Entire Cost Enhanced Multi-Task Model for Online-to-Offline Conversion Rate Prediction

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Abstract
Predicting users' conversion rate (CVR) is essentially important for ranking systems in industrial Online-to-Offline (O2O) applications. Numerous efforts have been made in CVR modeling to achieve state-of-the-art performance. However, existing methods mainly focus on the Business-to-Customer (B2C) scenario, which makes implementations to O2O meet with mixed success. This can be revealed via several scenario-specific challenges. For example, O2O users in different locations generally encounter different candidates of surrounding stores. This leads to users' behavioral regularity becoming essentially prominent. Besides, O2O users' conversion includes a two-stage cost, i.e., online order cost and offline transportation cost. This inspires that users' location sensitivity deserves additional attention compared with conventional scenarios. Motivated by these characteristics, we propose a novel CVR prediction method for the O2O scenario, named **E**ntire **C**ost enhanced **M**ulti-task **M**odel (ECMM): i) users' historical behavior sequences across different locations are modeled to capture the users' preference of behavioral regularity; ii) both online order cost and offline transportation cost are modeled to predict the users' aggregated preference for conversion. By designing two novel attention mechanisms, i.e., convert attention and sliding window attention, ECMM can be trained end-to-end to appropriately fit O2O characteristics. Extensive experiments have been carried out under a real-world industrial O2O platform Meituan. Both offline and rigorous online A/B tests under the billion-level data scale demonstrate the superiority of the proposed ECMM over the highly optimized state-of-the-art baselines.

Keywords
Online-to-Offline, Multi-Task Learning, Conversion Rate Prediction

1. Introduction

In the Online-to-Offline (O2O) scenario, industrial platforms generally rely on commission fees of successful conversion as profit. Hence, how to accurately predict users' conversion rate (CVR) is essentially important for ranking systems in O2O industry. However, the O2O scenario requires the conversion of users from not only online click to online order, but also to final offline consumption[1, 2]. In other words, O2O users' behaviors follow a sequential pattern of *impression→click→online order→offline consumption*, which is somewhat different from that of other online e-commerce forms[3, 4, 5], i.e., Business-to-Costumer (B2C). This raises several scenario-specific characteristics that make CVR prediction of O2O challenging, whereas conventional methods may not be perfectly suitable.

In this paper, two critical O2O characteristics summarized in our real practice are focused on: i) *online behavioral regularity*. As a typical form of Location-Based Service (LBS), the O2O scenario provides an online ranking list that only considers surrounding stores of a user's location. The limited candidates require CVR modeling to more accurately grasp users' preference of historical behaviors for online conversion since users' behaviors generally appear homogeneously on the platform in different locations[6, 7, 8] such as clicking/ordering stores with similar prices or distances showing online. ii) *offline transportation regularity*. Different from B2C purchases with only online order cost, O2O users should spend additional transportation cost for the offline consumption [9, 2]. Since user's preference for distance varies in different periods, offline cost should be counted for decision-making dynamically to predict the current transportation preference of the user. This inspires that CVR modeling should consider additionally location-sensitive factors when capturing O2O users' preferences.

Although numerous efforts have been made in CVR modeling to achieve state-of-the-art industrial performance , existing methods such as ESMM and its variants focus on addressing the problems of sample selection bias and data sparsity under the B2C scenario

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[10, 11, 12, 13, 14, 15] and some method solving domain specifically problem are proposed [16, 17, 18, 19]. However, where the intrinsic characteristics of O2O, i.e., online behavioral regularity and offline transportation regularity, are rarely considered.

One possible strategy to improve learning users' online behavioral regularity and offline transportation regularity is to consider user statistical features i.e. user's average online order cost and user's average offline distance features. However, in O2O scenarios, the spatiotemporal nature is inseparable, and using this strategy will lose time-series information when characterizing user preferences. Therefore, sequence representation techniques are also taken into account as shown in Figure 1.

Figure 1: The online order cost and offline transportation cost in user history. Such sequence can represent user online order and offline transportation preferences in time-series.

