AT-NCF: An Attention-based Time-aware Neural Collaborative Filtering Approach for Personalized Recommendation

1st Yimin Peng
Key Laboratory of Knowledge Processing &Networked Manufacturing
Hunan University of Sci & Tec
Xiangtan, China
yiminp@yeah.net

2nd Rong Hu
Key Laboratory of Knowledge Processing &Networked Manufacturing
Hunan University of Sci & Tec
Xiangtan, China
ronghu@126.com

3rd Yiping Wen
Key Laboratory of Knowledge Processing &Networked Manufacturing
Hunan University of Sci & Tec
Xiangtan, China
ypwen81@gmail.com

***Abstract*—With the explosive growth of data, how to apply these data with time characteristics to recommendation is particularly important. In order to do that, an attention-based time-aware neural collaborative filtering approach named AT-NCF is proposed in this paper. Concretely, short-term preferences of users are learned by a time perception network, and long-term preferences part are modeled by a historical interaction matrix. Then, the short-term preferences are concatenated with long-term preferences as the dynamic user preference vector. After that, high-order user-item feature interactions are learned by a general neural collaborative filtering framework which includes two types of DL models, Deep Matrix Factorization (DMF) and Multiple-Layer Perception (MLP). Finally, the predicted scores are output from the final layer of AT-NCF. Experimental results on the real-world e-commerce dataset verify the effectiveness of the proposed method.**

Keywords—time-aware, attention mechanism, user preference modeling, neural collaborative filtering, deep learning

I. INTRODUCTION

With the spread of the Internet, the world has entered a new era of information overload and abundance [1]. As an efficient implement to alleviate the difficulty, personalized recommendation system is widely used to supply personalized information service for various business and fields [2].

The current recommendation algorithm are based on several methods, such as Collaborative Filtering (CF) [3][4], Matrix Factorization (MF) [5][6], Deep Learning (DL) [7] methods and Neural Collaborative Filtering (NCF) [8][9][10]. The CF-based methods firstly map users and items to latent factors which share the same latent space, and then use a linear function, such as inner product or cosine distance, to predict the user's preference for items [11]. The MF algorithm use a latent feature vector to connect each user to the item. The DL-based models generally use neural networks to extract abstract feature representations of users and items or to learn the matching score [12]. The NCF combine nonlinear and linear models.

At present, existing NCF methods generally use historical interactions between users and items to build a user preference model or item similarity model without considering the interaction time [13]. Therefore, we propose an AT-NCF approach that takes interaction time into account in user preference modeling. Concretely, AT-NCF contains two parallel processes and a final fusion process: user preference modeling based on time-aware attention network, matching score prediction based on the fusion of two parts. The main contributions of our works are as follows:

- We use a time-aware attention workings to model the dynamic user preference, so as to obtain optimized input embedding for the training of the DL model.
- We use neural collaborative filtering layer to combine DMF and MLP, to model the multidimensional user-item feature interactions to get the prediction scores.
- We performed experiments with different dimensions on an e-commerce dataset, to demonstrate the validity and rationality of the proposed AT-NCF method.

II. RELATED WORK

In this part, we state the application of the attention mechanism and time factor and DL-based model in CF recommendations system, respectively.

A. Collaborative Filtering based on Deep Learning

In deep learning-based recommendation work, Deep Belief Network (DBM) [14] is the earliest neural network model used in recommendation systems. A hierarchical DL model called Collaborative Deep Learning (CDL) [15], which collectively performs deep representation learning based on content and CF recommendation based on the score feedback matrix. Gradually, hybrid recommendation models with both representational learning and deep learning capabilities have become the focus of research. The NeuMF is a specific method under the NCF [7] framework that explains in detail how to learn NCF which emphasizes the binary attribute of implicit data using probabilistic model. ConvNCF [9] which element cross products is used to explicitly model pairwise correspondences between embedded spatial aspect, and convolutional neural network is used to learn the higher order correspondence. Deep Collaborative Filtering (DeepCF) [2] which combining the advantages of presentation learning and matching equation learning, a deep learning network is built to predict the user-item interaction matrix.

