Prediction then Correction: An Abductive Prediction Correction Method for Sequential Recommendation

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ABSTRACT

Sequential recommender models typically generate predictions in a single step during testing, without considering additional prediction correction to enhance performance as humans would. To improve the accuracy of these models, some researchers have attempted to simulate human analogical reasoning to correct predictions for testing data by drawing analogies with the prediction errors of similar training data. However, there are inherent gaps between testing and training data, which can make this approach unreliable. To address this issue, we propose an *Abductive Prediction Correction* (APC) framework for sequential recommendation. Our approach simulates abductive reasoning to correct predictions. Specifically, we design an abductive reasoning task that infers the most probable historical interactions from the future interactions predicted by a recommender, and minimizes the discrepancy between the inferred and true historical interactions to adjust the predictions. We perform the abductive inference and adjustment using a reversed sequential model in the forward and backward propagation manner of neural networks. Our APC framework is applicable to various differentiable sequential recommender models. We implement it on three backbone models and demonstrate its effectiveness. We release the code at https://github.com/zyang1580/APC.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Sequential Recommendation; Prediction Correction; Abduction

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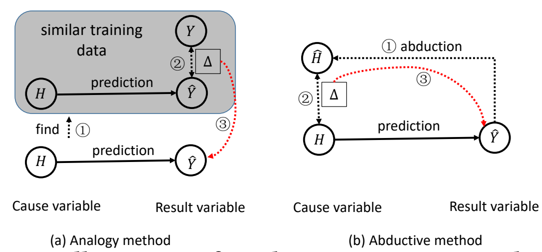


Figure 1: Illustration of prediction correction methods. H **and** Y **denote historical interactions (*i.e.,* causes) and future interactions (*i.e.,* results), respectively.** $\hat{Y}$ **is the model prediction, and** $\hat{H}$ **is the inferred historical interactions given the prediction** $\hat{Y}$**.** Δ **is the difference to guide the correction. The real and dotted lines represent the prediction and prediction correction processes, respectively.**

1 INTRODUCTION

Sequential recommendation [29] involves predicting the next item based on a user's historical interaction sequence. In recent years, many sequential recommender models have been developed, and they have achieved significant success [4, 6, 11, 20, 26]. However, these models typically make predictions in a one-shot manner, where recommendation decisions are made with a simple forward propagation of the trained models. This decision procedure appears to differ from that of humans, who often engage in further checking and revision of predictions, particularly when dealing with difficult samples. To further enhance the quality of recommendations, it is crucial to incorporate the ability of *prediction correction* into sequential recommendation.

Prior research has attempted to improve recommender model predictions by simulating one of the fundamental aspects of human thought: analogical reasoning [7]. As illustrated in Figure 1 (a), this approach involves retrieving similar training data for a testing candidate and adjusting the testing predictions by adding the prediction errors of such training data [15, 16]. However, we contend that this approach is unreliable to correct predictions for sequential recommender models due to inherent differences between the training and testing data [2, 6, 30, 31], including: 1) the model has already fitted the training data, but not the testing data; and 2) the training data pertains to the past, while the testing data pertains to the future. Such differences can lead to significant drifts in prediction errors between similar training and testing data, making it difficult to reliably correct testing predictions by analogy.

In addition to analogical reasoning, humans can also utilize abductive reasoning to evaluate their results, a key component of counterfactual thinking [17]. Abductive reasoning involves inferring the most plausible explanation, or causes, for the obtained results [1, 18]. As depicted in Figure 1 (b), during testing, humans can use abductive reasoning to infer the causes for their results and then adjust those results by making the inferred and observed causes more consistent. Unlike the analogy-based approach, this method corrects the results by referencing the observed part of the testing instance rather than other instances. Therefore, simulating human abductive reasoning could be a promising approach to correct model predictions in sequential recommendation without relying on the prediction errors of training data.

To simulate human abductive reasoning for prediction correction in sequential recommendation, a key step is to design an appropriate abductive reasoning task. Since causes typically precede results, a user's past interactions and future interactions can be regarded as the cause and result in abductive reasoning, respectively. Based on this, we can formulate the abductive reasoning task as inferring the user's historical interactions from the predicted future interactions. The predictions can then be corrected by minimizing the discrepancy between the inferred historical interactions and the true historical interactions. However, a critical challenge is how to transfer the obtained discrepancy information to the predictions for correction effectively. Furthermore, there is a trade-off between the degree of correcting predictions and the risk of introducing errors when applying abductive reasoning. Thus, it is essential to strike a balance between the correction of the predictions and the reliability of the inference results in the abductive reasoning process.

