Fake News vs Satire: A Dataset and Analysis
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Outline

Fake News ≠ Satirical News

Fake News

Figure: Fake News Example

- Factually incorrect
- Intended to deceive

Fake News ≠ Satirical News

Fake News

Figure: Fake News Example

- Factually incorrect
- Intended to deceive

Satirical News

Figure: Satirical News Example

- Factually incorrect
- Intended not to deceive, but rather to call out and ridicule

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Fake News is *Intentionally* Misleading

Categorizations of fake news

- News satire, news parody, fabrication, manipulation, advertising, propaganda (Tandoc et al.)
- Serious fabrications, large scale hoaxes, humorous fakes (Rubin et al.)

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Findings from user studies

- Readers are likely to believe fake news that are in favor of their preferred candidate or ideology (Alcott et al.)
- For readers with lower cognitive ability, the bias created by fake news is not fully reversed after being told it was fake. (Roets et al.)
- Most Americans believe that fake news is sowing confusion (Barthel et al.)

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Key Contributions of the Paper

- A hand-coded and verified **dataset** of **titles**, **URLs**, and **full-text** of **fake news articles**, **satirical news articles**, and a credible **rebutting article** for every fake news article
- Seven **themes** of content in news articles
- Naive-Bayes **classification** of news articles
  - Fake or satirical
  - 1 of 7 themes

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Outline

About the Dataset

Statistics

- **Focus** – American political news between Jan 2016 and Oct 2017
- **Diversity** – ≤ 5 news articles per website
- **Content** – *title*, *URL*, *full-text*, and *classification* of each article
- **Article Count** – Fake (283), Satirical (203) + Rebutting (283)

[1] Borderline articles have both fake and satirical elements (*e.g., fake news with a disclaimer of satire*)

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Data Collection and Annotation

- Identified fake news and satirical web sites
- Saved full-text of news articles (and rebutting articles for fake news)
- Reviewed and eliminated off-topic, out-of-time-frame, non-rebutted, and borderline articles[1]

[1] Borderline articles have both fake and satirical elements (*e.g., fake news with a disclaimer of satire*)

Similar Datasets

- 12,000+ fake news articles (Wang et al.)
  - Labels – truthfulness, subject, context/venue, speaker, state, party, prior history
- Assessing fake news articles by linguistic cues and network analysis (Conroy et al.)
  - Linguistic features – bag-of-words, sentiment (±), distance measure[2]
  - Network Analysis – in-links and out-links

[2] This distance measure is based on Rhetorical Structure Theory (RST)

Outline

Language of Fake/Satirical Articles are Different

0.791 Accuracy, 0.880 AUROC

- Article → word vector (x), fake/satire label (y)
- Naive-Bayes classifier on (x,y)
- 10-fold cross validation

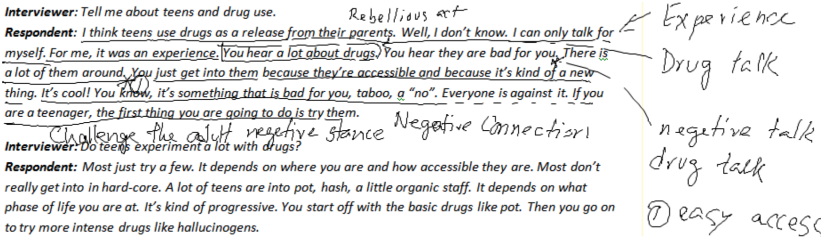
Table 1: Detailed accuracy measurements for classification of Fake News vs. Satire.

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.811	0.236	0.828	0.811	0.819	0.572	0.880	0.907	Fake
	0.764	0.189	0.742	0.764	0.752	0.572	0.880	0.847	Satire
Weighted Avg.	0.791	0.217	0.792	0.791	0.791	0.572	0.880	0.882	

Figure: Fake vs. Satire Classification - Detailed Metrics

Open Coding to Find Themes in News Articles

Idea – Identify *concepts* from text and assign *codes* to them[3]


Interviewer: *Tell me about teens and drug use.*

Respondent: *I think teens use drugs as a release from their parents. Well, I don't know. I can only talk for myself. For me, it was an experience. You hear a lot about drugs. You hear they are bad for you. There is a lot of them around. You just get into them because they're accessible and because it's kind of a new thing. It's cool! You know, it's something that is bad for you, taboo, a "no". Everyone is against it. If you are a teenager, the first thing you are going to do is try them.*

Interviewer: *Do teens experiment a lot with drugs?*

Respondent: *Most just try a few. It depends on where you are and how accessible they are. Most don't really get into in hard-core. A lot of teens are into pot, hash, a little organic staff. It depends on what phase of life you are at. It's kind of progressive. You start off with the basic drugs like pot. Then you go on to try more intense drugs like hallucinogens.*

Figure: An example of open coding

Open Coding Workflow

- **Build the concepts** – Identify parts of text with common semantics
- **Name the concepts** – Label the identified concepts
- **Categorize the concepts** – Group related concepts together

[3] Open Coding (Khandhkar et al.)

