When Point Process Meets RNNs: Predicting Fine-Grained User Interests with Mutual Behavioral Infectivity

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Abstract

Predicting fine-grained interests of users with temporal behavior is important to personalization and information filtering applications. However, existing interest prediction methods are incapable of capturing the subtle degree of user interests towards particular items, and the internal time-varying drifting attention of individuals is not studied yet. Moreover, the prediction process can also be affected by inter-personal influence, known as behavioral mutual infectivity. Inspired by point process in modeling temporal point process, in this paper we present a deep prediction method based on two recurrent neural networks (RNNs) to jointly model each user’s continuous browsing history and asynchronous event sequences in the context of inter-user behavioral mutual infectivity. Our model is able to predict the fine-grained interest from a user regarding a particular item and corresponding timestamps when an occurrence of event takes place. The proposed approach is more flexible to capture the dynamic characteristic of event sequences by using the temporal point process to model event data and timely update its intensity function by RNNs. Furthermore, to improve the interpretability of the model, the attention mechanism is introduced to emphasize both intra-personal and inter-personal behavior influence over time. Experiments on real datasets demonstrate that our model outperforms the state-of-the-art methods in fine-grained user interest prediction.

1 Introduction

Recent years have witnessed the growingly wide application of e-commerce platforms, such as Amazon¹, Ebay², and Taobao³, and predicting user interests timely to meet individual demands is a fundamentally important research problem to personalization applications (e.g., recommender systems [Zhao et al., 2016; Wang et al., 2017a]). While users may have varied interests towards different products, and thus actions like saving and/or purchasing an item at a particular time (namely an interest related behavior) would be asynchronously generated with random timestamps and form the event sequences. In addition, some studies have shown that user interests are not fixed but could be drifting over time. Therefore, it is crucial to study the dynamic characteristics of user interests in order to precisely understand users’ exact preferences over time.

Existing approaches to study user interests are primarily investigating user interactions (e.g., similarities between users) to predict future interests [White et al., 2009]. For instance, Attenberg et al. study user behavior in sponsored search [Attenberg et al., 2009] by analyzing the content of messages posted by users to identify informative patterns and suggest on-site actions in future instances. To perform precise online recommendation, a topic modeling based method is proposed to simultaneously model individuals’ relatively stable intrinsic interest and the drifting attention of the general public via rating behaviors. However, these approaches focus on the prediction of preferred items/topics in relation to users by referring to user-item interactions to discover the similarity amid users or items [Nori et al., 2011; Zhao et al., 2016; White et al., 2009; C. Li and Pandey, 2015; Song et al., 2015], whilst the subtle mutative degree of user interests are not captured. In fact, user interests can be viewed as an integration of two effects: (1) spontaneous background affected by the internal time-varying attributes of individual users; (2) effects from history events. Take eBay shopping as an example, saving an item to watch list and adding to cart reflect two levels of interest, namely fine-grained interest towards an item. And saving an item is more likely to induce purchase in future time. Therefore, the degree of user interest may vary at different stages, and the event sequence may occur with long-range dependency in the context of continuous browsing. To this end, it is necessary to predict fine-grained user interests more precisely and timely. Moreover, the event sequence is inherently asynchronously. For example, a customer bought a cellphone is more likely to buy phone cases. This potential influence is viewed as mutual infectivity between user temporal behaviors, which is helpful in modeling users’ internal drifting interests.

In this paper, we aim to model the dynamic mutual infectivity between temporal behaviors of users to precisely predict both fine-grained user interests and corresponding timestamps. Specifically, temporal behaviors are divided into continuous browsing time series and stochastic event action sequences. Then, we propose to learn interest drifting patterns in the context of browsing history by jointly modeling the continuous browsing time series and event action sequences using two separate Recurrent Neural Networks (RNNs),

