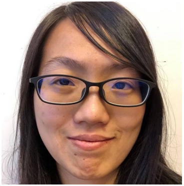
Discovering conflicting groups in signed networks

Ruo-Chun Tzeng[1] Bruno Ordozgoiti[2] Aristides Gionis[1,2]



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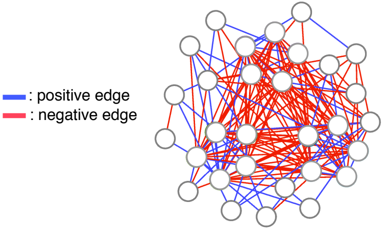
34th Conference on Neural Information Processing Systems

Problem: finding the conflicting groups

- Given a signed network, e.g., social networks with edge sign indicating agree/disagree.



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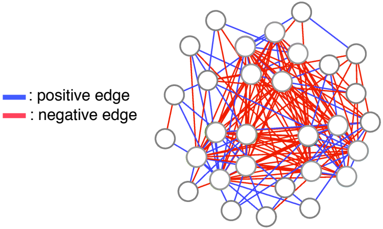

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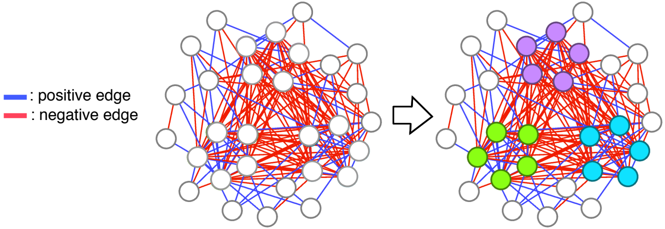
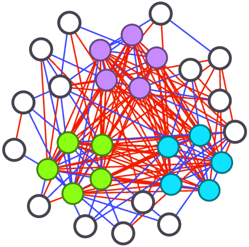


- People form into groups with likely-minded or common enemies.
- Our goal: find the conflicting groups with mostly $+$ intra-group edges and mostly $-$ inter-group edges.

Challenge: existence of neutral nodes



- Reason: e.g., not all people have strong opinions or firm stances.
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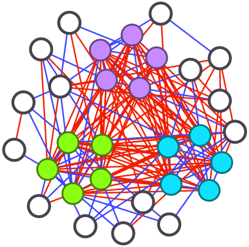

- Reason: e.g., not all people have strong opinions or firm stances.
- Neutral nodes might behave differently to both the conflicting groups or to themselves.
- Methods partitioning the entire network such as signed clustering [4, 5] and correlation clustering [1] are not efficient.

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  - Neutral nodes: $\{i : x_i^* = 0\}$.

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- It is APX-hard [2] to solve Eq (1) for $k = 2$.
- **Our contribution:** approximation algorithms by rounding the leading eigenvector of $A^{(j-1)}$.

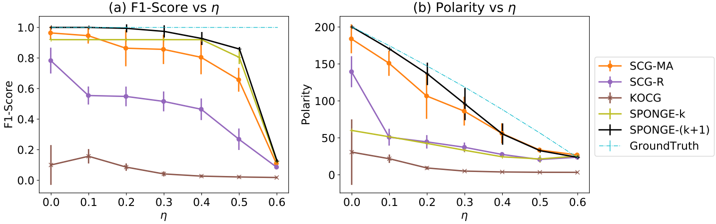
  (Minimum Angle) competitive in practice but hard to be analyzed.
  (Randomized) tight $\mathcal{O}(\sqrt{n})$ integrality gap when $k = 2$.

Experiment Results

- Real-world networks:

	Bitcoin	WikiVote	Referendum	Slashdot	WikiConflict	Epinions	Wikipolitics
$\|V\|$	5 881	7 115	10 884	82 140	116 717	131 580	138 587
$\|E\|$	21 492	100 693	251 406	500 481	2 026 646	711 210	715 883
$\|E_-\|/\|E\|$	0.2	0.2	0.1	0.2	0.6	0.2	0.1
SCG-MA	**14.6**	**45.5**	**84.9**	**37.8**	**102.6**	**88.8**	**57.5**
SCG-R	5.0	9.7	39.8	7.3	16.2	39.4	5.5
KOCG	4.4	5.5	8.8	2.6	4.5	8.7	4.8
SPONGE-k	5.0	15.8	41.5	—	—	—	—
SPONGE-(k+1)	0.8	1.0	1.0	—	—	—	—

- Synthetic:



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