Hence, in this paper, we propose a novel CVR prediction method for the O2O scenario, named **E**ntire **C**ost enhanced **M**ulti-task **M**odel (ECMM), to model users' aggregated preference under a online-offline cost perspective. Following the formation of state-of-the-art CVR modeling, two auxiliary tasks are focused on, i.e., predicting the click-through rate (CTR) and click-through conversion rate (CTCVR), which can be defined as follows:

$$p(cvr = 1|ctr = 1, \boldsymbol{x}) = \frac{p(ctcvr = 1|\boldsymbol{x})}{p(ctr = 1|\boldsymbol{x})}, \tag{1}$$

where $\boldsymbol{x}$ is $(\boldsymbol{u}, \boldsymbol{s}, \boldsymbol{t}, \boldsymbol{h}_c, \boldsymbol{h}_o)$, $\boldsymbol{u}$ is the user, $\boldsymbol{s}$ denotes the store, and $\boldsymbol{t}$ represents the current context, such as the current time, city, day of the week, and other information that is independent of user and store. $\boldsymbol{h}_c$ and $\boldsymbol{h}_o$ are the user's historical click sequence and order sequence, respectively. We note that the first three terms are the information widely used in conventional CVR modeling, while $\boldsymbol{h}_c$ and $\boldsymbol{h}_o$ are two newly considered ones to assist in the modeling of behavioral and transportation regularities. Moreover, the user's click and order sequences in ECMM are used from the online-offline cost perspective, i.e., online order cost and offline transportation cost, which are essentially different from that of conventional CTR prediction methods of modeling user's multiple interests [20, 21, 22, 23, 24, 25]. As a novel CVR prediction method for the O2O scenario, the contributions of ECMM are threefold:

- ECMM elongates the observation dimensions by learning users' online conversion preferences from historical behavior sequences. A new mechanism named *convert attention* is proposed to learn the user's behavior regularity from the global and local perspectives of online order cost.
- To the best of our knowledge, ECMM is the first method for CVR modeling from the perspective of offline transportation cost. We propose a new mechanism named *sliding window attention* to dynamically learn users' preference of offline transportation.
- ECMM is testified under a real-world industrial O2O platform, where extensive experiments are carried out. Both offline and rigorous online A/B tests under the billion-level data scale demonstrate the significant superiority of ECMM over the state-of-the-art baselines.

2. Related Work

Our work is closely related to traditional e-commerce CVR prediction, where the state-of-the-art model is trained by multi-task learning. Besides, for capture user behavior regularity, user history behavior sequence is considered in our model which is related to user behavior sequence representation. In this section, we give a brief introduction.

2.1. CVR Prediction

Inspired by the success within deep learning, recent CVR prediction model has evolved from traditional approaches to deep approaches. Traditional method used logistic regression [26, 27] and GBDT [28] for modeling CVR problem with feature interactions. However, nonlinear relationships of features are not considered in these models. Modern deep learning based method transforms CVR problem into a multi-task problem [10, 11, 12]. ESMM [10] make use of users sequential actions, "impression $\rightarrow$ click $\rightarrow$ pay", to solve sample selection bias and data sparsity problem over the entire space by simultaneous modeling of CTR and CTCVR tasks. ESM^2 [11] method extends users sequential actions to a more general situation, "impression → click → D(O)Action →pay", which simultaneous models CVR with CTR, CTAVR and CTCVR tasks. HM^3 [12] form "impression → click → D(O)Mi → D(O)Ma → pay" perspective models CVR with CTR, D-Mi, D-Ma and CTCVR tasks.

However, all these methods are based on B2C e-commerce platforms which makes implementations to O2O platforms meet with mixed success. Users have unique sequential actions in O2O, which can be represented as "impression→click→online order→offline consumption". Such situations require CVR model to consider not only user online behavioral regularity, but also offline transportation regularity.

2.2. User Behavior Sequence Representation

In the past decade, user behavior sequence representation have received much attention and achieved remarkable effectiveness. Many well designed recommender methods have been proposed and brought huge commercial revenues for companies and advertisers. In this models, users' history behaviors are transformed into low-dimension vectors after embedding to represent users' interest and other character. DIN [20] employs the attention mechanism to activate historical behaviors locally which capture user diversity interest to the given target item. DIEN [21] further proposes an auxiliary loss and attention mechanism with GRU to capture the dynamic evolution of users interest. DFN [29] jointly consider explicit/implicit and positive/negative feedbacks to learn user unbiased preferences. Moreover, inspired by the success of the self-attention architecture [30], Transformer is introduced in for session CTR prediction [31]. MIND [32] and DMIN [33] model multi-interest by multiple vectors with dynamic routing mechanism and capsule network.

