**Trump Tweets vs The Markets**

Final Report for CS39440 Major Project

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26th April 2018

Version 1.0 (Release)

This report is submitted as partial fulfilment of a BSc degree in  
Computer Science (G401)

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**Declaration of originality**

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By including my name below, I hereby agree to this dissertation being made available to other students and academic staff of the Aberystwyth Computer Science Department.

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**Acknowledgements**

I’d like to thank StackOverflow community for my Degree.

**Abstract**

“World events often have a great influence over international markets. Political uncertainty can often drive commodities up or down in value depending on where it occurs in the world. “[1]. Politicians of countries with the biggest markets have got a strong impact on the value of currencies and trading commodities. A simple message such as "With Mexico being one of the highest crime Nations in the world, we must have THE WALL. Mexico will pay for it…"[2] sent from the USA president's account can drop down Mexican Peso value. Trump’s infamous Twitter account, which is followed by almost 50 million people, can be an effective tool to influence the markets.

The goal of this project is to develop a system which considers the sentiment of tweets and can predict whether a stock index will increase or decrease depending on the current index, words, phrases and the sentiment of the tweet.

Python, Scikit-learn and NLTK (Natural Language Toolkit) are used to process the data in this project. The web interface is created using Flask framework.

The results show that when using a Naïve Bayes classifier, the accuracy of predicting the USD Index change is 53.6%, whereas the base rate of the three-class problem (up, down, no change) is 41%.

**Contents**

# **1. Background, Analysis & Process**

This section should discuss your preparation for the project, including background reading, your analysis of the problem and the process or method you have followed to help structure your work. It is likely that you will reuse part of your outline project specification, but at this point in the project you should have more to talk about.

# **1.1 Background**

# **1.1.1 Trump Tweets**

Trump is known for his controversial, outrageous and sometimes very hateful tweets. He tweets about 10 times every day and his account is followed by over 50 million people. His account is used to attack his opponents and BLBLBL

His tweets have got massive impact into markets and political scene. He admitted that without Tweeter he would not be a president.

(<https://www.independent.co.uk/news/world/americas/us-politics/donald-trump-tweets-twitter-social-media-facebook-instagram-fox-business-network-would-not-be-a8013491.html>)

His simple language makes them easy to analyse. He never uses a sarcasm or exquisite words. Due to the fact that his vocabulary is fairly small it is easy to build a machine learning classifier to do **WHAT**?

His tweets are also very emotional, petulant and sometimes aggressive what makes it easy to determine their sentiment by a computer. They also follow some patterns, most of his positive tweets end up with “Make America Great Again” phrase.

Analysing this data seemed to be very interesting because **BLALVLLV**

# **1.1.2 Machine Learning and Data Mining**

Machine learning and Data Mining becoming very popular nowadays. Internet is full of data that can be analysed and BLABALBA

## 1.1.3 Similar Systems

Tweets sentiment analysis, no clue what was used for

<https://dev.to/rodolfoferro/sentiment-analysis-on-trumpss-tweets-using-python->

Interesting was

<http://varianceexplained.org/r/trump-tweets/>

the analysis made by David Robinson (Chief Data Scientist at DataCamp)

comparing tweets content with the device they were send from (part of tweets is send from iPhone and some from Android). The results were interesting: most negative tweets attacking his rivals were sent from Android whereas iPhone was used more for benign announcements. The analysis concludes that tweets from these devices are written by different people. Almost all the tweets send with a picture or hashtags come from iPhone and most of “emotionally charged” words were common for Android device. What we can interpret from the analysis is that iPhone tweets are send by people involved in planning his schedule because words like “join” or “tomorrow” come from iPhone. Fact that Android tweets are more XXX can mean that these ones are sent by his public relations specialists or either be himself.

What was your background preparation for the project? What similar systems did you assess? What was your motivation and interest in this project?

## Analysis

Most of the twitter sentiment analysis examples in the Internet use ready-made analysers like the one build-in in the TextBlob. This approach is fast and XXX but too universal. It was assumed that it is better to build own classifier because peoples language is different and one people words can have different emotions when spoken by someone else. For example, words like “Mexico”, XXX, XXX are neutral but in Trump's tweets they usually have a negative attitude. Another example could be “Make America Great Again” which in all of the cases goes in positive tweets.

MUCH MORE THERE

## Process

You need to describe briefly the life cycle model or research method that you used. You do not need to write about all of the different process models that you are aware of. Focus on the process model that you have used. It is possible that you needed to adapt an existing process model to suit your project; clearly identify what you used and how you adapted it for your needs.

Deciding about the development process was simple. It was decided to use agile methodologies because

With waterfall methodology it would be very likely that there will not be enough time to do tests because implementing all of the features took too much time.

We are sure that if there would be too little time then we will still be able to deliver some working software. CZY TO DOBRY CZAS?

