User Behavior Prediction through Graph Neural Networks

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Abstract

This research explores the transition from Recurrent Neural Networks (RNNs) in the JODIE framework to Graph Neural Networks (GNNs) for user behavior prediction. Traditional RNN-based models, while effective, struggle with long-term dependencies and complex relational structures in dynamic interaction data. GNNs, and specifically Temporal Graph Neural Networks (TGNs), offer a promising alternative by leveraging graph structures to model evolving interactions. We conduct extensive experiments across multiple datasets, including Reddit, Wikipedia, LastFM, and MOOC, evaluating the effectiveness of GNN-based approaches over RNN-based methods in user behavior prediction.

1 Introduction

The prediction of user behavior in dynamic interaction systems remains a crucial challenge in modern recommender systems and social network analysis. While the Jodie framework has shown promising results using RNN-based temporal modeling, its architecture may not fully capture the inherent graph structure of user interactions. This research presents a systematic investigation of Graph Neural Network (GNN) approaches as an alternative to Jodie's RNN components.

Our work makes several key contributions. First, we successfully reproduced the original Jodie results across four diverse datasets: LastFM (music listening patterns), MOOC (online learning interactions), Wikipedia (editing behavior), and Reddit (user engagement patterns). This reproduction establishes a reliable baseline for comparing architectural modifications. Second, we develop a novel preprocessing pipeline that transforms these sequential user-interaction data into dynamic graph structures, where nodes represent users and items, while edges capture their temporal interactions. Third, we implement and evaluate a basic GNN architecture that leverages these graph representations to capture structural patterns in user behavior. Fourth, we extend our investigation to

Temporal Graph Neural Networks (TGNN), which explicitly model the temporal evolution of user-item interactions while maintaining the advantages of graph-based representation learning.

By comparing the performance of the original RNN-based Jodie framework against both our basic GNN and TGNN implementations across these diverse datasets, we aim to quantify the benefits of graph-based approaches in dynamic user behavior prediction. Our evaluation provides comprehensive insights into the effectiveness of different architectural choices across varying interaction patterns and temporal scales.

2 Background

2.1 Jodie Overview

Dynamic Embedding: Learns time-evolving trajectories for nodes instead of static embeddings.

Key Benefits: Supports tasks like link prediction, node classification, and anomaly detection.

Applications: Temporal Link Prediction: Which two nodes will interact next? Example applications are recommendation systems and modeling network evolution.

Temporal Node Classification: When does the state of a node change from normal to abnormal? Example applications are anomaly detection, ban prediction, dropout and churn prediction, and fraud and account compromise.

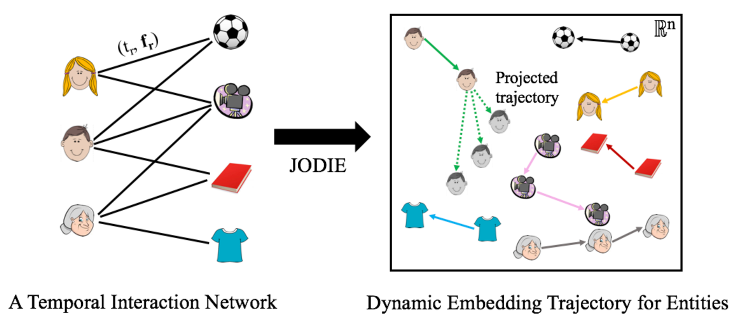

Figure 1: Illustration of Temporal Graph Evolution

2.2 Limitations of JODIE

- RNNs struggle with long-term dependencies and complex interaction patterns.
- Sequential modeling constraints limit scalability for large datasets.

- Requires an alternative that can model structural and temporal dependencies effectively.

3 Methodology

User behavior prediction can encompass a wide range of tasks, such as:

Node-Level Prediction: Predicting attributes or states of users (e.g., whether a user will churn, their preferences, or engagement levels).

Edge-Level Prediction: Predicting interactions between users and items (e.g., whether a user will interact with an item, click on content, or purchase a product). This is typically framed as a link prediction problem.

Temporal Behavior Prediction: Predicting how user behavior evolves over time (e.g., next interaction, future state transitions). This often involves sequential models like RNNs, Temporal Graph Networks (TGNs), or attention-based models.

