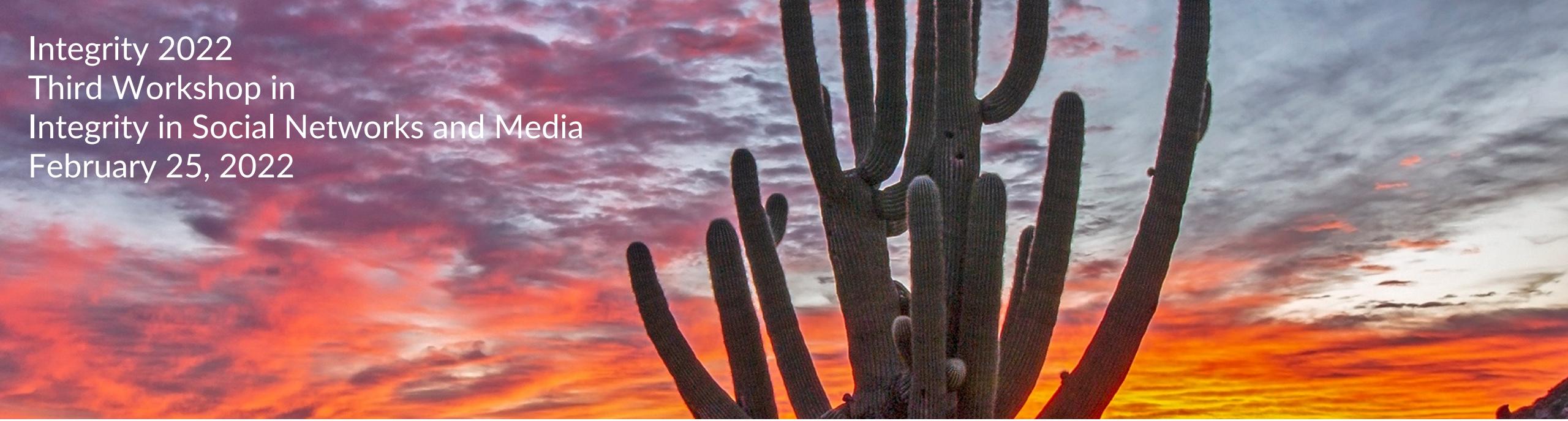


Integrity 2022
Third Workshop in
Integrity in Social Networks and Media
February 25, 2022

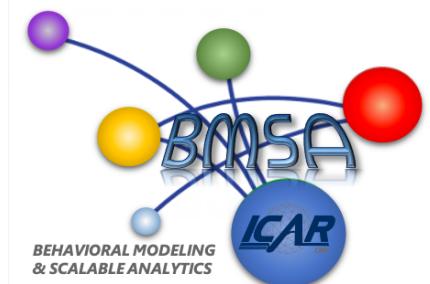


Characterizing Information diffusion

Social Influence, Propagation Speed, Polarization

Giuseppe Manco

Institute of High Performance Computing and Networking
National Research Council



Disclaimer & Acknowledgements

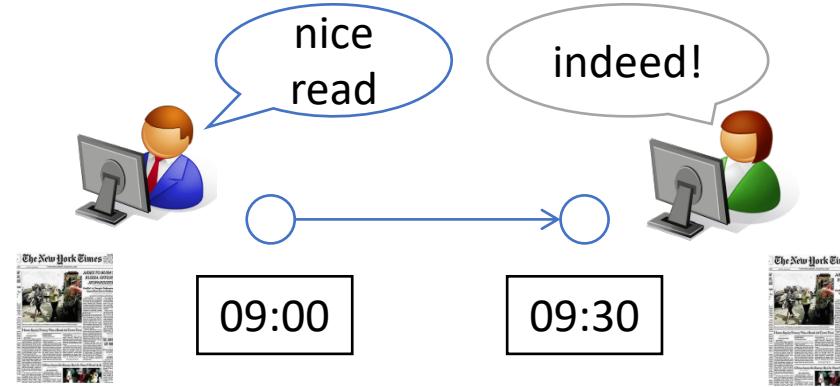
- Summary of results of joint works with Francesco Bonchi, Nicola Barbieri, Corrado Monti, Ettore Ritacco

Agenda

- The Information Diffusion flow
- Influence and susceptibility
- Speed of propagation
- Polarity and echo chambers

Context

Information propagation in on-line social networks



users perform actions

post messages, pictures, video

buy, comment, link, rate, share, like, retweet

users are connected with other users

interact, influence each other

actions propagate

Relevant Questions

- What makes a content popular?
- Which creators are able to trigger a cascade?
- Who will share a content?
- When will someone share a content?
- Who is expert in a topic characterizing a set of contents?
- Who is interested in a topic?
- Which are the most popular topics?
- ...



Basic Notation

- A graph $G = (V, E)$
 - Users u, v in V
- Items i
 - A cascade all (time-sorted) users who adopt that item

Node	Action	Time
u_1	i_1	t_0
u_2	i_1	t_1
u_3	i_2	t_3
...

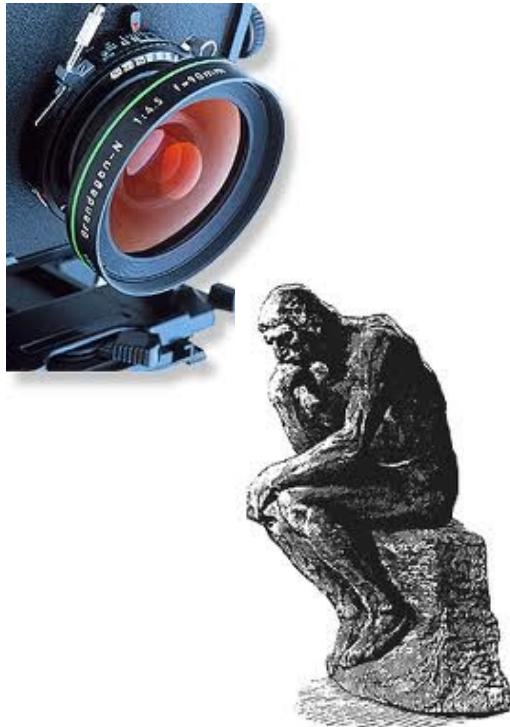
- $y_{i,u}$ binary indicator
 u adopts i

A Basic Tool: Probabilistic modeling

- Treat data as observations that arise from a generative probabilistic process that includes hidden variables
 - For cascade data, the hidden variables reflect the behavior of single users or the commonality in actions
- Infer the hidden structure using posterior inference
 - What are the latent behaviors that describe this group of users?
- Situate new data into the estimated model.
 - How does a new user fit into the estimated behavioral structure?

Key Insight 1

Propagations are topic-dependent



Key insight 1: Propagations are topic-aware

Generalization of the IC Model: the probability of a user become active depends on the strength exerted by one of its predecessors, which in turn depends on the **topic k of interest**.

$$\mathcal{L}(i, u) = y_{i,y} \cdot \log \left(\sum_k P_{u,k}^{i,+} \right) + (1 - y_{i,u}) \cdot \sum_k \log P_{u,k}^{i,-}$$

Probability that some of the potential influencers in activating u

Probability that none of the the “out-of-react” influencers succeeds in activating u

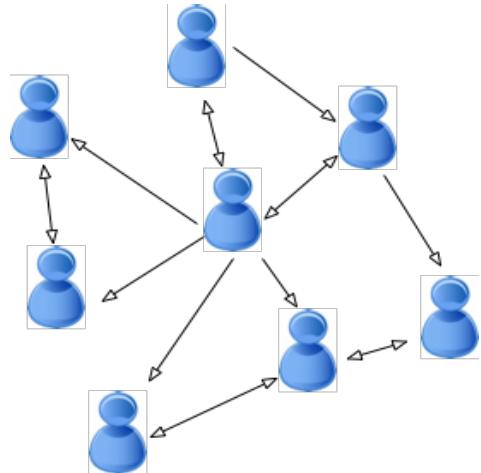
$$P_{u,k}^{i,+} = 1 - \prod_v (1 - p_{u,v}^k)$$

$$P_{u,k}^{i,-} = \prod_v (1 - p_{u,v}^k)$$

Topic-aware Social Influence Propagation Models

Input:

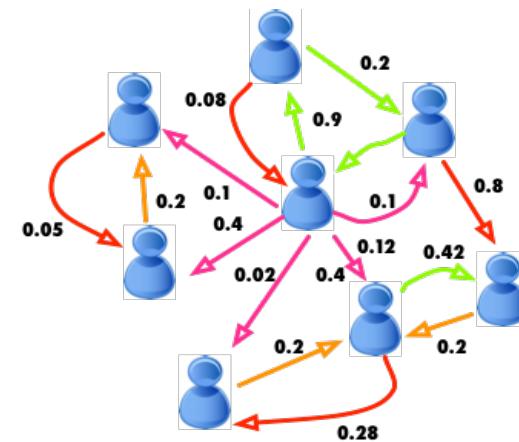
Social Network + Propagation Log
+ number of topics K



Node	Action	Time
u_1	i_1	t_0
u_2	i_1	t_1
u_3	i_2	t_3
...

