POLE: Polarized Embedding for Signed Networks

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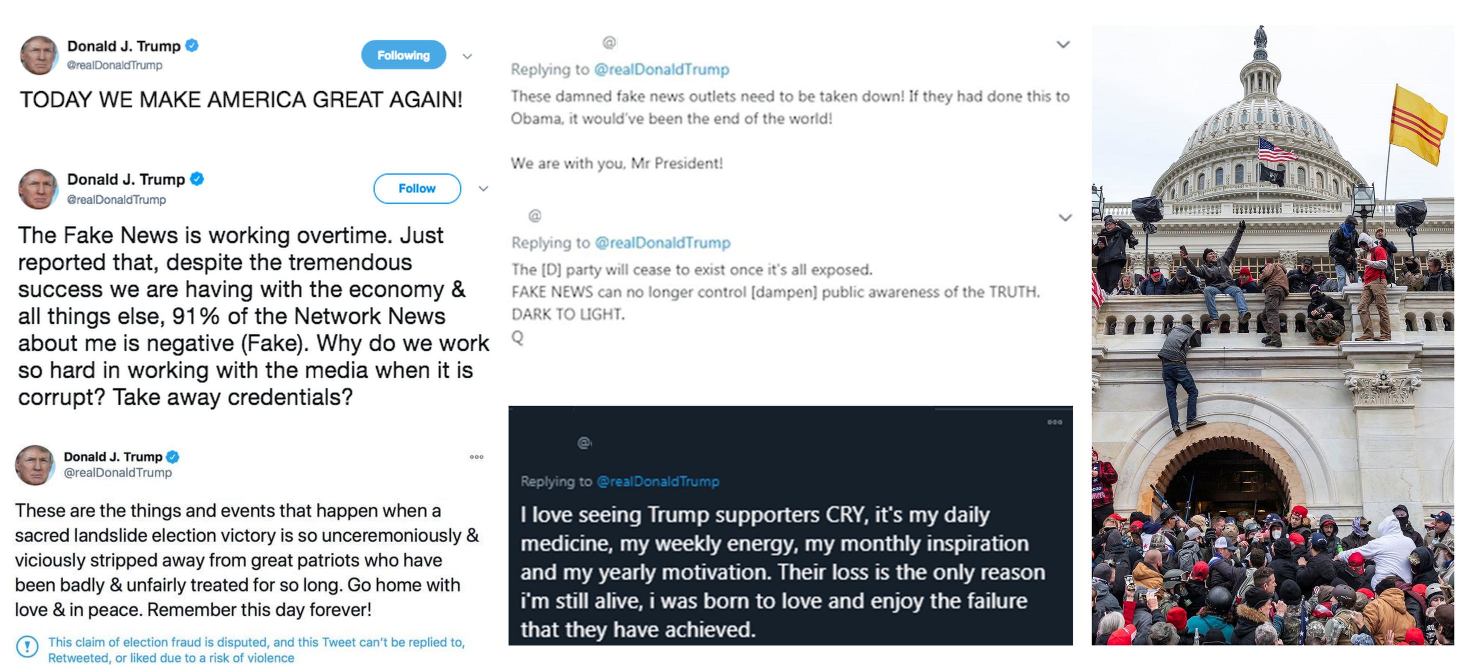
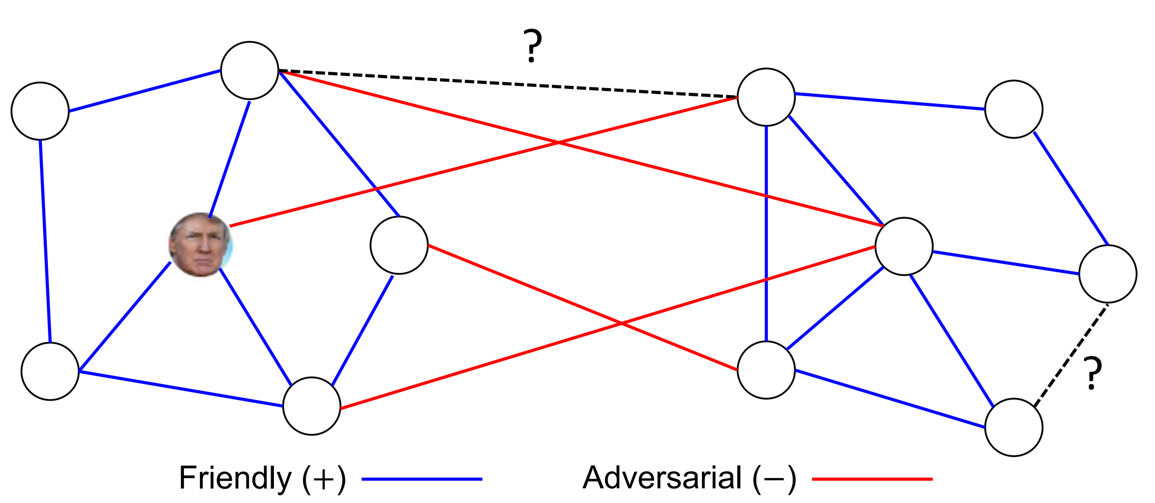
Social Polarization



