NetSciX2026: International School and Conference on Network Science
February 17^{th}-20^{th}, 2026 - Auckland, New Zealand

Graph Reduction in Multirelational Networks: A Spreading-Oriented Benchmark

Graph reduction, Benchmark datasets, Multilayer networks, Influence maximisation

Introduction

Despite extensive research on influence maximisation (IM), the impact of graph reduction methods on the accuracy and efficiency of IM algorithms has not been systematically assessed. Most existing benchmarks focus on single-relationship graphs and compare algorithms using diverse datasets, which makes systematic evaluation difficult and slowing progress. They also omit the impact of incomplete data and rarely reflect the multilayer nature of real systems. To address this gap, we propose a benchmark of graph reduction methods, evaluated systematically in the context of multilayer networks. Our work places graph reduction at the centre of the evaluation, by standardising datasets, diffusion settings, and representative tasks, it allows us to measure how different sparsification and coarsening strategies impact on IM models predictions in multilayer networks. This shifts the perspective from testing IM algorithms in isolation to assessing the suitability of reduction methods for supporting accurate and efficient analysis under realistic network conditions. The framework underlying the benchmark is extensible and operates on a representative collection of real-world multilayer graphs.

Approach

Our benchmark evaluates graph reduction methods with respect to influence-maximisation tasks on multilayer networks. We include representative approaches from two complementary families: sparsification (retaining only a subset of its edges and vital nodes) and coarsening (groups and amalgamates nodes into super nodes, with original inter-group edges being aggregated into super edges using a specified aggregation algorithm), systematically assessed in the context of spreading processes on multil [1], each applied at different reduction rates r. To capture spreading dynamics, we adopt widely used diffusion models, including the Linear Threshold Model (LTM) and the Independent Cascade Model (ICM), adapted for multilayer settings in accordance with [2]. Evaluation is based on comparing the results obtained on reduced graphs with those on the original networks. In particular, we measure the consistency of identifying the single most influential actor (“super spreader”), the cut-off of most significant spreaders and, as a preliminary task, the potential selection of seed sets, all computed on reduced graphs and compared to the original multilayer network. In addition, we record computational efficiency to assess trade-offs between accuracy and scalability. The complete benchmarking pipeline is presented in Figure 1. All experiments are conducted on a diverse collection of real-world multilayer graphs, ensuring coverage of different topologies and interaction patterns. The framework is extensible, enabling systematic comparison of additional reduction methods or networks.

Preliminary Results and Conclusions

The key contribution of this work is a unified benchmark of graph reduction methods, sparsification and coarsening, systematically assessed in the context of spreading processes on multilayer networks. Preliminary experiments, based on the comparison of super spreader potentials, presented in Table 1 using data from the Super Spreader Dataset [3], show mixed results.

While reduction often decreases agreement with the original predictions and reduces influence spread, the 12-course network exhibits consistent improvements, suggesting that coarsening in this case removes structural noise and sharpens the identification of influential nodes. These early findings highlight both the potential and limitations of applying current reduction methods in complex topologies. By the time of the conference, we plan to provide an extended dataset and additional evaluation scenarios to enable systematic comparisons across a broader range of networks.

Our benchmark operates exclusively on graph structures without storing confidential information about nodes or edges, ensuring that sensitive personal data is not exposed. Results obtained with our framework should be interpreted as indicative rather than predictive, and any practical application must account for the complexity and unpredictability of real systems.

References

[1] Mohammad Hashemi et al. "A comprehensive survey on graph reduction: sparsification, coarsening, and condensation (2024)". In: *arXiv preprint arXiv:2402.03358* (2024).

[2] Yaofeng Desmond Zhong et al. "Influence Spread in the Heterogeneous Multiplex Linear Threshold Model". In: *IEEE Transactions on Control of Network Systems* 9.3 (2022), pp. 1080–1091.

[3] Michał Czuba et al. "Identifying Super Spreaders in Multilayer Networks". In: *arXiv preprint arXiv:2505.20980* (2025).

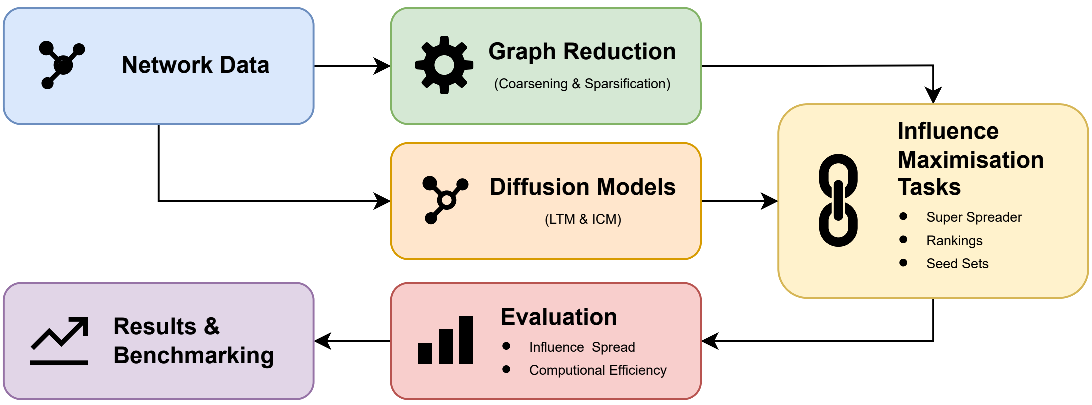

Figure 1: Benchmarking Pipeline for Graph Reduction in Multilayer Spreading Processes.

Table 1: Change in averaged IoU for super spreader cut-offs (Degree Centrality) caused by different reduction types and levels, compared to the original network.

r	arxiv		ckmp		12-course		timik	
	LDegree	GSpar	LDegree	GSpar	LDegree	GSpar	LDegree	GSpar
0.25	0.036	-0.078	0.004	-0.311	-0.254	0.803	-0.040	0.041
0.5	-0.127	-0.184	-0.081	-0.577	-0.222	0.585	-0.082	-0.357
0.75	-0.293	-0.184	-0.164	-0.577	0.389	0.341	-0.098	-0.431
base result	0.29		0.177		0.164		0.37	