Output:

Topics +
Topic-Aware propagation
Strengths



Better users' behavior modeling

Detection of influent authorities for different topics

Design of targeted viral marketing strategies

Applications:

Key insight 2

Adoptions and connections depend on influence

Probability of a link

$$P((u, v) \in E) = \vartheta_{u,k} \cdot \varphi_{v,k}$$

(source)

$$\vartheta_u = \text{SoftMax}(\Pi^s)$$

(destination)

$$\varphi_v = \text{SoftMax}(\Pi^d)$$

Probability of an action being propagated

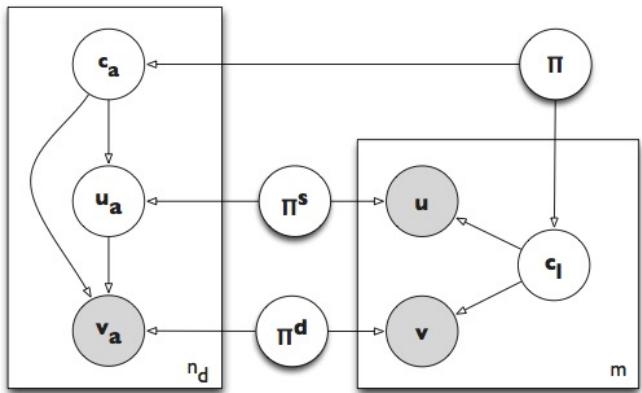
$$p_{u,v}^k \propto \theta_{u,k} \cdot \phi_{k,v}$$

(influencer)

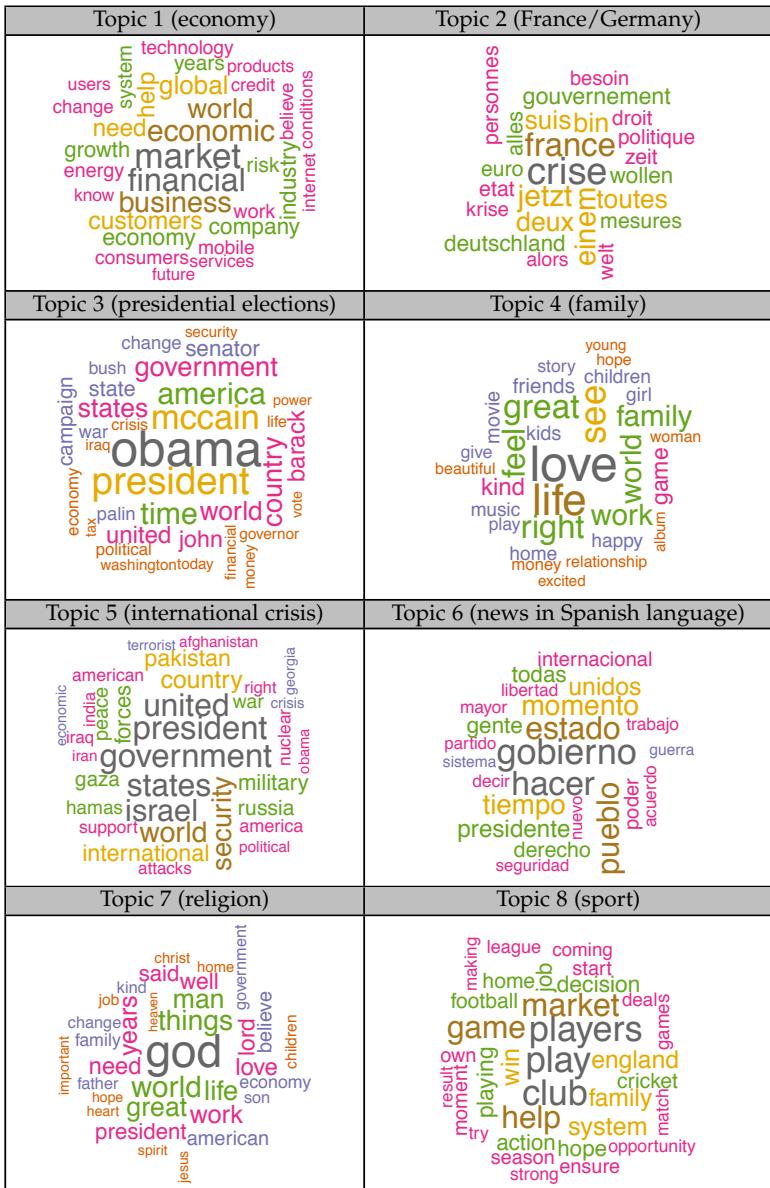
$$\varphi_v = \text{SoftMax}(\Pi^s)$$

(susceptible)

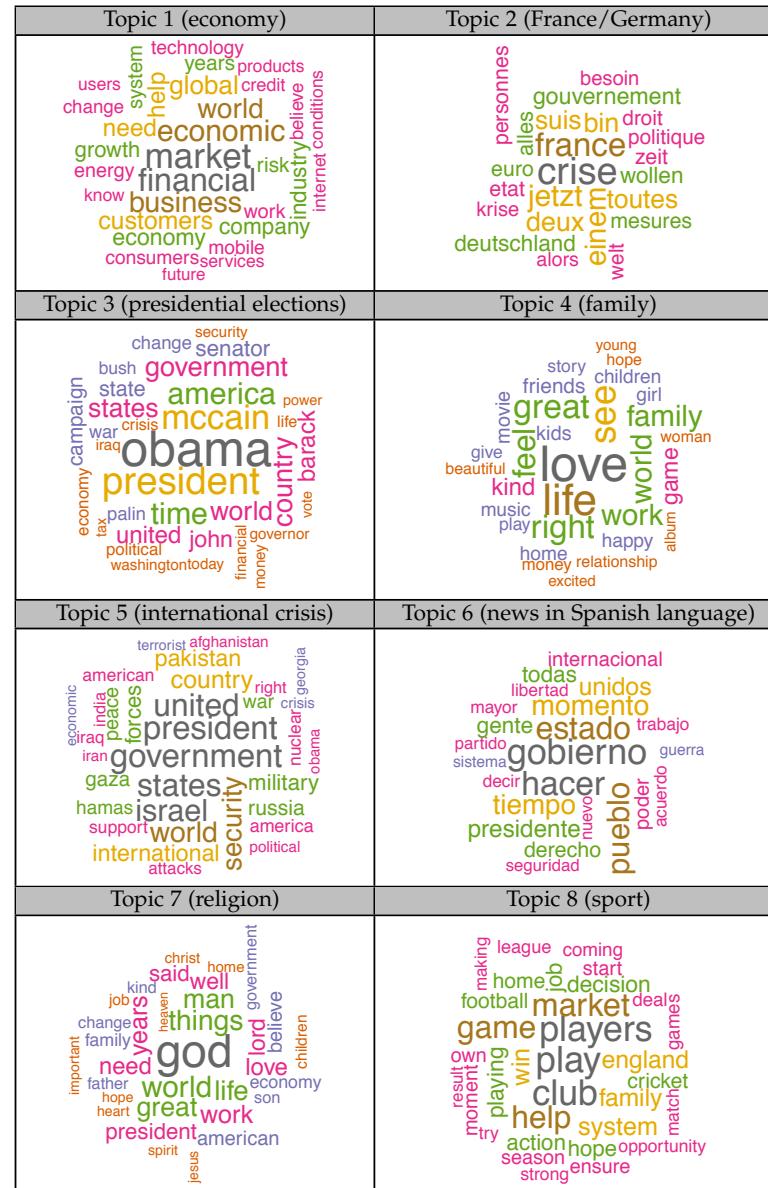
$$\theta_u = \text{SoftMax}(\Pi^d)$$



Topics on Memetracker

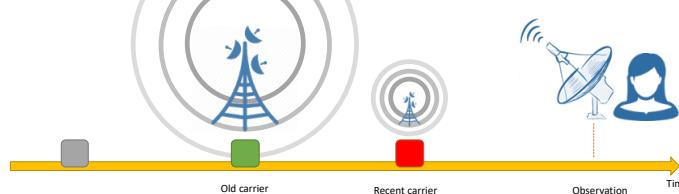


Influential nodes on Memetracker



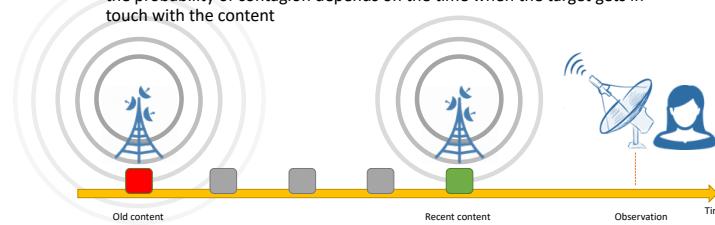
- Contagion is carrier-dependent

- Some carriers are more infectious than others
 - Influence exerted in the diffusion process



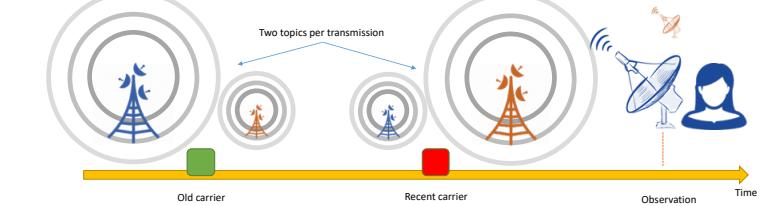
- Contagion is time-dependent

- the probability of contagion depends on the time when the target gets in touch with the content



