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# Dynamic Multi-Path Relationship: Preserved Embedding for Social Network

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***Abstract.*** In the contemporary era, human beings are living in a digital era, in which the issue of social network analysis has been constantly scrutinized and discussed. While the research regarding static embedding approaches has made significant progress, these approaches fail to deliver comprehensive solutions to circumstances with respect to dynamic embedding. This is a major defect, as the social network is constantly changing and evolving in a world that is developing rapidly and totally unpredictably. Therefore, this research paper focuses on dynamic social network embedding and investigates how to preserve multi-path relationships in dynamic social networks efficiently under rapidly changing topologies. The research is conducted through systematic and critical reviews of different varieties of dynamic embedding algorithms and models, followed by a comprehensive comparison. This research paper figured out that dynamic models and algorithms excel in the analysis of network users' connections in so many ways, which is mainly because of their ability to capture fleeting information and leverage information as social networks change and evolve continuously over time.

***Keywords:*** Dynamic network embedding, scenario-specific optimization, structure evolution.

## 1. Introduction

Social network analysis focuses on connections between individuals and has been a popular topic in the contemporary era. The main theme of this paper is the innovative ways of analyzing social networks, and for the sake of simplicity and practicality, the network will be abstracted as a graph, in which nodes and the relationships between individuals are represented by edges connecting nodes. This will enable researchers to use graph representation learning methods to have a closer insight into the graph, particularly the nodes, in terms of the low-dimensional representation vectors [1].

Dynamism has always been a key feature of social networks. The relationships between individuals vary over time as new connections form while some old connections dissolve. Traditional approaches to analyzing social networks involve static embedding methods, in which nodes are mapped into low-dimensional vectors to preserve their structural features. A typical example is Multi-Path Relationship Preserved Social Network Embedding (MPR-SNE). MPR-SNE employs a random walk to uncover multiple social relationship paths between individuals, and the sequences discovered are then used to establish a multi-path relationship between nodes [2].

However, it is also conspicuous that such static embedding approaches could not manage to capture temporal dynamics, which leads to a considerable amount of path degradation.

This paper will focus on the multi-path degradation issue in the dynamic social network embedding and will conduct a comprehensive investigation on approaches to preserve network structures that consist of multi-path relationships under topologies that vary continuously, unpredictably, and sometimes drastically. The edges may change frequently, resulting in rapid walk-based paths obsolescence [2]. Therefore, one of the major objectives is to conduct research on models and algorithms that can update paths in real-time as the edges evolve. This may include an extension of the Erdős–Rényi ML estimation, in which only walks for nodes that are affected by the incidents will be updated.

There is no doubt that dynamic path freshness plays a pivotal role in social network embedding. This paper systematically reviews some limitations of static path methods, as well as more advanced approaches to dynamic social network embedding, followed by a comparison between different algorithms. This paper also offers some critical views regarding how dynamic social network embedding excels in network analysis, as well as some limitations that it may have. Unlike prior surveys, this work systematically compares algorithms not only in terms of path preservation abilities but also in terms of adaptability to heterogeneous structures, overlapping clusters, and other more complicated scenarios.

## 2. Literature review

### 2.1. Early research regarding social network embedding

Social network embedding has been constantly scrutinized in recent years, and the following are some of the relatively early research studies conducted on this topic.

Dynamic network embedding offers several significant advantages over static network embedding [3]. This includes the ability to capture temporal information in time which will enhance the accuracy and preciseness of network analysis, the increase in efficiency of updating representation through simply applying a static model from scratch at each time step, and the ability to update representation in a fine-grained granularity of time by representing network as a series of snapshots or new node/edge with timestamp [3]. The Local-First mechanism can handle the issue of overlapping clustering through many innovative approaches, such as local perturbation [4].

### 2.2. State-of-the-art investigation of dynamic path preservation in embedding

Over the past approximately three years, dynamic path preservation technology has developed at a rapid rate, and the following reviews contain some typical newly developed algorithms for path and relationship preservation.

