A Brand-level Ranking System with the Customized Attention-GRU Model[*]

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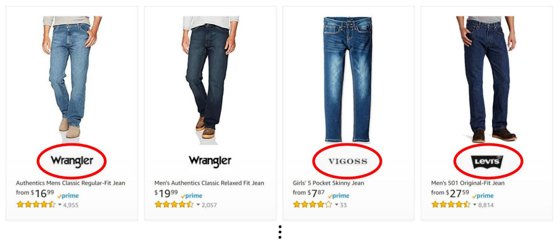
Abstract

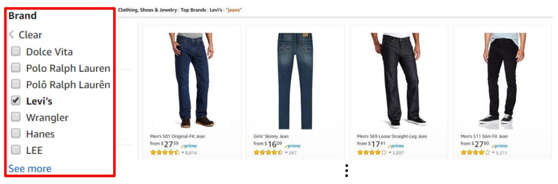
In e-commerce websites like Taobao, brand is playing a more important role in influencing users' decision of click/purchase, partly because users are now attaching more importance to the quality of products and brand is an indicator of quality. However, existing ranking systems are not specifically designed to satisfy this kind of demand. Some design tricks may partially alleviate this problem, but still cannot provide satisfactory results or may create additional interaction cost. In this paper, we design the first brand-level ranking system to address this problem. The key challenge of this system is how to sufficiently exploit users' rich behavior in e-commerce websites to rank the brands. In our solution, we firstly conduct the feature engineering specifically tailored for the personalized brand ranking problem and then rank the brands by an adapted Attention-GRU model containing three important modifications. Note that our proposed modifications can also apply to many other machine learning models on various tasks. We conduct a series of experiments to evaluate the effectiveness of our proposed ranking model and test the response to the brand-level ranking system from real users on a large-scale e-commerce platform, i.e. Taobao.

1 Introduction

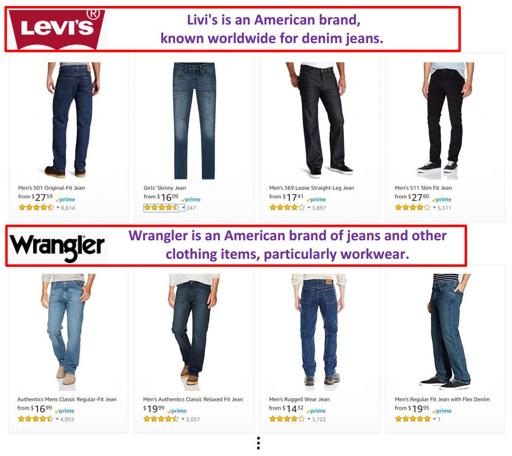
In e-commerce websites such as Taobao, the brand is having a growing impact on customers' decision of click/purchase [Zipser *et al.*, 2016]. There are numerous reasons behind this phenomenon. On one hand, users may prefer items with high quality, and brand is a good indicator of product quality. On the other hand, users may have preference bias to certain brands because of the brand image built from brand marketing and campaigns, e.g. basketball fans may prefer clothes under the brand endorsed by NBA stars.



(a) Results of existing ranking systems



(b) Results after clicking the checkbox Levi's



Livi's is an American brand, known worldwide for denim jeans.

Wrangler is an American brand of jeans and other clothing items, particularly workwear.

(c) Results of our brand-level ranking system

Figure 1: Results of different ranking systems given the query jeans. Red lines highlight the important brand-related information.

However, as shown in Figure 1(a), the ranking results from most existing retrieval/recommender systems aggregate the items of different brands together. This cannot well satisfy the users with strong preference towards certain brands, since they have to waste time browsing through large numbers of

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products from other brands. There exist several technical tricks to help with this issue: (1) Set the brand as a feature for the underlying ranking model, and then items with preferred brands would rank in the top of the list. However, items of different brands are still mixed together. (2) Set checkboxes/buttons to filter brands. As shown in Figure 1(b), on the result page of query "jeans", users can choose to only browse products under brand Levi's by clicking the checkbox filter for Levi's. However, only a few brands can be displayed here and there is no personalization. Moreover, users have to click the checkboxes multiple times if they want to browse several brands, which increases the interaction cost and creates negative user experience.

Due to the drawbacks of existing systems mentioned above, we design a new brand-level ranking system, where items of the same brand are grouped together and brand groups are ranked based on users' brand preference. A demo of our system is demonstrated in Figure 1(c). Jeans are first grouped by brands, e.g. Levi's and Wrangler. The system will then rank Levi's at a higher position, if it learns the user prefers Levi's to Wrangler.

