

Modeling Mass Protest Adoption in Social Network Communities using Geometric Brownian Motion

Fang Jin, Rupinder Paul Khandpur, Nathan Self, Edward Dougherty,
Sheng Guo, Feng Chen, B. Aditya Prakash, Naren Ramakrishnan



#Yosoy132 Protest



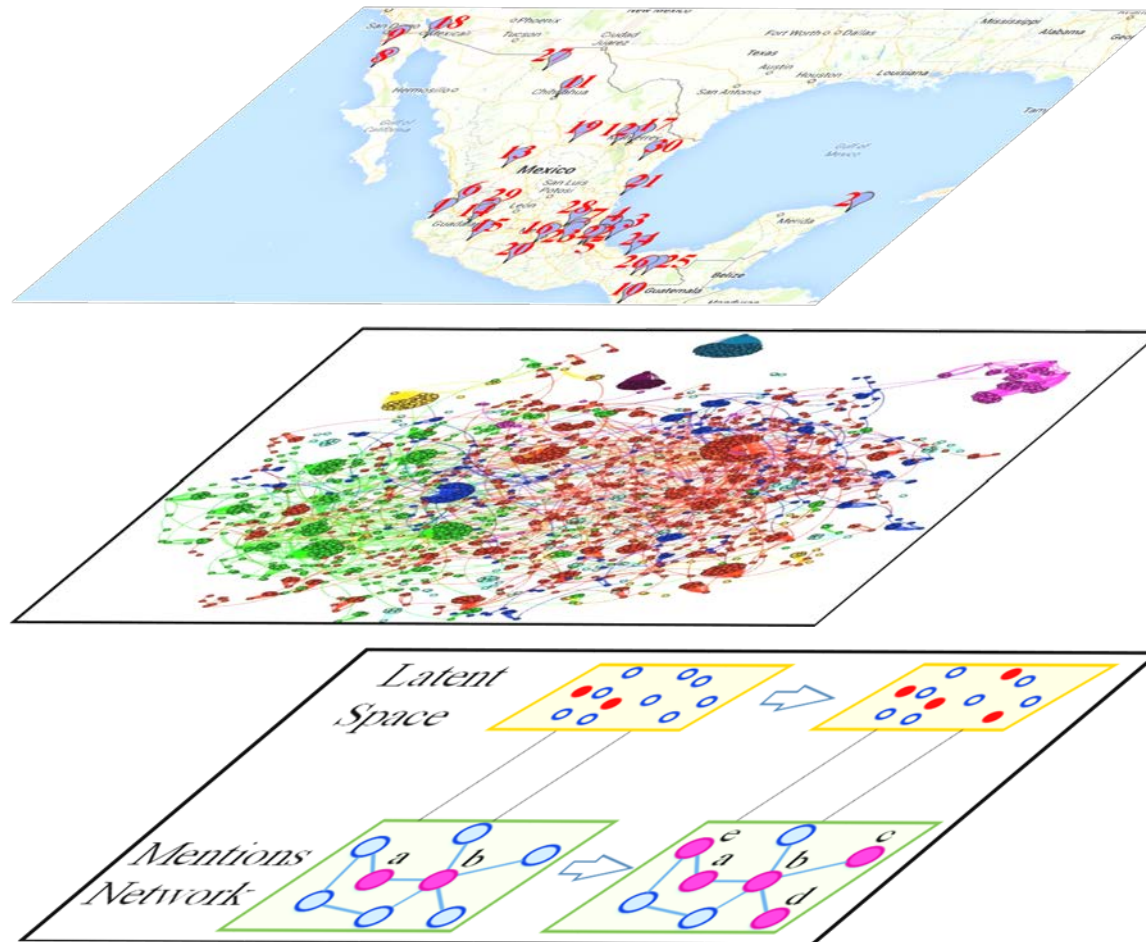
#Yosoy132 Protest



#Yosoy132 Protest



Motivation



Protest examples



Mass movement in
Twitter



Propagation model

Goal:

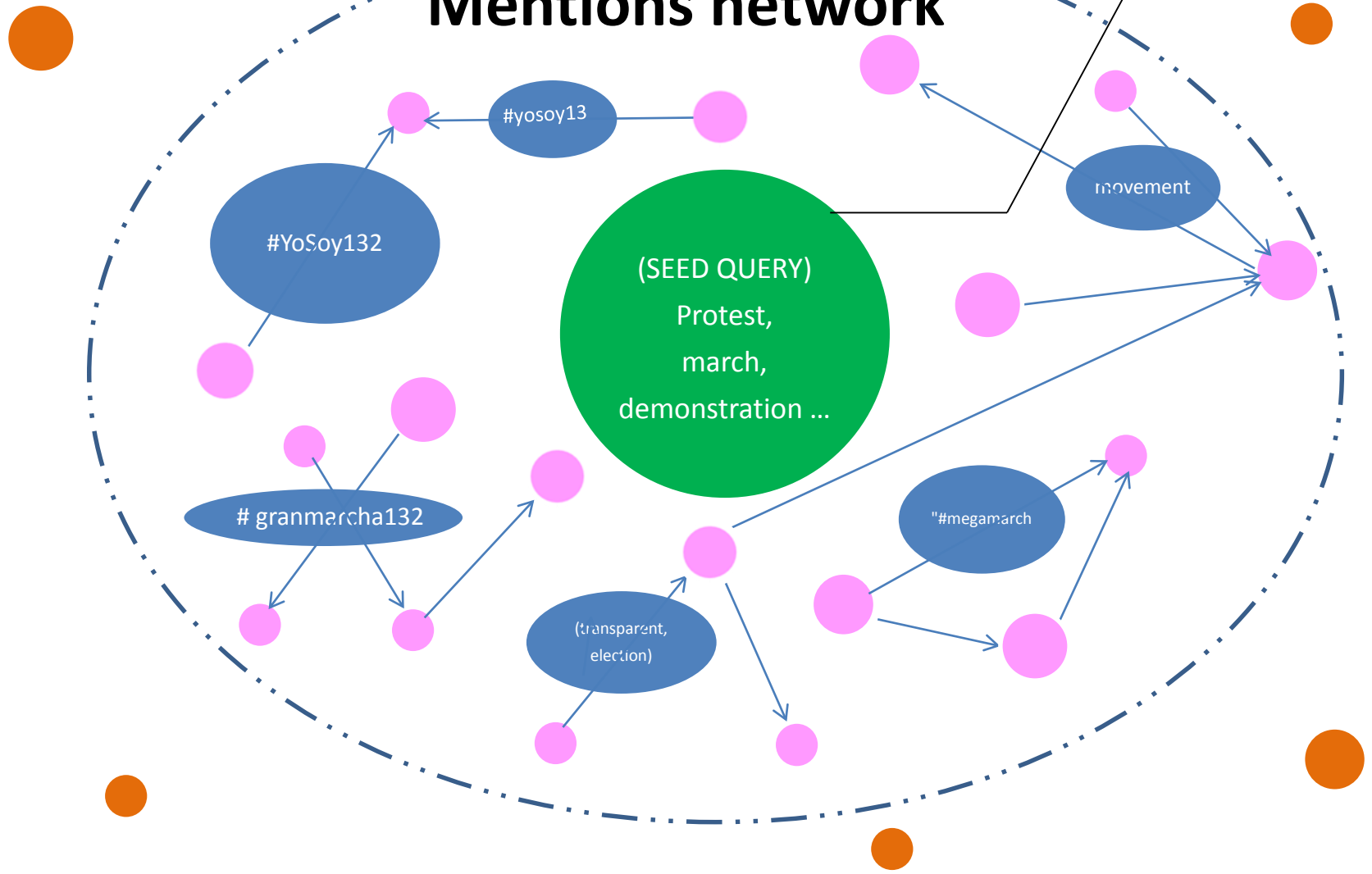
- Model the growth of protest participants within a social network.
- Understand the underlying social network and structural dynamics.

