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DIMES

Discovering Balance-Aware Polarized Communities in Signed Networks with Graph Neural Networks

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Neural discovery of balance-aware polarized communities

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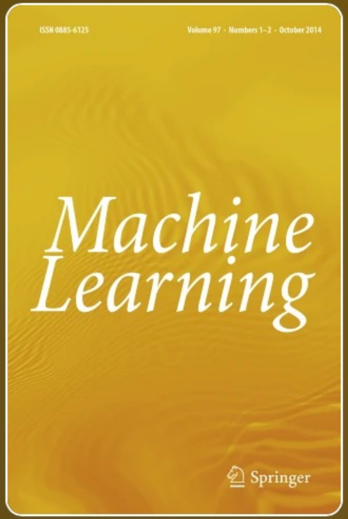


Outline

- Problem Statement
- Limitations of Existing Approaches
- Proposed Method
- Experimental Evaluation
- Conclusions & Future Work

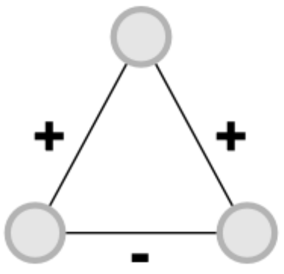
Introduction

- In real-world (social) graphs each interaction is *friendly* or *antagonistic:*
  - e.g. friend/foe, trust/distrust, agree/disagree etc.
- Increase of *polarization* around controversial issues is a growing concern with important societal fallouts.
- In order to study (and/or mitigate) polarization in large-scale online data, one first step is to *detect* it.

Signed Graphs

We denote a signed graph $G = (V, E^+ \cup E^-)$, where V is the set of nodes, E^+ (resp. E^-) denotes the set of positive (resp. negative) edges.

Signed adjacency matrix: $A = A^+ - A^-$



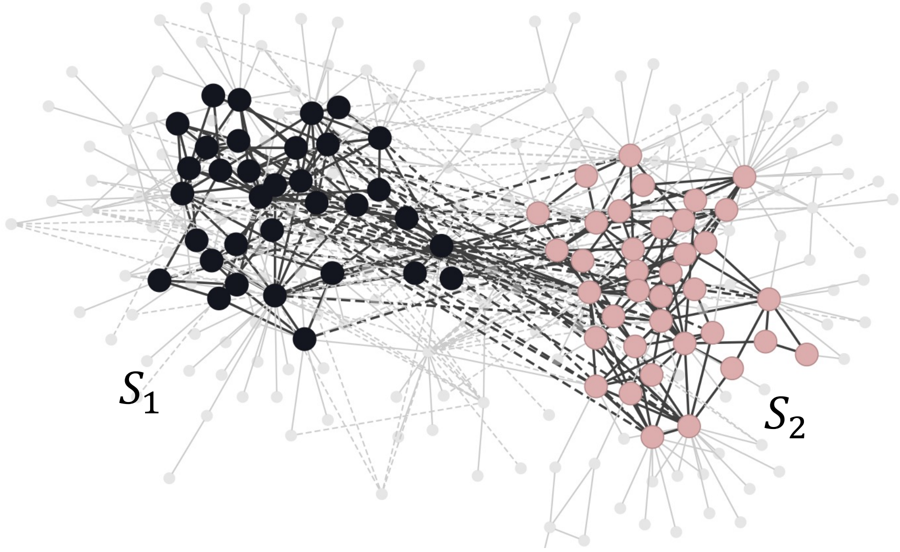
$$\mapsto \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & -1 \\ 1 & -1 & 0 \end{pmatrix}$$

2-Polarized-Communities (2PC) Problem

Find two communities $S_1, S_2 \subseteq V$ such that:

- (**R1**) within S_1 and S_2, there are mostly positive edges
- (**R2**) across S_1 and S_2, there are mostly negative edges
- (**R3**) the size of $S_1 \cup S_2$ is as small as possible

Note: S_1 and S_2 can be concealed within a large body of other network vertices (S_0), which are *neutral* with respect to the polarized structure



An example of two polarized communities in the Congress network. Solid edges are positive, while dashed edges are negative.

Bonchi Francesco, et al. "Discovering polarized communities in signed networks." CIKM 2019.

2PC: Problem Statement

PROBLEM 4 (2PC). *Given a signed network* $G = (V, E_+, E_-)$ *with* n *vertices and signed adjacency matrix* A*, find a vector* $\mathbf{x} \in \{-1, 0, 1\}^n$ *that maximizes*

$$p(\mathbf{x}, A) = \frac{\mathbf{x}^T A \mathbf{x}}{\mathbf{x}^T \mathbf{x}}.$$

polarity

Theorem. 2PC is **NP**-Hard

Bonchi Francesco, et al. "Discovering polarized communities in signed networks." CIKM 2019.

