MODULE-1

What is Machine Learning?

Machine Learning is a branch of Artificial Intelligence that deals with algorithms that learn and improve through experience. It is the science of getting computers to act and learn like humans through real world observed data by generalizing from the data given to it. These algorithms include patterns that are learnt and relationships between huge amounts of data given to the algorithm. They build Mathematical Models on training data in order to make predictions on unseen data without explicitly being programmed to do so. The key features of Machine Learning Algorithms is their ability to independently adapt to new data. Machine Learning algorithms are used in computer vision applications such as face recognition, object detection , video action Recognition etc. It also has a wide variety of applications ranging from simple classification to self driving cars.It is used in NLP to perform speech recognition, Image captioning etc. Machine Learning is used for predictive analysis and forecasting of weather data, fraud detection, in medical applications to analyse data and identify trends which can lead to faster diagnosis and treatment. Machine Learning has great significance in the Transportation Sector where it is used in finding the most efficient routes or routes with lesser traffic. [1]

SUPERVISED AND UNSUPERVISED LEARNING

SUPERVISED LEARNING

Supervised Learning involves the mapping between a set of input variables (features) X and a set of output variables (labels) y which is applied to unseen data. Supervised Machine Learning algorithms are applied when the training labels or the outputs are available in the dataset provided. Y=f(X). All the data is labelled. Learning stops when the algorithm achieves an acceptable level of performance.
Supervised Learning is grouped into Regressors and Classifiers.[2]
We use classifiers when the output variable is a category(0 or 1). We use regressors when the output is real data(For eg: Weight).

Regression

[3]Regression is a branch of supervised learning that models the input variables with the continuous output variables. This technique is used for forecasting and time series analysis. Simple Linear Regression sets an arbitrary line through the data points and calculates the distance between the data points and the line. This gives us the prediction error. Through each

iteration, in order to minimize the error, the algorithm moves the line in hopes of figuring out the best fitting line.(Minimum error). The distance by which we move the line through each and every iteration is governed by the learning rate which is multiplied to all the other parameters. The method used to find the best fitted line is called the Gradient Descent Method.

Gradient Descent

[4]Our main aim is to minimize the distance between the predicted values and the actual values i.e We need to minimize the following cost(squared error) function:

$$J(\theta_0,\theta_1)=(1/2m)\Sigma^{m}_{i=1}(h_\theta(x^{(i)})-y^{(i)})^2$$

The learning rate determines how big the steps are to decrease J .If the learning rate is too small, the algorithm takes infinite time to reach a global minimum. On the other hand, if the learning rate is too large, the algorithm may fail to converge at the global minimum. When the algorithm reaches the minima, the derivative of the cost function becomes 0 at a fixed learning rate. The derivatives calculated decrease as the algorithm approaches the minima. Using this method, we may reach the local minima rather than the global method which is not the most optimized solution and there aren't any ways to get out of it.
To address this we use a method called Stochastic Gradient Descent. [5] In stochastic gradient descent, one training sample at a time is passed to the network or the algorithm at a time and the weights of each layer are updated correspondingly with the gradient(Neural Networks). The weights are updated frequently and hence it can converge faster to the minimum(For larger datasets). [6] In Linear Regression, the training examples are fed into the model one at a time, the model predicts the output and then the model is updated in order to reduce the error.

$$W = W - \boldsymbol{\alpha} dW$$

As the weights are frequently updated, the steps taken have oscillations which helps the algorithm to exit the local minima. This feature however can prove to be problematic as frequent updates may lead to gradient descent in other directions.
[5]Batch Gradient Descent:
Here we pass the training data at once rather than one sample at a time. As a result of this, we get lesser oscillations and less noisy gradient descent with a stable convergence to the global minimum. It is computationally more efficient when compared to stochastic gradient descent. As the training datasets are usually large, additional memory might be required and the problem of the local minima still persists.
[7] Mini Batch Gradient Descent:
The number of samples per batch is taken between 1 and m(No of training examples). It is a trade off between stochastic and batch gradient descent. The cost is averaged over a smaller

number of samples. The noise or oscillations required to come out of the local minima , along with a stable convergence ,is retained.

Multiple Linear Regression:

[8]Multiple Linear Regression is a technique used when we have 1 dependent variable (y) and n independent variables(X). Here, we assume that the independent variables are not correlated with each other i.e they are not dependent on each other. The targeted values are selected independently and randomly. The reliability of the model is explained through the R^2 metric or the coefficient of determination. It measures how close the data fits to the regression line but this metric cannot indicate the bias of the predictions.

UNSUPERVISED LEARNING

[9] In some applications, the training data consists of input variables X without any labels and is required to find it's own structure in the input. In some places we may have to figure out the similarity in the data points and group them into clusters. These clusters can be later used for classification. An example of this approach would be extracting colors from an image. The pixel values extracted for every shade of each and every color are grouped together based on the distance between them. These groups can represent a particular color. We can choose how many clusters we require.

K means Clustering

Each data point's similarity is measured using euclidean distance metric or the correlation distance metric such that distance is minimum.The idea of this algorithm is to define k centers as far away from each other as possible in a 2D space. The algorithm is very sensitive to these randomly initialized centers. Next, we take each point and associate it with the nearest center. KMeans first starts with randomly selected centroids and performs repeated iterations to optimize the position of the centroids. Once the positions of these centers are stabilized, the iterations come to a halt.
Expectation-Maximization Approach:
The Expectation-Step is assigning the data point to the closest cluster and the Maximization-Step is computing the centroid for each cluster. This uses the Maximum Likelihood Estimation approach where the variables are first estimated and then optimized.

$$J=\Sigma_{i=1}^{m} \Sigma_{k=1}^{K} w_{ik}||x^{i}-\boldsymbol{\mu}_{k}||^{2}$$

If the data point(x^i) belongs to the cluster, w_{ik} is 1 or else w_{ik} is 0. $\boldsymbol{\mu}_k$ is the centroid of the respective cluster. Then we minimize J by finding the partial derivatives of J with respect to the

w_{ik} and $\boldsymbol{\mu}_k$. On differentiating with respect to w_{ik} (Extractive Step), we update the cluster assignments. Next we differentiate with respect to the $\boldsymbol{\mu}_k$ and recompute the centroids after the cluster assignments(Maximization step).

Fuzzy K Means Clustering :

Fuzzy K Mean Clustering discovers soft clusters where a data point can belong to more than one cluster with a certain probability. The algorithm is similar to k means.

CLASSIFICATION STUDY

[10]Classification Algorithms come under the Supervised Machine Learning Technique where the target variables are discrete,unordered values. [11]Natural Language processing uses classification algorithms to solve a wide range of problems.

Sentiment Analysis:

Sentiment classification is the most common application of NLP where the sentiment of the text or article is classified into a given set of categories. This is challenging even for humans. Sentiment analysis takes in the text as the input and classifies whether the comment is positive or negative. This is used to give movie reviews, to poll opinions on social media etc.

[12] Neural Networks have succeeded in a lot of NLP tasks such as machine translation, text summarization etc. However , it fails to address the aspects level sentiment analysis, where one part of the sentence may be positive and while the other may give a negative review. In order to capture relevant information in response to a given aspect,LSTM based Attention mechanism is used.Therefore Attention Mechanisms have proved to give superior results when compared to the others. Attention Mechanism , as the name suggests, figures out how much ‘attention’ it should pay to a given part of the sentence. This is handled by the parameter $\boldsymbol{\alpha}$. As it is possible to get opposite polarities from a sentence, the paper proposes to learn an embedding vector for each aspect . The embedding vector is calculated by multiplying the embedded matrix(similarity between the words of the sentence) with the one hot encoding of the word. This is the aspect embedding e. The attention weight($\boldsymbol{\alpha}$) is calculated from the embedding vectors with the formula:

$$\boldsymbol{\alpha}^{<t,t'>} = \exp(e^{<t,t'>})/(\Sigma_{t'=1}{}^{Tx}\exp(e^{<t,t'>}))$$

W is the word representation of the sentence with length N . This vector is passed through an LSTM to generate the hidden units H $\{h_1,h_2\ldots..h_n\}$ These hidden units are multiplied with $\boldsymbol{\alpha}$ to give the weighted representation of the sentence of a given aspect.