The core of the brand-level ranking system is to solve the personalized brand ranking problem. Various important information in e-commerce websites should be exploited to rank brands. Firstly, features such as brand pricing contribute to brand profiling. Second, the sequential information in user action (*click* or *purchase*) sequences and time intervals between actions are valuable in modeling users' interests on brands [Zhu *et al.*, 2017]. In addition, different types of actions (*click* and *purchase*) reflect users' different preferences on items (and in turn the corresponding brands), e.g. generally a user purchasing an item indicates he is more interested in the item than if he clicks it. The key challenge is how to well exploit these characteristics of user action sequences for brand ranking. We formulate it as a point-wise ranking problem. Specifically, a classifier is trained based on the various information in e-commerce websites. Then given a user, his probability of preferring each brand is predicted by the classifier and brands are ranked based on their probabilities. Items within the same brand group can be ranked by traditional ranking methods.

Two sub-tasks need to be accomplished for the brand-level ranking system. One is the feature engineering for the brand ranking problem. We propose a series of brand features that are important for brand ranking (details in section 4.1). The other one is the design of the ranking model. We propose an adapted Attention-GRU [Chorowski *et al.*, 2015] model to predict users' probabilities of preferring different brands. RNN (Recurrent Neural Network) methods have achieved state-of-the-art performance in capturing the sequential information in user action sequences [Zhu *et al.*, 2017]. GRU (Gated Recurrent Unit) [Cho *et al.*, 2014] is among the best RNN architectures and the attention mechanism [Chorowski *et al.*, 2015] helps to distinguish the influence of different previous actions on the current prediction. Therefore, Attention-GRU is chosen as the base model. We propose three major modifications to Attention-GRU for our task. (1) Combine the heuristically designed brand features and the model-learned brand embedding to better represent the brand. A brand embedding refers to a vector representation for the brand, which is learned from training data by our model [Zhu *et al.*, 2016]. (2) Consider different types of actions. (3) Integrate the time-gate [Zhu *et al.*, 2017] to model time intervals between actions, which can better capture users' short-term and long-term interests. The effectiveness of our adapted model and the brand-level ranking system is evaluated in our offline and online experiments on a large-scale e-commerce platform. This paper's contributions are outlined as follows.

- We propose the first brand-level ranking system, which provides explicit personalized brand-level ranking and better helps users to make click/purchase decisions based on their brand preference.
- We perform feature engineering tailored for the brand ranking task and propose an adapted Attention-GRU model as our ranking model. Specifically, we contribute three modifications which effectively improve the model performance.
- We conduct extensive offline and online experiments on a large-scale e-commerce platform. The results and feedbacks from real users prove the effectiveness of our adapted model and the brand-level ranking system.

2 Related Work

2.1 RNN, GRU and Attention-GRU

RNN [Elman, 1990] has been proved to perform excellently when modeling sequential data. It is formally defined as:

$$s_m = f(Wx_m + Us_{m-1}), \quad (1)$$
$$o_m = softmax(Vs_m), \quad (2)$$

where s_m, x_m and o_m are the hidden state, input and output at the m-th step. f is a non-linear activation function. W, U and V are the corresponding weights learned from training.

GRU [Cho et al., 2014] is an important ingredient of RNN architectures, which can avoid the problem of gradient vanishing. It replaces Eq. (1) with:

$$z_m = \sigma(W_z x_m + U_z s_{m-1}), \quad (3)$$
$$r_m = \sigma(W_r x_m + U_r s_{m-1}), \quad (4)$$
$$\begin{aligned} s_m = {} & z_m \odot tanh(W_h x_m + U_h(r_m \odot s_{m-1})) \\ & + (1 - z_m) \odot s_{m-1}, \end{aligned} \quad (5)$$

where z_m and r_m are the update and reset gates. σ and $tanh$ are sigmoidal and tanh nonlinearities. W_z, U_z, W_r, U_r, W_h and U_h are the weights. $\odot$ denotes the element-wise product.

Attention-GRU [Chorowski *et al.*, 2015] refers to GRU with the attention mechanism. RNN methods with the attention mechanism have been successfully applied to handwriting synthesis [Graves, 2013], machine comprehension [Pan *et al.*, 2017] etc. It typically focuses on the task that generates an output sequence $y = (y_1, \cdots, y_T)$ from an input sequence $x = (x_1, \cdots, x_L)$. x is often processed by an *encoder* to output a sequential representation $h = (h_1, \cdots, h_L)$. At the