Relaxed Version of 2PC

Problem 1 (2PC [8]). *Given a signed graph* $G = (V, E^+, E^-)$ *with signed adjacency matrix* $\mathbf{A}$*, find*

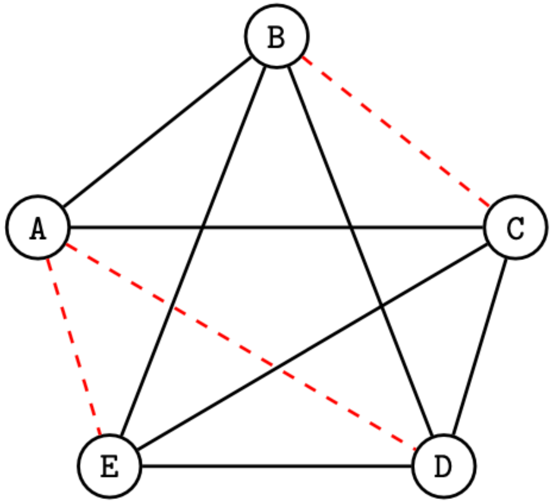
$$\mathbf{x}^* = \operatorname*{arg\,max}_{\mathbf{x} \in \{-1,0,1\}^{|V|}} p(\mathbf{x}, \mathbf{A}).$$

Problem 2 (2PC-RELAXED [8]). *Given a signed graph* $G = (V, E^+, E^-)$ *with signed adjacency matrix* $\mathbf{A}$*, find*

$$\mathbf{z}^* = \operatorname*{arg\,max}_{\mathbf{z} \in [-1,1]^{|V|}} p(\mathbf{z}, \mathbf{A}),$$

Limitations of Existing Algorithms to 2PC

Limitation 1: deriving a solution to 2PC starting from one optimal/approximate solution of the relaxed problem may be limiting in terms of polarity, i.e. suboptimal solutions to the relaxed problem can lead to better solutions to 2PC after rounding.



$$\begin{array}{cccccc} & A & B & C & D & E \\ \mathbf{z}^* = & [0.282, & -0.282, & -0.282, & -0.616, & -0.616] \\ \mathbf{z} = & [0.213, & -0.144, & -0.144, & -0.378, & -0.378] \end{array}$$

$p(\boldsymbol{z}^*, A) = 2.372$

$p(\boldsymbol{z}, A) = 2.363$

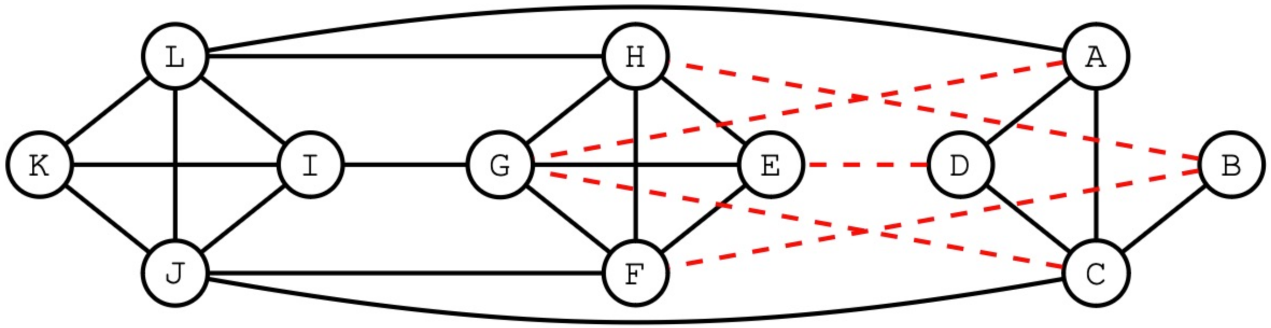
$ROUND(\boldsymbol{z}^*) = \boldsymbol{x}_1 = [1, -1, -1, -1, -1]$ (with threshold 0.282) $\quad p(\boldsymbol{x}_1, A) = 1.6$

$ROUND(\boldsymbol{z}) = \boldsymbol{x}_2 = [1, 0, 0, -1, -1]$ (with threshold 0.213) $\quad p(\boldsymbol{x}_2, A) = 2$

Limitations of Existing Algorithms to 2PC

Limitation 2: The polarity function does not require or foster the detection of *size-balanced* communities.

- Indeed, maximizing polarity can easily lead to *degenerate solutions* with a single sufficiently large community and another (almost) empty community, even if the input signed graph does contain "natural" polarized communities that are both non-empty and possibly of comparable size.



P1 = {{A,B,C,D}, {E,F,G,H}}

P2 = {Ø,{E,F,G,H,I,J,K,L}}.

Neural2PC: A Neural Approach to 2PC

A novel machine-learning approach to 2PC that addresses the aforementioned limitations:

- **Limitation 1**: by soundly and effectively exploring a variety of suboptimal solutions to the relaxed problem, so as to ultimately select the one that leads to the best discrete solution to 2PC after rounding.
- **Limitation 2**: by equipping a generalization of the polarity function, named γ-polarity that is designed to produce polarized communities that, depending on the setting of γ, can be either more balanced or larger than those yielded by standard polarity.

Francesco Gullo, Domenico Mandaglio, and Andrea Tagarelli. "Neural discovery of balance-aware polarized communities." Machine Learning. 2024.

