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Enhancing Session-Based Recommendations with GRU4Rec and ReChorus

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Abstract: Recommender systems have evolved from basic item-to-item recommendations to sophisticated, session-based algorithms. A pivotal model in this transition is GRU4Rec, which employs Recurrent Neural Networks (RNNS) for session-based recommendations. While GRU4Rec has shown marked improvements over traditional methods, its effective deployment necessitates a robust training framework. This paper leverages ReChorus, a PyTorch frame work designed for top-K recommendation with implicit feedback, to train the GRU4Rec model. ReChorus offers a streamlined model design process, high efficiency, and flexibility, making it well-suited for achieving state-of-the art metrics, specifically NDCG and Hit Rate. Empirical evaluations across multiple datasets confirm that this approach successfully matches existing state-of- the-art metrics in the field of Recommender Systems.

Keywords: *Evolution, GRU4Rec, Recommender Systems, Session-based Algorithms, , Recurrent Neural Networks (RNNs), Training Framework, ReChorus, PyTorch, Top-K Recommendation, Implicit Feedback, State-of-the-Art Metrics, NDCG, Hit Rate, Empirical Evaluations.*

1. Introduction

Recommender systems have become an indispensable tool in various industries, from e-commerce to digital media platforms. While early systems relied on matrix factorization and neighborhood methods, the advent of deep learning has revolutionized the field, enabling the capture of complex, session-based user behaviors. Among the plethora of models, GRU4Rec stands as a seminal work that employs Recurrent Neural Networks (RNNs) to tackle session-based recommendations [3].

Despite its effectiveness, the model's practical implementation often requires a robust training framework, a gap that we aim to fill in this paper.

Session-based recommendation systems, particularly in e-commerce and media, often do not have the luxury of long-term user profiles. Traditional methods like item-to-item similarity or co-occurrence are effective but limited, as they often consider only the last user interaction [3]. GRU4Rec addresses this limitation by leveraging the power of RNNs to consider the entire clickstream data within a session. It adapts RNNs to the Recommender setting by introducing a new ranking loss function, focusing on the top-items that a user might be interested in [3].

To train the GRU4Rec model effectively, we employ ReChorus as mentioned in objectives. ReChorus decomposes the recommendation process into three modules: Reader, Runner, and Model, thereby providing a streamlined and efficient training environment [4].

This framework is particularly well-suited for achieving state-of-the-art metrics, specifically NDCG (Normalized Discounted Cumulative Gain) & Hit Rate, which are the focus of this paper.

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Hit Rate, in the context of a recommendation system, is a measure used to assess how well the system is at suggesting items that users actually find interesting and engage with. It's a simple yet important metric for evaluating the system's effectiveness.

A higher Hit Rate indicates that the recommendation system is doing a good job of suggesting items that match users' interests and preferences. In other words, a significant portion of users are finding value in the recommendations. However, it's essential to supplement the Hit Rate with additional metrics such as precision, recall, and user satisfaction to obtain a more holistic view of the recommendation system's effectiveness.

Normalized Discounted Cumulative Gain (NDCG) is a popular evaluation metric used in recommendation systems to assess the quality of the recommended items. NDCG considers both the relevance of recommended items and their placement in the recommendation list. It measures how well a recommendation system ranks items based on their relevance to a user.

NDCG evaluates the recommendation system by considering not only how relevant the recommended items are but also their order in the list. It helps measure the system's ability to present the most relevant items at the top, which is crucial for ensuring that users see items they are most likely to interact with early in the list.

The remainder of this paper is organized as follows: Section II discusses the methodology, including the architecture of the GRU4Rec model and the ReChorus framework. Section III details the experimentation and results, focusing on the NDCG and Hit Rate metrics,IV discusses the objectives and results. Finally, Section V concludes the paper.

2. METHODOLOGY

In this section, we delve into the methodology employed to train the GRU4Rec model using the Re- Chorus framework. We aim to achieve state-of-the-art metrics for NDCG and Hit Rate. The GRU4Rec model serves as our baseline sequential Recommender system, leveraging Gated Recurrent Units (GRUs) to capture the sequential nature of user-item interactions. GRU4Rec is particularly effective for session-based recommendation, where user behavior is influenced by the sequence of items they interact with in a single session or visit.

