**Can data analysis be used on electricity usage data to effectively predict the occupancy of the household to identify circumstances in which elderly or   
disabled residents may require aid**

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By

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**ABSTRACT**

**ACKNOWLEDGMENTS**

**TABLE OF CONTENTS**

Member Profilesi

Declaration of originalityii

ABSTRACTIii

AcknowledgmentsIv

**CHAPTER 1 - INTRODUCTION1**

* 1. Overview2
  2. Problem description and motivation3

CHAPTER 2 - Literature Review4

2.1 What is Machine Learning?5

2.2 Supervised and Unsupervised Learning5

2.3 Algorithms6

2.3.1 k-NN Algorithm6

2.3.2 Linear Regression6

2.3.3 Neural Network Classification6

2.4 Related Work6

2.5 Inspection6

CHAPTER 3 - METHODOLOGY4

3.1 The Dataset5

3.1.1 Contender6

3.1.2 Compendium6

3.1.3 Collection Methodology6

3.2 Environment5

3.2.1 Tools6

3.2.2 Libraries6

3.3 Algorithms6

3.3.1 Regression & Classification6

3.3.2 k-NN Algorithm6

3.3.3 Linear Regression6

3.3.4 Neural Network Classification6

3.4 Statistical Analysis6

3.5 Definition and formulae of Statistical computations6

CHAPTER 4 - ANALYSIS4

4.1 Visual Aids5

4.1.1 k-NN Regressor6

4.1.2 k-NN Classifier6

4.1.3 Linear Regressor6

4.1.4 Neural Network Classifier6

4.1.5 Notation6

4.2 Statistical Analysis Report6

3.1.3 Collection Methodology6

CHAPTER 67 – PROJECT MANAGEMENT4

**LIST OF TABLES**

**CHAPTER 1 – LITERATURE REVIEW1**

Table 1. 2

Problem description and motivation3

**CHAPTER 1**

**INTRODUCTION**

* 1. **Overview**

This dissertation talks about and compares different data mining algorithms based on their ability to correctly predict the number of occupants of a household or simply just the presence of people using the homes electricity usage data. It comments on their accuracy and precision and concludes what specific algorithm best translates itself within the given dataset and type of computational environment. The findings are furthered by providing an application area where seniors or disabled residents can benefit by the implementation of such a system and continue living independently and abdicate assisted living or other equivalent unreasonably priced solutions to the challenges that come with age, disabilities and living by one’s self.

* 1. **Problem definition and Motivation**

In a research survey carried out by the NHS it was revealed that around one in three adults over the age of 65 are susceptible to fall over at least once a year (NHS, 2015). Around half of whom are likely to fall more frequently. Another similar extended research concluded that two thirds of those who have fallen once are more susceptible to fall again in the next 6 months (Senior Health & Wellness Blog, 2018). In the UK alone, the cause of death amongst seniors aged 75 and over is the most common and unfortunate occurrence (Age UK, 2017).

The government and private institutions are trying their best to get a hold on the situation and minimise these forlorn happenings. (1) Care homes, government allotted nurses, private carers and volunteer organisations are all viable solutions, but extortionate and according to a survey, unfavourable to the elderly as they fear losing their independence more than they fear illness and death.

<http://casas.wsu.edu/news/aging-at-home>

An article published by the Washington state university briefly outlined the average cost of assisted living being somewhere around 70,000 dollars per annum which equates to more than £49,000 per year.

There needs to be an affordable solution for seniors and citizens who, not only, want to keep their independence, but also need to be able to afford it, on their subordinate pension and income.

The application and motivation of this research project is aimed at the elderly and disabled people who reside on their own. As mentioned above, problems like getting around the house and doing daily chores etc can become a struggle at their fragile age and accidents often happen.

Many propositions and steps have already been taken to prevent such events from happening but most of the times they require additional equipment like infrared or heat sensors in homes to monitor movement of the residents which, yet again by being expensive, violates the conditions of a well-suited solution for people who want to be able to afford independence.

Electricity usage data is readily available for, if not all then, most households and the required data is being recorded but going to waste. The imminent implementation of smart meters will, more sooner than later, ensure the recording and storage of the consumption data for every household in the United Kingdom. Leaving us with workable and copious amounts of data that can mined for trends and patterns which in turn can be a less expensive, reasonable and economical alternative solution to the said problem.

Every human being on the planet has a contribution, a footprint. A footprint is described as the physical impression left sand or floor by a foot or shoe. There is another, deeper surrogate meaning of the word “Footprint”. It doesn’t relate to the physical aspects of impressions, but the ecological footprint of a human being. It is elementally defined as the demand of humans on nature. This specific footprint, much like fingerprints, varies from human to human. Every one of us leads a different lifestyle, works different jobs, has different hobbies and uses electricity differently. It’s only fair to have a just and customised judgement for a varying variable as such.

The Electricity consumption data of a household collected over a specific period can be analysed to learn trends. These trends, or “electricity footprint” if you may, once learned, can be used to perform additional actions such as prediction, plotting and forecasting using data science and data mining methodologies. This electricity footprint and trends in the data can, in the scope of this research, be compared with everyday usage to then, based on the electricity usage of the minute, predict the availability of a person at home.

Abnormalities in the data can range from between anything like an electricity spike not being shown roughly at around 7pm when the inhabitant uses the kettle for their evening tea. Or the system predicting the person not being home when the resident is in fact home.

When abnormalities as such are visible, the system can choose to notify a user of the curious occurrence and inconsistency in the predicted data.

* 1. **Application**

This is where the application of this research comes in. An affordable solution to independent living amongst the elderly and disabled.

In simple terms, this project aspires to implement different data mining algorithms that are capable of noticing abnormalities and deviations from normal trends, not directly and in a conventional straight-forward method but, by the uncomplicated comparison amongst the predicted data of occupancy against actual occupancy in electricity consumption entries. This will be made possible through the rigorous prospecting of data and uncompromising statistical tests on the algorithms used followed by a conclusion affirming which algorithm comparatively does the job with admirable accuracy.

try and overcome issues such as mobility and getting around the house that come with old age and disabilities and provide a secondary method of alerting emergency services if a problem arises. The only access to the problem being the persons electricity usage data.

* 1. **Implications**

The last sections assisted in grasping a reasonable understanding of the problem, motivation and need for such a system. This section very briefly outlines the intentions and methodology of this dissertation.

This research implements a diverse collection of data mining algorithm to predict the availability of people at home using supervised learning techniques and manipulating data. The success of the algorithm not only assures the partial implementation of a system that can be furthered to help in a real-world scenario, by making use of real-time power readings, but also counsels which machine learning algorithm works best from a handful of chosen and implemented ones.

The incessant need of the project to be implemented with limited resources and yet produce a capable solution dictated many paths in deciding aspects that were imperative to the project. For instance, the implementation of the algorithms. The algorithms were drafted in the programming language Python using Spyder as the Integrated Development Environment (IDE). The machine learning library “Scikit-learn” was used in the implementation of the algorithms, namely, k-NN regression and classification, Linear regression, Linear classification and Neural networks.

**CHAPTER 2**

**LITERATURE REVIEW**

This section outlines key areas of this research. Definitions, breakdown and related work done in affiliation with the primary research of this dissertation.

