Multi-interest Distribution based Diversified Recommendation

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ABSTRACT

Traditional sequential recommendations often utilize a single interest representation for users, limiting the modeling of their diverse interests and resulting in a lack of recommendation diversity. Therefore, multi-interest recommendations aim to enhance accuracy and diversity by considering users' multiple interests. However, existing methods fail to fully leverage these interests, which restricts diversity enhancement. To address this issue, we propose a diversified recommendation model called *MIND-DR*, which utilizes multiple interest distributions to enhance recommendation diversity. Specifically, during the reranking phase, we use KL divergence to align the interest distribution of the recommendation list with the average interest distribution of users, thus generating more diverse recommendations. Additionally, considering the interdependence and interference among different interests, we employ contrastive learning loss to encourage independence among users' multiple interest representations. Experimental results on three datasets demonstrate the effectiveness of the proposed model in improving recommendation diversity while maintaining high accuracy.

CCS CONCEPTS

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

KEYWORDS

Sequential Recommendation, Diversity, Multi-interest Distribution, KL Divergence, Reranking, Contrastive Learning

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1 INTRODUCTION

A recommender system can provide users with personalized goods, services, or information by analyzing their historical behaviors and interests. Traditional collaborative filtering models rely on the user-item interaction matrix to learn long-term and static preferences, which is not suitable for real-time scenarios [15][18][19]. Sequential recommendation, on the other hand, predicts a user's next behavior based on their historical behavior sequence, better addressing their current interests. However, traditional sequential recommendation only uses a single interest representation for each user, resulting in limited diversity in recommendation results and failing to meet diverse user interests [16].

Therefore, multi-interest recommendation models have emerged as a key research focus. These models not only address the limitations of traditional single-interest recommendation models but also enhance recommendation diversity and personalization. In recent years, researchers have proposed several models for diversified recommendation based on multiple interests. Cen et al. [3] introduced an approach that combines attention mechanism [22] and capsule network [17] to capture users' multiple interests, enhancing both accuracy and diversity of recommendations. However, these methods have limitations in fully leveraging users' multiple interests for diversity enhancement. Furthermore, the interdependence and interference among various interests will lead the model to favor a particular interest of the user while overlooking their other potential interests. These problems will result in the model's inability to effectively enhance recommendation diversity.

To address these issues, we propose a diversified recommendation model called *MIND-DR*, which incorporates multiple interest distribution to improve recommendation diversity and accuracy. The model follows these steps: 1) extracting multiple interest representations from users' historical behavior sequences, 2) recalling a subset of items as a candidate set based on these interest representations, 3) constructing interest distributions for each item and the user's average interest distribution, and 4) employing a greedy algorithm with multiple interest distribution constraints to rerank the candidate sets and provide diverse recommendations. Additionally, to promote independence among the user's multiple interest representations, we employ contrastive learning to constrain different interest representations. This will enable *MIND-DR* to learn to differentiate the features of different interests. The main contributions of this paper are as follows:

- We introduce interest distribution in the reranking stage to enhance recommendation diversity by aligning the average interest distribution of the recommendation list with that of the users.
- We introduce contrastive learning loss to promote independence among the user's multiple interest representations.
- Experiments on three datasets demonstrate the effectiveness and superiority of our proposed model, demonstrating its ability to improve recommendation diversity.

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2 RELATED WORK

2.1 Sequential Recommendation(SR)

Traditional sequential methods primarily employ Markov chains to depict the item transition pattern [16][7]. However, they struggled to handle complex sequential patterns. Recently, with the development of deep learning, a lot of works utilize different neural networks to encode the historical sequence to a hidden vector [6][29][11][23][26]. Hidasi et al. [6] first leverages recurrent neural network(RNN) to effectively handle long sequences and gains impressive improvements. Kang et al. [9] first employs self-attention to model the mutual influence between items and achieves remarkable results. Li et al. [11] extends SASRec by incorporating time interval information. However, these models often rely on a single user interest representation, neglecting diverse user interests. To address this, researchers have focused on incorporating multiple interest representations to enhance recommendation accuracy and diversity.

2.2 Multi-Interest Recommendation(MIR)

MIR aims to extract user's multiple interests and provide users with more accurate and diverse recommendations [3][10][29][12][27][20]. Li et al. [10] utilized dynamic routing to extract user's multiple interests for more refined recommendations. Cen et al. [3] extended MIND with self-attention and controllable factors to balance accuracy and diversity. Wang et al. [24] distilled target interest from multiple interest representations via knowledge distillation and aggregates user's multiple representations. Shi et al. [20] produced multi-interest by using user's sequential engagement more effectively and learned weights to represent preference over each embedding. In summary, MIR enhances accuracy and diversity by learning users' multiple interests.

