ABSTRACT
Recommender system (RS) has become crucial module in commercial systems. Most of RS are in waterfall flow form especially on mobiles. Specifically, we target to Taobao home-page feeds flow RS which is one of the largest e-commerce RS. Nowadays almost all the waterfall flow RS are based on client-and-server framework, in which computing overhead on cloud as well as network bandwidth and latency cause the delay for system feedback and user perception. So that the recommended contents may be not what users want at the moment, users' browsing and clicking willingness will decrease. Edge computing has the potential to address the concerns of response time, network bandwidth as well as data privacy. Our work takes the first to combine edge computing and RS. For system, we design and implement novel EdgeRec (Recommender System on Edge) aiming to do reranking on mobile device, which achieves Real-time Perception and Real-time Feedback. For algorithm, we propose Heterogeneous User Behavior Sequence Modeling and Context-aware Reranking with Behavior Attention Networks that captures users’ plentiful behaviors and models reranking considering about user behavior context respectively. We conduct extensive offline and online evaluations on real traffic of Taobao RS before fully deploying EdgeRec into production.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

1 INTRODUCTION
The explosive growth and variety of information (e.g., movies, commodities, news etc.) available on web frequently overwhelms users, while Recommender System (RS) is valuable means to cope with the information overload problem. RS usually provides the target user a list of items, which are selected from the overwhelmed candidates to best satisfy his/her current demands. In most scenarios of RS especially on mobiles, recommended items are shown in a waterfall flow form, i.e. users scroll the screen and items will be presented one-by-one. Taobao\textsuperscript{1} home-page feeds flow RS (a.k.a. Guess You Like) is one of the largest e-commerce RS, which serves hundreds of millions of users and generates billions of personalized recommendation pages every day.

Nowadays almost all the waterfall flow RS are based on client-and-server framework. Mobile client first initiates paging request to RS servers on cloud when a user scrolls on RS scenario. Then RS models (see Sec. 2) serving on cloud respond to the paging request and generate a list of ranked items which will be displayed to the user. User behaviors (i.e. user interactions with items) used by RS models to capture user’s personalized preference are collected on mobile client and sent to feature system on cloud over the network. Specifically in current Taobao RS illustrated in Fig. 1, the paging size is set to 50 due to the computing overhead for serving such complex RS models on cloud which affects system Response-Time (RT) and is now up to 1s including network transmission. Under such setting, Query-Per-Second (QPS) of system at traffic peak is about 20 thousands in common days and 90 thousands in some promotion days (e.g., Double 11 Global Online Shopping Festival\textsuperscript{2}). Furthermore the delay time of feature system receiving user behaviors can be up to 1min due to the limitations of network bandwidth and latency.\textsuperscript{3} Users in Taobao RS often find the items they want to buy gradually in the process of browsing. In this process, RS should capture

\textsuperscript{1}Yu Gong and Ziwen Jiang contribute equally.

\textsuperscript{2}We specifically refer to mobile Taobao App in our paper.

\textsuperscript{3}TimeTunnel (http://code.taobao.org/p/TimeTunnel/src/) and Blink (https://www.dataversity.net/year-blink-alibaba/) are involved as Message-Oriented Middleware and Streaming Computing systems.

ACM Reference Format:
Yu Gong, Ziwen Jiang, Kaiqi Zhao, Qingwen Liu, Wenwu Ou. 2020. EdgeRec: Recommender System on Edge in Mobile Taobao. In Proceedings of ACM Conference (Conference’17). ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnnn

© 2020 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/Y/MM. . . $15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnnn

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference’17, July 2017, Washington, DC, USA

Figure 1: The current client-and-server based system for waterfall flow RS in mobile Taobao.
the changes of users’ interests and recommend corresponding items that meet the requirements in time. However current client-and-server based system for waterfall flow RS fails to handle that as there are two major drawbacks as follows:

- **Delay for System Feedback**: Due to the paging mechanism in RS, system on cloud has few opportunities to respond so that it may fail to adjust the recommendation results in time to satisfy users’ varied demands. Take an example in Fig. 1, a user clicks an item with dress category in the 5th position of current page then asks customer service and adds it to cart in its detail page. These behaviors all reflect his/her preference to that item, but there may be no similar items in the rest of 45 positions that satisfy his/her demand before next paging request.

- **Delay for User Perception**: For RS models serving on cloud, there may be up to 1min delay time for capturing user behaviors due to network latency so that they fail to model users’ real-time preferences when responding to client. For example in Fig. 1, a user’s behaviors upon item in the 49th position reveal his/her preference to radios at present but RS may not recommend similar radios in the next page because of not receiving those behaviors in time. Furthermore network bandwidth also limits current RS models to capture more plentiful and detailed user behaviors on client.

To summarize, the problem of RS is that perception of users and timing of content adjustment for system cannot match the changes of users’ preferences, so that the recommended contents are not what users want at the moment, then users’ browsing and clicking willingness will decrease.

Edge computing is a buzzword now. It has the potential to address the concerns of response time, network bandwidth as well as data privacy [21], which is ideal for applications that require high real-time performance, e.g., smart home [23] and smart city [22]. Our work takes the first to combine RS and edge computing (here mobile device is the edge) to tackle the above discussed problems. Challenges include how to make RS on edge cooperate with existing RS on cloud, how to support serving large scale neural network models on edge and how to develop adaptive RS algorithms to take full advantage of edge computing. In our work, we propose novel **EdgeRec** (Recommender system on Edge) in mobile Taobao, which achieves **Real-time Perception** and **Real-time Feedback** without additional requests to RS servers. EdgeRec is a definitely new system both in industry and research, in which our main contributions can be summarized as follows:

- **System Architecture**: We design architecture of EdgeRec to do inner reranking on mobile device cooperated with RS on cloud that provides candidate items over traditional paging requests (see Sec. 3.1).

- **System Implementation**: EdgeRec supports serving large scale neural network models considering computing and storage efficiency on mobile device by distributing the model across edge and cloud (see Sec. 3.2).

- **User Behavior Modeling**: We propose **Heterogeneous User Behavior Sequence Modeling** to do user perception, we first design novel feature system (see Sec. 4.2) then simultaneously model positive and negative feedback interactions between users and items considering both interacted items and their corresponding actions (see Sec. 4.3). Based on EdgeRec, plentiful and detailed user behaviors in our feature system are collected and consumed on device so that our model can utilize in real-time. However it is impractical for RS models on cloud to model those due to the limitations of network bandwidth and latency.

