

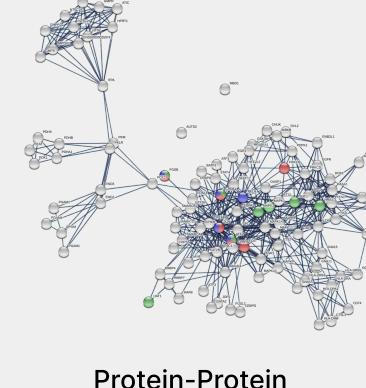
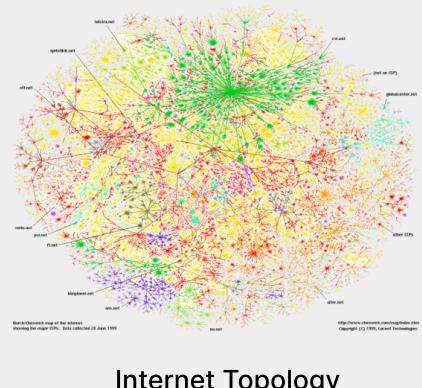
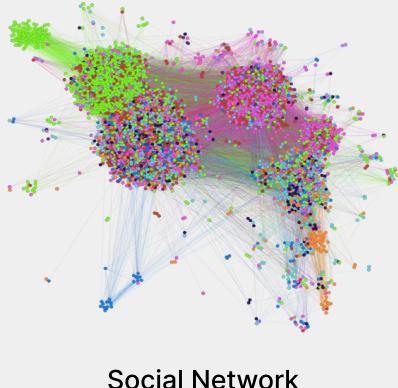


SparRL: Graph Sparsification via Deep Reinforcement Learning

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1. Motivation

- Graph size often dominates the efficiency of graph analytic workloads!
- Graphs are **ubiquitous** and **huge** in size in various domains



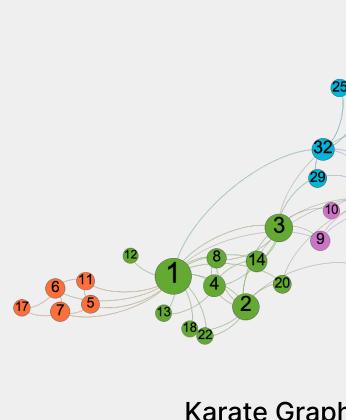
Social Network

Internet Topology

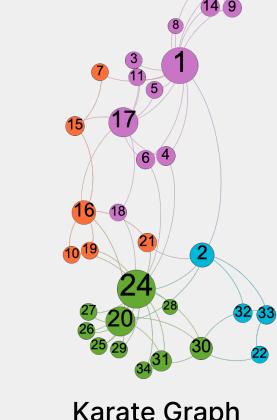
Protein-Protein Interaction Network

2. Problem

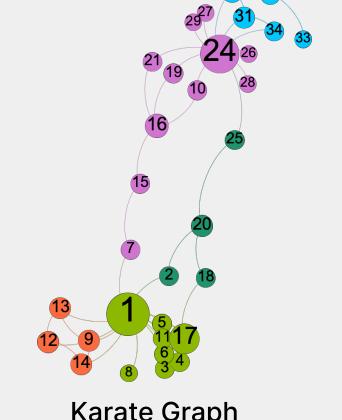
- **Graph sparsification** is a data reduction technique where an edge-reduced graph of similar structure is preferred.
- Derive $G' \subseteq G$ such that $F(G') \approx F(G)$



Karate Graph



Karate Graph (20% edge pruned)



Karate Graph (40% edge pruned)

3. Contributions

We propose a deep reinforcement learning algorithm for objective invariant graph sparsification