Methodology that fit the project specification the best is XP (Extreme Programming). Weekly meetings with a supervisor can be treated as client meetings during which a further direction is determined. Each week can be treated as a sprint within which there should be planned adding a small functionality to the project. Pair programming obviously could not be implement due to the only one developer but the rest of XXX fits the project perfectly.

The project was split into sprints:

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | W1 | W2 | W3 | W4 | W5 | W6 | W7 | W8 | W9 | W10 |
| Setting up Git, IDE, research |  |  |  |  |  |  |  |  |  |  |
| Data collection |  |  |  |  |  |  |  |  |  |  |
| Sentiment analysis |  |  |  |  |  |  |  |  |  |  |
| Phrases extraction |  |  |  |  |  |  |  |  |  |  |
| Markets model building |  |  |  |  |  |  |  |  |  |  |
| Feature selection |  |  |  |  |  |  |  |  |  |  |
| Creating a webpage |  |  |  |  |  |  |  |  |  |  |
| Adding new currencies |  |  |  |  |  |  |  |  |  |  |
| Integration tests |  |  |  |  |  |  |  |  |  |  |
| Writing a report |  |  |  |  |  |  |  |  |  |  |

Alternatives that were considered for the project were Scrum and XXX. Scrum would be rather more efficient in team work that in single person project.

# Design

## Overall Architecture

### 2.1.1 Tools and Technologies

Very important part of staring the project is to select programming language and libraries that will be used. More about blabla

**2.1.1.1 Programming Language**

When choosing a programming language, main criterias were usability for the project, its libraries, ease of use and experience. The language should provide:

* Machine learning and natural language processing libraries
* Simple Web framework
* Ease of experimenting
* Simple tools to gather the data from web APIs
* Simple tools to do data manipulations and analysis

In this project Python was the best choise. It provides very popular and in-depth machine learning libraries (NLTK, Scikit-learn, Textblob), web frameworks (Flask, Django, Pyramid) and Interpreter which is useful to do quick, ad hoc experimenting. It also provides a Pandas library that allows to form data into DataFrames what is very handy in data analysis and provides many build-in data processing functions. This language was also used by the student during the Industrial Year. Python is also very popular and has got documentation and there is many tutorials and snippets available in the Internet.

Other languages that were took into account are:

* **R** - has good ML and data processing libraries but has not got any libraries providing a way to create a web interface.
* **Ruby** – provides good web framework (Ruby on Rails) but does not provide good libraries/gems to do ML. There is Weka for JRuby or other ways to use Java Weka library in Ruby.
* **Java** – Provides many web frameworks such as Spring, JSF or Vaadin. XX also can use Weka (Waikato Environment for Knowledge Analysis) that is a very popular software suite.

Moreover, choosing Python is a good opportunity to develop skills that are used in the industry and meet the needs of the labour market.

In the project was used the most recent Python version what is 3.6.

**2.1.1.2 Libraries**

To do a language processing, firstly was used Textblob library which is built on top of NLTK but unfortunately due to the poor documentation and lack of its capabilities there was made a decision to move into NLTK.

To build a classificator which predicts market changes there was used Scikit-learn. It has got good documentation with many examples and there is also many topics about it on sites such as StackOverflow.

Other possibility would be to use Weka but it would require to use either Jython(implementation of the Python language for the Java platform[3]) or run Weka library using wrappers around JNI calls such as javabridge(package that allows Python to interact with JVM[4]) but both ways are too complicated.

The web interface of the program is very simple so I chose Flask. It is a micro web framework using Jinja2 template engine. It allows to create simple pages in very easy way. I did not use Django because it is rather better for more complex webpages. Pyramid is also good for creating simple webpages but is much less popular, what makes it harder to find some solutions ETC in the Internet.

I also used Mlxtend library to sue Apriori algorithm, Nose to do unittests and Flask-SQLAlchemy to quickly create a simple database in Flask.

To do data processing I also used Pandas and NumPy which are the most popular Python libraries providing …BLLBLB

To scrap tweets from Twitter API I used a Tweepy library which is the most popular and very simple.

# **2.1.1.3 Data storage**

CSV and SQLALCHEMY

**2.2 Detailed Design**

The project can be split into main two parts: market analysis and web interface. Therefore, it was split the into three packages separating project concerns:

* Markets package
* Webpage package
* Tests package

**2.2.1 Markets package**

All the code in “markets” package was split into modules that group together logically related code.

Write that python is not oop and that’s why there is almost no classes

**Dataset** – a module with a TweetsDataSet class that wraps a pandas Dataframe and represents a set of tweets with their features, sentiments and market affects.

**Tweeter Scrapping** – a module used to scrap tweets from Tweeter.

**Phrases Extraction** – contains a PhrasesExtractor class which builds a vocabulary of phrases and words found in the set of texts and then extracts those features from particular tweets.

