

RUMOUR CLASSIFICATION IN FOOTBALL TRANSFER WINDOW TWITTER DATA

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Table of Contents

Declaration…………………………………………………………………………………………………………………………..

Summary………………………………………………………………………………………………………………………………

Acknowledgments………………………………………………………………………………………………………………..

Table of Contents…………………………………………………………………………………………………………………

Table of Figures……………………………………………………………………………………………………………………

Table of Tables……………………………………………………………………………………………………………………..

1. Introduction…………………………………………………………………………………………………………………….

1.1 Research Question………………………..……………………………………………………………………

1.2 Hypothesis………………………………..………………………………………………………………………..

1.3 Overview of dissertation…………………………………………………………………………………….

2. Existing Work……………………………………………………………………………………………………………………

2.1 Fake News…………………………………………………………………………………………………………..

2.1.1 Overview………………………………………………………………………………………………

2.1.2 definition…………………………………………………………………………………………

2.1.3 Academic research……………………………………………………………………………….

2.2 Football Transfer Rumours………………………………………………………………………………….

2.2.1 Overview………………………………………………………………………………………………

2.2.1 Fake News……………………………………………………………………………………………

2.2.1AcedemicResearch………………………………………………………………………………

3. Methodology……………………………………………………………………………………………………………………

3.1 Introduction

3.2 Data Gathering……………………………………………………………………………………………………

3.1.1 Overview……………………………………………………………………………………………..

3.1.2 Methods Used……………………………………………………………………………………..

3.1.3 Implementation …………………………………………………………………………………

3.3 Data Labelling……………………………………………………………………………………………………..

3.2.1 Overview………………………………………………………………………………………………

3.2.2 Name Entity Recognition………………………………………………………………………

3.2.3 Tweet Processing………………………………………………………………………………….

3.4 Classification……………………………………………………………………………………………………….

3.3.1 Model Architecture………………………………………………………………………………

3.3.2 Classification Threshold………………………………………………………………………..

3.5 Conclusion………………………………………………………………………………………………………….

4. Implementation………………………………………………………………………………………………………………..

4.1 Data Collection……………………………………………………………………………………………………

4.1.1 Tweet Gathering…………………………………………………………………………………..

4.1.2 Ground Truth Knowledgebase………………………………………………………………

4.1.3………………………………………………………………………………………………………………

4.2 Labelling……………………………………………………………………………………………………………..

4.2.1 Part of Speech Tagging…………………………………………………………………………

4.2.2 Named Entity Recognition……………………………………………………………………

4.2.3 Rumour Detection………………………………………………………………………………..

4.2.4 Labelling……………………………………………………………………………………………….

4.2.5 Analysing Dataset…………………………………………………………………………………

4.3 Classification……………………………………………………………………………………………………….

4.3.1 Classification problem………………………………………………………………………….

4.3.2 Model Architecture/Methodologies……………………………………………………..

4.3.3 Training………………………………………………………………………………………………..

4.4 Conclusion………………………………………………………………………………………………………….

5. Results………………………………………………………………………………………………………………………………

6. Discussion of results…………………………………………………………………………………………………………

7. Conclusions………………………………………………………………………………………………………………………

1. Introduction

Fake news is a phrase which has been circulating through popular media and culture in recent years. Since the 2016 US presidential election the term has gained increasing traction and has been used to criticize all forms of media. The issue which originated with small groups manipulating social media algorithms and online advertising for personal financial gain didn’t stop there and went onto spark worldwide debate about the credibility of the news sources which we use today[[1]](#footnote-1). The term soon became a sound bite and theme coherent with the presidency of Donald Trump.

This scandal exposed a series of vulnerabilities in these platforms. It became intertwined with other scandals such as alleged Russian Government and other organizations interfering with elections using fake social media profiles and the hacking of personal emails[[2]](#footnote-2). This coupled with news that political consulting firms like Cambridge Analytica were able to develop digital profiles that represented individuals of certain political beliefs and demographics provided a scary outlook for the everyday social media user[[3]](#footnote-3). Not only are there groups creating fake accounts and profiles to manipulate these applications but the data they themselves provided was being used to facilitate political advert targeting.

