

**The Truth about Twitter**

Final Year Project Report

*DT228 B.Sc. (Hons) in Computer Science*

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# Abstract

The rise of social media platforms in the last few decades have led to the surge of numerous types of fake accounts across them. These platforms have struggled to keep up with the massive volume of nefarious fake accounts being created everyday due largely in part to how hard it can be to identify them as many are created to masquerade efficiently as human coupled with said platforms initial disinterest in dealing with such a problem. As pressure from their user base and governments mount though many are now actively pursuing the agenda to cleanse their platforms of this taint.

The purpose of this report is to show how data mining and machine learning algorithms can be used to deal with the issue of correctly identifying whether a Twitter account is real or a form of fake account. Machine learning models are created and used in a simple web application where a user can check any and as many accounts as the wish to see what type of account the models predict it to be. They are then able to share their results on different social media platforms and give feedback on the web application.

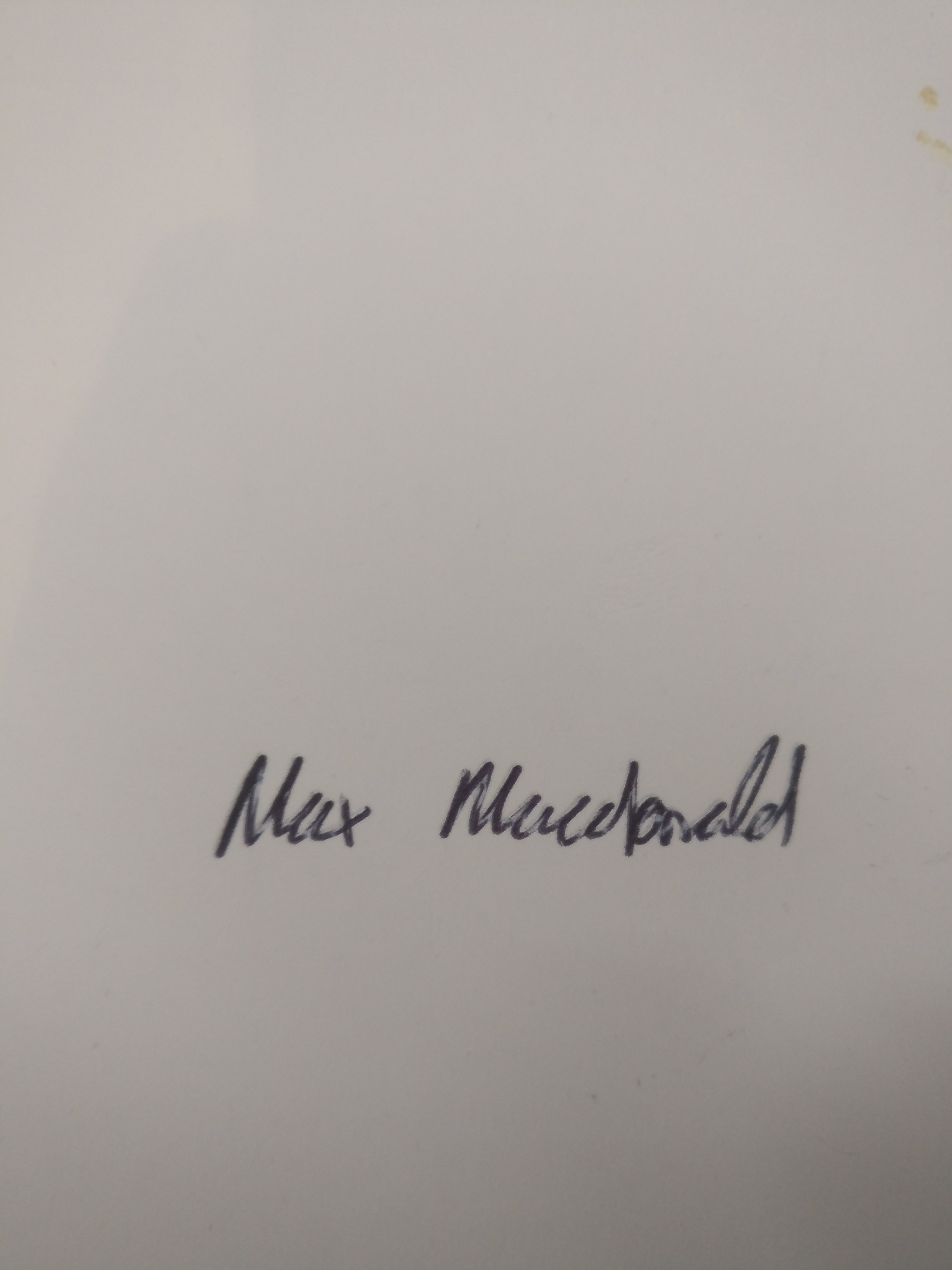
The report starts off by explaining the background of the project including description, objectives and roadmap and all the research that has gone into it. Next, the design and development stages are delved into in detail with the various decisions made during creation of the web application explained. Evaluation of the experiments done on the datasets to find the most accurate classifier, test and train data split technique and parameters and the various forms of testing on the website are discussed. Lastly all conclusions drawn from the report and any future work planned is reviewed.

Keywords: Data mining, Machine learning, Twitter, Fake accounts

# Declaration

I hereby declare that the work described in this dissertation is, except where otherwise stated, entirely my own work and has not been submitted as an exercise for a degree at this or any other university.

**Signed:**



\_\_\_\_\_\_\_\_\_\_\_

Max MacDonald

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**Table of Contents**

1. Project Statement 5

2. Research 5

2.1. Background Research 5

2.1.1. What is a Twitter Bot Account? 6

2.1.2. Types of Bots Accounts 6

2.1.3. Importance of Identifying Bots Accounts 6

2.1.4. Important Characteristics of Bot Accounts 7

2.2. Alternative Existing Solutions to Your Problem 8

2.2.1. Twitter 8

2.2.2. Botometer 8

2.3. Technologies Researched 9

2.3.1. Technologies for Data Mining & Machine Learning Models 10

2.3.2. Technologies for Web Application 12

2.3.3. Technologies for Web Server 13

2.3.4. Technologies for Version Control 14

2.3.5. Technologies for Data Storage 14

2.4. Other Relevant Research Done 15

2.4.1. Big Data 15

2.4.2. Data Mining 16

2.4.3. Machine Learning 17

2.5. Resultant Findings and Requirements 22

2.5.1. Chosen Technologies 22

2.5.2. Chosen DataSets 22

2.5.3. Challenges 23

3. Approach and Methodology 24

3.1. Agile & Kanban 24

3.1.1. Agile 24

3.1.2. Kanban 25

3.1.3. Project Use 25

3.2. Data Mining Project Management Models 26

3.2.1. CRISP-DM 26

3.2.2. SEMMA 28

3.2.3. Differences in Models 30

3.2.4. Conclusion 30

4. Design 31

4.1. Technical Architectures 31

4.1.1. Model View Controller 31

4.1.2. Model View Template 31

4.2. Technical Architecture Diagram 32

4.3. Other Design Documents 33

4.3.1. Use Case Diagram 33

4.3.2. Entity Relationship Diagram 33

5. Prototyping and Development 34

5.1. Vertical Prototype 34

5.1.1. Web Front-End 34

5.1.2. Basic Machine-Learning Model 35

5.2. Development 35

5.2.1. Web Front-End 35

5.2.2. Basic Machine-Learning Model 38

6. Testing 40

6.1. Data Mining & Machine Learning section 40

6.2. Web Front-End 41

6.3. Web-based Data Mining Application 41

7. Issues and Risks 41

8. Plan and Future Work 42

9. Bibliography 43

**Table of Figures**

[Figure 1 Botometer GUI [13] 9](#_Toc531620765)

[Figure 2 R code example 10](#_Toc531620766)

[Figure 3 Python code example 10](#_Toc531620767)

[Figure 4 PyCharm IDE 11](#_Toc531620768)

[Figure 5 Scikit-learn code example 11](#_Toc531620769)

[Figure 6 Pandas code example 12](#_Toc531620770)

[Figure 7 NumPy code example 12](#_Toc531620771)

[Figure 8 12 Agile Principles 24](#_Toc531620772)

[Figure 9 Sample Trello Board [40] 26](#_Toc531620773)

[Figure 10 CRISP-DM Model [41] 27](#_Toc531620774)

[Figure 11 SEMMA Model [43] 29](#_Toc531620775)

[Figure 12 Model View Controller 31](#_Toc531620776)

[Figure 13 Model View Template 32](#_Toc531620777)

[Figure 14 Application Technical Architecture 32](#_Toc531620778)

[Figure 15 User Use Case Diagram 33](#_Toc531620779)

[Figure 16 Entity Relationship Diagram 33](#_Toc531620780)

[Figure 17 Web Front End 34](#_Toc531620781)

[Figure 18 Web Front End with returned tweets 34](#_Toc531620782)

[Figure 19 Results of Model being run 35](#_Toc531620783)

[Figure 20 Saving Twitter credentials to file 36](#_Toc531620784)

[Figure 21 Basic form 36](#_Toc531620785)

[Figure 22 Creating or reading in form 36](#_Toc531620786)

[Figure 23 Twitter Authentication and tweet retrieval 37](#_Toc531620787)

[Figure 24 Render Index.html with variables passed 37](#_Toc531620788)

[Figure 25 Template directory added 37](#_Toc531620789)

[Figure 26 Index.html 37](#_Toc531620790)

[Figure 27 Load web\_style.css 37](#_Toc531620791)

[Figure 28 Enabling CSS file load part 1 38](#_Toc531620792)

[Figure 29 Enabling CSS file load part 2 38](#_Toc531620793)

[Figure 30 Enabling Django file use 38](#_Toc531620794)

[Figure 31 Read in all data 39](#_Toc531620795)

[Figure 32 Read in single dataset from CSV 39](#_Toc531620796)

[Figure 33 Data check example 39](#_Toc531620797)

[Figure 34 Adding data to database 39](#_Toc531620798)

[Figure 35 Get 2000 accounts 39](#_Toc531620799)

[Figure 36 Return random sub-set of accounts from database 40](#_Toc531620800)

[Figure 37 Convert arrays and initialise model 40](#_Toc531620801)

[Figure 38 Run model and output results to screen 40](#_Toc531620802)

[Figure 39 Project Gantt chart 42](#_Toc531620803)

# Introduction

## Project Background

Twitter, a free social networking microblogging service, is one of today’s leading digital platforms with 326 million active users worldwide in the third quarter of 2018. [1] Registered users can broadcast short posts called tweets which can be liked, retweeted and responded to by other users. Just like other social media platforms such as Facebook and Instagram, Twitter has and still is facing a massive problem with fake or bot accounts. Estimates place the percentage of bot accounts on Twitter anywhere from 9 to 15% of the total user count. [2]

### What is a Twitter Bot Account?

A Twitter bot account is an account that is controlled by a software application, via the Twitter API, which will automatically generate and publish new tweets, follow specific users, retweet other tweets and liking specific sets of tweets all based on content or hashtags included, depending on the settings of the controlling application. [2]

These bots can perform tasks at a much higher rate than a human user can and as such push out more content or tweets in the same timeframe, some even working around the clock. Bot accounts on other platforms are similar with any differences being based on the difference in platforms.