B. Collaborative Filtering based on Attention

Recently, the attention mechanism [16] has been widely used in various recommendation systems. For example, Attention CF (ACF) proposed by Chen et al. [17] in 2017 is the first CF recommendation model based on the attention network. ACF introduces two types cases: 1) item-level attention; 2) component-level attention. The former assumes that different historical interactive items have different contributions to user preference modeling and assign different weights to historical interactive items. Then, ATRank proposed by Zhou et al. [18] in 2018 models user preference by considering various heterogeneous behaviors. NAIS proposed by He et al. [8] is an item-based CF method that uses neural networks to model item similarity.

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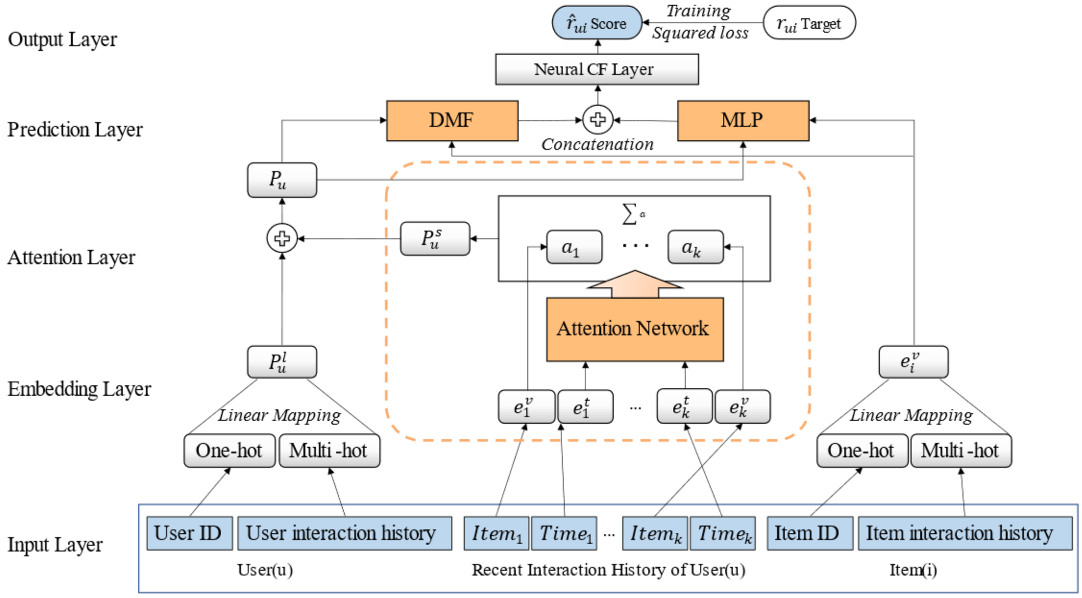

Fig. 1. Attention-Based Dynamic Neural Collaborative Filtering Framework

C. Collaborative Filtering based on Time-aware

The time-aware recommendation model is an intuitive and effective method for modeling time-series information. These methods generally adopt the recommend algorithm based on neighborhood, which pays more attention to the observation items closest to the current moment. TimeSVD++ proposed by Koren et al. [19] is a well-known time-aware recommendation model that improves SVD++ by introducing time-varying biases for each user and item at each time step. Wang et al. [20] proposed an attention model based on time perception. Absolute time signals are used to represent users' periodic behaviors, and relative time signals are used to represent the time relationship between items. TiSASRec [21] directly modeled the interaction timestamp to learn the influence of different time intervals on the next prediction.

III. The Proposed Method

A. General Framework

The general framework of the proposed AT-NCF model is shown in Fig. 1, and the model works as follows: (1) The input layer: this includes the user ID, the item ID, and the user-item interaction history. (2) The embedding layer: the user ID, the item ID are encoded as one-hot vectors, and the user-item interaction history are encoded as multi-hot vectors. (3) The attention layer: the network is used to get individual weights, for each recent historical interaction item with which the user interacts (4) The prediction layer: DMF part, the linear user-item feature interactions are representation by the inner product of the user and the item. MLP part, the user and item embedding vector are taken as the input, and the high-order user-item feature interaction is learned through the multi-layer neural network. (5) The output layer: here, AT-NCF predicted the user-item matching score by integrating the interaction vectors of the two models.