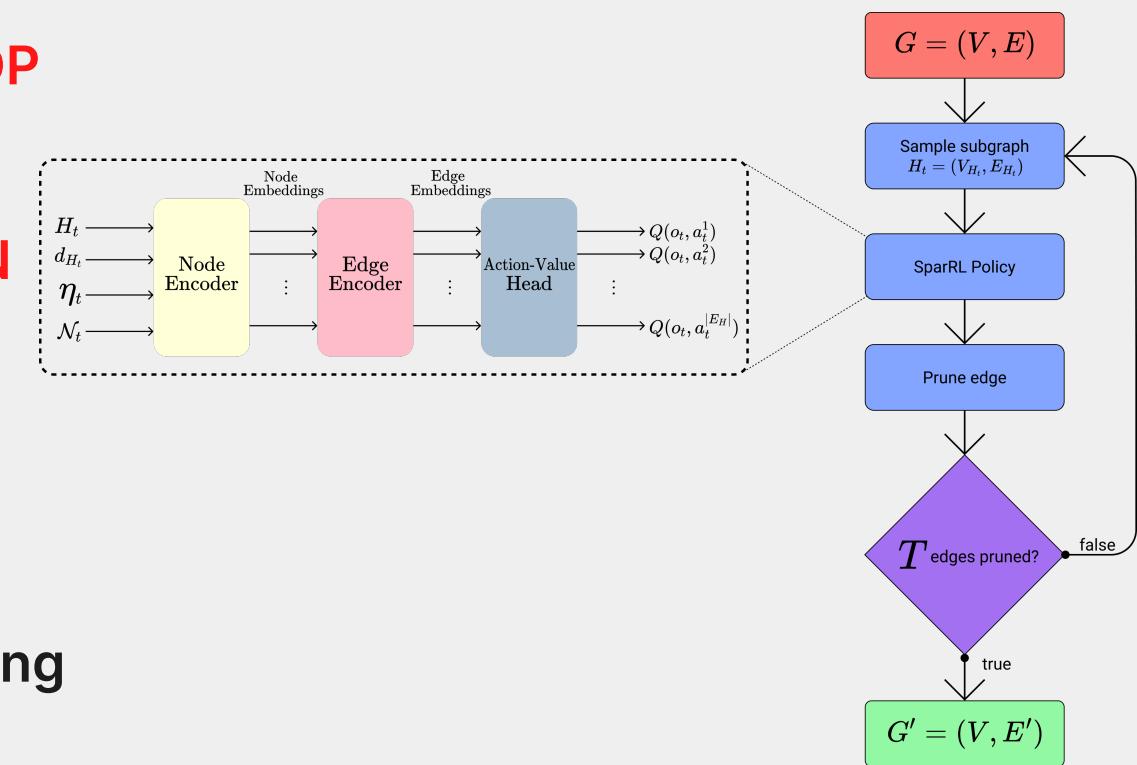
- Highly configurable through reward function
Any scalar objective that can be modeled as a function of the graph can be optimized!
- Shown to outperform all other baselines on all graphs and objectives

- We model graph sparsification as a POMDP $(\mathcal{S}, \mathcal{A}, P, R, \Omega, \mathcal{O}, \gamma)$

- Solved using Double DQN
The policy outputs a value for each edge and we prune the edge with the highest value

