

Polarized Communities meet Densest Subgraph: Efficient and Effective Polarization Detection in Signed Networks

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Overview

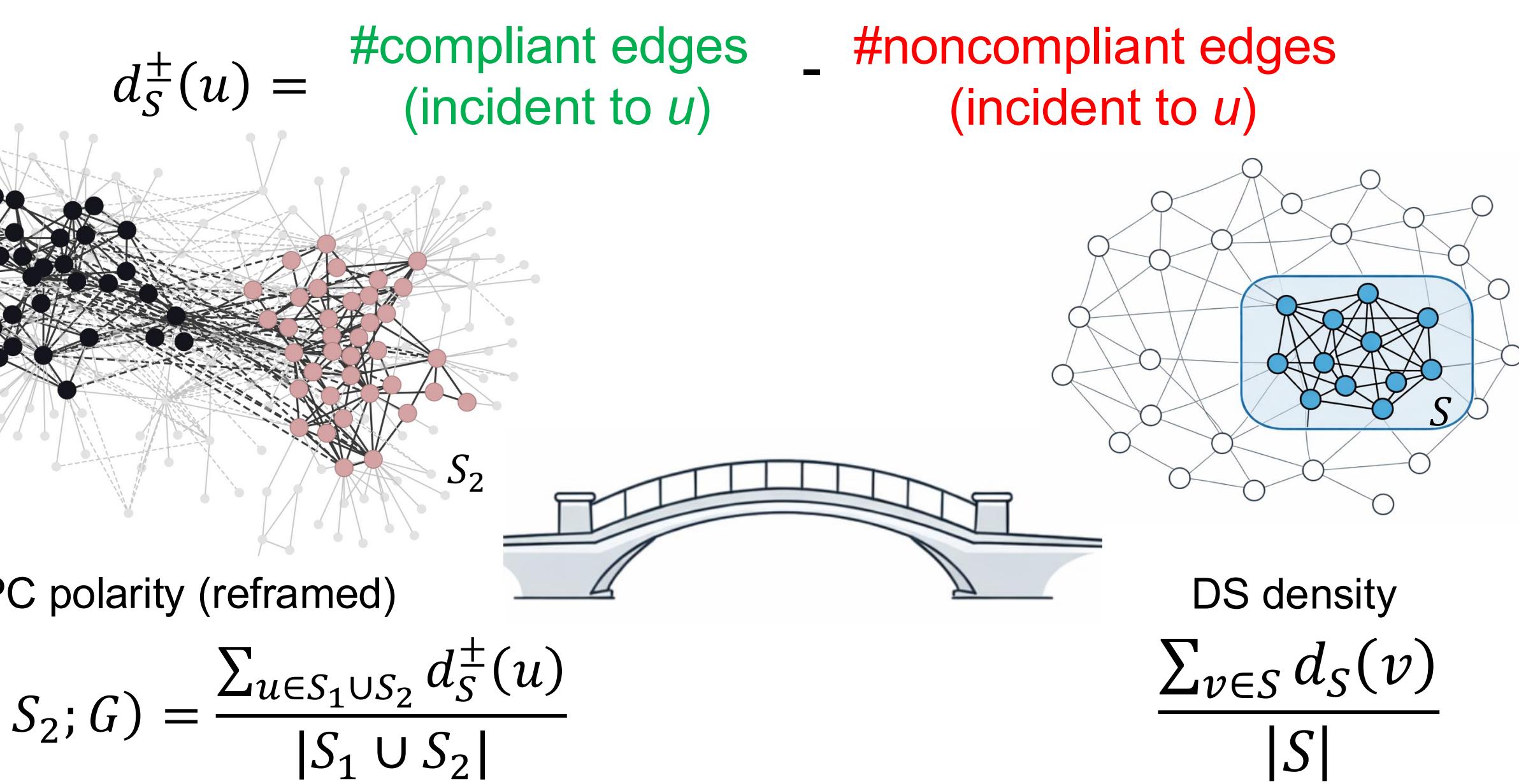
- **Problem & Motivation.** The **2-Polarized-Communities (2PC)** task (Bonchi et al., 2019) seeks two disjoint node sets in a *signed network* that are internally cohesive (mostly **positive intra-group edges**) and mutually antagonistic (mostly **negative inter-group edges**), while keeping their total size relatively small. Prior work has neither examined the implicitly optimized density measure by 2PC nor leveraged the rich algorithmic toolbox developed for the **Densest Subgraph (DS)** problem.
- **Key Idea.** We show that 2PC can be viewed as a densest-subgraph-like optimization problem on signed graphs, where the optimized density is defined via a signed degree measure, dubbed **net degree balance**, that rewards **compliant edges** and penalizes **noncompliant ones**.
- **Algorithm & Evaluation.** Building on this bridge, we propose Greedy-2PC, a **greedy peeling algorithm**, seeded by a spectral relaxation. We evaluate Greedy-2PC on real-world and synthetic signed networks, conducting a comparative evaluation against Pivot (Bansal et al., 2004), BNC (Chiang et al., 2012), SPONGE (Cucuringu et al., 2019), SSSNet (He et al., 2022), TIMBAL (Ordozgoiti et al., 2020), EIGEN (Bonchi et al., 2019), Neural2PC (Gullo et al., 2024), and RH (Chen et al., 2024).

