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This Just In: Fake News Packs a Lot in Title, Uses Simpler, Repetitive Content in Text Body, More Similar to Satire than Real News

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Abstract

The problem of fake news has gained a lot of attention as it is claimed to have had a significant impact on 2016 US Presidential Elections. Fake news is not a new problem and its spread in social networks is well-studied. Often an underlying assumption in fake news discussion is that it is written to look like real news, fooling the reader who does not check for reliability of the sources or the arguments in its content. Through a unique study of three data sets and features that capture the style and the language of articles, we show that this assumption is not true. Fake news in most cases is more similar to satire than to real news, leading us to conclude that persuasion in fake news is achieved through heuristics rather than the strength of arguments. We show overall title structure and the use of proper nouns in titles are very significant in differentiating fake from real. This leads us to conclude that fake news is targeted for audiences who are not likely to read beyond titles and is aimed at creating mental associations between entities and claims.

Introduction

The main problem we address in this paper is the following: Is there any systematic stylistic and other content differences between fake and real news? News informs and influences almost all of our everyday decisions. Today, the news is networked, abundant, and fast-flowing through social networks. The sheer number of news stories together with duplication across social contacts is overwhelming. The overload caused by this abundance can force us to use quick heuristics to gain information and make a decision on whether to trust its veracity. These heuristics can come in many forms. In deciding that content is believable by using reader's own judgment, readers may simply skim an article to understand the main claims instead of reading carefully the arguments and deciding whether the claim is well-supported. In some cases, other heuristics may rely on the trust for the source producing the information or for the social contact who shared it. Often the trust decision is a combination of these heuristics, content, source, and social network all playing a role. This trust decision strucure is supported by the well-studied notion of echo-chambers, in which the sharing of information often conforms to one's beliefs and is impacted by homophily (Bakshy, Messing, and Adamic 2015). Furthermore, misleading or wrong information have a higher potential to become viral (Bessi et al. 2015)and lead to negative discussions (Zollo et al. 2015b). Even more troubling, results show resistance by individuals to information challenging established beliefs and that attempts to debunk conspiracy theories are largely ineffective (Zollo et al. 2015a).

As an informed public is crucial to any operating democracy, incorrect information is especially dangerous in political news. As many widely discredited claims have become viral and distributed widely in social networks during the 2016 elections (Silverman 2016), the topic of "fake news" and effective methods for debunking it has gained renewed attention. While there is a great deal of work on the social factors leading to dissemination of misinformation in networks (Bessi et al. 2014), there is relatively little work on understanding how fake news content differs from real news content. We would like to understand whether fake news differs systematically from real news in style and language use. While some have argued that the distinction between fake and real news can be a rather arbitrary one, as well-established news organizations have been known to disseminate incorrect information on occasion, such organizations operate with a degree of transparency that is not found in fake news sites and risk their established credibility if their news stories are shown to be false. More importantly, their articles adhere to a journalistic style in making and presenting claims.

To conduct our study of "fake news", we study three separate data sets. Two of these data sets are novel: one has been featured by Buzzfeed through their analysis of real and fake news items from 2016 US Elections (Silverman 2016). The second data set, collected by us, contains news articles on US politics from real, fake, and satire news sources. Finally, we look at a third data set containing real and satire articles from a past study (Burfoot and Baldwin 2009). We include satire as a type of fake news that relies on absurdity rather than sound arguments to make claims, but explicitly identifies itself as satire. Fake news in contrast has the intention to deceive, making the reader believe it is correct. We study similarities between fake news and satire to understand different heuristics that they both employ to persuade their readers. The inclusion of satire as a third category of news is a unique contribution of our work. Through a statistical study of these three data sets, we show that fake news articles tend to be shorter in terms of content, but use repetitive language and fewer punctuation. Fake news articles differ much more in their titles. Fake titles are longer, use few stop words, and fewer nouns but more proper nouns. Furthermore, we find that fake news is more similar to satire than real news. When fake news is different than satire, the distinction simply exaggerates satire's differences with real news further. Fake news packs the main claim of the article into its title, which often is about a specific person and entity, allowing the reader to skip reading the article, which tends to be short, repetitive, and less informative. Given the arguments in the article are less of a factor, the persuasion likely relies on heuristics such as conformance of the information to one's beliefs. Lastly, we illustrate the predictive power of our features by utilizing linear kernel SVMs on small feature subsets. We hope that our study and data sets lead to further study of stylistic conventions used in persuading audiences with limited attention and effective methods to counter them. In the least, it suggests that more attention needs to paid to titles of such articles.

