Fake News Identification
4th Year Project

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Except where explicitly stated all the work in this report, including appendices, is my own and was carried out during my final year. It has not been submitted for assessment in any other context.

Signature: ____________________ Date: ____________________

Contents

Chapter 1

Introduction

Fake news on social media platforms have become prevalent over recent years, more notably during the 2016 Presidential election - where many criticised social media platforms Facebook and Twitter for a lack of censorship and ultimately blamed the outcome of the election (Naughton (2016)). Scotland's independence referendum had an outcome which was also a victim of voters being heavily influenced on ”news” they had read on social media platforms (Langer et al. (2019)). Individuals supporting either potential outcome used social media platforms in a form of scaremongering, swaying undecided voters to their respective causes.

1.1 Aims

The main aim of this project was to create a program that would be capable of being able to detect a Twitter post (also referred to as a ”Tweet”) containing fake news. This could be executed in a number of ways; allowing users to analyse single Tweets, a collection of Tweets containing a hashtag (a keyword or phrase given to describe the Tweet) or potentially as an automated program that could detect trends and spikes in social media activity and then be able to analyse larger sets of data to warn users of the sincerity of a Tweet - without requiring an analysis request from the user. Posts made on Twitter are uncensored and therefore are able to convey the raw emotion behind the words published, this sentiment can be analysed using many of the techniques available through certain programming practices.

1.2 Objectives

Throughout this project, there were multiple objectives to meet in order to achieve the desired outcome of this proposed project.

- Both learn and apply Python 3 in practice.
- Understand how various analysis algorithms operate and how suitable they may if applied in respect to this project.
- Implement a chosen Python 3 library and algorithm in an efficient and robust way, in order to correctly classify Tweets with minimal execution time.

Chapter 2

Related Work

To fully understand the aim of this proposed project, I carried out a rigorous analysis of any existing systems which are related to the project which was to be completed. The term "Fake News" was dissected to the following definition: **information with a heavily biased viewpoint from the source.** The aspect of sentiment analysis was largely focused on during my research as this plays a key factor in detecting fake news as well as it being a major lying undertone of this project.

2.1 What is Fake News?

Fake news can be defined as many things, it can be misinformation shared to favour one individual over another in the public eye. It can also be used for scaremongering such as anti-vax and nutritional diets. Or other times to simply draw attention for a follower/subscription boost. When deployed onto a social media network, fake news becomes a very powerful weapon for one to show an argument with a biased viewpoint (Reference of Social Media Effect Required). Fake is something that is not genuine, it is an imitation or counterfeit. The definition of news is to provide/receive noteworthy information. This report will use the term "Fake News" under the interpretation of **information being posted on social media with a biased viewpoint** in order to create an advantage for the individual(s) posting. This advantage may be political, business related, for a public movement - anti-vaxxers or simply for personal gain - such as a subscription boost for spreading viral information.

Historical Examples

During the first world war, in an attempt to rally the Chinese against the Germans, British papers portrayed the German soldier as repurposing the remains of both fellow and enemy soldiers for human consumption. As this was later proven as untrue, the Germans then used this to question the British media's credibility; Joseph Goebbels during the Second World war against allegations of concentration camps and mass massacre of the Jews (Lazer et al. (2018)).

