

# Contrastive Self-supervised Sequential Recommendation with Robust Augmentation

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## ABSTRACT

*Sequential Recommendation* describes a set of techniques to model dynamic user behavior in order to predict future interactions in sequential user data. At their core, such approaches model transition probabilities between items in a sequence, whether through Markov chains, recurrent networks, or more recently, Transformers. However both old and new issues remain, including data-sparsity and noisy data; such issues can impair performance, especially in complex, parameter-hungry models. In this paper, we investigate the application of contrastive Self-Supervised Learning (SSL) to sequential recommendation, as a way to alleviate some of these issues. Contrastive SSL constructs augmentations from unlabelled instances, where agreements among positive pairs are maximized. It is challenging to devise a contrastive SSL framework for sequential recommendation, due to its discrete nature, correlations among items, and skewness of length distributions. To this end, we propose a novel framework, Contrastive Self-supervised Learning for Sequential Recommendation (CoSeRec). We introduce two informative augmentation operators leveraging item correlations to create high quality views for contrastive learning. Experimental results on three real-world datasets demonstrate the effectiveness of the proposed method on improving model performance, and the robustness against sparse and noisy data. Our implementation is available: <https://github.com/YChen1993/CoSeRec>

## KEYWORDS

Contrastive Learning, Robustness, Sequential Recommendation

## 1 INTRODUCTION

Recommender systems aim at predicting potential interests of users toward unseen items [22, 29, 38] by leveraging historical interaction records. In order to model dynamic user behavior (and especially *short-term* dynamics), Sequential Recommendation (SR) [14, 16, 31, 32, 43] arguably represents the current state-of-the-art. SR models interactions between users and items as temporally-ordered sequences, with the goal of predicting the next interaction conditioned on recent observations.

The core idea to model SR problems is to capture relationships among items in sequences [14, 16, 31, 40]. Pioneering works [13,

31] employ Markov chains to learn pair-wise transition relationships. Later, RNN-based [14, 40, 50] models were proposed to infer sequence-wise correlations. More recently, the powerful ability of Transformers [5, 35] in encoding sequences has been adopted for applications in SR [16, 20, 32, 48]. Transformer-based SR models [16, 32, 43] encode sequences by learning item importances via self-attention mechanisms.

Despite the effectiveness of existing approaches, several issues remain less explored: (1) Data-sparsity. Transformers are motivated by NLP tasks [35], where large corpora are available to train complex models [5]. However, SR tasks usually involve rather sparse datasets [21, 25], which undermines the capability of a Transformer to model item correlations in sequences, *e.g.* performing poorly on short sequences [21]. (2) Noisy interactions. Occasionally, items in sequences may not reflect true item correlations, *e.g.* a user consumes an item because of promotion ads, ultimately resulting in negative feedback [37]. Inference from those noisy sequences spoils the performance of a model in revealing item transition correlations, thus producing less satisfying recommendation.

Inspired by recent developments of Self-Supervised Learning (SSL) [5, 8, 15, 19, 26, 42], this paper studies the possibility of contrastive self-supervised learning [2, 8, 42] for alleviating the aforementioned issues in SR. Intuitively, SSL constructs *augmentations* from unlabelled data, and enhances the discrimination ability of encoders by employing a contrastive loss [2, 12, 49, 51]. The contrastive loss maximizes agreements between positive pairs, which are different augmentations (*i.e.* views) from one instance. It is worth noting that this learning scheme is different from widely used contrastive losses in recommender systems, *e.g.* BPR [29] and NCE [11] losses, because contrastive SSL involves no prediction targets between two different entities but only the optimization of the consistency between two views of one instance. Nevertheless, it is challenging to devise a contrastive SSL framework for SR due to the following reasons:

- **Discreteness**: Items in sequences are represented by discrete IDs, which pose a challenge for popular augmentation methods designed for continuous feature spaces [2, 12]. Augmentation techniques for sequence data are still under-explored and require investigation.
- **Item Correlations**: Items in sequences are correlated with each other. However, existing techniques [2, 8, 42, 46] augment sequences based on random item perturbations. Those methods tend to destroy the original item relationships in sequences when

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constructing augmentations, thus impairing the confidence of positive pairs.

- **Length Skewness:** According to [21], the length distribution of sequences is skewed and suffers from the long-tail patterns. However, current contrastive SSL [2, 42, 46] frameworks employ identical augmentation methods across instances. This leads to less confident contrastive pairs in SR, *e.g.*, short sequences are more sensitive to random item perturbations.

To this end, we propose a new framework, **Contrastive Self-Supervised learning for Sequential Recommendation (CoSeRec)**. It contains three key components: (1) robust data augmentation that characterizes item correlations and sequence length skewness; (2) a contrastive SSL objective to maximize the agreement of positive views of sequences; and (3) a multi-task training strategy to jointly optimize the SR objective and the contrastive SSL objective effectively. To be more specific, we first propose two *informative augmentation* methods, *substitute* and *insert*, which advances current random augmentations [46, 52], such as *crop*, *reorder*, and *mask*. Random augmentations may yield less confident positive pairs, as those random perturbations of items break item relationships in sequences. Random augmentations can also hinder the quality of learned representations, because they (*e.g.* crop) often lead to fewer items in sequences, which exaggerates the cold-start issue. Unlike random augmentations, our informative augmentations leverage item correlations when constructing positive views, thus being more robust. Additionally, both ‘substitute’ and ‘insert’ operations expand user interaction records, which alleviates the cold-start issue. CoSeRec adopts a multi-task training strategy rather than a pre-training scheme [2, 44], because next-item prediction and the contrastive SSL share similar targets, *i.e.* modeling item relationships in sequences. Experiments on three real-world datasets verify the efficacy of CoSeRec. We summarize our contributions as follows:

- We devise a novel learning framework (CoSeRec), which addresses data-sparsity and noisy interaction issues by unifying contrastive SSL with sequential recommendation.
- We propose novel and robust sequence augmentation methods that exploit item correlations and alleviate length skewness problems in sequential recommendation.
- We conduct extensive experiments on three benchmark datasets with detailed analyses of the proposed paradigm and the optimal combinations of augmentations.

## 2 RELATED WORK

### 2.1 Sequential Recommendation

SR predicts future items in user sequences by modeling item transition correlations. Pioneering works [13, 31] adopt Markov chains to model the pair-wise item transition correlations. FPMC [31] directly factorizes item transition matrices. Fossil [13] extends this idea by leveraging similarities between items, which alleviates sparsity issues. Later, Recurrent Neural Network (RNN) have been adapted to solve SR [14, 40, 50], ostensibly modeling sequence-level correlations among transitions. Hierarchical RNNs [28] enhance RNNs using personalization information. Wu, et al. [40] apply LSTMs to explore both long-term and short-term item transition correlations. The major drawback of Markov chain and RNN models is that their

receptive fields of the transition function are limited. Therefore, they can only incorporate shallow item correlations, which limits their power to encode sequences [4].

