

Future Sight and Tough Fights: Revolutionizing Sequential Recommendation with FENRec

Yu-Hsuan Huang¹, Ling Lo¹, Hongxia Xie², Hong-Han Shuai¹, Wen-Huang Cheng³

¹National Yang Ming Chiao Tung University,

²Jilin University,

³National Taiwan University

{shan.ee08, linglo.ee08}@nycu.edu.tw, hongxiaxie@jlu.edu.cn, hhshuai@nycu.edu.tw, wenhuang@csie.ntu.edu.tw

Abstract

Sequential recommendation (SR) systems predict user preferences by analyzing time-ordered interaction sequences. A common challenge for SR is data sparsity, as users typically interact with only a limited number of items. While contrastive learning has been employed in previous approaches to address the challenges, these methods often adopt binary labels, missing finer patterns and overlooking detailed information in subsequent behaviors of users. Additionally, they rely on random sampling to select negatives in contrastive learning, which may not yield sufficiently hard negatives during later training stages. In this paper, we propose Future data utilization with Enduring Negatives for contrastive learning in sequential Recommendation (FENRec). Our approach aims to leverage future data with time-dependent soft labels and generate enduring hard negatives from existing data, thereby enhancing the effectiveness in tackling data sparsity. Experiment results demonstrate our state-of-the-art performance across four benchmark datasets, with an average improvement of 6.16% across all metrics.

Introduction

Recommendation systems enhance user experience by providing personalized suggestions tailored to individual preferences. Given their wide applications in online shopping, streaming services, and social media, extensive research has focused on optimizing their performance and effectiveness (Lu et al. 2015; Sharma et al. 2024; Alamdari et al. 2020). Among them, Sequential Recommendation (SR) stands out for its ability to capture and utilize the temporal dynamics of user behavior (Yu et al. 2019; Xie et al. 2022; Chen et al. 2022; Qiu et al. 2022).

Despite the strength of SR, they still face the common challenge of recommendation systems: the limited nature of user-item interaction. Usually, users only interact with a small subset of all available items. The sparsity in interaction data can impede the training of SR, making them struggle to learn meaningful preferences, which can affect the accuracy and the relevance of the generated recommendations. To address the data sparsity issue, previous methods have proposed incorporating contrastive learning, which leverages self-supervised signals to improve model performance (Xie

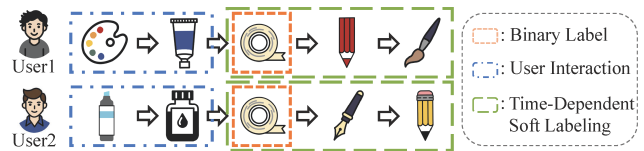


Figure 1: An illustration of binary labels compared to the Time-Dependent Soft Labeling we propose.

et al. 2022; Chen et al. 2022; Qiu et al. 2022). These methods create positive pairs through augmentation strategies and maximize their agreement. For instance, CL4SRec (Xie et al. 2022) uses data augmentations such as masking and cropping to generate positive pairs. DuoRec (Qiu et al. 2022) utilizes model-level augmentation and regards user sequence with the same next item as augmented positive view.

While contrastive learning has proven effective, we contend that sparse data can be used more efficiently within these methods due to two reasons. First, they use only the last item in sequence as a binary label and overlook the upcoming interactions. Second, they adopt random sampling for selecting negatives in contrastive learning, which may not yield sufficiently challenging samples later in training, reducing their effectiveness in addressing data sparsity issue. Therefore, to better utilize sparse data, we propose Future data utilization with Enduring Negatives for contrastive learning in sequential Recommendation (FENRec) including two components: Time-Dependent Soft Labeling and Enduring Hard Negatives Incorporation. For the first issue, we propose Time-Dependent Soft Labeling akin to using future interactions as labels, even though these interactions are rooted in the past. Our method traces back previous subsequences to generate labels based on interactions resembling potential future events, capturing finer patterns in user behavior. Unlike previous methods that assign identical binary labels to the two user sequences in Fig. 1, our approach incorporates subsequent events, allowing the model to capture more detailed insight in user behavior. Additionally, to address the second issue, we introduce Enduring Hard Negatives Incorporation. We generate hard negatives by mixing anchors with negatives throughout training, ensuring they remain consistently challenging. Fig. 2 shows how the similarity between original negatives and the anchor declines

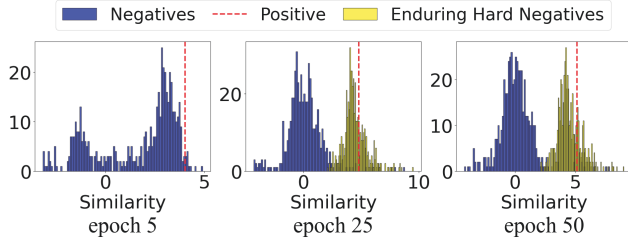


Figure 2: The distribution of similarity between samples and the anchor sample from a random sample batch at epoch 5, 25, and 50 on the Beauty dataset. Our enduring hard negatives are incorporated following a 20-epoch warm-up period. Similarity is calculated using the inner product.

over time, potentially hindering the model’s ability to learn discriminative features. In contrast, our hard negatives maintain higher similarity with the anchor, enhancing the model’s ability to differentiate user preferences.

The contributions of this work are summarized below:

- We propose Time-Dependent Soft Labeling to leverage the entire user interaction sequence. Our method generates labels based on interactions that resemble future events.
- We introduce Enduring Hard Negatives Incorporation to enhance contrastive learning. By generating enduring hard negatives, our method improves the ability of the model to differentiate complex samples.
- Extensive experiments on four benchmark datasets demonstrate the state-of-the-art performance of our FEN-Rec model, which comprises Time-Dependent Soft Labeling and Enduring Hard Negatives Incorporation.

Related Work

Sequential Recommendation

Sequential recommendation (SR) predicts future user interactions based on past sequences. Recent SR models have improved performance but still face data sparsity issues due to limited user interactions (Tang and Wang 2018; Hidasi et al. 2016; Kang and McAuley 2018; Yue et al. 2024; Shin et al. 2024). To address this, some methods use contrastive learning techniques (Xie et al. 2022; Du et al. 2022; Liu et al. 2021; Chen et al. 2022; Qiu et al. 2022; Qin et al. 2024), introducing self-supervised signals to more effectively utilize the available data for better learning. These approaches use augmentation techniques to generate positive pairs and maximize their agreement. CL4Rec (Xie et al. 2022) uses data augmentations like item masking to produce positive pairs, ICLRec (Chen et al. 2022) employs clustering to align intent and user representations, DuoRec (Qiu et al. 2022) leverages both supervised and unsupervised contrastive learning, and ICSRec (Qin et al. 2024) utilizes intent within subsequences for contrastive learning. However, these contrastive learning methods fail to utilize future interactions and adopt random sampling. Therefore, sparse data may not be fully utilized by these methods.