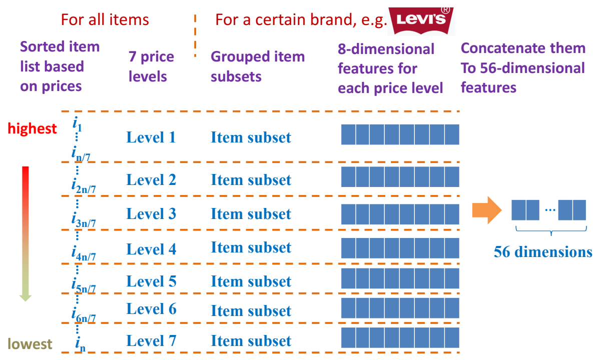
For all items
For a certain brand, e.g.
Sorted item list based on prices
7 price levels
Grouped item subsets
8-dimensional features for each price level
Concatenate them To 56-dimensional features
highest
lowest
Level 1
Level 2
Level 3
Level 4
Level 5
Level 6
Level 7
Item subset
56 dimensions

Figure 2: The general process to obtain the brand features.

m-th step y_m is generated by:

$$\alpha_m = Attend(s_{m-1}, h), \tag{6}$$

$$g_m = \sum_{j=1}^{L} \alpha_{m,j} h_j, \tag{7}$$

$$s_m = Recurrency(y_{m-1}, s_{m-1}, g_m), \tag{8}$$

$$y_m \sim Generate(y_{m-1}, s_m, g_m), \tag{9}$$

where $Attend$ and $Generate$ are functions. α_m is a vector whose entry $\alpha_{m,j}$ indicates the *attention weight* of the j-th input. g_m is called a *glimpse* [Mnih *et al.*, 2014]. $Recurrency$ represents the recurrent activation. In Attention-GRU, the recurrent activation is GRU.

2.2 RNN for Behavior Modeling

[Hidasi *et al.*, 2016; Tan *et al.*, 2016] focus on RNN solutions in a session-based setting. [Yu *et al.*, 2016] designs an RNN method for the next-basket recommendation. The setting in our task is different from these settings. The Time-LSTM model, proposed in [Zhu *et al.*, 2017], equips LSTM [Hochreiter and Schmidhuber, 1997] with time gates to better capture users' short-term and long-term interests. We propose that the time gate is a basic component and can be integrated into other RNN architectures (e.g. Attention-GRU in our task).

3 Task Definition and Models' adaptations

3.1 Task Definition

Let $\mathbf{U} = \{U_1, U_2, \cdots, U_M\}$ be a set of M users and $\mathbf{B} = \{B_1, B_2, \cdots, B_N\}$ be a set of N brands. For each user $u \in \mathbf{U}$, his behavior history H^u is defined by $H^u = [(b_1^u, h_1^u, t_1^u), (b_2^u, h_2^u, t_2^u), \cdots, (b_{n_u}^u, h_{n_u}^u, t_{n_u}^u)]$, where (b_m^u, h_m^u, t_m^u) indicates that u generates his m-th action h_m^u (*click* or *purchase*) on brand $b_m^u \in \mathbf{B}$ at time t_m^u. Our task is to predict the probability $p(B_{q_u})$ of u generating any type of action on brand B_{q_u} at a certain time T_u ($T_u > t_{n_u}^u$).

3.2 Adaptations of Traditional RNN Models

We first transform H^u to $\tilde{H^u} = [(b_1^u, h_1^u, t_2^u - t_1^u), (b_2^u, h_2^u, t_3^u - t_2^u), \cdots, (b_{n_u}^u, h_{n_u}^u, T_u - t_{n_u}^u)]$. The mathematical representations of b_m^u, h_m^u and $t_{m+1}^u - t_m^u$ are denoted as $R(b_m^u)$, $R(h_m^u)$ and $R(t_{m+1}^u - t_m^u)$, respectively. $R(b_m^u)$ is defined with two alternative ways: (1) a brand feature vector or (2) a one-hot vector. $R(h_m^u)$ is defined as a one-hot vector. Since

CTR (Click-Through Rate)	CVR (Conversion Rate)
GMV (Gross Merchandise Volume)	ATIP (Average Transacted Item Price)
Search Times	Click Times
Add-To-Cart Times	Transaction Times

Table 1: 8 Most Important E-commerce Metrics

there are two types of actions, i.e. *click* and *purchase*, in our task, thus they are represented as [0, 1] and [1, 0], respectively. $R(t_{m+1}^u - t_m^u)$ is set to be a scalar $t_{m+1}^u - t_m^u$ (in seconds). The label is 1 if u actually clicks/purchases B_{q_u} at time T_u and 0 otherwise.

