CS 2241 Status Report

Evan Jiang, Ryan Jiang, and Roy Han

Due: April 8 (Tue) 11:59pm, Eastern Time on Canvas.

1 Project Overview

This project focuses on the evaluation, comparison, and analysis of three established graph summarization techniques (node grouping, spectral coarsening, and community-based summaries). Our work systematically assesses how well these techniques preserve key structural and analytical properties of large-scale graphs. This evaluation is critical because modern web-scale graphs, such as internet hyperlink networks, are too often massive for direct analysis. By summarizing these graphs without significant loss of essential information–such as community structure, centrality distributions, and spectral characteristics–our study aims to inform researchers and practitioners about the relative strengths and weaknesses of different summarization strategies on variety of metrics.

1.1 Related Works

Our evaluation framework builds upon several studies in graph summarization. For instance, the work on Graph Summarization with Quality Guarantees by Riondato and Vandin (2017) provides initial quality metrics for assessing graph summaries. The framework also draws from Graph Reduction with Spectral and Cut Guarantees by Loukas (2019), which informs our spectral evaluation methods, and the study Graph Sparsification by Effective Resistances by Spielman and Srivastava (2011), which motivates several of our structural metrics. Additionally, Graph Summarization with Bounded Error by Navlakha, Rastogi, and Shrivastava (2008) contributes to our understanding of error bounds in summarization, while FrogWild! – Fast PageRank Approximations on Graph Engines by Mitliagkas et al. (2015) guides our use of PageRank approximation metrics.

2 Current Progress

Our current progress has been focused on implementation. Our code repository is structured to facilitate the evaluation and comparison of the main graph summarization techniques. Key progress includes:

- **Implementation of Evaluation Modules:**
  - Development of modules in `graphsum/summarizers/` for our main graph reduction techniques.
  - Implementation of the `GraphEvaluator` in `graphsum/evaluation/` for metric-based evaluations.
- **Organized Project Structure:**
  - `graphsum/summarizers/`: Contains the base class and individual implementations of community-based and spectral methods.

- `graphsum/io/`: Provides utilities for loading datasets, including SNAP-compatible graphs.

The evaluation metrics in our study serve as indicators of summary quality. We assess PageRank preservation through correlation and error metrics to ensure that the relative importance of nodes is maintained. Centrality measures, including degree and eigenvector centrality, evaluate whether influential nodes remain prominent in the summary. Additionally, community structure preservation is quantified using Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI), which indicate the fidelity of community partitions. Structural properties such as degree distribution, clustering coefficients, and path length characteristics are also compared to verify that the overall connectivity of the original graph is retained. Finally, runtime and compression ratios offer insight into the efficiency of the summarization process.

3 Preliminary Results

Initially, we developed a demo script `demo_community.py` to run our community Louvain method on a small dataset containing 34 nodes and 78 edges. This early test served both as a functional check for our implementation and as an initial validation of our evaluation metrics. In this experiment, the community detection algorithm identified 3 communities, yielding a summary graph composed of 3 nodes and 2 edges. The evaluation metrics reported a node compression ratio of 0.088 and an edge compression ratio of 0.026, while PageRank preservation showed a correlation of -0.025 with an L1 error of 11.408689. Additionally, both the Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) achieved scores of 1.000, confirming that the community structure was fully preserved in this small-scale scenario.

We then implemented the spectral coarsening method on the same dataset in `demo_spectral.py`. The evaluation summary for this method shows that the original graph (34 nodes, 78 edges) was reduced to a summary graph of 6 nodes and 8 edges, corresponding to a node compression ratio of 0.176 and an edge compression ratio of 0.103. In terms of PageRank preservation, the spectral approach achieved a correlation of -0.127 with an L1 error of 8.584412. The community preservation metrics were lower for spectral coarsening, with an NMI of 0.505 and an ARI of 0.251, indicating a less precise maintenance of the original community structure compared to the community Louvain method.

After observing the results from the quickstarts, we scaled our experiments to the SNAP `web-NotreDame` dataset, which comprises 325,729 nodes and 1,117,563 edges. Table 1 summarizes the evaluation results using the community Louvain method for this much larger dataset.

For the large-scale dataset, the community NMI of 0.7315 suggests that, overall, the community structure has been moderately well preserved in the summary. However, the low ARI of 0.0036 is expected due to the sparsity of the original graph, which reduces the accuracy of precise community matching. Despite this, the preservation of general community trends is still effectively captured by the relatively high NMI score.

Metric	Value
Original Nodes	325,729
Original Edges	1,117,563
Summary Nodes	570
Summary Edges	1,577
Node Compression Ratio	0.002
Edge Compression Ratio	0.001
Community NMI (Sampled)	0.7315
Community ARI (Sampled)	0.0036

Table 1: Evaluation results using the community Louvain method on the SNAP `web-NotreDame` dataset.

4 Next Steps

Our immediate objectives are to build upon our preliminary community-based results. In particular, we plan to complete the implementation of both the spectral coarsening method (since we're experiencing some problems with larger-scale datasets with this method, e.g. NotreDame) and the node grouping summary method. These additions will enable a comprehensive comparison across various evaluation metrics on the `web-NotreDame` dataset. Furthermore, we intend to expand our evaluation framework by incorporating a more diverse set of metrics, as the current set is limited. Additional steps include:

1. **Adding PageRank-focused Summary Method:** We will implement a PageRank-optimizing graph summary method and see how it performs on preserving PageRank while also examining its performance on the rest of the metrics. This way, we can compare it to the other summary methods at hand.

2. **Dataset Diversification:** We will experiment with other datasets to examine the similarities and differences in results across graphs with varying characteristics.

3. **In-depth Comparative Analysis:** A critical part of our future work is to analyze and compare why certain reduction methods perform better or worse on specific metrics, thus shedding light on the inherent trade-offs of each approach.

4. **Exploration of Novel Techniques:** Time permitting, we might explore developing a novel graph summarization approach and compare its performance against the established methods.