ELECRec: Training Sequential Recommenders as Discriminators

Yongjun Chen  
Salesforce Research  
Palo Alto, CA, USA  
yongjun.chen@salesforce.com

Jia Li  
Salesforce Research  
Palo Alto, CA, USA  
jia.li@salesforce.com

Caiming Xiong  
Salesforce Research  
Palo Alto, CA, USA  
cxiong@salesforce.com

ABSTRACT
Sequential recommendation is often considered as a generative task, i.e., training a sequential encoder to generate the next item of a user’s interests based on her historical interacted items. Despite their prevalence, these methods usually require training with more meaningful samples to be effective, which otherwise will lead to a poorly trained model. In this work, we propose to train the sequential recommenders as discriminators rather than generators. Instead of predicting the next item, our method trains a discriminator to distinguish if a sampled item is a ‘real’ target item or not. A generator, as an auxiliary model, is trained jointly with the discriminator to sample plausible alternative next items and will be thrown out after training. The trained discriminator is considered as the final SR model and denoted as ELECRec. Experiments conducted on four datasets demonstrate the effectiveness and efficiency of the proposed approach.

CCS CONCEPTS
• Information systems → Recommender systems; • Computing methodologies → Learning to rank.

KEYWORDS
Sequential Recommendation, Discriminate Modeling, Learning Efficiency

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1 INTRODUCTION
Recommender systems play an essential role in many applications [4, 12], including e-commerce, advertising, and grocery shopping, to alleviate information overload to users. Sequential recommendation [10, 17, 20, 22, 23] is one of the core tasks in recommender systems, aiming to capture the sequential dynamic of users’ behaviors from their historical behavior sequences.

Recent works [1, 2, 5, 7, 10, 13] commonly utilize Transformers [21, 25] to encode sequence and train the sequential recommender via a generative task: next-item prediction (NIP), i.e., take a user’s historical behavior sequence as input and then train the model to predict the next item. While Transformer itself has shown effective modeling sequential dynamics of item correlations [10, 14, 17, 31, 32], training via such generative (NIP) task can lead to a poorly trained model without enough representative training samples. For example, given a user behavior sequence “Jacket, Shoes, Pants, Sweater, Basketball”, the model can often fail to predict the next item as “Basketball” after the user purchases Sweater. Because purchasing “Basketball” is a rare consumer behavior right after purchasing a series of apparel. Without enough representative sequences such as “Shoes, Jacket, Sweater, Baseball”, “Hat, Jacket, Shoes, Football”, etc., the model cannot capture the sequential correlations between apparel and sporting goods, resulting in a poorly trained SR model.

Alleviating the issue mentioned above under the generative task is challenging because it requires more meaningful training data while recommender systems often facing cold-start and data-sparcity issues [15, 26, 29, 33]. S3-Rec [32] and CLASRec [30] propose to randomly “reorder”, “mask”, and “crop” sequence as the augmented user behavior sequence to enrich the training set. However, if a user behavior sequence is sensitive to the random permutations, these augmentations will bring additional noise into the training samples. As a result, the learned item correlations can be more inaccurate. ASReP [16] and BiCAT [9] propose to train unidirectional and bidirectional Transformers with reversed sequences to generate pseudo-prior items, respectively. Although they alleviate the user cold-start issue [26, 33], the aforementioned issue can still presence, i.e., the generated pseudo-prior items via Transformer are most likely did not include sporting goods because the Transformer is also trained via NIP task. Besides, training via NIP often requires more iterations to learn the accurate user preference to items well, which suffers a substantial computation cost. Adversarial training via generative adversarial networks (GANs) [6, 27] is challenging because of the difficulty of back-propagating from the adversarial networks to the generator. The training process is also not stable, leading to a worse-performed model.

Inspired by the success of ELECTRA [3] in efficient language model pre-training, we propose to train the sequential recommenders as a discriminative task rather than a generative task. The discriminator is trained to identify the ‘real’ next item from the plausible alternatives. To generate these plausible items, we jointly train a generator, an auxiliary model trained with the NIP task. Then a certain percentage of items in the original sequence is replaced with the items generated from the generator. Our training strategy is more effective because it generates high-quality plausible samples from a learnable generator rather than manually
crafter, making the discriminator steadily lift its ability to discriminate the true item correlations. Treating the task as a binary classification task is also more efficient. It only selectively updates item embeddings in the sequences without computing all items required in NIP. We denote the trained discriminator as ELECRec for Efficiently Learning an Encoder as a disCriminator for sequential Recommendation. Different from ELECTRA in NLP domain that distinguishes if a word token at “current” position is generated or from the training data for text understanding, our method aims at distinguishing the plausible “future” items, which is better aligned with the recommendation tasks.