Approach: Bispace model

Latent Space

We consider the mentions network to be stable

Mentions network

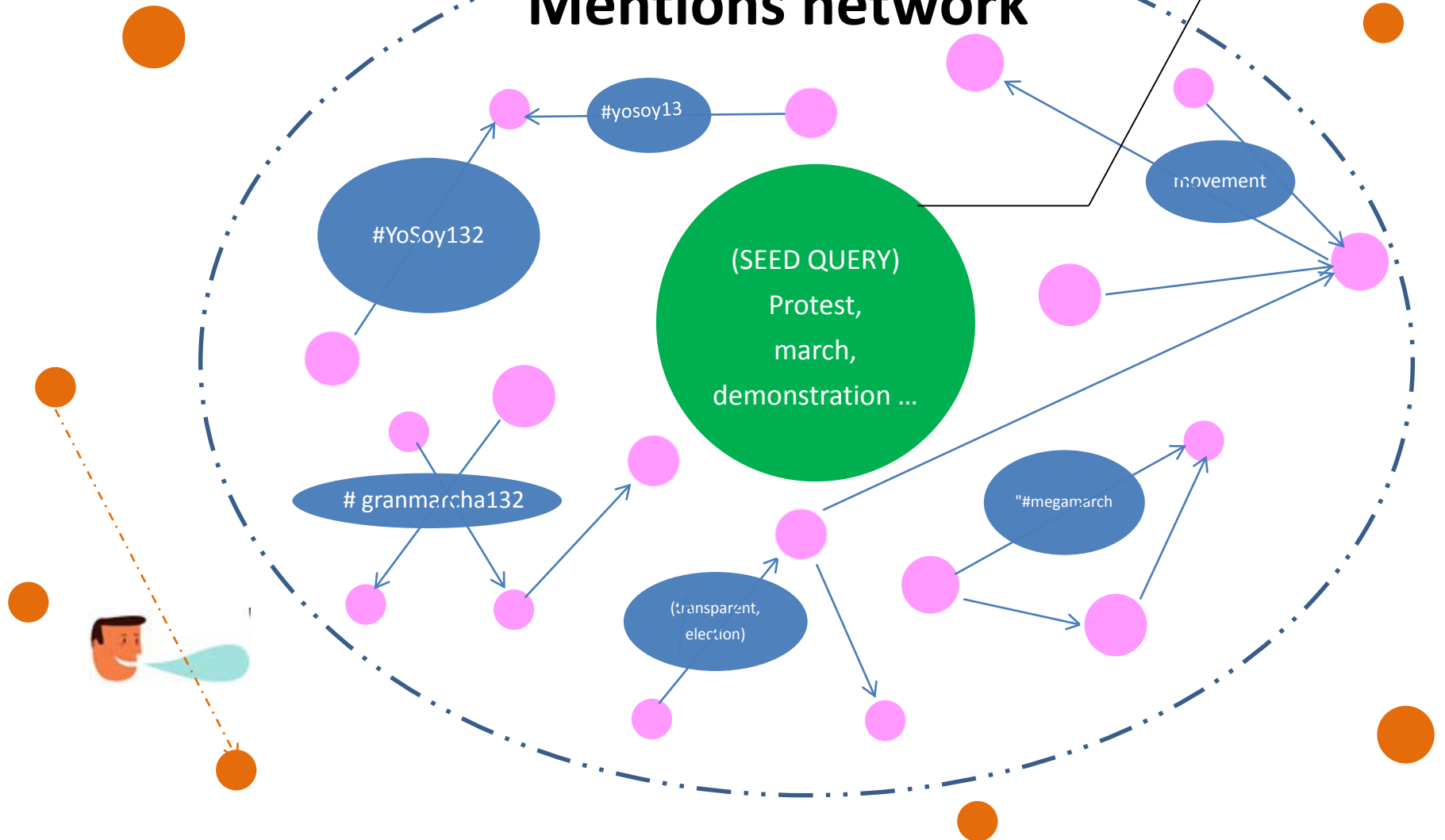


Approach: Bispace model

Latent Space

We consider the mentions network to be stable

Mentions network

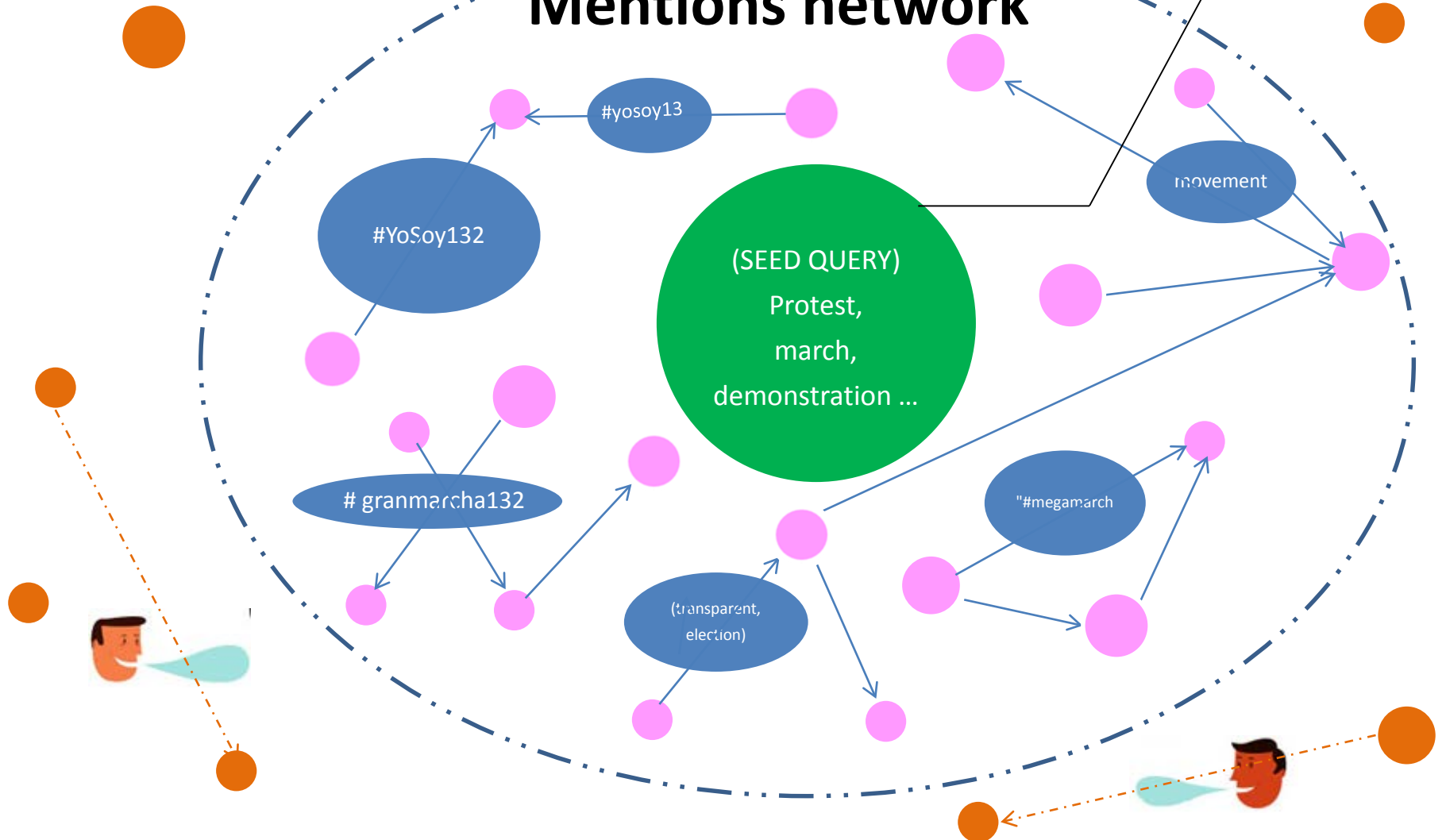


Approach: Bispace model

Latent Space

We consider the mentions network to be stable

Mentions network

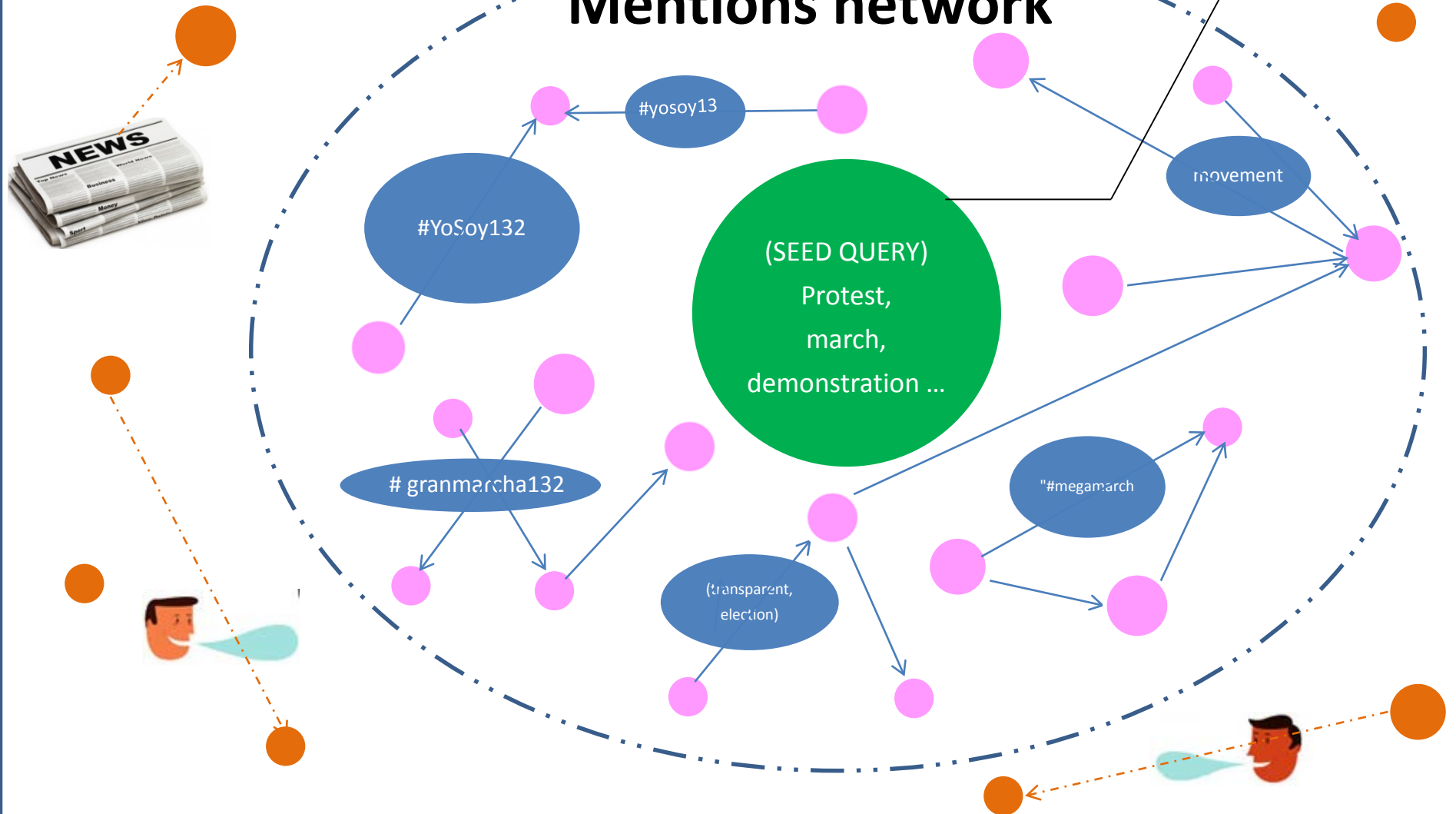


Approach: Bispace model

Latent Space

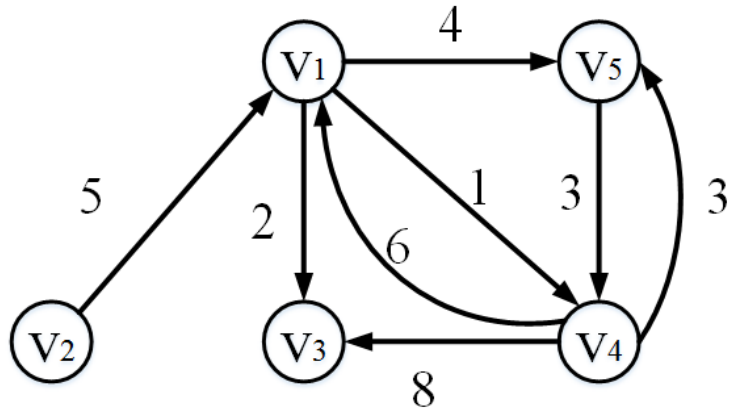
