

Use Cases in Big Data Software and Analytics

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Chapter 1

Preface

1.1 Disclaimer

The papers provided are contributed by students of the i523 class thought at Indiana University in Fall of 2017. The students were educated in plagiarizm and we hope that all papers meet the high standrads provided by the policies set at Indiana University in regards to plagiarizm. In case you notice any issues, please contact Gregor von Laszewski (laszewski@gmail.com) so we cn address the issue with the student.

1.2 Citation

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Big Data Analytics in E-commerce

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ABSTRACT

Humongous amounts of data gets generated every day in the domain of E-commerce industry. With the increasing competition and ever-changing market trends, it is a challenging task for the store owners to strategize business and marketing activities. If the companies are able to predict customer behavior, they can come up with business designs which can help them in making predictions about the customer purchasing patterns and thereby increase their revenue. In this project we have aimed to do analysis on the data of an E-commerce non-store online retail giant based in UK. The dataset, available in the UC Irvine repository by the name of 'Online Retail', consists of the goods purchased by different customers at a given time. Through this data available to us, we have done customer segmentation on the basis of the type and amount of goods purchased by a customer. We achieved this by doing a thorough exploration of the data, data pre-processing and then running different Machine Learning Classifiers to classify the customers in different categories.

KEYWORDS

HID 202, HID 205, i523, Machine Learning, Analysis, E-commerce, retail, Customer Segmentation, Python, Regression, Boosting, KNN, Random Forest.

1 INTRODUCTION

The E-commerce industry is in constant shifts due to the ever-increasing changes in the technologies used to develop and maintain the E-commerce systems, the services that they are willing to offer, the market strategies which gain popularity at the time, and most importantly- the customer behavior [3]. The online store owners are the ones who are most affected by these changes. And since the competition in the field of E-commerce is fierce, the online store owners need to come up with business strategies and technologies which provide better customer services leading to their satisfaction and earning customer loyalty. To achieve this, they need to address these ever changing issues to survive and thrive in the E-commerce market and come up with better decisions faster. The key to achieving this lies in better understanding of the customer behavior and their purchasing patterns. That is where analytics comes into play. Analysis of customer behavior and purchasing patterns helps in devising better and accurate marketing strategies which can not only help in generating more profits but also in saving both time and efforts that goes into trying and testing different marketing activities [3]. This ability to capture and analyze user data, and then provide useful and in depth insights in it is what Machine Learning empowers us with. In this project, we aim to do analysis on a data set 'Online Retail' from the UC Irvine Machine Learning Repository to determine the customer purchasing pattern by using

different machine Learning algorithms like K-Means Clustering, Logistic Regression, Random Forest, Gradient Boosting, etc.

2 BACKGROUND

Before the advent of the World Wide Web, transactions that happened on a day to day basis meant physical presence of customers, the brick-and-mortar setting of a store which offered a limited variety of goods. With the evolution of internet and its application in retail, the field of E-commerce emerged and changed the entire facet of shopping. Since a proper set-up of a store is no longer needed, customers can buy goods at much lower prices, with a wider variety to choose from and that too without the need of physical presence. The online market is expected to grow by almost 56% from the year 2015 to 2020 [16]. In the United States alone, 56% of the population prefers to shop online. The E-commerce industry is growing at an average rate of 23% every year, with 90% of the Americans having done online shopping at some point in their lives [15]. With so many transactions happening over the internet, naturally the amount of data getting generated is humongous. Also, with the constantly changing market trends, strategies to overcome the competition and make profits need to be constantly improved. The key issues therefore are managing the data and drawing insights from them which will help in bettering the business decisions. To store and maintain the magnanimous amounts of data getting generated *everyday* is a huge hassle, because along with the volume, this data gets generated at a break neck speed and in different formats from traditional numeric databases to unstructured text documents [12]. The big data technologies like Hadoop and Spark can be used in addressing these hurdles, namely the volume, velocity and variety.

2.1 The Three V's of E-commerce Big Data

Like other technologies which deal with a humongous amount of data, E-commerce must also respond to the 3 Vs, namely Volume, Velocity and Variety:

Volume Thousand of online transactions happen every day making the data generation a real time process. The integration of Big Data involves collection of relevant data like customer behavior statistics on the basis of their searches, transactions, demography, etc. The challenge here is not only gathering the data but also in analyzing it.

Variety The data from online transactions comes in different varieties, right from structured databases to unstructured text documents, videos, feedback emails and comments, and others. The retailers need to understand this for making the right business decisions by keeping a leeway for possible data fluctuations such as seasonal ad peak loads like Black Friday sales.

Velocity Handling the huge amounts of data which is generated at unprecedented rates is another challenge that needs to be taken care of. It is therefore imperative to do rapid analysis so that timely actions can be taken to sustain in the competition and boost the profit margins

Storing and maintaining the big data is a hassle in itself, but it will provide little value if proper analysis is not done on it. That is where we will be focusing on in this project - making sense of the data. Hence for the scope of this project, we have performed analysis on a small data set of around 45 MB. Machine Learning Algorithms learn from the data. Since we will be using Machine Learning Algorithms, the accuracy of Analysis will only increase with increase in the size of the dataset. We will be discussing this in further detail in the coming sections.

We have now established the fact that the E-commerce companies have a lot of data at their fingertips. Making use of this data is where the challenge lies. Machine learning is an approach by which insights can be drawn from digital data at a rate much faster than any human is capable of doing [7]. Following are some of the biggest challenges that are faced in the field of E-commerce which Machine Learning addresses successfully:

(1) Optimization of the Prices:

Pricing, and in that, online pricing is critically important. Since prices of the competitors are only a few clicks away, it is far easier for the customers to compare prices. Setting up the optimum price, by considering many factors like the prices set by the competitors, the time of the day, the type of the customer and the product's demand therefore is a difficult task. Machine Learning technology can set the prices by considering all these factors at once.

(2) Fraud detection:

The E-commerce industry, like the other industries, is susceptible to fraudulent activities. The consequences of these activities can lead to tarnishing the name of the company forever. Machine Learning helps in detecting and preventing the frauds by processing the repetitive data at a high speed.

(3) Search Ranking:

Machine Learning is capable of pulling information from patterns of search and purchase by considering the factors like preferences, content and search items and come up with a powerful search engine that shows what the customer exactly wants.

(4) Product Recommendations:

Machine Learning is capable of effortlessly quantifying the buying patterns of the customers and developing a recommendation engine which makes relevant product suggestions to them.

(5) Customer Segmentation and Personalization:

In any business, Customer base is the most important factor and therefore providing a satisfactory customer experience is of utmost importance. The biggest challenge that E-commerce systems endeavor to overcome is the separation from their customers. In person, a salesperson can quickly take in what the customers are saying, their economic status, their body language, and behavior to help them find better or desired products. The salesperson thus is able to *segment* customers, and provide them with a *personalized* shopping experience. With online shopping, it is very difficult to make this happen since an in depth understanding is needed of the vast amount of the data to provide tailored choices to the customers,

which can result in sale loss.

Machine Learning makes the biggest impact by making it possible to give personalized customer experiences which can boost the sales and thereby increase the revenue.

The type of analysis and Machine Learning Algorithm to be chosen depends solely on the data at hand. The data set we aim to analyze is a transnational data set that has been archived in the UC Irvine Machine Learning Repository under the name 'Online Retail'.

A thorough Exploratory Data Analysis on this data lets us know what kind of Machine Learning Algorithm needs to be used. Also, several models can be applied and the one which gives the best accuracy and precision against the test data can be chosen. To add icing to the cake, we can even combine the results given by the different models to make an ensemble model which gives an accuracy that is better than that of the individual algorithms. Machine Learning Algorithms are mostly classified as supervised and unsupervised Learning algorithms.

In Supervised Learning, each example is a pair of an input object and the corresponding output value, also called the supervisory signal. A supervised learning algorithm analyzed the training data to produce an inferred function which is used to map new, unknown output-value examples [8]. Since there is the output value to *supervise* the learning algorithm, such approach is called 'Supervised Learning'. The most commonly used Supervised Learning Algorithms are Logistic and Linear Regression, Bagging and Boosting Algorithms, Decision Trees and Random Forest. The Logistic Regression algorithm determines the relationship between the input and the output variables and generates a classifier model to predict the category to which a new example belongs to. Thus Logistic Regression is a classification algorithm [2]. Decision Trees are non parametric Supervised Learning Algorithms which create a model by learning simple decision rules inferred from data attributes to predict the value of a target variable. Decision Trees can be used either for Classification or Regression [5]. Bagging is a technique used to reduce the variance in the predictions by combining the result of multiple classifiers modeled on different sub-samples of the same data set. One of the most commonly and widely used implementation of Bagging is Random Forests. In Random forest, there are multiple trees which classify a new sample based on the set of attributes and a new sample is classified to that class which received the maximum 'votes' from the individual trees. In case of doing Regression with the help of Random Forest, the average of the outputs given by different trees is taken [10].

In Unsupervised learning, only the input data is known with no knowledge of the corresponding output variable. The goal therefore of the Unsupervised Learning Algorithms is to model the underlying distribution or structure in the data to understand the data more. Since there is no output available to validate or 'supervise' the answers, such learning algorithms are called Unsupervised. The most common application of unsupervised learning is clustering. Clustering enables to differentiate the data by discovering the inherent groupings of the input. The most common implementation of Clustering is the K-means algorithm. This algorithm works iteratively to assign each data point to one of the k-groups based on the feature similarity.

3 EXPLORING THE DATASET

The dataset taken for the analysis is the ‘Online Retail’ data set available on the UCI Machine Learning Repository. This is a transnational dataset which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers.

Data set consists of 5,41,909 transactions and 8 features which describe each of these transactions. There are missing values present in the dataset. All the attributes are integer and real numbers. The size of the dataset is 43.4 MB.

3.1 Attribute Information

InvoiceNo : This refers to the Invoice number. It is a Nominal, 6-digit integral number uniquely assigned to each transaction. If this code starts with letter ‘c’, it indicates a cancellation.

StockCode : This refers to the Product (item) code. It is a Nominal, 5-digit integral number uniquely assigned to each distinct product.

Description : This refers to the Product (item) name. It is of Nominal data type.

Quantity : This refers to the The quantities of each product (item) per transaction. It is Numeric in type.

InvoiceDate : This refers to the Invoice Date and time. It is Numeric, and represents the day and time when each transaction was generated.

UnitPrice : This refers to the Unit price. It is of Numeric type, and represent the Product price per unit in sterling.

customerID : This refers to the Customer number. It is a Nominal, 5-digit integral number uniquely assigned to each customer.

Country : This refers to the Country name. It is of Nominal type, and represents the name of the country where each customer resides.

4 DATA PREPARATION

4.1 Installation Steps

The project has been implemented in Python 2.7 version and we have used the Jupyter Notebook App for the program execution. The Jupyter Notebook Application is an application having server-client architecture which allows editing and executing notebook documents through a web browser. A notebook document is a human readable and machine executable document which can be executed for implementation of data analysis. The Jupyter Notebook Application can be executed on the local host or can be installed on a remote machine accessed via the internet [6].

The Jupyter Notebook can be installed very easily on a machine which has either Python 2 or Python 3 version. Since we have implemented our project in Python 2.7, following commands are to be run in the terminal:

```
pip install --upgrade pip
```

The above command will upgrade the Python package manager (pip).

```
pip install jupyter
```

The above command will install Jupyter in the local machine.

Once the Jupyter Notebook has been installed, it can be run using

Figure 1: Data set Contents

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART	6	2010-12-01 08:26:00	3.39	17850	United Kingdom

the following command in the terminal:

```
jupyter notebook
```

This command will run the Jupyter notebook in the default browser of the machine on the default port 8888 of the localhost.

4.2 Packages Installation

Before running the code the following packages were imported/installed in the Python environment.

Pandas Pandas provide a very fast and flexible data structures to make working with relational data easy and fairly intuitive.

Numpy This is a fundamental package for scientific computation with Python and can be used as an efficient multi-dimensional container of generic data.

Scikitlearn Scikit-learn makes a wide range of supervised and unsupervised machine learning algorithms available in python. We have implemented all the Machine Learning Algorithms using this library.

4.3 Null Value Treatment

Before going ahead with Data Exploration, a quick look through the data showed many missing values. Hence before doing any analysis, it is imperative to treat the missing values. The dataset has almost 25% of the entries that are not assigned to any of the customer i.e. customerID attribute for those entries is null.

Missing value treatment can be done by deleting the columns and/or rows which have missing values beyond a decided threshold, or replacing them with the attribute mean, median or mode. Since the missing values in our case is the customerID, the replacement method cannot be applied. Also, these entries are useless for the analysis since we aim to do Customer Segmentation and without knowing the customerID, it cannot be achieved. Hence we have deleted the rows with missing customerID. After removing these entries , the dataset left is with 4,06,829 transactions.

The content of the dataset appears as shown in the Figure 1.

We also removed the duplicate values present in the dataset. There are 5225 such entries present in the data set that are deleted.

5 EXPLORING THE CONTENT OF VARIABLES

The dataframe has 8 variables and we can draw some inferences by analyzing these variables.

5.1 Countries

From the data we can see that there are 37 different countries from which orders were placed. We can determine the number of orders per country by a ‘Chloropeth’ map. A Chloropleth map shown in

Figure 2: Distribution of Orders based on Countries



Figure 3: Customer Products Transactions

	products	transactions	customers
quantity	3684	22190	4372

Figure 4: Number of products per Customer

CustomerID	InvoiceNo	Number of products
0	12346	541431
1	12346	C541433
2	12347	537626
3	12347	542237
4	12347	549222

Figure 2 uses different colors and shades within predefined areas to indicate quantities in those areas.

The Figure 2 shows that maximum number of orders are placed from UK.

5.2 Customers and products

On observing the number of users, products purchased and number of transactions made; we can see that these are not proportional. This suggests that there were many transactions made for cancelling the orders shown in Figure 3

We can also determine the number of products purchased in each transaction. It shows that some customers purchased goods in bulk whereas some purchased a single product in a transaction. Also the orders with InvoiceNo starting with C are the cancelled orders. The details are shown in Figure 4.

Figure 5: Transactions for Cancellation

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
61619	541431	MEDIUM CERAMIC TOP STORAGE JAR	74215	2011-01-18 10:01:00	1.04	12346	United Kingdom
61624	C541433	MEDIUM CERAMIC TOP STORAGE JAR	-74215	2011-01-18 10:17:00	1.04	12346	United Kingdom
286623	562032	ARLINE BAG VINTAGE JET SET BROWN	4	2011-08-02 08:48:00	4.25	12347	Iceland
72260	542237	84991 60 TEATIME FAIRY CAKE CASES	24	2011-01-26 14:30:00	0.55	12347	Iceland
14943	537626	22772 PINK DRAWER KNOB ACRYLIC EDWARDIAN	12	2010-12-07 14:57:00	1.25	12347	Iceland

Figure 6: Stock Codes

POST	-> POSTAGE
D	-> Discount
C2	-> CARRIAGE
M	-> Manual
BANK CHARGES	-> Bank Charges
PADS	-> PADS TO MATCH ALL CUSHIONS
DOT	-> DOTCOM POSTAGE

5.3 Cancelled Orders

Almost 16% (3654) of the transactions are corresponding to the cancelled orders. In the dataset, corresponding to each cancelled transaction we should have an order placed with same quantity of products requested. While checking the same in the dataset, we found the details shown in Figure 5 for some of the orders.

This hypothesis should apply to the complete dataset, but on checking the whole dataset it is found out that there are some cancelled orders without the purchase order (the history of the order) made. This is done by locating the entries that indicate a negative quantity and then checking if there is an order indicating the same quantity (but positive) with the same description and the same customerID. We still get negative quantities. Going deeper in to this suggests that the entries with description 'Discount' have negative quantities associated with that transaction. And hence, to do the verification, we eliminated the 'Discount' entries. But again the initial hypothesis do not match; we still have negative numbers appearing in the quantity.

This can be because the buy orders were performed before December 2010 (the point of entry of the database). We can delete the records where a cancel order exists without the corresponding purchase order or where there is at least one counterpart with the exact quantity (since both records are logically cancelling each other). Total 8795 such records are found and deleted from the dataset.

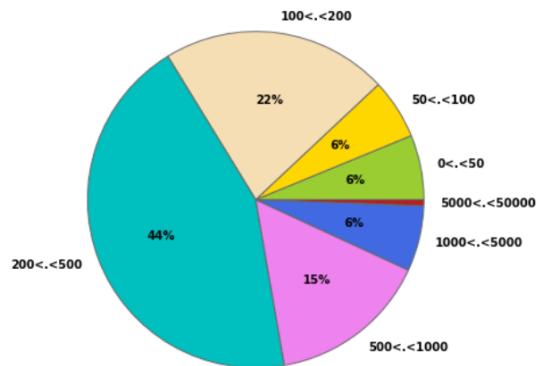
5.4 StockCode

The StockCode variable should ideally contain letters. So we have filtered out the codes with only letters. We can observe from Figure 6, different type of transactions based on these (example D is for discounted transaction).

Figure 7: Basket Price

CustomerID	InvoiceNo	Basket Price	InvoiceDate
1	12347	537626	711.79 2010-12-07 14:57:00.000001024
2	12347	542237	475.39 2011-01-26 14:29:59.99999744
3	12347	549222	636.25 2011-04-07 10:42:59.99999232
4	12347	556201	382.52 2011-06-09 13:01:00.000000256
5	12347	562032	584.91 2011-08-02 08:48:00.000000000
6	12347	573511	1294.32 2011-10-31 12:25:00.000001280

Figure 8: Pie-Chart
Distribution of the amounts of orders



5.5 Basket Price

We have added a new variable to indicate total price of the purchase (by multiplying unit price of each product with quantity purchased). Each transaction corresponds to the prices for a single product. On grouping the records based on a single order, we can see the complete price for that order as shown in Figure 7.

We can visualize the orders distinguished on the basis of total price of the basket. It can be shown as Figure 8 using a pie-chart.

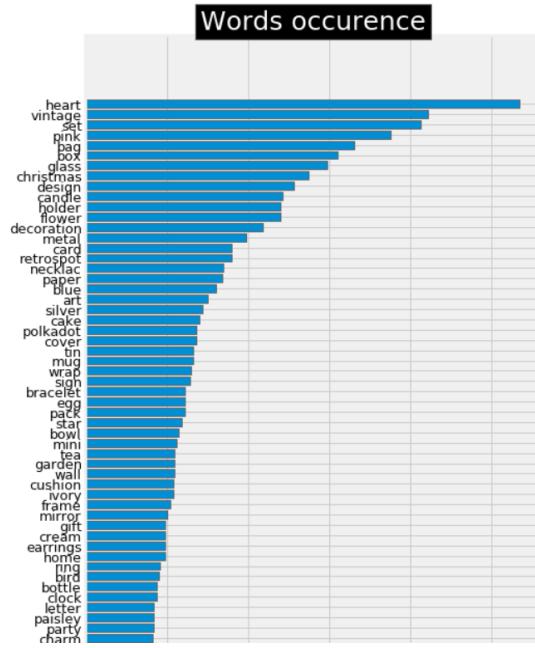
It shows that majority of the orders are the bulk purchases since 60% of the orders have amounts greater than 200 Sterling.

6 EXPLORING PRODUCT CATEGORIES

The dataset contains two variables- Stockcode and Description defining products. We can categorize the products based on the content of the description variable. This can be done in the following way. Firstly, the proper or the common names appearing in the products' description are extracted. Then the root of the word and combining set of names associated with this particular root is extracted. Lastly, the frequency of the word is found in the description variable of the dataframe.

Upon checking, we found that there are 1483 keywords present in the description variable of the dataset. The most common keywords can be determined based on the occurrences. The Figure 9 shows the top word occurrences.

Figure 9: Word Occurrences



6.1 Categorizing Products

We have obtained around 1400 keywords from the above occurrence list , most of which do not make sense. After discarding the keywords that are appearing less than 13 times, we are left with 193 keywords that we will consider for our analysis.

These significant keywords are used for creating categories of the products. The data has been encoded using the principle of one-hot-encoding.

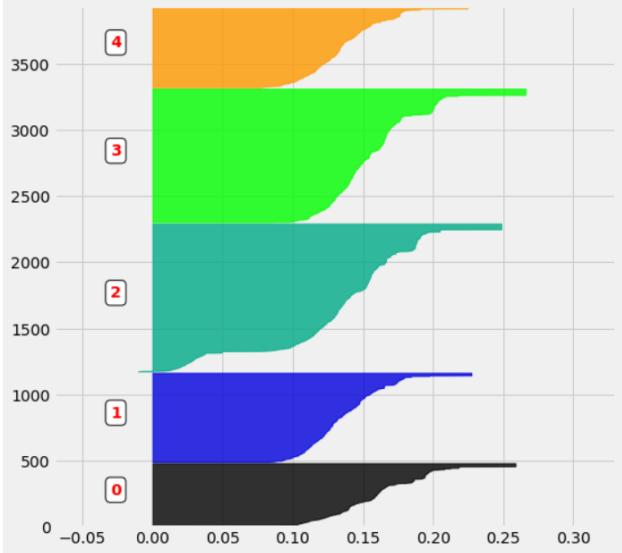
One hot encoding - One hot encoding is a process by which categorical variables are converted into a binary format of 0's and 1's that could be provided to ML algorithms to do a better job in prediction. The words present in the descriptions of the products are encoded. Also price range column is added as it will help in balanced grouping of the products.

6.2 Clustering of products

In the previous step we have created a matrix with encoded version of words present in the description variable. K-means clustering is used for the cluster assignment and since the data is in binary format because of encoding, the most appropriate distance method will be Hamming's metric (other distance functions are euclidean distance, Manhattan distance, binary distance, etc). It basically measures the minimum number of substitutions required to change one string into the other. But since the k-means package available in sklearn uses Euclidean distance by default, we have used it for our analysis.

Selection of optimum K-value:

Figure 11: Silhouette plot



The number of clusters can be selected using silhouette analysis on K-means clustering. It is used to study the separation distance between the resulting clusters. The silhouette plot displays a measure of how close each point in one cluster is to the points in the neighboring clusters and thus provides a way to assess parameters like number of clusters visually. This measure has a range of $[-1, 1]$. Silhouette coefficients (as these values are referred to) near +1 indicate that the sample is far away from the neighboring clusters. A value of 0 indicates that the sample is on or very close to the decision boundary between two neighboring clusters and negative values indicate that those samples might have been assigned to the wrong cluster.

The Figure 10 shows silhouette score for different values of k. These scores do not have significant differences, but since for k value greater than 5, the resulting clusters have very few elements in them, we have taken k as 5.

Figure 10: Silhouette Scores

```
('For n_clusters =', 3, 'The average silhouette_score is ::', 0.10158702596012364)
('For n_clusters =', 4, 'The average silhouette_score is ::', 0.12680045883937879)
('For n_clusters =', 5, 'The average silhouette_score is ::', 0.14553871352885445)
('For n_clusters =', 6, 'The average silhouette_score is ::', 0.15122077520906058)
('For n_clusters =', 7, 'The average silhouette_score is ::', 0.146368437259842)
('For n_clusters =', 8, 'The average silhouette_score is ::', 0.14764212603720744)
('For n_clusters =', 9, 'The average silhouette_score is ::', 0.13974230402472737)
```

6.3 Validating Quality of Classification

6.3.1 Silhouette Score. From the silhouette plot shown in Figure 11 we can see that cluster 1 has more number of elements than the other clusters. But overall distribution of elements in the clusters is comparative. Same can be seen from the Figure 12.

6.3.2 Principal Component Analysis. The main idea of principal component analysis (PCA) is to reduce the dimensionality of

Figure 12: Cluster Composition

2	1118
3	1009
1	673
4	606
0	472

Figure 13: PCA

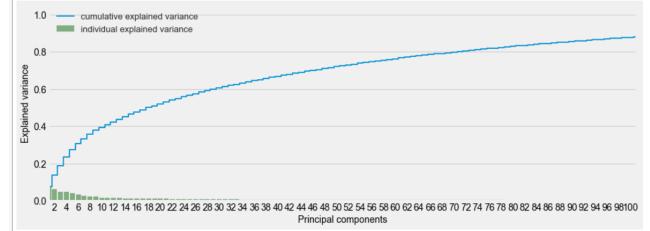
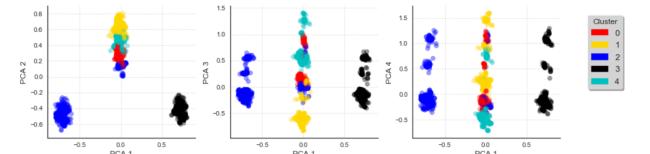


Figure 14: Biplot



a data set consisting of many variables correlated with each other, either heavily or lightly, while retaining the variation present in the dataset, up to the maximum extent. The initial matrix has large number of variables and hence, PCA is used for dimensionality reduction. From the Figure13 we can say that we need more than 100 components to explain 90% of the variance in the data.

Another application of PCA is that it sets the indication of cluster membership. Biplot is the best example that can be provided here to support this idea. Using biplot, we get the indication of number of clusters in a dataset. Below Figure 14 shows these on limited number of components (since it is only for visualizing cluster distribution). We can observe the groupings of points or clusters as expected.

Figure 15: Table

	CustomerID	InvoiceNo	Basket Price	categ_0	categ_1	categ_2	categ_3	categ_4	InvoiceDate
1	12347	537626	711.79	124.44	83.40	23.40	187.2	293.35	2010-12-07 14:57:00.000001024
2	12347	542237	475.39	0.00	53.10	122.59	130.5	169.20	2011-01-26 14:29:59.99999744
3	12347	549222	636.25	0.00	71.10	119.25	330.9	115.00	2011-04-07 10:42:59.999999232
4	12347	556201	382.52	19.90	78.06	41.40	74.4	168.76	2011-06-09 13:01:00.000000256
5	12347	562032	584.91	97.80	119.70	99.55	109.7	158.16	2011-08-02 08:48:00.000000000

Figure 16: Number of Purchases

	CustomerID	count	min	max	mean	sum	categ_0	categ_1	categ_2	categ_3	categ_4
0	12347	5	382.52	711.79	558.172000	2790.86	8.676179	14.524555	14.554295	29.836681	32.408290
1	12348	4	227.44	892.80	449.310000	1797.24	0.000000	0.000000	58.046783	41.953217	0.000000
2	12350	1	334.40	334.40	334.400000	334.40	0.000000	27.900718	23.654306	48.444976	0.000000
3	12352	6	144.35	840.30	345.663333	2073.98	14.301006	3.370331	53.725205	12.892120	15.711338
4	12353	1	89.00	89.00	89.000000	89.00	22.359551	19.887640	44.719101	13.033708	0.000000

7 EXPLORING CUSTOMER CATEGORIES

In the previous section, we have divided products in 5 clusters. We have added a dummy variable categ_product to indicate the cluster to which that customer belongs. Based on the clustering done on products we have created variables categ_0..4 which stores amount spent on each of the product category. And the categ_product variable which we have just created will have initial cluster assignment based on these variables. These can be further grouped on the basis of InvoiceNo as shown in Figure 15.

7.1 Subsetting dataframe based on Time

We have taken 12 months data for the analysis. This can be done on the basis of variable InvoiceDate present in the dataset. Using this data we have developed a model to characterize and anticipate the habits of customers using the site and this, we are doing it from the first visit.

In the previous section we have seen the basket price of each invoices. For further analysis we will combine these on the basis of customerID to analyze the number of purchases made by each customer as shown in Figure 16. A customer category of particular interest is that of customers who make only one purchase. So one objective may be, for example, to target these customers in order to retain them. In the dataset we have almost one-third of the customer base similar to this.

7.2 Categorizing Customers

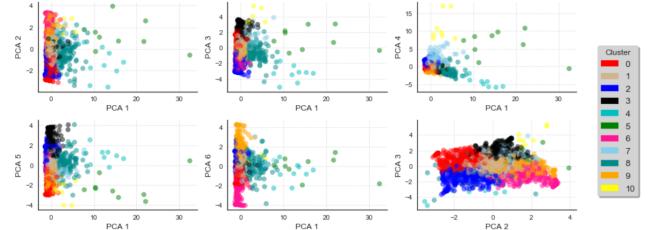
The information transactions per user is used for characterizing different types of customers. Because of different ranges of variations of different variables we have first scaled the data set. As done in the case of product categorization, we have again used K-means algorithm for cluster assignment.

Using the silhouette score, the optimum value of k comes out to be 11. The assignment of customers into different clusters is shown in Figure 17

Figure 17: Number of Purchase

	1	0	2	6	3	9	8	7	5	4	10
nb. de clients	1484	451	371	344	296	284	191	161	9	9	8

Figure 18: PCA



Now we will check validity of the cluster assignment using PCA and Silhouette plot as done in the case of product categorization.

7.2.1 PCA. There is a certain disparity in the sizes of different groups that have been created. So we have validated it using PCA. From the representation shown in Figure 18, it can be seen, for example, that the first principal component allow to separate the tiniest clusters from the rest. More generally, we see that there is always a representation in which two clusters will appear to be distinct.

7.2.2 Silhouette Plot. As with product categories, another way to look at the quality of the separation is to look at silhouette scores shown in Figure 19 within different clusters:

We can see that the different clusters are indeed disjoint.

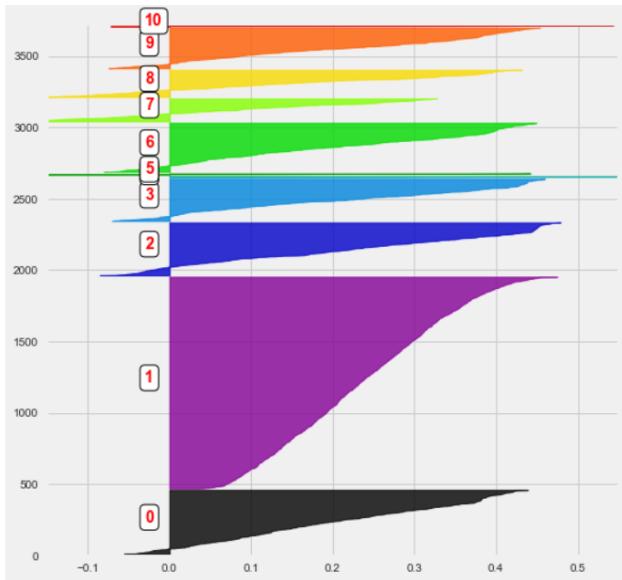
8 CLASSIFICATION OF CUSTOMERS USING CLASSIFICATION ALGORITHMS

In the previous section, we have made different client categories. In this part we will adjust a classifier so that the consumers can be classified in different client categories. The main aim of this is to enable the Classification on the first visit of the customer. To do this, we have defined a class that will allow interfacing the common functionalities to the different classifiers. Since we are going to classify the client on the basis of his/her first visit, the only parameters that we take into consideration are the contents of the basket and not the frequency of visits or the variation in the basket price over a period of time. Once this is done, we have split the dataset into train and test sets. The classification algorithms which we used to do this are mentioned below.

Before we delve deeper into the Classification Algorithm, some important concepts that need to be addressed are Cross Validation, Bias, Variance, underfitting and overfitting of the model.

Variance Variance essentially means how much the models estimated from the different training sets differ from each other. It measures how much the predictions made for a

Figure 19: Silhouette Plot



given point vary between the different realizations of the model [4]. When the training data tries to fit all the sample points to define the model, even the outlier data points, which are nothing but the noise, affect the model. Usually, the variance increases with increase in the complexity of the model.

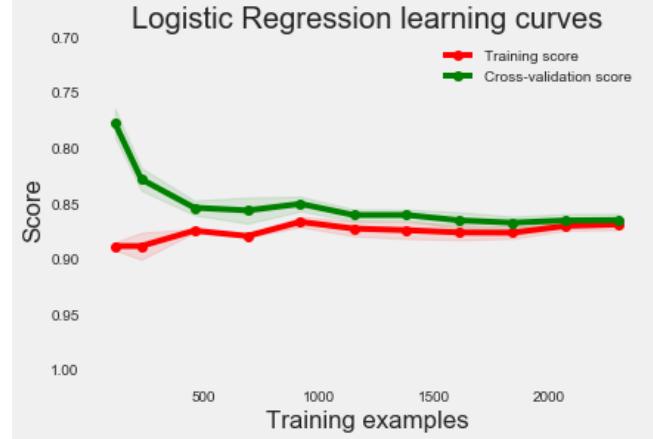
Bias Bias essentially means how much the average model over the training sets differ from the true model. Bias usually occurs if the model is over simplified or if some inaccurate assumptions are made. Thus Bias increases with increase in the over simplification of the model [4].

Underfitting Scientific study of mental processes and behaviour. Underfitting occurs when the model is too simple to make relevant classification of the testing data [4]. Thus when a model possesses high bias and low variance, we say there is underfitting of the model.

Overfitting Overfitting of a model occurs when the model is too complex and tries to fit in the irrelevant/outlier datapoints from the training set which is nothing but the noise [4]. Thus when a model possesses low bias and high variance, we say there is overfitting of the model.

Cross Validation Cross Validation is a technique for evaluating the predictive models by partitioning the original dataset into a training set to train the model, and a testing set to evaluate the model [11]. There are different ways to implement Cross Validation, the most effective of them all is the K-fold Cross Validation. In this method the dataset is divided into k subsets, out of which one is used as the test data and the remaining $k - 1$ are combined together to form training data. This process is done k times, ensuring that every single sample in the dataset gets to be tested exactly one time and gets trained upon exactly $k - 1$ times.

Figure 20: Logistic Regression Learning Curve



The variance therefore gets decreased as the k increases [11].

8.1 Logistic Regression

Logistic Regression as mentioned before is a Supervised Learning method which does analysis on a dataset containing two or more independent variables for determining the outcome. This outcome, i.e the dependent variable, is binary in nature, meaning it can have only two possible outcomes [9]. Multinomial Logistic Regression as the name suggests, generalizes the Logistic Regression to multiple classes, meaning the model can be used to predict the probabilities of the different outcomes of a categorically distributed dependent variable [17]. The goal of a Logistic Regression model is to determine a fitting model which best describes the relationship between the dependent variables (output variable) and a set of the input independent variables. Logistic Regression generates the coefficients along with the standard errors and significance levels of the below equation for predicting the logit transformation of the probability of presence of the characteristics of interest in a given sample example [9].

$$\text{logit}(p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \dots + \beta_k X_k$$

where p is the probability of the presence of a characteristic of interest. and $\text{logit}(p) = \log(p/1-p)$ In logistic Regression, the goal is to choose the parameters β in such a way that the likelihood of observing the new sample values is maximized [9].

In the Python code, we have imported the module ‘linear_model’ from the ‘sklearn’ package to perform Logistic Regression by using the function ‘logistic_regression’. And we have taken the $k = 5$ for k-fold cross validation. While performing Logistic Regression, we created an instance of the Class_Fit class and then ran the model on training data and see how the predictions are made as compared to the real values. The learning curve graph is as shown in Figure 20.

As we can see from the Figure 20, when the number of training examples increases, the cross-validation and train curves almost converge towards the same limit suggesting that the model has low variance. Thus we can say that model is not suffering from overfitting. Also one point to note is that the accuracy is high, which

means that the model has low bias, thus suggesting that it does not under-fit the data. The precision which we got from running the Logistic Regression model on the training data is 88.78%.

8.2 K Nearest Neighbours

KNN is a non parametric algorithm which means that there are no underlying assumptions that are made on the data. Also it is a lazy learning algorithm meaning that it does not do any generalization by using the training data. All the training data is needed during the testing phase [13].

KNN makes predictions using the training dataset directly. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances. For regression this might be the mean output variable, in classification this is be the model (or most common) class value. To elaborate on this, KNN makes predictions using the training dataset directly. These predictions are made for a new sample by going through the entire training set to find k such samples which are most similar or which are the ‘neighbors’ of the the new instance. Once these k instances are found out, the output variable corresponding to these is summarized and in case of Classification, it gives a class value to which the new instance belongs. The k ‘neighbors’, i.e., the most similar instances from the data set are found by using the distance measure- k such instances whose distance from the new instance is the least [13]. There are many distance functions which can be used, the most popular being the Euclidian distance function, the formula for which is given by:

$$\text{EuclideanDistance}(x, x_i) = \sqrt{\sum((x_j - x_{ji})^2)}$$

where x is a new data point and x_i is an already existing point [13].

The optimum value of K can be found by algorithm tuning, i.e. running the algorithm over several values of k and finding out and then figuring out for which k the algorithm gives the best results [14].

The output, i.e the class of the new sample can be calculated as the class which has the highest frequency from the k neighbours. Thus, each of the instances votes for their own class and the class which gets the maximum votes is taken as the prediction value [14].

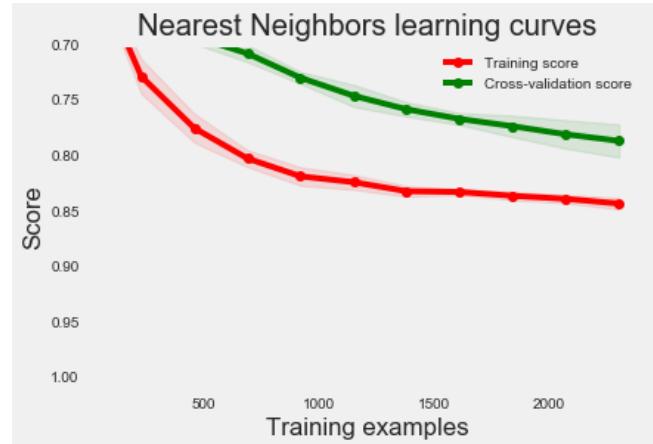
In Python, the ‘neighbors’ library is imported from the sklearn package which performs the KNN classification through the Kneighborsclassifiers function. The parameters that are used are ‘n_neighbors’ which represents the number of neighbors to use, in our case we have used the np.arange method to give sequence from 1 to 49. Also, we run the model using the K-fold Cross Validation with the value of $k = 5$. Once the model is run, we have drawn the learning curve graph which is as represented in the Figure 21.

The precision which we got from running the KNN model on the training data is 80.33%.

8.3 Random Forest

As the name suggests, Random Forest is an ensemble classifier which consists of many classification trees. An ensemble classifier is a multiple classifier algorithms, decision trees in the case of Random Forests, and the final output is the combined output of the all the classifier algorithms. In our case we will be using Random Forest

Figure 21: KNN Learning Curve



Algorithm for classification of the clients into different categories. A Random Forest grows many trees. For classifying a new object from an input vector, each tree in the forest gives a classification and vote for a particular class. And the forest then chooses the class having maximum number of votes over the other classes [1]. The question here that needs to be addressed is, how does the growth of a tree happen?

Each tree is grown as follows:

If the training set consists of N cases, then N cases are sampled with replacement from the original data. This is the training set for growing a tree. Thereafter, a number $m \leq M$ which is the number of input variables is taken such that the best split obtained on these m is used to split the node. The value of m is constant throughout the forest-growing. Each tree is allowed to grow to the fullest possible extension [1]. In Python, the ‘ensemble’ library is imported from the sklearn package which performs the Random Forest classification through the RandomForestClassifier function. The parameters given to this function are criterion, n_estimators and max_features. The criterion is used to measure the quality of the split. The Gini is for measuring the Gini impurity and Entropy is for information gain. The max_features are the number of the features that can be chosen when looking for the best split. For ‘sqrt’, the number of maximum features chosen are square root of the number of the features and for ‘log’, it is log of the number of the features. And the n_estimators is the number of trees in the forest. Once the model is run, we have drawn the learning curve graph which is as represented in the Figure 22 .

The precision which we got from running the Random Forest model on the training data is 90.17%.

8.4 Gradient Boosting Classifier

AdaBoost Classifier, short for Adaptive Classifier is another example of ensemble classifier. It is a general ensemble method which creates a strong classifier by combining the outputs of the weaker learning algorithms into a weighted sum to finally provide the output of the *boosted* classifier. This is done by building one model from the training set and then building a second one which attempts to rectify the errors from the first model and so on until either the

Figure 22: Random Forest Learning Curve

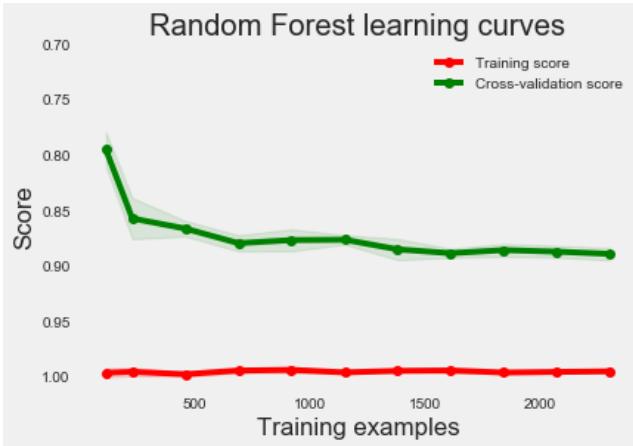
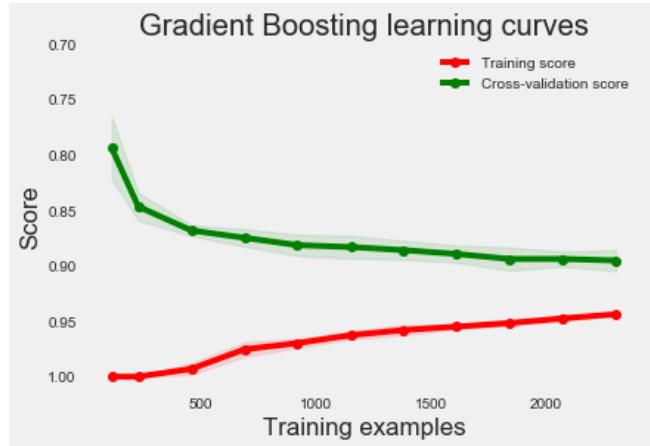


Figure 23: Gradient Boosting Learning Curve



limit of maximum models that can be added is reached or the training set is predicted accurately. AdaBoost is an adaptive algorithm, meaning that the weak learning algorithm can be tweaked to create a stronger classifier [6].

The Adaptive Boosting algorithm was recast into a statistical framework. “Arcing is an acronym for Adaptive Re-weighting and Combining. Each step in an arcing algorithm consists of a weighted minimization followed by a re-computation of [the classifiers] and [weighted input] [6]” This framework is called as Gradient Boosting.

Gradient Boosting involves three elements namely:

A loss function The selection of the loss function depends on the problem at hand. For example if it is a regression algorithm, then squared loss functions are used and if it is a classification algorithm then logarithmic functions are used. The main aim of the algorithm is to optimize the loss function.

A weak learner Regression trees are used as the weak learners in the Gradient Boosting Algorithm since they can output real values for splits which can be added together and the residuals in the predictions can be corrected. The weak learners are used for making predictions. These trees are constructed in a greedy manner usually up to 4-8 levels.

An additive model The additive model is made so as to add the weak learners to minimize the loss function. The trees are added one at a time with no changes to the existing trees in the model. A gradient descent model is used to reduce the loss when adding trees first by parameterizing the tree and then by modifying the parameters of the tree and moving in the right direction by reducing the loss in residuals. This approach is called Functional Gradient descent [6].

This framework was further developed by Friedman and called Gradient Boosting Machines. Later called just gradient boosting or gradient tree boosting [6].

In Python, the ‘ensemble’ library is imported from the sklearn package which performs the Gradient Boosting classification through the GradientBoostingClassifier function. The parameter given to

this function is n_estimators which is the number of boosting stages to perform. Gradient boosting is fairly robust to over-fitting so a large number results in better performance. Learning curve is shown in the Figure 23.

The precision which we got from running the Gradient Boosting model on the training data is 90.86%.

Now that we have the results of all the models, we can combine them using VotingClassifier method that we imported from the sklearn package to improve the classification model. Since we have already found the best parameters for each of the classifiers, we have adjusted the parameters of the classifiers accordingly. So now the best parameters are taken and merged to define a classifier which we then trained on the data. When we created a prediction on this, we got the precision value as 90.44%.

9 TESTING THE PREDICTIONS

Until now we have done all the analysis on the data from the first 10 months. After this we test the model on the set_test dataframe which contains the data of the last two months. The regrouping of the data is done according to the same procedure that we followed while regrouping the training data. But now we have to take into consideration the time difference in between the two datasets and the count(the total number of visits which the client made to the website) and sum(total amount that he/she spent) variables so that we have an equivalence in between the training set and testing set. The dataframe so obtained is now converted to a matrix and we retained only those variables that define the category to which the clients belonged. And just like on the training dataset the method of normalization was called, to maintain consistency, the same method is called on the test set as well.

Each row of the matrix obtained now represents the buying habits of the customers. Now all we have to do is to define the category to which the customer belongs by using these habits. The important point to note here is that this is just the test data preparation step by defining the category to which the consumer belongs for a period of two months through the variables count, min, max and sum. Thus this step does not correspond to the classification step itself. The classifier that we defined in the step 5 uses variables that were

defined from the client's first purchase.

So now, we have the data available for two months, and through that we can define the category to which the consumer belongs. The predictions now obtained by running the classifiers on test data can be tested against these categories. The instance of the k-means clustering method that we used in the Customer Categories section is used to define the category to which a client belongs. This contains the predict method which will calculate the distance of the consumers from the centroids of the 11 categories that we deduced, and the category which is closest to the clients' buying habits will define his/her category. Thus all we need after this for the execution of the classifier is to select the variables on which it acts, i.e. on mean, cat_0, cat_1, cat_2, cat_3 and cat_4. After examining the predictions of the different classifiers, we get precision scores as shown in Table 1.

Table 1: Algorithms with their Precision Scores

Algorithm	Precision(%)
Logistic Regression	72.99
KNN	68.44
Random Forest	75.93
Gradient boosting	75.74

And now, like we did in the Section 5, we will use the voting classifier method to merge the results obtained by these individual classifiers and see whether they combined result is better than the individual. It turns out that it is. We get the precision rate for the combined classifier to be 76.48% for the test data set. This concludes the analysis phase.

10 CONCLUSION

E-commerce is one of the emerging fields for Data Analysis since a lot of data gets generated every day at a break-neck speed in many different formats. To sustain in such a business, a very robust and extensive data analysis is needed to keep up with the ever changing markets by implementing different marketing strategies. And since the whole business revolves around the customers, they form the most important aspect of the analysis. We have tried to achieve Customer Segmentation on the basis of the purchasing patterns and frequency of client visits to their online portal. The dataset on which we performed analysis provided details on the purchases made by the consumers over a period of more than a year. Every entry in the dataset contained the purchase of a particular product on a given date by a particular customer. Out of the 591909 entries made in the dataset, approximately 4000 different consumers are present. From the information available for each consumer, we decided to go ahead with Customer Segmentation analysis by developing a classifier that predicts the type of purchase a consumer would make and his/her frequency of visits to the E-commerce website.

In the first step of this classification, we found out the different products sold by the company, and then classified the products into 5 categories of goods by using K-means clustering. In the second step we performed the classification of the customers on the basis

of purchasing habits in the first 10 months. The customers were classified into 11 categories on the basis of the types of products they usually bought, the number of visits they made to the website and the amount for which they shopped over a period of 10 months. Once we had the categories of the consumers, we performed training of the data of the first 10 months using different classifiers namely Logistic Regression, Random forests, KNN and Gradient Boosting algorithms to classify the consumers in these 11 categories, on the basis of their first purchase. The classifiers were based on these variables: the total price of the current purchase and the percentage of the amount spent in each of the 5 product categories. Once the customers were classified in the 11 categories, the quality of the data set was tested on the remaining two months of the dataset. This was achieved in two steps. In the first step, we assigned the category to which each customer belonged to, and then the classifier predictions were compared against these categories. And then we combined the results of the various classifiers by using the Voting Classifier method. The model performed with a 76.48% of precision, that is 76.48% of the times the clients were awarded the right classes.

One bias which we did not consider while doing the analysis is the seasonal fluctuations, like festive and seasonal sales. Since at these times the sales of products may rise and just before and after the sale duration, the sales may drop. Thus the purchasing habits of customers are dependent on the time of the year as well. Hence the seasonal effects may cause the actual sales in the last two months to be quite different from the ones which we extrapolated from the first ten months to the last two months. For overcoming such biases, it would be beneficial if the data were of a larger size and covered a larger period of time.

Knowing the type of a customer is critically important for an E-commerce business. By doing so, the store owners can provide personalized services to the customers, which will yield higher customer satisfaction. Customer satisfaction is directly proportional to the loyalty of the customers, thus Customer Segmentation and Personalization can help the company in increasing their brand name. Knowing the preferences and choices of customers also helps in catering to those needs of the customers which they may not be aware of in the first place. Thus by knowing the purchasing patterns of the customers, we can provide them with tailored suggestions, which can even increase the revenues of the company. Thus through proper implementation of the business strategies and marketing activities, which are motivated by a thorough Analysis of the data available can help the company in attracting loyal customers, increasing the revenue and establishing a better brand value.

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Big Data Analytics in Product development management

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ABSTRACT

The success of a new product is to a large extent due to whether the producer making efficient and accurate strategies between the different stages of a product lifecycle. Big Data analytic techniques have the potential to improve the efficiency of product development, making accurate product strategy, channel strategy, pricing strategies and promotional strategies in the different period of a product lifecycle. In this project, I will try to figure out how the data affect the decision making and try to use the relation between different twitter account to describe the potential of the Big data also I will describe decision trees and PageRank and how do these tools produce a good market segmentation and market positioning for a product.

KEYWORDS

i523, hid229, Big data, Product Development, Technology

1 INTRODUCTION: BIG DATA

The advent of technology has resulted in virtually all industries and organizations collecting large volumes of data. The data collected results from diverse source, which include product sales, customer information, historical industry data, and employee information just to mention a few. Computers and the internet in particular have made it easier to collect data of different kinds because they make it easy to create, store, transfer, and analyze data. As a result, data has become a critical asset for many organizations and corporations in their bid to control the markets of the products or services they offer consumers. Furthermore, According to Arora, big data also refers to large and complex dataset (13). This means that it is virtually impossible to use traditional processing applications to organize and analyze this data. Therefore, there are various challenges associated with big data due to its large volume and complexity [1]. These problems include data capture, data storage, data analysis, sharing of the data, making searches on the data and the privacy of the information [?]. Information increasingly becomes an important factor in determining the success of a product. A few years ago, manufacturing and the Internet have still belonged to two different separated industries, But as the mainstream consumer groups changed from old generation to Millennial generation, and the use of computers and the establishment and application of the Internet have produced a violent shock to the traditional way of product development, thus resulting in a new product development strategy. I have to say that the relation between the manufacturing and the Internet are getting closer and closer. One of the major changes might cause by using big data as a technique to develop right product and make effective promotion strategy.

information.png



Figure 1: Difference between various generations [10]

2 EXAMPLES OF BIG DATA

For example, organizations with an online presence such as online market places collect data from their clients. This includes different types of data such as customer information, purchases, and time spent on the website. For very large organizations (such as Amazon or eBay) dealing with thousands and probably millions of customers daily, this type of data soon becomes voluminous and difficult to analyze. For effective analysis, such data needs large physical storage space and organization in ways that will make it usable and of benefit to the organization [1]. The main solution to this problem is the use of a data warehouses since traditional databases are too basic to handle the complexities involved with big data. Data warehouses provide the much-needed processing power needed in handling and analyzing big data [1]. Another issue is Outdated decisions and information are bound to create disadvantages when competing with other companies, but the traditional data processing system is obviously not suitable for the era of big data. Corporate decision-makers must adopt new technologies to face the changes of the times and customer. For example, Hadoop technology is a new and widely accepted technology.

- “Hadoop is an open-source software framework for storing data and running applications on clusters of commodity hardware. It provides massive storage for any kind of data, enormous processing power and the ability to handle virtually limitless concurrent tasks or jobs[9].”



Figure 2: The Exponential Growth of Data [6]

2.1 Application of Big Data in Product Development

how to clean the data and find useful data more quickly in product development is even more important. Quickly identify the characteristics of the target customers and their possible needs for a variety of products. base on the analysis, we can develop some products that more suitable for marketplace needs, or we can be more accurate when we try to find our potential target customer. According to different consumer behavior, we can design different software, for example, during the financial turmoil we found that lots of users are price sensitive, we can design a kind of software that can provide local discount merchandise information in real time. If the target customer is a group which wants higher quality of life, we can push more high value-added product. One of the most vital areas where big data finds use is in product development management. The product development process allows for the design and release of new products into the market. Product development also involves processes such as forecasting, planning, and marketing of new products. The process adopted ensures that first the product developed meets a certain need in the market. Second, the process certifies that the price set reflects the amount consumers are willing to pay. Lastly, it guarantees the organization is making the product in such a way that it will be able to reach the targeted market. Typically, an organization will collect market data from various systems.

- For instance, transaction-processing systems provide invaluable data to organizations [11]. An example of a company that uses big data is the online market place Amazon. The market place has thousands of products stocked by the company and by third party sellers using the platform to sell their products. The checkout system in such an organization will collect very important data such as the products sold, the customers buying the products, the time of purchases and such details [14]. The details of the customers will probably include the age and gender of the customer. When the company analyzes such data, it provides the management with a vital insight into the business activities and performance. Such as SEM analysis, SEM analysis is a research and analysis methods which focus on customer satisfaction. This is a good way to make a classification for our users. One of the most typical examples is some recommender systems such as Pandora use songs or artist properties to create a radio station, all of these songs and artist have similar attributes. User feedback is used to adjust the content of the radio and recommend some music which is more attractive to the listener.

3 ANALYSIS OF CUSTOMER NEEDS AND MARKET DEMAND

3.1 Anticipating Customer Needs for New Products

For instance, using the data collected from the checkout system, the company can tell what type of products are likely to be bought and by which customers [14]. Using information about customers

contained in other systems such as customer relationship management (CRM) systems, the company can get information about the people likely to purchase a certain product, at what time they are likely to make the purchases, and the other goods they are likely to purchase with the products [14]. The company can then use such information to make decisions on which products to stock, what price to sell them, which products to suggest to clients as they are making purchases and the time of day, week and even year that such products are in demand. For instance, Walker points out that big data plays an important role in helping Amazon launch new products. In particular, the data collected by the organization on books played a central part in the establishment of the Amazon Kindle product, which is highly successful in the market [14].

3.2 Inventory Management

Therefore, with the help of big data, product developers and manufacturers are able to ensure that the products needed by the customers are available in the right quantities and at the right times [4]. For example, a person purchasing a large flat screen television is also likely to purchase wall brackets for mounting the television set. The company can also get information on what brand and size of TV sets are in demand. The company can then ensure that it stocks such products when they are in demand. Because of the increased competition, profit margins can be very small. This requires the company to ensure efficiency to ensure that it avoids issues such as dead stock, which have negative impacts on profitability. Getting the right amount of products is critical as it ensures that the company meets all the demand and there are no excess items, which are a cost to the organization [11].

3.3 Anticipating Customer Demands

hub node with high in-degree.png

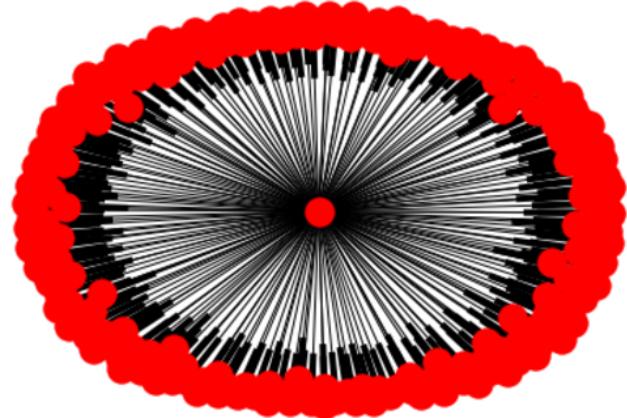


Figure 3: Hub Node in network

In addition, using big data, product developers able to anticipate demand for new products and it can therefore embark on developing such products and ensure that customers get the products. For example, Facebook the social media giant employs big data in making decisions on how to present its services for clients [8]. For

instance, the company collects data on user activity on its platform [8]. Using this information, the company is able to present an interface customized to a specific user. Such data also finds use in targeted advertising, which is one of the key ways in which such companies make majority of their revenues. In 2013, Morabito pegs the revenue drawn by Facebook from advertising at almost 8 billion dollars [8]. The use of big data by the company has made it able to forecast the needs of the market and provide users with products and services that the customers find useful. This has resulted in the company becoming the world's most used social media site and maintain its advantage over its rivals, some of which the company has ended up buying out. What is worth to mention is that some Big Data technique can help these companies decide which user are more worthy of advertising. According to what I got from my programming, some people with a high degree centrality in their tweet network have a higher value than other people with a sparse network. Because the dense network can spread the information faster with a lower cost.

4 MANAGEMENT OF THE PRODUCT DEVELOPMENT CYCLE

In product development management, a product passes through various stages in the lifecycle. The main stages are product research and development stage, the introduction stage, the growth stage, maturity stage and the decline stage [13]. Big data can help to ensure that a company develops a product that maximizes returns in each of the main stages. Once the product is in decline, the company also has the information needed to make decisions on the products it will introduce that will ensure that the company maintains its competitive advantage on the market.

4.1 Research and Development

In the product research and development stage, an organization will collect large amounts of data from the public, from its own internal systems or data from third parties [2]. Such data will contain information on the type of products favored by the market. The company will analyze this data and come up with information that its management can use to improve the overall decision-making process [2]. Using the example of the online retailer Amazon, the company can use big data to carry out research and development processes to determine that many customers want an easier way of making payments. The organization can obtain such information directly from customers, as well as, based on received feedback. For example, the company could notice trends in customers who browse for items but abandon the purchase when they are required to pay. This may be because the payment methods offered by the company are difficult or customers are not confident in them. Using such information, the company can decide to introduce alternative ways to make payments, which are easy to use.

4.2 Introduction Stage

Big data also proves to be very useful in the introduction stage. For instance, a company selling warm winter clothes would not be successful if such items in summer. The main reason for this is that

at the time, customers are not in need of the products. Organizations can derive such information by analyzing data on the type of purchases made by customers in different periods of the year.

4.3 Growth Stage

Furthermore, the growth stage is also vital for any product in the market. During this stage, the product introduced by the company gains a foothold in the market [13]. During this stage, more and more customers learn about the product and they are likely to make a purchase. Using big data can be advantageous to a company as it can help it to organize its marketing appropriately. The purpose of this is to ensure that the products reach the widest coverage [2]. Big data can also help the company in making decisions such as which locations to introduce the product.

4.4 Maturity Stage

Similarly, in the maturity stage of the life cycle of a product, the product has already gained a foothold in the market and its growth slows down [13]. Big data can help the company to make decisions that will enable the product to maintain growth during this stage for the longest time.

4.5 Decline Stage

The decline stage occurs after a product has been in the market for a while and probably newer technologies have become available reducing the usefulness of the product to the market [3]. Big data can help the organization in this stage of the product life cycle by ensuring that the product remains available for people who still need the product. For example, smartphone use has overtaken the use of feature phones in the market. Feature phones offering simple functions have therefore reached the decline stage of the cycle. Despite the noted decline in the global environment, in many developing countries feature phones remain in demand due to factors such as battery life and cost. Using big data, a company manufacturing feature phones can understand its market and therefore be able to ensure that supply to such markets remains available. Moreover, by the decline stage of the product life cycle, the company dealing with the product is likely to have begun the research into the next product that it will offer to clients that will meet their emerging needs. Big data, which will consist of data collected from the lifecycle of the previous product, will prove to be very useful in the development of the new product. As the name suggests, this is a lifecycle and the process should ideally continue indefinitely for the company. This ensures that the company is always ready with a new product that is able to meet the demand of clients in the market. Constant innovation is vital in the modern market where competition is very high. Nokia Corporation, once the largest manufacturer of cell phones is an example of a company that failed because of not innovating constantly. In the mid-2000s when competing firms introduced the first smartphones, Nokia was the dominant player. According to Robbins, Rolf, Ian, and Mary by 2007 Nokia controlled 40 percent of the global mobile phone market [3]. However, because of poor forecasting, the company continued to manufacture its previous phones and soon it lost its market share to other companies manufacturing smartphones such as Apple [12]. The use of big data in making decisions during the product lifecycle

can help a company to avoid making such mistakes, which may prove to be catastrophic. From the analysis above, it is evident that during the different stages of the product lifecycle, there are different strategies that organizations can employ. For example, product manufacturers and sellers can utilize different marketing strategies during the different stages of a product's lifecycle. The marketing strategy that is useful in the introduction stage may not be as effective during the growth stage of the product. The production strategy employed during the introduction stage may be very effective but the same strategy when employed during the growth stage or other subsequent stages may not be very effective. Big data therefore helps an organization to make the best decisions on different strategies based on the information obtained from analyzing the data. This ensures that the strategies selected for various activities during the different stages of the product's life are the most appropriate which ensures that the company is able to gain the most benefits from its products.

5 BIG DATA ANALYSIS METHODS

In big data, organizations can adopt different analytic methods in order to extract useful information. Data in its raw form is not very useful to an organization. Analysis of the data ensures organizations come up with patterns emerging in the data with the aim of improving the decision making process. The analytical method chosen for analysis of big data depends on various factors such as the type of data available (e.g. qualitative or quantitative), the amount of data available and the result desired. Among the most common analysis methods in big data are Decision tree analysis, PageRank, and kNN algorithm.

5.1 The Decision Tree Analysis

The decision tree analysis is a method of analyzing data that uses a graph in the shape of a tree, hence the name. In this method of analysis, a decision maker considers a decision and its resulting consequences [16]. These consequences include the chance of the consequence occurring, the costs involved when the consequence occurs and how useful the consequence is for the organization. The initial decision represents a node and the possible consequences are the branches [5]. Each consequence then becomes another node and the tree represents consequences in further branches [5]. When using a decision tree to make a decision, the decision maker selects the path that is most likely to lead to the desired solution. Big data requires the analysis of large amounts of data. A decision tree algorithm will analyze the data available and present a decision tree with all the possible paths (the connections between nodes and branches) based on the information available [5]. For example, the decision to select a particular marketing strategy will show the chance of it achieving the result, the costs involved, and the utility to the company, depending on the information obtained from the large data sets. This will therefore present different paths based on the different strategies chosen. Usually, the decision maker will make a decision by selecting the path of least resistance. Usually this path contains the best attributes needed by the organization. For instance, one path may be more costly than a different path based on the strategy chosen but they eventually lead to the same result. The path that costs less will therefore be best suited for

the organization since it will allow it to achieve its objective more efficiently. Lastly, because making a decision will lead to different consequences (which in themselves require other decision) the path that best suits the organization results from the final objective through the path of branches and nodes that best meet the needs of the organization [5].

5.2 PageRank

PageRank is an algorithm named after Larry Page who was a co-founder of the search giant and technology company Google. This algorithm finds use in ranking the search results on the search site [17]. This algorithm works by counting the number and quality of links to a webpage. This algorithm helps to determine the quality of the information on the different WebPages with information related to the search queries entered [7]. Based on the quality and number of links pointing to a page, the algorithm is able to determine the quality of the webpage [17]. This then results in the page receiving higher ranking in search results. PageRank is very important as it helps the search giant to present the most relevant answers to queries made on its site.

For instance, one webpage may contain very many links concerning the search query but the information contained on the webpage may not be of the highest quality. This means that another webpage with higher quality information even with fewer links can still rank higher than the other webpage [7]. This algorithm works by using data generated from previous searches with similar queries. Such an algorithm makes extensive use of big data to ensure that it presents the most appropriate results for a person making a query.

5.3 k-NN algorithm

The k-NN algorithm is an algorithm used in pattern recognition [15]. It finds use in both classification and regression. This is the simplest form of machine learning as it uses an approximation of values nearest to the value under analysis. For instance, in classification, the desired output is class membership. The algorithm achieves this by looking at the nearest neighbors of the value under inspection. The value receives assignment to the class to which most of its nearest neighbors belong. In regression, the desired output is typically the property value of the object under study. This is obtained by getting an average of the values of the objects that are the immediate neighbors of the object being inspected. This means that the nearest neighbors to an object contribute more towards its value than objects that are located further away from the object inspected. This means that using these algorithms, the values of an object can be predicted accurately, which helps in making complex decisions easier based on the immediate results expected [15].

6 BIG DATA ANALYTICS AND DECISION MAKING

6.1 Big Data and Competitive Advantage

Data as previously mentioned is one of the most important assets for any business. This data needs to be analyzed so as to come up with usable information that helps the management of the organization to make decisions that are likely to succeed in the market.

Because of the increased competition in the modern business environment, many organizations have employed big data to help them make decisions such as how to arrange items in stores, what items to stock, the prices that are best for the market and such decisions [14]. Although these decisions might look simple, it is very important for an organization to get them correct. Miscalculations made in such decisions could lead to losses including financial and market share losses. This is because modern customers want value for their money. This means that the organization must offer the best possible services at the lowest cost. Furthermore, this makes them attract more customers for their products or services and in the process enable them to make a higher margin. Because most competitors will use some form of data to make their decisions, it is very easy for an organization or company to lose its competitive advantage to its competitors [14]. Many organizations consider making accurate decisions in an efficient way a critical aspect of their competitive advantage. For instance, a company can release a product before the competition releases their version. Customers will buy the product already in the market allowing the organization to gain a market advantage over the rivals who have not released their product. Big data has made it possible for such organizations to obtain patterns from extremely large data sets, which are more accurate and therefore likely to produce accurate decisions [14]. Another strategy can help our product to attract more customers is using the internet hub node to spread the information about our product and advertising on the network, the network hub node is a node with a number of links that greatly exceeds the average. for example, Donald Trump's twitter is one of a most popular node in twitter network. If someone can lobby Trump to promote the product I believe we will have increasingly more customer growth. These hubs play the same role such as what Macy's used to play. Macy's used to be a big node for people's Holiday purchase. because it attracts most of the people living in that area to enter the store. The famous twitter account attract their follower because they have a fancy lifestyle or fulfill some value their follower admired. all of these are helpful for product promotion and the spread will have a more incredible efficiency and effectiveness.

7 CONCLUSION

In conclusion, despite the use of big data already being widespread in the business world, its importance will continue to grow with time. This is because of the large number of devices that are now generating data. The internet of things has resulted in a situation where even everyday appliances connect to the internet and they have the ability to collect large amounts of data. This results in more data that organizations can analyze to discover patterns in the market that organizations can exploit. Organizations are also overcoming the challenges facing big data with the collection of data now largely automated from different systems internal and external to the organization. Moreover, specialty companies have come up with the sole purpose of collecting and analyzing market data. Manufacturers are offering solutions to the technological challenges involved in big data by developing larger storage devices that are able to store increasing amounts of data efficiently. The security of such information has seen significant improvements with more secure communication and storage channels. The use of

big data is also set to increase as current analytic methods become efficient. New analytic methods are also likely to be developed that will ensure that the data collected from independent systems and the market are analyzed better in order to develop information that can be acted upon more readily in the market. This point to a future where big data will be more important than ever in ensuring that companies come up with products and strategies that enable them to be more competitive in the market and therefore increase their chances of survival in the market.

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Big Data in Safe Driver Prediction

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ABSTRACT

For years, people have been trying to reduce their automobile insurance bills. Insurance companies claim that price will be reduced for good drivers and raised for bad ones. However, inaccuracies in their data predictions lead to the exact opposite. The data-set being used is released by Porto Seguro, an auto and homeowner insurance company from Brazil. It consists of information from several hundred thousands of policyholders. The goal is to predict the probability an auto insurance policyholder files a claim the next year using classification algorithms. A good prediction with decent accuracy can correctly adjust prices for policyholders.

KEYWORDS

i523, HID233, HID204, Big data, Classification, Safe Driving, Predictive Analytics, Neural Networks

1 INTRODUCTION

Everyday, people die from car accidents and it should come as no surprise that automobile accidents are one of the most common causes of death in the United States [11]. As reported by the CDC, Centers for Disease Control, approximately over 40,000 people lose their lives to fatal automobile accidents each year. It should be clear that we need to enhance road safety for drivers all over the states [7]. However, as we are currently in the age of big data, these automobile accidents could be prevented by using modern technologies and methods such as artificial intelligence and predictive analytics.

Big data describes large quantities of data that are impossible to analyze using traditional data analysis methods. It includes structured and unstructured data. Structured data can be SQL database stores and unstructured data can be videos, images, social media feeds, etc. In industries, data analytics is often performed on big data in order to find specific patterns or anomalies that could prove useful for business decisions and choices. The amount of data is usually irrelevant in these cases. For example, smart cars utilize big data to improve their safety features and systems. They collect data such as driving patterns and routes as they travel from point A to B. This information is then sent to the computers onboard and gets transferred to the company servers where the data undergo analysis. The result is then collected and stored to enhance smart-car systems [13].

Big data is also helpful in providing insights for product development. It can find the causes for issues and problems in products through data analytics, which can then be used to improve the design. For example, the driver assistance feature on a Mercedes-Benz car not only has safety features but also collects data on driving habits. If large amount of drivers speed through intersections or

break hard during traffic hours, the company can obtain these information and use them properly to enhance their systems for better road safety. They could add a detector with GPS data to spot intersections or traffic jams. Furthermore, another data that are useful to collect are driving routes. Google Street View utilizes big data from driving routes to update their maps and display views of different places [13].

Aside from smart cars, we also need to master data collection in order to know how automobile accidents happen. For example, the technology behind the famous black box, which tracks planes and cockpit communications to determine the reason behind crashes, is getting used in cars as well. It is not expensive nor complicated to apply this technology onto the majority of vehicles out there. By recording the precise time, locations, speed and other variables, this technology can definitely help us collect valuable data and information in car accidents. The result from data analysis can also assist us in a deep understanding of causes behind automobile collisions in order to save more lives by preventing future accidents. The first country who thought to implement this technology on cars was South Korea. As a result, in the following year, a 14 percent decrease was saw in the number of car accidents along with a 20 percent decrease in the number of injuries and deaths of fatal automobile accidents [7].

Predictive analytics is a powerful method in big data analytics to help predict future events or outcomes based on current and historical data. It usually utilizes big data techniques such as data mining, predictive modeling and statistics. It uses a wide range of predictive models which depends on the type of event we are predicting. For example, most predictive models produce a number called a score where a higher score indicates a higher chance of that outcome happening in the future. It is a very useful tool for making business decisions and assessing potential risks in many industries such as insurance, retail, etc. Predictive analytics does not inform users about things that has happened before today. It tries to predict for a particular driver the probability that he or she may be involved in an car accident in the near future or any other chose time as accurately as possible [11].

For example, in order to find high-risk drivers, it is not enough to just have driving records, automobile incident reports or traffic tickets. We also need something called telematics. Telematics is defined as the combination of telecommunications and informatics. It collects, stores, sends and receives data and information via transmission-enabled devices. For example, the use of the car black box technology mentioned previously to collect and obtain information on driving behaviors or patterns is called vehicle telematics. With telematics data, companies can determine the possibility of a driver in a future car accident along with the expenses coupled with it. They can also take actions such as putting high-risk drivers

into training schools to correct their bad driving behaviors before an incident happens [11].

By studying the telematics data from a specific driver, we can learn his or her driving behaviors and create a report that details the potential danger this driver may inflict and use these data to correct those bad driving habits. The probability of a driver being involved in a car accident in the future can be used to categorize drivers into different groups. With these probabilities, companies can create a safety score to provide them with suggestions on which drivers to deal with first. The fundamental role for a safety score is to identify drivers with high risks before an accident happen to give the driver a chance to correct those bad driving habits and prevent incidents from happening [11].

However, just like other countless programs on risk evaluation, predictive analytics is not supposed to be flawless. In companies such as UPS, FedEx, USPS or any other services that use a large amount of drivers and vehicles called fleet vehicles, predictive analytics is just the first process and it requires the total cooperation and commitment from the company, drivers and fleet staff to achieve the highest efficiency. Companies that have numerous successful fleet operations are those who plan ahead and bring together all fleet personnel into the action. The most effective way to adjust the accuracy and precision of predictive models is to test the models every few days or few weeks or any other time that is suitable for the operations. Due to the fact that most operations have tight schedules, this leeway time will give companies enough room to call in safety personnel to step in to either train drivers to correct their driving habits or repair fleet vehicles beforehand to avoid major system failures [11].

Predictive analytics and telematics data are being used in almost all fleet companies as more of them start to see the value in predictive analytics. With the help of predictive analytics, fleet companies can be actively engaged in making better decisions about their fleets and companies by improving road safety, reducing expenses and risks or decreasing work load time [11].

2 BIG DATA IN THE INSURANCE INDUSTRY

For a long time, auto insurance companies have calculated insurance rates based on personal mileage through out the years [5]. Traditional auto insurance companies categorize users by demographics such as gender and other factors such as education. They then make predictions based on past statistics about their chances of getting involved in future car accidents. This means that the monthly payments insurance companies charge you are only calculated according to the information they have on you and these information has nothing to do with your driving behaviours. As a result, the premiums you pay every month is usually based on past data from people who have identical demographics as you. While a few of the factors are actually helpful in determining your risk score - for example, if you have had multiple accidents in the past, you are likely to be involved in a new one in the future - other factors such as how many cars you previously owned have little to do with your actual risk of being in an accident but yet they still matter when calculating the price. And no one ever use the most important factor in determining monthly premiums which is driving behaviors [9].

Major auto insurance companies have connection to large amount of information as well as data processing power in order to calculate risk scores and monthly premiums. It is no easy task for them to combine several different factors into one single price. Still, big data is not fully utilized. Even though these companies use a variety of different models to calculate monthly rates for drivers, not all of their methods are optimized. In a study conducted earlier this year, it was found, with the help of data mining, that there exists predictive models that have higher accuracy in categorizing drivers into high and low risk groups. Among those models was one that combined 16 factors which produced an extremely high accuracy in risk assessment [9].

Big data can help insurance companies in a big way to make better and smarter business decisions.

- Financial fraud has always been a big problem for both insurance companies and their clients ever since the invention of insurance. The expense that insurance fraud inflicts each year is more than 40 billion dollars as reported by the FBI. However, insurance companies now can put big data into good use as a brand new approach in detecting insurance fraud. Coupled with immense computing power and complex mathematical algorithms, insurance companies are now able to analyze their data to find abnormalities which might indicate possible fraud. For example, a variety of applications and computer software now have the ability to detect outliers automatically in the data. However, the anomalies detected do not always turn out to be fraud situations. There could be other reasons or explanations for them but this new approach certainly makes insurance companies a lot easier to detect potential fraud [3].
- Another benefit for insurance companies to use big data is that big data analytics applications such as Apache Hadoop are engineered to be simple to use with office software such as Excel. As a result, it is much easier to write reports in Hadoop which is intended to work with Excel. Insurance staff can now access huge amounts of data swiftly to obtain the information they need and produce a report in the form they already know how to use [3].
- Two years ago Google released a tool for residents of California to compare rates among different auto insurance companies. Since then, the competition has been increasing in the industry. However, there is no need for this useless competition because big data can help insurance companies find better ways to provide their customers with a good price while still earning profits. By collecting data and customer information from various sources such as social media, insurance companies can utilize these big data to accurately predict which customers are likely to file claims in the future and then try to bring in more of these customers [3].
- Aside from auto insurance, big data also has some interesting applications in the industry of health-care. With the accurate and effective collection of data on medical records, insurance companies can provide better health insurance plans for people so that they can have longer and better lives. As a result, people with better health insurance plans

file less claims which means insurance companies spend less money and earn higher profits. For example, insurance companies can advertise wearable technologies or devices such as apple watch to track customers well-beings in order to provide them with incentives to exercise or obtain better lifestyles [3].

- The insurance industry is continually changing. Insurance companies that can not match the pace will lose profits and resources. However, using big data, insurance companies can study and learn real time data such as social media feeds to obtain more information about customer styles and preferences. This can help insurance companies to design better marketing strategies, adapt faster to customer feedback and construct products that are more attuned with their customers' tastes [3].
- Last but not least, big data can also help insurance companies to provide insurance plans that are tailored to their customers. Every year, millions of money is lost because insurance companies do not have the means to personalize their insurance plans. However, with the help of big data analytics tools, employees in insurance companies now have the ability to gather more precision information on every one of their customers with ease so that they could create insurance plans according to each individual's needs. These tools and software can also give insights and advice based on the collected data to provide better support for employees to make decisions. This in turn will increase their customer satisfaction and lead to more customers in the future [3].

However, powered with advanced technology and big data analytics, insurance companies now-days have access to customers' driving behaviours for more personalized insurance rates. They collect specific data on how often you drive every day, how long you drive each time, how often you speed, how often you break hard and so on to determine the probability of you being in an accident in the near future. With these precise data on each individual customer, insurance companies can assess risk scores for everyone and use that information to calculate your monthly rates [5]. For example, an auto insurance company called Root is one of the first mobile auto insurance companies that are intended to help you on the go. They promise to only insure the good drivers to make sure they get the best rates. Their methods are simple. Download the app, take a test drive with the app on-board for several weeks and Root will send a personalized premium plan based on your driving behavior. Then you can just select the plan you want to purchase and buy via your phone [9].

These new and innovative mobile auto insurance plans are called UBI, short for Usage-Based Insurance and they calculate monthly premiums mostly based on driving habits. Applications on smart-phones and on-board diagnostic devices along with in-car tracking technology from manufacturer are used to record mileage and driving behaviours. These mobile insurance programs tend to give discounts for good drivers as a reward for their good driving behaviors. They are even adding new rewards such as roadside assistance on top of discounts for drivers who have maintained good driving behaviors for long periods of time. By collecting big data on driving

habits, auto insurance companies can promptly discover mistakes when accidents happen by knowing the exact positions of each car and driving habits data such as speeding or braking as well as environmental data such as weather or road conditions [10].

On the surface, these Usage-Based Insurance plans appear to be plausible and feasible. An application or a sensor is installed on your phone or car to track your driving behavior instead of estimating costs based on factors such as age, gender, education, traffic records, accident reports and so on. Several programs such as *Drivewise* from Allstate insurance and *Snapshot* from Progressive insurance have been released to the public for a couple of years in some states, completely based on customers' choices. You do not have to install them if you do not want to. However, the majority of drivers have been embracing these monitoring devices since it has no apparent downside. As long as your driving behaviors are considered to be safe, such as slow braking and accelerating or no driving around midnight, your should receive discounts like 5 to 10 percent or even up to 20 percent on your monthly premiums. On the other hand, customers are starting to worry about their privacy but we still do not know what the worst thing that might happen if we keep letting insurance companies monitor our driving behavior. According to the Wall Street Journal, these Usage-Based Insurance plans are growing exponentially. The biggest auto insurance company in United States, State Farm, announced their plans to expand their *Drive Safe and Save* program to the entire country soon. Their major advertising strategy is that by enrolling in the program, consumers can get discounts in their insurance premium by proving that they drive safely [12].

For example, one of the earliest Usage-Based Insurance programs available to the public was released about 10 years ago by Progressive and General Motors. This particular program, with the help of GPS, applied discounts based on customer mileage. Many of the Usage-Based Insurance programs these days still implement this strategy but many improvements have been made. Insurance companies nowadays know everything about the way you drive from where you drive to when you drive as well as how you drive. There are also a variety of options to choose from such as *pay as you drive* and *pay how you drive*, thanks to telematics. The advantage of having telematics in these insurance programs is to improve efficiency such as reducing response time for accidents. In addition, Usage-Based Insurance data can be analyzed using on-board diagnostic devices which are often plugged in via the on-board diagnostic 2 port on cars. These diagnostic devices do not have the ability to track car positions but they do generate more precise and meticulous data about car usage. Although telematics is the typical way to record driving habits, new creations in the future will possibly use smart-phone's location services or GPS abilities to track bad driving behaviors such as speeding and hard braking. Liberty Mutual and State Farm both tested their new tracking technology via smart-phones or other smart devices on-board cars in 2015. By 2020, the majority of auto insurance companies will be using Usage-based Insurance programs coupled with telematics data. It is no doubt that Usage-Based Insurance programs will continue to grow and achieve even higher precision and availability [4].

3 CURRENT APPLICATIONS

Predictive analytics are being utilized with telematics data to enhance and improve road safety. Telematics have been used for a long time in insurance industry to monitor driving behaviors such as speeding to identify high-risk drivers. Now coupled with predictive analytics, these data are being analyzed to predict the likelihood of a driver being involved in future accidents. SmartDrive Systems, a transportation safety and intelligence company, employs even more interesting ways to predict accidents. They record and gather video feeds from dashboard cameras in cars which are then integrated with telematics data. This way, they can improve their predictive analytics on driver safety and eventually leads to better predictions [1].

SmartDrive Systems uses a private cloud to provide their clients with predictive analytics solutions. All the data from their clients are collected by the company and stored on their cloud. The data includes telematics and video feeds from millions of clients with more than 4 billion mileage. SmartDrive constantly improves their predictive models because the agreements SmartDrive has with their clients permit them to study all the data they gather. The usage of both telematics data and video feeds is a great idea which enables SmartDrive researchers to better understand the data and interpret the results. By combining what they see through the video feeds and the results from telematics data analysis, the researchers can draw conclusions such as making a U-turn on a narrow road within some fixed radius is dangerous [1].

Indiana State Police came up with a different way to predict incidents and are making their predictive analytics methods open source. In their approach, they produced something called *Daily Crash Prediction Map* which finally completed in November. It contained data such as accident reports from all the police departments in Indiana going back to 2004 as well as data on daily weather, historical traffic amount and so on. This map highlights where potential accidents may happen categorized by their probabilities. It also features information about past accidents such as locations, dates, causes, fatalities and so on [2].

Liberty Mutual is the nation's third largest property and casualty insurance company. Last year, Liberty Mutual partnered up with Subaru. In doing so, customers was granted access to *Starlink*, Subaru's multimedia and navigation system, which can track and notify drivers via an app if they are speeding or braking too hard. By enrolling in the *RightTrack* program provided by Liberty Mutual, drivers can get up to 30 percent discounts for good driving behaviors [5].

4 DATA ANALYSIS

The data we are going to use for our analysis is of Porto Seguro. It is one of Brazil's largest auto and homeowner insurance companies. Inaccuracies in car insurance company's claim predictions raise the cost of insurance for good drivers and reduce the price for bad ones. The task is to build a model that predicts the probability that a driver will initiate an auto insurance claim in the next year. An accurate prediction will allow them to further tailor their prices, and hopefully make auto insurance coverage more accessible to more drivers.

4.1 Approach

We will be mainly discussing about the Exploratory data Analysis we have performed on the data. We will be using the help of both R and python environment and supporting packages to perform the necessary statistical analysis. Along with this, we will discuss about the Machine or Deep Learning algorithms or models that we will be using to achieve the near solution for the problem.

4.2 Feature Information

Dimensions of the data [Rows x Features] : [595212, 59]

The data-set constitutes different varieties of features.

Binomial Features [Count : 17] : ps.ind_06.bin, ps.ind_07.bin, ps.ind_08.bin, ps.ind_09.bin, ps.ind_10.bin, ps.ind_11.bin, ps.ind_12.bin, ps.ind_13.bin, ps.ind_16.bin, ps.ind_17.bin, ps.ind_18.bin, ps.calc_15.bin, ps.calc_16.bin, ps.calc_17.bin, ps.calc_18.bin, ps.calc_19.bin, ps.calc_20.bin.

Categorical Features [Count : 14] : ps.ind_02.cat, ps.ind_04.cat, ps.ind_05.cat, ps.ind_01.cat, ps.ind_02.cat, ps.ind_03.cat, ps.ind_04.cat, ps.ind_05.cat, ps.ind_07.cat, ps.ind_06.cat, ps.ind_08.cat, ps.ind_09.cat, ps.ind_10.cat, ps.ind_11.cat.

Integer Features [Count : 16] : ps.ind_01, ps.ind_03, ps.ind_14, ps.ind_15, ps.ind_11, ps.calc_04, ps.calc_05, ps.calc_06, ps.calc_07, ps.calc_08, ps.calc_09, ps.calc_10, ps.calc_11, ps.calc_12, ps.calc_13, ps.calc_14.

Floating Features [Count : 10] : ps.reg_01, ps.reg_02, ps.reg_03, ps.calc_01, ps.calc_02, ps.calc_03, ps.car_12, ps.car_13, ps.car_14, ps.car_15.

The remaining two features constitutes **id** and the **output (or target)**. All the features has been clearly represented using post script, **_cat** for categorical data, **_bin** for binomial data.

The **missing values** in the features are represented by -1.

4.3 Data Pre-processing

As shown in 1, missing values are found in 14 of the 58 columns. There are 6 features with more than 5000 missing row values. Owing to the shear size of the unavailable data, we have not performed any missing value treatment and removed these features from consideration. Of the remaining data, across rows, data is unavailable in almost 500 (smaller than 1 percent of the whole data-set) rows and these are promptly removed.

4.4 Distribution of the target variable

As shown in 2, target variable claims is a binary variable with a skewed distribution of classes. 96 percent of the customers did not make any claims. We wish to consider this distribution in measuring classification accuracy. Area under the ROC curve, recall and precision would be relevant metrics in this case.

4.5 Numerical Predictors (vs) Target Variable

Average value of most of the numerical predictors is higher when the claims are filed. This is a unique phenomenon and we intend to use this contrast in predicting the target variable.

4.6 Artificial Neural Networks

Artificial neural networks (ANNs) are computing models which are based on biological neural networks that constitute human brains. The idea of ANNs is based on the belief that working of human

Features	Missing Values Count
ps_ind_02_cat	216
ps_ind_04_cat	83
ps_ind_05_cat	5809
ps_reg_03	107772
ps_car_01_cat	107
ps_car_02_cat	5
ps_car_03_cat	411231
ps_car_05_cat	266551
ps_car_07_cat	11489
ps_car_09_cat	569
ps_car_11	5
ps_car_12	1
ps_car_14	42620

Figure 1: Missing Data

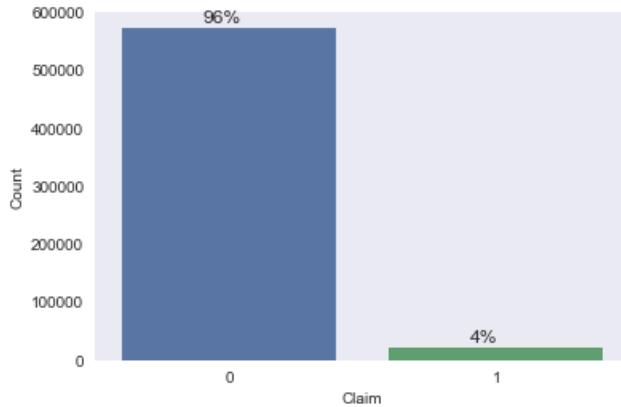


Figure 2: Target Variable Distribution

brain can be imitated for computers by using silicon and wires as living neurons. Such systems learn by progressively improving their performance to do tasks by considering examples, generally without task-specific programming. “The human brain can be considered as a complex network of nerve cells called neurons(about 86 billion)” [8]. They are inter-connected to other millions of cells by Axons. These neurons then react to stimulation from external environment or inputs from other organs. A neuron can then send the message to other neuron to handle the issue or does not send it forward.

ANNs also try to imitate biological neurons of human brain. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation. Each node is assigned with weight. ANNs are capable of learning, which takes place by altering weight values. If the network generates the desired output, there is no need to adjust the weights. However, if the network

generates an undesired output or an error, then the system alters the weights in order to improve subsequent results.

4.7 Types of ANNs

4.7.1 Feedback ANN. In this type of architecture, the output goes back into the network to achieve the best-evolved results internally. The feedback network feeds information back into itself and is well suited to solve optimization problems. Feedback ANNs are used by the Internal system error corrections [6].

4.7.2 Feed Forward ANN. A feed-forward network is a neural network which consists of an input layer, an output layer and one or more hidden layers of neurons. By evaluating its output by changing its input, the efficiency of the network can be noticed based on group behavior of the connected neurons and the output is decided. The main advantage of this network is that it learns to evaluate and recognize input patterns [6].

4.7.3 Radial Basis Function Neural Network. The RBF neural network is the first choice when interpolating in a multidimensional space. The RBF neural network is a highly intuitive neural network. Each neuron in the RBF neural network stores an example from the training set as a “prototype”. Linearity involved in the functioning of this neural network offers RBF the advantage of not suffering from local minima [6].

4.7.4 Kohonen Self-Organizing Neural Network. “Invented by Teuvo Kohonen, the self-organizing neural network is ideal for the visualization of low-dimensional views of high-dimensional data. The self-organizing neural network is different from other neural networks and applies competitive learning to a set of input data, as opposed to error-correction learning applied by other neural networks. The Kohonen self-organizing neural network is known for performing functions on unlabeled data to describe hidden structures in it” [6].

4.7.5 Recurrent Neural Network. The recurrent neural network is a neural network that allows a bi-directional flow of data. The network between the connected units forms a directed cycle. Such a network allows for dynamic temporal behavior to be exhibited. The recurrent neural network is capable of using its internal memory to process arbitrary sequence of inputs. This neural network is a popular choice for tasks such as handwriting and speech recognition [6].

4.7.6 Classification-Prediction ANN. It is a subset of feed-forward ANN and the classification-prediction ANN is applied to data-mining scenarios. The network is trained to identify particular patterns and classify them into specific groups and then further classify them into patterns which are unique for that network [6].

4.7.7 Physical Neural Network. This neural network aims to emphasize the reliance on physical hardware as opposed to software alone when simulating a neural network. An electrically adjustable resistance material is used for emulating the function of a neural synapse. While the physical hardware emulates the neurons, the software emulates the neural network [6].

4.8 Data Analysis Using Neural Networks

Rather than beginning our inquiry into the data-set with more traditional methods like regression we straight away tried to learn Artificial Neural Networks. Logistic regression itself, can be thought of as a special case of a neural network with a single neuron (perceptron).

After studying and learning the theory behind ANNs we proceeded to learn how to implement them – by ourselves at first, and later using TensorFlow. So far we have tried quite a bit of different models and learned some lessons about the data.

- **Data Cleaning :** As pointed out by the EDA above, there were a few columns which had a lot of missing data. For columns which had > 1000 values missing (6 columns), we disregarded them altogether. For the remaining data points, we disregarded the rows which had any one particular value missing. We started with a simple data cleaning strategy so as to not complicate it too much at the initial

stages, but we will probably want to look at it again as we go along.

- The first thing that we tried is using a simple **perceptron**. The input layer had 51 nodes (after removing the id, target and 6 other columns in data cleaning) and the output layer had a single perceptron with a sigmoid activation function. The best score that we got when we uploaded our code to Kaggle was 0.03 whereas the leader-board is hovering around 0.290 so this is not too impressive.
- However, now we added more hidden layers and nodes to see if we get a better job of fitting the data. To start off, we only consider the continuous variables so that we don't have to worry about handling binary/categorical data. We have 24 nodes in the input layer. The final layer has one node since it is a classification problem. We kept all activation to be logistic and experimented a bit with the number of hidden layers and nodes to get a best score of **0.211** with this simple approach.
- **Issued Encountered** Looking at the results from the neural network there is one major issue. Whenever we add too many hidden layers (> 3) the outputs for the test data are all ≈ 0 and the score drops. After some trial and error, we have diagnosed the issue to be the biased nature of the training data (96% of the training data are 0's). So the ANN sees too many zeros and consequently predicts mostly zeros. We aim to explore different sampling methods to train the neural network to improve the results further (along with cross validation which we haven't implemented).

5 OTHER TECHNIQUES THAT CAN BE USED

Among the machine Learning algorithms that are used in practice, gradient tree boosting is one technique that shines in many applications. Tree Boosting has been shown to give many state of the art results for many standard classification problem.

The most important factor for the success of XGBoost is its ability to scale in all the scenarios. The XGBoost algorithm run ten times faster than the existing popular solutions on a single solution and scales to billions of example in distributed or memory-limited settings.

The Porto Seguro data-set is clearly an classification problem, the data will be having only two outputs either the car insurance holder is going to claim or not.

While domain dependent analysis and feature engineering plays an important role in defining or modeling the solutions, the fact that XG Boost is the consensus choice for learners shows the impact and importance of our system in tree boosting. One problem with the Porto Seguro data-set we do not have have much information about the Features and all the feature must have to under go through strict statistical treatment to build an optimal solution.

6 CONCLUSION

Reducing insurance rates has always been a difficult task in the past. However, armed with advanced technology, insurance companies now have the ability to track personal driving behaviours to provide better suited personalized insurance plans. We performed Neural Networks algorithm on clients data from Porto Seguro, one of

Brazil's largest auto insurance companies in order to predict the probability of drivers filing claims in the next year. Our analysis proved to be a success and our model yielded a high accuracy.

7 APPENDIX

7.1 Links to iPython notebook:

https://github.com/bigdata-i523/hid233/blob/master/project/Shallow_Neural_Nets.ipynb

7.2 Links to iPython notebook pdf version:

https://github.com/bigdata-i523/hid233/blob/master/project/Shallow_Neural_Nets.pdf

7.3 Work Contribution

Jiaan Wang - Sections: Abstract, Introduction, Big data in the insurance industry, Current application, Data analysis (10 percent) and Conclusion

Dhawal Chaturvedi - Sections: Data analysis (90 percent), Other techniques that can be used and Conclusion as well as Jupyter notebook

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Big Data Analytics and Applications in the Travel Industry and Its Potential in Improving Travel Accessibility

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ABSTRACT

Big data applications and analytics have been influencing and improving tourists' experience. Travel accessibility refers to provide access for people with disabilities or limited mobility (such as seniors), who represent a growing market in the travel industry by spending billions on leisure and business trips. This report explored the implementation of big data analytics and applications in tourism, disabilities related studies and assistive technologies for people with disabilities. This report explored the potentials of big data applications and analytics in understanding the needs and travel experience of people with disabilities and improving travel accessibility and quality of life for people with disabilities.

KEYWORDS

i523, HID234, Big Data Analytics, Travel Accessibility, People with Disabilities, Quality of Life

1 INTRODUCTION

People with disabilities represented a large neglected tourism market. According to Amadeus annual report, 15 percent of worldwide population (around 1 billion people) lives with some forms of disability [3]. According to United Nation, people with disabilities are the largest minority group in the world [4, 16, 19]. Notably, the number of people with disabilities is expected to increase as a result of extension of human life-span, decreases in communicable diseases, the improvement of medical technology, and decrease of child mortality [42]. While some forms of disabilities might be genetic, but temporary or permanent disabilities can happen to anyone, such as spinal cord injury after car accident, or limited mobility at later stage of life [19].

Population aging trend also signifies that disability will be a more common and urgent issue in the future [22]. The World Health Organization estimates that by 2050, 21.5 per cent of the global population will be aged over 65 [3]. As a large and fast growing minority group worldwide, people with mobility limits and accessibility issues faces a large ranges of barrier when traveling, and travel and tourism demand of this group is often underestimated or completely ignored [3]. According to the Open Door Organization (ODO) market report in 2015, people with disabilities spend 17.3 billion dollars annually for their own travel [33]. Because people with disabilities usually needs a care giver or family member to accompany them when traveling, the potential economic impact could double [33].

Accessible travel or accessible tourism refers to the inclusive travel activities that enable people with access requirements, including mobility, vision, hearing and cognitive dimensions of access,

to function independently, with equity and dignity through the delivery of universally designed tourism products, services and environments [3]. However, the travel experiences for people with disabilities are more than access issues. In order to achieve travel accessibility, which means provide travel activities for people with disabilities, a variety of aspects for travel needs must be taken in consideration. An accessible destination and appropriate accommodation only lay the foundation for a particular travel experience to happen for people with disabilities [33]. More aspects that need to consider for people who are traveling with disabilities, such as accessible transportation, accessible online booking [3].

The ultimate aim for those involved in supporting accessible travel is to empower every individual to plan and travel independently, at their own will [50]. However, the task is not a easy one. Making the whole travel chain accessible, including the information and booking procedures, as well as the infrastructure and processes become a important task for travel accessibility [3].

The development of information communication technologies especially the creation and distribution of user-generated content (UGC) or consumer-generated content (CGC) has successfully changed how people travel and how people gather information for travel [12]. Big data application and analytics has become a trending topic for the tourism industry and tourism studies [12]. The fast development of information and digital technology has changed many people's lives, especially the life of people with disabilities has also been improved by technology [10]. People with poor visions can using cell phones to contact others, access information online with screen readers. People with hearing problems can text other people with their cell phone. The use of big data for disabilities related research, disability informatics and developing assistive technology has been studies to improve the quality of life for people with disabilities [22].

Although big data is becoming an important topic in both tourism studies and disability related studies. There are a gap in the literature about how big data can be used in accessible tourism practice and studies, the potential of big data analytics and applications for improving travel accessibility has not been discussed before. Travel for business and leisure, especially travel independently and with dignity, constitute an essential needs for people with disabilities, and plays a fundamental part in the quality of life for people with disabilities. This study is trying to explore the use of big data applications and big data analytics in tourism and disability related practice and research, illustrating and discovering the potential of using big data applications and analytics for accessible travel and tourism practice and studies.

2 TOURISM AND BIG DATA

Information Communication Technologies (ICTs) have been transforming tourism business globally and revolutionizing the world of Tourism. It transforms tourism from a labor-intensive to an information-intensive industry [45]. Tourists influence by the developments in search engines, network speed and capacity have been using use technologies for better planning and experiencing their trips [47]. In addition, ICTs enable travelers to access reliable and accurate information and make reservations faster, cheaper and more convenient than the traditional way [12]. The development of ICTs also enables Internet users to both create and distribute information (especially multimedia information), which is called user-generated content (UGC) or consumer-generated content (CGC) [12].

Big data is a new and trending topic in the tourism industry and tourism studies, however, it is not unfamiliar to tourist activities. Most activities in the tourism industry had been generating a huge amount of data for several years. Booking flight tickets, reserving a hotel room and renting a car all leaves a data trail [40]. These data could add up to more than hundred of terabytes or petabytes structured data in the conventional databases [2]. Discussions of travel planning on online travel community such as the Lonely Planet Community, status updates and posts on social media like Facebook and Twitter, compliments and compliant on review websites like TripAdvisor and Yelp, recording and sharing travel experience on travel blogs constructs more challenging and live unstructured data that arrives at a much faster pace than a conventional database [2]. Tourism practitioners and tourism scholars are trying to understand tourists' behavior by accepting and analyzing these big data [40].

Tourists in the digital age often use a variety of tools to access information that the tourism industry or other users have provided [46]. A tourist produces a high volume of data when they are searching for travel websites, reporting issues on mobile applications, sharing traffic information in the cities, searching and posting on social media, taking and sharing photos, reporting experience on travel websites and social media, documenting their trips on blogs [2, 40]. All these data that are produced constantly can demonstrate tourists' motivation, interests, and their planning patterns and so on [47].

Previous studies have demonstrated several different usage and formats of big data in the travel and tourism industry [47]. Social media is one of them that has a huge effect on the tourism industry. Social media includes social networks, review sites, blogs, media sharing, and wikis [46]. The exceptional growth of these data sources has inspired companies and institutions to come up with new strategies to understand the socio-economic phenomenon in various fields [40]. Discussions and information sharing on social media are considered as electronic word-of-mouth (eWOM) that has in some degree substituted tradition face-to-face word-of-mouth (WOM) for information exchange of tourist experience [12].

Most tourism research utilizing big data are focusing on CGC or UGC, especially online reviews for a hotel. A recent study conducted by Guo, Barnes and Jia used data mining approach and linguistic analysis to extract meaning from 266,544 online reviews for 25,670 hotels [24]. They mined their customer review data from

TripAdvisor using a web crawler [24]. Through their linguistic analysis of their data and cross-comparing with perceptual mapping of the hotels, they found 19 controllable dimensions that are important for hotels to manage their interactions with visitors (such as the price for value, check in and check out) [24].

Photo post on photographic sharing website also can also provide extensive information on the tourists. Previous studies have connected photos posted on Panoramio, Flickr, and Instagram [10, 29]. Because when a tourist post pictures on these websites, their photo is tagged with geographic locations and ordered chronologically. Therefore analyzing photos posted by tourists can provide a photo density map to better understand tourists' behaviors, and potentially provide opportunities to detect atypical tourists behavior and characterize communities behaviors [29]. However, the study also has its own limitation because of the limitation of technology to better exploit the data [10]. Another study focused on the sequence of locations in shared geotagged photos by tourist to identify and recommend travel routes which helped the travel recommender system to generate personalized recommendation according to interests and time available [29].

Overall for tourism industry and tourism research, big data has becoming more and more popular. Both tourism practitioners and tourism researcher has recognized the influence of big data and big data sources for tourism development. Big data in the tourism industry are generated by tourists directly, compared to traditional data sets that are gathered from surveys, they have argued that these direct data from tourists themselves can better represent their true travel experience [24]. Therefore, big data presented us opportunities to better understand tourist behavior, their motivations, and interests.

3 DISABILITY AND BIG DATA

There are many different definition of disabilities from different organizations. The most cited official definition is the 1976 definition of the World Health Organization [4]: "An impairment is any loss or abnormality of psychological, physiological or anatomical structure or function; a disability is any restriction or lack (resulting from an impairment) of ability to perform an activity in the manner or within the range considered normal for a human being; a handicap is a disadvantage for a given individual, resulting from an impairment or a disability, that prevents the fulfillment of a role that is considered normal (depending on age, gender and social and cultural factors) for that individual". While people with disabilities are those people who have limitations in their actions or activities resulting from physical, sensory or cognitive impairments, however, there are many types and levels of disabilities and their actions and activities are affected differently by their disabilities [4]. The complexity of disabilities presents difficulties and challenges to accommodate the different needs of people with disabilities and improve their qualities of life [35].

The number of individuals living with some sensory or cognitive impairment or assisting an affected person is enormous [38]. Researchers has been using disability informatics to better understand people with disabilities. Disability informatics is a sub-specialty of health informatics that is defined as "any application that collects, manages, and distributes information that are related to people

with disabilities, as well as to caregivers (including familiar members and health care providers) and rehabilitation professionals” [4]. Disability informatics is closely related to other health informatics areas such as medical informatics, public health informatics and consumer health informatics, because people with disabilities usually have some secondary medical condition such as poor health status and increased personal health care needs.

Gather medical and health information can help to better understand and accommodate people with disabilities [38]. A study from the early 2000 has identified the potential of public health informatics for prevention at all vulnerable points in the causal chains leading to disability and proposed that applications should not be restricted to particular social, behavioral, or environmental contexts, but in a more global context [48].

Another previous research has designed and deployed an extended version of Artemis system (a cloud system designed to acquire data and store physiological data of clinical information for real-time analytics) in a hospital. They have identified that high speed physiological data produced at intensive care units as big data, and the proper use of such data can promote health, reduce mortality and disability rates of critical condition patients and create new cloud-based health analytics [26]. Research also has shown that many disabilities are genetic, therefore, bioinformatics has implications in the education of genetic screening and gen therapy treatments in the future [4].

People with disabilities usually need some assistive technology in their daily life. These technology that assist them to perform basic physical and social functions. The use information technology and assistive applications in disability informatics are categorized into three areas: virtual, personal, physical.

- Virtual environment refers to use of digital technologies like website and the Internet [4]. The digital revolution had and will continue to have a profound positive impact on the life of people with disability by empowering them with the help of digital technologies [4]. However, there are still access issues in the digital world. One of the barrier is the use of the World Wide Web (WWW or Web). Therefore, virtual environment for people with disabilities is usually discussed regarding to web accessibility.
- Personal Environment refer to having a safe personal environment for people with disabilities, which includes personal management and health monitoring [4]. Safety monitoring and health monitor devices are essential in this personal environment, which enables a safer personal environment and also provide health information for their medical care providers [4]. However the ethic of such health monitor devices are always in debate, some believe it can be an invasion of privacy and a restriction of personal freedom, others hold the ground that its main purpose is to help people with disease or disabilities, since it can alert their caregiver if the individual are exposed to harm (such as a person with mental disability and has a history of self-harming, these device can prevent unwanted behavior [15].
- Physical environment refers to the actual living space, traveling environment for people with disabilities. People with

mobility disabilities, visual impairment or cognitive limitation all need special help in their physical environment. Since the American Disabilities Act passed in the 1990s, the accessibility of physical environment has been improved in a great degree. However, people with disabilities still would meet some barrier and problem, one of them is the lack of curb cuts. Assistive information technologies has been developed in an effort to solve this problem. One of them is MAGUS, which is a project using geographical information system to inform users about wheelchair accessibility in urban areas [4]

The contribution of Big data and cloud computing have been recognized and accepted by researchers in health informatics [44]. The potential of big data and cloud computing for disability informatics and for people with disabilities has been explored by a few researchers and organizations. Data-Pop Alliance is one of the organization has recognized the big data and potential for study and help people with disabilities for disability informatics and people with disabilities [35]. Their research has categorized three type of big data source used across disability research: exhaust data (mobile-based data, financial transaction, transportation and online trace), digital content (social media and crowded-sourced/online content), and sensing data (physical and remote) [35]. They also provided the potential for some of these data sources, for example, researchers can use transaction data to compare cost, availability, and use of services that offer accessible options (such as accessible hotel listings) [35]. They also suggested that researcher can use social media data to represent people with disabilities as a network of interaction and using crow-sourcing to map the locations of accessible businesses and public places [35]. The organization has also identify four functions of big data on disability: descriptive, predictive, diagnostic and engagement. Descriptive function of big data is to describing and presenting the collected information such as using location data to map workplaces that are accessible to people with disabilities [35]. Predictive function is making inferences based on collected information such as discovering trends in the growth of number of accessible businesses in a certain urban area, while the diagnostic function means establishing and making recommendations on the basis of causal relations such as showing what can help increasing accessible business in a certain area [35]. Finally, the engagement function refer to shaping dialogue within and between communities and with key stakeholders through communication of data [35].

Cloud computing in combined with big data can also provide great opportunities for research and improvement of quality of life for people with disabilities [7]. The term cloud “refers to everything a user may reach via the Internet, including services, storage, applications, and people” [25]. Depending on the type of using, the “cloud” can be use for different purpose, such as for companies, the cloud could be used for hosting services so as to avoid the costs and difficulties associated with hosting one’s own servers and software and for individuals, the could is often used as information storage [26]. Regardless of the types of usages for cloud, the end using must still access the information and services residing in the cloud through device like a smart phone or computer [25]. Cloud computing has been used to provide more accessible virtual environment,

especially Web access through project like WebAnywhere, which is a cloud based tool for blind using to access Internet [25].

Cloud computing and big data analytics can also be helpful in health monitoring. The Artemis project mention earlier provide a example of big data analytics and cloud computing usage in health monitoring, by creating new cloud-base health analytics solutions [26]. Previous researchers have developed a mobile app to collect motion data of Parkinson's disease (PD) which is a disease resulting in mobility disorder using the smart phone 3D accelerometer and to send the data to a cloud service for storage, data processing, and PD symptoms severity estimation, which provide an user-friendly and economically affordable system to monitor and assess the condition of PD [34]. Although this system is not for people with disabilities, but it provided potentials for similar systems to be developed for different kind of disabilities.

Another application of cloud computing and big data in assistive technology is the CloudCast platform, which is a cloud-based speech recognition services that can be used for many assistive technology application for people with speech difficulties and hearing impairment, it also facilitate the collection of speech data required for the machine learning techniques [15]. Similar to Alexa Voice Service, it provide reliable speech recognition which can be used with assistive devices for people with hearing impairments, but CloudCast platform also provide customization for assistive technology applications benefiting users with speech impairment [15]. This research provided a great example of using big data and cloud computing in combine to solve a certain problem for people with disabilities (in this case it is barriers for speech impairment).

The development of information technology and assistive technology has improved the life of people with disabilities. The use disability informatics and health informatics can help researchers and service and technology providers to better understand the needs and wants for people with disabilities. Studies has discussed and proposed the great potentials to use big data source to better represent people with disability and identity and study issues and propose actions and solution to the challenges faced by people with disabilities. Using Cloud computing and big data also helps improving assistive and information technology that are now used to help people with disabilities. To improve the quality of life for people with disabilities, travel as a necessary needs and right for human cannot be ignored and the travel demands from the population with disabilities have to be addressed. Therefore, it will be beneficial and necessary to study travel accessibility with the help of big data and digital technologies, in order to improve the quality of life for people with disabilities. By reviewing previous literature, this study is exploring the potential relationship between big data and travel accessibility as shown in Figure 1.

4 TRAVEL ACCESSIBILITY AND BIG DATA

To explore the potential of big data applications and analytics in improving travel accessibility, the complexity of travel accessibility have to be addressed. Accessible travel includes not only the point-to-point transportation (such as air travel, flights), but also the accessibility of destination [3, 16, 30]. For people with disability to actually make the trip, they will also require booking for transportation and hotel reservation to be accessible. This study is going

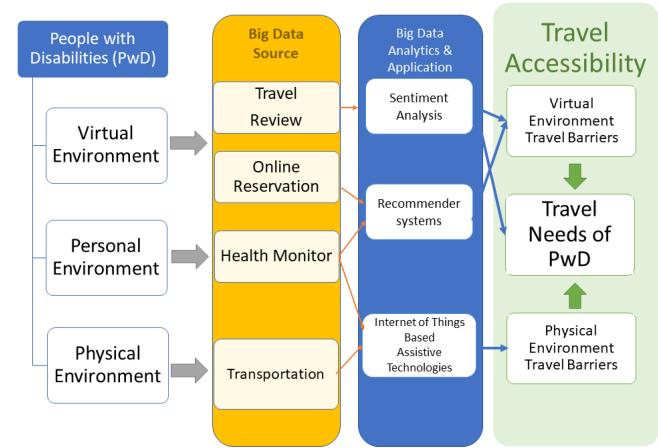


Figure 1: The Relationship Between Travel Accessibility and Big Data.

to explore the use of big data application and analytics in different aspect of travel such as reservation, long distance transportation (in the form of airline travel), and destination transportation, the existing evidence and potentials for using these big data to improve travel accessibility..

4.1 Big Data and Online Reservation

Nowadays, the majority of the travel planning process happens online. Tourists would use a variety of tourism website, search engines, and reservation domains. The Internet also plays an important part at during and post travel stage, as tourists report issues on mobile applications, share traffic information in the cities, search and post on social media, take and share photos, report experience on travel websites and social media [2, 40]. These activities seems mundane and easy to complete for the general public, but for people with disabilities they can huge hassles or barriers.

Previous studies in relation to disability informatics demonstrated the profound positive impact of that the digital revolution on the life of people with disability by empowering them with the help of digital technologies [4]. However, there are still access issues in the digital world, the most urgent one is the use of the World Wide Web (WWW or Web). The Web has always had a strong awareness and been advocacy for accessibility since early on in its evolution [4]. The World Wide Web Consortium (W3C) had passed the Web Accessibility Initiative (WAI) and Web Content Accessibility Guidelines in the late 1990s [4].

A number of assistive technologies were designed to help people with disabilities to use the Web. For example BBC Education Text to Speech Internet Enhancer (BESTIE) is a CGI Perl script that can help people with disabilities who are using text-to-speech systems for Web browsing to modified the web page removing images, Java and Javascript code that may cause difficulties to understand the BBC web page content [18]. However, the limitation of BESTIE is that it is only compatible with BBC website. Other researchers also came up with Personalizable Accessible Navigation (PAN), which is a set of edge services designed to improve Web pages accessibility

which allow personalization and the opportunities to select multiple profiles, making it compatible for web as well as mobile devices [34].

The online sector of the tourism industry has quickly adopted big data applications to better understand the need of customer and to improve online experience for customers [2]. The online sector of the industry include meta-search engines (like Google), online travel agencies (like Expedia) and some information website companies that distribute tourism information (TripAdvisor)[29]. Amadeus, a tourism company known for its global distribution system, has developed a program “Amadeus Airline Cloud Availability” that can generated special result and increase search for its customers [40].

Travel domain companies like Marriott, Southwest airline, and Amtrak also developed assistive devices specially for people with disabilities to use when browsing their websites. These assistive technologies can help people with disabilities to navigate online reservation website, and help them to independently booking their travel reservations for hotels, restaurants, airplane tickets and attraction passes.

These assistive devices was design to help people with disabilities to have access to the Web. However, current web accessibility standards do not respect disability as a complex and culturally contingent interaction. The needs and demand of people with different types of disabilities are certainly not the same and this make it hard to understand and pinpoint the real needs for people with disabilities to access the Web. Researchers have proposed to use big data to better understand of the relation between disability and technology and recognized the difference of disabled people in the “Global South” where different contexts constitute different disabilities and different experiences of web access [4].

4.2 Accessible Transportation and Big Data

An inaccessible transport network prevents many people from going to school or studying, working, going to the doctor, meeting friends, going shopping or to the cinema and other activities that are taken for granted. However, for people with disabilities, an inaccessible transport network would left them dependent and confined in their own home [3]. More importantly an inaccessible transport network would also prevent people with disabilities to travel for business or leisure [30]. Older adults, people with disabilities, individuals in low-income households, especially those living in rural areas can face significant mobility challenges [32].

Concerns about getting into an accident, congestion, price of travel, access to transit, and lack of walkways are important issues for a large percentage of the population, but they tend to be more important for people with disabilities [32]. For today’s travel and transportation businesses, it is important to address the issue of inclusion, which is the potential to enable a broader range of people to use transportation infrastructure regardless of their individual abilities or disabilities [30]. Accessibility transportation is essential for travel accessibility, because it represent two aspect of travel accessibility: first is long distance transportation accessibility, and the second is accessible destinations. For a destination to be accessible, it have to have an accessible transport network allow people with disabilities to navigate with the destination.

4.2.1 Airline and Big Data. The airline industry is very familiar with big data use in their daily operations and market research. Airline companies have been using their big data which is the large volume of structured information that has been produced internally [29] to analyze prices of plane ticket. Moreover, airlines have optimized the details of planning for the crew and routing [40].

Previous studies in airline network used Big Data mined from the U.S. air transportation system over the years from 1998?2014 to characterize the network’s behavior and determine what internal and/or external drivers result in structural changes to the airline network [14]. Airline delay patents has also been studied with the help of big data by identifying by the number of late arrivals as a percent of total operations [43].

In another previous study, researchers used data from 2006 to 2008 in order to provides the result about the total flight delay for a specific period of time caused due to climate, security, carrier, National Aviation System, Arrival and Departure based on total number of flights getting delayed over in the given period of time [43]. In the study, the authors used time series analysis along with the integration of heterogeneous database to identify and achieve the Airline Seasonal Delay which is implemented and visualized in R, they were able to identify a trend line to provide the insights for the aviation industry to take future measures to avoid delays and manage them [43].

Airline studies have also used big data analytics on passenger reviews data. The advance development of social media and mobile helped the passengers to post reviews in a ubiquitous way, allow them post real time feedback over Facebook, Twitter on airports, airlines, and other travel providers [11]. However, passengers’ review can be really complex since travel activities usually involve multiple parties, therefore, the travel domain application systems are also typically managed by different stakeholders like airlines, airports, travel agencies, security and other services providers like cars, bus, trains, hotels, events. In order to provide a holistic approach to manage complex passenger reviews with data gathering, processing and disseminating, a previous study has proposed a reference architecture to manage passenger reviews where multiple stakeholders are involved by using data lakes, which can store, manage and analyze structured and unstructured data with cheaper cost, well-distributed, open sourced and powerful set of tools.

Even though previous studies on airline using big data have not address the issues of accessibility. These previous studies still show the potential for using big data source from the airline industry and passenger reviews to study the interests, motivation, needs and demands from people with disabilities.

4.2.2 Transport Network Accessibility and Big Data. Accessibility in the transport network studies are different defined than travel accessibility, since the urban accessibility is focus on provide access of transportation and transit to general public, not specifically people with disabilities [32]. However, since transport network accessibility usually are connected to urban transport network, which represent an important part of physical environment for people with disabilities it can provide some insight for accessible destinations especially urban destinations. Accessibility has always been a key concept in urban and regional planning for its capacity to link

the activities of people and businesses to the possibilities of reaching them effectively. The accessibility of the transport network is already challenging for general public, for people with disabilities who require special needs, it becomes a tremendous and difficult barrier, because they are required to make rapid, real-time decisions that are especially difficult for special needs populations. Therefore, previous studies using big data on urban accessibility can provide some potentials for travel accessibility studies [5].

For Urban and regional planning, accessibility represents traffic capacity to link the activities of people and business to the possibilities of reaching them effectively [32]. Accessibility is defined as "a dynamic attribute of locations that varies over time due to changes in the transport network and in the attractiveness of destinations for certain activities" [32]. Since the emergence of big data generated by social media, smart phones, satellite navigation system and other technologies, the information on transport networks has improved conclusively in recent years [5]. Navigation companies such as TomTom; websites and applications like Bing Maps, Google Map; collaborative projects like Open-Street-Map; the public availability of Transit Feed Specification and data from other transit authorities opens up a rapid growing field of research on real time and time-of-day variations in private and public transit accessibility [32]. These companies and institutions have increasingly detailed systems with information on the features of roads and public transport networks, and their databases include information on speed variations on the roads and the frequencies of passage in public transport networks, all of which contribute a more efficient and dynamic vision to urban accessibility studies [32].

Researchers have just started using these new information sources in studies on urban accessibility. Previous studies utilized data obtained from global positioning system devices to calculate speeds, congestion levels and accessibility conditions at different times of day (morning, midday, evening), other studies analyzed data from Be-Mobile system (which provided the geo-located positions of 400,000 vehicles equipped with tracking devices) to calculate car travel times [32].

Previous studies also have gathered and analyzed information from web services (such as Google map API) to calculate travel times between origins and destinations. These studies were able to use new information source and big data provided by the development of technologies to retrieve information about local locations and traffic condition for local facilities like groceries, malls, restaurants, banks, recreation centers and others, and estimate accessibility by car, walking, cycling and public transit options [32]. Previous research also used data from social media such as Twitter in combined with data from satellite navigation system (like TomTom) to provide a dynamic approach and obtain profiles that highlight the daily variations in accessibility in urban cities, identify real time influence of congestion and population location changes, by providing different accessibility profiles from different transport zone, the researchers were able to analyze the relationship between the performance of the transport network and the attractiveness of the destination [32]. Although this study is not designed to provide information for people with disability, but such dynamic approach using real time big data can also benefit people with disabilities and help them identify places to go in the city and the most accessible route to the attractions.

Another study also proposed and developed a travel assistance device for people with disabilities by using real time data from global positioning system. According to this study, recent advancements in mobile technology enabled smart phones with global positioning system provide real-time location-based services and its related data. The researchers for this study designed, implemented and tested a travel assistance device (TAD) that is designed to help transit riders with special needs using public transportation [5]. This device is a navigation software program designed to prompt individuals via a cell phone to exit the bus at a pre-set location. This travel assistance device provides the people with disabilities customized real-time audio, visual and tactile prompts for exiting the transit vehicle by announcing "Get ready" and "Pull the cord now!", based on its real-time assisted GPS data provided by the embedded GPS chip in the cell phone [5]. Once the software is downloaded and installed to the cell phone, parents, travel trainers, or other authorized individuals can access the web management page to schedule bus routes to be transmitted to the cell phone [5]. The system also provides alerts to riders, their caretakers and travel trainers when the rider with disabilities deviates from the planned route. With a website allowing easy access for the design and planning of new trip itineraries, the device allows authorized personnel (usually caregivers, family members) to monitor the rider's location in real-time from any computer [5]. The travel assistance device was catered to the needs of people with disabilities, increasing their level of independence and their care-takers security. This travel assistance device represented beneficial practice for people with disabilities [5].

However, there are still many challenges for the development of such device or services. One of the main challenges is that different needs of people with disabilities making it difficult to completely satisfy and assist people with different disabilities. Since the device proposed by this study is still at experimental stage and their test sample are limited, although through the test, the device was proved to be easy to use, it still might pose as a challenge for other people with disabilities, especially people with cognitive limitations [5].

5 PROMISES OF BIG DATA IN TRAVEL ACCESSIBILITY

As mentioned above, big data has some potentials in studies and research that are intended to enable and improve the ability for people with disabilities to travel independently. This section will explore different big data related technologies, applications and analytics that can help people with disabilities to travel with ease and researchers to better understand the demand and need for people with disabilities.

5.1 Internet of Things and Travel Assistive Technology

5.1.1 Internet of Things Assistive Technology and Potentials for Travel use. Assistive devices or technology (AT) for people with disabilities are not a new concept. Assistive devices refers to "any item, piece of equipment, or product system, whether acquired commercially off the shelf, modified, or customized, that is used to increase, maintain or improve functional capabilities of individuals with disabilities", for examples, canes, crutches, walkers,

wheelchairs, and shower chairs, hearings aids, visual aids, other hardware, and software that improve ICT access or communication capacities are all assistive devices [5, 41]. People with disabilities are usually seen as depend, and in need of help from caregiver or family members [49]. However, with the technological growth that has been seen in the last 20 years, a wide array of devices have been adapted, created, and utilized with the potential to create independence for individuals with disabilities. Virtual reality, sensor monitoring devices, smart phone have all been used to assist those who require assistance in their day to day lives [32].

Older adults and individuals with physical, sensory, and mental/cognitive disabilities encounter many barriers to inclusion and accessing various opportunities and services that the society has to offer [41]. In order to overcome these barriers, people with disabilities needs some forms of assistive technologies or devices. Traditional technologies has many challenges, however, with the development of technology, the Internet of Things (IoT), smart homes, smart buildings, smart cities, and other smart environments can overcome some of these challenges due to their prevalence and diverse capabilities [9].

One of human's fundamental needs is the mobility and capability of independently traveling around, including for people with physical disabilities and even blind or visually impaired individuals [5]. In order for people with visual impairment to independently travel or moving around requires indoor and outdoor navigation capabilities, the blind and visually impaired people may rely on some type of AT to supplement their navigational abilities [41]. Previous studies has proposed using the advanced sensors of the smart phones in providing meaningful interactions with the environment for individuals with different abilities [41]. A typical modern smart phone has more than twenty sensors, which include GPS-based systems that can be useful for outdoor navigation, however in general, these sensors in smart phone still may lack the required precision and reliability for use by the blind or partially sighted individuals [41].

Previous research has proposed using Bluetooth beacons and audible instructions delivered through an interface device for navigation by the blind and partially sighted people is based on the use of such as bone conduction earphones or smart phones [5, 41]. A research team has designed and tested a system "with 16 Bluetooth beacons providing pin-point accurate indoor location mapping" for unassisted mobility in the London Underground [41]. The system is based on a mobile app, Wayfnder, which is a open platform that has the promise of promoting future development on assistive devices for people with visual limitations [41]. Microsoft, Guide Dogs, UK and several other organizations have also embarked on expanding similar concepts to respond to the challenges that people with sight loss face while navigating the cities [41]. These companies and organizations has developed technology and application that allow users to start a trip and they have a "Look Ahead" and "Find the way" mode that can help people with vision limitation to explore the city and let them stop at any point and check that they are heading the right direction [5].

5.1.2 The Big Data Challenge of IoT Based AT. While the growth and progress the IoT and smart environments, technologies such

as sensor technologies for comprehensive monitoring and surveillance progress and advance unbelievable fast, nevertheless, there still existed many challenges for these technologies [41]. One of the most important challenges is data availability. Because these technologies generated an enormous amount of data that surpasses the processing and use capabilities [41]. For instance, real-time localization and navigation systems that are designed to assist people with visual impairment to travel around, face two major related challenges: one is the allocation of computational resources that can process the large amounts of data coming from multiple sensors and cameras, fast enough in a real-time and synchronized manner, so that they can provide real-time guidance for people with special needs [41];the second issue relates to quick and real-time access to dynamic data sets through interfaces that are appropriate for the user [41].IoT devices typically have the issues of energy constrained, with small memory, limited processing power, and restrictive communication capabilities [41]. One positive aspect of this challenge is, these dynamic data obtained from IoT based AT device are extremely valuable and could help researchers and companies to better understand the needs of people with disabilities and analyzing such data can help researchers and companies to design better product for people with disabilities [17].

Another issues that AT adoption faces is its ability of meeting the usersfi needs and desires [41]. AT has been criticized because although AT devices "fimay have technical merit, and may solve obvious problems, but still fail to address the complex interplay of issues at work and to take the most appropriate approach to dealing with these matters. Furthermore, it is important to acknowledge that there may not even be a firightfi problem to tackle. Flexibility cannot be overvalued" [41]. Due to the complexity of the needs and wants for people with different disabilities, it can be challenging to develop an assistive device that can accommodate most people, however, a holistic understanding of the intended users is required [41]. It is important for researchers and AT device engineers to understand the wants and needs of people with disabilities, to be able to design an AT product that actually can fulfill what people with disabilities want, instead of just assuming what people with disabilities needs [5].

Some people may feel intimidated by the newer technologies such as those of the IoT-based AT [15]. First these device required some sort of learning and adapting period, and for people with disabilities, it might too longer time than for "normal" people, which can be taxing for people with disabilities and give them extra pressures [41]. For people who are used to being in control of their devices, some automate processes of IoT-based AT, which was intended to provide support for people with disabilities, ironically, may pose potential stress for operating and adapting to the devices [41]. A similar issue arises from the fast pace of the development of such advanced technologies. With the rapid advancement of technology, products and service become obsolete really quickly as the newer improved version become available. As mentioned above, people with disabilities do have a learning curve and need adapting process for IoT based assistive technologies, the constant and multiple upgrades of new version can make it harder for people with disabilities to adapt. Therefore, the elderly or people with disability or dementia may miss out on obtaining the full benefits of these devices or services [5, 15, 41]. The costs, learning curves,

or simply a lack of awareness can potentially prevent these people to use new technologies at all.

With the emergence of new technologies such as Internet of Things and large scale wireless sensor system, IoT based AT emerged as potential solution and promise for improving the quality of life for people with disabilities. They provide new opportunities and can aid people with disabilities in their travel, and help them overcome travel barriers. However, there is still manage challenges for people with disabilities, especially when it come to complex situations that they are going to encounter during their travel. There is a distinct gap in IoT based AT research: the lacking of holistic understanding of the needs and wants from people with disabilities. More studies needs to be conducted on the opinions and users experience of IoT based AT.

5.2 Sentiment Analysis on Online Reviews

The popularity of social media, especially review sites like TripAdvisor and blogs and wikis, leads to an enormous amount of personal reviews for travel-related information on the Web [37]. More importantly, the information in these reviews is valuable to both tourists and travel and tourism practitioners for various understanding and planning processes [49]. These UGC comes from all kinds of tourists with different demographic background, within with also has reviews from people with disabilities. Therefore, analyzing hotel reviews on various website and platform that are posted by people with disabilities can help us better understand the needs of this population group. One of the most common analytics method for large amount of review data is sentiment analysis [37].

Sentiment analysis, which is also called opinion mining, is one of the most active research areas in natural language processing [37]. The aim of sentiment analysis is to define automatic tools able to extract subjective information from text in natural language, and to create structured and actionable knowledge to be used by either a decision support system or a decision maker [23, 49]. The sentiments of reviews, online reputation or online documents are usually categorized in positive, negative and (in some studies) neutral sentiments [21]. The main goal of the sentiment classification is to extract “the global sentiment based on the subjectivity and the linguistic characteristics of the words within an unstructured text” [21]. Therefore, sentiment analysis provided a framework to transform unstructured text to structured data, which make it strongly applicable to both the academic field [8]. Because of the importance of sentiment analysis to business and society, it has spread from computer science to management science and the social sciences [36]. As a social science field and business industry, tourism and travel studies have already been using sentiment analysis in the research.

Previous studies have identified two primary approaches for sentiment analysis: methods based on the combination of lexical resources and Natural Language Processing (NLP) techniques; and machine learning approaches [21]. Since 2009, researchers have been using machine learning methods in the natural language processing (support vector machine (SVM), Nave Bayes, and the N-gram model) to do sentiment analysis on TripAdvisor reviews [49]. Their study analyzed online reviews related to travel destinations, using different supervised machine learning algorithms

The algorithms to evaluate the reviews about seven popular travel destinations in Europe and North America [49].

The etBlogAnalysis project developed a combined crawler /sentiment extraction application for the tourism industry, which used a simple and robust linguistic parsing methodology with information and terminology extraction methods in order to determine relevant utterances on expression level [37]. It will also provide a warning for tourism operator such as a hotel, if too many negative entries have been generated by their reviewers [21].

In tourism studies, sentiment analysis has been compared to traditional qualitative analytic methods. A previous study compared three alternative approaches for mining consumer sentiment (manual content coding, corpus-based semantic analysis, and stance-shift analysis) from large amounts of qualitative data found in online travel reviews [9, 13]. They applied three different approaches to study consumers' reaction to farm stays in order to demonstrate how large volumes of qualitative data can be analyzed quantitatively in a relatively efficient and reliable way [21]. Manual content coding is the same as traditional the content analysis approach involving two researchers collaborated in a manual coding process designed to extract consumer likes and dislikes from the qualitative data [20]. According to the comparison, computer generated sentiment analysis such as stance-shift analysis processing on both syntax and lexicon assures the coding maintains the statement's context identifying what is important to the informants by the way they express their comments. Most importantly, stance-shift analysis does not categorize what the researcher thinks is important in reviewer's words [9]. The study suggested by combining different approaches in sentiment analysis such as using stance-shift analysis first identifies the significant word segments then using corpus-based semantic analysis detects key themes in those segments helps uncover narrative themes of consumer experiences in large qualitative databases [9].

Sentiment analysis will help researchers to better understand people's travel experience, however, there are few studies have been done to identify demographic information of the reviewer and compare the sentiment analysis result across different demographic [23]. A recent invention present the possibility of identifying demographic characteristics while conducting sentiment analysis. The invention consist of a product or service review to determine demographic information of the reviewer [6]. A sentiment text analysis is performed on the product or service review, wherein the sentiment text analysis examines the product or service review to determine a sentiment of the product or service review. The sentiment of the product or service review is categorized based on the demographic information of the reviewer [6]. This invention presents the promise of using sentiment analysis on the travel experience of people with disabilities. However, challenges still remain for research of UGC generated by people with disabilities, such as the challenge presented by privacy concerns of personal data online [27].

5.3 Recommender System

Nowadays tourists faces a very challenging task of trip preparation because of the huge amount of information available on the Web about tourism and leisure activities [1]. Recommender systems

becomes essential for tourists and tourism operators. For tourists, recommender systems can be a useful tools to help them make decision for travel planning, such as the choices of destinations, attractions, accommodations and restaurants. As for tourism operators, it can be a great marketing opportunities for them to reach a variety of targeted potential consumers. Complex problems such as automated planning, semantic knowledge management, group recommendation or context-awareness have by now been heavily studied in this area [31].

There are already several tourism recommender system available for general public. TIP and Heracles systems provide recommendation service through mobile devices for tourism, through implement hybrid algorithms to calculate tourist preferences, using the defined tourist profile and location data [31]. Crumpet system provides new information delivery services for a variety of different tourist population based on location aware services, personalized user interaction, accessible multimedia mobile communication that uses Multi-Agent Technology [39]. CATIS is a Web based tourist information system using context-awareness, which include context elements such as location, time of day, speed, direction of travel and personal preferences. This system provided information to tourists relevant to his or her location and time [39]. TravelWithFriends using group recommendation service, the first step is to build a recommendation list for each user and to merge them to obtain a destinations shortlist. Afterwards, each group member rates all these options and a Borda count is used to determine the best five destinations to be recommended [31].

Classical recommender systems filter the domain items according to a particular user, using his or her demographic data, past ratings or purchasing history [28]. This approach are used to recommend specific items such as books, songs or films [28]. However, it may not be suitable for travel activities, since most of time travel is an activity that involves a group of people (such as family members, friends). Therefore, it is necessary to take into account the different preferences of all members of travel group when providing recommendations [31]. Previous studies and technology reports have identified two primary options for group recommendation: the first one is to merge the lists of items recommended to each group member, or creating a group profile with everyone's preferences and then compute a single list of group recommendations [20]. The second option's first step is the same as the previous option, by constructing of a list of recommendations for each group member. In a second step though, an automatic consensus-reaching process is applied, in which individual preferences are continuously updated until a high degree of agreement between all the group members is reached [20].

The use of semantic domain knowledge in the recommendation process has heavily increased in recent years. Previous studies have defined the semantic similarity between two concepts as "the ratio between the number of different ancestors and the total number of ancestors of both concepts" [31]. The items to be recommended are clustered according to this semantic similarity and the recommendation procedure selects the best item from random clusters [39]. Previous study has shown that this procedure keeps the accuracy and increases the diversity of the results [31]. Semantic information can also be used to determine the items to be recommended in a personalized visit to a museum or destinations,

by using a shortest-path semantic distance to determine which museum objects or attractions should be recommended to the user [31].

Previous study also proposed a hybrid tourism recommendation system for persons suffering from physical or intellectual limitation. This proposed recommendation system is not simply trying to improve experience, but to create and increase the confidence of users that despite of their limitations they can visit and experience certain places without being afraid, and to help them to truly live a touristic experience. As shown in Figure 2, the system models a user stereotype profile, by identifying the user's functionality and point of interest (POI) accessibility level, which represent user's related knowledge which is layered with several knowledge representation structures and models and produce an accurate touristic recommendation plan [39]. The study represent itself as an opportunity to provide needed information to people with disabilities through a hybrid tourism recommendation system.

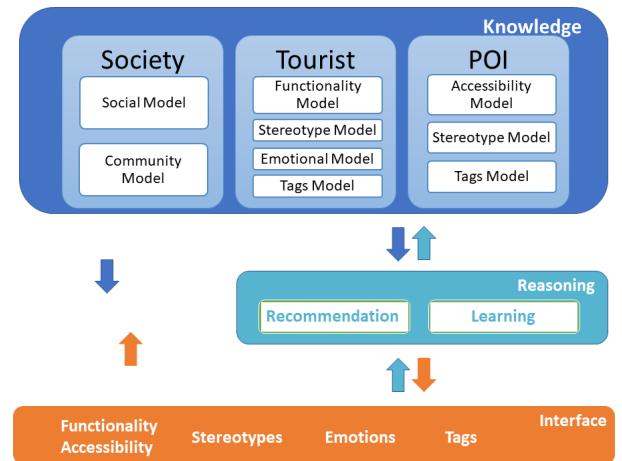


Figure 2: Hybrid Tourism Recommendation System[39].

6 CONCLUSION

This study has explored the big data applications and analytics in tourism industry and research, and disability related research. This study illustrated the importance of improving travel accessibility by recognizing the underestimated market for travel of people with disabilities. The lack of research on big data application and analytics in travel accessibility was identified. By recognizing the complexity of travel accessibility, this study present the potential of using big data analytics and application to better understand the need of people with disability in two travel accessibility aspects: online reservation, and accessible transportation. Although there are few studies on big data and accessible online reservations and accessible transportation directly, this study illustrate big data utilization in web accessibility, airline studies and urban accessibility. These previous studies show promises of using big data analytics and application to address accessibility issues and the needs of people with disabilities in these aspects. This study also explored the promise of big data in travel accessible by exploring:

- Potentials of Internet of Things (IoT) based assistive technology (AT): help people with disabilities overcome travel challenge presented by physical environment.
- Recommender systems: help people with disabilities to get more needed information online, and make it easier for them to navigate the virtual environment.
- Sentiment analysis on online reviews: help researchers and practitioners to better understand the needs and behaviors of people with disabilities.

However, there are still a lot challenge faced by researchers and organizations interested in improving the quality of life for people with disabilities. The most dominated challenge is the different needs for people with different disabilities types and function levels. Future studies could use sentiment analysis of reviews online generated by people with disabilities to better understand their needs and identify the differences between different disabilities groups. Future studies should also analyze dynamic data generated by the sensors on the assistive devices for people with disabilities to better understand their travel patterns and to provide more appropriate products for people with disabilities.

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Importance of Big data in predicting stock returns and price

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ABSTRACT

In this project, we will discuss the importance of big data in finance industry in predicting financial stock values. We will be using python libraries to fetch financial data from yahoo finance and will further predict the stock price returns of few selected technology companies such as Amazon, Yahoo depending on the historical data of x[16] years. Similarly, we will predict the returns based on y[10] years of data. The prediction will be based on SP 500 market return and market risk volatility. Here y is greater than x and then we will compare the predicted returns with the current returns. For the comparison we will be using the testing time frame as mentioned in the project later. This project will help us understand if more historic data helps in predicting the stock price returns or it adds noise. We will be using statistical approach and CAPM [capital asset pricing model] to predict stock price. Analysis will be done on the jupyter notebook

KEYWORDS

HID-301, Stock Price prediction, stock returns, SP500, risk free market, CAPM model, root mean square analysis, stock beta, Finance, Statistics, mean, variance, market premium, python, yahoo finance, i523

1 INTRODUCTION

By its nature of the business, the finance industry is always driven and dominated by data. The existence of Big data in the finance industry has exposed the big opportunity of growth and value extraction but at the same time imposed the various new challenges, which demand new skill set. [5] suggests that finance experts believe there is a huge potential in terms of value extraction from the financial big data. They also believe that finance industry can benefit more than any other industry. Historically, data was always there in some format either non-digital or digital. However, with digitization, this data has fallen into the prevalence of high volume of information, which we call as Big Data. Dominant drivers for the actuality of big data in the finance industry are mainly customer call logs, social media, news feed, regulatory data etc. Call logs, news feed and etc. fall into the category of unstructured data which is identified as an area where we can extract vast amount of business value.

[4] talks about the three V of big data in finance industry: volume, velocity and variety. [6] clearly depicts the amount of financial data pouring in the daily basis. TechNavio's forecast (TechNavio 2016) predicts data will grow at a CAGR [compound annual growth rate] of 61 percent over the period of 2017-2021. According to the

IDC financial insight 2016, every second there is around 10,000-payment card transaction and this number is expected to double by the end of this decade. The Capgemini/RBS Global payments study for 2012 suggests there were about 260 billion transactions in 2012 and is expected to grow between 15 and 22 percent for developing countries. Main drivers contributing to the big data in the finance industry are Data growth, increasing scrutiny from regulators, digitization of financial products, changing the business model and increased customer insight platforms such as customer service. [4] shows 76 percent of banks say the business driver for embracing big data is to enhance customer engagement, retention, and loyalty and seventy one percent of banks say that to increase their revenue, they need to better understand customers and big data will help them to do so.

Thinking about the data strategy, the financial industry has taken the business-driven approach to a big data. According to the IBM report, all financial organizations are not keeping the same pace as peer industry is keeping. Today because of increased competition, customers always expect more personalized banking service and at the same time, there is increased regulatory surveillance which in result creates big pressure on finance industry to better utilize the value of Big data. To achieve better-personalized experience, many banks have started the initiative to utilize the information gained from the vast ocean of data to offer better-personalized products and gain competitive advantage. Despite the fact that financial industry is data-driven, there is a gap in the amount of initiative financial industry has taken to extract the value out of big financial data. Technavio 2016 report has shown only 26 percent of financial organizations has focused on understanding the principal notation of Big data and most of those 26 percent are still struggling to define the clear roadmap. This clearly concludes that finance industry lag behind their cross-industry peers in using more varied data types. A good example to support this fact is that there are very less research and domain knowledge in extracting value out of retail bank call logs.

Big data technologies not only help in extracting the effective business value but analysis of unstructured data in conjunction with a wide variety of data set also helps in extracting commercial value. Big data in finance industry does not necessarily decode to valuable or actionable information. The real benefit lies in developing the technologies, which can be used to extract business and commercial value. [15] talks about what all advantage we can extract from the big data in the finance industry. Few examples are: Detection of false rumors that try to manipulate the finance market, Assessment of exposure to a reputational risk connected to consulting service offered by banks to their customer and Discover

topic trends, detect events, or support the portfolio optimization or asset allocation. Big data based pattern recognition can also help in enhanced fraud detection systems and prevention capability systems. Other benefits of utilizing big data include building a machine learning based algorithm to achieve higher performance and accuracy in the trading algorithm and Enhanced market trading analysis. There has been proven research [12] which states more data increases accuracy and precision of simulations which is the backbone of financial modeling based analytic. This research [12] states modern modeling techniques are data hungry. In this project we will extract inference if more financial data can be used to have better prediction.

2 USE OF STRUCTURED FINANCIAL DATA

This reflects the data which has a higher degree of an organization such as a relational database where information/data is easily searchable and we can easily apply standard algorithm to extract patterns out of it. In this project we will be using Yahoo finance structured data. Examples of such data set include yahoo financial data, trading applications, enterprise finance resource planner, Retail banking systems, Credit history database systems and other financial applications that use legacy application systems. Structured data always has a big advantage of being easily entered, stored, queried and analyzed. Most of the personal banking financial statements are stored in a structured way. Structured dataset combined with the distributed systems can be leveraged to achieve structured big data set on which we can run optimized SQL queries to retrieve patterns. [9] discusses various SQL based ways to specify information quality in data which can be used to filter out the noise. In this project we will be using structured data.

3 VARIOUS CHALLENGES UTILIZING BIG DATA VALUE IN FINANCE INDUSTRY

There are multiple challenges and constraints in extracting value out of big financial data. The biggest challenge is old IT culture and infrastructure. The much financial organization still uses old IT infrastructure which is not compatible with the big data application thus fail to take advantage of big data. Other challenges include lack of skill set and data privacy and security. With the emergence of digitalization, customer data is saved persistently because of which there has been continued concern regarding the customer privacy. Regulatory bodies guidelines on customer data are always ill-defined because of which there is always a concern regarding the use of customer data. In this project we will use standard python libraries to fetch financial data from yahoo finance. Analysis will be done on the jupyter notebook.

4 STOCK RETURNS PREDICTION - LITERATURE REVIEW

Authors of [1] discuss the importance of stock price and returns prediction based on the data extraction of historic data. This research [1] also shows historic financial data has definitive predictive relationship to the future value of stocks. Stock prediction always help investors to decide perfect timing of buying or selling stocks. There are various data mining, artificial neural networks and machine learning techniques available for the stock price prediction based

on the value extraction from the historic financial data. Based on the complexity of stock price matrix, pricing mechanism is essentially a non linear complex system. Authors of [14] and [13] state many predictive algorithm is based on the fundamental analysis of macroeconomics and company fundamentals. [11] states problem with the fundamental analysis is that it is too much focused on the intrinsic and lacks the quantitative aspect of the historic financial data. On the broad category we can define stock prediction analysis is based on two types of analysis: qualitative and quantitative. Choice of analysis is mainly based on the fact if we want to have short term analysis or long term analysis. In this project we have have ten and sixteen years of training data and used close to one year of testing data. Since our analysis is based on the historic data we have chosen to do quantitative analysis. Quantitative analysis is based on the pattern extraction, fact that history repeats and future financial drivers can be extracted based on the historic data. Advantage of using quantitative analysis is that we can use statistical confidence interval to validate the analysis.

There is a huge benefit of using machine learning algorithms in predicting stock prices. These algorithms made easy to cope up with the various financial events such as mergers acquisitions, bankruptcy, fraud, political changes, market crashes, housing bubble, dot net bubble and etc. In this project we have used hybrid approach of combined CAPM [Capital asset pricing] model and machine learning algorithm to mine data of sixteen and ten years of data and used close to 1 year of testing data. These machine learning algorithms can further be used to predict various financial events. Other approaches such as neural networks algorithms, SVM, logistic regression and multiple discriminant analysis can also be used to predict financial events. Example, [2] in their research they proved neural networks algorithms performs better in predicting financial events as compared to multiple discriminant analysis. There are other applications which use these algorithm to find predicted credit rating of a company. Credit rating plays a very important role doing qualitative analysis of the financial health of a company. On the other hand, accuracy of these algorithm is a big challenge because of the amount of huge data which it uses as input. Typically, accuracy of these algorithms is validated based on square root method.

In this project we have used several years of data for analysis which involves more than hundred thousands of rows with multiple columns. Then this data is analyzed two dimensionally with the same set of market return rows. Since this analysis is calculation intense, In the end we also have performed root mean square analysis.

Over the past few years there has been drastic changes in the way stock market operates. With the emergence of advance web services, there has been powerful enhancement in the data communication between various financial application. Because of which there is ocean of real time data is available, thus machine learning algorithm, neural networks algorithms, SVM, logistic regression and multiple discriminant analysis needs to be smarter. Forecasting stocks and financial parameter is of great interest to the investors. As discussed earlier these algorithms needs to modified depending on the fact if we want to have short term profit or long term profit.

[8] has shown the very interesting analysis of comparing the prediction of stock market with the random walk hypothesis. Author

of [8] ran an experiment in which he tossed a coin and recorded the results and mapped head with the company profit and tail with the company loss. Then result of this experiment was shown to the investors pretending these are the actual market profit and loss. Looking at the result graphs, investors believed it as a actual prediction. This research has shown the altogether different outlook which states stock price prediction and forecast can be fooled and stock prices are perfectly random in nature. On this theory many researchers have classified profit based on three hypothesis:

- Weak form Efficient Market Hypothesis: The weak form of the hypothesis states one can not generate profit by just looking at patterns and trends of stock market.
- Semi Strong Efficient Market Hypothesis: The semi strong form of the hypothesis states only possible way of generating profit is via inside trading.
- Strong form Efficient Market Hypothesis: The strong form of the hypothesis states its not possible to generate profit since stock market behaves in perfect random way.

However, if we are running root mean square analysis we can surely compare the accuracy of various algorithm and arrive at conclusion which algorithm is viable for prediction.

5 FINANCIAL DATA EXTRACTION

In this section, we will discuss various technical requirements needed to achieve value extraction from the big data in the finance industry. There are various technical requirements such as data Acquisition, data quality, data extraction, data integration, decision support. In order to fulfill requirements, a hybrid approach combining computer science, algorithms, statistics, data mining, machine learning and pattern recognition study needs to be adopted. To explore the advantage of big data there have been initiatives like data virtualization, multi-document summarization, pattern recognition from LOGS and many start-ups have been emerged. All big companies such as Microsoft, Google, IBM and Amazon are investing heavily in this field to leverage business and commercial value out of it. There has been changed in the industry pattern where financial industry is resorting big data to strategize their business. According to [6] with a very rapid pace, the financial industry is utilizing big data advantage in investment analysis, econometrics, risk assessment, fraud detection, trading, customer interaction analysis and behavior modeling. If we look at the Big promise the Big data holds in the finance industry, progress in this field is still in nascent stage and we expect more growth in upcoming years. In this project we will discuss jupyter notebook based solution for Data extraction.

In this project we have used jupyter notebook and rich python libraries to fetch financial stock data. Later in this paper we will discuss the stock data extraction in detail. Later we will also discuss what are different ways to fetch stock data and will discuss few important functions which python libraries

6 FETCHING FINANCIAL STOCK DATA

Fetching structured precise data is always a challenge. There are different ways to fetch the stock market data. In this project we will be fetching data from yahoo finance via python libraries which

internally makes remote web service call to the yahoo web server. There are also other ways to fetch data such as:

- Direct download of csv files from yahoo finance or google websites.
- Make web api call to download the data in the json/XML format
- Use python libraries to download data, which internally makes remote web service call to the yahoo web server. This is preferred way of doing since it allows you to save data to system variables directly.
- Call yahoo or finance web service from the application.
- Calling VBA function in excel to fetch yahoo stock data
- Quandl best for using core financial data and this website also includes access to rich python libraries.
- Google sheet has feature to fetch real time stock prices
- Install stocks macros in excel

In this project we have exhaustively used python for data manipulation. Reasons for using python are:

- Syntax is super easy which comes with very level of readability as compared to other programming languages.
- It is free and supports cross platform as python code can be called from any version of machine.
- Python has strong community support so if any problem is encountered, support is available online.
- Python has powerful tools available such as statsmodels, matplotlib, Pandas, Numpy and SciPy for calculation intense projects

Since we have exhaustively used the `get_data_yahoo` function from the `pandas_datareader` python library we will briefly discuss the parameters it takes. Please note we utilized only those arguments which are relevant to the project requirements. From [10] parameter list as listed below:

- `symbols` : string, array-like object (list, tuple, Series), or DataFrame Single stock symbol (ticker), array-like object of symbols or DataFrame with index containing stock symbols.
- `start` : string, (defaults to '1/1/2010') Starting date, timestamp. Parses many different kind of date representations (e.g., 'JAN-01-2010', '1/1/10', 'Jan, 1, 1980')
- `end` : string, (defaults to today) Ending date, timestamp. Same format as starting date.
- `retry_count` : int, default 3 Number of times to retry query request.
- `pause` : int, default 0 Time, in seconds, to pause between consecutive queries of chunks. If single value given for symbol, represents the pause between retries.
- `session` : Session, default None requests.sessions.Session instance to be used
- `adjust_price`: bool, default False If True, adjusts all prices in hist data ('Open','High', 'Low','Close') based on 'Adj Close' price. Adds 'Adj Ratio' column and drops 'Adj Close'.
- `ret_index` : bool, default False If True, includes a simple return index 'Ret Index' in hist data.
- `chunksize` : int, default 25 Number of symbols to download consecutively before initiating pause.

- interval : string, default 'd' Time interval code, valid values are 'd' for daily, 'w' for weekly, 'm' for monthly and 'v' for dividend.

In our analysis, for the symbol parameter we are passing ticker symbol one at a time. Though, we have an option to pass multiple tickers as an array argument. We are using get_data_yahoo function and utilizing only first three parameters: symbols, start and end. This function returns YahooDailyReader object which can further be manipulated to get Open, High, Low, Close, Adj Close and Volume stock values. Since default number of retry count is three we will be using this default value. Default value of pause which is zero is also good with respect to our requirement so we will not pass this as argument. Session argument should be used when we are handling multiple request in parallel in the code since our project we just need one session so we will not use this argument. adjust_price is not required in our analysis since we are interested only in returns which can be fetched using pct_change() function. Since return index is of no use in calculating the returns, we will not use this argument. Argument chunk size is used to modify number of consecutive downloads of stocks since we are just using single ticker so this argument is of no use. This function uses interval also as a parameter since we are only interested in daily values and daily value is the default interval so we didn't pass this argument in the function call. We could also use the contemporary google function which is get_data_google. Arguments which goes to the get_data_google are symbols, start, end, retry_count, pause, chunksize and session since we are not using get_data_google function in our project we will not discuss these in detail.

7 INTRODUCTION TO CAPM MODEL

CAPM [Capital asset pricing model] model was developed by William Sharpe and John Lintner in 1964. This model is considered so powerful that it is being used in current prediction models. There are few advantages of using CAPM model as compared to other pricing models:

- This model is a single dimensional model and easy to use, still powerful to model capital asset pricing.
- Since this model is based on the market portfolio and risk free rate, this model removes unsystematic risk.
- We can run root mean square algorithm to validate the algorithm.
- This model provides a flexibility to utilize various risk free rates and run model for various time range.
- This model can be applied to various financial objects such as stocks, put option, call option, bonds, and etc

This model can be used to evaluate the theoretical expected return on a security, security can be any financial object such as stocks, put option, call option, bonds, and etc. In CAPM model we evaluate how much financial object is sensitive to the market using statistical analysis. Then this sensitivity which is also known as beta is used to find the expected return on security. This expected return can be on daily basis, weekly basis, monthly basis or yearly. Here is the formula to evaluate expected return:

$$E(R_i) = r_f + \beta_i(E(r_m) - r_f)$$

Where

- $E(R_i)$ is expected return
- r_f is risk free interest rate example: Government bond
- $E(r_m)$ is return on market example SP 500
- β_i is sensitivity of stock with respect to market

β_i can further be defined how much stock is sensitive to the stock market. Example if β_i for a particular stock is two it means if market goes up by five percent then stock will go up by ten percent and if market goes down by two percent then stock will go down by ten percent. In terms of statistics β_i is defined as:

$$\beta_i = \frac{Cov(R_i, r_m)}{Var(r_m)}$$

Where covariance and variance are defined as

$$\begin{aligned} cov_{x,y} &= \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{N-1} \\ &= \frac{\sum_{i=1}^n (x_i - \mu)^2}{n} \\ var^2 &= \frac{\sum_{i=1}^n (x_i - \mu)^2}{n} \end{aligned}$$

β_i matrix can be used to illustrate β_i in a following way:

	β_i	MarketReturn	ExpectedReturn
Row1	+2	+5%	+10%
Row2	-2	+5%	-10%
Row3	+0.5	+4%	+2%
Row4	+0.5	-4%	-2%

Above matrix suggests how expected returns can be correlated with the the β_i . Example if for certain company has β_i of +2 and market returns is +5 % then company's expected returns can be predicted as +10 %. Please note β_i can be positive as well as negative.

8 PROPOSED ANALYSIS

In this project we will utilize structured data and use CAPM [Capital asset pricing model] to statistically find the expected daily return of selected technological stocks: Amazon and Yahoo. This daily expected return can be used to predict next day stock value given the condition we have current stock price. Following formula can be used to predict next day stock price:

Next Day stock price =: Today stock price * (1+Daily expected return)

Daily expected return will be calculated using CAPM model. Daily expected return sensitivity in CAPM terminology is also known as beta. In this project beta will be calculated based on two time frames:

Time frame 1: [01/01/2000 to 12/31/2016] 16 years of data
Time frame 2: [01/01/2006 to 12/31/2016] 10 years of data

Thus we we will have 2 β_i :

$$\beta_1 = \frac{Cov(R_1, r_{m1})}{Var(r_{m1})}$$

$$\beta_2 = \frac{\text{Cov}(R_2, r_{m2})}{\text{Var}(r_{m2})}$$

Where

- β_1 is β based on time frame 1
- β_2 is β based on time frame 2
- R_1 is actual return based on time frame 1
- r_{m1} is a mean market return based on time frame 1
- R_2 is actual return based on time frame 2
- r_{m2} is a mean market return based on time frame 2

Above two time frames will be our training data set. We will run two analysis: one on training time frame 1 and other on training time frame 2 to arrive at predicted CAPM variables. Then we will use this training data set to predict stock returns for test data set which will comprise of time frame:

Test data time frame: 01/01/2017 to 11/16/2017

Then we will run the statistically analysis on the test data to evaluate if 16 years of training data produced more accurate result or else it added noise compared to 10 years of training data. Please note this is purely a quantitative analysis not qualitative. Actual returns can also be impacted by a qualitative factors such as mergers acquisitions, bankruptcy, fraud, political changes, market crashes, housing bubble, dot net bubble and etc.

9 PROPOSED ALGORITHM

Code is written purely in python language and used the powerful rich python libraries such as statsmodels, matplotlib, Pandas, Numpy and SciPyfor. We have used jupyter notebook as interpreter tool to python. Code is started by importing above mentioned rich python libraries. Since we are interested only in technological stocks: Amazon and yahoo we need to initialize they stock ticker with the python variable. In CAPM model we need to know the market return in order to know the stock sensitivity we will also initialize market ticker with SP 500 index. As discussed above we will be using get_data_yahoo function from the pandas_datareader and in this project we will be only utilizing only first three parameters which is stock ticker, start date and end date. For first iteration we will be using get_data_yahoo to fetch stocks and market returns for time frame 1. For having better understanding of how the data looks when fetched using get_data_yahoo function, we will have amazon financial data matrix calculated like:

```
amazonData = dr.get_data_yahoo('AMZN', start_date, end_date)
```

Where

- dr is pandas_datareader.data class
- amazon is stock ticker for amazon which is 'AMZN'
- start_date is start date of time frame 1: 01/01/2000
- end_date is end date of time frame 1: 12/31/2016

and synopsis of above amazon data looks like:

	Open	High	Low	Close	Adj	Volume
23 - Dec - 16	764.54	766.50	757.98	760.59	760.59	1976900
27 - Dec - 16	763.40	774.65	761.20	771.40	771.40	2638700
28 - Dec - 16	776.25	780.00	770.50	772.13	772.13	3301000
29 - Dec - 16	772.40	773.40	760.84	765.15	765.15	3153500
30 - Dec - 16	766.46	767.40	748.28	749.86	749.86	4139400

Similarly using get_data_yahoo we will fetch Yahoo and market returns. Since we are interested in daily return, we fetched the daily data from yahoo finance which is evident from the above result data set. Now lets find the percentage change on the daily Close value to get the percentage change array which in finance terminology will be daily return on stock. For finding the percentage change we are using pct_change() function on the close column of result set. This function can be elaborated as follows:

```
return_amazon = amazonData.Close.pct_change()[1 :]
return_yahoo = yahooData.Close.pct_change()[1 :]
return_market = marketData.Close.pct_change()[1 :]
```

return_amazon, return_yahoo and return_market are two dimensional arrays and we need to convert them to single dimensional array in order to run statistical analysis. We can use dot values method to extract single dimensional array out of 2 dimensional array. This operation can be elaborated as follows:

```
X_amazon_actualReturns = return_amazon_testing.values
X2_yahoo_actualReturns = return_yahoo_testing.values
Y_market_actualReturns = return_market_testing.values
```

Please note these are actual returns - fetched from yahoo finance. Now in order to evaluate expected return for the testing period based on the calculated beta we need to calculate the risk free rate r_f as mentioned above in the CAPM formula. Please note get_data_yahoo formula will fetch the annualized rate but here we are dealing with the daily returns so this needs to be normalized to daily rate. Here we are using Treas Yld Index-10 Yr Nts bond. Ticker symbol for Treas Yld Index-10 Yr Nts bond is 'TDX'. Please note get_data_yahoo will return columns: Open, High, Low, Close, Adj Close and Volume. Dot values will convert to 2 dimensional array and then used index [0][4] to fetch annual rate. Detailed code with comments is mentioned on jupyter notebook.

Conversion of annualized return to daily return can be done using following formula:

```
riskFreeDailyRate = (1 + riskFreeAnnualRate)(1/365) - 1
```

Now we need to copy the content of X_amazon_actualReturns to new array X_amazon_predictedReturns and initialized each

element in X_amazon_predictedReturns using CAPM model as discussed above in Introduction:

```
X_amazon_predictedReturns = list(X_amazon_actualReturns)
```

We will do the same for Yahoo stocks:

```
X2_yahoo_predictedReturns = list(X2_yahoo_actualReturns)
```

In the code we have run the while loop and each element of X_amazon_predictedReturns and X2_yahoo_predictedReturns is assigned the value based on CAPM model. Now we have two returns arrays for amazon stocks based on sixteen years of data:

- X_amazon_actualReturns are the actual returns
- X_amazon_predictedReturns are returns based on the CAPM model.

Similarly we have two returns arrays for yahoo stocks based on sixteen years of data:

- X2_yahoo_actualReturns are the actual returns
- X2_yahoo_predictedReturns are the returns based on the CAPM model.

Now we can utilize mean_squared_error function from the sklearn.metrics python library to find how predicted returns are deviated from the actual returns. We will run this function on both stocks, amazon and yahoo:

```
a1 = Y_market_actualReturns
a2 = X_amazon_predictedReturns
y1 = Y_market_actualReturns
y2 = X2_yahoo_predictedReturns

rms_amazon = sqrt(mean_squared_error(a1,a2))
rms_yahoo = sqrt(mean_squared_error(y1,y2))
```

Here is the root mean square values for both the stocks under sixteen years of data case:

- Root mean square error for Amazon stocks analysis based on 16 years of data 0.0013770 or 0.137 percent
- Root mean square error for Yahoo stocks analysis based on 16 years of data 0.0014313 or 0.143 percent

Now we run the same analysis as discussed above for the ten years of data and will validate how much predicted stocks returns based on the ten years of data are deviated from the actual returns using root mean square method. Please note testing data set remains the same we are just using different training data set. This will let us compare if sixteen years of data is of more worth in predicting stock returns or it added noise to the analysis:

- Root mean square error for Amazon stocks analysis based on 10 years of data 0.0005310 or 0.053 percent
- Root mean square error for Yahoo stocks analysis based on 10 years of data 0.0014910 or 0.149 percent

Above analysis is purely quantitative and does not include any elements of qualitative analysis. It shows predicting yahoo stock price or its returns based on the sixteen years of data or ten years of data - both resulted in almost same results. However things are totally different for the amazon stocks, recent ten years of amazon stocks data produced more accurate results as compared

to using recent sixteen years of data. Author of [7] agrees with the fact that most recent financial data are the better predictors of the future price returns. Though, in the [7] author has used the neural networks and support vector machine for prediction. Author also stressed that neural networks algorithm produced better accuracy than other machine learning algorithms.

10 THREE PARADIGMS OF PREDICTION

Data prediction and analysis done in this project is purely quantitative. However there are other paradigms of predictions also which we will discuss here. Example in above analysis we totally missed the qualitative aspect of the data. This is why it explains recent data on amazon stocks produced better results. Here are the other prediction paradigms explained by the author of [3] :

- Quantitative research based prediction. This is a method where we utilize statistical tools to arrive at predictive value based on data
- Quantitative research based prediction. This is a method where we utilize conceptual knowledge to arrive at predicted value. Example of such study would be prediction of stocks based on the events such as mergers acquisitions, bankruptcy, Fraud, political changes, market crashes, housing bubble, dot net bubble and etc.
- Mixed research based prediction. This is a hybrid method where we utilize both qualitative and quantitative results to predict result.

In this project we used quantitative based approach to validate the fact if more data is good for prediction or it adds noise. Result of this project also showed there is a importance of recent data in predicting results. This is also validated by the research done under [7]

11 LIMITATION

In this project, analysis is based on two technological stocks: yahoo and amazon. We can extend our study to more diverse portfolio by including more stocks from various industries. Technological stocks tend to be more volatile than other stocks. Since this project is purely quantitative based prediction we deliberately chosen the technological stocks to leverage their volatility. More accurate prediction could also be made by encapsulating qualitative based prediction in the analysis which is more like a hybrid approach. Such hybrid approaches includes assigning weight to each predictions and taking cumulative result. As the part of future work we can also compare results across industry and arrive at conclusion which industry is more stable in prediction. Comparison can based on the root mean square analysis which is discussed in this project report.

12 CONCLUSION

Main objective of doing this project is to know the importance of big data in predicting financial variables. Analysis of this project is based on two stocks: amazon and yahoo. We started this project report with the discussion of importance of big data in financial industry. In the introduction we discussed how various industries are investing in the Big Data to attain higher standards in terms of quality and customer satisfaction. Then we discussed what are

the various types of data available: structured and unstructured. Since in this project we utilized only structured data so it was discussed deeply. This project report also touch base with various challenges financial industry takes in utilizing the value of big data. As the part of literature review we reviewed various researches done in the field of stock returns prediction. In the financial data extraction section we reviewed various technical requirements need for financial data extraction. As the part of data analysis for this project we discussed what are the various ways to fetch live stock data from yahoo or google server. In this project we used the rich financial python libraries for the analysis so we discussed them in details in this report. Financial model which we chose for the prediction is the CAPM model which is explained theoretically in this report. There are two different section where we discussed the proposed analysis and proposed algorithm. We finally concluded the report by discussing three paradigms of prediction. In the end we also mentioned what further can be done under future work section.

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A HID 301:GAGAN ARORA

- Identified Project topic.
- Collected the python financial libraries.
- fetched data from yahoo finance
- Studied, designed and reviewed CAPM model
- Implemented CAPM model using python libraries
- Created project report

B CODE REFERENCE

All code, notebooks and files for this project can be found in the githup repository: <https://github.com/bigdata-i523/hid301/blob/master/project/finalProject.ipynb>

Predicting Housing Prices

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ABSTRACT

In United States, more than 6 million residential homes sold in 2017. With ever-increasing demands, real estate is challenged with complex analysis of homes to provide accurate appraisals and predicting market fluctuations to react accordingly. Big data analytics helps mining the real estate data to provide valuable business insights. In this project, we have planned to analyze housing data to predict sale prices. Using well established datasets, with lots of exploratory variables, we could apply thorough exploration of the data, feature engineering and implement various advanced supervised learning algorithms, such as XGoost, Ridge, Lasso, Random Forest and Neural Network to predict accurate sale prices.

KEYWORDS

i523, hid306, Exploratory Data Analysis, Supervised Learning Algorithms, Ensemble Modeling

1 INTRODUCTION

Real estate, with \$235 million dollar yearly revenue, is a continued growing industry in United States. With more than 200,000 residential and commercial brokerage firms, there are millions houses getting sold every year [9]. In recent times, Big Data has changed the way real estate is getting operated and bringing the importance of data analysis to become major factor in the decision making process. The goal of our project is to predict the sale prices of residential homes listed in the test dataset as accurately as possible. Training dataset contains sale price of the homes, and using this training data set, how accurately we can predict sale prices of the homes in the test dataset by applying data preprocessing and thorough data analysis. In this project, we have applied various exploratory analysis techniques and engineer the features before applying a few advanced supervised learning algorithms such as SVM, XGoost, Ridge, Lasso, Random Forest and Neural Network, to create more accurately predicted models.

2 HOUSING DATA ANALYTICS

Traditional real estate forced buyers to have physical presence to see the homes and meet the realtors. Analyzing the sale price was challenging and require extensive understanding of the neighborhood; highly depend on knowledge of the realtor about recent homes being sold in the surroundings. Assessing the sale price is a daunting task even with a good understanding of the features of any specific home. The true value of mining the real estate data and analyzing it lies in making context-aware relevant data and converting the result to enterprise-grade, tangible and *actionable* business insights. In this project, we would like to predict *sale prices* of housing prices using two datasets - training and testing, each with 79

exploratory variables describing almost every aspect of residential homes in city of Ames, Iowa state. However, the datasets, we have got, are snapshots taken in 2010. As a result, these datasets may not reflect the latest trends in the housing sale prices but the analytical approaches taken in this project are generic and can easily be applied to newer datasets. The key to achieve this lies in getting better handle on the housing data and the trends in sale patterns. With proper housing analytics, not only the realtors get benefit in getting predicted appraisals but also help buyers analyze houses with accurate sale prices within their budget. Machine Learning is empowered with all the capabilities to analyze and provide in depth business insights. Interconnectivity between the economy and housing prices is vital motivating factor in doing this project.

Big Data is defined by *four Vs*: volume, variety, velocity and veracity [5]. (a) Volume: Millions of houses that are in the market for sales will generate high volumes of data. (b) Variety: Housing data comes in various formats: structured, semi-structured and unstructured. Structured data usually come from standard datasets collected at various sources. Video and housing pictures are examples of unstructured data. Traditional relational databases (RDBMSs) will not be suitable for scale out distributed processing to handle such volume and variety. Alternatives like *Hadoop ecosystem*, with Distributed File System, Map, Reduce, etc. aspects, allows complex data processing. (c) Velocity: Data can come in batches, near-real time and real-time. During the housing sale seasons, there will be very high velocity in getting the housing details and the sale transactional data. (d) Veracity: Housing datasets are going to have lots of noise and outlier data. Data mining will address these concerns using *data cleansing* and *normalization* techniques. Various types of analytics can be done using machine learning algorithms and data visualizations to see the classification and predicting model patterns.

Big Data Analytics, in the context of real estate, mainly refers to various analytical activities including population growth, buyer and seller profile matching and neighborhood public schools, using statistical tools and techniques with business acumen to explore hidden information from the available public data across United States. It applies data mining and machine learning algorithms to volume of data coming from multiple sources with various types of data formats. Typical data analytics work-flow include: gathering structured and unstructured data, cleaning the data before modeling, evaluating and visualizing to make them usable for business decisions. Data modeling is, the heart of analytics, to better understand, quantify using statistical algorithms and then visualize the model to comply to the business context. Exploratory data analysis and predictive analytics are two major groups of tasks in the data modeling. Exploratory data analysis uses various techniques to provide useful textual and visual summaries of the characteristics

of the data. Predictive analytics focuses on classification and numerical regression tasks. We will apply predictive analytics in this project, to model the predictions of the *sale prices*.

The real estate industry is tied with Big Data in many ways. Various real estate servicing companies providing advanced insights to buyers and realtors using big data analytics. These companies collect various types of high volume data, such as geographic, census and housing data for rent and sale. Just by using zip code or neighborhood information, one can easily analyze and get the information around potential value of neighborhood properties and trends in the sale. Real estate analytics can tap into *smart cities* data to provide in depth analysis of neighborhood health conditions and energy efficiencies. Banks are using big data sources to analyze and set the prices of foreclosure or short sales in the given neighborhood than offering some lower price which may not correlate with the surrounding similar homes [6]. Big data analytics is going to drive various housing aspects including: buyer identification, accurate pricing and geographic targets [10] along with connecting national and local real estate agents. Social networking datasets can help linking the buyers and sellers [12].

3 DOMAIN KNOWLEDGE

To predict accurate *sale price*, we will need to understand the domain well. We need to build the intuition around all the exploratory variables in the dataset and focus on which factors could influence the target variable: *sale price*. If we do not find all these factors, perhaps, we need to add new features to address the gaps in dataset describing the domain. Some of the factors which, we think, can directly influence house prices are:

- What is the overall Size or area of the house?
- How good is the location of the house - closer to highways?
- How good is the neighborhood?
- How old is the house?
- What is the quality of the construction?
- How many garages are there in the house?
- What are the floor plans?
- How many number of bedrooms are there in the house?
- How many number of bathrooms are there in the house?
- What is the size of living area?

4 EXPLORATORY DATA ANALYSIS

We can start the process with exploratory data analysis. There are 1460 rows in the training data set and 1459 rows in the test dataset. Out of the 80 variables, 23 are nominal, 23 are ordinal, 14 are discrete, and 20 are continuous. The nominal variables are related to material, garage, dwelling, and environmental conditions. All the 20 continuous variables are related to the area dimensions. The ordinal variables rate various items within the property. The home listing includes only few quantified variables like typical lot size and total dwelling square footage, but this data set has more specific variables. There are individual category variables derived from basement, main living area and porch based on quality and type. We have combined training and testing datasets for easier analysis. We excluded Id attribute as it does not add value in the modeling. We also removed Sale Price, the target variable, from the training dataset. All the variables are listed in the appendix section

as a reference. We applied univariate, bivariate and multivariate analytical techniques to analyze numerical and categorical variables. Various statistical and data visualizations were applied on each type of variable. The primary goal of exploratory data analysis is to amplify the insights of analysts onto given input dataset to analyze the aspects, such as:

- Good fitting of the model
- Analyzing impact of the outliers
- Missing value analysis and imputation
- Feature engineering and ranking
- Algorithm selection and tuning for optimal predictions

4.1 Analyze Missing Values

First part of the analysis was to check for any missing values in the training and testing datasets as shown in Figure (1). Using the bar plot shown in Figure (2), we have identified that there are 5 variables: *pool quality*, *miscellaneous features*, *alley*, *fence* and *fire place quality*, having the most missing data.

```
# python code - check for null values
train = pd.read_csv('../data/train.csv')
test = pd.read_csv('../data/test.csv')

#combine the data sets
alldata = train.append(test)
na = alldata.isnull().sum()
na.sort_values(ascending=False)
```

Figure 1: Code - Null Checks

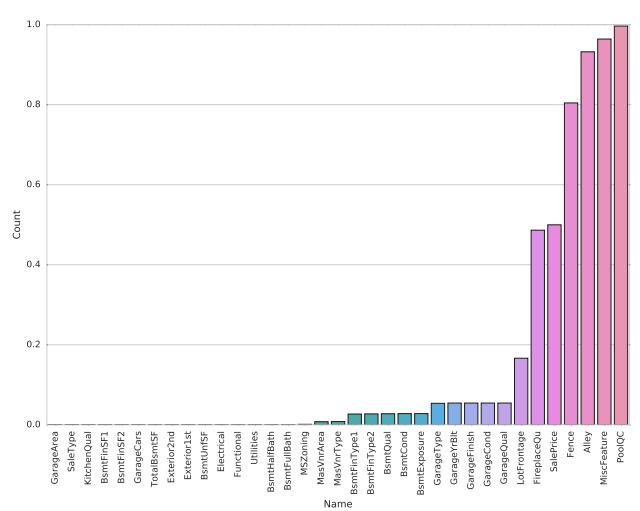


Figure 2: Graph - Missing Values

All the missed values of numeric variables are analyzed further to decide whether we need to delete the instances of all the data with missing values or impute them with something meaningful. There are various ways to find the estimate to replace the missing value including:

- Mean: Replace missed value with the mean value of the corresponding variable
- Regression: Some predicted value by regressing missing variable on all the other variables
- Interpolation and extrapolation: An estimated value from other observations of the same variable

4.2 Analyze Numerical Variables

There are 37 numerical variables after excluding the *Id* variable. List of numerical variables are: MS-Sub-Class, Lot-Frontage, Lot-Area, Overall-Qual, Overall-Cond, Year-Built, Year-Remod-Add, Mas-Vnr-Area, Bsmt-Fin-SF1, Bsmt-Fin-SF2, Bsmt-Unf-SF, Total-Bsmt-SF, 1st-Flr-SF, 2nd-Flr-SF, Low-Qual-Fin-SF, Gr-Liv-Area, Bsmt-Full-Bath, Bsmt-Half-Bath, Full-Bath, Half-Bath, Bedroom-Abv-Gr, Kitchen-Abv-Gr, Tot-Rms-Abv-Grd, Fireplaces, Garage-Yr-Blt, Garage-Cars, Garage-Area, WoodDeck-SF, Open-Porch-SF, Enclosed-Porch, 3Ssn-Porch, Screen-Porch, Pool-Area, Misc-Val, Mo-Sold, Yr-Sold and Sale-Price. *Interval* and *ratio* are the two types of numerical variables we encounter in most of the data analytical applications. Statistical aspects of the numerical univariate analysis include: count, minimum, maximum, mean, median, mode, quantile, range, variance, standard deviation and skewness. Data visualization techniques, such as histogram, box plot and scatter plot are used to analyze the numerical variables. We have shown *sale price*, *overall quality*, *garage live area* and *year built*, in the Figures (4) and (5) as a few sample plots from the numerical analysis. Corresponding code snippet is shown in Figure (3).

```
# python code - analyze numeric variables
numerical_features = [f for f in train.columns
if train.dtypes[f] != object]

nd = pd.melt(train, value_vars = numerical_features)
plt.figure(figsize = (5,3))
plot = sns.FacetGrid (nd, col=variable, col_wrap=4,
sharex=False, sharey = False)
plot = plot.map(sns.distplot, value)
```

Figure 3: Code - Numerical Analysis

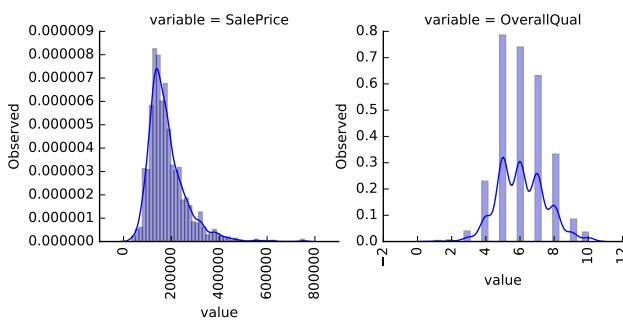


Figure 4: Graph - Sale Price and Overall Quality

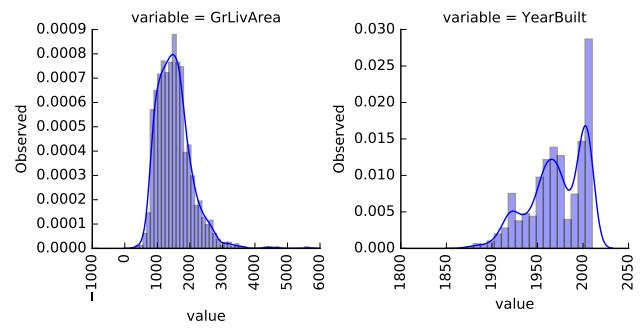


Figure 5: Graph - Ground Live Area and Year Built

4.3 Analyze Categorical Variables

There are 43 categorical variables in the combined dataset. List of categorical variables are: MS-Zoning, Street, Alley, Lot-Shape, Land-Contour, Utilities, Lot-Config, Land-Slope, Neighborhood, Condition1, Condition2, Bldg-Type, House-Style, Roof-Style, Roof-Matl, Exterior-1st, Exterior-2nd, Mas-Vnr-Type, Exter-Qual, Exter-Cond, Foundation, Bsmt-Qual, Bsmt-Cond, Bsmt-Exposure, Bsmt-Fin-Type1, Bsmt-Fin-Type2, Heating, Heating-QC, Central-Air, Electrical, Kitchen-Qual, Functional, Fireplace-Qu, Garage-Type, Garage-Finish, Garage-Qual, Garage-Cond, Paved-Drive, Pool-QC, Fence, Misc-Feature, Sale-Type and Sale-Condition. We have analyzed all categorical variables and found the ways to fill the missing values. We have also evaluated proper approaches to convert them into numerical factors. Bar and pie charts are used to visualize categorical variables. Later on in the feature engineering section, we will go through more details on numerical factors. Categorical variable factors and the corresponding code snippet for *neighborhood* and *sale type* are shown in Figure (6) and Figures (7).

```
# python code - analyze numeric variables
cat_features = [f for f in train.columns
if train.dtypes[f] == object]
print(cat_features)

plt.figure(figsize = (5,3))

p = pd.melt(train, id_vars=SalePrice,
value_vars=cat_features)

g = sns.FacetGrid (p, col=variable, col_wrap=4,
sharex=False, sharey=False, size=5)

g = g.map(barplot, value,SalePrice)
```

Figure 6: Code - Categorical Analysis

4.4 Analyze Correlations

Numpy package offers correlations functionality to analyze the variables that are positively or negatively correlated with the *sale price* and also analyze any interdependencies among the variables.

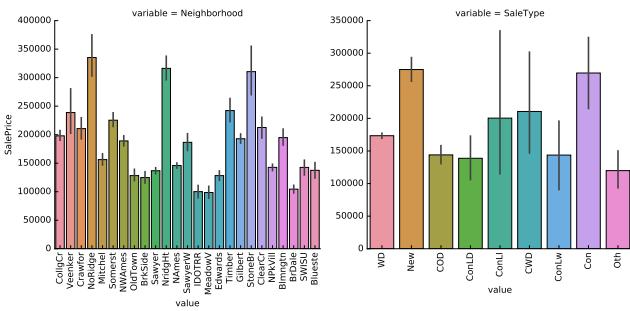


Figure 7: Graph - Neighborhood and Sale Type

Figure (8) and (9) shows the code snippet and the correlations plot. From that we can list the top 10 features those are strongly correlated with the target variable - *sale price*. We can visualize a few pair-wise correlation graphs with sale price for further detailed analysis. Figures (10) and (11) show how *overall quality*, *ground live area*, *garage cars* and *garage area* are positively correlated with *sale price*.

```
# python code
corr = alldata[numerical_features].corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
plt.figure(figsize = (15,8))
sns_plot = sns.heatmap(corr, cmap=YlGnBu,
linewidths=.5, mask=mask, vmax=.3)
```

Figure 8: Code - Correlations

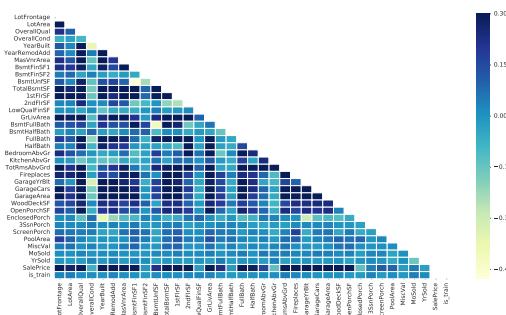


Figure 9: Graph - Correlations with Sale Price

- (1) OverallQual: Overall material and finish quality
 - (2) GrLivArea: Above ground living area square feet
 - (3) GarageCars: Size of garage in car capacity
 - (4) GarageArea: Size of garage in square feet
 - (5) TotalBsmtSF: Total square feet of basement area
 - (6) 1stFlrSF: First Floor square feet
 - (7) FullBath: Full bathrooms above grade
 - (8) TotRmsAbvGrd: Total rooms above ground

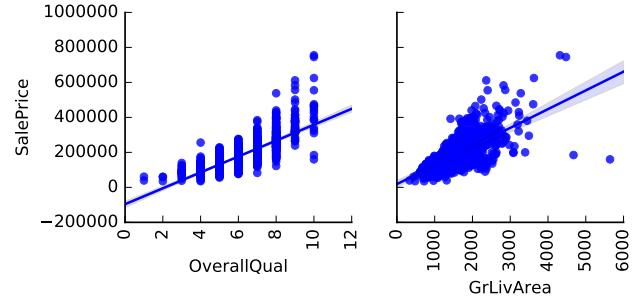


Figure 10: Graph - Overall Quality and Ground Live Area

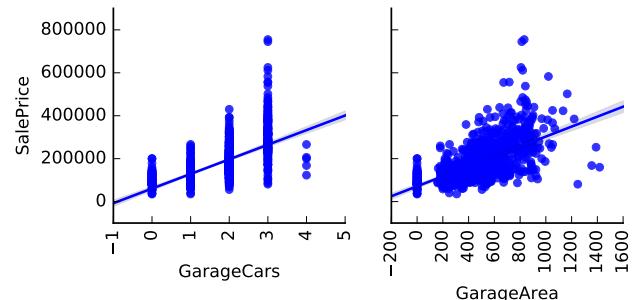


Figure 11: Graph - Garage Cars and Garage Area

- (9) YearBuilt: Original construction date
 - (10) GarageYrBlt: Garage built year

4.5 Skewed Data Analysis

From the numerical analysis, we have identified that there are a few numerical variables need further analysis to identify the skewed data. We did not find any key variables those have skewed more than 75%. However, we wanted to replace the *sale price* with corresponding logarithmic value for the predictive models and later convert it back to the exponential value before saving the predictions. Figure (12) shows the *sale price*, before and after applying the logarithmic value.

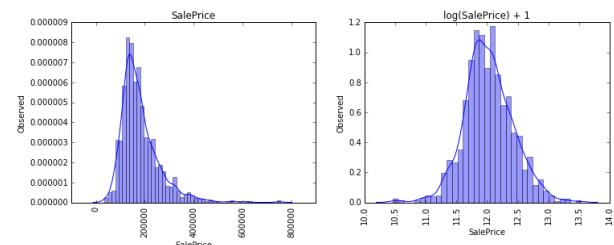


Figure 12: Graph - Sale Price skewness

4.6 Outlier Analysis

Continuing with exploratory analysis, we have analyzed the outliers using *Cooks distance*. Cooks distance is a measure calculated

from a regression model to find out the influence exerted by each observation (row) on the predictions. As a practice, those observations that have a Cooks distance greater than 4 times the mean value may be classified as an outlier. Outlier detection can be done using univariate and multivariate analysis. In univariate model, the outliers are those observations that are present outside of $1.5 * \text{IQR}$, where IQR (*Inter Quartile Range*) is the difference between 75th and 25th quartiles. Analyzing outliers in any observations based on single variable may lead to incorrect inferences. Cooks distance generalizes the outlier analysis using multivariate approach [7]. Figure (13) is the code implementing Cooks distance to find the outliers from training dataset and Figure (14) shows the scatter plot with outliers being marked as bubbles. The bigger the bubbles, the bigger outlier deviations from the mean value. We have further analyzed two key variables - *ground live area* and *garage area* that are in high correlation with the *sale price*. From the scatter plot shown in Figure (15), we can see that *garage live area* has 4 outliers with values greater than 4,000 sq ft. We can also visualize 4 outliers in *garage area* scatter plot with values greater than 1,200 sq ft. as shown in Figure (16). We have removed the 8 outlier rows related to these two variables from the training dataset, the corresponding code snippet shown in Figure (17).

```
# python code - outlier analysis
import statsmodels.api as sm
from statsmodels.formula.api import ols

model = ols(formula = SalePrice ~
GrLivArea + GarageArea, data=train)
fitted = model.fit()
plot = sm.graphics.influence_plot(fitted,
criterion=cooks)
```

Figure 13: Code - Outlier Analysis

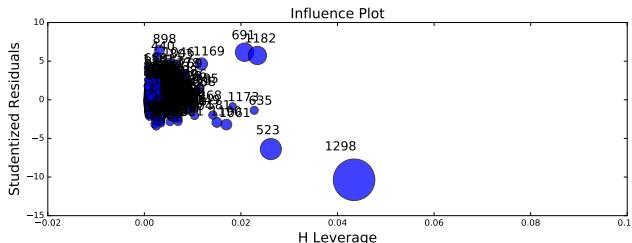


Figure 14: Graph - Outliers using Cooks distance

4.7 Feature Engineering

Feature engineering is a technique to analyze all the variables those influence target variable for better predictions. Part of feature engineering, we may need to create new features to make the data to be more expressive. One of the key intents, in analyzing categorical variables, is to convert them into numerical factors as most of the machine learning algorithms expect all the variables to be numeric for them to work more effectively. Feature engineering

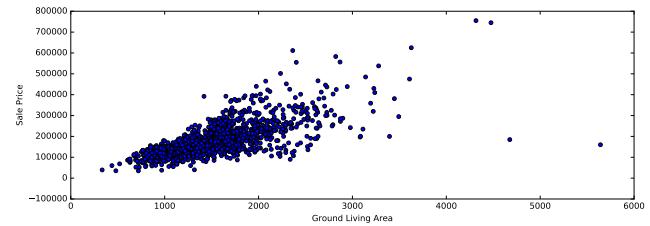


Figure 15: Graph - Garage Live Area Outliers

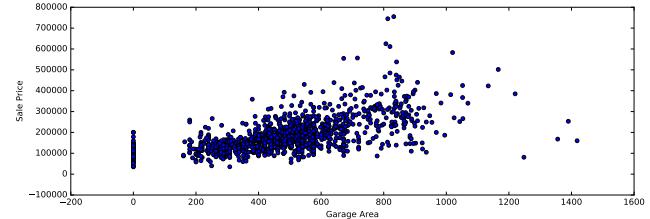


Figure 16: Graph - Garage Area Outliers

```
# python code - remove outlier rows
# fix all extreme outliers based on outlier analysis
# 8 rows will be deleted
train = train[train.GrLivArea <= 4000]
train = train[train.GarageArea <= 1200]
```

Figure 17: Code - Delete Outliers

is a difficult task; majority of the effort is manual and requires lots of domain knowledge.

4.7.1 Numerical Encoding. Some of the categorical variables are ordinal. we can use T-shirt sizes: small, medium and large as an example to explain an ordinal variable. When we convert this category variable into numeric encoding, we need to retain the fact that there is an implicit order within the values. Supposing, we give ordinal encoding as - small = 1, medium = 2 and large = 3; we will satisfy the implicit order or weightage and that helps in modeling the system by elevating the importance of this implicit ordering in the values of the ordinal variable. There are a few other encoding techniques, such as one-hot, binary, polynomial and helmert to factorize categorical variables. We will use ordinal and one-hot encoding techniques for this dataset. Following are a few categorical variables converted to numerical:

- *Lot shape* is encoded as: 1 - regular, 2 - Irregular-I, 3 - Irregular-II, 4 - Irregular-III
- *Alley* is encoded as: 1 - none, 2 - gravel, 3 - paved
- All quality variables such as *garage quality* are encoded as: 0 - none, 1 - poor, 2 - fair 3 - typical 4 - good, 5 - excellent
- *Building type* is encoded as: 1 - single-family, 2 - two-family, 3 - duplex, 4 - townhouse end unit, 5 - townhouse inside unit
- *Overall quality* is encoded as: 1 to 3 - bad, 4 to 6 - average, 7 to 10 - good

4.7.2 One-hot Encoding. One-hot encoding converts the category variable into many binary vectors, one new numeric variable for each value in the category. Assume that we have a categorical variable called signal-light with three possible values: green, yellow and red. We will need to convert these values into numeric - green = 1, yellow = 2 and red = 3. When we apply one-hot encoding on this variable, basically we are creating three new categorical variables - signal-light-green, signal-light-yellow and signal-light-red along with the original variable - signal-light, each is pretty much a binary vector having 1s for all the corresponding values; otherwise 0s. With hot-encoding, we are basically increasing dimensions in the model. After extensive feature engineering applied on the housing dataset, we have added 228 new features (variables). Figure (18) shows the python methods to factorize categorical variables using one-hot encoding techniques.

```
# python code - factorize and one-hot
def get_one_hot(df, col_name, fill_val):
if fill_val is not None:
df[col_name].fillna(fill_val, inplace=True)

dummies = pd.get_dummies(df[col_name], prefix=_ + col_name)
df = df.join(dummies)
df = df.drop([col_name], axis=1)
return df
#end def
```

Figure 18: Code - factorize and one-hot encoding

4.7.3 New Features. By adding new features that fill the gaps in domain model, we can guide the model predictions more accurately. We can easily, create more meaningful new features from existing features, such as:

- What is the total area of the house? - This variable is sum of 18 existing variables that are contributing to the overall size of the house, such as *lot frontage*, *lot area*, *ground live area*, *pool area* and *garage area*.
- Whether house has been ever remodeled? - We can find this out using two variables: *year built* and *year remodel added*.
- House remodeled since? - We can find this out using two variables: *year sold* and *year remodel added*.
- Is it a very new house? - This can be calculated based on *year built*
- What is the age of the house? - This is a calculated value from *year build* (formula: 2010 - *year built*)
- When was it last sold? - This is a calculated value from *year build* (formula: 2010 - *year sold*)
- Which season house was last sold in? - This is a calculated value from *month build*

4.7.4 Handling Null Values.

- LotFrontage: Calculated the median of the LotFrontage grouping by neighborhood and assigned the median value for the homes with null values.

- Street: Filled null values with *Grvl*.
- Alley: Filled null values with *NA*.
- Lot Shape: Filled null values with *Reg*.
- Land Contour: Filled null values with *lsl*.
- Land Slope: Filled null values with *Gtl*
- Neighborhood_Good: Filled null values with 0
- YearRemodAdd: Filled null values with Year Built value.
- GarageYrBlt: Filled null values with 0
- Exterior1st: Filled null values with Mode of this variable
- Exterior2nd: Filled null values with Mode of this variable
- MasVnrArea: Filled null values with 0
- ExterQual: Filled null values with *TA* (numeric factor = 2)
- BsmtQual: Filled null values with *TA* (numeric factor = 2)
- BsmtFinType1: Filled null values with Mode of this variable
- BsmtFinType2: Filled null values with Mode of this variable
- PoolQC: There are entries with *PoolArea* > 0 and *PoolQC* as NA, so filled the values with average condition - *TA*

5 ALGORITHMS AND METHODOLOGY

Broadly speaking, there are three types of machine learning algorithms: supervised, unsupervised and reinforcement learning. *Supervised learning algorithms*: decision trees, linear regression, support vector machines (SVMs), Naive Bayes, neural networks, etc. are popular for classification and regression problems by analyzing labeled training data. K-means clustering algorithms are good for *unsupervised* datasets to categorize based on the identified patterns in unlabeled data. While there are so many factors - nature of the domain, sample size of the dataset and number of attributes defining characteristics of the data - decide which machine learning algorithm works better, Deep Learning neural network algorithms are, getting greater traction, addressing complex analytics tasks including high-dimensionality and automatic creation of new features from existing complex hierarchical features, very well. *Reinforcement Learning* algorithms focus on how to maximize the learning based on rewards and punishments.

Linear regression predicts the target variable using best possible straight line fit to the set predictor variables. The best fit is usually the one that minimizes the root mean squared error (RMSE) between the actual and predicted data points. Logistic regression solves classification problems to predict discrete values based on given training dataset. Simple decision tree algorithms also target solving classification problems. Naive Bayes is also popular for classification type of problems where it assumes independence among the variables. However, with complex problem space such as the housing prices dataset, we have lots of variables relating to the target variable in a non-linear fashion. Trivial supervised learning algorithms will not be effective to provide accurate *sale price* predictions. To overcome this challenge, we have applied various advanced supervised learning algorithms, such as Support Vector Machine (SVM), Random Forest, Lasso, Ridge, XGBoost and Neural Network, to predict the test data housing prices. Following are some of the aspects that are common to all the algorithms:

5.1 Underfitting and Overfitting

Underfitting happens when the model is trivial and does not fit the data properly. As a result it is unable to learn the model properly

hence gives incorrect predictions. Underfitting suffers from low *variance* but high *bias* from the predicted model. Variance measures the variation in learning from different training sets. Variance does not properly filter outliers that are part of the model. Bias prevents generalization beyond the training dataset. Overfitting occurs when the predicted model learns the training dataset including the noise and results negatively impacting the performance and accuracy of the model. Overfitting happens more likely with non-linear and non-parametric algorithms those offer more flexibility. Overfitting, as expected, exhibits low *bias* and high *variance*. Balancing between bias and variance is a challenge and model may have to compromise one over the other.

5.2 Cross Validation

Before applying the trained model onto the testing dataset, we need to validate it. Cross-validation is a technique to validate the trained model by partitioning the original training dataset into two parts - training and cross validation datasets. The cross validation dataset is basically to evaluate the trained model before applying on the actual test dataset. Usually 70% of the original training dataset is kept for training the model and 30% of it for cross validation. This type of cross validation is called *holdout method*. *K-fold cross validation* is more improved and effective cross validation method, where the dataset is divided into k subsets, and the *holdout* method is repeated k times. In each iteration, one of the k subsets is selected as a test dataset and the remaining $k-1$ subsets will be part of the training dataset. In the end, the average error across all k attempts is computed.

5.3 Model Evaluation

We can use evaluation metrics to check accuracy of the trained model. Accuracy, precision, recall and f-score are typical metrics used to evaluate the classification models. Regression models use mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination and relative scored error (RSE) as metrics to verify the accuracy and performance of the model. MAE evaluates how close the predictions are to the actual target variable, hence a lower score is better. RMSE metric summarizes the error in predicted model. By squaring the error, the over and under predictions are controlled. RSE normalizes the total squared error by diving the total squared error of the actual target variable values. Coefficient of determination (R^2) represents the prediction as value between 0 and 1; 0 - means the model is random and 1 - means the model is a good fit.

5.4 Support Vector Machine (SVM) Algorithm

Support Vector Machine (SVM) algorithms can be used to solve classification and regression problems. SVM creates larger margins between categories of data so that they are linearly separable. SVM regression relies on kernel functions for modeling the data. SVM handles non-linearly separable data, mainly for regression problems, using kernel functions, such as polynomial, radial basis function (RBF) and sigmoid, to project the data onto a hyperplane. Figure (19) shows the python implementation for *sale price* predictions of the housing test dataset.

```
# python code - SVM algorithm
from sklearn.svm import SVR

_svm_algo = SVR(kernel = rbf, C=1e3, gamma=1e-8)
_svm_algo.fit(train, target_vector)

y_train = target_vector
y_train_pred = _svm_algo.predict(train)

#root mean squared error (RMSE)
rmse_train = np.sqrt(rmse(y_train,y_train_pred))

y_test_pred = _svm_algo.predict(test)
```

Figure 19: Code - SVM Algorithm

We have used *sklearn.svm* package to implement the SVM algorithm in Python. The SVM kernel used, for the *sale price* prediction, is *radial basis function*. Cost parameter, with a value of $1e3$, is used to increase the margin for better linear separability. Gamma controls the trade-off between error due to bias and variance in the trained model. We have used gamma value as $1e-8$. Once the SVM algorithm is instantiated, we fit the model by passing the training dataset and the *sale prices* vector of the training dataset as Y - target variable. After training the model is done, we checked the *root mean squared error* (RMSE) of the trained model predictions with the actuals to make sure the desired accuracy is being met. In this case, RMSE is calculated as 0.2069. Finally we predict the *sale price* of test dataset and make sure the sale prices are meaningful.

5.5 Random Forest Algorithm

Random Forest is an advanced machine learning algorithm for predictive analytics. Random Forest ensembles multiple decision trees to create an additive learning model from the sequence of base models created by each decision tree that worked on a sub-sample dataset. Random Forest models are suitable to handle tabular datasets with hundreds of numeric and categorical features. Along with missing values, non-linear relations between features and the target, will be handled well by random forest algorithms. By tuning the hyper-parameters of the random forest algorithm, it can perform well with decent accuracy in the predictions without overfitting the model. Random forest uses *voting* concept to predict the target variable and selects the highly voted predicted values as the final selected predictions. Unlike similar regression models, it does not offer feature coefficient information but it provides *feature ranking* functionality very nicely. Figure (20) shows the random forest algorithm details for the *sale price* predictions implemented using *sklearn* package and the Figure (21) shows the top 10 important features selected by random forest to model the predictions.

We have used *sklearn.ensemble* and *sklearn.metrics* packages to implement random forest algorithm. The hyper-parameters used in this algorithm are: *n_estimators* = 100, *oob_score* = True and *random_state* = 123456. Parameter: *n_estimators* is for the number of trees in the random forest. Parameter: *oob_score* is a boolean to indicate whether to use out-of-bag samples to estimate the generalization accuracy. Parameter: *random_state* is used as seed for

```

# python code - random forest algorithm
from sklearn.ensemble import RandomForestRegressor

_algo = RandomForestRegressor(n_estimators=100,
oob_score=True, random_state=123456)
model = _algo.fit(train, target_vector)

feat_imp = pd.Series(_algo.feature_importances_,
train.columns).sort_values(ascending=False)
feat_imp[:10].plot(kind=bar,
title=Feature Ranmkingt)
y_train = target_vector
y_train_pred = _algo.predict(train)

#root mean squared error (RMSE)
rmse_train = np.sqrt(rmse(y_train,y_train_pred))
y_test_pred = _algo.predict(test)

```

Figure 20: Code - Random Forest Algorithm

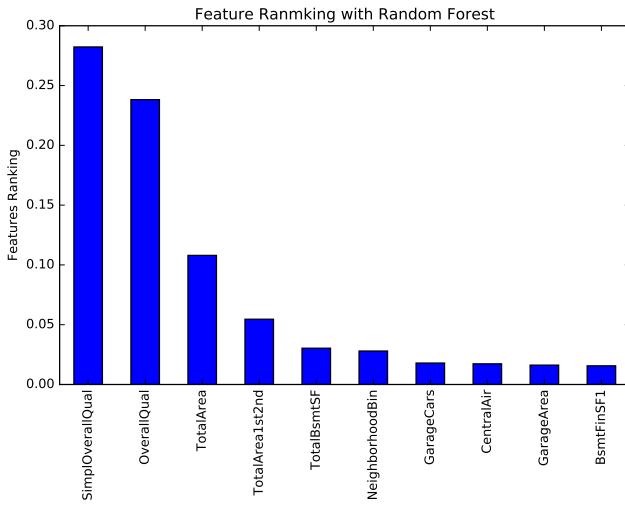


Figure 21: Graph - Random Forest Feature Ranking

the random number generator. Training dataset and the *Sale Price* vector are used as input to fit the model and verified the predicted output of the training dataset. The RMSE is calculated as 0.0519. Finished the implementation by predicting the *sale price* of the test dataset.

5.6 Lasso Algorithm

There are four techniques to model the predictions using linear regression - (1) simple linear regression, (2) Ordinary Least Squares (OLS), (3) Gradient Descent and (4) Regularization. First two techniques are basically using statistical analysis to calculate the coefficients, such as means, standard deviation, covariance and correlations, whereas gradient descent uses sum of the squared errors to scale down the coefficients to minimize the error. Regularization not only minimizes the squared error in the training dataset but

also reduces complexity of the overall model. Two well known algorithms to create the regularized regression models are - Lasso and Ridge regressions. While lasso performs *L1 regularization*, ridge applies *L2 regularization* techniques in modeling the predictions. L1 regularization adds penalty to the variables equivalent to *absolute value of the magnitude* of the coefficients, whereas L2 adds the penalty equivalent to *square of the magnitude* of the variable coefficients.

Lasso is a regression model that uses shrinkage to bring data points towards the center, similar to the mean value of all the data points. Lasso stands for Least Absolute Shrinkage and Selection Operator. It is a regularized linear model with penalty term *lambda* to minimize the error. Parameter penalization controls overfitting the input data by shrinking variable coefficients to 0. Essentially this makes the variables no effect in the model, hence reduces the dimensions. Figure (22) shows the lasso algorithm implementation for *sale price* predictions in python.

```

# python code - lasso algorithm
from sklearn.linear_model import Lasso

_best_alpha = 0.0001
_lasso_algo = Lasso(alpha = _best_alpha,
max_iter = 50000)
model = _lasso_algo.fit(train, target_vector)

y_train = target_vector
y_train_pred = _algo.predict(train)

#root mean squared error (RMSE)
rmse_train = np.sqrt(rmse(y_train,y_train_pred))
y_test_pred = _lasso_algo.predict(test)

```

Figure 22: Code - Lasso Algorithm

We have used *sklearn.linear_model* package to implement lasso algorithm. *sklearn.metrics* is used for RMSE calculations. The two key hyper-parameters used in this algorithm are: *alpha* = 0.0001 and *max_iter* = 50000. The parameter: *alpha* is used as a constant term that multiplies the L1 term. L1 is explained in the following Ridge Algorithm section. We have given alpha by finding the best value through cross validation. Training data and the *sale price* are sent to the *fit* method to fit the model. RMSE is calculated as 0.1015 to evaluate the accuracy of the trained model against the *sale price* of the training dataset. Finally the algorithm predicted the *sale price* of the test dataset.

5.7 Ridge Algorithm

Ridge algorithm is very similar to lasso algorithm with the same goal. Ridge uses *alpha* parameter to control the balance between minimizing the *residual sum of squares* (RSS) and minimizing sum of squares of square of coefficients. As the alpha value increases, the complexity of the model decreases. However, significant value of alpha might cause the model to go underfitting. Figure (23) shows the python implementation of the ridge algorithm for the *sale price*

predictions. Figures (24) and (25) show the top 10 positively and top 10 negatively influencing variables with *sale price*.

```
# python code - ridge algorithm
from sklearn.linear_model import Ridge
#found this best alpha value through cross-validation
_best_alpha = 0.00099
_ridge_algo = Ridge(alpha = _best_alpha,
normalize = True)
_ridge_algo.fit(train, target_vector)

y_train = target_vector
y_train_pred = _ridge_algo.predict(train)

#root mean squared error (RMSE)
rmse_train = np.sqrt(rmse(y_train,y_train_pred))

y_test_pred = _ridge_algo.predict(test)
```

Figure 23: Code - Ridge Algorithm

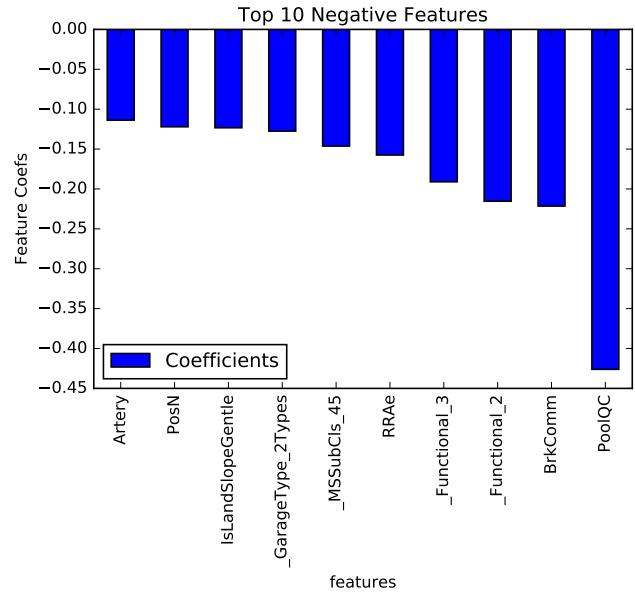


Figure 25: Graph - Ridge Top 10 Negative Features

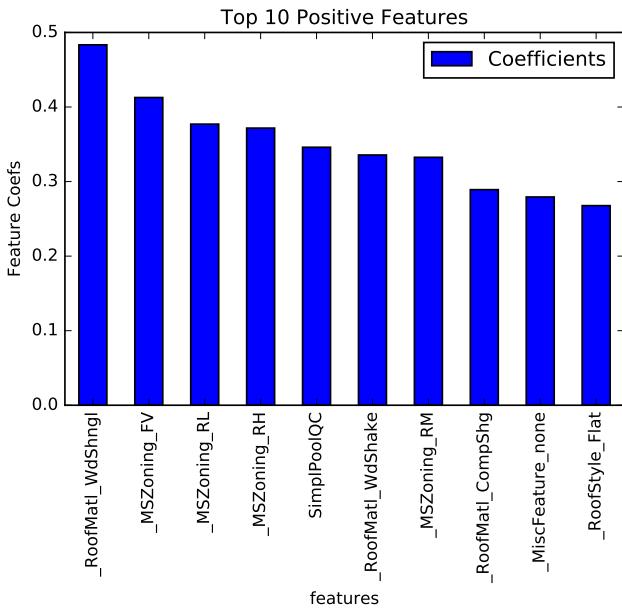


Figure 24: Graph - Ridge Top 10 Positive Features

We have used *sklearn.linear_model* package to implement ridge algorithm. The two key hyper-parameters used in this algorithm are: *alpha* = 0.00099 and *normalize* = True. The parameter: *alpha* is used to denote the *regularization* strength. We have given *alpha* by finding the best value through cross validation. Parameter: *normalize* is used when the value is True to normalize the regressors *X* before regression by subtracting the mean and dividing by the L2 norm. Training data and the *sale price* are sent to the *fit* method to fit the model. RMSE is calculated as 0.09888 to evaluate the accuracy.

of the trained model against the *sale price* of the training dataset. We have also extracted the top 10 positive and negative features influencing the target variable - *sale price*. Finally the algorithm predicted the *sale price* of the test dataset.

5.8 XGBoost Algorithm

XGBoost (eXtreme Gradient Boosting) is one of the Gradient Boosted Machine algorithms. It ensembles (combines) optimized model by taking trained models from all the preceding iterations. XGBoost regularizes the variables (parameters) using L1 and L2 regularizations to reduce the overfit and can work well with variables having missing values. It is empowered with built-in cross validation to reduce the boosting iterations; hence offers better performance along with parallel processing on multi-core CPU and also can also work with very large datasets in distributed environments. Execution speed and the performance of model creation make XGBoost a very good choice. There are many variations of XGBoost, such as gradient boosting machine, stochastic gradient boosting and additive regression tree, and all of them use gradient descent methods to minimize the loss function. By tuning the XGBoost hyper parameters, we can achieve well optimized model that can make more accurate predictions. XGBoost uses *F-Score* to measure the importance of variables. Our implementation of *sale price* predictions using XGBoost is shown in Figure (26). Following list explains the hyper-parameters of XGBoost algorithm.

- Maximum Iterations - Number of trees in the final model. More the trees, more accuracy.
- Maximum Depth - Depth of each individual tree to control overfitting.
- Step Size - Shrinkage, works similar to learning rate; smaller value takes more iterations.

