Hierarchical Multi-Interest Co-Network
For Coarse-Grained Ranking

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ABSTRACT
In this era of information explosion, a personalized recommendation system is convenient for users to get information they are interested in. To deal with billions of users and items, large-scale online recommendation services usually consist of three stages: candidate generation, coarse-grained ranking, and fine-grained ranking. The success of each stage depends on whether the model accurately captures the interests of users, which are usually hidden in users' behavior data. Previous research shows that users' interests are diverse, and one vector is not sufficient to capture users' different preferences. Therefore, many methods use multiple vectors to encode users' interests. However, there are two unsolved problems: (1) The similarity of different vectors in existing methods is too high, with too much redundant information. Consequently, the interests of users are not fully represented. (2) Existing methods model the long-term and short-term behaviors together, ignoring the differences between them. This paper proposes a Hierarchical Multi-Interest Co-Network (HCN) to capture users' diverse interests in the coarse-grained ranking stage. Specifically, we design a hierarchical multi-interest extraction layer to update users' diverse interest centers iteratively. The multiple embedded vectors obtained in this way contain more information and represent the interests of users better in various aspects. Furthermore, we develop a Co-Interest Network to integrate users' long-term and short-term interests. Experiments on several real-world datasets and one large-scale industrial dataset show that HCN effectively outperforms the state-of-the-art methods. We deploy HCN into a large-scale real-world E-commerce system and achieve extra 2.5% improvements on GMV (Gross Merchandise Value).

ACM Reference Format:
Xu Yuan, Chen Xu, Qiwei Chen, Tao Zhuang, Hongjie Chen, Chao Li, and Junfeng Ge. 2022. Hierarchical Multi-Interest Co-Network For Coarse-Grained Ranking. In Proceedings of ACM Conference (Conference'17). ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/nmmnnm.nmmnnm

1 INTRODUCTION
Due to the severe problem of information overload in online services, recommendation systems (RS) have gradually become an important tool to reduce users' time to acquire information. Industrial RS usually consists of the candidate generation stage and the ranking stage. The candidate generation stage aims to select items that users may be interested in from the billion corpora. These items are required to be sufficiently diverse to cover all potential preferences of users. The ranking stage is to select the items of interest to users under a relatively small data scale and finally expose them to users.

For large industrial recommender systems, the ranking stage is further divided into a coarse-grained ranking stage and a fine-grained ranking stage. Figure 1 shows the overview. This multi-stage cascade architecture has been widely used, and research on coarse-grained ranking has also achieved good results[18, 34].

![Figure 1: Overview of large industrial recommendations. The coarse-grained ranking stage is used to preliminarily score and filter the matched items, reduce data scale and pass it to the fine-grained ranking stage.](image)

Target attention mechanism proposed by DIN[48] is a powerful method for exploring user preferences, which has been widely used as a basic structure in the fine-grained ranking stage[47] with hundreds of candidates. Specifically, the candidate item is used to calculate the weight of the behavior sequence to activate the strongly correlated behaviors. However, due to the expensive computation and storage resources, DIN uses the recent 50 behaviors for target attention, which ignores the user's long-term interests hidden in the long user behavior sequence and is obviously sub-optimal[5]. Not to mention that it is not applicable to the coarse-grained ranking stage with tens of thousands of candidates.

Thus, in the coarse-grained ranking stage, we use the inner product model[1, 12] to avoid the delay and load caused by large-scale candidate sets. In the inner product model, candidates no longer interact with each user's behavior, but directly calculate the matching score by inner product of the user embedding.

However, without the help of target attention, how to capture users’ interest is a huge challenge. A lot of methods have been proposed to capture a user’s dynamic interests from his historical behaviors: recurrent neural networks (RNNs)[11], convolutional neural networks (CNNs)[31, 41], Graph Neural Network (GNN)[36],
Therefore, it is crucial to consider both long-term behaviors and multiple interest centers obtained by Hierarchical Multi-Interest iterative updating, the captured interest centers is more accurate through hierarchical multi-layer extraction modules. Through it-ver and self-attention as interest extraction methods and uses an aggregation module to aggregate items from different interests.