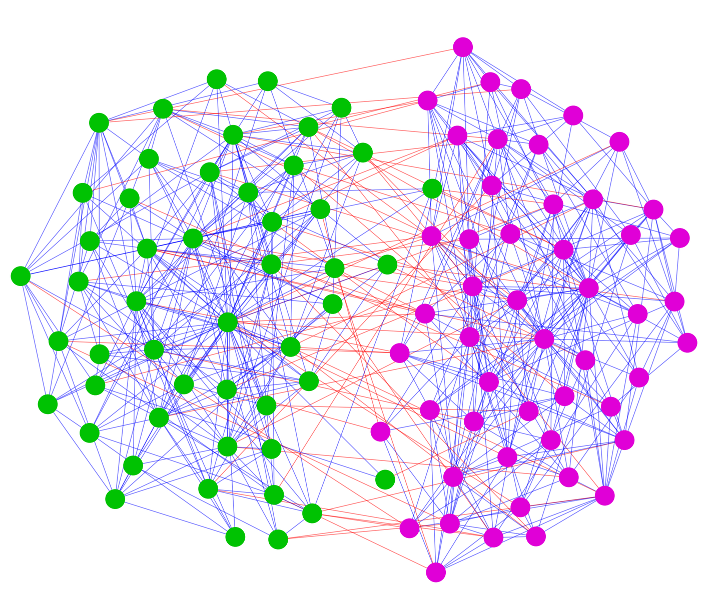


Can we predict future conflicts to reduce further polarization?

Signed Link Prediction in Polarized Networks

A polarized signed network comprises antagonistic communities with

- dense, positive intra-community links
- sparse, negative inter-community links



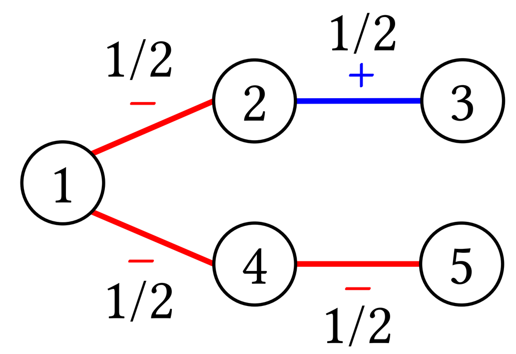
How can we predict signed links in a polarized network?

- To predict signs of links:
  - Signed embedding [1, 2] (capturing signed similarity)
- What about predicting link existence?
  - Unsigned embedding [3, 4] (capturing topological connectivity)
- **Cannot** predict negative links between polarized communities!
  - Because topology and link signs are interdependent
  - Need to capture signed/unsigned similarities jointly

Signed Random-Walk

Unsigned RW: $|M|_{uv}(t) = \Sigma_{\text{all length-}t \text{ paths } l \text{ between } u \text{ and } v}\,\text{Prob}(l)$

Signed RW: $M_{uv}(t) = \Sigma_{\text{all length-}t \text{ paths } l \text{ between } u \text{ and } v}\,\text{Prob}(l)\text{Sign}(l)$

