Link Classification and Clustering in Signed Graphs

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What it is a signed graph?

- Graphs model relationships between entities
- **homophily** assumption: linked entities tend to share common properties
- the strength of these relations is quantified by weights $w_{u,v} \in \mathbb{R}^+$
- allowing weights to be negative gives new semantics to edges:
  - dissimilarity
  - distrust
  - enmity

Problems and applications

1. Link classification: **predict the signs of a set of edges**, given the graph structure and the signs of the other edges. Applications in:
   - understanding trust dynamic and communities formation
   - testing social theories at a large scale
   - **recommending products**

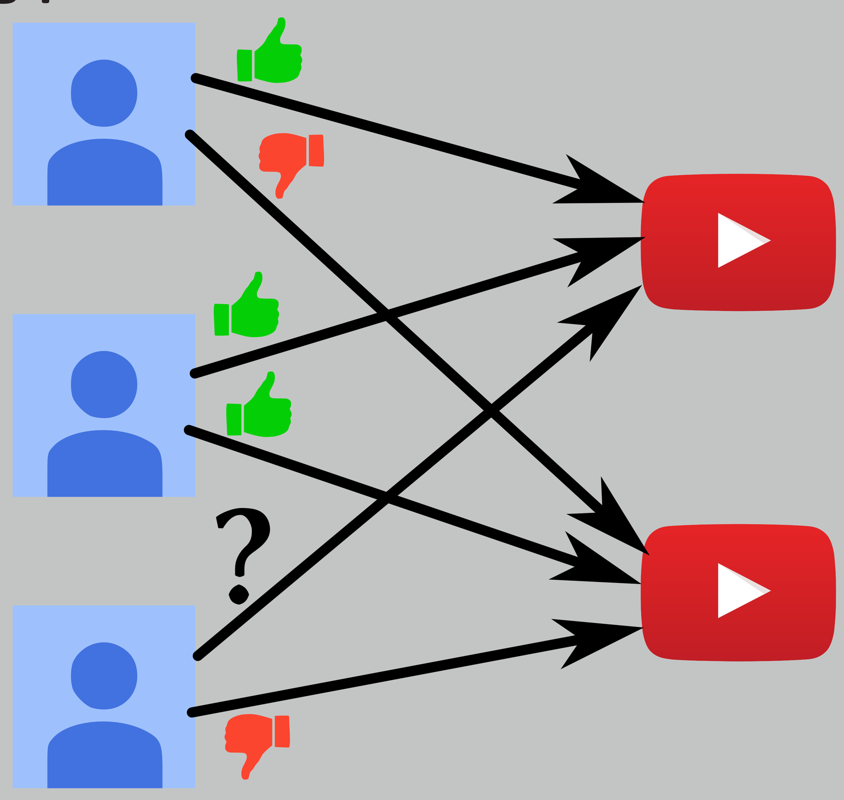


Figure: Youtube users/votes/videos bipartite signed graph

2. Correlation Clustering: **find a partition of the nodes minimizing the number of disagreement edges** (i.e. positive edges between clusters and negative edges within clusters). Used in:
   - image segmentation
   - solving co-reference task in natural language processing
   - identifying genes relationship
   - entity resolution
   - aggregation of clusterings