These studies have achieved good results in recommendation, yet they all have two apparent problems. First, it is not easy to extract multiple embedded vectors from the users’ behavior sequence in industry-level data. Items usually do not have clear clusters. The similarity and correlation of different vectors extracted by existing methods are too high, resulting in a lot of redundant information. Therefore, the performance of these multi-vector modeling methods is not much better than that of the single-vector modeling methods, because the extracted vectors can not really represent the diverse interests of users. Second, when people start surfing the Internet, their behavior will accumulate into a relatively long sequence. This long-term behavior expresses users’ potential preferences. At the same time, the more recent behaviors better represent the users’ precise interests. For example, if a user is a comic fan, he may click on a large number of comic-related items before. When he chooses to buy clothes now, clothes co-branded with comics will attract her/him more than other clothes. Therefore, it is crucial to consider both long-term behaviors and short-term interests. All existing multi-interest modeling methods directly model the sequence, and ignore this internal structure. Some studies have achieved good results in recommendation, yet they all have two apparent problems. First, it is not easy to extract multiple embedded vectors from the users’ behavior sequence. 

2 METHODOLOGY

2.1 Coarse-Grained Ranking for Industrial

For sizeable industrial recommendation systems like E-commerce, goods and users are often billions of levels. In such a large amount of data, coarse-grained ranking as a filter is critical in modern RS.

In the coarse-grained ranking stage, we mainly estimate the CTRs of all items selected in the candidate generation stage, and then use these CTRs scores to choose the top-k items for the next stage. The inputs of the prediction model are mainly composed of three parts. The first part includes user behavior, which records the history of items clicked by users. The second part includes user features, such as user ID, age, gender, etc. The third part includes item features, such as item ID, category, etc. Due to the large scale of the candidate set, the complexity of the prediction model and computing resources are strictly limited. Here, we use the inner product model to measure the item scores:

\[ f(X^U, X^I) = \langle \Phi_{W^U}(X^U), \Phi_{W^I}(X^I) \rangle, \]  

where the superscript \( U \) and \( I \) denote the user and item, respectively. \( X^U \) means a combination of user behavior and user features. \( \Phi_{W^U} (·) \) represents the non-linear mapping with learned parameter \( W \). \( \langle · , · \rangle \) is the inner product operation. As the user side and the item side are separated in Equation (1), during serving, we can compute the mappings \( \Phi_{W^U} (·) \) of all items off-line in advance. When a request comes, we only need to execute one forward pass to get the user mapping \( \Phi_{W^U} (X^U) \) and compute its inner product with all candidates, which is highly efficient. For more details, see the illustration in Figure 2. We conclude the notations and the corresponding descriptions in Table 1.

2.2 Hierarchical Multi-Interest Framework

The success of personalized recommendations depends on whether the model accurately describes the users’ interests, which are usually hidden in the users’ historical behaviors. Some studies show that the bottleneck of accurately capturing users’ interests is to express them through one representation vector. Therefore, many methods use attention, transformer, capsule network, etc. to capture or activate a variety of different interests of users.
behavior sequences. The basic structure is Multi-Head Attention, which has strong feature extraction ability and has been verified by many studies[6, 33]. However, it is found in the experiment that such transformation is not helpful to capture the users’ interests better than the recommended single header implementation[14, 30].

Poly-Encoders[13] proposed a new architecture with an additional learnt attention mechanism that represents more global features from sequence. We use it to extract multiple vectors from historical behavior sequence as the user’s interests, which are represented with n vectors ($y^t_{uuser}...y^n_{uuser}$) instead of just one. To obtain these n global representations, we learn n context codes ($c_1...c_n$) which are randomly initialized. Specifically, we obtain $y^t_{uuser}$ using:

$$y^t_{uuser} = \sum_j \omega^t_j q_j$$  \hspace{1cm} (2)

where $\left(\omega^t_1, ..., \omega^t_N\right) = \text{softmax} (c_1 \cdot q_1, ..., c_n \cdot q_n)$, $q_j$ represents each token of the sequence, $N$ is the length of the sequence.