Related Work

Fake news is certainly not a new phenomenon, and has been well studied in both the fields of journalism and computer science. In particular, it has been studied in two ways: (1) analyzing the spread of fake news and (2) analyzing the content of fake news.

Rubin et al. work towards a news verification system using Rhetorical Structure Theory (RST) on content data from NPR's "Bluff the Listener" (Rubin, Conroy, and Chen 2015), achieving a 63% prediction accuracy over a 56% baseline. Given its data source, this study aims at identifying subtle differences in narrative between different stories, which is not well-suited for news articles. Similarly, Burfoot and Baldwin use SVMs on lexical and semantic features to automatically classify true news content from satire news content. The content features specifically geared towards satire significantly outperform the baseline and achieve high classification precision. (Burfoot and Baldwin 2009). Some of our features and one of our data sets are common with this study, though we use a much larger feature set that also captures the readability of the text and its word usage. Along the same lines, Rubin et al. propose an SVM-based algorithm with 5 language features (Rubin et al. 2016). They achieve 90% accuracy in detecting satire news from real news. Our features and classification method has some overlap with this work. However, these studies do not explicitly target fake news. Yet, as demonstrated by the many events of the 2016 US Election (Silverman 2016), fake and satirical news are clearly different in motivation. Conversely, fake news is motivated by deceiving its readers into thinking a completely false story is real, many times with malicious intent (Sydell 2016). This distinction between the content of three classes of news: satire, fake, and real, is the key contribution of our work.

The spread of misinformation in networks has also been studied. Specifically, Bessi et al. study the attention given to misinformation on Facebook. They show that users who often interact with alternative media are more prone to interact with intentional false claims (Bessi et al. 2014). Very recently, Shao et al. launched a platform for tracking online misinformation called Hoaxy (Shao et al. 2016). Hoaxy gathers social news shares and fact-checking through a mix of web scraping, web syndication, and social network APIs. The goal of Hoaxy is to track both truthful and not truthful online information automatically. However, Hoaxy does not do any fact-checking of its own, rather relying on the efforts of fact-checkers such as snopes.com.

In our work, we concentrate on content analysis to study fake news for several important reasons. Readers' assessment of information play a significant role in decisions to disseminate it. Even though the abundance of information leads to limited attention given to each article, users engage with social media with the intention to find and share information. When controlling for attention and individual differences in the need to engage with information, the relevant arguments and message characteristics become the determinant in persuasion and attitude change (OKeefe 2008). Therefore, it is helpful to understand whether there are specific the message characteristics that accompany fake news articles being produced and widely shared. As, textual analysis is well studied in computer science and has been used for highly accurate document classification, it may prove quite helpful in stopping the spread of fake news (Sebastiani 2002). Furthermore, we hope that this type of analysis can be of benefit to grass-root fact-checkers by notifying them of potential fake articles earlier. This benefit in turn can provide more fact-checked content, ultimately helping systems like Hoaxy.

Methodology

To begin exploring the content of fake news, we develop strict definitions of what real, fake, and satire news stories are. Specifically, real news stories are stories that are known to be true and from well trusted news sources. Fake news stories are stories that are known to be false and are from well known fake news websites that are intentionally trying to spread misinformation. Satire news stories are stories that are from news sources that explicitly state they are satirical and do not intentionally spread misinformation. Satire news is explicitly produced for entertainment.

Data sets

With these definitions in mind, we use three independent data sets.