### Types of Bot Accounts

There are many different types of bot accounts from helpful and informative ones tweeting spiritual wellbeing tips to ones which retweet tweets that push extreme ideologies to advertising accounts which are set up to tweet content about specific brands, products or services at certain times of the day.

Some accounts are even used to boost a person’s fame or influence on Twitter by following that person’s account and can be bought in packages. This is a massive industry in and of itself reportedly being a $40 to $360 million-dollar business annually. [3] Major celebrities such as 50 Cent and brands like Mercedes-Benz have come under scrutiny for possibly engaging in this practice. [4]

Then there is the complexity of the software applications behind these accounts. Older and more traditional bot accounts tend to be easier to detect as they follow much simpler patterns in their activities while newer social bots need far more complex algorithms to detect as they are set up to masquerade effectively as human accounts by mimicking human behaviour better.

### Importance of Identifying Bot Accounts

The main reason why it is so important to be able to identify, unless the account states so itself, whether an account is real or not is the erosion of trust that can occur due to the account’s activities. If the account is followed by one million other accounts, even if most of them are fake themselves, and posts something that, while untrue, pushes a narrative that certain groups would be inclined to believe then that post can gain a lot of traction and spread quickly all over Twitter and beyond to other social media platforms causing untold damage.

Many individuals or groups wish to affect the perception of specific events or entities through Twitter and this ranges from boosting their own profiles through fake followers as mentioned above to trying to influence public campaigns such as the 2016 US Presidential elections. Studies have estimated that in the lead up to this election, a fifth of all Twitter traffic related to the election came from a legion of bots. [5] That much traffic would have had a massive influence on people’s views and how they voted and in turn the outcome of the election.

If a bot account is masquerading as a real human then, since it is inherently trying to deceive us, it is highly unlikely much good can come of its sustained existence and as such the sooner it is detected and shutdown the better.

### Important Characteristics of Bot accounts

When trying to identify if an account is a bot or not there are some key characteristics that can help [6,7]:

* How often per day an account tweets and if there is a regular interval between tweets can both lead to suspicions as this is a hallmark of automation.
* How anonymous that account is trying to be, does it have a profile picture and if so is it of a person? Same for the background picture. Does their bio information help identify them or add to their anonymity? Is the account handle just an alphanumeric scramble?
* Generic bio or lack of one as the programs which create these bots are not set up to make completely unique bios.
* Ratio of how many other accounts an account follows to how many follow it.

## Project Description

The focus of this project is to be able to differentiate between real and bot Twitter accounts and allow the public to make use of this ability. This will require a deep understanding into what constitutes each of the various types of bot accounts, research into the areas of data mining and machine learning, learning how to work towards the required insights from a procured dataset and lastly to create and deploy a web application. There are a lot of new subjects to learn about and interesting challenges to overcome that are detailed later.

## Project Objectives

The main goal of this project is first and foremost to create accurate mathematical models, employing various data mining and machine learning techniques and classifiers, that can tell a real Twitter account from a fake one. The secondary goal is to create a simple web application that makes use of these models to allow users to get a prediction for any Twitter account they wish.

To be able to achieve both goals, the following list of objectives must be completed:

1. Research into what makes a fake Twitter account and alternative solutions.
2. Research data mining, machine learning, the various technologies involved and Project Management and Data Mining methodologies.
3. Gather historical Twitter user account data that has both real and fake accounts.
4. Understand, clean and prepare gathered data.
5. Design the overall project architecture.
6. Design a database to store data and read the prepared data into it.
7. Experiment with the data and various classifiers until an acceptable level of accuracy is achieved.
8. Develop the web application to make use of the results from the previous part.
9. Deploy the web application onto the server.
10. Perform usability and \* testing to gain user feedback and ensure everything works as intended.

## Project Challenges

With all the main objectives set out for project set out, there will invariably be many challenges along the way in completion of these. Here are the main challenges that could be encountered:

### Time management

Time management for this entire project will be a major challenge as the year’s modules, their workloads and exams must all be juggled with this project. While everything has been planned out into a project plan and tweaked as progress is made, unexpected situations can arise within college and in outside life which can throw specific pieces of work’s timelines off.

### Data Preparation and Feature Selection

One of the longest and most important parts to any data mining project is preparing the data and then selecting the right features for use in training models. Any errors at either of these stages will lead to inaccurate predictions thereby losing users trust and interest in using the web application. The data must be explored carefully, and time invested in understanding how to prepare the data correctly and what features are important, and which are not.

### Accuracy of models

To be able to create accurate models requires that the previous challenge be overcome and then being to understand the various machine learning classifiers and how they arrive at their conclusions. This will require a significant portion of time dedicated to research and discerning between the different classifiers.

This challenge is the most important aspect that the success of the project relies on as without an accurate model the web application holds little value to the user as it cannot make accurate predictions.

### Deployment of Web Application

The deployment of the web application onto a server is potentially a complicated challenge due to a lack of experience in this area. Each provider of deployment servers has their own steps needed to be taken and settings altered to ensure a web application can be deployed smoothly and correctly. To overcome this challenge will very much be a process of trail and error and reading through tutorials.

## Dissertation Structure

***Chapter 1: Introduction***

An Introduction to the project background, a description of what it entails, a list of all major objectives requiring completion and what are the main set of challenges that will be faced to achieve completion.

***Chapter 2: Research***

Covers all research done before and throughout the design and development of the project. Alternative solutions to the core issue and similar past projects are investigated and detailed. Various relevant technologies are analysed, and an explanation given on why specific ones were chosen. Lastly the areas of data mining and machine learning are delved into, explaining the various techniques used.

***Chapter 3: Approach & Methodology***

The Agile and Kanban project management methodologies are explained and shown how they are used within this project. The CRISP-DM and SEMMA data mining methodologies are gone into in detail and compared with a conclusion on why one was chosen over the other.

***Chapter 4: Design & Architecture***

Details the various design elements of the project including the general technical architecture and how it was adapted for use, how the data mining and web application link together and discussions on Use Cases, Entity Relationship and Class Diagrams.

***Chapter 5: Development***

Goes in depth into all the development done for both parts of the project, describing how accurate machine learning models were created through the various stages of the CRISP-DM methodology and the construction of a website to make use of them such that accurate predictions are returned to the user.

***Chapter6: Testing and Evaluation***

Explains how the separate parts of the system were tested and evaluated. Usability and \* testing for the web application and what the results of these were. For the data mining side of the project, this revolved around the evaluation of various machine learning classifiers across multiple different output combinations. Various accuracy metrics are computed and explored leading to the final model/s selection used in the web application.

***Chapter 7:*** ***Project Plan***

Gives both the initial and final project plan, with explanations for any changes and how various Kanban boards were used to implement and keep track of the plan.

***Chapter 8: Conclusion and Future Work***

Wraps up the project, elaborating on the key points learned while undertaking this project, the parts that did and didn’t live up to expectation and what additional work could be done going forward.

***Chapter 9: Bibliography***

Details all references used throughout the document. Websites, books, academic papers and studies are all included.

# Research

This chapter will cover all research done for this project including applications or solutions akin this project, other final year projects like this, all technologies researched for this project, research into data science and its sub topics big data, data mining and machine learning and finally the results of all this research such as chosen technologies and areas that will prove challenging.

## Alternative Existing Solutions to the Problem

This section explains how Twitter deals with bot accounts and looks at a similar application to this project, Botometer.

### Twitter

It has only been in the last few years that Twitter has taken the detection and suspension of bot accounts seriously. Brexit and the US Presidential elections were the deciding factors as the activities of bot accounts in the lead up to these proved to be a liability for the company. After an internal investigation, Twitter announced it would not be selling any more advertising to Russia media outlets Russia Today and Sputnik as these organisations were found to have interfered with the Presidential election on behalf of their government. [8]

Twitter has also been quiet active this year in detecting and shutting down bot accounts, between May and July around 70 million fake and suspicious accounts were shut down, same in October to a bot network of a few hundred accounts, that were involved in a coordinated campaign to defend Saudi Arabia’s Government’s role in the disappearance of Jamal Khashoggi, and most recently in November around 10 thousand more, that were all aimed at discouraging Americans to vote in the midterm elections. [9,10,11]

While the company has been trying, it is not an easy fight as they will always be on a reactive footing rather than a proactive one since the creation and running of bots, which are constantly evolving, can be automated but their large-scale detection relies on human intervention. This combined with the sheer volume of users and content through the site makes it a daunting and never-ending task. [12]

### Botometer

Botometer is a joint project between Indiana University Network Science Institute (IUNI) and the Center for Complex Networks and Systems Research (CNeTS). It employs a machine learning algorithm trained to classify an account as real or bot based on a labelled dataset comprised of over 10 thousand. It uses the Twitter REST API to gather public data on an account and then passed to the Botometer API which “*extracts about 1,200 features to characterize the account's profile, friends, social network structure, temporal activity patterns, language, and sentiment*”. [13] These are passed onto its models to compute the various scores which in turn go towards the overall score.

Its web front allows a user to check the activity of a Twitter account, after having the user’s Twitter account authorised, and gives it a score, out of 5, based on how likely the account is to be a bot with the closer the number is to 5 the more likely it is. There is also an option to check that accounts followers and the accounts it follows as well. It is simple, easy on the eye and informative

I used my own Twitter account to test it and the results are shown below. As you can see it rates my account with a bot score of 4.6/5 and a Complete Automation Probability (CAP) of 83% which is the probability that this account is fully automated. I set my Twitter account up a few years ago, followed some people, sent out one tweet and then completely ignored it so it is not surprising that Botometer’s models gave back these results even if they are wrong.



Figure 1 Botometer GUI [13]

## Existing FYPs

This section looks at existing final year projects related to this one.

### Fantasy Premier League Predictive Analytics

This project involves the creation of a web application that allows the user to view important statistics about a football player from the Premier League and have recommendations made to them about what players to pick for their fantasy football team on a given week. Through use of this application, the user can gain an advantage over their friends and co-workers in any of the fantasy football leagues they participate in, with bragging rights or even a physical prize on the line.

Predictive data analytics was employed on historical Premier League player data using the CRISP-DM model, detailed later, and combined with various machine learning algorithms, mainly linear regression, to arrive at the recommendation system for the four sections of players: goalkeeper, defender, midfielder and striker. The web application was then a combination of said recommendation system, a Flask RESTful API and AngularJS to present everything in a neat and aesthetically pleasing way to the user. [14]

This project showed that you can combine your work, in this case college-orientated, with leisure subject matter and create something greater then the sum of the two parts. This is a critical piece of information to not just know but understand and realise that the more invested one gets in what they are doing, mind and body, the greater the outcome will be, in quality, scope and self-fulfilment.

### CrimAnalytics – A Crime Prediction Web Application

The creation of an accurate crime prediction model and subsequent use in a web application lies at the heart of this project. Users can avail of an interactive map to look up crime rates and other useful statistics within that area, based on the model and how local features are nearby. This is of great benefit to locals, as they can realise how big of a problem their area faces and can then move forward with positive action to try and reduce those rates and to tourists and those looking to move to a new area as this information can be a key factor in their decision making.

