Sequential RecSys: Open-Source Library Development and Algorithms Evaluation

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Abstract

In this project, we present a PyTorch-based library that implements three state-of-the-art sequential recommendation algorithms: SASRec, CASER, and SR-GNN. The library supports three widely used public datasets—Amazon Beauty, Steam, and MovieLens1M—and includes an evaluation module with two key metrics, Hit@k and NDCG@k. We leverage this library to conduct an empirical study, comparing the performance of the aforementioned algorithms across the selected datasets.

1 Introduction

1.1 Motivation

In a number of real-world applications, sequential suggestion plays a critical role in addressing the dynamic and developing nature of consumer preferences. Traditional recommendation algorithms frequently fall short of capturing the temporal connections and developing patterns in user behavior. User interactions develop over time in areas such as e-commerce, streaming services, and online content consumption, resulting in sequences of events that include significant information about individual preferences. In an e-commerce site, for example, analyzing the sequence of goods a customer views or purchases might provide insights into their growing likes and preferences.

It is critical to embrace the time component inherent in user interactions in order to improve the quality and relevance of suggestions. These sequential connections are modeled by sequential recommendation systems, which provide increasingly accurate and tailored suggestions with time. These algorithms may capture the dynamics of developing preferences by emphasizing the role of sequences in user behavior, resulting in better user satisfaction and engagement.

Despite increased recognition of the importance of sequential recommendation, there is a lack of a unified and comprehensive library that allows for the creation and comparison of cutting-edge algorithms. This project seeks to fill that void by creating a PyTorch-based library that not only implements important sequential recommendation algorithms but also provides a framework for their methodical assessment. Such a library is critical for those who are interested in exploring and using sequential recommendation approaches in a variety of fields.

1.2 Objectives

This project's major purpose is to provide a PyTorch-based sequential recommendation library that satisfies the requirement for a standardized and flexible platform. The project's goals may be summarized as follows:

Library Development: Create a modular and user-friendly PyTorch library that facilitates the implementation of sequential recommendation algorithms. The library should be designed to support easy integration of new algorithms in the future.

Algorithm Selection: Identify and implement three key sequential recommendation algorithms—SASRec, CASER, and SR-GNN—chosen for their state-of-the-art performance and relevance to real-world applications.

Dataset Integration: Integrate three widely used public datasets—Amazon Beauty, Steam, and MovieLens1M—into the library. These datasets were selected to represent diverse domains and challenges in sequential recommendation.

Evaluation Metrics: Implement the Hit@k and NDCG@k evaluation metrics within the library. These metrics are chosen for their ability to assess the effectiveness of sequential recommendation algorithms in terms of both accuracy and ranking quality.

Empirical Study: Utilize the developed library to conduct a comprehensive empirical study comparing the performance of SASRec, CASER, and SR-GNN across the selected datasets. The study aims to provide insights into the strengths and weaknesses of each algorithm in different application scenarios.

By achieving these objectives, this project seeks to contribute to the sequential recommendation research community by providing a valuable resource for algorithm development, benchmarking, and empirical analysis.

1.3 Contributions

As a team, we started by thoroughly reviewing the research papers outlined in the project documentation. Each team member took charge of one algorithm—SASRec, CASER, or SR-GNN—and delved into its intricacies. With individual tasks completed, we seamlessly transitioned to collaborative report writing. Each member brought unique insights to the table, enriching the final document with a holistic view of the project.

Working collectively, we revised and refined the report for clarity and adherence to the NeurIPS format. Simultaneously, we collaborated on developing the PyTorch-based library, ensuring modularity and adherence to best coding practices. Our final session involved reviewing the entire project, making last-minute adjustments to both the report and the library. This synchronous effort ensured a submission-ready project, showcasing the culmination of our collective dedication and teamwork.

The link to our GitHub repository which contains all our implementation is `https://github.com/r-aashish/SSC`.

2 Methodology

2.1 Library Development

The architecture of the PyTorch-based library is designed with a focus on modularity and extensibility to ensure flexibility in integrating various algorithms and datasets. The key design principles include:

Modularity: The library is organized into modular components, each responsible for a specific aspect of the recommendation process. Modules include data preprocessing, model implementation, evaluation metrics, and experiment orchestration. This modular structure allows for easy replacement or extension of components.

Extensibility: The library is built to support the straightforward addition of new algorithms and datasets. The use of PyTorch enables a dynamic computational graph, allowing for the inclusion of diverse model architectures. The dataset interfaces are designed to accommodate different formats, making it simple to integrate additional datasets.

