On Gender Bias in Fake News

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Abstract

Data science research into fake news has gathered much momentum in recent years, arguably facilitated by the emergence of large public benchmark datasets. While it has been well-established within media studies that gender bias is an issue that pervades news media, there has been very little exploration into the relationship between gender bias and fake news. In this work, we provide the first empirical analysis of gender bias vis-a-vis fake news, leveraging simple and transparent lexicon-based methods over public benchmark datasets. Our analysis establishes the increased prevalence of gender bias in fake news across three facets viz., abundance, affect and proximal words. The insights from our analysis provide a strong argument that gender bias needs to be an important consideration in research into fake news.

1 Introduction

Fake news, a terminology in use since 1890s, refers to false or misleading content presented as news. This has been a subject of intense academic and popular interest lately, especially coinciding with the emergence of online media, and professional management of political activity using it (Johnson, 2016). Disinformation or information disorder, as the phenomenon has been recently referred to, has been increasingly recognized as a grave threat to deliberative democracy (McKay and Tenove, 2021). While relationship between fake news and politics has rightly been subject to much scrutiny, fake news has been recently observed within the context of the COVID-19 pandemic (Springer and Özdemir, 2022) as well. In this paper, we analyze the relationship between fake news and gender, one that has been recognized within social sciences viz., media studies (Almenar et al., 2021) and politics (Stabile et al., 2019), and needs to be explored within quantitative NLP.

In this paper, for the first time to our best knowledge, we consider differences in how gender identities are portrayed within fake and real news within popular public textual fake news benchmark datasets. In particular, our interest is in understanding the relative abundance of gender references as well as gender-specific trends across affect and lexical references, and how they vary across fake and real news. Our analysis illustrates the nuanced but consistent nature of the relationship between news veracity and gender, and strongly suggests that gender needs to be an important consideration within critical studies and NLP research on fake news.

2 Related Work

It is interesting to note that what may be regarded as the watershed moment for the fake news phenomenon - 2016 US presidential election (Grinberg et al., 2019) - was a contest between female and male contenders. Yet, analysis focusing on gender has been very limited. A notable study (Stabile et al., 2019) on the gender aspect during the 2016 election uses quantitative analysis of tweets surrounding the election providing evidence that election-time fake news had indeed supported stereotypes such as women being unfit for leadership positions, hand in hand with villianizing or trivializing them. In contrast to this work centered on a particular election, our study has a broader scope and considers gender bias over popular benchmark datasets.

Research into gender and fake news located within media studies as well as broadly within social sciences have uncovered interesting insights. A survey study over Spanish respondents (Almenar et al., 2021) found that the perceptions of fake news varied across genders in terms of the degrees of concern, but remained underpinned by the same problems. An in-depth and comprehensive deliber-
3 Research Questions

In this work on data-driven analysis of gender vis-a-vis fake news, our research questions are:

RQ1: How do gender groups fare on their relative abundance within fake and real news?

RQ2: How do emotions and sentiments differ around gender mentions across fake and real news?

RQ3: How do trends on lexical references surrounding gender mentions differ across fake and real news?

We explore these questions over large benchmark datasets for fake news research.

4 Analysis Methodology

We first start with outlining the basic building blocks we use for our analysis. We intend that our analysis methodology embeds the ability to be be clearly verifiable by humans and be able to trace back the inferences to particular mentions within the textual articles. This makes lexicon-based approaches more suited than ML-based approaches for the task. Thus, our building blocks use simple and transparent lexicon-based analysis strategies. These building blocks, as we will see, would be used in a straightforward way for the analysis to address the separate RQs.

Gender Mentions: The first key component in our method involves the identification of gender references/mentions within (fake and real) textual news articles. We use a gender reference lexicon extracted from the NLTK corpus\(^2\) which contains separate lists of mentions of male and female genders, which includes gender-correlated names and pronouns. For example, words such as he and his are part of the male reference list, whereas her and girl are part of the female reference list. The separate lists contained thousands of words each. Lexicon word occurrences within news articles are regarded as respective gender mentions.