To address these issues, we propose a novel *Abductive Prediction Correction* (APC) framework, which includes a reversed sequential recommender model specifically designed for abductive reasoning tasks. Our framework corrects the predictions of a given recommender model through two key steps: abduction and adjustment. First, the APC framework uses the abductive model to infer the historical interactions that are most likely to have led to the predicted future interactions. Second, it adjusts the predictions of the original model by minimizing the difference between the inferred and true history using gradient descent. The difference information obtained from the abductive model is effectively utilized for correcting the predictions. To prevent over-correction, we only consider the top-N' ranked candidate items and reject the correction if it does not provide additional information gain for the abductive inference.

The main contributions of this work are summarized as follows:
- We propose to simulate human abductive reasoning to correct recommender predictions for further enhancing performance.
- We propose the APC framework for sequential recommendation, which is applicable to differentiable sequential recommenders.
- We conduct experiments with three sequential recommender models, verifying the superiority of our proposal.

2 RELATED WORK

Sequential recommendation. Early sequential recommendation methods focused on modeling transition information based on Markov Chain assumption [19]. Later, many neural networks have been employed to better leverage sequential information, such as RNN [10], CNN [22, 28], Attention networks [11, 20, 29], GNN [3, 24] and MLP [32]. Recently, contrastive learning has also been applied to sequential recommendation [12, 25]. However, to our knowledge, none of these works have studied prediction correction. One may think that our method is similar to bidirectional models such as BERT4Rec [20] and DualRec [29], as they both leverage future information for prediction. However, there are inherent differences: we leverage the information for correcting predictions during testing, while they are only during training.

Prediction correction. Prediction correction for machine learning models has gained increasing attention in various areas, *e.g.,* transportation prediction [13], medicine [23], trajectory prediction [21], and recommendation [15, 16, 27]. In recommendation, previous research can be divided into two lines. First, [15, 16] use analogy reasoning during testing to correct recommender predictions and enhance recommendation performance. Second, [27] focuses on knowledge distillation with ground-truth labels. All these methods rely on the prediction errors of training data, while we avoid using such prediction errors by employing abductive reasoning.

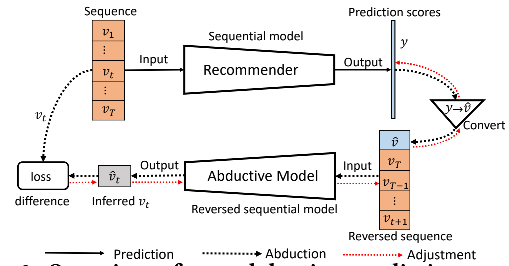


Figure 2: Overview of our abductive prediction correction framework. The real lines represent the initial prediction process. The dotted lines represent the correction process with two key steps: abduction inference and adjustment.

3 METHOD

Before presenting the proposed framework, we first introduce the problem, the basic concepts, and the notations in this paper.

3.1 Problem Formulation

Let $u \in \mathcal{U}$ and $v \in \mathcal{V}$ denote a user and an item, respectively, where $\mathcal{U}$ ($\mathcal{V}$) denotes the set of all users (items). Each user corresponds to a chronological interaction sequence $S_u = [v_1, \dots, v_t, \dots, v_T]$, where $v_t \in \mathcal{V}$ is the t-th item interacted by u, and T represents the length of the sequence[1]. Let $\mathcal{D} = \{S_u | u \in \mathcal{U}\}$ denote the interaction sequences of all users. We build a sequential recommender model f_R by fitting $\mathcal{D}$. During testing, given a sequence $S_u = [v_1, \dots, v_t, \dots, v_T]$ for a user u, f_R could generate a recommendation score for each candidate item, indicating how likely the item would be the $(T+1)$-th interacted item. Normally, the recommender generates the final recommendation list based on the prediction scores. Differently, we aim to further improve the recommendation performance by correcting the predictions generated by f_R.

[1]We apply padding if the sequence contains fewer than T interactions.

3.2 Abductive Prediction Correction Framework

We describe prediction correction using abductive reasoning, including the framework and its components.