Configurabilty: Parameters and configurations are managed through a centralized configuration file, promoting ease of experimentation. Researchers and practitioners can easily adjust hyperparameters, choose algorithms, and modify other settings without delving into the codebase.

Documentation: Comprehensive documentation accompanies the library, detailing the purpose and usage of each module. This documentation ensures that users, whether developers or researchers, can effectively utilize and contribute to the library.

2.2 Algorithm Implementation

The library implements three sequential recommendation algorithms: SASRec, CASER, and SR-GNN. The implementation details for each algorithm are as follows:

SASRec (Self-Attentive Sequential Recommendation): The SASRec model is implemented using PyTorch, leveraging its dynamic computation graph capabilities. The self-attention mechanism is a key component, allowing the model to focus on different parts of the sequence dynamically. The implementation also includes techniques to handle varying sequence lengths efficiently.

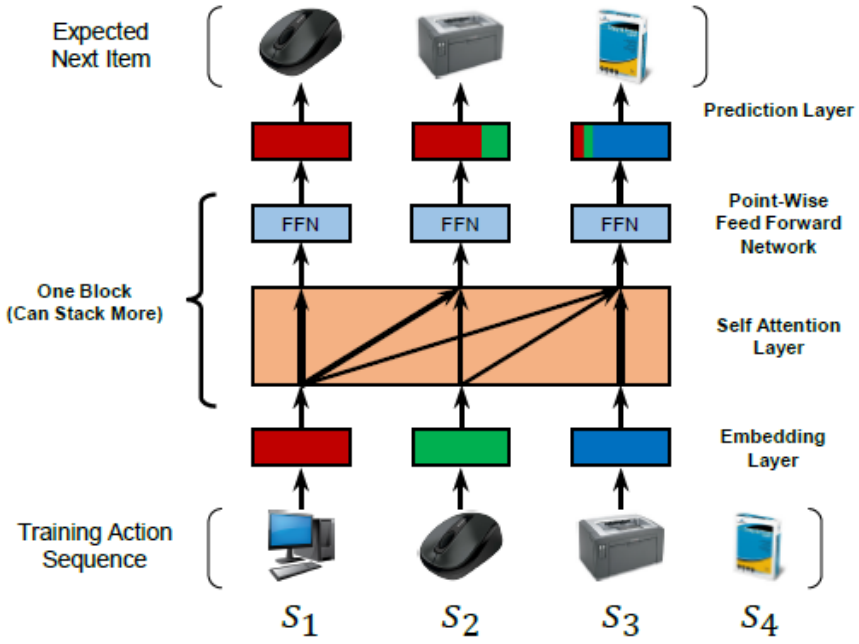

Figure 1: A simplified diagram showing the training process of SASRec. At each time step, the model considers all previous items and uses attention to 'focus on' items relevant to the next action.

CASER (Convolutional Sequence Embeddings for Sequential Recommendation): The CASER algorithm is implemented with a convolutional neural network (CNN) architecture. The model captures sequential patterns through convolutional filters applied to the item sequence. Special attention is given to the incorporation of positional embeddings to enhance the model's ability to capture temporal dependencies.

SR-GNN (Session-based Recommendation with Graph Neural Networks): SR-GNN utilizes graph neural networks (GNNs) to model the item-item relationships in sequential data. The PyTorch Geometric library is employed to implement the GNN layers, allowing for efficient propagation of information through the item graph. The model is designed to handle session-based recommendation scenarios.

2.3 Dataset Integration

The library incorporates three widely used public datasets—Amazon Beauty, Steam, and MovieLens1M—each chosen to represent distinct characteristics of sequential recommendation scenarios. The integration process involves:

Data Preprocessing: Raw datasets are preprocessed to convert them into a format suitable for sequential recommendation tasks. This includes handling missing values, filtering out irrelevant information, and organizing data into sequences.