- **Context-aware Reranking**: We propose **Context-aware Reranking with Behavior Attention Networks** to do reranking on device, particularly we model interaction between candidate items and real-time user behavior context by our proposed **Behavior Attention** mechanism (see Sec. 4.4). Depending on the ability to rerank items on device based on EdgeRec, we achieve real-time response to user’s demands without additional requests to RS servers.

We conduct extensive offline and online evaluations on real traffic of Taobao RS. Both quantitative and qualitative analysis justify the effectiveness and rationality of our proposed **Heterogeneous User Behavior Sequence Modeling and Context-aware Reranking with Behavior Attention Networks** algorithms targeting to user perception and reranking respectively. Furthermore EdgeRec contributes up to **1.57% PV, 7.18% CTR, 8.87% CLICK and 10.92% GMV promotions in online A/B testing**, which brings significant improvement to current Taobao RS. Now EdgeRec has already been deployed online and serves the main traffic.

2 **INDUSTRIAL RECOMMENDER SYSTEMS**

Industrial RS usually consists of the matching stage and ranking stage (see Fig. 1), in order to handle the billion-scale of users and items [7]. The matching stage [13, 28] is responsible for retrieving thousands of candidate items that are relevant to user interests. In the ranking stage, we first predict click-through-rate (CTR) [25, 26] and conversion-rate (CVR) [16] of users interacting with these candidate items (e.g., click or buy). And then apply learning-to-rank (LTR) method [15] based on features of CTR, CVR and other user preference scores (e.g., brand or shop preferences, etc) to rank the items and give the top-\(k\) results [14]. Furthermore reranking methods [1, 9, 19, 29] which consider local ranking context given initial ranked items from LTR will be applied.

Nowadays almost all the above RS models are serving on cloud servers (based on cloud computing [12]) and respond to the paging requests from mobile client when user scrolls on the waterfall flow RS (i.e. in client-and-server framework). So response-time (RT) is a critical metric that affects user experience. Queries-per-second (QPS) is a factor affecting RT, which causes computing overhead for serving such complex RS models on cloud servers. So that we cannot make the paging size much smaller, which prevents the adjustment of recommendation results in time. Network bandwidth and latency are other factors affecting user experience in RS. Almost

---

1[https://www.theverge.com/circuitbreaker/2018/5/7/17327584/edge-computing-cloud-google-microsoft-apple-amazon](https://www.theverge.com/circuitbreaker/2018/5/7/17327584/edge-computing-cloud-google-microsoft-apple-amazon)
all the models in both matching and ranking stages depend on user behaviors (i.e. user interaction with items) as input features to ensure the personalization. And user behaviors are collected on mobile client and sent to cloud servers over the network, in which network bandwidth and latency may limit the amount and timeliness of user behaviors. To summarize, RS based only on cloud computing does not work perfectly in waterfall flow scenario.

3 SYSTEM

The goal of EdgeRec system is to do inner reranking on mobile device before paging requests which provide candidate items. So the system can capture timely rich user behaviors (a.k.a. Real-time Perception) and respond to users’ demands in time (a.k.a. Real-time Feedback) without additional requests to RS servers, in which we need not consider about the overhead of cloud computing and network communication (e.g., RT, QoS, network bandwidth and latency). In the following we first give an overview of the system and then elaborate on implementations for the critical modules.

![Figure 2: EdgeRec system overview. The left part of modules are deployed in mobile Taobao client and the right part of modules are serving on cloud.](image)

3.1 System Overview

In Fig. 2, we show the overview of EdgeRec system for Taobao RS. It should be mentioned that EdgeRec doesn’t aim to replace RS on cloud but cooperates with it. The main modules and workflows are illustrated as follows:

**Client Native (CN)** first initiates paging requests as usual to RS servers and then caches the candidate items with corresponding item features returned from RS servers. In EdgeRec, the paging size is kept as the same as 50 with original RS in Taobao for the stability in production. However the number of returned items from RS servers to CN is set as 100 in order to provide more space for reranking on cloud for the candidate items before responding to CN.

**Offline Training (OT)** module first collects logs from MS and constructs data samples before model training. Then it splits the trained neural network model into three parts: (1) sub-model of User Behavior Modeling, (2) sub-model of Context-aware Reranking and (3) embedding matrices (e.g., category and brand). Finally sub-models of User Behavior Modeling and Context-aware Reranking will be sent and deployed on MS module, and embedding matrices will be kept in a key-value storage on cloud.

3.2 System Implementation

In this section we will introduce the implementation details for two critical modules deployed in mobile client supporting EdgeRec system in the left part of Fig. 2. We first introduce what client native module should provide to support EdgeRec models. Then talk about how EdgeRec neural network models serving on mobile device.

3.2.1 **Client Native.** One key module of client native is to collect user rich behaviors on client in mobile Taobao RS, including behaviors for user browsing items, clicking items, etc (more detailed behaviors can be seen in Sec. 4.1). These user behaviors are then stored in a database on device. As running of EdgeRec models (a.k.a. Model Serving) is triggered by client native, another critical module is the strategy when to trigger. Here we set the trigger points according to user’s online real-time behaviors and are summarized as follows: (1) user clicks an item, (2) user deletes an item (i.e. long press) and (3) k items have been exposed without clicking. We argue that these three types of user behaviors all reveal user’s current preferences on RS and RS should respond him/her in time (i.e. trigger Model Serving).

3.2.2 **Model Serving.** Deep neural network models serving on mobile device face a lot of challenges against traditional cloud serving, e.g., overhead of computing and storage. There are two critical implementations for EdgeRec model serving targeting on computing and storage efficiency respectively. The idea is to distribute the model across edge and cloud, which makes EdgeRec support serving large scale neural network models on mobile device for RS.