**Sentiment Analysis** – module containing a class responsible for tweets sentiment analysis. It wraps NaiveBayesClassifier from NLTK library and uses a PhrasesExtractor to extract features from tweets which are then used to train a model or predict a value of the particular tweet. All the functionality was wrapped in a class because it is more convenient to load and save the Analyser and perform any tests.

**Tweets Features Extraction** – contains all the functions used to extract features from the tweet such as sentiment and phrases/words in the tweet. To gather those informations uses SentimentAnalyser and PhrasesExtractor instances.

**Feature Selection** – module containing functions responsible for selecting the most significative sets of features to obtain the best accuracy.

**Currency Analysis** – a main module that connects all the functionalities. There is a CurrencyAnalyser class that is used to analyse a CSV file of stock prices and provide results of this analysis such as association rules, model to predict markets or the most coefficient features. It holds the functionality of reading files and saving the results.

**Association** – a module holding all the code that is responsible for reading stock prices from files and merging then with tweets datasets.

**Market** **Predicting**– contains all the code that is responsible for training a classifier that predicts stock changes. Contains 3 classes: Classifier representing a classifier model (MultinomialNB by default) and wrapping all its functionality, AnalysResult that represent a result of a single tweet analysis, MarketPredictingModel that contains two Classifier objects and decides which one to use to do a prediction.

**Rules** – contains functions used to do association rules learning.

The markets module has got also a “data” and “pickled\_models” directories. “data” folder stores all data used to do analysis such as a list of stop words, scrapped tweets and CSV files generated by the application. “pickled\_models” stores saved sentiment analysis and market predicting models.

**2.2.2 Webpage package**

Webpage module has got a typical structure for Flask projects.

It is split into:

* Static folder – holding static files such as images or CSS styles
* Templates folder – holding Jinja2 templates that are filled with content by views.
* Views.py – this is where routes are defined. It defines routes for each currency and gathers data that is send to the templates and presented.
* models.py – holds Currency model. This model stores information about currencies such as its name and accuracy of the model in database.
* \_\_init\_\_.py – Initializes the application, sets up its configuration and database.
* Currencies.db – stores Currencies models that can be loaded when application runs.

**2.2.3 Others**

Apart from these 3 packages there is few more files typical for a Flask project:

* -manage.py – a script used to init/drop database, fill database with some sample data and to run the webpage.
* -requirements.txt – file containing a list of packages that are used in the project and have to be installed
* -README – file explaining how to run the program

## Tools used to develop the project

For my Python IDE I chose PyCharm made by JetBrains company. I used it during my Industiral year and I really liked it. It has got all code assistance features such as syntax and error highlighting. It supports Flask projects and many file extensions such as html, css, js, csv which I used in a project. It also has got integrated debugger which I used a lot.

To keep track on changes and have a backup of the work I set up a Github repository. Backups of the work were kept on the Github repository and two machines the student worked on. As a Git client for the machine with Windows OS was chosen GitKraken and command line git for the machine with Linux.

# Implementation

**3.1 Data gathering**

**3.1.1 Tweets scrapping**

First step was to gather Donald Trump tweets. For this purpose, there was used TweePy library that allows to fetch data from Twitter REST API. To communicate with the API, it was necessary to create an account and obtain a customer key and access tokens.

The first task to do with tweets was a sentiment analysis, there had to be collected small amount (about 120) of tweets manually. Writing a scrapping script was very useful at this stage because it allowed to fetch particular tweets data from the API by the ID of the tweet. The data such as tweet id, creation date and text were saved to the CSV file.

Next step was to scrap all the tweets since the begin of 2017. It is a bit before Donal Trump become a president so his tweets began to have some influence on markets. Tweepy provides also a special function to get posts from users’ timeline. Unfortunately, it allows to get only 200 tweets at once so I had to do it sequentially. Twitter also allows only to scrap last 3240 of user tweets and hopefully there was obtained 2935 tweets from 01.2017 to 03.2018.

**3.1.2 Stocks data**

Obtaining stocks indices data was XX part of the project because all the webpages that archive historical stock data provide only daily-interval stock prices changes due to the amounts of this data. All the websites XXX during the project XX data with smaller intervals (such as hourly changes) for money. In consequence, all markets changes analysed in the project are daily open-close price changes.

**3.2 Sentiment Analysis and Phrases Extraction**

**3.2.1 Data selection**

To begin with a sentiment analysis there was scrapped 120 tweets manually and their sentiment was marked manually. It was decided that half of them had to be positive and half should be negative to have balanced classes – ADD WHY?

Tweets were selected regardless of the date. The most important aspect was to find ones that are clearly positive or very negative to train the model as best as possible.

Tweets were found using Google by searching phrases such as “Most positive Trump tweets”, “The worst Trump tweets”. Very useful was the website: <http://www.trumptwitterarchive.com/> where we can see the most popular keyword in his tweets and search for them.

**3.2.2 Building a model**

When the dataset was selected, the next step was to build a classifier.