B. Attention-based Dynamic User Preference

Generally, users' preferences are an organic combination of historical and recent preferences. Therefore, we learn the contribution weight of each of the nearest k interaction terms through the attention network. The optimal recent-k value, we get it through experiments. The contribution weight of each interaction item to recent user preference modeling is learned through the attention network, as follows:

$$a(j) = W_2^T \emptyset\left(W_{11} e_i^v + W_{12} e_j^v + W_{13} e_j^t + b_1\right) + b_2 \quad (1)$$

where $a(j)$ is the resulting importance weight of the historical interacted item j; W and b_k are weight matrices and biases of the attention network, respectively; $\emptyset(x)$ is the ReLU. The embedding vector weighted sum of recent interactive items is used as short-term user preferences, and the long-term user preferences are modeled as the arithmetic mean of user historical interactive items, as shown below:

$$P_u^s = \sum_{j=1}^{k} a(j) \cdot e_j^v \quad (2)$$

$$P_u^l = \frac{1}{|R(u)|} \sum_{j \in R(u)} e_j^v \quad (3)$$

where $R(u)$ is the items that user u has interacted with in the former time, and $|R(u)|$ is the numeral of items in $R(u)$. The dynamic user preference vector is modeled as a combination of short-term and long-term preferences, as shown below:

$$P_u = \alpha \cdot P_u^s + (1-\alpha) \cdot P_u^1 \quad (4)$$

C. DL-based feature interaction learning

Deep learning has been shown to approximate any continuous function, it's very suitable for learning complex matching purpose. The DMF interaction vectors and the MLP interaction vectors are fused in the output layer of AT-NCF for matching score prediction.

Since dynamic user preferences P_u and item embedding e_i^v as a given variable, two separate networks are used to learn the hidden representation vectors of users and items as follows:

$$U_u = M_{l_1}(\emptyset(M_1 P_u + c_1) + \cdots) + c_{l_1} \quad (5)$$

$$V_i = N_{l_2}(\emptyset(N_1 e_i^v + d_1) + \cdots) + d_{l_2} \quad (6)$$

where l_1 and l_2 are the layer numbers of the user model and the item model, respectively; M/N and c/d are the weight matrices and biases of the user/item model, respectively. The linear feature interaction between the user and the item is obtained by the inner product, as follows:

$$y_{ui}^{MLP} = (H_u U_u) \otimes (H_v V_i) \quad (7)$$

where $\otimes$ is the inner product between two vectors; H_u and H_v are mapping matrices. Meanwhile, we also use MLP to learn nonlinear high-order feature interactions, as shown below:

$$y_{ui}^{MLP} = L_l^T \sigma(\sigma(L_1[P_u, e_i^v] + g_1) + \cdots) + g_1 \quad (8)$$

where l is the layer number of the model, $[P_u,\ e_i^v]$ is the vector concatenation of the dynamic user preference vector and the item embedding vector. L and g are the weight matrices and biases, respectively.

D. Fusion and Learning

Since the model takes 2 ways to model users and items, it is a common practice to combine the features of the 2 paths by concatenation, which has been widely used in multimodal deep learning. To do this, we concatenate the prediction vectors of the two DL models into a fully connected layer to learn the user-item matching score. Therefore, the final prediction layer is created by concatenating the two models with a final hidden layer, it is formulated as follows:

$$\hat{r}_{ui} = \sigma(W_{out}[\beta \cdot y_{ui}^{DMF}, (1-\beta)\, y_{ui}^{MLP}]) \quad (9)$$

where, W_{out} is the output weight matrix of the model, σ is the sigmoid activation function. Our model is a CF model based on implicit feedback information, so the binary cross-entropy loss function is adopted as the objective function as follows:

$$\mathcal{L}\,(\Theta) = \sum_{(u,i)\in R^{+}\cup R^{-}} r_{ui}\, log\hat{r}_{ui} + (1-r_{ui})(1-log\hat{r}_{ui}) \quad (10)$$

where R^{+} and R^{-} denote positive and negative sample sets, respectively; r_{ui} is the real feedback, $\hat{r}_{ui}$ is the predicted matching score, Θ is the hyperparameter set of the model.

