A Truthfulness Stance Map for 2024 Election-Related Factual Claims

Zhengyuan Zhu, Zeyu Zhang, Haiqi Zhang, Chengkai Li

Department of Computer Science and Engineering, University of Texas at Arlington

zhengyuan.zhu@mavs.uta.edu, zeyu.zhang@mavs.uta.edu, haiqi.zhang@mavs.uta.edu, cli@uta.edu

The 2024 presidential election has intensified competition between Democratic and Republican candidates, each competing to capture public attention and secure votes. Alongside campaign rhetoric, conspiracy theories about the candidates and election administration are spreading widely. These factual claims (campaign statements and conspiracy theories) are frequently debated on social media platforms such as X (formerly Twitter). The discussions reflect public perceptions toward these claims, including users' sentiments, favorability, and evaluations of truthfulness. This study focuses on truthfulness perception. Specifically, the user's post perception is from one of three distinct classes — *positive*, *negative*, and *neutral/no stance*. The *positive* stance is for when the tweet conveys the belief that the claim is true. Conversely, the *negative* stance indicates that the tweet believes the claim is false. The *neutral/no stance* signifies that the tweet expresses uncertainty about the truthfulness of the claim (*neutral*), or the tweet does not express any opinion about the claim's truthfulness despite both the tweet and the claim discussing the same topic (*no stance*). Since factual claims can influence the electorate's voting decisions, understanding public perceptions of their truthfulness is crucial for assessing their potential impact on the election.

While previous research has explored truthfulness stance detection, much of this work has focused on non-election-related topics, such as COVID-19 [4] or general news [5, 2, 1]. In addition, they overlooked the importance of geolocation-based analysis. Understanding the geographic distribution of truthfulness stances at state and county levels is vital for assessing the localized influence of election-related claims. In this study, we introduce a truthfulness stance map as shown in Fig 1, an interactive interface that visually presents the distribution of truthfulness stances toward election-related factual claims across the United States. The map is developed using Streamlit [3]. The map allows users to select claims from a sidebar, drawing from two curated sources: (1) factual claims from Kamala Harris and Donald Trump, that have been fact-checked by Politifact [1] and (2) a dataset of conspiracy theories compiled by our research team. Once a claim is selected, the interface displays the stance results of social media posts on a U.S. map. Social media posts are gathered by querying tweets using a combination of keywords from the factual claims and geolocation data. The Twikit package [8] is used to collect these tweets. The collected tweet-claim pairs are then processed using our in-house truthfulness stance detection model [6] to classify the stance of each tweet-claim pair as one of the positive, neutral/no stance, negative stance. This stance detection model is based on a large language model, Zephyr [7], fine-tuned on a in-house truthfulness stance detection dataset comprising 3,105 labeled tweet-claim pairs. Below the map, bar charts summarize the stance distributions and provide a timeline of tweet volumes, displaying daily and cumulative counts leading up to election day.

This tool is designed to benefit multiple stakeholders. Political strategists can use the map to gauge public reactions to their candidates' statements and refine campaign strategies. Social

[1] https://www.politifact.com/

scientists can explore the spread and impact of conspiracy theories and test hypotheses on election-related misinformation. By integrating granular geolocation data with an intuitive, user-friendly interface, this work offers a valuable resource for understanding and addressing misinformation in the context of the 2024 election.

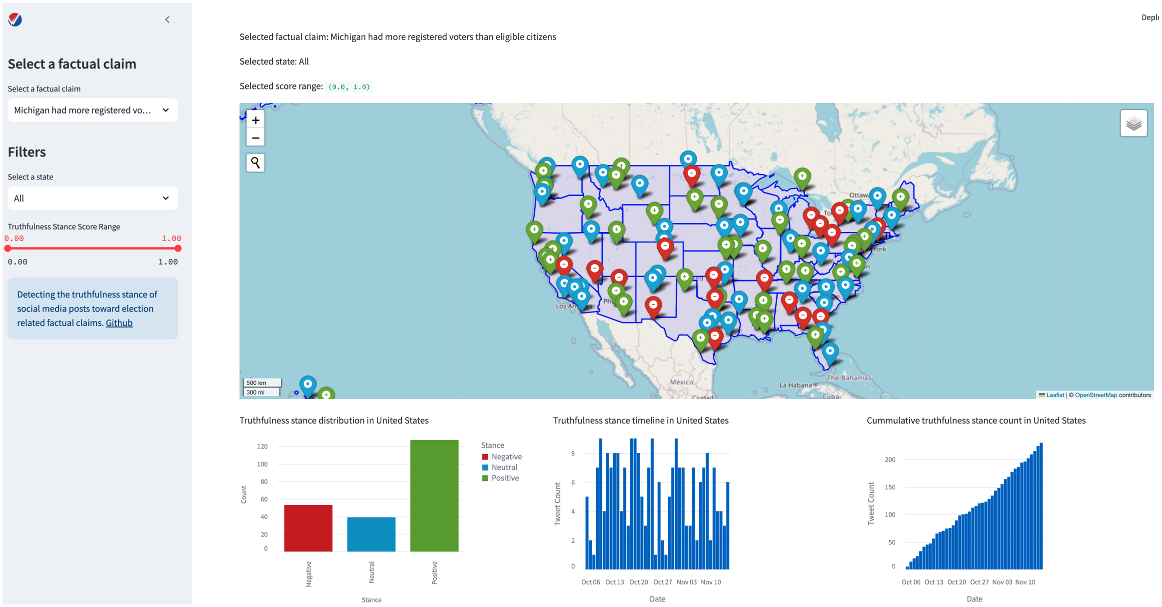

Figure 1: The truthfulness stance map.

References

[1] Dean Pomerleau and Delip Rao. *Fake News Challenge Stage 1 (FNC-1): Stance Detection*. `http://www.fakenewschallenge.org`. 2017.

[2] Genevieve Gorrell et al. "Semeval-2019 task 7: Rumoureval 2019: Determining rumour veracity and support for rumours". In: *Proceedings of the 13th International Workshop on Semantic Evaluation: NAACL HLT 2019*. Association for Computational Linguistics. 2019, pp. 845–854.

[3] Inc. Streamlit. *Streamlit: A faster way to build and share data apps*. `https://streamlit.io/`. Accessed: 2024-11-20. 2019.

[4] Tamanna Hossain et al. "COVIDLies: Detecting COVID-19 misinformation on social media". In: *Proceedings of the 1st Workshop on NLP for COVID-19 (Part 2) at EMNLP 2020*. 2020.

[5] Revanth Gangi Reddy et al. "Newsclaims: A new benchmark for claim detection from news with attribute knowledge". In: *arXiv preprint arXiv:2112.08544* (2021).

[6] Zhengyuan Zhu et al. "Detecting Stance of Tweets Toward Truthfulness of Factual Claims". In: *Proceedings of the 2012 Computation+Journalism Symposium*. 2022.

[7] Lewis Tunstall et al. "Zephyr: Direct distillation of lm alignment". In: *arXiv preprint arXiv:2310.16944* (2023).

[8] Twikit Contributors. *Twikit: A Framework for [description of purpose, e.g., Personalization].* https://github.com/d60/twikit. Accessed: 2024-11-20. 2024.