Overview of Neural2PC

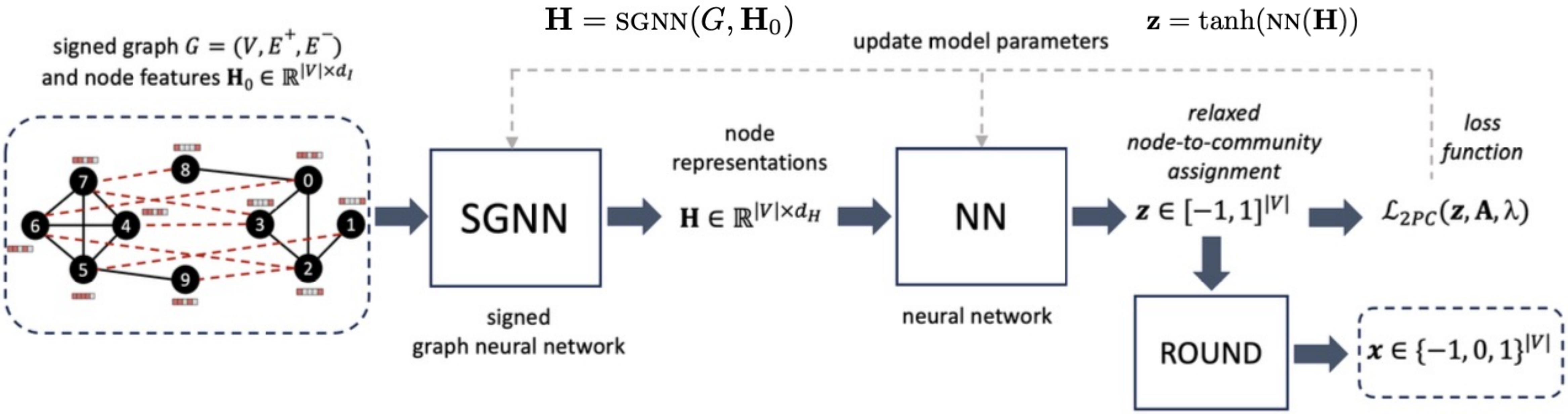


Fig. 2. Overview of the proposed Neural2PC approach.

$$\mathcal{L}_{2\mathrm{PC}}(\mathbf{z}, \mathbf{A}, \lambda) = -\underbrace{p(\mathbf{z}, \mathbf{A})}_{\text{polarity}} + \lambda \underbrace{||\rho||_2^2}_{\text{regularization}}$$

Penalizes solutions/assignments which are far from «discrete»

γ-Polarity Objective

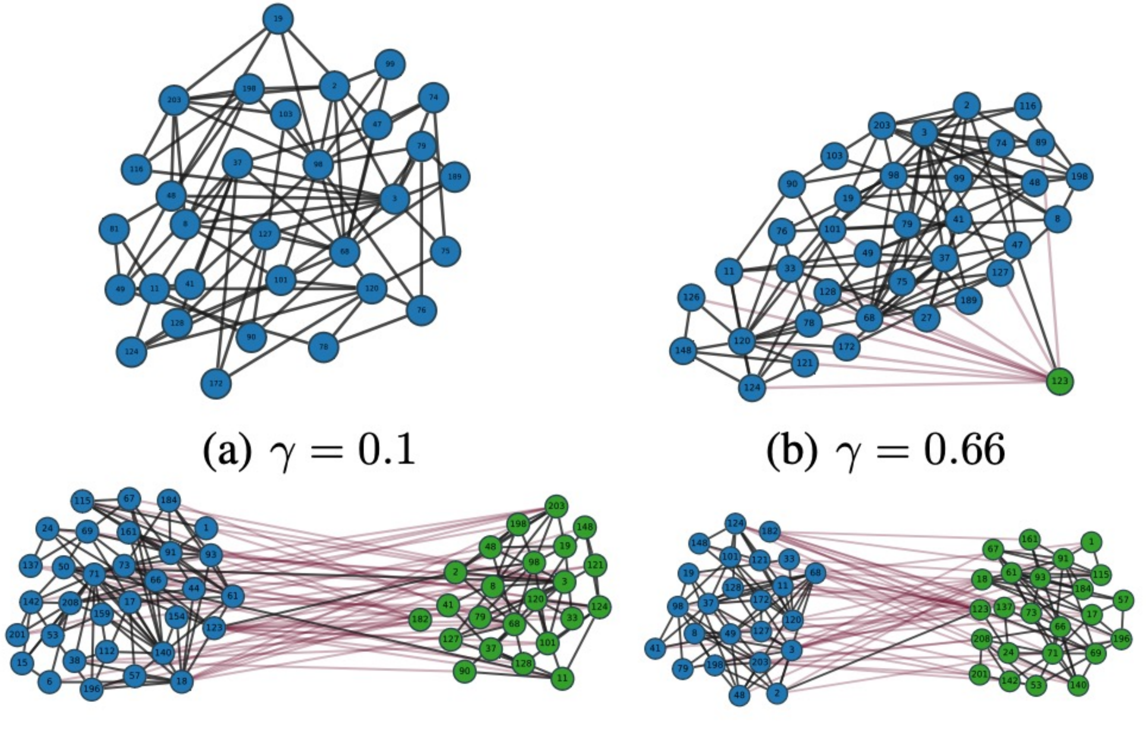
***Definition** 2 (γ-polarity):* Given a vector $\mathbf{x} \in \{-1, 0, 1\}^{|V|}$, a matrix $\mathbf{A} \in \{-1, 0, 1\}^{|V|\times|V|}$, and a real number $\gamma > 0$, the *γ-polarity* $p_\gamma(\mathbf{x}, A)$ of $\mathbf{x}$ with respect to $\mathbf{A}$ is defined as:

$$p_\gamma(\mathbf{x}, \mathbf{A}) = \frac{\mathbf{x}^\top \mathbf{A}\ \mathbf{x}}{(s_{max} - s_{min})\,\gamma + 2\, s_{min}}. \tag{7}$$

$$s_{max} = \max\{s_1, s_2\},\ s_{min} = \min\{s_1, s_2\}$$

- $\gamma > 1$ favors size *balance* among communities
- $\gamma = 1$ standard polarity
- $\gamma \in (0, 1)$ favors size *unbalance* among communities

Some Visualizations for γ-Polarity Results



(a) $\gamma = 0.1$ (b) $\gamma = 0.66$

(c) $\gamma = 1.0$ (d) $\gamma = 4.0$

Fig. 5. Solutions yielded by Neural2PC by optimizing γ-polarity (Def. 2), for different values of γ, on the Congress dataset.

Experimental Evaluation

Datasets: 10 real-world networks and synthetic networks (with ground-truth communities information).

Competing methods: state-of-the-art methods for discovering polarized communities (EIGEN[1], R-EIGEN[1]), as well as against non-trivial baselines inspired by methods devised for different yet related problems (PIVOT[2], GREEDY[3], SPONGE[4], BNC[5], SSSNET[6]).

1. Bonchi Francesco, et al. "Discovering polarized communities in signed networks." CIKM 2019.
2. Bansal Nikhil, Avrim Blum, and Shuchi Chawla. "Correlation clustering." Machine learning 2004.
3. Charikar Moses. "Greedy approximation algorithms for finding dense components in a graph." International workshop on approximation algorithms for combinatorial optimization 2000.
4. Cucuringu Mihai, et al. "SPONGE: A generalized eigenproblem for clustering signed networks." AISTATS 2019.
5. Chiang Kai-Yang, Joyce Jiyoung Whang, and Inderjit S. Dhillon. "Scalable clustering of signed networks using balance normalized cut." KDD 2012.
6. He Yixuan, et al. "SSSNET: semi-supervised signed network clustering." SDM 2022.

Experimental Evaluation

Evaluation goals: We assessed accuracy of the proposed Neural2PC and competitors/baselines on

1. real datasets
2. synthetic datasets
3. impact of different signed GNNs when used as a module of Neural2PC
4. runtimes of the considered methods
5. effectiveness of the individual components of Neural2PC through an ablation study
6. effectiveness of the γ-polarity measure in yielding communities that are both size-balanced and high-quality.

Real-World Datasets

TABLE II

MAIN CHARACTERISTICS OF REAL DATA (SIGNED GRAPHS) USED IN OUR EVALUATION. V: NODE SET; E^+: POSITIVE EDGE SET; E^-: NEGATIVE EDGE SET; DENSITY: $|E^+ \cup E^-|)/(|V|(|V|-1)/2)$; DEG$^+$, DEG$^-$: AVG AND STD-DEV OF POSITIVE AND NEGATIVE NODE DEGREES, RESP.; CC$^+$, CC$^-$: #CONNECTED COMPONENTS IN THE SUBGRAPH INDUCED BY E^+ AND E^-, RESP.; CC: OVERALL #CONNECTED COMPONENTS.

dataset	$\|V\|$	$\|E^+ \cup E^-\|$	$\|E^-\|/(\|E^+ \cup E^-\|)$	density	deg$^+$	deg$^-$	cc$^+$	cc$^+$	cc
Bitcoin [41]	5 881	21 492	0.152	0.00124	6.2 ± 19.93	1.11 ± 5.78	355	4 344	4
Cloister [34]	18	125	0.552	0.81699	6.22 ± 2.04	7.67 ± 3.06	1	1	1
Congress [34]	219	521	0.205	0.02183	3.78 ± 4.49	0.98 ± 1.71	8	127	1
Epinions [41]	131 580	711 210	0.171	8e-05	8.97 ± 43.21	1.84 ± 15.69	23 366	90 846	5 568
HTribes [34]	16	58	0.5	0.48333	3.62 ± 1.36	3.62 ± 1.76	2	2	1
Slashdot [41]	82 140	500 481	0.239	0.00015	9.28 ± 33.67	2.91 ± 13.16	7427	46 991	1
TwitterRef [37]	10 884	251 406	0.051	0.00424	43.85 ± 108.3	2.35 ± 16.05	69	6 801	11
WikiCon [41]	116 717	2 026 646	0.628	0.0003	12.9 ± 120.27	21.83 ± 62.11	70 284	1 788	1 785
WikiEle [34]	7 115	100 693	0.221	0.00398	22.05 ± 46.98	6.26 ± 14.78	892	2 926	24
WikiPol [37]	138 587	715 883	0.123	7e-05	9.06 ± 48.89	1.27 ± 11.76	14 458	97 459	305

