Browsing Behavioral Intent Prediction on Product Recommendation Pages of E-commerce Platform

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Abstract. User behavior data has always been the key for e-commerce platforms to make decisions and improve experience, especially when predicting users' behavioral intent. Nowadays, the Product Recommendation Page (PRP) has played an increasingly significant role of e-commerce platforms with the popularity of recommendation systems. However, past research on predicting user behavioral intent across e-commerce platforms may not be applicable to PRPs, where users have different characteristics. In this research, users' browsing behavioral intent of PRPs is studied and predicted. A large amount of user data of PRPs is collected and processed, and the corresponding dataset is built. After that, a user interest analysis method is proposed while five browsing intent prediction models are applied and compared. The method distinguishes users with different browsing interest degrees, and the models can better predict users' browsing behavior intent within different interest groups. A validation experiment on the large-scale dataset shows that the proposed method can predict user browsing intent with a decent performance.

Keywords: E-commerce · Product recommendation page · Intent prediction · Interest Analysis.

1 Introduction

The key component of e-commerce business is users, their behavior data is a significant analysis resource to boost e-commercial security, profitability, and stability. In the context of big data, many studies analyzing e-commerce user behavior data have been conducted in recent years. Understanding users' purchasing intent is an essential but troublesome task. The main challenge of predicting behavioral intent is to obtain valuable information and to ensure predicted speed. It is difficult to process behavior data correctly and extract the most useful information. Real-time is also necessary for the process of user intent prediction. If it is not fast enough to make decisions in response to user intent, it is likely to decrease user experience and even lose users. The focus of user behavioral intent prediction is also different for various scenarios in e-commerce platforms. The most common and influential intent study, user purchasing intent prediction [1] cannot be applied to all situations, especially where the purchasing intent is quite limited. In some scenarios, the main purpose is not to prompt users to make direct purchases, but to guide them in exploring products, which is typically represented by the Product Recommendation Page (PRP).

Nowadays PRPs have an increasing amount of traffic in e-commerce platforms, while the majority of research on user intent is geared towards the entire purchasing process, instead of PRPs of the platforms. In this work, users' browsing behavioral intent of PRPs is investigated and predicted. The users' behavior data are collected and then are processed to a browsing behavioral dataset. Based on this dataset, prediction models are constructed and used to predict users' browsing behavioral intent. In addition, the users' own characteristics are also modeled to distinguish different degrees of interest. Prediction models are retrained among different groups of people, which effectively improved predicted performance.

The contributions of this work are presented as follows:

1. A dataset of browsing-interactive behaviors, which contains detailed information about the path that users have browsed within PRPs. These data are easily accessible and can describe users from multiple perspectives for better users' interest analysis and browsing behavioral intent prediction.

2. A method of predicting users' browsing behavioral intent. The method requires only a small amount of easily accessible browsing behavior data, does not require building complex feature engineering to perform the prediction work, and has a fast response speed during the users' life-cycle in PRPs. Experiments are conducted on a large-scale dataset, and the results show that the model has great prediction performance.

3. A method for analyzing users' browsing interest using multiple metrics, and the results obtained contribute to improving the accuracy of browsing behavioral intent prediction.

2 Related work

2.1 Browsing Behavior Analysis

A survey in [2] shows user web browsing behavior, keystroke behavior, network transaction behavior, and mobile terminal behavior are the most common resources to optimize the scheme for designers and modelers. Specifically, browsing behavior analysis is mainly researching user features and behaviors by applying some machine learning algorithms based on users' historical behaviors [3]. [4] presents K-means clustering algorithm used for identification of user groups on the basis of their web access log record, while [5] uses PCA to identify the most significant features from the log file before clustering users by SOM algorithm. Historical behavior data are widely collected in forms of click-stream. [6]

conducts a comparative analysis of click-stream behavior of users from different countries, research in [7] applies a collaborative filtering-based method to recommend items for different consumers, and [8] addresses the problem of user intent prediction from click-stream data of an e-commerce platform. Interest analysis is also a popular method to find users' behavioral habits. [9–14] indicate that the frequency, duration and sequence of visits on web pages reflect browsing behaviours. [34] proposes Intent Contrastive Learning to investigate the benefits of latent intents and leverage them effectively for recommendation. [35] models the comprehensive compositional coherence on both global intent contents and semantic intent contents by a Content Attentive Neural Network.