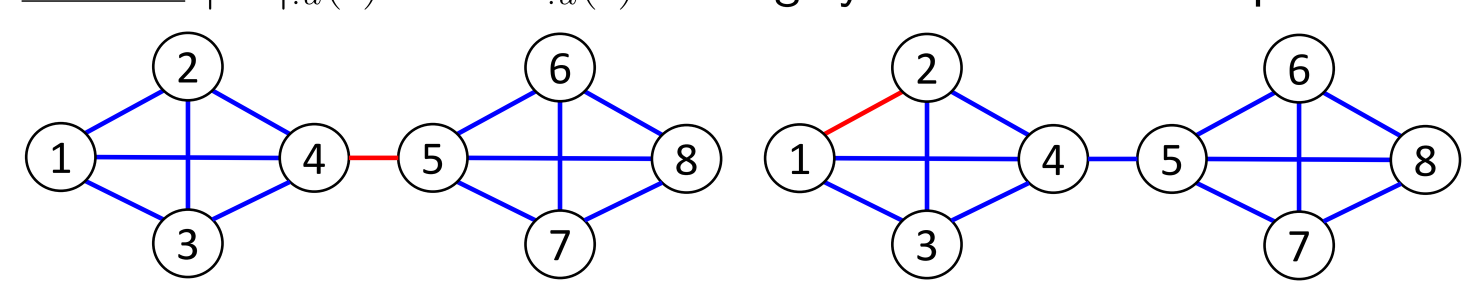


l	Prob(l)	Sign(l)
$\langle 1,2,3\rangle$	1/2 × 1/2 = 1/4	−1 × 1 = −1
$\langle 1,4,5\rangle$	1/2 × 1/2 = 1/4	−1 × −1 = 1

In close form: $M(t) = \begin{cases} (D^{-1}A)^t & \text{for discrete RWs} \\ \exp(-(I - D^{-1}A)t) & \text{for continuous RWs} \end{cases}$

A Measure of Polarization

Observ. $|M|_{:u}(t)$ and $M_{:u}(t)$ are highly correlated if u is polarized.



(a) (b)

$|M|_{:1} = [0.23, 0.21, 0.21, 0.18, 0.05, 0.02, 0.02, 0.02]$

$M^a_{:1} = [0.23, 0.21, 0.21, 0.18, -0.05, -0.02, -0.02, -0.02]$

$M^b_{:1} = [0.12, -0.01, 0.09, 0.07, 0.03, 0.01, 0.01, 0.01]$

$\text{corr}(|M|_{:1}, M^a_{:1}) = 0.9849$

$\text{corr}(|M|_{:1}, M^b_{:1}) = 0.6237$

Def. Node-level polarization: $\text{Pol}(u;t) = \text{corr}(|M|_{:u}(t), M_{:u}(t))$

Graph-level polarization: $\text{Pol}(G;t) = \text{mean}_{u \in G}(\text{Pol}(u;t))$

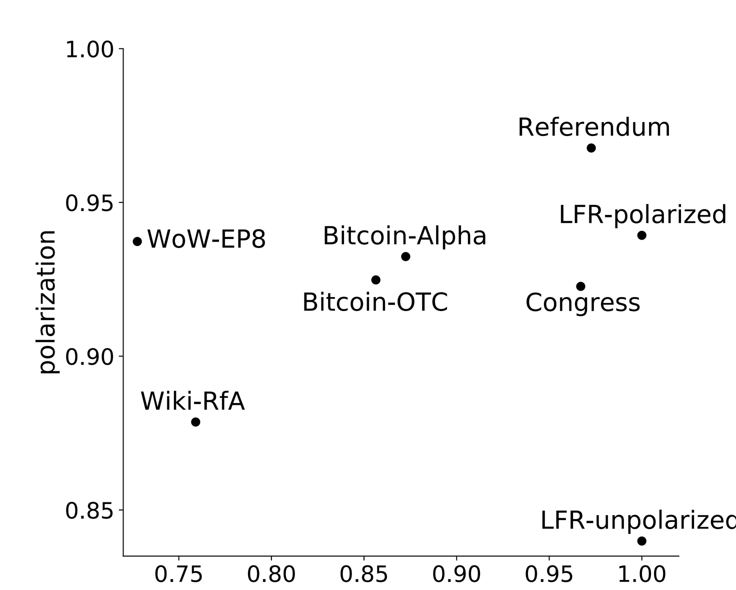
Polarization of Real-world Networks

Table: Least polarized members of the Congress by our polarization measure.

