

Misinformation Spread in Social Networks

A Monte Carlo Simulation by Akanksha Agrawal and Sara Kiel

Project Context and Motivation

In today's media environment, misinformation spreads rapidly, often faster than factual content, and can cause significant harm. People frequently share breaking news before verifying it, and social media platforms amplify such information due to their structure and virality mechanisms. Compounding this issue is the increasing difficulty in discerning authentic information online.

Inspired by studies such as the [2018 MIT research on Twitter misinformation](#), our project investigates how misinformation propagates through social networks and how factors like trust, user roles (influencers, fact-checkers, susceptible users), and competition from factual news impact this spread. We aim to simulate and analyze these dynamics using an agent-based Monte Carlo model, built from scratch in Python.

Baseline Setup

A baseline simulation was set up to enable robust validation against real-world findings and served as a control group for future hypothesis testing. We designed a baseline simulation using the following controlled parameters.

Network Composition

- **Size:** 1,500 agents (users), mimicking a mid-sized online community.
- **Structure:** We created a hybrid network using the **Watts-Strogatz (WS)** model for local clustering (echo chambers), and **Barabási-Albert (BA)** model to generate a few high-degree hubs (influencers).
- **Average Degree:** Tens of connections per user to simulate realistic social density.

User Role Distribution

- **Influencers:** 2.5% of users, chosen based on node degree.
- **Skeptical:** 57% of users, being split into the following additional roles:
 - **Fact-Checkers:** 30% of skeptical users, with a 30% probability of intervening when they see fake news.
 - **Susceptible Users:** 10% of skeptical users, divided into:
 - **Normal Susceptible**
 - **Highly Susceptible (5–10%)**
 - **Super-Spreaders (~0.1%)**
- **Regular Users:** Remaining population with moderate behavior.

Trust Modeling

- **Intra-Community Edges:** Higher trust, sampled from Uniform[0.8, 1.0].
- **Inter-Community Edges:** Lower trust, sampled from Uniform[0.1, 0.5].
- **Effect:** Trust modulates sharing probability by scaling it (i.e., actual share probability = $P_{\text{share}} \times \text{trust}$).

News Initialization

- One **fake news** and one **factual news** item introduced per run.
- Each seeded in a randomly selected user (with 10 users being initially seeded news) at round 0.
- News is treated as mutually exclusive in terms of belief - users typically adopt only one at a time.

Sharing Delays

- **Fake News:** Short delays; 85% share after 1 round, with the rest being shared in a 2nd and 3rd round.
- **Factual News:** 6× longer delays on average compared to fake news, matching real-world latency in verification and uptake.

Agent Behaviors

- **P_share_fake:** Ranges from 0.11–0.22 depending on role.
- **P_share_real:** 0.06–0.09, reflecting known slower spread of factual content.
- **Fact-checkers:** Intervene with 30% probability and reduce trust in flagged news connections by 70%.

Simulation Run

- **Monte Carlo Trials:** We ran the simulation 1,000 times to average out random fluctuations that may occur.
- **Termination:** Simulation ends when no new shares occurred or 50 rounds were reached.

Hypothesis Testing

We explored three main hypotheses through systematic experimentation:

H1: Fact-Checker Efficacy

- **H₀:** Varying fact-checker proportions has no effect on fake news spread.
- **Method:** Simulate networks with 10%–60% fact-checkers and compare outcomes.
- **Expected:** Higher fact-checker density significantly reduces fake news reach.

H2: Influence of Influencers

- **H₀:** Influencer behavior and presence do not affect misinformation spread.
- **Scenarios Tested:**
 - **A:** Increasing the number of initial influencer seeds
 - **B:** Influencer delay boost
 - **C:** Influencer trust boost
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H3: Competitive News Dynamics

- **H₀:** Introducing factual news does not affect the spread of fake news.
- **Method:** Run simulations where fake and factual news compete simultaneously.
- **Expected:** Factual news presence reduces the reach of fake news, but not symmetrically.