Although all these user behavior sequence representation methods have brought a huge boost to the business from the perspective of user interest, there are still opportunities for improvement in modeling user behavior sequences from other perspectives. Cost sensitivity [34] is an indispensable aspect of user modeling, and users of e-commerce often have certain restrictions on payment costs which makes it possible to further improve the user behavior sequence modeling from the perspective of cost.

3. The Proposed Approach

In this section, we introduce the proposed ECMM model. As shown in Figure 2, it consists of three modules, which are base module includes the online user, the offline store and context features, the entire cost module contain both the user's click and order sequence to capture the user's historical cost preference, and the cost combination module for combining online-to-offline cost to predict CTR and CVR. With this network, the model can capture the user's online behavioral and offline transportation regularities, which are hidden in users' historical behavior sequences. The details of each module are described as follows.

3.1. Motivation

As discussed in the previous section, users' online behavioral and offline transportation regularities are indispensable for O2O recommendation [9, 2, 20, 21]. However, how to define their relationship with users' behavior sequence as well as embody both online and offline cost into a unified framework for CVR prediction remains unexplored.

For one thing, we propose a novel CVR prediction method from the perspective of user historical behavior. We proposed *convert attention* to extract the local and global preference of users' online-to-offline behaviors from both depth and breadth perspectives. From a local view, an order placed by a user is affected by clicks. We design the local impact of a click on a order from the store perspective. From a global perspective, users' overall order sequence receives the impression of click sequence in terms of id, price, and relative distance. For another, to model users' transportation cost, we capture the information of the distance sequence implied in users' preference for offline cost in the O2O scenario, to assist the model in learning users' conversion preference in the offline stage. Each store of a user's historical click and order has distance features which means the offline transportation cost. Then we use *sliding window attention* method to calculate the user dynamic preference for offline cost during different timestamps.

3.2. Base Module

The base module is used to aggregate the basic features. Refer to [10, 11, 12], the embedding and MLP (multiple layer perception) structures are used in the base module. The user, store, and contextual features ($\boldsymbol{u} \in \mathbb{R}^{n_u}$, $\boldsymbol{s} \in \mathbb{R}^{n_s}$, and $\boldsymbol{t} \in \mathbb{R}^{n_t}$) are the inputs of the base module, which are mapped into a d-dimensional space via embedding operations. MLP are used to learn the aggregated vector b of basic features, with ELU [35] as the activation function:

$$\boldsymbol{b} = ELU(MLP(Embedding(\boldsymbol{u}, \boldsymbol{s}, \boldsymbol{t}))). \quad (2)$$