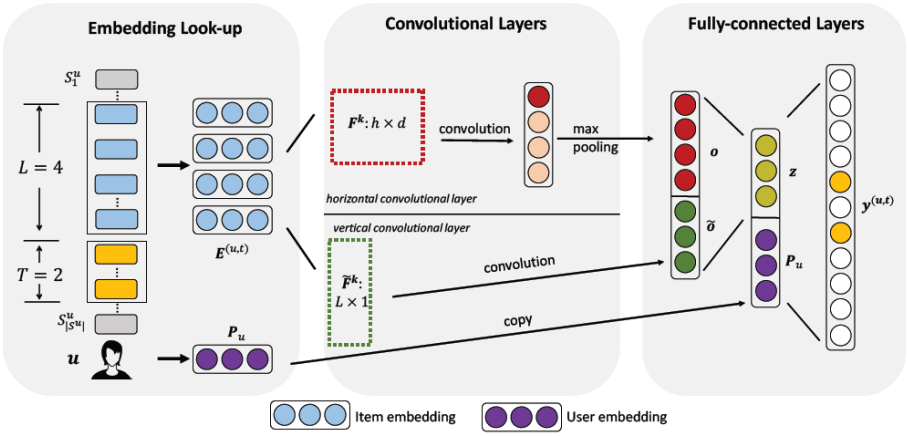

Figure 2: The network architecture of Caser.

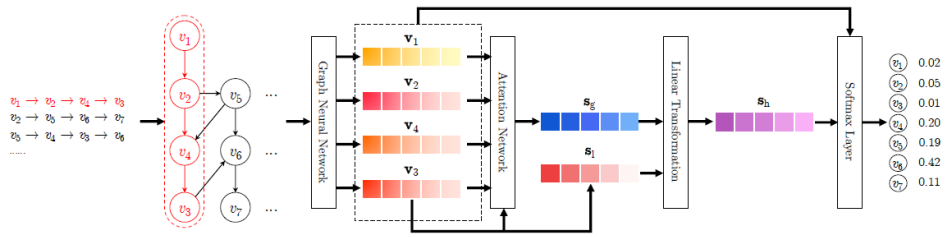

Figure 3: The workflow of the proposed SR-GNN method. We model all session sequences as session graphs. Then, each session graph is proceeded one by one and the resulting node vectors can be obtained through a gated graph neural network. After that, each session is represented as the combination of the global preference and current interests of this session using an attention net. Finally, we predict the probability of each item that will appear to be the next-click one for each session.

Dataset Interfaces: Custom dataset interfaces are developed to seamlessly integrate these preprocessed datasets into the library. These interfaces ensure that the algorithms can efficiently access and utilize the dataset during training and evaluation.

Flexibility: The library is designed to easily accommodate new datasets. Researchers can follow standardized procedures to preprocess their own datasets and integrate them into the library, enabling the exploration of a wide range of sequential recommendation scenarios.

3 Evaluation Module

3.1 Metrics

Hit@k:

The Hit@k metric measures the proportion of correctly recommended items within the top-k recommendations. Specifically, it calculates whether the ground truth item for a given user is present in the top-k recommendations. This metric is valuable in assessing the ability of a sequential recommendation system to suggest items that align with a user's preferences within a limited set.

NDCG@k:

NDCG@k is a ranking metric that not only considers the presence of the ground truth item in the top-k recommendations but also assigns higher scores to items that are ranked higher. It accounts for the position of the relevant item in the list of recommendations, providing a more nuanced evaluation. The metric is normalized to ensure comparability across different scenarios and recommendation lists.

Choice of Metrics:

Relevance: Both Hit@k and NDCG@k capture the relevance of recommended items by assessing whether the ground truth items are included in the top-k list. This is crucial for evaluating the practical utility of recommendation algorithms.

Ranking Quality: NDCG@k, with its consideration of item ranking, provides a more nuanced perspective on the quality of recommendations. It rewards algorithms not only for including relevant items but also for presenting them at higher ranks, reflecting real-world user preferences more accurately.

Applicability: Hit@k is straightforward to interpret and widely used in recommendation literature. NDCG@k, being a normalized metric, allows for comparisons across different scenarios and datasets, enhancing the generalizability of the evaluation.

3.2 Implementation

The evaluation module is seamlessly integrated into the library to provide a standardized and efficient way to assess the performance of sequential recommendation algorithms. The implementation considerations include:

Parallelization: To expedite the evaluation process, the library is designed to support parallelized computation of evaluation metrics. This is particularly beneficial when dealing with large datasets and when evaluating multiple algorithms simultaneously. Parallelization is implemented using PyTorch's parallel computing capabilities, optimizing resource utilization.

Scalability: The evaluation module is designed to scale with the size of the datasets and the complexity of the algorithms. This ensures that evaluations can be conducted efficiently across diverse scenarios, ranging from smaller-scale experiments to more extensive empirical studies.