2.3 Diversified Recommendation(DR).

To address diverse user interests, an increasing number of works begin to emphasize the importance of recommendation diversity [30][25][28][4][5]. Ziegler et al. [30] initially introduced diversity into recommender system by employing the MRR greedy algorithm [2] from information retrieval. Subsequently, a series of post-processing methods were proposed to improve recommendation diversity. Ashkan et al. [1] removed the balancing parameter by replacing weighted sum with multiplication. Pei et al. [14] presented a personalized reranking algorithm using a transformer to capture item interactions and introduces pre-trained user features. Cen et al. [3] modeled user's multiple interests and balance accuracy and diversity greedily. Additionally, Chen et al. [5] extracted users' multiple interests and improves recommendation diversity in an end-to-end way. However, these approaches fail to fully leverage user's multiple interests. This paper introduces a constraint on the user's multiple interest distribution during the reranking process, further enhancing recommendation diversity.

3 PROBLEM FORMULATION

In a recommender system, there are usually two entity sets: user set $U = \{u_1, u_2, \cdots, u_{|U|}\}$ and item set $I = \{i_1, i_2, \cdots, i_{|I|}\}$.

Sequential Recommendation Each user u has a behavior sequence $I^u = \{i_1^u, i_2^u, \cdots, i_n^u\}$ representing their interactions with items, sorted chronologically by timestamp. Here, i_t^u denotes the item that user u interacted with at time step t. The basic goal of SR is to predict the next item to be clicked by a user given the user's interaction sequence. In this paper, we adopt a common setting in SR, where we utilize the prefix sequence $I_u^t = \{i_1^u, i_2^u, \cdots, i_t^u\}$ $(1 \leq t < |I_u|)$ of I_u to predict the next item i_{t+1}^u that user u will click on at time step $t+1$. This item is referred to as the target item or positive sample(i^+). Subsequently, the prefix sequence I_u^t is used to generate ratings for all items in the candidate set, and the final $topN$ recommendation list will be obtained.

Multi-interest Recommendation For a user u, a multi-interest model is used to model the historical interaction sequence I_u^t and obtain K interest representations $\mathbf{V}_u \in \mathbb{R}^{K\times d}$:

$$\mathbf{V}_u = [\mathbf{v}_u^1, \mathbf{v}_u^2, \cdots, \mathbf{v}_u^K] \tag{1}$$

where d denotes the dimension of interest representation, $\mathbf{v}_u^k$ denotes user's kth interest representation. During the recall stage, each interest representation can recall N items from item set I, so that we can get $N \times K$ items as the candidate set S. Then, this paper proposes a diversified recommendation algorithm *MIND-DR* based on multiple interest distribution to enhance recommendation diversity by re-ranking the items in the candidate set S and finally obtain the $topN$ recommendation list.

4 APPROACH

Fig. 1 depicts the overall structure of *MIND-DR*, comprising two main modules: *Multi-interest Extraction Module*, and *Reranking Module*. Next, we will introduce each of them in detail.

4.1 Multi-interest Extraction Module

This section aims to acquire multiple interest representations that capture users' diverse interests. To achieve this, we employ an existing multi-interest framework ComiRec-SA [3] as the backbone to extract user's multiple interest representations. While multi-interest extraction is not our primary objective, we simplify the process into two steps: item embedding and multi-interest extraction.

Item Embedding. The embeddings of item set I are initialized as $\mathbf{H} \in \mathbb{R}^{|I|\times d}$, and the corresponding embedding for user u's historical interaction sequence I_u is $\mathbf{H}^u \in \mathbb{R}^{n\times d}$.

$$\mathbf{H}^u = \mathbf{H}\,[I^u, :] \tag{2}$$

where n denotes the max sequence length, and d denotes the dimension of the embedding.