To arrive at this, as in the previous project, predictive data analytics and modelling is performed over a dataset, a government crime statistics dataset, by cleaning and preparing the data and then using R to implement the model training and application. The web application that has the results integrated into it is comprised of a front-end of HTML and JSP scripts and a back-end split into a middle layer of Java code that process all the business logic and then a final layer of the servers running docker containers of a MySQL database, an R server and an Apache Tomcat server. All this combines for a full stack architecture that has each part fully separated out and independent. [15]

This is an ambitious project that delivers on all fronts, providing in-depth analysis of the subject material, efficient and organised structure to the application and an interesting user experience. There is much to learn in the area of data analytics and this project shows that the same subject can be of interest and utilised by the general public, businesses and governments

### Anti-Bullying with Machine Learning

This project revolves around being able to distinguish bullying content from normal text, in relation to messages and content shared on social media platforms such as Facebook and Twitter and then providing a simple web front end for any member of the public to check a piece of text to see would it be classified as bullying content. An incredibly sensitive and important subject, online bullying and trying to identify and stop it is something that always placed highly on any agenda within schools, the workplace and even government as most of the population as either been a victim of it or knows a friend who has.

Text analytics was done over various datasets, such as a Twitter dataset and a MySpace dataset both used in separate cyberbullying research. This involved various stages such as data cleaning, rebalancing and feature reduction before being used to train several different machine learning classifiers, including Naïve Bayes and Decision Trees across an array of experiments, each one tweaking the process with the aim of better classification of the data. The final models were then combined with an incredibly straightforward interface for demonstration purposes. [16]

The attention to detail in every part of the project from research and design to development and deployment and the similarities between it and the current undertaking are a welcome reminder that it is possible to see an idea through from start to finish no matter and that no matter what obstacles arise there is nearly always a solution even if that means taking a step backwards to eventually go forward.

## Technologies Researched

This section deals with all research into the various possible technologies that could be used in this project and their benefits and limitations.

### Technologies for Data Mining & Machine Learning

#### R

R, a GNU project, is a programming language and environment for statistical computing and graphics. It is a variation on the S language and can run code from other languages such as C, C++ and Foltran. It has a wide and enthusiastic community worldwide ensuring there is plenty of support for beginners and its functionality can be extended through numerous packages found online. It has a wide, coherent and well-developed suite of facilities for data handling, storage, data analysis and graphical displays. [17]

Even with all this it does have its limitations such as memory management, R can consume all available memory, since some packages are created by normal users they might not always be up to industry standard and a basic knowledge of statistical vocabulary is needed as it was written by statisticians for statisticians.



Figure 2 R code example

#### Python

Python is an interpreted, high level programming language that places a lot of emphasis on code readability. It is Open Source, friendly and easy to learn with one of the largest communities in the programming world. [18] It also has a wide variety of packages covering nearly any topic a user might need or need, entire frameworks that can be used to get a project up and running quickly and simply and is supported across multiple platforms and systems.

It does have its downsides though, due to the fact it is compiled at run time it can be quiet slow running, it is also not a good choice if mobile development is at the core of your work or if your project is a game with high-end graphics.



Figure 3 Python code example

#### PyCharm

PyCharm is a Python IDE developed by JetBrains that includes intelligent code compilations, error checking and quick fixes and easy project navigation. [19] The professional version being made available to students, allowing access to many great other features such as starting a project with a framework already in place, database and SQL support and a Python Profiler.



Figure 4 PyCharm IDE

Below are a few integral Python libraries for this project if it is to be used.

##### Scikit-learn

Easily the most important and fundamental library to this project, Scikit-learn facilitates machine-learning for users of all levels by supporting various classification, regression and clustering algorithms including gradient boosting, random forests, support vector machines and k-fold cross validation. [20] It allows a user to easily create models, run them and compare their accuracy scores.

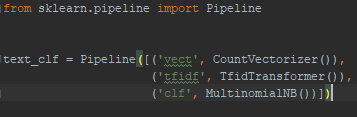


Figure 5 Scikit-learn code example

##### Pandas

The Pandas library provides high-performance, accessible data structures, such as Series and Data Frames, and data analysis tools. Data Frames are two-dimensional arrays while Series are only one-dimensional, and both offer huge array of features across them such as easily sorting them, iterating through them, searching across them for a count of specific entries or gaining stats on each column like mean or mode. [21]



Figure 6 Pandas code example

##### NumPy

The NumPy library offers numerous features for scientific computation and works well with the Scikit-learn library. It offers a powerful N-dimensional array object which can be used as an efficient container of generic data, as well as several sophisticated functions and tools. [22]

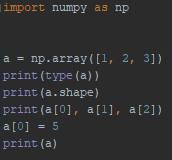


Figure 7 NumPy code example

### Technologies for Web Application

#### Flask

Flask is a web micro-framework for Python that provides users with a simple and effective core of tools, libraries and technologies to build a web application while also allowing it to be easily extended. [23] This has its benefits, as it is light with little need to keep an eye out for security bugs, but also has its limitations as the user will still have to do a lot of work themselves or increase the list of dependencies within the project.



Figure 8 Flask Logo [23]

#### Django

Django is a full web framework for Python that enables rapid deployment and elegant, practical design. It was built by skilful developers that abstracted much of the work required to get a web application of the ground such as managing views and templates, URL endpoints and security features, allowing users to focus on the nuts and bolts of their application instead. [24]



Figure 9 Django Logo [24]

#### Python to Twitter API

There are numerous Python libraries or wrappers that can connect to and gather data from the Twitter API such as Tweepy, Twython or Python Twitter. As Tweepy provides some great documentation and examples and is brilliantly supported I will be starting with that library. [25] If it does everything I need of it I will not need to use any of the other libraries.

### Technologies for Web Server

As Django and Flask web hosting only truly fulfil the role of development servers another web hosting service must be chosen for deployment onto a production server.

#### Apache HTTP Server

Apache HTTP Server is a free and open-source HTTP server built to operate on numerous different operating systems such as UNIX, Windows or Mac. [26] It is developed and maintained by an open community of developers, has a strong community of users willing to help first timers and is the most widely used web server in the market today. It does have its restrictions though: a strict updating policy must be put in place and the ability to modify its configuration can potentially cause a serious threat to the security of the web application.



Figure 10 Apache HTTP Server Logo [26]

#### Heroku

Heroku is a cloud platform as a service (PaaS) that allows users to deploy applications onto its servers and supports several programming languages including Python. It “*makes the processes of deploying, configuring, scaling, tuning, and managing apps as simple and straightforward as possible*” enabling developers to focus on building their app. [27] With this though comes a lack of control as the exact configuration of an application is set by them and if there is a high volume of data traffic then there is a premium charged.



Figure 11 Heroku Logo [27]

#### Amazon Web Services

Amazon Web Services (AWS) provides on-demand cloud computing platforms to users on a paid subscription basis. [28] This means that for many users it eliminates capacity constraints while mitigating the costs involved as well as adding in global reach and scalability. It is a high-tier grade service, but you are also paying for it unlike many others. It does offer a first-year free tier of all its services for first time customers and for students and educators there is an AWS Educate account that gives credits enabling hands on experience with their services.



Figure 12 AWS Logo [28]

### Technologies for Version Control

#### Git

Git is an open source distributed version control system that has seen a massive surge in popularity in recent years. It is free and easy to use and learn and can be run from the Git Bash client or from its integration in PyCharm, making it even easier to use and track changes in the process. Using either of these ways, it is simple to connect to GitHub, a web-based hosting service for Git repositories and ensure that a project is backed up with required access given to specific team members as well as giving public access to view the project and its code base. [29]



Figure 13 Git Logo

#### Mercurial

Mercurial is a free, distributed source control management tool that prides itself on how fast and powerful it is, it claims it can handle any project no matter the size or type. It is easy to learn and offers an instinctive interface. It is platform independent and extensible. For Mercurial, “history is permanent and sacred.” It only allows the rollback of the last pull or commit although there are extensions if more is needed. [30]



Figure 14 Mercurial Logo [30]

### Technologies for Data Storage

#### MySQL

MySQL is an open source relational database management system and one of the most popular systems in the world due to how easy it is to use, its nature as a relational database and how much investment and innovation has gone into it. It allows for powerful joins as well as standard features such as triggers, stored procedures and cursors. [31]

Due to its acquisition by Oracle though there have been some negatives: It is no longer completely open-source as some modules for it are now closed-source and it is no longer community driven.



Figure 15 MySQL Logo [31]

#### PostgreSQL

PostgreSQL is an open source object-relational database management system with a big emphasis on extensibility and creating features which safely store and scale the most complicated data workloads. [32] It essentially is a combination of relational and NoSQL databases, giving the best of both worlds through its extensions. It is highly scalable and supports JSON

Even with this it has some drawbacks: Its documentation has been known to be spotty and its configuration can be confusing to an inexperienced eye.



Figure 16 PostgreSQL Logo [32]

#### MongoDB

MongoDB is a free and open-source distributed NoSQL, or document, database that is scalable and flexible. It stores data in JSON- like documents which can be of any desired structure, removing the need for schemas, as in relational databases and allows for powerful ways to access and analyse data using Ad-hoc queries, indexing and real-time aggregation. [33] What is given up for this is the lack of functions or stored procedures as well as loss of strength in terms of ACID (Atomic, Consistency, Isolations, Durability).



Figure 17 MongoDB Logo [33]

## Other Relevant Research Done

This section covers all other relevant research done for this project. Research into approaches and methodologies will be dealt with in their own section later.

### Big Data

Over the last few decades the amount of data we have gone from using has increased from kilobytes to megabytes to gigabytes and has now hit terabytes in the everyday home. Many businesses have gone beyond this and are now dealing in petabytes or even exabytes of data.

These large datasets, both structured and unstructured, that are beyond the scope of traditional techniques to process due to their size or complexity and are used heavily within the domain of data science are what have been termed: Big Data. [34]

Organisations the world over have been investing into this area in the last number of years as the results that can arise from proper storage and use, through data mining and data analysis projects, of Big data can lead to massive returns or scientific breakthroughs.

### Data Mining

Data mining is the process of detecting anomalies, correlations and patterns within Big data to make predictions using a wide range of methods including various machine-learning algorithms. [35] There are various project models that can be used, although all of them are built upon the same foundation of stages

#### Data Acquisition

At the beginning of every data mining or analytics project, the first stage of the project is to ensure there is data to use. Where this data comes from varies from project to project as it may come from an inhouse databases or from surveys carried out with a business’s customer base.

The data used is referred to as a dataset with each row in the dataset being an instance of the data and each column being a descriptive feature of the data. [35]

#### Data Understanding

Understanding the business logic and context behind the acquired data and having a base knowledge of the project’s domain are integral parts of any data mining project as these helps to make sense of the relationships between features and enable easier selection of machine learning algorithms and improving their accuracy.

#### Data Preparation

This stage deals with the pre-processing of the data to ensure it’s in the correct state to be used for various business purposes such as in a machine-learning algorithm or data analysis. It includes the sub-stages of data cleaning and feature selection.