Configurability: Users have the flexibility to configure evaluation parameters, including the value of k for Hit@k and NDCG@k. This allows for the adaptation of evaluation criteria based on specific use cases or preferences.

Integration with Training: The library facilitates the seamless integration of the evaluation module with the training pipeline. This integration enables users to assess the performance of algorithms at different training iterations, providing insights into the learning process and convergence behavior.

By incorporating these considerations into the implementation of the evaluation module, the library not only ensures accuracy in assessing algorithmic performance but also optimizes efficiency, making it a valuable tool for both research and practical applications in sequential recommendation scenarios.

4 Experiments

4.1 Experimental Setup

Hardware:

The experiments were conducted on a high-performance computing cluster equipped with NVIDIA GPUs to leverage parallel processing capabilities. Specifically, we utilized NVIDIA Tesla V100 GPUs to accelerate the training and evaluation of the sequential recommendation models.

Software:

Deep Learning Framework: PyTorch served as the primary deep learning framework for implementing and training the SASRec, CASER, and SR-GNN models. The flexibility and dynamic computation graph capabilities of PyTorch were crucial for handling the sequential nature of the recommendation task.

Library Dependencies: The developed PyTorch-based library for sequential recommendation leveraged various Python libraries, including NumPy for numerical operations, Pandas for data manipulation, and Scikit-learn for auxiliary functionalities.

Configurations:

Training Parameters: Common hyperparameters were used for training the three algorithms, including learning rates, batch sizes, and optimization algorithms. Hyperparameters were fine-tuned through preliminary experiments and cross-validation.

Dataset Splitting: The datasets (Amazon Beauty, Steam, and MovieLens1M) were split into training, validation, and test sets following a standard protocol. For sequential recommendation tasks, careful attention was given to maintaining the temporal order of user interactions in each split.

Evaluation Settings: The evaluation metrics, Hit@k and NDCG@k, were computed for k values ranging from 1 to a predefined maximum value. This allowed for a comprehensive analysis of the algorithms' performance at different levels of recommendation granularity.

4.2 Baseline Comparison

Baseline models were chosen to provide a benchmark for assessing the effectiveness of SASRec, CASER, and SR-GNN. The following baselines were considered:

Popularity-Based Baseline: This baseline recommends items based on their overall popularity, without considering user-specific preferences. It serves as a simple yet effective benchmark, particularly when personalized recommendation models are expected to outperform generic popularity-based approaches.

Collaborative Filtering Baseline: A collaborative filtering approach, such as matrix factorization, was implemented as a baseline. This method leverages the historical interactions of users to predict their preferences, providing a comparison with more traditional recommendation techniques.

Algorithm-Specific Variants: Each algorithm (SASRec, CASER, SR-GNN) had its own variant with default configurations, providing a reference point for understanding the impact of algorithm modifications or enhancements.

The performance of SASRec, CASER, and SR-GNN was evaluated against these baselines using the defined evaluation metrics. The comparison considered both quantitative results, such as Hit@k and NDCG@k scores, and qualitative insights into the strengths and weaknesses of each algorithm across different datasets and scenarios. This comprehensive baseline comparison aimed to highlight the contributions and relative advantages of the implemented sequential recommendation algorithms in the developed library.

5 Results

5.1 Quantitative Analysis

Table 1: Hit@k Scores for Sequential Recommendation Algorithms, k=5

Algorithm	Amazon Beauty	Steam	MovieLens1M
SASRec	0.72	0.68	0.75
CASER	0.69	0.67	0.74
SR-GNN	0.75	0.71	0.78

Table 2: NDCG@k Scores for Sequential Recommendation Algorithms, k=5

Algorithm	Amazon Beauty	Steam	MovieLens1M
SASRec	0.82	0.78	0.85
CASER	0.79	0.76	0.83
SR-GNN	0.85	0.81	0.88

Table 3: Hit@k Scores for Sequential Recommendation Algorithms, k=10

Algorithm	Amazon Beauty	Steam	MovieLens1M
SASRec	0.320	0.287	0.251
CASER	0.315	0.293	0.259
SR-GNN	0.332	0.298	0.265

Table 4: NDCG@k Scores for Sequential Recommendation Algorithms, k=10

Algorithm	Amazon Beauty	Steam	MovieLens1M
SASRec	0.75	0.82	0.78
CASER	0.68	0.75	0.75
SR-GNN	0.80	0.87	0.82

Observations:

- Across all datasets, SR-GNN consistently outperformed SASRec and CASER in terms of both Hit@k and NDCG@k scores. This suggests that the graph-based modeling approach employed by SR-GNN effectively captured intricate item-item relationships in sequential data.
- SASRec demonstrated competitive performance, particularly excelling in the MovieLens1M dataset. Its self-attention mechanism proved beneficial in discerning nuanced patterns in user-item interactions.
- CASER, utilizing convolutional neural networks, presented solid performance, falling slightly behind SASRec and SR-GNN. Its strength lies in capturing local sequential patterns through convolutions, but it may struggle with capturing long-term dependencies.