- Contagion is topic-dependent

- Susceptibility and influence are relative the content
- Content is characterized by topics

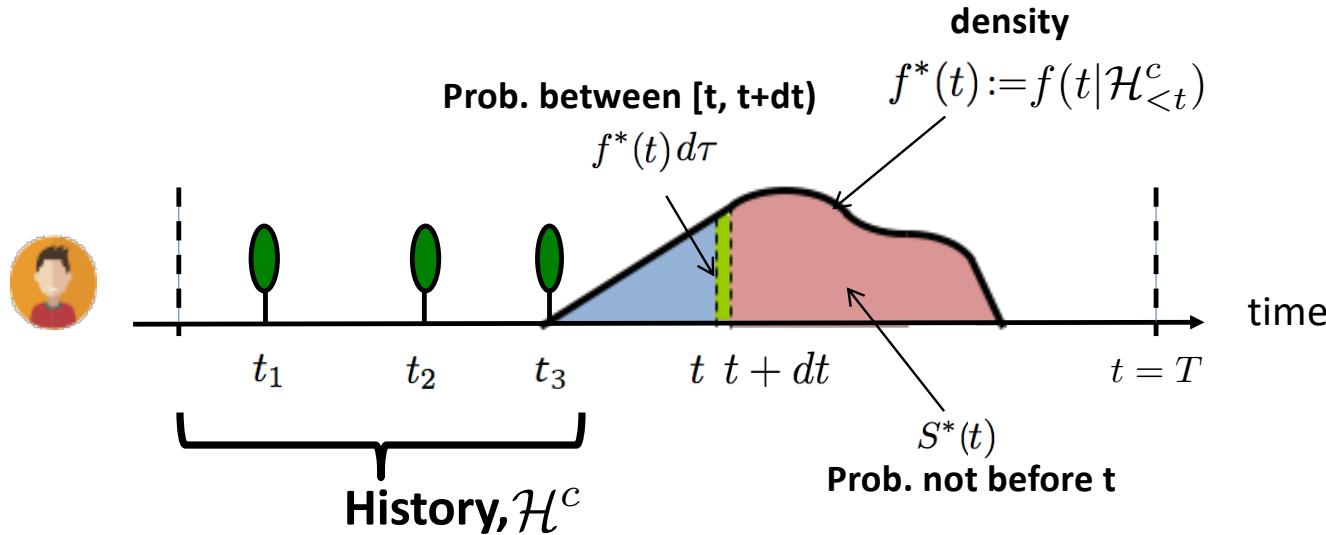


Modeling the contagion process

Key insight 3
The speed of propagations depend on influence

Modeling time as a random variable

Survival Networks



Intensity:

Probability between $[t, t+dt]$ but not before t

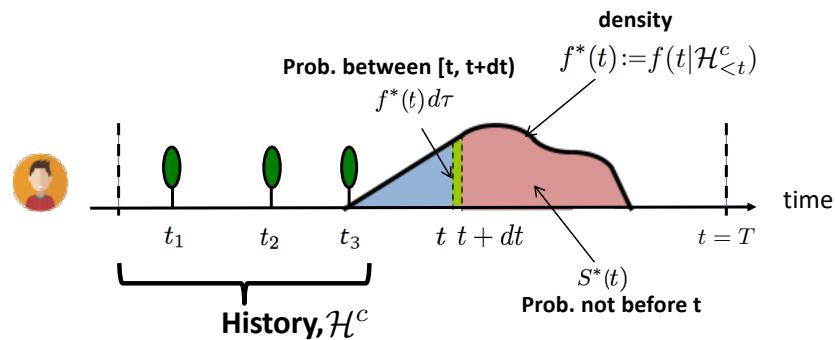
$$\lambda^*(t) dt = \frac{f^*(t) dt}{S^*(t)} \geq 0$$

$\lambda^*(t)$ It is a rate = # of events / unit of time

Modeling time as a random variable

Survival Networks

Idea: model the intensity function as the effect of influence and susceptibility



Intensity:

Probability between $[t, t+dt]$ but not before t

$$\lambda^*(t) dt = \frac{f^*(t) dt}{S^*(t)} \geq 0$$

$\lambda^*(t)$ It is a rate = # of events / unit of time

$$\lambda(t_i|u, v, k) \propto \theta_{u,k} \cdot \phi_{u,k}$$

Node	Action	Time
u_1	i_1	t_0
u_2	i_1	t_1
u_3	i_2	t_3
...

Summary so far

It's all about representation learning!

Authoritativeness of a user in a topic: $\varphi_{u,k}$

Interest of a user for a topic: $\theta_{u,k}$

Relevance of an item for a topic: $\gamma_{i,k}$



Lady Gaga @ladygaga

Justin Bieber @justinbieber



Barack Obama @barackobama

CNN @cnn

The Economist @TheEconomist



Key insight 4

Polarization and ideological leanings

- We can also use latent representations for modeling polarization
 - Authoritativeness of a user in a topic: $\varphi_{u,k}$
 - Interest of a user for a topic: $\theta_{u,k}$
 - Relevance of an item for a topic: $\gamma_{i,k}$
 - Polarization
- Probability of positive polarization

$$\phi_{u,k} \triangleq P(\ell_{u,k} = +)$$

Polarization and ideological leanings

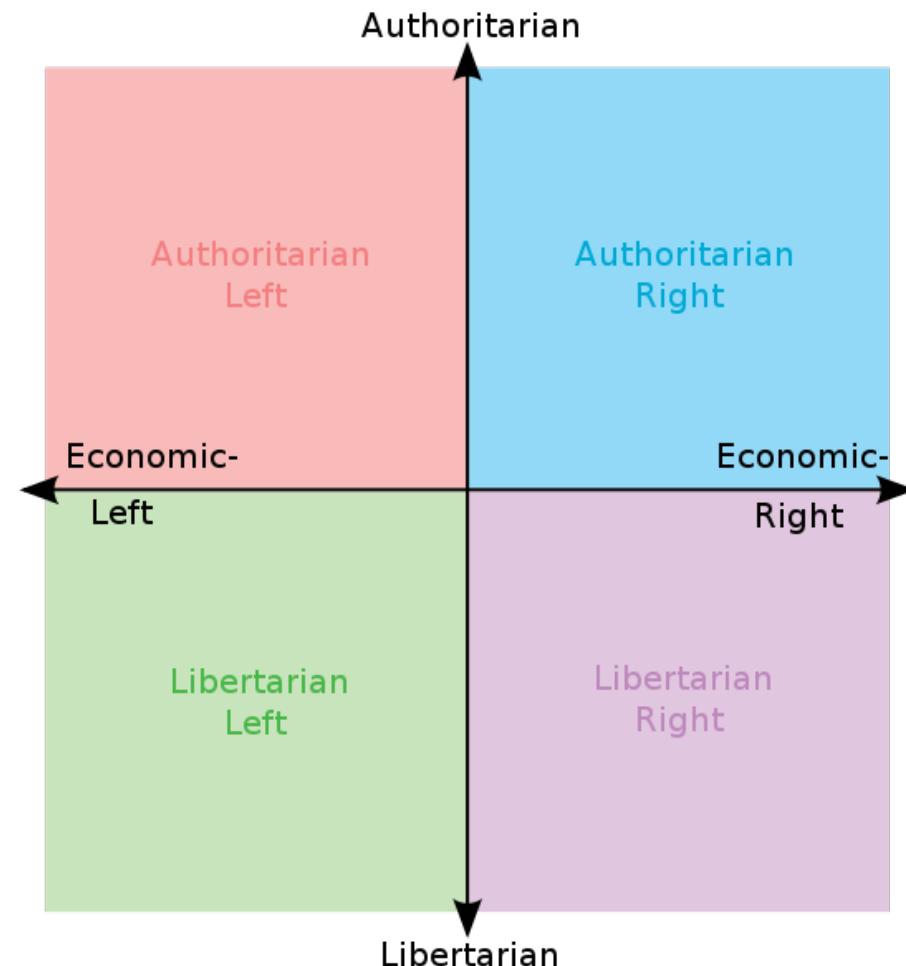
- Many works in opinion modeling assume a single axis
 - Often ill-defined too



