Auditing Crypto Currency Transactions: Anomaly Detection in Bitcoin

A report submitted in partial fulfilment of the requirements for the award of the degree of

B.Sc (hons)

in

Computing (Data Analytics)

By

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Declaration Cover Sheet for Project Submission

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ABSTRACT

Both “big data” and “analytics” have become popular keywords in many organizations. The power data analytics has on harnessing the increasing volumes, velocity and complexity of data in a world of constant change and disruptive technologies has been recognized. Many companies are making significant investments to better understand the impact of these capabilities on their businesses. One area with significant potential is the transformation of the audit. This project explores ways in which analytics can change and shape the work of accountants.

Anomaly detection plays a pivotal role in data mining since most outlying points contain crucial information for further investigation. In the financial world which the Bitcoin network is a part of, anomaly detection can indicate fraud. Using data mining tools such as Regression, we simultaneously examine the relationship among variables whilst visually inspecting the data for possible outliers. By doing so, I have chosen the world’s leading cryptocurrency, Bitcoin. This project will conclude with an in-depth analysis on whether or not data analytics can shape how effectively, and secure accountants can audit transactions by implementing analytics tools into their daily protocols.

Keywords: Anomaly Detection, Bitcoin, Transactions, Regression, Accountancy, Analytics

INTRODUCTION

"It's a massive leap to go from traditional audit approaches to one that fully integrates big data and analytics in a seamless manner."

– EY, How big data and analytics are transforming the audit.

Finance leaders are finding it very difficult to find accounting and financial professionals who possess the technical skills to implement data analytic initiatives. In a recent survey by Robert Half, *Building a Team to Capitalize on the Promise of Big Data,* 87 % of managers seek business analytics skills in financial analysis. These significant figures are having an impact on the future careers for accountants and whether or not there will still be a need for people with accountancy and financial skills over a person with data analytic skills.

One of the primary tasks as an accountant is auditing. For this investigation, we will use the world's leading crypto currency, Bitcoin, to audit transactions. Bitcoin is a special type of transaction system. It is traded on over 40 exchanges worldwide accepting over 30 different currencies and has a current market capitalization of 9 billion dollars. Interest in Bitcoin has grown significantly with over 250,000 transactions now taking place per day. It is on a sharing network known as the blockchain that has publicly produced a ledger that contains every transaction ever processed. The authenticity of each transaction is protected by digital signatures corresponding to the sending addresses, allowing all users to have full control over sending bitcoins from their own Bitcoin addresses.

With respect to transactional networks, comes those transactions who appear abnormally. We refer to those as anomalies or outliers. In terms of financial transactions, we can assume they may be fraudulent, or in fact may not be. A key goal would be to detect these anomalies to prevent future illegal actions. It can also allow for some interesting findings about our data. Big data are huge sets of information gathered that are so voluminous and complex that the average processing application are inadequate to deal with them. This is where the need for some personnel with analytical or technical experience is needed in order to optimize the data to gain as much knowledge as possible.

Big data challenges include capturing data, data storage, data analysis, search, sharing and transfer, visualization, querying, updating and information privacy. If the work of an accountant can be complete through these tasks, allowing for much more useless precise information, then will there eventually be a need for accountants over someone with analytical ability? This research project will investigate this using a large chunk of data from the bitcoin ledger.

MOTIVATION FOR THIS PROJECT

The underlying motivation for this project is the usefulness of analytic tools to audit a transactional dataset. Ultimately the initial goal is the same as that for an accountant when it comes them auditing a transactional ledger. But by applying highly technical algorithms, we hope for a more flawless process with an in-depth analysis report answering beyond our initial question. Allowing for a conclusion on accountancy versus analytics. To achieve this, we must clean, explore and optimise our data in a way in which an accountancy cannot do so manually. Whether this be down to lack of technical skill, resources or knowledge. By doing so, we can gain much more knowledge about our data and gain a competitive advantage. To condense this research, the aim is to produce a fully functional data mining model to represent our findings. Two areas' well researched and explored as an accountant, Outlier detection and Forecasting. Clustering and Regression are two models of motivation for this project.

"The primary task of accountants, which extends to all the others, is to prepare and examine financial records. They make sure that records are accurate and that taxes are paid properly and on time. Accountants and auditors perform overviews of the financial operations of a business in order to help it run efficiently."

- *https://www.allbusinessschools.com/accounting/job-description/*

DOMAIN CHALLENGES

The challenges of this project are as follows:

1. Collecting of data will be challenging. Although, Bitcoin ledger can be openly sourced online. The language of preference for this analysis was R. RStudio does not support libraries in which you can pull straight from the bitcoin ledger, so my data will have to be manually downloaded.
2. Choosing the right dataset in terms of size and complexity will be a big challenge for this project. To optimize this projects potential, the data we acquire must be of high dimensions.
3. Transforming the data to a manageable format will save future time spent loading data. Data for projects such as these, spend the entirety of the time cleaning and formatting.
4. With big data, involves high computational requirements. A challenge for all industries handling big data. The data must be reduced in size or else it will be unworkable even with modern computers.
5. An existing knowledge of the data to be able to filter out the bulk of the noise is crucial. The pre-processing stage will have a significant effect on the end results.
6. Defining what is an outlier will involve high technical ability. Targeting the features for my model.
7. Sampling and dimension reduction is an extremely complicated topic. When is too much and when is not enough? The risk of overfitting and underfitting can arise.
8. How the results are presented will play an important role in the interpretation of this project. Ensuring the initial idea is constantly being re-visited and evaluated.

BACKGROUND

Accountancy was my main area of interest when I began researching courses and colleges. As I began researching in further depth about the economy and degrees that would be “future proof”, I came across a noticeable demand for students with computing degrees which left me where I am today. The need for I.T experts has and still is a huge concern for many businesses. One area that consistently stands out is, the concept of handling Big data and the different techniques and methodologies to do so. Data Analytics is shaping businesses, especially in the financial sector which has left a huge strain on accountancy jobs and the need for accountants over a data analyst. This immediately caught my eye and I knew I wanted to research this further.

The first issue I ran into was what dataset could I analyse to explore this idea? It had to be relevant and one that corresponds to data an accountant would work with. Knowing this dataset would shape my project and the outcome I had to think long about it. At the project pitch, the dragons suggested using a bitcoin dataset. Bitcoin is the world’s leading crypto currency. Due to the open nature of Bitcoin it also poses another paradigm as opposed to traditional financial markets. It operates on a decentralized, peer-to-peer and trustless system in which all transactions are posted to an open ledger. This type of transparency is unheard of in other financial markets. I knew this would add to my project and enable me to explore the world of crypto currency and blockchain which has caught the eye of many huge companies recently.

RELATED WORK

There are many research projects and journals on Bitcoin as a crypto currency. Exploring any area of the blockchain in general, is well researched and documented. However, with that in mind, my aim is to compare my analysis on a transactional ledger using data and web mining algorithms and techniques to highlight and showcase the power of analytics from an accountancy perspective. This has not been done. To assist with this research, I have gained a lot of knowledge about anomaly detection through related work, which is a huge motivation for this project. Some findings from related work are documented as follows:

Anomaly Detection

The problem of anomaly detection has been explored for a long time. An anomaly can be defined as anything out of the ordinary. For this analysis, we are looking at identifying possible outliers through visualisation algorithms such as clustering. In financial markets, anomalies can be identified as thesis or illegal activities. These anomalies want to be detected as soon as possible. In 2017, Thai T. Pham and Steven Lee of Stanford explored Anomaly Detection in Bitcoin Network using Unsupervised Learning Methods. (https://arxiv.org/pdf/1611.03941.pdf) In their project, they particularly focused on the problem of detecting anomalies in the bitcoin network which is related to fraud detections study in all types of financial transactional systems. Three unsupervised learning methods including k-means clustering, Mahalonobis distance-based method and support vector machines on two graphs generated by the Bitcoin Transaction network. One graph to represent users and the other to represent the transactions through the use of nodes.

Using the following features, In-degree, Out-degree, unique in-degree, unique out-degree, clustering coefficient, average in and our transactions, average time, balance, creation date and active duration, each feature is plotted on the transactional and user graphs. The features mean different things for the two representations. The SVM method took a long time to run so therefore data points were limited to 100,000. This method detected one known loss. The k-Means cluster, which k=7 for both graphs, calculated the average of the ratios of detected anomaly distances to the centroids over max distances. Only the top 100 outliers were targeted. The Mahalanobis Distance based method detected one known theft. This studied concluded that only two known cases of theft and loss out of 30 known cases were detected from the three documented unsupervised techniques, resulting in the methods being unsuccessful in their entirety.

Clustering

Many metrics follow regular patterns correlated to determine normality. When that pattern becomes skewed or scattered, it can cause some alarms to go off. For example, when the metric is correlated to time, the key is to find its seasonality. Any activity outside of this "season" can be detected as anomalous and thus resulting in the identification of fraud, theft etc. or some other interesting discovery. K-means is one the most well-known and used algorithms for clustering. Clustering classifies your data based on similar features within a particular cluster. All points within a cluster have been identified by the algorithm as being similar among themselves and dissimilar to the data of the other clusters.

Varun Chandola, Arindam Banerjee and Vipin Kumar -Anomaly Detection: A Survey, from the University of Minnesota, evaluate clustering as an anomaly detection technique. (https://dl.acm.org/citation.cfm?id=1541882). According to the authors, clustering-based anomaly detection can be grouped into three categories:

1. Category one assumes that normal data instances belong to clusters while those anomalous does not belong to any cluster. DBSXAN, ROCK and SNN clustering are examples of category one.
2. Category two assumes normal data instances lie close to their closed cluster centroid whilst those anomalous lies far aware from their closest cluster centroid. K-means is an example of this.
3. Category three's assumption is that normal data instances belong to large, dense clusters, whist's those anomalous either belong to small, sparse clusters. Therefore, data belonging to clusters below are pre-declared threshold will be identified as outliers. An example of this category is CBLOF clustering approach where a local outlier factor is applied.

The survey concludes the section on clustering-based anomaly detection with an analysis on the advantages and disadvantages of the technique. Some advantages are speedy test phase, operational in an unsupervised mode and the complexity of the technique is small allowing it to adapt to other more complex data types. Disadvantages include the dependency of the algorithm on performance is based on the effectiveness of the clustering algorithm in capturing cluster structure of normal instances. Also, several clustering algorithms force every instance to be assigned to a cluster which may result in bypassing potential anomalies. Also, a good clustering-based anomaly detector is extremely computationally complex and difficult to implement on large data.

Regression

Xiufeng Liu and Per Sieverts Nielsen from the University of Denmark explore Regression based online Anomaly Detection for Smart Grid Data (file:///C:/Users/paris/Downloads/Regression-based_Online_Anomaly_Detection_for_Smar.pdf). In this survey, they are using a data analytics solution to an everyday problem, detection of unusual consumption behaviours of customers with the widely used smart energy meters. Proposed in a supervised learning and statistical-based approach, Regression. Effective use of regression as an anomalous detector would result in real-time in order to minimise the compromised to the use of the energy, according to Xiufeng and Per.

> *"The efficiency of updating the detection model and the accuracy of the detection are the important consideration for constructing such a real-time anomaly detection system. In this paper, we propose a statistical anomaly detection method based on the consumption patterns of smart grid data"*

The model is composed of a short-term prediction algorithm, periodic auto regression and Gaussian statistical distribution. This proposal was implemented and tested onto real-world data and the results have validated the effectiveness and the efficiency of the proposed system with the lambda architecture. The flexibility of regression was truly highlighted in this paper and used in a way I had no seen or heard of before. This caught my attention and made me want to experiment with it on a transaction dataset to see its limits. Ideally, we hope to detect anomalous behaviour with this model, whilst still fulfilling its general usability, forecasting.

Unsupervised and Supervised Anomaly Detection

Supervised anomaly detection techniques require a dataset that has labeled instances for "normal" and "abnormal" as well as a trained classifier. A typical approach would be to build a predictive model for normal vs. anomaly classes. Any unseen data instance is compared against the model to determine which class it belongs to. With supervised detection methods, we provide examples(labels) and train a model to "recognize" and differentiate between different labels. We are interested in predictions, i.e. using our feature vector X to predict or categorize label Y, or forecast our numeric dependent variable Y. One approach uses graphs for modelling the normal data and detect the irregularities in the graph for anomalies (Noble & Cook 2003). Another approach uses the normal data to generate abnormal data and uses it as input for a classification algorithm (Gonzalez & Dasgupta 2003).

Unsupervised anomaly detection techniques are more widely applicable because it does not make any assumption about the availability of labeled training data. Instead, the techniques make other assumptions about the data e.g. several techniques make the basic assumption that normal instances are far more frequent than outliers. This frequently results in occurring patterns appearing normal, whilst rare occurring patterns is typically considered as outliers. The unsupervised techniques typically suffer from higher false alarm rate, because often times the underlying assumptions do not hold true.

PROJECT AIM

Data analytics can certainly play a key role in many aspects of accounting. I will explore these roles and apply analytic tools and techniques to transform dated auditing concepts into a digitalized approach. Some of the key areas to concentrate on:

- Aim 1: **Boost competitiveness:** Exploring ways to boost a company's competitiveness through the use of Predictive analytics techniques. This would allow accounting professionals to make more accurate forecasts.
- Aim 2: **Manage Risks:** This is a huge concern for businesses and the role of managing risks for accountants have evolved from being solely based on compliance and internal controls to assessing risks arising from a diverse range of areas. Techniques such as continuous auditing and monitoring is proving to not be enough to monitor huge amounts of data.
- Aim 3: **Identify Fraud:** Data analytics techniques are well-suited for detecting fraud and this is an area I would like to highlight during this project. Similar, to managing risks, I will apply analytics outlier detection methods to my dataset to identify anomalies in my dataset. Emerging technologies in this area can allow a forensic accountant to quickly and effectively sieve through large volumes of transactions to identify anomalies in data which can often be indicative of fraudulent activity.
- Aim 4: **Explore Crypto currency and Blockchain:** Another aim for this project, is to become more knowledgeable and aware of the evolving world of blockchain. For this reason, I have chosen the world's leading crypto-currency, bitcoin, as my dataset.
- Aim 5: **Enhance Technical Skill and Knowledge:** If successful, I hope this research can allow for enhancement on not only my own technical ability, but for someone reading this and eager to apply my knowledge to their problem successfully. Additionally, a student potentially considering commencing a four-year course in accountancy becoming more leaning towards a career in IT would be a huge success for me.

TECHNOLOGIES USED

R:

R is a programming language and environment for statistical computing and graphics. It is a GNU project with similarity to the S languages. R is widely used for statistical and graphical techniques such as time-series analysis, classification, regression and clustering. It is high extensible and available as open-source online. I will use R to conduct in depth analysis on my data. It will be the main language of choice for this project due to its wide variety of libraries and low limitations.

RStudio:

RStudio is an Integrated development environment (IDE) for R programming language. I will use R in RStudio to create scripts to analyse the data sets. The R environment is successful in data handling and storage facility, applying calculations from basic mean methods to extensive for loop algorithms. It also graphically facilitates for data analysis. R is very extendable due to the vast number of libraries available, many of which I have optimized in this project.

