Fact-checking Effect on Viral Hoaxes:A Model of Misinformation Spread in Social Networks

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Introduction

- The spread of misinformation is a hot topic at the moment
- Spread of misinformation can be modeled as an epidemic:
  - Misinformation $\rightarrow$ virus
  - Believer of misinformation $\rightarrow$ infected
  - Debunker/fact-checker $\rightarrow$ infected
- This paper's contributions:
  - A model with four parameters, derived from established epidemic models
  - Simulations on synthetic and real networks
  - Conditions for hoax to be removed completely
  - Predict number of susceptible individuals as $t \rightarrow \infty$

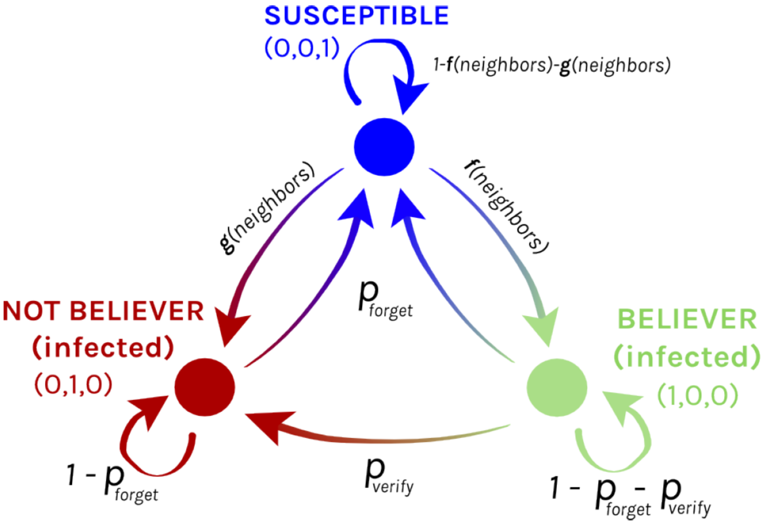
Epidemic Models

- Stochastic models used to simulate spread of infection
- Long history of literature since 1920s
- SIS: Susceptible-Infected-Susceptible
- SIR: Susceptible-Infected-Recovered
- These models are often used for information diffusion processes
- Classical results can be applied to new problems

The Model for Viral Hoaxes

- A graph where each node is in one of three states:
  - Believer
  - Fact-checker
  - Susceptible
- Captures three phenomena:
  - Spreading (based on neighbors)
  - Verifying (fixed probability)
  - Forgetting (fixed probability)

Helpful Diagram



The Spreading Functions

- Capture how each node is affected by neighbors
- $f_i(t)$ and $g_i(t)$ represent spreading of the hoax and debunking respectively

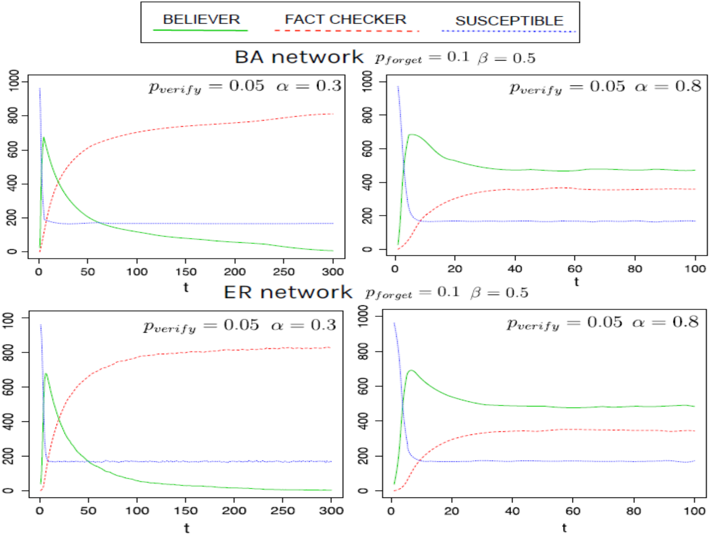
$$f = \beta \frac{n_B(1+\alpha)}{n_F(1-\alpha) + n_B(1+\alpha)}$$
$$g = \beta \frac{n_F(1-\alpha)}{n_F(1-\alpha) + n_B(1+\alpha)}$$

- Constants:
  - $\alpha \in [0,1)$ credibility of hoax
  - $\beta \in [0,1)$ spreading probability
- n_B, n_F: number of adjacent believers, fact-checkers for node i at time t

Results

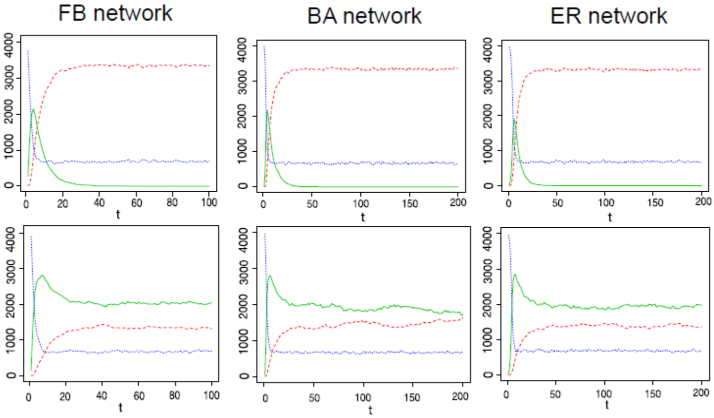
- S_∞ does not depend on topology, p_{verify} or β
- α and p_{verify} determine whether believers or fact-checkers prevail
- Hoax can be removed entirely if p_{verify} is high enough but "infection" (fact-checkers) will remain