For Time-LSTM [Zhu *et al.*, 2017], the input at each step is the concatenation $[R(b_m^u), R(h_m^u)]$ and $R(t_{m+1}^u - t_m^u)$. For the other RNN models, the input (i.e. x_m in section 2.1) is the concatenation $[R(b_m^u), R(h_m^u), R(t_{m+1}^u - t_m^u)]$. For RNN with no attention mechanism, the output (i.e. o_m in Eq. (2)) is a probability distribution over all brands, from which we can obtain $p(B_{q_u})$. For Attention-GRU, T and y_0 (i.e. y_{m-1} in Eq. (8) when $m = 1$) in section 2.1 are set to be 1 and B_{q_u}, respectively. We replace Eq. (9) with:

$$\tilde{o}_m = softmax(\tilde{V} s_m), \tag{10}$$

where $\tilde{V}$ is the weight and $\tilde{o}_m$ is a probability distribution over labels 1 and 0. $p(B_{q_u})$ is equal to the probability of label 1. These models are trained by AdaGrad [Duchi *et al.*, 2011] with the log loss calculated by $p(B_{q_u})$ and the label.

4 Proposed System

4.1 Feature Engineering

According to the market research conducted by the authors' company, the price range feature demonstrates great importance in user and brand profiling. Therefore, the brand features are carefully engineered by slicing into 7-level price ranges, with the details as follows (also shown in Figure 2).

(1) All items belonging to a certain category (e.g. "clothing") are sorted based on their prices. The sorted item list is denoted as $\{i_1, i_2, \cdots, i_n\}$. The price for i_t is denoted as p_t. We define 7 *price levels* as 7 price ranges, with Level 1 = $(0, p_{\frac{n}{7}}]$, Level 2 = $(p_{\frac{n}{7}}, p_{\frac{2n}{7}}]$,$\cdots$, Level 7 = $(p_{\frac{6n}{7}}, p_n]$.

(2) Given a certain brand, items belonging to this brand are grouped based on the price levels defined above. Specifically, an item is grouped to a price level if this item's price locates in the corresponding price range.

(3) Given a certain brand, 8 most important e-commerce metrics are aggregated within each price level, generating 8-dimensional features for each price level. Features from all 7 price levels are then concatenated into the final 56-dimensional brand features. Specifically, the 8 most important brand-related e-commerce metrics used in this paper is summarized in *Table 1*[1].

4.2 The Design of the Ranking Model

An adapted Attention-GRU model is proposed to predict users probabilities of preferring different brands.

[1]Due to page limit, please refer to the corresponding Wikipedia pages for definitions of CTR, CVR and GMV. ATIP = $\frac{\text{GMV}}{\text{Number of Transacted Items}}$.

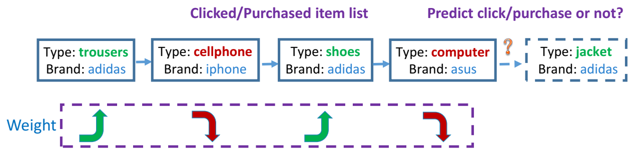

Figure 3: An example to show the motivation to apply the attention mechanism in our task.

(1) The Choice of Attention-GRU

RNN solutions have achieved state-of-the-art performance when modeling users' sequential actions [Hidasi *et al.*, 2016; Zhu *et al.*, 2017]. LSTM and GRU are two important ingredients of RNN architectures, both of which are able to avoid the problem of gradient vanishing. Compared to LSTM, GRU can yield comparable performance but has fewer parameters, thus it could train a bit faster and need less data to generalize [Chung *et al.*, 2014]. Figure 3 is an example to show the motivation to apply the attention mechanism in our task. When we predict whether the user would click/purchase the jacket with the brand Adidas, we want to increase the influence of the first and third items on the prediction since compared to the cellphone and computer, the trousers and shoes are much more related to the jacket. In the attention mechanism, this will be reflected with larger weights on the first and third inputs.

(2) Modifications to Attention-GRU

To achieve better performance, we propose three modifications to Attention-GRU (also explained in Figure 4):

Modification 1: Combining the brand features and brand embedding to better represent the brand

In a traditional Attention-GRU model, the brand can be represented by either a vector consisting of brand features defined in section 4.1, or a one-hot vector based on brand ID. However, the brand features are heuristically designed based on expert experience and may lack some important information useful for the brand ranking task. For example, two brands may have similar brand features but are of different interest for the same user. Using one-hot vectors can explicitly distinguish different brands but lacks the brand content information. Here we propose to combine these two representations. Specifically, following the denotations in section 3.1, assume b_m^u equals to B_k and the vector consisting of brand features for B_k is denoted as $\mathbf{v}_k \in R^{56\times 1}$. Its one-hot vector is defined as $\mathbf{o}_k \in \{0,1\}^{N\times 1}$, with the k-th entry equal to 1 and the other entries equal to 0. Matrix $\mathbf{M}_{embed} \in R^{56\times N}$ is defined to contain the embeddings of all brands. Then the combined mathematical representation considering both brand features and the brand embedding is defined as $R'(b_m^u)$, with

$$R'(b_m^u) = \mathbf{M}_{embed} \times \mathbf{o}_k + \mathbf{v}_k. \tag{11}$$

$\mathbf{M}_{embed}$ is learned from the training data. $\mathbf{o}_k$ is used to look up the embedding of B_k from $\mathbf{M}_{embed}$.

