Fake News Detection: building models with the determining features in the LIAR dataset

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Abstract. Detecting fake news has become one of the biggest issues in the world. There are already a lot of researches in this area. However, most of the previous research focused on the news content and ignored the importance of the headline. Also, with different research emerged, researchers are seeking for better features to build up more accurate models. Our research applied the newly built LIAR dataset, with two algorithms, KNN and the neuron network to try to build a better detection model. In addition, we also tested different feature combinations in this research to figure out the determining features in the LIAR dataset.

1 Introduction

Fake news continues to cause serious negative effects in society nowadays. In the past few years, fake news has become a popular approach for interested individuals to manipulate public opinion on international events. Moreover, anyone can spread fake news through social media to cause panic among the society. Since we observed that fake news is harming society, we decided to devote our ability to help the community to detect fake news with artificial intelligence.

Recently, researchers also explored how artificial intelligence techniques, particularly machine learning and natural language processing, can be leveraged to combat falsehoods online [1]. Furthermore, research has found that focusing on text analysis is not that effective, and the algorithms are not able to help people judge the authenticity of the news accurately. As a result, researchers today are focusing on searching effective features, and this is the topic that we would like to participate and make a contribution.

To train our algorithm, we use the LIAR dataset, which included a decade-long, 12.8K manually labeled short statements in various contexts [2]. Although there are also other researches based on the LIAR dataset, we still have not seen any significant results discussing the features. As a result, we will continue trying to optimize the algorithm in our research and to seek improving accuracy compared to previous studies. Besides, we would like to bring in further prospects to understand the features in this dataset better.

2 Related Work

Headlines provide more clue of detecting fake news

Most of the early researches on detecting fake news focused on the content text a lot. However, with the update of datasets and various features in upcoming researches, researchers found that the headlines or main statements of fake news might be one of the determining features that help us to develop the detection model. Ahmed (2018) developed his content-based detection models using the fake and real news dataset [3]. With rigorous data preprocessing and feature extraction from the content, Ahmed (2018) tested different classification model focusing on the fake news content. Although he got some good accuracy in some of the models, he still identified that the models would work better if there are more features being included. Vedova (2018) and his team built their model using data from Facebook posts combine with chatbots in their research [4]. They combined content-based and social-based methods to develop a better model for detecting fake news. Although the metrics of their model were pretty good, there are still rooms for improvement. Zhou (2018) discussed four perspectives that most of the fake news researches focused on [5]. When she talked about the credibility-based study of fake news, she mentioned how the headlines played an important role in detecting fake news. However, she focused more on the relation of headlines and click-bait, not using the headline as one of the features. Therefore, we think that the headlines might serve as an important feature in detecting fake news. For the past datasets that were used in the researches above, they don't have headlines as an independent feature. As a result, we will use the LIAR dataset, which didn't include the whole content text of the fake news; instead, it used statements or headlines as the main feature in this dataset. Through applying this dataset, we are able to study how headlines contribute as a feature in developing detection models of fake news.

Analyzing text content is not enough, but which features are helpful
In recent research, many articles have indicted that relying solely on text analysis to detect fake news is not enough. Therefore, researchers are trying to add other features to help the algorithm identify the authenticity of the news more effectively. According to Yunfei (2017) and his team included speaker 's profile, such as the speaker 's job title, partisanship, location, or even credit history, as a new feature in their research. As a result, their model outperforms the state-of-the-art method by 14.5% in accuracy using a benchmark fake news detection dataset [6]. Yaqing (2018) and her team introduced an end-to-end framework named Event Adversarial Neural Network (EANN), which can derive event-invariant features and thus benefit the detection of fake news on newly arrived events [7]. In the article, they utilized not only past news to train the algorithm, but also retrieved current news from social media platforms. With this new method, they were trying to solve one of the biggest difficulties encountered in building the detector of fake news, that is, to identify news that describes a new event. In their experiment design, they added the event itself as a new feature to address this problem. In the article "3HAN: A Deep Neural Network for Fake News Detection," the authors focused on the relationship between the content and headline. They proposed the method that was giving differential importance to parts of an article, on account of its three layers of attention [8]. Although they did not add any additional features, they were still able to deal with text con-

tent using this new method. These articles help us understand that it is almost impossible to achieve the desired results by merely analyzing the text content itself. There are more features we should include to detect fake news more effectively. Meanwhile, we also do not want too many features that would make our algorithm overfit and lead to poor accuracy. The articles above inspired us with some different perspectives, especially Sneha (2017) and her team's work. Nowadays, most researchers are discussing what new features can be added to achieve better accuracy; however, only very few researches focus on existing features. In this article, we continue to study the existing features in the LIAR database to find out which are more helpful for training algorithms to detect fake news. Our research result also indicates which feature would be possibly worth further collecting or labeling. We believe that this is a crucial issue for those who want to build new datasets in the future.

