Sequential Recommender Systems Deep Graph Evaluation and Denoising

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***Abstract*—Recent advancements in sequential recommender systems (SRSs) aim to provide users with better, personalized recommendations. While traditional models like collaborative filtering have been effective, SRSs focus on understanding user behaviors over time. However, SRSs, especially those using Graph Convolutional Neural Networks (GCNNs), face challenges such as complexity and inefficiency. This research compares traditional GCNNs with Graph Neighborhood Filters (GNFs), specifically neighborhood graph filters (NGFs). NGFs address challenges in GCNNs by providing a stable foundation using k-hop neighborhood adjacency matrices. The goal is to show the benefits of NGFs over traditional filters in practical applications like graph signal denoising and node classification. The study explores existing challenges in SRSs and contributes insights to improve recommendation systems. The research commits to evaluating NGFs' denoising performance against current methods, aiming to demonstrate their superiority in accuracy, scalability, and efficiency for sequential recommender systems. This is the GitHub repository for this report and implementation https://github.com/TxCorpi0x/sequential-recommendation**

***Index Terms*—Recommender Systems, GCNNs, NGFs.**

I. Introduction

THE field of sequential recommender systems (SRSs) has witnessed significant advancements in recent years, driven by the growing need to provide more accurate, personalized, and timely recommendations to users. While traditional recommendation models, such as collaborative filtering and content-based filtering, have proven effective, the emergence of SRSs addresses the limitations of these approaches by focusing on understanding and modeling the sequential user behaviors, interactions, and the evolution of user preferences over time. Despite their success, many SRSs, particularly those based on Graph Convolutional Neural Networks (GCNNs), face challenges related to computational efficiency, model complexity, and susceptibility to over-parameterization.

In this context, this research plans to build a comparison context for SRSs conventional GCNNs denoising with Graph Neighborhood Filters (GNFs). The motivation for this effort is rooted in the observed challenges of traditional GCNNs, such as numerical errors, limitations in practical depth, and sensitivity to graph topology variations [1]. The proposed GNFs, referred to as neighborhood graph filters (NGFs), present a family of graph filters that leverage k-hop neighborhood adjacency matrices, providing a more robust and numerically stable foundation for designing deep neighborhood GCNNs.

The primary goal of this research is to demonstrate the advantages of employing NGFs over classical graph filters in practical applications. To showcase the effectiveness of this approach, the study employs NGFs in the design of deep neighborhood GCNNs and evaluates their performance in graph signal denoising [1] [2] and node classification tasks using both synthetic and real-world datasets.

The subsequent sections of this research delve into the challenges faced by existing SRSs, particularly those utilizing GCNNs, and present a comprehensive exploration of the proposed GNF-based approach. The experimental results, supported by evaluations on various datasets, highlight the superior performance of the new model in terms of robustness, efficiency, and computational scalability. By addressing these key issues in SRSs, the research contributes to the ongoing evolution of recommendation systems, paving the way for more effective and scalable solutions in the era of dynamic user preferences and evolving content landscapes.

II. Literature Review

Sequential recommender systems (SRSs) have evolved as a crucial component in addressing the dynamic nature [3] of user preferences and the temporal aspect of interactions. Traditional recommendation models, such as collaborative filtering and content-based filtering, laid the foundation for personalized suggestions. However, the emerging landscape of SRSs, particularly those employing Graph Convolutional Neural Networks (GCNNs), has faced challenges that prompt researchers to explore novel alternatives.

1. Temporal Dynamics and Personalization

The importance of considering temporal information in recommendation systems is highlighted by various works. The SASRec model, inspired by the Transformer architecture, has demonstrated state-of-the-art results by leveraging attention mechanisms. However, limitations arise in terms of personalization, prompting the introduction of personalized models like SSE-PT, which outperforms SASRec by incorporating personalized user embeddings.

2. Multi-Behavior

The exploration of dependencies between different user behaviors is addressed by models like MB-AGCN [4]. This model focuses on personalized interaction patterns and cross-typed behavioral interdependencies, showcasing improvements over existing methods in multi-behavior recommendation scenarios.

3. Graph Neural Networks

The SURGE model [5] introduces a graph neural network approach to sequential recommendation, addressing challenges associated with implicit and noisy user behavior signals. The model leverages metric learning to cluster user preferences, demonstrating significant performance gains over state-of-the-art methods.

4. SR in Real-Time

Acknowledging the timeliness and contextual accuracy required in contemporary digital marketing, sequential recommendation systems based on autoencoders and GRU models offer promising results. Real-time predictions [6] in a production dataset of credit card transactions showcase the potential of sequential recommendation systems.

5. Hybrid

Hybrid recommender systems [6], [7], like U2CMS, aim to enhance personalized content recommendations by unifying similarity models, collaborative, and content-based approaches with Markov chains for sequential recommendation. The model proves effective in handling sparsity issues and outperforms existing state-of-the-art recommendation systems.

6. Complexities and Challenges

A systematic review on sequential recommender systems (SRSs) emphasizes the unique characteristics and challenges [8] in this research domain. The research categorizes key challenges, presents recent developments, and outlines important research directions in the evolving field of SRSs.

7. Attention Mechanisms and Over-Parameterization

Sequential recommender systems based on attention mechanisms [9], including RNNs, CNNs, memory networks, and attention networks, have gained popularity for their ability to capture dynamic preferences. However, the complexity and over-parameterization issues, particularly in Transformer models, pose challenges for effective deployment under limited resources.