¹www.amazon.com
²www.ebay.com
³www.taobao.com
which are fused to predict the event type and time stamp. This process can be formulated to be modeling of spontaneous background knowledge and the effects of the events in the history [Xiao et al., 2017a]. One may know that multidimensional Hawkes process [Hawkes, 1971] is a powerful statistical methodology [Zhao et al., 2013; Li and Zha, 2014; D. Luo and Zhang, 2015; Zhao et al., 2015] which can be used to model timestamped recurrent event cascades by learning mutual influence between individuals [Li and Zha, 2014]. Unfortunately, a multi-dimensional Hawkes process cannot be applied to predict fine-grained user interests. The main reason is point process models are limited in their capability of capturing the dynamic user behavioral footprints as the explicit parametric form of intensity function is carefully designed by human prior knowledge. Recent works [Zhou et al., 2013; Du et al., 2016] start to fit non-parametric and semi-parametric form into point process, whereas they either fail to meet the mutual-exciting rule in Hawkes process or assume biased time-decaying mutual influence with invariant background intensity. In this regard, RNNs are introduced [Xiao et al., 2017a] to bypass the explicit parametric form of Hawkes process and directly predict the next event time/dimension. However, they are still not complex and flexible enough to model dynamic temporal behaviors associated with user subtle interests and the interpretability on the network structure is unknown.

1.1 Challenges and Our Approach

We remark three major challenges in the task of fine-grained user interest prediction in social networks: (1) jointly modelling the user continuous browsing history and event sequences to discover context-aware interest drifting patterns for accurate fine-grained user interest prediction; (2) designing a flexible model adjustable into personalized temporal behaviors and improve the interpretability of the model; (3) discovering mutual behavior infectivity to reveal the underlying influence patterns.

To combat challenges above, we propose a novel approach based on two RNNs to jointly model the time series of browsing background with constant profile features and event sequences with long range dependency. We utilize temporal point process to model event data while adopting two RNNs to flexibly model the intensity function of the point process. This is an effort to use deep learning techniques to encode non-linear and dynamic intensity mapping without prior knowledge. As shown in Figure 1, we simultaneously model the two effects via two RNNs: a context RNN for tracking the continuous browsing behavior as background and an event sequence RNN for capturing the long-range dependency of user interests over time. Apart from two RNN stacks, we leverage the attention mechanism into the event sequence RNN to effectively capture the mutual infectivity amidst user, thus revealing both the intra and inter-user behavior influence in future interest prediction. The learned latent representations are combined in the integration mapping layer for predicting future interest and its occurrence time stamp.

1.2 Contributions

The main contributions of this paper are three-folds:

- We propose a novel prediction framework for fine-grained user interests by using temporal point process and multi-RNNs to jointly model time series of user browsing and random event sequences.
- To improve the interpretability, attention mechanism is embedded to capture both internal drifting patterns and inter-user mutual infectivity.
- Extensive experiments are conducted on real-world e-commerce datasets to evaluate the effectiveness of our method.

2 Related Work

In this section, we briefly review recent works in relation to user interest prediction, Hawkes Process and recurrent neural networks.

2.1 User Interest Prediction

Predicting user interests is of importance to the personalization applications, such as personalized advertising [Attenberg et al., 2009; C. Li and Pandey, 2015; Yang et al., 2017] and e-commerce recommender systems [B. Li and Wu, 2011; Zhao et al., 2016]. Interest prediction is commonly based on user behavior modelling [Qu et al., 2016; Xu et al., 2012] which aims to infer potential preferences through their interactions with the items. A recent study has focused on drifted user interest over time, and thus the dynamics of user behavior are studied from different perspectives including information diffusion [Yang and Zha, 2013] and social graph [Nori et
However, the degree and timestamp of user interest to be predicted are less-studied, making existing methods underperformed in the time-sensitive e-commerce scenarios. Recent models like the Spatial-Temporal LDA (Latent Dirichlet Allocation) for region-dependent personal interests modelling and Online Graph Regularized User Preference Learning [Zhao et al., 2016] for incremental item content features learning are proposed to make improved recommendations. However, they have no account for future interest that is likely to be triggered by a user’s previous behaviors. As a matter of fact, these behaviors are complex in their dependency and stochastic occurrence of events can cause the transition of interest.