Data set 1: Buzzfeed election data set First, we collected the news stories found in Buzzfeed's 2016 article on fake election news on Facebook (Silverman 2016). Buzzfeed gathered this data using the content analysis tool BuzzSumo by first searching for real and fake stories getting the highest engagement on Facebook using various methods during the 9 months before the 2016 US Presidential Election, divided into three 3-month segments. For fake stories, they targeted articles with the highest engagement for key election terms and filtered these by known fake news sources. For real stories, they found the stories getting the highest engagement from well-known news organizations in the same time period. The URL and Facebook engagement statistics of the chosen fake and real stories, 60 each, were made available. To keep the ground truth of real/fake within our definitions, we filtered out stories that are opinion based or were explicitly satire; leaving us with 36 real news stories and 35 fake news stories. Other than this filtering, we took the ground truth as is; thus, it is important to keep in mind the limitations of this data set. First, we do not know if there was any selection bias in collecting the data, which could impact our results. Second, while we can say these were news stories with high user engagement, we cannot say anything about the actual traffic the stories generated. Despite these limitations, this data set provides reasonable ground truth labels and we know all stories were highly shared on social media.

Data set 2: Our political news data set Given data set 1 contains political news only, we created our own political news data set to strengthen our analysis and control for the limitations of the first data set. Our data set contains 75 stories from each of the three defined categories of news: real, fake, and satire. We collected this data by first gathering known real, fake, and satire new sources, which can be found in Table 1. The fake news sources were collected from Zimdars' list of fake and misleading news websites (Zimdars 2016) and have had at least 1 story show up as false on a fact-checking website like snopes.com in the past. The real sources come from Business Insider's "Most-Trusted" list (Engel 2014), and are well established news media companies. The satire sources are sites that explicitly state they are satirical on the front page of their website. Once the sources were chosen, we then randomly selected political stories from each of the sources. Each of these stories must be a "hard" news story, and not an opinion piece. The sources used in this data set have some overlap with data set 1, but all collected stories are different than those in the first data set. While we cannot say anything about the engagement of the articles in data set 2, it avoids the possible limitations of the Buzzfeed data set described above. Furthermore, data set 2 allows us to explicitly analyze all three defined categories of news by having both satire and fake news stories in the same data set.

Both data sets 1 and 2 will be publicly available together with this paper at https://github.com/rpitrust/fakenewsdata1.

Data set 3: Burfoot and Baldwin data set Finally, we use a data set from (Burfoot and Baldwin 2009), which consists of 233 satire news stories and 4000 real news stories used in a classification task between these two types of news stories using lexical and semantic features. The authors collect the real news stories using newswire documents sampled from the English Gigaword Corpus. To select satire documents, they hand select satire stories that are closely related in topic to the real stories collected. They manually filter out "non-newsy" satire, similar to the method we use to construct our data set. While Burfoot and Baldwin do control for topic when matching articles, they do not limit themselves to only political topics; thus, this data may not be directly comparable to our other two data sets with respect to some of our more topic-driven features. We include this data set to strengthen our categorical comparisons between satire and real stories. A separate limitation of Burfoot and Baldwin's data set is that we do not explicitly know the sources of each story and cannot verify that the definition of real news sources by the authors corresponds to ours.

Real sources	**Fake sources**	**Satire sources**
Wall Street Journal	Ending the Fed	The Onion
The Economist	True Pundit	Huff Post Satire
BBC	abcnews.com.co	Borowitz Report
NPR	DC Gazette	The Beaverton
ABC	libertywritersnews	SatireWire
CBS	Before its News	Faking News
USA Today	Infowars	
The Guardian	Real News Right Now	
NBC		
Washington Post		

Table 1: Data set 2 sources

Features

To study these different articles, we compute many content based features on each data set and categorize them into 3 broad categories: stylistic, complexity, and psychological.