Soft Label for Recommendation Systems

Recommender systems often rely on one-hot labels, which overlook the ambiguity of unobserved feedback and can lead to poor generalization. To address this, some methods use soft labels to capture user preferences more accurately (Cheng et al. 2021; Zhou et al. 2023; Wu et al. 2024). Soft labels help the model to learn finer-grained user preferences. SoftRec (Cheng et al. 2021) uses item, user, and model strategies to create soft labels, MVS (Zhou et al. 2023) generates smoothed contexts with a complementary model, and CSRec (Wu et al. 2024) employs model-, data-, or training-level teachers to generate confident soft labels for SR. Unlike previous methods, we generate soft labels by leveraging upcoming interactions through a simple yet effective approach that requires no additional modules.

Hard Negative Mining in Deep Metrics Learning

Hard negatives have proved to be helpful in various domains (Suh et al. 2019; Xuan et al. 2020; Zhan et al. 2021; Robinson et al. 2021). Due to the advantage of using hard negatives, Mochi (Kalantidis et al. 2020) creates synthetic hard negatives by mixing the hardest negatives. MixCSE (Zhang et al. 2022) mix positive and negative samples to generate hard negatives. Despite the advantages of hard negatives and the prevalence of contrastive learning in SR, integrating hard negatives into these frameworks remains underexplored.

Preliminaries

Sequential Recommendation

Sequential recommendation (SR) aims to predict the next item a user will interact with by analyzing their historical interaction sequences. Denote the set of items as $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$ and the set of users as \mathcal{U} . The past interactions of each user $u \in \mathcal{U}$ can be arranged chronologically, forming a user interaction sequence $\mathcal{S}^u = [v_1^u, v_2^u, \dots, v_{|\mathcal{S}^u|}^u]$, where v_i^u represents the i -th interacted item in the sequence and $|\mathcal{S}^u|$ is the length of \mathcal{S}^u . Given a user interaction sequence \mathcal{S}^u , the goal of SR is to predict the item the user u is most likely to interact with at time step $|\mathcal{S}^u| + 1$. It can be formulated as follows:

$$\arg \max_{v \in \mathcal{V}} \mathbb{P}(v_{|\mathcal{S}^u|+1}^u = v \mid \mathcal{S}^u). \quad (1)$$

To effectively train models to achieve this goal, SR methods often divide the original sequence into multiple subsequences to enrich training data and train the model using them. Formally, given the interaction sequence \mathcal{S}^u of user u , the subsequences can be constructed as follows:

$$\mathcal{DS}(\mathcal{S}^u) = \{[v_1^u, v_2^u, \dots, v_t^u] \mid 1 \leq t \leq |\mathcal{S}^u|\}. \quad (2)$$

During the training phase, the next item of each subsequence is regarded as the target item for prediction.

After dividing user sequences, SR model is trained by calculating the probability of each item being the next of the subsequence and computing the cross-entropy loss based on this probability. Specifically, current SR systems first encode the interaction sequences into user representations using deep neural networks (e.g., RNN or transformer) and

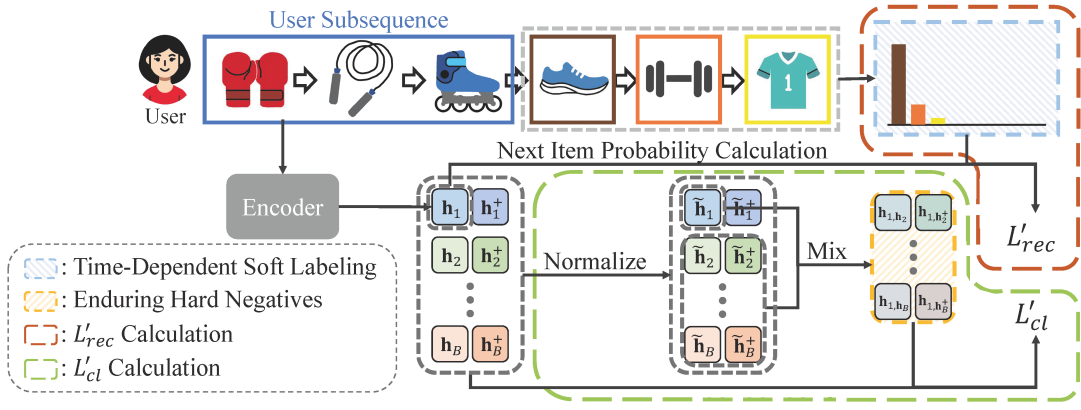


Figure 3: The framework of our method, FENRec, the user sequences will first be split into subsequences and encoded into representations, while soft labels are generated based on the subsequences. Next, the enduring hard negatives are produced and incorporated into contrastive learning framework. Finally, L'_{rec} and L'_{cl} are calculated.

calculate the probability of the next item based on it (Hidasi et al. 2016; Kang and McAuley 2018). Formally, a sequence encoder $f_\theta(\cdot)$ first encodes the interaction sequence $\mathcal{S}^{us} \in \mathcal{DS}(\mathcal{S}^u)$ and generates the user representation \mathbf{h}_{us} , denoted as $\mathbf{h}_{us} = f_\theta(\mathcal{S}^{us})$. Then, the probability that the next item of sequence \mathcal{S}^{us} is item v_j is given by:

$$\hat{\mathbf{y}}_j^{us} = \text{softmax}(\mathbf{h}_{us}^T \mathbf{v}_j), \quad (3)$$

where \mathbf{v}_j denotes the item embedding of the item v_j , and the cross-entropy loss is calculated as follows:

$$L_{rec} = - \sum_{j=1}^N \mathbf{y}_j^{us} \log \hat{\mathbf{y}}_j^{us}. \quad (4)$$

N represents the total number of items. \mathbf{y}_j^{us} denotes the true label of the interaction sequence \mathcal{S}^{us} for v_j . If v_i is the target item of \mathcal{S}^{us} (i.e., $v_{|\mathcal{S}^{us}|+1}^u$), then $\mathbf{y}_i^{us} = 1$ and $\mathbf{y}_j^{us} = 0$ for all other items (i.e., $j \neq i$). Minimizing the cross-entropy loss is equivalent to optimizing SR system with Eq. (1).