**Computing Efficiency.** User Behavior Modeling (see Sec. 4.3) and Context-aware Reranking (see Sec. 4.4) are trained together but deployed separately and run asynchronously on device. User Behavior Modeling utilizes recurrent neural network (RNN) [17] based sequence modeling approach which is much inefficient if it always does inference from start (i.e. with $O(n)$ time complexity). So it is independently inferred along with users’ online incoming behaviors in real-time by the recurrent characteristic of RNN (i.e. see Sec. 4.3) to capture timely user behaviors and Context-aware Reranking (see Sec. 4.4) to respond to users in time. Besides MS collects logs to cloud. Finally RS returns the ranking of candidate items to CN.

**Recommender System (RS)** on servers responds to paging requests from CN and provides candidate items with initial rankings (see Sec. 2). Here RS can be regarded as a recall module in EdgeRec. Besides it looks up item features and embeddings (e.g., category embedding) that models in MS module need from a key-value storage on cloud for the candidate items before responding to CN.

---

6We utilize MNN (https://github.com/alibaba/MNN) as our online deep neural network inference engine on device. ——

7The configurations are set empirically according to specific RS environment.
with O(1) time complexity) and produces behavior encodings which will be stored in database on device. Context-aware Reranking will first retrieve the behavior encodings from database and then do model inference based on them.

**Storage Efficiency.** ID type of features are common and important in RS models, we always utilize techniques of embedding [10, 26] to transform them. However they face challenge of storage efficiency when serving on mobile device. For example, item brand in our model is an ID feature with about 1.5 million size of dictionary and will be transformed into 40 size of hidden state by embedding layer, in which the embedding matrix will be size of 1500000×40 (i.e. about 230MBs). Models with such large embedding matrices will suffer from overhead of storage when deployed on mobile device. In our proposed system, we extract embedding matrices from the trained model to deploy in a key-value database on cloud. And these embedding matrices will be retrieved by corresponding items when RS on servers responds to the paging requests from client native and sent to client as item features. The rest parts of model without embedding layers serving on device (i.e. the model is about 3MBs) will take the embedding features as inputs and then do model inference.

Furthermore we design a model version strategy to ensure model synchronization when it is updated, because successfully deploying model on device may be far delayed against deploying model (i.e. the embedding matrices) on cloud, which depends on the current status of users’ mobile device (e.g., connected to wifi or 3G). In EdgeRec system, we will generate a unique version ID for every trained model. This version ID is kept along with the deployed on device and embedding matrices stored on cloud. Client native first initiates paging requests with the model version ID on device, then RS on cloud gets the model version ID and retrieves the embedding matrices with corresponding version before responding to the client.

4 ALGORITHM
We first give a formal definition of reranking on device particularly considering user behavior context in Sec. 4.1. Then we introduce the used features and our thoughts about them in Sec. 4.2. Finally we talk about our proposed models of user behavior modeling and context-aware reranking in Sec. 4.3 and Sec. 4.4 respectively.

4.1 Problem Definition
In this section, we formalize the problem of how to adapt reranking method on edge targeting waterfall flow recommendation scenario based on above EdgeRec system. Given the initial ranked item list \( S_r \) cached on edge which is generated by the existing RS on cloud, for the reranking request \( r \in R \) in Model Serving module triggered by Client Native module, our goal is to find a scoring function \( \phi \) considering (1) features of item \( x_i \), (2) local ranking context from initial model as \( s \) and (3) real-time user behavior context on current recommendation environment as \( C \). The way to find this optimal \( \phi \) is to minimize a loss function \( \mathcal{L} \) defined as:

\[
\mathcal{L} = \sum_{r \in R} \ell(\{y_i, \phi(x_i, s, C) | i \in S_r\}),
\]

where \( y_i \) is the label on item \( i \), e.g., click (labeled as 1) or not (labeled as 0) and \( \phi \) is ranging from 0 to 1.

Reranking models considering local ranking context are studied a lot in previous works. And the local ranking context is represented as the listwise interaction between initial ranked candidate items which can be modeled by RNN [1, 29] or Transformer [19]. Here we regard that local ranking context has become a default component in reranking models including ours. Furthermore we think real-time user behavior context is also important for reranking problem especially in waterfall flow recommendation scenario, while few works consider about it before. Sec. 4.3 introduces how we model real-time user behavior context with Heterogeneous User Behavior Sequence Modeling and Sec. 4.4 talks about how we model interaction between candidate items and real-time user behavior context with Context-aware Reranking with Behavior Attention Networks. The following algorithms are deployed in EdgeRec Model Serving module in mobile Taobao. By combining edge computing system and context-aware reranking model, we can achieve Real-time Perception and Real-time Feedback in RS to satisfy users’ online varied demands much better.

4.2 Feature System
In this section, we first give a discussion about our feature system then introduce the detailed user action features for item exposure and item page-view as well as corresponding item feature.

4.2.1 Our Thoughts. First of all, in personalized search and recommender systems, “personalization” mainly depends on user’s behavior data, e.g., Youtube-DNN [7], DIN [26], DUPN [18] and other works [13, 20, 25, 27], they all model user’s recent interacted item sequence as input of the personalized ranking model. However, previous works only consider the direct “positive feedback” interactions between users and items (e.g., clicking or transaction), and rarely consider the indirect “negative feedback” interactions (e.g., skipping or deleting). It is true that “positive feedback” features are relatively more clear and the noise is smaller. But real-time “negative feedback” interactions between users and items are also very important especially in waterfall flow RS. Take an intuitive example in online Taobao RS, after real-time multiple exposures of an item category, the corresponding CTR of its re-exposure will decrease significantly.

On the other hand, previous works of personalized ranking models only consider the characteristics (e.g., category, brand and others detailed in Sec. 4.2.4) of items interacted with users, and the central object is “interacted item”. However, the “interacted actions” between users and items should also be concerned. For example, after user clicking an item, the actions (e.g., add to favorite, add to cart and others detailed in Sec. 4.2.3) in its detail page (we call as item page-view) reflect the real user preference to this item. On the contrary, although user doesn’t click an item, the interacted actions on this item exposure (e.g scroll speed, exposure duration and others detailed in Sec. 4.2.2) can represent the degree of this item regarded as a “negative feedback”. Sometime if a user focuses on an item exposure for a long time without clicking it, it can’t absolutely indicate that he/she doesn’t like it. Especially in current waterfall flow RS, the display of item is getting more and more informative, e.g., with larger picture, various keywords and even automatically played video, clicking has become a very “luxury” positive feedback for some users.
Finally, based on our proposed EdgeRec system all the user behavior features are collected, extracted and consumed on edge (i.e. user’s mobile device). It can break through the limitations of network latency and bandwidth comparing to current client-and-server based RS system. So that we can utilize users’ more plentiful and detailed behaviors in a more real-time way. Furthermore, user’s raw behaviors are processed and utilized on his/her own mobile device, which can alleviate user data privacy issues to a certain extent.

