Dynamic Community Detection in Time Series Using Graph Neural Networks

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1 Introduction to Background

Dynamic community detection is becoming increasingly valuable in various fields involving time-series data, such as finance and transportation. In financial markets, detecting dynamic communities among stocks or assets enables investors to better understand how market structures evolve over time, helping them make informed investment decisions and effectively manage risks during market fluctuations. In transportation systems, this method helps urban planners discover changing traffic communities or emerging congestion patterns, thus supporting more effective and timely urban planning decisions.

Moreover, dynamic community detection can significantly improve spatial-temporal forecasting. Traditional static community detection models often overlook how relationships change over time, limiting their predictive accuracy. In contrast, dynamic approaches capture these evolving interactions among entities or regions, enhancing forecasting performance. For example, detecting dynamic communities among financial assets could lead to more accurate predictions of asset prices, as it considers both temporal changes and spatial interconnections simultaneously.

Although dynamic community detection has clear benefits, current research on this topic is still limited. Many existing studies have primarily concentrated on static community detection, leaving temporal dynamics relatively unexplored. Consequently, there is substantial room to investigate and develop innovative methods for dynamic community detection, making it a promising and valuable direction for further research.

In recent years, deep learning methods—such as CNNs, RNNs, and Transformer-based models—have notably improved time series analysis by capturing temporal patterns for single-target prediction. However, these models often focus solely on individual sequence representations, neglecting the intricate interdependencies among multiple targets. This shortcoming is especially critical in real-world applications where variables interact dynamically over time. Traditional models typically learn from isolated temporal patterns, ignoring the spatial correlations between different targets, which can lead to suboptimal performance.

To address this gap, researchers have proposed Spatial-Temporal network architectures that integrate both spatial and temporal information into a unified framework. These architectures aim to model each target's temporal evolution while concurrently capturing the interdependencies among targets, providing a more comprehensive representation of the underlying data. This research seeks to develop and evaluate a robust

Spatial-Temporal network architecture that not only enhances prediction accuracy but also yields deeper insights into the dynamic interactions among multiple targets.

2 Research Aims and Questions

2.1 Research Aims

This study is grounded in the concept of representation learning. By learning latent representations of the data, it further reveals the intricate interdependencies among multiple targets.

The primary aim of this research is to develop a novel framework for dynamic community detection in time-series networks, with an S&P 100 dataset from Yahoo Finance. Specifically, this study has implemented a static transformer-based graph convolution module combined with convolutional autoencoders that simultaneously extract spatial (cross-sectional) and temporal (longitudinal) patterns.

In summary, the core innovation of this research lies in the integration of Transformer-based graph convolution modules with convolutional autoencoders, explicitly designed to dynamically adapt graph structures and parameters, enabling deeper understanding and improved modeling of dynamic asset interactions in financial markets.

2.2 Ongoing Research Questions

2.2.1 Dynamic Relationship Modeling

How can this study effectively model the dynamic interdependencies using a combination of adaptive graph convolution (which allows the adjacency matrix to vary over time)?

2.2.2 Dynamic Weight Evolution

How can this study design and evaluate a mechanism (similar to EvolveGCN) that allows the model's weights to evolve over time, thereby transforming the representation from a static graph (e.g., processing data with static weight parameters) into a dynamic graph (e.g., updating weights via a recurrent mechanism to reflect time-varying relationships)?

2.2.3 Improve Enhanced Layer

This study is actively exploring alternative metrics or computational strategies (e.g., cosine similarity or Mahalanobis distance) to better capture the nuances of global dependencies without significantly increasing complexity.

3 Literature Review

Recent research has increasingly leveraged graph neural networks (GNNs) for capturing complex relationships in financial systems. For instance, Pacreau et al. (2021) [1] illustrate how GNNs can be applied in asset management by modeling inter-stock dependencies through graph-based representations, emphasizing the importance of structural information when analyzing market dynamics.

Another pertinent line of work focuses on community detection using GNNs. Qiu et al. (2022) [2] propose VGAER, a variational graph autoencoder reconstruction method specifically designed for community detection. Although VGAER integrates network structure and node features to extract modularity information and achieves notable improvements in clustering performance without requiring external labels, it does not account for time-series data.