Bridging 2PC and DS

2PC. Given a signed graph $G = (V, E^+, E^-)$, find $S_1, S_2 \subseteq V$, that maximizes:

$$p(S_1, S_2; G) = \frac{\sum_{i \in \{1,2\}} (|E^+(S_i)| - |E^-(S_i)|) + |E^-(S_1, S_2)| - |E^+(S_1, S_2)|}{|S_1 \cup S_2|}$$

Key concept. *Net Degree Balance:* For any node u , its net degree balance w.r.t. a pair of polarized communities $S = \{S_1, S_2\}$ is



The Greedy-2PC Algorithm

Algorithm 2 Greedy-2PC

Input: Signed graph $G = (V, E^+, E^-)$

Output: A pair $\widehat{S} = \{S_1, S_2\}$ of polarized communities

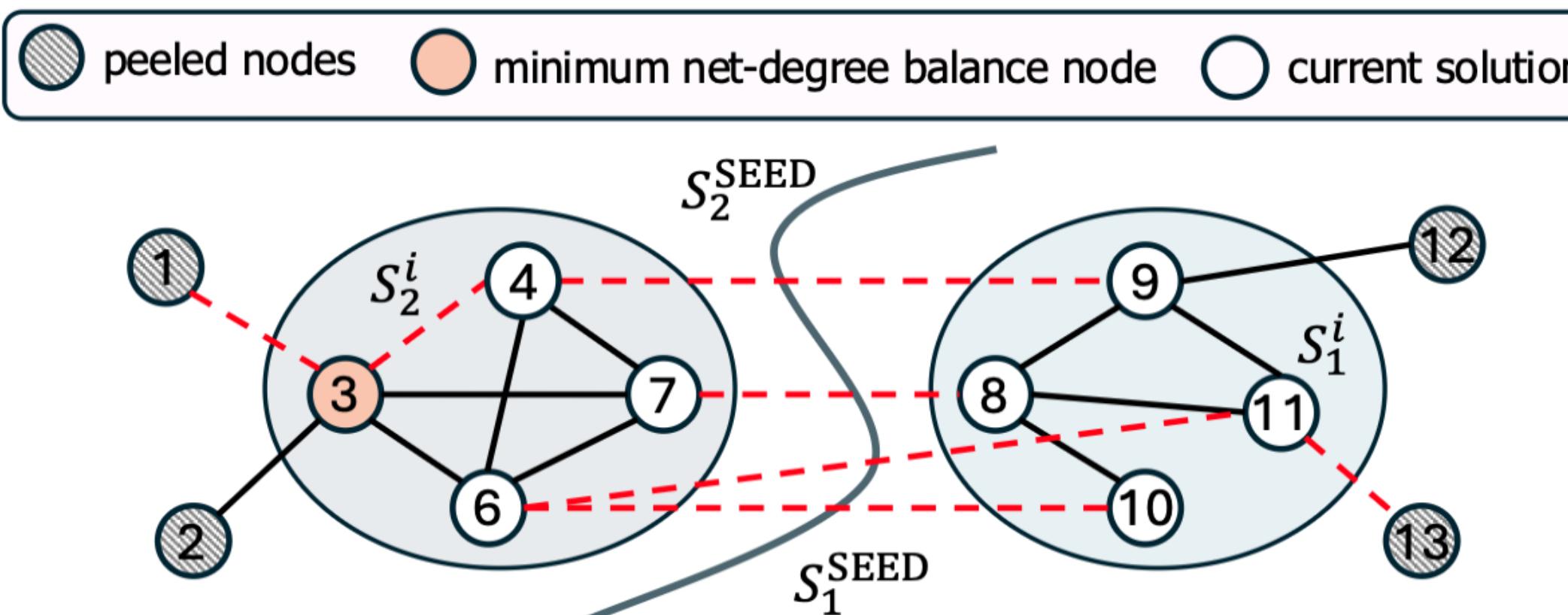
- $S^{\text{SEED}} \leftarrow \text{EIGEN-FULL}(G)$ {Algorithm 1}
- $\widehat{S} \leftarrow S^{\text{SEED}}, S^n \leftarrow S^{\text{SEED}}, i \leftarrow n$
- while** $|S_1^i \cup S_2^i| > 1$ **do**
- $u = \arg \min_{v \in S_1^i \cup S_2^i} d_S^\pm(v)$
- remove u from S_1^i or S_2^i in S^i
- if** $p(S_1^i, S_2^i; G) > p(\widehat{S}_1, \widehat{S}_2; G)$ **then**
- $\widehat{S} \leftarrow S^i$
- end if**
- $i \leftarrow i - 1$
- end while**
- return** \widehat{S}