IV. EXPERIMENTS

In this section, we introduce the experimental designs of this experiment and answer the following questions:

- **RQ1.** Does our proposed AT-NCF model achieve better performance than the correlation recommended methods?
- **RQ2.** Whether the key operations we proposed in this work improve the recommendation performance?
- **RQ3.** How do the hyperparameters of the AT-NCF model relate to the recommended performance?

A. Experimental Designs

TABLE I. DATA STATISTICS AFTER PRE-PROCESSING

Field	Taobao	Taobao-mini
Users	987,994	4,856
Items	4,162,024	242,329
Categories	9,439	5,070
Actions	100.15M	0.5M
Avg. actions/user	101.37	102.97
Avg. add-to-favor/user	2.92	2.67
Avg. add-to-carts/user	5.60	5.66
Avg. purchases/user	2.04	2.10

Datasets. This experiment selected the e-commerce dataset provided by Alibaba Group: Taobao user behavior data. The data format is like MovieLens-20M, with each row representing a user interaction with an item, and each column representing the user ID, item ID, item-category ID, interaction type (click, collection, shopping cart and purchase), and timestamp. The details are summarized in Table I.

Evaluation Metrics. To evaluate the performance of item recommendation, the "leave-one-out" evaluation method was used in this experiment. For each user, the most recent interaction is taken as the test set, and the remaining data is taken as the training set. In the ranking of test items, this experiment follows a general strategy, that is, to randomly sample 100 items without user interaction and rank the test items among them. In addition, the performance of the ranked list is judged by the Hit Rate (HR) and the Normalized Discounted Cumulative Gain (NDCG).

Baselines. To verify the effectiveness of our method, we compared the performance of the following methods:

- Item-KNN: Typical item-based CF algorithm. This experiment follows the settings in the reference so that it can be applied to implicit data.
- BPR-MF [22]: Bayesian personalized ranking is a ranking algorithm based on matrix decomposition, uses ranking loss to decompose the user-item interaction matrix.
- Deep-CF [2]: Combine the CF based, on presentation and on function learning. The implicit feedback information is used as the input of two different types of DL models.
- Neural-CF [7]: A general neural CF model with DL-based matching function learning, which combines hidden layers of GMF and MLP to learn the interaction function.
- NAIS [8]: A two-layer neural collaborative filtering method with item similarity information.
- TiSASRec [21]: It is a state-of-the-art time-aware model, it explicitly models the timestamps of interactions.

Parameter Settings. The comparison methods use the parameter settings given in the original literature. Our model is set up using the similar strategy.

B. Performance comparison (RQ1)

We record the convergence process of each model through experiments, Fig. 2 shows the performance of the seven methods in HR@10 and NDCG@10 for 20 iterations. Apparently, DL-based models (NCF and NAIS) are superior to similarity-based method and MF-based models (Item-KNN and BPR-MF), indicating that the DL models has high capabilities in high-order representation modeling and nonlinear feature interaction modeling. The time-aware recommendation method (TiSASRec) performs better than the DL-based recommendation method (DeepCF) by considering the interaction time-stamp information in user preference modeling. Overall, we can see that AT-NCF achieved the best performance. Compared with the base model (Deep-CF), it also leads by nearly 5% in both indicators. This shows that the attention mechanism and time-aware modeling has a great effect for recommendation performance.

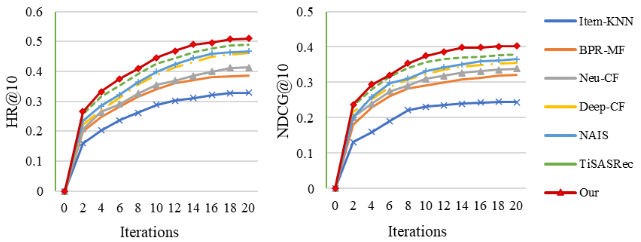

Fig. 2. Performance of HR@10 and NDCG@10 on Taobao-mini.