Tableau:

Tableau is a data visualization software application that allows the user to represent their findings in a clear and concise way. Once I have completed the analysis of my data sets in RStudio using R programming language I will use Tableau to represent my findings. Tableau uses the k-means algorithm for clustering. This will allow my audience to have a greater understanding of this project and my findings, both from technical and non-technical backgrounds. All graphs will be visible from my dashboard, which I have created in tableau.

Microsoft Excel:

Microsoft Excel is a spreadsheet program that extends from the Microsoft Office Suite of applications. It is a spreadsheet which represents tables of data arranged in rows and columns. Many statistical analyses can be conducted in excel. This program in particular would be often used by accountants for analysis. However, it would be about the limit in which they go technically. I used to excel to read one of my datasets. I also transformed my .txt datasets into .csv files through the use of R, as excel is a great way to visual your data on the spreadsheet and make minor changes without having to code them manually. Unfortunately, excel is not a good platform for handling large data.

ALTERNATIVE TECHNOLOGIES EXPLORED

Google BigQuery:

Due to the difficulty of acquiring suitable bitcoin datasets manually online, I decided to explore the idea of pulling data via an API. The method which stood out to me the most was via Googles API, BigQuery. BigQuery is Google's serverless, highly scalable, low cost enterprise data warehouse designed to make all your data analysts productive. BigQuery is free for up to 1TB of data analyzed each month and 10GB of data stored. (Google Cloud). The Bitcoin blockchain data that is accessible by google API, is updated every 10 minutes with new transaction. This data is extremely attractive as a source but unfortunately due to computational errors and time constraints I chose to stick with my manually downloaded Bitcoin datasets.

Python:

Python is an interpreted high-level programming language that has use potential and strengths when handling big data. As I explored the idea of implementing googles BigQuery API to pull my data, I discovered it could not be done through R and only Python. I attempted to pursue this and expand my language vocabulary for this project but again, due to computation error and other restrictions, this technology was not pursued.

Hadoop:

Hadoop is an open-source software framework for storing data and running applications. It provides massive storage for any kind of data, enormous processing power, and the ability to handle virtually limitless concurrent tasks or jobs. Hadoop is an option for safe efficient storage. When sampling my data, I needed to ensure my sampling was stratified. Stratified random sampling intends to guarantee that the sample represents specific sub-groups. Due to the huge amounts of data, RStudio did not have the processing power to do the job so I explored the idea of MapReduce, which is a sub-project of the Apache Hadoop project. Unfortunately, this type of sampling would not return stratified amounts, so I did not pursue this.

UNDERSTANDING CRYPTO CURRENCY

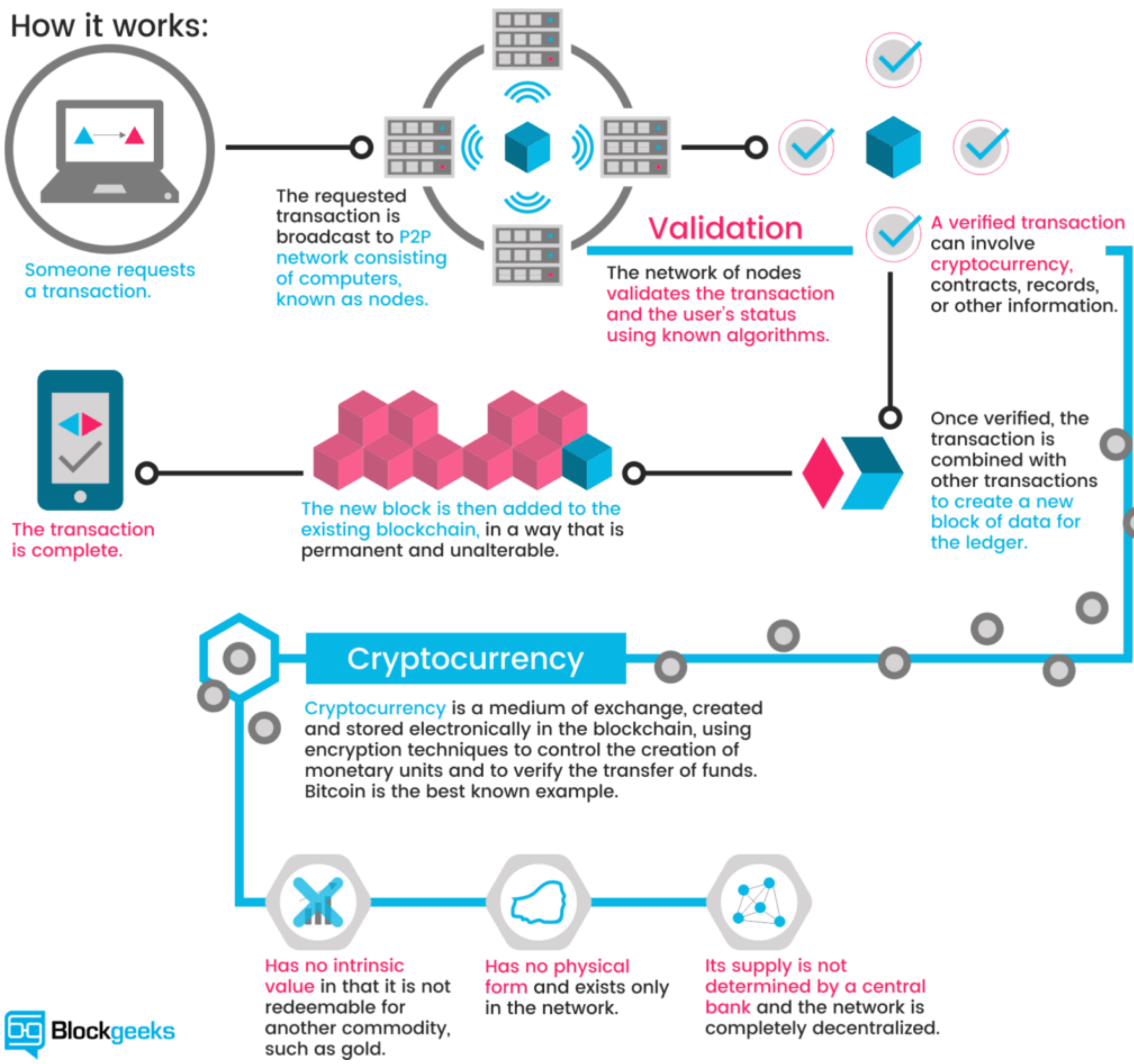


Figure 1: Matrix on how crypto currency works.

METHODOLOGY

The methodology that best describes the structure of this project is the knowledge discovery in Databases, KDD, methodology. The ultimate goal of the KDD process is to apply data mining methods to extract what is deemed as knowledge, according to specific thresholds previously declared in the algorithms. The steps are as follows:

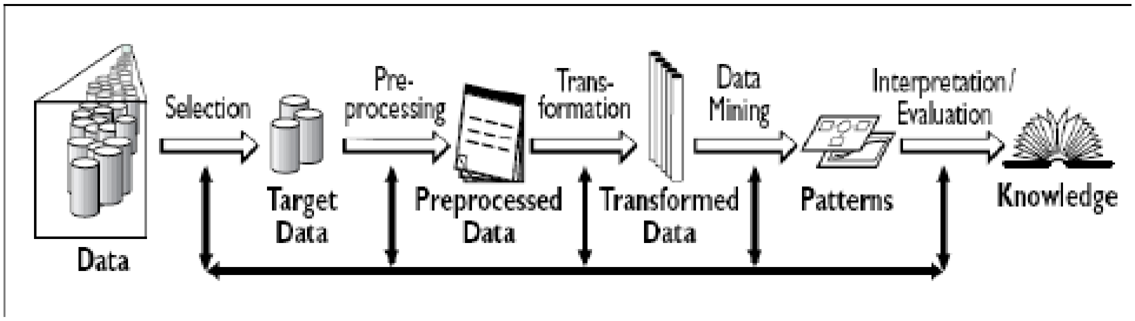


Figure 2: KDD methodology steps outlined.

Selection

The first stage of the following the KDD process is the selection stage. This is the acquiring of target dataset or datasets that will then be analysed to discover useful information about the chosen topic. This step was a lot more difficult than I had anticipated. Although, the bitcoin ledger is openly sourced online, I wanted to carry my analysis using R as my chosen language which limited my selection of which datasets I could use. Kaggle was my first choice when searching for datasets as I love the detail in which comes with the datasets from Kaggle. This data consists of data from 23.02.2010 to 20.02.2018 and has many attributes which can consider factors for affecting the price of bitcoin. We will explore this later when building our regression model.

Bitcoin in a very technical concept to understand and it's very important to understand the data you are working with. After a lot of research, I decided to take a medium sized dataset from Kaggle (Found here - https://www.kaggle.com/sudalairajkumar/cryptocurrencypricehistory/data). The dimensions can be seen below. This data set was formatted in a .csv file. As I finished my analysis on this dataset, I felt comfortable and confident to move onto bigger data. I acquired seven datasets (Found here -http://www.vo.elte.hu/bitcoin/downloads.htm) This data includes the list of all transactions up to 28.12.2013. Dimensions can be seen below. All files from site were downloaded as .txt files.

Data	
BitcoinData	2920 obs. of 24 variables

Figure 3: Dimensions of the dataset from Kaggle.

Data	
blockhash	277442 obs. of 4 variables
txhash	30048983 obs. of 2 variables
Txtin	1048575 obs. of 3 variables
tx	30048983 obs. of 4 variables
txout	73738345 obs. of 3 variables
txtime	30048983 obs. of 2 variables
txhash	30048983 obs. of 2 variables

Figure 4: Dimensions of each dataset from the ELTE site loaded into RStudio. Total 7 datasets.

Pre-processing

The next step is to pre-process my data. Considerably, this stage is deemed most important and can have a significant effect on your model's performance. This process was a smoothed with the Kaggle due to the size. In fact, the entire pre-processing stage with this dataset was relatively quick and easy. The basic read.csv function was used to read in this file. This step involves the removal of noise, outliers, collection of necessary information to build your model and strategies for handling missing fields of data. Luckily by applying the is.na(x) function to all datasets, no 'TRUE' values were returned, indicating no null values.

The anytime library in R was installed and loaded to convert the timestamp. This was then formatted using the as.Date method in R. An additional column was added for s count of days for each row. These changes can be seen in figure 3 and 4.

```
#converting unix timestamp
library(anytime)
anydate(df$Unix.Timestamp)
as.numeric(Sys.time(df$Unix.Timestamp))
```

Figure 5: Timestamp conversion

```
df$Days <- 1:nrow(df) #ADD COLUMN FOR COUNT OF DAYS FOR EACH ROW
df$Timestamp <- as.Date(df$Timestamp) #FORMAT DATE
```

Figure 6: adding columns and formatting date

Transformation

This stage was not needed for the Kaggle bitcoin set. After my ELTE datasets was pre-processed, I began the transformation process. Firstly, I had to sample my data as the sizes were extremely large and there were no resources available to handle that amount of data. I then came to learn about fread function which is an extension of the data.table library in R. This helped tremendously with runtime and eventually loaded all seven datasets into the one session in R. I then began my sampling process, which led to dimension reduction on all rows so they were equal and manipulated into one data frame.

Data Mining

The data mining stage of the KDD process involves deciding which goal I want to reach with my data and choosing the best model to showcase that goal. Ultimately, I want to gain as much knowledge as I can from my dataset. I also want to be able to detect outliers and showcase important patterns in my data as this will serve as very interesting information for an accountant. I have chosen to build a regression and clustering model to do this.

The Kaggle bitcoin dataset is extremely informative in terms of market value, share etc. This will be perfect to use when building my regression model. I can analyse the relationship among variables and look at the market of bitcoin as a crypto currency as whole, and not just from a transactional point of view. Is it worth investing in? What was the highest value of 1BTC? What was the lowest? Does x effect the price of Y? Is x decreasing in value wile y rises in value? Is my data normal? These, along with many more, are all questions a linear model can answer.

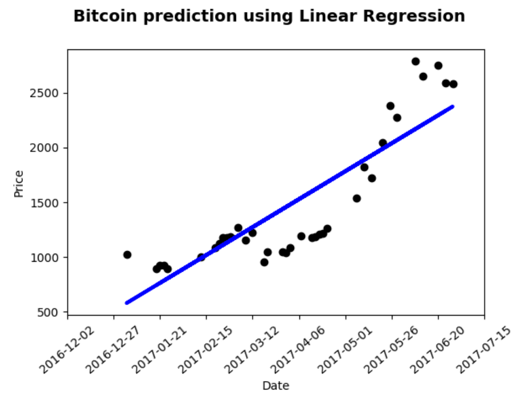


Figure 7. Example of a Linear Regression model predicting the price of bitcoin over time

Clustering is a great way to detect anomalies in your data. Those that don't fit in with your data are visually recognizable as outliers on your graph. Clustering is also a great way to visual your data and classify it. For this analysis, I have chosen to apply the k-means clustering algorithm. K-means is a type of unsupervised learning with the goals of grouping the data based on certain criteria's. The number of groups are represented by the number *K*. The algorithm works iteratively to assign each point to one of the K groups based on the features provided. This is based on the similarity of your data points as to where cluster it belongs to. Choosing K can be very difficult when you do not have pre -defined classes in your data. This will be a challenge for this project.

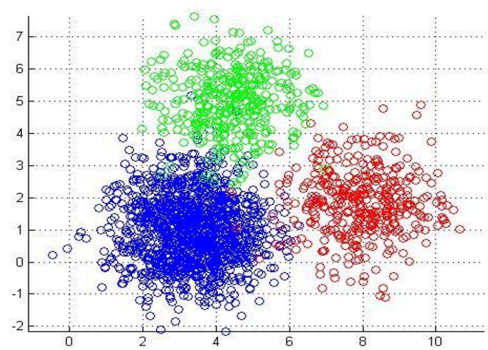


Figure 8: Example of a K means cluster on a 2D graph in R where K=3.

Interpretation/Evaluation

After my models have been built. I will run my data through them to see the results. Based on the results, I will visually represent my findings via tableau and graphs created in R. This allows for easier interpretation for those less technical minded and an easier comparison when I am referring back to the idea behind this project, which is the power of analytics vs. accountancy.