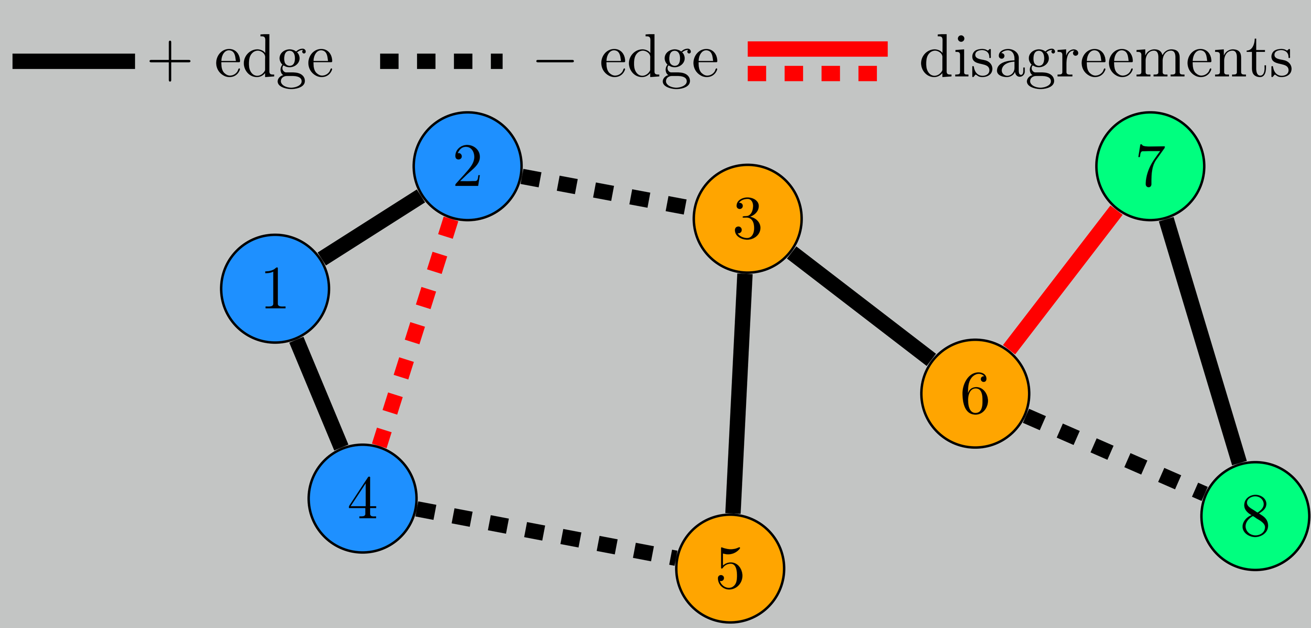


Figure: The optimal clustering of this signed graph has a cost of 2.

Link classification: current approaches

- Batch setting
  - train logistic regression on triangle patterns [7]
  - train logistic regression on higher order cycles [3]
  - train SVM on frequent subgraphs [9]

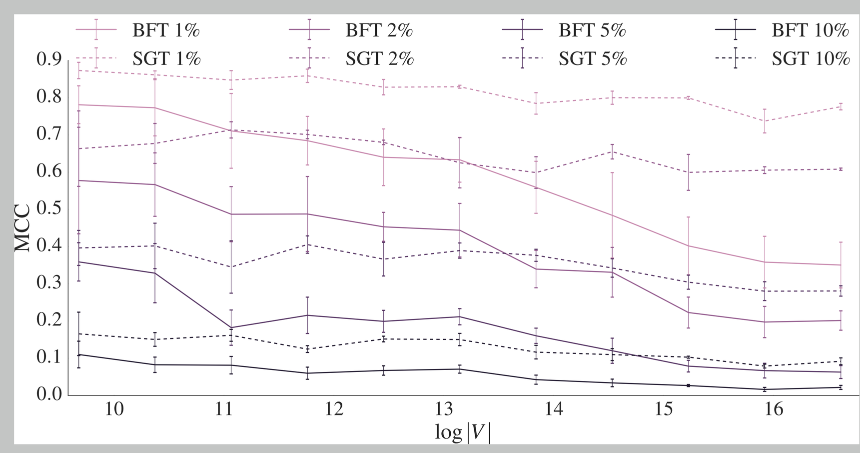
  Achieve good generalization but require a large training set
- Active setting: Parsimoniously select a training set to minimize the prediction error on the testing set [2]