To summarize, feature system in our work is novel and promoted (1) from “relying on only positive feedback interactions” to “simultaneously paying attention to positive and negative feedback interactions”, (2) from “concerning on only interacted items” to “considering both interacted items and their corresponding actions”, and (3) from “in quasi real-time way” to “in ultra real-time way”.

4.2.2 Item Exposure User Action Feature. Item Exposure (IE) user actions reveal how user behaves on an item exposure in RS’s current display page. Fig. 3(a) illustrates an item exposure in waterfall flow RS in mobile Taobao. And features for corresponding user actions on it can be classified as (see details in Tab. 1) (1) item exposure statistics ($e_1 \sim e_2$), (2) user scrolling statistics ($e_3 \sim e_5$), (3) user deleting feedbacks ($e_6$) and (4) time decay ($e_7$). Here we represent concatenation of $e_1 \sim e_7$ for corresponding item $i$ as item exposure action feature vector $a^i_{IE}$.

4.2.3 Item Page-View User Action Feature. Item Page-View (IPV) user actions reveal how user behaves in the item detail page after clicking an item. Fig. 3(b) illustrates an item page-view in mobile Taobao. And features for corresponding user actions in it can be classified as (see details in Tab. 1) (1) item page-view statistics ($d_1 \sim d_2$), (2) click or not on each block ($d_2 \sim d_{11}$) and (3) time decay ($d_{12}$). Here we represent concatenation of $d_1 \sim d_{12}$ for corresponding item $i$ as item page-view action feature vector $a^i_{IPV}$.

4.2.4 Item Feature. Apart from the features for user action, we need features for corresponding item. And they can be classified as (see details in Tab. 1) (1) discrete features which are learned by embeddings ($p_1 \sim p_5$) and (2) raw features which are provided from the base ranking models ($p_6$). Here we represent concatenation of $p_1 \sim p_7$ for item $i$ as item feature vector $p^i$.

4.3 Heterogeneous User Behavior Sequence Modeling

In this section, we will introduce how to model real-time user behavior context defined as $C$ in Eq. 1. Following the works [7, 18, 26], we apply sequence modeling approach as well. However previous works only consider user’s positive interacted items as we discussed in Sec. 4.2.1 so that they cannot handle user behavior sequence modeling well based on our proposed feature system. Challenge is that there are two aspects of heterogeneity in user’s behavior data. In our work, we propose Heterogeneous User Behavior Sequence Modeling (HUBSM) particularly targeting on the following two heterogeneities.

The first is heterogeneity of “item exposure behavior” and “item page-view behavior”. As item clicks are much more sparse compared to item exposures in RS, if they are encoded together in one sequence, we believe that item page-view behaviors will be dominated. So we chose to model them separately (i.e. Item Exposure Behavior Sequence Modeling and Item Page-View Behavior Sequence Modeling). The second is heterogeneity of “user behavior actions” and corresponding “user interacted items” which represents two kinds of feature space. User behavior action features reveal the distribution of how user behaves upon an item while item features represent the distribution of corresponding item characteristics. We choose to encode them separately first and then do the fusion for concerning about Behavior Attention mechanism in the following context-aware reranking model (see Sec. 4.4).

Here the used encoder function is a RNN [17] with gated recurrent unit (GRU) cell (see Fig. 4(c)). The GRU network is a technique...
aiming to control the problem of gradient vanishing in RNN [6]. Its basic idea is to control the update of network states with an update gate and a reset gate (see Fig. 4(b)). And we define the sequence encoder function with multi layers GRU networks as follows:

\[(\bar{X}, s) = \text{GRU}(X),\]

where \(X = \{x^i\}_{1 \leq i \leq n}\) is input sequence of feature vectors, \(\bar{X} = \{\bar{x}^i\}_{1 \leq i \leq n}\) is output sequence of encodings and \(s\) is final state of RNN. The fusion function here is a simple concatenation of two input sequence of feature vectors \(X = \{x^i\}_{1 \leq i \leq n}\) and \(Y = \{y^i\}_{1 \leq i \leq n}\), and is defined as follows:

\[Z = \text{CONCAT}(X, Y),\]

where \(Z = \{z^i\}_{1 \leq i \leq n}\) is the output sequence of fused encodings. Of course, more sophisticated encoding models (e.g., Transformer [24]) and fusion functions (e.g., DNN) can be adopted here. Considering the size of models on device, we use GRU and concatenation in our implementation respectively.

In the following two paragraphs, we will formally define our two specific Item Exposure Behavior Sequence Modeling and Item Page-View Behavior Sequence Modeling (see Fig. 4(a)), in which user behavior context \(C\) is represented by two corresponding tuples as \((P_{IE}, B_{IE})\) and \((P_{IPV}, B_{IPV})\). We deploy HUBSM on device in EdgeRec. Based on the recurrent computation characteristics of RNN, we model online incoming user behaviors synchronously and real-time as discussed in Sec. 3.2.2.

**Item Exposure Behavior Sequence Modeling.** We define IE input sequence of action feature vectors as \(A_{IE} = \{a^i_{IE}\}_{1 \leq i \leq n}\) and corresponding item feature vectors as \(P_{IE} = \{p^i_{IE}\}_{1 \leq i \leq m}\). Here \(n\) is the predefined maximum length of IE behavior sequence and we apply zero padding for shorter sequences. We get IE output sequence of action encodings \(\hat{A}_{IE}\), item encodings \(\hat{P}_{IE}\) and fused behavior encodings \(\hat{B}_{IE}\) respectively as following equations.

\[(\hat{A}_{IE} = \{\hat{a}^i_{IE}\}_{1 \leq i \leq \text{m}}) = \text{GRU}(A_{IE}),\]
\[(\hat{P}_{IE} = \{\hat{p}^i_{IE}\}_{1 \leq i \leq \text{m}}) = \text{GRU}(P_{IE}),\]
\[(\hat{B}_{IE} = \{\hat{b}^i_{IE}\}_{1 \leq i \leq \text{m}}) = \text{CONCAT}(\hat{A}_{IE}, \hat{P}_{IE}).\]