Recently, owing to the success of self-attention models [5, 35] in NLP tasks, a series of Transformer-based SR models have been proposed [16, 24, 32, 41]. SASRec [16] applies Transformer layer to learn item importance in sequences, which characterize complex item transition correlations. Later, inspired by BERT [5] model, BERT4Rec [32] is proposed with a bidirectional Transformer layer. Other works [6, 7, 20, 24, 43] also extend Transformer to incorporate complex signals in sequences, which verifies the efficacy of Transformer in solving SR. However, a recent work [21] argues Transformer is vulnerable to severe user cold-start issues in SR, where existing Transformer-based models yield unsatisfying results for short sequences. Therefore, augmentation for short sequences is desirable. S<sup>3</sup>-Rec [52] and CLS4Rec [46] also investigate contrastive learning in SR. However, both investigate weak self-supervised signals with random augmentations in sequences, but do not yet address the length skewness and item correlation challenges.

### 2.2 Contrastive Self-supervised Learning

Contrastive learning has recently achieved remarkable successes when coupled with the Self-Supervised Learning (SSL) framework, in areas ranging from Computer Vision (CV) [2, 12], Natural Language Understanding (NLU) [8, 9, 44], graph embedding [15, 49, 53], as well as recommender systems [42, 46, 52]. Contrastive SSL trains encoders by maximizing agreement between two augmented views of one instance, *i.e.*, positive pairs. As such, it encourages self-supervised training from the space of unlabelled data. The core of Contrastive SSL is to exploit strong augmentations [45] of data instances, which are diverse with respect to the data domains and objective tasks.

SimCLR [2] proposes a simple contrastive learning framework for visual representations, which studies stochastic image augmentations. Following this, [34, 45] argues that the optimal choice of augmentations is critically task-oriented and exists with balanced mutual information. As for NLU tasks, the augmentation [39] for text is of a discrete nature. Deleting [10, 44], reordering [44] and substituting [8, 44] words in a sentence leads to positive augmentation pairs, which also inspires this work. The augmentation in graph contrastive SSL differs from other domains in its structural characteristics. Thus, node-drop [49, 53], edge-drop [49, 53], and random walk [27, 36] are adopted as the augmentation operations.

In recommendation scenarios, contrastive learning is not a new technology, *e.g.*, the widely used BPR loss [30] and NCE loss [11], both adopt pair-wise contrastive losses on positive and negative samples. Their recent union with SSL shows promise in improving recommender systems [42]. S<sup>3</sup>-Rec [52] devises contrastive SSL to maximize the mutual information over attributes and sequence augmentations, which adopts random masks of attributes and items. [47] proposes two-stage augmentations by masking item embedding layers and dropping categorical features, which enables SSL for item encoders. SGL [42] advances graph-based recommender systems with SSL by employing graph structure augmentations. A recent work, CLS4Rec [46] proposes a contrastive SSL framework for improving SR. Although close to our paper, CLS4Rec adopt

random augmentation methods, ignoring crucial item correlations and length skewness for sequence augmentations.

### 3 PRELIMINARIES

#### 3.1 Problem Formulation

We denote user and item sets as  $\mathcal{U}$  and  $\mathcal{V}$  respectively. Each user  $u \in \mathcal{U}$  is associated with a sequence of items in chronological order  $s_u = [v_1, \dots, v_t, \dots, v_{|s_u|}]$ , where  $v_t \in \mathcal{V}$  denotes the item that  $u$  has interacted with at time  $t$  and  $|s_u|$  is the total number of items. SR tasks seek to predict the next item  $v_{|s_u|+1}$ , which is formulated as follows:

$$\arg \max_{v_i \in \mathcal{V}} P(v_{|s_u|+1} = v_i | s_u), \quad (1)$$

which is interpreted as calculating the probability of all candidate items and selecting the highest one for recommendation.

#### 3.2 Transformer for SR

Transformer [35] architecture is a powerful way to encode sequences, leading to successful application in SR [16, 20, 52]. It consists of two key components: a *multi-head self-attention module* and a position-wise *Feed-Forward Network* (FFN). We illustrate the structure of a Transformer in Figure 1(a). Multi-head self-attention models the item correlations in sequence. Position-wise FFN outputs a bag of embeddings, where the embedding at each position predicts the corresponding next item in the sequence. We present next-item prediction in Figure 1(b). To keep generality, we denote a Transformer encoder as  $\text{SeqEnc}(\cdot)$ , which can be an arbitrary sequence encoder. We formulate the encoding process as:

$$\mathbf{h}_u = \text{SeqEnc}(s_u), \quad (2)$$

where  $\mathbf{h}_u$  denotes the sequence embedding of  $s_u$ .  $\mathbf{h}_u$  is a bag of embeddings in Transformer. For each position  $t$ ,  $\mathbf{h}_u^t$  represents a predicted next-item [16]. We adopt the log-likelihood loss function to optimize the encoder for next-item prediction as follows:

$$\mathcal{L}_{\text{rec}}(u, t) = -\log(\sigma(\mathbf{h}_u^t \cdot \mathbf{e}_{v_{t+1}})) - \sum_{v_j \notin s_u} \log(1 - \sigma(\mathbf{h}_u^t \cdot \mathbf{e}_{v_j})), \quad (3)$$

where  $\mathcal{L}_{\text{rec}}(u, t)$  denotes the loss score for the prediction at position  $t$  in sequence  $s_u$ ,  $\sigma$  is the non-linear activation function,  $\mathbf{e}_{v_{t+1}}$  denotes the embedding for item  $v_{t+1}$ , and  $v_j$  is the sampled negative item for  $s_u$ . The embeddings of items are retrieved from the embedding table in  $\text{SeqEnc}$ , which is jointly optimized with Transformer.

### 4 METHODOLOGY

We first introduce data augmentations adopted in this paper, including both random and informative augmentations. Then we describe contrastive SSL with those augmentations. Finally, we present the overall training algorithm.

#### 4.1 Robust Sequence Augmentation

We first review and formulate existing random augmentation methods [44, 46, 52], and then introduce two novel informative augmentation methods. We also describe how to augment sequences based on their length. This section assumes the original sequence being

$s_u = [v_1, v_2, \dots, v_n]$ . Toy examples of those methods are illustrated in Figure 2, where  $n = 4$ .

**4.1.1 Random Augmentation.** Three random operators introduced by [46, 52] are included in this paper to create various views of original sequences:

- **Crop (C).** Randomly select a continuous sub-sequence of the original sequence starting from position  $i$ :

$$s_u^C = C(s_u) = [v_i, v_{i+1}, \dots, v_{i+c-1}], \quad (4)$$

where  $c = \lceil \eta n \rceil$  is the sub-sequence length that is controlled by a hyperparameter  $\eta$  and  $0 \leq \eta \leq 1$ .  $\lceil \cdot \rceil$  is the ceiling function.