Modern Examples

With the presence of the internet today, publication of such information has been completely transformed into immediate sharing of an article across the entire world as opposed to being confined to one country with paper print. After the outcome of the 2016 Presidential election, many commentators insisted that Trump would not have won a majority of votes if the fake news was not in his favour (Allcott & Gentzkow (2017)). The death of any celebrity is often an emotional ordeal for many people in the world, mix this with social media and they are given a 24 hour funeral of fans and admirers. However, there have been many death hoaxes posted online: an image of the actor Nicolas Cage was altered into an accident and shared on social media platforms (Evon (2016)), a fake Twitter account was able to spread the apparent death of actress Lindsay Lohan and Steve Job's death was given a seventeen page long article ... three years before his actual death (Rossi (2018)). These hoaxes were able to spread across the Internet without questioning the credibility of the source, reinforcing the claim that the public will believe almost anything the see or read on social media. Celebrity deaths come hand in hand with conspiracy theories, with heartbroken fans desperately trying to keep their idols alive with theories that can sometimes almost convince you. Platforms such as Reddit bear the brunt of these theories and they sometimes make their way onto mainstream newspapers such as The Telegram. Some may think that if a story is on a newspaper then surely it must be true. This stresses the fact that fake news on social media can also make its way into mainstream media. The reoccuring factor in these examples is that they are all biased for their own viewpoint, during the war - to make the enemy the enemy, for the 2016 Presidential election individuals only showed certain aspect of Trump's character against Clinton's. And for celebrity death conspiracies, these are usually created by fans in an attempt to make their "heroes" live that bit longer in the public eye.

2.2 Actions Against Fake News

After the controversial results of the 2016 Presidential elections, both social media platforms were criticised for their lack of countermeasures in place to suppress influential posts and ultimately leading to Trump's success. Facebook pledged to stop fake news on its platform (Pierson (2017)). A new search algorithm was adopted in

2017 by Facebook to show articles with high share and comment counts - this later proved to be disastrous as fake news articles were becoming viral and therefore ranked higher than genuine articles. Facebook reiterated their approach and implemented a fact checking algorithm for each article and also assigned a team of employees to manage approved articles. Twitter acquired a firm which specialises in the field of sentiment analysis of Tweets to help reduce the volume of false information on the platform (Agrawal (2019)).

Social Media Platforms

Both social giants, Facebook and Twitter have acknowledged that there is a growing epidemic with fake accounts and fake news on their respective platforms (Mosseri (2017)). Facebook has begun vetting adverts displayed on the platform to ensure that a strict set of guidelines is met before they are published (Wingfield et al. (2016)). Each prospect (advertising) account on Facebook is monitored closely on a regular basis to ensure that the material they are posting are indeed credible and not misleading. Facebook later released a feature to allow all users to flag potential fake news accounts or postings (Mosseri (2016)).

Twitter has very recently acquired a London based start up company - Fabula AI, which adopts a deep learning algorithm combined with powerful machine learning to analyse data from Twitter and flag unsafe materials for removal (Agrawal (2019)). The new in-house in team is currently tackling fake news accounts on the platform which will then expand to detect a wide variety of platform abuse.

Both Twitter and Facebook begun targeting fake news on their platforms after receiving mass criticism for the volume of democratic propaganda on their respective platforms during the Presidential election (Allcott & Gentzkow (2017)). Bot Sentinel and SparkToro are a few examples of the tools available online to the public which can track bot accounts and user Tweets.

Bot Sentinel

Bot Sentinel is a free web based program that was launched to allow users to track the suspension and termination of violating accounts on Twitter, these are mostly ”trollbots” - accounts which share propaganda. The website is a non-partisan platform which is capable of tracking both left and right wing accounts. It is able to detect “bot” accounts - automated accounts that execute actions such as following users, messaging user or retweeting posted Tweets. The machine learning model uses Twitter's policies as a guide to detect possible violating accounts, the accounts are then given a score of bot like behaviour. Accounts with higher scores are then tracked and added to a block list, which is available for users to download and add to their accounts to remove any untrustworthy or bot accounts from their Twitter accounts. When tracked accounts are suspended or terminated, Bot Sentinel adds these to its daily count. Users also have the option to analyse a specific account by Twitter handle.

SparkToro - Fake Followers Audit

SparkToro has a tool, fake follower audit, which allows users to analyse the nature of their followers, as inactive, spam, bots or other. Once users enter their Twitter credentials, they are given an analysis of percentage of fake, spam, unauthenticated and non-active accounts currently following them, a rating of their account in respect to accounts with a similar follower count is also provided, a breakdown of triggers which explain the account score can also be analysed. This tool is best suited for individuals who wish to measure their influence on their genuine followers - such as HR workers and politicians. SparkToro's initial model was trained to analyse a large spectrum of an accounts attributes, this was later compressed to six main factors to detect spam accounts: profile image, account age, follower count, date of last Tweet, display name and the number of times the account appears on lists (Fishkin (2018)).