**2.1 What is Machine Learning?**

<https://books.google.co.uk/books?hl=en&lr=&id=7f5bBAAAQBAJ&oi=fnd&pg=PR5&dq=machine+learning&ots=C45E1q7bJp&sig=FC5Iqs94GWx3ZNclmyqYeBEnKZE#v=onepage&q=machine%20learning&f=false>

Machine learning is a vital field in not only computers, but in every day professions such as retail, . In layman terms, it’s the ability to make a computer system learn and work intelligently using statistical techniques that are performed on data. It is believed that it has originated from the evolution of pattern recognition, computational learning theory and artificial intelligence. Machine learning is the technological modification and automation of a previously unreachable problem. Calculations and trends, patterns and behaviour of data that was once innumerable and computable by the naked eye, was made possible by astute algorithms that learn by reaching into depths and relations between seemingly one-dimensional data to extract meaningful results and outputs that prove to be extremely helpful in various application areas.

Data is constantly being produced and consumed.

**2.2 Supervised and Unsupervised Learning**

<https://machinelearningmastery.com/supervised-and-unsupervised-machine-learning-algorithms/>

Supervised learning is a machine learning approach which involves two separate attribute sets of data, an input set and a derivate output set. The job of this type of learning technique is to reckon the mapping between the input and output pairs. The aim for this approach is to learn and acquire this “mapping function” with such success that the system is then equipped to generate a probable output for a given input instance from the same data set. Examples of supervised learning methods include regression and classification algorithms.

Unsupervised learning, just by then name alone, displays a contradictory nature to its dissimilar sibling, the supervised learning technique. This approach, unlike supervised learning, considers input data that has no reciprocal or corresponding output data.

The goal of this technique is to deduce and extract features from the input unlabelled data. Its structure and elemental patterns and trends are learnt. This methodology is often referred to as “exploratory data analysis”. Due to the one-dimensional personality of this practice and the unavailability of a reference or labelled desired output, there is no way of telling if the results and findings from an unsupervised learning algorithm are, in fact, correct.

Its use is limited to areas where patterns, progressions and tendencies of results are to be analysed, predicted or foreseen.

Examples of unsupervised learning include Clustering, anomaly detection and some branches of neural networks.

<https://books.google.co.uk/books?id=Np9SDQAAQBAJ&printsec=frontcover&dq=machine+learning&hl=en&sa=X&ved=0ahUKEwi3ssmVvMXaAhVCK1AKHQNIDe4Q6wEIKjAA#v=onepage&q=supervised&f=false>

**2.3 Algorithms**

**2.3.1 k-NN Algorithm**

**2.3.2 Linear Regression**

**2.3.3 Neural Network Classification**

**2.4 Related Work**

There is plethora of research work that contributes to the area of computer science that deals with data mining and analysis, but only a handful of work that directly associates with my research could be found. The chosen literature’s, much like this research work, adapt different methods of data analysis to interpret and analyse the fitting of their work in a specific application. They also exhibit similarities ranging from the data collection methodologies to statistical analysis of algorithms.

<https://irjet.net/archives/V5/i3/IRJET-V5I3579.pdf>

The unpopularity, lack of full fledge implementation and availability of smart meters has forced many to take it upon themselves to create a homemade smart-meter. A paper published by the International Research Journal of Engineering and Technology (IRJET) implemented such a system using a microcontroller based design and implementation of an energy meter primarily to replace human interference in meter readings which makes the collections susceptible to error hence having an adverse effect on the economy. In addition to that, services such as monitoring energy consumption from a web page through device IP address and electricity theft detection by monitoring meter tampering were also made available. Due to these applications, a homemade smart meter was built based on the Internet of Things (IOT) technology in collaboration with existing electricity meters. The physical aspects of the sysem included an Arduino Nano Board, ESP 8266 Wi-Fi module (Node MCU), 16\*2 LCD display, buzzer, power supply and The Allegro® ACS712 for current sensing. The software aspects included the webpage. The webpage was used to display load energy usage reading in terms of Watts and present device information in a more detailed analysis in both description and visualization.

Coming towards algorithm based related work, a research extract from a book, that consisted of 29 contributions from researches all thoroughly reviewed and validated, analysed electricity data of a household to extract its specific trends which were then, along with the number of inhabitants of the household, used as input variables to a fuzzy model, to forecast how probable it was for a house apparatus to be used or started within the next 60 seconds (Zhu, 2016). The electricity data set collection for this research was long term and collected over a period of 12 months. A case-study on fuzzy tools along with neural network based algorithm for efficient energy management was presented. That was written to predict the electricity usage 24 hours ahead of its time. Lastly, a cost analysis was presented to signify the importance of energy management and its implications. The findings of this specific research in this book, heavily relates to the “Electricity data analysis” area of this dissertation.

Subsequently, a research specifically relating to electricity and anomaly detection with extensive results in the form of figures, diagrams and tables carried out data analysis on electricity consumption data using 2 different approaches namely statistical approach and clustering (Jakkula and Cook, 2010). The two methods were used with the aim of mining the electricity data and count the outliers using both techniques and compare them against the known outliers to see the efficiency of either methodologies. The dataset for this research was power consumption collected using a smart CASAS (Centre for Advanced Studies in Adaptive Systems) environment. It concluded that the 2 outlier detection mechanisms presented wrongly identified an outlier with a ratio of 1:43 in Clustering to Statistical approach. In layman terms, this means the possibility of wrongly identifying an outlier in clustering as opposed to statistical analysis was 1 in 43. The results and finding of this research paper showed that clustering would be inaccurate in its given task 2.3% of the times whereas Statistical approach would wrongly identify an outlier 97% of the time. The application of this research was, like in the previous related work researches, to ultimately conserve energy by identifying abnormal power consumption and hence taking a step towards energy efficiency and conservation, predict abnormalities earlier on, like in the case of too much power being consumed in a smart home the possibility to warn residents on the failure of appliances due etc.

<https://pdfs.semanticscholar.org/b9ba/4b0cfa5cf78d8d4f68da1882f2bb12489c7f.pdf>

Another similar research worked towards forecasting electricity demand in the UK. This research made use of existing deterministic calendar information of weekdays, weekends, bank and national holidays to create a data set of binary data, to distinguish between weekdays and weekends, In collaboration with a KNN- regression model for load forecast and prediction for the upcoming 24 hours. The existing calendar data was used as a base to compare input data against to sort what kind of day the load was being forecasted for (weekday, bank holiday, or weekends). The dataset used for this research dated from November 2001 to November 2008. Almost 8 years with values of power on an hourly basis making that up to be more than 66,500 instances. The results of this research were compared to existing benchmark models (Not created in the research) to the written Multivariate k-Nearest Neighbour Regression model. It concluded that amongst other benchmarks models. The method of choosing best algorithm being mean absolute percentage deviation value. The multivariate system, created within the research took the crown amongst other contenders including univariate k-NN regression model and other statistical benchmark models such as MOVAV (7)24, MOVAV (7)168, RW24 and RW168. This research coupled with the Clustering and statistical approach comparison research paper have made it credible that a benchmark methodology or linear statistical approach is not a strong method to go by when it comes to electricity data. The extensive, exhaustive and variating nature of the electricity data makes it rather impossible to fuse well and it takes complex much intelligent algorithms to learn the ways and motifs.

<https://www.researchgate.net/profile/Amir_Mosavi2/publication/46093676_Domain_Driven_Data_Mining_-_Application_to_Business/links/00b7d51c0a0025b857000000.pdf#page=32>

k-NN algorithms have been immensely popular in data analysis (CITE -) and specifically prediction applications, for the most part. There is a controversy revolving ‘k’ algorithms (k-NN, K-Means etc) when it comes to choosing an optimum value for the number of nearest neighbours (k), since it is user defined. In a research carried out by the Mu’tah University – Jordan tried out various values of n ranging from 1 to the square root of the sum of samples in the training dataset and proposed a solution to the selection of the value of ‘k’ depending on ensemble learning (CITE - <https://arxiv.org/ftp/arxiv/papers/1409/1409.0919.pdf>).