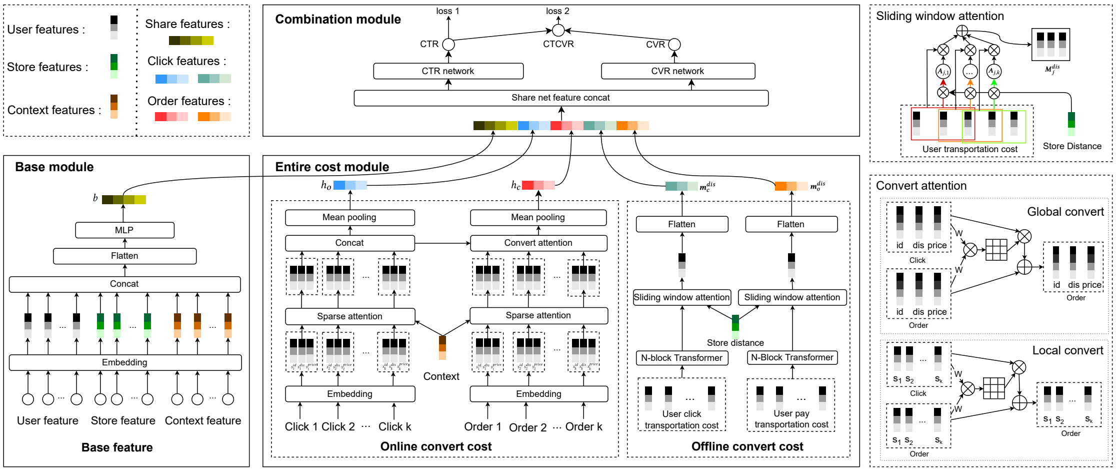

Figure 2: The structure of ECMM. Two auxiliary cost are introduced to model the entire cost, i) online convert cost calculate the behavior regularity of users when they face price and distance shown online, ii) offline convert cost calculate the transportation cost for offline consumption.

3.3. Entire Cost Module

Different from B2C purchase, O2O scenario generally considers surrounding stores of a user's location. Limited candidates actually reduce the possibility of matching with users' preference. Thus, it is critical to accurately capture the user's behavioral regularity from historical behaviors. Meanwhile, O2O users need to consider two-stage costs for decision making, i.e., online order cost and offline transportation cost, both of which should be considered. Entire cost module is designed to solve the above problems and is the most important part of the ECMM model. It contains two parts: online cost feature module and offline cost feature module.

Online Cost Feature Module. Each store that in the user's click or order sequence has side-information features of id s^{id}, distance s^{dis} and price s^{price} that represent the user cost that he decide to click/order an offline store in the online platform. Then we have embedding of the i-th store in user historical behavior,

$$\boldsymbol{h}_i^c = Embedding(s_i^{id}, s_i^{dis}, s_i^{price}), \boldsymbol{h}_i^j \in \mathbb{R}^{3d}. \quad (3)$$

$$\boldsymbol{h}_i^o = Embedding(s_i^{id}, s_i^{dis}, s_i^{price}), \boldsymbol{h}_i^j \in \mathbb{R}^{3d}. \quad (4)$$

Thus, the user's historical click and order behavior sequences, i.e., $\boldsymbol{H}_c$ and $\boldsymbol{H}_o$, can be represented as follows:

$$\boldsymbol{H}_c = concat(\boldsymbol{h}_1^c, \boldsymbol{h}_2^c, ..., \boldsymbol{h}_k^c), \ \boldsymbol{H}_c \in \mathbb{R}^{k\times 3d}, \quad (5)$$

$$\boldsymbol{H}_o = concat(\boldsymbol{h}_1^o, \boldsymbol{h}_2^o, ..., \boldsymbol{h}_k^o), \ \boldsymbol{H}_o \in \mathbb{R}^{k\times 3d}, \quad (6)$$

where k denotes the length of user's click and order sequences.

After embedding, the sparse attention is used to capture the user's historical preference under contextual restriction. The sparse attention takes the embedding of the user's current context feature, click and order sequences as input, and then get the most important user click and order behavior in the current context. The sparse attention [36] is defined as follows:

$$SparseAttn(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = softmax(topn(\frac{\boldsymbol{Q}\boldsymbol{K}^T}{\sqrt{k}}))\boldsymbol{V}, \quad (7)$$

where the *topn* operation takes the top n pieces of historical information most relevant to the current context.

Through the sparse attention, we can get the updated embeddings of user's click and order sequences:

$$\boldsymbol{H}_c^a = SparseAttn(\boldsymbol{Q}_s, \boldsymbol{K}_c, \boldsymbol{V}_c), \ \boldsymbol{H}_c^a \in \mathbb{R}^{k\times 3d}, \quad (8)$$

$$\boldsymbol{H}_o^a = SparseAttn(\boldsymbol{Q}_s, \boldsymbol{K}_o, \boldsymbol{V}_o), \ \boldsymbol{H}_o^a \in \mathbb{R}^{k\times 3d}, \quad (9)$$

where $\boldsymbol{Q}_s$ means converts context features as query vector, $\{\boldsymbol{K}_c, \boldsymbol{V}_c\}$ denotes converts the user click sequence as key and value vectors and $\{\boldsymbol{K}_o, \boldsymbol{V}_o\}$ as well.

In order to better capture the impact of the user click sequence H_c^a on the order sequence H_o^a from the retrieved click and order aggregation information, we propose a *convert attention* mechanism to capture these impacts from both local and global perspectives.

