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Inter-Basket and Intra-Basket Adaptive Attention Network for Next Basket Recommendation

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ABSTRACT Next basket recommendation with consideration of user sequential shopping behaviors plays a significant role in E-commerce to improve the user experience and service quality. Recently, recurrent neural networks (RNNs), especially attention-based RNN, have been widely adopted in the next basket recommendation. However, existing fixed attention mechanisms are not designed to model the dynamic and diverse characteristics of user appetites. In this paper, we propose an inter-basket and intra-basket adaptive attention network (IIAAN) for the next basket recommendation. Specifically, the inter-basket adaptive attention acts on all historical user baskets to model user's diverse long-term preferences, while the intra-basket adaptive attention is designed to act on item-level in the most recent basket to model user's dynamic and different short-term preferences. Then, we further integrate inter-basket and intra-basket adaptive attentions together to improve recommendation effectiveness. Finally, we evaluate the proposed model IIAAN using three real-world datasets from various E-commerce platforms. Our experimental results show that our model IIAAN significantly outperforms the state-of-the-art approaches for the next basket recommendation.

INDEX TERMS Basket recommendation, recurrent neural network, adaptive attention.

I. INTRODUCTION

With the rapid development of E-commerce, many companies like Amazon, TMall, and JingDong have established shopping platforms to ease user shopping. One of the most important tasks in E-commerce is detecting the purchase habits of customers and their evolution in time for next basket recommendation [1]. It can not only increase the traffic and profit for service providers, but also help customers find the items of interest more easily. With the user's shopping history represented as a sequence of baskets, it is natural to formalize the next basket recommendation to a sequential prediction problem. That is, given a sequence of baskets, we want to predict what the user will buy next with consideration of both users' general taste and sequential behaviors.

Existing next basket recommendation approaches can be classified into three categories: purchase pattern based methods, Markov Chains (MC), and Recurrent Neural Network (RNN). Pattern-based methods [2] consider the correlation between items in the same basket, and incorporate different product factors into the decision process. FPMC [3] only models both user's sequential behavior and general taste by conducting a tensor factorization over the transition cube. However, The MC-based method models the sequential behavior of users only between adjacent transactions. To address this problem, RNN is widely adopted in the sequential recommendation to describe the changing characteristics of user interest over time. Reference [4] employs RNN to mine dynamic user and item preferences in trajectory data. Since the monotonic assumption of RNN restricts the modeling of user's short-term interest, attention-based RNN solutions have been proposed to automatically assign different influences to previous baskets and achieved the state-of-the-art performance [5].

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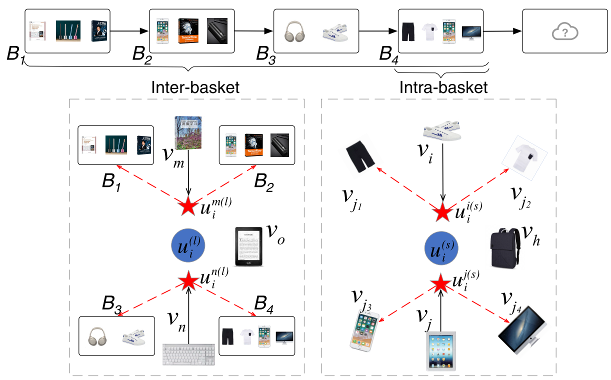

FIGURE 1. An example of dynamically adapting inter-basket and intra-basket adaptive user representations to candidate items.