Hybrid human-machine approach is emerging with unsolved issues
Many research papers in this field have proposed hybrid methods as solutions to fakes news. The main argument is that in specific scenarios, humans' ability to interpret the meaning of text content apparently outperforms the current artificial intelligence. Therefore, if the two can be combined, the accuracy of the algorithm will be improved. According to the work of Shabani and Sokhn (2018), they addressed the fake news and satire detection by proposing a method that uses a hybrid machine-crowd approach for detection of potentially deceptive new [9]. In their experiment design, the system detects news that requires judgment from human. Then, use the power of crowdsourcing to judge the authenticity of the news. With the power of crowdsourcing, its accuracy has been greatly improved, but the authors also pointed out that the improvement is the result of paying off the cost and latency of crowdsourcing. In the article "A hybrid approach to fake news detection on social media", the authors propose a hybrid model for detecting fake news on social media using a combination of both the human-based and machine-based detection approaches [10]. The hybrid approach seems to perform better; however, in the conclusion, the article mentioned that the measures which should be considered are still a question. Sebastian (2017) and his team worked on improving the accuracy of detecting fake news with crowdsourcing. They were inspired by a tool introduced by Facebook to let users label the fake news. In the article, the authors mentioned that any approach that is not learning about users' flagging behaviour is prone to failure in the presence of adversarial/spam users [11]. Therefore, they put a huge effort into training the algorithm to detect the user's behaviour. These articles remind us that although the algorithm for detecting fake news is a very attractive topic, due to the limitations currently faced, compared with human intelligence, some researchers have to seek the power of crowdsourcing to improve the accuracy of results. However, the crowd itself has become another huge research problem. Therefore, our work focuses on the algorithm and the features in the dataset. The LIAR dataset is based on a fact-checking website, PolitiFact. The website applies the Network Approach, which goes beyond the analysis of the questionable content itself to collect and compare a wide range of similar and related statements

from various sources (network) such as metatags and social network behaviour to ascertain the likelihood of the content being false [10]. With uncertainty as low as possible, we can focus more on algorithms and features selecting.

3 Methods

To find out which features are more important than others for fake news detection, we choose the LIAR dataset because it includes statements (which can be seen as headlines) and other related metadata as features. We want to know which features can effectively improve the accuracy of the model prediction. Before start to train and optimize the models, we utilize CountVectorizer and TfidfVectoerizer to achieve one-hot encoding for statements and contexts. Moreover, we apply k-nearest neighbor (KNN) and neuron network algorithms in our experiment, and use accuracy as the metric to evaluate their performances. In each training, we remove a feature. Eventually, we are able to compare the performances and to find out which features are more important than others.

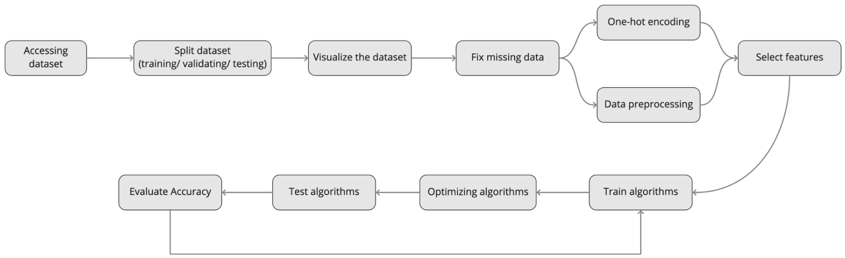

Figure 1. Research process flow chart

4 Experimental Design

We expect to compare the performance of each combination of features by deleting one feature in the LIAR dataset at a time. Therefore, in the experiments, the baseline is the performance of the model trained with all the features in the dataset.