Simulation Results on Synthetic Networks



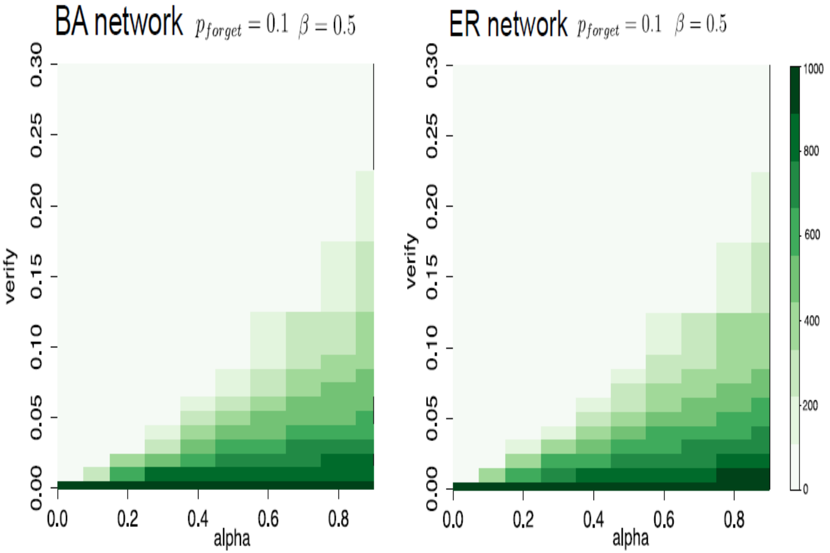
N $=$ 1000,mean degree $=$ 6, average over 30 iterations

Simulation results on real and synthetic networks of same size



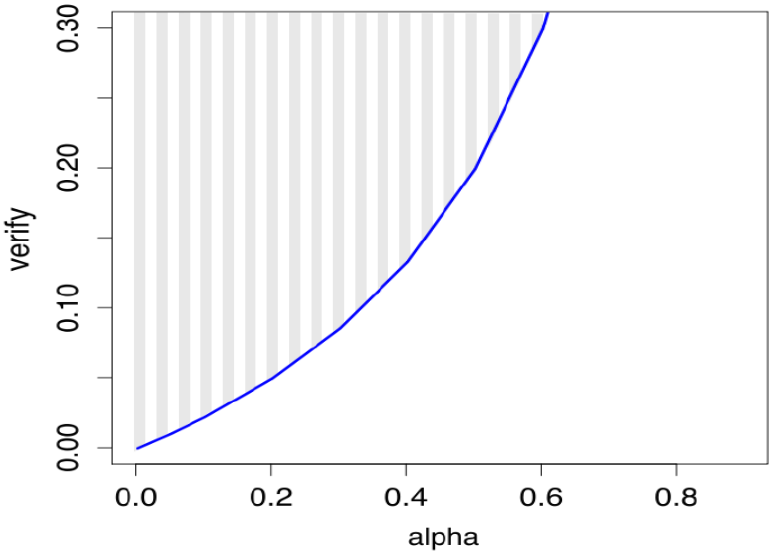
$\beta = 0.5$, $p_{forget} = 0.1$, $p_{verify} = 0.05$, $\alpha = 0.3$ (top) and 0.8 (bottom)

Phase Diagram for B_∞



Avg over 30 iterations

α and p_{verify}



$p_{forget} = 0.1$. Area above blue line represents total removal of hoax

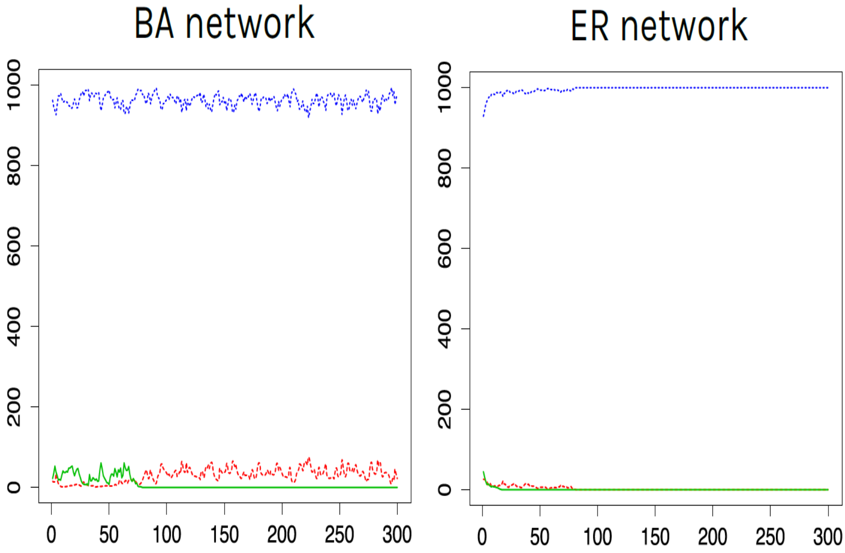
Comparison to Epidemic Models

- From epidemic theory, we have reproduction number R_0:

$$R_0 = \frac{\beta \langle k \rangle}{p_{forget}}$$

- Previously-known result: when *reproduction number* is greater than one, network topology does not matter
- When $R_0 < 1$, behavior is different for homogeneous and scale-free (like the Internet) networks
- Does this new model display this behavior?

Model Does What Was Expected



$\beta = 0.1$, $p_{forget} = 0.7$,$\alpha = 0.8$, and $p_{verify} = 0.05$

Critique

- Would have liked more detail on how spreading functions were created
- Does not account for variability in people (authors acknowledge this)
- What about cases where nodes can be removed entirely?

References

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