Detection and Characterization of Fake News Articles using Stylistic Features

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ABSTRACT

Fake news still remains a blight in today's media landscape, necessitating its automated detection. However, with most news sites being either in English or bilingual, only particular linguistic-based features can be employed in the classification. In line with this, the present study aims to detect fake news from a set of 5,000 English news articles using stylistic features. We first extracted the features from each cleaned article and selected the top 5, 10, 15 and 20 features based on the chi-squared test. We then fed differing number of top features to a logistic regression classifier, after which we assessed the performance of the classifiers based on accuracy and F-score. We found that both metrics increased as we increased the number of top features, with the 20-feature model yielding an accuracy of 85.2% and an F-score of 83.61%. Furthermore, comparing the results to a term count-based baseline model, we find that they do not differ significantly, although the stylistic feature-based model performs slightly worse.

KEYWORDS
text classification, fake news

1. INTRODUCTION

Social media has made it cheaper and easier for the general public to consume and share news. With this, however, the responsibility of curating and assessing news articles now falls upon the reader, who may not be well-equipped to do so. This is especially true in the Philippines, where the issue of fake news remains prevalent. The problem has become so entrenched in the country that Facebook's Global Politics and Government Outreach Director Katie Harbath has regarded Duterte's presidential campaign as "patient zero" in today's post-truth era, having come before the Cambridge Analytica scandal and Trump's own presidential campaign [19].

The prevalence of fake news is a serious problem, which can have long-standing consequences on society. For one, fake news instills false beliefs in its readers, encouraging them to act against their own best interests. The recent measles outbreak, for example, was in part due to growing distrust in vaccines due to the Dengvaxia scare. While the Dengvaxia vaccine's role in the death of the children who received it has yet to be established, many fake news sites have popped up suggesting otherwise, thus reducing the public's confidence in vaccines [6].

Fake news also tends to be more sensational, eye-catching and novel, making it diffuse farther and faster on social media compared to real news [20]. This is potentially dangerous, as fake news can change the way readers respond to real news. Since fake news tend to get to readers first, it can make readers distrust or outright condemn authentic news sources in favor of fake ones.

Hence, finding a means to detect fake news algorithmically is important, especially since humans have been found to correctly classify only around 70% of serious news articles [14]. This paper aims to do exactly that using linguistic-based features, as in [8]. By extracting stylistic features and comparing real news and fake news articles using said features, we can characterize the composition of typical real and fake news articles and use machine learning classifiers to algorithmically distinguish one from the other.

Traditionally, different features have been used to detect fake news articles – stylistic, sentiment-based and syntactic, among others (which will be discussed in Section 2). However, in the case of Filipino, the lack of a sentiment lexicon or a lexical database like WordNet hinders our ability to use features related to the sentiment or the sense of a text. Thus, this necessitates the use of stylistic features in the classification. While this paper will work with English news articles, it represents the first step in assessing the effectiveness of employing stylistic features in the automated detection of fake news articles in English. As such, the results of this study will be relevant in classifying Philippine-based news articles, as most articles are either bilingual or in English [18].

2. REVIEW OF RELATED LITERATURE

Most news articles can be described by the following attributes: (1) the source (author and publication), (2) the headline, (3) the body text and (4) any accompanying image/video attributes [17]. As such, we can extract two types of features from news articles – linguistic-based and visual-based.

Visual-based features, in particular, have been used in conjunction with linguistic-based features to aid in classification [7]. However, some studies have also made use of statistical image/video-based features, as in [10], to characterize fake news articles.

Linguistic-based features tend to be more popular, however, as fake news tends to have a stylistic fingerprint. Fake news pieces are often characterized by emotionally-charged and prejudiced writing, accompanied by clickbait headlines which tend to lure readers in [3].

In particular, Horne and Adali (2017) examined three sub-categories of linguistic-based features: (1) stylistic features, (2) complexity features and (3) psychological features. Stylistic features are based on the syntax and grammar in the articles and include word count, number of proper nouns and number of stop words, among others. Other papers extend this to include n-grams [4] and word-embeddings [13].