Meet
the
Libertarians

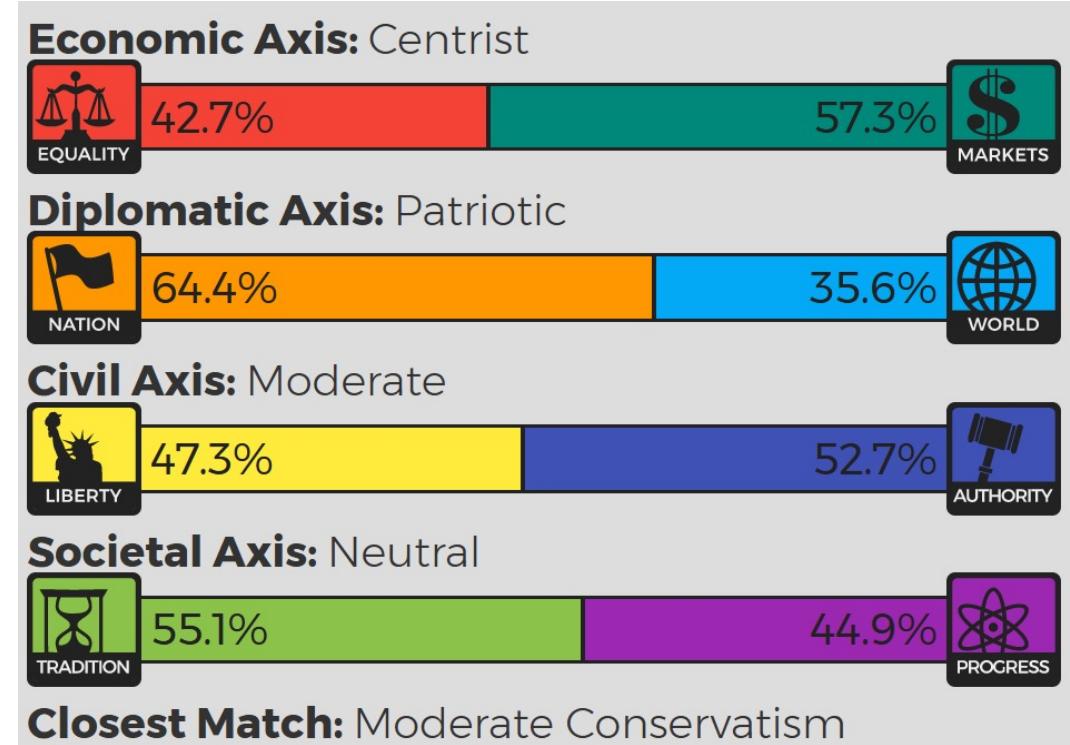
Why ideological embeddings?

- Multi-dimensional ideological spaces



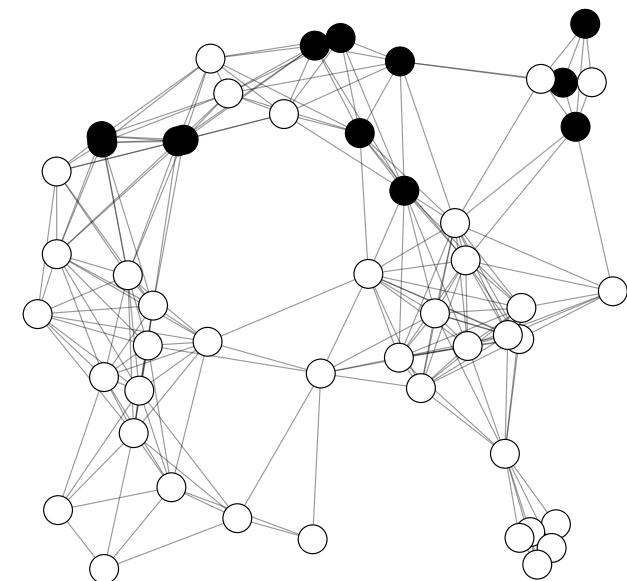
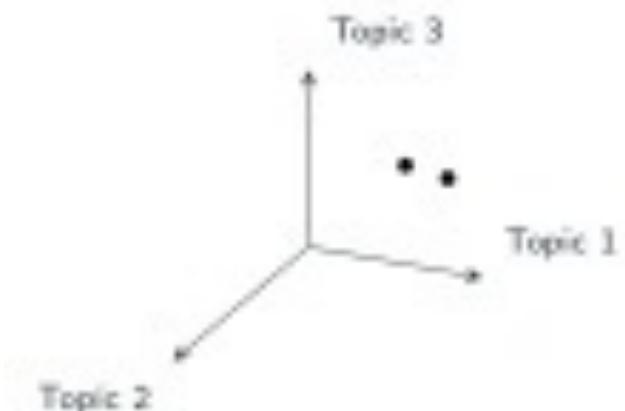
Why ideological embeddings?

- Multi-dimensional ideological spaces



Which behavior makes this observable?

- Spreading news on social media
 - A graph of agents that spread news content
 - They spread the same item if they are ideologically aligned



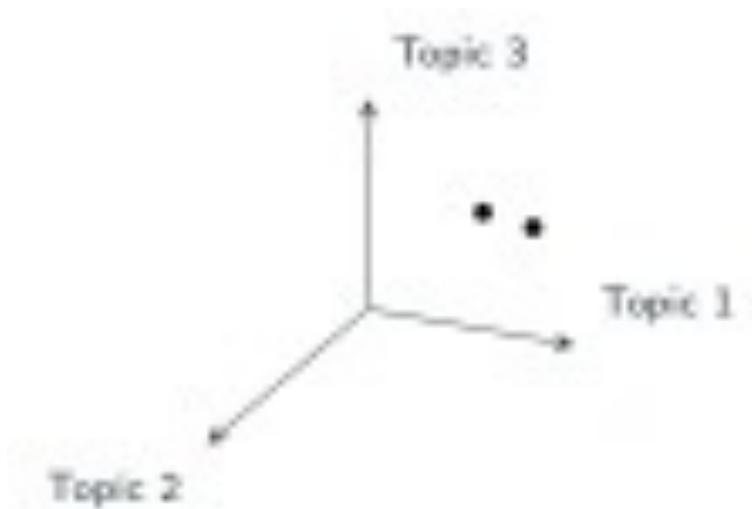
Which behavior makes this observable?

- We model actions that produce cascades on a graph through homophily:

a node imitates a neighbor
if they are similar in ideological
space.

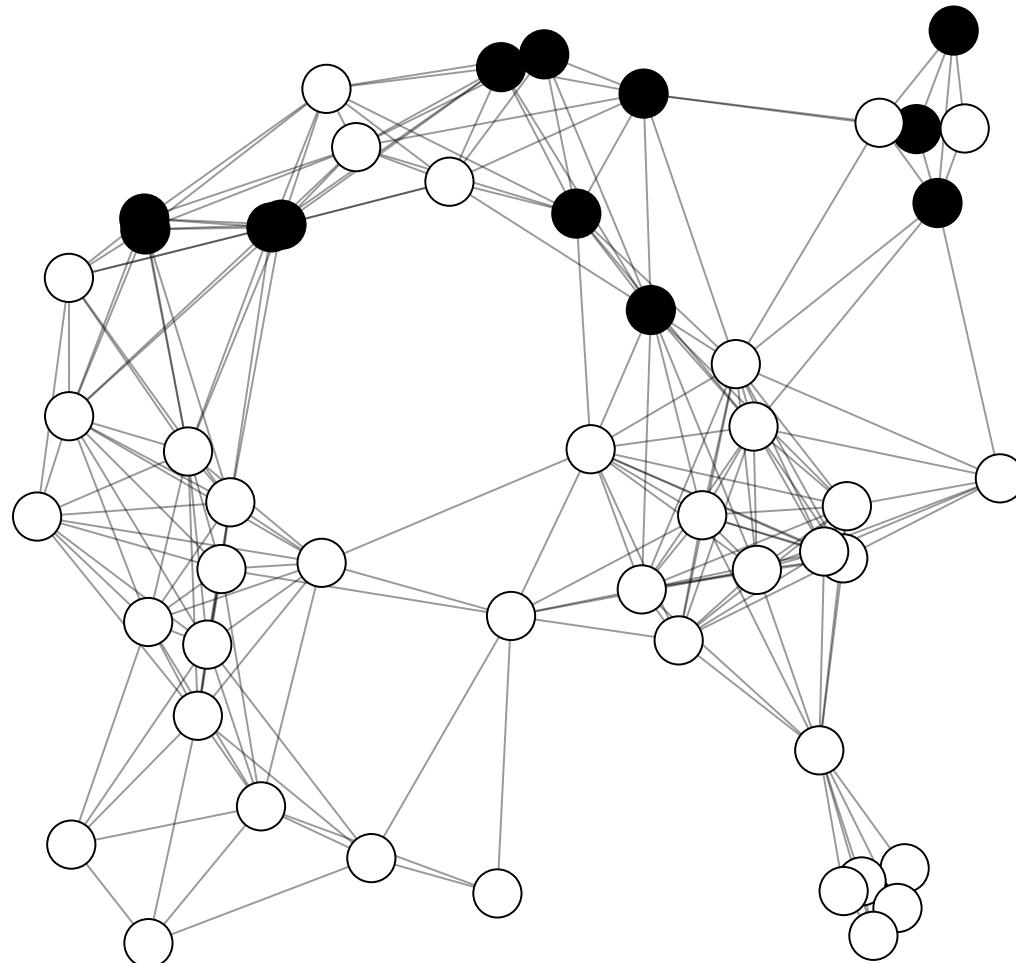
What is an ideological space?