From a local perspective, the preference of the user's conversion to store $\boldsymbol{h}_{o,i}^a \in \boldsymbol{H}_o^a$ can be characterized by the clicked store $\boldsymbol{h}_{c,i}^a \in \boldsymbol{H}_c^a$ related to where the order was placed:

$$\beta_i^j = (\mathbf{W}_c^l \times \boldsymbol{h}_{c,i}^a) \otimes (\boldsymbol{W}_o^l \times \boldsymbol{h}_{o,j}^a)^T, \quad (10)$$

$$\boldsymbol{s}_{o,j}^l = \Sigma_{i=1}^k \frac{exp(\beta_i^j) \times \boldsymbol{h}_{c,i}^a}{\Sigma_{o=1}^k exp(\beta_o^j)} + \boldsymbol{h}_{o,j}^a, \ \boldsymbol{h}_{o,j}^l \in \mathbb{R}^{3d}, \quad (11)$$

where $W_c^l, W_o^l \in \mathbb{R}^{3d\times 3d}$ is trainable parameters. β_i^j represents the correlation between clicked store i and order store j. $s_{o,j}^l$ means to use the aggregation of clicked stores information to obtain the local conversion preference to update the order store information. Here, we use the residual design to retain the original information of the order store.

From a global perspective, the user's preferences for different dimensions (i.e., store's id, price, distance) of order stores are affected by the relevant information of the clicked store. Hence, we separate the submatrix from the click and order sequences:

$$\boldsymbol{H}_{id}^a = (\boldsymbol{s}_i^{a,id}), \boldsymbol{H}_{dis}^a = (\boldsymbol{s}_i^{a,dis}), \boldsymbol{H}_{price}^a = (\boldsymbol{s}_i^{a,price}), \boldsymbol{H}_{ctxj}^a \in \mathbb{R}^{k\times d}. \tag{12}$$

For each dimension, we calculate the impact of the user's clicked sequence on the user's order sequence from a global perspective:

$$\gamma_{ctxi}^{ctxj} = (\boldsymbol{W}_c^g \times \boldsymbol{H}_{c,ctxi}^a) \otimes (\boldsymbol{W}_o^g \times \boldsymbol{H}_{o,ctxj}^a)^T, \tag{13}$$

$$\boldsymbol{H}_{o,ctxj}^g = \Sigma_{ctxi} \frac{exp(\gamma_{ctxi}^{ctxj})}{\Sigma_{ctxi} exp(\gamma_{ctxi}^{ctxj})} \boldsymbol{H}_{c,ctxi}^a + \boldsymbol{H}_{o,ctxj}^a, \quad \boldsymbol{H}_{o,ctxj}^g \in \mathbb{R}^{k\times d}, \tag{14}$$

where $ctxi, ctxj \in (id, dis, price)$, $\boldsymbol{W}_c^g, \boldsymbol{W}_o^g \in \mathbb{R}^{d\times d}$ is trainable parameters, γ_{ctxi}^{ctxj} represents the correlation between the click sequence in dimension $ctxj$ and the order sequence in dimension $ctxi$, $H_{o,ctxj}^g$ means that using the click additional information aggregation to obtain the global conversion preference to update the order sequence. The residual design is also used in this part.

Finally, the aggregation of order sequence and click sequence can be obtained :

$$\boldsymbol{h}_o = Meanpooling(\|_j (s_{o,j}^l) + \|_{ctxj} (\boldsymbol{H}_{o,ctxj}^a)), \quad \boldsymbol{h}_o \in \mathbb{R}^{3d}, \tag{15}$$

$$\boldsymbol{h}_c = Meanpooling(H_c^a), \ \boldsymbol{h}_c \in \mathbb{R}^{3d}, \tag{16}$$

where $\|$ means concatenate of vectors.

