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.
- **Skepticals**: 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_share x 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 0.11–1.0 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 500 rounds were reached.

Hypothesis Testing

We explored three main hypotheses through systematic experimentation:

H1: Fact-Checker Efficacy

- **H_0**: Varying fact-checker proportions has no effect on fake news spread.
- **Method**: Simulate networks with 50%, 70%, and 90% fact-checkers and compare outcomes.
- **Expected**: Higher fact-checker density significantly reduces fake news reach.

H2: Influence of Influencers

- **H_0**: Influencer behavior and presence do not affect misinformation spread.
- **Scenarios Tested**:
  - **A**: Increasing the number of initial influencer seeds
  - **B**: Influencer delay advantage (faster spreading)
  - **C:** Boost trust in influencer-originated content

H3: Competitive News Dynamics

- **H_0**: Introducing factual news does not affect the spread of fake news, nor does delaying its introduction.
- **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: 31.6 ± 17.6 agents
  - Real news: 20.5 ± 8.1 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.

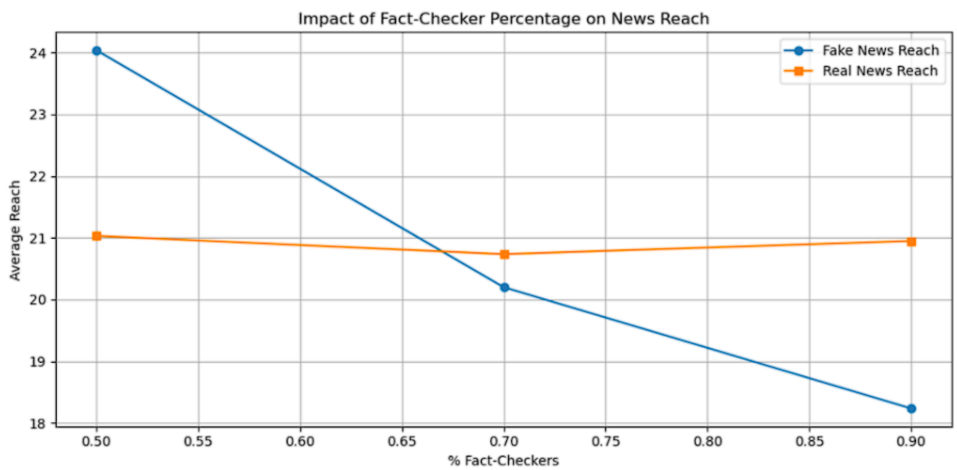
Experimental Insights

Fact-Checker Effectiveness

- As we increased the proportion of fact-checkers in the network, the simulation revealed a clear and consistent downward trend in the spread of fake news.
- Flagging and Trust Reduction: Fact-checkers intervened by identifying and flagging misinformation, which directly reduced the trust score on edges transmitting that content. This made downstream agents less likely to adopt or reshare fake news.
- Behavioral Influence: Since fact-checkers had lower probabilities of sharing fake news to begin with, their presence effectively diluted the high sharing rates driven by susceptible

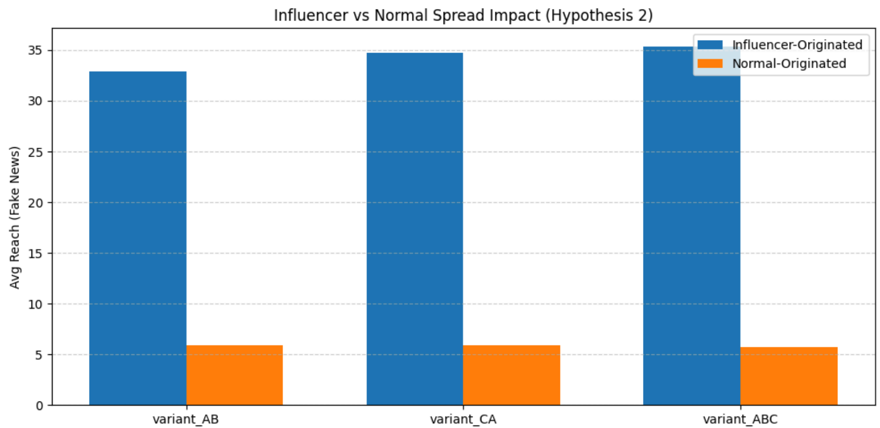
or influencer agents.