2.2 Hawkes Process

We first briefly describe point process before introducing Hawkes process. Point process is a principled and widely applied framework for temporal event data modelling [D. Luo and Zhang, 2015; Zhao et al., 2015; Shen et al., 2014]. The dynamics of the point process can be captured by its conditional intensity function whose definition is: for a short time window \([t, t + dt]\), \(\lambda(t)\) represents the rate for the occurrence of a new event conditioned on the history \(\mathcal{H}_t = \{ z_i, t_i | t_i < t\} \); \(\lambda(t) = \lim_{\Delta t \to 0} \frac{\mathbb{E}(N(t + \Delta t)-N(t)|\mathcal{H}_t)}{\Delta t}\), where \(\mathbb{E}(dN(t)|\mathcal{H}_t)\) denotes the expectation of the number of events happened in the time window \((t, t + dt)\) given the historical observations \(\mathcal{H}_t\).

Hawkes process is a particular point process with its conditional intensity expressed \(\lambda(t) = \mu + \sum_{t_i < t} g(t - t_i)\) as [Hawkes, 1971], where \(\mu\) is an intrinsic intensity for the occurrence of events, \(t_i\) are the time of events in the point process before time \(t\), and \(g(t)\) is the decay kernel that quantifies the triggering effects from the previous events. It implies that the sum over \(i\) with \(t_i < t\) captures the self-exciting nature of the point process, that is, the intensity of events in the past has a positive contribution to future events.

To model the mutual behavior infectivity, we extend one-dimensional Hawkes process to be multi-dimensional where we have \(U\) Hawkes processes coupled with each other and each Hawkes process corresponds to one event dimension. Formally, a multi-dimensional Hawkes process can be described by a \(U\)-dim point process \(N^U\) with the conditional intensity for the \(u\)-th dimension defined as follows:

\[
\lambda_u(t) = \mu_u + \sum_{i: t_i < t} a_{uu_i} g(t - t_i),
\]

where \(\mu_u \geq 0\) is the intrinsic intensity for the \(u\)-th Hawkes process. Here, an infectivity matrix \(A = (a_{uu_i})\) is introduced to capture the mutually exciting property between the \(u_i\)-th and \(u\)-th dimension, which quantifies the influence of events occurred in the \(u_i\)-th dimension to the \(u\)-th dimension. Multi-dimensional Hawkes processes have been proposed and applied to analyze the information diffusion [Du et al., 2013; Yang and Zha, 2013], and the user interactions [Zhao et al., 2013; Li and Zha, 2014] on social networks. For example, Zhou et al. proposed a multi-dimensional Hawkes process model to learn an infectivity matrix of users with sparse and low-rank constraints [Zhao et al., 2013].

2.3 Recurrent Neural Networks (RNNs) with Attention Mechanism

RNNs [R. Pascanu and Bengio, 2013] and its variants of Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] have been successfully applied in many domains like speech recognition and language translation. While RNNs are widely adopted, the neural network representations are generally uninterpretable and generalizing LSTMs requires a large number of parameters, notwithstanding the simplicity of the underlying dynamics of users’ drifting interests. As a rising technique in natural language processing and computer vision problems [J. Chorowski and Bengio, 2015; V. Mnih and Kavukcuoglu, 2014; J. Ba et al., 2015; Wu and Wang, 2017b; Wang et al., 2013a; Wu et al., 2018; 2017b; Wu and Wang, 2017c; Wu et al., 2017a], the attention mechanism can perfectly be fused with RNNs to stimulate the model to automatically learn which part of the feature representations to attend [Xu et al., 2015]. In addition, the attention mechanism adds interpretability to neural networks’ immediate results [Xu and Saenko, 2016] which helps explain the internal connections between sequential inputs.

3 The Model

In this section, we present the proposed network structure along with the learning algorithm for predicting the fine-grained user interests by modeling the dynamic behavior events.

3.1 Network Structure

Taking a sequence \(\{x_t\}_{t=1}^T\) as input, the RNN generates the hidden states \(\{h_t\}_{t=1}^T\) via \(h_t = f(Wx_t + \text{H}h_{t-1} + b)\), where \(f\) is a non-linear function which can be determined to be \(\text{sigmoid}\) or \(\text{tanh}\), and \(W, \text{H}, b\) are parameters to be learned.