Offline Cost Feature Module. In O2O scenario, offline transportation costs also play an important role in the conversion rate as users need to go to offline stores. We first construct the user's historical behavior sequences to represent the user's historical click and order transportation costs, and takes them as the input of the N-layers Transformer encoder:

$$\boldsymbol{T}_c^{dis} = Transformer(\boldsymbol{H}_c^{dis}), \ \boldsymbol{T}_c^{dis} \in \mathbb{R}^{k\times d}, \tag{17}$$

$$\boldsymbol{T}_o^{dis} = Transformer(\boldsymbol{H}_o^{dis}), \ \boldsymbol{T}_o^{dis} \in \mathbb{R}^{k\times d}. \tag{18}$$

We propose a *sliding window attention* mechanism that uses fixed-length windows to characterize the user's preference for transportation cost in different periods, because the user's preference for transportation cost varies in different periods. Note the mechanism has generation for not only O2O platform users but also for other scenario which need to capture user dynamic preference during different period.

Each offline store has a distance feature $\boldsymbol{s}^{dis} \in \mathbb{R}^d$ with respect to the current store, we match this feature with the user's historical distance sequence:

$$\boldsymbol{D}_{j,i} = \boldsymbol{T}_{c,i:i+ws}^{dis}, \ \boldsymbol{D}_{j,i} \in \mathbb{R}^{ws\times d}, \ j \in \{c, o\}, \tag{19}$$

$$\boldsymbol{A}_{j,i} = softmax(\frac{\boldsymbol{D}_{j,i}\boldsymbol{s}^{dis}}{\sqrt{ws}}), \boldsymbol{A}_{j,i} \in \mathbb{R}^{ws\times d}, \ j \in \{c, o\}, \tag{20}$$

$$\boldsymbol{M}_j^{dis} = \Sigma_{i=1}^k \boldsymbol{A}_{j,i}^w \boldsymbol{D}_{j,i}, \ \boldsymbol{M}_j^{dis} \in \mathbb{R}^{ws\times d}, \ j \in \{c, o\}, \tag{21}$$

where $ws \in \mathbb{N}$ denotes our window length, $\boldsymbol{D}_{j,i}$ denotes the subsequence in i-th window, $\boldsymbol{M}_j^{dis}$ denotes the user offline preference of the window length dimension matrix, and $\boldsymbol{m}_j^{dis} = Flatten(\boldsymbol{M}_j^{dis})$ denotes the user offline preference vector.

3.4. Cost Combination Module

In this section, we embody CTR and CVR prediction tasks into a multi-task framework. The input of this module is the concatenation of the outputs from base module and entire cost module. r^{ctr} and r^{cvr} are calculated by MLP network, respectively.

$$r^{ctr} = ELU(MLP([\boldsymbol{b}, \boldsymbol{h}_c, \boldsymbol{h}_o, \boldsymbol{m}_c^{dis}, \boldsymbol{m}_o^{dis}])), \tag{22}$$

$$r^{cvr} = ELU(MLP([\boldsymbol{b}, \boldsymbol{h}_c, \boldsymbol{h}_o, \boldsymbol{m}_c^{dis}, \boldsymbol{m}_o^{dis}])). \tag{23}$$

To this end, we calculate the post-view click through&conversion rate (CTCVR) by $r^{ctcvr} = r^{ctr} * r^{cvr}$. The loss function used here is lambda loss [37].

4. Experiments

In this section, we evaluate the model performance of the proposed ECMM. We describe the experimental settings and experimental results as follows.

4.1. Experimental Settings

Datasets. We selected 30 days exposure logs from August to September obtained from the online O2O business system to train the CVR model. We have two test sets: one is one day dataset in September and another is three days in October. Since user behavior evolves with time, the closer the time is to the training data, the closer the distribution of user behavior is to the training data,

Table 1
Offline experimental results on two testing sets.

Models	September		October		October improvement	
	CTR−NDCG	CTCVR-NDCG	CTR−NDCG	CTCVR-NDCG	CTR−NDCG	CTCVR-NDCG
ESMM	0.7560	0.8446	0.7515	0.8455	0.00%	0.00%
ESMM+DIN	0.7577	0.8456	0.7528	0.8463	0.17%	0.09%
ECMM wo *offline and convAttn*	0.7575	0.8458	0.7525	0.8464	0.13%	0.11%
ECMM wo *offline*	0.7574	0.8462	0.7532	0.8469	0.23%	0.17%
ECMM wo *online and slidWinAttn*	0.7577	0.8458	0.7533	0.8467	0.24%	0.14%
ECMM wo *online*	0.7579	0.8463	0.7534	0.8471	0.25%	0.19%
ECMM+dualInfo	0.7576	0.8462	0.7533	0.8469	0.24%	0.17%
ECMM+sepInput	0.7581	0.8465	0.7537	0.8472	0.29%	0.20%
ECMM	**0.7585**	**0.8480**	**0.7541**	**0.8487**	**0.34%**	**0.38%**