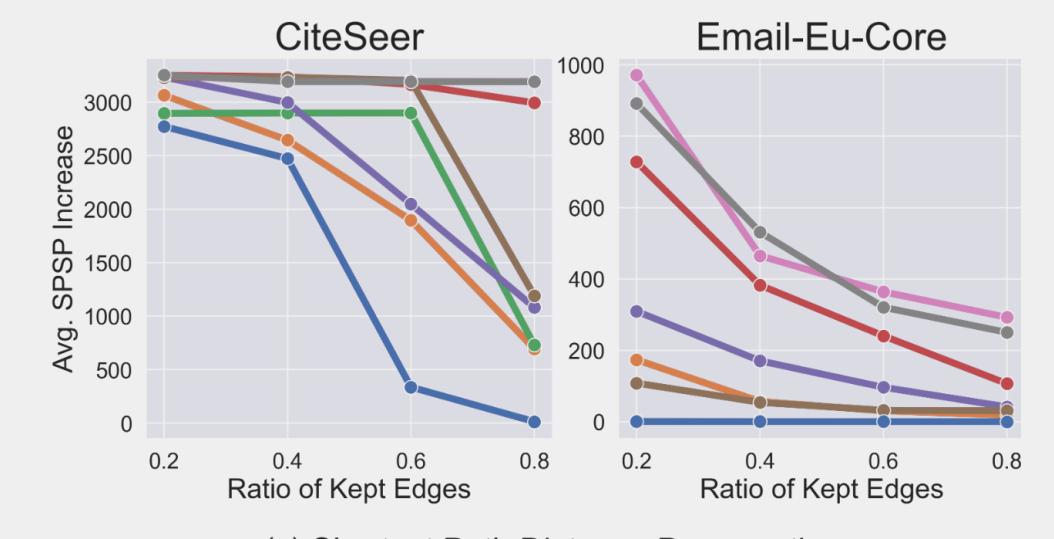
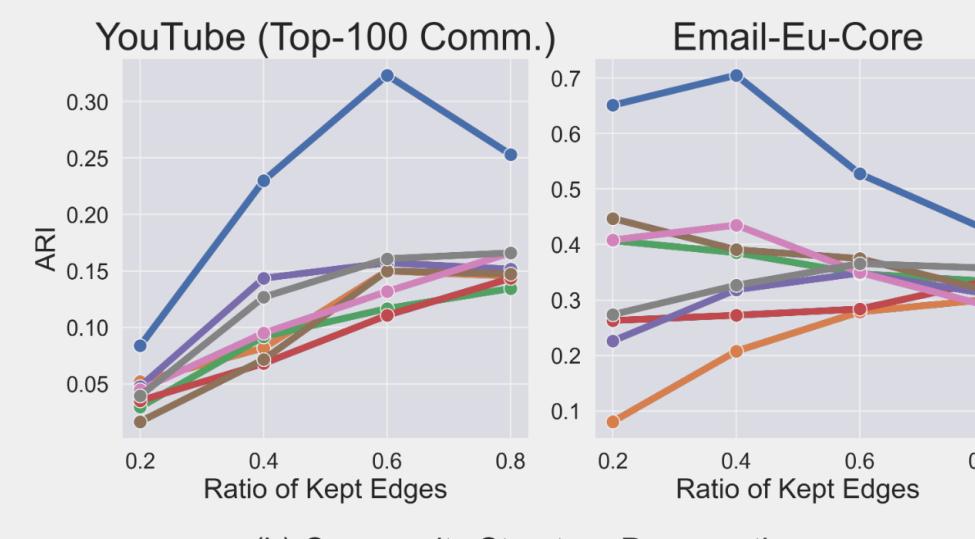
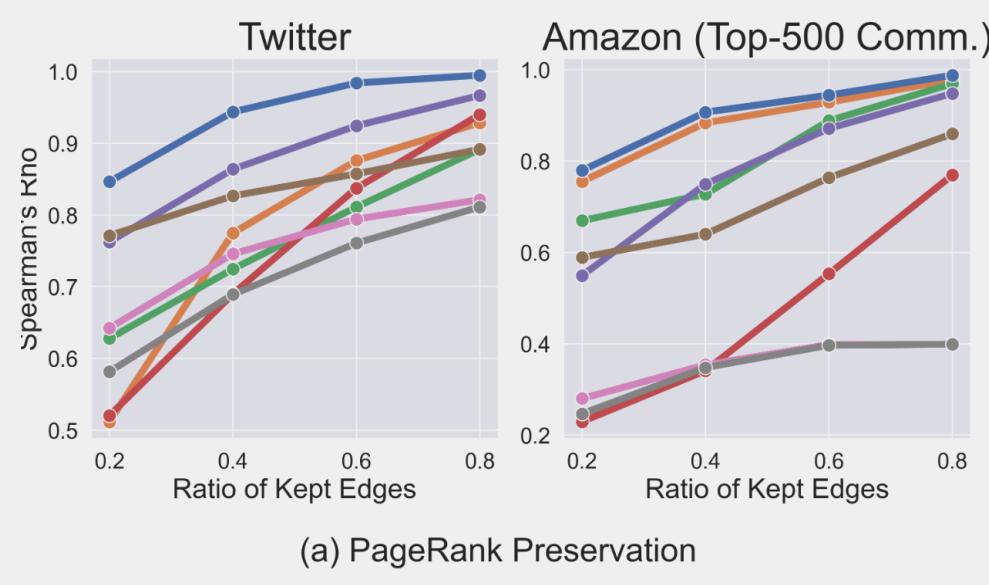
$$a_t = \arg \max_{a \in H_t} Q(o_t, a)$$
- Time Complexity of pruning T edges is $O(|E_H|T)$

4. Solution



5. Experiments & Conclusion

- Outperforms on all tested **benchmarks**:
PageRank, single-pair shortest path, community detection
- Outperforms all tested **baseline methods**:
Random Edge (RE), Local Degree (LD), Edge Forest Fire (EFF), Algebraic Distance (AD), L-Spar (LS), Simmelian Backbone (SB), Quadrilateral Simmelian Backbone (QSB)



- **SparRL** is the first task-adaptive and effective reinforcement learning-based framework for graph sparsification

Generality evident by its performance on multiple objectives on a variety of graphs

- In the future, we plan to extend SparRL

Test in a parallel setting, repurpose for graph learning tasks (e.g., link prediction, label classification etc.), and test on a dynamic graph setting

Table 1: SparRL compared against t -spanner for various stretch values t over CiteSeer. ($x\%$: edge kept ratio)

Method	$t=3$ (99.65%)	$t=4$ (99.63%)	$t=8$ (97.82%)	$t=16$ (93.74%)	$t=32$ (90.78%)
t-spanner	0.0082	0.0054	0.0405	0.1187	0.1911
SparRL	0.0031	0.0043	0.0350	0.0974	0.1820