Nevertheless, users' appetites within and between baskets are diverse and hard to be captured by existing fixed attention mechanisms. For example, we may find that a shopping basket usually contains different kinds of items, e.g., books and electronics in one basket. This indicates that user interests are diverse in Intra-basket. We also find that the principal item category in different baskets is usually different, e.g., Toys and Games in one basket and Beauty in another basket. This indicates that user interests are diverse in Inter-basket. In terms of user long-term preferences, attention-based RNN solutions use fixed strategies to allocate different influences to the previous baskets, but this is insufficient to capture the diversity of user long-term preferences. For instance, as shown in Figure 1, given a sequence of baskets (B_1, B_2, B_3, B_4), the aggregation representation of baskets formed two clusters for that B_1 is close to B_2 and B_3 is close to B_4. Fixed user long-term preference representation $u_i^{(l)}$ in terms of all baskets resides between two clusters. Fixed user representations will recommend item v_o for v_o is close to $u_i^{(l)}$. Adaptive user representations will recommend item v_m or v_n. Owing to the diversity of user interest, only a subset of the baskets can reveal whether a user is interested or not. The reason is that a candidate item book v_m is close to books in B_1 and B_2 rather than dress and electronics in B_3 and B_4. The adaptive user representation $u_i^{m(l)}$ is more precise than fixed user representation $u_i^{(l)}$ when considering candidate item v_m. This example shows that adaptive user representations can better reflect the correlation between candidate items and historical baskets, as well as better to express the diversity of user long-term preferences.

In terms of user short-term preferences, existing methods often project users and items of a recent basket B_4 into a low-dimensional space, in which similar items are projected closely. The distance between a user and an item represents how much the user is interested in the item, but the fixed user short-term preference representation does not effectively reflect user diversity preference. Due to the diversity of user preferences, different candidate items have different correlations with items in the historical baskets. As shown in Figure 1, items in the latest basket form two clusters for the diversity and fixed user representation $u_i^{(s)}$ resides between two clusters. Fixed user representations will recommend item v_h to user $u_i^{(s)}$ while adaptive representations will recommend item v_i or v_j. In other words, adaptive user representations can better reflect the correlation between candidate items and historical items, as well as better to express the diversity of user short-term preferences.

In this paper, we propose an adaptive attention mechanism on inter-basket and intra-basket for next basket recommendation. On the intra-basket, we adopt a memory component and a deep adaptive attention mechanism on item-level in the most recent basket to model the user's dynamic and diverse short-term preference. On the inter-basket, we adopt a deep adaptive attention mechanism on all historical user baskets to model user's diversity of long-term preference. Then, we integrate the diversity of user preferences intra-basket and inter-basket together into the long short-term memory (LSTM) layer and finally get the dynamic and adaptive user representation to further improve recommendation effectiveness. Experimental results on three real-world E-commerce datasets show our method significantly improves next basket recommendation performance.

To summarize, our contributions are listed as follows.

- We propose a novel adaptive attention network on inter- and intra-basket for next basket recommendation which introduces two layers adaptive attention to learn dynamic, diverse, and adaptive user representations.
- Benefiting from adaptive attention mechanism, our proposed model obtains good interpretability on explaining why items in the basket get recommended to a user by showing relevant baskets liked by the user.
- We perform experiments on three datasets which show that our model consistently outperforms state-of-the-art methods in terms of Recall, F1_score and NDCG.

II. RELATED WORK

Next basket recommendation is a typical sequence recommendation task. In this section, we will briefly review closely related work from two perspectives, which are sequential recommendation and attention mechanisms.

A. SEQUENTIAL RECOMMENDATION

Sequential recommendation can be classified into two categories: Markov chains and neural networks. Reference [3] (FPMC) combines the Matrix Factorization (MF) and Markov chains (MC) to model user general appetites and mine user sequential behaviors. Reference [1] (HRM) further extends the idea by employing a hierarchical structure to construct a user representation to capture sequential information and general tastes. These MC-based methods cannot model user's long-term preferences. Many researchers turn to use neural networks to solve this problem. Reference [6] proposes Dynamic Recurrent Basket Model (DREAM) based on RNN, which not only learns a dynamic representation of each user but also models global sequential features from item-purchase history. Reference [4] explores Gated Recurrent Unit (GRU) as a special form of RNN for the prediction of the