Complexity features, on the other hand, are meant to capture how "intricate" an article is. At the word level, Horne and Adali use three different readability indices: Gunning Fog, SMOG Grade and Flesh-Kincaid. All three compute a score based on particular features in the text (such as the number of syllables, number of sentences, number of difficult words, etc.) -- the score signifying how difficult it is to read the article. They also employ the type-token ratio (TTR), computed as the number of unique words in an article divided by the total number of words. This value is meant to capture the lexical diversity of an article; thus, lower TTR values signify more word redundancy.

Lastly, psychological features are primarily sentiment-based and make use of the Linguistic Inquiry and Word Count (LIWC) dictionaries. These include the number of analytic words, number of emotional tone words and number of personal concern words, among others [8].

In addition to the content of the news article, Shu et al. (2017) have also suggested the use of social context features. Fake news pieces tend to be spread by bots, so determining user-level features such as the registration age, number of followers/followees and number of tweets, among others can prove to be helpful in classifying fake news articles [2]. Moreover, social engagement can also be viewed at the post/tweet level. One can collate all posts/tweets pertaining to a particular article and characterize its stance/opinions [9], its topic [12] or its credibility [2]. We can also examine groups of posts/tweets to form a network. Co-occurrence networks [16], friendship networks [11] and diffusion networks [11] can be examined and their associated attributes can also be used to characterize fake news articles.

The present study, however, intends to focus simply on linguistics-based features, in particular stylistic and complexity features, as detailed in [8].

3. METHODOLOGY

3.1 DATA

The dataset was culled from two sources on Kaggle. The fake news had been obtained from the BS Detector dataset (source: https://www.kaggle.com/mrisdal/fake-news), which consisted of news articles whose sources had been deemed as fake by the BS Detector Chrome Extension by Daniel Sieradski. The real news had been obtained from the All the news dataset (source: https://www.kaggle.com/snapcrack/all-the-news) consisting of digital and print articles from 15 mainstream publications.

To balance the dataset, we kept real articles published within 5 days from the earliest/latest publication dates in the fake news dataset. That is, articles published 5 days before the earliest publication date and 5 days after the latest publication date in the fake dataset had been considered.

We removed articles that were not in English and articles with less than 200 words. We also removed Breitbart articles from the real news dataset and kept it in the fake news dataset due to Wikipedia editors deciding that the news site is a “conspiracy theorist and fake news website." [5]

Table 1 summarizes the news sources in the dataset.

TABLE 1. News sources for the dataset

NEWS TYPE	SOURCES
real news	Atlantic, Business Insider, Buzzfeed News, CNN, Fox News, Guardian, NPR, National Review, New York Post, New York Times, Reuters, Talking Points Memo, Vox, Washington Post (*14 in total*)
fake news	100percentfedup.com, 21stcenturywire.com, abcnews.com.co, abeldanger.net, abovetopsecret.com, activistpost.com, addictinginfo.org, adobochronicles.com, … (*233 in total*)

After cleaning, we find that there are 10,259 fake news articles and 11,105 real news articles in the dataset. For convenience, however, we perform a stratified sample on the dataset, resulting in 2,500 fake news articles and 2,500 real news articles.

3.2 FEATURES

In line with [5], we extract the following features from the news article content and headline:

TABLE 2. Features to be extracted

FEATURE	CONTENT?	TITLE?	DESCRIPTION
word count (WC)	✓	✓	number of words
sentence count (SC)	✓		number of sentences in the article
words per sentence (WPS)	✓		average number of words per sentence in the article
Dale-Chall readability index (DCRI)	✓	✓	gauges how difficult a text is to read based on word count and a list of words it deems difficult
type-token ratio (TTR)	✓		calculated as the number of unique words divided by the total number of words; measures lexical diversity
stop words (SW)	✓	✓	number of stop words
punctuation marks (PM)	✓	✓	number of punctuation marks
exclamation/ question marks (EQ)	✓	✓	number of exclamation/question marks
link count (LC)	✓		number of hyperlinks
all-caps (AC)	✓	✓	number of words that appear in all-caps
nouns (NN)	✓		number of nouns
proper nouns (NNP)	✓		number of proper nouns
adjectives (ADJ)	✓		number of adjectives
adverbs (ADV)	✓		number of adverbs

Not all features from [8] were included. Some features (e.g., psychological features) required the use of paid corpora/tools like the LIWC. Some others were excluded based on our own discretion. In total, 20 features were extracted per article.