To train a model tweets had to be split into folds to do a cross-validation what prevents overfitting and gives more reliable results. Due to the fact that scikit-learns Kfold functions seemed to be complicated there was a decision to write a folding function manually. The code was splitting a corpus into K chunks with preservation of stratification (each chuck had half of the tweets positive and half negative).

Building a text classification system with Textblob is very trivial:

cl = NaiveBayesClassifier**(**train\_data**)**

cl.classify**(**"This is an amazing library!"**)**

The Classifier object just has to be fed with list of tuples, and each tuple has to consist of tweet text and marked sentiment.

To ensure that results are reliable the training process was run 40 times with 10-folds cross validation and the result accuracy is a mean from those 40 runs. The results seemed to be surprisingly good. Naïve Bayes had 82% of test accuracy. Unfortunately, after investigating the most informative features it turned out that the most decisive features were words such as “are”, “there” or even punctuation marks such as brackets. That meant that the model was overfitted and instead of making decisions based on words such as “good” or “bad” was using the most common words in the language. Even the sentence contained many negative words like for example: “Crocked Hillary Clinton ….” Was marked as positive because it just had a word “AND”.

**3.2.3 Features extraction**

Once it had been discovered that TextBlob does not extract phrases properly and it does not provide easy option to change it, it was necessary to move into NLTKs’ classifier.

Next step was to write a custom feature extracting function that splits tweets into words. To do so were used very simple NLTKs’ functions: sent\_tokenize and word\_tokenize that split text into sentences and then into words. All the extracted words then had been lowercased because “Then” and “then” is the same word. Unfortunately, even that these functions are the part of so popular and reputable library, they had problems with splitting even simple sentences and words such as “doesn’t’ were separated into “does” and “’t”. Moreover, the model was still making decision basing on words such as “Did”, “of”, “And”. These senseless words are called stop words. These are words that are common in the language and do not tell anything about the meaning of the sentence.

Once it had been discovered that NLTK tokenizing functions cannot handle extracting words and phrases there was few alternatives checked out such as NLTKs ConllExtractor and FastExtractor. Most of them had problems with splitting the sentence properly. They either extract useless stop words or do not extract half of the important phrases. The only one that does it very well is a TextRazor – cloud service providing a deep learning analysis using their web API. Unfortunately, TextRazor is not free so the decision was made to write a custom phrase extractor.

After some research there was found easy to implement algorithm called RAKE(Rapid Automatic Keyword Extraction). There is many its implementations in the web but it was decided to write own extractor basing on LINK HERE. This one was selected because it is simple but it had to be modified because does not have enough configuration options and has too many redundant functions. Originally RAKE extracts also adjusted keywords (ones that include a stop word such as United States OF America). This functionality was also added but was dropped later on due to the lack of these phrases in the corpus and risk of leading to unnecessary False Positives.

Feature extractor algorithm basically extracts candidate phrases by splitting text by stop words. A list of stop words used in the project was downloaded from the Internet. LINK HERE

Then candidate phrases are sifted by their length and number of occurrences. Phrases that are not accepted are split into words.

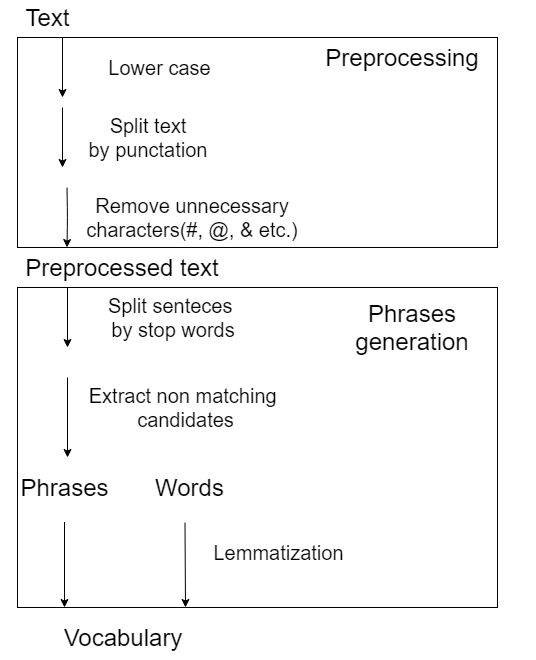
Accuracy of sentiment analyser while using a custom feature extractor increased to 84% and it is more reliable because the most informative words now are more sensible:

SCREEN HERE

The next step to improve the accuracy was to lemmatize words. It means that all inflected words were reduced to the root form (for example playing, plays, played into play). This time NLTKs lemmatize\_word function was sufficient. When subjected all the words to lemmatization, a test accuracy has increased to 86%.