Key Findings and Results

Baseline Results

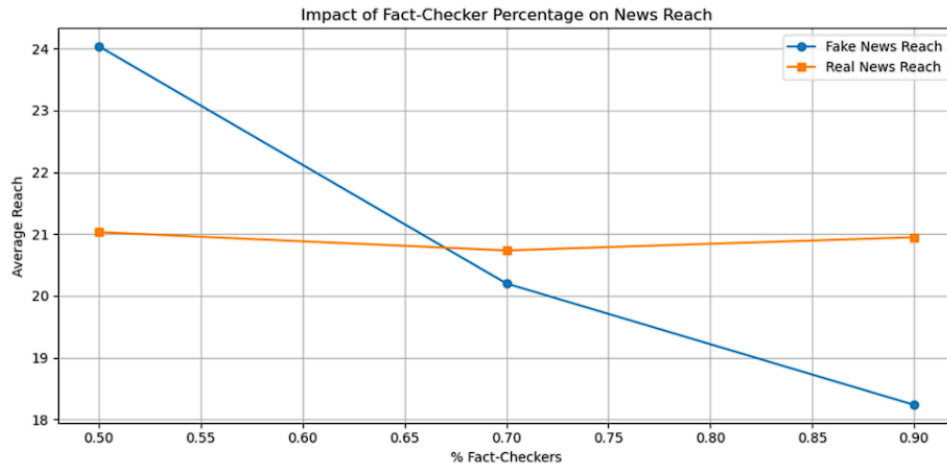
From 1,000 simulation runs, we saw the following results.

- **Average Reach:**
 - Fake news: 54.1 ± 41.4 agents
 - Real news: 18.2 ± 6.1 agents
- **Peak Spread Round:**
 - Fake: Round **1**
 - Real: Round **6**
- **Time to Peak:**
 - Real news takes **6× longer** than fake news to reach maximum velocity, aligning with the 2018 MIT study's finding that real news spreads significantly slower.

Experimental Insights

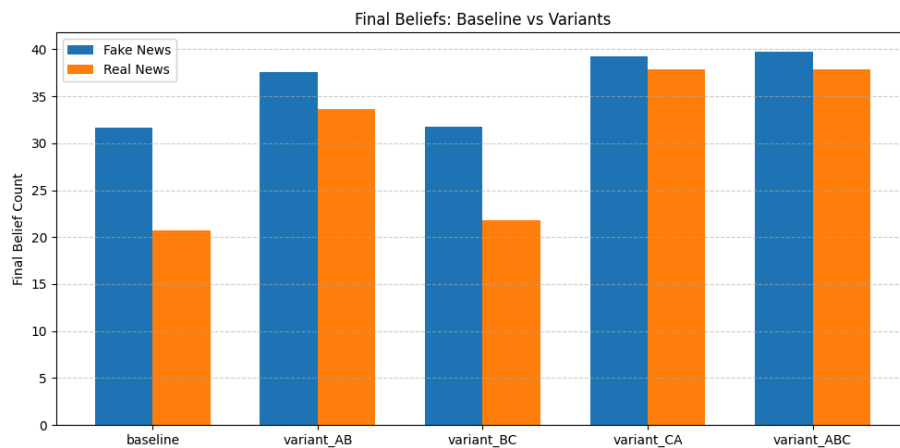
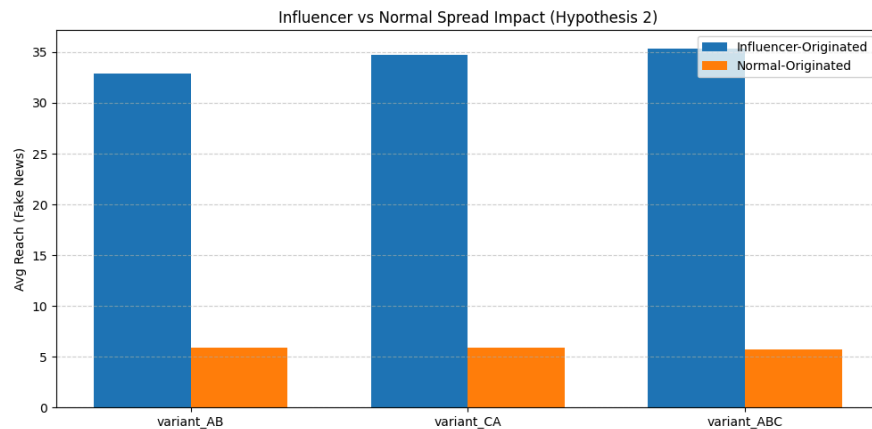
Fact-Checker Effectiveness

- As the proportion of fact-checkers increased, the spread of fake news declined substantially.
- Real news reach remained stable.
- **Conclusion:** Fact-checkers effectively suppress misinformation without suppressing truth.



