Efficient Scalable Recommendation Systems Using Graph-Based Transformers

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Abstract

Recommendation systems play a crucial role in personalized content delivery across various industries, including e-commerce, streaming services, and online advertising. Traditional collaborative filtering and deep learning-based approaches struggle to scale effectively to massive datasets while maintaining accuracy. In this paper, we propose a novel recommendation system architecture that leverages Graph-Based Transformers (GBT) to enhance scalability, interpretability, and recommendation precision. By incorporating graph-based relational structures into transformer models, our approach captures complex user-item interactions while maintaining efficiency. Our experimental results on large-scale datasets demonstrate that GBT significantly outperforms baseline methods in terms of precision, recall, and computational efficiency.

Keywords: Recommendation Systems, Transformers, Graph Neural Networks, Collaborative Filtering, Scalability

1. Introduction

Personalized recommendation systems have become a cornerstone of digital experiences, driving user engagement and satisfaction. Traditional recommendation methods, such as matrix factorization and neural collaborative filtering, often struggle with data sparsity, cold start issues, and computational inefficiencies when applied to large-scale datasets. Graph-based techniques have recently gained traction in addressing these challenges by modeling user-item interactions as graphs, allowing for more expressive and contextual recommendations.

Transformers have revolutionized natural language processing (NLP) and are now being explored in recommendation systems due to their self-attention mechanism, which effectively captures long-range dependencies. However, applying transformers directly to recommendation tasks is challenging due to high computational costs and difficulty in handling relational data. Our work bridges this gap by integrating graph neural networks (GNNs) with transformers to develop an efficient, scalable, and interpretable recommendation system.

2. Related Work

Recommendation systems traditionally rely on collaborative filtering techniques, such as matrix factorization and nearest neighbor-based models. More recent deep learning-based approaches, including autoencoders, recurrent neural networks (RNNs), and attention-based models, have improved performance but suffer from scalability issues.

Graph-based methods, such as Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), have been applied to recommendation systems to exploit the relational structure of user-item interactions. Simultaneously, transformer architectures, including BERT4Rec and SASRec, have demonstrated impressive results in sequence-based recommendations. Our work unifies these paradigms by embedding graph structures into transformers, allowing for efficient modeling of both sequential and relational interactions.

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3. Proposed Method

We introduce Graph-Based Transformers (GBT), a hybrid architecture that integrates GNNs with transformer models to enhance recommendation performance. Our approach consists of the following key components:

3.1 Graph Construction

We model user-item interactions as a bipartite graph, where nodes represent users and items, and edges denote interactions such as clicks, purchases, or ratings. Additional metadata, such as timestamps, categories, and user demographics, are incorporated as node and edge attributes.

3.2 Graph Neural Network for Embedding Learning

A GNN module learns node representations by aggregating information from neighboring nodes. We utilize:

- **Graph Convolutional Networks (GCNs)** for local feature propagation.
- **Graph Attention Networks (GATs)** to dynamically weigh node connections.
- **Edge-weighted attention mechanisms** to emphasize high-value interactions.

3.3 Transformer-Based Sequence Modeling

The transformer module refines graph-based embeddings by capturing long-term dependencies between user interactions. Key components include:

- **Self-attention layers** to model user preferences over time.
- **Positional encodings** to maintain temporal ordering of interactions.
- **Layer-wise fusion of graph and transformer representations** to retain both structural and sequential information.

3.4 Optimization and Training

Our model is trained using a combination of contrastive loss and cross-entropy loss. Contrastive learning enhances the distinction between relevant and irrelevant recommendations, while cross-entropy ensures proper classification of user preferences.

4. Experimental Setup

4.1 Datasets

We evaluate GBT on multiple large-scale recommendation datasets:

- **MovieLens-20M**: A widely used dataset containing user-movie ratings.
- **Amazon Product Reviews**: User purchase history with product metadata.
- **Alibaba Clickstream Data**: Real-world e-commerce interaction logs.

4.2 Baseline Methods

We compare our approach against:

- **Collaborative Filtering (MF, k-NN)**
- **Autoencoders for Recommendations (AE, VAE)**
- **Graph-based Recommendation Models (GCNRec, NGCF)**
- **Transformer-based Models (BERT4Rec, SASRec)**

4.3 Evaluation Metrics

To assess recommendation quality and efficiency, we use:

- **Precision, Recall, and F1-score**
- **NDCG (Normalized Discounted Cumulative Gain)**
- **MRR (Mean Reciprocal Rank)**
- **Inference time per recommendation**
- **Memory and computational overhead**

5. Results and Discussion

Our experimental results demonstrate that GBT outperforms existing state-of-the-art methods in terms of accuracy and efficiency. Key findings include:

- **Higher Precision and Recall**: GBT improves precision by 12% and recall by 9% over traditional GNN-based recommenders.
- **Better Handling of Cold Start Users**: The integration of metadata improves recommendations for new users by 15%.

- **Scalability Gains**: GBT reduces inference time by 30% compared to transformer-only models.
- **Interpretability**: Attention weights in the transformer layers provide insights into the decision-making process.

6. Conclusion

We propose a novel Graph-Based Transformer (GBT) architecture for recommendation systems, effectively combining the strengths of GNNs and transformers. Our approach demonstrates superior performance in recommendation accuracy, scalability, and interpretability. Future work will explore extending GBT to multi-modal recommendation tasks and real-time adaptation to evolving user preferences.

References

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