We consider the mentions network to be stable

Mentions network



Geometric Brownian motion (GBM)

Brownian distance



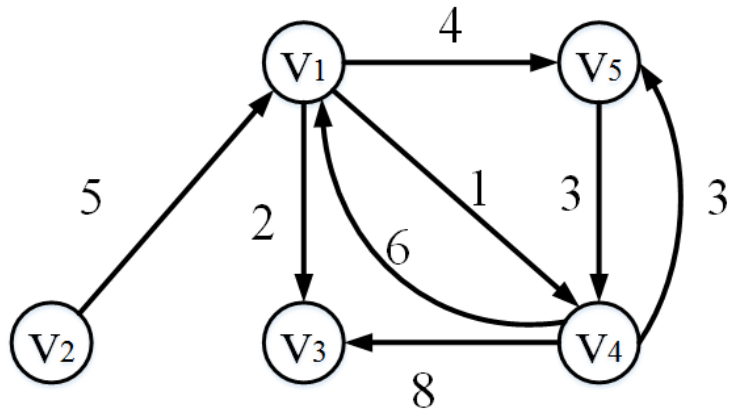
$$d_{ij} = \frac{1}{(\omega_{ij} + 1)(\omega_{ji} + 1)^\gamma(\eta_{ij} + 1)^\gamma}, \gamma \geq 1$$

$$eg : d_{14} = \frac{1}{(1 + 1)(6 + 1)(2 + 1)}, \gamma = 1$$

- We define the Brownian distance, which depends on the mention frequency and number of common direct neighbors
- Brownian distance is a measurement of the closeness and diffusion possibility of the nodes

Geometric Brownian motion (GBM)

