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Original Article

Fake News Detection using Machine Learning Algorithm

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Abstract - *Recent works have focused on understanding and detection of fake news stories that are information spread widely on social media. To accomplish this goal, these works explore several types of features extracted from news stories, including sources and posts from social media. Presenting a new set of features and measuring the Prediction performance of current approaches and features automatic detection of fake news discussing how fake news detection approaches can be used in practice, highlighting challenges and opportunities.*

Keywords - *Machine Learning, Supervised Learning, social media, Prediction*.

I. INTRODUCTION

Social media are interactive technologies that facilitate the creation and sharing of information, ideas, interests and other forms of expression through virtual communities and networks. A key problem today is that social media has become a place for campaigns of misinformation that affect the credibility of the entire news echo system. The characteristic of social media is that anyone can register and publish news without any upfront cost. Not only traditional news corporations are increasingly migrating to social media with this transition there are growing concerns about fake news publishers posting as the extensive spread of fake news can have a serious negative impact on individuals and society. The lack of scalable fact-checking approaches is exclusively troublesome.

Recent research efforts are dedicated to an automated approach to the fake news problem can be quite contentious and is still open for debate. A relevant research question is what is the prediction performance of current approaches and features for automatic detection of fake news?.

Table 1. The data set

News	Total number of articles	Type	Number of Articles
Real	21417	World News	10145
		Political News	11272
		Government News	1570
		Middle East News	778
		US News	783
Fake News	23481	Politics News	6841
		News	9050
		Left News	4459

II. FEATURES OF FAKE NEWS DETECTION

Most of the existing efforts to detect fake news propose features that leverage information present in a specific dataset. In contrast, we use a recently released dataset that allows us to implement most of the proposed features explored in previous works. It consists of news related articles.

A. Language Features (Syntax)

Sentence-level features, including bag-of-words approaches, "n-grams", and part-of-speech (POS tagging), were explored in previous efforts as features for fake news detection. 2,6 Here, we implemented 31 features from this set, including the number of words and syllables per sentence as well as tags of word categories (such as noun, verb, adjective). In addition, to evaluate writers' styles as potential indicators of text quality, we also implemented features based on text readability.

B. Lexical Features

Typical lexical features include character and word-level signals, such as the number of unique words and their frequency in the text. We implemented linguistic features, including the number of words, first-person pronouns, demonstrative pronouns, verbs, hashtags, all punctuations counts, etc.

C. Psycholinguistic Features

Linguistic Inquiry and Word Count (LIWC) 8 is a dictionary-based text mining software whose output has been explored in many classification tasks, including fake news detection. We use its latest version (2015) to extract 44 features that capture additional signals of persuasive and biased language.

D. Semantic Features

There are features that capture the semantic aspects of a text that are useful to infer patterns of meaning from data. As part of this set of features, we consider the toxicity score obtained from Google's API (https://www.perspectiveapi.com). The API uses machine

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learning models to quantify the extent to which a text (or comment, for instance) can be perceived as "toxic." We did not consider strategies for topic extraction since the dataset used in this paper was built based on news articles about the same topic or category (i.e., politics).

E. Subjectivity

Using Text Blob's API (http://text-blob.readthedocs.io/en/dev/). We compute the subjectivity and sentiment scores of a text as explored in previous efforts. News Source Features consist of information about the publisher of the news article. To extract these features, we first parsed all news URLs and extracted the domain information. When the URL was unavailable, we associated the official URL of the news outlet with the news article. Therefore, we extract eight indicators of political bias, credibility and source trustworthiness and use them as detailed next. Moreover, in this category, we introduce a new set composed of five features, called domain localization.

a) Bias

The correlation between political polarization and the spread of misinformation was explored in previous studies. In this paper, we use the political biases of news outlets from the Buzz Feed dataset as a feature.

b) Credibility and Trustworthiness

In this feature set, we introduce seven new features to capture aspects of credibility (or popularity) and trustworthiness of domains. We collect, using Facebook's API (https://.facebook.com), user engagement metrics of Facebook pages that published news articles (i.e., "page talking about" count and "page fan" count). Then, we use Alexa's API to get the relative position of the news domain on the Alexa Ranking (https://www.alexa.com). Furthermore, using this same API, we collect Alexa's top 500 newspapers. Based on the intuition that some unreliable domains may try to disguise themselves using domains similar to those of well-known newspapers, we define the dissimilarity between domains from the Alexa ranking and news domains in our dataset (measured by the minimum edit distance) as features. Finally, we use indicators of low credibility of domains compiled as features.

c) Domain Location

Ever since creating fake news became a profitable job, some cities have become famous because of residents who create and disseminate fake news (https://www./news/magazine). In order to exploit the information that domain location could carry, a pipeline was built to take each news website URL and extract new features, such as IP, latitude, longitude, city, and country. First, for each domain, the corresponding IP was extracted using the traceroute tool. Then, the IP stack API was used to retrieve the location features. Although localization information (i.e., IP) has been previously used in works on bots or spam detection, to the best of our knowledge, there are no works that leverage these data in the context of fake news detection.