The cross-social network User Identity Linkage (UIL) has several significant limitations. Still, the cross-social network UIL framework via dynamic embedding and clustering model driven by three-way decision (DECTUIL) is an ideal way of addressing the drawbacks of UIL in terms of extracting and classifying network users' features in a dynamic way and in terms of mitigating the shortcomings of heterogeneity and pre-aligned resources scarcity [5]. DECTUIL includes the Dynamic Embedding Algorithm (reduces the negative implications of heterogeneity through selecting embedding functions dynamically), the Vector Smoothing Algorithm (leverages neighborhood information to avoid disruption of inconsistent information in different platforms), and Three-Way Decision Driving Clustering (iteratively refines K-Means Clustering through a three-

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way decision, which will significantly increase the precision of clustering) [5]. High-order memory-guided temporal random walk for dynamic heterogeneous network embedding (HoMo-DYHNE) is an effective algorithm for conducting network embedding [6]. It could avoid the dependency of manually designed high-order structures and, in the meantime, capture networks' heterogeneous semantics [6].

### 2.3. Other algorithms to handle real-world issues

Apart from the algorithms above, these are some other algorithms related to social networks and dynamic embedding that could be used to handle an extensive range of social problems.

Algorithms like the Co-evolutionary memetic algorithm (COMA) can effectively identify key influential nodes [7]. The algorithm is constructed such that two types of population evolution, namely diversity direction evolution and influence fitness guided evolution, evolve in two different directions and compete in the selection of individuals based on two different strategies and goals [7]. One of the most striking advantages of this algorithm is that the premature convergence issue will not be an obstacle. Furthermore, the K-Anonymity algorithm can anonymize the graph through an artificial neural network and a support vector machine [8]. It ensures that each record must be identical to at least k-1 other records, which makes sure that all individuals are indistinguishable.

## 3. Methodology

### 3.1. Literature search strategy

A keyword-based systematic literature review on dynamic path preservation in social network embedding is conducted. Table 1 illustrates the three major literature retrieval websites across which the research was conducted and the respective search queries.

Table 1. Websites of literature retrieval used to conduct research

| Website | Search Query | URL |
| --- | --- | --- |
| IEEE Xplore | Dynamic and static path | Retrieved from https://ieeexplore.ieee.org/Xplore/home.jsp |
| ScienceDirect | Dynamic embedding | Retrieved from https://www.sciencedirect.com/ |
| Google Scholar | Network users' analysis algorithms | Retrieved from https://scholar.google.com |

The articles that are adopted are relatively modern, and they were published between 2019 and 2025.

### 3.2. Inclusion and exclusion criteria

Among the 27 research papers that are selected initially, some of them are included in the literature review, whilst other is excluded from the literature review based on the following criteria:

Inclusion Criteria includes whether a research paper proposes novel dynamic network embedding algorithms (Adapting creativity and novel algorithms are vital for the absorption of cutting-edge methodologies, which are more likely to be better at capturing network dynamics), whether it addresses path preservation explicitly, and whether it provides good examples of the practical application of social network dynamic embedding, even though it might not address the problem directly.

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A research paper is excluded if it lacks authoritative citations (Authoritative sources prevent misinformation, which will prevent the readers from having access to inaccurate or completely erroneous information, thereby reducing the probability of misleading), provides information that is not trustworthy, includes contents are completely irrelevant, or includes theoretical studies without any valid proofs or mathematical interpretations (Only studies with mathematical proofs can verify the fidelity of path preservation rigorously).

### 3.3. Quality assessment

Table 2 illustrates the evaluation process for each research paper. Papers whose total marks are greater than 20 (out of 30) are selected. As shown in Table 2, six different criteria are considered when evaluating research papers, and varying weights are assigned to these criteria based on their relative importance.

Table 2. Evaluation criteria and weights

| Criteria | Weights | 3 (out of five) | 5 (out of five) |
|---|---|---|---|
| Accuracy of information | 20% | Some information provided cannot be verified | Almost every information can be verified |
| Authority of citation | 20% | Only some of the resources are obtained from top academic journals | Most of the resources are obtained from journals |
| Rigorousness of mathematical proof or interpretation | 20% | Lack of academic proofs that are accurate and logical | Contain rigid mathematical proofs with clear elaborations of limitations |
| Practical Application | 10% | Only show some applications | Shows a wide range of applications in the real-world scenario |
| Ability of algorithms to tackle problems | 25% | May solve the problem but inevitably contains some obvious defects | Can solve the problem almost perfectly without conspicuous defects |
| Relevance | 5% | Does not have a strong connection to the topic regarding social network dynamic embedding | Shows a strong connection to the topic regarding social network dynamic embedding |

## 4. Results

### 4.1. Overview of models and algorithms

Table 3 is a summary of the models and algorithms in this research. The summary comprises the core advantage, key feature, relevance to the topic of dynamic network embedding, and application scenario of each model/algorithm.