Emotions and Sentiments: Similar to identification of gender mentions, we use the popular word-emotion association lexicon, EmoLex\(^3\), to identify affective contents within textual news articles across eight emotion classes, viz., anger, anticipation, disgust, fear, joy, sadness, surprise and trust. Given our intent of analyzing emotions and sentiments against the backdrop of gender references, we identify emotion mentions within a specified width word window - the width being a hyperparameter - on either side of the gender references. As an example, within the text excerpt: 'there was apparent anger in her face', the emotion word anger from the anger emotion class would be associated with the female gender pronoun her for window sizes set to ≥ 2; we set window size to 5.

Towards analyzing sentiments, we leveraged a popular Python lexicon-based library, VADER\(^4\). We aggregate the positive/negative sentiment-scores provided for mention-proximal words that appear in VADER’s sentiment dictionaries, to arrive at cumulative sentiment polarities around each gender mention.

Proximal Lexical References: Towards analyzing the nature of lexical references surrounding gender mentions, we use the same window-based approach as earlier, and associate all words within a fixed width word window to the gender reference. Thus, 'his premiership saw much violence’ would associate premiership, saw, much and violence with his under window sizes of 4 or 5.

RQ-specific Analyses: For a news article \(N\), let the bag of female and male gender mentions be \(N^F\) and \(N^M\) respectively. The bag of emotion words from emotion class \(e\) around female references in \(N\), denoted as \(N^e\) would be:

\[
N^e = \bigcup_{m \in N^F} \{m_e | m_e \in L(E = e) \land m_e \in W(m)\}
\]

where \(W(m)\) denotes the adjacency window

\(^1\)https://www.nltk.org/api/nltk.corpus.html
\(^2\)http://www.saifmohammad.com/
\(^3\)https://pypi.org/project/vaderSentiment/
around the mention \(m\), \(L(E = e)\) denotes the lexicon for emotion class \(e\) and all set notations above be interpreted as bag notations. \(N^W_M\), the bag of emotion words around male mentions, is defined similarly. The bag of words around the female mentions in \(N\) is then defined as:

\[
N^W_F = \bigcup_{m \in N_F} \{m_e | m_e \in W(m)\}
\]

The overall emotion density around female mentions in \(N\) is measured as:

\[
N^{ED}_F = \frac{\sum_{e \in E} |N^W_F|}{|N^W_F|}
\]

For sentiment analysis, a sentiment score is computed for each gender mention \(m\):

\[
S(m) = \sum_{w \in W(m)} \begin{cases} VADER(w) & w \in VADER \\ 0 & \text{otherwise} \end{cases}
\]

where \(VADER(w)\) denotes positive or negative sentiment score from VADER. Each mention is then associated with one of three sentiment labels, Positive, Neutral and Negative, based on the numerical nature of the sentiment score.

All such news article specific measures would be suitably aggregated over subsets of real and fake news towards addressing RQ1-3, as we will describe in the analysis.

5 Results and Analysis

Datasets and Setup: In the interest of generality, we conduct our analysis over three popular textual datasets that have been used for fake news research. ISOT\(^5\) comprises 40k+ articles split roughly evenly between real and fake. LIAR (Wang, 2017) comprises 12.8k statements labelled for veracity. Fake-Net (Shu et al., 2020) (FNN) comprises 21k news articles collected from across Politifact and Gossipcop. There is much variety in cardinality, type, distribution and source of news articles across these three datasets, facilitating a well-rounded analysis across them. Our observed trends were largely invariant with window size variations; the results reported are with window size set to 5.

5.1 RQ1: Abundance Analysis

Table 1 tabulates the relative abundance of genders across fake and real news, computed using a sum-based aggregation of \(N^W_F\) and \(N^W_F\) over fake and real subsets of the corpora, expressed as percentages to facilitate easy relative comparison. The results align with contemporary understandings of women’s under-representation in news media (Shor et al., 2019), but also indicate that such under-representation are mildly aggravated within fake news. The largest deterioration is in the case of ISOT, where women’s representation falls around 4% in real news to fake news.