Stylistic Features The stylistic features are based on natural language processing to understand the syntax, text style, and grammatical elements of each article content and title. To test for differences in syntax, we use the Python Natural Language Toolkit (Bird 2006) part of speech (POS) tagger and keep a count of how many times each tag appears in the article. Along with this, we keep track of the number of stopwords, punctuation, quotes, negations (no, never, not), informal/swear words, interrogatives (how, when, what, why), and words that appear in all capital letters. For features that need word dictionaries, such as the number of informal words, we use the 2015 Linguistic Inquiry and Word Count (LIWC) dictionaries (Tausczik and Pennebaker 2010).

Complexity Features The complexity features are based on deeper natural language processing computations to capture the overall intricacy of an article or title. We look at two levels of intricacy: the sentence level and the word level. To capture the sentence level complexity, we compute the number of words per sentence and each sentence's syntax tree depth, noun phrase syntax tree depth, and verb phrase syntax tree depth using the Stanford Parser (de Marneffe, MacCartney, and Manning 2006). We expect that more words per sentence and deeper syntax trees mean the average sentence structure complexity is high.

To capture the word level complexity, we use several key features. First, we compute the readability of each document using three different grade level readability indexes: Gunning Fog, SMOG Grade, and Flesh-Kincaid grade level index. Each measure computes a grade level reading score based on the number of syllables in words. A higher score means a document takes a higher education level to read. Second, we compute what is called the Type-Token Ratio (TTR) of a document as the number of unique words divided by the total number of words in the document. TTR is

Metadata				
Data set ID	description	# real news	# fake news	# satire news
1	filtered Buzzfeed 2016 election data set	36	35	0
2	our 3 class political news data set	75	75	75
3	Burfoot and Baldwins satire data set	4000	0	233

Table 2: Ground truth counts and ID number of each data set used in this study.

Abbr.	Description
GI	Gunning Fog Grade Readability Index
SMOG	SMOG Readability Index
FK	Flesh-Kincaid Grade Readability Index
med_depth	median depth of syntax tree
med_np_depth	median depth of noun phrase tree
med_vp_depth	median depth of verb phrase tree
flu_coca_c	avg. frequency of least common 3 words using all of the coca corpus
flu_coca_d	avg. frequency of words in each document using all of the coca corpus
TTR	Type-Token Ratio (lexical diversity)
avg_wlen	avg. length of each word

(a) Complexity Features

analytic	number of analytic words
insight	number of insightful words
cause	number of causal words
discrep	number of discrepancy words
tentat	number of tentative words
certain	number of certainty words
differ	number of differentiation words
affil	number of affiliation words
power	number of power words
reward	number of reward words
risk	number of risk words
personal	number of personal concern words (work, leisure, religion, money)
tone	number of emotional tone words
affect	number of emotion words (anger, sad, etc.)
str_neg	strength of negative emotion using SentiStrength
str_pos	strength of positive emotion using SentiStrength

(b) Psychology Features

Abbr.	Description
WC	word count
WPS	words per sentence
NN	number of nouns
NNP	number of proper nouns
PRP	number of personal pronouns
PRP$	number of possessive pronouns
WP	Wh-pronoun
DT	number of determinants
WDT	number of Wh-determinants
CD	number of cardinal numbers
RB	number of adverbs
UH	number of interjections
VB	number verbs
JJ	Adjective
VBD	number of past tense verbs
VBG	Verb, gerund or present participle
VBN	Verb, past participle
VBP	Verb, non-3rd person singular present
VBZ	Verb, 3rd person singular present
focuspast	number of past tense words
focusfuture	number of future tense words
i	number of I pronouns (similar to PRP)
we	number of we pronouns (similar to PRP)
you	number of you pronouns (similar to PRP)
shehe	number of she or he pronouns (similar to PRP)
quant	number of quantifying words
compare	number of comparison words
exclaim	number of exclamation marks
negate	number of negations (no, never, not)
swear	number of swear words
netspeak	number of online slang terms (lol, brb)
interrog	number of interrogatives (how, what, why)
all_caps	number of word that appear in all capital letters
per_stop	percent of stop words (the, is, on)
allPunc	number of punctuation
quotes	number of quotes
#vps	number of verb phrases