For the long-term and short-term behavior sequences, we initialize vectors ($c_1...c_n$) as matrix $C_0 \in \mathbb{R}^{n \times D}$ which called the SEED MATRIX. We take the user history interaction sequence as matrix $K \in \mathbb{R}^{L \times D}$ and matrix $V \in \mathbb{R}^{L' \times D}$ (for short sequence, they are matrix $K \in \mathbb{R}^{S \times D}$ and matrix $V \in \mathbb{R}^{S' \times D}$) to encode interests respectively. The calculation formula can be expressed as Equation (3):

$$H = \text{Concat}(head_1, ..., head_h)W^o,$$

$$head_i = \text{softmax} (\frac{C_0W^C_i (KW^K_i)^T}{\sqrt{d^KW^K_i}})W^V_i,$$  \hspace{1cm} (3)

where $H$ represents the encoded user interest centers, $W^C, W^K, W^V$ and $W^o$ are learnable parameters.

**Algorithm 1 Hierarchical Multi-Interest calculation process.**

**Input:** User history behavior sequence $I \leftarrow [q_1, q_2, ..., q_n]$; Iteration times $r$; head num $h$; Input user interest Centers $C_0$;

**Output:** Output user interest Centers $F_c$;

1. Random Initialize $C_0$
2. for $i = 0 \rightarrow r$ do
3. if $i > 0$ then
4. $C_i \leftarrow H_{i-1}$
5. end if
6. for $k = 0 \rightarrow h$ do
7. Init $W^Q, W^K, W^V$
8. $Q \leftarrow G_iW^Q$
9. $K \leftarrow IW^K$
10. $V \leftarrow IW^V$
11. $head_k \leftarrow \text{softmax} (\frac{QK^T}{\sqrt{d_K}})V$
12. end for
13. $H_i \leftarrow \text{Concat}(head_1, ..., head_h)W^o$
14. end for
15. $F_c \leftarrow W_c[H_0; H_1; ...; H_r] + b_c$
16. return $F_c$

2.2.1 Hierarchical Multi-Interest Network. Our framework starts by extracting users’ diverse interests from the users’ historical

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**Table 1: The notations and the corresponding descriptions.**

| Notation | Description |
|----------|-------------|
| $n$      | The number of user interest centers. |
| $D$      | The dimension of the embeddings. |
| $L$      | The embedding of users’ long-term interests. |
| $\hat{S}$ | The embedding of users’ short-term interests. |
| $X^U$    | The output on user side, a combination of user behavior and user features. |
| $X^I$    | The output on item side. |
| $\hat{X}^U$ | The embedded vector encoded by user history behavior sequence. |
| $\hat{X}^I$ | The embedded vector formed by user statistical features. |
| $\ell_S$ | The length of user long-term behavior sequence. |
| $\ell_L$ | The length of user short-term behavior sequence. |
| $C_0$   | Input user interest Centers. |
| $F_c$   | Output user interest Centers. |
| $\Phi_W(\cdot)$ | The non-linear mapping with learned parameter $W$. |
Comparing with the traditional self-attention, the calculation method we designed can reduce the complexity from $\ell^2 L$ to $n\ell L$ where $n \ll \ell L$. And it is also acceptable for ultra-long sequences.

However, such a simple calculation is not enough to obtain diverse and representative users’ interest centers. Researches on image representation learning show that the features become sharper and more distinguishable with the deepening of the network[15, 44]. Similar observations are also found in sentence representation learning[28]. Inspired by previous studies, we further introduce hierarchical structure as the extraction layer to get more representative interest centers.

We regard multi-interest extraction based on multi-head attention as an iteration. After one iteration, the interest centers are global, which cannot sufficiently represent the differentiation of users’ interests. Therefore, we use a hierarchical structure to update the users’ interest centers in multiple rounds. Starting from the second layer, we use the interest centers output from the previous layer as $Q$ and continue to encode the users’ historical behavior sequence as Equation (3). Finally, the output of each layer is concatenated together, and the users’ interest centers are obtained after a linear transformation. Through such iterative calculation, we get more diverse and representative interest centers. The whole hierarchical calculation process is listed in Algorithm 1.

