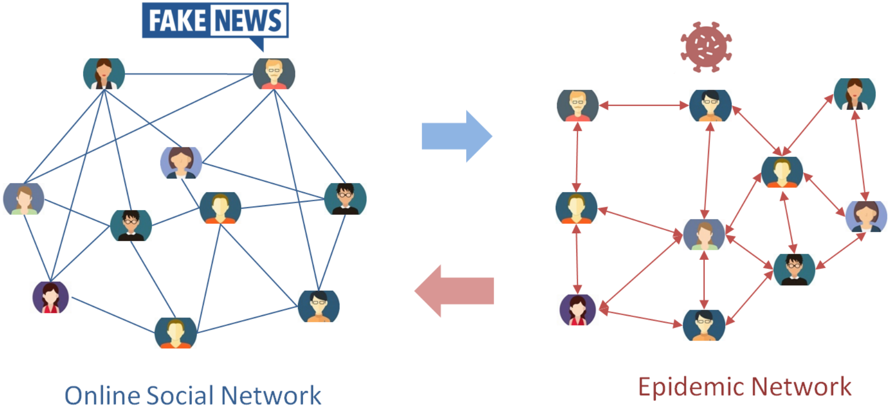
Interplay between Epidemic and News Propagation Processes

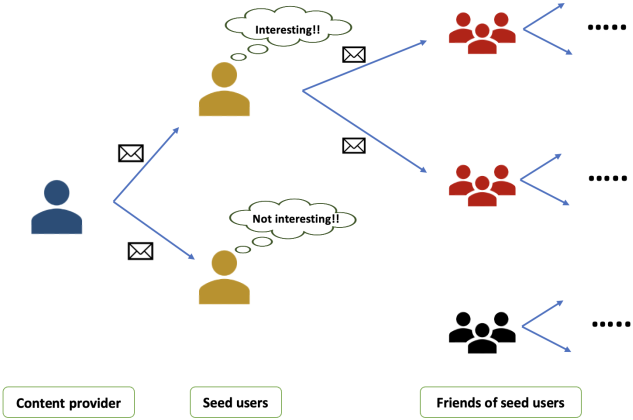
Workshop on Performance Evaluation

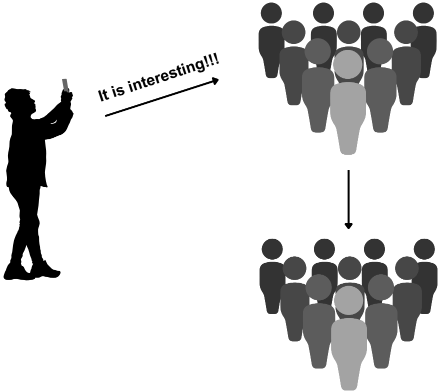
Madhu Dhiman, IEOR, IIT Bombay, India

Joint work with Veeraruna Kavitha at IEOR, IIT Bombay
and Chen Peng, Quanyan Zhu at ECE, New York University

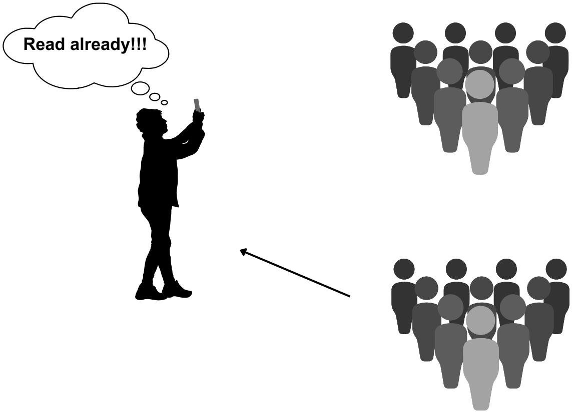
December 4, 2024


FAKE NEWS
Online Social Network
Epidemic Network


Interesting!!
Not interesting!!
......
......
......
Content provider
Seed users
Friends of seed users


It is interesting!!!

News Propagation Model – Read and unread copies



News Propagation Model-Regular Updates

After k-th user forwards the news-item,

$$\# \text{ unread copies, } \Psi_{k+1} = \Psi_k + \xi_{k+1} \underbrace{-1}_{\substack{\text{user read}\\ \text{the post}}} \quad \text{and}$$

$$\# \text{ total copies, } \Theta_{k+1} = \Theta_k + \xi_{k+1}$$

- Ψ_k — no. of unread copies of the post,
- Θ_k — no. of total copies of the post, and
- ξ_{k+1} – additional copies generated by new share/forward.