Iffy Quotient

Researchers at The University of Michigan have developed a tool - Iffy Quotient, which determines the percentage of fake news on Twitter and Facebook at regular intervals throughout the year. In 2018, Iffy Quotient reported that since 2016, Facebook's Iffy percentage steadily dropped in 2017 but then returned to its original 2016 percentage. It also reported that Twitter's Iffy percentage had not declined much in 2017 and was instead double the percentage from early 2016 (Thomas (2018)). A more recent report in 2019 claimed that the program had tracked a steady drop of questionable content on both major social media platforms. Facebook had dropped from 12.2% to just over less than half at 7.2% of data. Although Twitter's decline was not as drastic as Facebook's it was a welcome one, 11.1% to 10.9% (Thomas & Webster (2019)).

2.3 Approaches

To create a program in an attempt to track these instances of fake news, we can adopt one of the following programming languages: Python or R - both are very well suited for this project due to their data analysis capabilities and large volume of available libraries.

Technologies

R was designed for statistical analysis, making it a very powerful technology for data analysis. Once connected to the Twitter database - using the Twitter API, Tweets can be extracted for analysis. However, before the Tweet can be analysed for it's sentiment, the Tweet must be "cleaned" - removal of tags, handles, emojis, url links, leaving only words to create a word cloud with. Using libraries available to R, we can then create a sentiment score for each word in the word cloud and apply this model accordingly.

Python was designed to be both easy to read and powerful. It has a very large library of packages available to use, some of which are greatly suited for identifying fake news - TensorFlow, pyTorch and Keras. TensorFlow is the successor of Google Brain built "DistBelief", it is a symbolic math library which is also applied to machine learning such as neural networks. TensorFlow has many guides and resources available online as well as GitHub repositories with working examples. pyTorch is based on the Torch library, very useful for computer vision and language processing applications. boasts dynamic graphs which allows on-the-go edits to the directed acyclic graph, offering a more flexible approach when compared to TensorFlow's static DAG. Keras is a neural network library which is capable of running on top of other libraries such as Theano, PlaidML and in our case; TensorFlow. Keras is ideal for rapid production and rapid deployment but it is often criticised for being *too simple* in its approach to machine learning. When comparing both languages, it is clear that R has the larger number of libraries available to use, however, Python libraries are able to execute larger amounts of data in a more efficient time matter (Brittain et al. (2018)).

Techniques

There are many techniques available to us that we can implement to train a sentiment analysis model, these fall into three main categories; tree-based (decision trees), vector-based (supervised learning models) and analysis-based. Tree based techniques use a decision model to categorise data it is provided with, Random Forest (RF) is an application of this model. RF constructs multiple decision trees all using different features to process training data, the best suited decision tree based on the results of execution is then selected for data processing. Supervised learning techniques map input to output based on a training model's input-output pairs. After learning from training data, the algorithm is then capable of applying a deduced function to map provided data. Support-Vector Machines (SVM) use supervised learning techniques to classify data it is provided with. A supervised learning model is where the training dataset for an algorithm is labelled - desired outputs are given for inputs, this creates an inferred function to be created and used for new examples. An unsupervised learning technique does not have labelled training dataset and instead allows the AI to make logical decisions on the data to an output, semi-supervised is a hybrid of both supervised and unsupervised tasks. Analysis based techniques such as Artificial Neural Networks (ANN) "learn" to perform tasks after analysing similar data. Inspired from the human brain, ANN are capable of performing certain tasks using its network of (artificial) neurons to decide on the classification of input. To apply ANN to detect fake Tweets, a repository *of known fake* Tweets must be sourced and used to train a model which will then be able to identify certain patterns from new examples. ANN can be described as a weighted directed graph where input to the network is passed through multiple nodes based on mathematical equations to a final output. Deep learning is another technique based on artificial neural networks which can be any one of the three previously described machine learning tasks; supervised, unsupervised or semi-supervised. A distinction between deep learning and ANN, is that deep learning uses multiple hidden layers to classify data.