Through iterative multi-layer calculation, the final aggregated multiple vectors can represent the different interests of users. We get two vectors $\hat{L} \in \mathbb{R}^{n \times D}$ and $\hat{S} \in \mathbb{R}^{n \times D}$ to represent users’ long-term interests and short-term interests respectively. Figure 4 illustrates the Hierarchical Multi-Interest Network.

2.2.2 Co-Interest Network. Till now, we have extracted users’ long-term and short-term interests. Next, we need to integrate them. In the single-vector modeling method, we use a simple concat operation. However, since two sets of multi-vectors are extracted, how to align them has become an important problem. DIN[48] use a novel designed local activation unit to help behaviors with higher relevance to the candidate item get higher activated weights and dominate the representation of user interests. However, their approach is only applicable to the fine-grained ranking stage, which is not appropriate to the coarse-grained ranking stage with a larger sample size and strict complexity constraints. The cartesian product can capture the cross features of long-term and short-term interests[46], but the memory and computational overhead are also unacceptable.

In this paper, we design a Co-Interest Network to integrate the long-term and short-term interests with low consumption of computing resources. We regard the long-term interests as the users’
potential preference and the short-term interests as the users’ current preference. The goal is to capture the relationship between the potential and the current intentions.

Firstly, the local inference is determined by the attention weight \( e_{ij} \) computed as Equation (4), which is used to obtain the local relevance between long-term and short-term interests.

\[
e_{ij} = \hat{L}_i \hat{S}_j^T.
\]  
(4)

Then we use \( e_{ij} \) to reconstruct short-term and long-term interests, respectively. The motivation is to give higher weight to the embedding vector related to short-term intention and capture the cross features of long-term and short-term interests. The reconstruction process is as shown in Equation (5):

\[
\hat{L}_i = \sum_{j=1}^{t_L} \frac{\exp(e_{ij})}{\sum_{k=1}^{t_S} \exp(e_{ik})} \hat{S}_j, \forall i \in [1, \ldots, t_L],
\]

\[
\hat{S}_j = \sum_{i=1}^{t_L} \frac{\exp(e_{ij})}{\sum_{k=1}^{t_S} \exp(e_{ik})} \tilde{L}_i, \forall j \in [1, \ldots, t_S].
\]  
(5)

Finally, the fusion vectors are concatenated together and output, which defined as:

\[
\hat{X}^U = W^h [\hat{L}, \hat{S}, \hat{S}] + b^h.
\]  
(6)

Here, the embedded vector \( \hat{X}^U \in \mathbb{R}^{n \times D} \) represent \( n \) users’ interest centers which contains the cross features of users’ long-term and short-term preference. The embedded vector formed by users’ statistical features \( \hat{X}^U \in \mathbb{R}^{1 \times D} \), so we tile it into \( n \) parts and concat it with \( X^U \) as the output of user side, which defined as:

\[
X^U = W^U [\hat{X}^U; X^U] + b^U.
\]  
(7)

### 2.2.3 Aggregation Module

After obtaining the user side representation, we need to match it with the item side representation. We build an aggregation module layer to allow the candidate item \( \hat{X}^I \) to interact with multiple representations \( X^U \) gotten on the user side at the top level, so as to make full use of the information contained in the candidate item. The calculation process is shown in Equation (8):

\[
\alpha_j = \frac{\exp((X^I)^T \hat{X}^U)}{\sum_{j=0}^{k} \exp((X^I)^T \hat{X}^U)},
\]

\[
y = \langle X^I, \sum_{j=0}^{k} \alpha_j X^U_j \rangle,
\]  
(8)

where \( \langle \cdot, \cdot \rangle \) is the inner product operation. The model is trained by minimizing the loss of cross-entropy, which is defined as:

\[
L = -y \log \left( \frac{1}{1 + e^{-y}} \right) - (1 - y) \log (1 - \frac{1}{1 + e^{-y}}),
\]  
(9)

where \( y \) is label, and \( y \) is the output of the model, that is, the matching score.