Contrastive Learning in SR

One challenge in SR is data sparsity. Typically, users interact with only a small fraction of available items, leading to sparse history data. Since the sparsity can significantly hinder the learning of deep neural networks, recent works adopt contrastive learning to improve the learned features (Chen et al. 2022; Qiu et al. 2022). Generally, given an anchor sample¹ \mathbf{h}_i and the positive view of the anchor \mathbf{h}_i^+ generated by augmentation strategies², other samples within the batch are considered negative views, and the contrastive loss can be formulated as follows:

$$L_{cl}(\mathbf{h}_i, \mathbf{h}_i^+) = - \log \frac{e^{(\mathbf{h}_i^T \mathbf{h}_i^+)/\tau_1}}{e^{(\mathbf{h}_i^T \mathbf{h}_i^+)/\tau_1} + \sum_{\mathbf{n} \in \mathbf{H}_i} e^{(\mathbf{h}_i^T \mathbf{n})/\tau_1}}, \quad (5)$$

where $\mathbf{H}_i = \{\mathbf{h}_j, \mathbf{h}_j^+ \mid j \neq i, 0 < j \leq B\}$, and B denotes the batch size. τ_1 is the temperature parameter.

¹The anchor sample can be either the original representation or an augmented version from techniques like masking or cropping.

²Augmentation strategies such as model-level (e.g. dropout) or data-level augmentation (e.g. masking or cropping).

Method

Fig. 3 shows the overall framework of our method, Future data utilization with Enduring Negatives for contrastive learning in sequential Recommendation, FENRec. First, user interaction sequences are divided into subsequences and encoded into representations. We then generate time-dependent soft labels that assign probabilities to not only the next item but also the future interactions, enabling the calculation of the revised cross-entropy loss L'_{rec} , as depicted in the top half of Fig. 3. Next, enduring hard negatives are generated using user representations, as shown in the bottom half of Fig. 3. The revised contrastive loss L'_{cl} is then calculated using these enduring hard negatives. Finally, the total loss is computed by considering both L'_{rec} and L'_{cl} .

Future Interaction Utilization

By tracing back previous subsequences, the future interactions of these subsequences are identified. However, most existing SR models often overlook this valuable information. To fully leverage interaction data, we propose generating soft labels based on forthcoming interactions.

Time-Dependent Soft Labeling. Previous methods fail to leverage forthcoming interactions effectively since they use binary labels and focus solely on predicting the immediate next item. Therefore, to better utilize future data, we generate time-dependent soft labels by considering items the user will interact with in the near future (i.e., the second and third subsequent items) as items of interest. Items closer in time to the next item are assigned with higher probabilities. We define the time-dependent soft label as:

$$\mathbf{y}_i^{us'} = \begin{cases} p(i) & \text{if } v_i \in \{v_{|\mathcal{S}^{us}|+1}^u, \dots, v_{\min(|\mathcal{S}^{us}|+3, |\mathcal{S}^u|+1)}^u\}, \\ 0 & \text{otherwise} \end{cases}, \quad (6)$$

where

$$p(i) = \frac{\gamma^{(\text{pos}(v_i) - (|\mathcal{S}^{us}|+1))}}{\sum_{j=|\mathcal{S}^{us}|+1}^{\min(|\mathcal{S}^{us}|+3, |\mathcal{S}^u|+1)} \gamma^{(j - (|\mathcal{S}^{us}|+1))}}. \quad (7)$$

$pos(v_i)$ is the position of v_i in the user sequence \mathcal{S}^u (i.e., $pos(v_i) = |\mathcal{S}^{us}| + 1$, if $v_{|\mathcal{S}^{us}|+1} = v_i$). $\mathcal{S}^{us} \in \mathcal{DS}(\mathcal{S}^u)$ represents the subsequence derived from the original user sequence, and $|\mathcal{S}^{us}|$ is the length of the sequence \mathcal{S}^{us} . γ is a smoothing hyperparameter that controls the distribution of time-dependent soft labels. A higher value of γ results in a smoother probability distribution of soft labels, indicating greater uncertainty. Conversely, a lower value of γ leads to a more concentrated distribution, suggesting more confident predictions. We use time-dependent soft labels to replace the original binary labels. Hence, Eq. (4) can be altered as:

$$L'_{rec} = - \sum_{i=1}^N \mathbf{y}_i^{us'} \log \hat{\mathbf{y}}_i^{us}. \quad (8)$$

Enduring Hard Negatives Incorporation

Previous contrastive learning methods in SR often fail to provide challenging negatives in later training stages, limiting their effectiveness in alleviating data sparsity. Therefore, to better address data sparsity and enhance the model’s ability to learn discriminative features, we propose incorporating enduring hard negatives during training, ensuring that the model consistently learns from the challenging samples.

Enduring Hard Negatives. For contrastive learning in SR, we define hard negatives as user representations similar to the anchor sample but not its augmented view. Inspired by previous works (Kalantidis et al. 2020; Zhang et al. 2022), we proposed generating enduring hard negatives that remain challenging throughout training. As shown in the lower half of Fig. 3, we first normalize the user representations and mix the anchor with the negative samples to produce enduring hard negatives $\mathbf{h}_{i,n}^-$. It can be formulated as follows:

$$\tilde{\mathbf{h}}_u = \frac{\mathbf{h}_u}{\|\mathbf{h}_u\|_2}, \quad (9)$$

$$\mathbf{h}_{i,n}^- = \frac{\lambda \tilde{\mathbf{h}}_i + (1 - \lambda) \tilde{\mathbf{n}}}{\|\lambda \tilde{\mathbf{h}}_i + (1 - \lambda) \tilde{\mathbf{n}}\|_2} \cdot \|\mathbf{n}\|_2, \quad (10)$$

where $\mathbf{n} \in \mathbf{H}_i$. λ is a hyperparameter between 0 and 1 that controls the proportion of the anchor sample in the generated enduring hard negatives. We first normalize representations to ensure that anchor and negative samples contribute equally to the generated enduring hard negatives. Then, by mixing the anchor and negative samples, the enduring hard negatives maintain a consistently higher similarity to the anchor sample than the original negatives³. Finally, we divide the mixture of anchor and negative samples (i.e., $\lambda \tilde{\mathbf{h}}_i + (1 - \lambda) \tilde{\mathbf{n}}$) by their norm and multiply it by the norm of the negative samples, allowing enduring hard negatives to maintain their original norm range, ensuring their data distribution resembles that of the true user representations.