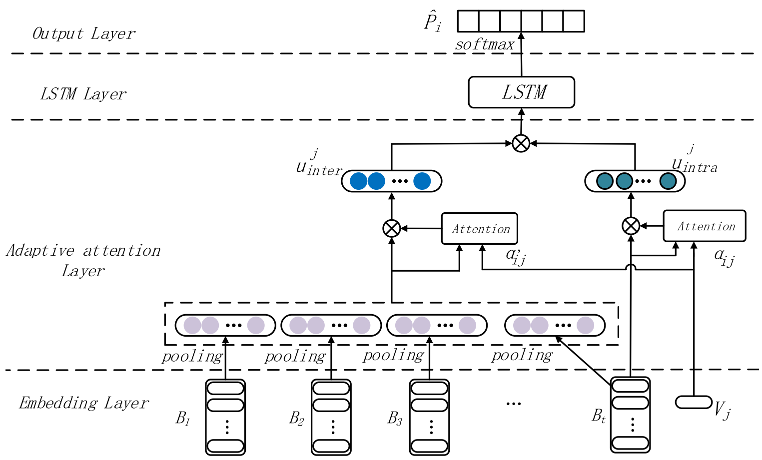

FIGURE 2. The architecture of our model IIAAN consists mainly of three layers. Firstly, we encode the information of items in each basket through the embedding layer. Secondly, we capture the dynamic and adaptive user representations within and between baskets through the adaptive attention layer. Lastly, we mine the user's sequential behaviors using *LSTM*.

action in a session. However, this method neglects the user's long and short-term appetites. Therefore, [7] introduces the attention mechanism to model user dynamic preferences and uses a hierarchical structure to learn the user's long and short-term preferences. Reference [8] employs the attention model to explain the user's attention to different aspects of the item. On the other hand, Convolutional Neural Network (CNN) based methods have achieved a comparable performance with RNN in sequential recommendation. Reference [9] regards the embedding matrix of recent items as an "image" and then uses convolutional operations to extract local item-item transitions for top-n sequential recommendation.

B. ATTENTION MECHANISMS

Attention mechanisms have been shown effective in various fields, such as image/video caption [10], [11], machine translation [12], and so on. The attention technique allows a model to focus on the most important parts of the target with different weights. For example, in the sequence recommendation, [13] proposed a two-layer hierarchical attention network to take both user-item and item-item interactions into account for sequential recommendation. Reference [5] employs a fixed attention mechanism to capture user's varying appetite toward items. These methods only capture a fixed user preference representation, which cannot dynamically and adaptively represent the diversity of user preferences. Nevertheless, in the traditional recommendation, [14] proposed an adaptive attention mechanism to model user diversity preferences for the traditional recommendation. However, it only learn the adaptive representation of the user, which cannot mine the sequence behavior of the user. Therefore, we introduce an adaptive attention mechanism and propose an Inter-basket and Intra-basket Adaptive Attention Network (IIAAN) for next basket recommendation. Our experimental results show the effectiveness of IIAAN.

III. INTER-BASKET AND INTRA-BASKET ADAPTIVE ATTENTION NETWORK

In this section, we first formulate the next basket recommendation problem and then introduce the details of our model Inter-basket and Intra-basket Adaptive Attention Network (IIAAN). Finally, we present the optimization procedures for IIAAN.

A. PROBLEM STATEMENT

We assume that we have a set of users and a set of items, denoted by U and I respectively, and $u \in U$ denotes a user and $v \in I$ denotes an item. The number of users and items are denoted as $|U|$ and $|I|$ respectively. For user u, his/her purchase records sorted by time is represented as a sequence of baskets $B^u = \{B^u_1, B^u_2, \cdots, B^u_t\}$. All items purchased by user u are history items, which are defined as $R^+_u = \{v_1, v_2, \cdots, v_n\}$. Given a user's history records, the task is to recommend items that the user probably buy at next visit. That is the recommendation problem can be reformulated as a ranking problem of all items, and then we recommend top K items to the user.

B. THE PROPOSED MODEL

Next we present the proposed model IIAAN, which utilizes an adaptive attention mechanism to model the diversity of user preferred intra-basket and inter-basket. As shown in Figure 2. Firstly, we encode the information of items in each basket through the embedding layer. Secondly, we capture the dynamic and adaptive user representations within and between baskets through the adaptive attention layer. Lastly, we mine user's sequential behaviors using *LSTM*. The details of each part of IIAAN are introduced as follows.