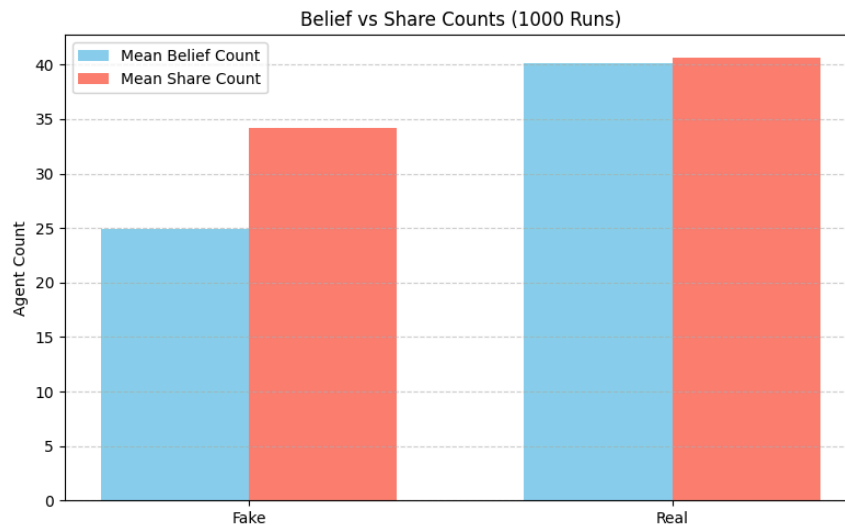
Influencer Behavior

- Scenario A (high $P_{\text{share_fake}}$): Led to much wider and faster fake news cascades.
- Scenario B (cautious influencers): Significantly suppressed misinformation, even with fewer fact-checkers.
- Increasing influencer density amplified spread, regardless of content.



Competing News

- The presence of factual news decreased fake news reach by 10–20%, showing limited but consistent suppression.
- However, due to higher sharing rates and speed, fake news still dominated in most simulations.
- **Timing mattered:** if real news lagged behind, its competitive influence weakened.



Conclusions and Reflections

This simulation demonstrates the multifaceted nature of misinformation spread and reinforces several key real-world dynamics:

- **Speed and virality favor misinformation**, making it difficult for factual corrections to catch up.
- **Fact-checkers are effective**, but only if present in sufficient numbers.
- **Influencers are critical levers:** their behavior can either suppress or supercharge misinformation.
- **Competing narratives matter**, but timing and network position shape the outcome.

Limitations and Future Work

Limitations

While our simulation captures key dynamics of misinformation spread, there are several limitations worth noting. These limitations highlight areas where future refinement, optimization, or real-world validation may enhance the robustness of our findings. Most limitations were results of favoring simpler code logic.

- **A manual toggling approach** was used to determine which simulations to run. This helps manage runtime and system resources, but is not ideal. To improve this, we could incorporate changes such as adding a progress bar to track simulation status or optimizing runtime performance across experiments
- **The current trust impact that fact-checking has** is a 70% direct drop in trust for later viewers of the news article. In a real world scenario, this would be a much more complicated process.
- **Similarly, trust between users** cannot simply be boiled down to whether they are direct or indirect connections, which is how we have it set currently. While this captures some aspects of real-world social dynamics, it oversimplifies the complexity of trust in online environments.
- **We ignored the content of the news itself** and how content influences shareability and fact-checking. For example, a news piece related to the newly appointed pope may be likely to spread faster than an article on how cheese is made.

Future Work

The other simulations we saw online related to misinformation spread or misinformation detection were primarily LLM-based and beyond the scope of our project assignment. However, these simulations provided thoughtful insights on additional variables that we could consider for future additions to our project.

- **Content-aware modeling:** We could incorporate factors like emotional tone or news source credibility, in addition to the aforementioned comparison of news topics/content and their spread.
- **Temporal network updates:** simulating evolving social structures.
- **More advanced user roles:** We could incorporate bots as a new user role in our simulation, or have more fleshed-out personalities for user groups.

References

- [Study: On Twitter, false news travels faster than true stories](#)
 - This study served as the inspiration for our project
- [From Skepticism to Acceptance: Simulating the Attitude Dynamics Toward Fake News](#)
 - Helped us consider incorporating fact-checker intervention
- [News Use Across Social Media Platforms 2018](#)
 - Provided us with our number of skeptical users: 57%
- [A survey of Twitter research: Data model, graph structure, sentiment analysis and attacks](#)
 - Based our probability of sharing real news range on results from this study
- [Who reports witnessing and performing corrections on social media in the United States, United Kingdom, Canada, and France?](#)
 - Our probability of fact-checker intervention was based on results from this study, as well as the proportion of fact-checkers in our baseline network
- [‘Who shared it?’: How Americans decide what news to trust on social media](#)

- This study helped us determine our ranges for inter- and intra-community trust
- [On Twitter, 'supersharers' spread majority of fake news](#)
 - Our proportions for total susceptibles and types of susceptible users were based on this study