Link classification: our goals

- Devise efficient graph sparsifiers T
  - In the p-stochastic two clusters case, all the signs of T are queried
  - For any $(u, v) \in E$, predict $\hat{y}_{u,v} = \prod_{e \in path^T_{u,v}} y_e$
  - Thus we want $path^T_{u,v}$ to be short for all $(u, v) \in E$
- Be adaptive, i.e. select at each step the edges adding the more information given those already revealed

Link classification: preliminary results

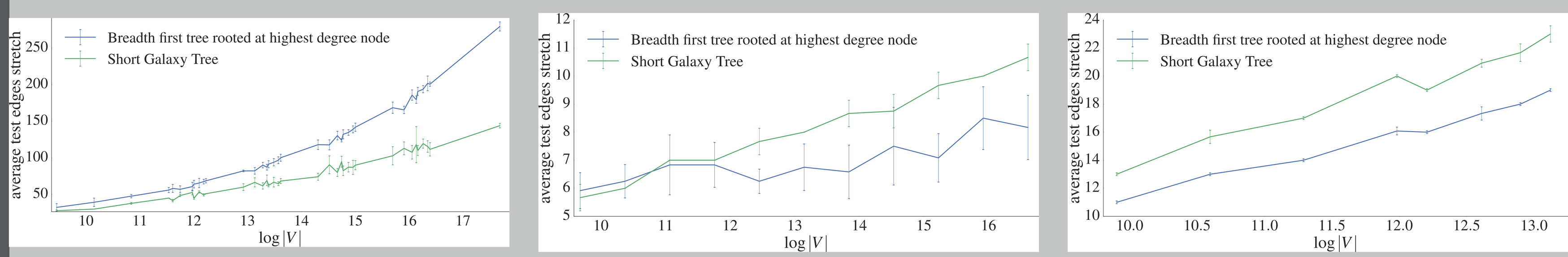
- T is a spanning tree of G
- $E_{test} = E \setminus T$
- $stretch = \frac{1}{|E_{test}|} \sum_{(u,v) \in E_{test}} |path^T_{u,v}|$
- The lower the stretch, the better the prediction
- Use Matthews Correlation Coefficient to assess binary prediction



$$\mathrm{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} = \pm\sqrt{\frac{\chi^2}{n}}$$

Table: MCC on 3 real datasets. Our method is more robust, albeit slightly less accurate

	Wikipedia	Slashdot	Epinion
$\lvert V \rvert$	7 065	82 052	119 070
$\lvert E \rvert$	99 936	498 527	701 569
fraction of + edges	78.5%	76.4%	83.2%
Breadth First Tree	.185 (.075)	.159 (.074)	.255 (.115)
Our Tree	.164 (.045)	.169 (.028)	.216 (.030)



Grid Pref. Attachment Triangle

Correlation Clustering: current approaches

- APX-hard problem
- On complete graphs, KwikCluster algorithm provides a simple and efficient combinatorial 3-approximation [1]

  function KwikCluster($G = (V, E)$)
    while not all nodes are clustered **do**
      $pivot \leftarrow$ pick a node in V at random
      put $pivot$ in its own cluster
      add all its positive neighbors
      remove them from G
- On general graphs, the approximation ratio is $O(\log n)$ and is obtained by solving a large SDP.

Correlation Clustering: our goals

- A combinatorial algorithm for general graphs, retaining the optimal $O(\log n)$ approximation ratio
- An idea would be to complete the graph through simple rules drawn from strong balance theory [5]
- Address the scalability issue, by studying parallel [8] and distributed (MapReduce or Pregel-like framework) [4] versions of KwikCluster, as well as parallelized BOEM post processing [6]

Correlation Clustering: preliminary results

- Planted model: k clusters of roughly n nodes each and consistent edge signs
- Flip the signs of 7% edges and assume it is the optimal number of errors ϕ

Table: The ratio of our number of mistakes to ϕ is constant

k	5	2	30	2	20	10	15
n_i	15	65	6	100	12	25	35
nodes	75	130	180	200	240	250	525
ratio	2.2	2.6	1.6	3.0	1.7	2.1	1.9

References

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