The fake news frenzy forced US, Irish and EU Government bodies to summon social media companies’ representatives before them and to seriously start thinking about heavier regulation for such companies. That being said these social media platforms are still being used daily by millions of Users and the same vulnerabilities that were present before still exist today. The potential for personal financial gain still exists on these platforms and the efforts made so far by these companies involve large teams sifting through accounts rather an automated, more scalable approach[[4]](#footnote-4).

The ability to extract meaning or sentiment from a piece of text is something which has been made increasingly possible through natural language processing. In the last decade companies have turned toward Machine Learning solutions to attempt to solve classification and prediction problems. A potential solution to the issue of “fake news” on social media may be possible through the creation of a model capable of classifying social media posts as “fake” or “real” news[[5]](#footnote-5).

An area where rumours and fake news is not new is in sport and particularly with relation to football transfers in the English Premier League. Twice a year there are transfer window periods where clubs can buy and sell players amongst one another. This leads to a lot transfer rumour speculation amongst the press, increasingly on social media platforms such as twitter. There are numerous accounts which have been set up with the sole purpose of reporting on this, claiming to be the some of the first individuals to be “in the know”[[6]](#footnote-6).

This area gives an ideal test case of a fake news in social media. By taking a specific transfer period in the past one can look at rumours posted on social media, specifically Twitter, and use them as ground truth to label whether this rumour actually became true. Twitter provides a medium to access the hundreds of thousands of rumours and true claims, all of which can be fact checked through official records of confirmed transfers. This gives a training set to develop a model capable of determining the veracity of a new, unseen transfer rumour or a social media post.

* 1. Research Question

The purpose of this research project is to answer the following question:

*“To what extent can supervised machine learning approaches be used to predict the accuracy of a Tweet or Twitter account, in relation to a football transfer?”*

From this question the following research objectives were defined:

* Data gathering and knowledgebase building: Create python scripts which handle the retrieval of football transfer Tweets. This process also involves creating a database of confirmed transfers which happened and English premier league club names and synonyms.
* A Natural Language Processing (NLP) technique for Name Entity Recognition (NER): This objective involves using existing models to extract information from the data in order to determine the meaning behind the text. This process is to be conducted to ensure the training set examples are labelled correctly.
* Classification model development: This objective involves creating classification models using different supervised machine learning techniques, using the training data gathered in the previous stages.
  1. Hypothesis

This research is aimed at identifying the set of text feature which can be used to accurately predict the accuracy of a rumour. It also aims to identify suited approaches to text classification in the context of fake news social media content. The research aims to measure the effectiveness of different text vectorization, feature set generation methods and supervised machine approaches at predicting whether or not and football transfer tweet is “fake news” or correct.

*(H0)*

*(H1)*

* 1. Overview of this Dissertation

The first section of this paper gives a background of the research and details the problem which it is trying to address. It also defines the research question itself and defines the hypothesis of the research.

Section two gives an overview of existing research on the topic and separate topics which are related. It also gives our definition of “fake news”. \*\*\*

Sections three details the methodology of the research. The methodology of this research can be spilt up into three distinct sections: Data Gathering; Named Entity Recognition; Classification.

The data gathering section details the process of gathering the corpus of transfer tweets, English football club names and past transfers which we know to have happened. In order to perform any supervised machine learning task suitable training data is necessary and this section details the steps taken in gathering this data.

The named entity recognition stage involved extracting meaning from the tweets gathered in data gathering. In order to correctly label each tweet as “happened/didn’t happen” the ability to entities and names from the texts of tweets was needed. The NER section details the methods used in extracting entities and player names from the tweets gathered, and how they were labelled.

Lastly once the training set was available classification experiments were carried out to investigate the accuracy of different methods. The classification section details the different methods involved in constructing the feature set and the different model architectures used.