The overall process of building a vocabulary looks as follows:

SCREEN HERE



The process of training a classifier looks as follows:

* Building a phrases extractor vocabulary from tweets
* Extract features from each tweet
* Train a model using market features and their target (sentiment)

Then the process of analysing a particular tweet looks as follows:

* Pre-process tweet (lower case, split by punctuation, remove unnecessary characters)
* Find matching phrases and remove them from tweet
* Split the rest by stop words to get rid of them
* Lemmatize words
* Mark words matching with the vocabulary
* Pass the features vector to the model to classify it

**3.4 Markets predicting**

Once the sentiment analysis part was done, the next step was to build a market predicting model.

MOZE TU WRZUCIC O TWEETERZE?

Before training a classifier, the dataset was preprocessed:

- all the tweets containing only video/image and no text were removed

- tweets written in languages other than English were removed

- Unicode characters were removed such as ✔💜 ➡✅

- some Unicode characters were changed into proper words or characters: &amp -> and

- from the tweets were removed all the links

- manually removed all the tweets that could not have any impact such as “Happy birthday”

- manually removed all short and meaningless tweets such as “Jobs, Jobs, Jobs”

- removed all retweets

- merged tweets that were separated into few tweets because were too long (Twitter allows tweets to be max 140 chars length so when they exceed the limit they are split into few separate ones that start or end with “…” ) EXAMPLE?

Then the dataset has decreased into 2026 tweets. All the tweets got the market change set up using the CSV file with stock prices. It was assumed that tweets affect the market within few hours so each tweet had got assigned a percent change of the index during the day it was published. It was also decided that all the tweets that are published after 10pm got the change value from the next day. MORE HERE

Market changes above 0 were marked as positive and the rest as negative what gave a binary target.

Then for each of the tweets sentiment was predicted and features extracted.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Tweet** | **Sentiment** | **Feature 1** | **Feat 2** | **Feat 3** | **…** | **Feat n** | **Change** |
| Tweet content | Pos | 1 | 0 | 0 | … | 1 | 0.05% |
| Tweet content | Neg | 0 | 1 | 0 | … | 0 | -0.12% |

That prepared dataset could be now used to train a model.

Experiments were performed using Weka J48 and SciKitLearns Naïve Bayes and Logistic. All of them was run with 10-fold cross validation. The base rate accuracy was 52.6%

To build a model there was used a Scikit-learn MultinomialNB and LogisticRegressionCV. First one is a Naïve Bayes classifier implantation that is suitable for classifying discrete values such as “Down”, “No change”, “Up. Logistic regression classifier used is also know as logit, MaxEnt (<http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegressionCV.html>)

It uses a cross validation to find the best hyperparameters to the data, what is very handy.

The data that is fed to the model has to be in proper format. Training data has to be split into 2D array of features and their marks for each instance and 1D array of results for each instance.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 2D array of 2 instances with 5 features:   |  |  |  |  |  | | --- | --- | --- | --- | --- | | 1 | 0 | 1 | 0 | 0 | | 0 | 0 | 0 | 1 | 0 | | 1 | 1 | 0 | 0 | 0 | | 1D array of targets for 3 instances:   |  |  |  | | --- | --- | --- | | Up | Down | Up | |

Using a DataFrame to store data was useful there because it was easy to format this data in such a way.

Then the model was built 30 times to take average of different randomized runs. 30 gave the same results as 100 so there was no point to run it more times.

Each run trained a model 10 times (10-fold CV) with stratified folds.

The model was build using XXX objects and over 6000 features and the accuracy that was obtained looks as follows:

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve bayes in scikit-learn | 54.9% | 90.6% |
| Logistic in scikit-learn | 51.6% | 100% |
| J48 in Weka | 51.2% | 81.5% |

Feature extractor was extracting over 6000 of features form the dataset what was a lot and the model needed a lot of time to train. The model was also trained using features that occurred only once or twice what just lead to overfitting.

Therefore, feature selection was necessary. Running any feature selector on that big dataset would result on a very long time of processing so it was decided to remove features that occur only few times. After a bit of experimenting it was decided to remove features that occur less than 7 times because it decreased a number of features to more practicable size (1185). It also diminished overfitting and gave a bit better test accuracy:

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve bayes in scikit-learn | 56.6% | 70.3% |
| Logistic in scikit-learn | 52.0% | 84.0% |
| J48 in Weka | 51.8% | 76.7% |

Once the number of features was dropped it was easier to try different feature selectors. The easiest way was to export the dataset to a CSV file and perform a selection in Weka. Many trials have been carried out with various selectors and finally the “Wrapper Subset Evaluator” proved to be the best.

It selected 116 best features what gave … Write how many features and tweets now

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve bayes in scikit-learn | 67.8% | 70.0% |
| Logistic in scikit-learn | 66.8% | 69.2% |
| J48 in Weka | 62.0% | 69.4% |

After that Weka was not used anymore to build a classifier due to the fact that uses only one thread, it is extremely slow and it is more convenient to process data and build classifier in python at one go without saving to file and bothering with opening it in Weka.