Multi-Interest Extraction. The ComiRec-SA framework adopts a self-attentive method to extract user's multiple interests. Specifically, given a user's historical sequence embeddings $\mathbf{H}^u$, the embedding of the item interacted at time step t is denoted as $\mathbf{h}_t$. In addition, we use position embedding to enhance item embedding.

$$\mathbf{e}_t = \mathbf{h}_t + \mathbf{p}_t \tag{3}$$

where $\mathbf{p}_t$ denotes the position embedding, $\mathbf{e}_t$ denotes the enhanced embedding. Then we can use a multi-headed attention mechanism to obtain user $u's$ multiple interest embeddings. First, we calculate

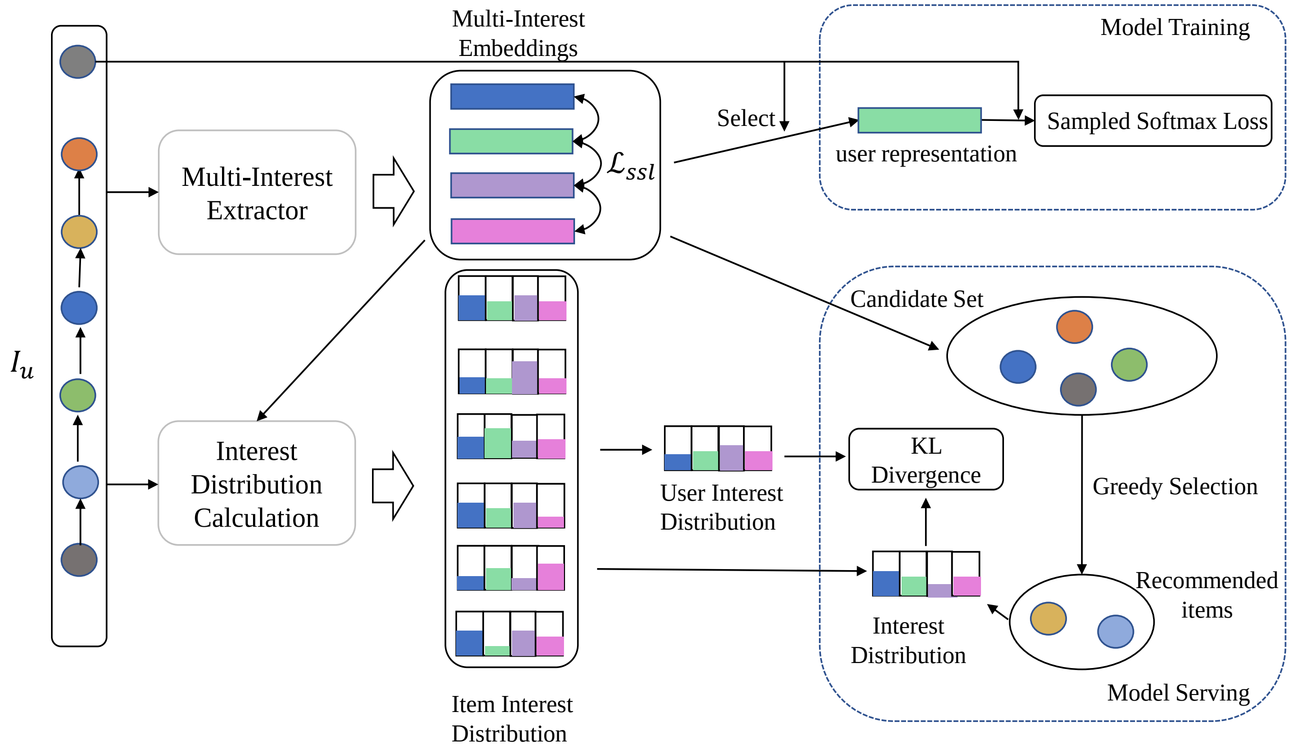


Figure 1: The overall structure of our proposed *MIND-DR*.

the user's attention $\mathbf{A} \in \mathbb{R}^{K \times n}$ for the items in the sequence from K different perspectives.

$$\mathbf{A} = softmax\ (\mathbf{W}_2^T tanh\ (\mathbf{W}_1 \mathbf{E}^T)) \tag{4}$$

where K denotes the number of interests, $\mathbf{W}_1 \in \mathbb{R}^{K \times d}$ and $\mathbf{W}_2 \in \mathbb{R}^{K \times K}$ denote trainable parameters, $\mathbf{E} \in \mathbb{R}^{n \times d}$ denotes the enhanced embeddings. Then we can obtain the multi-interest representation $\mathbf{V}_u \in \mathbb{R}^{K \times d}$ of user u according to Equation (5).

$$\mathbf{V}_u = \mathbf{AE} \tag{5}$$

4.1.1 Model Training. In the training phase, an arg max operator is used to select the most relevant interest representation $\mathbf{v}_u$ according to the positive item i^+.

