Modeling Dynamic Attributes for Next Basket Recommendation

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Traditional approaches to next-item and next basket recommendation typically extract users' interests based on their past interactions and associated static contextual information (e.g. a user id or item category). However, extracted interests can be inaccurate and become obsolete. Dynamic attributes, such as user income changes, item price changes (etc.), change over time. Such dynamics can intrinsically reflect the evolution of users' interests. We argue that modeling such dynamic attributes can boost recommendation performance. However, properly integrating them into user interest models is challenging since attribute dynamics can be diverse such as time-interval aware, periodic patterns (etc.), and they represent users' behaviors from different perspectives, which can happen asynchronously with interactions. Besides dynamic attributes, items in each basket contain complex interdependencies which might be beneficial but nontrivial to effectively capture. To address these challenges, we propose a novel Attentive network to model Dynamic attributes (named AnDa). AnDa separately encodes dynamic attributes and basket item sequences. We design a periodic aware encoder to allow the model to capture various temporal patterns from dynamic attributes. To effectively learn useful item relationships, intra-basket attention module is proposed. Experimental results on three real-world datasets demonstrate that our method consistently outperforms the state-of-the-art.

CCS Concepts:
- Information systems → Recommender systems;
- Computing methodologies → Neural networks.

Additional Key Words and Phrases: Dynamic Attributes, Context Interaction Learning, Next Basket Recommendation

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1 INTRODUCTION

Sequential recommendation systems have been successfully applied to various applications such as product recommendation, food recommendation, music recommendation, etc. There are two lines of sequential recommendation tasks based on different assumptions about users’ interaction behavior. Next item recommendation assumes that users interact with items sequentially, so that recommendations can be made by modeling the sequential semantics of the interaction history [10, 12, 14, 23], possibly including additional static attributes [29] (product category, brand, etc.).
Next basket recommendation [16, 28] assumes that users interact with multiple items during each round (i.e., a basket). The goal is to recommend a basket of items that a user is likely to interact with at the next time step. In the next basket recommendation task, in addition to the sequential patterns underlying historical interactions, items in each basket, and context of users or items often provides useful information.

Existing solutions for next-basket recommendation tasks train a sequential recommender based on the users’ interaction history [8, 11, 18, 28], or with additional static contextual attributes [2] (product category, brand, etc.) to extract users’ interests. However, extracted interests can be inaccurate and obsolete. Dynamic attributes, which change over time, appear in many applications, and can provide more accurate descriptions of the shift of a user’s interests or changes in item properties. For example, in a bank product recommendation scenario (see Figure 1), products from the bank are recommended to customers. Given only a sequence of monthly records of a customer’s products, the next basket recommended to the user is deterministic. Instead, dynamic attributes such as the household income and the customer membership type, which are changing overtime, help a recommender to better capture a user’s changing interests. Case 1 and 2 in Figure 1 illustrate that two customers with the same historical purchase behaviors but different household income and membership type sequences can have different interests.

![Fig. 1. An illustration of a recommender system with or without dynamic attributes.](image)

Although it is essential to model dynamic attributes, properly integrating dynamic attributes into sequential models is challenging. First, the temporal patterns underlying dynamic attributes can be diverse. There can be time-interval (i.e., two items purchased with different time-intervals has different impact on users’ future purchase behaviors.) and periodic patterns (i.e., seasons, weekday/weekend patterns, etc.). Second, dynamic attributes represent users’ behaviors from different perspectives, and can happen asynchronously with interactions. Directly concatenating basket items with dynamic attributes at each time step may not be stable to model diverse sequential patterns.

Besides dynamic attributes, in users’ historical interactions, items in each basket contain complex interrelationships (item correlations, co-purchases, etc.). Existing solutions [3, 11] either pre-define static item correlations based on co-occurring items, or (vanilla) attention to extract item correlations based on the whole items the last basket. However, multiple item interrelationships can exist based on multiple subsets of items in a basket and together influence next basket items. For example, in a grocery shopping, a customer bought apple, banana, TV and Speaker. The apple and banana are high correlated while TV and Speaker are also high correlated. The user may purchase some fruits again with TV accessories. Using multi-head attention allows the model to capture different item relationships under different subset of items in a historical basket.