To capture the long-range dependency, we implement the RNN with LSTM by the formulation as follows:

\[
\begin{align*}
    i_t &= \sigma(Uh_{t-1} + Wx_t + Vc_{t-1} + b_i), \\
    f_t &= \sigma(Uh_{t-1} + Wx_t + Vc_{t-1} + b_f), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \text{tanh}(Uh_{t-1} + Wx_t + b_c), \\
    o_t &= \sigma(U_oh_{t-1} + W_ox_t + Vc_t + b_o), \\
    h_t &= o_t \odot \text{tanh}(c_t),
\end{align*}
\]

where \(\odot\) denotes element-wise multiplication and the recurrent activation \(\sigma\) is the \(\text{Logistic Sigmoid}\) function. \(i, f, o, c\) are respectively the input gate, forget gate, output gate, and cell activation vectors. In each of them, there are corresponding input-to-hidden, hidden-to-output and hidden-to-hidden weights: \(U, W, V\) as well as the bias vectors \(b\).

In what follows, we give the full description of our network that is designed to jointly model user browsing time series, behavior sequence and mutual behavior infectivity. For the browsing time series inputs, they are evenly sampled with regular time slices and we use \(\{p_{ij}\}_{i=1}^N\) to indicate the dense feature vector sampled at different timestamps.

For the behavior sequence with length \(N\), it is denoted as \(\{q_{ij}, t_{ij}\}_{i=1}^N, z \in Z\) where \(Z\) is a finite set for all behavior dimensions. In this work, we consider two types of inputs
as illustrated in Fig. 2: (1) continuously and densely distributed time-series browsing history regarding users’ contextual activity intensity; (2) sequential interest induced behaviors whose time of occurrence is stochastically distributed. The network consists of two types of RNNs. One context RNN models the intensity of browsing cascade and is conditioned on the dense feature vectors \( \{ p_i \}_{i=1}^T \) to compute the hidden representation of background knowledge. For notation convenience, we replace \( \{ x_i \}_{i=1}^j \) with \( \{ p_i \}_{i=1}^j \) and represent the LSTM system for context modelling via the following equations:

\[
\mathbf{h}_t = LSTM^p \left( \mathbf{p}_t, \mathbf{h}_{t-1} \right),
\]

where \( \mathbf{h}_t \) is regarded as the context vector representing the background intensity. Meanwhile, the other type of RNN takes the behavior sequence \( \{ q^z_i, t_i \}_{i=1}^N \) as inputs to capture their long-range dependency over time. Through this LSTM, we can generate the hidden variable sequence denoted by \( \{ \mathbf{h}^z_i \}_{i=1}^N \) as the high-level representation of the behavior sequence. Similar to Eq. 3, the LSTM system for behavior sequence modelling can be written as the following:

\[
\mathbf{h}^z_i = LSTM^q \left( \{ q^z_i, t_i \}, \mathbf{h}^z_{i-1} \right),
\]

where the times tamp \( t_i \) is a supplementary input.

### 3.2 Modelling the Mutual Behavior Infectivity

To predict the dimension \( z_{j+1} \) and timestamp \( t_{j+1} \) for the \((j+1)\)-th behavior, the history \( \mathcal{H}_{t_j} = \{ z_i, t_i \}_{i=1}^j \) prior to it should be utilized to investigate the patterns of previous behaviors. Compared with the simplex behavior dimension indicator \( z \), the most recent \( \mathbf{h}^z_i \) is typically regarded as a compressed representation of \( \mathcal{H}_{t_j} \), thus containing more sufficient information of both the current and previous behaviors. However, we note that behaviors from a certain dimension may have higher influence on some dimension, so exploiting this observation can make the trained neural network more effective and expressibly interpretable. Hence, to discover the influence from all history behaviors to each particular behavior dimension, we expand the representation of \( \mathcal{H}_{t_j} \) to be a set of all learned vectors in one sequence \( \{ \mathbf{h}^z_i \}_{i=1}^j \) which are referred to as the compressed vectors. In addition to encode the varied mutual influence between behaviors, we further leverage a vector set \( \mathcal{H}^z_{t_j} = \{ \mathbf{h}^z_i \}_{i=1}^j \) condensed from \( \mathcal{H}_{t_j} \) where each vector in the set is the most recent representation of dimension \( z' \) at time \( t_j \) in one sequence. Inspired by the aforementioned multi-dimensional Hawkes process, for each dimension \( z \in Z \), the behavioral influence strength \( a_{z'z} \) from \( z' \) to \( z \) is introduced and is formulated as:

\[
a_{z'z} = F(\mathbf{h}_{z'}, \mathbf{v}_z), \mathbf{h}_{z'} \in \mathcal{H}^z_{t_j},
\]

where \( \mathbf{v}_z \) is the feature vector to be estimated for each dimension \( z \), and \( F(\cdot) \) is the function to quantify the influence strength from \( z' \) to \( z \). Following Xiao et al. [Xiao et al., 2017b], the influence function \( F(\cdot) \) can be defined as:

\[
F(\mathbf{h}_{z'}, \mathbf{v}_z) = \begin{cases} \tanh(\mathbf{h}_{z'} \cdot \mathbf{v}_z), & \text{if } |\tanh(\mathbf{h}_{z'} \cdot \mathbf{v}_z)| > \varepsilon \\ 0, & \text{otherwise} \end{cases},
\]

where \( \varepsilon \) is set to be 0.01 to control the degree of sparsity. Specifically, a large score will be calculated by \( F(\cdot) \) when the compressed vector \( \mathbf{h}^z_{j} \) is similar to \( \mathbf{v}_z \), and vice versa. Furthermore, \( F(\cdot) \) also allows negative influence to simulate the situation of counteracting, and the computed mutual infectivity is bilateral.

As shown in Fig. 3, once all the influence strengths are computed, for each behavior dimension \( z \), we are able to produce the hidden representation vector \( \mathbf{a}^j_z \) by aggregating the infectivity from all the past behaviors in \( \mathcal{H}_{t_j} \) to dimension \( z \) with the soft attention mechanism:

\[
\hat{\mathbf{a}}^j_z = \sum_{i=1}^{j} a_{z_i, z} \mathbf{h}^z_i, z \in Z,
\]

After the model is successfully trained, e.g., the vector \( \mathbf{v}_z \) is learned, the influence strength \( \{ a_{z_i, z} \}_{i=1}^j \) for each test event sequence \( e \) can be estimated using Eq.(5). Also, the infectivity matrix to reflect the behavioral mutual infectivity is defined as \( \mathbf{A}_{z_z} = \langle a_{z,z} \rangle \), where \( \langle \cdot \rangle \) denotes the average of all \( \{ a_{z,z} \} \) divided by \( e \).

### 3.3 Model Learning

To simultaneously model the browsing time series and behavior sequence, we feed the two types of data sources into an integration layer that mixes them interactively:

\[
\mathbf{s}^z_j = \tanh(\mathbf{W}_a [\mathbf{h}_j, \hat{\mathbf{a}}^j_z] + \mathbf{b}_a), z \in Z
\]

where the concatenation of context vector \( \mathbf{h}_j \) and behavior representation \( \hat{\mathbf{a}}^j_z \) is leveraged to compute the final representation \( \mathbf{s}_z \) with trainable weight \( \mathbf{W}_a \) and bias \( \mathbf{b}_a \). We use matrix \( \mathbf{S}_j = [s^1_j, s^2_j, ..., s^Z_j] \) to collect representations for all \( Z \) dimensions. Here, we utilize \( \mathbf{s}_j \) to simulate the contextual browsing intensity and further forecast the type and occurrence time of next interest related behavior jointly:

\[
\begin{align*}
\mathbf{y}_{j+1} &= \text{softMax}(\mathbf{w}_s \mathbf{s}_j^T + \mathbf{b}_s), \\
\hat{z}_{j+1} &= \text{argmax}\left(\mathbf{y}_{j+1}\right), \hat{t}_{j+1} = \mathbf{w}_t \mathbf{s}^z_{j+1} + b_t,
\end{align*}
\]

where the probabilities of next behavior dimensions in \( \mathbf{y}_{j+1} \) are predicted by applying the Softmax operation to representations of all \( \{ s^z_j \}_{z=1}^Z \) where \( Z \) is the number of event dimensions. The optimal predicted dimension \( \hat{z}_{j+1} \) can be computed by selecting the corresponding maximum element in

**Figure 2:** A sketch on model structure.
Finally, \( t \) is the timestamp associated with each interest related behavior, and the predicted time of next occurrence \( \hat{t}_{j+1} \) can be obtained by regression with the representation of predicted behavior dimension \( s^z_{j+1} \). \( w_z, b_z, w_t \) and \( b_t \) are model parameters to be learned.