- User-defined
- Each item must be tagged
 - a news can be “healthcare” or “migration”
 - Manually or LDA
 - Can be fuzzy



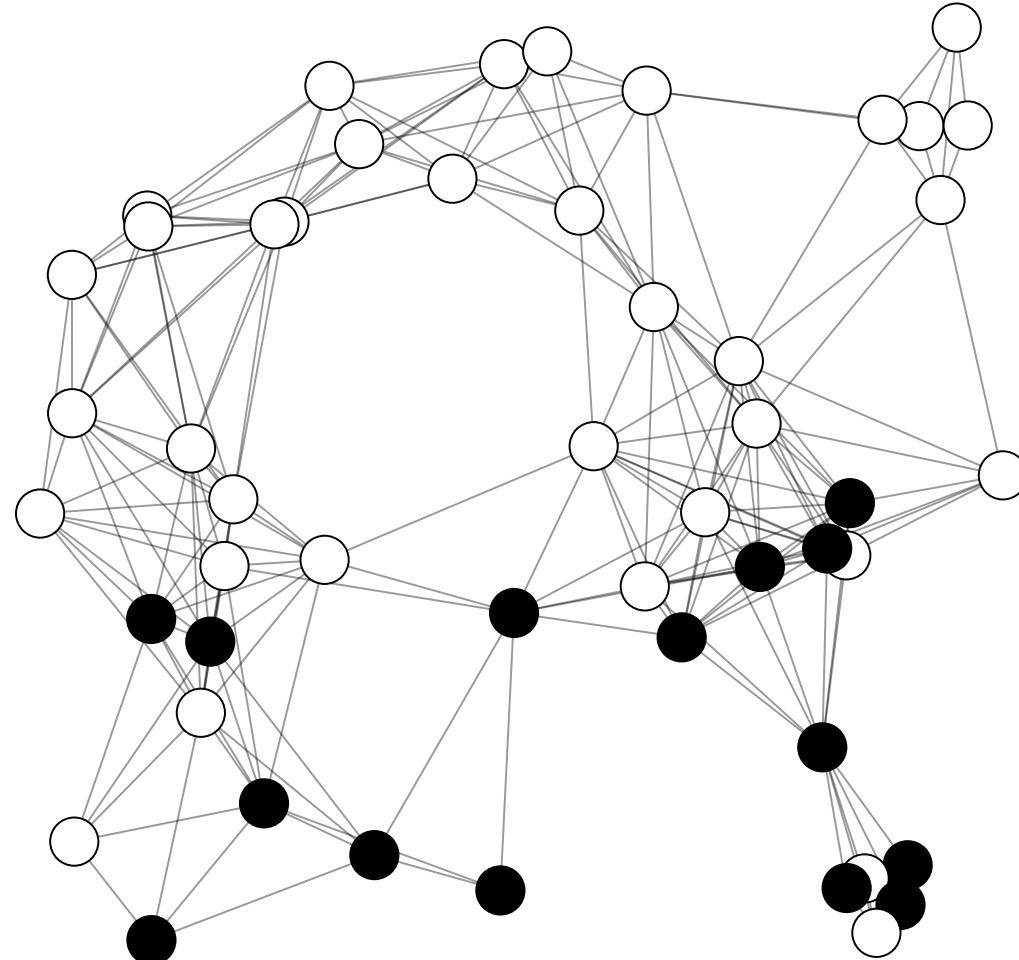
\circ = user, \bullet = user sharing an item

Item 1
0.9 healthcare + 0.1 migration



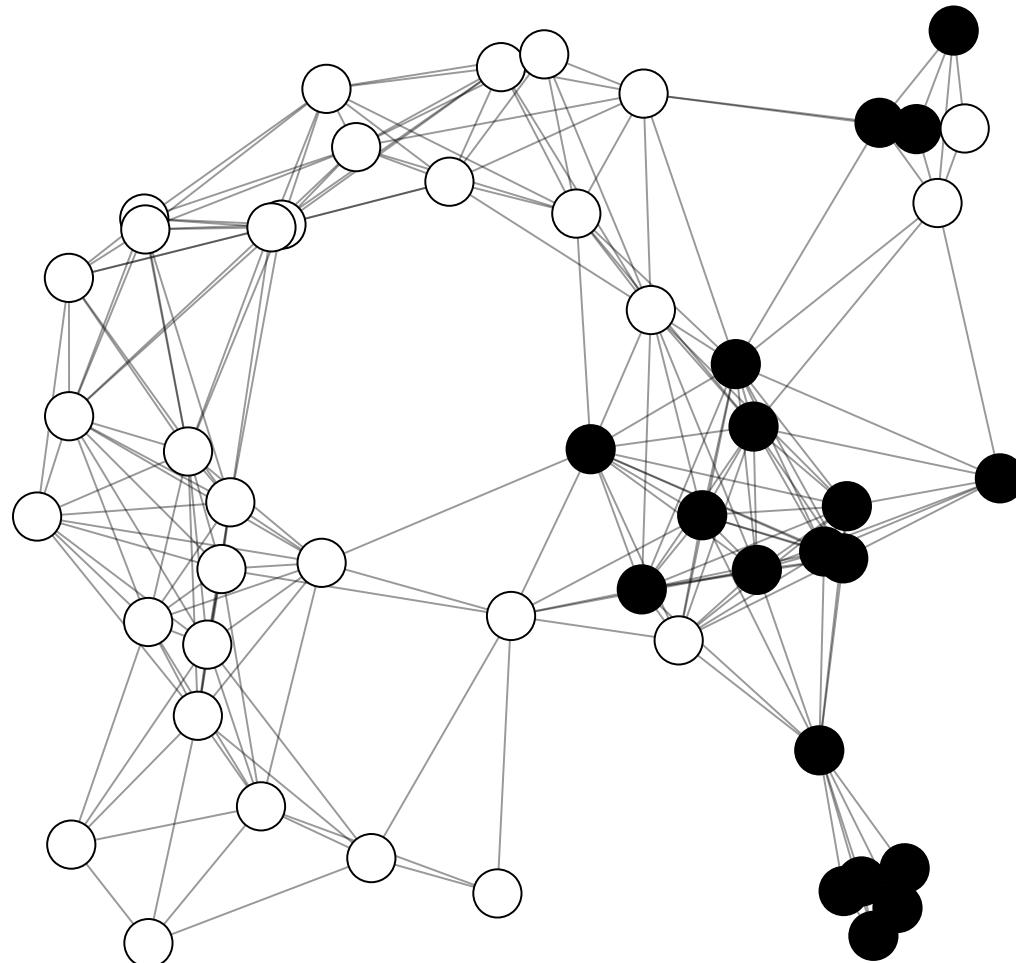
\circ = user, $*$ = user sharing an item

Item 2
0.9 healthcare + 0.1 migration



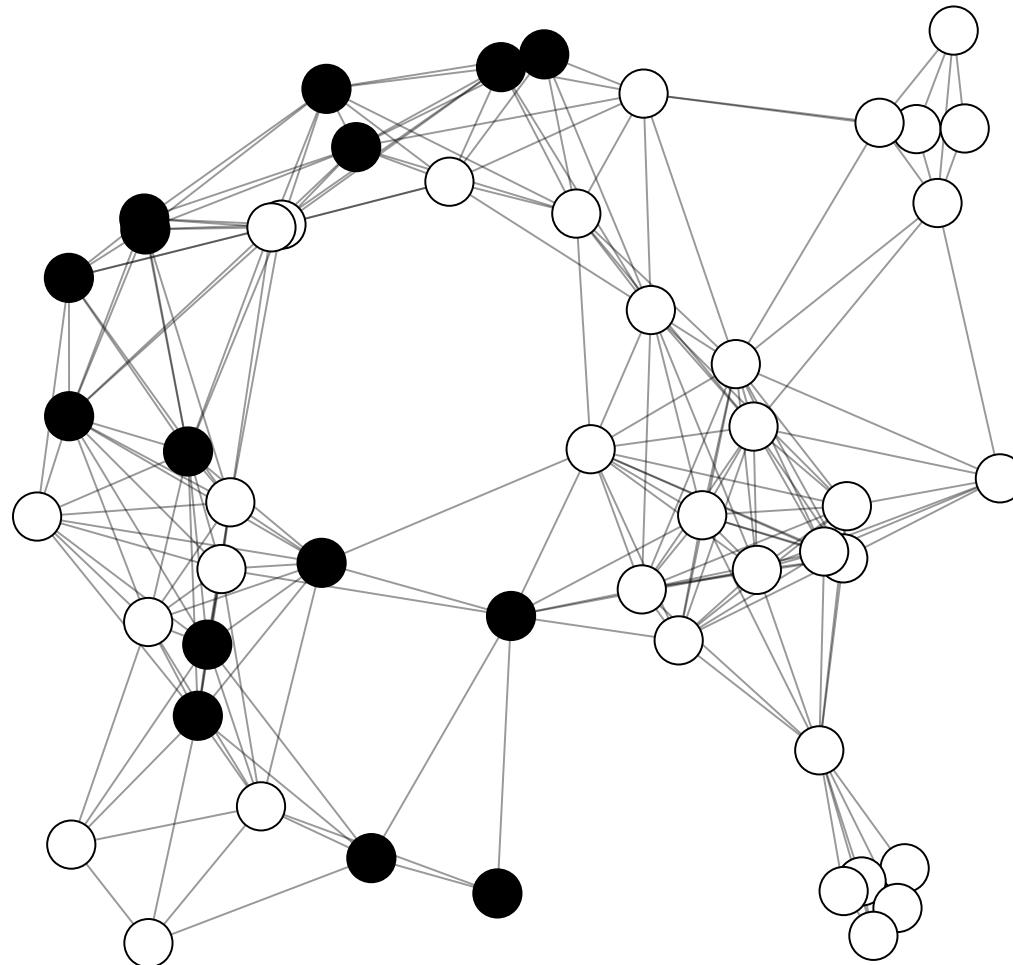
\circ = user, \bullet = user sharing an item