Based on [8], the features extracted can roughly be divided into two: (1) stylistic features and (2) complexity features. Stylistic features pertain to the syntax and grammar inherent in the writing style of the author. The features can point to particular attributes in the writing style and since fake news pieces are written specifically to catch attention and to incite strong emotion [3], we expect a significant difference between the stylistic features characteristic of fake news and of real news.

As an example, the number of words used, for example, can point to a news piece being either wordy or terse. Also, a high number of stop words can make an article readable, while a low number can point to the author sacrificing readability for the sake of squeezing as much information as possible.

According to [8], complexity features are meant to capture the "intricacy" of an article. However, the two complexity features extracted (Dale-Chall readability index and type-token ratio) can also be used to describe the author's writing style. The Dale-Chall readability index, for example, factors in the number of "difficult" (i.e., non-commonly occurring) words in an article, and a higher index can signify that an article may be trying to sound pompous or affected by using less commonly used words. Meanwhile, the type-token ratio measures lexical diversity, and lower values can point to an article being repetitive. Thus, the complexity features can reasonably be treated as stylistic features, as is done in this paper.

3.3 METHODS

We used Python in conducting all the steps outlined here. We first cleaned the dataset and performed a stratified sample, yielding 5,000 news articles – 2,500 of which are fake and 2,500 of which are real.

After cleaning the data, the succeeding procedures can be divided into four main phases. For the first phase, we extracted the features discussed in Section 3.2 and as an exploratory procedure, we compared the average value of each feature for both fake and real news articles and conducted a two-sample t-test (assuming unequal variances) to see if the features are significantly different from each other on average. The statistical test served to differentiate fake and real news based on the features extracted.

In the second phase, we split the dataset into training and testing sets, with 40% of the dataset going towards the testing set, after which we chose a baseline model employing the more conventional term frequencies/TF-IDF weighted frequencies as our features and applying the naive Bayes and logistic regression models as our classifiers. We examined two variants per classifier and per feature – one without the removal of stop words, stemming and considering only unigrams and the other with the removal of stop words, stemming (using the Porter Stemmer) and considering bigrams. From the eight resulting models, we chose the best-performing one as our baseline to compare to the model with stylistic features.

Meanwhile, for the third phase, we selected which stylistic features to feed to our classifiers based on the chi-squared test. The top 5, 10, 15 and 20 features were selected and fed into the model, with the baseline model as our reference. We then noted the performance of the classifier using accuracy and F-score as our performance measures.

Finally, in the fourth phase, we considered the effect of combining the stylistic characteristics of the article and term frequency/TF-IDF-weighted frequency as features in the classifier, noting whether the features complement each other using the resulting accuracy and F-score.

4. RESULTS AND DISCUSSION

4.1 STATISTICAL TESTING

After extracting the features, we first conducted a preliminary analysis by getting the mean value of each feature for both fake and real news articles and comparing the two using Welch's two-sample t-test.

This test is designed for unequal variances and assumes that the data is normally distributed (which can be assumed due to the large sample size). With the null hypothesis of identical averages, a small p-value indicates that the two means are significantly different from each other, and that we expect the features to be significantly different in the population.

Implementing Welch's two-sample t-test on the features and using a significance level of 5%, we obtain the following results:

TABLE 3. Comparison of content-based features

FEATURE	COMPARISON	P-VALUE
WC	Real > Fake	3.74e-6 *
SC	Real > Fake	2.73e-11 *
WPS	Fake > Real	4.17e-29 *
DCRI	Fake > Real	1.59e-47 *
TTR	Fake > Real	5.26e-29 *
SW	Real > Fake	3.48e-5 *
PM	Real > Fake	9.10e-5 *
EQ	Fake > Real	2.08e-91 *
LC	Fake > Real	8.02e-10 *
AC	Real > Fake	0.99
NN	Real > Fake	8.46e-9 *
NNP	Real > Fake	0.0048 *
ADJ	Real > Fake	0.0055 *
ADV	Real > Fake	0.0033 *

* - significant at 5%

The results of the statistical test show that the content of real and fake news differ considerably in terms of almost all features except one. The results show that real news articles tend to have more words and sentences on average. They also have more stop words, more punctuation marks and more nouns, proper nouns, adjectives and adverbs.