5.2 RQ2: Affect Analysis

The relative emotion densities - measured as percentage of emotion words among proximal words - across genders and news veracities are illustrated in Table 2. While there is an apparent invariance across genders and veracity classes for LIAR and FNN, ISOT illustrates a marked increase in emotion density, especially for females, in fake news. This illustrates that gender bias in fake news has an affective component.

Table 4 illustrates the relative trends across full emotion profiles computed across eight emotion classes. Apart from the expected deterioration in expressions of trust in fake news, it is also notable that the prevalence of fear and anger are much more than prevalence of joy and surprise. These are potentially aligned with popular perceptions of fake news. It is notable that there are no significant differences in trends across genders.

The sentiment analysis results appear in Table 3. Two broad trends are unmistakably visible. First, there is a shift from positive and neutral sentiments towards negative sentiments when one moves eyeballs from the real news statistics to fake. Second, this shift, at least for ISOT and LIAR, is higher in intensity for female mentions. These provide evidence to assert the prevalence of negativity towards females and to generalize extant observations of gendered narratives targeting women in political fake news (Stabile et al., 2019).

5.3 RQ3: Neighboring Lexicons

Our analysis of lexical references around gender mentions was much more revealing, than those above. Most words around gender mentions were salutations such as professor, governor and spokesman in real news and any gendered patterns were overshadowed by such words. But when it comes to fake news, words around female mentions contained gendered roles such as wife, in sharp contrast to non-gendered roles such as governor and ambassador in real news. This trend was seen to
deeper in fake news with words such as mother and daughter coming up additionally among top female proximal references in fake news. Similar trends were visible in LIAR and FNN, albeit much more subtly. A surprising observation is that attack happens to be the 3rd most common word beside female mentions, indicating victimization of women. We remark here that further studies using ML-style approaches, such as topic modelling, may facilitate deeper analysis of any gendered patterns around gender mentions.

6 Discussion

Our lexicon-based analysis of gender abundance and gender bias over affect and word references quantitatively reinforces the existence of gender stereotypes over popular datasets used in fake news research. Our main insight from the analysis is that of quantitative evidence on higher levels of gender bias against women within fake news (cf. real news) on all three facets of analysis across RQ1-3 viz., abundance, affect and word references. The accentuation is at varying degrees across various analysis facets, with the ISOT dataset illustrating highest degrees of bias variation. This indicates, among other consequences, that gender-agnostic processing of fake news could propagate and/or amplify gender biases. Our insights provide a strong argument to consider gender bias across the gamut of fake news research.

While we restricted our analysis to lexicon/dictionary based methods for transparency, our work provides a solid foundation for further studies such as ML-based analyses to uncover details of relationship between gender bias and fake news. In immediate future work, we intend to study ways of extending this analysis to non-binary genders. Usage of parsing-oriented NLP (e.g., dependency parsing) to address the same questions is another interesting direction.

Ethical Considerations: Our work provides insights into the prevalence and intensity of gender bias in fake news vis-a-vis real news, and helps raise awareness of the issue of gender bias in fake news among researchers in NLP, a positive ethical

7 Conclusions

We analyzed gender bias using lexicon-based methods over popular fake news datasets to gather quantitative evidence. Our analysis shows that the issue of gender bias - particularly bias against women - is accentuated within fake news on all three aspects of our analysis viz., abundance, affect and word references. The accentuation is at varying degrees across various analysis facets, with the ISOT dataset illustrating highest degrees of bias variation. This indicates, among other consequences, that gender-agnostic processing of fake news could propagate and/or amplify gender biases. Our insights provide a strong argument to consider gender bias across the gamut of fake news research.
impact. Based on a self-assessment, we have not identified any negative ethical impacts of our work.

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