#### Data Cleaning

Data cleaning is the process of finding and removing entries in the data that has been either entered or formatted incorrectly. [35] Without proper data cleaning, when passing the data into a model various errors can arise, leading to program failure or completely inaccurate results.

#### Feature Selection

In any data mining project, the aim is to produce accurate predictions as efficiently as possible. To do this, we want to minimise the number of features without affecting the accuracy. [35] Therefore, feature selection is a key component that must be carefully deliberated and decided on.

#### Training & Testing

The data is used to train and test the models using various splitting techniques and the results are saved to be used in the following stage.

#### Evaluation

Where the results from the previous stage are evaluated based on various accuracy metrics to see how certain models perform. If they have reached the required level of accuracy then they can start to be used in an application or to help make business decisions, otherwise a return to a previous stage is needed.

### Machine Learning

Acquiring and preparing large sets of data is only part of the battle, the next major stage is to be able to detect patterns within this data and then make predictions from this. This is the core of Machine Learning, enabling us to extract significant insight from Big Data through complex, mathematical algorithms with minimal human intervention. [36] These algorithms are trained on sub-sets of the data to grow more accurate in their predictions.

#### Algorithms

Machine learning algorithms are divided into two sections

* ***Unsupervised Learning***
  + An algorithm is given a set of inputs without any outputs known. It learns by itself, through specific methods, what outputs it should prescribe to each input.
  + Uses of Unsupervised learning algorithms
    - Find hidden patterns within data
    - Face recognition software
  + Example of Unsupervised learning algorithms
    - Clustering
* ***Supervised Learning***
  + An algorithm is given a set of inputs with all outputs known. Using these it learns what outputs to prescribe to any future inputs.
  + Uses of Unsupervised learning algorithms
    - Predicting Football scores based on previous years data
    - Selection of advertising to be displayed to specific users
  + Examples of Unsupervised learning algorithms:
    - Support Vector Machines
    - K-nearest Neighbour
    - Naïve Bayes
    - Decision Trees
* ***Examples of Both***
  + Artificial Neural Networks
  + Anomaly Detection

##### Unsupervised Learning Algorithms

###### Clustering

There are multiple different types of clustering algorithms such as K-Means Clustering and Hierarchal Clustering. All of them revolve around grouping the data based on each input’s feature similarity.

The difference between algorithms, for example, K-Means Clustering and Hierarchal clustering is that the former separates the data points iteratively into K clusters based on the features of the data while the latter considers each data point a cluster then identifies the clusters that are closest to each other and merging them, while taking note of the hierarchal relationship between them, and so on until only one cluster remains with one large hierarchy.[35]

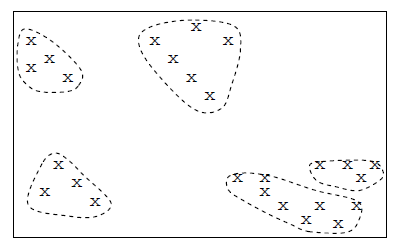


Figure 18 Clustering Feature Space Example [35]

##### Supervised Learning Algorithms

###### Naïve Bayes

Naïve Bayes classifiers belong to the family of probability-based classifiers and are based on Bayes’ theorem with the added assumption of conditional independence between all the features in the data. [36] This added assumption allows for the model to drastically reduce the amount of probabilities it must compute.

While this is quite a leap of faith to make, it still results in a robust model that delivers strong results and, when coupled with its scalability, efficiency and simplicity, is the reason it is normally the starting point for most data mining projects.

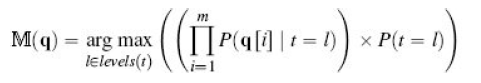


Figure 19 Naive Bayes Model [36]

###### Support Vector Machines

Support Vector Machine classifiers belong to the family of error-based classifiers. It maps all the data as points in an N-dimension space, N being the number of features, and then tries to find a hyperplane, or decision boundary, that distinctly classifies the data points. [36]

It tries to maximise the distance between the hyperplane and data points from both classes. Those points closest to the hyperplane are called support vectors and have a significant impact on its placement.

New points are mapped to this space and classified depending which side of the hyperplane they belong to. It has a high degree of accuracy, takes up less computation power than other algorithms and can be used for both regression and classification task.

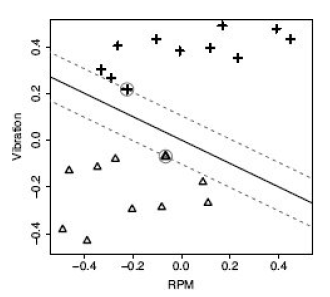


Figure 20 SVM Hyperplane selection [36]

###### K-Nearest Neighbour

K-Nearest Neighbour (KNN) is a simple, non- parametric classifier and belongs to the family of instance-based classifiers and as such has either no or a very small training phase to it.

To classify new data points, the feature similarity of its k-nearest neighbours is used, with the new data point going to the class with the majority count. [35] While it makes no assumptions about data and is versatile it can be computationally expensive and sensitive to irrelevant data.

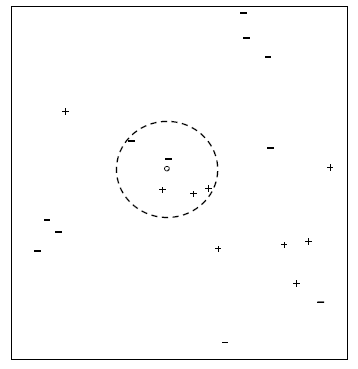


Figure 21 KNN Feature Space Example [35]

###### Decision Trees

Decision Tree classifier belongs to the family of information-based classifiers that takes a dataset and one feature at a time, branches out for all possible values if categorical and uses thresholds for continuous, until each branch can be labelled with only one classification. When trying to classify new instances, the tree is followed down to a branch based on its features the path those lead down the tree. [35]

The order in which the features are split upon depends on which metric is used, either the Information Gain, based on the entropy or measure of disorder of the feature, or the Gini Index, which is the measure of impurity of the dataset in regards that feature, with both trying to make the most efficient and smallest tree possible.

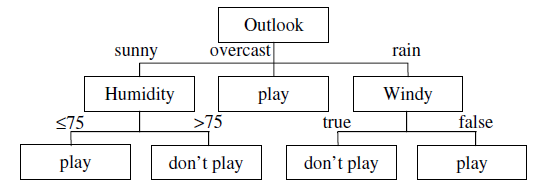


Figure 22 Decision Tree Example [35]

##### Both Learning Type Algorithms

###### Artificial Neural Networks

Artificial Neural Networks are “*biologically inspired computer programs designed to simulate the way in which the human brain processes information*”. Using artificial neurons, the computerized version of a brain cell, a network is formed by connecting the output of specific neurons to the input of other neurons, forming a directed, weighted graph. A neurons weights and activation functions can be tuned over the learning process to increase the networks accuracy. [37]

Neural networks can be used with datasets where either both the inputs and outputs are provided or only the inputs are provided allowing for use in a wider range of scenarios. [38]

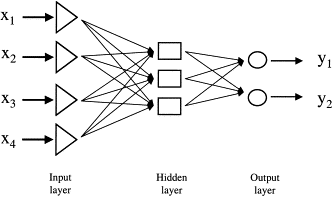


Figure 23 ANN Structure Example [37]

###### Anomaly Detection

Anomaly detection revolves around identifying outliers, those instances which display odd behaviour and can from unconventional patterns, within the dataset. These can be point anomalies, where a single instance has some features too far out of range when compared to other instances, or collective anomalies, where the behaviour of a group of instances helps to detect such anomalies. It is like noise removal but where that wants to clear noisy data from the dataset, anomaly detection wants to keep such abnormal data in and learn from it. [39]

Different techniques can be utilised with anomaly detection such as density-based which works like K-nearest neighbour detailed above and clustering-based, again like a previously mentioned algorithm: Clustering. Anomaly detection algorithms can be used with input and output pairs where it is known what the range of normal behaviour is to find ones that fall outside this or with just inputs and allow the algorithm to figure out what constitutes normal behaviour and raise a flag on instances that do not match this.

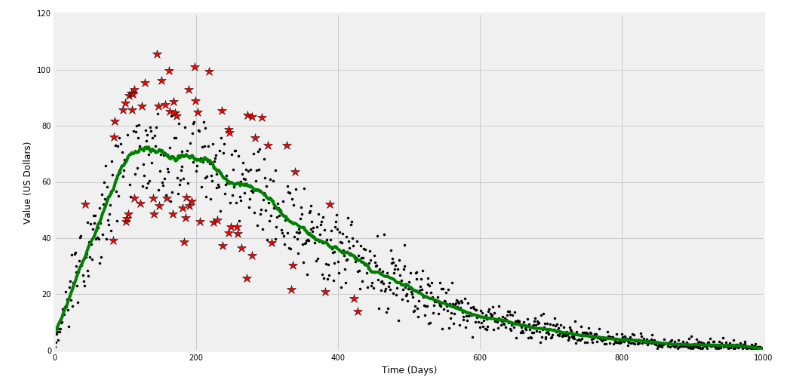


Figure 24 Anomaly Detection in Stock Value Example [39]

#### Training & Testing

Once a dataset has been fully prepared for use in a machine learning algorithm it must be divided up into training and testing datasets. The training dataset is a sub set of the original dataset used to train the model while the testing dataset is what is left. [35]

The training dataset is passed through a working model, with the results compared against the actual outcomes enabling the accuracy of the model to be measured. There are various ways that the base dataset can be divided up into training and testing datasets.

##### Holdout

This is the most basic division of the original set into training and testing sets with the partitioning of the original into two mutually exclusive sets. The split is usually taking a 2:1 ratio. The main problem with this method is that as more training data is used there is fewer testing data to be used. Ideally you want both the training and testing sets to be as large as possible. [36]

##### K-fold Cross Validation

Using this method, the original set is divided up into K partitions of equal size. Then for each partition, that partition acts as the testing set with the remaining partitions becoming the training set. A model is fitted using this training set and evaluated using the testing set. The model is discarded with the results being held onto before moving onto the next partition. [35]

This method deals with the main issue of the Holdout method, ensuring the entire dataset is used for both training, each partition being used K-1 times, and testing, each partition used once, with the results being of significant use at the end for evaluation.

#### Evaluation

After a model has been created and data run through it, results will have been produced. The accuracy of these results must be measured carefully. Only by truly understanding the accuracy of the results and what influenced it will someone be able to improve the model and its accuracy.

##### Classification Accuracy

Simply put, the accuracy of a model is the amount of predictions it got right. Put into formulaic terms: Accuracy = No. of correct predictions / Total no. of predictions. [36] This in and of itself is not enough in terms of detail for a proper model evaluation and as such other methods must also be employed.

##### Confusion Matrix

A confusion matrix is a table layout for the visualisation of the performance of a model. The totals of correct and incorrect predictions are calculated and broken down by class. These values are placed into a matrix with predicted across the top and expected down the side.

When looking at a two-class instance or one class against all the others this matrix will then hold the values for True Positives, False positives in the 1st row and False Negatives and True Negatives in the 2nd row. [36] This data holds much more meaning then the previous method of evaluation and can help in knowing what part of the model needs to be tuned to gain a better accuracy level.