Activation functions:

[14]Softmax Activation function - This activation function outputs a vector that represents the probability of all the outcomes. Hardmax classifier gives the outputs as 1 or 0 where 1 represents the predicted category.The value ranges from -1 to 1.

$$S(y_i) = e^{yi}/\boldsymbol{\Sigma}_j e^{yj}$$

Tanh activation function:

[15]Tanh activation function comes with the vanishing gradient problem where the gradient tends to get smaller and smaller in the backpropagation optimization. The earlier neurons tend to learn slower than the later neurons. This results in a decrease in the prediction accuracy and the model takes a long time to train.

$$\tanh(x) = 2/(1+e^{-2x})-1$$

Sigmoid Activation function:

The sigmoid activation function translates the input range from -inf t-+ inf to (0,1]. Softmax is a more generalized version of this activation function. The problem of vanishing gradients also persists in this case.

$$\boldsymbol{\sigma}(x) = 1/(1+e^{-x})$$

[16]SVMs for classification:

The objective of Support Vector machines is to find the hyperplane in N dimensional space that distinguishes all the data points from different classes. Hyperplanes are chosen in such a way that the distance from the hyperplane to the data points from each class should be maximum. This is called the maximum margin. This makes sure that future points are classified with more confidence. The dimension of the hyperplanes depend on the number of features present. The margin of the classifier is maximized by taking into consideration the data points which are closest to the hyperplane(Support Vectors). These vectors highly determine the position and the orientation of the hyperplanes. The threshold values in SVM are changed to -1 and 1, the range of values ([-1,1]) acts as the margin.

For the given training data D, the set of n points is in the form

$$D = \{(x_i,c_i) \mid x_i \in R^p, c_i \in \{-1,1\}\}_{i=1}^{n}$$

Where each x_i is a p dimensional vector and c_i is the class it belongs to {-1,1}.

Any hyperplane can be written as the set of points x satisfying w.x - b =0 where w is the normal vector perpendicular to the hyperplane. To maximize the margin, w must be minimized. To prevent the data from falling into the margins ,

$$c_i(w.x_i - b) >= 1 \text{ for all } i = 1,2,....,n$$

SVMs are greatly effective when we take into consideration the extreme cases. These data points are the support vectors. Sometimes the data points are not linearly separable. In this case, we use the non linear SVMs that transfer the data into high dimensional space, but this is computationally expensive. Hence, we use the kernel trick to transform non linear SVMs into linear SVMs. The cost function for the SVMs is called the hinge loss. If the predicted value and the actual value are of the same sign, this shows that it has been classified correctly. Therefore the cost is 0.

For the sentiment analysis problem statement, the data is linearly separable with two classes i.e 'positive' or 'negative'. Hence the kernel used here is the Linear SVM. Regularization parameter 'c' is added to decrease the overfitting and balance the margin maximization and loss.

The f1 score for the sentiment analysis on amazon review data with SVM was 91%. The f1 score is the harmonic mean of the precision and the recall values.

[17]Precision- The ratio of the correctly predicted positive values to the total number of positive values. High precision relates to low false positive rate.

Precision = True Positive/(True Positive+False Positive)

Recall- Recall is the ratio of correctly predicted positive labels to all the observations.

Recall = True positive/(True positive + False Negative)

F1 score works better than accuracy if we have uneven distribution of classes.

CLASSIFICATION METHODS:

[18]Logistic Regression:

Logistic Regression is a common method for solving binary classification problems. Multinomial Classification is used where there are multiple classes present. For ex: IRIS dataset. Logistic Regression can be used for diabetes prediction, spam detection and the type of cancer (Malignant or Benign). Logistic Regression uses the logit function to predict the probability of occurrence of a binary event. The dependent variable in logistic regression follows the Bernoulli Distribution. It is a discrete distribution having two possible outcomes given by the equation:

$$P(n) = p^n (1 - p^n)$$

where p is the probability and n is the label 0 or 1.

Logistic Regression is estimated using the Maximum Likelihood Estimation. This estimation determines the parameters that are most likely to produce the observed data. The mean and variance are the parameters used for predicting the data in the normal distribution.[19] Different values of variance and mean result in different curves. This estimation figures out those parameter values which results in a curve that best fits the data. The probability density of observing a single data point x is :

$$P(x ; \boldsymbol{\mu}, \boldsymbol{\sigma}) = 1/(\boldsymbol{\sigma}\sqrt{2})\exp(-(x - \boldsymbol{\mu})^2/2\boldsymbol{\sigma}^2)$$

The mean and variance are found out by maximizing the above function. We assume that the data points are independent of each other to avoid conditional probability. The natural log of the expression is taken to differentiate it. As natural logarithm is a monotonically increasing function, it ensures that the maximum value of the log of the expression occurs at the same point as the original expression. The sigmoid function is called the logistic function. If the output of sigmoid is greater than 0.5, we classify it as 1 or else 0.

[20]Tree Based Classification:

Tree based algorithms are considered as one of the most common supervised Machine learning techniques. They can handle linear relationships as well as non linear relationships with great accuracy. Tree based algorithms can be used for both regression and classification. This approach requires less cleaning when compared to the other modelling techniques and is not affected by missing values or outliers.

Decision Tree Classifiers- In this classifier, the population is split into two or more homogenous sets based on the significant splitter in the input variables, i.e the input feature which affects the target value the most. The root node represents the entire population or the sample. This further gets divided into sub nodes. When a sub node divides further, this is called the decision node. The terminal node or the leaf node does not divide into further nodes. The decision tree follows the 'top down greedy approach' as it cares only about the current split and doesn't care about future splits which might lead to a better position. The value obtained by the leaf node is the mode of the observations in that region while in regression, the mean of the observations is taken. Decision Trees uses multiple algorithms on how it decides the split. The common algorithm is the gini test.

[21]Gini algorithm:

Gini impurity metric evaluates how good a split is. A datapoint is randomly picked and classified according to the class distribution. The probability that the data point is classified incorrectly is called the gini impurity. The formula for the gini impurity is given by:

$$G = \sum_{i=1}^{C} p(i) * (1 - p(i))$$

Where C is the total classes and p(i) is the probability of picking a datapoint with class i.

A gini impurity of zero indicates the best possibility which can be achieved when everything is the same class. The gini impurity of the split will be low if the most effective input feature is taken as the root node for the split.

Random Forests - Decision Trees are more prone to overfitting as they can be too specific when we deal with smaller samples. Therefore, we use Random Forests. Random Forest consists of many decision Trees that have very low correlation with each other. If some trees provide wrong predictions, there are many more that provide the correct ones. This classifier decreases the chances of overfitting as different samples of the data are trained each time or random subsets of the feature are trained on. Decision trees are very sensitive to the data they are trained on. Small changes can result in a different tree. Random forest allows each tree to randomly sample from the dataset. This is called bagging (bootstrap aggregation). For data with different levels, Random Forests may be biased towards those attributes with different levels. They take up large amounts of memory and are slow to evaluate.

[22]XGBoost Algorithm

AdaBoost Algorithm - Adaboost Algorithm begins by assigning each observation with an equal weight while training the decision tree. After training, the observations which are difficult to classify are given greater weights while the others have lower weights. The second tree is trained on these weights. Therefore the new model is Tree1 + Tree2. The classifications are predicted from this tree and a new third tree is grown from the residuals. This process helps us classify observations that are very difficult and are not classified well by the previous ones. Prediction of the final model is the weighted sum of the previous models. The major difference between the AdaBoost and Gradient Boosting is how they identify the misclassifications. Adaboost uses high weights while Gradient Boost uses gradient descent in the loss function which is the measure of how well the coefficients fit the data. Gradient Boost allows the optimization of the cost function to achieve better results. XGBoost or Extreme Gradient Boost is a library for gradient Boost algorithms used widely for classification problems.

Naive Bayes Algorithm:
Naive Bayes assumes that each and every feature in a class is completely unrelated to the other features. This is a huge disadvantage as it barely occurs in real life. Bayes Theorem is as follows:

$$P(A|B) =(P(B|A)\ P(A))/P(B)$$

Where P(A) is the priori probability and P(A/B) is the posterior probability

Naive Bayes Classifier is used in text classification problems where the probability of each and every word of the sentence is calculated given that it is present in that particular category. For example, if we want to predict the class of the sentence ‘A very close game’ in the category of sports/ non sports, The probability of each and every word in that sentence given that it belongs to sports and the same for non sports must be calculated.