Target change

Since some of the tweets are completely neutral and have no influence into markets, there was add third target: No change…. BLABLBABLBA

In the USD Index dataset there is about 3% of days that the stock did not change at all. To get three classes more balanced there had to be some threshold set up to increase a set of “No change” objects. Following feedback from the project supervisor, it was decided that the threshold should be calculated using a standard deviation. To obtain about 1/3 of the targets as a no change the threshold is calculated by 1/3 of the standard deviation distance from the mean:

def calculate\_thresholds(stock\_prices):  
 mean = stock\_prices.mean()  
 sigma = stock\_prices.std(ddof=0)  
 lower\_threshold = (mean - (sigma / 3)).round(2)  
 higher\_threshold = (mean + (sigma / 3)).round(2)  
 return lower\_threshold, higher\_threshold

The base rate accuracy was changed into 41% due to the change into 3-class problem.

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve Bayes | 52.7% | 59.7% |
| Logistic regression | 49.1% | 54.0% |

Jakiś komentarzyk do tego?

After some investigation in was discovered that if a lot of features is removed then there is many objects left without any feature marked. For example if tweet “Happy Birthday” had marked “happy” and “birthday” features marked and they were deleted then the instance is useless. Those instances do not WPOWEADZAJA ZANDEJ on the decision process because only feature that was taken into account was their sentiment.

After removing tweets that do not have any feature the dataset length decreased into XX objects.

Model trained on that dataset gave better accuracy:

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve Bayes |  |  |
| Logistic regression |  |  |

XXXXXXXXXX

The next step was to mark features again. Due to the fact that the feature extractor extract features in more greedy?? Way words are not extracted from market phrases so if “Crooked Hillary Clinton” is found then words “Crooked”, “Hillary” and “Clinton” will not be marked. WHY IS IT BETTER

(Marking everything what was found was dropping the accuracy for about 2%)

If some phrases are found the text then they are removed and words that this phrase consist of are not marked.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Crooked** | **Mexico** | **Reform** | **Proud** | **Crooked Hillary Clinton** |
| Crooked Hillary Clinton is the worst loser of all time. | 0 | 0 | 0 | 0 | 1 |

After deleting “Proud” and “Crooked Hillary Clinton” it is needed to mark features again to mark words that may had been be in removed phrases.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Crooked** | **Mexico** | **Reform** |
| Crooked Hillary Clinton is the worst loser of all time. | 1 | 0 | 0 |

Marking features again resulted in better accuracy and X instances less to delete

|  |  |  |
| --- | --- | --- |
| **Classifier** | **Test accuracy** | **Train accuracy** |
| Naïve Bayes |  |  |
| Logistic regression |  |  |

The next change that was performed was making a sentiment to be a continuous value. Before the sentiment was marked as 0/1 (pos/neg). Some tweets could be more neutral and some evidently EMOCIONAL?. Therefore the sentiment values has been changed into continuous values from 0 to 1. Although it did not change the results for Naïve Bayes at all and Logistic regression train accuracy changed only for 0.01%. This is probably due to the large number of features and the fact that Naive Bayes treats features independently so chaning one feature, and moreover in a small extend, had no influence on the result.

Started trying to automate a process

TO AUTOMATE used REFCV but it was simplyfying the problem leaving small nr of features and tweets

Added running weka in process and new currencies

Results here

**3.5 Rules learning**

Once the model was working properly next thing that was done was association rules learing. It is a " is a rule-based machine learning method for discovering interesting relations between variables in large databases” (wiki).

The algorithm that has been used is Apriori. The outcome of the learning process is a a set of rules. Each rule consists of antecedents and consequents. Antecedents are words whose appearance is accompanied with consequents.

For example, this rule tells us that if in any tweet in the dataset has got words “Dossier, Hillary, Trump campaign” it also has word “Clinton”:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Antecedents** | **Consequents** | **antecedant support** | **consequent support** | **Support** | **Confidence** | **LIft** |
| dossier, hillary, trump campaign | clinton | 0.00185014 | 0.03607771 | 0.00185014 | 1.0 | 27.7 |

Support is an indication of how frequently the words set appears in the dataset.(wiki)

If there were 1080 tweets and this words set occurred twice the support is 2/1080 =

0.00185014.

Antecedant support is

Consequent support is

Confidence tells us how often the rule has been found to be true(wiki). In this case Everytime those atecendants occurred in a tweet, word “Clinton” occurred as well.

Lift is a the ratio of the confidence of the rule and the support of the consequents (<https://www.ibm.com/support/knowledgecenter/en/SSEPGG_9.5.0/com.ibm.im.model.doc/c_lift_in_an_association_rule.html>)

Greater lift values indicate stronger associations what can be interpreted as an importance of a rule. (source lift from wiki)

Rules are different for each currency because dataset used to build models are sifted differently. Rules presented on the webpage are filtered by number of occurencies(at least twice). It was decided that there is no point to present a rule that occurred only once.