- **Mask (M).** Randomly mask  $l = \lceil \mu n \rceil$  items in a sequence:

$$s_u^M = M(s_u) = [v'_1, v'_2, \dots, v'_n], \quad (5)$$

where  $v'_i$  is the ‘mask’ if  $v_i$  is a selected item, otherwise  $v'_i = v_i$ .  $l$  is controlled by a hyper-parameter  $\mu$ , where  $0 \leq \mu \leq 1$ .

- **Reorder (R).** Randomly shuffle a sub-sequence  $[v_i, \dots, v_{i+r-1}]$  of  $s_u$  as  $[v'_i, \dots, v'_{i+r-1}]$ :

$$s_u^R = R(s_u) = [v_1, v_2, \dots, v'_i, \dots, v'_{i+r-1}, \dots, v_n], \quad (6)$$

where  $r = \lceil \omega n \rceil$  is the sub-sequence length and  $0 \leq \omega \leq 1$ .

In general, good augmentations for one instance should give views sharing task-oriented information [34], thus being positive pairs. In our case, views from one sequence are supposed to maintain the original sequential correlations, which otherwise could yield less confident positive pairs. However, those random augmentations break the item correlations in sequences, especially for short sequences. For example, reordering a sequence leads to changed item correlations in the sub-sequence. This impact is enlarged when fewer items are present in sequences.

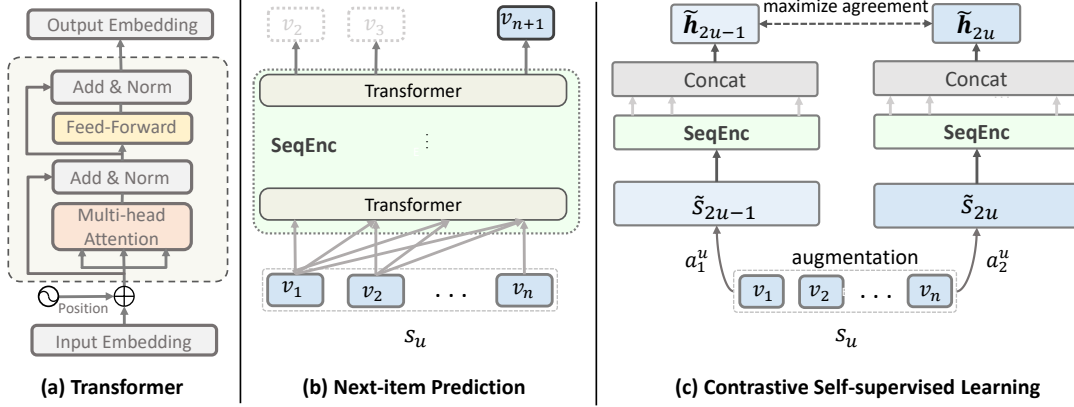
Moreover, random augmentations exaggerate cold-start issues in sequences, e.g. masking a short sequence induces few items in a sequence. As such, the sequence encoder may fail to learn high quality representations, and thus fail to characterize item relationships in sequences. Contrasting on low quality sequence representations further deteriorates the robustness of SSL.

Next, we will introduce two novel informative augmentation methods, which advance random augmentations regarding the mentioned concerns.

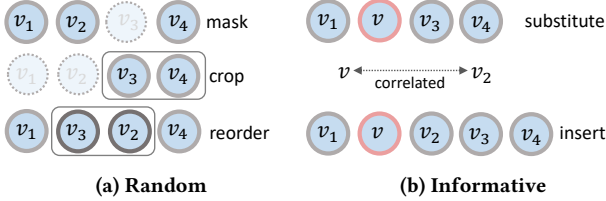
**4.1.2 Informative Augmentation.** We propose two informative augmentation operators leveraging item correlations to generate robust augmented sequences, as illustrated in Figure 2b.

- **Substitute (S).** The substitution augmentation is motivated by the real case [3] where recommending substitutable items to users expands the chance of discovering their actual interests. Correspondingly, substituting items in sequences with highly correlated item injects less corruption to the original sequential information, which thus yields confident positive pairs of views. Formally, we randomly select  $k$  different indices  $\{\text{idx}_1, \text{idx}_2, \dots, \text{idx}_k\}$  in the sequence  $s_u$ , where  $k = \lceil \alpha n \rceil$  and  $\text{idx}_i \in [1, 2, \dots, n]$ .  $\alpha \in [0, 1]$  is substitution ratio. Then we replace each with an correlated item based on the selected indices. The sequence after substitution will be:

$$s_u^S = S(s_u) = [v_1, v_2, \dots, v_{\text{idx}_i}, \dots, v_{|s_u|}], \quad (7)$$



**Figure 1: Overall framework.** (a) illustrates the structure of Transformer. (b) presents the sequence encoding and prediction of Transformer;  $v_i$  denotes an item at position  $i$  of the sequence  $s_u$ . (c) demonstrates the contrastive SSL of a sequence. It first augments a sequence as two views with two augmentation methods. Then, it encodes the sequence by concatenating embedding outputs from Transformer. Finally, it maximizes the agreement between the two views.



**Figure 2: Five augmentations adopted in this paper. The original sequence is  $[v_1, v_2, v_3, v_4]$ . Informative augmentations incorporate correlations among items.**

where  $\bar{v}_{idx_i}$  is a correlated item with  $v_{idx_i}$ . We will describe how to choose the correlated items in Section 4.1.3.

- **Insert (I).** In practice, recorded interactions are less than the complete consumption behavior of users, e.g. transactions from other sources are missing [23]. Consequently, training sequences may fail to track comprehensive user dynamics and item correlations. To this end, we construct augmentations by inserting items into sequences, in order to ‘complete’ the sequence. The number of inserted items is controlled by the ratio  $\beta \in [0, 1]$ . We first randomly select  $k$  different indices  $\{idx_1, idx_2, \dots, idx_k\}$  in the sequence  $s_u$ , where  $k = \lceil \beta n \rceil$  and  $idx_i \in [1, 2, \dots, n]$ . We then insert correlated items at those indices. After insertion, the sequence is:

$$s_u^I = I(s_u) = [v_1, v_2, \dots, \bar{v}_{idx_i}, v_{idx_i}, \dots, v_n], \quad (8)$$

where  $i \in \{1, 2, \dots, k\}$ , and  $\bar{v}_{idx_i}$  is the most correlated item with  $v_{idx_i}$ . The length of the augmented sequence  $s_u^I$  is  $k + n$ .

Both augmentations are informative as they perturb the sequence with correlated items. As such, augmented sequences have higher confidence of being positive pairs. Moreover, adding correlated items to sequences extends the number of user interactions, which alleviates user cold-start issues. Next, we introduce how to choose correlated items for informative augmentations.

**4.1.3 Item Correlations.** Informative augmentations require inferring correlations among items to perturb sequences. Thus, it is necessary to design a simple yet effective method for calculating item correlations. We first introduce two straightforward methods and then demonstrate a hybrid method adopted in this work.