##### F1 Score

The F1 score is another method of measuring a model’s accuracy. It is obtained by computing the weighted average of the Recall and Precision. [36] The closer this score is to 1 the more accurate the model is.

F1 = 2\*(Recall \* Precision) / (Recall + Precision).

Recall is found by dividing the total correct predictions by the sum of the total correct predictions and false negatives.

Recall = TP/ (TP + FN)

Precision is found by dividing the total correct predictions by the sum of the total correct predictions and false positives.

Precision = TP/ (TP + FP)

## Resultant Findings and Requirements

This section will deal with what technologies were chosen to use in this project and why and what datasets will be used to create my machine-learning models.

### Chosen Technologies

Python will be used over R for this project due to its familiarity, design tropes and high extensibility with a wide variety of libraries supporting every aspect of what is need in this project. PyCharm Professional IDE was chosen due to its wide variety of features including integrated Git support connecting to a GitHub repository with Git being the preferred VCS due to it being well supported, easily operated and widely recognised.

Django will be the framework of choice as it just provides more structure out of the box then Flask does. Amazon Web Services will be used for hosting the production server as the first-year free tier completely nullifies the costs and offers a great range of services, although if this project was to be extended beyond final year there would be more consideration to swapping to Apache HTTP Server due to fiscal reasons. For data storage PostgreSQL was chosen as it combines the best of both a relational and NoSQL databases.

### Chosen Datasets

For the data that my machine-learning models will use, the cresci-2017 dataset was selected. [40] This dataset has been used in academic studies in the field of Twitter bot detection, [7] is part of the datasets used by the Botometer application and covers an excellent range of different accounts.

It is split further into several smaller datasets. First there is a dataset of genuine account, then there are three groups of traditional spambots, the first group are general spambots without any focus, second group are spambots attempting to promote a web URL to try and get users to click it and lastly a group of spambots attempting to push job offers on users as well as getting them to click a specific URL.

Next is a group of fake follower bots which exist purely to make a user appear more popular or influential on the platform. Lastly are three groups of social spambots, the first group retweeted a specific political candidate in Italy, the second group were attempting to get people to download a specific mobile application and the last group were trying to sell products on Amazon.com.

# Approach & Methodology

This project will be performed iteratively, using the Agile and Kanban methodology for the overall scope of the project, including the web application, while for the data mining aspect of the project the CRISP-DM methodology was chosen from a few data mining project management models.

Both the Agile and Kanban methodologies and their use in this project as well as the CRISP-DM methodology and a similar methodology: SEMMA, will be explained in this section. A comparison will be made between them and reasons given why I chose the former over the latter.

## Agile & Kanban

### Agile

The Agile concept is an approach to project management within the domain of software development and includes various principles such as Feature Driven Design, Scrums, XP and Kanban, the last of which I have incorporated into my project and discuss later.

Agile and its sub-principles revolve around being adaptable, collaborative and versatile and with the focus on iterative and incremental development. [41] Projects that adopt Agile need an approach that facilitates rapid and flexible responses to change as well as continuous improvement.

The 12 Agile principles outlined in the Agile manifesto are:

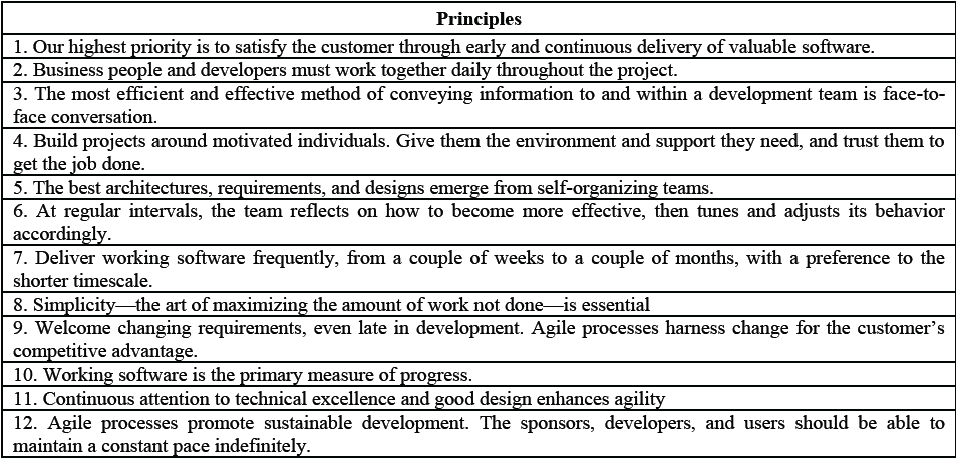


Figure 25 12 Agile Principles [42]

Some of the key differences between Agile and traditional methodologies are that the management style of a project is to lead and collaborate in the former and command and control in the later, that communication throughout the project is informal vs formal, that the developmental model is an evolutionary-delivery model vs a life-cycle model and that implementation is the focus vs spending large quantities of time on design. [41]

### Kanban

Kanban is a part of the Agile family with a heavy focus on continuous delivery while at the same time ensuring that the development team do not become overburdened. [43]

The Kanban methodology was named in 2007 after several presentations given by David Anderson of his management approach at various companies. The word “*kanban*” is the Japanese for sign or signal card and the methodology’s roots date back to the middle of the 20th century in Japan where Taiichi Ohno, while working for Toyota, employed the first Kanban system to regulate the workflow in the company. [44]

Kanban has three main principles behind it: [43]

* Visualise the flow of work: Set up an environment, either through post its on a board or digitally to visualise all the work items to give them context.
* Limit the work in progress: Limit each team member to at most 3 pieces of work at any given time to ensure the team does not start and commit to too much work.
* Enhance the flow: Once a team member has finished a piece of work, they take the highest priority work piece in the backlog.

Some of the benefits of the Kanban methodology are shorter cycle times ensuring that new features can be delivered quicker, easy adaption to frequent changes in work piece priority and requires less oversight ensuring team and project leads have more time to focus on other activities.

### Project Use

While Agile and Kanban methodologies revolve around a team of multiple members working together it isn’t hard to adapt them to this projects case of a team of one for this project. All roles will be taken on including all members of the team, the team lead and the shareholders that commission the project.

* Shareholders: All the requirements of this project were laid out by at its outset and priorities will continue to be assigned to all the deliverables and smaller pieces of work by the shareholders.
* Team lead & members: Every piece of work on this project has been and will be worked on and completed by the single team member. That member will oversee everything ensuring all the work is done in a timely manner and to a high quality.

Trello will be used, a free to use web-based project management application, to keep track of and manage the work load through the Kanban method. This was a piece of software that was introduced to during a previous piece of work and is extremely simple and easy to use. [45]

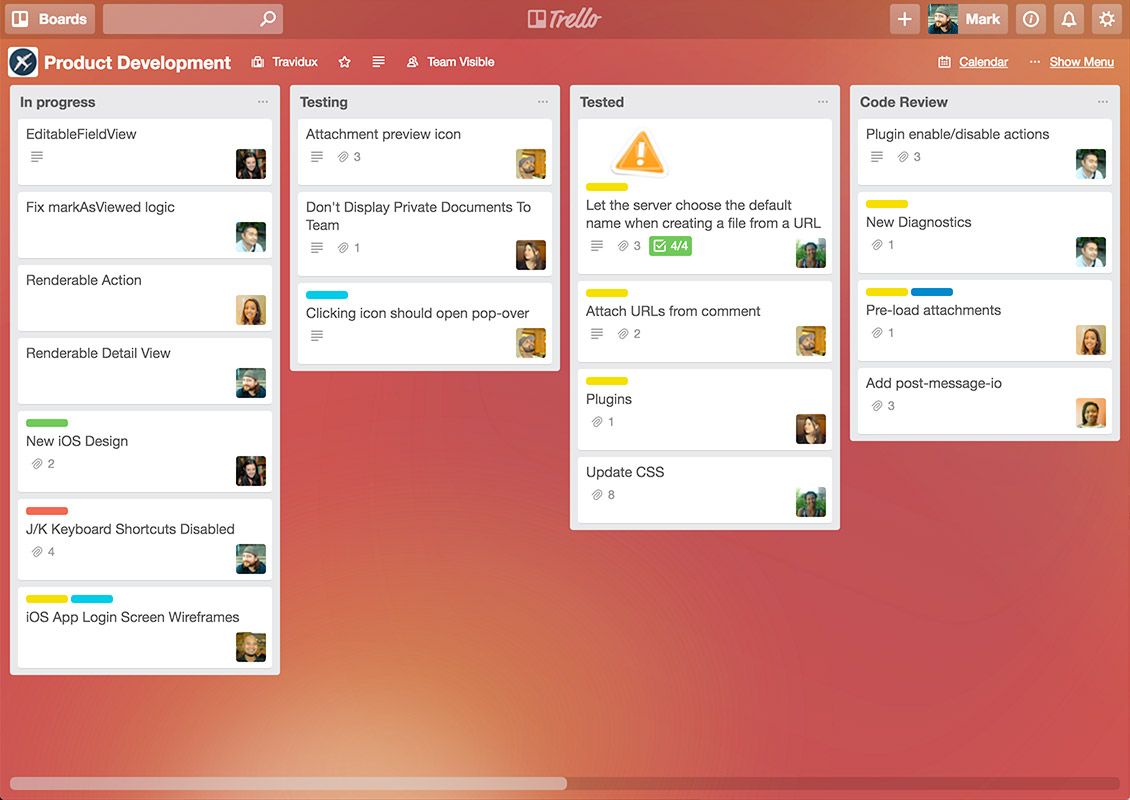


Figure 26 Sample Trello Board [45]

## Data Mining Project Management Models

### CRISP-DM

CRISP-DM model is an acronym that stands for Cross-Industry Standard Process for Data Modelling and is a cycle which consists of 6 stages. The sequence of these stages is not strict which allows for movement between any stage if so required. [46]

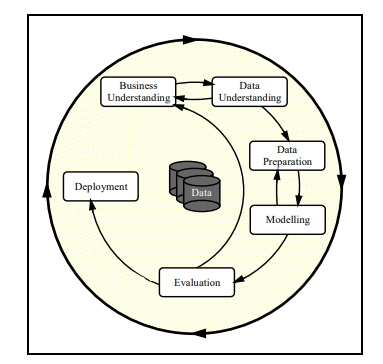


Figure 27 CRISP-DM Model [46]

#### Business Understanding

This stage revolves around understanding the business side of the data mining project:

* What is the domain of the business?
* Assessing the situation in terms of hardware, software, data sources and knowledge bases.
* Transforming business goals into data mining objectives.
* Producing a project plan.

#### Data Understanding

This stage is where data is acquired, and time spent exploring it, trying to understand any correlations between features as well as finding any data quality issues present in the data through a data quality report and data visualisations.

#### Data Preparation

This is the most important stage of the model and requires an excellent understanding of the previous two stages. This is where numerous tasks are performed on the data such as the pre-processing of data, cleaning and reformatting data to remove missing or fix corrupt values and feature selection. Aggregation or merging of data may also occur here. [46]

If the data is not prepared properly then the accuracy of any models it is passed to will suffer greatly and can take multiple iterations to get right.