ANALYSIS & DESIGN

USE CASES

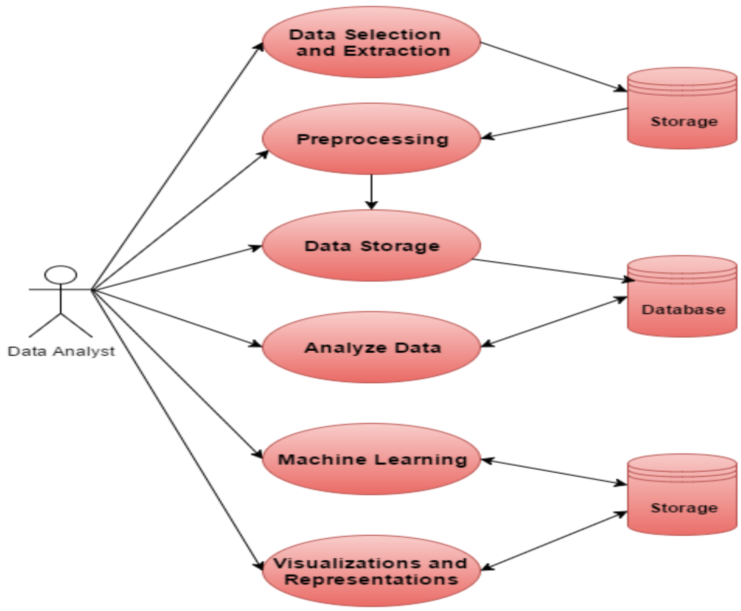


Figure 9: Use Case for this project

DATA REQUIREMENTS

The below datasets were required to complete my analysis. They were taking from Kaggle and the ELTE bitcoin project website. The timeframe is from 10th November 2009 until 7th November 2017. The Kaggle dataset has 2921 rows and 21 columns, whilst the other datasets combined have a total of 254,495,928 rows and 20 columns. The features of the datasets are split as follows:

Kaggle provided the dataset regarding the bitcoins transactions. *https://www.kaggle.com/sudalairajkumar/cryptocurrencypricehistory/data*
Date: Date of observation
btc_market_price: Average USD market price across major bitcoin exchanges.
btc_total_bitcoins: The total number of bitcoins that have already been mined.
btc_market_cap: The total USD value of bitcoin supply in circulation.
btc_trade_volume: The total USD value of trading volume on major bitcoin exchanges.
btc_blocks_size: The total size of all block headers and transactions.
btc_avg_block_size: The average block size in MB.

btc_n_orphaned_blocks: The total number of blocks mined but ultimately not attached to the main Bitcoin blockchain.
btc_n_transactions_per_block: The average number of transactions per block.
btc_median_confirmation_time: The median time for a transaction to be accepted into a mined block.
btc_hash_rate: The estimated number of tera hashes per second the Bitcoin network is performing.
btc_difficulty: A relative measure of how difficult it is to find a new block.
btc_miners_revenue: Total value of coinbase block rewards and transaction fees paid to miners.
btc_transaction_fees: The total value of all transaction fees paid to miners.
btc_cost_per_transaction_percent: miners revenue as percentage of the transaction volume.
btc_cost_per_transaction: miners revenue divided by the number of transactions.
btc_n_unique_addresses: The total number of unique addresses used on the Bitcoin blockchain.
btc_n_transactions: The number of daily confirmed Bitcoin transactions.
btc_n_transactions_total: Total number of transactions.
btc_n_transactions_excluding_popular: The total number of Bitcoin transactions, excluding the 100 most popular addresses.
btc_n_transactions_excluding_chains_longer_than_100: The total number of Bitcoin transactions per day excluding long transaction chains.
btc_output_volume: The total value of all transaction outputs per day.
btc_estimated_transaction_volume: The total estimated value of transactions on the Bitcoin blockchain.
btc_estimated_transaction_volume_usd: The estimated transaction value in USD value.

ELTE Bitcoin Project website and resources provided the below datasets. *http://www.vo.elte.hu/bitcoin/zipdescription.htm*
blockhash.txt -- enumeration of all blocks in the blockchain, 277443 rows, 4 columns:
blockID -- id used in this database (0 -- 277442, continous)
bhash -- block hash (identifier in the blockchain, 64 hex characters)
btime -- creation time (from the blockchain)
txs -- number of transactions
txhash.txt -- transaction ID and hash pairs, 30048983 rows, 2 columns:
txID -- id used in this database (0 -- 30048982, continous)
txhash -- transaction hash used in the blockchain (64 hex characters)

addresses.txt -- BitCoin address IDs, 24618959 rows, 2 columns:
addrID -- id used in this database (0 -- 24618958, continous, the address with addrID == 0 is invalid /blank, not used/)
addr -- string representation of the address (alphanumeric, maximum 35 characters; note that the IDs are NOT ordered by the addr in any way)
tx.txt -- enumaration of all transactions, 30048983 rows, 4 columns:
txID -- transaction ID (from the txhash.txt file)
blockID -- block ID (from the blockhash.txt file)
n_inputs -- number of inputs
n_outputs -- number of outputs
txin.txt -- list of all transaction inputs (sums sent by the users), 65714232 rows, 3 columns:
txID -- transaction ID (from the txhash.txt file)
addrID -- sending address (from the addresses.txt file)
value -- sum in Satoshis (1e-8 BTC -- note that the value can be over 2^32, use 64-bit integers when parsing)
txout.txt -- list of all transaction outputs (sums received by the users), 73738345 rows, 3 columns:
txID -- transaction ID (from the txhash.txt file)
addrID -- receiving address (from the addresses.txt file)
value -- sum in Satoshis (1e-8 BTC -- note that the value can be over 2^32, use 64-bit integers when parsing)
txtime.txt -- transaction timestamps (obtained from the blockchain.info site), 30048983 rows, 2 columns:
txID -- transaction ID (from the txhash.txt file)
unixtime -- unix timestamp (seconds since 1970-01-01)

IMPLEMENTATION

In this section, the main parts of the code will be explained using code snippets where appropriate. The majority of code was developed and tested using RStudio

SET UP THE ENVIRONMENT

Firstly, we need to set our working directory, so all files loaded are coming and going to the one folder. Next, we need to tell R environment which libraries will be used during the script. All R packages are first installed into libraries, which are directories in the file system containing a subdirectory for each package installed there. Then every time you open RStudio, you need to load the library function for each library, so R knows which libraries you are using on that script. This can be seen below. Now the data is ready to be read in and your analysis can begin.

```r
setwd("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_dataset")

library(bigmemory.sri)
library(bigmemory)
library(knitr)
library(pander)
library(tidyverse)
library(broom)
library(scatterplot3d)
library(DataCombine)
library(corrplot)
library(caret)
library(data.table)
library(bit64)
library(anytime)
library(ggplot2)
library(psych)
library(mvtnorm)
library(PRROC)
library(ggfortify)


df <- read.csv("BTC_df.csv", stringsAsFactors = F)
BTC <- read.csv("bitcoin_dataset.csv", stringsAsFactors = F)

#checking for NULL values
is.na(df)
is.na(BTC)
```

Figure 10: Setting up R environment

CLEANING THE DATA

The Kaggle dataset was relatively small, so a simple view() function in RStudio can allow for some visualisation on the data to check for any null values. Alternatively, on our much larger datasets, I applied a is.na(x) function and luckily no NULL's were found. Other pre-processing steps including renaming of columns for easier reading, removal of similar columns among the datasets before the transformation stage could begin. Unix Timestamp was converted and changed into date format.

```
#changing Column Names in the Datasets for easier reading
colnames(btc_hash)[colnames(btc_hash)=="X"] <- "Block.ID"
colnames(btc_hash)[colnames(btc_hash)=="X000000000019D6689C085AE165831E934FF763AE46A2A6C172B3F1B60A8CE26F"] <- "Block.Hash"
colnames(btc_hash)[colnames(btc_hash)=="X1231006505"] <- "Block.Time"
colnames(btc_hash)[colnames(btc_hash)=="X1"] <- "Num.Of.Transactions"

colnames(btc_Addresses)[colnames(btc_Addresses)=="X"] <- "Address.ID"
colnames(btc_Addresses)[colnames(btc_Addresses)=="x"] <- "Address"

colnames(btc_Input)[colnames(btc_Input)=="X"] <- "NULL"
colnames(btc_Input)[colnames(btc_Input)=="TxID"] <- "Transaction.ID"
colnames(btc_Input)[colnames(btc_Input)=="addrID"] <- "Address.ID"

colnames(btc_Output)[colnames(btc_Output)=="V1"] <- "Transaction.Output.ID"
colnames(btc_Output)[colnames(btc_Output)=="V2"] <- "Transaction.Output.Address"
colnames(btc_Output)[colnames(btc_Output)=="V3"] <- "Transactions.Output.Value"
```

Figure 11: Renaming of columns for easier analysis

Our Kaggle dataset variable, btc_median_confirmation_time, had a lot of '0' values. This could cause our data to have a skewered distribution and for our data to appear not normal. To avoid this, I created a subset which only includes instances greater than 0 for this variable. When I am comparing and analysing this variable, I will query my subset dataset, BitcoinData2.

```
> BitcoinData2 <- subset(BitcoinData, BitcoinData$btc_median_confirmation_time>0) #SUBSET OF D
ATA THAT IS CLEAN
```

Figure 12: creating a subset of data that is clean

SAMPLING THE DATA

Each dataset was individually read into RStudio.

The ELTE datasets (all 7) are massive in size so the reading process alone took hours. This was down to lack of computational power. However, my machine is less than a year old and has 8GB RAM and struggled immensely with handling this data so that highlights the volume of data that was processed. After a lot of restarting RStudio and machine, and a lot of unresponsive programs, I began experimenting with different packages in R that helps handle big data. Eventually I learnt of the fread() function which is a method from the Data.Table package. (This saved my day!) Fread is capable of reading in large amount of data and even gives a status report after it has been read as to how long it took and how much data was read. Also, whilst the data is being read, there is a percentage progress bar which shows you how much of the data has been read. A feature in which RStudio is lacking in itself, if I may add.

In Figure 5 you will see the time in which it took to read in some of the datasets. Figure 6 highlights even with a big memory function applied, the read time can still be very long when dealing with huge amounts of data. These datasets had to be read in numerous of times at the beginning until eventually RStudio and my machine worked up the processing power to read all 7 datasets in the one session. There were a lot of trial and error and a lot of time spent on this step before I could process to the next stages.

```
> addresses = fread("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_dataset/
addresses.txt")
Read 24618959 rows and 2 (of 2) columns from 0.998 GB file in 00:01:31
> tx = fread("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_dataset/tx.txt"
)
Read 30048983 rows and 4 (of 4) columns from 0.550 GB file in 00:00:21
> txtime = fread("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_dataset/txt
ime.txt")
Read 30048983 rows and 2 (of 2) columns from 0.549 GB file in 00:00:09
```

Figure 13: The fread function reading in 3 of the 7 larges datasets

```
> txhash = fread("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_dataset/txhash.txt")
Read 30048983 rows and 2 (of 2) columns from 2.061 GB file in 00:48:55
```

Figure 14: shows the time in which it took to read in one of the biggest datasets out of the 7. Almost 49 minutes!

Using another R method, sample(), I was able to specify how many samples I wanted from my set and apply different probabilities for each sample. I decided to split my data into train and test sets. The training set can be used when building my model and the test set can be used when my model is complete for testing purposes. After my data was sampled, I then wrote the two individual samples (test and train) to separate .csv files. This was so I would not have to spend the time reading in the entire datasets again and sampling them each time. This process was repeated for all seven datasets.

```
> txhash = fread("C:/Users/paris/Desktop/College/College/Software Project/bitcoin_datas
et/txhash.txt")
Read 30048983 rows and 2 (of 2) columns from 2.061 GB file in 00:02:48
> TransHash <- sample(2, nrow(txhash), replace=TRUE, prob = c(0.10, 0.025))
> trainTransHash <- txhash[TransHash==1, ]
> testTransHash <- txhash[TransHash==2, ]
> write.csv(trainTransHash, file = "trainTransactionHash.csv")

> write.csv(testTransHash, file = "testTransactionHash.csv")
```

Figure 15: txhash.txt dataset being read in, sampled, split into two sets then read individually to two .csv files.

DIMENSION REDUCTION

FROM THIS

```
> dim(btc_Output)
[1] 74045      4
> dim(btc_Time)
[1] 1048575        2
> dim(btc_Transactions)
[1] 1048575        4
> dim(btc_Transactions_Hash)
[1] 1048575        2
> dim(btc_Addresses)
[1] 1048575        2
> dim(btc_hash)
[1] 222112      4
> dim(btc_Input)
[1] 839163       3
> dim(btc_Output)
[1] 74045      4
> dim(btc_Time)
[1] 1048575        2
> dim(btc_Transactions)
[1] 1048575        4
> dim(btc_Transactions_Hash)
[1] 1048575        2
```

TO THIS

```
> dim(btc_Addresses)
[1] 74045     2
> dim(btc_hash)
[1] 74045     4
> dim(btc_Input)
[1] 74045     3
> dim(btc_Output)
[1] 74045     4
> dim(btc_Time)
[1] 74045     2
> dim(btc_Transactions)
[1] 74045     4
> dim(btc_Transactions_Hash)
[1] 74045     2
```

Figure 16: Dimension reduction on all training sets.

Once the seven datasets were successfully split into training and test sets. I rebooted R and only loaded in all the training sets. They were all of different dimensions, so I applied a dimension reduction method on the rows of each set and matched the size to that of the smallest train set, which was (btc_output 74047). This was the quickest most efficient way to reduce my data is size to all match so that they could then be combined into one data frame.

COMBINING THE DATA & BUILDING A DATA FRAME

The below code snippets show the steps in which I took to combine my seven training sets into one data frame. Once the row dimensions in all sets were equal, it was easy to then combine the data in the one frame using the data.frame() function in R.

```
dim(btc_Addresses)
dim(btc_hash)
dim(btc_Input)
dim(btc_Output)
dim(btc_Time)
dim(btc_Transactions)
dim(btc_Transactions_Hash)

btc_Input <- btc_Input[-c(74046:839163), ]
dim(btc_Input)

btc_Addresses <- btc_Addresses[-c(74046:1048575), ]
dim(btc_Addresses)

btc_hash <- btc_hash[-c(74046:222112), ]
dim(btc_hash)

btc_Time <- btc_Time[-c(74046:1048575)]
dim(btc_Time)

btc_Transactions <- btc_Transactions[-c(74046:1048575)]
dim(btc_Transactions)

btc_Transactions_Hash <- btc_Transactions_Hash[-c(74046:1048575)]
dim(btc_Transactions_Hash)
colnames(df)
#combining into a dataframe
df = data.frame(btc_hash, btc_Addresses, btc_Input, btc_Output, btc_Time, btc_Transactions, btc_Transactions_Hash)
colnames(df)

#writing to Csv file for furture analysis
write.csv(df, file = "BTC_df.csv")
```

Figure 17: combining train sets into a data frame

I then wrote the data frame to a .csv file so that I could not have to load the above code every time I want to analyse my data frame. This was a much easier option for going forward with the project. Also, my datasets have finally been condensed to a manageable size and I could view my data as a whole in excel. This also showed me there were a lot of duplicate 'ID' attributes which needed to be removed. For ease of use, I did this in a matter of seconds in excel.