Aim: A stochastic approximation (SA)-based iterative scheme – to aid analysis

Scaling

$$\psi_k = \frac{\Psi_k}{k}, \quad \text{and} \quad \theta_k = \frac{\Theta_k}{k}, \text{ for any } k \geq 1$$

SA-based iterative scheme

$$\psi_{k+1} = \psi_k + \frac{1}{k+1}\left(\xi_{k+1} - 1 - \psi_k\right)$$
$$\theta_{k+1} = \theta_k + \frac{1}{k+1}\left(\xi_{k+1} - \theta_k\right)$$

Suyog Kapsikar, Indrajit Saha, Khushboo Agarwal, Veeraruna Kavitha, and Quanyan Zhu, “Controlling Fake News by Collective Tagging: A Branching Process Analysis”. IEEE Control Systems Letters, 2020 and ACC 2020

- Any news-item can trend - copies grow exponentially
- After a while, saturates and replaced by new trending topic

- Saturation $\mathcal{E}_k^S$ captured by:
  - unread copies $\psi_k <$ a threshold
  - Total copies $\theta_k >$ a threshold
- $\mathcal{E}_k^S = 1$ iff $\psi_k < \delta_\psi$ and $\theta_k > \delta_\theta$

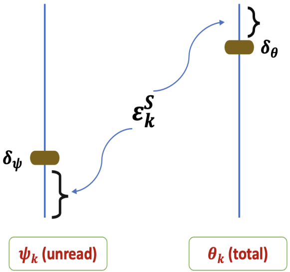


Figure: Saturated Regime

- Extra or fictitious iterates to model saturation
  - total copies reduce drastically – with a big rate, C
  - unread copies also reduce to zero.

The overall SA iteration

$$\psi_{k+1} = \psi_k + \epsilon \left(\underbrace{\left(1 - \mathcal{E}_k^S\right)\left(\xi_{k+1} - 1 - \psi_k\right)} - \underbrace{\mathcal{E}_k^S \ \psi_k} \right),$$

$$\theta_{k+1} = \theta_k + \epsilon \left(\underbrace{\left(1 - \mathcal{E}_k^S\right)\left(\xi_{k+1} - \theta_k\right)}_{\text{Regular news-item update}} - \underbrace{\mathcal{E}_k^S \ C\theta_k}_{Saturation} \right).$$

$$\mathcal{M}(\theta_k) := E_k[\xi_{k+1}|\sigma(\psi_s, \theta_s); s \leq k],$$

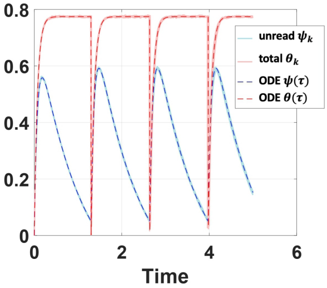
$\mathcal{M}(\theta)$ – expected number of shares, given θ (fraction of total copies)

$$\dot{\psi} = (1-\mathcal{E}^S)\Big(\mathcal{M}(\theta) - 1 - \psi\Big) - \mathcal{E}^S\psi,$$

$$\dot{\theta} = (1-\mathcal{E}^S)\Big(\mathcal{M}(\theta) - \theta\Big) - \mathcal{E}^S C\theta.$$

Theorem, under certain conditions

The news-update trajectory $\{\theta_k, \psi_k\}$ converges to ODE solution $(\theta(\cdot), \psi(\cdot))$ trajectory over any finite time horizon.



The Monte-Carlo estimates and the ODE solution trajectory are inseparable
Each cycle – one news-item (start to saturation)

Epidemic Model (SIRS)

Well-known dynamics

$$\underbrace{\frac{di}{dt} = i(\overline{\beta}(1-i-r)-\alpha)}_{\text{Infected fraction}}, \quad \underbrace{\frac{dr}{dt} = (i\alpha p_r - r l_i)}_{\text{Recovered fraction}},$$

- $(1 - i(t) - r(t))$ – susceptible fraction
- $\overline{\beta}$ – disease spread rate, α – recovery rate
- p_r – immunized fraction of recovered sub-population
- l_i – rate at which immunized individual looses immunity

Theorem

- When disease spread rate < recovery rate, disease eradicates eventually,
- Else, disease settles to non-zero (i, r).

News-items can influence public behaviour

- Spread of fake news about masks – influences mask behaviour
- Epidemic spread can increase/decrease
- Or panic can be created etc.