Dynamic graph representation learning has also emerged as a critical area, especially for systems where relationships evolve over time. EvolveGCN (Pareja et al., 2020) [3] introduces a framework where model parameters evolve via a recurrent mechanism to capture temporal dynamics in graphs, providing valuable insights into transforming static graph representations into dynamic ones. In a similar vein, Graph WaveNet (Wu et al., 2019) [4] proposes an adaptive dependency matrix that is learned through node embeddings. By dynamically adjusting the underlying adjacency structure and employing dilated causal convolutions for long-range temporal modeling, Graph WaveNet captures implicit spatial dependencies not present in fixed graphs. Inspired by this dynamic adjustment mechanism, our work explores a similar strategy for the dynamic updating of the adjacency matrix to reflect evolving inter-asset relationships. Despite the valuable contributions of these models, their effectiveness in spatial-temporal contexts could benefit from additional testing in more practical, real-world situations. For example, EvolveGCN uses recurrent neural networks (RNNs) to dynamically update its parameters. However, the effectiveness of this method might vary depending on the specific dataset or application scenario. Furthermore, alternative approaches, such as attention-based mechanisms, may provide improvements but remain relatively unexplored in this context. Therefore, this study recognizes the need for further experimentation and validation of these methods across different real-world datasets, highlighting an important direction for future research.

Complementing these approaches, recent studies on graph-based time series clustering (Cini et al., 2024 [5]; Peng et al., 2024 [6]) integrate hierarchical and relational inductive biases, demonstrating that joint modeling of temporal and relational information can further enhance clustering performance.

Together, these works provide motivation and context for this study. Specifically, this study proposes a transformer-based graph convolution module combined with convolutional autoencoders to capture spatial-temporal patterns from financial data. Unlike purely static approaches, the proposed framework inherently supports dynamic clustering within each distinct time window, effectively modeling evolving relationships among entities. Building upon this current model—which already learns dynamic spatial-temporal representations—this study aims to further enhance its capability by dynamically adapting the adjacency matrix and model weights over time. The goal is to explore whether these dynamic enhancements can lead to improved performance in detecting communities across changing time windows.