Results on Real-World Datasets: Polarity and Solution Size

TABLE III

POLARITY (DEF. 1) AND SOLUTION SIZE ($|S_1|/|S_2|$) OF THE PROPOSED NEURAL2PC METHOD VS. COMPETING METHODS ON REAL DATASETS. BEST RESULTS IN BOLD, SECOND-BEST UNDERLINED.

dataset	EIGEN		R-EIGEN		PIVOT		GREEDY		SPONGE(K)			BNC(K)			SSSNET(K)			Neural2PC		
	pol.	size	pol.	size	pol.	size	pol.	size	pol.	size	k	pol.	size	k	pol.	size	k	pol.	size	model
Bitcoin	<u>29.52</u>	136/2	14.12	725/103	21.65	21/19	29.01	140/0	8.36	26/2	3	5.27	5834/47	2	9.06	713/8	3	**30.28**	158/32	SGCN_{sum}
Cloister	**7.45**	8/3	6.23	14/3	4.17	9/3	6.11	15/3	6.11	15/3	2	1.0	17/1	2	6.93	6/3	3	**7.45**	8/3	All
Congress	<u>6.58</u>	28/24	5.38	50/50	3.1	6/5	5.77	36/33	4.43	115/104	2	2.75	216/3	2	4.43	115/104	2	**6.64**	29/24	SGDNET
Epinions	128.72	999/18	71.36	4057/407	156.38	248/5	<u>170.3</u>	269/0	7.12	131578/2	2	7.12	131225/355	2	73.19	953/0	3	**171.1**	268/1	$\text{SGCN}_{\text{mean}}$
HTribes	**6.18**	7/4	5.82	7/4	3.5	5/3	5.5	12/4	5.5	12/4	2	-0.5	10/6	2	5.0	11/5	2	**6.18**	7/4	All
Slashdot	79.7	233/1	29.21	2827/125	61.0	283/6	**82.72**	200/0	6.36	82138/2	2	6.36	82138/2	2	7.26	72915/9225	2	<u>82.25</u>	203/0	$\text{SGCN-DR}_{\text{mean}}$
TwitterRef	<u>174.1</u>	669/4	118.81	1487/20	116.25	1142/16	173.94	685/0	28.03	8274/2610	2	41.49	10882/2	2	41.49	10864/20	2	**174.35**	677/4	SGNN_{sum}
WikiCon	<u>175.65</u>	1993/449	99.93	9778/3109	129.33	368/134	127.96	1151/0	-8.92	116712/5	3	8.92	115730/987	2	28.56	50835/5401	3	**187.29**	1788/559	SGCN_{sum}
WikiEle	71.73	745/3	55.91	1054/67	37.59	407/7	**72.67**	730/0	15.79	7113/2	2	15.79	7102/13	2	17.09	6402/713	2	<u>72.17</u>	742/2	$\text{SGCN-DR}_{\text{sum}}$
WikiPol	88.44	646/2	35.72	6838/579	46.52	598/11	**90.02**	543/0	7.79	138585/2	2	7.79	138556/31	2	7.82	132566/6021	2	<u>88.89</u>	618/2	SGCN_{sum}

Conclusions & Future Work

We discussed a recent advancement in 2PC, which relies on a GNN-based neural approach and introduces the notion of γ-polarity to improve the balance in the size of the polarized communities.

Future work:

- Extend Neural2PC to detect *k* polarized groups
- Devise a custom GNN model for the 2PC task

Thank you!
Questions?

2PC Objective

- Given $G = (V, E_+ \cup E_-)$ with unit weight, the objective is to

$$\max_{S_1 \cap S_2 = \emptyset} \frac{\sum_{h\in[2]}(|E_+(S_h)| - |E_-(S_h)|) + \sum_{h\neq l\in[2]}(|E_-(S_h, S_\ell)| - |E_+(S_h, S_\ell)|)}{|\cup_{h\in[2]} S_h|},$$

  where $E(S_h, S_\ell) = \{(i,j) \in E : i \in S_h, j \in S_\ell\}$ and $E(S_h) = E(S_h, S_h)$.
- Idea: prefer the S_1, S_2 that
  - have many consistent edges and few inconsistent edges, and
  - the size of $S_1 \cup S_2$ is as small as possible.