$$\begin{aligned} k &= \arg\max\ (\mathbf{V}_u^T \mathbf{h}_{i^+}) \\ \mathbf{v}_u &= \mathbf{V}_u\ [:, k] \end{aligned} \tag{6}$$

where $\mathbf{h}_{i^+}$ denotes the embedding of the positive item. Then, the probability of positive item i^+ being clicked by user u can be obtained by Equation (7).

$$p\ (i^+|u) = \frac{exp\ (\mathbf{v}_u^T \mathbf{h}_{i^+})}{\sum_{j \in I} exp\ (\mathbf{v}_u^T \mathbf{h}_j)} \tag{7}$$

Since the denominator of Equation (7) contains a large number of negative samples, we use the sampled softmax technique [8] for efficiency. Then, for all positive sample pairs (u, i^+) in the training set, the negative log-likelihood $\mathcal{L}_1$ is formulated as follows.

$$\mathcal{L}_1 = \sum_{u \in U} \sum_{i^+ \in I_u} -\log\ p\ (i^+|u) \tag{8}$$

Contrastive Learning. To enhance the independence among different interest representations of users, we introduce a contrastive learning [13] loss $\mathcal{L}_{ssl}$ to guide the learning of the model. Specifically, for each user's K interest representations, we formed positive sample pairs by comparing each interest representation with itself, and negative sample pairs by comparing it with the other $K-1$ interest representations.

$$\mathcal{L}_{ssl} = \sum_{i=1}^{K} -\log \frac{exp(\mathbf{v}_u^i \cdot \mathbf{v}_u^i / \tau)}{\sum_{j=1}^{K} exp(\mathbf{v}_u^j \cdot \mathbf{v}_u^i / \tau)} \tag{9}$$

where τ is a temperature parameter. Through contrastive learning, we can constrain the correlations between different interest representations during the training process, allowing them to represent the user's diverse interests as independently as possible.

And we can obtain the final overall loss function as follows.

$$\mathcal{L} = \mathcal{L}_1 + \eta \times \mathcal{L}_{ssl} \tag{10}$$

where η is a trade-off parameter. By optimizing loss function $\mathcal{L}$, we can obtain multiple interest representations $\mathbf{V}_u \in \mathbb{R}^{K \times d}$ of user u and different interest representation will be independent as possible.

4.1.2 Modeling Serving. In the testing phase, each interest representation $\mathbf{v}_u^k$ can recall N items from I, so that we can get $N \times K$ items as the candidate set S. Then the final *topN* items to be recommended to the user can be obtained by the re-ranking algorithm described in the next section.

4.2 Multi-interest Distribution based Reranking Module

The goal of this section is to rerank the items in the candidate set S to obtain the final recommendation list. In this paper, we consider introducing multiple interest distributions of users to constrain the reranking process to improve recommendation diversity.

4.2.1 Calculation of Interest Distribution. For user u, we have obtained its K interest representations $\mathbf{V}_u$, and for each item in the candidate set S, its corresponding representation vector is $\mathbf{h}_i \in \mathbb{R}^{1\times d}$. Then we can calculate the probability of how candidate item i matches K interest representations.

$$\mathbf{p}_i = softmax\ (\mathbf{h}_i \mathbf{V}_u^T) \tag{11}$$

where $\mathbf{p}_i \in \mathbb{R}^{1\times K}$ is regarded as item $i's$ interest distribution. Then we can further obtain the average interest distribution vector $\bar{\mathbf{p}}_u$ of user u by averaging the interest distribution vectors of all items in user u's interaction sequence I_u.

$$\bar{\mathbf{p}}_u = \frac{1}{|I_u|}\sum_{i\in I_u}\mathbf{p}_i \tag{12}$$

where each dimension value $\bar{\mathbf{p}}_u^k$ represents the preference level of user u for the kth interest representation.

4.2.2 Greedy Selection. After obtaining the interest distribution of users and items, we can then rerank the candidate set S. Since the reranking problem has been proven to be an NP-hard problem [21], we adopt a greedy strategy to solve it. For user u, assume that the set of items already selected is R and its size is denoted by l. Initially, $R = \emptyset$, $l = 0$. We first consider the selection of the first item r_1. Since R is initially empty, we can't calculate the diversity of items in R and the average interest distribution of user u reflected in R. Therefore, we can only select r_1 based on the preference score of user u.

$$\begin{aligned} r_1 &= \arg\max_{i\in S} f(u,i) \\ f(u,i) &= \max_{1\leqslant k\leqslant K} (\mathbf{v}_u^k \mathbf{h}_i^T) \end{aligned} \tag{13}$$

where $f(u,i)$ denotes user u' preference score for item i. After finding item r_1, we add it to R and remove it from S. Now, $R = \{r_1\}, l = 1, S = S\backslash\{r_1\}$.