Brownian distance

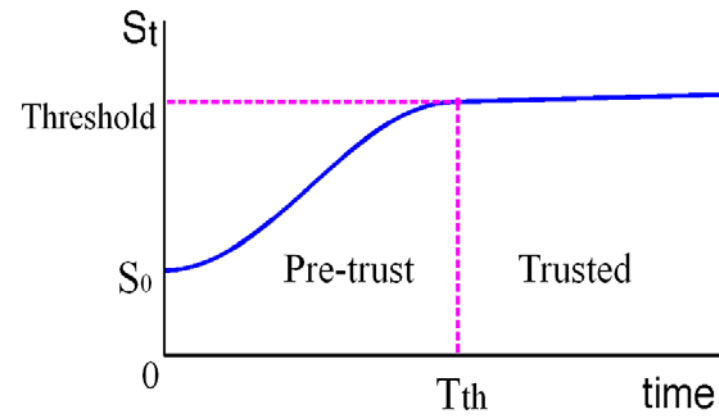


$$d_{ij} = \frac{1}{(\omega_{ij} + 1)(\omega_{ji} + 1)^\gamma(\eta_{ij} + 1)^\gamma}, \gamma \geq 1$$

$$eg : d_{14} = \frac{1}{(1 + 1)(6 + 1)(2 + 1)}, \gamma = 1$$

- We define the Brownian distance, which depends on the mention frequency and number of common direct neighbors
- Brownian distance is a measurement of the closeness and diffusion possibility of the nodes

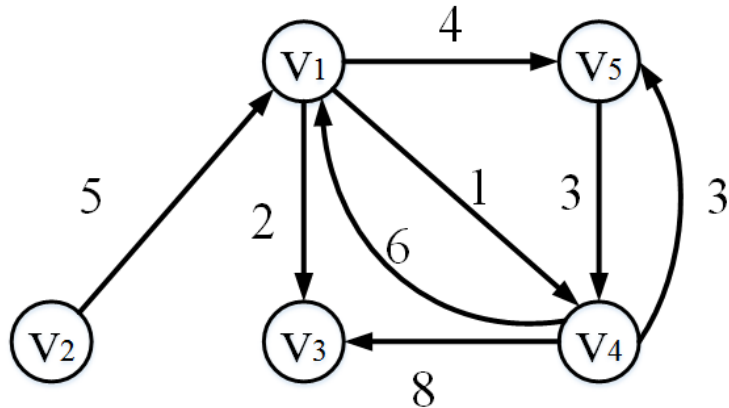
Trust function



- We define v^j trust function with v^i at time t as S_t^{ij}
- We modeled the trust function S_t as a GBM process: $S_t^{ij} \sim \text{GBM}$

Geometric Brownian motion (GBM)

Brownian distance

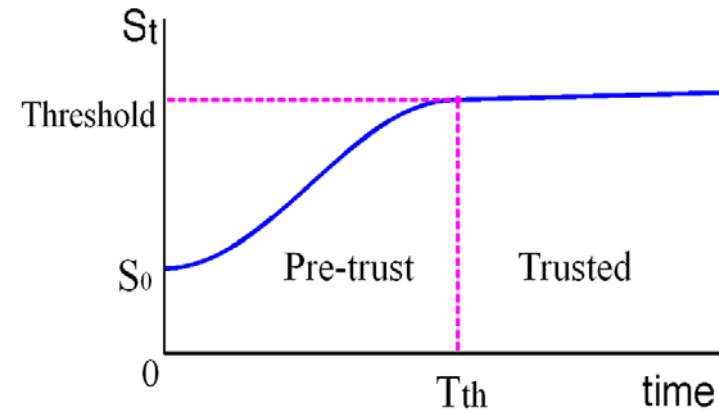


$$d_{ij} = \frac{1}{(\omega_{ij} + 1)(\omega_{ji} + 1)^\gamma(\eta_{ij} + 1)^\gamma}, \gamma \geq 1$$

$$eg : d_{14} = \frac{1}{(1 + 1)(6 + 1)(2 + 1)}, \gamma = 1$$

- We define the Brownian distance, which depends on the mention frequency and number of common direct neighbors
- Brownian distance is a measurement of the closeness and diffusion possibility of the nodes

Trust function



- We define v^j trust function with v^i at time t as S_t^{ij}
- We modeled the trust function S_t as a GBM process: $S_t^{ij} \sim \text{GBM}$

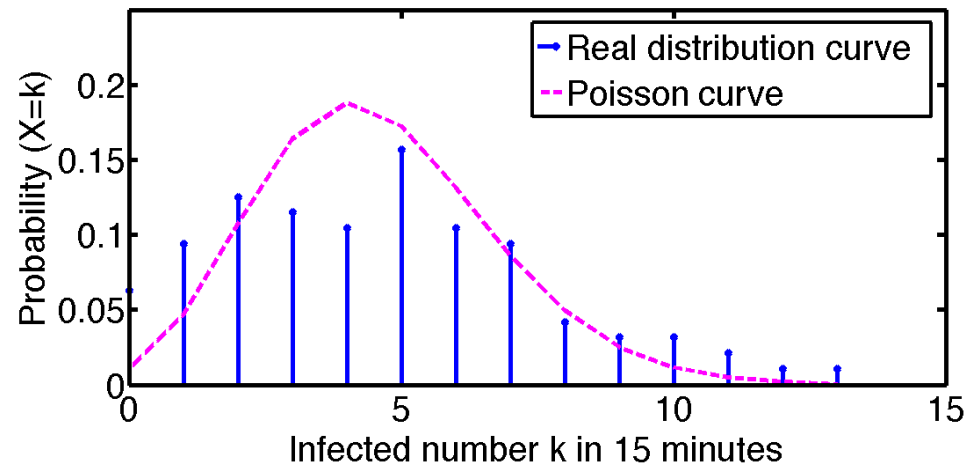
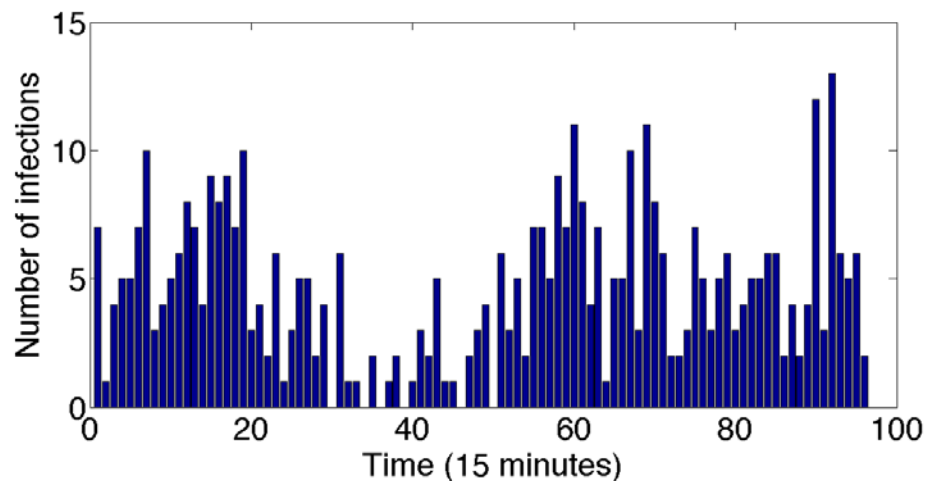
Infection condition:

$$\ln(S_t^{ij}) \geq d_{ij}$$

Latent space: Poisson model

- We assume the probability of the number of newly infected users, X , in a given time interval satisfies the Poisson distribution:

$$\Pr(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

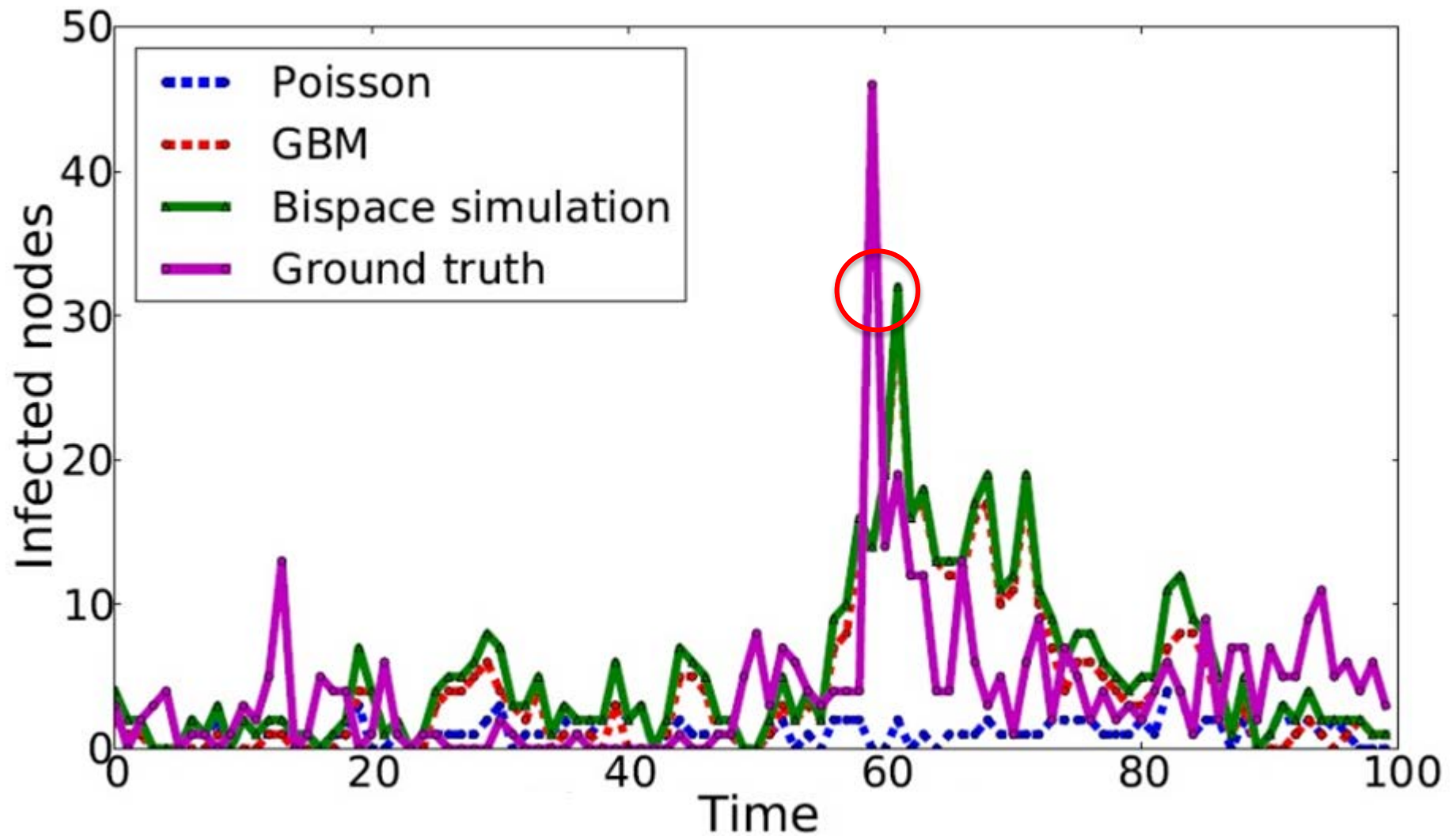


Infected nodes in latent space

Poisson distribution fit ($\lambda = 4.18$)