Therefore, the contrastive loss can be formulated as:

$$L_{cl}(\mathbf{h}_i, \mathbf{h}_i^+) = - \log \frac{e^{(\mathbf{h}_i^T \mathbf{h}_i^+)/\tau_1}}{C + \mu \sum_{\mathbf{n} \in \mathbf{H}_i} e^{(\mathbf{h}_i^T \text{SG}(\mathbf{h}_{i,n}^-))/\tau_1}}, \quad (11)$$

³More details are in Appendix(Huang et al. 2024).

where

$$C = e^{(\mathbf{h}_i^T \mathbf{h}_i^+)/\tau_1} + \sum_{\mathbf{n} \in \mathbf{H}_i} e^{(\mathbf{h}_i^T \mathbf{n})/\tau_1}. \quad (12)$$

μ is a hyperparameter to control the portion of enduring hard negatives in the contrastive loss. The “stop gradient,” denoted by $\text{SG}(\cdot)$, stops the gradient from propagating through the generated enduring hard negatives. This avoids incorrect backpropagation signals. Without $\text{SG}(\cdot)$, the anchor would be affected by the gradients passed through the enduring hard negatives. Since these negatives partially contain the anchor, anchor would be wrongly pushed away from itself.

Hard Negative Upweighting Contrastive Loss. In addition to enduring hard negatives, we further refine the contrastive loss by focusing on hard negatives, enabling the model to learn more effectively from challenging samples. Inspired by focal-infoNCE (Hou and Li 2023), we propose using hard negative upweighting contrastive loss in the contrastive learning framework for SR. The loss is as follows:

$$L_h = - \log \frac{e^{\mathbf{h}_i^T \mathbf{h}_i^+ \cdot s_i^+/\tau_1}}{e^{\mathbf{h}_i^T \mathbf{h}_i^+ \cdot s_i^+/\tau_1} + \sum_{\mathbf{n} \in \mathbf{H}_i} e^{(\mathbf{h}_i^T \mathbf{n} \cdot s(\mathbf{h}_i, \mathbf{n}) + m)/\tau_1}}, \quad (13)$$

where $s(\mathbf{a}, \mathbf{b}) = \tanh(\frac{\mathbf{a}^T \mathbf{b}}{\tau_2})$. and $s_i^+ = s(\mathbf{h}_i, \mathbf{h}_i^+)$. The hyperparameter τ_2 scales the similarity measure. m is a hyperparameter that allows flexible adjustment. Therefore, we reformulate Eq. (11) and Eq. (12) as:

$$L'_{cl}(\mathbf{h}_i, \mathbf{h}_i^+) = - \log \frac{e^{\mathbf{h}_i^T \mathbf{h}_i^+ \cdot s_i^+/\tau_1}}{C' + \mu \sum_{\mathbf{n} \in \mathbf{H}_i} e^{\mathbf{h}_i^T \text{SG}(\mathbf{h}_{i,n}^-) \cdot s_{i,n}^-/\tau_1}}, \quad (14)$$

where

$$C' = e^{\mathbf{h}_i^T \mathbf{h}_i^+ \cdot s_i^+/\tau_1} + \sum_{\mathbf{n} \in \mathbf{H}_i} e^{(\mathbf{h}_i^T \mathbf{n} \cdot s(\mathbf{h}_i, \mathbf{n}) + m)/\tau_1}, \quad (15)$$

and $s_{i,n}^- = s(\mathbf{h}_i, \mathbf{h}_{i,n}^-)$. Using Eq. (14), we upweight hard negative samples in contrastive learning, enabling the model to better distinguish between similar representations.

Multi-Task Learning

Similar to previous works (Qin et al. 2024; Qiu et al. 2022), we adopt a multi-task learning technique to simultaneously optimize the revised cross-entropy loss and the auxiliary contrastive learning objectives. Eq. (8) focuses on optimizing the main task of predicting the next item, while Eq. (14) optimizes the auxiliary contrastive learning task. The overall training loss function is formulated as:

$$L_{total} = L'_{rec} + \alpha (L'_{cl}(\mathbf{h}_i, \mathbf{h}_i^+) + L'_{cl}(\mathbf{h}_i^+, \mathbf{h}_i)), \quad (16)$$

where α is a hyperparameter controlling the weight of the revised contrastive loss relative to the revised cross-entropy loss. Notably, our FENRec can be integrated into different contrastive learning frameworks in SR by replacing the contrastive loss L_{cl} with our proposed L'_{cl} and the cross-entropy loss L_{rec} with our proposed L'_{rec} .