On the other hand, fake news articles have more words per sentence. They also have a higher Dale-Chall readability index indicating that they may be more difficult to comprehend, and a higher type-token ratio indicating that there is more lexical diversity in fake news articles. Fake news articles have also been found to contain more exclamation and question marks and more link counts.

The results point to the following conclusions. For one, real news articles tend to be longer on average and contain more stop words and punctuation marks, making them more fluid and thus easier to comprehend. Meanwhile, fake news articles have more words per sentence, less stop words and less punctuation, signifying that the authors of fake news articles try to cram as much information as possible into each sentence. Fake news articles have also been found to have a higher Dale-Chall readability index (which takes into account the occurrence of non-commonly occurring words) and a higher type-token ratio, meaning that there are more non-frequent words in fake news articles. Lastly, fake news articles have more question marks/exclamation points, possibly indicating more emotionally-charged content.

TABLE 4. Comparison of title-based features

FEATURE	COMPARISON	P-VALUE
WC	Fake > Real	1.00e-8 *
DCRI	Fake > Real	0.012
SW	Real > Fake	0.43
PM	Real > Fake	1.09e-9 *
EQ	Fake > Real	1.08e-9 *
AC	Fake > Real	2.16e036 *

* - significant at 5%

Similarly, we found that authors of fake news pieces tend to squeeze as much as possible into the headline, as evidenced by longer word counts and less stop words. Furthermore, fake news titles also tend to be more dramatic, as evidenced by more words being in all-caps and more question marks/exclamation points. These characteristics tend to be in line with those found in clickbait articles [3].

4.2 BASELINE MODEL SELECTION

In this section, we train a fake news classifier with term counts/TF-IDF weighted frequencies as the sole feature. Both have commonly been used as features in various text classification problems, including the automated detection of fake news [1]. As such, the TC/TF-IDF based model provides a reasonable baseline against which we can compare our stylistic features-based model.

As an initial step, we considered the words with the highest average term counts/TF-IDF weighted frequencies after removing stop words and stemming. The results are as follows:

TABLE 5. Top 10 most frequent words based on average term count and average TF-IDF weighted frequency

AVERAGE TERM COUNT		AVERAGE TF-IDF WEIGHTED FREQUENCY	
REAL NEWS	*FAKE NEWS*	*REAL NEWS*	*FAKE NEWS*
1. thi	1. wa	1. clinton	1. trump
2. wa	2. said	2. trump	2. said
3. ha	3. trump	3. thi	3. wa
4.clinton	4. hi	4. wa	4. hi
5. trump	5. ha	5. hillari	5. ha
6. hi	6. thi	6. ha	6. thi
7. would	7. would	7. email	7. clinton
8. peopl	8. one	8. elect	8. would
9. one	9. peopl	9. hi	9. state
10. state	10. state	10. us	10. elect

Based on Table 5, we found that the TF-IDF weighing scheme did not downweigh terms commonly occurring in both groups as much as we expected. TF-IDF is often employed in order to downweigh these terms and upweigh those that commonly occur in one group, so as to improve the classifier's performance [1]. In this case, however, we did not see a significant difference between the two.

We then fit a naïve Bayes model and a logistic regression model using either one as the sole feature, taking note of two variants – one without the removal of stop words, stemming and considering only unigrams and the other with the removal of stop words, stemming (using the Porter Stemmer) and considering bigrams. We choose the better-performing variant in each case and compare the four resulting models in terms of accuracy and F-score. Table 6 shows the results.

TABLE 6. Comparison of baseline models

CLASSIFIER	FEATURE	STOP WORD REMOVAL? STEMMING? BIGRAMS?	ACCURACY	F-SCORE
naïve Bayes	term counts	No	85.25%	86.08%
naïve Bayes	TF-IDF	No	80.5%	82.86%
logistic regression	term counts	Yes	87.7%	87.58%
logistic regression	TF-IDF	Yes	86.35%	86.21%

We found that the term counts-based models consistently performed better compared to the TF-IDF models. This is supported by the results in Table 5, which showed that TF-IDF did not considerably downweigh words that occurred commonly in both groups.

Comparing both term counts-based models, the logistic regression classifier performed better, achieving an accuracy of 87.7% and an F-score of 87.58%. Thus, we choose the term counts-based logistic regression model as our baseline model. To look into the results further, we can consult the normalized confusion matrix for our baseline model in Table 7.