The Halstead complexity was developed by Maurice H. Halstead and is capable of measuring a software metrics in respect to the complexity of operators and operands in the module (Munson & Kohshgoftaar (1993)). Please refer to Appendix A for a summary of complexity analysis carried out on machine learning techniques.

With 82% of young adults not being able to distinguish between adverts and actual news (Atodiresei et al. (2018)), it is to no surprise that social media has festered into such a playground for Internet trolls to spread fake news - and to have it slurped up by some of its gullible users. Both social media platforms have implemented features, in an attempt to reduce this ever growing threat. Facebook originally altered their search algorithm for posts that would rank those with higher comment and share counts first, however - due to the large percentage of users being unable to distinguish between real and fake news, this lead to fake news articles being ranked higher that genuine articles (Dwoskin (2019)). It then reiterated the algorithm again to include a metric referred to as 'Click-Gap' which analyses the source website of posts, if there is a large volume or articles originating from a single website, but this website does not have incoming links from other websites, the algorithm will lower the ranking for these posts (Dreyfuss & Lapowsky (2019)). Facebook also allows users to be able to report posts as untrustworthy, further aiding their search algorithm. A combination of automated sentiment analysis and human-agent interaction has been proven to provide a higher success rate in sentiment analysis (Clavel & Callejas (2016)). Twitter acquired a fake news detection firm - FabulaAI which uses deep learning algorithms called geometric deep learning. These are made of multiple neural networks that are able to detect and learn patterns on large data distributed data sets - such as social media. FabulaAI claim to run a GPU accelerated library from nVidia - cuDNN, on TensorFlow returning a success rate of 93% (NVIDIA (2019)).

For the purpose of this assignment, Python is a more suitable programming environment as it allows faster execution of large data sets which will be required when processing a large set of training data. Although R has more libraries at its disposal, Python is also capable of implementing those for sentiment analysis - using techniques such as Random Forests, Neural Networks and Support-Vector Machines. Learning and applying a language such as Python using the TensorFlow library will prove to be a greater advantage to my own learning and understanding as there is a larger number of companies with vacancies for this skillset.

The model will be trained with training dataset found online which contains sample Tweets from two accounts; GossipCop and PolitiFact. There are samples from both accounts containing links to both genuine and false news articles in politics and celebrity gossip. Figure 2.2 shows three examples of Tweets posted by users reporting Barack Obama's arrest for wiretapping Donald Trump:

(a) (b) (c)

Figure 2.1: Fake Tweets Stating Obama Arrest

One can easily identify at least one of these examples as being fake and possibly a second too. Figure 2.2 (a) is clearly posted by a Trump supporter (username "God Bless Trump" and handle "DTrumpThe45th") and based off the contents of the post, it shows Trump in a victim state of having been spied on - something that can benefit a presidential campaign. Figure 2.2 (b) can potentially be identified easily as fake news if the account posting is examined. A lack of a profile image, unstructured handle and mismatching of the handle and account name can all indicate a bot account reposting, in this case, fake news. Figure 2.2. (c), however, has both a profile image and a sensible handle along with account name. This is the scenario where a program or application such as the one proposed would be able to analyse and classify this Tweet as fake.

Chapter 3

Project Specification

I used the original specification provided by my project supervisor; John N. Wilson, as a starting point in order to fully understand the task at hand. After discussing this further with John, we were also able to come up with the best possible approaches to this project.

3.1 Functional and Non-Functional Requirements

Based from the specification outlined by John, this program must be able to execute the following tasks:

- Allow the user a choice of methods of how to fetch Tweets.
- Pull data from Twitter using the appropriate Twitter API based on the user's selection.
- Effectively 'strip' the Tweets collected into analysable data.
- Correctly categorise the data using the programming environment and technique chosen for this project.
- Notify the user of the outcome of their submitted Tweet(s).
- Allow the user to see Tweets which have been previously identified as containing fake news by the program.