To address the above challenges, we propose a novel Attentive network to model the Dynamic attributes as well as users’ historical interacted items (AnDa for short). AnDa separately encodes and learns representations from dynamic
attributes and interactions with basket items. To allow the model to capture time-interval aware and periodic patterns, we propose an input encoder containing a time-aware padding and periodic index embedding to encode dynamic attributes. To capture complex item relationships in each basket, an intra-basket attentive module is introduced. It is applied to each basket item to extract useful item relationships. We conduct experiments on three real-world datasets for next basket recommendation. Our experimental results demonstrate that our proposed method significantly outperforms baseline approaches.

2 RELATED WORK

2.1 Next Basket Recommendation

To capture sequential patterns at a basket level for next basket recommendation, DREAM [28] encodes items in each basket using max and average pooling and learns the sequence representation through an RNN-based network. ANAM [2] improves upon DREAM by considering static item attributes using vanilla attention. Sets2Sets [8] views the task as a multiple baskets prediction and proposes a RNN based encoder-decoder method to improve the performance. To capturing item relationships at each basket, Beacon [11] defines pre-computed static item correlation information based on the co-occurring items in the observed training baskets and then incorporates it into an RNN-based model. IIANN [3] learns the correlation between the most recent basket items and the target item to summarize users’ short-term interests. In this work, we use multi-head self-attention within each basket so that complex item interrelationships (e.g., co-occurrences) can be captured. MITGNN [15] focus on capturing users’ intention information in each basket and across different users’. In comparison, our work focus on leverage dynamic attributes for providing more accurate user interests.

2.2 Feature Interaction Learning

Factorization Machines (FMs) [4, 9, 17, 27] capture second-order feature interactions and have proven to be effective for recommendation [19]. With the success of deep neural networks (DNN), many works start to explore high-order feature interactions using DNN. NFM [7] combines FM with a DNN to model high-order feature interactions. The Wide&Deep [5] model uses a wide part to model second-order interactions and a deep part to model the higher-order interactions. Different from Wide&Deep, Deep&Cross [25] uses a cross-product transformation to integrate features, and xDeepFM [13] proposes a CIN module to take the outer product at a vector-wise level. These works, which use DNN to capture high-order feature interactions implicitly, lack good explanation ability in general. To this end, AutoInt [21] uses a self-attention mechanism to model high-order interactions with a more precise explanation of the interacted features. Inspired by this, we also apply multi-head self-attention to learn higher-order feature interactions and item interrelationships in each basket.

2.3 Attention Mechanisms

With the success of Transformer networks in machine translation tasks [24], purely attention-based models SASRec [10] is the first work that uses a pure self-attention mechanism to model sequential recommendation and demonstrates better performance than RNN-based methods. TiSASRec [12] extends SASRec using self-attention to model the time interval between two adjacent interactions. BERT4Rec [23] uses bidirectional self-attention with the Cloze objective. FDSA [29] further improves sequential recommendation by incorporating the usage of static item attributes and using vanilla attention to capture users’ interests. However, it does not incorporate dynamic user attributes and only models the sequential patterns at the item level instead of the basket level. Although this approach could be extended for
modeling dynamic features, it uses vanilla attention to average out different attributes at each time step. As a result, it is not able to learn high-order feature interactions. Also, it loses the temporal aspects of individual features. For example, if the trend of a usage metric is going up or down in the past three months, FDSA will not capture such a trend due to its averaging operation. Instead, our time-level attention module can capture these temporal patterns.

3 PROPOSED APPROACH

In this section, we first define the notation and formalize the next basket recommendation task with dynamic user attribute information. And then we present the proposed framework AnDa in detail. The framework is illustrated in Figure 2 and the notation is summarized in Table 1.

3.1 Problem Statement

In next basket recommender systems with dynamic attributes, historical basket interactions and dynamic attribute sequences are given, and the goal is to recommend the next basket’s items. Formally, we denotes \( U \), \( V \) and \( F \) a sets of users, items and user attributes respectively. For a user \( u \in U \), a sequence of baskets \( B^u = \{B^u_0, B^u_1, \cdots, B^u_{t_{max}}\} \) represents his or her item interactions sorted by time. \( T \) is the maximum time steps of each sequence, and \( B^u_t \in V \) is a set of items that user \( u \) interacted with at time step \( t \). A sequence \( A^u = \{A^u_1, A^u_2, \cdots, A^u_{t_{max}}\} \) represents the value of dynamic user attributes of user \( u \) ordered by time. Specifically, \( A^u_t \in F \) are all the attribute values of \( u \) at time step \( t \). The goal is to predict basket items that user \( u \) will interact with at time step \( T + 1 \) given \( T \) historical baskets \( B^u \) and attributes \( A^u \).