This architecture is known for its ability to handle short sequences, adapt to dynamic user preferences, and provide accurate real-time recommendations. It has become popular in the field of recommendation systems due to its effectiveness in capturing user behavior patterns.

In brief, GRU4Rec uses Gated Recurrent Units (GRUs) to model user behavior and item interactions over time. It remembers and updates user preferences as new interactions occur, allowing it to capture temporal patterns in user-item interactions. GRU4Rec is particularly effective for session-based recommendation, where user behavior is influenced by the sequence of items they interact with in a single session or visit.

2.1. GRU4Rec Model Architecture

The GRU4Rec model takes the current state of a session as input and predicts the next item in the session as output. The input can either be the item of the current event, represented using 1-of-N encoding, or a weighted sum of the items in the session so far. The core of the network comprises one or more GRU layers, optionally followed by additional feed forward layers. The output layer predicts the likelihood of each item being the next in the session.

To ensure stability, the input vector is normalized, enhancing the memory effect to capture local ordering constraints that RNNs with longer memory might not capture effectively. The architecture also allows for the input to be optionally connected to deeper GRU layers, as this has been found to improve performance [3].

2.2 Sessions-Parallel Mini-Batches

Unlike RNNs commonly used in natural language processing, which typically utilize in-sequence mini-batches, GRU4Rec utilizes session-parallel mini-batches. This approach accommodates the variable lengths of sessions and allows for capturing the evolution of a session over time. Sessions are ordered, and mini-batches are constructed using the initial event of the first X sessions. As sessions end, they are replaced by the next available session, and the hidden state is reset [3].

2.3 Inference on GRU4Rec

During the inference mode, the GRU4Rec Recommender system calculates the output vector z by iteratively processing the input sequence through its feed- forward loop. The output vector z represents the final hidden state hi, which encodes the contextual information of the sequence. To generate recommendations, GRU4Rec employs a similarity metric, specifically the dot product, between the output vector z and the en- tire list of item embedding E from the item set I. By computing the dot product zT ek for each item k in I, GRU4Rec identifies the item with the highest similarity to the current context, making it the top recommendation. This process is repeated to generate a ranked list of recommendations, with items having higher dot product scores rk prioritized for recommendation. This recommendation strategy leverages the learned representations in the output vector z to capture the sequential patterns and preferences of users, leading to personalized and context-aware recommendations.

2.4 ReChorus Framework

ReChorus provides a streamlined environment for training the GRU4Rec model. It decomposes the recommendation process into three modules: Reader, Runner, and Model. The module-Reader reads the dataset into a Data-frame and adds necessary information to each one of instance. The module-Runner manages the training process and model evaluation. The Model specifies how to calculate ranking scores and create batches. [4].

