Defending Against Fake News Booz | Allen | Hamilton

An internet browser plugin to help in the

fight against misleading information

Abstract

- Booz Allen Hamilton is an information technology consultancy that wants to help mitigate the rising fake news problem by offering a Google Chrome plugin that can inform readers about the validity of news.
- They requested Penn State to take their plugin and add a fresh approach to their existing methods.
- Accuracy can be added by implementing a machine learning algorithm based on the sentiment of an article which infers bias by judging overt positive or negative tones related to the article.
- The final product consists of a model which can take in an article from a webpage or news source and output a rating of fake or real. Adding this to the plugin can increase accuracy of the plugin's rating.

Motivation - Is this true?

- Social media and smartphones allow for fake news to be distributed quicker than ever before. It takes little effort to share an article or graphic that has no backing, but appears real.
- It takes facts over 6x longer to reach an audience of 1,500 people than sensationalized articles (Fox, 2008).
- By the time a fake article is circulated the damage is done. Retraction of articles gets little to no attention compared to the original news.

Methodology

- Sentiment indicates feelings in a certain direction of bias on the topic (positive or negative).
- Vader Sentiment analyzer used to gauge the sentiment and compound ranking of sentences.
- Sentiments of each sentence saved to "scores" vector = [Positive, Negative, Compound].
- The scores vector allows the following features to be generated to tune the model (right).
- Data consisted of 3,539 real articles and 3,646 fake (McIntire). This is illustrated below (left).

| No. | Title | Article | Label | |
|------|-----------------------|----------------------------|-------|--|
| | | , | | |
| 1 | Slim Prospects for Ch | Politicians can't agree on | Real | |
| | | | | |
| 3539 | The NY Giants Pick S | The Giant's Head Coach | Real | |
| 3540 | Superbowl Cancled | In a conference the comis | Fake | |
| | | | | |
| 7818 | Canada Declares Wa | The war between Mexico | Fake | |
| | | | | |

Dataset Visualization

Hypothesis

| Feature | Description | Feature | Description | | |
|---|--|--------------|-------------------------------------|--|--|
| article_pos | whole article positivity | end_pos | positivity of last 5 sentences | | |
| article_neg | rticle_neg whole article negativity end_neg | | negativity of last 5 sentences | | |
| article_comp | whole article compound rank | end_comp | comound rank of last 5 sentences | | |
| start_pos positivity of first 5 sentences | | pos_var | variance of positivity in article | | |
| start_neg negativity of first 5 sentences | | neg_var | variance of negativity in article | | |
| start_comp | tart_comp compount rank of first 5 sentences comp_ | | variance of compound rank in articl | | |
| tot_letters total letters in article | | sent_count | Average sentences per paragraph | | |
| tot_words | total words in article | word_count | Average words per sentence | | |
| tot_sent total sentences in article | | letter_count | Average letters per word | | |
| tot_para | total paragraphs in article | | | | |

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Features Available for Tuning Model

• Research and focus groups have helped identify good practices to validate a news source. This is illustrated below (Kiely, 2016).

Consider the source

- Reputation for serious and informative news
- Satirical or unreliable sources

Title of article

- Overt positive or negative can indicate bias
- Clickbait
- Unrelated to article content

Author's track record

Track record of good reporting

Check the date(s)

Does timeframe make sense

Read beyond the headline

- Does body match title
- Is the content absurd or fantastical





Implementing Sentiment Analysis

- NLP can be implemented to infer positive, negative, and various other "feelings" in text.
- Vader Sentiment Analyzer returns three rankings for each sentence which can then be manipulated. The most successful combination is shown below.

| | pos_diff | neg_diff | comp_diff | start_pos | end_pos | end_neg | word_count | letter_count | label |
|---|-----------|----------|-----------|-----------|---------|---------|------------|--------------|-------|
| 0 | -0.030951 | 0.061333 | -0.122836 | 0.08925 | 0.0946 | 0.1544 | 14.896552 | 4.776235 | FAKE |
| 1 | 0.010590 | 0.037960 | -0.114158 | 0.05225 | 0.0742 | 0.0846 | 17.840000 | 4.923767 | FAKE |

Example Feature Rankings of Most Accurate Model

Testing Algorithm

- Fitting the model one time is not sufficient to gain a confident estimate on accuracy.
- To gain the best accuracy learning was implemented 100 different times.
- This repetition confirms that the model did not simply get 'lucky' the first time it was ran.

accuracys = [] gnb = GaussianNB() for state in range(100): x_train, x_test, y_train, y_test = train_test_split(scores[:,:], label, test_size=0.2, random_state=state) gnb.fit(x_train, y_train) accuracys.append(accuracy_score(y_test, gnb.predict(x_test))) print(np.var(accuracys))

print(np.mean(accuracys))

0.0047084444444

0.722666666667

Script Used to Gauge Model's Accuracy with Output

The Booz Allen Hamilton Plugin

- Booz Allen began work on the project in 2017.
- The Penn State team received their work and then built their own plugin server, installed the plugin, and then proceeded to experiment with the existing code repository.



Instances of the plugin operating reading both fake (left) and true (right) articles

Objectives

Results

The following graphs illustrate various features and how they relate to real vs fake news.



• The table below shows the top 3 models and the associated ratings that were used to train them

| Accuracy | Features for | Machine Lear | ning Model | | | | |
|----------|--------------|--------------|--------------|--------------|------------|------------|--------------|
| 72.20% | article_pos | article_neg | article_comp | letter_count | word_count | sent_count | para_count |
| 71.38% | pos_var | neg_var | comp_var | letter_count | word_count | sent_count | para_count |
| 70.43% | start_pos | start_neg | start_comp | end_pos | end_neg | end_comp | letter_count |
| | | | | | | | |

Table of top 3 performing models with features included

Contributors

Citations Acknowledgments



• Create and test a fake news rating model which can be implemented in BAH plugin.

• Use features that are not already encompassed in the existing plugin.

• Find a more comprehensive data set to use for model training.

Team Members: Nick Baker, Paul Boehringer, Nina Brajovic, Peter Mathews, & Josh Norton Mentors: Matt Kremer, Jooyong Lee, Ryan Fischbach, & Wahab Jilani **Faculty Advisor:** Dr. Soundar Kumara



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