and the longer the relative time is, the user behavior distribution will change. Therefore the test sets in this experiment can effectively evaluate the accuracy and generalization of the model. The number of our training samples is approximately 1.1 billion, while the testing sets are 40 million and 100 million, respectively.

Metric. The goal of our ranking task is to provide a list that is more likely to facilitate users' conversion. The evaluation metric used in this paper is NDCG. We have two ranking strategies: sorting by CTR and sorting by CTCVR. So we have NDCG sorted by CTR to predict real click rate and NDCG sorted by CTCVR to predict real purchase rate. The calculation criteria are as follows:

$$NDCG = \frac{DCG}{IDCG} = \frac{\Sigma_{j=1}^{n}(2^r - 1)/log(1+j)}{\Sigma_{j=1}^{|rel|}(2^r - 1)/log(1+j)}, \tag{24}$$

where n represents the length of the list of stores ranked by the model, r represents the label of the sample including click and order differing from the model task, and $|rel|$ represents the number of stores that label is not zero.

Compared Methods. Our baseline is a highly optimized ESMM model that incorporates a large number of business features and handcrafted features. The total number of features is 473. The embedding matrix of dimension d is 10. We use the sequences feature from users' history for 180 days and the length k is 50. The numbers of Transformer layers N is 2. Because 80% of users click sequence length is less than 10 and order sequence length is less than 5, and considering the service performance, the n of the sparse attention we chose is 10. The dimension of the MLP used in the base module is 1024, and the dimension of the four-layer MLP used by the CTR and CVR networks is 512, 256, 128, 1 with ELU activation function, respectively. And all baselines take into account the statistical user features of online and offline costs for fair comparison. We conduct comparative experiments with three categories of methods:

(1) Baselines: a) **ESMM** [10]. An outstanding multi-task model for learning CTR and CVR in the industry. b) **ESMM+DIN** [20]. Based on ESMM, users' click sequence feature and the current store feature are introduced by DIN method.

(2) Ablation: a) **ECMM wo *offline and convAttn.*** Based on ECMM, we only use online convert cost without convert attention. b) **ECMM wo *offline.*** Based on ECMM, we only use online convert cost. c) **ECMM wo *online and slidWinAttn.*** Based on ECMM, we only use offline convert cost without sliding window attention. d) **ECMM wo *online.*** Based on ECMM, we only use offline convert cost.

(3) ECMM variants: a) **ECMM+dualInfo:** Based on ECMM, we calculate convert attention not only convert click sequence information to the order sequence but also convert order sequence information to the click sequence. b) **ECMM+sepInput:** Based on ECMM, we use the click feature as the input for the CTR network, the order feature as the input for the CVR network.

4.2. Offline Performance

The evaluation metric used in this paper is CTR-NDCG and CTCVR-NDCG. Table 1 shows the experimental results of the comparison methods on two testing sets, from which we have:

For the entire cost module, compared with ESMM, ECMM can obtain a 0.35% gain on CTR-NDCG and 0.38% gain on CTCVR-NDCG [1]. And all other ablation methods and variants can also improve the model performance after modeling users' behavior sequences.

For online cost feature, compared with ESMM, ESMM+DIN adding click sequence has a certain increase in CTR- and CTCVR-NDCG. As showen in Figure 3, ECMM wo *offline and convAttn*, which is further added to the order sequence, slightly decreases in the CTR-

[1]For large-scale datasets in industrial recommender systems, the improvement is considerable because of its hardness, and the testing results in Section 3.3 further verify the significant improvement of our proposal.

NDCG, but greatly improves the CTCVR-NDCG. ECMM wo *offline* indicates that the convert attention mechanism can learn users' order characteristics from click to order. These three methods show that it is effective to utilize historical features to improve CVR prediction. The convert attention brings 0.18% and 0.19% gains in CTR-NDCG and CTCVR-NDCG.