### 3 EXPERIMENTS

#### 3.1 Experimental Settings

##### 3.1.1 Data Sets

We conduct our experiments on five real-world datasets from several global E-commerce or other platforms. The data statistics after pre-processing are listed in Table 2. We truncated and padded the long-term and short-term behavior sequences for different datasets. These pre-processing method has been widely used in related works[22, 25].

- **Amazon Dataset** consists of product reviews and metadata from Amazon. In our experiment, we use the Books category of the Amazon dataset. And we select the data from October 2010 to October 2018.
- **MovieLens 25m** is a large stable benchmark which consists of movie ratings. The original data contains 25 million ratings and one million tag applications applied to 62,000 movies by 162,000 users.
- **Taobao** is a dataset consisting of user behavior data retrieved from Taobao, one of the biggest e-commerce platforms in China. It contains user behaviors from November 25 to December 3, 2017, with several behavior types, including click, purchase, add to cart, and item favoring.
- **Tafeng Dataset** released on Kaggle, which contains the transaction data of Chinese grocery store. It contains user behaviors from November 1, 2000 to February 28, 2001.
- **Industrial Dataset** is collected by one of the world’s largest e-commerce platforms. We chose the data from April 24, 2021 to May 22, 2021 as the training data. The total scale of the data is about 1600TB, and the ratio of positive and negative samples is 1:20.

#### 3.1.2 Evaluation Metric

We evaluate the performance with the area under the ROC curve (AUC). AUC[8] is a standard metric in coarse-grained ranking in industry[9, 26, 37], which measures the goodness of order by ranking all items with predicted CTR.

#### 3.1.3 Baselines

- **Mean Pooling** is a simple online baseline for aggregating users’ historical behaviors, which has the advantages of low complexity and low computation.
- **GRU4Rec** [11] adopts GRU to capture sequential dependencies and makes predictions for session-based recommendation.
- **SASRec** [14] uses stacking self-attention to capture user interests in user historical interaction behavior.
- **SAMRec** [32] is another common online baseline to extract users’ interests. Different from SASRec, it first obtains the high-level semantics of the sequence through the stacked self-attention and then aggregates them through mean pooling.
Table 3: Performance (AUC) comparison of baselines and our approaches, where our approach HCN’s best results are in bold.

| Method       | Taobao   | Amazon Books | ML25m   | Tafeng   | Industrial |
|--------------|----------|--------------|---------|----------|------------|
| Mean Pooling | 0.7320   | 0.6989       | 0.8248  | 0.7505   | 0.7218     |
| GRU4Rec      | 0.7544   | 0.7167       | 0.8304  | 0.7630   | 0.7382     |
| SAMRec       | 0.7691   | 0.7189       | 0.8340  | 0.7619   | 0.7407     |
| SASRec       | 0.7613   | 0.7205       | 0.8337  | 0.7611   | 0.7395     |
| MIND         | 0.7706   | 0.7293       | 0.8357  | 0.7690   | 0.7447     |
| SINE         | 0.7632   | 0.7284       | 0.8343  | 0.7730   | 0.7445     |
| ComiRec      | 0.7730   | 0.7267       | 0.8358  | 0.7724   | 0.7451     |
| HCN          | **0.7767** | **0.7341** | **0.8385** | **0.7785** | **0.7482** |
| Imprv.       | 3.7‰    | 4.8‰        | 2.7‰    | 5.5‰    | 3.1‰       |

3.2 Results and Analysis

3.2.1 Offline Results. Table 3 presents the performance comparisons between several baselines and our model (HCN). For fairness, the number of embedded vectors obtained by all multi-vector modeling methods is the same. HCN achieves the best performance on four public datasets and one industrial dataset, verifying our model’s superiority. HCN performs better than Mean Pooling, GRU4Rec, and SAMRec because HCN can capture a variety of users’ interests. It can also be observed that employing multiple embedding vectors (MIND, ComiRec, SINE, HCN) for a user generally performs better than single-embedding-based methods (Mean Pooling, GRU4Rec, SAMRec, SASRec).