We interpret Eq. (11) from three perspectives. *(1) Heuristic initialization + Fine tuning*. While $\mathbf{v}_k$ is heuristically designed, by learning from the training data, we fine tune the brand's representation to be $\mathbf{M}_{embed} \times \mathbf{o}_k + \mathbf{v}_k$, which would much better fit our task. *(2) Prior information + Posterior modification*. This perspective is similar to the first perspective, but in a Bayesian context [Berger, 2013]. Specifically, $\mathbf{v}_k$ is obtained based on our "prior" understanding of brands, then the training data enhances our understanding of them and allows us to give "posterior" estimations of their representations. *(3) Content information + Collaborative information*. $\mathbf{v}_k$ contains brands' content information, while $\mathbf{M}_{embed} \times \mathbf{o}_k$ is learned from users' click/purchase data in our task and thus captures the collaborative information. For some brands B_k that rarely appear in the training data, $\mathbf{v}_k$ can provide extra information to help with this "cold-start" situation [Wang *et al.*, 2016a; 2016b].

Modification 2: Considering different types of actions

When modeling user behaviors by RNN models, previous works such as [Hidasi *et al.*, 2016; Zhu *et al.*, 2017] usually consider single type of action. However, users can perform multiple types of actions on items, e.g. *click* and *purchase*. One way to handle different types of actions is to model each of them as a one-hot vector $R(h_m^u)$ (defined in section 3.2) and concatenate it to our combined brand representation $R'(b_m^u)$. However, this method allows no feature interaction between $R'(b_m^u)$ and $R(h_m^u)$ (or implicit interaction by the non-linear activation function), and thus would not well capture the interactive relation between the brand and the type of action performed on the brand [Rendle, 2012; Chen *et al.*, 2017].

Instead, we propose to define a matrix for each type of action (the total number of action types is usually not large). In our task, we define $\mathbf{M}_{click} \in R^{56\times 56}$ and $\mathbf{M}_{purchase} \in R^{56\times 56}$ for *click* and *purchase*, respectively. Then the representation considering both of the brand and the type of action is defined as:

$$R(bh_m^u) = \begin{cases} \mathbf{M}_{click} \times R'(b_m^u), & if\ b_m^u\ is\ clicked, \\ \mathbf{M}_{purchase} \times R'(b_m^u), & if\ b_m^u\ is\ purchased. \end{cases} \tag{12}$$

In this way, we explicitly model the interaction between the brand and the type of action by matrix multiplication.

Modification 3: Integrating the time-gate to model time intervals between actions

The time gate in Time-LSTM [Zhu *et al.*, 2017] is effective to capture users' short-term and long-term interests. We propose that the time gate is a basic component and adapt it to our model as follows. A time gate T_m is defined as:

$$T_m = \sigma(W_t x_m + \sigma(Q_t \triangle t_m)), \tag{13}$$

where

$$\begin{aligned} x_m &= R(bh_m^u), \\ \triangle t_m &= R(t_{m+1}^u - t_m^u) = t_{m+1}^u - t_m^u. \end{aligned} \tag{14}$$

W_t and Q_t are the weights of x_m and $\triangle t_m$ (time intervals), respectively. $\triangle t_m$ may be very large, thus we impose a sigmoidal function σ on $Q_t \triangle t_m$. Then we modify Eq. (5) to:

$$\begin{aligned} s_m = {} & z_m \odot T_m \odot tanh(W_h x_m + U_h(r_m \odot s_{m-1})) \\ & + (1 - z_m) \odot s_{m-1}. \end{aligned} \tag{15}$$

When modeling user behaviors by our model, x_m in Eq. (15) represents the user's most recent action, thus we can exploit x_m to learn his/her current short-term interest. s_{m-1} models this user's previous actions, thus s_{m-1} reflects his/her long-term interest. T_m is helpful in two ways, i.e. (1)