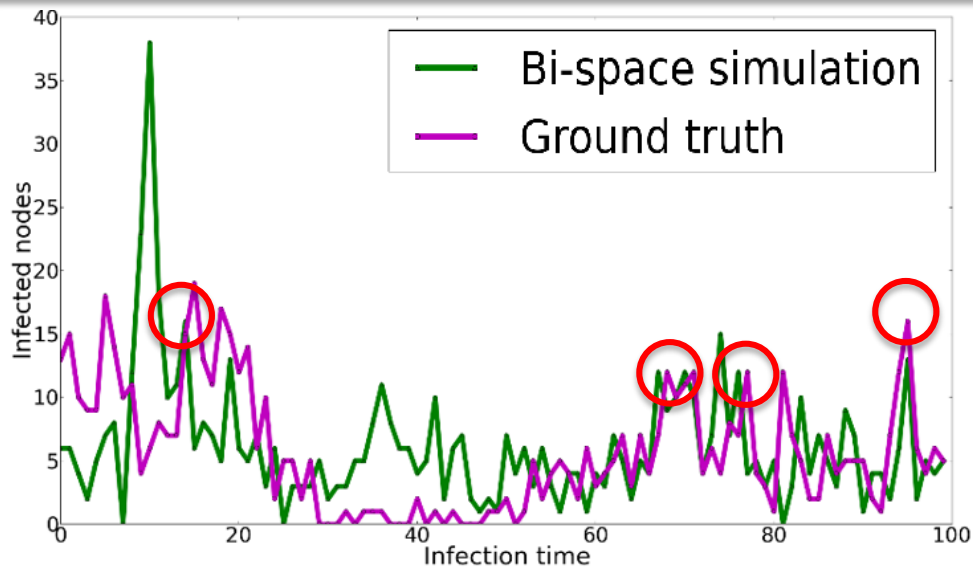


Simulation Result

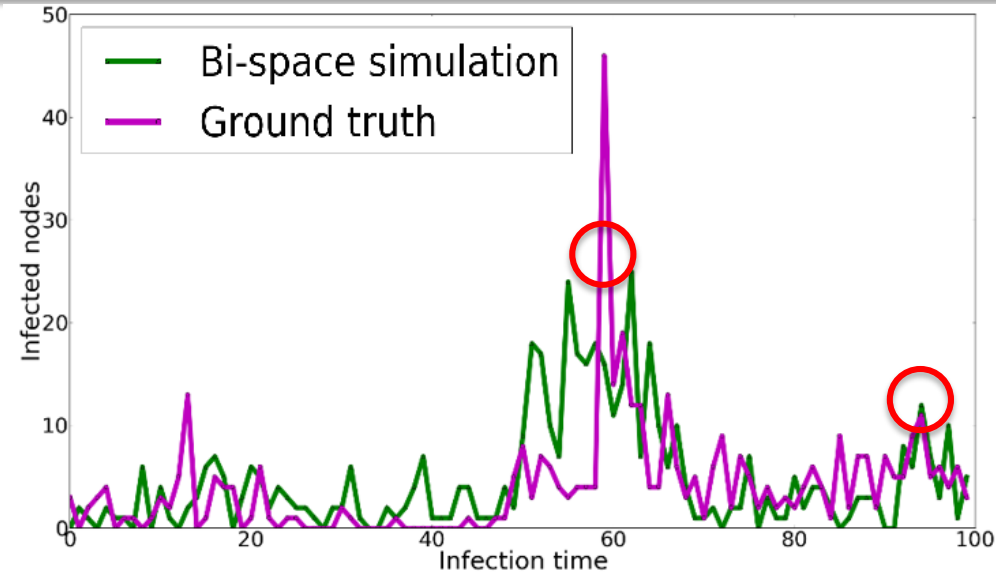


Bispase simulation value = Poisson value + GBM value

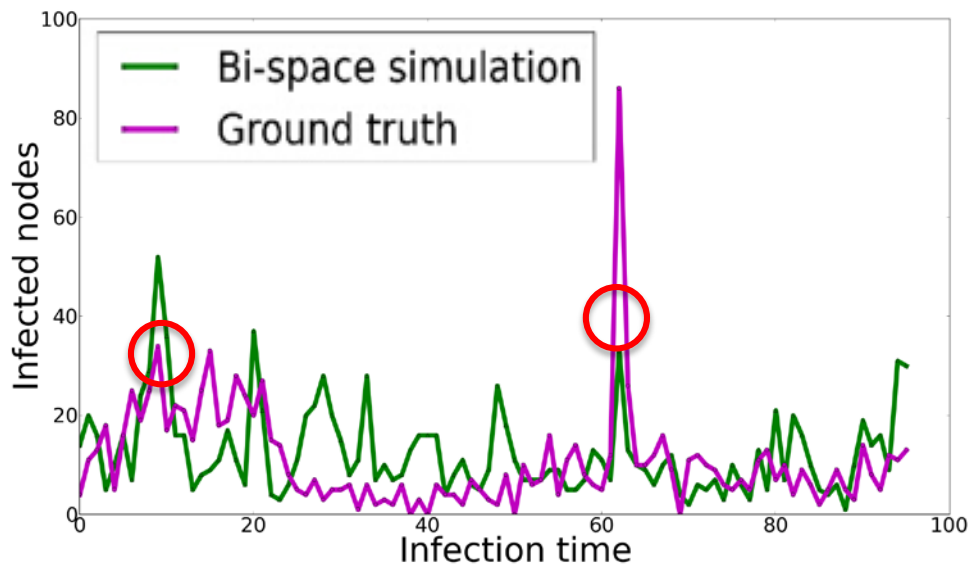
Simulation results for more cases



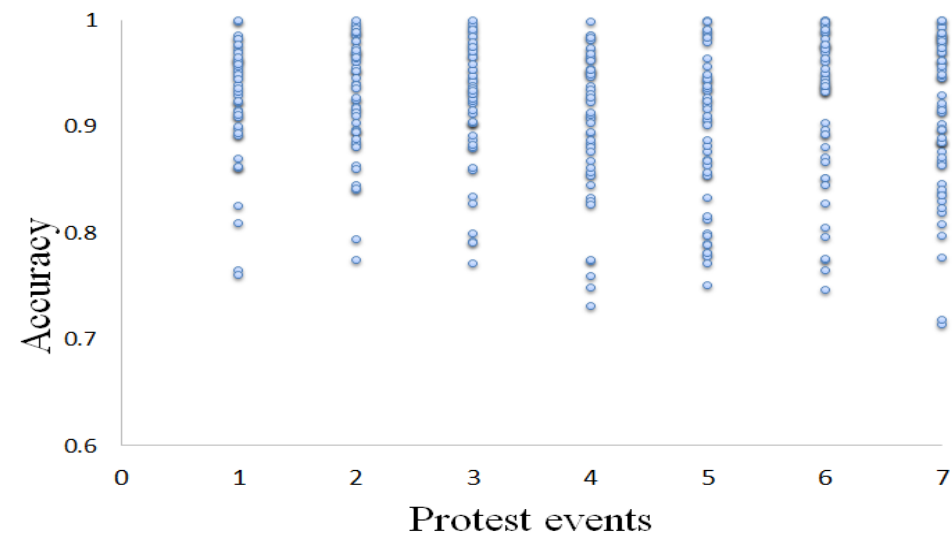
Mexican Yosoy132 protest



Colombian anti-government protest

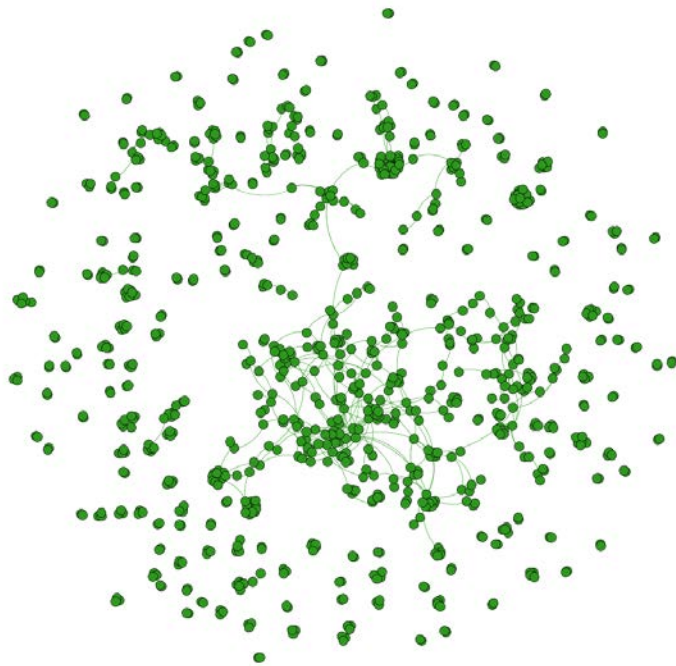


Mexican teachers' protest

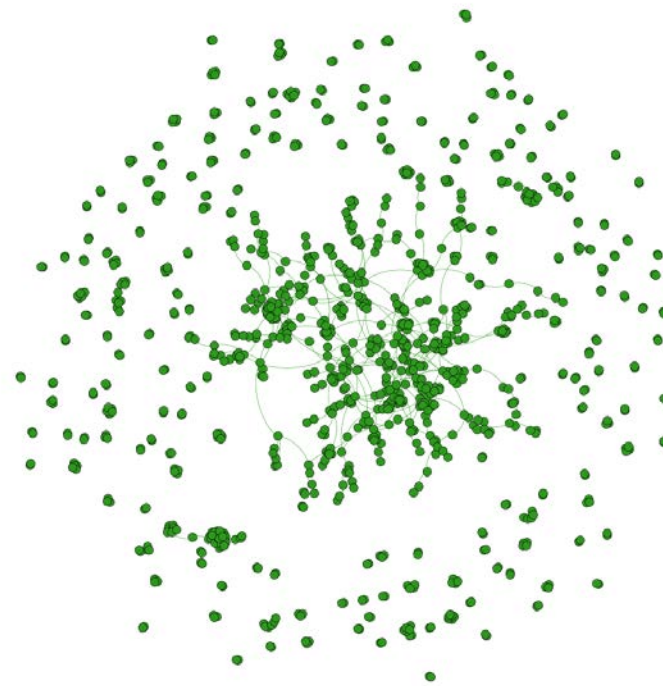


Accuracy for 7 protest events

Subgraph structure evaluation



Simulated infection subgraph



True infection subgraph

	Average degree	Diameter	Graph density	Connected components	Average clustering coefficient	Average path length
Simulation	1.791	11	0.002	183	0.083	4.786
Ground truth	1.726	18	0.002	204	0.008	6.261