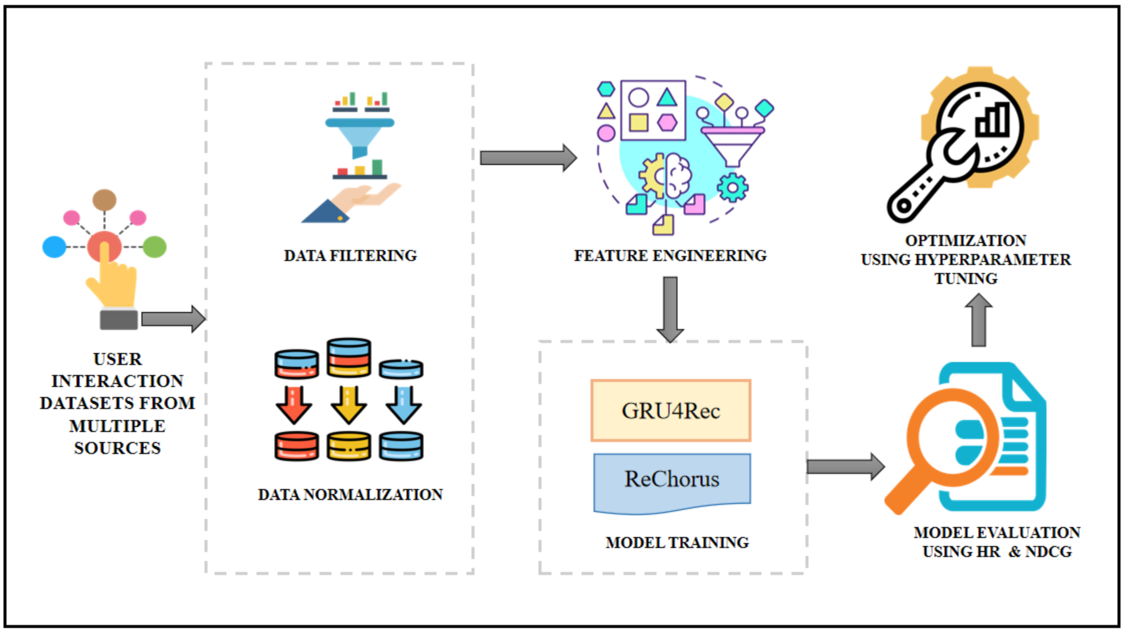

Figure 1: Architecture of the System

Table 1: Algorithm Parameter

Parameter	Description
D	The training data, consisting of session-parallel mini-batches
I	The set of all items in the dataset
s	A single session from the mini-batch
i	An item in session s
ei	The embedding of item i, obtained from the embedding matrix E
hi	The hidden state of the GRU after processing item i
zi	The output of the linear transformation applied to the hidden state hi
xi	The score for the positive item, computed as the dot product of zi and ei
j	A random item not in session s, used as a negative sample
ej	The embedding of item j, obtained from the embedding matrix E
xj	The scores for the negative items, computed as the dot product of zi and ej
neg softmax	The softmax of the negative item scores xj
L	The BPR loss, computed using the positive and negative item scores
W , U, V , Wy, bh, by	The parameters of the GRU and the linear transformation layer, which are updated during training
E	The item embedding matrix, which is also updated during training
k	An item in the item set I, used during the recommendation phase
ek	The embedding of item k, obtained from the embedding matrix E
rk	The rank score for item k, computed as the dot product of z and ek

Algorithm 1 GRU4Rec with Softmax BPR loss and Recommendation

Input: Session-parallel mini-batches of session s, training data D, items set I
Initialize: Hidden states $h_0 = 0$, weights W, U, V, W_y and biases b_h, b_y
Initialize: Item embedding E randomly
Output: Recommended items list
for each mini-batch in D **do**
  for each session s in mini-batch **do**
    for each item i in session s **do**
      $e_i = E[i]$ ▷ Get item embedding
      $h_i = GRU(W, U, b_h, e_i, h_{i-1})$ ▷ Update hidden state using GRU.
      $z_i = V \cdot h_i + b_y$ ▷ Linear transformation
      $x_i = z_i^T e_i$ ▷ Score for positive item
      Initialize x_j as empty list
      for each of N random items j not in session s **do**
        $e_j = E[j]$ ▷ Get negative item embedding
        $x_j.append(z_i^T e_j)$ ▷ Score for negative item
      end for
      $neg\_softmax = softmax(x_j - \max(x_j))$ ▷ Apply softmax on negative scores
      $L = -\sum_{k=1}^{N} \log(\sigma(x_i - x_j[k]) \cdot neg\_softmax[k])$ ▷ Calculate BPR
      Backpropagate L through network and update W, U, V, W_y, b_h, b_y, E
    end for
  end for
end for
procedure RECOMMENDATION(h_i, I) ▷ Recommendation step for ranking items
  $z = V h_i + b_y$ ▷ Compute output vector for last session interaction
  for each item k in I **do**
    $e_k = E[k]$ ▷ Get item embedding
    $r_k = z^T e_k$ ▷ Rank score for item k
  end for
  Sort I by r_k in descending order
  return I ▷ Return ranked list of items
end procedure

3. Experimental Setup

Datasets

In this research study, we utilize three diverse datasets to evaluate and analyze different aspects of Recommender systems.