**Item Page-View Behavior Sequence Modeling.** We define IPV input sequence of action feature vectors as \(A_{IPV} = \{a^i_{IPV}\}_{1 \leq i \leq n}\) and corresponding item feature vectors as \(P_{IPV} = \{p^i_{IPV}\}_{1 \leq i \leq n}\). Here \(n\) is the predefined maximum length of IPV behavior sequence and we apply zero padding for shorter sequences. We get IPV output sequence of action encodings \(\hat{A}_{IPV}\), item encodings \(\hat{P}_{IPV}\) and fused behavior encodings \(\hat{B}_{IPV}\) respectively as following equations.

\[(\hat{A}_{IPV} = \{\hat{a}^i_{IPV}\}_{1 \leq i \leq \text{m}}) = \text{GRU}(A_{IPV}),\]
\[(\hat{P}_{IPV} = \{\hat{p}^i_{IPV}\}_{1 \leq i \leq \text{m}}) = \text{GRU}(P_{IPV}),\]
\[(\hat{B}_{IPV} = \{\hat{b}^i_{IPV}\}_{1 \leq i \leq \text{m}}) = \text{CONCAT}(\hat{A}_{IPV}, \hat{P}_{IPV}).\]

### 4.4 Context-aware Reranking with Behavior Attention Networks

In this section, we will talk about how to model the reranking function \(\phi\) defined in Eq. 1 considering on both local ranking context \(s\) and real-time user behavior context \(C\). For modeling local ranking context, we follow the approach from DLCM [1]. Here we encode the sequence of candidate items ranked by initial ranking models with GRU networks, and apply the final state of RNN as local ranking context \(s\).

In the following, we will focus on discussing how we model interaction between candidate items and real-time user behavior context defined in Sec. 4.3. Attention mechanism is first proposed in natural language processing area, e.g., machine translation [2]. With the
help of attention technique, our reranking model can automatically (soft-)search for parts of user behavior context that are relevant to ranking a target item. Some previous CTR prediction models (e.g., DIN [26] and DUPN [18]) also utilize similar method, while they only learn to attend user historically interacted items with respect to the target item, in which they fail to model user behavior actions based on above attention mechanism. Our approach will first attend relevant interacted items (a.k.a. find similar interacted items) from user behavior context, and then attentively combine the corresponding user behavior actions which indicate user’s underlying intention to those items, together represented as context directing the prediction for target item. We call it Behavior Attention here. Specifically, our approach employs both item exposure behavior context and item page-view behavior context.

In the following paragraphs, we will introduce details for our reranking approach known as Context-aware Reranking with Behavior Attention Networks (see Fig. 4(a)). The Con-text-aware Reranking part of networks is deployed on EdgeRec based on User Behavior Modeling (see Sec. 4.3) as input. Depending on the ability to rerank items on device, we can achieve real-time response to the users’ demands without additional requests to RS servers.

**Candidate Item Sequence Encoder.** We define candidate item sequence as $P_{CN D} = \{p_{CN D}^t\}_{t \leq k}$, which is generated and ranked by the prior models (see Sec. 2) in RS servers. Here $k$ is the predefined maximum length of candidate item sequence and we apply zero padding for shorter sequences. We apply GRU networks to encode it and represent the final state of RNN as local ranking context in the following equation.

$$P_{CN D} = \{p_{CN D}^t\}_{t \leq k},  s_{CN D} = \text{GRU}(P_{CN D}),$$  \hspace{1cm} (10)

where $P_{CN D}$ is the output sequence of candidate item encodings and $s_{CN D}$ represents the local ranking context.

**Behavior Attention.** Specific for the target candidate item $t$ encoded as $P_{CN D}$, we first attend to the encodings of user behavior item sequence $\hat{P}_IE$ and $\hat{P}_IPV$ for item exposure and item page-view behaviors respectively. Then we indicate the attention distributions as $(att_{IE}^{t})_{1 \leq m}$ and $(att_{IPV}^{t})_{1 \leq n}$ following Bahdanau attention mechanism [2]. Finally we produce user behavior contexts known as $c^{IE}$ and $c^{IPV}$ by combining the attention distributions and fusion behavior encodings of user behavior sequence $\hat{B}_{IE}$ and $\hat{B}_{IPV}$.

Specifically following the notations of triplet (Query, Key, Value) in Transformer [24], we define $\hat{P}_{CN D}^t$ as Query, $\hat{P}_IE/\hat{P}_IPV$ as Key, and $\hat{B}_{IE}/\hat{B}_{IPV}$ as Value in our model. We consider that attention calculation here is to (soft-)find similar or relevant items, so that representations of the compared two feature spaces should be homogeneous. That’s why we choose to encode “user behavior actions” and corresponding “user interacted items” separately in Sec. 4.3, and employ user behavior item sequence as Key with respect to the Query of target item. You can see the following equations for details.

$$att_{IE}^{t} = \text{softmax}(x_{t}^{IE} \tanh(W_{IE}^{CN D} + W_{IE}^{\hat{P}_IE})), 1 \leq j \leq m,$$

$$c^{IE} = \sum_{j=1}^{m} att_{IE}^{t} p_{IE}^j,$$  \hspace{1cm} (11)

$$att_{IPV}^{t} = \text{softmax}(x_{t}^{IPV} \tanh(W_{IPV}^{CN D} + W_{IPV}^{\hat{P}_IPV})), 1 \leq j \leq n,$$

$$c^{IPV} = \sum_{j=1}^{n} att_{IPV}^{t} p_{IPV}^j,$$  \hspace{1cm} (12)

where weights $W_1, W_2, W_3, W_4, v_1$ and $v_2$ are trained parameters.