Rules presented on the webpage are grouped into words set. For example

daca, drug => military and drug military => daca are grouped into one set of words. Both of them have got the same confidence and support. That way of presenting results is more readable. By clicking on the words set, rules containing these words are presented.

****

**COEFFICIENT FEATURES**

**3.6 Flask webpage**

# Testing

How does this testing address the requirements and design for the project?

How comprehensive is the testing within the constraints of the project? Are you testing the normal working behaviour? Are you testing the exceptional behaviour, e.g. error conditions? Are you testing security issues if they are relevant for your project?

## Overall Approach to Testing

## Unit testing

Testing was carried out throughout the entire development process.

The chosen strategy was TDD (Test driven development) so while adding new functionalities, tests were written first and then was added code to fulfill those tests. Writing unit tests was a basic premise of the project because they prove the quality of the code and that it works at all. Having a set of tests is extremely helpful when modifying the code because we know that while adding one feature we do not break another. To write unit test there was used built-in python “unittest” module and “nose” to run them. Nose finds all the tests in the module and runs them in more user-friendly way, errors are more readable. There were also necessary “mock” and “parametrized” modules to mock out and monkey patch some parts of code and run parametrized tests to avoid code duplications.

There was a couple of exceptions of unit tests.

Scrapping code was not tested at all because the script was used just to download tweets and there was no point to test it. The code worked properly and tweets were scrapped as assumed. If the program was developed more, there was added a feature to choose any politicians’ tweets and scrapping was be done automatically, then tests would be obviously required.

Another code that was not unit tested was initially the code that processes DataFrames. At the beginning all the experiments were performed just in one go. The data was loaded into a DataFrame and processing was performed in a pipeline. That approach was quick for experimenting but hard to test. It would require some mocking, patching and writing many sample DataFrames, which structure also was changed many times at the begin.

When the tweets processing and classifying part of the code became more complex, the program was split into more object-oriented way. All the DataFrame code was wrapped into a DataSet class encapsulating all the DataFrame operations what testing easier because more units were **possible** to be test without involving DataFrames and creating whole datasets just to test one simple function.

Tests do not check too many exceptions that could occur during input files and dataframes analysis. The program assumes that they are in correct format. If the project was developed a bit more and allow users to add custom stock files then there would be much more tests to write and more corner cases to investigate?

Unit tests cover XX % of the code. Some of the functions were not tested because they were too simple like for example saving to file or using other libraries.

Most of the functionalities that are not tested separately in unit tests are tested in integration tests.

## Integration/Acceptance Testing

When it was certain that smaller bits of code work then next step was to write integration tests. This is also very important suite of tests that proves that all the bits of code will work together and the program They test functionality of every feature.

To write integration tests was used a Behave module. It is an equivalent of Cucumber – popular testing framework among Ruby on Rails’ community. All the features are tested by writing scenarios. All the scenarios are written in Gherkin – a simple human readable language for automated tests. Write how it works

It keeps high level concerns separated from the code and allows non-technical people to write tests. MORE

**Scenario:** Extract words  
 **Given** we have vocabulary of: cucumber, apple, banana, tomato  
 **When** we extract phrases from the sentence: I like to eat apples and bananas  
 **Then** we get apple, banana extracted

Functionalities that were tested are:

-Phrases extraction

-Sentiment analysis

-Stock prices prediction

Models use Scikit learn classifiers what would make testing hard and unrepeatable, therefore it was decided to mock out the models for tests. Anyway the tests should verify the correctness of links among the bits of the project and should not tests third-party code. Mocking out with auto-speccing (mock module makes sure that the patched code has got the same interface) should be sufficient in this case.

## ****Usability testing****

Usability testing is technique used to evaluate how easy is the interface to use. The webpage in this project is only used to present the results and only functionalities are changing currencies pages and analyzing tweets what was quickly tested by the student and supervisor.

# Critical Evaluation

such questions as:

* Were the requirements correctly identified?
* Were the design decisions correct?
* Could a more suitable set of tools have been chosen?
* How well did the software meet the needs of those who were expecting to use it?
* How well were any other project aims achieved?
* If you were starting again, what would you do differently?

The aim of this project was to determine if there is any connection between Trump tweets and the markets. It was also decided to analyze the tweets dataset and find out what we can learn and what information we can gather.

The goal has been achieved, there was found a relationship between tweets and the markets. The classifier is able to predict the currency change much better than if it was doing randomly (53% accuracy to XX base accuracy).

The most coefficient features while training the model turned out to be quite sensible:

FEATURES HERE

Python was a great choice for this project. It had all the functionality required for the task, all the needed libraries were available, up to date and well-functioning. Programming in this language was very quick and allowed to do quick experiments.

If you were starting again, what would you do differently?