#### Modelling

This stage revolves around the selection of modelling technique or machine-learning algorithms, decide how to measure the model’s validity or accuracy, the building of the model and its assessment to fix any mistakes that can occur in the building process. [46]

These mistakes arise due to *noise*: outliers or missing values in the data that have managed to slip through the previous stage. This then leads to *overfitting*, where the model is too complex for the data and therefore is highly sensitive to noise, or *underfitting*, where the model is too simplistic and unable to detect patterns within the data. Either of these have a negative impact on the accuracy. [35]

#### Evaluation

Evaluation of results from the models, once data has been passed through, is done here. This allows us to get an understanding of the suitability of the models as well as any errors we may have made at an earlier stage. The entire process is reviewed and the next iteration, if needed, is planned.

#### Deployment

Once a model has been created that hits a satisfactory accuracy level it can be deployed. This can have a variety of different meanings, dependent on the project itself, from being used in a work report or a scientific paper or in a data mining application. The deployment must be planned with any monitoring and maintenance considered.

### SEMMA

SEMMA is another model, developed by the SAS Institute, which is used to manage a data mining application and is an acronym for the 5 stages that comprise the model: [47]

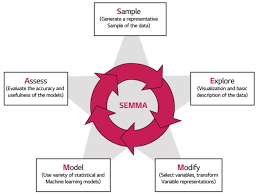


Figure 28 SEMMA Model [48]

#### Sample

This stage focuses on taking a sample of the dataset for use in the model. The sample must contain enough data such that accurate patterns can be drawn from it while small enough that it can still be used efficiently. Data partition of the sampled dataset into training and testing sets is also done here.

#### Explore

Exploration of the data is done here to detect any unexpected patterns, anomalies such as missing or corrupted data, or instances in the data that prove to be unnecessary while also gaining a better understanding of the data. This is done through visual representations and statistical techniques. [47]

#### Modify

The data is modified by creating, deleting, selecting and/or transforming variables within it to ensure the data being passed into the model is of high quality and considers any issues that arose in the exploration stage. Not every issue will be perfectly solvable, and it will be a case of applying the best fit solution. [47]

#### Model

The creation of the model is dealt with here, where selected modelling techniques are employed to build a model that will accurately make predictions based upon the data that is passed to it.

Again, like in CRISP-DM, the problems of *overfitting* and *underfitting* due to *noise* must potentially be dealt with.

#### Assess

The outputs of the model, after inputting the training set, that was set aside during the sampling stage, are compared to the actual outcomes of that dataset with the model’s accuracy and usefulness being evaluated.

### Difference in Models

Looking at both models it is easy to see that they are quite similar, in fact SEMMA appears to be akin to a slimmed down version of CRISP-DM with the first, Business Understanding, and last stage, Deployment, omitted such that all the focus is on data modelling aspect of the application, though realistically some knowledge of the business domain must be known or else the final product will be lacking in various areas.

This table clearly demonstrates this comparison:

|  |  |
| --- | --- |
| CRISP-DM | SEMMA |
| Business Understanding | ----------- |
| Data Understanding (Part 1) | Sample |
| Data Understanding (Part 2) | Explore |
| Data Preparation | Modify |
| Modelling | Model |
| Evaluation | Assess |
| Deployment | ----------- |

Figure 29 Model Comparison

### Conclusion

The CRISP-DM model was chosen for use within this project as it is an industry standard model that is used widely and as such is well proven, is robust and versatile allowing for movement between any stage if needed and finally inclusion of the deployment stage, which SEMMA is missing, as the data mining aspect of the project will need to be integrated and deployed within the overall web application.

# Design

This chapter details all the design elements of the project including the technical architecture chosen for this project and how it has been adapted from the Model View Controller design pattern and all other design documents such as the Use Case, Entity Relationship, Flow Chart and Source Code layout diagrams.

## Technical Architecture

### Model View Controller

The Model View Controller (MVC) architecture is used across a wide range of applications where there is a need to provide a User Interface through a desktop or web front-end. It is a three-tier architecture which uses the Controller, comprised of several classes such as a Command Factory class and Command, Service, and DAO classes, to pass information between the View, i.e. the front end, and the Model, i.e. the backend. [48]

This ensures the separation of roles between the different sections of code in a project. This makes it easier to divide up the work in a project as team members can focus on specific sections without worrying too much about the other parts enabling better development and testing.

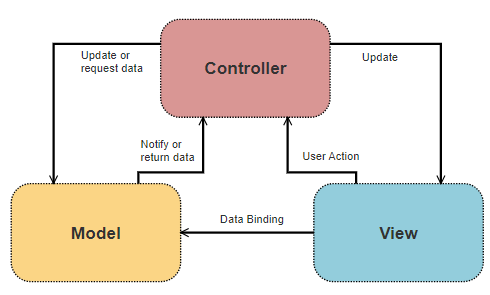


Figure 30 Model View Controller

### Model View Template

The Django framework has been chosen for the web application aspect of this project which uses its own modified version of the MVC called the Model View Template (MVT). In this adaption, Django takes care of the Controller role and replaces it with the Template section, which takes the role of the presentation layer by containing all the HTML and Static, such as CSS and image, files while the View section deals with all business logic and handles all requests from and responses to the User. The Model section stays the same and deals with everything to do with the database. [49]

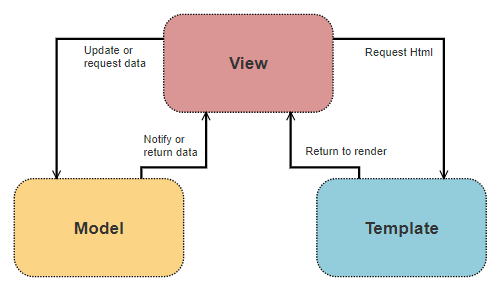


Figure 31 Model View Template

### Project Technical Architecture

The layout of the project technical architecture can be seen in Figure 32 and shows how each of the different parts of the project interact with each other. The model, or database, part of the Django MVT has been replaced with the prediction modals and act as the only link between the web application, which make use of them, and the data mining application, which creates and saves them to the web application.

Only the data mining app interacts with the PostgreSQL database, both of which are held locally with the web application being hosted on AWS. While the project has three tiers, the web application has a simple client-server architecture. Any change to the models requires only that the web application be quickly and seamlessly redeployed, meaning only minor disruption to the user experience, as those are the only changed elements.

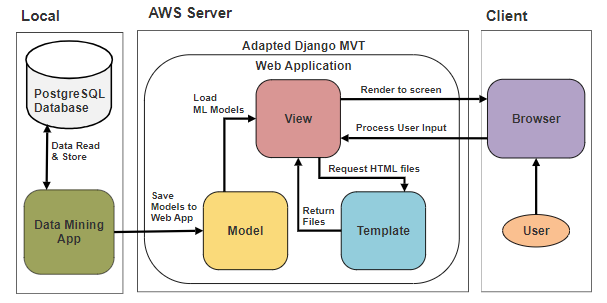


Figure 32 Project Technical Architecture Diagram

## Other Design Documents

### Use-Case

The Use-case in Figure 33 below details how a user will interact with the system. The user can enter in their own Twitter handle, if they have one, or any other one they wish, be it a celebrity’s, one of their friends or any other handle they wish to check. There is no need for any form of validation from the user due to the use of the OAuth2 validation system which will be discussed later.

They will then be able to view the prediction results about what type of real or fake account it is. They can then share this result to Twitter and/or Facebook, fill out a feedback form about the site and their experiences and go back to try another account. Lastly at the main screen they will also be able to view information about the site.

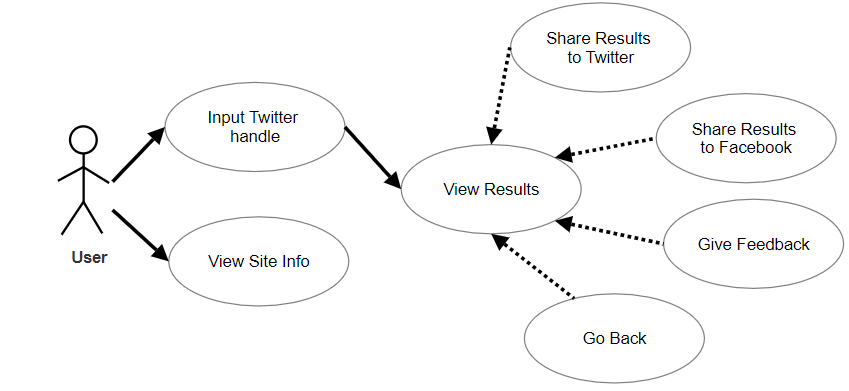


Figure 33 User Use Case Diagram

### Flow-Chart

The Flow-chart in Figure 34 below shows the entire process from the user entering in a Twitter handle to all the possible outcomes from this such as not being able to find data on that handle due to it not existing or predicting that handle’s account is a bot account.

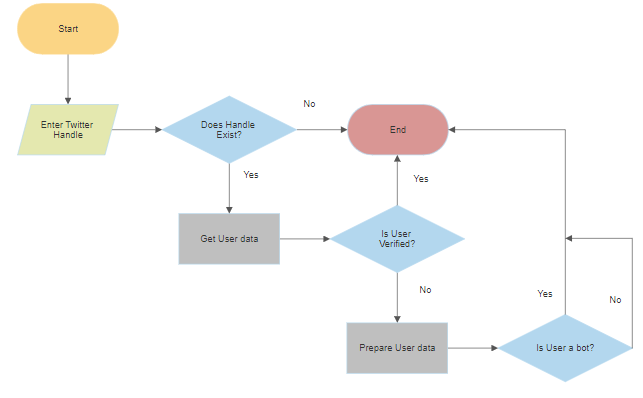


Figure 34 Prediction Flow Chart Diagram

### Entity Relationship

All the attributes for the Account table can be seen in Figure 35 below. This table is stored within the local PostgreSQL database as part of the Data Mining aspect of the project. Data is read in from csv files into this table and is detailed later.

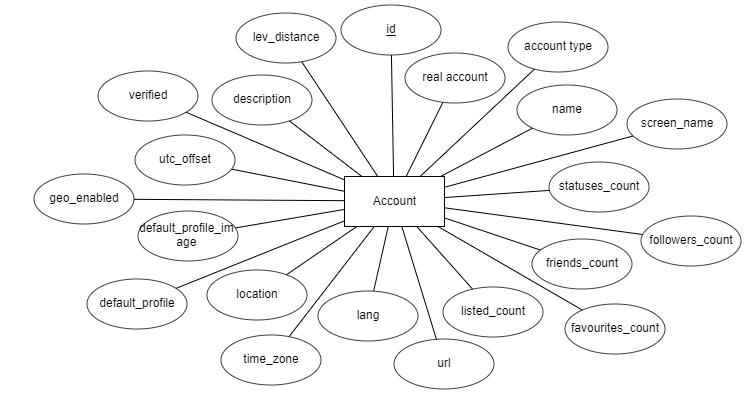


Figure 35 Entity Relationship Diagram

Attributes in Account Table:

**id**: big integer, unique identifier for each user account within the database.

**real\_account**: boolean, whether this account is denoted real or fake.

**account\_type**: integer, type of account, 1 for real, 2 for fake follower, 3 for traditional spambot and 4 for social spambot.

