Visualizing User Credibility and Cultural Influences in Misinformation Detection through Social Context

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GitHub
https://github.com/AidaCPL/INFOSCI301_Final_Project

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Introduction

The rapid spread of misinformation, especially through social media, continues to challenge societies worldwide. This study explores how cultural and social contexts shape the dissemination and detection of false information, focusing on patterns of user credibility and regional susceptibility. Drawing on data from Climate-FEVER and a global behavioral dataset, we examine the complex relationships between misinformation, audience behavior, and cultural influences.

Our approach combines geospatial mapping, network analysis, and machine learning to highlight key drivers of misinformation susceptibility. By incorporating interactive dashboards, we enable stakeholders to analyze regional vulnerabilities, explore user engagement patterns, and test intervention strategies in real time. The findings reveal cultural and demographic factors that increase susceptibility and identify high-risk regions, offering insights for targeted media literacy campaigns and content moderation policies.

Conclusion

This study highlights the complex factors influencing misinformation susceptibility, combining geospatial mapping, network analysis, and machine learning to uncover regional vulnerabilities and engagement patterns. Interactive geospatial visualizations reveal how cultural dimensions shape misinformation detection, while network analyses identify thematic distinctions in SUPPORTS and REFUTES claims, aiding content moderation strategies. Insights into social media use and cognitive performance underscore platform-specific behaviors and intellectual engagement's role in misinformation vulnerability. Machine learning further pinpoints key predictors, enabling targeted interventions for high-risk demographics.

This research demonstrates how thoughtful data visualization can make misinformation dynamics more accessible, equipping policymakers, media professionals, and educators with tools to develop culturally sensitive solutions to this pressing global issue.

Research Questions

1. How can interactive **geospatial visualizations** enhance the understanding of cultural influences on misinformation detection across different regions?
2. What novel insights emerge from visualizing the relationships between user credibility and misinformation spread using **network-based representations**?
3. In what ways can interactive visualizations reveal patterns in user engagement with misinformation **across various intellectual backgrounds**?
4. How can **machine learning** be utilized to illustrate the relative importance of cultural factors in misinformation susceptibility?

Geospatial Visualizations

- **Regional Focus:** This interactive map visualizes credibility scores by country using a color-coded representation created with the **Pyecharts** library. Countries are shaded on a gradient from dark to light colors, where lighter shades represent higher average scores derived from attention checks.
- **Interactivity:** Interactivity allows researchers to explore country-specific data in real-time, facilitating hypothesis generation about the relationship between cultural factors (e.g., individualism vs. collectivism, educational systems) and misinformation detection capabilities.