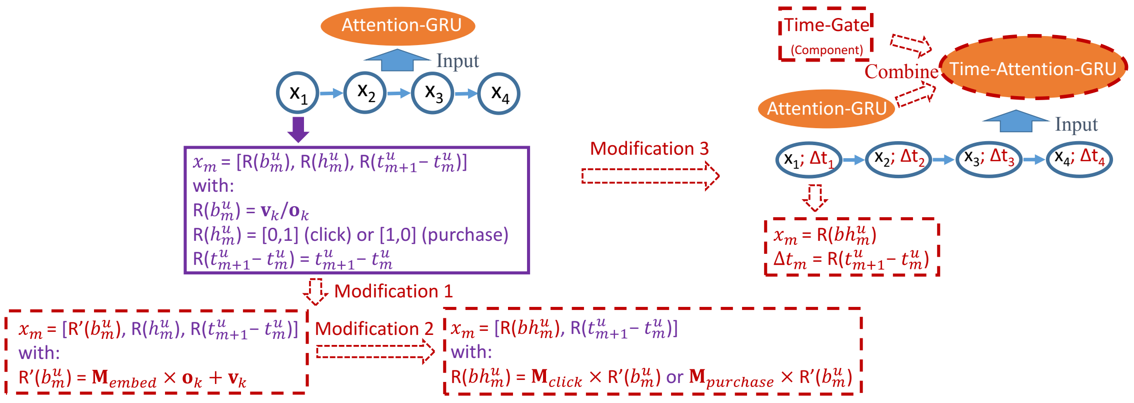
Attention-GRU
Input
x_1 x_2 x_3 x_4
x_m = [R(b_m^u), R(h_m^u), R($t_{m+1}^u - t_m^u$)]
with:
R(b_m^u) = $\mathbf{v}_k/\mathbf{o}_k$
R(h_m^u) = [0,1] (click) or [1,0] (purchase)
R($t_{m+1}^u - t_m^u$) = $t_{m+1}^u - t_m^u$
Modification 1
x_m = [R'(b_m^u), R(h_m^u), R($t_{m+1}^u - t_m^u$)]
with:
R'(b_m^u) = $\mathbf{M}_{embed} \times \mathbf{o}_k + \mathbf{v}_k$
Modification 2
x_m = [R(bh_m^u), R($t_{m+1}^u - t_m^u$)]
with:
R(bh_m^u) = $\mathbf{M}_{click}$ × R'(b_m^u) or $\mathbf{M}_{purchase}$ × R'(b_m^u)
Modification 3
Time-Gate
(Component)
Combine
Time-Attention-GRU
Attention-GRU
Input
x_1; Δt_1 x_2; Δt_2 x_3; Δt_3 x_4; Δt_4
x_m = R(bh_m^u)
Δt_m = R($t_{m+1}^u - t_m^u$)

Figure 4: Our proposed modifications to the Attention-GRU model, represented by dotted lines and red texts.

$tanh(W_h x_m + U_h(r_m \odot s_{m-1}))$ is filtered by not only z_m, but also T_m. So T_m can control the influence of x_m on current prediction. (2) $\triangle t_m$ is firstly stored in T_m, then transferred to s_m, and would be transferred to $s_{m+1}, s_{m+2} \cdots$. Thus T_m helps to better model users' long-term interest $(s_m, s_{m+1} \cdots)$ by incorporating $\triangle t_m$ for later predictions. We denote Attention-GRU with the time gate as Time-Attention-GRU.

It is notable that Modification 1 is rather general and can apply to many machine learning models where the designed features and one-hot vectors exist. Modification 2 can be generalized to handle tasks involving various interaction types with the input. In Modification 3, we propose that the time gate can be integrated into not only LSTM but also other RNN models, just as how we integrate it into Attention-GRU.

(3) Loss and Training

Similar to Attention-GRU, $p(B_{q_u})$ in our model is obtained from $\tilde{o}_m$ in Eq. (10). We define the loss for user u as:

$$loss_u = \begin{cases} -log(p(B_{q_u})), & \text{if } label_u = 1, \\ -w \times log(1 - p(B_{q_u})), & \text{otherwise}, \end{cases} \tag{16}$$

where $label_u$ is 1 if u actually generates an action on brand B_{q_u} at time T_u. We multiply the loss by w (< 1) for negative instances because some unlabeled positive instances may be mixed in the training data [Pan *et al.*, 2008]. Our model is optimized by AdaGrad [Duchi *et al.*, 2011].

5 Offline Experiments

5.1 Dataset

A large-scale dataset is collected from Taobao. Specifically, we extract tuples $<user\_id, brand\_id, action\_type, timestamp>$, with each tuple representing that user $user\_id$ has an action $action\_type$ on brand $brand\_id$ at time $timestamp$. Users and brands with few interactions are filtered. The final data set in our offline experiments consists of $M = 3,591,372$ users, $N = 90,529$ brands and 82,960,693 actions.