When l is larger than 1, the greedy selection will be performed according to Equation (14) because the diversity of items in R and the average interest distribution of items can be calculated at this time. Specifically, the accuracy and diversity of the recommendation list R are traded off while the average interest distribution reflected by the items in R is constrained to be closer to the real average interest distribution of user u.

$$r_l = \arg\max_{i\in S\backslash R} (\alpha\times f(u,i)+\beta\times div_{\{i\}\bigcup R}+\gamma\times(1-KL\ (\bar{\mathbf{p}}_{\{i\}\bigcup R}, \bar{\mathbf{p}}_u))) \tag{14}$$

$$div_{\{i\}\bigcup R} = \frac{|\{i\}\bigcup R|}{|\mathcal{D}|}, \qquad \bar{\mathbf{p}}_{\{i\}\bigcup R} = \frac{1}{l+1}\sum_{j\in\{i\}\bigcup R}\mathbf{p}_j \tag{15}$$

where $\mathcal{D}$ denotes the whole dataset, $|\cdot|$ denotes the number of category, $div_{\{i\}\bigcup R}$ denotes the diversity of items in the temporary set $\{i\}\bigcup R$, $\bar{\mathbf{p}}_{\{i\}\bigcup R}$ denotes the average interest distribution reflected by the items in $\{i\}\bigcup R$ and $KL\ (\cdot,\cdot)$ denotes the KL divergence between two distributions. KL divergence can be used to measure the difference between two distributions, the smaller the value, the smaller the difference. In the greedy selection process, we try to minimize the difference between these two interest distributions as much as possible, so that the average interest distribution reflected by the final recommendation list is closer to the real average interest distribution of users. This approach is based on the assumption that the different interests of users can reflect their preferences for different categories of items, and the smaller distance between the two distributions can make the categories of items in the final recommendation list as different as possible, thus enhancing recommendation diversity.

Table 1: The statistics of the datasets.

Datasets	#Users	#Items	#Inter	#Category	Sparsity
Food	14530	8714	151268	57	99.9%
Beauty	22363	12101	198502	38	99.9%
Music	5541	3568	64706	90	99.7%

5 EXPERIMENTS

In this section, extensive experiments will be conducted to demonstrate the effectiveness of *MIND-DR* model. Alternately, our extensive experiments intend to investigate and answer the following questions:

- **RQ1**: How does the proposed *MIND-DR* model perform on different datasets and how does *MIND-DR* perform compared to other comparative methods in terms of Diversity@N and F1-score@N?
- **RQ2**: Does the multiple interest distribution constraint and contrastive loss contribute to *MIND-DR* model?
- **RQ3**: How do the number of interests K, diversity coefficient γ and contrastive learning coefficient η of $\mathcal{L}_{ssl}$ affect the performance of *MIND-DR*?

5.1 Experimental Settings

5.1.1 Datasets. We selected three datasets, Food, Beauty and Music, from the amazon platform[1] for our experiment. In this paper, the datasets are preprocessed according to literature [3]. In order to satisfy sequential recommendation, we sort the user interaction records by timestamp, and the maximum length of each interaction sequence is set to 20. In the experiment, 80% of the interaction records are randomly selected as the training data, 10% as the validation set, and the remaining 10% as the test set. The statistical information of the dataset after preprocessing is shown in Table 1.

5.1.2 Evaluation Metrics. In this paper, we employ two commonly used metrics, HR@N and NDCG@N, to assess accuracy. Furthermore, as our primary goal is to enhance recommendation diversity, we introduce coverage as an evaluation metric and it is measured as the proportion of item categories in the recommended list among total categories in the dataset according to Equation (16). Additionally, we introduce F1-score@N to trade off the accuracy and diversity. For our evaluations, we consider the values of 5 and 10 for N.

$$Diversity@N = \frac{|R|}{|\mathcal{D}|} \tag{16}$$

[1]https://snap.stanford.edu/data/amazon/productGraph/categoryFiles/

Table 2: Overall comparison of our method and all baselines on three datasets.