Algorithm 1 EIGEN-FULL

Input: Signed graph $G = (V, E^+, E^-)$

Output: A pair $S = \{S_1, S_2\}$ of polarized communities

- Compute \mathbf{z}^* , the eigenvector corresponding to the largest eigenvalue λ_1 of the signed adjacency matrix \mathbf{A} of G
- $S_1 = \{u \in V : z_u^* \geq 0\}, S_2 = \{u \in V : z_u^* < 0\}$



Key Benefits of Greedy-2PC

- Highly efficient:** Greedy-2PC runs in $O(|V| + |E|)$ time.
- Effective in practice:** It consistently outperforms SOTA methods for 2PC.
- Theoretical (additive) guarantees:** Under condition $S_1^* \subseteq S_1^{\text{seed}}, S_2^* \subseteq S_2^{\text{seed}}$, $p(\widehat{S}_1, \widehat{S}_2; G) \geq OPT - c$, where c is a term related to the (maximum) #noncompliant edges of the peeled nodes.
- Simple to implement.**

Results

Comparative evaluation. Greedy-2PC outperforms competing methods on 11 real-world datasets in polarity and agreement ratio, and on synthetic graphs generated with a *modified Signed Stochastic Block Model* (with ground-truth communities) in F1 and polarity across noise levels η , while remaining highly efficient and scalable on large networks (poster: we report only the strongest competitors for effectiveness; full tables are in the paper).

method	criteria	Bitcoin	Cloister	Congress	Epinions	HTribes	Slashdot	TwitterRef	WikiCon	WikiEle	WikiPol	Word
EIGEN-FULL	pol. a.r.	6.23 0.93	6.11 0.72	4.37 0.96	8.89 0.91	5.50 0.88	8.08 0.83	39.03 0.92	28.78 0.91	19.58 0.85	8.57 0.91	9.87 0.76
EIGEN	pol. a.r.	29.52 0.95	7.45 0.94	6.58 0.98	128.72 0.95	6.18 1.00	79.7 0.99	174.1 0.99	175.65 0.95	71.73 0.93	88.44 0.96	24.02 0.98
RH	pol. a.r.	29.30 0.96	7.39 0.91	6.50 0.98	170.54 1.00	6.18 1.00	82.39 0.99	174.40 1.00	190.52 0.96	72.64 0.92	89.50 0.97	24.28 0.97
NEURAL2PC	pol. a.r.	30.28 0.95	7.45 0.94	6.64 0.98	171.1 1.00	6.18 1.00	82.25 0.99	174.35 0.99	187.29 0.95	72.17 0.92	88.89 0.96	24.32 0.97
Greedy-2PC	pol. a.r.	30.57 0.96	7.45 0.94	6.70 1.00	171.17 1.00	6.18 1.00	82.80 0.99	174.66 1.00	196.73 0.97	72.79 0.92	90.07 0.97	25.03 0.98

method	criteria	0	0.1	0.2	0.3	0.4	0.5	0.6
EIGEN-FULL	F_1 $pol.$.333 39.80	.334 44.86	.333 44.55	.333 40.51	.334 37.94	.333 30.23	.264 28.82
EIGEN	F_1 $pol.$	1.0 199	.998 168.04	.998 140.31	.998 110.5	.995 81.44	.972 50.02	.307 35.52
RH	F_1 $pol.$	1.0 199	.99 167.89	1.0 140.65	1.0 110.69	1.0 81.44	.81 45.83	.25 35.76
NEURAL2PC	F_1 $pol.$	1.0 199	1.0 168.62	1.0 140.65	1.0 110.69	1.0 81.44	.995 50.27	.341 36.16
Greedy-2PC	F_1 $pol.$	1.0 199	1.0 168.62	1.0 140.65	1.0 110.69	1.0 81.44	.988 50.28	.293 38.1