GBM simulation results for teacher protest events on Sep 2, 2013

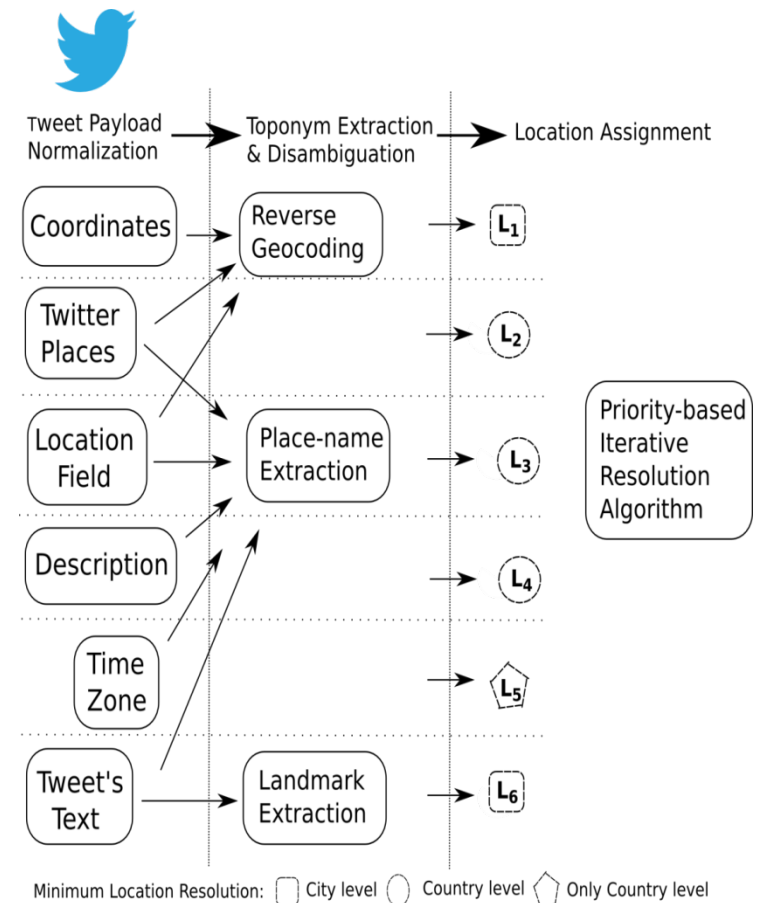
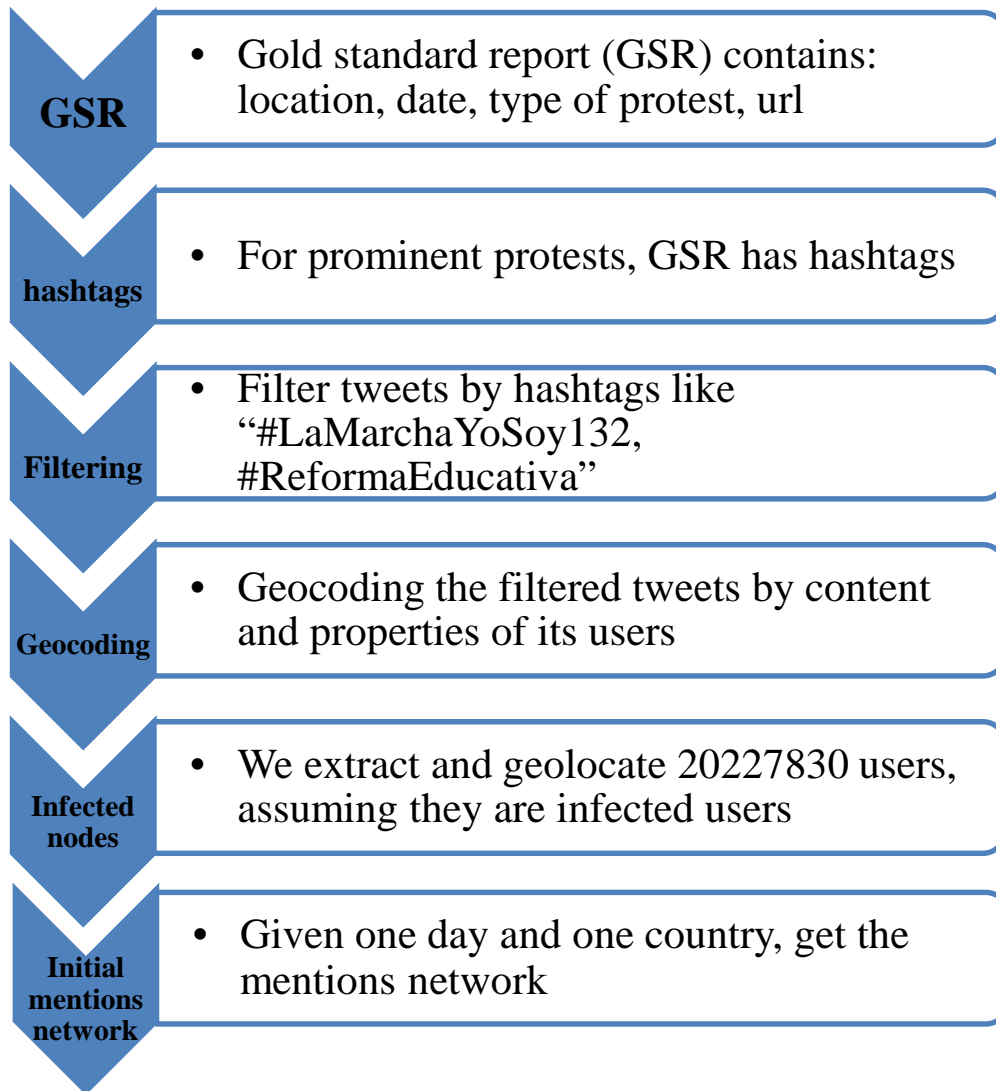
Conclusion

- The bispase model is effective at capturing the total number of infected nodes. We run 500 times experiments, the average accuracy is 0.90.
- The GBM model can simulate the protest burst, even though not at the precise moment.
- In the bispase propagation model, the GBM process is more influential than the Poisson process.
- The GBM model performs well for these network structure metrics: average degree, diameter, graph density, connected components and average path length
- Capturing the average clustering coefficient needs improvement.

Thanks!

Fang Jin: jfang8@cs.vt.edu

Data description



Geocoding process

GBM propagation

$$\ln(S_t^{ij}) \sim \mathcal{N}\left(\left(\mu - \frac{\sigma^2}{2}\right)t, \sigma^2 t\right)$$

At time t , $\ln(S_t^{ij}) \geq d_{ij}$.

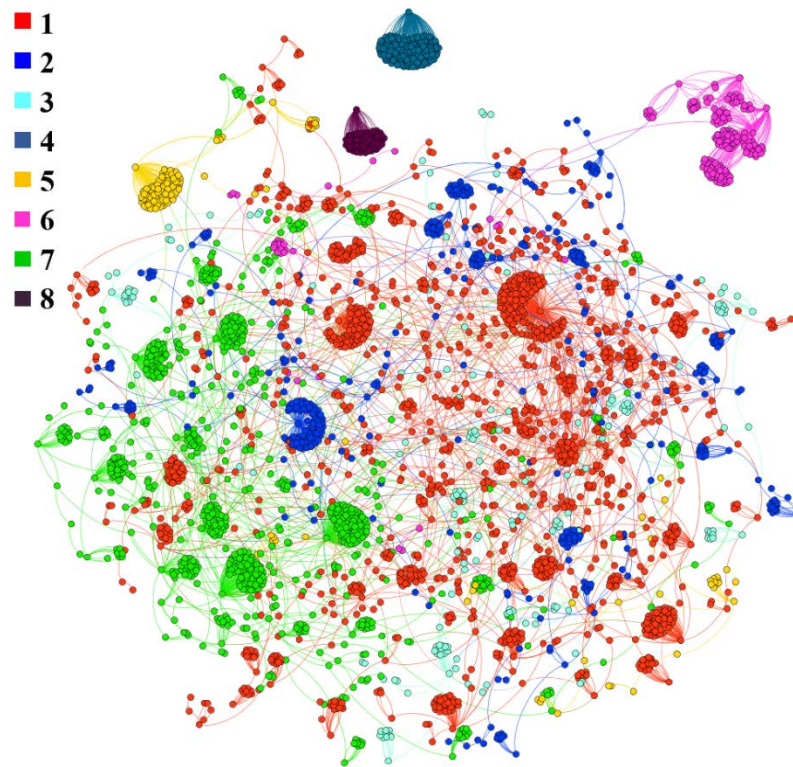
$$\text{At time } t + \delta t, \ln(S_{t+\delta t}^{ij}) \sim \mathcal{N}\left(\left(\mu - \frac{\sigma^2}{2}\right)(t + \delta t), \sigma^2(t + \delta t)\right)$$