- Column Subsample - Subset of the columns to use in each iteration.

```
# python code - XGBoost algorithm
import xgboost as xgb

_xgb_algo = xgb.XGBRegressor(
    colsample_bytree=0.8,
    colsample_bylevel = 0.8,
    gamma=0.01,learning_rate=0.05,
    max_depth=5, min_child_weight=1.5,
    n_estimators=6000, reg_alpha=0.5,
    reg_lambda=0.5,subsample=0.7,
    seed=42, silent=1)

_xgb_algo.fit(train, target_vector)

y_train = target_vector
y_train_pred = _xgb_algo.predict(train)

#root mean squared error (RMSE)
rmse_train = np.sqrt(rmse(y_train,y_train_pred))
y_test_pred = _xgb_algo.predict(test)
```

Figure 26: Code - XGBoost Algorithm

We have used *xgb* package to implement the XGBoost algorithm. Various hyper-parameters are used to tune the algorithm and a few of them are explained in the above list. The training dataset and the *sale price* vector are used to fit the model. Top 10 features selected by XGBoost algorithm are: TotalArea, LotArea, GarageArea, All_Liv_SF, BsmtUnfSF, 1stFlrSF, BsmtFinSF1, LotFrontage, TotalBsmtSF and Age, including the hot-encoded variables and new features created through feature engineering. We have captured the *feature ranking* as a graph and evaluated accuracy of the predictions by calculating RMSE on training dataset. Finally, we have predicted *sale prices* of the test dataset. Figure (27) shows the top 10 features selected by the XGBoost.

5.9 Neural Network Algorithm

Neural Network is, a *directed graph*, organized by layers and layers are created by number of interconnected neurons (or nodes). Every neuron in a layer is connected with all the neurons from previous layer; there will be no interaction of neurons within a layer. The performance of a Neural Network is measured using *cost or error function* and the dependent input *weight* variables. *Forward-propagation* and *back-propagation* are two techniques, neural network uses repeatedly until all the input variables are adjusted or calibrated to predict accurate output. During, forward-propagation, information moves in forward direction and passes through all the layers by applying certain weights to the input parameters. *Back-propagation* method minimizes the error in the *weights* by applying an algorithm called *gradient descent* at each iteration step.

Deep Learning is an advanced neural network, with multiple hidden layers (thousands or even more deep), that can work well with supervised (labeled) and unsupervised (unlabeled) datasets.

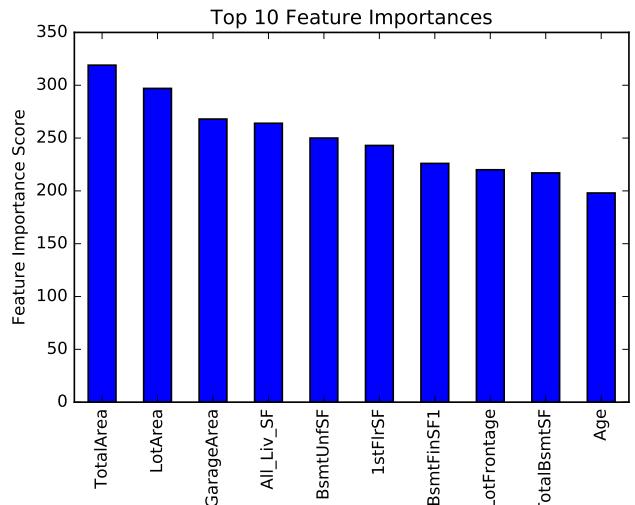


Figure 27: Graph - XGBoost Feature Importance

Applications, such as speech, image and behavior patterns, having complex relationships in large-set of attributes, are best suited for Deep Learning Neural Networks. Deep Learning vectorizes the input and converts it into output vector space by decomposing complex geometric and polynomial equations into a series of simple transformations. These transformations go through neuron activation functions at each layer parameterized by input weights. Deep Learning makes neurons learn new features themselves, in an unsupervised manner, from existing features distributed in several hidden layers. *Stacked Autoencoder* (AE) is, a Deep Belief Network algorithm, to create advanced predictive models for large datasets having thousands or even millions of dimensions, automatically, with complex hierarchical attributes in non-linear fashion for simpler computing. Though AE is sophisticated, it is very difficult to understand the algorithm logic and so unable to reuse the learnings from the modeling to other systems. We have used *TensorFlow* python library to predict the *sale price* of housing dataset using simple feed-forward neural network. TensorFlow uses *tensors*, special multi-dimensional arrays to store the datasets for easier linear algebra and vector calculus operations.

We have implemented Neural Network algorithm by creating a TensorFlow based work-flow. We have created various objects, such as input variables, loss computation, optimizer and the predictions for TensorFlow to create the model. TensorFlow tunes the hyper-parameters using number of cross-validation iterations before finally predicting the *sale prices* of test dataset. Deep Learning, by design, allows parallel programming, as each module - with all the dependencies among neurons - can run independently and parallelly from other modules within the network. Using Graphics Process Unit (GPU), module networks can achieve parallel programming without needing much of Central Processing Unit (CPU) allocation of a computer. Though GPU is intended for graphical processing, it works efficiently to run thousands of small mathematical functions, such as matrix multiplications, in parallel. Cloud computing and edge analytics offer flexible scale out distributed processing

options using virtualization and containerization. Sophisticated algorithms and distributed computing make Deep Learning scale and perform well to process huge datasets.

5.10 Model Ensembling

We can create a robust predictive model with better accuracy by merging two or more machine learning algorithms. This technique is called *model ensembling*. Ensembled algorithms may be similar in functionality or may entirely be different from each other. Individual algorithms may not perform great but by ensembling them, the overall system can offer much better performance and accuracy. Variations in the predicting logic in each of these individual algorithms will bring unbiasedness into the unified model. *Bagging*, *boosting* and *stacking* are popular ensembling techniques. Many of the advanced machine learning algorithms use ensembled approaches to achieve accurate classifications or predictions. Random Forest uses bagging, XGBoost uses boosting and Neural Network applies stacking ensembling techniques. To optimize the predictions, we have created an ensembled model by averaging *Sale Price* of the top 3 performing ensembled algorithms - XGBoost, Lasso and Neural Network. As predicted, ensembled model has predicted better with less RMSE (*root mean squared error*), compared to all the individual algorithms. Following list displays each algorithm and the corresponding *root mean squared error* (RMSE).

- SVM - RMSE = 0.2069
- Random Forest - RMSE = 0.0519
- XGBoost - RMSE = 0.0432
- Lasso - RMSE = 0.1015
- Ridge - RMSE = 0.0988
- Neural Network - RMSE = 0.20

6 DEVELOPMENT ENVIRONMENT

6.1 OS and Programming Language

We have used *Ubuntu 16.4* Operating System that runs in Windows 10 through Oracle Virtual Box 5.2. Python 2.7 has been used as the programming language for this project. Data visualizations are done using *seaborn* and *matplotlib* packages. Most of the algorithms implemented in this project are using *sklearn* package. For the neural network algorithm, we have used *tensorflow* package as it offers simple programming interface to the complex processing needed by the algorithm. Our code is placed in gitHub repository at <git@github.com:bigdata-i523/hid306.git>.

6.2 Project Folder Structure

Project is organized in three folders - code, data and images. Code folder has all the python code files. Data folder contains the *house pricing* sample datasets that we used for the exploratory analysis and *sale price* predictions. We also stored all the *sale price* prediction output files from various algorithms in the data folder. Images folder contains all the data visualization files that we have created during the analysis and in processing the algorithms. We wanted to create interactive and sharable code files that contain not only the python code but also corresponding explanation along with data visualizations. Jupyter Notebook application is ideal for such

facilitation with python code components. Using Jupyter Notebook, it would be easy to share live code with the reviewers. Such environment allows to explore the code-base easily along with the interactive code execution and visualize all the corresponding exploratory analysis results with the graphs.

6.3 Project Files

We have a total of 11 Jupyter Notebook driven python code files. First 4 files are focused on doing the exploratory data analysis and the next 6 files are meant for six supervised machine learning algorithms - SVM, Random Forest, Ridge, Lasso, Neural Network and XGBoost. Last code file is dedicated for ensembling the top 3 algorithms with best predictions of housing sale prices in the test dataset. We have named them in a sequence as there is an implicit order in the execution of these files. We wanted to do the data analysis first before running the predictive algorithms.

6.4 List of Code Files

Following is the list of code files:

- Exploratory Analysis Numerical - To load datasets and analyze all numerical variables
- Exploratory Analysis Categorical - To analyze categorical variables in the dataset
- Outlier And Skewed Data Analysis - Handles outlier and skewed data analysis
- Feature Engineering - All the feature engineering is done in this file
- SVM Algorithm - Implementation of SVM algorithm
- Random Forest Algorithm - Implementation of Random Forest algorithm
- Ridge Algorithm - Implementation of Ridge algorithm
- Lasso Algorithm - Implementation of Lasso algorithm
- Neural Network Algorithm - Implementation of Neural Network algorithm
- XGBoost Algorithm - Implementation of XGBoost algorithm
- Ensembled Model - Implementation of Ensembled algorithm

6.5 List of Data Files

Following is the list of data files:

- Housing Dataset with Sale Price - Sample training dataset with housing attributes along with the sale price
- Housing Dataset without Sale Price - Sample testing dataset similar to training dataset without the sale price
- SVMs Algorithm Predictions - Predicted Housing Sale Prices from SVM algorithm
- Random Forest Algorithm Predictions - Predicted Housing Sale Prices from Random Forest algorithm
- Ridge Algorithm Predictions - Predicted Housing Sale Prices from Ridge algorithm
- XGBoost Algorithm Predictions - Predicted Housing Sale Prices from XGBoost algorithm
- Lasso Algorithm Predictions - Predicted Housing Sale Prices from Lasso algorithm

- Neural Network Predictions - Predicted Housing Sale Prices from Neural Network algorithm
- Ensembled Model Predictions - Predicted Housing Sale Prices from Ensembled algorithm

7 CONCLUSION

Though the datasets we have used are old, the complexity of the dataset is challenging enough for us to find the optimized algorithms to get the accurate predictions. Generally, ensemble models performs better compared to individual algorithms. However, there are a few factors that influence accuracy and performance of the algorithms, such as handcrafted feature engineering, proper cost function with regularized input to address non-linearities in the training datasets and tuning hyper-parameters of the algorithms. While Deep Learning Neural Networks are good for image processing, K-Nearest Neighbor algorithms can handle unsupervised datasets with less complexity. Domain knowledge and algorithm selection play vital role in getting accurate predictions. XGBoost, Random Forest, Lasso and Neural Networks are advanced machine learning algorithms dominating in the Big Data analytics for classification and regression related tasks. With ensembling and iterative learning techniques, they can scale well and offer better predictions for huge datasets having large number of features.

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A SAMPLE DATASET FILE DETAILS

The training and testing sample datasets contain the same variables explaining the housing real estate aspects. Training dataset contains the sale price information whereas the testing dataset does not the sale price as that is the target variable we need to predict using supervised machine learning algorithm. Following are the list of variables describing the housing real estate domain. Good understanding of the domain is needed for better exploratory data analysis and to apply the matching machine learning algorithms to the problem space.

- Id: Row Id
- SalePrice: Sale price of the house in dollars. This is the target variable to predict.
- MSSubClass: The building class
- MSZoning: The general zoning classification
- LotFrontage: Linear feet of street connected to property
- LotArea: Lot size in square feet
- Street: Type of road access
- Alley: Type of alley access
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LotConfig: Lot configuration
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits
- Condition1: Proximity to main road or railroad
- Condition2: Proximity to main road or railroad (if a second is present)
- BldgType: Type of dwelling
- HouseStyle: Style of dwelling
- OverallQual: Overall material and finish quality
- OverallCond: Overall condition rating
- YearBuilt: Original construction date
- YearRemodAdd: Remodel date
- RoofStyle: Type of roof
- RoofMatl: Roof material
- Exterior1st: Exterior covering on house
- Exterior2nd: Exterior covering on house (if more than one material)
- MasVnrType: Masonry veneer type
- MasVnrArea: Masonry veneer area in square feet
- ExterQual: Exterior material quality
- ExterCond: Present condition of the material on the exterior
- Foundation: Type of foundation
- BsmtQual: Height of the basement
- BsmtCond: General condition of the basement
- BsmtExposure: Walkout or garden level basement walls
- BsmtFinType1: Quality of basement finished area
- BsmtFinSF1: Type 1 finished square feet
- BsmtFinType2: Quality of second finished area (if present)
- BsmtFinSF2: Type 2 finished square feet
- BsmtUnfSF: Unfinished square feet of basement area
- TotalBsmtSF: Total square feet of basement area
- Heating: Type of heating
- HeatingQC: Heating quality and condition

- CentralAir: Central air conditioning
- Electrical: Electrical system
- 1stFlrSF: First Floor square feet
- 2ndFlrSF: Second floor square feet
- LowQualFinSF: Low quality finished square feet (all floors)
- GrLivArea: Above grade (ground) living area square feet
- BsmtFullBath: Basement full bathrooms
- BsmtHalfBath: Basement half bathrooms
- FullBath: Full bathrooms above grade
- HalfBath: Half baths above grade
- Bedroom: Number of bedrooms above basement level
- Kitchen: Number of kitchens
- KitchenQual: Kitchen quality
- TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
- Functional: Home functionality rating
- Fireplaces: Number of fireplaces
- FireplaceQu: Fireplace quality
- GarageType: Garage location
- GarageYrBlt: Year garage was built
- GarageFinish: Interior finish of the garage
- GarageCars: Size of garage in car capacity
- GarageArea: Size of garage in square feet
- GarageQual: Garage quality
- GarageCond: Garage condition
- PavedDrive: Paved driveway
- WoodDeckSF: Wood deck area in square feet
- OpenPorchSF: Open porch area in square feet
- EnclosedPorch: Enclosed porch area in square feet
- 3SsnPorch: Three season porch area in square feet
- ScreenPorch: Screen porch area in square feet
- PoolArea: Pool area in square feet
- PoolQC: Pool quality
- Fence: Fence quality
- MiscFeature: Miscellaneous feature not covered in other categories
- MiscVal: Dollar Value of miscellaneous feature
- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale

A.1 Factorization of categorical variables

Following are the factorized categorical variable details:

A.1.1 Street (Nominal). : Type of road access to property

- Grvl - Gravel
- Pave - Paved

A.1.2 Alley (Nominal). : Type of alley access to property

- Grvl- Gravel
- Pave - Paved
- NA - No alley access

A.1.3 Lot Shape (Ordinal). : General shape of property

- Reg - Regular
- IR1 - Slightly irregular

- IR2 - Moderately Irregular
- IR3 - Irregular

A.1.4 Land Contour (Nominal). : Flatness of the property

- Lvl - Near Flat /Level
- Bnk - Banked - Quick and significant rise from street grade to building
- HLS - Hillside - Significant slope from side to side
- Low - Depression

A.1.5 Land Slope (Ordinal). : Slope of property

- Gtl - Gentle slope
- Mod - Moderate Slope
- Sev - Severe Slope

A.1.6 Utilities (Ordinal). : Type of utilities available

- AllPub - All public Utilities (E,G,W, and S)
- NoSewr - Electricity, Gas, and Water (Septic Tank)
- NoSeWa - Electricity and Gas Only
- ELO - Electricity only

A.1.7 Lot Config (Nominal). : Lot configuration

- Inside - Inside lot
- Corner - Corner lot
- CulDSac - Cul-de-sac
- FR2 - Frontage on 2 sides of property
- FR3 - Frontage on 3 sides of property

A.1.8 Neighborhood (Nominal). : Physical locations within Ames city limits (map available)

- Blmngtn - Bloomington Heights
- Blueste - Bluestem
- BrDale - Briardale
- BrkSide - Brookside
- ClearCr - Clear Creek
- CollgCr - College Creek
- Crawfor - Crawford
- Edwards - Edwards
- Gilbert - Gilbert
- Greens - Greens
- GrnHill - Green Hills
- IDOTRR - Iowa DOT and Rail Road
- Landmrk - Landmark
- MeadowV - Meadow Village
- Mitchel - Mitchell
- Names - North Ames
- NoRidge - Northridge
- NPkVill - Northpark Villa
- NridgHt - Northridge Heights
- NWAmes - Northwest Ames
- OldTown - Old Town
- SWISU - South and West of Iowa State University
- Sawyer - Sawyer
- SawyerW - Sawyer West
- Somerst - Somerset
- StoneBr - Stone Brook
- Timber - Timberland
- Veenker - Veenker

A.1.9 *Condition 1 (Nominal)*. : Proximity to various conditions

- Artery - Adjacent to arterial street
- Feedr - Adjacent to feeder street
- Norm - Normal
- RRNn - Within 200 feet of North-South Railroad
- RRAAn - Adjacent to North-South Railroad
- PosN - Near positive off-site feature-park, greenbelt, etc.
- PosA - Adjacent to positive off-site feature
- RRNe - Within 200 feet of East-West Railroad
- RRAe - Adjacent to East-West Railroad

A.1.10 *Condition 2 (Nominal)*. : Proximity to various conditions
(if more than one is present)

- Artery - Adjacent to arterial street
- Feedr - Adjacent to feeder street
- Norm - Normal
- RRNn - Within 200 feet of North-South Railroad
- RRAAn - Adjacent to North-South Railroad
- PosN - Near positive off-site feature-park, greenbelt, etc.
- PosA - Adjacent to positive off-site feature
- RRNe - Within 200 feet of East-West Railroad
- RRAe - Adjacent to East-West Railroad

A.1.11 *Bldg Type (Nominal)*. : Type of dwelling

- 1Fam - Single-family Detached
- 2FmCon - Two-family Conversion; originally built as one-family dwelling
- Duplx - Duplex
- Twnhse - Townhouse End Unit
- Twnhsl - Townhouse Inside Unit

A.1.12 *Variable: MS Zoning*. MS Zoning (Nominal): Identifies the general zoning classification of the sale.

- A - Agriculture
- C - Commercial
- FV - Floating Village Residential
- I - Industrial
- RH - Residential High Density
- RL - Residential Low Density
- RP - Residential Low Density Park
- RM - Residential Medium Density

A.1.13 *House Style (Nominal)*. : Style of dwelling

- 1Story - One story
- 1.5Fin - One and one-half story: 2nd level finished
- 1.5Unf - One and one-half story: 2nd level unfinished
- 2Story - Two story
- 2.5Fin - Two and one-half story: 2nd level finished
- 2.5Unf - Two and one-half story: 2nd level unfinished
- SFOyer - Split Foyer
- SLvl - Split Level

A.1.14 *Overall Qual (Ordinal)*. : Rates the overall material and finish of the house

- 10 - Very Excellent
- 9 - Excellent
- 8 - Very Good
- 7 - Good

- 6 - Above Average
- 5 - Average
- 4 - Below Average
- 3 - Fair
- 2 - Poor
- 1 - Very Poor

A.1.15 *Overall Cond (Ordinal)*. : Rates the overall condition of the house

- 10 - Very Excellent
- 9 - Excellent
- 8 - Very Good
- 7 - Good
- 6 - Above Average
- 5 - Average
- 4 - Below Average
- 3 - Fair
- 2 - Poor
- 1 - Very Poor

A.1.16 *Roof Style (Nominal)*. : Type of roof

- Flat - Flat
- Gable - Gable
- Gambrel - Gabrel (Barn)
- Hip - Hip
- Mansard - Mansard
- Shed - Shed

A.1.17 *Roof Matl (Nominal)*. : Roof material

- ClyTile - Clay or Tile
- CompShg - Standard (Composite) Shingle
- Membran - Membrane
- Metal - Metal
- Roll - Roll
- Tar and Grv - Gravel and Tar
- WdShake - Wood Shakes
- WdShngl - Wood Shingles

A.1.18 *Exterior 1 and 2 (Nominal)*. : Exterior covering on house

- AsbShng - Asbestos Shingles
- AsphShn - Asphalt Shingles
- BrkComm - Brick Common
- BrkFace - Brick Face
- CBlock - Cinder Block
- CemntBd - Cement Board
- HdBoard - Hard Board
- ImStucc - Imitation Stucco
- MetalSd - Metal Siding
- Other - Other
- Plywood - Plywood
- PreCast - PreCast
- Stone - Stone
- Stucco - Stucco
- VinylSd - Vinyl Siding
- Wd Sdng - Wood Siding
- WdShng - Wood Shingles

A.1.19 *Mas Vnr Type (Nominal)*. : Masonry veneer type

- BrkCmn - Brick Common
- BrkFace - Brick Face
- CBlock - Cinder Block
- None - None
- Stone - Stone

A.1.20 *Bsmt Cond, Exter Qual and Exter Cond (Ordinal)*. : Evaluates the quality of the material on the exterior

- Ex - Excellent
- Gd - Good
- TA - Average/Typical
- Fa - Fair
- Po - Poor

A.1.21 *Foundation (Nominal)*. : Type of foundation

- BrkTil - Brick and Tile
- CBlock - Cinder Block
- PConc - Poured Concrete
- Slab - Slab
- Stone - Stone
- Wood - Wood

A.1.22 *Bsmt Qual (Ordinal)*. : Evaluates the height of the basement

- Ex - Excellent (100+ inches)
- Gd - Good (90-99 inches)
- TA - Typical (80-89 inches)
- Fa - Fair (70-79 inches)
- Po - Poor (<70 inches)
- NA - No Basement

A.1.23 *Bsmt Exposure (Ordinal)*. : Refers to walkout or garden level walls

- Gd - Good Exposure
- Av - Average Exposure (split levels or foyers typically score average or above)
- Mn - Minimum Exposure
- No - No Exposure
- NA - No Basement

A.1.24 *BsmtFin Type 1 (Ordinal)*. : Rating of basement finished area

- GLQ - Good Living Quarters
- ALQ - Average Living Quarters
- BLQ - Below Average Living Quarters
- Rec - Average Rec Room
- LwQ - Low Quality
- Unf - Unfinished
- NA - No Basement

A.1.25 *BsmtFin Type 2 (Ordinal)*. : Rating of basement finished area (if multiple types)

- GLQ - Good Living Quarters
- ALQ - Average Living Quarters
- BLQ - Below Average Living Quarters
- Rec - Average Rec Room
- LwQ - Low Quality
- Unf - Unfinished
- NA - No Basement

A.1.26 *Heating (Nominal)*. : Type of heating

- Floor - Floor Furnace
- GasA - Gas forced warm air furnace
- GasW - Gas hot water or steam heat
- Grav - Gravity furnace
- OthW - Hot water or steam heat other than gas
- Wall - Wall furnace

A.1.27 *Electrical (Ordinal)*. : Electrical system

- SBrkr - Standard Circuit Breakers and Romex
- FuseA - Fuse Box over 60 AMP and all Romex wiring (Average)
- FuseF - 60 AMP Fuse Box and mostly Romex wiring (Fair)
- FuseP - 60 AMP Fuse Box and mostly knob and tube wiring (poor)
- Mix - Mixed

A.1.28 *HeatingQC (Ordinal)*. : Heating quality and condition

- Ex - Excellent
- Gd - Good
- TA - Average/Typical
- Fa - Fair
- Po - Poor

A.1.29 *Central Air (Nominal)*. : Central air conditioning

- N - No
- Y - Yes

A.1.30 *KitchenQual (Ordinal)*. : Kitchen quality

- Ex - Excellent
- Gd - Good
- TA - Typical/Average
- Fa - Fair
- Po - Poor

Big Data Applications in Real Estate Analysis

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ABSTRACT

Big Data analysis reveals and comforts buyers with knowledge and facts about the neighborhood, its people and trends. Reducing risk of buying and predicting changes in home value for potential buyers.

KEYWORDS

i523, hid320, Big Data Applications and Analytics, Real Estate

1 INTRODUCTION

When one mentions American dream, home ownership is first aspect that comes to mind. Another part of the American dream is financial success and wealth building. Buying your dream home to raise the family is obvious part of the real estate. For most Americans buying a home is the largest purchase they will ever make. Coupled with the fact that most conventional mortgages span 30 years research and analysis required to make educated choice should not be taken lightly as it will have implications on lifestyle for practically 40 percent of your lifetime. Successful investment in your home, potential rental property or land can lead to financially windfall. Failure to make right choices in real-estate purchases may have disastrous consequences. Financial ruin is obvious part of the equation. Majority of divorces in the united states are caused by financial duress in the households. Resulting in stress negatively affecting one's health.

The latest trend in real estate is application of Big Data. Big Data manipulation is booming and transforming the industry. We are seeing a huge move in usage of Big data and analytics. Companies build property matching online software based on customers behavior and their needs. The opportunities of Big Data are truly endless. It creates the power to change our thinking in decision making and develops efficient business approach by extracting variety of collected data points and reducing risks for consumers.

Big Data is already changing real estate industry by optimizing consumers search, offers recommendations on real estate websites to potential buyers and sellers. Utilizing Big Data in real estate could match customers with their desired home. It might include how many bedrooms they need, what neighborhood fits best, affordability, schools, crime rates, potential business property for rent, location and communities.

When using Big Data and analytics, it is possible to review patterns to understand whether the property is a good investment and a great match to potential customer. It is also possible to analyze what buyers are selecting more often and based on that data create a model.

When selecting a specific house for sale, Big Data integration within online websites made it possible to analyze local surroundings, sale patterns and neighborhood personality of each area. It created a knowledge comfort by having facts of the neighborhood, its people; and therefore reducing the risk of buying or investing in the wrong property.

2 BIG DATA IN REAL ESTATE BUSINESS

Risk mitigation is essential part of the way Big Data is transforming real estate. Open data across the internet and variety of Big Data tools added strong force for analysis in decision making of choosing right property or home. It equipped customers with the valuable information by extracting the data and cross analyzing it.

Big real estate agencies such as Realtor [13], Zillow [22] and Trulia [16], are pioneering those tools and provide estimated forecast of the property value from 1 to 10 years. Additionally, they provide information about the neighborhood trends, estimate mortgage payment, cost of ownership, history of the property and current value. The calculation is based on variety of public data records, market information, user data points [21] by using Big Data analysis formula developed in-house.

2.1 Real Estate Industry Evolution

Automated valuation methods have been used for a very long time. For decades banks utilized "Automated Valuation Model" to estimate home values. At one point banks wanted to exclusively rely on this model more than home values provided by professional appraisers. That practice led to problems with by omitting important nuances about condition resulting in overvaluation and undervaluation of properties. Big Data analysis and property estimates generated by online real estate giants are the next step in the evolution of real estate industry. This evolution diminishes importance and need for a real-estate agents as it is able to gather a lot of tribal information known only to experts in the area. That means this change can impact job market for over six hundred thousand active agents in the US.

2.2 Real Estate and Artificial Intelligence

Real estate businesses worry that unlocking the vast amount of data about properties could transform the business to be powered by artificial intelligence.

However, based on the GeekWire article [7] big data and artificial intelligence will not replace real estate agents. Robots are just big help and enrichment to the business. It created much better and safer decision making models. Artificial intelligence will help to deliver information about real estate transactions and trends to consumers. It says that in future Amazon voice or Siri could provide

useful information about popular housing trends and market value. Additionally, it can reveal the data on how many people were interested in the property and bids.

So far it is not a robot that is thinking and proactively making decision, it is just a voice based system that extracts the information from Big Data.

For the last twenty years, industry worries about loosing jobs in that area. However, the industry stayed the same. People still want an advice before making an important decision. Even thought, there so much more information and streamlined sales, individuals that want relationships, empathy and connecting with people are still there.

Obviously, there is some fear in real estate that robots can rock the world for real estate business. However, Big Data empowers agents with information and data, it is making them better providers with higher service.

2.3 Online Real Estate Agencies

Online real estate agencies calculate market value by using proprietary formulas. They are not providing expert estimation but a starting point in estimated property monetary worth. It is calculated from public data and surveys, by utilizing special features, market conditions and location. Additionally, they encourage consumers and homeowners to expand online data by doing other investigations such as comparing market prices for around areas, working with a real estate agent, getting an appraisal from an expert and visiting the house [21].

For example Zillow, developed a Zestimate prediction[21], which is Zillow's estimate of a home that currently on sale, one to ten years from now. The provided information based on current house and market condition. Other real estate agencies with online presence competing with Zillow, like Trulia and Realtor for example have developed similar proprietary formulas to assist customers.

Also, the companies provide rent estimates that would help evaluate potential monthly rental price by developed in-house algorithmic formula. Variations in rental prices can also happen because of different factors, additional investments, or length of lease.

Big Data information affects the forecasting. As an example, the amount of rental listings in a specific area affects how much we know about approximate prices in that area for condos, apartments and houses. Based on number of properties for rent, the prediction becomes more accurate. Homeowners can also update and provide information online about their needs or property, which helps even more for predicted accuracy.

The formula they use to estimate rent prices is comparing similar homes and apartments in the given area. Comparing bedrooms, square footage and other details. Then prices are being compared, and pattern to rental prices is shown.

Big data analysis provides unbiased information. Although, majority of real estate agents are esteemed professionals looking out for client's best interests they are still. There are still those that would like to manipulate client's opinion to benefit themselves. For example, if a particular house have been on the market too long and the agent might lose the listing there is a possibility that some shortcoming of the property will be omitted by the agent in order to complete the sale. Same can be said about agents trying

to achieve some sales goals or quotas. However, if the potential buyer conducts the research using Big Data all information will be available. Put simply, data does not lie.

3 REAL ESTATE ANALYSIS

Big Data is widely used by agents and real estate agencies to understand and improve how to target potential buyers. But the great thing about Big Data is that customers benefit from it as well. They can use free public resources with tons of data and information maps with different data analyzing tool options.

Latest tools allow to utilize Python to cross mix and match different values and data sets to analyze complex data. Prior to having these tools available such analysis would be an impossible task for individual users and required immense human and computing effort to complete. It is possible to visualize it by rendering correlations and trends. It reveals stunning insights in to chosen property for rent, business or home.

There is so much information that it is important to understand which data is relevant to consumers and improves decision making. It is useful to analyze the data-sets when considering investing [3]. The analysis can provide variety information and make the educated decision on the investment.

3.1 Big Data Tools

Analysis of these featured data points could be done with Python tool sets and libraries.

Python is a great programming language with variety of options. It is object oriented, semantically structured and great for scripting programs as well as connecting other programmable components. Python is considerably easy to learn and because of its high productivity and also became one of the favorite tools for programmers and data scientists. It contains libraries that are script importable and usable for a lot of use cases, such as image modification, scientific data analysis and server automation. Python world has been around for thirty years and a lot of code was written with multiple contributors. Variety of options built up on how to visualize the data [19].

The most common type of visualization is a simple bar chart and line graph [14]. It is popular and commonly used type of visualization to make comparison between values and variety of categories. It can be vertically or horizontally oriented by adjusting x and y axes, depending on what kind of information or categories the chart requires to present. Parameters need to be identified, such as axes, similarities, title and decided on what exactly the visualization supposed to show.

To make a simple bar chart, a number some of the most popular tools and libraries that have been invented for plotting the data could be utilized. These include the most used and common tools such as: Pandas, Seaborn, Bokeh, Pygal and Plotly.

Additionally, just like any other programming language issues, errors or questions with the libraries can be found on stack overflow page by Google search.

3.2 Data Analysis

For the purpose of this project, bar chart and graphs visualization methods with pandas modules in Python have been rendered and

explained. The simple form of this plot looks acceptable and easy to read.

The techniques were done within Jupiter notebook [9].

Jupiter notebook is great for running data sets analysis and for calculation projects. Jupiter notebook documents are readable files having the analysis description and the results in figures and tables as well as exportable files which can be executed to perform data analysis. It allows to render images and move values back and forth between different modules and coding languages.

The data-sets collected from clsearch.com [5], data.gov [17], zillow.com [22] and uploaded to the class's Google Drive to demonstrate the trends and patterns between each output.

The data includes both geographic and social data-sets evaluated by ratings in rows and titles in columns to keep it simple. The data set for both cities is being used for all examples that are demonstrated below. The point of the visualization is to understand the data in visual platform and make an informative decision based on rendered data.

A simple example of two properties in Tarzana, California versus Calabasas, were compared and exported for read.

Tarzana City is a wealthy neighborhood in the San Fernando Valley region of the city of Los Angeles, California. Tarzana was purchased in 1919 and developed on the site of local elites and named by Edgar Rice Burroughs, author of the popular Tarzan books. He established Tarzana and later sold it to local farmers [20].

Calabasas City located in the hills west of Malibu, in the San Fernando Valley region of the city of Los Angeles, California. The area established in 1991 and the name was derived from Spanish word "calabaza", meaning pumpkin. The legend has it that in 1824, a Mexican rancher spilled a wagon of pumpkin seeds and it spouted alongside the road. Therefore, the area was named Calabasas, the pumpkin land [20].

From a quick glance both areas are very similar and are located within 10 miles of each other. Both Tarzana and Calabasas are influential and desirable neighborhoods with lots of high priced homes. How does one differentiate between the two in order to find the right investment?

Big Data is the answer. Specifically in states like California. In California Big Data application benefits greatly from availability of public records such as sale price as apposed to certain "non-disclosure" states. There sale prices for homes are not disclosed in public records.

The analysis combines several main components, including property characteristics in the area, crime rate, quality of life, pollution, race and ethnicity, population growth, family household, house value, business field, employment, schools and future home value.

3.3 Property Characteristics

Big Data analytics can help in connecting needs of a buyer and providing neighborhood demographics. The quality of population in the neighborhood will influence who buys the house and who lives there. It is important to identify what is important to you and make sure those items are covered in the research. For example, if you are a student you will probably look for a densely populated

location around universities, closer to food locations and communities. Things like public transportation, nightlife, and bars will be very important to you and will be prioritized over other things. If you are married with kids, your best choice would be location with good schools and low crime. Parks, playgrounds and traffic and noise pollution around the house will be paramount. Most parents would love to find a nice quite cul-de-sac house. Young working professional would prefer to be right in the middle of things on a busy boulevard.

Latest Big Data collections made it all possible for real estate website to provide that information to potential buyers. Websites such as United States Zip-codes [2] collect information from public records and make it available in exportable format as well as for reviewing and analyzing local neighborhoods by states and zip codes input.

3.4 Crime Rate Indexes

Crime Big Data is available now and helps to see patterns and avoid areas with unfavorable statistics. The Los Angeles Police Department [1] already uses the data to show which areas in Los Angeles are hot-spots of crime.

Crime rates are being calculated by comparing the national levels of the average 100 [6]. For example, if score is 150 it means that it is 1.5 higher risk of crime than national average level. The data is coming from police department reports and public records. Additionally, the Federal Bureau of Investigation also provides factual information for ranking [18]. Furthermore, the research on crime can be extracted from United States Department of Justice via Uniform Crime Reporting Program [11].

In this example [9], running the crime data sets of Tarzana and Calabasas showed that Calabasas is in much better shape and safer place to live as compared to Tarzana, which is around the average of national rate. The total crime risk in Tarzana slightly higher than national average, it is 108, meanwhile Calabasas is almost 3 times lower, it is 24. The murder risk is 118 compared to 24 in Calabasas. Rape risk is 70 in Tarzana and 35 in Calabasas. Robbery risk in Tarzana is almost twice higher than in Calabasas, it is 125 versus 77. Assault risk three times higher in Tarzana, it is 127 versus 48 in Calabasas. Burglary risk twice higher in Tarzana as well, it is 55 versus 27. Larceny risk in Tarzana is overwhelmingly high, it is 73 versus 9 in Calabasas. Motor vehicle theft risk in Tarzana is 118 versus 39 in Calabasas. Based on these findings, it is defiantly safer to live in Calabasas [fig 1].

Based on these finding, it is defiantly safer to live in Calabasas as shown in Figure 1 [9].

3.5 Education Levels

Next run was done on educational level of residents. Big Data includes data of resident's education level and makes it possible to collect data about an individual resident and provides insightful information about social level interaction. The data extracted and combined from variety of sources including international school districts.

The education rating filtered by zip codes represents the percentage of people in the area who have attended colleges and received degrees. It does not represent performance and specific schools.

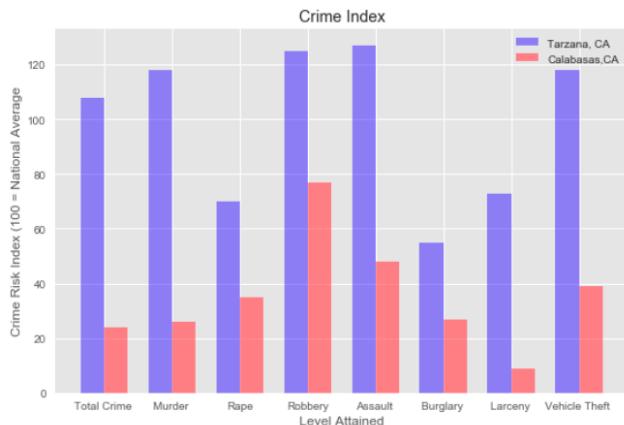


Figure 1: Crime rate in Tarzana, CA compared to Calabasas, CA (100 = National Average) [9].

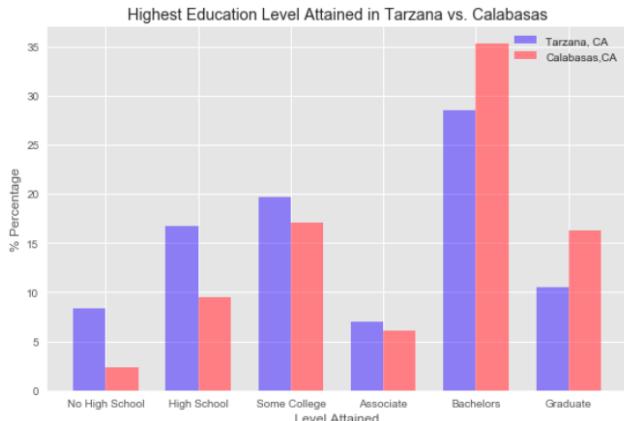


Figure 2: Educational percentage of people in Tarzana, CA compared to Calabasas, CA (Population Age 25+) [9].

The rendered data showed [9] that residents in Calabasas are higher educated by 7 percent with Bachelor degrees and 6 percent higher with graduate degree, as shown in Figure 2 [9].

Based on the Economic Policy Institute study [4], there is a clear correlation between higher educated workforce and economic success within state and ability to grow. Additionally, higher educated people are good for state budgets, since workers with higher income contribute more through taxes.

3.6 Life Quality Standards

The next important consideration in buying a property, searching for a house and making a decision is quality of life standards in that area. Big Data and latest methods of data collection can lead to improvements in quality of life for residential areas. It can find neighborhoods that are safer, cleaner, more entertaining and a better place to live specifically tailored to potential buyer.

The data-set of life quality obtained from variety of sources, including public Google searches, social media and local study

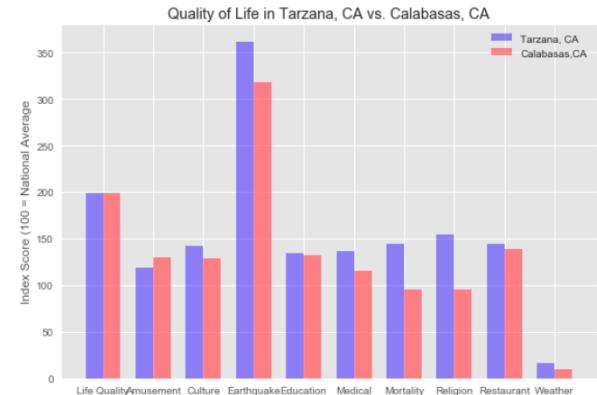


Figure 3: Life quality of people in Tarzana, CA compared to Calabasas, CA [9].

groups. The quality of life is being measured by how residents are being effected by crimes, weather, education, entertainment, religion, medical support and food supply. The positive decision variables calculated by amusement, education, culture, media, religion, weather and restaurants. The negative decision is based on the level of crime, natural disasters and mortality. The national level is being compared to 100 [5].

Rendered data showed that amusement index equal to 110 in Tarzana and 130 in Calabasas. What that means is that in Calabasas there are more community events and entertainment. Culture is 142 in Tarzana versus 129 in Calabasas. Culture refers to artistic development. Earthquake index 362 in Tarzana compared to 318 in Calabasas. this is a very interesting point considering that both neighborhoods are very close to each other. But since Tarzana's Earthquake index is higher associated insurance will likely be higher as well. Raising cost of ownership. Medical index is 137 in Tarzana and 116 in Calabasas. If you are working in the medical field this might be an important topic for you as it will help you find employment closer to home. Reduce your commute time, minimizing wasted time spent in California's infamous gridlock traffic. Mortality is much higher in Tarzana, it is 144 versus 95 in Calabasas. Religion is better in Tarzana, it is 154 compared to 96 in Calabasas. Religion refers to houses of worship and religious establishments. Restaurant index about the same, it is 144 in Tarzana and 139 in Calabasas. Weather is better in Tarzana, it is 16 versus 10 in Calabasas. That is another interesting observation considering that both neighborhoods are minutes away from each other.

Based on the data, overall quality of life is equal between two cities, as shown in Figure 3 [9].

3.7 Air Pollution

Big data can control and reveal pollution levels of particular area [8]. It is one of the main causes of health problems in the population and preventive cause death.

Over 80 percent of residents living in urban areas are vulnerable to poisoning from pollution. Cancer is one of the leading cause of deaths for both men and women; and exposure to pollution at early may have life-long negative consequences.

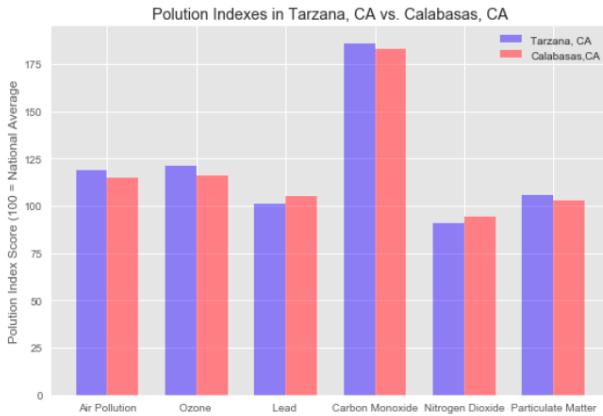


Figure 4: Air Pollution Indexes in Tarzana, CA compared to Calabasas, CA [9].

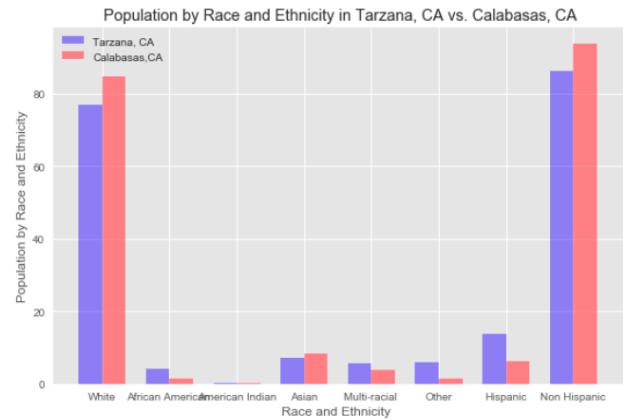


Figure 5: 2012 Population by Race and Ethnicity in Tarzana, CA compared to Calabasas, CA [9].

Monitored areas show that air quality levels exceed the safety levels [12]. Additionally, the World Health Organization warns that most populated states are most affected.

Government is aware of this problem, therefore collecting and monitoring the data regarding air quality has increased. The data is being shared between universities and air quality maps for further development. The data is openly shared and prepared for Big Data analysis.

Even though Big Data will not reduce the pollution by itself, it provides tools to visualize the problem which is especially helpful when choosing a place to live.

The exported data-sets showed [9] that carbon monoxide is extremely high in both cities. It is 186 in Tarzana and 183 in Calabasas. The national level is being compared to 100 [5]. Based on the data, overall air pollution index is about the same in both areas, as shown in Figure 4 [9].

3.8 Race and Ethnicity

Big Data can reveal a lot of information about population by using zip codes. It shows profiles of people who live there. Understanding ethnicity and identity of the community influence will help with decision.

The standard of maintaining, collecting and presenting federal data on race and ethnicity [10] were revised and improved on collecting quality about two decades ago. In accordance to best analysis practices, federal agencies conducting researches to better understand ethnic and race diversity.

The language to describe the ethnicity and race keeps changing to resonate with the category of residence and adding new meaning to not make it discriminatory. The general rule became that race and ethnicity should not be interpreted as being a science.

Based on the rendered graph, most population in Tarzana and Calabasas consist of white and non-Hispanic residents, as shown in Figure 5 [9].

That information provides insight about communities and relatedness to the buyer.

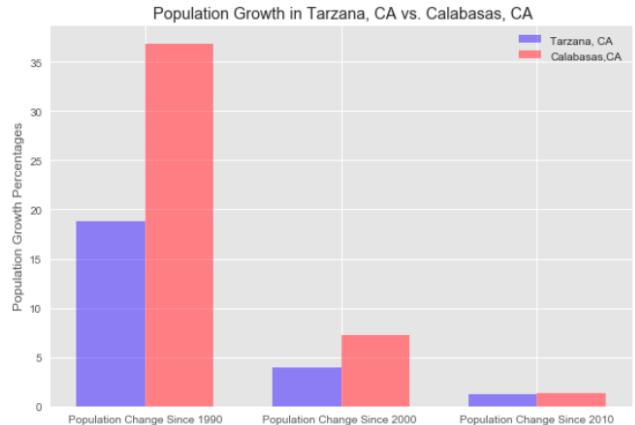


Figure 6: Population change since 1990 in Tarzana, CA compared to Calabasas, CA [9].

3.9 Population Growth

Leveraging Big Data in population growth might be helpful for economic growth prediction and future development.

For the recent centuries, population growth jumped dramatically [15]. How fast the population is growing can influence area homes and businesses development. Allowing for more business opportunities.

Educated people can contribute to the development with increased skills and knowledge. However, it is also important to look not only on the total population size, but also population growth rate.

Based on the data visualization, population size in Tarzana is higher by 3,000 residents than in Calabasas, as shown in Figure 6 [9].

Both in Calabasas and Tarzana, the rate was rapidly increasing from 1900-2000, and there was not much progress since then. Population density in Tarzana is 4,048 versus 856 in Tarzana. City area

size in square miles is 7.44 and 31.67 in Calabasas. This information provides insight that Calabasas has much more opportunities for future growth and development. New housing and real estate development is Achilles heel in California. State struggles to provide all existing residents with affordable housing. Compiled with population growth and migration of new residents the problem becomes even harder resolve. By having additional development space Calabasas growth potential is much higher compared to Tarzana.

3.10 Family Household

Big Data and internet of things are making its existence common place in each household. Only 15 years ago home computers were the only smart device in the house. Now even vacuums and thermostats are connected. Our homes are goldmines of data. Getting family household data summary instantly tells about the type of people in these areas and obtained knowledge can be used to help with buying decision.

Household definition refers to type of family and people living in a household structure. Household data is useful when consumer wants to know about the type of people living in that area and relativity.

Based on the combined data-set results [9], full family household is 64 percent in Tarzana and 76 percent in Calabasas. 48 percent are married in Tarzana, and 62 percent in Calabasas. Therefore for married families with kids it makes more sense to live in Calabasas.

3.11 Property Value

Big Data is being used to analyze property values. Real estate agencies, such as Zillow [22], estimate values based on Big Data collection tools and using their algorithm [21]. They combine information from variety of sources and provide insightful information to buyers, sellers or brokers.

Based on the data analysis [9], it shows that Calabasas prices are higher than in Tarzana by 23 percent. That insight shows that more financially able residence live in Calabasas.

To confirm that, the income data was calculated. Based on the rendered data as shown in Figure 7 [9], it proves that residence in Calabasas are more influential with higher income than in Tarzana.

The total income in Calabasas is higher by approximately 20 percent.

3.12 Employment and Occupation

The employment breakdown that derived from data, published by the Bureau of Labor Statistics showed that business field compared with employment field could help with predicting job opportunities.

Based on compared data sets, Health-care is leading employment field in Tarzana and Management in Calabasas, as shown in Figure 8 and Figure 9 [9].

3.13 Public Schools

Big Data in public schools are being used to fix education institutions and improve student scores and results. Whereas in the past school performance was judged simply on average API scores of the students now student attributes data is further analyzed. This allows to identify subgroups of under-performing students. For example income levels of households are tracked to make sure that

students from low-income families have the same opportunities to have better scores and grades as families from high-income families. It also provides tracking and comparison with schools in different districts. This helps school boards to allocate additional resources to schools that lack them. It also helps parents and home buyers identify schools and neighborhoods where their child could flourish academically.

The mined data could be used for decision making in property investment as well. Prospective buyers with kids are not only looking for good education and safe schools for their own kids, but also from stand-point of property value since homes located in good school districts are more desirable. The detailed information that can be found online made it easy to be properly informed. Compared data between two cities, showed that elementary schools have 38 percent higher rating in Calabasas, middle schools are 25 percent higher and high schools are the same. Schools in Calabasas are better based on these rating scores, as shown in Figure 10 [9].

3.14 Available Houses for Rent and Sale

Another shift in demographic preferences that has been observed is related to home ownership vs renting. Millennials are changing their spending habits when compared to previous generations. Food, health and entertainment take priorities over burdens expenses associated with home ownership. If that trend continues return on investment generated by buying rental properties will rise.

The best way to know if a house is a good investment is to check the rental properties near the area.

There is also a 1 percent rule of thumb to keep in mind. The rule is that a purchased home should be rented for 1 percent of the cost.

Based on the rental data, medium price in Tarzana 4,210 dollars per month, and Calabasas 4,085 dollars per month. It actually reveals that Tarzana rental properties are more expensive than Calabasas, even though the home prices in Calabasas are higher, as shown in Figure 11 [9].

Additionally, square footage was calculated. To get the price per square footage, the price of the area was divided by its square footage. The results showed that in Tarzana rent is slightly higher than in Calabasas, as shown in Figure 12 [9].

Therefore, it makes more sense to buy renting properties in Tarzana.

The lowest price of property in Tarzana is 700,000 US dollars, and in Calabasas it is 975,000 US dollars [9].

Based on the 1 percent rule, it does not make sense to buy and rent out in Tarzana or Calabasas.

3.15 Future Value

California housing is booming and crashing. Massive home equity destruction happened few years ago and reversed back.

When data-sets are analyzed, they can reveal insightful information and guide consumer decision making.

Based on the sales data was taken and generated, suggests that in spite of price drops the value of houses goes up, as shown in Figure 13 and Figure 14 [9].

Calculated housing investment for the last 20 years had a growth rate of 5.46 percent [9]. By knowing a starting and ending value, it is

Household Income Statistics in Tarzana, CA vs. Calabasas, CA

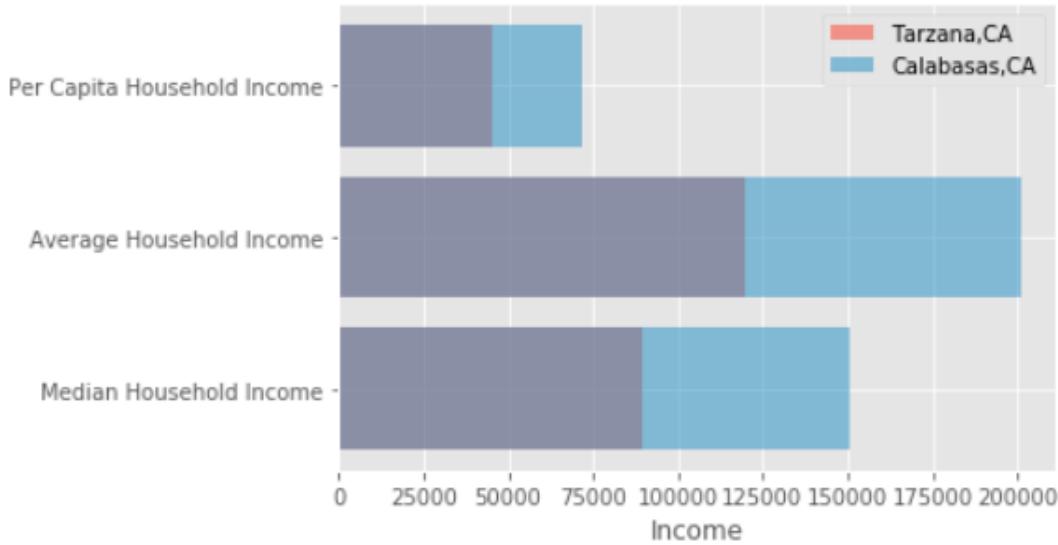


Figure 7: Income in Tarzana, CA compared to Calabasas, CA [9].

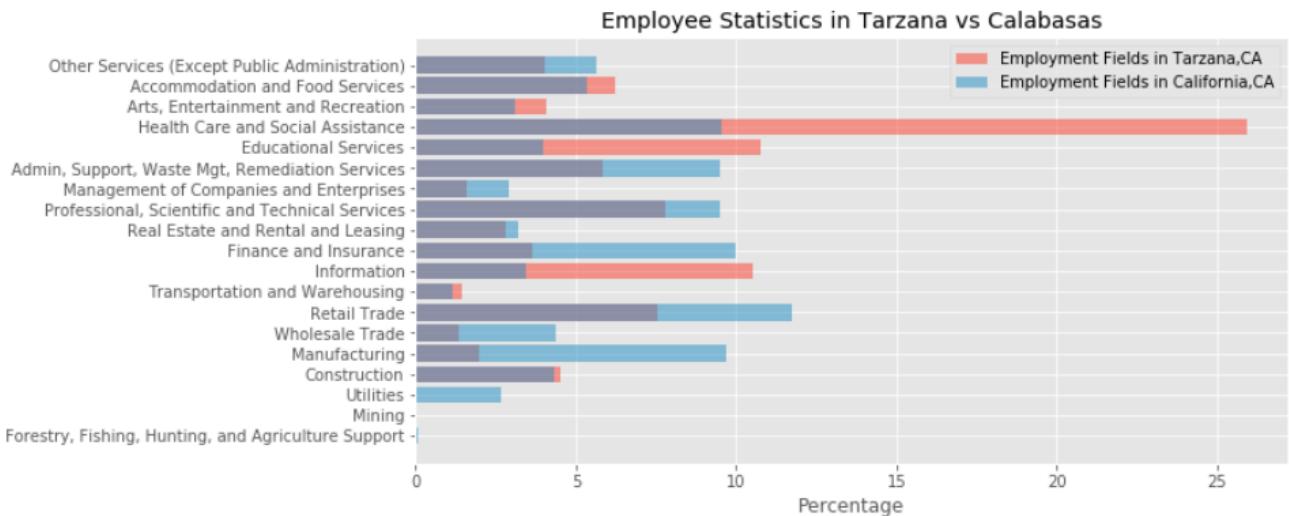


Figure 8: Employment field in Tarzana, CA compared to Calabasas, CA [9].

possible to calculate the future value of an investment. Referencing the previous calculations [9], it predicts that house value will grow by 63 percent in the next 20 years.

4 CONCLUSION

Big Data potential to transform decision making in real-estate is immense. Home ownership is part of the American dream and Big Data will play a huge role in that process. It will allow potential buyers to have a better understanding of historic data and how it correlates to investment potential.

Big data will provide powerful insight to augment decision making process. Yet, it will not eliminate all risks associated with investment in real-estate. All risks must be evaluated and analyzed before buying and big data will provide plenty of tools for that.

Based on this analysis, it was determined that Tarzana and Calabasas properties are overpriced. Currently, renting is low compared to buying a property.

It is impossible to find properties in California that generate rents at around 1 percent of total property cost. You can not justify

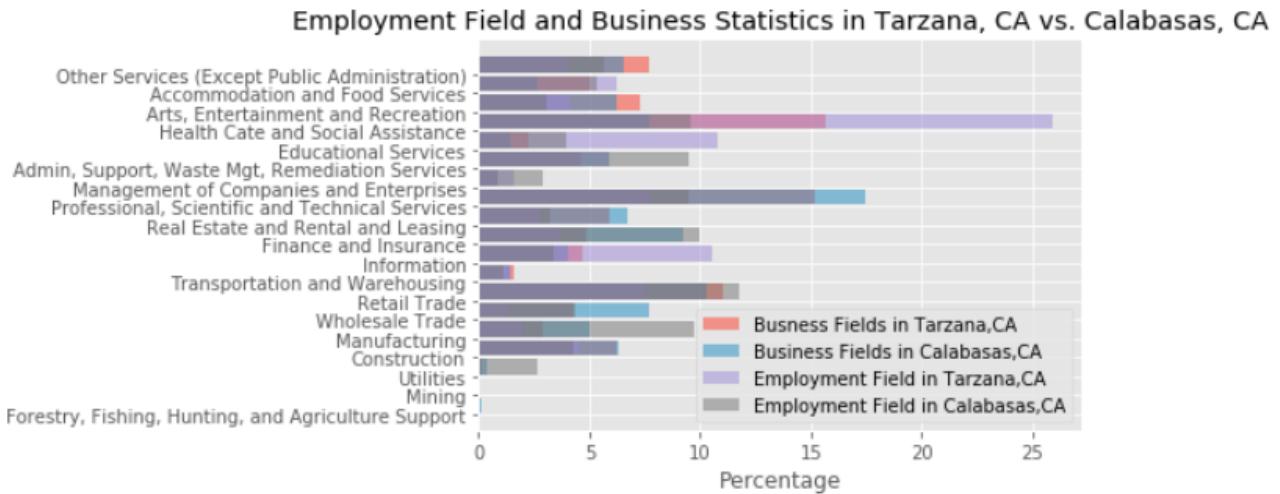


Figure 9: Business fields in Tarzana, CA compared to Calabasas, CA [9].

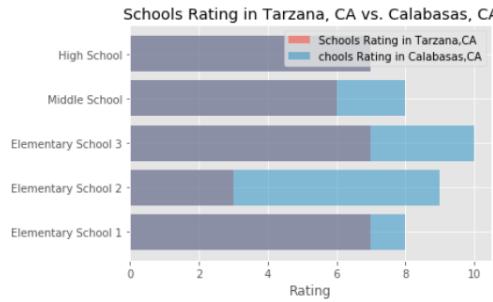


Figure 10: Public schools in Tarzana, CA compared to Calabasas, CA [9].

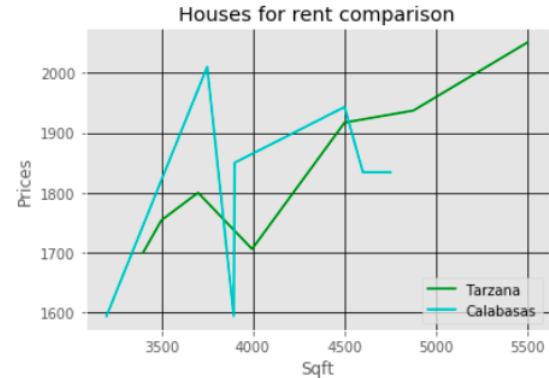


Figure 12: Price per sqft for rent in Tarzana, CA compared to Calabasas, CA [9].



Figure 11: Houses for rent in Tarzana, CA compared to Calabasas, CA (3bd+ House For Rent (1,500-2,500 Sqft)) [9].

the prices and it is only for the privilege of living in San Fernando Valley region of the city of Los Angeles, California.

However, if you do still want to invest, Calabasas is a better choice for investing in a family home property and Tarzana for a rental property.



Figure 14: Prices Growth Index in California [9].

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Big Data Analytics in Identifying Factors Affecting Bitcoin

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ABSTRACT

Pricing of Blockchain based cryptocurrencies are like a black box, as per theory the pricing compared to U.S dollar is based on a number of transactions however lot other factors like Dollar price, social media, Online threats supersede the transaction count. Big data and Analytics helps to identify the metrics impacting this variation and identify the correlation between them.

KEYWORDS

i523, hid324, Big data, Predictive analytics, Random Forest, correlation, Blockchain, Bitcoin, Ethereum

1 INTRODUCTION

The start of the 21st century witnessed the evolution of various disruptive technologies, right from Big data, IoT, VR to Blockchain. When it comes to the blockchain, the sole winner is Bitcoin, with the growth rate of over 1327 percent [5], Bitcoin is disrupting the way banking system works. As the Bitcoin grows the acceptance and adoption grow along with that. Similar to any other currency in the world, Bitcoin's price deviates widely towards the positive side which created the opportunity for investment in it. Even though the same is not widely accepted everywhere, there is a grace to own Bitcoin citing its growth rate. Though the transaction counts haven't grown up, the retention of the coin has grown up making it a Digital Gold [17].

2 BITCOIN

Bitcoin is a progressed cryptographic cash and shared ledger that is completely decentralized, which implies it relies upon peer-to-peer trades with no bureaucratic oversight. Trades and liquidity inside the framework are somewhat based on cryptography. The concept was first introduced in 2009 [8] and is at this moment a prospering open-source gathering and portion sort out. In perspective of the uniqueness of Bitcoin's tradition and its creating choice, the Bitcoin is grabbing stacks of thought from associations, clients, and monetary experts alike. Specifically, for this technology to thrive, we need to recreate budgetary organizations and things that starting at now exist in our traditional, fiat cash world, make them available and specially fitted to Bitcoin, and other rising computerized types of cash. In technical terms, Bitcoin's is a shared ledger or a database running by a set of clusters, as the clustering is involved, a competition is set for the individual machines to acquire and update the ledger. The competition is in terms of hashing problem. The hashing needs multiple GPU's to perform validations and update the ledger. This competition eliminates the slower machines to be part of the network and improve the infrastructure's capacity, only by winning the competition a machine can be awarded some

Bitcoin as an incentive. Since one machine cannot process the competition problem, a set of peers come together to form a Mining pool and share their capacity and the incentives. We can gather useful mining statistics information from these mining pools.

3 PRICE PREDICTION

The Bitcoin market's cash-related basic is, clearly, a securities trade. To support money related to reward, the stock market prediction has turned out to be known ground which can be reused with the presence of high-repeat, low-dormancy trading hardware joined with solid machine learning figurings. Henceforth, it looks good that this desire is imitated in the domain of Bitcoin, as the framework expands more conspicuous liquidity and more people develop an excitement for placing profitably in the structure. To do accordingly, it is essential to utilize machine learning and Big data advancements to foresee the cost of Bitcoin [10].

3.1 Data Source

As Bitcoin is a decentralized and a transparent system, all the source of data can be gathered from the peer-to-peer networks. This peer-to-peer network is called as Bitcoin-mining pool [2]. The rate of block creation is adjusted every 2016 blocks to aim for a constant two week adjustment period (equivalent to 6 per hour.) The number of Bitcoins generated per block is set to decrease geometrically, with a 50 reduction every 210,000 blocks, or approximately four years. The result is that the number of bitcoins in existence is not expected to exceed 21 million [6]. The true source of data for Bitcoin analysis would be from Bitcoin mining pool. Coinbase is one of the main members of bitcoin pool from which we can gather mining statistics. In the process of identifying the features impacting Bitcoin's price fluctuations, not only the transaction volume impacts, even the popularity and people's trend towards it impact the price of the coins. Hence, data from Google is also gathered. As a currency's price also been altered by its exchange, supply, and demand, Ethereum's price data and transactional data is also acquired from Ethereum's exchange point. With all these data sources, we analyze the features impacting the Bitcoin's market price.

3.2 Feature Selection

Feature selection is one of the vital steps in any meaningful analysis of an expected outcome. A set of features have been selected to analyze its interdependence with Bitcoin's evaluation. The features are selected based on three wide areas, the first is Bitcoin mining data, second is social data and the last one is exchange data. The internal activities in the Bitcoin's infrastructure definitely reflect the changes or the fluctuations in the Bitcoin's network, Bitcoin's mining data is gathered from Coinbase. This is extracted from the

web service API provided by Quandl.com [9]. By making a REST call, CSV files containing the historical data is downloaded and processed. The second is the social data, which is extracted as a static data from Google trends [7], the main reason behind this data is when the popularity grows people tend to know or show interest in being part of the growth. With the impressive growth of more than 1000 percent in a year, this is considered as an important data. The last one is the exchange data, as a currencies price is directly proportional to the supply and demand, the supply of the currency can be impacted by the exchange to other currencies or commodity [18]. Ethereum is known to show a similar pattern in terms of growth and deviations [3]. Hence, there's price in US dollars and transaction volume is considered one of the features.

4 BIG DATA IN FEATURE ANALYSIS AND ALGORITHM'S EXECUTION

Feature extraction, transformation, and prediction can be synonymous with a conventional ETL methodology. Though few of the extraction is handled manually and the volume is comparably low, it is assumed that the data volume will be increased by modifying the extraction to real-time systems. When the extraction systems are changed, our code must be able to handle streaming data which can be related to "variety and volume " of the data. The next step is validating the data for anomalies, data miss and cleanse the data of issues which is synonymous with data cleansing. The later one is data processing, which includes data processing with multiple iterations and permutation consuming a lot of memory and other resources. These processing needs lead us in adopting Big data technologies in the entire lifecycle of the implementation. Apache Spark framework is identified as the end-to-end processing environment which is pre-loaded with redundancy, fault tolerance, in-memory processing, parallel processing, streaming, and Machine learning modules.

4.1 Execution with Apache Spark

"Apache Spark is a fast and general-purpose cluster computing system. It provides high-level APIs in Java, Scala, Python and R, and an optimized engine that supports general execution graphs". It also provides extensive support to Machine learning libraries(MLLib) and to streaming through Spark Streaming. The in-memory processing is implemented with the help of Resilient distributed dataset (RDD) [12].

Spark's architectures given in the figure 1 provide a glimpse of how different system in Spark is interfaced. The first level of interfacing to Spark is with high-level languages like Scala, Java, Python and R. Users implement their functionalities in these high-level languages. The primary executing components in Spark are Driver and Executor modules. The driver is the entry point for any implementation, the written programs will be executed in the main function of the Driver module, later converted to set of Directed Acyclic graph by the Spark APIs. DAGs are then executed in executors in the data nodes based on the data placement policy of the infrastructure. Four modules built on spark for serving the user's needs are SparkSQL, Spark Streaming, MLLib, and GraphX. Spark SQL and Machine Learning libraries(MLLib) are consumed in our implementation and the future improvement would be on Spark

Spark Architecture

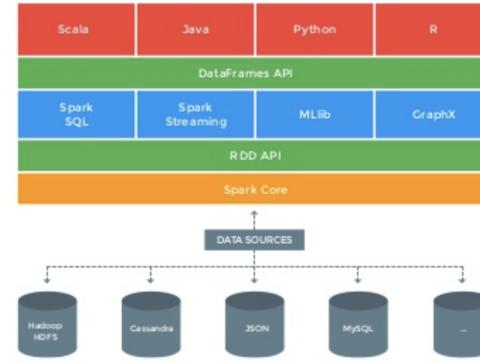


Figure 1: Spark Architecture [11]

Streaming which is used for Streaming requirements. SparkSQL and MLLibs modules contain the implementation for DataFrames, SQL functionalities, and Machine learning libraries. The next level of the modules is data abstraction layer. Spark's basic data abstraction is Resilient Distributed Dataset (RDD), which is a fault tolerant partitioned data encapsulation datatype. The RDDs are lazily evaluated, hence a Directed Acyclic Graph is implemented to persist the state of the RDDs at each stage. With RDD, Spark can execute the transformation in parallel with fault tolerance. This implementation widely differentiates from conventional Python implementation which lacks this advanced logic. Apache's Spark 2.2 is used to implement all the ETL functionality. Spark is installed in the local system along with Anacondas, so Spark libraries can be consumed inside Python shell. To consume and process Pyspark libraries, sparkcontext is created which initiates the driver program. The spark context is bootstrapped with SQL and Spark session libraries so that Spark RDD and Data frames could be accessed under a single window.

As the abstract describes the necessity of the features impacting Bitcoin's price, the best metric to identify the relation between Bitcoin's price and its features is by identifying the correlation matrix provided by Charles Spearman. Spearman's function describes the relationship between two variable using a monotonic function [16]. Apart from identifying the correlation, these features can be modeled to predict the value of the dependent variable which is Bitcoin's value. The algorithm consumed for the predictions are Random forest and gradient boosted regression the Machine learning modules of Spark.

5 ARCHITECTURE

The architecture flow consists of three levels of components, first one is the Data extraction, second is processing and the final is visualization. The Figure 2 describes how the implementation is fitted over Spark's architecture. The logical implementation starts with extracting the data from the source and loading it over RDDs. With RDDs on the base, source data is validated for data miss and anomalies. With RDDs, all validation happens in parallel irrespective of

5.3 Data Cleansing

The data cleansed with multiple Python and feature cleansing libraries in Python and Pyspark. Major efforts of cleansing are needed to standardize the date columns from all the data sources. The date format was in the different format in different sources. To stitch back all the data points, Date Time libraries were used and joined with a single standard format. Another important activity in the cleansing is data miss. For some instance, the values are missing resulting in incorrect predictions and correlations. To resolve these missing values, Imputer [13] functionality is used from feature library of Apache Spark. The imputer is an Imputation estimator for completing missing values, either using the mean or the median of the columns in which the missing values are located. The input to this function is dataframe columns and output are renamed dataframe columns. The processing happens in-memory with the spark.

5.4 Data Visualization

The visualization is provided in the form of static plots. Static plots are built-dimensional plots and scatter plots to represent correlation and projections.

6 SPEARMAN'S CORRELATION

Spearman's correlation function is used to identify the correlation between Bitcoin's price and the features selected. In Spark, a separate function is defined to calculate Spearman's correlation. The input is in Pyspark RDD's and the output value is returned between -1 to +1. The positive ratio indicates the feature is directly proportional and the negative values indicate indirect proportionality.

Spearman's Correlation on the selected features are :

- BTC-volume :0.348540857386
- High :0.998581861669
- Low :0.995190604708
- Open :0.997943642437
- Google-trend:0.260343238604
- ETH price :0.68683414787
- ETHTRAN :0.720031468617
- BTC-price-Label:1.0

Per Spearman's correlation algorithm, highest correlations with Bitcoin's price are with trading data like High, low and Opening values of Bitcoin. The second highest correlation is with the Ethereum's transaction data. The least ones are Google's trend and Bitcoin's own transaction volumes. These features are selected and used for the pattern analysis and prediction with regression algorithms.

The Figure7 describes the growth pattern between Bitcoin transaction count and its value. The y-axis is the count of Bitcoin's transactions and the x-axis is the date progression, it means day 0 on considered as the July 30,2015 and the next day is considered as 1. What is inferred from the correlation is that the volatility of the transactions increased as the price increases and in other perspective the transaction counts are moderately consistent even though the value is increasing which means some other feature impacting the price more than the number of transactions.

The Figures 8,9 and 10 describes the growth pattern between open, low and high prices of Bitcoin on the recorded date. The

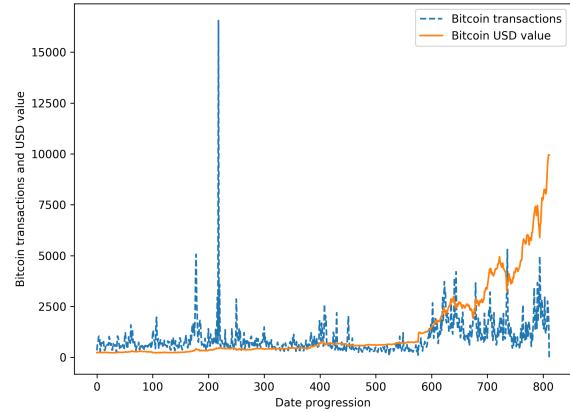


Figure 7: Bitcoin Transaction and USD value

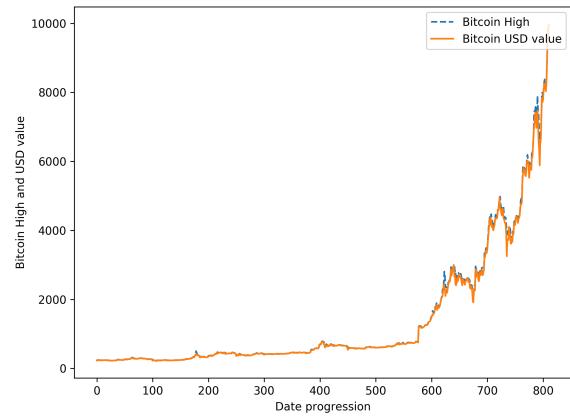


Figure 8: Bitcoin Highest exchange value and Closing value

x-axis is date progression and the y-axis is the value of Bitcoin's price and Bitcoin's highest, opening and lowest price on that day. This is obvious that these prices are highly correlated with the price change.

The figure 11 describes the pattern between the Google search trend and the hike in Bitcoin's price, the x-axis in the Date progression and the y-axis defines the counts of the features.

Figure 12 and 13 describes the growth trend of Ethereum's price and its transaction volumes with Bitcoin's price in which the transaction pattern of Ethereum is more similar to Bitcoin's pattern.

As far as processing is concerned, all the RDDs are cached before feeding into Spearman's correlation function, the reason being, when the RDDs are transformed multiple times, it has to calculate data lineage every time it is computed and lineage is the basic quality of resilience in Apache Spark. If the RDDs are cached and persisted in-memory, the iteration and other transformations happen in memory avoiding costly I/O operations, this feature cannot

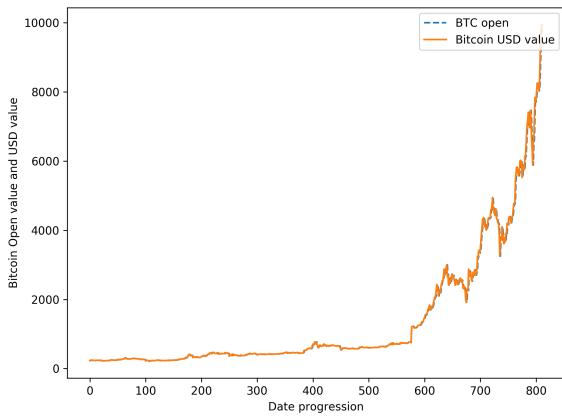


Figure 9: Bitcoin Lowest exchange value and Closing value

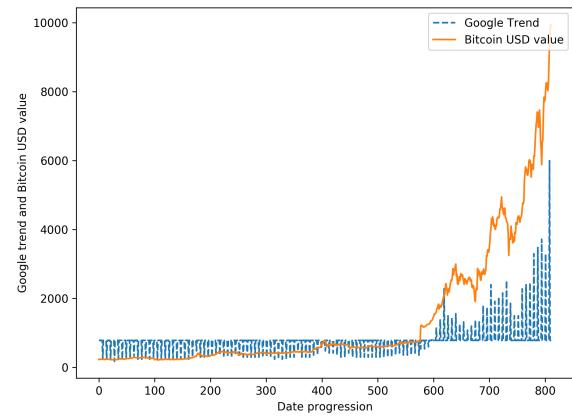


Figure 11: Bitcoin USD value and Google search trend

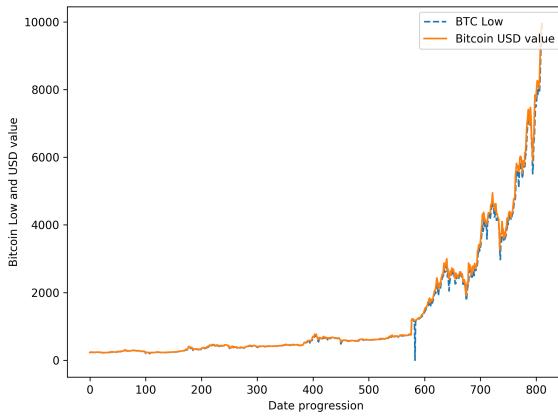


Figure 10: Bitcoin Opening exchange value and Closing value

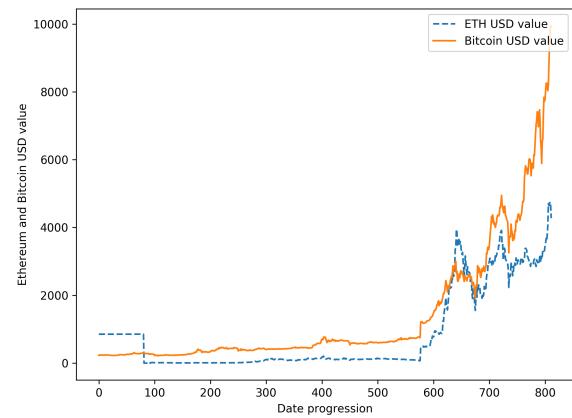


Figure 12: Ethereum price and Bitcoin price

be easily implemented when executed in conventional python libraries.

7 DECISION TREE REGRESSION

With the availability of features, we can take the processing to the next level of predicting Bitcoin's price. Here, supervised learning model is used to predict the price of Bitcoin.

Figure 14 give some basic idea of how decisions are made with the supervised decision tree based model.

Ensemble method models are derived from another base model. The base model used here is Decision trees and ensemble models are Random forest and Gradient Boosted tree(GBT) Algorithms.

Though the base model for both the algorithms is same, both are different in terms of training the dataset. GBT can train only one tree at a time whereas Random forest can train multiple trees resulting in reduced overfitting caused by GBTs.

"Random forests or random decision forests operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of mean prediction (regression) of the individual trees and GBTs iteratively train decision trees in order to minimize a loss function. Like decision trees, GBTs handle categorical features, extend to the multiclass classification setting, do not require feature scaling, and are able to capture non-linearities and feature interactions" [14].

All the execution is implemented in Apache Spark, hence all the transformation and processing happens in-memory, even if the data volume is high, the processing will spawn across the clusters and will be processed with consistent redundancy.

The model is implemented by first splitting the data into two sets of different volume, i.e test data and training data. The training data will be used by the model to derive the logic and the built logic will be tested with the test data for accuracy. Here, 70:30 ratio is selected for training and test data respectively. And by altering this

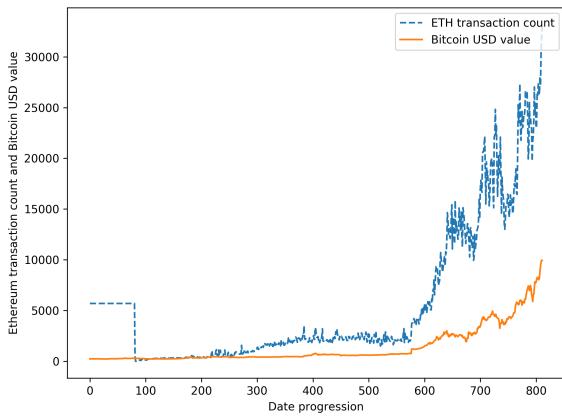


Figure 13: Ethereum Transaction volume and Bitcoin transaction volume

```
TreeEnsembleModel classifier with 3 trees

Tree 0:
  Predict: 1.0

Tree 1:
  If (feature 0 <= 1.0)
    Predict: 0.0
  Else (feature 0 > 1.0)
    Predict: 1.0

Tree 2:
  If (feature 0 <= 1.0)
    Predict: 0.0
  Else (feature 0 > 1.0)
    Predict: 1.0
```

Figure 14: Sample Decision tree [1]

ratio we can adjust the performance of the model. Upon completion of the modeling, the accuracy of the models is calculated based on Metrics library in Spark. The metrics identified for the accuracy calculations are mean Squared Error, Root Mean Squared Error, r-square and mean Absolute error. Mean Squared error can be defined as an estimator to measures the average of the squares of the errors or deviations [15]. "R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression" [4].

7.1 Random Forest

As we are predicting Bitcoin's USD value per day, Bitcoin's price is considered as a label and all other columns are marked as features, and only the features having a decent level of correlation is marked as Features. These features are loaded into the model with Labelled Points as a Spark datafram.

Random forest requires parameters to tune the model for the highest accuracy.

The parameters used in the functions are [1] :

- Training dataset: RDDs as LabeledPoint
- NumTrees: Number of trees in the random forest

- FeatureSubsetStrategy: Number of features to consider for splits at each node
- Impurity: Criterion used for information gain calculation
- MaxDepth: Maximum depth of tree
- MaxBins: Maximum number of bins used for splitting features
- Seed: Random seed for bootstrapping and choosing feature subsets

The first parameter is the training dataset, the training datasets are constructed as LabelledPoint RDDs, the LabelledPoint RDD is a local vector associated with a label, it acts as a optimized data structure for datasets with association. The next one is the number of trees allowed to construct in the algorithm, as the decision tree is based on deriving mean of multiple decision trees, in general, more trees gives better results. However, the improvement decreases as the number of trees increase more than the threshold of the given dataset. Hence, number of trees selected is 10, which gives us better efficiency. The FeatureSubsetStrategy defines how the features are sampled at each split in a tree, we have selected *auto*, so the algorithm will take care of the split. The Impurity parameter is the criteria followed for Information gain calculation, *variance* is the default considered by Spark. The next parameter is MaxDepth, which defines the limit of the depth of the tree, beyond which decision tree will not be extended, the maximum depth allowed in Spark is 30. The next one is MaxBins, which describes the number of bins used for splitting which we have defaulted and the last one is Seed parameter, which induces randomness while multiple trees are created which is defaulted as well.

With all parameters were carefully selected and the model is tuned to give the highest accuracy, Avg.closeness index of the algorithm is closer to 0.95. After deriving the model, the closeness/correctness of the predicted results was also analyzed and it is described in the plot 15.

7.2 Gradient Boosted Tree

In the Gradient Boosted algorithm, the training and test data are used in similar to the Random Forest algorithm. The implementation is less complex compared with Random forest. As GBT trains the model based on iterative execution of sequence of decision trees. Upon execution of three iterations, it is clearly evident with the closeness index that the data is little bit over-fitted with the closeness index of 0.96, slightly greater than Random forest.

The parameters used in the functions are [1] :

- Training dataset: RDDs as LabeledPoint
- CategoricalFeaturesInfo: A Map of categorical features
- Loss Function: Loss function used for minimization during gradient boosting
- NumIterations: Number of iterations of boosting
- LearningRate: Learning rate for shrinking the contribution of each estimator
- MaxDepth: Maximum depth of tree
- MaxBins: Maximum number of bins used for splitting features.

Similar to Random Forest, the first parameter is LabelledPoint RDD, the second one the map of categorical features. Most important parameters used in GBT's functionality are Loss function,

NumIterations and Learning rate. Loss function selected is *least-SquaresError*. Number iteration is the number of times the tree is iterated to derive the result, the default value of 100 is selected. The learning rate is optional which is defaulted to 0.1 in Spark.

By altering these parameters, the performance and the decision of the model can be optimized. The alteration includes thorough analysis of the data consists of data gap analysis and feature transformation. By selecting the default parameters, the output decision tree tend to perform better in the selected scenario.

8 RESULTS

From the observation of scatter plots of regression model Random forest 15 and GBT 16, it is evident that GBT's single tree iterative model has predicted the values with over-fitting. Some predicted values are consistent with some particular time scope and changes happening in steps. The prediction distribution looks like a single line and not widespread. Whereas, in the Random forest, the predicted values are widespread and closely aligned.

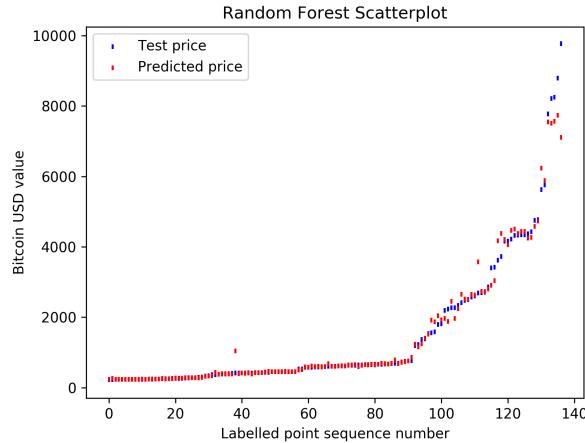


Figure 15: Randomforest Scatterplot

We have came up with a metric called *Closeness indicator*, which tells us mean ratio of test and predicted label. If it is less than 100, then the predicted value is less than the actual and if it is more than 100, then the predicted value is more than the actual value. For both algorithms, the closeness index is near 100%, hence both predictions achieved optimal results. Other important metric includes r-square values which above 95% in both the cases, hence our model fits with the expectation and the parameter selected for the algorithm holds good.

9 CHALLENGES FACED

Most of the challenges are with the data and casting to the required data types as the correlation and regression functions need data either in float or double data types. The other challenge faced is the data source availability, though the Bitcoin network is open to the public, gathering all the statistics data from all the mining pool available in BTC infrastructure is tedious. And, in the Bitcoin network, we do not know which user performs the transaction, we

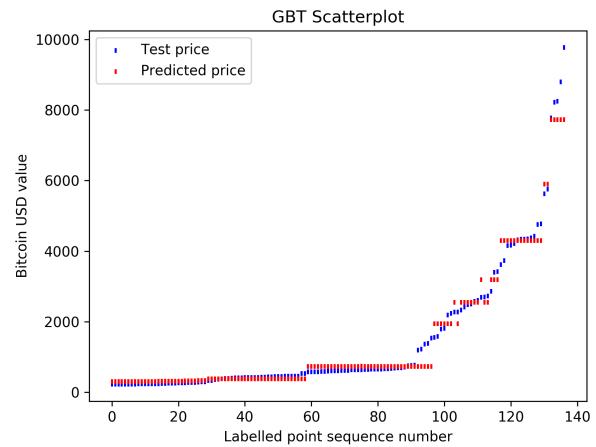


Figure 16: Gradient Boosted Tree Scatterplot

have no open option to classify the user and identify the feature inducing that transaction. Due to the void of these inducing factors, we may need to assume few features and start the analysis with the correlation. And handling all these constraints along with Big data specifics in mind adds up to the challenge, thanks to Apache Spark which handles the data lineage and persistence through RDDs.

10 PROJECT STRUCTURE

Three folders are created, the first one is for scripts which retain the actual code to be executed and two Korn shell scripts to install dependencies and to download the required source files. The second one is the data folder which retains the data required for the model and correlation algorithm. The extract folder is to persist the plot figures extracted out of the python script. The versioning and multiuser synchronization is supported by Git.

11 LIMITATIONS

There are a some of improvement opportunities that can be implemented. One of them includes fetching the data in near real-time directly from the Mining-pool instead of a third party data service, the second one would be increasing the granularity of data which would increase the performance and the Spark would make more sense with that level of granularity and volume. The other improvement opportunities include gathering more features like illegal market transaction data, mining exchange data, wallet exchange data, world's inconsistency data which will increase correlation factors and result in the accurate prediction of models. Other visualization opportunity includes real-time presentation capabilities with Big Data at the back end. Matplot API has minimal options for real-time reporting which can be upgraded. Other important improvement opportunity includes implementing the prediction logic with Neural network based models like Long Short-Term Memory(LSTM) as decision tree based models sometimes fail to adapt to the changes based on their past experience. These LSTM based model keep the memory of the previous experience and improve the learning upon training.

12 CONCLUSION

After the analysis of the Bitcoin data, the Bitcoin transaction count does not impact the Bitcoin's value which proves that the users are not using the Bitcoin for any day to day transactions instead they are exchanging it with US Dollars and saving as an asset like Gold. By retaining it, the demand for the Bitcoin coin increases. As the new-coins can only be generated through mining and the growth is controlled, coins in circulation keep reducing, increasing its cost further. It clearly proves that Bitcoin bought are saved in the wallets are not used in the regular transaction much. Most of the Bitcoin's are retained to earn the profit over its demand and its price variation with US Dollars. Other important inference is that the exchange rate of Ethereum is changing along with Bitcoin's, the only possibility of close correlation is the exchange of both the currencies. By logically linking the findings, people are using Bitcoin as an asset and using other cryptocurrencies as the transaction medium exchanged from Bitcoin's market instead of directly from the US Dollar market.

With all prowess of Big Data and its technologies, Blockchain technologies are not only evolving, it also equips humans with the opportunity to make the world more transparent, ethical and a viable place to live. As the technology has evolved so far, it is expected to understand its growth story in terms of its microscopic level to push it to the next level of improvement. Such microscopic level of qualities was missed in legacy methods and Big Data comes to the rescue in identifying those qualities and nurture them.

ACKNOWLEDGMENTS

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Predicting Profitable Customers in Banking Industry

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ABSTRACT

Banks often want to know the profile of their profitable top 1% or 20% customers looks like. Conversely, they may also wonder what the general profile is of the customers in the worst 1% and 20% of profit. Based on customer's data variables at any given time, a good predictive model can predict which profit group (extremely unprofitable, average, extremely profitable etc) customers fall into. This helps financial institutions to better understand what drives the customer profit and accordingly take decisions to sell their products to the right customers. Further down in banking sector, it is a challenge to identify customers who are most likely to repay the loan. Recent big data and machine learning technologies have the potential to predict good customers and open doors for banks to profitable growth. Since the banking sector has evolved over the periods, there are tremendous amount of historical data available to analyze. We show how bank's big data can be analyzed and create a model based on that, to classify customers. In addition to big data technologies, we use machine learning algorithms to build a predictive model to predict creditworthy and uncreditworthy customers from a list of new customers. Various classification algorithms like Decision Tree and Random Forest are used to build the models and trace the best model among them to achieve the goal.

KEYWORDS

i523, HID328, Big Data, Spark, Python, Decision Trees, Random Forest

1 INTRODUCTION

Big data as the name implies, refers to large and complex data which continues to grow enormously day by day. Industries like financial firms, in particular, have widely adopted big data analytics to obtain better investment decisions with consistent growth. Recent survey research indicates that 71 percent of firms in the financial services industry at a global level are exploring big data and predictive analytics [22]. This number continues to grow and sectors like government, business, technology, universities, health-care, finance, manufacturing etc make use of big data to obtain meaningful information using big data technologies [32].

The finance sector contributes to the daily data generation from products and marketing, banking, business, share market etc [14]. Banking is a very sensitive field and any useful insight can make a positive impact on the overall turnover. Historic data analysis and real time data analysis are equally important in banking sector. The era of big data helps financial firms to take quality business decisions related to expanding revenues, managing costs, hiring resources etc, based on effective data analysis which provide access

to real-time insights. Data-driven decision making is one of the key advantages of big data technologies.

1.1 Project Goals

We aim to help banking sector to identify trustworthy customers. Specifically, help banks to take a decision driven by data, whether to approve or reject a loan application. When a new customer approaches the bank for a loan, banks would be able to identify the customers who are most likely to repay the loan by analyzing the applicant's profile and background information.

There can be two scenarios of risks associated with the bank's decision. First, if the customer is creditworthy and if the bank rejects the loan, then it is a loss to the bank in terms of interest. Second, if the customer is uncreditworthy and if the bank approves the loan, then it is a loss to the bank in terms of loan amount and interest [15]. Approving loan for an uncreditworthy customer will end up in more financial loss for the bank and accordingly is a greater risk. Hence banks would require a decision rule to follow for whom to approve the loan. We show how to build a predictive model using machine learning algorithm and a sample dataset with customer records classified as "Good" or "Bad" according to bank's opinion on the customer. With our model, we try to mitigate these risks for the banks by contributing to the decision rules. In other words, our model helps to minimize the risks and maximize the profit for the bank by understanding the customers.

1.2 Methods and Technologies Involved

The goal of most of the big data projects is to analyze the data and derive knowledge out of it. In other words, data is the input to the model and knowledge is the output. We also follow the same methods and processes for our project. We wrote the project code using Python3.

1.2.1 Project Workflow. Overall workflow of the project is shown in Figure 1. We have taken a sample data set of loan applications received by a bank. We explored the data and the requirements of the bank and based on that set the project goals as discussed in the section 1.1, before starting the project. In the real scenarios, we will not be able to apply analytical methods directly on the raw data as it likely be imperfect and containing irrelevant information. Hence we do data cleaning (data preprocessing) as the first step. Data cleaning is done using PySpark. The cleaned data has 1000 customer records with 1 classifier and 20 feature variables.

Exploratory analysis like Chi-square test is done to understand the data and feature selection for analysis as part of the data mining process. We have done graphical representations to show how the actual data is related and what are the direct insights available from the cleaned data set.

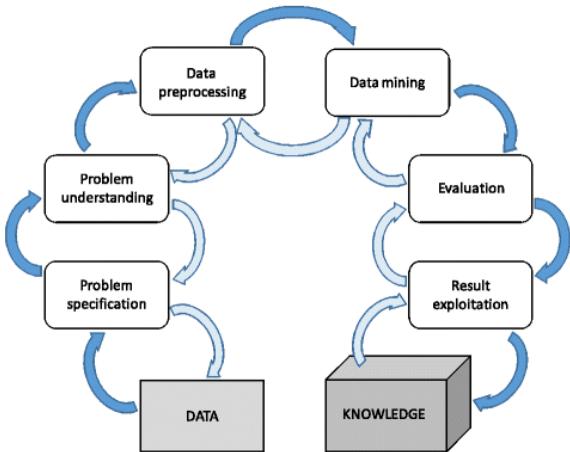


Figure 1: Project Workflow [9]

Machine learning approaches are used for the data evaluation and to build our predictive model. We develop various models using machine learning algorithms and compare them to identify the best model to choose for our problem solution [23]. To develop the models we first split the data set into two parts - training data and test data. We defined 2 baseline models, Decision trees and the Random Forest model. We compare all these models to identify the most effective and least penalty model. We use python as the programming language to build these models and display visualizations for easy comparison and results discussion.

1.2.2 Python. Python version 3 is the programming language used to develop the models and visualizations in this project. Python is a general purpose programming language that is open source, easy to use, faster to write, flexible and powerful. It has a rich set of libraries and utilities for data processing and analytics tasks [27]. Other important features of Python include the ability to process big data, scalability of applications and easiness to integrate with web applications. We use Python libraries like pandas, matplotlib, seaborn and numpy.

Pandas: Pandas is one of the most popular libraries in Python. Pandas is used for data manipulation and analysis [17], read data files from different sources, create data frames and some built-in visualizations [11].

Matplotlib: Matplotlib is the library used for plotting arrays and histograms of data in python [6].

Seaborn: Seaborn is a Python visualization library used for statistical visualization of data [31].

Numpy: Numpy is Python library which is used to operate mathematical functions on large multi dimensional arrays [35].

1.2.3 PySpark. Even though Python is powerful to handle complex big data analytic tasks, it alone cannot handle the big data processing. A distributed framework would require to handle a large amount of data. Spark is a distributed computing framework which supports Python [7].

PySpark is used to carry out the data preprocessing tasks and it is the Python API for Spark.

1.2.4 Jupyter Notebook. Jupyter notebook is an open source web application that allows to edit, run and share Python code and visualizations into a web view. It can be used to modify and re-execute program parts in a flexible way [5]. The files created in Jupyter notebook use extension ".ipynb".

1.2.5 Machine Learning. Machine learning enables computers to learn automatically and act accordingly without human assistance or being explicitly programmed. It is an application of Artificial Intelligence. It focuses on computer programs that can access data and learn by itself. Learning process starts by observing the data for patterns and make better decisions in future on the given scenarios [25]. There are mainly 2 categories of machine learning - Supervised and Unsupervised.

Supervised Machine Learning Algorithms: Supervised machine learning algorithms enable machines to get trained using a known training data set. Using these labeled examples, supervised learning algorithms can predict future events by applying already learned knowledge. These systems can be used for target definitions for new set of data after required training. Also, it can compare new data input with the intended output and give error indications [25].

Unsupervised Machine Learning Algorithms: Unsupervised machine learning algorithms are used when there is not a preferred output and the data is not labeled or classified. It helps to find the hidden patterns in the data. It can describe the hidden structure of the unlabeled data but would not be useful to provide a correct, intended output [25].

There is another categorization of the machine learning algorithms depending on the preferred output. That include *Classification Algorithms* (Used for supervised learning with discrete output), *Regression Algorithms* (Used for supervised learning with continuous output), *Clustering Algorithms* (Unsupervised) etc [34].

We use supervised machine learning approaches in this project. In particular, the classification algorithms - Decision Tree and Random Forest.

1.2.6 Decision Tree. Decision Tree is a supervised machine learning algorithm used to solve both classification and regression problems. In Decision Tree, a trained model with a set of rules will be created based on the training data. The target class or value of a test/new data set will be predicted based on this training rules. Decision Tree algorithm is simple to understand as it uses a tree model representation to solve the problem. It starts from a root node and continues with other decision nodes. Each internal decision nodes corresponds to the feature variables and each leaf nodes corresponds to the class label [24]. Figure 2 shows the decision tree classifier.

The best attribute will be chosen as the root node. To identify the root node there are 2 methods. They are, *Information Gain* and *Gini Index*. There are statistical approaches to calculate Information gain and Gini index values for each feature variables. Attribute with better value will be considered as the root node and other attributes will be placed in the internal nodes according to the values in recursive order. Step 1 to model the decision tree is placing the root attribute. In step 2, the training data set will be divided into

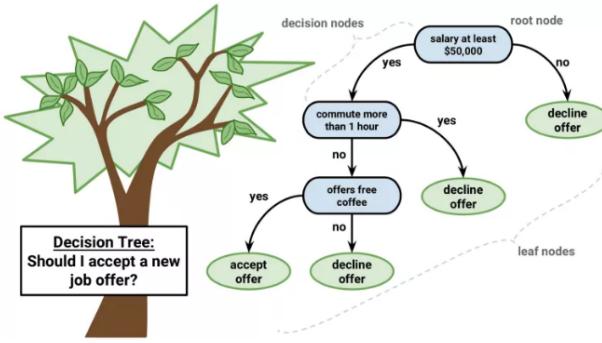


Figure 2: Decision Tree Classifier [24]

2 sub data sets in such a way that, both subsets will contain same attribute values for that variable. Step 1 and 2 will be repeated until we reach the leaf nodes with predicted class value [24].

Overfitting: Overfitting is a practical issue that can happen while building a decision tree. When the algorithm goes deeper and deeper it builds more branches because of the irregularities in data and the prediction accuracy of the model goes down accordingly. There are 2 methods can be used to avoid overfitting issues - *Pre-Pruning* and *Post-Pruning*. In Pre-pruning, we set a threshold value as a goodness measure and if it crosses, further split of the node will be stopped. In Post-Pruning, tree construction continues until all leafs are reached and pruning will be done if the model shows overfitting issues. Cross-validation data will be used to measure the improvement in this method [24].

1.2.7 Random Forest. Like Decision Tree, Random Forest algorithm also can be used for classification as well as regression problems. It is a supervised machine learning algorithm. It uses decision tree concept as well but there will be more than one trees in a Random Forest. As the number of trees increases in the Random forest, the accuracy of the prediction also will increase accordingly. Random forest algorithm can handle missing values in the data. Also with more trees in the forest, overfitting issues will not occur in Random Forest algorithm [19]. Figure 3 shows the Random Forest model.

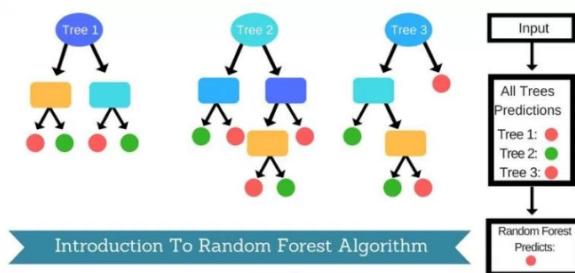


Figure 3: Random Forest model [19]

Random Forest algorithm progresses via 2 stages - Random Forest creation and Perform prediction. To create the Random Forest, we select a random number of feature variables from the total list of

feature variables in the training data and create a Decision Tree out of it. We repeat this process to create desired number of trees. These randomly created trees will form a Random Forest. Figure 4 shows how random forest algorithm works.

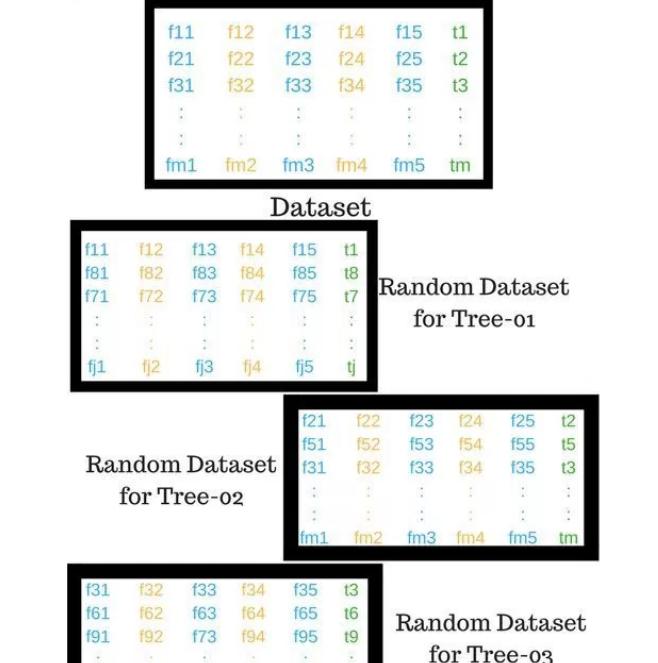


Figure 4: How random forest algorithm works [19]

The test data set will be analyzed against the rules developed by each of the trees to predict the output. To predict Random Forest output, the outputs of each of the trees are considered as votes. The top voted output is the final predicted value of the Random Forest.

1.3 Installations

Technologies used in this project are discussed in detail in section 1.2. The installation commands on Ubuntu 16.04 OS for each of these technologies are given in this section. Installations can be done from the terminal window.

- (1) Python installation steps for ubuntu OS are available in the askubuntu website [4].
- (2) Install pip to manage the libraries in the Python. Pip is a Python package management software used to install and manage Python libraries. pip can be installed using command "sudo pip install -U pip" [18].
- (3) Install PySpark using command "sudo pip install pyspark" [1].
- (4) Install Jupyter notebook using command "sudo pip install jupyter" [20].
- (5) Install Pandas using command "sudo pip install pandas" [16].
- (6) Install matplotlib using command "sudo pip install matplotlib" [3].
- (7) Install seaborn using command "sudo pip install seaborn" [26].

Table 1: Variables and description [15]

Variable	Description
Credit	Creditability: Good or Bad
Account Status	Balance of current account
Credit Months	Duration of Credit (month)
Credit History	Payment Status of Previous Credit
Purpose	Purpose of credit
Credit Amount	Amount of credit
Savings	Value Savings or stocks
Employment	Length of current employment
Installment Rate	Installment in % of current income
Personal Status	Sex and Marital Status
Guarantors	Further debtors
Residence	Duration in Current address
Property	Most valuable available asset
Age	Age in years
Other Installments	Concurrent Credits
Housing	Type of apartment
Credit Cards	No of Credits at this Bank
Occupation	Occupation
Dependents	No of dependents
Telephone	Phone number
Foreign Worker	Foreign worker

(8) Install numpy using command "sudo pip install numpy" [2]

All these installation steps are included in a make file referred in appendix A.1.

2 DATASET

We used the German Credit data which is publically available in the UCI Machine Learning Repository [10] and also in the website of PennState Eberly College of Science [15]. Both these sites have the cleaned dataset and not the original one. The dataset that we used (german-credit.csv) is taken from the website of PennState Eberly College of Science [15] and it is uploaded in the Github repository [12]. We recreated the original one from these data sets to understand and try out the data cleaning processes. We start our project with the recreated original data set (credit-data.csv) which is available in the Github repository [12].

Dataset includes 1000 customer records with 20 feature variables and a class variable. In the class variable, the actual class of the customer is specified - good or bad. The complete list of data set variables and their description is given in Table 1.

3 DATA CLEANSING

A massive amount of raw data is piling up in the recent years from different sources and it has been continuously getting stored as the storage mechanism is getting cheaper and the storage capacity increases day by day. This raw data cannot be analysed as it is by human or traditional applications, as the processing capacity of traditional tools has been exceeded because of the volume of the data. That is the reason why big data technologies have evolved and they use distributed systems like MapReduce, Spark, Flink etc.

Even if we have a big data solution to process the high quantity of raw data, it is not the efficiency and performance of the solution that determines the quality of the knowledge extracted but it depends on the quality of the data as well. The raw data likely to be imperfect and may contain noise, irrelevant information, missing values etc. It is well known that low quality data will lead to low quality knowledge [9]. Hence data cleaning is the major step to be performed before we continue with data mining algorithms to make sure that we are using a suitable and relevant data set.

Data cleaning has 2 parts. First part is data preparation and second part is data reduction techniques.

3.0.1 Data Preparation. The data going to the analytics model should be clean and noise free. Hence data preparation part includes tasks like data cleaning, data normalization, data transformation, missing value imputation, data integration and Noise identification. Figure 5 shows the data preparations tasks [9].

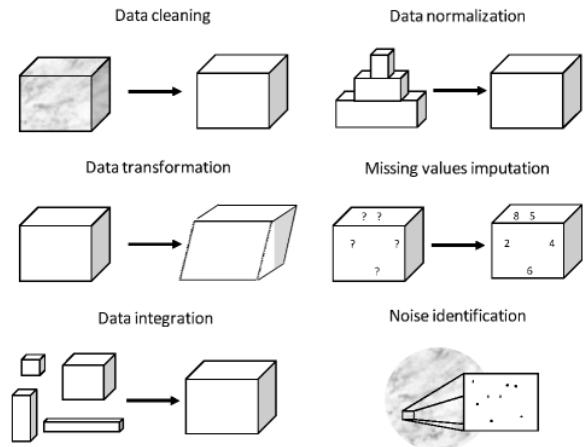


Figure 5: Data Preprocessing and preparation tasks [9]

3.0.2 Data Reduction Techniques. To reduce the dimensionality problem and the computational cost, because of a large number of variables and instances in the data set, we try to gather only the required set of quality data. Data reduction techniques include feature selection, instance selection and discretization. Figure 6 shows data reduction techniques [9].

With respect to our chosen data set, data reduction techniques were already applied to the raw data and 1000 customer records and 21 variables were shortlisted. All these variables are either categorical (like Account-Balance, Previous-credit, purpose etc) or continuous (Duration-of-credit, Installment-percent, dependents). As part of data preparation for our analysis, we transform the values of categorical variable's from string to scores (numerical values). For example, the variable "creditability" got 2 values - good and bad. After transformation process, "good" get replaced by "1" and "bad" get replaced by "0". Likewise, we gave scores for the values of the variables, Foreign-Worker, Telephone, Previous-Credit, Purpose, Sex-MaritalStatus, Guarantors and Type-apartment.

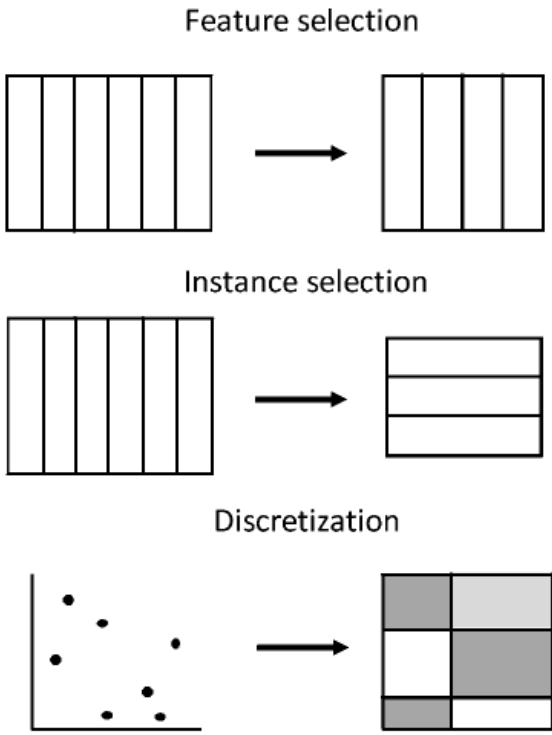


Figure 6: Data Reduction Approaches [9]

4 DATA ANALYSIS

Big data analysis is the process of obtaining knowledge by analyzing and understanding hidden patterns, market trends, unknown correlations, customer preferences and other relevant information from large and varied datasets [21]. Big data analytics methods include exploratory analysis, data mining, predictive analytics, machine learning, deep learning etc. The results of the analysis can be visualized using tools like Tableau, Infogram, Plotly etc or by using Python scripts. This project utilizes methods like exploratory analysis, predictive analysis, machine learning algorithms and visualizations of results using Python scripts. Python codes for all these analysis methods are given in appendix A.3.

4.1 Exploratory Analysis

Exploratory analysis is basically to explore the data and understand what it actually contains. It is an approach to summarize the general characteristics of the data set before we attempt to model it. Statistical methods or direct visualizations can help in data exploration [33].

4.1.1 Direct Visualization. After data preprocessing, our dataset includes 1000 customer records with 20 feature variable and 1 class variable. Feature variable values can be visualized to understand the characteristics and how they are related to each other - proportionally or inversely.

Figure 7 shows the histogram of credit amount disbursed with respect to frequency. From this diagram, we understand that most

of the customers are requested for loans for up to 2500 German Marks. The number of customers decreases as the loan amount increases. And very few customers fall under the loan amount category over 10000 German Marks.

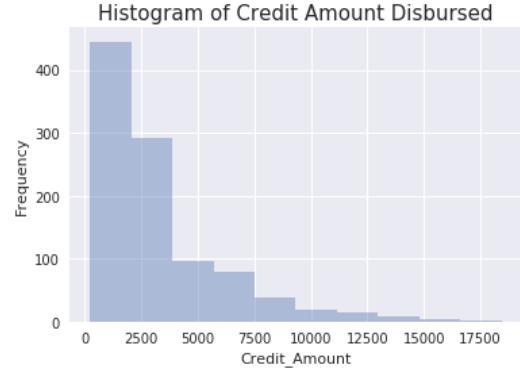


Figure 7: Credit amount vs. Frequency [28]

Figure 8 and Figure 9 shows the credit amount availed by bad customers and good customers respectively. The trend is almost the same. Maximum customers from both the classes fall under the category of up to 2500 German Marks. But there is a noticeable difference in the number of customers under 12500 range. Bad rated customers are more in this category.

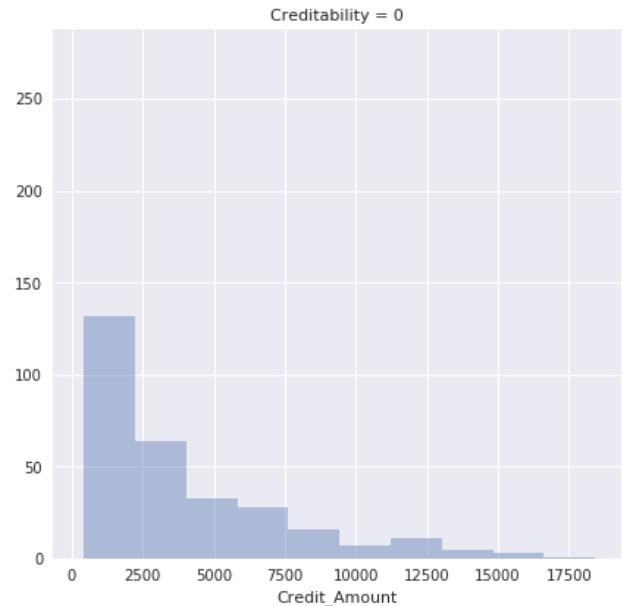


Figure 8: Credit amount vs. bad customers [28]

Figure 10 shows the duration of credit in months vs. number of customers. From this graph, we can understand that maximum number of customers opted for 10 to 15 months duration.

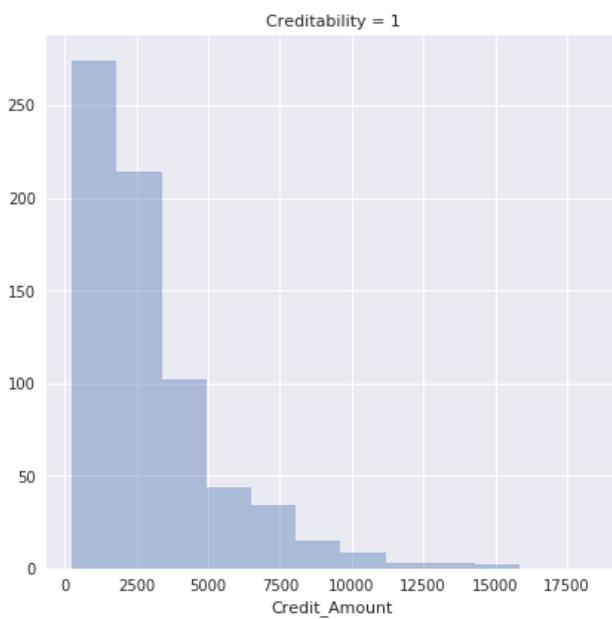


Figure 9: Credit amount vs. good customers [28]

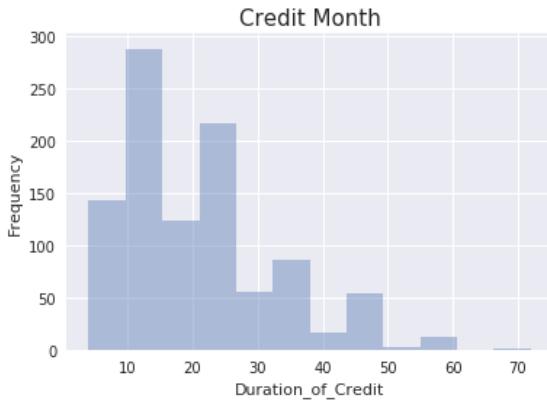


Figure 10: Duration of credit in months vs. frequency [28]

Figure 11 and Figure 12 shows the duration of credit in months vs number of bad customers and good customers respectively. It shows that there is not much difference in the trend.

Figure 13 shows how customers are scattered with respect to age. Most of the borrowers fall under the age group of 23 to 28.

4.1.2 Data Classification. We have one class variable "Credibility" to classify the customers based on the bank's opinion on the actual applicants. We could extract this class information from dataset using PySpark Python script "GroupBy". Table 2 shows the output of the script.

Customers in our dataset are classified into 2 classes - Good (1 = Creditworthy) and Bad (0 = Uncreditworthy). We have 700 customers in the Good class and 300 customers in the Bad class.

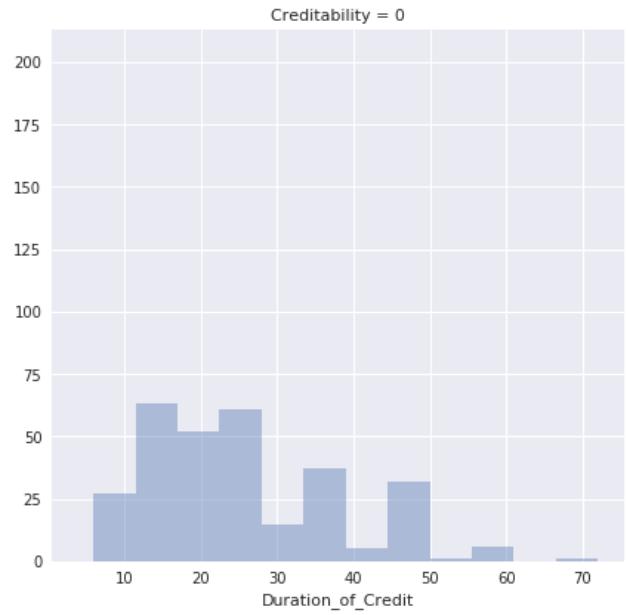


Figure 11: Duration of credit in months vs. bad customers [28]

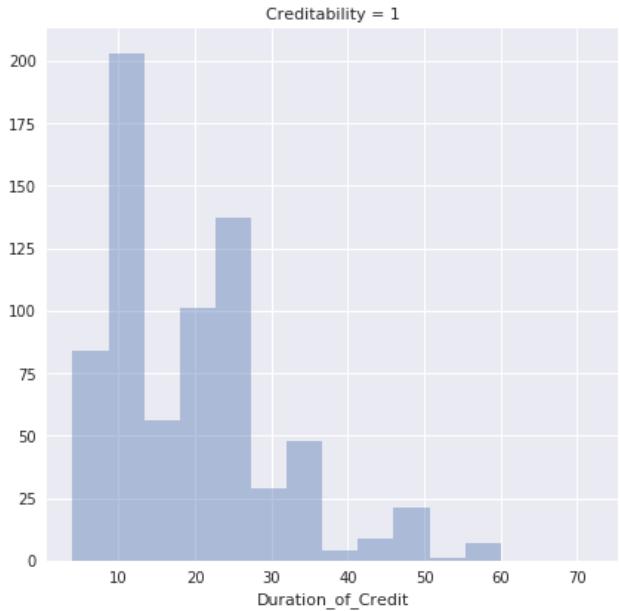


Figure 12: Duration of credit in months vs. good customers [28]

We divide our dataset of 1000 customer records randomly into 2 parts. First part is the training dataset with 700 customer records and second part is the test dataset of 300 customer records.

4.1.3 Interquartile Range. Interquartile Range is a statistical method to measure the variability of the data. This will be applicable

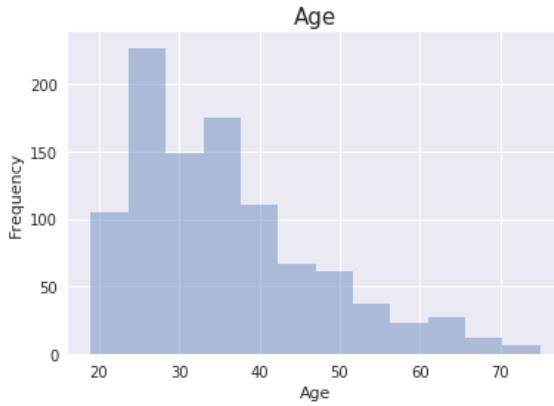


Figure 13: Age vs. frequency

Table 2: Data classification

Creditability	Count
0	300
1	700

Table 3: Variability in Credit-Amount

Min	1st Qu	Median	Mean	3rd Qu	Max
250	1365.5	2319.5	3271.248	3972.25	18424

Table 4: Variability of Duration of credit

Min	1st Qu	Median	Mean	3rd Qu	Max
4	12	18	20.90	24	72

only for the continuous variables (Credit-amount, Duration of credit and Age). The rank-ordered data will be divided into 4 equal parts called quartiles. Values are called the First (Q1) Second (Q2) and Third (Q3) quartiles. Q2 is the Median value of the dataset [30].

We used pandas quantile function to extract this information for all the continuous variables.

Table 3 shows the variability of Credit-Amount.

Table 4 shows the variability of Duration of credit.

Table 5 shows the variability of Age.

4.1.4 Cross-Tabulation. Cross-Tabulation is a statistical method used to compare the relationship between categorical variables. In our scenario, we examine the relationship of the categorical variables with the class variable "creditability". We create a *contingency table* which displays the frequency of categorical variables with respect to the class [36].

Table 6 shows the contingency table created for the variable sex-marital status against class. It shows the number of good and bad customers distributed among the 4 categories of the variable sex-marital status. Category "male: married/widowed" has the maximum number of Good customers. Contingency tables are used to create the Chi-square values.

Table 5: Variability of Age

Min	1st Qu	Median	Mean	3rd Qu	Max
19	27	33	35.5	42	75

Table 6: Contingency table of sex-marital status

		Sex-Marital Status					
		1	2	3	4	Row Total	
Creditability	Good	30	201	402	67	700	
	Bad	20	109	146	25	300	
	Column Total	50	310	548	92	1000	

4.1.5 Test of Independence. We need to identify the features that are closely related to the class/credit rating to build a predictive model. We do a test of independence on all our feature variables to identify the ones to be selected for data modeling. The method we use to do the Test of Independence is the Chi-squared test. The output of the Chi-squared test is the input to the Logistical Regression Algorithm. Variables which are not related to the class variable will be discarded from further analysis of Logical Regression.

Pearson's Chi-squared test: Chi-squared test is used to determine the significant difference between expected values and observed values in one or more categories. There are 2 types of Chi-squared test - Goodness of Fit and Test for Independence.

We use the second method - *Test of Independence*. It compares 2 variables in a contingency table to check if they are related. In other words, it examines if the distributions of categorical variables are different from one another.

If the calculated value is small that means, the variables are related. If the value is large that means, the data is not related and not fit for analysis [29].

p-value: p-value is the probability value that, when the null hypothesis is true, the chi-square value will be greater than the empirical value of the data. There is a p-value distribution chart available where it is calculated against the significance value, degrees of freedom and chi-square test value [13].

Degrees of freedom: Degrees of freedom is the number of scores that can be varied. It is calculated using the formula,

$$\text{Degrees of freedom} = (r - 1) * (c - 1) \quad (1)$$

The calculated values are shown in Table 7.

5 MODELS

Predictive models can be created using different Machine Learning algorithms such as Logistical Regression, Decision Trees, Random Forest etc. Machine learning algorithms generate models from the training data and tested against the test data to estimate the accuracy level. Before building predictive models, there are few baseline models can be created to compare and see what improvements we are actually trying to achieve. By comparing the accuracies of different predictive models against the base models, we can come up with the best model for that particular problem. The best model is saved for the future predictions on new datasets.

Table 7: Chi-square, df and p values

All	Chi-square	D.F	PValues
Account-Balance	123.720944	3	0.000000e+00
Duration-of-Credit	78.886937	32	7.784572e-06
Previous-Credit	61.691397	4	1.279199e-12
Purpose	33.356447	9	1.157491e-04
Credit-Amount	931.746032	922	4.045155e-01
Value-Savings-Stocks	36.098928	4	2.761214e-07
employment	18.368274	4	1.045452e-03
Instalment-percent	5.476792	3	1.400333e-01
Sex-MaritalStatus	9.605214	3	2.223801e-02
Guarantors	6.645367	2	3.605595e-02
Duration-address	0.749296	3	8.615521e-01
asset	23.719551	3	2.858442e-05
Age	57.626982	52	2.749531e-01
Concurrent-Credits	12.839188	2	1.629318e-03
Type-apartment	18.674005	2	8.810311e-05
No-of-Credits	2.671198	3	4.451441e-01
Occupation	1.885156	3	5.965816e-01
dependents	0.009089	1	9.240463e-01
Telephone	1.329783	1	2.488438e-01
Foreign-Worker	6.737044	1	9.443096e-03

Table 8: Baseline Model 1

Good	
Good	210
Bad	70

5.1 Baseline Models

Baseline models use simple summary statistics. In classification problems like our scenario, baseline models are created based on the class values. As mentioned in the data classification section 4.1.2, our total list of 1000 customer records are divided into training dataset and test dataset. Training dataset has 700 customer records and test dataset has 300 customer records. For the baseline models, we evaluate the test data of 300 customer records.

In this project we create 2 baseline models.

Baseline Model 1: In this model, we assume all the input test customer records (300 customer records) belongs to the "Good" class. Since out of 1000 customers, 700 falls under "Good" class, we assume among the 300 customers in test dataset 70% will fall under "Good" class and rest in "Bad" class, which means this baseline model holds 70% accuracy.

Table 8 shows the assumption in baseline model 1.

Baseline Model 2: In this model, we assume all the input test customer records (300 customer records) belongs to the "Bad" class. Since out of 1000 customers, 300 falls under "Bad" class, we assume among the 300 customers in test dataset 30% will fall under "Bad" class and rest in "Good" class, which means this baseline model holds 30% accuracy.

Table 9 shows the assumption in baseline model 2.

Table 9: Baseline Model 2

Bad	
Good	210
Bad	70

5.2 Decision Tree Model

To build this model, we use the machine learning algorithm - Decision Tree which is explained in section 1.2.6. PySpark's class "DecisionTreeClassifier" is used to build different Decision Tree models from training data based on different tree attributes like MaxBins, Maxdepth, Impurity etc. Impurity measures are calculated internally by this classifier to identify the root node and other internal nodes. Gini Index is the method opted in our project.

Formula to calculate Gini Index is,

$$GiniIndex = \sum_{i=1}^C f_i(1 - f_i) \quad (2)$$

We created 2 Decision Tree models to compare the accuracy.

Decision Tree with maxDepth None: In this model, we set the maxDepth value of the Tree to None and we calculated the accuracy using PySpark's "MulticlassClassificationEvaluator". In this case, the tree can become arbitrarily deep and complex and more chances of overfitting issues.

The accuracy of the output of this model is 0.679. Maximum number of Bins are 32. Depth is None.

Decision Tree after adjusting the attribute values: In this model, we set the maxDepth value to 6 and maxBins value to 20. We used the same PySpark's "MulticlassClassificationEvaluator" to calculate the accuracy. Since we have limited the maxDepth and maxBin values, the overfitting issues decreases.

- The accuracy of the output of this model is 0.716
- Number of Bins are 20
- Depth is 6

5.3 Random Forest

Random Forest Machine Learning algorithm which is explained in the section 1.2.7 is used to build Random Forest model. We use PySpark class "RandomForestClassifier" to generate the model from training data. We build 2 Random Forest models one with default attribute and another one with chosen attribute values.

Random Forest with Default Settings: In this case, the attributes of the Tree are selected by the "RandomForestClassifier" itself internally and accuracy of the model is calculated based on that.

The accuracy of the output of this model is 0.756. Maximum number of Bins are 32. Maximum Depth is 5. Maximum number of Trees are 20.

Tuning Random Forest with cross-validator: In this case, we tune the Random Forest model by trying different attribute values for tree attributes - maxDepth, maxBin and numTrees. We can provide multiple values for each attribute. We provided 3 values for maxDepth, 2 values for maxBins and 3 values for numTrees. We will start with some random values for these attributes.

Table 10: Prediction matrix - Decision Tree

Prediction	0.0	1.0
Label		
0.0	35	55
1.0	34	184

Table 11: Prediction matrix - Random Forest

Prediction	0.0	1.0
Label		
0.0	40	50
1.0	18	200

We use *cross-validation* techniques in this type of Random Forest model to get the best model. PySpark "CrossValidator" will analyze the values of the attributes. In this scenario, the "CrossValidator" will choose 3 values of attributes from $3 * 2 * 3$ values. It will then try different combinations of the attribute values internally and finally, the model will get tuned to a final set of attributes which derive the best model with maximum accuracy.

- The accuracy of the output of this model is 0.779
- Number of Trees are 100

As we identified the best model with maximum accuracy is the Random Forest model, we passed the actual dataset to this model and received an accuracy of 0.845

6 RESULTS

Now we have all the desired models created which can predict the class of a new customer. We can compare and analyze the outputs of each of these models and conclude with the best model. We can analyze the results based on accuracy and mean penalty matrix.

6.1 Prediction matrix

Prediction matrix can be extracted using the "groupby" option in PySpark. Table 10 and Table 11 shows the prediction matrix of Decision Tree and Random Forest respectively. Decision Tree has got 219 right predictions and Random Forest has got 240 right predictions out of 300 customer records.

6.2 Feature Importance

Feature Importance is the list of important predictors that are the top contributed variables towards building the predictive model. Normally the variable with maximum dependency would be treated as the root node by the algorithm. We could calculate the feature importance only for the Random forest algorithm by using the class "bestModel.featureImportances". Figure 14 shows the list of predictors. We could see that the variable "Account Balance" contributes maximum to the predictions.

6.3 Model Accuracy Comparison

Figure 15 shows the accuracy of different predictive models that we created. We plotted the output of "MulticlassClassificationEvaluator" for Decision Tree and Random Forest. We can understand

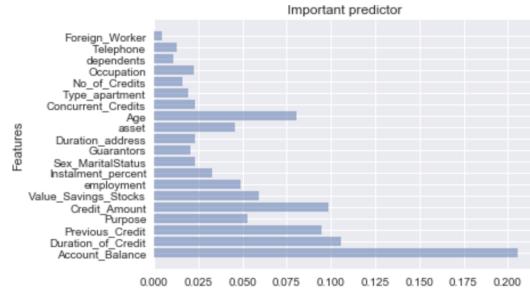


Figure 14: Random Forest Important Predictors

Table 12: Penalty Matrix [15]

Actual	Predicted 'Good'	Predicted 'Bad'
Good	0	1
Bad	5	0

from the graph that baseline model 2 has got the least accuracy and Random Forest has got the most.



Figure 15: Model accuracy comparison [28]

6.4 Penalty Matrix

One important aspect to consider while choosing a predictive model is the accuracy. When considering the actual goal of this project, the model should be apt to minimize the risks and to maximize the profit. The model should ensure good prediction accuracy to achieve the goal.

A penalty matrix is defined to calculate the loss to the bank. Penalty will be applied to each misclassifications and penalty value differs for wrong classifications - 'good as bad' and 'bad as good'. As discussed in the project goals section 1.1, approving loan for an uncreditworthy customer will end up in more financial loss for the bank and accordingly is a greater risk. Hence classifying a bad customer wrongly as good customer will have more penalty.

Table 12 shows the penalty matrix. For right predictions penalty is 0. If a good customer predicted as bad, the penalty is 1 and if a bad customer predicted as good, the penalty is 5. The sum of the

penalty values multiplied with the respective number of misclassified customers will provide the total amount of loss / penalty.

Figure 16 shows the penalty comparison of different predictive models. Baseline model 1 has more chances of predicting bad customers as good because it blindly assumes that, all the incoming customers are good. Hence it has got more penalty value. Baseline model 2 has got least chances of classifying bad customers as good because it assumes all incoming customers are bad. Hence baseline model 2 has minimum penalty.



Figure 16: Model penalty comparison [28]

6.5 Accuracy and Penalty Comparison

Figure 17 shows the accuracy and penalty comparison for all the 4 models. Random Forest is the most accurate model and with minimal penalty. Hence Random Forest is the best model out of all.

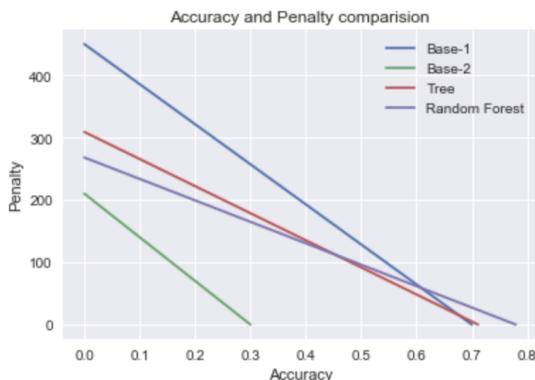


Figure 17: Model accuracy and penalty comparison [28]

7 DISCUSSION

We have built 4 predictive models. Baseline model 1 and 2, Decision Tree and Random Forest. We did a small study on Logistical Regression model as well. There are many other machine learning algorithms available which are suitable for classification analysis. Current analysis uses only 20 feature variables and 1000 customer records to populate the predictive models. In predictive analysis, the bigger the training dataset, the better the outcome. Current

analysis can be extended to really big data with more feature variables customer records and also data from multiple years. Data processing can be done using distributed big data processing systems available today for better accuracy. Unfortunately, such a large data is not publicly available for studies in finance area right now. Hence we tried big data technologies in a comparatively smaller dataset.

8 CONCLUSION

Out of 4 predictive models created, Random Forest has the maximum accuracy in classifying the customers in the right class. Even if it gives an accuracy of around 85% it is not an error free model. There are 15% chances for misclassification. The size of the dataset that we considered to develop this model may have a direct impact. If we can train the model with a larger data set with tens of thousands of customer records and feature variables, the accuracy may increase close to 100%. There might be other more advanced machine learning algorithms and tools coming up to explore the chances of increasing the overall accuracy of the predictive models in common.

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A PROJECT REFERENCES

All project related documents are available in the github repository i523/hid328/project: <https://github.com/bigdata-i523/hid328/tree/master/project> [12].

A.1 Makefile

Make file is created assuming that the target system has Ubuntu OS and Python3 installed already. This can be executed from terminal window from folder i523/hid328/project/code using command "make run". Makefile is available in the github repository i523/hid328/project/code [8].

A.2 Data Set

"credit-data.csv" is available in Google Drive /project-data/hid328/.

A.3 Project Code

Project code is available in the Jupyter notebook "project.ipynb" in the github repository i523/hid328/project/code [8].

Big Data and the Customer Experience Journey

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ABSTRACT

A customer's experience journey consists of multiple touchpoints along the way as they make choices in which companies and brands to interact with and ultimately, purchasing decisions. While the customer experience journey may differ based on product, service, audience, time, as well as a company's capabilities and strategic initiatives, the need to understand the customer transcends all industries. These touchpoints are increasingly moving to the digital space through online search, mobile interaction, social media, email, in addition to other methods that may not even be in existence as of yet. Given the number of these touchpoints across customers and the ability to track customers across multiple methods, understanding the experience of customers through the use of big data provides opportunities for companies to better enhance the customer experience journey. Real-time recommendations, personalized marketing messages, and geo-targeted advertising can all play a role in *nudging* the customer appropriately when companies are looking to drive customer interaction and behavior. We will seek to explore this customer experience journey in the digital environment and introduce relevant case studies where companies and industries have started to utilize big data and analytics to better understand and customize the customer experience journey through digital efforts.

KEYWORDS

i523, hid329, big data, analytics, customer experience journey, consumer behavior, digital marketing

1 INTRODUCTION

The customer experience journey has been largely explored from a psychological and behavioral standpoint [50]. Dating back to the near 1800s, marginal and expected utility of actions were detailed by Nicholas Bernoulli, among others, to better understand how purchasing decisions were made [50]. From related work that followed in this field of studying behavioral economics, research has shown that purchasing decisions are not linear and at times, are not even rational as cognitive, emotional, and social factors can all play a role into how a customer makes a purchasing decision [50]. As described by Stoicescu, the reason why researchers started to study purchasing behavior was due to the "diversification of need" [50].

However, with diversification also comes complexity. The more choices a customer is given, the harder it can become for them to make a decision [50]. With every product choice, there also is an opportunity for interaction or *touchpoints* along this customer experience journey [34]. These series of touchpoints can occur through a variety of ways and the time frame in which they take place can also vary greatly by the product or service being offered and to which audience. In figure 1 example of a customer setting

up utilities after the purchase of a new home and the multiple touchpoints they may encounter along their journey [41].

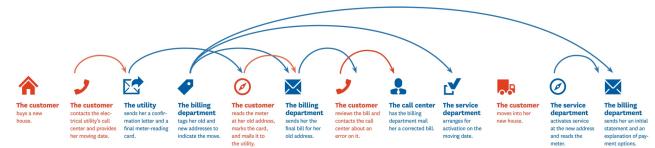


Figure 1: Customer Experience Journey Touchpoints [41]

However, not all touchpoints are created equal [34]. There are some touchpoints that every customer may have to go through to get to the next step in the process and others that will produce a more valuable action, such as a purchase [34]. There are further questions today that did not exist in years past due to the advances in technology and how that affects customer behavior [29]. These advances in technology not only could influence customer behavior but also provide companies direction on which products they should produce, where these products should be placed, what price point is most optimal and how should they properly promote a particular product to their audience [29]. Big data and analytics can provide opportunity to inform the promotional piece as companies have utilized this feature to provide personalized and relevant content along the customer journey as defined in figure 2 [50].

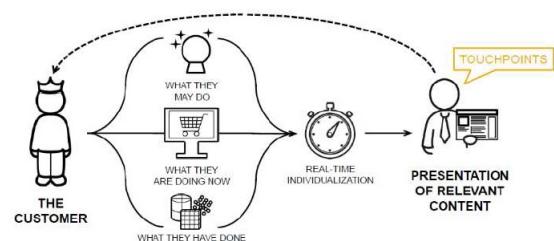


Figure 2: Customer Experience Journey [50]

While traditional advertising and marketing methods have included outdoor, print, television, and radio, among others, there is a growing shift in reaching customers via the digital space [29]. As of 2016, digital advertising spend reached 72 billion dollars, a 20% increase from the year prior and now accounting for a third of all advertising revenue spent in the United States [5]. With the increased move to digital from more traditional outreach methods, the customer relationship is also being managed via digital platforms such as email, social, and mobile [29]. A customer's *digital journey* can provide opportunities for big data and analytics to better understand the touchpoints along the way as well as where a

company may be able to *nudge* a customer appropriately to make a purchase decision.

The objective of this work is to provide a view into the customer experience journey as it relates to big data and analytics. This overview of existing work is to allow one to see how a company or industry may start to match their big data efforts with the purchase decision that customers make as well as the multiple touchpoints included along the way. The move towards digital outreach and marketing efforts will also be defined to ensure the reader understands what is meant throughout as it relates to outreach and personalization efforts. Rather than the analysis of a specific dataset, real-world examples will be showcased across a variety of industries to provide detail as to how big data is being used to better understand the customer and enhance the journey they go through along the way. Lastly, this work will highlight the need of matching big data with the customer experience journey, challenges with pursuing this work going forward, along with recommendations on how to overcome these challenges.

2 WHAT IS THE CUSTOMER EXPERIENCE JOURNEY?

The way *customer experience journey* is defined can differ by industry, product, and even by place. While past work has defined the customer experience journey as the process of purchasing a product or service, in today's landscape, it has become more than that. The Harvard Business Review would define the customer experience journey as the "sum-totality of how customers engage with your company or brand, not just in a snapshot of time, but throughout the entire arc of being a customer" [42]. Traditionally, the customer experience journey and buying process were used interchangeably where a customer moves through a decision making process. Some key areas that were highlighted in a typical customer experience journey include:

- **Need Identification:** At this stage, this is where the customer decides whether they have a particular need that they believe the product or service could fill. There are times where properly identifying the need or problem can be an area of opportunity for a company [13].
- **Awareness:** In order for customers to even engage with a product or brand, they first need to be aware that it exists. Further, the customer has to decide whether the product, service, or brand is relevant to them [13].
- **Evaluation of Alternatives:** Here, a customer starts to investigate the options available and educate themselves on the benefits and drawbacks of each. This is an area where companies seek to differentiate themselves from competitors as customers go through this stage in the progress [13]. As customers continue in their research state, they can be influenced in a variety of ways such as through advertising and marketing, word-of-mouth or reviews from others, in addition to information they obtain in other ways through their own search process [29].
- **Purchase:** After a customer has gone through their choices to the best of their satisfaction, they move to the stage where they decide to make (or not make) a purchase [29].

• **Post-Action Evaluation:** After a decision is made, one way or the other, this is place where the consumer evaluates their decision which may include key questions such as [13]:

- Were my needs adequately met?
- Am I satisfied with my choice?
- If given the same circumstances, would I make the same choice again?
- Would I recommend the choice I made to others?

While the list of questions could be endless the intent is to move customers through this purchase decision process so companies create loyal customers and advocates [29]. However, that model is evolving with the shift to a multi-prong outreach approach via digital and non-digital methods [13]. A longer customer experience journey is outlined in figure 1 as a customer can enter at any stage in the process. Pre and post purchase measures can be collected, stored, and analyzed at any point along the way as shown in figure 3 [13].

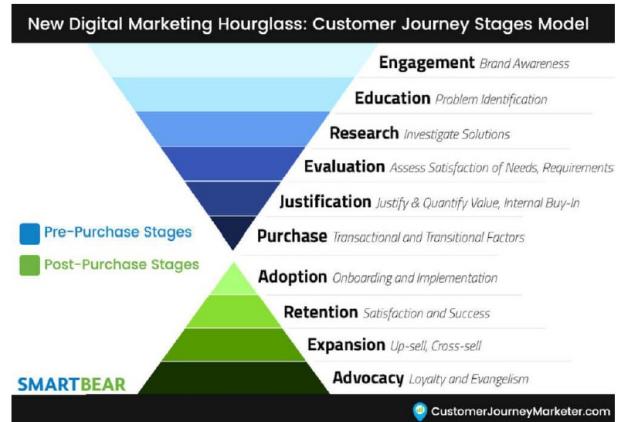


Figure 3: Digital Marketing Customer Stages Model
[13]

3 WHAT DOES DIGITAL MEAN?

With the influx of big data, analytics, and technology, there is often a rallying cry among leadership teams for an effort to be more *digital*. However, when exploring the definition of *digital*, it can greatly differ by audience, industry, and objective. Even within a singular company, alignment on what digital means can vary. Instead of trying to decide what digital *is*, it may be more beneficial to think of what digital can *do*. McKinsey highlights that digital should create value of some kind and offers various ways in which this can apply to an organization [14]. Despite varying definitions, methods, and applications of what digital is (and is not), there are commonalities in digital efforts that can be used to better understand this environment [26]:

- **Customer-Centric:** Digital efforts entail putting the customer first as they examine data and processes to enrich the customer experience [26].

- **Real-Time:** Long gone are lag times between collecting, analyzing, and processing data to decision-making. Now, data collection is always on and can be pulled at any time [26].
- **Connected:** With the volume, veracity, variety, and velocity of big data alone, the ability to have data sources and storage systems talk to one another is crucial to develop meaningful insights and inform decision making appropriately and effectively [1]. This not only has to happen from a technology standpoint but also from a company culture standpoint as well to ensure appropriate units and individuals are also talking to one another to better understand the customer experience journey overall.

It's important to note that while *digital* can mean *online*, one should not assume that these actions and behaviors only occur in the online environment. However, the collection, storing, and analyzing or these behaviors can be *digital* or *online* even though they may be reflective of what is happening in an *off-line* setting. Overall, implementing digital capabilities should improve business processes, challenge new ways of thinking, and deliver ways to enhance the customer experience journey [1].

4 WHAT IS DIGITAL MARKETING?

While advertising and marketing methods go as far back as the 1800s where customer lists were used to determine how individuals could be influenced via direct mailing efforts, digital marketing has only come to be with the creation of the internet [10]. The internet has created opportunity for brands to directly connect with customers and likewise, for customers to engage with brands in a myriad of ways in the digital space [17]. While varying definitions of digital marketing exist, it is often categorized as a subset of traditional marketing where the “use of digital technologies create an integrated, targeted, and measurable communication” to not only attract potential customers but engage with current ones for retention and loyalty purposes [23]. Digital marketing became even more prevalent in the 2000s as companies such as Google, Yahoo, and Facebook provided opportunity to deliver ads at an individual level based on demographic and behavioral characteristics [10]. Other data collection firms offered the ability to track users across the web space to see which pages were viewed, clicked, and time explored to help further understand the experience of a customer across the web space [10]. With these advances in technology and understanding, the customer experience journey began to also transform along with the changes in advertising from traditional to more digital.

5 HOW IS BIG DATA INVOLVED IN THE CUSTOMER EXPERIENCE JOURNEY AND DIGITAL MARKETING?

As the typical customer experience journey moves away from a traditional linear process and more towards an iterative approach, there is a need to understand the pathway among customers with data [17]. As of 2016, there are now approximately 3.7 billion individual users on the internet [3]. This population size coupled with the multiple methods of interaction present an opportunity for companies to better understand potential customers in an effort

to deliver the right message, to the right person, at the right time. A Gartner report states that the amount of data companies are collecting is growing by nearly 40 percent year-after-year [30]. Nearly one of out of every four state that there is a need to tie big data back to marketing-related efforts [30]. At the time of the report, it was estimated that only three percent of companies surveyed had a dedicated individual responsible for big data analytics and customer intelligence insight [30]. As the touchpoints with customers increase and also move more towards digital, so does the ability to collect and track the data from these touchpoints to better understand the customer experience journey [17].

One could argue that marketing data has been *big* for quite some time given the sheer number of people exposed to efforts typically exceeds millions [10]. However, what has changed in this space is marketing’s increased use of digital technologies to reach potential customers in the digital landscape across various channels including search, display, social media, email, etc. [29]. For companies to be successful in utilizing big data to inform digital marketing efforts and to better track and enhance the customer experience journey, incorporating the necessary technologies and talent is a must along with shifting the organizational culture to making data driven decisions [23]. This process can be difficult as an individual user alone can generate “billions of data signals” and attempting to understand which ones may be tied directly to a product or brand’s marketing efforts can be a daunting and overwhelming task [10]. However, there are a few well-known companies that have started the shift in tracking the customer experience journey through big data analytics and applications. We will examine key industries that have leveraged this knowledge and insight to better understand and enhance their relationship with customers.

6 BIG DATA IN ONLINE RETAIL

Companies like Amazon and eBay are often cited as pioneers in utilizing big data analytics considering these were companies that were *born digital* [3]. While other retail companies have made their way into the big data analytics environment, often times they are brick-and-mortar establishments in addition to offering electronic commerce (e-commerce) capabilities, such as Target, Sears, or Wal-Mart. Growth in e-commerce has taken place around the world with nearly 1.3 billion customers in existence as of 2016 [3]. In the online space, there are multiple opportunities for these companies to track the customer experience from number of visits, keywords used in search, orders and products placed, frequency of purchases, in addition to when items in their virtual cart are abandoned or even when items are returned or complaints are filed [3]. Amazon and eBay, among others, have utilized big data analytics to their advantage to create recommendations for their customers, develop predictive models, and also offer real-time changes in the customer’s experience journey.

6.1 How Does Amazon Use Big Data?

In 1995, Amazon started its life in the online space as an electronic bookstore [25]. While early sales were still impressive totaling nearly \$20,000 a week, during their popular campaign of *Prime Day* in 2017, analysts estimated that sales for that one day alone to be

around \$500 million [47]. As of July 2017, Amazon has approximately 300 million users with nearly eight out of ten that make a purchase at least once a month [47]. The amount of information tracked per user continues to increase at an exponential rate as Amazon's growth has moved beyond their days of an online book-store and into the realm of an *everything* store, including acquiring other large companies such as Whole Foods [40]. With this, there are a number of ways that Amazon uses big data to enhance the customer experience:

- **Personalized Recommendations and Predictive Modeling:** As customers are exploring products on Amazon, they are often shown other suggested products either based on their own past purchase behavior or by what others who purchase similar items also bought [3]. These recommendations are shown in real-time, often on the same web pages as customers are exploring other products [3]. It is estimated that based on this ability alone, utilizing both structured and unstructured data, that 35% of all sales are attributed to the recommendation algorithm, which would show that their predictive efforts are meeting the needs of their customers [3].
- **Efficient Delivery:** Even though Amazon utilizes and houses large amounts of data about its customers to offer personalized recommendations and offers, the company also has to maintain a tremendous amount of data about its own operations to inform logistics and supply chain management to meet customer expectations [3]. A key selling message of Amazon is delivering product in two business days, even in some cases offering same day delivery on certain items if they are ordered within a certain timeframe CITE[21]. With the increase number of products, suppliers, and customers, Amazon is still able to rely on big data analysis to maintain a consistent experience that doesn't compromise delivery for the customer which in turn leads to a better customer experience overall [3].

6.2 How Does eBay Use Big Data?

eBay is a website that also started in 1995 which offered a unique opportunity to bring together buyers and sellers in the online space [15]. Sellers could place their items online where buyers could potentially place bids, similar to if they participated in a live auction, where the item may go to the highest bidder. This allowed for others around the globe to connect and purchase items directly from another person while paying for the item through online methods. It is estimated today that there are nearly 180 million buyers and sellers and nearly 250 million search inquiries made per day on eBay [31]. Like Amazon, eBay seeks to understand and tailor the online experience for customers through the use of big data in a multitude of ways as eBay itself states "understanding the customer is key" [44]. Various methods utilized to better understand and tailor the customer experience journey include:

- **Web Page Metrics to Inform Layout:** It is estimated that among eBay customers, there is "100 million hours of interactions collected per month" [44]. Through an extensive number of experiments and A/B testing, eBay is able to optimize the web experience for customers. From

their big data analytics, they can find preferred layouts of web pages which can customize anything from navigation feature to the size of photos displayed on the screen [3].

- **Ease of Finding Items:** Buyers and sellers alike utilize the search feature provided on the eBay website to find necessary items or to compare price points of like items when deciding which price point to utilize [31]. Behavior patterns of customers have been used to inform how to best optimize the search feature in an effort to get customers to the necessary items more quickly which in turn will, hopefully, produce a sale [31]. While in the past, the search algorithm would have taken words and terms in a more literal sense, though optimization eBay has been able to make the search algorithm more intuitive which has lead to more sales [31]. Such examples show that originally when customers would shorten words used in the search feature, they may not find what they need. However, after analysis of customer inputs and changes in the search algorithm, this ability was taken into account so customers could still find the necessary product without changing their behavior.

7 BIG DATA IN THE FINANCE INDUSTRY

There are a number of products and services available in the finance industry ranging from personal and business loans, to stocks, retirement accounts, and credit cards. Companies such as JP Chase Morgan, American Express, and Bank of America are capitalizing on big data use to inform their offerings and also better understand their customer base [52]. These companies are monitoring the customer experience journey through all touchpoints which could include web visits, phone calls, and even in-person interactions [24]. This information can also be used to detect fraud on certain accounts when activity occurs that may not be typical of their customer [52]. These algorithms and techniques can in turn ensure customers are protected which help with customer retention. Conversely, those in the finance industry may also be able to utilize big data and mining techniques to determine if they are about to lose a customer. One such company that utilized these methods to their advantage is American Express, which accounts for nearly a quarter of all credit cards transactions and totals more than \$1 trillion annually in customer purchases [35].

7.1 How Does American Express Use Big Data?

In 2010, American Express invested in big data technologies and resources, including Hadoop, to increase capabilities to detect fraud, provide recommendations to current customers, predict who may close their accounts, as well as acquire new customers [52]. These methods are used to assist in efforts to maximize the customer experience journey through the use of:

- **Fraud Detection:** To minimize loss, fraud alerts have to happen quickly. To achieve this, American Express implemented machine learning algorithm techniques [32]. Data points included in the model consisted of information about the merchant where the purchase occurred, purchase details such as items bought and price, and even customer

information [32]. By analyzing patterns in real-time, American Express was able to flag possible fraudulent activity in a matter of milliseconds which then allows the company and customers more time to prevent further loss with the increased capability [32]. American Express was able to identify an additional \$2 billion in fraudulent activity that they were not able to identify before and therefore protect their customers and ensure a more positive customer experience as a result [32].

- **Personalized Recommendations:** Along with protecting their customers, American Express also seeks to understand how to better engage their customers through personalized recommendations. One such example is based on analyzing customers past transactions along with geographic location information to push specific recommendations to customers in real-time [52]. Through the use of big data analytics, the company can send recommendations on similar restaurants in the area if they see from a customer's transactions they frequent a certain genre or area [52]. These recommendations also work on behalf of the merchants who accept American Express as the company can provide information on purchases in the area which merchants can use to create offers to entice customers to purchase products and services by using their American Express card at their particular store [16].
- **Churn Prediction Models:** American Express also uses its vast amounts of data to see if they can predict whether a customer will close their account [32]. By incorporating machine learning models, they can better understand the customer experience and appropriately jump in at different points along the journey in an effort to deter customers from closing their accounts. Through analysis of past transactions as well as nearly 100 other variables incorporated to understand customers, the company estimated that for one model, they were able to identify nearly one out of every four accounts they believed would have closed in the near future [32]. With this information, tailored marketing and messaging could be implemented to help with retention rates.
- **Acquiring New Customers:** Despite the large base of customers, merchants, and transactions, there is always a need for businesses to grow to increase revenue and capabilities for the future. One way to achieve this is through digital marketing efforts targeted at those who may be potential customers for American Express. Through their efforts, American Express was able to grow their customer base by nearly 40% through online marketing efforts [32]. With these more targeted and cost-effective measures, American Express was able to efficiently acquire new customers as compared to more traditional marketing efforts of the past, such as direct mail [32]. These optimizations further enhance the customer experience journey by delivering them a message at the right time through the right medium.

7.2 How Does Bank of America Use Big Data?

While big data, analytics, and predictive models can be used to better understand how to reach out, retain, and attract customers, these same techniques can be applied when determining how to optimize the customer experience journey from an internal perspective. Considering the journey can take place across a series of touchpoints, Bank of America was one major bank, among others, that utilized big data to better understand how to better serve their nearly 50 million customers [12]. One method included:

- **Customer Segmentation:** Through the use of big data, Bank of America acknowledged that their customer base could be divided into segments and therefore their behavior and needs differed [12]. By analyzing online correspondence, calls from a call center, and even visits to area branches, appropriate offers could be tailored to the customer [12]. Utilizing data points provided in the online space along with the ones that occurred elsewhere, a new program was developed by Bank of America [12]. With this new program and customized offerings, customers were more highly engaged with by Bank of America which increased customer satisfaction and experience as a result [12].

8 BIG DATA IN THE HEALTHCARE INDUSTRY

Rising patient volumes, increasing aging population, and mounting costs have all contributed to the growth, importance, and complexity of the healthcare industry [37]. As of 2016, it is estimated that nearly \$4.1 trillion will be spent on healthcare costs in the United States alone [37]. Nearly 290 million people in the United States have some form of insurance or healthcare coverage but that also leaves nearly 28 million who are uninsured [19]. A typical customer can interact with a number of stakeholders throughout their healthcare journey ranging anywhere from their initial doctor's visit, to filling a prescription at the pharmacy, to paying a bill to their insurance provider. One may then ask based on these interactions: how does the online space play into the healthcare industry at all?

With the move to electronic medical records (EMR), the ability to now aggregate years of information on an individual, as well as an entire population, becomes more of a reality [20]. Even though the healthcare industry has lagged behind other industries regarding their collection and use of big data, they are one of the most important as it relates to utilizing their information to create a better experience for customers as it pertains to their health [20]. The ability to link this data across various stakeholders is also critical in understanding the full journey of a customer (or patient) to ensure effective treatment decisions are made. Health Information Exchanges (HIEs) allow for this opportunity and the HIE has information on more than 10 million patients, over a span of nearly 80 connected hospitals, and approximately 18,000 physicians have access [20]. Big data in the realm of healthcare provides tremendous opportunity to create value for customers and healthcare professionals alike. One such software company explored this use of connected data sources to better inform healthcare providers with

practice-based evidence in an effort to tailor care for an individual patient [6].

8.1 How Does Apixio Use Big Data?

As others have stated about healthcare related data and reporting, “the problem in healthcare is not lack of data, but the unstructured nature of its data” [33]. Apixio, a cognitive computing firm based in California, wanted to take on the challenge of making unstructured healthcare related data available and easier to use in order to better aid decision making in patient treatment [33]. Their work involved taking clinical charts of patients and combining them with notes from physicians, test results, and even hospital stays to develop a more complete picture about an individual [33]. From there, Apixio was able to provide benefits based on this big data process:

- **Patient Model Development:** Data at an individual level was used to develop patient models from a series of text processing and coded healthcare data [33]. By creating a profile per individual, like individuals could then be grouped together which in turn helped to inform what treatments or procedures would work best in those individuals who fit a certain criteria [33]. Considering this information is derived from actual practice of medicine, it can better inform clinical care and also ensure that patients are set up for best optimal outcomes if treatment decisions are made based on big data collection and analysis [33].
- **Healthcare Cost Savings:** Cost of healthcare continues to be a growing concern for both customers and other key players such as healthcare professionals and insurance companies [37]. With the move to EMR and big data analytics, it is estimated that anywhere between \$300 and \$450 billion dollars can be saved in healthcare costs [37]. With the use of big data technology and methods, Apixio developed a system that could read and code patient chart information [33]. Typically, this method of coding would have been performed manually by a person or set of individuals, and with that comes a laborious and expensive process [33]. Apixio’s capabilities were also found to be more accurate resulting in 20% improvement in accuracy which in turn lead to better decision making among healthcare providers [33]. This also helped individual customer to ensure they were getting billed appropriately for the right treatment or procedure as well as for the insurance company who may be providing coverage [33]. These techniques then allow for an improved customer experience journey if costs can be mitigated through the use of big data initiatives that allow for better efficiency and accuracy.

9 BIG DATA IN THE ENTERTAINMENT INDUSTRY

The entertainment industry includes a wide array of forms including newspapers, movies, books, television programs, and radio [22]. As of 2016 it is estimated that this industry is worth approximately 1.8 trillion dollars in the United States alone [49]. Streaming video services such as Netflix and Hulu have entered the market in recent years and provide a further opportunity to deliver content directly to customers. As of 2016, video streaming services are the second

largest category for home entertainment with customers in the United States spending \$6.2 billion [4]. The wealth of data collected from these streaming services include but are not limited to the type of content watched, when content is watched and on which type of device, as well as how often it takes for customers to make a selection down to an individual user level [8]. Netflix is one of the many video streaming leaders and has made big data and analytics a foundation to their business strategy and outreach initiatives [28].

9.1 How Does Netflix Use Big Data?

While Netflix once started out as a mail-subscription video rental service, the business model has shifted to provide content entirely online and caters to nearly 60 million subscribers in over 50 countries [28]. Netflix’s competitive advantage in the market place stems from their ability to use big data as they estimate that they process over 10 petabytes of data a day which includes more than 400 billion new events [28]. Utilizing programs and data scientists, Netflix began to seek out additional opportunities to understand customer preferences and to also optimize the experience journey through a variety of different methods:

- **Personalized Recommendations:** Netflix not only analyzes what a particular person may watch but also what others who *look like* that user may enjoy based on data such as age, gender, or even zip code [28]. With the sophistication of the recommendation algorithm, viewers spend an average of 17.8 minutes browsing through the selections before picking a program to watch [28]. Spending more time increases the level of engagement with users and also extends the lifetime value of the customer in an effort to help with retention [8]. By delivering relevant content, Netflix estimates they save more than \$1 billion per year by their efforts in keeping customers happy [8].
- **User Choice:** In addition to providing the right recommendations, ensuring that the image or artwork for films is appropriate to the user also aids in choice [8]. Netflix engages in A/B testing of program thumbnails images and also seeks out feedback from users on which images they prefer [8]. From this process, Netflix was able to increase video viewing between 20-30% when utilizing the right images and listening to customers’ preferences [8].
- **Customized Content:** Analyzing what audiences enjoy watching can provide insight as Netflix sought to create their own content [28]. One common cited example includes the development of *House of Cards* as an original Netflix series that was created with big data information [28]. Netflix found that the original series from the British Broadcasting Corporation (BBC) did well with audiences and that Kevin Spacey movies were also popular [28]. Further using customer data, Netflix understood that customers *binge-watched* seasons of shows and therefore releasing an entire season at a time would best meet the needs of their customers versus one episode at a time [28]. The year the *House of Cards* series premiered, subscribers grew from 27.1 to 33.4 million and the show received countless Emmy and Golden Globe nominations and awards [28]. By utilizing big data, Netflix was able to create and deliver

content that customers wanted and also help their bottom line [28].

10 BIG DATA IN THE GAMING INDUSTRY

In addition to the entertainment economy, the gaming sector also is substantial in size and revenue. In 2016, the commercial gaming industry grew to \$38.7 billion across 24 states and nearly 600 casinos [43]. Las Vegas, a leader and popular gaming destination had a record year of visitors at nearly 43 million [43]. With increased competition among entertainment resorts and casinos in Las Vegas, as well as other parts of the United States, the need to create an optimal customer experience is crucial to attract customers and also keep them engaged. Metro-Goldwyn-Mayer (MGM) Resorts International and Caesars Entertainment are two conglomerates that have capitalized on big data use to better tailor the customer experience journey.

10.1 How Does Caesars Entertainment Use Big Data?

Caesars has described their customer relationship optimization process as utilizing a “data-driven and closed loop approached to deliver a personalized experience” [51]. A few ways they have implemented this include:

- **Creating Customer Loyalty:** Demographic, gameplay, and other transactional data is kept on each guest to create a detailed profile [51]. Employees then across the establishment can utilize this data to personalize offerings and incentives to customers, anywhere from how he or she is greeted by staff to whether complementary services should be offered to improve the customer experience [51]. This type of treatment isn’t just limited to big spenders at the casino but translates across all customers in an effort to create loyalty across multiple segments [51].
- **Efficiencies Through Mobile Application:** Caesars also offers guest the ability to utilize their mobile device to conduct tasks such as checking into a property or even ordering a drink from the bar to avoid long lines [51]. Incentives can also be pushed directly to customers based on their location and preferences such as tickets for shows or dining options in the area [51]. Considering most guests carry their phone in their pocket, engaging with them on the casino floor can create a better customer experience to give them what they need, when they need it [51].
- **Customized Experiences:** The vast amounts of data collected on customer behavioral patterns in terms of which machines are played, when, where, and by whom can provide insight into how to best tailor offerings [46]. For example, it was observed that an elderly population visits the casino at a certain time of day and therefore with the influx of that audience, casinos are able to adjust game offerings in real-time offering enlarged text for better viewing among the visually impaired in that age group as well as bet levels for certain games [46]. By analyzing heat maps of popular games and parts of the casino, it also allows for companies to staff appropriately to ensure customer needs

are being met based on predicted demand [46]. These real-time changes enhance the customer experience journey by tailoring offerings to specific customer segments.

10.2 How Does MGM use Big Data?

Similar to other casinos and resorts, MGM has utilized past customer data in an effort to better predict future behavior [36]. However, they have also utilized this data to create personalized marketing offers to entice frequent (and non-frequent) visitors back into the experience [36]. Though sophisticated modeling efforts, MGM is able to tailor marketing efforts to include a variety of different incentive types and levels. The final result of this process created 120 models of customer behavior with approximately 180 variables in each as well as 20,000 parameters across all which showcased an increase in revenue at a lower cost [36]. These models were used to inform marketing efforts across a variety of areas, including but not limited to [36]:

- **Hotel Room Rates:** Attributes such as room type, discount, number of times, etc., all play a role in which aspect will draw a customer back into the establishment [36].
- **Entertainment Add-Ons:** Type of entertainment offered, ticket price, or even facility features were all used as inputs in the model [36].
- **Other Offers:** Air packages, limo rides, resort credits, and many others were also used as way to determine which customers would respond to which offers [36].

11 BIG DATA IN THE TRANSPORTATION INDUSTRY

Whether by plane, train, car, or other means, today’s American customer relies on some sort of transportation to get them to varying destinations whether it be work, school, or even vacation. An average person spends 20% more time commuting today than they did 30 years ago [7]. With this come questions to the transportation industry as to where they should expand highways, add public transit, or open additional hubs or destinations for travel. Big data can be one avenue in exploring and answering these questions as well as create a more enjoyable experience for the customer if they can spend less of their life commuting. The introduction of the ride sharing mobile application of Uber also arose based on customer needs and preferences and through the use of big data is thriving as alternative transportation option [9]. Large airline carriers have made use of big data as they seek to understand buyer behavior so they can effectively plan flights and other amenities to meet customer needs [39].

11.1 How Do Airlines Use Big Data?

In just one day’s time, it is estimated that there are nearly 42,000 commercial flights and 2.5 million passengers [2]. From purchasing a ticket, to taking a flight, and (hopefully) receiving their checked baggage at their final destination, airlines collect a wealth of information on their customers throughout their flying experience [39]. When looking at key attributes that are analyzed and down to an individual level, airlines collect information about purchase history, arrival, departure cities, and dates, in-flight food choices, connecting cities, travel companions, as well as miles and credit

card points earned and used [18]. While airlines have succeeded in collecting this data, using it to better enhance the customer experience journey is still a work in progress [39]. Those who work in the travel software environment and frequently provide products and services to those in the airline community to better understand their data even state they have “not seen a single major airline with an integrated big data business solution” [39]. With that in mind, highlights from major airline players are explored even though full development of utilizing big data may still be on-going in this industry.

11.2 How Does Southwest Airlines Use Big Data?

One way that Southwest Airlines is utilizing big data is by trying to identify new opportunities for revenue [39]. By analyzing customer behavior online, Southwest is able to support their relationship with customers by offering the best rates in real-time [39]. They are also able to look at searches for destination pairs and make determinations on whether certain flights should be added to keep their customer base loyal and ultimately satisfied by getting to where they need to be, when they need to be there [18]. Not only is Southwest looking to meet the needs of customers as they make a flight choice, but they also seek to comprehend customer interaction at other points in the purchase process [18]. By utilizing a speech analytics tool, the company can better understand recorded conversations that take place with representatives as well as social media chatter [18]. These real-time insights can then inform customer service representatives as they interact with customers and guide them to deliver the optimal solution in various situations [18]. In addition to optimizing the customer experience from a satisfaction standpoint, Southwest airlines has also partnered with NASA on potential safety initiatives where machine learning algorithms can be used to spot potential abnormalities [18]. These efforts enhance the customer experience journey by not only looking out for safety of individuals but by also meeting their needs based on behavioral data.

11.3 How Does Delta Airlines Use Big Data?

In a quest for customer loyalty, Delta Airlines has made an intentional effort in investing in their baggage tracking system to better meet customer needs [45]. With this \$100 million dollar initiative, it not only gives airport operation teams the opportunity to identify trends in mishandled luggage situations but also real-time information to baggage handlers when transferring or sorting through bags [45]. Similar information is also shared with travelers so they can track the progress of their bags down to the minute [45]. With approximately 130 million bags checked in a given year on Delta Airlines, there is a common concern among customers on whether their bag will arrive at their final destination [39]. Giving customers a piece of mind allows for a more beneficial customer experience and also increases satisfaction and loyalty. The luggage tracking app has been downloaded 11 million times and has reduced the rate of mishandled luggage by nearly 71% since 2007, which is better than any other airline [45].

11.4 How Does Uber Use Big Data?

Founded in 2009, Uber started as a technology company and created a mobile application that connected those seeking transportation with those who were drivers [9]. Now, with nearly 8 million users who have connected with over 160,000 drivers, nearly half of the United States population has access to Uber in their city [27]. The only opportunity to connect riders and drivers is through the mobile app consolidating data collection and tracking from the start; however, the sheer volume and real-time application of data use to inform pricing and availability still presents on-going challenges [9]. Demographics, frequency of trips, destinations, price, as well as sessions that do not end with a purchase are all recorded from the application [9]. Several ways in which Uber utilizes big data to meet customer needs includes:

- **Matching Supply and Demand:** By analyzing travel transactions, Uber can appropriately plan for busy nights so customer travel needs are met [9]. Customers are also able to give feedback about their ride experience and rate drivers [6]. With this capability, the company can inspire trust and improve satisfaction if they find that certain drivers are not meeting expectations [6]. UberPool is also a new feature that has been added that allows for carpooling of customers where real-time analytics search for other customers in the area by geography [6]. This can therefore improve the customer experience for those who want to share a ride and split the cost appropriately [6].
- **Dynamic Pricing Model:** Uber is also able to adjust pricing models accordingly based on time of day [9]. Fair estimates are also able to be given in real-time which allow the customer to adjust their travel plans if needed and also pick the type of transportation, such as a sedan or sports-utility-vehicle (SUV) [9]. However, there are times that Uber uses these models to the company’s advantage and offer *surge* pricing in the events of heavy demand or traffic [9]. All financial transactions take place via the application with no exchange of cash. Pre-set and transparent pricing structures allow customers to select what fits their needs, even if they find their choice is to not take a ride at a particular time. Having the necessary and accurate information provided at time or purchase makes for a more enjoyable customer experience journey [6].

12 WHY IS USING BIG DATA TO OPTIMIZE CUSTOMER EXPERIENCE JOURNEY IMPORTANT?

These examples are a select few to showcase how companies can better understand and further the customer experience journey by leveraging big data. The average customer is presented with more choices today than ever before [34]. With this, companies today have to be more strategic to get the attention, time, and loyalty of customers to remain in the marketplace. Doing so can provide many advantages to both companies and customers as they utilize big data to better understand the customer experience. As Rawson et al state: “companies that excel in delivering journeys tend to win in the market” [41]. Trends presented showcase how big data can provide big benefit:

- **Retention of Customers:** It is estimated that “acquiring a new customer can be between five and 25 times more expensive than retaining an existing one” [21]. Utilizing big data to predict when customers may close accounts can help to inform company efforts and ultimately prevent potential revenue loss if they can keep existing customers. American Express showed that by using big data and predictive analytics, the company could identify these customers sooner versus wait until the customer is already lost.
- **Personalized Outreach:** Tailored communication messaging, and recommendations can give customers a better experience in getting what they need from companies but also benefit the company’s bottom line as well. As Netflix and Amazon have showcased, providing recommendations to customers increases engagement and purchase behavior.
- **Company Process Efficiencies:** Utilizing big data to understand customer behavior can help companies determine whether changes or improvements need to be made in how they deliver products and services to customers. As the Delta example showed, tracking baggage was not only a concern to customers but by doing so, the company improved their mishandled luggage rates. These efficiencies not only create satisfied, and possibly loyal, customers but also ensure that companies are spending their resources effectively by not making costly and time-consuming errors.

13 WHAT CHALLENGES EXIST IN UTILIZING BIG DATA FOR THE CUSTOMER EXPERIENCE JOURNEY?

While big data use is going to be a crucial component going forward in understanding the customer experience journey, companies do face challenges in making this a reality, specifically:

- **Data Ownership** Customer data can live in a variety of places within one organization. The departments in which this data lives can be in silos with multiple departments not talking to one another or not willing to share what they feel their department owns [48].
- **Company Culture** Cooperation across the organization can be a significant barrier in truly understanding the full customer experience. [48].
- **Lack of Strategy** Without a clear strategy, it can also create issue in trying to determine how to best interpret and apply the findings in the data. This can lead to gaps in the organization if it is unclear what the ultimate goal is and which parties play a role [48].
- **Resources and Skills** The technical aspects of understanding the customer experience journey can be a barrier as well. Having the right technology, people, and time in place to understand the full customer journey can also be a challenge for companies. [11]
- **Consumer Behavior Volatility** Not all decisions made by customers are rational ones and there can be a variety of factors in play that big data can not track [50]. As further detailed in other work “people do not behave like robots,” so even when all the variables are optimized, outside forces

beyond the control of a company could influence choice along with a customer’s own emotions which big data doesn’t always include [42].

Since within one company there can be different systems, different processes, and a variety of people employed with different skillsets, trying to address all of these challenges can be overwhelming. However, with challenges come opportunities and areas in which companies can focus on as they strive to have data that is connected, customer-centric, and available to look at in real-time [48].

14 HOW CAN A COMPANY OVERCOME THESE CHALLENGES?

As companies seek to better understand their customer base through the use of big data and analytics, from the research performed, there are some steps that companies can take as they further explore opportunities to optimize the customer experience journey. Some key areas and questions to consider include:

- **Seek to Understand Your Customer:** Big data and analytics can be a valuable starting point in understanding the pathway to purchase among your customers as well as which areas where you may be losing customers in the process. However, big data should be used in conjunction with small data as companies seek to understand the *why* behind customer behavior. Gathering feedback from customers is essential in the process in optimizing their journey.
- **Set Clear Objectives and Roles:** Given that earlier research highlighted that a very small percentage of companies have a dedicated person for customer analytics, first establishing a dedicated person or team could help in developing a better understanding of the data involved in tracking the customer experience journey [38]. This person or team of people can provide guidance to others within an organization by being a central source of knowledge about the customer. A key part of research is also setting clear questions and objectives at the beginning. Which data points are truly a part of the customer experience journey? What connections do we need to establish in order to move our strategy forward? How will we measure the return on our efforts?
- **Make the Necessary Investment:** As other companies in this research highlighted, big data skillsets are necessary in understanding the customer experience journey which may mean a company may need to add data scientists, analysts, or other like positions within an organization. Additional technologies and tools may also be needed such as Hadoop or languages such as R or Python in an effort to process big data to derive insight.
- **Test, Assess, and Optimize:** As companies look to establish dedicated resources, time, and people in the process of understanding the customer experience journey, there must also be acknowledgement that this process is iterative. There could be efforts that are not fruitful or plainly, do not work. However, as other companies have shown, the ability to test can provide this insight and allow the opportunity for a company to change course if needed.

While there are likely other areas to consider, this initial outline described can provide companies and those within an opportunity to start understanding the customer experience journey from a big data and analytics perspective. A company has to also prioritize these different efforts accordingly as it may not be possible to implement these changes at once. A company must also consider what their own *success* will look like over time as progress is made.

15 CONCLUSION

The customer experience journey will continue to evolve as new technologies are developed that can influence the multitude of touchpoints one experiences along the way as they make purchasing decisions. While big data and analytics can provide a picture as to what customers are doing, leveraging learnings from this work to better understand the customer experience journey will be key as competition in the marketplace continues to increase across a variety of industries. These examples show that by having the right tools, skillset, and objectives in place that utilizing big data to better meet the needs of customers can be successful. While the undertaking of this endeavor may not be quick or necessarily easy, it can provide great benefit to both companies and customers to deliver relevant products and services with the customer experience in mind. Even though big data is a means of tracking the customer experience, big data is also changing the customer experience through digital marketing and outreach efforts in a way to effectively and efficiently engage and connect with customers. With this approach, the ability to deliver the right message, to the right person, at exactly the right time in the customer experience journey can provide tremendous opportunity for companies but also benefit the customers to have a more fulfilling experience journey with a company or brand.

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IoT Application Using MQTT and Raspberry Pi Robot Car

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ABSTRACT

As the number of connected edge devices increases there is a need for fast communication between these devices, and to analyse the data collected by these devices, which is made possible by the use of a scalable lightweight communication protocol such as MQTT, which is easy to use, data agnostic, and application independent. We look at one such application of the protocol, to control a robot car remotely, over wireless network, navigating with the help of a raspberry pi camera on the car.

KEYWORDS

i523, HID201, Edge Computing, Raspberry Pi, MQTT, Robot Car, IoT

1 INTRODUCTION

As the number of edge devices increases, and sensor networks become more and more common in Internet of Things (IoT) applications, the need arises to allow these resource constrained devices to communicate with each other in a power efficient and secure manner. In many cases these devices may not be able to process traditional HTTP requests efficiently, and as the number of devices increases, sending an HTTP request to each of the devices in order to get data may not be efficient [3][11].

Message Queue Telemetry Transport (MQTT) is a lightweight machine to machine (M2M) messaging protocol, that uses a client/server based publish/subscribe model and is ideal for IoT applications. The protocol has been designed on top of TCP/IP protocol for us in situations where network bandwidth and available memory are limited [39][22]. The Eclipse Paho Project currently provides support for MQTT [5]. MQTT clients are available for various languages like Python, C, and Lua.

We look at one such application here that uses MQTT for communication between a raspberry pi and a desktop. The raspberry pi controls the stepper motors of the robot car according to the message it receives over mqtt, and drives the car accordingly. Another program running on the raspberry pi uses the raspberry pi onboard camera to capture pictures and send them back to the desktop to help in navigation. Thus we create a simple robot car that can be used remotely for monitoring purposes. The robot car can be controlled from anywhere in the world, as long as both the controlling device (desktop) and the raspberry pi can connect to the MQTT broker.

We can use multiple such cars and controlling devices to control the cars independently or from a common device to drive multiple cars together, thus controlling a swarm of cars. As these cars may be using different platforms like raspberry pi or arduino, Using MQTT allows us to write the controller program independent of the subscriber programs running on the different robot cars and

even in different languages. All that is needed to control a car is that the subscriber can understand the messages sent by the controller.

2 RELATED WORK

There have been many edge computing applications that involve robot cars or swarm of cars.

[28] provides an example of a raspberry pi car that uses distance sensor, and face detection on the raspberry pi 2. The car is controlled over wifi and is built using the GoPiGo robot car kit [14]

Zheng Wang used raspberry pi in [38] to build a sophisticated self driving car that can detect stop signs and traffic signals and drive appropriately on a small test track. The car has a camera and a distance sensor that stream data to a TCP server running on a desktop. The system uses Haar Cascades provided in opencv to detect objects like stop signs and traffic signals and a trained neural network which uses the image to predict the direction in which the car should move. The distance is calculated using the image from the raspberry pi camera with the help of a monocular vision method proposed by Chu, Ji, Guo, Li and Wang in 2004 [16].

As the part of Eclipse IoT open challenge [2] built a robot car that is controlled using the Constrained Application Protocol (CoAP) which snaps images and communicates the images over MQTT

OpenHAB provides a vendor neutral platform that allows users to integrate various home automation systems and provides an application interface to control those devices [25]. It allows integration of various devices with MQTT.

The FloodNet project at University of Southampton [12] aims at "providing a pervasive, continuous embedded monitoring presence". The system is intelligent and obtains "environmental self-awareness and resilience to ensure robust transmission of data", ensuring data quality and allowing exploration of environments in new ways. The project uses MQTT for communicating data from the sensors on field to visualization and simulation applications.

As a part of IBM's Extreme Blue projects, Say it Sign it [32] is a sophisticated, innovative speech to sign language translation system. The application uses speech recognition and renders an avatar that signs the corresponding words in British sign Language, using MQTT and microbroker for communication.

3 TECHNOLOGIES AND HARDWARE

The project uses MQTT to communicate between a controller running on a desktop and a raspberry pi that drives the robot car with the help of stepper motors. We describe these technologies in detail.

3.1 MQTT

MQTT works via a publish-subscribe model that contains 3 entities: (1) a publisher, that sends a message, (2) a broker, that maintains

queue of all messages based on topics and (3) multiple subscribers that subscribe to various topics they are interested in [29].

This allows for decoupling of functionality at various levels. The publisher and subscriber do not need to be close to each other and do not need to know each others identity. They need only to know the broker, as the publisher and the subscribers do not have to be running either at the same time nor on the same hardware [19].

MQTT implements a hierarchy of topics that are related to all messages. These topics are recognised by strings separated by a forward-slash (/), where each part represents a different topic level. This is a common model introduced in file systems but also in internet URLs.

A topic looks therefore as follows: *topic-level0/topic-level1/topic-level2*.

All subscribers subscribe to different topics via the broker. Subscribing to *topic-level0* allows the subscriber to receive all messages that are associated with topics that start with *topic-level0*.

This is different from traditional message queues as the message is forwarded to multiple subscribers, and allows for a more flexible approach with the help of topics [19]. The basic steps in an MQTT client application include connecting to the broker, subscribing to some topics, waiting for messages and performing the appropriate action when a certain message is received [39].

MQTT allows the publisher and subscriber to respond to messages with the help of callbacks that are executed on different events, in a non-blocking manner. The paho-mqtt package for python provides callbacks methods like `on-connect()`, `on-message()` and `on-disconnect()`, which are fired when the connection to the broker is complete, a message is received from the broker, and when the client is disconnected from the broker respectively. These methods are used in conjunction with the `loop-start()` and `loop-end()` methods which start and end an asynchronous loop that listens for these events and fires the relevant callbacks, allowing the clients to perform other tasks [6].

MQTT has been designed to be flexible and options are provided to easily change the quality of service (QoS) as required by the application. Three basic levels of QoS are supported by the protocol, Atmost-once (QoS level 0), Atleast-once (QoS level 1) and Atmost-once (QoS level 2) [20][6].

The QoS level of 0 can be used in applications where some dropped messages may not affect the application. Under this QoS level, the broker forwards a message to the subscribers only once and does not wait for any acknowledgement [20] [6].

The QoS level of 1 can be used in situations where the delivery of all messages is important and the subscriber can handle duplicate messages. Here the broker keeps on resending the message to a subscriber after a certain timeout until the first acknowledgement is received. A QoS level of 2 should be used in cases where all messages must be delivered and no duplicate messages should be allowed. In this case the broker sets up a handshake with the subscriber to check for its availability before sending the message [20] [6].

The MQTT specification uses TCP/IP to deliver the messaged to the subscribers, but it does not provide any form of security by default to make it useful for resource constrained IoT devices. “It allows the use of username and password for authentication,

but by default this information is sent as plain text over the network, making it susceptible to man-in-the middle attacks” [27] [21]. Therefore, in sensitive applications some form of additional security measures are recommended which may include network layer security with the use of Virtual Private Networks (VPNs), Transport Layer Security, or application layer security [21].

Transport Layer Security (TLS) and Secure Sockets Layer (SSL) are cryptographic protocols that establish the identity of the server and client with the help of a handshake mechanism which uses trust certificates to establish identities before encrypted communication can take place [4]. If the handshake is not completed for some reason, the connection is not established and no messages are exchanged [21]. “Most MQTT brokers provide an option to use TLS instead of plain TCP and port 8883 has been standardized for secured MQTT connections” [27].

Using TLS/SSL security however comes at an additional cost. If the connections are short-lived then most of the time can be spent in the handshake itself, which may take up few kilobytes of bandwidth. In case the connections are short-lived, temporary session IDs and session tickets can be used to resume a session instead of repeating the handshake process. If the connections are long term, the overhead of the handshake is negligible and TLS/SSL security should be used [27][21].

Although MQTT protocol itself does not include authorization, many MQTT brokers include authorization as an additional feature [4]. OAuth2.0 uses JSON Web Tokens which contain information about the token and the user and are signed by a trusted authorization server [10].

When connecting to the broker this token can be used to check whether the client is authorised to connect at this time or not. Additionally the same validations can be used when publishing or subscribing to the broker. The broker may use a third party resource such as LDAP (lightweight directory access protocol) to look up authorizations for the client [10]. Since there can be a large number of clients and it can become impractical to authorize everyone, clients may be grouped and the authorizations may be checked for each group [4].

MQTT allows easy integration with other services, that have been designed to process this data.

Apache storm is a distributed processing system that allows real time processing of continuous data streams, much like Hadoop works for batch processing [1]. Apache storm can be easily integrated with MQTT as shown in [36] to get real time data streams and allow analytics and online machine learning in a fault tolerant manner [42].

ELK stack (elastic-search, logstash and kibana) is an open source project designed for scalability which contains three main software packages, the *elastic-search* search and analytics engine, *logstash* which is a data collection pipeline and *kibana* which is a visualization dashboard [7]. Data from an IoT network can be collected, analysed and visualized easily with the help of the ELK stack as shown in [34] and [33].

MQTT broker services can be utilized for enterprise and production environments. EMQ (Erlang MQTT Broker) provides a highly scalable, distributed and reliable MQTT broker that can be used in enterprise-grade applications [9].

3.2 Raspberry Pi

The raspberry pi is a credit card sized development board that was developed by Eben Upton with the goal to create a low cost device that can be used for education and prototyping [26]. Since its creation the board has been adapted for various different projects by educators hobbyists and in the industry [31]. The board is developed as open hardware except for the Broadcom chip that controls the main components of the board, and most raspberry pi projects are available openly with detailed documentation.

The board's Broadcom system on chip consists of an ARM processor and it can be used just like a normal computer by connecting a monitor, a keyboard and a mouse. The raspberry pi can communicate to other devices with the help of wifi and bluetooth and is capable of accessing the internet. All this put together makes the raspberry pi a very useful device [31].

The raspberry pi comes in various models, Model A+, which is one of the smallest form factors, raspberry pi2 Model B, raspberry pi3 Model B and Model B+ that have more gpio pins. The raspberry pi 3 Model B is the newest design and consists of on board wifi and bluetooth, eliminating the need to use usb wifi and bluetooth attachments. It has a 1.2 GHz ARM 8 microprocessor, 1 GB RAM, a dual core Videocore IV GPU, and 40 general purpose input and output (GPIO) pins. The board has an ethernet port and four USB ports and an HDMI port to connect to a monitor [18][17].

The raspberry pi Zero is the development board that has the smallest form factor. Even though the raspberry pi zero includes no ethernet or USB ports, and does not come with GPIO pins soldered on, its small size and cost effectiveness make it extremely useful in applications such as IoT where space is constrained [30].

The raspberry pi uses a micro SD card to boot and various operating systems, that support the ARM architecture can be used. The most common operating systems are Raspbian, a derivative of the Debian linux, and Pidora, a derivative of Fedora. There are other operating systems centered around using the raspberry pi for various purposes, like openELEC and RaspBMC, which make it easy to use raspberry pi as a multimedia center. For, users who want non-linux operating system, RISC OS may be a good choice. The raspberry pi foundation provides new users the opportunity to try out various operating systems with the help of their New Out Of The Box Software (NOOBS), which allows the users to pick which operating system they want to use [26].

Various different shields are available for the raspberry pi that make it simple to connect to various peripherals, and extend the functionality of the raspberry pi, such as the GrovePi shield, provided by Dexter Industries, which allows simple interface with many digital and analog sensors and actuators provided by Dexter.

3.3 Stepper Motors

Stepper motors are brushless motors that divide the complete rotation into a number of parts known as steps. The motor consists of electromagnetic coils and a rotating core that aligns itself according to the combined magnetic effect of the coils. The stepper motor can move from one step to another and remain in a single step based on which coils are turned on. The torque of the motor can be increased or decreased with the current supplied to the coils, and the speed

of rotation can be controlled by setting the time interval between switching the coils on and off [41].

Stepper motors can be controlled in various ways, depending on the application. Figure 1 shows how a stepper motor with a resolution of 90 degrees can be made to complete one full rotation. In practice however, the resolution (the degrees moved at each step) of most stepper motors is much higher. The process mentioned in figure 1 is known as half stepping [15].

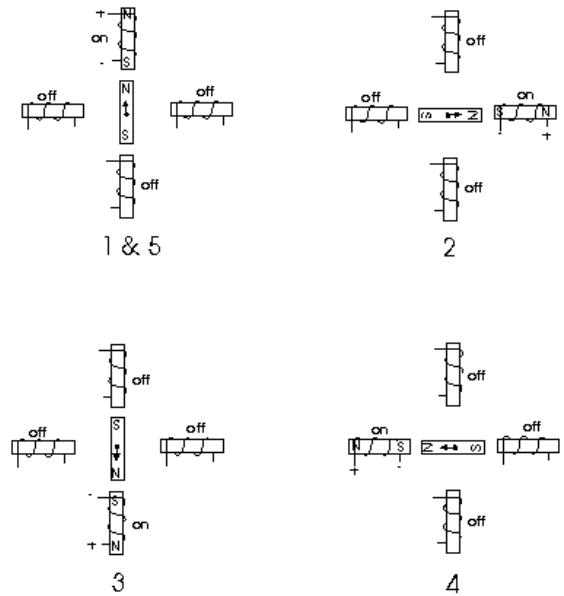


Figure 1: Working of a stepper motor : Full stepping using one coil at a time [15]

In the above method, only one coil is turned on at a time. This can be improved upon to get a higher torque. To get a higher torque, two adjacent coils are turned on at the same time, as shown in figure 2. This results in double the torque generated when using only one coil at a time [37].

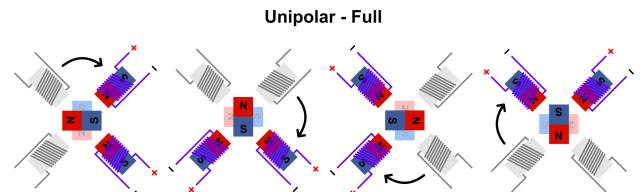


Figure 2: Working of a stepper motor : Full stepping using two coils at a time [37]

With full stepping however, the transition between two consecutive steps is not very smooth. Therefore, a technique called Half

stepping is used, where two adjacent coils are turned on similar to full stepping, but between two steps one of the coils is turned off, so that the transition between steps is smooth. This results in a torque 70 percent of that generated in using full stepping with two coils turned on at the same time. This process is shown in figure 3 [15].

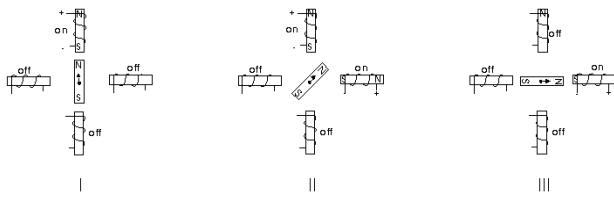


Figure 3: Working of a stepper motor : Half stepping [15]

For this project, the stepper motor 28BYJ-48, provided by Elegoo Industries is used. The motor is driven with the help of a ULN2003 motor driver. The motor is a unipolar stepper motor, with a five wire connection to the motor controller and can work with 5 and 12 Volts of DC power supply. When using Half stepping, the step angle of the motor is about 5.625 degrees per step, and when using full stepping the step angle is 11.25 degrees per step. The motor weighs 30 grams, and a gear ratio of 64:1 [13][35].

3.4 OpenCV

The Open Source Computer Vision library (openCV) is a library of functions aimed at real time computer vision and machine learning and providing a common infrastructure to allow fast progress in the field of computer vision and machine perception [40][23].

The library was originally built by Intel and is now maintained by Itseez and is available freely under open-source BSD License. The library was originally written for C++ but has been developed as cross platform library and supports Python , C++, MATLAB and Java [23]. for Python the library has been built on top of Numpy, a library that optimizes matrix and vector operations, and takes advantage of MMX and SSE instructions whenever possible. For C++ the library uses the Standard Template Library (STL) as its backbone.

The library has more than 2500 algorithms which include a combination of simple and advanced operations allowing a wide range of operations from edge detection, color detection to object detection, face detection and automatic video stabilization, and motion detection. The opencv-contrib which is an extension to the library built collaboratively by the community contains advanced algorithms that allow processing video in real time [23].

OpenCV is widely used in the industry by startups as well as well established organizations like Google, Yahoo, Microsoft, IBM and Intel [23].

OpenCV can be used to detect faces in real time. The Haar cascades function in the library allows detecting any kind of objects. The algorithm uses a series of simple classifiers to predict whether a given image has the desired object or not. After training on a large set of positive examples (images containing faces) and negative examples (images not containing faces), the algorithm learns

various classifiers, that classify different sections of the image in a manner similar to Adaboost algorithm. Only the portions of the image that are promising are analysed further by more detailed classifiers. This allows the algorithm to run in real time, and detect multiple objects [24][43]. Once the classifiers are learned, they can be stored in an XML file which can be used to classify new images. This allows users to obtain XML files available openly for classifiers trained to detect the required object and use them in their programs. OpenCV provides XML files for classifiers trained to detect faces and eyes.

The performance of the Haar cascades suffers however, when detecting objects in new images that are present in a different orientation than the ones used to train the classifiers. The classifiers may also fail to differentiate between the object that needs to be detected and similar objects if enough negative examples are not shown while training that include similar objects.

4 ARCHITECTURE

The solution includes two entities the raspberry pi and the desktop, each running two programs. The raspberry pi is connected to the robot car and the raspberry pi can drive the robot car according to the message it receives from the desktop.

There are two programs running on pi, controller stepper sub.py and video pub.py, and two programs running on the desktop, controller pub.py and video sub.py.

The programs on both the raspberry pi and the desktop connect to a common broker. The broker may be running on the desktop, or any other place, as long as the IP address of the broker is known. The IP address can be passed as a command line argument when running these programs.

The controller pub.py program running on the desktop continuously reads characters from the user and publishes them to the broker under the topic *topic/control*. The subscriber controller stepper sub.py running on the raspberry pi waits for these messages from the broker and when a message is received it uses the *on_message()* callback to make the robot car move forward, move backward, turn left or turn right, using the half stepping technique described in the previous section.

For monitoring purposes, another program, video pub runs on the raspberry pi. This program uses the raspberry pi on board camera with the help of the picamera module and captures images. The images are converted to greyscale, and opencv is used to perform face detection using Haar Cascades. If a face is found, a box is drawn around the face in the image. The image is published to the broker under the topic *topic/video_frames*. The video sub.py program running on the desktop subscribes to this topic on the broker and displays the images received. These images can be used for the navigation of the robot car remotely figure 4.

Using separate programs allow changing the functionality or replacing different parts of the program easily, while keeping the interface same. The program, controller sub.py, can be used if continuous rotation servo motors are used instead of the stepper motors without changing any other part of the application.

The programs can be run easily with the help of a Makefile as described in the next section

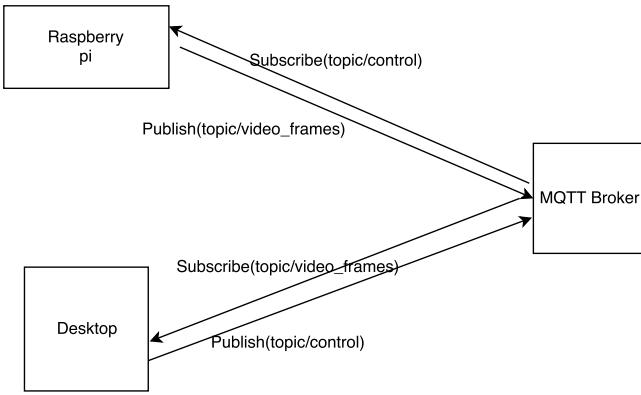


Figure 4: Architecture of the Application

5 RESULTS

This section covers the setup instructions for the project and the observations. The robot car that was built is shown in figure 5.

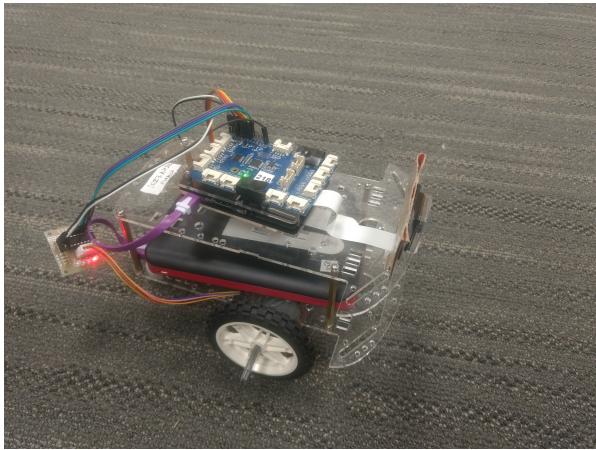


Figure 5: Raspberry Pi Robot Car

5.1 Setup Instructions

To run the application successfully on both the raspberry pi and the desktop, it must be ensured that all the required libraries are installed. A Makefile has been provided that can do this on both the raspberry pi and the desktop.

- First, the motors should be connected to the raspberry pi correctly. The program uses the raspberry pi GPIO pins, and assumes that for the left motor, the pins IN1, IN2, IN3, IN4 are connected to GPIO pins 7, 11, 13, and 15, and for the right motor, they are connected to GPIO pins, 8, 10, 12, 16, as shown in the connection diagram in figure 6
- On the raspberry pi, dependencies for openCV need to be installed. Since the openCV is not available in pip for the arm processor in raspberry pi, we it must be installed from

source. This takes a few hours on the raspberry pi. To complete the setup including installation of a MQTT client and opencv on the raspberry pi, clone the repository from github on the raspberry pi and navigate to the code folder, open the terminal and run the command

`make setup_pi`

- Next, install opencv and an MQTT client and MQTT broker on the desktop. For this, clone the repository from github, navigate into the code folder and run the command
`make setup_server`
- Note the IP address of the desktop so that we can connect to the MQTT server running on it. Connect the raspberry pi and the desktop on the same wireless network.
- To run the code on the desktop, run the command
`make run_server IP=[IP address of the MQTT broker]`
- Finally to run the code on the raspberry pi, run
`make run_pi IP=[IP address of the MQTT broker]`
- Now the raspberry pi car can be controlled by typing in W, A, S, or D keys on the desktop in the terminal where the program is running.
- The program can be stopped on both the raspberry pi and the desktop by running
`make kill`

5.2 Observations

It was observed that the communication between the raspberry pi and the desktop controller application is pretty seamless. The robot car responds without any observable delays when the network is strong. When the network is weak, however, some delays may be observed. The delay becomes more evident in the case of the images sent by the raspberry pi back to the desktop when the network is not strong.

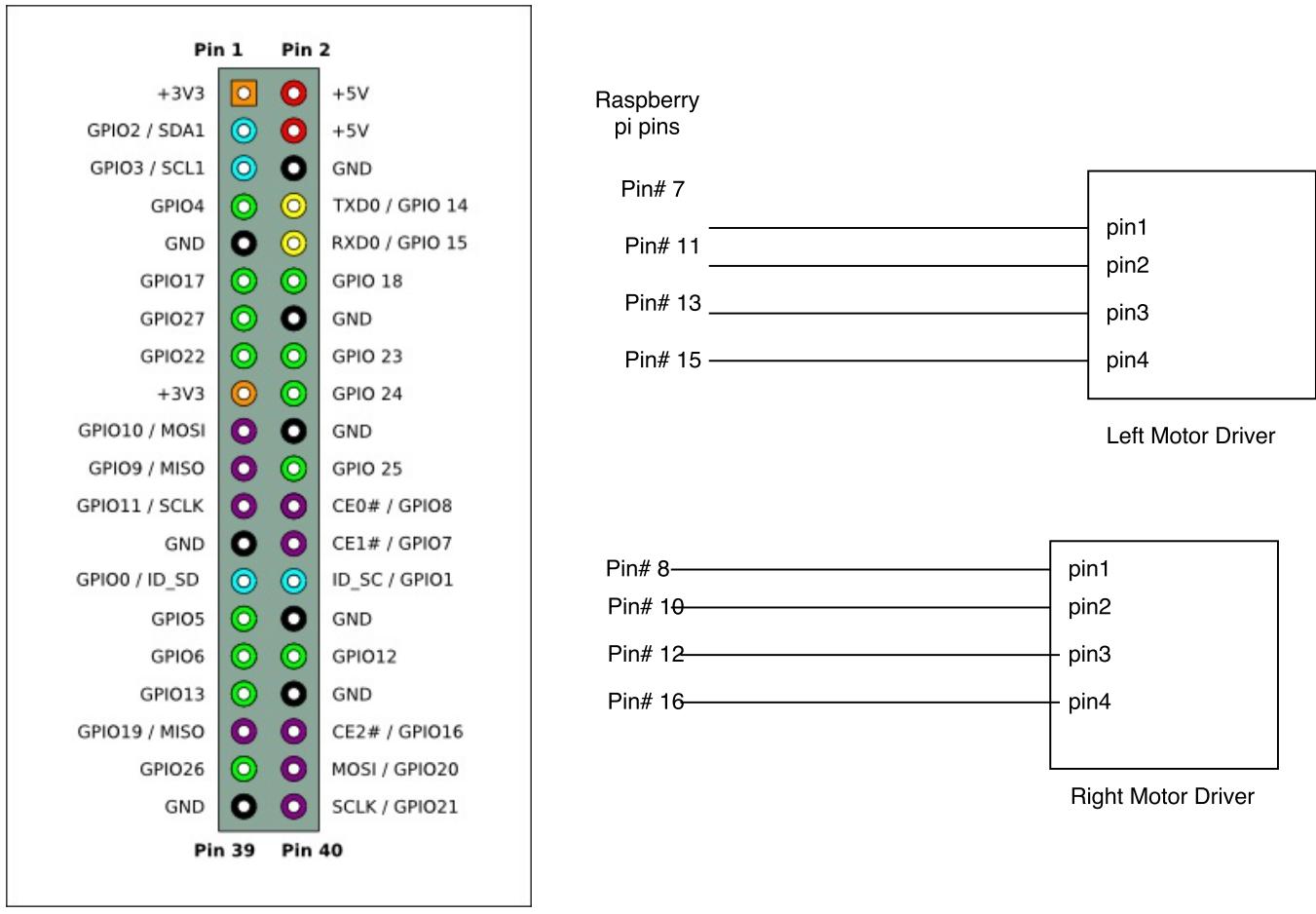
Using the stepper motors, it is difficult to set a how much a motor should turn when it receives a message. If the motor is not allowed to turn long enough, then between two messages the motor will be idle and if it is turned longer than the interval between two messages, there can be conflicts if in response to each of the messages the subscriber running on the raspberry pi tries to set a different step on the motor. Therefore, the movement can seem a little jerky at times.

However, this is not a problem with 360 degrees continuous servo motors. Since the continuous servo motors use pulse width modulation, the speed and direction of rotation can be controlled by sending a square wave with different duty cycles depending on the motor. Since, the motor can be stopped and started easily, there are no conflicts even if the motor is allowed to turn longer than the interval between two messages. However, the motor would respond to the two messages one after the other.

Thus the raspberry pi robot car can be successfully controlled over wifi using MQTT for communication

5.3 Improvements

The project can be improved in various ways. Firstly, even though the deployment with makefile is easy, installing opencv on raspberry pi takes around 4 hours. This can be avoided if we use docker for deployment on the raspberry pi. Two separate images would me



Raspberry pi 3 GPIO header

Figure 6: Connection Diagram [8]

needed however one for the processor on the desktop and another one for the arm 8 processor on the raspberry pi.

Machine learning can be incorporated, by collecting the images and the corresponding messages that were sent to the raspberry pi and use it to train a neural network, which could then be used to drive the robot car autonomously. This would be complicated however since car needs to be driven for a long time to get enough data for the neural network to perform well regardless of the surroundings.

Using Haar cascades for face detection leads to a problem that faces can be recognised only if they are resent in the image in the same orientation as that in the training examples. Therefore, it is challenging to recognise all faces in all orientations since it is not possible to train the classifier on images of different faces from all possible angles and rotations. A better option would be to use Convolutional Neural Networks, that help in improving accuracy for the purpose of object detection. Since training and running neural networks may be computationally expensive, it would be a good idea to run it on a server and not on the raspberry pi.

Many different sensors could be added to help improve the monitoring capability of the car, and get more information about the environment. If many controlling devices and cars are present, the cars may be controlled in groups and other functionality added to behave as a swarm of cars to complete tasks collaboratively.

6 CONCLUSION

MQTT is a fast and reliable data agnostic and platform independent protocol that allows communication between devices. Raspberry pi is small but powerful development board that allows users to build prototypes easily and can be used in various applications because of the significantly powerful arm 8 microprocessor. OpenCV is an open source library for computer vision that is optimised to perform operations on images efficiently and is commonly used in computer vision applications. All these technologies were used to build a robot car, controlled via MQTT over a wireless network. MQTT allows us to easily scale up the number of such cars if needed.

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Big Data and Edge Analytics in Weather Monitoring and Forecasting

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ABSTRACT

General Topic: The gathering of weather data and forecasting used to be a task left only to meteorologists or scientists with expensive, often unreliable, and heavily centralized scientific equipment. With an estimated 260,000+ weather stations in use around the world today[9], collecting and analyzing weather data has not only become inexpensive and more reliable, it has become far more decentralized. This decentralization has prompted more of the analysis to be conducted locally as opposed to in a central repository managed by large centralized weather institutions such as the National Weather Service or NOAA (National Oceanographic and Atmospheric Administration). It has also allowed reporting to achieve greater accuracy by enabling the monitoring to occur a few yards away from the person collecting the data, instead of 20 or 30 miles away. Reliability has also increased with the increased number of data points being fed to the cloud.

Specific Question: The purpose of this project is to build a versatile and compact PWS (Personal Weather Station), write a program to collect local weather data, upload it to Weather Underground, and perform an analysis of the data compared to other local weather stations collecting similar data in roughly the same geographic area. The project also explores other options for using this data with other IoT devices in order to achieve maximum energy efficiency in the home.

Method: Utilizing a Raspberry Pi 3 and Sense Hat, local weather data was collected using a Python script, and then streamed to Weather Underground's distributed weather station network. Three data types were evaluated: 1) Temperature (in Fahrenheit) 2) Humidity and 3) Barometric Pressure (in Hg). The data was analyzed along with other home weather stations in the immediate geographic vicinity to determine variance and accuracy between the weather stations as well as with the general forecast for the tested geographic area. An official non-PWS weather station was also selected as a control test. The feasibility of using the concept of edge analytics based on this data to enhance the efficiency of a Nest thermostat and Tesla solar array was also explored.

Results: Localized weather from PWS was far more accurate and reliable compared with distant, commercial weather stations and IoT devices such as Nest and the Tesla solar array, and moreover the environment, would benefit significantly from utilizing localized weather data sourced from a PWS.

KEYWORDS

i523, HID316, Big Data, Edge Analytics, Raspberry Pi 3, Sense Hat, Python, Personal Weather Station, Weather Underground,

Meteorology, Energy Efficiency, Clean Energy, IoT, Nest, Tesla, Solar Array

1 INTRODUCTION

A world burgeoning with IoT devices and connected everything is upon us. As the trend in computing shifts from cloud-based computing to localized computers sending data to the cloud, weather reporting has similarly shifted in a more localized direction. Long gone are the days in which a person needs to wait until the top of the hour to hear a radio broadcast of the latest weather conditions. Even the Weather Channel itself is becoming obsolete. With the widespread availability of cheap computing and components, it is now not only possible for someone to build their own PWS for less than \$100, but they can also become a reliable source of data from which more accurate weather forecasts can be derived.

Having a general idea of what the weather might be like 12-36 hours from now isn't exactly a new concept. As conversations about the weather can attest, it is one of the most foundational elements of human interaction between two strangers. Everyone has a pretty good idea of what the weather's going to be like in the relatively near future, but this is typically based off of either secondary information or, at best, from sources in which the data was measured and analyzed many dozens of miles away. A person's decisions about when to go to a particular place, what to wear, or when to stay home may all be based on information that is only loosely tailored to their needs. Likewise, IoT devices such as thermostats and solar arrays might be indexed to the same weather data sources and might not, as a result, operate nearly as efficiently as they otherwise could be.

By pushing the currently available technology as far as it can possibly go with commercially available components and software, it was the intent of this project to explore the extent to which a small and inexpensive scratch built IoT device could be used to gather and analyze local weather data to potentially be used as an enhancement to existing energy saving IoT appliances such as Nest and a Tesla solar array. The IoT weather data collection device, will be referred to as a personal weather station, or PWS, throughout the rest of this paper. This project explored how the PWS was constructed and the Python code required to interface with the Sense Hat sensors and stream the data to Weather Underground. In order to do this, an account was required on Weather Underground. The PWS was registered as one the 260,000+ PWS submitting weather data to the site. Once submitted, this data was tracked and stored by Weather Underground at regular intervals which was and is used by the site to present a holistic picture of the weather for a given geographical

area. The data can also be downloaded and used offline for other purposes, such as the analysis for this project. Data gathered by the PWS used for this project will be compared to other various types of PWS as well as one non-PWS weather station in the general geographic area.

This data was then used to determine the variances with other PWSs and show the benefit of feeding localized weather data to other nearby IoT devices. Both of the devices used in this project meet the minimum requirements of being connected to the internet and would benefit from being connected to up-to-date and accurate weather data. The Nest connects to Weather Underground for its weather data, which is the site used to stream the PWS data used for this project, but currently connects to the site via zip code. Users have also identified many issues with the weather data not being accurate for their locations[4]. Often readings are off by 10-15 degrees Fahrenheit[10].

At some point in the future, it may be possible for Nest users to select a particular PWS, with their own being the obvious best choice. Likewise, local PWS weather data could be useful in conjunction with a Tesla solar array, both in terms of forecasting daily sunlight and energy consumption as well as temperature and increased air-conditioning use. This data could also be used to determine if solar panels would be a smart investment for a home in a particular area with a given set of weather conditions.

2 A BRIEF HISTORY OF METEOROLOGY

In order to understand the pressing need of getting localized, up-to-date, and accurate weather data, it is important to understand the evolution of gathering, analyzing, and modeling weather data and to do that, it is important to understand the science behind weather. The science of weather is more commonly referred to as meteorology. Meteorology is a type of atmospheric science that has its roots going back millennia, although it wasn't comprised of much more than observation and forecasting based on historical data collection until the late 1800s. It wasn't until the late 19th and early 20th centuries that the science of meteorology evolved into roughly what it is today; a network of weather observation stations sharing information on a global scale. In the beginning, weather observation stations were nothing more than a collection of scientific instruments read by a human and recorded on paper. Over time, inferences could be made about the historical data collected in order to make rudimentary weather forecasts, though the predictive accuracy of weather forecasting was somewhat low until further work had been done in the field of physics and chemistry.

The dawn of the computer age brought about significant change and rapid advancement to the world of meteorology. As weather data began to be tracked electronically, the advent of big data, and eventually weather modeling allowed for very sophisticated weather observation and forecasting. Weather data and forecasting went from cable television to mobile phone apps by the early 21st century, allowing users to have on-demand weather information available to them. Still, in its early stages, this data was mostly limited to what was gathered by expensive and highly sophisticated weather equipment at labs, research facilities, academic institutions, and meteorological centers.