**Loss.** To model $\phi(x_t, s, C)$ defined in Eq. 1, we first simply concatenate (defined as $[\cdot]$) the following: 1) user behavior context $c^{IE}$ and $c^{IPV}$ known as $C$, 2) representation of target candidate item $P_{CN D}^t$ known as $x_t$ and 3) local ranking context $s_{CN D}$ known as $s$. And then we apply multi-layer perception (MLP) before a sigmoid function $\sigma$ to get the output score $\hat{o}$. Finally, we apply cross-entropy loss to train the model. The following equations define the output and loss in details.

$$o^{t} = [c^{IE}; c^{IPV}; P_{CN D}^t; s_{CN D}],$$  \hspace{1cm} (13)

$$\hat{o} = \sigma(\text{MLP}(o^{t})), $$  \hspace{1cm} (14)

$$\mathcal{L} = \sum_{r \in R} \sum_{t=1}^{T} y_i \log(\hat{o}^r) + (1 - y_i) \log(1 - \hat{o}^r),$$  \hspace{1cm} (15)

where $y_i$ is the label on target item $i$ and $r \in R$ represents the reranking request triggered by client in EdgeRec.

### 5 EXPERIMENTS

In this section, we evaluate our model on real-world Taobao RS dataset and demonstrate the effectiveness of our model in Sec. 5.1. Moreover we do online A/B testing on Taobao RS to show the business performances in production in Sec. 5.2.1. Then we report some critical online system performances to verify the efficiency of our system in Sec. 5.2.2. Demo and case study are also involved to help understand how our method works intuitively in Appx. B.

#### 5.1 Offline Evaluation

**5.1.1 Dataset.** We collect online logs from EdgeRec system (see Sec. 3) in mobile Taobao and construct the dataset with statistics shown in Tab. 4. In our offline dataset, the label $y_t$ for each item is whether clicked ($y_t = 1$) or not ($y_t = 0$). The predefined maximum length of IE behavior sequence, IPV behavior sequence and candidate item sequence are $m = 100$, $n = 50$ and $k = 100$ respectively. Training and testing datasets are random sampled from the logs in two different days (2019-11-14 and 2019-11-15) to prevent the problem of overfitting. Finally we train the models with distributed Tensorflow supported by PAI\(^8\) with training settings in Appx. A.2.

**5.1.2 Comparing Methods.** We compare our model with the following representative methods.

- **DNN-rank** [5]: A popular ranking method in production which applies DNN to model the score function $\phi(x_t)$.
- **DLCM** [1]: A reranking model which considers local ranking context encoded by GRU networks to model the score function $\phi(x_t, s)$.

To verify how proposed Heterogeneous User Behavior Sequence Modeling (HUBSM) and Context-aware Reranking with Behavior Attention Networks (CRBAN) works, we do the following ablation tests:

- **CRBAN+HUBSM(IE&IPV)**: The complete method we propose in which we model $\phi(x_t, s, C)$ with CRBAN. And user behavior context $C$ is modeled with HUBSM considering both Item Exposure Behavior Sequence Modeling (IE-BSM) and Item Page-View Behavior Sequence Modeling (IPV-BSM).
- **CRBAN+HUBSM(IE)**: HUBSM only considers IE-BSM.
- **CRBAN+HUBSM(IPV)**: HUBSM only considers IPV-BSM.
- **CRBAN+HUISM(IE&IPV)**: User behavior context $C$ is only modeled by user interacted item sequence like DIN [26]. Thus

\(\text{https://data.aliyun.com/product/learn}\)
Key and Value in Behavior Attention are both encodings of user behavior item sequence \( P_{IE}/P_{IPV} \) (see paragraph Behavior Attention in Sec. 4.4). Here we consider both item exposure and item page-view user behavior item sequence known as HUISM(IE&IPV).

5.1.3 Evaluation Protocol. AUC \(^8\) is the metric to evaluate ranking performance and is commonly used in production. Here we apply GAUC which is also adopted in DIN \(^{26}\) which measures the goodness of intra-user order by averaging AUC over users. In our paper, we extend GAUC by averaging AUC over Client Native requests \( r \in R \) in EdgeRec system which can be regarded as a reranking session. It is calculated as follows:

\[
GAUC = \frac{\sum_{r \in R} \#\text{impression}_r \times AUC_r}{\sum_{r \in R} \#\text{impression}_r},
\]

where \( \#\text{impression}_r \) and \( AUC_r \) are the number of item impressions and AUC corresponding to the request \( r \).

5.1.4 Result Analysis. Tab. 2 shows the performances of GAUC with respect to different methods. We can see that DLCM outperforms DNN-rank (row 2 vs. 1) which verifies the effectiveness of involving local ranking context to reranking model. Furthermore, we can see that all the CRBAN based methods outperform DLCM significantly. Especially we achieve significant 2X relative improvement of GAUC (row 6 vs. 2) for our complete method CRBAN+HUBSM(IE&IPV). This demonstrates the advantage of considering real-time user behavior context in reranking model. So that how to model user behavior context is what we will focus on in the following discussions.

To verify our proposed Heterogeneous User Behavior Sequence Modeling method, we compare HUBSM(IE&IPV) with HUBSM(IE) (row 6 vs. 3) and HUBSM(IPV) (row 6 vs. 4). Results show that user behaviors of “positive feedback” (known as IPV) and “negative feedback” (known as IE) both contribute to modeling user behavior context. We also find that HUBSM(IPV) outperforms HUBSM(IE) (row 4 vs. 3) which shows that IPV user behaviors can be more important than IE user behaviors. Finally, results by comparing HUBSM(IE&IPV) and HUISM(IE&IPV) (row 6 vs. 5) indicates the promotion by considering both interacted items and their corresponding actions with Behavior Attention mechanism.

Table 2: Overall performances. Here * indicates statistical significance improvement compared to the baseline (DLCM) measured by t-test at \( p \)-value of 0.05.

| Method                   | GAUC   |
|--------------------------|--------|
| 1 DNN-rank               | 0.62531|
| 2 DLCM                   | 0.63552|
| 3 CRBAN-HUBSM(IE)        | 0.63618|
| 4 CRBAN-HUBSM(IPV)       | 0.64039|
| 5 CRBAN-HUBSM(IE&IPV)    | 0.64281|
| 6 CRBAN-HUBSM(IE&IPV)*   | 0.64825*|

5.2 Online Performance

5.2.1 Online A/B Testing. We conduct online experiments (a.k.a. A/B testing) on our EdgeRec system deployed in mobile Taobao. In

\(^9\)We utilize a strategy named "hierarchical bucketing" in which different algorithms on cloud servers will be transparent for online experiments on edge.