3.2.1 Overall Framework. Inspired by human abductive reasoning, we develop a generic Abductive Prediction Correction (APC) framework for sequential recommendation (Figure 2). The framework simulates abductive reasoning to construct a task of inferring the historical interactions based on the predictions of the recommender model f_R, and then corrects the predictions according to the inferred results. To achieve this, apart from the recommender model f_R, we additionally build an abductive model f_A, a reversed sequential model, which could infer the past interactions given the future interactions. Then, we utilize the abductive model to correct the predictions generated by f_R with two key steps:

1) abduction (black dotted lines in Figure 2), which infers the most possible historical interactions given the predicted scores of f_R,
2) adjustment (red dotted lines in Figure 2), which updates the prediction scores by minimizing the difference between inferred and observed historical interactions in a gradient descent manner.

The two steps iterate until convergence or a maximum number of iterations is reached. Next, we present details for each key part.

3.2.2 Recommender and Abductive Models. In our framework, the recommender model f_R could be any well-trained embedding-based sequential recommender model, *e.g.,* SASRec [11]. That means, f_R deals with the input interaction sequence by converting the interacted items to corresponding embeddings. Formally, given a testing sequence $S_u = [v_1, \dots, v_t, \dots, v_T]$, f_R generates a recommendation (prediction) score $y_v \in [0, 1]$ for each candidate item v as:

$$y_v = f_R(v; [e_{v_1}, \dots, e_{v_T}]), \tag{1}$$

where e_{v_1} denotes the learned item embedding for item v_1 in f_R, similarly for others. The abductive model f_A is a reversed sequential model which infers the past interactions according to the future interactions. To simplify, we keep the model architecture of f_A the same as that of f_R. We train f_A by fitting the reversed interaction sequences $\mathcal{D}^{-1} = \{S_{u'}^{-1} | u' \in \mathcal{U}\}$, where $S_{u'}^{-1}$ is the reversed $S_{u'}$ (*e.g.,* $S_u^{-1} = [v_T, \dots, v_1]$), and keep the training process[2] similar to that of the recommender model f_R.

3.2.3 Prediction Correction. After the recommender model f_R generates predictions scores for user u, we take two key steps to correct the prediction scores with the well-trained abductive model f_A:

Step 1. Abduction. In this step, we use the abductive model f_A to infer the historical interactions with the prediction scores generated by f_R. The abductive model f_A is an embedding-based sequential model that cannot directly utilize the prediction scores. To address the issue, we convert the prediction scores into a dummy item embedding, making them manageable by f_A. Specifically, we generate the dummy item embedding $\hat{e}$ via embedding fusion with the prediction score-related weights as follows:

$$\hat{e} = \sum_{v \in \mathcal{V}_u'} w_v e_v, \tag{2}$$

where $\mathcal{V}_u'$ denotes the candidate items considered during the correction process for user u, e_v is the learned embedding for item v in f_A, and w_v is a prediction score-related weight to control the contribution of e_v to $\hat{e}$. Formally,

$$w_v = \frac{(y_v)^\eta}{\sum_{v' \in \mathcal{V}_u'} (y_{v'})^\eta}, \tag{3}$$

where $\eta > 0$ is a hyper-parameter to smooth the prediction scores, and y_v is the prediction score generated by f_R with Equation (1).

Here, $\hat{e}$ could represent a dummy item $\hat{v}$ that f_R predicts as the $(T+1)$-th interacted item for u. We first inject $\hat{v}$ into the first position of the reversed interaction sequence of u. Then, we take f_A to infer how likely the historical item v_t $(t < T)$ was interacted by u at the t-th position, with the sub-sequence $[\hat{v}, v_T, v_{T-1}, \dots, v_{t+1}]$ as model input. Formally,

$$p_A(v_t | [\hat{v}, v_T, \dots, v_{t+1}]) = f_A(v_t; [\hat{e}, e_{v_T}, \dots, e_{v_{t+1}}]), \tag{4}$$

where $p_A(v_t | [\hat{v}, v_T, \dots, v_{t+1}])$ denotes the inferred probability, and e_{v_T} denotes item embedding in f_A for v_T, similarly for others. Next, we take the following loss ℓ to quantify how the inferred results match true historical observations:

$$\ell = -\,log(p_A(v_t | [\hat{v}, v_T, \dots, v_{t+1}])). \tag{5}$$

A small ℓ means less difference between the abductively inferred and true historical interactions.