As the cost curve for personal computers, and electronic components generally, continued to bend downward over the course of the early 21st century, it became possible for individuals to build, maintain, and read the data from their own personal weather stations (PWS). In tandem with this, the internet could then be used to transmit this data to central weather databases, which were only getting highly regionalized data from the aforementioned scientific facilities. Both the localization and volume of data enables much more accurate weather models, and subsequently, much more accurate weather forecasting.

3 PWS OVERVIEW

Personal Weather Stations can be built in a number of different ways, using a variety of components, and with virtually limitless coding possibilities. For this project, a Raspberry Pi 3 was used as the platform on which the other components - in this case a Sense Hat - were connected. The Sense Hat has three sensors for measuring temperature, humidity, and pressure. It also has an 8x8 full-color LED matrix for displaying text and symbols, which for this project, was used to indicate whether the temperature had gone up, down, or remained the same during a given period of time. Some other options for the display were experimented with, such as displaying scrolling text, but ultimately this was determined to be unreadable, as the LED matrix is only capable of displaying 1-2 characters at a time. Though it was not used regularly for this project, the Sense Hat also has a mini 5 button joystick, which can be used to control the completed IoT PWS when it's not connected to any peripherals. The Raspberry Pi 3 and Sense Hat were then wrapped in a C4 Labs Zebra Case with the add on for the Sense Hat. The add on leaves the sensors and LED matrix exposed to the elements.

4 BUILDING THE PWS

The physical act of building the PWS itself is relatively easy and doesn't have a significant time requirement. These are the steps that were followed:

- (1) Unboxed the Raspberry Pi 3 and Sense Hat (see Figure 1).
- (2) Connected the Sense Hat to the Raspberry Pi 3.
- (3) Attached heat sink to the Raspberry Pi 3 that were included with the C4 Labs Zebra Case. These needed to be mounted prior placing the Raspberry Pi 3 and Sense Hat into the Zebra Case.
- (4) With the Sense Hat and heat sinks attached, the Zebra Case is assembled in layers around the components, beginning with the bottom and building upward. The heatsinks should fit through the precut holes in the Zebra Case, facing downward and the Sense Hat LED matrix and sensors are facing upward.
- (5) As the layers were added, it was important to ensure the various components, especially the Raspberry Pi 3 and the Sense Hat remained aligned in the case.
- (6) Insert the screws and rivets and close the case.
- (7) Before powering on, insert a mini SD card pre-loaded with the NOOBS operating system. A 32GB card was used for this project, but since data is only being read and streamed to the cloud, a not a lot of disk space is required. Even so,

disk space still needed to be expanded during the initial setup.

5 INITIAL CONFIGURATION OF THE RASPBERRY PI 3

After building the physical infrastructure of the PWS, it was configured with the NOOBS operating system that was pre-loaded on the mini SD card and then updates were installed. These were the steps that were followed:

- (1) Plugged mini USB plug into the Raspberry Pi 3.
- (2) Plugged peripherals (monitor, keyboard, mouse) into the Raspberry Pi 3.
- (3) The device booted and began automatically installing the NOOBS operating system.
- (4) After NOOBS completed its installation, the Raspberry Pi preferences could be configured.
- (5) By selecting Preferences -> Raspberry Pi Configuration, disk space could then be expanded by clicking the "Expand Filesystem" button. This was required because the default setup ultimately leaves too little disk space for all the software required for the project. SHOW IMAGE
- (6) The hostname can also be renamed so that it can easily be found on your home WiFi network.
- (7) It's also a good idea to update the Raspberry Pi 3's software, which was done by opening a terminal window entering the following command - which updates the Raspberry Pi 3's indexes of the most up-to-date software packages:

```
sudo apt-get update
```
- (8) After software packages were updated, entering the following command then updated the Raspbian OS to the most current configuration available:

```
sudo apt-get upgrade
```
- (9) At this point, the device was ready to begin configuration of the PWS specific software and coding.

6 CONFIGURATION OF THE SENSE HAT

Once the Raspberry Pi 3 was correctly configured, the next major step was installing and configuring the Sense Hat. Since the Sense Hat utilizes its own Python libraries, they needed to be installed as well. These were the steps that were followed:

- (1) Enter the following command to install the Sense Hat libraries:

```
sudo apt-get install sense-hat
```
- (2) Once the Sense Hat libraries were installed, a directory was created for the Python code. This was done using the following set of commands:

```
cd ~
mkdir pi_weather_station
cd pi_weather_station
```

7 PWS PYTHON SOURCE CODE

Overall the Python source code used for this project is fairly straightforward[8]. In essence, it is telling the Sense Hat to measure temperature, humidity, and pressure during specific intervals and to send them to



Figure 1: Unboxed Raspberry Pi 3 with heatsink attached prior to mounting on case bottom



Figure 2: Sense Hat attached to the Raspberry Pi 3 with the Zebra Case assembled upward from the bottom in layers



Figure 3: SD Card inserted through the slot on the bottom of the PWS



Figure 4: PWS powered on for the first time

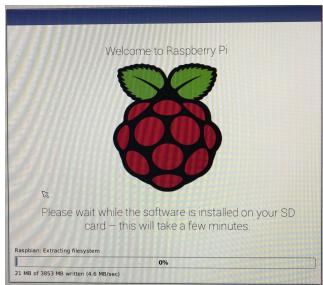


Figure 5: NOOBS OS is in the process of installing

Weather underground. In the figure below, the code begins by initiating contact with the Weather Underground and defines variables for data upload.

```
if WEATHER_UPLOAD:
    print("Uploading data to Weather Underground")
    weather_data = {
        "action": "updateraw",
        "ID": wu_station_id,
        "PASSWORD": wu_station_key,
        "dateutc": "now",
        "tempf": str(temp_f),
        "humidity": str(humidity),
        "baromin": str(pressure),
    }
    try:
        upload_url = WU_URL + "?" + urlencode(weather_data)
        response = urlopen(upload_url)
        html = response.read()
        print("Server response:", html)
        response.close()
    except:
        print("Exception:", sys.exc_info()[0], SLASH_N)
    else:
        print("Skipping Weather Underground upload")
```

Figure 6: Section of Python code instructing the Sense Hat to initiate contact with Weather Underground and define various variables for data upload.

The code also makes use of the Sense Hat's 8x8 full-color LED matrix to display with a "W" for Warmer if the moving average of the temperature has increased since the past interval or a "C" for Cooler if the moving average of the temperature has decreased since the past interval, as shown in the figure below. If the moving average of the temperature remains the same since the past interval, it displays a red and blue equal sign for no change in temperature.

There are a few nuances to the code, as seen in the figure below, which converts the standard Sense Hat measurement of temperature from Celsius to Fahrenheit. Pressure is also converted from millibars to inHG.

Celsius to Fahrenheit:

Another issue that had to be overcome was the warmth of the Raspberry Pi 3 and Sense Hat causing the temperature readings to

```
b = [0, 0, 255] # blue
r = [255, 0, 0] # red
e = [0, 0, 0] # empty
warm_up = [
    r, r, e, r, r, e, r, r,
    r, r, r, r, r, e, r, r,
    r, r, e, r, r, e, r, r,
    r, r, r, r, r, r, r, r,
    e, r, r, r, r, r, r, e
]
cool_down = [
    e, b, b, b, b, b, b, e,
    b, b, b, b, b, b, b, b,
    b, b, e, b, b, e, b, b,
    b, b, e, b, b, e, e, e,
    b, b, e, b, b, e, e, e,
    b, b, e, b, b, e, b, b,
    b, b, b, b, b, b, b, b,
    e, b, b, b, b, b, b, e
]
bars = [
    e, e, e, e, e, e, e, e,
    e, e, e, e, e, e, e, e,
    r, r, r, r, r, r, r, r,
    r, r, r, r, r, r, r, r,
    b, b, b, b, b, b, b, b,
    b, b, b, b, b, b, b, b,
    e, e, e, e, e, e, e, e,
    e, e, e, e, e, e, e, e
]
```

Figure 7: Section of Python code instructing the Sense Hat how to display various symbols indicating temperature changes on the LED matrix

```
def c_to_f(input_temp):
    # conversion of the temp from Celsius to Fahrenheit
    return (input_temp * 1.8) + 32
```

Figure 8: Section of Python code converting the temperature from Celsius to Fahrenheit

be about 10-15 degrees warmer in Fahrenheit than the ambient temperature. Weather Underground will eventually disconnect PWSs which display erroneous and incorrect data. This was overcome by employing a "hack" available from the Pi, shown in the figure below. Foundation[1]:

Another nuance to the data collection aspect is the moving average. Though the PWS is only sending weather data to Weather Underground every 10 minutes, it is reading the data locally on the device every 5 seconds and sending the moving average to Weather Underground using the follow code:

For this project, the above source code was saved as

```

def get_temp():
    t1 = sense.get_temperature_from_humidity()
    t2 = sense.get_temperature_from_pressure()
    t = (t1 + t2) / 2
    t_cpu = get_cpu_temp()
    # Calculation for the real temperature
    t_corr = t - ((t_cpu - t) / 1.5)
    # average over 3 readings
    t_corr = get_smooth(t_corr)
    return t_corr

def main():
    global last_temp
    last_minute = datetime.datetime.now().minute
    last_minute -= 1
    if last_minute == 0:
        last_minute = 59

```

Figure 9: Section of Python code correcting for the higher CPU temperature

```

def get_smooth(x):
    if not hasattr(get_smooth, "t"):
        get_smooth.t = [x, x, x]
    get_smooth.t[2] = get_smooth.t[1]
    get_smooth.t[1] = get_smooth.t[0]
    get_smooth.t[0] = x
    # average of the last 3 smooth temps
    xs = (get_smooth.t[0] + \
           get_smooth.t[1] + \
           get_smooth.t[2]) / 3
    return xs

```

Figure 10: Section of Python code averaging temps taken over a short time period

personal_weather_station.py
and placed in the
pi_weather_station
directory that was created during steps we did for configuring the Sense Hat. In addition to the personal_weather_station.py code, a configuration file is also required in order for the PWS to be able to interface with Weather Underground. The configuration file is fairly simple, comprised of just 3 lines of code:

```

class Config:
    STATION_ID = ""
    STATION_KEY = ""

```

Figure 11: Section of Python code for inputting Weather Underground Station ID and Station Key

Both the Station ID and the Station Key are obtained when setting up an account on Weather Underground. More on that next.

8 REGISTERING THE PWS ON WEATHER UNDERGROUND

Why Weather Underground? Weather Underground started in 1995 as an internet weather service, initially with the sole purpose of displaying real-time weather data on the web. By 2012 the Weather Channel (The Weather Company) had acquired Weather Underground and by 2017 Weather Underground had over 260,000+ PWSs feeding weather data into its cloud-based weather tracking and analysis system. These observations are used in conjunction with official National Weather Service weather stations to provide very detailed and dynamically-updated features on Weather Underground and Weather Channel's forecasting service as well as Google's Map base.

Setting up a PWS on Weather Underground network wasn't particularly difficult, but some basic requirements need to be met. First, the PWS of choice must be able to interface with Weather Underground's servers. The Raspberry Pi 3 and Sense Hat are perfect for this and hence why they were used for this project. The following are the steps that were followed for setting up the device:

- (1) From the <http://www.wunderground.com> web page, an account must be registered following the standard procedure for doing something like this. Given that the PWS that was registered is keyed into a particular geographic location, an address as well as elevation must be provided.
- (2) A name was also picked for the PWS, and for the purposes of this project, the name "Deer Ridge" was selected.

After completing these steps, the Station ID and Station Access Key were provided but were not yet entered into the config.py file in the pi_weather_station directory on the PWS. It was only after successful completion of testing and automation that this final step was taken.

9 INITIAL TESTING AND AUTOMATION

Prior to placing the PWS outside (where it will no longer be easy to plug in its peripherals), some initial testing was conducted before automating the startup of the personal_weather_station.py script and submitting potentially false and inaccurate data to Weather Underground. It was also during this testing that the Sense Hat warm temperature sensor issue first presented itself and it was determined that it needed to be fixed prior to configuring the device to send data to Weather Underground.

After plugging in the device and manually launching the main source code script, it was confirmed that the script was working as expected, including the readouts on the LED matrix display. Data began populating at 5 second intervals in the terminal window and the correct readouts were displaying on the LED matrix. However, according to the Nest in my home the ambient temperature in the house was 70 degrees Fahrenheit. Yet the PWS was registering at 81 degrees Fahrenheit and climbing. Thus, as it was explained in the above section on the project source code, a workaround had to be implemented in the code to compensate for this temperature.

Once that issue was resolved, it was time to configure the PWS scripts to run automatically upon PWS startup. The advantages to doing this allowed the PWS to be moved (unplugged from its power source) and to maintain a constant stream of weather data

to Weather Underground in the event of a power outage or WiFi reboot.

This automated startup can be accomplished by opening a terminal window and navigating to the pi_weather_station directory on the PWS. Once there, the project's Bash script file can be turned into an executable using the following command:

```
chmod +x start-station.sh
```

Figure 12: Section of Python code for creating the auto start script

Once this command was entered, then the autostart file can be opened and the following line of code can be added:

```
@lxterminal -e /home/pi/pi_weather_station/start-station.sh
```

Figure 13: Section of Python code for the auto start script itself

After rebooting the PWS, the personal_weather_station.py then started automatically. The script was then stopped and the Station ID and Station Access Key that were provided by Weather Underground during registration were entered into the config.py file in the pi_weather_station directory on the PWS.

10 PWS LOCATION SELECTION

Before turning on the PWS and transmitting data to Weather Underground, a suitable location needed to be selected for the PWS. The basic requirements for this were that the sensors need to be as out in the open and exposed to the outdoor elements as much as possible while also not getting wet or exposed to too much wind and dust. Weather Underground suggests placement of at least 5 feet off the ground and away from concrete, asphalt, and any other heat-producing appliances such as air conditioners or solar inverters.

The most reasonable location available for this project was the inside of a fence post, tucked under the eves of the house. This way, the PWS was not in direct sunlight, in danger of getting wet, and also near a power supply. The PWS was mounted on the fence post about 5 feet off the ground and plugged into a power source.

The geographic location chosen for the PWS was Northern California with the time setting for this project over the course of an 8 day period during the month of November, from 11/21/2017 to 11/28/2017. This is a time in which weather conditions in this part of the country are in flux and make for some interesting readings. The PWS is also at roughly 300 feet of elevation in the foothills east and in the rain shadow of large mountain with approximately 4,000 feet of elevation. The PWS is located roughly 60 miles east of the Pacific Ocean and therefore is exposed to rapidly changing weather patterns in the fall. These patterns are born out in the data.

11 OFFICIAL WEATHER DATA SOURCE SELECTION

Both the geography and topography of the area around the site of the PWS built for this project vary greatly within 1-5 miles let alone

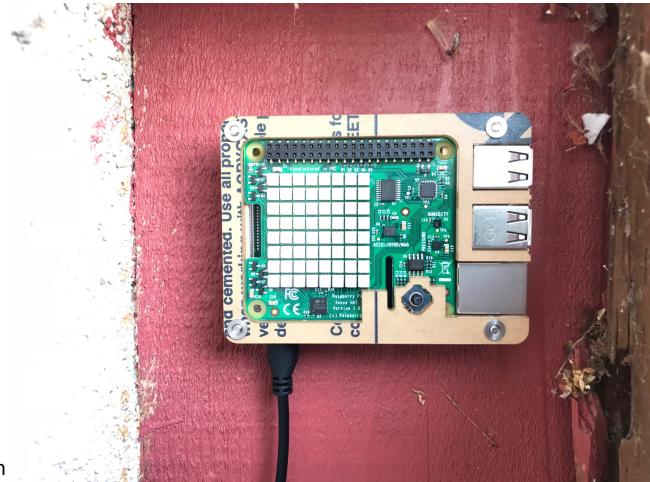


Figure 14: PWS mounted in an outdoor, protected area, out of direct sunlight

10-20 miles. Roughly half of the people who live in the United States live within 17 miles of an airport, while 90 percent live within 58 miles of an airport.^[7] In nearly all cases, airports are equipped with the most advanced weather station and data collection technology, so they are often most cited for their data. As an official weather source for this project, the KSCK Stockton Airport WS weather station is 31 miles away and is the closest major airport to the location of the PWS built for this project. The Stockton Airport WS weather station collects a variety of comprehensive weather data, though for this project, we are only comparing temperature, humidity, and pressure.

12 ADDITION PWS DATA SELECTION

In addition to the official weather source from Stockton Airport WS, 3 additional PWSs in varying proximity to the Deer Ridge PWS (but not further away than Stockton Airport WS) were selected to collect temperature, humidity, and pressure data for a date range of 11/21/2017 to 11/28/2017. The stations selected were (ordered by distance from Deer Ridge PWS):

13 ADDITION PWS DATA SELECTION

13.1 Deer Ridge Country Club PWS

Type: Netatmo Weather Station, located less than 1 mile from the Deer Ridge PWS at an elevation of 173 feet.

13.2 Campanello PWS

Type: Netatmo Weather Station, located 2.2 miles from the Deer Ridge PWS at an elevation of 88 feet.

13.3 Morgan Territory PWS

Type: AcuRite Pro Weather Center, located 4.8 miles from the Deer Ridge PWS at an elevation of 820 feet.

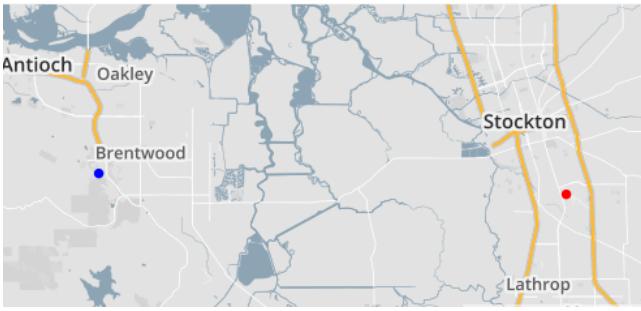


Figure 15: Location of the Deer Ridge PWS (Blue Dot) in relation to Stockton Airport PWS (Red Dot)

14 PWS DATA ANALYSIS

Once making these selections, collecting the data was as simple as pulling down the data from Weather Underground as each PWS and the Stockton Airport WS have their own webpages with relevant data hosted on Weather Underground.[5] Data was collected in CSV format and added to the local Python Directory. Using iPython Notebook, Pandas, and Matplotlib, analysis was performed on the temperature, humidity, and pressure data collected that is useful in determining whether or not:

- (1) Weather data coming from local PWSs is more accurate than weather data observed at the nearest major weather station, which in the case of this project, is Stockton Airport WS.
- (2) Weather data coming from local PWSs can be used to interface with Nest and a Tesla Solar Array

A total of 6 data elements were collected from 5 weather stations:

- (1) Date
- (2) Time
- (3) PWS Name
- (4) Temperature (Fahrenheit)
- (5) Humidity (Percentage)
- (6) Pressure (inHG)

14.1 Outliers

The first part of the analysis that was performed as to determine if there were any outliers in the data that could, if used to feed a Nest or Tesla Solar Array, cause equipment to operate inefficiently. Obviously, given that the over-arching goal of this project is to conserve energy and allow equipment to function in the most efficient manner possible based on the most localized weather data possible, it must be determined if these sources are usable. In order to do this, Pandas was used to create a DataFrame from a CSV in iPython Notebook and Matplotlib was used to generate a bar graph. The first analysis performed was weekly record (max values) with regard to temperature, humidity, and pressure for each PWS. While the differences in pressure were negligible, there were some significant variances in both temperature and humidity, not only between the various local PWSs, but also when compared to Stockton.

The most significant differences were between Campanello PWS and Deer Ridge Country Club PWS, which are less than 5 miles apart and yet there was a full 12 degree difference between the

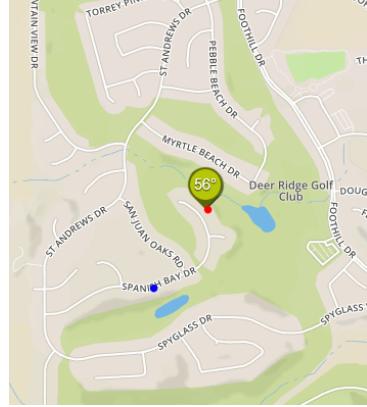


Figure 16: Location of Deer Ridge PWS (Blue Dot) in relation to Deer Ridge Country Club PWS (Red Dot)

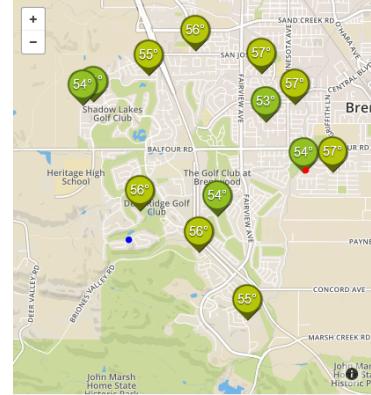


Figure 17: Location of Deer Ridge PWS (Blue Dot) in relation to Campanello PWS (Red Dot)

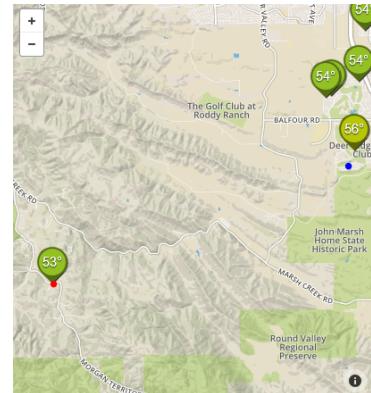


Figure 18: Location of Deer Ridge PWS (Blue Dot) in relation to Morgan Territory PWS (Red Dot)

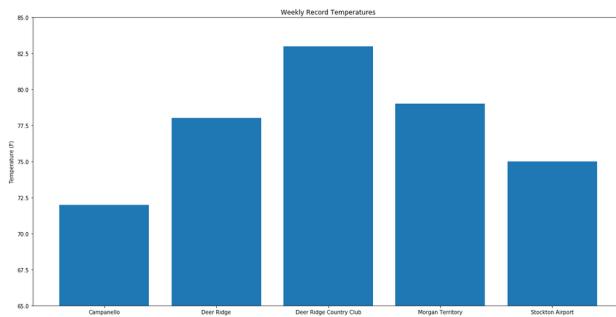


Figure 19: Weekly Record High Temperatures

two in terms of highest temperature recorded during the period in which data was collected. Another striking observation was the 5 degree difference in record high temperature between Deer Ridge PWS and Deer Ridge Country Club PWS. There is also a 5 degree difference between Campinello PWS and Deer Ridge PWS, but in the opposite direction from Deer Ridge PWS vs. Deer Ridge Country Club PWS.

With Deer Ridge PWS falling near the average of the 5 weather stations, it would seem that the Deer Ridge Country Club PWS is either having calibration issues or is mounted in a place that is less than ideal, such as on or near a concrete surface or in direct sunlight. The Deer Ridge PWS is also closest to the Stockton Airport WS, so this is very positive news in terms of furthering the goal of obtaining the most accurate, local weather.

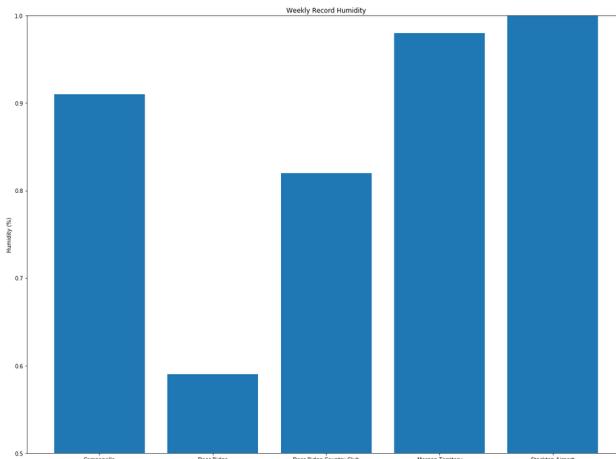


Figure 20: Weekly Record High Humidity

With just a cursory glance at the weekly records for humidity for each of the 5 weather stations, one would have to conclude that the seems to be an issue with Stockton Airport WS. The average humidity for this part of California tends to be pretty low as the climate is generally a mix between Mediterranean/Semi-Arid. Even with the onset of the fall and winter season and the ensuing rain that comes with it, there doesn't seem to be any reasonable explanation for why Stockton Airport WS's humidity should register at greater

than 70 percent more than 14 percent of the time. One explanation for this could possibly be that it has inadvertently come into contact with water, perhaps from an errant sprinkler nozzle or something similar. This might explain why the humidity hangs at 100 percent for such long periods of time and then tapers off, which is a totally unrealistic scenario.

In fact, despite the fact that the Deer Ridge PWS seems like it is reporting low humidity, it in fact is not when compared with other PWSs that were not factored into the data, as well as from reports from the National Weather Service[6], which reported the average humidity for the period of observation to be 54 percent. This coincides with the humidity measurements that were observed on the Deer Ridge PWS, which is yet another positive aspect in proving the theory that local weather is better weather.

14.2 PWsaaS

Broadly speaking, PWS data would be a far better candidate for feeding IoT home devices such as Nest and a Tesla Solar Array than the currently available data from Weather Underground. As was demonstrated above, even data provided by the Stockton Airport WS contained significant outliers. Though not even other local PWSs in closer vicinity to the Deer Ridge PWS were providing accurate readings. This means that selecting the correct location for a weather station is probably even more crucial than selecting the type of equipment itself. Even with a Raspberry Pi 3 and rudimentary sensors, the data collected by it was far more close to the average than other more expensive weather stations. As was mentioned in the introduction section of this project, the cost of the Raspberry Pi 3 and its components came to less than \$100. With all of its accessories, the Netatmo PWS can cost upwards of \$ 500[2]. The Stockton Airport WS is no doubt many thousands if not tens of thousands more than these price points, though no details are provided on Weather Underground as to type or specifications for this particular WS.

The bottom line for the Nest is that if Weather Underground can come up with an inexpensive method of certifying PWS data, it would make sense, based on the findings of this project, to release an update to their existing software that would allow Nest users to select the PWS of their choice, rather than the currently configured generic Weather Underground data.

In terms of the Tesla Solar Array, according to Tesla's website, the only way they are currently utilizing weather data is during the design phase when they are determining feasibility for installing a solar array at client's home or business[3]:

"We will review past utility bills, sunlight patterns, and weather data for your area and create a custom system design for your home."

What Tesla doesn't say is from where they are sourcing their data. If similar to Nest's sourcing, then Tesla's design process would also benefit from using more accurate, localized weather data. Additionally, given that Tesla solar systems are also IoT devices in that they interface both with the utility company and Tesla for the purposes of metering and monitoring, respectively, it would also be beneficial for Tesla to begin utilizing real-time weather data as well for the purposes of enhancing efficiency and energy productivity. Moreover, Nest (owned by Google) and Tesla could partner to use

localized, highly accurate weather data observation and forecasting to automate two systems that manage virtually all of the energy needs of 21st century living. Personal Weather Stations as a Service (PWSaaS) could quickly become another fixture of the wired home.

15 CONCLUSION

As technology continues to progress in the 21st century, it is clear that many of the rapid advances with IoT devices once thought impossible even a decade ago are not only possible now, but are inexpensive, more accurate, and wholly underutilized. The results of this project are clear and undeniable: Individually and locally sourced weather data is far more accurate and reliable than it ever has been in the past and is clearly superior to weather data sourced from legacy weather stations at airports and meteorological centers. Given the pressing need to conserve energy and use our limited natural resources more efficiently, the need for the most accurate weather data is now far more pressing, now that IoT energy management devices such as Nest and Tesla's solar array utilize weather data for design and operation. The findings of this project are that local weather data is more accurate, but only if PWS are well-placed. This localized data will only be truly beneficial if PWSs can be certified for accuracy. If this issue of consistency can be overcome, the possibilities for integrating this data with household IoT devices are virtually limitless.

ACKNOWLEDGMENTS

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Face Detection and Recognition Using Raspberry Pi Robot Car

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ABSTRACT

Face recognition is an exciting and emerging field of computer vision with many applications to hardware and devices. Using embedded platforms like the Raspberry Pi, a camera module and open source computer vision libraries like OpenCV, purpose is to add face recognition to Robot car and also facial recognition using free developer version of Kairos Facial Recognition software. In today's modern world, face recognition playing an important role for the purpose of security and surveillance and hence there is a need for an efficient and cost effective system. So the main goal is to explore the feasibility of implementing Raspberry Pi based facial recognition system using conventional face detection and recognition techniques such as Haarcascade detection and Kairos. An obstacle avoidance Robot car is integrated with Raspberry Pi and a camera module aiming at taking face recognition to a level in which the system can identify the humans who are stuck in buildings during earth quakes. Raspberry Pi kit provides the system cost effective and easy to use, with high performance.

KEYWORDS

Raspberry Pi, Robot Car, Face Recognition, Face Identification, I523, HID319

1 INTRODUCTION

A Computer Vision application which has always encouraged people, concern about the capability and capacity of robots and computers to determine, detect, recognize and interact with human beings [4]. We will prevail the advantage of cheaper tools that are available in market for computing and detecting human face from the image, recognizing the face using hardware like Raspberry Pi and a video camera that is dedicated to Raspberry Pi. Simple and open source software like OpenCV is used to detect human face from the video that is being captured and the image will be sent to Kairos facial recognition software which allows a high level approach to this process.

In this fastest information era, every information is travelled in split of seconds. There is much more need for accurate and fastest methods in identifying, recognizing and authentication of humans. In the present world, Facial recognition had became most important and crucial form of human identification methods. As per Literature survey statistics in face recognition, the two trends to receive significant attention for the past several years are; the first is the law enforcement applications and also wide range of commercial techniques, and the second is exponential booming of applications and feasible technologies after 30 years of research [6].

The aim is achieved by a possibility to locate human beings or their parts like faces from the live video capture and within the

pictures context. Most advanced human detection applications have this functionality already available. When the picture is capture and loaded into the system, it will scan the picture and will look for human faces in it. Current implementation is to detect face and register them with a name. If the face is detected and not recognized, Robot car will ask to register the detected face with a name. If the human is already registered in Kairos, then once the face is detected, Robot car will greet the human with the associated name. This whole process determines the Face detection and Face recognition techniques using Raspberry Pi and Robot car.

Facial biometric data is to be computed first in creating a complete recognition system. This biometric data is then compared with the face database and to associate with the human identity. The difference between a human and machine is, a human can easily and quickly identify characteristics of a human face but then can only save few hundreds of faces. Whereas a machine or computers prevails at storing and mapping human characteristics and meta data. In current generation, facial recognition softwares can identify a human face with in millions of images from the database in seconds. Humans tend to forget human faces as time pass by. Machines stores them forever. Most of the Law firms across the world follow the process and spend huge money with development of these facial recognition systems that can easily identify criminals in real-time. A well-known example is studying human faces in airports and bus stations.

The design of the Robot car integrated with Face recognition system will navigate through dangerous or natural disaster locations where humans unable to enter. Robot car while avoiding obstacles on its way, will continuously monitor for human faces who got stuck or in danger and will recognize the faces based on the user database. Once the human face is recognized, it will intimate to corresponding authorities about the human and will help in guiding assistance.

2 FACE DETECTION

Face Detection is a technique referred to computer vision technology which is able to identify human faces within digital images [3]. Face detection applications works using algorithms and machine learning formulas for detecting human faces in the visual images. Identifying only human faces from these images which can contains landscapes, houses, animals is called Face Detection technique.

Face Detection is termed to only identify if there are any humans present in the image or a video. It lacks in ability to recognize which human face is present. Common widely used face detection techniques are in auto-focus of a digital camera. During auto-focus, camera lens will look for human faces in the range and identify them to have focus in that particular area. Face Detection techniques will

be widely used in counting how many number of visitors attending a particular event.

2.1 How Face Detection Works

While Face Detection process is somewhat complex, the algorithms will start off by searching for human eyes at first. Eyes usually represents a valley region and its the easiest feature in human face to detect. Once the eyes are detected, then the algorithms will look for rest of the characteristics of a human face such as iris, nose, mouth, eyebrows and nostrils. Face detection algorithm then summarizes the data and shows that it has successfully detected a human face from the facial region. An additional tests can be conducted by the algorithm to make sure and validate if its detected human face or not [8].

3 FACE RECOGNITION

Like most of the biometrics solutions, face recognition technology will be used for identification and authentication purposes by measuring and matching the unique facial characteristics of a human face. Using a digital camera connected to raspberry pi, once the face is detected, facial recognition software will quantify the characteristics of face and then will match with the stored images in database. Once the match is positive, then the corresponding name will be displayed as output [2].

Face biometrics can be integrated to any system having a camera. Border control agencies use face recognition to verify identities of the travellers and can separate them from the trespassers. Government Law agencies replace all the security cameras around the world with biometric applications to scan faces in CCTV footage, and to identify persons of interest in the field. Face recognition has become one of the fastest and human unintervention techniques to find out the identity of a particular human [2].

For the past few years, Face recognition has become one of the most commonly used bio-metric authentication techniques. It mainly deals with the Pattern recognition and analyzing the images. Two main tasks of Facial recognition are: Face verification and Face Identification. Face Verification is comparing a human face in an image with a template image and recognizing the correct patterns. Face Identification is comparing human face in an image with multiple images in the database. Face recognition techniques have more advantages than any other biometrics. With well sophisticated algorithms and coding, Face recognition has a high recognition rate or high identification rate of more than 90% [6].



Figure 1: Block Diagram of a Face Recognition System

4 SOFTWARE AND HARDWARE SPECIFICATIONS

OpenCV is to be installed in Raspberry Pi to detect human faces with in the captured images. Kairos Facial recognition software is

used to recognize human face and identify with the corresponding name.

4.1 Software Used

4.1.1 Raspbian OS. This is the recommended OS for Raspberry Pi 3. Raspbian OS is debian based OS. It can be installed from noobs installer. Raspbian comes with pre-installed softwares such as Python, Sonic Pi, Java, Mathematica for programming and education.

4.1.2 Putty. PuTTY is an SSH and telnet client, developed originally by Simon Tatham for the Windows platform. PuTTY is open source software that is available with source code and is developed and supported by a group of volunteers. Here we are using putty for accessing our raspberry pi remotely.

4.1.3 OpenCV. OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code. The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects and extract 3D models of objects [5].

4.1.4 Python 2 IDE. Python 2.7.x version Integrated Development Environment is used to compile python program in Raspberry Pi. IDE is a text editor plus terminal combination which is used to work on large projects with complex code bases.

4.1.5 Kairos Facial Recognition Software. Kairos is an artificial intelligence company specializing in face recognition. Through computer vision and machine learning, Kairos can recognize faces in videos, photos, and the real-world. A captured image is sent to Kairos using an API call and then Kairos will search with the face database. If it matches then will reply with the human name.

- Identity
- Emotions
- Demographics

Kairos navigates the complexities of face analysis technology.

4.2 Hardware Used

4.2.1 Raspberry Pi 3. Raspberry Pi 3 is the latest version of Raspberry Pi. Unless previous versions, this have an unbuilt Bluetooth platform and a wi-fi support module. There are total 40 pins in RPI3. Of the 40 pins, 26 are GPIO pins and the others are power or ground pins (plus two ID EEPROM pins.) There are 4 USB Port and 1 Ethernet slot, one HDMI port, 1 audio output port and 1 micro usb port and also many other things you can see the diagram on right side. And also we have one micro sd card slot wherein we have to install the recommended Operating system on micro sd card. There are two ways to interact with your raspberry pi. Either you can interact directly through HDMI port by connecting HDMI to VGA cable, and keyboard and mouse or else you can interact from any system through SSH(Secure Shell) [7]

4.2.2 Raspberry Pi Camera. The Raspberry Pi camera module can be used to take high-definition video, as well as stills photographs. It's easy to use for beginners, but has plenty to offer advanced users if you're looking to expand your knowledge. There are lots of examples online of people using it for time-lapse, slow-motion and other video cleverness. You can also use the libraries we bundle with the camera to create effects.

4.2.3 Robot Car Chassis Kit. The Mechanical design of the Robot car includes hardware such as motor and wheel placement and body setup. Robot car uses two gear-motors attached to wheels and one free wheel for forward, backward, left and right movements. Free wheel ball is placed at rear side of the robot which helps for 360 degrees free movement [1]. L298N DC Stepper Motor Drive controller is used to control the speed and direction of the two gear motor wheels. Ultrasonic sensors are placed at front side of the robot which is capable to detect the objects on its path.

5 SYSTEM ARCHITECTURE

System Architecture consists of following blocks :

- a) Raspberry Pi
- b) Raspberry Pi Camera Module
- c) L298N Dual H-Bridge Stepper Motor Controller
- d) DC power supply 12v and 5v
- e) Robot Car chassis kit
- f) HC-SR04 Ultrasonic Sensor
- g) SG90 Servo Motor.
- h) Wires, Breadboard, Small PCB.

The Mechanical design of the Robot car includes hardware such as motor and wheel placement and body setup. Robot car uses two gear-motors attached to wheels and one free wheel for forward, backward, left and right movements. Free wheel ball is placed at rear side of the robot which helps for 360 degrees free movement. L298N DC Stepper Motor Drive controller is used to control the speed and direction of the two gear motor wheels. Ultrasonic sensors are placed at front side of the robot which is capable to detect the objects on its path. Raspberry Pi Camera module is used to monitor the live stream and recognize the face if its detected.

6 SETUP

6.1 Connect Raspberry Pi

This section includes connectivity of Raspberry Pi over Wifi.

- Download Raspbian OS to an SD card with a minimum capacity of 8GB.
- Plug in USB power cable, keyboard, mouse and monitor cables to Raspberry Pi.
- Insert the SD card with Raspbian OS into Pi and boot the system. Once the Pi is booted up, a window will appear with Raspbian operating system. Click on Raspbian and Install.
- When the install process has completed, the Raspberry Pi configuration menu (raspi-config) will load. Here set the time and date for your region.
- Enable wifi on upper right corner and connect to wifi sid.

6.2 Connect Raspberry Pi Camera Module

- Install the Raspberry Pi Camera module by inserting the cable into the Raspberry Pi.
- The cable slots into the connector situated between the Ethernet and HDMI ports, with the silver connectors facing the HDMI port.
- Boot up your Raspberry Pi and run below commands in command prompt.
 - sudo apt-get install python-pip
 - sudo apt-get install python-dev
 - sudo pip install picamera
 - sudo pip install rpio
 - From the prompt, run "sudo raspi-config".
 - If the "camera" option is not listed, you will need to run a few commands to update your Raspberry Pi. Run "sudo apt-get update" and "sudo apt-get upgrade"

6.2.1 Enable Camera. For Face Detection, PiCamera should be enable from Raspberry Pi. Below list of figures shows the detailed steps on how to enable PiCamera from Raspberry Pi.

6.3 Install OpenCV and Required Libraries

OpenCV computer vision library is used to perform face detection and recognition. For this, first need to install OpenCV dependencies on Raspberry Pi. Below commands needs to be executed.

- sudo apt-get update
- sudo apt-get upgrade
- sudo apt-get install build-essential
- cmake pkg-config python-dev libgtk2.0-dev libgtk-2.0-dev libpng-dev libjpeg-dev libtiff-dev libjasper-dev libavcodec-dev swig unzip
- Select yes for all options and wait for the libraries and dependencies to be installed

Download opencv-2.4.9 zip file to Raspberry Pi. Change the directory and execute cmake command as follows:

```
cd opencv-2.4.9
sudo apt-get install build-essential cmake pkg-config
sudo apt-get install libjpeg-dev libtiff5-dev libjasper-dev libpng-dev
sudo apt-get install python-dev python-numpy libtbb2 libtbb-dev \
libjpeg-dev libpng-dev libtiff-dev \
libjasper-dev libdc1394-22-dev
sudo apt-get install python-opencv
sudo apt-get install python-matplotlib
```

After executing the commands the latest version of OpenCV is now installed in Raspberry Pi.

6.4 Integration of Raspberry Pi with Robot Car

Raspberry Pi connected with PiCamera is integrated with Robot car to navigate using webserver. During the navigation, robot car will look for human faces using PiCamera and then detects the face. Once the face is detected, python program will call Kairos facial detection software to identify the person and greet with the name. If the human face is unidentified then robot car will ask human to register their name.

```
The programs included with the Debian GNU/Linux system are free software;
the exact distribution terms for each program are described in the
individual files in /usr/share/doc/*/*copyright.

Debian GNU/Linux comes with ABSOLUTELY NO WARRANTY, to the extent
permitted by applicable law.
Last login: Mon May 29 18:17:10 2017
pi@raspberrypi:~ $ sudo raspi-config
```

Figure 2: Edit raspi-config file from command line

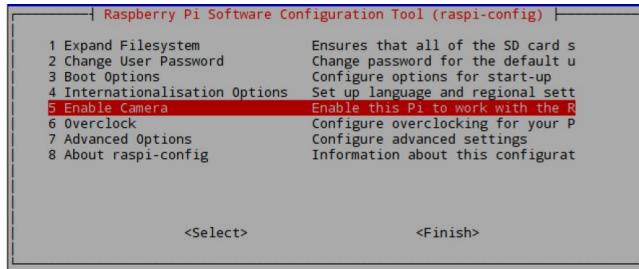


Figure 3: Select Camera from the options

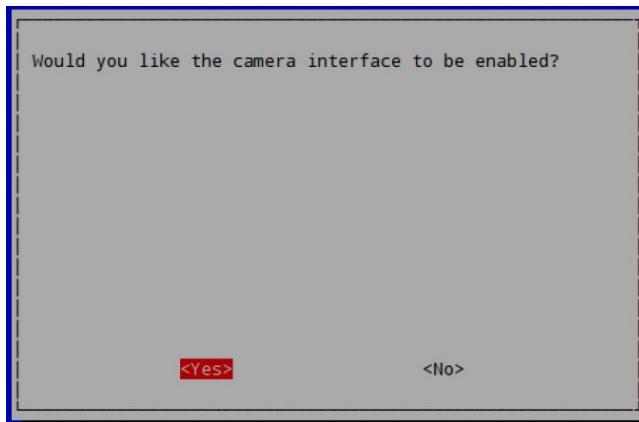


Figure 4: Enable Camera

As shown in the figure below, connect a Robot car chassis to raspberry pi and follow the circuit connections.

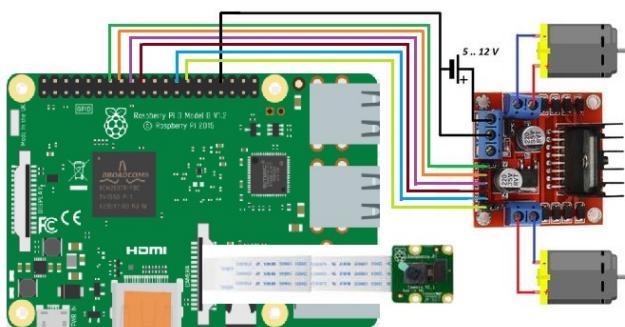


Figure 5: Raspberry Pi Robot Car Integration

In Table 1 we show

Table 1: WHat is this

Actuator	Pin	????
Motor1A	16	GPIO 23 - Pin 16
Motor1B	18	GPIO 24 - Pin 18
Motor1Enable	22	GPIO 25 - Pin 22
Motor2A	21	GPIO 9 - Pin 21
Motor2B	19	GPIO 10 - Pin 19
Motor2Enable	23	GPIO 11 - Pin 23

6.5 Kairos Face Recognition Setup

Kairos Face Recognition system has a free developer account which is used to identify the human name from the images. Once registered a human name with an image, the code will call Kairos API with a newly detected human face and will look for the registered name. Kairos will do a quick lookup in human database from the registered account and if it matches, will send the name of the human back to the code.

Setup as follows:

- Register will <https://www.kairos.com> as a free developer account
- Login with regisered username and password
- Create an Appname
- An App ID and a key are generated. Save this for future use
- Enroll users and a gallery name with the user images

```
POST /enroll HTTP/1.1
Content-Type: application/json
app_id: your-app-id
app_key: your-app-key
{
  "image": " http://media.kairos.com/user.jpg ",
  "subject_id": "User",
  "gallery_name": "MyGallery"
}
```

7 CODE EXPLANATION

7.1 Face Detection

Import all the related libraries including PiCamera and PiRGBArray libraries for camera to operate in Raspberry Pi. These libraries will help to capture video and images from the PiCamera.

```
from picamera.array import PiRGBArray
from picamera import PiCamera
import time
import cv2
import sys
import imutils
from fractions import Fraction
import base64
import requests
import json
import random
import os
```

Haarcascade is a tool to capture the frontal features of face. This tool will help to continuous monitoring for any human face to detect. Once detected a human face, the output values will provide as Human Face Detected from the capturing video.

```
# Get user supplied values
cascPath = './haarcascade_frontalface_default.xml'

# Create the haar cascade
faceCascade = cv2.CascadeClassifier(cascPath)
```

Camera settings needs to be updated in the code as per below suggestions. The capture image is to be sent to Kairos for Facial recognition and so we will set the resolution to a lower level. This will help to send the image faster over the network without any delay.

```
# initialize the camera and grab a reference to the raw
    camera capture
camera = PiCamera()
camera.resolution = (160, 120)
camera framerate = 32
rawCapture = PiRGBArray(camera, size=(160, 120))
```

Below code represents PiCamera continuously monitor for human faces detected from the grayscale video capture. Once the human face is detected, espeak function in Raspberry Pi will send the voice to a connected speaker and will output as "Human face detected". This detected image is then saved as "User-Image.jpg" which is then will be sent to Kairos during Face recognition.

Here are the front, sideviews of the face detected images.



Figure 6: Front View of Face detection

```
# allow the camera to warmup
time.sleep(0.1)
lastTime = time.time()*1000.0
# capture frames from the camera
```



Figure 7: Side view 1 of Face detection



Figure 8: Side view 2 of Face detection

```
for frame in camera.capture_continuous(rawCapture,
    format="bgr", use_video_port=True):
    # grab the raw NumPy array representing the image, then
    # initialize the timestamp
    # and occupied/unoccupied text
    image = frame.array
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    # Detect faces in the image
    faces = faceCascade.detectMultiScale(
        gray,
        scaleFactor=1.1,
        minNeighbors=5,
        minSize=(30, 30),
        flags = cv2.cv.CV_HAAR_SCALE_IMAGE
    )
```

```

print time.time()*1000.0-lastTime," Found {0}
faces!".format(len(faces))
lastTime = time.time()*1000.0

# Draw a circle around the faces
for (x, y, w, h) in faces:
    cv2.circle(image, (x+w/2, y+h/2), int((w+h)/3),
               (255, 255, 255), 1)
# show the frame
cv2.imshow("Frame", image)
key = cv2.waitKey(1) & 0xFF
if len(faces) == 1:
    print("Taking image...")
camera.capture("foo.jpg")
os.system('espeak "Human face detected"')
inputImage= "./foo.jpg"
del camera
break
# clear the stream in preparation for the next frame
rawCapture.truncate(0)

# if the `q` key was pressed, break from the loop
if key == ord("q"):
    del camera
    exit()

```

7.2 Face Recognition

For the Face Recognition, we use Kairos to detect the facial characteristics. A json config file is to be placed in the same folder as of the code with Kairos API app id and key value. When the human face is detected, code will generate an API call to Kairos software along with the gallery name, API app id and key values. Image when sending to Kairos, it will be base64 encrypted and will send over the network for security purpose. This encrypted image will then be decrypted at Kairos platform.

```

KAIROS = "api.kairos"
KairosGallery = 'MyFace'
KairosConfig = './kairos_config.json'

def trainKairos(image, name):
    global KairosGallery
    headers = {
        'app_id': 'your-app-idd39fc1b1',
        'app_key': 'your-app-key'
    }
    data = {
        'image': base64.b64encode(image),
        'gallery_name': KairosGallery,
        'subject_id': name
    }
    r = requests.post('http://api.kairos.com/enroll',
                      headers=headers, data=json.dumps(data))
    print(r.text)
    return(None)

```

```

class Recognize():
    def __init__(self, API, config_file):
        self.api = API
        self.config = config_file

    #def recognize(self, image_path):
    #    return self.__recognizeKairos(image_path)

    def recognizeKairos(self, image):
        with open(image, "rb") as image_file:
            encoded_string =
                base64.b64encode(image_file.read())
        with open(self.config, "rb") as config_file:
            config = json.loads(config_file.read())
        data = {
            "image": encoded_string,
            "gallery_name": config["gallery_name"]
        }

        headers = {
            "Content-Type": "application/json",
            "app_id": config["app_id"],
            "app_key": config["app_key"]
        }

```

Output from Kairos software is in json format. The output is then segregated as per the key value pairs and then saved into local variables. When the image is recognized, a success transaction message will be obtained from Kairos along with subject id and face id.

```

try:
    r = requests.post("https://api.kairos.com/recognize",
                      headers=headers, data=json.dumps(data))
    data = r.json()
    print data
    # print json.dumps(data, indent=4)
    faces = []
    if "images" in data:
        for obj in data["images"]:
            if obj["transaction"]["status"] == "success":
                face_obj = {}
                face_obj["person"] =
                    obj["transaction"]["subject_id"]
                    .decode("utf_8")
                #face_obj["faceid"] =
                #    obj["candidates"][0]["face_id"]
                #    .decode("utf_8")
                face_obj["confidence"] =
                    obj["transaction"]["confidence"]
                faces.append(face_obj)
            elif obj["transaction"]["status"] == "failure":
                face_obj = {}
                face_obj["person"] = "unidentified"
                face_obj["confidence"] = 0
                faces.append(face_obj)
            else:

```

```

        print "its in last loop"
        return faces
    except requests.exceptions.RequestException as exception:
        print exception
        return None

    Output from Kairos face recogniion software is to be read to
    understand if the person name is identified or not. If its identified
    then the person name sill be listed according to the corresponding
    person in the image. If the human is not identified, then code will
    suggest if the user wants to registered for face recognition. Once
    the user key in the name, Kairos API call is generated while sending
    newly registered name and the gallery name to that corresponding
    app id. Here the newly recognized user will be registerd with the
    name and his image. When the user is reconized by camera in next
    corresponding events, then Robot car will greet the user with his
    name.

if __name__ == "__main__":
    r = Recognize(KAIROS, "kairos_config.json")
    x = r.recognizeKairos(inputImage)

    #print x
    #print x["person"]
    #print x[0]["person"]
    string1 = x[0]["person"]
    #print string1
    os.system('espeak "Hello...""{}''.format(string1)')
    if x[0]["person"] == "unidentified":
        os.system('espeak "Please enter your name to
                    Register"')
        nameToRegister = raw_input("Please enter your name
                                   to Register :")
        binaryData = open(inputImage, 'rb').read()
        print('Enrolling to Kairos')
        trainKairos(binaryData, nameToRegister)
        print "You are now Registered as :", nameToRegister
        os.system('espeak
                    "Hello...""{}''.format(nameToRegister)')
        exit()

```

7.3 Robot Car Navigation

```

import RPi.GPIO as GPIO
from time import sleep

GPIO.setmode(GPIO.BOARD)

#Connecting two wheel motors to Raspberry Pi GPIO
#Left Motor (Motor 1) connections
Motor1A = 16 #(GPIO 23 - Pin 16)
Motor1B = 18 #(GPIO 24 - Pin 18)
Motor1Enable = 22 #(GPIO 25 - Pin 22)

#Right Motor (Motor 2) Connecctions
Motor2A = 21 #(GPIO 9 - Pin 21)

```

```

Motor2B = 19 #(GPIO 10 - Pin 19)
Motor2Enable = 23 #(GPIO 11 - Pin 23)

#Output of Morors to set as OUT
GPIO.setup(Motor1A,GPIO.OUT)
GPIO.setup(Motor1B,GPIO.OUT)
GPIO.setup(Motor1Enable,GPIO.OUT)
GPIO.setup(Motor2A,GPIO.OUT)
GPIO.setup(Motor2B,GPIO.OUT)
GPIO.setup(Motor2Enable,GPIO.OUT)

# Defining function for Robot car to move forward
def forward():
    GPIO.output(Motor1A,GPIO.HIGH)
    GPIO.output(Motor1B,GPIO.LOW)
    GPIO.output(Motor1Enable,GPIO.HIGH)
    GPIO.output(Motor2A,GPIO.HIGH)
    GPIO.output(Motor2B,GPIO.LOW)
    GPIO.output(Motor2Enable,GPIO.HIGH)

    sleep(2)

# Defining function for Robot car to move backward
def backward():
    GPIO.output(Motor1A,GPIO.LOW)
    GPIO.output(Motor1B,GPIO.HIGH)
    GPIO.output(Motor1Enable,GPIO.HIGH)
    GPIO.output(Motor2A,GPIO.LOW)
    GPIO.output(Motor2B,GPIO.HIGH)
    GPIO.output(Motor2Enable,GPIO.HIGH)

    sleep(2)

# Defining function for Robot car to turn right
def turnRight():
    print("Going Right")
    GPIO.output(Motor1A,GPIO.HIGH)
    GPIO.output(Motor1B,GPIO.LOW)
    GPIO.output(Motor1Enable,GPIO.HIGH)
    GPIO.output(Motor2A,GPIO.LOW)
    GPIO.output(Motor2B,GPIO.LOW)
    GPIO.output(Motor2Enable,GPIO.LOW)

    sleep(2)

# Defining function for Robot car to turn left
def turnLeft():
    print("Going Left")
    GPIO.output(Motor1A,GPIO.LOW)
    GPIO.output(Motor1B,GPIO.LOW)
    GPIO.output(Motor1Enable,GPIO.LOW)
    GPIO.output(Motor2A,GPIO.HIGH)
    GPIO.output(Motor2B,GPIO.LOW)
    GPIO.output(Motor2Enable,GPIO.HIGH)

```

```

sleep(2)

# Defining function for Robot car to stop
def stop():
    print("Stopping")
    GPIO.output(Motor1A,GPIO.LOW)
    GPIO.output(Motor1B,GPIO.LOW)
    GPIO.output(Motor1Enable,GPIO.LOW)
    GPIO.output(Motor2A,GPIO.LOW)
    GPIO.output(Motor2B,GPIO.LOW)
    GPIO.output(Motor2Enable,GPIO.LOW)

response = make_response(redirect(url_for('index')))
return(response)

#set up the server in debug mode to the port 8000
app.run(debug=True, host='0.0.0.0', port=8000)

```

7.4 Controloing Robot Car using webserver

```

from flask import Flask, render_template, request,
    redirect, url_for, make_response
import RPi.GPIO as GPIO
import motors

#set up GPIO
GPIO.setmode(GPIO.BOARD)

#set up flask server
app = Flask(__name__)

#when the root IP is selected, return index.html page
@app.route('/')
def index():

    return render_template('index.html')

#recieve which pin to change from the button press on
# index.html
#each button returns a number that triggers a command in
# this function
#
#Uses methods from motors.py to send commands to the GPIO
# to operate the motors
@app.route('/<changePin>', methods=['POST'])
def reroute(changePin):

    changePin = int(changePin) #cast changePin to an int

    if changePin == 1:
        motors.turnLeft()
    elif changePin == 2:
        motors.forward()
    elif changePin == 3:
        motors.turnRight()
    elif changePin == 4:
        motors.backward()
    else:
        motors.stop()

```

8 APPLICATIONS

There are lots of applications of face recognition. Face recognition is already being used to unlock phones and specific applications. Face recognition is also used for biometric surveillance. Banks, retail stores, stadiums, airports and other facilities use facial recognition to reduce crime and prevent violence.

9 CONCLUSION

A Face detection and a recognition system is developed using Raspberry Pi. Using Python programming language, system is being built such that it can face detect and recognize in real time scenarios. For this solution Kairos Facial recognition software is being used which have a free developer account. Facial recognition is tested with various types of faces ie, front view, sideview. The Round Trip Time for robot car to take picture and recognize face is nearly 3seconds. Efficiency of the system was analyzed based on the rate of face detection in real time. As per this analysis, this current system shows tremendous performance efficiency where the face detection and recognition can be performed even with a very low quality images.

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The Intersection of Big Data and IoT

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ABSTRACT

Big Data and IoT share a symbiotic relationship with one another that is leading to incredible innovations that were inconceivable just 18 years ago. As a result of this relationship, it has become easier than ever for individuals to customize and monitor various elements of their life if they choose to do so. We examine a few of the emerging technologies within IoT, highlight some of the most interesting current use cases and show how Big Data plays a role before presenting a challenges that lie ahead for the technology. Finally, a demonstrative project is undertaken via the Raspberry Pi to illustrate how accessible IoT has become to leverage Big Data analysis.

KEYWORDS

i523, HID 334, Edge Computing, Raspberry Pi, IoT

1 INTRODUCTION

In 2020, it is estimated that 95 percent of electronics will contain IoT technology [41]. This technology, commonly abbreviated for the “Internet of Things”, is expected to be so pervasive due to how the technology is defined and how impactful it has already become.

At the highest level, IoT is intended to describe devices that collect and relay information via the Internet. This leaves IoT is broadly defined in the type of application, which could come in the form of a phone, vehicle, a home device like a thermostat or television, but the technology is rather specific in its intended application. That is, these devices are generally made to serve a single purpose and they are extremely adept at that function. In its most powerful applications, massive data sets are created from these individual IoT devices as they are synthesized together to meet a larger need, as we will see.

The specific purpose of an IoT device is what differentiates this emerging technology from traditional computers. With the exception of recent developments, which will be explored in depth, early IoT devices were not intended to do the heavy computing like a computer would do. However, with rapid advancements in computing power and speed, the line differentiating the two has begun to blur. It is this increase in computing power that has lead IoT and Big Data to have a cooperative relationship to create some of the most exciting technology that's available today.

The ability to collect and process more data has increased the utility of these devices as they're able to become more personalized, spurring tremendous growth recently, on the order of 30% annually. In 2017, it is expected to be the year that the number of IoT devices exceeds the number of people on Earth [18]. This personalization is not without consequence though, which will be discussed later, so the relationship between IoT and Big Data is still evolving.

To begin, we examine how the IoT came to be and continuously evaluate how it is integrated with Big Data. Next, we discuss high

level implementations of these technologies in modern use before discussing some of the challenges the industry is facing. Finally, a demonstrative project will be outlined to show how Big Data can be used in an IoT device.

2 EMERGENCE OF IOT

Given the massive and recent popularity of IoT, it might be a surprise to some to learn that this concept has been around since 1999. The idea to have multiple, remote devices communicating with one another to gain insights to a single problems was originally conceived by Kevin Ashton as a solution to supply chain management [16]. At that point, the idea was ahead of its time as the internet was still gaining widespread adoption. However, as computing power and sensor costs have declined, IoT has become a main an indispensable aspect of most people's lives. One such example could be the integration of global positioning systems (GPS) into cellphones, which was introduced in just 2004, but has become a staple for nearly every phone released [50].

2.1 What Defines IoT?

Given the ascension of so many new technologies, it could be helpful to understand what technically constitutes an IoT device. This will be useful later when discussing the sample project undertaken and how these both relate to Big Data analysis.

As stated earlier, at a high level, IoT is meant to describe devices that use internal or external sensors to connect to the Internet. These sensors could come in the form of the well known types, such as Wi-Fi, Bluetooth or RFID, to the perhaps less widely known, such as NFC (Near Field Communication) or Zigbee [43].

For these IoT devices, the Internet allows them to be tremendously influential in the advancement of Big Data by virtue of the amount of data the devices are able to collect. Specifically, IoT allows its users to quantify the world around them in ways that were previously not possible. For corporations, this yields tremendous advantages when it comes to business planning or equipment monitoring. For example, the average wind farm can generate 150,000 data points *per second* and an engine turbine could give 500 gigabytes of data [28]. Additionally, for individuals, IoT enables people to monitor their activity on a daily basis through wearable fitness devices and customize their homes to save on energy consumption. It has been estimated the average household generates approximately 2,000 gigabytes of data a year and this is expected to increase five fold by 2020 [52]. As we will explore, this rapid increase is due in large part to the computing power of the individual devices, which allow for a greater volume of data to be collected. For example, if a person enjoys a simple bike ride and purchases the Garmin Edge 500 watch, on a single ride they are producing data across 61 different variables for statistics such as heart rate, elevation gained, cadence and output produced continuously for the duration of their ride [17].

3 EDGE COMPUTING

Edge computing is currently one of the most transformative technologies within IoT because it is changing the way the cloud is being utilized for Big Data analysis.

The technology gains its name from how the information being processed by the device. Prior to this recent innovation, information was gathered, sent to the cloud, processed there, and then the output is pushed back to the device. Namely, it was a centralized process. However, with edge computing, devices are more intelligent in what information they choose to send, providing a much more efficient process. For example, rather than having a camera monitor an area constantly, even when there is no motion, modern IoT cameras have been equipped with motion detection so information is only sent when there is something to actually record. Since this decision and processing is made on the actual device, it is considered to be at the *edge* of the network.

Traditionally, IoT devices that were intended to work in conjunction, such as surveillance cameras, were simple in their functionality and storage. Namely, a group of cameras would record individually and send their results back to a central server. However, with improvements in image quality, this becomes a Big Data problem very quickly as these cameras are running around the clock collecting footage. In the historical model of a centralized server, this setup eventually creates problems as bandwidth and storage issues emerge. These limitations are the problems that edge computing seeks to circumvent and has become a major catalyst in the growth of IoT devices [51].

One of the primary reasons this technology is possible is due to the dramatic decrease in computing costs. The demonstrative project that is undertaken later on is an example of how much computing power is now available in the simplest devices. For the cost of \$10 one can get a single-board computer with 1 GHz and 512 MB RAM through the Raspberry Pi.

For these reasons, this type of processing is close to becoming the majority as it is expected that by 2019, 45% of all data collected by IoT devices will be processed at the edge of the network [37]. As we will see by examining several commercial use cases, this technology is allowing early adopters to gain unique, real-time insights through Big Data analytics into the health and composition of their businesses.

3.1 Use Case: Fraud Detection

Fraudulent transactions represent just 1% of all transactions. However, while the relative size of these transactions to the overall market are small, their absolute impact is enormously detrimental to merchants and financial services companies. In 2015, total fraudulent transactions created damages of \$22 billion [29].

The economic impact of these transactions has given these companies a tremendous incentive to innovate their way out of this problem. The marriage of IoT and Big Data has now provided them the opportunity to have near real-time analytics, which is necessary to effectively manage the problem. This is because the approval process for a transaction needs to be as close to instantaneous as possible. If shortcuts are taken in the analysis to increase speed, fraudulent transactions could slip through and not get flagged. IoT

has helped make this trade-off between accuracy and speed less of an issue with new innovations, such as Visa's Ready program.

Visa Ready is an innovative program enables payments through IoT for both security and convenience. Instead of traditional means of payment authorization, such as simply swiping your credit card at a vendor, IoT enables Visa to take advantage of improvements in biometric technology [57]. Visa has introduced multi-dimension verification through biometrics by letting users endorse a payment through their fingerprint, iris scan, face scan and even their voice [58]. This type of technology is gaining adoption and there are expected for be 500 million devices with biometric sensors by 2018 and 26 billion by 2020 [48].

Complementing biometric data, as IoT devices become more mainstream, companies such as FICO are using behavioral data in fortifying their analysis of whether a transaction is fraudulent or not. This type of analysis is not new in and of itself as it has been established as a way to identify e-commerce fraud, but the application through IoT is providing a new dimension of analysis. Traditionally, behavior data was tracked to see how a user interacts with a website to reduce the number of false positives that get flagged, which could occur if a user was on a business trip and abruptly logged into their account to buy something from an IP in another country [14]. With IoT, this adds a tremendous amount of data to an already Big Data problem. Now these companies will have data on how users interact with an IoT device, such as how they hold their device in the case of a phone or their tendencies when using the keyboard [25]. From a business perspective, this all occurs in the background without the user's experience without the product being interrupted.

As a testament to the future of this relationship between IoT and Big Data, Visa has partnered with IBM. This was done in an effort to gain maximum benefit from this new biometric technology by leveraging Visa's payment infrastructure with IBM's efforts in artificial intelligence and Big Data analysis with IBM Watson [31].

3.2 Use Case: Autonomous Vehicles

In many ways, autonomous vehicles represent the pinnacle of edge computing to date in unifying IoT and Big Data. Among its many goals, this technology is trying to use Big Data to resolve one of the modern tragic realities of our modern world - automobile fatalities. Automobile accidents cause 1.2 million deaths a year, 94% of which are attributable to human error [30]. For this reason, in conjunction with expected energy savings from car designs with this technology, the technology is expected to experience adoption rates that rivals mobile phones with significantly more impact [23]. Traditional car makers have taken notice of the potential future and as an example of this, General Motors recently hired an Uber engineer to lead its self-driving initiative as the company's first ever Chief Technology Officer [5].

The relation of autonomous cars to IoT via edge computing is once again out of necessity for real-time functionality. A car that processes it should stop two seconds too late is as potentially useful as never making the calculation in the first place, so timing is of the utmost importance. Amazing progress has already been made in the speed and complexity of calculations these autonomous vehicles can handle. One of the highest profile graphic card manufacturers,

Nvidia, recently announced their system for autonomous vehicles at the rate of 320 *trillion* operations a second [21]. Since these vehicles are equipped with various types of sensors to process its environment, this type of computing power is a near necessity to tackle this Big Data problem in real-time.

Kevin Ashton's original vision for the IoT was to have an accurate view of inventory as RFID scanners synced over the Internet. In just 18 short years, these autonomous vehicles are achieving the same end of communication with one another on an incredible scale. In what's known as "vehicle to vehicle communication" autonomous cars will be able to send one another information on important considerations, such as road hazards or conditions, allowing GPS to take the most optimal route to its destination. Similarly, speed limit signs can take weather conditions into account, dynamically adjust the speed limit of the road and relay this to the car's navigation system [1].

The companies that are pursuing autonomous driving are largely having the cars learn through the experiences of its sensors. It would be impossible to code every possible scenario a car could face, so instead, data is collected from the various sensors and loaded to the cloud for later analysis. For example, Tesla is accumulating a million miles worth of data across its sensors every 10 hours, leaving it with 780 million through mid-2016 [7]. These sensors on board, which will be briefly described to show their application, are expected to generate 4,000 gigabytes of data *daily* [38] [19]. This is another instance of the familiar union between IoT and Big Data.

3.3 Use Case: Health Care

The United States, like the world as a whole, is experiencing an aging crisis in its population. In both the world and the United States, the number of adults aged 65 and over is expected to double by 2025. In the United States, this demographic of the population will move from 15% to 25%. While this jump is not negligible, the most alarming aspect of this statistic is that in 2010, the elderly portion of the population was just 10%, but accounted for 34% of medical expenditures [34].

For this reason of high future expenditures, much of today's public policy debates center around how resources will be pooled to meet this not so distant future need. Currently, one of the most promising use cases for edge computing is coming from health care and how the technology can be used to provide better care to a wider range of people.

Through edge computing, doctors have the ability to gain insights into their patients through sensors that can be worn by their patients, such as a heart monitor. This allows for early identification of irregular patterns and allows for an earlier diagnosis, potentially saving the patient's life compared to earlier times when a heart attack could strike abruptly without warning. This usage is directly related to Big Data as doctors now can get continuous, real-time assessments of their patients. This makes way to more accurate future diagnoses as more insights can be gleaned between the true cause and effect of a particular ailment [42].

Outside of data analysis by doctors, the patients themselves are expected to receive numerous benefits from this type of monitoring. Namely, those who are less mobile no longer need to make

a physical trip to see the doctor as the doctor has the diagnostics they typically need and at a much more granular level [6].

In addition to the elderly, this type of real-time feedback system through edge computing can be incredibly transformative for those with health conditions that require nearly continuous monitoring. One such example has been demonstrated with epileptic patients. An edge computing solution has been introduced that epileptic patients can use and if a patient experiences an epileptic episode, an immediate alert is sent to family members and doctors [53]. This type of technology is only possible through edge computing because the alerts are triggered by monitoring historical metrics versus live readings in areas like heart rate and sudden movements. The delay that would be incurred by sending this data to the cloud and waiting for a response would have too much latency to be an effective solution to this problem.

Another promising area for edge computing within health care is for those suffering from mental diseases, such as dementia or Alzheimer's. With this technology, family members can monitor and set alerts if a particular perimeter is breached from where their loved one is supposed to be staying [8].

3.4 Use Case: Retail Shopping

Worth \$2.6 trillion, the United States retail industry comprises 15% of national gross domestic product [13]. The ground is shifting underneath this industry though as brick and mortar stores are under siege from a surging market share by Amazon, which is up 150% since 2013.

These traditional stores still hold the top rankings in the retail sales by size, but the ability of Amazon to utilize Big Data for a personalized shopping experience online is forcing these top retailers to adapt with a competing level of customization. Amazon's recommendation engine allows them to see into a user's purchase history, viewing history, rating history and search history, which are all used to point the customer to the most likely product they're looking for. In fact, Amazon is even working on an IoT sensor that they intend will act as a personalized stylist. The device will take a picture of your outfit and make recommendations of what would look best, based on the recommendations of its algorithms that are supplemented by fashion stylists to reflect current trends [33]. As a result, IoT gives Amazon a level of scalability to its entire customer base to create more information and data about the customer that is simply not available to the brick and mortar stores.

To try and compete with this personalization though, brick and mortar retailers are using edge computing to introduce technology that was science fiction 15 years ago in the movie Minority Report. In the movie, which takes place in 2054, the main character is rushing through a busy shopping center when he passes various kiosks that address him by name and ask about his recent purchases in the store. This is the reality that retailers are now using through real-time facial recognition, enabled by edge computing to integrate IoT and Big Data. With this, they are also collecting broader demographic statistics by tracking customers' ages, ethnicity and gender [32]. In fact, America's largest retailer, Wal-Mart, is currently using facial technology to sense customer's moods and find those who are dissatisfied [40].

While we haven't quite hit the personalization depicted in Minority Report for the general public, those with celebrity can expect that high-end stores they visit will recognize them upon entry. For example, one such jewelry store in Los Angeles is equipped with facial recognition technology, stocked with a database of celebrity pictures from Google Images and when someone is recognized, an alert is sent to the manager with purchase history and sizes [46].

Outside of custom shopping, facial recognition is also being used by traditional stores to deal with a risk that e-commerce is not exposed to - shoplifting. With this technology, a retail store can identify when a known shoplifter is most likely to re-visit the store and when, which were previously unquantifiable. Once they are identified on site, management is sent an instant alert and the customer is escorted from the store to prevent further loss in the future [11]. Additionally, RFID sensors are being used on items individually to better track items outside of the store for loss prevention like this and better supply chain management [10].

4 CONCERN WITH IOT

As exciting as these use cases are about what the future might hold, innovation is outpacing legislation for IoT. As we will expand upon below, a race to release products has left consumers susceptible to hacking in some cases as security measures have not been fully developed yet for these devices. Additionally, with the customization that comes with IoT, consumer information is being sold to advertising agencies in many cases without the consumer's knowledge.

4.1 Security

While we have discussed some of the most exciting and interesting developments in IoT, this blistering pace of innovation has come at a price. There are experts in this field that believe the connectivity of these devices are a gateway of vulnerability as many IoT devices do not have sufficient security measures, allowing malicious actors direct access into some of people's most private details.

For most utilizing IoT, the technology is used to make their lives easier in some respect. However, when it comes to security, it is believed this approach of a "hands off" relationship with IoT leaves users susceptible to security breaches. Specifically, users need to be diligent in making sure their software is up to date across *all* devices. The reason for this is that with a large network of IoT devices, hackers now have multiple fronts on which they get behind the firewall whereas their only avenues traditionally were the computer and more recently, smart phones. As a result, negligence in one area could be enough of an opening for a comprised network where hackers could take control of a device, which is particularly worrisome in the case of an autonomous car.

Another dimension of risk for IoT security sits with the creators of this technology. Underlying in the assumption about users being diligent in updating their software to prevent breaches is that the developers of the software are actually making continuous updates to adapt along with hackers. However, as time goes on, new products are likely to draw a company's limited resources away from maintaining older products.

In response to these risks, two significant changes have been undertaken to mitigate some of the risks. Namely, companies have

introduced automatic updates and used the same operating system across later models of a particular product. These automatic updates then take the burden off of the user of IoT technology, which is an attractive feature as many adopt the technology to simplify their daily life. Additionally, when companies are able to use the same underlying operating system across later products, they're able to update all products in lockstep with the developing security community, ensuring no older products are left behind as an opening behind the firewall [39].

Fortunately, these security concerns with IoT have largely played out in the hypothetical. In fact, surveys have found that the majority of consumers are unaware of IoT security risks and once made aware, do not consider the risks serious. In fact, surveyors even found that if a device had a known security flaw, 20% of consumers are still willing to buy the product [9].

For this reason, with no major attacks to date, adopters of IoT have possibly felt insulated as an overwhelming majority are not threatened by the security risks IoT could pose. This is not to insinuate that IoT attacks do not regularly happen, but instead that they have not occurred on the scale that some of the largest security breaches in recent years have occurred, such as the Target Corporation's incident in 2013. In that breach, 110 million consumer credit card numbers were stolen, along with personally identifying information like their address, e-mail and phone number. The entire episode was estimated to have cost Target \$162 million [2].

While an IoT originated attack like this has not happened yet on this scale, these attacks do occur with frequency. One such statistic demonstrating this unsettling fact is that half of all companies that have adopted some element of IoT technology have experienced a security breach. In the end, these breaches have cost an average of 13% of annual revenue [45].

The closest demonstration of IoT risks came in October 2016 through the "Mirai" malware, which was used to attack DNS servers and bring down high traffic websites, such as Netflix and Amazon. Disturbingly, "Mirai" translates to "future" in Japanese. With Mirai, the program is continuously scanning the internet for IoT connected devices that have left the default user name and password. Then, once a device is found, it is turned into a bot that is used to amplify a DDoS attack. Incredibly, the average IoT device is scanned every two minutes with this bot, leaving an extremely small margin for error in being compromised [44].

This breach demonstrated the downside of the highly connected nature of IoT. Against the benefit of having devices that can communicate with one another, in the event of an attack, these devices are intertwined and will be equally compromised. The network of IoT devices has gotten so complicated for some companies that one survey found 66% of IT professionals aren't sure how many devices are in their environment [35].

4.2 Privacy

It is rather commonplace knowledge, for better or worse, that the apps we use daily are collecting data on us. We're aware that it is on going, but in many cases it's unclear what data is actually being collected. This data aggregation is one of the main debates around IoT. Ironically, one of IoT's primary benefits makes it also one of the most unsettling for others, fearing how the data could

be used in the wrong hands. In fact, in 2014, it was found that of the top 200 free apps in the Apple store, 95% were engaging in “risky behavior” [36]. These risky behaviors, are defined as activities such as tracking locations, accessing users’ contact lists or selling registration data to ad agencies.

Due to this pervasive data collection, one of the consequences of a security breach via an IoT device would be having personal information comprised. However, outside of this direct relationship, there are concerns on privacy as it relates to usage as laws are behind technology in how this data can be used. The only major pieces of legislation that concern privacy at the federal level are through HIPAA for medical records and the Fair Credit and Reporting Act. Outside of these, the task of regulating privacy is left to states, which are behind the curve in today’s fast paced, data driven world.

In a similar conundrum as the security concerns with IoT, one of its greatest features in its ability to continuously monitor and collect this data into Big Data sets is also the reason some hold reservations on the technology. This is mainly due to the fact that this data is not collected into a central repository, like your credit, to see what information is being associated with you. To take it a step further, it is not even clear who has what data on a particular user.

In a shock to most on how little personal privacy may exist in our technology saturated world, it was discovered that the CIA and MI-5 intelligence agencies were using “smart” TVs to eavesdrop on conversations in people’s homes. For security experts, this was no surprise and known to be an easily accessible device, but those outside of that community felt an invasion of privacy [49]. Discovered in 2016, the program was used in 2014 by exploiting the voice enabled features that Samsung included in its TVs to listen to conversations. The power button was even programmed to look as if the TV was off while this recording was happening [56].

While this spying was alleged to have just been on “people of interest”, the average consumer with a smart TV has likely experienced spying they were unaware of through their viewing habits. By default, Vizio TVs were found to be recording their customers activities by logging metrics such as date, time, show, whether it was live or recorded and how long it was watched. This is estimated to have affected 11 million TVs in the end before the FTC outlawed the practice of having these settings turned on by default [27]. This would be a utilization of IoT and Big Data that few would be comfortable forfeiting without their consent.

5 IOT PROJECT

5.1 Goal

The goal of this demonstrative project is to illustrate how Big Data analytics can be easily leveraged and customized through an IoT device.

5.2 IoT Device

The Raspberry Pi 3 (Model B) was the IoT device used with this goal in mind. The Raspberry Pi has drawn tremendous accolades for its initiative to get inexpensive, but powerful computing power into the hands of aspiring programmers and hobbyists. Equipped with

1GB of RAM, a 1.2GHz quad-core processor and Bluetooth/Wi-Fi capability, one can purchase the device for just \$35.

5.3 Description

In this project, an application is created via the Raspberry Pi. Specifically, an interface is created that gives the user a morning snapshot for relevant, important information to begin their day. As it relates to IoT, this project uses IoT technology through Wi-Fi to source the output of Big Data projects undertaken by others (ie. Google and Weather Underground as will be shown).

5.4 Implementation

For those unfamiliar with the Raspberry Pi, the initial setup could be somewhat intimidating the first time around. Specifically, the Raspberry Pi comes as a truly blank slate and to begin using it, one will need to write the OS, Raspbian, onto the Pi. Several tutorials are available online to get to the desktop, so in the interest of brevity, the discussion below will assume that the user has been able to successfully get the Pi operational and to the Linux prompt with Python installed to run the script.

The application was developed using Python, utilizing the Kivy package for GUI development, the requests and Beautiful Soup packages for the user location, news stories and sports scores along with Yahoo Weather/Weather Underground via the Weather package. Outside of these, standard Python library packages were used.

5.5 Results

The final product of our application on the Raspberry Pi is shown in Figure 1.

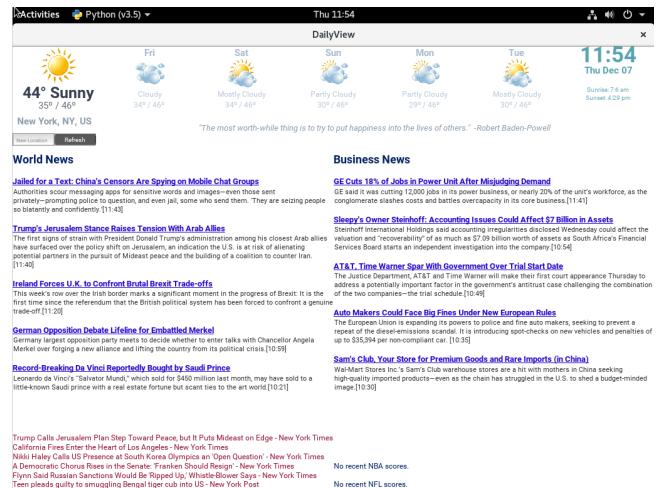


Figure 1: Raspberry Pi IoT Application

As part of the display, a continuous running clock was added, which necessitated the application to be on a constant refresh. This was implemented successfully and at a relatively low cost with no significant delays. The total build of the application consumed 966,565 bytes with each refresh using just 1032 bytes. At the initialization of the program, the application uses the user’s IP address to find their zip code to populate the local weather forecast and local

news. For the weather, the user will get the current temperature with a high/low for the current day and each day in the five day forecast.

Additionally, as news stories are published to the WSJ news feed, they will be read into the application and refreshed. Stories are shown in chronological order along with their time stamp of publication and each is hyperlinked directly to the full story if the user wants more information.

5.6 Application to Big Data

One of the main benefits of IoT is synthesizing data across numerous platforms and data sources into a desired output. Our desired output is a one-stop interface with interesting information that can be displayed anywhere with an outlet, internet connection and monitor.

The various components of the monitor are only made possible by the creativity by the providers in solving difficult Big Data issues, such as the clustering of news (Google) and weather forecasting (Yahoo/Weather Underground). Each provider's relationship to Big Data is worth examination and will be the topic of the following sections.

5.7 Google News

5.7.1 Big Data Description. Google News has evolved into a central source of information for how a large share of the population receives its news. In fact, as a display of the trust that users place in Google to deliver the most information in the most efficient manner, it was found that users are more likely to trust a Google news headline than that same headline from the original source [26]. Additionally, 44% of users were found to read nothing more than the headlines [22]. This is a testament to their ability to simplify the universe of world news into succinct rankings.

Entering into its fifteenth year, Google News aggregates from 50,000 news sources worldwide across 30 different languages. In 2012, they reported the division was receiving 1 billion unique visits a week[4]. For reference, major individual news providers, such as CNN and the New York Times receive 125 million and 99 million unique visitors per month [3]. These statistics further demonstrate Google's successful navigation of the Big Data problem for news stories in the eyes of its users. It's relatively clear why this is an important Big Data problem, but one might be curious how they're able to effectively navigate the problem. Unfortunately, the full design from start to finish is a well kept secret, but pieces have been released and one can piece together a mosaic view of what might be going on under the hood. The decision to not disclose the techniques for ranking news stories is understandable, but it has been a lightening rod of controversy nonetheless. Some view the decision of Google's scoring as effectively acting as a censor for the internet while they maintain it is to keep the integrity of the algorithm so that news stories cannot be written purely for traffic, known as search engine optimization [12].

On the surface, one might question the economic value of Google News to the larger company since it is a free service for both users and providers. However, there is a tremendous amount to be gained in solving this Big Data problem. Even though Google does not show ads on its news site, it was estimated to generate spillover

traffic into its search engine that leaves the News entity worth \$100 million in 2008 [60]. The current valuation is undoubtedly higher, but it remains undisclosed. So while there are profits to be made for Google in this quest, publishers of these stories have a tremendous amount of interest in this problem as well. Some providers don't believe content should be indexed to Google's search algorithm for free and Google should pay them for their investigative research. One such provider, who happened to be Germany's largest news source, decided to remove themselves from the index for two weeks. The results were devastating for the site as traffic through the site dropped by 40% [59]. It was a quick lesson in how critical positioning can be in the Big Data world of news aggregation.

5.7.2 Big Data Solution. Just as news is constantly evolving, so are Google's solutions to this Big Data problem. As we've seen recently, news aggregation services are under pressure to become more intelligent on what news is shown in the hopes of preventing fake news from making it into the top results.

The technical specifics of what Google is implemented has largely been kept under wraps, but we did learn a few of the techniques and platforms in 2007. In at least the early versions, Google used MinHash, Probabilistic Latent Semantic Indexing and Covisitation to solve this Big Data. Specifically, these methods will compare historical clicks with other similar users for recommendations, decipher key words and phrases from an article for grouping and track how news stories are clicked within a certain time frame to find stories that were read successively. For processing these queries, Google uses MapReduce and Hadoop architecture [55].

For the inputs into these algorithms, Google will analyze several metrics of a provider to see how they should be ranked along with the user preferences. These metrics include things like how large the staff is, how many articles they put out, how many websites reference that news source (PageRank) and the breadth of news topics covered [15].

5.8 Weather Underground via Yahoo API

5.8.1 Big Data Description. Weather is a primary concern in business planning for many industries, such as airlines or agriculture. As a result, companies are willing to dedicate a tremendous amount of resources towards accurate forecasts. One of the most innovative companies and a great example of the intersection of IoT and Big Data is Weather Underground.

Weather Underground is a weather forecasting service that was once owned by the Weather Channel and recently, partially by IBM to integrate with its growing IoT ecosystem. What makes the company unique is how their forecasts are formulated. In their model, they couple traditional forecasting tools with IoT. The traditional readings come from the National Weather Service (NWS), which aggregates data from airports and weather balloons. IoT has lead to a new dimension of forecasting as personalized weather stations are distributed to its users for live forecasts in places that traditional instruments might not be available. As of now, they have 250,000 users set up on the platform. This setup provides an additional layer of information, yielding more frequent data, longer forecast windows and greater certainty for a given area. Namely, users can get new forecasts every 15 minutes (versus every 4 hours on the NWS) and forecasts up to two weeks in advance (compared

to one week for NWS) [54]. This use of the IoT, specifically edge computing, which will be expanded on later, provides a tremendous example of how IoT can be used to enhance Big Data analysis.

For those that choose to participate in the service, they will purchase a Personal Weather Station (PWS) that allows them to measure temperature, humidity, pressure, rainfall, wind speed and direction via sensors. The major advantage of the PWS comes from its pressure and wind metrics as users can get a better idea of humidity and wind chill, giving a more accurate representation of current conditions. Neither of these are available through the NWS. In the end, this amounts to around 3 billion data points for the Weather Underground model, servicing around 26 billion inquiries a day [24]. This is a great demonstration of edge computing that was explained earlier for its ability to collect and process relevant information before sending it to the cloud for synthesis with other devices.

5.8.2 Big Data Solution. To process its data in the past, which amounts to multiple terabytes daily, Weather Underground has stored its forecasts, radar data and satellite data using Apache Hadoop and Amazon Web Services [47]. In fact, IBM has stated a large reason for their motivation to have an ownership stake in the company was due to the cloud infrastructure that Weather Underground had built for fielding the massive volume of requests and forecasts it processes daily.

5.9 Limitations

While this application shows what an IoT device can achieve with Big Data, the most influential uses of IoT come when devices are able to communicate with one another and create more data that can be implemented back into future improvements in the device, as we have seen. The limitation of this current program is that it is a singular instance of the application. Allowing multiple applications to be deployed where information can be collected on *volunteered* information would be orders of magnitude more difficult to implement, but could be an interesting addition to gain better insight on the user base. Then, this data can be pooled together for how the application could be tailored to meet geographic or demographic preferences.

Additionally, with a large enough user base, we would be interested in tracking the number of downloads, active users and which panels of the display are clicked most often. All of these metrics can be readily accessed through integration with Google Analytics, which allows one to analyze different events within the application [20].

6 CONCLUSION

As we've seen, IoT cannot realize its full potential without Big Data. The IoT universe represents the senses by which Big Data is collected for later insights and innovations. For this reason, the IoT revolution has the potential to completely change the world as we currently know. It could be a world in which automobile accidents are no longer a tragic reality or a world where health care delivers the most personalized plan with attention on every minute detail. Additionally, users are able to benefit from the increase in computing power per dollar spent, allowing them more flexibility than ever to design their own IoT device, as was demonstrated in

the application made for this paper. However, against this rapid pace of innovation in IoT, some of its most attractive features of interdependency among devices expose the technology to some of its greatest vulnerabilities. Keeping this growth rate in the products in step with security will prove to be one of the biggest challenges in coming years.

A CODE COMPILATION AND SAMPLE OUTPUT

The following urls are intended to direct to various parts of the project.

- Packages required to compile the project along with sample input
 - <https://github.com/bigdata-i523/hid334/tree/master/project>
- Python code to create the monitor:
 - <https://github.com/bigdata-i523/blob/master/project/code/project.py>
- Weather codes:
 - <https://github.com/bigdata-i523/blob/master/project/weathercodes.py>
- Kivy file:
 - <https://github.com/bigdata-i523/blob/master/project/DailyView.kv>

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Big Data and Its Application in Education

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ABSTRACT

The development of big data is changing the society in a dynamic way. With high speed internet and high penetration rate of mobile devices, every individual becomes a source of data and is constantly provide these data to various organizations who want to make profits or want to utilize these data to contribute to a certain end. Big data helps online retailers to add new strategies to increase their selling; it also helps medicare organizations to make more accurate diagnosis to patients; it even changes the sports industry. Because big data is changes various industries profoundly, it will certainly in a point change the way people acquire new knowledge. For this reason, it is important to review how big data bring changes to different industries and how education strategies could adjust to the fast-change world. In order to have a clear picture of in what ways big data will influence educational strategies, we will use education recommendation system and medicare education which is transformed by big data, as a case to see how educators should adjust their strategies with the benefits brought by big data..

KEYWORDS

i523, HID236,HID218, big data, education

1 INTRODUCTION

When we search the definition of education, we will find that it is defined as process of facilitating learning or the acquisition of knowledge, skills, values and beliefs and habits [43]. However, when we talk about education, we regard education as academic education such as K-12 education and higher education. In reality, education is happening all the time and everywhere. When you are sitting in a classroom, you are learning to get a degree and plan for your career life. When you are working in the office, you gradually learn how to accommodate what you learn at school to what the reality is in the workplace. When you are watching TV, you are getting information about what is happening around the world and you gain your first impression of different countries around the globe. And even when you are shopping online, you are learning how to identify the product is good or bad by reading the reviews. Therefore, in the 21st century when educators look into education, it will cover not only school education but also corporate training and other forms of informal learning.

2 A LOOK BACK AT LEARNING

It is very difficult not to think of Confucius and Socrates, two great men who are regarded as the most important people in terms of influence on education in the East and West. Confucius emphasized the importance of education and proposed that education should be equal to everyone. He was a teacher himself and taught students

morality, proper speech, government and refined arts. “He never discourses at length on a subject. Instead he poses questions, cites passages from the classics, or uses apt analogies, and waits for his students to arrive at the right answers” [30]. Confucius set an example of teachers in ancient China and other regions in Asia such Korea and Japan. Teachers in these parts of world should be much better learned than students and are examples in terms of morals. Because of this, students should imitate teachers. By contrast, Socrates adopted a different view of learning. fSocrates does not believe that any one person or any one school of thought is authoritative or has the wisdom to teach “things.” Socrates repeatedly disavows his own knowledge and his own methods. However, this appears to be a technique for engaging others and empowering the conversator to openly Dialogue [2]. This may be one of the reason why the learning style in the East and the West is so different. But when we look back at education in schools in the past, no matter where the school or the learning place is located, learning is highly teacher-centered. In ancient China, teachers still follow the learning style of confucius. The teachers had authority over their students and students were supposed to treat their teachers like their fathers. In return, teachers should be selfless enough to pass what they knew to their students. In the West, the situation was similar. And one of the reasons might be the lack of resources in teaching. In ancient times, only limited number of books were available due to printing technique and the number of scholars who could write books. In the year of 1500, the illiteracy rate of men and women in English is 90 and 100 respectively. And in Qing Dynasty around 1880, literacy rate is around 30-45 in men and 2-10 in women. It is not hard to deduce that these numbers are much lower in 1500s [28]. Knowledge or information was in the hand of the top 10 of people which make knowledge more precious. Therefore, teaching must be teacher-centered and teachers have much authority over the students. However, it is never true today. The volume of books will take a person’s whole life to read; TV has changed the way of how people get information; and the internet revolutionizes how information is created and transmitted. As a result, teachers are no longer just knowledge providers and it is impossible for them to be mere knowledge providers because learners have access to almost infinite source of knowledge.

3 WHAT IS INSTRUCTIONAL DESIGN?

“Educational technology is the study and ethical practice of facilitating learning and improving performance by creating, using, and managing appropriate technological processes and resources” [13]. Instructional technology started from instructional media , the use of which can date back to the first 10 years of 20th century in school museums. The use of different media in instruction or

learning have gone through visual instruction, audio-visual instruction and the use of communication theories to today the integration of computers and internet technologies [29].

However, the turning point of the birth of educational technology began as visual education. At the turn of the 20th century, educators were exploring the potentials of motion pictures and projected slides. In the 1950s, the advent of television added new dimension of widespread of audio-visual programming. At this time, the design materials only focused on creating attractive and creative presentations which are pleasing to learners' eye and ears. But a shift happened in the next decade. Educators not only cared about the appeal of the teaching or learning materials, but also cared about what learners are doing. In the next a few decades, the focus of learning design continued to change because of the advent of the internet which allows learners to collaborate anytime anywhere. Also, computers became a powerful assistant in learning with the advances made in CPU and storage [25].

Instructional design has several names such as instructional system technologies, learning design and educational technology. Although universities which have program on instructional design prefer different names, they have similar courses and goals of training. The definition of instructional design has been revised several times in history and those changes were caused by different opinions held by experts in the field and most important caused by advances of science and technology.

4 THE DEVELOPMENT OF EDUCATION PSYCHOLOGY

Behaviorists believe that performance of people can be changed by contingencies of reinforcement combined with changes in the environment [42]. For example, drivers or passengers of a car may not want to or forget to fasten the safety belts. In order to prevent that from happening, a machine would give out a loud "beep" noise which is annoying to tell people in the car that you need to fasten the belt. This is called a negative reinforcement. In order to avoid something awful to occur, people will behave in certain way. Opposite to this is positive reinforcement. For instance, teachers would give a student who has the high scores in a exam a gift and verbal appraise as a way to encourage all the students to study harder. Behaviorism has great impact on programmed instruction in both academic education and military training [34]. However, the behaviorist approach to learning has two problems. The first one is the use of proper reinforcement. As learners grow older, instructors have to find reinforcement that learners will value. But it is really difficult to provide such reinforcement to adult learners. The other problem is that behaviorists seem to ignore the process of learning.

By contrast, cognitivists focus on how people process information. The core components of cognitive approach to learning are perception and sensory stores, short-term memory, and long-term memory. Perception is about how people select what information to pay attention to; "sensory stores are capable of storing almost complete records of what we attend to but hold those records very briefly"; short-term memory helps people to rehearse the information coming through sensory stores but it has limited capacity; Long-term memory is where information is stored in a certain

way permanently and is ready to be retrieved [41]. A example of using cognitive theory in learning or information is the design of presentation slides. A good PowerPoint presentation may contains clear contrast between the texts and the background or different categories of information. It also only contains keywords of a topic so viewers will be well-guided by the slides when listening to the speakers. Although cognitive approach of learning helps learners to process information, what learners can do if they need to learn a ill-defined topic?

Constructivism made one more step forward towards learning. Learning, according to constructivist theory, is a process of meaning making, a process of solving problems when encountering cognitive conflict and a social activity such as collaboration and negotiation [44] Put it simply, constructive theory advocates simulation of the real world environment. A topic is ill-defined and learners are required to formulate their own strategies to look for relevant information and experiment potential solutions to solve a problem.

5 PROBLEM-BASED LEARNING AND MEDICAL EDUCATION:

Problem-based learning is based on constructive approach to learning. "Participation in valued activities within different domains is fundamental to how students learn." People who advocate this problem-based approach suggest that learning happens when other people involve such peers, tutors or mentors. And cooperation in activities can lead to higher reasoning level. Students may change their perspective of thinking and their opinions about a topic because in collaboration more ideas are involved and those ideas will be discussed in an environment in which sharing and collaboration are promoted. Lev Vygotsky found the construct of the zone of proximal development to explain how people can facilitate knowledge construction. This framework shows that if instructors can reduce the distance between what the learners can do completely by themselves and the things that can be accomplished by themselves with the assistance from others, then the instruction can be successful. "PBL is a form of education in which information is mastered in the same context in which it will be used" [6]. Another definition of PBL is "a learning method based on the principle of using problems as a starting point for the acquisition and integration of new knowledge" [23]. Problem-based learning can also refers to problem-and -task-centered approaches of learning. It is one of educational technologies designed to situate instruction in authentic or meaningful settings. It has been employed in many different fields of studies such as medicine, science, law, business and mathematics. And the goals of PBL differs from each other. In medicine PBL requires learners to work in groups to practice their skills to diagnose patient cases and the ability to use clinical knowledge in practice. But in science and humanities, students in a PBL class to come up with explanations for a certain phenomenon through activities such as defining a question, seeking evidence, and outlining and argument. Moreover, in law and business related courses students will engage in the study of cases and they will be encouraged to seek and summarize critical information from those cases and present their finds to peers in the classroom. By the end of their presentation, instructors will provide feedback. In math and science PBL courses, students work together in an environment in

which constructive feedback is provided to each other or by tutors or teachers. Although the goals of learning in different fields are different, in PBL the core value is to put education in authentic tasks so the learning is more meaningful.

Savery and Duffy proposed a framework of how to conduct problem-based learning: Anchor all learning activities to a larger task or problem

Support the learner in developing ownership for the overall problem or task

Design an authentic task

Design the task and the learning environment to reflect the complexity of the environment they should be able to function in at the end of learning

Give the learner ownership of the process used to develop a solution

Design the learning environment to support and challenge the learner's thinking

Encourage testing ideas against alternative views and alternative contexts

Provide opportunity for and support reflection on both the content learned and the learning process [35]

Medical education is very suitable for Problem-based learning because the advances made in medicare makes it impossible to include everything in lectures. And in the field of medicare, doctors will face various problems with patients which are highly likely beyond what medical students can learn from school. Therefore, in order to foster the ability to solve problems, critical thinking and experiment potential solutions, PBL serves as a critical part of medical education. PBL has been employed in many medical schools around the world. "It was introduced in the medical school at Mc-Master University in Canada in the late 1960s and is now a common curriculum component in medical and health science schools around the world" [23]. "The University of New Mexico was the first to adopt a medical PBL curriculum in the United States and Mercer University School of Medicine in Georgia was the first U.S medical school to employ PBL as its only curricular offering" [6].

Here we will present how to use this framework with medical education. The first step of designing PBL for medical students is to find an authentic task. By saying authentic task, we don't mean the task must be the same with what happens in a hospital every day. It means the task will require similar cognitive load to a real problem. The specific difficulty of the task is designed by the instructor according to the level of the course. As is often the case, instructors will create scenarios to represent an authentic task. Before creating a scenario, instructors should formulate objectives of the course, and create a scenario in which all of these objectives will be accomplished. The complexity or the difficulty of the problem should be appropriate to the curriculum and the level of students' understanding. It is better if the scenario is appealing enough to attract students' attention. Basic science should be included in the context of a clinical scenario to encourage integration of knowledge. Although the problem presented in a PBL class should be ill-defined, the PBL scenario should have cues to stimulate discussion and push students to seek reasonable explanation to the issues involved in the scenario. At last, the scenarios should promote participation by

the students in the seek of explanation [46].

The next step is to gather all relevant information which can be useful or useless to the final solution to the diagnosis. However, this information will not be provided to students directly. Besides relevant information, the instructor should also have other resources such as equipments, lab or simulation of the environment in a real hospital. Then students will have a meeting with the instructor to talk about the basic information of the patient such as age and gender and symptoms he or she has. Then the task will almost completely hand to the students. Here comes to an important point of the whole learning experience. The learners should be told that there is no correct answer to the task and it is the students' responsibility to find a possible solutions.

A tutor should be assigned to the students and the tutor is not necessarily an expert in medicare because the tutor's job is not to provide suggestions to the students. Or the instructor can be the tutor. But the responsibility of the tutor is to ask leading questions such as why do you choose this? or how did this happen? By asking these questions we hope students will spot their own mistakes or loopholes in the process of finding a solution to the diagnosis. In this way students will revise their strategy of work. Another responsibility of the tutor or instructor is to provide key information if the students are seriously off the track. And in order to ensure the quality of the course, tutors or instructors have to do so. Speaking of the roles of tutor in PBL, we have to talk about scaffolding. A real or physical scaffold is a structure to support learners to complete a task and it is not permanent. When a task is accomplished, the structure will be removed. It is still the same when we talk about scaffolding in education. It will be removed when it is not needed. Scaffolding is designed to assist learners to complete tasks which are otherwise beyond their reach. This suggests that the design of scaffolding must be very careful. So there are several questions for tutor and instructors to think when they design such a structure: what is needed to support, when and in what way to support the students, how much support should be provided to learners, and when and how to fade scaffolding.

In PBL in a medicare course, students are required to write reports weekly or bi-weekly on how they collaborate, what problems occur and how they solve these problems. Also, by knowing the progress students make, it is much easier for instructors to see how they grow and how they should adjust some elements of the learning environment. And a final report to summarize the whole process of collaboration and the working process will be submitted at the end of the semester.

Such courses can also be conducted in multiple groups. Every group will have their own way of collaboration and propose different solutions to a diagnosis. And instructors should create an environment where different groups are eager to share their own progress because they can always get constructive feedback from their peers. Moreover, such a sharing environment will make the learning more dynamic and accelerate the growth of learners. Tutorials are also an important element in PBL. Usually, the PBL tutorial has a group of students which has no more than 10 and a tutor who provides scaffolding to the session. The duration of the session varies. It depends on how long it takes for a certain group to have good dynamics. Moreover, for each tutorial session, a different

leader or chair should be elected so every member of the team will contribute and free ride can be avoided [46].

Here we want to elaborate tools and activities can be included in PBL in the Internet era. Basically, PBL courses can include activities such as generating lists, scaling down the scope of topics, making outlines of options, debating issues, and even voting. Today, many activities can happen in virtual environment. Wikis enable learners to have meeting in a virtual community and collaborate on projects and solve problems. And meeting tools such as Zoom, Goggle Hangouts and Adobe Connect enable online meetings of a large group of students and share screens and notes. Moreover, blogs also provide virtual space for learners to practice their writing skills and share their writing with audiences beyond their teacher. In a PBL class, web 2.0 tools can also be included such as Skype, Twitter, Instagram.

Here are some examples of how Mercer University conducted PBL in its medical courses. At Mercer University, a series of tutorial sessions were used to substitute the lectures. And during each session, faculty members and students would meet to discuss the actual case problems. In other programs which are related to clinical skills and community science, students need to deal with simulated patients and spend some afternoons with local primary-care practitioners. "In this way, real life clinical practice in a rural community becomes a laboratory exercise for the illustration of basic science theory." In Mercer University, tutors were called "faculty overseers" who are neither to be the source of all information nor even to have information about every area being discussed. The responsibility of these overseers is to keep student participation and knows enough to prevent gross mistakes. On the contrary, students were teachers and learners. Without giving lists of what to know, students need to generate a list of what to look for according to importance of relevant information.

Although small groups of meeting played essential role in the PBL of Mercer University, lectures are still used to some extent. The students may have some lectures on one or two basic science lectures every week but these sessions were not mandatory. The evaluation of the course was intense. Students at Mercer University were tested by both intramural and extramural means. At the end of each of the thirteen curricular phases, students would have a 200-item, cross-disciplinary, objective examination and a forty minutes case analysis oral examination.

The majority of faculty members favor PBL over the conventional way of teaching. The reason is very simple: it is a more natural way of learning. PBL simulate the environment where people generate knowledge. For example, students became better prepared in the learning process. That is the ownership was handed to the students instead of the instructors. If a student came to the discussion session without any preparation, she or he would be complaint by other members. Another benefit of PBL is that students became more flexible in learning. Students at Mercer University used texts, mono graphs, periodical literature and various resources in their learning. In the past, the learning is very lecture centered and students were actually not actively engaged in the learning. By contrast, when they were on their own, they tried every alternatives to find useful

resources and developed flexibility in learning [23].

From the history of the evolution of educational technology we can see the changes are brought by technological development made in other fields of studies. Those technologies were not intended to contribute to education but they are all utilized in education. And to successfully employ PBL in an academic learning environment, instructors and instructional designers must build a proper environment. As a result, the development of big data can provide new thoughts in how to advance current instructional design and improve the building of a proper PBL learning environment.

6 CHALLENGES OF LEARNING IN THE INFORMATION ERA

The challenges of learning in 21 first century is that the explosion of information brought too much information whose credibility is uncertain. Many people, especially scholars, questions the accuracy of information of Wikipedia. However, Wikipedia may be the most popular sites for all kinds of information ranging from entertainment to academia. And because of the affordable and high speed internet, everyone has a say in the virtual world. One can find people argue on an issue in online forums, express their own opinions in blogs and social media. However, these information could be wrong and there is no third party to verify if the information is correct. By the end, people tend to believe in the opinions presented by the most popular sites or people. For example, in China a high school history teacher go visual on the internet and he starts to have his own online courses about history in China and other parts of the world. His courses are pretty interesting because a lot of humor is involved and various media are used such as animation and movies. Therefore, a lot of students prefer to watch his online courses instead of taking the face-to-face class at school. However, the opinions presented by this history teacher are very different from main-stream scholars especially in the history of the second world war and civil war in China. And this caused problems at schools. In this case I presented, the teacher actually unconsciously took advantage of the populism of teenagers at high school. Students at this age can be very disobedient and do not want to engage in the old tradition.

And here comes another problem and the internet era. It is often the case that who has the most resources to populate a opinion will finally be the person who has the most say. It seems that the internet give people equal opportunity to express. However, what really happens is that people can only find limited opinions or values. For examples, many news agency can use the resources they have to control media on what to be reported and what not to be reported. The fake news of several US news agency proves that it is real. In addition, the internet world is actually not so different from the physical reality. One is likely to find that the best resources on the internet are also expensive and only open to a few instead of the public general. That is also one of the reason why Wikipedia can be so popular because it is free to everyone. Because the best resources are only open to a small group of people that may widening the gap between the well-educated and the ill-educated. That is also the reason why the education community are working on Open

Education Resources. Work with people from the academia, these open resources can be affordable or even completely free and still they have high quality. Massive Open Online Courses can be viewed as the most popular representatives of OER. However, there is still a long way to go in promoting education equality due to political and financial reasons.

Challenges to instructional design The last challenge is how to do a thorough analysis of learning. In instructional design, ADDIE model is the most used model of doing the design process. ADDIE stands for analysis, design, development and evaluation. In the analysis phase, instructional designers need to work with subject-matter experts to formulate learning objectives. The learning objectives are specific performance which can be observed or evaluated in other ways. And learner analysis will include the traits of learners, the learning styles of learners, the motivation, confidence, prior knowledge of learners and the potential satisfaction of learners. Also a context analysis will also include. In the design phase, instructional designers will script and finalized learning strategies and tactics for the entire learning experience based on the analysis made in the first phase and the learning materials given by instructors. Then they enter the development phase in which the final education product is made. In the evaluation phase, instructional designers will conduct trials of the course and general a report on what needs to be modified and summative evaluation will be formulated to test learners' performance change in the end.

However, in the internet internet era, the number of online learners can be bigger than 2,000. In many popular MOOCs, there are more than 2,000 people registered. As a consequence, it is impossible to do a learner analysis. Not only the number of students is big, the learning styles, motivations and level of prior knowledge vary drastically. Even if a comprehensive learner analysis is possible, the result might be that the learning environment is too complex and the course may be out of control of the instructors' hand. And in reality it is true. In many MOOC courses, learners have different expectations toward the same course, once they feel disappointed about the course, they drop. And the result is only a very small percentage of learners finally complete the course. And because of the huge number of students, the discussion forum goes out of control and instructors and teaching assistants cannot monitor the discussion and the discussion result in nothing.

7 HOW BIG DATA INFLUENCE DIFFERENT INDUSTRIES

Before we look at how big data will influence education or more specifically influence instructional design of medical courses in a PBL environment, we will first examine how big data have influenced other industries. The experience from these industries will provide guidance on how education community utilize big data. Big data has become the buzz words for today's world. One of the reasons is that big data increase benefits of many business. The traditional way of costumer consumption has lasted for centuries. In the ancient time, people would go to fairs to buy groceries, hardware and clothes. But at that time, fairs were not standardized, and the conditions of those fair can be terrible. It was impossible to guarantee the quality of the goods bought by customers. Later, in

the industrialized world, cities were built and shopping mall appeared. In a shopping mall, customers could buy good qualities in different stores. Instead, they would go to supermarket to buy groceries. This mode of doing business remained until the beginning of e-commerce. In the web 2.0 era, search engines enabled consumers to look for products in virtual shops and sellers can collect feedback of consumers' satisfaction in their website [3]. Today, with big data technology, it is possible for online retailors to monitor activities of consumers online. Business owners can have better understanding of consumers and formulate more targeted strategies of how to increase profits. Because of the ability of monitoring online activities and better understanding behaviors of consumers, online retailers can provide personalized services. This is realized through the use of recommender system. Online buyers will be labelled according to their online activities and they will receive emails or suggestions of what to buy on the internet. 35 percent of Amazon's revenue is created by the recommendation system. Users of Amazon can click the recommendation section and see the products selected by the recommendation system. For example, if a learner is looking for a backpack, he or she will probably see some recommended backpack [17]. Dynamic pricing is also a strategy brought by big data technology. "Some business set different prices for their products or services based on algorithms that take into account competitor pricing, supply and demand and other external factors in the market. It is a common practice in industries such as hospitality, travel, entertainment, retail, electricity and public transport" [43]

Before big data was brought to the face of the healthcare system, the role of data in the healing process of patients was minimal. Data such as name, age, disease description, diabetic profile, medical reports and family history of illness were collected. These data could only reflect limited view of a patient. For example, a doctor may know that the reason of a patient with heart disease can be traced back to his or her family, but there are many possible perspectives on why the patient has such disease.(Pal2016) "The influence of big data on medicine is that we can build better health profiles and predictive models around individual patients so that we can better diagnose and treat disease." The pharmaceutical industry is facing the limitation of insufficient understanding of the biology if disease. But big data can help in building the understand of what constitutes a disease such as causes from DNA, proteins and metabolites to cells, tissues, organs, organisms, and ecosystems [36]. The problem for the medical research is that enterprise is unable to follow the pace of the information needs of patients, clinicians, administrators and policy makers. fiThe flow of new knowledge is too slow, and its scope is too narrow.fi The consequence of the medical research community not adopting big data technology is that hospitals are ill prepared for a more precise diagnosis. Now the medical research community need new thinking in their work. The new thinking must involve the integration of new technologies. "For instance, researchers can use big data to reveal clusters of patient groups that might suggest new taxonomies of disease based on how similar they are according to a broad range of characteristics, including outcomes." Advances in prediction can simply attribute to the learning of data and creating a mechanism which is highly reproducible and has consistent performance [18]. "Big data has helped healthcare

institutions take a 360 degree view of a patient's health problems." With the help of big data, new findings, innovative methods of treatment plans and more precise diagnosis can be realized. Here is an example of how it is possible to build better health profiles. Some diseases are more common among a certain race of people due to genetical reasons. When a patient from this race is found suffering from heart disease, the doctors can look at the data of patients belonging to the same race who have same problems. By examining their life style, genetic structure, family DNA and other elements, they can build health profiles for these group of people. Wearable devices can also play a role in the detection of potential health problems even if no apparent symptoms are presented. Wearable devices can help see some indicators of health. And doctors can make certain conclusions and decide on the future action on them. The devices today are already able to record data such as heart rate, pulse, glucose levels and calorie levels. And big data will also have the potential to personalize medicine. The NCI-MATCH trial is examine 1000 people who have tumors that do not respond to standard cancer treatments. Researchers hope that they can match drugs to this kind of tumor to produce the best result [27]. "In the very near future, you could also be sharing this data with your doctor who will use it as part of his or her diagnostic toolbox when you visit them with an ailment. Even if there's nothing wrong with you, access to huge, ever growing databases of information about the state of the health of the general public will allow problems to be spotted before they occur, and remedies - either medicinal or educational - to be prepared in advance" [24].

8 HOW BIG DATA WILL INFLUENCE EDUCATION IN GENERAL

The first change we will see in education is the rise of adaptive learning. Adaptive learning means that students can learn knowledge whose difficulty is suitable for their ability. This is enabled by the availability of online application, classroom activity software, social media, blogs and surveys of staff. With adaptive learning comes the universities' ability to provide personalized feedback to students, monitor student satisfaction, increase attainment and give students' opportunities to reflect on their own learning. On the other hand, instructors will receive real-time reports which will enable them to adjust teaching strategies for the best outcomes [20]. Because learning is more adaptive, students can advance their learning in different paces. Big data and data analysts will inform instructors who is learning faster and can advance to a more difficult class and who need support from teachers [14].

Since learning of different learners will at different paces, it is important for learners to develop self-management. For example, in a PBL class, students need to solve an ill-defined problem and the process of learning is almost unguided. As a result, students need to take the initiatives and actively contribute to the project. Also learners will monitor their own process of learning and submit a report to summarize this process. So they must develop their meta-cognitive skills which means the learners are able to learn how to learn. Another reason why self-management is more important in the big data era is the widespread of informal learning. As mentioned before, people today are learning anytime anywhere. Social media, blogs, news and anything connected to the internet

will serve as a source of learning. Therefore, it is impossible for teachers to monitor learning of students all the time.

9 BIG DATA MINING

Big data mining refers to the procedure in which a gigantic amount of data from a wide variety of source is collected, and analyzed with a wide spectrum of means to discover inner mechanism or other information via pattern [45]. Being used in almost every field such as business marketing, science and engineering, medicine, design and education industries to provide such functions as intelligence, research and marketing. Oftentimes, big data mining will be carried out on individual persons. When someone is doing activities online, their data will be collected. They could also be providing these data via questionnaires, surveys or other means. This massive amount of data collected on everyone are commonly called big data by the industry and corporations and companies will utilize them to figure out what need one have or what kind of personal trait one may carry. As the big data industry found itself in rapid development, concerns and other critiques are also rising on the ethical issue of big data. Heated discussions were talking about the insult to privacy and abuse of such data. However, big data have already set foot in so many industries and almost all aspects of our daily lives[40].

Data mining sees Artificial Intelligence and Machine Learning as its inception. During data mining, patterns are discovered, and data scientists could utilize such patterns to carry out more versatile functions. The system could get to understand an individual via the data collected about this one. The Recommendation Engine, or so called the Recommender System, is one application for data mining. The recommendation engine filters information and uses data mining techniques to figure out the specific suggestion to one person for information or other assets that may help them with current or future needs.

One commonly used example of the recommender system would be the online shopping websites. When someone shops on it, he or she will be given information about merchandise that related to this purchase. Such recommendations require various kinds of variables, such as this person's shopping history, the gender, age, and occupation of the person, or the items other bought after purchasing the same item. Another example will be after someone searched for a merchandise or service online, the advertisement will pop out for them showing related products.

These kinds of systems require algorithm with high complexity to give out recommendations following patterns discovered via enormous amount of data from mining. Such presentation will be oftentimes beneficial to individuals as they no longer need to go through such amount of information to find their desired service or product. Instead, targeted recommendation will be directly presented to the individual and sometimes the individual will have little awareness that they may need such product or service. As a result, the system will greatly enhance the efficiency for the user, it will also be a blessing for the services or products so that they could be utilized more often.

With such benefits, the recommendation engine is wildly used amongst all online websites, including but not limited to online shopping, searching, streaming and social media websites[39].

9.1 Types of Recommendation Engines

A good deal of recommendation engines is backed with such technique called as collaborative or content-based filtering technologies. Collaborative filtering resembles a person making purchases on the gathered information from other via verbal or other means. It could also be understood as crowdsourcing[38]. In many online websites, people could give out ratings or feedbacks for others to reference. It is an interesting phenomenon that customers will more likely to read crowdsourcing comment first rather than the information provided by the seller. The collaborative filtering based system took one step further by categorizing commenters into different subcategories and present different person with different information or resources that might only be beneficial to him or her. Such patterns as statistical models are utilized to calculate everyone's correlation, thus giving out a value of recommendation. Some examples might be Twitter, eBay, Steam and Apple Store. They are all using collaborative filtering systems.

On the other hand, content based systems focus on different properties of a resource, in comparison with the properties of a person. As a person's total using time accumulates, the system will become more and more accurate as the user will demonstrate more personal traits and preferences in using the system. Examples of this kind of content based system will be Netflix and other streaming websites. Moreover, a developed recommendation engine could involve both collaborative and content based filtering techniques to bring prediction accuracy to a new level.

9.2 Math Models of the Recommendation Engine

The math models that standing in the back of the data mining engines include such technologies as association, classification and clustering means. Clustering refers to the procedure of combining individual with certain characteristics and trait being recognized as high value in the recommendation system. Such values as ratings, tones of comments are taken weighted average of all members in the cluster to identify the how the individuals in this cluster would recommend this product or service. More complicated systems would involve multiple clusters and calculated overall weighted averages across all the clusters that one individual belongs to[37]. Classification identifying technique are also utilized as the cornerstone of interconnecting different person with different appreciation to different items. Fundamental version of classification systems only works as primary filter to figure out how relevant individuals with desired kind of resources. As an example, only providing infant nutrition food for those who just give birth to a baby. This example only provides a crude vision of classification while more complicated ones will be able to perform prediction recommendations with higher complexity, and thus higher accuracy[33]. Association on the other hand provide more sophisticated recommendation rules with the introduction of correlation amongst different items or different individuals. With such rules, the system will be granted the ability to determine what a person needs most currently, rather than giving recommendations based on the person's previous activity history in the system. One example will be that if someone is looking for an oven in the kitchen, but he or she was browsing a dishwasher 2 months ago, the system will begin to give

recommendations on oven or other cooking utensils, rather than kitchen cleaning utensils. Like mentioned before, a more complicated version of the association rule will give out recommendation with more complicated consideration and calculations. The recommendation system will be referencing different traits of a person or by viewing at a variety of items being browsed in the system by the user. One supplementary of the association recommendation system will be using dynamic analyzing to provide recommendations for future use when the user wished to need some resources that related to the current inquiry. An example would be a person who bought or browsed an oven today may be provided information of recommendation on oven recipe, or aluminum foil tomorrow.

9.3 Big Data Recommendation Engines in Education

As we have mentioned before, recommendation engines based on data mining are proving to be beneficial to almost all fields in our lives, and education is one of them.

The field in education that involves big data mining are often referred as learning analytics. It focuses on how big data mining could be utilized for teaching and learning purposes ranging from personalized teaching, learning, evaluations and assessments for individuals to providing data to decision makers of various levels of education (for example, a director of a department or a government official of education). Big data mining has provided benefits to many aspects of education such as teaching, learning, education leadership, adult education, special education, enrollment decision, talent education, etc. The new millennium has seen the rapid development of educational big data mining and the field is hunger for talents that possess not only profound understanding in educational theory, but also the capability to carry out statistics, research and evaluation in education[32].

As the examples mentions above, the educational recommendation systems have deep similarities with commercial recommendation systems as they both strive to introduces the user to their desired products or services. However, educational recommendation system could also provide interconnection between learners, their desired course, their personal traits and educational resources that could serve the learners to help them reaching maximum efficiency in learning and to reach their academic goals. These beneficial factors make the educational recommendation engines a state-of-the-art asset for students to excel in personalized online learning systems. In such system, learner's characteristics, track selection and knowledge gained in previous learning could all be quantized into values to serve as a filtering and weighing standard to learners in e-learning. As one can see, such system has great flexibility and are highly adaptive to different learners. In this way, the efficiency of learning is greatly enhanced, and students are more motivated in engaging in learning[31].

The history of the e-learning recommendation system could be traced back to computer assisted instruction systems, also known as CAI. One major concept called Time-shared, Interactive, Computer-Controlled, Information Television (TICCIT) was invented in the last 70s. This could be the cornerstone of nowadays educational recommendation engine. TICCIT is developed so that the learner

could have higher control in their own learning with the help of a mentor giving suggestions and advices from time to time. The education recommendation has met its rapid development afterward ever after the introduction of TICCIT as they could provide personalized advice and suggestions to learners according to their daily usage and browsing history of the system. Students could spend less time on looking for the education resources on their own or filtering out valued teaching and learning resources from a gigantic amount of information on the internet or within the e-learning system. In such way they could devote all their valuable time to learning, rather than being in a frustrated state without guidance[22].

As mention before, the recommendation system's ability to provide an accurate result relies on massive amount of data collected from individuals and their behavior on the e-learning website. In this way, e-learning websites with a considerable number of users could better contribute to the learning process of the recommendation engine. For instance, Massive Open Online Courses (MOOCs) could have hundreds or thousands of active users on the website, or even learning the same course at one time. In such way, the recommendation engine evolves quickly, and user could benefit from it. Moreover, online learning websites have a social learning ecosystem which have great resemblance to social media networks. This lays the groundwork for the recommendation system to make full utilization of its huge user database to provide more relevant courses for learners. It is worth mentioning that these e-learning systems with social element are more likely to be involved with informal or professional learning. An example would be info of a user in career development system will be put under comparison to his or her colleague's information to carry out a performance evaluation[16].

Also, when he or she wishes to visit some of the resources on the career training website, the system could filter out his or her colleague's recommendation, comment, rate of one course and then utilize algorithm to provide this user with resources not only capable of helping him or her reaching current goals, but also courses and information that may become useful in the future[21]. Lots of educational teaching and learning systems with data mining and recommendation feature are established on online learning systems that could be easily visited from a mobile phone or a tablet. Such convenience no doubt made collecting data at great ease and allows more users to participate in such process. This could be a beneficial cycle: the ever-growing user base allows the algorithm to be more accurate and provide more personalized learn guidelines, and such feature will not only attract more user but will also let remaining users to provide more data to the system.

Learning analytics could also find itself useful other than the scenario of teaching and learning systems. Data mining and recommendation engines could be also used in supporting students in daily learning. For instance, a system that feature in college application could use a recommendation engine to provide learning track for students to better prepare for a certain university's requirements. Such method could be also used with other kinds of online learning motivation techniques such as badges. Badges are like achievement system in which when a student accomplish certain goals, he or she will be award a badge. He or she could get to know the global percentage of student holding that badge and get

motivated in making more accomplishments[19].

One more application would be the student retention system, in which students' data are monitored and a baseline is set based on the overall performance of all the student within. If one student's performance is below par, the system will receive alert and will send support or intervention staff as soon as they can to help the student and prevent him or her from dropping the course. In addition, big data also provide new thinking on how to conduct the PBL learning process. For example, when learners are working in the virtual environment, tutors can monitor the contribution of students in a certain group. In this way, the tutor can quickly identify who is not contributing to the team and take certain measures to intervene the performance of this student. Moreover, in a conventional PBL environment, the timing of proving scaffolding and removing scaffolding is very hard to master. But with the help of big data, tutors can analyze the process of learning in a team and spot the time when the team make minimal progress[15]. In this way, the instructors and tutors can provide in-time support. And tutors can also spot the time when a team have sufficient knowledge and ability of accomplishing the task, so tutors can fade scaffolding. From the learners' perspective, big data give them space to try new ideas. Instead of having group discussions and debates of different ideas, students can also learn from what the data tells them and gain empirical experience. With big data technology, learners can also formulate more up-to-date solutions to a task[18].

Big data also provide powerful tools to instructional designers. With the help of data, instructional designers can label learners just as the way online retailers label customers. Then those labels will be put into different categorizes. This is very important for conducting learner analysis. Instructional designers will be able to see clearly the motivations they have, the prior knowledge they possess to determine the scope of learning. Also with such data, instructional designers can design proper strategies to motivate learners and increase the satisfaction rate. The learning style data will help the development of teaching strategies. Designers and subject-matter experts can integrate different ways of learning in one semester based course and let learners with different learning habits to collaborate to foster flexibility in learning.

10 WEB ANALYSIS

Web analysis is also an uprising branch that belongs to the learning analytics and being supported by big data mining. It focuses on how to collect and analyze data gained on websites or applications that needs to connect to internet before using. These kinds of data are often a result of user's activities on the internet. Web analytics are often utilized to boost the study and learning efficiency of students in a specific Learning Management System(LMS). It could also help the administrator of the website to monitor and support student's learning progress and to help oversee the functioning of the website[17].

Web analytics are also utilized by administrators to get a better understanding of what kinds of personal traits one user may carry and how would this one interacts with various function on the website. It could be utilized to make a prediction on what kind of educational

products or courses will be more welcomed by certain students and learners. After analyzing such data as how many people have visited one page and what kind of activities they are most likely to carry out, the administrator could be informed that what kind of needs one student possesses and how they can develop in the future to cater to their needs. For the education website owners, the web analysis can also be used as a mean to find out any hidden security risks online and could help them gaining evidence for court should an attack really happens.

In the world of academics, web analytics is also beneficial in helping the college to make strategic plans. For instance, with a growing number of traditional courses, tutoring services are going to be changed into their online version, web analytic will find out how to deploy these courses and servers better so that they could get maximum visit from those who are interested in them. Since many data and information are distributed on different websites, they call for the facilitation of web analytics to perform an integration to the scattered resources. Moreover, the educational corporations, both online and offline, could easily get to know how the traffic flow changes every day on their online learning systems[1].

10.1 Web Analytics Anatomy

Normally, the history of web analytics could be traced back to last 60s when scientists start to analyze web logs. These logs could be transaction or search types. The transaction type takes direct actions such as user's clicks, how long they have spent on one page into consideration while search type focuses more on the behavior on how the users carry out the searching activities.

Depending on the data provided by the servers, web analytics send small package of data (commonly known as cookies) to the user. Cookies will start collecting data and send them back to the server. Such process is called as server-side data collection. On the other hand, this kind of data collection would render itself not accurate. Internet service provider (ISP) provides IP address to users while user many set blockade to some cookies. To the contrary, client-side data collection is more flexible and can be more accurate. By implanting tags into the website being visited by the client, client-side data collection could carry out more versatile missions.

The word Human Computer Interaction(HCI) have been a buzzword nowadays and it have been embedded into our daily lives. Web analytics could also have utilized such different methods as interviews, questionnaires to establish more convincing reports. Key Performance Indicators (KPI) are set up to differentiate various kinds of web analytics. As of an example, one university that introduced with a new kind of LMS are facing difficulty because too much people are using its social features and it needs some backup support. The web based analysis will be performed to assess the resource the university possesses and evaluate the need to figure how to employ capable person to perform certain kinds of maintenance work as well. The KPI within could be able to indicate how many clicks can one user click before reaching the help page, how long will a user spend on the help page, how easy the help material could be comprehended, how visible are the various icons to the viewer and so on. Then the KPIs are collected and analyzed to compose a report[4].

10.2 Web Analytics and Education

In the field of education, web analytics are utilized to form reports that are driven by data to help such functions as facilitating students, managing staffs and supporting researches. Also, web analytics are used to figure out how well a student could perform, how would the student and online tutor would normally interact, how effective one course could be and how well the student is progressing in the course. One specific kind of web analysis is called as academic analytics. It would evaluate the overall performance on an online teaching website to provide information so that administrators could better make decisions.

Learning analytics, as mentioned before, focuses on the collection and analysis of data that have relation to the learners and the courses and learning materials. Learning analytics are also utilized in documenting students' overall learning efficiency in computer facilitated learning and could facilitate student to get accustomed to the online teaching and learning environment better. With big data gained and stored in the systems, learning analytics made many contributions to lots of fields that could help students reaching their academic success. For example, they could note down where the students are now in the middle of a course; if a student misses too much class, they could figure it out and send intervene staff quickly; assess different aspect of the Learning management system; give out help and facilitation that could cater to a student's need[5].

As one way to lead students to academic success, learning analytics could trace all students' activity and other behaviors in the online environment, with data collected via the student information system (SIS). In a class that is one hundred percent online, instructors could fully utilize learning analytic to carry out formative evaluation, which could help the teacher to learn about how the students are performing, how could they make modification to ongoing courses, and how he or she could demonstrate such course materials to the students. An example would be that the teacher could track how many time the student have entering the LMS in the allotted time and use it as evidence of attendance record. Also, the teacher could record how many clicks are carried out in one content page or during one course, or how long the student has spent in different sections of the course. All the data collected above could give out information on how the user behave and how the relations of learners and teaching and learning materials have been. With the deployment of web learning analytic in the LMS, the instructor could figure out abnormal activities of students and give out interventions that cater to the student's needs.

To boost the efficiency of the learning analysis system to the maximum level, learning analytic could also reach to qualitative data such as the discussions in students' forums, students' cooperative wiki pages, and many other social learning assets to form more persuasive and convincing data to website administrators. This requires natural language processing kit (NLTK) to perform semantic analysis so that these qualitative data could be better transcribed into data that would be better analyzed. These data gained could be utilized to perform some higher-level assessments, such as the creativity and critical thinking level of a student[7]. With different teaching and learning goals, KPI could help student, or make modifications of online course in the online learning website with the facilitation of quantitative and qualitative data. They can also

run course diagnose for learners and teachers. The KPI mentioned could be collected and analyzed with such techniques as students' characteristics and performance tracking, investigating a group of students with same traits, giving out content recommendations of learning materials on history activities and make prediction to future developments.

11 THE INTELLIGENT TUTORING SYSTEMS

The term intelligent tutoring system are used to describe a computer system that could act as a human mentor to some extent to facilitate a student in getting to understand and have firm understanding of the learning materials. Such system is often designed to make learning with a higher efficiency as well as providing inspiration to students while learning. It requires the support of big data and are considered one of the rising learning technologies in the field[26]. Taking a human mentor for example, he or she will be preparing for the learning material for the student first, then he or she will try the best to get the student motivated for learning. When the student is facing difficulties in learning, he or she will stand out and provide necessary guidance for them to overcome the barrier. Likewise, AI of the intelligent tutoring system could be evaluated and determined whether it could qualify as a human teacher. Such system need to negotiate and communicate with a student to get accustomed to newer conditions, and when a student make requests of learning materials or asks question on certain items, the system will adjust automatically to cater to student's need better. In a word, intelligent tutoring system is different from commonplace e-learning websites as it is more flexible and could provide more detailed education contents. This system could store gigantic amount of data, ready to respond to unique needs of students under different scenarios[12].

11.1 Anatomy of the ITS

Such system has provoked the wide interest amongst researcher and programmer thus many have devoted themselves into designing it, which makes one kind of such system greatly differs from another. It is worthwhile to notice that even these systems have distinctive design theories, they are share the similarities of the following elements: domain, learner, pedagogical and interaction model.

Domain model mainly answer the question on how to represent the core knowledge on the computer. It could be demonstrated as flow charts, diagrams, semantic networks, etc. It is mainly consisted of the fundamental logic, strategies and rules to solve ongoing questions. It is the logical core of the system, as it will provide assessment standard when the student's progress is going through evaluation. Moreover, it will also serve as a detector of abnormal behaviors[8].

Learner's model will be demonstrating the systematic evaluation on how well the student is going through one course, what kind of error the student will most likely to make, what kind of learning style the student prefers, what characteristic the student possesses, etc. Such information is collected via students' activities on the system. This kind of model is also utilized in self-regulated learning,

which relies little on the help of other human instructors.

Pedagogical model focuses more on using best teaching and learning strategies to the student according to the teaching environment. It will check on the student's learning progress, and give out appropriate information or facilitation accordingly.

Interaction model, also known as the interactive model are more like a translator between the system and the student. It will need to receive student's input and give out response that could meet the student's needs. Not only this model requires information on the learning material, it would also need information on the common sense of mankind. It was based on verbal texts but nowadays one could identify users' interaction from a variety of sources such as facial expressions, body temperature and moisture, minor gestures, etc.

These four models are all under the management of a database. Moreover, the models are designed under the guidance of different educational theories and uprising technologies. As for interactive model, it is based on various multimedia means. To better understand one student's input, NLTK is involved as well as voice recognition software. AIs are introduced to interactive model to automatically output text and voice messages. Capturing technologies are also involved to capture the student's facial expressions and body gestures. Researchers are also trying to bring virtual and augmented reality to the model. This model involves psychology related content as well as researchers are managing to deploy emotional detection technology to determine one's affection state as it might cast profound impact on the learning effect of an individual. When the internet haven't reached today's popularity, many of the ITS were installed on the PC and cannot get frequent upgrade. Due to the hardware limitations of PCs at that time, the function of such ITS is highly limited, as there was little storage space, and PC didn't have high processing speed at that time[9].

With the rapid development of the internet and PC, ITS have entered an new era as many calculation and data could be processed on the cloud. This have removed the blockade of those who with to be guided by ITS and it is making a growing number of learners benefit from ITS. Nowadays the needed learning materials could be searched and retrieved in no time thanks to ever-developing searching techniques. Moreover, more online wikis are being established which provided supplementary source of domain knowledge to help broaden the borders of domain models.

Learners have also witnessed the rapid development of mobile learning in the field of ITS. Wherever there is internet, learner could easily get in touch with ITS at every corner of the world. As smart cell phones and tablets became almost necessities of everyone, ITS have also taken a leap forward and keep absorbing the newest discoveries in such field as machine learning and big data mining. Learners nowadays could get authentic and quick feedback from ITS, which could be a great motivation to the process of learning.

11.2 Designing ITS

To design an ITS system, researchers have to follow certain procedures, which have certain resemblance with designing a learning management system, or a teaching and learning software. It is commonly agreed that such process take place in four steps: Needs

assessment to carry out the anatomy of learner goals and discussion with the instructor and course material designer for the course; Cognitive task analysis to start building models mentioned before, preparing to tackle any issues in the developmental process; Initial mentor implementation to set up the ecosystem of the ITS and to provide learning facilitation; Evaluation to start trial runs of the ITS and to testify the overall steadiness and robustness of the ITS and give out a holistic assessment to the system.

11.3 Applying ITS

One of the most outstanding feature of ITS is that it possesses the capability to give out immediate response to students' needs without a human teacher. Moreover, it can also give timely support, choosing different learning goals for students with different demands, giving individualized coaching and provide mental reinforcement. As a consequence, ITS are more likely to be deployed at institutions, army camps, and business where tutoring and mentoring is required in training yet lacks enough human tutor. Ergo, it have a wide spectrum of application, ranging from kindergarten education, to training on jobs, and even lifelong learning. Researchers have profound interest in studying the efficiency and other benefits of ITS. Such aspects of students as how well they could comprehend the course materials, how eager are they when learning about new contents, how much would they devote themselves into learning and how satisfied they will be after the learning are all taken into consideration. They will even arrange human tutoring session to compare the overall efficiency between human and computer tutors. Some researchers have found out that there is only Little difference between the effect of human tutoring and machine tutoring[10].

As the developers have reached the goal of giving response immediately and provide escalated tutoring techniques, they are facing new challenges now. Due to the complexity of such system, ITS is not economy-friendly to design and deploy. As a result, researchers and developers are researching and developing means to make deploying these systems at a lower cost.

11.4 Envisioning ITS

As mentioned before, the most vital feature of ITS is it does not require extra human tutor to give help to the student. What is more, it could also generate and comprehend natural language for better communication between the machine and the learners. There are many undiscovered areas for researchers to venture in as the recognition rate of the system are still in a moderate level and still have rooms for development. Also, the natural language output give by the ITS sometimes are not considered authentic enough for students to understand. Researchers are also calling for the research on the identification of students' affection state so that the dialogue may change to different mood the student is in accordingly. The system should also be capable of know how the student will be most motivated, thus planning for motivation strategies.

The researchers also have the ambition to upgrade the ITS from a system to an environment. It could adapt to more kinds of learners, providing more reliable content and support to learners, and have greater flexibility in the tutoring process. The most advanced ITS

could still only function in questions that have clear boundaries and finite solutions. It is all researchers' hope that in the future the ITS will be able to support student with question that have open answers[11].

12 CONCLUSION

For centuries, the learning style of countries around the world remains similar. The teachers are served as the center of information. Students go to school to acquire information they otherwise do not know if they just stay at home. That is the reason why behaviorism was proposed as the main theory of learning. However, with the development of science of technology, people have more tools of getting information such as radio, television and movies. Such development pushed educators to revise their educational strategies in order to make education attractive. Then cognitive theory came into being and provided guidance of how to facilitate the process of learning. However, with the increase of publishing of books and the development of affordable and high speed internet, teachers can no longer serve as people who provide information to students in the fast-changing world. Therefore the strategy of teaching must again change the suit the world. The shift is to foster students ability to solve ill-defined problems through collaboration with minimal guidance from instructors and develop meta-cognitive skills. Data mining and recommendation engine have proven their importance nowadays and will continue to shine and make more impact in the foreseeable future in the field of education. The specific field of learning analytic will continue to make more contribution to online learning. However, we must take the ethical use of big data into consideration and make sure we maximize the benefit of big data in education while preventing misusing the data and protect individual's privacy at all costs. Another issue might be the ever-complex algorithms and codes will be a challenge to education specialists and school or learning website admins while the programmer may have limited knowledge in education. However, with the rapid development of educational recommendation system, many new job opportunities will be created, thus encouraging specialists to carry out interdisciplinary research and there will be a growing number of talents that excel both in education theories and programming. It also calls for the tight collaboration between education expert and programmers to make sure that the ever growing education recommendation system backed by big data mining will lead countless of learner to their academic success. The potential of big data on education is still not clear. Although big data have been employed in commerce, healthcare, artificial intelligence and other industries, educators are still waiting to see its implication on learning. However, we can predict big data will bring positive changes to learning as a whole and provide new perspective to instructional design.

A CONCLUSION OF ROLES IN THE TERM PAPER

In this term paper my partner Weipeng Yang and I participated in the discussion of the general topic of the paper. We finalized the topic through a meeting. Since we are all students of the Instructional System Technology department at the school of education, we reached an agreement that the topic should be how big data can

influence instructional design.

Then in the following meetings we had , we generally came up the the structure of the paper. Instructional design is a subject of education. However, instructional design itself is still a broad topic. Therefore, we want to put our focus on Problem-based learning which is an important learning strategy. In addition, we also took our audience into consideration. The potential readers of the paper are not necessarily in the field of instructional design, so we thought it is important to introduce this field of study, the development of instructional design first. And then we will focus on Problem-based learning and give a few examples.

And because we are not in the field of big data and this field is really strange to us, we wanted to summarize topics involved in big data and then present how big data will influence instructional design.

In this term paper, my responsibility was to focus on the instructional design part and Weipeng was in charge of the big data part. But we also participated in each other's work to keep the group go smoothly.

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Big Data Analytics in Monitoring Outdoor Air Quality

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ABSTRACT

Outdoor air pollution is one of the risk factors of public health. Air pollution adds burden to public health. Both developing and developed world use new technology and expertise to monitor outdoor air quality. United States Environmental Protection Agency (USEPA) collects outdoor air quality data from state, local and tribal agencies through outdoor air quality monitors across the country. The data get collected into the Air Quality System (AQS) database. This data can be used for variety of purposes such as education, research and regulatory. Data from this data-mart is available for different time-series like hourly, daily, weekly, monthly and yearly. It gives us a real picture of outdoor air quality and measurements of pollutants present in the air in a particular time period. The data can be used for comparing air quality among different regions, raise awareness to general public so that they can play a role in reducing household air pollutants, to see the trend of air pollutants at different time periods in a day or a season, it can also be combined with emissions data for comparative study. Data analysis of pollutants help identify pollution hot spots. Since air quality is vital for public health and environmental health, air quality monitoring possesses great significance from public health perspective. It is worth looking at simple statistical values and level of air quality index value for the pollutants described as criteria pollutants as described by World Health Organizations. Simple statistical calculations in bigger datasets help understand the extent and source of problem. It helps in comparing past statistics with the present so helps in evaluations of action being taken during past periods. Looking at the overall mean value of criteria pollutants of 2016 and 2006 reveals improved air quality level to some extent for all core-based statistical areas. But the mean value of carbon monoxide has significantly increased over the ten years period.

KEYWORDS

i523, hid330, Outdoor Air Quality, Big Data, Air Quality Index

1 INTRODUCTION

Outdoor air is a valuable natural resource that is vital to the health and existence of human beings and other forms of life. The outdoor air not only has clean air but has presence of various pollutants. Several health research have revealed that air pollutants are contributing factors for lung cancer, cardiovascular disease, acute and chronic respiratory conditions. World Health Organization (WHO) in 2013 has assessed that air pollution is carcinogenic to humans [14]. "In 2012 WHO estimated that 72 percent of outdoor air pollution-related premature deaths were due to ischaemic heart disease and strokes" [14]. Being aware of this fact, governments along with the scientists and the environmentalists help make policies to

combat air pollution. Each country has set their own standards for outdoor air quality to protect their citizen's health. Every nation's standards depend upon their economic, cultural, social and political needs. "The United States enacted its Clean Air Act (CAA) in 1970 and was amended in 1990 as a way to set stage for combating air pollution challenges" [1]. Since then, the country has made a lot of progress in improving air quality while sustaining a constant economic growth. After the enactment of CAA significant progress has been made in improving the outdoor air quality, reducing emissions levels from vehicles and power-plants. Over the period of 1990 and 2015, "national concentrations of air pollutants improved 85 percent for lead, 84 percent for carbon monoxide, 67 percent for sulfur dioxide (1-hour), 60 percent for nitrogen dioxide (annual), and 3 percent for ozone" [1]. Particulate matters "concentrations (24-hour) improved 37 percent and coarse particle concentrations (24-hour) improved 69 percent" between 2000 and 2015 [1]. Today, United States, European nations, India, China and other developing countries monitor outdoor air quality and use the collected data for identifying the particles present in the air, their contribution to various health problems, their sources, health research and also to find out the solutions to minimize their production level.

Thousands of air quality monitors are placed across the united States including US Virgin Islands and Puerto Rico. They are stationed based upon the significance of air quality effects on health. These monitors stream outdoor air quality data to a national air database system called Air Quality System (AQS). As a result big outdoor air data is generated constantly everyday. Air Quality System database is a national database where state, local and tribal agencies submit all of the data collected from thousands of air quality monitors across the United States. These huge databases are easily accessible in EPAs air data website via AQS. Besides air data, AQS database system has weather and emissions data. Emissions data provides data from vehicular, industrial and powerplants emissions records. Weather plays an important role in the quality of outdoor air. For example, high wind may disperse concentration of chemical particles. AQS database also called AQS Data Mart, has summary of yearly air quality data since the year of 1957. These data give an understanding of outdoor air quality and different particles present in the air and their sources. Source of air particles can be natural or human generated. Pollen, smoke from wildfires, mold, dust are some of the natural air pollutants. Similarly, emissions from power-plants, industries and vehicles, different substances and solutions that human have generated for various purpose are human generated air pollutants.

To set standard for air quality, Air Quality Guidelines was published by WHO in 1987 and have been revised in 1997 [11]. WHO guidelines set an international standard for air quality based on which countries around the world set their own standards to achieve

the goal set by WHO. Nitrous Oxide (NO₂), Sulphur dioxide (SO₂), Carbon Monoxide (CO), ground level Ozone, Particulate Matter (PM) among others, are some of the common hazardous air pollutants. Particulate matters are categorized into two categories, PM2.5 and PM10, based on the size of fine particle. Based on the value of Air Quality Index (AQI), USEPA has classified Outdoor air quality, AQI level as ‘Good’, ‘Moderate’, ‘Unhealthy for sensitive Groups’, ‘Unhealthy’, ‘Very Unhealthy’ and ‘Hazardous’ [7]. The AQI value range from 0 to 500. The agency has assigned colors (‘Green’, ‘Yellow’, ‘Orange’, ‘Red’, ‘Purple’ and ‘Maroon’ respectively) to each of the air quality categories [7]. It is shown in figure 2.

2 BIG DATA AND OUTDOOR AIR QUALITY

In US there are about 4,000 outdoor air quality monitors operated by state environmental agencies [6]. They constantly collect air data on harmful suspended particles present in the air and send them to a national database center which is AQS database. EPA has air quality database from last 27 years from around the states [2]. The size of EPA’s database is 25 GB. The data contains valuable information about the concentrations of different air pollutants in different time series; hourly, daily, weekly and yearly. Besides air quality data, AQS database also contains emissions data and weather data which are vital to the outdoor air air quality. Emissions data is basically data from vehicular and industrial emissions. They help to understand the source of different air pollutants and their role in air quality as well as they can be used for furthering research in limiting their emissions. Yearly summary data of AQS Data Mart can also be used to see the progress made in reducing harmful air pollutants over the years. For example, EPA reported that emission of SO₂ has reduced by 73 percent from 1990 to 2011 which is resulted primarily from electric utilities. Study of Emissions and air quality data gives an insight into the source of air pollutants and scientists can use these data to build a better industrial and vehicular models that reduces the emissions of pollutants. Similarly policy makers set vehicle emissions standards and industrial waste management.

India and China, two bigger economies in the world are battling worst air pollution. In recent years IBM is doing collaborative work with local authorities to combat air pollution in cities like Delhi, Beijing and Johannesburg by providing its data analysis platform called ‘Green Horizons’ [3]. The platform uses machine learning tools to analyze past weather forecasts data along with near real time data from optical sensors, air quality monitors and satellites to understand past forecasting models and build a better prediction models for future forecasts [3]. This prediction model helped Beijing enforce air quality control measures on traffic, construction and industry.

Weather directly affects outdoor air quality. For example in a windy day PMs can easily be spread in a neighboring regions and high temperatures increases ground level ozone [3]. Similarly, another example of relationship between big data analysis and air pollution is use of Microsoft’s tools in incorporating Beijing’s outdoor air data collected from conventional monitors along with data from “environmental monitoring stations, traffic systems, weather satellites, topographic maps, economic data, and even social media” [4].

Furthermore, OpenAQ is another platform besides EPA–AQS repository, which holds and hourly updates near–live air quality data from around the world. It claims to have “collected 133,494,377 air quality measurements from 8,054 locations from 47 countries. Data are aggregated from 98 government level and research-grade sources” [2]. The platform helps general public identify global hotspots for poor air quality and allow to have a look at the outdoor air quality where they live [2]. There is another open forum site called ‘Air–Now International’ where users from around the world can participate in sharing and information about air quality data. “It is an international version of USEPA’s air now system”[8]. Big volume of EPA’s data can be combined with another big data, census data to find out the portion of population breathing polluted air. This gives an understanding of health effects among general public. Since, monitoring stations generate big volume of air pollution data and regularly stream into, EPA’s open source, air database, any concerned individual can access live raw data from the website to find out about the quality of air they are breathing.

3 AIR POLLUTANTS

EPA has prioritized six major air pollutants that are commonly found all over the US. They pose significant threat to public health and environment. They are called ‘Criteria Pollutants’ and they are ground level ozone, fine particles or particulate matter (PM2.5 and PM10), nitrogen dioxide, sulphur dioxide, lead and carbon monoxide [1]. WHO has set the guidelines for each of these pollutants as shown in figure1.

PM_{2.5} are particles less than or equal to 2.5 micrometers in diameter while PM 10 are particles less than or equal to 10 micrometers. “Sulfate, nitrates, ammonia, sodium chloride, black carbon, mineral dust and water are the main components of PM ” [14]. These components combine with each other to form variety of mixtures in the air and can easily enter our lungs. Longer exposure to these substances increases the risk of lung cancer and cardiovascular disease [14].

Data on emissions from powerplants, industries and motor vehicles shows that emitted pollutants like various volatile substances and various forms of nitrogen oxides (NO₂) are responsible for the formation of ground level ozone. Chemical reactions between these substances create ground level ozone directly in the air [1]. Chest pain, coughing, throat irritation and inflammation are common problems caused by ozone air pollution. The main source of NO₂ is emissions from heating, power generation and engines in vehicles and ships. SO₂ is another air pollutant produced mainly from burning of fossil fuels. Volcano is a natural resource so₂ release in the outdoor air. Longer exposure to this pollutant causes inflammation of respiratory tract [14]. The data on these pollutants have been regularly analyzed to see their trend. They have also been used in health research to have an understanding of their impact on people’s health. Keeping track of problems and source of problems help us in keeping problem at check. Some air pollutants are characterized as hazardous or toxic air pollutants. Some of the examples include benzene, cadmium, mercury, lead and asbestos.

4 HEALTH HAZARDS

Air pollutants, such as hazardous air particles can easily reach our lungs when we breathe. The effects are itchy, irritated throat, nose and inflammation of respiratory tract. Pollutants such as PM 20 block our airtubes. These pollutants badly affects people with asthma and bronchitis. WHO had estimated that in 2012, 3 million premature deaths worldwide due to outdoor air pollution, particularly due to exposure to particulate matter of 10 microns or less [14]. And in 2014 WHO has reported 7 million premature deaths worldwide [14]. Other pollutants such as lead, pesticides, arsenic also called as toxic pollutants are carcinogenic hence are responsible for lung cancer which is one of premature deaths. Carbon monoxide a very common air pollutant generated by combustion has been called a silent killer. Its health effects include nausea, vomiting and reduced neuro and cardiovascular behavior as it blocks oxygen transfer inside the body thereby might lead to death without knowing the real cause of death. Exposure to higher level of ground level ozone have serious health issues, while it affects people with asthma and bronchitis, other groups of people also experience coughing, shortness of breath, eventually inflammation of airways and development of chronic obstructive pulmonary disease [9].

Sulphur dioxide (so₂) is a highly poisonous gas present in ambient air. It is a byproduct of burning of sulphur or product containing sulphur. Its main source is burning of fossil fuels especially in the powerplants and other industrial facilities. This pollutant can harm the environment by causing acid rain [10]. It harms human health by causing breathing difficulty and coughing. It combines with other particle pollutants present in the air causing haze.

5 AIR QUALITY INDEX

AQI is the index, for five major air pollutants discussed above, calculated by special formula developed by EPA. EPA uses its own formula to convert daily concentrations of measurement of each pollutant into AQI value of each pollutant [7]. Among all the highest AQI value is reported as the daily AQI value for that day [7]. Generally AQI 100 is the acceptable index set by EPA to protect public's health and it ranges from 0 to 500 [7]. The higher the value of AQI, greater is the pollution level and greater is the health risk. Based on hourly data collection from air quality monitors, stakeholders can constantly monitor AQI value in their cities or respective location. So weather channels in different media outlets such as local radio, television stations and newspapers also report about AQI index in order to inform general public about air quality in their area. Figure 2 shows the AQI classification for each pollutant as recommended by WHO and implemented by U. S. EPA. EPA is requires to report any AQI value greater than 100 specifically in larger cities with population more than 350,000 [7].

6 OUTDOOR AIR QUALITY MONITORING STATIONS

Outdoor(Ambient) air quality monitors are specified based on the significance of monitoring a particular pollutant [8]. The purpose might be to protect public health or environment in a densely populated areas. They might be stationed nearby, schools, hospitals, parks and recreational areas. While they are operated by several different agencies they are regulated by U. S. EPA. According to

EPA these stations should meet all the requirements for designs and operations as regulated by EPA themselves. These stations not only provide data on air quality they help in evaluating the effectiveness of programs and policies on emissions control.

7 WHO GUIDELINES AND CLEAN AIR ACT

WHO guidelines for air quality is applied worldwide. This guidelines was revised in 2005 [14]. The guidelines set standards for different air pollutants. According to the guidelines which is based on scientific evidence WHO has set standards for Ozone (o₃), SO₂, NO₂ and PM. WHO guidelines try to limit the lowest possible values for these pollutants. For example WHO limit values for PM2.5 is 10 micrograms per cubic meter is annual mean and 25 micrograms per cubic meter is 24-hour mean and limit value for PM10 is 20 micrograms/m³ annual mean and 50 micrograms/m³ 24-hour mean [14] 1. "The 2005 WHO Air quality guidelines" offer global guidance on thresholds and limits for key air pollutants that pose health risks. The Guidelines indicate that by reducing particulate matter (PM10) pollution from 70 to 20 micrograms per cubic metre, we can cut air pollution-related deaths by around 15 percent [14].

United States' Clean Air Act (CAA), first enacted in 1970 and with major revisions in 1990, is a federal law which is defined as "The Act that regulates air emissions from area, stationary, and mobile sources" [1]. CAA . EPA is the administrator of CAA [12]. As required by law, EPA regulates emissions standards for vehicles, industries, aircrafts and powerplants among others in order to protect environment and public health. Today, with the availability of new technology and analytical tools air quality data from the monitors across the regions can be accessed in an instant and can be analyzed for daily reporting. Based on daily AQI value, respective authorities can take appropriate actions to save outdoor air quality in areas where pollution level is insignificant and to identify measures to be taken in areas where air quality is poor.

8 METHODS

8.1 Air Quality Dataset

Outdoor air quality data sets are available in the USEPA.gov website called 'Air Data'. The data on 'Air Data website comes from AQS database where outdoor air data generated from thousands of air quality monitors from all over the country is collected. As mentioned, all states, local and private monitoring agencies send outdoor pollutants concentrations measurement data to the AQS database [1]. Besides, Air Data there are other sources of data as well, they are briefly discussed below;

- 'Air Now' which has air quality forecasts and real-time data in visual form.
- 'AirCompare' that has data about Counties' AQI summaries.
- 'AirTrends' data is about trends of air quality and emissions.
- 'Air Emissions Sources' has emissions data with national, state and county-level summaries for criteria pollutant emissions.
- 'Remote Sensing Information Gateway (RSIG)' that has air quality monitoring, monitoring and satellite data.
- 'Air Data' datasets have raw dataset, AQI summary datasets. Summary reports consists of AQI report which displays a

- yearly summary of AQI values in a county or city or Core Based Statistical Area (CBSA). The AQI values are summarized by maximum percentile and median and count of days in each AQI category and the count of days when AQI could be attributed to each criteria pollutant [1].
- “ Quality Statistics Report has yearly summaries of air pollution values for a city or county. It shows the maximum values reported during the year by all monitors in CBSA or county” [1].
 - Monitor Values Report that has yearly summary of the measurements at individual monitors and has descriptive information about the site [1].
 - Monitor Values Report-Hazardous Air Pollutants that shows HAPs summary data for individual monitoring sites [1].
 - Air Quality Index Daily Values Report that has information about AQI values for specified year and location [1].

The dataset that are being used for analysis are “Daily AQI by CBSA 2016” and “daily AQI by CBSA 2006”, from EPA’s air data website. Air data has different categories of outdoor air quality data. There are datasets for hourly as well as monthly time period broken down by single criteria pollutant of ‘Hazardous Air Pollutants’ (HAPs). There are county level monitors and stations and datasets grouped by “Core Based Statistical Area (CBSA)”. Each datasets have more than 17,000 data points.

CBSA is designed by Office of Management (OMB) as a geographical area that consists of one or more than one counties and similar surroundings that are associated with at least one core urbanized area of at least 10,000 population plus adjacent counties which are associated with each other in terms of social, economic and daily commutes [5]. CBSA collectively refers to Metropolitan and Micropolitan statistical areas. “OMB defined Metropolitan and Micropolitan statistical areas in 2003 based on application of the 2000 standards with Census 2000 data. It became effective in 2003” [5]. There are 922 CBSAs in total [5]. Metropolitan statistical areas are urbanized areas with population of 50,000 and its adjacent areas while Micropolitan statistical areas are areas with population of at least 10000 or less than 50,000 [5].

CBSA AQI datasets fits the scenario for monitoring outdoor air quality. Because the designed statistical areas are significantly populated along with higher concentrations of motor vehicles running, higher number of day to day activities, less natural habitats or and most of the areas are within industrial areas and powerplant generators. Also, the first look at the dataset give a general information about AQI value of each ‘Criteria Pollutant’ for a day in a year of each monitoring stations in CBSAs.

8.2 Methods

The comma separated dataset “daily aqi by cbsa 2016” was downloaded from data source “<https://aqs.epa.gov/aqsweb/airdata>”. The dataset shows AQI value of each “criteria pollutants” for each CBSA recorded per day per station for the year 2016. Criteria pollutants recorded in the dataset are, PM2.5, PM10, Ozone, SO2, NO2 and CO. It also has a column for number of stations for each CBSA and location of the monitoring stations per CBSA.

In order to have a comparative study of any changes in AQI value for each parameter for the listed CBSA, dataset for the year

2006 is also being analyzed. This gives us a picture of changes if any for the duration of 10 years. Since real world datasets may not be perfect, there are slight or negligible amount of discrepancies among the two datasets. Criteria pollutants recorded in the dataset varies within each CBSAs depending on their significance in the region or monitoring stations. Similarly, record date per station per CBSA is not continuous, there are certain interval for recording and reporting data. For example, data is recorded on January 1st 2016 and the next date is January 3rd and 6th and so on. This pattern is seen in the whole dataset. Also, number of monitoring stations varies per CBSAs.

Using jupyter notebook with python2.7 as the interpreter, the dataset is fetched and converted into pandas dataframe for and analysis. Next, only the columns needed for analysis are selected and created a clean pandas dataframe ready for manipulation. Jupyter Notebook is an open source web application which is powerful in data cleaning, manipulation, data analysis and visualizations. The notebook is not sufficient in itself for a variety of data manipulations, it needs to have all sorts of python packages as per requirement of data analysis. Matplotlib, pandas, numpy and pandas datetime are the packages used for air quality data analysis.

9 ANALYSIS

The requirements for the analysis are python’s jupyter notebook and the packages pandas, matplotlib and numpy. Using the pandas dataframe, average AQI value is calculated for each ‘Defining Parameter’ grouped by CBSA. Since AQI value determines the level of risk factor as shown in figure 2, it is worth calculating the mean of that value which helps in determining which CBSA is affected by which ‘defining Parameter’. It also helps identify the source of the pollutant so that responsible stakeholders can take required actions to solve the problem. The purpose of using the data set is to find out level of AQI per CBSA for the year 2016. The reason of using 2016 data set is it the most recent complete set of data for a year. While 2017 data set would have been the most recent look at AQI level in the United States but as of this analysis the 2017 data set contains air quality data until the month of May 2017. This data set wold be completed as a full years data only in the upcoming spring [6]. In order to do a general comparison of the changes, positive or negative, if any similar data set for the year 2006 is selected. This would allow us to look at differences in AQI values in a decade time frame.

9.1 CBSA Average AQI for 2016

Simple statistical measures such as mean, maximum, count and minimum value for any variable provides some insights into the degree of variation between each measure of the variable within a period of time. So, as a first test mean value of “Criteria Pollutants” for all the listed CBSAs have been calculated. Then the results have been plotted into a bar-chart as shown in figure 5. It shows that among all, Ozone and PM 2.5 have highest average among CBSAs while CO, NO2, SO2 and PM10 have slightly lower average AQI for the year 2016.

Furthermore, figure 3 illustrates the average AQI value for overall CBSAs for the year 2016 by month. The table illustrates that AQI value, which is 53.56, for Ozone is the highest during the month of

June of last year. This AQI value of ozone comes under the category of 'unhealthy for sensitive groups'. This value is followed by CO which has the highest mean value for two consecutive months, May and June. From the table it can be said that during 2016 the most significant criteria pollutants were Ozone, CO, and PM2.5.

In order to look at monthly average AQI per 'Defining Parameter', first 'Date' series is converted into pandas datetime format and then the series is bucketed into month of the year column. Then mean is calculated by using 'groupby' function, mean is calculated grouped by 'Defining Parameter' and 'month of year'. The result illustrated in figure 7 shows that there is no significant change in mean AQI for SO2 and PM10 while significant change can be seen for CO and Ozone. AQI average for CO shows a sharp increase in May.

For the purpose of finding out CBSA with highest and lowest average AQI value for the year 2016, for specified pollutant, aggregate function is used with groupby function with descending value of AQI. The result is shown in figure 9. The table shows CBSA 'Madison, WI' has lowest AQI value for SO2, followed by Fayetteville, NC for the same parameter. Similarly, as seen figure 10 Hilo, Hawaii has the highest AQI value for parameter SO2 which is 151.79. This means AQI value is unhealthy and people may experience health effects with sensitive groups people with asthma, bronchitis and chronic obstructive pulmonary disease (COPD) might have very serious health effects as stated in figure 2. The reason for highest AQI value for SO2 might be the release of SO2 gas from active volcanoes around the CBSA region as SO2 is one of the gases released from volcanoes. Hilo, HI is followed by 'Riverside– San Bernardino–Ontario, CA with AQI value 126.53 for 2 with category 'unhealthy'. Other CBSAs in the top ten list are Lansing–East Lansing, MI, San Juan–Carolina–Caguas, PR, Bishop, CA, Durango, CO, Riverside–San Bernardino–Ontario, CA, Philadelphia–Camden–Wilmington, PA–NJ–DE–MD, Los Angeles–Long Beach–Anaheim, CA and Minneapolis–St.Paul–Bloomington, MN–WI. All of these CBSAs have at least one defining parameter with 'Unhealthy' AQI value. It is also significant that Riverside–San Bernardino–Ontario, CA have two highest AQI value for two defining parameters that is ozone and PM 10.

In order to have a visual picture of level of AQI value, count measure is used grouped by 'CBSA', 'Defining Parameter' and 'Category' and visualized the result in a boxplot. This basically counted number of days in each category of AQI. The figure 11 shows, that there are significant number of 'good days' during 2016 followed by 'moderate', 'unhealthy for sensitive groups' and rest of the three categories have less range of days. As seen in bar chart the mean value for Ozone is higher for the months May and August in comparison to other pollutants Columns for the months of June and July are missing at this point.

9.2 Comparative AQI for 2006 and 2016

To compare AQI per CBSA for criteria pollutants, exactly similar data set for the year 2006 is used to calculate average AQI value and plotted into a bar chart which is shown in figure 6. As the result can be compared with that of 2016. average AQI value for ozone and SO2 is significantly higher compared to 2016 while that of carbon monoxide (CO) has increased significantly from 2006 to 2016. For other parameters there are not so significant changes.

Similarly, average AQI for SO2 is also higher in 2006 compared to 2016. There is also some changes in overall average AQI value. This figure shown here 4 illustrates the AQI average for the year 2006. As seen in barplot this figure shows the highest mean for Ozone at the top of the list when mean is grouped by month of the year and output is sorted in descending order by mean. Interestingly, most of the highest mean value are for the month of June, July and August. To be more specific AQI value for Ozone is mostly during above listed months. Similar result can also be seen in the analysis of 2016 dataset.

While comparing top ten CBSA with highest average AQI value for 2016 with that of 2006, top ten CBSAs with highest average AQI for 2006 is shown in figure 8. Compared to 2016 there is no sharp increase in mean value for CO any of the month as has been in 2016. Its mean value remains comparatively in same range, in between 17 and 16. Whereas, the value for Ozone is significantly higher for the months of March, April, May, August and September. For other months as well it has higher level of mean AQI compared to other pollutants except for SO2 which has the second highest AQI throughout the months. Average value for all of the pollutants throughout the months have higher values compared to that of year 2016 except for CO. Average CO AQI for 2016 is higher than that of the year 2006.

Another comparison can be done by looking at the list of top most CBSAs with higher mean AQI. We have already discussed about this for year of 2016. Now we will look at similar output for 2006 which is shown in figure 12. The mean output is generated by grouping the CBSA and defining parameter. Here, Bishop, CA has highest yearly average for PM10 which is 435.21 followed by CBSA Phoenix–Mesa–Scottsdale, AZ, Carlsbad–Artesia, NM have yearly mean value of 127 for SO2. In comparison to the same statistics for year 2016, mean value is lower than that of 2006. This indicated that there is progress made in lowering the measurement in air pollutant.

10 FURTHER STUDIES

It would be effective to look at the factors that helped lower the mean AQI value within a decade. Are there any policy differences between now and then? Are there less economic activities compared to 2016 or did any of the technology have any role to play to make such change? It would be effective to look at the factors that helped lower the mean AQI value within a decade. As can be seen from the analysis above average ozone has highest average value among all. Finding out or looking at the contributing factors can be another area of furthering this research. and it would be interesting to see any changes if any during the year of 2017. The analysis presented here showcases just the level of pollutants by AQI value. For furthering the studies different models for lowering AQI value for a single pollutant within certain periods of time can be developed. Since vehicular, industrial or air transportation emissions are some of the main sources of criteria pollutants, it would be very effective to analyze monthly emissions data with AQI data to have an understanding of level of pollutants generated from these sources. This analysis can be combined with weather data in order to find out the effects of weather or seasonal variations on increasing or lowering pollutants. There is an increased AQI value

for CO from 2006 to 2016. Factors responsible for poor AQI value can be the next research topics.

Looking at difference in emissions policy during the past decade will also provide some insight into why certain parameters have lower AQI value. Looking at effects of AQI value in international boundaries that is effect evaluation of pollutants of country affecting the air quality of surrounding country could be a whole new topic of outdoor air quality study.

11 CONCLUSION

Air quality monitors across the United States and its territories, Puerto Rico and Virgin Islands collects everyday air data in order to collect data on pollutants present in outdoor air. These generates a huge volume of data. Air data contains measurements of concentrations of pollutants, commonly called as criteria pollutants, present in outdoor air. These monitors are under the management of state, local or private environmental agencies. They collectively send these data to a national database system called air quality system. For analytical purpose the air data from the AQS website which is an source of air data, is directly accessed through jupyter notebook. Simple statistical measures are calculated to have a look at the level of pollutants present in ambient year.

The air data by CBSA, for the year of 2016 have been analyzed to see the average value of AQI for each defining parameter or criteria pollutants. This analysis identifies that average AQI value for Ozone is significantly higher compared to other pollutants. The analysis also shows that AQI value varies by month of the year. The results shows that Ozone AQI is higher in the months of March to August. While calculating overall average AQI, among all of the criteria pollutants level of ground level ozone has the highest value during the year of 2016 as well as 2006. It can also be concluded that overall level of AQI value have been improved over the years period while comparing the value from 2006 with that of 2016. Interesting enough AQI value of CO have been significantly increased from 2006 to 2016.

Air quality monitoring have become an important and effective policy for reducing the concentrations of different criteria pollutants. Since the adoption of clean air act in United States significant progress has been made in improving outdoor air quality. Thereby reducing the development of health risk factors for general public. Air quality monitoring stations collect everyday measurement values of criteria pollutants which generates a big volume of air data. This gives us information on daily level of pollutants present in the air thereby letting us know the quality of air that we breathe everyday. This information is shared to the public through various media outlet. This raise awareness among general public about the importance of outdoor air and their health.

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Pollutant	Source types and major sources	Health effects	WHO guidelines
Particulate matter	Primary and secondary- Anthropogenic: burning of fossil fuel, wood burning, natural sources (e.g., pollen), conversion of precursors (NO _x , SO _x , VOCs) Biogenic: dust storms, forest fires, dirt roads	Respiratory symptoms, decline in lung function, exacerbation of respiratory and cardiovascular disease (e.g., asthma), mortality PM _{2.5} Annual mean: 20 µg/m ³ 24-hour mean: 50 µg/m ³	PM ₁₀ Annual mean: 10 µg/m ³ 24-hour mean: 25 µg/m ³
Ozone	Secondary- Formed through chemical reactions of anthropogenic and biogenic precursors (VOCs and NO _x) in the presence of sunlight	Decreased lung function, increased respiratory symptoms, eye irritation, bronchoconstriction	8-hour mean: 100 µg/m ³
Nitrogen dioxide	Primary and secondary- Anthropogenic: fossil fuel combustion (vehicles, electric utilities, industry), kerosene heaters Biogenic: biological processes in soil, lightning	Decreased lung function, increased respiratory infection Precursor to ozone. Contributes to PM and acid precipitation	Annual mean: 40 µg/m ³ 1-hour mean: 200 µg/m ³
Sulfur dioxide	Primary Anthropogenic: combustion of fossil fuel (power plants), industrial boilers, household coal use, oil refineries Biogenic: decomposition of organic matter, sea spray, volcanic eruptions	Lung impairment, respiratory symptoms, Precursor to PM. Contributes to acid precipitation	Annual mean: 20 µg/m ³ 10-minute mean: 500 µg/m ³

Figure 1: WHO Guidelines Source And Health Effects [13]

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warnings of emergency conditions. The entire population is more likely to be affected.

Figure 2: Air Quality Index [7]

month_year	Defining Parameter	Mean
2016-06	Ozone	53.56
2016-05	CO	51.96
2016-06	CO	51.61
2016-05	Ozone	49.07
2016-07	Ozone	48.35
2016-04	Ozone	47.86
2016-07	CO	47.27
2016-08	Ozone	44.83
2016-11	PM2.5	43.21
2016-01	PM2.5	42.18

Figure 3: Top Ten Mean AQI Value for the Year 2016

month_year	Defining Parameter	Mean
2006-07	Ozone	69.58
2006-06		69.29
2006-08	Ozone	61.31
2006-05		58.31
2006-04	SO2	54.97
		54.70
2006-08	PM2.5	51.20
2006-07	PM2.5	50.58
2006-05	SO2	50.36
2006-12	PM2.5	48.96

Figure 4: Top Ten Mean AQI Value for the Year 2006

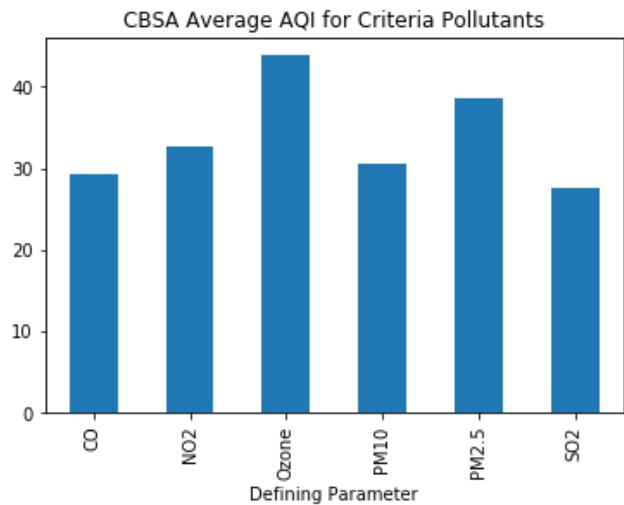


Figure 5: CBSA Average AQI for Criteria Pollutants

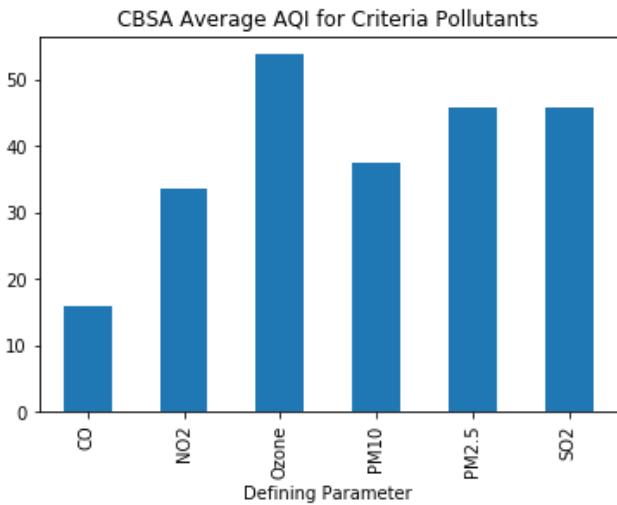


Figure 6: CBSA Average AQI for Criteria Pollutants 2006

Defining Parameters	2016-01	2016-02	2016-03	2016-04	2016-05	2016-08	2016-09	2016-10	2016-11	2016-12
CO	7.19	4.00	8.20	26.00	51.96	16.77	31.25	NA	26.00	2.60
NO ₂	33.18	33.07	33.69	39.00	34.41	22.90	40.43	31.27	33.11	30.39
Ozone	33.97	38.48	41.20	47.86	49.07	44.83	40.91	37.61	34.75	31.07
PM10	19.67	28.82	33.31	30.04	28.67	28.01	32.62	36.89	32.55	25.61
PM2.5	42.18	38.99	35.76	33.30	35.21	36.74	35.90	36.71	43.21	40.82
SO ₂	25.89	26.83	26.83	29.64	24.92	27.51	32.42	32.20	25.99	23.33

Figure 7: Mean AQI per Month per Criteria Pollutant 2016

Defining Parameters	2016-01	2016-02	2016-03	2016-04	2016-05	2016-08	2016-09	2016-10	2016-11	2016-12
CO	17.06	15.07	12.40	15.59	15.15	13.75	20.15	17.97	17.22	16.74
NO ₂	31.93	38.34	37.99	39.54	33.84	24.79	34.36	32.77	32.60	31.97
Ozone	32.99	37.80	46.22	54.70	58.31	61.31	46.37	38.06	33.51	29.79
PM10	45.46	48.20	32.75	36.07	36.64	31.49	37.91	36.17	40.79	33.55
PM2.5	43.23	45.92	43.81	39.97	43.43	51.20	47.00	41.82	47.47	48.96
SO ₂	43.84	44.25	44.65	54.97	50.36	48.75	45.89	47.61	43.86	42.40

Figure 8: Mean AQI per Month per Criteria Pollutant 2006

CBSA	Defining Parameter	mean
College Station-Bryan, TX	SO ₂	1.75
Wilmington, NC	SO ₂	1.44
Rochester, MN	SO ₂	1.00
Corning, NY	SO ₂	1.00
Jamestown-Dunkirk-Fredonia, NY	SO ₂	1.00
Kapaa, HI	SO ₂	0.50
Gulfport-Biloxi-Pascagoula, MS	SO ₂	0.50
Seneca, SC	SO ₂	0.46
Fayetteville, NC	SO ₂	0.38
Madison, WI	SO ₂	0.00

Figure 9: Lowest Mean AQI per CBSA 2016

CBSA	Defining Parameter	mean
Hilo, HI	SO ₂	151.79
Riverside-San Bernardino-Ontario, CA	Ozone	126.53
Lansing-East Lansing, MI	SO ₂	123.00
San Juan-Carolina-Caguas, PR	SO ₂	119.61
Bishop, CA	PM10	117.66
Durango, CO	NO ₂	109.00
Riverside-San Bernardino-Ontario, CA	PM10	108.20
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	SO ₂	107.00
Los Angeles-Long Beach-Anaheim, CA	Ozone	105.46
Minneapolis-St. Paul-Bloomington, MN-WI	SO ₂	105.00

Figure 10: Highest Mean AQI per CBSA 2016

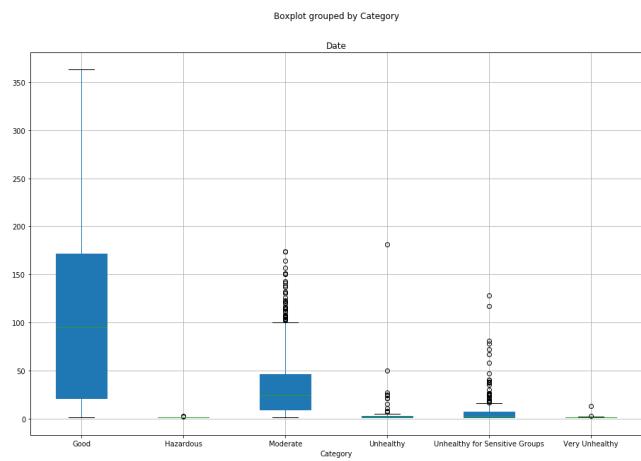


Figure 11: Boxplot Grouped by Category, 2016

CBSA	Defining Parameter	mean
Bishop, CA	PM10	435.21
Phoenix-Mesa-Scottsdale, AZ	PM10	185.33
Carlsbad-Artesia, NM	SO ₂	161.00
El Centro, CA	SO ₂	127.50
Riverside-San Bernardino-Ontario, CA	Ozone	123.17
Bakersfield, CA	Ozone	119.92
Atlanta-Sandy Springs-Roswell, GA	Ozone	119.33
Houston-The Woodlands-Sugar Land, TX	Ozone	118.44
Birmingham-Hoover, AL	Ozone	114.16
St. Louis, MO-LI	SO ₂	112.85

Figure 12: Highest Mean AQI per CBSA 2006

Agricultural Data Science: Then, Now, and Beyond

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ABSTRACT

As the human population swells to staggering numbers that historians of yesteryear could not imagine, one very important question seems to keep coming up over and over again. How do we feed all of these people? Thankfully, humans are intelligent beasts and are figuring out ways to farm and produce larger amounts of food using methods and techniques more sophisticated than ones humanity has relied on in the past. The party is just getting started as farming meets the era of big data. As more and more data is generated from farming, techniques and processes become more sophisticated, cleaner, and more efficient. The kind of data being analyzed to improve agricultural endeavours comes in many forms, and can be statistical data like amount of food grown using how much land, actual data generated from using farm tools and other smart farming equipment, or any other kind of agricultural activity that can produce datafies actions and procedures. However, data science is helping in other ways, too, as scientists and engineers are taking advantage of all this newly available data and helping create new technology to improve food production and increase yields. With all this new information available, new farming endeavours are being undertaken. Farming within closed systems such as urban or vertical farming, practicing precision agricultural techniques, or even laboratories using genetics data on different plant strains to crossbreed the various plant strains in order to produce new breeds that can grow in the harshest of environments while using minimal resources. As the population grows, we are finding that not only is the production of food vital, but also that sustainable farming techniques are of paramount importance for long term agricultural need. Data Science and its applications are most definitely changing the way people produce food and the very nature of farming itself.

KEYWORDS

i523, HID345, Agricultural Data Science, Smart Farming, Vertical Farms, Urban Farming, Big Data Farming, Smart Farming Tools, Precision Agriculture

1 INTRODUCTION

Humans have not always lived in the amazing concrete and technological jungles that we have surrounded ourselves with today. Indeed, the ability to stop being nomadic and settle down in one area is a relatively new development in regards to the grand scale of human existence. However, if there is one technological advancement which is considered to be the most directly responsible for allowing humans to change how they lived and thrive in a harsh and unforgiving world, it would be when ancient humans evolved into the first agrarian societies by figuring out how to plant crops and grow food. By making their societies agriculture based instead of hunting based, humans were able to live in one place and do a lot of gathering, in addition to the hunting they were used to. This

regular supply of food and less dependency on hunting allowed ancient humans time to develop other aspects of human society, such as language, writing, and building. This was about 12,000 years ago and ever since that time, humanity has been gathering data on farming and slowly but surely refining the techniques we use for food production. Humanity has not just been gathering data and knowledge on how to grow food, but also information on what kinds of crops to grow when and where, how to deal with insect, rodent, and pests and other external threats to crops, and how what to do and how to manage different weather and environmental setbacks. These are a few of the many examples of information that humanity has accumulated over the millennia that have allowed humans to improve their farming and agricultural techniques, which has enabled humanity to thrive around the world.

The advances humans have made in their early years of farming will pale in comparison to the advances that humanity has the potential to make in the modern era using big data analytics and sophisticated technology that improves farming methods. With population statistics indicating that there is no sign of our population growth slowing down, the question is becoming even more relevant today than it has been in the past. With estimates putting the world population at 11.2 billion by the year 2100, solving the hunger problem is imperative [13]. Using data science and modern data analysis techniques and models, humans are able to look at the concept of agriculture as a whole and start making decisions based on data that had never been readily available in the past. This data is useful to farmers and serves as kind of risk management system through which farmers can make informed decisions about changes they might want to implement on their farms. The rise of smart farming with a focus on sustainability, the ability to analyze information in ways not possible in the past, and the invention of tools like monitoring sensors and machines that datafie work are changing agriculture for the better. The desire for more efficiency, greater food production, and meeting the demands of a steadily growing population are the driving forces behind why this field continues to be researched and expanded. Closed farms that eliminate the need for pesticides and rodenticide use while also helping the environment by cleaning the air in urban areas are a couple of unique ways this field has branched off from traditional farming practices and techniques.

Modern technology and data science are making new agricultural endeavours possible in ways that previously could not have been attempted with any hope of such success modern farmers are finding. One new technique is called urban, or vertical farming. A vertical farm is a farm constructed in an urban area that goes up instead of out. Ideally built in a parking garage like structure, vertical farms use data analysis to make their crop yields extremely efficient. There are plans for their construction coming up in more and more cities over the next couple decades and they are already beginning

to appear in developing nations that have problems meeting the demand for fresh fruits and vegetables in major urban centers. Other examples of how data science is changing the agriculture game is through the invention of more sophisticated computer software and languages that allow for the analysis of farming and crop data in ways that could never have been done in the past. This new way of looking at growing, storing, and transporting food and agricultural goods is making humanity second guess a lot of the ways we used to do things with regard to food. The explosive growth of big data and the rise of data science are already changing the way the world works and how we go about our daily lives. Data science is already improving agricultural endeavours in a myriad of ways, just like it does in most fields that it used to solve problems in. The positive benefits of this transition to new approaches in agriculture are already beginning to be seen.

2 HISTORICAL AGRICULTURAL DATA SCIENCE

The rise of big data analytics software and technology was the turning point where society began to really be able to take advantage of the ever growing amounts of data being produced by farms and their workers. As computer components began to get smaller, cheaper, and more powerful, this enabled more wide spread use of data analysis to be performed, which made it easier for companies and other organizations to adopt these new techniques and get in on the ground floor of solving agricultural problems and changing the way people farm around the world. Despite all these positive steps happening in the fields of technology, data analysis, and data creation, only small groups of people, usually limited to college university campuses, were actually receiving funding to analyze agricultural research data. This lack of funding meant that, although models for agricultural analysis were being developed, they were not being improved upon, leaving the power of data science in the field of agriculture unrealized until it could be adopted by more people and organizations [16].

2.1 Early Agricultural Analysis

In early to mid 1950s, computers and funding were still only available mostly at universities, which meant that universities were where most data analysis was being done in that era. Despite this, great steps were still being made to lay the foundation of modern agricultural data science and all that that encompasses. From the mid 1950s and onward, modeling was done by various institutions to find things like best water balance, photosynthesis and growth statistics, models to evaluate land and zoning properties, and pinning down economic risk management models, to name a few [16]. These models acted as guidelines and risk management tools in food production decisions making processes. As the availability and use of modeling technology became more widespread and more people and organizations began adopting them, so too did their positive impact on the real world become more apparent and visible. The changes, technological advances, and new techniques that were being proposed to farmers may have been met with some skepticism at first, but by the mid 1970s, these new processes were reportedly responsible for saving the lives of billions of people around the world by helping aid world hunger relief efforts. Like dominoes

falling, this led to increases in funding, which led to better and more accurate models being developed, which led to even more advances, which led to more funding, and so on. This self sustaining cycle of budget increases and technological innovation at the beginning of the agricultural data science boom led to the development of new ways of thinking about growing food and led to the development of tools that are still used today. These agricultural systems were developed for many reasons, but the top three reasons they are developed are typically “the intended use of the model, approaches taken to develop the models, and their target scales” [16]. Whatever their intent for development, very quickly it was evident that the proof was in the pudding.

2.2 New Tools for Agricultural and Risk Modeling

One data analysis tool for statistical decision making that was developed during the early days of agricultural data analysis was a software called Statistical Analysis System, or SAS for short. SAS was developed and “started out as a tool for statisticians: Goodnight originally developed it to analyze agricultural-research data in North Carolina” [16]. The development and utilization of SAS made sifting through the piles of random agricultural data much more manageable, and helped proto-data scientists find patterns, make connections, and gleam wisdom from the available agricultural data that they would not have been able to find without using SAS. Being able to manipulate and understand all the available data gave the farmers and data scientists a statistical edge when making choices about changing their farming practices. Economic risk management models would later be developed which helped make farmers more knowledgeable and able to hedge their bets whenever they were attempting new processes and techniques for improving their crops and growing capacity [25]. All of these new models made it easier for farmers to make decisions about making changes in how they produced their crops. The ability to make informed decisions about potentially big changes made farmers less reticent to try new approaches to farming and different techniques in how they produced their crops.

Since the development and implementation of SAS, other techniques have been developed to help take the pressure off of farmers when making educated and informed decisions. Commonly referred to as decision support tools, they have been developed to help farmers and data scientists make heads or tails of all the data that their trade is generating on a day to day basis. Thanks to the development of these kinds of tools and models and their improvement over the years, the decades since their adoption by farmers have seen farms produce more food per acre and increase their own sustainability for the years to come. These tools are incredibly useful to farmers, and “lead users through clear steps and suggest optimal decision paths or may act as information sources to improve the evidence base for decisions” [25]. These tools were slow to be developed because of funding problems, but once they began to catch on, they were quickly adopted by farmers to help improve their yields. A statistical analysis of farmers and the tools they used found that the odds of using decision support tools and software increased greatly depending on the size of the farm. The bigger the farm, the better the chances are that they use some kind of

decision support tools software [25]. The growth of urbanization and major cities meant that there were less farmers, which means that the farms that did exist were becoming bigger and bigger to fill the vacuum. Larger farms led to more widespread of adoption of the then modern technology and approaches to increase yields, improve efficiency, and improve farming conditions and overall food production.

2.3 Food Explosion, Courtesy of Data Science

Slowly but surely, the world, and especially developing nations, began to see the effects of applied data science to agricultural and farming endeavours. It was in the 1960s that a kind of critical mass was reached where the benefits of this field became undeniable. This led to the eventual development of precision farming with a focus on sustainability. All of these new breakthroughs in environmental science helped plant the seeds for what would be the growing environmental movements. In the mid to late 20th century, scientists like Norman Borlaug, who would later win a Nobel Peace Prize for his research, pioneered the way in using analysis models on plant genetics in order to improve yield by finding which breeds were best to cross and grow in different environments. These experiments led directly to the development of high yield crops in 1960s Mexico, and would later do the same in India [5]. Analysis of crop data allowed for the scientist to breed genetically superior strains of cereal grains that could withstand harsher climates, thrive on fewer resources like water and fertilizer, and produce a greater yield per acre than strains that Mexican farmers had previously been using. These new strains were potent and unlike anything the world had ever seen. When the Mexican farmers adopted these strains that Borlaug and his team had developed, they immediately began to see an improvement in their ability to meet the food demand of their population. While not alleviating the problem of hunger entirely, these developments proved that applying data science solutions to agricultural problems yields great results. These developments helped stymie off a hunger epidemic, and when Borlaug received his Nobel Peace Prize in 1970, it was officially for “saving over a billion lives” [4]. This quick turnaround showed definitively that research and development in agricultural data science was worth the investment, as less than 25 years after these new processes and models were being worked out, they were able to be used to save billions of lives.

These achievements, fantastical as they may be, only helped stymie off the threat of hunger around the world temporally, as these kinds of advances could only go so far. Growing populations steadily defeat advancements in food production, and humanity has to keep adapting and refining our methods and techniques in order to continually meet the needs of the many [22]. Luckily, humans are clever creatures, and our innovation and technological achievements have grown exponentially with our massive populations. More powerful computers and data analysis methods are constantly making humans better at producing food and meeting the staggering population demands. The gradual advance in sophistication of humankind’s ability to produce food and knowledge of best techniques and practices continues to evolve with technology and available data. Data science is just the newest and sharpest tool

in humanity’s toolbox and its use is improving farming in every way.

2.4 The End of the Past

History is a gradual process which only seems instantaneous when reading about it in a history book. When talking about agricultural data science and its past, present, and future, it would be easier to think about it like stepping stones. The future did not just come to be, but contributions from the farmers and data scientists in the past helped to build it up to where it is today. But which stepping stones are the most important ones to be looking at when thinking agricultural data science’s past? Ultimately, the best example the past can provide is that working together and openly is the most beneficial approach for everyone involved.

Some of the biggest developments from the 20th century of agriculture came about because of the open nature of the field, but there were other circumstances that led to great leaps in agricultural data science. Other circumstances that have led to advances in this field are: 1) the ability to capitalize on a crisis, 2) advances in technology and hardware, 3) keeping the data open and harmonized, 4) making the data easily applicable so that it can be used in other disciplines, 5) developing and maintaining standards and protocols, and 6) making sure the data remains user friendly and user-driven [16]. These approaches represent ideal ways to handle and manage agricultural data so that it can be used and expanded upon by all parties that might be interested. Keeping the data open allows for greater innovation as it becomes a problem that is solved on a societal level, not an individual one. This helps keep the data user friendly and driven as well. All of these different examples represent the various stepping stones that have worked together to bring the field of agricultural data science from its roots in human history and changes in the 20th century, to the modern way we look at agriculture and farming in the 21st century.

3 MODERN AGRICULTURAL DATA SCIENCE

In the 21st century, humanity has the hindsight to know that data science and its endeavours yield their own rewards. As a result, funding for the study of agricultural endeavours using data science is no longer too difficult to come by. The different areas under the umbrella that is agricultural data science have, in many ways, become fields unto themselves. Urban and precision farming, net-worked farms, and agricultural technological innovation all have their own sub-fields, but they all belong to the field of agriculture data science in one way or another. All of these different fields that make up modern agricultural data science have one attribute in common, however, and that one attribute is a focus on sustainability in whatever agricultural endeavour that is being undertaken. Indeed, modern data scientists and farmers would have a difficult time encouraging and practicing new processes that did not take sustainability into account. With the world’s population expected to keep growing, and the amount of food needed to feed the population expected to double by 2050 [13], this new focus on sustainability is an ever growing piece of the modern farming puzzle, whose importance and juxtaposition along side traditional and modern beliefs about agriculture can no longer afford to be overlooked. Data science factors into this tremendously as it enables farmers

and agriculturalists to analyze their data and figure out if their new approaches and techniques are actually working and worth continuing.

Focusing on sustainability and changing things around the farm are not the only new tricks that modern farmers and data scientists have up their sleeves. New techniques and advances in computing technology, both hardware and software, have helped pave the way towards making the analysis of farming data easier and more available than ever so that farmers and agriculturalists can make informed decisions about how they grow their crops and produce food. One example of a new technique that has been developed is based on an old approach: selective breeding. Selective and cross breeding different strains of plants is nothing new. However, thanks to modern technology and new techniques, farmers can work with data scientists to dig down to an even greater degree of analysis based on data that was not available in the past. One study's model, for example, analyzed how different nighttime temperatures and amounts of nitrogen fertilizer used impacted growth rates of rice. The study found that high night time temperatures "substantially reduces yields of cereal crops" [26]. Studies and experiments like this are specific examples of how agricultural data science is changing the ways farmers grow food. Because of studies like this, farmers are now breeding their rice strains selecting for traits that tolerate high nighttime temperatures. All of this data was obtained from sensors that were developed for the express purpose of gathering this kind of data. It is in this way that data science is encouraging agricultural advancement. But will improving the success rates of plants and a focus on sustainability be enough to help farmers provide food to so many people in the future? Time will tell, but data science is an incredibly useful tool when applied to producing food.

The focus on sustainability and hardier plants that produce more food, while an important part of the food puzzle, are not the only pieces that humanity needs to focus on in order to feed future populations. Architectural endeavours like vertical farms, designing and implementing a connected farms that take advantage of Internet of Things technology in farm equipment, using drone and wireless sensor monitoring systems technology, and using computing networks and sensors to figure out new information about insect and rodent infestation rates and crop losses are just a few examples of the kinds of outside the box thinking that is being done to improve agriculture. Through the use of technology and approaches developed from the use of data science practices, the agriculture sector as a whole continues to improve and is stepping up to meet the modern demands of an ever growing population.

3.1 Growing Urban Populations and the Greater Demand for Food

More and more humans are beginning to live in centralized places like major urban cities while at the same time, people are leaving rural areas and communities in greater and greater numbers. This is having an impact on farming and agriculture in a number of ways. First and foremost, this is leading to a major reduction of the number of farmers and agriculture workers. According to the 2012 US Census of Agriculture data, less than 2% of the population of workers in the United States classify themselves as farmers - about

Number of U.S. Farmers, 2007 and 2012

Operators	2007	2012	% change
Principal	2,204,792	2,109,303	-4.3*
Second	931,670	928,151	-0.4
Third	145,072	142,620	-1.7
All	3,281,534	3,180,074	-3.1

*Statistically significant change.

Source: USDA NASS, 2012 Census of Agriculture.

Figure 1: The decline of US farmers [30].

Gender, Primary Occupation, and Years on Farm, 2012 (percent)

Farm Operators	Gender		Primary Occupation		Years on Farm	
	Male	Female	Farm	Other	<10	10+
Principal	86	14	48	52	22	78
Second	33	67	37	63	31	69
Third	61	39	43	57	45	55
All	70	30	44	56	26	74

Source: USDA NASS, 2012 Census of Agriculture.

Figure 2: Farm occupation statistics [30].

3.2 million people classify themselves as farmers, ranchers, or some other kind of agriculture related occupation [30]. This reduction in available farmers and agricultural workers means that the job of providing food to an ever growing population and society falls to fewer and fewer people. It also means that providing fresh fruits and vegetables to the growing and expanding urban populations is going to become more and more difficult due to the logistics of growing larger quantities of food, storing it, and then by getting it from point A to point B. One upside to this population shift is that the farms that still exist are getting much bigger to meet demands, and larger farms typically use more support tool and decision management data science tools. This means that more data than ever is being created, and more data is the cornerstone to using data science as a tool to improve agricultural production, efficiency, and sustainability.

Being able to produce food within urban areas is a dynamic approach to helping solve several problems. This process of growing food and other greenery in urban areas would not only help ease the demand for food from sources outside the urban areas, but it also helps to create less of an environmental impact while simultaneously promoting a sustainable model. By again causing even less strain on the farming resources outside of the urban sectors, this enables them to focus on a more manageable demand [21]. Growing what is needed locally within urban areas is a great way to help the environment, increase availability while also providing food and agricultural goods for a growing population, and encourage a sustainable agricultural model. One major benefit of farming in a close system like an urban farm is that since the system is closed, the urban farmers do not have to worry about insects, rodents, or other pest infestations that might destroy their crops. But more

importantly, the nature of the closed system means they do not have to used insecticides, pesticides, or rodenticides. This means the urban crops are safer for consumption and that they leave a much smaller environmental foot print than their rural cousins [21]. This closed system method also allows the urban farmers to use the precise amount of resources that their data indicates they should be using to grow their plants. This increase in efficiency is not only an economic boost, but further improves this model of sustainability by making the environmental footprint of farming even smaller. Data science is also helping improve these endeavours in the same way it helped with farmers in the mid to late 20th century: by applying rigorously tested computing models to agricultural jobs, urban farmers are pushing the envelope in regards to how much food they can grow with limited spaces while saving on resources [1].

The United States and other developed nations are not the only places taking advantage of these advances in farming technology, newly developed processes for improving production, and taking advantage of agriculture data analysis. Developing nations are also benefiting from this new era where agriculture is meeting modern technology. As world populations grow and nations develop further, the demand for more and varied goods increases, including a demand for more varied foods. By taking advantage of data science practices, farmers and food providers in developing nations are discovering new and innovative ways to meet this new demand placed on them for their goods. These new approaches are helping developed nations two fold: not only are they helping farmers to produce greater and more varied quantities of food, but they are also helping to limit the environmental footprint, created from farming, in places that are more sensitive to environmental change, or where environmental laws are not as heavily enforced [12]. The ability to meet food demands, curtail the effects of climate change on the surrounding environment, maximize the efficiency of resource use, and take advantage of advances in food storage and distribution are helping to transform developing nations in ways that all of their citizens can benefit from. Limiting and reducing the environmental footprint of farming and other agriculture processes is also extremely beneficial for developing countries and places that are facing more extreme, contemporary threats from climate change, as opposed to other nations whose economies and well being are less dependent upon their agriculture sector [12]. The direction that modern farmers in developing nations are taking, and their focus on sustainability, are only possible because data analysis tools have brought the world's agricultural expertise to this point. Keeping the data open and friendly allows for cross applicability of the data, which leads to more insights and discoveries, which in turn continues to benefit the farmers and agriculturalists even more.

3.2 Focusing On Sustainability

As mentioned previously, the growing focus on sustainability is helping to drive technological innovation and advancements and new techniques that produce more and better food while also limiting and reducing the environmental footprint required to do so. This is good news for farmers who are facing a shrinking population of

agricultural workers in the face of growing demand for food in centralized urban areas. This growing demand has not gone unnoticed by the governments of the world, and many of them are actively taking steps by working with farmers and providing resources for research and development of farming practices that leave the ones farmers have been using in the dust. This focus on sustainability is not just for places like the United States who have the resources to explore new and dynamic avenues for agricultural experimentation. These new techniques and processes are also being quickly adopted by developing nations around the world in order to combat their countries' own hunger and resource problems. With the looming threat of climate change, whose impact is already beginning to make itself more and more apparent around the world, the demand and pursuit of data oriented precision agriculture is increasing at an exponential rate [29]. Since the well being of many developing nations is tied so closely with their agricultural production, they are the most susceptible to climate changes and the damage it can cause to food production [22]. Humanity is good at overcoming adversity, however, and data science is clearly helping to tackle the effects of climate change on agricultural endeavours and food production. The threat of climate change itself is driving entirely new agricultural fields whose sole focus is on sustainability.

There are many factors driving the technological innovation in data science focused agriculture. But of all of them, human caused climate change is perhaps one of the biggest factors driving the changes and modern focus on sustainability, especially in developing nations. "Because most developing countries depend heavily on agriculture, the effects of global warming on productive croplands are likely to threaten both the welfare of the population and the economic development of the countries" [22]. Since developing nations are more sensitive to the effects of climate change because their economies and well being are often directly dependent on their agriculture sector, they are the ones who are benefiting the most from all the advancements in this field. These benefits are having a stabilizing effect in areas where these practices are being used, allowing for these places to develop further in areas that they ordinarily would not be able to focus on if they were still struggling to meet food requirements. By being able to focus on other parts of their society, these nations are able to further develop themselves and achieve greater and greater standards of living and freedoms for their citizens [20]. This is just one example of how agricultural data science has positive effects on society outside of the agricultural and environmental sectors. These effects, when used with noble intentions, are good for everyone.

3.3 Urban and Vertical Farming

As touched upon briefly earlier, when farmers begin producing some of the fruits and vegetables that people need inside of urban areas instead of on farmlands, this helps ease another one of the biggest problems farmers have encountered in the past, the problem of land availability. Again, as populations continue to grow, the stress they put on the demand for resources becomes more and more extreme. Land and resources becomes more and more scarce, not only because they are required for people to live on, but also because lots of other resources are required to handle large populations. Land resources for building roads for transportation, food and

retail zones, resources such as land fills, waste removal, hazardous storage, water treatment, and power plants are just a few of the many other land resource demands that increase hand-in-hand as urban populations increase. One novel solution being used by many countries to tackle the problem of scarce geographic resources comes from thinking dynamically about the problem and realizing that, technically, farmland is not required in order to grow food and have a farm. Instead of expanding outward in order to grow more food, some modern farms are being rethought and built upwards or in repurposed, closed and controlled facilities in major urban areas. By utilizing or building multi-level structures laid out over a semi large area, farmers are able to grow different crops at different levels. These installations can be built in major urban areas, but any open urban space will do. This has the bonus side effect of reusing old buildings that might not have previously been in use anymore, which adds to and promotes a sustainable model. These structures allow for the same kind of closed system farming techniques that precision farming benefits from, while also allowing farmers to control everything that is done to their crops [11]. Having all the plants in urban areas also has the benefit of naturally cleaning the air. Plants use many of the gases released in vehicle emissions for their life functions. Taking these harmful gases out of the air is beneficial to humans, the plants, and the surrounding environment [11]. Building urban farms like this is a win for everyone involved, and as people and governments begin to take a more active role in regards to improving and pursuing sustainable models of food production and environmental protection, urban farms are likely to gain in popularity and start popping up all around the world.

Another angle that can be taken in regards to vertical farming is the idea of growing plants on all available flat surfaces. Not only floors, but also ceilings and walls where available. One problem major urban areas can have is a lack of green spaces available. This takes away from the aesthetics of these urban locations, while also allowing for pollution to go to choke out major areas in cities. Growing plants on some walls and buildings around major cities will help reduce the impact of both of these problems on the people and their environment. The plants being around the city take care of the lack of green places on its own, transforming concrete jungles into lush, semi-green cities. Meanwhile, the plants themselves will help clean up pollutants in the air from human emissions and simultaneously reduce amounts of noise pollution in their immediate vicinity. These green walls can even be limited to urban agricultural buildings themselves and would still be effective and have a positive impact on their immediate environment [28] Again, data science makes all of this possible by allowing analysts and farmers to figure out the best ways to execute their agricultural endeavours, how to grow their plants, which and how much of their resources they need to use, and so forth. Technically, all of this could have and has been done in the past; it is not difficult to grow plants on the sides of buildings. But now urban populations are reaching heights that have never been seen, and the demand on environmental resources and human emissions are ever increasing. These simple approaches to the problems presented above are a means for cities to tackle a lot of the problems in city living, along with helping ease their dependency on farmlands for resources [28]. When urban farmers and city planners have access to data science and analysis tools that allow them to review and analyze information at a much deeper

level, they are able to find new insights into the problems they are trying to solve. These new insights are driving urban farming to the level it needs to be at in order to meet the needs of an ever growing population and increased urban demand on resources.

3.4 Precision Farming: Networked Farms

The idea of a connected farm is paramount in moving beyond the historical approach to farming and agriculture. The cornerstone of understanding and finding better techniques to improve farming is data, and a networked, or smart farm, does just that. By using technology that networks the farmland, the farmer now has access to a decisions support network, which allows farmers the ability to keep track of all the happenings taking place on their property in ways they have not been able to in the past. This new attention to detail taking place allows farmers and agriculturalists to engage in a practice called precision agriculture. Precision agriculture “concentrates on providing the means for observing, assessing, and controlling agricultural practices” [17]. In essence, precision agriculture, or smart farming, focuses on sustainability and finding the sweet spot between resource use and crop growth and food production. Being able to hit that efficiency spot allows farmers to save on resource use while getting the most bang for their buck in regards to crops grown and sold per acre. Farmers are able to take advantage of all kinds of new data at their disposal. They have access to modern technology, which allows them access to things like satellite telemetry data on not only the weather, but also insect populations and blooms, as well as a myriad of data on other farming techniques and practices that are still evolving to improve efficiency and production.

By taking advantage of new technology, as well as Internet of Things based technology, farmers and agriculturalists are able to tap into a source that humans have never been able to use in the past. Examples of modern agricultural technology include advances in wireless sensor technology that allow for the monitoring and changes in environmental conditions, resource use and precision agriculture, warehouse and storage management for storing crops and other perishables, technology that allows for large amounts of automation, and RFID technology that allows for tracking of the distribution of goods from farms [32]. All of these new technologies work in conjunction with one another to improve all aspects of the farm by making it possible to accurately monitor for and detect small problems that might arise and get them taken care of before they turn in to big problems. This proactive process of monitoring for problems fits with the growing importance of sustainability. Getting to problems and fixing them before they become larger issues can help the farm in countless ways. Practical ways in which data science technology can help improve farms are detecting insects, rodents, or other pests before they become an infestation, monitoring environmental conditions outside or in storage spaces in order to ensure that the crops they have stay fresh longer and do not become tainted in any way, determining the precise amount of resources required for individual plots of land or crops being grown so the farm’s resources are being used more efficiently, soil analysis to determine the best kinds of plant strains for their specific farmland, and tracking the distribution of their farm goods in order to more accurately distribute them to retailers. All of these

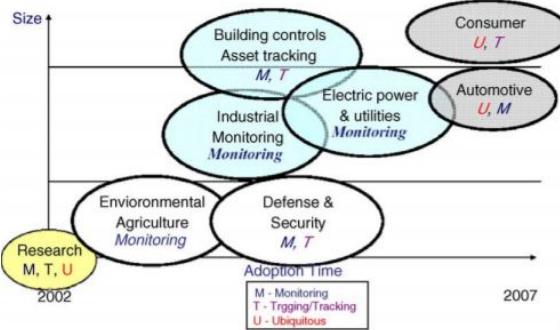


Figure 3: Projections show how quickly the technology was growing at the start of the 21st century [32].

agricultural techniques come together to form the larger picture that shows how much data science has really changed the agriculture sector. All of these technologies only came into existence in the last 25 years [32].

3.5 Modern Agricultural Data Science Beyond Food

Data science has the power to improve farming and agriculture in ways beyond just precision agriculture and growing food in ways and places that have never been done before. By taking a look at the entire picture, it is possible to shave even more off the proverbial top in terms of efficiency and improving sustainability in relation to farming and agriculture. Data science can improve the economic returns of local farmers while also helping to minimize the environmental footprint that is produced from the production and transportation of goods. Modern technology and machines enable for the harvesting, gathering, and preparation of food goods to be automated, faster, and much more efficient than if it was done by hand [32]. Modern technology also allows for the farmer and business owners to keep track of how much of their products are being sold and in which locations. This allows the retailer to order more precise amounts to fit their needs while also informing the farmer which crops are best to grow, when to grow them, and what quantities to shoot for. GPS and other transportation technology can be used in the transportation process to make sure that the drivers have the most direct and efficient routes possible while delivering their goods, and advances in communications technology make it easy for orders to be changed or updated at the last minute [29]. The goal of all of this is to produce less overall waste and put less stress on the environment. Data science helps mitigate problems that would produce more waste and add stress to the environment, so in this way, it is one of the most important tools humanity has in solving these problems and continually improving the agriculture sector to meet the demands of bigger populations.

3.6 Setbacks and Steps Towards the Future

The ability to analyze agriculture data with modern technology is leading to many unexpected discoveries. With sustainability and combating climate change being two of the most important driving

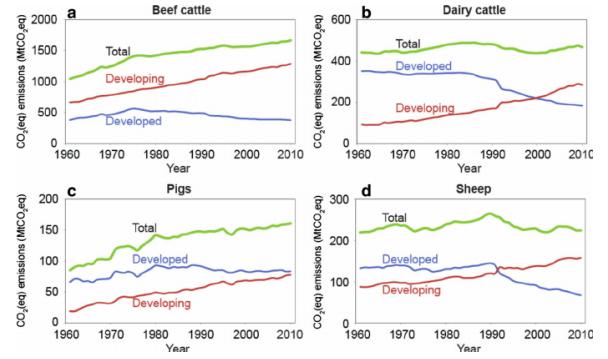


Figure 4: Cattle emissions rate trends over the years [7].

factors in innovation, scientists and farmers and finding are using data science models to find dynamic solutions to problems, both old and new. At this point one of the biggest problems holding back agricultural data science, despite the fact that more and more data is being generated everyday, is the distinct lack of data. There are many challenges that must be overcome as we move towards the future of agriculture, but one of the greatest obstacles “is to obtain reliable data on farm management decision making, both for current conditions and under scenarios of changed bio-physical and socio-economic conditions” [6]. In other words, it is not a question of having reliable data, as much as it is a question of having reliable data that pertains to scenarios and circumstances that are difficult to reproduce, that have not happened yet, but are speculated to happen as the climate change. Despite this, the modern data that has been collected is obviously still being put to good use and helping to solve major problems that humanity knows will be immense obstacles in the future.

One example of a modern solution to an old problem is fighting emissions that pollute the earth. Although it is often thought that vehicle and airplane emissions cause the most air pollution, but of all of humankind’s endeavours, it is factory farming that is having the biggest impact on our environment and exacerbating the effects of climate change [7]. Agricultural data science is being used to help combat the effects of factory farming in a number of unorthodox ways. One recent example of agricultural data science making a breakthrough in this area came when scientists discovered that feeding cows, who are by far the biggest producers of methane and other remissions, ground up bits of seaweed with their regular feed will radically reduce the amount of methane they produce while having no negative affect on the animals [19]. The wireless monitoring sensors and models used to ascertain these findings were only available because they were created from investments in the pursuit of agricultural data science practices. As findings like this become more common and see widespread adoption, the environmental footprint of factoring farming will begin to decline. This will be incredibly useful for developed nations whose factoring farming emissions levels are continuing to rise [7].

4 THE FUTURE OF AGRICULTURAL DATA SCIENCE

The future of agricultural data science is concerning itself with not only continuing to solve and improve the same old problems, but also exploring entirely new, out of this world concepts in regards to farming and growing foods. In the past, agricultural data science was focused on gathering data and growing the field. Modern agricultural data scientists are taking on problems like climate change, staggering populations and their demand for food, and finding new ways to improve sustainable agricultural models. So, then, it seems that the future of agricultural data science is beginning to come into focus. Although new problems and fields are bound to arise, the focus of the future of agricultural data science seems to be on automation and enhanced sustainability through disturbing the environment as little as possible [18]. Since machines are able to perform tasks more efficiently than humans can, reaching a point of agricultural automation is one of the potential goals of sustainable models. A mostly automated farm is much more efficient than one that relies on the human element to perform jobs and work. That is not to say that there will never be a human element involved, but the future farmers may have more in common with data scientists and programmers than they do with their modern and historical counterparts who worked in fields most of the day [23]. As technology improves in ways we cannot imagine right now, the possibilities of how data science will influence agriculture in the future are great.