1) EMBEDDING LAYER

Traditional matrix factorization only captures low-level, bi-linear and static representation, which has limited representation capability [15]. Embedding representation, which embeds users and items into two continuous low-dimensional spaces, solves the shortcomings of the matrix factorization model. Therefore, IIAAN first employs lookup layer to transform the one-hot encoding of users and items into continuous low-dimensional spaces. For every item v, we formulate the item embedding vector as

$$V = LOOKUP(W^T, v^I), \tag{1}$$

where $W \in R^{K\times|I|}$ is the transformation matrix for *LOOKUP* and K is the embedding dimension of each item. In order to represent the basket information of the user at different time slots in low-dimensional spaces. We apply a memory module to store the latent representations of all items in the basket at time t. This memory matrix M at time t is constructed as

$$M_t = \{m_1, m_2, \ldots, m_l\}, \tag{2}$$

where l is the number of items in the basket at time t, $m_l \in R^{K\times 1}$ corresponds to the latent representation of an item liked by the user. Hence, the matrix M_t reflects the user's interest in the basket at time t.

2) INTRA-BASKET ADAPTIVE ATTENTION

Items in a basket liked by a user naturally reflect the user's interests. Existing methods only use the attention mechanism to describe users' appetites for different items, and learn a fixed user preference representation. However, these methods cannot reflect the diversity of user interests in a basket. Therefore, we introduce a novel adaptive attention mechanism [14] to reflect the diversity of user preference in the basket. The goal of the novel adaptive attention mechanism is to select items that are closely related to the target item from M_t, and then aggregate the representation of informative items to characterize the interests of a specific user. Hence, we learn the correlation score between the M_t and item v_j, and the item v_j is randomly selected from history items R_u^+. Each element of the relevance score w_{ij} is defined as follows:

$$w_{ij} = m_i^T v_j, \quad \forall i = 1, 2, \ldots, l \tag{3}$$

where $m_i \in R^{K\times 1}$ is the i-th column vector of memory matrix M_t. Then we normalize the relevance score w_{ij} by a *softmax* as follows:

$$\alpha_{ij} = softmax\left(w_{ij}\right) \tag{4}$$

We generate an intra-basket user representation in the basket by focusing on items in M_t, which are highly activated, *i.e.*, adaptively selecting valuable features from the memory matrix M. Hence, the intra-basket adaptive user representation u^j_{intra} is derived by weighting M_t as follows, according to the candidate item v_j.

$$u^j_{intra} = \sum_{m_i \in M_t} m_i \alpha_{ij}, \tag{5}$$

where $u^j_{intra} \in R^{K\times 1}$ can adaptively represent users' diverse appetites in the basket.

3) INTER-BASKET ADAPTIVE ATTENTION

From the user basket records, we can see that the basket contains user interests that change over time and uses' appetites between baskets are diverse. Hence, from a long-term preference, learning a fixed user preference representation cannot express the diversity of user preference between baskets. To solve this problem, we reuse the novel adaptive attention mechanism to learn the dynamical and adaptive user representations between baskets.

For a user purchase records sorted by time is a sequential of baskets $B = \{B_1, B_2, \ldots, B_t\}$, we firstly generate the latent representations of each basket $B' = \left\{B'_1, B'_2, \ldots, B'_t\right\}$ by aggregating representations of all items in each basket [6]. Therefore, the latent representation for each basket is formulated as follows.

$$B'_t = max\_pooling(B_t) \tag{6}$$

where $B'_t \in R^{k\times 1}$ means the latent representation of the basket B_t at time t.

Then, similar to the way of learning the intra-basket adaptive user representation, we also introduce a novel attention mechanism into the latent representation of the basket B'_t and the item v_j to reflect the diversity of user preference between baskets. Formally,

$$w'_{tj} = (B'_t)^T v_j, \quad \forall t = 1, 2, \ldots; \tag{7}$$

$$\alpha'_{tj} = softmax(w'_{tj}), \tag{8}$$

$$u^j_{inter} = \sum_{B'_t \in B'} B'_t \alpha'_{tj}, \tag{9}$$

where B'_t is the t-th column vector of the latent representation of the basket B'. The $u^j_{inter} \in R^{k\times 1}$ is the inter-basket adaptive user representations between baskets.