The LIAR dataset was created by Wang (2017), he collected a decade-long, 12.8K manually labeled short statements in various contexts from POLITIFACT.COM, which is a website that identifies whether a news is fake or not with detailed analysis and references. In the dataset, each instance are lableled in six categories, "True", "Mostly true", "Half true", "Barely true", "False", and "Pants on fire". Also, there are eight features: statements, subjects, speakers, job titles, states, parties, credit histories, and contexts.

After visualized, we observed that the instances labeled as "Pants on fire" are much less than other instances with different labels. In "state" and "party" features, serious bias can be found. Most instances do not come from any state, and also they come from Republican and Democrat, the two huge political party in the United States. The huge bias may make us to receive a model with bad performance.

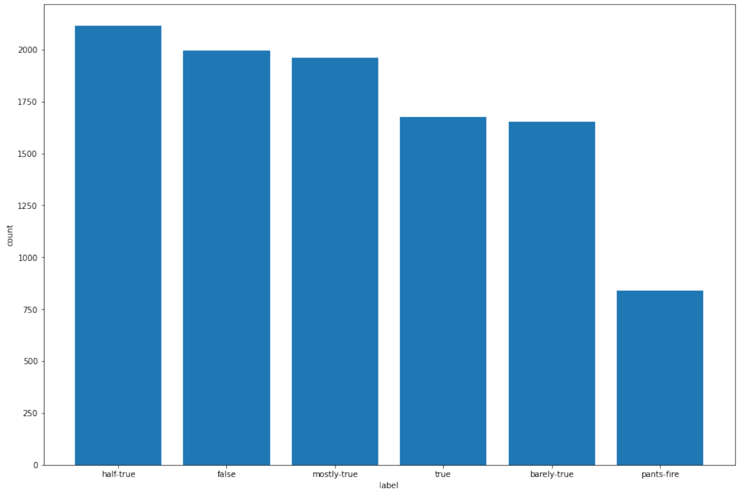

Figure 2. The Numbers of instances with different labels

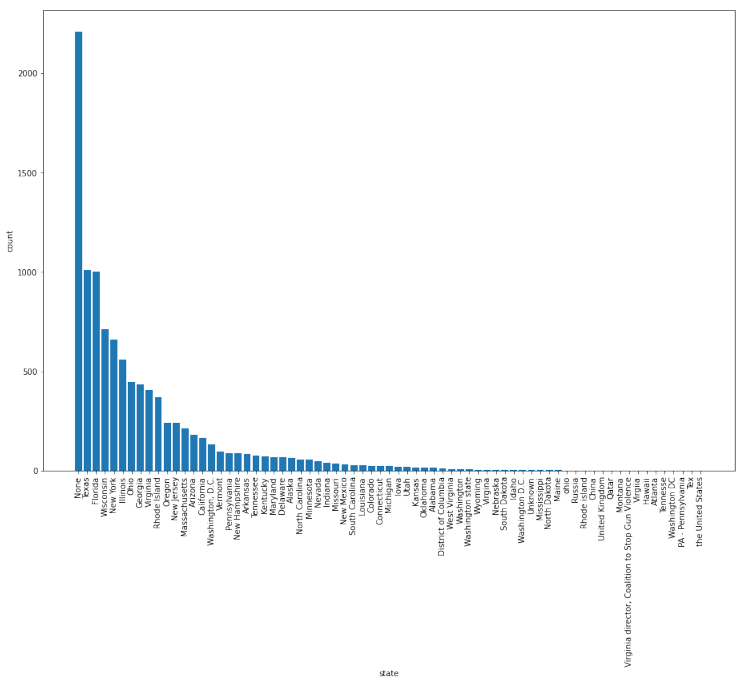

Figure 3. The Numbers of instances from different states

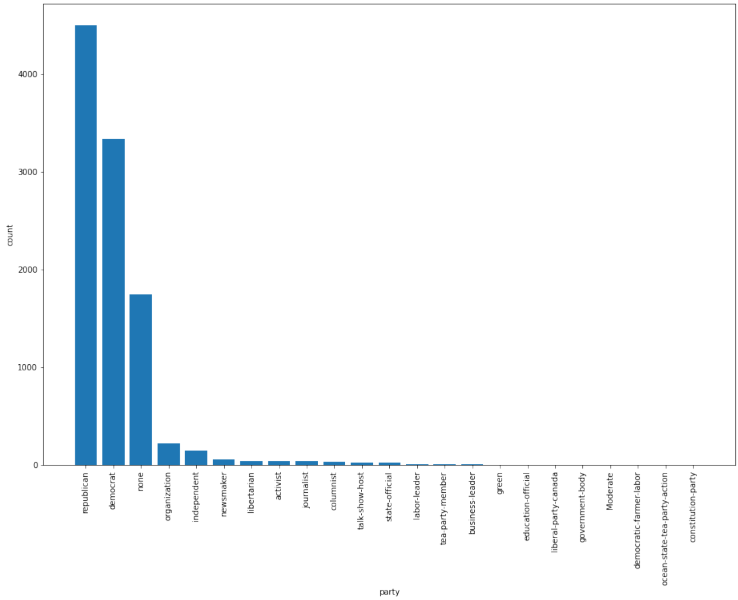

Figure 4. The Numbers of instances from different parties

As a result, We choose accuracy as the evaluation metric to see whether the instances are correctly classified. Also, Wang (2017) also use accuracy as the evaluation metric. By choosing the same accuracy, we can compare the performances of our models to his work.

5 Experimental Results

The average test accuracies of our two models are 0.1597 for KNN, and 0.168 for neuron network. The highest accuracy we got is from the neuron network with all features except for context, which is 0.1965. Another close accuracy is also from the neuron network model with all features except for "party," which is 0.1918. As for the KNN model, the best accuracy is 0.1736, with all features except for "state." Overall, the performances from our two models are not as good as the previous research. The possible reason is that we applied different preprocessing approaches to our data. However, there are still some clues about which feature might not really contribute to the detection accuracy in this dataset.

	KNN		Neuron	
	Validate	Test	Validate	Test
All	0.1667	0.1515	0.2025	0.1492
All - Context	0.1651	0.1523	0.155	**0.1965**
All - credit	**0.1783**	0.1641	**0.2033**	0.1618
All - Job title	0.1651	0.1586	0.1503	0.1476
All - Party	0.1659	0.1555	0.1604	0.1918
All - Speaker	0.1729	0.1713	0.148	0.1736
All - State	0.1682	**0.1736**	0.1495	0.1602
All - Subject	0.1643	0.1507	0.1519	0.1634
Average	0.1683	0.1597	0.1651	0.1680

Figure 5. Experiment result