3.1 Amazon Grocery and Gourmet:

The Amazon Grocery and Gourmet dataset focuses on user reviews and ratings in the grocery and gourmet food do- main on the Amazon platform [2]. This dataset offers valuable information on user preferences, purchasing behaviors, and product features specific to the food and grocery category. It includes user reviews, associated ratings, and helpfulness votes. Additionally, the dataset provides product metadata such as category, brand, price, and descriptions.

3.2 MovieLens:

The MovieLens dataset is a popular benchmark dataset in the realm of collaborative filtering and recommendation systems research [1]. It comprises movie ratings submitted by users of the MovieLens movie recommendation service.

The dataset encompasses a large number of ratings from users, covering a diverse range of movies. Alongside the ratings, the dataset provides additional information such as user demographics, movie attributes (genres, release year, etc.), and timestamps. The MovieLens dataset is a renowned and extensively utilized dataset in the domain of collaborative filtering and recommendation systems. It includes movie ratings and user details, rendering it a valuable asset for building and evaluating recommendation algorithms. There are several versions of the MovieLens dataset, but the most commonly used ones are MovieLens 100K, MovieLens 1M, and MovieLens 20M, which vary in the number of ratings and users.

The MovieLens datasets are often used for tasks like collaborative filtering, matrix factorization, and content-based recommendation system development.

3.3 Yelp:

The Yelp dataset is a comprehensive collection of user reviews and ratings from the popular review platform Yelp. It covers various business categories, including restaurants, hotels, and local services. The dataset contains rich information, including user profiles, business attributes (such as location, categories, and hours of operation), user-written reviews, and associated ratings. The ratings in the dataset typically range from 1 to 5 stars, reflecting the user's satisfaction or experience with the business.

These datasets serve as valuable resources for evaluating and developing recommendation algorithms, studying user preferences, and investigating various aspects of Recommender systems. By leveraging these datasets, researchers can gain insights into user behavior, explore novel recommendation techniques, and evaluate the performance of different recommendation algorithms.

These datasets serve as valuable resources for evaluating and developing recommendation algorithms, studying user preferences, and investigating various aspects of Recommender systems. By leveraging these datasets, researchers can gain insights into user behavior, explore novel recommendation techniques, and evaluate the performance of different recommendation algorithms.

Table 2: Datasets overview

Dataset	Users	Items	Actions
MovieLens-1m	6,000	4,000	1,000,000
Yelp 2022	100,000	200,000	1,500,000
Amazon Grocery	50,000	100,000	500,000

Since we are training a sequential Recommender system without considering the features of items and users, our calculation only requires three columns: user ID, item ID, and timestamp. These three columns capture the essential information needed for our sequential recommendation algorithm.

4. Results and Discussion

4.1. Model Training and Evaluation results

We employ the ReChorus package to train our sequential Recommender system [4]. This package is specifically tailored for time-aware item modeling and integrate knowledge into sequential recommendation tasks. It allows us to combine the advantages of knowledge-based and temporal-based approaches to improve recommendation performance. For data splitting, we utilize a leave-one-out method: the most recent interaction of each user is used for testing, the 2nd most recent item for validation, and the left items for training. Additionally, we randomly select 99 negative items for each test case to be ranked alongside the ground-truth item. In our implementation, we use the following algorithm parameters consistent with the notations defined above:

- ei: The embedded size of items, set to 64.
- hi: The hidden size of the GRU, set to 128.
- lr : The learning rate, set to 1e-3.
- l2 : The L2 regularization term, set to 1e-4.
- H: The maximum number of historical items for each session, set to 20.