5.2.2 Online System Performance. Apart from online A/B testing to show the business performances in production, we also conduct the efficiency of EdgeRec in mobile Taobao RS. Tab. 3 reveals the significant improvements of system efficiency from three key aspects after deploying EdgeRec.

Delay time for user behaviors influences the timeliness for system to capture user personalized preference to items which may affect user experience in RS. Due to the limitations of network bandwidth and latency, RS based on only client-and-server framework...
may lead to up to 1min delay time for capturing user behaviors. However after deploying EdgeRec, user behaviors can be collected and consumed on device without any network communication overhead, which can make the delay time within 300ms (e.g., time for reading user behaviors from on-device database).

**Response time of system** is another factor affecting user experience in RS. When client native initiates a request to system along user scrolling on RS scenario, the system should respond in time and provide the ranked items to user, otherwise the user will be waiting which may make him/her leave. Due to the computing overhead of serving such complex RS models (see Sec. 2) for hundreds of millions of users in Taobao RS, based on only cloud computing may lead to 1s response time including network transmission. While in EdgeRec, the models are serving on each user’s mobile device, which solves the problem of centralized computing overhead and makes the response time within 100ms without any network communication.

**Average times of system feedback for users** is another key factor affecting user experience in RS. It reflects how often system can adjust the ranking of items which will be shown to user when he/she browses in RS. The more frequently the system can adjust results, the more it can satisfy the users’ varied demands in RS. However RS without EdgeRec cannot make the times of system feedback much larger because it will aggravate computing overhead on cloud servers. So average times of system feedback for users in Taobao RS without EdgeRec is 3 and paging size is 50 in current client-and-server framework (i.e. users make 3 paging requests on average). In comparison, there is no explicit paging point in EdgeRec but triggered by client native depending on user behaviors (see Sec. 3.2.1). Without increasing additional computing overhead on cloud, the average times of system feedback can be 15 in EdgeRec (i.e. client native triggers 5 reranking requests on average in one page so total is 15).

### Table 3: System performances in Taobao RS with (w/) or without (w/o) EdgeRec. They are observed at traffic peak and calculated by averaging over users.

|    | w/ EdgeRec | w/o EdgeRec |
|----|------------|-------------|
| delay time for user behaviors | ≤ 300ms | ≤ 1min |
| response time of system | ≤ 100ms | ≤ 1s |
| times of system feedback | 15 | 3 |

## 6 CONCLUSION AND FUTURE WORK

Our work takes the first to combine RS and edge computing. We design and implement EdgeRec (Recommender System on Edge) in mobile Taobao to tackle the problem of delay for user perception and system feedback in waterfall flow RS. Meanwhile we propose **Heterogeneous User Behavior Sequence Modeling and Context-aware Reranking with Behavior Attention Networks** to model users’ plentiful behaviors and reranking. After successful offline and online evaluations on real traffic of Taobao RS, EdgeRec has been deployed to production. We believe that EdgeRec will bring a lot of interesting topics to both industry and research of RS in the future, e.g., thousand people with thousand models (a.k.a. model personalization) based on on-device training and federated learning [3, 11], interactive recommendation [4], etc.

## REFERENCES

[1] Qingyao Ai, Keping Bi, Jiafeng Guo, and W Bruce Croft. 2018. Learning a deep listwise context model for ranking refinement. In *SIGIR*.

[2] Dmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. arXiv (2014).

[3] Fei Chen, Zhenhua Dong, Zhenguo Li, and Xiuping He. 2018. Federated meta-learning for recommendation. arXiv (2018).

[4] Tie-Yan Liu et al. 2009. Learning to rank for information retrieval. *Foundations and Trends® in Information Retrieval* 3, 3 (2009), 225–331.

[5] Yu Gong, Yu Zhu, Lu Duan, Qingwen Liu, Ziyu Guan, Fei Sun, Wenwu Ou, and Kenny Q. Zhu. 2019. Exact-k recommendation via maximal clique optimization. In *SIGKDD*.

[6] Mihajlo Grbovic and Haibin Cheng. 2018. Real-time personalization using embeddings for search ranking at airbnb. In *SIGKDD*.

[7] Andrew Hard, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaudaux, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage. 2018. Federated learning for mobile keyboard prediction. arXiv (2018).

[8] Brian Hayes. 2008. Cloud computing. *Commun. ACM* 51, 7 (2008), 9–11.

[9] Yabo Ni, Dan Ou, Shichen Liu, Xiang Li, Wenwu Ou, Anxiang Zeng, and Luo Si. 2018. Perceive your users in depth: Learning universal user representations from multiple e-commerce tasks. In *SIGKDD*.

[10] Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Cernocký, and Sanjeev Khudanpur. 2010. Recurrent neural network based language model. In *ICSLP*.

[11] Yabo Ni, Dan Ou, Shichen Liu, Xiang Li, Wenwu Ou, Anxiang Zeng, and Luo Si. 2018. Perceive your users in depth: Learning universal user representations from multiple e-commerce tasks. In *SIGKDD*.

[12] Chao Li, Zhiyuan Liu, Mengmeng Wu, Yuchi Xu, PIPEI HUANG, Huan Zhao, Guoliang Kang, Qiwe Chen, Wei Li, and Dik Lun Lee. 2019. Multi-Interest Network with Dynamic Routing for Recommendation at Tmall. arXiv (2019).

[13] Xi Shi, Jie Yuan, Bei Zou, Guorui Zhou, Qi Pi, and Kun Gai. 2020. Practice on Long Sequential User Behavior Modeling for Click-Through Rate Prediction. arXiv (2019).

[14] Weisong Shi, Jie Cao, Quan Zhang, Youhuizi Li, and Lanyu Xu. 2016. Edge computing: Vision and challenges. *IEEE Internet of Things Journal* 3, 5 (2016), 637–646.

[15] Tarik Taleb, Sunny Dutta, Adlen Ksentini, Muddasser Iqbal, and Hannu Flinck. 2017. Mobile edge computing potential in making cities smarter. *IEEE Communication Magazine* 55, 3 (2017).

[16] Carlo Vallati, Antonio Virdis, Enzo Mingozzi, and Giovanni Stea. 2016. Mobile-edge computing come home connecting things in future smart homes using LTE device-to-device communications. *IEEE Consumer Electronics Magazine* 5, 4 (2016), 77–83.