P(A very close game|sports) = P(A|sports)P(very|sports)P(close|sports)P(game|sports)

P(A very close game|sports) = P(A|non sports)P(very|non sports)P(close|non sports)P(game|non sports)

All of these probabilities are calculated by the Laplace Smoothing method i.e

$$P(word) = (word\ Count + \boldsymbol{\alpha}) / (Total\ number\ of\ words + Number\ of\ unique\ words)$$

Where $\boldsymbol{\alpha} = 1$ (Laplace Smoothing)

This makes sure that we do not get zero probabilities.

The probability with the highest score is taken . It was found that P(A very close game|sports) > P(A very close game|non sports). Therefore ‘A very close game’ most probably belongs to the category sports. Gaussian Naive Bayes Classifier assumes that the data follows a normal distribution. The above problem implements the MultiNominalNB naive Bayes algorithm where it counts how often a word occurs in the document. If a variable present in the test dataset is not present in the training data, a zero probability is assigned and we do not get the correct prediction. This is called Zero Frequency. Laplace Smoothing addresses this problem.

[23]CNN for classification:
Convolutional Neural Networks are one of the most common and most powerful Neural Network architectures used for various Computer Vision problems ranging from a simple dog- cat classifier to self driving cars. However Convolutional Neural Networks can also be used to address many problems that come under NLP also. Convolutions are nothing but ‘sliding windows’ applied to the input matrix be it image or text. We perform an element wise multiplication of a 3x3 filter over the input matrix and then sum it up. CNNs are several layers of convolutions and non linear activations on relu, tanh applied to results. During the training phase, these CNNs learn the values of filters based on the task we want to perform. Probably in the first layer, it might detect the vertical and the horizontal edges, the second layer, it might detect simple shapes and as the Network progresses, it might be able to detect high level features in the last layers. Therefore each filter composes a local path from low dimensionality to high level dimensionality which is why CNNs are so powerful.
Zero padding- As the filters cannot be applied to the edges of the matrix, zeros are appended to all elements outside the matrix. This is known as ‘wide convolution’.
In NLP tasks, the inputs are usually sentences or documents represented as matrices. Each row is a vector that corresponds to a word. These are usually word embeddings(word2vec or Glove) of n dimension. If there are m words in a sentence, the resultant matrix is of the size mxn.
Stride size - This is defined by how much you want to shift the filter over the matrix. Larger the stride size, smaller the output size.
Pooling - The pooling layer usually comes after the convolution layer. The most common pooling used is the ‘max pooling’. Pooling can be applied to the whole matrix or to just the window. The maximum value of each window is taken to construct the output matrix. For nlp purposes, usually the whole matrix is considered and then we get only 1 output after passing it to the pooling layer. One useful property of the pooling layers is that the output size is always fixed. If we have n filters, we get an n dimensional output regardless of the size of the filters or the size of the input. It keeps the salient features, applying max pooling gives information on whether or not the feature appeared but losing information about where it appeared. You are losing the global information about the locations but keeping the local information captured by the filters.
Given this RNNs are considered to be a better fit for NLP applications rather than CNNs.
Channels - In image recognition, you have RGB channels i.e how the data is viewed and in NLP you might have channels for different word embeddings.
Applications of CNN in NLP:
CNNs can be applied to spam detection , Sentiment Analysis etc. For sentence classification, the input layer is a sentence composed of word2vec embeddings followed by convolutional layers with multiple filters, then max pooling layers and then finally a softmax layer for classification. Some CNN models have been trained from scratch that is passing the one hot encoded vector of each word as the input. Research has also been done on applying CNNs to characters without

any pre trained word embeddings. Direct character level inputs work on large datasets but fail on simpler models.

[24]RNN for classification:
Recurrent Neural Networks are networks with loops in them that allow information to persist. They can be considered as a chain of networks where each of them pass a message to its successor. RNNs are applied to a variety of problems such as Speech Recognition, Image Captioning, translation etc. These networks have the capability of retaining past information and predict the next word based on this information. In cases where the gap between relevant information and places that it's needed is small, RNNs can learn from past information. Sometimes we need more context. If the gap between relevant information and place of the word increases, RNNs face difficulty in learning. For example: 'I grew up in France.. I speak fluent French'. If the word 'French' is to be predicted, the network requires the context 'France'. In this case, the gap is considerably large.
LSTMs(Long Short Term Memory):
LSTMs are used to address the above issue. The key parameter of the LSTM is the cell state. The cell state consists of information that may be removed or added by the LSTM. The information stored in the cell state is controlled by the gate which contains a sigmoid layer and a pointwise multiplication operator. It decides as to how much information must be passed through.
For example: we might want to store the gender of a subject. When we see a new subject, we might want to forget the gender of the old subject.

$$f_t = \boldsymbol{\sigma}(W_f . [h_{t-1} , x_t] + b_f)$$

If the output of this layer is 0, the cell state forgets the previous information but if the output is 1 it retains it.
Next, we decide on what to update to the cell state. First we have the sigmoid layer that decides which values we will update to the cell state. Then a tanh layer that gives a vector of new values that could be updated to the cell state. These two are combined to give the update state.

$$i_t = \boldsymbol{\sigma}(W_i . [h_{t-1} , x_t] + b_i)$$
$$C^{\sim}_t = \tanh(W_C . [h_{t-1} , x_t] + b_C)$$

We then multiply the old cell state with the f_t and then add it to the product of the above equations.

$$C_t = f_t * C_{t-1} + i_t * C^{\sim}_t$$

Next, we decide on what we are going to output. We run a sigmoid layer to get what parts of the cell state we are going to output, then we pass the cell state through the tanh layer(to get values between -1 and 1). We multiply this to the output of the sigmoid layer.

$$o_t = \boldsymbol{\sigma}(W_o . [h_{t-1} , x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

In language models , LSTMs might want to output the relevant verb based on whether the noun is singular or plural. For example $C_t = 1$ if singular and 0 if plural. An extension for LSTM is a Bidirectional LSTM which takes in information from both earlier and later parts of the sentence. [13]They have many applications in handwriting recognition, emotion recognition, translation, phoneme classification , human behaviour analysis, audio video data etc.

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MODULE - 2 - Data Preprocessing

Why is data preprocessing required in general?

The desired outcome of any problem statement is highly correlated with the data we pass to the algorithm. Machine Learning Algorithms learn by creating patterns in the huge amounts of data passed to it and they get better by gaining more and more experience while training. Therefore it is required to pass relevant data of a particular data type if we expect the model to give us good results. [1] Real world data comes in different forms broadly categorised into unstructured(images,text,audio) and structured data(tables). This data needs to be processed into information readable to the machine. Raw Data collected is almost always unclean which consists of missing attributes, noise,outliers,duplicate or wrong data. Data Preprocessing techniques are used to handle these difficulties posed by raw data. Data passed to the algorithm is known as Feature which represents the characteristics of an object or a phenomena in measurable scales. The types of features in Structured Data include :
Categorical Data - The Data whose values are taken from a predefined set or whose values always fall under a category in a set. If the Data has a particular order, it is called ordinal data For example: movie ratings out of 5. If there is no particular order, it is called Nominal Data.
Numerical Data - The features whose values are continuous or integer.
<u>Data PreProcessing Steps:</u>

→ Dealing with Missing Values - Sometimes eliminating the feature which consists of a large percentage of missing values can prove to be effective. However we can't apply this if many objects have missing values. If the percentage of missing values is small, we use interpolation methods to fill in the values.
[2] Interpolation: Interpolation is a model that adjusts the function to the data and extrapolates it to calculate the missing value. The most common type of interpolation is Linear Interpolation. It takes the mean of the values before the missing data and after. Missing values are easily approximated if the temporal data has a clear cut pattern. If this is not the case, the mean of the entire series is taken. Missing data can also be filled with the data around it . The mean of the previous data point and next data point can fill the missing value.
If the data is categorical, we fill the missing values with the mode of the data.