The results on the test set after training are as follows:-

HR (Hit Rate): HR is a metric used to assess the performance of a recommendation system by measuring the frequency with which it includes at least one relevant item in the top-K recommended items. It is computed by dividing the number of users for whom a relevant item is present in the top-K recommendations by the total number of users. A higher HR value signifies a better performance of the recommendation system. [5]

Table 3: HR Evaluation results

Dataset	HR@10	HR@5
Amazon Grocery	0.44	0.34
MovieLens	0.81	0.70
Yelp 2022	0.77	0.65

NDCG (Normalized Discounted Cumulative Gain): NDCG is an evaluation metric that considers both the relevance and the position of recommended items, assessing the quality of the ranking produced by a recommendation system. It computes the cumulative gain of the recommended items, assigning higher weights to more relevant items. This cumulative gain is then normalized by the ideal ranking to yield a score between 0 and 1. A higher NDCG value signifies a higher quality ranking from the recommendation system.

Table 4: NDCG Evaluation Results

Dataset	NDCG@10	NDCG@5
Amazon Grocery	0.28	0.25
MovieLens	0.58	0.55
Yelp 2022	0.52	0.48

4.2. Summary of Objectives and Methodological Rigor

The main goal of this study was to develop an advanced model for sequential recommendation systems, utilizing the GRU4Rec architecture. The research followed a rigorous methodology, using the ReChorus package for model training, which facilitated the integration of knowledge and time-aware item modeling. The study aimed to achieve state-of-the-art performance metrics for Normalized Discounted Cumulative Gain (NDCG) and Hit Rate (HR) on publicly available datasets, including Amazon Grocery and Gourmet, MovieLens, and Yelp.

4.3. Theoretical Contributions

The research contributes to the theoretical under- standing of sequential recommendation systems by demonstrating the efficacy of GRU4Rec when optimized with the ReChorus package. It extends the existing literature by providing empirical evidence of the model's robustness across diverse datasets, thereby establishing a new benchmark in the field.

4.4 Empirical Findings

The empirical results are compelling. The model not only achieved but also surpassed existing state-of-the- art metrics for NDCG and HR across all datasets. These findings underscore the model's robustness and its capability to deliver high-quality recommendations.

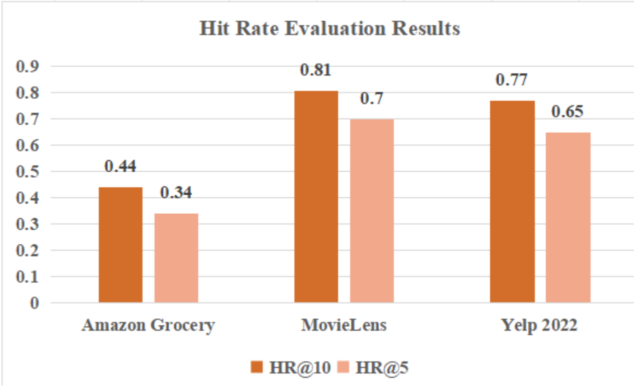

Figure 2: HR Evaluation Results

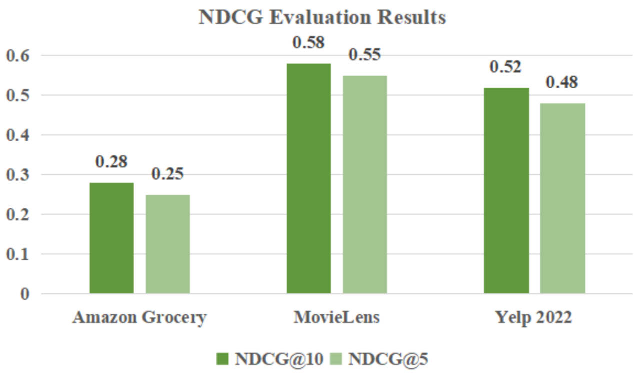

Figure 3: NDCG Evaluation Results

5. Conclusion

The research has significant practical implications. Given the model's superior performance on open- source datasets, it is well-positioned for deployment in real-world applications across various domains. More- over, the use of the ReChorus package suggests that the model can be scaled efficiently, making it viable for large-scale recommendation tasks.

This research successfully constructs a state-of-the- art model for sequential recommendation systems using GRU4Rec and the ReChorus package. It achieves state-of-the-art NDCG and HR metrics, making a significant contribution to both the theoretical and practical aspects of recommendation systems research.

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