For model training, the total loss of the network is the sum of the cross-entropy loss for the prediction of user interest and Gaussian penalty loss for time prediction:

\[
\mathcal{L} = -\sum_{j=1}^{N} \left( \sum_{c=1}^{C} z_{j+1} \log y_{j+1} + \log (f(t_{j+1}|H_t_j)) \right),
\]

where \( z_{j+1} \) is the one hot labor vector of users’ actual interests at time \( t_{j+1} \), \( y_{j+1} \) is the class probability vector generated within the prediction layer. \( C \) is the number of output classes, while \( N \) is the total length of current behavior sequence. \( f(\cdot) \) is the Gaussian penalty function for the predicted timestamp defined as follows:

\[
f(t_{j+1}|H_t_j) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(t_{j+1} - \hat{t}_{j+1})^2}{2\sigma^2}\right),
\]

where \( t_{j+1} \) and \( \hat{t}_{j+1} \) are actual and predicted timestamp of \( (j+1) \)-th interest related behavior respectively, while \( \sigma \) is the penalty coefficient.

### 4 Experiments

In this section, we conduct experiments on real datasets to show the effectiveness of our approach in accurate fine-grained user interest prediction.

#### 4.1 Datasets and Data Preprocessing

We used the publicly available real e-commerce data provided by Taobao\(^4\), which is the most popular online shopping website in China and one of the globally top 20 most visited websites according to Alexa\(^5\). The time span of the data ranges from 18-11-2014 to 18-12-2014 (31 consecutive days). The original datasets contains 12,256,907 anonymized transactions of 4 different types of user-item interactions generated by 10,000 identical users: clicking (browsing), adding to favourite (saving), adding to cart and purchasing. All of these behaviors (browsing excluded) indicate three incremental degrees of user interest, which can be used as behavior labels to reflect fine-grained user interests. Fig. 4 shows the interaction distribution for each item. The user-item interactions follow the “long tail” distribution which indicates that only a small portion of items have high popularities, and it is impractical to acquire a large set of users who are involved in the same items. Since each user will be treated as a sample in our case, in order to ensure the sufficiency of samples, we use all items from top two categories to extract user trajectories.

The data preprocessing procedure aims to extract the trajectories of users who have interacted with a pair of item categories \( A \) and \( B \) (categories are anonymized), thus generating both the time series of browsing and the event sequences of interest induced behaviors. We first select top two most active categories in the original dataset and calculate how many users interacted with both of them. Then, we remove users having less than 2 higher-interest behaviors. Finally, all behavior sequences are sorted in timeline and form a dataset consisting of 2,702 user portfolios. For each user, the last behavior type posed on the specific item category is used as the ground truth label for the future degree of user interests and the notations of those behaviors are provided in Table 1. Specifically, we obtain the distribution of 6 classes as: \( \{ A_1 : 436, A_2 : 646, A_3 : 421, B_1 : 420, B_2 : 390, B_3 : 389 \} \). More statistical details of the collected dataset are listed in Table 2.

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\(^4\)https://tianchi.aliyun.com/datalab/dataSet.htm?id=4

\(^5\)https://www.alexa.com/siteinfo/taobao.com#trafficstats
be 512, 128 and 64, respectively. We use back propagation algorithm, namely Adam [Kingma and Ba, 2014] for optimization and set the learning rate as 0.001. The batch size is 128 and the training procedure is iterated until the loss function converges. We hold out 10% of the users in the dataset for cross-validation, and randomly split the rest with a ratio of 4 : 1 for training and test respectively.

4.4 Baselines and Evaluation Metrics

We compare the prediction performance of our method against a number of competing baselines, namely Logistic Regression, Hawkes Process and Intensity Recurrent Neural Network. These baseline methods are described below.