4 Current Progress

4.1 Algorithm Architecture

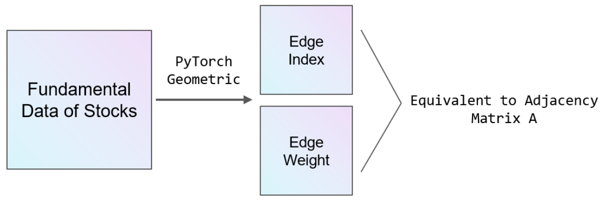

Figure 1: Graph Creation

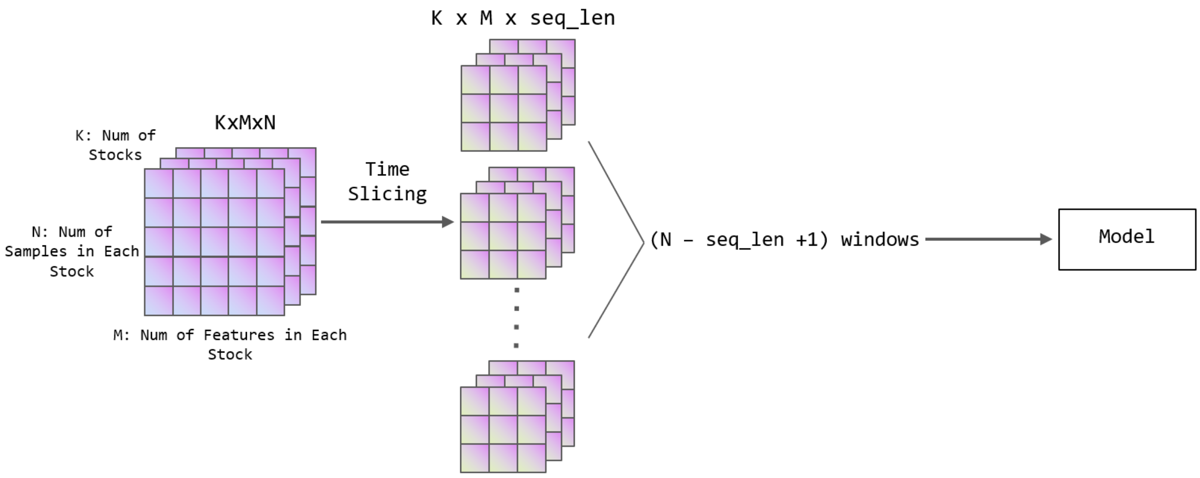

Figure 2: Time Slicing

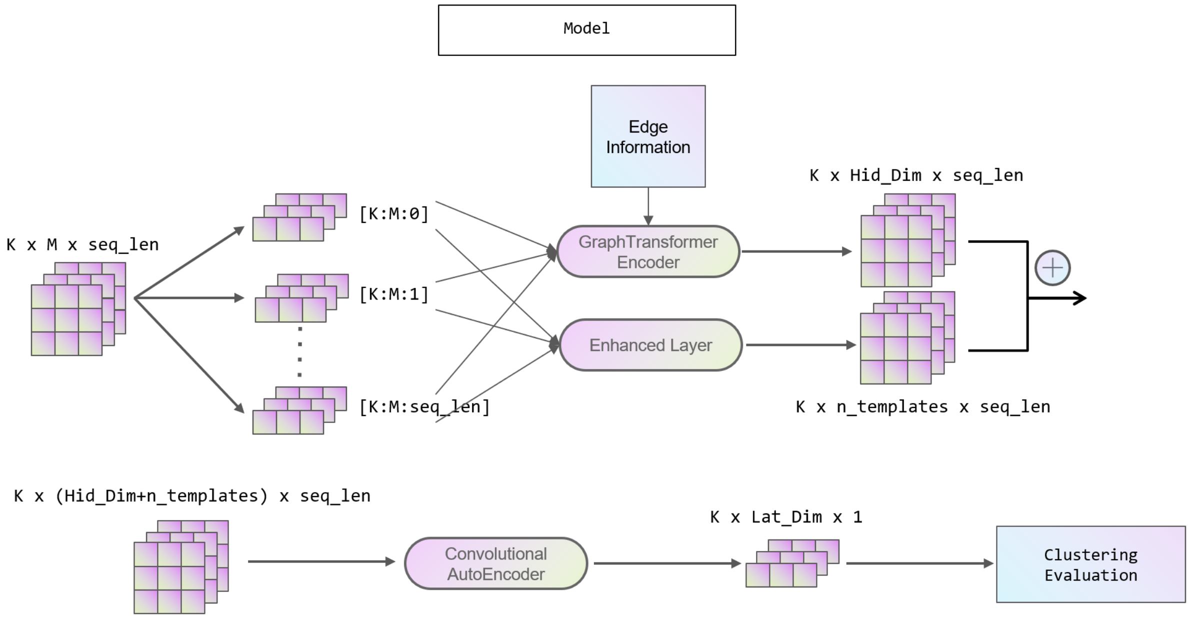

Figure 3: Model & Evaluation

4.2 Current Results

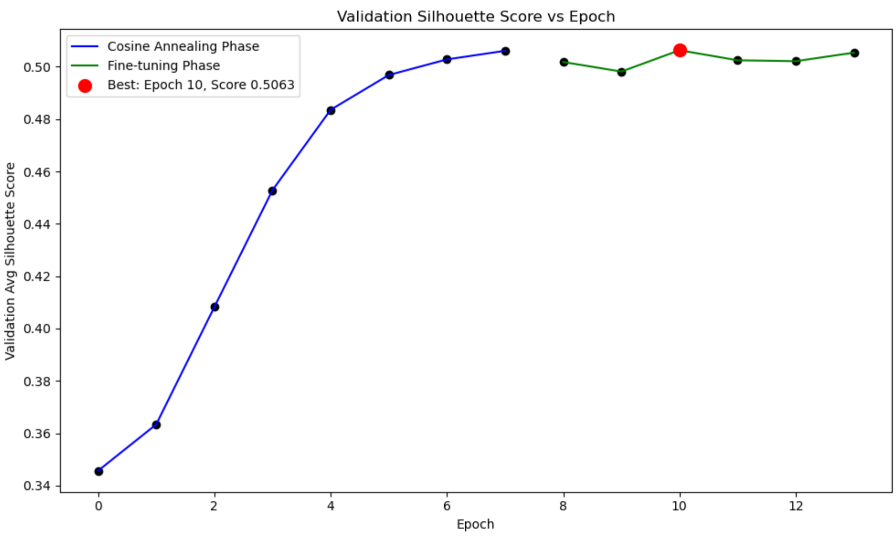

Figure 4: Average Silhouette Score of All Time Steps in Each Epoch

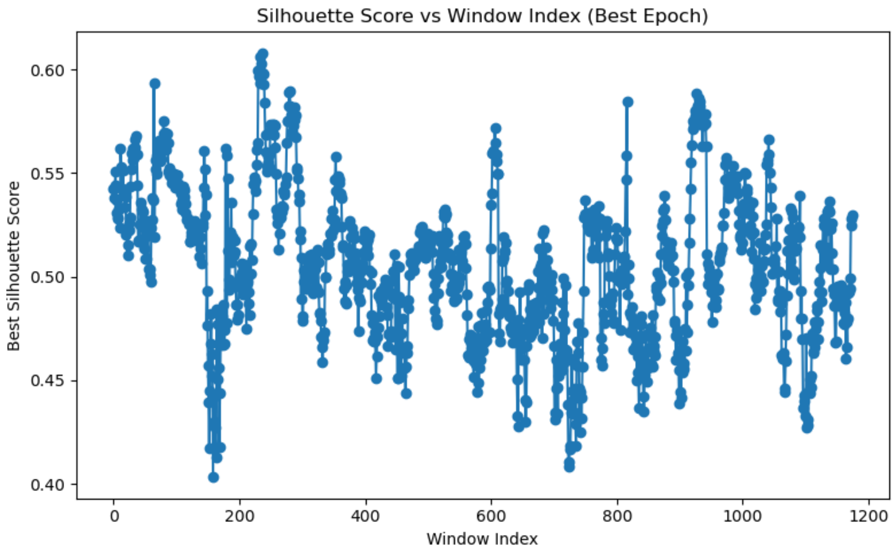

Figure 5: Time-Varying Silhouette Score

It is quite encouraging that many windows achieve an average silhouette coefficient above 0.5, especially for financial time series. However, it is also clear that some windows show noticeably lower silhouette coefficients, which might be due to the limitations of using fixed weights and a static adjacency matrix. Therefore, it would be worthwhile to explore methods that can address these lower-performance intervals and further enhance the model's overall performance.