2PC Objective

- Given $G = (V, E_+ \cup E_-)$, the objective is to

$$\max_{S_1 \cap S_2 = \emptyset} \frac{\sum_{h \in [2]}(|E_+(S_h)| - |E_-(S_h)|) + \sum_{h \neq l \in [2]}(|E_-(S_h, S_\ell)| - |E_+(S_h, S_\ell)|)}{|\cup_{h \in [2]} S_h|},$$

- Denote $A \in \{0, \pm 1\}^{n \times n}$ the signed adjacency matrix of G.

2PC Objective

- Given $G = (V, E_+ \cup E_-)$, the objective is to

$$\max_{S_1 \cap S_2 = \emptyset} \frac{\sum_{h\in[2]}(|E_+(S_h)| - |E_-(S_h)|) + \sum_{h\neq l\in[2]}(|E_-(S_h, S_\ell)| - |E_+(S_h, S_\ell)|)}{|\cup_{h\in[2]} S_h|},$$

$$= \max_{S_1 \cap S_2 = \emptyset} \frac{\sum_{h\in[2]} \sum_{(i,j)\in E(S_h)} A_{i,j} + \sum_{h\neq\ell\in[2]} \sum_{(i,j)\in E(S_h,S_\ell)} (-A_{i,j})}{|\cup_{h\in[2]} S_h|}$$

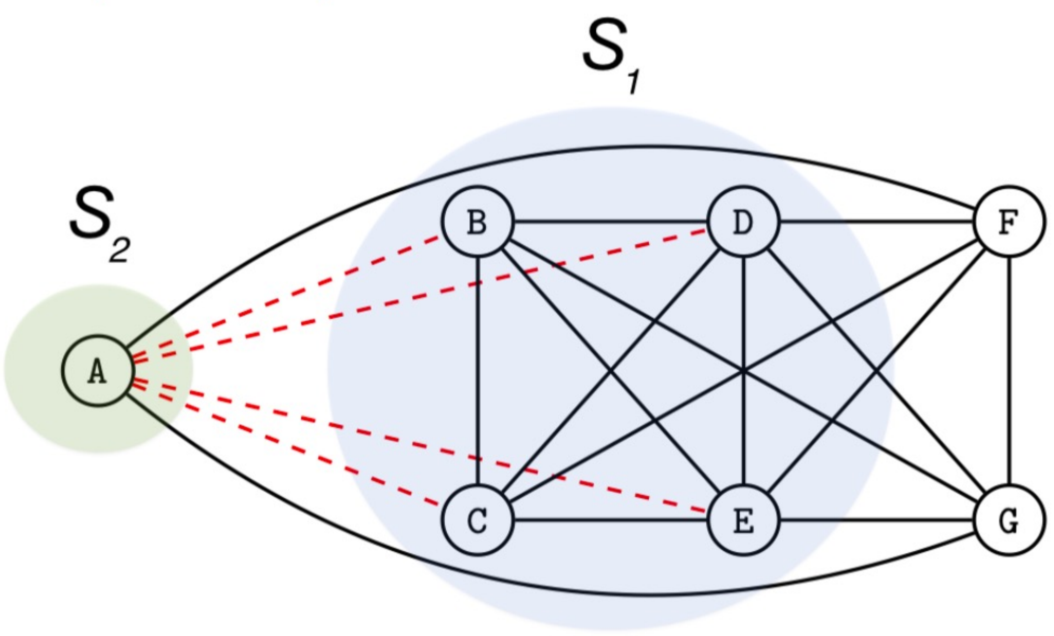
$$= \max\{\frac{x^T A x}{x^T x} : x \in \{-1, 0, 1\}^n \backslash \mathbf{0}\}. \qquad (1)$$

x is an assignment vector that encodes S_1 and S_2 (and S_0)

Limitations of Spectral Algorithms to 2PC

Limitation 2: The polarity function does not require or foster the detection of *size-balanced* communities.

- Detecting fine-grained polarization phenomena within signed networks is crucial, being essential to recognize minorities in polarization which might correspond to harmful situations like *isolation*



Both Eigensign and Random-Eigensign yield $\{\{B, C, D, E, F, G\}, \emptyset\}$ instead of the desired output $\{S_1, S_2\} = \{\{B, C, D, E\}, \emptyset\}$

2PC-Relaxed is in PTIME

Theorem 10 (Rayleigh–Ritz Theorem[3]). *Let* $\mathbf{A}_r$ *be a symmetric matrix with eigenvalues* $\lambda_1 \geq \ldots \geq \lambda_n$ *and corresponding eigenvectors* $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_n$. *Then*

$$\begin{aligned} \lambda_1 &= \max_{\boldsymbol{x} \neq \mathbf{0}} R(\mathbf{A}_r, \boldsymbol{x}) = \max_{\boldsymbol{x} \in \mathbb{R}^n, \|\boldsymbol{x}\|=1} \boldsymbol{x}^T \mathbf{A}_r \boldsymbol{x} \Longrightarrow \boldsymbol{x} = \boldsymbol{u}_1 \\ \lambda_n &= \min_{\boldsymbol{x} \neq \mathbf{0}} R(\mathbf{A}_r, \boldsymbol{x}) = \min_{\boldsymbol{x} \in \mathbb{R}^n, \|\boldsymbol{x}\|=1} \boldsymbol{x}^T \mathbf{A}_r \boldsymbol{x} \Longrightarrow \boldsymbol{x} = \boldsymbol{u}_n. \end{aligned} \tag{7}$$

$$R(\mathbf{A}_r, \boldsymbol{x}) = \frac{\boldsymbol{x}^T \mathbf{A}_r \boldsymbol{x}}{\boldsymbol{x}^T \boldsymbol{x}}, \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{x} \neq \mathbf{0},$$

Good news: finding the largest eigenvector of the signed adjacency matrix can be done through the Lanczos method in $O(t \cdot |E|)$, where t is the number of Lanczos iterations and E is the overall set of edges (positive and negative) in the signed graph.