→ [1]Feature Sampling - Feature Sampling involves the selection of a subset from the dataset That represents the properties of the original dataset. This reduces the memory consumptions and the time complexity of the algorithm. *Simple Random Sampling* is commonly performed which sets the condition that there must be equal probability in choosing a sample of the dataset.Sampling without Replacement creates a bias in the dataset where the probability of selecting a sample is not equal to the others. If the dataset contains objects that vary drastically with the others, we use *Stratified Random Sampling.* A dataset is said to be imbalanced if the number of objects of one class is significantly higher than the objects of the other classes. [3]A stratified sample divides the entire population into subgroups or strata based on the shared characteristics. These subgroups adequately represent the whole sample population in a study.A simple version of stratified sampling is to pick an equal number of objects from each class irrespective of the size of the class in the dataset. In proportionate Stratified Sampling, the sample size is proportionate to the population size. One of the disadvantages of this is method is that sometimes one entity can fall into more than 1 stratum. This introduces a bias where those present in multiple groups are likely to be chosen while performing simple random sampling.

→ Dimensionality Reduction - Most Real World problems have a large number of features that describe an entity especially in Image Processing problems. When the number of dimensions increases, the number planes occupied by the data increases which increases the sparsity to the data (More empty space). This becomes harder to visualize and model. This is called the *Curse Of Dimensionality.* [4] As there is an increase in the number of dimensions, the number of entries in the feature vector increases that represents each observation in a Euclidean Space. We measure distance in a vector space using the Euclidean distance.

$$d(p,q) = \sqrt{\Sigma^{n}_{i=1}(p_i - q_i)^2}$$

Where p and q are 2 feature vectors.

If new features are added, the distance increases which means that the feature space becomes sparse or emptier. Curse of Dimensionality is the main cause for overfitting while performing K Nearest Neighbours. Dimensionality Reduction is used to address this problem.

Principal Component Analysis(PCA) -

[5]After preprocessing the data , we perform Principal Component Analysis on the features values to reduce the dimensions. The idea of PCA is to reduce the number of dimensions of the dataset correlated to each other while preserving the variations in the dataset to a maximum extent.In short PCA is nothing but an eigenvalue method to reduce while preserving important information. The principal components are nothing but the measures of variations in the data.Basically,Principal Components are given by an orthogonal linear transformation of a set of variables optimizing a certain algebraic criterion.The two main steps required in finding out the principal components are to subtract the mean from the data point and to find the covariance matrix i.e the relation between the dimensions.The Variance of the data is defined as the deviation of each and every term from it's arithmetic mean.Co-variance is nothing but the variance that is taken with respect to multiple dimensions.

$$Cov(X,Y) = (\Sigma_{i=1}^{n}(X_i - X')(Y_i - Y'))/(n-1)$$

Where X' is the arithmetic mean of data X Y' is the arithmetic mean of data Y and n is the number of observations

On multiplication of any random vector to this matrix, we get a vector of greater magnitude with direction turned towards the vector with highest variation that is principal component 1 or PC1.The Principal Components are highly sensitive to the units of measurements which is a major drawback in PCA on covariance matrices.Further multiplication with random vectors reaches a point where the direction of the vector does not change.This vector is known as an eigenvector. An Eigenvector of a matrix A is a vector when multiplied by A returns a vector which is a scalar multiple of itself.

$$Av = \lambda v$$

Covariance matrices are symmetric and symmetric matrices have orthogonal vectors. Therefore PCA always leads to orthogonal components.Next, we project these eigenvectors onto our new dimensions, that is the reduced dimensions(n). The first step involved in this is to center our data around the mean i.e to subtract the mean from each datapoint. The first n eigenvectors are chosen and the dot product of these vectors with the transposed center data gives the projection and results in an n dimensional vector which is the PCA'd vector of the original dataset.

[6]Singular Value Decomposition - It is a matrix factorization technique that decomposes a matrix into 3 matrices.

$$A= USV^T$$

Where S is a diagonal matrix of singular values. This represents the rank of the matrix A. A is a matrix of size m x n . U is a matrix of size m x r and V is a matrix of size n x r.

We can think of U as a matrix representing the similarity of the rows of the data with the concept the data is trying to represent. V can be thought of the similarity of columns and the concept. For example, if we consider the rows of the matrix A as users ratings and the columns of A as the movies. The concept would be either romantic or scifi. Based on the user ratings, we can figure out the concepts that are mostly represented. SVD represents the best axis to project the data on. By 'best', we mean the projection that results in the minimum sum of squares of the errors of all the movie ratings. S represents the variance('spread') on the projection axis. As we saw in PCA, the value with the most variance represents the dataset the most. Therefore, we replace the element of the least variance from matrix S and it's corresponding rows in U and V with zero. Next we multiply, all the resultant matrices. Let's say this matrix is B. The Frobenius distance between the two results in a very small value.

$$||A-B||_F = \sqrt{\Sigma_{ij}} (A_{ij} - B_{ij})^2$$

What are the difficulties involved in handling text data in particular?

[7] Text analysis allows us to extract information such as sentiment, intentions, reviews and responses from documents,tweets, reddit etc. The most common application is the sentiment analysis of tweets, language translation, etc. To perform tasks related to text data, the machine is required to understand the emotion and the hidden meaning behind the text. Each word from the given text is tagged, this helps the algorithm to identify the relations and associations between

the words. A popular application of text analysis is priority detection . The machine must be able to identify which text must be prioritised over another. A common problem while handling similar applications may be the ambiguity in detecting sarcasm, idioms or slang language in the text. This may result in the algorithm in giving a completely different output. Speech to text translation can face difficulty in translating homophones. It also needs to take into account various different accents of the user. While performing sentiment analysis there might come a situation where the text has mixed emotions. This is where we use Attention Mechanism with LSTMs to consider only the important features.

[8] Difficulties in Sentiment Analysis - Sentiment Analysis looks just like a simple text classification problem from the outside but there are many difficulties faced while addressing this problem statement. Sentiment analysis has 3 broad categories namely, positive,negative and neutral sentiments. Sarcastic comments are usually positive comments but with negative sentiment.These comments make it very difficult for the algorithm to classify the text without understanding the context of the situation or the environment. Sarcasm is also sometimes hard for humans to understand it . The most common type of sarcasm was found to be numeric sarcasm found in a lot of social media platforms. These are the types of conversations where numerical values can affect text polarity. Example :

We drove slowly ,only 20kmph (non sarcastic)

We drove slowly , only 160 kmph (sarcastic)

[9] Neural Network architectures, such as CNN , DNN and RNN have shown excellent capabilities. A sarcastic text can be considered elementally as a sequence of text signals or word combinations. RNN is a perfect fit for modelling temporal text signals as it includes a memory component that stores contextual information directly into the model. CNNs have the ability to reduce frequency variations in the input and map the input features into robust features which are fed into the LSTM. The main disadvantage of CNN is that it has only fixed filter widths and is not suitable to handle text with different lengths. CNNs can catch patterns in temporal text with shorter lengths only. Element wise multiplication is performed between the input matrix and filter to produce composite features to be passed into the LSTM model. The sigmoid activation function is used to ensure non linearity. RNN includes a memory component which allows the model to store temporal contextual information. If the gap between two time steps becomes large, we use LSTMs that define a memory cell and a set of gates. LSTMs do not suffer from vanishing or exploding gradients while performing backpropagation. The output of the LSTM layer is passed to the Deep Neural Network layer which produces a high order feature set. This feature set can be easily categorized into the required classes.

[8] Negation Detection - Negation is a way of reversing the meaning of a sentence or a phrase. Negation Detection can prove to be difficult as it is necessary to figure out the range of words that are affected by this negation word which isn’t fixed. Negation words include ‘not’ , ‘diss’, ‘less’. Most sentiment analysis techniques negate all the words that occur after the negation

word. This method will not work if the sentence does not have any negation word but conveys negative meaning . Example :

'If this kind of behaviour continues, this would be the last time you go.'

Various LSTM models outperform other models in detecting negative emotions.