TABLE 7. Normalized confusion matrix for the baseline model

		PREDICTED LABEL	
		FAKE	REAL
TRUE LABEL	FAKE	0.89	0.11
	REAL	0.14	0.86

From Table 7, we found that roughly 90% of the news articles in each group were correctly classified.

4.3 FEATURE SELECTION AND STYLISTIC FEATURE-BASED MODEL

After selecting the baseline model, we proceed to selecting the stylistic features to employ in our model using the chi-squared test. This statistical test returns a score for each feature based on the computed chi-square test statistic. A larger value indicates that the feature can potentially provide important information about the class of the article (i.e., whether it is real or fake) to the classifier. Based on these scores, we choose the highest 5, 10, 15 and 20 and use the attributes associated with them as features in the model, using the baseline model as our reference. Using this as our basis, we get the top 5, 10, 15 and 20 features as shown in Table 8.

TABLE 8. Top features based on feature selection

TOP	FEATURES
Top 5	• WC • SW • PM • LC • NN

Top 10	• SC • AC (title) • NNP • ADJ • ADV
Top 15	• WPS • DCRI • EQ • WC (title) • QE (title)
Top 20	• TTR • AC • SW (title) • PM (title) • DCRI (title)

After feeding the top 5, 10, 15 and 20 features into our logistic regression classifier, we assessed the performance of the classifiers, taking note of their accuracy and F-scores. Table 9 summarizes these results.

TABLE 9. Comparison of stylistic feature-based models

FEATURE	ACCURACY	F-SCORE
Top 5	80.37%	75.81%
Top 10	82.49%	79.91%
Top 15	84.75%	83.06%
Top 20	85.20%	83.61%

Comparing these figures to those in Table 6, we find that the fake news classifier relying only stylistic features performed slightly worse compared to our baseline model.

In addition to this, we also examined if adding the stylistic features can improve the performance of the term counts-based logistic regression model. Table 10 summarizes the results.

TABLE 10. Comparison of stylistic feature-based models

FEATURE	ACCURACY	F-SCORE
Baseline	87.7%	87.58%
Baseline + Top 5	87. 92%	87.98%
Baseline + Top 10	88.37%	88.47%
Baseline + Top 15	89.33%	89.35%
Baseline + Top 20	89.38%	89.37%

The results outlined in Table 10 show that adding the stylistic features to the baseline model improve its accuracy somewhat, but not significantly. Thus, stylistic features do not offer a lot of information that is not contained in the term counts. If we wish to improve the accuracy of the baseline models, we would have to search for other features such as those explained in Section 2.

5. CONCLUSION

Various accounts in section 2 ([8] in particular) have been able to employ the linguistic-based attributes of a news article to determine whether it is genuine or not. Through our results in section 3, we have been able to show that stylistic attributes can viably be used as features to a fake news classifier.

In the first part, we used statistical testing as a preliminary method to determine if fake and real news had any significant stylistic differences. We were able to determine that real news articles were lengthier on average but had more stop words, more punctuation and were easier to understand. The content of fake news pieces, on the other hand, were harder to understand and were possibly more emotionally-charged. In terms of the titles, we found that fake news titles were more dramatic as evidenced by the use of all caps and exclamation marks/question marks and as with the body, authors tried to cram as much information as possible, inflating word count and skipping stop words and punctuation altogether.

After analyzing the stylistic differences between the two, we selected a baseline model with term counts/TF-IDF weighted frequencies as the sole feature. We ended up selecting a term counts-based logistic regression model with stop word removal, stemming and bigrams. We then selected which stylistic features to use and then fed the top 5, 10, 15 and 20 features to the logistic regression classifier. Comparing our reference model with the stylistic feature-based classifier, we find that the two do not differ significantly in terms of performance. We also find that the two complement each other slightly, as considering them both leads to a minor uptick in performance.

In general, we can conclude that stylistic attributes can be considered as important features in the automated detection of fake news articles, although they do not offer much more information than is already offered by term counts or TF-IDF. Future research can focus on the use of other lexicon-based features, as in [8]. It may also be important for future researchers to gather their own news data, as section 2 suggests that social context features are gaining credence in the literature. One may also want to expand the study by distinguishing between hoaxes, propaganda news and satirical news, as in [15].

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