2. Existing Work

2.1 Fake News

2.1.1 Overview

Manipulating news and media outlets for personal, political and financial gain is not a new concept, and has been around so far as news and media has itself[[7]](#footnote-7). However, in 2016 we appeared to witness and ill-fitting combination between these practises and social media. The origin of the fake news social media as we have come to know it today can be traced back to the unlikely and infamous Macedonian town of Veles. In a town with an average monthly salary of $371, a group of young teens had figured out a way to make $16000[[8]](#footnote-8), around about the same time a report found that over one hundred pro-Trump fake news websites were registered to Veles. These two happenings of course were not a coincidence and as it turned out this group of teens had found a way of exploiting social media websites such as Twitter and Facebook to generate thousands of clicks to their websites which would in turn lead to a payday via Google ads for themselves.

This idea of enticing users to a click onto a website in the hope of revenue is also not new, and these so called “clickbait” tactics to generating clicks have emerged ever since it has been incentivised to prioritise clicks over good journalistic reporting[[9]](#footnote-9). However, its relevance has become increasingly important in this post-truth politics era, due to the easy access to advertising revenue and polarizing political beliefs.

Aside from groups using these techniques for financial gain, a number of reports have alleged that states such as Russia have faced allegations of disseminated false information to influence the 2016 US presidential election[[10]](#footnote-10).

The phrase quickly turned into a sound bite to refer to the “lying press” for politicians as the social media fake news epidemic became mainstream news itself. Although many primarily associate the phrase with political jargon, the problem of groups using fake news to exploit social media algorithms is still an ever-present issue[[11]](#footnote-11). Facebooks CEO Mark Zuckerberg even testified before the US Congress as a result. In late 2018 some of the world’s leading tech firms agreed upon a code of conduct to do more to tackle the spread of fake news. However, as many reports have suggested this code of conduct provided little transparency on how to implement it. Most efforts to deter these practises have come in the form of manual human labour of shutting down payments and preventing the setup of fake accounts. However, automated detection of fake news accounts and posts still poses a real challenge[[12]](#footnote-12).

2.1.2 Definition

Irrespective of the research which has gone into the area, there does not seem to be one agreed upon definition of “Fake News”. However, the consensus from most studies is that it can be defined as news which include false information designed at purposefully misleading readers [[13]](#footnote-13) [[14]](#footnote-14). At the core of the definition of Fake News definition is comprised of misinformation and intent. This is true for both articles and social media posts as the intent behind one binds it to the other. In other words, the sole reason for a fake news social media post is to generate clicks to the article linked in it. Therefore, for the purposes of this research, we define the definition of fake news as follows,

*Fake News: A social media post or news article that is created with the intention of misinforming the reader.*

2.1.3 Academic research

In term of fake news there have numerous studies conducted with the aim of investigating fake news and researching possible detection methods. One research paper detailing the BuzzFeed-Webis[[15]](#footnote-15) fake news corpus investigation detailed the research into what mainly comprises of a fake news post. The report found that hyper-partisan and mainstream publishers all earned verified checkmarks (official account badge) with no favourable bias toward any one type earning the badge. The same report concluded that manual binary classification between fake and real news was infeasible, as most linked articles included true and false news. Despite this, it was noted that the majority of mixed fake/reals news articles belonged to hyper-partisan “right-wing” sources. Another report aimed at defining fake news[[16]](#footnote-16) also confirmed the mixed true/false news nature of articles in their corpus, as it was in the BuzzFeed-Webis report.

Aside from research into investigating the contents of fake news and defining it, research has also gone into possible methods of fake news detection. Fake news detection using a naïve Bayes classifier [[17]](#footnote-17)on the same BuzzFeed data set names above produced interesting results. The implementation aimed to correctly classify the BuzzFeed article dataset as True or Fake news. The research showed that even using a simple classification approach can yield classification accuracy of 75.4%. Despite having a precision value of 0.71 and a high classification accuracy, the classifiers recall value was only 0.13. Each research paper using this corpus of articles reported the presence of mixed true/fake news articles and this low recall value further backs up their claim. The aforementioned paper results suggest that machined learning techniques could be successful in tackling this problem.

Another research papers approach[[18]](#footnote-18) to the detection issue was to extract linguistic features and create linguistic feature sets. Then using said feature sets define and SVM classifier with Five-fold cross validation was used in the experiment. This approach showed promise, with one classifier producing accuracy scores of 0.73 and 0.74 on different datasets. The input features were a combination of punctuation, Ngrams, syntax and readability features. The same models achieved recall value of 0.74 and 0.73 respectively.