The future may seem like science fiction in many ways, but modern technology and agricultural procedures may have seemed like science fiction if they were explained to a farmer from the 1950s. That does not mean that we are not able to see where a lot of different areas or advancing, to theorize technology and procedures that farmers and agriculturalists are not able to take advantage of now because they are too expensive. But as technology becomes cheaper and new methods and data science models are built, the future quickly becomes the present as humans catch up with their imaginations. Advances in automation, bloodless food production, extra-solar farming, and eventually terraforming, when realized, have the potential to transform our society in astonishing ways, possibly even leading to a post scarcity society where everyone's basic needs are met. Where agriculture itself enabled humankind to stop focusing on strictly survival and evolve into societies, so too might automated agriculture and food production allow for humanity to achieve a new level of societal evolution [10].

The coming changes in agricultural data science are not simply limited to technological or physical. Indeed, even now as humanity's understanding of its impact on the climate and surrounding environment is coming to be better understood, world governments are beginning to realize the important of sustainability and limiting the environmental footprint that is created from food production. World governments taking an active interest is having a positive effect on the research and development being done in the fields related to agricultural data science [6]. This new emphasis is changing the way many politicians think about agriculture and making them eager to use political leverage to enact changes in government which put guidelines into place and make resources available

that enable agricultural researches to analyze their data and make informed decisions when attempting new agricultural endeavours.

4.1 The Future and Automation

Much as sustainability and environmental impact are big tent poles driving innovation in agricultural data science and technology, so too will they continue to be in the future. However, a third piece of the puzzle is being thought of as more data is generated and analyzed, and that piece is automation. Automation is when technology and machines work to perform the jobs and tasks that humans would ordinarily do. Automation makes work far more efficient because, typically, a machine requires less resources to perform work than a human does. The resources a machine requires come largely in the form of costs upfront, but they quickly pay for themselves [18]. Automation allows for producers to produce their product around the clock, so too would the crops on an automated farm receive constant care and attention that a human would be unable to provide. This fine attention to detail would increase the amount of food produced and improve resource use efficiency for growing food.

This concept is not referring to an enormous, single intelligent farm that knows all. Instead, an automated smart farm would actually be a collection of many smaller, automated systems that all work together to ensure the success of the farm and its food production requirements. Not all farms would need to be completely autonomous in order to benefit from this technology. For example, some farms are already taking advantage of available technology to automate simple tasks and jobs that humans used to perform, such as automated irrigation systems [14] and tools that automatically extract key data bits from current crop conditions and executes automated commands to tend the farm, based on a set of predefined variables [9]. Nonetheless, as more and more automated systems are made available and become less expensive, more farms will be adopting them, leading to an even greater level of automation and requiring even fewer workers with diverse skill sets than ever before.

4.2 Meat Grown in Labs

Climate change is one of the biggest threats spurring research and interest in efforts to improve sustainable agriculture practices. As mentioned earlier, the one human activity that by far has the greatest impact on the environment is factory farming, which is a process of raising cattle and other livestock in controlled conditions [7]. Similar in approach to precision agriculture, factory farming in developed nations is having a substantial impact on the environment from all the emissions the animals produce, as well as the resources that are required to operate factory farming facilities. This poses a problem for future generations since it is an unsustainable model. One solution being aided by data science that is currently too expensive is the possibility of growing meat in a laboratory setting without requiring the growing and slaughtering of actual animals. Basically, this process is "a novel idea of producing meat without involving animals with the help of tissue engineering techniques" [2]. At present levels of technology, this process is possible but far too expensive to be a practical solution to producing food on a large scale. However, data science models are helping to drive

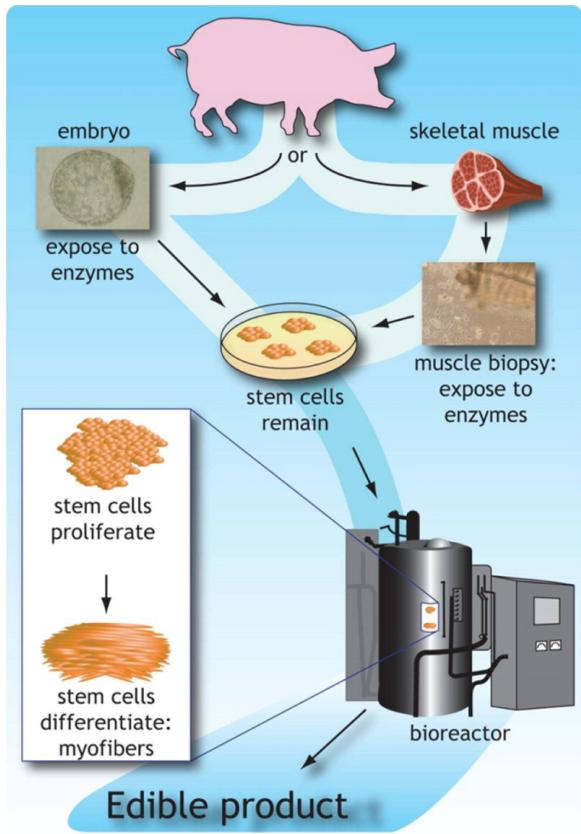


Figure 5: Simplified process by which stem cells grow edible meat [27].

down costs by allowing scientists to analyze their data and find more efficient ways to accomplish their goals. Once it becomes less expensive to grow meat in a lab that is indistinguishable from traditional meat, protein farms will likely start popping up all over the world [2].

There are other benefits to think about when considering the impact of switching from traditional meat production to lab grown. The biggest, as mentioned slightly above, is that it will help to dramatically reduce the environmental footprint being created by factory farming practices. Growing meat in labs, once costs and techniques are worked out, has the potential to be radically more sustainable model than humankind's current practices [15]. Once it becomes possible and feasible to be able to grow all the healthy meat needed to satisfy the demands of the growing population in a labs, this model will begin to be adopted because of the economic and environmental advantages to its use that come with following a model focused on sustainability. Data science is helping to make this more of a reality by producing more advanced models that help scientists and engineers get their jobs done and find newer, cheaper ways to produce this lab grown meat [15].

4.3 Farming in Space

One undeniable truth about humanity is that humans expanding and exploration seem to be hardwired into our genetic makeup.

Since the beginning of humankind's history, exploration and settlement have been a big part of what drives human innovation. Necessity is the mother of invention, as the saying goes. It is in the spirit of that saying that future agricultural endeavours are being theorized and planned for today. One big possibility on the horizon is the necessity to grow food and farm off-world because of lack of space, resources, or environmental factors making the available farmland incapable of meeting the demands of future populations [23]. Once agricultural development and food production reach a tipping point in regards to demands and human population, there will be no choice but to start farming in space. Enormous and fantastical space stations could be constructed where food could be grown in closed systems. This endeavour, though expensive, would eventually pay for itself and allow for a level of control, efficiency, and automation not available on Earth [23]. By designing and constructing a station like this from the ground up, with things like sustainability and efficiency in mind, food will be able to be produced in a way never before practiced by humanity. This has the added benefit of having absolutely no impact on the environment, since it is not even being done on Earth. Right now, space travel and getting super structures like this built are prohibitively expensive. However, the costs of such things are expected to go down as technology advances and methods of space travel become more available [31].

4.4 Terraforming Worlds: the Height of Agriculture

At the most extreme end of outside the box thinking comes the most fantastic sounding concept yet: terraforming. Terraforming is the process of making another planet or heavenly body habitable for humans to live and thrive on. In the distant future there may come a time when humanity needs to take steps to become a multi-planet species. Data science will be invaluable when achieving this level of agricultural endeavour as the amount of data to be processed and understood will require data analysis models and techniques that have not even been invented yet [8]. The ability to adapt a planet to human life would require a complete mastery of agriculture which could only be obtained through refined understanding of unimaginably large amounts of data created from attempting such a task. Right now, scientists can only re-create extraterrestrial soil in a labs and perform experiments to grow food there, so any work done in this field is mostly hypothetical, but not outside the realm of possibility. If humans continue to advance at the exponential pace at which they are, one thing begins to become undeniable clear. Given a long enough timeline, environmental, societal, or geographical conditions will come about that will one day make it a necessity for humans to start living on multiple planets. Although this is science fiction now, data science and the insights its use grants us are making the impossible possible everyday.

One applicable experiment that was performed to test the validity of adapting the soil on Mars to growing terrestrial flora was when scientists looked at the recent volcanic iron deposits in Santorini, Greece. The bizarre lifeforms that were found living in this environment "provides a potentially useful ecosystem for Mars terraforming experiments" [24]. Using data science to gather and make sense of the data generated on terrestrial locations that are

similar to extraterrestrial ones brings humanity one step closer to terraforming, even if it is a baby step. As fantastical a concept as bending another planet to humanity's will is, if you stop to think about it, this is nothing new. Humans have been terraforming the Earth for thousands of years already, just not in the ways we would prefer. Terraforming on a large scale is theoretically possible, but it will never be possible without the data science tools and techniques to analyze the mountains of data that would be need to be analyzed to achieve such a advantageous goal that may one day be a neccesity.

4.5 Restructuring Society

The possibility of achieving a post-scarcity society, while seemingly outlandish considering humanity's current problems, could become a reality in the future. Having all of humanity's food needs met automatically through space aged inventions like massive orbiting space farms and home or lab grown meat would lead to a restructuring of society humans have not seen since we first started farming twelve thousand years ago [10]. Should humanity ever achieve this level of societal progress, data science methods and models will be largely to thank for allowing humans to understand and improve their work by analyzing the data it produces. A largely automated society would produce an enormous amount of data to be analyzed, which as previously discussed, has the benefit of becoming even more sophisticated as more data is generated to learn from [3]. This self reinforcing system of generating data, improving from it, then generating more is showing no signs of slowing down as humanity is only just now beginning to see the benefits of complex automation. Self driving vehicles and automated farms are on the horizon, as well as a myriad of other technological innovations, and data science and its versatile applications are one of the biggest reasons that humanity has to thank for these technological possibilities.

5 CONCLUSION

Humanity's modest roots as simple nomads who discovered that they could grow their own food and use agriculture as a tool to build civilizations lasted for thousands and thousands of years. There were advancements, sure, but they were slow in coming and lacking in sophistication. However, in the last 75 years or so, humanity has seen the agriculture sector explode with new developments in techniques, technologies, and practices that have increased food production and allowed the agricultural sector to keep pace with growing populations that have a greater demand for food and agricultural resources. How was the agricultural sector able to revolutionize itself when in the past, changes came about much more slowly and incrementally? The answer, of course, is that the field of data science has been one of the chief tools used to solve agricultural problems and find solutions that meet the demands of today.

Technological advancements in hardware and modeling systems are ushering in a whole new era of human agriculture that focuses on sustainability. Producing as little waste as possible, while also impacting the environment in ways that contribute to climate change in as few of ways as they can are among the most important goals of modern day agriculture and food production, and data science is helping farmers and agriculturalists achieve these beefy

goals. By creating vast networked farms, modern day farmers and agriculturalists have access to a level of data analysis that has not been available in the past, enabling them to make informed decisions and change the way they do things in order to improve the efficiency and output of their farms. This analysis is also leading to improved sustainability practices on farms by allowing the farmers to understand statistics about resource use and relation to crop growth like they could not in the past. Urban farming is also proving to be a modern solution to food distribution problems in highly populated areas, while also having the beneficial side effect of the plants helping to clean and detoxify the potentially harmful human made emissions that are found in major cities around the world.

The field of data science, from its origin to its current state as one of the premiere methods of human problem solving, is only going to continue to become more and more sophisticated as time goes on. With computer technology continuing to become smaller, cheaper, and more powerful, as well as data analysis models increasing in their reach and sophistication, the future of decision management tools and informed decision making that is going to be available to farmers and agricultural workers will be staggering. The future that agricultural data science is enabling seems like science fiction, but it is rapidly becoming a reality. Major projects like orbiting farms that meet the demands of the Earth's people to terraforming entire planets are going to require advanced tools and models that only sophisticated data science techniques and models will be able to provide in the future. Although humanity is still going through the growing pains of becoming a global, connected community, the future looks bright, statistically speaking. World hunger is still a problem humans are trying to solve, but data science has empowered us to fight it on a level battlefield where. Assuming human innovation continues at the exponential rate it has set for itself, the struggle to feed every human is a battle data science will help us to win.

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Gerrymandering Detection Using Data Analysis

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ABSTRACT

Can the evergreen issue of partisan gerrymandering be solved using data and algorithms? That question is closer to being solved than ever, as a method developed by University of Chicago researchers in 2014 is currently pending approval by the United States Supreme Court. We give a brief overview of the issue of partisan gerrymandering in American politics and why an objective data-informed measure is needed. We examine the method, known as the efficiency gap model, using data from Indiana's recent State Senate and House elections. We then evaluate the effectiveness of this model and take stock of any substantial critiques.

KEYWORDS

Big Data, Elections, Gerrymandering, Voting, Efficiency gap, i523, HID310

1 INTRODUCTION

In 1964 the Supreme Court established in constitutional law the principle of "one-person, one-vote".[14] The idea appears self-evident; the value of any citizen's vote is equal to that of any other citizen's vote. But could anything still exist in our institutions of our democracy that resists this principle? Beyond obvious impediments to voting such as the since-repealed prohibition on women or racial minorities voting, what other barriers could exist? And why has "one-person, one-vote" become an issue as important, and contentious, as ever?

The barrier, many will argue [7][18][23], lies in the concept of "gerrymandering", or the manipulation of legislative district lines for the benefit of one political player over another. But determining whether something is gerrymandered has proven to be a difficult task. And even once you decide something is gerrymandered, what can be done about it? Answers to these questions may be coming in the form of both advanced data analysis, and simple arithmetic.

In this paper we will lay the foundation of the issue: what is gerrymandering, when has it been used successfully, and what have people done to attempt to curb it? It is important to have meaningful context to the loaded political realities behind the term as well as why it is so relevant today. This will lead us into court cases currently being debated today which set up the necessity for data and objective measures to determine the existence of gerrymandering.

We will explore possible tests to identify gerrymandering, particularly the efficiency gap method which is the centerpiece to a court case currently awaiting a decision from the United States Supreme Court. This case could have the potential to make our data-informed measure a legal reality.

We will replicate the efficiency gap method in Python using data from Indiana's recent State Senate and House elections to gauge the

level of partisan gerrymandering baked into the state's legislative maps. We will discuss any complicating factors in this data and make provisions to account for them. We will evaluate these results, seek to find corroborating evidence for the model's accuracy, and suggest further courses of study.

It is our hope that this analysis will provide a clear picture of the state of gerrymandering politics in America today, explain how big data can be used to bring clarity and objectivity to the debate, and showcase how to put these ideas into practice using data-powered applications.

2 WHAT IS GERRYMANDERING?

The building blocks of America's democratic republic are legislative districts. Any one American lives in three overlapping districts: their State Senate district, their State House of Representatives district, and their U.S. House of Representatives (congressional) district. There is a set limit of 435 congressional districts dispersed to the 50 states based on population measured at the last U.S. Census. Within each state, each congressional district must be exactly the same size. Across the nation as a whole, the average population of a district is 710,000 residents. State House and Senate districts are given a 10 percent population range, as long as it is not systematically used to give one party an advantage. The federal government leaves it to the states to draw the lines all three of these maps. While there is some variance, most states have these lines drawn by the state legislature themselves. The lines are redrawn every ten years, after the census is conducted, in a process called redistricting.[6][1][10]

Gerrymandering, simply put, is the process by which a political party in power uses redistricting to "manipulate district boundaries to create maps that systematically advantage the party in control and lock in an advantage for the party in future elections", according to the NYU Brennan Center of Justice.[17] In other words, the political party seeks to maximize the efficiency of each vote for their candidates, while decreasing the efficiency of the opposite party. This is done primarily through by "cracking" and "packing" the district maps:

- *Cracking* means splitting up a bloc of voters loyal to one party into several other districts, thus diluting the power of their collective vote and maximizing the amount of districts the preferred party is competitive in.
- *Packing* means concentrating a bloc of voters loyal to the opposing party into one district, giving them an overwhelming share of the vote in that district, but decreasing their power in several other districts. [18]

The overall effect of cracking and packing is maximize the "wasted votes" of the disfavored party, while minimizing those of the favored party. The concept of wasted votes is crucial to the model we

will examine further. A wasted vote can be defined as one of the following:

- For the winning candidate (party A), a wasted vote is any vote beyond the threshold needed to win, or 50 percent of the vote.
- Every vote for the losing candidate (party B) is considered wasted, as the vote did not net a seat for that party.[18]

You can clearly see the potential for cracking and packing to greatly effect the amount of wasted votes a certain party receives. When a party's voters are cracked into several different districts, the net effect is that their votes go to various losing candidates, thus the votes are all wasted. When a party's voters are packed into one concentrated district, the net effect is that their votes overwhelmingly elect just one candidate, well beyond the needed threshold to win. Thus, all the votes beyond that threshold are wasted.

2.1 History

This is not merely a theoretical exercise. Gerrymandering has been utilized throughout the history of the United States by virtually every political party that has been in power. In fact, the term "gerrymander" dates back to 1812, when the *Boston Gazette* used the phrase to decry a unfairly-drawn redistricting plan signed into law by Massachusetts Governor Elbridge Gerry.[11] A famous political cartoon depicts one particularly contrived looking district as a dragon-esque creature, while others compared its shape to that of a salamander. The colloquial term became "gerry-mander" after the governor who enabled such a result.

The utilization and effectiveness of gerrymandering does not appear to have lessened with time. One of the most effective uses of the practice happened earlier this decade.

In 2008, the national Republican Party was in a dire position. Barack Obama had just been elected president in a sweep that included control of both houses of Congress. They held the House of Representatives by the largest margin seen in almost 20 years.[22] Journalist Michael Grunwald presented a grim narrative for the party in Time magazine in 2009, writing that "polls suggest that only one-fourth of the electorate considers itself Republican, that independents are trending Democratic and that as few as five states have solid Republican pluralities." In addition, he pointed out that the overall population was decreasing in demographics that had proven to be solidly Republican - "less white, less rural, less Christian".[12]

Fast-forward to 2017: Republicans control the White House and Congress, owning the House by almost as large a margin as the Democrats did just 8 years earlier.[22] What happened to produce results that so starkly contrast with the outlook Grunwald predicted?

2.2 REDMAP

In the wake of the 2008 election, the Republican State Leadership Committee launched the Redistricting Majority Project (REDMAP).[16] The strategy of the plan was brilliant in its simplicity: use their funding to target state legislature races in order to control as many state legislatures as possible when the next redistricting occurred in 2011. In most states, the task of drawing new district boundaries is left to the state legislatures.[6] Redistricting occurs after each census to reflect changes in population densities and demographics.

The strategy paid off in giving Republicans control of the redistricting process in many of the states. From there, partisan politics began its work.

REDMAP was a clear success as evidenced by the ensuing 2012 election, the year in which Barack Obama won reelection. In Michigan, for example, voters cast 240,000 more votes overall for Democrats in congressional races, but 9 Republicans were elected and only 5 Democrats. In Pennsylvania, voters cast 83,000 more votes overall for Democrats in congressional races, but 13 Republicans were elected and only 5 Democrats. Across the nation, Republicans won 54 percent of house seats and 58 out of 99 state legislative chambers, while winning only 8 out of 33 Senate races (which are gerrymander-proof as they do not rely on district lines).[16]

The effect of gerrymandering is evident in the results of REDMAP. Republicans maximized the wasted votes of the Democrats and minimized the wasted votes of the Republicans. Although in many cases Democrats had more votes statewide, more Republicans candidates were sent to Congress.

Gerrymandering is an issue seen by many in both parties as problematic. Representative Brian Fitzpatrick (R-PA) wrote in *The Hill* that gerrymandering has caused the nation to stray from its ideal of representative leadership, as it has "has undermined community-focused representation by forcing lawmakers to ideological extremes and exacerbating electoral complacency that causes lawmakers to focus on accumulating power rather than serving constituents".[9]

However, despite bipartisan efforts in the legislature such as those lauded by Fitzpatrick, the most promising avenue for curbing gerrymandering may lie in a different branch of government: the United States Supreme Court.

2.3 The Supreme Court and Gerrymandering

The court has already banned racial gerrymandering in the decision on *Thornburg v. Gingles* in 1986. They determined that a district map in North Carolina violated the Voting Rights Act by gerrymandering the districts in a way that unfairly diluted the power of black voters.[23]

But up until recently, partisan gerrymandering has been left to the states to police themselves. The Supreme Court has heard around 50 cases in its history imploring the court to intervene against a partisan gerrymandered map, and each time has deferred.[18] The last major case was *Vieth v. Jubelirer* in 2004. Justice Antonin Scalia, since deceased, delivered the majority opinion stating that the courts were not responsible for partisan gerrymandered maps as they were "non-justiciable".[7]

But the court is not unanimous in the opinion that partisan gerrymandering cannot be solved through judicial means. The vote in *Vieth* was a narrow one, and even those following Justice Scalia's lead had a range of views on the subject. Justice Anthony Kennedy, for example, is reliable in his unreliability - he serves as the court's "swing vote", as court observers are often unsure which way he'll fall on a given issue until the decision is handed down. Given the court's ideological polarity often leads to close votes, this arguably makes him the most powerful justice on the bench.

In *Vieth*, Kennedy voted along with the majority opinion that upheld the allegedly-gerrymandered maps. However, he left open

the possibility of the court adjudicating gerrymanders, if a clear standard could be found for determining whether a map is gerrymandered or not.[7] Kennedy's logic was clear - the objective nature of a partisan map should not be left up to the subjective nature of a given judge's disposition. Any given judge could invent his or her own criteria for a map to be gerrymandered, and the nation would be buried in lawsuits alleging every map was gerrymandered. But if there were one, universally agreed upon measure that could serve as a standard from which to judge gerrymandering, this problem would not arise. Kennedy had not yet seen such a standard by the time he had voted in *Vieth*, but he did not write off the possibility that a standard could be developed that satisfied his criteria.

Such a standard has not been apparent until, perhaps, now.

3 THE EFFICIENCY GAP

In 2017, a case reached the Supreme Court alleging that the Wisconsin State Assembly was gerrymandered in such an extremely partisan way as to render it unconstitutional. The plaintiffs, savvy enough to recognize Justice Kennedy as the potential swing vote and remembering his desire for a clear standard, argued their case using the "efficiency gap" method.[7]

The efficiency gap method was developed by University of Chicago law professor Nicholas Stephanopoulos and Eric McGhee, a researcher at the Public Policy Institute of California.[18]

The efficiency gap is a relatively simple formula, based on the aforementioned concept of wasted votes. The formula takes the total statewide wasted votes of party A and subtracts the total statewide wasted votes of party B, and then divides that number by the total number of statewide votes to find the efficiency gap score.[19]

$$\text{Gap} = \frac{\text{Waste}(A) - \text{Waste}(B)}{\text{TotalVotes}}$$

Another way it can be written:

$$\text{Gap} = (\text{Seat margin}) - (2 \times \text{Vote margin})$$

The "seat margin" is the percentage of seats you win from the statewide allotment minus 50 percent, and the "vote margin" is the total percentage of the vote you win minus 50 percent. A negative result means the map is biased against you.[19] This is a helpful format when we begin measuring the net effect of gerrymandering in congressional districts.

If the two parties have similar numbers of wasted votes, or neither party has a significant amount of wasted votes, the efficiency gap score for that state will be low indicating acceptable levels of map bias. However, if one party has a disproportionate number of wasted votes compared to its opponent, the result will be a higher efficiency gap score indicating unacceptable levels of map bias.

This method captures the effects of both cracking and packing: packing will be detected by the wasted votes from an excessive victory, and cracking will be detected excessive amounts of losing votes statewide.

Let's apply this to an example. Let's say Party A and Party B are competing in a state with ten congressional districts of 100 people each.

Per 1, in Districts 01, 04, 06, and 09, Party A wins by an overwhelming margin. In the rest of the districts, Party B wins by

Table 1: Election Scenario A

District	Party A votes	Party B votes
01	90	10
02	49	51
03	45	55
04	95	5
05	45	55
06	90	10
07	49	51
08	45	55
09	95	5
10	45	55

Table 2: Scenario A Total Votes and Net Seats by Party

	Party A	Party B
Votes	648	352
Seats	4	6

Table 3: Scenario A Wasted Votes by Party

District	Party A Wasted votes	Party B Wasted votes
01	40	10
02	49	1
03	45	5
04	45	5
05	45	5
01	40	10
02	49	1
03	45	5
04	45	5
05	45	5
Total	448	52

narrow margins. This results in more votes being cast for Party A statewide, but Party B gets more seats as shown in 2:

These races result in an overwhelming amount of wasted votes for Party A, and a minimal amount for Party B as shown in 3.

We can see that Party A has many more wasted votes than Party B, indicating the map may be drawn to minimize the efficiency of Party A. We then add up the total number of votes cast statewide and plug these numbers into our efficiency gap formula:

$$\frac{448 - 52}{1000} = \frac{396}{1000} = 0.396$$

So our efficiency gap, written as a percentage, is 39.6 percent. The map is clearly tilted in favor of Party B. But is it considered illegal gerrymandering? In their paper, the authors establish thresholds for when an efficiency gap indicates levels of illegal gerrymandering:

- For state legislature maps, an efficiency gap score above eight percent is considered illegally gerrymandered. The mere percentage is used as each legislature is an entity unto itself, elected wholly by voters in the state. This along with variances in size among state legislatures, makes efficiency

gap the best way to normalize disparate state houses for comparison.

- For congressional maps, a state is considered illegally gerrymandered if the map costs a party two seats. In contrast to state houses, the authors contend, "aggregate House seats are the parties' main objective". In that regard, seats are the best way to normalize disparate state sizes for comparison.[20]

If we write our formula in the format (Seat margin) - (2 x Vote margin), we can measure how many seats were lost as a result of the biased map. In this example, Party A won 64.8 percent of the vote, but was awarded only 4 out of the 10 seats. For Party A:

$$\begin{aligned} (.40-.50) - (2 \times .148) \\ -.10 - .296 \\ -.396 \end{aligned}$$

Now let's give Party A enough seats to make the efficiency gap score as close to 0 as possible. We will say that Party A in this alternate scenario received 8 seats, represented as .80 in the seat share value:

$$\begin{aligned} (.80-.50) - (2 \times .148) \\ .30 - .296 \\ .004 \end{aligned}$$

We have brought the score effectively to 0. So using this formula, we have determined that the efficiency gap derived from the biased map cost Party A a total of 4 seats, well above the threshold for illegal gerrymandering.

The question remains whether this standard will be used to measure map bias and judge gerrymandering. During oral arguments for *Whitford* in October 2017, Chief Justice John Roberts referred to the theory as "sociological gobbledegook".[25] But some court observers are anticipating Justice Kennedy, the swing vote, to vote in favor of the efficiency gap test.[27]

3.1 Criticism

As with any politically-charged debate, the efficiency gap has drawn criticism for simplifying the electoral process too much to come to its result. Critics contend that there are several factors the method ignores that may explain the phenomenon of gerrymandering. Two such critics, Chris Winkelman, an attorney for the National Republican Congressional Committee and Phillip Gordon, an outside attorney, filed a brief with the Supreme Court in the *Gill v. Whitford* case exposing what they saw as flaws in the efficiency gap formula.[26] These are indicative of the major arguments against the efficiency gap that we have found.

- (1) The method assumes that voters' party loyalties are static.

In predicting the future, the model assumes that voters never change their minds and are not swayed by the contextual candidates involved. Winkelman and Gordon point to the 2012 and 2016 elections. They contend that studies have shown between 11 to 15 percent of voters chose Barack Obama, a Democrat, in 2012 and then chose Donald Trump, a Republican, in 2016. In addition, in 2016 12 Democrats won in districts that elected Trump while 23 Republicans won in districts that elected Clinton.

- The efficiency gap method accounts for this by taking into account several elections in a row, rather than one single election. With more data smoothing out any abnormalities in partisan preference (for example, voters in blue-collar districts turning out in overwhelming numbers in 2016 to vote for Donald Trump), this should lessen any "pendulum" effect on the overall efficiency gap score.

- (2) The method ignores the effect of partisan geometry. The method assumes that partisan loyalties are spread out evenly among a state, when this is not the case. Typically, Democrats tend to concentrate heavily in urban areas, while Republicans are more thinly spread out among rural and suburban areas. This makes drawing maps in a compact and contiguous manner, which most agree is the ideal way to draw a map as opposed to winding, snake-like districts that are clearly to lump chosen groups of voters together, naturally beneficial to Republicans.

- The efficiency gap authors concede that the measure may capture legitimate redistricting methods under the purview of gerrymandering. Thus, in outlining their proposed court test, they allow that states above the threshold could show that the the gap was the result of either the "consistent application of legitimate policies", or "inevitable due to the states' underlying political geography".[20]

4 APPLICATION

We implemented the efficiency gap method into a python application powered by real-world election data in order to determine whether the district maps for Indiana's House of Representatives and State Senate pass or fail the efficiency gap thresholds.

Indiana was chosen arbitrarily, primarily because it is the home to both the author and institution of this paper. In addition, Indiana's legislature gives us clean and uniform data to work with, as there are an even number of senators and representatives elected, no special elections, and no run-off elections to complicate the data. However, after implementation of the application, it became apparent that it was fortunate Indiana was chosen as the results showcase important teaching moments in understanding the efficiency gap and its applications.

Because we were evaluating state legislatures, we did not have to calculate seats lost, so the results are given in raw efficiency gap score.

4.1 Data sourcing and cleaning

For our data, we use the election results from the 2016 Indiana House of Representatives races[3], and the 2014 and 2016 Indiana State Senate races[2][4]. The data was collected from Ballotpedia, an online election and candidate encyclopedia. For context, each member of the House is elected every even year for a two-year term. There are 100 representatives. Each member of the Senate is elected to a four-year term, with elections occurring every two years to elect half of the members. There are 50 senators. Thus, to receive a full sample of the House races, we only needed to collect

data from one election year. But for the Senate, we needed two election years in order to collect data for the full senate.

There were two complicating factors with the data that needed to be cleaned before implementation into our model:

- (1) One third of the races in 2016 were uncontested, meaning the winning candidate had no opposition to compare to. In 2014, almost half were uncontested. Depending on the county data recording, these are represented in one of two ways.
 - (a) The votes cast for the winner are displayed, resulting in an election that looks like 20,000 votes were cast for candidate A, and 0 votes were cast for candidate B.
 - (b) No votes are displayed, and the winner is simply displayed as a default.

Both of these taken at face value are problematic for our model. In the first case, plugging these results into our model could overstate how many wasted votes there were for the winning candidate, as the model would think that the winner received 20,000 more votes than they needed to, and the loser received no wasted votes. This is unlikely to occur in reality if the opposing party had fielded a candidate. Even if it is not a close race, the loser would accumulate enough votes to alleviate the amount of wasted votes accrued by the winner and increase the amount of wasted votes for the loser.

In the second case, rather than overstating the wasted votes, they are understated. The race is treated as a draw in terms of wasted votes, when uncontested elections would in reality be a major symptom of an efficiency gap and wasted votes should be accrued.

Clearly, they cannot be ignored. The efficiency gap authors provide guidance on what to do with these races. For state house races, they ran a multi-level model using a fixed effect for incumbency and random effects for year, state, and district. If the district had been contested in its past, the value was derived from other districts in the state during that year along with the same district in other years. If not, they had a random draw of random effects. [21]

The results were a mean Democratic vote share of 66 percent for uncontested Democratic candidates, with 90 percent of values falling between 52 and 83 percent. Democratic vote share for races with uncontested Republicans was placed at 36 percent, with 90 percent of values falling between 22 and 43 percent. The authors do not hold this solution to be the be-all-end-all model for computing vote shares of uncontested candidates, as they "encourage scholars to explore a range of imputation techniques." [21]

Our solution was to uncritically use the authors' figures of 34 percent share for Republicans in uncontested Democratic seats, and 36 percent share for Democrats in uncontested Republican seats. For those seats that had no winning vote data available, we took the average population of a district, adjusted for that year's vote turnout, and applied the percentages to that number. For those seats

with winning vote data, we simply took half of the winning votes as the loser's share of votes.

- If further work to be undergone on this application, we would recommend fine tuning these calculations, particularly if one were to specifically focus on a particular state legislature, as vote shares for a given political party would most likely vary from state to state.
- (2) The other complicating factor for this experiment was the existence of third parties. In the efficiency gap calculations, third party votes are ignored, relying on the two-party vote.[24] For most districts, the effect that third parties have is marginal:

- The United States is a two-party system, mostly due its "winner take all" election rules (where the party with the most votes is the singular winner in a given race, whereas a proportional system would give distribute legislative seats proportionally based on vote share). Third parties therefore have a difficult time gaining any sort of power:
 - The highest vote share of any third party in the 2016 presidential election was 4 percent for the Libertarian Party, the highest share the Libertarian Party had ever received in a presidential election.[5]
 - There are no third party members of the Indiana House of Representatives and the Indiana State Senate.[4][3]
 - There are no third party members of the U.S. House of Representatives.[22]
- Third parties are varied; there is no one singular third party to claim a stake in the redistricting process. Thus, their voice is diluted by diversification.
- When we establish that we are operating under a binary party system, third parties make no difference in the efficiency gap formula, as a vote cast for a third party candidate is wasted for Democrats and Republicans equally, thus cancelling itself out.

The solution was straightforward - we simply removed third party votes from our calculations and operated under a two-party vote system.

4.2 Implementation

The application made moderate use of the Python Pandas module. We began by importing two dataframes: the 2016 House results, and the 2014 and 2016 Senate results combined into one dataframe. Because the efficiency gap is a simple formula, the values needed are similarly simple. The only values needed were the Republican votes and Democratic votes for each district as seen in 4:

With the data imported, the first step is to calculate the wasted votes for both parties. We have two separate functions to calculate Democratic wasted votes and Republican wasted votes.

```
def dwaste(row):  
    if row['dvotes'] > row['rvotes']:  
        val = row['dvotes'] - ((row['dvotes'] + row['rvotes']) * .5)  
    else:  
        val = row['dvotes']
```

Table 4: Indiana House votes sample [3]

district	dvotes	rvotes
1	15561	7780
2	24820	12786
.	.	.
99	24820	12786
100	14110	7055

return val

The Republican wasted votes function is identical except the 'dvotes' and 'rvotes' values are switched. This portion of the script goes line by line through the dataframe to calculate the wasted votes for each party per district. This needs to be done row by row as wasted votes cannot be found as an aggregate statewide total, but by looking at each individual district race.

Next, we applied the rwaste() and dwaste() functions to our data frames, and then we can get our statewide totals of wasted votes by party:

```
df['rwaste'] = df.apply(rwaste, axis=1)
rtotal = df['rwaste'].sum()
```

From there, we plugged the statewide wasted votes totals into our efficiency gap formula:

```
((dtotal-rtotal)/((df['rvotes'].sum()+df['dvotes'].sum()))*100
```

Finally, we implemented a simple function that serves as our threshold test. If the formula falls above 8, it triggers an "UNCONSTITUTIONAL GERRYMANDER" response:

```
def eg():
    if final >8
        print("UNCONSTITUTIONAL GERRYMANDER")
    else:
        print("ACCEPTABLE")
```

Since the data used for this particular experiment is small, the application was able to be executed on a personal computer using an Ubuntu virtualbox.

In short, the input for this application is a .csv dataframe of every seat's Democratic and Republican votes, and the output is the efficiency gap score in percentage form and an indication whether the legislative map exceeds the threshold for unconstitutional gerrymandering. This framework is simple in the data needed and could easily be replicated for any state legislative body.

4.3 Results

The application revealed that the House of Representatives, with 2,992,624 votes cast, had 838,675 Democratic wasted votes and 657,637 Republican wasted votes resulting in an efficiency gap score of 6.05 percent in favor of Republicans. This falls under the 8 percent threshold, indicating that if the efficiency gap were to be adopted as a court standard by the Supreme Court, this map would be ruled constitutional.

On the other hand, the Senate, with 2,107,263 votes cast, has 661,509 Democratic wasted votes and 347,122 Republican wasted votes resulting in an efficiency gap score of 15.58 percent in favor of Republicans. This lands well above the gerrymandering threshold.

Table 5: Indiana Gubernatorial results by year

Year	Republican	Democrat
2008	58.8%	40.0%
2012	49.4%	46.5%
2016	51.3%	45.4%

If this standard were to be adopted by the Supreme Court, there is a decent chance the Senate map would be ruled unconstitutional.

There are a few factors to consider that may be used to explain the discrepancy with the Senate vote:

- If we take at face value that the Senate is twice as gerrymandered as the House, a major reason could be district size. The House has twice as many districts as the Senate over the same land area. The more granular a district is, the more difficult it becomes for a map to be gerrymandered, as you have smaller populations and smaller land areas per district. People of similar ideologies and political leanings tend to group together, so with smaller parameters, it becomes more difficult to group some of these individuals with opposing parties in order to "crack" their vote.
- If we are skeptical, the results could be explained by the fact that half of the Senate data was taken from the 2014 midterm election, while all of the House data was taken from the 2016 presidential election.
 - Midterm elections tend to have lower voter turnout, so the data may not be as accurately reflect the true political landscape of a region. In 2014, Indiana had a voter turnout rate of 28 percent, the lowest in the nation that year[15], compared to 58 percent in 2016.[13]
 - Historically, Republicans tend to have higher turnout in midterm elections. Nationally, Republicans were 20 percent more likely to vote in 2010 and 2014 than Democrats were, according to an analysis by the New York Times' Nate Cohn. [8]

Further analysis would need to be done in order to determine if this explanation suffices. It would, in fact, be in the Republicans best interest to find an alternative explanation other than gerrymandering. Again, it can be allowed that states above the threshold could show that the the gap was the result of either the "consistent application of legitimate policies", or "inevitable due to the states' underlying political geography".[20]

However, when compared to other Indiana political measures, the Senate result is not especially surprising. While the Indiana is admittedly a "red state", or a state predominantly partial to Republicans, the Senate seat share appears to be out of sync with other measures. Currently, there are only 9 Democrats to 41 Republicans in the Indiana State Senate[2][4], meaning the Democrats have a 18 percent seat share. Compare this with the last three statewide elections for governor in Indiana in 5:

Meanwhile, the House of Representatives has 30 Democrats to 70 Republicans [3], which, while slightly lower than the gubernatorial vote share, can be explained as a "winner's bonus", or a small surplus of votes for the overall winning party. This is accepted by the efficiency gap authors and political scientists as a common

feature in American political systems. They also accept that the USA is not a proportional representation system, where vote share corresponds virtually 1:1 with seat share.[19] Therefore measures like gubernatorial vote share versus legislative seat share cannot be used to prove partisan gerrymandering on its own, however, when drastic enough, it can certainly be used as a symptom to correspond with a more direct objective measure.

5 LIMITATIONS

Considering we developed an application for one state out of 50 from just one election cycle, and we did not develop an application for a congressional analysis, the scope of our analysis is limited.

If further research and applications were to be conducted, especially in the realm of big data, it may prove to be beneficial to scrape data from all 50 states to create a time series of state legislature efficiency gap changes across the entire country. This could be coded to import election results dynamically as they are held. This would be useful in observing changes in efficiency gap scores in response to implementations of redistricting plans, identifying ideal redistricting methods, and generating data for use in speculative algorithm-based redistricting applications.

There is also much big data potential in gerrymandering solutions and redistricting methods, while we have been limited to detection. AI and machine learning applications applied to the currently human-driven redistricting effort could prove to be revolutionary for this aspect of our electoral system.

6 CONCLUSION

An objective way to measure gerrymandering? Or, as Chief Justice John Roberts so colorfully put it, "sociological gobbledegook"? That definitive answer to that question lies outside the scope of this analysis, and the relevance of that question lies solely with the United States Supreme Court. They have the power, in coming months, to either make this measure the standard with which to measure all district maps moving forward, or toss it aside and continue this country's long history of ignoring partisan gerrymandering as far as the law is concerned.

We have shown how data can be used to transform the debate around partisan gerrymandering, taking what used to be a heated back and forth based on the arguers' political persuasions and elevating it to a debate on which mathematical standard should be used to measure gerrymandering. Though, some still contend that it cannot be measured objectively whatsoever.

We have demonstrated on a preliminary basis some correlation between an excessive efficiency gap score and a disproportionate vote share in the case of the Indiana State Senate.

At the very least, we have sought to prove that the efficiency gap is indeed easy to calculate based on the parameters specified by the method's creators. For someone such as Chief Justice John Roberts, simpler may be better.

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Can Blockchain Adoption Mitigate the Opioid Crisis Through More Secure Drug Distribution?

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ABSTRACT

Like TCP/IP in the 1970s and 1980s, blockchain is a new, intriguing but grossly misunderstood technology that is still in its infancy. It is commonly misunderstood as just a technology for Bitcoin and cryptocurrencies. However, blockchain's use cases extend beyond just financial transactions and cryptocurrencies, and have the potential to transform nearly every industry including healthcare and supply chain. As the technology matures, additional transformative use cases could expand into drug distribution and specifically to opioid supply chains. Despite this potential, a publicly-available blockchain specifically for opioid supply chains was not found. Therefore, to demonstrate how a blockchain would function on a simplified opioid supply chain, a blockchain, using Python code, was developed as a proof of concept. This source code is publicly available to allow others to further develop the blockchain model for more complex and real-world opioid supply chains. The collective review and analysis of blockchain, pharmaceutical supply chains, the opioid crisis, and the demonstrated blockchain model suggest that the adoption of blockchain systems for prescription opioid supply chains would enable numerous capabilities that could mitigate certain aspects of the opioid crisis.

KEYWORDS

HID212, HID210, HID225, i523, blockchain, opioid epidemic, pharmaceutical supply chain, healthcare

1 INTRODUCTION

1.1 The Need to Modernize Global Record Keeping

Contracts, transactional records, and verification systems are part of the foundational core of the global economy. However, as Iansiti and Lakhani [37] explain, these tools have not modernized to keep up with the needs of the rapidly evolving global economy and are “like a rush-hour gridlock trapping a Formula 1 car.” Records and transactions are still being managed as they were in the 20th century which creates broad consequences for nearly every industry including supply chain and healthcare.

In supply chain, data management methods for records and logistics are usually inconsistent across the different levels of a supply chain [7]. The outdated record management method encourages redundant data to be stored at the same organization as well as across the supply chain which increases IT maintenance costs and decreases trust and transparency [30]. These issues prevent a tertiary party, like the government, to effectively scrutinize records.

Outdated data management processes also negatively impact healthcare. In the USA in 2014 healthcare fraud cost an estimated

\$272 billion [22], and in 2016, healthcare data breaches impacted over 27 million patients [16]. Today, medical data management is stifled by antiquated technology that limits patients' ability to manage and control access to their electronic medical records [23].

In addition, pharmaceutical supply chains are enervated by current record-keeping technologies. Transactional records are rarely shared across pharmaceutical supply chain organizations which consequently increases inventory levels [52]. As a result, total healthcare cost and the opportunity for counterfeit drugs increases [66]. In addition, verification systems are often independent among supply chain retailers and prescribers. The lack coordination opens the door for “doctor shopping” and greater prescription medication abuse [24].

1.2 Rational Exuberance for Blockchain

The adoption of blockchain, “an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way” [37], has the potential to resolve these and other fundamental problems of the global economy by overcoming many of the antiquated shortcomings of the traditional means of managing and verifying contracts and transactions. However, like TCP/IP in the 1970s and 1980s, blockchain is an immature technology that faces numerous challenges to mass adoption. In spite of its current limitations, blockchain is already seeing promising applications in various industries extending beyond just finance including healthcare and supply chain.

One particularly exciting use case sits at the intersection of healthcare and supply chain. Blockchain could provide a more secure distribution system for opioid medications that would develop enabling and foundational capabilities that would potentially mitigate certain aspects of the opioid crisis. To further develop and evaluate this potential use case, a blockchain model based on a simplified pharmaceutical supply is presented with publicly-available source code for further development.

2 BLOCKCHAIN OVERVIEW

Blockchain's secure distributed ledger framework includes three data types and has the potential to deliver numerous benefits but faces major hurdles toward mass adoption. Proper application of design principles can overcome these hurdles and accelerate the realization of these benefits.

2.1 The Blockchain Framework

Blockchain is a foundational technology comprised of numerous technological processes and entities [37]. Some of the most significant pieces follow.

2.1.1 Node. Nodes are the individual units connected to the blockchain network. They are computers with adequate software to maintain a blockchain. The blockchain network connects all the nodes and can read and write data to a block [65] [40].

2.1.2 Block. Blocks are the group of records, bundled together by nodes. They follow a specific set of rules and have limited size. Blocks are also linked to the last generated block, thus forming a chain [65].

2.1.3 Smart Contracts. Smart contracts are the codes with timestamps to represent a contract [65]. Iansiti and Lakhani [37] believe that “smart contracts” may be the most transformative blockchain application at the moment,” because they allow for automatic payments whenever contract conditions are met.

2.1.4 Submit Transaction. In case of a new transaction submission to the network, an individual node circulates it to all the other nodes in the network [65]. The main purpose of circulation is approval.

2.1.5 Transaction Approval. When a transaction is submitted and circulated in the network, each node verifies it. Invalid transactions are deleted [65].

2.1.6 Consensus. For multiple systems to work in a distributed network, they must have an agreement. Such a structure is useful in case of fault tolerance when those agreed set of protocols help to restore the data [65].

2.2 Data Types in Blockchain

There are three major types of data stored on a blockchain, namely un-encrypted, encrypted, and hashed [30].

2.2.1 Un-encrypted Data. All the organizations have read access to the un-encrypted data. Such data is fully transparent and facilitates immediate dispute resolution [30].

2.2.2 Encrypted Data. The encrypted data can only be read by the organizations with the access to such data. This means an organization should have a decryption key to read to read the encrypted data. Encrypted data provides restricted access but is also stored in every node in the blockchain. In case of a dispute, the decryption key could be used by different organizations to rectify the entry or deletion of any record [30].

2.2.3 Hash Data. Hash data is also a hidden data type, where hash keys act like fingerprints to represent changes or entry for any data record. Each organization can easily confirm their hash keys. Breaking the hash key is nearly impossible. Only the hash key is in the blockchain while the record data is stored off-chain by individual organizations. Data could be revealed, in case of a dispute, by the respective organization [30].

2.3 Benefits of Blockchain

The exuberance surrounding blockchain stems from the fundamental benefits that are cornerstones to nearly every industry.

2.3.1 Trust. Blockchains enable parties that do not know each other to trust each other. No single organization is trusted to maintain the records. Instead, all organizations must approve the contents of the record in order to avoid disputes. Therefore, records should have a timestamp and an origin proof. Normally, a third party facilitates this requirement. Blockchains can provide an alternate solution, where organizations jointly manage the records and preventing corruption by a single organization [30].

2.3.2 Access. Blockchains allow for greater control over what information is and is not accessible. The technology enforces identical data to be stored by each organization. When one copy is updated, all the other copies are also updated. This eliminates the need for a third party to facilitate management of records [38]. Alternatively, different levels of read and write access could be provided to different organizations. Although some meta data should be stored in the public ledger.

2.3.3 Redundancy. Blockchain also assists in providing security by disallowing redundancy at the same node. The core logic of blockchain does not allow duplicate entries to be created in the same place which obviates the risk of duplicate entry, either intentional or accidental [7]. For example, one of the major benefits of Bitcoin is that the same coins can be spent in multiple places, overcoming the so-called “double spend” problem [69].

2.3.4 Transparency. Transparency in a business helps to grow trust among organizations. Sharing information can improve relationships among these organizations. Without blockchain, transparency is hard to achieve. Blockchains can help improve the visibility of contracts, legal documents as well as other inter-organization data [65]. Organizations are not obligated to show all of their data. Varying levels of access can be provided for data that could be useful to other organizations and a shared collection of records can also be stored and managed by co-operation from different organizations [69].

2.3.5 Low Transaction Costs. Through by-passing third-party verification systems such as brokers, lawyers, or banks, blockchain could significantly reduce transaction costs. Not only will this lower costs for existing transactions, it could open up the market for micro-payments [37].

2.4 Challenges to Blockchain Mass Adoption

While blockchain adoption has the potential to help a wide variety of the world’s problems, it should not be viewed as a panacea. Blockchain is not mature enough to support mass-market adoption and faces numerous challenges. Rabah [62] states that to be effective, blockchain needs to overcome its shortcomings of lacking standard protocols, unclear regulation, large energy and computing power consumption, privacy, cultural adoption, and high initial capital requirements. Tapscott and Tapscott [69] agree that its current technical infrastructure is not sufficient, its energy consumption and computational requirements are not sustainable, and user-friendly systems have yet to be designed that would allow for mass market adoption.

Society would have to dismantle many technological, governance, organizational, and cultural barriers to create new foundations for a new world economy that relies heavily on blockchain [37]. This will come at the cost of some existing societal norms, core business functions, and people's jobs [37] [62].

2.5 Technology Adoption Lifecycle

Iansiti and Lakhani [37] argue that the process for mass adoption of blockchain may take longer than expected but will follow a fairly predictable technology adoption pattern that parallels the adoption of TCP/IP (transmission control protocol / internet protocol). TCP/IP started as *single-use* and matured to *localized uses, substitutions, and transformations*. It was introduced as a *single-use* in 1972 for e-mail in ARPAnet, a precursor to commercial internet for the US Department of Defense. Met with skepticism, this technology slowly gained traction among some firms in the 1980s and early 1990s for *localized use* and did not become mainstream until the emergence of World Wide Web in the mid-1990s. This then paved the road for infrastructure companies to provide the necessary hardware and software to establish "plumbing" systems for the internet. Once the technical infrastructure was mature enough, companies then developed businesses that *substituted* existing services with online services (such as Amazon books instead of Borders). Finally, a wave of companies created *transformative* applications that fundamentally changed service experiences (such as Napster in the music industry or Skype in telecommunications).

Similarly, blockchain was also launched for a *single use* in 2009 for Bitcoin, a virtual currency. Blockchain has matured to extend beyond cryptocurrencies and is now being applied for various *localized uses* including in healthcare and supply chain. It took over 30 years for TCP/IP to realize its potential, and blockchain will likewise require decades to mature into a revolutionary economic force. However, companies can start planning for this revolution today and implement blockchains that follow seven key design principles [37] [69].

2.6 Seven Design Principles for Blockchain

Tapscott and Tapscott [69] in their book *Blockchain Revolution* propose seven design principles that, when appropriately applied, can help blockchain move down the technology adoption lifecycle and create more honest, cost-effective, and accountable systems.

2.6.1 Networked integrity. Because all organizations on the blockchain must approve updates, "Participants can exchange value directly with the expectation that the other party will act with integrity" [69].

2.6.2 Distributed Power. Since the blockchain is distributed across a broad network, it cannot be dismantled by authoritarian power, hackers, or other bad actors. There are no single points of failure and the blockchain can still perpetuate even if numerous nodes are compromised [69].

2.6.3 Value as Incentive. Blockchains can align incentives of individual participants with the interests of the entire blockchain. This minimizes organization problems and conflicts of interests [69].

2.6.4 Security. Blockchains can protect against hackers, malware, ransomware, and identity theft by using a variety of security features. Public key infrastructures, private keys, public keys, and verification methods verify participant activities and prevent bad actors from overriding the network [69].

2.6.5 Privacy. Blockchains can and should provide participants with the freedom to expose as little or as much information about themselves as they desire. This allows a participant to act anonymously when desired or to share sensitive information with only appropriate parties when needed [69].

2.6.6 Rights Preserved. To protect against counterfeit items, a blockchain can serve as a public ledger of ownership [69].

2.6.7 Inclusion. Currently, access to certain financial services is limited to those who are deemed "creditworthy". Blockchains can and should have significantly lower bars of entry that are not managed by banking institutions so that even a poor rural farmer on a remote corner of Earth who isn't creditworthy, could participate in the blockchain [69].

3 BLOCKCHAIN APPLICATIONS IN SUPPLY CHAIN AND HEALTHCARE

In the broad public's view, blockchain is mostly known for Bitcoin; however, people are beginning to realize its potential to transform nearly every industry [37]. Two such industries include supply chain and healthcare.

3.1 Supply Chain

Blockchain, being a public ledger, can be used in different domains with slight variation in its core attributes. While the general implementation says that the data of a single block is public to all the nodes, different sets of access rights could be provided to different classes of users. Such implementation of blockchain could be applied to a supply chain network.

A supply chain requires the involvement of various parties helping each other. This is generally a one-to-one chain network. Often, each organization uses different technologies for record keeping. Record keeping could involve any information ranging from direct communications to logistics. Trust is an important issue between organizations. Most of the organizations in a supply chain keep individual records, which are not public to other organizations in the supply chain. Organizations share some information like contracts or notarized data. An efficient management of such shared data can be accomplished using a blockchain. The blockchain provides the ability to collect, record, and notarize different types of shared data [30].

Blockchain could also facilitate storing and maintaining logistics data. Such an application could be useful in the field of healthcare, where the government wants to monitor the supply of drugs. By simplifying the storage and management of information, blockchain could provide easy access of such critical public sector information to government organizations while providing data security [10]. Blocks comprise of the data records. When these blocks are added to the chain, they become immutable. This means they cannot be deleted or changed by a single organization [10]. A consensus has to be reached by a majority of the organizations for changing any

record. Such a feature helps to maintain the security of the records by eliminating data corruption. Each block is verified and managed using some shared protocols. This process can be automated to allow ease of data entry.

3.2 Healthcare

Representing over 17% of the United States' GDP, healthcare costs continue to soar [24]. Healthcare data in the United States reached 150 exabytes in 2011 with Kaiser Permanente, California's health network, reportedly having between 26.5 and 44 petabytes alone [14]. The volume of healthcare data is likewise soaring, doubling every 12-14 months [20], and the diversity of this data scattered across disparate systems further complicates its analysis [28]. More effective data management could address many of healthcare's fundamental issues, and according to a 2011 McKinsey report [48], more effective health data management could save \$300 billion annually. Current innovations focus on placing patients at the center, privacy and access, completeness of information, and cost [24]. Three interesting applications of blockchain for healthcare are in claims adjudication, cyber security and healthcare IoT, and electronic medical records [16].

3.2.1 Claims Adjudication and Fraud Prevention. The Economist [22] estimated that in 2014 the United States wasted \$272 billion dollars on healthcare fraud. Blockchain could not only minimize fraudulent billing; but, by automating claims adjudication and billing processes, obviate the need for administrative and transactional costs through third parties. Gem Health and Capital One are developing a blockchain-based solution for healthcare claims management [16].

3.2.2 Cyber Security and Healthcare IoT. In 2016, there were 450 reported health data breaches, impacting 27 million patients. Hacking and ransomware were responsible for 27% of these breaches. Each additional connected medical device serves as a potential entry point for bad actors. With an estimated 20-30 billion healthcare IoT devices by 2020, blockchain could secure these devices and protect confidential data. Telstra, IBM, and Tierion are three companies that are developing cyber security solutions for connected healthcare devices [16].

3.2.3 Electronic Medical Records. Beleaguered by stifled technology development, limited ownership control by patients, fragmented information systems, and risks of electronic protected health information hacking, electronic medical records have perhaps the most important use cases for blockchain [76]. Blockchain can provide interoperability of healthcare information, improved security, patient-centric control, and immutable records [16]. Three examples of blockchain-based EMRs include MedRec, Medicalchain, and the Estonian eHealth Foundation. First, by leveraging smart contracts on the Ethereum blockchain, MedRec is a prototype system that provides patients with "one-stop-shop access to their medical history" and shows promise to give ownership of health information back to the patients who can selectively share access through a modern API interface in a secure manner [23]. Second, Medicalchain is a permissioned blockchain distributed on networks of international healthcare providers that allow patients to transfer medical records across national borders [24]. Third, a data security

company called Guardtime is using its Keyless Signature Infrastructure system in partnership with the Estonian eHealth Foundation to store Estonian health records on a blockchain.

4 THE OPIOID CRISIS

The United States opioid crisis is an overwhelming, tangled web of issues with increasingly severe health and financial consequences. The private sector, government, and academia are suggesting and implementing critical mitigation strategies to combat the crisis.

4.1 Addiction Risk

Since the late 1990s, pharmaceutical companies have downplayed the addictive risk of opioids [55]. However, the addictive nature of prescribed opioid painkillers increases the "potential for unforeseen adverse events for the patient, including overdose, experience of physiological dependence and subsequent withdrawal, addiction, and negative impacts on functioning" [72]. Patients with wholesome medical intentions often fall victim to the pills' addictive nature. Misuse and eventual abuse of prescribed opioid painkillers is common: 21%-29% of patients prescribed opioids for chronic pain misuse them while 7.8%-11.7% develop an addiction [72]. Moreover, an opioid addiction often serves as a gateway to other illegal drug use. With similar highs, prescription opioid addicts often transition to heroin, an illicit street-made opioid, since it is cheaper and easier to obtain. In fact, 4%-6% of patients using prescribed opioids develop a heroin addiction [55]. Whereas, 75% of heroin users began their opioid addiction with prescription opioids [12].

Despite these risks, opioids are still prescribed at alarming rates. In fact, the United States, with about 5% of the world's population, consumed 80% of the world's opioid prescriptions from 2001-2010 [72]. Between 1999 and 2015 the number of prescribed opioids painkillers such as codeine, fentanyl, oxycodone, Demerol, and Vicodin quadrupled. In the same time period, opioid-related deaths also quadrupled.

4.2 Health Impact

The epidemic has become so severe that in October 2017 President Trump was forced to declare it "a national health emergency" [54]. With no signs of stopping, this epidemic is burgeoning across America killing nearly 91 people a day [61].

In 2015, 33,091 Americans died from an opioid overdose with rural white males at the greatest risk of an opioid overdose. White Americans (27,056) died the most, followed by black Americans (2,741), and Hispanic Americans (2,507). Generally the middle-aged population was most at risk with the following percent mortality distributions by age group [27]:

- Aged 0-24: 10% of the opioid-related deaths
- 25-34: 26%
- 35-44: 23%
- 45-54: 23%
- 55+: 19%

Males die nearly twice as frequently from an opioid overdose, representing 65% deaths compared with 35% for females [27].

4.3 Financial Impact

The health impacts are the primary reason for concern, but the financial liability associated with the epidemic is also increasing. The estimated financial impact of the crisis grew from \$55.7 billion in 2007 [5] to \$78.5 billion in 2013 [25]. Of the total economic burden, roughly 25% or \$20 billion is conveyed to the public sector [25]. Partitioned between workplace, healthcare, and criminal justice costs, the overall financial burden will continue to rise until a reversal in current opioid abuse trends.

Opioid drug makers are also exposed to significant financial and legal liabilities as lawsuits accusing pharmaceutical companies of deceptive marketing are commonplace. After a U.S. Justice Department probe in 2007, the maker of OxyContin pleaded guilty to federal charges and paid \$634.5 million. In later cases, OxyContin maker Purdue Pharma LP settled two additional cases for a combined \$43.5 million. Similar to the tobacco industry in the 1990's, over 100 state, city, and county governments are taking their turn litigating drug makers role in the rise in opioid addictions. In fact, lawsuits against tobacco companies resulted in over \$200 billion in court-ordered payouts and similar payouts are expected for opioid makers [60]. Most cases follow the same legal jargon. For example, in a suit filed in April 2017 against the three largest drug retailers in the USA - CVS, Walgreens, and Walmart - lawyers for plaintiffs Cherokee Nation claim that the "Defendants turned a blind eye to the problem of opioid diversion and profited from the sale of prescription opioids to the citizens of the Cherokee Nation in quantities that far exceeded the number of prescriptions that could reasonably have been used for legitimate medical purposes" [34].

4.4 Responses to Mitigate the Crisis

The private sector, government, and academia alike recognize the importance of solving this crisis and are implementing strategies to help mitigate the opioid crisis.

4.4.1 Private Sector. Drug retailers are taking immediate action. In September 2017, CVS pharmacy announced actions to limit patient supply of prescription opioids to seven days, to restrict the strength of opioids dispensed for first time patients, and to install 750 more in-store drug disposal kiosks [9] [31].

A longer-term private sector solution is through the use of radio frequency identification (RFID) technology as a method to improve supply chain security [70] [74]. RFID tracking tags are small microchips that are either printed, etched, stamped, or vapor-deposited onto product labels and are intended to replace barcodes. RFID can be read without direct line of sight and at distances up to 30 feet. Research shows that RFID tags have the potential to reduce costs, increase transparency, and identify counterfeit lots. RFID tags have many advantages over current barcode tracking methods. RFID tags can hold up to 32,000 alphanumeric characters compared to just 20 in a barcode. RFID tags have a much higher upfront cost but decrease total supply chain cost due to the timely process to scan each individual barcode. And unlike RFID tags, barcodes are susceptible to wear and tear and are easily replicated. RFID technology also has its flaws. In addition to the higher upfront cost, each tag costs between 5-10 US cents, significantly higher than bar-

codes. Moreover, they are vulnerable to electromagnetic interference and poor manufacturing, are larger, and require a much larger IT infrastructure [70] [39].

4.4.2 Government. Through policy and politics, the federal government is attempting to find solutions to the epidemic. In the same address President Trump declared the opioid epidemic a national health crisis, he proposed "really tough, really big, really great advertising" [19]. Tom Price of the U.S. Department of Health and Human Services (HHS) outlined a more detailed federal long-term plan including, "improving access to treatment and recovery services, promoting use of overdose-reversing drugs, strengthening our understanding of the epidemic through better public health surveillance, providing support for cutting edge research on pain and addiction, and advancing better practices for pain management" [59]. Additionally, President Trump's Commission on Combating Drug Addiction and the Opioid Crisis repeatedly mentions "data sharing" as a method to cope and limit the opioid crisis [54].

Multiple studies indicate that states with strong prescription drug monitoring programs (PDMPs) show a significant reduction in the number of opioid-related deaths [57] [58]. Unfortunately, evidence suggests that 72% of physicians were aware of their states' PDMPs in 2015, but only 52% used their services. Physicians noted difficulties understanding the data formats and retrieval systems as the main barriers to continual use of PDMPs [64]. As a result, low registration rates are common in the 49 states that offer some form PDMPs [32].

Increasing access to Naloxone, an opioid antagonist that rapidly reverses the opioid overdose damage, may be the most important immediate solution to reducing opioid-related deaths [32]. Between 1998 and 2014, 52,283 naloxone kits were distributed among the 30 states with naloxone distribution programs resulting in 26,453 overdose reversals [32]. 27 states have "third-party prescription" laws that allow physicians to prescribe Naloxone to family and friends of individuals with an opioid addiction [32]. To further reduce opioid-related deaths states must reduce malpractice liability for physicians prescribing Naloxone and make Naloxone available without a prescription [32].

In addition, states have started to pass legislation protecting Good Samaritans. As of 2014, 23 states had laws protecting cooperating bystanders, from low-level misdemeanors and drug possession. Without these laws, bystanders are subject to criminal charges and even murder if it is proven they supplied the deadly drugs. Consequently, these laws are necessary to encourage immediate life-saving calls to 911 [8] [32].

Other solutions states should consider is access to medical marijuana, as Pardo [57] found that states with legal medical marijuana dispensaries have lower opioid-related deaths.

4.4.3 Academia. Academic research is helping to propose effective solutions to the opioid crisis. For example, Indiana University announced plans to commit \$50 million and 70 researchers to find solutions that lead to a decline in opioid-related deaths [63]. In a similar proposal to the HHS, researchers at the Network for Public Health Law, Boston University, and Northeastern University proposed a four-step solution including "improving clinical decision making and access to evidence-based treatment, investing

in comprehensive public health approaches, and re-focusing law enforcement response” [18].

5 PHARMACEUTICAL SUPPLY CHAINS

At the intersection of supply chain and healthcare, pharmaceutical supply chains have not substantially evolved with the adoption of new technologies. Stifled by outdated processes, the weaknesses of existing pharmaceutical supply chains contribute to problems in the opioid crisis which has led several to look towards blockchain to transform the industry.

5.1 Supply Chain Participants

Participants in pharmaceutical supply chains engage in both forward and reverse activities. Forward facing supply chain activities occur before a customer purchase. In a pharmaceutical supply chain, forward facing nodes includes manufacturers, warehouses, distributors, and retailers. Reverse facing supply chain activities occur after the sale and include collecting, recycling, redistributing, and disposing of unwanted medications.

5.1.1 Primary Manufactures. Primary manufactures produce the main active ingredient [67].

5.1.2 Secondary Manufactures. Often at a different geographic location for tax and labor reasons, secondary manufacturers combine the active ingredients produced by primary manufacturers and excipient substances. Secondary manufacturers produce distribution ready SKU medications through one or more of the following processes: granulation, compression, coating, and packaging [67].

5.1.3 Market Warehouses and Distribution Centers. Due to the cost of setup and cleaning, it is common for primary manufacturers to produce a years’ worth of active ingredients for a particular medication in one batch. This strategy creates a lot of excess finished and work-in-progress inventory which is then stored in warehouses and distribution centers [67].

5.1.4 Wholesalers. Wholesalers sell large quantities to retailers at low costs. Roughly 80% of demand flows through wholesalers. The pharmaceutical wholesaling industry is highly competitive and consolidated. The largest five wholesalers accounted for roughly 45% of industry revenue [67] [36].

5.1.5 Pharmacies and Hospitals. Pharmacies and hospitals are the last node on the pharmaceutical forward facing supply chains before medications are distributed at a patient level. Major retailers include pharmacies CVS, Walgreens, Walmart, and Rite Aid and hospital systems such as Community Health Systems, Hospital Corporation of America, and Ascension Health [67].

5.1.6 Patients. Patients are prescribed opioids for pain management. They are the end consumer and represent the final nodes of the supply chain.

5.2 Weaknesses

The nature of the current pharmaceutical production and supply chain system creates multiple weaknesses.

5.2.1 Lead Time. Lead times, the time it takes between manufacturing and end sale, can take up to 300 days [67]. As a result, high safety stocks are needed to react to future demand.

5.2.2 High Service Levels. The necessity for on-time pharmaceutical products forces retailers to maintain high service levels, the targeted rate of stock-outs. In many cases and especially in hospitals, patient health relies on having the right medication at the right time. A failure to meet this immediate demand could lead to fatal consequences [43] [51].

5.2.3 Imbalance of Information. Another major disadvantage is the lack of collaboration between raw material suppliers, manufacturers, warehouses, wholesalers, and retailers. “The problem is that the different decision-makers do not have access to the same information regarding the state of the entire supply chain network, and in addition they usually operate under different objective functions” [66]. In this decentralized method, manufacturers have a difficult time forecasting demand. In addition, an imbalance of information between supply chain nodes increases cost and stock-outs. However, Nematollahi, Hosseini-Motlagh, and Heydari [52] found that collaborative decision making through information sharing can increase economic benefits for the entire supply chain while also increasing drug fill rate.

5.2.4 Manufacturing Strategy. The mixture of manufacturers ‘push’ strategy and retailers ‘pull’ strategy, results in high safety stocks. At any given point, there is usually 4 to 24 weeks of finished goods that have yet to be delivered to patients [67].

5.2.5 Large Network. Medications pass through several nodes before they are delivered to the market. Safety and security issues face organization conflicts as the capital cost to prevent theft and mismanagement is not equally spread across the supply chain. The number of nodes also increases the likelihood for counterfeits to enter the market. Between each node, medications are shipped and handled between multiple parties and often times across national and state borders [67].

5.2.6 Counterfeits. High inventory levels increase supply chain cost, the potential for theft, and the introduction of counterfeits. It is estimated that 10% of the worldwide pharmaceuticals are counterfeit and approaching 25% in developing countries [42]. Pharmaceutical companies lose an estimated \$200 billion annually due to counterfeit drugs [16].

5.2.7 Disposal. The reverse supply chain is often overlooked as a key component of the pharmaceutical supply chain network. Few people take their unwanted medications to proper collection sites. Instead, medications are discarded in the trash and sewage. In fact, in 2003 at least \$760 million worth of prescription medications were inappropriately disposed around the world [51]. By 2014, this number ballooned to an estimated \$5 billion [47]. The roughly 10 million unused and unexpired prescription medications could be recycled and reused, but instead improper disposal leads to dangerous compounds in water ranging from sewage to drinking water [51] [47]. Hua, Tang, and Wu [51] suggest a combination of government subsidies, penalties, and marketing to encourage drug makers to collect unwanted and expired medications.

5.3 Government Response

In response to these problems, the government heavily regulates pharmaceutical supply chains to ensure a safe and steady supply of medications. The Drug Quality and Security Act [1] signed by President Barack Obama in 2013 introduced new regulations for the manufacturing and the distribution of pharmaceutical products. The policy mandates the creation of systems to trace lot-level transactions and systems to verify product legitimacy. In addition, any company within the supply chain must obtain federal licensure and authenticate the licensure of their trading partners. These required changes place immense financial pressure on pharmaceutical companies, drug distributors, and prescribers to develop sustainable supply chain solutions. The 2023 deadline gives pharmaceutical companies time to test and implement the most sustainable and practical solution [26].

5.4 Moving Drug Distribution onto the Blockchain

The shortcomings of existing pharmaceutical supply chains contribute to the opioid crisis. Inefficiencies lead to higher costs which could create financial strain for patients. Imbalanced information presents difficulties to appropriately track opioid distribution, counterfeit risk exists but is largely unknown, and improper disposal opens the door for others to use opioids not prescribed to them, which could contribute to further addictions. As such, in addition to the previously mentioned responses to mitigate the opioid crisis, researchers are suggesting blockchain as a solution. However, there are no comprehensive models or suggestions on how to implement blockchain in opioid distribution. Rather, current research and commentary focuses on the benefits of blockchain implementation [21] [29]. More broadly, commentary on the benefits of blockchain in healthcare exists [46] [2] [68] [50] [17], but again the authors present little evidence towards tangible implementation steps.

The first step to moving opioid distribution onto the blockchain rests in the initial infrastructure investment plan for development and maintenance. The next step is to establish the policies and security clearances of each organization [11]. Once these critical questions are answered, an opioid distribution blockchain would be similar to blockchains in other industries. Each blockchain would start with the genesis node created by the primary manufacturer. From there on, each additional downstream node would timestamp an additional hash. When the opioid eventually reaches the patient, the block would contain information on all supply chain nodes with timestamps and distribution information including prescribing physician and pharmacist.

An opioid blockchain should follow the Hyperledger design principles [13] [71], Tapscott and Tapscott's seven design principles for blockchain [69], and BlockSci [41] analysis protocols.

In the first tangible step towards creating a blockchain network for drug distribution, The Centers for Disease Control and Prevention (CDC) recently announced plans to research ways to implement blockchain [56]. Creating more open source research can help quicken blockchain adoption.

6 A BLOCKCHAIN MODEL FOR OPIOID DISTRIBUTION

Despite the discussion surrounding blockchain's potential to mitigate the opioid crisis, none of the researched sources provide an actual blockchain model. Such a model is an important initial step along the long road of blockchain adoption for drug distribution.

6.1 The Supply Chain Model

To develop an initial blockchain model for opioid distribution, a simplified, hypothetical supply chain was conceptualized. This supply chain includes a limited number of participants across seven different stages:

- (1) Raw Material Provider ($\text{raw}_1, \text{raw}_2, \text{raw}_3$): Three suppliers of opioid raw materials.
- (2) Primary Manufacturer (m_1, m_2): Two primary manufacturers who mix the active ingredients in opioids.
- (3) Secondary Manufacturer (sm_1): One secondary manufacturer to create the consumable opioid.
- (4) Warehouse (w_1): One secure warehouse facility to store the opioids.
- (5) Distributor (d_1, d_2): Two distributors who move opioids from the warehouse to the retailers.
- (6) Pharmacies (rp_1, rp_2, hp_1): Three retail and one hospital pharmacy. Each pharmacy includes a pharmacist who provides prescriptions for the purchase of the drug. The prescriber is not directly in the supply chain but plays an important role.
- (7) Patient (p_1, p_2, \dots, p_{99}): 100 patients who are prescribed opioid medication. Each patient receives opioids from at least one pharmacy and possibly all three.

The opioids flow through the supply chain participants as diagrammed in Figure 1.

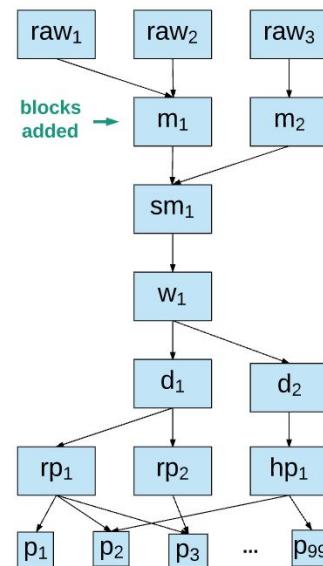


Figure 1: The flow chart for a pharmaceutical supply chain

```

print ("Data for 1012th block\n")
print (blockchain[1012].data)

Data for 1012th block

rawmaterial_supplier          raw2
manufacturer_id                m1
manufacturer_t1                2009-10-23 12:47:13.412781
manufacturer_t2                2009-11-25 21:53:47.774749
smanufacturer_id               sml
smanufacturer_t1              2009-12-04 00:05:09.454538
smanufacturer_t2              2010-01-01 05:15:57.344100
warehouse_id                   wl
warehouse_t1                  2010-01-13 04:19:37.169847
warehouse_t2                  2010-02-15 13:26:11.531815
distributor_id                d2
distributor_t1                2010-02-25 02:09:30.423126
distributor_t2                2010-03-06 14:52:49.314437
pharmacy_id                   hp1
pharmacy_t1                  2010-03-14 20:51:50.723182
pharmacy_t2                  2010-03-25 12:26:34.086122
prescriber_id                 pres1
patient_id                     87
zipcode                        zip1
pharmacy_returntime           None
distributor_returntime         None
warehouse_returntime           None

```

Figure 2: The data fields that are stored in a block

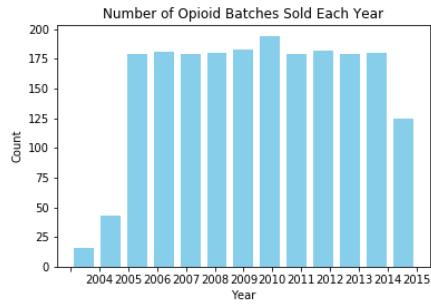


Figure 3: Number of opioid batches sold each year

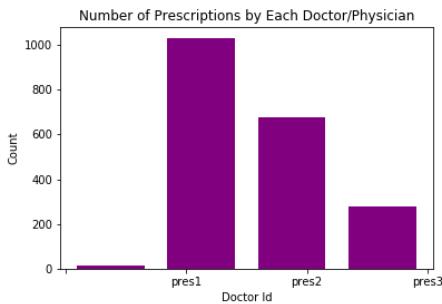


Figure 4: Number of prescriptions by each doctor/physician

6.2 The Blockchain Model

Primary manufactures create a new block for every new opioid batch. As a manufacturer creates a new block, they update the block with raw material data. Only the primary manufacturer has the rights to create a block, as primary manufacturers are the only nodes that creates a new batch of opioids. All other nodes update

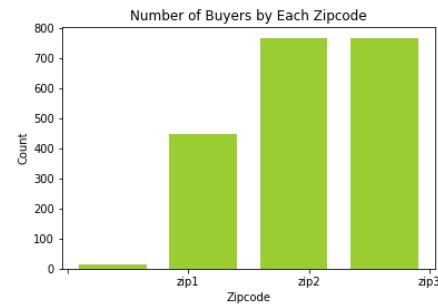


Figure 5: Number of buyers by each zipcode

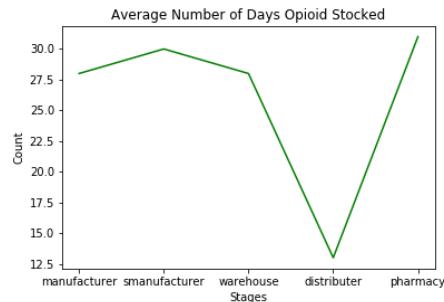


Figure 6: Average number of days opioid stocked

the block data as the opioids move downstream through the supply chain.

The primary manufacture assigns a unique hash key for every new block. These keys are shared across the supply chain for others to update the block. Only nodes with the hash key table are able to update the block data. When a batch of drugs pass through each stage of the supply chain, the ID of the stage node is updated. In addition, The timestamp when the batch of drug arrived and left the facility is also added to the block data. In the model, we assume data entry is integrated with on-site scanners at each node. When a batch of drugs is scanned, the information is automatically added to the block data. For example, the purchase data for any batch is represented by the timestamp that the pharmacy provides as to when the drugs left their facility. In regards to the reverse supply chain, pharmacies, distributors, and warehouses have the capability to update the block with the corresponding node ID and timestamp. Data present in each block is shown in Figure 2.

6.3 Blockchain Model Development

The blockchain model is implemented in Python2.7. The model uses a self-generated data set which is created through Python code.

6.3.1 Data Curation. The model creates a blockchain with 2000 blocks [44]. Each block has its separate piece of data. Blockchain is implemented as a Python class and each block is an object of the Python class.

Most of the data is created using random package in Python. The model uses random normal function to create data points for the

2000 blocks. Data is created for every stage in section 6.1. Hash keys are created using the hash lib library in Python. Different nodes at each stage, like the distributor 1 or 2, is also chosen using random functions. Data is completely created using the create data function.

6.3.2 Code Overview. The model [45] defines a blockchain class and the first block added to the class is called the genesis block. The primary manufacturers create these blocks and the subsequent blocks. New block function creates a new block as well as assigns it with essential data like timestamp, ID, and hash key. Each new block added is linked to the last block to form a chain. The create data function is used for randomized creation of data for each block. Previous block object is used for creation of next block.

The hash key information is stored separately as a table containing the block ID and the respective hash key. This table should be provided to every node in the supply chain network. The update function uses the hash key table for verification. Then a node is allowed to update the data for any block.

The model provides few analysis results. These results can be used by the government to scrutinize the details of opioid crisis and find any disturbing trends. While creation of data, the randomization has been done in such a way, that few clear trends are visible through simple analysis.

6.3.3 Blockchain Execution. The model is executed on a local virtual box on Ubuntu version 16.04 with four gigabytes of ram on an i7 processor. The run time for the complete model, along with data creation took 9.166 minutes.

The model was also executed on the Chameleon Cloud virtual machine on a single node. The execution time for the complete model was 6.015 minutes.

6.4 Blockchain Model Limitations and Future Work

The demonstrated blockchain model presented should not be viewed as practical but rather as an initial model that could be further developed for academic and eventual industry use. Shortcomings include over simplification, security, mutual agreement, data management, the lack of user-friendly features, and the lack of counterfeit detection and reverse supply chain functionalities. The source data [44] and source code [45] are publicly available for others to build towards a more functional blockchain model.

6.4.1 Overly Simplified. The most obvious shortcoming of the blockchain model is that it is built for an unrealistic and overly simplified drug supply chain. The model has been used on a simplified stem of a supply chain distribution tree. Many more variables are required to actually scale it to a real supply chain. For a country-wide or even a state-wide network, it will become a big data problem, and a robust data architecture must be required to handle the huge number of variables.

6.4.2 Security. Advanced level of security must be applied to safeguard the creation and adaption of data. The model uses hash key table which is to be shared with every node in the distribution network. This is a trivial method of security which can be easily hacked. A dedicated security system is needed with regular patches

to update the system. The security system can be developed in-house or through a security vendor.

6.4.3 Mutual Agreement. All the stages in the supply chain will have to come to a mutual agreement of making the supply data transparent and setting up a system for conducting such a model. A non co-operation from a single stage or node will make the data non-transparent. This will also make the blockchain model ineffective as track of data flow will be lost.

6.4.4 Data Management. Data management for a shared database system like a blockchain should should meet the few basic requirements like maintaining consistency and providing security. The data should be changed dynamically across the network, when a block is added or updated. Single node in the distribution network cannot be trusted with the data management. The model uses a single data set that is shared across the network. A voting mechanism must be made to notify and request approval from each node in the distribution network before adding or updating a block in the blockchain. Only then the model will become a truly decentralized data management system, that is required for a blockchain.

6.4.5 User-Friendly. The model is a piece of python code, that is either run through a command line or an iPython notebook. A practical application would have a user interface for wider use. For each stage, the system that scans the bar codes must be connected with the blockchain model, to provide hassle-free updates to a block's data. It will internally require approval from the security system for the scan. This will require front-end application development. The model will also require servers for database and running back-end code. Either the nodes in the supply chain network or the government must bear the initial cost of setting up the system.

6.4.6 Counterfeit Detection. The model does not take into consideration the theft or counterfeit replacement during transportation. The hash keys are connected to the block ID, which in the real-world represents a bar code for a batch of drugs. If the drugs are replaced while keeping the original packaging, then duplicate drugs can be entered into the supply chain.

6.4.7 Reverse Supply Chain. The model does not currently have functionality to accurately represent the reverse supply chain. The model used only three variables which represent the return time of a batch across different stages. The field of reverse supply chain must be explored further as it is important when distributors and pharmacies overstock the drugs.

7 DISCUSSION

An analysis of blockchain, the opioid crisis, pharmaceutical supply chains, and the demonstrated blockchain model for opioid distribution provides a more comprehensive picture for how blockchain could be applied to drug distribution. In particular, sample analytics were generated from the blockchain model and are provided as a snapshot of the overall analytic capabilities of a blockchain. Benefits of blockchain adoption are diverse but broadly fall into administrative capabilities and analytic capabilities. Effective use of these capabilities provide numerous benefits, including several which could mitigate certain issues of the opioid crisis. However,

actual implementation must overcome significant challenges to adoption.

7.1 Sample Analytics from Blockchain Model

7.1.1 Spikes in Sale Over Time. The basic analysis to perform on the supply chain data, keeping the opioid crisis in mind, is to show the drug sale over time. Figure 3 shows the number of batches of opioid sold every year. An increase in sale can be noted after year 2005. The sale remains high for the later years. Such an analysis for country wide data can be helpful in finding the spike in sale of drugs and look further into the causes. The model uses sold date provided by the pharmacy for this task.

7.1.2 Number of Prescription Over Time. This is another important analysis that should be performed in case of a crisis like opioid crisis. The increase in sale of prescription drug is mainly due to increase in prescriptions that are provided by the doctors and physicians. Such a case should be looked into depth. After finding the areas with most sale of drug over time, the prescription data should be analyzed to find any defaulter. Since the opioid crisis is mostly due to over prescription of drug, this analysis is very important. Figure 4 shows ids for doctors that gave away too many prescriptions. The prescription data is provided by the pharmacy. In the figure 4, the doctor with id pres1 gave away most prescriptions while pres3 id doctor was the most nominal in giving away prescriptions.

7.1.3 Zip-codes that Abuse the Drug. In any drug crisis, the main analysis is localizing the point in time when the excessive sale happened and the area in which it happened. To find the area of excessive sale the model performs analysis on the zip code data provided by the pharmacy. Figure 5 shows results of such an analysis. Zip3 and Zip2 contribute towards most of the sale of opioid. Such areas should be studied into further. This analysis simplifies the process of finding the factors contributing towards the drug crisis.

7.1.4 Average Number of Days for Stocking Drug. Another major factor in the opioid crisis was overstocking of drugs by different nodes in the supply chain. To dive deeper into this problem an analysis should be done finding the average number of days a batch of drug was stocked across the different nodes in the supply chain. The defaulters can be easily found out, when the average number of stock days for that node is high. Figure 6 shows such an analysis on the supply chain. Stocked days are found out by the difference in time as to when the batch of drugs arrived at that node and when it left the node. This time data is provided by each node in the supply chain. Figure 6 shows that the manufacturers, warehouses and pharmacies, for this given example, stocked the drugs for higher number of days. Some stocking should be allowed, as sales cannot be predicted accurately, but excessive stocking should be looked into further and rules against excessive stocking should be implemented. Especially for drugs like opioid.

7.2 More Comprehensive Capabilities

A more fully-functioning blockchain can provide numerous benefits that allow for administrative efficiencies and provide richer information and analytics.

7.2.1 Cost Savings. As a proactive cost saving maneuver, drug makers and retailers can move onto the supply chain to prevent future litigation [53]. In addition, blockchain automation saves time and operating costs [71].

7.2.2 Reduced Lead Times. Collaborative record-sharing is the foundation and ultimate strength of blockchain technology. Nematiollahi, Hosseini-Motlagh, and Heydari [52] show that collaborative record-sharing among pharmaceutical nodes increases both the social and economic effectiveness of the supply chain. The economic benefits realized through the reduction of the total supply chain inventory levels also decreases lead times.

7.2.3 Post-Sale Opioid Collection. Blockchain technology can also increase the usefulness of post-sale opioid collection. Current medication packaging lacks 2D Data Matrix bar codes making it nearly impossible to identify historical information such as who is returning their medication, who prescribed and sold the medication, and when the medication was prescribed and returned [73]. Blockchain can trace this information leading to better post-sale analysis. In turn, this information can be studied to improve prescribing methodology.

7.2.4 Payment Facilitation. The blockchain provides a framework from which smart contracts can be written for the automatic transference of payment based upon certain conditions being met [37] [69]. By adding smart contracts to the pharmaceutical supply chain blockchain, payments will transfer seamlessly and automatically with significantly lower transaction costs and risks for payment dispute. The end impact results in lower costs.

7.2.5 Collaborative Information Sharing. The adoption of blockchain technology provides capabilities that have the potential to reduce the opioid epidemic through transparent and decentralized record keeping. In particular, blockchain adoption has the potential to identify prescription drug fraud. Currently without blockchain, opioid addicts can take advantage of the incomplete feedback between physicians and pharmacists by "doctor shopping", modifying, and duplicating prescriptions [24]. With pharmaceutical records on the blockchain, this type of activity is easily identifiable.

Blockchain can reduce illegal opioid prescribing and distribution. In the current centralized record keeping system, the U.S. Drug Enforcement Administration (DEA) relies the Controlled Substances Act of 1970, that requires drug companies to disclose large or suspicious drug purchases [35]. Drug makers, on the other hand claim their responsibility to report is too vague. As a result, identifying "pill mills" is unnecessarily difficult and time-consuming. The DEA's pharmaceutical unit has 600 investigators [35]. With blockchain, record keeping is standardized and accessible to all parties with the correct cryptographic keys.

7.2.6 Counterfeit Detection. Blocks are immutable, that is once a block is created it cannot be deleted or erased. In addition, each batch of product can be traced back to its origin. This means that each batch will have a block of code associated with it. If a batch does not have its presence in the blockchain, then it can be deemed as a counterfeit [10]. Furthermore, blocks with abnormal distribution patterns can be flagged and removed from the supply chain. Creating illicit blocks is easily identifiable as all new blocks must

be approved by all parties on the blockchain. Consequently, drugs that are distributed through a blockchain supply chain enable doctors, pharmacists, and patients identify whether the medication is genuine with much greater certainty [24].

7.2.7 Traceability. In the areas of logistics and inventory data, blockchain provides a new approach to supply chain management. The core logic of blockchain does not allow duplicate entries to be created in the same place [7]. A unique inventory can have a single entry with multiple updates, but not duplication. This prevents the organizations from creating false information. In the example of a drug inventory, the shipment status for a batch of drugs will be updated for everyone, everywhere. Each entry could be traced back to its origin [7].

7.2.8 Data Analysis. Academic institutions and researchers should have access to superkeys to analyze the blockchain [49]. Data analysis can provide both a descriptive and predictive overview of the opioid supply chain. Blockchain can also improve the repeatability of clinical studies and allow access to the raw data [4]. Because the information streams are more comprehensive with lower lag times, high-risk scenarios and communities could be predicted or identified in time for agencies to intervene and provide outreach and emergency planning that could mitigate the risk of fatalities.

7.3 Adoption Challenges and Recommendations

Moving drug distribution onto the blockchain without a full understanding of its capabilities is perilous [37]. Rather the reality for such a system is likely still at least a decade in the future as the pharmaceutical and supply chain industries need to overcome numerous hurdles before effective adoption.

In addition to the general blockchain adoption challenges discussed by Tapscott and Tapscott [69], Rabah [62], and Iansiti and Lakhani [37], an opioid distribution blockchain must overcome its own unique barriers prior to adoption.

7.3.1 Security. The need to protect patient data is critical as inaccurate information could lead to fatal consequences. One unique weakness to blockchain is a 51% attack. This occurs when one node or a coalition of nodes controls at least 51% of the network. When this happens, the single node or coalition of nodes controls the entire network. A 51% attack is more likely in a network with a small amount of genesis nodes [3]. In addition, future quantum computing power may be strong enough to break cryptographic keys [24]. Security setup must meet the standards of the Security Rule, a subset of the Health Insurance Portability and Accountability Act (HIPPA), which provides rigid administrative, physical, and technical safeguards [33].

7.3.2 Regulation. Beyond just the Security Rule, the entire Health Insurance Portability and Accountability Act (HIPPA) must be at the forefront of designing any portion of an opioid distribution blockchain that involves electronic Protected Health Information (ePHI). Also, like most transformative technology, regulations are slow to conform. A lack of uniform regulations will create a roadblock and slow blockchain adoption [33].

7.3.3 Transparency and Confidentiality. One of the major strengths of blockchain technology is transparency, but current in-use blockchain technology, Bitcoin, only provides pseudonymity. This poses a major threat to patient confidentiality as users are identifiable through the transnational location of IP addresses [6]. Encryption technology is necessary for adoption in opioid distribution. Collaboration between drug makers, supply chain organizations, and patient representatives must reach an agreement on specific protocols to protect patient identity and company level trade secrets.

7.3.4 Speed and Scalability. Blockchain adoption will require adequate transnational speeds for full-scale adoption. Currently, the most widely adopted blockchain network, Bitcoin takes at least ten minutes to confirm transactions and can only process seven transactions per second. Comparatively, Visa Credit Cards can confirm transactions within seconds and can process up to 56,000 transactions per second [15]. Speed and scalability requirements for an opioid supply chain blockchain have yet to be determined.

7.3.5 Size. Current standards limit the size of one block to 1 megabyte, which limits each block to roughly 500 transactions [75]. In opioid distribution, the genesis node is created at the primary manufacturer. One batch of opioids may easily have over 500 transactions.

7.3.6 Bandwidth. At current throughput levels, the Bitcoin network is over 50,000 megabyte. Adoption of blockchain in healthcare could increase the throughput to levels seen in credit card companies. At that level, the blockchain network would grow up to 241 petabyte a year [75]. Reducing the cost of acquiring bandwidth and storage is necessary for adoption. Research shows that at current prices, each transaction costs \$0.0154 [15].

7.3.7 Error Handling. It is reasonable to assume mistakes will occur during shipping, handling, and retailing of opioids. Since blocks are immutable, these errors would remain permanently attached to the block. Updates can be made to correct these mistakes but the record-keeping may not be easily interpretable. One mitigating strategy is to implement a one hour grace period before transactions are confirmed. For example, a hospital doctor may scan an opioid prescription to a patient, but then never give the patient the drugs. A system of confirmation is needed to prevent misleading data in the network.

7.3.8 Data Input. Blockchain technology allows for more automatic data creation but ultimately manual entry will still be required. Encouraging accurate data entry will ultimately define the usability of blockchain in opioid drug distribution [24].

7.3.9 Status Quo and Learning Curve. The current system of opioid distribution has been in place for decades. Blockchain has immense social benefits, but companies may be unwilling to invest in the new and relatively unknown technology. Due to the initial learning curve, lead times may increase in the early days of implementation. Businesses may ignore the idea based on the hassle and the initial investment for setting up such a model. Training cost will also be substantial, but with the fast approaching 2023 mandate of The Drug Quality and Security Act [1], pharmaceutical

supply chain organizations may have the necessary regulatory incentives to invest in blockchain technology more quickly than in an unregulated market.

8 CONCLUSION

Although still in its infancy, blockchain has the potential to be just as transformative as TCP/IP. Early and potential applications in healthcare and supply chain suggest that blockchain is indeed moving along the path of technology adoption. Because blockchain is a low-cost solution for supply chain management and provides security and transparency, it could theoretically be used for digital data and communication to overall the distribution of controlled substances such as opioids.

From a technical feasibility standpoint, the blockchain proof of concept presented shows that the blockchain can be applied to a hypothetical and simplified drug supply chain. Although useful as a starting point, this model is far from practical adoption. The authors welcome other collaborators to build upon the source code to further expand the blockchain model for use in more complex and realistic drug supply chains.

The presenting question: “Can blockchain adoption mitigate the opioid crisis through more secure drug distribution?” has yet to be tested in practice. However, blockchain use cases in healthcare and supply chain, the technical maturation of blockchain including the drug distribution blockchain proof of concept presented, and scholarly, business, and health industry articles suggest that blockchain can become an effective foundational tool that would open a Pandora’s box of innovation. In turn, smart applications built into or on top of the blockchain framework would enable numerous capabilities that could help mitigate certain problems of the opioid crisis. Specifically, effective development and adoption of such innovations could reduce prescription costs, help match supply with demand, shorten lead times, and enable more secure post-sale opioid collection. Moreover, by arming administrators, organizations, and regulatory agencies with more comprehensive real-time information and analytics, they will be able to more securely track opioids, help identify counterfeits and fraud, conduct thorough research, and intervene in communities that are predicted to have an increased risk of fatalities.

Realistically, this transformation will require at least a decade before its benefits can be fully realized. Blockchain progression for highly regulated industries such as drug distribution where consequences could literally be fatal will develop even more slowly than in other industries. Yet, with lives at stake, the government, researchers, and private industry should take steps now that progress toward functional blockchain solutions for drug distribution. This progress should not be viewed as a single monumental task but rather as a series of incremental improvements that collectively provide capabilities to help mitigate the opioid epidemic and provide broader benefits. Application of agile product management philosophies and open source collaboration are key to the maturation of this blockchain concept. The authors invite others to build upon their incremental work as one of the numerous steps toward an effective blockchain solution for drug distribution.

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Big data and hearing disability

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ABSTRACT

Big Data is rapidly becoming a crucial component in the majority of the fields, be it from medicine to software. Big data technologies help in processing humongous amounts of data in a rapid manner while enabling us to achieve results fast and accurately. Hearing disability is a huge problem to the very fabric of society. It causes great discomfort among those who suffer from it and in some extreme cases can cause alienation. Thus there is a need for society to accept the difficulties faced by those affected with hearing disabilities and enhance the traditional solutions offered with the latest technologies so that they can lead a life without difficulties and live a normal life. The paper shows how the latest big data trends can be applied to existing traditional solutions like hearing aid, captions and also suggests how it can be used to proactively avoid situations that could lead to hearing loss. It is hoped that an interest will be generated towards further research and implementation towards combining Big data with hearing difficulty solutions.

KEYWORDS

Big Data, i523 , HID 232 , Rain Water Harvesting

1 INTRODUCTION

Hearing loss or impairment is defined as the partial or total inability to hear and may occur in one or both ears and may result in a person having little to no hearing. This loss can be either temporary or permanent depending on the mode of affliction. The causes of hearing loss are many but the most prominent factors can be narrowed down to genetics, ageing, exposure to noise, some infections, birth complications, trauma to the ear, and certain medications or toxins, chronic ear infections and the like. Infections that may have no relation to hearing loss like syphilis and rubella may also cause hearing loss if infected during pregnancy. If a person feels that their hearing is not sharp they can undergo tests to confirm which sets the bar at 25 decibels, if a person cannot hear at that range then they can be diagnosed as suffering from hearing loss. Hearing loss can be categorized as mild, moderate, moderate-severe, severe, or profound[19]. Hearing loss can further be categorized into two sections Congenital Hearing Loss and Acquired Hearing Loss. Under Congenital Hearing Loss two chief factors are Genetic and Prenatal Issues. Under Acquired Hearing Loss the chief factors can be listed as Chronic ear infections, medications that can affect aspects of hearing, Diseases that affect hearing (Mnire's Disease, etc.), Head injury, Perforated eardrum[1].

Generally, genetic factors have been found to be responsible for pediatric hearing loss. This occurs when inherited genes work against the development of the patient's body and this impacts the development of the hearing system as a result. As it is with genetics

it can target any part of the body in this case it spares no part of the ear and can target any part from the outer ear to the deepest part of the inner ear. The degree of hearing loss can vary depending on which part is affected. When applicable solutions like hearing aids, implants etc provide for some relief [19].

As of 2013 hearing loss affects about 1.1 billion people to some degree[19]. It causes disability in 5% (360 to 538 million) and moderate to severe disability in 124 million people [19]. Of those with moderate to severe disability 108 million live in low and middle-income countries. Of those with hearing loss, it began in 65 million during childhood. Those who use sign language and are members of Deaf culture see themselves as having a difference rather than an illness. Most members of Deaf culture oppose attempts to cure deafness and some within this community view cochlear implants with concern as they have the potential to eliminate their culture. The term hearing impairment is often viewed negatively as it emphasizes what people cannot do. Despite all of the solutions and rationalizations being made, it cannot be denied however that hearing loss is becoming an important problem in today's society and one whose numbers is constantly increasing[19].

Big data is perhaps the most interesting technological advancement made in the current era, it has roots in almost all fields right from health care to education to even government policies. It is the far reach that makes big data important, it allows users and clients to make better-informed decisions by taking into account almost all factors. Doctors are looking towards big data to make more accurate diagnostics and look for new medicines, economists are looking towards big data to make more accurate models. The paper will look into how it can enhance some of the solutions provided for those hard of hearing like hearing aids, closed caption etc. It will also suggest enhancements towards preemptively preventing situations that could lead to hearing loss[19].

2 BIG DATA IN HEARING AIDS

2.1 Introduction

Hearing aids are small electronic devices that you wear in or behind your ear they improve the hearing and speech comprehension of people. It makes some sounds louder so that a person with hearing loss can listen, communicate, and participate more fully in daily activities. A hearing aid can help people hear more in both quiet and noisy situations. A hearing aid has three basic parts: a microphone, amplifier, and speaker as can be seen from the figure 1.

The microphone receives sound, which converts it into electrical signals and sends them to an amplifier. The amplifier increases the power of the signals and then sends them to the ear through a speaker basically it is magnifying sound vibrations entering the ear. The eardrum then passes these vibrations to the nerve cells which

1. Microphone
2. Microchip
3. Amplifier
4. Battery
5. Receiver



Figure 1: parts of hearing aid

then passes these signals to the brain. The more severe the hearing loss, and the greater the hearing aid amplification needed to make up the difference. However, there are practical limits to the amount of amplification a hearing aid can provide. However, if the inner ear is too damaged, a hearing aid would be ineffective [11]. Hearing aids can be classified into three distinct categories [11] they are Behind-the-ear (BTE), In-the-ear (ITE) and Canal as can be seen in the figure 2. BTE hearing aids consist of a hard plastic case

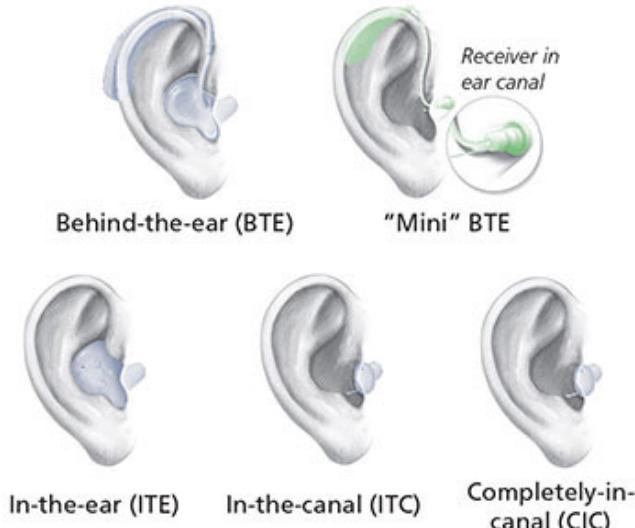


Figure 2: types of hearing aids

worn behind the ear and connected to a plastic earmold that fits inside the outer ear. The electronic parts are held in the case behind the ear. Sound travels from the hearing aid through the earmold and into the ear. BTE aids are used by people of all ages for mild to profound hearing loss. ITE aids fit completely inside the outer ear and are used for mild to severe hearing loss. The case holding the electronic components is made of hard plastic. Canal Aids fit

into the ear canal and are available in two styles. The in-the-canal (ITC) hearing aid is made to fit the size and shape of a person's ear canal. A completely-in-canal (CIC) hearing aid is nearly hidden in the ear canal. Both types are used for mild to moderately severe hearing loss[11].

Hearing aids can further be classified based on their inner circuitry which is analogue and digital. Analog aids convert sound waves into electrical signals, which are amplified. The aid is programmed by the manufacturer according to the specifications recommended by your audiologist. An audiologist can program the aid using a computer, and you can change the program for different listening environments from a small, quiet room to a crowded restaurant etc. Digital aids convert sound waves into numerical codes, similar to the binary code of a computer, before amplifying them. Because the code also includes information about a sound's pitch or loudness, the aid can be specially programmed to amplify some frequencies more than others. Digital circuitry gives an audiologist more flexibility in adjusting the aid to a user's needs and to certain listening environments and can be programmed to focus on sounds coming from a specific direction[11].

Hearing aids are a fairly popular solution among most age groups and users use them for about 8-9 hours a day [2]. The process of getting a hearing aid is fairly simple. First, you confirm with an ENT / audiologist that you are indeed in need of one. Then a series of audiometry tests are performed to determine the extent of damage / hearing loss incurred. Hearing sensitivity can be measured for a range of frequencies and plotted on an audiogram. Another method for quantifying hearing loss is a speech-in-noise test, which gives an indication of how well one can understand speech in a noisy environment. A person with a hearing loss will often be less able to understand speech, especially in noisy conditions. This is especially true for people who have a sensorineural loss [11] which is by far the most common type of hearing loss. A recently developed digit-triplet speech-in-noise test may be a more efficient screening test. The audiologist then programs the hearing aid to amplify at an acceptable level.

2.2 Big data in hearing aids

The working of hearing aids was covered in detail in the previous section now we shall focus on the areas where big data can be applied to help both the doctors and the patients as much as possible. We know that in order to determine the extent of hearing loss an audiometry test will be performed. The test proceeds with a patient being made to sit in a soundproof room and being subjected to listening to a wide variety of sounds ranging from the softest possible sound they can perceive to the loudest possible. The audiologist then charts a graph to figure out the extent of hearing loss. It will look like the below graph shown as per the figure 3. The problem with this process is it's still random and despite audiologists having great skill and lowering the margin as much as possible they can never be totally accurate nor can they test too much because it is physically demanding on the patient too. Big data can be a great help here. Data collected from multiple patients (with their consent) can be stored making use of technologies like apache pig , hive etc. Then when an initial audiometry analysis has been performed we can use deep learning or simple statistical sampling to obtain

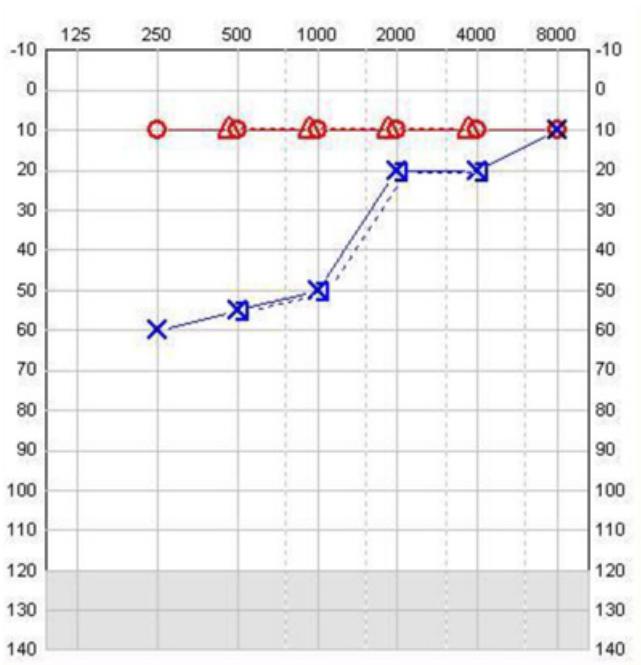


Figure 3: audiometry graph

a few similar cases via technologies like say apache-spark. From these cases, we can perform a more streamlined audiometry test rather than guesswork and further accurately narrow down the loss coefficients.

After the hearing loss estimates are charted down. It is time to program the hearing aid (a hearing aid model is selected by the audiologist in accordance with the hearing loss estimates). The aid is programmed to amplify sound waves in the range where losses are observed and then various simulated environments are performed to determine the level of comfort and extent to which the hearing aid is helping and perform fine-tuning. The problem is the same as previous a very limited range of environment that may / may not be useful to the patient is observed. Using big data once again a more accurate test can be conceived. A user can be presented with the environments patients from the similar range of hearing loss faced and this can be used as a basis for fine-tuning. This process has slowly been making its way into research [13] and a few companies [14] have already started commercialising it.

These days most people make use of digital hearing aids. As previously mentioned digital hearing aids are well equipped to make use of big data in a way they do make use of it albeit in a micro manner. The behavioural patterns of the patient are recorded like the range of volume increase or decrease in various modes, amount used etc. When the patient visits the audiologist the next time this data is analysed and then corrective changes are made towards the programming of the hearing aid. Big data can play a very big role in proactively doing so. These days most hearing aids have moved on from using a separate remote control towards making use of smartphone apps as a remote. This can be viewed as a huge enabler for big data technologies. Since mobile phones will most

of the time be connected to the internet this will enable (with consent) real-time load and store of data using technologies like pig and hadoop of user environments and the current sound wave patterns and amplification used along with other useful data like if the patient is increasing or decreasing volume. Hearing aids are certainly growing smarter in the sense when a mobile communication device is brought near the aid the electromagnetic pulses from the phone is detected by the aid and automatically switches to a phone mode, however for most of the part the user has to switch manually to other modes like theatre, noisy etc. Big data can play a huge role in automatic detection. For starters, big data can be employed to dynamically observe the fluctuations in loudness levels as well observe the fluctuations in background noise to help determine what mode should aid change to. Aside from observing fluctuations it can also compare the current scenario to those who have already encountered such scenarios under similar conditions (and with a similar hearing loss) rate and then perhaps adjust the volume/setting to a safe appropriate level. note that this would be highly experimental and could also create more problems than it solves. As much as we have powerful machine learning algorithms like deep learning it is impossible for them to predict a solution that best suits a patient after all different patients have different problems and conditions but as it learns more and gains more data (the hallmark of deep learning to learn with more data) there will be a good chance that the algorithms will provide a solution that really suits the patient.

So far we have looked at how big data can make use of sound waves in terms of loudness background noise etc, but there is one more aspect in which big data can help us. Analysing the contents of the speech itself. It has been previously mentioned Big data in language and speech processing is a well-established topic and plenty of papers and discussions exists [3] [17]. Most speech can be well predicted these days and when we take into account that hearing aids these days can make out the direction of which the sound is coming from. Making use of this and the ability of deep learning to possibly predict parts of speech we can leverage this to accordingly increase or decrease volume. certain words will have pronunciations that are hard to understand or have lower tones or have a high frequency to be repeated. we can take advantage of this. Also, the hearing aid can be programmed to automatically increase the volume when it detects a repetition of sentences/words either due to the patient asking the opposite person to repeat his/her sentence. this can be achieved either by listening to keywords like what, sorry, repeat yourself, etc or by analysing the sound waves and learning from that if the same pattern is being repeated.

2.3 Data processing and Technologies

Pattern recognition is a branch of machine learning that focuses on the recognition of patterns and regularities in data. Pattern recognition systems are in many cases trained from labelled "training" data (supervised learning), but when no labelled data are available other algorithms can be used to discover previously unknown patterns (unsupervised learning). In machine learning, pattern recognition is the assignment of a label to a given input value. An example of pattern recognition is classification, which attempts to assign each input value to one of a given set of classes (for example, determine

whether a given email is "spam" or "non-spam"). However, pattern recognition is a more general problem that encompasses other types of output as well. Other examples are regression, which assigns a real-valued output to each input; sequence labeling, which assigns a class to each member of a sequence of values (for example, part of speech tagging, which assigns a part of speech to each word in an input sentence); and parsing, which assigns a parse tree to an input sentence, describing the syntactic structure of the sentence [12].

From the above explanation, it becomes clear the manner in which we can apply pattern matching for hearing aids. We could use the binary stream as a basis for calculation and from this stream try to match it to existing patterns and predict the future patterns. If any of the generated patterns are found to have speech that is hard to decipher at that range signals can be sent to the hearing aid to accordingly raise the volume of the hearing aid. Aside from that we can make use of the binary sequences and try to find the best fit pattern match, we can eliminate noise because most hearing aids these days have excellent noise cancelling technology so we can be assured that the sound stream is that of the person who is speaking to the patient. Once we get the best fit we can make a correlation between the pattern identified and the next action to be performed. The discussed methods need not only be limited to merely volume increase and decrease. they can also be applied to the fitting process as we have discussed in detail previously, after obtaining the initial estimate graph we can take the plot points and use it to find the best-fit match of another patient and fine-tune the hearing aid accordingly saving a lot of time and effort and allowing the entire experience to be pleasant and more productive.

Apache hadoop, hive etc are just data warehousing software, used for distributed storage and processing of dataset of big data using the MapReduce programming model. It consists of computer clusters built from commodity hardware. All the modules in Hadoop are designed with a fundamental assumption that hardware failures are common occurrences and should be automatically handled by the framework. we have previously seen how data is being made available for us the next logical question that comes to mind is how do we store it and using what. The answer to what is somewhat easier to explain. As mentioned previously we can make use of sound waves which gets converted to numerical codes. Mobile phones used to control the hearing aids which have access to the internet can make use of hadoop framework. We can send this data to some API which then uses map reduce to accordingly save it to a location which represents that pattern. while looking for a pattern the analysis made at real time can be used to query the API which will use map reduce to obtain all patterns relevant to the range of hearing loss and then use pattern matching to figure out best fits and suggest feasible solutions. Audiologists can make use of this in the same manner only instead of making use of the API via mobile phones they can do it conventionally by a computer which will allow for stronger processing.

2.4 Section Summary

Hearing aids are the most assistive technology a person with hearing impairments could receive which do not require surgery. They are fast becoming an important industry especially with the rising

problem of hearing loss. The process of obtaining a hearing aid is simple and straightforward and for a long time it remained static. However with the advent of big data the world of hearing aids has been shaken from its static foundations and is undergoing a paradigm shift in the same manner mobile phones evolved to the current smart model. Right from the process of fitting to using the hearing big data can be applied to almost every stage. the entire process is still in its infancy and there is a huge scope for further development. Pattern matching , deep learning all the concepts are only the tip of the iceberg there are many algorithms and designs that can Be implemented. Thus there is a huge market both towards improving the current crop of hearing aids available and as well as creating jobs.

3 BIG DATA IN CLOSED CAPTIONING

3.1 Introduction

The importance of video in today's world cannot be stated enough. in the field of education, more and more classes are being shifted to the online model, professors are moving towards keeping their lecturers in places like udemy, youtube, pluralsight etc because there they are allowed the total freedom to take the course in their own direction without the constraints of time and classroom size. Certain sites like youtube even offer a source of remuneration. Thanks to the advancements in technology like smartphones and cheaper internet the general public is not satisfied with just listening to the audio, they want to watch the video and embrace the whole experience and artists have contributed to it by making their videos so colourful. TV is ever present with people preferring to watch news comfortably and be updated on the go rather than rifle through a newspaper. Even in communication, there is a paradigm shift from normal audio based conversations heading towards video calls, facetime, Whatsapp video chat are just a few of the most popular options available.

Now that an accord has been reached on how popular the video format is becoming, its time to talk about how difficult it's becoming for people who have hearing disabilities to cope with this changing world. These are people who are struggling to understand communication face to face and now are tasked with trying to understand something available on a digital platform and something they may not even have the power to ask for a repeat in case they misheard. the problem with digital media is mainly the distortion that comes with it. If it is too loud it becomes illegible to understand if it's too soft it is not loud enough to understand and the middle ground isn't much of a help more often than not. Aside from videos hearing impaired patients also find it difficult to perform most of their daily life activities like attending a class etc.

So what solution do we have that is capable of solving most of the above problems. It can be observed that the community has gone about finding different ways to solve their problems. Sign language translators, lip reading etc. They are all convenient methods of getting by but the problem with them is as good as they are they are way too situational. A more reliable method would be that of closed captions. Note that the art of captions is one that already exists and is made mandatory by governments to make such resources available on request and in general people are very receptive towards these technologies and often go out of their way

to enable them. For students perhaps the most common use of captions is the CART(Communication Access Real Time) systems, where an individual types a captioning of what the teacher is saying and the students view this in real time there will always be a delay of a few microseconds but it is still extremely useful [19]. In the case of tv, most channels already have implemented a subtitle system. Pre-recorded shows already have subtitles generated in advance and they are displayed. In case of live settings, the same text from the teleprompter is used as a subtitle or a cart like a system is used where a person types in the text being spoken and it is displayed a few seconds later. In the case of online videos, most content providers have provided the option of loading the subtitle file. The problem now lies in generating/obtaining the subtitle files. Good Samaritans always exist and for important videos more often than not the uploader or someone else will generate their own subtitles. The society is slowly recognizing the need for subtitles and in general, you will find the subtitles of the files you are looking for if you look hard enough. There also exist professional agencies who will create subtitles either for free or for a price, though in general, the free ones are already hard at work.

The issue at hand today is generating good quality subtitles and fast. The traditional method of generating subtitles by having a person listen and then type the subtitles is fine but it is too slow and cumbersome. It would be faster to have a computer generate the subtitles and have a human change/modify errors. Youtube has its own automatic subtitle generation, Facebook too is developing a similar feature on the same lines. Watson IBM have developed an API that leverages the power of Watsons AI to generate subtitles.

3.1.1 Manual caption generation. Manual caption generation as previously stated is a very tedious job it involves a person listening to the audio and then accordingly typing out the captions and storing them for later use. Big data can play a significant role in making thing easier for both the generator and the consumer. First lets deal with the generator. In terms of manual caption generation, there is not much that can be done to aid the person unless he switches to an automatic caption generation system. A few simple steps, however, can make his/her life much simpler. Using big data the video could be analysed for segments which have very common phrases / repeated segments and then these segments could be stored using map reduce. the next could be using map reduce find if there were translations available previously and generate the captions or store it till the user enters the caption. There are multiple benefits of such a method, perhaps the most important benefit would be it serves as an error detection mechanism improving the subtitle accuracy. Another benefit is it serves as a great training tool for supervised and semi-supervised learning algorithms. For the consumers, the biggest problem is finding subtitles. Using Apache Hadoop etc we can create an API that acts as a centralized database. However, this is an initiative that should be encouraged by the government. This is a problem that affects all citizens and having the government take care of it adds responsibility and accountability.

3.1.2 Automatic caption generation. Automatic caption generation has made huge strides in the recent years thanks to the development in the field of AI, semantic web, statistical models etc. In the case of automatic caption generation, the process is amazingly straightforward. First, you select the video for which you want

to generate. then you upload/send the data to the respective API. The API then generates the captions you need which you can then embed into the video or load into the video. The favourite method seems to be that of youtube API which gives a very high accuracy rating of around 94%. [18]. Aside from youtube, there exists IBM Watson which boasts of one of the most powerful deep learning features [22]. It should be noted that the youtube method is not exactly real-time sure it can work in real time with a delay of a few seconds but it requires the video to be clipped and sent at regular intervals in order for it to be real time to return a caption response with a slight delay. That being said it doesn't mean that youtube cannot do it in real time its a feature that has not been made available to the public yet, to clarify the speech to text conversion happens at a real-time rate it is just the communication between sender and server that will take some time. Youtube API much like Watson makes use of powerful and complex deep learning neural networks. While the exact process has not been made to the public quite understandably so the general concept will be explained along with an additional Hidden Markov model method.

3.1.3 Automatic caption generation markov model. First, we shall explain a simple and relatively straightforward hidden Markov model a simple but powerful AI algorithm. A formal definition from Wikipedia that helps in understanding the concept of Markov models is given as " In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters, while in the hidden Markov model, the state is not directly visible, but the output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states. The adjective hidden refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a hidden Markov model even if these parameters are known exactly." [20]. A markov model looks like this figure 4

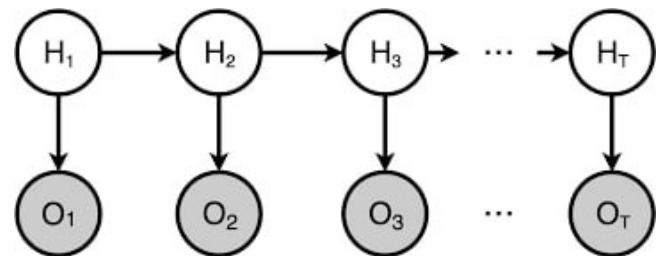


Figure 4: markov model

The thought process that follows the following explanation is that of a semi-supervised learning. The training data will compose of just words(audio) with their respective speech tag. Also, the training data will comprise a good set of perfectly captioned videos. More than the videos it is the caption files that are important. The individual words file merely provide us with a corpus file of what words to expect. it is the caption files however that allow us to build the Markov model around which the entire caption generation

process will be built upon. Now that we have our corpus file we can begin analysis on the caption file to build the model. What we will be doing is using a very simple probabilistic equation[20], The probability of observing a sequence $Y = y(0), y(1), \dots, y(L-1)$ of length of L is given by,

$$P(Y) = \sum_X \frac{P(Y/X)}{P(X)}$$

. To explain this in a more understandable manner we are looking for relationships between words. For example, when a person is introducing themselves a common sentence is "Hello my name is xyz" or "hello I am xyz". Another assumption we will have to make at this point at least with respect to the current Markov method is that we will work with more complete words that span at least 3 or more syllables so that the model can detect them better. With that, the previous sentences become "hello name xyz" and "hello xyz", from this reduction we can now get a new relationship, two of them in fact. the word hello leads to the follow up of the word name and this leads to the follow up of xyz whatever and hello leads to xyz. Now this relationship will be remembered. Now we can also make use of this concept but towards sentences. First, we will have to determine via some statistical method what would be the best average length [time duration] for sentences. Now we can use the previous principle to observe if there exist any relationship between sentences and remember them. Now we get on to processing the data to generate the captions. First, we have to eliminate noise from the audio. Then we need to split it into appropriate sections [n = total length of video/time of average sentence calculated previously]. Now using MapReduce we can quickly determine how many segments already have a translation [ie find if there are any perfect/reasonable matches] and obtain the captions for those. If there are none available then we go to the next stage of getting captions word by word. After converting it to a data format appropriately [this has been discussed this previously in the hearing aid section, another alternative manner will be discussed shortly]. Now we determine the first word, again using map reduce we can match the word to a list of probable similar sounding words. To obtain the actual word the magic of probability comes into play. remember the Markov model we had discussed earlier, from it we can calculate the probabilities of a word occurring as the first word and accordingly make a very educated guess on which word is the right word. Following that using the Markov model once we can determine what the next word could be after first narrowing down the suspects we can use the model to infer what the next word could be. that is, given the current word what is the probability that the next word will be the selected word.

This way we go about generating captions for every word in the sentence. After this is done for all sentences we can generate a caption file for the entire duration of the video. This method is likely to have a lot of errors since the Markov model described here is rather simplistic therefore the onus will have to be on the administrator to go over the captions generated and accordingly make the corrections. This will not only be useful to the people with disabilities but also help improve the accuracy of the system on the whole. Studies have been carried out and more complex implementation of the same idea has been performed with a rather

high accuracy rate can be found here [6].

3.1.4 Automatic caption generation Deep neural network model.
Now the concept of a neural network will be explained. A neural network is based on the same idea of how our brains work [21]. A collection of neurons for information processing and to model the world around us. A very brief explanation would be a neuron sums all the inputs and if the resulting value is higher than a specified threshold it fires. A neural net can be represented as the following figure 5.

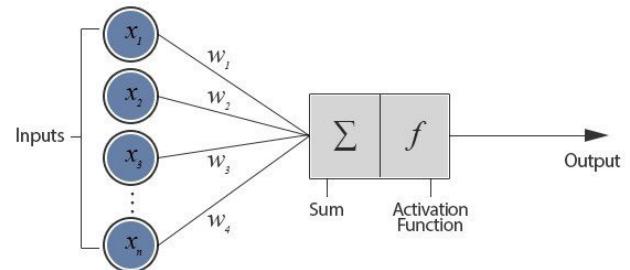


Figure 5: neuralnetwork image

The above configuration is called a perceptron. It has n inputs and n weights are real numbers and can be positive or negative. The perceptron consists of weights, summation processor and an activation function. the inputs are multiplied by the individual weights and the summation of all of these is passed to an activation function, we will make use of a step activation function which fires 1 if above the threshold a 0 otherwise[21]. We need to train the perceptron now. This essentially means modifying weights after observing the inputs such that the activation function fires correctly. For all inputs, i , $W(i) = W(i) + a^*(T-A)*P(i)$, where a is the learning rate, here, W is the weight vector. P is the input vector. T is the correct output that the perceptron should have known and A is the output given by the perceptron [21]. When an entire pass through all of the input training vectors is completed without an error, the perceptron has learnt. A deep neural network is thus a collection of perceptrons or to be more accurate it is a multiple layered architectures which compromises of an input and output layer and in between them multiple hidden layers [15].[multilayer network image] From the image we can observe Each input from the input layer is fed up to each node in the hidden layer, and from there to each node on the output layer. We should note that there can be any number of nodes per layer and there are usually multiple hidden layers to pass through before ultimately reaching the output layer. But to prepare this we require a learning calculation which ought to be able to tune not as it were the weights between the output layer and the hidden layer but moreover the weights between the hidden layer and the input layer. Clearly, it becomes obvious that we will need to tune the inputs between the input layer and hidden layer for this we shall make use of a technique called backpropagation which essentially means we carry the error to the next stage of input and then use these errors to modify the input stage of every layer. to be brief we can summarize it as follows We present a training sample

to the neural network (initialised with random weights). Compute the output received by calculating activations of each layer and thus calculate the error. Having calculated the error, we readjust the weights (according to the above-mentioned equations) such that the error decreases. We continue the process for all training samples several times until the weights are not changing too much [7].

Now that we have a good understanding of how neural networks work we shall look into how ASR happens via neural networks [5]. We shall go about this step by step. The first problem will be converting sound to bits. We have previously seen digital hearing aids automatically convert sound waves into numerical codes and have extended this concept in multiple places. We shall now go into this a little more in detail and provide an insight into how this could happen. Consider the below wave of sound 6. This can be



Figure 6: soundwave

represented on a graph as a simple expression of height vs time. The annotations towards height can be amplitude, frequency whatever a person chooses that suits their purpose best. However, note that this is a bit too scattered and not very uniform which is understandable because over digital media the voice can break. Let us attempt to smooth this signal using one of the many transformation algorithms available [Nyquist theorem for example]. The result will look like this 7. Recall it was mentioned that we can simply take



Figure 7: smooth wave

the graph as a function of height vs time, so to help visualize this consider the 8. To represent this in a text format it would look like [100,-20,30,89,789,-400,...,345] where each value is a measure of height over a designated unit of time. We need to be careful about how we select this unit of time. The idea is that different syllables have a different pitch we want to exploit that [4]. Hence we want to select a unit of time such that each unit possibly corresponds to one letter. The figure 9. gives an insight into how the overall model should look. So after we have trained the network to recognize each letter based on value/set of values we proceed with feeding the current input stream and thereby obtaining each letter. We can then pair these letters to form a word. Note that there is a high

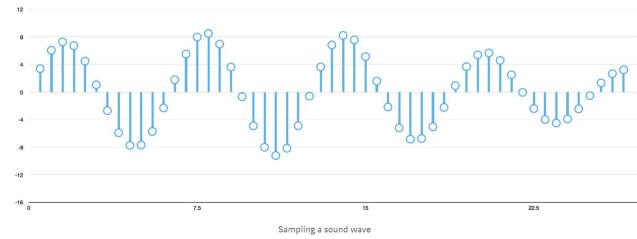


Figure 8: sampled wave

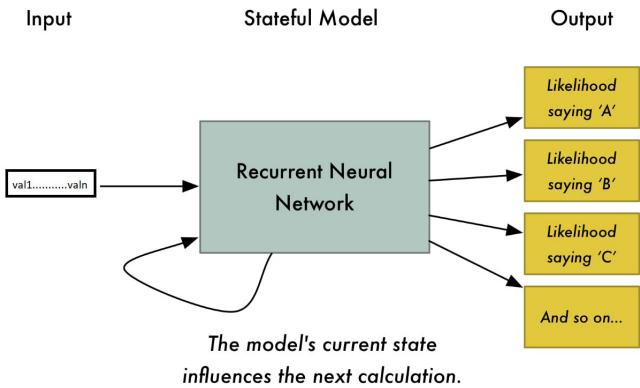


Figure 9: overall neural net model

chance that many letters could be repeated, decisions must be made based on observations if we need to replace repetitions. Once we have obtained these words there is a possibility of spelling errors using an auto-correct program [there are many good algorithms available on the internet] we can then use the Markov model we previously explored to verify its correctness [if the word generated fits the model observed]. To save some time we could use map-reduce again to find out if similar patterns exist before and then use it accordingly to determine if there were similar instances before.

3.1.5 Using Image Processing to generate captions. It is well known how powerful OCR is it can convert text images into a text file by "reading". What if we could apply a similar concept when people are speaking. People who have hearing disabilities especially those who have severe hearing disabilities and cannot always make use of sign language to get by make use of lip reading. Lip reading has existed for a long time and there is no particular skill or technique about it. People familiarize themselves with the movements of the lips with respect to different sounds and then make use of that pattern. We will not go too deep into the specifics of how to process features and use them to recognise these patterns, we have already exhaustively covered neural networks and Markov models in great detail. Depending on how the features were extracted and stored learning can occur. We shall instead focus on the process of obtaining the images for processing the features. Since we are going to be focusing on extracting the facial features we need a device that can focus on the face. Two devices that could be used are the smartphones and perhaps a not so popular option in Google Glass. Both devices have powerful cameras with which pictures

can be taken. Note that captions generated will be with some delay. Converting these devices into IoT devices shouldn't be particularly hard. Using map reduce we can effectively store these images and in a quick manner, to save data however we could probably convert the image into an rgb matrix text file and send. Map reduce plays a very very important role here, rather than sending the same image again and again if a mapping is found to exist already we can make use of it. To extract features OpenCV has a great library that could aid in the feature extraction making use of these features for processing depends on the implementation. Note that big data here if a good bunch of people are observing the same thing, like for example watching a news broadcast, seminar etc. We can use a combination of big data and IOT to determine these similar users and make one person the central hub, he/she will process while the results are shared between all or alternatively each person can send sections at regular intervals to reduce the processing time. For example, if 4 persons are detected person each person can do 10 seconds order depending on implementation this should help keep the process more real time. Note that however, this would be very situational but in situations where transcripts are not made available and the environment is way too noisy for a speech to text caption system to be implemented this comes very handy. While we are on the topic of using these devices as IoT a future possible implementation, especially for smart TVs, would be to do detect such devices and send the subtitles to the device. Too many times if watching from a distance subtitles from a distance a person am not be able to read them having it sent n the device would mean the person can see the tv and read comfortably especially in the case of google glass.

3.1.6 Captions for the blind and deaf. It has been covered in detail how we can go about to help those who are hard of hearing. But there are many people who are both deaf and blind. It is appropriate that we consider the difficulties these people face too and think of a possible solution. All considered one of the most important thing blind and deaf people would need is a braille machine (provided they know braille). There exists technologies that create Braille on the fly and are IoT supported. Combining all of the previous discussed technologies with this wont be particularly hard the only note able difference is instead of outputting captions they need to be converted to a braille format instead.

3.2 Data Processing and Technologies

Data processing has been covered in advance very well in the previous sections. For those who are unable to build a custom neural network or are struggling to implement it can make use of the Watson API. Watson was created as a question answering (QA) computing system that IBM built to apply advanced natural language processing, information retrieval, knowledge representation, automated reasoning, and machine learning technologies to the field of open domain question answering. When created, IBM stated that, "more than 100 different techniques are used to analyze natural language, identify sources, find and generate hypotheses, find and score evidence, and merge and rank hypotheses." In recent years, the Watson capabilities have been extended and the way in which Watson works has been changed to take advantage of new deployment models (Watson on IBM Cloud) and evolved machine

learning capabilities and optimized hardware available to developers and researchers. It is no longer purely a question answering (QA) computing system designed from Q&A pairs but can now 'see', 'hear', 'read', 'talk', 'taste', 'understand', 'reason', 'interpret', 'learn' and 'recommend' [22]. This article [8] provides a very good explanation on how to use the watson API to generate captions.

3.3 Section conclusion

Captions are a very important methods of understanding conversations and proceedings. with advancements being made it AI the challenge is now geared towards generating captions with 100% accuracy. Players both big and small are starting to take up the process of caption generation more seriously. Aside from helping people who are hard of hearing caption generation is important because of its other uses , it can overcome the language barrier and become a very powerful tools for envoys possibly removing the need for interpreters. There should be more funding and activity from the government over this issue. Getting captions most of the time is not easy and the current guidelines are reactive rather than proactive. Technologies exist , personnel exist , motivation for doing such helpful work is at an all time high all that is needed is a little push. On the technical front as mentioned all the big tech giants are actively focusing on AI but they all are looking at the bigger picture. AI to perform tasks on the whole. there is always a chance for smaller corps to pick up small important pieces of detail that could really make a difference. for example, the google glass project has not really made much progress and caption generation is not their priority. However, companies exist who have made facial expressions to captions a reality on devices like smart phones. Someone could put two and two together and make a device that costs lesser than a hearing but delivers the same impact.

4 BIG DATA AND NOISE POLLUTION

4.1 Introduction

Every day, we experience sounds in our environment, such as the sounds from television and radio, household appliances, and traffic. Normally, these sounds are at safe levels that don't damage our hearing. But sounds can be harmful when they are too loud, even for a brief time, or when they are both loud and long-lasting. These sounds can damage sensitive structures in the inner ear and cause noise-induced hearing loss (NIHL). NIHL can be immediate or it can take a long time to be noticeable [10]. It can be temporary or permanent, and it can affect one ear or both ears. Based on a 2011-2012 CDC study involving hearing tests and interviews with participants, at least 10 million adults (6 percent) in the U.S. under age 70fi! and perhaps as many as 40 million adults (24 percent)fi! have features of their hearing test that suggest hearing loss in one or both ears from exposure to loud noise [10]. Loud noises like explosions, repeated exposure to loud music for extended periods of time are few of the factors that lead to NIHL. Sound is measured in units called decibels. Sounds of less than 75 decibels, even after long exposure, are unlikely to cause hearing loss. However, long or repeated exposure to sounds at or above 85 decibels can cause hearing loss. The louder the sound, the shorter the amount of time it takes for NIHL to happen.

4.2 Big data and how to tackle noise pollution

So far a very reactive approach was taken towards tackling hearing loss and while they all are good approaches as the saying goes prevention is better than cure. Now we shall take a look at how integrating big data with the IoT devices we have at hand can go towards helping us curb NIHL. The device is none other than the mobile phone. The mobile phone is one of the pinnacle devices that leads the IoT trend. The fact it has the high processing power and can access the internet almost anytime allow for many desirable solutions. So how do we go about tackling this problem, quite straightforwardly it is a good practice to avoid sources of loud sounds. How can we do this, two ways one we can proactively scourge the internet and google maps for situations like traffic, construction sites and other such noise pollutants and then analysing these chart routes to avoid them. This works well only if we have such data available via maps, internet. The other way is to use the same implementation of the previous but rather than depending on internet and maps have people update this information via an API. One more possible implementation is to use the speakers on the phone and use it as a sensor and then use GPS data to accordingly update information. If the majority of the public agrees to this then the amount of data will be humongous and definitely big data technologies like Hadoop, pig, hive will be required to store efficiently but this method will have loads of data charges and will be a drain on the battery life. It could help if governments could fund for specific IoT devices that listen to crucial junctions like signals that the government and or public could use. This way the governments could have a portal maintained by them that actually suggests places of high noise pollutions. The added benefit to this is that the government can monitor round the clock violators of noise pollution and can proactively set out to catch these offenders. While the above may/may not be implemented yet one way we can protect ourselves is by using ear plugs, But the most common complaint would then be that of boredom and discomfort. Most head and earphone companies these days make use of excellent noise cancellation technology. We can use big data and mobile phones to play music that is at the opposite frequency of the sound to cancel out such unwarranted noise. Aside from external noise we now must consider how harmful is the music we listen to. Music has evolved the music of these days have evolved from peaceful melodies to high-intensity powerful tunes. More often than not we get lost in the euphoria of these tunes and subconsciously increase the volume to maximize the effect of this rush. Using big data we can control these habits via big data we can dynamically analyse which songs are most likely to cause such situations by looking at the loudness distribution of the music and then collectively comparing the instances when other people suddenly increase their volumes. note that no one can dictate a person what to do unless they have explicitly given permission settings to do so. What we can do is whenever a person suddenly increases the volume that way past a safe threshold we can display warning messages that will alert the user that he/she is at risk of damaging their eardrums.

4.3 Section Conclusion

There are many unique possible solutions to counter the problem of NIHL. Ultimately both the government and its people need to

be proactive and neither should wait for the other to make the first move. Governments need to start creating more awareness about the effects of NIHL and need to start funding research into tracking NIHL digitally if they do not have the required personnel to track manually. With everything going digital ultimately this implementation will have to happen somewhere down the line. However the sooner they get a start to it the sooner this problem can be curbed. People too can be proactive about this and try to keep their environment as sound friendly as possible. noise cancellation technology at the minute is rather limited towards to just ear and headphones but if the current noise pollution level trends continue it won't be long before we look at buildings being built with a mandatory soundproofing scheme.

5 BIG DATA AND HEARING LOSS, MEDICAL

5.1 Introduction

Hearing loss can occur due to a myriad of medical reasons from colds to trauma to accidents. While a lot of these don't have facets where we can apply big data to reduce the probability of hearing loss occurring Big data can help in identifying the early symptoms of these problems and suggest preventive actions. The first-way and most hearing loss can occur due to medical reasons is that of the common cold. When we contradict a common cold the ear nose and throat being interconnected the infection spreads everywhere. this infection causes a buildup of fluid in the middle ear, making it difficult for sounds to travel efficiently from the outer ear to the eardrum. Individuals may notice a clicking sound in their ear or that conversations and noises are muffled. The congestion may also lead to an ear infection, caused by bacteria or a virus in the middle ear, and lead to temporary hearing loss [19]. The other factor that leads to hearing loss is the disease meningitis. Meningitis is an inflammation of the membranes (meninges) surrounding your brain and spinal cord. The swelling from meningitis typically triggers symptoms such as a headache, fever and a stiff neck [9]. Studies have shown how dangerous meningitis in particular bacterial meningitis is towards causing hearing loss [9]. The cause for the hearing loss enters the realm of biology, but the article [16] states that meningitis leads to lesions developed in the meninges layer and causes neurological damage. The next cause of hearing loss we shall look at is that caused due to trauma to the head due to accidents.

5.2 Applying Big data

It should be noted that leading a healthy lifestyle to prevent illness is an onus that should remain on the person. There are very detailed national registries that provide checklists of which vaccines to take and when. The prerogative thus remains on the person to be healthy and vaccinated. That being said using big data and IoT one can track their everyday activities and then use these details to compare it to a centralized plan and modify their activities. plenty of such apps exist but they are not entirely smart as they require manual input but are a good start. Improvements in terms of implementations of IoT devices to track such changes would be very useful. We can make use of these features to lead a healthier lifestyle and build more robust immune systems a natural way. Aside from this we also would be able to track any sudden changes in our health, if

we suddenly show symptoms of a cold etc the change in regular pattern would be detected, a cold could lead to body temperature to increase , lethargy, etc these changes could be compared to people with similar fluctuations and then a plan for corrective action could be suggested this is very much like looking up your symptoms online through a portal like WebMD only that you now have data to back it up. Also, this data could be very vital to when you visit a doctor as a doctor could analyse these logs and they could provide a more detailed information than the normal guesswork of replies the doctor would normally receive. A lot of research has been done in detecting diseases like meningitis using big data however this enters the realm of biology and is another paper in its own right. We instead shall focus on analysing MRI images to detect anomalies that could be caused by diseases like meningitis. Note that we would be able to just detect anomalies but there is a high chance these anomalies could be just noise. The purpose of using big data is to minimize the risk of being misdiagnosed as treatments for meningitis could cause more harm if misdiagnosed. Ultimately it is safer to get a second opinion and treat the analysis provided by the big data with a pinch of salt.

Safety of an individual ultimately lies in their own hands, discounting factors such as bad luck and freak accidents things that cannot be controlled. Also, note there is nothing much that can be done in the event of an accident occurring other can call paramedics, it more risky to make the situation worse by performing actions that could be detrimental to the situation it is best to remain calm and wait for help and follow very basic first aid practices. That being said big data can be sued to help the respective authorities reach and react faster to accidents and lessen the damage trauma can cause. IoT devices installed in accident prone/ busy zones can be trained to detect crashes. When a crash occurs it can be used to notify the nearest hospital with enough available resources. So we are looking at an implementation of having data of all hospitals in a region and their available resources by this we mean available ambulances ready for use and perhaps logistics like available trauma specialists and the like, this way people in distress won't have to wait too long for medical attention and everyone is covered better. Aside from separate IoT devices personal devices like mobile phones, wrist health meters can be trained to detect sudden changes in the body like falling blood pressure, etc and alert the user if the user doesn't respond then the device alerts the nearest hospital. A specialist in the hospital can monitor these details to decide if this is due to negligence or a person is actually in distress.

5.3 Section Conclusion

Big data has a lot of applications in the field of medicine, but the motivation to stay healthy should come from the persons themselves. There is a lot of research happening in the field of medicine to make the process of getting a diagnosis at least a lot cheaper than the current rates. But these diagnoses always should be taken with a pinch of salt. most programs only look at what is in front of them and may not be able to determine relationships between different diseases, they may however at least bring to attention potential anomalies which may have been missed and suggest a second opinion may be a good idea. In terms of hearing loss and medical big data cannot yet play a big part, once more co-relations

have been made between data and meningitis detection it will have to be limited towards potential MRI detection, but by no means is this a small feat MRI is very costly and big data may reduce the need to undergo multiple MRIs as it could help it confirming the presence of anomalies or rule them out altogether. The same can be said of trauma prevention. Big data can be merely sued to make sure help is received sooner. It can be used as a preventive measure to make sure people don't use accident-prone routes etc.

6 CONCLUSION

Hearing loss is a problem and once upon a time it could be considered creating a liability on the society, however, the application of big data and emerging technologies could help turn this liability into something positive. It certainly is creating a lot of job opportunities for one. there are multiple new startups created to develop on facets like speech to text conversion via a mobile phone, big players are trying to reach overall 100% accuracy. people affected by hearing disabilities now find themselves with much more options than before and also have opportunities to contribute and be a part of something big. Another positive is that the application of big data is providing a paradigm shift and is now creating more new kinds of hearing aids each of which incorporates more and more powerful features. it may not be too soon before this hearing aids down the line become new "smart earphones". Caption generation has a huge potential market too but it is only the big players who are making significant headlines. The race for 100% is wide open and anyone stands a chance to make a name for themselves. The current set of government policies and funding are more that of a reactive than proactive approach changes can help drive research and also create new jobs to make resources available everywhere for anyone to use. Big data has a lot of applications in healthcare which is constantly evolving there will always be new avenues to apply big data, it is, however, a risky move because any misdiagnosis or wrong suggestion could lead to fatalities which could lead to lawsuits. The benefits, however, outweigh the risks and most patients are smart enough to know that predictions from a computer are to be used as a reference and not the rule.

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Analyzing everyday challenges of people with visual impairments

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ABSTRACT

People with visual impairments face varieties of problem in their daily lives. Nowadays, modern technology especially camera-based technologies are helping people with visual impairment in their everyday tasks ranging from daily household activity to navigation. Users are using camera based applications where they are sharing photos and asking questions. Based on the asked question and shared photo, automated tools or human crowd workers are helping the visually impaired people in their tasks. By exploring the questions, it is possible to understand the problems and challenges of people with visual impairments. However, the volume of such data makes it impossible to analyze the questions manually. Big data analytics could help us to understand the challenges of people with visual impairments. To understand the challenges, we analyzed the VizWiz data set which contains more than 33,500 questions asked by people with visual impairments. In this paper, we report on the data and shed light on the challenges.

KEYWORDS

E534, HID 237, Big Data, Accessibility Issues, People with Visual Impairments

1 INTRODUCTION

People with visual impairments face a variety of problems in their daily lives and need assistance. They need assistance with detecting objects, identifying money, navigation, transportation, household activities, cooking, and various other activities. Sighted person rely on vision on so many things that it is almost impossible to visualize and understand the problems of people with visual impairments. Although there are variety of tools available to simulate the challenges and experiences of people with visual impairments, the challenges of people with visual impairments is not well understood. To help visually impaired people with technologies, we need to understand their problem first.

One possible to understand the challenges of people with visual impairments is qualitative analysis or ethnographic studies with people with visual impairments. Simply, researchers can follow or conduct interviews with people with visual impairments. Although qualitative studies are widely accepted research methods, it has limitations. Specially to understand the problems of people with visual impairments, qualitative studies have severe limitations. As the challenges vary with the experiences of people with visual impairments, these studies can not capture or depict the whole picture. Besides, these studies are very expensive and need ample

human effort. Therefore, we need a better way to understand the challenges of people with visual impairments.

Big data analytics could be a potential alternative. To understand how big data can help people with visual impairments, we need to understand the background first. Nowadays, people with visual impairments uses different technologies for their problems. A wide range of technologies such as talking watch, braille reader, navigation helper are available in the market to help the visually impaired in their daily tasks. Since the introduction of smartphone, smartphone based applications gained huge popularities among people with visual impairments. Now, mobile and smartphone applications like Seeing AI [7], AiPoly [2], LookTel [9], and other such camera based applications are helping people with visual impairments in object recognition, face recognition, color detection, human emotion detection, activity recognition, and other such tasks that was not possible before. Figure 1 depicts an example from Seeing AI which shows that how camera based applications are helping people with visual impairments by describing nearby person's activity (Figure 1b) and their facial emotions (Figure 1a).

Most of the camera assisted assistive applications works in one simple way. The user uploads an intended photo and asks a question about that. Applications have its simple iq engine which tries to answer the problem first. If it's not able to answer that question, it shares the questions and images with the user's friends and family. Sometimes, the image is shared with a web based human worker. This crowd worker is essential for such system, because the iq engine is not sophisticated yet. We can not completely trust the automated approaches. Besides, visually impaired user's can not efficiently take photos. Sometimes they point at totally wrong objects or items, sometimes they share blurry photos, and even sometimes the question does not match with the photos [3, 5, 6]. Therefore, to give a correct answer of the questions, technologies require human intelligence. Questions and answer based applications like TapTapSee [8] and VizWiz [3] uses this approach. LookTell [9] and BeMyEyes does not have any automated approach, it directly broadcasts the video feed to the volunteers and volunteers answer their questions. Some applications are trying to move towards the fully automated approach, however, due to the limitations of automated approaches they did not gain much popularity yet.

Human based systems have privacy issues, because these users are uploading their photos which may contain sensitive information. Often they ask about medical information, their address, and various other sensitive information which can be exploited by the malicious crowd workers. Even sometimes, the users shares their credit card image and asks the system to about their credit card information which have severe privacy and security implications.



(a) Age, gender, appearance, and facial expression



(b) Age, gender, and activity of a nearby person

Figure 1: Seeing AI providing various information about people nearby [7].

Moreover, cameras and images shared by them can be extremely risky for people with visual impairments, because often they do not know the contents of the photo. Photos can be uploaded in error, sensitive data can be shared unintentionally. Ahmed et al. [1] reported a scary story of one of the VizWiz users, who accidentally shared her naked photo with a crowd worker. Such evidents suggests that such systems has severe privacy and security implications. However, visually impaired needs such tool in their daily lives. Therefore, the ideal solution would be an completely automated approach. However, to design a flawless system we need to improve the existing tools first and we need to understand the challenges first.

The challenges of people with visual impairments can be easily understood from the images uploaded and questions asked by the user. Although it is extremely difficult for people with visual impairments to take a good photo, still they are using these tools because of their challenges. Therefore, the data uploaded in these applications are probably a good way to understand the challenges. However, due to the volume of the data it is not possible to manually identify the problems. Therefore, big data analytics can be helpful in this context to understand the challenges of people with visual impairments. However, due to privacy issues all but one data sets are not publicly available.

In this paper, we analyzed the VizWiz data set containing more than 35000 images and questions [3]. Based on the questions asked, we tried to categorize their problems which eventually help the researchers to design and develop a fully automated system. Previous researches [4] explored the same problem with the same data set. However, they only explored 1000 images and performed a qualitative study and identified four categories of problem. Since manual analysis is not possible on 35000 data, we used big data tools to automatically analyze the questions and images. In this paper, we report on analysis performed and the visual challenges of people with visual impairments.

2 METHODOLOGY

In this section, we discuss the methodology for identifying the challenges of people with visual impairments.

2.1 Data Set

We used VizWiz data set which is the only available data set in this category. VizWiz is an iPhone application that allows visually impaired users to get quick responses of their challenges. The app tries to find an answer by using automatic IQ engine and anonymous crowd workers [11]. VizWiz was released in May, 2011.

VizWiz application helped more than ten thousand users by answering more than 100,000 questions. However, they only shared half of their data from those participants who gave consent. Therefore, around 50,000 data are available for the researchers. However, the researchers removed around 6,000 data due to sensitive contents in the images. The rest of the 43,543 images were made public. All images and questions redundantly checked and anonymized. We downloaded this data set for research purposes in May. Recently, the data is not available to download. Therefore, we urge the instructors to not distribute the data.

Based on the images shared and questions uploaded, we found only 33,580 images and their related questions. The questions were shared in json format and images are shared in a compressed directory. The questions data set have three columns which I described next:

- **image:** The name of the image file.
- **private:** If the image is marked as private.
- **question:** Asked questions of the user. Some questions are missing.
- **response:** Each question can have multiple responses. As mentioned earlier, some questions were tried to answer using the IQ engine and some questions were sent to the web workers. For each question, there can be one to 11 responses. However, on average three responses were received. The distribution of the responses shown in Figure 2. From the figure, we can see that most of the questions either received three or four responses.

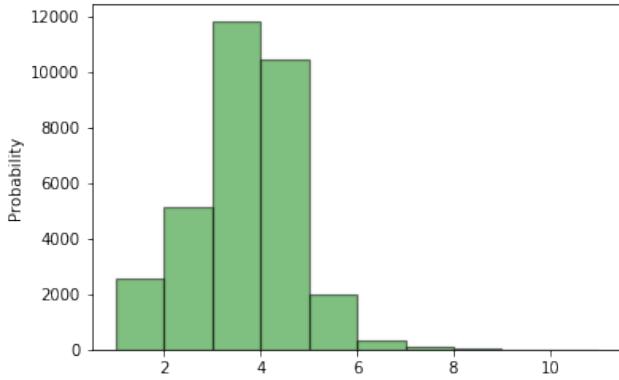


Figure 2: Distribution of the number of responses

2.2 Data Cleaning and Preparation

Since this data was collected from a research group, the data is very clean. We did not need any further cleaning except we discarded the private column. Since the researchers did not share the private images, therefore, all the rows in private columns shows false. Therefore, this column does not add any values to our analysis. We also noticed that lot of questions are missing, but an image is available. We can safely assume that these images were asked without questions and the users assumed that the images are self describing. Since the images can be interesting, therefore, we still kept the questions and labeled those questions as ‘NoQues’. We used

‘pandas’ for storing the data. We also uploaded the images in the specified Google Drive folder.

2.3 Data Analysis

We performed analysis on both the questions and image data sets. The image data set only used to detect the blurred images. However, we rigorously analyzed the questions to identify various issues of people with visual impairments. In this section, we mainly discussed the text analysis methods. The full analysis can be found in ‘question_analysis’ jupyter notebook. The image analysis can be found in ‘image_analysis’ notebook.

2.3.1 Question Analysis. To understand the challenges of people with visual impairments we performed unigram, bigram, and trigram analysis. Based on the analysis, we identified several issues which is presented in the results. The process of identifying the challenges is discussed in next section.

3 RESULTS

In this section, we present our results that we identified from the analysis:

3.1 Identifying the challenges of people with visual impairments

The questions asked by people with visual impairments explains some of their challenges in their daily lives. Whenever they are facing issues, they are asking questions in VizWiz. Therefore, the questions asked could give us some insights about their challenges. To understand the challenges, we first calculated the frequency of

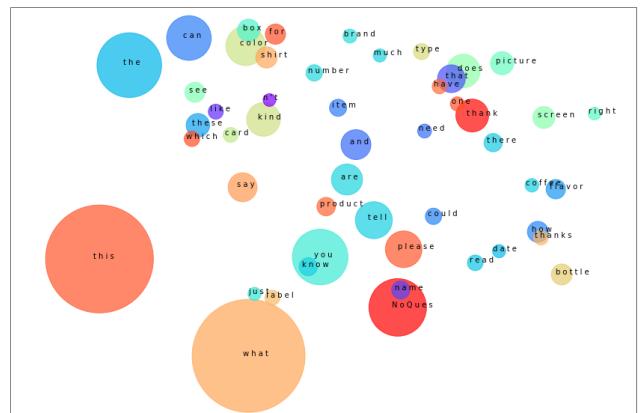


Figure 3: Most frequently used words in the questions asked

the words. There are around 4500 unique words in the questions. The most frequent 50 words is shown in Figure 3. If we closely examine the words, we can see that the most frequently used word is ‘what’. ‘What’ appeared 22793 times which is approximately 70% of all of the worlds. The second and third most frequent words are ‘this’ and ‘the’. Since, this is a set of questions, therefore, all the above words are justifiable. Although, ‘what’ is somewhat giving us an indication that users are asking about objects or subjective questions mostly, ‘this’ and ‘the’ is not adding that much value. Next,

we performed the same analysis by removing the most commonly used words in English. That unigrams gave us some additional insights. The list of most frequently used interesting words can be found in Figure 4. If we remove the commonly used words, then for the majority of the questions had no questions. Those questions were asked by just uploading the photos. We assume that the users thought that the app could automatically answer those questions. Other three most frequently used words are 'color', 'tell', and 'please'. Among these three the most interesting is 'color'. Combination of 'what' and 'color' indicates that people with visual impairments face issues with color detection, and often they ask the workers about the color of the objects and items. Therefore, we found **color detection** problem of people with visual impairments from the analysis. If we just consider the nouns and pronouns from the 30 most frequently used words, we find 'box', 'picture', 'color', 'screen', 'shirt', 'bottle', 'flavor', 'brand', 'coffee', 'label', and 'product'. From this keywords, we can safely assume three other problems: they face issues with screens (screen), there are issues with objects (brand), and the users face issues with reading labels. Therefore, from the initial analysis we found four problems that people with visual impairments regularly face: **color detection**, **object detection**, **reading screens (mobile/ computer)**, and **reading labels**.

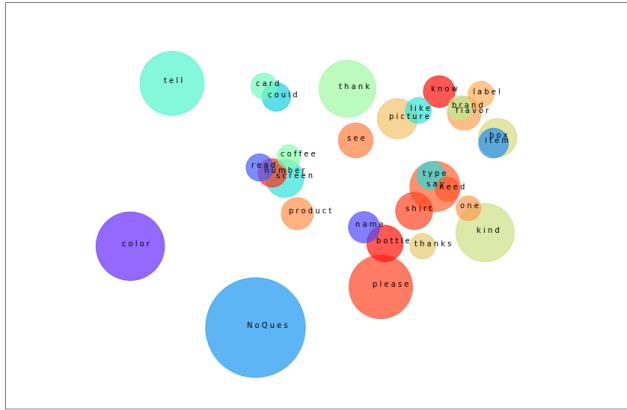


Figure 4: Most frequently used interesting words

After checking the most frequently used words, we explored the most interesting pairs of words. If we check the bigrams (Figure 14 and 15 in Appendix), it gives confidence of our identified problems. The most frequently used two words are 'what' and 'this' which suggests that most questions were asked to identify the object. Therefore, people with visual impairments definitely face problems with detecting objects. 'What' and 'color' also suggests that users face color detection problem frequently. If we check the bigrams of most frequently used interesting words (Figure 15), we find some additional insights. If we ignore 'NoQues', then we again see color detection and computer screen reading problem. However, now we can find another interesting pairs of words 'look' and 'like'. This pair indicates a subjective question, where the user is asking how the user is looking like. This identifies another challenges of people with visual impairments **Impression Management**. Another

interesting common pair of words are 'long' and 'cook' which indicates reading label issues, however this can be a household activity issue. The trigrams also gave us some new interesting insights (Figure 16). Most of the trigrams confirms above mentioned challenges, however, there are some new issues. One interesting trigram is 'display', 'treadmill', and 'tell' which indicates the health fitness related issues or **Health Management Issue**. Due to the accessibility issues in health monitoring and fitness monitoring issues, they can not manage health effective. Therefore, the users often seek help for reading the display. Another interesting three words are 'pregnancy', 'test', 'show' which can also be put into health Management category. However, this seems a private information, but still people with visual impairments have to share this information due to their visual challenges.

3.2 Challenges

Based on the rigorous analysis, we identified some challenges of people with visual impairments. In this section, we discuss the challenges:

3.2.1 Object Detection: The most frequently asked question in VizWiz is 'What is this' or 'What is that'. 'What' appeared more than 22,000 questions. Among those 22,000 questions around 7,000 questions are 'What is this?' and 'What is that?'. People asks variety of object detection questions ranging from everyday objects to personal objects. Some examples of object detection problem is shown in Figure 5. By manually analyzing some photos, it seems most of them are related to household activities. Therefore, with better tools it is possible to detect the objects.

3.2.2 Color Detection: Another most frequent problem that people with visual impairments face is to detect colors. Most of the time they use VizWiz to identify colors of their cloths, items, foods, and others. Some examples of color detection is shown in Figure 6. Based on the images, automatically detecting the colors seems a challenging task. Because, if we examine figure 6 we can see in the image there can be other objects. Automatically detecting the object of interest will be difficult. For example, in the right most photo the user is asking about the color of the dress in hand, however, there are other objects visible in the photo. Therefore, identifying the color automatically will be challenging.

3.2.3 Reading Screens: Nowadays, people with visual impairments use smartphones and computers. They use screen reading software which generates synthesized speech to relay the information from screen. However, sometimes these software fail and visually impaired need to seek help from crowd workers. Another issue is the accessibility issues of CAPTCHA, people with visual impairments struggle with CAPTCHA. Therefore, they seek people who can read the CAPTCHA for them. Some examples of reading screen problems are shown in Figure 7.

3.2.4 Reading documents or labels: Another obvious challenges of people with visual impairments is reading documents. The paper documents are not often accessible and people need help from others to read that. People might use scanners to read documents, however, scanning documents can be time consuming. Especially, for scanning food or medicine labels can be difficult. Therefore,

participants seek help to read labels for them. Figure 8 shows some examples of reading issues. However, there can be potential score for technology for this types of problem. If the user is asking for reading helps, a simple OCR can help. However, OCR might not work well with food labels. One suggestion could be for food related reading question, the system could look for barcode and identify necessary information.

3.2.5 Impression Management: Based on the analysis, we explored that managing impressions can be challenging. As a social norm, we often present our better selves to others by wearing consistent dresses. For example, we do not want to present ourselves in social places in such way that may misrepresent ourselves. Some words that we found in the questions are ‘look’, ‘like’ which we assume that users are asking to understand their appearance. Therefore, impression management for people could be challenging. Sometimes, the questions can be appearance related. Some examples of impression management challenges is shown in Figure 9.

3.2.6 Health Management: Health management is important for everyone. However, people with visual impairments face lot of challenges to maintain healthy behavior. They struggles to cook, therefore, they need to eat outside or eat packaged foods. They can not read the package’s well, so miss the nutrition info. Managing medicine can be issue. Some other issues can be attributed to visual representation of results. For examples, weight scales show visual weights, pregnancy scales convey visual feedback, health monitoring instruments like treadmill convey visual information. All these visual information makes it difficult for managing health issues. Therefore, health management can be challenging. For that reasons, people with visual impairments often ask such applications to help them with various visual indicators in health and fitness. Figure 10 shows three different health realted issues of people with visual impairments. Figure 10a depicts the issues of medicine management, users often can not identify the required medicine. Figure 10b shows asking the result of pregnancy test, which can be sensitive. Figure 10c asking questions about the weight of the user. Since, such applications can forward these questions to friends and family members all these images can be sensitive. However, technology can potentially address this issue by automating the responses.

3.2.7 Taking Photos: Like sighted people, visually impaired people also wants to take photos. However, taking photos are challenging since the users can not seen the image. Therefore, they often struggle to take photos. The irony of applications like VizWiz is that these services require a challenging task to solve other challenges. Although none of the questions mention anything about taking photos, the responses of the web workers illustrates the photo taking challenges of people with visual impairments. Around 4000 images have been detected as blurry and not understandable by human workers. Apart from blurry images, sometimes photos can be out of focus and misplaced.

Figure 11 depicts the some not understandable photos taken by people with visual impairments. However, such images takes resources and often cost money. If the system can early detect such images and prevent those images from sending then it can

save resources. Misplaced or blurry photos can be early detected. Another potential scope of technology is to automatically fix the blurry images.

We identified various challenges of people with visual impairments. There can be other challenges, however, from the VizWiz data set these seven seems some major problems. We also discovered that there can be privacy issues with the shared images (i.e., pregnancy test results) and such data need to be handled carefully. Although existing services require manual efforts, technology has various scopes to help people with visual impairments. Due to poor quality of images, such system may consume significant user resources and early detection of the quality of images can save the resources. In the next section, we discuss one such approach and the evaluation of the approach using VizWiz data set.

3.3 Automatically Detecting Blurry Images

We have already give some examples of the struggles of taking photos by the user. Often their photos are out of focus and blurry. Using OpenCV, we can detect blurry images. From the web workers responses we have an estimation that some photos are very blurry and can not be recognizable by human. If the system can early detect the blurry photos and asks the user to retake the photos it could reduce human effort. In this analysis, our task is if we can automatically identify the blurred images. The ‘Image Analysis’ jupyter notebook shows some the analysis that we performed in this section.

3.3.1 Estimation of Ground Truth Data. We set up the ground truth from the web workers responses. If any of the web workers mentioned that the image is blurry, then we set the image as blurry. From that, we found a list of 3580 images which can be considered as blurry. We then divided the data frame into two different sets: blurred set and not blurred set.

3.3.2 Detecting Blurry Photos. We followed pyimagesearch’s tutorial to detect the blur images [10]. Following that tutorial, we used variance of the Laplacian to detect the blurred images. Then, we run the algorithm on 33,580 images.

3.3.3 Calculating F1 score. We made an assumption for the accuracy of blur detection. If we consider the real case scenario, if the user need to take a photo more than once to avoid blurring that is not a problem. Although, they have difficulties of taking photos but it is still possible to take a better photo and there is no cost of taking photos. However, if we send a blurry photo to web worker it wastes resources. The system need to pay the web workers for their tasks and the system somehow charges that money to the users. Therefore, taking a blurry photo is costly. Therefore, for such a system it is better to be some false positives than false negatives. Therefore, this system tries to reduce the false negatives. Hence, we tried to improve the recall. However, too much false positive can affect the usability of a system. Therefore, Our target is to find the best accuracy over blurred images minimizing false positive rates. F1 score will help us to find a correct threshold. Our initial threshold of 150 gave us F1 score of 21.36%.

3.3.4 Identifying a good threshold. We run the algorithm with various thresholds. The F1 score graph against various thresholds

did not improve the accuracy. Figure 12 shows the accuracy of blur detection.

3.3.5 Implications of result. The poor accuracy of the blur detection algorithms depicts some problems of real world data set. Although Laplacian blur detection is a good indicator is a good indicator of blurred images, the algorithm failed in this case. The failure of the blur detection algorithm can be attributed to poorly taken images and inconsistent image sizes. We tried to change the size of the images, however, it did not improve the accuracy of the results. Probably using new deep learning based methods will be more effective.

3.4 Privacy implications of VizWiz

In the analysis of VizWiz, we have seen various issues of people with visual impairment. Definitely, such applications are helping the users, making them more independent. However, there are privacy risks. We have seen people share their medical health information, often they share their address web workers. The authors of VizWiz data set did not share 5000 photos due to privacy reason. However, people often share their credit card information which can have severe consequences. The information given to unfamiliar people can be exploited. Therefore, additional care is required for such data. Based on the analysis, we have seen multiple times that it is not always possible to automatically answering the questions. We need human intelligence for some challenges. If the data requires human intelligence, then instead of sending the complete data the system can send partial data so that the privacy implication can be reduced.

Another potential privacy threat can be arose from the inability to know what is in the picture. The user can mistakenly capture sensitive photos and share it with the web workers. The bystanders of such devices are also in risk, because they can also inadvertently captured by the user and shared with the crowd workers. One such example is shown in Figure 13. If we check the figure, we can see that a bystander is present in the picture. The question asked for this question was ‘What is this?’. We can assume that the user probably was trying to detect an object but took a photo of nearby person. Similar privacy leakage can happen with credit cards, and other sensitive information. Photos can be shared in error. Therefore, such systems should consider such implications and should take extra precaution to reduce such incidents.

4 CONCLUSION

People with visual impairments faces different challenges and by analyzing the VizWiz data set we identified and explored some challenges. Although some challenges could be identified by analyzing portions of the data, big data analytics helps us to get a better exploration of the challenges. Moreover, big data analytics also helps to discover some solution space. In future, if other such services similar analysis it would be possible to reduce the human effort that is required to operate such services. Moreover, with more data it would be possible to early detect the risks. By early detecting the risks, the system would be more helpful for people with visual impairments. Only in that way, they can enjoy the similar quality like other sighted people.

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Figure 5: Object Detection Questions

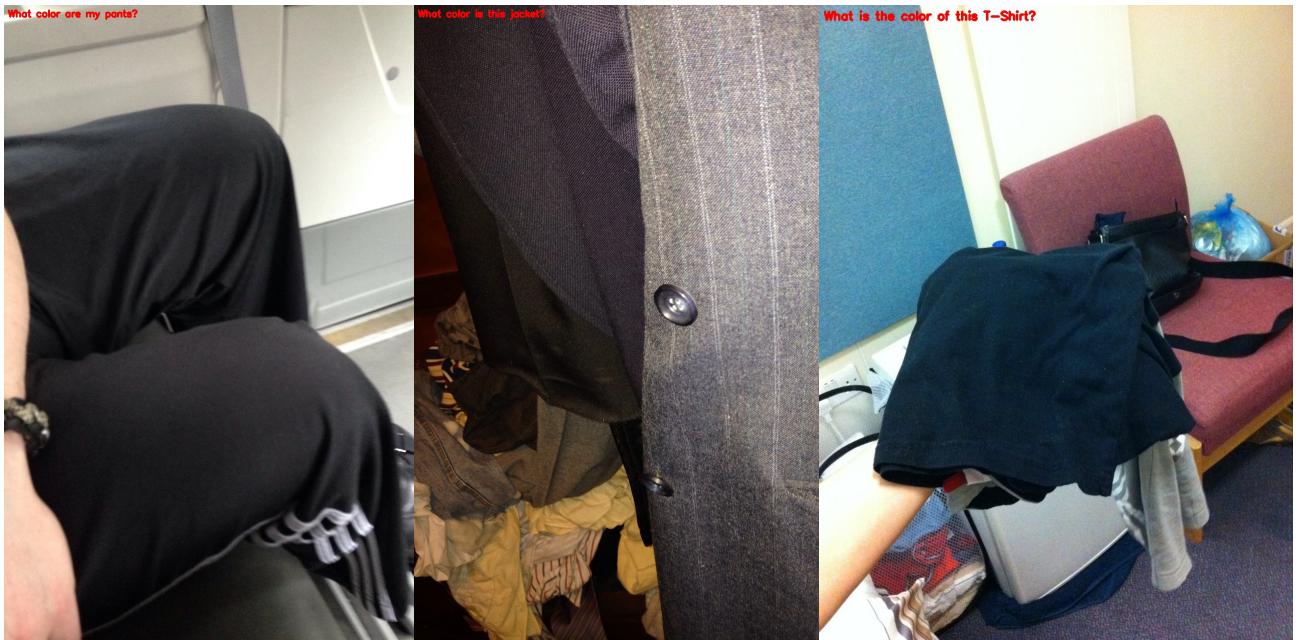


Figure 6: Color Detection images

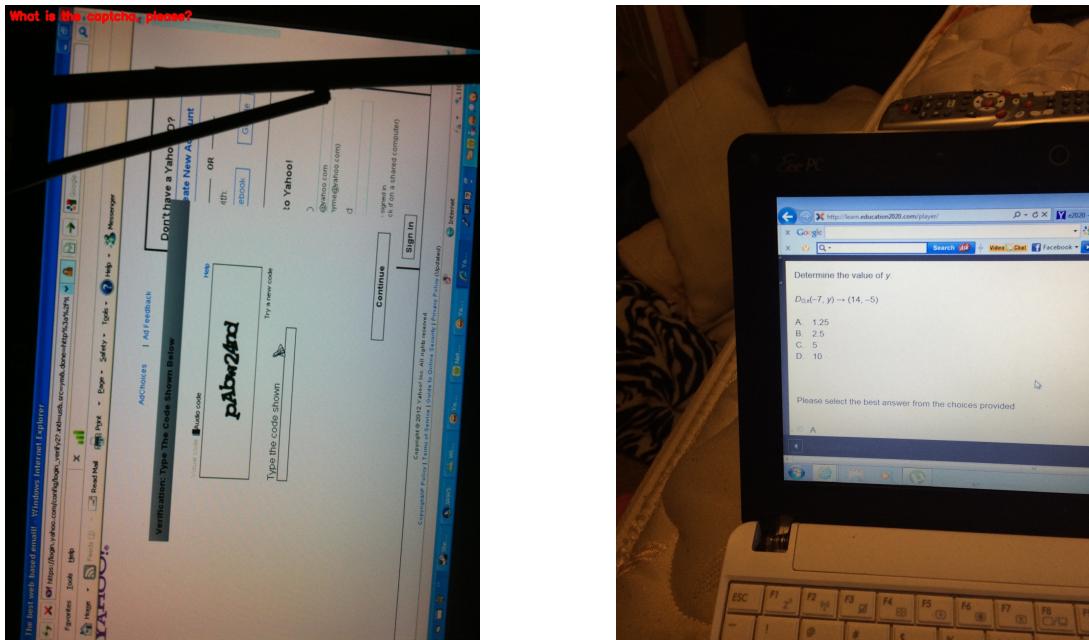


Figure 7: Screen Reading images



Figure 8: Reading problems related images

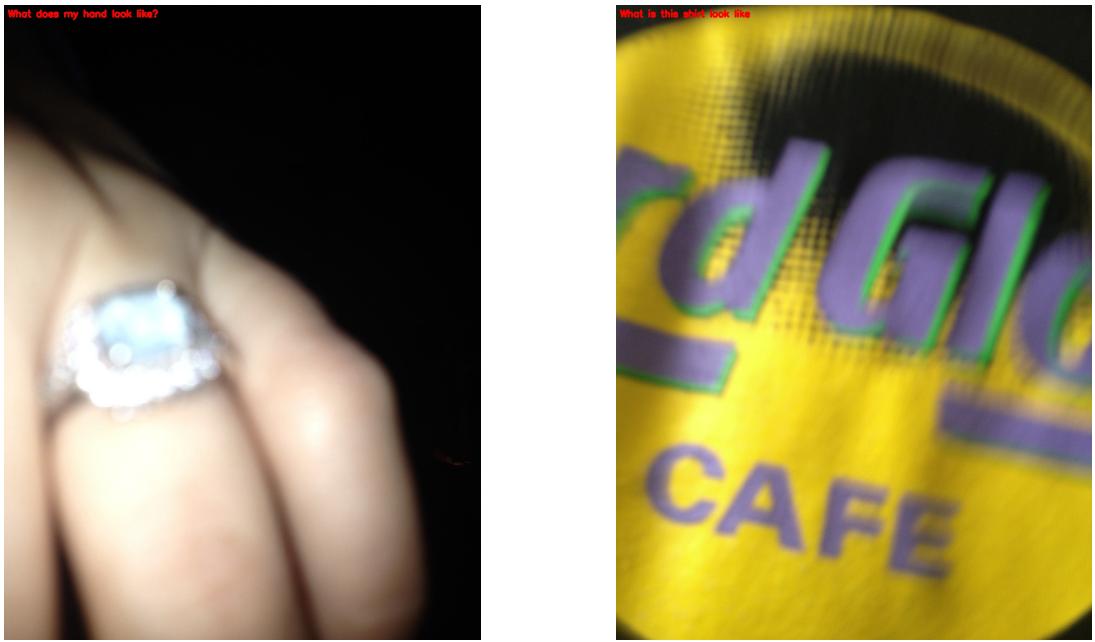
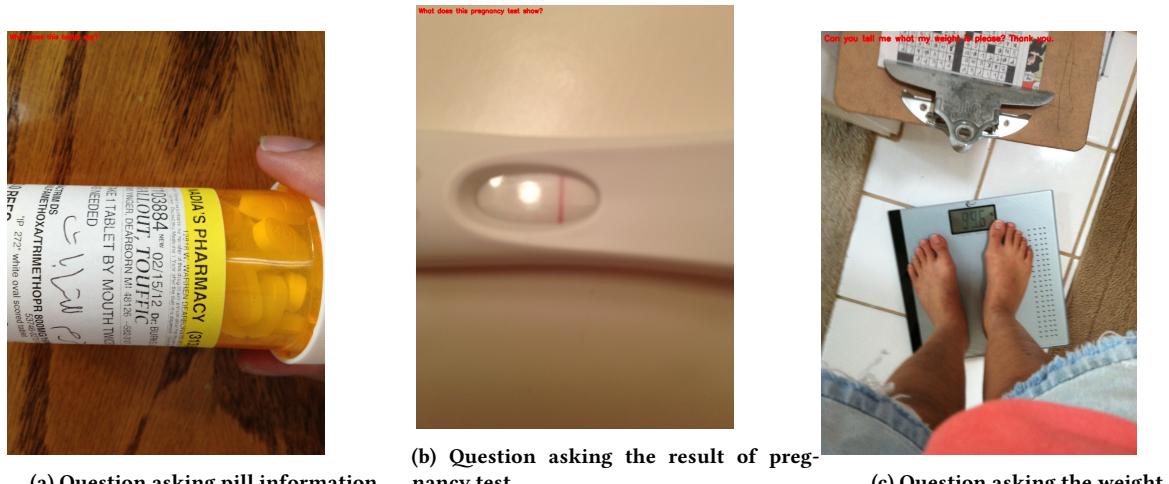


Figure 9: Questions asked containing 'look' and 'like'



(a) Question asking pill information

(b) Question asking the result of pregnancy test

(c) Question asking the weight

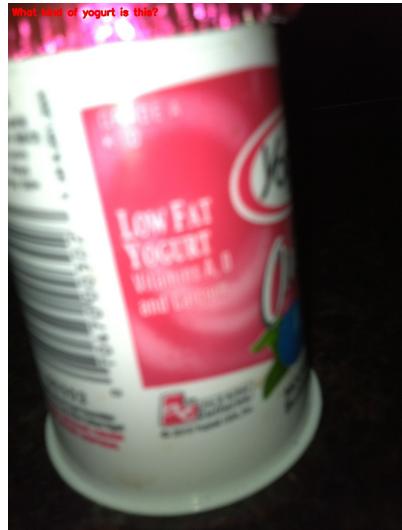
Figure 10: Various health related questions



(a) Blurry Photo



(b) Poorly Focused photo



(c) Off Focused photo

Figure 11: Poorly captured images

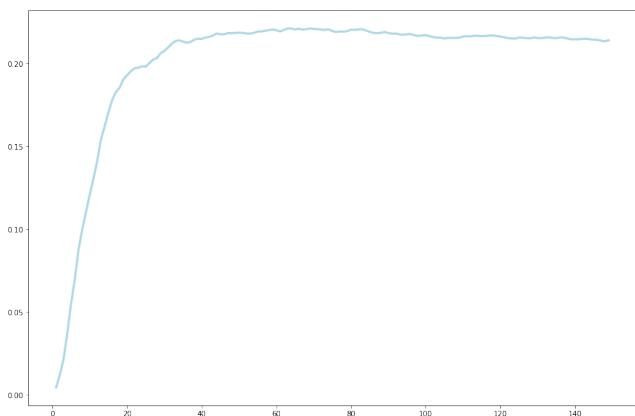


Figure 12: Accuracy of Laplacian blur detection



Figure 13: Privacy Implications of VizWiz

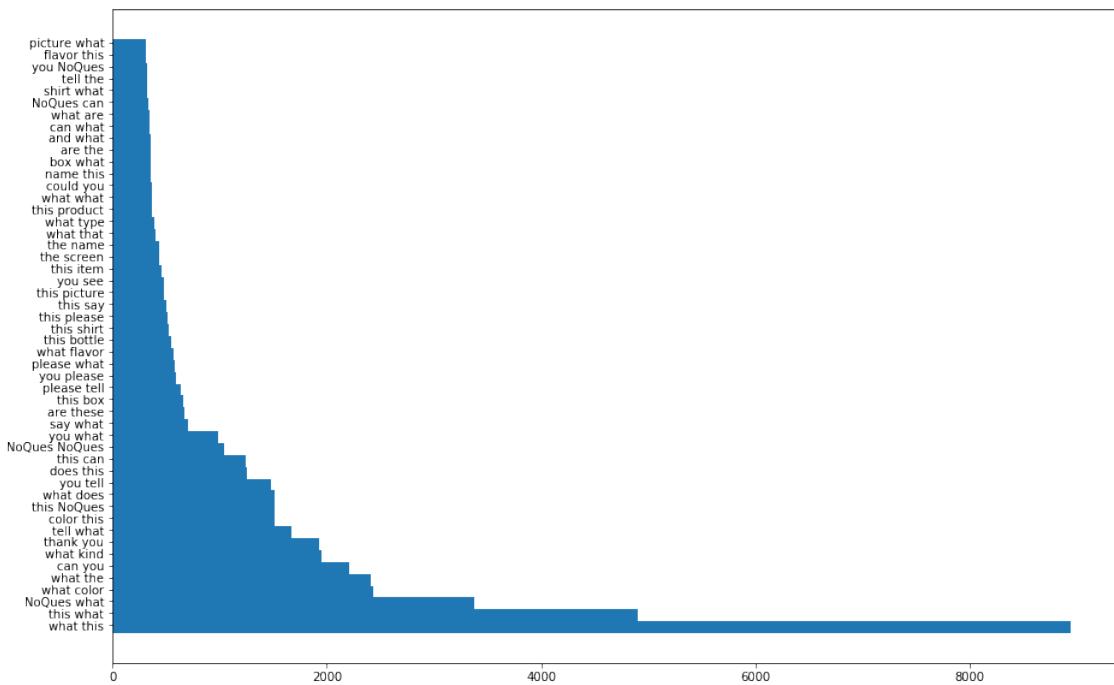


Figure 14: figure
Most frequently used pair of word

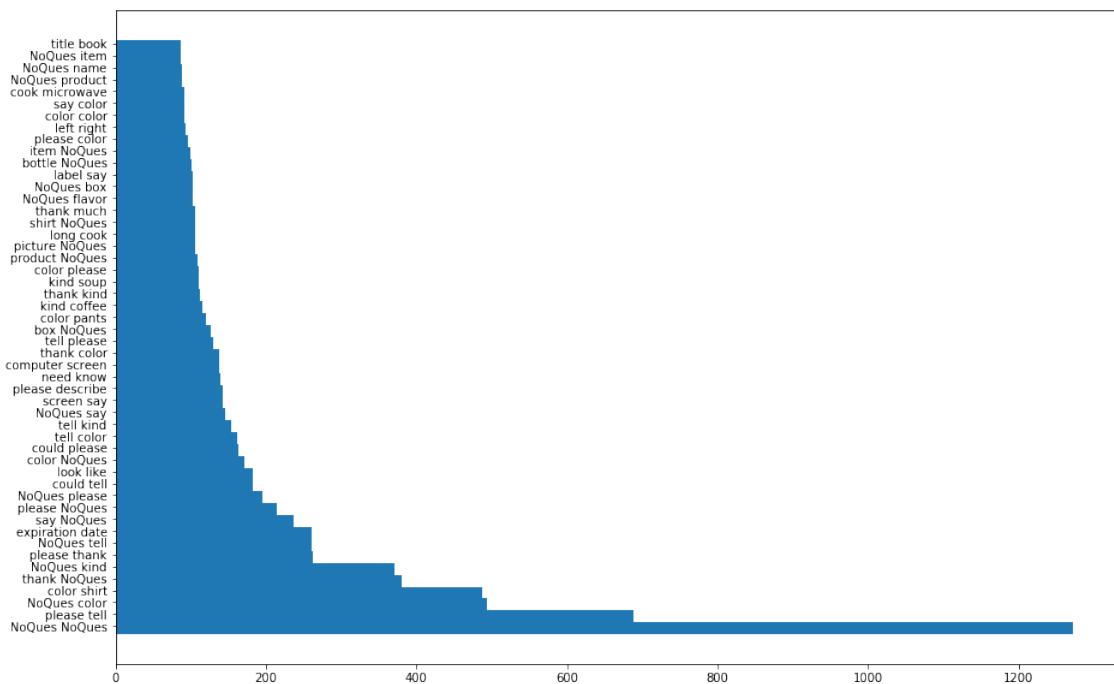


Figure 15: figure
Most frequently used pair of interesting words

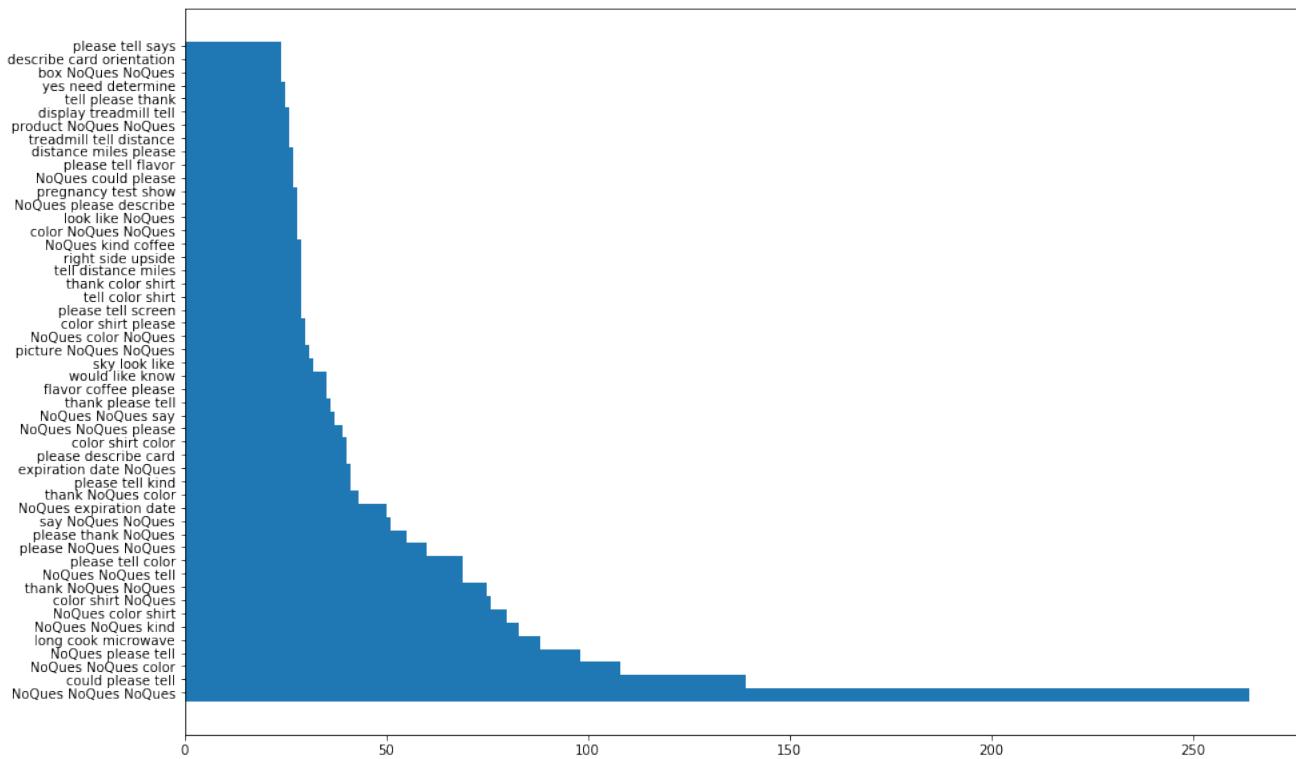


Figure 16: Most frequently used interesting words

Big Data in Genomics and Medicine

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ABSTRACT

The entirety of the human genome was sequenced in 2003, ushering in a new era of molecular biology, genetics and medicine. Since that time, technologies have advanced significantly, and next generation sequencing allows increasingly rapid and affordable sequencing of the entire human genome. Beyond the human genome, we can also sequence the entire RNA transcriptome, proteome, and metabolome. We can compare these entities in health and disease, and across populations. These new technologies produce massive datasets. Big Data applications and analytics allow interpretation and utilization of these data sets. However, analyzing and interpreting these datasets lags behind sequencing technology, as the rate limiting step. Still these technologies hold great potential for advancing medicine and human health. Combining this omics data with the electronic health record, wearable technology, pharmaceuticals and procedures, moves us towards personalized, precision, medicine.

KEYWORDS

i523, hid311, Big Data, genomics, genetics, species reintroduction, environment, conservation

1 INTRODUCTION

1.1 Health and Genomics

The current state of healthcare system in the United States is often described as a crisis. The term comes with good reason, as spending accounts for 17-18% of GDP, dwarfing other nations, and is exponentially rising at an unsustainable rate. For all of our spending, we have poorer health than most developed and many developing nations. The healthcare industry is behind in technology, with recent adoption of an electronic medical record, and prior reliance on paper charting. Communication is most often by decades old technology including phone or fax. Internet communication between healthcare providers, and with patients, is a recent novelty. We have the poorest health, including obesity due to poor diet, lack of exercise, and substance abuse. We pay more for pharmaceuticals than any other country, and most pharmaceutical budget goes to marketing as opposed to research and development. To determine a familial or genetic risk for disease we mostly rely on patient interview.

Big Data has major potential to impact health. Massive data sets related to human health and genomics are compiled by insurance companies, pharmaceutical companies, public health institutions and research institutions. [6] Healthcare is making strides and big data collection is visible everywhere. The electronic medical record EMR is close to universal and is improving constantly. Medical

resources are accessible around the world through smartphones. Wearable technology and fitness tracking apps, nutrition apps are improving personal health. One of the biggest potential impacts to health comes with the advances in next generation sequencing and genomics. These new technologies allow us to determine genetic disease risk, determine prognosis, and predict response to pharmacology and other treatment, all by measuring the genetic code. The most powerful application will be to combine genomic data with the data generated from the EMR, wearable technology, model systems, etc. to develop personalized medicine strategies.

1.2 The Genetic Code

For centuries we have known much disease is heritable. Taking a thorough family health history via patient has been a mainstay of medical interview. Previously the medical provider merely noted ailments that ran in families and maintained vigilance in subsequent generations. All of that changed in 1953 when James Watson and Francis Crick reported the molecular structure of Deoxyribonucleic acid, or DNA [27]. DNA is a relatively simple structure is made up of four nucleotides, adenine, guanine, cytosine and uracil on a carbohydrate background. Different triplicate combinations of these four nucleotides, code for 20 amino acids, and these 20 amino acids make up every protein in all living things. This relative simple system is called the genetic code. Much like the 0's and 1's in computer code, giving rise to the complexity of the internet, the genetic code gives rise to the complexity of all living things. Each organism has a unique genetic code, and this molecular blueprint is utilized to create their protein, carbohydrate, lipid structure. Furthermore this DNA code is replicated, blended through reproduction, and passed to future generations. This genetic code is often interrupted in disease such as cancer. Differences in the genetic code lead to differences in disease susceptibility, and treatment response. The human genome refers to humans over 3 billion nucleotides. We have the ability to sequence the human genome, or determine the order of these nucleotide bases.

1.3 The Human Genome

The first human genome was sequenced in 2003 [3]. This colossal global effort took over 10 years and thousands of scientists working at great expense. In the end, a private and public group collectively sequenced the first genome. Initially, the technology was extremely expensive and took great deal of time. Through technological advancements including sequencing cores and big data, the cost of the genome has plummeted. The 1000-dollar genome project is an attempt to make sequencing more affordable [6]. We are a long way away from being able to utilize the genome to deliver care.

Bioinformatics expertise has lagged behind sequencing technology. Groups still do not agree on a standard way to process the information. Still this technology improves rapidly, and recently a group published 24-hour genome sequencing for intended us in clinical decision making [19]. Soon it may be a reality for physicians to utilize genomic information, whether about drug susceptibility, or prognosis, to guide medical care. Here we review the methods to asses genetic changes. We discuss issues that present with each method.

2 GENOME ANALYSIS

2.1 Chromosome Analysis

Historical mainstays to asses changes in the human genome include a method known as a karyotype analysis. A karyotype visualizes the 23 chromosomes that contain our genetic information. Aneuploidy is duplication of a chromosome. Trisomy 21 is a well known syndrome characterized by duplication of the 21st chromosome. Duplication or deletion of all other chromosomes is not compatible with life. However, portions of chromosomes can be duplicated or deleted, giving rise to well known syndromes. Karyotype analysis is capable of visualizing large deletions and duplication in chromosomes, generally greater than 10Mb. Chromosome analysis has been largely surpassed by newer technologies. Given established use and accessibility, it may have a clinical role in rapidly confirming a suspected aneuploidy.

2.2 Flourescent In Situ Hybridization

Fluorescent In Situ Hybridization utilizes fluorescent labeled probes to identify portions of DNA which match the probe sites. In this way the chromosomal material can be visualized. Fluorescent In Situ Hybridization can identify chromosomal duplication and deletions up to 2MB. This is helpful, to identify large duplication's and deletions leading to disease. However we know even single nucleate changes lead to disease. Therefore Fluorescent In Situ Hybridization has been replaced by other technologies [2].

2.3 Genome Wide Association Studies

Historically research has focused on aneuploidy and syndromes representing large duplication or deletion of genetic material, or on single gene mutations leading to disease. However pathogenesis likely involves multiple common and rare single nucleotide variants (Single nucleotide variation) in parallel leading to most disease. Genome Wide Association Studies emerged to study common variants on large scale, and studies have showed multiple susceptibility loci8. However, Genome Wide Association Studies failed to identify all forms of genetic disease [24].

2.4 Copy Number Variation

A large part of the human genome consists of repetitive sequence, including both long and short repeated segments. There are distinct regions that vary in the number of repeats between individuals, and this variation leads to phenotypic differences between these individuals. This variation is referred to as copy number variation (Copy Number Variation). It is thought that up to 10% of the genome consists of Copy Number Variation. Most Copy Number Variation is inherited but it can also occur de-novo. Copy Number

Variation is increasingly understood as contributing to disease, where varying amounts, or doses, of a particular gene and therefore protein lead to disease [32].

2.5 Chromosomal Microarray

Chromosomal microarray is the baseline genetic testing for individuals with disease. Chromosomal Microarray is a technology that detects the presence or absence of patient DNA by measuring hybridization of patient sample to small segments of DNA attached to a surface. Chromosomal Microarray detects deletions and duplications of chromosomal material much smaller than FISH and karyotype. As technology improves, Chromosomal Microarray is able to detect increasingly small changes down to, but excluding, Single nucleotide variation. As many common diseases are due to Single nucleotide variation, sequencing is often necessary. [26]

2.6 Sanger Sequencing

In 1977 a paper was published entitled “A rapid method for determining sequences in DNA by primed synthesis with DNA polymerase”. This technique, now known as Sanger sequencing, revolutionized molecular biology. Using termination of sequence and dye detection, it provided a fast and easy way to determine the DNA sequence of living organisms. It is still extensively utilized. Many newer technologies have been developed and are known as “next generation sequencing.” [20]

2.7 Next Generation Sequencing

Next Generation Sequencing refers to a variety of technologies and a number of different methods for high throughput sequencing of DNA samples [16]. The technology utilizes massive number of parallel sequencers to copy short fragments of DNA and assemble transcripts utilizing big data and bioinformatics techniques. According to the illumina website “With its unprecedented throughput, scalability, and speed, next-generation sequencing enables researchers to study biological systems at a level never before possible.”

2.8 Targeted Gene or Gene Panel Sequencing

Disease is often due to Single nucleotide variation necessitating sequencing for diagnosis. Targeted sequencing is commercially available to detect Single nucleotide variation in a specific gene, or an entire panel of genes, often depending on the disease. Gene panels are available for particular syndromes. Commercial panels utilize both traditional sanger sequencing and NGS technology. Targeted sequencing often provides better coverage of specific genes than does Whole Exome Sequencing. This targeted sequencing circumvents the significant burden of analyzing thousands of variants of unknown significance, a problem inherent to Whole Exome Sequencing, but misses variants in genes outside of the panel, or in novel genes.

3 NEXT GENERATION SEQUENCING

3.1 Whole Exome Sequencing

With advancements in technology, exome sequencing is approaching the affordability and efficiency of targeted gene panel sequencing. Whole exome sequencing involves sequencing the entire coding region, or exome, of the genome. This consists of around 20,000 genes and over 30 million nucleotides. The exome, though massive, consists of only 1% of the total genomic DNA. Most genetic diseases involve alteration of this coding exome. Sequencing only 1% of the genomic material is a fraction of the time, cost, and burden of analysis, compared with Whole Genome Sequencing. Due to errors in Whole Exome Sequencing, a portion, (up to 1%), of the coding exome is missed. Coverage varies by gene and by region, with particular genes of interest, such as the HRAS gene implicated in Costello Syndrome, difficult to capture by Whole Exome Sequencing at all. Copy Number Variation, insertions, and deletions are also difficult to detect. Targeted sequencing is often advantageous, but Whole Exome Sequencing is improving and is increasingly accessible to clinicians [30].

3.2 Whole Genome Sequencing

Despite the massive amount of information produced in Whole Exome Sequencing, it represents only 1% of the total genome. Transcription enhancers and promoters, often involved in disease pathogenesis, are outside of the exon and missed by Whole Exome Sequencing. In addition, Whole Genome Sequencing better captures Copy Number Variation, insertions and deletions, frequently involved in disease. Whole Genome Sequencing adds significantly to expense, data storage, analysis, and the burden of determining variant significance. For this reason Whole Genome Sequencing is predominantly used in the research setting, but this is changing. In 2012 a group used rapid Whole Genome Sequencing in the newborn ICU to identifying disease causing pathologic variants. The process, from sample collection to automated bioinformatics analysis, was complete within in 48 hours. This rapid turnaround was intended as a model for utilization of Whole Genome Sequencing in clinical decision making. As technology improves Whole Genome Sequencing will likely become a useful clinical tool [13].

3.3 Variants of Unknown Significance(VUS)

Whole Exome Sequencing produces tens of thousands of variants, and Whole Genome Sequencing exponentially more. Another major hurdle is determining significance. Each variant must be assessed for disease pathogenesis, distinguishing it from a previously unreported polymorphism. Variants can be filtered for pathogenic nature based on conservation across populations and location in a protein. It is often necessary to obtain parents samples and perform sequencing on patient-parent trios to determine novelty. When a novel variant is identified, ideally biologic mechanism is investigated through animal and cell culture models. Genetic variation can now be introduced into animal and cell culture models with greater ease and efficiency utilizing the CRISPR-Cas9 system. Variants are often damaging only in conjunction with other variants. In some cases it is impossible to narrow down a single candidate when a

disease with incomplete penetrance and variable expressivity affects a small family. Efforts are ongoing to improve and streamline variant analysis for clinical utilization [14].

4 BEYOND DNA

Initial estimates placed the number of genes at $\approx 100,000$ [1]. Looking at the massive amount of diversity and the billions of unique human beings on this earth, this was an appropriate estimate. The current number is estimated somewhere around 20,000. The question is what accounts for the rest of phenotypic diversity and disease. The picture of development is complex with networks of genes turned on and off at different locations and timepoints. Regulation of this process occurs to some extent outside of the coding region, through promoters and enhancers, epigenetic alterations, splicing variation, and noncoding RNA. Altered noncoding sequence is increasingly implicated in disease. The human genome project utilized whole exome sequencing. The exome, though massive, consists of only 1% of the total genomic DNA. Many genetic diseases involve alteration of this coding exome but we are discovering that many diseases are due to problems outside of this coding region. Whole genome captures this noncoding region, although with far greater cost, burden of analysis, etc. We have also come to realize that splicing and other post transactional regulation introduces much diversity. We have the technology to sequence the entire RNA transcriptome and the proteome as well. This produces a data set which dwarfs the genome and genomic DNA sequence information. These technologies are currently only utilized in the research setting. Despite our advanced technology, we have very little idea of how to interpret the data in a clinical setting. Again the bioinformatics expertise lags behind. There is amazing potential to advance knowledge and study human disease and a tremendous amount of big data analytics along the way.

4.1 RNA Sequencing

Splicing variation leads to multiple different proteins resulting from a single gene due to differential splicing during transcription. Non-coding RNA also influences expression and modifies proteins after translation. Technologies to examine the elements, include Whole Genome Sequencing to measure DNA outside of the exome, RNA sequencing to measure the splice variants and the transcriptome, and ChIPSeq to measure DNA methylation. These noncoding regulatory elements have important clinical implications, and need further exploration. [25]

4.2 Epigenetic Sequencing

Mutations in transcription factors are well established in pathogenesis and regulation is often through enhancers and promoters outside of the coding sequence. The term epigenetics refers to alterations outside of, or on top of, the genetic material or DNA, that influence phenotype. Common epigenetic factors include DNA methylation, where methylation of DNA bases represses DNA expression, and also histone modification, where the degree to which DNA is wrapped around histones influences its expression. Epigenetic factors are heritable, and also influenced by the environment. [11]

4.3 Proteome

Ultimately DNA codes for RNA and RNA is translated into proteins. Proteins are the building blocks of all living things. The proteome is the term for the entire protein content of an organism. New technologies allow us to measure the proteome. The proteome is generally measured through tandem mass spectroscopy or finger-printing. Tandem mass spectroscopy breaks proteins into smaller portions and measures a signature and electrophoresis techniques involve separating proteins on a gel and measuring their fingerprint. These techniques require sophisticated chemistry and data analysis techniques and produce massive datasets. [8]

4.4 Metabolome

The Metabolome involves the entire set of small molecules within an organism. Analyzing the metabolome involves measuring every amino acid, organic acid, vitamin and mineral in a cell, tissue or organism. Measurement is usually by mass spectroscopy or nuclear magnetic resonance spectroscopy. requires extensive data analysis.

5 OTHER GENOMICS TOOLS

Sequencing technology is not the only factor revolutionizing personalized medicine. There is a separate and equally exciting revolution in cell culture technology integral to personalized medicine. All of these technologies rely on genomics measurements that produce massive datasets and rely on Big Data for analysis.

5.1 Model Systems

The optimal diagnosis and treatment of pediatric disease requires an understanding of physiology and pathophysiology. Throughout medical research history animal and cell culture models have been critical to this process. Mouse models, in particular, are extensively utilized because they are relatively convenient, and similar to humans at the chemical, molecular, cellular, and some anatomic levels. Furthermore, the use of transgenic mice allows for genetic manipulation to help elucidate molecular mechanisms. However, given that mice and humans diverged millions of years ago, there are critical physiological differences between the two species. Human diseases often lack a mice ortholog. The equivalent disease in mice may be fatal or benign, and we cannot model some high level human organ functions or late onset diseases. Even non-human primates, despite being our closest ancestors, have important phenotypic differences. For example, because of these differences, it is particularly difficult to develop animal models for neurodegenerative or neurodevelopmental disorders. Differences in mouse disease morphogenesis have led difficulty modeling human congenital heart disease. These limitations drive the need for human cell, tissue, and organ systems models. Many human diseases involve terminally differentiated cell types, such as neurons and cardiomyocytes. These cell types are nearly impossible to sample, culture, and maintain. Even after generating primary cell lines from diseased tissues, ability to derive meaningful conclusions is often hampered by inconsistent replicability, dedifferentiation, and variability due to culture conditions. In this light, tissues derived from human induced pluripotent stem cells (h induced pluripotent stem cellss) has the potential to overcome many inherent limitations of animal and cell culture models

and provide an unprecedented new paradigm to model human diseases.

5.2 Pluripotent Stem Cells

During human embryogenesis, the ovum and spermatozoa fuse at fertilization, begin to divide, and differentiate into all cell lineages and tissue types in the human body. During development, these cells lose their pluripotency as they terminally differentiate into specific cell types. Embryonic stem cells (ESC) were first isolated from the blastocyst of developing mouse embryos in 1981, and from human embryos in 1998 [17]. These cells have the remarkable ability to retain pluripotency. The ESC discovery generated great excitement over their potential applicability in human disease modeling and regenerative therapies. However, limitations and controversies soon emerged. The isolation of ESCs from human embryos is ethically controversial. Disease models utilizing ESC are limited to diseases identified through preimplantation genetic diagnosis. Genome editing ECSs provides an opportunity to generate particular mutations of interest, but technique remains largely limited to monogenic diseases. In this light, recent breakthroughs in induced pluripotent stem cell (induced pluripotent stem cells) technology circumvent many of these drawbacks.

5.3 Induced Pluripotent Stem Cells

In 2006, Shinya Yamanaka identified four transcription factors, (OCT4, SOX2, KLF4, and c-MYC), that were capable for reprogramming somatic mouse cells into a pluripotent state [22]. This extraordinary feat was recapitulated one year later in human cells. These induced pluripotent stem cells (induced pluripotent stem cellss) behave like ESCs with capability to differentiate to most other cell types, and circumvent the ethical controversy and sample limitations. As opposed to human embryos, induced pluripotent stem cellss can be generated from readily accessible tissue samples, such as peripheral blood mononucleated cells (PBMCs). Patient samples can be reprogrammed to induced pluripotent stem cellss, serving as an autologous, continuously renewing supply of pluripotent cells. This has resulted in the dramatic expansion of the stem cell field, with development and improvements in reprogramming protocols, and directed cellular differentiation. Patient-specific induced pluripotent stem cellss can be generated from wide variety of patient samples, including PBMCs from blood samples, to dermal fibroblasts from punch biopsies, and epithelial cells from urine samples. induced pluripotent stem cellss can then be differentiated to most other cell types including cardiomyocytes, neurons, and hepatocytes. Because the lines are patient-specific, they are expected to recapitulate features of many disease phenotypes, whether due to simple monogenic mutations or complex polygenic disease susceptibilities. The patient-specific induced pluripotent stem cellss hold potential for disease modeling, predicting drug response, assessing environmental triggers of diseases, and regenerative tissue engineering. Thus, they provide great potential for research and clinical applications in personalized medicine.

5.4 Gene Editing induced pluripotent stem cellss

Mouse models allow genetic alteration using transgenesis and gene knock-outs. Measuring the resulting phenotype is extremely valuable in the study of genetics and development. induced pluripotent stem cellss allow us to utilize these same genetic approaches using human cell lines. The past decade has seen tremendous advances in gene editing technology, including ZFNs (zinc finger nucleases), TALENs (transcription activator like effector nucleases), and CRISPRf!Cas9 (clustered regularly interspaced short palindromic repeat) [21] [10]. The common mechanism of these genomic editing approaches is that they create double stranded breaks (DSBs) at desired locations in the genome, which then can be repaired by either nonhomologous end-joining (NHEJ) that can result in insertion/deletions (indels) or homology directed repair (HDR), which results in precise gene modifications. Of these, the CRISPR-Cas9 technology, which appropriates the prokaryote defense mechanism, has quickly become dominant due to ease with which it can be adapted to precisely edit virtually any region in the host genome. Genome editing, coupled with the induced pluripotent stem cells technology, allow us to study disease mechanism like never before. These technologies allow us to precisely correct mutations, and insert reporters under the endogenous regulatory control. They have also been used to demonstrate feasibility of genomic editing as a therapeutic modality. Recently, a group corrected a pathogenic mutation in preimplantation human embryos, demonstrating the feasibility of gene correction therapy. While still a long way from clinical applications, many disease phenotypes have been corrected in cell culture. These studies show the potential of these powerful technologies for disease modeling, and for therapeutic genome engineering.

5.5 Organoid Models

Sometimes a simple, two-dimensional induced pluripotent stem cells-derived tissue culture model cannot fully recapitulate complex organ systems involving three dimensional (3D) architecture; such cases necessitate organoid modeling. In vitro organogenesis, the exciting new frontier in in vitro disease modeling, aims to organize induced pluripotent stem cellss into 3D structures that better recapitulate in vivo physiology. Previous attempts at organoid modeling utilized primary tissue cells, but primary cells are difficult to obtain and often fails to propagate in vitro. In principle, induced pluripotent stem cellss are an ideal cell source to make tissue organoids. The most comprehensive organoid model to date involves a fully vascularized and functional human liver. A 3D gastric organoid was created that progresses through developmental stages adopts similar architecture to the stomach. This organoid provided valuable insights into the gut development, as well as H. Pylori infection. Human induced pluripotent stem cellss were grown also on rat intestinal matrix, to engineer a humanized intestinal graft for nutrient absorption in patients with short bowel syndrome. The established protocol for generating 3D cerebral organoids from induced pluripotent stem cellss, replicates brain developmental stages. The organoid reproduces a variety of brain structures, including the cerebral cortex, ventral telencephalon, choroid plexus

and retina. Manipulating specific developmental signaling pathways in ventral-anterior foregut spheroids recently generated an induced pluripotent stem cells-based human lung model. Lastly, an induced pluripotent stem cells-based human kidney organoid model was recently developed displaying glomerulus-like structures and renal tubules. Future in vitro organogenesis effort must address the need for chemically defined synthetic extracellular matrices, and incorporation of support cell types such as interspersed neurons, immune cells, and other regulatory cells. While the regenerative medicine field is still in infancy, transplantation of functional tissues derived from patient's own cells could profoundly improve the health of patients with end-organ failure. [15]

6 BIOINFORMATICS

Each of the steps in analyzing disease models relies heavily on bioinformatics and big data analytic. Bioinformatics is the field combining computer science, biology, mathematics, medicine, engineering, etc. [18] When Watson and Crick first identified the DNA structure, discover quickly led to the DNA coding mechanism and the interpretation of sequencing information. The interpretation and analysis of sequencing data was very amendable to computer science. We began to sequence and interpret larger datasets including entire genes, entire chromosomes, the entire human exome, the entire human genome, and now the entire transcriptome and metabolome. Further we need to compare these large datasets to one another. Bioinformatics has gone far beyond sequence analysis to involve image analysis, mass spectroscopy, and countless other integration between biology and computer science. there are also distinct field of Biomedical informatics, which refers more specifically to the integration of computer science and medicine. This often involves running multiple subsequent computer programs in established pipelines. Projects like the Galaxy project work to streamline these pipelines for ease of use. We will discuss some common applications of bioinformatics.

6.1 Sequence Assembly

Sequencing technologies produce millions of fragments of DNA. Sequence assembly is the process of identifying overlapping sequence, aligning the overlapping portion and combining into a complete genome. Once the genome is assembled it is possible to compare a sample of DNA to a known sequence in a database. One of the most popular tools involves the program Basic Local Alignment Search Tool(BLAST.) Scientists can input any obtained sequence and check for matching to a known sequence in the database.

6.2 Sequence Annotation

Sequence annotation involves identifying the important regions in a sequence. It includes identifying the regions that code for proteins, regulatory regions, and other biologically significance sequence. It is performed by popular programs such as

6.3 Comparison of two states

Another set of software tools involves the comparison of two datasets. This includes the comparison of two disease states, two individuals, or any other two datasets that need comparison and analysis.

6.4 Examples of a Popular Bioinformatics Pipelines

The programs utilized for RNA Sequencing analysis include the Tuxedo Suite open source software package which includes Tophat, Bowtie, Cufflink, CuffCompare and CuffDiff [23]. The compressed BAM file type is utilized by these programs. Tophat aligns sequencing reads to the human genome using the high output short read aligner Bowtie and then analyzes the results to identify splice junctions. Cufflinks assembles transcripts, mapping segments of transcripts to genes and individual transcripts of a reference genome. Cufflinks uses fragment counts as a measure of relative abundance, which are reported as Fragments Per Kilobase of exon per Million fragments mapped (FPKM). Assembled transcripts from can be compared using Cuffcompare. CuffDiff to compare transcript expression level, splicing and promoter use. Cuffdiff uses the Cufflinks to compare transcript expression levels in two data sets. It allows the user to find differentially expressed and regulated genes at the transcriptional and post-transcriptional level by reporting the log-fold-change in expression.

7 COST OF HEALTHCARE

7.1 The Current State

One of the most troubling issues facing the United States, and the world, is the increasing cost of healthcare. The problems are different around the globe. Much of the developing world lacks access to adequate healthcare, which is a serious problem. This paper focuses on a different problem, in the crisis facing the United States. Current healthcare spending is greater than 3 trillion dollars [5]. This makes up 17 percent of GDP. This number grows every year and is unsustainable. This number affects citizens deeply, and currently healthcare costs are responsible for 50% of bankruptcy claims in the United States [6]. All of this extra spending does not equal better health. In most measures of health, from infant mortality to life expectancy, the United States find itself far from the top. There are major issues at play ranging from a massive bureaucracy, to the poor health and obesity of participants.

7.2 The Future

It is projected that the average family will spend over 25% of income on to healthcare [6]. The problem is not projected to improve. As the *baby-boomers* age, the population over 60 with high cost chronic healthcare problems, increases exponentially. In Medical School, we were taught about this *silver tsunami* approaching the US healthcare system (prompting me to go into Pediatrics.) Many individuals, including myself, look to Big Data to uncover these problems and help fix them. Before it is too late. There are technology solutions including the electronic health record, medical reference technology, genomic medicine, telemedicine, wearable health technology, and personalized medicine.

8 ELECTRONIC HEALTH RECORD

8.1 Electronic Medical Record and Genomics (eMerge)

There is currently a massive effort undertaken by multiple companies and branches of government to combine genomics data and the

electronic health record. According to the website: "eMERGE is a national network organized and funded by the National Human Genome Research Institute (NHGRI) that combines DNA biorepositories with electronic medical record (EMR) systems for large scale, high-throughput genetic research in support of implementing genomic medicine." This method of combining genomics data and electronic health information holds great potential.