3.2 Time-Interval and Periodic Aware Input Encoder

**Embedding Lookup:** For each basket of dynamic attributes \( A^u_t \), we model categorical and numerical attributes differently. Categorical attributes \( A^u_{t,\text{cat}} \) are represented by an \( |F_{\text{cat}}| \)-dimensional multi-hot vector denoted by \( e^V_{t,\text{cat}} \in \mathbb{R}^{|F_{\text{cat}}| \times 1} \). Numerical attributes are normalized into the range \([-1, 1]\) using min-max normalization, denoted as \( s^V_{t,\text{num}} \in \mathbb{R}^{|F_{\text{num}}| \times 1} \). Each basket of items \( B^u_t \) is represented by a \( |V| \)-dimensional multi-hot representation, denoted by \( e^V_t \in \mathbb{R}^{|V| \times 1} \). After that, we apply a concatenation-based lookup function [2] to encode \( e^V_{t,\text{cat}} \) and \( e^V_t \):

\[
\begin{align*}
    s^V_{t,\text{cat}} &= \text{CONCAT} - \text{LOOKUP}(R, e^F_{t,\text{cat}}), \\
    s^V_t &= \text{CONCAT} - \text{LOOKUP}(Q, e^V_t)
\end{align*}
\]

where \( R \in \mathbb{R}^{|F_{\text{cat}}| \times D} \) and \( Q \in \mathbb{R}^{|V| \times D} \) are learnable embedding matrices for categorical attributes and items. The “CONCAT-LOOKUP” function retrieves the corresponding embedding vectors and then concatenates them together to form matrices \( s^F_{t,\text{cat}} \in \mathbb{R}^{|F_{\text{cat}}| \times D} \), and \( s^V_t \in \mathbb{R}^{|V| \times D} \). \( D \) is the embedding dimension of each item and categorical attribute. \( |V_t| \) is the total number of items in \( B^u_t \). Since the number of items in each basket varies, we set the maximum number of items in the basket as the largest basket size in the training set \( |V_{\text{max}}| \), and add padding vectors for baskets smaller than \( |V_{\text{max}}| \).
Time-aware Padding Operation: We set the maximum sequence length as $T$ to get up to the latest $T$ position steps’ information. If the sequence length is shorter than $T$, a zero-pad operation will be applied to empty positions. Otherwise, we truncate to the last $T$ positional steps. Unlike previous works [10, 23, 29] that pad zeros to the left until the sequence length is $T$, we pad zeros to the missed time steps to keep the time interval information. We denote $F_{\text{cat}}$ and $F_{\text{num}}$ as the padded basket item, categorical attribute, and numerical attribute sequences respectively.

Periodic Index Embedding: We introduce a periodic index embedding $M \in \mathbb{R}^{T \times D}$ for attention modules to discover periodic patterns. The index repeats over every $T'$ time steps of a sequence. For example, $T' = 12$ can be used for capturing seasonal patterns when the time interval between each two baskets is one month. Positional embeddings [20] that commonly used to identify item positions is also used in this paper. Formally, we concatenate the periodic and positional index embedding with $s_i^V$ as $l_i^V = [s_i^V, p_t, m_t]$, where $t \in \{1, \cdots, T\}$, $m_t \in M$ and $p_t \in P$ are $D$ dimensional periodic and positional embedding vectors. Then a basket sequence is represented as $L^V = \{l_1^V, l_2^V, \cdots, l_T^V\}$. We also add positional and periodic index embeddings to $S^{\text{cat}}$ and $S^{\text{num}}$ to form $L^{\text{cat}}$ and $L^{\text{num}}$ respectively.

3.3 Time Level Attention Module

To capture temporal patterns from $L^V$, $L^{\text{cat}}$ and $L^{\text{num}}$, we separately encode them via multi-head self-attention (MHSA) [24]. Formally, let $L^0 = L = L^{\text{cat}}$, and then fed into a MHSA block as shown below: Eq. 2

$$M^{(1)} = \text{MHSA}(L^{(0)}, h) = [\text{head}_1, \text{head}_2, \ldots, \text{head}_h]W_{\text{Concate}},$$

$$\text{head}_i = S\text{A}(L^{(0)j}_{\text{Query}}, L^{(0)j}_{\text{Key}}, L^{(0)j}_{\text{Value}}),$$