ANALYZING AND EXPLORING THE DATA

The first step I always take in exploring my data is to run the summary command. This command is so simple yet so powerful in summarizing your data. You get results in a matter of seconds which is a great thing about R as a language. Below we can see some interesting things about our data frame, the mean number of inputs are 0.52 and the mean number of outputs are 1.168. This shows there is a greater amount of transactions being sent than received, which makes sense really! Although, these numbers are extremely small. This could be down to the security measures behind the blockchain which provide each transaction with a unique address, making it hard to trace back to the seller, so again making it difficult to determine exactly how many transactions have come from the same seller.

```
> summary(df)
       X              Blockhash            blocktime          Hash.Number.of.Transactions
 Min.   :    1   Length:74045       Min.   :1.231e+09   Min.   :  1.000
 1st Qu.:18512   Class :character   1st Qu.:1.253e+09   1st Qu.:  1.000
 Median :37023   Mode  :character   Median :1.269e+09   Median :  1.000
 Mean   :37023                      Mean   :1.266e+09   Mean   :  1.702
 3rd Qu.:55534                      3rd Qu.:1.280e+09   3rd Qu.:  1.000
 Max.   :74045                      Max.   :1.290e+09   Max.   :776.000
   Address.ID       Address          Input.Transaction.ID Input.Address.ID
 Min.   :    0   Length:74045       Min.   :   171       Min.   :    147
 1st Qu.:23187   Class :character   1st Qu.: 66295       1st Qu.:1507964
 Median :46335   Mode  :character   Median : 90733       Median :3132254
 Mean   :46341                      Mean   : 86768       Mean   :3185608
 3rd Qu.:69537                      3rd Qu.:109111       3rd Qu.:4874247
 Max.   :92680                      Max.   :127685       Max.   :6486284
  Input.Value         Transaction.Output.ID Transaction.Output.Address
 Min.   :9.900e+01   Min.   :     206      Min.   :       1
 1st Qu.:5.000e+07   1st Qu.: 8032885      1st Qu.: 3575893
 Median :5.000e+09   Median :15683616      Median : 8995634
 Mean   :1.244e+10   Mean   :15378789      Mean   : 9999718
 3rd Qu.:5.000e+09   3rd Qu.:22766208      3rd Qu.:15567295
 Max.   :5.000e+12   Max.   :30048678      Max.   :24618773
 Transactions.Output.Value Time.Transaction.ID  Timestamp          Unix.Timestamp
 Min.   :0                 Min.   :    0       Length:74045       Min.   :1.231e+09
 1st Qu.:0                 1st Qu.:23168       Class :character   1st Qu.:1.253e+09
 Median :0                 Median :46272       Mode  :character   Median :1.269e+09
 Mean   :0                 Mean   :46266                          Mean   :1.264e+09
 3rd Qu.:0                 3rd Qu.:69394                          3rd Qu.:1.277e+09
 Max.   :0                 Max.   :92482                          Max.   :1.280e+09
 Transaction.ID      Block.ID      No.of.Inputs     No.of.Outputs   Transaction.Hash
 Min.   :    1   Min.   :    1   Min.   :  0.00   Min.   :1.000   Length:74045
 1st Qu.:23207   1st Qu.:23060   1st Qu.:  0.00   1st Qu.:1.000   Class :character
 Median :46263   Median :45781   Median :  0.00   Median :1.000   Mode  :character
 Mean   :46352   Mean   :41800   Mean   :  0.52   Mean   :1.168
 3rd Qu.:69592   3rd Qu.:62270   3rd Qu.:  0.00   3rd Qu.:1.000
 Max.   :92731   Max.   :70389   Max.   :965.00   Max.   :2.000
```

Figure 18: summary command in RStudio on df

I separately ran a command to get the average time as it was in Unix and I wanted the time as well as the date displayed. By using the anytime() library in R this was done and can be seen below.

```
> mean(df$Unix.Timestamp)
[1] 1263836532
> anytime(1263836532)
[1] "2010-01-18 17:42:12 GMT"
> MeanTimestamp <- anytime(1263836532)
```

Figure 19: Mean time of transactions

Below is a code snippet on the code I ran to display a correlation matrix of my Kaggle dataset. I felt this would be very interesting considering the attributes in this set. A correlation matrix displays, usually in a percentage, the relationship among two variables. In this case, my variables are my attributes. A score close to 1 displays a strong relationship among variables x and y. A score near .5 displays a medium relationship among x and y variables. Anything below would be considered weak.

```
> cor <- cor(BitcoinData[,c(2:4,6:25)])
> colnames(cor) <- c("MarketPrice", "TotalBTC", "MarketCap", "BlocksSize","AvgBlockSize",
+                    "OrphanedBlocks", "Ntransactions","MedConfirmTime","HashRate","BTCDifficulty",
+                    "MinersRevenue","TransactionFees","CostPerTransaction%","CostPerTransaction",
+                    "NumUniqueAddresses","NumTransactions","NumTansactionsTotal","TransactionsExPop",
+                    "TransactionsExLong100","OutputVolume","EstTransactionVolume","EstTransactionVolUSD"
,
+                    "Days")
> rownames(cor) <- c("MarketPrice", "TotalBTC", "MarketCap", "BlocksSize","AvgBlockSize","OrphanedBlocks"
,
+                    "Ntransactions","MedConfirmTime","HashRate","BTCDifficulty","MinersRevenue",
+                    "TransactionFees","CostPerTransaction%","CostPerTransaction","NumUniqueAddresses",
+                    "NumTransactions","NumTansactionsTotal","TransactionsExPop","TransactionsExLong100",
+                    "OutputVolume","EstTransactionVolume","EstTransactionVolUSD","Days")
> corrplot(cor, method = "square", tl.srt = 70, tl.col = "black",
+          tl.cex=0.4, title = "Correlation of Variables", mar=c(0,0,1,0))
> corrplot(cor, method = "square", tl.srt = 80, tl.col = "black",
+          tl.cex=0.4, title = "Correlation of Variables", mar=c(0,0,1,0))
> View(cor)
```

Figure 30: code snippet from RStudio of correlation matrix

For easier reading, I worded my column names before displays the correlations as a matrix. Below you can see a thermostat output of the relationship among variables. The darker the blue, the stronger the relationship. The whiter the colour, then we would conclude a medium relationship. Then we can look at any red as the “danger zone” concluding an extremely weak correlation and no relationship. It is clear to see there is a lot bluer tones, showing a lot of strong relationships. There are absolutely no red tones but a lot of white tones. White tones indicated a correlation coefficient close to 0 which signifies that there is no linear relationship between the variables. This matrix is a good indicator to analyse when building a model as it specifies which variables have an impact on one another.

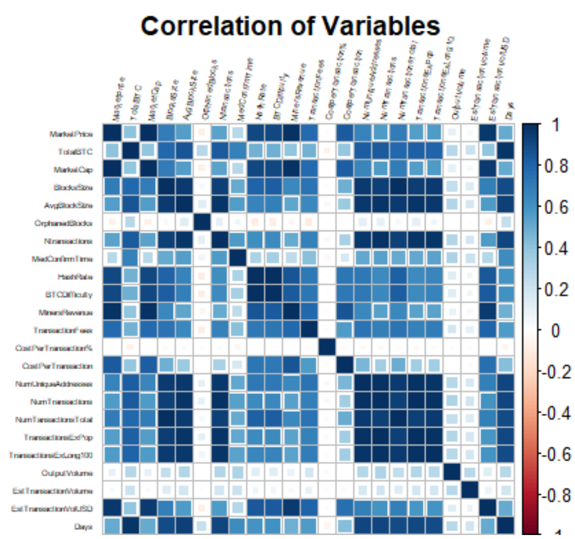


Figure 21: Correlation Matrix

MarketPrice and MarketCap have a correlation coefficient of 0.99. This is extremely high showing a strong relationship. This makes sense as generally market caps do have an effect on market price.

BTCDifficulty, HashRate, MinersRevenue, EstTransactionVolUSD are also all highly correlated with MarketPrice with coefficients of .9+.

OutputVolume, and TotalBTC have low correlations with MarketPrice suggesting they do not contribute to one another.

VISUALIZING THE DATA

The next step was to visualise my data. This step only makes sense after you have done enough research to understand your data. Otherwise it would be too difficult to comprehend the graphs.

A common question to ask about the strength of any currency, is it getting stronger or weaker over time? The graph to the left represents our Kaggle data which clearly shows the value of bitcoin is getting higher as time progresses. The right graph represents our transactional dataset, ELTE, and shows the number of transactions being sent are relatively small and don't seem to be increasing as time goes on too much. This could suggest users are more inclined to receives bitcoins but not send them.

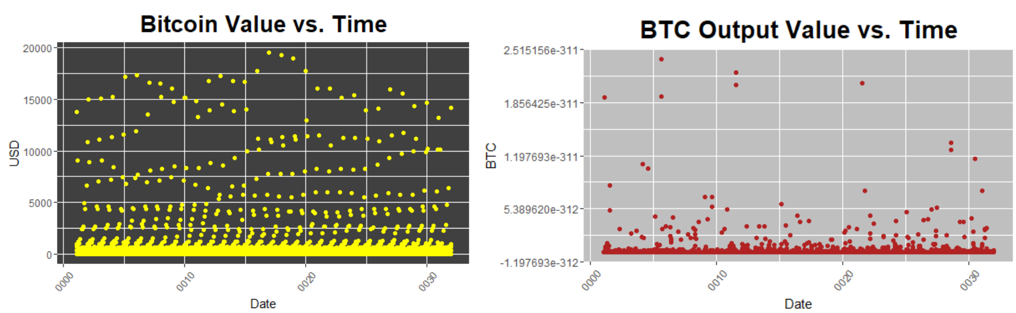


Figure 22: ggplot from R. Left image is Kaggle data and right is ELTE data.

Below I plotted bitcoins market capitalization which is the total USD value of bitcoin supply in circulation versus the Market Price (Average USD market price across major bitcoin exchanges). The data points were graphed onto a linear model. Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data. Additionally, we can see our datapoints are all on the linear regression line which shows our data is normal. It is clear to see that both variables are dependent on one another. As market price rights so does Market capitalization and visa versa. I referred back to my correlation matrix and seen a coefficient of 0.99 between them which confirms this.

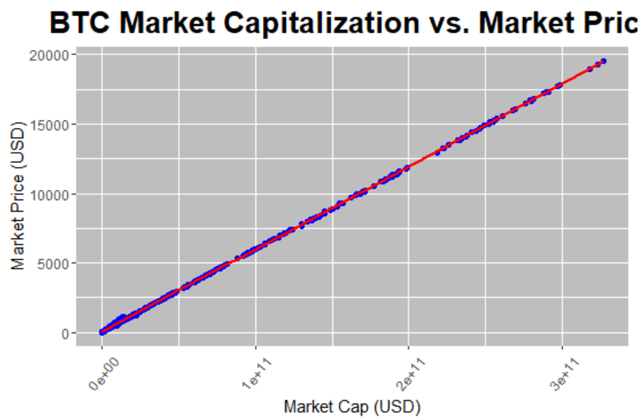


Figure 23: ggplot of Market Capitalization vs. Market Price

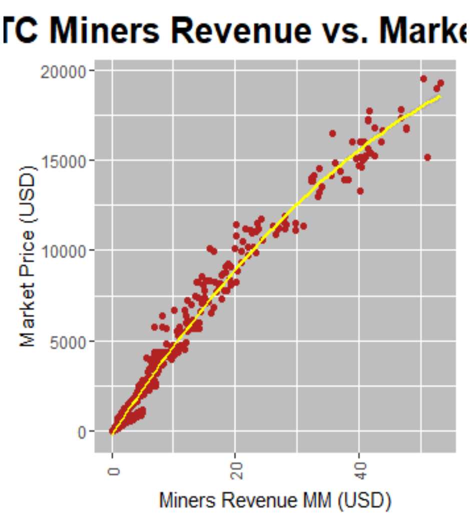


Figure 24: ggplot of Market Capitalization vs. Market Price

BUILDING THE MODELS

In statistics, linear regression is an approach at modelling the relationship between a dependent variable y and one or more explanatory variables (or independent variables) denoted X.

Market Price vs. Estimated Transaction Volume Linear Model

	t value	Pr(>|t|)
poly(BitcoinData2$btc_estimated_transaction_volume_usd, 2)1	168	0
poly(BitcoinData2$btc_estimated_transaction_volume_usd, 2)2	-15	5.5e-50

```
                **(Intercept)**                    76        0
---------------------------------------------------------------------------
```

The t statistic is the coefficient divided by its standard error. The standard error is an estimate of the standard deviation of the coefficient, the amount it varies across cases. It can be thought of as a measure of the precision with which the regression coefficient is measured.

```
> lm1 <- plot(BitcoinData2$btc_market_price~ BitcoinData2$btc_estimated
_transaction_volume_usd)
> meanlm1 <- mean(BitcoinData2$btc_market_price)
> abline(h=meanlm1)
> R2=summary(lmfit2)$r.squared
> cat("R-Squared =", R2)
R-Squared = 0.9262094
```

R- Squared, also known as the coefficient of determination, is the proportion of variability in y that is explained by the independent variable, x, in the model.

Our independent x variable is btc_estimated_transaction_volume_usd and our dependent variable y is btc_market_price. Our R-Squared value tells us that 92% of bitcoins market price is due to bitcoins estimated volume of transactions. Although this value of R-Squared is high, the x and y variables by themselves or together, do not tell us enough about our data.

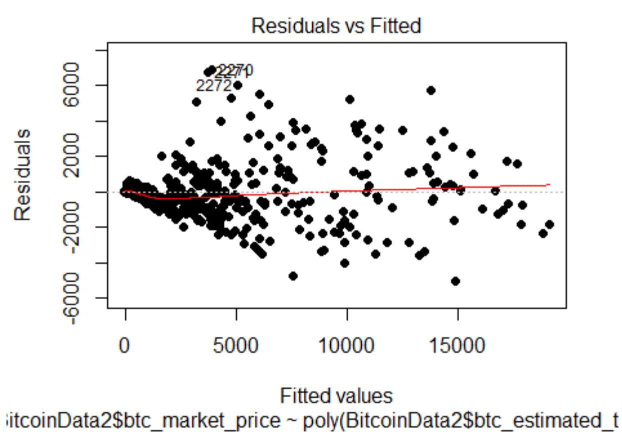


Figure 25: Graph of the residuals of lmfit2b

These plots exhibit “heteroscedasticity”, meaning that the residuals get larger as the prediction moves from small to large (or from large to small). There appears to be a pattern in the residuals plot above starting at zero and increasing linearly to approximately 1000 on the x-axis. Also meaning as the price increases the variability increases. One way to remedy this may be to transform a variable in the model. This will be considered when selecting variables for a regression model.

Market Price vs. Estimated Transaction Volume Linear Model Second Iteration

In the second iteration, a log transformation was applied due to the model being bottom heavy in the x and y axis. The code for this can be seen below.

```
> lmfit2b <-
+   lm(log(BitcoinData2$btc_market_price)~log(BitcoinData2$btc_estimate
d_transaction_volume_usd))
> panderOptions("digits", 2)
> pander(lmfit2b, caption = "Linear Model: Market Price ~ Estimated Tra
nsactions Volume(USD) Squared")
```

Figure 26 : Applying a log transformation to lmfit2b

```
> R22=summary(lmfit2)$r.squared
> cat("R-Squared=", R22)
R-Squared= 0.9262094
```

Figure 27 : R-Squared value since a log transform was applied

This R-Squared value is the exact same as that before the log transform was applied. This suggests this has not made a difference to our model. We will visually inspect this below for further confirmation.