8.2 Adoption of and EMR

Throughout history, medical records were taken on paper, but after 2000 the slow transition to electronic records began [12]. The handwritten records were kept in large file cabinets, and when records needed to be shared between physicians or institutions (across the country or across the street), the paper records were faxed over a telephone line. This technology is decades old. As technology raced forward with supercomputers and the worldwide web, medicine continued to use these antiquated forms of communication. Finally, government mandates forced healthcare systems into the modern era and electronic records went online. Currently over 84% of health records are online [6].

8.3 The Current State

A majority of healthcare systems around the world are under a government regulated socialized medical system which comes with a universal health record. The healthcare system in the United States is privatized, therefore the transition to EHR came with individual health entities purchasing a multitude of different EHRs. The problem comes in that a patient presenting to two different healthcare facilities, even if across the street or within the same building, will have two different medical charts that do not communicate with one another. The other problem comes with accessing this information. The two largest companies Epic and Cerner have a commercial interest, with a primary goal to increase revenue to the shareholder. It is exceedingly difficult for the nonprofit entities including academic centers and hospitals to access the patient information within the EHR. There is tremendous potential within the EHR. Beyond data collection, storage, data retrieval, and analysis, we should move towards real time guidance and guidelines for medical decision making to improve health.

8.4 Phenome-wide association studies]

The first established linkage of the electronic health record and genomics datasets took place at Vanderbilt University. Vanderbilt Medical Center began to collect biospecimens from patients (using an ethically controversial opt-out consent process.) They performed Whole Exome Sequencing on the specimens. They then linked the specimens to the electronic health record and compiled the data in a database called BioVUE. Phenome-wide association studies is the name of a method used to measure the number of phenotypes or diseases reported in the electronic health record, in relation to single nucleotide changes in the human genome [4]. Researchers can assess whether each variant is related to any disease state. The database started in 2012 and is growing rapidly. As the dataset grows, so will its power to predict disease based on single nucleotide variants. An early version of the catalog is currently available online to all individuals.

9 KNOWLEDGE

9.1 Online Genomic Resources

Most of the Genomics data is available to the public online. The National Center for Biotechnology Information (NCBI) provide a massive cache of information. Most people know about NCBI's PubMed database of over 27 million citations from biomedical literature. NCBI also hold a massive nucleotide database, with nucleotide information compiled from almost every genomic study performed to date. Their genome site holds the sequences, maps, chromosomes, assemblies, and annotations of every version of the human genome, along with mouse, drosophila, rat, EColi, Yeast, and countless other model organisms. Not only does NCBI provide a genome browser, but numerous other organizations provide this information, including Ensembl, UCSC, etc. Researchers spend hours pouring over the genome browser of their choosing, to design experiments, interpret results, and hypothesize.

9.2 Online Medical Resources

Only 10-20 years ago, Hospital libraries and medical school libraries were once filled with books and journal articles. If a healthcare practitioner wanted information relevant to clinical care, they went to libraries to pour through the resources with exhaustive efforts. Today, those libraries are mostly void of books. Almost every individual in Whole Exome Sequencingtern medicine has access to a computer, and usually to a handheld device, capable of accessing far more information than could ever be stored in a library. There are massive information sources, such as PubMed, and Up To Date, a point of care medical reference similar to Wikipedia, commonly used on a handheld device, with evidence based clinical guidelines contributed by over 5,000 physicians [29]. The massive amount of data now accessible to most healthcare providers and scientists is changing healthcare rapidly. Still, there is much room for improvement as care is commonly delivered based on anecdotal evidence, and cost and quality should continue to improve. Combining this online genomic information, and online medical information will provide a valuable tool to improve health.

10 WEARABLE TECHNOLOGY, NUTRITION AND WELLNESS APPS

Massive data sets exist, collected by insurance companies, in electronic health records, by pharmaceutical companies and genomics data sets collected by research institutions. There is another very exciting source of big data on the horizon, in personal wearable technologies, and also fitness, wellness and nutrition apps [6]. Individuals wearing FitBits, with fitness apps on their mobile devices, wearing smartwatches, etc. can track health and wellness measures in ways that once required inpatient hospital monitoring and sophisticated research lab settings. They track sleep and activity throughout the day and night. In addition, there are countless apps which track nutrition and health. People log meals and nutrition to keep accountable. Often these apps work with time tested and well researched diets including weight watchers, etc. This technology has already changed the way many individuals look at health and wellness. This exciting new dataset has great potential to advance human health and improve disease that may be the root cause of

our healthcare epidemic. Combining the massive datasets produced through wearable technology, with genomics data, holds immense potential. Measuring exercise response and sleep endurance, to nutrition and weight gain, in light of genetic background, provide incredible insight into health and disease.

10.1 Visual Technology

Currently procedural technology is one of the greatest expenses to the health care system. Genomics analysis holds great potential to help reduce these costs. Telemedicine involves a virtual visit between a physician and patient [9]. There are obvious benefits, especially when a patient population is spread across a wide geographic space either due to a high level of physician specialization, or a rural patient population. Highly specialized, but critical subspecialists are often in great shortage. This places a great burden on the available providers, with often unsustainable schedules. Video technology allows doctors, nurses and practitioners to visualize patients, perform a limited physical, and to communicate with individuals at a distance. There is great potential to improve cost and reduce burden. There are limitations. Many physician specialists are valued for their technical, hands on skills. Telemedicine is not much of a help, the technical procedures, such as inserting airways into the trachea of small babies, and insert central arterial lines into major vessels to deliver lifesaving medications, require hands on skills. The same goes for surgeons and other highly skilled technical professions. Interventional techniques and robotics are increasingly being used to perform procedures, but while these operations are performed, a surgeon needs to be very close, in case unforeseen accidents problems necessitate a conventional correction. Procedural specialties are the greatest expense to our healthcare system and their procedural skills are a long way from being performed through telemedicine or robotics. Genomics data will help to triage individuals, indicating response to particular treatment or technology.

11 COMMERCIAL GENOMICS

The company 23 and me offers genetic testing directly to consumers [31]. For around 100\$ an individual can obtain *Ancestry Services* or *Health and Ancestry Services*. Given the massive expense and resources required to analyze genomic data, the service likely provides little to no valuable information. However the market for these novelty services has exploded in recent years, as consumers grasp to understand their own genetic information. Much of the advertising, distribution, and sharing of this genetic information is done through social media. There is a multitude of health information shared over social media networks. Blogs, columns, and posts providing information about nutrition and wellness, news stories, and information sharing. The story reporting googleflis flu prediction trends ahead of the CDC, based on search history, spread virally over facebook [7]. The field will continue to expand. Soon, as technology improves, consumers will have access to their own genomics data sets. how they access in share this information is unknown.

12 PERSONALIZED MEDICINE

Wikipedia summarized personalized medicine as: "a medical procedure that separates patients into different groupsfi!with medical

decisions, practices, interventions and/or products being tailored to the individual patient based on their predicted response or risk of disease.” [28] In a way the culmination of big data and health is with personalized medicine. In a hopefully not so distant future the electronic health record, pharmaceutical data and genomic data will provide a more tailored, affordable, and high-quality approach to healthcare. The revolutions in cellular reprogramming, genome sequencing and genome editing have opened up tremendous opportunities for the study of human disease. Based on the dizzying rates of advances in the revolutionary technologies, it is not unreasonable to believe that patient-derived and genome-edited induced pluripotent stem cells models may become a dominant model for the study of disease and the search for new therapies.

Whole Exome Sequencing and Whole Genome Sequencing can be utilized to measure all genomic changes, and newer technologies allow us to perform personalized omics measurements in affected tissue including metabolomics, transcriptomics, proteomics, etc. For example, we can take a patient blood sample, derive cardiomyocytes, neurons, smooth muscle, etc, and perform analysis to measure tissue metabolics, RNA transcriptional differences, and pharmacologic response of the tissue. At some point in the future we may move toward autologous transplantation with genetically edited organs derived from the patients own tissue. Bioinformatics analysis and interpretive steps lag behind. Clinically actionable results would be needed in hours to days, versus the months this type of analysis usually require. This rapid analysis is a rate limiting step, but is improving exponentially.

13 CONCLUSION

As the population continues to grow, we will continue to utilize and increasing amount of resources. Optimal utilization of these resources is the only way to ensure survival and proper living standard for the human population. Many look to the revolutions in genomic medicine combining this omics data with the electronic health record, wearable technology, pharmaceuticals and procedures to move us towards personalized, precision, medicine. Big Data is plays an increasing role in sustaining and improving our world.

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Big Data Mental Health Monitoring: A Private and Independent Approach

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ABSTRACT

Big data holds great promise in a number of fields, and mental health treatment is no exception. Effective big data applications have been developed for every stage of treatment, but not without difficulties. This is particularly true for passive monitoring using smartphones. While it provides improved resolution of consumer behavior, it has complications with privacy and implementation connected with use of commercial software and streaming data. This project created an open source program which uses discrete exported data from smartphones to implement passive monitoring in a way that promotes consumer control of their data and independence from commercial interests. A working program which parses and analyzes smartphone data was created to demonstrate concepts, but would benefit from further development of parser options, analyses, and input/output file management in the future.

KEYWORDS

i523, passive monitoring, open source, mental health treatment, big data

1 INTRODUCTION

Can big data contribute to the treatment of mental illness? Are there any unique issues that hinder big data being used for mental health treatment? Big data has certainly gained the reputation of being a formidable remedy for analytical problems. Corporate empires such as Google, Facebook, and Amazon were built on a foundation of handling and managing big data, and scientists have explored everything from the structure of galaxies to the language of our genes using the power of big data. Perhaps it can work such wonders in the field of mental health as well.

1.1 What is Big Data?

First of all, what is big data? This proves to be a difficult question to answer, as definitions vary based upon industry and often shift as technology evolves and adapts. However, there are three generally accepted traits of big data: high volume (amount of data), high velocity (rate of data creation), and/or high variety (number of data sources). It is when these data traits become increasingly extreme, and require non-traditional analytic methods to extract insights, that it becomes big data [9].

The need for big data analytics has arisen, partly because data storage capabilities have increased at a faster rate than that of data processing. This paired with the proliferation of data collecting devices creates a surplus of stored data that is growing faster than it can be processed traditionally. This drives the demand to develop new ways to extract insights from big data [6].

Big data approaches can be applied to every stage of the data life cycle. Unworked data can be extracted from varied and possibly streaming sources and cleaned and organized automatically. Then predictive analytics can be applied to identify patterns in the data, relying on either regression techniques or machine learning. These approaches attempt to scale these extreme data sets to the level of human insight by reducing noise and identifying patterns via automation and intelligent algorithms [9].

1.2 Mental Health Treatment

Mental illness has been a prevalent issues for all societies worldwide. It has been estimated that 29.2 % of the world population will personally struggle with mental illness, and that 17.6 % had a mental illness in 2014 [30]. In the United States, 17.9 % of the population was estimated to have mental illness [21]. The negative impact of these disorders is high. It is estimated by the Center for Disease Control and Prevention that 36,035 Americans died by suicide and 666,000 visited acute care for harm to self in 2008 [7]. 1,947,775 Americans drew social security/disability due to a psychotic or mood disorder according to the Social Security Administration in 2013, making up around 19 % of recipients [29]. In 2002, mental health issues are estimated to have had \$ 100 billion negative effect on the US economy [21], and over 12,000 facilities were providing mental health services in 2015 in the United States [31]. It is evident given the scale of the negative impact mental illness has on individuals and societies, that effective solutions are needed.

Services provided to meet this need vary depending on a variety of factors, but typically involve a screening and assessment process [1], assignment of interventions [32], and monitoring of treatment progress [10]. Mental health screening is an initial contact that takes a relatively succinct amount of information and seeks to guide the person towards the right services. They are designed to not be time consuming or overly invasive to distribute them to a wide group of people. Assessment is more comprehensive, with the goal of identifying primary mental health needs and clinical diagnoses for the purpose of informing treatment decisions [1].

After the treatment team has determined a person's needs and diagnosed clinical disorders, appropriate interventions are chosen, and added to the person's treatment plan. Typical services are talk therapy which targets developing positive change strategies, medication management which seek to manage symptoms through psychiatric drugs, and case management and related support services which assist in coordinating details of their care and applying skills learned in treatment [32].

Treatment monitoring is where clinicians assess if treatment is resulting in positive change for the person receiving treatment.

Without this feedback, it is easy for clinicians to lose sight of how the person is doing. Though most clinicians have methods of assessing progress, it can be difficult to do so objectively [10].

The majority of the activities of mental health treatment involve gathering data about the treatment consumer and extracting clinically meaningful insights. This frequently generates considerable amounts of data, which is often from a variety of sources, thus making big data approaches appropriate for consideration.

1.3 Big Data Mental Health Applications

Given the problem-solving potential of big data analytics, many researchers have explored ways to apply these techniques to the problem of treating mental health difficulties. Providing quality mental health treatment involves considerable information gathering and insight extracting work, thus making big data techniques relevant for every stage of the treatment process.

1.3.1 Screening and Assessment. Mental health screening typically is the first contact people have with mental health services, and serve the important role of identifying mental health needs at a larger scale. Thus screening methods that are easy to implement and capture information from a large group are ideal. Many big data approaches to this problem have been attempted, often using data found on social media. This provides a large, if not messy dataset, but the accuracy of these methods was found to be better than that typical of primary care providers, but worse than self-reporting tools [11].

Assessment and diagnosis is more information intensive and traditionally requires the skills of a highly trained clinician. Many studies have looked at how to streamline that task by using data gathered through data mining and natural language processing to group people into diagnostic categories using machine learning techniques. While this approach has some success, it has not demonstrated more accuracy than traditional assessment methods, thus suggesting that it may primarily serve an assisting role for the time being. Related to big data assessment techniques, outcome prediction using machine learning has been used to attempt to identify a person's likely treatment trajectory, given certain factors. These predictive models sought to connect risk factors with negative outcomes, and was able to do so with a fair degree of accuracy (69% to 99%). However, sample sizes were small, so further research is needed to fully assess their efficacy [15, 19].

1.3.2 Interventions. Treatment interventions are the actual delivery of services, such as therapy or medication management. They are very personalized and focus on facilitating positive change in the treatment consumer. Thus there are not as many Big Data opportunities, as intervention itself does not generate massive amounts of data. However, certain web-based interventions could use big data techniques by delivering interactive services to a large number of consumers at one time, thus requiring specialized analytic techniques to respond to user input [17, 18].

1.3.3 Treatment Monitoring. Just as screening and assessment provide the clinician with information to guide what treatment they are to receive, treatment monitoring aims to inform the clinician on the efficacy of treatment. Though this is just as important, it is often difficult to be objective and to engage the consumer in

providing needed information. Active monitoring via smartphones has been explored as a possible solution. Through apps or text messages, a consumer is reminded of treatment goals and symptoms are assessed in real time. This data can be generated multiple times a day, and takes a variety of forms, which indicates a possible big data opportunity [18].

Passive monitoring is a similar approach, but instead of relying on consumers to actively respond, it gathers data from them throughout the day. This data can be collected in a number of ways, including smartphones and wearable devices. Many studies have paired this active monitoring data with machine learning techniques to create predictive models [18]. One example of this is an initiative to develop a program which can identify whether someone is experiencing symptoms of bipolar disorder from input on their smartphone such as data from the devices sensors or from keyboard input [34]. The app is being developed in Apple's ResearchKit, which is an open source medical research application development tool [3].

While these techniques are promising, implementing them can be challenging, given the variety of data sources involved from different devices. It is also difficult to test the approaches with consumers, due to lack of engagement [19]. Provision of technical support and clinical engagement concerning passive monitoring techniques has shown to help improve consumers' level of engagement [28].

1.4 Barriers to Big Data for Mental Health Treatment

Every stage of treatment can benefit from big data applications to differing degrees. The screening and assessment process is the most information intensive stage, and thus has received considerable attention from Big Data application research. These efforts have had some success, though they have not surpassed traditional methods, and have not been validated on larger samples sizes [19].

However, treatment monitoring, particularly passive monitoring is considerably information intensive as well, and can potentially produce datasets with more volume, variety, and velocity than initial assessment services. As seen above, development of these approaches appears to be slower, due to a number of issues inherent in many Big Data applications, which are accentuated in passive monitoring. For this reason development of this approach has been slower, though it has elicited considerable interest and discussion [18].

A primary concern is that privacy will be compromised for persons who participate in treatment that utilizes big data techniques, particularly passive monitoring. The use of commercial software for data analysis often requires that the analytics company process the data themselves rather than the treatment provider. This is especially true of mobile device apps, which usually take data, and send it back to their own servers to be processed. These applications do not necessarily have the same privacy rules that medical records due concerning protected health information [19]. A key part of privacy is one's ability to control what information about them goes where, and to prevent unwanted information from being shared [14]. With streaming personal data from smartphones, consumers begin lose some of their privacy, because they lose control of their

data. As it is constantly being sent to the treatment provider, and requires action on the part of the consumer for it to stop, the person has sacrificed some of their privacy in order to receive this service. Though this is a common trade off in medical and mental health contexts, research indicates that people prefer to have more control of the private data, and that they want to be able to share it in portions, rather than have to share all of it [4].

Another issue related to using activity monitoring in mental health treatment is that the variety of competing smartphone and wearable sensor companies creates an environment with plenty of human behavior Big Data, but it is not easy to integrate. This data is stored on separate private databases and each company has fiscal motivations to resist collaboration. Thus the product which a treatment provider intends for use as a clinical tool, is also being used for a commercial purpose, and to create a comprehensive application which is not encumbered by the independent economic interest of a private business is difficult [12].

Some companies attempt to avoid this by providing some open source products. Open source software is freely distributed, can be modified and integrated into other software, the source code is available, and it is not associated with any specific product. Benefits of such code is that they can be improved by a large number of programmers, they can be widely implemented, and it is not tied to any product or corporation [22]. An example of such as Apple's ResearchKit [3]. However, though the product is free, it is still tied to the company's resources, in this case Xcode [33]. Though some development can be done freely, Apple controls this, and extensive work cannot be easily distributed without paying for a developer account [2]. While there are some truly free open-source software solutions for mental health, they tend to target administrative problems, rather than treatment itself [16].

1.5 Open Source and Discrete Data Transfer

A true open source big data solution could make passive monitoring an ethical and workable tool for mental health treatment. A program written in the open source programming language Python would be free of corporate entanglements and costs, but would benefit from the massive amount of documentation, packages, and ready-made code produced by the Python community [26]. Run on open source Ubuntu Linux [5] installed on open source Oracle Virtual Box [23], such a program would be independent of commercial interests, completely reproducible, and free of charge. Besides these direct benefits, open source programs often have performance and security advantages of commercially developed products [20].

The data source for the passive monitoring would still be smartphones, but instead of using commercially provided apps for analysis, the data would be extracted and analyzed using the open source based program. The iPhone step count data collected by the built-in accelerometer, and stored in the Health App can be exported via email as an xml file [24]. Though this method losses the benefits of streaming data, it increases the consumers' control over their data by making data transfer definite and discrete. Instead of agreeing to install an app on their device which will track their behaviors forever unless they ask for data to stop streaming or the app is uninstalled, the consumer can agreed to provide a defined amount of information now, and may do so again later. As the Health export

file stores all detected steps, no data is lost, it is just not seen in real-time. This would still provide useful information for treatment monitoring purposes.

Using this method also allows for the steps data of numerous people to be parsed and analyzed in an automated fashion, which would be necessary from a mental health treatment perspective, as numerous consumers data would need processed. As datasets increase, some way of address the increasing extremity of the data needs to occur. There are other approaches that would be insightful, but this approach is a good fit when the output is a file for each individual participant, rather than aggregate date about a group.

1.6 Thesis

Private and independent passive monitoring can be utilized in mental health treatment by leveraging open source programming tools to analyze aggregate movement data provided from smartphones in discrete amounts. This approach avoids the cost and entanglements of commercial software and wearable technology, as well as increases consumer control over their personal data.

1.7 Project Goals

This project attempts to demonstrate this concept by developing a simple open-source program written in Python which can perform full data life cycle analytics on automatically collected iPhone Health App data. The program was designed to accommodate Big Data by automatically iterating over multiple files without user input.

2 METHODS

2.1 Design

This current research utilized the Python programming language to develop a program which could parse, analyze, and report clinically relevant information from a folder of exported individual iPhone 6 Health App data files. This program consisted of four sub-programs: acceleparser.py, Tables.py, Visualizations.py, and makefile.py. Also included with the program code was a folder named iPhoneData which contained the test xml files, and a bash script named make_install.sh which installed program packages.

The acceleparser.py program which imports the xml file and parses it using the ElementTree python package. The xml file is imported and parsed into a tree structure. It then iterates through the tree and appends date/time data and steps data to corresponding lists. Those lists are then used to create a dataframe using the pandas python package, which is then returned.

The Tables.py program takes the dataframe returned from acceleparser.py, and formats it for display and for use by the Visualizations.py program. Tables.py consists of two functions, stepsBYdata and stepsBYweekday. The stepsBYdata function formats the dataframe to show the total steps for each date using the pandas groupby functionality. The stepsBYweekday function formats the dataframe to display the mean steps for each date in columns of weekdays, and rows of weeks labelled by the first Monday's date. This was accomplished using pandas pivot table functionality to aggregate the mean function over the dataframe, and then a new dataframe was made with the weekday columns. Each function returns a dataframe object.

The Visualizations.py program takes input dataframes from either acceleparser.py or Tables.py, and returns graphs. Visualizations.py consists of two functions. The stepsBYdateGraph function takes the dataframe created by the stepsBYdate function of Tables.py and creates a time series line graph using matplotlib.pyplot python package. The stepsBYweekdayGraph function takes the dataframe returned by acceleparser.py, and creates a list of mean steps for each day of the week and a list of days of the week. From these lists, a bar graph of the mean of steps for each day of the week is generated using matplotlib.pyplot.

The makefile.py program iterates over the xml files stored in the iPhoneData folder, and for each file ran the acceleparser.py program, and directed that dataframe to the Tables.py and Visualizations.py programs to output the table and graphs. The table was then saved as a txt file and the graphs saved as pdf, each named by which iteration the original file was in the for loop.

This program utilized the module design of small sub-programs to provide ease of customization and expansion of program features. Later functions can be added to their appropriate subprograms, and the makefile.py modified to include the new function, and thus generate a new report. Multiple reports could even be added to the makefile.py, and executed when called.

2.2 Data

The test data consisted of xml files exported from the Apple Health App on iPhone 6. To export the data, the export health data option was selected in the app, which compiled as export.zip. This file was then emailed to researcher and the file unzipped as folder named apple_health_export. This folder contained two files, export.xml and export_cda.xml. The export.xml file contained the steps data, and was renamed “Client1.xml”. It was then placed in the folder “iPhoneData” in the github repository [8].

Health data was exported from two devices, which contained a variety of data, but only date/time and step count data were used in this project. The xml files were 5.58 MB and 8.33 MB in size, containing 203 days and 888 days of steps data respectively. Data was also tested from iPhone 8 models, but the program would not parse the files, and thus were excluded from the final test set.

2.3 Analyses

Basic descriptive statistics were utilized to explore patterns of step activity over time. Daily step counts were organized in table fashion by day of the week columns and rows of weeks. Visual analyses consisted of a bar graph of the mean steps taken for each day of the week and of a time series line graph of daily steps taken over time. These analyses were chosen to show basic patterns in data in a way which could be quickly assimilated.

2.4 Specifications

Project development and testing was done in Ubuntu Linux operating system version 16.04 (download available at [5]) installed on an Oracle Virtual Box Graphical User Interface (download available at [23]). Code was written in Python version 3.5.2 (download available at [27]) installed within pyenv Python Version Management System (download available at [36] per installation instructions available here [35]). External Python libraries utilized in project were pandas,

matplotlib, and numpy (download available from the Python Package Index [25]). With this configuration, it was necessary to install tk-dev system wide prior to creating pyenv virtual python environment (instructions found at [13]), and to install python3-tk within the virtual python environment in order to utilize matplotlib.pyplot. Completed source code can be found at Neil Eliason’s bigdata-i523 github repository [8].

2.5 Procedure

Program tests were done per instructions found in the README.md file of the project sourcecode [8].

3 RESULTS

After executing the program, the output was one txt file and four pdf files for every one input xml file. Thus, for the test data of two xml files, ten files were created. All files were generated in the code directory from which makefile.py was ran.

The txt file contained a table with columns of daily steps for each day of the week and rows labelled as the date of the first day of the week, with each week starting on Monday. It also contains the spearman correlation of daily steps with day of the week. The file name was determined by where in the order the original xml data was parsed in the program iteration. For example, the output txt file for the first parsed xml file would be named “Client1.txt”.

Table 1: Output table of daily steps by day of the week

Client1 Report							
Week Of	Mon	Tue	Wed	Thu	Fri	Sat	Sun
2017-05-08	[5766]	[9956]	[3605]	[2590]	[1955]	[3471]	[5097]
2017-05-15	[10236]	[10624]	[3861]	[6464]	[6358]	[7473]	[32511]
2017-05-22	[4884]	[6999]	[3233]	[3796]	[7056]	[2858]	[2174]
2017-05-29	[3579]	[6357]	[7232]	[5091]	[5076]	[5761]	[7443]
2017-06-05	[8717]	[5276]	[7870]	[5658]	[7986]	[3999]	[3950]
2017-06-12	[8018]	[5195]	[3246]	[8261]	[8501]	[6930]	[4284]
2017-06-19	[8568]	[3871]	[33]	[127]	[3811]	[3484]	[8264]
2017-06-26	[645]	[5922]	[6309]	[6272]	[148]	[5905]	[1938]
2017-07-03	[3831]	[6986]	[5413]	[3823]	[3074]	[4517]	[974]
2017-07-10	[6040]	[3938]	[9701]	[4309]	[3292]	[14241]	[1423]
2017-07-17	[9911]	[8529]	[2545]	[4485]	[3416]	[10684]	[2562]
2017-07-24	[3296]	[5949]	[4651]	[2529]	[5423]	[17880]	[4017]
2017-07-31	[4718]	[5910]	[9783]	[2178]	[6599]	[802]	[4146]
2017-08-07	[6714]	[2555]	[9921]	[3544]	[2115]	[6874]	[2536]
2017-08-14	[4568]	[5198]	[3473]	[3378]	[4136]	[83]	[2455]
2017-08-21	[4877]	[4141]	[3241]	[3481]	[5952]	[134]	[1186]
2017-08-28	[5774]	[3310]	[4330]	[4362]	[6347]	[4951]	[2028]
2017-09-04	[2102]	[3124]	[5619]	[3286]	[4236]	[1219]	[3186]
2017-09-11	[7976]	[3939]	[6293]	[3262]	[2610]	[1545]	[3437]
2017-09-18	[1442]	[4586]	[3420]	[4111]	[4484]	[11554]	[2759]
2017-09-25	[2564]	[2841]	[2733]	[2959]	[4901]	[4790]	[8063]
2017-10-02	[5124]	[2248]	[1774]	[4046]	[5142]	[7477]	[2276]
2017-10-09	[4787]	[2663]	[4525]	[3840]	[6244]	[1681]	[3175]
2017-10-16	[2692]	[4149]	[4667]	[2463]	[2988]	[8118]	[6127]
2017-10-23	[2163]	[2744]	[5631]	[4805]	[3134]	[1902]	[2025]
2017-10-30	[3976]	[5048]	[7557]	[3065]	[2378]	[6034]	[2963]
2017-11-06	[1800]	[4362]	[5793]	[2332]	[3186]	[1723]	[1719]
2017-11-13	[14382]	[2648]	[5592]	[5482]	[2561]	[2230]	[2704]
2017-11-20	[3631]	[3463]	[2485]	[2390]	[1509]	[2906]	None
2017-11-27	[3691]	[2503]	[4328]	[2005]	[11]	None	None

Correlation of Steps with Day of the Week	
weekday	steps
1.000000	-0.198758
-0.198758	1.000000

The pdf files were graphs of different analytics and relationships of the parsed data. The first was a time series line graph of daily step information for the whole time period of the xml file. The second was a bar graph of the mean steps for each day of the week

of the whole time period of the dataset. The third was a bar graph of the standard deviation of daily steps for each day of the week. The fourth was a scatterplot with points representing number of daily steps on the y axis and the day of the week on the x axis. These files were named similarly to the above txt file, with each file named according to its order in the iteration. For example, the first xml file parsed would generate “Client1StepsByDate.pdf” for the first graph and “Client1MeanStepsByDayOfWeek.pdf” for the second, “Client1StDvStepsByDayOfWeek.pdf” for the third, and “Client1ScatterplotOfStepsByDayOfWeek.pdf” for the fourth.

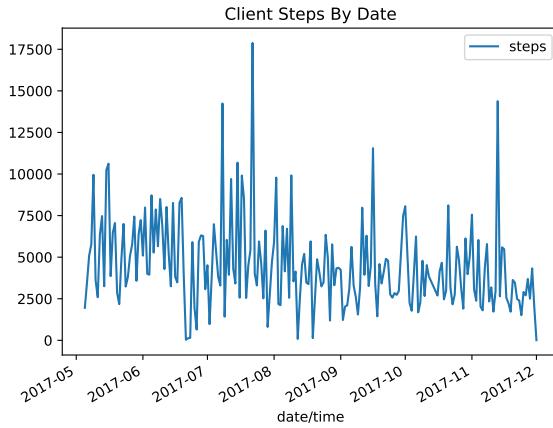


Figure 1: Output graph of time series of daily steps

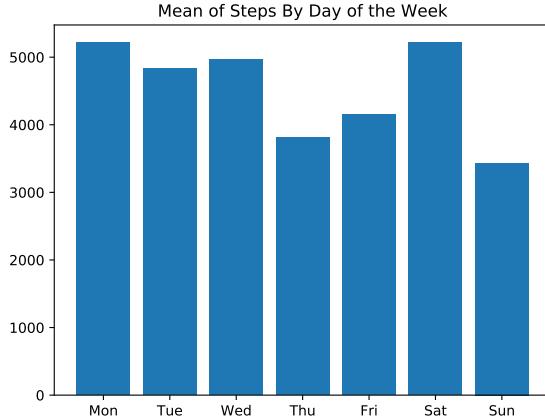


Figure 2: Output graph of mean steps for each day of the week

4 DISCUSSION

4.1 Project Goal Assessment

The goal of this project was to address the common issues of privacy concerns and ease of implementation that hinder applying Big Data

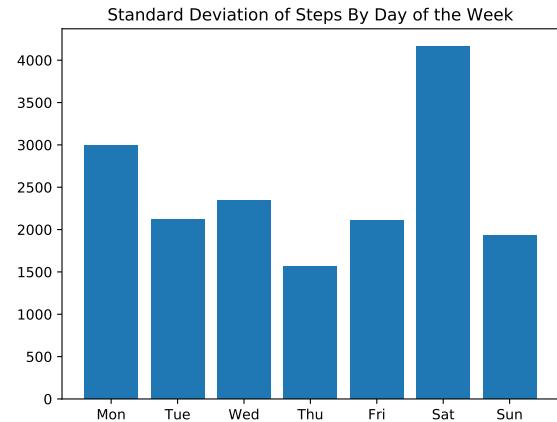


Figure 3: Output graph of standard deviation of steps for each day of the week

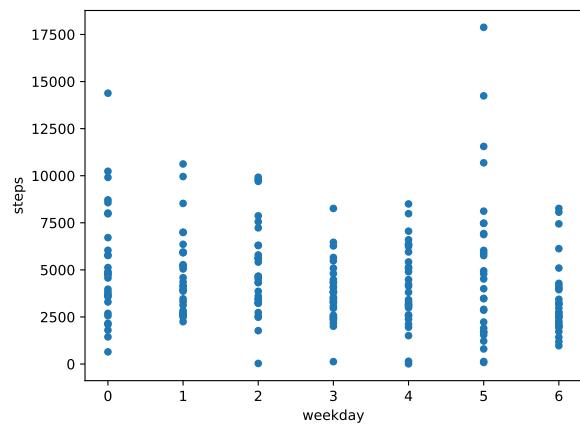


Figure 4: Output graph of scatterplot of steps by each day of the week

techniques to Mental Health Treatment. The strategy was to write a program that leveraged open source software, used smartphone data provided by the consumer in discrete and definite ways, and allowed for applications in a Big Data setting.

4.1.1 Open Source. The source code for the program was written in Python 3.5.2, and utilized the pandas, matplotlib, and numpy packages to perform data cleaning, organization, and visualization. All these resources are available online free of charge, and with substantial technical support and documentation. By following the installation instructions found in the README.md, this program can be installed on the open source Ubuntu operating system on Virtualbox, thus making the program configuration reproducible on any standard operating system with sufficient hardware. This allows for distribution in various settings with no cost or input

from outside commercial interests. The project successfully created a working program using open source programs.

4.1.2 Discrete Data Delivery. Data was exported from the iPhone Health app, and emailed to the researcher as a single file. By using a discrete dataset, the person providing the data did not have to install invasive apps on their phone or agree to releasing information for an indefinite amount of time. They made the decision to provide a set amount of data, and can make a subsequent decision to do so at a later time, but they do not have to make a decision to stop sharing the data. They must be active to share in the future, rather than needing to be active to stop sharing. The project successfully utilized discrete data as the data source for the program.

4.1.3 Big Data Informed. By utilizing a design that iterates the program through a folder of data files, one command from the terminal can theoretically produce the output files for hundreds of consumers. This functionality is necessary when dealing with big data, as it would be incredibly tedious, if not impossible to do such a task through the graphical user interface. While the program was designed to be useable with big data, testing was not done with a dataset which would qualify as big data. Also, no big data analytics, such as machine learning were utilized. The project successfully developed a starting platform for big data analytics, but needs further development.

4.2 Thesis Assessment

This project was able to create an open-source program which analyzes readily available behavior data from smartphones provided in discrete samples, rather than streaming. While the project goals were met, how do they relate to the thesis? Do these results support the thesis that open-source programs and discrete data collection address issues of consumer data control and flexible implementation of passive monitoring in mental health?

The diverse selection of technology companies fighting for a larger piece of a lucrative market share certainly creates numerous products which could be used for passive monitoring applications. However, corporate competition hinders collaboration and integration of these tools into a comprehensive mental health Big Data approach [12]. Also, by utilizing commercial software, data is not always guaranteed to be protected, and may be gathered from apps and analyzed by the corporation for business purposes [19]. By utilizing completely open source products for the project, to analyze multiple persons' accelerometer data from a popular smartphone device, this project demonstrates that a corporate interference free approach to passive monitoring is possible. By avoiding corporate interference, the implementation of this approach is completely flexible and the fate of data is clear and transparent encouraging safety of consumer data.

Much attention has been given to the power of streaming data, which is not unwarranted. In the context of passive monitoring, streaming data can provide an incredible level of information resolution about a consumer's behavior [12], and safety planning and monitoring could utilize such approaches to identify when someone may be more symptomatic and in danger [18]. However, these approaches to passive monitoring remove control of the data from the consumer, and force them to take action if they want that data

sharing to stop. Given that people generally prefer to have greater control over what data is shared and when [4], this may contribute to some of the lack of engagement found in some implementations [18]. By using discrete streaming data, this project allows for consumers to have more control over their personal data, while still benefiting from the clinical insights afforded by passive monitoring. Another ancillary benefit of utilizing discrete data transfer is that it actually facilitates more interaction between the consumer and the service provider about the health data. This can provide opportunities for insight development for the consumer by increasing awareness of their behaviors and activity.

4.3 Limitations and Future Directions

This project's aim was to develop a prototype passive monitoring program using open source and discretely provided consumer data that could be utilized with Big Data. While this was accomplished, the actual work the program does is fairly basic. The hope would be for more robust and effective models of passive monitoring to be built expanding on these approaches. As it is, the current project has the following limitations.

4.3.1 Depth of analysis. As seen above, a number of powerful analytic techniques are available for use on big data sets. From traditional inferential statistics, to machine learning, to advanced visualizations, more extensive analytics could provide increased insight from this data. This project included a simple spearman correlation to demonstrate how inferential analysis modules can be added to the functions of the program, and thus provide more in-depth insights. By including another variable, such as reported mood, hours of sleep, etc. machine learning techniques could attempt to identify patterns between the variables. This particular data may especially benefit from exploring patterns at different levels of resolution, attempting to identify patterns in activity based on time, day, week, or month, and pair this with more information rich and refined visualizations.

4.3.2 Narrow data sources. As the project progressed, it became apparent that the format of the xml files differed between iPhone versions. The xml parser program which was written using iPhone 6 test data, would not read the iPhone 8 data. The utility of the program would be greatly increased if it was able to read the xml files from other iPhone models. Given the module design of the program, a smart parser could be developed, which would identify which version of iPhone exported the file, and have utilize a parser algorithm which is compatible with the xml structure. Further work could even explore creating an Android parser module, which could create compatible dataframes for the subsequent analysis modules.

4.3.3 Requires some technical knowledge. Though to implement this program requires no ability to code, the creation of a Virtual Box, installation of Ubuntu, and executing commands via terminal would be difficult for a novice with no guidance. This could be problematic for real-world implementation, and many mental health providers may not feel comfortable using the commandline. Future implementations would benefit from detailed documentation with the technical layman in mind, in order to facilitate utilization by clinical staff who may not be familiar with the technology. Another approach would be to develop a more comprehensive installation

script and graphical user interface for those who are not comfortable with command line.

4.3.4 Input and output files could be more organized. The program as developed does not place the output files in any specific location, but rather allows them to generate within the code folder. While workable, this could become a bit cluttered as large numbers of files are generated. Also the program's file naming technique consists of assigning a number to the consumer's data based on which iteration of the program in which it is parsed. This means that in order for the identity of the person to remain connected to their data, care must be taken to order the files correctly in the iPhoneData folder. Otherwise, if the xml file for Client1 is accidentally put third in the iPhoneData folder, then that record and all following records will be connected to the wrong person. One possible solution is to utilize a database program, perhaps the open source SQL database MySQL, to manage the original files and their relationships to consumer identifying information and output files. This could prevent the likelihood of errors occurring, and also introduce some of the functionality brought to bear from the SQL programming language.

5 CONCLUSION

Big Data techniques have demonstrated great success in a variety of fields, but can they positively impact the provision of mental health treatment? The question is an important one, given the prevalence of mental health difficulties worldwide, and the large cost they have on individuals and societies.

Researchers have explored big data approaches for every stage of the treatment process, and found effective applications, such as using social media to detect depression, assigning diagnostic criteria using machine learning, or detecting a manic episode by the way a consumer is typing. The research focuses on the more information intensive areas of screening/assessment and treatment monitoring, which lend themselves to Big Data analysis. With the prevalence of smartphones and wearable devices which people take with them throughout the day, treatment monitoring is of particular interest. Active monitoring approaches require intentional interaction from the consumer and passive monitoring gathers data from the various sensors and inputs of the device without any intentional action from the consumer.

While these technologies have great potential, concerns of privacy and effective implementation hinder their growth. Many commercial methods exist for activity monitoring, but they do not integrate well with each and have corporate enforced restrictions, largely driven by business competition. Commercial apps also often utilize data in methods that are not bound by protected health information rules. The focus on streaming data and apps also creates a loss of consumer control of their data. Once they have agreed to send streaming data to a provider, actions must be taken to stop the data sharing. This conflicts with healthcare consumers' preference to have control of what data is shared and when.

By utilizing data shared in discrete portions, consumers could remain in control of their data while gaining the insights which can be leveraged by passive monitoring, and by creating this program using open source software, it would be free of conflicting corporate interests. Such a program would need to be able to process

numerous samples automatically in order to manage the Big Data requirements of a mental health provider.

This project sought to demonstrate this model by developing a program written in the Python programming language, running on Ubuntu Linux, installed on Virtual Box Machine which would perform analyses of multiple exports of iPhone 6 Health App data. All software utilized was open source, and the data available in discrete portions. This allowed for the program to be developed without restrictions and costs inherent with commercial software and for the consumer to remain in control of their data.

When the program was run with test data, it was able to parse the iPhone xml files and generate a reference table and a time series of steps graph and a weekday mean of steps graph. The program successfully met the project objective of producing a working passive monitoring program using only open source programs and discrete data transfer, and thus demonstrated that this approach is a viable way to utilize passive monitoring while encouraging consumer control of data, avoiding interference from corporate restrictions, and being Big Data informed.

The project had various limitations related to the small scope of each particular function of the program, but further development could work on increasing the robustness of each individual module. Specific areas of development would be creating a smart parser which would use different algorithms for different iPhone versions, increasing the depth and aesthetics of the visualizations, and exploring android parsing applications. The project also sacrificed some ease of use in order to leverage the open source program, and may not be the best solution in clinicians are not familiar or willing to learn the commandline. The program also requires development in organizing the input and output files and more effectively preserving identification information, possibly using an open source database application, like MySQL.

This project was able to demonstrate how open-source programs could be paired with smartphone data exported discretely to create a program which could conduct passive monitoring while maintaining consumer control of personal data and independence from conflicting corporate interests. Continued exploration of ways to increase control of personal data and transparency is critical, especially for mental health consumers. As big data analytics and applications continue to develop, the potential for them to be misused is great. Governments, corporations, and other powerful entities have the resources to leverage control over data in ways that people may not generally be aware of or approve of.

This also can be true of mental health providers to consumers. There is a power differential, partly driven by systemic elements of the legal, medical, and mental health, but also driven by the person's need for change. People struggling with mental illness (and everyone else) often are desperate to change some circumstance in their life, and may be willing to give up something to get it. The danger for the mental health provider is to use that take away a freedom from that person for the sake of their greater good. In this context, that would be asking the person to give up their privacy in order that they can receive better services. A time comes when drastic measures may be necessary, such as when a person is a danger to themselves or others. However, if an option to preserve some of their dignity remains, it should be chosen. That is part of the motivation of this project, to provide a way to help people,

while preserving their dignity. Sometimes all it takes is to rewrite the script.

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The Impact of Clinical Trial Results on Pharmaceutical Stock Performance

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ABSTRACT

While many relate stock market trading to gambling, successful traders have turned stock picking into a science. The likes of Warren Buffet tell us that successful stock buying is all in the research. So what kind of research aids in the prediction of companies within the highly volatile pharmaceutical market? The use of available, open-source APIs and Google Alerts are used to explore if clinical trial results can directly impact stock performance in small, mid, and large cap pharmaceutical companies. Key words and/or phrases in results and related news articles are identified as possible predictors of market effect. As well as a comparison to already established analyst ratings from Barclays, Goldman, and J P Morgan Chase which have already been shown to impact stock performance.

KEYWORDS

Big Data, HID313, i523, Stock Market, Pharmaceutical

1 INTRODUCTION

A “stock” is a piece of ownership in a company. Offering stocks for sale provides capital to the selling company in exchange for a stake in the company. A stock market is a collection of exchanges where trading of stocks takes place [13]. Evidence of early stock markets date back to the fourteenth century with the offering of state loan stocks throughout Italy. Even prior to the organization of stock markets, price fluctuations for goods such as wheat and barley were tracked by early economists. The first “modern” stock market appeared in Amsterdam in the seventeenth century where the volume of stocks traded and the fluidity in which they were traded reached a new high [4].

The biggest stock markets in the world are currently the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), and the London Stock Exchange. NYSE started in 1792 with twenty four stock brokers. The initial focus was government bonds which provided secure, long term income. The early days of the 1800 saw stocks traded through telegraph. Telephones replaces the telegraphs in 1878. Current trading on the NYSE can surpass 1.4 billion shares each day across almost 4,000 companies [8]. NASDAQ began as an all-electric equities exchange in 1971 and today provides trading, technology, and information services for financial markets. Today over 4,000 companies are traded on the NASDAQ with over 1.8 billion trades per day [20]. The London stock exchange was founded in 1801. Currently over 2,600 companies across 60 countries are traded on the London Stock Exchange each day [6].

Throughout the history of markets, prices have been tracked and insightful traders have attempted to predict and capitalize on price fluctuation. The age of computers opened new doors for stock

analysis and trend prediction to facilitate capital gains for traders. Financial companies like Goldman Sachs and JPMorgan Chase & Co. have hired mathematicians, statisticians, and trade analysts since the early days of trading in an effort to predict the market in a consistent manner. Once an algorithm is established and used consistently the algorithm itself but be considered as a variable that could effect the prediction outcome [?].

A major complexity in creating algorithms for the stock market is that the market tends to follow the erratic emotions and feelings of humans. If computers were running the market, making trade decisions based on logic and reason, then the market would be much more stable. The volatility of human emotions about money and stocks creates tremendous volatility in the market. The revolution of social media has provided a means of measuring the mood of possible traders. For this reason, the ability to predict society’s reaction to news has developed into a field of study within the data science world [3].

How big of an impact can news articles have on the stock market? In September 2008, an article published on a South Florida News website reported that United airlines had files Chapter 11 bankruptcy. The news struck so hard that United’s stock plummeted 75% from \$12 to \$3. Interestingly enough, the article was just about six years old and had originally been published by the Chicago Tribune in December 2002. Even though the report was literally “old news” it did not prevent massive panic from investors [28].

1.1 Pharmaceutical Sector

The pharmaceutical industry has evolved around the need to establish drugs and treatment options for diseases. Research and development within pharmaceutical companies range from compound identification to disease characterization. This market is directly affected by the results of drug tests such as clinical trials and the establishment of new treatment options. Market growth also comes from manufacturing and licensing of drugs and treatment methods. Innovation is the key driver of this industry [9].

Like the financial sector trying to predict the stock market, the pharmaceutical industry has devoted resources to developing prediction algorithms and machine learning systems. The efforts of drug manufacturers are aimed to create a system that consistently predicts or aids in identifying drug targets. One such approach is the development of virtual screening for drug discovery meant to reduce the experimental failures associated with high throughput screening. High throughput screening is carried out to test many chemicals, molecules, compounds, proteins, hormones, viral vectors, etc all at once on large grids or plates which can test many different treatment combinations all together. Large costs and big

data sets are associated with high throughput screening which is now becoming virtual with the help of advanced molecular profiling [14].

1.2 Clinical Trials

A clinical trial is a planned experiment involving patients with the intent to elucidate an appropriate or effective treatment option(s) for the population of patients afflicted with the same medical condition. A big concern with clinical trials is that inferences are made for the entire population of patients from a relatively small sample size [22]. One of the first clinical trials recorded was carried out in the eighteenth century to evaluate six treatments on twelve patients with scurvy. Two patients that were given oranges and lemons recovered very quickly. Fisher introduced the concept of randomization in the nineteenth century [7].

Clinical trials have four defined phases. Phase I trials identify how well a drug is tolerated by determining the maximally tolerated dose (MTD) on a very small sample size. Phase I trials have very simple experimental designs as the only intent is to examine toxicity. Phase II explores biological activity or effect on a small patient sample size. The design of a Phase II trial is dependent on the design on the Phase I trial as both share the intent to evaluate adverse events. Phase III trials follow the design of Phase II trials but on a bigger sample size with the intent to solidify a treatment's effectiveness in clinical practice. Phase IV trials are prolonged Phase III trials that can track a drug, procedure, or instrument for decades with continuous efficiency reflection [7].

Clinical trial designs have been very slow to evolve due to restrictions enforced by governing agencies such as the US Food and Drug Administration (FDA) and the Centers for Disease Control and Prevention (CDC). While these restrictions are intended to minimize patient risk, they also greatly restrict the potential of clinical trial data collection. Other limiting factors include difficulty enrolling high quality participants for each trial phase, problems monitoring how well patients are following protocol, difficulty sorting out "the placebo effect" or the ability for patients to feel as if they are recovering without actually receiving treatment, and overall minimizing poor quality of data [7].

1.3 Established Analyst Ratings

Companies within the financial sector often publish rankings of the top stocks that the company invests in. The ratings are a way to attract investors with proof that the company is diligently analyzing the market and "picking winners". These published rankings have been shown to boost or deflate rallies behind particular stocks that are added or removed for these prestigious lists [1].

The Goldman Sachs Group, Inc. was founded in 1869. The company provides a full stack portfolio of banking and investment services. Goldman Sachs career website states that the company is driven to achieve superior returns for their clients which include pension funds, hedge funds, and mutual funds. The company boasts that their research analysts are curious and creative [26]. Goldman Sachs Global Investor Research group provides stock ratings on a scale of Buy, Neutral, and Sell [25].

J P Morgan Chase (JPM) is one of the largest investment banks in the world [27]. The company's investment mechanisms include currency, emerging markets, equities, and fixed income. JPM publishes quarterly market insight reports with "buy" and "sell" ratings for the companies of interest to the firm. Subscribers to JPM's services can even get an audio version of the report which details market trends [18].

Barclays was founded in London in 1896. The bank currently serves over forty-eight million customers and releases stock picks every quarter but for a limited number of stocks [27]. Because Barclays is so selective with their stock promotions, only selecting some 50 stocks to support, it is possible that they have a greater impact on the market than other companies in the stock prediction game.

1.4 Data Resources

An Application Programming Interface (API) acts as the middleman between the requesting service and the performing service. When a user or system submits a request the request is passed to the API which translates it for the processing system then returns the results in a receivable format. This project uses the free Gmail API provided by Google to read and extract data from specific email messages.

Machine learning is the study using computer language to recognize patterns and make data-driven decisions based off of them. It is based on the theories of statistics. Bayes' Theorem gives the probability of an event occurring given some evidence. Bayes' Theorem is vital in Machine Learning because it provides evidence to how probabilities should be updated given new evidence. Markov's theory describes properties that can be predicted based only on past events. Some of the first learning programs were designed to play boardgames such as checkers and chess [30].

NASDAQ's website provides historical stock performance data that can be exported as a Comma-Separated Values (CSV) file. The disadvantage of NASDAQ's free export service is that each stock must be exported separately. The free quote service can be accessed at [21]. NASDAQ provides API services for subscribers starting at \$5,000 per year [19]. Access to NASDAQ's API services can also be granted through corporate sponsorship. NASDAQ's free CSV export services were used to collect initial project data. In this example, the stock history for Celsion Corporation during the week of August 21, 2017 is shown in 1.

Table 1: NASDAQ CSV file format example

date	close	volume	open	high	low
2017/08/25	1.3700	179097.0000	1.3600	1.4100	1.3000
2017/08/24	1.3600	149832.0000	1.3100	1.3600	1.2810
2017/08/23	1.3100	223451.0000	1.2500	1.3300	1.2430
2017/08/22	1.2800	164594.0000	1.3200	1.3200	1.2400
2017/08/21	1.3300	169037.0000	1.3300	1.3700	1.2800

Exports such as this one offered by NASDAQ and API interfaces for stock data are provided by numerous companies. The Yahoo! Finance API is explored below and the Google Finance API was used to perform the stock data extraction for the analysis presented.

Additional resources such as stock tracking apps and free exports are available. CSV exports such as the one listed above can be downloaded from Google Finance, Yahoo! Finance, and many others. This publication does not provide a complete list of available resources, but attempts to present a few for comparison.

Python.org provides a python module to pull stock data from Yahoo! Finance [23]. The package can be installed through Git by cloning the Git directory where the package is available: [17]. To install the python package without Git the tape archive can be downloaded from [24]. Tape archives allow for compression of multiple files which can be restored to their original format using the tar command in the command line [15]. Apply the tar options: z - filter archive through gzip, x - extract an archive file, and f - filename of archive, use “cd” to change the current working directory, and then install the python module using the package management command “pip”:

```
tar -zxf yahoo-finance-1.4.0.tar.gz
cd yahoo-finance
pip install yahoo-finance
```

While Yahoo! Finance is a great resource, the API does not function consistently, and as of this writing the API has been turned off by Yahoo!.

2 METHODS

2.1 Data Collection

Data collection was initiated with the use of Google Alerts. Google allows for alerts to be configured from Google [11]. Gmail users can configure these alerts to be sent through email when news or other types of articles pertaining to a defined subject are released to the web. The Google Alerts for this project were: “Phase III Trial”, “Phase 3 Trial”, and “Meets Primary End Point”. When these phrases are detected by Google, the link to the webpage and a short description are sent via email to the configured email address. On busy days, an excess of 100 alerts were received for these alert phrases. On slow days, only a couple alerts were received. Only very infrequently were no messages received.

To collect data from the received Google Alerts without too much manual clicking, Gmail has an available API which allows users to pull data from a Gmail account. To start using the Gmail API, a user must first configure their Authentication credentials through Google’s developer console. The JSON format is shown in Table 2. Once credentials are received in the form of a JSON file, the

Table 2: Google Gmail API JSON format

```
{"installed":{"client_id": "###.apps.googleusercontent.com",
"project_id": "###",
"auth_uri": "[URL]",
"token_uri": "[URL]",
"auth_provider_x509_cert_url": "[URL",
"client_secret": "###",
"redirect_uris": ["urn:ietf:wg:oauth:2.0:oob",
"http://localhost"]}}
```

Google Client Library can be installed using pip to install google-api-python-client. The Google Development team has provided a quickstart file which facilitates the first authentication run. Running this quick start guide will open a browser window and prompt the user to log into a Gmail account. The user then accepts the authorization and can run the Gmail API from command line or other compilers.

Headlines of the received alerts, usually the title of the article and the first couple of lines, are referred to as “Snippets” by Google’s Gmail API. This project pulled only the Snippets and the date from the Google Alerts. The Snippets do not contain the whole article but may still provide enough evidence of sentiment for further analysis and prediction of the associated stock. Unfortunately, no solution was identified for extracting the appropriate stock symbols from the Snippets so this task had to be performed manually.

The google-api-python-client provides a number of helpful modules that are designed to provide simple access to Google APIs. The main components of authenticating the API are apiclient which build the credential string which will be added to each execution string for the API. Auth2client provides the authentication library [10]. Access to HTTP connections are provided by httplib2 [12]. Dates are managed and manipulated with time, dateutil, and datetime. Csv, io, and json provide text and file parses and manipulators.

The Python code calls the Gmail API and writes a .csv from the data. After calling all needed libraries, the scope of the authorization is defined. Google mail can be opened with a Readonly or Modify authentication. Next, the credentials are established by the JSON file received during the API authentication setup. This JSON must be saved in the same directory as the code being run. The code sets the variables for User ID and Label then runs an execution command calling the Messages.List API, which looks like this:

```
GMAIL.users().messages().list(userId='me', labelIds=
[INBOX], q='from:[ALERTS] before:[DATE]').execute()
```

Google has defined the user ID “me” as the global for the authenticated account in use. The label ID “INBOX” designates that the messages will be pulled from the inbox folder, but any other folder could be called here as well as a collection of labels that Google has defined such as “UNREAD”. The “q” designates a query. The query will return only messages from the Google Alerts email address which have been received by the twenty-fourth of November 2017. This data was selected so that all returned records would have five market days of stock prices to compare. This execution returns a dictionary which contains message IDs for all the messages that matched the query.

The next step is to “get” the messages with the use of the Messages.Get API. While looping through the dictionary of message ID from the defined query, the script retrieves the Date and Snippet for each. Additional options could return the Sender, Receiving Email, Email body, among others. The syntax is shown here:

```
GMAIL.users().messages().get(userId='me',
id=m_id).execute()
```

The user ID is the same as described previously with the ID being the current message ID within the loop. This execute command returns a dictionary which is parsed from “payload” to “headers” to extract the Date. The Snippet is also grabbed from the message

dictionary and along with the Date, passed to a final list to be written to a .csv file.

Figure 1 shows the entire code to extract Google Alerts data using the Google provided Gmail API.

The Python package pandas is an incredible resource that provides a number of tools to read, parse, extract, and manipulate delimited file or data types. The Pandas package has a resource for getting stock market data from free online sources such as Yahoo! mentioned above and Google. To install this package through Git, simply clone the directory, use the “Change Directory” command “cd” to change the current working directory, and installing the python module as follows: “ git clone git://github.com/pydata/pandas-datareader.git cd pandas-datareader python setup.py install ”

If the Python setup returns the error: “python: command not found” run the following with the path to the python installation:

```
“PATH=$PATH:/c/Python27”
```

Pandas-datareader and many other packages can also be installed via pip. In example, many additional packages are needed to run a python script using pandas-datareader. These packages can be configured all at once or one at a time as follows: “ pip -m install -user numpy scipy matplotlib ipython jupyter pandas sympy nose urllib3 chardet idna ”

Unlike the NASDAQ export, using Google as a data source for pandas-datareader requires each attribute to be called separately. This means calling the Close Price, Open Price, High Price, etc individually and joining them through code. Also, unlike NASDAQ’s export but this time in a positive light, multiple tickers can be passed together. This allows for all historical data to be pulled for many stocks with a single code.

The Python code for collecting historical stock data is propelled by pandas_datareader. The script starts by reading in the .csv created using the Google API script described previously. The data is read in as a dictionary using DictReader and the output file is opened/created right afterwards to allow for writing out with each loop through the starting file’s dictionary. For each line the stock ticker and date of the Google Alert are passed to a function that returns the highest price of the stock 5 days after the Google Alert, the stock and ticker are then passed to a function that pulls the opening price on the day that the Google Alert was received. The highest price and starting price are the used to calculate the percent change using the formula: “ round(((high-startPrice)/startPrice) × 100,2) ” If the high price is 10% higher than the starting price the line is given a “W” for “Winner”. If the high price is less than 10% of the starting price then the line is marked with a “L” for loser. The whole line with the addition of the Win or Lose designation and the percent change is written to a new .csv file with the intention of attempting sentiment analysis with the Win or Lose designations as the outcome and the Snippets as the sentiment.

Figure 2 shows a portion of the code to combine the data produced by the Google Alert mining and available historic stock price data.

Twelve out of over one hundred stock tickers returned by Google Alerts were flagged at “Winners” for increasing in price by 10% within five days after the Google Alert was received and are shown in Table 3.

ABEO Snippet appears to reflect a number of disappointments followed by something positive: “ Abeona Therapeutics - String Of

Table 3: Winning Stock Tickers

Ticker	prctChange	High	Open	Date
['ABEO']	27.39	10.0	7.85	2017-08-22
['ARRY']	15.41	10.11	8.76	2017-08-22
['CLSN']	160.9	3.47	1.33	2017-11-23
['EARS']	20.83	0.87	0.72	2017-11-18
['EGLT']	15.04	1.3	1.13	2017-11-17
['HCM']	39.87	35.01	25.03	2017-11-19
['NLNK']	57.8	10.02	6.35	2017-11-18
['NWBO']	45.0	0.29	0.2	2017-11-19
['NWBO']	45.0	0.29	0.2	2017-11-17
['ONCE']	11.53	83.19	74.59	2017-08-21
['OTIC']	11.47	20.9	18.75	2017-08-23
['PSTI']	32.23	1.6	1.21	2017-11-22
['VTVT']	10.92	5.08	4.58	2017-11-23
['VTVT']	24.24	5.69	4.58	2017-11-19
['VTVT']	24.24	5.69	4.58	2017-11-18

Pearls Strategy With Numerous Catalysts And A Lot Of Upside ” This Snippet was received August 22, when ABEO’s stock opened at \$7.85. The stock hit its five year high of \$19.95 on October 10.

ARRY is a bio-pharmaceutical company that was call out in the training set as a “winner” for August 22. J P Morgan Chase & Co confirmed a “buy” rating for ARRY on September 11, three weeks after it was identified by this model as a “winner”. Goldman Sachs increase their buy in to ARRY on October 22 by 33%. The Snippet for ARRY does not appear to reflect a positive sentiment about the company: “ Array Biopharma (ARRY) Reaches \$8.58 After 7.00% Down Move; Per Se Technologies ”

CLSN started the year just under \$10 a share and slowly declined to its current \$2.40. The Snippet for CLSN was received on November 23 when the stock briefly rose 160% before falling again: “ After Reaching Milestone, Is Celso Corporation (NASDAQ:CLSN)’s Short Interest Revealing ”

EARS is a small tier stock with a market cap of \$19 million. The stock rose to \$0.93 per share on November 24 before falling to \$0.42 on November 28. The Snippet depicts analysts predictions of negative earnings: “ Analysts See \$-0.20 EPS for Auris Medical Holding AG (EARS) BZ Weekly The Company’s advanced product candidate, AM-101, is in ”

Egalet Corporation (EGLT) develops abuse resistant formulations of opioids. The Snippet is overwhelming positive and describing stock increases: “ Egalet progressing second abuse-deterring opioid med The Pharma Letter Egalet (Nasdaq: EGLT) says its share move up a hefty 38.55% ” This Google Alert was receive on November 17, just prior to another 30% stock increase.

HCM is a pharmaceutical company headquartered in China. The Snippet reflects the companies one year growth of over 160%: “ Will Hutchison China MediTech Limited (HCM) Run Out of Steam Soon? BZ Weekly ... Hutchison China MediTech Limited (LON:HCM) were ”

NLNK received positive feedback from established analysts on November 18. Causing the stock to briefly rise and then return. This Snippet and change may reflect the power on analyst ratings: “

```

...
Portion of Reading GMAIL Alerts using Python
Tiffany Fabianac Modified code from:
    - https://github.com/abhishekchhibber/Gmail-Api-through-Python
    - Abhishek Chhibber
...
# Creating a storage.JSON file with authentication details
SCOPES = 'https://www.googleapis.com/auth/gmail.modify'
store = file.Storage('storage.json')
creds = store.get()
if not creds or creds.invalid:
    flow = client.flow_from_clientsecrets('client_secret.json', SCOPES)
    creds = tools.run_flow(flow, store)
GMAIL = discovery.build('gmail', 'v1', http=creds.authorize(Http()))

user_id = 'me'
label_id_one = 'INBOX'

alert_msgs = GMAIL.users().messages().list(userId='me', labelIds=[label_id_one],
    q='from:googlealerts-noreply@google.com').execute()

# We get a dictionary. Now reading values for the key 'messages'
mssg_list = alert_msgs['messages']

final_list = []

for mssg in mssg_list:
    temp_dict = {}
    m_id = mssg['id'] # get id of individual message
    message = GMAIL.users().messages().get(userId=user_id, id=m_id).execute() # fetch the message using API
    payld = message['payload'] # get payload of the message
    headr = payld['headers'] # get header of the payload

    for two in headr: # getting the date
        if two['name'] == 'Date':
            msg_date = two['value']
            date_parse = (parser.parse(msg_date))
            m_date = (date_parse.date())
            temp_dict['Date'] = str(m_date)
        else:
            pass

    temp_dict['Snippet'] = message['snippet']

    final_list=json.dumps(temp_dict) # This will create a dictionary item in the final list
    re.sub(r'\u22c5', '', final_list)

```

Figure 1: The Google API Python code calls the Gmail APIs Messages.list which lists reduced properties of Gmail messages and Messages. Get which returns the messages themselves. Lists is used to query the messages that are wanted based on the defined criteria: userId=me, labelIds=INBOX], q=from:googlealerts-noreply@google.com. Get then retrieves the messages identified in using List and returns the messages content for Date and Snippet.

NewLink Genetics Corporation (NASDAQ:NLNK) Given Buy Rating at Cantor Fitzgerald StockNewsTimes Indoximod is expected to enter a ”

NWBO held steady through October at \$0.16 and between until November 15 and November 28 rose 87%. The Snippet was received on November 18 in the prime of the increase. “ Here’s Why Northwest Biotherapeutics, Inc (OTCMKTS:NWBO) Just Ripped Higher

```

...
Collect Historical Stock Data
Tiffany Fabianac Modified code from:
- http://pandas-datareader.readthedocs.io/en/latest/remote_data.html
...
def stockData (startDate, endDate, ticker):
    # Define which online source one should use
    data_source = 'google'

    # Use pandas_reader.data.DataReader to load the desired data.
    panel_data = data.DataReader(ticker, data_source, startDate, endDate)

    close = panel_data.ix['Close']
    volume = panel_data.ix['Volume']
    op = panel_data.ix['Open']
    high = panel_data.ix['High']
    low = panel_data.ix['Low']

    # Getting all weekdays between 01/01/2017 and 12/31/2017
    all_weekdays = pd.date_range(start=startDate, end=endDate, freq='B')

    # Align new set of dates
    close = close.reindex(all_weekdays)
    volume = volume.reindex(all_weekdays)
    op = op.reindex(all_weekdays)
    high = high.reindex(all_weekdays)
    low = low.reindex(all_weekdays)

    result = pd.concat([close, volume, op, high, low], axis=1, join='inner')
    result.columns=['close','volume','open','high','low']
    return result

def findHigh (startDate, ticker):
    # Get date and five days after
    temp_date = datetime.datetime.strptime(startDate, "%Y-%m-%d")
    endDate = temp_date + BDay(5)

    result = stockData(startDate, endDate, ticker)
    tempHigh = result.nlargest(1,'high')
    high = tempHigh.iloc[0]['high']
    return high

def openPrice (startDate, ticker):
    temp_date = datetime.datetime.strptime(startDate, "%Y-%m-%d")
    endDate = temp_date + BDay(1)

    result = stockData(startDate, endDate, ticker)
    open = result.iloc[0]['open']
    return open

```

Figure 2: This Python script takes in the Date, Stock Ticker Symbol, and Snippet from the Google API.csv that was produced using both manual mining of the stock symbols and the python script provided for getting the Date and Snippet from Gmail. This code returns a modified .csv which lists an "L" for stocks that did not increase by 10% in five days and a "W" for stocks that increased by at least 10%. It also prints the stocks that increased by at least 10% along with the highest price over 5 days, the starting price on the day that the Google Alert was received, and the percent change.

The Finance Registrar The Company's lead program orthwest Bioth Cmn (NASDAQ:NWBO) Stock fi? Is it Overbought? First News 24 The Business's lead product, DCVax-L, is in an ongoing "

ONCE is a large cap therapeutics company which showed growth through September. The Snippet reflects news of a changed analyst rating: " Spark Therapeutics Inc (ONCE) is Initiated by Evercore ISI to "In-line" "

OTIC rose in August just before crashing from \$20.18 to \$3.20 after a failed Phase III clinical trial in September. The Snippet captured analyst confidence in the company: " Otonomy (OTIC): Reiterating Outperform Ahead Of Catalysts - Cowen "

PSTI is a leading developer of cell therapy products derived from placenta. The Snippet received on November 22 reflects news of a granted patent application: " Pluristem Therapeutics (PSTI) Granted US Patent for Skeletal Muscle Regeneration StreetInsider.com This very important patent comes"

VTVT's Snippets reflect stock decreases, low sentiment scores, and drug treatment competition: " vTv Therapeutics (VTVT) Reaches \$5.01 After 5.00% Down Move; FMC (FMC) Shorts Down By vTv Therapeutics (VTVT) Receives Media Sentiment Rating of 0.25 The Lincolnian Online vTv Therapeutics Inc is a clinical-stage Head-To-Head Comparison: vTv Therapeutics (VTVT) versus Its Competitors The Ledger Gazette Its drug candidate for the treatment of " These sentiments do not reflect positive news and should be cause to look more deeply at the stock comparison being performed.

2.2 Data Analysis

There are many methods for analysis that could be implemented for this dataset. Time series prediction could be used to identify trends in the stocks of interest [2]. Regression analysis is very common to identify key factors that contribute to the accuracy of a prediction. TextBlob sentiment analysis allows for sentiment analysis to be performed in as little as four lines of code. TextBlob returns a number between -1 and 1 for how negative (-1) or positive (1) a defined sentiment or group of text is [16]. Tensorflow is another popular way of creating sentiment analysis which takes an input of words with the intent of returning a sentiment of positive, negative, or neutral. In order to do this Tensorflow uses a build in learning and training set called tflearn to compare previously established sentiments. For example, words like "love" and "happy" return a positive sentiment while words like "hate" and "sad" return a negative sentiment [5].

Random Forest algorithms create decision trees for each variable. Each tree represents the sequence of events or decisions that led to the outcome or result. With each branch or step through the decision tree a probability is calculated for the outcome and the collection of trees work are combined to create multiple "regression lines" that are used to predict an outcome when presented with new data that does not have an outcome. The model or collection of trees form what is called a random forest can then be used to predict sentiment or outcomes. For stock data or other time series datasets, it is essential to continuously re-train the model to perform at its best. As mentioned above it is possible for additional models and even the model itself to begin to influence the prediction model.

The code that performs random tree analysis starts with some dependencies. Os is imported to allow for command line functionality,

the machine learning library sklearn is used because it has a very fast learning rate, KaggleWord2VecUtility is a utility that processes raw text into segments for learning, pandas as mentioned before helps with delimited file manipulation, nltk that already contains a number of words and phrases that are not useful for sentiment analysis importing this library helps to eliminate those elements from the dataset we are training on. To install KaggleWord2VecUtility visit the DeepLearningMovies github directory [29].

In this code the Kaggle module removes special characters associated with HTML. It was intended to return a URL from the Google Alerts and run the website associates with each alert through beautiful-soup to use the entire article as training data, but the Gmail messages were encoded in such a way that it was not possible to extract the URL from the Google Alert. Nltk removes words such as "to" or "the" which do not hold any inherent meaning that could be applied to the sentiment analysis. The cleaning process converts the first Snippet as follows: " Abeona Therapeutics - String Of Pearls Strategy With Numerous Catalysts And A Lot Of Upside abeona therapeutics string pearls strategy numerous catalysts lot upside "

Once the Snippets are free of special characters and non-sentiment words, they are parsed into a vector. This process creates what is called a "Bag of Words" by creating a dictionary with the count of each word in the text. This is also called tokenization or vectorizing and is performed easily with the sklearn package's countVectorizer process. Here the analyzer is set to word, there is no defined tokenizer, pre-processor, or stop words needed so these are set to "None". The maximum number of features controls the limit on the maximum number of words and frequencies contained in the bag of words.

A model is easily created from the defined bag of words using sklearn's fit_transform which is converted to an array. The method for classification is a random forest which builds decision trees for each variable in the dataset. In example, the first Snippet describes a "winning" variable and contains the word "Upside" if other Snippets contain the word "Upside" it might be indicative of a "winning" classifier. The last step calculates predictions for the new dataset based on the established classifiers. This is simple done with the RandomForestClassifier's predict function.

Figure 3 shows the entire code to train on the dataset provided by the historical stock data and Google Alert sentiments.

The Python code for verifying the random tree analysis by pulling historical stock data for each ticker analyzed is propelled by pandas_datareader. The script starts by reading in the .csv created using the random tree analysis script described previously. The data is read in as a dictionary using DictReader and the output file is opened/created right afterwards to allow for writing out with each loop through the starting file's dictionary. For each line the stock ticker and date are passed to a function that returns the highest price of the stock from the date of the received alert to the current date, the stock and ticker are then passed to a function that pulls the opening price on the day that the Google Alert was received. These two prices are compared to verify if the stock increased by 10% from the time of the alert.

Figure 4 shows a portion of the code to combine the data produced by the random forest analysis and combine it with available historic stock price data.

```

...
PORTION OF: Use KaggleWord2VecUtility to produce random forest analysis
Tiffany Fabianac Modified code from:
- https://youtu.be/AJVP96tAWxw
- Siraj Raval
...

# Cleaning and parsing the training set
for i in xrange(0, len(train['Snippit'])):
    clean_train_reviews.append(" ".join(KaggleWord2VecUtility.
review_to_wordlist(train['Snippit'][i], True)))
#Creating the bag of words
vectorizer = CountVectorizer(analyzer="word", tokenizer=None, preprocessor=None,
stop_words=None, max_features=5000)
train_data_features = vectorizer.fit_transform(clean_train_reviews)
train_data_features = train_data_features.toarray()

#Training Random forest
forest = RandomForestClassifier(n_estimators=100)
forest = forest.fit(train_data_features, train['W/L?'])
clean_test_reviews=[]

#"Cleaning and parsing
for i in xrange(0,len(test['Snippit'])):
    clean_test_reviews.append(" ".join(KaggleWord2VecUtility.
review_to_wordlist(test['Snippit'][i], True)))
test_data_features = vectorizer.transform(clean_test_reviews)
test_data_features = test_data_features.toarray()

print "Predicting test labels...\n"
result = forest.predict(test_data_features)

```

Figure 3: The Sentiment Python code takes the .csv exported by the historical stock script and parses the Snippets to train on the stock script and apply it to more recent stock quotes and Google Alerts

3 RESULTS

The resulting CSV file contains the accuracy of the prediction, if the stock did not increase by atleast 10%, the date that the Google Alert was received, the Sentiment that was calculated by the random forest algorithm, and the stock ticker. The results export to a .csv as shown in Tables 4, 5, and 6.

This analysis shows the stock ticker ABBV for the pharmaceutical company AbbVie as a “loser” twice as two alerts were received about the company on December 3 and 4. As of December 4 ABBV is down 1.08% post Google Alert receipt. ACAD is the ticker for ACADIA Pharmaceuticals Inc. which is down 1.09% since receipt of the Google Alert on November 30. Alnylam Pharmaceuticals, Inc (ALNY) is down 1.06% since December 2. ARGX is down 0.97% since receipt of the Google Alert but up over 18% for the prior five days. ARGX did not appear in the training data set so it might be worth while to explore factors that contributed to it’s recent increase, if not clinical trials. Interestingly, BABA is a Chinese e-commerce site which is down 2.88%. This ticker appearing is cause to look closer at the article that was link to the Clinical Trial Alert but returned a retail chain.

3.1 Comparison to Established Analyst Ratings

One of the important aspects of professional analyst ratings is that the intent is to identify the best long term investments. This project only looked at short term success over a period of five days. Further research should refine additional models to compare success in shorter term, one day, and longer term, six months to a year or more.

ABBV, a predicted “losers”, is marked “Neutral” by JPM. The two Snippets stored for ABBV are: “ Cornercap Investment Counsel Has Raised Abbvie Com (ABBV) Stake; Profile of 7 Analysts ... NormanObserver.com The firm also develops AbbVie Inc. (NYSE:ABBV) Updates On Phase III Murano Trial MMJ Reporter AbbVie Inc. (NYSE:ABBV) reported that the American Society of ” The ABBV Snippets do not appear to be negative, and may even swing more in the positive light. AbbVie being a large cap pharmaceutical company may create lower volatility for the stock. Reanalyzing the data and splitting companies into small, mid, and high tier categories may give very different results over long term and short term growth. Larger companies, with many more investors, tend to be more stable.

ACAD, a predicted “losers”, is marked as “Neutral by Goldman Sachs. Interestingly enough, the Snippet about ACAD mentions a

```

...
PORTION OF: Validate random forest analysis
Tiffany Fabianac Modified code from:
- http://pandas-datareader.readthedocs.io/en/latest/remote_data.html
...
with open('randomForestResults.csv', 'rb') as csvfile:
    with open('resultsData.csv','wb') as f:
        datareader = csv.DictReader(csvfile)
        writer = csv.DictWriter(f, fieldnames=datareader.fieldnames, extrasaction='ignore',
                               delimiter=',', skipinitialspace=True)
        writer.writeheader()
        for line in datareader:
            if (line['Ticker'] == '' or line['Sentiment'] == ''):
                pass
            else:
                ticker = [line['Ticker']]
                date = line['Date']
                high = findHigh(date, ticker)
                startPrice = openPrice(date, ticker)
                prctIncrease = round(((high-startPrice)/startPrice)*100,2)
                if (high > startPrice*1.1 and line['Sentiment']=='W' ):
                    line['Accuracy']='W'
                    print ticker, prctIncrease, high, startPrice, date
                else:
                    line['Accuracy']='L'
                writer.writerow(line)

```

Figure 4: This Python script takes in the Date and Stock Ticker Symbol from the sentiment .csv that was produced using the sentiment python script provided for performing a random forest analysis on the Google Alert results. This code returns a modified .csv which lists an “L” for stocks that did not increase by 10% from the time the Alert was received to the current date and a “W” for stocks that increased by at least 10%. It also prints the stocks that increased by at least 10% and were marked as “winners” by the sentiment script.

sentiment ranking which is actually what would be considered a positive rating: “ EPS for The Kroger Co. (KR) Expected At \$0.41; Acadia Pharmaceuticals (ACAD)s Sentiment Is 1.05 San Times The Company ” Increasing the Google Alert scope to include data related to sentiment for pharmaceutical companies may be beneficial to the model.

ALNY, a predicted “losers”, is marked as “Buy” by JPM, Goldman Sachs, and Barclays. These analyst ratings may indicate that the model is not a good indicator of long term success as the analyst ratings suggest. This requires greater research which should include increasing the historic interval from five days to six months or more. The Snippet does not seem to reflect anything positive or negative about the company: “ How Analysts Rated Alnylam Pharmaceuticals Inc. (NASDAQ:ALNY) Last Week BZ Weekly The company’s clinical development programs ” ARGX, a predicted “losers”, is ranked as “Underweight” by Barclay, as recently upgraded to “Buy” by Goldman Sachs, and has been downgraded to “Neutral” by JPM. The Snippet used to rate this company mentions a number of other stock tickers but gives the impression that ARGX should be a stock of interest for would be investors: “ Here’s Why You Need To Keep An Eye On ARGX MGNX KURA AGIO Nasdaq argenxs lead oncology asset is ARGX-110 currently ”

It is important to note that the intention of the model is not to predict winning long term stocks, but to predict stock that will have a 10% increase within five business days.

BABA, a predicted “losers”, is also marked as a “buy” by all investing firms and reaffirms that additional data is needed for long term investments. This Snippet does show negative sentiment. Reducing holding in a company is not a good sign of positive things to come for a company. Even if this sentiment appears accurate, it does not on its own confirm the model’s accuracy. “ Tiger Legatus Capital Management Cut Alibaba Group Hldg LTD (BABA) Position By \$2.80 Million ... UtahHerald.com The company ”

4 CONCLUSION

The codes provided for this project take Google Alert data directly from a Gmail account, write the date the alert was received and the Snippet to a .csv, use the stock tickers identified in the Google Alerts to pull relevant historical stock price data to create a training set which is then analyzed using a random tree approach. The random tree analysis then produces a prediction for stocks that have received alerts more recently (within five days of the analysis). While all the sentiments drawn in the final calculation were indicated as “losers” none of the stocks were reconfirmed by recent historical data as significant increases. The lack of true negatives

Table 4: Final analyzed results and accuracy

Accuracy	Date	Sentiment	Ticker
L	2017-11-24	L	CLSN
L	2017-11-24	L	KMDA
L	2017-11-25	L	CLSN
L	2017-11-25	L	VTVT
L	2017-11-25	L	NKTR
L	2017-11-26	L	PRTD
L	2017-11-26	L	ADMA
L	2017-11-26	L	KALA
L	2017-11-26	L	SNDX
L	2017-11-26	L	GALE
L	2017-11-26	L	SNDX
L	2017-11-26	L	EVOX
L	2017-11-27	L	CPRX
L	2017-11-27	L	AZN
L	2017-11-27	L	TSRO
L	2017-11-27	L	CLSN
L	2017-11-28	L	MRK
L	2017-11-28	L	REGN
L	2017-11-28	L	EARS
L	2017-11-28	L	MRK
L	2017-11-28	L	CPRX
L	2017-11-28	L	AZN
L	2017-11-28	L	AERI
L	2017-11-29	L	CLSN
L	2017-11-29	L	EARS

does not confirm the model, but could be an indication of the model being on the right track for success.

The analysis presented herein represents the possible impact of sentiment expressed in news reports about clinical trials has the potential to predict the movement of stock prices. Further analysis should work with a bigger data set, possibly by increasing the number of configured Google Alerts and certainly by identifying how to pull stock tickers from the Snippets. An idea to do this might be to create a dictionary of stock tickers and company names and compare this dictionary with the sentiments. This could then pull out any company names or tickers defined in the Snippets and associate the relevant ticker symbol.

Next steps should also include more in depth analysis on the timing of stock increases by changing the historical stock data from five days after an alert is received to two days or one day. This would allow for a more immediate reflection on the cause and effect of the reported news. The scope should also be scaled to consider historical data over six months or more and compared again to the results of dedicated investor houses. In addition, adding sentiment analysis reports for pharmaceutical companies may benefit the long and short term predictions.

This project was run on ubuntu and took approximately four minutes to process from pulling Google Alerts to producing the analysis after Nltk was downloaded. Nltk took some seven minutes to download for the first run. Future projects, with bigger datasets, could be run from cloud environments like AWS, Chromeleon, or the server node of a big red environment.

Table 5: Final analyzed results and accuracy continued

Accuracy	Date	Sentiment	Ticker
L	2017-11-29	L	MRK
L	2017-11-29	L	TEVA
L	2017-11-29	L	NVS
L	2017-11-29	L	TEVA
L	2017-11-29	L	MRK
L	2017-11-29	L	EARS
L	2017-11-29	L	APVO
L	2017-11-29	L	EARS
L	2017-11-29	L	CLSN
L	2017-11-29	L	EARS
L	2017-11-30	L	ACAD
L	2017-11-30	L	MRK
L	2017-11-30	L	TEVA
L	2017-11-30	L	VKTX
L	2017-11-30	L	MRK
L	2017-11-30	L	TEVA
L	2017-11-30	L	VKTX
L	2017-11-30	L	CLSN
L	2017-11-30	L	NVS
L	2017-12-01	L	ABBV
L	2017-12-01	L	BAYN
L	2017-12-01	L	CLSN
L	2017-12-01	L	CLSN
L	2017-12-01	L	NTNX
L	2017-12-01	L	PAIOF

Continued improvement of the code would test running Kaggle and Nltk from the Google API script to reduce the size of the output file by eliminating stop words and special characters before the first export is even produced. This process would also improve speed with the historical stock price collection script as the Snippets are also written here.

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Table 6: Final analyzed results and accuracy continued

- | Accuracy | Date | Sentiment | Ticker |
|----------|------------|-----------|--------|
| L | 2017-12-01 | L | SNDX |
| L | 2017-12-01 | L | SNY |
| L | 2017-12-01 | L | SNY |
| L | 2017-12-01 | L | CLSN |
| L | 2017-12-01 | L | NTNX |
| L | 2017-12-01 | L | ABBV |
| L | 2017-12-02 | L | ALNY |
| L | 2017-12-02 | L | BABA |
| L | 2017-12-02 | L | CISN |
| L | 2017-12-02 | L | CLSN |
| L | 2017-12-02 | L | MDXG |
| L | 2017-12-02 | L | OCRX |
| L | 2017-12-02 | L | PTCT |
| L | 2017-12-02 | L | RTRX |
| L | 2017-12-02 | L | CISN |
| L | 2017-12-02 | L | RTRX |
| L | 2017-12-02 | L | CLSN |
| L | 2017-12-03 | L | ABBV |
| L | 2017-12-03 | L | ARGX |
| L | 2017-12-03 | L | BPMX |
| L | 2017-12-03 | L | CLSN |
| L | 2017-12-03 | L | CLSN |
| L | 2017-12-03 | L | CSX |
| L | 2017-12-03 | L | GERN |
| L | 2017-12-03 | L | OMER |
| L | 2017-12-03 | L | SGEN |
| L | 2017-12-03 | L | SPHRF |
| L | 2017-12-03 | L | TILE |
| L | 2017-12-03 | L | TJX |
-
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How Big Data Will Help Improve People's Health Worldwide

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ABSTRACT

Aside from people changing their habits, big data analytics may hold the best possibility for the improvement of worldwide health. It will enable the ability to correctly diagnose patients more quickly, even when the patients may not be able to be physically seen by a provider. It will be used to create treatment plans specific to not only an illness, but to the patient's overall health condition and history, demographics, environment, and access to resources. While it may not solve the problem of everyone not having access to the best of care, it can help to make sure everyone can get the best care possible for them. This paper explores the ways in which big data is evolving in the field of healthcare to make these possibilities become realities and looks at some of the social concerns which could hold it back.

KEYWORDS

i523, hid327, healthcare, patient treatment, genomics, diagnosis

1 INTRODUCTION

There have been many advances in big data analytics over the last several years. More and more data is able to be processed in a shorter amount of time. There are also many new sources of data. Data is not what big data is about though. It is about taking data and turning it into information that can be useful. The application of big data can vary, but very few may be more important than the ability to use data for the betterment of people's health across the globe. This is one way in which data science can make a substantial contribution to humanity.

Making this a reality is not, nor will be, a simple task. Health data itself requires the proper handling of the information as it is very sensitive. On one hand people have a right to privacy. On the other, if data is kept isolated, not combined with records from other people, then this limits the ability to gather insight and find breakthroughs. The key is to ensure privacy, but keep the integrity and relationships of the data in order to preserve privacy while gaining insight. The insight gained has endless possibilities.

One issue facing the medical profession today is a lack of trained professionals. The number of patients per healthcare worker around the world can vary from more than six per 1,000 people to less than one half per 1,000[43]. It is easy to see how this one fact greatly impacts the expected lifespan of people. But what if a patient could be examined, diagnosed, and have access to a treatment plan without a human doctor needed? It may sound futuristic, but the technology is being implemented today thanks in part to data analytics.

The impact of big data on healthcare doesn't stop there. The cost of treating 5 percent of the most chronic conditions can consume up

to 50 percent of the money spent on healthcare[42]. One reason for this is prevention, diagnosis, and treatment plans are not optimized. There is not one way to help patients avoid chronic conditions. It is based on many inputs depending on the person, their environment, and other factors. These same aspects impact the effectiveness of treatment plans as well. One size does not fit all. Through analytics many factors are being analyzed along with the results of prior plans to determine which methods would be the most effective. Avoiding a chronic condition not only saves money, but extends a patient's life and improves the quality of their life.

The ability to take many factors into account for a patient goes well beyond chronic conditions. Genomic technology is progressing which is allowing for a person's individual genome to be one of the inputs. Each person on earth has their own specific genome with billions of combinations, some of which directly impact their health and susceptibility to illnesses. Through big data analytics, this type of analysis may one day be commonplace like taking blood pressure and other vital statistics into account.

The discovery of new drugs and how they can be used to treat people is being sped up by the power of big data techniques. Drug research requires an immense amount of information to be correlated and processed. Big data is helping to speed this up and even helps speed up clinical trials by matching the right set of circumstances to provide viable results.

Progress does not always come without drawbacks, and big data analytics in healthcare is no exception.

2 HANDLING THE DATA

2.1 Security

Any use of healthcare data must take into account the ability to protect the data. Therefore a brief understanding of the task must be addressed. Healthcare information usually has two forms of protected information: Personally Identifiable Information (PII) and Protected Health Information (PHI). In order to be able to keep data with this type of information you must follow very strict rules on safeguarding it. The best known regulations are based on the Health Insurance Portability and Accountability Act (HIPAA) of 1996. Among the governmental standards to comply with HIPAA are the Security Control Assessment[18] and Defense Information Systems Agency's Security Technical Implementation Guides[1]. These types of requirements can be costly and require constant changes to remain secure.

Even with the ability to secure the data properly, any company wishing to obtain data must have an approved reason to get the information or the approval of the patients involved. Obtaining approval from each patient in a big data application is not practical.

Data is needed from too many people to obtain approval for each of them. A common way to handle this is through de-identification.

De-identification is the ability to alter the data in such a way that you cannot link health information to a person or identify individuals in the data. However, in order for the data to be useful for analysis it cannot be changed randomly so the links between certain data elements from record to record is lost. For instance, a diagnosis of a specific cancer in a patient must still be able to be linked to treatment data, x-rays, blood tests, etc. from that patient. In other words, de-identification has to be done in such a way that the data integrity remains in place, but the individual's identity is protected. This can become complicated because data elements such as age, sex, and geographical location are important.

Fortunately there are software solutions to assist in the de-identification of medical information. The software is broken into two categories: structured data and free-form text. De-identification of structured data is generally easier. The data has a known set of fields of which the ones which can identify a person and their health are known. These fields are added to the software and algorithms are run against them. The resultant data is useful for analysis, but the identity of any individual is safe. This is because the algorithm changes data in such a manner that it protects the person and the data integrity. Examples of tools in this arena include PARAT from Privacy Analytics, Inc., mu-Argus from the Netherlands national statistical agency, Cornell Anonymization Toolkit (CAT), an anonymization toolkit from the University of Texas at Dallas, sdcMirco from r-project.org[25]. Commercial tools like Privacy Analytics Eclipse claim to de-identify 10 million records per day from a variety of sources[50].

Unstructured data is more complex. The data which needs to be de-identified can be located anywhere within the dataset. This includes the text or metadata attached to images such as x-rays. Vital clinical, diagnosis, treatment, and other medical information is also included throughout unstructured data. Not being able to identify all PHI and PII can cause privacy concerns. Not linking all the correct data together reduces data integrity which reduces the usefulness of the data being studied.

Being able to properly de-identify and link unstructured data is being studied and refined. There are challenges for solutions to the problem. Informatics for Integrating Biology and the Bedside[24] has held challenges to help further solutions for this problem. The most recent was held in 2014. Track 1 of this challenge noted that "Removing protected health information (PHI) is a critical step in making medical records accessible to more people, yet it is a very difficult and nuanced"[24]. The ability to properly de-identify the data is rooted in the ability for the software to perform natural language processing. The focus of the challenge was all eighteen HIPAA defined PHI types[35]. While not as mainstream as de-identifying structured data, the ability to de-identify unstructured data will continue to progress and be solved through commercially available products over time.

2.2 Data Sharing

There are many sources of healthcare data. This is a major hurdle as the data is in different systems which are governed by different entities and used for purposes[32]. Data is stored in claims systems,

clinical settings, pharmacies, and others. It is stored in different formats. These sources may not contain similar key data that allows it to be easily brought together. Individual patients usually have a single provider who is their primary insurer. This data is usually in standard formats. However the same patients may have many providers of care using different systems. While most providers leverage electronic health records, these systems can contain many free-form text fields, images, and other types of fields. These data sets contain a wealth of information, but they are missing data which could be vital such as social, environmental, and community data. Other sources of data which could be useful are habits which people store on themselves such as food and activity tracking they may enter into any number of online applications[10].

While more data is being collected, there are still barriers to sharing it. There are the security and privacy concerns discussed earlier, but also the costs and who pays for them which must be addressed. There are tools and strategies being worked on in the industry to make sharing data across disparate systems possible. So far a widely adopted solution has not emerged[9]. Until such time that it does, data analytics in healthcare will be hampered.

3 BIG DATA IN A CLINICAL SETTING

Being a doctor can be like being a human big data machine at times. They take in many variables, process it against the history of information they have, and come to some sort of conclusion. In many cases there are multiple diagnosis that can be made. In fact sometimes there a lot of diagnosis that can be made. Unfortunately while much of the work is very scientific it does not mean that coming to a conclusion is a precise science.

Different doctors have different backgrounds. They have seen different patients, seen different diseases, studied at different locations, and read different literature. In short, their diagnosis is based off of their experiences. Unfortunately experiences are a form of bias. It is not that someone is doing this on purpose for the betterment or detriment of someone, but it is how our brains are wired. Physicians are not immune to this and it can affect the ability to treat all patients and conditions equally or appropriately[11]. When set up correctly and fine-tuned over time, data analytics can minimize biases.

3.1 Electronic Health Records

The ability to use big data in a clinical setting is growing out of the movement to storing records electronically. Historically these records were stored in paper format. The amount of data to use for big data analysis continues to rise as adoption of Electronic Health Records (EHRs) increases. Countries such as Norway and the Netherlands adopted EHRs more quickly than others and were at 98% adoption by 2012. The United Kingdom (97% in 2012), New Zealand (97%), and Australia (92%) were early adopters as well.[13] The United States is potentially a large source of EHR information, but has lagged other countries when looking at adoption rates. However, by the end of 2016 over 95% of hospitals and over 60% of United States based doctors have achieved meaningful use certification for EHRs from the Centers for Medicare and Medicaid Services.[40] As all countries continue to move toward storing

health records electronically then the body of information available for analysis will grow.

3.2 Big Data as a Physician Assistant

What if each doctor had the collective knowledge of others? That could make for better and more accurate diagnoses around the globe. A doctor in the United States would have the knowledge of thousands of years of alternative medicine which may only be taught in schools in the far east. Not only is it possible, but big data is making it happen today through technologies such as IBM's Watson.

3.3 IBM's Watson Health

One of the challenges facing doctors today is the ability to keep up with changes in healthcare. Even doctors who specialize in a field cannot keep up with the amount of information that is being published. One estimate is that 8,000 medical journal articles are published each day[59]. This makes medicine a good fit for big data. Watson Health, IBM's name for their cognitive supercomputer focused on healthcare, is able to ingest millions of pages of information in seconds. This information becomes part of the core information Watson has at its disposal as it assists clinicians by offering recommendations for them to consider. In this way Watson is not the final decision maker, but helps doctors be better at what they do[29].

While Watson is delegated to a physician's assistant currently, it may not always be so. In order to test how accurate it is, IBM tried it on 1,000 patients. In this test Watson and the attending physician agreed 99 percent of the time. In fact, in 30 percent of the cases Watson offered pathways which the physician had not considered. Armed with information like this IBM believes that computer cognitive thinking will be mainstream in the next ten years[59]. Because of advances in other technology areas have been progressing so quickly, it is hard to disagree with them. For instance, computers are now able to instantaneously make decisions that seemed unimaginable just a few years ago which as lead to the realization of autonomous driving vehicles. The question may not be the technology, but if people will accept a diagnosis from a computer program such as Watson.

Watson was also tested to see how examining a patient's entire genome would be more beneficial than simply running a panel which focuses on a limited number of areas most commonly known to be related to the cancer a patient may be experiencing. While the cost of and speed of sequencing a person's genome has been reduced, there is still a lot of work to using this data for a specific diagnosis and treatment plan. Both Watson and team from the New York Genome Center analyzed a patient's genome. Each of them was able to identify gene mutations which would have pointed to a clinical trial or drug which may have been a better match than the treatment the patient received. The difference being that it took the team of physicians approximately 160 hours to come to their conclusion. Watson provided its results in 10 minutes[58]. While not perfect, Watson adds another tool doctors can leverage which would allow them to better diagnose and treat patients.

How does Watson do it? It is actually very similar to how a human doctor works. The patient's symptoms and other information is made available to Watson. From there it deduces the relevant elements and leverages any background information it may have such as patient and family history, labs, x-rays, and other test results. It then accesses other sources of information it has accumulated over time: treatment guidelines, relevant articles and studies, and potentially information from other patients similar to this patient. Watson develops hypotheses and runs them through a process to test its hypotheses and provide a confidence score for each. Watson then provides its recommended treatment options with its confidence rating to the physician[19].

One advantage of Watson, or any such system, is that every time it is used that patient is getting all of its collective knowledge. Today when a patient see a physician they are diagnosed by that physician and maybe one or two other people generally from the same office. However as Watson gets *trained* by specialists in such fields as Oncology, every doctor who uses Watson's assistance becomes as or more knowledgeable than the collective group. This means that each doctor is providing top of the field care even if they are being seen nowhere near a facility that is considered as the best world[36]. A patient in a country not seen as having world-class healthcare can get diagnosed as if they were at the Sloan-Kettering Cancer Center. It also means that a patient who may be seeing a specialist in one area may be diagnosed with an ailment outside of their field. This can save time in receiving the appropriate diagnosis and subsequent treatment which gives patients the best chance for recovery.

There are obstacles to making Watson available worldwide and that is the ability to understand different languages. Watson knows English, Brazilian Portuguese, Japanese, and Spanish and is learning others. As an example, IBM, the Cleveland Clinic, and Mubadala are teaming up and are building a hospital in the Middle East. The Cleveland Clinic is already a user of Watson Health and is expected to leverage that in the new facility as many chronic conditions in the United States are present in the Middle East as well. To prepare for this, IBM is teaching Watson Arabic[62]. As Watson learns more languages it will be able to be leveraged in areas around the world which that language is spoken allowing for those populations to advance their healthcare knowledge.

Another advantage that Watson has over human physicians is that it never forgets. Even doctors who try to keep up with changes in healthcare, they will never be able to remember information as precisely as Watson. And Watson is also consistent. A single doctor may be mostly consistent, but different doctors will provide different diagnoses given the same input. Watson will not unless it is programmed differently or new knowledge is ingested which can create a more accurate diagnosis. It also does not have bad days, get tired, and is available 24x7x365. Watson's incremental costs, the cost of using it for one or one million patients, is low. IBM has spent billions on it and is continuing to invest, but those costs will be spread out as usage goes up thus making Watson cheaper over time[19].

3.4 Implementing Big Data Diagnostic Systems

Leveraging such technologies can be implemented in various ways. The easiest way is to look at them as another tool in a physicians' tool chest. Once fully implemented the inclusion of big data assisted technologies will be seamless. Clinical information is being collected digitally on an increasing basis. As vital signs, x-rays, diagnostic images, lab results, and even discussions with the patients are collected digitally they will become part of the patient's electronic health record and the overall collective knowledge base. Watson or other software could provide insight to the physician. It may be present a collection of diagnoses scored in likelihood based on the evidence collected so far[28]. It could provide recommendations for next steps or information which could lead to a more complete recommendation.

The idea behind such a system, Watson or any similar tool, is to make physicians better through more accurate diagnosis. It allows for the use of big data without removing the human aspect of medicine. This will help to begin to include the big data and computer health diagnosis to patients who would otherwise not be open to it. For many people their relationship with their doctor is personal. They discuss items with their doctor they do not discuss with anyone else. They may not trust a computer with their health[28]. A non-caring, non-breathing inanimate object cannot be trusted with something so human. In this implementation a doctor would still be there providing the personal interaction with the patient and thus providing them with the best care including the collective knowledge of the system.

3.5 Replacing Doctors for Routine Visits

Having a doctor meet with a patient initially may not always be required. The ability for big data to leverage healthcare data could lead to helping alleviate the shortage of doctors and nurses in the United States and around the world. Worldwide there is an estimated shortage of skilled health professionals of 17.4 million of which 2.6 million are doctors. The problem does not get much better over time as the estimate for 2030 is over 14 million[45]. It takes a lot of time and money for a student to achieve the level of knowledge to fill these positions. Unless the students are already in the pipeline then there is not a good response to the problem. People cannot switch careers and be a doctor or a nurse in twelve months or some short time-frame.

Adding new big data doctors is simple. It is mostly a hardware problem. Buy the right equipment, install the right software, train the staff, and Dr. Data can see patients. Leveraging automated machines to take vital signs will free up time for staff[14] similar to how checking out via automated tellers at the grocery store has reduced the number of cashiers and baggers needed. A physical office offering virtual doctor's visits could be staffed with people trained on the technology more than medical professionals. They would be there to help make sure that people are using the machines correctly and to wipe down equipment after a patient has used it. A nurse would be there in case certain patients are unable to use the equipment and their information must be taken manually. They could also be there to take blood samples which would be processed by automated machines and included in the patient's profile.

Automated diagnosis systems are in use today in a limited basis. In the United Kingdom the National Health Service has approved the use of Your.MD (an AI powered mobile app) for diagnosis. When people are comfortable using a technology like this it limits the number of more basic cases a doctor has to see and allows them to concentrate on more difficult tasks. Another tool, Ada, learns a user's history, provides an assessment, and adds an option to contact an actual doctor if needed. Babylon Health takes it one step further by adding follow-ups with users to see how they are doing and can even set up a video consultation with a live general practitioner if needed[14].

4 LIMITING EPIDEMICS

Incorporating big data analytics into the healthcare environment has the ability to limit the spread of disease by taking current circumstances outside of the immediate patient into account. In a linked system data from other local, regional, national, and global patients can be leveraged. Are there other patients presenting similar circumstances? Did the other patients provide more details or mention something slightly different? Taking this into account may help to diagnose a specific person and to identify an outbreak of something. Is a disease spreading? Did patients come from a similar location such as a building? By being able to correlate this information immediately there is the potential to stop an outbreak from spreading thus saving an untold number of patients from pain and suffering and saving healthcare dollars by not having to treat more patients. Epidemics have an economic impact at many levels including "the micro (individual and household), meso (establishment, village or city) and macro (national and international)"[46].

5 INSURANCE

The option of having fully automated doctors' visits could alter the insurance market as well. Health insurance is about numbers. Actuaries spend time estimating the health of the consumers they cover and many other factors to determine what premium rates to set[38]. Insurers make a profit by taking in more money than the costs to administrate the plans and the cost of paying for claims combined. To reduce the costs of claims they set predetermined prices for services rendered by hospitals, physicians, and sometimes pharmacy companies. The lower they can drive the cost of the claims they cover the less they charge or the more money they make. Charging less can result in making more money as well as more people may choose to purchase coverage from that insurer.

By creating an option for autonomous doctor's visits or tele-medicine an insurance company could save money. The more methods can be deployed which can reduce overall healthcare costs, the less people will pay. There are multiple ways in which this can be included to reduce health insurance premiums, a high cost item for most people in the United States and other countries. Insurers can work with healthcare providers who leverage this technology to create a reimbursement policy that is less for services such as tele-medicine[33]. They could also offer plans to potential customers which require basic treatments to take place with autonomous or tele-medicine options before they go to a doctor's office. This would offer an economic advantage to people which in turn can not only lower costs, but help to increase the adoption of new technologies.

Such a system is not for everyone or every condition. The idea is not to replace all doctor's visits, but to allow those who are comfortable to take advantage of lower cost coverage. It will encourage younger people to keep insurance if it is made more affordable. Currently the highest rate of not having insurance in the United States is when someone can no longer be covered as part of their parents plan, starting around the age of 25[4].

6 PORTABILITY

More importantly than lowering the cost of healthcare or making seeing a doctor more convenient is the ability to make exceptional healthcare available almost anywhere. Big data using an automated doctor can have an impact on under-served areas the like of which no one has ever seen. Today there are people who do not have access to healthcare of any kind. When they get sick they may not have a place to turn. In developed countries the number of patients per doctor is generally in the low hundreds. In poor, *third world countries* the number of patients per doctor is in the thousands or tens of thousands[26]. There are people who try to help, such as Doctors Without Borders, by making visits to these areas to provide some support but it does not reach a level anywhere near what people in some countries have available to them. If each doctor could multiply their impact with technology then the under-served would be helped more. As technology advances so people could be seen by experts without one being physically present then even more people could be seen.

7 PATIENT DATA COLLECTION

7.1 Actual Data vs. Circumstantial Insight

The more valid data which can be collected on patients the better big data will be able to help improve treatment for people around the world. The more accurate the data, the more accurate the analysis and results will be. Fortunately technology is helping in this area as well. Many people around the world have access to devices which monitor different aspects of our daily lives. Hundreds of millions of people around the world have purchased wearable devices, many of which can be used to monitor activity and inactivity[57]. By the end of next year it is expected that over one-third of people in the world will own a smart phone which can also track this type of activity[56]. While they are not seen as a medical device, they can help to track activity which is useful for diagnosis and treatment. They are another input into the data about a patient which can be used to more accurately gather information. Today doctors rely on a patient to answer questions about their level of activity. With such a devices they can get a more accurate picture.

These devices are useful for more than just activity levels. They also provide insight into areas of people's lives they are not really able to answer accurately such as how they sleep. Many people may sleep they sleep well or not so well, but in fact they are basing this more on how they feel than how much rest and how good of rest they get. Activity trackers are able to track sleep patterns as well. They actively monitor your inactivity. When used correctly a wearer pushes a button to indicate they are going to sleep and when they get up in the morning. The monitor is then able to track how long it takes for someone to get into a motionless/restful state. It continues to track them throughout the night recording if they

move around, get up, etc. Getting good sleep is a key element of maintaining overall health[54].

More advanced features of activity trackers include the ability to monitor vital signs like heart rates. They can be extremely important to a diagnosis providing input similar to a mini stress test. This is especially true if a person exercises, such as during jogging. The device can monitor how far a person is moving and their associated heart-rate. By gathering this information, the data can be fed into patient's profile when they visit a doctor (virtually or physically) instead of having to wait for a patient to get a test done and receive that feedback. Shortening the time to collect data and accurately analyze the patient can be the difference between life and death.

One aspect of activity trackers which must be noted is their accuracy and consistency. This is something big data can help with as well. Steps from person to person are not of consistent stride, tracker accuracy changes from device to device, heart rate monitors vary, and sleep are not be tracked similarly across all products and types of activities[55]. Big data can help normalize this input so that it can become a reliable input. Analysis has been done on different monitors to see how accurate they are. In order to bring them into health analysis more tests can be performed to get an accurate picture of how the devices correlate to the actual distances walked and level of sleep.

Activity trackers are only the beginning. *Wearable technology* is an expanding field which is enhancing the collection of passive data. Sensors are being built into clothing which track more accurately and include more types of data[20]. This includes information like breathing rate and muscle activity. They not only collect more types of data, but can wirelessly transmit the data via Bluetooth[31]. This means they can create a more accurate picture based on electronic data which can be used as an input. The more this type of technology becomes commonplace, the more data which can be fed into a patient's health record and the collection of health information.

7.2 Follow-Up Visits

All of these devices also have the ability to not only be used in diagnosis, but in the monitoring of treatment plans. Is the patient exercising as they say they are? Is a medicine or other corrective action helping them to lower their heart rate or get more restful sleep? It can also help to notify the patient or doctor when they are exceeding a prescribed level of respiration or heart rate. This can trigger an alert for a patient if they are at risk or even that they may need to seek treatment. These levels will not only be set based on standards, but patient specific information[3]. They can also take into account the environment the person is in. Are they in a hot location or one with high allergy levels which could negatively impact them? This is what separates the treatment plans of today with those of tomorrow. Use the technology to more accurately collect data on the patient, use it to create a diagnosis, monitor the patient using the technology, feed that data back into the patient's health record, and adjust as needed based on factual information.

Beyond the use of commercially available monitoring systems, there are devices which collect data similar to the information collected by a physician. Simple systems such as a blood pressure monitors are common. Many other pieces of equipment can be prescribed by a physician for home monitoring. These systems

not only collect information, but are able to digitally transmit the data so that it can be automatically analyzed with other sources of information. A patient will get feedback without having to visit a doctor[3]. This helps to close another gap in healthcare which affect many people: not following up with their doctor. Missing these visits can negatively impact the patient. By easing the ability to be monitored, automating the data collection, and instantly analyzing that data will lead to better overall prognosis.

Big data will also help to change people's habits. By using the data collected a picture of potential outcomes can be made for a patient to contemplate. Instead of generalities, patients will receive advice based on their medical history, other patients like them, treatment plans, and other inputs based on the variables specific to the patient's circumstances. It can show a patient how they impact their recovery based on what they are doing or not doing. For instance if they miss taking their medicines on time, do not lose weight, continue to smoke, or whatever other variables they are in control of and how it affects their specific recovery or health status. Showing them in advance may give them the motivation they need to follow the plan more closely. Throughout their treatment the model can be updated based on the patient's actual adherence to the plan. This provides another feedback loop for the patient to course correct their habits if they have not been following it as outlined[3].

Not only will big data help to diagnosis patients more accurately, but it will also allow for the customization of treatment plans at levels not available today. Instead of relying on more general treatment plans, patients will have their plans customized by their specific set of circumstances. Demographic information about the patient will be used to compare to historical plans and outcomes of patients most closely related to their characteristics. This includes not only the patients themselves, but the environments they live in. Pollution, weather, access to ongoing care, income (the patient may have to work whereas a long period of rest would be better) and other circumstances will be variables which may not be controllable by the patient, but can be used to help treat them. The plan will not necessarily be the best treatment course, not everyone has the access to the best care or the ability to abide by it, but will instead be the best plan for them and their circumstances. Each patient will be able to maximize their chances of recovering or otherwise leading the most normal life possible.

8 ACCESS TO HEALTHCARE

It is estimated that over 400 million people do not have access to basic healthcare around the world and others are forced into extreme poverty because of what they pay for healthcare[47]. Through tools referred to as telemedicine, these numbers can be lowered. Telemedicine itself is the ability for people to get evaluated, diagnosed, and treated while the physician is not located where they are. When combined with a mobile diagnostic unit a patient can get similar care to someone who is seen at a clinic[52]. As advances in automated solutions such as IBM Watson evolve, there could be a day when these remote services are performed in very remote areas where communication with a physician would be technically challenging.

9 COST SAVINGS

Another reason why big data will be helping with healthcare more and more in the future is the most basic of reasons: Economics. Regardless of the country or political system, there is always an economic element which must be addressed. No country, no system has an endless supply of any services or funds. Because of that ideas which make the most economic sense have a better chance to be adopted. The economics of automating healthcare with big data analytics will reach a tipping point as time progresses.

Simply put, healthcare is getting more and more expensive every year and computing resources become cheaper every year. Worldwide the per capita expense of healthcare has risen from \$661 to \$1,059 (numbers in United States Dollars or USD) in the last 10 years[21]. That is a 60.21% increase in one decade. The average per capita may seem low to some but that is due to it being worldwide number. Many countries spend almost nothing on healthcare per capita while others spend thousands. For instance, in 2004 Vietnam spent \$30 USD per capita and \$142 USD in 2014. This is a 373% increase, but in total dollars it is still a fraction of \$6,369 (2004) and \$9,403 spent in the United States[21].

In contrast to this the cost of computing power has decreased year over year. Computer power is not as straightforward to analyze, but cost trends are easily seen. One way is to compare the cost using a baseline year and showing other years as a percentage of the cost of the baseline. Using December of 1997 as a baseline (100) of cost for computers, the cost of computers and peripherals in January 2004 had dropped to 16.2. In other words, to get the same amount of computer power in 2004 you only had to spend 16.2 cents for every dollar spent in December of 1997. By January of 2014 it had dropped to 4.9. Comparing the 2004 and 2014 numbers, the same ones used above for healthcare spending, the cost of computing had been reduced by 69.75%[41].

A specific component when it comes to big data is the cost of storage. The decline in the cost of storage over time is staggering. In the early 1980's the cost of one gigabyte (GB) of storage was in the hundreds of thousands of dollars. Using early 2004 as our baseline the cost for one GB of storage had dropped to just under \$2.00. By 2014 the cost had declined further to between three and four cents per GB[30]. The speed at which the data can now be retrieved as compared to 2004 is like comparing the speed of light to the speed of sound. Today's storage units are that much faster.

Using this data one can see that as we are able to leverage big data solutions to provide better healthcare we can also begin to slow the incline of healthcare costs and then lower the cost of healthcare over time. Adding a new virtual doctor will not take years of schooling which can cost hundreds of thousands of dollars in some countries. It will be the cost of some piece of common technology and a licensing fee for the software. As with most everything technology based, increasing the volume decreases the cost. So as more and more virtual doctors are brought online the cost of each will decrease.

10 CHRONIC CONDITIONS

Chronic conditions are ones that "are preventable, and frequently manageable through early detection, improved diet, exercise, and treatment therapy"[61]. They are also very expensive to manage

and treat. Worldwide in 2010 the total cost of heart disease alone was \$863 billion dollars (USD) and is expected to be \$1.44 trillion by 2030. Between 2011 and 2031 the cost of the top five chronic diseases (cancer, diabetes, mental illness, heart disease, and respiratory disease) will cost \$47 trillion (USD) globally[27].

It is not only the economic impact of chronic diseases that make them a target for big data analysis. Chronic diseases reduce people's quality of life. This cannot be factored into simple terms such as money. Chronic diseases are the cause of 60 percent of deaths worldwide[44]. In a 2002 study it was estimated that 84 percent of deaths were due to chronic diseases in Europe and Central Asia[12]. Chronic disease is so prevalent and impactful to people's lives that it has been labeled as "the most expensive, fastest growing, and most intricate problem facing healthcare providers in every nation on earth[7]." With data like this it is easy to see why advances in chronic diseases is important. The question becomes how do fight them.

10.1 Prevention

The best way to fight chronic disease is to never have one in the first place. The best way to reduce the number of people who get a chronic condition is early intervention. Big data analytics can be used to help with population health management when it comes to chronic diseases. That is by identifying those who are at a high risk of getting one of these costly, harmful conditions[7]. The ability to leverage big data in prevention is a two part process. First risk factors which are modifiable must be identified and then interventions need to be created which will have an impact on changing the factors[5].

Modifiable is the key word in the first aspect of using big data. A key to fighting many chronic conditions is for people to stop behaviors such as smoking, to eat healthier, and to exercise more. However, if it was as easy as letting people know this then there would be a lot less chronic disease already. Big data can take many factors into account and help to create a more precise message for a people with specific risk elements. For instance instead of telling a patient to eat more nutritious foods, by leveraging elements of their specific health factors a doctor can recommend more precise information such as asking them to include a particular dietary nutrient[5]. Big data can also help with the timing of the message. In a survey patients wanted more information from analytics that would have warned them before they developed a chronic condition[8]. When someone is presented with more personalized information (they are on a path and about to reach a point of no return) vs. general (a healthy lifestyle may prevent you having issues years down the road) they are more compelled to heed that information and act upon it.

Newer technologies outside of a clinical setting are helping to add to the data available to analyze and care for patients. Combining data from a patient's activity monitor, fitness tracking website, or food logs into their plan helps to create a feedback cycle for the healthcare provider. Many applications track food by scanning the USB code from the package. Making it simple helps to get people to do things. The easier it is, the more likely they are to do it. Taking this data and combining it with clinical data such as blood labs and vital statistics can show a patient how they are directly

impacting their health in a positive or negative manner. It changes the conversation from more of a public service announcement general message to one unique to them.

A special sub-section of patients are very high-cost patients. In the United States there are roughly five percent of patients who account for almost 50 percent of healthcare spending[6]. Identifying these patients and creating intervention plans that work can have an enormous impact on their lives and the cost of healthcare overall. Patients with seemingly similar risk factors may have very different prognoses. Obvious factors such as age, weight, sex, and vital statistics may be the same. In order for big data to help identify the five percent more data is needed. Including mental health data, genetic information, socioeconomic, marital status, living conditions, and even cultural factors into the analysis will allow for better predictions and better ways to intervene which will lead to better outcomes[6].

10.2 Management

Even with the best of preventive measures there will still be too many people with chronic conditions for years and decades to come. Approximately 25 percent of people with chronic conditions have restrictions in what tasks they can perform for themselves, at work, or at school[23]. Because of this big data must also be leveraged to help manage those with chronic conditions. Managing it is not only based on cost, but helping them to live a better quality of life with less trips to the doctors and less admissions to a hospital. Data analytics can help to customize treatment plans to the circumstances of each patient. It can see patterns in patient's data and help to determine better follow up schedules. This could mean the difference between a visit with their doctor or a costly hospitalization[2].

Part of the solution for using big data to help tackle chronic conditions is leveraging new sources of information from technologies such as wearables. As mentioned earlier they allow for real-time data to be collected, combined with other sources of information including that of other patients, and provide better treatment plans for patients. Historically the medical profession had to rely on subjective input from patients when they came in for a visit. How often were they active, did they log information like their heart rate and blood pressure when they should have. With some wearables all this information and more is gathered in real-time and can trigger an alert to a care management professional[23]. This means that changes can be made when they are needed and the patient can get immediate attention, not days or weeks later.

Another issue with chronic care for providers is that patients may have multiple conditions. They may be overweight, have diabetes, and hypertension. This leads a patient to having multiple doctors each working on a specific condition, but no real coordination across the diseases. A treatment for one condition may have a negative impact on the patient because of treatment or drugs prescribed for another condition. And this situation is not unique as there are many patients suffering from the same conditions simultaneously. Big data analytics can bridge this gap. By combining data from multiple sources, patients, and treatments physicians can create a customized treatment plan for a patient to combat all three illnesses in the best manner without adverse interactions[60].

The result of this is that big data can help people see that treatments are tailored to them and are making a difference. Data analytics allows for patient-centric care, not disease-centric care. Patient managers would work with patients providing details on their plan, their results, and will be able to show patients how the care plan affects their quality of life. It can help to create a healthcare environment “where patients are not only engaged in time but see improved health results at affordable costs”[53].

11 GENOMICS (PERSONALIZED HEALTHCARE)

The field of Genomics is investigating how healthcare can be more personal. How diagnosis and treatment plans will be based on a specific person instead of how the factors or ailment is normally seen and treated in the general population. This is essential work because in the United States up to 47 percent of the cost of healthcare is spent on interventions that do not provide any value. While the actual percentage may vary in other countries, this is a worldwide problem[29]. Any easy way to understand the difference is over the counter medicine. Generally speaking the instructions on a bottle are broken down into children and adults. Following the directions adults will take the same amount of medicine regardless of their age, weight, or overall health.

Genomics aims to make medicine very specific to an individual by breaking down each person’s genome. This is only possible through big data as a single person’s genome produces a lot of data because it has up to 25,000 genes with three million base pairs. One human genome can produce up to 100 gigabytes of data[17]. And the information from one individual is not what is required for personalized health. It requires genomes from many individuals. The more data available, the better the analysis can be on similarities between people and how they may react to certain treatments. This multiplies 100 gigabytes by thousands, then millions, then hundreds of millions.

Through advances in technology such analysis is possible. In 2003 the first human genome was sequenced. It was only after 13 years and approximately \$3 billion dollars. By 2015 the same work can be done in a few hours at a cost of just over \$1,000[37]. This means that more and more people can have their genomes sequenced and used for analysis and personalized diagnosis and treatment of diseases. As more and more genomes are collected and analyzed treatment can be based on their personal genome and their family traits through family based analysis. This analysis lets doctors see how people may have inherited a propensity to be susceptible to certain diseases based on mutations in their genomes. In addition, through population based analysis environmental and cultural factors can be included. It is estimated that by 2025 over 100 million genomes could be sequenced[22]. Analyzing the details of the building blocks of so many individuals will be an a big data challenge which can have an enormous impact on healthcare.

12 DRUG DISCOVERY

Discovering new drugs which can help us live a better life is something like finding a needle in a haystack. Large libraries of molecules have to be examined “against millions of data points spanning chemical, biological, and clinical databases”[15]. This is done looking for

relationships between diseases and drugs to see if a particular drug could be used to treat the disease. While the process is not new, this work is the basis of many new drug discoveries, the ability of current big data techniques speeds up the process allowing for drugs to be discovered more quickly[15].

One of the reasons for it being so complicated goes back to the discussion of the human genome: each person is a unique individual. If you have seen a commercial or advertisement for a prescription drug there is always a list, sometimes a very long list, of possible side effects. These are adverse impacts which can range from minor annoyances to death. Part of the challenge of drug discovery is attempting to identify and quantify the impact a drug may have on people. To speed this process healthcare big data has developed solutions such as array-based technologies which are purpose built to combinatorial problems. This lets researchers find patterns in the data more quickly, speeding up the overall process[16].

Once a drug is thought to have a potential positive use it must go through a testing phase before it is approved for use. This can be long process which has successes and failures. Big data is being used for “the improvement of clinical trial designs (e.g., endpoints, inclusion/exclusion criteria, etc.)”[34]. This not only allows for potentially a quicker time to market, and thus the ability help people sooner, but a cost savings without paying for trials which do not produce viable results.

13 INCENTIVES FOR ADOPTION

In the end many of the advances will only be possible if people accept them. So how can this number be influenced? The most logical way to do so is to make the adoption of these advances financially beneficial. People are more willing to take a chance when they can see a hard benefit. Insurance premiums can help to drive this and provide an immediate benefit. Plans could be offered in which a person’s primary care is provided by a big data doctor. People would have to consent to having their information stored electronically and compared against the data sets. Visits to physical doctors including for second opinions would be limited. They could even have different reimbursement models similar to preventive tests. Most insurance today covers preventive services at 100 percent and are not subject to a deductible. Electronic visits could be treated similarly. They could be covered at 100 percent, or some number higher than regular doctors visits, and may or may not be subject to a deductible. Leveraging these types of incentives will help to promote the use of advanced analytics in the healthcare field. As usage grows so will the basis of data available to analyze and the ability to create better analysis models.

Another incentive for leveraging big data analytics by physicians is being led by the governments and private insurance. Instead of paying for services as they are performed, alternate payment models are being explored. For instance, in the United States the Centers for Medicaid and Medicare services is creating Alternate Payment Models to stimulate high-quality, cost-efficient care[39]. Physicians are able to earn more income and profit by achieving better outcomes. They will be willing to invest in computer analysis which will help them to diagnose and treat patients better. The financial incentive will drive change in providers’ habits which will benefit the healthcare big data analytics and patients.

14 DRAWBACKS

Leveraging big data innovations does not come without hurdles. One of the first is that people are generally slow or not open to change. The more personal the need for change, the less open they are. Organizations (hospitals, physician groups) are no different. Part of being an individual is making choices based of what information you can gather and leveraging your ability to make a determination. This is part of what makes each person unique. It is also how we learn. The more we become dependent on machines, the less we store in our own brains and we stop “building the networks in our brains to solve a whole host of problems.[51]” As those in the healthcare field rely more on technology to diagnosis and treat patients, the less human innovation may leveraged which can have a detrimental effect over time.

A major complication in big data analytics in any setting is the quality of data. The term emphasis garbage in, garbage out has probably been applied to computer systems since the beginning. There are techniques used to combat this, but when it comes to people’s health it is a bit more important. A portion of the healthcare data used as a base for analysis comes from existing diagnosis and treatment performed by humans. In looking at second opinions for patients, it was estimated that “10% to 62% of second opinions yield a major change in the diagnosis, treatment, or prognosis”[49]. Extrapolating this number to the base of information in big data for analysis means that a significant portion of the data would be different if a patient simply went to a different doctor.

Aside from the data itself, there is the potential for the algorithms behind big data analysis to be biased or having discrimination built into them. There has been a lot of talk about a lack of diversity in the technology world, especially with companies in Silicon Valley. This lack of diversity could become manifested into the analytics behind healthcare analytics. Different cultures and different races have some unique healthcare challenges. With a lack of diversification in key jobs the developers of healthcare systems could under-serve large portions of the world’s population due to a lack of understanding of how certain diseases affect their everyday lives. The United States Federal Trade Commission has asked companies in general to look at how representative their big data is and whether their models have built in biases[48]. The fact that healthcare around the world varies based economic factors makes it easy to understand how the data itself can be discriminatory. More wealthy people will be proportionally more represented than the poor thus skewing the data toward conditions afflicting the wealthy.

While big data will help to diagnose patients and create treatment plans, it does not come without its drawbacks. One of the biggest may be innovation. Part of being human is the ability to think of what has not already been done before. As algorithms and data analysis based on the historical variables begin to become more commonplace, there will be a reduction in the human factor of the medical profession. When faced with what can seem like a dire situation, the human mind can think of new options not previously discovered. Trying something which may not seem to have an impact on the surface, but something completely unrelated to any prior decision made can lead to new alternatives. What will a computer do with a patient when it does not see any hope? A human physician may opt to take a risk. It is a well-informed risk

with the patient knowing that there are no guarantees. It is easy to assume when an automated course of action without a substantial chance of a positive outcome is encountered that a physician would be able to intervene. This is true for a while, but as more and more of medicine is turned over to computer diagnosis and treatments the pool of capable physicians will shrink. With less people involved the less chance there is that the truly gifted individuals who make strides in the field will even decide to enter the field in the first place. In other words, these individuals may decide on a different career path and their discoveries would be left undiscovered.

15 CONCLUSIONS

Big data is an expanding science in many fields. The ability to digitize, collect, store, and analyze data has never been more than it is today. The type of information that can be used in data analysis is expanding every day as well. Images, videos, and sound are all part of the inputs into big data. Computers are now able to leverage natural language processing to make inputs that much easier to collect. As this field continues to grow, the ability to leverage it in improving healthcare around the world will grow as well.

We are on the edge of a shift in healthcare for the betterment of humankind. Advances will not be limited to one nation or one class of people. While healthcare may not be universal in its application, not every person will be able to access the same level of care, there will be benefits which can eventually help all people. A mobile unit which can be taken to almost any part of the planet will be able to have the knowledge better than most doctors practicing today. Doctors will have access to new drugs, diagnostic information, and treatment plans than they ever had before. They will be able to leverage new advances in medicine without having to read as many publications as they can. They will have a tool that reads and learns for them and provides that insight on case by case basis.

Through the use of data analysis of sources of data which did not exist a decade or so ago, we will be able to identify when a disease is starting to spread and react, thus limiting its impact. Because of technology people will be spared from suffering and they will never even know it. By understanding the human genome people who may be more susceptible certain diseases can be treated before they take hold. Babies will have their genome sequenced while they are still in their mother’s womb. This one aspect of the power of big data, the ability to process and understand a human genome, may be the single largest breakthrough in healthcare. It can provide insight into how each person individually reacts to the world around them and what science can do to make that interaction better. What science can do to help each person avoid potential chronic conditions which are not only financially costly, but that severely reduce their quality of life or end their life. Through advances in big data we will not only live longer, but live better.

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into the collection of the class. With access open to all, and potentially future classes, the collection of projects becomes a big data collection unto itself.

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Big Data Applications in Predicting Hospital Readmissions

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ABSTRACT

Hospital readmissions occur when a patient is discharged from a hospital and subsequently readmitted to a hospital within a short time frame. Hospitals are held accountable and penalized for readmissions that occur within 30 days of the initial inpatient stay. In 2016, nearly 2,600 hospitals were penalized \$528 million collectively for readmissions. Machine learning is increasingly being used to build models that predict if a patient has a high probability of being readmitted, which allows hospital staff to prioritize resources around high-risk patients and potentially prevent the otherwise likely readmission. Healthcare providers possess every-growing stores of medical data that are essential for building accurate predictive models. While most of this information is private and not widely available for research, there are a few public datasets that researchers can use to build models and gain a better understand of which information is significant in the task of identifying high-risk patients. One such dataset includes over 100,000 patient admissions that occurred at 130 US hospitals between 1999 and 2008 and includes many features that can be used to build models. Open-source Python tools such as scikit-learn, pandas and matplotlib have tools necessary for preparing, modeling and visualizing data. These tools can be used to define algorithms that describe the problem of hospital readmissions by creating classifiers that categorize patients based on the probability of readmission. Machine learning techniques, such as logistic regression, are capable of modeling data for classification problems, and these tools include methods for assessing and optimizing the algorithms. In this analysis, the model created using logistic regression performed better than random guessing, but not well enough to reasonably be considered a highly effective model. The sensitivity of the model is rather low for a problem where there is a high cost of missing an opportunity to intervene on a patient at high-risk of readmission. The lack of behavioral and social attributes in the dataset may lend to lower predictive power. In any case, the effectiveness of machine learning in classifying patients for risk of readmission is a growing topic of study and implementation of tools for assisting healthcare providers will likely continue to increase.

KEYWORDS

hid331, i523, Big Data, Hospital Readmissions, Machine Learning, Classification, Python

1 INTRODUCTION

Hospital readmissions are problematic for both patients and health-care providers. Even a single hospital admission for a patient can be an inconvenient, expensive and anxiety-inducing major life event.

For a patient to be subsequently readmitted to the hospital, the patient again experiences the negative aspects of being in a hospital, along with a diminished quality of life that accompanies a recurrent disease or medical issue. Healthcare providers are increasingly being held accountable and often penalized for an inability to keep recently discharged patients from being readmitted. It has been estimated that nearly 1 in 5 Medicare patients discharged from a hospital will be readmitted within 30 days [5].

The Hospital Readmission Reduction Program (HRRP), which originated in 2013 as a provision in the Affordable Care Act, serves as an example of an initiative that punishes hospitals for readmissions by administering financial penalties on hospitals with disproportionately high readmission rates among Medicare beneficiaries [1]. The HRRP levies a reduction in Medicare reimbursement, and uses the ‘all-cause’ definition for readmissions, which means that a subsequent hospital stay that occurs for any reason within 30 days of the initial stay counts against the hospital [1]. The program focuses on patients initially admitted with a heart attack, heart failure, pneumonia, chronic obstructive pulmonary disease, a coronary artery bypass graft procedure or a hip/knee replacement procedure [1]. If a hospital’s risk-adjusted readmission rate is higher than the national average, then that hospital will be penalized. Further, the excessiveness of the rate is considered as well, ensuring that providers with the worst readmission rates have proportionately higher penalties [1]. In 2016, the US government penalized 79 percent of US hospitals, which amounts to 2,597 institutions [9]. The penalties for those readmissions, applied to the 2017 fiscal year reimbursements, amounted to \$528 million nationally, \$108 million higher than the previous year [9].

Effectively this means that the care provided to readmitted patients is uncompensated care, which still requires valuable resources such as medical supplies, pharmaceuticals, the occupancy of hospital beds and the attention of medical staff. HRRP has had the intended effect of bringing increased attention to readmissions, and some healthcare providers are leveraging their ever-increasing medical data stores to better understand their patients. Several organization are using machine learning to identify high-risk patients. Assessing patients for the likelihood of readmission presents a binary classification problem, where a model’s goal is to come to one of two conclusions on each case. The model analyzes each patient and the patient’s accompanying attributes and concludes either that the patient will be readmitted or will not be readmitted.

1.1 Applying Machine Learning to Hospital Readmissions

There are several studies pertaining to the effectiveness of using machine learning to build predictive models that address this problem.

A 2011 study conducted a systematic review of the topic and found 26 studies discussing predictive models related to hospital readmissions. These models were created using administrative claims data, electronic medical record (EMR) data, or a combination of each type of dataset [4]. Administrative claims data is primarily gathered for billing purposes and contains information about procedures, diagnoses, length of hospital stay and location of care [7]. The advantage of this type of data is that it typically describes large populations and is inexpensive to acquire because it's already gathered for billing [5]. EMRs contain the basic information contained in administrative claims data, and also include lab data, image data and the results of various diagnostic tests, as well as social and behavioral information. Of the 26 studies reviewed by this paper, only 4 reported an area under the curve (AUC) value greater than 0.70, indicating that the other 22 models performed relatively poorly at classifying high-risk patients. Interestingly, 3 of the 4 studies with a moderately high AUC built models with clinical information found in EMRs in addition to administrative claims data, which suggests that the rich information available in EMRs adds discriminative power to the predictive models [5].

One study that demonstrates the power of incorporating EMR data was conducted at Mount Sinai Health System in New York, NY. Mount Sinai developed a model to predict readmissions among patients with heart failure, which is the top cause of readmission among Medicare beneficiaries [10]. To build the model, Mount Sinai leveraged their EMR system to mine 4,205 patient attributes, including 1,763 diagnosis codes, 1,028 medications, 846 laboratory measurements, 564 surgical procedures, and 4 types of vital signs. The study used a cohort of 1,068 patients, 178 of whom were readmitted within 30 days [10]. The model achieved a prediction accuracy rate of 83.19 percent and an AUC value of 0.78. Commenting on this outcome, Mount Sinai said that the model would benefit from the inclusion of several years of data from several different hospital sites [10]. In other words, even more data is needed to further improve the accuracy of the model.

2 ANALYSIS

Though the data used by institutions to build models is not widely available, there are a few public datasets that can be used by machine learning practitioners to better understand how predictive modeling techniques can be applied to the task of predicting readmissions. One such dataset comes from the Cerner Corporation's Health Facts database, which is comprised of comprehensive clinical EMR records voluntarily provided by hospitals across the United States [11].

Researchers extracted a subset of 101,766 encounters from the nearly 74 million records in the Health Facts database for the purpose of studying diabetic inpatient encounters. The admissions span 10 years from 1999 to 2008, and occurred at 130 different hospitals across the United States. The researchers used the following criteria to narrow down the dataset [11]:

- 1) The encounter is an inpatient encounter.
- 2) It was a diabetic encounter, meaning at least one diabetic diagnosis code was associated with the episode of care.
- 3) The length of stay was between 1 and 14 days.
- 4) The patient had at least one lab test.

- 5) The patient was administered at least one medication.

This dataset is now publicly available on the UCI Machine Learning Repository. Each observation in the dataset has up to 55 attributes, or features, that are potentially related to hospital readmissions, including diagnoses defined by ICD9 codes, in-hospital procedures, hospital characteristics, individual provider information, lab data, pharmacy data, and demographic data, such as age, gender and race. Each patient encounter record also has a label indicating whether or not the patient was readmitted within 30 days. Since the dataset includes these labels, supervised machine learning techniques can be used, as opposed to unsupervised machine learning techniques. Logistic regression is a supervised machine learning technique capable of binary classification of observations, and is well-suited to predict the likelihood of readmission for the observations in this diabetes dataset.

2.1 Overview of Supervised Machine Learning

2.1.1 Minimization of Error. The goal of a machine learning algorithm is to minimize the error made in the predictions. The general form of this concept can be represented by the formula:

$$Y = f(x) + \epsilon$$

Y is the actual outcome associated with the sample. x represents the attributes associated with each sample and typically takes the form of a matrix where the columns are the features and the rows are the individual observations. $f(x)$ is a function that represents the systematic information x provides about Y , and ϵ is the error term describing the differences between the predicted value returned by $f(x)$ and the actual value represented by Y [6]. A perfect prediction means $f(x)$ equals Y and ϵ equals zero. In reality, the error term will rarely be zero, so each prediction yields a certain amount of error. The prediction accuracy for each sample is evaluated by this formula, and sum of the error terms from each evaluation represents the magnitude of error made by the model. The goal is to make the sum of errors as low as possible [6].

The error term is minimized through optimization of $f(x)$, which is intended to describe the patterns that exist between the independent variables, represented by x , and the dependent variable, represented by Y . Said differently, the equation describes the relationship between the features and the outcome label. The way that this function describes this relationship is through coefficient weights. Each feature in the dataset is paired with a numerical weight that accentuates or diminishes the impact of a feature on the predicted outcome. The way in which these coefficients can be interpreted differs by which algorithm is used, but the intuition remains the same: the coefficients are adjusted to highlight the important features in the dataset. Once the coefficients are determined, the model has been fit to the data.

2.1.2 Training Set vs. Test Set. The coefficient weights of the model are defined by analyzing the samples in a dataset. In a practical sense, the value of a model depends on its ability to accurately predict the outcomes of new samples that were unseen at the time the model was determined [4]. A model that performs well when making predictions with new data is said to generalize well.

A machine learning practitioner will want to have confidence in the model's ability to generalize before deploying the model

to make predictions in real-time, and will not necessarily have a new dataset of previously unseen observations to run through the model. To get around this, the original dataset is often split into two parts. The first part of the dataset is referred to as the training set and is used to determine the coefficient weights. The second part of the dataset is referred to as the test set, and this set is run through the model derived from the training set. The accuracy of the predictions on the test set is compared to the accuracy of the predictions on the training set to determine the extent to which the model generalizes [4].

A model that has high training accuracy, but low test accuracy, is said to be overfitting the data. This means that the model, in its efforts to minimize ϵ , has become too complex and focuses too closely on the samples in the training dataset. By chasing patterns in the training data caused more so by random chance than by the true characteristics of x , the model no longer generalizes to the unseen samples in the test set [6][4]. An overfit model describes characteristics in the training data that are not in the test data, leading to poor predictions on the test set.

A model can also underfit the data, which means the model is failing to capture the relationship between Y and x and will likely perform poorly on both the training and test datasets.

2.1.3 The Bias/Variance Trade-off. Bias and Variance are two important components related to training models using machine learning. Variance describes the extent to which a model changes due to small adjustments in the training data. Since the training data used to fit a model can vary, it is reasonable to expect that a model will change when different samples are selected into the training dataset, but ideally the model changes only slightly [6]. If a model is quite complex and is overfitting the training data, then slight changes in the training samples can have a large effect on the coefficient weights. Low variance is preferable [6].

Bias refers to the error that occurs when trying to describe a phenomenon using a model. For example, if a machine learning technique assumes a linear relationship between the independent and dependent variables, but the relationship is highly non-linear, then the model has high bias [6]. A model with high bias will make many erroneous predictions because the estimated relationship between x and Y is not closely aligned with the actual relationship between x and Y .

As a model becomes more complex and able to fit to the perceived important information in the training data, variance will increase and bias will decrease. The model will become more flexible and therefore more sensitive to variations in the training data, but will reduce bias by better estimation of the relationship between x and Y , resulting in a reduction in the prediction error. The important part of the relationship between these two components is that as a model becomes more complex, the bias decreases more rapidly than the variance increases, so the trade-off of increasing variance while decreasing bias leads to a net gain in improvement of the model [6]. However, there is a point at which the model becomes too complex and the net gain begins to disappear. Increased model complexity leads to significantly higher variance without appreciable improvement in bias [6].

2.1.4 Model Evaluation. Several statistics can be used for evaluating model accuracy. For classification problems, a basic technique for evaluation is the confusion matrix.

$$\begin{Bmatrix} TN & FP \\ FN & TP \end{Bmatrix}$$

This is the general framework of a confusion matrix which shows the counts of each type of prediction and the accuracy of that prediction. A true positive (TP) is an outcome that is predicted to be positive and is positive in reality [2]. A true negative (TN) is an outcome that is predicted to be negative and is negative in reality [2]. These are the preferred responses. In the context of hospital readmissions, a true positive is a prediction that a patient in the test dataset, according to the trained model, will be readmitted to the hospital within 30 days, and this occurs in reality. A true negative is a prediction that a patient in the test dataset will not be readmitted, and this occurs in reality.

On the other hand, a false positive (FP) is an outcome that is predicted to be positive but is negative in reality [2]. A false negative (FN) is an outcome that is predicted to be negative but is positive in reality. These are errors in prediction [2]. If a healthcare provider acts on a false positive, that could mean that a patient, who without intervention would not have been readmitted within 30 days, received resources and attention that were not necessary. In the case of a false negative, this means a patient who eventually did get readmitted within 30 days, but was said to be of low-risk of readmission, could have benefited from additional attention and resources from a healthcare team.

These four components - true positives, true negative, false positives, and false negatives - can be combined to create more nuanced metrics. Two of those metrics are sensitivity and specificity. Sensitivity refers to the true positive detection rate. This is the percentage of positive occurrences that are successfully identified [2]. Specificity is the true negative detection rate. This is the percentage of negative occurrences that are successfully identified [2].

In the context of readmissions, low sensitivity means many patients who eventually get readmitted are not predicted to be high-risk before the readmission occurs. Low specificity means that many patients who would not otherwise be readmitted are predicted to be readmitted. There is a trade-off between sensitivity and specificity, and an improvement in one often causes the other to worsen. Preference toward sensitivity or specificity often depends on the cost of incorrect predictions.

A patient who otherwise would not be readmitted who is predicted to be high-risk is the type of case that will incur unnecessary resources. While this requires healthcare providers to invest resources that are not needed, the readmission is nevertheless avoided and there are potentially other benefits achieved by the hospital, such as increased satisfaction of the patient and their family. On the other hand, a patient who eventually gets readmitted but was not identified beforehand will likely be costly to a hospital in a couple ways. The provider must dedicate resources to stabilizing and healing the patient, while also incurring penalties if this type of readmission occurs frequently. If the expense of an unexpected readmission is higher than the expense of deploying unnecessary resources to low-risk patients, then a model that favors higher sensitivity at the expense of lower specificity is preferable.

Sensitivity and specificity can be assessed in tandem by the receiver operating characteristic (ROC) curve, which is quite useful for evaluating supervised classification models. The ROC curve plots the true positive rate against the false positive rate (100 minus the true negative rate) for varying decision thresholds. This illustrates the trade-off between sensitivity and specificity and can provide guidance on which decision threshold is appropriate for the task [2]. ROC curves are often leveraged to evaluate the performance of models by calculating the area under the ROC curve, also known as the AUC. The goal is to maximize the AUC value, and that value points to the optimal balance between sensitivity and specificity [2].

2.2 Logistic Regression

2.2.1 Logistic Regression - Intuition. Logistic regression models the probability that a sample belongs to a certain class given the feature values of the sample [4]. This probability can be represented as:

$$p(x) = Pr(Y = 1|X)$$

In the context of predicting hospital readmissions, this translates to the likelihood that a patient will be readmitted within 30 days of discharge given the patient's characteristics. To determine the probability, logistic regression utilizes the logistic function, which takes in the coefficient weights and feature responses for each sample and returns a the probability - a number between 0 and 1 [4]. In the case of logistic regression involving multiple features, the model takes the form:

$$f(x) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}$$

The model is fit to the data by adjusting the coefficient weights using a method called maximum likelihood. The intuition of this process is that the estimates for the coefficients are set such that the predicted probability of a certain outcome corresponds as closely as possible to the actual label of that sample. This means that the ideal coefficient weights, when plugged into the logistic function, return a number close to one for the readmitted patients and a number close to zero for the patients not readmitted [4].

2.2.2 Logistic Regression - Data Pre-processing. Data often need to be processed prior to using logistic regression because this machine learning technique requires numerical data. The diabetes dataset contains a combination of continuous and categorical features. For example, 'num_procedures' and 'num_lab_procedures' are continuous features that describe the number of procedures and the number of lab procedures, respectively. Since these columns already contain numerical data, these features are ready to use as-is. Other columns such as 'A1Cresult' includes values such as 'A1Cresult_>7', 'A1Cresult_>8', 'A1Cresult_None' and 'A1Cresult_Norm'. The first issue is that this features is represented by text values, which will not work with logistic regression. These values must be encoded to work properly. If a categorical feature with four unique values, or levels, has an ordinal scale, the text values can be encoded as sequential numbers, such as 1, 2, 3 and 4. If a categorical features with four levels has a nominal scale, as is the case with the feature

'A1Cresult', an effective encoding strategy is to create one dummy column for each level in the original categorical column.

The Python library pandas has a function called 'get_dummies' that will create one column for each level in a categorical column, and each of those dummy columns will only contain 0's and 1's. In the case of the column 'A1Cresult', this process will yield 4 columns. For each observation, a 1 will appear in the column corresponding to the value of the original feature. For example, if an observation had a value of 'A1Cresult_>7', the observation will have a 1 in the 'A1Cresult_>7' dummy column and 0's in the other three A1C dummy columns. This process is repeated for all nominal categorical variables.

Three categorical columns in the dataset have several hundred unique values, which can be problematic. The columns 'diag_1', 'diag_2' and 'diag_3' have 695, 724 and 757 unique values describing ICD9 diagnosis codes, respectively. The first diagnosis column is considered to be the primary diagnosis of the stay, and 'diag_2' and 'diag_3' contain any additional diagnoses documented during the stay. Running these columns through the 'get_dummies' procedure would yield a total of 2,176 dummy columns, which would greatly increase the dimensionality of the dataset. Further, many ICD9 codes are used only a few times in the dataset, which means it is quite likely that, depending on how the training and test data is split, all observations of a particular code only fall in either the training set or the test set.

One solution to this problem is to 'bin' the information into categories. Each ICD9 code belongs to a category. For example, ICD9 code '250.62 - Diabetes with neurological manifestations, Type II, uncontrolled' is in the ICD9 category 'Endocrine, Nutritional, Metabolic, Immunity'. Each ICD9 code can be binned into one of 19 categories. Further, instead of having three columns for each ICD9 category (because each unique ICD9 code can appear in any of the three diagnosis columns), the data can be processed such that there is one column for each ICD9 category, and each observation can have up to three 1's in these 19 dummy columns. This loses the distinction between primary and secondary diagnoses, but reduces computation time and reduces the likelihood of the rare diagnosis codes only appearing in the test set or training set.

Another column in the dataset called 'medical_specialty' has a high number of unique values with 71 different responses, and also is null in nearly half of the observations. Rather than turning this feature into 71 different dummy variable columns, it is noted that there is redundancy between the 'medical_specialty' and the diagnosis code columns. For example, if a patient has a diagnosis code in the 'Pregnancy, Childbirth, and the Puerperium' category, they are often in the obstetrics medical specialty. Given this redundancy, the high percentage of null values and in the interest of reducing the complexity of the dataset, the 'medical_specialty' column is not included in the final dataset.

Several patients have multiple observations captured in the dataset. Logistic regression requires that the observations be independent, so including multiple inpatient encounter for individual patients violates this requirements. To solve this problem, the initial count of 101,766 observations is reduced down to 69,988 observations by keeping only the first encounter for each 'patient_nbr'. The first encounter per patient is considered to be the observation with the lowest 'encounter_id', which operates on the assumption that

IDs are incremented by 1 and allocated sequentially as inpatient admissions occur.

Lastly, the response label in the original dataset is represented with three levels and is described in text. The column ‘readmitted’ contain the values ‘NO’, ‘>30’ and ‘<30’. Since observations with the label ‘>30’ days were not readmitted within thirty days, these labels were converted to ‘NO’. The remaining responses of ‘NO’ and ‘<30’ were encoded as 0 and 1, respectively.

2.2.3 Logistic Regression - Data Quality Evaluation. When creating dummy columns, whether through simple methods, such as the ‘A1Cresult’ transformation, or more complex methods, such as the ICD9 diagnosis binning transformation, special consideration must be given to collinearity and multicollinearity between features. For example, if a feature called ‘gender’ contains two values, male and female, and this feature is converted into two dummy features, these two features will be collinear. Where one feature column has a value of one, the other will have a zero, and visa versa. This means that one feature column can perfectly predict the value of the other feature column. We only need the female column to know if the observation pertains to a male or female, so the inclusion of the male column would be redundant. This is problematic for the model because the two feature columns provide an identical explanation of the variance in the dependent variable, and neither adds additional value while in the presence of the other. When this issue manifests between two columns, this means the columns are collinear. Multicollinearity refers to a situation where this redundancy occurs between three or more columns. If the combination of three columns explains most of the variation explained by another single column, then there is multicollinearity in the data.

Collinearity and multicollinearity increase the variance of the coefficient weights, which would make the model very sensitive to changes in the training data. This instability of the weights means that it can be difficult to decide which predictors have a high influence on the outcome, and can even cause the sign of the coefficient to change [3]. Under stable conditions, a positive coefficient can be interpreted to mean that the associated feature contributes to a higher probability of readmission, and a negative coefficient can be interpreted to mean that the associated feature contributes to a low probability of readmission [6]. The instability that multicollinearity creates in the coefficient weights make it dubious to make inferences from the signs of the weights.

Datasets with collinearity and multicollinearity issues are considered to be ill-conditioned, which will reduce the ability to create a meaningful model with the data. Problematic features need to be strategically identified and removed. A dataset can be evaluated for problems using several linear algebra methods. The matrix rank is a single value that can give an overall assessment of the relationship between features. In a dataset, which can be represented as a matrix, that has more rows than columns, the ideal matrix rank value is equal to the number of columns. When the matrix rank value is equal to the number of columns this means the matrix is considered to be full rank [12]. A full rank matrix contains only linearly independent features. On the other hand, if a feature in a dataset is linearly dependent, then the rank of the matrix is reduced. For example, if we were to keep both the male and female gender

dummy columns, these features would be considered linearly dependent, and would therefore reduce the rank of the matrix. Each linearly dependent feature in a dataset reduces the matrix rank.

A correlation matrix provides a correlation statistic for each pair of variables. The values fall between -1 and 1, and the closer the value is to -1 or 1, the stronger the relationship between the two variables. Features with high correlation are considered to be collinear. This technique is effective at finding collinearity, but is not well-suited to finding multicollinearity because the correlation matrix only shows the relationship between pairs of variables.

The correlation matrix can also be used to find the determinant of the dataset. The determinant is a single value and will reveal if there are any highly or perfectly correlated columns, which suggests there is collinearity among features. The determinant value ranges between 0 and 1. A value of zero means the correlation matrix is singular. In other words, the correlation matrix contains at least one pair of perfectly correlated features. A near-zero determinant value means there is one or more pair of features that is nearly correlated. A higher determinant value is preferable.

These methods are effective at describing the overall health of the dataset and simple relationships between pairs of features. To find multicollinearity, more nuanced techniques need to be deployed. One approach is to determine the variance inflation factor (VIF) for each independent variable. The VIF measures the increase of variance in the coefficient estimates that is caused by the inclusion of a particular variable [8]. This technique fits each independent variable, one at a time, against all of the other independent variables. This can be represented by the following sequence of equations:

$$\begin{aligned} X_1 &= \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \dots + \beta_kX_k \\ X_2 &= \beta_1X_1 + \beta_3X_3 + \beta_4X_4 + \dots + \beta_kX_k \\ X_3 &= \beta_1X_1 + \beta_2X_2 + \beta_4X_4 + \dots + \beta_kX_k \\ &\dots \\ X_k &= \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \dots + \beta_{k-1}X_{k-1} \end{aligned}$$

For a dataset with k-features, the dataset is fit k-times, once for each independent feature. The VIF for each feature is calculated by the equation:

$$VIF_k = \frac{1}{1 - R_k^2}$$

Each fitted model has an R^2 , which is the coefficient of determination, or R-squared, and it describes the proportion of variation in the ‘dependent’ variable that is described by the independent variables. A high R-squared means that the independent variables explain a significant amount of variation in the dependent variable. In the context of VIF, if one independent variable is thoroughly explained by the other independent variables, the R-squared will be high which will lead to a high VIF. While the threshold for acceptable VIF values differs, the documentation for the Python library statsmodels recommends using a threshold of 5 [8]. To achieve a value of 5 or less, the R^2 for an independent variable must 0.80 or less. In other words, the independent variable being considered by the VIF method must be less than 80% explained by the other independent variables.

The elimination of problematic variables in this dataset is handled by a custom Python function that identifies the features with

the highest VIF and selectively removes those features from the dataset. The Python functions works by calculating the VIF for each independent variable. It then iterates through each group of dummy columns that stemmed from a single categorical column, and, for each group, deletes the column with the highest VIF value if that value is above the threshold. The function also removes ratio-scaled features, such as ‘num_procedures’, that have a high VIF value. This whole process is looped until zero features have a VIF above the threshold.

Before trimming features based on VIF, the dataset included 175 features, with a matrix rank of 150 and a correlation matrix determinant of zero, meaning the coefficient matrix was singular. This means there were several linearly dependent features and at least one pair of perfectly correlated features. After trimming 52 features based on VIF, the dataset includes 123 features with a full rank of 123 and a correlation matrix determinant of 0.00697. While this determinant value is still relatively low, the determinant increased over each iteration of the Python function from 0.0 to 2.85e-26 to 0.0056 to 0.00697, representing several orders of magnitude in improvement from the originally singular matrix. Most importantly, the matrix now has full rank with 0 linearly dependent features.

2.2.4 Logistic Regression - Feature Selection. With the issue related to multicollinearity among the independent variables largely resolved, the coefficient weights of the model will be more stable, allowing for inferences to be made based on the sign and magnitude of the weights. The next step is to strategically choose which features to use when training the model. Recursive feature selection (RFE) is one strategy for choosing which features have the highest significance in predicting the likelihood of readmission within 30 days. The intuition behind RFE is that it repeatedly fits the model on the training data. The first iteration includes all features, and each subsequent fitting of the data drops the least significant feature or features from the previous iteration. Python has a library called scikit-learn which includes tools to execute RFE on a dataset. The user may choose how many features to trim after each iteration, as well as choose how many features the final model should have. The process will repeatedly fit the narrowing set of features to the data until the preferred number of the most important features is reached.

There is an extension of RFE called RFECV, which helps to determine the ideal number of features. When using RFE on its own, the user must arbitrarily choose the preferred number of procedures. RFECV functions by calculating the accuracy of the model after each iteration of trimming features and re-fitting the model. The number of features used at the step in which the model performance is best is determined to be the ideal number of features to use. The ‘transform’ method of RFECV will then trim down the original dataset to the selected features. After running RFECV on the remaining 123 features, the process selected 57 features that led to the highest accuracy rate.

2.2.5 Logistic Regression - Execute Analysis. The set of independent variables is trimmed down further to the 57 features selected by RFECV as being the most important for predicting likelihood of readmission within 30 days. The next step is to train the logistic regression model, and then test the accuracy of the model. Scikit-learn has a function that randomly splits the dataset into training

and test sets, and also allows the user to decide the size of the test dataset in terms of proportion of overall data. After splitting the features and labels into training and test sets, the data is ready for fitting.

Scikit-learn also has a process for executing logistic regression, and there is a parameter that controls the way the algorithm minimizes coefficients. The default setting is L2 regularization, which determines coefficients that can approach zero (meaning the associated feature does not have a large effect on the outcome) but never fully reach zero. This regularization of coefficients effectively determines how much effect each feature has on the prediction. The less significant features will have a coefficient close to zero. L1 regularization is another option, which sets the less significant features to exactly zero, which can be viewed as another form of feature selection [4].

There is another parameter called C, which dictates the strength of the regularization. Higher values of C lead to less regularization. This means that a model trained with a high value of C will value fitting each observation as closely as possible, whereas a lower value of C will train the model in a way that tries to fit the data more generally [4]. A high value of C will lead to higher weight values, and a low value of C will lead to weights that are much closer to zero.

2.2.6 Logistic Regression - Evaluate Analysis. The model is trained using both L1 and L2 regularization, and each regularization type is fit using three different values for C: 0.01, 1.0 and 100.0. Figure 1 shows the coefficient weights using L2 regularization and the three different values of C. It is evident that higher values of C lead to larger weights. Figure 2 show the coefficient weights using L1 regularization, again with the different values of C. In addition to the observation that higher value of C lead to larger weights, it is also interesting to note that using 0.01 for the value of C sets all but four weights equal to zero. The four features chosen by this model are the numbers of inpatient encounters, age 50-60, transferred to a skilled nursing facility and discharged to another rehabilitation facility. This pair of L1 regularization and 0.01 for C has the highest training and test set accuracy. The training accuracy is 91.063% and the test accuracy rate is 90.0827%. In the original dataset of the 69,998 observations, 63,704 were not readmitted. This is a rate of 91.02%. This is only slightly smaller than the training accuracy and larger than the test accuracy, which means the model performs closely to the rate that would be achieved if a person guessed that every case would not be readmitted. The confusion matrix for L1, C = 0.01 model is:

$$\begin{Bmatrix} 12713 & 2 \\ 1282 & 1 \end{Bmatrix}$$

12,713 true negatives were identified and 1 true positive, for a total of 12,714 accurate predictions. There were 2 false positives and 1,282 false negatives. The model is effective at predicting patients who will not be readmitted, but the high number of false negatives, compared to the extremely low count of true negatives, demonstrates that the model is not performing well at identifying patients who eventually get readmitted. The models with C values of 1.0 and 100.0 have a true negative detection count of 4, slightly

higher than the 1 observation classified correctly by the L1, C = 0.01 model.

The relationship between the true positive and false positive rates can be visualized with an ROC curve. Figure 3 show the ROC curve for the L1, C = 0.01 model. The black dotted line represents the 50/50 chance curve, which is equivalent with guessing. The ROC curve extends slightly above the 50/50 chance curve, which means the predictive power is slightly higher than random guessing. This is described by the AUC, which has a value of 0.50013. This is consistent with the conclusion that model is only slightly better than chance. Figure 4 shows the ROC curve for the L1, 100 model, and the ROC curve bends further away from the 50/50 chance curve, and the AUC is slightly higher at 0.5013. This is consistent with the observation that the model with the higher value of C has a higher true negative detection rate. Ideally, the ROC curve is as close to the upper left hand corner as possible, which would represent a high true positive rate with a low false positive rate.

3 CONCLUSION

The predictive power of the logistic regression model chosen for this analysis appears to be slightly better than random guessing, but not significantly better. The high proportion of false negatives means many patients who are at high risk of readmission within 30 days, and later get readmitted, are not being identified by the model. This is a domain where high sensitivity is favored over high specificity, but the model conversely has low sensitivity and high specificity. To improve the predictive power of the model, it might be helpful to include features that have more to do with behavioral and social characteristics, as well as socioeconomic indicators. Attributes such as literacy, obesity, annual income, smoking status, medication regimen adherence, utilization of family and community support and employment status are a few features that come to mind that may lend to better explaining the likelihood of readmission within thirty days. Features of this type may help describe the extent to which a patient is able to manage his or her own care outside of the hospital. Patients who cannot read or who do not adhere to the recommended medication regimen, for example, are patients who can reasonably be said to be less capable of providing consistent and effective care to themselves in the home setting. Attributes such as this are not available in the dataset, but common sense suggests this information would be helpful.

Further, logistic regression is just one type of machine learning technique capable of performing classification. Support vector machines and decision trees are two other techniques that would be worth exploring to see if modeling the data using different machine learning algorithms improves the sensitivity of the model.

A ACCOMPANYING JUPYTER NOTEBOOK AND REQUIREMENTS

The accompanying Jupyter Notebook is available at: <https://github.com/bigdata-i523/hid331/blob/master/project/project.ipynb>

The requirement file is available at: <https://github.com/bigdata-i523/hid331/blob/master/project/requirements.txt>

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B FIGURES

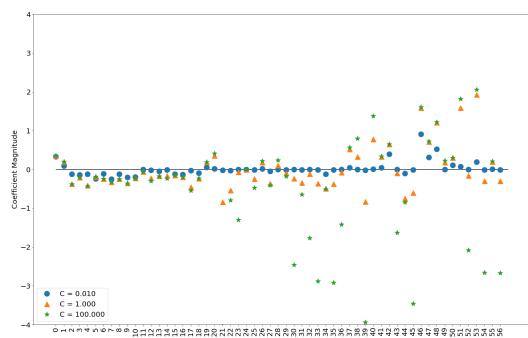


Figure 1: Logistic Regression Weights By C-Value, L2 Regularization

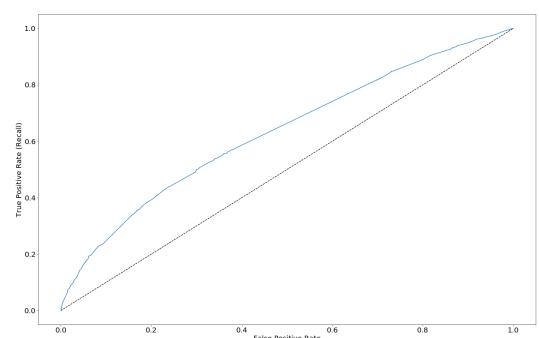


Figure 4: ROC Curve, L1 Regularization, C = 100.0

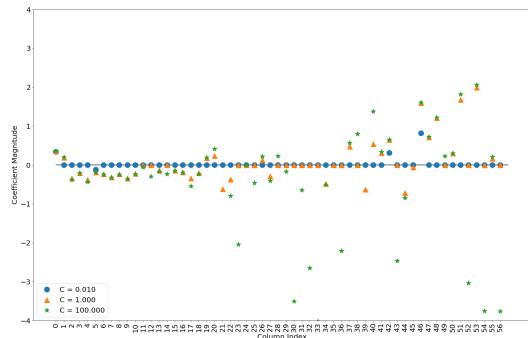


Figure 2: Logistic Regression Weights By C-Value, L1 Regularization

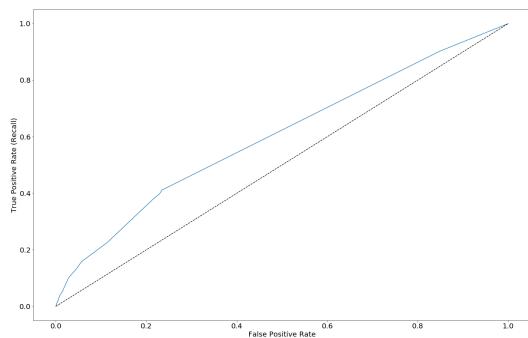


Figure 3: ROC Curve, L1 Regularization, C = 0.01

Big Data Analytics Role in Reducing Healthcare Costs in the United States

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ABSTRACT

In the United States more money is spent on health care than in any other industrialized country in the world. Yet, health care access is often problematic and health care quality indicators are lower or mediocre as compared to other countries with similar economic status. Insights offered by Big Data Analytics can find solutions that will significantly lower costs and improve delivery of health care in the United States. These solutions have the potential to save billions of dollars in health care costs and to improve the quality of care for millions of Americans.

KEYWORDS

I523, HID332, health care costs, predictive analytics, electronic health records, big data

1 INTRODUCTION

Health care spending in the United States greatly exceeds the spending of other industrialized countries. Americans spend 3 trillion dollars annually on health care. Health expenditures currently account for 17.6 percent of the Gross National Product (GDP) and are expected to increase at an average rate of 5.8 percent through 2025. Health care spending has exceeded growth of the Gross National Product (GDP) in 42 of the previous 50 years [2]. Health spending threatens the nation's fiscal health [29]. Despite the excessive spending, the United States ranks among the worst on measures of health care quality, health access equity, and quality of life [22]. Policy makers do not know how to respond.

Big data analytics has the potential to help manage and address some of the cost issues while simultaneously improving patient health outcomes. Big Data ability gives us the ability to combine and analyze data from a wide variety of sources in ways that have never before been possible. This new information is providing new and valuable insights into ways to provide more effective and efficient patient care. The associations, patterns, and trends in big data may hold the key to reducing expenditures, improving care, and saving lives [29]. The information is being used to achieve more accurate and timely diagnoses, better match treatment plans to patient needs, and predict and identify at-risk patients and populations [22]. Mobile applications are being used to monitor patient care in real time. Big data can reduce health care waste, improve coordination of care, expose fraud and abuse, and to speed up the research and development pipeline.

The cost savings estimates are substantial. McKinsey and Company estimates that Big data analytics has the potential to reduce health care costs in the United States by 12 to 17 percent. This

equals to a savings of between 348 to 493 billion dollars annually [6].

Some of the tools and methodologies that big data uses to introduce efficiencies into the American health care system include: Outcome based reimbursement methodologies, electronic health records, medical device monitoring, predictive analytics, evidence based medicine, genomic analysis, and claim prepayment fraud analysis. Big data technologies are adding value and improving efficiency in almost every area of health care including clinical decision support, administration, pharmaceutical research and development, and population health management.

2 COMPARISON TO OTHER COUNTRIES

According to the Organization for Economic Cooperation and Development (OECD), the United States spends 2.5 times per person than the average of OECD related industrialized nations. In 2016, the United States spent 9822 dollars per person annually on health care. In comparison, the average amount spent per person among all OECD nations was 4033 dollars. The next highest spender was Switzerland at 7919 dollars per person [28]. The average spending as a percentage of Gross National Product (GDP) among OECD nations was 9 percent. Switzerland was again the next highest spender at 12 percent of their Gross National Product (GDP) being spent on health care. According to a McKinsey and Company analysis, the United States spends 600 billion dollars more annually than the estimated benchmark amount as calculated based upon the country's size and wealth as compared to other OECD related nations [18].

The United States lags in many standard indicators of health quality. According to a Commonwealth Fund study of 11 developed countries in 2013, the United States ranked fifth in quality and worst in infant mortality. The United States also ranked last in the prevention of deaths from treatable conditions such as strokes, diabetes, high blood pressure and treatable cancers. The average life expectancy in the United States is 76.3 years. The average life expectancy among all OECD countries is 77.9 years. The incidence of obstetric trauma is 9.6 per 100,000 births in the United States compared to 5.7 incidents per 100,000 in other countries. The statistics for preventable hospital admissions also compare poorly in comparison to other nations. In the United States the hospital admission rate for asthma and COPD was 262 per 100,000 in comparison to the average of 236 per 100,000. Thirty eight percent of the population in the United States is obese. The average obesity rate in other countries is nineteen percent. The United States has fewer physicians and hospitals. In the United States, there are 2.6 practicing physicians and 2.8 hospital beds per 1000 population.

This compares to an average of 3.4 physicians and 4.7 hospital beds on the average in the other countries [28].

The United States has material problems with health care access. Most other OEDC countries have achieved almost universal insurance coverages. On the average, 98 percent of persons in OEDC countries have health insurance. In the United States only 90 percent have health insurance. In addition, cost sharing requirements often make access additionally prohibitive. In 2016, 22.3 percent of the persons in the United States had skipped a medical consultation due to cost concerns. In comparison, the average percentage of individuals who had skipped medical visits due to cost in OEDC nations was 10.5 percent. In the United States 11.6 percent of the population had skipped taking a prescribed medication due to cost in 2016. This compares to an average of 7.1 percent of the population in other OEDC countries who reported foregoing foregone a prescribed medication due to cost [28].

3 HEALTH COST DRIVERS

Why is health care so much more expensive in the United States than it is anywhere else in the world? Some of the contributing factors include: the basic health care economic payment structure, inefficient and wasteful use of resources, medical errors, lack of transparency within the system, unnecessary administrative costs, and fraud and abuse.

3.1 Health Care Payment Structure

Many of the cost issues can be contributed to the complex, un-coordinated, multi-payer payment structure. Private insurance companies, Medicaid, and Medicare are the primary payers. An individual's eligibility by payer is dependent upon factors such as employment status, income level, age, and whether or not they are disabled. Most citizens obtain private insurance through their employment. Individuals who are 65 years of age or older or disabled are eligible for Medicare. These individuals may also purchase private Medicare Supplement insurance on their own to pay expenses that Medicare does not cover. Low income individuals may be eligible for Medicaid. If an individual is not eligible for any of these programs, he can purchase individual health insurance from a private insurance company on his own. However, individual health insurance is expensive. According to data from E-care, in 2016, the average monthly premium for an individual was 393 dollars per month. The average cost for family coverage was 1021 dollars per month [39]. In addition, individual insurance policies often include fairly high cost sharing features. Even though subsidies are available through the Affordable Care Act to offset some of these costs, many people choose to forego insurance entirely due to the prohibitive expense.

The system is inefficient and flawed because the basic economic concepts such as supply and demand and competition do not work in this sector. This is because none of the players are incentivized to manage or reduce costs [3]. Consumers do not manage medical utilization because it is being paid for by a third party, the insurance company. Insurance coverage thus insulates patients from the true costs of medical care [3]. Providers are not incentivized to provide efficient, cost effective care. Most providers are paid via a traditional fee for service methodology. That is, providers are

paid for each service that they provide. Traditional fee for service provider payment methodologies that reward health caregivers for quantity instead of quality often result in overutilization of unnecessary tests and treatment procedures. The structure is such that it encourages the production of inefficient and low value services [3]. Insurance companies pass the cost of services on to the consumers in the form of higher premiums year after year. The cost inflation cycle goes on and on.

Administrative waste is another result of the complexity of the United States multi payer payment structure. Each payer has their own rules and standards. Benefit and coverage options can vary dramatically among individuals even within the same insurance company. According to the OEDC 2008 estimates, the United States spends 7.3 percent of health care expenses on administrative activities. This is more than any other country. Comparatively, Germany spends 5.6 percent, Canada spends 2.6 percent and France spends 1.9 percent [28]. Administrative activities include transaction related activities such as billing and claims payment, and regulatory compliance such as those required to comply with government and nongovernment accreditation and regulation including licensing requirements.

3.2 Clinical and Operational Waste

McKinsey and Company estimates that clinical waste amounts to 273 dollars annually [29]. According to the Congressional budget office, 30 percent of United States spending is wasteful or not necessary [8]. There are two types of waste: operational, and clinical [3].

Operational waste results from duplication of services or inefficient production processes. An example would be a duplicate medical service because of lost medical records or the same service already being provided by another caregiver [3].

Clinical waste is created by the creation of low value outputs or care that is not optimally managed. One type of clinical waste is the spending on goods and services that provide marginal or no health benefit over less costly alternatives. Some clinical waste is the result of the uncertainty in the science of medicine. An example would be when a patient is misdiagnosed or when the treatment protocol is uncertain [3]. Other types of clinical waste may be symptoms of a flawed fee for service payment structure. These may include such things as over screening, excessive office visits, or the use of branded instead of generic drugs. Another example is when a newer or more modern treatment is marketed and sold even when it does not provide a better outcome as compared to the traditional treatment. An example was a 2 million dollar prostate cancer machine that was being marketed in 2014. It made the price of the procedure significantly more, but it did nothing to improve the health outcome [8]. Other examples of types of treatment that are the result of clinical waste include avoidable emergency room use, unnecessary hospital admissions, and excessive antibiotic use [3].

3.3 Medical Errors

Medical errors cost the United States system between 17 and 29 billion dollars annually [3]. This amount could be as much as 1 trillion dollars a year if lost productivity is taken into account [27].

This compares to an estimate of 750 million in Canada [3]. The Institute of Medicine estimates that preventable medical errors claim between 44000 and 98000 lives in hospitals each year [3].

3.4 Fraud and Abuse

The National Healthcare Anti-Fraud Association estimates losses due to health care fraud at 80 billion dollars annually. Other industry sources estimate fraudulent related losses to be around 200 billion. This accounts for approximately 2 to 3 percent of total health care spending. Research indicates that only 5 percent of these losses are ever recovered [10].

4 BIG DATA

Big data refers to electronic data sets that are so large and complex that they cannot be managed with traditional hardware and software. A report delivered to the United States Congress in August 2012 defines big data as large volumes of high velocity, complex, variable data that require progressive techniques and technologies to capture, storage, distribution, manage, and analyze the information. Big data characteristics include variety, velocity, and veracity, and volume [29]. Health care data is big data because it involves the processing of overwhelmingly large complex data sets, from a wide variety of sources and a very rapid speed [29]. In addition, the data is extremely difficult to sort, organize, and decipher [11]. Recent advances in Big Data technology gives us the ability to capture, share and store healthcare data at an unprecedented pace.

4.1 Volume

The health care industry has always generated large amounts of data. Data is needed for record keeping, compliance and regulatory reporting and patient care. Historically, this data has been stored in hard copy format. Now, more and more data is being created and stored digitally. In 2011, there were estimated to be 150 Exabytes of health related data. The amount of health related big data is growing rapidly. It is expected to soon reach the zettabyte scale and then soon after that, into the yottabytes [29].

4.2 Velocity

Traditionally, health care data has been static: for example, paper files, x-ray films, and prescriptions [29]. Ironically, in many medical situations, the speed of the response can mean the difference between life and death. Increasingly, more and more of the data is being collected in real time and at a rapid pace. For example, medical monitoring devices information collect data continuously, and can support immediate response [29].

4.3 Variety

There is an enormous variety of data being collected. The data is in multimedia including images, video, text, numerical, multimedia, paper, and electronic records. Formats include structured, unstructured, and semi-structured. Sources of data include patients, physicians, hospitals, laboratories, research companies, insurance companies, and government agencies. Data comes from web and social media such as Facebook, twitter, health plan websites and smart phone applications. Machine to machine data comes from patient sensors. Biometric data is available such as fingerprints,

genetics, hand writing information and imagining reports [29]. Physicians generate electronic medical records, physician notes, and medical correspondence. Pharmaceutical companies maintain research and development information in medical databases. The United States government houses databases concerning clinical drug trials. Data is collected by the United States Centers Disease Control and Prevention [6].

4.4 Veracity

The characteristic Veracity addresses whether the information is credible and error free. Veracity is extremely important in health care because life or death decisions on being based upon the information provided. There is a particular concern because interpretations of unstructured data such as physician notes could be incorrect or imprecise. Big data architecture, platforms, methodologies and tools are designed to take into account the uncertainties of big data analytics [29].

4.5 Unstructured Big Data

Unstructured data now makes up about 80 percent of the health care information that is available and is growing exponentially. Sources of unstructured data include: medical devices, physician and nurses notes, and medical correspondence. Being able to access to this information is an invaluable resource for improving patient care and increasing efficiency [22]. Big data technology gives us the ability to capitalize and make use of the valuable clinical information that is unstructured [15].

Traditional databases have well defined structures. The data exists in a table and column format, tables have well defined schemas, and each piece of data is stored within its own well defined space. Big data is not like that at all. Data is extracted from the source systems in its raw format. Massive amounts of this data are stored in a somewhat chaotic fashion in a distributed file system. For example, the Hadoop Distributed File System (HDFS) stores data in directories of files in a hierarchical form. The convention is to store files in 64 Megabyte files in the data nodes using a high degree of compression [15].

Big data is raw data. Big data is not cleansed or transformed in any way. No business rules are applied. The approach is to transform and apply business rules or bind the data semantically as late in the process as possible. In other words, the approach is to bind as close to the application layer as possible [15].

Big unstructured data is less expensive than traditional databases. Most traditional relational databases require propriety software that is associated with expensive licensing and maintenance agreements. Relational databases also need significant specialized resources for design, administration, and maintenance. Because of its unstructured format and open source concept, big unstructured data is much less expensive to own and operate. Big data needs little design work and is easy to maintain. A Hadoop cluster is built using inexpensive commodity hardware and runs on traditional disk drives using a direct attached (DAS) configuration instead of an expensive storage area (SAN). The practice of storage redundancy makes the configuration more tolerable to hardware failures. Hadoop clusters are designed so that they are able to rebuild failed nodes easily [15].

Big unstructured data is more difficult to use. Traditional relational database users are able to access the data using a simple structured query language (SQL) that uses a sophisticated query engine that has been optimized to extract the data. Unstructured data is much more difficult to query. A sophisticated data user, such as a data scientist may be needed to manipulate the data. However tools are being developed to solve this problem. One tool is SparkSQL. This tool leverages conventional SQL for querying and works by converting SQL queries into MapReduce jobs. Another example is Microsoft Polybase which can join data from Hadoop and traditional databases and return a single result set [15].

To summarize, advances in Big Data technology, including data management of unstructured datasets and cloud computing are facilitating the development of platforms for more effectively capturing, storing, and manipulating large data sets sourced from multiple sources [29].

4.6 Big Data Trends for Healthcare

The costs for storing and parallel processing are decreasing [22]. Previously, we had to choose what data to capture and store because storage costs were so high. Now we can capture and store everything [17]. The use of the Internet of Things is growing. Internet connected technology is everywhere and has become a common and accepted part of our culture. For example, wearable fitness devices are continuously generating health information and sending it to the cloud.

Another trend is the establishment of standards and incentives in the industry that encourage the digitization and sharing of health care data. The Health Insurance Portability and Accountability Act (HIPAA) establishes national standards for electronic healthcare transactions for the submission of claims. Claims are the documents that health providers submit to insurance companies to get paid. Such standards encourage the widespread use of Electronic Document exchange. These standards have made it possible to effectively and easily share and exchange medical information between providers and insurance companies [22]. Medicare and Medicaid have set up Electronic Medical Record (EHR) incentive programs to encourage professionals and hospitals to adopt and demonstrate meaningful use of EHRs. The Affordable Health Care Act (ACA) encourages the shift from fee for service to value based payment structures by financing initiatives to test new payment models [33].

5 VALUE BASED REIMBURSEMENT

One of the most important strategies that we can take to reduce health care in the United States is to change the way that we reimburse providers from the traditional fee for service methodology to outcome based reimbursement. McKinsey and Company estimates that this strategy alone could reduce health care spending in the United States by 1 trillion dollars over the next decade [23]. This will also mitigate medical inflation because it will automatically promote preventative care and discourage the use of low value expensive technologies. Other benefits include: improved care coordination and the reduction of redundant care. All of this results in better health outcomes, and enhanced patient satisfaction.

With the fee for service payment structure providers are paid a fee for each and every service that they perform. This tends to

encourage overutilization instead of the efficient use of medical resources. The United States tends to perform more and more expensive diagnostic services and treatment services than any other country in the world. The United States is well known for over testing and over treatment [26]. Hospitals are rewarded for preventable readmissions. Physicians are rewarded as much for a failed medical procedure as they are for a successful one. It is up to each individual physician to determine what tests and treatment services to order. From a clinical perspective, many of these tests are not medically necessary. This is a wasteful use of resources.

The goal of value based reimbursement structures are to align payment incentives with the administration of efficient, high quality medical care. Basing provider reimbursement on performance and patient outcomes encourages providers to work towards optimizing patient health instead of just providing more health care services. Caregivers are also incentivized to be more innovative and to search for ways to improve health care delivery [5].

Many payers, including private health insurance companies, Medicare, and Medicaid are starting to base reimbursement on value based incentives. The Affordable Health Care Act includes provisions to encourage the development and adoption of more effective care delivery models. Some payers are also starting to reward pharmaceutical companies by basing reimbursements on drug effectiveness [18]. Systems that have been adopted to date include: patient centered medical homes, episode based payments, global payments, shared savings programs, value based contracting, and population models, including accountable care organizations.

In the patient centered home model, the primary care physician coordinates the patients care and is rewarded for improving quality and reducing costs for individual patients. Another value based system is a population model that rewards providers for improving the health of the entire population [20]. An example of this type of program is an Accountable Care Organization (ACO). In Accountable Care Organizations, groups of doctors, hospitals, and other providers work together to provide coordinated care for patients. In Medicare supported Accountable Care Organizations, providers share in Medicare savings when they deliver high quality care and manage costs wisely [7].

Big Data Analytics can play an integral role in the development and testing of new payment model methodologies. The development and adoption of such models are still in the infancy stage. Big Data Analytics has the potential to provide information that will result in innovative payment structure and reward insights. Big data can also play a role developing clinical best practices and in identifying reasons for unjustified clinical variability in current practices.

Big Data will help to support the implementation of models that have already been adopted. Value based health care depends upon quality data collection and precise data analytics [20]. First, the data must be collected and analyzed in order to define what defines quality care. Big Data is collected and analyzed in order to establish clinical guidelines that promote a more rational use of specific diagnostic tests and treatment protocols. Second, this information must be made available to health care givers in a format that they can use for day to day clinical decision making. This is often in the form of a cloud based integration platform [20]. Next, data must be collected on an ongoing basis to provide feedback indicating

whether the providers are meeting the defined standards and if not, what can be done to improve performance. In addition, the same data can benefit future patients when data analytics are taken beyond the initial reporting and are used to develop care protocols for entire patient populations [20].

One example is in which big data is being used to track and modify provider behavior is at Memorial Care, a six hospital system in Fountain Valley, California. Memorial Care uses physician performance analytics to analyze performance of hospital doctors and outpatient providers. So far, such tracking has resulted in the reduction 280 dollars per hospital stay for the average adult patient. This equates to a 13.8 million annual dollar savings for the Fountain Valley Hospital system [9].

6 ELECTRONIC HEALTH RECORDS

An Electronic Medical Record (EMR) is a digitized version of a patients medical chart. Whereas, an electronic medical record (EMR) typically includes information from one health provider, an electronic health record (EHR) includes information from multiple providers and documents all of the available information about the patient. The objective is to provide in one place, an electronic record of a patients health. This enables the sharing of information between providers. An electronic health record (EHR) contains medical history, diagnosis, medications, immunizations dates, allergy information, radiology images, and test results [36]. These records are made available to providers in real time. Electronic health record (EHR) systems often include electronic prescription subscribing systems. Also, they can include and be integrated with evidence based tools that help providers make immediate decisions about patients care. For example, an Electronic Health record system can also automatically check for problems such as medication conflicts and notify clinicians with alerts [13].

Electronic Health Records (EHRs) improve patient health care in so many ways. Physicians have better organized, more accessible, and more complete information about the patient. A clinicians ability to make an accurate diagnosis is improved. Easily accessible patient information reduces medical errors and unnecessary tests. There is a reduction in the incidence of duplicate tests. Coordination of care is improved because every caregiver is made aware of simultaneous care that is being provided by other caregivers. It easier to communicate critical clinical information to all applicable providers in a timely fashion. Because information is made available to providers in real time, there is a drastic reduction in the probability of errors caused by such things as allergic reactions or drug interactions, especially in emergency situations. Because electronic subscribing allows physicians to communicate directly with the pharmacies, prescriptions are no longer lost or misread [13]. Preventative care improves because it is easier to track and manage when patients are due for vaccinations and screenings. It becomes possible to track prescriptions to determine if a patient has been following doctors orders [34]. Productivity is increased, overlap care is reduced, and coordination of care is enhanced [5]. In general, electronic health records (EHRs) improve quality of care enhance patient safety, and contribute to better outcomes [13].

Electronic Health records (EHRs) have significantly improved the ability to treat chronically ill patients. In the past, providers

had to limit the decisions to the amount of information that was available to them at the time. The planning of care of a chronically diseased patient that had many symptoms was often mismanaged or delayed. Electronic health records (EHRs) enable the physicians to facilitate personalized treatment for these patients in a way that has never before been possible [5]. Providers have a comprehensive record of historical treatments, diagnostic data, medical history, and meticulous medical information all in one place [5]. The result is more efficient and effective treatment for chronically ill patients. There is a reduction in the number of potential side effects and an increase the patients quality of life all at a much reduced cost. [5].

Electronic health records (EHRs) also save money by reducing administrative costs. They reduce transcription costs and eliminate chart storage and access costs.

Between 2001 and 2014 Electronic Health record (EHR) usage in physician offices rose from 20 percent to 82 percent. According to Health Information Technology for Economic and Clinical Health (HITECH) research, electronic health records are being used in 94 percent of hospitals in the United States [34]. This amount of data that is being collected by large health systems and treatment centers around the country is massive [31].

7 PREDICTIVE ANALYTICS

7.1 Definition

Predictive analytics is the process of learning from historical data in order to make predictions about the future. The objective of predictive health analytics is to provide insights that enable personalized medical care for each individual patient [30]. Traditionally, physicians have always used predictive analytics, as they have always provided health care based upon what they know about the medical history of each individual patient. Predictive Health analytics seeks to supplement that knowledge with software tools that enable physicians to make more informed choices about the patients treatment based upon data from population cohorts [31]. Patients are directed to specific treatment plans based upon their specific conditions as compared to other patients in a similar cohort. This additional knowledge has the potential to provide physician with the information they need to provide a more effective treatment plans [31]. This becomes especially important for patients with complex medical histories who are suffering from multiple conditions [34]. Predictive analytics can also improve the accuracy of diagnosing patient conditions, better match treatments with outcomes, and better predict the specific patients at risk for disease [34].

Predictive analytics takes advantage of disparate data sources including: clinical, claims, research, sensors, social media, and genomic analysis.

Predictive analytics has the potential to materially reduce health care costs and improve patient care. Insights provided can in clinical decision support, prevent hospital readmission preventions, aid in adverse incidence avoidance, and help chronic disease management. In addition, predictive analytics can identify treatments and programs that do not deliver demonstrable benefits or that cost too much [29]. Some predictive models reduce readmissions by identifying environmental of lifestyle factors that increase risk

or trigger adverse events so that treatment plans can be adjusted according. [29].

7.2 Patient Profile Analytics

Patient Profile Analytics is a specific type of predictive analysis in which patient profiles are developed to identify individuals who may be at risk for developing a disease and who could benefit from proactive management, such as lifestyle modifications. For example, patient profile analytics can be used to identify patients who may be at risk for developing diabetes.

7.3 Risk Stratification

One area in which predicting patients at risk can yield the greatest results is in identifying the patients who are at the greatest risk for the most adverse outcomes or costliest diseases [29]. Risk stratification is a methodology that can be used to identify and track the sickest and potentially costliest patients. The tool ranks or stratifies patients by potential risk and flags high risk cases for additional management. A risk stratification predictive tool takes into account risk factors such as missed doctors appointments in addition the symptoms. The tool enables doctors to intervene earlier to avoid hospital admissions and costly treatment [9].

7.4 Predictive Analytic Examples

Hundreds of thousands of dollars are spent on cancer care. Big data can be used to develop individualized, personalized cancer care programs. There is a web based application, which was sponsored by the National Cancer Institute that uses data from the Prostate, Lung, Colorectal, and Ovarian Cancer Screening trial together with patient risk factor and demographic data to help develop patient specific treatment regimens [6].

Congestive heart failure accounts for more medical spending than any other diagnosis. The earlier this condition is diagnosed, the easier it is to treat and to avoid dangerous and expensive complications. However, early manifestation is difficult to recognize and can easily be missed by physicians [22]. Machine learning algorithms have the ability to take into account many more factors than doctors alone. Predictive modeling and machine learning using large sample sizes can identify nuances and patterns that were previously impossible to see. As a result, machine learning models in the form of predictive analytics substantially improved clinicians ability to accurately diagnose persons with congestive heart failure [34].

Optum labs has developed a database with the electronic health records of over 30 million patients. They use the database to develop predictive analytic tools, the objective of which is to help doctors make Big data informed decisions that will improve patients treatment [22].

Parkland Hospital in Dallas, Texas uses predictive modeling to identify high risk patients in the coronary care unit and to predict likely outcomes when the patients are sent home. To date, Parkland has reduced readmissions for Medicare patients with heart failure by 31 percent. This equates to a 500000 dollar annual savings for this one hospital [9].

8 INTERNET CONNECTED MEDICAL DEVICES

Internet connected medical devices are becoming more affordable and are being used more and more commonly. Gartner, the analysis firm, estimates that there will be more than 25 billion connected health devices by the year 2020 [15]. These devices collect data in real time and send information into the cloud. Devices include blood pressure monitors, pulse oximeters, glucose monitors, and electronic scales [15]. Some of these devices are being used as preventive care devices. Other devices are being used by health care providers to aid in the monitoring of patient conditions. Big Data is required because the process involves the capture and analysis of large volumes of fast moving data from in hospital and in home devices in real time.

8.1 Preventative Care

Millions of people are using mobile technology help live healthier lifestyles. Smart phone applications together with wearable devices such as Fitbit, Jawbone, and Samsung Gear Fit are designed to track the wearers exercise and activity levels [12]. Measures that are typically tracked include: the number of steps taken, number of calories burned, and number of stairs climbed. The objective is to encourage the users to take a more active role in their own health and wellbeing by being more physically active. Such devices can provide individuals with the information that they need to make more informed decisions, better manage their health, and to more easily track and adopt healthier behaviors [3]. In the future, it is conceivable that it will be routine to share this information with personal physicians and that it will be incorporated into regular health care management.

An individuals data can be uploaded from the device to the cloud where it is aggregated with information from other users [15]. In an initiative between Apple and IBM, a big data platform is being developed that will allow iPhone and Apple Watch users to share their data with IBMs Watson Health cloud health care analytics service. The information will use the combination of real time activity information in combination with biometric data to discover new medical insights [12].

8.2 Medical Monitoring

Remote monitoring enable medical professional to monitor a patient remotely using various technological devices. The devices can be worn by patients with health conditions at home and in medical facilities to stream data continuously to provide real time remote patient monitoring. The devices can improve care by giving patients the ability to self-manage their conditions. Processing of real time events can be supplemented with machine learning algorithms to help provide physicians with information they need to make lifesaving interventions [22]. Patient care tends to be more proactive as patient vital signs are can be monitored constantly [22]. Medical alerts can be sent to care providers such that they immediately aware of changes in a patients condition and can respond accordingly. Devices are often used for adverse risk prediction. Remote monitoring is typically used to monitor conditions such as heart disease, diabetes mellitus, and asthma. One example of the

use of personal devices in patient care is pediatricians monitoring asthmatics to identify environmental triggers for attacks [6].

Real time systems analysis improves patient care while simultaneously reducing health care costs [5]. The devices are especially advantageous to individuals who reside in remote areas. Other advantages include: a reduced incidence of severe events, improved in patient safety, and high patient satisfaction levels.

9 PUBLIC HEALTH

Data science is being used in cities throughout the United States to predict and impede potential public health issues before they even start. For example, the Chicago Department of Public Health is modeling a program to target lead exposure in children. Information is collected from multiple sources such as, home inspection records, assessor values, health records, and census data. Predictive analytic algorithms then determine which houses have the highest potential risk. This information is then being incorporated into Electronic health records (EHRs) to automatically alert physicians to possible lead exposure risk concerning their pediatric and pregnant patients. Chicago has similar programs in place for food protection and tobacco control [14].

In San Diego, California the public health department routinely gathers big data health related information and publishes it on a user friendly web site. Information is gathered from sources such as marketing companies, mobile apps and demographic data. The data includes everything from vegetable consumption to diabetes occurrences. In one initiative, Live Well, the information was able to reduce the obesity rates at a local elementary school by 5 percent. A project that is currently in progress is the study and analysis of areas that have high rates of Alzheimers [19].

10 TRANSPARENCY

In the United States, health care price information is rarely made available to the health care consumers when they receive the care. Patients usually become aware of the costs when they receive the bill. The price of health procedures can vary radically by provider. Prices can even vary by payer for the same provider. In one study, it was estimated that consumers paid 10 to 17 percent less when they were given access to comparative price data. According a paper that was published by the American Economic Journal Economic Policy, if patients had access to price data and were willing to shop around, they could be pay significantly less for everything from routine screenings to knee surgery [2]. This tended to work best for consumers who had to pay for at least some portion of their own care.

Online pricing is a potential Big Data solution. Health related price web sites provide approximate prices for health services and procedures in fairly transparent formats. Online resources are now being made available by insurers, government agencies, internet companies and medical care providers. National insurers such as Anthem, United Health group, Humana, Aetna, and Cigna offer pricing tools to their customers. Some states, including New Hampshire, Maine, Oregon, and Massachusetts publish health pricing websites. The internet company Healthcarebluebook.com publishes information for all consumers in the United States [35].

The trend towards pay for performance reimbursement agreements will also help the cost transparency issue. This is because these pricing structures encourage health care providers to share information [5].

11 EVIDENCE BASED MEDICINE

Evidence based medicine (EBM) is an approach to medical practice that emphasizes the use of evidence from well designed and well conducted research to optimize decision making [37]. Evidence based medicine is an approach that supplements a clinicians knowledge, which may be limited by knowledge gaps or bias, with the formal and explicit information such as scientific literature or best practice methodology. Evidence based medicine eliminates guesswork for health care providers. Instead of having to rely only on their own personal judgement, providers can base treatment and protocols on credible scientific data [5].

Big Data analytics supports the research and development of evidence based best practice treatment protocols. Structured and unstructured data from a variety of sources is combined and big data algorithms are applied. Sources may include electronic medical records, financial and operational data, clinical data, and genomic data [29]. The aggregating individual data sets into big data sets enable analysis for conditions that typically have small populations. An example is the study of individuals with gluten allergies [18].

12 DRUG COSTS

It is a well known fact that drugs in the United States are priced higher than they are in other countries. There are many complicated contributing factors. One factor is lack of price regulation. Another factor is the economic structure of the health care system. Because the system includes multiple payers, there is no one payer with the power to effectively negotiate with the pharmaceutical companies as there are in other economies. Therefore, drug companies typically set drug prices at whatever the market will bear. Newly developed drugs usually have higher price tags. Big Data analytics cannot fix all of the problems with the drug market, but there are some areas in which it may have an impact: medication therapy management capabilities, drug comparison technology, and pharmaceutical research and development process improvements [4].

12.1 Medication Therapy Management

Big data analytics can play a significant role in improving the Medication Therapy Management process. Adverse drug events cost billions of dollars and result in thousands of patient deaths. Physicians and pharmacist are often overwhelmed to the point of not having the time to implement appropriate drug therapies. Drug therapies are becoming more difficult to manage as more patients are taking multiple medications. Big Data cloud analytics are helping clinicians better co manage drug therapies, and to identify drug interactions, adverse side effects, and additive toxicities in real time. The results include a reduction in the number of patient deaths, emergency room visits, hospital admissions, and hospital readmissions [9].

12.2 Comparison of Competitor Drugs

In the research, there tends to be a lot of information about individual drugs. However, there is not much information about how drugs perform in comparison to their competitors. There needs to be more drug comparative information so that physicians are better informed about the true benefits of prescribing a more costly medication as compared to a less expensive or generic drug [4]. Big data technology can play a role in making such comparisons easier to accomplish.

12.3 Pharmaceutical Research and Development

Big Data can help to streamline the Pharmaceutical Research and development process. As a result, important drugs can be delivered to the market more quickly and the cost of drug development will be reduced.

Big data can enhance the process of identifying appropriate patients to enroll in the clinical trials. First, multiple sources are now available from which to select patients. For example, social media can be incorporated into the selection process and used in addition to physician information. Secondly, the participate selection criteria can include more inclusive factors, such as genetic information. This will enable better targeting of potential trial subjects which will result in more pertinent information, while at the same time shorting trail times and reducing expenses [24].

Trial can be monitored and tracked in real time. Real time trial monitoring can decrease the number of safety and operational issues. The result is the avoidance of potentially costly issues such as adverse events or unnecessary delays [24].

Electronically captured data can improve communication. Information can be shared easily between functions and external parties. All interested individuals can have access to the data at the same time including all departments, external partners, physicians, and contract research organizations (CROs). This will replace the issue of having rigid departmental data silos that hinder interaction [24].

Genomic and proteomic data can be used to speed drug development by providing the capability to better target treatments based upon genetic indicators [17].

13 ADMINISTRATIVE COSTS

According to the Institute of Medicine (IOM), the United States spends 361 billion annually on health care administration. This is more than twice our total spending on heart disease and three times our spending on cancer. Also according to the IOM, fully half of these expenditures are unnecessary [9].

One way that providers can save money is to digitize billing processes such as benefit verification, denial management, and claims submission. A benefit verification that is done electronically costs 49 cents per patient. Comparatively, the same process done manually costs 8 dollars. It is estimated that providers could save 9.4 dollars annually by transitioning to electronic processing [21].

One example in which digitized processes are being used to streamline billing processes effectively is at the Phoenix Childrens Hospital in Arizona. They use a tool that automatically converts the clinical notes in the electronic health record (EHR) system to billable diagnostic codes [21].

14 FRAUD AND ABUSE

Common types of fraud and abuse include: billing for services that are not rendered, billing for more expensive procedures than were actually delivered, and the performance of unnecessary services.

In the past, the process of identifying misrepresented claims was tedious and time consuming. Big Data analytics makes it possible to easily identify and tag such claims. According to an article by RevCycle Intelligence, when there is repeated misrepresentation of some key fact or event, patterns are created in the data that can be detected by comparing the information to legitimate claims [10]. Anthem Health Insurance, one of the nations biggest insurance payers, uses big data and machine learning algorithms to tag suspicious claims as the claims are being processed. Tagged claims are then sent to clinical coding experts for review. The objective is to identify and address fraudulent claims before they are actually paid [10].

The Center for Medicare and Medicaid Services used predictive data analytics to identify and recover 210.7 million [22] in health care fraud in 2015. They did this by assigning risk scores to claims and providers via algorithms. This enabled the identification of abnormal billing patterns in claim submissions [10].

United Healthcare realized a 2200 percent return on their investment in a Hadoop Big Data platform that was used to identify and tag inaccurate claims using a systemic and repeatable methodology [22].

Other uses of Big Data analytics in fighting fraud and abuse include: identifying links between providers to access whether an identified unethical activity is being practiced by related providers, identification of a hospitals overutilization of services in a short time period, recognizing patients who are receiving health care services from different hospitals in different locations at the same time, and detecting prescriptions that are filled for the same patient in multiple locations at the same time. Big Data analytics can also utilize machine learning algorithms combined with historical information to detect trends in anomalies and suspicious data patterns.

15 GENOMICS ANALYTICS

Big data is playing a major role in the field of genomics and precision medicine. These technologies are helping clinicians choose the best treatment plan for individuals based upon their genetic makeup. Combining data from electronic health records (EHRs), clinical trials, and genetic testing gives researchers information to develop more effective treatments for complex diseases such as cancer and diabetes [25], and HIV. Genetic testing that has been made possible by the mapping of the human genome will cut costs and improve survival rates [1].

One area in which genomics can have a dramatic impacts is in pharmaceuticals management. In the United States, 300 million dollars are spent annually on pharmaceuticals. Studies indicate that between 20 to 75 percent of patients are not responsive to prescribed drug therapies. This can often be contributed to incorrect dosing or drug mismatches. However, 50 percent of the time it is because of a molecular mismatch between the patient and the drug. According to Alan Mertz, president of the American Clinical Laboratory Association, an estimated 30 to 110 billion can be saved

by using genetic test to select a drug that is a precise match for the genetics of the patient. By using each patients unique genomic profile, therapy can become more targeted and the instances of inappropriate care will be reduced [1].

For breast cancer patients, genetic testing can identify which 30 percent of women of an overabundance of the HER2 protein. Regular chemotherapy will not help these women, but a drug called Herceptin does. Having this information not only provides doctors with the information they need to prescribe the correct medication, it enables thousands of women avoid needless harsh, expensive chemotherapy treatment. As a result, genetic testing has been shown to reduce the risk of death by 33 percent and the risk of recurrence by 52 percent for breast cancer patients. The resulting savings are estimated to be 24 thousand dollars per patient [1].

Genetic tests can help physicians select the appropriate drug for patients with metastatic colon cancer. According to one estimate, 700 million dollars could be saved annually be obtaining this information before administering treatment [1].

According to a 2006 Brookings/AEI estimate, using genetic tests to determine the appropriate dose of the blood thinner, warfarin, could save the United States 1.1 billion dollars annually. According to a study in June 2010 by the Journal of American College of Cardiology, this test could reduce hospital admissions that are caused by inaccurate dosages by 31 percent [1].

Genomic technology is also good for the United States economy. According to Battelle, a global research organization, human genome sequencing projects generated 796 billion in economic output, 244 billion in personal income and 3.8 million job-years of employment in the United States [1].

The process of gene sequencing continues becomes more efficient and cost effective. It is expected to become a regular part of medical care in the near future [15].

16 TELEMEDICINE

Telemedicine is receiving medical treatment and advice remotely, on a computer over the internet with a physician [12]. Telemedicine has been in the market for 40 years, but the with availability of internet connected technology such as smartphones, wireless devices, and video conferences, it is becoming commonplace. It is primarily used for initial diagnosis, remote patient monitoring, and medical education. However, it is also being used for more complicated care such as telesurgery. Telesurgery is a technique in which doctors perform surgery via robots with the assistance of high speed real time data delivery technology [34].

Telemedicine is especially beneficial to patients who live in rural communities who may have to travel long distances to see a doctor or specialist. Telemedicine also gives doctors who are located in multiple locations the ability to discuss and share information. Telemedicine facilitates medical education by giving caregivers the ability to observe and be trained by subject experts no matter where their location.

Telemedicine has the potential to significantly reduce costs by reducing the number of outpatient and hospital visits [38].

17 USE CASES

Valence Health has built a data lake that they use as their primary data repository using a MapR Converged Data Platform. The system includes 3000 inbound data feeds and contains 45 different types of data including: lab test results, patient vitals, prescriptions, immunizations, pharmacy benefits, claims information from doctors and hospitals. The system reports dramatically better system performance than legacy system technology. For example, previously, it took 22 hours to process 20 million laboratory records. Now the processing time for the same number of records is 20 minutes. In addition, the new system requires less hardware [22].

The National Institute of Health developed a data lake which combines data sets from separate institutions. Now that all of the data is housed in the same location, analysis is more efficient and can be more easily shared [22].

United Healthcare uses Hadoop to maintain a platform with tools that they use to analyze information generated from claims, prescriptions, provider contracts, plan subscriber, and review information [22].

Novartis, a global healthcare company, uses Hadoop and Apache Spark to build a workflow system that aids in the integration, processing, and analysis of Next Generation Sequencing research as it relates to Genomic Analytics [22].

18 CHALLENGES

One of the most compelling challenges is clinicians willingness and ability to change behavior based upon the information provided by the data. Studies have shown that it takes more than a decade of compelling clinical evidence before a new finding becomes common clinical practice. Therefore, we need to do a better job of working with clinicians on finding ways to use the data to provide higher quality care [17].

In health care, the privacy, security, and confidentiality of the patient is paramount [15]. Big data technology has inconsistent security technology. The Health Insurance Portability and Accountability Act (HIPPA) is a federal law that was passed in 1996 that sets a national standards to protect the confidentiality of medical records and personal health information. The HIPAA law is applicable to any component of the information can be used to identify a person. The protections apply to both electronic and non-electronic forms of information [32]. HIPAA regulations make it a federal offense to breach patient security. It is important to work with vendors who understand the importance of security [15]. Liason Technologies is one company that provides solutions to the healthcare and life sciences industry that has experience meeting the HIPAA security requirements [22].

Health care data has inconsistent formatting and definitional issues [17]. There is proliferation of data formats and data representations. There are inconsistent variable definitions. A value may have different meanings for different groups. For example, a cohort definition for an asthmatic patient often differs from one group of clinicians to another [16]. Big data has the challenge of bringing all of this information together.

Another issue is lack of technical experts. The manipulation and extraction of data from often unstructured data sets require special knowledge. There have been some recent changes in tooling that

will make it easier for individualized with less specialized skills to manipulate the data. For example, Big data is starting to use include SQL as a tools for querying and data manipulation. Examples are Microsoft Polybase, Impala, and SQL Hadoop [15].

19 CONCLUSION

Big data analytics has huge potential to save the United States billions of dollars in health care costs while drastically improving health outcomes. Vast amounts of information is being captured, stored and combined in ways that offer insights have never before been possible. Innovative Big data tools are reducing medical waste, decreasing medical errors, fighting fraud, and keeping people healthier. Value based reimbursement solutions have the potential to revolutionize the health delivery system in the United States by motivating providers to find ways to deliver the best possible medical care with the most economical use of resources. The development of most of these tools is only in the preliminary stage. Therefore, we are only beginning to realize some of the potential benefits. Big data really does have the potential to bend the cost curve. Big data in health care is here to stay.

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Using Machine Learning Classification of Opioid Addiction for Big Data Health Analytics

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ABSTRACT

Classification of opioid misuse and abuse can identify important features relevant for predicting drug addiction and overdose death. Machine learning procedures were applied to data from a large National Survey of Drug Use and Health (NSDUH-2015) to classify individuals for illicit opioid use according to demographic characteristics and mental health attributes (e.g., depression). Classification models of opioid addiction can be extended for big data health analytics to include high-dimensional datasets, data collected over previous years, or expanded to the larger population of patients taking prescription opioid medication. The results seek to raise awareness of risk factors related to opioid addiction among patients and medication prescribers, and help decrease the risk of opioid overdose death.

KEYWORDS

Big Data, Health Analytics, Classifier Algorithms, Opioid Addiction, i523, hid335

1 INTRODUCTION

Big Data offers tremendous potential to fuel innovation and transform society. Can this momentum be harnessed to address a serious health crisis such as the opioid overdose epidemic? [7] Health informatics is generating huge amounts of data at a rapid pace, from electronic medical records (EMRs), clinical research data, to population-level public health data [5]. This project considers health analytics from two levels, the research questions being addressed and the data used to answer them. The question of interest in this project is whether opioid dependency and addiction can be predicted from demographic attributes and psychological characteristics. Survey research provides data on a wide range of issues that people may be reluctant to disclose, including mental health disorders, personal medical health concerns, prescription medications, and illicit drug use. Responses to surveys may be biased to some degree, but measures of confidentiality and anonymity help to assure more accurate disclosures. The goal of this project is to use machine learning procedures to classify individuals susceptible to opioid abuse and dependence. Understanding the features that contribute to opioid addiction can identify underlying risk factors and increase awareness of potential opioid abuse for patients and health care providers. The results could be extended to big data from previous years of the opioid crisis and to the larger population of patients taking prescription opioid mediation. Different machine learning classification methods are discussed.

1.1 Opioid Overdose Epidemic

The abuse of prescription opioid medication in the U.S. has become a major health crisis of epidemic proportions [26]. Over 2 million Americans were dependent or abused prescription opioids such as oxycodone or hydrocodone in 2014[3]. Overdose deaths from prescription opioids have quadrupled since 1999, resulting in more than 180,000 deaths between 1999 to 2015 [11]. Drug overdose deaths increased significantly for males and females, between 25-44 years, ages 55 and older, for Non-Hispanic Whites and Blacks, in the Northeast, Midwest, and Southern regions of the U.S. [7]. Mobile health applications can monitor patient medication consumption and provide an early warning system for potential abuse, detecting sudden changes in medications, higher dosages, or rapid escalation of a prescribed dosage [25]. Reliable information about medication dosages can be difficult to obtain based on self-reports. Individuals dependent or addicted to prescription opioids may obtain synthetic opioids such as fentanyl or illicit drugs such as heroin. Because the dosage levels and potency of illicit opioids are largely unknown, there is greater risk of drug overdose death. The sharp increase in overdose deaths due to synthetic opioids (other than methadone) has coincided with the increased availability of illicitly manufactured fentanyl, which is indistinguishable from prescription fentanyl. The findings indicate the opioid overdose epidemic is getting worse, and requires urgent action to prevent opioid dependence, abuse and overdose death. The target group for this project is individuals who reported misusing or abusing prescribed opioid medication who also used heroin, shown in Figure 1.

1.2 Machine Learning Approaches

Machine learning is a set of procedures and automated processes for extracting knowledge from data. The two main branches of machine learning are supervised learning and unsupervised learning. Supervised learning problems involve prediction about a specific target variable or outcome of interest. If a given dataset has no target outcome, unsupervised learning methods can be used to discover underlying structure in unlabeled data. The goal of this project is to classify opioid addiction and focuses on supervised learning. Supervised learning is used to predict a certain outcome from a given input, when examples of input/output pairs are available [10]. A machine learning model is constructed from the training set of input-output pairs, to predict new test data not previously seen by the model. The two major approaches to supervised learning problems are regression and classification. When the target variable to be predicted is continuous, or there is continuity between the outcome (e.g., home values, or income), a regression model is used to test the set of features that predict the target variable. If the target is a class label, set of categorical or binary outcomes (e.g., spam or ham, benign or malignant), then classification is used to

predict which class or category label that new instances will be assigned to.

1.3 Classification Algorithms

Comparing the performance of different learning algorithms can be helpful for selecting the best model for a given problem [14]. One of the simplest classification algorithms is K-Nearest-Neighbors (KNN) which takes a set of data points and classifies a new data point based on the distance (e.g., Euclidean, by default) to its nearest neighbors. The main parameter for KNN is the number of neighbors, and k of 3 or 5 neighbors works well. The advantage of the KNN classifier is that it provides a solution that is easy to understand. A limitation of KNN is that it does not perform well with a large number of features (100 or more) or sparse datasets. Several different classification algorithms are considered below.

1.3.1 Logistic Regression Classifier. Logistic regression is a commonly used linear model for classification problems. The decision boundary for the logistic regression classifier is a linear function of the input; a binary classifier separates two classes using along a line, plane, or hyperplane. Linear classification models differ in terms of (1) how they measure how well a particular combination of coefficients and intercept fit the training data, and (2) the type of regularization used [10]. The main parameter for linear classification models is the regularization parameter C. High values of C correspond to less regularization and the model will fit the training set as best as possible, stressing the importance of each individual data point to be classified correctly. By contrast, with low values of C, the model puts more emphasis on finding coefficient vectors (i.e., weights) that are close to zero, trying to adjust to the majority of data points. In addition, the penalty parameter influences the coefficient values of the linear model. The L2 penalty (Ridge) uses all available features, but pushes the coefficient values toward zero. The L1 penalty (Lasso) sets the coefficient values for most features to zero, and uses only a subset of features for improved interpretability. This analysis used a logistic regression classifier to predict Heroin use from demographic attributes, mental health, prescription opioids, medication use, misuse, and illicit drug use.

1.3.2 Tree Based Models. Decision tree models are widely used for classification and regression. Tree models “learn” a hierarchy of if-else questions that are represented in the form of a decision tree. Building decision trees proceeds from a root node as the starting point and continues through a series of decisions or choices. Each node in the tree either represents either a question or a terminal node (i.e., leaf) that contains the outcome. Applied to a binary classification task, the decision tree algorithm *learns* the sequence of if-else questions that arrives at the outcome most quickly. For data with continuous features, the decisions are expressed in the form of, “Is feature x larger than value y?” [10] In constructing the tree, the algorithm searches through all possible decisions or tests, and find a solution that is most informative about the target outcome. A decision tree classifier is used for binary or categorical targets, and decision tree regression is used for continuous target outcomes. The recursive branching process of tree based models yields a binary tree of decisions, with each node representing a test that considers a single feature. This process of recursive partitioning

is repeated until each leaf in the decision tree contains only a single target. Prediction for a new data point proceeds by checking which region of the partition the point falls in, and predicting the majority in that feature space. The main advantage of tree based models is that they require little adjustment and are easy to interpret. A drawback is that they can lead to very complex models that are highly overfit to the training data. A common strategy to prevent overfitting is *pre-pruning*, which stops tree construction early by limiting the maximum depth of the tree, or the maximum number of leaves. One can also set the minimum number of points in a node required for splitting. Another approach is to build the tree and then remove or collapse nodes with little information, which is called *post-pruning*. Decision trees work well with features measured on very different scales, or with data that has a mix of binary and continuous features.