**name**: 60-character varying, the accounts display name.

**screen\_name**: 16-character varying, accounts handle.

**statuses\_count**: integer, total amount of statuses this account has posted.

**followers\_count**: integer, total amount of other accounts that follow this account.

**friends\_count**: integer, total amount of accounts this account follows, otherwise known as friends

**favourites\_count**: integer, total amount of statuses this account has favourited.

**listed\_count**: integer, total amount of lists this account has been put into by other accounts.

**url**: 100-character varing, URL for the accounts Twitter page.

**lang**: 25-character varying, the language the user has chosen for their account.

**time\_zone**: 40-character varying, the time zone the account operates in.

**location**: 70-character varying, location the user has set for the account.

**default\_profile**: integer, whether the account uses the default profile.

**default\_profile\_image**: integer, whether the account uses the default profile image.

**geo\_enabled**: integer, whether geolocation is turned on or not for the account.

**utc\_offset**: integer, difference in time between UTC time and the time of the account’s location.

**verified**: integer, whether this account has been verified by Twitter to be who they say they are.

**description**: 320-character varying, a public summary about the account.

**lev\_distance**: integer, the minimum levenshtien distance between tweets by the account, which is the lowest number of single-character edits to change one string to another.

### Source Code Layout

#### Data Mining Application

The data mining application consists of a data folder for the dataset that is split up between 9 sub-folders containing user and tweet csv files, a results folder for storing the results of the various experiments done with the data, different classifiers and different account type comparisons and then several python files to process each of the tasks required.

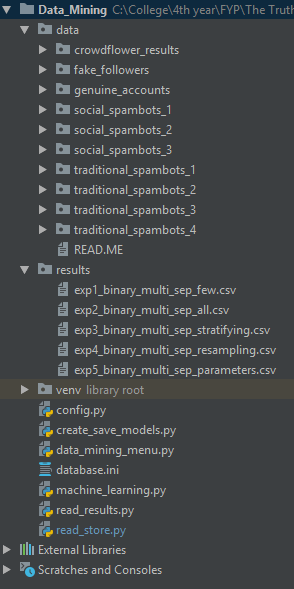


Figure 36 Data Mining Code Layout

#### Web Application

The web application uses the Django framework and builds upon it by adding in both base and home HTML files for rending to screen, staticfiles folder for all CSS, font and image files, credentials folder to save all required keys to make calls to the Twitter API, ml\_folders for the machine learning models from the data mining application to be saved to and the requirements.txt and .ebextensions and .elasticbeanstalk folders to facilitate the applications deployment to an AWS Elastic Beanstalk instance.

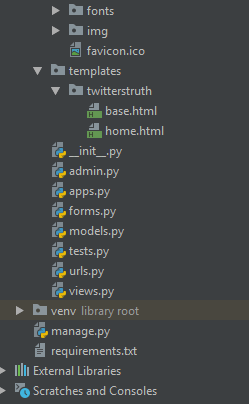
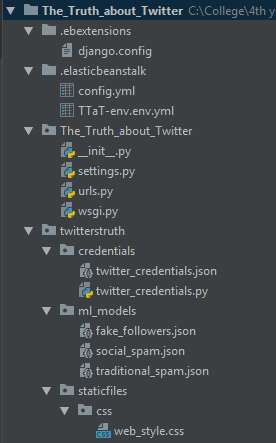


Figure 37 Web Application Code Layout

# Development

This chapter covers all the development undertaken for both the data mining and web applications and the major challenges that arose during this phase and how they were solved.

## Data Mining Application

This section dives into how the CRISP-DM methodology was implemented in this project with the aim of creating accurate models to classify different types of real and bot Twitter accounts and the various pieces of code used to facilitate this.

### Business Understanding

### Data Understanding

### Task Menu

### Data Preparation

### Modelling

### Evaluation & Deployment

## Web Application

This section details how the web application was created and then deployed, including the initial setup of the Django framework, the logic used behind the scenes, the presentation layer and finally how it was deployed to an AWS Elastic Beanstalk instance for use by the public.

### Getting Setup

### OAuth2 Authorisation

### Views

### Templates

### Static Files

### Deployment

## Challenges Encountered

While there were a wide range of challenges encountered at nearly every stage across the entire project life, only the major ones are explained here and how they were overcome.

### Time Management

This issue was touched on as a potential challenge at the start of the project and it most certainly proved to be. Everything from other college work to family commitments and slight mental health issues worked to derail tasks and extend the time it took to complete them ensuring that there were constant revisions to self-set task deadlines.

There was no easy solution to this issue and while the use of Trello boards certainly helped to keep track of things and try to keep the daily motivation going, they could be quite conveniently ignored if so desired.

What did work though was a combination of parental support, where they would check in and see how everything is going, offering an ear to talk to and words of encouragement, weekly meetings with the project supervisor as progress was expected to be made from week too week and finally seeing the progress others in the year were making with their projects as this proved quite the personal motivator.

### User & Tweet Data Storing

As all the account data was split up between various users and tweets CSV files, this needed to be stored for use in the various parts of the data mining application. The format to store it in went through various iterations in the first half of this project as there were various ways of going about it.

Should all the data just be stored raw, some form of it stored with the parts that were not needed left out or features be derived from the data first and then stored. Initially the last option was chosen but upon the realisation that to change any of those features would require that the data within the database be changed partially or completely, a time intensive task due to either the volume of data being read in from the CSV files or implementing SQL to make the changes, other options had to be explored.

Finally, after trying a few different approaches, it was decided that the best way to proceed was to read in the user’s account data in its normal form, while dropping a variety of columns that held no value and adding three columns, including one to hold what type of account it is and one to hold the minimum Levenshtein distance between that users tweets thereby eliminating the need to store anything from the tweets files.

### Model Accuracy

Another challenge that was brought up at the start of the project was gaining a high level of accuracy in the machine learning models and turned out to be quite a time consuming and vexing challenge to overcome.

Vast quantities of time were devoted to researching what were the characteristics of the various types of bot accounts, various machine learning classifiers, how to make full use of their parameters and other techniques that can be employed on a dataset to gain a higher-level accuracy such as K-fold cross validation and resampling.

Five large scale experiments were undertaken parallel to a lot of this research and incorporating all the knowledge learned. This investment of time and effort payed off as the final models created had approx. 90% accuracy in their classification of a Twitter account.

### Web UI Design

Designing and creating the UI for the web application proved to be rather troublesome due to a lack of confidence and ability in this domain. Coming up with a fresh and trendy design and implementing all the CSS that went along with it ended proved a bridge too far for the time span off this project without going out and either completely ripping off another website or purchasing a website framework design.

The solution to this proved rather boring and it was decided to keep all design elements of the web application as simple as possible. This is one challenge that is passed onto future iterations of the project to complete as it would require a substantial amount of time to complete and priorities at that stage lay elsewhere.

### Saving Models for Deployment

The only connections between the data mining and web application are the final models used to predict the classification of Twitter accounts. Initially to create and save these models across from one application to the other, they were serialised using the pickle Python library and then saved within the web application.

When the web application was run locally, there was no issue with using the pickle library to then de-serialise the models for use in making predictions. The issue only arose once the application was deployed onto an AWS Elastic Beanstalk instance when trying to load the models from their SAV files to make a prediction with the error “Buffer dtype mismatch, expected 'SIZE\_t' but got 'int'” being given.

After investigation, it was found that there was no easy fix for this error as this error had to do either with a mismatch between Python versions or environments, Windows and Linux, locally and on the server instance. The solution found was to change what was being saved across so instead of the models, the training data used to create them was saved across by writing the data to dictionaries and then to their respective JSON files. Within the web application, these files are then loaded up and the data extracted and used to recreate the models once more for use.

# Testing & Evaluation

This chapter covers the various model experiments undertaken in pursuit of the most accurate way to identify the different types of accounts and their evaluation as well as all forms of testing done across the project, including usability testing of the web application, ad-hoc testing and unit testing.

## Model Experiments

### Getting Ready

#### Data

#### Classifiers

#### Training & Testing

#### Evaluation

### Experiment 1: Minimal Features

### Experiment 2: Maximum Features

### Experiment 3: Stratifying

### Experiment 4: Resampling

### Experiment 5: Classifier Parameters

### Conclusions

## Usability Testing

## Ad Hoc Testing

## Unit Testing

# Project Plan

This chapter covers the creation of the initial project plan, what the final one looked and explanations for the differences and how Kanban boards were implemented to manage the project and all tasks and objectives.

## Initial Plan

The initial plan can be seen below in Figure \* in the form of a Gantt chart and includes all deadlines for the project including the vertical prototype and the dissertation. Analysis was done on each major task within the project, with estimated times of completion made and filled out in the chart with one block corresponds to one week. Background reading for example nearly reaches across the entire timespan of the project as there is always different subject matter to be researched or solutions looked up. The time estimates for each task were liberally made to try and consider unexpected delays, inexperience in certain domains and balancing the rest of the years’ workload.

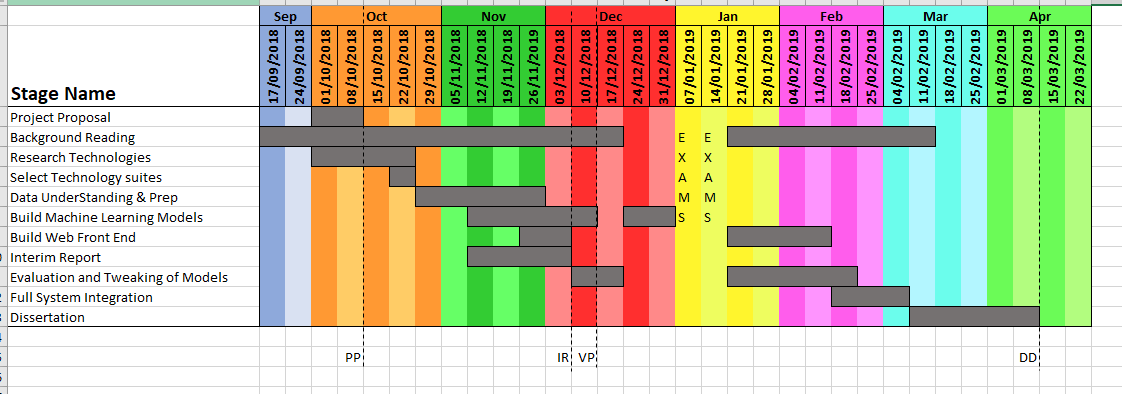


Figure 38 Initial Project Gantt Chart

## Final Plan

The Final plan can be seen below in Figure \* and shows a great deal of change in the second half of the timespan. This indicates that no matter how well you plan out something things can still go awry due to a variety of reasons. The main one in this instance is the fallout after finishing winter exams and how draining they can be.

It took a lot longer than originally anticipated to recuperate from them and once again have the mental drive to continue onwards with the project and even when this happened it was at a much slower pace. This meant that not only was there a delay in work but there was a decrease in the speed at which that work was getting done.

