Determining Credibility in the News: Do We Need to Read?

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Outline

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Fake News Flavors

The New York Times.

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Facebook To Ban Fake News, Says Mark Zuckerberg While Eating Dolphin

Facebook will take measures to remove fake news stories from peoples' news feeds, Mark Zuckerberg announced this morning while consuming a live dolphin.

In 2016, the prevalence of political fact abuse – promulgated by the words of two polarizing presidential candidates and their passionate supporters – gave rise to a spreading of fake news with unprecedented impunity.

Fake news: Hillary Clinton is running a child sex ring out of a pizza shop.

Fake news: Democrats want to impose Islamic law in Florida.

Fake news: Thousands of people at a Donald Trump rally in Manhattan chanted, "We hate Muslims, we hate blacks, we want our great country back."

None of those stories – and there are so many more like them – is remotely true.



Fake News and the Modern Web









- Motive: Clickbait revenue streams and political campaign funding incentivizes low quality articles to attract readers
- Means: The democratization of online media allows anyone to setup a website and publish unadjudicated content
- Opportunity: Social media provides huge platforms for attracting clicks

Our Approach

"Structural Method"

Probabilistic inference using a domain (publisher) web link network





Find-Class

Conservative

Credible

Non Credible

"Bias Detection"

Class label denotes political ideology

"Credibility Assessment"

Class label denotes source reputation

"Content Model"

Traditional supervised learning classifiers using textual features



Bias Detection

Humans can pick up on nuanced but powerful signals of bias in terms of *semantics*, *sentiment* (tone) and content.



Content Model

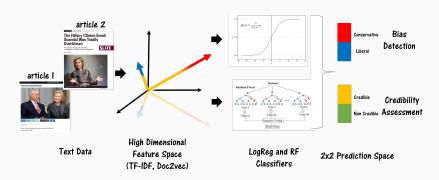
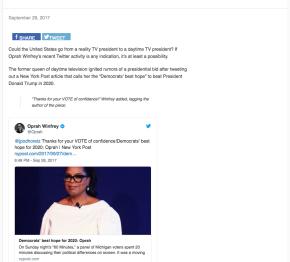


Figure 1: Content Model Pipeline



Credibility Assessment: Fake or Not Fake?

Oprah Stokes 2020 Rumors with Tweet: 'Thanks for Your Vote'



Source: HillaryDaily.com



- New Book Reveals That Obama Pushed Hillary to Concede in 2016 Election
- 2016 Democratic Presidential Candidate Blasts Media for Being Against Trump "Right from the Beginning"
- Michelle Obama: If I Ran Against Trump I Would Have Beaten Him Easily!
- Kellyanne Conway Shuts Chelsea Clinton Down: "You Lost the Election"
- Former President Obama Spotted Partying in Caribbean with Billionaire
- Trump Admin Says Pakistan May Be Next Country He Includes in Ban James Fairbanks, Natalie Fitch, Nathan Knauf, Erica Briscoe

Structural Method

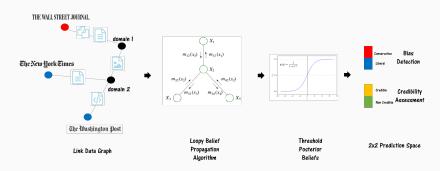


Figure 2: Structural Method Pipeline



Structural Method: Graph Creation

HTML Tag	Description
<a>	Mutually linked sites (text content)
k>	Shared CSS (visual style)
<script></td><td colspan=2>Shared JavaScript files (user interaction)</td></tr><tr><td></td><td>Common images, logos, or icons (visual content)</td></tr></tbody></table></script>	

Table 1: Link Types used in Graph Construction

 An undirected and unweighted graph was constructed using link structure from 19,786 domains (nodes) with 32,632 links (edges)

Structural Method: Belief Propagation

BP is an iterative semisupervised method based on:

- Node potential: $\phi(x_i)$ "a priori belief of node i's assignment"
- Edge potential: $\psi(x_i, x_i)$ "probability node j in class x_i given node i in class x_i "

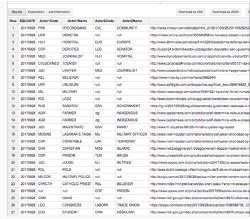
$$\begin{array}{ccc} \psi_{ij}(x_i, x_j) & x_i & x_j \\ x_i & 1 - \epsilon & \epsilon \\ x_j & \epsilon & 1 - \epsilon \end{array}$$

- Nodes pass messages: $m_{ij}(x_i)$ "node i's belief about node i belonging to class x_i " $m_{ij}(x_j) \leftarrow \sum_{x_i \in X} \phi(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in N(j)/j} m_{ki}(x_i)$
- Compute Posterior: $b_i(x_i)$ $b_i(x_i) = k\phi(x_i) \prod_{x_i \in N(i)} m_{ji}(\mathbf{G})$

Experiments: The GDELT Database

Contains events extracted from online news sources and includes:

- two actors
- the action
- source url
- geographic information
- temporal information



We augment GDELT with text and links from news sources

Experiments: Media Bias Fact Check



Figure 3: Volunteer run fact checking site mediabiasfactcheck.com

- Rubric based ratings for domains for 4 categories:
 - Biased wording/headlines
 - Factual/Sourcing
 - Story Choices
 - Political Affiliation/Endorsement
- Labels are converted to binary labels for classification



Results

- Content problem used textual information from 124,300 articles from 242 domains
- Structural problem used link information from 19,786 domains (nodes) and 32,632 links (edges)

	Bias	Credibility
Model		
Content	0.926	0.358
Structure	0.931	0.889

Table 2: Test Set AUC for Bias and Credibility problems. While content is sufficient to detect bias, structure is required to detect fake new **Georgia**

Conclusions

- We can discover and combat propaganda with structural analysis of the web, which leverages informative features ignored in linguistic models
- Text based models are less effective for credibility because of changing topics of fake news
- Future research should focus on:
 - Combining article link structure with traditional NLP textual features
 - Current method is vulnerable to large connected components without any labels.
 - Extracting links from the text "according to AP"