1.3.3 Random Forests Classifier. A random forest is a collection of decision trees that are slightly different from the others, which each overfits the data in different ways. The idea behind random forests is that overfitting can be reduced by building many trees and averaging their results. This approach retains the predictive power of trees while reducing overfitting. Randomness is introduced into the tree building process in two ways: (a) selecting a bootstrap sample of the data, and (b) selecting features in each node branch [10, 14]. In building the random forest, we first decide how many trees to build (e.g., 10 or 100), and the algorithm makes different random choices so that each tree is distinct. The bootstrapping method repeatedly draws random samples of size n from the dataset (with replacement). The decision trees are built on these random samples that are the same size as the original data, with some points missing and some data points repeated. The algorithm also selects a random subset of p features, repeated separately each node in the tree, so that each decision at the node branch is made using a different subset of features. These two processes help ensure that all of the decision trees in the random forest are different. The important parameters for the random forests algorithm are the number of sampled data points and the maximum number of features; the algorithm could look at all of the features in the dataset or a limited number. A high value for *maximum-features* will produce trees in the random forest that are very similar and will fit the data easily based on the most distinctive features, whereas a low value will produce trees that are very different from each other, and reduces overfitting. Random forests is of the most widely used ML algorithms that works well without very much parameter tuning or scaling of data. A limitation of this approach is that Random forests do not perform well with very high-dimensional, data that is sparse data, such as text data.

1.4 Project Goals

The general idea of the project is that prescription opioid dependency and addiction will in many cases lead to the use of illicit opioids such as heroin or fentanyl. According to this reasoning, it was hypothesized that individuals who report using heroin may also be susceptible to misusing or abusing prescription opioid medications. The goal of the study was to identify the set of features important for predicting opioid addiction. The data used in the project is from the National Survey on Drug Use and Health from 2015 (NSUH-

2015) [1], which is the most recent year available. The NSDUH-2015 is a comprehensive survey that covers all aspects of substance use, misuse, dependency, and abuse, including questions related to both prescription medications (opioids, tranquilizers, sedatives) and illicit drugs (e.g., heroin, cocaine, methamphetamine), drug dependency, addiction, and treatment, demographic measures of education and employment, physical health, depression, and mental health treatment. Several classification models were constructed to classify heroin use in the sample by demographics attributes and mental health characteristics (e.g., adult depression). This method addresses the following issues related to opioid dependency and addiction: (i) Identify factors related to illicit opioid use, (ii) Identify factors related to prescription opioid misuse and abuse, and (iii) Examine the relationship between prescription opioid misuse, abuse and heroin use.

2 METHOD

The project workflow pipeline is outlined in a readme markdown file in the project folder [22]. The steps included in the workflow were (1) Download and Extract the Data, (2) Data Cleaning and Preparation, (3) Exploratory Data Analysis, (4) Data Visualization, (5) Analysis of Classification Models for Heroin Use, and (6) Analysis of Classification Models for Prescription Opioid Pain Reliever Misuse.

2.1 Data

Data from the 2015 NSUH was downloaded from the Substance Abuse and Mental Health Data Archive (SAMHDA) [1] URL using the get-data.py function written to unzip the data files, extract the data as a Pandas data frame, and write the file to CSV file [4]. The dataset consists of 57,146 observations with 2,666 features representing individual-level responses from a survey of the U.S. population. According to the NSDUH codebook, sampling was weighted across states by population size for a representative distribution selected from 6,000 area segments. The sample design used five state sample size groups drawing more heavily from the eight states with the largest population (e.g., CA, FL, IL, MI, NY, OH, PA, TX) which together account for 48 percent of total U.S. population aged 12 or older. All identifying information was collapsed (e.g., age categories) and state identifiers were removed from the public use file to ensure confidentiality. The NSDUH public-use files do not include geographic location, or demographic variables related to ethnicity or immigration status. The weighted survey screening response rate was 81.94 percent and the weighted interview response rate was 71.2 percent.

2.2 Data Cleaning and Preparation

2.2.1 Data Cleaning. All steps of this analysis was completed in a python interactive notebook [16] based following examples from *Python for Data Analysis* [9]. After saving the NSDUH-2015 as a data frame object, the dataset was subset by columns to include demographic characteristics (e.g., age category, sex, marital status, education, employment status, and category of metropolitan area), measures of physical health (e.g., overall health, STDs, Hepatitis, HIV, Cancer, hospitalization), mental health (e.g., Adult Depression, Emotional Distress, Suicidal Thoughts, Plans), Suicide Attempts,

Pain Reliever Medication Use, Misuse, and Abuse (over past year, past month), Prescription Opioid Medications Taken in Past year (e.g., Hydrocodone, Oxycodone, Tramadol, Morphine, Fentanyl, Oxymorphone, Demerol, Hydromorphone), Heroin Use, Abuse (over past year, past month), Tranquilizer Use, Sedative Use, Cocaine Use, Amphetamine and Methamphetamine Use, Hallucinogen Use, Drug Treatment (e.g., Inpatient, Outpatient, Hospital, Mental Health Clinic, ER, Drug Treatment Status), and Mental Health Treatment History. A codebook was created to provide a complete list of variables included with summaries of response categories [19]. The following steps were taken to detect and remove inconsistencies in the data [13]:

- (1) Remove missing values (i.e., NaN)
- (2) Recode blanks, non-responses, or legitimate skips (e.g., 99, 991, 993) to zero
- (3) Recode dichotomous responses (e.g., Yes=1 / No=2) so that No=0
- (4) Recode categorical variables to be consistent with amount or degree (e.g., 1=low, 2=med, 3=high)
- (5) Rename selected variables for better description (e.g., Adult Major Depressive Episode Lifetime changed from AMDELT to DEPMELT)

2.2.2 Aggregated Variables. Because the majority of features were represented as dichotomous Yes / No variables, related features were summed to create aggregated variables. For example, overall health, STD, Hepatitis, HIV, Cancer, and hospitalization were aggregated to create a single health measure. The health measure was recoded so that higher scores indicated better health. Questions related to depression, emotional distress, and suicidal thoughts were summed to create a single variable for mental health (MENTHLTH) with scores ranging from 0 to 9. Responses to pain reliever medication use, misuse, abuse, or dependency, were aggregated to create a single variable of pain reliever misuse or abuse (PRLMISAB). All prescription painkiller medications used in the past year were summed. Similarly, all related responses were summed to create single variables for Tranquilizers, Sedatives, Cocaine, Amphetamines, Hallucinogens, Drug Treatment, and Mental Health Treatment. The target outcome of interest for classification, lifetime heroin use (i.e., “Have you ever used heroin before, at any time?”) is a dichotomous variables. The demographic characteristics and aggregated variables were subset and saved to a new data frame consisting of 2 features and 57,146 observations, which was exported to CSV file.

3 RESULTS

3.1 Exploratory Data Analysis

Of the total sample of N=57,146 respondents, 26,736 were male and 30,410 female; 6,343 individuals reported misusing pain medication at some point (570 males, 386 females), but only 956 respondents had used heroin (570 males, 386 females). Table 1 shows the raw counts of individual substance use by age group (with the sample size for each age group), listing the ten most commonly used opioid pain medications, self-reported misuse of prescription opioid pain relievers (i.e., PRL Misuse Ever), use of prescription Tranquilizers, Sedatives, and Methadone. In addition, self-reported use of illicit drugs such as heroin, cocaine, amphetamines, methamphetamine,

Table 1: Substance Use by Age Group Counts - NSDUH 2015 [1]

Age Group	12-17	18-25	26-34	35-49	50+
Sample Size	13585	14553	9084	11169	8755
Oxycodone	545	1632	1132	1345	1044
Hydrocodone	831	2936	2233	2781	2103
Tramadol	241	753	654	829	734
Morphine	251	431	236	313	286
Fentanyl	28	97	81	96	86
Demerol	26	74	49	64	71
Buprenorphine	43	197	167	124	51
Oxymorphone	46	88	57	47	41
Hydromorphone	24	94	107	118	81
PRL Misuse Ever*	798	2127	1475	1343	600
Tranquilizers	405	1469	1064	1405	1153
Sedatives	204	242	157	256	226
Methadone Ever	32	83	96	71	46
Heroin Use Ever*	22	261	259	250	164
Cocaine Use Ever	109	1645	1626	1954	1406
Amphetamines Ever	932	1836	627	383	164
Methamphetamine	42	481	700	898	492
Hallucinogens	450	2660	2020	2127	1197
LSD Use Ever	190	1114	874	1442	907
Ecstasy (MDMA)	199	1867	1403	947	149

Hallucinogens, including LSD and Ecstasy (MDMA). This summary table shows that substance use seems to be highest for individuals between the ages of 18 to 25 and from 35 to 49 years. Of the prescription relievers, Hydrocodone use (e.g., Vicodin) was almost double the rate of Oxycodone use (e.g., Oxycontin) for each age group, and was significantly higher than any other prescription opioid medication. Use of prescription Fentanyl and Demerol, two powerful opioids, and synthetic morphines such as Oxymorphone and Hydromorphone, was very low. The rate of prescription Tranquillizer use was several orders of magnitude higher than Sedative use or Methadone use. Compared to other illicit drugs such as Cocaine, Amphetamines, Hallucinogens, heroin use was not very common in this sample. The highest rates of heroin use were seen between the ages of 18 to 49, and was lowest for respondents in the youngest age group 12 to 17, and individuals over 50.

Table 2 shows the frequency of individuals reporting that they had experienced mental health issues such as depression, suicidal thoughts, whether they had received mental health treatment, received treatment from a private therapist, or believed that they needed drug treatment, but had not sought treatment, across each age category. Frequency of depression was not included for respondents between 12 to 17 years, because the survey measure was for adult depression.

Figure 1 shows the proportion of individuals who reported misusing prescription opioid pain relievers and who reported using heroin. The left column of the Figure 1 shows the majority of respondents (89 percent) stated they had never misused prescription

Table 2: Frequency Table of Mental Health Issues and Treatment NSDUH 2015 [1]

Age Group	12-17	18-25	26-34	35-49	50+
In Hospital Overnight	730	1149	821	890	1173
Adult Depression	0	2413	1395	1766	967
Mental Health Treatment					
Private Therapist	0	592	434	554	311
Treatment Gap*	469	931	321	239	90

opioid pain medication or used heroin, although 10 percent reported misusing opioid pain medication at some point. The right panel of Figure 1 shows that, of those individuals who reported using heroin, the proportion who also reported misusing opioid pain medication was almost twice as large as the proportion of those who only used heroin. This is consistent with the hypothesis that misuse of prescription opioids is linked with heroin use for some individuals.

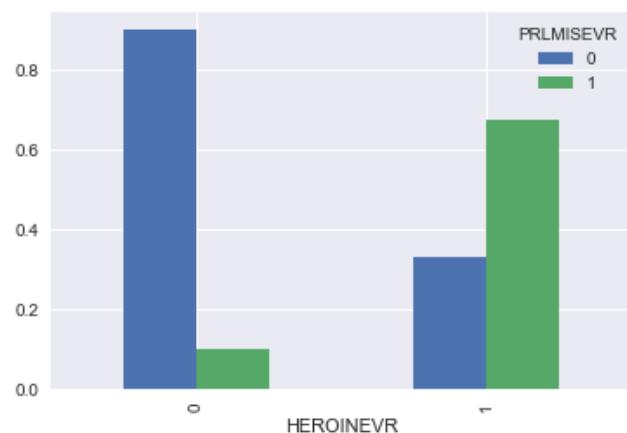


Figure 1: Proportion of Individuals Who Reported Ever Misusing Prescription Opioid Pain Relievers and Proportion Who Reported Using Heroin

Figure 2 shows the aggregated measure of Opioid Pain Reliever misuse and abuse plotted against the aggregated measure of Heroin use (which includes misuse, abuse, lifetime use, past year use, 30 day use), with weighted regression lines grouped by size of City Metropolitan region (from none to large). The largest proportion of the sample who report prescription opioid misuse, abuse, and heroin use is represented by observations from large metropolitan areas (red circles) with large population size. However, a small number of observations from rural or small metropolitan regions (blue and green circles) showed very high rates of prescription opioid misuse and abuse. Regression lines (i.e., line of best fit) shown are weighted by the City/Metro region attribute, with a steeper slope shown for smaller metropolitan regions than large metropolitan regions. The difference in slope may be due to the influence of the small number of outliers who had high degrees of prescription opioid misuse, and

heroin use. The plot also shows a clear divide on the y-axis, which separates the sample according to high and low or no prescription opioid misuse, although the continuum of heroin use from no, low, to high is distributed fairly evenly along the x-axis.

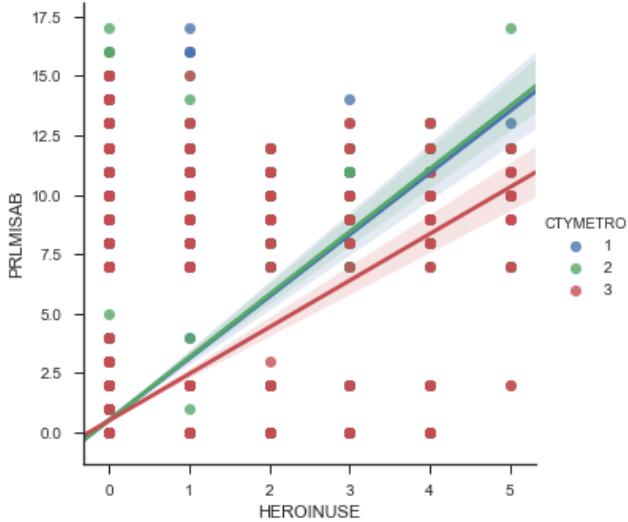


Figure 2: Plot of Opioid Pain Medication Misuse and Abuse and Heroin Use with Regression Slopes Weighted by Metropolitan Area Size

Figure 3 shows the pairplots of demographic features including mental health (higher scores equal to more depression), Prescription Opioid Pain Reliever (PRL) Medication (aggregated), Heroin Use (aggregated measure), and Size of City/Metropolitan region. The top row shows that the majority of the sample reported no mental health concerns, whereas a small proportion of the sample reported depression, emotional distress, or suicidal thoughts. Only few people self-described as high in depression reported low Prescription Opioid PRL misuse and abuse. The plot also reveals that prescription opioid misuse and heroin use were distributed approximately evenly for individuals reporting either low, moderate, or high levels of depression, which suggests that depression was not a factor in predicting opioid misuse. The second row shows a small number of individuals from rural areas or small cities who reported very high levels of prescription opioid misuse, although the majority of respondents misusing or abusing prescription opioid were from large metropolitan areas. As described above, the majority of respondents (about 90 percent of the sample) reported they had never misused prescription opioids. In the second row and third and fourth columns, a natural break is seen between individuals who reported high levels of prescription opioid misuse and abuse and those who reported very low or no opioid misuse. A very small proportion of the entire sample reported both misusing and abusing prescription opioids and using heroin, but this is a group of interest. The last column of the second row shows the individuals reporting high levels of opioid misuse and abuse were distributed evenly across city/metropolitan areas of different sizes, with only slightly higher numbers for small cities or rural areas. As

stated above, only few participants reported using heroin, and of these, the majority were from large metropolitan areas. Finally, the sample seems to have slightly higher proportions from small and large metropolitan areas, which is likely due to weighted sampling, which drew more from heavily populated regions.

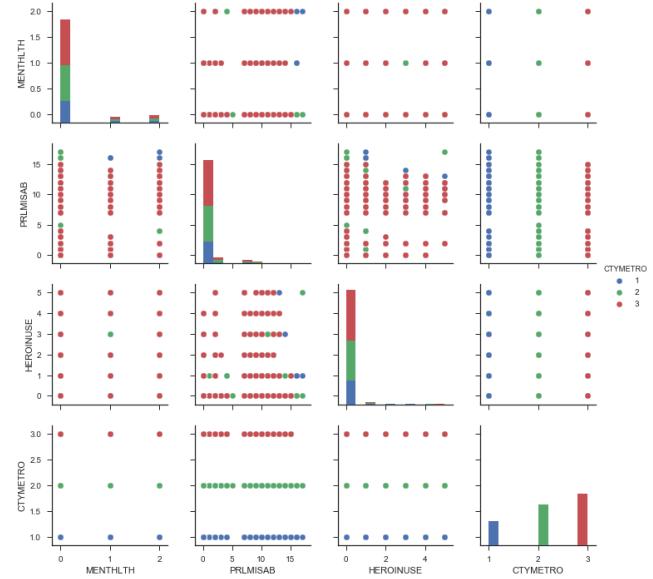


Figure 3: Pairplots of Mental Health, Prescription Opioid Misuse and Abuse, Heroin Use, and Size of City Metropolitan Area

3.2 Classifier Models of Heroin Use

This analysis classified individuals according to whether they had ever used heroin (i.e., “Heroin Use Ever”). All classifier models were constructed using SciKit Learn [10] using an interactive python jupyter notebook [17]. The features of interest were demographic characteristics, health, mental health (adultdepression), prescription opioid misuse and abuse (PRLMISEVR, PRLMISAB, PRLANY), prescription tranquilizers use and sedatives use (TRQLZRS, SE-DATVS), use of illicit drugs (COCAINE, AMPHETMN), drug treatment (TRTMNT), and mental health treatment (MHTRTMT). The target variable was Heroin Use (HEROINEVR). Next, the dataset was split into the training set and test sets using the train-test-split() function in sklearn. Model accuracy for the training set and test set are reported, with different parameter values, and features importance.

3.2.1 Logistic Regression Classifier. Logistic Regression Classification is based on a linear equation that calculates the relative weight of each feature for a categorical target or binary outcome (yes / no) [14]. The logistic regression classifier was fit to the training data in Scikit-Learn, and the model was validated on the test data. By default, the model applies L2 penalty (Ridge). The training set accuracy was 0.983 and the test set accuracy was 0.984. The parameter ‘C’ determines the strength of regularization, with higher values of C providing greater regularization. The L1 penalty

(Lasso) limits the values of most coefficients to zero, creating a more interpretable model that uses only a few features. Figure 4 plots the coefficients of logistic regression classifier for heroin use with the L1 Penalty (Lasso) under different values of parameter C. The default setting, C=1.0, provides good performance for train and test sets, but the model is very likely underfitting the test data. Using a higher value of C fits a more flexible model and generally gives improved accuracy for both training and tests sets. Using a value of C=100 yielded training set accuracy of 0.98 and test set accuracy of 0.98. Figure 4 shows that the features coefficient values did not change much according to the values of parameter C, and the accuracy values were approximately the same for all values of C. Examination of the coefficients from the logistic regression classifier revealed the three features which were most closely associated with Heroin use were: Prescription Opioid Pain Reliever (PRL) Misuse ever (as predicted), Cocaine Use, and Amphetamine use, respectively.

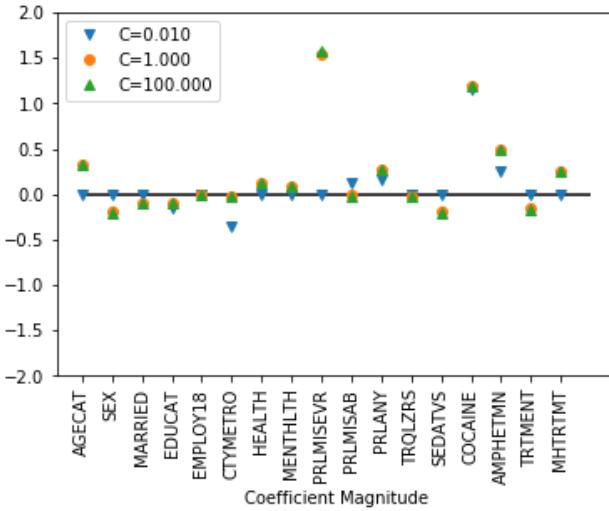


Figure 4: Coefficients of Logistic Regression Classifier of Heroin Use (With L1 Penalty and Values of Regularization Parameter C)

3.2.2 Decision Tree Classifier. The following analysis used the *Decision Tree Classifier* package in Scikit-Learn, which only does pre-pruning. First, the decision model was build using the default setting of a fully developed tree until all leaves are pure. The random state' features is fixed to break ties internally. Accuracy on the training set was 0.99 and test set accuracy was 0.974. Without restricting their depth, decision trees can become complex; unpruned trees are prone to overfitting and do not generalize well to new data. Limiting the depth of tree decreases overfitting, which results in lower training set accuracy, but improved performance on the test set. Next, pre-pruning was applied, with a maximum depth of 4, which means the algorithm split on four consecutive questions. Training set accuracy of the pruned tree was 0.985 and test set accuracy was 0.984. Even with a depth of 4, the tree can become a bit complex. Figure 5 shows a partial view of the decision tree

classifier of heroin use (the entire tree was too wide to include as a legible Figure), and the full tree image is available in the notebook BDA-Analytics-Classifier-Heroin.ipynb [17]. The decision tree shows the top features that the algorithm split on to classify heroin use. One way to interpret a decision tree it by following the sample numbers represented at the test split for each node. The classifier algorithm selected Cocaine Use (aggregated score) as the root node of the decision tree. The branch to the left side of the tree represents samples with a score equal to or less than 1.5 (n=40956), whereas the branch to the right represents samples with a Cocaine Use score greater than 1.5 (n=1903). The second split on the right occurs for Any Prescription Opioid Pain Reliever Use (PRLANY), with n=1443 having a score less than or equal to 3.5, and n=460 respondents with a PRL score greater than 3.5. In other words, of those respondents who reported relatively high Cocaine use, a small portion also reported relatively high Prescription Opioid PRL use. Instead of looking at the whole tree, features importance is a common summary function that rates how important each feature is for the classification decisions made in the algorithm. Each feature is assigned an importance value between 0 and 1; with a value of 1 indicating the feature perfectly predicts the target and a value of 0 meaning that the feature was not used at all. Feature importance values also always sum to 1. A feature may have a low feature importance value because another feature encodes the same information. The top two important features for classifying Heroin Use were Cocaine Use and Any Prescription Opioid PRL Use, with smaller importance given to Opioid PRL Misuse Ever and Prescription Opioid PRL Misuse and Abuse.

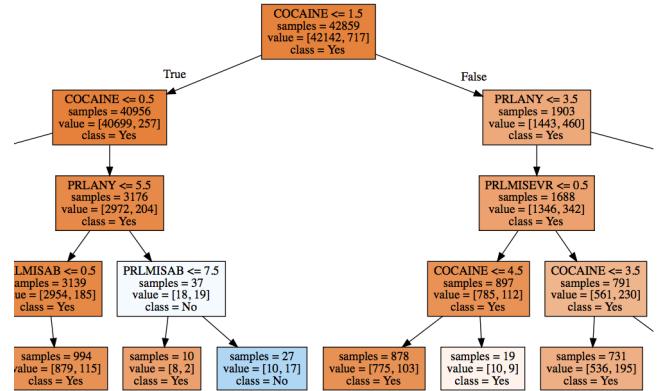


Figure 5: Decision Tree Classification of Heroin Use (Partial View)

3.2.3 Random Forests Classifier. Random forests is an ensemble approach that builds many trees and averages their results to reduce overfitting. The model was build using the *Random Forest Classifier* package in Scikit-Learn. The parameters of interest for building random forests are: (a) the number of trees (n-estimators), (b) the number of data points for bootstrap sampling (n-samples), and (c) the maximum number of features considered at each node (max-features). The max-features parameter determines how random each tree is, with smaller values of max-features resulting in trees in the random forest that are very different from each other. This

analysis applied a random forest consisting of 100 trees to classify Heroin Use, and the random state was set to zero. The training set accuracy was 0.999 and the test set accuracy was 0.984. Often the default settings for random forests work well, but we can apply pre-pruning as with a single tree, or adjust the maximum number of features. Feature importance for random forests is computed by aggregating the feature importance over trees in the random forest, and random forests gives non-zero importance to more features than a single tree. Typically random forests provide a more reliable measure of feature importance than the feature importance for a single tree. Figure 6 shows the feature importance of the random forests classifier for heroin use with 100 trees. Similar to the single tree, the random forest selected Cocaine Use as the most informative feature in the model, followed by Any PRL Use, which is an aggregated measure of prescription opioid medication use. Following after that, several features were tied for third place of importance, namely Education Level, Overall Health, Age Category, and Pain Reliever Misuse and Abuse. Random forests provides much of the same benefit as decision trees, while compensating for some of their shortcomings of overfitting. Single trees are still useful for visually representing the decision process.

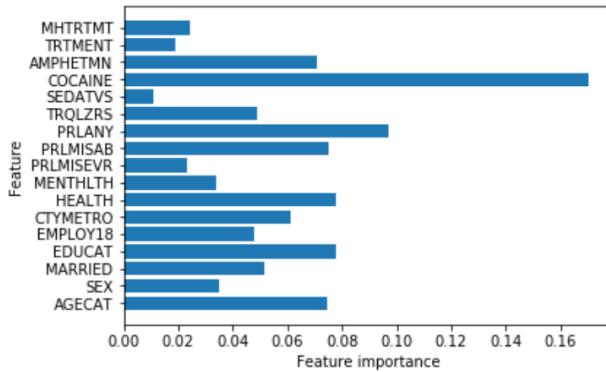


Figure 6: Feature Importance for Random Forests Classifier for Heroin Use

3.2.4 Gradient Boosting Classifier Tree. Gradient boosting machines is another ensemble method that combines multiple decision trees for regression or classification by building trees in a serial fashion, where each tree tries to correct for mistakes of the previous one [10]. Gradient boosted regression trees use strong pre-pruning, with shallow trees of a depth of one to five. Each tree only provides a good estimate of part of the data, but combining many shallow trees (i.e., “weak learners”), the use many simple models iteratively improves performance. In addition to pre-pruning and the number of trees, an important parameter for gradient boosting is the learning rate, which determines how strongly each tree tries to correct for mistakes of previous trees. A high learning rate produces stronger corrections, allowing for more complex models. Adding more trees to the ensemble also increases model complexity. Gradient boosting and random forests perform well on similar tasks and data; it is common to first try random forests and then include

gradient boosting to attain improvements in accuracy of the learning model. This analysis used the *Gradient Boosting Classifier* from Scikit-Learn to classify Heroin Use, with the default setting of 100 trees of maximum depth of 3, and a learning rate of 0.1. The model was build on the training set and evaluated on the test set, with both training set and test set accuracy equal to 0.984. To reduce overfitting, pre-pruning could be implemented by reducing the maximum depth, or by reducing the learning rate. Figure 7 shows that the feature importance for the gradient boosting classifier tree looks similar to the feature importance for random forests, but the gradient boosting has decreased the importance of many features to zero. Again Cocaine is selected as the most informative features, followed by Any Opioid PRL Use. In addition to Prescription Opioid PRL Misuse and Abuse, the gradient boosting classifier selected Amphetamine Use as an informative feature of Heroin Use.

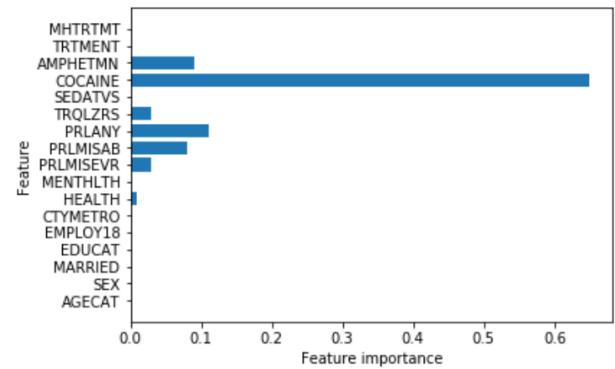


Figure 7: Feature Importance for Gradient Boosting Classifier for Heroin Use

3.3 Classifier Models of Prescription Opioid Pain Reliever (PRL) Misuse

This section reports results from the same set of classification analyses described above using *Prescription Opioid Pain Reliever Misuse* (PRLMISEVR) as the target variable. Attributes related to Heroin Use were now included as features (e.g., HEROINEVR, HEROINUSE, HEROINFQY). The classifier models were built using SciKit Learn in a python notebook [18]. The dataset was split into the training set and test sets using the train-test-split function in sklearn and the target variables was designated. Model accuracy for the training set and test set are reported, for different parameter values, with feature importance.

3.3.1 Logistic Regression Classifier. The logistic regression classifier was fit to the training data using the L1 penalty (Lasso), using different values of the regularization parameter C, and the model was validated on the test data. Higher value of parameter C typically gives improved accuracy for both training and tests sets; however, in this case, the training set accuracy was 0.901 and test set accuracy was 0.903, and these values were consistent for all values of parameter C. Figure 8 plots the coefficients of logistic regression classifier for Prescription Opioid PRL Misuse under different values of C. As

shown in Figure 8, the features with the highest coefficient values were Treatment (for substance use), Heroin Use (as predicted), as well as Cocaine and Amphetamine use. This result indicates that Prescription Opioid Misuse is positively related to Drug Treatment, meaning that respondents who reported higher levels of opioids misuse were also in treatment, but that people who were misusing opioid medications were also more likely to have used illicit drugs such as heroin, cocaine, and amphetamine.

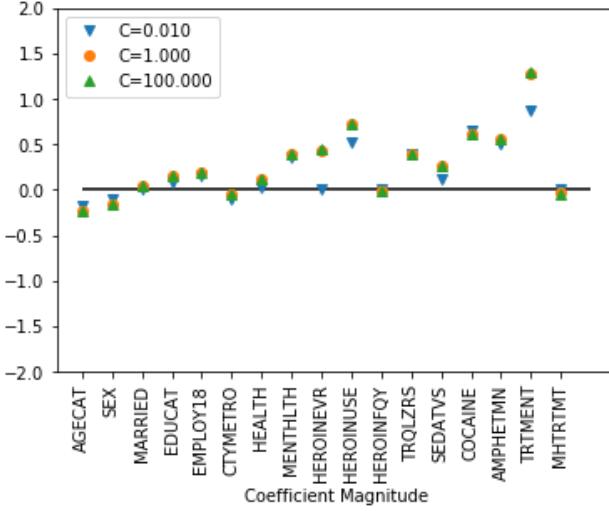


Figure 8: Logistic Regression Classification of Prescription Opioid (PRL) Misuse with L2 Penalty

3.3.2 Decision Tree Classifier. The Decision Tree Classifier package in Scikit-Learn was used to build the tree model, pre-pruning was applied with a maximum depth of 4, which means the algorithm split on four consecutive questions. The training set accuracy of the pruned tree was 0.902 and test set accuracy was 0.902. Figure 9 shows a partial view of the decision tree classifier of prescription opioid misuse (the full tree is included in the BDA-Analytics-Classifier-PRL.ipynb notebook) [18]. As Figure 9 shows, the decision tree classifier selected Cocaine Use as the root note, that branched by the test score equal to or less than 0.5 (any Cocaine Use). At the second node, on the branch to the right n=5015 samples were further divided according to heroin use, with n=1913 having a score greater than 0.5 (any Heroin Use). At the third node on the right branch, samples were selected according to Tranquillizer medication use, with n=1419 scoring positively. On the left branch, the second node selected was Drug Treatment, with n=2844 respondents scoring positively that they had received Drug Treatment. Feature importance of the decision tree classifier selected Cocaine Use as the most informative feature for Prescription Opioid PRL Misuse. Following afterwards, Tranquillizer Use, Drug Treatment, and Heroin Use were tied for second place.

3.3.3 Random Forests Classifier. The Random Forest Classifier package in Scikit-Learn was used to classify Prescription Opioid PRL Misuse as the target variable, with 100 trees. The model accuracy for the training set was 0.955 and the test set accuracy was 0.896, which

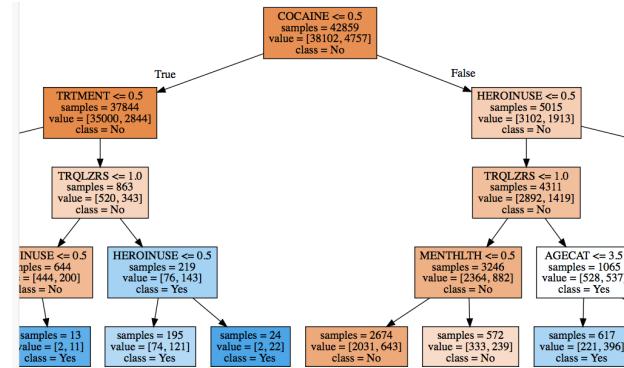


Figure 9: Decision Tree for Prescription Opioid (PRL) Misuse

suggests that the model overfit the data. Figure 10 shows the feature importance of the random forests classifier for Prescription Opioid PRL Misuse. As Figure 10 shows, several features were identified as important for classifying Prescription Opioid PRL Misuse. The random forest selected Overall Health as the most informative feature in the model, followed by Cocaine Use, Education Level, Age Category, and Size of City Metropolitan region. Because of the additional features included as important, gradient boosting was performed to clarify the feature importance.

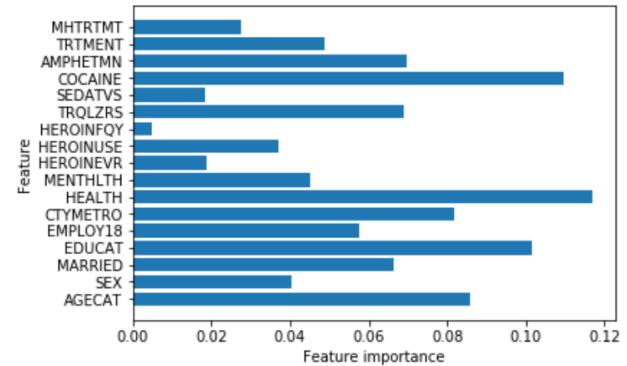


Figure 10: Feature Importance for Random Forest Classifier of Prescription Opioid (PRL) Misuse

3.3.4 Boosted Gradient Classifier. The Gradient Boosting Classifier from Scikit-Learn was used to classify Prescription Opioid PRL Misuse, using the default setting of 100 trees, of maximum depth of 3, and a learning rate of 0.1. The model accuracy for the training set was 0.894 and accuracy for the test set was 0.893. Gradient boosting typically improves test set accuracy by using many simple models iteratively. In this case, model accuracy for gradient boosting was no better than random forests, and this is because the default parameter settings were used; further parameter tuning is needed to improve model performance. Feature importance was a primary interest for identifying features related to 'prescription opioid abuse. Figure 11 shows the feature importance for the gradient

boosting classifier tree. As Figure 11 shows, several features were important for classifying prescription opioid misuse, and contrary to the random forests, gradient boosting selected Tranquillizer use as the most informative feature. Following closely in importance were Heroin Use and Age Category. Tied for fourth place were Cocaine Use and Treatment, with Mental Health (depression) coming in fourth in terms of feature importance. This result illustrates that several features are important for understanding Prescription Opioid Misuse, and the relations among features may be complex.

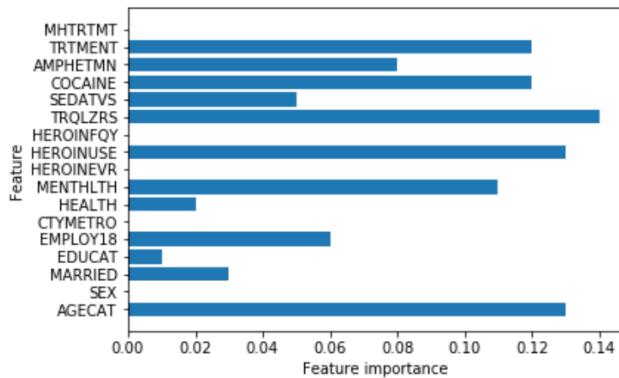


Figure 11: Feature Importance for Gradient Boosted Classifier Tree of Prescription Opioid (PRL) Misuse

4 DISCUSSION

The results show that rates of prescription opioid use, misuse, and abuse are much higher than use of illicit opioids such as heroin and fentanyl. The use of Hydrocodone (Vicodan) was double the rate of Oxycodone use (Oxycodone) across almost all age groups. The use of traditional prescription opioids was greater than reported use of synthetic opioids. Illicit drug use was highest for respondents between the ages of 18 to 25. In terms of mental health, more individuals between 18 to 25 years reported experiencing a major depressive episode (in adulthood) than any other age group. In terms of the so-called *treatment gap*, almost twice as many respondents between 18 to 25 years who felt a need for substance use treatment, had not received treatment, than younger individuals between 12 to 17 years. The large majority of respondents (approximately 90 percent) had not misused prescription opioid pain relievers or used heroin. However, of those individuals who reported misusing prescription opioid pain relievers, almost twice as many had also used heroin than had not (see Figure 1), which partially supports the hypothesis that prescription opioid use is associated with use of illicit opioids such as heroin. Prescription opioid misuse and heroin use was also higher in large metropolitan areas than smaller cities or rural areas, but a small portion of individuals in non-metropolitan regions reported very high levels of prescription opioid misuse. These data points may represent outliers, but a large sample would allow for analysis of how opioid misuse and addiction differ for smaller rural regions versus large urban areas.

4.1 Comparison of Classifier Models

Several classifier algorithms were used to identify relevant features for predicting heroin use and prescription opioid misuse. Comparing the performance of different algorithms is helpful for selecting the best model. Test set accuracy was comparable across models for both Heroin Use (0.98) and Prescription Opioid PRL Misuse (0.89-0.90). Logistic Regression provided the feature coefficients for different values of the regularization parameter C. The Decision Tree classifier provided an easy to use, interpretable visual of the decisions involved at each step of classification. Random forests provides a more reliable indication of features importance than a single tree, whereas the gradient boosting classifier included additional tuning parameter for a more powerful model and more interpretable analysis of feature importance. Each classifier method provides a different level of analysis. For classifying heroin use, the logistic regression classified showed that Prescription Opioid PRL Misuse had the highest coefficient value, but the tree-based classifiers each identified Cocaine Use as the most informative feature for predicting heroin use. For classifying Prescription Opioid PRL Misuse, logistic regression showed that Treatment had the highest coefficient value, but the tree based models each differed in selecting the most important features. Decision trees indicated that Cocaine Use was most informative, the random forests classifier selected health as the most important feature, and the gradient boosting model selected Tranquillizer use as most informative of prescription opioid PRL misuse. The different model each have their advantages and limitations, logistic regression provides the coefficients, but random forests and gradient boosting are helpful for identifying sets of important features.

4.2 Study Limitations

The main goal of this project was to identify features relevant for predicting opioid addiction by classifying cases according to heroin use. Only a small proportion of the sample reported having used heroin, and scores for mental health issues were very low. A limitation of survey data is that responses may be biased by under-reporting or minimizing the use of illicit or illegal substances. People may also be reluctant to disclose mental health issues or health problems (e.g., STDs, HIV status, suicide attempts). It is possible that this sample is representative of the frequency of opioid use and misuse in the larger population. Recent statistics from the CDC show that heroin use has increased among most demographics groups, with an average estimated rate of approximately 2.6 percent between 2011-2013 [7]. The rate of heroin use reported in the NSDUH-2015 sample was 1.6 percent. Therefore, it seems that the actual rate of heroin use in the U.S. population may not be accurately reflected in this sample. Another limitation is that the project dataset was constructed as a subset of features from the NSDUH-2015 data. Ninety attributes out of 2666 features in the original data were selected, and many features were combined to create aggregated variables for health, mental health, prescription opioid misuse and abuse, drug treatment, mental health treatment. Future research could include a more comprehensive selection of features to identify the set of features relevant for predicting opioid dependency and addiction. An important challenge for making

sense of big data is developing analytic tools adequate to handle large volumes of data.

4.3 Extension to Big Data

A general tenet of big data is that, “More data is always better.” The methods used in this project could be extended to better approximate big data for predicting opioid use in the following ways: (1) Include a larger selection of features from the attributes in the NSDUH-2015 dataset; (2) Include survey data from previous years (e.g., 2005-2015) for a larger sample; and (3) Obtain a broader sample from the population of patients who are taking prescribed opioid medications. The most immediate step would be to include additional features for use with the classifier models. Additional data from the NSDUH was downloaded from previous years (2012 to 2014); preliminary examination of the data revealed inconsistencies in questions and prescription opioid medications that would need to be resolved in order to combine data from multiple years. Data cleaning can be a time consuming process, but important for obtaining usable data. Unfortunately, owing to constraints of time for completing the project, it was not possible to integrate data from previous years into the project dataset. In working with big data, there are several steps involved in the consolidation of data from multiple sources into a single dataset (in addition to data cleaning), which include extraction, integration, and aggregation of features [13]. A future study could integrate data from different years, using a broader set of features, with more inclusive sample representative of the larger population, and integrate data from multiple sources.

4.4 Opioid Addiction and Epidemic Spreading

Drug addiction has many similar characteristics to other chronic medical illnesses, but there are unique challenges to the treatment of addiction [8, 23]. In drug rehabilitation treatment programs, patients undergo intense detoxification that reduces their drug tolerance, but are then released back into the environments associated with their drug use, putting them at high risk for relapse and potential drug overdose [6]. If the prescription opioid crisis is a genuine epidemic, we must consider the process of spreading or diffusion of contagion. Epidemic spreading is a dynamic process based on networks of direct person-to-person contact and indirect exposure via transportation pathways [2]. Epidemics are quantified in terms of the proportion of the population infected, those yet to be infected, and the rate of transmission. Potentially everyone is at risk of becoming dependent or addicted to prescription medications or illicit opioids. In terms of the opioid epidemic, rather than labeling persons as infected or uninfected, it is more useful to consider people as either susceptible to dependence and addiction or less susceptible. Furthermore, the structure of the contact network can influence epidemic spreading [12]. For example, in the case of simple contagion, weak ties among acquaintances or infrequent associations provide shortcuts between distant nodes that reduce distance within the network [?] which can facilitate the spread of contagion, or in this case drug use. Furthermore, contact networks for drug use may have “small world” properties where a small number of nodes have a high number of connections that can rapidly transmit contagion throughout the network [?].

Network analysis may help to identify the underlying structure of the contact network of opioid use, to examine pathways and points of contact in the misuse and abuse of prescription opioid medications. According to a classical conditioning model of addiction, situational cues or events can elicit a motivational state underlying relapse to drug use. Addictive behavior can be also be reinstated after extinction of dependency by exposure to drug-related cues or stressors in the environment [15]. Future research could use social network modeling to explore how drug dependency and addiction are subserved by patterns of social interaction.

5 CONCLUSION

This project compared several classification algorithms to predict heroin use and prescription opioid misuse and abuse. The results provided partial support for the hypothesis that prescription opioid misuse is associated with the use of illicit opioids such as heroin. Several features were identified as important for classifying heroin use, including Cocaine Use, Amphetamine Use, and any prescription opioid medication use. In regards to predicting heroin use, it appears the use of other illicit drugs such as Cocaine and Amphetamine was perhaps more informative than any prescription opioid use or misuse. Heroin use was selected as important for classifying prescription opioid pain reliever misuse, but additional factors also played a role, including tranquilizer use, age category, overall health, cocaine use. Substance treatment had the largest regression coefficient, suggesting that people who are misusing prescription opioid pain medication are also more likely to be in drug treatment programs. The direction of these effects cannot be determined owing to the nature of the analyses. On the one hand individual misusing or abusing prescription opioids may also be using heroin. Alternatively, individuals with a susceptibility for opioid use may be equally likely to have used heroin and also to have misused prescription opioids. A general conclusion is that of those individuals who reported misusing prescription opioid medications, twice as said they had used heroin than reported they had not used heroin. The results do not provide sufficient evidence to rule out alternative hypotheses. Given the relatively low rates of opioid and heroin in this sample, additional evidence is needed to resolve this question. The study can provide information to raise awareness about the risk factors for prescription opioid addiction and may help reduce opioid overdose deaths.

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A CODE REFERENCES

All code, notebooks, files, and folders for this project can be found in the i523/hid335/project github repository: <https://github.com/bigdata-i523/hid335/tree/master/project>. An outline of the workflow pipelines was included as a readme.md markdown file [22].

A.1 Download and Extract Data

The get-data.py function was written to download the data, unzip the data files, extract the data, and write the NSDUH-2015 dataset to CSV file [4].

A.2 Data Cleaning and Preparation

Data cleaning and preparation steps was conducted using an interactive python Jupyter Notebook [16] based on examples in Python for Data Analysis [9] and the Python Data Science Handbook [24].

A.3 Exploratory Data Analysis

Exploratory Data Analysis of the NSDUH-2015 dataset was conducted using an interactive python notebook [20] based on examples from Python for Data Analysis [9], and the Python Data Science Handbook [24].

A.4 Data Visualization

Several plots and graphs were constructed in a Data Visualization interactive python notebook [21] using Matplotlib and Seaborn python visualization packages [9, 24].

A.5 Classification Algorithms

Machine learning classification models were constructed using SciKit Learn [10, 14] in two separate Jupyter Notebooks, one for classifier models of Heroin Use as the target variable [17], and another for classifier models of Prescription Opioid PRL Misuse as the target [18].

IoT and Big Data Analytics for Equipment Predictive Health Management (PHM)

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ABSTRACT

The predictive health management (PHM) is an enabling discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk. The PHM system will monitor environmental, operational, and performance related characteristics of the product and gathered data analyzed to assess product health and predict remaining life.

In this application, the industrial rotating equipment such as compressors, vacuum blowers, pumps, and valves etc. are considered to monitor and analyze their operational behavior. The product critical operational parameter data such as vibration, temperature, and load current will be collected from field sensors and analyzed to predict the failure using kNN machine learning classification algorithms. The data will be collected from the field using wireless sensors and stored on the cloud based AWS database server. The product data will be analyzed and made available to all stakeholders to take appropriate preventive actions via web/mobile applications.

KEYWORDS

i523, HID333, HID337, KNN, IoT, Big Data, Analytics

1 INTRODUCTION

The PHM technology can be put within a broader business context by relating it to the Product-Service System (PSS) business model. PSS can be defined as an integrated combination of products and services where the emphasis is put on the “sale of use” rather than the “sale of product” [2]. Central to this new business model is a shift from selling a product, and its related spare parts as required, to selling a solution that supports customer needs in the form of a service delivering a fully maintained and useable product [2]. As shown in Figure 1, There are several wireless technologies such as 802.11, cellular, and short distance wireless protocols can be used to collect and send data to the centralized servers. Also, data can be stored in cloud based technologies such as AWS, Microsoft Azure, IBM and Google etc. for processing.

Problem Statement: in the manufacturing operations, automotive and other process industries rotating equipment such as pumps, valves, compressors, and blowers are commonly used equipment for various purposes. These equipment are severely suffered from wear and tear, bearing degradation, shaft misalignment, corrosion, and other mechanical breakdowns. Due to the limitations of wireless enabled sensors based data acquisition it was very difficult to collect this data in the past. Also, due to real-time nature of the data acquisition, it was a huge challenge to store the data locally and

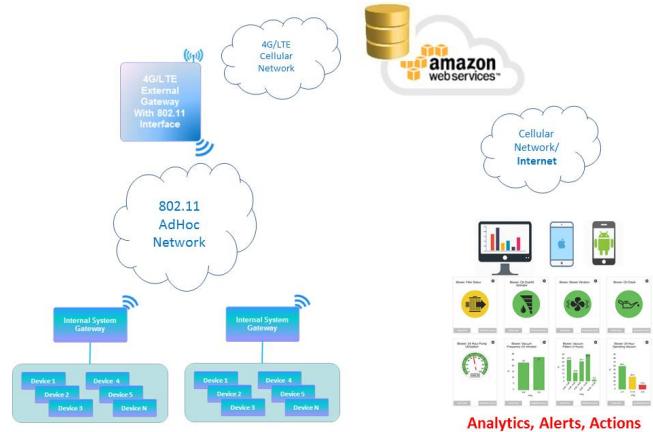


Figure 1: System Architecture

process the information for applying machine learning algorithms. All these technological and infrastructure limitations caused industrial equipment health monitoring had become one of the sector businesses are losing the money due to operation shutdowns and unplanned maintenance etc.

Solution Approach: with the wireless sensors and cloud based server technologies, it has become possible to deploy hundreds of sensors in the manufacturing plant and collect the data and store with minimal costs. Once the data is stored on the servers with high computing power, machine learning algorithms can be used to process the sensor data to predict the equipment failures with reasonable accuracy. This approach has been named as predictive or prognostics health management of the equipment which is widely available in the recent times due to the availability of technological infrastructure.

The PHM generally combines sensing, collecting, storing and analyzing of environmental, operational, and performance related parameters to assess the health of a product and predict remaining useful life. Assessing the health of a product provides information that can be used to meet several critical goals [1]:

- Providing advance warning of failures
- Minimizing unscheduled maintenance, extending maintenance cycles, and maintaining effectiveness through timely repair actions
- Reducing the life cycle cost of equipment by decreasing inspection costs, downtime, and inventory

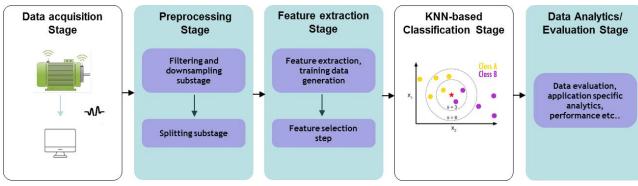


Figure 2: PHM Design Process [6]

- improving qualification and assisting in the design and logistical support of fielded and future systems

The PHM is not a new concept, however, with the advent of sensors, machine learning algorithms, and computing capacity of the servers it has become more prevalent in the recent days. In this application, an attempt has been made to prove the concept of simple PHM implementation and use in real world applications. The application can be re-architected to address more complex products/systems with considerations of scalability, performance, cost and reliability. The limitations of the current application are described in the end of this report.

The parameter monitoring and the analysis of acquired data using prognostic models are fundamental steps for the PHM methods. The sensors are the essential devices used to monitor parameters and obtain long-term accurate information to provide anomaly detection, fault isolation, and rapid failure prediction [1].

Firstly, PHM requires monitoring a large number of product parameters to evaluate the health of a product. Depending on the complexity of the monitored product, it is possible to monitor thousands of parameters in the entire life cycle of the product to provide the information required by PHM. These parameters include operational and environmental loads as well as the performance conditions of the product, for example, temperature, vibration, shock, pressure, acoustic levels, strain, stress, voltage, current, humidity levels, contaminant concentration, usage frequency, usage severity, usage time, power, and heat dissipation. In each case, a variety of monitoring features such as magnitude, variation, peak level, and rate of change may be required in order to obtain characteristics of parameters [1].

In this application, commonly used equipment in industrial and automobile operations such as air compressors, vacuum blowers, and smart valves are considered for analysis. The critical operational parameters of these products will be collected using applicable sensors from the field and fed to a database at regular intervals.

In general design, the frequency of data collection and storage depends on the number of parameters to be analyzed, cost of the system and operational behavior of the equipment. For this application, since products with rotating parts are considered, the critical parameters that would define the health of the equipment are: input or load current, internal ambient temperature, and vibration of the equipment.

The PHM application design process is shown in Figure 2, which describes various steps of the processes involved. For the implementation of this project, the sensor generated data is simulated using SQL scripts due to development time constraints. However, a detailed step-by-step approach is provided if we need to plug-in the sensor modules in to the application.

Data Acquisition Stage: It is required to have a description of a machine behaving normally that can be used for early detection of anomalies. This calls for a proper characterization of machine health. As part of this process, various methods are identified to extract health information from vibration measurements and investigate strengths and weaknesses of these methods as health descriptors. This stage will be the core part of PHM application where vibration data were experimentally obtained from a compressor using triaxial accelerometer to collect transverse, longitudinal and vertical axes vibration signals. For the experimental data collection, ACC301A triaxial accelerometer and National Instruments data acquisition system was used. A total of 8 parameters

- (1) Input Current
- (2) Input Voltage
- (3) Internal ambient temperature
- (4) External ambient temperature
- (5) Transverse vibration
- (6) Longitudinal vibration
- (7) Vertical axis vibration
- (8) Acquisition time

were captured at one second rate, which generated about 65000 records. This data has been analyzed for identifying the feature classification.

Pre Processing stage: During this stage collected data will be filtered and processed for accuracy in order to adapt them to subsequent feature extraction stage. In this application, all the pre-processing has been done manually to validate the accuracy of the data based on the system conditions. Since spectral analysis of vibration signals are not done (one of the limitations for this application, captured in the end), the data generated from the compressor is considered as the primary frequency of the equipment (which is isolated from the rest of the attachments).

Feature extraction and selection stage: during this stage domain specific vibration spectral analysis has been performed but only considered time-domain behavior for various system operational conditions such as increased load, modified input voltage, and modified external ambient temperature etc. Based on the response of the machine vibration to various external conditions were noted down. This data is used to identify the following feature vectors.

- NORMAL OPERATION AT 30 DEG CENTIGRADE
- OVER CURRENT FAULT OPERATION
- OVER TEMPERATURE FAULT OPERATION
- INPUT OVER VOLTAGE FAULT OPERATION
- ABNORMAL OPERATION AT 30 DEG CENTIGRADE
- BEARING DEGRADATION OPERATION

KNN classification stage: this stage is core part of the PHM application, which will predict the unknown test data to be classified in to a known label based on the training data set using nearest neighbor algorithm.

Classifier performance evaluation stage: this stage will be used to evaluate the classifier accuracy of prediction. In this application, k-fold cross-validation method has been used to perform the evaluation.

The data is generated and made available in Oracle database on AWS cloud to perform analysis. The application developed in this project will consist of the following components:

- Sensor Data Generator
- Machine Learning Algorithm
- Big Data and IoT
- PHM Dashboard
- Decision Alerts
- Application Script

The following sections will describe the architectural and design aspects of the PHM system implementation in detail.

2 PROGNOSTICS MODEL EVALUATION

The prediction is typically performed only after the *health* of the component or system deteriorates beyond a certain threshold [7]. In this application, faults and failures are identified in the training data set. The faults identified are: Over current fault, over temperature fault and over voltage fault. If over current fault is occurred, the equipment will tend to draw higher current than nominal values which if continued further several times eventually leads to a permanent failure of the equipment. In this application, when motor bearing starts degrading, the first observation will be over current followed by over temperature conditions. Often times, that threshold is tripped because a fault occurs. A fault is a state of a component or system that deviates from the normal state such that the integrity of the component is outside of its required specification. A fault does not necessarily imply that the overall system does not operate anymore; however, the damage that characterizes the fault often grows under the influence of operations to a failure. The latter is the state at which the component or system does not meet its desired function anymore. It is the task of prognostics to estimate the time that it takes from the current time to the failed state, conditional on anticipated future usage. This would give operators access to information that has significant implications on system safety or cost of operations. Where safety is impacted, the ability to predict failure allows operators to take action that preserves the assets either through rescue operation or through remedial action that avert failure altogether. Where minimizing cost of operations is the primary objective, predictive information allows operators to avert secondary damage, or to perform maintenance in the most cost-effective fashion. Often times, there is a mix of objectives that need to be optimized together, sometimes weighted by different preferences [7].

As emphasized above, predictive models evaluation needs to take domain specificities into account. Such specificities cover two aspects: capability of failure prediction and TTF estimation. From the point of view of TTF, it is desirable that a predictive model can generate alerts in a *targeted* time window prior to a failure. A model that predicts a failure too early leads to non-optimal component use which will impact the reliability or availability of the system [9].

As shown in the Figure 3, the time to failure prediction will be estimated based on the classified result data set and alert the stakeholders to take relevant actions. The target alert zone will be identified based on the abnormal behavior of the equipment over the period.

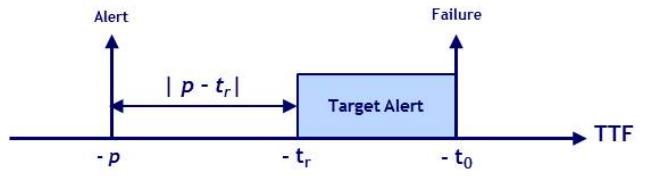


Figure 3: Time relation between alert time and failure time [9]

3 APPLICATION DESIGN ANALYSIS

The PHM application in this project considered to use rotating equipment temperature, load current and vibration data for analyzing and predicting the future operational behavior. Vibration signals from rotating components are usually analyzed in the frequency domain, because significant peaks in the signal spectrum appear at frequencies that are related to the rotation frequency of the component. In this application, only time domain parameters with peak vibration magnitudes irrespective of the frequency component. The training data set consists of normal, abnormal, and fault conditions vibration patterns describes the system characteristics from which its status can be estimated. The PHM application for industrial equipment machine failure detection problem directly correlates to the pattern classification problem. From the vibration data collected, each accelerometer will output values of X, Y, and Z data then using a KNN we can similarly identify which vibration parameter(s) determines problems in our machines, or *likely to experience failure*. The typical defects or failures that can be detected are: machine imbalance, shaft misalignment, pumps cavitation, structural and rotating looseness, early stage bearing wear, gear teeth problems, and other high-frequency defects.

This application used *Sensor Data Gen* SQL script module to generate the sensor data and store in Oracle database on AWS. This is the critical module as we have not used the real data collection from the field. However, the sensor hardware and necessary environment to generate the data is identified and experimented to work with. A brief description about the hardware is provided in the end of this report.

The PHM application is designed such that the fundamental concepts can be verified to open a discussion on limitations, performance, scalability, ROI and reliability of the system.

The following sections describe the application design components with necessary implementation details:

3.1 Sensor Data Generator

The SQL data generator script is designed to generate training data as well test data for this application with following eleven parameters: Acquisition time, equipment name, part number, serial number, internal ambient temperature, external ambient temperature, input voltage, input current, and vibration data for x, y, and z axes. The following database design architecture followed for Sensor Data Gen module:

- Sensor Data Generator PL SQL Objects
 - Tables
 - * SENSOR TRAIN DATA for storing training data

- * SENSOR TEST DATA for storing testing data
- Views
 - * SENSOR TRAIN DATA VIEW: Created View on top of SENSOR TRAIN DATA with logic to translate string label data into numbers
 - * SENSOR TEST DATA VIEW Created View on top of SENSOR TEST DATA with logic to translate string label data into numbers
- Packages BIG DATA 503 PRJ PKG
 - * Generate Test Set: PL/SQL procedure to insert sensor test data into SENSOR TRAIN DATA table
 - * Generate Train Set: PL/SQL procedure to insert sensor train data into SENSOR TRAIN DATA table
 - * Delete Data Set: PL/SQL procedure to delete all training and test data.
 - * Update Test Data Labels: PL/SQL procedure to update SENSOR TRAIN DATA table with KNN algorithm predicted label values

3.2 Machine Learning Algorithm

3.2.1 Classifier evaluation. Typical classifier evaluation methods include ROC Curves, Reject Curves, Precision-Recall Curves, and Statistical Tests. The statistical tests consists of following methods to perform evaluation:

- Estimating the error rate of a classifier
- Comparing two classifiers
- Estimating the error rate of a learning algorithm
- Comparing two algorithms

Out of the listed statistical tests, the error rate estimation method is used in this application to evaluate the performance. An experimental data is used to estimate the error rate or accuracy of various classifiers. Then a comparison has been made to choose the classifier to use in the application.

The following list of performance for various classifiers is observed during the accuracy calculation. The same set of training data has been used for all the classifiers, which has resulted the following performance. All values are mentioned in percents between 0 to 1, 1 means 100 percent accuracy.

- LogisticRegression: 0.963636
- KNN: 0.981818
- DecisionTreeClassifier: 0.964394
- SVM: 0.972727

Based on the performance as shown in Figure 4, kNN has been selected to use for this application.

3.2.2 *k* Nearest Neighbor - kNN. In this application, neighbors-based classification is chosen to classify the unknown instance to the known trained labels [10]. Neighbors-based classification does not attempt to construct a general internal model, but simply stores instances of the training data.

Classification is computed from a simple majority vote of the nearest neighbors of each point: a query point is assigned the data class which has the most representatives within the nearest neighbors of the point.

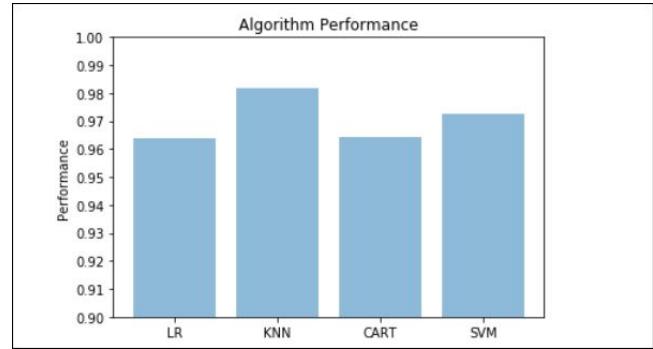


Figure 4: Algorithm performance

KNN falls in the supervised learning family of algorithms. Informally, this means that we are given a labelled dataset consisting of training observations (x,y) and would like to capture the relationship between x and y . More formally, our goal is to learn a function

$$h : X \rightarrow Y$$

so that given an unseen observations x , $h(x)$ can confidently predict the corresponding output y .

In the classification setting, the K-nearest neighbor algorithm essentially boils down to forming a majority vote between the K most similar instances to a given unseen observation. The number of neighbors for k -nearest neighbors (k) can be any value less than the number of rows from dataset. Looking at only a few neighbors makes the algorithm perform better but the less similar the neighbors, the worse the prediction will be. Similarity is defined according to a distance metric between two data points. A popular choice is the Euclidean distance given by:

$$d(x, x') = \sqrt{(x_1 - x'_1)^2 + (x_2 - x'_2)^2 + \dots + (x_n - x'_n)^2}$$

But other measures can be more suitable for a given setting and include the Manhattan, Chebyshev and Hamming distance. An alternate way of understanding KNN is by thinking about it as calculating a decision boundary (i.e. boundaries for more than 2 classes) which is then used to classify new points.

Another characteristic of KNN is it is instance based learning algorithm. Means it doesn't explicitly learn a model. Instead, it chooses to memorize the training instances which are subsequently used as knowledge for the prediction phase. It is also means the algorithm does not build a model until the time that a prediction is required. It is also lazy learning because it only does work at the last second. This has the benefit of only including data relevant to the unseen data, called a localized model. A disadvantage with lazy model is it can be computationally expensive to repeat the same or similar searches over larger training datasets.

In the application design, sci-kit open source python libraries are used for implementing the kNN algorithms. Scikit is built on NumPy, SciPy, and matplotlib. The k -neighbors classification in KNeighborsClassifier is the more commonly used of the two techniques. The optimal choice of the value k is highly data-dependent:

	precision	recall	f1-score	support
ABNORMAL_OP_30_DEG_C	1.00	1.00	1.00	997
BEARING_DEGRADE_OP	1.00	1.00	1.00	100
INPUT_OVER_VOLT_FAULT_OP	0.99	0.96	0.98	1059
NORMAL_OP_30_DEG_C	0.96	0.99	0.97	931
OVER_CURRENT_FAULT_OP	1.00	1.00	1.00	1005
OVER_TEMP_FAULT_OP	1.00	1.00	1.00	1130
avg / total		0.99	0.99	0.99
5222				
[[997 0 0 0 0]]				
[[0 100 0 0 0]]				
[[0 0 1018 41 0]]				
[[0 0 10 921 0]]				
[[0 0 0 0 1005]]				
[[0 0 0 0 1130]]				

Figure 5: KNN Classification and Confusion matrix report

in general a larger k suppresses the effects of noise, but makes the classification boundaries less distinct.

The `sklearn.neighbors.KNeighborsClassifier` class has the following methods, which are used in the application design [8]:

- fit: Fit the model using X as training data and y as target values.
 - get params: Fit the model using X as training data and y as target values.
 - kneighbors: Finds the K-neighbors of a point.
 - kneighbors graph: Computes the (weighted) graph of k-Neighbors for points in X.
 - predict: Predict the class labels for the provided data.
 - predict_proba: Return probability estimates for the test data X.
 - score: Returns the mean accuracy on the given test data and labels.
 - set_params: Set the parameters of this estimator.

3.2.3 *K-fold cross-validation*. To estimate the test error in the model, a cross-validation approach followed in which a subset of the training set will be held out from the fitting process. This subset, called the validation set, can be used to select the appropriate level of flexibility of our algorithm. There are different validation approaches that are used in practice, and we will be exploring one of the more popular ones called **k-fold cross validation**. The k-fold cross validation (the k is totally unrelated to K) involves randomly dividing the training set into k groups, or folds, of approximately equal size. The first fold is treated as a validation set, and the method is fit on the remaining $k - 1$ folds. The misclassification rate is then computed on the observations in the held-out fold. This procedure is repeated k times; each time, a different group of observations is treated as a validation set. This process results in k estimates of the test error which are then averaged out.

In this application, an average k-fold cross validation accuracy of 0.99 percent achieved, which is explained in the appendix section of the report. Figure 5 shows Classification and Confusion report output obtained from the KNN model we used for this project.

3.3 Big Data and IoT

In PHM systems big data is characterized by one or more 3Vs: volume, velocity and variety due to streaming of real-time IoT sensors. Most of the IoT systems present challenges in combinations of velocity and volume. The important feature of the IoT application is that by observing the behavior of “many things” it will be possible to gain important insights, optimize processes, etc. This requires

storing all the events (velocity and volume challenge) to run analytical queries over the stored events and perform analytics (data mining and machine learning) over the data to gain insights. In general PHM applications, data will be collected through field sensors at specific rate which accounts for large amount of data per day in the order of multi-million records. This data will be stored in any NOSQL or RDBMS based database for storage and processing. Since the big data infrastructure is much reliable and available widely from multiple vendors, it would help to build complex PHM systems with large number of feature vectors for classification.

In this application, for the demonstration of the concept, the real vibration data from the compressor equipment has been collected via accelerometer sensors. This vibration data has been analyzed in time domain and established the labels based on the compressor design performance parameters. Later, this data analysis is used to design a SQL script for generating training and test data sets. However, the real-time PHM system will have continuous streaming of data coming from hundreds of devices at faster rates (in the order of milliseconds to tens of seconds). This data needs to be captured by reliable and scalable platforms such as AWS IoT or similar and use the machine learning algorithms to classify the unknown data.

3.4 PHM Dashboard

Once all the test data set has been classified into appropriate labels, the prediction of the failure can be performed based on the trending of the equipment behavior over the period. In order to understand the equipment performance insight, following queries will be used on the classified data:

- Faults Reported by Equipment Part Number
 - Faults Reported by Serial Number
 - Abnormal Behavior by Equipment Part Number
 - Abnormal Behavior by Serial Number over the period range

There can be more application specific information obtained from classified data set to take various decisions. Figure 6, Figure 7 and Figure 8 show various PHM data analytics for this project. Figure 6 displays all the serial numbers of equipment 1 with bearing degradation problems. The X axis gives serial numbers while the Y axis gives number of occurrences of bearing degradation for that particular serial number. Similarly Figure 7 and Figure 8 give the details of over temperature and over current faults of various serial numbers.

As part of data visualization, result data file is queried based on the analytics metrics interested. The python matplotlib package has been used to draw the charts as needed for showing the analytics. In real world application, a more sophisticated business intelligence tools such as Tableau, Microsoft BI, and Amazon Quick Sight can be used to show the PHM dashboards. These dashboards are targeted for business users so that they will be able to customize the views, add filters and drill down in to specific information as needed.

Sample screen shots for the following scenarios are included from python code output:

- Bearing Degraded Serial numbers for Equipment Part Number1: Figure 6
 - Over Temperature Fault Serial numbers for Equipment Part Number1: Figure 7

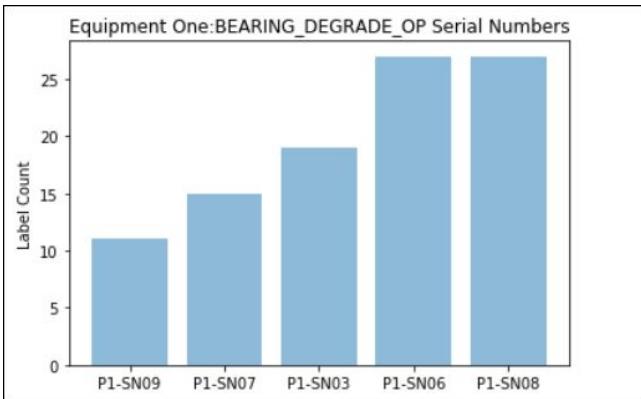


Figure 6: Bearing Degradation

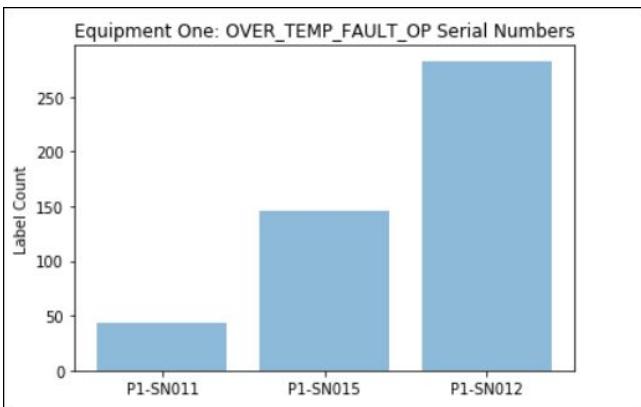


Figure 7: Over Temperature Fault

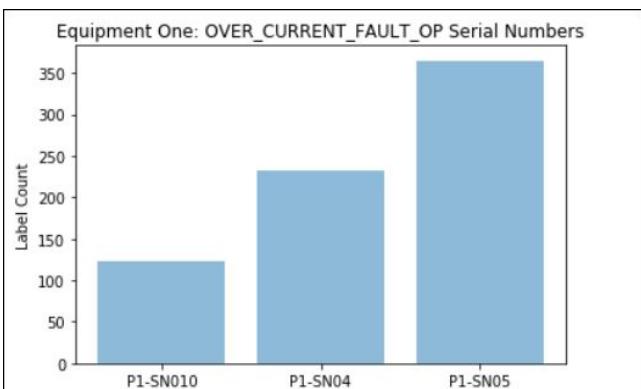


Figure 8: Over current Fault

- Over Current Fault Serial numbers for Equipment Part Number1: Figure 8

3.5 Decision Alerts

Once the results data set has been generated by the prediction algorithm, and then based on the analytics queries, PHM system

can send out the alert messages to appropriate stakeholders. The typical messages include the following s minimum:

- SN 10002: Faulted X times on over temperature in last Y days, needs maintenance to clean the filter
- SN 10005: Consistently indicating bearing degradation from last X days, needs lubrication maintenance
- SN 10009: Consistently drawing over current from last X days, needs mechanical load maintenance

In this application all the unseen test data is classified and labeled in the result data file. However, in real world application, along with the dashboards a comprehensive alerting capabilities can be built. The application checks for out of range alert conditions on selected incoming report parameters, looking for warning or alarm conditions that are higher or lower than expected under normal operating conditions.

3.6 Application Code Development

Code required for this project is divided into two categories

- Python Coding: We used **Anacoda Navigator ver 1.6.9** installation on windows7 laptop which includes Jupyter notebook application for python coding [3]. **Anacoda Navigator** also supports multiple installation and management of python environments using gui interface. The location of the Jupyter notebook file we developer for this project is mentioned in appendix b.
- PL/SQL Coding: This application specific training/test sensor data has been created/generated on AWS cloud database using pl/sql coding which will be accessed during the run time by python notebook. We used **Orcale Sql Developer** for pl/sql coding [4].

3.7 Python - Oracle Interface

For this project we used python library called **cxOracle** to enable access to Oracle Database [5]. It can be installed easily using **pip** and it supports both Python 2 and 3. This library supports:

- SQL and PL/SQL Execution. The underlying Oracle Client libraries have significant optimizations including compressed fetch, pre-fetching, client and server result set caching, and statement caching with auto-tuning.
- Extensive Oracle data type support, including large object support like CLOB and BLOB)
- Batch operations for efficient INSERT and UPDATES

In the following scenarios we used **cxOracle** libraries:

- To read sensor training data from Oracle database
- To read sensor test data from Oracle database
- After classification of labels, to update test data with classified labels

4 APPLICATION LIMITATIONS

The PHM application developed in this project has several limitations. Typically, PHM applications suffer from the prediction accuracy rate which influences the ability to take decisions that will have broader impact on the business operations and financial aspects. However, with the advanced machine learning classifiers and model evaluation methods this can be addressed to achieve

reasonable confidence. Following are some of the limitations of this application, which can be addressed and improved in large real-time PHM systems.

Data acquisition hardware: in this application the data is not collected from real-time sensors for voltage, current, temperature and vibration data. There will be inherent accuracy in the raw data generated by SQL script. However, a sample vibration dataset has been collected from the field, which is used as basis to generate the simulated data set.

Feature extraction analysis: the equipment performance parameters of interest need to be down selected from large set of incoming parameter data.

When analyzing vibration data in the time domain only few parameters are available in quantifying the strength of a vibration profile: amplitude, peak-to-peak value, and RMS. The amplitude is valuable for shock events but it does not take into account the time duration and thus the energy in the event. The same is true for peak-to-peak with the added benefit of providing the maximum excursion of the wave, useful when looking at displacement information, specifically clearances. The RMS value is generally the most useful because it is directly related to the energy content of the vibration profile and thus the destructive capability of the vibration.

This requires in-depth domain specific analysis, in this case a detailed mathematical modeling of vibration spectral analysis to precisely select the features and corresponding behavior patterns. Such analytical data should be used for training data feature set. In this application, a primitive approach of time-domain analysis of vibration magnitudes used for determining features. However, in real application these features need to be mathematically analyzed to identify the features that represent the system behavior as close as possible.

Model accuracy and scoring : the kNN algorithm used in this application validated using k-cross fold cross-validation. There are several other model evaluation and scoring methods such as accuracy (or error rate), True Positive Rate (TPR), False Positive Rate (FPR), False Negative Rate (FNR), True Negative Rate (TNR), sensitivity etc. These metrics provide a simple and effective way to measure the performance of a classifier. This application can be further improved by applying more performance measurement methods to increase the effectiveness of the algorithm design.

Scalability: the application designed in this project is very primitive to understand the basic concepts of PHM and kNN classifier implementation. This application cannot be used for PHM application in business use. To implement real world PHM application, a more comprehensive design needed by considering modularity, service oriented architecture, large number of sensors integration, big data and analytics integration etc.

5 RECOMMENDATIONS

Generality: since each rotating equipment vibrates in a different manner, a monitoring method needs to be retrained for each machine. The training on several repeated measurements on several similar equipment in several operating modes may allow for a more general monitoring method.

Feature extraction and dimensionality: In this application it has been assumed that a proper feature (selection) has been chosen,

such that the feature dimensionality is not too high. If the data lies in a subspace, application of an initial dimensionality reduction may be a good idea. It is highly recommended to perform spectral analysis on vibration data and identify various fault frequencies and their sources. This would help to extract the optimized feature vectors for the given application followed by selecting the more relevant ones.

Model evaluation: classifier accuracy and effectiveness will be varied based on the test data set. It is highly recommended to evaluate multiple models with appropriate test data to choose the best classifier for the given application.

Domain specific modeling: It is highly recommended to perform more and more domain-oriented feature vector analysis to meet the needs of predictive model evaluation for PHM applications. Domain-oriented approaches helpful and useful in evaluating classifier for applications. Generic evaluation methods could help developers in investigating overall performance of a model from the statistical viewpoint at the initial stage of model development. Domain-oriented approaches should be further used to evaluate the usefulness and business value [9].

6 CONCLUSION

In this project, the problem statement around industrial rotating equipment maintenance is described and solution principle to address the same using PHM concept is defined, experimented and results are discussed. Since this application is developed to prove the only concept but not the complete solution a section with limitations and recommendations for real world system development is described. Overall, PHM application with kNN classifier algorithm and cross validation accuracy of 0.99 percent has been implemented, verified and results are analyzed for business decisions.

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A WORK BREAKDOWN

A.1 HID 333:Anil Ravi

- Identified Project topic.
- Created architecture of the application.
- Ran experimental test to collect vibration data
- Extracted and analyzed feature vectors
- Studied, designed and reviewed kNN algorithm
- Created draft project report
- Reviewed the draft project report.

A.2 HID 337:Ashok Reddy Singam

- Implemented sensor data generation SQL script.
- Implemented kNN algorithm in Python
- Implemented k-fold cross validation design
- Created data analytics charts
- Reviewed the draft project report.

B CODE REFERENCE

All code, notebooks and files for this project can be found in the githup repository: <https://github.com/bigdata-i523/hid337/blob/master/project/jupyter>

Big Data Application in Precision Medicine and Pharmacogenomics

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ABSTRACT

This article focuses on the impending impact of big data analytics improving health, preventing and detecting illness at a preliminary stage of illness and personalize interferences. The complexity and diversity of biological data are pouring the need of big data analytics and how it is applied in biological field especially in Pharmacogenetics, personalized/precision medicine. Big data is particularly very useful in the healthcare industry as a whole for its data handling intensive nature. Over the past decade, electronic health records (EHR) have become an extensively accepted in hospitals and clinics worldwide and the amount of information is generally daily from a single patient is increasing day by day. Important clinical acquaintance and a deeper understanding of patient disease patterns can be deliberate from such data. It will help to improve patient care as well improve efficiency of patient care and disease prevention. There are few applications pointed out to be effective using big data such as Healthcare data solutions and big data in cancer therapy, continuous monitoring of patients symptoms, healthcare intelligence, fraud prevention and detection. Many people heard about the proposition of precision medicine in State of Union speech of President Obama in 2012. Since then the revolutionary process of precision medicine started to grow rapidly in healthcare industry. On January 30, on the same Precision based medical initiatives, the Obama administration exposed facts about the Precision Medicine tentative plans. Threw with a 215 million dollar investment in the US President's 2016 budget,, the Precision Medicine Initiative will product a new model of patient driven research that eventually support delivering the right treatment to the right patient at the right time[9]. On March 11, 2015, it is reported that China is planning to invest 60 billion Yuan almost 10 billion) in precision medicine (20 billion from the Central Government and the remaining 40 billion from local governments and companies) before 2030 [[9]]. There is a similar necessity of big data application to this latest emergence of biomedical domain. . Big data in precision medicine is the most widely used methods in precision and personalized medicine which is a life changing event in healthcare industry. Personalized medicine or called as Precision medicine is product and services that leverage the science of genomics and proteomics and take advantage of on the trends concerning wellness to enable preventive care. By using big data analytics, prevention and detection of diseases are in a new era of healthcare which essentially improving daily life of every patient. Personalize medicine is the in an era of new modern healthcare innovation. The role that big data analytics may have in interrogating the patient electronic health record headed for improved clinical decision support is discussed. In this paper we try to examine developments in pharmacogenetics

that have enflamed our appreciation of the reasons why patients respond inversely to chemotherapy in cancer treatment. We also try to measure the development of online health infrastructures and the way healthcare data may be capitalized in order to detect public health warnings and control or comprise epidemics. Finally, this paper talks about how a new generation of body sensors in form of implanted in human body may improve comfort, rationalize management of chronic diseases and progress the superiority of surgical implants which could be effectively used in near future. So, let's talk about what is precision medicine? How is it related to other dealings such as personalized medicine and omics technologies (especially in Pharmacogenomics and in Pharmacoproteomics)

KEYWORDS

Keywords- HID348, Precision Medicine, Pharmacogenomics, Pharmacoproteomics. Big data Application, Data analytics, Big data infrastructure

1 INTRODUCTION

The complexity, diversity, and rich context of data being generated in healthcare are driving the development of big data for health [3].The data captured at these portals can also help significantly reduce the cost of drug discovery as improved predictive analytics to determine which drugs work well and which are not as effective for certain conditions. Big data analytics may even allow for uploading the genomics of large populations that can be warehoused for researching new generations of drug remedies. Big data analytics is becoming increasingly popular in modern world with almost every domain. Big Data means lots of data used for analysis and get the insight from the data. Big data applications in general is applicable to any domain such as Retail, Healthcare, Finance and Supply Chain efficiently but in current world the application of Big Data has a major impact on healthcare sector where daily volume of data quadruple in every minute around the globe. Organizations are using Big Data to envisage the future with the goal of making them smarter and competitive in daily work. Applications from Big Data has become from retail industry where Big Data helps retailers gain insights into the customer needs and by monitoring customers' habits future can be effectively utilized, HealthCare and Hospitality[3]. Government agencies are progressively integrating Big Data analytics to control crime and sustain law by foresee the circumstances and by using social media, it is trying to achieve other benefits out of it. So, to get actionable data and perform analytics requires specialized tools which can handle this

massive amount of data as well as help in analysis of the information. There are thousands of Big Data tools available in the market right now which contribute significantly to healthcare analytics. There are open source tools like Hadoop, which is named as big data umbrella and in big data ecosystem. Today's healthcare data are beginning analyzed using aforesaid big data tools such as Pig, Cassandra, MongoDB and others. The quality of health care services in US and across the globe have been enhanced tremendously because of the advancement in health care services, advancements of technologies and Artificial intelligence process which improved the accuracy of healthcare as a service to next level. According to Google Trends analysis, the number of searches using the keyword "big data" started to increase dramatically in 2011 and reached the peak in 2017 [3]. Although the term "big data" resonances as if it is connected to the area of data science, big data and data science both play a significant role in healthcare research especially in precision and emergency medicine. Conventionally, scientists have adopted the traditional 4Vs criteria to describe big data: volume of data, velocity of data which is speed of incoming and outgoing data and variety which is range of data types [5]. However, from the perspective of medical science, this classification may not be real world sufficient as the 3Vs criteria are forceful and time-reliant. Big Data is a capacious collection of data that cannot be achieved by traditional database management systems (RDBMS). Big Data is an umbrella term used for the enormous amount of data produced from countless of sources such as mobile, web, sensor devices, enterprise applications and rigorous digital repositories. In big data umbrella, data can be structured as well as unstructured or semi-structured. The data varieties from terabytes to exabytes of data [5]. The relational database management systems (RDBMS) have proven inefficient to handle such huge volumes of data in form of patient records such as X-ray, Scan and routine checkup results. Another important factor which renders the conventional database systems inappropriate is that the majority of data being generated as unstructured, the RDBMS systems are only adept to handle structured relational data. Hereafter new tools and systems for data analysis and management have emerged. Volume, velocity, variety, veracity, variability, and value are the three must have Vs of big data and these are condensed in the integral challenges of biomedical and health informatics. Effective ways of confronting these challenges would cover the way for more intellectual healthcare systems focused on early detection, prevention and personalized treatments. As Big data is characterized by the 4 Vs. We discussed about the 4Vs below which essentially contributed to the success of healthcare management [3]. 1. Volume- As data are increasing day by day, it is always in light of voluminous collection of data. The complete volume of data generated these days by real-time applications such as X-ray machines and MRI systems and other external data sources such as Facebook comments, tweets or even patients' data, it runs to petabytes and exabytes of data. Big Data technology empowers us to store this amount of data on dispersed systems [5]. 2. Velocity- is the proportion at which data is arrived. As an example, in whole gene sequencing process, one sequence generates huge volume of data and when the sequencing process is completed data arrives at a very higher speed having few time to store and analyze the data. 3. Veracity- When the volume increases so does the quality. Veracity refers to the quality of the data.

There are doubt of good quality of accurate data being generated in recent times. Big Data applications empower working with data which are large in volume, accurate and insightful [5]. 4. Value- Everything in the world has a value so does the data. There is an intrinsic value that the data holds and discovers for analysis. Value is the heart of Big data analytics and the way data generated value in healthcare is just enormous. Modern technologies have made it possible to find the insight from data. Since data is huge and storage capacity leads to an expensive turnaround. Apache Hadoop is the savior in these kind of applications by processing gigabytes of data in a very short span of time and Hadoop ecosystem consisting of MapReduce a different language processing system or Hive and Drill an analytical SQL platform on Hadoop or Spark, in memory data flow system or HBase/MongoDB in memory database systems or HDFS, capable of storing petabytes of data or streaming systems such as Apache Storm and Kafka, overall these all highly capable tools can be profoundly effective in healthcare biomedical data analytics.

2 WHAT IS PRECISION MEDICINE

Precision medicine in broader terms is another name of preventive medicine. According to the Precision Medicine Initiative and American Healthcare Association, precision medicine is an emerging approach for disease treatment and prevention that takes into interpretation of individual heterogeneity in genes, environment and routine and lifestyle for each person. This approach will allow medical professionals and researchers to predict more accurately about the treatment and prevention approaches for any particular disease about its effectiveness. It is in divergence to a one-size approach in which disease treatment and prevention strategies are developed for the average person with less deliberation for the genetics-based differences between each individual. Though the term precision medicine is relatively new in medical industry, the concept has been there and as a part of healthcare for many years. As an example, a patient who needs a blood transfusion is not given random blood from blood bank storage rather it will be from a process of donor's blood type is matched to the recipient to decrease the risk of future problems [10]. Although illustrations can be found in numerous areas of medicine the role of precision medicine in day-to-day healthcare is relatively restricted. Medical researchers expect that this approach will increase in many areas of health and other healthcare domains in upcoming years. Precision medicine is being sought to transform how we as a whole improve health, treat and prevent disease. Today most of the medical treatments are intended for the average patient using the one-and-one approach. However, in many cases, this approach is not at all effective because treatments can be very successful for some patients but not for every patient [5]. As an example, if Patient A and Patient B both have stage 3 lung cancer, giving the same chemotherapy to both the patient helps one but not the other. In precision medicine with the help of big data technology, medicines are targeted to specific genomic sequences rather than a random selection. In advanced countries like USA, a rigorous process is already in place to target particular genes after finding the root cause of the disease. It is a big data application which enables to store the data and use analytical tools to get useful information out of it. Overall, Precision medicine is a field

of medicine that takes into interpretation individual differences in people's genes, environments, microbiomes, habitual effects, and family history to make diagnostic and beneficial strategies accurately personalized to individual patients. Precision medicine is a newer term referring to a similar ground compared to another word if personalized medicine. The term if precision medicine arrived the scientific dictionary in the year 2008 when business strategist Clayton Christensen, of Harvard Business School in Boston, invented the appearance to describe how molecular diagnostics allows physicians to unambiguously diagnose the cause of a disease without having to rely on perception [5]. The name precision medicine didn't gain enough attention until 2011 when a committee convened by the US National Research Council placed out a plan for modernizing the classification of disease on the foundation of molecular information such as causal genetic variants instead of a symptom based cataloguing system. The committee called the report Toward Precision Medicine [3]. There are many areas where precision medicine is vastly applicable and are very much beneficial such as, finding correct dose of prescription drugs, root cause analysis of a disease and so on. The field of pharmacogenomics aims to understand how genetic variations influence individual responses to medications. Genetic tests for supervisory treatment decisions are becoming increasingly available across miscellaneous areas of medical care. These kind of tests provide more effective drugs to patients earlier in their treatment and with fewer negative side effects and in less costly than previous tests. Precision medicine is also pertinent in Cancer detection, Genomics and cure process. Oncology is the target of some of the most auspicious precision medicine approaches available today. Cancer forms through the gradual accumulation of genetic DNA changes in genes that regulate cell growth. That is why, cancer is very much an illness of the genome. Depending on where in the body the cancer started and the types of genetic changes the cells grow, different types of cancer have very different genetic profiles which completely varies person to person and highly dependent on their family history. These genetic sequences can be used in a number of ways to help medical professionals choosing the best treatments for each individual patient. Growing tissues replacement is another way to apply precision medicine in pharmacogenomics [3].

2.1 Personalized Medicine

The concept of personalized medicine dates back many hundreds of years although the term seemingly similar meaning with precision medicine. Mere from 19th century, scientists started to measure the chemistry of root cause of any illness and the research improvements are granular over time. With the growth of the pharmaceutical industry and medical technology industries in recent times came the rise of genetics, data mining and imaging. Halfway over the period, comments of specific alterations in retort to drugs contributed growth to a body of study attentive on classifying crucial enzymes that play an important role in disparity in drug absorption and reaction and this is helped as the basis for pharmacogenetics. In recent times, sequencing of the human genome customary in motion the transformation of personalized medicine from an knowledge to a practice. Personalized diagnosed tools are now created with rapid developments in genomics along with advances high critical areas

such as computational biology, medical imaging, and regenerative medicine and treatment [5]. Personalized medicine first appeared in available mechanism in 1999 with the creation of some of the domain specific core concepts even dating back to 19th century [2]. So basically personalized medicine is referred to treatment depending on each individual's personal structure and history. Initially, personalized medicine is the idea that assortment of a treatment should be custom-made giving to the individual patient's specific physiognomies, including age, sex, gender, height, ethnicity, diet, and environmental factors against traditional clinical trials on group of people which has been happening since the invention of medicine happened [5]. Scientists got interested on personalized medicine when medical professional started understanding the essence of gene in human development. Several human genome projects have been conducted since then and the importance of personalized medicine started in limelight. With deceitful out in order the 3.2 billion units of our DNA, scientists flashed a blaze of detection and a detonation of genomic knowledge in medical science history [2]. Novel omics technologies including microarrays, whole genome single nucleotide polymorphism [SNP] chips, RNA interference high-throughput transmission, next generation sequencing are the few procedure which accompanied with this revolution. All the above launch a new epoch in personalized medicine which is called genomic revolution era which bids us limitless probable and countless promise containing the expansion of personalized medical products for each individual based on their sole genomic information [10]. Advancement of genomics science along with the developing of new omics technologies, personalized medicine is today frequently well-defined as a combination of molecular profiling (omics methods) and customary methods such as family history, lifestyle and environment, which create analytic and beneficial strategies precisely personalized to individual patients [2, 5].

3 BIG DATA IN PRECISION MEDICINE

Once again the term Big data is signifies in collection of large and complex data sets which are difficult or sometimes impossible to process using common database management tools or traditional data processing applications even with modern advancement of traditional data warehousing tools such as Amazon Redshift. In 2012, the Obama administration announced the Big Data Research and Development Initiative [7], which explored how big data could be utilized to address important problems faced by the overall healthcare system. Since then, Big Data becomes such a big term that people tend to claim any kind of data analysis to be if Big Data if characterization. The overall concept of big data can be explained in various ways. One way is, Big data is a comprehensive term for any collection of data sets are so voluminous that processing the data in the begging stage itself is very hard. With four if Vif characterization of big data m, complexity arises more to collect data and make meaningful information out of it. Omics data, mobile internet real-time data and electronic health record data are the top three areas for Big Data in medical research. Precision medicine will use all of these three Big Data. In fact, among the 215 million investment in the USA President's 2016 Budget, 130 million (over 60 percent) will be used for building a large US cohort for precision research [7]. In this regiment study, the scientists will use widespread omics

data, electronic health record data gathered from several hospital and private practices along with mobile internet data [*]. Thus, omics and medical big data are one of the key pairs in the success of precision medicine in healthcare industry as a whole.

4 BIG DATA CHALLENGES IN HEALTHCARE

- Whenever anything benefits us, that comes with its own challenges and problems. The primary idea of big data to be applied in healthcare is to roll massive healthcare dataset with individual information. As the need of more data driven enterprise grows Besides general challenges inherent to the analysis of big data such as missing data, vague data, and varied data, employing big data in health care systems imposes new challenges which includes the lack of reliability and a solid data governance of some biomedical data, issues of privacy and security and confidentiality, insufficient data from random clinical trials including successful and failed trials, and overall low quality data. Challenges in machine learning and statistical applications also put the analytics in challenging situation where model development and execution are critical to success[2]. Healthcare providers who have hardly come to grasps with driving data into their electronic health records (EHR) are now being questioned to pull actionable insights out of them and apply those learnings to complex initiatives that straight impact their repayment rates. Organizations who can integrate this data driven technological innovation to their healthcare operations are in the most benefit[6]. Data assets and data insights can be achieved by using healthier patients, increased visibility in operational excellence, lower care costs and higher staff and consumer satisfaction rates are among the many benefits of turning data assets into data insights. The journey to evocative healthcare analytics is difficult challenge and problems by solving those will benefit the industry to the highest extent. The way overall big data analytics work, collecting, storing, analyzing the data require clear presentation to the staff members to understand the overall workflow process[5]. Analyzing genomic data is a computationally are some of the top challenges organizations typically aspect when striking up a big data analytics program and how can organizations overawed these issues to attain their data driven clinical and financial goals are the most important aspect of big data implementation. Understanding unstructured clinical nodes, storing unstructured patients health records are complex in nature and specialized training is required in implementing the analytics platform is essential. Some of the pitfall of big data application in precision medicine is discussed below.

4.1 Data Collection

This is the most crucial stage in any data driven technologies, capturing the patient's behavioral data through several sensing processes; with their numerous social interactions and communications. The data many come from many sources or in different format but not everywhere data governance is properly applied while collecting the data. Capturing data which is clean, comprehensive, correct, and well formatted for use in diverse systems is an ongoing combat for organizations, many of which are not on the endearing side of the battle. As an example, electronic health record capturing in right movement help physicians to access the accurate picture

of the patient's history. Oftentimes, delay in collecting this data create problems which eventually leads to unhealthy environment and future risks. Revolving Healthcare Big Data into Actionable Clinical Intelligence Providers can start to recover their data capture procedures by ranking valuable data categories for their specific plans, conscripting the data governance and honesty knowledge of health information management professionals and evolving clinical documentation improvement programs that tutor clinicians about how to confirm that data is valuable for downstream analytics [5]

4.2 Data Cleaning

Healthcare providers are well familiar with the importance of cleanliness in the clinic and the operating room but they are not aware on many things which could lead to a clear picture of the meaningful data. Data which is dirty and raw might have a potential impact on big data analytics projects and can screw up the true insight completely. Data cleaning also known as data scrubbing always ensures that data is not inconsistent, proper and useful in perspective and predictive analytics. Though when everything started, data cleaning was a manual process, but now with the help of big data quality tools, cleaning data has been easier than ever before. Since data cleaning is complex and tedious process in particular healthcare system, oftentimes big data analytical tools stand by the first door where data streamline occurs. Which eventually cleans the data with a global standard before it entered to main stream pipeline.

4.3 Data Storage

This is the most critical place where big data application play a key role. As the volume of healthcare data grows exponentially many healthcare providers are not able to manage the costs and effects of on premise data centers. Although many organizations are most happy with on premise data storing which also leads to security issues and data governance issues. With the help of cloud storage almost 90 percent of healthcare providers have chosen cloud based data storage centers which provides better flexibility and availability of data. Amazon web services, Microsoft Azure cloud and Salesforce cloud have put the data storage industry to the utmost point where no longer organizations need to worry about the cost and capacity of storing humongous amount of data. The cloud offers sprightly disaster recovery, lower set up and upfront costs and easier development, although organizations must be extremely careful about choosing partners that understand the significance of HIPAA law and other healthcare related compliance and security issues [3]. Many organizations finish up with an amalgam approach to their data storage agendas, which may be the furthestmost supple and workable approach for providers with variable data access and storage necessities. When creating hybrid substructure providers should be cautious to safeguard that dissimilar systems are able to interconnect and portion the data through extra segments of the organization when necessary [6].

4.4 Data Security

Data security is the number one priority for healthcare organizations, particularly in the wake of a hundreds of data breaches, hackings, and intrusion incidents. Data is so sensitive especially

in healthcare systems that a proper security measure has to be taken to protect the data. Healthcare privacy law such as HIPAA and others put the organizations in the front door where every healthcare providers must conform the law to protect the data. For precision based medicine era, this has become more important with each individual patient's data being captured and analyzed. Since genomic science is completely depending on data architecture, one data breach can push the healthcare provider in a tremendous reputation and financial loss. Due to this, security is one of the most talked topic in personalized medicine [2].

4.5 Data Governance

Healthcare data, particularly on the clinical side has a long ledger life. In accumulation to existence required to keep patient data available for at least six years of time frame, providers might request to use de identified datasets for scientific projects, which makes continuing stewardship and curation an important concern [2]. Any data can be used for variety of other purposes as long as data masking is properly applied to the dataset. Understanding of the data when it is created by whom and for purpose can lead to positive results while in research.

4.6 Data Querying

Vigorous metadata and robust stewardship procedures make organizations to comply with data querying very effectively. There are many tools in the market which can give access to query from databases to get the useful information. Azure datalakes, different programming based API, Hadoop Sqoop are the few tools which help in big data query language extraction. Many organizations use Structured Query Language (SQL) to dive into large datasets and relational databases, but this can only be true if end user can trust the data they are working on which can provide useful information to them [2]. Data Reporting: Reporting is the end to end product of any data collection and process. Big data reporting can help transform virtually all aspects of the enterprise. From quickly producing actionable intelligence to driving productivity to gain real time visibility into customers and markets, big data analysis and big data reporting promise to deliver a wealth of benefits for competitive advantage [*]. Many companies including not for profit hospitals use reporting as their sole decision making procedure. Data reporting helps unveils the insight into charts and graphs and visualize the insight to the target audience. In healthcare organizations especially in precision medicines, reporting of the finding is must have to take informed decision. Data reporting has the potential to show about the result of an ongoing research study or data findings. [2].

4.7 Data Visualization

In patient care, a clean and attractive data visualization can make it much easier for a clinical staff to understand the fundamental very easily and take decision based on it. Color visualizations are a popular data visualization technique that typically yields an immediate response as an example, red, black color divergence is. Organizations must also consider good data presentation practices such as charts, graphs, scatterplot. Common examples of data visualizations include heat maps, bar charts, pie charts, scatterplots,

and histograms, all of which have their own specific uses to prove concepts and material.

4.8 Data Update

Healthcare data is non-static and almost all the elements requires an update in daily interval. Some datasets such as patient vital signs and symptoms, may require frequent update. But patient's demographic information may change once in a while. Since in genomic since changes are captured in every interval or procedure, there has to be constant update to the proper and existing dataset. The most critical phrase comes when incremental data is gathered and new data is added to existing dataset. In precision medicine, medical professional compares whole gene sequences in different timeframe of the disease and in different medicine stages. In these case, data has to be updated regularly in order to analyze the proper data [?]. Organizations should also confirm that they are not making needless identical records when endeavoring an update to a single component which may make it problematic for clinical staff members to access needed information for patient decision making.

4.9 Data Sharing

With the essence of electronic medical record, data sharing become easier but complicated in healthcare analytics. With large volume and the structure of the data, healthcare providers and researchers are immensely beholding data which may contribute finding to their scientific invention. Data exchange is a perpetual worry for organizations at any costs. With the increase data volume and nature of the data, it is getting more and more difficult for the organization to move data from one to place to another without losing information and change in pattern on data lineage can lead to significant mislead information. [6].

5 PRECISION MEDICINE AND OMICS

With the growth of big data, organizations move into NOSQL databases where security is a growing concern. Though we found there are severe security issues in most of the NOSQL databases which are used today in big data environment. Lack of security measures put extra sensitivity to the overall big data applications being NOSQL databases are heart of any big data project. Though not reached at pick, constant evaluation and research are in process to make NOSQL databases more secure in near future. The evolution of omics outlining technologies significantly benefited studies are conducted on diseases mechanism, molecular diagnosis and personalized treatment [5]. The study of omics is strongly related to the study of biology as a whole and precision medicine. There is a strong connection between Omics and Precision medicine and big data as a whole has become the core of precision medicine. The advancement of precision/personalized medicine depends heavily on the ability to acquire biological aces at omics interval though the training of precision medicine does not use sole omics data and omics knowledge [1]. This happens due to molecular characteristics found from omics data can categorize diseases and classify population of patients appropriate to assured common treatment more exactly [5]. Biology has become more data intensive and technological intensive subject .Following this trend, many of the emerging fields of large-scale data rich biology are designated by

adding the suffix *fi*-omics to previously used definitions. Particularly, the word omics refers to a field of study in biology ending in the suffix *fi*? omics and it is related addresses the objects of study of such a field[5][2]. Pharmacogenomics is the study of how a person's response to drugs is affected by his genetic makeup [3]. It combines pharmacology which is also called the science of drugs and genomics which is the study of gene and their functions to develop effective, proper medications that will be personalized to a person's genetic makeup. Pharmacoproteomics, essentially a sub discipline of functional pharmacogenomics which is a study of how the protein content of a cell or tissue changes qualitatively and quantitatively in response to treatment or disease, what the protein-protein and protein ligand interactions are in related to drug response, and how a person's protein variants in quality and quantity affect a person's response to a drug [10]. In modern days, the pharmaceutical industry has developed strong interest in Pharmacoproteomics with the anticipation that this technology will lead to the empathy and authentication of protein targets and eventually to the detection and growth of feasible drug candidates. Pharmacogenomics and Pharmacoproteomics will help the prescription of drug and related doses to a patients based on response to a drug which greatly indorsing the advance and practice of precision/personalized medicine [10]

6 MANAGEMENT AND PROCESSING OF OMICS DATA

There is no shortage of data in healthcare and it is growing 40 percent annually according to IDC. Data in healthcare is not always about volume in healthcare but there are several factors can contribute to it as well such as *fiRegulations*, *fiComplexity* and *fiIntegrity*. To process the volume and complexity of Omics data, there is a need of major investments in research laboratories in form of computational and storage capabilities. Laboratories need servers or cloud service storage access to store this massive amount of data. In traditional way, servers are costly in maintenance and ended up in profligate or sub optimal servers which are even more added cost load. In the past decade, cloud computing is closing the gap in handling omics data. Cloud computing is a high scalable multi-processing semantic environment which operate virtually with some of the great benefits to any organization such as costs, speed, global scale, productivity, performance and reliability. A good example comprise the *fiEasyGenomics* cloud in Beijing Genomics Institute (BGI) and *fiEmbassy* clouds as part of ELIXIR project in collaboration with multiple European countries (UK, Sweden, Switzerland, Czech Republic, Estonia, Norway, the Netherlands, and Denmark) [8]. In several circumstances, Graphic Processing Units or GPUs are also used in cloud environment as GPU's are named to provide faster processing of data compared to Central Processing Units or CPU's. There is also a high need of parallel computing in processing of Omics data along with data validation need in research platforms before Omics data are utilized. Along with software application in storage which is only one side of the medal there is a huge need of integration between biological system and the Omics data. Moreover, analysis of big data requires most recurrent data access to turn data into real knowledge. Even though we can take up the occurrence of an appropriate volume

of bandwidth inside a cluster, there is a great need to have use distributed computing infrastructure in effective solution adaption. In big data technological umbrella there are two highest performance parallel file systems are the General Parallel File System (GPFS) [8] a product of IBM, and Lustre [] which is an open source platform. Predominantly most supercomputing systems such as Lustre is used in Titan, the second supercomputer of the TOP 100 list (December 2017) [8]. The storage capability of Titan contains more than 20,000 disks which is equivalent to 40 Petabyte of storage and almost 1 Terabyte per second of storage bandwidth. Among many software companies in big data business. IBM file management solution is operational as a regulator plane for smooth data handling. Since the access of data is so frequent, modern software's can automatically switch less frequently accessed data to the less expensive storage available in the infrastructure keeping the most expensive storage for critical and sensitive data. Nowadays, moving the data from less expensive storage to expensive storage is completely depending on analytics supported decision making which includes pattern, storage characteristics and network pattern. Hadoop file systems plays a very important role in Omics data storage and overall data processing capabilities as explained above. Besides HDFS, Middleware is also essential in development of user specified custom solutions. A suitable example is R, considering a statistical programming tool, R is more robust now to handle high volume of data in biomedical data analytics and with help of middleware it can be used best in Omics data analysis as well.

7 ANALYSIS OF BIG DATA IN OMICS USING COMPUTATIONAL FACILITIES

HPC clusters along with grid computing used as customary platform for big data applications. Over the years it has been documented so many drawbacks of these platform in real environment where data manipulation and data integration were critical for success. Through cloud computing small and medium size laboratories can now leverage the power of data by accessing the data they want through cloud storage devices. Cluster computing which is a data parallel approach processes data independently with a high scalability. De Nova assembly algorithm is a renowned algorithm which is developed on cluster computing. This system can process daily genome sequence and find sequenced reads overlaps using in memory distributed approaches. Here the data is held in memory clusters unless it is sequenced differently [4]. Another high computing big data application is Intel's Xeon Phi which can deliver massive parallelism and vectorization to support high performance computing applications. Xeon Phi is an excellent support systems application in data discovery workloads and high dimensional matrices can be used to a level which can significantly benefit the thread level parallelism. Along with some established and newly added big data application which can great change the biomedical industry, we have documented the used of data semantics in many research laboratories in their data discovery process. Semantic data uses RDF or Resource description framework, Web Ontology Language or OWL, SPARQL or Protocol and query language for semantic web data sources and extensively use of XML (Extensible

Markup Language). Oftentimes these have a dense use in bioinformatics and biostatistics to integrate all data formats and standardize existing ontologies [4].

8 CONCLUSION

Personal medicine, Omics technologies and pharmacogenomics are the evolutionary invention in medical industry, holding the hands of these medical concepts scientist can not only find the cancer cell in human body parts as well as start of cancer as a disease in a particular cell. These all is possible due to the essence of big data which not only helped organizations to tackle the voluminous data effectively but to use them in a way to get meaningful insight out of it. Massive parallel computing and clustering are now opened up new window in medical research where processing of huge amount data is better than ever before as well as build automated model on top of it. Whole gene sequencing is an example of how a big data can help strong millions of genetic information in a single storage system and take useful information out of it. With the help of big data in precision based medicines scientists are now able to predict the origin of the disease, track and cure it more effectively.

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Diversification of Big Data

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ABSTRACT

There are some ideas around the conception of big data and how it is used in the market outside of a programmer's computer. What I mean to try, and state here is that there is an idea of how big data is used and functions in the world. As a programmer, we cannot just focus on what we contribute to the programs, meaning we cannot only look at our computer data and creation of such programs as a means for our own scientific endeavors and egos, we must understand how such creation are reflected into the world and how such programs create a very interesting market exposure. Therefore, we write this paper to analyze the enterprise of big data. We will use this paper to seek out the multiplicity of avenues in which big data is used by our technological world (mainly those that seek to use big data to create diversified consumer experiences).

KEYWORDS

i423, hid109, Big Data; Social Media; Online, Shopping, Customers; Pricing; Dynamic, Internet, application

1 INTRODUCTION

In order to begin a type of observation around this topic, we need to first establish what types of enterprise we will look into in order to make our observations. We will look at Online Shopping, streaming services, and Social media. These forms of enterprise concentrate their use of big data to create a diversified user experience, one which looks to creating more possibilities and other forms of consumer products for consumers. We would also like to use such an observation to understand the use of big data in these types of enterprises and how such uses render experiences and technology of big data as a good form of consumer study.

2 OBSERVATION

Before we begin our in-depth observation, it is important to showcase the Big Data technologies, some components of big data that make it what it is. There is of course an array of technologies that facilitate and create big data. In the creations of big data, we can see many enterprises like the generations of web pages (in which individuals, corporations, government, and the like, produce these pages with data). We can also see digital imagers that facilitate data collection as well. These types of data can come from telescopes, MRI Machines, and Video Cameras. Another source of data production can come from biological and chemical sensors, things like microarrays and environmental monitors [21].

From production of data there must be a medium that collects this data, that is of course usually computers. These data can be collected in things like the internet and localized sensor networks.

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These sources of course can both collect and analyze the data. From collection, there are also storage capacity for these data. In that, we find that there are many storage type disk (magnetic disk) that can hold tons of data. There are also cloud services with which data can be stored.

Big data is crucial to the developments of many businesses that drive on the interactions and recommenders of their clientele. When we are looking to understand big data and how it is used by big contenders, we must first look to the companies to see what uses they have for big data. Let us begin with looking at Amazon, an empire built on e-commerce, the selling and recommending of products to consumers at efficient and effective rates. When we look at how this company succeeds, we can see that the main component to its success comes from its unique and bold use of big data.

3 ALGORITHMS, PREDICTIONS, AND BIG DATA CRAZE WITH ONLINE SHOPPING

When a consumer is shopping on Amazon, they can click on the image of the product they would like to view. During this process, they will probably go back and look at other products to compare the product to other products that are similar. Therefore, what can a company do to ensure that they are helping their consumers with this process? By pooling this data into other similar consumer searches and sells. For Amazon to do this they have a very complex system of enterprise that is meant to survey this, their use of big data. But it also comes down to very simple standards that are used by consumers.

When a consumer is shopping on Amazon they can administer filters to help them narrow their searches of products that they like. But during this process of administering these filters, the consumer is also being surveyed of searches made in the past to better associate what the consumers wants and needs within the products that they are shopping for.

This type of use of big data allows for any company (mainly Amazon like companies) to focus their resources on the calculation of products that an individual consumer would want based on searches that they have made. But the best part about this is that the information is pooled on multiple similar searches and consumers to best devise the necessary searches to show a consumer what to buy [25].

But beyond this simple observation of the big data usage, we need to understand what forms of implementation must be taken into consideration when creating these types of programs. Now,

what really needs to be focused on here is the interpretation of the data that is collected by Amazon to provide consumers with their recommendations.

Within big data itself, the name gives away what it is, it is a cluster of data, a large, almost seemingly insurmountable amount. There must be some sort of way to interpret the data results as they come in. For this process, it needs to be understood that this data interpretation cannot happen within a void, rather what is done for these data to be interpreted and re-designated as recommendations back to a user would be through a process of examining detailed assumptions and rethinking the analysis [1].

This process of observing and interpreting big data itself can have issues, such as those of bug interference based on programs that are being used in order to interpret these large data pools, and data can become erroneous. However, a way in which these types of issues can be resolved comes in the form of predetermined data assumptions. Data assumptions that are made to help companies who use big data to narrow in on data pools to create a seamless connection of data gathered to products showcased based on data that is collected, interpreted, and re-designated to users. This is done to help devise the necessary sales goals or recommendation services that come from these companies use of big data.

Also, when we are looking at the process by which data is collected, there will be data that is of no importance to the necessary processes by which the data is collected for. The difficult task becomes that of filtering out the useless information without removing the information that is of importance. To do this, there have been advancements made within the scientific community to reduce the plausibility of such turn out to happen. The process seeks to monitor faultiness that can be caused by sensors to lower the chances of data that is useful to not be discarded alongside data of no importance. This is also where algorithms that are made to establish key components of data come into play as well.

These forms of interpretation of course come from algorithms that are used to detect the data in forms of patterns. A perfect example of this would be comparing both Amazon and Netflix's use of algorithms that recommend to users what to buy or watch next. Machine learning within the recommendation system is what enterprises this use of algorithms. The machine learning itself will compare the histories of purchase and views to establish a statistical model of a collective pool of millions of other users to generate the necessary continued recommendations to users. The use of algorithms and machine learning also helps to establish a base line of what it is that users like and are more attuned. The use of algorithms is to ensure that the data that is being collected is correctly sorted and re-designated to users in the forms of recommendations. This is because large quantities of data require these types of assumptions to calculate and extract knowledge from the data that is collected [21].

As a programmer, machine learning and the creation of these algorithms truly fascinate when they are being used in order to create a recommendation system. Since the collection of data is

pooled, the use of algorithms to reach a particular end, based on data analysis, makes for a very interesting usage. As the use of data algorithms not only seek to facilitate the necessary recommendations, but also filter through millions of data informatics to agitate the necessary products to ensure the transparency of recommendations created. This can also be seen in what was stated above regarding consumers being able to filter products with precise search options. These filters can act as filters for filters. As in the filters chosen by consumers help to facilitate precise sifters and allows for algorithms to pinpoint precise outlines of data that help to recommend even finer tuned recommendations for consumers.

Big data, from this perspective, can be seen as a general tool that can be created to make precise measurements that are used in order to facilitate the necessary recommendations for consumers. This is of course a process that is keyed out by the use of interpretations and algorithms that are necessary to the specifications made on big data that is collected. Therefore, big data is used precisely well as a tool to pool and narrow pattern like data to ensure that completed data of particular patterns can always correctly correlate to consumers as well as viewers who use services such as Amazon and Netflix (This paper will not observe Netflix in full as it did with Amazon since the use of big data analyzes and processes to creating recommendations for consumers are very similar).

Therefore, when we are looking at companies like Amazon and Netflix, we are looking at companies that use big data to create predictive analytics. Predictive analytics has many uses however and cannot just be subjected to Amazon and Netflix's use on commercial needs. The use is mainly attributed to uncovering patterns and highlight relationships with the data that is being observed. Because of this very nature, big data that goes under predictive analytics are being done soon to search out these two main components. There is also the process of trying to find past data patterns outcome variables and trying to deduce them for the use of the future (observing patterns from a specific time-period to see if such trend continues again at another given future based on certain functions that existed in the data of the past and then comparing that to the future) [14].

Further delving into predictive analytics, which is the main use of big data for our commercial subjects, we see that there are also forms of linear regressions. The use of this is to find interdependencies within outcome variables and explanatory variables in order to use them in the process of making predictions or to right out make the prediction itself. This looks to focus the data that is collected into predictive measures that are precise to the sets of data that are collected and distributed through this type of analysis. Above, when looking at machine learning, this is categorized as a neural network. Neural networks are a collective entity, something like that of the human brain, if an artificial neural network can be defined as a computing system made up of number of simple highly interconnected processing elements which processes information by their dynamic state response to external inputs. Within the neural networks, machine learning works within the sphere of the networks to generate and learn from data collected to predict,

showcase patterns, and classifying input data [22].

To finish up the observation here on big data uses for predictive analytics and the basis of enterprise that is that of Amazon and Netflix's ability to use big data to create such systems, the paper needs to understand a little further into the principles of how this portrays use in consumer settings. What is meant to be clarified here is how big data effects the process by which consumers use services and are data mined. To affectively understand this component, there needs to be an understanding that big data and it cultivation are just as it is named, a collection of data on a mass scale meant to just be data. It is however, the enterprise of the scientific community as well as commercial bodies that induce a specific plethora of uses to assimilate the necessary components to use big data effectively. Such things make it to where consumers have an easier time with their collective use of these commercial branches (Amazon and Netflix, as well as unnamed companies). Consumers use of these sites creates data, a process by which these companies then use the process of data mining to achieve the best standards of prediction and analytics that help them to enforce their use of big data as their tool in apprehending consumers by prediction. Because of this process, consumers are the ones who are helping these companies further develop their own uses of big data by allowing these corporate bodies to data mine them, collect data, and analyze the data provided. But this process is crucial to the experience of the consumer, as this data helps with creating the necessary components of these corporate bodies, allowing them to further create advanced algorithms that help these corporate bodies devise the necessary recommendations and make the predictions to the habits of these consumers. That makes it easier for consumers to use these products offered by these corporate bodies.

In all, big data, with modifications from things such as data mining, data collection, machine learning, algorithms, and prediction analyst are all components which excel the use of big data (because of the necessary enterprise that it takes to stay updated with this matter) and insure the that consumers and users of big data can reach out to their own platforms easily.

4 PRODUCT RECOMMENDER SYSTEM

In the recent past, Amazon has moved from operating as a pure e-commerce firm to a major player in the internet services industry, with focus on offering a wide variety of services to both individuals as well as companies. The firm started to shift its focus on big data and started the journey to transition from a typical online retailer into one a major force in the realm of big data. Around 2000, the company, along with other internet firms such as Google, Yahoo, and Twitter realized that they had voluminous data about their customers, which could be put used to improve their performance. Although the other firms did not initially concentrate majorly on big data, Amazon swiftly moved to take advantage of the invaluable database of individuals who used its e-commerce platforms around the world to shop. The team charged with the responsibility of recommending the products to the customers came up with innovative strategies that the firm could make use of the data collected

by the firm about their customers. The end result of the move was a huge success in big data, which revolutionized how the company did business.

As a major player in the e-commerce domain, the success of Amazon was always pegged on availing the right products to the customers. The efficacy of providing the right products for the customers in turn largely depended on a proper understanding of the needs of the consumers. A proper market research was necessary in order to understand the customer's needs and tastes. Since it was founded, Amazon has created a name for itself because of its superior product recommender system, which suggests products to consumers on the basis of their last purchase. The major driving force behind the recommender system is the data gathered from the customers.

The product recommender system is essential for the personalization of each customer's experience when they are shopping in the firm's online store [25]. The firm employs collaborative filtering and clustering algorithms to classify clients on the basis of preferences. Customers are grouped on the basis of same search as well as collaborative filtering between items. Content-based search employs the shopping history of customers and item ratings to establish a search query capable of finding other items that match the tastes of consumers. For instance, if a customer purchases a book, the product recommender systems will suggest books from the same author, publisher, or subject area. The product recommendations are not only used by the company in the online stores, but it also doubles up as a marketing tool useful in conducting email campaigns. There is a recommendation link that enables shoppers to filter products by several criteria depending on the items that they have in their shopping carts.

5 BIG DATA FOR DYNAMIC PRICING

Dynamic pricing entails the use of big data such as clickstreams, purchase history, cookies, etc. to offer customized discounts to customers or to alter the prices of items being sold dynamically. The technology enables the real-time price customization for an item to suit a specific customer. This explains why it is sometimes possible for two different sets of customers to buy the same item at different prices from the same online store [23]. Despite the immense benefits of this technology, some customers may always feel discriminated against due to the price differences. Amazon has successfully used the power of big data to implement a price discrimination system. For example, there was an incident in which some Amazon customers were aggravated about price variations of a certain DVD. One of the customers noted that there was a difference of nearly two points five dollars in the price if the cookies were deleted from the computer. Price discrimination was also experienced in the sale of a product known as Diamond Rio MP3 Player.

Big data also enables price optimization. This enables the firm to manage the prices of commodities and grow its profits by twenty-five percent annually. Several factors are used to set the prices of commodities. Some of them are: activity of the customer on the

firm's shopping portal, availability of the product, competitor's prices, order history, item preferences, and the anticipated profit margin [23]. The prices are normally refreshed every ten minutes as big data become updated. Due to this, Amazon provides customers with discounts on best-selling commodities and accrue large profit margins on the items that are less popular with customers.

6 BIG DATA AND CUSTOMER SERVICE

Big data is also extensively being used for customer service at Amazon. The acquisition of Zappos has often been viewed as a major element in the same. Since it was founded, Zappos has enjoyed a good reputation for the excellence in customer service and was usually viewed as a world leader in this domain. Much of the success can be attributed to their advanced relationship management systems which extensively employed their own customer data. After the acquisition of the firm in 2009, the procedures were integrated together with those of Amazon. Today's business environment is changing at a rapid rate, and consumers are also using their voices faster. Within a few moments after undergoing a bad experience, customers can swiftly move into social media and spread the news about their negative experience [17]. The only strategy for an organization to survive under such conditions is to employ the power of analytic to streamline and shorten the response time, as well as fix the customer support issues. The customers of the present day are not only looking for a product that works, but also one that is personalized and able to recognize their interests and save them time.

7 ONE CLICK ORDERING

Amazon used big data to create one-click ordering. This feature is activated automatically when the customer places his first order, enters a shipping address as well as a method of payment. When using the one-click feature, the customer is given thirty minutes to change his mind about the particular purchase. This system was created on the premise that a simplified path to purchase would increase conversion rates. Since the introduction of the technology, the firm's revenues have increased year after year. The significance of this application pushed the company to patent it to prevent other companies from using it without authorization. Reorganizing the purchase process is currently one of the most significant differentiates in the current marketplace. The service enables users to make payments without having to exchange cards or money physically. Amazon has also greatly benefited from impulse buying, which is accelerated by one-click buying. Research has shown that the largest percentage of people normally purchase things they don't require or did not plan to purchase in the first place [5].

8 USING BIG DATA TO SUPPORT OTHER COMPANIES

Amazon also uses its big data platform to support and help other companies improve their operations. Organizations can employ AWS toolkit provided by Amazon to create scalable big data applications that have the capacity to improve business performance [25]. Besides, they would be able to secure these applications easily without the need to spend on expensive infrastructure and hardware. The big data applications including data warehousing, clickstream

analytic, fraud detection, internet of things, and several others are delivered via cloud computing. Hence, there is no need for an organization to incur additional costs in setting up a data center. The Amazon web services can enable companies to analyze spending habits, customer demographics, and other related information to enable them effectively cross-sell some of the firm's products in patterns similar to Amazon. That is to say that the retailers will also be able to stalk their customers, recommend products to them, and improve their customer experience.

9 BIG DATA TECHNOLOGIES

Amazon EMR: This technology offers a managed Hadoop framework that simplifies and hastens the processing of huge amounts of data across scalable Amazon EC2 instances. Amazon EMR also supports other common distributed frameworks including HBase, Apache Spark, Flink, and Presto [3]. Besides, it reliably and safely handles a wide range of big data use cases, such as web indexing, log analysis, financial analysis, machine learning, and bioinformatics.

Amazon Athena: It denotes an interactive query service that simplifies data analysis in Amazon S3 via standard SQL. Since it is service less, one only pays for the queries they run and there is no infrastructure to be managed [3]. The technology is quite straightforward and delivers results within the shortest time possible. Moreover, it does not require complex ETL jobs to prepare data for analysis.

Amazon Kinesis Firehouse: This is one of the simplest methods to import streaming data into Amazon Web Services. The technology can be used to gather, transform, and import streaming data into Amazon S3, Amazon Kinesis analytic, and Amazon Redshift, to permit instant analytic with the current BI tools and dashboards currently being used. It is a comprehensively managed service that can expand automatically with the increase in data throughput.

10 UNSTRUCTURED DATA AND AI COMPONENTS OF SOCIAL MEDIA

Next, we will look to observe big data and its uses within social media. First and foremost, it is important to understand that social media is an outlet that is massive. The many posts, tweets, likes, shares, and other social media actions all develop unstructured forms of data that are then considered by corporations to understand the market of users. It is within the creation of this unstructured data that creates such an importance to talking about social media and its perfect relationship to big data. Because of the importance of social media to businesses (due to trend and the fast-paced living environment we live in, if a business is behind on trend it becomes behind on sales and other forms of innovations), there is a large component of dependence towards retrieving big data from social media to calculate and predict trend. But beyond just trend, businesses are also trying to get their hands on the enormous amount of big data that exists within the social media sphere. There is recognition of the value of unstructured data that is sourced within social media. The value comes from consumers using social media to broadcast what they are thinking, want, and are doing. These

types of information, one might think it private, but the internet is a very transparent source of data. In so, businesses value the perspective of consumers and create ways in which they can follow through with interacting on a very contingent basis, they data mine and from that, they advertise based on the collected big data from social media [12].

This brings to focus the use of advertisement and the necessity for big data to be used. Within digital advertising, the one who collects and analyzes big data effectively and efficiently with accurate uses is king. To be successful in this method of advertising, businesses need to be prodigious at their collection of data, integration of that data and analysis of that data. The reason being is if these three things are managed well, the use of the data is much more successful. What is challenging about this type of work however is that a majority of the data that is collected from social media is unstructured, it is in a word, messy. These forms of unstructured data are in our own use of social media, usually within posts, videos, tweets, photo post to Instagram, mass use of Snapchat, etc. Because these forms of data are so much more unstructured and more difficult to analyze using traditional analysis methods, businesses needed to enterprise methods for them to collect these data forms and have the necessary big analytics platforms to analyze the data. Keep in mind the data has the most information about us, therefore the use of these unstructured data is key to devising targeted and precise marketing executions [20].

There is also the collection of real-time data. Because of the advances within the technology, the process by which real-time data can be analyzed has sped up exponentially compared to the past where this process would be impossible and yield no results. With the ability to now look real-time data and have the capacity to analyze it, businesses (those that are marketers) have the possibility of taking action instantly to provide consumers on social media with their own personalized ad. The use of personalized ads of course comes from the massive amounts of data that consumers put out on social media, allowing marketers to collect these data (things we like, talk about, and do daily). And because they have these data, they can target specific ads to consumers without missing a beat. But what happens when we begin to incorporate other technologies that allow us to always be able to access our social medias? Mobile devices provide the quintessential provisions needed for data to have a constant flow to advertisers. Big data then is a facet within the life of social media. It must be done effectively in order to continue its uses of data collected and then expounded on to get customers to buy products or even interact with specific businesses. With the development of the mobile device, location also becomes part of big data, as it allows for your location to be collected, you leave not only a digital footprint, but also a physical one which can be collected as data and used [20].

Because of such enterprise, big data can gather almost every facet of information that is readily available to the internet. Such a mass look on data also comes back to the revision on algorithms that are meant to specify what is being observed and analyzed in the data. Of course, for these algorithms to work, there has to be a steady stream of data in order for the algorithms to process and do

its job. Because of the accessibility of data through the means of mass social media and how quickly consumers use and are exposed to social media (due to mobile phone), businesses are more creative in their approach to their algorithms. These algorithms can now pop up wherever consumers are on the social sphere. In doing this, big data itself changed the advertising platform. Advertiser now must create enticing messages from big data to continue their reach to consumers. The change is incredibly eye opening. As the use of data itself can create a massive alteration in how a marketer begins to try and craft their ads to highlight what it is that individuals want. Advertising becomes more individualized and work closely around the sphere of social media to allocate their ads effectively [9].

Within the use of big data, there is also the use of AI to help with the process of analyzing big data. AI creates a much more effective measure when it comes to analyzing hundreds and thousands of data in detail. Because AI can do that, it allows for businesses to have a better idea around what perspective they themselves must take when advertising based on detail production from AI technology. AI technology becomes a very important component to being able to go analyze big data in order to provide the necessary specific information that would help with creating the necessary ads [12].

We are then looking to see how this affects the user, or better how this type of big data in social media affects consumer experiences. The use of big data comes back to the work of the consumer and the business. The consumer creates big data from their usage of social media, social media in turn collects and responds to the data that is being created by the consumer (user). Through the process of facilitating the data, analyzing it, interpreting it, pooling it, and filtering it through algorithms and AI technology, consumers using social media get access to tailored advertisements. The consumer experiences a personalized social media experience and personalized advertisement trail based on the collected data that is reinforced by big data that is pooled together in order to do this. Does big data have any other uses in social media then? Yes, it does.

Social media can also use big data in order to create studies and infiltrate certain components of a consumer's private life. Facebook for example, a top social media company prides itself in its technological advances that use big data. Facebook uses is considered a top user of digital advertisement, so it begs to question what else does Facebook do with the mass big data that it collects? Facebook has also used its big data resources to try and act on social media experiments. During a time when there were the I Voted stickers sprawled on Facebook for users to share and gimmick that they had voted, Facebook was using this in order to incite and boost voter turnout. The method was to first isolate and use the stickers with particular groups of people, small groups at first in order to test the role. After having enough data collected on the presence of the stickers and what they meant for users, Facebook began to mass data span by incorporating the stickers in a much more massive turnout. With midterms of 2010, there is studied on behalf of Facebook scientist, that say 340,000 more people voted in the 2010 midterms [18].

From these the observation of these big data uses, we can showcase the how and what makes big data so important to the creation of diversified consumer experiences but also showcase the necessary components to how big data is used by the new technologies we have. It is however imperative that we understand these different phenomena that come from the use of big data.

11 SOCIAL MEDIA IS SIGNIFICANT FOR COMPANIES AND INDIVIVUALS

Although big data is said to come from several different sources, the largest proportion of it is said to originate from unstructured sources. As it can be imagined, social media makes up the largest source of unstructured content for big data. All the activities that users perform on social media such as views, retweets, comments, favorites, likes, etc. can be gathered and explored by interested individuals.

In the current digital world, social media plays a vital role in many companies. Having a presence on various social media platforms such as Instagram, Facebook, and Twitter is imperative since it enables individuals to interact with an organization on an ostensibly personal level and at the same time helps businesses across several domains get in touch with their customers. Currently, Facebook alone has over two billion users on their platform; this is roughly twenty-six percent of the world population [12]. It is therefore important to consider the fact that big data, from the social media platforms, can reach any people in different forms. Besides that, social media interactions have continued to play a big role and will continue to play a big role in business decisions. For example, some insurance companies have declined to offer life insurance policies to individuals solely based on their social media posts. If you frequently post, on any of these platforms, about how you are drinking or going to drink, insurance companies would be reluctant to offer you a life insurance policy as this is a risk to them.

It will not be long before organizations discover new and better strategies for making sense of big data. But, at the moment, the concept of big data is still new and rapidly evolving. Nevertheless, some businesses have found ways of interacting and using this data, which is just but the beginning, but still a good way to begin. To elaborate, a marketing company whose interest is promoting a new product could employ machine learning algorithms that enable it to gather data from individuals who meet certain attributes [12]. Consequently, by employing artificial intelligence technology, they will also be capable of drawing insights from millions of users and create campaigns. This will increase their levels of precision and focus, a technique usually referred to as targeted marketing, and present an excellent opportunity for finding the perfect audience and satisfy its preferences.

12 BIG DATA IN SOCIAL MEDIA ADVERTISING

Fundamentally, advertising revolves around communication since it is all about sensitizing consumers on products and services that an organization is selling. However, different consumers will always want to hear varied messages, which is a vital fact to consider when

new clients are being recruited into the internet bandwagon due to the growing popularity of smart phones. Big data has the capacity to customize these messages, project what consumers would like to hear, and establish new perceptions on what customers like or prefer [8]. The above steps are all revolutionary and are expected to have a significant impact on how marketers in various organizations advertise.

Furthermore, there are some occurrences which several people do not view as advertising but are still interactions between big data and marketing like product recommendation. An obvious example is Netflix [9]. Although the company does not have a concrete advertisement plan, it employs a lot of algorithms to recommend various movies and shows to its customers. The approach saves the organization a lot of money by reducing the rate of customer exit and ensures that the right shows are marketed to the right individuals. The company's strategy is to target consumers with shows specifically tailored for them. Apart from them, other firms such as Amazon, YouTube, etc. also do the same by using product recommendation to target their customers [9]. In order to stay up to date, the algorithms need constant flow of data to help it work more efficiently. With the growth of the internet, users leave huge volumes of data not only on social media platforms but also on other places they visit online in the form of a digital footprint. This provides advertisers with new avenues to tailor their messages to meet their customer demands.

The digital footprints left by online advertisers provides new insights to marketers on what a consumer really needs, and this sometimes may be more accurate than what the customer actually says on social media. However, marketers are worried about how to safeguard the privacy and security of their consumers and therefore companies that are careless in handling data collected from consumers usually ignite a backlash which greatly impact their business. Even though targeted advertising has been in existence for quite a while [9] the more the data that is collected by advertisers, the more personalized and effective marketing is expected to be. Organizations will strive not just to gather as much data as they can, but also to gather information which typically represents the individual consumer's needs in order to enable them to market to their personalized tastes.

13 ANALYZING LINKS

Big data collected from social media can lead to the discovery of new information regarding each individual customer that can help in creating a customized appeal to that specific customer. However, with the new insights, marketers can enhance how advertising is approached as they create new strategies. The new growth in content marketing is usually perceived as a primary beneficiary of big data, although the concept of content marketing could be older than the internet itself.

Another essential point is that big data enables digital marketers to target users effectively with more personalized advertisements which they might prefer to see. Facebook and Google are among the biggest players in this domain of digital advertising. They have

discovered excellent ways of creating and delivering more appealing advertisements in ways that do not intrude on the rights and preferences of the consumers [10]. Most of their advertisements feature services and goods that consumers would like most to enhance their lives and almost all of these advertisements are reliant on huge amounts of personal data that users usually provide from what they are up to, what they share and like things online.

Experts contend that it is possible to accurately make predictions on an array of individual attributes that are more sensitive merely through an analysis of an individual's Facebook or Twitter likes [20]. For example, the likes on these social media websites are critical in predicting one's religion, sexual orientation, emotional stability, life satisfaction, age, relationship status, and many other attributes. Companies like Facebook successfully linked political activity with user commitment when they created a sticker enabling most of their users to declare on their profiles that they had voted. The initiative was conducted during the 2010 midterm polls and was very effective as more people turned up to vote as compared to the 2006 midterm elections [18]. Individuals who saw the feature had high chances of voting and actively engaged in a conversation about the same after seeing their friends and peers participate in the activity. Later on, during the 2016 polls, Facebook escalated their role into the voting process by providing users with not only constant reminders but also with directions about their polling stations [19]. Apart from that, they also enabled users to easily get access to registration information, news, voting guides and other tools that would have made them more equipped to go through the election process.

14 USER RATING AND POP UP ADS

Depending on the user preferences and the content that they often access on social media, pop-up advertisements can be created to target users every time they are online. For example, an ad can be created on the Facebook Messenger app to open inside that particular app every time the user hits the CTA button. When clicked, such ads would redirect the user to a page where they would be required to answer some question, claim a reward or send some feedback regarding a product or service. Before creating such ads, it is imperative to establish a custom audience of the individuals who would be targeted with that particular pop-up ads. For instance, individuals who have previously liked the company's products on their Facebook page or other social media sites can be included on the list of target audience to receive the ad [4]. Another strategy that can be employed is to rate users by tracking their cookies. In most cases, user activities are usually tracked across the internet using cookies whenever a user logs into one of the social media sites and is concurrently browsing other sites. Whenever this happens the other sites that the user is visiting can be easily tracked and the data used accordingly.

15 RELEVANCY OF BIG DATA ANALYTICS IN GROCERIES STORES

15.1 Increases the customer shopping experience

As per a current SHSFoodThink white paper "Are We Chain Obsessed?" 64% of customers said that the previous shopping experience is what makes them keep coming back! not the items themselves [24]. By utilizing bits of knowledge received from the information transaction database, online networking, promotional activity, customers purchasing behavior, and client movement patterns, grocery stores can find a way to guarantee they are engaged with their customers that matter most.

For instance, they can investigate customers shopping movement to enhance the layout of their store, or recognize attrition risks for clients who have not as of late bought staple things, similar to milk. In like manner, chains can construct item varieties demonstrated with the customer needs and purchase patterns in certain regions [2, 13, 24]. Regardless of whether it is through reconsidering store layout or furnishing store attended with mobile apps to better serve clients, analytics can enable grocers to change consumer's expectations.

15.2 RESTRUCTURE THE SUPPLY CHAIN

Grocery stores can likewise utilize analytic to investigate the production of their products, monitor production processes, and quality control, and improve straightforwardness with buyers about their sustenance production practices of foods [16]. Suppliers remain to profit from the evaluation also, with access to secure, customized content of information identified with performance sales of the product, stock, margins, and marketing effectiveness. Giving supplier an opportune profitable business knowledge that supports joint ventures, drives performance, and decreases waste products

15.3 BUILD SUPERIOR MARKETING PROGRAMS

Loyalty programs furnish grocery merchants with an abundance of data to enable them to distinguish client segments and precisely characterize item preferences. By joining this information with different data sources! like healthful patterns, favored technique for accepting marketing promotion, customer movement patterns, and weather-related event! grocery merchants can concentrate on enhancing, and derive income from, the general shopping experience [24]. For instance, grocery retailers can utilize analytics to customize the advancements they offer to clients given what they are well on the way to buy. They can likewise time advancements fittingly, and offer codes to customers who often as possible buy certain things.

15.4 IMPROVES HR STRATEGIES

Supermarket stores utilize analytics to manage work-related decisions. Information freely accessible through online networking accounts and different means can be examined in conjunction with a grocer's internal information to direct decision identified with selection and recruitment, employee termination, and performance management and advancements [11]. For example, an investigation

of late action on LinkedIn can reveal insight into which representatives are destined to leave an organization.

Grocery merchants can likewise break down information to control the advancement approaches that will build workforce performance. For example, they could explore different avenues regarding organizing a social gathering for representatives at a subset of their stores, and analyze information on profitability, morale, and turnover in the preceding months [13]. They may find that the gathering information prompted a more positive workplace where workers feel more noteworthy engagement at work, and soon after that, they could roll the strategy out to different stores.

15.5 USING BIG DATA FOR COMPETITIVE ADVANTAGE AND ATTRACTING CUSTOMERS

Numerous grocery stores have been utilizing transaction and client information for a considerable length of time, despite the fact that many still have not completely used all that can be proficient with these types of information. For Small to Medium Sized grocery merchants, many have swung to subcontracted point solutions because of an absence of available analytics assets and potential framework investment required [11, 24]. The issue with point solutions recently is that if? they independently work out for a particular business section and the evaluation is cookie cutter. In this way, the 'information' is not coordinated and hard if not difficult to give an all-encompassing picture of client conduct overall touch focuses for instance. Nor are the investigations offering a cross-functional observation that is pertinent to all business partners as far as driving differentiation in the commercial center in promoting, advertising, store operations and supply chain.

As far as utilizing 'new' data sources, for example, mobile, social and text, the industry is particularly occupied with a discovery phase of investigation with an assortment of center sections, testing and figuring out how to extricate an incentive from these rich new sources of information. There are two common paths grocery merchants takes with little respect of the 'size' of the organization: to start with is Strategic Commitment, in which there is C-level (hierarchical) commitment making the venture in the assets to get the majority of the in-house data and evaluated it [13].

Presently like never before, information, analytics, and IP are seen as vital resources and competitive discriminators. The other is Business Discovery; in which grocery merchants outsource to an Analytics as a Service firm to use internal and external information. Performing analytics speeds the construction of business advantages creating new users case and helps catch 'quick wins' before making resource commitment to technological innovation and human capital in advance [11]. In view of progress, and a wit, trusted stakeholder willing to share the techniques and explanatory models, can assist grocery merchants to proceed with an outsourced administrations supplier or relocate the data, analytics in addition to IP in-house.

16 RECOMMENDATIONS

16.1 Real-time insight on product demand

Nowadays, retailers can get to information on item demand levels instantly on a chain of stores. Nevertheless, numerous merchants are still in the earliest stages in regards to evaluating and monetizing the huge amount accessible data [2]. This prompts stocking deficits, for example, evaluating item demanded based exclusively on past historical information. It can likewise convey about wrong promoting endeavors: If a customer purchased ketchup on Saturday, an email coupon for it on Sunday is not well planned and make little sense to the shopper.

This is the place data from store loyalty programs in addition to credit card sales can prove to be useful. Its data can be utilized to define needs of the customers in future. For example, grocery merchants can use data analytics to decide how regularly customers purchase sugar, flavors, or different items, and after that send every family unit coupons given their propensity to buy [24].

16.2 Enhancing in-store stock management

Perishable basic supplies, for example, dairy, meat, and fish call for precise stock administration, regularly on an hourly premise. Client analytics and prediction tools can enable grocery merchants to calibrate their inventory levels by assessing buyer purchasing behavior and requested products from various viewpoints and situations [24].

For example, grocery retailers might need to screen cycles like when customers go for particular nourishment, purchasing patterns amid sales deals when storing activity peaks or seasonally inspired buys. As indicated by a report from Manthan, this methodology worked for U.K. food grocery merchant Waitrose: a deeper understanding of buyer purchasing behavior and demand outlines using cutting edge client analytics and predicting tools helped the store [11]. Concurrently, retailers can utilize these systems to all the more deftly change their stock levels and amplify high-buy products.

16.3 Leveraging Predictive Analytics

Amazon spearheaded item proposal engine: the "if you purchased that, you may like this" invention. This strategic changing web-based shopping feature mirrors the retailer's profound assessment of buyers' shopping basket. Proposal engine is intended to enable customers to find items they were not sorting out but rather would be interested in purchasing [13]. Today, general grocery merchants are progressively tapping the global innovation behind proposal engine: predictive analytics. This kind of assessment measures future patterns in light of present and past information, and it can enable stores to improve business. Information is driven, all-encompassing assessment of "purchasing triggers, for example, regularity, weather, stock, and advancements, is progressively informing grocery stores' product blend, marketing plans, and sales forecast [2]. Furnished with these information-driven tools, stores can better distinguish what items customers need today and what they will be demanding in future, and this learning will enable them to stay competitive for a considerable length of time to come.

17 INTRODUCTION

Digitization set apart by an increasing number social media and mobile devices is shifting the business landscape in every sector insurance included. The opportunity presented by this aspect for insurance companies are immense. Communities and social networks enable insurers to interface with their clients better, which to their advantage improves branding, customer retention, and acquisition [24]. Insurance companies additionally get a plenty of contributions from computerized data as feedbacks, which likewise can be utilized to develop unique products and aggressive valuing. Digitization of big data analytics offers numerous opportunities that Insurances Company can harness to detect fraud among their customers. Dealing with fraud manually has dependably been expensive for insurance firms regardless of the possibility that maybe a couple of minor fraud went undetected [6]. What's more, the trends in big data (the evolution in unstructured information) are prone to numerous fraud, which can go without notice if analysis is performed correctly. In the proceeding section, the article will examine important of big data in insurance fraud detection and its relevancy.

18 IMPORTANCE BIG DATA AND INSURANCE FRAUD DETECTION

Conventionally, insurance firms utilize statistical models to recognize fraudulent cases. These models have their limitation [15]. To start with, they employ sampling techniques to assess information, which prompts at least one fraud going unnoticed. There is a punishment for not performing a proper assessment of the data provided. Subsequently, this strategy depends on the cases analyzed before. Therefore, every time different fraud takes place, insurance firms need to manage the impact for the first time. Lastly, the conventional strategy works in silos and is not correctly equipped for taking care of the natural developing wellsprings of data from various diverts and diverse capacities in an integrated way. Analytics tends to be difficult and assumes an exceptionally pivotal part in fraudulent recognition for insurance firms. In the proceeding section, the significant benefits of utilizing big analytics in fraud detection assessed.

18.1 Identification of low incidence events:

Utilizing sampling methods accompanies its particular arrangement of acknowledged mistakes. By using analytics, insurance can manufacture frameworks that go through every fundamental datum. This like this distinguishes events with low frequency (0.001%) [7]. Methods such as predictive modeling can be utilized to altogether break down processes of fraud, channel clear cases, and allude low-rate fraud cases for facilitating analytics.

18.2 Enterprise-wide solution:

Analytics help in building a global point of view of the anti-fraud endeavors all through the undertaking. Such a point of view regularly prompts dominant fraud location by connecting related data inside the association. Fraud can happen at various source focuses premium, claims or surrender, application, employee-related or outsider fraud. In the meantime, insurance channel broadening is

adding to the breakdown of identifiable information. Insurance-related exercises should be possible using cell phones separated from the conventional face-to-face and online Insurance [15, 25]. This can be seen as an expansion to data storehouses in the Insurance business. Given more prominent channel enhancement and the development of ranges where fraud can happen, it is vital for insurers to have reachable enterprise-level data about their business and clients.

18.3 Data Integration:

Analytics assumes a vital part in incorporating information. Viable fraud recognition abilities can be worked by joining information from different sources. Analytics additionally help in integrating inside information with outsider information that may have predictive significance, for example, public records. Information sources with derogatory properties are on the whole public documents that can be incorporated into a model. Cases include liquidations, liens, criminal records, judgment, abandonment, or even deliver change speed to show transient conduct. Different sorts of outsider information can be useful in upgrading effectiveness, for example, audit evaluating data to decide whether harms coordinate portrayal or misfortune or injury being guaranteed [6]. A standout amongst the most under-used information sources is doctor's visit expense audit information. This information, if utilized as a part of a model legitimately, is a gold dig for organizations researching medical fraud. Revealing peculiarities, in charging and adding these to the next scoring motors or interpersonal organization analytics will diminish the measure of time an agent or expert spends endeavoring to pull the majority of the pieces together to recognize deceitful action.

18.4 Harnessing Unstructured Data:

Analytics is useful for getting the best incentive from unstructured information. Fraud can be delicate or hard. This depends on whether it comprises of a policyholder's misrepresented cases, or on the off chance that it contains of a policyholder arranging or creating a misfortune. At an abnormal state, fraud can happen amid commission discounting, because of false documentation, an arrangement between parties or from is offering [24]. Albeit bunches of organized data is put away in an information distribution center as a component of numerous applications, a significant portion of the vital data about a fraud is in unstructured information, for example, outsider reports, which are not assessed. In most insurance firms, data accessible in online networking is not suitably stored. An uncommon investigative-unit specialist will concur that unstructured information is vital for fraud examination. Since textual information is not straightforwardly utilized for reporting, it does not discover a place in most information stockrooms [7]. This is the place content examination can assume a crucial part in checking on this unstructured information and giving some valuable experiences in fraud discovery.

19 RELEVANCE OF BIG DATA IN INSURANCE FRAUD DETECTION

Big data analytics is a reality for the insurance company because of its capability to enhance various conventional technologies and

be used to detect fraudulent acts. In the proceeding section, the relevance of big data and insurance fraud detection will be examined.

19.1 Text analysis

In numerous Insurance fraud recognition ventures, from 33% to oneportion of factors utilized as a part of the fraud location model originate from unstructured content data. This is particularly helpful for long-tail claims, for example, damage claims, because the best information frequently is found in claim notes [15]. Content mining is something beyond keyword sorting. Excellent content analytics apparatuses translate the importance of the words to establish context. Innovation that is adroit at preparing common dialect can help remove factors from the unstructured content that can be utilized for assist fraud modeling.

19.2 Data Management

Regardless of where your information is stored from legacy frameworks to the valid information stockpiling structure, Hadoop an information administration framework can enable insurers to make reusable information rules. They give a standard, repeatable strategy for enhancing and incorporating information [7]. Preferably, you need a framework that interfaces with different information sources. It ought to have streamlined information league, relocation, synchronization, organization, and visual assessment.

19.3 Event Stream Processing

This enables insurers to investigate and processes in movement (i.e., process streams). Rather than putting away information and running questions against data, you store the inquiries and stream the data through them [24]. This is foundational to both ongoing fraud identification (invigorating fraud scoring) and successful utilization of great high-speed information sources similar to vehicle telematics.

19.4 Hadoop

A free programming structure that assesses and prepares of tremendous collected information in a distributed environment of computing. It offers gigantic details stockpiling and super-quick processing at around 5 percent of the cost of convection less-adaptable databases. Hadoop's mark quality is the capacity to deal with organized and unstructured information (counting sound, text, and visual), and in expansive volumes. Insurers either can employ Hadoop specialists to exploit the structure or purchase items that scaffold to existing databases and information distribution centers[6, 7]. This foundational innovation for making predictive analytics models stays one-step in front of fraudsters and spillage of paid-out cases cash. The exchange observing advancement innovation used to battle regularly complicated illegal tax avoidance utilizes Hadoop as a center stockpiling and sorting out innovation. Complex organized crack rings and therapeutic factories, for instance, are conveying progressively modern techniques for laundering cash stolen from auto insurers.

19.5 In memory

In-memory analytics is a processing style in which all information utilized by an application is put away inside the principal memory

of the computing condition. Instead of being available on a disc, the data stays suspended in the mind of useful sets of PCs. Different clients can share this information with numerous applications in a quick, secure, and simultaneous way. In-memory analytics likewise exploits multi-threading and distributed registry [6, 24]. This implies clients can disseminate the information (and complex workloads that process the data) over different machines in a group or inside a single server condition. In-memory analytics manages questions and information analytics, yet also is utilized with morecomplex procedures, for example, predictive analytics, machine learning, and analytics. The sorts of neural-network analytics that assist insurer in discovering association among suspects sustaining claim and premium fraud depending on the kind of processes

19.6 Software as a Service (SaaS)

Predictive modeling and different analytics were accessible to large insurance net providers willing to introduce the innovation on location as of not long ago. Software as a service has advanced to even where genuinely little insurers can exploit Big Data analytics [6]. Insurance providers subscribe to a service keeps running by a seller as opposed to paying for the vast buy, establishment, and support of in-house frameworks. SaaS likewise is named "on-demand software."

20 DISCUSSION

Form such progress we can see the diverse reach that big data has and how it affects the users in their experiences with big data. Not only do we see big data creating advertising products to consumers, we are also seeing social media sites using big data to influence other functions of consumeris daily lives. To further that observation, there is necessity behind seeing the claims that Facebook makes on its ability to influence its consumers to influence those within the social media sphere. If big data has the access to arrange itself around the sphere of the consumer to have the consumer act on certain task, what does that mean the uses of big data are to social media sites? We can assume from our knowledge that social media sites like Facebook could be interjecting into the private lives of their users by instigating on the data that is collected in processed to pinpoint user habits. It can also be seen that big data facilitates the necessary components of information to allow social media sites to specify their own approaches to their consumer in ways that can be seen as going over the line when it comes to their connection with their consumers. It is however, still a very enterprise avenue of using big data. As it allows for the social media to influence social, economical, and political landscapes. But that in itself is also a very dangerous power to have. As those who use the big data and direct their resources into specific marketing strategies can alter nearly whatever they fid like to in front of the irrational consumer.

As we have observed of big data above, we also learn of the prediction value and how big data escalates the ability for businesses to predict and recommend to consumers different products. The use of pooling data and sifting it through algorithms in order to precisely choose methods of spawning products before consumers

is a fundamental use of big data. Big data becomes a tool that assimilates the data that is created to businesses to create more big data. The process is unending and constantly provides businesses with unlimited amounts of data that can be used to spearhead their campaigns. Does big data then become a commodity that is used like currency to businesses? Well, it is very possible. As the use of big data is how businesses maneuver their strategies to get consumer to consume. If these algorithms meant to increase sales were used for something else, say medical awareness to the issues that exists within smoking cigarettes, how will the big data be used and what forms of algorithms would be used? The use of prediction analyst suits sales, but based on the observation made above, it is probably even more effective in helping to create a knowledgeable public. By facilitating the big data and being able to sort out the necessary public images that have control over social sphere through mass social medias, there can be an exchange of data between consumers. Because of the interplay between data and how consumers absorb them and create more data that is spawned for more information, big data can in turn control knowledgeable outcomes in public opinions. The use of big data is vast then when it comes to understanding the many components that make up what big data is.

Our observation above also places the consumer experience as an important facilitator for big data to exist. The habits and practices of consumers as well as the opinions and locations of the consumer can truly inhibit how big data is filtered to facilitate the necessary components of data to market and process information. This process can of course be seen using AI technology in order to expedite the data that is coming in. It does this so that the data is filtered and able to be used to immediately influence commercial markets, social media spheres, and consumer habits. That in turn regulates and begins to push out even more big data from the interactions that consumer have with the new platforms that are created from old big data that was used in order to create their new purchases or opinions. AI technology then becomes a fundamental component to the access, collection, analysis, and interpretation of big data. Its use of manipulating and translating data in order to be used to create enterprise is crucial to the development of more big data. From the observation above, it can also be said that AI technology will has also positioned itself in a way where it has become fundamental to the big data analysis and because of that, AI technology is part of big data.

The paper also sought to observe the nature of consumers having the capacity to control the big data that flows into collection. The use comes from filter settings like those included on Amazon in order to help narrow searches of items or on Netflix in order to create the right kind of streaming that the consumer requires or likes. If that is the case, the consumer actually holds a lot of power when it comes to the collection, analysis, and interpretation process of big data. Within how the consumer chooses to reside over these social medias and commercial businesses determines how the social media sites and businesses get their data. Beyond that, the consumer has no knowledge of how to analyze or interpret big data, yet holds the key to the very idea of big data. Because of this notion, the discussion here seeks to try and highlight the importance of

businesses maintaining and using data collected responsibly.

Big data is used in order to interact with consumers in order to sell or sway. The use of data however is also created by consumers. For this symbiotic relationship to exist and stay peaceful, businesses must be sure that they are not over stepping privacy issues when it comes to the use of big data. By enterprise methods to help consumers with choices and options through their recommendation systems and early predictive measures of trend by their collected big data, that is fine. But when business pressure consumers with the use of big data, the business will most likely end up losing new data to collect. As if no one is using their sources to create data, their lack of data causes them to have slow flow, and that leads to isolation of data.

Take for instance the process of data mining. Data mining is used in order to receive particular forms of information about consumers. This information is in the form of data, this data is put through special filters to narrow in on what it is that businesses want to know about particular groups of consumers to achieve the best methods of interacting with the consumers in order to highlight necessary products to the consumer. What happens if the algorithms for this particular data mine was off? This would mean that the data that was supposed to continue in the line of procession ends up lost. Because missing the mark with data mining and interpretation means that businesses loses their edge with their consumers.

Big data is a very complex topic to talk about. It is however, a very interesting topic to look at. As when we are observing what forms of big data are used in order to create experiences for consumers and business practices for businesses we can see the importance of having a very strong handle on the idea of big data. It is not just a process by which you collect massive amounts of information and then through it back out into a market. Big data must be molded around using algorithms, AI technology, studies done to mine particular forms of data, and even understanding the complex notions of unstructured data. Because of these reasons, the study of big data is still relatively incomplete. The use of big data however, should be understood as a relationship between consumers and those who seek to use big data to facilitate their individual means.

21 CONCLUSION

The paper sought out to examine the complexities of big data, but to be more precise, this paper seeks out to the multiplicity of avenues in which big data is used by our technological world in regards to Online shopping, Streaming Services, and Social Medias. The conclusion is that the multiple complex systems which make up the forefront and system of enterprise around big data falls under the very distinctive relationship that exists around the users of these services, and the sources the users use in order to create more big data.

Such complex multiplicity of diversified uses alter the understanding of big data by showcasing that big data in itself is easily

manipulated and altered. This becomes the case because of the multiple layers of data that exists in any given moment. The use of these data are incorporated in a way that there are many organization that are still trying to spearhead further in the endeavors of big data. The papers observation of the multiple forms of big data conversions, analytics, prediction standards, and even experimental uses of data reinforces the concept that big data is as it is called, massive. Because of such presence, to truly be able to look into the multiplicity of big data would mean a massive overhaul of research meant to showcase the existence. This paper however does not do that, but would also rather seek to showcase that.

Online shopping and streaming sites uses a multiplicity of tools alongside big data in order to function with consumers and creates a diversified experience for consumers. The tools that are used by these shopping and steaming businesses alter big data into sustainable forms of information that are then used in order to predict and recommend to consumers what products to purchase and recommendations. These are all done through algorithms used to analyze the data. The paper observes and concludes that the standing made by these businesses are diversified and are meant to showcase the suitable substance of the big data to consumers. The use their procedures not only diversify the consumer experience but also diversifies the way that big data is collected and used. Big data within these forms of principles are collected and retained under algorithmic databases that are then filtered out when it is being generated by consumers. The process of big data filtering is not only done by businesses, they are also given as options to consumers. Through the process of filtering consumers can do the exact same thing.

Social media sites use big data just at online shopping and streaming services do, but social media also has another power. One which allows them to facilitate their studies into experiences around the consumer. By doing this, social media can use big data in order to influence and manipulate consumers into specific acts of studies that are being done by the social media sites. This form of big data usage not only diversifies but also includes possibility for growth in collection of information. As when social media analysis these complex forms of data known as unstructured data, they are having a deeper perspective into consumer habits, wants, and additional personal information that expands their usage of big data.

Big data is a very diversified entity. Even though it can be narrowed down to certain institutions or entities, it in itself is able to expand largely in those narrowed views. The diversification of big data is very crucial to the survival and usage of big data. Without multiple sources to collect necessary data, there would be no big data. Therefore, the userfis experiences around big data needs to be one that is flexible and seeks to incorporate the right amounts of AI and Algorithms in order to maintain steady flow of data which encapsulates the very idea of diversified big data.

In summary, the multiplicity of avenues that exists around big data creates the very core study that it takes in order to understand the practices and exhibits which are induced by the use of big data itself. By observing real world applications of big data we can see

that the diversification of big data does not need to be mellowed or shallowed out from the perspective of a programmer, as it seems that the market capitalizes on big data and therefore creates the very enterprise of multiplicity within its diversification.

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Big Data Analytics on Food Products Around the World

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ABSTRACT

Food is one of the basic necessities of human-being. It helps us gain energy to recharge our body to do the daily activities of moving, playing, and thinking. From being a cave man to producing a wide variety of foods, we have come a long way. The civilizations shaped the food habits of the world and there is a lot of variance in the food habits across countries. We analyze the *Open Food Facts* database that gathers information on food products from around the world to unearth some food habits of the world and we predict the food grade based on the nutrition facts of the food products.

KEYWORDS

i523, hid231, hid203, big data, food habits, food products, nutrition

1 INTRODUCTION

Open Food Facts is a non-profit initiative started by Stephane Gigaandet and run by thousands of volunteers around the world. Any person around the world can contribute to the database by simply scanning a product using a mobile app which is made available to IOS and Android. This massive database of food products opens up a lot of opportunities to analyze the food products around the world and understand the food habits. We are particularly interested in the consumption of nutrients that come along with the food items across the world, the composition of different fat content, and the prediction of nutrition grade based on the nutrients.

2 FOOD ANALYSIS: IMPORTANCE AND RELATED WORK

In recent times, more and more companies try to market their food as low-fat or low-calories in order to fool consumers into buying their products. The increasing concern of public health has led to a significant interest in detecting the health-related properties of food products [2]. Thus, there is no question about the importance of analysis of the nutrition grade and food safety in today's world. The analysis of food requires more robust and efficient methodologies in order to ensure the quality and safety of the food products [2]. Previous methods based on the so-called wet-chemistry have now evolved into more powerful techniques which are used in the food laboratories. These methods provide a massive improvement in analytical accuracy thus expanding the limits of food applications [2]. The traditional methods of food analysis can be classified based on the underlying principle. Some of these categories are spectroscopic, biological, electrochemical, supercritical fluid chromatography [2]. All these techniques provide information about the sample under study and this information is derived from a specific physical-chemical interaction [2]. A different approach to analyzing and detecting the food quality is by using machine

learning techniques. We will discuss one of these modern methods of food analysis which can be widely used across countries.

3 ANALYSIS OF NUTRIENTS IN FOOD

Fat is definitely a nutrient that the body needs and is an essential nutrient that aids in cell growth, helps with energy generation, maintaining body temperature, protect organs, help absorb other essential nutrients that aid in producing energy, improve blood cholesterol level, help reduce inflammation in case of injury, and help in storing energy that can be used for survival when you go without food for few days [1]. But we do need to keep a track of the consumption because anything that is remotely excess leads to a variety of serious health issues [1].

3.1 Dietary Fats

There are different types of fat if? some are good and some are bad and some needs to be taken within a certain limit [1].

3.1.1 Saturated Fat. More intake of saturated fats results in the cholesterol levels in the blood which increases the risk of heart-related diseases [1]. The American Heart Association suggests around 5 percent of daily calories from foods containing saturated fat [1]. Meat, cheese, and milk are some of the sources of saturated fat [1].

3.1.2 Trans Fat. Any type of trans fat whether it is natural or artificial is not good [1]. The reason why food manufacturers use trans-fat is that they are less expensive, can be produced artificially, easy to use with other ingredients, last for a long time and also aid in improving the taste of the food [1]. Trans fats raise the bad fat levels and decrease the good fat levels [1]. The American Heart suggests to completely cut off trans-fat from the diet [1].

3.1.3 Monounsaturated Fat. Monounsaturated fats have a good effect on the body when taken within limit [1]. They help reduce the bad cholesterol levels in the blood and thereby decrease the risk of heart diseases [1]. They also help in gaining vitamin E which is a good nutrient that acts as antioxidant [1]. Olive oil, avocados, and sesame oil are some of the sources of monounsaturated fats [1].

3.1.4 Polyunsaturated Fat. Polyunsaturated fats have a good effect on the body when taken within limit [1]. They help reduce the bad cholesterol levels in the blood and thereby decrease the risk of heart diseases [1]. They also provide some nutrients that are essential for the body [1]. Soybean oil and sunflower oil are some of the sources of polyunsaturated fats [1].

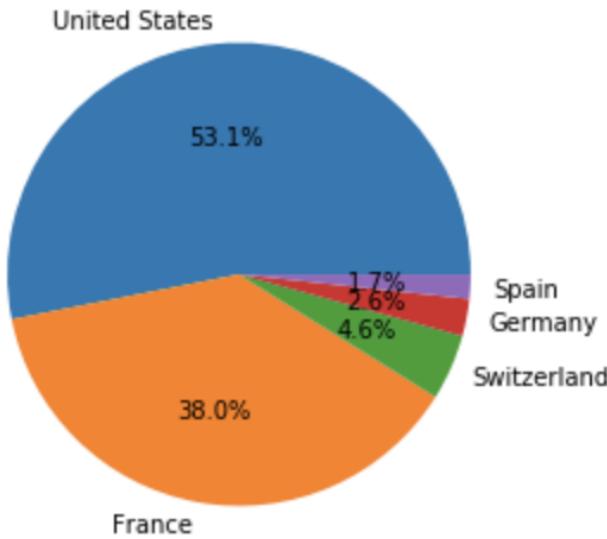


Figure 1: Top 5 countries [9]

3.2 Data Cleaning and Transformation

To make the analysis more interesting, the top 20 countries with most value counts for the attributes have been considered. The countries with names combined with other countries were also cleaned in the process. The data was analyzed for missing values and the attributes with more than 60 percent missing values were removed from the analysis to add consistency. Only the columns that are meaningful in the analysis were retained and the rest were removed from further analysis.

We then display the top 5 countries as a pie-chart and the 5 countries are namely United States, France, Switzerland, Germany, and Spain as shown in Figure 1.

We then impute all the null values with zeroes and we then check the dietary fat content in the foods and check the top countries with fat content using a histogram. The analysis with respect to the fat countries is as follows

3.3 Fat Content

The top 5 countries with most fat content in the food items are Serbia, United States, Switzerland, Germany, and Sweden as shown in Figure 2.

The top 5 countries with most saturated fat content in the food items are Serbia, United States, Germany, France and Switzerland as shown in Figure 3

The top 5 countries with most trans-fat content in the food items are United States, Brazil, Canada, Australia, Russia, and Serbia as shown in Figure 4.

The top 5 countries with most cholesterol content in the food items are United States, Canada, Portugal, Brazil, France, and Italy

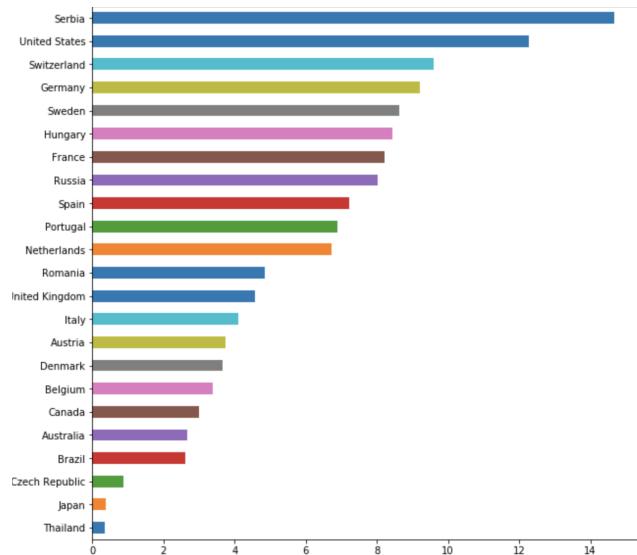


Figure 2: Top 5 countries with most fat content [9]

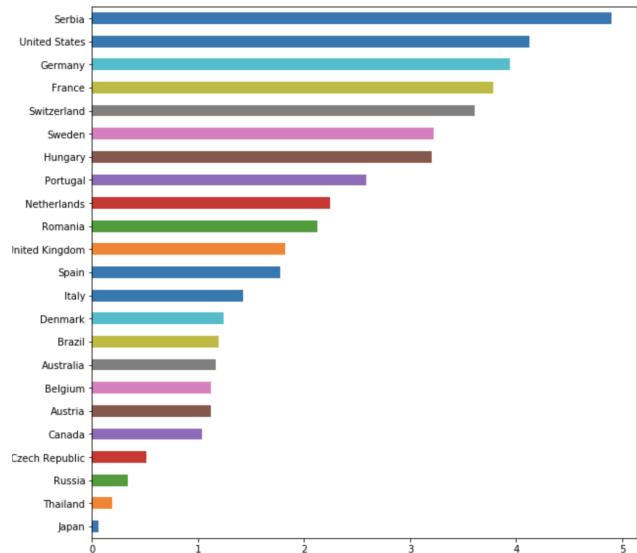


Figure 3: Top 5 countries with most saturated fat content [9]

as shown in Figure 5.

3.4 Sugar and Salt Content

Although the body needs sugar, high intake of artificial and processed sugar is bad for health as it does not add any nutrients but only adds calories [5]. It is always better to rely on the natural sugar that comes with fruits and milk [5]. Artificial sugars tooth decay and diabetes [5]. Just as fat, sodium which is the main source of iodine is essential for health although its intake should be within limit [5]. Increase in intake of salt leads to blood pressure and has

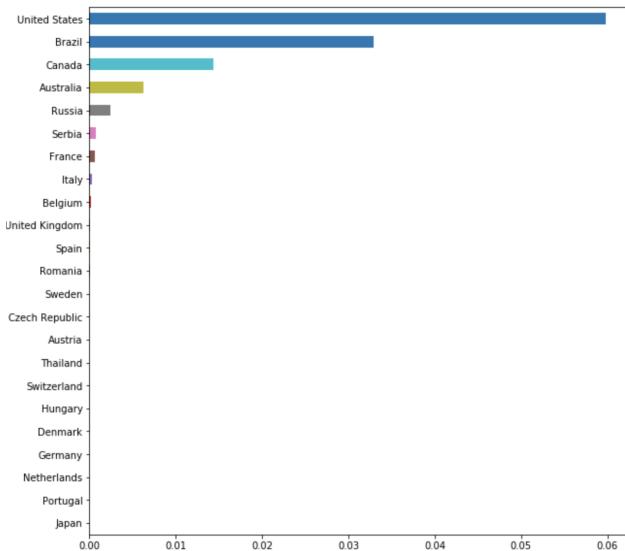


Figure 4: Top 5 countries with most trans-fat content [9]

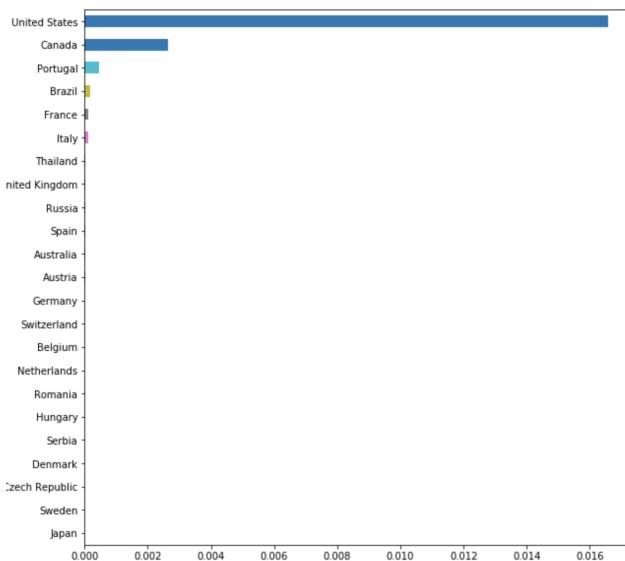


Figure 5: Top 5 countries with most cholesterol content [9]

an effect on the heart [5].

The top 5 countries with most sugar content in the food items are United States, Serbia, Switzerland, France, and Sweden as shown in Figure 6.

The top 5 countries with most sodium content in the food items are United States, Hungary, Serbia, Sweden, and France as shown in Figure 7.

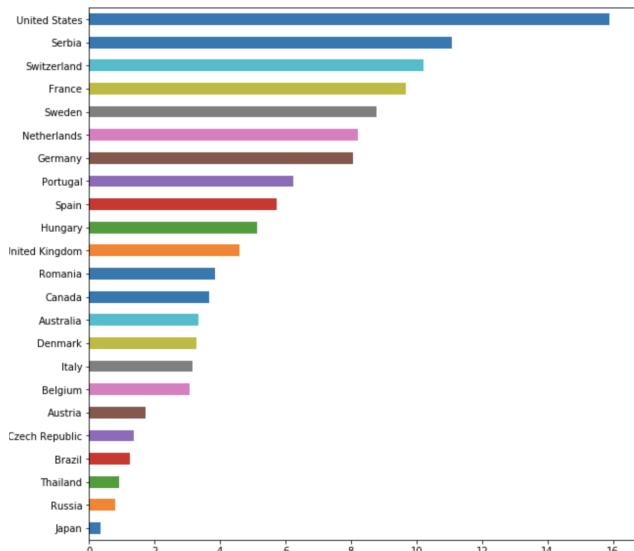


Figure 6: Top 5 countries with most sugar content [9]

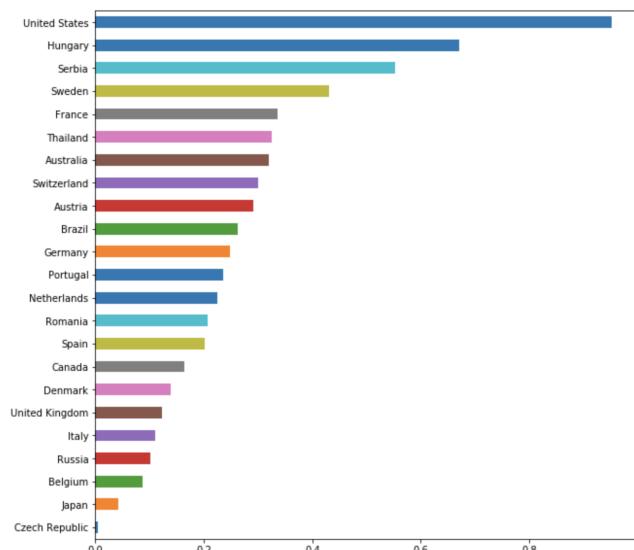


Figure 7: Top 5 countries with most sugar content [9]

4 NUTRITION GRADE LABELLING SYSTEM

France recently took a decision to implement a nutri-score system which will use a color coding mechanism to label the food products that will help consumers know the nutrition grade of the product [3]. The World Health Organization regional office for Europe as a part of its 5-year action plan from 2015-2020 recommends a labeling mechanism for the consumers to know about the quality of the food products at a first glance [3]. This will not only make it easier for the consumers to pick healthier options but it will also regulate food manufacturers to resort to healthier ingredients instead of going for low cost artificial or less healthy ingredients [3].

France after the United Kingdom became the second country to implement this system to indicate the main ingredients like fat, salt and sugar content in the food items [3]. France made use of an evidence-based system to study different labeling systems to arrive at the best one [3]. By implementing this system, the World Health Organization will keep a check on the growing number of diet-related diseases in the Europe region [3]. Europe being the largest consumer of cheese wants to regulate the ingredients that go into the manufacturing process so that people are well informed about their food choices [3].

4.1 Nutrition Grade Prediction as a Big Data Problem

We build a predictive classification model to predict the food nutrition grade based on the ingredients of the food. The goal is to apply various machine learning algorithms to the problem at hand, measure the prediction accuracy to compare and contrast the different algorithms and arrive at the best algorithm that suits the given data and the problem. This problem can be solved using Big Data and Machine Learning techniques given the size and the complexity of the data.

5 MACHINE LEARNING

Machine Learning is a field in which we train computers in a way that they can learn from the input data [6]. The ideology is that computers use the training data that is made available to them, learn from it, build a model and use this experience to build knowledge that can be applied on new unseen data [6]. A wonderful example to demonstrate machine learning is the application to detect spam emails where the machine builds knowledge from previously seen emails which are marked as spam, checks new emails to see if they match the historic spam emails and label them as spam or non-spam [6].

5.1 Types of Machine Learning Algorithms

There are primarily two types of machine learning algorithms, descriptive models and predictive models [6]. A *Descriptive Model* is described as the analysis done and insights gained from slicing and dicing the data in new and interesting ways [6]. One example of a descriptive model is pattern discovery that is often used in market basket analysis where transnational purchase details are analyzed [6]. A *Predictive Model* on the other hand involves predicting one value using one or more variables [6]. The learning algorithms tried to build a model that captures the relationship between a response variable and the independent variables [8].

5.2 Types of Learning

Unsupervised Learning is the process where there is no explicit training data to learn from, so there is simply no mechanism where the machine can learn from previously available data [6]. The same email example can be looked at in a different way where we now want to do anomaly detection in emails [6]. Here the main goal is to detect unusual messages from the bunch of messages and we do not have experience of previous data [6].

Supervised Learning in contrast is the process of gaining knowledge or expertise from the training data which can be applied to future unseen data [6]. Here the model is first trained by using a bulk of training examples and this model is applied to testing data to measure the accuracy [6]. The variable that we need to predict is identified which is called the response variable and the variables that are used to predict the response variables, called the predictor variables are identified [6]. If the existing variables are not sufficiently giving the accuracy that is expected, a method called feature engineering is done where new variables are derived by combining existing variables [6].

6 PREDICTION ANALYSIS

Prediction analysis is the process of working on a large dataset using a combination of statistical, data mining and machine learning algorithms to predict the outcome based on past data [6]. There are primarily two types of prediction analysis in machine learning, namely regression and classification [8]. In regression, we try to predict a continuous variable from the predictor variables [8]. A good example of regression is to predict the housing prices from different parameters like the year of construction, location, amenities, number of bedrooms etc [8]. Here the response variable is continuous and it is not predefined [8]. Classification, on the other hand, tries to predict a categorical variable in which we assign each record with a predefined label or a class [8].

Classification is the task of assigning each data record to a predefined class [8]. In machine learning, classification is categorized as a supervised learning technique [8]. This problem has applications in various fields like spam detection, medical applications, astronomy, and banking to identify fraudulent transactions from genuine transactions [8]. It is the task of coming up with a model which is essentially a function that maps every data record to a class label [8].

The task at hand is a classification problem since we are trying to predict the food nutrition grade of the products based on the ingredients that go into the product. For this problem, we are considering only the data for the country France, since the nutrition grade is available for most food products from the country. Another reason is that France is the first country in the region to come up with the idea of adding a color-coded label to the food products mentioning the nutrition grade. In the subsequent sections, we discuss the machine learning techniques used to solve this problem.

6.1 K Nearest Neighbors

6.1.1 Overview. Some of the classification algorithms in machine learning work on the principle of eager learning that involves a two-step process where first a model is built from the training data and the model is applied on testing data [8]. In contrast, K nearest neighbors is a lazy learning algorithm where the process of modeling the training data is not done until the test examples are classified [8]. *Rote Classifier* is a good example of lazy learning algorithm which memorizes the entire training data to perform classification but has the drawback of not being able to map every test example against the training example [8]. K nearest neighbors algorithm overcomes this drawback by finding all the records that

Algorithm 5.2 The k -nearest neighbor classification algorithm.

```

1: Let  $k$  be the number of nearest neighbors and  $D$  be the set of training examples.
2: for each test example  $z = (\mathbf{x}', y')$  do
3:   Compute  $d(\mathbf{x}', \mathbf{x})$ , the distance between  $z$  and every example,  $(\mathbf{x}, y) \in D$ .
4:   Select  $D_z \subseteq D$ , the set of  $k$  closest training examples to  $z$ .
5:    $y' = \operatorname{argmax}_v \sum_{(\mathbf{x}_i, y_i) \in D_z} I(v = y_i)$ 
6: end for
```

Figure 8: K nearest neighbors algorithm[8]

are closest or nearest to the training records [8].

The nearest neighbor puts each attribute list as a data point in the n -dimensional space, given n the number of attributes [8]. Once we have the training examples, we take each test example and compute its distance to the training example classes and assign a class label [8]. Any of the popular distance measures among Euclidean distance, Manhattan distance, Minkowski distance and Mahalanobis distance can be used [8]. The k denotes the k closest points to the test example [8]. Figure 8 shows the algorithm [8].

6.1.2 Support in Python. KNeighborsClassifier is available in the scikit learn python library.

6.2 Logistic Regression

Logistic regression or logit regression is a special type of regression analysis where the response variable that we need to predict is a categorical variable [8]. Typically, logistic regression models the response variable to take two values, 1 or 0, pass or fail, win or lose [8]. Logistic regression that takes more than two values for the response variable is called multinomial logistic regression [8]. Here the probability of the response variable to take a categorical value is modeled as a function of the predictor variables [8].

Like a lot of machine learning algorithms, logistic regression works by making a lot of assumptions which should be taken care as a part of the data cleaning and transformation process [6]. It does not assume a linear relationship between the response variables and the predictor variables [6]. Since it applies a log transformation on the predicted probabilities, it can handle a variety of relationship between the predictor variables [6]. If the predictor variables are multivariate normal, the algorithm achieves the best result although it works even if they are not [6]. The stepwise method must be used in the logistic regression to ensure that we are neither overfitting nor underfitting the data [6]. A very important assumption to be noted in logistic regression is that each attribute list must be independent, in the sense, the data records must not be derived from a before-after setup experiment [6]. It also requires a decently large sample size to work on [6].

6.2.1 Support for Python. LogisticRegression is available in the scikit learn python library.

6.3 Random Forest Classifier

Random forest is an ensemble classification algorithm which is very powerful [8]. Ensemble method is a special process to improve the accuracy of the prediction [8]. The classification algorithms we have seen so far predict the response variable using a single

classifier on the test data but ensemble methods use multiple classifiers in tandem and aggregate the predictions to boost the accuracy by a huge margin [8]. Using a combination method, the ensemble method derives a set of base classifiers from the training data and on each iteration takes a vote of all the base classifiers to arrive at a result [8].

Random forest is an ensemble method which works very well for classification problems [8]. It combines the predictions made by multiple classifiers where each classifier independently works on the training data and casts its vote [8]. Unlike methods like AdaBoost which generates values based on independent random vectors using a varied probability distribution, random forest generates values based on fixed probability distribution [8].

6.3.1 Rationale for Random Forest. Consider an example, where we have 25 base classifiers and each base classifier has an error rate of 0.35 [8]. As discussed, the random forest takes the majority vote given by the base classifiers [8]. The model makes a wrong prediction if half or more base classifiers predict inaccurately. The accuracy is improved with an error rate of 0.06 which is far better than using just a single classifier [8].

6.3.2 Support for Python. RandomForestClassifier is available in the scikit learn python library.

7 EXPERIMENTS AND RESULTS

In this section, we will introduce the algorithm along with the details of experiments and methodology for predicting the nutrition grade of food products in France.

7.1 Algorithm

The problem at hand is to correctly identify the nutrition grade of the food item. The possible labels are, a to e , with a being the best and e being the worst grade for a food item. For this task, we have used machine learning techniques that help in predicting the label of each food item. Before getting into the details of each step of the method, we first present a concise version of the algorithm used for this task:

- (1) Select all the records for the country, France. Drop records where nutrition grade is not populated.
- (2) Separate the predictors from the response variable in order to perform data cleaning and data transformation steps.
- (3) Check for missing values in the predictors obtained in the step above. Drop columns with more than 60% missing values.
- (4) Impute the missing values with 0 for remaining columns.
- (5) After imputing the missing values, standardize all the numerical predictors using the standard scaler.
- (6) Check for the correlation between different numerical predictors. Drop one predictor from each pair of predictors that show high correlation.
- (7) Combine the pre-processed predictors and the response variable in a single data frame.
- (8) Divide the data obtained in step above into training and test data using stratified sampling.

- (9) Train different classifiers on the training data and check the performance of each classifier on the test data.

7.2 Data set

For the classification problem, we selected the records for country France.

Number of examples: 123,961

Number of variables: 12

Response variables: *Nutrition Grade*

Predictor variables: *Energy per 100g, Fat per 100g, Saturated Fat per 100g, Carbohydrates per 100g, Sugars per 100g, Fiber per 100g, Proteins per 100g, Salt per 100g, Trans-fat per 100g, Sodium per 100g*

7.3 Python Packages Used

The following Python packages were used to solve the classification problem:

- Pandas: Provides high-performance data structures for data analysis and data munging
- Matplotlib: Plotting library that helps to embed plots into applications using GUI
- Seaborn: Visualization package based on matplotlib used for drawing high-level statistical graphics
- Scikit-learn: Toolbox with solid implementation of machine learning and other algorithms
- Scipy: Package that supports scientific computing with modules for linear algebra and integration

7.4 Data Cleaning

7.4.1 Step 1: Data Sparsity. Data sparsity refers to the situation where a lot of attributes have missing values which is an advantage in some cases because you only need to store and analyze the data that is available to you and save on computation time and storage [8]. We first check the data value counts for each country. United States, France, Switzerland, Germany, and Spain come as the top 5 countries with most data. Since the food nutrition grade was implemented in France, it has most products for which nutrition grade is labeled. So for this classification problem, we use the food data from France for analysis.

7.4.2 Step 2: Handling Missing Values. Missing values is a common scenario and they can be handled in different ways. You could choose to eliminate the data objects with missing values but at the expense of missing some critical analysis [8]. Estimating the missing values is also a good way to handle them, especially when the data comes from time series etc, where you could possibly interpolate the missing values from the ones that are closer to it [8]. Ignoring the missing values is another technique which can be applied to tasks like clustering where the similarity can be calculated using the attributes other than the missing ones [8].

The data set was first analyzed to check the missing values in all the columns. The threshold limit has been set at 60 percent. All the columns with missing values more than 60 percent were removed from the analysis to make the result more consistent. Once

the columns were removed, the data set has to be re-indexed to maintain the order. Only the columns that are important for the prediction task have been retained from the original dataset. In this case, all the ingredients which are primarily the predictor variables were included. The missing values in the response variable also need to be taken care of. Removing the records with missing values for the response variable proved to be the best option for trying out various things.

Imputation was used to handle the null values in the predictor variables. Imputation can be done in a variety of ways, for example, replacing the missing values with zero or imputing the missing values for numerical columns with the mean and the categorical columns with the mode. Since all the predictor variables have numeric values, all the null values have been replaced with zero. To ensure that the imputation process has been done correctly, the sum of missing values is calculated since post-imputation, this sum should be zero.

7.4.3 Step 3: Outlier Treatment. Outliers are data objects with quite distinct characteristics from the other data records [8]. There is a considerable difference between anomalies and outliers, where anomalies refer to data records that have bad data, which is noise and need to be ignored, anomalies often contain interesting aspects and can lead to some good analysis [8]. In applications like *Fraud Detection*, anomalies could be of utmost importance [8]. The outliers in the data have been looked at by using box plots and have been handled as a part of the data cleaning process.

7.5 Exploratory Data Analysis

For exploratory data analysis, we used the Seaborn package along with Matplotlib for visualizations. The measure of spread, that is the range and variance of the values, is a good way to understand the different aspects of the predictor variables. Box-plots are a method of visualization to look at the distribution of values for a numerical attribute [8]. The box plots show the percentiles where the lower and upper ends of the box indicate 25th and 75th percentile, the line inside the box indicates the 50th percentile, the tails indicate the 10th and 90th percentile respectively [8].

7.5.1 Bi-variate box-plots. Bi-variate box-plots go beyond univariate box plots by showing the relationship between the predictor variable and the response variable [8]. We look at the bi-variate box-plots for each of the important predictor variables namely, saturated fat, polyunsaturated fat, sugars and salt and the response variable, nutrition grade. Figure 9 shows the bi-variate box plots.

By looking at the box plots, we can understand some important aspects of how the response variable is related to the predictor variables. We see that as the average saturated fat content increases, the food grade decreases and as the average polyunsaturated fat content increases the nutrition grade is better. When the sugar levels increase, the health quotient of the food comes down. The energy levels behave in an interesting manner where the energy for the nutrition grade A is higher whereas in general, the average energy level slightly increases with the decreasing nutrition grade. While

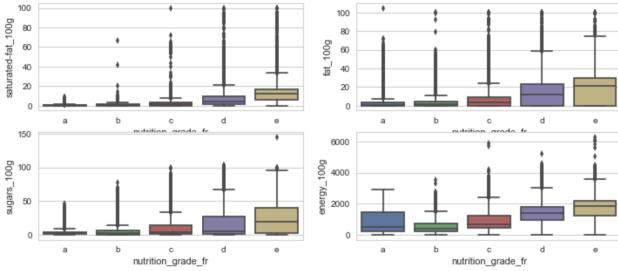


Figure 9: Bi-variate box plots [9]

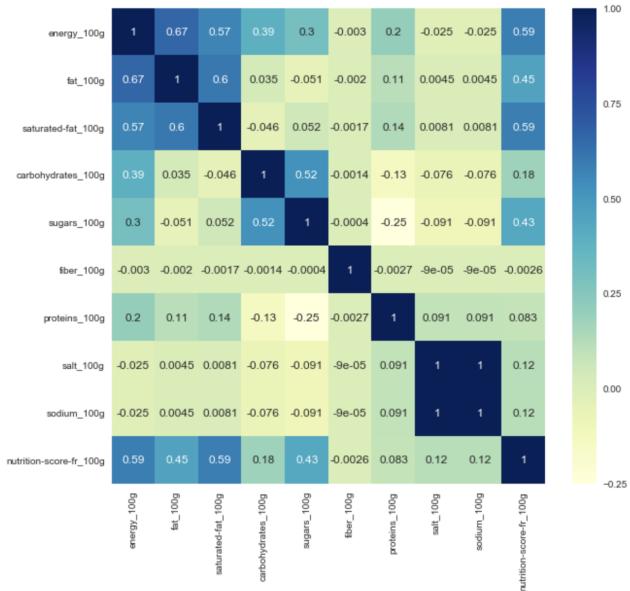


Figure 10: Correlation Plot [9]

increase in energy does not necessarily imply that the nutrition quality is high, as there are a lot of instant energy foods that have a lot of additives, but they are often rated low when it comes to health.

7.5.2 Correlation. Correlation between data objects is the measure of the linear relationship between the attributes of the object that are continuous variables [8]. Correlation analysis is the process of finding of the correlations between the different predictor variables and identify high collinearity problem [6]. The relationship could be either linear or non-linear based on the given data [8]. The correlation coefficient can range anywhere between -1 and 1, where 1 indicates a very high positive correlation and -1 indicates a very high negative correlation [6]. Correlation plot visually shows the correlation coefficient between the variables in a nicely laid out plot. Figure 10 shows the correlation plot.

By looking at the correlation plot, we can see that sugars, fat, energy are positively correlated with the nutrition grade. This indicates that these variables will play an important role in the prediction algorithm. However, sodium and salt are highly correlated

with each other and this may lead to collinearity problem if not handled. Collinearity is the state where the independent variables are highly correlated with each other which can add a lot of noise to the data [7]. Some of the problems because of collinearity are that the regression coefficients may not be estimated correctly. Also, collinearity makes it very difficult to explain the response variables using the predictor variables [7]. So we remove sodium from the predictor variables and proceed to the next step.

7.5.3 Data Transformation. Data transformation refers to the transformation that is applied to the variables [8]. For each data object, we apply a transformation function to all the attributes of the object to ensure that the attributes do not have a lot of variance in the data [8]. This process is also called standardization since we are applying a standard function to make sure all the attributes fall within a given range [8]. There are different methods that can be applied to achieve scaling namely log transformation, absolute value, square root transformation [8].

We use the method called normalization where all the values fall in the range, 0 to 1. To achieve this, we use the prepossessing package from sklearn which provides utility functions and transformer classes to change raw data into a standard representation. A lot of machine learning algorithms work well on standardized data. If some of the variables have extreme values, they might dominate the model function and might disturb the estimation parameter. Thus, for such extreme values, standardization helps achieve better results.

On scaling the data, there was a massive improvement in the prediction accuracy of the algorithms, implemented for this task. Thus, this proves the importance of data standardization with respect to machine learning algorithms.

7.6 Data Sampling

In a supervised machine learning approach, the model is trained on one sample of the data and later tested on a different sample of the data. Thus, in order to test the performance of the nutrition grade classifier, the data for the country France was divided into two samples, training and testing. There are various ways to achieve this split or sampling of the data. Some of these sampling methods are:

- **Simple Random Sampling:** This is one of the simplest sampling techniques. In this technique, every data point has an equal chance of being selected. In other words, it works similar to a lottery system where every outcome has an equal probability. The biggest advantage of this technique is the ease of implementation and its unbiased nature while generating the sample. However, random sampling might not always result in a sample that can represent the true population. It generally works well when we have huge data to sample from.
- **Stratified Sampling:** This technique is a more sophisticated method of sampling data. Stratified sampling generates a sample such that the proportion of each class in the sample is same as that in the true population. In this technique, the entire population is divided into groups or strata. The next

step is to randomly select data points from each stratum such that the final sample has the same proportion for each stratum as that present in the true population. Thus, the sample generated by this technique is a good representative of the true population. Stratified sampling is a very useful technique when the classes in the data are highly imbalanced.

For our classifier, we chose to divide the data for France into training and test samples using stratified sampling technique. The strata or groups were created based on the response variable, i.e., food grade. This ensured that the training and test data had the same proportion of each food grade.

7.7 Data Modeling

Once the data was divided into training and test data, the next step was to train different classifiers and tune their respective parameters for better accuracy. We implemented three different models for classifying the food grade. Each of these models along with their parameters is:

- K Nearest Neighbors (kNN): For kNN, the grade of a food item in test data is classified by first finding the k most similar food items in the training data. It then takes the vote (food grade label) from each of these neighbors and based on the majority vote, the food item from the test data is assigned a food grade. Thus, one of the most important parameter for kNN is k , i.e., the number of neighbors to consider from the training data. We tried different k values and found that $k = 3$ gives the best accuracy.
- Logistic Regression: For logistic regression, one of the important parameters is the penalty. This parameter specifies the kind of regularization to be applied. This parameter can take two possible values, l_1 regularization and l_2 regularization. Both these values penalize high magnitude of the coefficients of the predictors in order to prevent the model from over-fitting. For our model, we have used l_2 regularization as it works well even in the presence of highly correlated features.
- Random Forest: For the random forest, there are many parameters, such as the number of trees in the forest, the maximum depth of the trees, maximum number of features to consider at each split, the minimum number of samples required in a sub-tree to qualify for a further split, the minimum number of samples required to qualify as a leaf node, etc. For our data, we have kept most of the parameters at their default values, except for, the number of estimators or trees in the forest. We have set this value to 100, as the classifier resulted in very high accuracy with 100 trees in the forest.

7.8 Evaluation Metrics and Results

There are various evaluation metrics for assessing the performance of classifiers. Some of these evaluation metrics are [4]:

- Accuracy: This metric gives the proportion of the total number of correctly classified instances
- Precision: This gives the proportion of the true positive instances from the total instances classified as positive

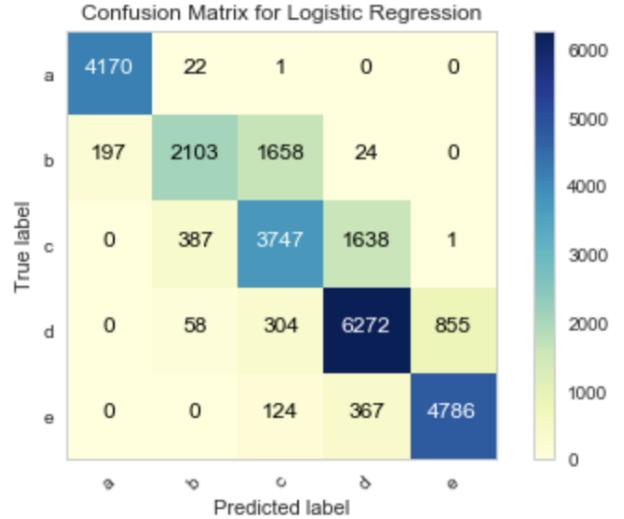


Figure 11: Confusion matrix for Logistic Regression [9]

- Recall: This gives the proportion of the positive instances that are correctly classified
- F-Measure: This gives the harmonic mean between precision and the recall values
- Confusion Matrix: This is a useful way of checking the accuracy of the classifier. It clearly shows the number of instances correctly classified for each label. Thus, if we know that the classes in the data are not well-balanced, it's always a good idea to check the confusion matrix along with accuracy. Consider a case where 95% of the instances belong to class A and only 5% of the instances belong to class B. If a classifier is trained on a dataset with such imbalance, there is a high chance that the classifier would return label A for each test instance. The classifier would still be able to correctly classify 95% of the test instances resulting in 95% accuracy. This is a case where accuracy can be misleading and thus a quick look at the confusion matrix can help understand the problem with the classifier. For such a case, the confusion matrix will clearly show that all the instances of the minority class, B, have been misclassified.

For our model, we used accuracy as well as confusion matrix for evaluating the results. The confusion matrix did not show any serious issues for any of the classifiers. The accuracy for each of the three classifiers was:

- (1) Logistic Regression: With l_2 penalty, the accuracy of logistic regression was 78.9%. Figure 11 shows the confusion matrix.
- (2) K Nearest Neighbors: With k as 3, the accuracy of kNN was 95.74%. Figure 12 shows the confusion matrix.
- (3) Random Forest: With a number of trees as 100, the accuracy of random forest classifier was 99.68%. Figure 13

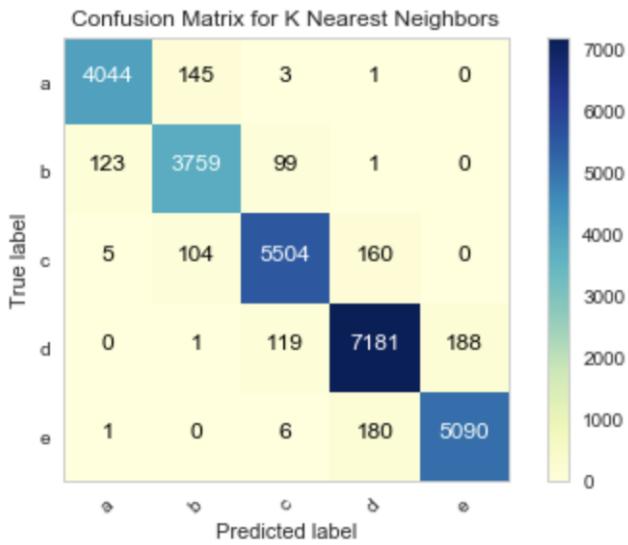


Figure 12: Confusion matrix for K Nearest Neighbors [9]

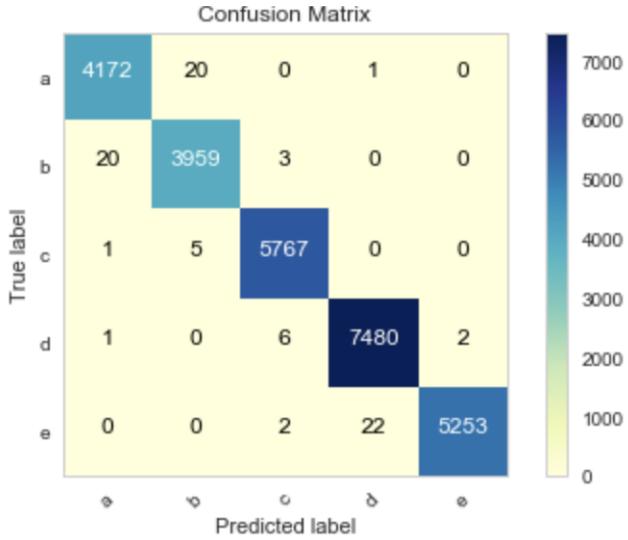


Figure 13: Confusion matrix for Random Forest [9]

shows the confusion matrix.

Thus, we obtained the best results with Random Forest classifier.

8 CONCLUSION

Analysis of food content is very important in today's world as most of the companies try to fool consumers by labeling their product as low-fat. It's important for the consumers to know the true nutrition grade while purchasing any food item. Thus, we analyzed the nutrition grade based on the composition of various components of the food items. We developed a model that labels a food item purely on the basis of its nutrients, thus eliminating any bias, such as, the

production company or the brand name. For accurate labeling, we applied different data cleaning and data transformation techniques. With this transformed data, we tried various machine learning models. We got the best results using random forest classifier which was able to accurately label 99% of the food products. Since the model is trained only for France, as part of future work, we can try and scale our model for different countries. However, to achieve similar results for other countries, we need to collect more data. The current data has many missing values for countries other than France. Once we collect enough data for these countries, we can also try and implement more sophisticated models like neural networks in future.

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A WORK BREAKDOWN

Dataset identification: Karthik Vegi, Nisha Chandwani: work equally split between.

Requirement Gathering: Karthik Vegi, Nisha Chandwani: work equally split between.

Learning Machine Learning Concepts: Karthik Vegi, Nisha Chandwani: work equally split between.

Data analysis and implementation of the Logistic Regression: Karthik Vegi.

K nearest neighbors and Random Forest algorithms: Nisha Chandwani

Writing the project report: Karthik Vegi, Nisha Chandwani: work equally split between.

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Recipe Ingredient Analysis

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ABSTRACT

Food is the unavoidable part of day to day of human life. Ingredients play a major role or are the basic requirement in preparation of any kind of food. We can find the humongous list of ingredients getting used across globally along with other details which constitute to big data. We explore ingredients getting used in various recipes across the globe to understand most used ingredient, key ingredients of various cuisine and the relationship between the ingredients to find out closely related ingredients which can always provide great dish if used together.

KEYWORDS

i523, hid302, big data, ingredient, recipe, analysis, python, gephi

1 INTRODUCTION

Ingredients are vital for human existence as well as for food or restaurant industry. We use it every day for cooking and food industry uses it to produce consumable for their customers. Ingredient inspires chefs to come up with new culinary artistry. So what do we know about this essential element of the life and what data tell us? Ingredients come in different size, color, shape, flavor, nutrition, taste, texture, grows in specific weather conditions and this provides a great opportunity for various analysis which can be useful for the human being as well as business industries. There can be multiple analysis carried out on the ingredients but main focus of this study is on the ingredients used in various recipes across the cuisines understand most used ingredients, key cuisine ingredients and ingredient relationship.

This study is organized as follows, section *Big Data and Food* touch open big data and its application in food industry, section *Ingredient* defines ingredient and it's various characteristics. section *Ingredient Analytics and Related Studies* describes various analytics which can be performed on the ingredient with some examples and studies. Section *Project* describes the aim of this study. Section *technologies* provides information on the tools and technologies used for this project. Section *Methodology* covers overall process carried out in this project. Section *Dataset* describes data structure used along with loading process and data findings. Section *Analysis and Findings* describes various analysis carried out on the data and the visual representation of the analysis. Section *Shortcomings* captures shortcomings of the project. Section *Limitations* talks about limitations and what else can be done with this dataset which is not covered in the current scope of the project. Section *Conclusion* concludes the study.

2 BIG DATA AND FOOD

Big Data is defined in lot many different ways but one of the interesting ways it has been defined is in terms of three V's which are Volume, Velocity, and Variety. Big data is generated in great volume

typically in the gigabyte or more which makes data processing difficult. Data *velocity* has been increased due to the real-time data streaming from various applications like social media or different type of sensors recording data continuously. Big data comes in *variety* of format like structured or unstructured data. Data varies in various format like text, pictures, audio, videos, 3D, social media and so on. These big data characteristics pose challenges in terms of overall data lifecycle management. Some of the examples of big data usage are the recommendation service, predictive analytics, data analytics, pattern identification, and machine learning.

Over the period of time, food has grown from basic necessity to big food industry. Food industry covers lot many businesses under its umbrella like agriculture which is growing/raising/catching food, food production or manufacturing, food processing, food safety and compliance, distribution, marketing, food retailing and food service [9]. Ultimately this wide array provides us with a huge opportunity for big data application in food industry.

Agriculture is moved on to precision agriculture with the rise of new technologies. Precision agriculture is a practice of farming more accurate and controlled when it comes to the growing of crops and raising livestock. A key component of this farm management approach is the use of information technology and a wide array of items such as GPS guidance, control systems, sensors, robotics, drones, autonomous vehicles, variable rate technology, GPS-based soil sampling, automated hardware, telematics, and software. Big data gathered by these technologies are used to guide both immediate and future decisions on when it is best to apply chemical, fertilizer or seed [19].

The distribution includes all activities of moving food from food producer to the consumer. Big data can provide valuable analytics in determining the best transportation methods and routes. By analyzing transport methods and making them more efficient, spoilage and damage can be reduced, allowing a greater percentage of products to make it from the farm to the customer. This is important as lot many time food contains perishable items which can result in bio-waste if not handled properly during the transportation. Reducing this waste will increase profits, as well as the amount of food produced, and will have a positive impact on the environment [17].

Food safety is another growing concern in the food industry as it has direct implication to the human health. Analyzing data about food quality helps to detect spoiled food, preventing it from reaching the customer. This analysis can also help producers and distributors in the food industry identify contaminated food, and isolate its source and current location. Not only does this allow for faster recalls, minimizing the number of people exposed to the food, it also allows for targeted recalls rather than blanket ones. This saves the company significant amounts of money, as fewer items need to be removed from shelves and replaced [17].

Big data is allowing restaurant chains to closely monitor every aspect of their business. By collecting information from every

individual restaurant, it is possible for food analytics to detect patterns such as what menu items perform best in which regions, how much food needs to be stocked and prepared for a given week or even a particular time of day, and what building layout provides the best and most efficient experience [17]. Sentiment analysis can help in understanding the customer emotions. Preventive action can be taken to address the customer dissatisfaction.

3 INGREDIENT

Food is defined as “Edible or potable substance (usually of animal or plant origin), consisting of nourishing and nutritive components such as carbohydrates, fats, proteins, essential mineral and vitamins, which (when ingested and assimilated through digestion) sustains life, generates energy, and provides growth, maintenance, and health of the body” [4]. Thus food is the basic necessity for human for the sustainability. Food can be eaten raw, cooked or processed. As human race evolved over the period of time, the way we eat food is also evolved. Food cooking is just not the basic necessity but its an art and science in today’s era. Food preparation consists of various cooking techniques, tools, and ingredients to make it palatable or edible by humans. The ingredient is by far the most important part of any food or recipe preparation. The recipe consists of the list of ingredients and the set of instruction to cook particular food dish [8]. An ingredient is defined as “Any of the foods or substances that are combined to make a particular dish” [16]. Ingredients impart various flavors, aroma, texture, and color to the cooking dish. Ingredients are mostly derived from vegetables, fruits, nuts, grains, living organisms, herbs, flowers, and spices. It comes in both solid and liquid forms. Another characteristic of ingredients is the nutritional value they provide which is essential for the human body.

4 INGREDIENT ANALYTICS AND RELATED STUDIES

Ingredients characteristics and the combination of other related data provides various opportunities to analyze ingredient in different ways. Flavor network and the principle of food pairing by Yong-Yeol Ahn et al. [1] is the most referenced study in terms of ingredient analysis. They built a bipartite network consisting of ingredients and flavor compounds imparted by those ingredients. This flavor network connects two ingredients if there is at least one flavor compound is shared by those ingredients. More the flavor compound ingredient they share more strongly they are related. This network revealed that fruits and dairy products are close to alcoholic drinks, and mushrooms appear isolated, as they share a statistically significant number of flavor compounds only with other mushrooms. They further studied food pairing hypothesis and found out that in North American recipes, the more compounds are shared by two ingredients, the more likely they appear in recipes. By contrast, in East Asian cuisine the more flavor compounds two ingredients share, the less likely they are used together. Analysis of the flavors present in ingredient can provide us with the categorization of the different ingredient by the flavor profile which can be helpful in deciding substitute ingredient if a certain ingredient is not present or pairing ingredient from different flavor categories

to construct the dish as per the taste required. This analysis also helps to understand which ingredients cannot be used together.

Another analysis is carried out to correlate ingredient across recipes to come up with top 50 combinations of ingredients which can be used together [11]. Some of the combinations finding from this study are interesting and fun to experiment

- tomato, garlic, oregano, onion, basil
- vanilla, cream, almond, coconut, oat
- onion, black pepper, vegetable oil, bell pepper, garlic
- cumin, coriander, turmeric, fenugreek, lemongrass

Flavourspace application provides functionality to search recipe based on the ingredients, suggests alternate ingredient if not present, adjust the recipe as per the taste which is a good example of big data analytics in food industry [18].

Foodpairing application takes another approach to form the connection between unfamiliar ingredients and provides information on how to use such ingredient to make a dish, this is very helpful in terms of sustainability as we can use ingredient which is ample available but not in use due to the absence of information on using such ingredients [14].

Recipe recommendation system uses users recipe browsing history or rating history to suggest the recipe. It also relay on the ingredient present in the recipe and look for the overlap or key ingredients while matching other recipes. Another approach is to recommend recipe based on the nutritional values or healthy food choice which is dependent on the ingredient used in the recipe. Models are made to recommend recipe based on the available ingredients and personal nutrition needs. Chen-Yuen et al. [6] derived network of complimenting and substituting ingredients. They also demonstrated that network can be used to predict which recipe would be successful. To understand the complimenting ingredient they constructed network based on pointwise mutual information (PMI) defined on pairs of ingredients. This PMI provides the probability of those two ingredients occurring together. Their study found out 2 main cluster as savory and sweet dishes along with the a satellite cluster of mixed drink ingredients. This study also finds out ingredient adjustment and substitution based on the comments on the recipe. Recipe comments provides insight into which ingredients quantity is increased or decreased to get more flavors or which ingredient is used instead of some ingredient in the recipe since ingredient mentioned in recipe is not present or to get different taste. The words like add, omit, instead, adding, using, more etc in comments provides this insight. Ingredient which are considered as unhealthy like sugar, fats are often reduced and ingredient which adds flavors like soy sauce, lemon juice, cinnamon are added more in quantity. Chicken can be substituted by turkey, beef, sausage, chicken breast, bacon and olive oil by butter, apple sauce, oil, banana, margarine, and Tilapia by cod, catfish, flounder, halibut, orange roughy to name few.

The researcher at IBM have built a program that uses math, chemistry, and vast quantities of data to churn out new and unusual recipes. The new recipes are generated by ‘mutating’ the ingredients of existing recipes, and then fusing these with other recipes, resulting in all sorts of new hybrid concoctions. This idea, known as a genetic algorithm, is modeled after the process of genetic change [3].

Another study conducted on most used ingredient provides insight that sugar, oil, pepper, and salt are most commonly occurring ingredient, among spices clove, in vegetable onion, garlic , and tomatoes, butter in milk product, eggs followed by chicken in the animal product are the most used ingredient in the categories [5]. This information can help in better planning and sourcing of such ingredients which are in high demand.

Ingredient nutrition analysis can help find out nutrition of the food prepared by those ingredients. This would be helpful in menu planning where nutrition information is the key factor such as school, hospitals or any other dietary program [7].

Yannick Kimmel [13] analyzed top 20 recipes on allrecipes.com website for last 20 year to understand the food trends in the USA. Word cloud analysis on recipe title revealed that cookie, chicken, chocolate, banana, salad, bread, potato, pie, cake, and bake are most frequently used in the top recipe titles. The ingredient word cloud includes sugar, white, ground, butter, salt, bake, and chop which are fundamental words in cooking. Recipe calorie analysis shows that there is jump in calories in initial year but it drop slowly over period of time which can be reflection of focus on healthy food. Analysis also reveals that there is increase in usage of olive oil which might be the result of health benefits provided by olive oil.

Recipe cost is calculated by including the cost of the ingredient used in that recipe. Ingredient cost as per the quantity used in recipe provides base information to calculate the price of any recipe. This ingredient cost analysis provides an avenue to reduce the cost of the recipe by using substitute ingredient of lesser cost. This can also help in household budget to keep in check as well as make restaurant industry profitable.

Ingredient used in recipe can provide insight into type of weather received by that cuisine as ingredient can grow in certain weather condition. This can help chef locally source the ingredient and maintain local agriculture sustainability.