		@5				@10			
Datasets	Models	HR	NDCG	Diversity	F1-score	HR	NDCG	Diversity	F1-score
Music	POP	0.0175	0.0116	0.0112	0.0114	0.0285	0.0152	0.0221	0.0180
	GRU4Rec	0.0664	0.0425	0.0281	0.0338	0.1050	0.0549	0.0418	0.0474
	GRU4Rec-MRR	0.0610	0.0401	0.0285	0.0333	0.0975	0.0514	0.0427	0.0466
	SASRec	0.0958	0.0649	0.0279	0.0390	0.1435	0.0801	0.0416	0.0548
	SASRec-MRR	0.0960	0.0649	0.0292	0.0402	0.1419	0.0795	0.0432	0.0559
	TiMiRec	**0.1025**	**0.0696**	0.0283	0.0402	**0.1520**	**0.0855**	0.0425	0.0568
	MDSR	0.0978	0.0676	0.0299	0.0414	0.1512	0.0841	0.0435	0.0568
	ComiRec-SA	0.0998	0.0659	0.0296	0.0408	0.1502	0.0826	0.0438	0.0572
	MIND-DR	0.1002	0.0667	**0.0315**	**0.0428**	0.1505	0.0831	**0.0467**	**0.0598**
Food	POP	0.0044	0.0029	0.0175	0.0050	0.0080	0.0041	0.0175	0.0066
	GRU4Rec	0.0275	0.0171	0.0202	0.0186	0.0456	0.0230	0.0232	0.0231
	GRU4Rec-MRR	0.0263	0.0167	0.0217	0.0189	0.0443	0.0225	0.0245	0.0235
	SASRec	0.0342	0.0206	0.0210	0.0207	0.0504	0.0257	0.0241	0.0249
	SASRec-MRR	0.0331	0.0201	0.0222	0.0210	0.0490	0.0251	0.0250	0.0250
	TiMiRec	**0.0372**	**0.0218**	0.0220	0.0219	**0.0572**	**0.0281**	0.0247	0.0263
	MDSR	0.0351	0.0210	0.0239	0.0224	0.0510	0.0264	0.0261	0.0262
	ComiRec-SA	0.0365	0.0214	0.0231	0.0221	0.0514	0.0275	0.0256	0.0265
	MIND-DR	0.0340	0.0203	**0.0271**	**0.0232**	0.0493	0.0267	**0.0289**	**0.0278**
Beauty	POP	0.0080	0.0044	0.0787	0.0083	0.0113	0.0054	0.1449	0.0104
	GRU4Rec	0.0249	0.0150	0.0905	0.0257	0.0399	0.0201	0.1420	0.0352
	GRU4Rec-MRR	0.0220	0.0145	0.0913	0.0250	0.0388	0.0195	0.1435	0.0343
	SASRec	0.0291	0.0187	0.0910	0.0310	0.0468	0.0243	0.1461	0.0417
	SASRec-MRR	0.0290	0.0186	0.0918	0.0309	0.0464	0.0242	0.1489	0.0416
	TiMiRec	0.0333	0.0201	0.0915	0.0326	0.0542	0.0275	0.1475	0.0463
	MDSR	0.0318	0.0196	0.0923	0.0323	0.0524	0.0268	0.1493	0.0454
	ComiRec-SA	0.0325	0.0200	0.0920	0.0328	0.0532	0.0272	0.1489	0.0460
	MIND-DR	**0.0334**	**0.0205**	**0.0937**	**0.0336**	**0.0544**	**0.0277**	**0.1511**	**0.0468**

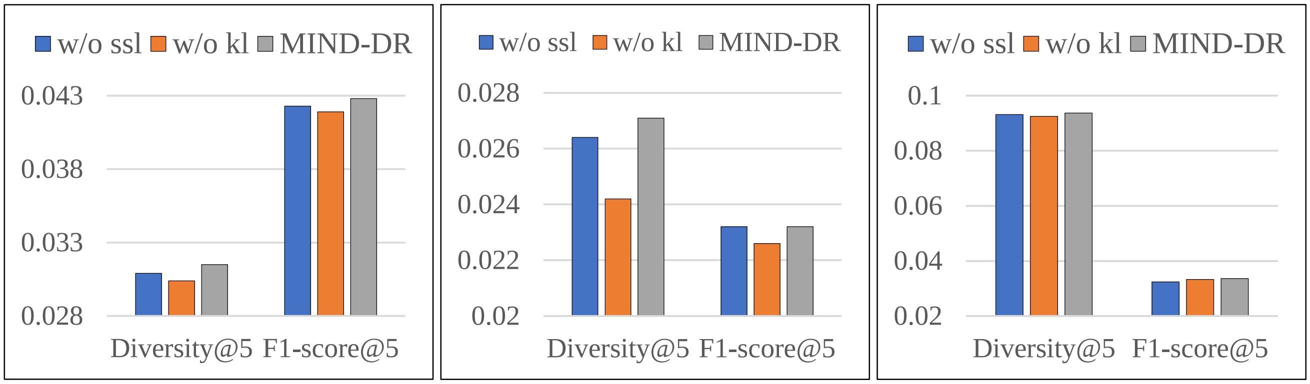
where $\mathcal{D}$ denotes the whole dataset, R denotes the top@N recommendation list and $|\cdot|$ denotes the number of categories.