An archaic yet substantial research paper proposed that “large values of K smoothen the results of classification” (CITE - <http://cs.du.edu/~mitchell/mario_books/Neural_Networks_for_Pattern_Recognition_-_Christopher_Bishop.pdf>). With insufficient evidence as to why, but it is also considered that the square root of the sum of samples in the training dataset is an optimal assigned value for ‘k’.

<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.727.486&rep=rep1&type=pdf>

Neural networks happen to be immensely popular with electricity data in arguably one application. Electricity price predictions. The complex multiple layer model and nature of the artificial neural networks makes it possible to work with much convoluted scenarios with more than one variable and attributes. A comparable research that made use of a 3 layered ANN model forecasting price, based on the electricity usage data, for the next 168 hours. This research, however, used the Levenberg-Marquardt algorithm for training purposes. The accuracy and efficiency of the systems predictions were computed using a real-world case study established on the electricity market.

<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.193.1235&rep=rep1&type=pdf>

A comprehensive research, in the field of Neural Networks, read and compared published papers dating from years 1990-1996 and 2000-2005 listing 5 areas having attracted most attention amidst which was Load forecasting. A reasonable and in-demand application of electricity data seems to be load forecasting and outlier detection in order to battle energy inefficiencies. Even load forecasting can further be broken down into three sub categories of prediction areas based on periods of forecasts: Long Term (LTLF), Mid Term, and Short-Term Load forecasting. The forecasts lasting anywhere 5 – 20 years for long term, a month to 5 years and short term being defined as anywhere between an hourly to weekly forecasting system. All three of which have different applications and scenarios that call for different forecasting periods.

The conclusion of this research is conflicting yet informative. Despite the many benefits of using Neural networks for power based training and predictions like its ability to deal with stochastic pattern of variating increasing data and fast classification and implied filtering of results, it also stated how and when it would be discouraged to use ANN model. Problems such as training time, training vector and “noisy” data (data containing errors such as missing elements due to faults in recording etc) can cause complications in the algorithm. It also stated that such an algorithm should be used as an “additional tool” not as a “replacement” to other AI techniques.

Anomaly detection is another area that hugely relates to this project. The application of this dissertation is to detect, effectively, occurrences and instances of data that can be considered as anomalous and swiftly acting upon those said occurrences. A survey-based journal article spoke in depth about the different kinds of outliers in data analysis and the challenges faced in isolating a given anomaly from normal regions in a traditional 2-dimensional dataset (Chandola, Banerjee and Kumar, 2009). This survey particularly proved helpful in narrowing down concepts and techniques most effective in successful outlier isolation and detection. In addition to that, it also spoke about techniques for Anomaly detection such as Neural networks, rule based, Bayesian Network, Support vector, Clustering and Nearest neighbour based techniques etc. Most of the mentioned techniques in this survey have been used for this dissertation for not outlier detection, but prediction based on a training dataset.

Another research relating to anomaly detection proved to be more practical than survey based and aimed to detect abnormalities between an aged and a new transformer in the UK based on data and variables from the transformers such as temperature, vibration, moisture, load current etc in the 2 transformers (Catterson, McArthur and Moss, 2010). The data readings were calculated using sensors. This paper concluded that the Conditional Anomaly Detection (CAD) technique can be used in the online monitoring of the transformers.

<https://pdfs.semanticscholar.org/ff0b/d954443338708279f97feb05d6b29e41382c.pdf>

<https://link.springer.com/chapter/10.1007/11941439_114#citeas>

The final deliverable of this research, in addition to implementation of assorted predictive machine learning algorithms, covers a section for statistical analysis and comparison of the enforced algorithms based on their predictive performance and success using various arithmetic formulary. However, it primarily relied on F Score to calculate, prove and thereupon crown one algorithm victor.

One such research study, published by the Australasian Joint Conference on Artificial Intelligence, discussed evaluation measures for different characteristics of machine learning algorithms. It speaks of commonly-accepted performance measuring techniques and touches base with and proposes new unconventional approaches for measures derived from “fault avoidance” such as Youden’s index γ, the likelihood values ρ−, ρ+, and Discriminant Power DP. It is argued in this paper that performance measures other than accuracy, F-score, precision, recall or ROC do apply and can be beneficial.

Although the work Ms. Sokolova was aimed towards providing an unprecedented approach to algorithm measure, the areas of her research that resonated with this research work was the discussion of conventional measures such as precision, recall, sensitivity, specificity, accuracy and F measure. There is substantial evidenced work done using these statistical methodologies and a “fault avoidance” approach was unbefitting.

**The research rudimentarily defined the measures as follows (**For extensive and apprehensible definitions with corresponding formulae refer to the methodology section**):**

* **Receiver Operating Characteristic (ROC):**

Shows a relation between the sensitivity and the specificity of the algorithm

* **Accuracy:**

Approximation of the effectiveness the algorithm displays by showing the probability of the true value of the class label; in other words, it assesses the overall effectiveness of the algorithm;

* **Specificity:**

Specificity approximates the probability of the negative label being true; in other words, it assesses the effectiveness of the algorithm on a single class;

* **Sensitivity:**

Sensitivity approximates the probability of the positive label being true; in other words, it assesses the effectiveness of the algorithm on a single class;

* **F score:**

A composite measure which benefits algorithms with higher sensitivity and challenges algorithms with higher specificity.

For said measures, quality of classification is measured and built from a confusion matrix which records correctly and incorrectly recognized examples for each class. These classes are determined by the nature of the prediction.

A prediction instance can be classified as one of the following:

* **True positives (TP)**

The algorithm correctly classifies the subject of prediction in a binary environment, as ‘1’

* **False Positives (FP)**

The algorithm incorrectly classifies the subject of prediction in a binary environment, as ‘1’

* **True Negatives (TN)**

The algorithm correctly classifies the subject of prediction in a binary environment, as ‘0’

* **False Negatives (FN)**

The algorithm incorrectly classifies the subject of prediction in a binary environment, as ‘0’

The confusion matrix below outlines the elemental method of categorization and determination of the prediction type based on the above-mentioned counts.

|  |  |  |
| --- | --- | --- |
|  | **Recognized Positive** | **Recognized negative** |
| **Class Positive** | **TP** | **FN** |
| **Class Negative** | **FP** | **TN** |

Table 1. Prediction Classification

**2.5 Inspection**

Most of the existing work done in relation to this project takes things as far as analysing electricity usage data to extract trends, test different data analytical techniques and anomaly detection. The major application of those finding being the need to make electricity consumption more efficient and conserve energy where possible. The Anomaly Survey research discussed entirely different application areas of anomaly detection but none of them came close to the intended work and application of this project which, along with other related work, makes it evident that the deliverable is new and hence will contribute to a novel application of occupancy and outlier detection.

The Multivariant k-NN regression model research showed sweeping results in the success of a nearest neighbour regression model in the forecasting of load data which stands to show that a k-NN model might be a viable technique for triumphant results while working with electricity consumption data.

This project intends to take things in a different direction, it aims to predict the occupancy of a household in not just a Boolean value, but in number of occupants as well. The intended application of this project is to identify an anomaly in data and alert emergency services to get the independent senior or disabled resident the help they need. The abnormality detection will root as an extension to the proposed occupancy predicative system. If the system produces a false negative, that is, no inhabitant is predicted against the known data telling us that there is in fact someone home, it’s clear that something is wrong. The said application of this project, with hope, stands out and is derived from personal motivation and empathy towards the human race.