[10] The method described in this paper aims at extracting and analysing data about a specific topic from social media networks. It performs sentiment analysis by combining the unigram model with the Word Sense Disambiguation(WSD) Technique on bigram. WSD is a technique in finding out which meaning of the word is to be considered given the context of the sentence. It is usually applied in Machine Translation, Information Retrieval and Text Mining. The text analysis process includes text tokenization, parts of speech tagging (POS),lemmatization and finally the sentiment scores of the words that are -1,0 or 1 for negative, neutral or positive sentiment. The algorithm worked poorly while handling negative data reaching a 64.4 % . Therefore the Negation Handling technique was introduced. Bag Of Words is an algorithm that takes into account only the multiplicity of the words. Due to this simplicity, it fails to handle the negation words in a sentence. A possible approach may be to use dependencies or grammatical relations among words. This kind of parser produces a list of relations between word pairs. However sometimes a negative word in a sentence may not result in a negative sentiment . For example:

I do not hate my enemies

This will be classified as a negative sentiment even if it is a positive one. This paper proposes to build a dependency parse tree with both grammatical relations and the order of appearance of terms. The algorithm builds this tree and explores it to find the negation words using the DFS approach. It is assumed that the negative words only affect the nearby words of the same clause. If the negation word is the tree node, the algorithm inverts the polarity of the sibling nodes as they belong to the same clause. The sentiment score of the negation word is 0 itself. The WDS along with the Negation Handling approach gave an improved accuracy of 67%.

Basic steps involved in preprocessing/ cleaning of text data.

[11]Before we pass our data into any model, it is necessary we first preprocess the data. Data preprocessing when it comes to text has many stages. The 3 main important tasks to be performed for data preprocessing are -

Tokenization - Tokenization is the process of splitting sentences or longer strings precisely into words. We use the inbuilt tokenize( ) from the nltk package. It may seem like we could accomplish this task manually by splitting the string based on punctuations but there are many examples where this approach will not work. This approach would give bad results when we have to figure out all the sentences from a document. For example :

Dr.Ford asked the name of Mr.Smith's dog.

Note that *Dr.Ford* and *Mr.Smith* are two entities where Dr and Ford would have been separated by using traditional methods.

Normalization - Normalization of text refers to tasks where the text is brought down to the same level. Steps include converting all the text to lower or upper case, removing punctuations, removing stop words (and,or..) according to the problem we are required to solve,converting the numbers into their word equivalents etc. Stop words do not contribute to the inner meaning of the context. For example in classification of positive or negative sentiments, these stopwords have an equal probability of being in the positive sentiment column or the negative sentiment column. Further, normalization is divided into stemming and lemmatization. [12]Stemming is the process of removing the prefixes and suffixes of words and mapping a group of words to a single stem even if it is not valid. For example :

Playing - play
Plays - play
Played - play

PortStemmer uses *SuffixStripping* for stemming. The reason why PortStemmer does not often output English words is because it does not keep a lookup table for actual stems of words but uses algorithmic rules to generate these stems . It decides whether or not to keep the suffixes through these rules. PortStemmer is known for its simplicity and speed. LancasterStemmer is an iterative algorithm with rules specified externally. A table contains about 120 rules indexed by the last letter of the suffix of a word. Based on this last letter, it decides the rule i.e whether to delete the letter or to replace it. Heavy stemming during the iterations may cause the algorithm to over - stem i.e the words might seize to have any meaning.

[11] Lemmatization is similar to Stemming but this algorithm is able to catch the canonical form of the word. For example *Better* would result in *good* on lemmatization. Lemmatization ensures that the root word belongs to the English vocabulary. You need to specify the context in which you want to lemmatize.

Another method that is necessary for pre processing is the removal of contractions. For example:

What's is replaced with *What is*
You're is replaced with *You are*

Noise removal - Usually , we obtain our textual dataset by web scraping from websites using tools such as BeautifulSoup. To extract the exact data that we need, we must remove the text file header, footers, HTML.XML, metadata etc. We might need to extract valuable data that is in the JSON format .

[13]Parts Of Speech Tagging - POS tagging is a mechanism used for labelling each word in a sentence with it's appropriate part- of - speech. Rule- based POS tagging uses dictionaries to get the possible tags for a word. If the word contains more than one tag, the algorithm considers the features of the preceding tag as well as the following one to assign the appropriate tag for the

word. For example : If the preceding word is an article, the following word must be a noun.The rules in Rule Based tagging are manually written which are limited to around 1000 rules.
Stochastic POS tagging performs tagging by calculating the probability of a tag occurring. It might consider the most frequent tag of the corresponding word in the train corpus for unseen or ambiguous situations in the test corpus.This is called Word Frequency Approach. Another approach would be to assign the best tag to a word by calculating the probability of the tag with *n* previous tags.
Transformation - Based Tagging shows similarity between Rule Based as well as Stochastic tagging. It is a rule based algorithm for automatic assignment of POS tags to a word.It also uses rules that decides what tags need to be assigned to a word and these rules are derived by ML models from the data.
Hidden Markov Model for POS tagging - The idea of this algorithm is to find the sequence of tags which most likely generated the sequence of words. We can model this POS process by using HMM where we specify the tags as hidden states that produced the words. We need to maximize the probability of a tag sequence given a word sequence.

Advanced text processing steps.

[14]Ngram Model - Ngram Model is a simple model that assigns probabilities to a given sequence of words or sentences. Ngram is nothing but a sequence of N words. Bi-Gram is a sequence of two words while tri- gram is a sequence of 3 words.
P(w|h) is the probability of a word w given it's history h . For example :

$$P(the|It\ rained\ so\ hard\ that)$$

To find this, we will need to count the number of times *'It rained so hard that'* and the number of times '*the'* followed it. This becomes practically impossible and infeasible to compute in a large training corpus. Therefore we use the Bi-Gram approach where we calculate the probability of a given word with respect to its history by just considering the previous word. This assumption is known as the Markov Assumption i.e :

$$P(W_n \mid W_1^{n-1}) = P(W_n \mid W_{n-1})$$

To calculate this probability, we use Maximum Likelihood Estimation. We get the n grams count from the corpus and normalize the values so that it lies between 0 and 1. For example, if we need to find the probability of a word *y* given the previous word *x*, we need to count all the bigrams *C(xy)* and normalize it by the sum of all the bigrams that share the same first word.
Markov models make an assumption that we can predict into the future without looking far into the past. Any training corpus is limited therefore acceptable English sequences might be missing. This might result in the N gram model giving a zero probability. The N gram model is highly dependent on the training corpus. The accuracy can change if we convert bi gram into tri gram.

[15]Term Frequency - The main purpose of Term Frequency and Inverse Document Frequency was for document extraction and information retrieval. It's proportionate to the number of times a key word occurs in the document as well as the number of documents containing this word. This ensures that stop words are not considered as they do not add meaning to the document. It helps us associate the words of a document with its relevance to that document. Similar words will have similar relevance to a document which is what our algorithm needs to find out. Tf-IDf approach can help in extracting relevant keywords from a document. The higher the tf-idf score,the more weight it carries. Term Frequency is the raw count of the instances that occur in a document. The frequency of this can be adjusted. Inverse Document Frequency is how common or rare a word is in a document.The closer the value is to 0,more common the word is. The metric can be calculated by taking the total number of documents and dividing it by the number of documents that contain that word and then applying logarithm to that. Multiplying these two frequencies, we get the TF-IDF score of the word in the document.

$$tf(t,d,D) = tf(t,d).idf(t,D)$$

[16]Bag Of Words - Textual data is usually messy and machine learning algorithms usually prefer fixed length inputs. We cannot send in raw text directly to the model, therefore we will need to convert the text into a vector of numbers. This is called feature encoding. Bag-Of-Words is a technique for extracting features from a text. It's a representation that gives the occurrence of words in a document. It involves the vocabulary of the given words and how often they occur in the document. The algorithm does not take into consideration the location of the word in a document but only the histogram of words within a text i.e the word count in the text. The Bernoulli Document model represents documents as Bag Of Words using Naive Bayes assumption. A document is represented by a feature vector with binary elements taking the value 1 if the corresponding word is present in the document or 0 if it is not. Example of Bag Of Words-

Sentence 1 : The cat sat on the hat

Sentence 2: The dog ate the hat

Vocabulary :{ *The,cat,sat,on,hat,dog,ate*}

The encoding for sentence 1 is {2,1,1,1,1,0,0}

Sentence 2 is {2,0,0,0,1,1,1}

In computer vision, the bag of visual words is the vector of occurrence counts of a vocabulary of local image features.