According to study food also contains medicinal properties and can be used for the healing. Traditional healing methods like *Ayurveda* in India and Chines medicine relay on food or various herbs medicinal properties for the healing. Ingredients has medicinal properties like Decreasing and Controlling Inflammation, Balancing Hormones, Alkalizing the Body, Balancing Blood Glucose, Detoxifying and Eliminating Toxins and Improving Absorption of Nutrients. Green vegetables like kale, wheat grass and spinach, sea vegetables are considered some of the healthiest foods and known to help slow aging [2]. Analysis of food ingredients for the medicinal properties to classify those food with various medicinal values and effect on human body can greatly help as this treatment can be low cost as compare to other medical treatments.

We also found ingredient relationship analysis and network graph generated in another study [20]. This analysis shows ingredient cluster of 5 cuisines.

5 PROJECT

This project study is conducted to analyze ingredients getting used in various recipes across the cuisines to find out

- Most used ingredients across cuisines or globally
- Key ingredients used by cuisines

- Ingredient relationship to understand the related ingredients and provide complimentary ingredient network

5.1 Technologies

Technologies and tools used in this projects are

- Python version 3.6 is used for data load and processing
- Gephi 0.9.2 for visualization
- Spyder 3.0 as a Python IDE

5.2 Code Organization

Code is checked-in in Github at location

<https://github.com/bigdata-i523/hid302/tree/master/project/code>

Code is organized as described in Figure 1

code

```
- ingredientAnalysis.py
- ingredientAnalysis.py
- data
  - train.json
  - nodes.xlsx
  - edges.xlsx
- images
- gephi
  - geph Ing big data.gephi
```

Figure 1: Code Structure

Python Scripts

- *ingredientAnalysis.py* - This python script loads dataset from datafile train.json present in *data* directory and process dataset to find out recipe distribution across cuisines, top 20 ingredient used across cuisines and top 10 key ingredients for every cuisine. The graph generated during analysis is stored in *images* folder. This codes inspiration can be found out at Kaggle's What Cooking competition which we modified as per our project need [15], [10].
- *ingCluster.py* - loads dataset from datafile train.json present in *data* directory and process dataset to create relationship file required by Gephi in excel format. It establishes ingredients relationship by relating ingredient in recipe with each other to generate *nodes.xlsx* and *edges.xlsx* files and stores in *data* directory. These generated files are then imported into the Gephi to create the visualization.
- *geph Ing big data.gephi*
 - This is project file from Gephi which can be re-opened in Gephi software to view or re-run the analysis.

5.3 Methodology

We followed methodology as described to complete our study

- *Identify Data Source* - We analyzed various sources of ingredients and finalized the data source
- *Collect/Extract Data* - We analyzed various ways of extracting data from the data source and finalized our approach on data extraction process
- *Load Data* - Load data using Python script for the analysis

- *Clean/Filter Data* - Process loaded data for the clean up to avoid unwanted data
- *Process Data* - Process cleaned up data through python scripts to analyze most used ingredient, ingredient distribution across cuisines and per cuisine
- *Generate Ingredient Relationship Network* - Gephi software is used to analyze the relationship and to find out the ingredient modularity. We investigated what kind of data is needed for Gephi for the analysis and we understood that Gephi needs node and edges which is nothing but the relationship between the nodes. Node contains node id and edges contains source node id and target node id which depicts source node is related to target node and this file can be generated in excel file format. Python script is used to create the network files required by the Gephi tool. Python script generated Node and Edges file in excel format so that it can be imported into Gephi. Distinct ingredients used in recipes becomes the nodes. Edges or relationship between ingredients is derived by relating ingredients appearing in the same recipe. All ingredient in the same recipe is considered related to each other.
- *Import Data to Gephi* - Network files created by Python are imported in Gephi to produce the graph for the visualization.
- *Clean/Filter Data in Gephi* - Gephi tools data laboratory is used to clean up the data and filters are applied to provide usable network visualization.
- *Data Processing in Gephi* - Process data in Gephi by applying layouts and statistics to generate the graph
- *Visualize and Publish Results* - Gephi tools data laboratory is used to clean up the data and filters are applied to provide usable network visualization.

Figure 2 shows pictorial representation of the methodology used for this project to analyze ingredient data.

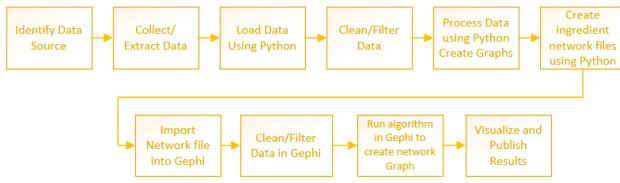


Figure 2: Flowchart of the Methodology to Analyze Ingredients

5.4 Data Gathering

The first step was to source the data. We were interested in the dataset which provides recipe information along with the ingredient used in the recipe. Since we wanted to analyze distribution across cuisines, data should also contain cuisine tagging. We evaluated 2 ways of gathering the data, generate the data ourselves or use publicly available data.

The dataset can be generated by pulling recipe data from various online applications or pick from publicly available datasets.

There are lot of applications online like allrecipes, Food, Yummly etc which hosts thousands of recipes and not to forget about recipe site available in every country, if we consider all these sources then it can easily contribute to huge dataset. Yannick Kimmel [13] demonstrated in his recipe analysis project how recipe data can be source directly from the application. He did analysis of top 20 recipes from allrecipes website which is the largest web application hosting the recipes. He used Selenium package in Python to scrap allrecipes which can handle AJAX used in the application. Each recipe in allrecipe can be identified using unique identifier and follows generic format as [allrecipes.com/recipe/\[Unique ID number\]](http://allrecipes.com/recipe/[Unique ID number]). This generic URL is used by passing different unique id number to retrieve the recipe page and then find-element method is used to read various attributes like title, rating, reviews, calories per serving, prep time, cook time, total time and ingredients. We can follow the same approach to generate the dataset from different recipe sites for our analysis but we finalized publicly available dataset at Kaggle application satisfying need for this project to save the time.

5.5 Dataset

The dataset for this study is sourced from Kaggle application [12]. This dataset is publicly available and featured in *What's Cooking?* competition. This dataset is provided to Kaggle by Yummly which is the application which hosts recipes online. This dataset is in JSON format and of 12MB size. This dataset contains recipe id, cuisine and list of ingredients as described in Figure 3. This dataset contains

```
{
  "id": 24717,
  "cuisine": "indian",
  "ingredients": [
    "tumeric",
    "vegetable stock",
    "tomatoes",
    "garam masala",
    "naan",
    "red lentils",
    "red chili peppers",
    "onions",
    "spinach",
    "sweet potatoes"
  ]
}
```

Figure 3: Ingredient Data Structure

total 39774 recipes across various cuisines. We used two different methods to load this data. Cuisine and ingredient analysis is done by loading data into *pandas dataframe* and to analyze ingredient relationship data has been loaded into *json* object. Figure 4 shows the code for data loading used in this project.

Ingredient extraction from the data structure and processing was challenging as ingredients are listed comma separated for each recipe. Also, ingredient list can vary by recipe and there is no proper structure. We observed shortcoming of dataset as

- *Ingredient Duplication* - ingredient appears in the ingredient list in various forms but it's the same ingredient which

```

#read the ingredient data using pandas
dfTrain = pd.read_json('./data/train.json')

#load data using json
dataFilePath='./data/train.json'
with open(dataFilePath) as data_file:
    data = json.load(data_file)

```

Figure 4: Data Loading

gives duplicate data. For example, salt appears as salt, kosher salt, Morton Salt, sea salt, table salt, Himalayan salt, fine sea salt, low sodium salt, fine salt. This is the same ingredient but come across in recipe as a different ingredient and getting counted as a separate ingredient in the analysis

- *Ingredient Name along with measure* - ingredients are listed along with measures like (10 oz.) frozen chopped spinach, (10 oz.) frozen chopped spinach, thawed and squeezed dry, (14.5 oz.) diced tomatoes and getting counted as a separate ingredient
- *Branded Ingredients* - ingredients are listed along with the brand name like KRAFT Reduced Fat Shredded Mozzarella Cheese, Johnsonville Smoked Sausage, Johnsonville Mild Italian Sausage Links etc and also constitutes to the ingredient list
- *CountryName with Ingredients* - ingredients are listed along with the country name like japanese cucumber, korean chile paste, Japanese soy sauce etc and also constitutes to the ingredient list
- *Ingredient name too long* - some ingredient name are too long to be an ingredient like *wish-bone light asian sesame ginger vinaigrette dressing*
- *Ingredient with application* - ingredient names like chopped onion, diced tomatoes, chopped cilantro, grass-fed beef, grass-fed butter, cut up chicken

This variation makes difficult to get the proper ingredient list for the analysis. Extensive work is needed to clean and correct the noisy data so that proper analysis can be carried out. This correction process is not carried out as part of this project.

Certain ingredients like salt or water etc should be avoided from the analysis as those are not the ingredient we are looking for the analysis. We tried to clean such elements during ingredient relationship analysis but we had little success as those ingredients are present in the dataset in various forms.

5.6 Analysis and Findings

5.6.1 Recipe Distribution By Cuisine. We first analyze entire dataset to understand the total number of recipes and their distribution across various cuisines. We use Pythons Panda library to get the total recipe count as 39774 and plot the distribution. Figure 5 shows number of recipes per cuisine. Our observations from this analysis are

- Dataset is heavily dominated by Italian cuisine followed by Mexican cuisine which shows popularity of those cuisines

- Very fewer recipes from Russian and Brazilian cuisines which shows very less contribution from those areas
- No recipes from some regions like Germany, Canada which might be due to the recipes are not uploaded by users from that regions
- This also highlights another shortcoming of the dataset that it doesn't have equal representation of all cuisines which might give us biased analysis

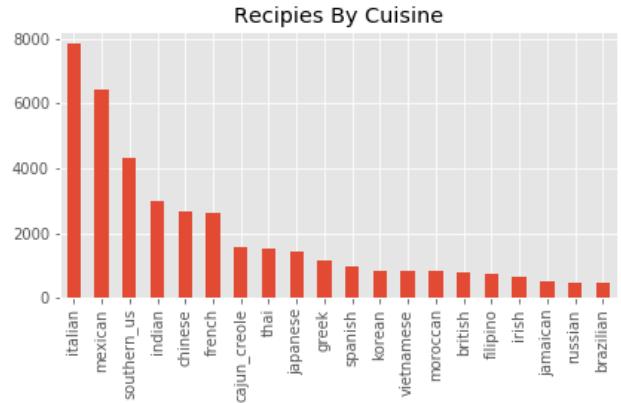


Figure 5: Recipe Distribution By Cuisine

Table1 describes recipe count for every cuisine.

Table 1: Recipe Count By Cuisine

Cuisine	Recipe Count
brazilian	467
british	804
cajun creole	1546
chinese	2673
filipino	755
french	2646
greek	1175
indian	3003
irish	667
italian	7838
jamaican	526
japanese	1423
korean	830
mexican	6438
moroccan	821
russian	489
southern_us	4320
spanish	989
thai	1539
vietnamese	825

5.6.2 Most Used Ingredients All Cuisines. The second analysis is carried out to understand top 20 ingredients getting used across cuisine or globally. As per our study most used distinct ingredients across cuisines in order are

- Salt
- Olive Oil
- Onions
- Water
- Garlic
- Sugar
- Butter
- Black Paper
- All-purpose flour
- Vegetable Oil
- Eggs
- Soy Sauce
- Green Onions
- Tomatoes
- Carrots

Ingredient *Salt* is obvious topper followed by *Oil and Onions*. This also proves our craving for salty and fatty food. Top 20 ingredient also contain duplicate ingredient like garlic and garlic clove, salt and kosher salt, eggs and large eggs which shows shortcoming of the dataset. Also ingredient like salt, oil and water could be avoided to get analysis of real ingredients as these are commonly use ingredient and doesn't contribute much to the study. Figure 6 shows top 20 ingredient across cuisines.

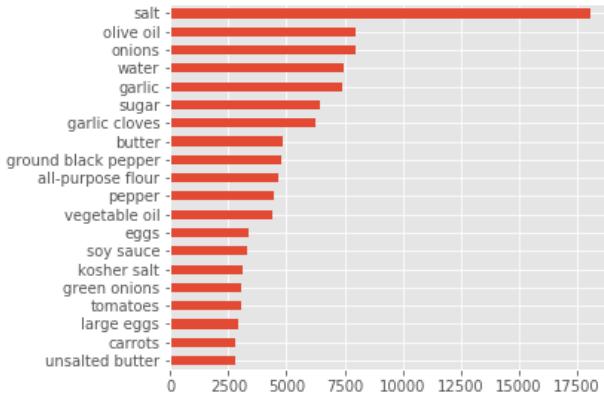


Figure 6: Top 20 Ingredients

5.6.3 *Ingredients Distribution By Cuisines*. The third analysis is carried out to understand key ingredient for each cuisine. These key ingredients define those cuisines and provide unique test characterized by that cuisine. We limited ingredient list to top 10 to get the key ingredients for each cuisine. Study shows key ingredient for our top 5 cuisines as follows

- *Italian* - Olive oil, garlic, cheese, black pepper, onion and butter
- *Mexican* - onion, cumin, garlic, chili powder, jalapeno chilies, sour cream, tortillas and avocado
- *Southern US* - butter, all-purpose flour, sugar, eggs, baking powder, milk and butter milk
- *Indian* - onion, garam masala, turmeric, garlic, cumin and oil

- *Chinese* - soy sauce, sesame oil, corn starch, sugar, garlic, green onions and scallions

Similarly we show key ingredient of all other cuisines present in the dataset and we observe that it is very close representation of all cuisines. Figure 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26 shows top 10 key ingredient used in the corresponding cuisines.

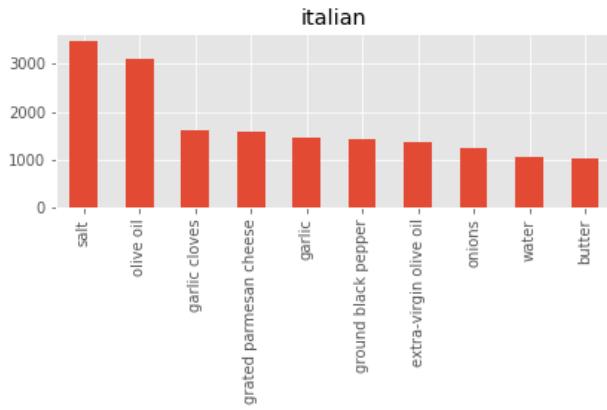


Figure 7: Top 10 Ingredients

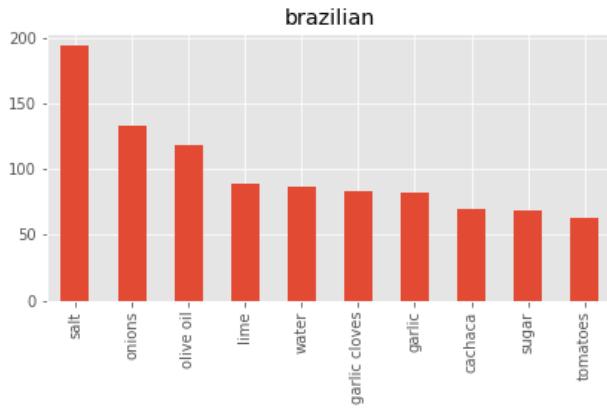


Figure 8: Top 10 Ingredients

5.6.4 *Ingredients Relationship*. Forth analysis is carried out to understand the relationship between the ingredient to find out ingredient clusters. This analysis helps us understand the ingredient combinations which can be used together to provide great dish every time. This model can be used to predict ingredients for certain recipe based on the cluster. We used Gephi tool to analyze and produce the graph for this analysis. Gephi accepts network structure in terms of Node and Edge relationship. We created this network using python by relating all ingredients present in the recipe with each other. Ingredients become the node and source and target nodes become the edges. These network files generated in excel spreadsheet and converted to CSV format and imported

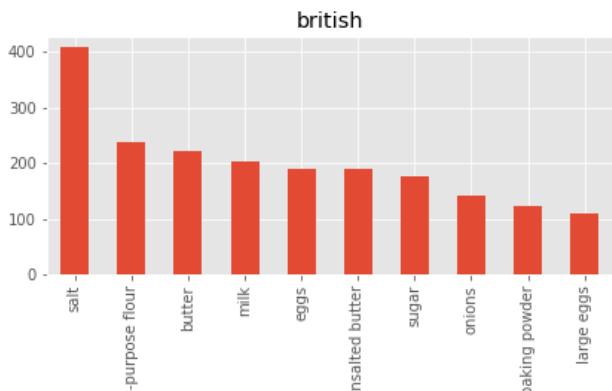


Figure 9: Top 10 Ingredients

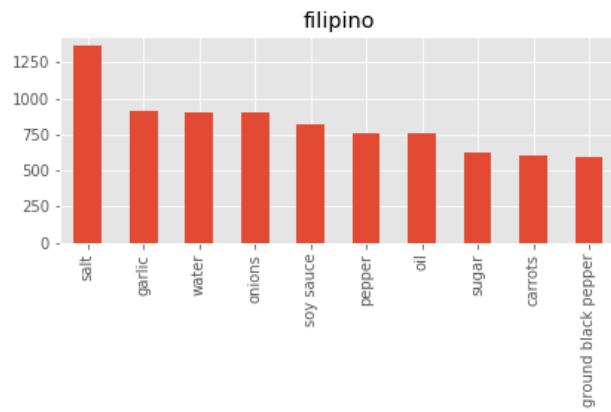


Figure 12: Top 10 Ingredients

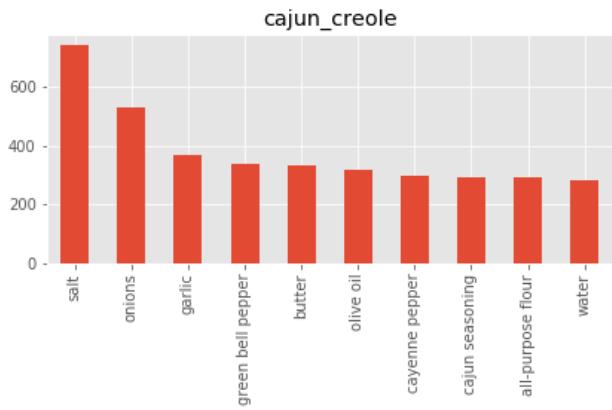


Figure 10: Top 10 Ingredients

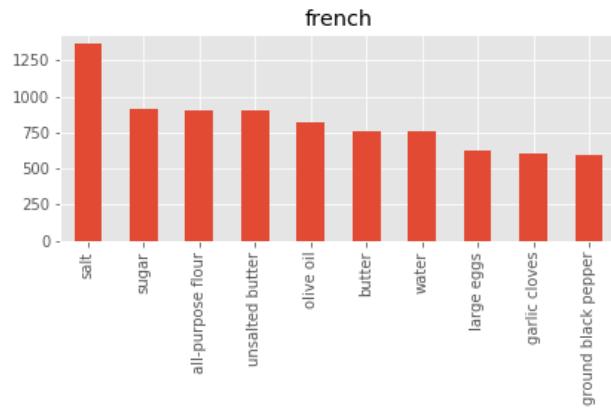


Figure 13: Top 10 Ingredients

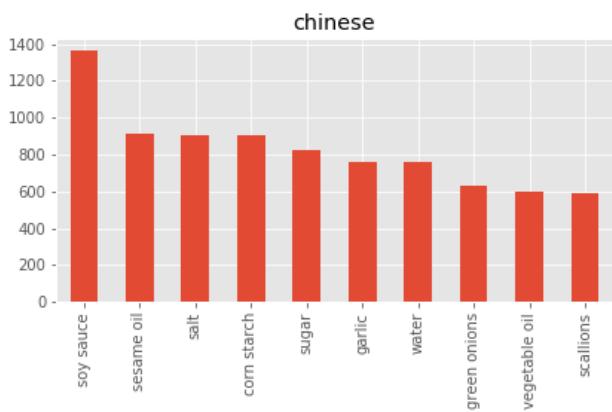


Figure 11: Top 10 Ingredients

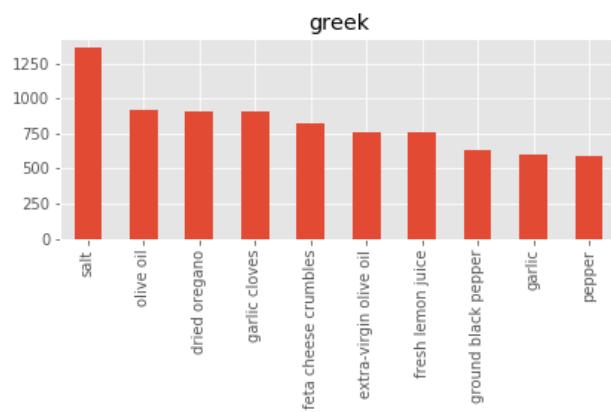


Figure 14: Top 10 Ingredients

into the Gephi tool. Import created 5405 Nodes and 290828 edges for processing and analysis. Force Atlas 2 layout present in Gephi has been applied to the network which brings nodes with higher

weights and shared connections closer to each other. We also used Gephi Data Laboratory to clean up duplicate or unwanted nodes. Filtering based on Degree Range and Edge Weight has been applied

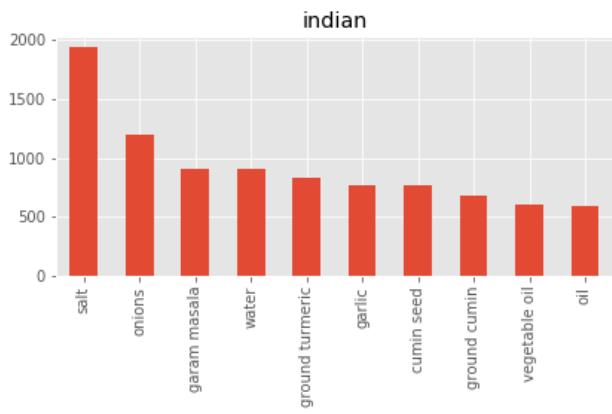


Figure 15: Top 10 Ingredients

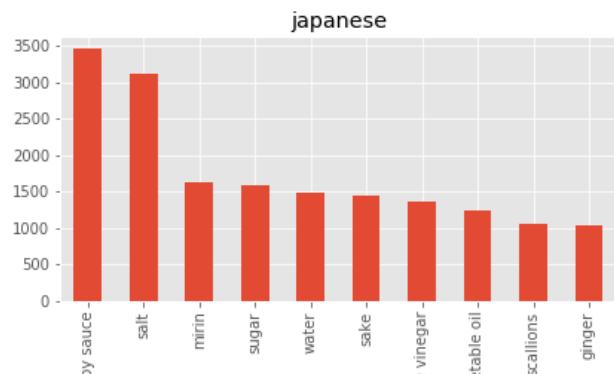


Figure 18: Top 10 Ingredients

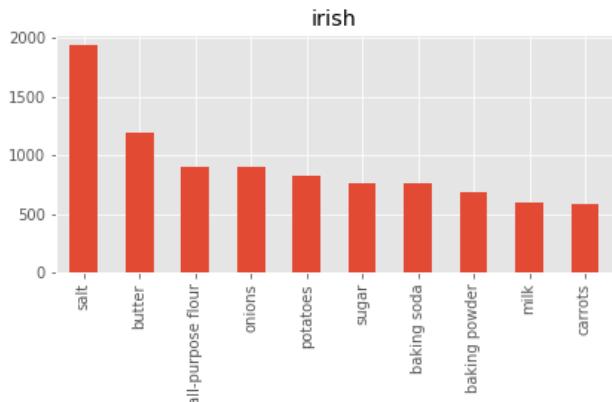


Figure 16: Top 10 Ingredients

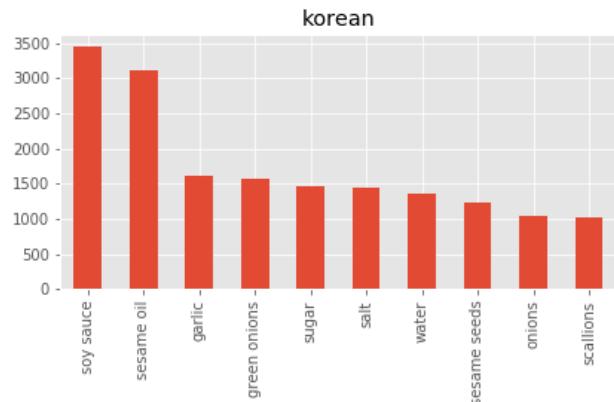


Figure 19: Top 10 Ingredients

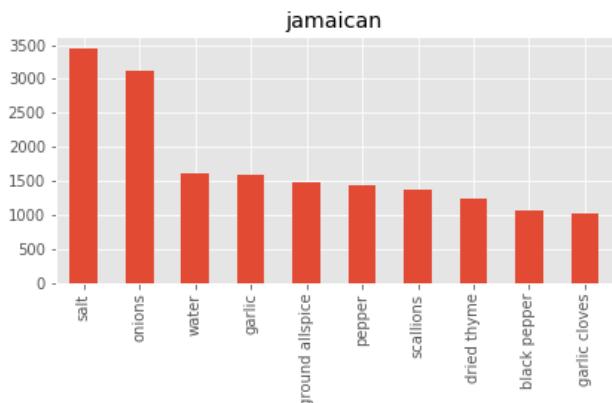


Figure 17: Top 10 Ingredients

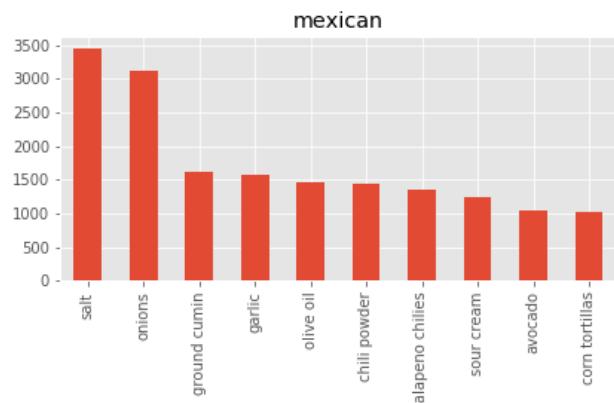


Figure 20: Top 10 Ingredients

to data to reduce node and edges to get the graph which can be used for analysis and avoid crashing Gephi due to large data. Modularity statistic uncovered 5 ingredient clusters which can be identified

by different colors in the graph. This cluster can approximately relate to the cuisines present in our dataset and confirms our earlier analysis of ingredient by cuisine.

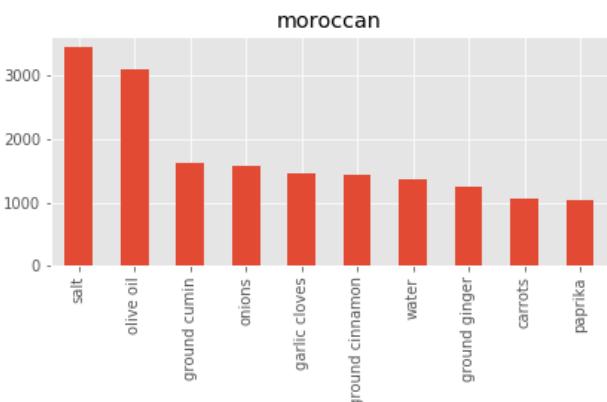


Figure 21: Top 10 Ingredients

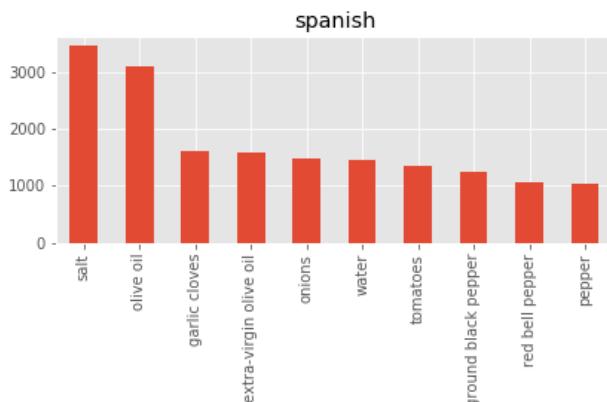


Figure 24: Top 10 Ingredients

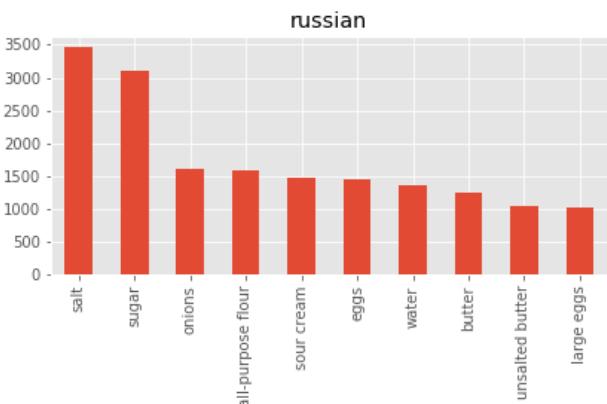


Figure 22: Top 10 Ingredients

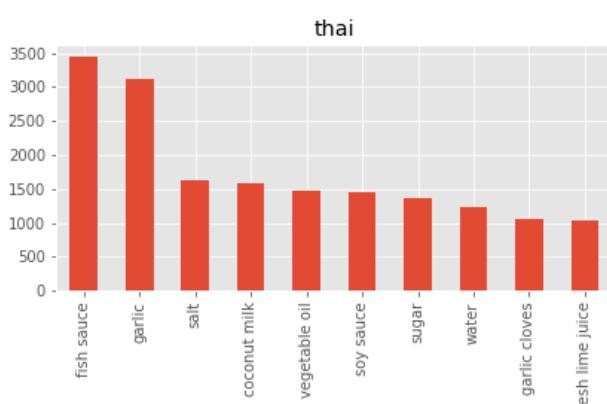


Figure 25: Top 10 Ingredients

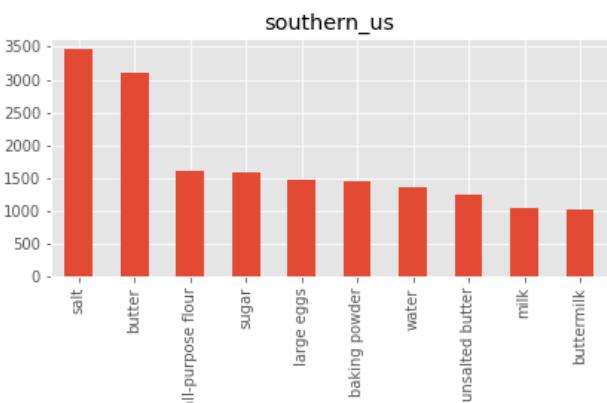


Figure 23: Top 10 Ingredients



Figure 26: Top 10 Ingredients

- Orange - Mexican
- Brown - Indian
- Blue - Chinese

- Green - Italian
- Gray - Southern US

This analysis also provides us with the complimentary ingredient network which can be used together to construct tasty dish. We can see that there are two type of combination one is savoury and another is sweet. The complimentary ingredients as per our study are

- Sugar, butter, all-purpose flour, large eggs, heavy cream, baking powder, cinnamon, flour, lemon, vanilla
- Olive oil, garlic, black paper, onion, cheese, basil, parsley, oregano, white wine, shallots, lemon juice, bell paper
- Onion, garlic, pepper, tomato, bay leaves, paprika, potatoes, chicken, shrimp, celery, green paper, garlic powder, dried thyme
- Tomato, ground cumin, chicken, cilantro, jalapeno chilies, ground beef, sour cream, chili powder, avocado, corn tortillas, black beans, salsa, lime, green chilies, oil, turmeric, garam masala, coconut milk
- Oil, green onions, scallions, carrots, garlic, ginger, fish sauce, soy sauce, rice vinegar, sesame oil, corn starch, brown sugar, honey

Graph also shows overlap between following ingredients which confirms that those are the commonly together used ingredients in the recipes. We observe those combination in Indian and Italian cuisine.

- Onion, garlic
- Olive oil, black paper

Figure 27 shows ingredient cluster of more than 1000 nodes. This graph is nice to look at but difficult to read due to lot many nodes and edges in the graph.

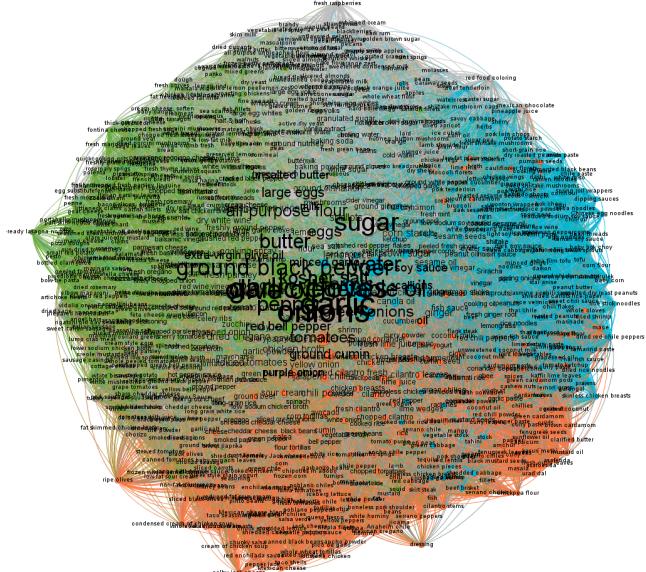


Figure 27: Ingredient Cluster

Figure 28 shows ingredient cluster of around 100 nodes. We generated this graph by reducing nodes and edges to make it more readable. This graph provides us with our top 5 cuisine clusters.

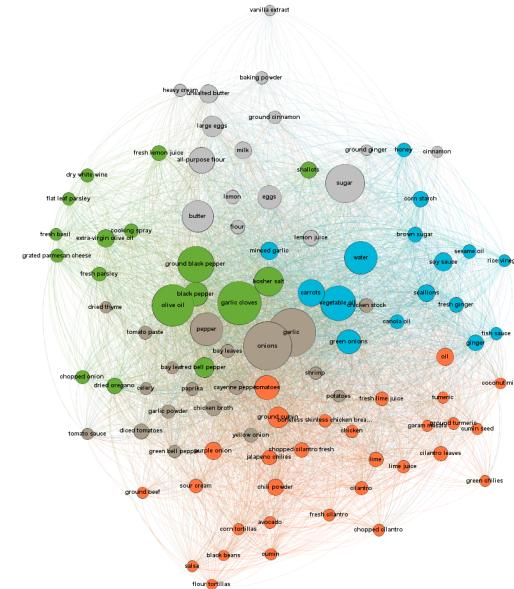


Figure 28: ingredient Cluster 100 Nodes

5.7 Shortcomings

Improper documentation of ingredient names in the dataset reduces the correctness of this analysis. In absence of proper ingredient name and duplication of ingredient name prevents getting exact ingredient weight into the analysis. A dataset with uniform ingredient name can help this analysis to achieve its best. If we don't find proper ingredient name then this analysis needs to include extensive data cleaning process which can be considered an improvement to this project.

Network file creation algorithm can be enhanced further by considering the number of recipes for the ingredient to provide additional weight to the relationship which can provide the stronger bond between the ingredients.

5.8 Limitations

This dataset can be analyzed to find out ingredient overlap between various cuisines and can provide insight into the influence of one cuisine on another which is not covered as part of this study. Usually, geographically neighboring cuisines are influenced by each other as they share common ingredients.

6 CONCLUSION

This project shows most used ingredient, ingredient distribution by cuisine and predictive ingredient relationship model as per the goal of the project. We also show various opportunities present with ingredient data analysis and role of big data analytics. We prove

human craving for salty and fatty food as salt and oil are most used ingredient across cuisines as per the analysis. We understand now based on our analysis key ingredient of any cuisine. Ingredient cluster shows why those ingredients are the base of certain cuisine and recipe of those ingredients always turn out delicious. We also crave for the good data so that we can provide more accurate analysis of the ingredients. Ingredient analysis has potential not only to help restaurant and food industry but it can help with our social responsibility of sustainability and understanding different cuisines and culture. As food industries interest grows in big data analytics, we will continue to see more evaluations of the ingredients.

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Analysis of Digit Recognizer classification algorithms in big data

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ABSTRACT

Digit Recognizer is becoming more and more important in many different areas, such as zip code recognizer, banking receipt and balance sheet. Many technology companies are trying to use Big Data to develop more efficient and accurate algorithm for Digit Recognizer. This project uses Digit Recognizer data set from Kaggle.com. There are more than 42000 samples in the data set. Each sample contains 784 features which contain pixel information from a 28×28 graph. Each pixel has a value between 0 to 255. We use binary classification technique for data cleaning and PCA for feature extraction. For the classification model, we choose five most commonly used classification algorithms, which include Decision Tree (DT), Naive Bayes (NB), Logistic Regression (LR), Random Forest (RF) and Support Vector Machine (SVM). From the result, SVM classifier on PCA data produces the highest accuracy with 0.9813. The time spend is 127 seconds. Naive Bayes classifier on PCA data spends the least amount of time to finish the classification task. It takes less one second and reaches a 0.8651 accuracy.

KEYWORDS

I523, HID213, HID214, HID209, Big Data, Digit Recognition, Cross Validation, Decision Tree, Naive Bayes, Logistic Regression, Random Forest, Support Vector Machine

1 INTRODUCTION

People have made a great improvement in digital recognition in recent years. And it plays significant roles in many different areas. Zip code recognizer can scan zip code for post office automatically. Recognizer in banks can help managing user account by scanning their account number. They help people a lot in increasing working efficiency. And many new productions use digital recognition to authenticate password. In this situation, the accuracy and efficiency of recognition become more and more essential and methods in order to increase the accuracy and efficiency are also required.

Fortunately, people have already developed many different types of techniques to avoid faults and decrease running time in recent few years. Several algorithms will be mentioned here. Logistic regression, the most frequently used algorithm in the field of machine learning, also has a good performance in digital recognition. Decision tree is commonly used in decision analysis. It can identify strategies to get a result, in this case, it can also play an important role in digital recognition. Naive Bayes classifier would also be used. Random forest is also a widely used technique in the field of classification and regression. Its special structure with the multitude of decision trees would help it get a fantastic result. Support vector machine can efficiently perform non-linear classification

hence it also be considered frequently. These algorithms have different structures so that they have different performance. We can also observe running time and accuracy of different algorithms with different kind of data. In this paper, we are going to talk about this and make the comparison between algorithms in accuracy and efficiency.

2 DIGIT RECOGNITION APPLICATION IN BIG DATA

Digit recognition have many applications in our daily life. More and more organizations start using Digit recognition technique to save cost and increase accuracy in large-scale data entry jobs.

First, Digit recognition can be used in large scale statistic. For example, it can be used in industry annual inspection and population census [4]. The United States Census Bureau will lead a population census every year in United States, the data volume is huge. A large amount of data needs to be input. In the past, all the data need to input into the database manually. This process required large amount labor force and human resources. In recent years, more and more companies and countries start to use OCR and Digit recognition technique for these jobs. Because the dataset from these applications are centrally organized. Usually, we can build forms automatically and impose restrictions on writing to facilitate automatic Digit Recognition. At present, most of these applications required user to fill in the assigned boxed according to specific requirements. Also, in order to check the accuracy of the recognition, these systems tend to use a user interface to make a comprehensive examination of the recognition results [8]. Currently, more and more advanced algorithms are used in Digit recognition.

Second, Digit recognizer has a widely used in finance and tax administration. As the development of the economy in the world, there are more and more reports, forms, checks and bills waiting to be dealt. The person may deal with these in a comparable lower efficient. It is fantastic for the appearance of digit recognizer to work with these [24]. It has a higher efficiency and longer working hours. And machines do not need the salary. It is more difficult in recognize checks and forms because of higher demand for accuracy. In the meanwhile, there may be several kinds of forms. Recognizer should have the capability to deal with them all. Furthermore, recognizer has to face millions of handwriting some of them are hard to recognize [3].

Third, this technology is also popularly applied in mail sorting. With the improvement of people's living standards, the development of economic activities, the demand for communication causes a substantial increase in the exchange of letters. For example, the post offices in metropolitan areas of China have already reached

to a few million pieces per day in 2000. This sharp rise in business volume has made the sorting of mail pieces automated and becoming the trend of the times. In the automatic sorting of mail, handwritten digit recognition (OCR) often combined with optical bar code recognition (OBR) and artificial identification to complete the postal code reading. Currently, the most common used OVCS sorter has the performance with 30% OCR rejection rate and 1.1% OCR sorting error rate [21].

3 EXPERIMENT PREPARATION

In this paper, we choose the data of Digit Recognizer from Kaggle.com in order to test different classification algorithms [7]. The goal of this experiment is to correctly identify digits from a data set of tens of thousands of handwritten images. Thus, we could compare the pros and cons of each technique through the recognition accuracy and time-consuming.

3.1 Data Set Description

In train.csv data file, it contains 42000 gray-scale images of hand-drawn digits, from zero through nine. Each image is a 28×28 pixels matrix with a total of 784 pixels [7]. Each pixel has a single pixel-value which is an integer from 0 to 255 associated with it, indicating the lightness or darkness of that pixel (higher numbers meaning lighter). In this experiment, we have plotted the graph in order to see the appearance of these digits easily. Figure 1 shows the first 70 samples.

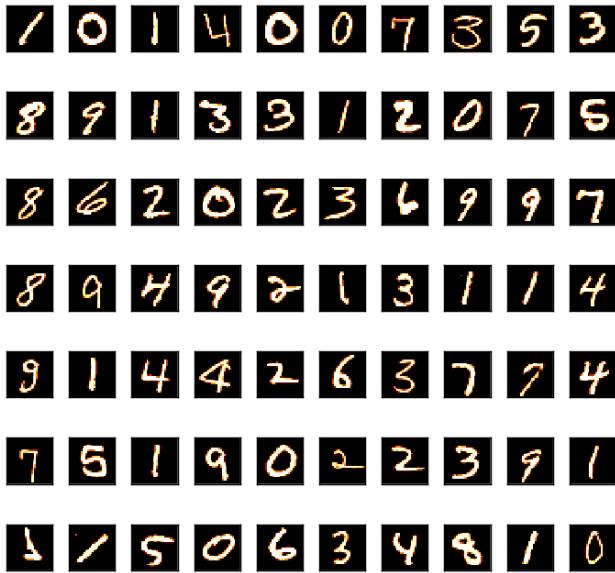


Figure 1: 70 samples of hand-drawn digits in this data set

The training data set has 785 columns. The first column called “label”, is the digit that was drawn by the user. The rest of the columns contain the pixel-values of the associated image. Each pixel column in the training set has a name like $pixelx$, where x

is an integer between 0 and 783. To locate a pixel on the image, suppose that we have decomposed x as $x = i * 28 + j$, where i and j are integers between 0 and 27. Then $pixelx$ is located in row i and column j of this matrix [7]. Visually, if we omit the “pixel” prefix, the pixels make up the image like the following form:

000	001	002	003	...	026	027
028	029	030	031	...	054	055
056	057	058	059	...	082	083
:	:	:	:	:	:	:
728	729	730	731	...	754	755
756	757	758	759	...	782	783

3.2 Data Cleaning

As we mentioned above, it can be seen from both the figure and the pixel-value that the value varies from 0 to 255, which means each feature is a continuous value. Thus, it is possible that such continuous values might affect our later feature selection. Our observation shows that the values are not very high at the boundaries of 0 and > 0 . So here exist three ways to handle it [28]:

- (1) Not do any processing on image;
- (2) Binarize the image. That is, for the values which are 0, keep them as 0; for the values which are greater than 0, change to 1;
- (3) Binarize the image by setting a threshold. That is, for the values which are greater than this threshold, change to 1; otherwise, change to 0.

Obviously, method (2) and (3) will cause the loss of the original information. However, this information may not as important as our expected during the execution of classification algorithms, it could play a positive role in increasing the performance without reducing the accuracy.

In our experiment, we selected method (2) to clean the raw data. The main codes in Figure 2 shows this operation.

```
from numpy import *
# The data is from 0-255 for each cell.
# Normalize data by set all value > 0 to 1
def data_clean(data):
    m, n = shape(data)
    new_data = zeros((m, n))
    for i in range(m):
        for j in range(n):
            if data[i, j] > 0:
                new_data[i, j] = 1
            else:
                new_data[i, j] = 0
    print("Data clean completed.")
    return new_data
```

Figure 2: The core codes about data clean

3.3 Feature Extraction

Dimension reduction in the field of machine learning refers to using a mapping method to map the data points in the original high-dimensional space into the low-dimensional space. The essence of dimension reduction is to learn a mapping function $f : x \rightarrow y$, where x is the expression of the original data point, y is the low-dimensional vector representation after the data point mapping [12].

The reason why we use data after dimension reduction is that the redundant information and noise information are contained in the original high-dimensional space, which reduces the accuracy of our model. By dimension reduction, we hope to reduce the error caused by redundant information and improve the accuracy of identification. We also hope to find the intrinsic structure of the data structure through the dimension reduction algorithm. Also, in this example, there are 784 features in our data. Space, time and computation complexity are all unacceptable. There are many different dimension reduction algorithms for us to choose. In this project, we choose to use Principle Component Analysis (PCA).

3.3.1 PCA

Principal Component Analysis (PCA) is the most commonly used method of supervised linear dimension reduction. Its goal is to map high-dimensional data to a low-dimensional representation of space by some kind of linear projection. The variance of the data is expected to be maximized in the projected dimension. By keep the variance of data as high as possible, PCA can reduce the dimension of data and keep the loss of information of the data as a minimum [5].

A common understanding is that if all the points are mapped together, almost all information (such as the distance between points) is lost. If the post-mapping variance is as large as possible, the data points are spread apart to preserve more information. It can be proved that PCA is a linear dimension reduction method that loses the original least data information.

One of the questions we faced while we are using PCA is that: how many components should we choose for the model after dimension reduction. In order to solve this problem, we use Explained Variance as our threshold standard. Explained Variance is an important indicator of PCA dimension reduction. The Explained Variance shows the amount of variance explained by each of the selected components. The first column of the PCA model always explains the most variance and the variance explained will keep decrease as the number of column increase. Generally, a dimension with a cumulative contribution rate of about 90% is selected as a reference dimension for PCA dimensionality reduction. In this project, in order to get a more accurate result, we choose 95% as our threshold.

After calculating the explained variance for each component, we decide to choose 30 components for our model. Which shows that there will be 30 features in our model.

4 EXPERIMENT ALGORITHMS

We aim to select five most commonly used classification algorithms which include Decision Tree, Naive Bayes (NB), Logistic Regression (LR), Random Forest (RF) and Support Vector Machine (SVM). This section offers a broad overview of these algorithms before applying

```
from sklearn.decomposition import PCA

def feature_selection(data):
    pca = PCA()
    pca.fit(data)
    ev = pca.explained_variance_
    ev_ratio = []
    for i in range(len(ev)):
        ev_ratio.append(ev[i] / ev[0])

    # select number of component which have a higher ratio
    # than 0.05 with the first components
    n = 0
    for i in range(len(ev_ratio)):
        if ev_ratio[i] < 0.05:
            n = i
            break

    # Then, PCA the model by the number of components
    pca = PCA(n_components=n, whiten=True)
    return pca.fit_transform(data)
```

Figure 3: The core codes about PCA processing

them to the digit recognizer problem to compare their characteristics. Then, the result of the different algorithm on different data will show on a table.

For each algorithm, we use:

- (1) PCA data - data after using PCA to reduce the dimension on raw data
- (2) Clean data - data after our data cleaning process, which set all values greater than 0 to 1 in our data
- (3) PCA Clean daata - data after using PCA to reduce the dimension on clean data after data cleaning process

4.1 Cross-Validation

When we build the model, it is normal to follow the principle of simplification since the simpler model we built, the better performance we will get. However, for some complicated problems, our model will also become more complex which might cause the overfitting problem. In order to solve this problem, we introduce the cross-validation technique. Cross-validation is a technique to evaluate predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it [16].

The purpose of cross-validation is to select the model with the optimal parameters. After the model is set up, tuning the parameters is a very time-consuming process. Through cross-validation, we can get the model with the optimal parameters much easier. Here are some steps about cross-validation procedure:

- (1) Prepare the candidate models, M_1, M_2, M_3, \dots (the model framework is consistent, only different on the parameters);
- (2) For each model, use cross-validation to return the accuracy and error rate information of the model, the result should be the average of cross-validation;

- (3) Select the best model by comparing the accuracy or error of the different models.

There are some types of cross-validation which are common to use: K-fold cross-validation and Leave-one-out cross-validation.

- K-fold:

This method is to divide the data set into k subsets. Each time, select one of the k subsets as the test set and the other $k - 1$ subsets become a training set. Then the average accuracy or error across all k trials is computed [16]. In general, we choose 10 as the value of k .

- Leave-one-out (LOO):

This method is K-fold cross-validation taken to its logical extreme, with $k = n$ ($n > k$), the number of data points in the set [16]. That is, it randomly select n samples as a training set and the rest as a test set. Since the time complexity of this cross-validation is factorial, it is not an appropriate method for big data set.

In this project, we use K-fold cross validation technique to reduce over-fitting of our model and increase the accuracy in each model. We use the function `cross_val_score` from the `sklearn` package. It have several important parameters to set [10].

- (1) CV: int, cross-validation generator or an iterable, optional
This parameter determines the cross-validation splitting strategy, which determined the number of fold we need to use. In our project, we use the default 3-fold cross-validation. Because 3-fold provide us the result in a reasonable time and accuracy.
- (2) Scoring: string, callable or None, optional, default: None
The scoring parameter determines what to return after we call the function. We just this parameter to ‘accuracy’, which will return the accuracy between 0 to 1 for each model.

After we receive the result for each validation, we generate the mean of each result and use the result as the accuracy of the model.

```
from datetime import datetime
from sklearn.cross_validation import cross_val_score

def model_acc(data, label, model):
    start = datetime.now()
    acc = cross_val_score(model, data, label, cv=5,
                          scoring="accuracy").mean()
    end = datetime.now()
    time_use = (end - start).seconds

    print("Time use: ", time_use)
    print("Accuracy by cross validation: ", acc)
```

Figure 4: The core codes about cross-validation

4.2 Decision Tree

4.2.1 Introduction

Decision tree builds classification or regression models in the form of a tree structure (either binary or non-binary) [20]. Each of its non-leaf nodes represents a test on the characteristic attributes, and each leaf node stores a category. The process of decision making using decision tree has the following steps [23]:

- (1) Start at the root node;
- (2) Test the corresponding characteristic attribute of the items that need to be classified;
- (3) Select the branch based on the value until the leaf node is reached;
- (4) The category of stored in the leaf node is the result.

The decision tree construction process rely on attribute selection metrics in order to choose the attribute which has the capability to divide tuples into different classes best. The key step in constructing a decision tree is split attributes which means to construct different branches according to the different partition of a certain characteristic attribute at a node. The goal of this step is to make each split subset as “pure” as possible. Split attributes are divided into three different situations:

- (1) Attributes are discrete values and do not require to generate a binary decision tree. This time, each partition of an attribute becomes a branch;
- (2) Attributes are discrete values and require to generate a binary decision tree. This time, a subset of attribute partitions is used for testing, broken down two branches according to “subordinate to this subset” and “not subordinate to this subset”;
- (3) Attributes are continuous values. This time, determine a value as a `split_point` and generate two branches according to $> \text{split_point}$ and $\leq \text{split_point}$.

There are many attribute selection metric algorithms (e.g. ID3, C4.5, CART, etc.), generally using top-down recursive method with non-backtrack greedy strategy. In our experiment, we applied optimized version of the Classification And Regression Trees (CART) algorithm from scikit-learn library.

The CART algorithm uses a binary recursive segmentation technique [1]: the current sample set is divided into two sub-sample sets, so that each non-leaf node have two branches. Therefore, the decision tree generated by the CART algorithm is a concise binary tree with the root node represents a single input variable (x) and a split point on that variable and the leaf nodes contain an output variable (y) which has the capability to make a prediction [1].

The first key step of CART algorithm is creating the tree model, it examines each variable and all possible partitions of this variable to observe the best partitions. For discrete values such as $U = \{x, y, z\}$, there are three cases of partitions [9]:

$$\{\{x, y\}, \{z\}\}, \{\{x, z\}, \{y\}\}, \{\{y, z\}, \{x\}\}$$

except \emptyset and U ; for continuous values, it introduces the idea of “split point”. Suppose one attribute of a sample has n continuous values, it then has $n - 1$ splitting points where each of them is the average of two consecutive values $(a[i] + a[i + 1])/2$. Partitions of each attribute are sorted by the amount of impurities that they can reduce. The reduction of impurities could use the most popular method of

impurity metric which is: Gini index. If we use k ($k = 1, 2, 3, \dots, C$) to represent the class, where C is the dependent variable number of the category set. Thus, the Gini impurity of a Node A could be defined as [9]:

$$Gini(A) = 1 - \sum_{k=1}^C p_k^2$$

Where p_k denotes the probability of observation points which belong to class k . When $Gini(A) = 0$, all samples belong to the same class. When $Gini(A)$ is the maximum, which is $\frac{(C-1)C}{2}$, all classes occur with the same probability in nodes.

The second key idea in the CART process is to prune the trees of the training set with independent validation data sets. Analyzing the recursive tree construction of classification and regression tree, it is easy to find that there exists a data over-fitting problem [1]. In the construction of decision tree, many branches reflect the abnormality in training data due to the noises or outliers inside. Using such decision tree to classify the data with unknown categories, the accuracy of classification is not high. So it is essential to detect and subtract these branches. Generally, tree pruning method uses statistical metrics, subtract the least reliable branches, which results in faster classification and improves the ability to separate correctly from the training data. The CART algorithm often adopts the post-pruning method, which is implemented by pruning the branches in a fully grown tree. By deleting the branch of the node to cut tree nodes, the bottom non-pruned node becomes a leaf.

The main codes of Figure 5 shows how we called CART algorithm in our experiment.

```
# Import Library
from sklearn import tree

def dt_classifier(data, label, data_type):
    dt_model = tree.DecisionTreeRegressor()
    dt_model.fit(data, label)
    print("Test " + data_type + " using DT: ")

    # Train the model using the training sets and check
    # score
    model_acc(data, label, dt_model)
```

Figure 5: The core codes about CART algorithm (decision tree)

4.2.2 Advantage and Disadvantage

Decision Tree has advantages as follow [6]:

- (1) Decision trees are easy to understand and implement, and people have the ability to understand what the decision tree means by explaining it.
- (2) Data preparation is often simple or unnecessary for decision trees, and other techniques often require first generalizing data, such as removing redundant or blank attributes.
- (3) Feasible and effective results for large data sources in a relatively short period of time.

- (4) Not sensitive to missing values
- (5) Can handle irrelevant feature data
- (6) High efficiency. Decision tree only needs to build once. The maximum number of calculations for each prediction does not exceed the depth of the decision tree

Decision Tree also has disadvantages as follow [6]:

- (1) Hard to predict features with continues value
- (2) Need to do a lot of data reprocessing work for time-series data
- (3) When the category is too large, the error rate may increase.
- (4) It does not look good when dealing with data that has a strong correlation between each feature.

4.2.3 Result

From table 1, we can find that the Decision Tree algorithm has a highest accuracy 0.8378 when we using Clean data. That's because the Clean data contains all 784 features in the data set. It has the minimum information loss among all three data set. Clean data also have the longest running time, which is 20 seconds.

PCA Clean Data have the second highest accuracy with the lowest running time. By using the PCA to reduce the dimension of the clean data, the running time reduced a lot. The accuracy only decreases by 0.01, which shows that the process of PCA did not lose a lot of information.

When we use decision tree algorithm, PCA data have the lowest accuracy. That's may because the raw data have may noise and redundant information. After we remove this information from our data pre-processing step, our accuracy increased.

4.3 Naive Bayes

4.3.1 Introduction

Naive Bayes algorithm is a classification technique based on Baye's Theorem with an assumption of independence among predictors [18]. That is to say, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. For example, we may guess a fruit is an orange if it is yellow, round and about 3 inches in diameter. Even if these features depend on each other, all properties independently contribute to the probability that this fruit is an orange, which explain the term 'Naive' [18].

The Baye's Theorem is particularly useful and not complicated. It solves many problems encountered in our life. The purpose of this theorem is that given a conditional probability of a certain condition, obtain the probability of exchanging two conditions. That is, to get $P(B|A)$ while given $P(A|B)$. $P(A|B)$ is the posterior probability which is also the conditional probability (likelihood) and $P(A)$ or $P(B)$ is called a prior probability. We use the following equation to express this theorem:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

The idea of Baye's Theorem is very simple and directly: For the given item which need to be classified, compute the probability of each category under this item. We consider this item belongs to the category with the largest value. The work process of Naive Bayes classification is as follows [25]:

	PCA Data	PCA Clean Data	Clean Data
Time	12	9	20
Accuracy	0.8012	0.8234	0.8378

Table 1: Result For Decision Tree

- (1) Let D be the set of training tuples associated with their class labels. Each tuple is represented by an n -dimensional attribute vector $X = x_1, x_2, \dots, x_n$;
- (2) Suppose there are m classes C_1, C_2, \dots, C_m . For the given tuple X , the classification algorithm will predict that X belongs to the class with the highest posterior probability. That is, Naive Bayes classification predicts that X belongs to class C_i if and only if $P(C_i|X) > P(C_j|X), 1 \leq j \leq m, j \neq i$. Thus, the class C_1 with the largest $P(C_i|X)$ is called the maximum posterior probability according to the Baye's Theorem: $P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}$;
- (3) Since $P(X)$ is a constant for all classes, we only require the maximum of $P(C_i|X)P(C_i)$. If the prior probability of a class is unknown, then generally assume these classes are equiprobable (i.e. $P(C_1) = P(C_2) = \dots = P(C_m)$) and maximize $P(C_i|X)$ based on this assumption. Otherwise, maximize $P(C_i|X)P(C_i)$;
- (4) Given a data set with multiple attributes, the computational cost of $P(C_i|X)$ is very large. In order to reduce this cost, we could make the naive assumption about conditional independent of the class. For the label of a given tuple class, assuming the attribute values are conditionally independent. Therefore, we have

$$P(X|C_i) = \prod_{k=1}^n P(x_k|C_i)$$

To examine whether the attribute is classified or continuous value, we need to consider the following two cases:

- (a) If A_k is a classified attribute, then $P(x_k|C_i)$ is the number of tuples of class C_i whose value is x_k for attribute A_k in D divided by the number of tuples of class C_i in D ($|C_i, D|$);
- (b) If A_k is a continuous value attribute, then assume the attribute obeys a Gaussian distribute with the mean η and standard deviation σ , as defined by:

$$g(x, \eta, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\eta)^2}{2\sigma^2}}$$

Thus, $P(x_k|C_i) = g(x_k, \eta_{C_i}, \sigma_{C_i})$.

- (5) To predict the label of class X , calculate $P(C_i|X)P(C_i)$ for each class C_i .

The whole Naive Bayes classification could be divided into three stages:

- (1) Preparation stage. The task of this stage is to make the necessary preparation for the Naive Bayes classification. The main work is to determine the characteristic attributes according to the specific situations and make the appropriate partition for each characteristic attribute, and then

manually classified some of the items to constitute a training sample set. The input of this stage is all data that need to be classified and the output is the characteristic attribute and the training sample.

- (2) Classifier training stage, the task of this stage is to generate a classifier. The main work is to compute the occurrence frequency of each class in training sample and the conditional probability of all partitions in each category, and then record the results. The input is characteristic attributes and a training sample, the output is a classifier. This stage could be completed automatically by a program.
- (3) Application stage. The task of this stage is to classify items using classifier. The input is classifier and items, and the output is the mapping between items and categories. This stage could also be completed by a program.

The main codes of Figure 6 shows how we called Naive Bayes algorithm in our experiment.

```
# Import Library
from sklearn.naive_bayes import GaussianNB

def nb_classifier(data, label, data_type):
    nb_model = GaussianNB()
    nb_model.fit(data, label)
    print("Test " + data_type + " using NB: ")

    # Train the model using the training sets and check
    # score
    model_acc(data, label, nb_model)
```

Figure 6: The core codes about Naive Bayes

4.3.2 Advantage and Disadvantage

Naive Bayes has advantages as follow [13]:

- (1) Naive Bayesian model originated in classical mathematical theory, which is stable.
- (2) Have a good performance on small-scale data,
- (3) Can handle multi-category tasks.
- (4) For incremental training, especially when the amount of data exceeds memory, we can use batch training to save training time.

Naive Bayes also has disadvantages as follow [13]:

- (1) In theory, the naive Bayes model has the smallest error rate compared to other classification methods. However, this is not always the case. This is because the naive Bayesian model assumes that the features are independent of each other. This assumption often does not hold in practice.

- When the number of attributes is large or the correlation between attributes is large, the error rate will be huge.
- (2) Need to know the prior probability, and the probability of prior probability depends on the assumption. There are many kinds of hypothetical models, so the prediction results will be poor at some time due to the choice of hypothetical model.
 - (3) Because we determine the posterior probability by priority and data to determine the classification, there is a certain error rate in the classification decision.
 - (4) Sensitive to the type of raw data.

4.3.3 Result

From table 2, we can find that Clean Data have a really low accuracy with the highest time spent. That's because the raw data set did not match the assumption of Naive Bayes. The features are not conditionally independent of each other. The pixels are continues. For example, if pixel1 and pixel3 are both greater than 0, pixel2 will have a more probability to have a value greater than 0.

After we use the dimension reduction technique to reduce the dimension of the data, each component of the data becomes a linear combination of the original data. The new data fits the assumption of Naive Bayes more. Therefore, the PCA Data and PCA Clean Data have a much better performance than Clean Data. They also have the lowest running time compare to any other algorithms.

The PCA Clean Data have the highest accuracy of 0.8710 which higher than the PCA Data. That's may because of the noise and redundant in the original data.

4.4 Logistic Regression

4.4.1 Introduction

Logistic regression is a static regression model with a category of the dependent variable. It uses a binary logistic model to estimate binary response probability on predictor variables. In this case, we can know which specific factor makes influence in the presence of risk increasing odds when getting outcomes. We use logistic regression to find the best fitting model to conclude the relationship between variables. Logistic regression generates the coefficients (and its standard errors and significance levels) of a formula to predict a logit transformation of the probability of the presence of the characteristic of interest [22]:

$$\text{logit}(p) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \dots + b_kX_k$$

p is the probability of the presence of the characteristic of interest and odds is logical transformation.

$$\text{odds} = \frac{p}{1-p} = \frac{p(\text{presence of characteristic})}{p(\text{absence of characteristic})}$$

$$\text{logit}(p) = \ln \frac{p}{1-p}$$

There are four ways to input independent variables into the model:

- (1) Enter: enter all variables at the same time
- (2) Forward: enter essential variables one by one
- (3) Backward: enter all variables first and delete non-essential variables one by one

- (4) Stepwise: enter essential variables one by one and check the importance of each variable, delete non-essential ones.

It still has other options:

- (1) Remove variable. Variables would be removed from the model if its significant level is greater than P-value.
- (2) Classification table cutoff value: a value between 0 and 1 which will be used as a cutoff value for a classification table. The classification table is a method to evaluate the logistic regression model. In this table the observed values for the dependent outcome and the predicted values (at the selected cut-off value) are cross-classified [22].
- (3) Categorical: Identify variables in the category.

The main codes of Figure 7 shows how we called Logistic Regression algorithm in our experiment.

```
# Import Library
from sklearn.linear_model import LogisticRegression

def lr_classifier(data, label, data_type):
    lr_model = LogisticRegression()
    lr_model.fit(data, label)
    print("Test " + data_type + " using LR: ")

    # Train the model using the training sets and check
    # score
    model_acc(data, label, lr_model)
```

Figure 7: The core codes about Logistic Regression

4.4.2 Advantage and Disadvantage

Logistic Regression has advantages as follow [14]:

- (1) Very simple to implement and use, widely used in industrial issues
- (2) The amount of computation is very small when classified. Therefore the running time is low and the requirement for the storage space is also low.
- (3) The sigmoid score for each sample is easy to observe. The threshold can be easily determined by user.
- (4) For logistic regression, multicollinearity is not a problem, it can be solved in conjunction with L2 regularization;

Logistic Regression also has disadvantages as follow [14]:

- (1) When the feature space is large, the performance of logistic regression is not very good.
- (2) May have the under-fitting problem, the general accuracy is not high.
- (3) Can only deal with the binary classification problem (based on this, softmax can be used for multi-classification), and must be linearly separable.
- (4) For non-linear features, normalization is required.

4.4.3 Result

The result of logistic regression is pretty impressive. This is a 10-categorical classification problem, and logistic regression did a good job on this task.

	PCA Data	PCA Clean Data	Clean Data
Time	0	0	20
Accuracy	0.8651	0.8710	0.5397

Table 2: Result For Navie Bayes

	PCA Data	PCA Clean Data	Clean Data
Time	27	21	218
Accuracy	0.8891	0.8862	0.9064

Table 3: Result For Logistic Regression

When we get this result, we are thinking if we having an over-fitting result. Therefore, we add a regularization parameter to penalize the features. We use l2 regularization as our parameter when we create our logistic classifier. We also use cross-validation skill to increase our sample size. The results show that the accuracy is still around 90%. Therefore, we are not having an over-fitting problem.

The running time of logistic regression is relatively high. For Clean Data, it received the accuracy of 0.9064 with 218 seconds. PCA Data and PCA Clean Data have a lower accuracy with a much lower time spend. Also, we noticed that the PCA Data accuracy is a little bit higher than the PCA Clean Data. That's may because the clean data make some of the information loss in the raw data.

4.5 Random Forest

4.5.1 Introduction

Random forest uses a random way to build a forest within many decision trees. There is no correlation between each tree in a random forest [26]. After getting the forest, when a new input sample comes in, each decision tree required to make a judgment separately in order to see which class the sample belongs to (for the classification algorithm), and predict the sample for the category which has most selected.

Random forest is mainly used for regression and classification. It is somewhat similar to the bagging which utilizes decision trees as a basic classifier. Bagging could generate a decision tree after replay a sample in each bootstrap and do not make more intervention while generating these trees. Random forest is also sampling with bootstrap, but the difference is that when constructing each tree, every node variable is generated only in a small number of randomly selected variables. Therefore, not only the samples are random, but also the generation of each node's features. Since the combination classifier is more effective than the single classifier, random forest could classify the data and give the importance evaluation of each variable.

The basic principle of random forest is to get a new training sample set by selecting k samples from the original training sample set N , and then make up a random forest according to k classification trees. The classification result of the new data depends on the score of the tree votes [17]. In essence, it is an improvement on the decision tree algorithm: it combines multiple decision trees, each tree established depends on an independently sample and has the same distribution. The classification error relies on each the classification ability of a tree and the correlation between them.

Feature selection uses a random method to split each node, and then compare the error generated in different situations. The inherent estimation error, classification ability and relevance determine the number of features [17].

Since there are many decision trees in the forest, once a new input sample comes in, each decision tree make a decision to check what the class the sample belongs to, and which one is chosen most to the prediction. There are two selection metrics for decision trees to split attributes [23]:

- (1) Information gain
 - (a) $I(s_1, s_2, \dots, s_m) = -\sum_{i=1}^m p_i \log_2(p_i)$, where S is the data set, m is the number of categories, $p_i \approx \frac{|S_i|}{|S|}$ is the probability for any sample belongs to C_i , C_i is a class label and s_i is the number of samples on C_i ;
 - (b) The smaller $I(s_1, s_2, \dots, s_m)$, the more ordered of the sample and the better the classification effect;
 - (c) Entropy of the subsets partitioned by attribute A : A has V different values, S is partitioned by A into V subsets s_1, s_2, \dots, s_V , where s_{ij} is the number of samples of C_i in subset s_j . Then, we have
 - (d) $E(A) = \sum_{j=1}^V \frac{(s_{1j} + \dots + s_{mj})}{s * I(s_{1j}, \dots, s_{mj})}$
 - (e) $G = I(s_1, s_2, \dots, s_m)E(A)$;
 - (f) Select the attribute with the maximum information gain as the split attribute.
- (2) Gini index
 - (a) Set S contains N categories of records, then its Gini index is the frequency of the occurrence of p_j ;
 - (b) If set S is partitioned into m parts s_1, s_2, \dots, s_m , this segmentation is the Gini split;
 - (c) Select the attribute with the smallest Gini split as a split attribute.

In order to implement random forest, we should follow these steps:

- (1) The input original training set is N , use bootstrap to extract k samples randomly and build k decision trees;
- (2) Suppose there are m_A variables, then randomly extract m_T variables from each node of each tree to find one of the variables with the highest classification ability in m_T variables. The threshold of the variable classification is determined by checking each classification point;

- (3) Maximize the growth of each tree without any pruning;
- (4) Constitute the random forest with these decision trees. Use random forest to determine and classify the new data, and the results are based on votes amount of the tree classifier.

The main codes of Figure 8 shows how we called Random Forest algorithm in our experiment.

```
# Import Library
from sklearn.ensemble import RandomForestClassifier

def rf_classifier(data, label, flag):
    rf_model = RandomForestClassifier(n_estimators=100)
    rf_model.fit(data, label)
    print("Test " + flag + " using RF: ")

    # Train the model using the training sets and check
    # score
    model_acc(data, label, rf_model)
```

Figure 8: The core codes about Random Forest

4.5.2 Advantage and Disadvantage

Random Forest has advantages as follow [2]:

- (1) It can handle very high-dimensional data, and do not have to do feature selection, feature subset is randomly selected
- (2) It can provide which feature is more important after training.
- (3) When creating a random forest, the use of generalization error is an unbiased estimation, which shows that this model has a high generalization ability.
- (4) Easy to make a parallel method, training tree and tree are independent of each other.
- (5) In the training process, the algorithm is able to detect the interaction between the features.
- (6) For unbalanced data sets, it can balance the model automatically.
- (7) If a large part of the features is lost, the model can still maintain the accuracy.

Random Forest also has disadvantages as follow [2]:

- (1) There may be many similar decision trees that mask the real results.
- (2) Small data or low dimensional data may not produce the best classification.
- (3) Much slower than single decision tree algorithm.
- (4) Random forests can be over-fitting on some noisy classifications or regression problems
- (5) For feature with different value range, the more value-separated features will have a greater impact on random forests

4.5.3 Result

From table 4, we can find that Clean Data performed perfectly in this case. It takes the shortest time and reached a 0.9647 accuracy.

The result shows an interesting phenomenon: Clean Data cost less time than PCA Data and PCA Clean Data. In order to explain this phenomenon, we have to check what parameter we choose when we build our random forest classifier. From sklearn API document, we can find that the first default parameter is the number of trees in the forest. For all the data, we set the number of trees to the default number, which is 10. However, in Clean Data, many features are correlated to each other, which means that there may many similar decision trees. For PCA Data and PCA Clean Data, most of the features are independent of each other. Therefore, the running time for Clean Data is higher than PCA Data and PCA clean Data.

Also, we know that when there are similar decision trees in the random forest, the real results may be masked. Therefore, although the Clean Data have a really high accuracy, it may still not as good as the PCA Data and PCA Clean Data result. When we running the classifier on an untested data set, the classifier made by PCA Clean Data may have the best performance among the three.

4.6 Support Vector Machine

4.6.1 Introduction

Support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis [27]. It is mostly used in classification. People can plot each data as a point in an n-dimensional space and give each feature a value. Finding the hyperplane which can differentiate two classes very well can complete classification. As for hyperplane, we must know the notation used to define a hyperplane [15]:

$$f(x) = \beta_0 + \beta^T x$$

β is weight and β_0 is bias. The optimal hyperplane can be represented in an infinite number of different ways by scaling of β and β_0 . The one we choose is [15]:

$$|\beta_0 + \beta^T x| = 1$$

x is the training sample who is the most closest to hyperplane. It is known as canonical hyperplane. Distance between point and hyperplane is [15]:

$$\text{distance} = \frac{|\beta_0 + \beta^T x|}{\|\beta\|}$$

$$\text{distance}_{\text{support vector}} = \frac{|\beta_0 + \beta^T x|}{\|\beta\|} = \frac{1}{\|\beta\|}$$

$$M = 2 * \text{distance}_{\text{support vector}} = \frac{2}{\|\beta\|}$$

$$\min L(\beta) = \frac{1}{2} \|\beta\|^2 \text{ subject to } y_i(\beta^T + \beta_0) \geq 1, \forall i$$

In Python, scikit-learn is a widely used library for implementing machine learning algorithms, SVM is also available in the scikit-learn library and follows the same structure (Import library, object creation, fitting model and prediction). Let's look at the below Python code [19] in Figure 9:

The e1071 package in R is used to create Support Vector Machines with ease. It has helper functions as well as code for the Naive Bayes Classifier. The creation of a support vector machine in R and Python

	PCA Data	PCA Clean Data	Clean Data
Time	126	107	56
Accuracy	0.9483	0.9497	0.9647

Table 4: Result For Random Forest

```

# Import Library
from sklearn import svm

# Assumed you have, X (predictor) and Y (target) for
# training data set and x_test(predictor) of test_data
# set

# Create SVM classification object
model = svm.SVC(kernel='rbf', C=10)

# there are various option associated with it, like changing
# kernel, gamma and C value
# Train the model using the training sets and check score
model.fit(X, y)
model.score(X, y)

# Predict Output
predicted= model.predict(x_test)

```

Figure 9: The core codes about SVM in Python

follow similar approaches, let's take a look now at the following R code [19] in Figure 10:

```

# Import Library
require(e1071) #Contains the SVM

Train <- read.csv(file.choose())
Test <- read.csv(file.choose())

# there are various options associated with SVM training;
# like changing kernel, gamma and C value.

# create model
model <-
  svm(Target~Predictor1+Predictor2+Predictor3,data=Train,
  kernel='linear',gamma=0.2, cost=100)

# Predict Output
preds <- predict(model,Test)
table(preds)

```

Figure 10: The core codes about SVM in R

4.6.2 Advantage and Disadvantage

Support vector machine has advantages as follow:

- (1) More efficient in high dimensional space.
- (2) Effective when the number of samples is smaller than the number of dimensions.
- (3) Can memorize efficiently by using a subset of training sample in decision function.
- (4) Flexible by changing Kernel functions for different customers.

And it also has disadvantages as follow:

- (1) It would over-fitting in choosing Kernel functions when the number of samples is much smaller than the number of features.
- (2) Must pay more attention to regularization term.
- (3) It can only get probability by an expensive five-fold cross-validation instead of calculating directly.

4.6.3 Result

By using SVM to build our classifier, we received a really great accuracy score. The PCA Data received a 0.9814 accuracy of 127 seconds. The running complexity of SVM is $O(N^3 + LN^2 + d * L * N)$, which N is the number of support vector choose, L is the number of samples and d is the number of features of the data set. Therefore, SVM algorithm will run really slow on the large data set. Therefore, when we use the Clean Data, which include more than 42000 samples and 784 features, it takes 1029 seconds to finish the job. We also try to use SVM direct on our raw data. It takes forever to get a result.

SVM can get much better results than other algorithms in the small sample training set. SVM has become one of the most commonly used and effective classifiers. By using the concept of margin, a structured description of the data distribution is obtained, thereby reducing the need for data size and data distribution.

SVM model has three very important parameters kernel, C and γ [11].

- (1) Kernel: string, optional. This parameter specifies the kernel type to be used in the algorithm. There are many different kernels that can be used in SVM. For example, linear, polynomial, sigmoid, Radial basis function (RBF) and pre-computed. In this project, choose to use RBF. Because:
 - (a) The RBF kernel function can map a sample to a higher dimensional space, and the linear kernel function is a special case of RBF. That is to say, if RBF is considered, then it is unnecessary to consider the linear kernel function.
 - (b) Compared with polynomial kernel function, RBF needs to determine fewer parameters, the number of kernel function parameters directly affect the complexity of the function. In addition, when the order of the polynomial is relatively high, the elemental values of the

	PCA Data	PCA Clean Data	Clean Data
Time	127	90	1029
Accuracy	0.9814	0.9785	0.9575

Table 5: Result For Support Vector Machine

kernel matrix will tend to positive infinity or negative infinity, while the RBF will reduce the numerical calculation difficulties.

- (c) RBF and sigmoid have similar performance for some parameters.
- (2) C is the penalty coefficient, which shows the tolerance of the bias. If your C is small, it will give you a great distance, but as a trade-off, we have to ignore some misclassified samples; on the other hand, if you have a large C, you will try to correctly classify all the samples, but the price is the margin space will be small. In our example, we choose c equals to 10, which is a relatively large c value, which brings us a more accurate classifier.
- (3) Gamma defines how much influence a single training example has. It determines the distribution of the data after mapping to a new feature space. The larger the gamma is, the less the support vector it will be. The smaller the gamma value is, the more the support vector it will be. The number of support vectors affects the speed of training and prediction. Also, if we set gamma large, it will have the over-fitting problem. Therefore, in this project, we decided to use the default gamma value, which is

$$\gamma = \frac{1}{\text{number of features}}$$

In this task, SVM have a really great performance, the running time is also acceptable.

5 CONCLUSION

From table 6, we can easily find that when we use SVM classifier on PCA Data, we will receive the highest accuracy among all 5 different algorithms. The highest accuracy we reached for this project is 0.9813, which shows that our classifier predicts 98.13% of the sample correct by using our SVM classifier. The time of training the model takes 127 seconds. The time spent is acceptable. The accuracy of SVM on PCA Clean Data has the second highest accuracy, which is 0.9785. The difference between first and second highest accuracy is about 0.0028, which is really small. However, the time spent saved 41.1%. Therefore, SVM on PCA Clean Data is also a reasonable choice for the Digit Recognition task.

Random Forest can be explained as a combination of many decision trees. Decision tree can be explained as a special case of Random Forest, which set the number of trees in the Random Forest to 1. Therefore, Random Forest has a much better performance than decision tree in all three data set. As a trade-off, the time spent for Random Forest is much higher than Decision Tree.

Compare to other four Classifiers, Naive Bayes has the fastest training speed. For PCA Data and PCA Clean Data, Naive Bayes Classifier takes less than one second to train the classifier. And for

Clean data, which contains all 784 features, it takes only 6 seconds to train the classifier. The reason why Naive Bayes is fast is that:

- (1) The algorithm does not need to iterate to get the result. The running time is approximately linear.
- (2) It makes an assumption of independence between its features, so that parameter estimates can be calculated independently and thus possibly very quickly.
- (3) The prior probability values do not change. Therefore, the prior probability can be calculated and store in memory in the first place.

However, we have to be very careful about the assumption made by Naive Bayes, or we will get a very low accuracy.

Logistic Regression received an average performance among the 5 algorithms. It achieves a 0.8891 accuracy in 27 seconds on PCA data. However, when we using logistic regression, we have to pay a lot of attention to over-fitting problem. We should use regularization and cross-validation to reduce the probability of over-fitting problems.

To conclude, we decide to use SVM classifier for Digit Recognition Task. We should definitely use feature extraction on the data because of the running time and over-fitting problem. The Binary Data cleaning method is optional. If we want to have higher accuracy, we should not use Binary Data cleaning. As a trade-off, if we want to have faster training speed, we should use Binary Data cleaning.

6 LIMITATIONS

Our analysis is far from perfect. There are several points that we want to point our as discussion and also opportunities for future improvement.

- (1) We can try several more classification algorithms. For example, K^{th} Nearest Neighbour (KNN) and Neural Network. We can use some more complex algorithms too, such as Convolution Neural Network (CNN).
- (2) We can focus more on tune parameter. For example, we can use the Grid Search on SVM to get a better parameter combination.
- (3) We can choose a different Data Cleaning Method. For example, we can set a threshold on data. Any value greater than 50 will be set to 1.
- (4) We can choose a different Feature Extraction or Feature Selection method. For example, LDA. Unlike PCA, LDA is an unsupervised dimension reduction method.

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	Decision Tree	Naive Bayes	Logistic Regression	Random Forest	Support Vector Machine
PCA Time	12	0	27	126	127
PCA Accuracy	0.8012	0.8651	0.8891	0.9483	0.9813
PCA Clean Time	9	0	21	107	90
PCA Clean Accuracy	0.8234	0.8710	0.8862	0.9497	0.9785
Clean Time	20	6	218	56	1029
Clean Accuracy	0.8378	0.5397	0.9064	0.9647	0.9575

Table 6: Result For Different Algorithm with Different Data Cleaning & Feature Extraction method

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A CODE ATTACHMENT

```

##Author: Yuchen Liu HID213, Wen Xuanhan HID209, Junjie Lu
##ID: 214
##Data: 2017.12.01
##Reference:
http://blog.csdn.net/tinkle181129/article/details/55261251

from datetime import datetime
import matplotlib.pyplot as plt
import pandas as pd
from numpy import *
from sklearn import svm
from sklearn import tree
from sklearn.cross_validation import cross_val_score
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB

# 1. read data from csv
def read_data():
    data_set = pd.read_csv("train.csv")
    data = data_set.values[0:, 1:]
    label = data_set.values[0:, 0]
    print("Data load completed.")
    return data, label

# plot 70 samples
def show_pic(data):
    print(shape(data))
    plt.figure(figsize=(7, 7))
    for digit_num in range(0, 70):
        plt.subplot(7, 10, digit_num + 1)
```

```

grid_data = data[digit_num].reshape(28, 28)
plt.imshow(grid_data, interpolation="none",
           cmap="afmhot")
plt.xticks([])
plt.yticks([])
plt.tight_layout()
plt.savefig("data_samples.png")

# 2. Data Cleaning
# The data is from 0-255 for each cell.
# Normalize data by set all value > 0 to 1
def data_clean(data):
    m, n = shape(data)
    new_data = zeros((m, n))
    for i in range(m):
        for j in range(n):
            if data[i, j] > 0:
                new_data[i, j] = 1
            else:
                new_data[i, j] = 0
    print("Data clean completed.")
    return new_data

# 3. Feature Selection by PCA
def feature_selection(data):
    # First, use explained_variance to get recommended
    # number of component
    pca = PCA()
    # pca_parameter = pca.fit(data)
    pca.fit(data)
    ev = pca.explained_variance_
    ev_ratio = []
    for i in range(len(ev)):
        ev_ratio.append(ev[i] / ev[0])

    # select number of component which have a higher ratio
    # than 0.05 with the first components
    n = 0
    for i in range(len(ev_ratio)):
        if ev_ratio[i] < 0.05:
            n = i
            # print(n)
            break

    # Then, PCA the model by the number of components
    # pca = PCA(n_components=n, whiten=True)
    pca = PCA(n_components=n, whiten=True)
    print("Feature selection completed.")
    return pca.fit_transform(data)

# 4. Model Selection
def model_acc(data, label, model):
    start = datetime.now()
    acc = cross_val_score(model, data, label,
                          scoring="accuracy").mean()
    end = datetime.now()
    time_use = (end - start).seconds
    print("Time use: ", time_use)
    print("Accuracy by cross validation: ", acc)

def dt_classifier(data, label, data_type):
    dt_model = tree.DecisionTreeRegressor()
    dt_model.fit(data, label)
    print("Test " + data_type + " using DT: ")
    model_acc(data, label, dt_model)

def nb_classifier(data, label, data_type):
    nb_model = GaussianNB()
    nb_model.fit(data, label)
    print("Test " + data_type + " using NB: ")
    model_acc(data, label, nb_model)

def lr_classifier(data, label, data_type):
    lr_model = LogisticRegression()
    lr_model.fit(data, label)
    print("Test " + data_type + " using LR: ")
    model_acc(data, label, lr_model)

def rf_classifier(data, label, flag):
    rf_model = RandomForestClassifier(n_estimators=100)
    rf_model.fit(data, label)
    print("Test " + flag + " using RF: ")
    model_acc(data, label, rf_model)

def svm_classifier(data, label, flag):
    svm_model = svm.SVC(kernel="rbf", C=10)
    svm_model.fit(data, label)
    # svc_clf = NuSVC(nu=0.1, kernel='rbf', verbose=True)
    print("Test " + flag + " using SVM: ")
    model_acc(data, label, svm_model)

def main():
    data, label = read_data()
    # show_pic(data)
    clean_data = data_clean(data)

    test_type = 3
    for i in range(1, 3):
        print("In %d test" % i)

        if test_type == 0:
            input_data = data
            str = "raw data"
        elif test_type == 1:

```

```
    input_data = clean_data
    str = "clean data"
elif test_type == 2:
    input_data = feature_selection(data)
    str = "pca data"
elif test_type == 3:
    input_data = feature_selection(clean_data)
    str = "pca clean data"

dt_classifier(input_data, label, str)
nb_classifier(input_data, label, str)
lr_classifier(input_data, label, str)
rf_classifier(input_data, label, str)
svm_classifier(input_data, label, str)

main()
```

Income Prediction based on Machine Learning Techniques

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ABSTRACT

This project takes a closer look to some of the most used supervised learning algorithms in machine learning. We start with the description of the each of the algorithms then we move it to analytics and findings by using that particular algorithm in our data-set. We also provide advantages and disadvantages of each supervised machine learning algorithm for future reference. We mainly focus on our prediction of the income level of individuals by looking at their age, gender, education, location, and other features given by our data-set. We will try each algorithm and try to pick the best features from our data-set to have an optimal prediction.

KEYWORDS

i523, HID343, Machine Learning, Income Prediction, Logistic Regression, Ensemble methods

1 INTRODUCTION

In this project, we try to showcase the performance of the machine learning algorithms on data which we gather from UCI machine learning repository [22]. This data used by Kohavi R. and Becker B. for their research in improving the in Naive Bayes Classifier's accuracy [21].

Data consists of 15 variables, and we try to predict the income of the individuals. To do this prediction task, we first started with data preparation because the data we receive from UCI machine learning repository [22] not fully prepared for any machine learning algorithm. Our first task was the clean the data while applying some statistical techniques to get insights from the dataset. We also used data transformation methods like One-Hot-Encoding[45] to apply logarithmic functions for improving the machine learning algorithms performance before training the data.

Machine Learning algorithms that we discuss in this paper are Gaussian Naive Bayes [46], K Nearest Neighbors [29], Ensemble Methods (Boosting) [8], Support Vector Machines [6], Logistic Regression [34], and Decision Trees [49]. We try to show their weakness, advantages, and their time consumption while training each of them in machine learning algorithms section.

After providing a brief introduction of each of the supervised machine learning algorithms, we will discuss our findings for of each of the algorithms by comparing their accuracy score, F-1 score, recall, and lastly time comparison.

2 IMPORTANCE OF BIG DATA ANALYTICS FOR PREDICTIVE CLASSIFICATION

Importance of big data analytics is getting higher every day since the algorithms become more powerful to predict, classify and cluster any given data set. Importance of our case is any company can be used to predict individuals income to refer them goods in their

income range or governments can provide additional support for the areas that have lower income range. There can be many possible things that can do with this kind of classification predictions.

3 DATA PREPARATION

We first used the pandas [28] to help to load the data in data frame format. This gave us a unique advantage, and faster processing of comma separated values for putting into data frame [48]. Our data consist of 15 variables. Some of these variables are continuous, and some of them are categorical variables, and our target variable was "income" attribute. After putting the data into data frames, we first got a statistical snapshot of continuous variables (age, education, capital gain, capital loss, hours worked) by using the pandas [27] functions as shown in Table 1.

	age	education	cap gain	cap loss	hours
count	32561	32561	32561	32561	32561
mean	38.581	10.08	1077.64	87.303	40.437
std.	13.640	2.572	7385.292	402.960	12.347
min.	17.0	1.0	0	0	1.0
25%	28.0	9.0	0	0	40.0
50%	37.0	10.0	0	0	40.0
75%	48.0	12.0	0	0	45.0
max	90.0	16.0	0	4356.0	99.0

Table 1: Statistical Summary of The Continuous Variables

3.1 Data Cleaning

After getting a snapshot from income data frame, we recognized that there is a column which has no meaning. The first task was to remove this entire column from our dataset we used pandas drop function for doing this task. After removing this column, we had more concise dataframe to analyze.

Moreover, removing the column we have encountered some missing values which labeled as "question marks" in data frame. In order to remove this values we first changed all the "question mark" values to "NaN" values by using pandas "replace" function [26]. After replacing all the question marks with "NaN" values, we used pandas missing value dropping function to remove all the "NaN" values from our dataset.

Furthermore, we start investigating the types of the variables, and in our case, we found two types of variable one of them labeled as "int64" which stands for integer values, other one labeled as object type of variable. From our previous example especially in "scikit-learn" it is better to use float object rather than "int64" for training the machine learning algorithms. Because their numerical output most of the time is "float64" object. We transferred all the

“int64“ objects to “float64“ objects. This was the last step of the cleaning process.

Our last process is changing the string values to numerical values on our target data which consist of string values (“\$ 50K”) for machine learning algorithms to understand this target data we need to transfer it to numerical values. Since we have only two categories, we will assign 1 and 0 as numerical values as shown in Table 2.

Description	Assigned Value
Individuals who makes more than \$50K	1
Individuals who makes at or less than \$50K	0

Table 2: Description of the Binary Values

Our shape of the data will also receive impact from changing to numerical. Our number of futures will go from 14 to 103. This is because we implemented one-hot-encode to our dataset. It is called one hot encoded because we transform the categorical variables into a more acceptable shape for the machine learning algorithms to perform well [45]. In other words “we implement binarization of the category to include as a future to train model [45]“. As we can see in Table 3 and Table 4.

Company Name	Categorical Variable	Price
VW	1	2000
Acura	2	10011
Honda	3	50000
Honda	3	10000

Table 3: Example of One Hot Encoding Before [45].

VW	Acura	Honda	Price
1	0	0	20,000
0	1	0	10,011
0	0	1	50,000
0	0	1	10,000

Table 4: Example of One Hot Encoding After [45].

4 DATA EXPLORATION

After cleaning the data, we started our data exploration to learn little bit more from our data and make necessary changes if needed before putting into our machine learning algorithms. The first step in this process is getting the total count of the individuals as well as the count of the individuals who are making more than \$50K and less than \$50K which can be seen in below Table 5.

Moreover, we also look at the statistical values of each of the continuous variable we have. Those values given in Table 6. As we can see we have individuals who’re age ranging from 17 to 90 years old with a mean of 38.58. If we look at the capital gains and capital losses, we have a standard deviation of 7385 and 402 respectively this is also another indication of skew in these variables.

Description	Count
Total Number of Individuals	30162
Individuals who makes more than \$50K	7508
Individuals who makes at or less than \$50K	22654

Table 5: Count of Income Variable Regarding to Individuals

	Age	Gain	Loss	Hours
Number of Instances	32,561	32,561	32,561	32,561
Mean	38.58	1077.64	87.303	40.437
Standard Deviation	13.640	7385.292	402.960	12.347
Minimum Value	17	0	0	1
25th percentile	28	0	0	40
50th percentile	37	0	0	40
75th percentile	48	0	0	45
Maximum Values	90	99999	4356	99

Table 6: Statistical Summary of Continuous Variables [44].

We used scatter matrix plot and applied the correlation function to see if we have any reliable correlation between any of the variables. As we can see from the correlation matrix Table 7 and correlation numbers Figure 1 we do not have the high correlation between any variables. Correlation values range between -1 to 1. The correlation value of 1 is an indication of perfect positive correlation and correlation number -1 indicates a negative correlation between variables [15]. Because of lower correlation values, it will be tough to determine the classification by just looking at the correlations; this indicates we have sophisticated algorithms to determine the relationship between variables to classify individuals incomes.

	Age	Education	Capital Gain	Capital Loss	Hours Per Week
Age	1.0	0.043	0.080	0.060	0.101
Education	0.043	1.0	0.124	0.079	0.152
Capital Gain	0.080	0.124	1.0	-0.032	0.080
Capital Loss	0.060	0.796	-0.032	1.0	0.052
Hours Per Week	0.101	0.152	0.080	0.052	1.0

Table 7: Correlation Matrix [44].

Furthermore, we also explore the capital gains, capital losses, and hours per week variables which we used a histogram to plot the data into distribution form so we can see how all these attributes distributed. The reason we do the histogram is we want to see any skewness in our data. As shown in the histogram graphs in Figure 2 and Figure 3 in capital gains and capital loss we have highly skewed data which can cause issues later on in our algorithms. We apply a logarithmic function to do highly skewed data to less skewed [24]. Using logarithmic functions adds more value to data from the interpretable standpoint and “it helps to meet the assumptions of inferential statistics [24]“.

Moreover, applying logarithmic function had an impact on distribution. We can see the changes on skew data in Figure 4 after applying logarithmic function.

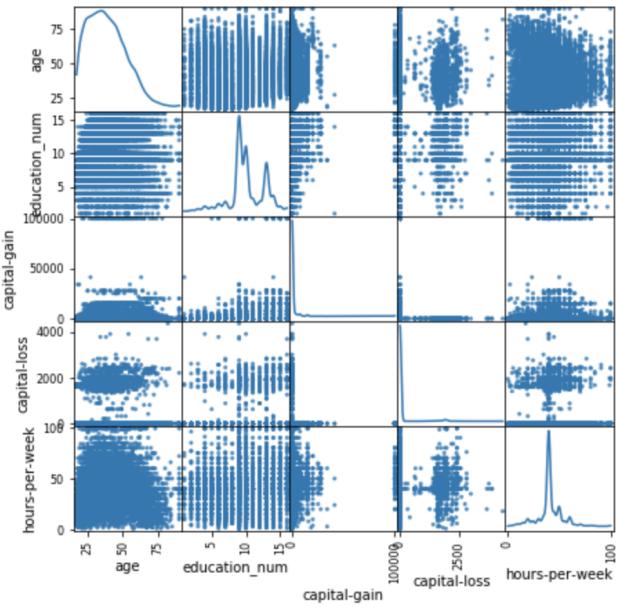


Figure 1: Scatter Matrix Plot [44].

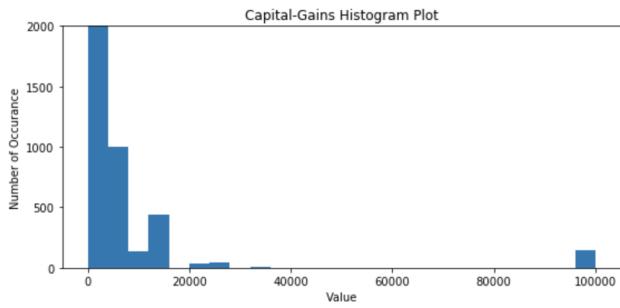


Figure 2: Histogram of Capital Gain [44].

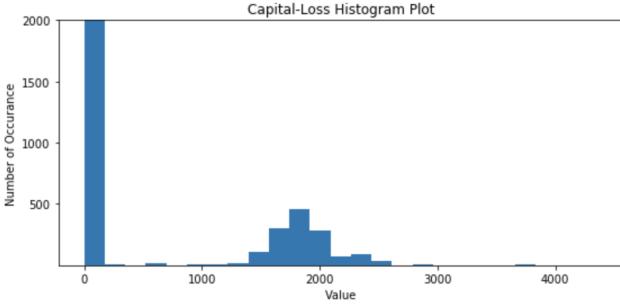


Figure 3: Histogram of Capital Loss [44].

5 MACHINE LEARNING ALGORITHMS TO CONSIDER

We have multiple algorithms to consider when we are doing the supervised learning. Each algorithm has its benefits and drawbacks.

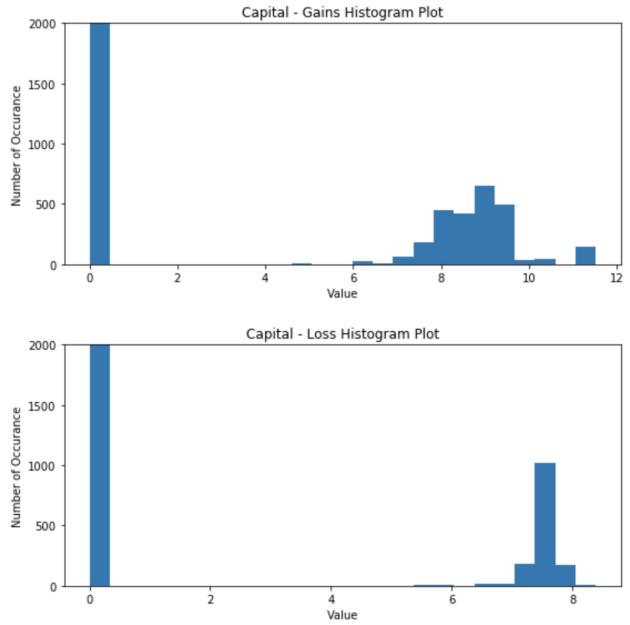


Figure 4: After Logarithmic Function Applied Histogram of Capital Gain [44].

We will consider several supervised machine learning algorithms for our predictions. The application we will use to implement these algorithms will be Python Scikit-Learn library. We will briefly explain each parameter included in these algorithms in Scikit-Learn.

First we'll look at the Scikit-Learn in Python framework we will go through the advantages in Scikit-Learn how we can implement any machine learning in just couple of simple line of codes in Scikit-Learn.

5.1 Why Scikit-Learn?

Scikit-learn developed by David Cournapeau in 2007. The development came from while he was working on summer code project for Google. After recognized and published by INRIA in 2010 project start to get more attention among worldwide. There are more than 30 active contributors and has secured several sponsorships from big technology companies[17]. “It also has a goal of providing common algorithms to Python users through consistent interface[2]”. Scikit-Learn consists of several elements to make analytical predictions. These elements are shown below[23]:

Supervised Learning Algorithms: One of the most fundamental reason that Scikit-Learn’s popularity comes from highly available supervised learning algorithms. These algorithms vary from regression models to decision trees and many more[23].

Cross Validation: Scikit-Learn includes various techniques to check the accuracy or any statistical measure between training and unseen testing set[23].

Unsupervised Learning Algorithms: Scikit-Learn had also various algorithms to support many unsupervised algorithms some of these include clustering, factor analysis, and neural network analysis[23].

Various example data-sets: Scikit-Learn comes with different data sets included in its package so users can start learning Scikit-Learn without the need of any data-sets[23].

Feature extraction: It has rich feature for extracting images or text from data-sets[23].

Algorithms that we will investigate shown below; we will go more deep analysis on each of these algorithms.

- Gaussian Naive Bayes
- Logistic Regression
- K-Nearest Neighbors (KNN)
- Stochastic Gradient Descent Classifier
- Support Vector Machines
- Decision Trees

5.2 Gaussian Naive Bayes

Naive Bayes bring many beneficial features; it is widely popular among machine learning applications[41]. The popularity of Naive Bayes comes from being able to handle large projects and data-sets faster than most algorithms[41]. It also can handle complex data-sets with categorical and non-categorical inputs [41]. Naive Bayes based on probabilistic classifier of Bayesian theory. It is also a favorite way of doing text categorization [46].

Term naive comes from it is the method of use probability among categories which assumes of independence among given class of attributes as shown in Figure 5. In other words, if we try to classify individuals from their email communications it will not take the order of words into account. Whereas in the English language we can tell the difference between sentence makes sense or not if we randomly re-order our words in the sentences. So it does not understand the text, it only looks at word frequencies as a way to do the classification. This is why it is called “Naive”.

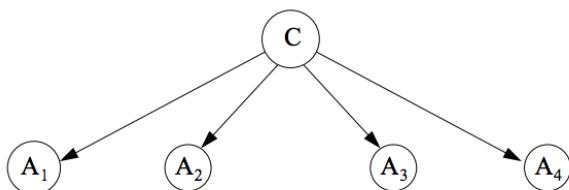


Figure 5: Example of Naive Bayes [50].

As we state above Naive Bayes derives from Bayesian Theory where the dimensionality of inputs is relatively high. Bayesian Theorem is stated below [16].

$$P(C | X) = \frac{P(X | C) \times P(C)}{P(X)} \quad (1)$$

Naive Bayes Classifier works as follows [16]:

Advantages of Naive Bayes [16]:

- Faster classification time for training data-set.
- Because of independent classification it improves classification performance.
- Performance is relatively good.

Disadvantages of Naive Bayes[16]:

- Often it requires a large number of data-sets to give adequate results.
- On some occasions which are relative to data-sets, it can give less accuracy.

5.3 Logistic Regression

Logistic Regression widely used for predicting “probability of failure in a given system, product, and process [34]“. Logistic Regression also used in natural language analysis, it is an extension of conditional random fields [34]. It works as a classifier which learns the features from the input given and classifies them by multiplying the input value with the weight value [14].

$$P(C | X) = \sum_{i=1}^N W_i \times f_i \quad (2)$$

Main reason that Logistic Regression differs from Linear Regression is output variable for Logistic Regression is binary whereas output variable in Linear Regression is discrete(continuous) [12].

Advantages of Logistic Regression:

- It does not have any assumptions over distribution of classes [18].
- It is fast to train [18].
- Logistic Regression has fast classifying method of unknown data [18].
- We can easily extend to other regression for multiple classes like multinomial regression [18].

Disadvantages of Logistic Regression:

- One of the disadvantages of linear regression is it is not providing flexibility in some instances. What we mean by the “lack of flexibility is the linear dependency, and linear decision boundary in the instance space is not valid [42]“. This disadvantage can be improved changing from Logistic Regression to Choquistic Regression[42].
- Logistic regression can provide poor results when there are more complex relationships in data [9].
- Logistic models also have over-fitting problems which come from a result of sampling bias [31].
- Because of Logistic Regression’s predictions comes from the independent variable if the researcher includes wrong independent variables then model’s prediction will have no value [31].
- Because it is predictions based on 1 and 0 model will have poor performance when predicting continuous variables [31].

5.4 K-Nearest Neighbors (KNN)

K Nearest neighbor has been primarily studied, and this popularity comes from it has been applied to many applications some of these applications are “spatial databases, pattern recognition, geographic information, image retrieval, computer game, and many other applications [29]“. Due to an increase of mobile devices and people tends to use of applications like navigation K-nearest neighbor found itself another widely used area of location-based services due to an ability to found a target location [29].

Intuition behind the K Nearest Neighbor can be described as follows: “ for a set P of n objects and a querying point q, return the k objects in P that are closest to q [29].”

Advantages of K Nearest Neighbors:

- K Nearest Neighbor is a basic and simple approach to implement [35].
- K Nearest Neighbor can perform well and efficiently with the large amount of data [43].
- K nearest Neighbor also does effectively well with noisy data sets (“if the inverse square of weighted distance used as the distance [43]”). In other words, it is flexible to feature and distance choices [35].

Disadvantages of K Nearest Neighbors:

- K Nearest Neighbor typically require large dataset to perform well [35].
- Time complexity could be high due to computing distance of each query to all training data points [43]. This time might be improved with some indexing (K-D Tree) [43].
- Determining the value of K can be time-consuming [43].
- It can be unclear to know which type of distance to use, as well as which variability to use to get the optimal results [43].
- Switching the different K values can result in the predicted class labels [30].

Many of these disadvantages are improving with the help of parallel distributed computing. Recent improvements in MapReduce framework allows users to run KNN algorithms in the cluster which had a significant effect on reducing the computation time [19].

Another area of improvements on KNN, is to implement different mapping functions such as kernel KNN, kernel difference weighted KNN, adaptive quasi-conformal kernel nearest neighbor, angular similarity, local linear discriminant analysis, and Dempster-Shafer [10].

5.5 Decision Trees

Decision Tree is another widely used algorithm model for classification and regression. Decision Trees uses a recursive split model where each recursive split is identified by each data point; this is an example of non-parametric hierarchical model [13].

Representation of decision trees is as follows; we sort the instances from root to leaf nodes, this sorting gives insights about the classification of the instance, every outcome descending from the root node corresponds to possible values for that variable [33]. We can classify an instance by starting from the root node and checking the attributes labeled on that node and moving down from that node based on attribute given attribute values [33] as shown in Figure 6.

Advantages of Decision Trees:

- Decision Tree applications are easy to interpret and understand [32]. This ease comes from their schematic representation [32]. Interpretation between alternatives can be expressed with single numerical number which is the expected value (EV) [32].

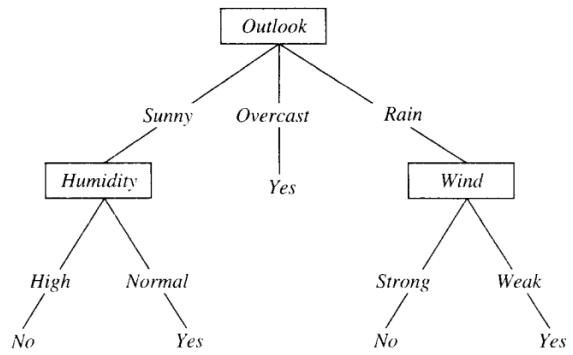


Figure 6: Example of Decision Tree Construction[33].

- Decision Trees can handle noisy or incomplete data-sets [32]. In other words it requires little effort of data preparation because of it is flexibility [7].
- It can handle both nominal and numerical variables [32].
- It can be modified easily whenever the new information is available [32].
-

Disadvantages of Decision Trees:

- Because of it is a use of divide and conquer method they can demonstrate good performance if there are few attributes exists when the attributes level goes into large number decision tree become more complex which will result in poor performance [32].
- Decision Trees are also susceptible to training set which can give a result of over-fitting [32]. In other words, it can believe the training set completely which will give an abysmal performance on testing set.
- ID3 and C4.5 decision tree algorithms require discrete values as input data.

5.6 Stochastic Gradient Descent Classifier (SGD)

Stochastic Gradient Descent recently got became more popular because of it is large-scale learning ability in machine learning problems [11]. It is a useful and straightforward way approach of linear classifiers under convex problems which is Support Vector Machines or Conditional Random Fields [3]. The originality of SGD derives from “Stochastic Approximation” which is a work from Robinson and Manroe [5].

Advantages of Stochastic Gradient Descent:

- One of the advantage of stochastic gradient descent is, it is easy to implement [38].
- Stochastic Gradient Descent is also efficient because of each step only relies on a single derivative which makes the computational cost $1 / n$ than normal gradient descent [37].

Disadvantages of Stochastic Gradient Descent:

- Stochastic Gradient Descent can be required to have many iterations, and it also requires some hyper-parameters [38].

- Feature scaling is a practice which used in the standardization of range of independent variables [47]. SGD also used this feature scaling technique and it can be sensitive to feature scaling [38].
- Another drawback of Stochastic Gradient Descent is while using GPU they are hard to parallelize or distributing them using computer clusters [25].

5.7 Support Vector Machines

Support Vector Machines is fallen under the classification methods in machine learning [6]. It is also a robust classification method that has been widely found itself an area ranging from pattern recognition to text analysis [6].

Fitting a boundary between data points is the principle of the support vector machines. This boundary divides the data points between classes, and each similar data point puts under the same class classification [6]. After training the support vector machines with training data-set, we only need to check whether the test data lies under the boundaries for testing set. Another thing to consider is after it creates the boundaries of the data remaining training data becomes obsolete because we only need the core set of points which supports the boundaries to classify the new data set. This core data points called “support vectors”. It is called vector because of each data point contains a row of observed data values for attributes [6].

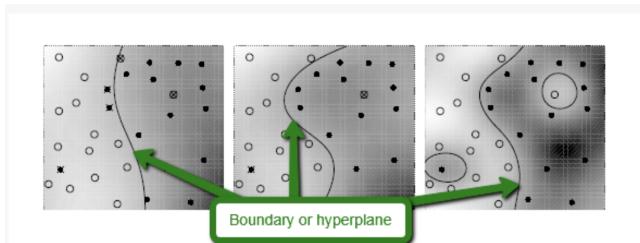


Figure 7: Example of Shows the Hyperplanes [6].

Traditionally boundaries are called “hyperplanes” and it is used to describe boundaries in more than three dimensions because they are hard or sometimes impossible to visualize.[7]. Figure 7. Optimality of hyperplane expressed as a linear function which requires maximum distance between the identified classes. It only considers a small number of training example to build this hyperplane. SVM hyperplanes based on “ separation of positive (+1) and negative (-1) with the largest margin [39]“.

One of the main characteristic of the machine learning is to generalization. In other words, we want to give a general idea that tends to fit any of our testing datasets optimally. Support vector machines are a perfect regarding generalizations because once the training data fitted by the support vector machines other than support vector data inside the training data becomes redundant which means that even with the small changes inside the data will not have a significant effect on general boundaries [6].

Advantages of Support Vector Machines:

- Generalizes the data well with the help of boundaries. Which reduces the overfitting [6].

- Classification accuracy in basic support vector machine will yield a 95 percent accuracy with a default settings [6].
- SVM can deliver a unique solution, because of optimality solution is convex. This will give an advantage over Neural Networks which has multiple solutions in local minima [1].

Disadvantages of Support Vector Machines:

- One common disadvantage of SVM, is the lack of transparency because of its non-parametric techniques [1].
- Another biggest disadvantage of SVM is it requires high algorithmic complexity and high level of memory for the large-scale implementations [39].
- According to Burgees, biggest limitation of the SVM is in the choice of kernel [4].

5.8 Ensemble Methods

Ensemble methods goes into classification algorithm category, they are learning algorithms which uses weighted vote for it is prediction methods, in other words, it is learning rules over a small subset of data then we combine these rules which we learn from the small subset of data to make predictions and/or classification on the testing data [8]. The originality of the Ensemble method comes from Bayesian averaging, but with the recent algorithms include “Bagging, error-correcting, and boosting [8]“.

Bagging refers to simply the looking at data-sets and dividing the data-set to it is small subsets then learning the rules of that particular small subset. Next step is combining each learned rule from subsets to apply to more significant data set. Combining method mostly done with averaging the learned rules. Bagging also does better on testing set than standard Linear Regression analysis and linear regression does better on training set especially in third order polynomial [8].

Stacking

Boosting is another method used in Ensemble Methods. The difference from bagging is in boosting we need to pick subsets or examples that we are not good at in other words hardest examples. Then we combine these learned rules with the weighted mean instead mean used in bagging method.

Boosting is little different then bagging.

Advantages of Ensemble Methods:

- Prediction of the ensemble methods is better than most of the algorithms because of the combining methods intuition makes the model less noisy [36].
- They are more stable than other algorithms. [36]

Disadvantages of Ensemble Methods:

- Over-fitting may cause some disadvantages for ensemble learning but bagging operation will reduce this overfitting [36].

6 FITTING DATA INTO MACHINE LEARNING ALGORITHMS

In this section, we will show the techniques we used on the execution of the prepared data into machine learning algorithms. Before fitting the data into the machine learning algorithms, we split the data into two sets. These sets are the training set and the testing

set. We do splitting because of gaining an access of the future data will most likely be hard before future occurs, and because of this fact, it is a good idea to test our model with a dataset which our model has not seen it [40].

We used scikit-learn for splitting data into train and test we saved 20% of data for testing purposes as shown in Table 8 .

Splitting the Data	Sample Size
Training	24129
Testing	6033

Table 8: Train-Test-Split [44].

Furthermore, after splitting the data we put all of our training data into to each of the machine learning algorithm to get their prediction results. We also provided code at the beginning and the end of each algorithm to calculate their running time.

Before we move further we need to discuss critical characteristics of a machine learning algorithm. These are;

- Confusion Matrix
- Accuracy
- Recall
- F-1 Score
- Precision

6.0.1 Confusion Matrix: Confusion matrix develops from 4 key elements. These elements are true positive, true negative, false negative, and false positive. As shown in Figure 8 about the constructing a confusion matrix. If we want to build a confusion matrix by targeting individuals who are making more than \$50K our true positive, true negative, false positive, and false negative explained below.

Actual Class	Predicted class	
	Class = Yes	Class = No
Class = Yes	True Positive	False Negative
Class = No	False Positive	True Negative

Figure 8: Example of Confusion Matrix Construction [20].

True Positive (TP): We can explain true positive as if the individuals make more than \$50K and our model correctly classifies them as individuals who makes more than \$50K, then this individual is in higher income range, in this case, we call it a true positive [20].

True Negative (TN): Intuition of true negative is if an individual makes less than \$50K and our model correctly classifies them as individuals who makes less then \$50K, then this individual is in lower income range. We call this true negative [20].

False Negative (FN): When an individual makes less than \$50K and our model incorrectly classifies them in higher income range by making a mistake causes a false negative to happen [20].

False Positive (FP): When an individual is making more than \$50K and our model classifies them in lower income range by mistake. This is called false positive [20].

6.0.2 Accuracy: Accuracy answers the question of how good is the model is. In our case this question will be out of all the individuals, how many did the models classify the individuals correctly. The mathematical expression of the accuracy is the ratio between the number of correctly classified points and the number of total points. We can think that if we have high accuracy, our model is excellent, but this is only where we have identical false positive and false negative values in our dataset [20].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

6.0.3 Precision. Precision answers the questions of out of all the points predicted to be positive how many of them were actually positive? If we translate this question into our case, we will have out of all the individuals that we are classified as lower income how many were actually have lower income. Higher precision indicates that we have low false positive rate [20]. Mathematical expression of precision is;

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

6.0.4 Recall (Sensitivity). Recall answers the question of “out of the points that are labeled positive how many of them were correctly predicted is positive ? ”. If we translate this to our case, we will have “out of the points that are labeled higher income how many of them correctly predicted is in higher income range ? ”. Mathematical expression of the recall is;

$$\text{Precision} = \frac{TP}{TP + FN} \quad (5)$$

6.0.5 F-1 Score. The F-1 score is the idea of giving a decision by looking at only one score which will include precision, and recall scores. We cannot just take the average of precision and recall because if either of them is very low. We need a number to be low, even if the other one is not. This will leads us to look at the harmonic mean, and it works as follow. Let’s say we have two numbers X and Y. X is smaller than Y, and we have the arithmetic mean, and it always lies between X and Y. It is a mathematical fact that the harmonic mean is always less than the arithmetic mean which is closer to the smaller number than to the higher number. Mathematical expression of F-1 score is;

$$\text{F1Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

6.1 Results

Now we can look at the results from each of the machine learning algorithm. Results also showed in Table 9 with the visualization of Figure 10. We can also see the running time of the each of the algorithm in Figure 9. Support Vector Machines is the winner for the highest running time for training the algorithm.

6.1.1 Naive Bayes. As shown in the Figure 10 we have a comparison of several supervised machine learning algorithms on our dataset. We can see that from the accuracy standpoint Naive Bayes algorithms have the lowest score which means that it did not do a good job for labeling true positives regards to all data but it did a good job in precision standpoint while doing a bad classification

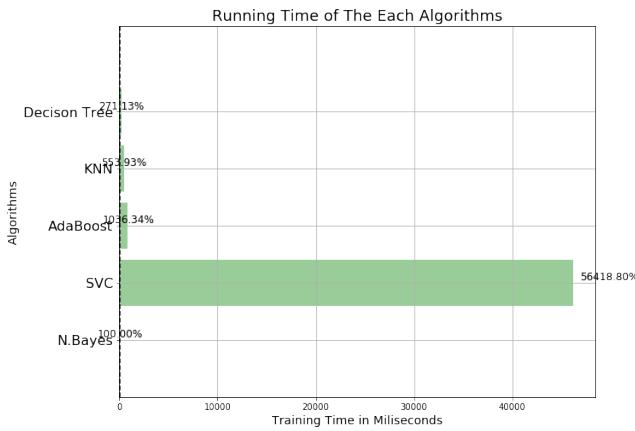


Figure 9: Supervised Learning Algorithm Running Time Results [44].

Name	Accuracy	Recall	Precision	F1 Score
Naive Bayes	0.4442	0.4642	0.9680	0.3053
SVC	0.8301	0.5969	0.5056	0.7284
AdaBoost	0.8499	0.6724	0.6189	0.7361
KNN	0.8184	0.6090	0.5682	0.6561
Decision Tree	0.8161	0.6231	0.6109	0.6459

Table 9: Results of the Algorithms [44].

from recall standpoint. Two key element for us in this situation is accuracy and f1 score(which consist of precision and recall).

6.1.2 Support Vector Machine. Support Vector Machine is the second best algorithm in our case. This algorithm did very well job on classification it has the second highest accuracy and f1 score.

6.1.3 AdaBoost. As we stated before ensemble algorithms learn from the small portion of the data and combine these learning to do the predictive task. As shown in Figure 10 adaboosting has the highest accuracy score among all the other algorithms. This algorithm should be our first choice to do predictive modeling. We believe that there is still an improvements on accuracy

6.1.4 K-Nearest Neighbors. K-Nearest Neighbor algorithm in our project we set the k value to 5. K Nearest Neighbor algorithm also did a good job by placing itself third in accuracy score.

6.1.5 Decision Tree. Decision Tree is gave a good accuracy but fall behind on f1 score as shown in Figure 10.

7 CONCLUSION

We presented the importance of analytical approach with machine learning algorithms and how they can be used to predict or classify the individuals with many different attributes like age, education, income, etc. We also presented weaknesses and strengths of these algorithms along with their precision, accuracy, recall, and F-1 scores by presenting with the visualizations. We also demonstrated the running time for each algorithm while using big data sets.

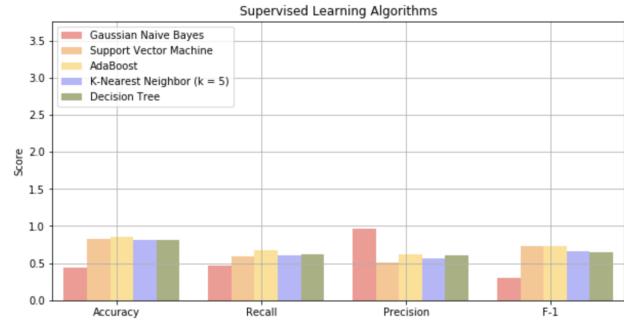


Figure 10: Supervised Learning Algorithm Results [44].

The source code of this project can found Github website which presented in reference section [44].

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Big Data Analytics on Influencers in Social Networks

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ABSTRACT

Social Networking has become a part of people's lives with millions of posts made every day. This huge volume of data paves the way to find interesting insights from data. Applying Big Data analytic methods on Twitter data helps in identifying the most influenced users. The Twitter data used for analysis is taken from Kaggle website. Performing feature selection tasks on this data has helped in identifying the important features that differentiate a user's influence over the other. By applying various Machine learning classification algorithms iteratively on these features obtained can be used to classify a user as more influential over the other.

KEYWORDS

I523, hid215, hid208, Machine Learning, Artificial Intelligence, Data Analysis, Multi layer Neural Network, Logistic regression, Random Forest Classifier, Support Vector Classifier(SVC), Stochastic Gradient Descent(SGD), K Nearest Neighbours(KNN), Naive Bayes.

1 INTRODUCTION

Social Media is a powerful tool to express one's thoughts, ideas and experiences. With the exponential growth in active users across various social media platforms such as Facebook, Twitter, Instagram etc, a mammoth amount of data is being generated across these platforms. With such huge volume of data readily available, a lot of research is being carried on in the recent time in analyzing this data using various tools and extracting useful insights from it. With such large number of active users on these platforms, organizations are looking to capitalize on the opportunity to reach out to a large mass of population with absolutely low marketing costs.

Post made on Twitter are short and concise making it one the most used social media platform used by millions all around the world. Contrary to other social media platforms, Twitter has a limit on the number of words used by its users to make posts, making it the most professional way to interact with people. Most influenced people around the world such as politicians, sportsmen, businessmen, artists are active users of Twitter. With such large number of celebrities using Twitter to express themselves, it is interesting to find how influential they are when compared to their counterparts. One can argue that a user's influence on Twitter is directly proportional to the number of followers he/she has. This is debatable as a set of people argue that with the number of followers a celebrity has, a post made by he/she influences a large population. While others argue that many other factors come into picture when quantifying how influential is a person rather than raw follower count. This can be analyzed by collecting a large volume of Twitter data and identifying the key factors that contribute to the influence of a user. Many methods are in use for collecting data from Twitter with the most popular ones being Twitter API and GOT3 or using readily

available data online. Identifying influenced users across Twitter can be helpful in multiple domains. For example, this analysis can be used to formulate marketing strategies by organizations so that they can approach the more influenced people to make a post on their products for them to reach out to a large population. Also identifying most influenced persons during election campaigns can be used to predict the winning presidential candidate. Candidates can even deploy strategies to make themselves more influential on Twitter which indeed helps in their campaigning.

That data for the analysis is obtained from Kaggle data science competition. The train datasets has 5500 rows and 13 columns. The approach here is to classify each of users which has attributes from both the A user and the B user into the classes making it a Binary classification problem. The data is split into train and test datasets using 5 fold cross-validation. This is because we do not have test data and to test the model performance we need test data to work with. Many approaches for binary classification such as Multilayer Neural Network, Logistic regression, Random Forest Classifier, Support Vector Classifier(SVC), Stochastic Gradient Descent(SGD), K Nearest Neighbours(KNN), Naive Bayes have been used to classify every row in the data into either of the two classes. The models are fitted on the train part of the split dataset and tested on the testing data set for obtaining the model accuracy.

Prior to fitting the models, it is important to obtain the features that are most useful for classification. Using all the features in the dataset is not a good approach as the model tends to memorizes the data points which eventually leads to overfitting. Random forest feature importance is used to rank the features in the dataset based on their importance towards the classification task. While there are many approaches towards feature reduction, Random forest is most followed approach giving the best possible results for the data in many situations. Then a subset of these features of the variable importance is taken for model fitting and discarding the remaining features. The random forest approach is run multiple amounts of times before feature selection since there is randomness involved in the approach and it is optimal to normalize the results from various iterations.

The above-stated models are then fitted on this subset of features in an iterative fashion. Various parameters of these models must be taken into consideration when fitting the models. The parameters should then be tweaked according to the data set and obtain the best parameter set for every model. Once the models are fitted it is important to evaluate the performance of these models and compare them against one another to obtain the best model that fits the data. The performance is tested on the test data obtained from the split using metrics such as accuracy score, precision score, recall score, F1 score and confusion matrix. These are various metrics that describe various properties of the performance of the model.

2 LITERATURE REVIEW

Previous research on determining the user influence in twitter by Krishna P. Gummadi suggests that the indegree, reweets, and mentions play a major role in determining a user's influence on Twitter. Where, in-degree refers to how popular a user is, re-tweets is the number of re-tweets received by a post made by the user and mentions is the number of mentions he got from his post. Krishna P. Gummadi says that a user being more popular may not be equally influential in terms of re-tweets and mentions. In his paper, he only used these three attributes to determine the influence of a user on Twitter.[5]

Whereas, the approach proposed currently uses more attributes than that and hence is expected to perform better than Krishna P. Gummadi's model. It is always better to have more attributes or more data so that we can then perform feature selection to select the most important features. We can also calculate the correlations between different features to see how they influence each other. It is better to consider re-tweets or mentions received and sent and also the follower as well as the following count to determine the influence to model a better classifier.[5]

Katz, E., and Lazarsfeld discuss a useful method to determine the most influential customer using social network so that the companies can market their product to so that they can market it to an exponential number of people. They say that if instead of viewing a market as a set of independent entities, we view it as a social network and model it as a Markov random field. Their method focuses on calculating a network for a given customer. The current method proposed is an extension to this, predicting who is the most influential user, instead of calculating the network value of each user.[7]

3 DATA DESCRIPTION

The data for classification and analysis is taken from Kaggle's competition on "Influencers In Twitter". The idea was to use bigger data set, but due to scalability issues, have only used a smaller data set. The data set has 5500 rows and 23 columns. Each row in the data corresponds to two users A and B. Each row is independent of one another i.e. the A user and B user in each row is independent of each other. The first column 'Choice' in the data set represents the class label. This column has a value of 1 if B user is more influential than the A user and has a value of 0 if A user is more influential than the B user. The next 11 columns belong to attributes of the A user followed by 11 columns belonging to the attributes of B user. The following are the 11 attributes of each user:

- (1) Follower-count
- (2) Following- count
- (3) Listed-count
- (4) Mentions-received
- (5) Mentions-sent
- (6) Retweets-received
- (7) Retweets-sent
- (8) Posts
- (9) Network feature-1
- (10) Network feature-2

- (11) Network feature-3

Follower count, Following count: These attributes in the data specifies the number of users following the A or B user and number of users followed by user A or B respectively.

Listed count: This attribute specifies the number of private lists the A or B user is a part of.

Mentions Received and Retweets Received: These attributes specify the number of mentions and the number of re-tweets A or B user received from other users.

Re-tweet Sent: specifies the number of re-tweets A or B user sent to other users.

Post: This attribute describes the number of tweets made till date by the users.

Network feature attributes: These are obtained as a result of PCA analysis and are included in the data. They correspond to some variance in the data from the network point of view.

4 FEATURE SELECTION

Due to the existence of a large number of features available in the data set, this feature should be reduced and only the most important features that help to model the data needs to be selected. If all the features are used to model the data the model performs exceptionally well on the training data set but fails to perform well on the testing data set. This is called 'Over-fitting'. This is a general phenomenon that occurs across most Machine learning algorithms when using a large set of features for classification because the model learns to memorize these features resulting in a good accuracy score for train data set, but when we encounter a new set of values for these features in the testing data the models fail to classify them correctly resulting in a poor accuracy score.

There are many approaches to feature selection. One approach is to have domain knowledge on the data i.e. having prior knowledge on the data set and by intuition selecting features from the data. For example, if we are predicting sales prices of a house based on the features of the house, having an in-depth knowledge on what feature make the house price go up or down can help in selecting the features of interest. This often requires a professional who experts in that domain to make the decision. But this approach often fails for two reasons, firstly it is hard to find an expert opinion on every data set and secondly the intuition of the expert can be trusted as humans are prone to make mistakes in estimation.

The ideal approach would be to use some algorithm that can predict the features of interest by iterating over the model multiple times. Random forest for feature selection is one such algorithm. As the word random suggests, the algorithm builds small decision trees using a different subset of features in each iteration and then combines the insights from all of these decision trees and ranks the features in the dataset based on their importance. Since the algorithm builds thousands of trees based on the random selection of features, the feature ranking, for the most part, is accurate. Once the features with its ranking are obtained, one has to select a subset of these features and use them for model classification. Since the ideal number of features that best suits the model is still unknown, the approach is to iterate over the important feature and select the best possible subset. For the Twitter dataset, the random forest ranked the features according to their importance and selecting 8 of

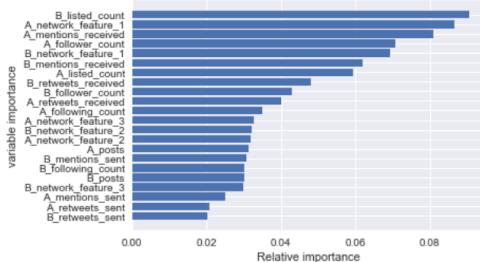


Figure 1: Variable importance

the top most important feature given the best possible results. The features are follower count, listed count, re-tweets received and Network features 1 for both A and B users. Figure 1 shows the features ranked according to their importance.

5 CLASSIFICATION METHODS

Since we have only two classes (either 0 or 1) in our class label, it becomes a binary classification problem. A lot models can be used for binary classification. The approach is to fit 8 of these models for the data set and evaluate the performance of each of these models by using the evaluation metrics.

5.1 Logistic Regression

Logistic regression is one of the Generalized Linear Models that describes the relationship between the response variable and the explanatory variables[1]. The response variable can either be binary or multinomial. If the response variable is binary, it is called binary logistic regression and if it is multinomial, it is called multinomial logistic regression.

The cumulative distribution function for logistic regression is given by:

[1]

$$F(x) = P(X \leq x) = \frac{e^{\frac{(x-\mu)}{\tau}}}{1 + e^{\frac{(x-\mu)}{\tau}}} \quad (1)$$

Where μ is the mean of the given set of data points and τ is a scaling parameter.

Using the cumulative distribution function for logistic regression[1], the logistic regression function is given by:

[1]

$$\log\left(\frac{\pi(x)}{1 - \pi(x)}\right) = \alpha + \beta x \quad (2)$$

where:

[1]

$$\pi(x) = \frac{e^{\alpha+\beta x}}{1 + e^{\alpha+\beta x}} \quad (3)$$

π is the probability of occurrence of an event. Where

[1]

$$\alpha = -\mu/\tau \quad (4)$$

$$\beta = 1/\tau \quad (5)$$

The relationship between $\pi(x)$ and x is mostly non-linear. The influence of x on $\pi(x)$ is more when it is near 0 or 1 rather than when it is in between. π either increases or decreases with an increase in $x[1]$. The rate of increase or decrease depends on β . If $\beta > 0$, then $\pi(x)$ increases with an increase in x and if $\beta < 0$, then $\pi(x)$ decreases with an increase in x and remains constant when $\beta = 0$. The random component for the response variable in logistic regression has a binomial distribution. The link function is 'logit'. The logistic regression model is also sometimes referred to as logit model. If it is a multinomial logistic regression model, then the random component would be multinomially distributed[1].

5.2 Random Forest Classifier

The Random forest algorithm apart from its use as feature selection method can also be used a Classifier. Random forest in one of the ensemble classification methods currently in use."Ensemble learning is a machine learning paradigm where multiple learners are trained to solve the same problem"[11]. Typical methods for example Decision tree algorithm build trees by iterating over the features in the train data set. But ensemble method uses a different approach, for example, Random forest build a number of small decision trees based on a subset of training features and combine the results from all these decision trees and obtain a better accuracy. It eventually builds a forest of decision trees, hence the name Random Forest.[2]

Each of the decision trees has a decision as to which class a new data point belongs to. Random forest algorithm classifies the data point by combining the decisions from all the decision trees. Hence it provides better performance while at the same time over-fitting on most occasions. The random forest classifier has two stages, the training phase, and the classification phase. [2]

In the training phase from the corpus of training features, a random subset of features is sampled with replacement. Three-fourths of the data is sampled leaving out the remaining data for formulating the classification error. It is called out of bag data (OOB). In the classification phase, proximities are calculated for every decision tree for each of the two classes. If two decision trees have the same proximities for each of the two classes the proximity is increased by one. Once all the proximities are determined it is then divided by the total number of decision trees to normalize it.[2]

While building the decision trees typically the Gini importance is used.Gini index splits the tree based on whether the Gini impurity criterion of the current node is less than the parent node.

[2]

$$I_G(p) = 1 - \sum_{i=1}^J (p_i)^2 \quad (6)$$

Where $I_G(p)$ is gini impurity of p

J is the number of classes (J=2 for binary classification) p_i is the number of items classified into class i

Here there are a few design choices to be made

Max iterations: - Have to specify the maximum number of iterations the classifier has to run. It is hard to find an optimal number for every problem. Need's to be iterated across multiple values.

Max depth:- Specifies the maximum depth to which the decision

tress are built.

N estimators:- specifies the maximum number of trees built in each iteration.

Max features- specifies the number of features to be considered when splitting the decision tree.

Criterion - specifies using either gini impurity index or entropy. By default it uses gini impurity index.[2]

5.3 Stochastic Gradient Descent

Gradient descent is one of the machine learning algorithms which is used for updating the weights of a neural network to optimize the prediction error of machine learning algorithms[4]. The weights are updated so that the classification or regression error of training samples is minimized over the iterations. Gradient descent is classified into three types based on the number of training samples used for updating the weights. They are:

- (1) Batch Gradient Descent
- (2) Stochastic Gradient Descent
- (3) Mini-batch Gradient Descent

In batch Gradient descent, the weights of the network are assigned randomly initially and the model is designed by updating the weights accordingly to minimize the prediction error after all the training samples are classified. [4]

Stochastic Gradient Descent is another type of gradient descent in which the error is calculated for each training sample. The weights are updated for every training sample. Because of the kind of update the Stochastic Gradient Descent uses, it is called as online machine learning algorithm. There are both advantages and disadvantages of using this approach. One of the advantages is that the model is less prone to arrive at local minima as the update process is noisy[4]. As the error is calculated frequently, the error in the prediction can be corrected at that stage itself, instead of propagating it to next stages. Also, the frequent updating of weights may result in fast learning. On the other hand, one of the major disadvantages of this approach is that updating the weights for every training sample may be much time consuming and delay the convergence. Also the updates being noisy might cause the algorithm to arrive at a error minimum with high variance[4].

To combine the advantages of both Batch Gradient Descent and Stochastic Gradient Descent, Mini-batch Gradient Descent can be used[4]. In this method, the training data is divided into a number of subsets and the error is calculated and weights are updated for each subset.

5.4 Support vector Classifier

Support Vector Machines is an advancement over Neural Network. A neural network converges if the two classes are linearly separable. Every time we run a neural network on the train data and plot the points and the line on a 2-D plane, we get a different line that separates the two classes, this happens due to the randomness in the initial weights chosen for the perceptrons. Since we get a different classifier every time we run it, it is obvious that one classifier is better than the other. The neural network does not guarantee the best possible classification. This is where SVC shines with its improvements over neural networks. SVC can be used both

for classification and regression tasks but are typically used for classification. There mainly three types of SVC,[10]

1.Linear SVC

2.Nu SVC

3.SVC

Ideally, the goal of SVC is to place the decision boundary i.e. the line that separates the two classes as far away from the classes as possible. The distance between the decision boundary and the data points in each class is called margin. Most often some of the data points exist within the margin and are close to the boundary, these points are called as 'Support vectors'. The distance from the vector to the boundary is given by,[10]

$$r = \frac{g(x)}{\|w\|} \quad (7)$$

where,

$$g(x) = w^T x + b \quad (8)$$

where r is the distance, g(x) is the decision boundary and $\|w\|$ is the absolute value of the weight vector and b is the bias.

Since the goal here is to find the optimal decision boundary, the corresponding w and b should be estimated. This can be achieved by using the Primal problem which is a constraint minimization problem. The formulation of this is,[10]

$$d_i(w^T x_i + b) \geq 1 \quad (9)$$

$$\Phi(w) = \frac{1}{2} w w^T \quad (10)$$

The above minimization can be solved using the Lagrangian formulation,

$$J(w, b, \alpha) = \frac{1}{2} w w^T - \sum_{i=1}^N \alpha_i [d_i(w^T x_i + b) - 1] \quad (11)$$

where α_i is called the Lagrangian multipliers. We obtain the optimal values of w and b by partially derivating the above equation and equating it to zero. We get,

$$w = \sum_i \alpha_i d_i x_i \quad (12)$$

$$Q(\alpha) = \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j d_i d_j x_i^T x_j \quad (13)$$

here $\alpha_i > 0$ only for support vectors and Q is quadratic. Finally after getting α_i , the optimal w_0 is,

$$w_0 = \sum_{i=1}^{N_s} \alpha_0 d_i x_i \quad (14)$$

where N_s is the number of support vectors.

$$b_0 = \frac{1}{d(s)} - w_0^T x^{(s)} \quad (15)$$

Since now we have the optimal value for w and b, we get the

optimal decision boundary. SVC generally gives a better accuracy over perceptron and it can be used efficiently for high dimensional planes.[10]

5.5 Multi layer Perceptron

The neural network came into existence in the early 1960's but was not very popular approach since it had some limitations in solving complex problems. But with the introduction of backpropagation algorithms and its application on Multi-layer Neural networks. Each neural network comprises of individual neurons which are also called perceptions. These neurons are connected to one another with edges. A simple neural network has three layers, input layer, an output layer and the hidden layer. The inputs layers consist of data points these data points are connected to the neuron in the hidden layer by an edge which has weights and biases associated with them. The hidden layer is then connected to the output layer with edges which also has weights and biases.[9]

Based on the type of the problem, the output layer either output a binary value(0 or 1) or any continuous value. The input data point is multiplied by the weight of the neuron and the bias of that neuron is added. All output from each neuron is added together and is fed to an activation function and produces an output. Once an iteration is completed the weights of the network are updated based on the output obtained from the first iteration using the perceptron learning algorithm. The learning stops when there is no significant improvement from one iteration to the other. The error is calculated after each iteration which quantifies the number of misclassified data points.[9]

$$w(n+1) = w(n) + \eta[d(n) - y(n)] * x(n) \quad (16)$$

where,

w(n+1)-new weight of the neuron

w(n)- old weight of the neuron

d(n)- desired output

y(n)- acutal output

x(n)- data point

This simple neural network can only be used yo solve a handful of problems. For example, it cannot solve the XOR problem. To deal with much more complicated problems we require the use of Multi-layer Neural networks with the back-propagation algorithm to update the weights in each iteration. The back-propagation algorithm uses gradient descent to update the weights by cost minimization. There are two steps in the back-propagation algorithm. One is the feedforward step where the network feeds forward and find the output. In the back-propagation step the algorithm back-propagates and update the weights in each layer by using gradient descent. This is done is a backward fashion starting from the output layer and then the hidden layers. There are two methods for updating the weights, batch update and the online update. While batch update method updates the weights after one iteration of all the data points, the online update method updates the wights after each data point is passed through the network.[9]

Here there are lot of design choice to made

1.Initializing weights - weights are usually initialized random normal manner.

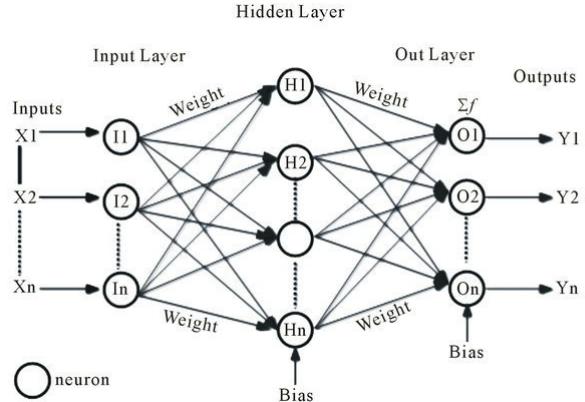


Figure 2: Architecture of a Multi-layer Neural network [9]

- 2.Choosing the number of hidden layers- This parameter cannot be determined in advance. One has to iterate through multiple values of the hidden layer unless the best accuracy is obtained.
- 3.Update method- The weights can be updated typically using the batch update on the online update. In most application typically the online method is used as it is much more efficient.
- 4.Choosing the Activation function- This is a difficult task, most commonly non-linear activation functions are used. Example Re-Lu activation function. Figure 2 shows the architecture of a Multi-layer Neural network

5.6 K Nearest Neighbours

K Nearest Neighbours is one of the simplest machine learning models that can be easily implemented and it surprisingly works well for most classification problems. K Nearest Neighbours can be used for both classification and regression problems giving it the flexibility to solve most problems.

The algorithm assumes all the data points are scattered on a 2-dimensional plane and it tries to find clusters of these data points. The algorithm mainly has two phases, the training phase, and the classification phase. The training phase of KNN is fairly simple as it just stores the values of each of the variables and also the class label. The classification phase is the most important one as all the calculation are made in this phase. Since cross-validation is being used to split the data set into train and test, in the training phase the algorithm stores the values of each of the 8 attributes used for model fitting and also the values of the class label for each fold of the cross-validation.

In the classification phase for each data point in the test data set, the algorithm iterates over all the data point in the train data set and finds the k nearest neighbors to the current data point by calculating the distance between them. A variety of distance metrics can be used to find the nearest neighbors. The most commonly used ones are Manhattan Distance and Euclidean Distance. But based on the type of data other distance metrics can be used to obtain better performance. Once the k nearest neighbors are obtained the algorithm looks for the class labels for these neighbors and assigns the most occurring label among these neighbors to the current data

point. This happens for every data point in the test data set and every fold in the cross-validation. The algorithm then assigns the most occurring class labels across all folds.

The value of k is unknown for a given problem and one has to iterate over multiple values of k to find the best accurate model. The most common approach to find k is to iterate over multiple values of k starting from 1 and stopping when the difference in performance from the previous value of k is below a certain threshold. This threshold can be set based on the type and volume of data. Ideally, the threshold should not be too large or too small. Some advantages of this model involve low training cost and it often works well with enough training data and a good distance metric. It also has few drawbacks which involve choosing the apt distance metric can be cumbersome without prior knowledge, it is easily prone to over-fitting and usually takes a lot of time and memory for the classification phase.

5.7 Naive Bayes

Naive Bayes is one of the machine learning algorithms. It is known for its simplicity. It is a classification approach based on the Bayefis law. In this approach, prior knowledge is very essential. The basic idea is to compute the prior of each class and the likelihoods. Then, the posterior probabilities are calculated using Bayefis law for each class and the data point is assigned to the class with highest posterior probability. The prior represents the probability of occurrence of a class among all the given classes. The likelihoods or likelihood probabilities are a measure of how likely is a given data point prone to belong to a given class. Posterior probability is the probability of a class is one of the given classes, given a set of data points.[6] There are two phases in the Nave Bayefis classification as that of any other machine learning algorithm, training, and testing. In the training phase, the prior probabilities of the classes are calculated by computing the number of times the class has occurred in the given data among all the classes. If there are n classes C_1, C_2, \dots, C_n and m data points X_1, X_2, \dots, X_m , then the prior of a class is represented by $P(C_i)$ for i ranging from 1 to n. After computing the priors, the likelihood of each data point belonging to each one of the classes are calculated. The likelihood ratio is given by:[6]

$$P(X_j/C_i) = \frac{P(X_j, C_i)}{P(C_i)} \quad (17)$$

where $i = 1$ to n , $j = 1$ to m

Where, $P(X_j, C_i)$ is the probability of occurrence of the data point X_j in class C_i . X_j represents the j^{th} data point in a given set of data points and C_i represents the i^{th} class.[6]

In the testing phase, the posteriors probabilities are using the Bayefis law:

$$P(C_i/X_j) = \frac{P(X_j/C_i)P(C_i)}{P(X_j)} \quad (18)$$

Where, $P(X_j)$ represents the total probability of X_j , given by:

$$P(X_j) = \sum_{i=1}^n P(X_j/C_i)P(C_i) \quad (19)$$

Naive Bayes model makes the assumption that the data points are conditionally independent of each other given the class or label.

Hence, the likelihood probability of a set of data points belonging to a class becomes:[6]

$$P(X_1, X_2, \dots, X_n/C_i) = \prod_{j=1}^n P(X_j/C_i) \quad (20)$$

Then the posterior probability of a set of data points can be written as:

$$P(C_i/X_1, X_2, \dots, X_n) = \frac{\prod_{j=1}^n P(X_j/C_i)P(C_i)}{P(X_1, X_2, \dots, X_n)} \quad (21)$$

For a given set of data points, $P(X_1, X_2, \dots, X_n)$ remains constant and hence, equation(6) can be written as:

$$P(C_i/X_1, X_2, \dots, X_n) \propto \prod_{j=1}^n P(X_j/C_i)P(C_i) \quad (22)$$

Naive Bayes derives its name from making the naive assumption that the data points are conditionally independent of each other. There are three types of Naive Bayes classifiers:[6]

- (1) Gaussian Naive Bayes
- (2) Multinomial Naive Bayes
- (3) Bernoulli Naive Bayes

Gaussian Naive Bayes can be used for the classification when the given set of data points have Gaussian distribution.[8]

Multinomial Naive Bayes can be used when for the data if it is multinomially distributed[8]. Bernoulli Naive Bayes can be used when all the attributes or features in a given data are binary[8].

5.8 AdaBoost

Ensemble learning is one of the machine learning methods which is based on decision trees. The basic idea is to create an ensemble of hypotheses and combine their predictions instead of predicting using a single hypothesis[3]. Boosting is one of the ensemble methods which attempts at learning a strong classifier from a set of weak classifiers. At first, an initial model is created and then the next model attempts to correctly classify the training samples which have been misclassified by the previous model. This process continues until a predefined number of models have been generated or there is nothing much to be done with the training data.

AdaBoost is one of the Boosting algorithms which is used for binary classification. It can only be used when the response variable is binary. AdaBoost can be used with any machine learning algorithms to improve the performance. It is most commonly used with decision trees. The decision trees used in AdaBoost are only of depth one, i.e., they only have one decision to make. Hence, the decision trees in AdaBoost are called decision stumps[3].

There are two phases in the AdaBoost as well, like any other machine learning algorithms. In the training phase, all the given training samples are assigned with uniform weights. If there are n training samples, then each sample is given a weight of $1/n$. Hence, the initial weights of the training samples can be written as[3]:

$$w(x_i) = \frac{1}{n} \quad (23)$$

Where x_i is the i^{th} training sample and $w(x_i)$ is the initial weight of i^{th} training sample. Using these weighted samples, a weak binary classifier is modeled which can only make one decision and output either -1 or 1, where 1 represents the first class and -1 represents

the second class. Then, the misclassification rate is calculated for the trained model as follows[3]:

$$\text{error} = \frac{(c - n)}{n} \quad (24)$$

Where c is the number of correctly classified samples and n is the total number of training samples. Now, weighted aggregate of the misclassification rate is calculated to further use it to modify the weights of the training samples. It is modified as[3]:

$$\text{error} = \frac{\sum_{i=1}^n w(x_i)e(i)}{\sum_{i=1}^n w(x_i)} \quad (25)$$

Where $e(i)$ is the prediction error of the i^{th} training sample which is either 1 or 0. It is 0 if the sample is classified correctly and 1 if it is misclassified.

Then, stage value is calculated from the aggregated error as follows[3]:

$$\text{stage} = \ln\left(\frac{1 - \text{error}}{\text{error}}\right) \quad (26)$$

The stage value is used to assign greater importance to classifiers which are more accurate. The weights of the training samples are updated using the stage value so that samples which are correctly classified have less weight and the incorrectly classified samples have more weight. The weights are updated using the below equation[3]:

$$w(i) = w(i) * e^{\text{stage}*e(i)} \quad (27)$$

We can observe from the above equation that if a sample i is correctly classified, then prediction error of that sample $e(i)$ will be 0 and hence the weight of the sample remains as it is. Whereas, if the sample is misclassified, then $e(i)$ would be 1 and the weight of the sample increases by a factor e^{stage} . This process is continued by updating the weights and modeling weak classifiers until a predefined number of weak classifiers have been modeled or when there is nothing more to be gained from the training data.[3]

In the testing or prediction phase, when a test sample is to be classified into one of the two available classes, it is classified using all the weak classifiers designed in the training phase and the predicted values are given weights according to the stage value of the corresponding classifiers[3]. The final predicted value is taken to be 1 if the weighted sum of these predicted values is positive and -1 if the sum is negative.

6 EXPLORATORY DATA ANALYSIS

6.1 Missing values

Since the data is sparse, null values can exist in the data. These null values if not treated can be catastrophic to the model accuracy. The null or missing values can be treated either by removing the rows which have these values or replacing them with apt data. For example, if a data frame has 10 null values in a column, the approach would be to replace the values with either the mean, median or mode of that column. The data here does not consist of any null or missing values in any of the rows.

6.2 Outliers

If a data point diverges very much from the rest of the data points it is called an outlier. These outliers if not addressed will eventually lead to overfitting of the model i.e. the model fits each and every

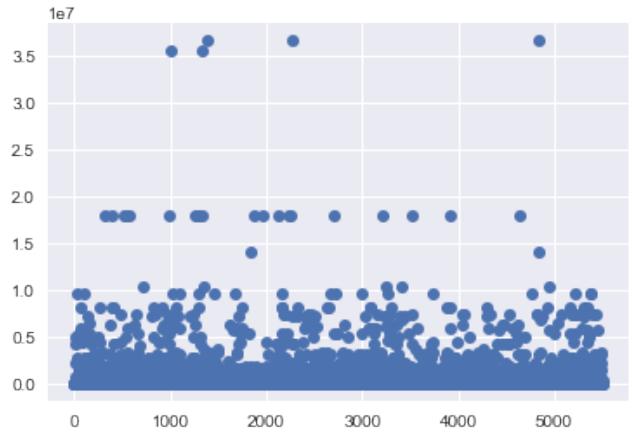


Figure 3: Scatter Plot

point in the train data and gets a good accuracy, but when tested on unseen data it will result in a poor accuracy score. To overcome overfitting the outliers need to be addressed. The outliers in the data can be identified by either plotting a box plot or scatter plot of each of the variables in the train data and check for the distribution of data points.

Just like missing values the outlier can either be deleted from the data or can be modified to better suit the model. The ideal approach would be to use binning of the columns which have outliers. In binning data, we bin the data into small categories based on a range. The Twitter data here consists of a few outliers in almost all the attributes. Binning the data improved the accuracy score of all the models. Figure 3 shows the scatter plot of A follower count variable with outliers.

From the scatter plot it is evident that for all the attributes the data point is concentrated in the lower range. Hence after binning each attribute into two the first two lower categories, null values are generated in the higher categories. Hence the rows with Null values have been dropped thereby removing the outliers. The data is reduced to 5209 rows after the removal of outliers.

6.3 Correlation among attributes

Since the data consists of 22 columns apart from the class label, correlations among these attributes might be. Correlation is the measure of association between two attributes. It indicates how closely two attributes are related to each other. The range of correlation is between -1 and 1. A positive correlation indicates the two variables are directly proportional and a negative correlation indicated that they are indirectly proportional. If the value is zero then there is no association between the attributes. Figure 4 shows a heat map displaying the correlation among the variables.

The color of the heat map indicates the level of correlation among attributes. As the color tends to get closer to yellow, it shows a positive correlation and shows a negative correlation if color tends to get bluer. For example, there is a strong correlation between network feature 1 and mentions received. This correlation also

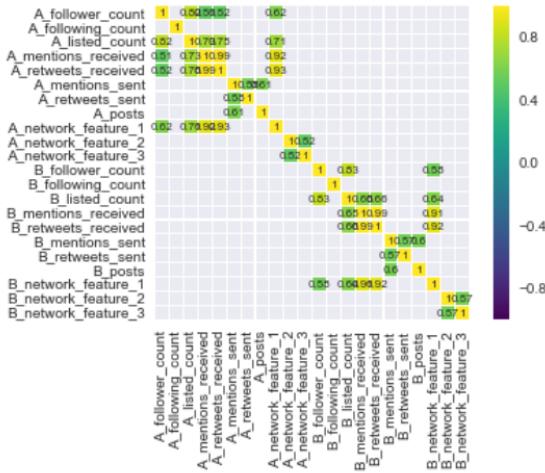


Figure 4: Correlation Plot

helps in feature selection as we can ignore one of the two features if they are closely related. The variables which are closely related to the class label are found to be follower count and listed count of both A and B. This is not very surprising as a person with high follower count or listed count on Twitter is expected to be more influential than others. These insights proved to be useful in the further analysis when performing feature reduction.

7 EXPERIMENT AND RESULTS

To avoid overfitting, the training data has been further split into train and test using cross-validation. 80 percent of the data has been used for training the classifier and the remaining 20 percent is used to evaluate the performance of the classifier.

Feature selection has been performed on the train data using Random Forest Classifier to obtain the most important attributes. A bar plot has been plotted to know the top most important variables which are shown in the figure. The top four important attributes are identified to be follower-count, listed-count, mentions-received and network feature-1 of both A and B. Further analysis or classification has been performed on these eight attributes.

7.1 Evaluation Metrics

One the model is fitted, there is a need to evaluate the performance of the model. Various evaluation metric can be used to measure how well the model performs. Accuracy score, precision score, F1 score, Confusion matrix and recall score are the most commonly used metrics to evaluate the performance of classifiers. They indicate various measure of evaluation

1. Accuracy score: Ratio of number of correctly classified data points to total number of data points.

2. Precision score: Ratio of True positives to sum of True positives ,False positives for each class.

3. F1 score: Twice the ratio of product of precision and recall to the sum of precision and recall for each class.

4. Recall score: Ratio of True positives to sum of True positives ,False negatives for each class

	accuracy score	precision score	recall score	f1 score	confusion matrix
logistic regression	0.774472	[0.76334519573, 0.7875]	[0.80790960452, 0.739726027397]	0.774443	[[429, 102], [133, 378]]
Knn	0.744722	[0.747663551402, 0.741617357002]	[0.753295668655, 0.735812133072]	0.744696	[[400, 131], [135, 376]]
Random forests	0.776392	[0.762323943662, 0.793248945148]	[0.81544261205, 0.735812133072]	0.775956	[[433, 98], [135, 376]]
LinearSVC	0.772553	[0.761565836299, 0.785416966687]	[0.80602036365348, 0.737769080235]	0.772221	[[428, 103], [134, 377]]
Adaboost	0.786948	[0.804733727811, 0.770093457944]	[0.768361581921, 0.806262302092]	0.786929	[[408, 123], [99, 412]]
Multinomial NB	0.757198	[0.756457564576, 0.758]	[0.772128060264, 0.74168297456]	0.757121	[[410, 121], [132, 379]]
SGD	0.759117	[0.7482269690355, 0.771966527197]	[0.79472693032, 0.722113502935]	0.758728	[[422, 109], [142, 369]]
MLP	0.687140	[0.92531120332, 0.615480649189]	[0.419962335217, 0.964774951076]	0.662954	[[223, 308], [18, 493]]

Figure 5: Evaluation Metrics

5. Confusion matrix: To know how well the classifier performs in each class in the data. It gives the number of True positive, False positives, True negatives, and False negatives. The rows in the matrix correspond to actual class label and the columns to the predicted class label.

If a classifier has very high precision then it may miss many true instances of a label, similarly, if it has very high recall score it is prone to misclassify many data points. Hence a good classifier should have a trade-off between precision score and recall score. For the Influence analysis, the Ada boost Classifier has the best performance with an accuracy score of 0.78 and an F1 score of 0.78. The MLP classifier performed the worst with an accuracy score of 0.68 and an F1 score of 0.67. This is because the classifier performed extremely well in one class and very poorly in the other class. This is evident from a high precision score in class 1 and a low recall score, and vice-versa for class 0. Whereas for the AdaBoost classifier both class 1 and 0 have decent precision and recall scores, hence finding a good trade-off between them. Figure 5 shows the evaluation performance of each classifier with all the evaluation metrics

8 FUTURE WORK

Predicting the Influence of users based on various attributes paves the way for much more research in the area. Instead just classifying two users based on their influence it can be extended to a larger audience, which can be quite interesting. But it becomes a regression problem rather than a classification problem. This analysis can also be extended to address how an individual is influential i.e. in a good or a bad way. This can be achieved with the help of sentiment analysis performed on the users. But this would require the actual tweets that the users make.

9 CONCLUSION

Twitter being one of the most popular social media platforms, serves as a source for various thoughts expressed by people across different domains. These tweets or tweet data if analyzed in an efficient way can answer many questions. One of such questions is which user on Twitter is more influential. Given the tweets made by the user and other statistics like a number of retweets received, follower count, etc the user with more influence can be predicted using various machine learning classification techniques. AdaBoost is found to be the most efficient classification technique for this research question with an accuracy score of 0.78 and the least appropriate method was found to be the Multi-Layer Perceptron classification.

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Big Data Analytics in Detection of DDoS (Distributed Denial-of-Service) attacks

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ABSTRACT

With the increase in internet traffic, threats on the network have also increased. Denial-of-service attacks are cyber attacks wherein a perpetrator, due to any kind of malicious intent, tries to make a resource on the network unavailable to its intended users and carries it out by swamping the system or resource with excess requests in order to overload it and prevent users from accessing it. A much more dangerous variety of such an attack is if it is distributed i.e. coming from various sources. Big Data analytics, however, can be used to detect such attacks by having the ability to store the voluminous logs of such attacks and using the data and machine learning techniques to design an anomaly detection system (using a classification model) to detect and prevent these attacks. This project will aim to explore such classification models, design and train the most optimum model and display its effects using a DDoS network traffic logs dataset.

KEYWORDS

i523, HID224, Denial-of-Service, Intrusion Detection, KDD Cup'99 dataset, Machine Learning, Apache Spark

1 INTRODUCTION

The Internet allows us several comforts and functionalities in our day-to-day lives. With the increasing flexibility and accessibility provided by technology, the Internet has become an indispensable part of our life. However, this same accessibility often provides openings for malicious attackers to enter. Security over the Internet is an interdependent factor, with the security of one user depending on rest of the global network [1]. Denial-of-Service attacks are attacks by such malicious users in order to disrupt the accessibility of other legitimate users to a Web Service or application [7]. The objectives of such attacks are mainly malicious, driven out of revenge or for some material gain. The attacks seriously hinder the productivity of the victim, as the resources available are not sufficient to handle the oncoming flood of requests. This attack increases in complexity when there are multiple sources of attacks, resulting in a Distributed Denial-of-Service attack. “In the case of a Distributed Denial-of-Service (DDoS) attack, an attacker uses multiple sources - which may be compromised or controlled by a group of collaborators - to orchestrate an attack against a target” [7]. A small batch of requests sent by an attacker may be enough to generate a large amount of unwanted traffic. The earliest of these attacks was when a DDoS tool called Trinoo, deployed in at least 227 systems, flooded a University of Minnesota computer, which was subsequently rendered useless for more than two days [1]. Figure 1 shows how a Distributed Denial-of-Service attack occurs.

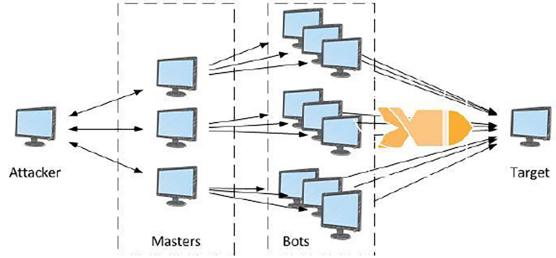


Figure 1: Distributed Denial-of-Service Attack [7]

As the connectivity increases in our everyday lives, so have the risks for DDoS attacks. The Internet of Things (IoT) for example, has opened up a whole new avenue for Denial-of-Service attackers. Earlier, limited to attacks over the Internet which mostly affected a user’s computer, with the advent of IoT, the scope of attacks on other smart devices has increased considerably. These devices could be used as pawns in a DDoS attack network and could even be the intended targets for such an attack. Some of the largest DDoS attacks till date are as given: In March of 2013, the DDoS attack on Spamhaus saw 120 Gbps of traffic on their network, in August of 2013, a “part of the Chinese internet went down in one of the largest DDoS attacks”, in the Spring of 2015, UK-based phone carrier Carphone Warehouse got attacked and hackers stole millions of customers’ data and in January of 2016, some HSBC customers were inhibited from accessing their online banking accounts, which caused a great upheaval as it was “two days before the tax payment deadline in the United Kingdom” [11]. We can see that these attacks, if allowed to happen, have great damage potential. Hence, DDoS mitigation service providers like Imperva Incapsula Enterprise, Arbor Cloud, Verisign, DOSarrest and CloudFlare, have their work cut out for them to detect and prevent such attacks, which are increasing in their reach and complexity [10].

2 DDoS ATTACK TYPES AND ARCHITECTURE

In order to prevent a DDoS attack, it is important to know the points in a network where the attack is expected to occur and the type of attack that can occur. Referring to an Open Systems Interconnection(OSI) model, we can usually narrow down the layers which could be affected by a potential attack to the Network, Transport, Presentation and Application layers [7]. Figure 2 shows an Open Systems Interconnection Model with the layers highlighted where DDoS attacks are most common.

#	Layer	Unit	Description	Vector Examples
7	Application	Data	Network process to application	HTTP floods, DNS query floods
6	Presentation	Data	Data representation and encryption	SSL abuse
5	Session	Data	Interhost communication	N/A
4	Transport	Segments	End-to-end connections and reliability	SYN floods
3	Network	Packets	Path determination and logical addressing	UDP reflection attacks
2	Data Link	Frames	Physical addressing	N/A
1	Physical	Bits	Media, signal, and binary transmission	N/A

Figure 2: Open Systems Interconnection Model [7]

Apart from this, the DDoS attacks generally have a specific architecture and follow certain strategies. Knowledge of the pathway which a Denial-of-Service attack follows is essential to detecting and mitigating it.

2.1 DDoS Attack Types

The DDoS attacks in the Network and Transport layers are generally of the User Datagram Protocol (UDP) reflection and synchronize (SYN) flood types [7]. The UDP protocol can allow the attacker to fake the source of a request sent to a server and generate a larger response. The amplification factor of a protocol (request to response size) will result in an overwhelming response to a comparatively smaller request. “For example, the amplification factor for DNS can be in the 28 to 54 range - which means an attacker can send a request payload of 64 bytes to a DNS server and generate over 3400 bytes of unwanted traffic” [7]. A SYN flood attack is based on employing all the resources of a system and exhausting them by leaving connections half-open. For example, when an user connects to a TCP service, the client will send a SYN packet and the server will return a SYN-ACK, expecting the client to return an ACK and completing the handshake. In a SYN flood attack, the ACK is not returned and so the server is stuck in this state which prevents other users from connecting to it [7].

In the Presentation and Application layers, the DDoS attacks are slightly different. The most common of such attacks are “HTTP floods, cache-busting attacks, and WordPress XML-RPC floods” [7]. In an HTTP flood attack, the attacker sends HTTP requests under the guise of a real user or web service. These attacks target a resource or try to emulate human behavior. Cache-busting attacks are a specialized version of HTTP flood attacks that use “variations in the query string to circumvent content delivery network (CDN) caching which results in origin fetches, causing additional strain on the origin web server” [7]. A WordPress XML-RPC flood (WordPress pingback flood) is used by an attacker to misuse the XML-RPC API function of a website hosted on WordPress software to generate HTTP flood requests. This type of attack has *WordPress* present in the HTTP request header and so is clearly recognizable [7].

2.2 DDoS Attack Architecture

“DDoS attack networks follow two types of architectures: the Agent-Handler architecture and the Internet Relay Chat (IRC)-based architecture” [1]. The components of an Agent-Handler architecture are clients, handlers, and agents. In this type of architecture, the attacker connects with the rest of the attack system at the client point. The handlers are generally software packages available over

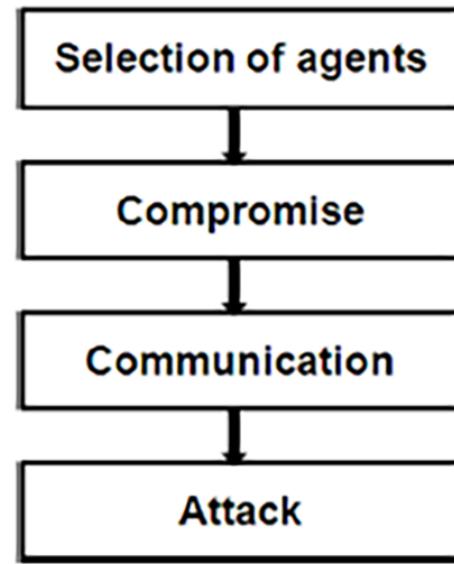


Figure 3: Steps of a Denial-of-Service attack [1]

the Internet which are used by the client to connect to the agents. The agent softwares are placed in the vulnerable systems that are finally used to implement the attack. Often, the users of the agent systems are not aware of the attack being carried out [1]. In the IRC-based architecture, “an IRC communication channel is used to connect the client(s) to the agents” [1]. IRC ports are employed to send commands to the agents, making the DDoS command packets harder to trace (as these channels have a lot of traffic) [1]. When launching a DDoS attack, the attacker goes through some steps common to both types of architectures [1]. First, the attacker tries to identify vulnerable systems that can be used as agents. The resources of these systems are used to generate a powerful attack stream. Next, the attacker plants the handler software code in the compromised system and ensures steps to prevent the code from being detected. These compromised systems are often referred to as *zombies*. Sometimes, the attacker creates several intermediate layers between the *zombies* and the victim to hinder traceability. Thirdly, the attacker communicates with the handler codes placed via protocols like TCP or UDP, and decides the scheduling of the attacks. Post the complete setup, the attacker launches the attack on the victim’s machine or server and renders it unusable [1]. In an IRC-based architecture, most of the above steps remain same, but an IRC-channel is used for communication purposes. This helps the attacker as even if one *zombie* or *bot* is discovered, the identities of the others is still hidden, as IRC-channels are difficult to detect [1]. Figure 3 shows the steps of a Denial-of-Service attack execution.

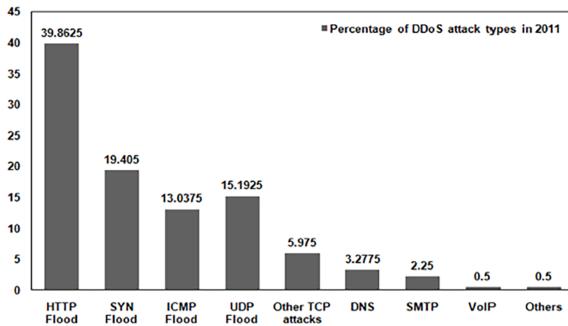


Figure 4: Different Denial-of-Service attack type statistics [1]

3 DDoS ATTACK DEFENSE METHODOLOGIES

In the previous section, we explored the common types of DDoS attacks and the general architecture that they follow. These different types of attacks are used with variation by attackers in their attempts to obstruct utilization of resources. Figure 4 shows the percentage of different Denial-of-Service attacks in 2011 by type. The different types of DDoS attacks and their improvement throughout time has also invoked different defense mechanisms against these attacks. DDoS defense mechanisms are usually employed at three points in the attack network : Victim-end, Source-end and Intermediate-Network [1]. Victim-end detection approaches are generally incorporated in the routers of victim networks. A detection system is used to detect intrusion based on different techniques. Detecting DDoS attacks at this point is relatively easy and the most practically applicable, but has the disadvantage of detection only after the attack has reached the victim and legitimate users have already been denied services [1]. Source-end detection system works similarly to the victim-end detection system apart from “a throttling component”, which is added to force a rate limit on outgoing connections. The detection system then compares both incoming and outgoing network traffic with normal traffic benchmarks to detect an attack. This is probably the ideal defense mechanism, but faces challenges in the deployment of a detection system at the source and difficulty in identification in case of multiple sources [1]. The intermediate-network defense mechanism acts like a middle-ground between the victim-end and source-end systems. It acts like a collaborative model which depends upon communication and sharing of information between all routers on the network. Hence, this too suffers from the problem of deployability, as even one router missing on the network could hinder the traceback process [1].

From the above defense mechanism schemes, we can garner that detection of these attacks forms a major part of the preventive process. The most commonly used detection methodologies for defense against DDoS are as follows: Statistical Methods, Soft-Computing and Machine Learning Methods and Knowledge-Based Methods [1].

3.1 Statistical Methods

Statistical Methods follow the statistical properties of the distribution of incoming and outgoing network traffic for detection of DDoS attacks. The distributions (or statistical estimates generated using it) are compared with those for a normal traffic signature. An example of the same is the use of cumulative deviation from normal to detect DDoS attacks. Similarly, a periodic deviation analysis from the normal pattern can be used to detect intrusions [1]. Another example, is the use of a two-sample t-test to detect DDoS signatures by comparing the SYN arrival rate distribution with the distribution of a normal SYN arrival rate (after confirming a gaussian distribution for it). If the difference is considered significant according to the t-test, the traffic is marked as potentially containing attack packets [1]. A prediction method designed by Zhang et al. [12] uses an Auto Regressive Integrated Auto Regressive (ARIMA) model for their detection system.

3.2 Soft-Computing and Machine Learning Methods

The voluminous network traffic data generated can be leveraged by a soft-computing system like a neural network or a data mining/machine learning model to design a classifier that differentiates between normal traffic and intrusions. An example is the use of statistical preprocessing for extraction of relevant features from the traffic followed by an unsupervised neural net to classify traffic signatures as either a DDoS attack or normal [1]. Another case is the use of a Radial Basis Function (RBF) neural network to analyze attack packets and classify them as normal or harmful [1]. Machine learning algorithms like K-Nearest Neighbors and Support Vector Machines can be used as excellent classifiers for incoming network traffic. Fuzzy networks can also be used in the decision-making process while separating normal traffic packets from potentially harmful ones [1].

3.3 Knowledge-Based Methods

In knowledge-based methods, network traffic features are compared with predefined patterns of attack. Some examples of knowledge-based methodologies include “expert systems, signature analysis, self organizing maps, and state transition analysis” [1]. Heuristics can be used to analyze traffic characteristics and classify them as DDoS or otherwise. An excellent example is that of a DDoS detection system which used a “gossip based communication mechanism” to exchange information about network attacks among independent detection nodes in order to use the aggregate data to identify network attacks [1]. Another model, used temporal-correlation based method to extract features and spatial-correlation for detection to correctly identify DDoS attacks [1].

4 DDoS ATTACK DETECTION MODEL

For this project, we have worked on the design and implementation of an optimal DDoS detection model (based on Soft-Computing and Machine Learning algorithms) by training and implementing several potential models and creating an ensemble model from the best ones. We have also explored the traffic logs dataset to identify patterns via unsupervised means.

4.1 Data Description

The KDD Cup'99 dataset [6] has been used for our data analysis. This dataset has been derived from the 1998 DARPA Intrusion Detection Evaluation Program dataset [8] which was prepared and managed by MIT Lincoln Labs. The data was simulated to evaluate study in intrusion detection. It comprises of a “wide variety of intrusions simulated in a military network environment” [6]. The original data comprised of around five million records. Hence, we use a 10 percent subset of the original train and test datasets for our analysis purposes.

4.2 Data Exploration and Processing

The data exploration and analysis for this project has been implemented using Python on *Jupyter Notebook*. The *Jupyter Notebook* provides us with “an open-source web application that allows us to create and share documents that contain live code, equations, visualizations and narrative text” [5].

For data loading, we use the *Pandas* library in python, which is one of the largest and most flexible data managing libraries and offers a wide variety of options for data handling and manipulation using data frames. After loading the datasets, we explore some of the features of the dataset. From the documentation on the KDD Cup'99 dataset, we know that the data consists of a wide variety of network attacks, but the five main classes of network traffic are as follows: normal (normal network traffic), DoS/DDoS (Denial-of-Service network traffic), R2L (unauthorized access from a remote machine traffic), U2R (unauthorized access to local superuser privileges traffic) and probing [6]. Also, the test dataset consists of an additional 14 attack types which are not present in the training data. However, these new attack types are also a part of the above five categories and the purpose behind their addition in the dataset was to prove that new variants can also be detected using signatures of the preexisting types of attacks [6].

For plotting and visualization purposes, we use *Matplotlib* and *Seaborn* - two excellent visualization libraries offered by Python. First, we check for nulls in the train and test dataset, but find none. Secondly, we check the three categorical columns in the data, to ensure same levels in both the training and test dataset. We find that the training dataset has an additional level in the *service* column. For simplicity, we remove the categorical columns from our analysis dataset and continue our work on only the numerical columns. We now explore the target label column which specifies the *attack type* or the network traffic class. We map the labels to five core categories discussed previously and compare them for the training and testing set. Figure 5 shows the Attack Type distribution in the training and test datasets

We can observe that DoS attacks form the majority of all the attack types (98.67 percent out of all attacks in training set; 91.78 percent out of all attacks in test set). Hence, we broadly classify the target labels as *normal* and *bad* for intrusion detection. We also include the individual labels for the multi-label classification part.

Post this, we create pair plots for the first few variables in order to view individual distributions as well as correlations. Figure 6 shows the pair plot between the first 15 variables in the training dataset. We observe that the data seems to be skewed, indicating the need for standardizing the features. Also, there do not seem to

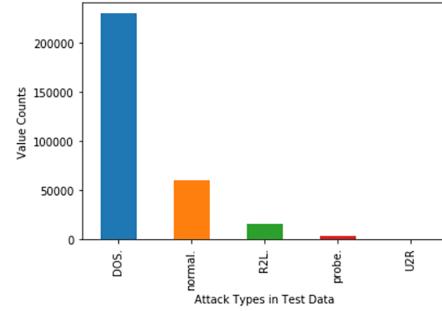
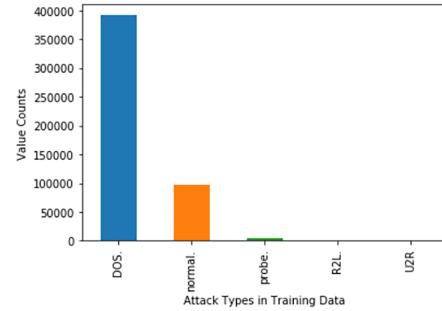


Figure 5: Attack Type Distributions

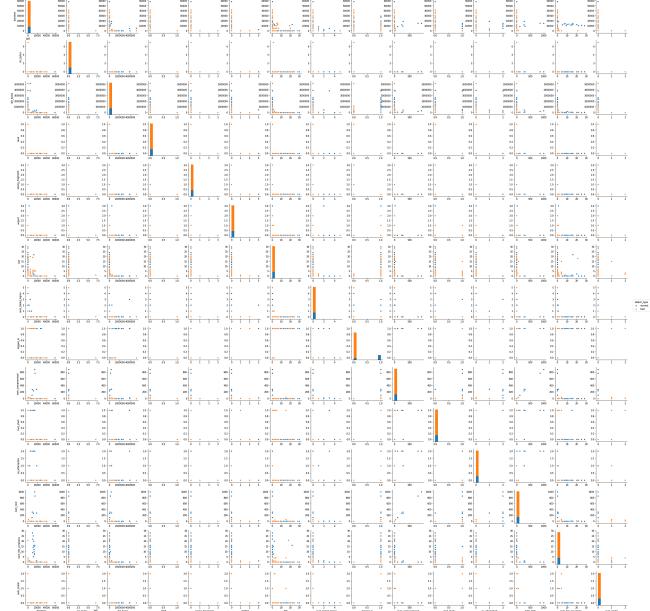


Figure 6: Pair plot for Training Features

be a lot of correlated variables in the dataset.

We proceed with separating the binary variables (mentioned in the documentation) from the continuous variables and scaling the continuous variables using mean normalization in the training dataset. We then apply the same transformations to the test dataset. Post

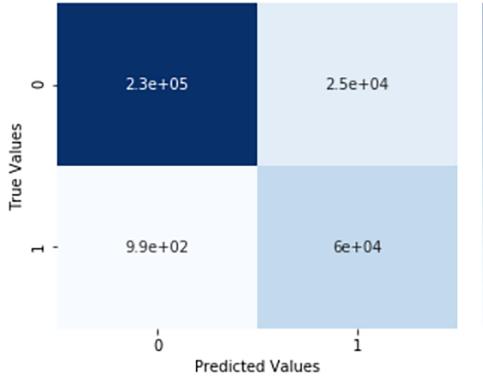


Figure 7: Logistic Regression Confusion Matrix - 2-class classification

this, we consolidate all our features and get the final processed datasets for training and testing.

4.3 Data Analysis

Once we are ready with our final datasets, we design the required detection models by training them on the training data and testing their performance on the test data. For the design of the models, we use the *scikit-learn* or *sklearn* package in python, which contains a plethora of resources for statistical and machine learning methodologies. For most models, we also employ the *n_jobs* parameter present in the models for parallelization purposes [9]. For performance tests, we calculate the accuracy, precision, recall and F1 score for the model (for both 2-label and multi-label classification). The confusion matrix generated in each case displays the classes as follows: 2-class classification (0 - bad, 1 - normal) ; Multi-class classification (0 - Dos/DDoS, 1 - R2L, 2 - U2R, 3 - normal, 4 - probe).

4.3.1 Logistic Regression. Logistic Regression is a machine learning algorithm based on the regression model which is used to fit a model to describe the relationship between a dependent (categorical target) and one or more independent variables. Used mainly for classification purposes, the target variable in a logistic regression model is mainly binary, although the method can be used for multi-class classification too. The basis of logistic regression is a *logistic function* (usually a sigmoid function) which keeps the output values bounded between 0 and 1. This function is fit using a *maximum likelihood* methodology which attempts to estimate the coefficients of the regression equation such that the probability outputs match as closely as possible to the true output values [4].

We train two logistic regression models - one for the 2-class classification and one for the multi-class classification. The model for the 2-class classification is fit as per the default parameters, with the regularization parameter as 0.01 for stronger regularization. For the multi-class classification (since this is not the default type for a logistic regression model), we use a specific solver method known as *Stochastic Average Gradient Descent Solver* [9]. Figure 7 shows the 2-class confusion matrix for logistic regression. Figure 8 shows the multi-class confusion matrix for logistic regression.

The overall accuracy, recall, precision and F1 score for the 2-class

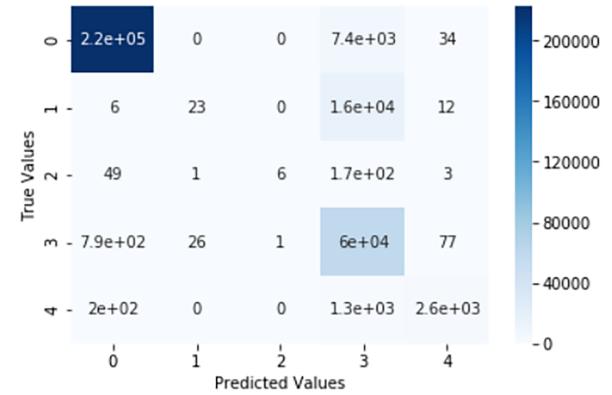


Figure 8: Logistic Regression Confusion Matrix - Multi-class classification

classification are as follows: 91.7, 94.2, 85.0 and 88.3 percent. The same for the multi-class classification are as follows: 91.5, 52.2, 79.4 and 52.3. We can observe that the accuracy of the model seems to be good for the 2-class classification but the recall and F1 scores decrease for the multi-class classification (due to the decrease in recall for the U2R and R2L classes, which have a higher proportion in test as compared to train data).

4.3.2 K-Nearest Neighbors. The K-Nearest Neighbors algorithm selects the k nearest points to the test data point (depending upon a predefined distance metric), present in the training data point, and assign it the class label depending on the majority class label present among the k training data points. Being a non-parametric method, KNN does not assume any initial distribution or form of data [4].

We train two KNN ($k=5$) models - one for the 2-class classification and one for the multi-class classification. For both the classification models, instead of taking the *brute force* or traditional approach, we use an optimized approach known as *Ball Tree Method* [9], which is a tree based method that endeavors to reduce the number of distance computations by encoding the distance information more efficiently. It recursively divides the data according to a hyper-sphere determined by a particular centroid and radius, and reduces the participants for a neighbor search using triangle inequality [9]. This method works better for data in high dimensions (similar to the dataset for our analysis). Also, we take the distance metric as Manhattan Distance instead of the commonly used Euclidean Distance metric, due to better properties of Manhattan distance in higher dimensions.

Figure 9 shows the 2-class confusion matrix for KNN. Figure 10 shows the multi-class confusion matrix for KNN. The overall accuracy, recall, precision and F1 score for the 2-class classification are as follows: 92.35, 94.64, 85.95 and 89.20 percent. The same for the multi-class classification are as follows: 92.08, 55.90, 80.16 and 55.17. We can observe that the accuracy of the model increases as compared to a simple logistic regression model for the 2-class classification. The recall and F1 scores too increase for the multi-class classification case.

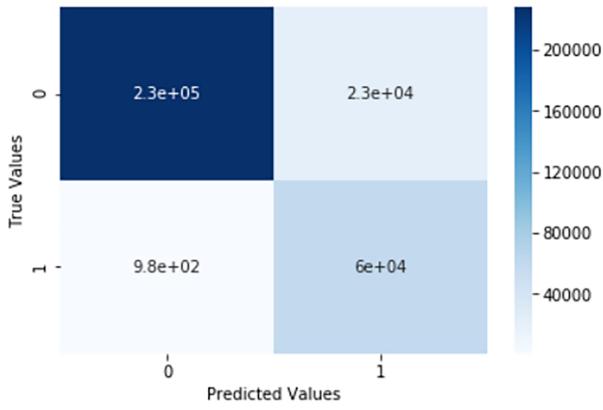


Figure 9: KNN Confusion Matrix - 2-class classification

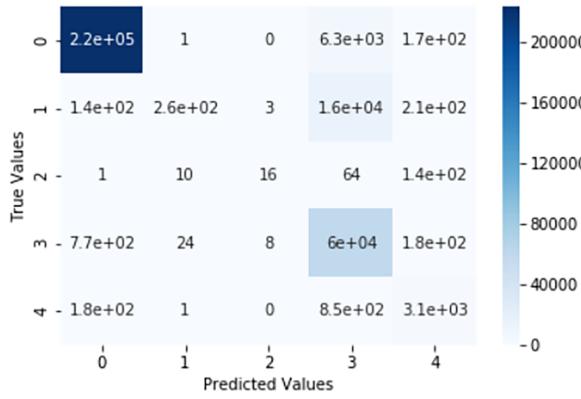


Figure 10: KNN Confusion Matrix - Multi-class classification

4.3.3 Support Vector Machine - Linear. A Support Vector Machine is a model based on the maximal margin classifier i.e. classification based on an optimal separating hyperplane. The support vector machine extends this concept further and to non-linear decision boundaries as well. It uses a function referred to as the *kernel* which acts as quantification of the similarity between observations. Therefore, for non-linear cases a variety of kernels such as radial or polynomial can be employed for classification purposes [4].

We train two linear SVM models - one for the 2-class classification and one for the multi-class classification. We implement this classifier using a *Bagging Classifier* which uses the base SVM classifier on different subsets of data drawn with replacement (also referred to as bootstrapping) and aggregates the results to given the final output [9]. Figure 11 shows the 2-class confusion matrix for linear SVM. Figure 12 shows the multi-class confusion matrix for linear SVM.

The overall accuracy, recall, precision and F1 score for the 2-class classification are as follows: 92.23, 94.55, 85.78 and 89.04 percent. The same for the multi-class classification are as follows: 89.14, 54.91, 83.44 and 55.81. We can observe that the accuracy of the model increases as compared to a simple logistic regression model

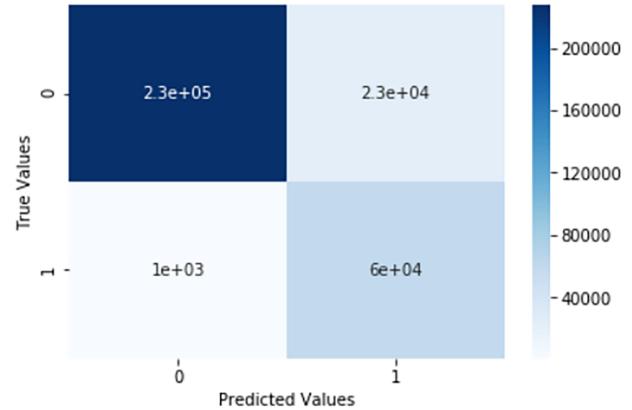


Figure 11: Linear SVM Confusion Matrix - 2-class classification

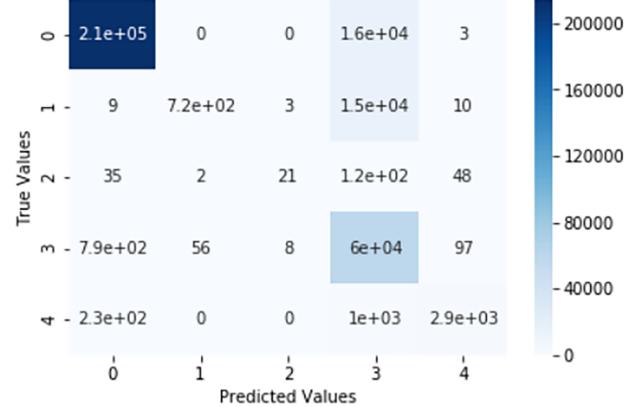


Figure 12: Linear SVM Confusion Matrix - Multi-class classification

but is lower than the KNN model for the 2-class classification. The recall and F1 scores too increase compared to logistic regression but are similar to that of KNN for the multi-class classification case.

4.3.4 Support Vector Machine - Polynomial. Here, we train two SVM models (with polynomial kernels of degree=3) and using a *Bagging Classifier* - one for the 2-class classification and one for the multi-class classification. Figure 13 shows the 2-class confusion matrix for polynomial SVM. Figure 14 shows the multi-class confusion matrix for polynomial SVM.

The overall accuracy, recall, precision and F1 score for the 2-class classification are as follows: 92.28, 94.41, 85.87 and 89.08 percent. The same for the multi-class classification are as follows: 91.95, 56.74, 84.60 and 56.38. We can observe that the accuracy of this model too is lower than the KNN model for the 2-class classification. However, the recall and F1 scores are higher than KNN too (correctly classifies more DoS/DDoS and probe attacks than linear

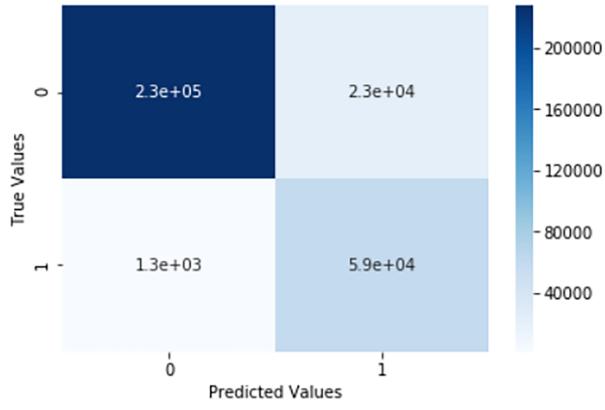


Figure 13: Polynomial SVM Confusion Matrix - 2-class classification

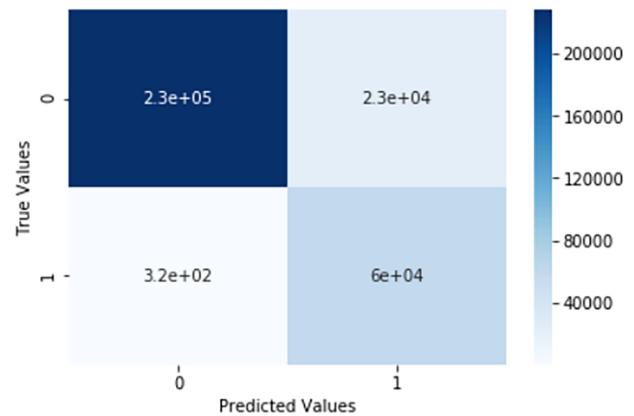


Figure 15: Random Forest Confusion Matrix - 2-class classification

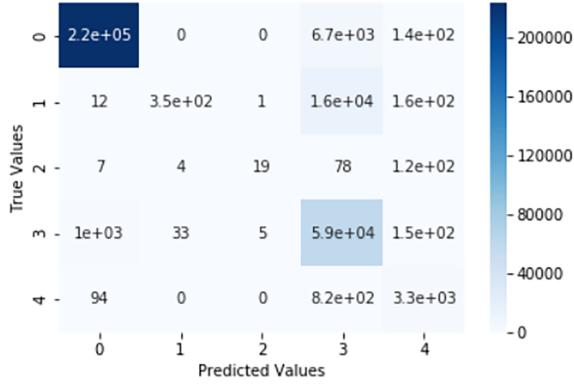


Figure 14: Polynomial SVM Confusion Matrix - Multi-class classification

SVM and more R2L and probe attacks than KNN) for the multi-class classification case. Overall, the performance is similar to KNN.

4.3.5 Random Forest. A random forest model works as an improvement over individual decision trees through building a number of decision trees on bootstrapped samples along with decorrelating the individual trees by choosing only a random subset of predictors out of the total predictors while constructing trees. At each split, a fresh subset of predictors is used which implements the decorrelation of features [4].

We train two random forest models - one for the 2-class classification and one for the multi-class classification. The selection of the subset of features is taken as the default parameter i.e. square root of the total number of features [9]. Figure 15 shows the 2-class confusion matrix for a Random Forest. Figure 16 shows the multi-class confusion matrix for a Random Forest.

The overall accuracy, recall, precision and F1 score for the 2-class classification are as follows: 92.64, 95.22, 86.31, 89.63 percent. The same for the multi-class classification are as follows: 92.44, 55.74, 80.39 and 54.26. We can observe that the accuracy of this model

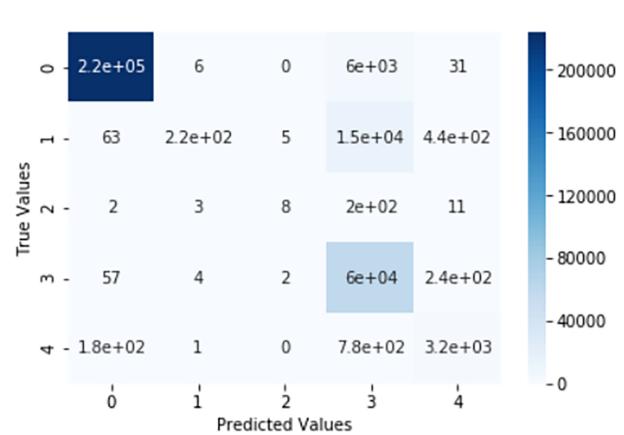


Figure 16: Random Forest Confusion Matrix - Multi-class classification

higher than all the previous models for the 2-class classification. The recall and F1 score for multi-class classification is comparable to the SVM models.

4.3.6 Neural Networks : Multi-Layer Perceptron. Neural Networks are soft-computing techniques that attempt to replicate information processing in biological systems, and thus have excellent learning capabilities. When used for pattern recognition or classification purposes, the most useful Neural Network is that of Multi-Layer Perceptron which basically acts as multiple layers of logistic regression models [2].

We train two MLP models (with a hyperbolic tan activation function as it has better convergence properties than a logistic or sigmoid function) - one for the 2-class classification and one for the multi-class classification. Figure 15 shows the 2-class confusion matrix for a Multi-Layer Perceptron. Figure 18 shows the multi-class confusion matrix for a Multi-Layer Perceptron.

The overall accuracy, recall, precision and F1 score for the 2-class

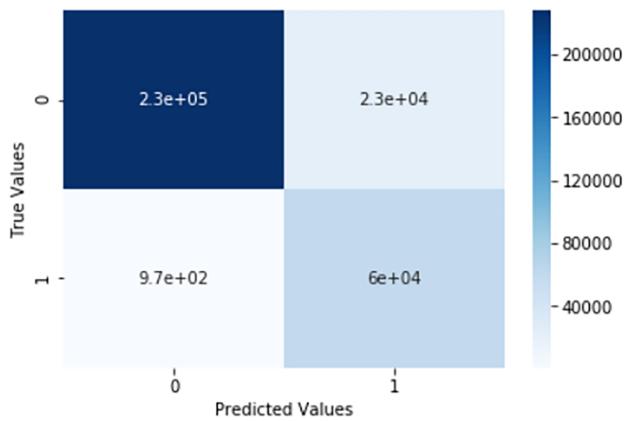


Figure 17: Multi-Layer Perceptron Confusion Matrix - 2-class classification

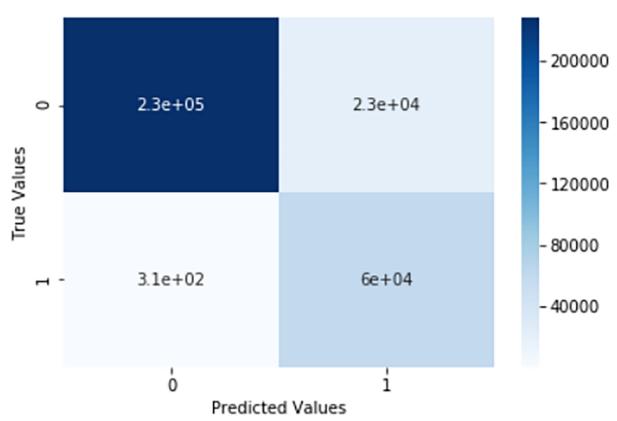


Figure 19: Ensemble Model Confusion Matrix - 2-class classification

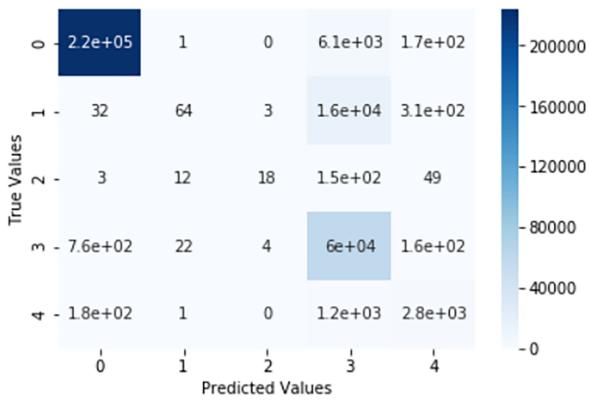


Figure 18: Multi-Layer Perceptron Confusion Matrix - Multi-class classification

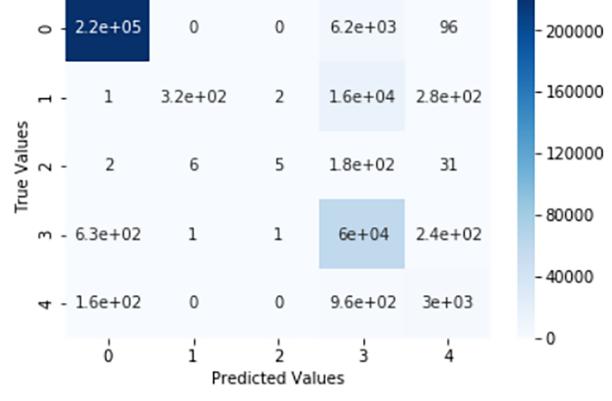


Figure 20: Ensemble Model Confusion Matrix - Multi-class classification

classification are as follows: 92.40, 94.68, 86.02 and 89.27 percent. The same for the multi-class classification are as follows: 91.98, 54.18, 77.53 and 53.90. We can observe that the accuracy of this model is similar to that of a random forest model for the 2-class classification. The recall and F1 score for multi-class classification is comparable to the random forest model.

4.3.7 Ensemble Modeling. Ensemble modeling deals with the combination of two or more machine learning models to generate a model with better accuracy. We have already observed that Random Forests have the highest accuracy for the 2-label classification whereas a polynomial SVM has better recall for the multi-label classification. Therefore, we try to get the best of both worlds by creating an ensemble of two Random Forest (with different rules for selection of the feature subset - square root of features and log of features) and one polynomial SVM model.

We train two ensemble models - one for the 2-class classification and one for the multi-class classification. Figure 19 shows the 2-class confusion matrix for an ensemble model. Figure 20 shows the

multi-class confusion matrix for an ensemble model. The overall accuracy, recall, precision and F1 score for the 2-class classification are as follows: 92.66, 95.25, 86.33 and 89.65 percent. The same for the multi-class classification are as follows: 92.26, 56.85, 84.77 and 55.41. We can observe that the accuracy and F1 score of this model is higher than all individual models for the 2-class classification. The recall and F1 score for multi-class classification is balanced between that of the random forest and the polynomial SVM but is higher than most individual models.

4.3.8 Unsupervised Learning - Clustering. Up till here, we observed and evaluated a variety of supervised learning models. As a result, we came to the conclusion that an ensemble of two good models often results in a better and more balanced result than individual models. In this section, we will examine how exploring the test data by means of a clustering algorithm (with no support from the training data) helps provide a good idea of the patterns within the data. The clustering algorithm we will use for this purpose is K-Means which is used to partition data into a given number of

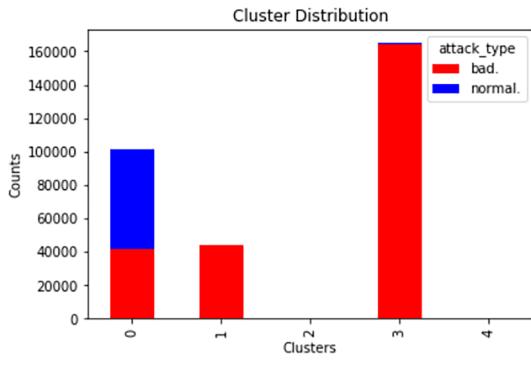


Figure 21: Chart for k-means clustering (clusters=5) - 2-class classification

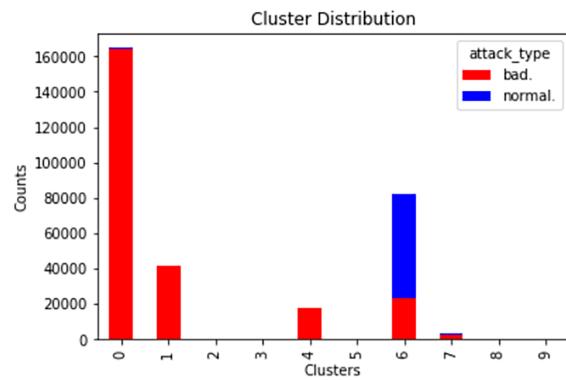


Figure 23: Chart for k-means clustering (clusters=10) - 2-class classification

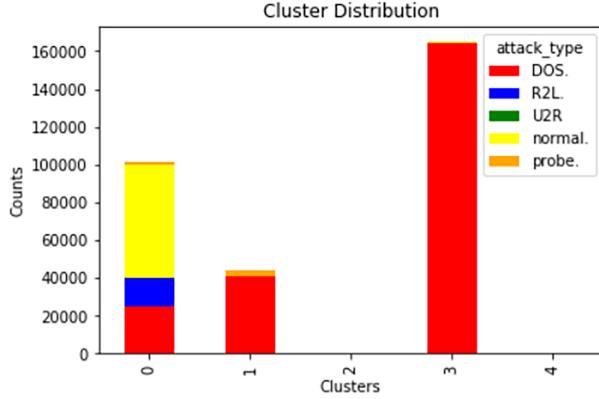


Figure 22: Chart for k-means clustering (clusters=5) - multi-class classification

non-overlapping clusters based on a distance metric [4]. We train two k-means clustering models for both 2-class and multi-class classification - one for clusters=5 and the other for clusters=10 (for greater granularity).

Figure 21 shows the 2-class chart for k-means clustering with clusters=5 (some clusters not visible due to small size). We see that most of the clusters show one of the classes as a dominant proportion of the cluster. We can validate the same by comparing with the multi-class labels as well.

Figure 22 shows the multi-class chart for k-means clustering with clusters=5 (some clusters not visible due to small size).

We also run the analysis for clusters=10, for greater granularity. Figure 23 shows the 2-class chart for k-means clustering with clusters=10 (some clusters not visible due to small size).

Figure 24 shows the multi-class chart for k-means clustering with clusters=10 (some clusters not visible due to small size).

We can observe the same trend here as well.

4.4 Results

Among the supervised models, we observe that on comparison, some models perform better in terms of accuracy whereas some

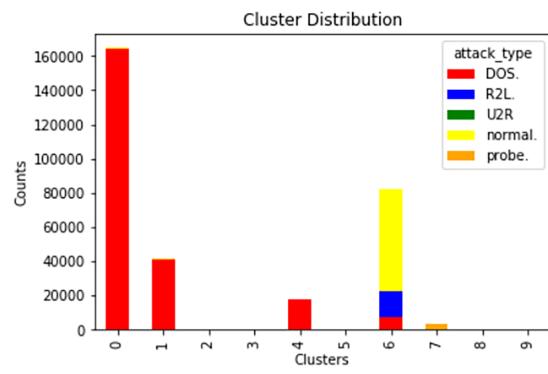


Figure 24: Chart for k-means clustering (clusters=10) - multi-class classification

perform better in terms of recall. We also observe that most models find it easier to perform a 2-class classification (due to the high volume of attack labels in both the datasets as compared to normal labels), but face difficulties in identifying the individual classes (especially R2L and U2R which have a higher proportion in the test data compared to the training data). Overall, for the purpose of Dos/DDoS and intrusion detection, we see that most machine learning models give good results (KNN for example), and an ensemble of a random forest and polynomial SVM model gives the best accuracy among all.

When we venture into unsupervised learning we observe that clustering algorithms too can work well on network traffic data by creating clusters of traffic logs through pattern recognition. Though clustering does not provide us with exact labels, it can be useful in cases where we do not have any training or benchmark data, by giving us a fair idea of the direction in which to proceed.

5 APACHE SPARK - USING PYSPARK

The volume of network traffic data generated is generally quite huge, and thus requires Big Data technologies to deal with it. Our demonstration was for a smaller subset of the actual dataset (which in itself consists of five million records). However, this larger dataset

too consists of logs only for seven weeks of monitoring. We can therefore imagine how voluminous the datasets would begin to get with constant monitoring of systems. In such cases, Big Data cloud technologies can come to the aid of analytics, and help create a sustainable system for such intrusion detection purposes.

Our analysis was carried out using Python on an individual system. But often for larger datasets, we need additional resources. The PySpark API, from Apache Spark (an open-source processing engine), can help us gain “access to the extremely high-performance data processing enabled by Spark’s Scala architecture - without the need to learn any Scala” [3]. The smallest building blocks of Spark are referred to as RDDs (Resilient Distributed Datasets) and these along with Spark’s DataFrame can act as useful alternatives to the *Pandas* data frames, in case of large datasets, where the distributed processing power of Spark can come into play [3].

We can install PySpark on a Windows machine using GOW (incorporates Linux commands in Windows like gzip, curl and tar) and Anaconda (an open-scale distribution containing Jupyter Notebook and other resources for Python). The package can be installed from the Apache Spark website, following which we perform *gzip* and *tar* operations on it. After adding the windows binary for Hadoop and modifying a few environment variables, you can launch Spark locally from Command Prompt. We have not used Spark for our analyses further as Python was able to handle the 10 percent datasets locally. However, PySpark can prove to be a great tool for analyzing data and creating models for larger datasets using a familiar and flexible language like Python. The presence of libraries like *mllib* in PySpark can offer us a wide variety of learning algorithms (similar to the *sklearn* library in Python).

6 CONCLUSION

The detection and prevention of DDoS attacks is a crucial problem for the safety and stability of networks. With the increasing use and dependence on technology and connectivity, this affects a huge cohort of people today. The data generated from day-to-day network traffic is huge and largely unstructured, but it can be captured and modified into an understandable structure, to be analyzed and used to generate efficient solutions. Through our analysis, we affirm the efficiency of machine learning technologies as tools for Big Data analytics and the use of open-source distributed processing systems as supports towards utilization of these tools. We observe that not only do supervised learning methods work well towards this objective, but unsupervised learning techniques such as clustering also provide us with helpful insights on pattern detection in the data. Therefore, Big Data technologies along with intelligent analytic solutions can help create new and improve existing defense systems to ensure security from such malicious attacks and intrusions.

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Predictive Model For English Premier League Games

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ABSTRACT

We discuss a model for predicting the outcome of soccer matches based on the previous matches played by each team. The model we produce is based on a model discussed in a previous paper, which claims to predict match results extremely accurately based on the previous two meetings between the teams and the previous five matches of each of the teams. While the model we based the project on used a genetic tuning algorithm combined with a neural network, this was too complicated for our purposes. Instead, we first attempted to use a multivariate regression model. This model uses matrix algebra to generate coefficients based on the sample data given to it. These coefficients are then what is used to make predictions. The next model was a basic neural network model. This model creates different layers of perceptrons, which can solve more complicated problems than a single perceptron. Both of these models make use of python's sklearn package, and the code for our model is in the project.ipynb file. We evaluate both models and compare the predictive accuracy of each using a number of metrics. Potential uses for this type of model could include setting gambling lines or for the evaluation of the importance of certain games relative to one another. Furthermore, the analysis of the data could be used on any sets of data which are in the dataframe format. The neural network, multivariate regression model, and evaluation code is very flexible and could easily be used for other purposes.

KEYWORDS

HID105, I523, sports, analytics, predictive, neural network

1 INTRODUCTION

Prediction of sporting events is an extremely difficult problem due to the enormous number of factors involved and the unpredictability of those factors. While a lot of data about sports is generated, it is still extremely difficult to create models which account for every factor involved. In the model we attempt to imitate, a match's result is hypothesized to be predictable based on the last five matches each team has played and the last two matches between the teams. The model we imitated created a three layer neural network using these features, and was initiated with weights created by a genetic tuning algorithm. The model we use loads data on the English Premier League, England's highest league and arguably the best league in the world. Using this data, we create features for each match based on the previous games played by those teams. In this way, we attempt to circumvent far more complicated methods of analyzing sports such as per possession models or spatial recognition and player tracking software. Common thought among soccer players indicates that a team's 'form', or how well they have played in their

last five matches, is a significant indicator of how well a team will do in their next match. Similarly, it seems to follow common sense that if team 1 has beaten team 2 the previous two times they have played, that team 1 is likely to beat team 2 again the next time they play.

There are many supporting factors to the assumption that a team that has beaten another repeatedly will do so again. For one, teams in the premier league with more money consistently do significantly better than those with less money. According to Gerhards, "success in national football championships is highly predictable. The market value of a team is by far the most important single predictor". [3] In comparison to variables such as diversity of a team or the amount of turnover in team personnel, market value was far more positively correlated to success. Furthermore, those teams that find success sell more jerseys and are featured on television more, thus generating even more wealth and ensuring that the wealth generated by soccer stays with the wealthier teams. These facts seem to support the statement that plugging the form, or last five results of each team, and the previous results between the two teams, into some model, we could expect to predict with some consistency the results of soccer matches. Market value implies consistent success of some teams over others, which would seem to indicate that the previous two meetings between two teams should consistently correlate to results. Given previous results, some of the unpredictability of sporting events in general is taken away. While random chance should still certainly be accounted for, we expect significant correlation between previous match results and future match results.

Although numerous other statistics are available that describe English Premier League soccer in more detail, we chose not to incorporate any other variables in our models. In general, the models discussed in paper 2 which performed well used fewer variables. The models that used a lot of different kinds of data were less effective. Therefore, the project model used only match results as data. In order to create models for predictive analytics, we used sklearn's python packages. The first is the multivariate linear regression model, which takes any number of variables and weights them according to their correlation to the true results. This model produces a continuous range of predictions. We also created a similar linear regression model using less features. Lastly, we created a neural network using the sklearn neural network package. This package takes an array of inputs, in this case match results, and produces layers of perceptrons, or 'neurons'. By combining multiple 'neurons' making use of stochastic gradient descent, more complicated problems and models can be represented than when using just one. Furthermore, "The use of SGD In the neural network setting is motivated by the high cost of running back propagation over the full training set. SGD can overcome this cost and still lead

to fast convergence.”[8] Although sklearn offers various additional variables for tuning implementations of its neural network package, we chose not to use them in our code. This was due to a lack of experience tuning neural networks.

2 LEARNING MODELS EXAMINED FROM PAPER 2

In order to come up with our model, we examined models in paper 2 in order to develop a strategy to solve the complicated problem of predicting soccer games. We evaluated effectiveness and ease of implementation. Furthermore, we evaluated the different forms of data and models used in order to learn and implement the best parts of each model in our own model. This section is largely excerpts from paper 2.