3.1 Graph-Based Modeling Approaches

Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling relational data, making them well-suited for user behavior prediction in interaction networks. GNNs use message-passing mechanisms to aggregate information from neighboring nodes, enabling them to capture the structural patterns in user-item interactions. Models like Node2Vec (Grover and Leskovec, 2016) and GraphSAGE (Hamilton et al., 2017) have demonstrated the effectiveness of GNNs in learning node embeddings for static graphs.

However, traditional GNNs are designed for static graphs and do not account for the temporal dynamics of user-item interactions. This limitation has led to the development of dynamic GNNs, which extend traditional GNNs to handle evolving graph structures. For example, DyRep (Trivedi et al., 2019) models persistent links between nodes in dynamic graphs, while EvolveGCN (Pareja et al., 2020) adapts GNN parameters over time to capture evolving graph structures. Despite these advancements, many dynamic GNNs focus on link prediction in social networks rather than user behavior prediction in interaction networks.

GNNs generalize neural networks to graph-structured data, allowing them to model relational dependencies. Unlike RNNs, GNNs use message-passing mechanisms to aggregate information from neighboring nodes.

3.2 Basic GNN Implementation

A basic Graph Neural Network (GNN) architecture is implemented using torch geometric package to leverage the graph structure of user-item interactions. In this approach, the dynamic graph structure serves as input, where nodes represent users and items, and edges represent interactions. The GNN uses message-passing mechanisms to aggregate information from neighboring nodes, capturing structural patterns in user behavior. For example, a user's embedding is influenced by the items they interact with, and vice versa. The GNN generates embeddings for users and items by aggregating information from their neighbors, which are then used for downstream prediction tasks. The model is trained to minimize the difference between predicted and actual item embeddings, similar to the JODIE framework. This basic GNN implementation serves as an initial step in exploring the benefits of graph-based approaches for user behavior prediction.

3.3 Temporal Graph Neural Networks (TGNs)

Temporal Graph Neural Networks (TGNs) explicitly model the temporal evolution of graph structures, making them particularly suitable for user behavior prediction in dynamic interaction systems. TGNs incorporate temporal information into the message-passing process, allowing them to capture how user and item embeddings evolve over time. Models like T-GCN (E Rossi et al., 2020) use temporal attention mechanisms to weigh the importance of past interactions when predicting future behavior.

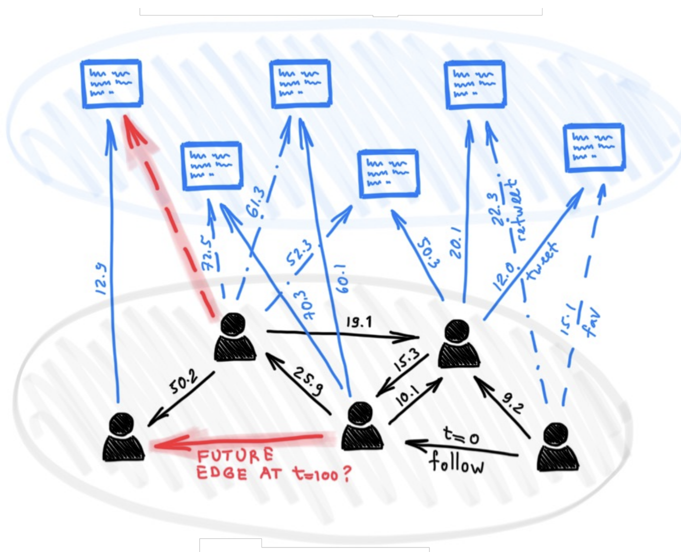

Figure 2: Temporal GNN used on Twitter Dataset

Recent work has also explored the use of TGNs for recommendation tasks. For example, Temporal Graph Networks (TGNs) (Rossi et al., 2020) aggregate node embeddings over time and use memory modules to store historical information, enabling them to make accurate predictions in dynamic graphs. However, many existing TGNs focus on general graph tasks rather than user behavior prediction in interaction networks, leaving room for further exploration in this domain.