Spectral Algorithms for 2PC

Algorithm 1 EIGENSIGN

Input: adjacency matrix A

1: Compute $\mathbf{v}$, the eigenvector corresponding to the largest eigenvalue λ_1 of A.
2: Construct $\mathbf{x}$ as follows: for each $i \in \{1, \ldots, n\}$, $x_i = sgn(v_i)$.
3: Output $\mathbf{x}$.

Algorithm 2 RANDOM-EIGENSIGN

Input: adjacency matrix A

1: Compute $\mathbf{v}$, the eigenvector corresponding to the largest eigenvalue λ_1 of A.
2: Construct $\mathbf{x}$ as follows: for each $i \in \{1, \ldots, n\}$, run a Bernoulli experiment with success probability $|v_i|$. If it succeeds, then $x_i = sgn(v_i)$, otherwise $x_i = 0$.
3: Output $\mathbf{x}$.

- Both algorithms first compute the optimal solution to the 2PC-Relaxed problem (line 1)
- The two algorithms differ in their approach to constructing a solution to 2PC from the optimal solution to 2PC-Relaxed

Enhancements for practical use: Rounding Step

Limitation: EIGENSIGN always outputs a solution involving all the vertices in the network

Solution: rounding the continous vector $z \in [-1, +1]^{|V|}$ with a threshold

$$Z_i = \{\lceil \mathbf{z}[u] \rfloor_i \mid u \in V\}.$$

$$\forall u \in V: \ \mathbf{x}_\tau[u] = \begin{cases} \operatorname{sgn}(\mathbf{z}[u]), & \text{if } |\mathbf{z}[u]| \geq \tau. \\ 0, & \text{otherwise.} \end{cases}$$

$$\text{ROUND}(\mathbf{z}) = \underset{\mathbf{x} \in \{\mathbf{x}_\tau \mid \tau \in Z_i\}}{\arg\max} \ p(\mathbf{x}, \mathbf{A}).$$

Neural2PC Framework

Algorithm 1 Neural2PC

Input: Signed graph $G = (V, E^+, E^-)$ with signed adjacency matrix $\mathbf{A}$; node feature matrix $\mathbf{H}_0 \in \mathbb{R}^{|V| \times d_I}$; positive integer e_{max} (number of epochs); positive real number α (learning rate); real number λ (regularization hyperparameter)

Output: vector $\mathbf{x}_{best} \in \{-1, 0, 1\}^{|V|}$

```
x_best ← 0^{|V|},  p_best ← −∞,  θ ← parameter initialization
for e = 1, ..., e_max do
    z ← f_θ(G, H_0)
    x ← ROUND(z)
    if p(x, A) > p_best then
        x_best ← x,  p_best ← p(x, A)
    end if
    θ ← gradient-descent step over θ, with loss L_2PC(z, A, λ) (Eq. (5)) and learning
    rate α
end for
```

$$f_\theta(G, \mathbf{H}_0) = \tanh(\textsc{nn}(\textsc{sgnn}(G, \mathbf{H}_0)))$$

Example: Issues with the Polarity Objective

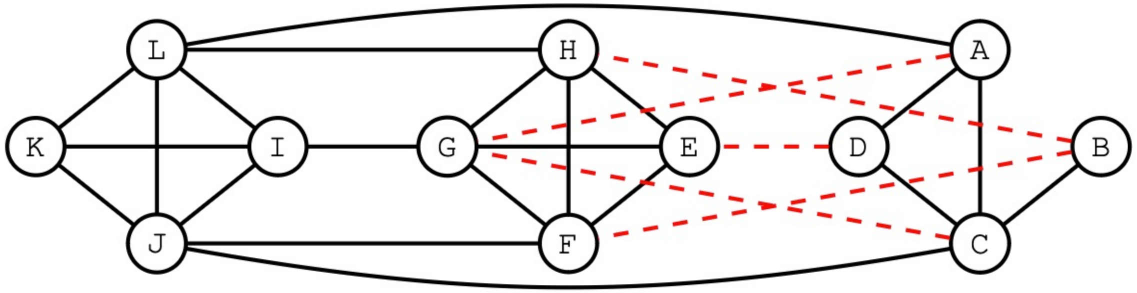


Fig. 3. Example signed graph where, unlike basic polarity, γ-polarity detects effective polarized communities that are also size-balanced.