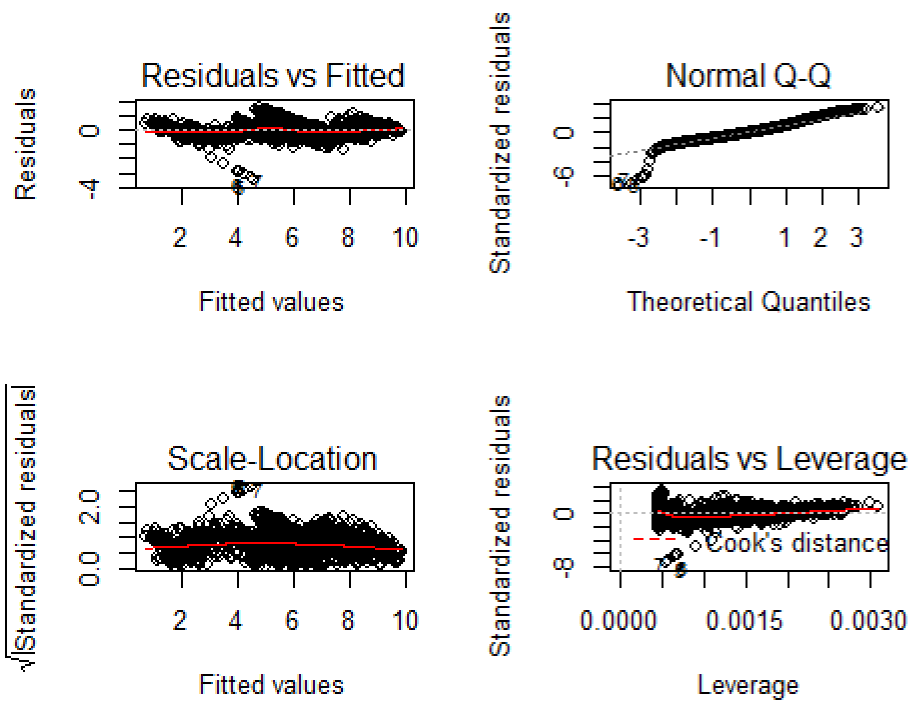


Figure 28: Plots of residuals for the lmfit2b model after the log transform

As your can see from the plots above that the log transform has impacted the heteroscedasticity issue significantly in the x-axis direction. Perhaps these two variables do not work together in the way we hoped they would. Our QQ plot for normality (top right corner) indicates our data is normal in distribution.

Market Price vs. Miners Revenue Linear Regression Model

A linear model was built to see whether there was a relationship between the market price of bitcoin and the miners revenue. The miners revenue is the total value of coinbase block rewards and transaction fees paid to miners. The market price is based on the average USD market price across major bitcoin exchanges. The output is as follows:

```
> lmfit3<-lm(BitcoinData2$btc_market_price~poly(BitcoinData2$btc_miners_revenue
,2))
> panderOptions("digits", 2)
> pander(lmfit3, caption = "Linear Model: Market Price ~ Miners Revenue (USD) S
quared")

---------------------------------------------------------------------------
                                       Estimate   Std. Error   t value
----------------------------------------- ---------- ------------ ---------
 **poly(BitcoinData2$btc_miners_revenue,    125159       375         334
                  2)1**

 **poly(BitcoinData2$btc_miners_revenue,    -12954       375         -35
                  2)2**

             **(Intercept)**                 1152        7.9         147
---------------------------------------------------------------------------

Table: Linear Model: Market Price ~ Miners Revenue (USD) Squared (continued bel
ow)


----------------------------------------------------
                                       Pr(>|t|)
----------------------------------------- ----------
 **poly(BitcoinData2$btc_miners_revenue,      0
                  2)1**

 **poly(BitcoinData2$btc_miners_revenue,   7.8e-211
                  2)2**

             **(Intercept)**                  0
----------------------------------------------------

> R3=summary(lmfit3)$r.squared
> cat("R-Squared = ", R3)
R-Squared =  0.9802747
```

Figure 29: Code output of our linear model for comparing the relationship between bitcoins market price and bitcoins Miners revenue.

R-Squared value indicates that 98% of our market price is due to Miners Revenue.

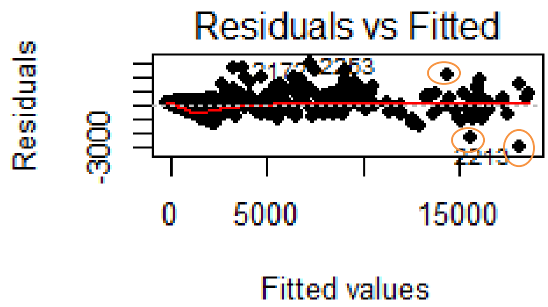
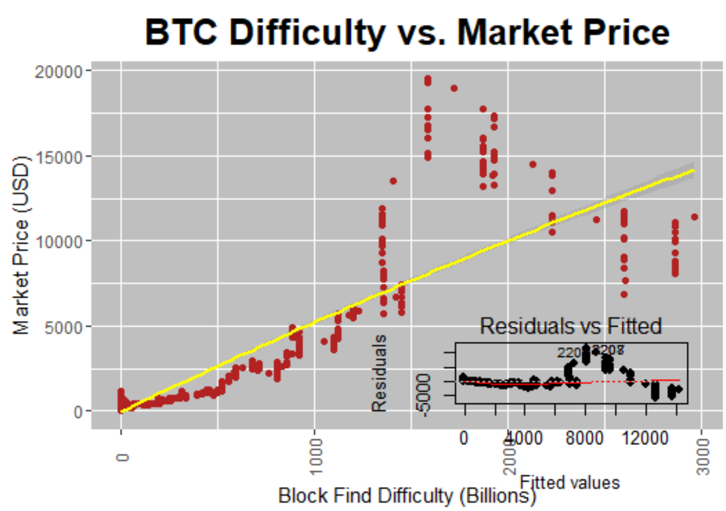


Figure 30: Residuals vs Fitted for lmfit3. I have circled possible outliers.

Again, there are signs of heteroscedasticity. Also, we can see a lot of our data have formed into clusters. This graph clearly indicates there are outliers in our data. This could be a factor in our graph having dispersions. Perhaps a very large or very small data point far from the mean have caused our data to appear this way. This graph highlights how versatile regression is as data mining method. It is a great visualisation method for viewing your data and checking for anomalies. I have circled these above. This fits very well with my project.

Market Price vs. Block Find Difficulty Linear Model

Next, we look at a relative measure of how difficult it is to find a new block in the blockchain and consider whether this has an effect on the market price.



This graph is really interesting. There is a lot of variance around the linear but the graph is still a good indicator that there is a linear relationship in the data. Our R value can help with determining this as sometimes we cannot say visually. Again, we can see some outliers among our data which could be worth investigating.

```
> R5=summary(lmfit5)$r.squared
> cat("R-Squared = ", R5)
R-Squared =  0.8129002
```

There is an 81% chance that the block find difficulty has an effect on the market price.

Market Price vs. Hash Rate Linear Model

The linear model below represents the relationship between bitcoins hash rate and market price. There is an 81% chance that the model explains all the variability of the response data around the mean.

```
> R5=summary(lmfit5)$r.squared
> cat("R-Squared = ", R5)
R-Squared =  0.8129002
```

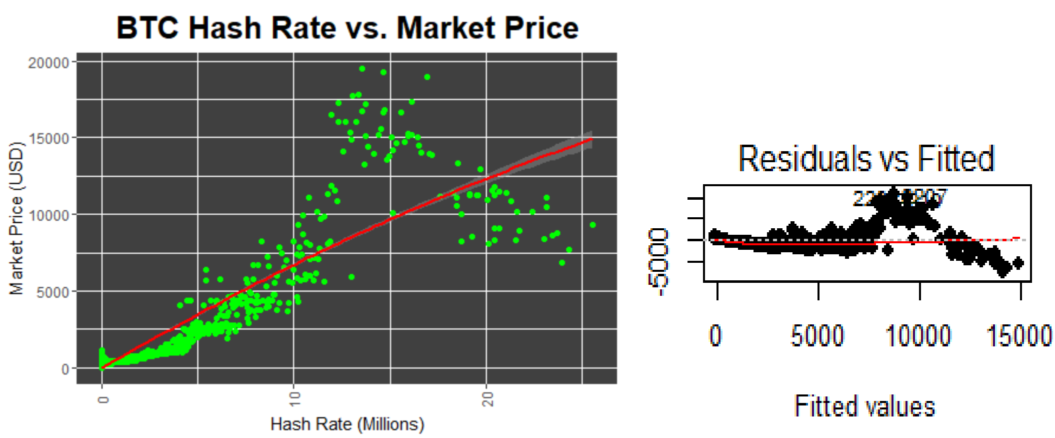


Figure 31

There are signs of some heteroscedasticity, but residuals are relatively flat. Evidence of some obvious outliers can be seen in the graph to the left above. This is an indicator of possible anomalous behaviour that can be skewing our data. In regression, outliers are known as influential points. This is because an outlier greatly affects(influences) the slope of the regression line. Our coefficient of determination is 81%. Due to evidence of outliers, we can assume our R-squared value has been affected by these resulting in it being bigger or smaller

Market Price vs. All Variables

Now its time to look at all variables as a whole and how these are significant to the market price.

`> pander(lmBTCm, caption = "Linear Model: Market Price vs. All Variables")` (Output can be seen in the Appendix for this function, includes estimate, standard error, t-value and p-value for all variables.)

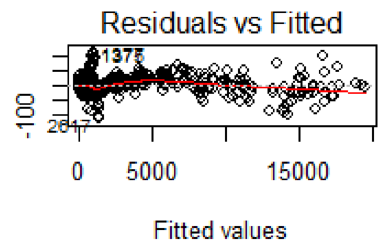


Figure 32 residuals of all variables versus market price.

What's really interesting to see from the graph is the number out outliers. By changing the pch to 1, this has become a lot clearer and easier identifiable.
We can also see that the majority of the volume is located in the lower x-axis region. Our data see ms to be very clustered around this region. In general, the trend line is relatively flat.

Now we look at the relationship between market price and our highly correlated variables only.

```
> lmBTCm2 <- lm(BitcoinData2$btc_market_price~BitcoinData2$btc_market_cap+
+                 BitcoinData2$btc_hash_rate+BitcoinData2$btc_difficulty+
+                 BitcoinData2$btc_miners_revenue+
+                 BitcoinData2$btc_estimated_transaction_volume_usd, BitcoinData2)
There were 12 warnings (use warnings() to see them)
> panderOptions("digits", 2)
> Rb2=summary(lmBTCm2)$r.squared
> cat("R-Squared = ", Rb2)
R-Squared =  0.9997442
```

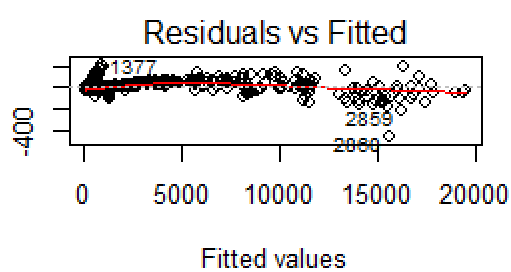


Figure 33

We have an extremely high R-squared value. This suggests our model is doing a good job. It appears our highly correlated variables are significant to the market price. Our trend line is not very flat nor is our data evenly dispersed.

If we condense our variables further, this may have a positive impact. Market Capitalization and Estimated Transaction Volume are highly correlated, only one will be included in the model. Also, because Difficulty and Hash Rate are highly correlated, the model will only include one.

```
> cat("R-Squared = ", Rb6)
R-Squared = 0.9736494
```

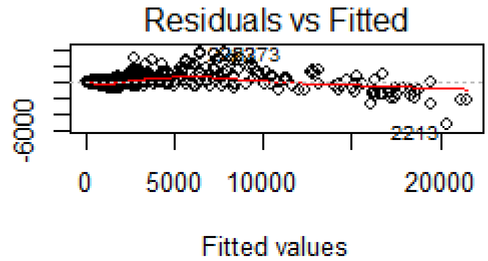


Figure 34

Still some heteroscedasticity, but the best model so far.

Polynomial Multivariable introduced to "Linear Model: Market Price ~ Miners Revenue Squared + Count of Transactions Squared" linear model

Polynomial regression is a special case of multiple linear regression when the relationship between the independent variable x and dependent variable y is modelled as a nth degree polynomial in x.

Our R-squared value is extremely high in comparison with the non-polynomial multivariable regression.

```
> lmfit7 <- lm(BitcoinData2$btc_market_price ~ poly
+               (BitcoinData2$btc_estimated_transaction_volume_usd, 2)
+               + poly(BitcoinData2$btc_miners_revenue, degree=2))
> R7=summary(lmfit7)$r.squared
> cat("R-Squared = ", R7)
R-Squared =  0.9827218
```

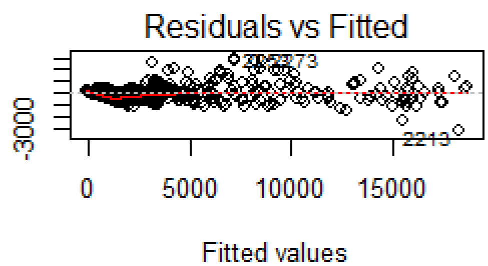


Figure 34

With polynomials introduced, we can see our graph does not have as much dispersion as recommended and it also results in a flatter line. We can consider this model, the best thus far.

Now its time to train the model and test it

For this model I will use the same model features as above for lmfit7.

```
> set.seed(1)
> train.index<-sample(1:nrow(BitcoinData2),0.80*nrow(BitcoinData2), replace=FAL
SE)
```

```
> train <- BitcoinData2[train.index, ]
> test  <- BitcoinData2[-train.index,]
> lmtrain <- lm(btc_market_price~poly(btc_estimated_transaction_volume_usd,2) +
poly(btc_miners_revenue,2) , train)
> test$p1 <- predict(lmtrain,test)
```

Figure 36: Splitting the data into training and testing

```
> ggplot(test, aes(test$Days)) +
+   geom_point(aes(y=test$btc_market_price),color="red") +
+   geom_line(aes(y=test$p1), color="Blue")+
+   ggtitle('BTC Prediction vs. Actuals') +
+   theme(plot.title = element_text(size=16, face="bold",
+                                   margin = margin(10, 0, 10, 0)))+
+   labs(x="Days", y="Market Price (USD)")+
+   theme(axis.text.x=element_text(angle=90, vjust=0.5)) +
+   theme(panel.background = element_rect(fill = 'grey75'))+
+   labs(title = paste("BTC Linear Regression Model Prediction vs. Actuals",
+                      "\n\nAdj R2 = ",signif(summary(lmtrain)$adj.r.squared, 5
),
+                      " P =",signif(summary(lmtrain)$coef[2,4], 2)))
```

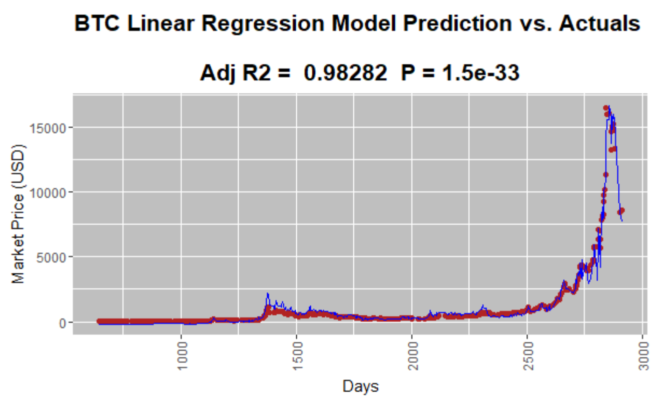


Figure 37: Output for the above code snippet

We can see the model does a great job at tracking the test set. If we add a column for the percentage of change for the market price this is our output…. (this was done using the mutate() and lag() function.)