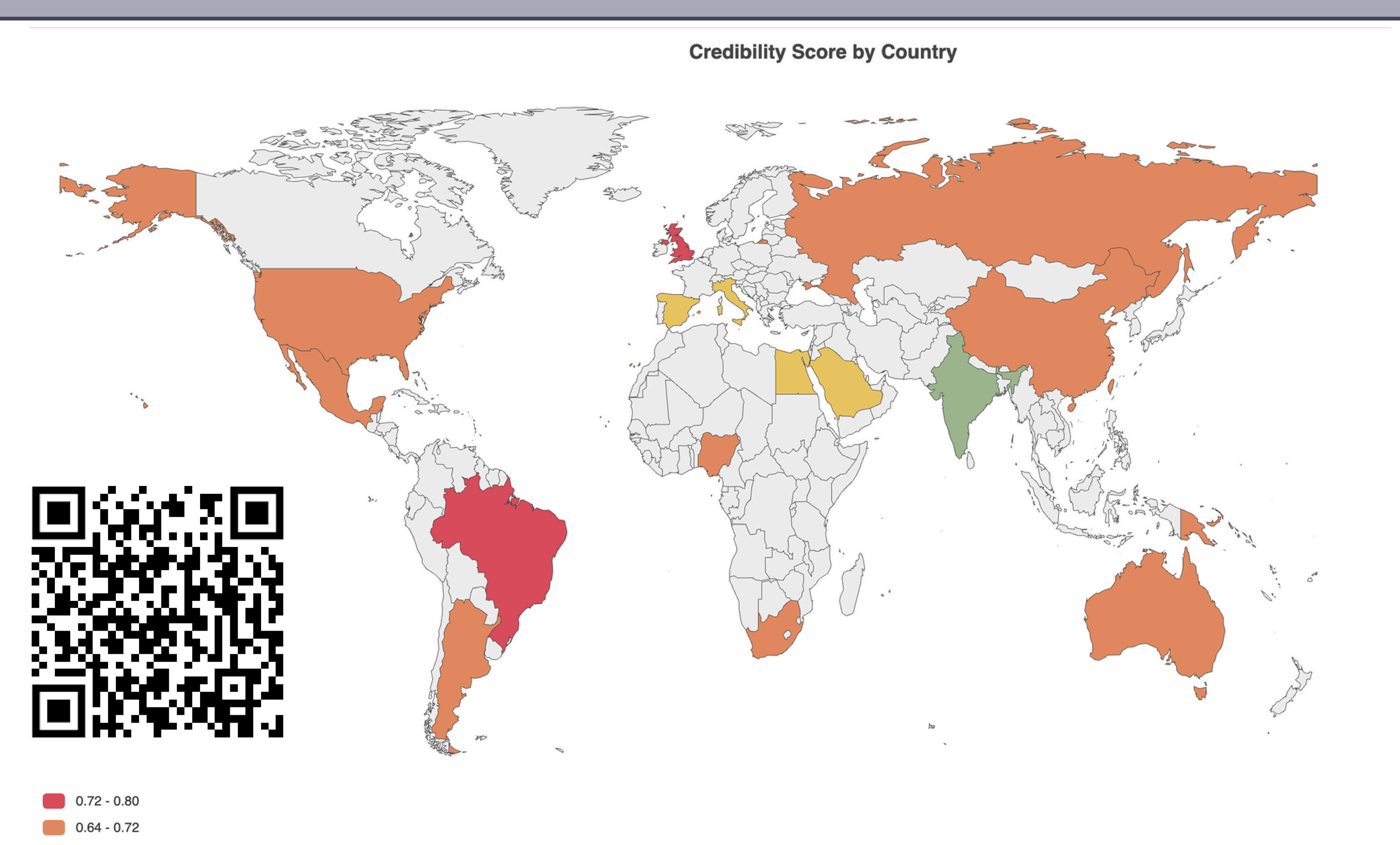

Figure 2. Interactive map of Credibility scores by country.

Network-based relationships

Methodology & Interpration: The visualizations represent word networks derived from claims categorized as SUPPORTS (figure 4) and REFUTES (figure 3), generated using **Gephi**. Words are nodes, and their co-occurrences within claims form weighted edges. Node size corresponds to word frequency, and edge thickness reflects the strength of their association.

Nodes are color-coded to indicate clusters identified through modularity analysis, highlighting groups of words with stronger interconnections. The layouts were optimized for clarity using a force-directed algorithm, ensuring a balanced distribution and clear representation of relationships. These visualizations reveal the structural differences in word usage and associations between the two claim types.

The visualizations reveal distinct patterns in word usage and associations between SUPPORTS and REFUTES claims. **Modular clusters** highlight thematic groupings, indicating key terms that frequently co-occur. Larger nodes signify central words integral to the argument structure, while thicker edges suggest stronger connections. Differences in clustering and word relationships between the two claim types underscore variations in argument composition and focus.