Previous academic research into defining fake news and fake news classification methods provides confidence that further advancements can be made through the use of supervised machine learning techniques to addressing the detection of fake news.

2.2 Football Transfer Rumours

2.2.1 Overview

Fake news within reporting on football transfers has is also prevalent. During each January transfer and Summer transfer window journalists and supposed sports media accounts report on player transfers, of which they claim to be “in the know”, in advance of the deal being confirmed or publicly announced. Tactics used during the election are also at play here, however it has undergone the same scrutiny, most likely due to the difference in nature between the two. Nonetheless, the thousands of football transfer rumour tweets available gives the opportunity to investigate the feasibility of a model capable of classifying the veracity of a rumour, or the account which posted it.

2.2.2 Fake News

It is important to point out the similarities between football transfer fake news and the political fake news mentioned above. If we take our definition of fake news a lot of these accounts claiming to be “in the know” are intended to misinform the reader with exaggerated scenarios and eye-catching premises. Furthermore, they usually contain links aimed at re-directing the user to a cite in hope of financial gain rather than true news.

2.2.3 Academic research \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

In term of football transfers themselves there has been numerous cites of research. One frequent point of research within the area Is the relationship between club expenditure and success[[19]](#footnote-19). Research into the increasing prices of players and even using transfer markets to investigate labour mobility and globalization[[20]](#footnote-20) have been conducted. However, this paper finds that research into football transfer rumours is limited, especially in relation to the rumour veracity detection.

It is important to note that due to the similar nature and outcome and nature of political and football transfer rumours social media rumours, that one can employ some of the existing techniques discussed in the other. In other words, this paper aims to take some the previous academic research in political fake news social media account is completely relevant to football transfer rumours.

3. Methodology

3.1 Introduction

This section details the methodology of carrying out this research. This methodology can be split up into three distinct sections. The first section is the data gathering section. This involved gathering the tweets to be used as the training set for performing the classification experiment. It also involved gathering other information to be used in NER. The second section involved Named Entity Recognition (NER). This section involved ensuring that the data gathered was labelled correctly, in other words was a tweet about a past transfer correctly labelled “happened” or “didn’t happen” (rumour/fact).

The last section involved constructing different feature sets using different methods. It also involved constructing different classification models using different supervised ML approaches.

3.2 Data Gathering

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2. https://www.theguardian.com/us-news/2016/dec/16/qa-russian-hackers-vladimir-putin-donald-trump-us-presidential-election [↑](#footnote-ref-2)
3. https://www.nytimes.com/2018/03/19/technology/facebook-cambridge-analytica-explained.html [↑](#footnote-ref-3)
4. https://uk.reuters.com/article/us-eu-tech-fakenews/facebook-google-to-tackle-spread-of-fake-news-advisors-want-more-idUKKCN1M61AG [↑](#footnote-ref-4)
5. https://www.ll.mit.edu/news/using-machine-learning-detect-fake-news [↑](#footnote-ref-5)
6. https://www.bbc.com/news/blogs-trending-40574049 [↑](#footnote-ref-6)
7. https://www.wired.com/story/free-speech-issue-tech-turmoil-new-censorship/?CNDID=50121752 [↑](#footnote-ref-7)
8. https://www.wired.com/2017/02/veles-macedonia-fake-news/ [↑](#footnote-ref-8)
9. https://www.bbc.com/news/uk-wales-34213693 [↑](#footnote-ref-9)
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11. https://www.theguardian.com/commentisfree/2019/feb/28/facebook-twitter-fake-news-eu-elections [↑](#footnote-ref-11)
12. https://uk.reuters.com/article/us-eu-tech-fakenews/facebook-google-to-tackle-spread-of-fake-news-advisors-want-more-idUKKCN1M61AG [↑](#footnote-ref-12)
13. https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.31.2.211 [↑](#footnote-ref-13)
14. [arXiv:1703.06988](https://arxiv.org/abs/1703.06988) [cs.SI] [↑](#footnote-ref-14)
15. arXiv:1702.05638 [↑](#footnote-ref-15)
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20. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9485.2007.00423.x [↑](#footnote-ref-20)