The first is **memory-based correlation**. Collaborative signals are crucial in recommender systems. Therefore, we employ item-based collaborative filtering considering inverse user frequency (ItemCF-IUF [1]) to measure item correlations due to its simplicity and effectiveness. Formally, the memory-based correlation score between item  $i$  and  $j$  is defined as:

$$\text{Cor}_o(i, j) = \frac{1}{\sqrt{|\mathcal{N}(i)| |\mathcal{N}(j)|}} \sum_{u \in \mathcal{N}(i) \cap \mathcal{N}(j)} \frac{1}{\log(1 + |\mathcal{N}(u)|)}, \quad (9)$$

where  $u$  is a user,  $|\mathcal{N}(i)|$ , and  $|\mathcal{N}(j)|$  are the number of users who have interacted with  $i$  and  $j$ , respectively. Memory-based correlation treats two items as being more correlated if they share a higher ratio of common users.

The other is **model-based correlation**. This correlation directly infers correlations by measuring the similarity between item representations. Since item representations are jointly learned with the encoder, this method is thus model-based. In this work, we adopt the dot-product as the similarity metric. Given the representations of items  $i$  and  $j$  as  $\mathbf{e}_i$  and  $\mathbf{e}_j$ , the model-based correlation score is defined as:

$$\text{Cor}_e(i, j) = \mathbf{e}_i \cdot \mathbf{e}_j. \quad (10)$$

In this paper, we fuse the *memory-based* and *model-based* correlations as a *hybrid* correlation  $\text{Cor}_h$ , which is defined as the highest value between memory-based and model-based correlations as:

$$\text{Cor}_h(i, j) = \max(\overline{\text{Cor}}_o(i, j), \overline{\text{Cor}}_e(i, j)), \quad (11)$$

where  $\overline{\text{Cor}}_o$  and  $\overline{\text{Cor}}_e$  are the normalized score of memory-based and model-based correlations, respectively. We normalize (min-max normalization) them to be comparable. Additionally, since item representations learned at early epochs are not informative,



we initially use  $\text{Cor}_0$  to infer correlated items. Then, after training with  $E$  epochs, we switch to  $\text{Cor}_h$ , where  $E$  is a hyper-parameter.

**4.1.4 Augment w.r.t. Sequence Length.** The length of interaction sequences tends to follow a long-tail distribution [21], in which most sequences are short. Considering that short sequences are more sensitive to random item perturbations, we should carefully choose augmentation operations on short sequences. In this work, we employ different augmentation operators sets to sequences with respect to their lengths. We use a hyper-parameter  $K$  to decide whether a sequence is short or long, and then apply data augmentation as follows:

$$s_u^a = \begin{cases} a(s_u), a \sim \{S, I, M\}, & |s_u| \leq K \\ a(s_u), a \sim \{S, I, M, C, R\}, & |s_u| > K \end{cases} \quad (12)$$

where  $a$  is an augmentation operator selecting from the corresponding augmentation set. Though  $M$  is a random augmentation, we also include it in the augmentation set for short sequences. The reason are twofold: Firstly, mask augmentation implicitly models item relationships in sequence, which is similar to the next-item prediction target. Secondly, masking operation encourages items near masked items being closer, which models high-order item relationships in the original sequence.

## 4.2 Contrastive Self-Supervision

Contrastive SSL optimizes encoders by maximizing the agreements between ‘positive’ pairs, which are two augmentations from one sequence. To be specific, given a minibatch of sequences  $\{s_u\}_{u=1}^N$ , we sample two augmentation operators for each sequence  $s_u$ , which obtains  $2N$  augmented sequences as:

$$\{\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_{2u-1}, \tilde{s}_{2u}, \dots, \tilde{s}_{2N-1}, \tilde{s}_{2N}\}, \quad (13)$$

where  $u \in \{1, 2, \dots, N\}$ . Following [2], each pair  $(\tilde{s}_{2u-1}, \tilde{s}_{2u})$  is treated as a positive pair, and the other  $2(N-1)$  augmented views are considered as negative samples for this pair. The augmented sequences are then encoded as in Eq. (2) with a shared sequence encoder. For each sequence pair  $(\tilde{s}_{2u-1}, \tilde{s}_{2u})$ , their representations are  $(\tilde{h}_{2u-1}, \tilde{h}_{2u})$ . We adopt the NT-Xent loss [2] for optimization as follows:

$$\mathcal{L}_{ssl}(\tilde{h}_{2u-1}, \tilde{h}_{2u}) = -\log \frac{\exp(\text{sim}(\tilde{h}_{2u-1}, \tilde{h}_{2u}))}{\sum_{m=1}^{2N} \mathbb{1}_{m \neq 2u-1} \exp(\text{sim}(\tilde{h}_{2u-1}, \tilde{h}_m))}, \quad (14)$$

where  $\text{sim}(\cdot)$  is a dot product to measure the similarity between two augmented views, and  $\mathbb{1}_{|m \neq 2u-1|} \in \{0, 1\}$  is an indicator function. Since the output embeddings from a Transformer encoder are position-wise, we thus concatenate representations at all positions as the sequence representation. We illustrate the contrastive SSL framework in Figure 1(c).

## 4.3 Multi-Task Training

Because next-item prediction and contrastive SSL both model item relationships in sequences, to boost sequential recommendation performance with the contrastive SSL objective, we leverage a multi-task strategy to optimize them jointly as follows:

$$\mathcal{L} = \mathcal{L}_{rec} + \lambda \mathcal{L}_{ssl}, \quad (15)$$

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### Algorithm 1: CoSeRec training.