2.2 Browsing Behavioral Intent Prediction

The problem of user intent or session classification in an e-commerce setting has been heavily studied, with a variety of classic machine learning and deep learning modeling techniques employed. [15] uses Recurrent Neural Networks (RNNs) on a subset of the same dataset to predict the next session click on the user intent classification problem. [16] compares [15] to a variety of classical machine learning algorithms on multiple datasets and finds that performance varies signally by datasets. [17] extends [15] with a variant of LSTM to capture variations in dwell time between user actions. User dwell time is considered a vital factor in multiple implementations. For browsing behavior prediction, [18] uses a mixture of RNNs and treats the problem as a sequence-to-sequence translation problem, constructing a model both including prediction and recommendation. [19] shows that short sessions are very common in e-commerce datasets, moreover, a user's most recent actions are often more vital in deciphering their intent than older actions. Therefore we argue that all session lengths should be included. RNNs are used in [20] to incorporate temporal features with user preferences to improve recommendation performance, and to predict behavioral directions instead of purchase intent.

The task of browsing behavioral intent prediction is closely related to sequence classification. A brief survey by [21] categorizes the sequence classification methods into three groups: feature-based methods [22], sequence distance-based methods [23], and model-based methods [24–27]. This research is related to the model-based approach, which applies end-to-end algorithms to model the sequences and save extensive feature engineering work. The work is also related to sentence classification in natural language processing [28–30]. Text sentences and time series data are similar to each other in that they are both ordered sequences in nature. This work differs from the previous work in that the dwell time in the sequence is also concerned, while in traditional sequence classification, usually, only the data in the sequence needs to be processed.

3 Methodology

In PRPs, user browsing path and dwell time are often the most concern by researchers, and these data are also easy to obtain in many cases. Therefore, this research collects users' browsing path in the form of a sequence of pages, while each page contains detailed information about browsing behaviors and the dwell time.

The main purpose of predicting user browsing behavioral intent in this work is to predict what a user is going to browse next, i.e., to predict which page the user will go to next. However, there are many types of pages in PRPs, including not only PRPs' home page and sub-pages, but also different product pages and many other types of pages. Moreover, the naming and coding of pages are often irregular, and also unrelated to users' intent.

Based on the above, the PRPs are classified into five types by the nature of the pages, considering both the compatibility of PRPs in different e-commerce platforms and the relevance of data to user intent. The classification is helpful to make better predictions, and each type of pages has its own independent page nature rather than a name. Thus different types of pages are more likely to represent users' intent. For example, frequent browsing of the "product exploration page" can indicate that a user is more interested in a wide range of products and eager to obtain inspiration from its exploration experience. After processing the raw data, the corresponding large-scale dataset is built.

Based on the processed dataset, the browsing behavioral intent prediction in this study can be described as a sequence classification task which has five possibilities regarding output. To find the best prediction method, this work constructs five models to predict user browsing behavioral intent, that contain three deep neural network models and two traditional machine learning models. Taking into account real-time requirements of e-commerce platforms, these models are not designed to be too large and all have applicable prediction speed.

In order to improve the effectiveness of the prediction model, this work presents a deeper analysis on user behaviors and proposes a user interest analysis method. The method produces two indicators from browsing data and uses a clustering algorithm to distinguish the group of users who have a distinguishing interest in PRP. Finally, the prediction model was retrained and predicted in the different interest groups to verify the effectiveness of the proposed method. The workflow of behavior analysis and prediction are shown in Fig 1.

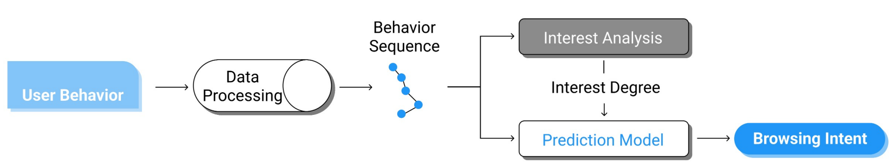

Fig. 1. Workflow diagram of user browsing behavior analysis and prediction system.