2.1 Expected Goals Model

Arguably the most common method of predicting the results of soccer games is to create a prediction of the number of goals scored by each team. The result of subtracting these two numbers gives not only a prediction of which team will win, but an inherent level of confidence proportional to the difference of each predicted number of goals [1]. This model creates an “expected goals value” by predicting the number of shots and assigning each of these shots a value. These values are based on attributes such as angle from the goal, distance to the goal, body part used to take the shot, what type of approach was used to obtain the shot (dribble, short pass, long pass, etc.), and even the relevant FIFA video game ratings of the player taking the shot. Each value represents the predicted likelihood of scoring, with 0 being an impossible shot and 1 being a sure goal. By summing these values and incorporating the FIFA rating of the opposing goalkeeper, an expected goals value for a team is obtained. This model is able to predict the number of goals scored by each team about 20% of the time. The correct result of the match was found about 56% of the time [1]. While the data was extremely specific, the general assumption that a team’s goals in a given match correlate to the quality of the shots the team gets plus the quality of the striker was extremely ineffective. [5]

2.2 Bivariate Expected Goals Model

We drew some inspiration from this model discussed in paper 2: A flaw with the previous example of an expected goals model is that it accounted only for the attack team’s ability in its goal predictions. Apart from the ability of the goalkeeper, there is no accounting for the defensive ability of an opponent in prediction of expected goals. In a different model, defensive ability and attacking ability are both incorporated. The authors of this method created their model based on the idea that the goals scored two competing soccer teams are negatively correlated with one another. By using a bivariate Poisson model for soccer data, the authors created predictions for the number of goals scored by each team in a given match, and therefore the results of each game[4]. The covariates used in the bivariate Poisson regression model include: GDP per capita, population, home advantage, bookmaker’s odds, market value, number of Champion’s League players, number of club teammates, and the age of the coach. By running 1,000,000 simulations on the European Championships in 2016, predictions for each match were created,

along with odds for each team to reach each round of the tournament. The odds of the model outperformed bookmakers’ odds 42.22% to 39.23% in predictive accuracy[4]. The authors used their model in placing equal bets on every bet in the tournament with the service that provided the most favorable odds to the outcome predicted by their model. In doing so, they obtained a return of 30.28% after the tournament. The authors concluded that the scores of two soccer teams are indeed negatively correlated and that this is a sound notion to base a predictive model on [4]. [5]

From that model, we gained insights into how to make our model. First of all, the authors of that model gave an example that used a relatively simple to implement bivariate poisson model. Secondly, the authors of the model concluded that two team’s goals were strongly negatively correlated. It is therefore important to take both teams into equal consideration. Finally, the authors of this model classified their results into simply home team win, home team loss, or draw, which provided an easy and effective way to evaluate the model. Our model is similarly able to predict a home win, home loss, or home tie, and the results are evaluated in this way as well.

2.3 NCAA Analysis

In college basketball, the committee that decides who gets into the NCAA tournament makes use of a ranking system called Ratings Percentage Index, or RPI. RPI weights .25 of a team’s ranking on their win percentage, .5 on their opponents’ win percentage, and .25 on their opponents’ opponents’ win percentage. [9] This system is designed to encourage teams to schedule difficult opponents, as a large portion of the rankings is based on strength of schedule. This formula has significant influence on where teams are ranked. Unfortunately, “the RPI lacks theoretical justification from a statistical standpoint.” [9] In general, it is believed that the model places too much emphasis on strength of schedule and not enough on performance. Attempts to utilize an improved version of this model have made an impact on seeding in college soccer and baseball as well. In these sports, wins are weighted to give more ranking points to an away win than a home win.[9] These types of alterations, however, do not address the fact that 75% of this ranking comes from a team’s strength of schedule. This type of bias favors teams that are in strong conferences, even if they have poor records in their conference. [5]

2.4 Per Possession Analysis

A proposed alternative to RPI is to use a “per possession model,” or a model that predicts outcomes using statistics that are used in the context of efficiency with possessions. For example, offensive efficiency is found by dividing points scored by possessions and defensive efficiency is found by dividing points allowed by possessions [10]. These statistics are then used to calculate an offensive efficiency adjusted by the perceived strength of the opponent. Adjusted offensive efficiency, for example, is calculated by multiplying offensive efficiency by the average national offensive efficiency then dividing this number by the adjusted defensive efficiency of an opponent [10]. By combining these adjusted efficiencies with other factors such as home court advantage, the authors made several models which created an estimation for “win probability,”

which can in turn be used to predict individual match outcomes or create a ranking system. By using win probability, the study we examine created models based on decision trees, rule learners, artificial neural networks, naive Bayes, and ensemble learners. The neural network and naive Bayes models were the most effective models, both predicting outcomes with about 72% accuracy[10]. A surprising observation from the authors is that simpler models tend to work better than more complicated ones. Similarly, attempting to incorporate more features into the models tended to decrease predictive accuracy. The authors believe that there is a "glass ceiling" when it comes to accuracy predicting sporting events of around 74% [10]. Each of these models is unable to predict any individual season at a rate greater than 74%[10]. [5]

2.5 Fuzzy Neural Network Model

In a paper 2, we discussed a method of prediction solely uses past results to predict future results. This model was extremely accurate and a under strong consideration for a model to base our project on. This section is an excerpt from [5]: In this method, a predictive model is based on the intuitive proposition that if team 1 has won their previous few games, team 2 has lost their previous few games, and team 1 has beaten team 2 the last two times they have played, team 1 will beat team 2 [6]. The model proposed in this article assigns a value in the range [-5, 5] to the last five games played by each team as well as the last two games played between the two teams. The higher the number, the bigger the win. The lower the number, the bigger the loss. The predicted result of a game is a function of these numbers. Through a combination of a fuzzy logic table and a neural network algorithm, a result is predicted. First, the authors created a table with every possible value of $x_1 \times 12$. Each of these combinations was then associated with a predicted result and a weight in the interval [0, 1] that indicated the confidence in the predicted result. These initial confidence intervals were then tuned. The predicted result is drawn from the range [Big loss (BL), Small loss (SL), Draw (D), Small win (SW), Big win (BW)] [6]. Using a sample size of 1056 matches, the network assigned weights to the nodes in the neural network. The trained model was applied to 350 results from other seasons and was correct when predicting a big loss 91.4 percent of the time, a small loss 83.3 percent of the time, a draw 87 percent of the time, a small win 84 percent of the time, and a big win 94.6 percent of the time [6]. The authors do cite flaws that come from not considering factors such as injured or suspended players, refereeing, or weather conditions [6]. [5]

Furthermore, this method's already impressive predictive accuracy could also be improved by taking into account strength of schedule, as a team that has narrowly won its last five games against very weak opponents would be favored against a team that has narrowly lost against very strong opponents. The machine learning techniques implemented in this study could have been improved by incorporating opponents' results into the model, giving more weight to wins against good teams. [5] It would also be interesting to see whether using a continuous model would decrease the accuracy of predictions or give similar accuracy with more specificity than the fuzzy logic model. It seems possible that using the fuzzy logic model provides a neural network with more occurrences of samples that are similar to each other due to grouping results

together, thereby providing a better prediction. In a continuous model, the features may be too varied for a neural network to pick up on without a greatly increased sample size.

After examining these models, we chose to create a multivariate linear regression model and a neural network. These models would use match results. The predictions would be continuously distributed, and would indicate the degree to which the home team would be expected to win, lose, or draw by. Python was chosen to implement these solutions due to the ease of use in machine learning and data analytics applications, as well as being the default language for this course. The Sklearn package was chosen due to the ease of implementation. Instead of having to construct a neural network or linear regression model from scratch, the implementation was straightforward and contained many ways to customize the models they provided. Our predictions will be evaluated based on percent of correct match results predicted, matches correctly predicted within 1 goal, matches correctly predicted to within half a goal, and mean squared error.

3 PROJECT MODEL

In order to select the parameters for our model, we examined several models in paper 2. The most common type of predictive model for other sports was a per possession model. This model attempts to gauge the number of possessions each team will get, then gauge how efficient each team will be with their possessions. By multiplying the number of predicted possessions by the projected efficiency of the team, a prediction for the number of points scored by that team occurs. This means that a match prediction would be the difference of the predicted goals for each team. In soccer, this could be done with time of possession, a commonly tracked statistic. A model could for example predict that for each minute a team is expected to possess the ball, they are expected to score a certain number of goals. By incorporating the opposing team's predicted minutes of possession and predicted goals conceded, a prediction of goals scored and conceded could be obtained. However, after considering this type of model, we decided it had too many flaws to be implemented. Firstly, the model would not use a simple, readily available set of data. Secondly, the model would have to incorporate a greatly varying set of data. In paper 2, we concluded that "simple inputs, especially those involving neural networks, provide the greatest accuracy in predicting the outcome of sporting events." [5] Therefore, we decided to reject models that had several forms of data and stick to only match data. It was also important to figure out what kind of data to use. In paper 2, models used features such as FIFA ratings, possession statistics, match results, and expected goals. We decided to move forward using match results due to the simplicity of that variable, as well as the abundance and ease of access for that data in a number of leagues. Ultimately, we chose to focus on just one league in order to attempt to keep the data consistent and to try to make predictions based on the highest level soccer possible. It could be an interesting topic to compare models' effectiveness in evaluating other leagues, but we chose to use match data from just the English Premier League.

In general, we attempted to imitate the model discussed in the section 'Fuzzy Neural Network Model'. We used match data from <http://www.football-data.co.uk> [2]. The data includes numerous

statistics about English Premier League soccer matches dating back to 1993, including the team names and goals scored by each team, which were the data we were interested in. In order to load the data from the .csv files included in the website into a usable format, we used panda's read csv function. Three years of the data was in an unreadable format for the csv loader and was skipped in the analysis, which included data from 2001-2003. We then narrowed the data down to the names of each team involved in each match and the number of goals scored by each team. We then created a function last5 to determine the last five matches the last team played, which returned the number of goals scored by the team minus the number of goals that had been scored on them over the course of those five games. This function partitioned off the dataframe with all results to include just the results which had occurred before the match in question. Next, we used a boolean indexer in the dataframe to determine which rows contained the team name in either the home team or away team column. Each entry was added to a different list. That list was then negatively indexed to find the last five entries in the list, and each item was summed. This sum was what the function returned. We also created a function prevMeetings to determine the results of the last two times the teams played. This function took the data and the index of the match to be observed. Next, the names of the teams involved were found. Next, the data was slimmed to only include match results from the past. Next, we used a boolean indexer in the dataframe of past matches to determine which rows contained the home team name in either the home team column or the away team column, and the away team name in either the home team column or the away team column. We negatively indexed the dataframe produced to include only the last two results. Each of these results was summed. In each of these functions, we used goal difference to represent each result. Goal difference was found by subtracting the number of goals allowed in a match by the home team from the number of goals scored in a match by the home team. We kept individual match results within the range [-4, 4] in order to prevent very large wins or losses from having too much influence on the statistics. A 7-0 win, therefore, counted the same as a 4-0 win, and a 7-0 win followed by five losses couldn't result in a positive goal difference for the team. Next, we created a function sampler, which used prevMeetings and last5 to turn each row in the data into an array of the features about each match that we wanted. We referred to the last5 of the home team as 'z1', the last5 of the away team as 'z2', and the previous two meetings of the teams as 'z3' and 'z4' respectively in order to more consistently imitate the model discussed in the Fuzzy Neural Network Model. Finally, we created a function that found the true results of each match by iterating through every match result and subtracting the away team's goals scored from the home team's goals scored, thus representing the "true" prediction. This model has the benefit of inherently giving value to the home team due to z1 always being the home team and z2 always being the away team. When two teams did not have previous results, z3 and z4 were entered as 0 and 0 so as not to affect the prediction either way. Because of this, we trimmed the first 250 results out of the data so as not to have too many z3 and z4 data points equal to 0. When a team did not have five previous matches in the data, last5 returned a -5, as this typically indicates a team recently promoted to the league and therefore the team would not

be expected to find much success. These functions slightly differed from the more complicated model we were imitating, as this used the last five results from each team as individual features in the first input layer of a neural network and the previous two meetings as input nodes in the second layer of a neural network. Furthermore, the model we were imitating used fuzzy logic to model the problem as a classification problem, using big loss, small loss, draw, big win, and small win as the classifications. Our model, however, attempts to create a continuous solution. In order to do so, we take the results of sampler as our sample data used for prediction and the output of another function, results, as our true data. Sklearn's multivariate linear regression model uses matrix algebra in order to create coefficients for each variable in the sample X. Each coefficient indicates the strength of the correlation between the variable in X and the actual result. Therefore, the coefficient is the weight which the variable is multiplied by when using the model to predict. Using sklearn's model, we fitted the sample data to the results and created an array of predictions, which we then compared to the true results. We also used sklearn's neuralnetwork package to create a MLP Regressor neural network with the hidden layer sizes attribute set to 50, which we found to produce the smallest mean squared error. In order to reduce the bias towards z1 and z2, which are typically bigger in absolute value than z3 and z4, the data was scaled during preprocessing for this model. Next, the neural network fit the scaled data to the true results. Finally, evaluation of the model was done based on mean squared error between predictions and true results and percentages of correct predictions or predictions that were within a certain range of the true result. In our model, a correct prediction was classified as simply predicting within the same category as the result, with the categories being less than -.5, greater than .5, or in between .5 and -.5 goal difference, each representing a draw, home win, or home loss respectively. We also tested whether each prediction was within .5 or 1 of the true result. These predictions represent the expected goal difference of the home team, meaning the predicted value of the home team's goals scored minus the away team's goals scored. After the prediction sets for each model were created, we changed the mean of the data to fit the mean goal difference of the results, which was just over 0.4. We also changed the standard deviation to match the standard deviation of the results.

4 EVALUATION

4.1 Efficiency

Extraction of the data was relatively fast. The retrieveEPL function extracts 7832 rows of a dataframe relatively quickly. The last5 function is slow due to running 7832 times and checking a large portion of the dataframe for previous results each time. The sampler function is by far the slowest to run due to the large number of comparisons and indexes it has to do. Running last5 and prevMeetings on each row of the dataframe is less than quadratic time, but still ends up being extremely costly computationally. The results function runs in linear time, which is optimal. Finally, the models are fitted to the data extremely quickly as well.

4.2 Prediction Performance

The performance of the predictions was far less effective than the fuzzy neural network model we attempted to replicate. This was to be expected, however, as our model was simply a more basic version of the other model. In order to evaluate our model, we measure the mean squared error between the actual results and the predicted results of both the multivariate linear regression model and the neural network. Each had an almost identical mean squared error, with the neural network scoring 2.851 and the linear regression model scoring 2.868. Each model also had nearly identical proportions of games predicted within .5 of the correct result (.264 for the neural network and .263 for the multivariate linear regression model), games predicted within 1 of the correct result (.49 for both models), draws correctly predicted (.147 for the neural network and .144 for the multivariate linear regression model), home wins correctly predicted (.249 for the neural network and .255 for the multivariate linear regression model), home losses correctly predicted (.020 for the neural network and .019 for the multivariate linear regression model), and percent total correct predictions (.417 for the neural network and .419 for the multivariate linear regression model). The effect of z1 and z2 was as would be expected: z1 was a positive coefficient for the regressino model and z2 was negative. This indicates that the home team was favored, which was reflected in the mean value in both the prediction and true results sets being about 0.4. It was interesting to note, however, that the z3 and z4 features had almost no effect on the accuracy of the predictions. The linear regression model's coefficient for these two features was almost 0. This is extremely counter intuitive and could be a result of inserting 0 for z3 and z4 at times where no previous results could be found, although it seems that these should still be significant features for prediction. Both models' prediction sets' standard deviation was far lower than the actual results, which could be a significant factor in the mean squared error. After hypothesizing that this may have increased the number of home losses predicted correctly, we tried increasing the standard deviation. After subtracting the mean of each array from each element in the array, then multiplying each value by 1.76, the standard deviation of the true results, and adding the mean back to each element, the percent of correct results predicted increased to 45.00 and 45.50 percent for the multivariate linear regression model and neural network model respectively. Doing this, however, decreased the number of results predicted within .5 goals and 1 goal by about 7 percent for the multivariate linear regression model and by about 8 percent for the neural network model. This is most likely due to the fact that a large portion of soccer games end with a goal difference within 1 and -1, so pushing predictions farther from the mean reduces the number of predictions close to this range. The highest final predictive accuracy obtained by any of the models, therefore, was 45.5 percent. This compares favorably to the bivariate poisson distribution model discussed earlier in the paper, which claims "The odds of the model outperformedbookmakersfi odds 42.22 percent to 39.23 percent in predictive accuracy" [4]. Therefore, it appears our model has predictive accuracy significantly greater than some odds or models.

4.3 Limitations

In retrospect, it seems that the models' biggest flaws are both their lack of ability to incorporate the z3 and z4 features into their prediction. Going into the project, I had hypothesized that this should be the biggest indicator of which team would win, regardless of their play during their last five matches. This hypothesis was supported by the fuzzy neural network model we attempted to imitate as well. Furthermore, the repeated success of a handful of teams over the rest of the league would seem to indicate that a team that beats another team multiple times would continue to do so. This is due in large part to the fact that certain teams have far more money than others to spend on players, facilities, etc., and this does not typically change from year to year. Neither model in this project seemed to indicate that previous matches between teams had a significant affect on the match prediction. Common sense would therefore seem to indicate significant issues with the implementation of the model in our project. In future implementations, we could try a different way to handle cases where there are not two previous meetings between the teams. We could, for example, give the benefit of the doubt to the team that has been in the league the longest, as we did with the last5 function. It may also be that the hole in our data in the early two thousands could be significantly affecting that feature. The csv files for those years were significantly different and could not be processed with the same function used to load the data from the other years. This is another problem with our model, as it is based on data that is incomplete and skips three years. The model we attempted to imitate had a much smaller sample size (about 1000 compared to about 8000 for ours), but presumably had accurate data points for each sample. Finally, more work with tuning neural networks would be extremely helpful, as this is a first attempt at any sort of data analysis to this degree. More experience with setting up models and more knowledge of advanced statistics would presumably greatly strengthen a model such as this. It may also be helpful to take each season independently, as teams undergo significant change over the course of the offseason. In the model in this project, a team's first game of the season is predicted using the last five games from last season, which could have been a very different set of players. In the future, it could be useful to run comparisons between our project model and a model that ignored the first five games of the season for each team so as to "get a feel" for the way a team starts out the year instead of assuming they will pick up right where they left off from the season before. Further improvements could take into account other factors such as injuries, suspensions, refereeing or weather. Clearly, we were unable to replicate all facets of the other model. The genetic tuning was extremely complicated and tough to figure out, and the neural network had more sophisticated layers and tuning. Our sample size was greater, but the data was arguably less precise due to not having previous results for every game. Furthermore, breaking results down into categories using fuzzy logic could potentially enable the model to make more accurate predictions. The fuzzy logic is less specific than a prediction across a continuous range, but this could be a good thing when tuning or fitting a model because each permutation of potential inputs would be more likely to have been seen before a prediction is made. Another potential improvement could be to simply include more features. As indicated in the

introduction, the financial value of a team is a significant indicator of a team's success, particularly in the premier league. According to [7], Chelsea is worth 631 million Euros, while Huddersfield Town is worth just 58 million. This great divide in value is seen consistently across top European leagues and could be a significant indicator of the results of matches due to the importance of being able to buy the best players. While this statistic could be partially accounted for in the previous two meetings between teams, it could be valuable to include it as its own feature in the predictive model. A potential problem would be the skyrocketing value of clubs over the last twenty years, as it would be difficult to scale the data appropriately before fitting the model. Another feature to consider would be to augment the last five played and previous two meetings features in this model by taking into account the strength of schedule. For example, beating a team that was on a win streak would be more valuable than beating a team that had lost its last five games. This could be incorporated as a multiplier in the last5 and prevMeetings functions. In this way, more information could be included in the predictive model.

5 CONCLUSION

In the future it would be interesting to compare an improved model to gambling lines to see how different the results are and whether there were any patterns to predicted results differing from betting lines and actual results. It could be possible, for example, that if there is a big enough discrepancy between a model's predictions and a gambling line that it would actually be worth betting. As it is, the model is not nearly accurate enough to be used to reliably predict results of sporting events, as it only out predicts random chance by twelve percent. An improved model could potentially be used to set betting lines or to inform how to beat betting lines. As this was a first attempt at this sort of data analysis and the problem is quite complicated, this was a reasonable result. However, this is again not a model to be used for practical applications. It would be interesting to see how much more of the model in the example from paper 2 could be recreated. If a more accurate predictive model like this was created, it could potentially be used by soccer teams in order to predict which matches are more likely to be won or lost so as to determine which matches would be best to rest key players. A match that is predicted to be a three goal win for your team, for example, would be a much better game to rest a key player than a game predicted to be a draw. The tactics of a team could change based on the prediction, such as a coach playing more defensively in a game their team was predicted to lose, and instead bank on tying in order to get some sort of positive result out of it. Furthermore, the model could be applied to other sports quite easily. By properly scaling data, data from sports such as football and basketball could put into the model and used in the same way. If the range for the goal difference of each game was changed, the theory behind the model could be tested for other sports as well. A future project could be to examine the difference in the correlation of past results in basketball or football versus soccer. Another potential change to this model would be to predict the number of goals each team will score instead of only predicting the goal difference. The model could be quite similar. Instead of the last5 function returning only the goal difference, it could return a list of lists, each

of which stores the number of goals scored and the number of goals conceded for each of the last five matches. Next, the prevMeetings function would change to the same format. The sampler function could return a prediction for the number of goals scored and the number of goals conceded by each team using a regression model or neural network. Next, these predictions would be fed into another regression model or neural network that predicted the number of goals scored or conceded by either team. These second layer models would combine a team's goals scored prediction and the opposing team's goals conceded prediction in order to predict the number of goals scored. Similarly, they would combine a team's goals conceded prediction and the opposing team's goals scored prediction in order to predict the number of goals scored. Both a multivariate linear regression model and a neural network could be used for this format. These predictions could give a more accurate representation of a game and incorporate some of the variables that a "per possession" model would use, while still using the same data as before, albeit in a slightly different way. By diversifying what the model is able to incorporate but still using simple and accurate data, the new model could obtain the best qualities of the previous models described without adding significant computational time. Each function might be expected to take longer, but these changes would not alter the big-O worst case time complexity of the model in general. The advantages of this sort of model's prediction is that it could be used to make more specific types of gambling lines, such as over/unders. Furthermore, it could better inform a coach on tactical decisions about how aggressive or defensive to align his team. The models described in this paper could make a great starting point for predictive modeling of any kind, as the models included are extremely flexible. Although the majority of the work ended up being actually finding, parsing, and formatting the data correctly, the methods used to analyze the data would work with any big sets of data in a dataframe format.

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Big Data Analytics in Indian Premier League

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ABSTRACT

Cricket is one of the most admired sports across the globe. Indian Premier League is one of the professional cricket leagues conducted by Board of Cricket Control India in the months of April and May. This league is famous for its diversity of players and breath-taking cricket match endings. The factors of winning change for each moment as the game progresses. As there are many players and franchises involved in the game, these factors for winning changes for each team. Data related to each player is required to analyse his performance and predict his future scope in team. Data related to factors of winning is crucial and can be analysed for predicting the results of the game. This analysis would help the team management, league administration to wisely chose the players and modify rules according to the impact of each decision. Data related some of the important factors which plays major role in deciding the match winner are analysed. Their impact is predicted and compared with the actual results. Impact of these factors are studied for each individual team and individual season of this cricket tournament. Impact of each factor is plotted and its impact in next season is predicted.

KEYWORDS

Big Data, Cricket, Indian Premier League, i523

1 INTRODUCTION

Fast paced games are gaining more importance in near future. This because there are many factors which contribute to the result of the game. These factors are minor but could change the results of the game dramatically. Indian Premier League is one such type of cricket league where there are a lot factors which have their influence on the results of the game. These factors are though minor or major, will have bigger part in deciding the results of the game. These factors from the previous games can be utilised wisely to predict their influence in the upcoming matches. These factors can be quantitatively represented in the form numbers, graphs or Booleans. This quantitative representation of data related the factors can be analysed using various analytic techniques to predict their impact on the game.

However, Analytics is a good way to go about this prediction, but there are several problems which should be addressed. Considering the role of batsman, it will be having parameters like balls faced, dot balls, number of boundaries, strike rate etc. Considering the role of bowler, there are various parameters like matches played, overs bowled, economy rate. There are many similar kinds of roles in the game and above-mentioned parameters are specific to one player playing only one role in the team. According to, around 500 players play for each season of cricket. These 500 players will be

filtered on various factor from the pool of nearly 5,31,253 cricket players across the globe. These players can play any of the role or play multiple to roles to contribute to the result of the match. These players and cricket matches produces large amount of data which when analysed to produce structured data and analytics. Hence, there is good scope of analytics ad big data in this sport.

The data produced by the matches happening in Indian Premier League can be used to fit in mathematical models. These mathematical models are then used to study the nature and trends of the factors which influence the results of the game. Extending this model to the known values of the input factors can produce the predicted values of the impacts of these factors. Models like Linear regression, polynomial regression, radial-basis approach can be applied to do these kinds of predictive analysis.

2 PROBLEM STATEMENT

There are various factors influencing the results of the game. As part of this analytics, data related to four of the most influencing factors is gathered and modelled for analysis. This data was available in raw formats which requires some amount of modelling for predictive analysis. The modelled data is used for building a mathematical model which would fit closely to the trend of these factors in matches played in all the past seasons. A part of data is assumed to be unknown. This unknown part of data is predicted by using the fitted mathematical models. Results obtained by these predictions are compared with the actual results from the data source. Impact of these factors are calculated to the ratio of one. These data is analysed for each independent team and each independent season.

The report is in regard to the predictive analysis conducted on only five of the most influencing factors in the game. There are other factors in the game which might influence the result of the game. This predictive analysis will only be considered reliable only if the predicted values of the results will have high accuracy with respect to the actual results of the available data. The data is divided into two parts. All the available data is sorted with respect to date. The latest match comes later in the dataset and the earliest first. The first part of data is used to train the mathematical model. The parameters in the later part of the dataset are used to predict the result of the match. These predicted results are then compared with the actual results in the datasets to determine the accuracy of the predictive model which is used to build the analytics. This analysis produce valuable insights on the influence of these factors and the mathematical model.

3 SCOPE

The scope of the analysis is:

1)The analytics uses the data for only five factors. These five factors are namely toss, Batting position, Range of score, portion of runs in boundaries.

2)The data is collected for all the seasons completed for this tournament. However, this data is sorted with respect to date and partitioned into training and testing data sets for calculating the accuracy of the model.

3) The values of these factors are represented in usable data formats like range, Boolean, integers for analysis.

4 FACTORS IN CONSIDERATION

4.1 Batting Sequence

Order of batting is considered as one of the factors in consideration. Batting order is one crucial parameter which depends on various other factors of the game. Some of these parameters are the status of the pitch for the game, climate conditions of the game, previous statistics of the game and the history of the team in similar situations. The toss winner will have the privilege to decide the order of the batting. As this factor is conglomeration of various other factors stated above, batting order is considered for the analytics. This data can be represented in the form of Boolean. Where true Boolean indicates that the team referring to the statistics have batted first in the game. False indicates that the team referring to the statistics have batted second in the game. This Boolean value depends on the values in for toss winner and toss decision.

4.2 Total Score

Score indicates the total number of runs scored by the team in any match. Score of the team depends on various other parameters of the game like team statistics and composition, impact of the opponents, and situation of the match. This parameter can be calculated from other values of extra runs, scored runs. This categorized into four categories. This first category of the innings scored not more than 100 runs. The second category of the innings scored more than 100 and less than 150 runs. The third category of the innings scored more than 150 and less than 200 hundred runs. All the other innings which scored more than 200 are categorised into fourth category. This categorization is done in accordance to the range of scores. The least scored innings were given least category value. The highest scored innings were given highest category value.

4.3 Score Composition

Composition of scored runs. The runs are majorly scored in the form of boundaries, players individual running, and the extra runs given by then bowling team. As IPL is a T20 game which is played for short duration of time, scoring runs quickly at right time is crucial factor. Boundaries contribute to runs scored in the form of fours and sixes in the game. This is the easiest way to quickly score the runs. Team scoring high majority of runs in the form of boundaries have higher chance of imposing a higher target to the opponents or chasing down the target imposed by the opponents. Hence, this parameter is considered for analysis. This value for this parameter is a Boolean. This value is set to true, if most of the runs scored by any team in any innings are from boundaries and vice versa.

4.4 Toss

The batting sequence is decided by the winner of the toss. Winner of the toss will have the initial upper hand in the game to decide the sequence of the game. The winner's decision will vary on various other factors of the game like, duration of the match, pitch behaviour throughout the game, statistics of the game. These various factors play an important role in deciding the toss winner's decision. The value for this parameter is Boolean. The true value of the parameter indicates the team has won the toss and the false value indicates the team has not won the toss.

5 DATA MANIPULATION

5.1 Team data

There are thirteen teams participated in IPL which was held for nine seasons. Each team was having its team name and teamId. These details are taken from the data source team.csv. Python's csv module is used to read the data from this csv file. As this data represents a key value pair, csv module's dictreader method is used to read the row in these files. Using this method, a dictionary was created which consisted of the teamId as keys and team name as value objects.

5.2 Match data

Details pertaining to a specific match are published to the Match.csv file. These details include host team name, guest team name, toss winner id, match winner id, decision of the toss, win type. This data was used and modified for calculating the impact of each factors stated in the factors description. Python's pandas dataframes were used to read the data from these csv files. All the missing values in the dataframes are replaced with 0 to ease the complexities that arise with null values. For each value in the team dictionary, the teamId is matched with the opponent team id column and team name id column in the match.csv. Python's operator module is used to obtain the or condition between these values. Dataframe is modified with the given conditions. This dataframe is converted to list. This way, list of matches played by a team is defined and stored into a list.

From the dataframe which contains the list of matches played by the team, column matchwinnerid is used to define if the match winner. A new dataframe is created with a condition if the matchwinnerid's value in the column is equals to the id of the current team. If the above-mentioned condition is true, then this value is added to the dataframe, else the value is removed from the dataframe. This way, list of matches won by a team is determined.

A new dataframe is created to store the Booleans of the toss decision. From the teamdata dataframe, the column toss winner id is used to determine the toss winner for each match. If the id value in this column is same as the team id of the current team, Boolean true is appended to the toss list. Else, Boolean false is appended to the toss list. This list contains only Booleans.

5.3 Ball-by-ball data

Ball by ball analyses will be required to calculate the scores for each ball. These details will include the number of runs scored in the ball, extra runs scored, bowler details, batsman details, over details. This

data is extracted from the ballbyball.csv file. This file contains ball by ball analysis of all the matches. This data is sorted according to the match id and is extracted for further analysis. Pandas readcsv method is used to read the csv file. A new data dataframe called balldata is created.

Balldata csv is used to for calculating the runs scored by a team in a specific match. The balldata dataframe is filtered for useless columns and null values. All the null values are replaced with 0 to ease the complexities which comes with usage of null values. Balldatadfis team batting id and match id are used to calculate the runs scored by a team in a specific match. This data frame is modified such that, the values in the match id column is equal to the current match id and the values in the team batting id is equal to the current team id. Python operator module is used to achieve the and condition in the above case. The modified ball data data frame is used to calculate the score. The sum method on the dataframe is used from the pandas library. This score is categorised into four categories. The first category included the score which are less than hundred. The second category included the scores which are between hundred and one hundred fifty. The third category included the scores which are between one hundred fifty and two hundred. The fourth category of scores contain scores which are above two hundred.

A new list is created which stored the category of the scores. If the score falls in first category, then an integer 1 is appended to the list. If the score falls in the second category, integer 2 is appended to the list. If the score falls in the category falls in the third category, an integer 3 is appended. If the score falls in the category four, an integer 4 is appended to the list. The other factor which was stated in the factors in consideration teamfis score composition. It is highly probable that a team scores a high total or chase down the target imposed by the opposition team quickly is the majority of runs are scored in the form of boundaries. The ball data dataframe which is created in the previous case is utilised with other conditions to calculate the contribution of boundaries to the total score. This dataframe is filtered with the match id and team id condition to obtain the current match and current batting team. This is again filtered for all the scores that are having values either four or six. The minified frame is filtered for all values of four and summed. The same is repeated with the sum of six values. Adding together these two sums will give the total amount of runs scored in form of boundaries.

A new list is created for storing the Booleans related to the contribution of boundaries to the score. This list is appended with value true, if the contribution of boundaries is more than other forms of runs, false if, the contribution of boundaries is less than the contribution of other forms of runs.

The lists which are created for each factor are used to define factorsfi impact on the gamefis result. These lists contain the values in the form of integers and Booleans which are obtained by using the existing parameters. These lists are created for each value in the team.csv file. Thus, they are independent to each team. A new DataFrame is created with these lists as columns in the frame. For each team, these frames are stored into another csv file using the pandas write csv function with the file name same as the value in the team dictionary.

6 PREDICTIVE ANALYSIS

The factors and their values are written in to a csv file which contains the factor names as the columns headings and their respective values in the rows. Each team has its independent statistics files mentioned in the above statement. These files will be used for conducting the predictive analysis. For each value in the team dictionary, these csv files which are specific to the team are read using the pandas csv reader function. There are two types of columns in these statistics file. The first type is predictors and the other type is targets. Columns related to the factors which impact the results are considered as the predictor columns, Columns related to the result of the match are considered as the targets column. Columns battingfirst, boundaries majority, wontoss, scorerange are predictors. Wonmatch column is target in the given scenario.

The data available in the statistics files is split into test and train sets. This is done by the function train test split in the sklearn library in the python. The data is split in the ratio of 3 is to 2. Sixty percent of the data is used as training set. Forty percent of the data is used as testing set. The predictors and target of the training set are used to build the mathematical model. The predictors of the testing set are used to predict the values of the targets. These predicted values are compared with the actual target values. This comparision is used to determine the accuracy of the prediction.

6.1 Implementation

Decision trees and Random forest are used in making the predictions. Decision trees are tree like structures which are built based on the values of the parameters. These trees are useful in defining the probability of the target value being attained. Trees are build with various stems which are drawn from conditional statements. Decision trees has three kinds of elements. The first element i.e., are the decision elements which refer to the block which checks for the condition or logic of the tree. Chance elements are the elements which occur depending on the condition or logic of the function. End elements are the results or outcome of the decision tree. These are basically leaf nodes of the tree. These nodes represent the result. Random Forests are conglomeration of decisions from various decision trees. In random forest approach, a dataset is divided into various subsets which will have some or all the input parameters as the decision makers and some or all the data which are the values for the parameters. Each subset is used to build a tree by using principles of decision tree. The predictions from these prediction trees are used in determining the final value. When a given set of input parameters are giving, they are predicted with all the decision trees developed by the forest. The outcome from all the decision trees are noted. The majority of these outputs is decided as result. This way, the errors which might arise in using only one decision tree can be eradicated. An error from one model of decision tree will be dominated by the results from all the other decision tree.

Random forest classifier from the module sklearn is used to build the various decision trees and predict these values. Classifier type object is instantiated in the code/cite. This object is assigned with the RandomForestclassifier and an attribute called n estimator. The variable n estimator will define the number of decision trees to be build for the analysis. Fit function from the sklearn module is used to develop the model for the random forest algorithm. Fit function

will take the training parameters and training targets as inputs. These are divided into fifty subsets in this scenario. Predict function is used to predict the value of the target given test predictor variable as inputs.

6.2 Accuracy

Generation of only one decision tree as the model for the given training data would produce erroneous results. Using the random forests, fifty decision trees are built to predict the correct value of the target. This way, errors produced by one of the decision tree will be corrected by the predictions from the other trees.

In the graph 3, the accuracy of using various number of decision trees are plotted against the number of decision trees. It can be observed that using less than five decision trees, the accuracy for the prediction for all the teams is around sixty percentage. As the number of decision trees increased, the accuracy of all the prediction is increased by at least ten percent. The hundred percent accuracy is because, those teams have played less number of games.

7 IMPACT OF FACTORS

This indicates the contribution of each factor for predicting the result of the game. These values will determine the probability of the value of result on any given values for the input variables. In the first step, the distinct values of the target value are noted. For all the distinct values of an input parameter from the set of values of one of the input parameter, the probability of different kind of results are calculated. This calculation is repeated for the distinct values in the set of input parameter and summed at the end. This produces the importance of the feature. The above procedure is repeated for all the decision tree and all the value are averaged for getting the overall value of the importance feature for that feature. This procedure is repeated for all the input parameters. This will give the contribution of each parameter to the result values.

7.1 Batting First

The first importance feature for all the teams are plotted in the graph 4 . It is clear from the graph that the importance feature batting first is highest for Rising Pune super giants. This indicates that this team have won most of their previous matches with while batting first in the game. While the Chennai Super kings and Kochi Tuskers are also high, but they are less than half. This indicates that batting first in the match will be a favourable condition for the above mentioned teams. For all the other teams except Kings xi Punjab, Pune warriors and Sunrisers Hyderabad, the batting first importance factor is nearly around 0.1. This implies, out of all that matches which were present in the training set, these team batted first for only ten percent of the games.

However, the total number matches should also be considered while validating this condition. Though the value for Kochi Tuskers is high, this might also be because they have played less number of matches and they have batted first in all the winning matches.

7.2 Score Composition

Score Composition composition is the combination of different ways of getting runs. For any high scoring and successful game, a team will have to score runs at faster rate. Hence, scoring runs in

form of boundaries will help a team a lot in turning the match in their favour. In the graph 5 , Contribution of this factor against each team is plotted. This graph summarises the contribution towards of the score composition factor towards the factor. This factor is very high for Kochi Tuskers team, because they have played considerably less number of games.

A factor around 0.2 to 0.3 seems around the average value for all the teams. It is clearly seen from the graph that this factor is high for Rising Pune Supergiants. That means, out of all the matches this team have won in all the season, in most of the matches, this team have scored most of their runs in form of boundaries. Then, Rajasthan royals and Delhi Daredevils are having next higher values. A lower value of this factor means, that out of all the matches which this specific team have won, they have scored most of them in form of another form. Sunrisers Hyderabad and Royal challengers are one such team.

This factor is calculated independent of the team composition. This factor can be normalised with respect to the team composition.

7.3 Score Range

Score is the total number of runs scored by a team in a specific innings of the match. This factor is categorised into four categories. Each category has a range of value for runs. Based, on this runs, the team is classified into categories. The first category of team will have scored less than hundred runs. The second category of team have scored less than one hundred fifty. The third category of team have scored less than two hundred runs. The remaining teams comes under the fourth category.

This categorisation is used as one factor in determining the results. From the graph, it can be seen that this value is very high for some of the teams and considerably less for other teams. A higher value of this factor means that out of all the matches the specific team has won, most of the matches they have scored the runs in the higher categories ,or out of all the matches they lost, they have scores in the lower categories of the score.

From the graph 7 ,It is clear that, teams Kolkatta Knight Risers and Sun Risers Hyderabad have a value around 0.6. This implies that the wonmatch of column for this teams was mostly decided by the score range category column. For the teams like Gujarat Lions and Rising Pune Super giants, this value is low. It can be inferred that the wonmatch column for this table is mostly decided by other columns in the team statistics table.

7.4 Toss

Toss is another important factor considered for this analysis. The winner of the toss has the power to decide the sequence of the match. This decision of the winning captain will effect the results of the match. Given this opportunity, any captain would take decision in favour their side. Hence, toss is one important factor in deciding the results of the match.

A higher value of this factor implies, that out of all the matches the specific team has won, they have also won the toss in most of the matches. It also implies that the column wontoss have contributed a large amount to the target column. A lower value of this factor implies that out of all the matches a specific team has lost, most of the matches they have lost the toss.

From the graph 6 it is clear that the this value is higher for teams Delhi Daredevils, Gujarat Lions and Royal challengers bangalore. This implies that out of the matches they have won, most of the matches they have won the toss. This implies toss is one of the important factor for this team to win a specific match. It is clear from the graph that this value is lower for teams like Kolkatta Knight risers. This implies that out of all the matches won by this team, they have won toss in less number of matches. This implies that toss is not one of the important factors for this team to win.

For the other teams, this value is around 0.15 which is considered as average contribution. For these teams, toss decision have a fair impact on the decision of the match. The wontoss column in the team statistics have contributed fair amount to the target column.

8 STATISTICAL ANALYSIS

This analysis will give the statistics of each factors and their importance in the previous matches for each team. This is done by gathering the data from the team statistics which is prepared as part of the first step in the predictive analysis.

A dictionary of team names is prepared using the teams.csv file from the source. This file is read using the read csv method in the csv library. An empty list is created for the factors batting order, score range, toss. As there is only one kind of value for all these factors, they are grouped and studied together. The score range is studied in a different program.

These empty lists are used for storing the percentage contribution of each factor towards the results of analysis. In this case, the data is not divided into test and training sets. All the data in the data sets are taken into consideration. The values used in the analysis are the actuals value and no predictions are made in defining these values.

For every element in the team dictionary, we iterate over the specific team statistics csv file created in the first step of this predictive analysis. From these csv files , we read the columns battingsfirst, majorityscore, wontoss columns. For each columns in the csv file, we create a corresponding dataframe in the python program using the pandas dataframe. This dataframes are constructed on based on two values. The wonmatch column value and the value of the factor being studied. We append the corresponding row to the dataframe only if both the conditions are satisfied. This kind of conditional statements can be achieved by python or operator.

For every factor, now independent dataframes are defined after both the conditions are satisfied. Total matches is the length of the csv file. From the above calculate the percentage of the dataframe which we have captured with respect to the total length of the csv file. This percentage value determines the percentage contribution of the factor towards determining the winning chances of the team.

These percentages are calculated for all the teams in the team dictionary. These values are stored in the respective factors list. This list is used for plotting the bar graphs using the pythons matplotlib.

8.1 Analysis of individual team

From the the lists of percentage contributions from the above analysis. Analysis of each factor and their contribution towards the

individual team has been plotted in the graph. These plots are plotted against the team name and the percentage bars which show the percentage of each factor. Graph 2 has been plotted with above lists.

For the team Kolkatta knight riders, out of all the matches they have won, in forty percentage of those matches, they have score majority of their score in form of boundaries. Out of all the matches they have won, they also won toss in thirty percentage of the matches and batted first in twenty percentage of the matches. This implies that the probability of winning a match for kolkatta Knight riders team is high if they score moajority of their score in form of boundaries. Then decision of toss and sequence of matches have considerable effect in the matchesf decision.

Team Royal Challengers bangalore have followed the same trend as the kolkatta team in the analysis. Out of all the matches they have won, they also scored majority of the runs in the form of boundaries. While ,out of these matches, they won only twenty percent of the tosses, they batted first in nearly twenty five percentage of the matches. Runs have been major contributing factor in this team also.

Chennai Super Kings have majority of their contribution from the toss factor and batting sequence factor together. That implies that, from the all the matches they have won, they either won the toss or batted first in the match. This implies that the team Chennai Super kings will have to win toss or bat first to win the match.

Teams punjab and Kochi Tuskers have followed trend similar to that of Kolkatta Knight risers and royal challengers bangalore. They scored majority of their score in the form of boundaries in nearly forty percent of the matches played by them. The other factors toss and batting sequence have contributed to nearly twenty percentage of their winnings. This implies that scoring majority of runs in form of boundaries will favour these teams.

Mumbai Indians team have the second highest percentage contribution from the factors toss and batting sequence compared to other teams. This team also have third highes contribution from the score composition factor. That implies, this team have higher chance of winning given any factor. Though the value from the any one factor is against them, the other factor will over ride the effect of the previous factor.

Gujarat Lions have the highest contribution from the factor batting order. That implies, out of all the matches won by this team, they have scored majority of runs in the form of boundaries. The other two factors are considerably low. This implies that Gujarat team will have to score most of the runs in the form of boundaries to win the match.

It can be inferred from the graph that rising pune super giants have not won a match while batting first in the game. Out of all the matches won by them, they have either batted second in the game or score majority of runs in the form of boundaries.

Team Deccan chargers have almost same amount of contribution from all the three factors. This team is consistently performing in any values of the factors. They have good balance of the conditions in the previous games.

Team Pune warriors has the lowest values for the factors toss and sequence of the match. They are also have less contribution from the factor composition of score. This implies that this team is under performing in any given condition.

8.2 Analysis of Range of Scores

The scores were divided into categories. This analysis will contribute the percentage contribution of each range of the score to the result of the matches played by the specific team. This analysis can be used as to determine the safe score range for every team.

Team dictionary is taken from the team.csv file. The team statistics csv file which is created in the predictive analysis will be utilised for the value for range of scores. The values from the columns score range and wonmatch will be utilised. The data in this csv file is not partitioned into training and testing sets. This analysis is performed on complete data. No data is predicted in this analysis also. This is analysis on all the available data.

For every value in the team dictionary, we locate the team statistics csv file which is generated as part of the predictive analysis. Four empty lists are generated to store the number of matches won by each team with score in the given score range. Total number matches can be calculated by using the length of team statistics csv file that is being studied upon. For every value in the team dictionary, we divide the csv file into four different data frames. Each data frame corresponds to each range of scores. This partition can be achieved by using pandas data frame.

This dataframes are extracted using the two conditions. They are the value of score range must be equal to the range we are fetching data for and the other condition is the wonmatch column must be true.

After corresponding data frames are extracted from the team staistics csv, we calculate the percentage of each range data frame length against the total length of the team statistics csv. This percentage value will give us the percentage contribution of each range towards the result of the match.

8.3 Graphical Analysis on scores

From the graph 1, it is clear that most of the wining scores fall in the second and third category. That implies for any team to win the match, it is most likely that the team must score atleast hundred runs in the match and come under second category or score atleast one hundred fifty runs and come under third category.

Teams Gujarat lions and pune warriors have never won match scoring less than hundred runs or more than two hundred runs. This implies that the range from hundred to two hundred is the safe score range for these teams. Gujarat have won most number of matches scoring in the third category that is atleast scoring one hundred fifty runs and atmost two hundred runs. This is more safe zone for them. While, for pune warriors team they have almost similar winning percentage in both the categories. Teams rising pune supergiants and kochi have never won a game scoring more than two hundred runs. This might be bacuse, they have not scored more than two hundred runs in any given match or they have not won in the matches in which they scored more than two hundred runs. That implies that they are having a safe scoring in the range of one hundred fifty and two hundred.

Sunrisers Hyderabad team has more contribution from the the second and third categories of scoring in the game compared to the other two teams. This indicates that they are consistent in this category of scoring than other teams. They do not have major difference in contribution from these categories. This indicates that

they are consistently scoring around one hundred fifty mark score which makes the assumption that this team have good batting side. From the statistics on this team it is clear that they have also won matches scoring less than hundred. It is clear that they are also having a good bowling side as well.

Team Royal Challengers bangalore has highest contribution from the fourth category of scoring when compared to other teams. That implies, the team royal challengers banglore have highest probability of winning the matches , if they are scoring more than two hundred runs in the match. Then their next contribution comes from the score range of third category. That implies this team has a good batting side. Because they are having high scoring percentages from the third and fourth categories.

Following the royal challenger banglore team is Chennai super kings team. This team have contributions from all the four categories of the scoring range. This implies this team is fairly consistent in both the categories of the game.

Team Mumbai Indians have the highest contribution from the third category of the scoring range after Gujarat lions. They are also having contributions from all the categories of range of scores. This will clearly show that Mumbai Indians team has an inconsistent batting team. If these totals are from the second innings, it can also be assumed that whenever their batsman failed to score many runs, bowler won the match.

Kolkatta team has the highest contribution from the first category of scoring after Kochi team and Pune super giants. This implies that the above three teams have a good batting side. Scoring less than hundred and winning match is sight of team having a good bowling side. Upon having good contributions from category one, kolkatta knight riders also has good contributions from the other three categories as well. This implies, that this team not only has good bowling side,it also ahs a good batting side as well.

9 CONCLUSION

Predictive Data analytics have provided promising solutions to various problems in wide variety of fields. As part of this study, predictive and statistical data analytics on data related to a cricket League, Indian Premier league is conducted. As part of predictive analytics, the available data is split into training and testing data sets. The values from the model are used to predict the target value. These values are compared to the original values for accuracy. Method of improving the accuracy of model is studied. This study would be useful to determine the impact of a factor on the result of the game. This analysis would help in predicting the results of the matches acuurately with the model developed from the training data.

Statistical analysis on the same data is conducted to get the details related to the impact of a factor quantitatively on a specific team. This analysis pertains to the available data and no predictions are done. This kind of analysis would be useful in determining the strengths of individual team. This kind of analysis can be conducted to the nature and strengths of each team.

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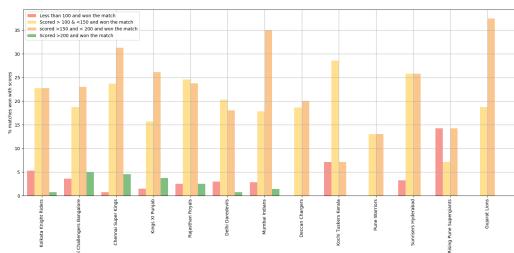


Figure 1: Score Staistics

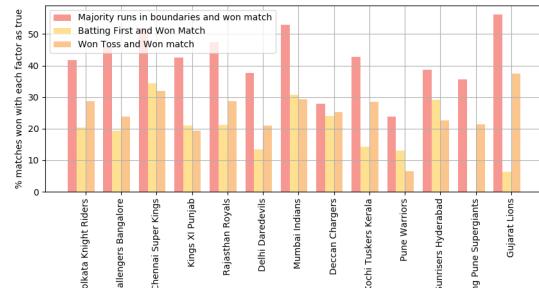


Figure 2: Other Factors Staistics

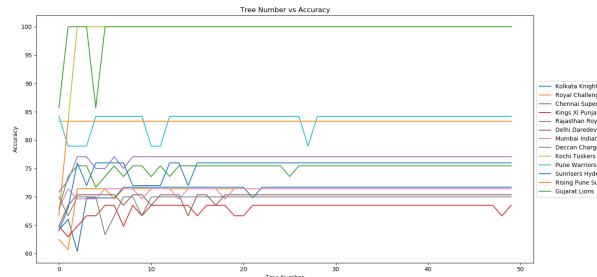


Figure 3: Tree number vs Accuracy

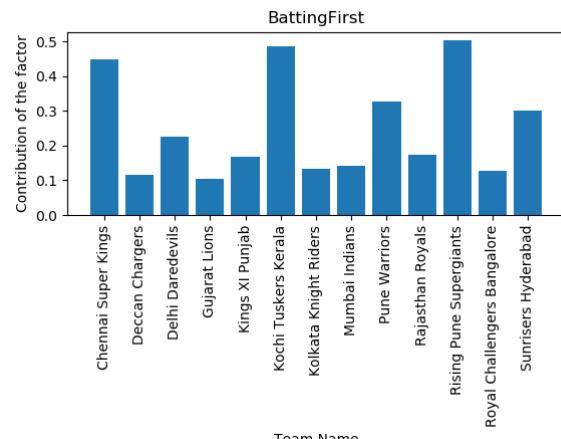
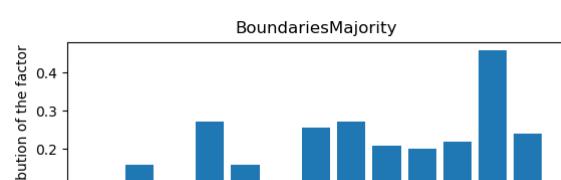


Figure 4: BattingFirst



TBI: A Data Driven Journey Beyond Contact Sports that Puts Data In The Driver's Seat

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ABSTRACT

The data journey into concussions starts with the confluence of contact sports, long-term neurological diseases, and well known athletes. Lots of fascinating technologies to help the hockey player, football player and others that play contact sports. And hey, sports matter! But the data journey leads down other roads. The Data Scientist has an opportunity to help the athlete but also an opportunity to help many others as well. This data journey is not well known and has far less panache but is important nonetheless. This road leads to military veterans, those injured in auto-accidents, and the elderly. We will take a deep dive into data from the Veterans Affairs department, and see what it tells us and what else can be done.

KEYWORDS

i523, hib315, Big Data, TBI, Veterans Affairs, Concussion

1 INTRODUCTION

Be it a researcher, a developer, a scientist, a doctor, an accountant, a stay-at-home mom, or a DJ, we all want to know that we are making a difference. For some, it's through one-time or episodic opportunities: service projects for some, for others it comes in the form of making a monetary donation, and for others, it's less formal: simply helping someone in person. But for others, there is an opportunity to know that what they are doing day in and day out could help someone in a meaningful way. It's particularly satisfying that what you may do for a living could indeed help someone in a consequential way. For most of us we wonder if we are fulfilling that yearning within us. The manager in the business that is trying to make a buck, or the employee at the license bureau, or the teaching assistant...those may have to seek out that extra bit of fulfillment or satisfaction.

Yes, indeed, we can all make a difference....even a Data Scientist! Yes, in a small or large way a Data Scientist can make a real difference. Is it the keen Python skills that Data Scientists possess that make the difference? Or is it the machine learning and R-programming that sets the data scientist apart? Not likely, if not, then surely the ability to query a database, provide documentation, and manage a keen bibliography is the critical piece. All of these are important to be clear. However, a Data Scientist can make a true and meaningful difference by knowing and exercising two essential cornerstones of big data: 1) Knowing your data. 2) Being willing to take the road down which the data leads. Sometimes its the journey that determines the destination. Are you willing to go?

2 THE BEGINNING

When the author was young, around 10 or 11 years old, he fell off his bike directly in front of his house. He hit his head on the side of a cement sewer and received a concussion. At the time, it was uncommon for a youth to wear a helmet. The idea of wearing a helmet was not even thought about. He was not taken to the hospital or doctor for any treatment or diagnosis. Therefore, there was nothing definitively diagnosed, medically speaking. Nothing was quantitatively documented. No X-Rays or MRI to test or verify. The only tangible *data* was a large knot on the side of his head, a loss of balance so bad that he could hardly walk or even stand upright, and tremendous nausea.

Today there are concussion protocols. At the slightest sign of concussion symptoms, the footballer is taken into a tent and examined by a physician. We have learned the importance of a quick diagnosis and immediate treatment. In today's professional game, we have means of measuring the g-force of each hit, using sensors within the helmet. Wikipedia describes g-force (the "g" referencing gravity) as "a measurement of the type of acceleration that causes a perception in weight. Despite the name, it is incorrect to consider g-force a fundamental force, as "g-force" is a type of acceleration that can be measured with an accelerometer. Since g-force accelerations indirectly produce weight, any g-force can be described as a 'weight per unit mass'. Helmet sensors can indicate the direction of the impact in addition to the g-force measurement. This information is collected and real-time notifications are sent to trainers and even parents of young athletes.

3 YOUTH ATHLETICS

In recent years, due to health issues of high profile professional athletes, we are learning more about the long-term health impacts of head injuries sustained as a young adult or as a child. Along with medical research, data has helped to pave the way for a growing understanding of the impacts of TBI (Traumatic Brain Injury) as well as impacts to the head that are not traumatic. This is indeed critical as the incidents occur at a "rate of 1.6-3.8 million in the United States per year with accumulated costs approaching \$60 billion annually. Recent studies have identified relationships between magnitude, frequency and location of these sustained head impacts with post event symptoms and decrements in neurocognitive function." [2]

With mounting evidence that head impacts, as young adults, can impact our long-term neurological health, the previously quoted report from Shockbox research (one of several independent studies) drew still further concern. It concludes, "when monitored for head impacts across a regular season, it was seen that the elementary age players (average age of 13) experience a similar magnitude and frequency of impacts compared to the high school players (average

age of 17). The frequency and magnitude of high peak g impacts in elementary (71 impacts with 50 g average) causing 6 concussions is also similar to the high school team players (84 impacts with 51 g average) who did not have any team concussions. It is also seen that youth players are still developing skills and techniques leading for increased impacts at the front of the head.” [2]

While the “data road” is showing us information in terms of numbers, is the data diverse and comprehensive? That is, we can measure force and impacts to the brain but what about other data sources like biological tests (*markers*) or images? Patrick Bellgowan, a scientist at the University of Tulsa’s Laureate Institute for Brain Research, focused his effort on measurement and *form* of the hippocampus. The hippocampus is a major portion of the human brain and is part of the limbic system and thus plays a role in spacial memory, long and short-term memory, and is linked to processing and likely emotional control. Bellgowan’s research is published in the *Journal of the American Medical Association* and shows some very stark numbers. “A group of 25 players with no history of reported concussions had hippocampuses that were, on average, 14 percent smaller than those of a control group of 25 males of similar age and health who didn’t play contact sports.” [3] Further, the report shows that while “much of the health and safety debate over football and other contact sports focuses on the risk of developing severe, headline-grabbing neurodegenerative diseases like amyotrophic lateral sclerosis (ALS) and CTE, a growing body of evidence suggests that both concussions and subconcussive blows can alter mood, cognition and behavior while causing damage and structural changes to the brain.” [3]

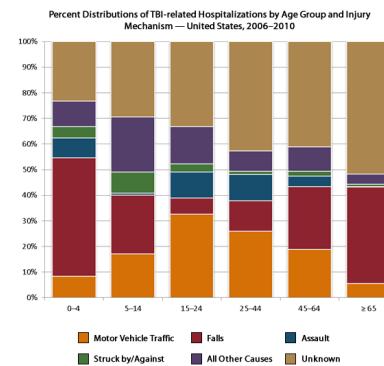
Traveling down this “data road” there is no shortage of information around concussions, TBIs, and athletics. We can certainly understand the concern with the potential long-term impacts on one’s health. Fear for our young athletes’ health would concern any doctor, pediatrician and most certainly parents. Based on the quantity of information one would think that it’s the athlete that is most susceptible. The youth are vulnerable to be sure, but is it only the athlete? It’s clear that professional athletics is big business in our country and around the world. It wasn’t until the deaths of the big name professional athletes that this issue came to the public’s eye. Researchers were already looking into this but focus was not sharpened until we heard the names of Mike Webster, Dave Duereson, Andre Waters and Junior Seau. These athletes made millions and the big business of athletics was at stake. With all this money comes more concern and interest and, in this case, data availability.

However, this “data road” if you will, did not originate with athletics. While the bulk of the data is based on TBI concerns for athletics, it originated with the military. Military personnel have tremendous challenges with head trauma due to the force of explosions and projectiles. With the military, the measured force of explosions and the speed of projectiles is tremendous especially when compared to the trauma experienced by most athletes. Add to this, a soldier is under significant stress as part of his job. How both head trauma along with significant levels of stress impacts the soldier’s neurological health requires much more research, as do related TBIs in the general population due to auto accidents, falls and violence. While culturally the impacts of TBIs on athletes garners greater attention, it’s the military and the population at

large that provides opportunities for the Data Scientist, if we let the data do the driving.

4 THE GENERAL POPULATION

The Center for Disease Control and Prevention (CDC) is a great source for detailed information regarding TBI’s and the general populous. They are involved in providing detailed reports to congress and to the citizens regarding items related to our health. While access to raw data is not available, the breadth and scope of the data that is available is worth studying. The CDC provides data regarding the rates of hospital visits, emergency department visits, and death broken out by age group and type or cause of trauma. Much of this data is available going back several years. In addition, there are numerous reports including broad level statistics. For example:



	Motor Vehicle Traffic	Falls	Assault	Struck by/Against	All Other Causes	Unknown
0-4	1,116	6,184	1,044	589	1,327	3,123
5-14	2,306	3,077	111	1,118	2,887	3,976
15-24	13,257	2,590	4,131	1,230	5,949	13,517
25-44	15,522	7,045	6,134	777	4,670	25,539
45-64	12,178	15,962	2,668	1,296	6,091	26,775
≥ 65	5,282	36,525	285	912	3,774	50,197

Figure 1: CDC TBI Type 2006-2010

It’s by knowing the data that you can better understand the quality of the data. If we want to make a difference, in data science, we have to know the source of the data. The CDC leverages a few sources for their TBI related reporting. The Healthcare Cost and Utilization Project (HCUP) is a part of the US Health and Human Services Department. It’s a comprehensive repository or collection of databases related to hospital stays and patient care data. HCUP has yet another collection of databases called NEDS (Nationwide Emergency Department Sample) and NIS (National Impatient Sample). The databases rely on data that is input and managed by hospitals at the time of the patients stay. The CDC feels that the data “sample size is large enough to provide stable annual estimates of TBI.”

One way that these databases are created is due to the efforts at the hospital using the International Classification of Disease (ICD), in this case the ICD-9-CM, which is the *International Classification of Disease, Ninth Edition, Clinical Modification*. To a Data Scientist this is a standardized basis of input of the source data - a very good

thing. During a patient's stay in the hospital, there is a standard in identifying the diagnosis as well as classifications, used for patient releases or secondary diagnoses. For example, lets say a patient is admitted into the hospital with a TBI due to an auto accident in which the patient's head hits the steering wheel, causing injury. Code 804: multiple fractures involving skull or face with other bones, could be used. Multiple codes could also be used to further define the extent of the injuries or diagnosis. While this approach has inherit challenges for a data scientist, for example, how do we manage analysis tied to multiple codes, or potential administrative issues (loss of data or mis-classification)? The good thing is that we do have a standard and data that we can build upon. And in this case, the data source has a standardization which is important. To help alleviate some of the aforementioned data concerns, we could minimize some of the data challenges by increasing the sample size or extrapolate by leveraging other similar sources to increase our certainty.

The CDC's published report "Traumatic Brain Injury - Related Emergency Department Visits, Hospitalizations, and Deaths - United States, 2007 and 2013," concluded the following: "In 2013, approximately 2.8 million TBI-related ED visits, hospitalizations, and deaths occurred in the United States, representing an increase in 2007 that was largely attributed to an increase in the number and rate of TBI - related ED (Emergency Departments), *i.e.*, Emergency Room visits. Although much public interest has been devoted to sports-related concussion in youth, the findings in this report indicate that older adult falls account for a much larger proportion of the increase in TBI-related ED visits during this period. In addition, although the modest increase in ED visits that might be attributed to youth sports concussions do not extend to increases in TBI-related hospitalizations and deaths, the same cannot be said for TBIs attributed to older adult falls. From 2007 and 2013, increases in TBI-related hospitalizations and death attributable to older adult falls suggest the need for greater attention to preventing older adult falls. Empirically validated prevention measures can help reduce the incidence of older adult falls." [5]. By quantifying the causes of some of the TBI's for the general public, using data, we could indeed make a difference and help to "empirically validate prevention measures".

If the ICD codes were expanded to include more details around causation, or if during the hospital visit the symptoms were tagged to *potential cause* we could build upon that from a data perspective. Knowing that some will not know the cause of the fall (elderly), or a patient could have been concussed due to domestic violence and is unwilling to discuss it, building upon what we currently have could help us use the data to help prevent TBIs in the general public. The CDC created the STEADI program (Stopping Elderly Accidents, Deaths and Injuries), which is an effort to help identify older adults at risk and help prevent falls. A Data Scientist research could marry results to those in the medical field for an opportunity to help with predictive analytics and preemptively provide support to the elderly and others at risk using the data we have and are building upon. While there is so much attention paid to athletes and data tied to youth head injury prevention, there is a vast opportunity to help others, of all ages, and truly make a difference.

5 THE VETERANS

On the playing field, athletes like to call it the "Field of Battle". This analog represents the arena in which the athlete challenges himself to beat his opponent and win the game. While the "Field of Battle" for the athlete offers a competitive challenge, it is not life or death. The soldier, fights on THE field of battle. He doesn't play to win but to live. Balls are not flying but bullets! This places an immeasurable amount of stress on the soldier. Imagine adding a TBI to a critically stressed soldier. The dynamics increase, and so does the need to understand the causes, health, history, and symptoms of the soldier. In short, we need more data in order to help.

"While most people fully recover from a concussion within three to six months, soldiers who suffer concussions in battle can experience symptoms for years following the injury, says Michael K. Rauls, an experimental psychology student at Augusta State University in August. Combat-related stress may prolong soldiers' recovery, and, at the same time, concussions may hamper soldiers' ability to recover from stress."^[1]

The following url provided raw data for examination. This is data from the Veterans Affairs database accessible under the catalog of government data. The data sets are available under the catalog section and is intended for public access and use. In addition, Metadata has been created and was updated in November, 2017.

url - <https://catalog.data.gov/dataset/mild-tbi-diagnosis-and-management-strategies> [4]

From the website, once you have accessed the catalog you will notice the source data used is JSON data via the website. JSON (JavaScript Object Notation) is easy to access and is considered “human-readable”. We chose to convert the JSON to CSV (Common Separated Values) then uploaded via Python as well as input into excel. We converted CSV to XLSX, a Microsoft Excel format. We analyzed the data for any obvious issues as this is normally a good time to do some data cleaning. It’s also a good time to do some realigning if need be, i.e., move some data around to align more cleanly. At this point, we used the pivot function within excel. The pivot function is one of excel’s most powerful features. It allows the user to align large data sets in order to extract meaning. The result is a table like format that is easily used to make charts or graphs.

Below is a snippet of the JSON data downloaded from the Veterans Affairs (VA) website.

Using a simple conversion tool, this image is a snippet of the

Using Python, via Jupyter Notebook, to pull in the CSV for JSON parsed data translated to CSV.

additional programming work.

There are two data sets: (1) Mild TBI Diagnosis and Management Strategies: Implications for Assessment and Treatment in Veterans (2) Mild TBI Diagnosis and Management Strategies: VA's TBI Screening and Evaluation Program. The Screening and Evaluation Program document contains primarily data, in terms of total numbers, related to the Veterans symptoms. We will however dig deeper into the Assessment and Treatment in Veterans data.

DataElement	DataType	DataValue	TBIFlag
Patients	Characteristic	47,845	Y
Patients	Characteristic	636,288	N
Age Mean	Characteristic	33	Y
Age Mean	Characteristic	36	N
Age Standard Deviation	Characteristic	8	Y
Age Standard Deviation	Characteristic	10	N
Female	Characteristic	6%	Y
Female	Characteristic	14%	N
Male	Characteristic	94%	Y
Male	Characteristic	86%	N
White Only	Characteristic	75%	Y
White Only	Characteristic	67%	N
Black Only	Characteristic	13%	Y
Black Only	Characteristic	18%	N
Native Amer	Characteristic	1%	Y
Native Amer	Characteristic	1%	N
Asian Only	Characteristic	2%	Y
Asian Only	Characteristic	2%	N
Native Hawa	Characteristic	1%	Y
Native Hawa	Characteristic	1%	N
Multiracial	Characteristic	3%	Y
Multiracial	Characteristic	2%	N
Unknown	Characteristic	6%	Y
Unknown	Characteristic	10%	N
Non-Hispanic	Characteristic	85%	Y
Non-Hispanic	Characteristic	82%	N
Hispanic	Characteristic	13%	Y
Hispanic	Characteristic	11%	N
Unknown	Characteristic	3%	Y

Figure 3: Veterans Affairs CSV

This data from the Assessment and Treatment dataset is small and straightforward. The data variables have four categories: DataElement, DataType, DataValue and TBIFlag. TBIFlag is used to differentiate those that were diagnosed with TBI as the data set includes both those diagnosed with TBI and those that were not identified. The working assumption is that there could be some that actually did have a Traumatic Brain Injury that may not have been officially diagnosed and flagged in this data. If you looked at it hierarchically, DataElement is the more granular of the two key characteristic variables. So DataElement would be the “child” to the DataType, and is dependant on the DataType.

The specific parsing and analyzing effort was to take the CSV file and import it into Microsoft Excel. Using excel, for both datasets, we created a workbook in which to analyze the data, similar to a Jupyter Notebook used for Python. We created a “data tab” which

```
In [3]: import csv
import pandas as pd
data=pd.read_csv('tbl_assessment.csv')

ModuleNotFoundError: No module named 'pandas'
In [4]: import csv
with open ('tbl_assessment.csv') as file:
    reader=csv.reader(file)
    for row in reader:
        print (row)

[DataElements, 'Data-Type', 'DataValue', 'TBIFlag']
[Patients, 'Characteristic', 'Population', '47,845', 'Y']
[Patients, 'Characteristic', 'Population', '636,288', 'N']
[Age Mean, 'Characteristic', 'Population', '33', 'Y']
[Age Mean, 'Characteristic', 'Population', '36', 'N']
[Age Standard Deviation, 'Characteristic', 'Population', '8', 'Y']
[Age Standard Deviation, 'Characteristic', 'Population', '10', 'N']
[Female, 'Characteristic', 'Gender', '6%', 'Y']
[Female, 'Characteristic', 'Gender', '14%', 'N']
[Male, 'Characteristic', 'Gender', '94%', 'Y']
[Male, 'Characteristic', 'Gender', '86%', 'N']
[White Only, 'Characteristic', 'Race', '75%', 'Y']
[White Only, 'Characteristic', 'Race', '67%', 'N']
[Black Only, 'Characteristic', 'Race', '13%', 'Y']
[Black Only, 'Characteristic', 'Race', '18%', 'N']
[Native American/Alaska Native Only, 'Characteristic', 'Race', '1%', 'Y']
[Native American/Alaska Native Only, 'Characteristic', 'Race', '1%', 'N']
[Asian Only, 'Characteristic', 'Race', '3%', 'Y']
[Asian Only, 'Characteristic', 'Race', '2%', 'N']
```

Figure 4: Veterans Affairs ipynb

held the CSV data that we copied and placed into a pivot table. Leveraging the two primary data variables of DataElement and DataType we analyzed the data. Based on what the data told us we set up additional tabs as a work space in the workbook to look at particular DataTypes. At this point, we created charts to illustrate the data findings, the most pertinent charts of which are included in this project. This was done by the charting capabilities within excel.

The DataType includes several categories, but we will focus on a few. One area was the “category of care by patient with and without TBI”. This data set included a total of 684,133 veterans that were patients. Of that, 47,845 (7%) had the TBI flag while the remaining 636,288 did not. Included are some charts created from the data based on the *category of care* and as we expected, those with TBI (flagged for TBI) had a higher percentage of treatment related to Psychiatry and Mental Health.

Additionally, we looked into another DataType category of “Prevalence of Mental Health and Pain”. This category includes DataValues of: depression, bipolar, psychosis, PTSD (Post-Traumatic Stress Disorder) and others. While it was not clear, we are assuming this diagnosis of the prevalence of mental health and pain was made as a result of the treatment of TBI, though the data does include numbers on veterans who had been (prior to) receiving services from the VA (Veterans Affairs/Administration), listed as a “VA User”. The point here is there is some uncertainty as to whether their diagnoses were pre-TBI or were as a result of having a TBI. The results, however, were particularly stark in that the veteran with TBI had a marked increase in areas around mental health, PTSD, headache and depression. The chart shows the comparisons.

One DataType that caught our eye was the “Category of Care Inpatient Length of Stay”, since veterans with TBI and other stress related health issues should have a marked increase in the length of stay. However, the TBI flagged veterans did not show an increase in the time of stay, the data did not represent a length of time. Since time was not a DataElement option, we decided to compare the “In-patient Stay” percentages to the total number of patients and found that it was the result of the two. Therefore, “Category of

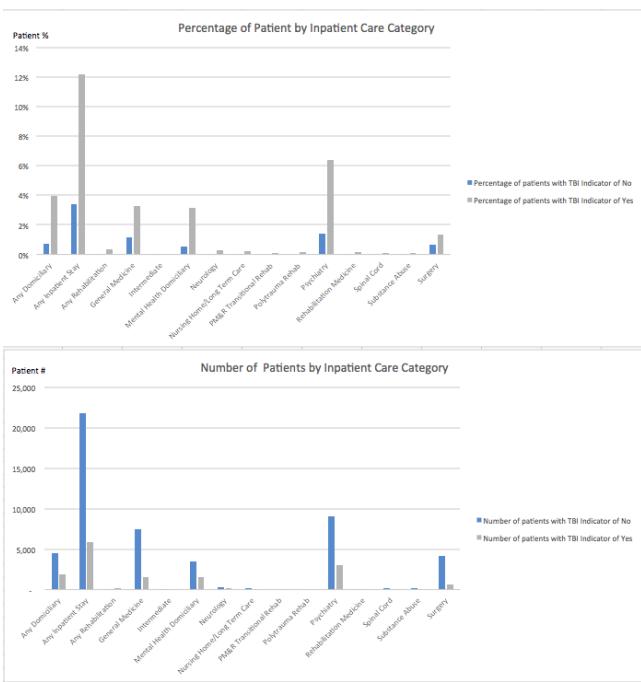


Figure 5: Veterans Affairs Care Category

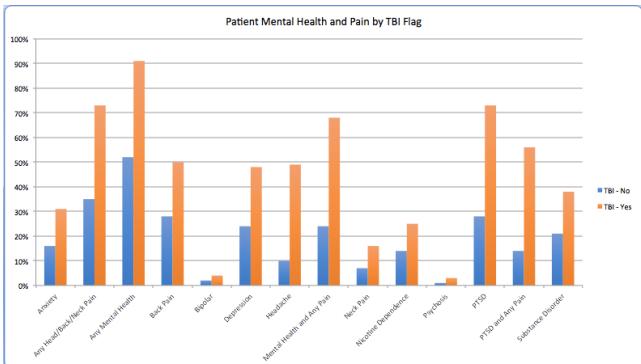


Figure 6: Veterans Affairs mental health and pain

Care Inpatient Length of Stay”, was not a representation of time but the number of patients. The simple chart illustrates the result. So *specifically* the length of stay is actually the “Number of Patients by Inpatient Care Category” shown in a prior chart. While we feel this is an error with the data, the general feeling is that we think it is minor but will reach out to the VA and advise. However, it would have been interesting for this researcher to see that data.

While we do have errors in the data, the fact that the data does include Diagnosis Codes as a DataType variable is promising. These are the same codes described prior as ICD (International Classification of Disease). This helps to provide us with additional information that can be used to further help medical personnel and support of veterans who have prolonged rehabilitation due to TBIs and the various levels of stress, including PTSD.

Length of Stay Data	N	Y	Inpatient Stay % * Total
Patients	636,288	47,845	
Any Domiciliary	4,540	1,878	
Any Inpatient Stay	21,822	5,844	
Any Rehabilitation	88	170	
General Medicine	7,469	1,573	
Intermediate	18	—	
Mental Health Domiciliary	3,429	1,514	
Neurology	264	140	
Nursing Home/Long Term Care	203	102	
PM&R Transitional Rehab	-	44	
Polytrauma Rehab	-	75	
Psychiatry	9,044	3,074	
Rehabilitation Medicine	76	83	
Spinal Cord	131	49	
Substance Abuse	110	34	
Surgery	4,147	655	
Patients	636,288	47,845	
Any Domiciliary	1%	4%	4,518 1,880
Any Inpatient Stay	3%	12%	21,825 5,842
Any Rehabilitation	0%	0%	64 172
General Medicine	1%	3%	7,445 1,574
Intermediate	0%	0%	19 —
Mental Health Domiciliary	1%	3%	3,436 1,512
Neurology	0%	0%	255 139
Nursing Home/Long Term C	0%	0%	191 100
PM&R Transitional Rehab	0%	0%	- 43
Polytrauma Rehab	0%	0%	- 77
Psychiatry	1%	6%	9,035 3,072
Rehabilitation Medicine	0%	0%	64 81
Spinal Cord	0%	0%	127 48
Substance Abuse	0%	0%	127 33
Surgery	1%	1%	4,136 655

Figure 7: Veterans Affairs incorrect length of stay

The second of the two JSON data sets “VA’s TBI Screening and Evaluation Program”, includes yearly diagnosis numbers and “Postconcussive Symptoms in the last 30 days”. The yearly diagnosis numbers at first blush appear to provide meaningful information as it includes a yearly total of patients as well as the percentage of those that were diagnosed with pain, or PTSD or TBI, which was very similar to the data in the first JSON data set. Additionally, the overall year to year numbers should be reflective of the amount of military activity within that given year, assuming the concussions were directly related to military activity. That is, I would expect to see the overall numbers, as well as those particular diagnosis numbers, increase when there is military activity. This data does not provide any information regarding the level of activity by the military, within the given year.

However, the second JSON data set includes the “Postconcussive Symptoms in the last 30 days”, which helps to support that data in the first JSON data set “Implications for Assessment and Treatment”. This data set evaluated 55,070 postconcussive veterans within 30 days. My working assumption is that these veterans would have been diagnosed within the last 30 days, but could have sustained the concussion more than 30 days ago. The postconcussive symptoms in this data set are numerous and center around the general categories of: Anxiety, depression, fatigue, forgetfulness, headache, irritability among others. For each symptom category the symptom is measured as either, none, mild or moderate to severe.

The postconcussive symptoms that had the highest number of veterans, that was diagnosed with that symptom, all had moderate to severe measured symptoms. The top five identified symptoms, all having a moderate to severe rating are: 1) Irritability (easily annoyed), 2) Sleep Disturbance, 3) Forgetfulness, 4) Anxious or tense and 5) Headaches. For example, of the 55,070 postconcussive veterans, 45,389 felt irritable and were easily annoyed; which is 82 percent. Over 72 percent complained of moderate to severe headaches. It would be interesting to compare similar raw data from concussed athletes to these numbers to see how they compare.

So what does all this data tell the Data Scientist? The data driven direction has found that veterans and active soldiers with TBI are diagnosed at a higher rate in terms of levels of stress, and thus have a need for mental health treatment and psychiatric care. As a result, recovery takes much longer than say the general population or for athletes and, based on the first JSON dataset, a majority of veterans were Veteran Affair or services users. Given the data that we have, it appears that TBI veterans have as many symptoms and likely many more, and for a longer period of time, than athletes. To that, veterans have the additional complication of stress that increases the symptoms and the severity. Imagine a TBI veteran

that is experiencing moderate to severe headaches, anxiety, fatigue and irritability. Not only is the concern around the long-term neurological health, like Alzheimer's or CTE (Chronic Traumatic Encephalopathy), the veteran has to deal with a prolonged recovery *short-term*.

How can the Data Scientist make a difference? Given the data we have, we can start to create some models to help align the symptoms to care and start to leverage this based on each military mission. In essence, prepare for the TBI patient, coming in from the battle field, regarding long-term care. Since we have the ICD codes (diagnosis codes) in this data, can we use these or enhance the data to draw a connection to the causes of the TBI. If so, by linking the causation, to the symptoms and recovery, we can prepare earlier, plan for the impact and the cost. With the goal of ultimately working with the military to help limit TBIs. The idea would be to use the information to help proactively identify soldiers at risk, diagnose quickly, and be prepared with the necessary treatment as quickly as possible, which includes planning for the future, as unlike the athlete who may need to quit playing a game, the soldier may be giving up his job. Anything the Data Scientist can do to help, would make a difference.

6 THE CHALLENGES

The desire of this research was to pull together a fascinating story to show that head trauma, even mild trauma, over a period of time could cause long-term debilitating neurological effects. Furthermore, we wanted to show the benefit of documenting the daily head trauma of football players in both practice and games and then add all the data together and tell the story of how we now know that mild regular head trauma is just as dangerous as TBIs and maybe more so, as you may not know you are in long-term neurological danger. This would have been supported by the output of helmet sensors and collection of data each and every day. The daily data for each player would have been collected, cleaned and organized to show the direction of head impacts (what part of the brain was affected). The data would have included a *g-force measurement* for each hit, again on a daily basis.

All of the aforementioned would be linked to, and compared with, a regular MRI or another type of image. Say for example, an annual MRI of the brain to compare year to year changes or to look for any changes due to the helmet impact data gathered throughout the year. Any potential correlation from these two data sources would be documented. From a data science perspective, we had envisioned a method to represent the images quantitatively so that we could more easily align the image to the daily impact data. For example, we could divide the brain up alphabetically, each letter representing a different area within the brain. To each alphabetically designated section, we could apply a combination of numeric value and a word, say a color, to illustrate both the location, type and severity of injury, or changes to the brain from the MRI. For a Data Scientist then you can start to build some correlation between the daily data and the specific message in the image. Gathered on an annual basis we could build some history and move towards doing some predictive-analytics. To both the daily impact data and the images we could also include biological markers, that could be analyzed from blood to show concussions and other biological

changes, further adding *richness* to the data. However, we never found that data. Yes, medically speaking, some correlation or cause-and-effect data exist but not in an overall quantifiable manner and not available in a data set for the Data Scientist.

Finding medical data sets is a challenge to be sure. We researched for days trying to find any data set with little luck. We would expect that medical data sets would be limited due to privacy concerns and how quickly data in the medical world can become stale. We would expect that some data sets were very challenging and expensive to gather and that the owner would not want to freely offer such an asset. Then there is the likely challenge of the complexity of a given medical data set. We would assume that most medical, in particular head trauma based, data sets would be complicated and challenging to access, parse, clean, read, etc. However, it was a learning experience to find so little. It also has us wondering if the medical community might be well served to have some other *eyes* looking at the data. We read several medical studies and journals and know that there is indeed data available based on the research that was found, but nothing that was accessible. As a result, this might be an excellent opportunity for data science, computer science and medical worlds to work together towards a shared goal, and make a difference. This created a question for us that we were not able to have the time to further investigate.

Since the data drove us to the general public and in particular head injuries to the military, we were not able to pull together information around the causes, other than high level information. That is, by knowing more about the cause of the head trauma we may be able to better work toward limiting them. We simply assumed one thing, but the data steered us in a different direction. It would have been interesting to pursue any roll that big data could have played in helping to limit TBIs in the military. Just the concussion from the delivery of a large artillery piece is significant. Imagine being on the receiving end.

Not only was there limited data, but the JSON data sets were small. The actual patient numbers were reasonable but the lack of historical data based on diagnosis types, or symptoms related to any long-term neurological diseases, or additional data on the patient recovery would have been welcomed. Imagine then comparing this to a similar data set for athletes who had experienced TBI, which would have been very interesting. It's from this point that we could build a cost-estimate related to treatment and recovery and then show the difference in cost for treatment of the athlete and the veteran. For the Data Scientist, working towards pulling together a cost-estimate for veterans would help in preparing the necessary care as well as doing analysis on the benefits of prevention and additional research. As for the veteran, their likely short-term treatment will take much longer than the athlete, not to mention the expense of the veteran not being able to work as well as any potential long-term impacts to the veteran, complexities not all athletes have to endure. In theory, we might find that research dollars are better spent dealing with TBIs in veterans than the athlete.

Another challenge is trying to better understand what we don't know. For example, the JSON data sets were based on those veterans receiving care from the VA. We also know from the data that about 80% of them had been receiving care from the VA prior, but we don't know how far back their VA based treatment and diagnosis went.

We also do not know how many soldiers were diagnosed on the battle field or training and are not receiving care from the VA and are therefore not identified in these numbers. To the Data Scientist, it would be important to know of all the military personnel that were diagnosed with TBI, how many are in treatment with the VA?

Lastly, as the paper outlines, we have a concern about the long-term effects of head trauma, especially repeated trauma. Alzheimer's, CTE, Parkinson's diseases are catastrophic, and building an open relationship between these diseases and concussion are ongoing. This is a growing area of research, as the medical research of the brain is complicated and still maturing. Additionally, this type of research is a long-term endeavor as some of these diseases are not diagnosed until years after the head trauma. So the challenge of gathering actionable data can take years - even decades. Also, some of the disease identification requires research of the brain after the death of the patient. It was not until after the doctors were able to examine the brains of athletes that they identified what is now called CTE.

7 CONCLUSION

"The road goes ever on and on, down from the door where it began. Now far ahead the road has gone, and I must follow, if I can, pursuing it with eager feet, until it joins some larger way where many paths and errands meet. And whither then? I cannot say." - J.R.R. Tolkien, The Fellowship of the Ring.

The availability of data drove us down a different road than we expected. It also opened our eyes to a brand new group affected by brain injuries - The Military! While the data sets were limited, the research process placed us on a road that opened our eyes. A road that was built upon not only concern of TBIs for athletes, but for the general population and the military.

When compared to the athlete, the soldier needs so much more to recover. The TBI's are worse, requiring a longer period of time to recover. The extended recover time impacts life in the military and at home, thus impacting the quality of life as well as vocation, as they may be forced to retire or ultimately be disabled. The potential long-term impacts are not insignificant. Their road is one with hills. We can't help but dream of what we can do to help.

With more data, we can make a difference in identifying the injured. With more data we can build towards complete rehabilitation and treatment. And with more data we can help prepare for the financial challenges. With all the resources and companies lined up to help the athlete, as well as substantial financial resources from sports leagues and institutions...we wonder if our veterans will be treated similarly. Will we maintain the quality of helmet sensors for our soldier that the star football player receives? Will we keep a database and track impacts to our soldiers like Riddell helmet company does for the high school football player? If not, the data may just show us what we are not doing for our veterans. That is a road worth traveling one that is making a difference....welcome to Data Science.

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Big Data = Big Bias? An Analysis of Google Search Suggestions

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ABSTRACT

While Big Data can make the world a better place, blind optimism in its infallibility can cause irreversible damage to society if left unchecked. With the mission of ensuring accountability, we debunk the fallacious narratives people tend to tell about Big Data, offering a more realistic discussion of its merits and its limitations. We then explore how analytical or algorithmic bias and sampling bias, two problems that statisticians have faced since long before the onset of Big Data, present pitfalls for deriving knowledge from data. We examine how the ethical implications of these pitfalls can cause serious damage in society. We determine that effective, credible, and ethically sound Big Data analysis must obey the principles of transparency, clear and appropriate objective definition, and self-correcting feedback mechanisms. We examine case studies where academicians and businesses have tested algorithms to study how well they exhibit these principles. We then implement our own test to check for potential algorithmic bias in Google. Based on evidence that certain individuals have been corrupted in part by Google searches allegedly bias against racial minorities, we hypothesize that Google's algorithms systematically exhibit biases against minority groups. We test this hypothesis by examining how Google search suggestions associate certain negative words with names that typically belong to minority groups. We conclude that while our study alone cannot prove or disprove our argument, the evidence in our analysis contradicts our hypotheses, thus suggesting that no systematic bias is exhibited. We discuss end by discussing what the results could mean for future studies of potential algorithmic bias in Google.

KEYWORDS

i523, hid104, hid216, Big Data, Ethics, Algorithmic Bias, Sample Bias

1 INTRODUCTION: FALLACIOUS NARRATIVES ABOUT BIG DATA

Since its origins, Big Data has promised to revolutionize the world. Scholars have wisely noted that it represents a paradigmatic shift from conventional norms of data, but the public has latched onto provocative yet unrealistic narratives that deify Big Data as omniscient, infallible, and impervious to bias. Confiding in such narratives diminishes the integrity of credible science and poses serious ethical challenges, but these challenges are more likely overlooked because the problematic narratives seem to reject the need for ethical discussion.

In 2008, *Wired.com*'s Chris Anderson wrote an article that captures the general optimism with which people conceptualize Big Data. The article, with its self-explanatory title "The End of Theory: The Data Deluge Makes the Scientific Method Obsolete", argues that

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Big Data provides such a complete, infallible view into reality that we no longer need conventional methods of scientific inquiry but need only to look at what the data tell us. According to Anderson, "With enough data, the numbers speak for themselves"[1]. This fervorous optimism was further extended in a 2013 book by Mayer-Schonberger and Cukier titled *Big Data* where authors assert that Big Data is synonymous with all data. In the past, researchers could only look at samples of data with limited scope, but Big Data, the authors claim, represents not a sample but a complete set[11]. A dataset of Twitter posts is viewed as synonymous with a complete, unbiased set of all of society's thoughts. By analyzing such a dataset, they conclude that they can confidently answer any question about how all of society thinks and behaves[9].

Cheerleaders for Big Data, such as Anderson, Mayer-Schonberger, and Cukier to make five exciting but yet flatly incorrect claims: that bigger is always better; that data analysis produces indisputably accurate results; that every data point can be studied, eliminating the need for archaic statistical sampling techniques; that studying causation is no longer needed since correlational patterns tell us all we need to know; and that scientific and statistical models are obsolete, since Big Data is itself sufficient. They have tended to extrapolate from the early success of the Google Flu Trends which at the time successfully embodied such grandiose, idealistic views. The Google Flu Trends project employed a theory-free set of algorithms that studied search engine results to predict flu outbreaks faster and more accurately than the Center for Disease Control. Allowing the numbers to "speak for themselves", Google determined that the number of searches about the Flu were correlated with flu outbreaks, so they concluded that more searches could accurately predict a greater spread[9].

At first it worked brilliantly. But in February 2013, just a month before the $n = all$ proposition was published in *Big Data*, it made headlines for failing miserably, overestimating actual trends in 2013 by over 140 percent, leading Google to humbly terminate the program. The overconfidence of such an enormous dataset, viewed as a complete representation of reality free of gaps or inconsistencies, blinded them to its inherent flaws. For one, searches involving the term *influenza* are hardly an unbiased determinant of flu prevalence. They committed a classic statistical mistake by failing to consider confounding variables: the other reasons why people might search for the word *influenza*. Rather than adapting their model to fit changing patterns in the data, they assumed that the numbers could speak for themselves[9].

But blind proponents of Big Data bury the Google Flu Trends fiasco as just one not particularly convincing counterexample, giving superficial explanations that do not challenge Big Data's position as an infallible deity. In reality, such failure is the rule rather than the exception. Even Gartner, a company publicly known for pushing the importance of Big Data, estimated that 60 percent of Big

Data projects would fail[8]. But it's not just a matter of occasional success or failure; many people in all disciplines misunderstand the nature of Big Data and therefore have unrealistic expectations. The narrative of the Target coupon case shows that society still regards the potential of Big Data as omniscient even if its execution is occasionally flawed. The story is narrated somewhat as follows.

In 2012, Target had collected enough purchasing data about pregnant women that they determined a particular high school girl was pregnant. When coupons for baby care items mixed in with general coupons started showing up in the mail, the father angrily visited the store manager to complain, suggesting that the store was encouraging teen pregnancy. The manager understood his frustration and called twice to apologize, but on the second call, the father's mood was different. The father offered his own apology because Target was right. His daughter was pregnant, and Target's Big Data analytics managed to discover this before him[6].

While such a rose-colored narration fits well within the aforementioned grandiose conceptions of Big Data, a closer look shows that this successful case is overblown. While the anecdote seems to prove that Target's algorithms are infallibly accurate – that everyone receiving baby care coupons is pregnant – this is very unlikely. While the popular account suggests that Target mixes in coupons targeted towards pregnant women with other coupons to avoid spooking such women about their algorithmic accuracy, a much more credible explanation is that many women see mixed advertisements precisely because Target is unsure which ones actually are pregnant[9]. Even women who Target does suspect are pregnant have shopping interests outside of baby care items. While the algorithms help not to waste money by sending the coupons to, say, a single male adult living alone, they hardly indicate any reliable accuracy of pregnancy prediction. Of course, this is an empirical question that could be answered by researching how often pregnancy-targeted ads are sent to pregnant women versus those who aren't. But without having a methodologically sound study prove consistent accuracy, it's unwise to extrapolate from the anecdote and assume that Big Data done right is omniscient.

Critiquing the dominant reading of the Target case is not meant to suggest that Big Data has no value. Afterall, Target likely improved the efficiency of targeted advertising through Big Data by more accurately segmenting those who *might* be pregnant. But the important thing to keep in mind is that ultimately, models of the world and the data that feed them are imperfect. Models reflect the biases of those who create them, and data reflect biases inherent in sampling methods, time periods, and society in general. Cathy O'Neal, a former professor and Wall Street algorithm specialist with a mathematics degree from Harvard, observes that any model of the world "begins with a hunch, an instinct about a deeper logic beneath the surface of things"[13]. Human potential for bias and faulty assumptions can creep in. Of course, hunches or working thesis provide a necessary part of the scientific method of inquiry. Human intuition can be useful, as long there exist mechanisms by which those hunches can be evaluated and revised when necessary[13].

Perhaps the most common example of successfully wielding insightful models is depicted by the movie *Moneyball*, based on a true story. Oakland A's General Manager Billy Beane hypothesized that conventional performance metrics were overrated whereas

more obscure measures better predicted overall success. He worked with statistician Bill James to create models that helped Beane decide which players to acquire and which to let go. The once obscure method has become a staple of baseball analytics. According to O'Neal, the model works for three main reasons: it allows for transparent analysis; its objectives are clear and appropriately quantifiable; and it includes a self-correcting feedback mechanism of new inputs and outputs, allowing it to be honed and refined. Models go wrong when they lack these three healthy attributes: "the calculations are opaque; the objectives attempt to quantify that which perhaps should not be; and feedback loops, far from being self-correcting, serve only to reinforce faulty assumptions"[13].

But models are only one factor in determining the efficacy of Big Data analysis. Since the very nature of data analysis is to extrapolate from limited samples, not only must researchers realize that models include human bias, but data itself is imperfect. It's true that data never lie. But it's false to assume they tell the truth. Data by themselves don't say anything; they simply are[4]. No matter how large and complex a dataset, it is always up to researchers to interpret the data to make meaningful claims. This is the essence of the scientific method that some want to reject.

2 ALGORITHMIC AND SAMPLE BIAS: THE THREATS THAT NEVER DISAPPEARED

Humans, as imperfect beings, should never assume that our creations are without flaw and bias. In many ways, mistakes and flawed thinking can trickle into the processes we come up with. This is the idea behind the fallibility of models created by humans with respect to algorithms used for handling Big Data. Some algorithms come with biases based on narrow thinking with a broad scope to cover. Other biases come from the assumption that the Big Data set being used is representative of the population when it really isn't. In any scenario, the creator is prone to introducing bias into any given algorithm, which can make it difficult to trust the results that the algorithm produces. With this in mind and considering the importance of specific findings, there is a lot at stake here. In some cases, lives can be changed for better or worse.

Sometimes algorithms, as models laden with the biases of their creators, can unintentionally manipulate readings of data in ways that reinforce false positives. But not all algorithms are wrong. In fact, machine learning shows us that often a well-written algorithm fed with good data can outperform human knowledge on everything from chess to medical diagnosis. But there's a problem with Big Data; it's inherently messy, complex, and distorted. Contrary to popular opinion that views it as a perfect representation of reality – recall the $n = \text{all}$ proposition – Big Data is a black box where typical issues with data quality hide themselves rather than disappearing. No matter how large or complex the dataset, the old adage still remains true: garbage in, garbage out.

The Literary Digest experienced the concept of garbage in, garbage out firsthand during the 1936 US presidential election, which pitted the Republican Alfred Landon against the wildly popular democrat Franklin D. Roosevelt. Roosevelt was particularly popular among the working class, the US majority, whereas Landon resonated well with the upper middle class and elites[9]. *The Literary Digest* Tried to predict the outcome of the election by sending out surveys to its

own subscribers and by looking people up in phone and automobile registries. During the great depression, the people that owned phones, cars, and subscribed to the *The Literary Digest* tended to be more affluent and republican. After sending out 10 million ballots and receiving back nearly a fifth of them, they predicted that Alfred Landon would win with an astonishing 57 percent of the popular vote. They could not have been more wrong. Landon earned less than 40 percent of the popular vote, losing by a landslide[5]. This case has become the archetype example that data from a bias sample will lead to bias results. Increasing the volume of bad data only succeeds in producing a very precise incorrect conclusion, creating a false sense of confidence in something inherently wrong.

Although the *The Literary Digest* used lots of data, by definition their sample did not involve Big Data[11]. But if we reject the $n = all$ proposition, we can see that Big Data is still a sample and is therefore potentially vulnerable to sample bias. But while any statistically literate person can understand what went wrong with *The Literary Digest*, sample bias with Big Data is much more complicated and difficult to identify. For many people, random samples of social media data appear impervious to sample bias. Researchers conducting Twitter sentiment analyses often claim objectivity in representing the real world accurately, concluding that patterns observed in these vast, complex webs occur the same way offline. Despite the conflation of people and Twitter users, the two are not synonymous. Twitter users are by no means representative of the population. A Pew Research project in 2013 found that US-based Twitter users “were disproportionately young, urban or suburban, and black”[2]. To complicate things further, we cannot assume that Twitter data accurately represent how users behave because users and accounts are not a one-to-one relationship. Some accounts have multiple users, and some users own multiple accounts. Some accounts are just bots that automatically produce content, and some accounts are created and forgotten, going years without use. Furthermore, among active accounts, data are skewed by how some accounts dominate the discourse. Whereas some users post multiple times per day, others use the site only to view content. In fact, 40 percent of active users view content without making contributions, according to 2011 data from Twitter Inc[2]. The notions of what it means to be active, to participate, and to be a user require critical examination that’s almost universally lacking.

The aforementioned examples highlight problems with available Twitter data, but there’s also a problem with the integrity of available data. Twitter only makes a fraction of its data publicly available through its APIs. The supposed firehose of data theoretically contains all public tweets but explicitly excludes data that a user chooses to make private. Furthermore, theory does not match reality as the firehose lacks some publicly available tweets. Very few researchers get adequately full access. Research by Microsoft’s Danah Boyd and Kate Crawford found that rather than a firehose, most have access to a “gardenhose (roughly 10 percent of public tweets), a spritzer (roughly 1 percent of public tweets),” or just select access through whitelist accounts[2]. Not only are protected data excluded, but data samples are not always randomized. So, a more reasonable description of Twitter data would say it takes a skewed sample of the real world population, further skewed by how users and bots create or do not create content, and then it limits the scope of the skewed data in an often opaque, arbitrary manner[2].

Is this data useful? Without a doubt. Is the data so perfect and infallible that we need not concern ourselves with basic principles of statistical and scientific credibility because “the numbers speak for themselves”[1]? Not even close.

If an algorithm could analyze a large, random sample of every word ever thought, spoken, or written by every human throughout their entire life, we could confidently believe that $n = all$ and make a sentiment analysis that accurately captures how people feel about a certain topic without regard for methods of scientific inquiry; the numbers would “speak for themselves”[1]. But we do not, and probably never will, have that kind of data. Twitter or other social media platforms are no substitute. While understanding the fallibility of Big Data is perhaps not as clear and straightforward as the *Literary Digest* case, society must be responsible by diligently scrutinizing data. To paraphrase loosely from world-renowned consultant Meta S. Brown, the biggest problem with data analysis will always be people failing to admit that data imperfections exist, failing to look for them, and refusing to do anything constructive about the ethical implications of these imperfections[3].

3 ETHICAL IMPLICATIONS OF ALGORITHMIC AND SAMPLE BIAS

As we’ve seen, the massive failure of the Google Flu Trends caused embarrassment and wasted Google’s money. But the consequences they faced are relatively trivial, and given the company’s history of learning from the past, they are probably a better company because of the failure. But when Big Data goes awry, the consequences are not always so trivial and localized. Big Data used unwisely has very serious, irreversible impacts upon society. Pervasive overconfidence can make it harder to acknowledge and confront such impacts until too late.

Society’s current failure to address these issues is the topic of Cathy O’Neal’s book *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. She argues that these WMDs, referring to Big Data algorithms, have good intentions but often reinforce harmful stereotypes, especially of minorities and the poor, and become opaque models wielding arbitrary punishments. Through her work in the private sector, she has experienced numerous Big Data horror stories, and the book discusses several different failings of Big Data in various contexts.

One common issue associated with Big Data is the notion of self-fulfilling prophecy: the idea that expectations change reality to make it reflect the expectations. If police suspect African Americans to be more likely to commit crimes, they may patrol black neighborhoods more often and proactively hunt criminal activity. Increasing patrols increases the number of arrests, which provides justification to further increase patrols, causing more arrests, and so on. The prophecy that African Americans are more likely to commit crimes becomes adequately reinforced with their higher incarceration rates. But higher likelihood of arrest is not the same thing as being more likely to commit crimes[12].

It should be easy to see how the example of arrest rates is problematic, but somehow incorporating Big Data tends to make people fail to recognize the possibility of self-fulfilling prophecy. In fact, numerous police departments use algorithms that do just this, inadvertently instructing their officers to focus on areas with high

concentrations of blacks. Crime prediction software that attempts to adjust police deployments according to anticipated patterns fail when they confuse more data with better data. Even though they attempt to prioritize violent and serious crime, data generated by relatively insignificant petty crimes, which occur far more often in poor and predominantly minority communities, can overwhelm the system, making it prejudice. Once the petty crime data enters a predictive model, more police deploy into those neighborhoods, and they are more likely to arrest people by their sheer presence and by the perceived threat that those people pose. The increased arrests justify the deployments in the first place[13].

But the danger does not end there. Once people are arrested by these inherently discriminatory processes, Big Data can work to keep them in prison for longer. This is usually not by intention but by flaws in design. Recognizing how unconscious bias can affect sentencing decisions, courts in 24 US states have started to use computerized models to help assess the risk of recidivism, the likelihood of repeat offense. The models attempt to use Big Data to avoid a common, serious problem with human reasoning, and they certainly show some promise in this regard. But over reliance on the models can prove even worse than trusting potentially biased judges. “By attempting to quantify and nail down with precision what are at root messy human realities”, the recidivism models shroud sentencing bias in a veil of unwarranted confidence and precise accuracy that disadvantages minorities by subjecting them to harsher prison sentences[13].

How does one quantify something as complex as the risk of recidivism? One popular model uses a lengthy questionnaire that attempts to pinpoint factors related to this risk. The questionnaire inquires about things such as previous police incidents. Given how much more often young black males get stopped by the police, partly because of the aforementioned self-fulfilling prophecy, such questions easily become a proxy for race, despite intentions to reduce this very prejudice. Other questions, such as whether or not the respondent’s relatives or friends have criminal records, would be flagrant violations of court procedures and surely elicit objections from a defense attorneys if raised during a trial. But the opacity “of these complicated risk models shields them from proper scrutiny”[13]. Discriminatory police strategies feed into the recidivism models used to call for harsher sentencing, creating “a destructive and pernicious feedback loop”[13].

It is no secret that racial tension has become a dominant source of discussion when it comes to the American justice system. However, this issue is compounded with bias produced within the data itself as well. When there is a bias in how arrests are made based on the color of someone’s skin, this bias feeds into an algorithm which opens up for more bias down the road. As more people of a given color are arrested and given harsher sentences, this data builds up in the system. The root of the cause may be human bias, but there is definitely a healthy amount of algorithmic bias that compounds and builds on the issue as most algorithms lack the ability to look beyond the face value of the data provided[7].

Big Data is, of course, not only used in attempts to more effectively dole out punishments. Facing international competition, Corporate America has latched onto its potential for increasing profits through more effective marketing, financial trading, and personnel decisions. With the prevalence of the internet, social

media, and information literacy, Big Data presents an enormous opportunity for market personalizing. Rather than targeting advertisement campaigns on broad, general audiences, Big Data can segment down to the individual level, targeting people based on their own personal data and patterns of behavior. However, this type of marketing is still a very inexact science and raises tricky ethical issues, including gender bias. Like racial bias, gender bias comes about in scenarios where profiling usually happens. For instance, advertising on the internet aims to reach its intended audience in order for businesses to sell products and make profits. Big Data and the statistical analysis involved might suggest that a certain gender has specific tendencies or lean on embedded societal stereotypes which cause some serious bias in an algorithm. One example might be a job opportunity being advertised. In this case, we want to say that either gender should be shown the advertisement a near equal amount, but we know from experience and outrage that this is not the case. It is almost staggering how it would favor the male population at times, especially when dealing with high paying jobs. Here, we also have a combination of Big Data and algorithmic bias working hand in hand to create biased results that ultimately lead to insult and faulty representation[3].

Beyond marketing, Big Data has found particular popularity among Wall Street investment firms, and for good reason. The ability to incorporate Big Data into decision making has tremendous potential for profitability. But the subprime mortgage crisis demonstrated how this can also have tremendous destructive potential. Financial models exhibited a particular bias, reinforcing the idea that what has worked in the past or what works currently will continue working indefinitely. But the sophisticated mathematical models lacked self-correcting feedback that could indicate inherent flaws. Since the models were driven by the market, if they led to maximum profits, they were considered infallible. Otherwise, why would the omniscient invisible hand of the market reward it? In hindsight we all recognize that betting on the subprime mortgage bubble was a losing proposition, yet the myopic reliance on the market proved disastrous in 2008. During the financial crisis, the algorithms used to assess securities risk became smoke screens. Their complex, mathematically intimidating design “camouflaged the true level of risk”[13]. The opaque models also lacked a healthy feedback mechanism that could have identified the problem[13]. The severity of the 2008 recession shows that companies are not only accountable for their own success and failure. Their misuse of Big Data had broad sweeping effects across the entire economy.

Perhaps it is reasonable to understand why companies might get carried away in a practice that, at least on the surface level, does not appear to affect humans directly. A trader working on the top floor of a Wall Street skyscraper might not see how the work of his mathematicians might hurt or harm average people. But Big Data also plays a role in ways that very clearly affect individuals, especially with the increasing popularity of integrating technology into personnel decisions. Since personnel decisions directly impact company performance, workforce management has become popular, particularly programs that promise to eliminate the guesswork from hiring by screening potential employees [13]. Many of these programs use personality tests to try and automate the hiring process; 60 percent to 70 percent of prospective employers, according to Deloitte Consulting.

Despite the optimism, such tests face the same problem as the recidivism surveys: they try unsuccessfully to quantify and precisely measure “what are at root messy human realities”[13] The high use of personality tests goes against research that consistently shows them to be poor predictors of future job performance. They don’t provide this goal but rather an illusion of objectivity and simplicity. They generate raw data that get plugged into efficient algorithms and give clear answers, as opposed to the time consuming and obviously subjective process of human interviewing. Not only does this illusion coolly deceive companies, it leaves prospective employees disgruntled and confused by results from a opaque systems. Rejected employees don’t know if they’ve been flagged or what caused them to be. The personality tests also lack important feedback mechanisms. There is no way to identify inherent errors in the model and use those mistakes to refine the system[13]. Far too often, personality tests fail both the companies that use them and the prospective employees that get arbitrarily denied a chance.

In each of these cases, the story repeats itself where ethical issues that are normally fairly obvious become invisible when Big Data enters the picture. The argument is not that we should reject the positive potential of a reality that will only grow stronger with time. Rather, we should remain cognizant that a failure to adhere to basic principles of scientific credibility and ethical reasoning can affect people in unseen but deadly ways.

4 POTENTIAL ALGORITHMIC BIAS IN GOOGLE: THE DYLANN ROOF CASE

Sometimes, algorithmic bias can morph and distort opinions in ways that almost seem like indoctrination in nature. In some cases, it can seem like this bias can be the root of a terrible downward spiral into blatant racism, but when do we justifiably point blame at the machine rather than a person’s inner desires? In today’s society, it can be tempting to take the easy way out of tough situations and place the blame anywhere else that might make sense as long as it provides some kind of vindication. That being said, we do live in a generation that is gradually becoming more influenced by the internet and technology in general as the years fly by. With that in mind, it is reasonable to see where a flaw or bias in an algorithm can have a monumental impact in a negative way on some people. Unfortunately, there have been cases where people are significantly effected by these algorithmic biases in ways that trigger a violent disposition towards another group or race.

In 2015, a man named Dylann Roof shot and killed nine people at a church in Charleston, South Carolina. The interesting details hanging around this massacre to make it stand out were the people he shot and the line of reasoning he used to explain how he was eventually led to commit such an act. The attack was done on what was reported to be a predominantly black church which led people to label the offense as a hate crime. However, Roof’s explanation on what might have led him to that point is what makes this story stand out from other hate crimes. In an article that the National public radio published titled “What Happened When Dylann Roof Asked Google For Information About Race?” it was reported that Roof’s defense had made a case that there was more to the act than just simple racism and white supremacy[10]. The argument that the internet had a direct influence on what Roof believed and

that he was acting on the information he was being fed through other sources was being made. Roof elaborated on the subject and explained that it had all begun with the growing popularity of the Trayvon Martin case. Trayvon Martin was an unarmed black teenager who was shot and killed in 2012. After researching the details of the case and coming to his own conclusions he states in a quote in the article “this prompted me to type in the words ‘black on White crime’ into Google, and I have never been the same since that day”[10]. The article continues to dive deeper into what Roof might have encountered. Anyone who has encountered a search engine in general has been faced with the auto complete feature that provides calculated, popular options to give the user some direction. In this case, the potential algorithmic bias surrounding the racial tensions might have led Roof down the path of searching for examples of crime committed by people of color on white people. The National Public Radio itself reported that they tested out Google’s search engine by typing out the beginning of the phrase Roof mentioned and they were prompted with the auto complete option of the exact phrase before they could even type in the word white[10]. Even today, you can perform the same experiment and come up with the same results.

Unfortunately, the main factor in driving this algorithmic bias is popularity and relevance which are hard variables that are difficult to counter and account for in most cases. This means the objective of removing the type of algorithmic bias that Dylann Roof encountered would be difficult and require a major change in how search suggestions and results are calculated. However, this needs to be discussed and changes need to be made or more people will continue to be influenced negatively by algorithmic bias which would put more lives at risk down the road. After all, Roof was only seventeen when he began down the line of thinking that led him to commit those murders. There are numerous children and young adults that have unlimited access to the internet and are wide open to the same influence. So, preventative measures need to be taken in order to assure that we do not see similar stories surface. In order to get that done, there has to be some kind of analysis of bias within specific algorithms to understand them and create ways to account for this bias. If unchecked, not much can be done, but the knowledge from understanding the potential bias in these algorithms could prove invaluable.

5 CASE STUDIES IN CHECKING FOR ALGORITHMIC BIAS

Before we can test for algorithmic bias, we have to have a grasp or understanding on how typical algorithms implemented in concepts such as prediction work. In many fields where predictive work is being done in research, there is a common use of natural language processing algorithms such as Support Vector Machines, Neural Networks, and Naive Bayes. Each algorithm uses a specific type of processing that makes it stand out from the others, but the different aspects to each come with advantages and drawbacks that make each one valuable in certain circumstances. However, it is the internal structure of what makes up the algorithm that allows for bias to get in.

5.1 Support Vector Machines

A Support Vector Machine is a supervised learning model that is known for the analysis of data for classification and regression. This algorithm is much better at classifying problems than normal logistical regression, and it always converges to a global minima when classifying data. However, this algorithm can be complex especially when the data isn't linearly separable. In the case that the data set being used is non-separable, the data can be transformed using a kernel function, such as a log function in some cases, in order for the algorithm to fit the data and classify correctly. The main bias that we can see from this algorithm is in the case of it classifying data to the point where patterns form based on things like popularity and relevance which could lead to something similar to what we discussed in the case involving Dylann Roof. Since Support Vector Machines are supervised learning models, any bias can be accounted for in the manual make up of the model because it does need some direction. In that case, bias might come in the form of human error though.

5.2 Neural Networks

Neural Networks are algorithmic models in which weighted inputs are fed into a function to compute an output. In a predictive setting, Neural Networks are fairly flexible in structure which allows it to be applied in many scenarios. In this type of model, we can expect to utilize logic gates in order to understand how certain scenarios must be weighted to account for a specific outcome or result that we want. If an outcome relying on three variables hinges on a specific variable being untrue and requires at least one of the other variables to be true, we would assign a higher weight to the first variable than the other two because that one variable to ruin the outcome. We can see how this type of modeling can be used to model complex predictive problems and could possibly be used in a search engine if desired. Based on input strings that make up common and popular words and phrases, we could make an auto complete function using neural networks to put weights on certain inputs to predict the possible resulting desired search for the user. Unfortunately, placing weight on certain inputs and pieces of the function can inherit some bias along with it. Even if those weights aren't manually decided, popularity and relevance can have a large impact on calculation of weights which would still lead to some bias down the road. In the search engine example, this would lead to people being influenced to search something based on the beginning of their search query.

5.3 Naive Bayes

The Naive Bayes classifier is a probabilistic model that applies Bayes' Theorem that makes predictions based on a set of training data consisting of predetermined features. However, Naive Bayes places the assumption on the features that each one is independent of the other. Although this stipulation does well enough in real word situations, this assumption can hold it back from working in more complex situations where features are highly dependent on one another. In the world we live in today, we rarely encounter situations in large data sets, especially in Big Data settings, where the features involved are independent. This strong assumption of independence here is where the source of a decent amount of

bias could come from when using this algorithm. Because of this, there is a limitation to how well one can make predictions in more complex situations. After all, Naive Bayes is a probabilistic model, but probabilities tend to rely on a multitude of varying factors which may include the influences of other features involved. With this in mind, we can see how the results may be skewed or flawed, but how exactly does that introduce bias? Other biases can come within and there are undoubtedly some in this algorithm, but another major source of bias can come after the work is done. A critical piece comes from the analytic interpretation of the results. If the probabilities are flawed, then the conclusions made from the results could be flawed as well. In this case, we would call it analytical bias. Even though this type of bias isn't an internal problem of the algorithm, it is a byproduct of it in the end result.

5.4 How to Check and Account For Algorithmic Bias

After getting to know what kind of algorithms we are working with and what kind of biases can arise from them, our attention should naturally gravitate towards ways we can check and account for these biases. In some of these algorithms, we can recognize and pinpoint potential biases based on how it acts and the conditions set, but we can also account for a lot of it since Support Vector Machines and Neural Networks are, for the most part, supervised models. This means that some of the biases stem from some programming error which can be accounted for by fixing and tweaking the algorithm. This works for these models because there are main points such as variable weighting and classification in Neural Networks and Support Vector Machines respectively. However, the Naive Bayes classifier is a little more ambiguous. This algorithm struggles with over fitting the data which means that it caters too closely to the data set and prevents it from effectively predicting and adding future data points. In this case, more bias or alteration to the model may be needed to find an equilibrium and allow proper analysis. This requires that less influence be put on handpicking features and allow for a hands off approach. This is often considered soft feature selection in data analytics and is a way of removing the harshness of imposing desired features. With all of this in mind, it is near impossible to completely remove the influence of bias in any given algorithm. There will usually be a flaw somewhere no matter how hard we try to create a perfect model. This is clear when looking back on the Dylann Roof case study about Google algorithmic bias. In the same article, Google indicates that they are aware of biases in their algorithm and that they have worked on eliminating and fixing the issues[10]. Even with this awareness and implementation of fixes, we need data and analysis to help us evaluate how well Google improved their algorithm. This was one of our many motivations for testing Google's search suggestions for bias.

6 OUR CASE STUDY: TESTING GOOGLE FOR NEGATIVE SEARCH SUGGESTIONS BIAS AGAINST CERTAIN RACES

Based on the observed need for scrutinizing algorithms and inspiration from researchers who have successfully done so, we devised an experiment to test Google's search suggestions for potential

bias against names associated with particular races. In the following sections, we discuss our methodology, our hypotheses our algorithm, and our results.

6.1 Methodology

Building off of several researchers and the anecdotal record which have identified cases of bias against certain names, we decided to test for such biases by identifying how negative word associations correlate with searches for particular names. We decided to look for instances of the words associated with *arrest*, *murder*, *crime*, *homicide*, and *prison*, including the words *arrested*, *arresting*, *arrests*, *murderer*, *murderers*, *murdering*, *crimes*, *criminal*, *criminals* *criminality*, *homicides*, *homicidal*, *prisoner*, and *prisons*.

Since we expected these associations to carry bias based on race and ethnicity, we decided to use data that separated names into racial and ethnic categories. To make as objective of an assumption as possible regarding which names were associated with which race, we used data from the 2010 Census that identifies what percentage of people self-identify with which types of names. This allowed us to classify a name as belonging to a certain racial or ethnic group if most people with that name identified under that race. However, one complication of using Census data is that we only had access to surnames. Whereas, based on intuition, a person might be able to distinguish a predominantly Black first name from a predominantly white first name, this is much more difficult for surnames. However, whereas black and white surnames are less distinguishable, Asian and Latino or Hispanic names are much easier to identify because they are usually not based on the English language. For these names, we can be confident that Google recognizes the name and can make associations based partly on these racial and ethnic identities.

Given that the central argument from our qualitative analysis of Big Data suggests that Big Data analysis often has inherent flaws, we determined that avoiding many of the common pitfalls observed with such research should be a top priority. We wanted to study something with which we could be completely confident that the results reflect the true nature of Google's algorithms, whether they support our hypotheses or not. For this reason, despite initially considering it, we decided to avoid studying web page data for such information. Data from web pages would have been problematic because it is difficult to infer the context behind word associations. Simple word counts could create potential false positives. For instance, if a web page from the search *Mueller arrest* uses the word *arrested* n amount of times, it could be an arrest record report for someone with the last name Mueller, a decidedly negative view, or it could a page talking about the people arrested by order of former FBI director James Mueller. Since our study depends on isolating not only words but negative associations, this lack of context introduces an irreconcilably high level of uncertainty: it would be far too difficult to determine which sites held negative views of the particular name and which ones had positive views. For this reason, we decided instead to look at search suggestions. Google's algorithms play the central role in search suggestions, and the simplicity of the searches largely eliminates the problem of insufficient context. By just typing in a name and the first few letters of a search term, we can be more confident that whichever

suggestions are revealed reflect clearly distinguishable sentiments (negative or positive) regarding the name itself.

6.2 Hypotheses

Given the anecdotal evidence and from a history of racial and ethnic bias in the United States, we expected to see a bias toward and ethnic minorities. However, we expected that words associated with criminality would apply much more to Blacks and Latinos than to Asians. Therefore, we hypothesized the following:

H1: Surnames that most often identify Black people will, on average, have more negative word associations than names which most often identify White people.

H2: Surnames that most often identify Black people will, on average, have more negative word associations than names which most often identify Hispanic or Latino people.

H3: Surnames that most often identify Hispanic or Latino people will, on average, have more negative word associations than names which most often identify White people.

H4: Surnames that most often identify Hispanic or Latino people will, on average, have more negative word associations than names which most often identify Asian and Pacific people.

H5: Surnames that most often identify White people will, on average, have more negative word associations than names which most often identify Asian and Pacific Island people.

6.3 Algorithm

The coding for our analysis was conducted with Python 3.5.2. The necessary import modules include: *requests*, *json*, *csv*, *urllib.request*, *matplotlib*, *pandas*, *scipy*, *numpy*, and *timeit*, all of which we installed using *pip install*. We gathered the data for our project from the website for the 2010 Census. Their .csv provided us with a list of 162,254 surnames. We read in the file, which is posted in our github account, using *csv.DictReader*. We isolate the name and race/ethnicity columns. For each name, the race/ethnicity categories include the percentage of people that identify as part of a particular race or ethnicity. Because increasingly obscure names are likely less identifiable, we decided to use only the first 500 names. None of these 500 names were predominantly multiracial or predominantly Native American, so these categories were excluded from our analysis. We created a dictionary with the analyzable categories, *pctwhite*, *pctblack*, *pctapi*, *pcthispanic* and sorted the 500 names into the appropriate categories using a series of *for loops* that checked for the highest percentage.

We then move to the main goal of the experiment: capturing Google search suggestions. Using Mozilla Firefox 5.0 as a user agent, we use a url that automatically outputs a two-dimensional list with the search term and ten Google suggestions. We then define a function to modify the url for each search term and for

every name. When, for a given name, a search suggestion contains one of the target words described in the methodology section (arrest, crime, homicide, etc.), the function adds a point to the name's value. We run the function five times for each target word, creating five dictionaries that store names as keys and the number of negative word associations as values. We add the five dictionaries to a list that we can iterate through. This section involves a lot of searching, so we use `timeit` to make sure it runs efficiently. It typically takes about 200 seconds to run with 8 gigabytes of ram and an Intel i7 processor with 500 names, so we estimate that this step would take about 65,000 seconds or over 18 hours to run with the full data.

Now that the search results are appropriately organized by name and by search term, we need to calculate the scores for each race/ethnicity category. We create two dictionaries for each of the four race/ethnicity categories, with search terms as keys and values defaulted to empty lists. For each pairing, one will be later converted to averages and the other will stay as raw data. We then define a function that will appropriately fill the values so that we know how many negative word associations go along with each search term for each race. As inputs, the function takes the name of the racial/ethnic category, the name of the dictionary for that category (from the four we just created), and the list containing the five search term dictionaries we created earlier. The function uses three for loops to iterate through the various dictionaries and lists to match names with their racial categories and add the values to the scores accordingly. We run this function eight times in total for the four pairs of dictionaries.

To calculate the aggregate word associations for each racial category, all we need to do is sum the values of each key for each dictionary. However, to be completely sure that the function for the previous section worked properly, we implement a set of for loops to calculate the aggregates instead of just summing the dictionary values. We create a dictionary with keys set to the racial category and values defaulted to zero and allow the for loops to calculate the proper scores. We also create a dictionary with racial categories as keys and empty lists as values. We append the numerical values for each word association to the empty list. With the data arranged as such in raw form, we are now able to analyze more measures of central tendency, including the median and the 1st and 3rd quartiles. This data arrangement enables us to create the box plot displayed in the results section. Now, for every pair of category dictionaries, we use one of the dictionaries to calculate averages of the aggregate data so that we know how many negative word associations go along with each name and each search term on average.

As a final data preparation step, we are now ready to conduct statistical analysis through a separate .csv file. We write out the data name-by-name to a .csv file by using a series of *for loops* that arrange the data row-by-row grouped by the race it belongs to. The *for loops* arrange everything into a long string with new line characters to separate where each row should be, and then we write it out in one step. From there we read in the new resultsdata.csv file with `csv.DictReader` and sort the data totals data into numpy arrays by racial/ethnic category. We then conduct two sample t-tests to compare each array to calculate statistical significance. With this step, we now have all the data summarized and organized as needed and can move on to creating a bar chart, a box plot, and a series of radar charts using matplotlib. Details on how to recreate these

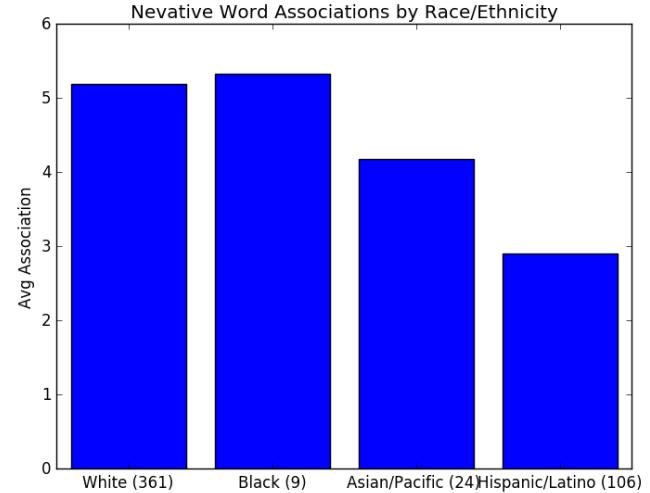


Figure 1: Bar chart comparing average word associations by race.

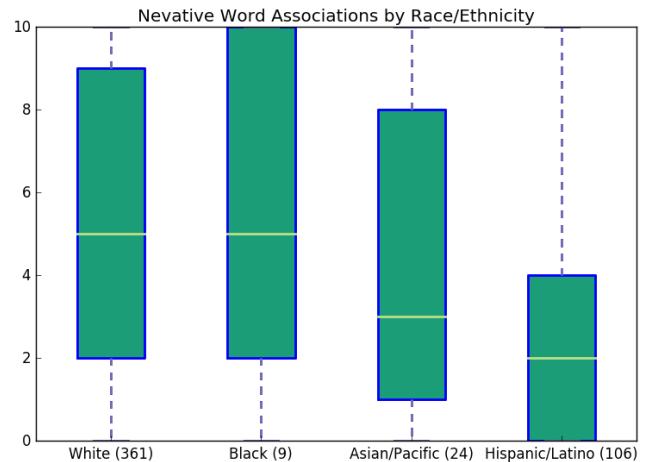


Figure 2: Box plots showing distribution of average word association by race.

visuals are available on the Jupyter notebook on our github project folder.

6.4 Results

While we had qualitative data that suggested Google's algorithms could be biased against Black and Hispanic/Latino minorities, the results do not support most of our hypotheses. Regarding H1, while Figure 1 and Figure 2 appear to show that Black surnames do have more negative associations than White surnames, the results were not statistically significant at the .95 confidence level ($p > .85$), so we conclude the null hypothesis in this case. This lack of statistical significance is likely due to the very small number of Black surnames (9) compared to White names (361) in the top 500.

Comparing Blacks to Hispanics with H2, however, Figure 1 and Figure 2 do clearly support our conclusion. The difference in means is about 2.4, and this difference is significant at the .95 confidence level ($p < .002$). With a mean of just 2.9, the average negative associations for Hispanic/Latino was actually the lowest in the data set, so H3 was not just nullified, but the exact opposite is true with statistical significance: White names had more associations than Hispanic/Latino names. Hispanic/Latino names also had fewer negative than Asian/Pacific Island names, so we also reject H4. While Asian/Pacific Island names did not have the lowest amount of negative associations, the group did have significantly fewer than both White and Black names, so we can confirm H5. H5 and H2 were the only hypotheses that were supported by the data; H1 was nullified, and for both H2 and H3, the opposite was shown to be true. Given that our hypotheses were not supported, we cannot support our central claim that Google search suggestions would have inherent biases against Black and Hispanics/Latino surnames based on negative word associations dealing with the identified search terms.

Along with our other visualizations, we included a few radar charts showing the distribution of negative search results based on the word we focused on, as seen in figure 3 and figure 4. One with the four races separated into their own chart and the other with all four races overlapping in one radar chart. The idea behind this observation was to get an idea of which words impacted the negative results the most. The charts do not have a significant impact on our original hypotheses, but are there to just give us general insight into the data. However, by observing the charts, we can see that the three most negatively associated search words across all races were crime, arrest, and prison in no particular order across all races.

7 DISCUSSION

While our results did not support our assumptions, this does not necessarily mean that Google does not exhibit any forms of algorithmic bias. However, it does suggest that, Google is probably quite aware of accusations of bias, like the ones following the Dylan Roof case, and has taken active steps to minimize such bias. It could also mean that just analyzing surnames instead of first names is too generic for Google to recognize racial differences, or perhaps that our search terms did not accurately capture common negative word associations that people relate to certain races. In either case, these provocative results establish the need for more complex algorithmic bias analysis to continue holding such algorithms accountable and rewarding ones that effectively minimize bias.

ACKNOWLEDGMENTS

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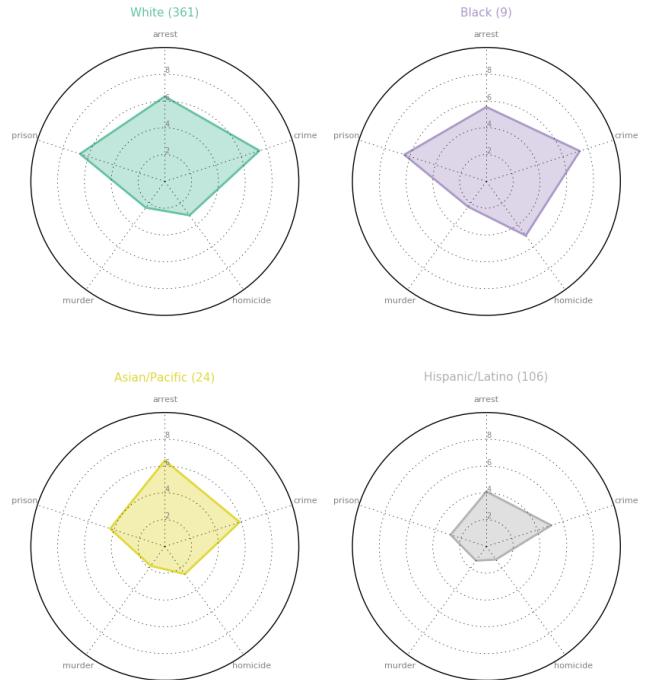


Figure 3: Series of radar charts showing average word association by race and by search term.

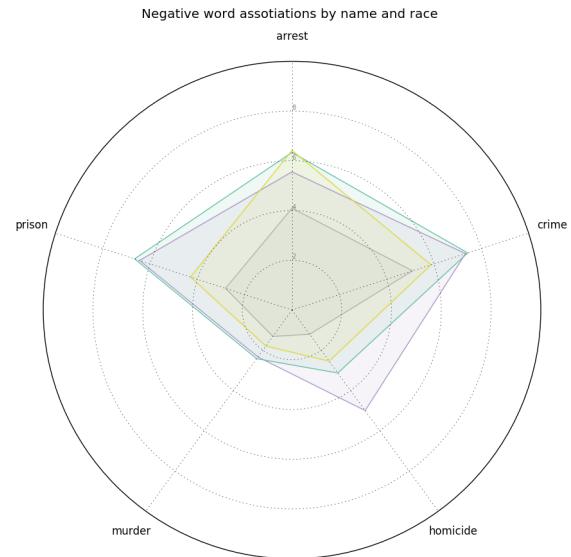


Figure 4: Consolidation of the previous four radar charts into one image that shows how each race compares.

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Big Data Analytics in Support Filtering Wrong Informations On Social Networking Sites

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ABSTRACT

In an era of information, people are more likely to get information from the ciber world. Due to the conflict of interest, many organizations hire “Spammers” to post a mass of wrong comments under some famous person’s post on Social Networking Sites for control the trend of public opinion[2]. So when user want to see the public opinion under some famous person’s post, they usually get the wrong information which doesn’t represent the real public opinion. Big Data analytic can provide information filtering to screening the fake comment based on data mining technique, and let the user be able to see the true of public opinion on social networking sites.

KEYWORDS

523, HID 107, project, big data, weibo, spammers, data visualizationThChina

1 INTRODUCTION

In highly informatization modern society, internet especially for social networking website carried mass information data. Along with the growth in users at social networking websites, social networking website become a platform which content infinite potential business opportunities and interests. Famous social networking website like Facebook and twitter already became leader which can drive the public opinion direction. I think the influence by social networking websites is completely different than traditional social media, social networking websites are more emphasize on audience’s acceptance and follow suit. For example, some politician announce some idea on news paper and TV news, the influence from it only work when it can make arouse sympathy to the audience, which mean it only work when the audience think it make sense for them. But social networking websites are difference, Seiter mention that“ Comments are a powerful emotional driver. Make the most of them by engaging often with your Facebook community and replying to fans’ comments to keep the conversation going.”[?]. Social netorking website can make the user believed their opinion by drive their user follow the crowd because people love to view the comments and post comment, “A previous study showed that 45% of users on a social networking site readily click on links posted by their fifriendfi accounts, even if they do not know that person in real life” [?]. For example, the President of United states Trump really like post his opinion via twitter, we can see lot of people post comments under his tweets, and also many people retweet his tweets. According to Seiter’s statistic, “to let others know what I believe in and who I really am (37%)” [2] is place on the fourth position at social website seeking primarily ranking. This draw a conclusion that if people saw retweets or comments from some Twitter who they believe that twitter is believable, people

will believe the retweets and comments from that twitter is making sense for them. Furthermore, the power of comments under the hot tweets is really powerful because making comment make user no longer be a spectator, they are actually involve into the event and be part of the society. Then, the comments with most retweets will gain people’s trust, and making people think that comment is represent the main strain. So this is how social networking websites impact the main social opinion trends.

2 THE ADVERSE EFFECT FROM SPAMMERS

The social opinion trend at social networking community will drive personal and even company decision, then some trends might harm someone’s benefit because the power of social opinion trend is so powerful. Then people hired spammers to spread wrong information that lead the trend become advantage for them, but the users are become victim because they will make wrong decision because of the trend is control by someone on purpose. “Brown showed how it would be possible for spammers to craft targeted spam by leveraging the information available in online social networks.” [5], every spammer post must for some reason that beneficial for their employer, the most famous case for spammers the shampoo case at 2010. ”BaWang shampoo” is the most famous shampoo at China which advertised by super star Jackie Chan, ”Next Magazine” post a fake news claimed that using ”BaWang shampoo” could cause cancer [3]. I clear remember at that time, almost all social websites post new claim ”BaWang shampoo” is harmful at the same time without any authority judgment, and they put this new at the headline position to abstract user’s eye-ball. Even the authority department proof this new is unreliable, the business reputation of ”BaWang shampoo” had been damaged, lot of people around me stop using this shampoo any more. This case seems have no spammers involved, but actually the spammers for this case is social networking websites themselves instead of single person. The reason why they post slander is because they can get benefit from other shampoo companies in china, other shampoo companies can have more sales because the market-share of ”BaWang shampoo” will be decrease at this case.

The other reason why spammers getting so popular at social networking website is the operating cost of spammers is supper low. Try searching ”buy Facebook like” at Google, and there are over hundred million results come up. And the price of buying like and followers from that website is pretty low, so spammers can get an account with 1000 followers which look like a real account for only 5 dollar [6]. So spammer can create thousands this kind of fake account for posting the wrong information at social networking website, and the detected system is hard to find out those kind of account is real account or Zombie account those accounts have actually followers and like, even feeds. Then spammers can

use script to post batch of wrong information via those account. Furthermore, the cost for post batch of wrong information is unbelievable low; according to the internal information which provided from my friend who working at a IT company, there two ways to post wrong information at social networking website, first one is money reward system, second one is posting AI. For the reward system, a professional spammer company usually have about 10 teams, each team has 500 people; They use reward instead of constant salary, each feed related to the order topic is worth 0.5 Chinese dollar(equal to 5 cent in dollar), and each comment on the target feed is worth 0.2 Chinese dollar(equal to 3 cent in dollar), and the price of long text post is negotiated. The spammers accounts are provide from the company, the price for those account is also low; Most social networking websites only require email address for registered, then they buy email accounts from the retail like 100 Chinese dollar(equal to 15 dollar) for ten thousand accounts, and using script to register social websites accounts and making follow with each fake accounts. This is how they operate the spammer, now most social networking websites register require phone number verify, then they working with local sim card retail which infinity phone number on hand, but the price for each fake account is increase a lot like 3 Chinese dollar(like 50cent) per one, but still pretty cheap compare with other advertise way. Cheap labor force and the development of script technology rising the spammer company, but the lower the user experience at social websites because lot of trash information full of the social websites, people are hard to see the true at social websites any more. According to the network sites worldwide ranking[7], we can see WeChat has almost twice active user than Weibo, and WeChat is the most popular social networking app in China because spammer can not do any at that app. In WeChat, they post feed at the module which call "Friends circle", the feed formatting is pretty similar as weibo, but the app is semi-closed which mean it is complete private, user can only see their friend's post and the comment, no retweet allowed, and if someone who not in the user friend's list comment at user's feeds, user can not see that guys comments. Plenty of users quit traditional social networking website, and the semi-closed social networking app is getting popular, so the adverse effect of spammer is not only for the spam target but also for the platform. If we let spammer keep development, and don't have any way to filter their information, the traditional social websites will die soon.

3 BACKGROUND

According to the worldwide statistics data, "Sina Weibo" has 368 millions active users which more than 328 millions of twitter active user [?], so I would like to use "Sina Weibo" as my investigate target instead of using Twitter. The other reason why I choose "Sina Weibo" as my investigate target is because I'm familiar with Chinese culture and I have been using "Sina Weibo" for more than 8 years. I think my knowledge about "Sina Weibo" will help me a lot at this project and better understand how spammers works at "weibo". The page frame at "weibo" is pretty similar to Twitter [figure1].

The four buttons under each feed are "collect, retweet, reply, like", and the capability for each button is same as twitter. When user click into the "rely" button, user can see all the comments



related to the current feed, and sort them by the amount of "like" that comments get from other user. The only things different at "weibo" is user not only can see the comments but also can see the retweet information, twitter only allow user to see who retweet the feed. Then user can see the retweet's comments and sort the list by the retweet's times of the retweet feed. So people would love to check the retweet list to see which famous person retweet the feed, and what comment they put into the retweet. Spammer control the public opinion trends by putting wrong information that doesn't represent real public opinion into the comment for some hot feed, they utilize user's habit to reach their goal.

4 RELATED WORK

There are many researcher done previous research about how to distinguish the authenticity of information that post on social networking websites. Kr point out the user's social networking structure and the user's feed can represent the credible of the user, and kr using different order algorithm to rank the credible order based on the user's social networking structure and user's feed, and use it to judge the user whether is spammer or not [7]. According to Liu's idea, personal information source is really important for judge the source is reliable or not, like the user register time, the user operating frequency, and the relationship between the user and comment target will be three factors for supervise fake account [17]. In lou's article, he mention that we need to analysis the content and feed for judge the reliable level of information, he also point out the if only investigated the comment, retweet for detect spammer, it is hard to reach automatically fast and accuracy result, which mean it still require operator to control the analysis application [15]. Xu has really unique investigate area, she investigate the spammer in online business platform, and her idea can be work on social networking website [14]. In her article, she focusing on the speciality of spammer's behavior in online business websites, she collect sixty thousand comments and thirteen thousand product

information that related to those comments at Amazon, she use those data to analysis the characteristic of user behaviour and set up a classifier for different characteristic of user behaviour; she also use the relationship between different spammers to improve the level of accuracy for detecting spammer.

5 METHOD

The method for Filtering spammer's Information at social networking websites can be divided into two part, first part is collecting data and the second part is produce data. Collecting data is the main part at this project because any analysis must base on the data, if the application can not collect the target data from third party platform, then is no way to start analysis.

5.1 Data Collection

Using python 2.7 to collecting data from Weibo, and using the official SDK as my accessed method. First, setting a feed as the investigated target, I using https://weibo.com/5305999252/Fy0sio7nQ?from=page_1005055305999252_profile&wvr=6&mod=weibotime&type=comment this feed to investigated the comment content. The person send this feed is my favorite gaming live streaming player, his name is LuBen Wei. He is the most popular gaming live streaming in China, there are over four million audiences what his playing game every night. Moreover, this is his second account, so he always post some feeds that can not be post at his official account at Weibo, but there are still thirty thousand comments under this feed , the number of comments at this feed even more than the comments under every signaler feed from Donald J. Trump's account. And the feed's content is he complain about the cheating case, he announced that he never cheating at "PlayerUnknown's Battlegrounds", he claim that the rumor about his cheating is come from the spammers. After he post this feed, this feed became the top 1 hot feed at the feed ranking at Webo, and most comments under this feed are abuse him cheating. So I thought there are must be spammer working under this feed, the comments at a feed from a gaming live streaming player's second account is more than the comments from United states's president's feed which is so ridiculous. Therefor I think there must be spammer involved into this feed, that is how we pick up the feed which involved spammer in social networking website. If a feed has unusual comments and likes amount compare with other feed post from the owner, that feed have huge possibility that involved spammer work.

First of all, Weibo require we use Weibo API with authentication, so we need to create a personal application first at the weibo application apply page [13]. Then the weibo official suggest us to use SDK to access the the API, so I came to the sdk websites [8] to get the Weibo SDK package. Normally can just type "pip install sinaweibopy" to install this sdk package to python, and also can download the sdk package, and put the webo.py with the py files I using to collect data into the same fidder to use this sdk. I using the second method becuase I have issue pop this sdk. User can get the direction of how to use sdk via the weibo sdk wiki page [10], they provide many tutorial about how to use sdk on different environment not only for pyhton. For using Offical sdk, we need to use the "app_key" and "app_secret", we can find those code from the application page which I create the app apply before using my

account. Those two codes are represent the user identity of who using the API, so weibo will ban the user's weibo account if they do something bad via weibo API because those two codes are directly link to user's weibo account. For getting the autorized for using the weibo API, I using Thinkgamer_gyt's idea to get the authorized code [9], Weibo using OAuth 2 to check the user identity for using API. After the authorized page pump up, enter code which from the page url link which look like <https://api.weibo.com/oauth2/default.html?code=2024222384d5dc88316d21675259d73a>, and the code we need to enter is the string that after "code=" at the url link. ; then weibo will return an the access token for the API, then we using "Client" to activate the API, so we can get our target information via "Client".

After finishing open the API, the next step is to allocate the target feed page. For target the specific feed, we need to find out the id for each feed. Weibo is pretty tricky, they hide the real id and replace it as some codes at the feed URL, so we need to decode the Url to get the real feed id. https://weibo.com/5305999252/Fy0sio7nQ?from=page_1005055305999252_profile&wvr=6&mod=weibotime&type=comment this link is my target feed link, take a look on the link, we can find out the the code before the question mark is pretty much look like the encryption feed id. Xuebuyuan find out the encryption rule for feed id [16], based on his idea, each four characters from back to front is a group as sixty binary, and switch those sixty binary to ten binary and then link them together. I using his code to decode the feed id at the ipython notebook, so user want to change their focus feed, they can enter the different codes from their focus feed's url, then they can get their feed id.

Once we get the feed's id, we can use this id to allocate the target feed at API. The next step is to get the target information we want to analysis from the feed. We are looking for the comments information from this page, so we need to know the code about the API port for our target information. Weibo provide a API port instructions to guide the user how to access different information via API [12], the access port we are looking for is comment. The code of comment port can not directly use at python, then use dot instead of slash for the comment for fit the python coding rule. Then following the access port guide, setting the parameter like feed's id, the number of page we want to have for the comment, and the number of comment we want to have for each comment page. For here, I only set up return 200 comments from page one because set limited usage of API for each account, so each account only get 2000 comments via API if the account is using free API connection, I don't want to use all the attempts chances at once. Then we use the access token which we got in the previous section to open the API and active the data port we set up for the target information. Finally set a variable to storage the data which return from the comment port.

The last step for collecting data is to storage the target data as txt file. All the data that related to comment are saved into the variable now, so if we want to get our target return object from this data set, we need to use the special code for different kind of category inside this data set; Weibo also provide a specific instruction for the code of return object [11]. The data we need for wrong information filtration are the content of comments and the user information for each comments, the numbers of follower and the number of friends for the user who post the comments, also we need to get

the number of feed that post from the user who comments the feed. Then use special code "follower_count", "FRIENDS_count", and "statuses_count" to get those information, and save them into the txt file for next step data visualization. The reason why I save my target date into txt file because of the coding knowledge shortage, I don't know how to using the data analysis model at 2.7 python version, so I decide to using Python 2.7 to collecting data and using python 3.5 to do the data analysis.

5.2 Data visualization

The data visualization in this paper will be simple and straight forward, because of even I have some idea to analysis the data, but I can not represent it due to coding knowledge shortage. The models I decide to use for this data visualization are matplotlib, nltk, wordcloud, pandas, numpy, jieba and codecs. First, open the content.txt file at python and using readlines and appends to create a list that content all the comments. I intend to use worldcloud to visualize the words that has most frequence on the comment list, and I find out the worldcloud don't support chineeses really well, so I use the module "jieba" to reproduce the comments list. Jieba is the best module to support Word Segmentation, wen can using this module to pick up the words which most frequently appear at the comment list[4]. I using FontTian's formatting as my main structure of jieba code [4], also we can add some new word into our word list and use it to make the jieb module can be able to indentify the new world, and we use "stopwords_path" to filter the common word like "hello", and the we are using outside txt source which is Chinese vocabulary words out file as our stop word dictionary [1]. And during using this stop word file inside the jieba code, we have to encoding the file to "utf8" formatting, otherwise it will have some error that the jieba module can not distinguish the content inside the stop word file; also we need to set up the right font for the wordcloud by using the ttc file from the fonts document on the computer, if the font use on wordcloud doesn't support chinese, the final result will be a retangle for each word instand of actually Chinese.

The first outcome I got from the word cloud is look like this: So

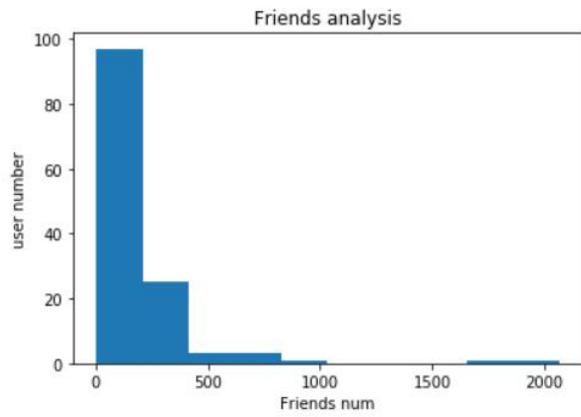


now people can really quickly have a pretty idea that what is the main trend of the comments, and what is all the comment talking about. But we can still find some noise inside the plt, like "fhh" which means reply. It doesn't contain any meaning, so we can add this word to our stop words list, then we try to create world cloud again, the new plot is look like this: It seems more meaningful than before, and contain more information than before. So we can see that their lot

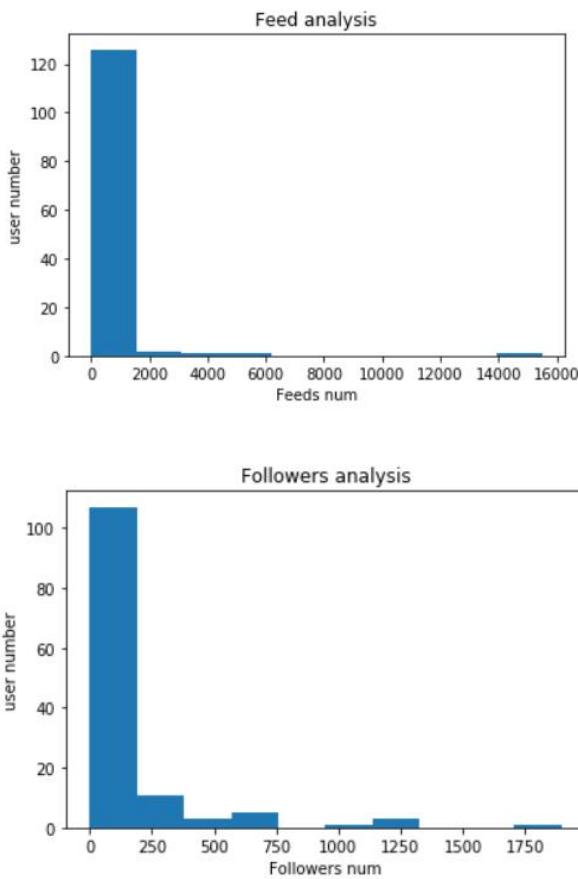


of words like "fhh" inside the comments data is useless, then we can add those word into our stop words list to rip it up. Also we can use this method to filter the spammer's information, so the user can see the true information from the word cloud.

Then for detecting the spammer, analysis the user who post the comments is very important. To visualize the user data, using readlines to open the each txt file, and using solit and strip to reproduce the data formatting. Then putting all the data into the dataframe via pandas modules. When I look at the data type in dataframe, I found out that the data type inside the dataframe for each catory is not number, then I use astype to change the data type to number for calculator. Here is the three histograms I plot out for the the Feeds, Friends, and followers data:



The result is pretty interesting and surprise for me. The data represent those three histograms are pretty obviously, even the number of my sample is only 200 comments because of the limitation of weibo API. We can see that all the histograms are right-skewed distribution, according to the definition of histogram, the mean at right skewed distribution is the peak of the right side [1]. It doesn't look like normal because of the curve is not bell shape, if this data is from the real commets which mean post by the actual user not spammer, the curve of this three histograms will looks like normal distribution. The peal of those three histograms show us the majority of those three elements, for the number of friends, the majority is between 0 to 250; for the majority of feeds is between 0 to 1800, and the majority for followers is between 0 to 200. we can see most majority are fall into the first interval, which mean it represent the friends, followers, and feed from the accounts I



pick are pretty much same type of fake account. So it is pretty luck that I can dig out so much spammer account with small number of simple, so there no doubt that their are lot of spammers involve into this feed's comment because the comments post by the majority accounts are pretty much same type of account.

6 FUTURE WORK

The above sections bring out the idea about how to detect the spammer, and the method is pretty sample because of it just to use for proof my idea is feasible. To rise the filter wrong information to the big data level, we can using database to storage our data instead of storage the data into a txt files. We can make a connection between API and mysql, and the programming will automatically storage the data inside each table for different data category. Also the authorized code can be automatically get from the authorized page, so user no need to enter it by hand. All the analysis will be integration into one application, so user only need to copy and paste the feed link that they want to see the true for that feed, and the application will decode the feed id and collecting all kind of data into the mysql database. For collecting huge size of data like over ten thousand comments, we can using different virtual machine to get data from the API, so we don't need to worry about the daily API usage any more. Furthermore, using machine learning to train a model that can recognize the most frequency word that spammer use to post the wrong information, and use it the find

out the spammer on the comment list. Finally, according to the comment list data analysis, save the user name which are define as spammer in database, and then remove the comments that related to those user in the comments content list, use this new comments content list to create wordcloud to represent the true trend and focus point for user's target feed. Moreover, the spammer data on the database will be cumulative, so the application analysis more fee, the spammer list will be increase, then each time the application can remove the comments which post by the spammer on the spammer list before analysis the spammer on the comments list which can improve the precision ratio of eliminate spammer information a lot. I think big data is based on the data precipitation, so most big data application won't have good performance at the begin because lack of data, when the application produce and save data until certain level, the performance the application will be increase.

7 CONCLUSIONS

The power of social opinion not only effect the ciber world, but also have great impact on real world. Therefore, it is really important to let the user in ciber world getting right information for the content that they are interesting in; the best way to achieve this gold is using application that base on big data analysis to filtering the wrong information that post by the spammer. There lot of ways to filtering the wrong information, but the collecting related data are always same, because no matter using which way to analysis the data, getting data is top priority than any things. I believe current technology can support big data storage really well, when the data storage reach certain amount, we can use it to decontaminate the ciber world, and maintain the ciber world envirnment that allow people gain real information and create real social relationship on it. Therefore, improve the accuracy and adaptation for spammer will be meaningful to investigated.

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The Importance of Data Sharing and Replication, But What About Data Archiving?

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ABSTRACT

With the increase of digital information, scientists have faced many challenges when it comes to the topic of big data management, including data archiving and data sharing. While it is unproblematic to share and archive quantitative data, qualitative data remains a puzzle that social scientists need to solve when it comes to what data to share, where to house the data, who will pay to store the data, how long the data should be kept for, etc. Many researchers are skeptical to engage in the practice of sharing digital information due to privacy concern, fear of stigmatization, the problem of funding, repository of data, transparency, and so forth. While it is important to keep these challenges in mind, it is critical to take a look at the different advantages of data sharing and data archiving.

KEYWORDS

i523, HID325, Data Sharing and Data Archiving

1 INTRODUCTION

Nowadays, many fields are witnessing a large influx of data due to the increase usage of technology. The digital data generated from scientific research is integral to the advancement of different scientific fields. While these data sets exist in abundant quantities, one challenge that many fields face is the lack of and/or prohibition of data being shared among researchers. Data sharing and its subsequent replication is a subject matter that is in dispute within in the sciences [13]. This is a significant area of contention in the United States; however, in other countries like the United Kingdom (U.K.), this issue has been addressed by making data sharing a matter of great importance; so much so, that the Joint Information Systems Committee of the U.K. made "data-sharing a priority, and has helped to establish a Digital Curation Centrefit to be national focus for research and development into data issues" [16]. On one hand, opponents of data sharing are skeptical about this practice due to privacy concerns, fears of stigmatization, funding problems, repositories for data, transparency, etc. On the other hand, some researchers are open to data sharing because it allows their work to be reviewed and creates opportunities to further their findings; however, the actual practice is stunted by researchers concerns [15]. Proponents of data sharing continue to advocate for an open access policy that would allow data to quickly respond to societal problems and crises, as well as advance the sciences. While it is as important to keep in mind the different challenges to data sharing, like data archiving, sharing data among fellow scientists can be very beneficial, not only can this practice help to maximize profits, make new discoveries, and respond to crises more quickly, but also it can play a vital role in advancing science and research.

2 THE RELEVANCE OF DATA SHARING AND DATA REPLICATION

2.1 Define Big Data, Data Sharing, and replication

Big data "is data that exceeds the processing capacity of traditional databases. The data is too big to be processed by a single machine. New and innovative methods are required to process and store such large volumes of data" [10]. The data sets are so voluminous and complex that traditional way of data processing application software are insufficient to deal with them.

Data sharing can be understood as the ability to share research findings with multiple users. This technique implies that the digital information is being archived in one or multiple servers in the network and that there is other technique to prevent this information from being altered by two or more users at the same time. It is the practice of making data used for scholarly research available to other investigators. Data sharing is nothing but making the data available for other users to use for the common good of society. [1].

Data replication is the process of copying data from one location to another. The technology helps an organization to possess up-to-date copies of its data in the event of a disaster."Replication can take place over a storage area network, local area network or local wide area network, as well as to the cloud. For disaster recovery (DR) purposes, replication typically occurs between a primary storage location and a secondary offsite location" [2].

2.2 The Advantages of Big Data

we cannot talk about the advantages of Big data without quickly acknowledge that its numerous challenges, which include data collection, data storage, data analysis, search, sharing, transfer, visualization, etc.

Big data analysis presents numerous advantages. For instance, it helps businesses to increase their productivity. This has done through a process of analyzing raw data that produces information that identifies trends and patterns that will help businesses make cost effective decisions. It is also helpful in aiding government agencies to improve public sector administration, and assists global organizations in analyzing information that has wide-reaching impact on the world. The information produced by big data can help medical professionals to detect diseases in earlier stages. Some other advantages of big data analysis is present in many different areas, such as: smart grids, which monitor and control electricity use; traffic management systems, which provide information about transportation infrastructure like roads and highways, mass transit, construction, and traffic congestion; retail by studying customer

purchasing behavior to improve store layout and marketing; payment processing by helping to detect fraudulent activity, etc [23]. Data is being collected everywhere due to the use of the internet; therefore, businesses and scientists are trying to make the maximum profits from it. Data sharing, for instance, can help scientist to respond to epidemic and crisis in a quickly manner.

2.2.1 Data Sharing Helps to Respond to Crisis Quicker. Sharing data among fellow scientists and researchers is crucial. This process can help to respond to crisis quicker. By sharing (digital) data, researchers do not always have to start from scratch when they are responding to societal problems, such as medical epidemics, economic instability issues, natural disasters, etc. As previously mentioned, an important aspect of data sharing is its ability to be used to respond to and help expeditiously resolve societal issues. As found in [26], data sharing is encouraged among fellow researchers and scientists to quickly respond to outbreaks. The authors centered their arguments around the rise of Ebola back in April 2015 that raised serious panic around the whole world due to the dangerous impacts of the disease that could result in death from just one exposure. They explained how the rapid availability of research data had facilitated a more amenable response time to the rapidly spreading threat of Ebola. The data accessed allowed it to be determined that the virus had circulated from Guinea to Sierra Leone and that it was being sustained by person-to-person contact.

The fact that the data was recoverable from the GenBank, a public database, allowed researchers ready access and assisted with tracking the source of the deadly virus; thus, leading to the advocacy for the sharing of data among researchers to allow for quicker responses to life-threatening crises. This is one example of how data sharing can have a crucial impact on the response time researchers have when responding to disasters that have a global impact.

Moreover, [25] wrote about the problem that public health policies faced when it came to responding to outbreaks like Ebola. He explained how bureaucracy and a lack of record keeping often delayed the ability of scientists to respond. A lack of collaboration among researchers can hinder progress when scientists need to respond to crises. Not only does data sharing help scientists to respond to and help provide critical solutions to outbreaks like Ebola, but access to the data can also contribute to the advancement of science through data replication. Thus, the importance to encourage this practice among fellow researchers.

Certain research studies have supported the idea that big data allows for real time tracking of diseases and the development, prediction of outbreaks, and facilitates the development of personalized healthcare. Big data can also be used to maximize profits in many disciplines, including healthcare if harnessed properly [24]. "By harnessing big data, businesses gain many advantages, including increased operational efficiency, informed strategic direction, improved customer service, new products, and new customers and markets" [11]. While data exists in huge quantities in many fields, including the health care field, individual privacy concerns remain a big problem that policymakers have to tackle to meet current trends in data collection. Improved methods of protecting very personal, private and sensitive health information is needed in order to allow

for safe, necessary and adequate access to protected health information within the health care industry. Without proper policies related to data use, access, and protection, this big data potential can not be realized [17]. Data sharing and replication contribute to increase the availability of the amounts of digital information and make the access to information easier.

2.2.2 Data Sharing and Replication Contribute to Increase the Availability of Digital Information. Furthermore, data sharing and replication (the availability of multiple copies of a data set to different users) is an important practice that plays a crucial role in the advancing of the sciences. The way sciences grow is through scaffolding, which means that one must rely on the work of previously published research to come up with new findings; thus, further supporting the necessity for a collaborative effort among researchers and scientists. Data sharing has been shown to help spot errors in research. In 2013, for example, a graduate student pointed out a calculation error made by two Harvard professors. This discovery was only possible because the professors shared a spreadsheet of their research findings with the particular student [13]. In this case, and possibly in many other cases, data sharing has helped to build community among fellow researchers, uncover honest mistakes and, in worst-case scenarios, expose possible fraud. Another researcher made a series of observations about the relevance of sharing data and asked many poignant questions regarding content, parameters and the necessity for sharing information. One observation she made was that "science progressed for centuries without data sharing policies and then questioned, why is data sharing deemed so important to scientific progress now?" [6]. She challenged the notion of free and unhindered distribution of data and cautioned that preliminary questions must first be answered to determine what data to share, how much and in what context data should be released to advance the changes in sciences. Her point was that the data should not stand alone, but rather it ought to be accurately defined and contextualized within the means that identified, developed and synthesized the data into usable information. While Borgman's scrutiny has its place in the argument regarding the absence of policies! which she argues ought to be based on accurately defining the data parameters! and their ability to facilitate data sharing, it is also important to acknowledge that the various scientific fields have been faced with different types of data and challenges.

Nowadays, scientists are being bombarded with an abundant presence of digital data, which has made it difficult to manage and store, and far more difficult to compare data exchanges to what it was centuries ago. If digital data that is generated through research is not being replicated, the world of science will face far more challenges in the years ahead due to a lack of evolving data to build upon. Data replication involves open access to data so that researchers can continually study, analyze, and make new discoveries about existing data. Now, if data sharing opens the door to the replication of scientific research and advancement, then why is there so much opposition to such a practice? Without replication, the sciences may become stagnant in their advancement of theories and potential solutions to global problems. Not only data sharing makes access to information easier, but also helps to mitigate/eliminate unnecessary cost.

2.2.3 Data Sharing Help Reduce Unnecessary Cost. Another reason to encourage data sharing is that data sharing help to reduce unnecessary cost. As digital information is made available in the cloud system, researchers will be able to access the same type of information at different locations. "Data sharing is driven by the need to maintain more accurate and up-to-date spatial databases, but at the same time reduce data acquisition and maintenance costs" [21]. If data becomes more accessible, not only this will contribute to lowering the cost to access data, but also will it encourage researchers in their endeavors to respond to social outbreak quicker. Data sharing can also play a crucial role in advancing science, which is our next point.

2.2.4 Data Sharing Advances the Science. Contrarily to what many might think, the advancement science occurs through replication of existing findings; scientists must rely on the work of previous researchers to make new discoveries. Just like human being cannot live in vacuum; the way science develop is through collaborative effort among fellow scientists."Placing research data online allows instantaneous access by a globally dispersed group of researchers to share, understand, and synthesize results. This aggregation and synthesis provide an opportunity for insight, progress, and that uniquely human quest for larger understanding. Data repositories also allow for the publication of previously hidden negative data, essentially experiments that didn't work" [3]. One advantage of this practice is that by sharing their work, scientists will be able to spout errors that previous researchers have made, reveal fraud, build community, etc [13]. As found in [5] policy makers must develop policies that explain how to embark in this process. If data are not being replicated, the world of science will face far more challenges in the future. Data replication involves open access to data so that researchers can continue to study, analyze, and make new conclusion about existing data. Now, if data sharing allows the replication of the sciences, why are many people opposed such practice?

3 BLOCKS TO DATA SHARING

There are numerous barriers to data sharing. One of the barriers to data sharing is transparency.

3.1 Transparency Issue

Some researchers fear that their work is going to be poached and that they will not get credit for their findings, so they hold on to it and do not disclose it. The concerns of obscurity and/or credit being assigned to other researchers who might advance the original researcher's findings will cause a serious reluctance to sharing data. As found in [13], the term data parasites is used to describe the practice of utilizing data without giving proper credit to prior publishers. Thus, to overcome this challenge, there should be honesty and allowance for intellectual probity; a sort of fair play between researchers where appropriate credit would be given. In addition to giving appropriate credit for findings, another important aspect of disclosure is the appropriate compensation for the release of intellectual property. Oftentimes, researcher have sacrificed their time, income potential, energies, and relationships to do the work they do; incentive needs to be provided to encourage the sharing of their findings that they have worked hard to develop. "The call for

transparency is not new, of course. Rather the emphasis is on access to data in a usable format, which can work to create value to individuals" [23]. Access to digital information can engage individuals, invite scrutiny, and expose misuses of data.

Another concern pointed out by this author is that data sharing may open the door for data analysts to disprove and/or scrutinize the work of the data producers. A potential solution that he proposed to this issue was co-authorship. He believed this would discourage the misuse of data by allowing collaboration among researchers [13]. Another researcher also asserted that researchers ought to agree on the standards of practice needed to responsibly share data. She advocated that both data and its means of publication deserve equal status in scholarly communications to determine how to cite data in non-trivial ways [6]. If data sharing and collaboration among researchers is to be effective, there need to be norms and regulations of how to do so. Collaboration among scientists can be a good thing to help mitigate and even eradicate the sense of fear that many researchers have in sharing their findings and the methodologies used to produce them. This leads us to our next potential block and challenge to data sharing, privacy concern.

3.2 The Problem of Individuals' Privacy

Another barrier to data sharing, specifically in the healthcare field, involves the protection of patient privacy; a lack thereof can lead to stigmatization and potentially hamper patients participation in healthcare research and treatment. "Privacy is a major concern in outsourced data. recently some controversies have revealed how some security agencies are using data generated by individuals for their own benefits without permission. Therefore, policies that cover all user privacy concerns should be developed. Furthermore, rule violators should be identified and users data should not be misused or leaked" [11]. In so doing, individuals will feel more at ease to engage in the process of sharing information for the benefits of everyone.

As [26] highlighted, some uncertainties that are involved data sharing, like whether data belongs to public or private domains. Still, another barrier is patient consent and their ability to fully understand how their participation can make them vulnerable to being potentially shunned and ostracized in their community based on their diagnosis and/or treatment. The researchers advocated for the responsible sharing of pertinent information among researchers to avoid this problem. It should also be mentioned that preclusion to the sharing of unnecessary information would also weaken the barriers to data sharing. Although data sharing is important, particularly during a medical outbreak, researchers ought to do their best to protect patient privacy to avoid any threat of stigmatization or isolation of patients. Rigorous ethical standards should be applied to safeguard patients' privacy and dignity to allow for easier sharing of relevant data [26]. Shelton (2011) advanced that "Rather than viewing privacy concerns as impediment, policy makers, scientists and HIT specialists should embrace privacy as an opportunity that, if addressed, can enhance the flow of information" [19]. If patients' privacy is protected, this will ease and mitigate skepticism within those who are refusing to share their personal information for fear

that their privacy will be violated. These steps in the research process can facilitate the progression of scientific research through the increase of public participation and collaboration.

Besides addressing privacy concerns, researchers can focus on understanding what aspects of data need to be preserved and dispensed for the public good. As another potential barrier, data preservation and the awareness of what data needs to be preserved raises concerns about data quality, the absence of scientists to analyze data, and data storage options. Funding for research needs to be contingent upon the determination of the importance of digital data. Policies ought to be developed that relate to the use of data, such as what data to be preserved as well as what exceptions need to be made to data preservation. In addition, regulations about data hosts (warehouses for storing data) should be determined. For example, "Agencies and the research community together need to create the digital equivalent of libraries: institutions that can take responsibility for preserving digital data and making them accessible over the long term" [16]. Moreover, an effort to teach information management should be prioritized to facilitate data acquisition, data cleansing, data storage, and effective uses of data. While most scientific disciplines found that a data deluge is extremely challenging, great opportunities can be realized with better organization and open access to data [8]. It is important to train scientists, establish better policies to regulate data sharing, and increase the incentives for researchers from every fields to collaborate as they tackle the many issues that are faced by the modern sciences.

For data sharing and replication to be effective, scientists from diverse fields ought to come together because very rarely can progress happen in isolation. Currently, very few fields like astronomy, genomics, social sciences, and archaeology practice data sharing. The lack of success in implementing data sharing policies conveys the need for greater understanding of the roles of data in various sciences; highlighting the need to also seek the development of new models of scientific practice [6]. A new model can be in the arena of archiving; archiving data can be very expensive and difficult to manage, thus while it is encouraging that scientists share their work with each other, it is also crucial to have serious conversation about data housing, and the financial responsibility that involves in this practice. Until researchers come together to satisfy the response to those barriers, data sharing will remain a challenge among scientists. And if today's scientists and researchers do not make the effort to work together to facilitate effective and essential data sharing, future generations will experience the problem of lost data due to a lack of effective stewardship.

3.3 Ways to Overcome Privacy Concern

Three types of data are being identified: 1. personal and proprietary data, which are controlled by individuals and non-government organizations; 2. government controlled data, which includes, for instance, personal tax, census data, and personal health records; and finally, open data commons, which are available to everyone to access and use. The author advocated for policy makers develop strategy to link personal, proprietary, and government data to pursue health care care objectives [24]. When we think about privacy concerns it is crucial to see collaboration between scientists

from different sectors. By working together they will be more equipped to develop policies that can help to mitigate the risk of data leaking.

One way policymakers can protect individual privacy is by making the data anonymous. Researchers have identified three types of data: personal and proprietary data that is controlled by individuals; government-controlled data, which government agencies can restrict access to; and, open data commons, which means that the data is centrally located and available to all. Big data analysts and researchers have advocated for linking data together that can help to improve health care planning at both the patient and population levels. They also argued for an increase in the amount of information that is available in open data commons [17]. Although the anonymization of data appears to be a great technique that policymakers could espouse to address privacy concerns, other studies have indicated that some data can be traced back to their respective individual; thus, destroying the argument for anonymity [24]. "Every copy of data increases the risk of unintended disclosure. To reduce this risk, data should be anonymized before transfer; upon receipt, the recipient will have no choice but anonymize it at rest...And re-identification is by design, in order to ensure accountability, reconciliation and audit" [7] If proper norms are established for data analysis, this can potentially contribute to improvements in the health care industry, and businesses can maximize profit from it.

3.3.1 Privacy Principles and Data Architecture. Privacy principles should be introduced during the process of data architecture; privacy should be incorporated into the design and operational procedures [7]. In so doing, personal health care data, for example, will be protected against malicious hackers who try to access individuals' personal health information for the purposes of stealing individuals' identity. Another type of data that has been introduced to the healthcare industry is concept quantified self data. It can be understood as the data produced by individuals that engage in self-tracking of personal health information, such as heart rate, weight, energy levels, sleep quality, cognitive performance, etc. These individuals use devices like smart-phones, watches, and wearable technology sensors in the collection of their personal data and biometrics. It has been shown that 60 percent of U.S. adults are tracking their weight, diet or exercise routines, while 33 percent are monitoring their blood sugar, blood pressure, sleep patterns, etc. This indicates that there is a vast amount of health information that has been produced by individuals. What is done with all of this data? This massive supply demonstrates the need to develop policies and protocols that involve individual patient consent to share their collected data; this data can be critical to the advancement of health-care with the support of data analysis. Before that can be done; however, we must first establish the proper norm to use this type of data so that the privacy of individuals can be protected; this ought to be the primary action to take [22]. Because many individuals are willing to collect information about themselves without being prompted to do so; this is a good sign that is proper norm is established around data management and incentive is given to encourage data sharing, individuals will be willing to engage in the process of sharing their personal data. Although it is often

complicated to share qualitative data, the challenge to share seems to increase when dealing with healthcare data.

In the healthcare industry, Patients often do not want their health information to fall in the hand of other entities without their consent; however, with proper informed consent, patients seemed to become willing to share their personal health information. As agencies work with patients to disclose the purposes of collecting certain, sometimes sensitive, health information, they can empower patients to make informed decisions about their personal health information, thus engaging patients in the process. This can then serve to increase and improve the set of personal health information utilized for clinical research purposes, and subsequently improve people's lives [19]. "Privacy concerns exist wherever personally identifiable information or other sensitive information is collected and stored in any form" [12]. Thus, to protect privacy, other techniques, like encryption, authentication, and data masking may be utilized to ensure that the information is available only to authorized users.

4 SAVING SCIENTIFIC DATA FOR FUTURE GENERATIONS

4.1 Data Archiving

Along with the conversation surrounding data sharing and replication, another important conversation that needs to take place is around the infrastructure needed to archive data. While many people engage in a debate to encourage data sharing among scientists, the infrastructure to preserve the data does not yet fully exist. In reference to data, Nelson (2009) drew on a proverbial question, is it the chicken or the egg; what comes first, data sharing or the space to store data? He contends that while data sharing is encouraged among scientists, the infrastructure to store data is nonexistent and it is arduous task to pursue the development of it [15]. Thus, it is tantamount to talk about data saving as we encourage data sharing because if scientists resort to sharing their findings then there also need to be a safe place to house the data. This preservation is critical for future generations to build upon the work that has already been done to advance scientific research. As the advocacy for data archiving increases, a new challenge arises: who will pay for all of this?

4.1.1 Who Should Pay to Store the Data? Serious conversation needs to continue to happen around data management. "Access to data requires that the data be hosted somewhere and managed by someone" [4]. Although they acknowledged the effort of public and private sectors to archive data in certain fields like the life sciences, they also stipulated that many federally funded research data are at risk due to the lack of long-term structure that can ensure continual access and preservation of data. If data are not housed well, it could be said that a lot of efforts, money, and energies, are being wasted away due to lack of a secure and sustaining system of storage. As found in [14], the author posited that scientists are not the best stewards of data and suggested the job of data archiving be entrusted to the institutions that employ the researchers. Ensuring that data is well preserved will lay the important groundwork for allowing data to be accessible in the future. Lynch also emphasized the idea that for data saving to be effective, collaboration between funders, institutions and scientists are crucial. He gave the example,

such as the GenBank and the U.S.'s National Institutes of Health (NIH) genetic sequence database, as well as the U.S. National Virtual Observatory, to show the possibilities of what can be done. It appears that collaboration between sectors is key when it comes data management, including data archiving. It is not the job of one sector, but it is the job of all of us. Only when all of the sectors converge their effort together, we will be able to respond the quandary of Big data management.

Some researchers proposed four approaches that can help improve the partnership among sectors: 1) incentivize the private sector to be stewards of public research, 2) utilize the power of partnership between the public and private sectors to fund viable solutions, 3) create clear policies for the management of public data, and finally 4) encourage openness to new and diverse methods of research to advance public research abilities. Furthermore, they theorized that there should be adequate safeguards to prevent private sector's control, access and use of public data [4]. While these measures are applicable, there not be all great because by relinquishing the work of data saving to the private sector solely, it can create a very expensive problem to accessing data via private organizations that are highly incentivized by financial gains. It would probably be more effective if the federal government would pay for their own data scientists to be trained on how to effectively manage the data, and establish the requirements and expectations that all federally funded research remains in the public domain.

Other research corroborates the idea of licensing all research data to the public domain. This is the case, in the Netherlands, where for example, all the data retrievals are kept by the National Library. The U.S. can espouse this model by creating a center for data to be stored, and develop policies on how to access the data. This would prevent the private sector from having a monopoly on accessing, interpreting, sharing and store data that belongs in the public domain [18]. Another researcher advanced and noted that, in its effort to encourage peer review, the National Science Foundation (NSF), makes data sharing a requirement in the grant contract, where researchers are required to submit a 2-page report of their research that can be used to facilitate peer review. This technique used by NSF was revealed to be a great example of how the federal government can overcome the conundrum of data sharing and archiving among scientists [5]. This technique is applicable, however, proper norm stills to be established and proper security measure needs to be created to preclude the data leaking, which can compromise the privacy of research participants.

4.2 Electronic Versus Physical Archives

Another conversation that needs to happen when it comes to Big data management is how to archive the data. Scientists need to decide between electronic archiving versus physical archiving. "Digital archives face specific challenges linked to physical storage media as well as hardware and software longevity. In reality, every method of recording information, whether on paper, stone, or photographic film, has a limited resistance to time. The value of any information is dependent on the ability to decode it after a long storage period. The difference with digital archives is that these limits are ignored because of the addition of complex and versatile technology to the overall equation" [20]. Thus, it is important that researchers figure

out which form they want to espouse to archive that will allow long term access to the data. It can be argued that both forms have its advantages and disadvantages. Physical archiving allows access to the data locally and no sophisticated knowledge or programming skills are needed to access the data; however, the data is not available everywhere; this form of archiving data is quite limited. On the other hand, electronic archiving allows multiple users to access the data at the same time. It can be said that the digital information is not limited to physical location and space; the data is located in the cloud; it is unbound and can be accessed from everywhere. "The advantages of a digital archive in the pharmaceutical sector cover four areas: accessibility, selectivity, fidelity, and compliance" [20].

The only disadvantage to digital information is probably the lack of skills to access and manipulate the data. "As we move into the electronic era of digital objects, it is important to know that there are new barbarians at the gate and that we are moving into an era where much of what we know today, much of what is coded and written electronically, will be lost forever. We are, to my mind, living in the midst of digital Dark Ages; consequently, much as monks of times past, it falls to librarians and archivists to hold to the tradition which reveres history and the published heritage of our times" [20]. Thus, the necessity to continue to train more data scientists and analysts who can extract, manipulate, and analyze the information from the cloud system.

5 TRAIN NEW SCIENTIST TO HELP TO MANAGE DATA

If we are talking about data sharing, data replication and data archiving, it is critical to address the how to do so? The skills to extract, collect, and store data have not been taught yet in regular school. If we want to develop a generation of data driven society, we need to start teaching computer skills in elementary school all the way to college and university. Just like we teach natural language, like English, French, Spanish to children at a very young age, it is important to teach programming language skills to these kids, so that we can increase their awareness and develop incentive to become data analysts, scientists who will be able to manipulate the data sets. There is an old proverbial that states that " You can teach an old dog new tricks." Thus, the earlier we start teaching those skills, the better. While there are many institutions that have shown interest in developing Data Scientists by teaching programming language skills, like python, java, C++, machine learning, data analysis, etc. so that data can be extracted and analyzed, it would be great to start teaching programming skills to students at a lower level, like elementary school. The same way certain math skills like probability has been taught in high school, it is relevant to start incorporating programming language skills in high school to develop interest and incentive to engage in the process of collecting, manipulating, and housing digital information.

5.1 Why Data Repository?

Data repository facilitates access to existing documents. "Besides being a good thing for the sharing and verification of data-driven research results, data research repositories are now necessary for

university campuses. Placing one's research data online has become mandatory for any researcher wishing to receive grants from any public U.S. agency. This includes the National Institutes of Health (NIH), National Science Foundation (NSF), U.S. Department of Agriculture (USDA), and National Endowment for the Humanities (NEH). The rationale is that if a researcher is drawing from the public taxpayers' trough, the research must be publicly accessible through both the article and original data. Sharing this data helps keep the wider economy vital, facilitating healthy competition toward commercialization and dissemination of discovery. If researchers do not have data management plans in place, their chance of obtaining a grant decreases. Currently, a majority of grant-funded researchers do not share data. With recent mandated changes, this situation is rapidly changing. Ivy League institutions have already capitalized on it by sharing data leverages and enhances faculty, departmental, and a university's global research standing" [3]. If research data is made available, this can contribute to lessen and even mitigate the stress level of graduate students when they work on dissertation and final project for their respective institutions. Not only it would save them the time to go to different libraries to hunt for documents to start working on their project, but also it gives them access to all the work that has been done on the topic chosen, and what else is left to be done.

Data repositories can play a vital role in making research findings available to everyone and making access to data an easy process. "Online research data repositories are large database infrastructures set up to manage, share, access, and archive researchers' datasets. Repositories may be specialized and relegated to aggregating disciplinary data or more general, collecting over larger knowledge areas, such as the sciences or social sciences. Online repositories may also aggregate experts' data globally or locally, collecting a university or consortium of universities researcher's data for mutual benefit. The simple idea is that sharing data improves results and drives research and discovery forward. A repository allows examination, proof, review, transparency, and validation of a researcher's results by other experts beyond the published refereed academic article. Placing research data online allows instantaneous access by a globally dispersed group of researchers to share, understand, and synthesize results. This aggregation and synthesis provide an opportunity for insight, progress, and that uniquely human quest for larger understanding. Data repositories also allow for the publication of previously hidden negative data, essentially experiments that didn't work. This enables other researchers to avoid previous dead ends of those who have tried a path before them to better find their way toward more fertile territory" [3].

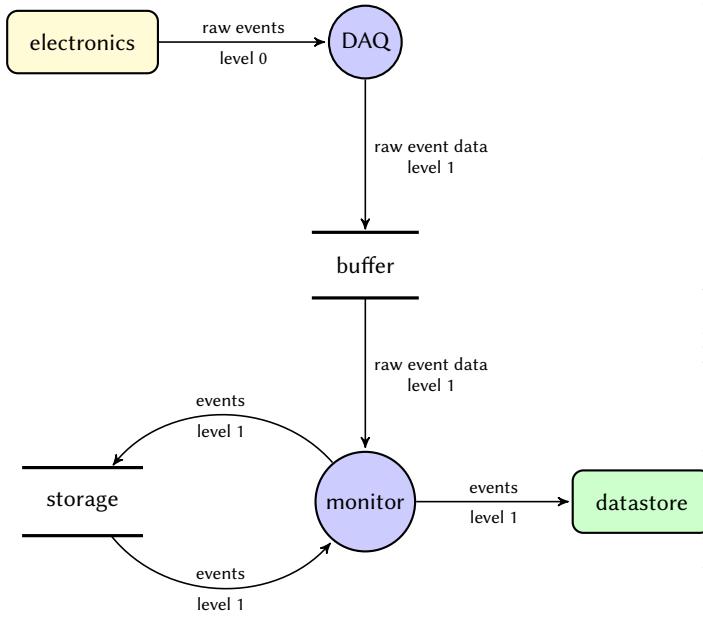
6 FLOW OF INFORMATION

The following data flow diagrams convey the flow of information in a system. This figure shows experimental data being collected, reported, processed and stored [9]. This figure is depiction, an example of how data management works. The data go through a series of process before it can be archived and reused.

As we can see, managing big data requires that highly individuals to collect, clean, analyze, store, and share the data. It is not the work of one individual; it is the work of all of us. We need more data analysts who can engage in analyzing the data; we need more

data collectors to collect and create raw data and spreadsheets to be analyzed; we need more individuals who can create structures and security around data storing, etc. It was never the work of one individual, all of us need to be involved.

Thus, it is critical to converge our effort in passing the management tools and skills to current students and developing scientists who will be highly skilled in managing Big data analysis. Considering all of the different breakthroughs that are happening in the digital realm, it is safe to say that Big data is bigger and bigger; thus the necessity to train scientists to face the challenges that await us ahead.



6.1 A simple Example of Data lifecycle

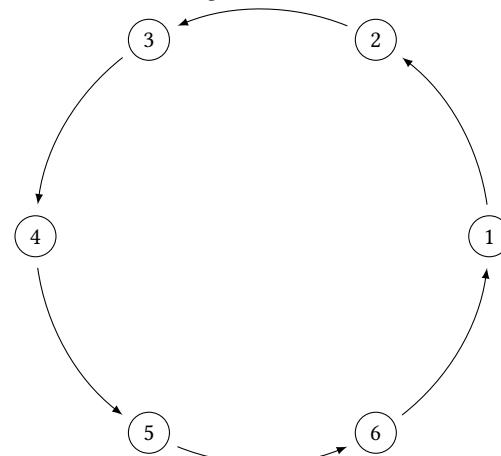
This data lifecycle was created by Jerome Tremblay and is adapted to explain the different phases that the data take before it can be destroyed [9].

The following figure is a depiction of the data lifecycle. The data often follows a number of steps, which are: in 1 we have (data creation), followed by 2 (data maintenance), 3 (data utilization), 4 (data publication), 5 (data archiving) and 6 (data destruction). In phase 1, the data gets created. Spreadsheets are often used by companies to keep the data. In this active process, the data is often stored locally on a server or multiple servers, or in the cloud, or a host data center. In phase 2, the data is data gets processed and synthesized in a variety of tasks. This is a fairly broad range of management actions, such as how data is supplied to the end users and how analytics such as modeling are performed on the data. In phase 3, the data is ready to be used by end users. In this phase the challenge of data governance and data compliance arise. In phase 4, the data can be published. In phase 5, the data is archive. At some point in time, the data in your system will have no immediate use, and it's time to archive it in case it might be needed in the future. This removes the data from your active environment and moves it off to storage. In phase 6, When the data is no longer

useful and needed, it must be destroyed. In this phase of the data lifecycle governance and compliance challenge might be surfaced. It's important to ensure that the data has actually been destroyed properly for several reasons, among those reason to make sure that privacy of individuals are protected. Briefly, these are the difference phases that data take before it falls into desuetude.

It is important to note that there are other types of data lifecycle in the realm of big data management that follow different stages, such as: data collection, in the this stage large amounts of raw data is being created; this stage is a significant aspect in the management of big data because it helps to capture the data that will later transition from raw data to published data. The second stage is data filtering and classification, in the stage the data is being filtered, cleaned and structured to eventually be ready to be analyzed. In the third stage, that data is ready to be analyzed. certain techniques and technologies are being used in the process of analyzing the data, such as data mining algorithm, cluster, correlation, statistical regression, indexing, graphics. Visualization and interpretation of the information happen in this very stage. The next stages that the data are storing, sharing, and publishing. After the data is being analyzed, the data is store for future use. "Data and its resources are collected and analyzed for storing, sharing, and publishing to benefit audiences, the public, tribal governments, academicians, researchers, scientific partners, federal agencies, and other stakeholders (e.g. industries, communities, and the media). Large and extensive Big data datasets must be stored and managed with reliability, availability, and easy accessibility, storage infrastructures must provide reliable space and a strong access interface that can not only analyze large amounts of data, but also store, manage, and determine data with relational DBMS structures. Storage capacity must be competitive given the sharp increase in data volume; hence, research on data storage is necessary" [11]. Thus, the importance to develop good policies that will address privacy and different challenges that involves storing and sharing Big data for the benefits of every sectors.

The codes for this figure was borrowed from Jerome Tremblay.



7 CONCLUSION

This document put forth the dialogue needed to assist researchers to address the different challenges they have experienced when

it comes to data sharing and replication as well as data saving. The advantages and disadvantages of Big data analysis have been discussed. We have seen that though Big data applications has its advantages, it has its poses many challenges as well. The importance of data sharing has been explored, and examples of how sharing information can help scientists to respond to global crises in a timely manner, like in the Ebola outbreak, have been provided. It has also been shown how data sharing and replication have helped to advance scientific research. It was postulated that in order for data to continue to exist, scientists need to embrace the idea of replicating their information.

As research continues to occur and scientists increase their agreement to collaborating with one another, they will be better equipped to discover potential errors from previous retrievals, fix those errors and clean the data, and make other discoveries based on existing data. Scientists cannot operate as an Island. Policies need to be put in place, to understand what data to share, when to share, where to store the data, and what data to store etc. For the continued advancement of the sciences, data sharing and archiving will require resources that facilitate the access, interpretation and maintenance of data. The importance of data sharing, data replication, and data archival cannot be overlooked. This work is far from exhaustive, More discussion around data management need to happen; new policies and regulations regarding how to share, store and replicate data are needed as well as effective parameters for how these processes will be funded and used in the future.

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Continuous Motion Detection Using Convolutional Neural Network and Recurrent Neural Network

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ABSTRACT

Object detection is fundamental and important Computer Vision task. Continuous object detection is an extension of object detection for continuous motion scenes. Traditional methodologies include estimating object displacement in subsequent scenes using optical flow methodology. Optical flow can be computationally expensive to compute making it unattractive for online learning methodologies. Deep Neural Network learning techniques present an alternative approach for determining continuous motion without explicitly computing the optical flow between subsequent frames.

KEYWORDS

I523,HID211, Continuous Motion Detection, Convolutional Neural Networks, Object Detection, Deep Neural Networks

1 INTRODUCTION

Object detection is fundamental and important Computer Vision task. Continuous object detection is an extension of object detection for continuous motion scenes. In section 2, we discuss the scope and applications driven by continuous motion detection. In section 3, we present the data that we use for our experiments.

In section 4, we discuss traditional techniques used for continuous motion detection. Traditionally, hand crafted features [14] and optical flow [13] between subsequent frames was used to detect continuous motion detection. We discuss the major drawbacks of using traditional optical flow and hand crafted feature based methods. These drawbacks can be overcome using newer deep learning techniques.

We begin section 5 by discussing about deep convolutional neural networks and their application for object detection. We introduce certain naive methods that can be used to achieve continuous object detection. In section 5.3, we introduce Recurrent Neural Networks and their application for continuous object detection. We discuss long-short-term-memory networks a form of recurrent neural network which is designed to retain scene memory over long periods of time. We discuss implementations which use long-short-term-memory networks along with deep convolutional neural networks to improve the performance of the naive methods.

In section 6, we present an end-to-end approach and algorithm which can be trained in a single shot fashion with the gradient generated by long-short-term-memory network to train the object detection network.

In section 6.1, we discuss the our training methodology and training resources used for our experiment. In section 7, we present

the results we achieved for training the model in an end-to-end fashion. In section 8, we conclude our discussion.

2 APPLICATIONS

The applications and scope of motion detection and object tracking has risen exponentially over the last decade. In recent years, we have seen several concepts of automated vehicular driving, physical robots aiding human-centric activities, aerial drone technologies replacing traditional delivery schemes, virtual reality based systems tracking human movement habits and learning from those and use of motion tracking in popular sports for crucial decision making[8]. Continuous motion detection and robotic vision remain at the crux of all the above applications. Traditionally, motion detection has also been used for security monitoring [1] and tracking suspicious activities. Researchers have traditionally used object tracking methodologies to study human movement patterns, track bird, mammal and aquatic migration patterns and draw conclusions from them. Thus it remains important to introduce computationally efficient and online learning methodologies which can be used for real time object motion detection.

3 DATA

One of the major difficulties in training architectures for continuous motion detection is lack of availability of labelled data. Videos are a sequence of image frames and speed of motion is determined using the rate at which these frames are presented to the naked human eye. Additionally motion changes in subsequent frames is minimal and can be approximated to zero or no-motion. Human experts are required to annotate images by drawing bounding boxes around objects of interests in image frames. Few second long videos can have thousands of frames depending upon the frame rate. Several online platforms including amazons mechanical turk are used by researchers to create labelled data. Participants are paid for labelling scenes and hand annotating object locations. This makes the annotation task expensive and tedious.

For this experiment we use Visual Object Tracking challenge dataset [5]. The dataset has 16 videos corresponding to different action sequences, each action has on an average 400 motion frames. Each frame is further labelled with the object of interest and bounding box annotations. Each frame presents a single object of interest. Each object is under varied illumination, colour and shape conditions. Additionally the images are noisy and blurry replicating low resolution tracking devices traditionally found in the wild.

4 TRADITIONAL APPROACHES

Traditional methods involve use of hand crafted features including hand annotating interest points on objects within images and then tracking the motion of interest points in subsequent frames. Another traditional approach uses the bag of words representation of images or uses the histogram of oriented gradients [14] approach to locate objects of interest in the images. These approaches have multiple severe drawbacks which we discuss further.

- These approaches fail to scale for larger dataset with different objects of varied size and shapes. They suffer further from scale and illumination variance in continuous frames.
- Researchers are tasked with detecting feature points within images, thus making this mechanically tasking and expensive.

Another important and popular approach for tackling continuous motion problems involves the computation of optical flow. Optical flow [13] computes the relative motion between pixels in subsequent frames. Optical flow uses the following assumption, given motion of the pixels in subsequent frames is small or negligible, the changes in intensity or brightness in subsequent frames will be constant or near zero.

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t) \quad (1)$$

In equation 1 I represents the pixel wise intensity across frames. If the movement is small the right hand side of the above equation can be approximated using the first order Taylor series

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\delta I}{\delta x} \Delta x + \frac{\delta I}{\delta y} \Delta y + \frac{\delta I}{\delta t} \Delta t \quad (2)$$

$$\frac{\delta I}{\delta x} \Delta x + \frac{\delta I}{\delta y} \Delta y + \frac{\delta I}{\delta t} \Delta t = 0 \quad (3)$$

$$\frac{\delta I}{\delta x} \frac{\Delta x}{\Delta t} + \frac{\delta I}{\delta y} \frac{\Delta y}{\Delta t} + \frac{\delta I}{\delta t} \frac{\Delta t}{\Delta t} = 0 \quad (4)$$

$$\frac{\delta I}{\delta x} \frac{\Delta x}{\Delta t} + \frac{\delta I}{\delta y} \frac{\Delta y}{\Delta t} + \frac{\delta I}{\delta t} = 0 \quad (5)$$

$$\frac{\delta I}{\delta x} V_x + \frac{\delta I}{\delta y} V_y = -\frac{\delta I}{\delta t} \quad (6)$$

Here V_x and V_y represent the optical flow in directions x, y and the partial derivative represent the derivative of the image at pixel x and y . The equation has 2 unknowns and requires additional constraints and equation to solve for the unknowns. Two popular approaches to estimate the optical flow include Lucas-Kanade method and Horn-Schunk method. Lucas-Kanade [13] method solves for the unknown using the assumption, the motion for all pixels in a window centered around p between frames will be constant. Thus they solve for the equation.

$$\begin{aligned} I_x(p_1)V_x + I_y(p_1)V_y &= -I_t(p_1) \\ I_x(p_2)V_x + I_y(p_2)V_y &= -I_t(p_2) \\ &\vdots \end{aligned} \quad (7)$$

Here $I_{x,y}(p_n)$ represents the partial derivative of the intensity at location x, y and $V_{x,y}$ is the optical flow at pixels within the window centered around p .

Horn-Schunk [4] method assumes the flow of pixels across the image in subsequent frames is smooth and distortion free. It approximates the optical flow by solving the equations

$$\begin{aligned} I_x(I_x u + I_y v + I_t) - \alpha^2 \Delta u &= 0 \\ I_y(I_x u + I_y v + I_t) - \alpha^2 \Delta v &= 0 \end{aligned} \quad (8)$$

where $\Delta = \frac{\delta^2}{\delta x^2} + \frac{\delta^2}{\delta y^2}$ is the Laplacian operator. The above approaches suffer from multiple drawbacks which we discuss below.

- These approaches require calculation or approximation of the higher order polynomials making it computationally inefficient for scaling.
- These approaches are make several assumptions about the images. These assumptions fail to hold in the wild.
- These approaches heavily depend on the constant brightness principle and fail to perform well for images with varying brightness, illumination, distortion and color.

5 NEWER APPROACHES

5.1 Convolutional Neural Networks

Recent research on continuous motion detection is heavily focused on the use of deep convolutional neural networks for the task object detection. Deep convolutional neural networks [6] are characterized by the movement of the convolution operator over the input image. Each convolution operator is called a filter and the filter is responsible for capturing unique patterns appearing within the input image. Filters use non-linear activation helping the network capture non linear relationships that may exist within the input data. One complete traversal of a filter over the input results in a feature representation. Multiple such representations are stacked at every convolution layer to create feature maps. Feature maps capture the various patterns that occur across images. Further, these feature maps extract patterns at different scales and intensities making the model robust to affine transformations and scale invariance. These feature maps are further mapped to an embedding layer which extracts important features that appear across these feature maps. This embedding is further fed to a fully connected network which is responsible for making output decisions. Similar images or images belonging to the same class have repetitive patterns. These repetitive patterns are captured within the low representation embedding of the image. Thus, neural networks are invariant to scale, illumination and affine transformation.

5.2 Object Detection

Object detection is the task of identifying various objects that are present within the image scene. Feature maps capture various object level information at different scales. The approach to object detection is simple. Along with the classification output the network outputs multiple regression outputs, the regression outputs signify the approximated location of an object in a scene. During backpropagation, neurons which generated the feature map for the object are penalized using mean squared error for misidentifying the location of the object. With a large dataset and over multiple iterations, the network learns to identify feature maps corresponding to objects within the scene. As the network is invariant to scale and affine transformations it generalizes well for similar objects with different sizes, shapes and colours under different illumination and environmental constraints.

Multi-object detection is task of identifying multiple objects within the scene. The task is complex as compared to single object detection problem. Traditional approaches involved using a sliding window of fixed dimension across feature maps and feeding each window to the fully-connected network. The network decides whether the window contains an object. This approach has the following drawbacks

- As the window slides per pixel, large number of input vectors are generated and fed to the fully connected network making it computationally inefficient
- Since the size of the window is fixed, it fails to capture objects of varying scale
- Overlapping of windows leads generates large number of false positives.

Girshick et al. [2], use external image processing techniques such as histogram of oriented gradients and pixel wise unsupervised segmentation to generate candidate object boxes, thereby reducing the number of possible input vectors. Ren et al. [10], use the existing annotations available within the dataset to generate the candidate boxes and generate equal random boxes from different part of the image to generate negative examples, classified as background. Redmon et al. [9], propose a single sweep over the input image and train the network for multiple object detection in an end-to-end fashion.

5.3 Recurrent Neural Networks

Recurrent neural networks [7] are a variant of traditional neural networks. They are characterized by a recursive loop which feeds the output of the network back as an input to the network. This allows information to persist within the network. Recurrent neural networks have successfully been used for addressing multiple challenges. They are extensively used for natural language modelling, speech recognition, cognitive science and time-series analysis. This is due to their excellent ability to model and memorize sequences for long temporal duration. Vanilla recurrent neural network has two major drawbacks. We discuss them below.

- Recurrent neural networks can have several input units depending upon the temporal duration of the activity. When the input signal flows from one unit within the network to

the next, it is attenuated using non-linear activation. After flowing through several units within the network, the input signal dies off. This problem is traditionally known as the gradient vanishing problem. If the gradient vanishes during the forward pass of the network, the ability of the network to learn via gradient descent through back-propagation is weakened. Thus, the network fails to learn sequences over longer duration.

- Recurrent neural networks also suffer from gradient explosion problems. An unrolled version of a recurrent neural network is equivalent to feed forward neural networks. During backpropagation the gradient generated by the final layer is accumulated over the layers, leading to drastic unstable changes in the weights of the networks.
- Vanilla recurrent neural networks also suffer due to lack of inbuilt correction mechanism. Advanced versions of Recurrent neural networks can correct the weights of the recursive loop to control the influence of previous inputs on the correct input thereby preventing the weights from exploding.

5.4 Long Short Term Memory Network

Long short term memory network [3] is an advanced variation of the vanilla recurrent neural network. They overcome the gradient explosion and gradient vanishing drawbacks of the traditional recurrent network. They are characterized by a memory cell which holds sequential information. This characteristic of the network is important in tracking motion of objects in subsequent frames of video. The memory cell is connected to 4 gates which determine the flow of information to and from the memory cell and within the network.

- Forget gate: Forget gate determines the influence previous outputs have on the current unit of the long short term memory network. The decision of the gate is driven by the rest of the network. This is essential, as blocking the flow of information to the memory cell reduces the compounding error, stabilizing the training and preventing the gradients to explode during backpropagation
- Input gate: Input gate determines, the joint influence of the current input and the output of the previous layer has on the unit of the long short term memory network. The decision of the gate is driven by rest of the network. Input gate along with the forget gate determine the sequence the network is tasked to remember.
- Output gate: Output gate determines the influence the current unit has on future units.

5.5 Working

The network first determines the importance of the previous output with respect to the state of the current unit. The units within the forget gate f_t are driven to either 1 or 0 by the rest of the network.

$$f_t = \sigma(W_f[h_{t-1}, x_t]) \quad (9)$$

The network then determines the influence of the input to the current unit of the long short term memory network. The weights of the input gate I_t unit is driven to either 1 or 0 by the rest of the network.

$$i_t = \sigma(W_i[h_{t-1}, x_t]) \quad (10)$$

$$\hat{C}_t = \tanh(W_c[h_{t-1}, x_t]) \quad (11)$$

\hat{C}_t determines the intermediate update vector of the unit

The memory cell of the current unit is then updated with the new update vector determined by the following equation

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (12)$$

The network outputs the following to drive the future units

$$o_t = \sigma(W_o[h_{t-1}, x_t]) \quad (13)$$

$$h_t = o_t * \tanh(C_t) \quad (14)$$

6 APPROACH

We present an end-to-end approach for continuous motion detection and object tracking using deep convolutional neural network and long short term memory networks. As the approach is end-to-end, we can train all networks in a single shot and optimize neural network layer weights using a single loss metric and gradients.

Algorithm 1 Single Shot motion tracking

- 1: Load video frames f_i , ground truth labels l_i , bounding box annotations $b_{i,j}$
 - 2: Pre-process $f_i, l_i, b_{i,j}$
 - 3: **procedure** MODEL(f_i, l_i, b_i)
 - 4: Create arbitrary input batch of 64 frames, labels, annotations
 - 5: Feed batch to CNN
 - 6: Generate embedding E_{CNN} , annotations b_{CNN} , label l_{CNN}
 - 7: Concatenate E_{CNN} , b_{CNN} , l_{CNN} to form long vector V_{CNN}
 - 8: Feed V_{CNN} to LSTM
 - 9: Predict approximated location of object in future frame b_{+1}
 - 10: Compute joint loss and gradients g and update network weights
 - 11: Save Model
-

Our approach is pretty similar to the one presented by Valipour et al. [11] which was used for end-to-end video segmentation. The approach is simple, we begin by feeding a video frame from an arbitrary position within the video through a deep convolutional network. We concatenate lower dimensional embedding of the input frame along with the class of the object and its location to

form a one dimensional long vector. This vector is then fed to a stacked long short term memory architecture. The output of the long short term memory network is approximated location of the object in the subsequent frame.

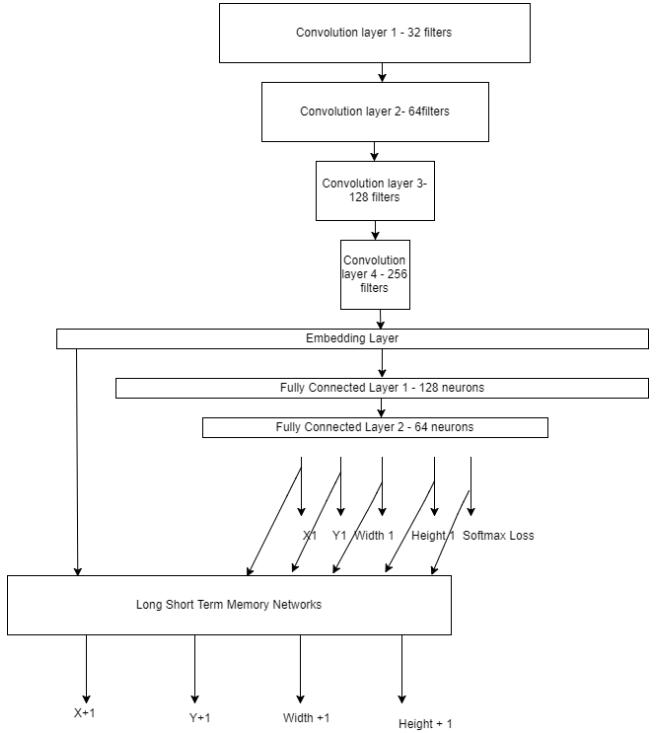


Figure 1: Model Architecture

We pre-train the deep convolutional neural network for the dataset [12]. Pre-training the neural network helps it to converge faster and stabilizes the training of the long short term memory networks which we introduce further. We believe a pre-trained deep neural network architecture trained on the ImageNet dataset will further improve the performance and generalizability of the model for unseen data samples. We do not present results or analysis for ImageNet trained architectures in this experiment. We use the deep convolutional network to extract a lower level embedding of the input image. Lower level embedding captures features present within an image.

We believe, the class of the object plays an important role in determining the rate of change in motion of the objects in subsequent frames e.g. Divers leaning forward, motion change of a car as compared to bicycles will be higher. Additionally, we use the current location of the object as a correction mechanism for the long short term memory network to prevent it from diverging from the actual motion of the object in subsequent frames. We use a time stamp of 5 frames to determine the location of the object in the 6th frame. We believe 5 frames captures the relative motion of the object between frames. We jointly try to minimize a multiple loss function.

6.0.1 Cross-entropy loss.

$$\mathcal{L} = -\frac{1}{n} \sum_{i=1}^n y^{(i)} \ln \delta(x^{(i)}) + (1 - y^{(i)}) \ln (1 - \delta(x^{(i)})) \quad (15)$$

x_i is the input samples and y_i is the output for the corresponding input samples. $\delta(x_i)$ is the output of the activation function

$$\delta(x) = \frac{1}{1 + e^{-Wx-b}} \quad (16)$$

W and b represent the weights and bias of the neural network. We minimize the cross-entropy loss for the classification task.

6.0.2 Mean-square loss.

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{Y}_i - \delta(x^{(i)}))^2 \quad (17)$$

x_i is the input samples and y_i is the output for the corresponding input samples. $\delta(x_i)$ is the output of the activation function

$$\delta(x) = \frac{1}{1 + e^{-Wx-b}} \quad (18)$$

W and b represent the weights and bias of the neural network. We minimize the mean square error loss for the regression task.

We minimize the cross-entropy and mean squared loss generated by the deep convolutional network in predicting and localizing the object in the video frame. In an end-to-end fashion, we allow the loss generated by the long short term memory network to flow through the convolutional neural network to jointly minimize the loss in predicting the location of the object in the next frames.

6.1 Salient Features of Architecture

- The input size of frames vary for different videos. Frame heights are centered on 240 pixels and width on 360 pixels. We use a fixed dimension of 120 x 120 pixels for this experiment. The number of frames per video is high, to prevent computational bottlenecks we use a lightweight convolutional neural network architecture. Another benefit of a light weight architecture is it allows the network to be deployed on low powered devices.
- We use 5 convolutional layers with 32, 64, 128 and 256 filters respectively. Each filter is of the size 3 x 3. We use the Adam optimizer for our experiments.
- with each convolutional pass, we reduce the dimensions of the image by half thereby further improving the computational efficiency of our model. We use strides instead of the traditional pooling architecture. Pooling leads to loss of visual information and deteriorates object localization performance.
- We use Rectified linear units for activation in each of our layers. Rectified units prevent gradient saturation and are computationally efficient to calculate.
- Additionally, as we are dealing with a medium sized dataset, our model is prone to over fitting. To prevent over fitting,

we couple every convolutional neural network layer with a dropout layer. Dropout serves as a regularizer for neural network architectures as it randomly drops out multiple neurons in the every hidden layer, leading to high misclassification and mean square error and penalizing the neurons forcing them to generalize for all classes.

- We use affixed batch size of 64 temporal frames for our experiment. We randomly select the starting frame so as to prevent our network from over fitting on the sequence of the video frames.
- We use a 2 layered stacked long short term memory network with 16 and 4 units each. We use hyperbolic tangent as an activation for the recurrent neural network. We use categorical cross-entropy loss for the classification task and we use mean squared error for the regression task

6.2 Training

We train our model on Indiana University's cluster computing resource Big Red 2 and Karst. We use a total of 6 CPU's to pre-train our model for the classification and regression task and we use one graphical processing unit along with 6 CPU's and 96 cores to train our end-to-end model. We train our model for 100 iterations. For each iteration during pre-training we randomly sample a batch of 64 images, labels and bounding boxes for the classification and regression task. As we are dealing with a medium sized dataset, the error converges quickly. It takes 6 hours to pre-train our model on the above stated configuration. For end-to-end training we use the following approach. We train the model for 75 iterations. In Each iteration, we sample a sequence of 128 video frames randomly and pass it to our model to generate future location of our object in context. We repeat this procedure for 100 randomly sampled sequences of 128 video frames. Random sampling improves the generalizability of our approach. Additionally as we sample randomly, we are required to repeat this approach multiple times to ensure our model trains on all action sequence. Training the model in an end-to-end fashion requires 12 hours on CPU configuration and takes about 3 hours with the Graphical Processing Unit.

7 EVALUATION

We evaluate multiple metrics during training. We try and minimize the cross-entropy loss for the classification task, and minimize the mean-squared error loss for the object position in current frame and future frame. We achieve a cross-entropy loss of 2 % in relative context. Additionally, each iteration uses a randomly sampled sequence of video frame thus indicating our model generalizes well for different actions being performed in the video. The mean squared error loss for the future frame decreases with every iteration indicating our model is able to learn motion sequence in continuous frame. The loss decreases to a minimum of 5 % in relative context which is significant as the loss is jointly computed for all 4 coordinates of the future frame simultaneously. Figure 1, shows the training loss compared to validation loss. We can clearly infer that the model performs well on the validation set, at times exceeding the training accuracy.

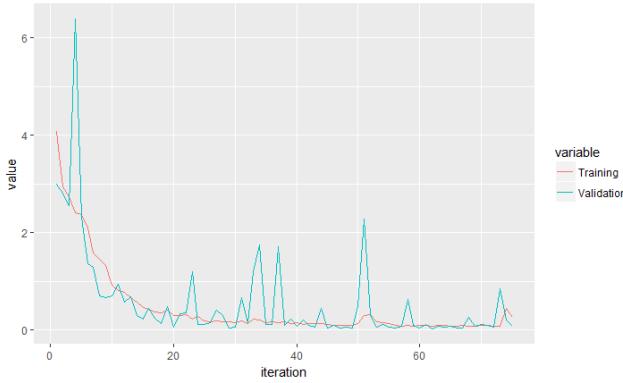


Figure 2: Train versus validation loss function

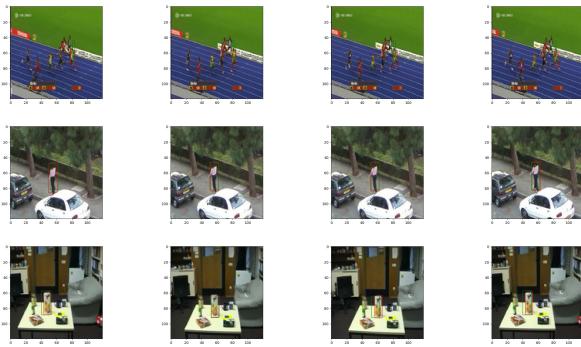


Figure 3: Predicted Examples, green indicates predicted value, red indicates actual location

Table 1: Loss Table-Training

Iteration	Training Joint Loss	Training LSTM Loss	Training Cross Entropy Loss
1	2.9984	0.0174	2.7480
10	0.7004	0.0069	0.6378
20	0.0588	0.0035	0.0175
30	0.0470	0.0067	0.0014
40	0.0862	0.0044	0.0372
50	0.4786	0.0120	0.4142
60	0.0349	0.0041	2.3931e-04
70	0.0726	0.0038	0.0141

Table 2: Loss Table- Validation

Iteration	Validation Joint Loss	Validation LSTM loss	Validation Cross Entropy Loss
1	4.0735	0.0296	2.8767
10	0.9193	0.0071	0.8033
20	0.2893	0.0044	0.2122
30	0.1720	0.0035	0.1120
40	0.1459	0.0041	0.0836
50	0.1347	0.0040	0.0678
60	0.1028	0.0034	0.0510
70	0.0745	0.0028	0.0306

8 CONCLUSION

Object and motion tracking is a difficult task. We presented traditional approaches to motion tracking and their computational flaws. We further presented a low powered light weight approach to tackle object and motion tracking using convolutional neural networks and recurrent neural networks. Our model fails to generalize for certain video sequences and tracks well for others. This we believe is due to reduced training time and small sized dataset. Use of heavier architecture introduces computation bottlenecks and places high emphasis on object detection. By using recurrent neural networks we compensate for object localization mistakes made by our lightweight convolutional neural network by studying the apparent motion of the object in frames. We present competitive results on difficult benchmark dataset. We emphasize pre trained deeper networks on ImageNet dataset can improve the performance and generalizability of our approach but it loses the essence of the light weight architecture. We propose further improvements can be achieved by combining the best of both worlds. A two stream convolutional neural network with video frames and low resolution computationally efficient optical flow can improve the performance of our approach.

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