According to the formulas 5 and 9, we can generate the intra-basket and inter-basket adaptive user representations respectively. To generate the hybrid adaptive user representations, we merge u^j_{intra} and u^j_{inter} by a simple element-wise product operation, which is defined as follows.

$$u^{hybrid} = u^j_{intra} \cdot u^j_{inter} \tag{10}$$

To conclude, u^{hybrid} reflects not only the diversity of user preference intra_basket and inter_basket, but also differentiates contributions of items for predicting items in next basket.

4) LSTM LAYER

Through the adaptive layer, we can learn a hybrid adaptive user representation. However, it only reflects the diversity of user interest within the basket and between baskets at the time, but it cannot reflect the user's sequence behaviors. Therefore, we model the user's sequence behaviors through *LSTM*. For each time step t, the input of *LSTM* is u_t^{hybrid}, and the output of *LSTM* is the users' preference representation $u_t^h \in R^{K\times 1}$ at step t.

TABLE 1. The performance comparisons of different methods on the next basket recommendation task, and the boldface results are the best while the second best is underlined.

Datasets	Ta-Feng			Taobao			JingDong		
Models	Recall@5	F1@5	NDCG@5	Recall@5	F1@5	NDCG@5	Recall@5	F1@5	NDCG@5
TOP	0.015	0.008	0.009	0.007	0.002	0.002	0.083	0.028	0.029
FPMC	0.028	0.010	0.011	0.008	0.003	0.002	0.095	0.031	0.031
HRM	0.030	0.011	0.012	0.008	0.003	0.003	0.100	0.032	0.032
DREAM	0.033	0.032	0.041	0.010	0.005	0.006	0.115	0.038	0.040
SHAN	0.054	0.039	0.036	0.015	0.008	0.007	0.129	0.067	0.053
ANAM	<u>0.145</u>	<u>0.122</u>	<u>0.144</u>	<u>0.023</u>	<u>0.015</u>	<u>0.014</u>	<u>0.285</u>	<u>0.158</u>	<u>0.153</u>
IIAAN	**0.159**	**0.134**	**0.158**	**0.034**	**0.022**	**0.021**	**0.295**	**0.164**	**0.157**

5) LEARNING AND PREDICTION

For a user u and his/her historical baskets $B^u_{1,t-1}$, we define the probability of an item i being purchased in the next basket B^u_t by *softmax* function

$$p\left(i \in B^u_t | u, B^u_{1,t-1}\right) = \frac{exp\left(V^T_i \cdot u^h_t\right)}{\sum_{j=1}^{|I|} exp\left(V^T_j \cdot u^h_t\right)} \tag{11}$$

To effectively learn from the training data, we adopt a weighted cross-entropy as the optimization objective at each step of *LSTM*, which is defined as follows.

$$L = \sum_{u \in U} \sum_{B^u_t \in B^u} \sum_{i \in I_t} -m \cdot y_i \cdot log\hat{p}_i - n\left(1 - y_i\right) \cdot log(1 - \hat{p}_i) \tag{12}$$

where $\hat{p}_i$ is the probability of item i being purchased in the next basket in IIAAN. If item i is purchased in the next basket, $y_i = 1$. Otherwise, $y_i = 0$. Since the positive instances and negative instances are extremely unbalanced in datasets, we use parameters m and n to balance the positive and negative instance distribution.

IV. EXPERIMENTS

In this section, we conduct experiments to answer the following questions:

$Q1$: What is the performance of our model IIAAN, comparing with other state-of-the-art methods?

$Q2$: What are the influences of intra-basket and inter-basket adaptive attention components in IIAAN?

$Q3$: How do the parameters affect the performance of IIAAN, including its hyper-parameters and the number of dimensions?

A. EXPERIMENTAL SETUP

Datasets We evaluate IIAAN on three real-world datasets, i.e., Ta-Feng,[1] Taobao,[2] and JingDong,[3] to demonstrate the effectiveness of IIAAN. The Ta-Feng dataset contains 4 months (Nov 2000 to Feb 2001) of shopping transactions of the Ta-Feng supermarket. The Taobao dataset contains 9 days (Nov 25 to Dec 03, 2017) of users' behavior dataset. The JingDong dataset contains 3 months (Feb 1, 2016 to Apr 20, 2016) of users' behavior dataset. Similar to [5], the users having less than 20 purchases in all datasets are removed, so are items purchased less than 15 times. The statistics of the three datasets are summarized in Table 2.