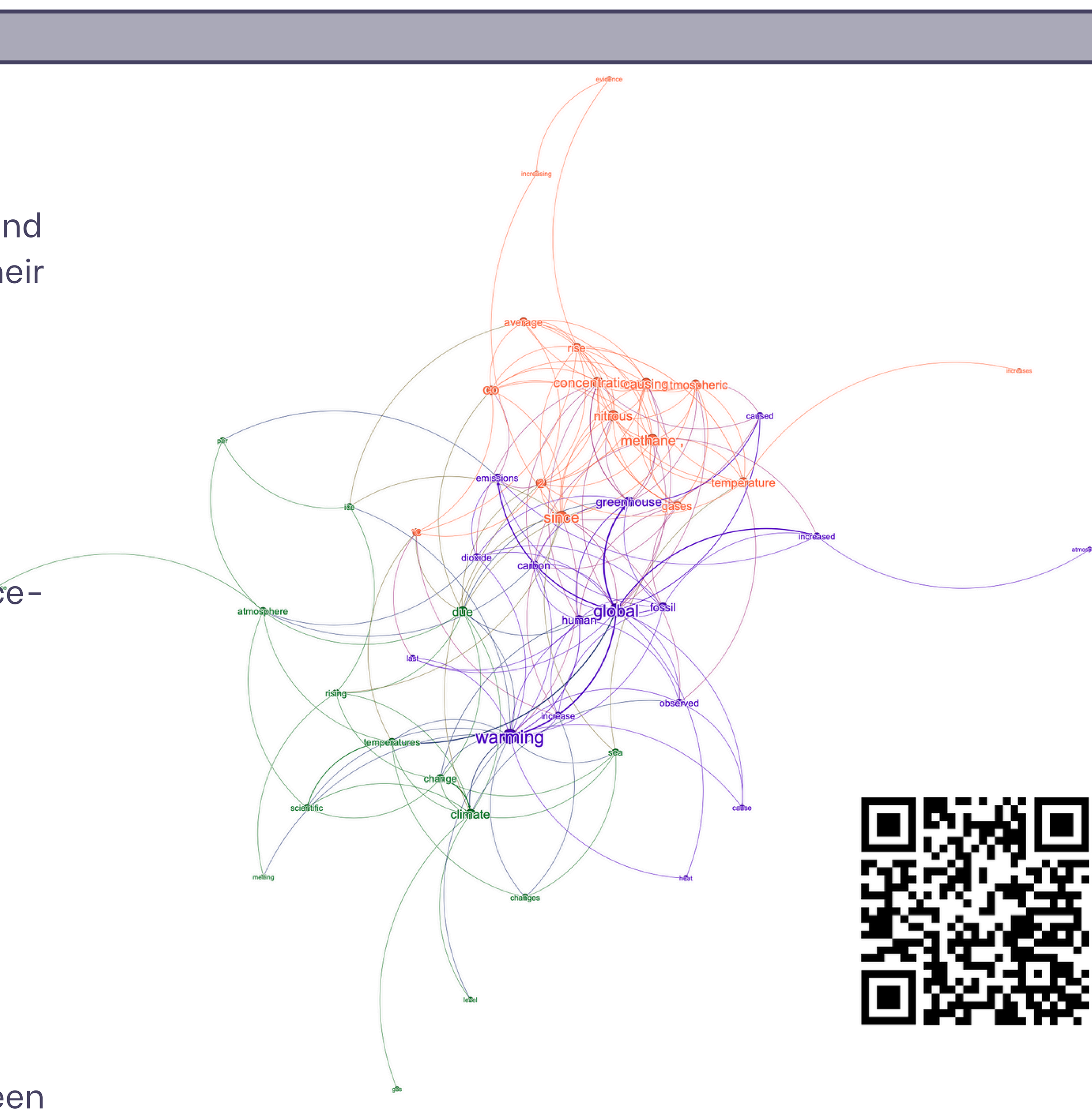

Figure 3. Networks of identified Fake data on the Climate-FEVER Dataset. Created with Gephi.