Step 2. Adjustment. We next minimize ℓ, the difference between the inferred and true history, to update the prediction scores in the gradient descent manner. That is, we treat the prediction scores $\{y_v | v \in \mathcal{V}_u'\}$ as learnable parameters, and take the gradient descent method to update $\{y_v | v \in \mathcal{V}_u'\}$ with the optimization goal of minimizing ℓ. Formally,

$$y_v \leftarrow y_v - \alpha \frac{\partial \ell}{\partial y_v}, \tag{6}$$

where $\frac{\partial \ell}{\partial y_v}$ denotes the gradient of y_v *w.r.t.* ℓ, and α refers to the learning rate to control the update step size. Obviously, the abduction and adjustment steps correspond to the forward and backward propagation of f_A, respectively. We iteratively run the two steps until convergence or a maximum number of iterations is reached.

3.2.4 Preventing Over-correction. As the abductive model could also make mistakes, we take two strategies to avoid over-correction:

Controlling $\mathcal{V}_u'$. Instead of correcting the predictions for all candidates, we only focus on correcting the candidate items with top-N' (initial) prediction scores. That means,

$$\mathcal{V}_u' = \{v | y_v \text{ ranks in the top } N' \text{ among all candidate items}\}. \tag{7}$$

Here, N' is greater than the length of the final recommender list. Besides avoiding over-correction, this strategy could also help reduce computation costs, which is crucial for recommendation since there are usually efficiency requirements during online serving.

Information gain-based strategy. Another strategy is to reject the correction if the corrected results cannot bring information gain for inferring historical interaction, compared to only using the sequence without injecting $\hat{v}$, *i.e.,* $[v_T, \dots, v_{t+1}]$. Specifically, after the last iteration is finished, we compute ℓ defined in Equation (5) again and compare it with another ℓ' gotten with $[v_T, \dots, v_{t+1}]$. Formally, ℓ' is computed similarly to ℓ, having: $\ell' = -log(p_A(v_t | [v_T, \dots, v_{t+1}]))$, where $p_A(v_t | [v_T, \dots, v_{t+1}]) = f_A(v_t; [e_{v_T}, \dots, e_{v_{t+1}}])$ is the probability — how likely v_t was the t-th interacted item of u — abductively inferred by f_A without using $\hat{v}$. Then, we reject the prediction correction if $\ell > \ell'$, and recover the initial prediction scores.

[2] We use the training method taken by the paper proposing the recommender model.

Table 1: Performance of backbone models, DTEC, and our APC compared. 'R@10'/'N@10' is Recall@10/NDCG@10. 'Ori' is the backbone model without prediction correction, and '+DTEC'/'+APC' is with DTEC/APC applied.

Backbone	Dataset	Beauty		ML1M	
	Method	R@10	N@10	R@10	N@10
SASRec	Ori	0.0294	0.0157	0.2481	0.1284
	+DTEC	0.0295	0.0158	0.2479	0.1283
	+APC	**0.0325**	**0.0176**	**0.2505**	**0.1297**
DualRec	Ori	0.0590	0.0359	0.2173	0.1214
	+DTEC	0.0592	0.0360	0.2171	0.1215
	+APC	**0.0594**	**0.0360**	**0.2240**	**0.1237**
Caser	Ori	0.0195	0.0098	0.2775	0.1469
	+DTEC	0.0193	0.0097	0.2770	0.1468
	+APC	**0.0198**	**0.0102**	**0.2787**	**0.1474**

Recommendation. After finishing the prediction correction, we re-rank the candidate items in $\mathcal{V}_u'$ based on the corrected prediction scores, and select the top-N ranked items as final recommendations.

4 EXPERIMENTS

We conduct experiments to verify the effectiveness of our proposal.

4.1 Experimental Setting

Datasets. We conduct experiments on two representative datasets: Amazon-Beauty (Beauty) [14], which includes user reviews of products in Amazon, and MovieLens-1M (ML1M) [8], which is a movie rating dataset collected by GroupLens Research[3]. We preprocess the dataset following the setting in the SASRec work [11]. Specifically, we discard users and items with fewer than five interactions, and for each user, we select the most recent interaction for testing, the second most recent interaction for validation, and the remaining interactions for training.