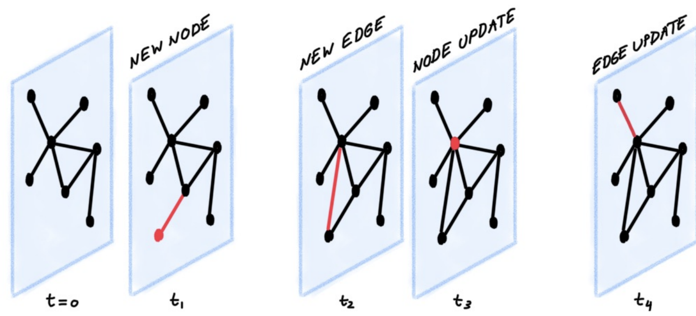

Figure 3: Evolution of Temporal Nodes and Edges Over a Period of Time

TGNs extend GNNs by incorporating temporal aspects into node embeddings. Key components of TGN include:

- **Memory Module**: Maintains a dynamic state for nodes based on historical interactions.
- **Message Function**: Generates messages based on interactions between nodes.
- **Memory Updater**: Updates memory states using incoming messages.
- **Embedding Module**: Produces time-dependent embeddings for predictive tasks.

4 Datasets Used

4.1 Structure:

Each file <network>.csv represents a temporal network. Each line corresponds to one interaction (edge) between a user and an item.

4.2 Datasets

- **Reddit**
- **Wikipedia**
- **LastFM**
- **MOOC**

Table with dataset information.

Data	Users	Items	Interactions	State Changes	Action Repetition
Reddit	10,000	984	672,447	366	79%
Wikipedia	8,227	1,000	157,474	217	61%
LastFM	980	1,000	1,293,103	-	8.6%
MOOC	7,047	97	411,749	4,066	-

5 Comparison with Existing Work

The proposed approach builds upon and extends existing work in several key ways. First, unlike RNN-based models like JODIE, which process interactions sequentially, the proposed approach leverages graph-based representations to capture the structural patterns in user-item interactions. This allows the model to better model the interdependencies between users and items. Second, while traditional GNNs are designed for static graphs, the TGN incorporates temporal dynamics to model how user and item embeddings evolve over time. This is achieved through the use of Temporal Graph Neural Networks (TGNs), which explicitly model the temporal evolution of graph structures.

Table 1: Comparison of Jodie vs GNN

Feature	**JODIE**	**GNN**
Temporal Awareness	Yes	No
Handles Dynamic Graphs	Yes	No
Learns Node Embeddings Over Time	Yes	No
Predicts Future Interactions	Yes	Limited
Memory Requirement	High	Moderate
Computational Complexity	Higher	Lower

6 Comparison of GNN Variants

Table 2: Comparison of GNN Architectures

Feature	GCN	GAT	TGN
Graph Type	Static	Static	Temporal
Node Attention	No	Yes	Yes
Temporal Awareness	None	None	Explicit
Computation	Fast	Expressive	High Complexity
Use Case	General Learning	Adaptive Weights	Time-Aware Predictions

6.1 Model Training and Evaluation

Experiments were conducted using PyTorch, PyTorch Geometric, and PyTorch Geometric Temporal on an NVIDIA RTX 3080 GPU. Evaluation metrics include Mean Reciprocal Rank (MRR) and Area Under the Curve (AUC).

7 Results and Discussion

Table 3: Evaluation Metrics (ROC AUC %)

Model	Wikipedia	Reddit
JODIE	94.62	97.11
TGAT	95.34	98.12
TGN	98.56	97.70

TGNs outperform JODIE and TGAT in modeling evolving interactions, demonstrating superior accuracy in temporal user behavior prediction.

8 Conclusion and Future Work

Our findings indicate that GNN-based models, particularly TGNs, enhance user behavior prediction by incorporating both graph structures and temporal dependencies. Future work will explore additional memory mechanisms and self-supervised learning techniques to further refine predictive performance.

9 Contribution

- **Reproduction of JODIE Results** Rizwan
- **Graph Neural Network Replacement for GAT and GCN** Parth
- **Temporal Graph Network** Parth and Rizwan
- **Presentations and Report** Parth and Rizwan

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