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**Input:** hyperparameters  $\alpha, \beta, K, E$ , and  $\lambda$ , max training epochs  $B$ , batch size  $N$ , and a memory-based correlation matrix  $\text{Cor}_0$ .  
**Output:**  $\text{SeqEnc}(\cdot)$ .

```

1 while  $epoch \leq B$  do
    // Item correlation selection (Sec. 4.1.3)
2   if  $epoch \leq E$  then
3     | Leverage  $\text{Cor}_0$  for informative augmentations.
4   else
5     | Leverage  $\text{Cor}_h$  for informative augmentations.
    // End-to-end optimization
6   for sampled minibatch  $\{s_u\}_{u=1}^N$  do
7     for  $u \in \{1, 2, \dots, N\}$  do
8       | // Construct two augmentations.
9       | if  $|s_u| \leq K$  then
10        | | sample two operators:  $a_1^u, a_2^u \sim \{I, S, M\}$ 
11        | else
12        | | sample two operators:  $a_1^u, a_2^u \sim \{I, S, M, C, R\}$ 
13        |  $\tilde{s}_{2u-1} = a_1^u(s_u), \tilde{s}_{2u} = a_2^u(s_u)$ 
14        | // Representation learning via SeqEnc
15        |  $\tilde{h}_u = \text{SeqEnc}(s_u)$ 
16        |  $\tilde{h}_{2u-1}, \tilde{h}_{2u} = \text{SeqEnc}(\tilde{s}_{2u-1}), \text{SeqEnc}(\tilde{s}_{2u})$ 
    // Multi-Task optimization
     $\mathcal{L} = \frac{1}{N} \sum_{u=1}^N \mathcal{L}_{rec}(\tilde{h}_u) +$ 
     $\lambda \frac{1}{2N} \sum_{u=1}^N [\mathcal{L}_{ssl}(\tilde{h}_{2u-1}, \tilde{h}_{2u}) + \mathcal{L}_{ssl}(\tilde{h}_{2u}, \tilde{h}_{2u-1})]$ 
    update network  $\text{SeqEnc}(\cdot)$  to minimize  $\mathcal{L}$ 

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where  $\lambda$  is a hyper-parameter to control the intensity of contrastive SSL. Algorithm 1 summarizes the training process of CoSeRec. Alternatively, a two-stage optimization, i.e. first pre-training the encoder with SSL and then fine-tuning with next-item prediction, can be adopted. We provide comparisons in Section 5.5.3, which indicates joint training is better than two-stage training.

## 5 EXPERIMENTS

In this section, we conduct experiments on three public datasets and answer the following Research Questions (RQs):

- **RQ1:** How does CoSeRec perform on sequential recommendations compared with existing methods?
- **RQ2:** What are the optimal augmentation methods for sequential recommendation?
- **RQ3:** Can CoSeRec perform robustly against data-sparsity and noisy interactions issues?
- **RQ4:** How do different settings influence CoSeRec’s performance?

### 5.1 Experimental Setting

**5.1.1 Datasets.** We conduct experiments on three public datasets collected from two real-world platforms. *Beauty* and *Sports* are two

subcategories of Amazon review data introduced in [25]. The Yelp<sup>1</sup> dataset is a dataset for business recommendation.

We follow common practice in [46, 52] to preprocess the datasets. The numeric ratings or the presence of a review are treated as positive instances while others as negative instances. We only keep the ‘5-core’ datasets, i.e. every user bought in total at least 5 items and vice versa each item was bought by at least 5 users. Table 1 shows the statistics of the datasets after preprocessing.

**Table 1: Dataset information.**

Dataset	# Users	# Items	# Actions	Avg. length	Sparsity
Beauty	22,363	12,101	198,502	8.9	99.73%
Sports	35,598	18,357	296,337	8.3	99.95%
Yelp	30,431	20,033	316,354	10.3	99.95%

**5.1.2 Evaluation Metrics.** We follow [16, 32] to evaluate the model as next-item prediction. We rank the prediction on whole item set without negative sampling, which otherwise leads biased discoveries [18]. Performance is evaluated on top- $k$  ranking metrics including *Hit Ratio@k* (HR@ $k$ ), and *Normalized Discounted Cumulative Gain@k* (NDCG@ $k$ ). We report HR and NDCG with  $k \in \{5, 10, 20\}$ .

**5.1.3 Baseline Methods.** We include three groups of baseline methods for comparison.

- *Non-Sequential models:* PopRec is based on the popularity of items; BPR-MF [30] is a matrix factorization model with a pairwise Bayesian Personalized Ranking loss.
- *Transformer-based SR models:* SASRec [16] is one of the state-of-the-art Transformer-based baselines for SR, Bert4Rec [32] extends SASRec with bidirectional self-attention modules. S<sup>3</sup>-Rec [52] uses self-supervised learning to capture relationships among item and associated attributes. We remove its modules for mining on attributes as we have no attributes for items, namely S<sup>3</sup>-Rec<sub>m</sub>. CL4SRec [46] fuses contrastive SSL with Transformer-based SR model. It only has random augmentation methods for SSL.
- *Other SR models:* GRU4Rec [14] is an RNN-based approach, and Caser [33] is a CNN-based model.

**5.1.4 Implementation Details.** We use code provided by the authors for S3-Rec<sup>2</sup>, Bert4Rec<sup>3</sup> and Caser<sup>4</sup> methods. We implement GRU4Rec<sup>5</sup> and BPRMF<sup>6</sup> methods based on public resources. We tune the mask proportion of BERT4Rec with  $\{0.2, 0.4, 0.6, 0.8\}$ . We set all other hyper-parameters of each method as reported in the papers.

We implement our method in PyTorch. For common hyperparameters, we follow [46] to set the number of the self-attention blocks and attention heads as 2, the embedding dimension as 64, and the maximum sequence length as 50. We tune  $\alpha$ ,  $\beta$ ,  $K$ ,  $E$ , and  $\lambda$  within the ranges of  $[0.1, 0.9]$ ,  $[0.1, 0.9]$ ,  $\{4, 12, 20\}$ ,  $\{0, 20, 40, 60, 80, 100\}$ ,

and  $\{0.1, 0.2, 0.3, 0.4, 0.5\}$  respectively. For hyperparameters in random augmentation operators  $\eta$ ,  $\mu$ , and  $\omega$ , we set the optimal values reported by [46]. We adopt early stopping on the validation set if the performance does not improve for 40 epochs, and report results on test set. The model is optimized by Adam optimizer [17] with a learning rate of 0.001,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ , and batch size of 256.

## 5.2 Overall Performance Comparison (RQ1)

Table 2 shows the performance of all methods on three datasets. We make the follow observations:

- *Overall Comparison.* (1) Non-sequential models perform worse than sequential recommendation methods. This suggests the importance of mining sequential patterns for next-item prediction. For sequential models, Transformer-based methods achieve better performance than other type of SR models, which indicates that self-attention mechanisms are more effective at capturing sequential patterns than CNN and RNNs. (2) S<sup>3</sup>-Rec<sub>m</sub>, though leveraging self-supervision signals by masking items in sequences, performs worse than SASRec. We hypothesize the poor performance results from two reasons: the two-stage training preventing information sharing between SSL and next-item prediction targets, and the weak supervision signals without informative augmentations. (3) CL4SRec consistently performs better than other baselines, which verifies the efficacy of employing contrastive SSL in sequential recommendation. However, it still performs worse than CoSeRec, since it has no informative augmentations. (4) The proposed CoSeRec consistently outperforms other models on all datasets in all evaluation metrics. The improvements comparing with the best baseline range from 3.54% to 30.88% in terms of HR and NDCG. Different from baselines, our proposed method leverages contrastive SSL signals with informative augmentation methods, incorporating length skewness of sequences, and optimize the model with multi-task strategy.
- *Comparison with SASRec and CL4SRec.* (1) We observe that compared with SASRec, the performance of CoSeRec is significantly better, ranging from 14.54% to 54.14% in HR and NDCG on three datasets. Since both CoSeRec and SASRec adopt the same sequence encoder, those results demonstrate the necessity of leveraging the contrastive SSL signals for SR. (2) Compared with CL4SRec which employs random augmentations for contrastive SSL task, CoSeRec achieves 22.47%, 23.39% and 4.67% average relative improvement on Beauty, Sports, and Yelp datasets respectively. The performance gains result from the informative augmentation, which is first proposed in this work. (3) We also observe larger average improvements on Sports and Beauty compared with Yelp. We hypothesis the difference is because the average sequence length of Sports and Beauty is shorter than that of Yelp, thus suffering severer ‘cold-start’ issues. Therefore, SSL contributes more benefits to the sequence encoding on the Sports and Beauty datasets.

## 5.3 Augmentation Analysis (RQ2)

In this paper, we include five augmentation operators for the contrastive SSL task. To study impacts of these augmentation methods and find the optimal choice, we conduct three groups of ablation

<sup>1</sup><https://www.yelp.com/dataset>

<sup>2</sup><https://github.com/RUCAIBox/CIKM2020-S3Rec>

<sup>3</sup><https://github.com/FeiSun/BERT4Rec>

<sup>4</sup>[https://github.com/graytowne/caser\\_pytorch](https://github.com/graytowne/caser_pytorch)

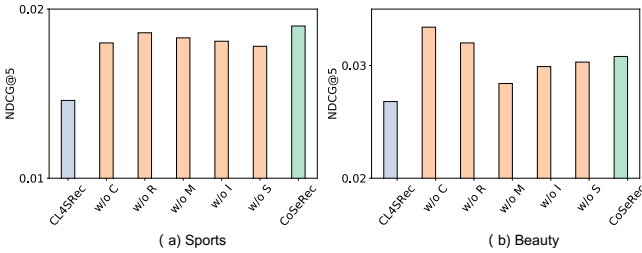
<sup>5</sup>[https://github.com/slientGe/Sequential\\_Recommendation\\_Tensorflow](https://github.com/slientGe/Sequential_Recommendation_Tensorflow)

<sup>6</sup>[https://github.com/xiangwang1223/neural\\_graph\\_collaborative\\_filtering](https://github.com/xiangwang1223/neural_graph_collaborative_filtering)

**Table 2: Performance comparisons of different methods. The best score is bolded in each row, and the second best is underlined. The last two columns are the relative improvements compared with SASRec and the best baseline results.**

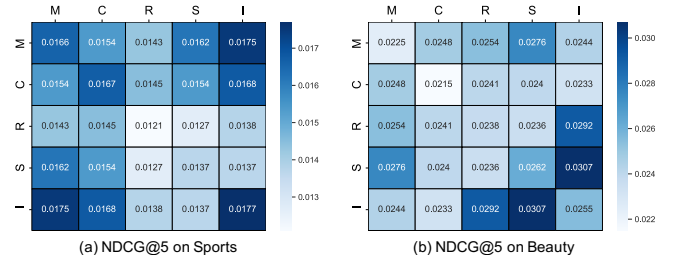
Dataset	Metric	PopRec	BPR	GRU4Rec	Caser	SASRec	BERT4Rec	S <sup>3</sup> -Rec <sub>m</sub>	CL4SRec	CoSeRec	Improv. v.s.	
											SASRec	All
Beauty	HR@5	0.0080	0.0212	0.0111	0.0251	0.0374	0.0351	0.0189	<u>0.0401</u>	<b>0.0537</b>	43.58%	33.92%
	HR@10	0.0152	0.0372	0.0162	0.0342	0.0575	0.0601	0.0307	<u>0.0642</u>	<b>0.0752</b>	30.78%	17.13%
	HR@20	0.0217	0.0589	0.0478	0.0643	0.0901	0.0942	0.0487	<u>0.0974</u>	<b>0.1041</b>	15.54%	6.88%
	NDCG@5	0.0044	0.0130	0.0058	0.0145	0.0241	0.0219	0.0115	<u>0.0268</u>	<b>0.0361</b>	49.79%	34.7%
	NDCG@10	0.0068	0.0181	0.0075	0.0226	0.0305	0.0300	0.0153	<u>0.0345</u>	<b>0.0430</b>	40.98%	24.64%
	NDCG@20	0.0084	0.0236	0.0104	0.0298	0.0387	0.0386	0.0198	<u>0.0428</u>	<b>0.0503</b>	29.97%	17.52%
Sports	HR@5	0.0056	0.0141	0.0162	0.0154	0.0206	0.0217	0.0121	<u>0.0231</u>	<b>0.0287</b>	39.32%	24.24%
	HR@10	0.0094	0.0216	0.0258	0.0261	0.0320	0.0359	0.0205	<u>0.0369</u>	<b>0.0437</b>	36.56%	18.43%
	HR@20	0.0192	0.0323	0.0421	0.0399	0.0497	<u>0.0604</u>	0.0344	0.0557	<b>0.0635</b>	27.77%	8.60%
	NDCG@5	0.0041	0.0091	0.0103	0.0114	0.0135	0.0143	0.0084	<u>0.0146</u>	<b>0.0196</b>	45.19%	34.25%
	NDCG@10	0.0053	0.0115	0.0142	0.0135	0.0172	0.0190	0.0111	<u>0.0191</u>	<b>0.0242</b>	40.7%	26.7%
	NDCG@20	0.0078	0.0142	0.0186	0.0178	0.0216	<u>0.0251</u>	0.0146	0.0238	<b>0.0292</b>	35.19%	15.14%
Yelp	HR@5	0.0057	0.0127	0.0152	0.0142	0.0160	0.0196	0.0101	<u>0.0227</u>	<b>0.0241</b>	50.63%	6.17%
	HR@10	0.0099	0.0216	0.0248	0.0254	0.0260	0.0339	0.0176	<u>0.0384</u>	<b>0.0395</b>	51.92%	2.86%
	HR@20	0.0164	0.0346	0.0371	0.0406	0.0443	0.0564	0.0314	<u>0.0623</u>	<b>0.0649</b>	46.5%	4.17%
	NDCG@5	0.0037	0.0082	0.0091	0.008	0.0101	0.0121	0.0068	<u>0.0143</u>	<b>0.0151</b>	49.5%	5.59%
	NDCG@10	0.0051	0.0111	0.0124	0.0113	0.0133	0.0167	0.0092	<u>0.0194</u>	<b>0.0205</b>	54.14%	5.67%
	NDCG@20	0.0067	0.0143	0.0145	0.0156	0.0179	0.0223	0.0127	<u>0.0254</u>	<b>0.0263</b>	46.93%	3.54%

studies on the Sports and Beauty datasets. The first is a ‘leave-one-out’ setting in which only one augmentation operator is removed from the augmentation set  $\{M, C, R, S, I\}$  at a time. The second is ‘pair-wise’ where we only apply two augmentations to create two types of views for contrastive SSL tasks in each model. Lastly, we investigate the optimal augmentations for short sequences.