Methods	Dataset	H@5	H@10	H@20	N@5	N@10	N@20	Dataset	H@5	H@10	H@20	N@5	N@10	N@20
GRU4Rec	Sports	0.0116	0.0197	0.0320	0.0074	0.0100	0.0131	Beauty	0.0188	0.0315	0.0516	0.0114	0.0154	0.0205
Caser		0.0123	0.0210	0.0336	0.0078	0.0105	0.0137		0.0234	0.0386	0.0585	0.0148	0.0197	0.0248
LRURec		0.0389	0.0551	0.0771	0.0276	0.0329	0.0384		0.0671	0.0928	0.1257	0.0481	0.0564	0.0647
SASRec		0.0189	0.0307	0.0491	0.0122	0.0161	0.0207		0.0359	0.0580	0.0905	0.0233	0.0304	0.0385
BSARec		<u>0.0400</u>	<u>0.0583</u>	<u>0.0830</u>	<u>0.0280</u>	<u>0.0339</u>	<u>0.0401</u>		<u>0.0707</u>	<u>0.0978</u>	<u>0.1345</u>	<u>0.0503</u>	<u>0.0590</u>	<u>0.0682</u>
BERT4Rec		0.0264	0.0408	0.0622	0.0175	0.0221	0.0275		0.0489	0.0735	0.1065	0.0330	0.0409	0.0492
MAERec		0.0285	0.0435	0.0645	0.0191	0.0239	0.0292		0.0557	0.0789	0.1094	0.0397	0.0472	0.0548
CBiT		0.0235	0.0365	0.0528	0.0157	0.0198	0.0239		0.0612	0.0871	0.1202	0.0435	0.0518	0.0602
CL4SRec		0.0235	0.0375	0.0575	0.0156	0.0201	0.0251		0.0492	0.0706	0.0990	0.0348	0.0417	0.0488
CoSeRec		0.0264	0.0403	0.0605	0.0177	0.0221	0.0272		0.0459	0.0696	0.1020	0.0301	0.0378	0.0460
ICLRec		0.0271	0.0422	0.0632	0.0179	0.0227	0.0280		0.0493	0.0726	0.1055	0.0325	0.0400	0.0483
DuoRec		0.0311	0.0446	0.0640	0.0220	0.0263	0.0312		0.0560	0.0800	0.1088	0.0406	0.0483	0.0555
ICSRec		0.0388	0.0551	0.0767	0.0272	0.0324	0.0379		0.0681	0.0936	0.1273	0.0487	0.0569	0.0654
MVS		0.0384	0.0548	0.0775	0.0268	0.0321	0.0378		0.0691	0.0961	0.1305	0.0494	0.0581	0.0667
FENRec	0.0431	0.0621	0.0890	0.0299	0.0361	0.0429	0.0728	0.1019	0.1393	0.0514	0.0608	0.0702		
Improv.	7.75%	6.52%	7.23%	6.79%	6.49%	6.98%	2.97%	4.19%	3.57%	2.19%	3.05%	2.93%		
GRU4Rec	Toys	0.0164	0.0277	0.0461	0.0104	0.0140	0.0187	Yelp	0.0129	0.0227	0.0386	0.0082	0.0113	0.0153
Caser		0.0180	0.0277	0.0421	0.0117	0.0149	0.0185		0.0137	0.0246	0.0419	0.0086	0.0120	0.0164
LRURec		0.0707	0.0941	0.1228	0.0523	0.0598	0.0671		0.0240	0.0410	0.0652	0.0152	0.0207	0.0267
SASRec		0.0481	0.0699	0.0982	0.0326	0.0396	0.0468		0.0147	0.0254	0.0418	0.0091	0.0125	0.0166
BSARec		<u>0.0792</u>	<u>0.1066</u>	<u>0.1405</u>	<u>0.0574</u>	<u>0.0662</u>	<u>0.0747</u>		<u>0.0252</u>	<u>0.0432</u>	<u>0.0704</u>	0.0159	0.0217	0.0285
BERT4Rec		0.0476	0.0690	0.0974	0.0332	0.0401	0.0472		0.0215	0.0361	0.0608	0.0134	0.0181	0.0243
MAERec		0.0589	0.0823	0.1108	0.0424	0.0499	0.0570		0.0255	0.0423	0.0687	0.0162	0.0216	0.0282
CBiT		0.0632	0.0865	0.1166	0.0453	0.0529	0.0605		0.0164	0.0281	0.0474	0.0102	0.0140	0.0188
CL4SRec		0.0630	0.0863	0.1143	0.0447	0.0522	0.0592		0.0238	0.0404	0.0655	0.0150	0.0204	0.0266
CoSeRec		0.0576	0.0818	0.1121	0.0399	0.0477	0.0553		0.0221	0.0375	0.0618	0.0141	0.0190	0.0251
ICLRec		0.0576	0.0826	0.1137	0.0393	0.0473	0.0552		0.0232	0.0394	0.0645	0.0147	0.0198	0.0262
DuoRec		0.0609	0.0816	0.1080	0.0449	0.0515	0.0582		0.0236	0.0402	0.0663	0.0150	0.0202	0.0268
ICSRec		0.0776	0.1035	0.1355	0.0566	0.0650	0.0731		<u>0.0260</u>	0.0431	0.0700	<u>0.0165</u>	<u>0.0220</u>	<u>0.0288</u>
MVS		0.0748	0.1008	0.1323	0.0547	0.0631	0.0710		0.0243	0.0409	0.0654	0.0156	0.0210	0.0271
FENRec	0.0818	0.1109	0.1462	0.0592	0.0686	0.0775	0.0286	0.0485	0.0776	0.0182	0.0246	0.0319		
Improv.	3.28%	4.03%	4.06%	3.14%	3.63%	3.75%	10.00%	12.27%	10.23%	10.30%	11.82%	10.76%		

Table 1: Performance comparison of different methods. The best results are in boldface and the second-best results are underlined. ‘Improv.’ indicates the relative improvement against the best baseline. More details are in Appendix (Huang et al. 2024).

Experiments

Experimental Setup

Metrics. We assess model performance using Hit Ratio@K (HR@K) and Normalized Discounted Cumulative Gain@K (NDCG@K), with K selected from {5, 10, 20}. We refer to HR@K as H@K and NDCG@K as N@K.

Datasets. We use the Amazon dataset with three categories: *Sports*, *Beauty*, *Toys*, and the Yelp dataset.

Baselines.⁴ We compare our FENRec with 3 categories of SR approaches: 1) **General sequential models:** Caser (Tang and Wang 2018), GRURec (Hidasi et al. 2016), SASRec (Kang and McAuley 2018), LRURec (Yue et al. 2024), and BSARec (Shin et al. 2024), 2) **Sequential models with self-supervised learning:** BERT4Rec (Sun et al. 2019), MAERec (Ye, Xia, and Huang 2023), CL4SRec (Xie et al. 2022), CoSeRec (Liu et al. 2021), CBiT (Du et al. 2022), DuoRec (Qiu et al. 2022), ICLRec (Chen et al. 2022), and ICSRec (Qin et al. 2024), 3) **Sequential models with label smoothness:** MVS (Zhou et al. 2023)

⁴Details are provided in Appendix(Huang et al. 2024).

Implementation Details.⁵ For our evaluation framework, we integrate our FENRec method into the ICSRec system to facilitate a comprehensive comparison. To ensure uniformity in our representations, we employ a noise-based negative sampling method on sentence representations as outlined by (Zhou et al. 2022). Parameter tuning is meticulously carried out; τ_2 is varied within the set {8, 10}, while τ_1 was fixed at 1, μ at 0.1, and m at 0.2. The parameters γ and λ are each tuned over {0.1, 0.2, 0.3, 0.4, 0.5}. We incorporate enduring hard negatives into the training process after a 20-epoch warm-up period. All experiments were conducted three times, and results were averaged for comparison.