[17] Ashish Varghese, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *NIPS*.

[18] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep interest evolution network for click-through rate prediction. In *AAAI*.

[19] Guorui Zhou, Xiaoqiang Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqin Jin, Han Li, and Kun Gai. 2018. Deep interest network for click-through rate prediction. In *SIGKDD*.

[20] MeiZi Zhou, Zhuyue Ding, Jiliang Tang, and Dawei Yin. 2018. Micro behaviors: A new perspective in e-commerce recommender systems. In *WSDM*.

[21] Han Zhu, Xiang Li, Pengyu Zhang, Guozheng Li, Jie He, Han Li, and Kun Gai. 2019. Learning Tree-based Deep Model for Recommender Systems. In *SIGKDD*.

[22] Tao Zha, Wenwu Ou, and Zhigong Wang. 2018. Globally optimized mutual influence aware ranking in e-commerce search. In *AAAI*.
A EXPERIMENTAL SETTINGS

A.1 Dataset

| Table 5: Statistics of dataset. |
|--------------------------------|
| Training | Testing |
|--------------------------------|
| No. of samples (a.k.a. requests) | 22,072,671 | 200,000 |
| No. of users | 7,245,411 | 195,692 |
| Avg. of IE behavior sequence length | 56 | 55 |
| Avg. of IPV behavior sequence length | 26 | 26 |

A.2 Training Settings

We report the settings of input features in Tab. 5 and hyper-parameters for training in Tab. 6.

Table 5: Type and size of input features in our model. For embedding type, the size is shape of embedding matrix.

| Var | Attribute | Type | Size |
|-----|-----------|------|------|
| e_1 | exposure_duration | bucketize | 10 |
| e_2 | exposure_count | bucketize | 3 |
| e_3 | scroll_speed | bucketize | 10 |
| e_4 | scroll_duration | bucketize | 10 |
| e_5 | scroll_count | bucketize | 3 |
| e_6 | delete_reason | one-hot | 3 |
| e_7 | expose_decay | bucketize | 30 |
| d_1 | ipv_duration | bucketize | 10 |
| d_2 | cart | binarize | 1 |
| d_3 | buy | binarize | 1 |
| d_4 | favorite | binarize | 1 |
| d_5 | comment | binarize | 1 |
| d_6 | select_SKU | binarize | 1 |
| d_7 | WDI | binarize | 1 |
| d_8 | wangwang | binarize | 1 |
| d_9 | detail | binarize | 1 |
| d_10 | shop | binarize | 1 |
| d_11 | recommendation | binarize | 1 |
| d_12 | ipv_click | bucketize | 30 |

Table 6: Hyper-parameters for training the models which are tuned as the best.

| Hyper-Parameter | Value |
|-----------------|-------|
| batch size | 512 |
| learning rate | 0.005 |
| epochs | 1 |
| exponential decay steps | 1000 |
| exponential decay rate | 0.98 |
| gradients clip | 10 |
| GRU layers | 3 |
| GRU hidden units | 32 |
| attention hidden units | 32 |
| MLP hidden size | 32 x 1 |
| optimizer | Adam |

B DEMO AND CASE STUDY

We conduct case study experiment and select a case in mobile Taobao to illustrate how our raranking model works in Fig. 7.

The top part visualizes Heterogeneous User Behavior Sequence Modeling (HUBSM). Specific to item page-view (IPV) and item exposure (IE) in left column and right column, the first row represents sequence of user’s interacted items as \( \tilde{P}^{IPV} \) and \( \tilde{P}^{IE} \), the second row shows sequence of the corresponding actions for each item as \( A^{IPV} \) and \( A^{IE} \), the third row indicates sequence of the predicted user’s intention. For case study, the degree of intention (i.e. from Dislike to Like) for IPV item \( i \) and IE item \( j \) is estimated by \( MLP^{IPV}(\tilde{a}^{IPV}) \) and \( MLP^{IE}(\tilde{a}^{IE}) \) in which \( MLP^{IPV} \) and \( MLP^{IE} \) are trained by the following loss.

\[
\begin{align*}
    c_r^{IPV} &= \sum_{i=1}^{m} att^{IPV}_i MLP^{IPV}(\tilde{a}^{IPV})_r, \\
    \hat{c}_r &= \sigma(c_r^{IPV} + c_r^{IPV}) \\
    \mathcal{L} &= \sum_{r \in R} \sum_{i=1}^{m} y_i \log(\sigma') + (1 - y_i) \log(1 - \sigma'),
\end{align*}
\]

where \( r \) represents target candidate item in reranking, \( \{att^{IPV}_i\}_{1 \leq i \leq m} \) and \( \{att^{IPV}_i\}_{1 \leq j \leq n} \) are consistent with Eq. 11 and Eq. 12. We should mention that only MLP^{IPV} and MLP^{IE} are trainable here and other parameters are transfered and fixed from our already trained reranking model. From left column in Fig. 7, we can see that user actions in item page-view reveal his/her preference to that item with positive intention degree, e.g., adding to cart or asking for customer service. On the contrary in right column, user actions in item exposure usually infer negative intention to that item, e.g., scrolling quickly or deleting. Above discussion indicates that our proposed HUBSM is able to capture user’s underlying positive and negative intentions to the historical interacted items.

The bottom part visualizes Context-aware Reranking with Behavior Attention Networks (CRBAN). In our case study, the intention contexts for target item \( t \) are represented as \( c_t^{IE} \) and \( c_t^{IPV} \) in Eq. 17 and Eq. 18. As shown in Fig. 7, for the first candidate item which is a shirt, it finds two similar shirts (i.e. with high attention values) in IPV with higher positive intention degrees which help to predict the target shirt as positive (i.e. label as 1). On the contrary for the second candidate item which is a hat, it finds two similar interacted items in IE with lower negative intention degrees which leads to predict it as negative (i.e. label as 0). Above discussion indicates that our proposed CRBAN is able to model the interaction between candidate items with user behavior context which directs the prediction for target item better.
Figure 7: A case in mobile Taobao to illustrate the impact of our proposed Heterogeneous User Behavior Sequence Modeling and Context-aware Reranking with Behavior Attention Networks.