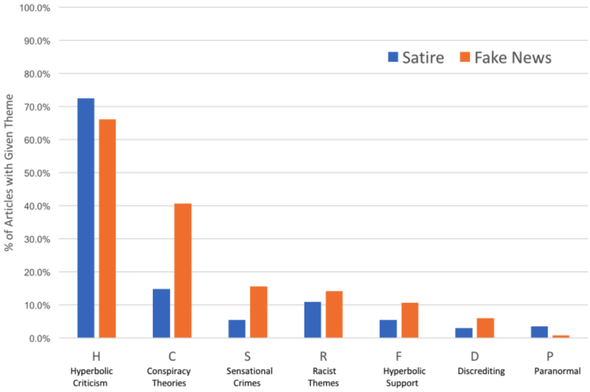
Found 7 Themes using Open Coding

- **Hyperbolic Criticism** – *"Obama Signs Executive Order Banning the Pledge of Allegiance in Schools Nationwide"*
- **Hyperbolic Support** – *"Because Trump Won the Presidency, Ford Shifts Truck Production from Mexico to Ohio!"*
- **Discrediting Credible Sources** – *"MIT Researchers: Global Warming Data is Complete Bunk"*
- **Sensational Crimes** – *"George Zimmerman Found DEAD Just Hours After Bragging About Killing Trayvon Martin"*
- **Racist Themes** – *"Trump has Fired Muslim Sharia Judge Arrested and Charged"*
- **Paranormal Theories** – *"Donald Trump Says the Earth is Flat"*
- **Conspiracy Theories** – *"Hilary Clinton Busted in the Middle of Huge Pedophilia Ring Cover Up at State Department"*

Themes Across Fake/Satirical Articles

- **Most Common**: Hyperbolic Criticism, Conspiracy Theories
- **Fake** > **Satirical**: Conspiracy Theories, Sensational Crimes
- **Fake** < **Satirical**: Paranormal Theories

⇒ a good theme classifier could possibly detect fake stories



Theme **Pairs** Across Fake/Satirical Articles

Pair	C-H	H-S	C-S	H-R	D-H	C-R	C-D	F-H	C-F	R-S	H-P	F-R	D-S	F-S	D-R	C-P	D-P
Overall	19.50%	6.40%	4.10%	7.00%	2.90%	1.90%	1.20%	1.20%	1.40%	1.20%	1.20%	1.00%	0.40%	0.40%	0.40%	0.40%	0.20%
Satire	9.40%	3.40%	0.00%	7.40%	1.50%	1.50%	0.00%	0.50%	1.50%	1.50%	2.00%	1.50%	0.00%	0.00%	0.50%	1.00%	0.50%
Fake	26.90%	8.50%	7.10%	6.70%	3.90%	2.10%	2.10%	1.80%	1.40%	1.10%	0.70%	0.70%	0.70%	0.70%	0.40%	0.00%	0.00%

Most Common Pairs – CH, HR, HS, and CS

- **Overall**: **CH** (9.50%) > **HR** (7.00%) > **HS** (6.40%)
- **Fake**: **CH** (9.40%) > **HR** (7.40%) > **HS** (3.40%)
- **Satirical**: **CH** (26.90%) > **HS** (8.50%) > **CS** (7.10%)

- **CH**: Conspiracy Theories + Hyperbolic Criticism
- **HR**: Hyperbolic Criticism + Racist Messaging
- **HS**: Hyperbolic Criticism + Sensational Crimes
- **CS**: Conspiracy Theories + Sensational Crimes

Language of Differently-Themed Articles are Different

- Article → word vector (x), theme (y)
- One Naive-Bayes classifier on (x,y) **per theme**

Theme	Accuracy	ROC AUC
H	56.3%	0.583
C	80.1%	0.754
S	89.3%	0.750
R	89.8%	0.669
F	92.4%	0.610
D	96.3%	0.433
P	98.7%	0.672

Figure: Theme Classification - Detailed Metrics

Classifiers (C) and (S) performed the best.
Having good (H) and (C) classifiers could improve fake news detection.

Summary

- The authors curated a **dataset** of **titles**, **URLs**, and **full-text** of **fake news articles**, **satirical news articles**, and a credible **rebutting article** for every fake news article.
- Using open coding, they identified 7 **themes** in their news articles. (H) Hyperbolic Criticism, (F) Hyperbolic Support, (D) Discrediting Credible Sources, (S) Sensational Crimes, (R) Racist Themes, (P) Paranormal Theories, (C) Conspiracy Theories
- By converting each article into a word vector, they performed two Naive-Bayes **classifications**.
  - Fake/Satirical Classification – 0.791 Accuracy, 0.880 AUROC
    $\Rightarrow$ Significant difference in language of fake/satirical articles
  - Theme Classification – Classifiers (C) and (S) performed the best. Having good (H) and (C) classifiers could improve fake news detection.