Comparison to SOTA

Tab. 1 shows the recommendation performance for all datasets across all metrics. First, contrastive learning methods CL4SRec, CoSeRec, ICLRec, DuoRec, and ICSRec significantly improve upon their backbone, SASRec, by mitigating data sparsity issues in SR, demonstrating the effectiveness of contrastive learning. Second, MVS also demonstrates improvements over its backbone, SASRec, due to the

⁵More details are provided in Appendix(Huang et al. 2024).

Dataset	Metric	C	+F	I.	D	+F	I.
Sports	H@5	0.0235	0.0249	6.0%	0.0311	0.0330	6.1%
	H@10	0.0375	0.0389	3.7%	0.0446	0.0473	6.1%
	H@20	0.0575	0.0585	1.7%	0.0640	0.0681	6.4%
	N@5	0.0156	0.0167	7.1%	0.0220	0.0231	5.0%
	N@10	0.0201	0.0212	5.5%	0.0263	0.0277	5.3%
	N@20	0.0251	0.0261	4.0%	0.0312	0.0329	5.4%
Beauty	H@5	0.0492	0.0492	0.0%	0.0560	0.0586	4.6%
	H@10	0.0706	0.0718	1.7%	0.0800	0.0834	4.3%
	H@20	0.0990	0.1028	3.8%	0.1088	0.1145	5.2%
	N@5	0.0348	0.0345	-0.9%	0.0406	0.0421	3.7%
	N@10	0.0417	0.0418	0.2%	0.0483	0.0501	3.7%
	N@20	0.0488	0.0496	1.6%	0.0555	0.0579	4.3%
Toys	H@5	0.0630	0.0641	1.7%	0.0609	0.0648	6.4%
	H@10	0.0863	0.0890	3.1%	0.0816	0.0871	6.7%
	H@20	0.1143	0.1208	5.7%	0.1080	0.1177	9.0%
	N@5	0.0447	0.0455	1.8%	0.0449	0.0477	6.2%
	N@10	0.0522	0.0535	2.5%	0.0515	0.0549	6.6%
	N@20	0.0592	0.0615	3.9%	0.0582	0.0626	7.6%
Yelp	H@5	0.0238	0.0243	2.1%	0.0236	0.0246	4.2%
	H@10	0.0404	0.0409	1.2%	0.0402	0.0421	4.7%
	H@20	0.0655	0.0676	3.2%	0.0663	0.0687	3.6%
	N@5	0.0150	0.0155	3.3%	0.0150	0.0155	3.3%
	N@10	0.0204	0.0208	2.0%	0.0202	0.0212	5.0%
	N@20	0.0266	0.0275	3.4%	0.0268	0.0279	4.1%

Table 2: Applying our method to other frameworks. “C” and “D” represent CL4SRec and DuoRec, respectively. The “+F” notation indicates the integration of our method. “I.” represents the improvement over the original methods.

context and label smoothness it introduces, which helps the model capture user preferences and reduces overfitting. Finally, FENRec outperforms all other models across all metrics, achieving an average improvement of 6.34% in HIT and 5.99% in NDCG over the second-best results on all datasets. Notably, it shows greater gains in metrics at larger k values compared to those at 5. This is likely due to the inclusion of enduring hard negatives and time-dependent soft labels, which enhance the model’s ability to differentiate similar user preferences. The increased discriminative power also improves rankings across the list, not just at the top.

Compatibility to Existing Methods

Here, we examine the integration of our FENRec model into different frameworks, specifically CL4SRec and DuoRec. As demonstrated in Tab. 2, FENRec enhances the performance of contrastive learning frameworks for sequential recommendation (SR) across most evaluated metrics, underscoring its versatility and effectiveness in diverse SR systems. Notably, the integration of FENRec with DuoRec yields more pronounced improvements compared to CL4SRec. This discrepancy can largely be attributed to the nature of the augmentation strategies employed by each framework. CL4SRec relies on methods such as masking and cropping to generate positive pairs. While effective, these strategies can sometimes alter the underlying user intent and diminish semantic similarity. Conversely, DuoRec

Dataset	M	H@5	H@10	H@20	N@5	N@10	N@20
Sports	F	0.0431	0.0621	0.0890	0.0299	0.0361	0.0429
	-S	0.0403	0.0578	0.0806	0.0282	0.0339	0.0396
	-N	0.0422	0.0616	0.0869	0.0292	0.0354	0.0417
Beauty	F	0.0728	0.1019	0.1393	0.0514	0.0608	0.0702
	-S	0.0693	0.0968	0.1317	0.0496	0.0585	0.0673
	-N	0.0707	0.0991	0.1363	0.0501	0.0593	0.0687
Toys	F	0.0818	0.1109	0.1462	0.0592	0.0686	0.0775
	-S	0.0789	0.1055	0.1392	0.0573	0.0659	0.0744
	-N	0.0806	0.1092	0.1437	0.0582	0.0675	0.0762
Yelp	F	0.0286	0.0485	0.0776	0.0182	0.0246	0.0319
	-S	0.0275	0.0455	0.0740	0.0174	0.0232	0.0304
	-N	0.0268	0.0454	0.0738	0.0170	0.0230	0.0301

Table 3: Ablation study results. “M” represents methods under evaluation. “F” denotes FENRec. “-N” and “-S” represent removing Enduring Hard Negatives Incorporation and removing Time-Dependent Soft Labeling, respectively.

preserves user intent more effectively by aligning sequences that share the same subsequent item as positive pairs. This method enhances the semantic coherence between pairs, thereby amplifying the benefits when combined with FENRec. This analysis highlights the critical role of augmentation strategies, particularly when augmented with FENRec.

Ablation Study

To evaluate the critical role of each component within the FENRec framework, we executed an ablation study. The results, detailed in Tab. 3, underscore the individual contributions of each element. Notably, the removal of Time-Dependent Soft Labeling from FENRec resulted in a larger performance decline compared to the exclusion of Enduring Hard Negatives Incorporation. This impact probably stems from the role of time-dependent soft labels in enhancing the model’s capacity to handle uncertainty and capture potential user interest. While the integration of enduring hard negatives is pivotal, it primarily assists the model in refining the accuracy of items that users might seem interested in but are not the main targets of prediction. However, this approach carries the inherent risk of incorrectly dismissing genuinely appealing items as irrelevant, leading to potential false negatives. Moreover, soft labels effectively counterbalance this risk by allowing the model to better capture and represent user interest ambiguity, thus optimizing the effectiveness of hard negatives. This synergy underscores the necessity of incorporating both components to achieve optimal performance in FENRec, as shown in our ablation study findings.