TABLE 2. Statistics of the three datasets.

Datasets	Ta-Feng	Taobao	JingDong
Users	6263	7181	10000
Items	11203	72510	9136
Transactions	199971	108398	207749
Sparsity(%)	99.71%	99.97%	99.77%
Avg.basket per user	7.05	6.7	8.8
Avg.basket size	4.53	2.26	2.36

Metrics To evaluate the performance of each method for the next basket recommendation problem, we employ three widely used metrics Recall@N, F1-score@N, and NDCG@N. Recall@N evaluates the fraction of ground truth items that have been rightly ranked over top-N items in all testing baskets, F1-score@N calculates the harmonic mean of the precision and recall measurements, and NDCG@N is normalized discounted cumulative gain using to measure rank quality. Note that a larger value of all three metrics indicates better performance.

Baselines We compare our model IIAAN with following baseline algorithms.

- ***TOP***: The method recommends items to users according to their popularity.
- ***FPMC*** [3]: This method models user preferences through matrix factorization and sequential information through first-order Markov chain simultaneously, and then combines them by the linear way for next basket recommendation.
- ***HRM*** [1]: This method captures sequential behaviors and users' general tastes by generating a user hierarchical representation.
- ***DREAM*** [6]: This method adopts RNN to model global sequential features that reflects interactions among baskets and users, and the hidden state of RNN presents user's dynamic interests over time.
- ***SHAN*** [13]: SHAN adopts hierarchical attention network to model the user's long-term preferences and short-term preferences over time.
- ***ANAM*** [5]: ANAM adopts an attentive RNN to model the user's sequential behaviors over time, and relays the user's appetites for items and their attributes to the next basket through attention weights shared across baskets on the two different hierarchies.

[1] http://www.bigdatalab.ac.cn/benchmark/bm/dd?data=Ta-Feng
[2] https://tianchi.aliyun.com/datalab/dataSet
[3] https://www.datafountain.cn/competitions/247/details/data-evaluation

B. PERFORMANCE COMPARISON

Table 1 shows the performance of all methods on the three datasets in terms of three evaluation indicators. From the experimental results, we can conclude that:

Firstly, among all baseline models, TOP has the most unfavorable performance under all cases, since it is a non-personalized and non-sequential method. The classic model FPMC performs better than TOP in all cases because it takes adjacent baskets into account. The experimental results verify that sequential and personalized information can help improve the recommendation performance.

Secondly, HRM is significantly better than FPMC on the three datasets. It demonstrates that the nonlinear operations among multiple factors are significantly better than linear operations. DREAM consistently outperforms HRM and FPMC in terms of three metrics on the three datasets. These results show that RNN-based architecture is able to capture user sequence features and dynamic interests of users. However, SHAN is better than the previous three models in terms of the three metrics on the three datasets. It demonstrates that complicated nonlinear information can be captured by attention network. Furthermore, refining user preferences to long-term and short-term preferences can more accurately capture user preferences. In addition, the ANAM model outperforms the SHAN model. This demonstrates that the user's preferences can be better captured by an attention mechanism in the basket, and incorporating the attribute information about items is helpful to promote model's capability.

Finally, our model IIAAN is superior to the second best method ANAM. The recall@5 is increased by 9.7%, 47.8% and 3.5% on the three datasets respectively, although IIAAN does not use category information while ANAM uses it. We think that ANAM learns user preferences through a fixed attention mechanism, and it cannot mine the diversity of users' appetites on intra-basket and inter-baskets. Our model IIAAN captures the diversity of user preferences by adaptive attention on intra-basket and inter-basket. It demonstrates that for the next basket recommendation, capturing the diversity of user interests on intra-basket and inter-baskets can better promote model capability.

Surprisingly, all methods have a significantly better effect on the Ta-Feng and JingDong datasets than on the Taobao dataset. The reason may be that the Taobao dataset is most sparse. However, our model IIAAN increases the most on Taobao dataset compared to the other two datasets.