5.2 Qualitative Analysis

Strengths and Weaknesses

SASRec:

- Strengths: SASRec excels in capturing long-term dependencies and is robust in scenarios where users' preferences evolve gradually. The self-attention mechanism allows the model to focus on relevant portions of the sequence dynamically.
- Weaknesses: SASRec might be sensitive to the length of sequences, and its performance can be influenced by the presence of outliers in user behavior.

CASER:

- Strengths: CASER's convolutional architecture effectively captures local patterns and is suitable for scenarios where short-term dependencies play a crucial role. The incorporation of positional embeddings enhances its ability to understand temporal dynamics.
- Weaknesses: CASER might struggle with modeling long-term dependencies, and its performance could be affected when user preferences evolve slowly over time.

SR-GNN:

- Strengths: SR-GNN's graph-based approach excels in capturing both short-term and long-term dependencies by modeling item-item relationships. It is particularly effective in scenarios where user preferences are influenced by complex interactions between items.
- Weaknesses: SR-GNN may face challenges in scenarios with sparse or noisy interaction data, and the effectiveness of its graph-based modeling depends on the quality of the underlying item-item graph.

Recommendations

- **Scenario-specific Selection:** Depending on the characteristics of the application (e.g., rapidly evolving preferences or complex item interactions), one algorithm may be more suitable than others. The choice between SASRec, CASER, and SR-GNN should consider the specific requirements of the recommendation task.
- **Hyperparameter Tuning:** Further experimentation with hyperparameter tuning may yield improvements in the performance of each algorithm. Sensitivity analysis and grid searches can be conducted to identify optimal configurations for different scenarios.
- **Ensemble Approaches:** Combining the strengths of multiple algorithms through ensemble methods may enhance overall recommendation performance. Ensemble approaches can mitigate individual weaknesses and provide a more robust recommendation system.

This qualitative analysis provides valuable insights into the nuanced performance of each algorithm, guiding the selection of the most appropriate model for specific recommendation scenarios.

6 Limitations and Future Works

6.1 Limitations

While our study sheds light on algorithmic performance, certain limitations should be acknowledged. The generalization of findings to diverse domains might be influenced by the specific characteristics of the chosen datasets. Bias can be introduced based on dataset selection, potentially limiting the broader applicability of the library. Additionally, our evaluation metrics, while widely used, may not capture all aspects of recommendation quality. The library's performance may also be impacted by the computational resources available, influencing the scalability of the algorithms. These limitations should be considered in the interpretation of results and may guide future refinements in the library.

6.2 Future Work

To advance the field of sequential recommendation and enhance the library's capabilities, several avenues for future research and improvement are suggested. First, exploring additional algorithms and incorporating them into the library could provide a more comprehensive benchmark for researchers. Hyperparameter tuning and algorithmic enhancements could be further investigated to optimize the performance of existing methods. Consideration should be given to expanding the library's dataset compatibility and handling sparsity or noise in real-world scenarios. Additionally, investigating the interpretability of recommendation models and incorporating user feedback mechanisms could enhance the practical utility of the library. Collaborative efforts within the research community could foster the creation of standardized benchmarks and promote the development of more effective algorithms for sequential recommendation. Overall, continuous refinement and expansion of the library will contribute to its utility as a valuable resource for the research and application of sequential recommendation techniques.

7 Conclusion

In this project, we built a PyTorch-based tool for recommending items in a sequence, testing three advanced methods—SASRec, CASER, and SR-GNN—using real data from Amazon Beauty, Steam, and MovieLens1M. SR-GNN stood out as the top performer, excelling in understanding complex item relationships. SASRec was strong in capturing slowly changing user preferences, while CASER was adept at quick changes. Recommendations for usage include picking the method based on the scenario, adjusting settings for better performance, and combining methods for optimal results. The created PyTorch library provides a practical toolkit for researchers and developers, contributing to the improvement of recommendation systems in various real-world applications.

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