The program must also require the following non-functional requirements:

- Accuracy - Be able to accurately classify the Tweets collected by the API.
- Performance - Be able to perform calculations in a timely fashion so as to not keep the user waiting large amounts to process data.
- Transparent - The interface must be clear and concise to the user.

Chapter 4

Methodology

Development

I will be undertaking an Agile approach to the development of this project. Throughout the implementation of this project, the research carried out will prove to show a capricious nature, making this approach very suited for this project. I will be tackling different aspects of the program on a weekly/biweekly basis. I plan to meet with my project supervisor on a weekly basis to provide updates of my progress with the project and to also discuss best next steps.

Design

Implementation

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Testing and Evaluation

The program will constantly be tested throughout development. Known fake news Tweets will be entered into the program whilst the model is being trained and the outcome will be noted, this will give an idea of how the model is capable to adapt to Tweets with no knowledge of its sentiment. The functional and non-functional requirements will be used as a guide to gauge the completeness of the final program.

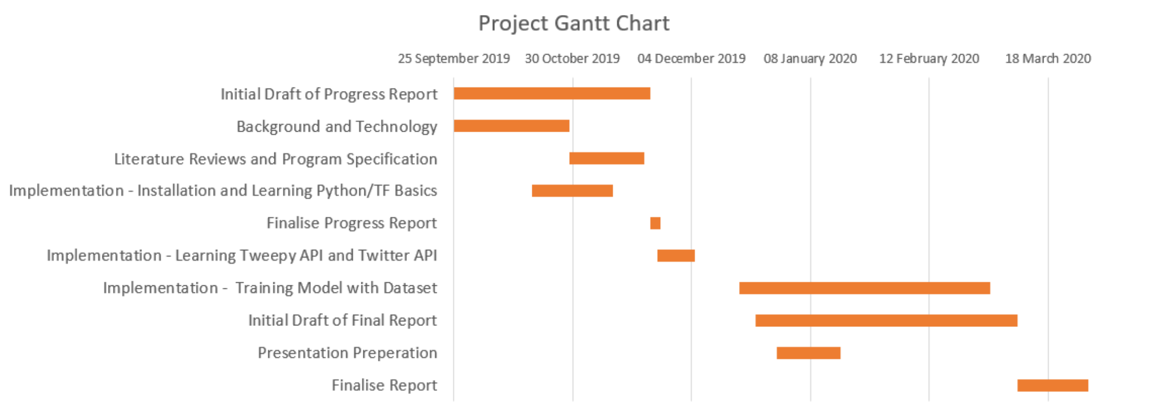
Chapter 5

Project Plan

5.1 Table of Dates

Start Date	End Date	Task Description
25/09/2019	22/11/2019	Initial Draft of Progress Report
25/09/2019	29/10/2019	Background and Technology
29/10/2019	20/11/2019	Literature Reviews and Program Specification
18/10/2019	11/11/2019	Implementation - Installation and Learning Python/TF Basics
22/11/2019	25/11/2019	Finalise Progress Report
24/11/2019	05/12/2019	Implementation - Learning Tweepy API and Twitter API
18/12/2019	01/03/2020	Implementation - Training Model with Dataset
23/12/2019	09/03/2020	Initial Draft of Final Report
29/12/2019	17/01/2020	Presentation Preperation
09/03/2020	30/03/2020	Finalise Report

5.2 Gantt Chart



5.3 Development

As discussed in the Technologies and Techniques sections of this report, theuse of Python over R would be more beneficial for myself for both the purpose of this project as well as my own skills development as there is a larger job field for Python developers. As Python 2 will be coming to its End of Life (EOL) in early 2020, I will be using Python 3 with the TensorFlow 2 library to train a model to learn sentiment from Tweets processed by it. Tweets will be collected using Tweepy, another library which allows usage of the Twitter API. I may also make use of the Google Cloud Platform (GCP) to store large volumes of data which may be required when training the model or for any new functionality which may be added - such as storing all processed and *known* fake news Tweets.