5.1.3 Baselines. We selected traditional recommendation methods without considering sequences (POP), single interest SR methods (GRU4Rec [6], SASRec [9]), and MIR methods (MDSR [5], ComiRec-SA [3], TiMiRec [24]) for comparison. The details are listed as follows:

- **POP**: This method recommends the most popular items to users according to the items' popularity.
- **GRU4Rec** [6]: This method uses gated neural units (GRUs) for the first time to model the user's behavioral sequences, and is one of the classical RNN-based sequential recommendation algorithms.
- **SASRec** [9]: This method uses a self-attention mechanism to model the user's behavior sequences and predict the next items that user might click.
- **MDSR** [5]: This model extracts users' multiple interests and improves recommendation diversity in an end-to-end way for sequential recommendation.
- **ComiRec-SA** [3]: This model uses a self-attentive mechanism to model multiple users' interests, and introduces a balancing factor to trade-off the accuracy and diversity.
- **TiMiRec** [24]: This model extracts target interests from multiple interest representations by knowledge distillation, and then aggregates multiple representations based on the target interests.

Additionally, we construct two baselines **GRU4Rec-MRR** and **SASRec-MRR** which reranks the predicted list of GRU4Rec and SASRec respectively.

5.1.4 Parameter Settings. To obtain the best performance, we tune the hyper-parameters over validation set and employ early stopping with the patience of 20 epochs to prevent overfitting. Some common hyper-parameters are set as follows. For a fair comparison, the



(a) Music (b) Food (c) Beauty

Figure 2: Ablation study: Performance comparison between *MIND-DR* and its variants.

dimension of item embedding for all methods is $d = 64$, the length of the maximum historical interaction sequence of users is set to 20, and the size of each batch of training and validation data is set to 256. The hyperparameters $\alpha = 0.5$, $\beta = [0.15, 70, 5]$ for three datasets respectively, γ in Equation (14) range from $[6, 8, 10, 12]$. The learning rate is set as $lr = 0.0001$. We initialize the network parameters with Xavier initialization and adopt Adam as the optimizer.

5.2 Experimental Results

5.2.1 Overall Performance. To answer **RQ1**, we compare the performance of our *MIND-DR* with all baselines. Table 2 reports the best results achieved by all models across three datasets. We can observe that *MIND-DR* surpasses all baselines in terms of diversity on all datasets. Compared with the start-of-the-art baselines, *MIND-DR* gains 5.4%, 13.4%, and 1.5% on Diversity@5 and 6.6%, 10.7%, and 1.2% on Diversity@10 on the three datasets respectively. Notably, *MIND-DR* achieves increased diversity without compromising accuracy significantly. Regarding F1-score metric, *MIND-DR* achieves gains 3.4%, 3.6% and 2.4% on F1-score@5 and 4.5%, 4.9% and 1.1% on F1-score@10 on the three datasets respectively, which indicates that *MIND-DR* strikes a favorable balance between accuracy and diversity. The slightly lower f1-score compared to the start-of-the-art baselines on the Beauty dataset could be attributed to its smaller number of item categories, which presents challenges in achieving trade-offs. These experiments validate the effectiveness of our proposed model. Different from ComiRec-SA, our approach incorporates interest distribution to fully leverage multiple interest representations, thereby further enhancing diversity.

5.2.2 Ablation Study. To answer **RQ2**, we conduct ablation studies by progressively removing multi-interest distribution constraint and contrastive learning from *MIND-DR*. The results on three datasets are shown in Figure 2. We can observe that each variant yields a performance drop on both Diversity@5 and F1-score@5 metrics compared to *MIND-DR*, which demonstrates that both multi-interest distribution constraint and contrastive learning can contribute to our proposed model. Furthermore, the variant w/o kl leads to a significant decrease in performance suggesting that multi-interest distribution constraint plays a vital role in improving recommendation diversity while contrastive learning contributes in an auxiliary manner.