We conduct extensive experiments on four datasets. The empirical results demonstrate the effectiveness and efficiency of our proposed framework for training a sequential recommendation model. The detailed analysis also shows the superiority of ELECRec. We summarize our contributions as follows:

- We propose a novel training framework, which alternatively trains a sequential recommender as a discriminator rather than a generator.
- We propose to generate plausible alternative items via a jointly trained generator and suggest sharing the item embeddings between generator and discriminator networks to boost efficiency.
- We empirically demonstrate the effectiveness and efficiency of ELECRec, which is trained via our proposed training framework.

2 PRELIMINARY

2.1 Problem Statement

We denote a set of users and items as $U$ and $V$, respectively. Each user $u \in U$ is associated with a sequence of interacted items that are sorted in chronological order: $I^u = \{i^u_1, i^u_2, \ldots, i^u_{n_u}\}$. Specifically, $i^u_{n_u}$ is the item that user $u$ interacted at step $n_u$. The goal of Sequential Recommendation (SR) is to accurately predict the next item $i^u_{n_u+1}$ based on the truncated (with the “padding” operator) \cite{8, 10, 24} prior interactions $\{i^u_1, i^u_2, \ldots, i^u_{n_u}\}$ during training stage. The common training loss to achieve that goal is this kind:

$$
\mathcal{L}_{\text{NIP}}(u, t) = -\log p_G(i^u_{t+1}|i^u_1, i^u_2, \ldots, i^u_t),
$$

where $\theta$ describes a neural network $f_\theta$, which encodes sequence latent representation space: $h^u_t = f_\theta((i^u_j)_{j=1}^t)$ and the probability is often defined to measure the similarity between the encoded sequence $h^u_t$ and the next item $i^u_{t+1}$ in the representation space.

3 METHODOLOGY

In this section, we present a novel training framework, which contains a generator $G$, a data sampler, and a discriminator $D$. The sequence encoders that used in both $G$ and $D$ are Transformer networks \cite{21, 25} (denoted as $f_G(\cdot)$ and $f_D(\cdot)$), which are widely used on modern SR models \cite{10, 14, 17, 31, 32}. Figure 1 illustrates the overall learning framework.

3.1 Generator

The role of generator $G$ is to generate plausible next items to improve the discrimination ability of discriminator $D$. To achieve that, $G$ is trained with the NIP task (Eq. 1). At each time $t$, the probability of an item is considered to be generated defined with a Softmax layer:

$$
p_G(i^u_{t+1}|h^u_t) = \exp((i^u_{t+1})^T h^u_t) \sum_{i' \in V} \exp((i')^T h^u_t),
$$

where $h^u_t = f_G((i^u_j)_{j=1}^t)$ and $i'$ denotes the embedding of item $i' \in V$.

3.2 Data Sampler

For a given sequence $I^u$, the data sampler samples $\alpha$ percentage of items from the generator $G$ to replace the original target items. Formally, we first sample total $\text{ceil}(\alpha \cdot T)$ positions of the sequence: $\{r^u_j\}_{j=1}^{\text{ceil}(\alpha \cdot T)} \sim \text{uniform}(1, T)$, where $j \in (1, \text{ceil}(\alpha \cdot T))$. Then we sample the items from the generator $G$ for every sampled position.
where \( r_j \) as follows: \( \hat{t}_j \sim \pi_G(i_t^G | h_{t-j+1}) \) for \( j \in r \). Finally, we replace the original target items with the sampled items for each position \( r_j \) to form the new input sequence \( \tilde{t}_j \) for discriminator \( G \).

### 3.3 Discriminator

For a given input sequence \( \tilde{t}_j \), the discriminator aims at predicting that whether \( \tilde{t}_j \) is a “real” or “fake” target item. Notes that if the sampled items from the generator are indeed the target items, they are considered as target items instead of “fake” ones. Formally speaking, the discriminator \( D \) distinguishes items with a sigmoid function:

\[
p_D(\tilde{t}_j) = \text{sigmoid}(w^T \tilde{h}_j^D),
\]

where \( w \) is a learnable parameter and \( \tilde{h}_j^D = f_D((\tilde{t}_j^D)_{j=1}^T) \).