4 Experiments

4.1 Data collection and processing

From a mobile App of the largest e-commerce platform in China, the browsing behavior data of 284,202 users of PRPs are collected by means of end-to-end buried points. The time span of the data is one week in March 2022. The raw data of browse-interactive behaviors contain three fields, including "Scene", "Id" and "Timestamp". "Scene" and "Timestamp" identify where and when an action occurs. "Scene" also indicates the function of the page, e.g. the page is used to represent a product or advertisement. "Id" helps identify the exact page when browsing in the App.

Fig. 2. An example of five types of pages and their flow directions. "PRP_mainpage", "Product_detail", "Product_explore", "Out_page", "PRP_otherpage" are indicated by yellow, red, orange, blue and green boxes respectively.

Combining "Scene" and "Id", the pages are divided into five types. An example of five types of pages and their flow directions is shown in Fig 2, where the type is indicated by bounding box with five different colors. The process of page jumping is represented by lines, of which the dots represent the clicking area that triggers the jumping of the starting page and the arrows point to the pages after the jumping. Each type contains a specific definition. The definition and distribution of five types of pages are described in Table 1. Statistics show that the two largest distributions are "Product_detail" and "PRP_otherpage", accounting for 67.9% of the pages. However, in general, there is no situation where a certain page occupies the majority of browsing activities, so we can use accuracy as the metric to evaluate the prediction performance.

To process the data into a format suitable for model recognition, pages are encoded as one-hot codes of a length of five. The dwell time between pages browsed by users is normalized within sixty seconds, as 94% of the dwell time is less than sixty seconds. Then a massive dataset is built and contains 284,202 complete user browsing behavioral sequences. [19] argues user real-time browsing intent tends to be most closely related to the most recent behaviors that occurred, while behavioral actions that occurred long ago can be used to assess

Table 1. The definition and distribution of five types of pages.

Type	PRP_mainpage	Product_detail	Product_explore	Out_page	PRP_otherpage
Definition	Recommended products page	Product detail page	Sub-page of product detail page	The off-site page of PRP, but still in the App	Within PRPs and do not belong to "PRP_mainpage", "Product_detail" and "Product_explore"
Percentage	17.3%	24.5%	11.2%	3.6%	43.4%

users' habits. Considering the applicability of historical data to current data, the model uses only five most recent occurrences in predicting user browsing intent, but the complete sequence is processed when analyzing browsing interest. So our prepared dataset for prediction consists of 2,301,388 sequences of a length of six while the first five pages and dwell time are used as input data and the sixth page is used as label.

This method just takes a few easily obtained browsing data, which can not only reduce the time consumption of data collection to ensure prediction speed but also minimize the impact on the normal operation of business in the actual production environment.

4.2 Model architecture

The prediction model is designed to consume the input representation and predict user browsing behavioral intent in an end-to-end, sequence to prediction manner. The model in this work is not designed to be large and complex in order to ensure the speed of prediction and lightweight requirement in real online business scenarios. This research investigates two traditional machine learning models and three neural network-based models for intent prediction.

Traditional machine learning models This work tests two traditional machine learning models that can be used to handle sequence classification, namely, RF-HMM model and Compact Prediction Tree (CPT) [31] model. In the RF-HMM model, the raw data are used to train the Random Forest (RF) and Hidden Markov Model (HMM) respectively, and the HMM is used to estimate the state transfer matrix. At the prediction stage, RF is first applied to predict the probability distribution, and then the state transfer matrix of the HMM is combined to obtain the resultant values.

Neural networks models Three neural network-based models are used to make browsing behavioral intent prediction. RNNs, which are good at modelling sequential data, are chosen to build the prediction model. The first neural network model uses LSTM among many RNN variants because of its ability to extract features from a long sequence. The model's main structure consists of a network of four layers with 512 LSTM neurons in each layer. Inspired by [22], considering the ability of CNN for feature extraction, the second model combines CNN and LSTM, using a one-dimensional CNN to extract the features of the sequence before applying LSTM for the prediction output. The third model is based on the Temporal Convolutional Neural (TCN), which is tiny and has achieved several SOTAs in time series tasks since it was proposed by [32] in 2018. The TCN model is consisted by a TCN layer and two hidden dense layers and a linear layer used to be output.