Compared with MIND, our model shows much better performance. On the one hand, the infrastructures of the two methods are different. We use Multi-Head Attention as the basis, which is better than the dynamic routing used by MIND. In complex behavior sequences, the feature extraction ability of the Multi-Head Attention mechanism plays a very important role. It is also verified in ComiRec[4]. On the other hand, in our model, long-term and short-term interests interact and guide each other. While MIND does not model long-term and short-term preference, respectively, thus ignoring the cross features.

HCN outperforms SINE and ComiRec. We conjecture that the hierarchical structure leads to more diverse and representative of multiple embedded vectors extracted by the model. To verify it, we introduce the Pearson correlation coefficient, which reflects a linear correlation of variables. It is the ratio between the covariance of two variables and the product of their standard deviations. The lower the Pearson correlation coefficient, the lower the correlation between multiple embedding vectors. The Pearson correlation coefficient calculation process is as shown in Equation (10):

$$r(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}[X] \cdot \text{Var}[Y]}}$$

where Cov(X, Y) is the covariance between X and Y, Var[X] is the variance of X, and Var[Y] is the variance of Y.

Table 4: Correlation Coefficient comparison between various state-of-the-arts models and HCN. The lower the value, the lower the correlation between embedded vectors.

| Method  | Taobao   | Amazon Books | ML25m   | Tafeng   | Industrial |
|---------|----------|--------------|---------|----------|------------|
| SINE    | 0.8859   | 0.7023       | 0.8051  | 0.8586   | 0.7994     |
| ComiRec | 0.6697   | 0.6696       | 0.8136  | 0.8421   | 0.8769     |
| MIND    | 0.5963   | 0.6645       | 0.7702  | 0.8084   | 0.5587     |
| HCN     | 0.5485   | 0.6269       | 0.7523  | 0.7965   | 0.5019     |

We calculate the multiple interest vectors obtained by the model in pairs and get the overall correlation coefficient score after averaging on the whole testing set. Table 4 presents the result. It can be seen that the multiple user interest centers captured by HCN are the most independent. MIND as another method of iteratively updating the user interests, the correlation of embedded vectors is also lower than SINE and ComiRec. The slight correlation between vectors means that there are few redundant features, which can contain more information. It is consistent with the goal of multi-vector modeling. Combined with the experimental results, we find that the embedded vector with lower correlation can often provide more incredible help for the recommendation. It is the fundamental reason why HCN is superior to SINE and ComiRec.
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Table 5: Effect of Hierarchical Multi-Interest Network (HIN) and Co-Interest Network (CIN).

|                  | Taobao AUC | Improve | Amazon Books AUC | Improve | ML25m AUC | Improve | Tafeng AUC | Improve | Industrial AUC | Improve |
|------------------|------------|---------|-----------------|---------|-----------|---------|------------|---------|----------------|---------|
| w/o HIN and CIN  | 0.7711     | -       | 0.7254          | -       | 0.8344    | -       | 0.7705     | -       | 0.7449         | -       |
| w/o CIN          | 0.7742     | 3.1‰   | 0.7293          | 3.9‰   | 0.8359    | 1.5‰   | 0.7772     | 6.7‰   | 0.7472         | 2.3‰   |
| HCN              | 0.7767     | 5.6‰   | 0.7341          | 8.7‰   | 0.8385    | 4.1‰   | 0.7785     | 8.0‰   | 0.7482         | 3.3‰   |

3.2.2 Online A/B Testing. We have deployed the proposed solution in mobile e-commerce platforms. From 2021-08-21 to 2021-09-21, we conduct a strict online A/B testing experiment to validate the proposed HCN model. Compared to our last online model based on SAMRec, HCN achieves great gain, which shows in Table 6. Now, HCN has been deployed online and serves the Homepage of Taobao app every day, which contributes significant business revenue growth.