Analysis

Robustness Across Varying Sequence Lengths. We tested the robustness of FENRec by evaluating its performance across user groups with different interaction sequence lengths. As shown in Fig. 4, contrastive learning methods enhance the performance of the backbone (i.e., SASRec) across all sequence lengths, highlighting their effectiveness. On Amazon datasets, contrastive learning meth-

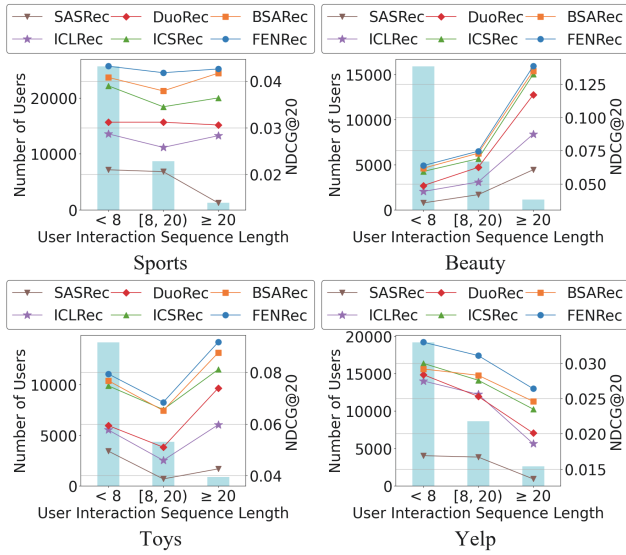


Figure 4: Comparison of model performance across different user interaction sequence lengths. The bar chart represents the number of users, and the line chart indicates NDCG@20.

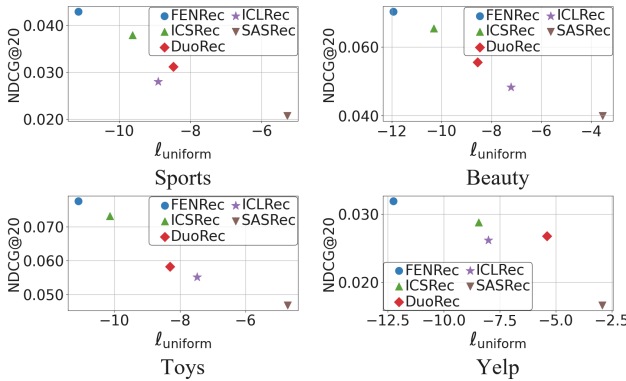


Figure 5: Comparison of ℓ_{uniform} and performance.

ods show greater improvements for users with longer interaction sequences, while on the Yelp dataset, shorter sequences benefit more. This may be due to users with longer sequences having a lower average number of interactions per item within their sequences on the Yelp dataset. The statistics are in Appendix (Huang et al. 2024). Overall, our method consistently outperforms baseline methods across all sequence lengths, showing the robustness of FENRec.

Model Discriminative Capability Analysis. In this section, we evaluate the model’s discriminative capability using item uniformity, which indicates the model’s ability to differentiate between semantically similar items. Lower uniformity suggests higher semantic similarities, indicating that the model may struggle to distinguish between items, while higher uniformity indicates a more even distribution of item embeddings, enabling effective differentiation. We compare item uniformity across various contrastive learning methods and their backbone, SASRec. The uniformity loss

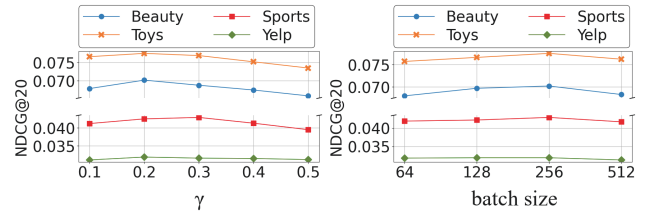


Figure 6: Performance of FENRec w.r.t. different hyperparameters.

ℓ_{uniform} measures data uniformity. It is calculated using the definition in DuoRec (Qiu et al. 2022). A smaller ℓ_{uniform} represents a more uniform data distribution. As shown in Fig. 5, there is a negative correlation between ℓ_{uniform} and NDCG@20 since lower uniformity indicates that the model has not learned sufficiently discriminative features, leading to lower performance. Results demonstrate that FENRec helps increase item uniformity and performance, indicating its effectiveness in helping the model learn discriminative features. This improvement is likely because hard negatives help the model differentiate similar preferences, while soft labels provide finer labels, enhancing the discriminative power of the learned representations and thereby improving the model’s comprehension of item semantics.

Hyperparameter Tuning

We tune each hyperparameter individually while keeping others optimal to observe performance changes, as shown in Fig. 6. First, we adjust γ . A higher γ creates smoother soft labels, while a lower γ makes it more concentrated. FENRec shows the best performance when γ is 0.2 or 0.3, indicating that a low γ can make the model overly confident and a high γ can make it unsure about the next item. Next, we assess the impact of batch size, finding FENRec performs best at 256. A smaller batch size lacks sufficient negative samples, while a larger one increases the risk of false negatives. This risk is amplified as FENRec generates hard negatives by mixing anchor and in-batch negatives, causing false negatives to be pushed further away from positives. Due to the space constraint, other results are in Appendix (Huang et al. 2024).

Conclusion

In this paper, we tackled the issue of data sparsity in sequential recommendation systems by introducing FENRec, an innovative approach that integrates Time-Dependent Soft Labeling and Enduring Hard Negatives Incorporation within contrastive learning frameworks. By utilizing future interactions in Time-Dependent Soft Labeling, our method effectively captures finer user preferences. Additionally, Enduring Hard Negatives Incorporation ensures the model learns from more challenging samples, enhancing its ability to learn discriminative features. Extensive experiments on four benchmark datasets highlight FENRec’s effectiveness in enhancing performance and improving the differentiation of user preferences. For future work, we would like to incorporate auxiliary time information to improve the performance.

Acknowledgments

This work is partially supported by the National Science and Technology Council, Taiwan under Grants NSTC-112-2221-E-A49-059-MY3 and NSTC-112-2221-E-A49-094-MY3.

