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Evaluating Community Structure Preservation of Network Embedding Algorithms

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Abstract. Network embedding compresses network information into low-dimensional vectors while retaining structural and semantic details. Preserving community structure is vital. Existing evaluation metrics often overlook community structure. This study assesses network embedding algorithms across various community strengths, demonstrating performance variation in mesoscopic quality metrics.

Keywords. *Network Embedding, Community Structure, Evaluation Metrics, Quality Metrics*

1 Introduction

Networks often exhibit a modular structure, where nodes cluster into communities with shared characteristics or functions [6, 15, 12]. Understanding these community structures is crucial for various applications, from recommendation systems to the optimal spread of information and disease control [2, 13, 14, 4, 5, 11, 3, 10]. With network sizes increasingly increasing, generating lower order representation, known as network embedding, has gained significant attention in recent years [7]. This technique transforms networks into low-dimensional vector representations. While certain techniques are designed to explicitly maintain or enhance the community structure through the embedding process, others may not consider community structure preservation a primary objective. Nonetheless, one of the fundamental goals of all network embedding techniques is to project the similarity of the nodes of the original network onto the lower-dimensional space. Further, network embedding techniques are commonly evaluated through classification metrics [7]. Nonetheless, these metrics are agnostic about the community structure: they do not indicate whether it is well preserved after the embedding process. In other words, they offer information about the overall quality of results but do not reveal the fine-grained details of community structure within a network. Consequently, there is a need for a comprehensive comparative analysis of network embedding algorithms from a modular perspective. This paper reports the performance analysis of the most prominent network embedding algorithms on controlled synthetic networks [1].

2 Experimental Evaluation

A bird’s-eye view of the experimental setup to evaluate the network embedding algorithms’ efficacy in maintaining the community structure is illustrated in Figure 1.

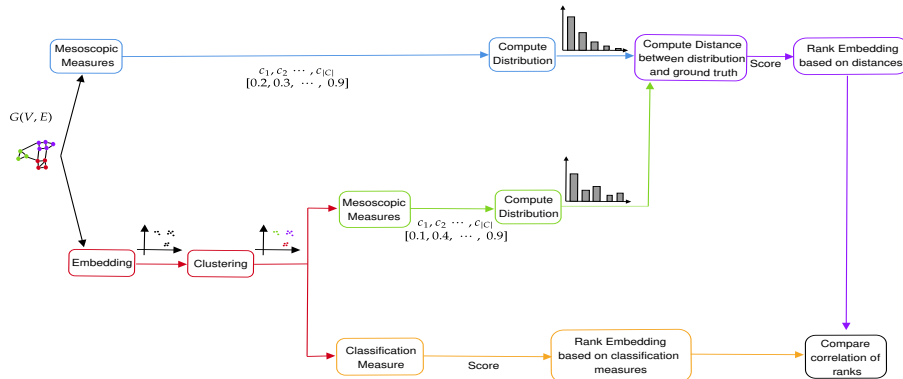


Figure 1: Flowchart of the experimental setup to evaluate the performance of the network embedding algorithms. Mesoscopic metrics are calculated individually for each of the network’s communities.

Synthetic networks are generated with the help of the ABCD network generator. ABCD offers the ability to change multiple parameters of the network generation process. We fix all its parameters except the mixing parameter (μ) to study the influence of the community structure strength [8].

We use ten embedding algorithms to embed generated networks into a 128-dimensional space: DeepWalk, Node2Vec, Diff2Vec, Walklets, Modularity-Normalized Matrix Factorization (M-NMF), Laplacian Eigenmaps (LEM), Randomized Network Embedding (RandNE), Boosted Network Embedding (BoostNE) and Network Matrix Factorization (NetMF) [1]. We use Classification metrics and community structure quality measures to assess the ability of the embedding process to preserve the community structure. The classification measures used are classically used in the machine-learning community. We rely on the adjusted mutual information score (AMI), normalized mutual information score (NMI), adjusted random score (ARI), Micro-F1 score, and Macro-F1 score

Multiple community structure quality metrics are also used. We compute these metrics for each community. Therefore, we can approximate their distribution for a given graph[1] and compare it with the distribution in the original network.