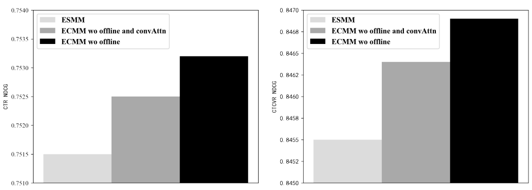

Figure 3: Improvement in conversion rate prediction from online behavioral regularity in October.

For offline cost feature, the ECMM wo *online and slidWinAttn* model that uses distance sequence features brings stronger effects improve both CTR- and CTCVR-NDCG. As showen in Figure 4, comparing ECMM wo *online and slidWinAttn* with ESMM, it can be seen that the offline transportation cost is indispensable for the conversion rate prediction of O2O platform. And ECMM wo *online* model introduced by our proposed slide window attention brings greater gains by dynamic matching user preference during different times. The sliding window method brings 0.02% and 0.05% gains in CTR-NDCG and CTCVR-NDCG.

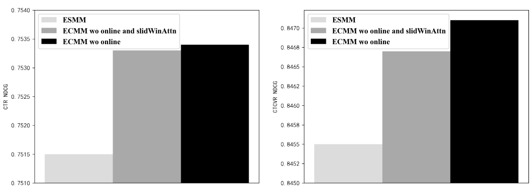

Figure 4: Improvement in conversion rate prediction from offline transportation regularity in October.

In order to explore whether the user's historical order will affect click, we further study with the ECMM+dualInfo model that the order sequence transmits information to the click sequence. It can be seen that the click NDCG decreased by 0.05%, and the CTCVR-NDCG decreased by 0.06%. We separate the click and the order features into the CTR network and CVR network to obtain the ECMM+sepInput model to verify the feature impact of different task, and found that separate features will reduce model performance.

To verify the generalization of our model instead of fitting users over a certain period, we further evaluate our method on a test set in October. The results are

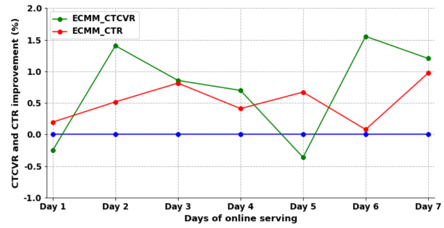

Figure 5: Online performance. The improvements of CTCVR and CTR are significant with the significance level α=0.05.

consistent with the assessment in September. The ECMM model shows that the advantage of considering users' online behavioral and offline transportation regularities is helpful in predicting users' current CTR and CTCVR.

4.3. Online Evaluations

Online A/B test was conducted in the recommender system in 7 days in January 2022. For the control group, 10% of users were randomly assigned and presented in a recommender system presented by a highly optimized ESMM algorithm. For the experimental group, 10% of users were randomly selected to use the ECMM method. In the online experiment, we choose CTR and CTCVR as evaluation indicators, where CTCVR represents the purchase rate of each request. The result is shown in Figure 5. We can see that our proposed ECMM method improves the CTR by 0.52% (p-value=0.00<0.05) compared with the baseline model, and the CTCVR by 0.73% (p-value=0.02<0.05), which has a 1.8% (p-value=0.02<0.05) increase in total revenue. Here, total revenue increases to 1.8% with a 0.45% increase in CTCVR means the model provides users with higher price list. So far, the ECMM method has been applied to the main online traffic and has served more than hundreds of millions of users, bringing a significant increase in the total revenue of Meituan.

5. Conclusion

In this paper, inspired by the user sequential behaviors in O2O platform, a novel model is proposed to predict conversion rate. Further, introduce *covert attention* and *sliding window attention* in the cost module to learn users' online behavioral regularity and offline transportation regularity. At the same time, offline experiments have proved the effectiveness of our proposed method to learn users' conversion from users' click sequence to order sequence, and the accuracy of the ranking list is improved by evaluating NDCG. Online experiments show that ECMM method has a significant effect on improving the total revenue of the O2O platform. For now, the ECMM method has been applied to the main online traffic, bringing a significant increase in the total revenue of the enterprise.

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