Compared methods. To show the effectiveness of the proposed APC framework, we apply it to three representative sequential recommender models: 1) SASRec [11], which is a left-to-right self-attention model, 2) DualRec [29], which is a bi-directional self-attention model, and 3) Caser [22], which is a CNN-based model. On the one hand, we directly compare with these backbone models to study whether our method could further enhance the performance of these models. On the other hand, we compare APC with a SOTA analogy-based prediction correction method named DTEC [16].

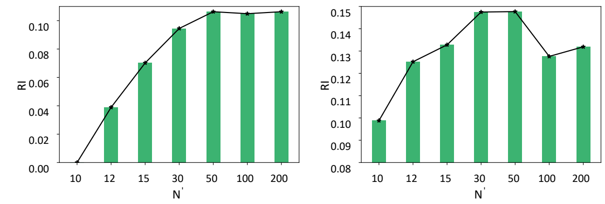
Evaluation metrics and hyper-parameters. To evaluate the top-N (N=10) recommendation performance, we take two metrics: Recall@N and NDCG@N, and compute them with the all-ranking protocol — all non-interacted items are the candidates. For all methods, we search the learning rate, L_2 regularization coefficient, dropout ratio in [1e-2, . . . , 1e-4], [1e-1, 1e-2, . . . , 1e-6], and [0, 0.3, . . . , 0.7], respectively. For the special hyper-parameters of backbone models, we search them in the ranges provided in their paper. For our APC, we set the N' in Equation (7) as 50, and search η of Equation (3) in [0.5, 1, 2, 3]. When computing ℓ in Equation (5), we take the items interacted by other users in the same mini-batch as negative items.

4.2 Results and Discussion

Overall performance. We summarize the results in Table 1, where we have the following observations:

- When applying our APC to the three different types of backbone models (SASRec, DualRec, and Caser), our APC consistently improved recommendation performance in all metrics on both datasets. These results demonstrate that conducting prediction correction can further enhance recommendation performance.
- In contrast, DTEC cannot consistently improve the recommendation performance and may even harm it. DTEC corrects the predictions of candidate items for a user by drawing analogies with the prediction errors of similar training items the user has engaged with. However, inherent differences exist between training and testing data, particularly in sequential recommendation where temporal drifts exist, making its correction unreliable. The results confirm the superiority of simulating abductive reasoning to correct predictions in sequential recommendation.
- SASRec outperforms DualRec on ML1M, but DualRec performs better on Beauty. However, our method enhances the performance of DualRec on both datasets, indicating its distinctiveness from other bidirectional methods. It effectively utilizes the future-to-past information of sequences through abductive reasoning.

[3]https://grouplens.org/datasets/movielens/.



(a) **Recall@10** (b) **NDCG@10**

Figure 3: The effect of the size of $\mathcal{V}'$ (*i.e.,* N') on the performance of APC. 'RI' denotes the relative improvements of APC over SASRec on Beauty in corresponding metrics.

In-depth analyses. To prevent over-correction, during prediction correction, we only consider the candidate items with top-N' initial prediction scores, *i.e.,* $\mathcal{V}_u'$ in Equation (7). We next investigate how the size of $\mathcal{V}_u'$ (*i.e.,* N') affects the relative improvements (RI) of our APC over backbone models in recommendation performance. Figure 3 summarizes the validation results on the Beauty dataset regarding the backbone model SASRec. We find that as N' increases, the RI in Recall@10 first increases and then slightly decreases, while the RI in NDCG@10 first increases and then decreases significantly. This suggests that a larger N' is beneficial for recalling related items, but an excessively large N' may reduce the ranking quality of related items. Therefore, it is crucial to choose an appropriate value of N' to avoid over-correction or under-correction. Additionally, when $N' = N = 10$, the RI in NDCG is greater than 9%, further verifying that APC can improve the ranking quality for a fixed item list. Besides, we find that N' has much greater impacts than the information gain-based strategy, so we omit the latter here.

5 CONCLUSION

In this work, we introduce a universal APC framework for sequential recommendation inspired by human abductive reasoning. The framework formulates an abductive task of deducing the past interaction based on future interaction and minimizes the discrepancy between the inferred and actual history to correct predictions. We apply this framework to three representative sequential recommender models and validate its effectiveness. In the future, we plan to extend the framework to other recommendation tasks such as collaborative filtering [9]. We also plan to leverage advanced techniques such as uncertainty [5] to prevent over-correction.

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