**Figure 3: Performance comparison (in NDCG@5) w.r.t. different augmentation sets on Sports and Beauty datasets. ‘w/o’ indicates one type is removed from the full augmentation set  $\{M, C, R, S, I\}$ . CoSeRec adopts the full set.**

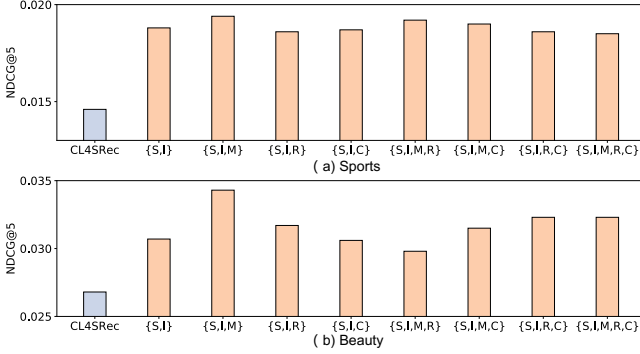
**5.3.1 Leave-One-Out Comparison.** Figure 3 shows the comparison results under the ‘leave-one-out’ setting. We included CL4SRec for comparison since it utilizes random augmentations  $\{M, C, R\}$ . We observe that without the ‘Insert’ or ‘Substitute’ operator, the performance consistently decreases on both datasets. Without random operators such as ‘Crop’ or ‘Reorder’, performance even significantly *increases* on the Beauty dataset. This phenomenon implies that existing random augmentations, such as randomly cropping or reordering a sequence without considering item correlations,

demolish item relationships in sequences, which leads to less confident positive pairs and thus impairs the efficacy of the contrastive SSL learning.

**Figure 4: Performance comparison (in NDCG@5) w.r.t. different augmentation pairs on Sports and Beauty datasets.**

**5.3.2 Pair-Wise Comparison.** Figure 4 shows the comparison results on the Sports and Beauty datasets under the ‘pair-wise’ setting. We observe that: (1) For pair of the same operator (diagonal values), the best performance is I and S on Sports and Beauty dataset, respectively. This demonstrates our proposed informative operators are better than those random augmentations for contrastive SSL. (2) A pair of different operators performs better than two which are the same in general. For example in Beauty, (I, S) pair achieves 0.0307 while (I, I) and (S, S) pairs achieves 0.0255 and 0.0262 in NDCG@5 respectively. Comparing with Figure 3(b), we observe that having multiple augmentation operators perform better than one or two augmentation operators. For example, with  $\{M, R, S, I\}$  augmentation set, the model achieves 0.0334 in NDCG@5 on Beauty which is

higher than all pair-wise based model results. These observations imply that having multiple views for contrastive SSL is beneficial as it allows the model to capture more mutual information from different views. (3) ‘S’ performs well on Beauty but not on Sports under the pair-wise setting. However, in Figure 3(a), model without ‘S’ augmentation has the largest performance drop compared to others. This indicates that the ‘S’ operator is more suitable for providing a complementary view for contrastive SSL learning.



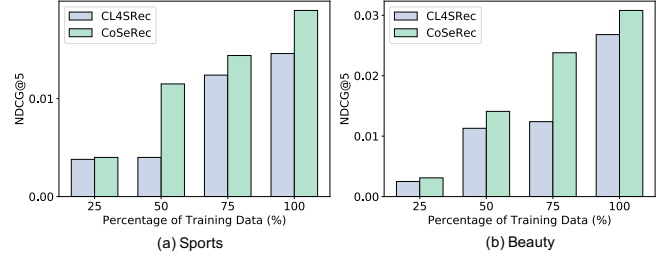
**Figure 5: Performance comparison w.r.t. different augmentation sets for short sequences on Sports and Beauty datasets.**

**5.3.3 Augmentation Set for Short Sequences.** As described in Sec. 4.1.4, short sequences are more sensitive to random augmentations, for which we only augmented by ‘M’, ‘S’, and ‘I’ augmentation operators. In this section, we explore the optimal augmentation combinations for short sequences to verify our claims.

Figure 5 shows the performance with different combinations of augmentations for short sequences. For example, ‘{S, I, M}’ denotes adopting all ‘S’, ‘I’, and ‘M’ augmentations for short sequences. We observe that all combinations which include informative augmentations outperform CL4SRec, which demonstrates the necessity of using informative operators for short sequences. With the additional ‘M’ augmentation, the performance improves most. This is because ‘M’ operator shares the same information as the next-item prediction target, and it encourages the encoder to capture high-order item relationships. Additionally, the model with ‘{S, I, M}’ operators outperforms ‘{S, I, M, R, C}’ indicating that applying different augmentation operators to short and long sequences is meaningful as short sequences can be more sensitive to randomness.

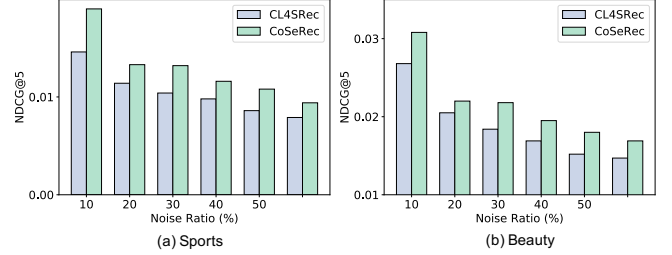
## 5.4 Robustness Analysis (RQ3)

Recommender systems usually suffer data-sparsity issues where there are limited historical records. To simulate this scenario, we train a model with only partial training data (25%, 50%, 75%, and 100%) and keep the test data unchanged. We compare the proposed method with the best baseline (CL4SRec) on the Sports and Beauty datasets, which are presented in Figures 6 (a) and (b), respectively. We observe that performance substantially degrades when less training data is used, but CoSeRec consistently performs better than CL4SRec and the performance degradation is slower than CL4SRec. For example, on Sports, CoSeRec achieves similar performance with only 75% of training data as of CL4SRec with full training



**Figure 6: Performance comparison w.r.t. sparsity ratio.**

data. Moreover, CL4SRec drops 76.19% of its original performance while CoSeRec only drop 34%, when both with 50% training data. These observations demonstrate that informative augmentations in CoSeRec can alleviate data-sparsity issue. We also observe that the impact of data sparsity varies on different datasets. With 50% training data, CoSeRec’s performance drops 34% on Sports while dropping 52.14% on Beauty.



**Figure 7: Model performance comparisons w.r.t. noise ratio.**

We also evaluate the robustness of CoSeRec to noisy interactions in the inference phrase. Specifically, we train a model with the original training data, and randomly add a certain proportion (10%, 20%, 30%, 40%, and 50%) of negative user-item interactions to every test sequence. Figures 6 (c)-(d) show the results on the Sports and Beauty datasets. We see that the performance of both CoSeRec and CL4SRec decreases. CoSeRec can consistently perform better than CL4SRec under any noise ratio. This implies that with additional high quality augmentation operators (‘Insert’ and ‘Substitute’), CoSeRec creates higher confident positive views for the contrastive SSL objective to maximize agreements, which thus endows the encoder with more robustness against the noisy interactions during the inference stage.