- Every trending post has an explosion phase followed by saturation
- Different people interact with post at different times of its life-time.
- Capture the influence via the total copies shared

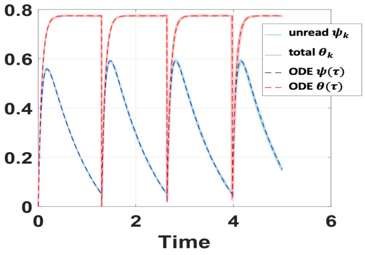


Figure: Limit Cycle

Mean number of shares

$$\mathcal{M}(\theta) = \eta(1 - a\theta),$$

- η – attractiveness factor
- a – proportion factor

Epidemic ODE solution has a limit cycle, solving it

$$\theta^*_\infty(\eta) \approx \frac{\eta}{a\eta + 1}$$

- News propagates at faster time scale (hours)
- Disease propagates at slower time scale (days)
- Influence is not instantaneous – rather over the entire cycle
- Influenced disease spread parameter

$$\beta = \overline{\beta} + w\frac{\eta}{a\eta + 1}$$

Disease spread parameter influenced by one news-item

$$\beta = \overline{\beta} + w\frac{\eta}{a\eta + 1}$$

- No influence on recovery α and immunization rate parameters p_r
- $w = w(i)$, $\eta = \eta(i)$ – depend on infected population
  - when infection is high, people are more sensitive, more attracted to news-items

Influence of all trending topics, assuming similar post-characteristics

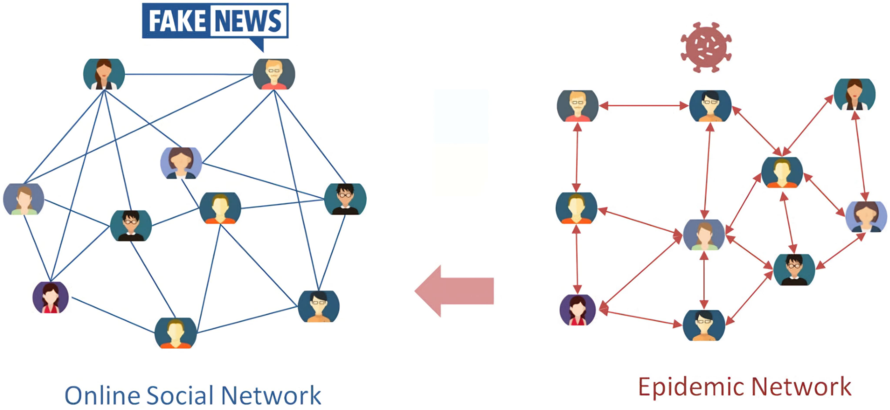
$$\beta(i) = \overline{\beta} + \sum_{m \text{ is trending}} w_m(i)\frac{\eta_m(i)}{a\eta_m(i) + 1}$$

$$= \overline{\beta} + \overline{w}(i)\frac{\eta(i)}{a\eta(i) + 1}$$

Integrated ODE

$$\underbrace{\frac{di}{dt} = i(\overline{\beta}(i)(1-i-r)-\alpha)}_{\text{Infected fraction}}, \quad \underbrace{\frac{dr}{dt} = (i\alpha p_r - rl_i)}_{\text{Recovered fraction}},$$

$$\overline{\beta}(i) = \overline{\beta} + \overline{w}(i)\frac{\eta(i)}{a\eta(i)+1}$$


FAKE NEWS
Online Social Network
Epidemic Network

As infection level i increases

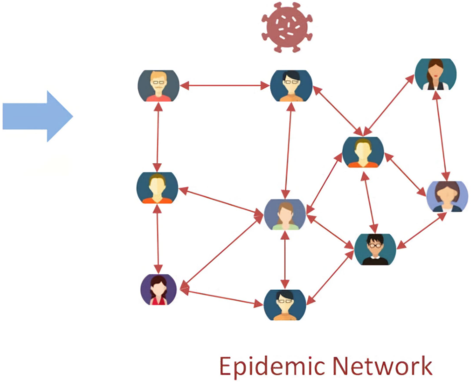
- $\eta(i) = \overline{\eta}(pi + q)$ — public show more interest in reading and sharing posts
- $\overline{w}(i) \equiv \overline{w}$ — not reacting significantly over consumed information

$\beta(0)$ – disease spread rate near zero infected fraction

Theorem

- When $\beta(0) < \alpha$, disease eradicates.
- Otherwise,
  - either disease eradicates – example when $\overline{w} < 0$ (authentic information)
  - or settles to non-zero value.