The dataset is split into a training set and validation set in an 80:20 ratio. During the training period, these three models are trained using the Adam optimizer, coupled with a categorical cross-entropy loss metric and a learning rate automatic controller. Training is halted after two continuous epochs of worsening validation Accuracy.

4.3 Interest Analysis Method

In this section, an interest analysis method is proposed to analyze users' interest in PRPs, and users are divided into three groups with different interest degrees. Models are trained separately in different groups of users and make predictions of them. It can improve the models' prediction accuracy utilize different preferences of different groups. Unlike the predictive models, which use only the five most recent pages, the method uses all the pages a user has browsed since entering the PRPs.

Two indicators are used which are most concerned about by real online environment to measure users' interest patterns [33].

Indicator 1: visiting frequency

For user_i, click_i^j consists of the number of visits to type_j. Visiting frequency is defined as the ratio of type clicks to the length of the user's full browsing path. This work uses freq_i^j to denote the visiting frequency to type_j by user_i in a session:

$$\text{freq}_i^j = \frac{\text{clicks}_i^j}{\text{len}\,(P_i)} \quad \left(0 \leqslant \text{freq}_i^j \leqslant 1\right) \tag{1}$$

Indicator 2: relative duration

In this study, the time spent browsing each page will be accumulated according to the type. Relative duration is utilized as one of the main indicators to reflect a user's interest. Relative duration redu_i^j is defined as the ratio of time user_i spends on type_j to the entire session.

$$\text{redu}_i^j = \frac{\text{duration}_i^j}{\text{time}\,(P_i)} \quad \left(0 \leqslant \text{redu}_i^j \leqslant 1\right) \tag{2}$$

After processing, each user has a feature vector of shape (2, 5), that is, each user has two indicators in five types. K-means algorithm is used to cluster users into different interest groups, the algorithm allows to customize the number of clusters.

The "Score" function measures the clustering effect, which is the negative number of the sum of the distance between the samples and their cluster center, and will increase with the increase of clusters. Therefore, the optimal value of the number of clusters is set according to the elbow criterion. Intuitively, the scores for the number of clusters from one to ten are mapped into (0, 1) and plotted in Fig 3.

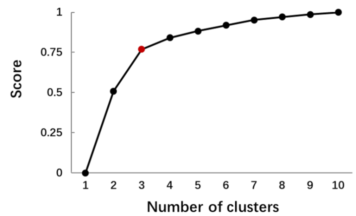

Fig. 3. Scores for different numbers of clusters.

In addition, the optimal number of clusters should also make samples evenly distributed to ensure that each model is well trained. The proportions of each group with K value of two, three and four are 1:2.10, 1:1.07:1.13 and 1:1.09:1.93:2.15, respectively. Therefore, three is the best number of clusters considering it is an elbow point and gives an even data distribution. These three groups of users are defined into high, middle, and low interest groups, which are described in detail in Section 4.3.

5 Results and discussion

5.1 Prediction results

In the testing phase, the data in the validation set are used for testing, and the prediction results for both cases with and without interest analysis are counted separately, shown in Table 2.

Without using interest analysis, models are trained by all users' data of the training set. Neutral network based models perform much better than traditional machine learning models. LSTMs model takes highest accuracy at 88.72% without using interest analysis, indicating that it can learn behavioral characteristics and habits of users better from these few and easily obtained browsing data. However, the accuracy of RF-HMM and CPT models does not exceed 70%, probably because these models are too simple to learn users' behavioral habits from little information.

Table 2. Prediction results for different groups of users of different models.

Model	Accuracy			
	Without interest analysis	High interest group	Middle interest group	Low interest group
CPT	0.6425	0.6861	0.6874	0.6682
RF-HMM	0.6632	0.7233	0.6922	0.6598
TCN	0.8734	0.8936	0.8872	0.8698
CNN-LSTM	0.8612	0.8878	0.8827	0.8606
LSTMs	**0.8872**	**0.9211**	**0.8958**	**0.8842**

To test the running speed of the models, the time consumption (milliseconds) of each prediction of the five models is shown in Table 3. The single prediction time of the five models is less than 50 ms, which is satisfactory in real application scenarios. The best model, LSTMs, predicts at 28.92 ms per session. Two traditional machine learning models are faster than the neural network models and can reach around 10 ms or less.