[17]Continuous Bag Of Words - This algorithm tends to predict a probability of a word given a context which may be a single word or a group of words. If we have a corpus C , we first need to construct a matrix with the one hot encoding of each word. The matrix is sent into a shallow neural network with an input layer, hidden layer and an output layer. If we have 3 context

vectors for a single target word, we will have 3 initial hidden activations which are then averaged element-wise to obtain the final activation.

$$p(wo|wi) = \exp(v'_{wo}{}^{T}| v_{wi})/(\Sigma_{w=1}^{W} \exp(v'_{w}{}^{T} v_{wi})$$

$$CBOW = -\log(p(wo/wi))$$

wo : output words

wi : context words

CBOW takes the average of the context of words. For ex: Apple can either be a fruit or a company. CBOW takes the average of these two contexts and places it in between a cluster for both fruits and companies.

[18]Skip Gram Model - The skip gram model achieves the reversal of the CBOW algorithm. It predicts the context vector i.e the surrounding text given a target variable(center text). For example this model aims to predict the context *[quick,fox]* given the word *[brown]* or *[the, brown]* given the target word *[quick]*. We feed the model with a pair of words (X,Y) where X is the input target word and Y is the context. We feed in ([target,context],1) to specify a positive label which means that the target and the context are related . The negative example passed is in the form ([target,context],0) which signifies that the pair of words are irrelevant. This makes sure we get the similar word embeddings for semantically similar words.

Word2Vec is the most popular method of learning features from text and transforming them to their associated embeddings. It can use either the CBOW approach or the Skip Gram approach. It was found that the Skip Gram approach showed better results for small amounts of data and the CBOW approach works well for more frequent words.

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Module-3:
Data Exploration & Visualization

3.1 Why is Exploratory Data Analysis (EDA) for text data required?

Exploratory Data Analysis or EDA is important for both structured and unstructured data As it gives us insights on the underlying features of the data and helps us find trends ,patterns so that we can apply the appropriate models as well as give our own hypothesis on the data. The EDA for structured data and unstructured data differ greatly. Common visualization tools like bar plots.histograms,correlation matrices are not suited for textual data.[1] Visually representing the contents of a text document is one of the most important steps in any NLP problem. It helps us get a heuristic idea of the events in the summary and on how we can create storylines from that data. However, we can use histograms and bar plots for problem statements that predict categorical data.For example: Sentiment Polarity Distribution using tools like Plotly.[2] Visualization of textual data comes after the text cleaning and preprocessing stage as described in the previous module.This blog mainly focuses on the the sentiments of the reviews on amazon products. In this blog, a Document Term Matrix was created to provide frequency of words in a corpus. It helps in analysing the frequency of words in each document.

Exploratory Data Analysis on Amazon Product Reviews - The first step is to plot the most common words which can be obtained from the Document Term Matrix and visualize it using WordClouds. WordCloud is a visualization tool that gives the frequencies of different tools in the document. It gives more importance to frequent bigger words when compared to the less frequent words. It was found out that LOVE,EASY,BUY and GREAT were the most common words in the document. This shows us that probably most people love purchasing their products on amazon. It also can give us a start in the error analysis in cases we get much varying predicted outputs. To find the polarities, they have used the TextBlob library that classifies the positive and the negative sentiments. This was visualized easily using barplots where it was concluded that Amazon had room for improvement in their Fire Kids Edition Tablet. Another way we can analyse textual data is by analysing the readability of the data that is how understandable the text data is. There are various methods to achieve the same which include Flesch Reading Ease, Dale Chall Readability Score and Gunning Fox index.

Flesch Reading Ease - Flesch Reading Ease is a technique used to understand how difficult a passage in English is easy to understand. Higher the score, easier the material is to understand and read. Flesch Reading Ease test is given by :

206.835 - 1.0.15(total words/total sentences) - 84.6(total syllabus/total words)

Dale Chall Readability Score - It provides a comprehension difficulty that readers come upon while reading a text. It uses a list of 3000 words that groups of fourth grade American students could reliably understand. The Dale Chall Readability score is :

0.1579((difficult words/words) x 100) + 0.0496(words/sentences)

Gunning Fog Index - It’s a readability test that estimates the years of formal education required by a person to understand on the first reading . The formula for the test is :

0.4[(words/sentences) + 100(complex words/words)]

3.2 What are the basic statistics on the text data?

[3]Word Frequency Analysis - Word Frequency involves the occurrence of every n-gram model that can be uni gram or bi gram in a corpus that can be counted to classify it into a potential category.In the example given in this particular blog, they have used term frequency to categorize the words into categories of *trustworthy* and *untrustworthy*.

For example consider the corpus of words to be :

He is a cheater and never stops lying.

She is incompetent and has a history for lying

He is a lying racist.

The most common words in this text corpus are *is,a* and *lying* in which *lying* is the most significant word and *is,a* can be removed in the preprocessing stage. If the test corpus contains the word *lied* or *cheated*, by using lemmatization, we would be able to correctly classify the words to the untrustworthy category as lemmatization takes into consideration the base words.

[4]Collocation - Collocation helps in giving us insights in how often two words co-occur. Analysing bi-grams and trigrams can give us the hidden semantic patterns in the text which is more efficient than using uni grams. For example *‘water park’* can be a collocation in a given context and *‘water heater’* in another context can be very useful in analysing text data.

Concordance - Concordance is used to identify the context and instances of a word or a set of words. The example used in the blog uses *simple* as a target and analyses the preceding context as well as the following context of the target in each of the reviews. For example :

Preceding context : *Hate the new update*

Target: *simple*

Following Context : *as that*

Preceding context: *It’s quite good*

Target: *simple*

Following Context: *to use*

Simple is used in two complete different ways expressing negative as well as positive emotion. This method gives us insights on how users use the target word and can also be used to eliminate human ambiguity to some extent. From this example we can make out two different contexts and analyse more complex phrases.

[5] Handling unknown words (OOV or Out-Of-Word Vocabulary Model) - The limitations of word embeddings is that they are learnt by Natural Language Models and therefore words must have been part of the training dataset. If we encounter an OOV word, we sequence the words in the sentence and try to predict the meaning of the word in the sentence by comparing it with other sentences. We aim at producing embeddings for the OOV words

depending upon the context of the OOV word. We use Bi-Directional RNN LSTM. We predict the most probable word embeddings in the place of the OOV word and then taking the weighted average of their mapped word embeddings.The step by step process for this includes the preprocessing of a large corpus of text with tokenization ,encoding the words as unique integers and then the Embedding Prediction Model to predict the OOV words. The Forward as well as the Backward sequences of text are prepared as we are required to predict the embedding with respect to the former and the latter words of the OOV text. These sequences form the inputs and are required to have the same length. Next, we define the layers of the Neural Network required. The first layer is the embedding layer to get the vector representation of each sequence. The second layer is the Bi Directional layer that can be tuned to fit the training corpus. The last layer is the output layer with the softmax activation that outputs the probability distribution of the vocabulary based on the sequence we input the Neural Network. We take in a sample input text and locate the OOV word in the vocabulary. The embedding for the OOV word is generated and updated. In the end, this embedding is added to the pretrained models such as GLOVE,Word2Vec etc.

[6]Feature Engineering - The most important part of any text classification is feature engineering where we transform raw text data into embedded vectors or features that can be passed into the model. We may even want to consider checking if the corpus belongs to the same language or not.All of these steps can be included in the preprocessing of the textual data before a classification model is created.

Length Analysis - It is important for us to visualize the count of words and the lengths of the sentences in the corpus for sequence models and it gives us insights on the data. There are many ways to measure length in textual data. Word Count gives the count of the number of words or tokens in the corpus, character count gives the number of characters of each token, sentence count counts the number of sentences, average word count gives the sum of the number of words divided by their word count, average sentence count gives the number of sentences divided by the sentence count. Using these variables, we can find the distribution of those variables with respect to the target. In the example given this blog, we divide the dataset into 3 categories that is Entertainment,Politics,Tech. We compare the histograms and densities of the samples. If the distributions are different, then the variable is predictive because it can be easily classified into the 3 categories. We check these plots for each of the variables that is character count,word count etc with the target (y) and arrive at some insights as to what can be a predicting factor for the samples. Since the distribution plots turned out to be similar, we can conclude that character count is not really a good factor to analyse the category of the data.