(c) Stylistic Features

Table 3: Different features used in our study

meant to capture the lexical diversity of the vocabulary in a document. A low TTR means a document has more word redundancy and a high TTR means a document has more word diversity (Dillard and Pfau 2002). Third, we compute a word level metric called fluency, used in (Horne et al. 2016). Fluency is meant to capture how common or specialized the vocabulary of a document is. We would say that a common term is more fluent, and easier to interpret by others; while a less common term would be less fluent and more technical. This idea is captured by computing how frequently a term in a document is found in a large English corpus. We use both the Corpus of Contemporary American English (COCA) (Davies 2008) corpus to compute this feature.

Psychological Features The psychological features are based on well studied word counts that are correlated with different psychological processes, and basic sentiment analysis. We use Linguistic Inquiry and Word Count (LIWC) dictionaries (Tausczik and Pennebaker 2010) to measure cognitive processes, drives, and personal concerns. Along with this, we use LIWC to measure basic bag-of-words sentiment. We then use SentiStrength (Thelwall et al. 2010) to measure the intensity of positive and negative emotion in each document. SentiStrength is a sentiment analysis tool that reports a negative sentiment integer score between -1 and -5 and a positive sentiment integer score between 1 and 5, where -5 is the most negative and 5 is the most positive.

Statistical Tests and Classification

Due to our use of small data sets and large number of features, we choose to first approach the problem using two well known hypothesis testing methods, the one-way ANOVA test and the Wilcoxon rank sum test, to find which features differ between the different categories of news.

A one-way ANOVA test is used to compare the means of different groups on a dependent variable. ANOVA uses the ratio of the treatment and residual variances to determine if the difference in group means is due to random variation or the treatment. In our case, the treatment is grouping news as fake, real, or satire. ANOVA assumes that the variables are approximately normally distributed. While these assumptions are true for most of our features, we cannot assume it is true for all of them. Thus, we also utilize the Wilcoxon rank sum test to compare two distributions that are not normal. Specifically, for each feature that passes a normality test, we use the one-way ANOVA, otherwise, we will use Wilcoxon rank sum. In both cases, we are looking for a large F-value and a significance level of at least 0.05.

These statistical test cannot say anything about predicting classes in the data, as a machine learning classifier would. However, these test can illustrate a shift in the use of a linguistic feature based on the category the article falls in. We would expect that the more significant the difference in a feature, the higher chance a machine learning classifier would be able to separate the data. To better test the predictive power of our features, we will use a linear classifier on a small subset of our features. We select the top 4 features from our hypothesis testing methods for both the body text and title text of the articles. With these 4 features, we will run a Support Vector Machine (SVM) model with a linear kernel and 5-fold cross-validation. Since we are only using a small number of features and our model is a simple linear model on balanced classes, we expect to avoid the over-fitting that comes with small data.

Results

In this section, we present the most significant features in separating news, referring to each data set by its ID number found in Table 2. The complete results can be found in Tables 4 and 5. Classification results can be found in Table 6.

Feature	Data set 1	Data set 2	Data set 3
WC	**Real > Fake**	**Real > Fake > Satire**	Satire > Real
flu_coca_c	Fake > Real	Satire = Fake > Real	
flu_coca_d		Satire = Fake > Real	
flu_acad_c		Satire > Fake = Real	
avg_wlen	Real > Fake	**Real > Fake = Satire**	Real > Satire
quote	Real > Fake	**Real > Fake = Satire**	
allPunc	**Real > Fake**	Real > Fake = Satire	
GI		Real = Satire > Fake	**Satire > Real**
FK		Real = Satire > Fake	**Satire > Real**
analytic		Real > Fake = Satire	
all_caps		Fake = Satire > Real	
NN		Real > Fake = Satire	
PRP		**Satire > Fake > Real**	Satire > Real
PRP$		Satire > Fake = Real	Satire > Real
DT		Fake = Real > Satire	
WDT		Fake = Real > Satire	
RB		**Satire = Fake > Real**	
i		Satire > Fake = Real	Satire > Real
we		Fake > Real = Satire	
you		Satire > Fake > Real	Satire > Real
shehe		Satire > Real = Fake	Satire > Real
CD		Real = Fake > Satire	**Real > Satire**
compare		Real > Fake = Satire	
swear		Satire > Real = Fake	
TTR	**Fake > Real**	**Satire > Fake > Real**	**Satire > Real**
avg_negstr	**Fake > Real**		
avg_posstr	Real > Fake		
med_depth	Fake > Real		Satire > Real
med_np_d	Fake > Real		
med_vp_d	Fake > Real		