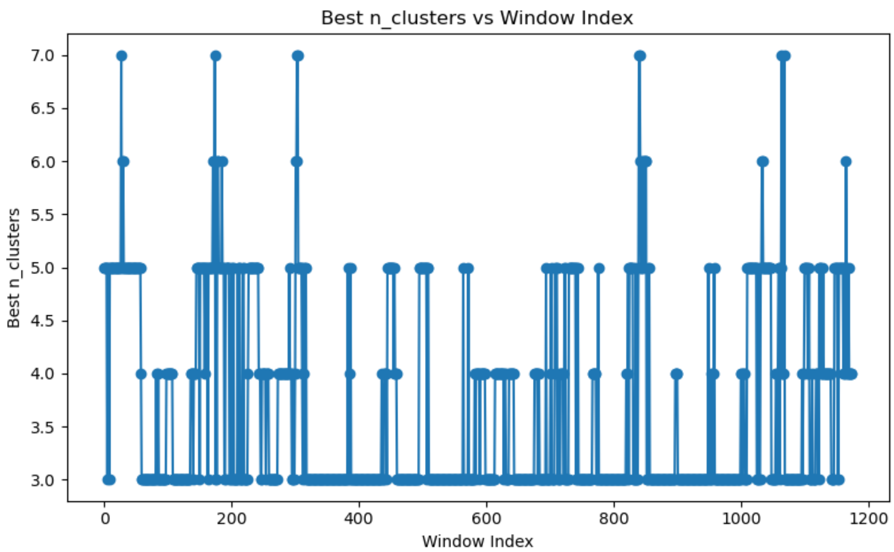

Figure 6: Time-Varying Best Community Number

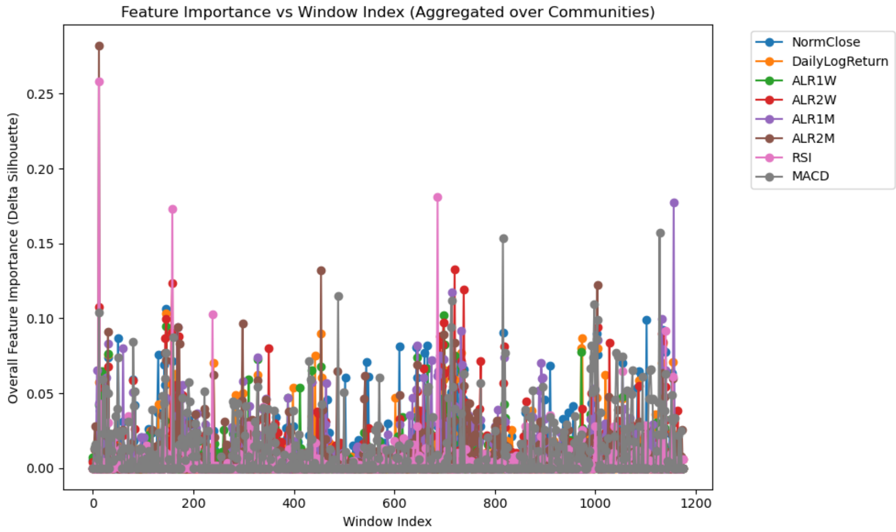

Figure 7: Time-Varying Feature Importance Based on Feature Perturbation

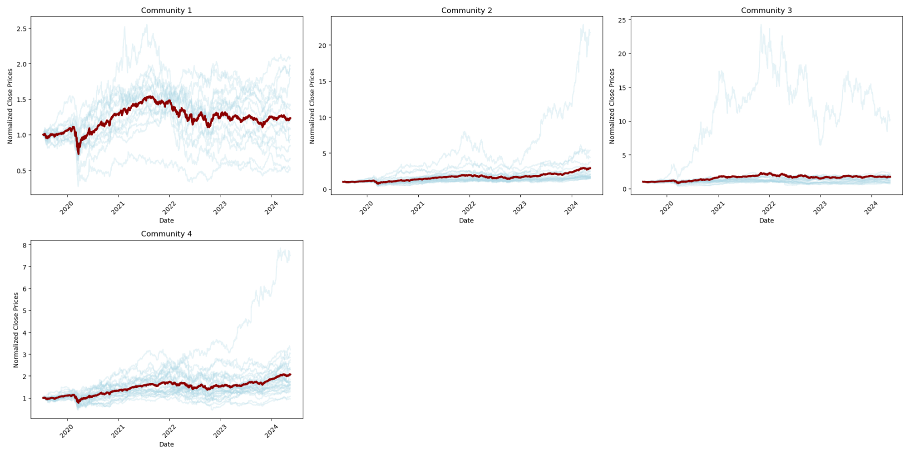

Figure 8: Clustering Visualization of the Last Window

5 Time Line

Timeline	Progress
Before April 1, 2025	Attempt to migrate the EvolveGCN idea to achieve a dynamic weight matrix.
Before April 15, 2025	Attempt to migrate the Graph WaveNet idea to achieve a dynamic adjacency matrix.
Before April 30, 2025	Experiment with alternative metrics or computational strategies to better capture the nuances of global dependencies.
Before May 14, 2025	Determine the optimal combination of advanced techniques and establish a sound theoretical foundation.
After May 14, 2025 (as needed)	Complete the full paper writing.

Table 1: Research Milestones Timeline

6 Expected Outcomes

This study anticipates that the proposed transformer-based graph convolution module combined with convolutional autoencoders will achieve better performance compared to existing graph neural network (GNN)-based models for unsupervised community detection in time series data. Specifically, this study aims to demonstrate at least a 10% improvement in average silhouette scores compared to baseline GNN approaches. Additionally, the proposed model is expected to reduce the standard deviation of silhouette coefficients across different time windows by approximately 10%, indicating more stable community detection over time. Furthermore, by integrating dynamic components—such as time-varying adjacency matrices and adaptive model weights—this study expects an additional improvement of at least 5% in the average silhouette score relative to the static version. These results would confirm the effectiveness and potential of dynamic spatial-temporal modeling in capturing evolving relationships.

7 References

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