P1 = {{A,B,C,D}, {E,F,G,H}}
P2 = {∅,{E,F,G,H,I,J,K,L}}.

The polarity of P1 and P2 is (15×2)/8 = 3.75, and (15×2)/8 = 3.75, respectively. Despite, P1 and P2 *both* exhibit the highest polarity, P1 is much more *size-balanced*, thus intuitively preferable. Instead, the γ-polarity of P1 is higher than P2 for any $\gamma > 1$.

Results on Synthetic Datasets

Table 6 Performance of the proposed Neural2PC vs. competing methods on synthetic datasets, in terms of F_1-score and polarity (Def. 1) as a function of the noise parameter η.

method	criteria	η						
		0	0.1	0.2	0.3	0.4	0.5	0.6
EIGEN	F_1	**1.0**	.998	<u>.998</u>	<u>.998</u>	**.995**	<u>.972</u>	.307
	pol.	**199**	168.04	<u>140.31</u>	<u>110.5</u>	**81.44**	<u>50.02</u>	35.52
R-EIGEN	F_1	**1.0**	.911	.861	.829	.755	.678	.309
	pol.	**199**	144.23	112.96	87.55	61.98	39.4	30.67
PIVOT	F_1	.997	.584	.426	.338	.305	.28	.236
	pol.	198	61.66	32.56	17.06	8.5	4.06	3.1
GREEDY	F_1	.667	.644	.621	.63	.605	.334	.264
	pol.	99	79.79	62.64	50.76	38.77	30.31	28.86
SPONGE(K)	F_1	**1.0**	**1.0**	.714	.714	.714	.551	.247
	pol.	**199**	**168.62**	28.01	23.96	15.81	23.36	23.85
	k	3	3	2	2	2	3	3
BNC(K)	F_1	.5	.5	.5	.167	.167	.476	**.374**
	pol.	-0.2	-0.26	-0.75	1.86	-0.98	1.01	1.09
	k	2	2	2	2	2	3	2
SSSNET(K)	F_1	**1.0**	**1.0**	.99	.99	.976	.365	.267
	pol.	**199**	**168.62**	140.2	109.97	74.99	34.83	26.89
	k	3	3	3	3	3	2	3
Neural2PC	F_1	**1.0**	**1.0**	**1.0**	**1.0**	**.995**	**.997**	.341
	pol.	**199**	**168.62**	**140.65**	**110.69**	**81.44**	**50.27**	**36.16**

Synthetic datasets generated with the *modified signed stochastic block model* (M-SSBM) as a generator, that has 3 parameters:

- number of nodes n
- size of the ground-truth communities $n_c = |S_1| = |S_2|$
- a noise parameter $\eta \in [0, 1]$ to control edge probabilities

Parameters setting: $n = 1000$, $n_c = 100$ and varied $\eta \in [0, 0.6]$ with stepsize 0.1

Execution Times

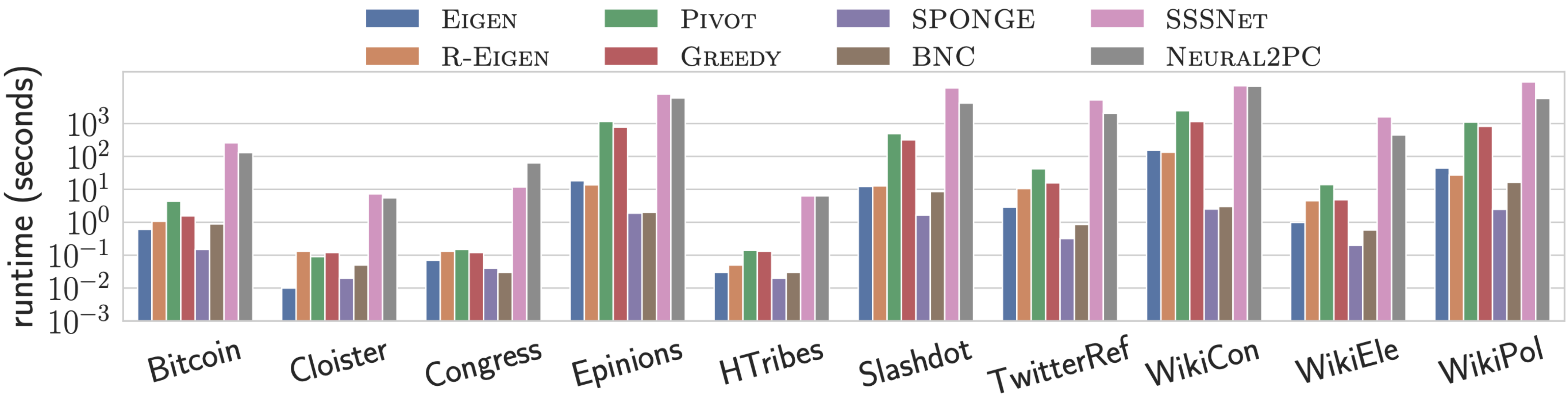


Figure. Execution times (in seconds) of the proposed Neural2PC method vs. competing methods on real-world network datasets.