The next analysis done in this blog is the sentiment analysis and whether the sentiment can be an effective way of classifying the data point into the three categories. TextBlob and Vader can be used as pretrained models to extract the sentiments of a text. Next we find if there is any pattern between the categories and the sentiments. It was found out that the Politics news is more skewed towards the negative tail while the Tech news is skewed more towards the positive tail.

Named Entity Recognition(NER) - NER is the process of tagging an entity in the dataset into categories such as person, organizations, locations, buildings ,objects etc. SpaCy is an open source tool that is used to recognize such entities. To make use of this feature for visualizations, we run this tool on every observation in the dataset. In this dataset, we take each observation to be a news headline. For each text , we make a dictionary with the entity,tag and number of times it occurs. For example :

Will Smith ***Person*** *Joins Diplo* ***Person*** *And Nicky Jam* ***Person*** *For The 2018 World Cup's* ***Event*** *Official Song*

{('Will Smith','PERSON'):1,
('Diplo','PERSON'):1,
('Nicky Jam','PERSON'):1,
('The 2018 World Cup's','EVENT'):1}

Next we create a column for each category and find the number of entities in each tag.

PERSON :3
EVENT:1

We can visualize the three categories that are ENTERTAINMENT,POLITICS and TECH with respect to the most frequent tags found. For example in 'Entertainment' , we find that the 'Person' tag is most frequently found when compared to the other tags. We may run into problems while considering names like *'Will Smith'* with stopwords like 'will'. We use SpaCy to recognize a person's name, we can use **name detection** to change the string.

3.2 What are the steps involved in EDA of text data?

Word Frequency
A single word can tell us a lot about which category the sentence should belong to. We can visualize these words using n-grams. An n gram is a sequence of words given from a sample text. We can visualize the most frequent words in each category using bar plots. We can create new features based on how frequently the n grams appear in a category. In the Bag Of Words approach we use all words as features. In this example, we find that 'box office' is most commonly used in Entertainment, 'President' in politics and 'apple' in tech. We use these as features to represent the text corpus using CountVectorizer that returns a matrix of each of these token counts. We can visualize these using Word Clouds. The size and color of the font signifies the frequency of each tag.
Word Vectors - Neural Network Architectures used for feature learning and vectorization of text corpus has been replacing traditional N gram models. The real numbered vectors that are a result of word transformation are called Word Embeddings. These are estimated by calculating the probability distributions of what words may appear before or after the concerned word. Using these vectors, it would be fairly simple to estimate the similar words using the Euclidean distance between the vectors. A popular package used to obtain word embeddings is the gensim model. Gensim is an unsupervised model for obtaining vector representations of vocabulary size 300. We can figure out the most similar word from this model and plot these vector representations by reducing their dimensions to only 2. This can be done by many dimensionality reduction techniques like PCA or t SNE.
Topic Modelling - Gensim package is widely used in Topic modelling. Topic modelling is

the process in discovering the most appropriate topics for a set of documents. Statistical models are available that can explain why some data points are similar to others.(Latent Dirichlet Allocation). We will need to specify how many topics we desire in a text corpus beforehand. We can visualize all the n grams divided into their respective topic and have an idea of the models performance by inspecting how many of those n grams are actually similar.

[7] Qualitative Comparisons
As explained in the previous section, word embeddings give us a great description of the text with respect to the dataset in the form of numerical values. They can provide us with qualitative comparisons of words as they represent words with high dimensional vectors whose dimensions can be reduced for visualizations using dimensionality reduction techniques. We can provide understandable visualizations using bubble charts where the color can imply the average word length and the similarity measure can be based on anything like the frequency of the bigrams appearing in a particular topic or the vocabulary length etc. Another visualization technique that can be used is the treemap visualization. This visualization is effective when we want to figure out length related patterns in the data. For example if we want to differentiate between complaints and praise, we generally observe that the complaint messages are usually longer than praises. The treemap generally divides the data into a particular topic and checks for any such differentiating tokens in those samples.The box size indicates group sizing and the color indicates the average length.
In some cases we might also want to compare the proportions of complaints through various products or companies. Here a stacked bar might come in handy. Pie charts can also be visualized if we are comparing proportions. We can also use the top 50 bigrams and compare the frequencies of these bigrams for each company or product. We can get insights into which product might be overperforming the other or which company has better feedback from the public. We can also visualize the increase or decrease in the complaint rate for any company over a period of time or plot the histograms of all companies complaints over a period of time. However, we can get most out of the Exploratory Data Analysis by visualizing the n grams and using word embeddings for similarity checks.

References:

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[6]https://towardsdatascience.com/text-analysis-feature-engineering-with-nlp-502d6ea9225d#:~:text=The%20most%20important%20part%20of,to%20build%20a%20classification%20model.

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MODULE - 4 (PRACTICAL)

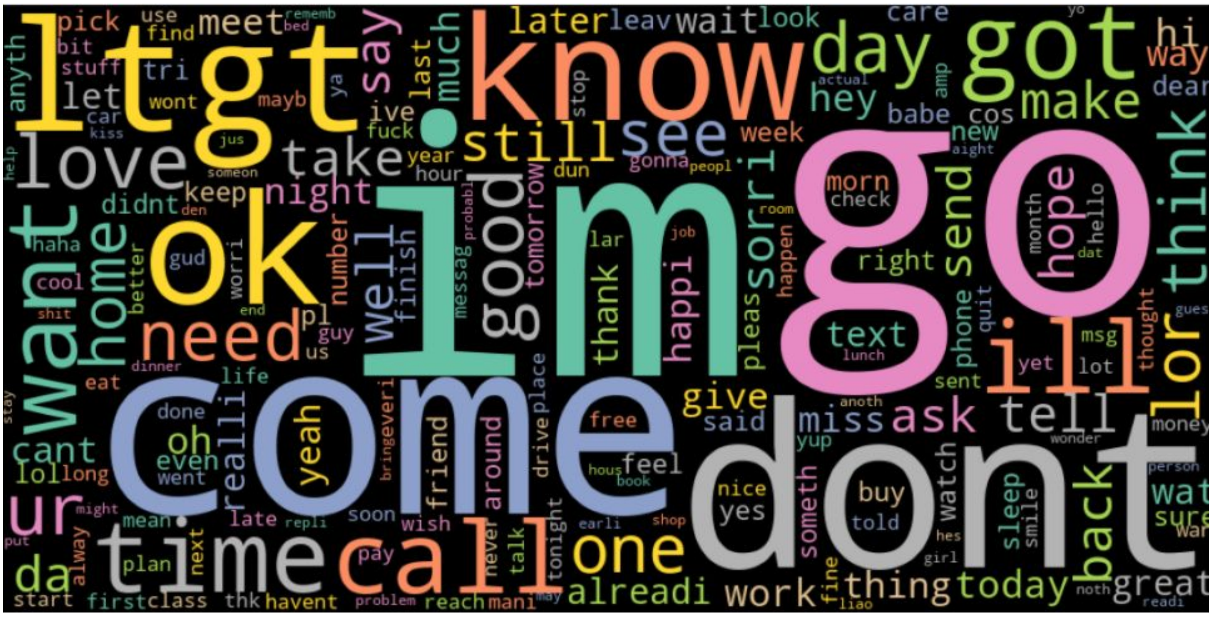
Dataset

SMSSpamCollection Dataset - https://archive.ics.uci.edu/ml/datasets/sms+spam+collection
This dataset contains SMS messages divided into 2 categories ‘ham’ and ‘spam’. There are 5574 rows in total.