References

- Alamdari, P. M.; Navimipour, N. J.; Hosseinzadeh, M.; Safaei, A. A.; and Darwesh, A. 2020. A systematic study on the recommender systems in the E-commerce. *Ieee Access*, 8: 115694–115716.
- Chen, Y.; Liu, Z.; Li, J.; McAuley, J.; and Xiong, C. 2022. Intent contrastive learning for sequential recommendation. In *Proceedings of the ACM Web Conference*, 2172–2182.
- Cheng, M.; Yuan, F.; Liu, Q.; Ge, S.; Li, Z.; Yu, R.; Lian, D.; Yuan, S.; and Chen, E. 2021. Learning recommender systems with implicit feedback via soft target enhancement. In *Proceedings of the International ACM SIGIR Conference on Research and Development in Information Retrieval*, 575–584.
- Du, H.; Shi, H.; Zhao, P.; Wang, D.; Sheng, V. S.; Liu, Y.; Liu, G.; and Zhao, L. 2022. Contrastive learning with bidirectional transformers for sequential recommendation. In *Proceedings of the ACM International Conference on Information and Knowledge Management*, 396–405.
- Hidasi, B.; Karatzoglou, A.; Baltrunas, L.; and Tikk, D. 2016. Session-based Recommendations with Recurrent Neural Networks. In Bengio, Y.; and LeCun, Y., eds., *International Conference on Learning Representations*.
- Hou, P.; and Li, X. 2023. Improving Contrastive Learning of Sentence Embeddings with Focal InfoNCE. In *Findings of the Association for Computational Linguistics: EMNLP 2023*.
- Huang, Y.-H.; Lo, L.; Xie, H.; Shuai, H.-H.; and Cheng, W.-H. 2024. Future Sight and Tough Fights: Revolutionizing Sequential Recommendation with FENRec.
- Kalantidis, Y.; Sariyildiz, M. B.; Pion, N.; Weinzaepfel, P.; and Larlus, D. 2020. Hard negative mixing for contrastive learning. *Advances in neural information processing systems*, 33: 21798–21809.
- Kang, W.-C.; and McAuley, J. 2018. Self-attentive sequential recommendation. In *IEEE International Conference on Data Mining*, 197–206. IEEE.
- Liu, Z.; Chen, Y.; Li, J.; Yu, P. S.; McAuley, J.; and Xiong, C. 2021. Contrastive self-supervised sequential recommendation with robust augmentation. *arXiv preprint arXiv:2108.06479*.
- Lu, J.; Wu, D.; Mao, M.; Wang, W.; and Zhang, G. 2015. Recommender system application developments: a survey. *Decision support systems*, 12–32.
- Qin, X.; Yuan, H.; Zhao, P.; Liu, G.; Zhuang, F.; and Sheng, V. S. 2024. Intent Contrastive Learning with Cross Subsequences for Sequential Recommendation. In *Proceedings of the ACM International Conference on Web Search and Data Mining*, 548–556.
- Qiu, R.; Huang, Z.; Yin, H.; and Wang, Z. 2022. Contrastive learning for representation degeneration problem in sequential recommendation. In *Proceedings of the ACM international conference on web search and data mining*, 813–823.
- Robinson, J.; Chuang, C.-Y.; Sra, S.; and Jegelka, S. 2021. Contrastive Learning with Hard Negative Samples. In *International Conference on Learning Representations*.
- Sharma, K.; Lee, Y.-C.; Nambi, S.; Salian, A.; Shah, S.; Kim, S.-W.; and Kumar, S. 2024. A survey of graph neural networks for social recommender systems. *ACM Computing Surveys*, 56(10): 1–34.
- Shin, Y.; Choi, J.; Wi, H.; and Park, N. 2024. An attentive inductive bias for sequential recommendation beyond the self-attention. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 8984–8992.
- Suh, Y.; Han, B.; Kim, W.; and Lee, K. M. 2019. Stochastic class-based hard example mining for deep metric learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 7251–7259.
- Sun, F.; Liu, J.; Wu, J.; Pei, C.; Lin, X.; Ou, W.; and Jiang, P. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the ACM International Conference on Information and Knowledge Management*, 1441–1450.
- Tang, J.; and Wang, K. 2018. Personalized top-n sequential recommendation via convolutional sequence embedding. In *Proceedings of the ACM international conference on web search and data mining*, 565–573.
- Wu, S.; Xin, X.; Ren, P.; Chen, Z.; Ma, J.; Rijke, M.; and Ren, Z. 2024. Learning Robust Sequential Recommenders through Confident Soft Labels. *ACM Transactions on Information Systems*, 43.
- Xie, X.; Sun, F.; Liu, Z.; Wu, S.; Gao, J.; Zhang, J.; Ding, B.; and Cui, B. 2022. Contrastive learning for sequential recommendation. In *IEEE International Conference on Data Engineering*, 1259–1273. IEEE.
- Xuan, H.; Stylianou, A.; Liu, X.; and Pless, R. 2020. Hard negative examples are hard, but useful. In *European Conference on Computer Vision*, 126–142. Springer.
- Ye, Y.; Xia, L.; and Huang, C. 2023. Graph masked autoencoder for sequential recommendation. In *Proceedings of the International ACM SIGIR Conference on Research and Development in Information Retrieval*, 321–330.
- Yu, L.; Zhang, C.; Liang, S.; and Zhang, X. 2019. Multi-order attentive ranking model for sequential recommendation. In *Proceedings of the AAAI conference on artificial intelligence*, 5709–5716.
- Yue, Z.; Wang, Y.; He, Z.; Zeng, H.; McAuley, J.; and Wang, D. 2024. Linear recurrent units for sequential recommendation. In *Proceedings of the ACM International Conference on Web Search and Data Mining*, 930–938.
- Zhan, J.; Mao, J.; Liu, Y.; Guo, J.; Zhang, M.; and Ma, S. 2021. Optimizing dense retrieval model training with hard negatives. In *Proceedings of the International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1503–1512.

Zhang, Y.; Zhang, R.; Mensah, S.; Liu, X.; and Mao, Y. 2022. Unsupervised sentence representation via contrastive learning with mixing negatives. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 11730–11738.

Zhou, K.; Wang, H.; Wen, J.-r.; and Zhao, W. X. 2023. Enhancing Multi-View Smoothness for Sequential Recommendation Models. *ACM Transactions on Information Systems*, 41(4): 1–27.

Zhou, K.; Zhang, B.; Zhao, W. X.; and Wen, J.-R. 2022. De-biased contrastive learning of unsupervised sentence representations. In *Proceedings of Annual Meeting of the Association for Computational Linguistics*.