Despite there being many such algorithms capable of successful prediction of occupancy based on electricity data, like load forecasting, not a lot of research is done in this domain of predicting occupancy based on electricity consumption let alone a statistical comparison of such algorithms and the intended application of this project.

The existing work seems to be aimed at crowning technology victor against the existing linear benchmark and statistical methods. It is a given that an expert learnable algorithm will perform well than a system with a linear standard point of reference. To some extent it’s safe to say there is no comparison there. But even amongst the various learnable algorithms there must be one that performs better than the other. In addition to the many ways listed above, this specific reason of a rigorous statistical analysis and comparison between different algorithms, also, makes this dissertation project novel and different from its related existing work.

CHAPTER 3

METHODOLOGY

This section of the research focuses on the methods applied and implemented to set the objectives into motion. The dataset, algorithms, testing and statistical analysis methodologies implemented.

**3.1 The Dataset**

**3.1.1 Contender**

The search for a dataset was a crucial part of the research as it would lay the foundations on which the primary research would be based. Not many datasets were even considered but one specific dataset that was taken into close consideration was an open-source Electricity consumption dataset of 19 households in London over the course of 2 years. The data set consisted of separate csv files for household information, half-hourly electricity consumption, daily electricity consumption, acorn details, half hourly weather and daily weather. These separate 6 csv files contained information such as tariff, what block the house is in, its acorn group, a smart meter measurement of power on a half hourly and daily basis, power measures, minimum, maximum, mean, median, sum and std. Details of the acorn group, their profile and the people in the group. In addition to that it had 2 other files containing weather readings, again, on a half hourly and a daily basis.

Despite the data being publicly available, clean, workable and with the added benefit of having data from 19 different households and exhaustive readings, it was ruled out as the project aimed to display no threat or necessity of peoples personal and sensitive information. It was stressed and an unescapable part of research to make the system starved to maintain economic implications yet yield comparable results.

Working with this dataset would have been easy and not challenging because of its resourceful definition and extensive variables, but people would have been led to believe that minimum requirement for the application and implementation of a system as such requires innumerable readings and a convoluted combination of attributes. Ultimately this dataset was dropped as it was aimed to keep the project unambiguous for people yet competent in its goal.

**3.1.2 Compendium**

The dataset that was ultimately chosen for the project was not a publicly available one. It was a personal household electricity dataset that was recorded and belonged to my supervisor.

The dataset was a singular csv file containing three attributes, namely, Date and time, Power and “at home”. The power was calculated and recorded for every minute of each over the period of 2 months (January and February 2018) adding up to 37270 instances.

Since there is a reading for every minute of each day, there are roughly 1448 occurrences of the attributes for a single day. This makes the data highly exhaustive and broken down hence very specific and precise.

|  |  |
| --- | --- |
| Attribute | Description |
| datetime | The date and time |
| power | The number of watts consumed in kw/h |
| unit | An additional field added to serialise the datetime variable to represent minutes. |
| athome | A variable denoting the presence and availability of people inside the household with 0, 1 and 2 (indicating number of people) |

Table 2. Dataset Variables

The benefits of this data set were the additional variable “athome” which can be used to and linked to patterns and behaviours in the electricity usage and how the power goes up or down based on occupancy, which will make the system more learnable and proficient.

**3.1.3 Collection Methodology**

<http://www.reuk.co.uk/wordpress/solar/flashing-led-on-electricity-meter/>

Given that the use of smart meters is not popular in every household thus far, this specific dataset was collected using manual techniques which will, soon enough in the future, become frivolous once smart meters installation is enforced by law.

A homemade smart meter was created for the effective collection of the electricity data which included the following components:

* **Node MCU:** <http://ijireeice.com/upload/2017/november-17/IJIREEICE%204.pdf>  
  A Lua (scripting language) based ESP8266-E12 Wi-Fi SOC (System on Chip) module used commonly for the implementation of internet of things. It has 16 GPIO (General Purpose Input Output) and works on 3.3v. The term "NodeMCU" by default refers to the firmware rather than the dev kits. The firmware uses the Lua scripting language
* **Raspberry Pi:** <https://www.raspberrypi.org/help/what-%20is-a-raspberry-pi/>“An inexpensive credit card-sized computer that plugs into a computer monitor or TV, uses a standard keyboard and mouse. It is a capable little device that enables people of all ages to explore computing, and to learn how to program in languages like Scratch and Python. It’s capable of doing everything you’d expect a desktop computer to do, from browsing the internet and playing high-definition video, to making spreadsheets, word-processing, and playing games.”
* **SQL Lite Database:**For storage of the recorded electricity data.
* **Light Sensor:**For registering light flashes and hence computing the time between consecutive flashes.

Electricity meters that were installed over the past few years have been electronic and come equipped with an LED light. The job of this LED is to flash, proportionally to the amount of power passing through the meter. A light detector was used to calculate the power consumption. The sensor would register the time between consecutive light flashes on the electricity meter. The relationship between the meter LED to the number of kWh being passed is known, so it is just a matter of computing the rate of flashes to determine the power being exported per minute.

Given the rate of flashing of the LED, the power being consumed is simply calculated by the formula:

The process of calculating the seconds between the light flashes can be done manually but, as the flashing is dependent on power consumption which is seldom constant hence inconsistent, inaccurate results can be registered. To limit any chance of error this process was automated using microcontroller called NodeMCU and Raspberry Pi. This flashing rate can be stored or used to make immediate calculations of power consumption which were the stored in an SQL Lite database.

The “athome” variable was calculated using “pings”. Defined as “Query (another computer on a network) to determine whether there is a connection to it” (CITE - <https://en.oxforddictionaries.com/definition/ping>) which would administer how many specified mobile phones were connected to the internet at a given time. To make this calculation more accurate the use of push notifications was also used.

This dataset was chosen because of its simple precise nature. It consisted of limited but necessary variables. Another reason of preference for this this dataset was its temporal proximity. The lifestyles of people today largely differ from the way of living of people as recent as 5-10 years ago. Factors such as weather, routine, job, lifestyle, activity, insulation and occupancy etc are all factors that influence the consumption of electricity. They are also factors that tend to differ which makes older datasets, if not outdated then at least, irrelevant. Leaving recent data being more relatable and accurate in its ability to determine anomalies in the modern-day electricity consumption patterns.

**3.1.4 Dataset split (Testing and training)**

The split for the training and testing data is an area worthy of attention. It was advised in the end of term presentation feedback to ensure that the split wasn’t right down the middle or that the training included all the dates of January and some of February and testing data of just February but rather make the split more random and distributed.

The percentage of the split was also a concern and there is debate when it comes to a fair value. A research journal paper similar in terms of data mining methodology split its data to an 80:20 – training to testing ratio (CITE - https://pdfs.semanticscholar.org/15e9/7c52dceeb88a9e69ac404a137c2ca0216eb7.pdf). It is considered a fair split, whereas in some cases and scenarios even a split of 70:30 is justified. But then again, these split ratios are also highly dependent on the size of the data set and refinery capability of an algorithm.