Table 4: Features that differ in the *body* of the news content (bolded results correspond to p values of 0.00 or less, all other results have p values of at least less than 0.05)

Feature	Data set 1	Data set 2	Data set 3
WPS	Fake > Real	Fake > Real = Satire	
flu_coca_c	Fake > Real	**Satire > Fake = Real**	Satire > Real
avg_wlen		**Real > Fake = Satire**	
all_caps	Fake > Real	Satire > Fake > Real	
GI	Real > Fake	**Real > Satire = Fake**	Real > Satire
FK	Real > Fake	**Real > Satire = Fake**	**Real > Satire**
NNP	**Fake > Real**	**Fake = Satire > Real**	**Satire > Real**
NN	Real > Fake	**Real > Satire > Fake**	
PRP	Real > Fake		Satire > Real
PRP$	Real > Fake		Satire > Real
DT	Real > Fake		
CD			Real > Satire
per_stop	**Real > Fake**	**Real > Satire = Fake**	**Real > Satire**
exclaim		Fake > Real = Satire	
focuspast		**Fake > Satire = Real**	
analytic	**Fake > Real**		
#vps		**Fake > Real = Satire**	

Table 5: Features that differ in the *title* of the news content (bolded results correspond to p values of 0.00 or less, all other results have p values of at least less than 0.05)

The content of fake and real news articles is substantially different. Our results show there is a significant difference in the content of real and fake news articles. Consistently between data sets 1 and 2, we find that real news articles are significantly longer than fake news articles and that fake news articles use fewer technical words, smaller words, fewer punctuation, fewer quotes, and more lexical redundancy. Along with this, in data set 2, fake articles need a slightly lower education level to read, use fewer analytic words, have significantly more personal pronouns, and use fewer nouns and more adverbs. These differences illustrate a strong divergence in both the complexity and the style of content. Fake news articles seem to be filled with less substantial information demonstrated by having a high amount of redundancy, more adverbs, fewer nouns, fewer analytic words, and fewer quotes. Our results also suggest that fake news may be more personal and more self-referential, using words like we, you, and us more often. However, this result is not consistent between data sets and is less significant.

	Baseline	Fake vs Real	Satire vs Real	Satire vs Fake
Body	50%	71%	91%	67%
Title	50%	78%	75%	55%

Table 6: Linear kernel SVM classification results using the top 4 features for the body and the title texts in Data set 2. Accuracy is the mean of 5-fold cross-validation.

This stark difference between real and fake news content is further strengthened by our SVM classification results on the content of fake and real articles in Dataset 2. To classify the content, we use the top 4 features from our statistical analysis: number of nouns, lexical redundancy (TTR), word count, and number of quotes. We achieve a 71% cross-validation accuracy over a 50% baseline when separating the body texts of real and fake news articles. Similarly, when classifying fake from real content in Data set 1 using the same 4 features, we achieve a 77% accuracy over a 57% baseline. These results are shown in Table 6.

Titles are a strong differentiating factor between fake and real news. When looking at just the titles of fake and real news articles, we find an even stronger dissimilarity between the two, with high consistency between the data sets and high statistical significance in the differences. Precisely, we find that fake news titles are longer than real news titles and contain simpler words in both length and technicality. Fake titles also used more all capitalized words, significantly more proper nouns, but fewer nouns overall, and fewer stopwords. Interestingly, we also find that in data set 1 fake titles use significantly more analytical words and in data set 2 fake titles use significantly more verb phrases and significantly more past tense words. Overall, these results suggest that the writers of fake news are attempting to squeeze as much substance into the titles as possible by skipping stop-words and nouns to increase proper nouns and verb phrases.