Table 6: HCN’s Lift rate of online results compared with previous online system from Aug 21 to Sep 21, 2021, in Guess What You Like column of Taobao App Homepage.

| Metric | IPV | CTR | GMV |
|--------|-----|-----|-----|
| Lift rate | 3.2% | 3.1% | 2.5% |

3.2.3 Case Study. In order to deeply explore the knowledge learned by the model, we visualized multiple interest centers. Concretely, we leverage its embedding vectors to retrieve the top-4 closest items under their similarity for each center. Figure 5 illustrates six exemplar centers to show their clustering performance. As can be seen, our model successfully groups some semantic-similar items into a latent concept. Multiple embedded vectors can capture various commodity sets from the user’s historical behaviors and then give different weights through candidate items.

Figure 5: A case study of an e-commerce user. We draw six interest centers, ”Dress”, ”Earrings”, ”Shoes”, ”Down Jackets”, ”Snacks”, ”Phone Shell’ with the top-4 closest items.

3.2.4 Ablation Study. We perform the ablation study to see the effectiveness of the proposed Hierarchical Multi-Interest Network (HIN) and Co-Interest Network (CIN). Table 5 reports the results on different datasets. It can be seen that both HIN and CIN significantly improve the recommendation performance. HIN continuously updates users’ interest centers through iteration aggregation to make them more diverse and representative. CIN focuses on the potential connection between long-term and short-term preferences ignored by the existing models, which significantly strengthens the expression ability of n embedded vectors. It emphasizes the strong correlation between a small number of long-term preferences and current short-term behaviors, while captures multi-level user preferences. In particular, even without the help of the Co-Interest Network, our proposed model can obtain better results than state-of-the-art.

Figure 6: Sensitivity of Hyper-parameter $n$.

3.2.5 Sensitivity of Hyper-parameter. We study the sensitivity $n$ of the HCN hyper-parameter. Figure 6 shows AUC scores of HCN with different $n$. It can be seen that when the number of embedded vectors increases from one to multiple, AUC increases significantly, which once again proves the importance of multi-vector modeling. In particular, different datasets have different sensitivity to the hyper-parameter $n$. Large E-commerce datasets such as Taobao and Amazon Books need eight or more embedded vectors to represent users’ interests because of their rich user historical behaviors. However, when $n$ continues to rise, AUC does not increase obviously. The user’s interests have an upper limit, which can be expressed by a specific number of embedded vectors, and more vectors are redundant.
Table 7: Performance on two public datasets, where our approach HCN’s best results are in bold. The underlined numbers are the best results besides HCN. All the numbers in the table are percentage numbers with ‘%’ omitted.

|               | Amazon Books |               | Taobao       |               |
|---------------|--------------|--------------|--------------|--------------|
|               | Metrics@50   | Metrics@100  | Metrics@50   | Metrics@100  |
| Hit Rate      | NDCG         | Hit Rate     | NDCG         | Hit Rate     | NDCG         |
| Mean Pooling  | 1.54         | 0.35         | 2.31         | 0.42         | 1.59         | 3.14         | 10.03        | 3.18         |
| GRU4Rec       | 1.70         | 0.51         | 2.74         | 0.67         | 9.41         | 3.60         | 12.43        | 4.08         |
| SAMRec        | 3.07         | 0.98         | 4.22         | 1.17         | 13.55        | 5.71         | 16.19        | 6.94         |
| SASRec        | 3.17         | 1.01         | 4.43         | 1.28         | 13.36        | 5.64         | 15.37        | 6.38         |
| MIND          | 3.94         | 1.45         | 5.87         | 1.66         | 17.81        | 10.31        | 20.55        | 10.93        |
| SINE          | 4.36         | 1.59         | 6.14         | 1.72         | 16.37        | 9.28         | 18.96        | 9.52         |
| ComiRec       | 4.01         | 1.52         | 5.98         | 1.67         | 16.45        | 9.56         | 19.18        | 10.06        |
| HCN           | 4.76         | 1.64         | 6.52         | 1.80         | 18.21        | 11.09        | 21.96        | 11.95        |

3.2.6 Results of HCN in candidate generation stage. Although HCN is developed based on the coarse-grained ranking stage, it can also adapt to the candidate generation stage. We employ Hit Rate and NDCG [17] to evaluate the recommendation performance. Hit Rate indicates the proportion of cases when the rated item is amongst the top-k items. NDCG is the normalized discounted cumulative gain at k, which takes the rank of recommended items into account and assigns larger weights on higher positions. To evaluate the recommendation’s performance, we split each dataset into training/validation/testing sets. We hold out the last two interactions as validation and test sets for each user, while the other interactions are used for training.