The final percentage split that was adapted for this research was 67:33 training to testing ratio. Given the total 36210 instances, it divided into a seemingly healthy split of 24300 learnable instances to 11970 predicting/testing instances. The split randomness of the split was also ensured by the python built-in data split function having the ability to add a “random\_state” which would shuffle the instances before splitting based on the percentage provided. As shown in the figure below, the first 20 instances of both the training testing data (along with their serial numbers) was random.

|  |  |
| --- | --- |
| **Training dataset (67%)** | **Testing dataset (33%)** |
|  |  |

Table 3. The training and testing data split

\*The numbers on the right-hand side is the additional field that was added to the data set to serialise the headings of the power and ‘athome’ variable readings. Although the first 20 values only aren’t sufficient to display the randomness in the collection and split of the data it is still apparent that the data was not collected serially.

This part of the code is responsible for the split. The split ratio and the randomness of the split. The sklearn library has a function “model\_selection**.**train\_test\_split” which takes in attributes such as the output variables, the size of the testing data and the random state.

X\_train**,** X\_test**,** Y\_train**,** Y\_test **=** sklearn**.**model\_selection**.**train\_test\_split**(**X**,** y**,** test\_size **=** 0.33**,** random\_state **=** 4**)**

**3.2 Environment**

**3.2.1 Tools**

* **Programming Language:** Python 3.6
* **Integrated Development Environment (IDE):** Spyder 3.2.6

Spyder is an open source IDE designed to solemnly work with Python. It enhances the language’s ability given its many beneficial characteristics like syntax highlighting, debugging support, variable exploration, GUI based editor for most data structures, step-by-step execution, ability to run parts of code at a time, code prediction and completion, built-in editor and various other productivity tools. Its IPython (Qt) console makes for an able prompt data visualisation and visual communication area. in the form of graphs, tables and the display of regular outputs. CITE - <https://books.google.co.uk/books?hl=en&lr=&id=N1InCgAAQBAJ&oi=fnd&pg=PP3&dq=spyder+development+environment+python&ots=9GL4id3oTs&sig=JW7RFBACriK53R_dzatWwRIZZto#v=onepage&q=spyder%20development%20environment%20python&f=false>

Like most IDE’s for python, it tackles the linear nature and inflexibility of the regular Python programme interface and provides a more participating candidate as opposed to the stand-alone Python programme.

The IDE “Rodeo” was initially considered, but it was found to be inflexible and caused conflicts in the existing programmes. The library import function was unable to detect to the location of the module where they were downloaded.

<http://www.southampton.ac.uk/~fangohr/blog/installation-of-python-spyder-numpy-sympy-scipy-pytest-matplotlib-via-anaconda.html#what-is-what-python-python-packages-spyder-anaconda>

* **Dataset (.csv file):** Microsoft Excel
* **Statistics computation:** Manual

**3.2.2 Libraries** <https://www.frontiersin.org/articles/10.3389/fninf.2014.00014/full>

* **Scikit learn**

Scikit-learn is a Python module that includes a wide range of state-of-the-art machine learning algorithms for supervised and unsupervised problems. This package emphasises ease of use, performance and documentation while focusing on bringing machine learning to non-experts using a general-purpose high-level language. It has minimal dependencies and is distributed under the simplified BSD license, encouraging its use in both academic and commercial settings. <https://hal.inria.fr/hal-00650905v1/document>

* **Numpy**

In the Python world, NumPy arrays are the standard representation for numerical data and enable efficient implementation of numerical computations in a high-level language. Performance of computations are improved through techniques such as vectorizing calculations, avoiding copying data in memory, and minimizing operation counts.

<https://ieeexplore.ieee.org/document/5725236/>

* **Pandas**

An open source, BSD-licensed library for the Python Language which provides rich data structures and functions which makes working with structured data fast, east and expressive. It enables Python to be a powerful and productive data analysis environment.

<https://books.google.co.uk/books?hl=en&lr=&id=v3n4_AK8vu0C&oi=fnd&pg=PR3&dq=python+pandas&ots=rgFI3qxxqA&sig=5c6fMIuXR_1PqxahUdn_MDPfLDE#v=onepage&q=pandas&f=false>

* **Matplotlib**

A 2D graphics package used by Python for application development, interactive scripting and publication-quality image generation across user interfaces and operating systems.

<https://ieeexplore.ieee.org/document/4160265/>

**3.3 Algorithms**

**3.3.1 Regression & Classification**

<https://books.google.co.uk/books?hl=en&lr=&id=X2Y6OkXl8ysC&oi=fnd&pg=PR5&dq=Linear+regression&ots=sdjQFZrPgv&sig=pAazfHuFMtk71nq_TKYfhtmhluY#v=onepage&q=Linear%20regression&f=false> **Page 391**

The basic difference between the said algorithm is that the outputs and behaviour of the algorithms. The aim of regression models is to discover relationships between response ‘Y’ and explanatory variable ‘X’. Ultimately to make predictions of the variable Y based on the observation of the input ‘X’ variable. (CITE – BOOK). It finds the similarity of the input testing dataset to predict an attribute. The attribute prediction is “measured” based on a similarity function. In the regression model the output is an actual independent value. The value is calculated based on the average of its given nearest neighbours.

<https://web.stanford.edu/~hastie/THESES/gareth_james.pdf>

The classifier model, as the name implies, “classifies” or “categorizes” its predicted output in a defined set of possible outputs based on the similarity function. The output for a classification algorithm takes the value of the nearest neighbour most popular and in majority. This is known as majority vote. (CITE – Majority vote)

**Example:**

Figure 1. Example supposed scatter for a data set.

**Classification method:**

Referring to the visual aid in Fig 1 above and in the case of *classification*, in a k-NN algorithm with a defined training dataset of 10 instances and 4 possible outputs: either ‘Blue’, ‘Red’, ‘Green’ or ‘Yellow’, If the family of a testing instance (Bigger, black dot) needs to be determined in a situation where k = 3, It is visible, in Fig 1, that out of the 3 closest points to the testing instance (black dot) on the graph, 2 are green and one is red hence the testing instance will be “classified” into the “Green” family based on the “Majority Vote” phenomenon discussed in chapter 2 – Literature Review.

**Regression Method:**

When it comes to regression, it becomes a little more complex than that. Regression will also produce a result that ultimately crowns the testing instance to belong to the green family but it technique of determination is different.

First the algorithm will assign the 3 possible instances (Blue, green, yellow and red) numeric values:

|  |  |  |
| --- | --- | --- |
| **Colour** | | **Assigned Numeric Value** |
| Blue |  | 1 |
| Red |  | 2 |
| Green |  | 3 |
| Yellow |  | 4 |
| Black |  | To be predicted |

Table 4. Regressor, classifier example colour assigning

Given that k = 3, and that as visible in the graph out of the 3 closest points are 2 green and a red dot the algorithm will place the testing instance using the average of the nearest neighbours using their numeric values.

Nearest neighbours = [Green, Green, Red]

Numeric Values = [3, 3, 2]

Testing instance:

The produced value is closest to the numeric Value 3 and hence the testing instance is computed to belong in the green family.

Although the actual execution of the algorithms is far more complex and doesn’t rely on numeric assigning, the motive for the above example was to, in layman terms, explain the difference in operation of the two algorithms. In reality, the outcomes aren’t assigned numeric values rather the similarity function uses values based on the Euclidean distance of the testing instance to first determine the nearest neighbours, then compute the testing instances illegibility in every possible family.

**Actual case:**

Keeping in mind the example for the nearest neighbour models above, in the case of the electricity dataset being used for this project, the training and input data set being ‘kwh’ (power) and ‘athome’ (Number of occupants of the household), the possible classes for classification for output data becomes 0, 1 and 2 from the “athome” variable. Based on the similarity function, the algorithm ‘classifies’ every instance of the testing dataset into the three possible classes.