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Table 3. Strengths and application backgrounds of dynamic network embedding models and algorithms

| Algorithms/Models | Core Advantages | Relevance to the Topic | Application Scenarios |
|---|---|---|---|
| General Dynamic Embedding | Can capture temporal information | Strong | General cases |
| Local-First Mechanism | Can handle overlapping clusters | Intermediate | Overlapping structures |
| DECTUIL Framework | Optimize clustering via three-way decisions and vector smoothing | Strong | Cross-network UIL and heterogeneous networks |
| HoMo-DYHNE | Capture high-order structures and preserve heterogeneous semantics | Strong | Heterogeneous dynamic network |
| COMA | Identify key nodes and prevent premature convergence through co-evolution | Intermediate | Diffusion network |
| K-Anonymity | Achieve privacy preservation | Weak | Network privacy and graph anonymization |

## 4.2. Closer insights into models and algorithms

In this section, COMA and K-Anonymity are no longer considered, as they are not particularly helpful for preserving the path. To deepen the understandings of the models and algorithms, and take a further look at how effective they will be to help researches carry on the investigation of path preservation, the rest of the algorithms and models (i.e. General Dynamic Embedding, Local-First Algorithm, DECTUIL Framework, HoMo-DYHNE) will be further scrutinized and their qualities and usefulness will be compared based on their accuracy, runtime efficiency, memory usage, and generality. Table 4 provides more detailed insights into the algorithms and models that will be discussed later.

Table 4. Quality and scope of use of algorithms and models

| Models/Algorithms | Accuracy | Runtime Efficiency | Memory Usage | Generality |
|---|---|---|---|---|
| General Dynamic Embedding | Intermediate | Low | High (history snapshots storage is needed) | High (manage to tackle many general cases) |
| Local-First Algorithm | Superior on overlapping communities | Intermediate | Low (overlap structures only) | Low (overlap structures only) |
| DECTUIL Framework | Relatively good for alignment | Very low | Very high (boundary cache required) | Intermediate (dependent on stable communities) |
| HoMo-DYHNE | Superior on heterogeneous graphs | Low | High (heterogeneous features are involved) | Very low (heavily dependent on meta-path) |

## 5. Discussion

In Tables 3 and 4, many important algorithms and models in the field of Dynamic Network Embedding (DNE) are systematically and critically reviewed and compared. In this section, the points of view on this topic will be elaborated, particularly the reasons why dynamic embedding

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outperformed many static methods. There will be a summary of the key findings and some root causes, followed by a reflection on the limitations of this research as well as the possible future research directions of this field.

### 5.1. Key findings

According to the analysis, the core advantages of DNE models come directly from the ability to capture, construct models, and leverage information as the nodes and edges evolve over time.

Dynamic networks are inevitably and inherently complex, and many issues related to dynamic networks, such as overlapping structures and heterogeneity, cannot be directly addressed by static approaches, as they only involve a single model that aims to solve problems in all circumstances, which often fails to work properly in many cases. Algorithms like Local-First Mechanism, DECTUIL, and HoMo-DYHNE successfully handle the issue of network evolution, which demonstrates the effectiveness of dynamic and adjustable models that are designed for a particular purpose.

It is noteworthy that almost no DNE models or algorithms emphasize high efficiency or generality as their key advantage. This indicates that while those models are in pursuit of the ability to tackle specific issues, computational efficiency and wide applicability may be compromised.

### 5.2. Why dynamic embedding works

Static embedding is basically a stationary snapshot of the network at an instantaneous moment, which makes it unable to obtain continuous changes in nodes, edges, or the overall structures of the entire network. By comparison, DNE manages to tackle structural complexity through its flexibility. Table 5 provides a brief summary of how each DNE algorithm excels in handling rapidly evolving networks, highlighting the differences between these algorithms and static approaches.

