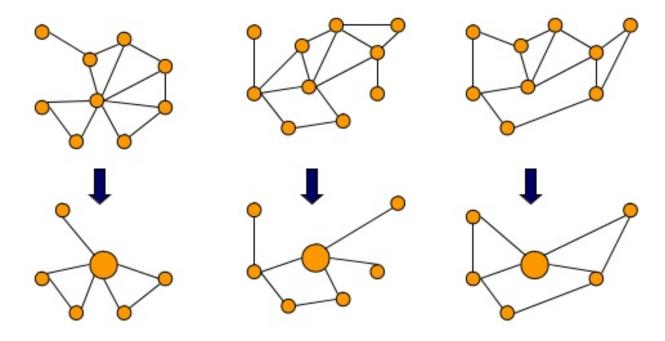
Solving graph compression via optimal transport

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Graph compression



- Improved performance
 - reduced storage requirements
 - faster algorithms
 - removal of spurious features for downstream tasks
- summarization/better visualization

Image source: Houw Liong The, Lecture 12 on graph mining.

Standard approach 1: Compression via coarsening

Find a matching, merge the matched vertices, and repeat.

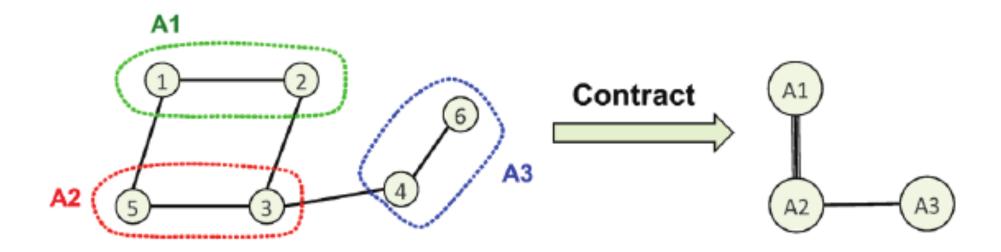


Image source: Aydin Buluc, SIAM Journal on Scientific Computing, 2011.

Standard approach 2: Compression via sparsification

Keep the vertices intact, and delete edges instead.

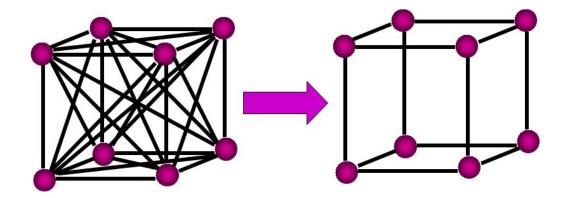


Image source: Daniel Spielman, Workshop on Algorithms for Modern Massive Datasets.

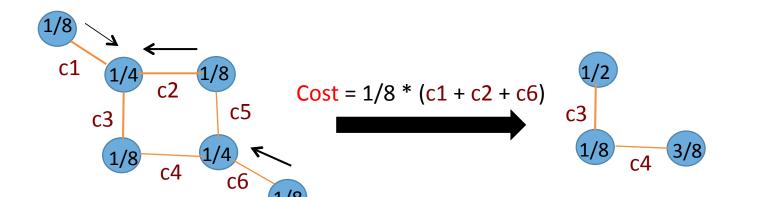
What's missing?

- Existing approaches try to preserve the graph spectrum, cuts etc.
 - oblivious to attribute information, e.g., graph labels and node features
- Compression criteria not given as an optimization problem
 - less suitable for robustly linking with downstream tasks

Optimal transport cost on a graph

Suppose we fix an initial distribution and a target distribution on the nodes.

What's the minimum cost to transfer mass if we only allow flow along the edges?



Note that here the target distribution is over a smaller support (only 3 nodes)

Example: Cost associated with the indicated flow (not necessarily optimal)

How do we compute the optimal transport (OT) cost?

Previously known for directed graphs only. We extend to the undirected setting.

$$\min_{\substack{J^+,J^-\in\mathbb{R}^{|E|}\\ \mathbf{0} \leq J^+,J^-}} \sum_{e\in E} c(e)(J^+(e)+J^-(e))$$

$$\mathrm{s.t.} \qquad F^\top(J^--J^+) = \rho_1-\rho_0$$

$$c(e): \text{ cost of transporting unit flow on edge } e$$

$$J^+(e),J^-(e): \qquad \text{flow on } e \text{ in two directions}$$

$$F: \text{ unoriented (unsigned) incidence matrix}$$

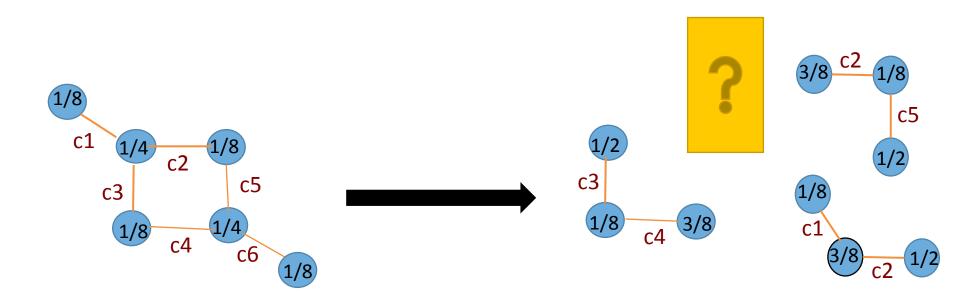
$$\rho_0,\rho_1: \qquad \text{initial and target distributions}$$