(2)

where $h$ is the number of sub-spaces, $W_{\text{Query}}^j \in \mathbb{R}^{C \times C}$, $W_{\text{Key}}^j \in \mathbb{R}^{C \times C}$, $W_{\text{Value}}^j \in \mathbb{R}^{C \times C}$ and $W_{\text{Concate}} \in \mathbb{R}^{C' \times C}$ are learned parameters ($C = (|F_{\text{cat}} + 2| \cdot D)$, and $C' = h C$). Similar, $L^V$ and $L^{\text{num}}$ are also encoded via Eq. 2.
We stack multiple attention blocks to capture more complex feature interactions:

\[ L^{(1)} = \text{MHSAB}(L^{(0)}, h) \]  

(3)

We stack multiple attention blocks to capture more complex feature interactions:

\[ L^{(k)} = \text{MHSAB}(L^{(k-1)}, h^k), k > 0 \]  

(4)

where \( L^{(0)} = L \) and \( h^k \) is the number of heads at the \( k^{th} \) attention block. \( L^{(k)} \) is the output after stacking multiple time-level attention layers. The extracted representation vector at time step \( t \) can be denoted \( L_t^{(k)} \) and contains information extracted from time 1 to time \( t \) of the input sequence.

### 3.4 Intra-Basket and Intra-Attribute Self-Attention Modules

Item correlations in each basket can reveal some useful information such as co-purchase relationships. The key problem is how to determine which items should be combined or are correlated. In this paper, we use multi-head self-attention to learn information such as items’ correlation relationships. Specially, given representations of all items in a basket \( L_t^k \), a single-head self-attention module will first compute the similarity matrix which is seen as item correlation scores, and then it updates the item representation \( h^k_t \) by combining all relevant items using the similarity coefficients (generated based on the similarity matrix). We use MHSAB to enhance the model’s capability of capturing complex item correlations, which is formed as follows:

\[ L_t^{(k+1)} = \text{MHSAB}(L_t^{(k)}, h_t^{k+1}), k > 0, t \in \{1, 2, \cdots, T\} \]  

(5)

where \( L_t^{(k)} \) is the output of the time level attention module at time \( t \), and \( h_t^{k+1} \) is the \((k+1)^{th}\) attention block.

We stack Eq. 5 \( m \) times to capture more complex item relationships \( L_t^{(k+m)} \). Similarly, we can stack Eq. 5 on dynamic attribute (named Intra-Attribute Attention) to get higher level categorical attribute interactions \( L_t^{(k+m) \text{cat}} \).

### 3.5 Model Training

The encoded user representations are projected as: \( L_t^{\text{all}} = \text{FFNN}([L_t^{(k+m) \text{Fv}}, L_t^{(k+m) \text{Fcat}}, L_t^{(k+m) \text{Fnum}}]) \), where FFNN is a feed forward network. \( L_t^{\text{all}} \in \mathbb{R}^{1 \times D} \) is the final representation given dynamic attributes and basket items from time step 1 to \( t \). We then adopt the binary cross-entropy loss as the objective for training the model defined as:

\[ - \sum_{B^u \in B \cdot u \in \{1, \cdots, T\}} \sum_{i \in |B^u|} \left( \sum_{j \not \in |B^u|} \log(\sigma(L_t^{\text{all}} \cdot Q_i)) + \sum_{j \in |B^u|} \log(1 - \sigma(L_t^{\text{all}} \cdot Q_j)) \right) \]  

(6)

where \( \sigma \) is the sigmoid function \( \sigma(x) = 1/(1+e^{-x}) \). \( Q \) is the item embedding matrix which is shared for encoding basket items in input encoders. The target basket items for user \( u \) are a shifted version of \( B^u \), denoted by \( \{B^u_2, B^u_3, \cdots, B^u_{t+1}\} \).

### 4 EXPERIMENTS

#### 4.1 Experimental Setting

4.1.1 Datasets. Table 2 summarizes the statistics of the datasets. EPR is a private dataset sampled from a leading enterprise cloud platform. The task is to recommend products to businesses. Examples of the dynamic attributes are
behavior metrics on the website, sales information, and marketing activities of the business. SPR\(^1\) is a public dataset on product recommendations for the Santander bank. Ta-Feng\(^2\) is a grocery shopping dataset. We followed Beacon [11] to create train, validation, and test sets by chronological order. The \(<\text{train, validation, test}>\) sets for EPR, SPR, and Ta-Feng datasets are \(<1^{\text{st}}-20^{\text{th}}, 21^{\text{st}}, 22^{\text{nd}}-24^{\text{th}}>, <1^{\text{st}}-16^{\text{th}}, 17^{\text{th}}, 18^{\text{th}}>\), and \(<1^{\text{st}}-3^{\text{rd}}, \text{successive 0.5, last 0.5}>\) month(s) respectively. The interval between each two time steps is 1 month for EPR and SPR datasets, and 1 day for Ta-Feng dataset.