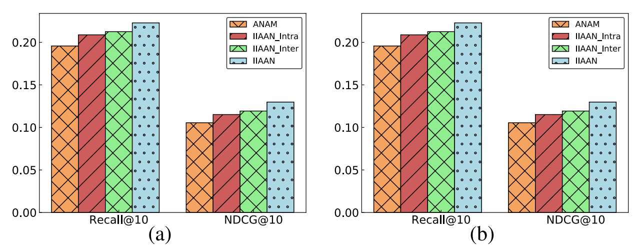

FIGURE 3. Influence of components at recall@10 and NDCG@10. (a) Ta-Feng. (b) Taobao.

C. INFLUENCE OF COMPONENTS

To evaluate the contribution of each component for forming the final dynamic and adaptive user representation, we conduct experiments to analyze the influence of each component. As shown in Figure 3, IIAAN_Intra only considers the diversity of users' appetites from intra-baskets, IIAAN_Inter only considers the diversity of users' appetites from inter-baskets.

Firstly, IIAAN_Intra achieves better performance compared with ANAM. It demonstrates the effectiveness of highlighting the user's preference from intra-baskets through an adaptive attention mechanism. Furthermore, considering the diversity of user preferences intra-baskets will promote model capability. Secondly, on the Ta-Feng dataset, IIAAN_Inter outperforms IIAAN_Intra with a slight advantage, but the experimental results are reversed on the Taobao dataset. From these two datasets, we find that the user shopping interval on the Taobao dataset is significantly shorter than on the Ta-Feng dataset. Hence, the reason may be that when the time interval between users' baskets is too long, it may result in the inability of capturing the diversity of user preferences inter-baskets. Finally, IIAAN performs better than two single component models in all cases. It shows that combining intra-basket and inter-basket into account simultaneously is helpful to predict the next basket.

TABLE 3. The influence of different ratios of m and n in terms of recall@10.

Datasets / $m:n$	Ta-Feng	Taobao	JinDong
100	0.169	0.028	0.338
500	0.192	0.032	0.371
1000	0.202	0.035	0.370
1500	0.203	0.037	0.372
2000	0.204	0.037	0.374

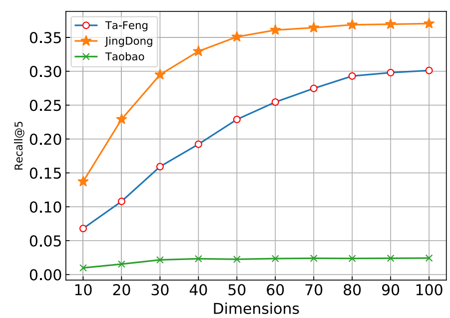

FIGURE 4. The impact of the dimension size in terms of recall@5.

D. INFLUENCE OF HYPER-PARAMETERS

In our model IIAAN, we utilize m and n to balance the positive and negative sample imbalance. Table 3 shows the influence of different ratios of m and n in terms of recall@10. We can see that when the ratio of m to n is greater than 500, the performance of IIAAN will tend to be stable. This demonstrates that the ratio of m to n is helpful for balancing positive and negative sample imbalances. Furthermore, we investigate the impact of the dimension size K, which is relevant to item embedding size. From Figure 4, we can observe that high dimensions can embed better for items.

However, when the dimension is greater than 100, the model does not benefit from a larger dimension. Overfitting could be a possible reason.

V. CONCLUSION

In this paper, a novel Intra-basket and Inter-basket Adaptive Attention Network, named IIAAN, was proposed for next basket recommendation. Specifically, we utilized a novel adaptive attention mechanism to capture the dynamic and diversity user appetites on intra-basket and inter-basket. Then, we integrated user preference on inter-basket and intra-basket together to improve the recommendation performance. Experimental results on three real-world datasets demonstrated that IIAAN outperforms the state-of-the-art methods in terms of Recall, F1-scores, and NDCG.

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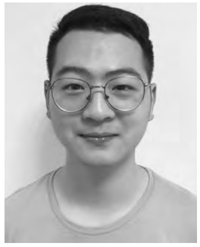

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