The evaluation and tweaking or experimentation of the machine learning models took longer to complete and work on the web front end didn’t resume until the start of March. This added some additional pressure knowing that the final stages of the project were being entered but through support from certain family members and friends, the rate of work got not just back on track but increased past the normal rate to make up for the few weeks in limbo. This meant that everything was in high gear when it came time to close out the last few objectives of the project.

*“Starting strong is good. Finishing strong is epic.” [\*]*

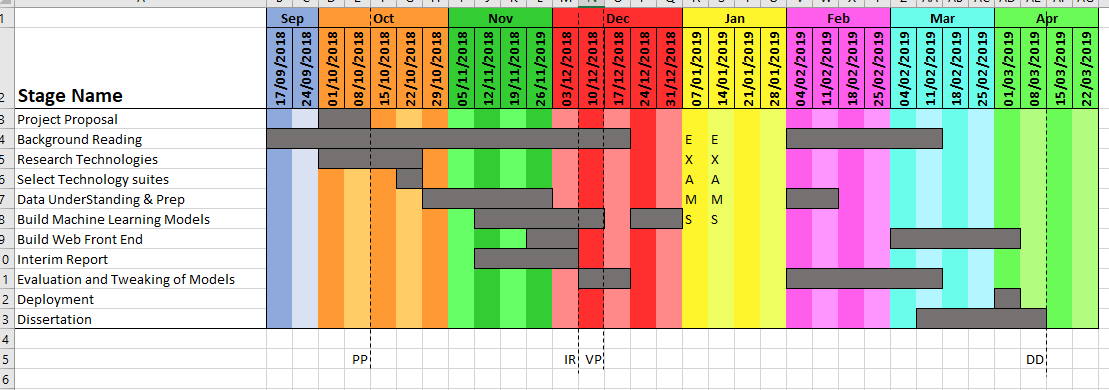


Figure 39 Final Project Gantt Chart

## Kanban & Trello

As mentioned previously in chapter 3, the Kanban subdiscipline of the Agile methodology was chosen to provide day to day management of the project while keeping track of the overarching objectives. A Trello account was created and two kanban boards created through it.

The first board, shown in Figure [\*], was used to keep track of the major objectives of the project, helping to keep the overall project on track without focusing on the individual tasks needing completion. This would be used at the start of the day to reflect on what stage the project was at and help figure out what tasks to work on in the second board.

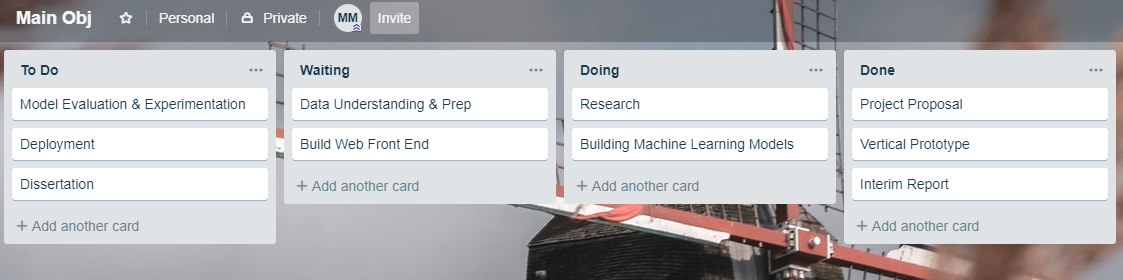


Figure 40 Main Objectives Trello Board

The second board, shown in Figure [\*], was used to for the day to day management of the project and had all the major objectives broken down into all their respective sub-tasks with some again broken down if they were too big. Every day the priority of all the tasks in the To-Do and Waiting columns were reassessed with new tasks being added throughout. Only two tasks were worked on at most at any one time, with tasks sometimes being moved back to Waiting so that other tasks could be completed. As tasks were completed, they were moved into the Done column and after a month archived from there to remove clutter on the board. This proved an incredibly effective way of managing the workflow for this project and even helped get everything back on track as mentioned previously as the focus was always on one or two tasks instead of the entire project looming over.

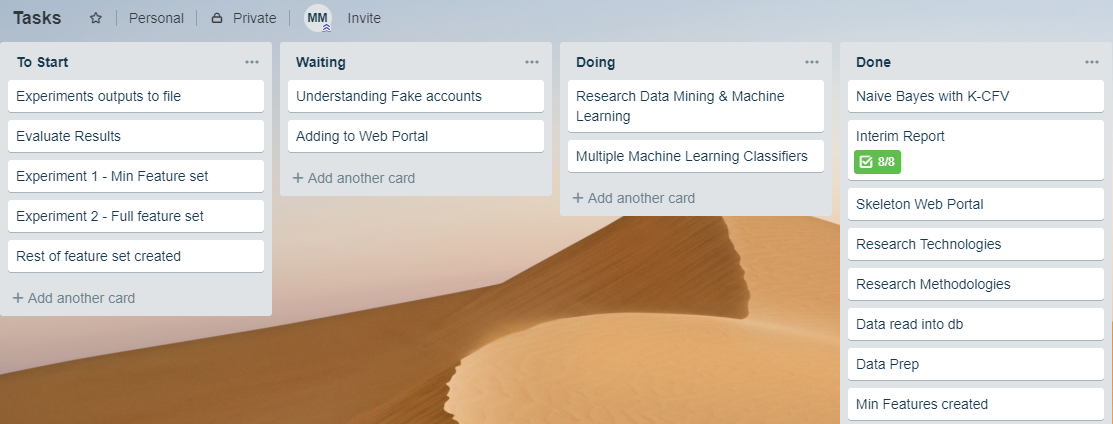


Figure 41 Tasks Trello Board

# Conclusions & Future Work

This chapter wraps the project up, giving reflections on the project and the personal growth achieved and lessons learned from start to finish and detailing several ideas for future iterations of the project, both for the data mining application and the web application.

## Conclusions

### Personal

This project has had its many highs and lows spread across the entire timespan. Some of the highs have directly followed some of the lows as a wall is hit during the completion of a specific task and attempt after attempt fails to solve the issue, leading to incredible frustration and a slight sense of hopelessness until finally a solution is found or thought of leading to a complete swing in mood and outlook as one feels nothing can stop you now.

Other highs have been simply making weekly progress with certain stages of the project and the feeling this consistent output of work gives. One of the main lows, as discussed when evaluating the project plan, was how long it took from the end of winter exams to get back fully into working on the project although this experience in the end will no doubt prove invaluable moving forward.

So much has been learned from every obstacle overcome, every topic researched, and every stage of the project completed that it seems weird to think back to the start of the project and compare how personal knowledge levels from then to now. All of this has contributed to a massive surge in personal growth that when combined with the experiences of work placement ensure that everything is in close to perfect order to make the leap from college to the workforce in a smooth and quick manner.

### Project

The project itself has shown how numerous different disciplines, methodologies and technologies can come together to achieve nearly any realistic, even some not so realistic, goal a person or group can come up with, albeit also reliant on that person or groups various skills too.

For example, while Python was used for both the data mining application and the web application, it could have been substituted with R for the former and Java for the later if someone preferred or needed to work with those languages. Next the CRISP-DM and Kanban project management methodologies could have been replaced with the SEMMA and Scrum methodologies with little disruption to the overall project.

The overall outcome of the project was rather satisfactory, as while some parts could have been implemented better, all the main objectives of the project were hit. The data mining application proved incredibly fruitful with a high level of accuracy achieved when making predictions about Twitter accounts. The web application did everything that was required of it although looking back, this is one part of the project that should have been expanded upon with more features implemented.

There was plenty of good feedback given during testing and self-analysis done once development was finished that means there are various ideas for the project in the future past college if so inclined and these are explored next.

## Future Work

### Data Mining Application

#### Find More Data

One of the most important and fundamental parts of the entire project was the procurement of relevant Twitter account data to be used to design accurate machine learning models in the classification of bot accounts. While the dataset used proved extremely helpful and up to the task, within the scope of the project, it is two years old and only contains data on approx. twelve thousand and five hundred accounts.

Being able to add to this dataset with more labelled Twitter accounts, both real and bot, would help with identifying them as some patterns may have been missed within the original dataset. Unless others have already done this and made their dataset available for public use, this would require a significant amount of work, as accounts would need to be chosen, labelled correctly and have their details and tweets saved.

The main issue is labelling them correctly as while the models built and used in this project are largely accurate, any inaccurate predictions made and used in an extended dataset would lead to further inaccurate models being made. The method used to label the original dataset would need to be investigated for use here.

#### Identify New Types of Bots

Completing the previous task would then potentially allow for the identification of new types of bot accounts that were either not identified back when the original dataset was being created or have arisen in the meantime.

These could be the same types of bot accounts that have had their parameters changed in a way such that their behaviour has changed significantly and as such can be classified as their own type or completely brand-new types of bot accounts that have been engineered with various new techniques to masquerade even more efficiently as human and as such pose even more of a threat to society as a whole.

Due to the ever-changing nature of technology and in this instance rise of new types of bot accounts, this is an especially important task as being able to at least keep up somewhat with this pace and identify them allows for Twitter users to be able to know more often then not when they are interacting with these new bot types.

#### Changes to Feature set

One of the main areas that would help with being able to better identify a real person, the known types of bots or any potential new types of bots identified in the previous task, would be to look at the set of features derived from user data and used to train and test the machine learning models.

Through further investigation and new insights gained from the previous two tasks, the feature set could be modified by either adding, removing or changing some of the features within it. These could range from simple tweaks to some of the ratios used between friend and follower counts of a user to more in-depth text mining on the users tweets and even looking at how if at all various bot accounts have interacted with each other and is there anything with those relationships that could be used to help better identify them.

### Web Application

#### Better UI

One of the main points taken away from the usability testing was that the UI was a bit plain and that the colour scheme could do with a slight change. Moving forward, the UI could be redesigned to take this and a few other minor response into consideration, leading to a much better layout and user experience. As UI design is not a strong point, a course on it would need to be taken to be able to rectify this area of inadequate skill and fully implement the changes in a way that will satisfy the userbase.

One part of the redesign would be to give an in-depth explanation of the predictions made around an account. This would take the form of what features are used in making the prediction, how they relate to the type of account that is predicted and which ones the predicted account satisfies.

#### Look at Friend and Follower accounts

A feature that could be added would be the ability to not just make a prediction on an account but also look at all accounts that account follows and is followed by and have predictions made on them. The results for these could then be presented via various types of charts such as a Pie chart or a Bar chart showing the totals of the different types of accounts predicted and then the user can drilldown and see the result for each individual account.

This would prefer immensely helpful for a person checking their own account as it would illuminate whether they interact with any bots or for someone checking an account to see has it paid for a number of follower boosting accounts to see if they really are as influential as they appear to be.

#### Mobile Application

One task that could be done in the future is to create a simple mobile application version of the web application that would also incorporate any changes made to the latter in the previous two task. This would allow mobile users to quickly check a Twitter account by opening the app on their phone instead of having to open a browser’s app and then navigate to the web page before being able to check an account.

It would have some inherent design differences from the web application as there are different design systems to follow when creating a mobile app compared with a web application. The mobile app would also be created independently of the web application as Python is not suited for this so Android Studio would be used. How the results from the data mining application is passed to and used by the mobile app would also need to be taken into consideration.

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