Item 3
0.1 healthcare + 0.9 migration



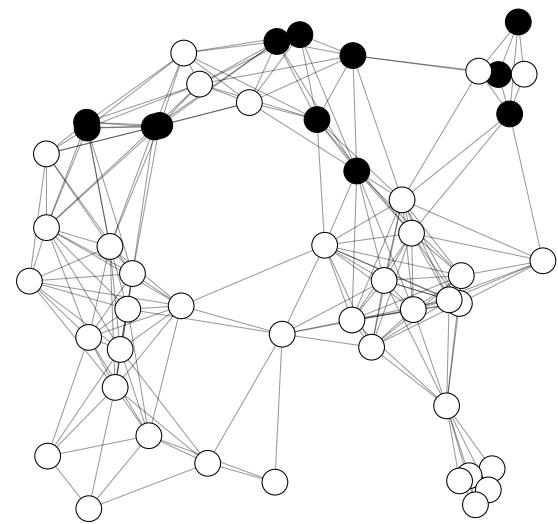
\circ = user, \bullet = user sharing an item

Item 4
0.1 healthcare + 0.9 migration



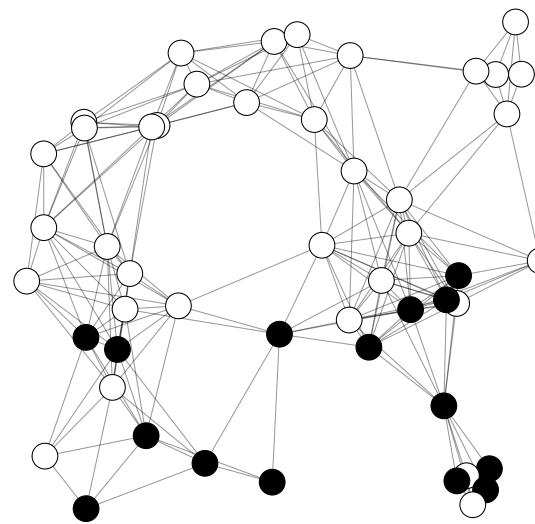
Item 1

0.9 healthcare + 0.1 migration



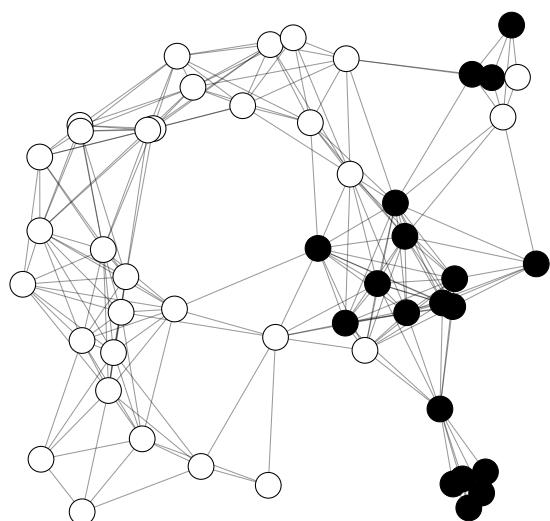
Item 2

0.9 healthcare + 0.1 migration



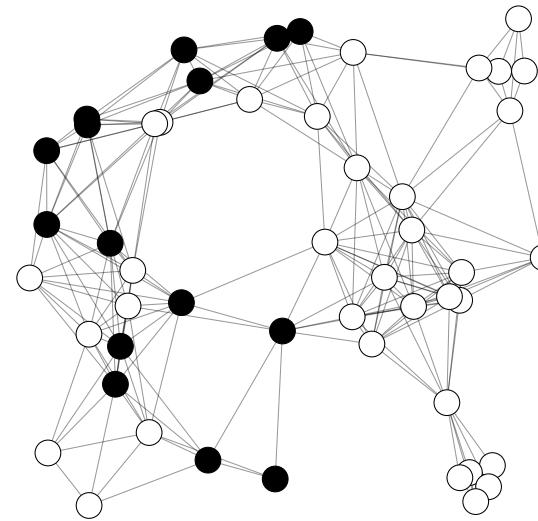
Item 3

0.1 healthcare + 0.9 migration



Item 4

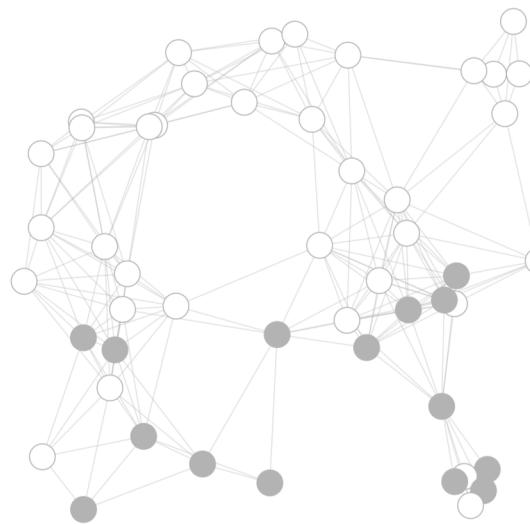
0.1 healthcare + 0.9 migration



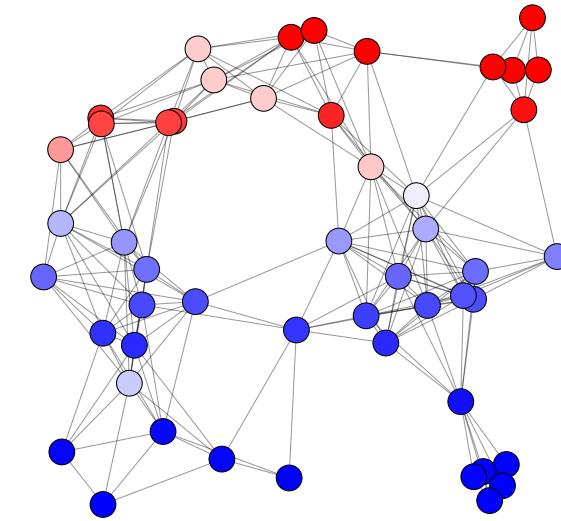
Item 1
0.9 healthcare + 0.1 migration



Item 2
0.9 healthcare + 0.1 migration



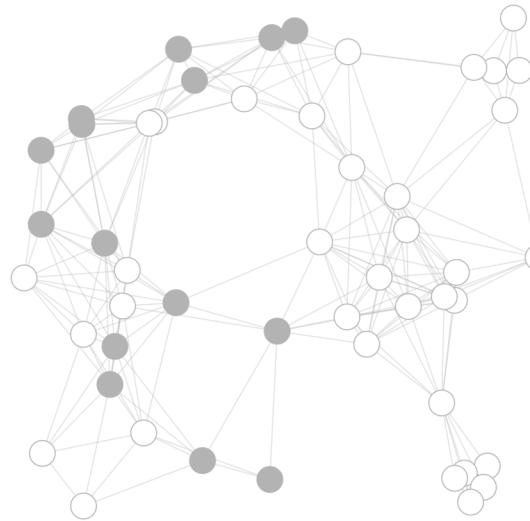
Healthcare



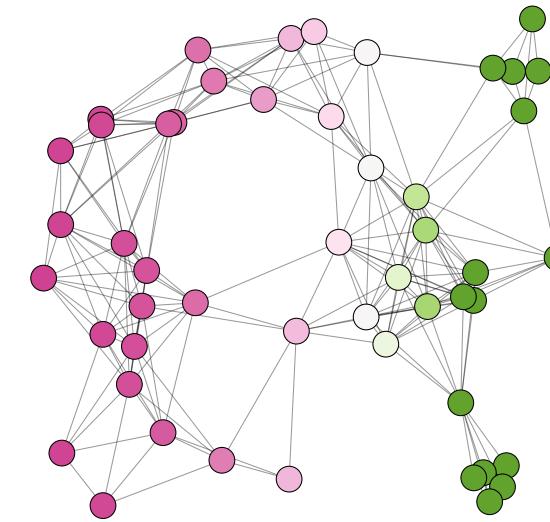
Item 3
0.1 healthcare + 0.9 migration



Item 4
0.1 healthcare + 0.9 migration



Immigration



The Generative model

- Interests $\vartheta_{u,k} \sim \text{Beta}(\alpha, \beta)$
- Polarities $\phi_{u,k} \sim \text{Beta}(p^{-1}, p^{-1})$
- Generate an item i :
 - topic distribution $\gamma_i \sim \text{Dir}(\mathbf{q})$
 - initial activator $v_i \sim U(V)$
 - For $(v, u) \in E$ s.t. v activated and u has not seen i :
 1. Node u sees i from v
 2. topic $k \sim \text{Multinom}(\gamma_i)$
 3. u is interested with probability $\vartheta_{u,k}$
 4. If interested, attitudes of u and v are Bernoullis with $\phi_{u,k}$ and $\phi_{v,k}$
 5. If equal attitudes, u activates on i

Modeling diffusion as ideological alignment

$$\mathcal{L}(i, u) \approx \sum_v \{y_{i,u} \cdot \log(P_{u,v}^{i,+}) + (1 - u_{i,u}) \cdot \log(1 - P_u^{i,+})\}$$

$$P_{u,v}^{i,+} = \sum_k \gamma_{i,k} \cdot \theta_{u,k} \cdot p(u, v, k)$$

The diagram illustrates the components of the probability $P_{u,v}^{i,+}$. Three blue arrows point from the labels "Relevance", "Interest", and "Alignment in polarities" to the terms $\gamma_{i,k}$, $\theta_{u,k}$, and $p(u, v, k)$ respectively in the equation.