The discriminator is trained with the binary cross-entropy loss as follow:

\[
L_{\text{Disc}} = \sum_{i=1}^{N} \sum_{t=2}^{T} \left( \mathbb{1}(\tilde{t}_t^G = \hat{t}_t^G) \log(p_D(\tilde{t}_t^G)) \right. \\
\left. - \mathbb{1}(\tilde{t}_t^G \neq \hat{t}_t^G) \log(1 - p_D(\tilde{t}_t^G)) \right), \tag{5}
\]

### 3.4 Training and Inference

During the training stage, we perform joint training to minimize the following losses:

\[
L = L_{\text{NIP}}(I, G) + \lambda L_{\text{Disc}}(\tilde{I}, D), \tag{6}
\]

where \( \lambda \) controls the strength of the discriminator. The item embeddings in both generator and discriminator are shared. We also explore the potential of sharing the Transformer encoder parameters. See Section 4.3 for detailed comparisons. The training objective is different from a GAN-based approach because the generator is trained with the NIP task following the maximum log-likelihood principle instead of aiming at adversarial fool the discriminator. If the generator generates the true target items, then these items are considered as next items rather than ‘fake’ ones. The generator will be thrown out in the inference stage, leaving the trained discriminator as the final SR model.

## 4 EXPERIMENTAL STUDY

In this section, we conduct extensive experiments to answer following research questions (RQs):

- **RQ1:** Is ELECRRec effective and efficient for sequential recommendations compared with other baselines?
- **RQ2:** How does each component of ELECRRec influences ELECRRec’s performance?
- **RQ3:** What’s the optimal sampling rate \( \alpha \) and weights of discriminator \( \lambda \)?

### 4.1 Experiment Setup

#### 4.1.1 Data

We conduct experiments on four datasets with various data distributions: Yelp\(^2\) is a dataset for business recommendation. Sports, Beauty, and Toys are three datasets collected from Amazon.

\(^2\)https://www.yelp.com/dataset

in [18]. We follow [17, 19, 32] to prepare the datasets. Specifically, we discard all users and items that have fewer than 5 related interactions. For each user, we use her last interacted item for testing, the second from the last item for validation, and the rest items for training.

#### 4.1.2 Evaluation Metrics

We follow previous works [11, 28] to rank the predictions over the whole item set without negative sampling. Performance is evaluated on a variety of Top-K evaluation metrics: Hit Ratio@k (HR@k), and Normalized Discounted Cumulative Gain@k (NDCG@k) where \( k \in \{5, 10\} \).

#### 4.1.3 Baseline

We compare our method with eight different baselines. An item popularity-based method: PopRec; four deep SR methods that trained with next-item prediction task: Caser [24], GRU4Rec [8], SASRec [10], and S3-Rec [32]; Two deep SR methods that trained with other generative tasks: BERT4Rec [23] and Seq2Seq [17].

#### 4.1.4 Parameter Setting

The number of attention heads and layers for all Transformer-based methods are tuned from \{1, 2, 4\} and \{1, 2, 3\}, respectively. The embedding size is searched from \{32, 64, 128\}. The number of latent factors in Seq2Seq is tuned from \{1, 2, \ldots, 8\}. We fixed the batch size and maximum sequence length for all methods as 256 and 50, respectively. We implement our method in PyTorch. The sample rate \( \alpha \) and the strength of discriminator \( \lambda \) are both tuned from \{0.0, 0.1, \ldots, 1.0\}. We tune hyper-parameters on the validation set, and stop training if validation performance does not improve for 40 epochs. We evaluate the final performance of all methods on test set.