The regression model, calculates the average of the 3 closest neighbours to the testing instances and produces a float value which can be rounded off to produce a prediction of the class the testing instance might belong to.

ELABORATE^^^^

**3.3.2 k-NN Algorithm**

In all ‘k’ type algorithms where the value of a certain variable is user defined (Like number of clusters ‘K’ in K- Means algorithm), the value of ‘k’ becomes a cause for concern.

Ultimately the value of ‘k’ (nearest neighbour to be taken into consideration) in both the models was assigned the value of 3 and kept constant for both the algorithms to maintain a fair environment as the algorithms were to be compared and the value of k can influence the performance of the algorithm drastically. However, this number wasn’t established right away.

As mentioned earlier Chapter 2 - Literature Review, the debate on the value of ‘k’ in k-NN algorithms and the research surrounding it being vague and contradictory. Since the lack of a bespoke determination and work done surrounding the optimal value of ‘k’ for electricity datasets, additional extensive measures were taken to determine which k value is custom best suited to the electricity data set.

Code was adapted to run the k-NN regression algorithm for a total of 53 different Values for “k” ranging between 1 and 156 (Square root of training data set) with increments of 3. The code would, as a result, calculate the precision of the predicted data, accuracy of the result based on correct and incorrect predictions and mean square error for every given value of “k”. There were built-in functions for measuring the precision, and mean square error, but the accuracy was computed based on code that was written to compare the testing dataset with the predicted data set to determine the number of correctly identified instances. Accuracy was then calculated using the formula:

**Accuracy Percentage Formula:**

The total values of ‘k’ used were 53, but the table below highlights

**The accuracy variation for said values of k were as follows (based on both distance and uniform):**

|  |  |  |  |
| --- | --- | --- | --- |
| **Values of ‘k’** | **Accuracy (%)** | **Precision score** | **Mean Square Error** |
| 1 | 96.75 | 0.968 | 0.0345 |
| 3 | 90.21 | 0.966 | 0.0246 |
| 9 | 74.77 | 0.964 | 0.0287 |
| 99 | 19.18 | 0.938 | 0.0571 |
| 156 - Square root of training data set | 9.87 | 0.930 | 0.0662 |

Table 5. Variance of performance with changing values of 'k'

The values of “k” and their resulting accuracies, precision and Mean Square Error (MSE) values were stored in lists.

Since the values of k considered were 53 and the linear representation of it in a table wouldn’t have aided, the said data was plotted in graph format to visually display the findings for a superior understanding of the effect of the values of “k”:

**The Graph for Values of “k” against Accuracies is as follows:**

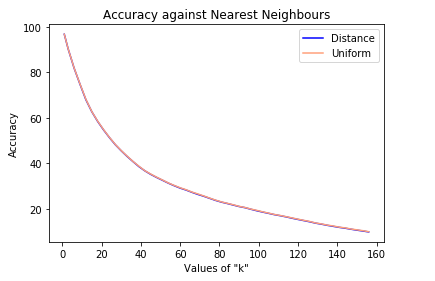


Figure 2. Accuracy against values of 'k'

There is a visible decrease in the accuracy of prediction with increasing members considered during the categorization and placement of a test dataset instance.

Although the highest percentage of accuracy visibly being achieved at K = 1, the realisation that a number so small may and is capable of being influenced by noise and hence increasing the probability of inaccuracy incorrect prediction, it was decided to find middle ground and settle for K = 3. Because it seemed like a reasonable number and it seemed to be better suited to the given dataset.

**The Graph for Values of “k” against Precision score is as follows:**

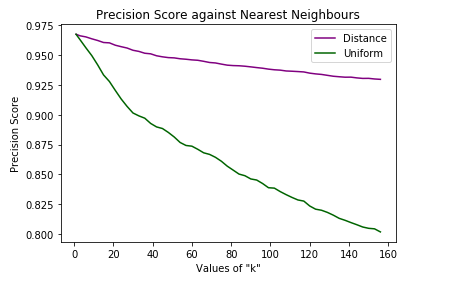


Figure 3. Precision Score against values of 'k'

**The Graph for Values of “k” against Mean Square Error is as follows:**

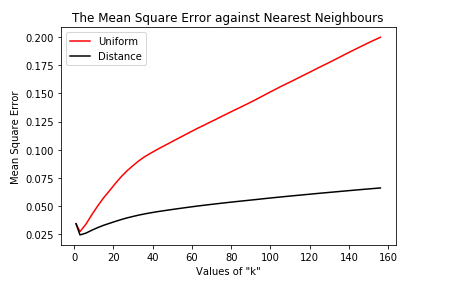


Figure 4. Mean square error against values of 'k'

Despite the research that has been carried out for the sole purpose of figuring out a suitable value for the number of nearest neighbours taken into consideration, during this research through personal experience it was explored that the value of ‘k’ is dependent on the type of dataset and shouldn’t be merged with existing notions of it working best when equal to the square root of the training dataset or some constant number. There is a reason that the value of nearest neighbours is not predefined and remains flexible as different types of datasets might call for different considerations. And the random assigning of different values for it reveals which one works best and gives an acceptable result.

All in all, it makes sense that a small value for ‘k’ might make the algorithm too influenced by individual cases whereas on the other hand, larger values may include too much of a deviation and complexity in a non-complex situation ultimately producing a prediction that is in either case not the most reliable and accurate as it can be.

However, there is obvious sense in the fact that it shouldn’t be too small either, but then again there is a pattern that shows that keeping it too large can cause deviations and the majority vote can get influenced given if the data, being worked with, is noisy. Having said that, increasing the value of K also saw a visible constant being reached, although the overall accuracy of the system came down arguably significantly, at a point increasing the value of ‘k’ would produce accuracy very close to that for a closer k value and the difference would not be substantial. This showed that whilst accuracy was being compromised, a large value for the number of nearest neighbours would also make the system less prone to be persuaded by noise and irregularities in data.

**Algorithm Implementation**

The determination of ‘k’ was the principle errand for both the k-NN algorithms (Regression and Classification). But the actual implementation of the algorithm was straight forward. Having said that, the outputs from the regression model were floats as it is the resulting calculation of an average of nearest neighbours and division often leads to a decimal number. This algorithm posed a challenge in the classification of correctly and wrongly determined instances. The result had to be “round up” using the built-in python function for exploitation.

**3.3.3 Linear Regression**

Implementation, problem with the detection of 0, critical reflection

**3.3.4 Neural Network Classification**

Unlike the other algorithms that were implemented in this research, neural networks had a margin and capability to be refined and hence better the results. Due to the composition of the classification algorithm to include loss functions, activation function, dropout, number of layers, number of iterations and batch size, which are all variable factors they heavily influence the results and the overall performance of the algorithm.

NUMBER OF LAYERS, NUMBER OF NEURONS, critical reflection

**Amidst other factors, the most important dynamic factors were:**

**Loss function:** 'categorical\_crossentropy'

**Activation Function:** ‘relu’

**Epochs:** 100

**Batch Size:** 32

Defined as the split or number of data instances taken to train the system in one go or iteration.

**Dropout:**

Dropout is a technique for addressing overfitting. Its purpose is to randomly drop units (along with their connections) from the neural network during training. This prevents units from co-adapting too much. (CITE - https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf)

Since no background knowledge or experience with the algorithm was at hand, the sole method of refining the results were to alter the variables and functions randomly with hopes of incurring a better result. The ‘AccuStats’ self-written function was used to measure the correct instances after every change made to the variables and the algorithm run. It is safe to say that not all possible combinations were tested but the mentioned variable values above gave the best result in comparison and to the best of knowledge. It was noted that a significant change in results was observed when Epochs was increased. The adjustment of others didn’t provoke any notable consequences.

