

Fake News Detection

1. Introduction

The rise of the social media platforms all over the Internet over the last decades is considered to be like a double-edged sword. On one hand, technological developments grow exponentially, and communicating with a person anywhere on the globe can be done within seconds. This enabled many useful advents such as online courses and has been on particular importance during the pandemic lockdowns. On the other hand, the outstanding amount of information out there is simply too much to handle. With over 4 million YouTube videos watched every minute [6] in a day and with over 500,000 comments, photos and tweets posted per minute continuously [6], there is no practical way of controlling all the information that is spread out there. As such, we witness the rise of fake news, a critical problem that needs to be fixed. According to a new Pew Research center study, it's not just making people believe false things—it's also making them less likely to consume or accept information [7]. This can lead to potentially disastrous consequences, able to impact everything in our daily lives, whether we're talking about simple, unimportant news, or extremely sensitive subjects, such as religion and politics. Fig. 1 shows an example of such fake news.



Figure 1: Fake news example

Since we cannot devise any group of people, no matter how large the group, to keep under control all of the fake news out there, we need to use computers to our advantage.

Specifically, we can create software that can recognize fake news. Many different techniques already exist for this, although all are not 100% perfect. Some leverage Artificial Intelligence systems, while other are simpler statistical techniques.

2. Related work

First of all, there has been a great community effort from researchers around the world, which led to the creation of datasets for fake news. [8-10] are some quick examples. Ma et al. (2016) collected 5 million posts from Twitter and Sina Weibo micro blogs that comprised 778 reported events from which 64% are rumors [11]. The FA-KES dataset comprises news events around the Syrian war (Salem et al., 2019). The dataset consists of 804 news articles of which 376 are fake [12]. There are many more out there.

Many methods have been developed. Ahmad et. al [1] explore fake news detection through different machine learning ensemble methods. Nasir et. al [2] try a more complex approach by combining CNN and RNN for detection. Zellers et. al [4] analyze the use of multiple high-end models for fake news detection, suggesting a unidirectional model, called Grover, may be the best. While Thota et al. [5] used NN architectures, Bhatt et al [3] suggest that one class of methods isn't enough, and proposes a combination of neural and statistical methods, aided by external features (hand crafted with the help of engineering heuristics).

3. Methods

The dataset used [13] was taken from Kaggle. It contains approximately 25k train samples and 5.8k test samples, where the label is either 1 or 0 (fake news or not).

id	title	author	text	label
0	House Dem Aide: We Didn't Even See Comey's Letter Until Jason Chaffetz Tweeted It	Darrell Lucas	House Dem Aide: We Didn't Even See Comey's Letter Until Jason Chaffetz Tweeted It By Darrell Lucas 0...	1
1	FLYNN: Hillary Clinton, Big Woman on Campus - Breitbart	Daniel J. Flynn	Ever get the feeling your life circles the roundabout rather than heads in a straight line toward th...	0
2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, 2016 The tension between intelligence analysts and po...	1

Figure 2: Samples from the dataset

The methods tested consist of both classical approaches, such as Support Vector Machines, and advanced ones such as BERT.

For the classical methods, we additionally tested using TF-IDF versus Bag of Words, with and without stop words removal and with or without stemming.

Model	Bow/TF-IDF	Stemming	Stop words removal	Accuracy
SVM	TF-IDF	NO	YES	97.83%
	TF-IDF	NO	NO	96.97%
	TF-IDF	YES	YES	95.91%
	TF-IDF	YES	NO	95.52%
	BOW	NO	YES	94.42%
	BOW	NO	NO	95.52%
	BOW	YES	YES	92.98%
	BOW	YES	NO	92.78%
Naïve Bayes	TF-IDF	NO	YES	90.38%
	TF-IDF	NO	NO	91.15%
	TF-IDF	YES	YES	89.71%
	TF-IDF	YES	NO	88.36%
	BOW	NO	YES	89.9%
	BOW	NO	NO	91.49%
	BOW	YES	YES	86.82%
	BOW	YES	NO	87.78%
Logistic Regression	TF-IDF	NO	YES	96.34%
	TF-IDF	NO	NO	95.33%
	TF-IDF	YES	YES	94.18%
	TF-IDF	YES	NO	94.8%
	BOW	NO	YES	96.15%
	BOW	NO	NO	96.44%
	BOW	YES	YES	93.94%
	BOW	YES	NO	94.37%

Table 1: Results for classic ML models with different mixes of preprocessing

For the advanced deep learning methods, we tried to apply **BERT** [14]. This model did much better, obtaining an accuracy of **99.23%**, outperforming all of the above models.

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