GBM parameter estimation

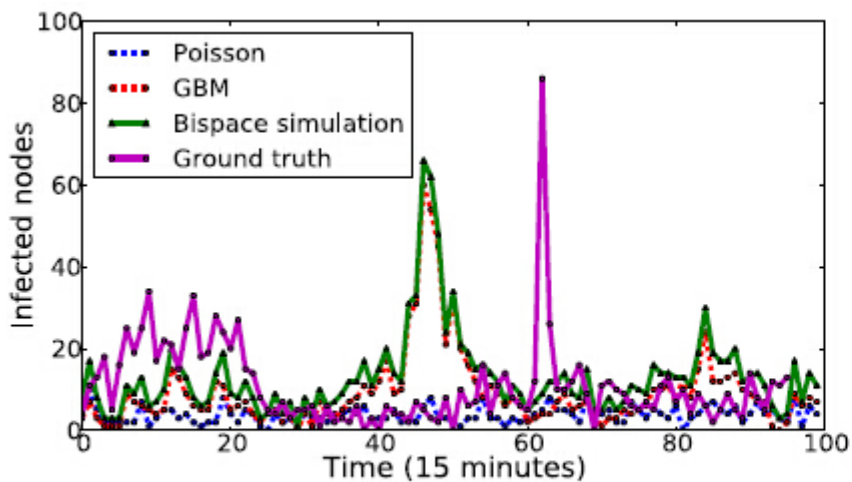
$$\mathcal{L}(\theta, \sigma^2 | v_1, \dots, v_n) = \prod_{j=1}^n \frac{1}{\sigma \sqrt{2\pi\tau_j}} \exp\left(-\frac{(x_j - (\mu - \frac{\sigma^2}{2})\tau_j)^2}{2\sigma^2\tau_j}\right)$$

GBM with community

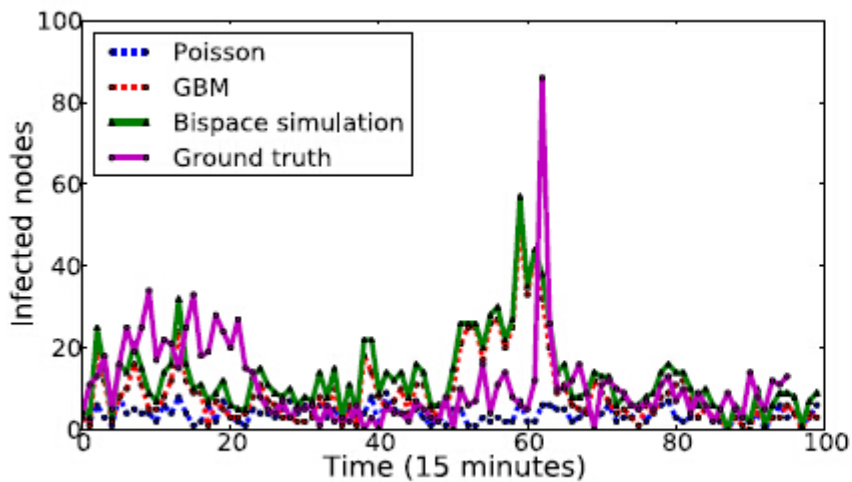
- Assumptions:
 - Each community has its own parameter
 - If v_i and v_j are in the same community c_i , the propagation will follow c_i parameters.
 - Propagation from one community to another happens as per the source community's model parameters.



Results

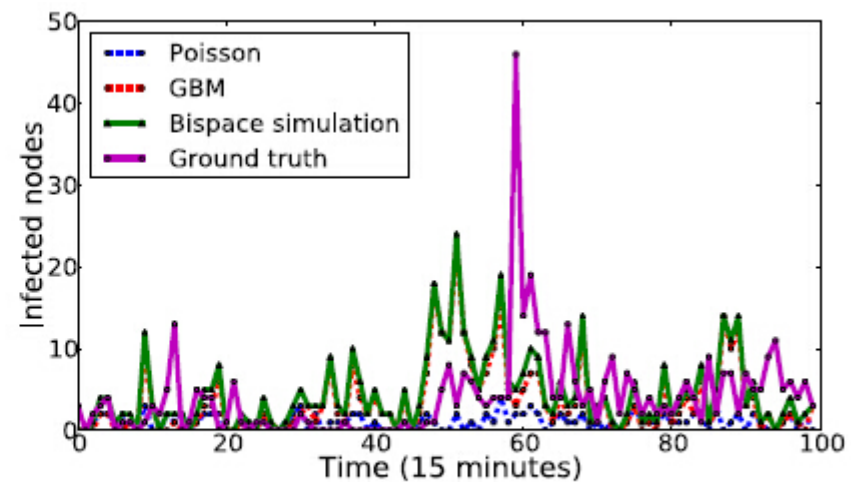


(a) Simulation without community

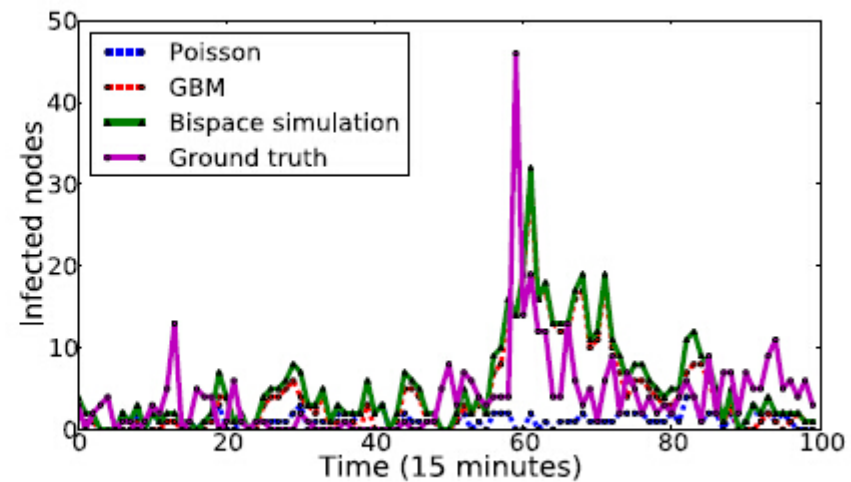


(b) Simulation with community

Mexico teachers' protest



(a) Simulation without community



(b) Simulation with community

Colombia anti-government protest

Model set up

- Select one protest event from GSR, find the protest hashtags, keywords, location, beginning day, ending day
- Geocoding tweets
- Initial mentions network: specify the date to be the beginning day, and country to be the protest country, collect all the mentions network of that day and that country, as the initial mentions network.
- Infected users: filter tweets by hashtags/keywords within the protest country.
- Latent space users: Twitter users out of mentions network.