| Datasets/Information | # Users | # Items | # Attributes | Sparsity | Avg. Baskets | Avg. Basket Size |
|----------------------|---------|---------|--------------|----------|--------------|-----------------|
| EPR                  | 229314  | 23      | 169          | 7.92%    | 17.04        | 1.34            |
| SPR                  | 956645  | 24      | 24           | 4.92%    | 14.51        | 1.47            |
| Ta-Feng              | 13541   | 7691    | 5            | 3.58%    | 7.12         | 5.8             |

4.1.2 Baselines & Evaluation Metrics. We include three groups of baseline methods: PopRec considers no sequential patterns; FMC [18] and FPMC [18] are Markov Chain-based sequential methods; and Neural Network based methods with (FDSA+) or without (DREAM [28], Beacon [11], Sets2Sets [8], and CTA [26]) dynamic attributes. We evaluate all methods on the whole item set without sampling. All the items are first ranked and then evaluated by Hit Rate (HR@K), Normalized Discounted Cumulative Gain (NDCG@K), and Mean Average Precision (MAP). In this work, we report HR and NDCG with K=5.

4.1.3 Parameter Settings. We tune the embedding dimension \(C\) from \(\{10, 15, 30, 50\}\), learning rate from \(\{0.0001, 0.001, 0.01\}\), and dropout from \(\{0.0, 0.1, 0.2, 0.5\}\). For DREAM, we tune with RNN, GRU, and LSTM modules. AdamOptimizer is used to update the network with moment estimates \(\beta_1 = 0.9\) and \(\beta_2 = 0.999\). For AnDa, we tune the self-attention layers from \(\{1, 2, 4\}\) and head number on each attention block from \(\{1, 2, 4, 6\}\). Maximum sequence lengths are set as 12, 16, and 30 in EPR, SPR, and Ta-Feng respectively. We report the hyper-parameter sensitivity study results in Figure 3.

4.2 Overall Performance Comparison

Table 3 shows overall results compared with baseline approaches. We observe that, first, our proposed approach consistently outperforms all baselines significantly in terms of Hit Rate, NDCG, and MAP by 3.65% - 21.87%, 9.09% - 43.76%, and 2.32% - 24.53%, which demonstrate the effectiveness of our proposed method. Beside, The next basket recommenders (DREAM, Beacon, CTA, and Sets2Sets) outperform those for next item recommendation (FMC, FPMC). This indicates that learning the sequential patterns with the encoding of the intra-baseket information can better capture users’ dynamic interests. The FDSA+ method performs the best among baselines in the EPR and SPR datasets, while Sets2Sets performs the best in the Ta-Feng dataset. The main reason is that FDSA+ leverages attribute information where EPR and SPR have more attributes. We also report the models’ average inference time (milliseconds per sequence) on 400 sequence inputs in Table 3 (last row). The proposed method takes more time to generate recommendation lists than baseline methods, though is comparable with Set2Sets, DREAM, CTA, and FDSA+.

\(^{1}\)https://www.kaggle.com/c/santander-product-recommendation
\(^{2}\)https://www.kaggle.com/chiranjivdas09/ta-feng-grocery-dataset
Table 3. Performance Comparison of different methods on next basket recommendation. Bold/underlined scores are the best/second best in each row. The last column shows AnDa’s relative improvement over the best baseline.