### 4.2 Overall Comparison

Table 1 shows the overall performance comparisons on four datasets. First of all, our method consistently performs best among all methods over all datasets. The improvements range from 38.28% to 137.16% in HR and NDCG, respectively, compared with the best baseline method. This observation demonstrates the effectiveness of ELECRRec and shows that an SR trained with the proposed training framework can learn a more accurate sequence and item representations. Seq2Seq achieves the second-best results in three out of four datasets, verifying the efficacy of leveraging multiple future items to perform additional self-supervised learning. S3-Rec fuses item attributes via contrastive self-supervised learning in pre-training stage and achieves the second-best results on Yelp. It verifies that contrastive self-supervised learning is an effective way of leveraging additional item attributes in SR. BERT4Rec replaces the next-item task with a mask-item prediction task to leverage contextual information in the sequence and perform better than SASRec in Yelp and Sports. It shows that considering contextual information can benefit model learning. However, BERT4Rec fails to outperform SASRec on Beauty and Toys, which indicates that the mask-item prediction task may not align with the goal of recommendation (next-item prediction) well. SASRec that encodes sequence with Transformer outperforms CNN and RNN based approaches (Caser and GRU4Rec), demonstrating the effectiveness of Transformer for capturing user dynamic changed behaviors. The static method PopRec performs worst on all datasets as it ignores the sequential dynamics of user behaviors.
We also study the proposed method’s efficiency on the Sports dataset compared with the typical SR model SASRec trained with a NIP task. Figure 2 shows the performance on validation set over training epochs and training time. We can observe that, firstly, ELECRec can outperform SASRec under any training time and training epochs. The faster converge rate of ELECRec demonstrates the efficiency of the proposed training strategy. Besides, ELECRec can converge to much higher performance than SASRec. This phenomenon shows the crucial of distinguishing plausible items for improving the accuracy of users’ preferences towards large vocabulary items.

Figure 2: Efficiency comparison (Performance on validation set). ELECRec that trained with discriminator can consistently outperform a typical SR model that trained with NIP task (e.g., SASRec) under any training time.

4.3 Ablation Study

We conduct a detailed ablation study on Yelp and Beauty to verify the effectiveness of each component and report the results in Table 2. (A) ELECRecES and (B) ELECRecFS are two types of ELECRec that either sharing the weights of item embeddings or with additional Transformer parameters between generator and discriminator, respectively. (C) only trains the generator as the final SR model. (D) is SASRec for comparison. The key difference between (C) and (D) is that (D) trains the generator via a sequential binary cross-entropy (BCE) loss while (C) trains the generator via a sequential multi-classes cross-entropy (Softmax) loss so that all item embeddings are updated densely during training. From (A), (B), and (C) we can see that the discriminator does benefits the model learning. Intuitively, the discriminator tries to update the embeddings of plausible items, either sampled from the generator or present in the original sequence so that the SR model can distinguish them more easily. From (C) and (D) we can also see that a model trained with Softmax can achieves better performance than its binarized approximation (sequential BCE).

Figure 3: Performance w.r.t. the sampling rate $\alpha$. The black dash line is the performance of SASRec for comparison.

4.4 Influence of the sampling rate $\alpha$ and discriminator weight $\lambda$

ELECRec introduces two hyper-parameters: the sampling rate $\alpha$ and the weights to control the strength of the jointly trained discriminator. We conduct experiments on Beauty and Toys and show the influence of these two hyper-parameters in Figure 3 and Figure 4, respectively. From Figure 3 we can see that $\alpha = 0.5$ is the optimal value on Beauty and Toys. When $\alpha$ is too large, most of items in the sequence are replaced by the generator and viewed as
negative class. When α is too small, most of items are from original input and are viewed as positive class. The brought of data imbalance issue can affects learning thus deteriorates performance. From Figure 4 we can observe λ = 0.5 gives the best performance on Beauty and Toys in HR@5. While model with λ = 0.3 perform best on Beauty in terms of NDCG@5. In general, the λ less than 1.0 benefits the model learning most. This phenomenon indicates that the discriminator’s job is to identify the plausible items sampled from the generator, which are a small group of items. In comparison, the generator takes more responsibility for training the whole item embeddings, thus requires larger weights to update the parameters.

Figure 4: Performance w.r.t. discriminator weight λ. The black dash line is the performance of SASRec for comparison.

5 CONCLUSION & LIMITATIONS

In this work, we propose to train sequential recommenders as discriminators instead of generators so that the user behavior sequence and item representations are more accurate. We propose to generate high-quality training samples for the discriminator via a jointly trained generator so that the discriminator can steadily improve its ability to discriminate the true item correlations. Extensive experiments on four datasets with eight baseline methods demonstrate the effectiveness of our propose training framework. Detailed ablation study and analysis also shows the superiority of ELECRec that trained via our propose training scheme. A limitation of our work is that the model performance needs to be carefully tuned and optimal hyper-parameters vary over datasets.

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