Congressperson	State	Party	Score
Henry Cuellar*	Texas	D	-0.6542
Jane Harman†	California	D	-0.5376
Curt Weldon	Pennsylvania	R	-0.4381
Dutch Ruppersberger	Maryland	D	-0.4318
Jim Moran	Virginia	D	-0.3832
Dave Obey	Wisconsin	D	-0.3588
Wayne Gilchrest	Maryland	R	-0.3503
Duke Cunningham	California	R	-0.3248
Al Edwards	Texas	D	-0.3063
Lincoln Davis	Tennessee	D	-0.2901

* "Voted with President Trump 75% of time",538
† "Best Republican in Democratic Party",LA Times

Figure: Polarization and social balance of real-world graphs and benchmarks.



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POLE: Polarized Embedding

POLE: extends autocovariance similarity [4, 5] to signed RWs

$$R(t) = M(t)^T W M(t)$$

where $W = \frac{1}{\text{vol}(G)} D - \frac{1}{\text{vol}(G)^2} dd^T$. And embedding $U = \text{SVD}(R(t))$.

Similarity consistency: Positive links → large positive similarity
Negative links → large negative similarity
Non-links → small similarity.

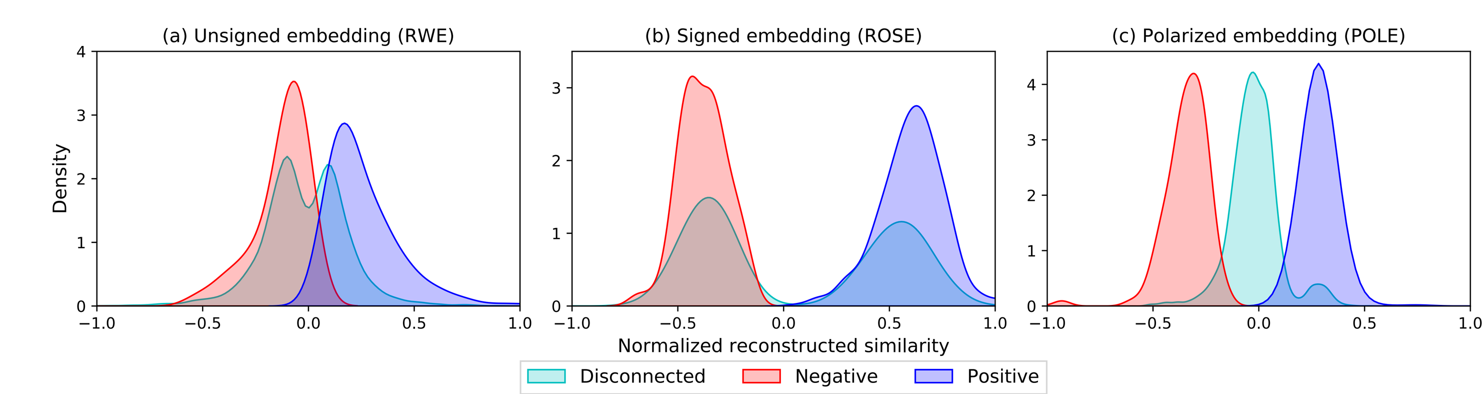

Figure: Distributions of the similarity for different node pairs in a polarized network using (a) unsigned [4], (b) signed [2], and (c) polarized embedding.