## 5.5 Study of CoSeRec (RQ4)

In this section, we first explore the effects of hyperparameters  $\alpha$ ,  $\beta$ ,  $K$ , and  $\lambda$  in CoSeRec, which control the ‘Substitute’ ratio, ‘Insert’ ratio, threshold of deciding whether a sequence to be short, and the intensity of contrastive SSL, respectively. Then we compare different item correlations. Lastly, we investigate an alternative two-stages optimization strategy, which first pre-trains from SSL and then fine-tunes on next-item prediction targets.

**5.5.1 Hyperparameter Study.** We study the hyperparameters one by one meaning that all other hyperparameters are assigned



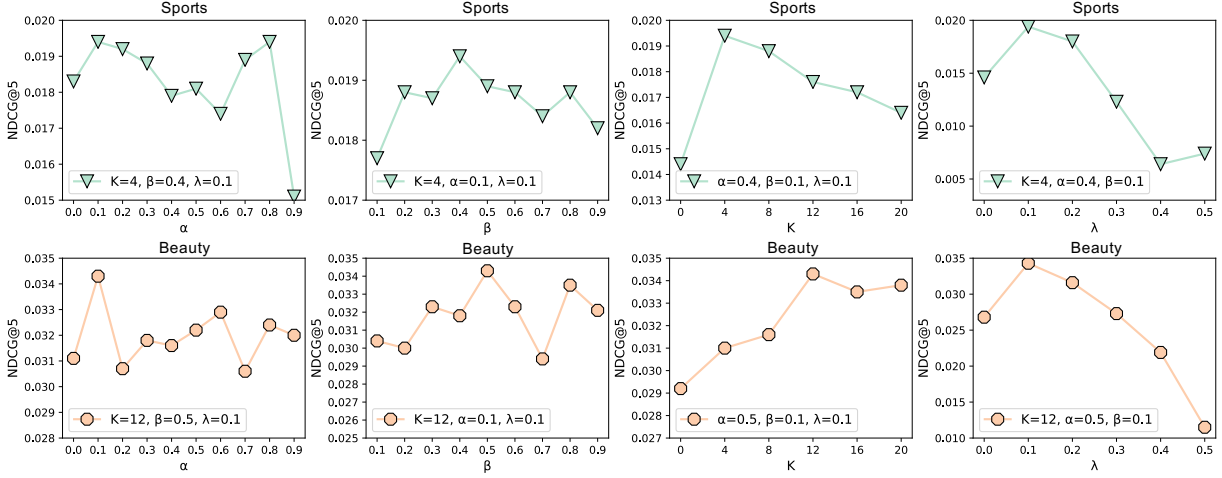


Figure 8: Performance comparison of CoSeRec w.r.t. different  $\alpha$ ,  $\beta$ ,  $K$ , and  $\lambda$  on Sports and Beauty datasets.

the optimal tuned values when studying a certain hyperparameter. Figure 8 shows overall comparisons.

We observe that: (1) A general pattern for  $\alpha$  and  $\beta$  is that the performance reaches to a peak as the ratios increasing and then start to deteriorate. The reason is that there is no informative augmentation when the ratio is 0 and increasing the ratios too high leads heavier corruptions, thus constructing false positive samples to impair the SSL. Specifically,  $\beta = 0.4$  performs the best while  $\alpha = 0.1$  performs the best in the Sports and Beauty datasets, respectively. The larger  $\beta$  indicates that due to the long-tail distribution of short sequences, the dataset requires more ‘Insert’ operator to alleviate the cold-start problem. (2) The best values of  $K$  are 4 and 12 on Sports and Beauty, respectively. We hypothesis that the difference between the optimal  $K$  of two datasets is because the length skewness is different. (3) We can see that having the contrastive SSL signal ( $\lambda > 0$ ) is important as it significantly improves the performance 32.88% and 12.82% in NDCG@5 on the Sports and Beauty datasets. We also observe that performance starts to deteriorate when  $\lambda > 0.1$ . This indicates that the contrastive SSL signal complements but should not dominate the learning goal.

**5.5.2 Effect of Item Correlations.** We study the effect of different correlations introduced in Section 4.1.3 including *memory-based*, *model-based* and *hybrid* correlations. Table 3 shows comparison results. We can see that using any type of item correlations helps improving performance compared with CL4SRec. Among these correlations, model-based correlation performs worse than memory-based and hybrid correlations. This might be because item representations learned from the model at early epochs are not informative. Hybrid correlations performs best with  $E \geq 160$ . This indicates that it is beneficial to incorporate both model-based and memory-based correlations.

**5.5.3 Effect of pre-training.** We have demonstrated that jointly optimizing the recommendation objective with the contrastive learning objective leads to an effective training of CoSeRec. However,  $S^3$ -Rec claims that a *two-stage* training, i.e. pre-training with contrastive SSL and fine-tuning with next-item prediction, is also

Table 3: Performance comparison w.r.t. different item correlations for informative augmentations.

Correlation Type	Sports		Beauty	
	HR@5	NDCG@5	HR@5	NDCG@5
None (CL4SRec)	0.0231	0.0146	0.0401	0.0268
Memory-based	0.0284	0.0194	0.0528	0.0357
Model-based	0.0251	0.0164	0.0497	0.0338
Hybrid ( $E = 80$ )	0.0270	0.0179	0.0503	0.0342
Hybrid ( $E = 160$ )	0.0287	<b>0.0196</b>	<b>0.0537</b>	<b>0.0361</b>
Hybrid ( $E = 200$ )	<b>0.0290</b>	0.0194	0.0530	0.0357

effective. This two-stage training is also widely adopted in other areas [2, 5]. Therefore, we conduct experiments to compare the performance of our multi-task training strategy and an alternative two-stage one. Table 4 shows the result comparisons between multi-task training and two-stage training on the Sports and Beauty datasets. We observe that a two-stage training performs worse compared with the multi-task strategy. The better performance of the multi-task strategy of CoSeRec reflects that contrastive learning objectives and recommendation objectives can benefit from each other when jointly training, while two stage training can lead to the pre-trained self-supervision information being forgotten in the fine-tuning stage.

Table 4: Performance comparison under multi-task and two-stage training strategies on Sports and Beauty datasets.

Strategy	Sports		Beauty	
	HR@5	NDCG@5	HR@5	NDCG@5
Multi-task	0.0287	0.0196	0.0537	0.0361
Two-stage	0.0242	0.0388	0.0435	0.0283

## 6 CONCLUSION AND FUTURE WORK

In this work, we studied the contrastive SSL in sequential recommendation, which alleviate the data-sparsity and noisy interaction issues. We proposed a novel learning framework, CoSeRec, which jointly optimizes the contrastive SSL objective and the next-item prediction objective. We proposed two novel informative augmentation methods, *i.e.* substitute and insert, which advances existing random augmentations by leveraging item correlations. Additionally, we endowed augmentations with sequence length awareness, which addresses the length skewness in sequential dataset. We conducted extensive experiments on three benchmark datasets and justified the effectiveness and the robustness of CoSeRec. Moreover, we investigated the optimal augmentation for sequential recommendation, which verifies the efficacy of informative augmentations.

In the future, we plan to investigate more advanced model-based item correlation functions. For example, searching for correlated items under a reinforcement learning framework so that more accurate correlation information can be leveraged. Additionally, we will explore finer-grained exploration of the relation between augmentations and the sequence length. Moreover, we plan to study the effects of different contrastive learning functions in the self-supervised learning of sequences.

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