1. **Internal distance:** is the average shortest distance of nodes inside a given community
2. **Internal density:** is the edge density inside a given community
3. **Maximum-out degree fraction (Max-ODF):** is the maximum ratio of inter-community links vs. intra-community links.
4. **Average-out degree fraction (Average-ODF):** same as Max-ODF, but averaging.
5. **Hub dominance:** is based on the intra-community links of a node that has the highest intra-community links in its community
6. **Flake-Out degree fraction (Flake-ODF):** is the percentage of the out degree fraction.
7. **Embeddedness:** quantifies intra-community links. It is the opposite of Average-ODF.
8. **Hub dominance:** is based on the intra-community links of the node that has the highest intra-community links in its community

After embedding, K-means clustering is applied to group embeddings into the same number of clusters as the ground truth. The Kullback-Leibler divergence is computed between the ground truth and embedded distributions. The distance between the two distributions measures how good the embedding is. The smaller the distance, the better the algorithm. For classification Metrics, we can just look at the performance of each algorithm. A ranking scheme utilizing Schulze’s voting model is employed to evaluate the overall quality of the algorithms based on performance metrics[14]. KL-divergence scores and classification metrics serve as voters, while algorithm ranks act as candidates. The model compares candidates in head-to-head matchups to identify the algorithm with the broadest preference, aiming for a consensus winner. The final ranks represent a consensus across all metrics, providing a comprehensive assessment of network embedding algorithm performance. As shown in Table 1, LEM demonstrates outstanding performance within a robust community structure, excelling in community awareness and classification metrics. However, as the strength of the community structure diminishes, its effectiveness declines prominently with classification metrics. The opposite behavior is seen with NetMF. In contrast, M-GAE maintains outperformance across both community-aware and classification metrics, regardless of the community structure strength, by ranking either first or second.

μ	Metrics	Ranks									
		1 st	2 nd	3 rd	4 th	5 th	6 th	7 th	8 th	9 th	10 th
$\mu \leq 0.4$	Meso	LEM	M-GAE	RandNE	NetMF	Deepwalk	Node2Vec	Diff2Vec	Walklets	M-NMF	BoostNE
	CL	LEM	M-GAE	RandNE	Walklets	NetMF	M-NMF Node2Vec		Deepwalk	Diff2Vec	BoostNE
$\mu > 0.4$	Meso	M-GAE	NetMF	RandNE LEM		M-NMF	Deepwalk	Diff2Vec	Node2Vec	BoostNE	Walklets
	CL	M-GAE	NetMF	M-NMF	BoostNE	LEM	Deepwalk	Node2Vec RandNE		Diff2Vec	Walklets
Total	Meso	LEM	M-GAE	RandNE	NetMF	Deepwalk	Node2Vec	Diff2Vec	M-NMF	Walklets	BoostNE
	CL	M-GAE	LEM	NetMF	M-NMF	RandNE	Node2Vec	Deepwalk	BoostNE	Walklets	Diff2Vec

Table 1: The ranking of the embedding algorithms based on Schulze’s method for mesoscopic (Meso) and classification metrics (CL) with respect to the mixing parameter(μ)

3 Conclusion

Preserving network community structure is crucial, and network embedding techniques offer significant potential. However, the evaluation metrics commonly used in the literature fail to capture this preservation effectively. This study highlights the need for a comprehensive comparison of network embedding algorithms from a modular perspective. Our work is limited to evaluating the effect of the mixing parameter on the embedding quality. Our study specifically aims to determine the adequacy of classification metrics employed in the literature to comprehend the effectiveness of network embeddings. Results reveal that these metrics do not comprehensively reflect the network’s community structure. Furthermore, the efficacy of certain embedding techniques, such as LEM, M-GAE, and NetMF, is influenced by the strength of the community structure. These findings underscore the need for a more attentive approach in evaluating embedding techniques tailored to the specific application. Finally, it is worth mentioning that we only considered the effect of the mixing parameter in this study, further research can be done to check for other parameters’ influence such as the dimensionality of the embedding, and other coefficients that describe community structure.

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