

RUMOUR CLASSIFICATION IN FOOTBALL TRANSFER WINDOW TWITTER DATA

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1. Introduction

Fake news is a term which has been circulating through popular media and culture in recent years. Since the 2016 US presidential election the term has gained traction and has been used to criticize all forms of media. The issue which originated over 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 2016 US election and presidency of Donald Trump.

A truth which exposed a series of vulnerabilities in these platforms became intertwined with other scandals such as organizations and alleged Russian Government interfering with elections using fake social media profiles and accounts 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).

Determining the legitimacy of a social media account through language style is a problem which falls out of the imperative programming capabilities. In the last decade companies have been turning toward Machine Learning solutions to solve classification and prediction problems. The advancements and research into Machine Learning and AI are leading to trivial human cognitive tasks being replaced. A potential solution to the issue of “fake news” social media may be possible through creating a classification model capable of classifying social media posts as “fake” or “real” news[[5]](#footnote-5).

An area where rumors and fake news is not new is in sport and particularly in the Premier League football transfer windows. Twice a year there are transfer window periods where clubs can buy and sell players amongst one another. This leads to a lot transfer rumor speculation amongst the press, specifically on twitter. There are numerous accounts set up with the sole purpose of reporting on this, claiming to be the some of the first individuals “in the know”[[6]](#footnote-6).

This area gives an ideal sample set of a fake news in the media. By taking a specific transfer period in the past one can look at public tweeted rumors and use them as ground truth to label whether this rumor actually became true. Twitter provides a medium to access to hundreds of thousands of rumors and true claims, all of which can be fact checked through official records of confirmed transfers. This gives a sample set to develop a model capable of determining the veracity of a transfer rumor or a social media account.

* 1. Research Question

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

*“To what extent can supervised machine learning practices used to determine the accuracy of a Twitter rumor or Twitter account in predicting football transfers?”*

From this the following research objectives were created:

* A rumor Twitter API query generation method
* A Natural Language Processing (NLP) technique for Name Entity Recognition (NER).
* Classification model development using various ML techniques and labelled Twitter data.
  1. Hypothesis

This research is aimed to determine whether the accuracy of a twitter football transfer rumor can be determined by developing a model using supervised machine learning techniques. The research is aimed to find evidence that there are supervised Machine Learning techniques which can be used to train a model capable of predicting rumor accuracy.

*(H0) The research finds no method of developing a supervised machine learning model capable of producing a model with the aforementioned capabilities.*

*(H1) The research finds a method supervised machine learning method capable of producing a model with the aforementioned capabilities.*

1.3 Overview of this Dissertation

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 we have come to know today can be traced back to the unlikely and infamous Macedonian town of Veles. In a town who’s average monthly salary was $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 hope of revenue is also not new, and these so called “clickbait” tactics to generating clicks have been since it’s been incentivised to priorities clicks good journalistic reporting[[9]](#footnote-9). However, its relevance has become more important in our 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 suggested that states such as Russia have faced allegations of disseminating 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 setup of fake accounts. However, automated detection of fake news accounts and posts still poses a real struggle[[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). The core of the 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 fake news social media post is to generate click to the article linked in it. Therefore, 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 and re-directing 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 fake/reals news mixture 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 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 should 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. The conclusion of the research was also boded well. One classifier produced 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 a faith in further possible supervised machine learning techniques to addressing the fake news problem.

2.2 Football Transfer Rumours

2.2.1 Overview

Fake news within the football transfer window news has also been around since the transfer windows existence itself\*. During each January transfer and Summer transfer window journalists and supposed sports media accounts report on player transfers which they claim to be in the know of in advance of the deal being publicly announced. It has seen the same explosion of the same fake news tactics used in during the 2016 US Presidential election, however it has never gained similar interest 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. By drawing these parallels between the two we can state that the fake news tactics are much the same between the two.

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.

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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)
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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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