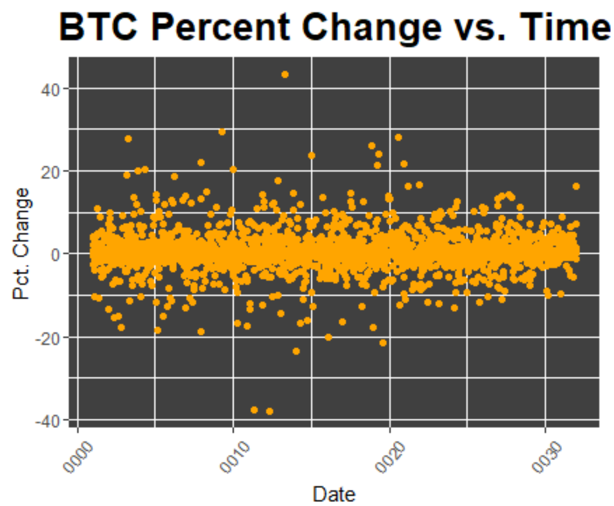


Figure 38: Bitcoin market price percentage of change over time

```
> library(zoo)

Attaching package: 'zoo'

The following objects are masked from 'package:base':

    as.Date, as.Date.numeric

> BitcoinData2$AVGtransactionvolume<-BitcoinData2$btc_estimated_transaction_volume_usd
> BitcoinData2$AVGminersrevenue<-BitcoinData2$btc_miners_revenue
> BitcoinData2$AVGmarketcap<-BitcoinData2$btc_market_cap
> BitcoinData2$pctChange<-BitcoinData2$btc_market_price
> BitcoinData2$AVGtotalbitcoins<-BitcoinData2$btc_total_bitcoins
> BitcoinData3<- subset(BitcoinData2, BitcoinData2$AVGminersrevenue>0)
> BitcoinData3<-mutate(BitcoinData3, pctChange=(BitcoinData2$btc_market_price-lag(BitcoinData2$btc_market_price))/lag(BitcoinData2$btc_market_price)*100)
> BitcoinData3<-mutate(BitcoinData3, AVGtransactionvolume=(BitcoinData2$AVGtransactionvolume-lag(BitcoinData2$AVGtransactionvolume))/lag(BitcoinData2$AVGtransactionv
olume)*100)
> BitcoinData3<-mutate(BitcoinData3, AVGminersrevenue=(BitcoinData2$AVGminersrevenue-lag(BitcoinData2$AVGminersrevenue))/lag(BitcoinData2$AVGminersrevenue)*100)
> BitcoinData3<-mutate(BitcoinData3, AVGmarketcap=(BitcoinData2$AVGmarketcap-lag(BitcoinData2$AVGmarketcap))/lag(BitcoinData2$AVGmarketcap)*100)
> BitcoinData3<-mutate(BitcoinData3, AVGtotalbitcoins=(BitcoinData2$AVGtotalbitcoins-lag(BitcoinData2$AVGtotalbitcoins))/lag(BitcoinData2$AVGtotalbitcoins)*100)
> ggplot(BitcoinData2, aes(BitcoinData3$Date, BitcoinData3$pctChange)) +
+   geom_point(color="firebrick") +
+   ggtitle('BTC Percent Change vs. Time') +
+   theme(plot.title = element_text(size=20, face="bold",
+                                   margin = margin(10, 0, 10, 0)))+
+   labs(x="Date", y="Pct. Change")+
+   theme(axis.text.x=element_text(angle=50, vjust=0.5)) +
+   theme(panel.background = element_rect(fill = 'grey75'))
Warning message:
Removed 1 rows containing missing values (geom_point).
> ggplot(BitcoinData2, aes(BitcoinData3$Date, BitcoinData3$pctChange)) +
+   geom_point(color="orange") +
+   ggtitle('BTC Percent Change vs. Time') +
+   theme(plot.title = element_text(size=20, face="bold",
+                                   margin = margin(10, 0, 10, 0)))+
+   labs(x="Date", y="Pct. Change")+
+   theme(axis.text.x=element_text(angle=50, vjust=0.5)) +
+   theme(panel.background = element_rect(fill = 'grey25'))
Warning message:
```

Figure 39 : The code snippet for the above output.

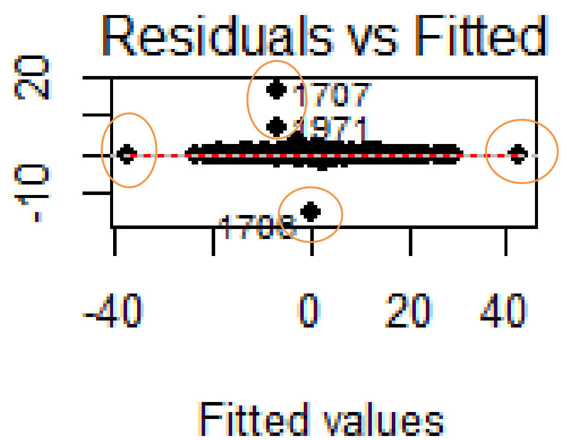
As you can see from the code snippet above, I used the library zoo in R to transform the variables to percentages by multiplying 100 by each variable. I then created another correlation matrix based on the transformed variables.

	% Change Transx Volume	% Change Miner Rev.	% Change Market Cap	% Change Market Price	Change Total Coins
% Change Transx Volume	1.00000000	0.11162116	0.14576288	0.141099695	0.020772266
% Change Miner Rev.	0.11162116	1.00000000	0.33408262	0.330541045	0.083660537
% Change Market Cap	0.14576288	0.33408262	1.00000000	0.993199714	0.015189932
% Change Market Price	0.14109970	0.33054105	0.99319971	1.000000000	0.009823925
Change Total Coins	0.02077227	0.08366054	0.01518993	0.009823925	1.000000000

Figure 40: Correlation Matrix output in R on transformed variables.

We can see from our matrix, the percent in market price is highly correlated with the percent change in market capitalization.

"Linear Model: Market Price Change ~ Market Cap Change + Total Coins Change"



Creating a linear model of the percent of market price change versus market cap change plus the total number of coins change. Our model is extremely flat with a very even distribution. There are some obvious outliers which I have circled orange. Not only is this the best model yet, but we have found a model which displays our outliers very clearly. Again, highlight the versatility and power of a good regression model! Now its time to test our model.

```
> set.seed(1)
> train2.index<-sample(1:nrow(BitcoinData3),0.90*nrow(BitcoinData3), replace=FALSE)
> train2 <- BitcoinData3[train2.index, ]
> test2  <- BitcoinData3[-train2.index,]
> lmtrain2 <- lm(pctChange~AVGmarketcap+AVGtotalbitcoins, train2)
> test2$p1 <- predict(lmtrain2,test2)
> error=mean(abs(test2$p1-test2$pctChange))
> cat("Mean Error = ", error)
Mean Error =  0.07705158
```

Figure 41: Testing and training our model

Thankfully we have a relatively small amount of error when train and test our model. Below is a visualization of the final model. From the above implementation, we have learnt it is better to create a model based on percent change. As prices rise, so does a lot of associations with the value of currencies such as market capitalization, miners revenue etc. Otherwise, our models were showing a lot of heteroscedasticity in a non-zero scenario.

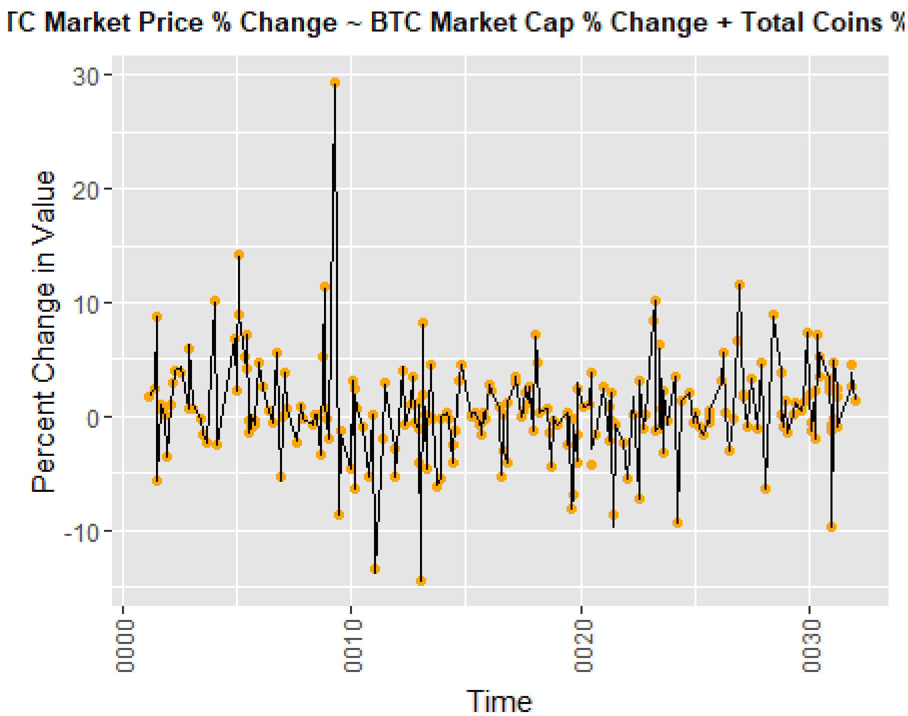


Figure 42: Final Model Representation

We now know, percent change in the value of Bitcoin is highly dependent to the percent change in Market Capitalization and percent change in total bitcoins in Circulation. This makes a lot of sense as how can you make money from bitcoins that are not available?!

#sources include: http://www.statisticssolutions.com/conduct-interpret-linear-regression/, https://www.kaggle.com/sudalairajkumar/cryptocurrencypricehistory, http://www.vo.elte.hu/bitcoin/zipdescription.htm https://www.kaggle.com/alisaaleksanyan/prediction-of-bitcoin-price-linear-regression/code

TESTING

The data analysis throughout this process consisted of sampling large amounts of data, manipulating data frames and reading data from comma separated and text files. A function as created using one of RStudio's assertr packages to conduct a test to test the output of a given data frame.

```
data <- read.csv("bitcoin_dataset.csv")
data %>%
  assertr::verify(nrow(.)>2919)
...
```

Figure 43 : Function Testing the output of a Data Frame

The function above is expects that in the data frame there is greater than 2919 rows. The function returns no error's, so it is successful.

```
> data %>%
+   assertr::verify(nrow(.)>2921)
Error in assertr::verify(., nrow(.) > 2920) :
  verification failed! (1 failure)
```

Figure 44: Error occurring in function when number of rows is greater than expected

Above is an example of the function displaying an error. There are 2920 observations in the data frame and the function was manipulated to test for more than this amount which return an error.

Unit testing: Programmatic tests that evaluate a unit of your code at a low level. These tests are small bits of code that can often be automated. East test was conducted in RStudio using the testthat package. You can see the code for this below.

```
library(testthat)

source('C:/Users/paris/Desktop/College/College/Paris Moore Software Project/Code/test_Regression.R')

test_results <- test_dir("C:/Users/paris/Desktop/College/College/Paris Moore Software Project/Code/test.R", filter = NULL, reporter="summary"
```

CONCLUSION & FURTHER WORK

To conclude this analysis, I have created a matrix below of a list of technical and non-technical skills, associated with auditing and accounts. Followed by a column for Analytics and a column for Accountants. This is a comparison table of skills for both parties.

Skills	**Analytics**	**Accountants**
Audits — in which computers excel at executing structured processes and rigorous checking	✓	✓
Regulatory compliance — ensuring complex transactions comply and facilitate necessary reporting	✓	✓
Receipt reconciliation — turn receipts into machine-readable data can then reconcile them with transaction data eliminating the need to ever "balance the checkbook"	✓	✗
Risk management — fraud detection and prediction	✓	✓
Trend analysis and Forecasting	✓	✓
Data mining and extraction	✓	✗
Operational analysis	✓	✓
Technological acumen	✓	✗
Statistical modeling and data analysis	✓	✓
Decision analysis & Strategic thinking and execution	✓	✓

Figure 45: Comparison table of skills of an accountant vs. analytics person

As you can see, there isn't a lot that an accountant is lacking in comparison to that of an analytic minded person. However, if we were to add a constraint to this table, such as carrying out the above task in less than a matter of minutes, the accountant's columns would consist of nothing but red X's, whilst the analytics column would look the same as it does now. Additionally, if we were to add constraints based on complexity such as data size, again, we would suspect the accountant would struggle a lot more/take a lot longer than that of an analytic mindset. My comparison is not suggesting in any way that an analytic minded person is "smarter" than an accountant, but the resources and skillset a data analyst holds is much more powerful in conducting the above tasks. Also, during my analysis I was constantly comparing the work load between the two and realised the limits to which each can go. I understand an accountants job has digitally transformed the past decade, in line with technology evolving. However, the point I have learnt is, how powerful is taking someone else's output and interpreting it yourself versus someone who creates the output, manipulates it until the optimized output is achieved? Also, how much can you rely on a computer program to continuously run commands over and over again without missing any "unusual" noise? Would this risk be better managed and reduced by a more technical minded person running the programs with a complete understanding of what is going on in the background? These are many questions I have begin asking myself since carrying out my analysis.

Additionally, my linear regression implementation has opened my eyes immensely at the power of this data mining tool alone. I began this project with the idea of applying clustering to my data as it seemed like the most obvious solution in detecting outliers, but that was the problem, it was too “obvious”. It did not align in with auditing transactions, where as regression allowed for a full analysis on the bitcoin market. I was really intrigued by the fluctuation in the market price of bitcoin that I wanted to figure out which variables impacted this the most. Along the way, it became clear that linear regression was a lot more than a relationship among two variables (my initial understanding). It allowed for outlier detection as well as being able to determine if your data was normal and how it was distributed. Dealing with large amounts of data is difficult in all aspects, but plotting your data using linear regression made this a lot easier and allowed me to fully understand my data and decide on my end result.

