Modeling the Spread of Misinformation in Online Networks

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Abstract (Background)

The rapid spread of misinformation across online social networks has become a global issue, shaping public perception, social polarization, and even democratic stability. This study builds a computational model to simulate misinformation diffusion, drawing methodological inspiration from open-source projects such as *FakeNews Simulator* (FraLotito, 2021) and *Fake-News-Network-Modeling* (Kymry et al., 2021). Using agent-based network simulations, the research aims to identify the **critical tipping point** at which misinformation transitions from local containment to viral propagation. The project focuses on how **network topology** (random vs. scale-free) and **user susceptibility** interact to trigger large-scale diffusion.

Introduction (Hypothesis, Literature Review, Falsifiability)

Hypothesis:

Misinformation in online networks exhibits a **tipping-point dynamic**—when a small but critical fraction of users begin sharing false content, diffusion accelerates nonlinearly, reaching most of the network.

Literature Review:

Prior studies in complex contagion and network diffusion (Watts, 2002; Centola, 2010) show that collective behaviors spread through threshold-based mechanisms rather than continuous growth. Early rumor models (Daley & Kendall, 1965) conceptualized information spread as an epidemic process but lacked network structural realism. More recent open-source simulations, including *FakeNews Simulator* and *Fake-News-Network-Modeling*, demonstrate how social connectivity, node influence, and message virality interact to produce cascading effects.

Falsifiability:

The hypothesis is falsifiable: if simulation results display steady, linear diffusion across all probabilities p, it would indicate the absence of a nonlinear tipping point.

MVE (Data Generation, Sample Size, Tipping Point)

Data Generation:
Simulations are implemented in Python using the *NetworkX* library, extending methodologies from *FakeNews Simulator* (FraLotito, 2021). Two synthetic network structures were generated:

- **Erdős–Rényi (ER)** random networks representing decentralized social structures.

- **Barabási–Albert (BA)** scale-free networks reflecting influencer-dominated online platforms.

Each node is assigned a probability *p* of retransmitting misinformation upon exposure. The diffusion process is modeled through iterative propagation across connected nodes, with transmission outcomes determined by random sampling.

Sample Size:
For each configuration, 200 independent simulation runs were conducted across network sizes from 500 to 5000 nodes and varying connection probabilities.

Tipping Point Definition:
The critical threshold p_c is defined as the minimum value of *p* at which misinformation reaches ≥80% of nodes within 10 propagation rounds.

Analysis (Statistical Analysis, Scaling, and Validation)

Statistical Analysis:
A logistic regression was fitted to model the relationship between the retransmission probability *p* and final adoption rate *A(p)*.
The first derivative of the fitted curve identifies the inflection point—interpreted as the tipping threshold.

Scaling and Pivoting:
To evaluate model robustness, experiments were scaled across multiple network sizes.
Pivoting on clustering coefficients revealed that higher community density delays the tipping point, indicating that strong local ties restrict global diffusion.

Model Validation:
Simulation trends were compared with existing open-source models (*Fake-News-Network-Modeling*, Kymry et al., 2021), both showing consistent nonlinear diffusion patterns. The similarity validates the robustness of the implemented model and supports the presence of a critical phase transition.

Conclusion

Results indicate that misinformation diffusion is **nonlinear** and **network-dependent**. Once the critical probability threshold p_c is exceeded, the spread accelerates exponentially, transforming isolated interactions into a system-wide cascade.
This supports the existence of a tipping-point phenomenon in online misinformation dynamics.
Future work will incorporate **real-world datasets** from Twitter and Reddit to analyze how algorithmic amplification, echo chambers, and polarization modify contagion thresholds in realistic environments.

References:

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