Relevance

Interest

Alignment in polarities

Polarity alignment

$$p(u, v, k) = \underbrace{\phi_{u,k} \cdot \phi_{v,k}}_{\text{Positive alignment}} + \underbrace{(1 - \phi_{u,k}) \cdot (1 - \phi_{v,k})}_{\text{Negative alignment}}$$

Learning the model

$$\mathcal{L}(i, u) \approx \sum_v \left\{ y_{i,u} \cdot \log(P_{u,v}^{i,+}) + (1 - u_{i,u}) \cdot \log(1 - P_u^{i,+}) \right\}$$

- Fast and effective gradient-based optimization
 - Each potential activation $u \rightarrow v$ is an example
 - Scales to a large number of cascades
- Extensible to support variational inference

Algorithm 1 Inference algorithm.

Input:

- Graph (V, E)
- For every item $i \in \mathcal{I}$:
 - Its topic distribution γ_i on K topics
 - Its activated nodes $\mathcal{D}_i \subseteq V$

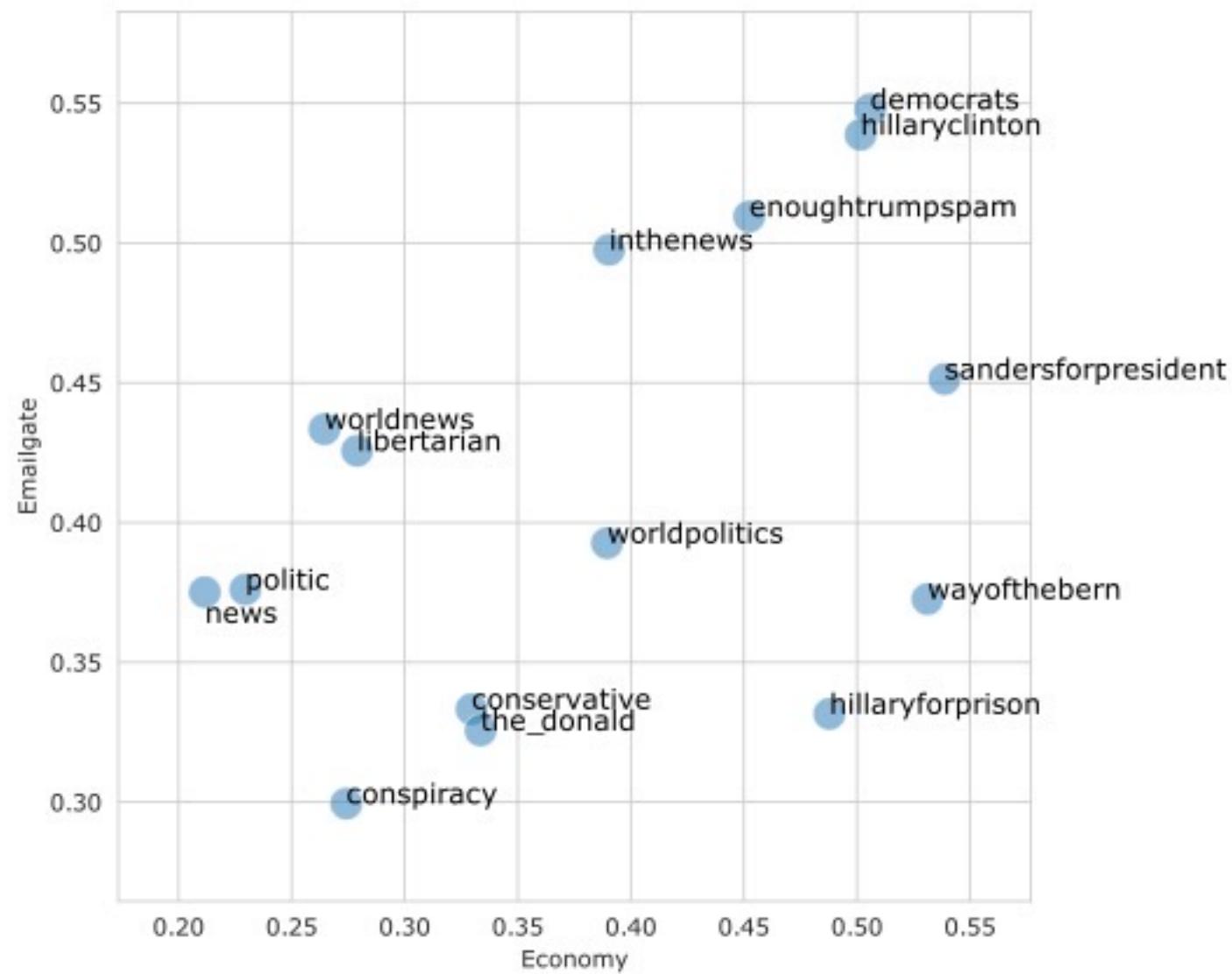
Output: Polarities ϕ_u and interests θ_u for all $u \in V$.