As I just outlined, big data – how I underestimated this. The sampling phase of the ELTE datasets was by far the most complicated and time-consuming part of this project. Whether this was down to computational power I am still unsure. RStudio definitely struggled with this phase as much as I did. Nevertheless, my knowledge, respect and handling of big data has definitely grown throughout this project.

To finally summarise this report, I refer back to my first question, “Can data analytic’s shape the work of accountants?”, personally I say 100% it can. The knowledge defined within the huge volumes of data processed every second of everyday is never ending. People like accountants who work with data day in and day out, are being relied on by companies to report back as much information as they can from the data, this cannot be done without the necessary tools and skillset of that of a data analyst.

Final Thoughts

Overall this project has been of huge interest and an exceptional learning curve. I began this project not know what Bitcoin nor the blockchain was and have soon become, what feels like, an expert in the area. (not really!) A special thank you to all who contributed towards this project. An extra special thanks to my Supervisor, Simon, for having the patience of a saint and guiding me from start to finish with this. A final thanks to the staff at the National College of Ireland for teaching me to progress to this level over the last four years. It’s been a pleasure.

APPENDIX

SUPERVISOR INTERACTION

4th year Template – Learning Agreement/Minutes

Student Name	Paris Moore
Student Number	X14485758
Course	BSc Computing
Project Title	Auditing Crypto Currency Transactions, Anomaly Detection in Bitcoin

Overview of Project

Looking for ways in which analytics can shape the work of accountants was the initial idea of this project. When the question was proposed as to which dataset I could acquire to carry out my analysis, the idea of using the world's leading crypto-currency's bitcoin ledger posed as a great solution and one that would add flavour to my project.

Meeting 1

Date	16th November 2017
Time	10:00am
Duration of Meeting	30 minutes

Current Challenges

Discuss November Technical Report. Which bitcoin dataset to use. Size, interpretation and complexity all play a pivot role.

Goals of Meeting:

I had previously spoken to Simon about my final year project. He had some great insight and idea into my idea and I want to elaborate on it with him to get more guidance for my final report. I also have questions on which dataset I should be using and what type i.e. .csv, API etc.

Goals/Actions for next Meeting:

Explore the idea of anomaly detection in more detail. Which methodology to follow. Size of the dataset which is required and whether I need multiple data sources.

Learning Agreement Student Signature	*PARIS MOORE*

Meeting 2

Date	13th February 2018
Time	13:30pm
Duration of Meeting	30 minutes

Current Challenges Still undecided on what data to use. Which anomaly detection method would be best.	
Goals of Meeting: Simon has helped me find a site online which has several versions of bitcoin datasets. The dimensions are massive. There are seven datasets in total. Simon kindly provided me which his clustering tutorial for his master students. This should assist with my understanding of k-means clustering for anomaly detection.	
Goals/Actions for next Meeting: Right now, there is no specific goal for the next meeting. However, we have scheduled to meet every Wednesday at 1:30pm going forth.	
Learning Agreement **Student Signature**	*PARIS MOORE*

Meeting 3

Date	2nd May 2018
Time	3:30pm
Duration of Meeting	45 minutes
Current Challenges I am still unsure whether I can handle the volume of data I have. I am considering totally changing my data source and using google bigQuery API to pull data using Python.	
Goals of Meeting: Discuss bigQuery Idea. Ask about technical report.	
Goals/Actions for next Meeting: Ensure my data is successfully sampled, hopefully have all models built and I am ready to move onto the technical document.	
Learning Agreement **Student Signature**	*PARIS MOORE*

Meeting 4

Date	9th May 2015
Time	2pm
Duration of Meeting	45 minutes
Current Challenges The biggest challenge I am facing is whether I have the technical ability to produce a k-means clustering model for anomaly detection by Submission on Sunday.	
Goals of Meeting:	

Discuss K-means. Look at grading rubric. Ask about presentation and second marker. Discuss what is left to do to produce a good project. Get tips and hints.
Goals/Actions for next Meeting: This could possible be my last meeting with Simon. However it has been said that it may be possible to meet next week to discuss the presentations.

Learning Agreement **Student Signature**	*PARIS MOORE*

PROJECT PROPOSAL

Objectives

The objective for this project is to specify, design, implement and document a medium to large scale project in the chosen area of specialization. My chosen area of specialization is Data Analytics. I am expected to choose a dataset from an area of interest and using Analytics tools and techniques, inspect, extract and clean this data. I will further investigate my dataset to draw conclusions about my data based on the areas I choose to investigate. The dataset I have chosen is the online bitcoin ledger. Bitcoin is a worldwide cryptocurrency and digital payment system called the first decentralized digital currency. I will inspect this dataset using the R programming language and RStudio as my chosen software. I will investigate the anomalies in this dataset and try to draw some conclusions around these bitcoin transactions. Also, as part of this project I will also look for ways to implement data analytics within Accountancy. I will use the bitcoin ledger as my dataset for this and audit crypto currency transactions and investigate for any anomalies.

During the cycle of this project, I will look at ways of improving and enhancing my developing and presentation skills. I will communicate monthly with my supervisor and work on my project continuously referring to a strict project plan. I will draft up a comprehensive requirement specification document to help with the process of my project.

Motivation

The world of auditing is evolving. Digital transformation is transforming businesses and how they operate. Through this, accountants and auditors have huge amounts of data and are looking for more ways to optimize that data and draw out some conclusions/predictions to help benefit their business. Data analytic methodologies have the power to focus on outliers and exceptions, identifying the riskiest areas of the audit.

The massive volumes of data now available inside and outside companies, and the power of new data analytics technologies, are fundamentally changing the audit. The general view is that big data will have a dramatic impact on enhancing productivity, profits and risk management. But big data in itself yields limited value until it has been processed and analysed.

Analytics is the process of analysing data with the objective of drawing meaningful conclusions. Major companies and organizations have recognized the opportunity that big data and analytics provide, and many are making significant investments to better understand the impact of these capabilities on their businesses. One area where we see significant potential is in the transformation of the audit.

Technical Approach

Data Analysis:

When analyzing the data, I will use a CRISP-DM approach:

- Business understanding: This phase concentrates on making sure I understand the project objectives and requirements from a business point of view. Then taking this perspective and converting it into a data mining problem and designing a plan on how to approach the problem and solve it.
- Data understanding: This phase involves data collection and pre-processing. This involves looking for data integrity, ensuring the data is of high quality and fits in with the requirements for this project. In order to move onto the next phase, it is crucial I understand my data at this point.
- Data preparation: This phase involves preparing your data to the point where you construct your final dataset. Tasks include table, record, and attribute selection, data cleaning, construction of new attributes, and transformation of data for modelling tools.
- Modelling: Once you have your final dataset, you can begin applying various modelling techniques.
- Evaluation: This stage involves re-evaluating your steps and ensuring your model meets your business objectives and requirements. You can re track back through some phases if needs be until your model is at the standard required for deployment.
- Deployment: This phase is how you decide to represent your model; this can be as simple as generating a report or as complex as implementing a repeatable data mining process. This will depend on customer’s needs.

Special resources required

As of this moment I require no special resources.

1. Clustering

Clustering is the process of partitioning a group of data points (m nodes in the graph) into a small number of clusters. The goal is to assign a cluster to each data point. K-means is a clustering method that aims to find positions of the clusters that minimize the distance from the data points to the cluster. It does this through an algorithm. It firstly decides the number of clusters and gives this number a value k. Then:

This algorithm will fit very well as it will visually represent my data in a way that will make any outliers visually obvious. We first need to represent each node as a multi-dimensional vector in the Euclidean space.

2. Depth-based Approaches Model-based

3. Deviation-based Approaches

4. Distance-based Approaches based Approaches

5. Density-based Approaches

6. High dimensional Approaches

Project Plan

Task Mode	Task Name	Duration	Start	Finish	Predecessors	Resource Names
Manually Scheduled	**Project Proposal**	**25 days**	**Mon 18/09/17**	**Fri 22/10/17**		
Auto Scheduled	Brainstorming Project Ideas	5 days	Mon 18/09/17	Fri 22/09/17		
Auto Scheduled	Email Lecturer for	1 day	Mon 25/09/17	Mon 25/09/17	2	
Auto Scheduled	Project Pitch	1 day	Wed 04/10/17	Wed 04/10/17		
Manually Scheduled	First Monthly Journal Entry	1 day	Fri 06/10/17	Fri 06/10/17		
Auto Scheduled	Project Proposal	12 days	Thu 05/10/17	Fri 20/10/17	4	
Manually Scheduled	Meeting with Supervisor	1 day	Tue 12/09/17	Tue 12/09/17		
Manually Scheduled	Meeting with Supervisor	1 day	Tue 19/09/17	Tue 19/09/17		
Manually Scheduled	Proof read Project Proposal	1 day	Fri 20/10/17	Fri 20/10/17		

Manually Scheduled	**Requirement Specification**	**15 days**	**Mon 23/10/17**	**Fri 10/11/17**		
Auto Scheduled	Acquire all data sets for the	5 days	Mon 23/10/17	Fri 27/10/17		
Auto Scheduled	Requirement Specification	15 days	Mon 23/10/17	Fri 10/11/17		
Manually Scheduled	Meeting with Supervisor	1 day	Thu 02/11/17	Thu 02/11/17		
Manually Scheduled	Requirements Specification	1 day	Fri 10/11/17	Fri 10/11/17		
Auto Scheduled	Second Monthly Journal	1 day	Fri 03/11/17	Fri 03/11/17		
Manually Scheduled	**Project Prototype**	**25 days**	**Sat 11/11/17**	**Thu 14/12/17**		
Manually Scheduled	Data Cleansing	5 days	Mon 06/11/17	Fri 10/11/17		
Manually Scheduled	Start to create prototype for	14 days	Sat 11/11/17	Wed 29/11/17		
Manually Scheduled	Meeting with Supervisor	1 day	Thu 16/11/17	Thu 16/11/17		
Manually Scheduled	Third Monthly Report	1 day	Fri 08/12/17	Fri 08/12/17		
Manually Scheduled	**Mid-Point Presentation**	**4 days**	**Mon 11/12/17**	**Thu 14/12/17**		
Manually Scheduled	Meeting with Supervisor	1 day	Thu 14/12/17	Thu 14/12/17		
Manually Scheduled	Finish Prototype and					
Manually Scheduled	**Post Mid-Point Presentation**	**31 days**	**Mon 18/12/17**	**Mon 31/01/18**		
Manually Scheduled	Process feedback from	5 days	Mon 18/12/17	Fri 22/12/17		
Manually Scheduled	Christmas Break	5 days	Sat 22/12/17	Thu 28/12/17		
Manually Scheduled	Fourth Monthly Report	1 day	Fri 29/12/17	Fri 29/12/17		
Manually Scheduled	Continue to develop	10 days	Mon 01/01/18	Fri 12/01/18		
Manually Scheduled	Meeting with Supervisor	1 day	Fri 26/01/18	Fri 26/01/18		
Manually Scheduled	Analyze Datasets and	12 days	Sat 13/01/18	Tue 30/01/18		
Manually Scheduled	**Prepare Final Working**	**40 days**	**Thur 01/02/18**	**Wed 28/03/18**		
Manually Scheduled	Design my Application	5 days	Thur 01/02/18	Wed 07/02/18		
Manually Scheduled	Fifth Monthly Report	1 day	Sat 03/02/18	Sat 03/02/18		
Manually Scheduled	Meeting with Supervisor to	1 day	Fri 09/02/18	Fri 09/02/18		

Manually Scheduled	Finish Analysis of	17 days	Thur 08/02/18	Fri 02/03/18		
Manually Scheduled	Completion of application and	14 days	Fri 09/03/18	Wed 28/03/18		
Manually Scheduled	**Testing**	**5 days**	**Thur 29/03/18**	**Wed 04/04/18**		
Manually Scheduled	Create and Implement Test	3 days	Thur 29/03/18	Sat 31/03/18		
Manually Scheduled	Create and Implement Test	3 days	Sun 01/04/18	Wed 04/04/18		
Manually Scheduled	**Final Report**	**31 days**	**Thur 05/04/18**	**Thur 17/05/18**		
Manually Scheduled	Prepare Final Document					
Manually Scheduled	**Upload Software**	**1 day**	**Thur 17/05/18**	**Thur 17/05/18**		
Manually Scheduled						

PROJECT RESTRICTIONS

Data

All transactions analysed will be historical data. This report acknowledges that bitcoins datasets are all open source.

Time:

The project timeline spans from September 2017 until May 2018.

Cost:

The poster is a project requirement which will cost €20 to be printed.

Software:

Student resources and open source platforms provide the necessary tools. For the duration of this project I have been working from my own machine.

Legal:

Datasets in relation to the bitcoin are open source and provided by the many sites online. For this project, I will be using Kaggle, a platform for predictive modelling and analytics, to gather the majority of my data. All data gathered will be referenced accordingly. An ethics form was also filled out to ensure against data protection laws.

FUNCTIONAL/NON-FUNCTIONAL REQUIREMENTS

SECURITY REQUIREMENTS

Security is a fundamental aspect to the system. The data provided will be securely stored in local disk and backed up to the cloud. The Data Administrator will have full rights and access to the account and will only allow others to authorise when necessary.

- The system shall be secure.
- Authorization shall be granted if necessary.
- The data will be backed up.

AVAILABILITY REQUIREMENT

Data shall remain available to the system throughout the project scope.

INTEGRITY REQUIREMENT

Data must remain accurate and consistent over the entire project-cycle

USER REQUIREMENTS

The User Requirements Definition defines the objectives and requirements for the project that through in-depth analysis either verifies or rejects the idea that data analytic technique can help shape the work of accountants.

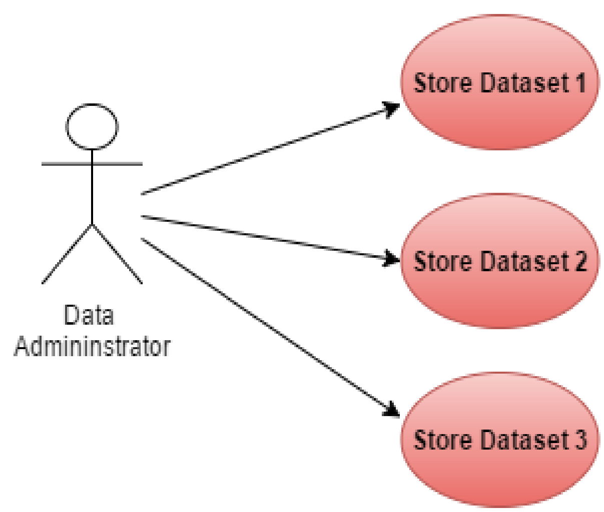
TECHNICAL REPORT USE CASES

Requirement 1 <Gather Data>

Description & Priority

This requirement is crucial in order for this project to be successful. We must have access and authorisation to access and gather required data.

Use Case



Flow Description

Precondition

The user must have access to their email account and relevant website to download the required data.

Activation

This use case starts when the data administrator retrieves data.