Signed Link Prediction Performance

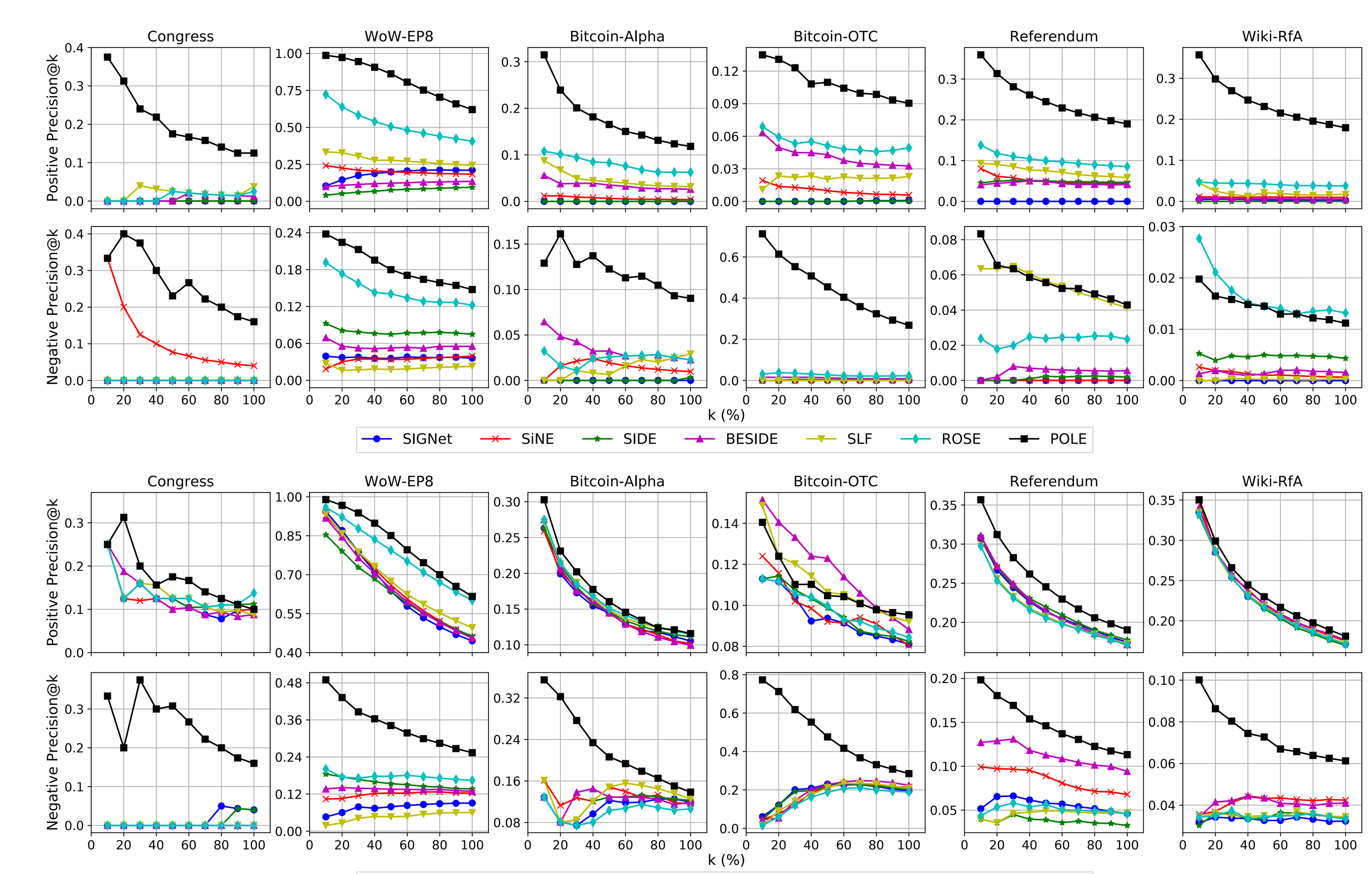

Figure: POLE significantly outperforms all baselines in almost all datasets in signed link prediction, especially for the negative links. (Upper: without unsigned embedding; lower: with unsigned embedding)

References

[1] Junghwan Kim, Haekyu Park, Ji-Eun Lee, and U Kang. Side: representation learning in signed directed networks. In *WebConf*, 2018.

[2] Amin Javari, Tyler Derr, Pouya Esmailian, Jiliang Tang, and Kevin Chen-Chuan Chang. Rose: Role-based signed network embedding. In *WebConf*, 2020.

[3] Aditya Grover and Jure Leskovec. node2vec: Scalable feature learning for networks. In *SIGKDD*, 2016.

[4] Zexi Huang, Arlei Silva, and Ambuj Singh. A broader picture of random-walk based graph embedding. In *SIGKDD*, 2021.

[5] Michael T Schaub, Jean-Charles Delvenne, Renaud Lambiotte, and Mauricio Barahona. Multiscale dynamical embeddings of complex networks. *PRE*, 99(6):062308, 2019.