8. Temporal Graph Networks for Cold-Start Problem

Temporal graph networks emerge as powerful tools for addressing the cold-start problem in sequential recommender systems. The proposed exploration method using Rooted PageRank and bipartite graphs aims to mitigate feedback loops and data distribution shifts, providing competitive results on popular benchmarks [10].

9. Deep Attention-based Sequential Models

The DAS model tackles the challenges of modeling both short-term and long-term preferences in user-item interaction sequences. By incorporating an embedding block, an attention block, and a fully-connected block, the model demonstrates superiority over state-of-the-art approaches in SRSs through extensive experiments [9].

10. Challenges in Graph Convolutional Neural Networks (GCNNs)

Classical graph filters in GCNNs are prone to numerical errors and limitations in practical depth. The proposed NGFs, a form of graph neighborhood filters, address these challenges by leveraging k-hop neighborhood adjacency matrices, offering a more robust foundation for designing deep neighborhood GCNNs.

11. Transformer Models in Recommender Systems

Transformer models have become the backbone of many SRSs due to their ability to capture long-range dependencies and sequential patterns. However, the growth in model size raises concerns about computational efficiency, prompting researchers to explore compression techniques for these architectures [11].

III. Contribution of Study

In response to the challenges and complexities outlined in the existing literature on sequential recommender systems (SRSs), particularly those employing Graph Convolutional Neural Networks (GCNNs), this study aims to make a contribution by evaluating and tuning the denoising of Graph Neighborhood Filters (GNFs) [1] [2] to evaluate or improve the overall efficacy of SRSs. The key contribution of this research lies in addressing the limitations associated with traditional graph filters and leveraging GNFs or alternative approach to enhance various aspects of sequential recommendations.

While GCNNs have proven effective in capturing graph-structured data, their generalization capabilities may be hindered by over-parameterization. Graph Neighborhood Filters are anticipated to contribute to improved generalization by providing a more parsimonious representation of graph relationships. This, in turn, enhances the model's adaptability to diverse datasets and recommendation scenarios.

The study plans to conduct a comprehensive evaluation and improve denoising performance of the proposed Graph Neighborhood Filters by benchmarking them against state-of-the-art methods on various real-world datasets. This thorough assessment aims to demonstrate the superiority of the proposed approach in terms of recommendation accuracy, scalability, and computational efficiency.

IV. Methodology

1. Data Collection

- **Datasets**: Select diverse real-world datasets representing denoising performance of the GNFs.
- **Data Preprocessing**: Clean and preprocess datasets, handling missing values, encoding categorical features, and ensuring a standardized format.

2. Graph Construction

- **User-Item Interaction Graph**: Build a graph representation of user-item interactions, considering temporal dynamics and denosing dependencies.
- **Graph Neighborhood Extraction**: Define k-hop neighborhood adjacency matrices to capture local graph structures.

3. Graph Neighborhood Filters Integration

- **Graph Neighborhood Filters (GNFs) Tuning**: Modify GNFs denosing mechanism and Hyper-Parameter manipulation.
- **Denosing Performance**: Optionally, explore graph noise filtering techniques to further enhance efficiency and scalability.

4. Model Architecture

- **Sequential Recommender System (SRS)**: Establish a baseline SRS model using traditional Graph Convolutional Neural Networks (GCNNs).
- **Graph Neighborhood Filters Integration**: Integrate the designed GNFs into the SRS architecture, replacing traditional graph filters with improved denoising capabilities.

5. Model Training

- **Loss Function**: Define appropriate loss functions for the SRS model with GNFs, considering the nature of the recommendation task (e.g., ranking loss for sequential recommendations).
- **Optimization**: Utilize optimization algorithms such as stochastic gradient descent to train the model.

6. Evaluation Metrics

- **Performance Metrics**: Employ standard evaluation metrics for recommender systems, including precision, recall, F1 score, and ranking metrics like NDCG@k.
- **Comparison**: Benchmark the performance of the enhanced SRS with GNFs against current implementation of GFNs [1].

7. Experimental Setup

Baseline Comparison: Include a comparison with traditional GCNN-based SRS to highlight the impact of GNFs and denoising mechanisms.

8. Open-Source Implementation

- **Code Repository**: Share an open-source implementation of the enhanced SRS with GNFs, including preprocessing scripts, model training, and evaluation code.
- **Documentation**: Provide comprehensive documentation for researchers and practitioners to reproduce the study's results and extend the proposed approach.

V. DATASETS

- **Movie Lens 1M**
- **IMDB**

VI. EXPERIMENTAL RESULTS

Compression of Numerical Errors

Classical graph filters (GFs) in Graph Convolutional Neural Networks (GCNNs) are prone to numerical errors, especially with high-order polynomials, The application of Neighborhood Graph Filters (NGFs) effectively mitigates numerical errors, allowing for smoother and more accurate computations during the training and inference phases

Enhanced Robustness to Graph Topology Errors

Traditional GFs face challenges in maintaining robustness to errors in the topology of the graph, leading to suboptimal performance in real-world scenarios. NGFs demonstrate enhanced robustness to errors in the graph's topology. This improvement is crucial for applications in dynamic and evolving graph structures commonly encountered in real-world datasets.

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