Main flow

1. The Data Administrator (DA) logs onto email account and downloads data to secure location.
2. The DA accesses the relevant webpage and downloads the dataset to a secure location.
3. The DA checks data integrity by opening and reading files in relevant software.
4. Data is stored to a secure location.

Exceptional flow

1. The relevant webpage is down.
2. Email account cannot be accessed.
3. The datasets are corrupted.

Termination

The process of selecting, extracting and storing the data has been completed. Therefore, this process is terminated.

Requirement 2 <Pre-processing>

Description & Priority

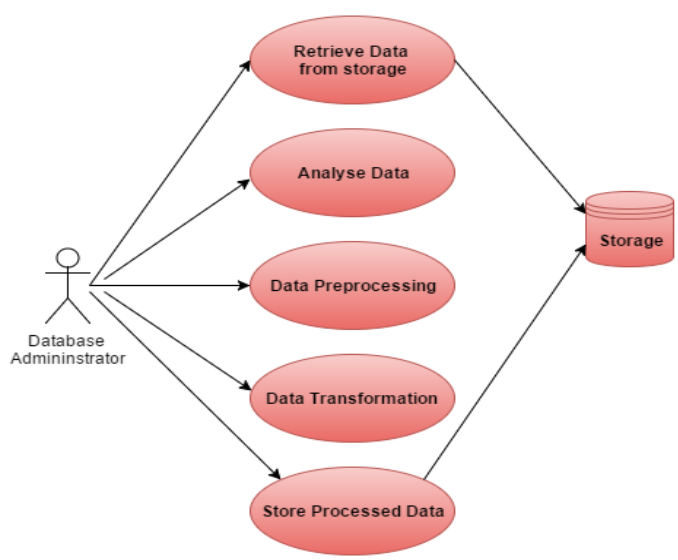
The Preprocessing use case entails augmenting the dataset which will enable the possibility of in depth analysis at a later stage. The preprocessing requirement is of priority 2.

Use Case

Scope

The data is Pre-processed in order to achieve the best analysis possible.

Use Case Diagram



Flow Description

Precondition

The data must be accessible.

Activation

This use case commences when the data is retrieved.

Main flow

1. The Data Administrator retrieves the data.
2. The data is analysed and cleaned.
3. Pre-processing commences.
4. The data is transformed.
5. The processed data is stored.

Alternate flow

Various different platforms can be adopted to apply this use case.

Exceptional flow

The data is not retrievable.

Termination

The Pre-processing use case terminates when the data is cleansed, transformed and pre-processing is completed.

Requirement 3:<Data Storage>

Description

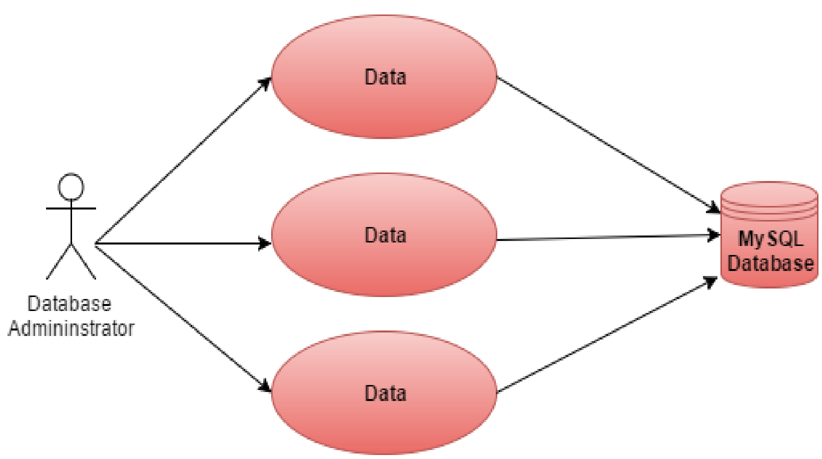
The data storage requirement entails storing the datasets in database tables to ensure the data is secure and accessible at all times.

Use Case

Scope

A Database is created with specific tables to store the data.

Use Case Diagram



Flow

Description

Precondition

The data must be Pre-processed and Transformed to the correct format before it can be stored in a database.

Activation

This use case is activated when the data administrator makes the data available.

Main flow

1. The Database Administrator (DBA) retrieves the data.
2. The DBA creates suitable tables within the database that will store the data.
3. The data is loaded into database tables.

Alternate flow

Alternative storage is a viable option.

Exceptional flow

The data cannot be retrieved.

Termination

The termination of the data storage requirement occurs when the data is successfully stored in a database.

Post Condition

The data is accessed while residing in the database.

Requirement 4: <Analyse Data>

Description & Priority

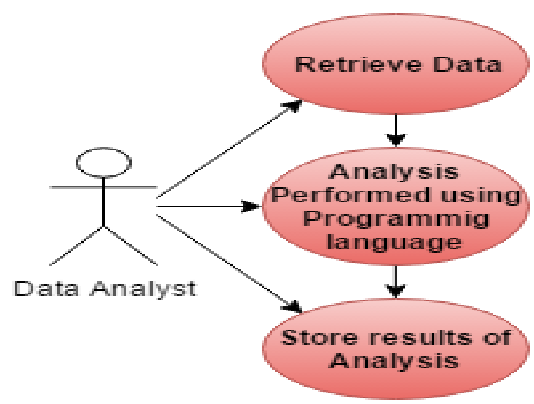
The Analyze Data requirement is a fundamental requirement to the project and is ranked priority 1. The analysis of the datasets requires significant attention to detail and will help to achieve the project goals.

Use Case

Scope

Data is retrieved from the database where analysis is performed using several programming scripts. Results are produced and interpreted.

Use Case Diagram



Flow Description

Precondition

The data must be residing in a database and be accessible to the data analyst.

Activation

This use case starts when the data analyst calls the data from the database.

Main flow

1. The Data Analyst retrieves the data from a database.
2. Data is analysed using specific programming language.
3. The results are interpreted.
4. The results are saved to a secure location.

Exceptional flow

The data cannot be retrieved from the database.

Termination

The use case is terminated when the analysis is complete.

Post Condition

The data is residing in a database waiting for further analysis.

Requirement 5: <Machine Learning>

Description & Priority

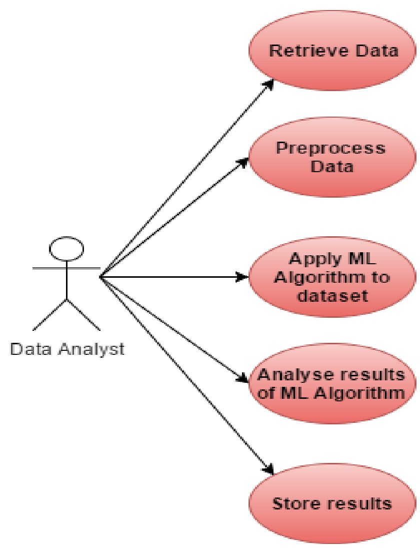
The Machine Learning Requirement is an exploratory requirement and ranked priority 2. An algorithm is applied to the data to produce in depth analysis and comparisons between the datasets.

Use Case

Scope

Datasets are retrieved and Pre-processed. A Machine Learning (ML) algorithm is applied to the data. The results are analysed and finally the results will be stored.

Use Case Diagram



Flow Description

Precondition

Data is retrievable.

Activation

The use case is activated when the data is retrieved.

Main flow

1. The Data Analyst retrieves the data.
2. The data analyst Pre-processes the data.
3. A Machine Learning Algorithm is applied to the data.
4. Results are analysed.
5. Results are stored.

Exceptional flow

The problem cannot be solved.

Termination

The Machine Learning use case is terminated when the problem is solved to a satisfactory standard.

LINEAR REGRESSION OUTPUT IN R

Market Price vs All Variables

	Estimate
Date	9e-05
btc_total_bitcoins	-3.9e-06
btc_market_cap	5.8e-08
btc_trade_volume	4.1e-09
btc_blocks_size	-0.017
btc_avg_block_size	2.8
btc_n_orphaned_blocks	-0.28
btc_n_transactions_per_block	-0.0099
btc_median_confirmation_time	0.36
btc_hash_rate	-1.7e-05
btc_difficulty	2.8e-11
btc_miners_revenue	2.7e-07
btc_transaction_fees	-0.14
btc_cost_per_transaction_percent	-3.6
btc_cost_per_transaction	3.2
btc_n_unique_addresses	0.00018
btc_n_transactions	2.4e-05
btc_n_transactions_total	9e-06
btc_n_transactions_excluding_popular	-1.4e-05
btc_n_transactions_excluding_chains_longer_than_100	6.7e-05
btc_output_volume	6.1e-08
btc_estimated_transaction_volume	-7.4e-06
btc_estimated_transaction_volume_usd	2.2e-08
Days	-0.014
(Intercept)	102

Table: Linear Model: Market Price vs. All Variables (continued below)

	Std. Error	t value	
Date	0.00011	0.85	
btc_total_bitcoins	3.4e-06	-1.1	

btc_market_cap	1.3e-10	464
btc_trade_volume	2.4e-09	1.7
btc_blocks_size	0.00074	-22
btc_avg_block_size	6.8	0.42
btc_n_orphaned_blocks	0.44	-0.64
btc_n_transactions_per_block	0.0031	-3.2
btc_median_confirmation_time	0.15	2.4
btc_hash_rate	1.2e-06	-14
btc_difficulty	1.1e-11	2.6
btc_miners_revenue	8.7e-07	0.32
btc_transaction_fees	0.008	-18
btc_cost_per_transaction_percent	0.33	-11
btc_cost_per_transaction	0.057	57
btc_n_unique_addresses	1.6e-05	11
btc_n_transactions	4.6e-05	0.53
btc_n_transactions_total	3.8e-07	24
btc_n_transactions_excluding_popular	3.4e-05	-0.4
btc_n_transactions_excluding_chains_longer_than_100	4.5e-05	1.5
btc_output_volume	1.6e-07	0.39
btc_estimated_transaction_volume	1.7e-06	-4.3
btc_estimated_transaction_volume_usd	2.6e-09	8.5
Days	0.019	-0.75
(Intercept)	78	1.3

Table: Table continues below

	Pr(>|t|)
Date	0.4
btc_total_bitcoins	0.26
btc_market_cap	0
btc_trade_volume	0.084
btc_blocks_size	7.1e-100
btc_avg_block_size	0.68
btc_n_orphaned_blocks	0.52
btc_n_transactions_per_block	0.0015
btc_median_confirmation_time	0.017
btc_hash_rate	1e-44
btc_difficulty	0.0089
btc_miners_revenue	0.75
btc_transaction_fees	8.2e-67
btc_cost_per_transaction_percent	2e-27

```
                **btc_cost_per_transaction**              0
           **btc_n_unique_addresses**                    7e-29
              **btc_n_transactions**                     0.6
         **btc_n_transactions_total**                    3e-112
         **btc_n_transactions_excluding_popular**          0.69
**btc_n_transactions_excluding_chains_longer_than_100**0.14
           **btc_output_volume**                          0.69
       **btc_estimated_transaction_volume**              1.7e-05
        **btc_estimated_transaction_volume_usd**       2.6e-17
            **Days**                                     0.46
             **(Intercept)**                             0.19
--------------------------------------------------------------------
```

BIBLIOGRAPHY

Ey.com. (2017). How big data and analytics are transforming the audit | EY Reporting. [online] Available at: http://www.ey.com/gl/en/services/assurance/ey-reporting-issue-9-how-big-data-and-analytics-are-transforming-the-audit [Accessed 14 Nov. 2017].

Anon,(2017).[online]Availableat:https://www.researchgate.net/post/What_is_the_best_approach_for_detection_of_outliers_using_R_programming_for_real_time_data [Accessed 24 Nov. 2017].

Google.ie. (2017). data analytics into accountancy - Google Search. [online] Availableat:https://www.google.ie/search?q=data+analytics+into+accountancy&rlz=1C1CHBD_enIE773&oq=data+analytics+into+accountancy&aqs=chrome..69i57.12944j0j7&sourceid=chrome&ie=UTF-8 [Accessed 27 Nov. 2017].

reddit. (2017). Outliers: Living, Breathing, & Betting on Bitcoin • r/Bitcoin. [online] Availableat:https://www.reddit.com/r/Bitcoin/comments/75t8nm/outliers_living_breathing_betting_on_bitcoin/ [Accessed 29 Nov. 2017].

Accounting is More than Crunching Numbers: Read an Accounting Job Description https://www.allbusinessschools.com/accounting/job-description/ [Accessed May 11th 2018]

9.7 - Polynomial Regression | STAT 501 [WWW Document], n.d. URL https://newonlinecourses.science.psu.edu/stat501/node/324/ (accessed 5.13.18).

Accounting Job Description | What You'll Do [WWW Document], n.d. . All Business Schools. URL https://www.allbusinessschools.com/accounting/job-description/ (accessed 5.11.18).

Anomaly Detection Using K-Means Clustering, 2015. . Anomaly.

AnomalyDetection.pdf, n.d.

BigQuery - Analytics Data Warehouse [WWW Document], n.d. . Google Cloud. URL https://cloud.google.com/bigquery/ (accessed 5.11.18).

chandola09_anomaly-detection-survey.pdf, n.d.

Choudhary, P., n.d. Introduction to Anomaly Detection [WWW Document]. URL https://www.datascience.com/blog/python-anomaly-detection (accessed 2.26.18).

Cryptocurrency Historical Prices [WWW Document], n.d. URL https://www.kaggle.com/sudalairajkumar/cryptocurrencypricehistory (accessed 5.13.18).

FAQ How do I interpret a regression model when some variables are log transformed?, n.d. . IDRE Stats.

Interpreting residual plots to improve your regression | Statwing Documentation [WWW Document], n.d. URL http://docs.statwing.com/interpreting-residual-plots-to-improve-your-regression/#hetero-header (accessed 5.13.18).

KDD Process/Overview [WWW Document], n.d. URL http://www2.cs.uregina.ca/~dbd/cs831/notes/kdd/1_kdd.html (accessed 5.12.18).

Leung, K., Leckie, C., 2005. Unsupervised Anomaly Detection in Network Intrusion Detection Using Clusters, in: Proceedings of the Twenty-Eighth Australasian Conference on Computer Science - Volume 38, ACSC ’05. Australian Computer Society, Inc., Darlinghurst, Australia, Australia, pp. 333–342.

Linear Regression [WWW Document], n.d. URL http://www.stat.yale.edu/Courses/1997-98/101/linreg.htm (accessed 5.12.18).

Mishra, B.K., Rath, A., Nayak, N.R., Swain, S., 2012. Far efficient K-means clustering algorithm. ACM Press, p. 106. https://doi.org/10.1145/2345396.2345414

R: What is R? [WWW Document], n.d. URL https://www.r-project.org/about.html (accessed 5.11.18).

Sönmez, F., Zontul, M., Kaynar, O., Tutar, H., 2017. Anomaly Detection Using Data Mining Methods in IT Systems: A Decision Support Application.

Udacity, n.d. Building the Linear Model - Data Analysis with R.