| Dataset | Metric | FMC | FPMC | PopRec | CTA | Sets2Sets | DREAM | Beacon | FDSA+ | AnDa | Improv. |
|---------|--------|-----|------|--------|-----|-----------|-------|--------|-------|------|--------|
| EPR     | HR@5  | 0.1024 | 0.1297 | 0.4099 | 0.3108 | 0.4155 | 0.2285 | 0.3211 | 0.4613 | **0.5622** | 21.87% |
|         | NDCG@5 | 0.0691 | 0.0889 | 0.2189 | 0.2065 | 0.2207 | 0.1082 | 0.1453 | 0.3211 | **0.4616** | 43.76% |
|         | MAP    | 0.0938 | 0.1103 | 0.1805 | 0.1789 | 0.1912 | 0.1324 | 0.1385 | 0.2556 | **0.3183** | 24.53% |
| SPR     | HR@5  | 0.2197 | 0.3246 | 0.4527 | 0.4783 | 0.5632 | 0.1441 | 0.5027 | 0.6834 | **0.7481** | 9.47%  |
|         | NDCG@5 | 0.1026 | 0.1358 | 0.1192 | 0.2137 | 0.3021 | 0.0694 | 0.2259 | 0.3123 | **0.4049** | 29.65% |
|         | MAP    | 0.1196 | 0.1271 | 0.1465 | 0.1842 | 0.2365 | 0.0991 | 0.1699 | 0.2476 | **0.2638** | 6.54%  |
| Ta-Feng | HR@5  | 0.0064 | 0.0089 | 0.0414 | 0.0379 | 0.0498 | 0.0401 | 0.0442 | 0.0301 | **0.0573** | 15.06% |
|         | NDCG@5 | 0.0035 | 0.0044 | 0.0155 | 0.0214 | 0.0271 | 0.0226 | 0.0256 | 0.0141 | **0.0308** | 13.65% |
|         | MAP    | 0.0027 | 0.0039 | 0.0229 | 0.0202 | 0.0259 | 0.0200 | 0.0255 | 0.0188 | **0.0265** | 2.32%  |

Inference Time msec./seq. **0.1697** 0.1929 0.8428 1.8341 2.3212 2.2542 0.6911 1.9521 2.5172 -

4.3 Ablation Study

To understand the impact of different components in AnDa, we conduct a detailed ablation study using the SPR dataset in Table 4. AnDa(P) is AnDa without periodic index embedding. The results show that the periodic index can help capture users’ seasonal purchase patterns, and thus helps to improve performance. AnDa(B) is AnDa with basket information only. Without dynamic attributes, AnDa(B-) removes the intra-basket module from AnDa(B). AnDa(T) is AnDa without using intra-basket and intra-attribute modules on both items and attributes, and AnDa(I) is AnDa without applying the time level attention module. The performance degradation on the sub-models shows the benefits of each component.

Table 4. Ablation Study on the SPR Dataset.

| Models  | HR@5 | NDCG@5 | MAP | Average | Models  | HR@5 | NDCG@5 | MAP | Average |
|---------|------|--------|-----|---------|---------|------|--------|-----|---------|
| FDSA(+) | 0.6834 | 0.3123 | 0.2476 | -13.91% | AnDa(P) | 0.7340 | 0.3961 | 0.4749 | -1.42% |
| AnDa(B) | 0.7408 | 0.4037 | 0.2605 | -0.90% | AnDa(B-) | 0.7280 | 0.3933 | 0.4753 | -1.89% |
| AnDa(T) | 0.7401 | 0.3977 | 0.2610 | -1.06% | AnDa(I) | 0.7182 | 0.3813 | 0.4666 | -3.61% |
| AnDa   | **0.7481** | **0.4049** | **0.2638** | - | AnDa | **0.7481** | **0.4049** | **0.2638** | - |

4.4 Attention Visualization

We visualize the attention weights of time-level, intra-attribute, and intra-basket attentions on sampled sequences from the SPR dataset in Figure 3 (B) to gain more insights. (a) and (b) are attention weights from two different layers (layer 1 and 4) of time level basket attention, (c) and (d) are from two different heads of the first intra-attribute layer, and (e) and (f) are from two different heads of the first intra-basket layer. From (a) and (b), we can see the attention varies over different layers. While the weights in layer 4 focus more on recent items, the weights in layer 1 attend more evenly to all previous histories. From (c) and (d), we observe that the attention weights vary over different heads, and the module captures meaningful feature interactions. For example, in (c), the position (11, 1) (marked by a red square) corresponding to interacted feature value <"Foreigner index": NO, "Customer’s Country residence": ES> (the bank is based in Spain, so a customer who lives in Spain is not a foreigner). We can also observe that intra-basket attention can capture different item relationships under different heads comparing with (e) and (f).
5 CONCLUSION

In this paper, we propose a novel attentive network AnDa, which models dynamic attributes to better capture users’ dynamically changing interests and intentions. AnDa separately extracts temporal patterns from dynamic attributes and user historical interactions with a novel input encoder. AnDa also generates feature interactions and uncovers item interrelationships in each basket with proposed intra-attribute and intra-basket modules respectively. We evaluate AnDa on three real-world datasets and demonstrate the usefulness of modeling dynamic attributes for next basket recommendation.

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