Looking at an example from our data will solidify this notion:

1. **FAKE TITLE:** ”BREAKING BOMBSHELL: NYPD Blows Whistle on New Hillary Emails: Money Laundering, Sex Crimes with Children, Child Exploitation, Pay to Play, Perjury”
2. **REAL TITLE:** Preexisting Conditions and Republican Plans to Replace Obamacare

There is a clear difference in the number of claims being made in each title. The fake title uses many verb phrases and name entities to get many points across, while the real title opts for a brief and general summary statement. This broad pattern shown in the example is consistent across the first two data sets. Interestingly, this finding in the titles of fake news is closely related to Rubin et al's finding in the quotations of satirical articles (Rubin et al. 2016) where a large number of clauses are packed into a sentence. Saliently, this title structure is not as similar to clickbait as one might expect. Clickbait titles have been shown to have many more function words, more stopwords, more hyperbolic words (extremely positive), more internet slangs, and more possestive nouns rather than proper nouns (Chakraborty et al. 2016).

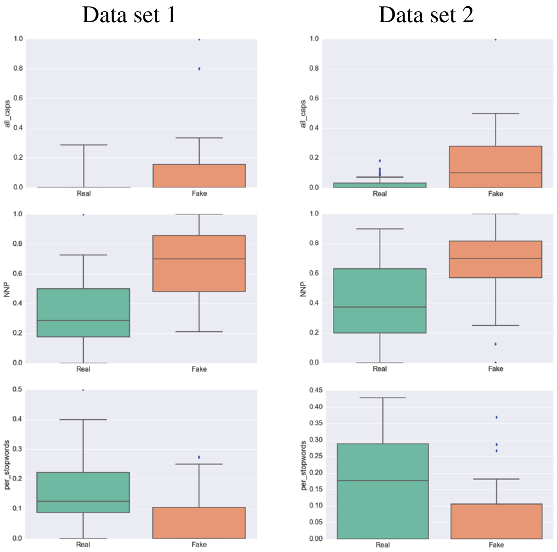

Table 7: 95% Confidence plots of all_caps, NNP, and per_stop. These features were found to be significant across both data sets 1 and 2 for fake and real titles. **Top:** all_caps **Middle:** NNP **Bottom:** per_stop

Once again, these differences are further strengthened by our SVM classification results on Data set 2. To classify fake and real news articles by their title, we use the top 4 features from our statistical analysis on titles: the percent of stopwords, number of nouns, average word length, and FKE readability. We achieve a 78% cross-validation accuracy over a 50% baseline, demonstrating the importance of the title in predicting fake and real news. These results are shown in Table 6. In addition, when classifying fake from real titles in Data set 1 using the same 4 features, we achieve a 71% accuracy over a 49% baseline.

Table 7 shows the distributions of select features that are significant and consistent between data sets.

Fake content is more closely related to satire than to real. When adding in satire articles to the analysis, we find that the majority of our features distributions are common between satire and fake. Specifically, both satire and fake use smaller, fewer technical, and fewer analytic words, as well as, fewer quotes, fewer punctuation, more adverbs, and fewer nouns than real articles. Further, fake and satire use significantly more lexical redundancy than real articles.

These claims are further supported by SVM classification results in Table 6. When using the number of nouns, lexical redundancy (TTR), word count, and number of quotes for the body text, we achieve a 91% cross-validation accuracy over a 50% baseline on separating satire from real articles. On the other hand, when separating satire from fake articles, we only acheive a 67% accuracy over a 50% baseline. Similarly, when classifying the titles of articles using the percent of stopwords, number of nouns, average word length, and

FKE readability, we achieve a 75% cross-validation accuracy when separating satire titles from real titles, but only achieve a 55% accuracy when separating satire titles from fake titles. While this accuracy is a reasonable improvement over baseline, it is not nearly as high as big of an improvement as separating satire from real or real from fake.