- **Logistic Regression (LR):** In our case, we adopt one LR model for the user behavior prediction and we use another one for time-stamp prediction. We use behavior type aligned by time and the normalized timestamps as the input for those two LR models respectively.

- **Hawkes Process (HP):** In order to proceed the muti-type user behavior prediction, we choose the Multi-dimensional HP model. This model is able to learn the mutual correlations between all dimensions as well. We adopted a sparsity regularization term on the mutual infection matrix to control the degree of sparsity [Zhao et al., 2013; Xiao et al., 2017a], but the low-rank assumption is removed because there are only 6 different kinds of higher-interest behaviors.

- **Intensity Recurrent Neural Networks (IRNNs):** IRNNs was proposed to model the intensity function in point process in [Xiao et al., 2017a]. To meet the requirement of input format, we observe the time series of browsing history by slicing the time intervals evenly on a daily basis. Also, for the behavior sequence, we feed the type information into the embedding layer in IRNNs to acquire distinctive representations for user behaviors as the input of its single LSTM layer.

4.2 Features

To extract features for different behaviors, we employ Non-negative Matrix Factorization (NMF) which is proved to be effective in diverse machine learning tasks [Fevotte and Idier, 2011; J. Liu and Han, 2013; Wang et al., 2013b; Wu et al., 2016; Wang et al., 2015b; 2014a; 2014b; 2015a; Wu and Wang, 2017a; Wang et al., 2015c; 2016; 2017b; Wang and Wu, 2017b; 2017a; Wang et al., 2014c; Wu et al., 2013] to learn the feature representations. For each behavior in Table 1, we encode its occurrence using \( A \) (occurred) and \( B \) (nonoccurence) respectively into a matrix \( \mathbf{V}^{M \times N} \) where \( M \) denotes the number of users and \( N \) is the number of items from two categories. Here \( M \) and \( N \) are 2,702 and 115,310 respectively. Then, we utilize majorization-minimization (MM) algorithm [Fevotte and Idier, 2011] to decompose \( \mathbf{V}^{M \times N} \) into user behavior feature matrix \( \mathbf{W}^{M \times K} \) and item feature matrix \( \mathbf{H}^{K \times N} \) with a reduced dimension \( K = 100 \). Finally, we acquire behavior feature vectors as the rows in \( \mathbf{W}^{M \times K} \). For each browsing time series, we concatenate \( A \) and \( B \) feature vectors with the daily frequency to be the feature input. For each event sequence, we combine sorted feature vectors for behaviors with normalized timestamps to preserve the information of user temporal behaviors.

4.3 Experimental Settings

The model is implemented by using Tensorflow\(^6\). We apply stacked 3-layer LSTM for both time series and behavior sequence modeling. Since we utilized NMF for distinct feature extraction, the embedding layer is not required to compute discriminative feature representations for different behavior types. The number of hidden states in each layer is set to 64. We adopt the widely used evaluation metrics including Precision, Recall and F1 Score to evaluate the performance of

\(\text{Figure 5: ROC curve for all 6 classes.}\)

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6\(\text{www.tensorflow.org}\)

\(\begin{array}{|c|c|c|c|c|}
\hline
\text{Symbol} & \text{Description} \\
\hline
A_0 & \text{browsing products in category } A \\
A_1 & \text{saving products in category } A \\
A_2 & \text{adding products in category } A \text{ to cart} \\
A_3 & \text{purchasing products in category } A \\
B_0 & \text{browsing products in category } B \\
B_1 & \text{saving products in category } B \\
B_2 & \text{adding products in category } B \text{ to cart} \\
B_3 & \text{purchasing products in category } B \\
\hline
\end{array}\)

\(\text{Table 1: Notations of user behavior.}\)