For each user u, his/her action sequence is cut into short ones with the length equal to 11. The first 10 actions form H^u. The brand and timestamp in the last action are assigned to B_{q_u} and T_u respectively, serving as the positive instances ($label_u = 1$) in training. The negative instances ($label_u = 0$) are generated by replacing B_{q_u} with another random brand.

5.2 Compared Models and Evaluations

Our proposed model, Attention-GRU with three modifications, is denoted as Attention-GRU-3M, and is compared with the following baselines.

GRU: GRU [Cho *et al.*, 2014] is among the best RNN architectures. Thus we choose GRU as a representative of the original RNN models.

Attention-GRU: Similarly, Attention-GRU [Chorowski *et al.*, 2015] is selected to represent RNN models with the attention mechanism.

Time-LSTM: Time-LSTM [Zhu *et al.*, 2017] has achieved state-of-the-art performance for sequential behavior modeling. Thus it would be a competitive baseline in our task.

Session-RNN: Session-RNN [Hidasi *et al.*, 2016] exploits RNN to capture users' short-term interest based on sequential actions within a session. We use the publicly available python implementation[2] of Session-RNN, with the session identified by *timeout* [Huang *et al.*, 2004].

libFM: Our task can also be treated as a brand recommendation problem. Therefore, many hybrid recommendation methods that simultaneously capture the content and collaborative information can be applied. We use the popular libFM model [Rendle, 2012] as a representative of these methods.

GRU, Attention-GRU, Time-LSTM and Session-RNN are adapted to our task as described in section 3.2. For libFM, we extract tuples $<user\_id, brand\_id, label>$, where $label$ is 1 if user $user\_id$ has an action on brand $brand\_id$ and 0 otherwise. Then the one-hot vector for $user\_id$, the one-hot vector for $brand\_id$ and the corresponding brand feature vector are concatenated to be $\mathbf{x}$ and $label$ is $\mathbf{y}$ in libFM. The number of units is empirically set to 256 for RNN models. The other hyperparameters in all models are tuned via cross-validation or set as in the original paper. Our code is public [3].

AUC and F1 score [Kim and Leskovec, 2013] are used to evaluate the prediction performance of different models.

5.3 Results and Discussions

Model Comparison

As shown in Table 2, our proposed model significantly outperforms all baselines and we attribute it to the adoption of

[2]https://github.com/hidasib/GRU4Rec

[3]https://github.com/zyody/Attention-GRU-3M

	50% training data		100% training data	
	AUC	F1	AUC	F1
GRU	0.5831	0.5573	0.5952	0.5752
Attention-GRU	0.5918	0.5698	0.6059	0.5843
Time-LSTM	0.5926	0.5704	0.6062	0.5849
Session-RNN	0.5839	0.5561	0.5967	0.5733
libFM	0.5891	0.5663	0.6009	0.5802
Attention-GRU-3M	**0.6051***	**0.5801***	**0.6283***	**0.6050***

Table 2: Model Comparison (bold typeset indicates the best performance. * indicates statistical significance at $p < 0.01$ compared to the second best.)

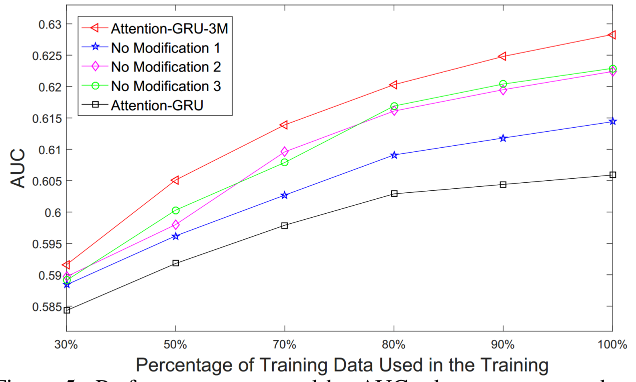

Figure 5: Performance measured by AUC when we remove three modifications one at a time and vary the training data size. No Modification i refers to our model without Modification i.

the attention mechanism and three proposed modifications. In comparison, baselines GRU and Session-RNN, exploiting none of these merits, perform the worst. Compared with GRU, Attention-GRU adopts additional attention mechanism and Time-LSTM adopts Modification 3 proposed in section 4.2. Thus, they both outperform GRU and Session-RNN. As a hybrid recommendation approach, libFM captures content and collaborative filtering features at the same time, but fails to capture the sequential information of user behaviors, while our model captures all these information. This explains why libFM performs worse than our model.