C. Effectiveness of dynamic preference modeling(RQ2)

Due to the dynamic user preference modeling based on attention time-aware network is the key operation in ATNCF, we conduct experiments to demonstrate its effectiveness in this section. We set the variables of the experiment as 1) Do not use the attention network, named AT-NCF-un-a; 2) Use the attention network but not the time factor, named AT-NCF-un-t. Then, we compared the performance of several related models. The details of the above experiments are shown in Table II. The experimental results show that the method using time factor is better than the method without time factor among all the methods using attention mechanism. At the same time, it shows that interaction time information plays an important role in modeling user preferences and accurate top-k recommendations. In general, the experimental results demonstrate the advantages of time factor embedding and attention mechanism combination.

TABLE II. EFFECTS OF KEY OPERATIONS ON THE MODEL

Method	Hit Rate	NDCG	Avg. Ranking
Neu-CF	0.4257	0.3516	6
Deep-CF	0.4613	0.3652	5
NAIS	0.4739	0.3718	3
AT-NCF-un-a	0.4716	0.3693	4
AT-NCF-un-t	0.4964	0.3928	2
AT-NCF (both have)	**0.5172***	**0.4169***	**1**

D. Sensitivity Analysis of Hyperparameters (RQ3)

The control variable method was used in all the following experiments. Relevant parameters include [vector/model fusion coefficient, the number of latent factors/recent-k item]. From Figure 3 (I), we can see that the fusion coefficient in dynamic user modeling has a great impact on the model performance, because accurate user modeling is the key to high-quality recommendation. When the fusion coefficient is set to 0.5, the model gets the best performance, which shows that short- and long-term preferences is equally important in our model. Fig.3 (II) shows the ranking gets better and better as the number of factors increases. From Fig.4 (I), that 0.5 is the most appropriate coefficient, indicating that model based on linear method and the DL method are equally important in the integration model. Finally is the fusion coefficient of the two models, from Fig.4 (II), In modeling short-term user preferences, the results in the figure indicate that the recommended performance of the last 10 interactive items is a better value.

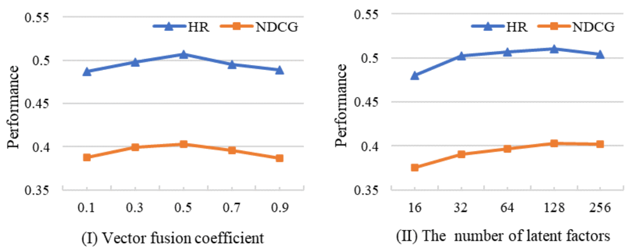

Fig. 3. Effects of fusion coefficient of the two vectors, and effects of the number of latent factors.

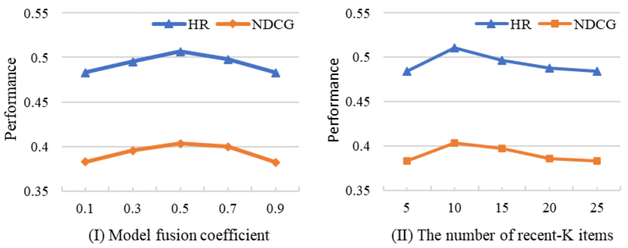

Fig. 4. Effects of fusion coefficient of the two models, and effects of the number of recently interacted items.

V. Conclusion and Future Work

In this work, we proposed an attention-based time-aware multi-layer NCF recommendation model, AT-NCF, for personalized recommendation. Specifically, long- and short-term interests of users are combined to construct the finally user preference model. For matching function learning, we use DMF and MLP to learn the linear and nonlinear user-item feature interaction. In the final fusion layer of our model, the feature interaction vectors of the two models are fused to obtain the final prediction score. Extensive experiments show that our method outperforms the existing CF methods.

In the future, our method can be further studied. Actually, in the real recommended scenario, there is a lot of explicit data, social network data, and other related auxiliary information available. That is one of the focuses of our future work.

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