**Initial vs final results**

Although not drastic, changing epoch from 20 to 100, reduced error, courtesy of the loss function given a chance of more iterations to work over. The initial accuracy ((Correct determined instances/total instances) \* 100) was 48. Increasing the epoch to 100 significantly increased algorithms runtime but yielded a better result of 58% accuracy. Logically it would be perceived that further increase of epoch would harvest better results but it only increased program runtime and produced a result that was 0.0002% worse.

**3.4 Statistical Analysis**

There are many procedures at hand to determine the success of algorithms in reaching a given target. The algorithms can be tested on their ability using markers such as speed of computability, solution quality, simulation, run time, errors encountered, optimisation etc. Many of these units are computable within the scope of code and the language being worked with. With an import of a library and the administration of parameters to a function and running the said code, these units of measure can be determined with the click of a button.

Such methods of algorithm analysis can be computed in one line of code. They are in most cases considered sufficient but it can be argued that they tend to be incomprehensive and in some cases, rendered meagre. In a professional environment however, there is a call for a far more encyclopaedic analysis especially in areas where a heavy part of research is formulated of a comparative statistical analysis.

Upon meeting with statistical expertise for mentoring regarding the most viable possible method that could be devoted to the investigation, Chi squared error was initially considered but on further description of the nature of the system and its outputs, it was rendered unprofitable and precision recall and F score was suggested instead.

Hence, this dissertation makes use of many notable techniques and manual mathematical calculations in collaboration with the results acquired from the algorithms and code to put forward a reasonable and thorough analysis of the algorithms that were worked with.

The statistical techniques and calculations applied to the results from each algorithm are as follows:

* F1 score
* True positive rate
* False negative rate
* True negative rate
* False positive rate
* Prevalence
* Positive predictive value precision
* False discovery rate
* Accuracy
* False omission rate
* Negative Predictive Value
* Positive likelihood ratio
* Negative likelihood ratio

*\*Some of the above are already listed in Chapter 2 – Literature Review, but as a recap and additional calculations carried out for this research they are mentioned again.*

The mentioned calculations make use of computed variables based on the results from the prediction algorithms. The variables used are:

* **True positives (TP)**

The algorithm correctly predicts the presence of a person as positive. Meaning predicting that a person is home when they in fact are.

* **False Positives (FP)**

The algorithm incorrectly predicts the presence of a person as positive. Meaning predicting that a person is home when they in fact aren’t.

* **True Negatives (TN)**

The algorithm correctly predicts the presence of a person as negative. Meaning predicting that a person is not home when they in fact aren’t.

* **False Negatives (FN)**

The algorithm incorrectly predicts the presence of a person as negative. Meaning predicting that a person is not home when they in fact are.

* **Condition Positives (CP)**

The total instances in the data where the person is home, where person occupancy or presence is positive.

* **Condition Negatives (CN)**

The total instances in the data where the person is not home, where person occupancy or presence is negative.

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | Positive | Negative |
|  |  | Actual data (+)  (Person(s) home) | Actual data (-)  (Person(s) not home) |
| Positive | Predicted Occupancy (+)  (Person(s) home) | **TP** | **FP** |
| Negative | Predicted Occupancy (-)  (Person(s) not home) | **FN** | **TN** |

Table 6. Prediction Classification

**3.5 Definition and formulae of Statistical computations**

**Following is a brief explanation and formulas of the above-mentioned methods to test the prediction algorithms:**

**F1 score – (Primary Method)**

Also known as “F score” or “F measure”, this calculation measures the accuracy of a subject. It can be explained as the weighted average between the precision and recall of the subject. Its best possible value is 1, denoting a highly efficient and accurate subject and worst possible outcome is 0, signifying a subject without the possibility of having performed more poorly.

The actual formula based on the definition of F1 score is as follows:

But through methods of substitution, a more direct and applicable formula for it can be derived:

**True positive rate (Sensitivity) - Recall**

Also referred to as the sensitivity or “hit rate” of a subject. As the name suggests, measures the proportion of positives identified correctly. Example the proportion of times the algorithm predicted occupancy of the household as positive (Someone home) when there was someone home. (*Sensitivity And Specificity* 2018)

Formula:

Since False Negatives are ultimately all the instances that are true, total positives = True Positives + False Negatives

**False positive rate**

Is defined as the proportion of negatives that return positive outcomes. The probability of a positive prediction result produced given that the condition being looked for is not present (negative). the expectancy of the false positive ratio. It is calculated as the ratio between number of negative events incorrectly classified as positive to the total number of negative events. (*False Positive Rate* 2018)

Formula:

Since False Positives are ultimately all the instances that are negatives, total negatives = True Negatives + False Positives

**True negative rate (Specificity)**

Also referred to as the specificity or “miss rate” of a subject. As the name suggests, measures the proportion of negatives identified correctly. Example the proportion of times the algorithm predicted occupancy of the household as negative (No one home) when there was no one home. (*Sensitivity And Specificity* 2018)

Formula:

Since False Positives are ultimately all the instances that are negatives, total negatives = True Negatives + False Positives

**False negative rate**

Clearly complimentary to “False Positive Rate”. Defined as the proportion of positives that return negative outcomes. The probability of a negative prediction result produced given that the condition being looked for is present (positive). (*False Positives And False Negatives* 2018)

Formula:

Since False Negatives are ultimately all the instances that are true, total positives = True Positives + False Negatives

**Prevalence**

Is defined as the proportion of a specific condition to be true. In our case of household occupancy, it will be defined as the fraction of times when a person is truly home to the total number of readings. Although not a unit of measurement of the accuracy of an algorithm, this measurement will not remain same for every algorithm and only signifies the popularity of occupancy.

Formula:

**Positive Predictive Value (PPV) - Precision**

A second more broken down name for precision which makes the formula more understandable. Defined as the probability that instances where the positive was predicted (person is home) is true. (*Positive And Negative Predictive Value* 2018)

Formula:

**Negative Predictive Value (NPV)**

Defined as the probability that instances where the negative was predicted (person is not home) is true. (*Positive And Negative Predictive Value* 2018)

Formula:

**False discovery rate**

Defined as the percentage of false predictions in a given set of predictions. (*False Discovery Rate | Columbia University Mailman School Of Public Health* 2018)

Formula:

**Accuracy**

Generally defined as the calibre to which the outcome of an assessment, calculation or measurement is precise or correct. In a statistical environment, error is taken into consideration. In order to achieve a high accuracy both precision and correctness of a measurement need to be high.

Formula:

**False omission rate**

False Omission Rate a measure of False Negatives that are incorrectly rejected. It is a compliment of the Negative Predictive Value.

Formula:

**CHAPTER 2**

**ANALYSIS**

**4.1 Visual Aids**

Theoretical analysis of scenarios can bode well in situations where they are being thoroughly explained since they tend to be lengthy and hard to absorb and differentiate between. Visually presented data, however, can be instantly analysed and understood.

The following figures display the Predicted ‘athome’ variable against the actual testing set for each algorithm.