The Effects of Three Modifications

As described in section 4.2, three modifications are proposed to enhance Attention-GRU. We now remove them one at a time to evaluate how each modification affects the prediction performance. We also change the size of data used in training to evaluate its effect on the performance. As shown in Figure 5 (The results of AUC and F1 are similar. Due to page limit, we only show the results of AUC), AUC declines when we remove each type of modification and declines the most when removing Modification 1, which indicates that all the proposed modifications contribute to the performance improvement and Modification 1 is more effective. As the size of training data increases, the influence of Modification 1 becomes larger (i.e. the gap between "Attention-GRU-3M" and "No Modification 1" becomes larger). One explanation may be that, compared to the other two modifications, Modification 1 brings much more parameters (i.e. entries of $\mathbf{M}_{embed}$), thus it needs more training data to learn their optimal values. This also explains that in Table 2 and Figure 5, our model has a larger performance improvement than the other models as the data size increases.

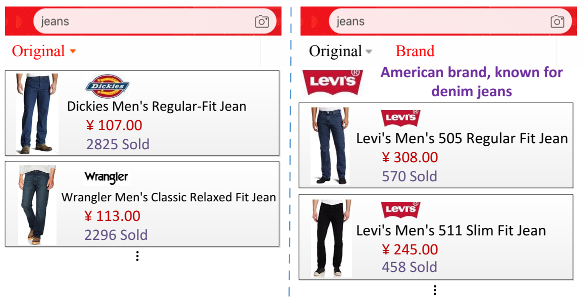
jeans
Original
Dickies Men's Regular-Fit Jean
¥ 107.00
2825 Sold
Wrangler
Wrangler Men's Classic Relaxed Fit Jean
¥ 113.00
2296 Sold
jeans
Original
Brand
American brand, known for denim jeans
Levi's Men's 505 Regular Fit Jean
¥ 308.00
570 Sold
Levi's Men's 511 Slim Fit Jean
¥ 245.00
458 Sold

Figure 6: The original ranking system of the platform is shown in the left. Users can switch to our brand-level ranking system by clicking the button "Brand" as in the right.

	CTR	ATIP	GMV
Baseline	50.17%	CNY 140.13	CNY 4824001.84
New Version	50.37%	CNY 144.90	CNY 4993468.95
Improvement	0.39%	3.40%	3.51%

Table 3: Performance of Online Experiments (*Baseline* corresponds to the left system of Figure 6 and *New Version* represents the right system. *Improvement* is a relative growth of *New Version* compared to *Baseline*, e.g. 3.40% $\approx (144.90 - 140.13)/140.13$).

6 Online Experiments

To better evaluate users' real response to our brand-level ranking system, we conduct a series of online experiments on the Tmall search scenario in Taobao. In this scenario, there are about 5×10^8 *clicks* and 2×10^6 *purchases* on items of nearly 10^5 brands from over 10^7 customers within one normal day. A standard A/B test is conducted online. As shown in Figure 6, we design two user interfaces, one adopts the original ranking system (left), and a button "Brand" is added to the other one (right), where users can switch to our brand-level ranking system by clicking the button. We preserve the original ranking system in the right for users who have no brand preference. For each setting, the same number (about 5×10^5 per day) of users are randomly selected for A/B test. We perform the online experiments for seven days, and the average CTR, ATIP and GMV (described in section 4.1) per day are reported.

The results are shown in Table 3. We can see that compared with the baseline, CTR and ATIP in the proposed new ranking system are both improved, which indicates that by incorporating the brand-level ranking system, users are more likely to click the items and at the same time, they tend to purchase items with higher price (likely to be of higher quality). As a result, the key metric to optimize in this platform, i.e. GMV, has an improvement of 3.51%. Considering the traffic of the platform, it would result in a significant boost in revenue. Our brand-level ranking system has already gone production on the platform, currently serving as a feature requiring user's proactive opt-in to be activated. Nearly 4×10^5 users actively use this system per day.

7 Conclusion

In this paper, we propose a brand-level ranking system to better satisfy the demand of users who have preference bias to certain brands. The core of this system is to solve the personalized brand ranking problem. In our solution, we firstly carefully design the brand features, then rank the brands by an adapted Attention-GRU model. In future work, we will explore the effectiveness of our modifications on other machine learning models (e.g. Modification 1 on Convolutional Neural Network [Krizhevsky *et al.*, 2012], Modification 2 on Matrix Factorization [Qian *et al.*, 2016]). In addition, we would improve the design of our ranking model (e.g. considering the exploration of new brands by reinforcement learning).

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