Overall, these results paint an interesting picture where satire and fake news articles are written in a less investigative way. This conclusion is in sync with what we know of satire (Randolph 1942) (Burfoot and Baldwin 2009). Satire news articles do not have the goal of creating sound arguments, but often make absurd and eccentric claims, whereas real news articles must back up the information they are providing with direct quotes, domain specific knowledge, and reasonable analysis.

Real news persuades through arguments, while fake news persuades through heuristics. To better explain our findings, we look at the Elaboration Likelihood Model (ELM) of persuasion, well-studied in communications. According to ELM, people are persuaded through two different routes: central and peripheral (Petty and Cacioppo 1986). The central route of persuasion results from the attentive examination of the arguments and message characteristics presented, involving a high amount of energy and cognition. In opposition, the peripheral route of persuasion results from associating ideas or making conjectures that are unrelated to the logic and quality of the information presented. This method could be called a heuristic method as it does not ensure to be optimal or even sufficient in achieving its objective of finding correct or truthful information. The peripheral route takes very little energy and cognition.

This model fits well with both our results and recent studies on the behavior of sharing online information. Given the similarity of fake content to satire, we hypothesize that fake content targets the peripheral route, helping the reader use simple heuristics to assess veracity of the information. The significant features support this finding: fake news places a high amount substance and claims into their titles and places much less logic, technicality, and sound arguments in the body text of the article. Several studies have argued that the majority of the links shared or commented on in social networks are never clicked, and thus, only the titles of the articles are ever read (Wang, Ramachandran, and Chaintreau 2016) Titles of fake news often present claims about people and entities in complete sentences, associating them with actions. Therefore, titles serve as the main mechanism to quickly make claims which are easy to assess whether they are believable based on the reader's existing knowledge base. The body of fake news articles add relatively little new information, but serves to repeat and enhance the claims made in the title. The fake content is more negative in general, similar to findings in past work (Zollo et al. 2015b). Hence, fake news is assessed through the peripheral route. We hypothesize that if users were to utilize the central route of persuasion, they would have a much lower chance of being convinced by the body content of fake news, as we have shown the fake news content tend to be short, repetitive and lacking arguments.

Conclusions and Future work

In this paper, we showed that fake and real news articles are notably distinguishable, specifically in the title of the articles. Fake news titles use significantly fewer stop-words and nouns, while using significantly more proper nouns and verb phrases. We also conclude that the complexity and style of content in fake news is more closely related to the content of satire news. We also showed that our features can be used to significantly improve the prediction of fake and satire news, achieving between 71% and 91% accuracy in separating from real news stories. These results lead us to consider the Elaboration Likelihood Model as a theory to explain the spread and persuasion of fake news. We conclude that real news articles persuade users through sound arguments while fake news persuades users through heuristics. This finding is concerning as a person may be convinced of fake news simply out of having low energy, not just contempt, negligence, or low cognition. Unfortunately, misleading claims in the titles of fake news articles can lead to established beliefs which can be hard to change through reasoned arguments. As a starting point, articles that aim to counter fake claims should consider packing the counter-claim into their titles.

This work has some limitations and room for improvement. First, we would like to extensively expand the news data set. Typically it is very difficult to obtain a non-noisy ground truth for fake and real news, as the real news is becoming increasingly opinion based and many times more detailed fact checking is needed. We would like to make more objective clusters of fake, real, and satire news through unsupervised machine learning methods on a variety of news sources. With an expanded data set and stronger ground truth comes the ability to do more sophisticated classification and more in-depth natural language feature engineering, all with the hope to stop the spread of malicious fake news quickly. With more data and more in-depth features, our arguments could be made much stronger. Second, we would like to conduct user studies to more directly capture the persuasion mechanisms of fake and real news. For users studies such as this to be valid, careful planning and ethical considerations are needed. Largely, we hope this work helps the academic community continue to build technology and a refined understanding of malicious fake news.

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