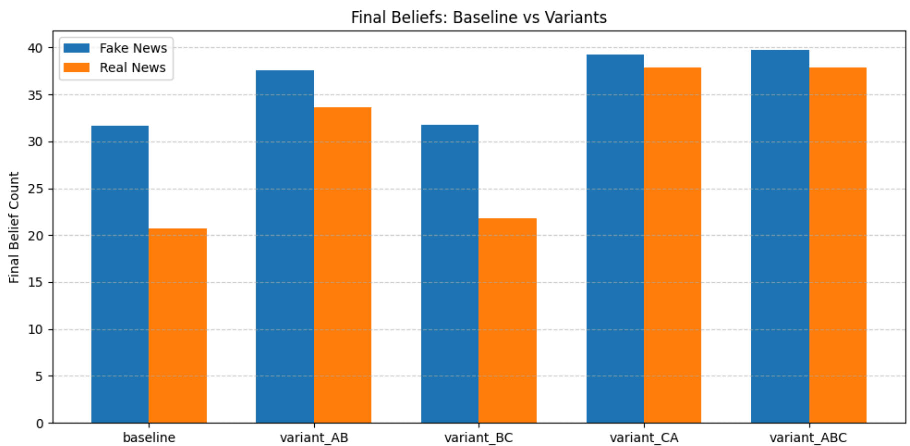
- Despite this strong suppression of fake news, the spread of real news remained largely unaffected. This is because fact-checkers are designed not to intervene in or suppress factual content, and their cautious behavior did not hinder real news from reaching agents with high enough trust to believe and share it.
- **Conclusion:** By reducing the reach of misinformation without interfering with factual communication, fact-checkers enhance the integrity of a social network without throttling overall information flow and are a non-disruptive defense against misinformation. With this, we reject the null hypothesis.



Influencer Behavior

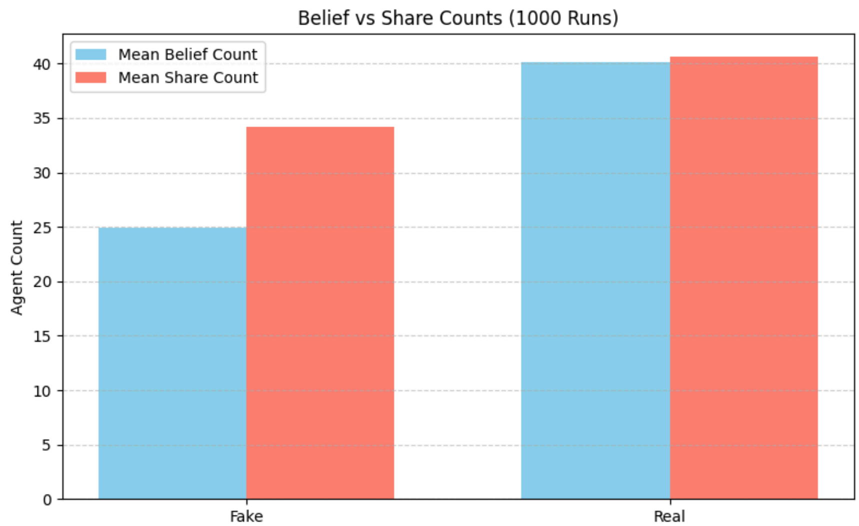
- Variant A (Influencer Seeding): Resulted in dominant cascades driven by high P_share influencers. On average, over 80–90% of fake news spread originated from influencer-seeded paths. Their structural advantage (higher degree and trust) and lower delay accelerated spread rapidly.
- Variant B (Reduced Delay): Despite enabling influencers to share faster, the spread was more tempered. Influencers still contributed significantly, but their cautious behavior (via controlled delay tweaking) slightly limited breadth.
- Variant C (Trust Boost): When influencer-shared news gained an artificial trust bump, it further amplified their reach. This led to more aggressive early-stage diffusion, as seen in slightly increased influencer reach metrics.
- Across All Variants with A Enabled: A significantly larger proportion of the network is reached through influencer-initiated cascades compared to those triggered by normal users.
- **Conclusion:** Influencers are powerful accelerators of misinformation. Their behavior, seeding, and network position strongly shape overall spread dynamics, and we reject the null hypothesis.





Competing News

- Introducing real news concurrently with fake news reduced fake news reach by ~10–20%, showing consistent, albeit modest, competitive suppression.
- The overlap between belief and share metrics for real news suggests that many agents revised their beliefs upon encountering real news after initially believing fake news. This supports the belief-switching logic implemented for fact-checkers and some normal agents.
- When real news was introduced with delays (e.g., 3 rounds later), its suppression capability diminished. Misinformation, due to faster delays and higher P_share, often established dominance before real news gained traction.
- **Conclusion:** Real news can compete with and suppress misinformation, but effectiveness hinges on timing and the presence of fact-checkers who facilitate belief correction. Without intervention, misinformation dominates due to inherent spread advantages. We once again reject the null hypothesis.



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