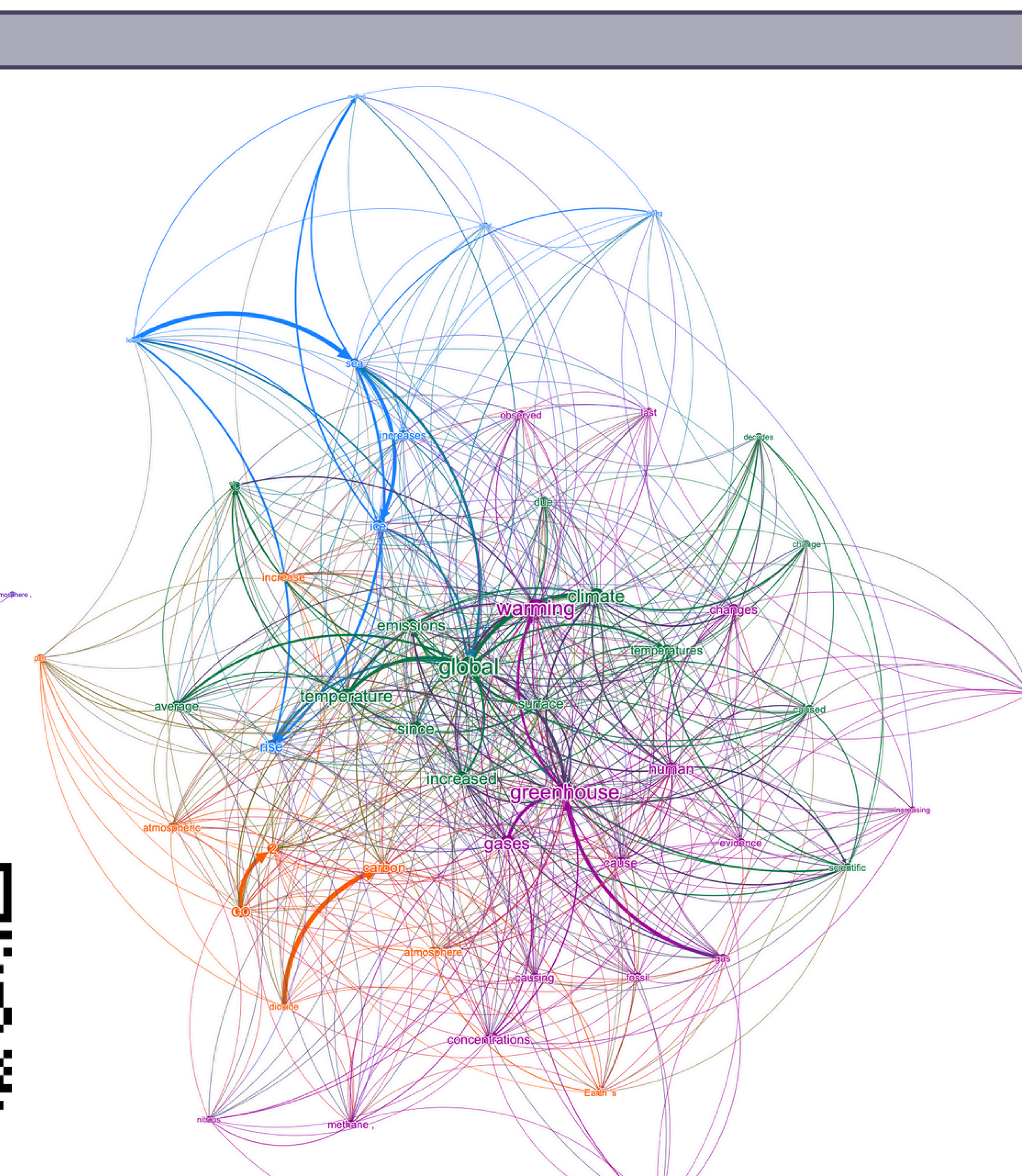

Figure 4. Networks of identified Real data on the Climate-FEVER Dataset. Created with Gephi.