My development for this project so far has been mainly learning and understanding Python and some libraries which may be vital in this program. I have been using a Jupyter notebook (Google Colab) to develop and execute Python 3 code as well as libraries such as Tweepy and TensorFlow. By following tutorials available online, I have learned how to use basic functions of the Tweepy API as well as accessing the Twitter API to gather data. Tweets can be either searched for by a predefined term such as *"#fakenews"*, or from user input - to which I have decided to convert into a hashtag to search Twitter for e.g user searched *"brexit"*, this will instead search for Tweets which contain the term *"#brexit"*. After searching the Twitter database, a list of Tweets will be returned, and for testing purposes, these are also being stored (appended) in a text file on my personal Google Drive.

Initially, there was an issue with the versions of both Python and TensorFlow installed, as Colab will use the oldest stable releases regardless of (stable) updated versions being available, Python 2 and TensorFlow 1 were both installed in the environment. I was able to overcome this issue by simply updating and adapting all my code to Python 3 and running a script which removed the pre installed TensorFlow version from the environment and installed the version which I would be using for this project; TensorFlow 2. To access Twitter data, I had to acquire a developer account and request access to their resources by stating my intent to use their API. My requests for both the developer account and app were successful and I was able to obtain keys required to use Tweepy to access the Twitter API.

Appendix A

The Halstead Complexity

Theoretically, this measure can indicate how efficiently an algorithm can execute with reference to the manipulations of data within the algorithm. An analysis has been carried out on a data set containing 25,000 real and fake news articles, sourced from Retuers (real) and Kaggle (fake), using multiple approaches and models to classify articles (Traore et al. (2017)). The study compared multiple machine learning techniques - support vector machines, decision trees and logistic regression to name a few. After running the different methods on the same data set, the results of this study were as follows:

N-Gram Size	TF-IDF				TF			
	1000	5000	10,000	50,000	1000	5000	10,000	50,000
Uni-gram	84.0	86.0	84.0	84.0	85.0	72.0	69.0	69.4
Bi-Gram	78.0	73.0	67.0	54.0	68.0	51.0	47.0	47.0
Tri-Gram	71.0	59.0	53.0	48.0	53.0	47.0	53.0	47.0
Four-Gram	55.0	37.0	37.0	45.0	47.0	48.0	40.0	47.0

(a)

N-gram Size	TF-IDF				TF			
	1000	5000	10,000	50,000	1000	5000	10,000	50,000
Uni-gram	88.0	88.0	89.0	89.0	83.0	88.0	88.0	80.0
Bi-gram	85.0	85.0	85.0	84.0	84.0	87.0	87.0	84.0
Tri-Gram	86.0	86.0	87.0	85.0	86.0	86.0	84.0	86.0
Four-gram	74.0	74.0	71.0	74.0	67.0	67.0	70.0	67.0

(b)

N-Gram Size	TF-IDF				TF			
	1000	5000	10,000	50,000	1000	5000	10,000	50,000
Uni-gram	83.0	89.0	89.0	89.0	89.0	89.0	83.0	89.0
Bi-gram	87.0	87.0	88.0	88.0	87.0	85.0	86.0	86.0
Tri-gram	86.0	85.0	88.0	87.0	83.0	83.0	83.0	82.0
Four-gram	70.0	76.0	75.0	81.0	68.0	67.0	67.0	61.0

(c)

Figure A.1: Accuracy Results of SVM, DT and LR (Traore et al. (2017))

Figure 2.1 (a) shows the results of accuracy for SVM, (b) are the results of DT and (c) depicts the accuracy results of LR algorithms. If we compare only the uni-gram results for TF-IDF applications - this is a more accurate method of applying each algorithm. We can see that SVM had the lowest average score for 5,000 to 10,000 applications, followed by LR and DT being the most accurate.

Appendix B

Sample Title

App

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