5.2.3 Parameter Sensitive Test. To answer **RQ3**, we conduct some experiments with varing K, γ, η on Music and Food datasets. The results are shown in Figure 3.

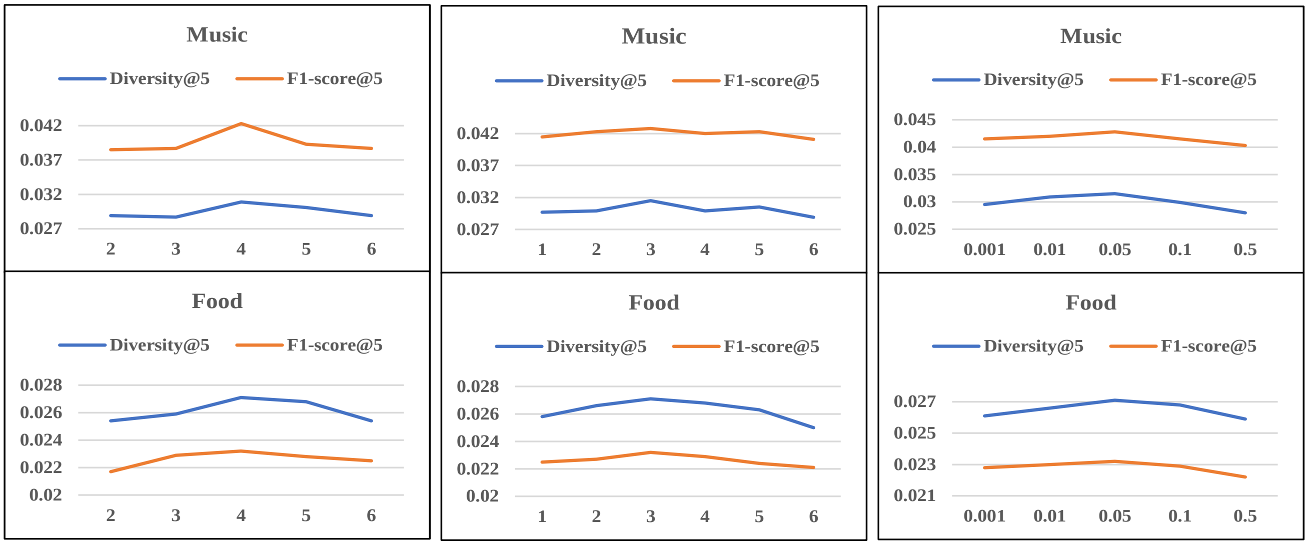
Interest Number K. Figure 3(a) depicts the outcomes of our proposed model in terms of Diversity@5 and F1-score@5 while varying the number of user interests. For both datasets, Diversity@5 and F1-score@5 first increase and then decrease with increasing K. The optimal results are achieved when $K = 4$. These experimental findings further validate that incorporating multiple interest representations of users can enhance recommendation diversity.

Diversity Coefficient γ. From Figure 3(b) , we can find that Diversity@5 and F1-score@5 of *MIND-DR* increases and then decreases with the increase of γ in both datasets, and the optimal results are obtained at $\gamma = 3$ for all datasets. The results show that, with the strengthening of the multiple interest distribution constraint, recommendation list will not be biased towards some specific interests, and the recommendation diversity is thus improved.

Contrastive Learning Coefficient η. Figure 3(c) shows the change of Diversity@5 of *MIND-DR* with increasing the contrastive learning coefficient. The optimal results are achieved at $\eta = 0.05$. The results indicates that promoting independence among the user's multiple interest representations can enhance the diversity of recommendation results.

6 CONCLUSION

Existing MIR models underutilize users' multiple interests, limiting their ability to enhance recommendation diversity. To address this issue, we propose a model called *Multi-INterest Distribution based Diversified Recommendation* (*MIND-DR*). In *MIND-DR*, we incorporate interest distribution in the reranking phase, which enhances recommendation diversity by minimizing the gap between the average interest distribution of the recommendation list and that of users. Additionally, to foster the independence of users' multiple interest representations, we introduce a contrastive learning loss to



(a) Influence of K (b) Influence of γ (c) Influence of η

Figure 3: Parameter sensitivity analysis on *MIND-DR*.

guide the model's learning process. Extensive experiments on three datasets validate *MIND-DR*'s effectiveness. Future research can integrate additional information sources like social networks and user profiles to enhance the accuracy and diversity of recommendations.

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