Cleaning and EDA

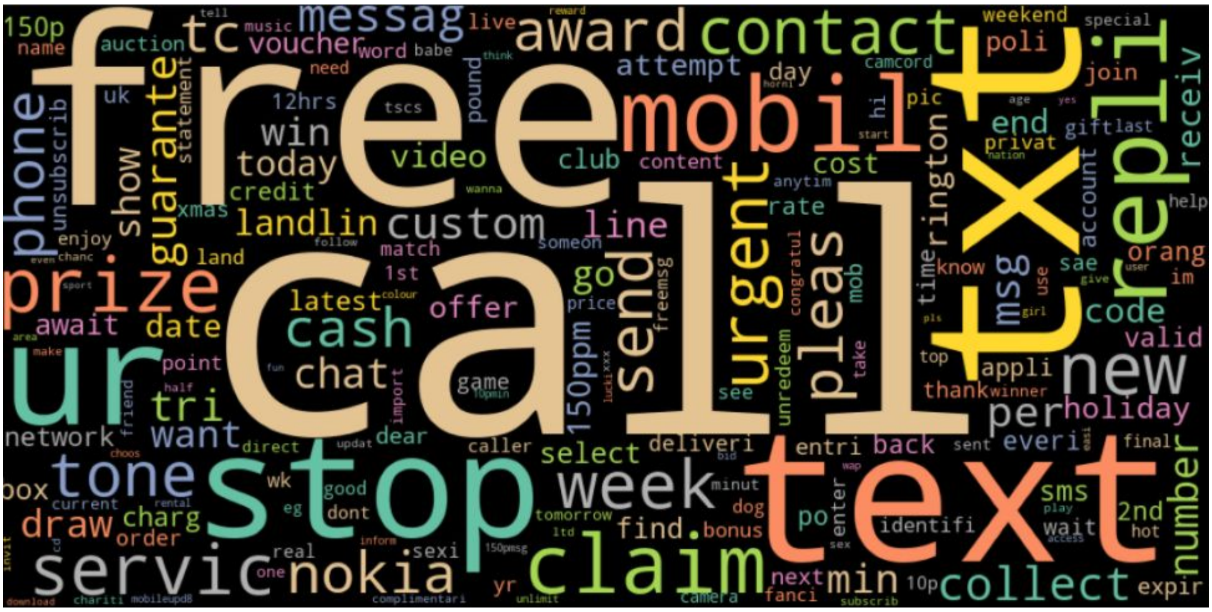
The data contains 444 duplicate values mostly from the ham category. While cleaning the text, we remove all the punctuation,stopwords and apply stemming to the data. We do not remove numbers from the text data as it has been observed that the ‘Spam’ text contains a lot of numbers when compared to the ham data and can be used as a good differentiating factor. The dataset is highly imbalanced even after removing the duplicates, there are 4281 rows in the ‘Ham’ category and 543 rows in the ‘Spam’ category. Therefore to increase the data in the minority class, we use SMOTE, an oversampling technique to balance the data.
The number of unique words in the ‘ham’ are 44 and in ‘spam’ are 39. The mean length of each sentence in ham is 42.129 and the mean length in the ‘spam’ is 98.20994475138122 .

Word Count Visualization ‘ham’ text:



In ‘ham’ messages, we see that the most common words are ‘im’, ‘come’, ‘go’,’dont’ which signify normal text messages and can be easily differentiated between ‘Spam’ messages. The larger the size of the word, the more frequent it is in the category and more weightage it must be given for categorizing.

Word Cloud For Spam :



Here we see that most of the ‘Spam’ messages contain words like ‘free’,’call’,’service’,’win’,’prize’, ‘award'   which are the most frequent words that can be found in spam texts. Therefore these words can be given more weightage while classifying ‘spam’ from ‘ham’. We also notice that spam messages tend to be more formal than ham messages.

We use TF-IDF vectorizer to vectorize the feature values.

Modelling Techniques:

SVM(Support Vector Machines):

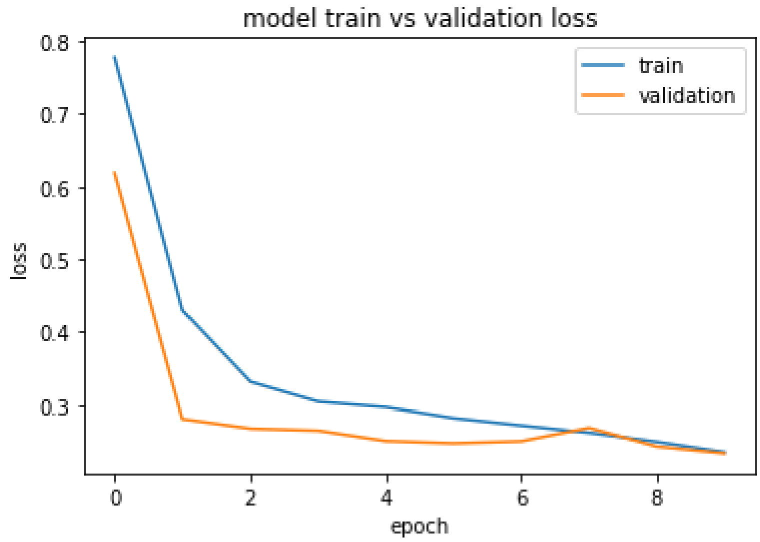
SVM is one of the approaches I have used for modelling and prediction of the data. The C value in Support Vector Machine indicates to what extent we would tolerate the misclassification of the samples. Larger the C value, smaller the marginal hyperplane. With the C value as 1000, I was able to achieve 95.2 test accuracy and the model misclassified 41 samples.

RNN(Recurrent Neural Network) with LSTM:

In most NLP text classification techniques, RNNs are used to maintain or ‘remember’ the context of the word which is used later in predictions. Each and every word that we input relates to each other. Predictions are made at the end of each data point once the context of each word is stored.

Before we create the RNN, we must map each vector to a number. The number of unique words we took is 600 which gave a perfect fit on many trials. Anything above this number would overfit the model and anything below would underfit it. We also need to make each encoded input the same length. Therefore we pad zeros to some vectors and we take 25 as the maximum length. The labels must also be encoded from ‘ham’,’spam’ to class 1 and class 2. We use the Tokenizer( ) to encode the labels. Once encoded, we must balance the dataset as explained above. We use SMOTE to equalize the classes. After equalizing, we one-hot encode the labels i.e represent the labels in terms of 3 classes since our labels contain 1 and 2. Next, we build our model.

In our model, we add an Embedding layer where words are encoded as high dimensional vectors and closeness of vectors indicate words with similar meanings. We map each word to 8 dimension vectors and the number of words is 600. Next, we initialize the LSTM layer, we pass the dimension as the input. The last Dense layer we have 3 output dimensions with activation ‘softmax’. The loss function is ‘categorical cross entropy’ and metrics accuracy. The optimizer function is ‘adam’.



This graph shows the perfect fit which is not overfitting nor underfitting. The train accuracy is 91.1% and test accuracy is 90.14%.

Naive Bayes Algorithm:

The main assumption made by this algorithm is that it assumes all words are independent of each other and each feature makes an equal contribution.

Therefore:

$$P(A,B) = P(A)P(B)$$

This is a fairly strong assumption which does not hold good in most real world applications. Words that heavily depend on the context they are used in and also on surrounding words are not handled by Naive Bayes algorithm due to the independence assumption. Sentiments in more difficult datasets may also include the use of sarcastic contexts that c

Naive Bayes calculates the probability of ‘ham’ or ‘spam’ given the word. We use the bayesian formula to calculate this probability. Higher the value, more probable the word or the feature belongs to that class.

$$P(\text{'ham'}|\text{word}) = (P(\text{word}|\text{'ham'})P(\text{'ham'}))/P(\text{word})$$

Naive Bayes algorithm, due to the independence rule assumes that

$$P(\text{word1},\text{word2},\text{word3}\ldots\text{wordN}|\text{'ham'}) = P(\text{word1}|\text{'ham'})P(\text{word2}|\text{'ham'})\ldots P(\text{wordN}|\text{'ham'})$$

To account for zero probability or words that the model has not seen before, we apply Laplacian smoothing to cancel out the zero effect on multiplication. We usually take the parameter to be 1. Therefore, we add 1 to the numerator and add a total number of unique words to both classes in the denominator.
Here, we use MultiNomialNB( ) for the classification. In this example Naive Bayes algorithm worked fairly well with 96.21%.