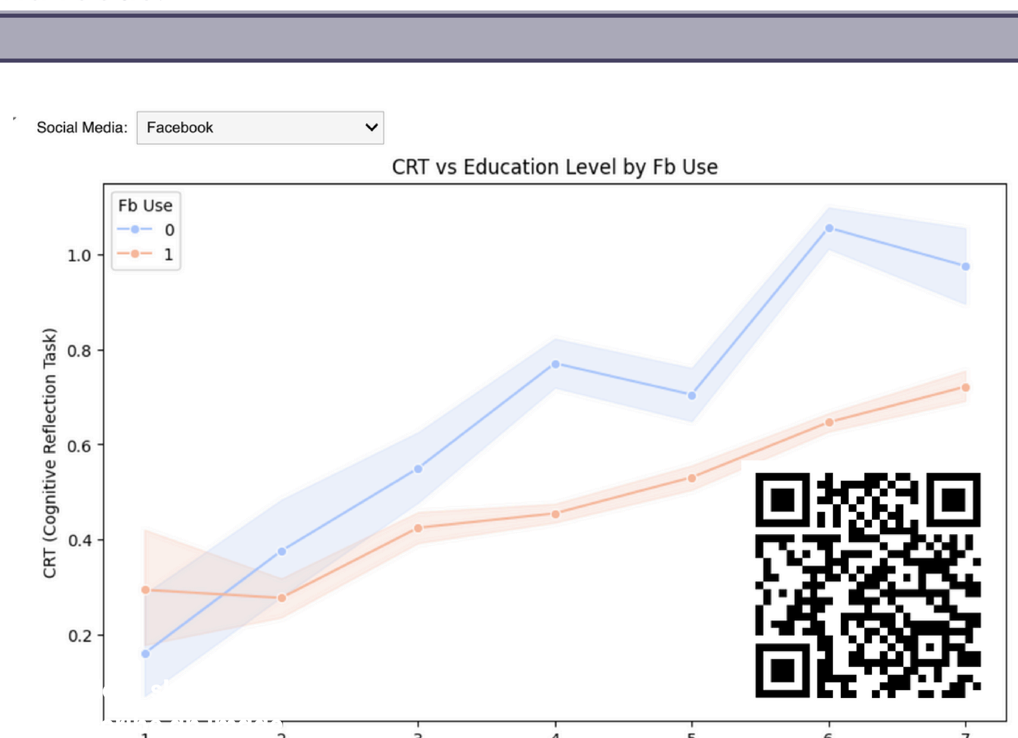

Figure 5. Interactive plot showing CRT scores by education level and Facebook use. Explore on GitHub to compare other social media platforms.

Impact of Social Media use on Intellect

Methodology & Insights: This visualization explores the relationship between education level and cognitive reflection task (CRT) performance, stratified by social media usage. CRT scores are plotted against education levels for users and non-users of specific platforms, with an interactive dropdown allowing platform comparisons.

Machine Learning Implementation

The feature importance plot highlights the most influential factors in predicting the target variable. Merging datasets enriches the feature set, allowing machine learning models, like **Random Forest,** to handle complex, non-linear relationships and uncover hidden patterns and interactions. This approach provides actionable insights, such as targeting specific demographics for interventions or tailoring strategies to combat misinformation based on key predictors, all while maintaining robust performance and interpretability.

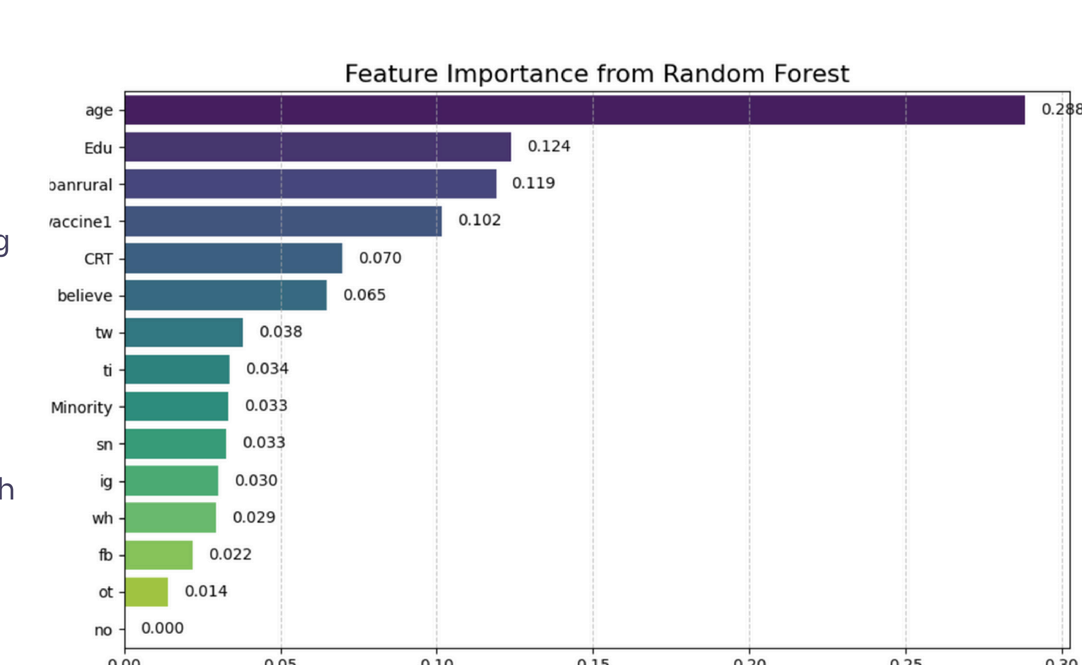

Figure 6. Feature importance plot from a Random Forest model.