Due to the space limit, only the results on Amazon Books and Taobao are reported in Table 7. The comparison results show that HCN consistently performs better on two datasets in terms of all evaluation metrics than state-of-the-art models. Similar results are obtained for other cases. It is consistent with our experimental results on the coarse-grained ranking stage. HCN, MIND, SINE, and ComiRec perform better than the single embedded modeling methods represented by GRU4Rec in Hit Rate and NDCG. This further shows that it is necessary to use multiple embedded vectors to express users’ preferences in a system with highly complex user behaviors.

4 RELATED WORK

4.1 Sequential Recommendation

Nowadays, many approaches have been proposed to model the user’s historical interaction sequence. The methods based on the Markov chain predict the subsequent user interaction by estimating the probability of transfer matrix between items [50]. RNN-based methods model the sequential dependencies over the given interactions from left to right and make recommendations based on this hidden representation. Except for the basic RNN, long short-term memory (LSTM) [35], gated recurrent unit (GRU) [11], hierarchical RNN [27] have also been developed to capture the long-term or more complex dependencies in a sequence. CNN-based methods first embed this historical interactive information into a matrix and then use CNN to treat the matrix as an image to learn its local features for subsequent recommendation [31, 41]. GNN-based methods first build a directed graph on the interaction sequence, then learn the embeddings of users or items on the graph to get more complex relations over the whole graph [36]. Attention models emphasize those important interactions in a sequence while downplaying those that have nothing to do with user interest [39]. To further enhance the expression ability of sequence model, there are also some valuable works in sequence modeling, which combines self-supervised learning [42, 49], aggregates side information [43, 45], and so on.

4.2 Attention Mechanism

Attention was first applied in the image field [3, 23, 38] for dynamic control in identifying objects, and then widely used in seq2seq tasks, such as machine translation [2, 19]. Traditional methods, such as RNN and CNN, can not reflect the importance of different sequence parts, and the attention mechanism can capture it well. In natural language processing, BERT [7] has achieved great success by using transformer. In recommendation, it also plays a significant role. For example, DIN [48] uses attention to obtain information strongly related to the candidate item in the user’s historical behavior sequence. ICAI-SR [43] uses the attention mechanism to aggregate various attributes of items.

4.3 Multi Interest Modeling

In previous studies, we expressed the user’s interest as a single embedded vector. With the development of the Internet and the accumulation of data, more and more studies show that users’ behavior history is dynamic, and users’ interests are diverse. It isn’t easy to completely represent the genuine interest of users with a single vector.

MIND [16] uses dynamic routing to aggregate the user’s historical behavior sequence into the user’s interest expression. It does not capture the cross features of long-term and short-term preferences. SINE [30] proposes a sparse-interest embedding framework which can adaptively activate users’ multiple intentions. ComiRec [4] uses dynamic routing and self-attentive as interest extraction methods and uses an aggregation module to aggregate items from different interests. The difference of the proposed HCN from existing Multi-Interest models is in that we built the extraction module hierarchically and noticed the relationship between long-term and short-term interests. These make the performance of the recommendation system get a significant improvement.
5 CONCLUSION
In this work, we extract multiple interests from users’ behavior sequences with Hierarchical Multi-Interest Co-Network for the coarse-grained ranking stage. First, users’ long-term and short-term interests are extracted by a Hierarchical Multi-Interest Network and updated iteratively to get more diverse and represent centers. Then a Co-Interest Network captures the cross features of users’ long-term and short-term preferences and integrates them through an aggregation module. Experimental results and analysis demonstrate the superiority of the proposed model. The total GMV are improved by 2.5% in online A/B test compared to previous online system.

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