* Write data processing in more object-oriented way instead of using DataFrames. I would just make a DataSet class that would have a list of tweets and each tweet would store information about its features and sentiment. I think that I would make processing slower but it would help to achieve more modularity and lower cohesion. Therefore, testing would be easier.
* I think that if code was written more modular then it would be easier to test and mocking would not be so much need in some places.

Some of the tasks that were specified as additional, to do in the spare time were not accomplished because required more work to do. The program is ready to implement an option to add custom stock prices or even select from them on the webpage to be scrapped from the internet but it would require to verify the input ,check a lot of corner cases and handle all of the possible exceptions . It was decided to do not even start doing this because it would require a lot of time to do it properly.

# Appendices

If you have taken an agile approach to developing the project, then you may be less likely to have developed a full requirements specification. Perhaps you use stories to keep track of the functionality and the ’future conversations’. It might not be relevant to include all of those in the body of your report. Instead, you might include those in an appendix.

# **A. Third-Party Code and Libraries**

TextBlob – a free library for processing textual data.( FROM http://textblob.readthedocs.io/en/dev/index.html) Was dropped and scikit learn was used in lieu

SciKit-Learn – Python machine learning library. It was used to do cross-validation and build classifiers It is free and open source. This library is released using BSD license.

Weka – is a suite of [machine learning](https://en.wikipedia.org/wiki/Machine_learning) software written in [Java](https://en.wikipedia.org/wiki/Java_(programming_language)). It is [free software](https://en.wikipedia.org/wiki/Free_software) licensed under the [GNU General Public License](https://en.wikipedia.org/wiki/GNU_General_Public_License). (<https://en.wikipedia.org/wiki/Weka_(machine_learning)>)

It was used to for experimenting with the data and to do a feature selection. It is run by the program by a subprocess XXX command. Weka Jar file is included into the project directory. Version 3.8.2 was used.

Mlxtend – The project used this library to do association rule learning with Apriori algorithm. It is released under BSD licence. Version used 0.11. (https://github.com/rasbt/mlxtend)

Pandas – library used to do data manipulation and analysis. Library is released using BSD license. Version used 0.22.0

TweePy – Python library used to access the Twitter API. It is released using MIT license. Version used 3.6.0 (<https://github.com/tweepy/tweepy/blob/master/LICENSE>)

Behave

Flask, ChartJS bootstrap

All those libraries were used without modification.

1. Ethics Submission
2. Code Samples

ANYTHIING THERE?

Only include code in the appendix if that code is discussed and referred to in the body of the report.

# Annotated Bibliography

This final section should list all relevant resources that you have consulted in researching your project. Each reference should also include a brief annotation.

1. Neil Mac Parthaláin, “MMP: Project descriptions”, 2018 (Online) Available at: https://teaching.dcs.aber.ac.uk/mmp Accessed April 2018.

2. <https://twitter.com/realdonaldtrump/status/901802524981817344>, 27th Febuary 2017. Accessed April 2018.

This is of Donald Trumps’ Tweets.

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4. https://pypi.python.org/pypi/javabridge/1.0.17

1. Sylvia Duckworth. A picture of a kitten at Hellifield Peel. <http://www.geograph.org.uk/photo/640959>, 2007. Copyright Sylvia Duckworth and licensed for reuse under a Creative Commons Attribution-Share Alike 2.0 Generic Licence. Accessed August 2011.  
     
   This is my annotation. I should add in a description here.
2. Mark Neal, Jan Feyereisl, Rosario Rascunà, and Xiaolei Wang. Don’t touch me, I’m fine: Robot autonomy using an artificial innate immune system. In *Proceedings of the 5th International Conference on Artificial Immune Systems*, pages 349–361. Springer, 2006.   
     
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3. W.H. Press et al. *Numerical recipes in C*. Cambridge University Press Cambridge, 1992.  
     
   This is my annotation. I can add in comments that are in **bold** and *italics*and then further content.
4. Various. Fail blog. <http://www.failblog.org/>, August 2011. Accessed August 2011.  
     
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5. Apache Software Foundation (2014) “*Apache POI - the Java API for Microsoft Documents*” (Online) Available at: [http://poi.apache.org](http://poi.apache.org/) Accessed: 14th March 2014.
6. Apache Software Foundation (2004) “Apache License, Version 2.0” (Online) Available at: <http://www.apache.org/licenses/LICENSE-2.0> Accessed: 14th March 2014.
7. Neil Taylor, “MMP: Final Report and Technical Work”, 2017 (Online) Available at: <http://blackboard.aber.ac.uk/> Accessed 26th April 2017.

A document that outlines information about the marking guide for the Final Report and Technical Work. This document was referred to as Structure of the Final Report before academic year 2016-2017. This is published in the Assignments folder. If you are logged in to Blackboard, you can access the folder using <http://jump.aber.ac.uk/?sxxpt>.