Outline of our approach

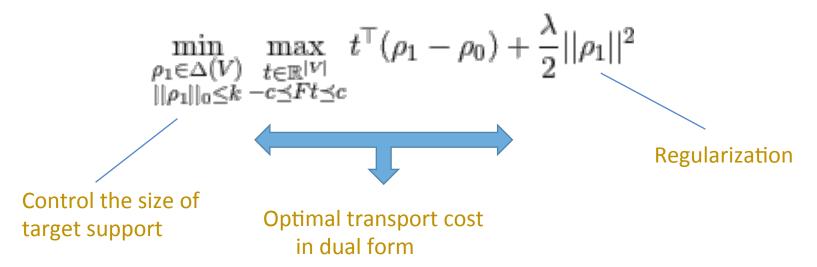
- Define OT on a (directed/annotated) graph
 - cost depends on specified prior information
 - e.g. importance of nodes and their labels or attributes
 - thus can be informed by the downstream task
- Optimize the target distribution (its support)
 - using a regularized OT cost as the criterion
 - key step: we show how subgraph selection is found (yet to be illustrated)

Challenge: Target distribution is not known

 Combinatorial problem! Need to compute optimal cost relative to every target distribution over the specified size of support



Optimization formulation



Solving the optimization

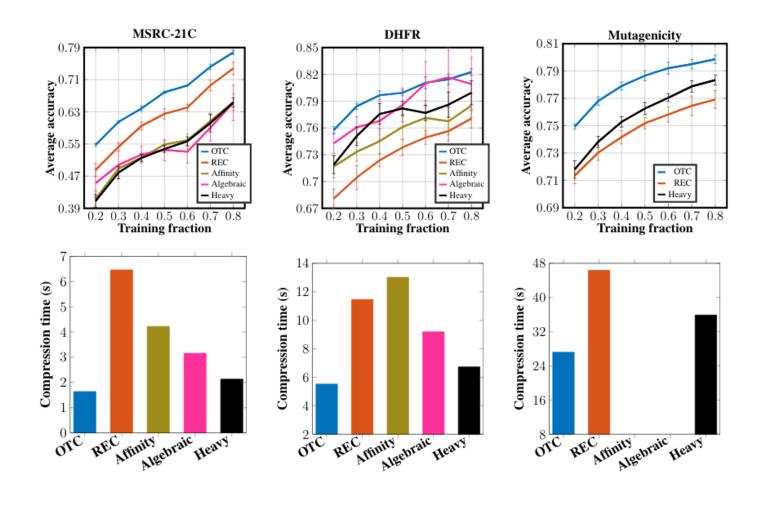
• Non-convex due to sparsity constraint $\|\rho_1\|_0 \le k$

$$\min_{\substack{\rho_1 \in \Delta(V) \\ ||\rho_1||_0 \le k}} \max_{\substack{t \in \mathbb{R}^{|V|} \\ -c \le Ft \le c}} t^{\top} (\rho_1 - \rho_0) + \frac{\lambda}{2} ||\rho_1||^2$$

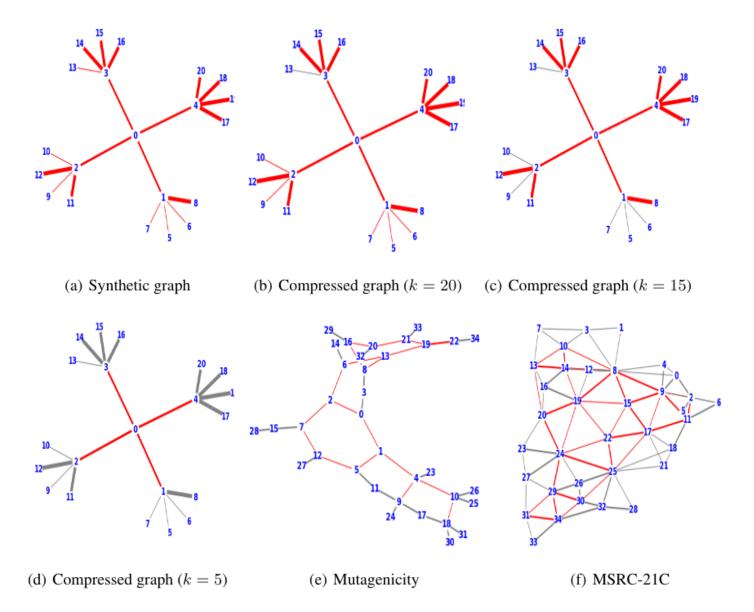
• Introduce Boolean variables
$$\epsilon$$
 and deduce $\min_{\epsilon \in \{0,1\}^{|V|}} \min_{\substack{\overline{\rho}_1 \in \mathbb{R}^{|V|} \\ \overline{\rho}_1 \odot \epsilon \in \Delta(V) - c \preceq Ft \preceq c}} t^{\top}(\overline{\rho}_1 \odot \epsilon - \rho_0) + \frac{\lambda}{2} ||\overline{\rho}_1||^2$

• Relax each coordinate of ϵ to [0, 1] and solve. Perform rounding to have at most k vertices. The spanned subgraph is our compressed graph.

Performance on standard graph datasets



Qualitative results on synthetic and real data



Conclusion

- A new principled approach to compressing graphs
- Prior information can be seeded easily
- Suitable for downstream tasks such as classification
- Interesting directions
 - complement encoding (compression) with decoding (decompression)
 - expand the framework to allow additional constraints (e.g. requiring the compressed graph to be connected)
 - higher order, structured graph compression