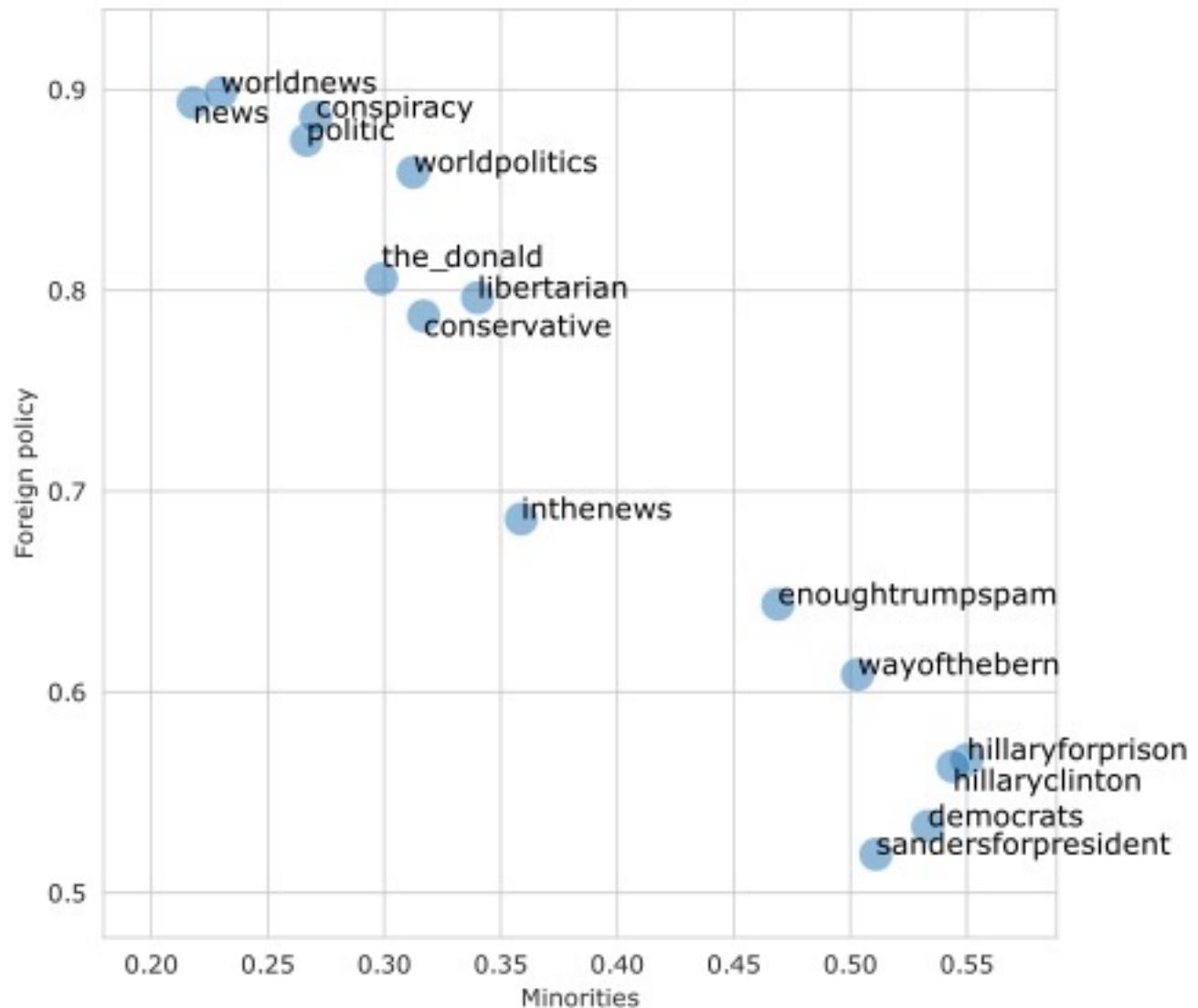
```
1: Initialize  $\phi$  and  $\theta$  as  $|V| \times K$  matrices.  
2: for number of epochs do  
3:   for  $i \in \mathcal{I}$  do  
4:     for  $v \in \mathcal{D}_i$  do  
5:       for  $u \in \{u \in \mathcal{D}_i | (v, u) \in E\}$  do  
6:         Update  $\phi, \theta$  by ascending the gradient:  
7:           
$$\nabla_{\phi, \theta} \log \left( \sum_k \gamma_{i,k} \cdot \theta_{u,k} \cdot p(u, v, k) \right)$$
  
8:       end for  
9:       for  $u \in \text{SAMPLE}(\{u \notin \mathcal{D}_i | (v, u) \in E\})$  do  
10:        Update  $\phi, \theta$  by ascending the gradient:  
11:          
$$\nabla_{\phi, \theta} \log \left( 1 - \sum_k \gamma_{i,k} \cdot \theta_{u,k} \cdot p(u, v, k) \right)$$
  
12:        end for  
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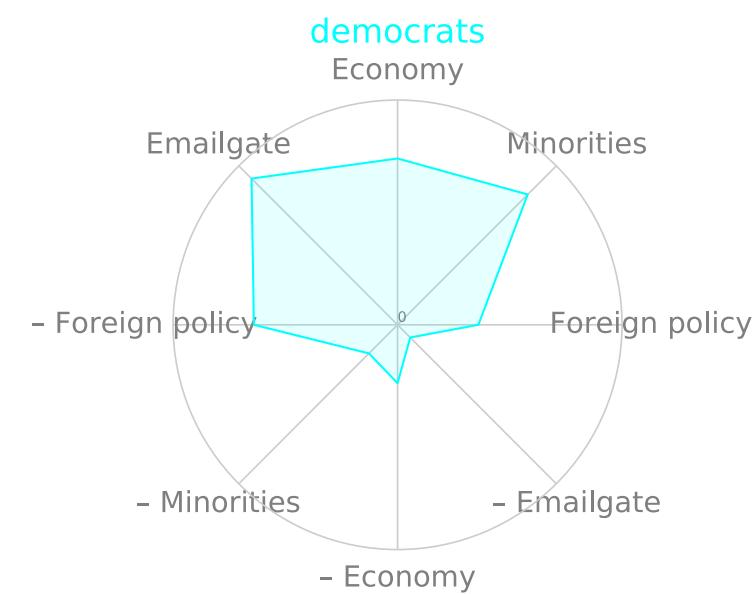
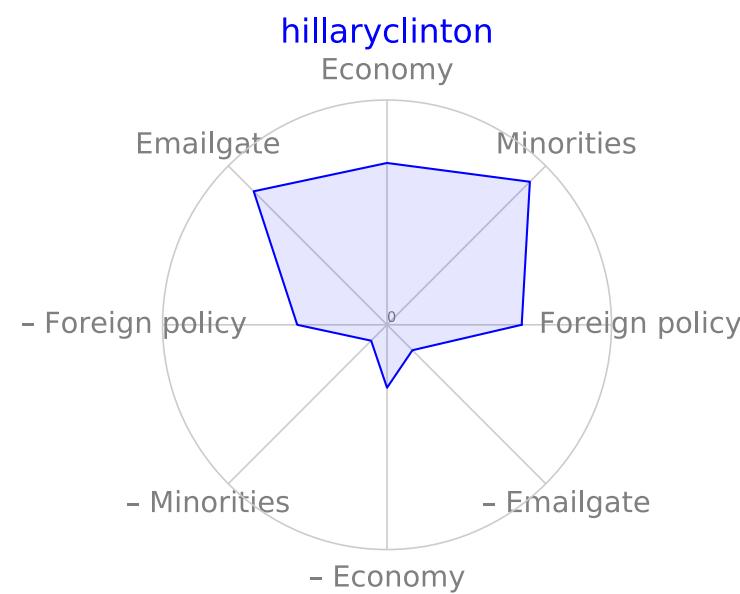
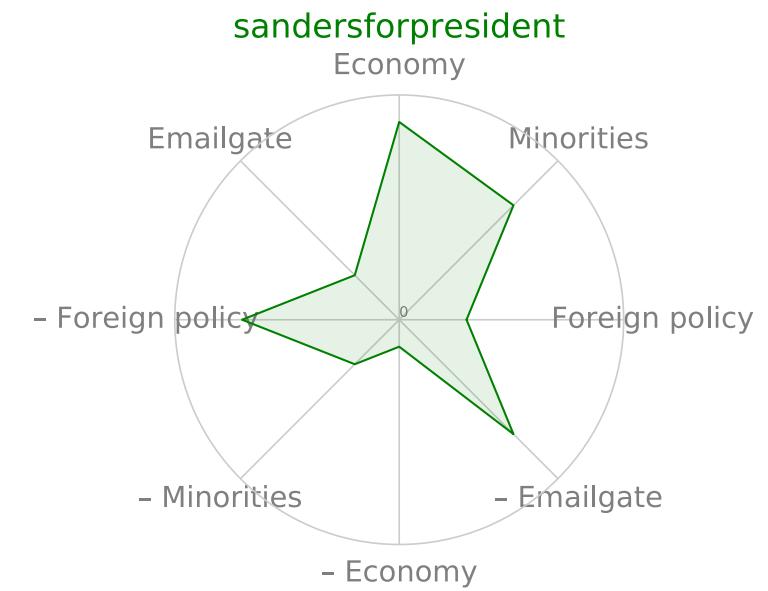
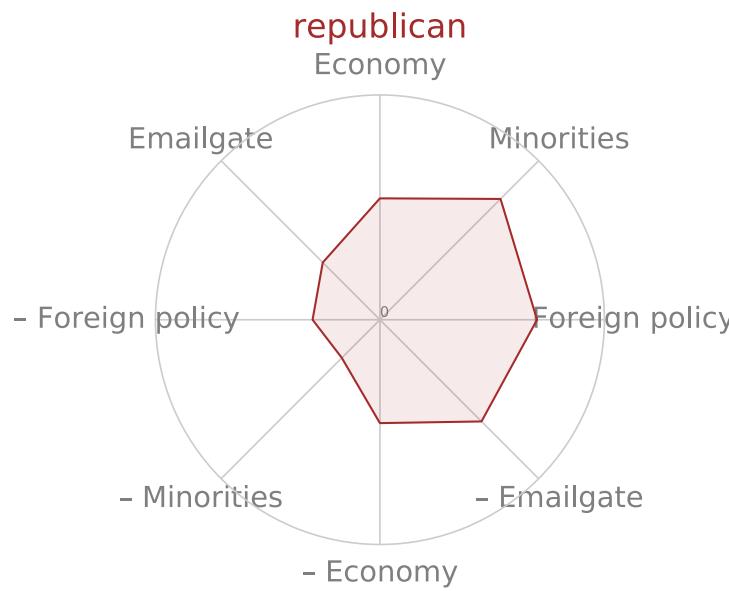
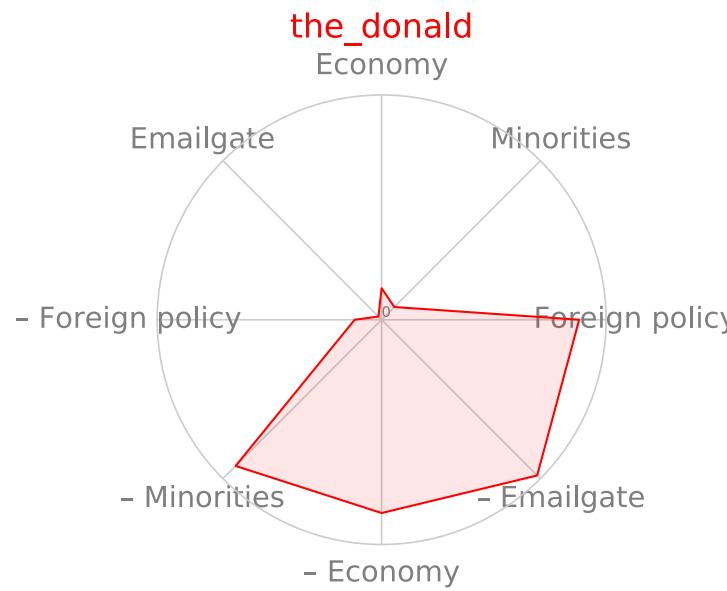
Results

Real data & Interpretability

- Reddit
 - Nodes: 50 political subreddits
 - Actions: Posting a Url
 - 22.047 items
 - 5 topics identified
 - Economy, emailgate, Foreign policy, Campaign, Minorities







Conclusions

- Representation learning for modeling information propagation
 - Susceptibility and influence
 - Interest and relevance
 - Speed of the propagation process
 - Polarity and alignments
- Advantages
 - Interpretability, predictive power, scalable learning
- A unified perspective
 - Can we put all these pieces together?
- Why is it important?
 - Echo-chamber detection
 - Moderating discussions, mitigation policies
 - Fighting misinformation

Thank you

Questions?



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@beman