From the eight different feature combinations in our experiment, we highlighted the best and the worst three in each of our models. Then we found that, overall, if we include all features from the LIAR dataset, the performance of our two models is both in the worst three with the average accuracy around 0.15. This result clearly showed that there must be some features in this dataset that are not really contributing to better detecting the fake news. To identify which feature caused this issue, we can look into the combination of all features excepts for ”speaker.” The performance of this combination in both models is in their best three, with significant accuracies increase to over 0.17. This result suggested that the feature ”speaker” in the LIAR dataset is not contributing to detect fake news; moreover, it even limits the accuracy of the detection.

Test Accuracy		
Algorithm	KNN	Neuron
All	0.1515	0.1492
All - Context	0.1523	0.1965
All - Credit	0.1641	0.1618
All - Job title	0.1586	0.1476
All - Party	0.1555	0.1918
All - Speaker	0.1713	0.1736
All - State	0.1736	0.1602
All - Subject	0.1507	0.1634

Best three accuracies   Worst three accuracies

Figure 6. Experiment result with best three and worst three

The possible reason that speaker is not a good feature for detecting fake news is that human beings are complicated creatures. We tell the truth or lies based on different circumstances and intentions. We don’t really have a pattern of always telling the truth or lies. Furthermore, some people might purposely tell truths to increase their credit so that when they need to lie, people would be more likely to trust them. As a result, detecting fake news includes the information of the speaker might not be beneficial as we thought.

6 Conclusions

Detecting fake news has become one of the most popular and important issues for researchers in the machine learning field. In the past, researchers have made a lot of contributions to the structure and context of fake news articles. These contributions make current researchers widely understand that it is difficult to improve the detection accuracy of the algorithm with the text content of fakes news. In recent years, the research on fake news is moving in many different directions.

From our experiment, we applied the newly formed LIAR dataset, which included not only the content of the news also abut the headlines, to try to build a better detection model. We also tested different feature combinations to identify the determining features in this dataset. Although our models are not accurate as of the previous research, we still identified one feature that is not contributing and even hinders the accuracy of the detection. For future research, we would like to suggest researchers look for other new features instead of including the speaker as one of the features. We also encourage to have more research on identifying the importance of the features we currently have than to seek for more, not really worthy features.

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