**4.1.1 k-NN Regressor:**

Predicted data as a plot:

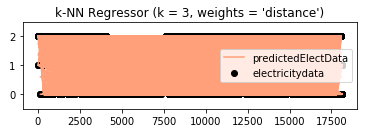


Figure 5. k-NN regression actual VS predicted data (plot)

Predicted data as a scatter:

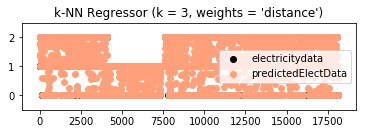


Figure 6. k-NN regression actual VS predicted data (scatter)

As seen in the figures above, the predictions lie within the definition of the actual data set. Since the plot was plotted using ‘scatter’ for actual data and ‘plot’ for the predicted, the predictions are displayed using one conjoined line which is why it takes over and overlaps most of the visible graph. Although inefficient this method was chosen because the scatter failed to show the actual data set.

**4.1.2 k-NN Classifier:**

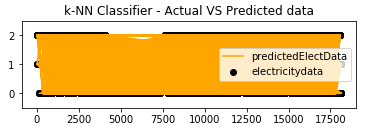


Figure 7. k-NN classification actual VS predicted data (plot)

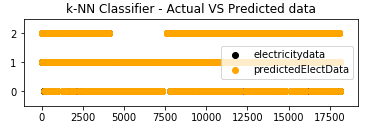


Figure 8. k-NN classification actual VS predicted data (scatter)

In the case of regression, there is a possibility to predict any float value between or relatively close to the definition of the actual data (0 - 2). In the case of classification, the only possible outcome is one of the three, 0, 1 or 2.

**4.1.3 Linear regressor:**

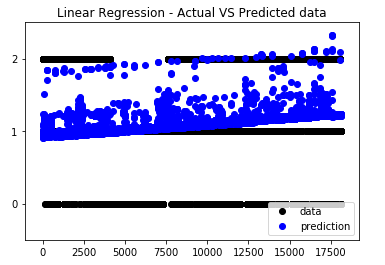


Figure 9. Linear regression actual VS predicted data

**4.1.4 Neural Network Classifier:**

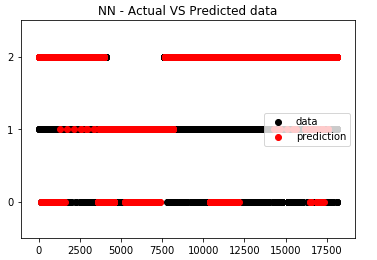


Figure 10. Neural Network Classifier actual VS predicted data

**4.1.5 Notation**

**Talk about all the above diagrams here collectively and compare**

**4.2 Statistical Analysis Report:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | k-NN Regressor | k-NN Classifier | Linear Regressor | Neural Network regressor |
| False omission rate | **0.011** | **0.017** | **0.000** | **0.425** |
| False discovery rate | **0.008** | **0.009** | **0.511** | **0.295** |
| True negative rate (Specificity) | **0.982** | **0.980** | **0.000** | **0.360** |
| False positive rate | **0.018** | **0.020** | **0.000** | **0.640** |
| False negative rate | **0.005** | **0.007** | **0.000** | **0.148** |
| Negative Predictive Value (NPV) | **0.989** | **0.983** | **0.000** | **0.575** |
| Precision (Positive Predictive Value) | **0.992** | **0.991** | **1.000** | **0.705** |
| Recall (True positive rate /Sensitivity) | **0.995** | **0.992** | **1.000** | **0.852** |
| Accuracy | **0.991** | **0.989** | **0.488** | **0.670** |
| F1 Score | **0.994** | **0.992** | **0.656** | **0.772** |

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**CHAPTER 2**

**CONCLUSION**

A relatively imperative objective of this research was the establishment of one data analysis algorithm as superior to the rest, not entirely but, in the specific scenario it was adapted into. Having said that, amongst the various algorithms used – Falana worked best – with an accuracy of blah% and an f1 score of blah, meaning it would correctly predict the occupancy of the house blah% of the times and wrongly determine it only 1 out of 50 times.

The findings of these research have positive educational repercussions and if they don’t push the boundaries of knowledge they have at least stood up to standards and to the borders of knowledge in terms of comparison between two, of each, regression and classification models written with the intent of prediction.

Researches regarding algorithms have been carried out immeasurable number or times across the world but keeping in sight the related work that was sought after for the population of section ADD literature review and all that lead up to it, it is safe to say that the findings of this research are unique and next to none in terms of the composition, application, choice of algorithm and statistical analysis of their performance. Individually countless researches have been done in these areas but this research work incorporates all these

These wrong determinations lie False Negatives. In the case of our project False Negatives can be defined as the set of those predictions that wrongly predicted a person not being home when the person, as per testing data, was available at home. This is a clear auditee. Given the possibility of determining auditees from sufficiently good results – the system can be used to identify problems – In more specificity the problem of someone being home but not using their electricity like they usually do perhaps because they have likely fallen victim to the unfortunate occurrences that come with independent living amongst the senior and disabled. This clearly highlights the tree of events starting from electricity data analysis to getting the said parties the help they need. This, in turn, proves and answers the research question “Can data analysis be used to get the elderly and disabled the help that they need”. Yes. In fact, it can. It is safe to say, with slight maturing of this dissertation work, data analysis can successfully be used, in collaboration with external real-time data readings and a little furtherment and linking of the written code for this research, to help getting the reliant the help they need.

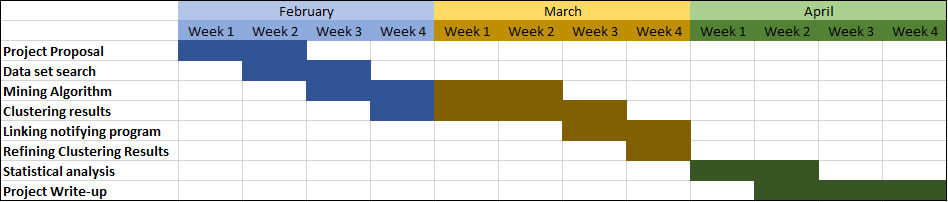
**CHAPTER 7**

**PROJECT MANAGEMENT**

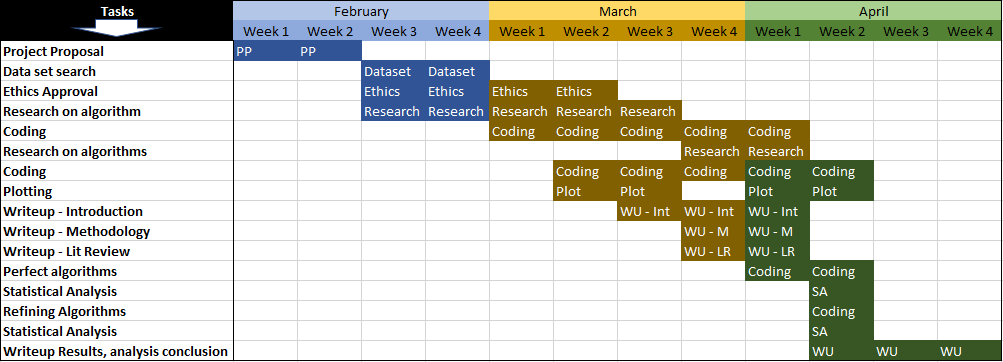
This research took inspiration from iterative Agile techniques as its basic execution plan. Sprints every week were planned, executed and sought after. The initial sprint defined and allotted minimum functionality which was then refined and further worked-on on every consecutive sprint or increment.

An initial project plan in the form of a Gantt Chart was designed for task break down.

**Initial Gantt Chart:**



**Final Gant Chart:**



The underestimation of tasks at the initial stages of the project is evident. It is for this reason that agile project management techniques were applied to the project. The drawbacks of conventions sequential management techniques are far too many and its inflexibility renders projects unsuccessful and failing in terms of time budget etc.

**Sprint Backlog:**

**REFERENCES**

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