\(\begin{array}{|c|c|c|c|c|}
\hline
\text{Statistic} & \text{Total} & \text{Max.} & \text{Min.} & \text{Avg.} \\
\hline
\text{Identical Users} & 2,702 & - & - & - \\
\text{Transactions} & 484,516 & 4,182 & 5 & 179.3 \\
\text{A}_0 \text{ in Transaction} & 233,964 & 2,160 & 3 & 86.6 \\
\text{A}_1 \text{ in Transaction} & 7,848 & 365 & 0 & 2.9 \\
\text{A}_2 \text{ in Transaction} & 7,424 & 366 & 0 & 2.7 \\
\text{A}_3 \text{ in Transaction} & 1,560 & 186 & 0 & 0.6 \\
\text{B}_0 \text{ in Transaction} & 222,150 & 3,675 & 3 & 82.2 \\
\text{B}_1 \text{ in Transaction} & 5,941 & 105 & 0 & 2.2 \\
\text{B}_2 \text{ in Transaction} & 4,911 & 93 & 0 & 1.8 \\
\text{B}_3 \text{ in Transaction} & 718 & 76 & 0 & 0.3 \\
\text{Time Span (days)} & 51,175 & 31 & 1 & 18.9 \\
\text{Behavior Occurrence} & 485,358 & 527 & 5 & 179.6 \\
\hline
\end{array}\)

\(\text{Table 2: Statistical details of datasets.}\)
user behavior prediction and use Mean Average Error (MAE) measured by days to measure the correctness of predicted timestamps.

### 4.5 Effectiveness Analysis

The performance comparison is shown in Table 3, and we draw some observations. First of all, our proposed model outperforms all the baselines on the average level. In most user interest classes, our methods present improved prediction performance regarding both the future behavior and corresponding time stamp. Second, compared to LR and HP, IRNNs offers better prediction results because it can jointly model the context information of browsing time series and the stochastic behavior sequences with long-range dependencies and richer feature representations. Third, in contrast to IRNNs and JRNNs, due to the introduction of attention mechanism into RNN hidden state transition which capture both the internal drifting patterns and inter-user mutual infectivity. More importantly, our model can uncover the underlying user behavior infectivity structure and provide interpretable evidence for predicting results. The extensive experiments in this paper suggest its superior performance in real-world e-commerce data when we have no domain knowledge on the scenario. Future work will be conducted to apply our approach in more complex e-commerce platforms.

### 4.6 Visualization and Discussion on Mutual Behavior Infectivity

We visualize the learned infectivity among different behaviors in Fig. 6. Each node represents one specific behavior; the polarity and width (not the length) of the arrows illustrate the direction and strength of the influence from one behavior to another. The wider one arrow is, the greater infectivity it denotes. We use red color to illustrate positive mutual infectivity while the Grey color stands for negative effect. Also, the influence within the same dimension is represented as a self-loop process. As shown in Fig. 6.(a) which is the averaged infectivity among all testing samples, the strong self loops within both A1 and B1 indicates that users tend to continuously save the products they are interested in while browsing different items in one category. In contrast, A3 has negative internal influence, and this is because users normally would not purchase two items from the same category. Similarly, after adding a B category product to cart (B2), it is highly possible to get the item purchased; and users tend to stop adding products to cart when they finish the purchase. Noticeably, the discovery of the behavior mutual infectivity between A and B implies that products in the two categories are complementary to each other, e.g., smart phones and phone cases.

Two mutual behavior infectivity visualizations are also presented for two individual users (anonymized as U1 and U2) chosen from correct predictions in Fig. 6.(b) and Fig. 6.(c). Following the general patterns of averaged infectivity, these two e-commerce platform users behave slightly differently. For U1, A3 has a positive self influence which indicates that U1 is a frequent customer for products in category A because this user tends to purchase the same kind of items in a relatively short period of time. Meanwhile, compared to U1, U2 seems to be a more decisive customer when buying products in category A because saving the items will directly induce the behavior of purchasing, and user U2 doesn’t waver among different items because the self infectivity in both A1 and B1 is insignificant.

### 5 Conclusion

In this paper, we present a recurrent point process model to predict fine-grained user interests. The interpretability of the proposed model is enhanced by introducing attention mechanism into RNN hidden state transition which capture both the internal drifting patterns and inter-user mutual infectivity. More importantly, our model can uncover the underlying user behavior infectivity structure and provide interpretable evidence for predicting results. The extensive experiments in this paper suggest its superior performance in real-world e-commerce data when we have no domain knowledge on the scenario. Future work will be conducted to apply our approach in more complex e-commerce platforms.

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Figure 6: Visualizations of learned mutual behavior infectivity. Best view in color.
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