Table 5. Summary of how DNE models excel

| Name of algorithm/model | How it excels | Degree of practicality |
|---|---|---|
| Local-First Mechanism | It is designed for dynamic optimization and can adjust node community assignments in time so as to dynamically adjust to overlap and evolution. | high |
| DECTUIL Framework | It conducts users' identifications across multiple platforms and merges information from various sources. It utilizes three-ways decisions effectively. | high |
| HoMo-DYHNE | It manages to preserve and fuse diverse semantic relationships between individuals in a very heterogeneous network system. It can adjust its representation based on structural changes that it observes, which enables them to tackle extremely complex network with tremendous amounts of node/edge types and drastically- and unpredictably- changing relationships. | intermediate |

### 5.3. Limitation

The research paper involves the following limitations.

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#### 5.3.1. Lack of efficiency

Due to the fact that DNE requires a significant amount of computational overhead, the efficiency of the processing of large-scale dynamic networks is limited, especially in real-time. For instance, in the DECTUIL Framework, three-way clustering iterations require repetitive complicated calculations, thereby significantly driving up iterative costs. Another example is that in HoMo-DYHNE, parallel processing involves multiple meta paths, which will increase the rate of growth of computational scales exponentially. This study could not quantify the actual computational time, computational costs, or scalability.

#### 5.3.2. Lack of generality

In this study, most models are designed in a scenario-based way. For instance, the Local-First Mechanism is optimized only for overlapping structures, so it will inevitably fail to deal with networks with clear modular boundaries. This will limit the applicability of the models in this research study.

### 5.4. Further study

These are the directions that should be worked on regarding the field of DNE.

#### 5.4.1. Develop an embedding that is efficient and lightweight

Further research should be conducted to develop dynamic embedding algorithms that are both computationally time- & money- saving and convenient for storage. This may include adapting some more advanced strategies that only perform minor updates on the changed parts, which will avoid large-scale re-computation.

For instance, incremental updates can be included in future models, which will undoubtedly increase the efficiency considerably through enlarging storage and saving a significant amount of computational power. Furthermore, datasets selecting techniques such as sampling optimization can also be merged into models that are developed in the future, because it can divide data into different subgroups and queries different samples iteratively based on the uncertainty of the model, and not only will it increase the speed for a model to be trained, it will also reduce the expenses to store and to compute, allowing an efficient and effective analysis of large datasets.

#### 5.4.2. Construct robust and universal dynamic frameworks to increase generalization

Approaches to reduce model dependency are also a key part of future study. The aim should be to make the models suitable to tackle issues in a wide range of scenarios using a wide range of datasets. This may include the construction of AI models that can adjust the internal structures or parameters automatically based on changes in external inputs. This may also include the exploration of the relationships between relatively stable information structures and rapidly evolving information, which will significantly increase the robustness of the model, as well as the ability of models to transfer between one another.

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## 6. Conclusion

This research paper critically and systematically reviews some important and state-of-the-art dynamic network embedding algorithms and models, including prominent examples such as DECTUIL and HoMo-DYHNE. Results clearly show that such dynamic embedding approaches have the ability to leverage information as the nodes, edges, and entire network structures evolve continuously over time, which are within low-dimensional vector spaces. It can handle the fundamental and major challenges associated with representing a complex network. The strengths of dynamic embedding approaches are revealed in complex network analysis. Notably, the superior performances of the models and algorithms in scenario-specific optimization cases like overlapping structures handling (in which individuals simultaneously belong to multiple clusters) and cross-network alignment (which requires the mapping of individuals across different networks) are explicitly highlighted in the research paper, despite some possible drawbacks associated with a lack of efficiency and generality.

In addition, the study emphasizes that the future of this research area lies in balancing efficiency, scalability, and generalization. While existing methods demonstrate strong capabilities in capturing heterogeneous semantics and dynamic structural changes, their reliance on scenario-specific assumptions limits their broader applicability. By exploring incremental update mechanisms, lightweight embeddings, and robust universal frameworks, researchers may overcome the existing bottlenecks.

Overall, this work not only provides readers with crucial algorithms and practical, evidence-based model selection guidelines but also outlines promising pathways for further innovation. It reinforces the importance of dynamic network embedding as a foundation for analyzing complex evolving systems, and it calls for continued efforts to enhance efficiency and generality while maintaining accuracy and robustness. The insights and recommendations presented here are expected to guide researchers and practitioners in designing more effective models that can adapt to diverse and rapidly changing networked environments.

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