FAKE NEWS
Online Social Network


Epidemic Network

As infected fraction increases

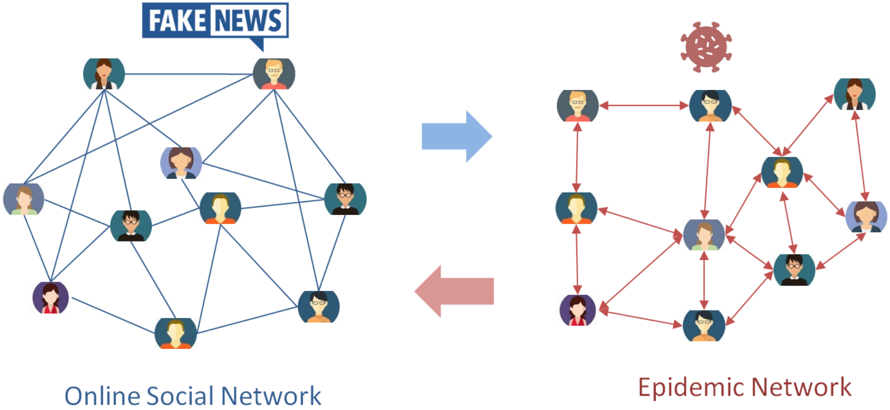
- $\eta(i) \equiv 1$ – interest towards consuming and spreading news remains the same
- $\overline{w}(i) = ui$ (linear influence) – reactions are more pronounced at higher i

Theorem

- when $\beta(0) < \alpha$, disease eradicates.
- otherwise, either disease eradicates or settles to non-zero value or leads to limit cycle.

When public responds to news more sensitively

Limit cycles are created even without change in disease parameters !


FAKE NEWS
Online Social Network
Epidemic Network

As infected fraction increases

- $\eta(i) = \overline{\eta}(pi + q)$ – more interest in reading and showing posts
- $\overline{w}(i) = \overline{w} + ui$ – more reaction towards posts

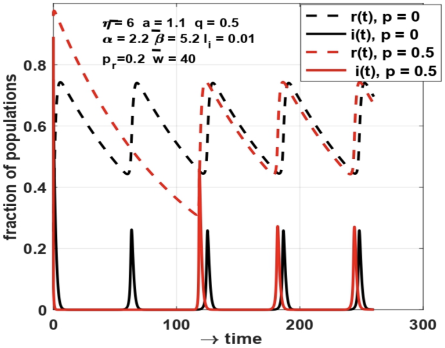


Figure: IBIN ($p = 0$), IBIN and I3N ($p = 0.5$)

$p = 0$ – increasing behavioural influence by News (with higher i)
$p = 0.5$ – interest towards posts increases as well as the response
Limit Cycle seen in either case

Conclusions

- When the disease characteristics remains the same and epidemic is not influenced
  - the epidemic converges to a fixed fraction of infected, recovered fraction
  - the disease is either eradicated or non-eradicated.
- We developed a integrative two time scale ODE
  - that captures the influence of epidemic on trending topics and vice versa
  - the two time scale is different type than usually considered in literature
- Studied variety of influences
  - Public interest towards posts on OSN increases with increase in disease
    - the number of shares, total number of copies shared grow non-linearly
  - Public react more strongly with higher infection levels
    - the disease spread rates are modulated accordingly.

Conclusions contd

- The integrated model indicates several interesting phenomenon
  - disease can be cured probably when sufficient authentic posts get viral
  - infection level can increase significantly when fake news spreads
  - More interestingly, one can see limit cycles
    - disease fluctuates between small and large values of infection levels
    - this happens not due to variations in disease characteristic
    - rather due to public response towards available information

References

- Fung, Isaac Chun-Hai, King-Wa Fu, Chung-Hong Chan, Benedict Shing Bun Chan, Chi-Ngai Cheung, Thomas Abraham, and Zion Tsz Ho Tse. “Social media’s initial reaction to information and misinformation on Ebola, August 2014: facts and rumors.” Public health reports, 2016.
- de Oliveira, Nicollas R., Pedro S. Pisa, Martin Andreoni Lopez, Dianne Scherly V. de Medeiros, and Diogo MF Mattos. “Identifying fake news on social networks based on natural language processing: trends and
- Suyog Kapsikar, Indrajit Saha, Khushboo Agarwal, Veeraruna Kavitha, and Quanyan Zhu, “Controlling Fake News by Collective Tagging: A Branching Process Analysis”, IEEE Control Systems Letters, 2020.
- Benveniste, Albert and Métivier, Michel and Priouret, Pierre, “Adaptive algorithms and stochastic approximations”, Springer Science & Business Media, 2012.
- Palis, J Jr and De Melo, Welington, “Geometric theory of dynamical systems: an introduction”, Springer Science & Business Media, 2012. challenges.” Information, 2021.

Thank You!