Environment Features consist of statistics of user engagement and temporal patterns from social media (i.e., Facebook). These features have been extensively used in previous efforts, especially to better understand the phenomenon of fake news. Next, we detail the features of this category.

1) Engagement

We consider the number of likes, shares, and comments from Facebook users. Moreover, we compute the number of comments within intervals from publication time (900, 1800, 2700, 3600, 7200, 14400, 28 800, 57 600, and 86 400 s), summing up to 12 features.

2) Temporal Patterns

Finally, to capture oral temp patterns from user commenting activities, we compute the rate at which comments are posted for the same time windows defined before.

III. CLASSIFICATION RESULTS

We evaluate the discriminative power of the previous features using several classic and state of the art classifiers, including k-Nearest Neighbors (KNN), Naive Bayes (NB), Random Forests (RF), Support Vector Machine with RBF kernel (SVM), and XGBoost (XGB). Given that we used handcrafted. Features, there was no need to include a neural network model in the comparison since it would only associate weights with the features rather than find new ones.

IV. METHODOLOGY

This section presents the methodology used for the classification. Using this model, a tool is implemented for detecting fake articles. In this method, supervised machine learning is used for classifying the dataset. The first step in this classification problem is the dataset collection phase, followed by preprocessing, implementing features selection, and then performing the training and testing of the dataset and finally running the classifiers. Figure [1] describes the proposed system methodology. The methodology is based on conducting various experiments on the dataset using the algorithms described in the previous section named Random forest, SVM and Naïve Bayes, majority voting and other classifiers.

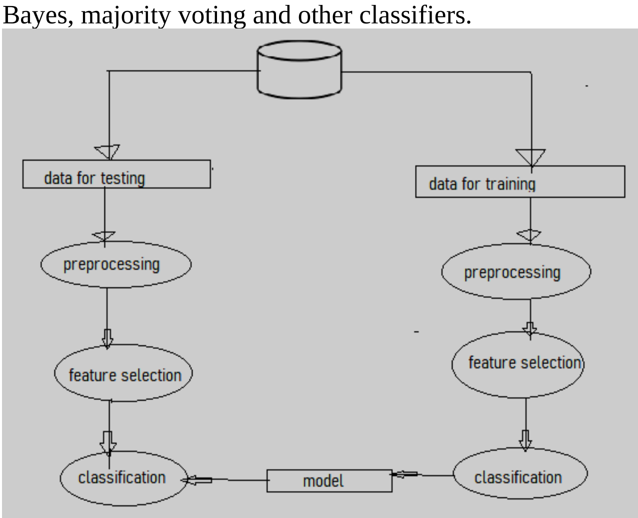

Fig. 1 Describes the Proposed System Methodology

The main goal is to apply a set of classification algorithms to obtain a classification model in order to be used as a scanner for fake news by details of news detection and embed the model in python application to be used as a discovery for the fake news data.

The classification algorithms applied in this model are k-Nearest Neighbors (k-NN), Linear Regression, XGBoost, Naive Bayes, Decision Tree, Random Forests and Support Vector Machine (SVM). All these algorithms get as accurate as possible. Where reliable from the combination of the average of them and compare them.

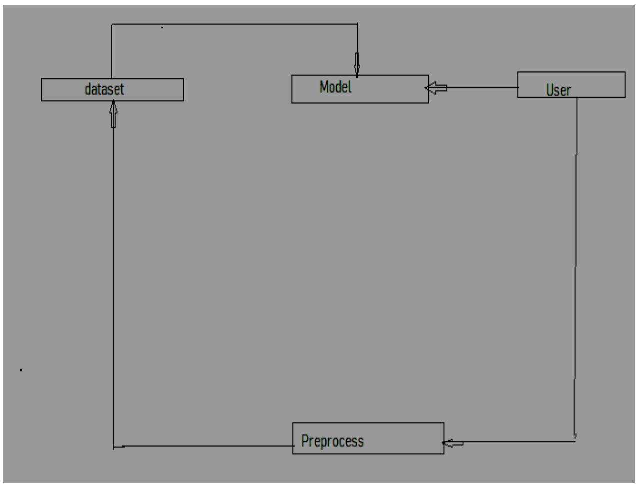

Fig. 2 Fake detector model

V. CONCLUSION

In the future, larger volumes of labelled data will enable us to explore other techniques such as deep learning and push the boundaries of prediction performance.

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