Table 3. Time consumption per prediction for five models.

Model	CPT	RF-HMM	TCN	CNN-LSTM	LSTMs
Time(ms)	2.38	10.93	47.29	27.90	28.92

5.2 Interest analysis results and discussion

This section describes the results after using the interest analysis method, which analyzes the characteristics of three different groups of users. The prediction results with the interest analysis are also discussed.

Two indicators of a user on the same page type have a strong correlation. Their distributions for the three groups of users on the five page types are shown in Fig 4 and these distributions are easy to distinguish.

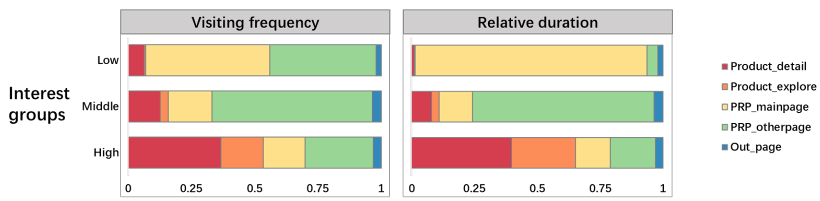

Fig. 4. Distributions of the two indicators for the three groups of users on the five pages.

According to the definition of page classification, when users spend more time visiting the "Product_detail" and "Product_explore", it means that they are more interested in products; otherwise, they just wander aimlessly in PRPs. Therefore, the group with high visiting frequency on these two types is considered the high interest group, and other two groups are considered the middle and low interest groups, respectively.

Users with different interest degrees differ greatly in the prediction results. As described in Table 2, the Accuracy of high interest group has the greatest improvement of three groups and can reach 92.11% in the best model LSTMs. The middle interest group also has better results among five models. However, there is no significant increase in the prediction results for the middle interest or even a decrease for low interest groups.

Combining the visiting frequency and duration distributions shown in Fig 4, It can be inferred that the high interest group is more evenly distributed across the five pages and they prefer to browse pages that are directly related to the products. Delightfully, these people are often the most useful people in e-commerce because they have a higher purchase rate. In contrast, the middle interest group spends the most time on "PRP_otherpage" in PRPs, accounting for about 63.3%, but also focuses on some productive pages, so their behavioral pattern is harder to capture. The most irregular pattern is the low interest group, who barely browses the products after entering the PRPs.

Table 4. Full path length and total dwell time statistics for three groups.

	Full path length (steps)			Total dwell time (seconds)		
Interest degree	High	Middle	Low	High	Middle	Low
Mean	12.7	10.3	2.1	207.2	196.9	43.7
Median	12.0	10.0	2.0	147.9	127.0	17.8
S.D.	7.9	6.2	2.8	202.3	216.0	111.9

To further verify the division of interest groups, this research also calculates the mean, median, and standard deviation of the full path length and total dwell time of three groups. The full path length is the number of pages browsed by a user from entering the PRPs to leaving the PRPs. The total dwell time is the total time spent in this process. The results shown in Table 4 find that high interest group has the longest full path length and total dwell time, while users in low interest group performs much shorter on both dimensions than the other two groups. Therefore, the obtained interest group division is reasonable.

For middle interest group, their browsing path length and dwell time are similar to those of high interest group, but they are less likely to browse products in PRPs, so PRPs may need to help them find products they like. For low interest groups, they not only do not browse the products but also have a short browsing path and dwell time. Their irregular pattern causes the predictive Accuracy of "Low interest group" to be worse than that "Without interest analysis". So PRPs may first consider how to retain them.

6 Conclusion

In this study, the browsing behavioral intent of online users in PRPs is investigated and predicted. This work first collects a large amount of user data in a mobile App for processing and analysis. Then five models for browsing intent prediction are proposed, while a method of analyzing users' browsing interest is further studied to boost prediction performance. Finally, the prediction models are tested and the results show that LSTMs achieved the best and it could have better performance when combined with the interest analysis method in which users are divided into different interest groups, especially in the case of high interest group who are also the most concerned by e-commerce platforms. Moreover, the prediction process of the model is speedy enough to predict the current user behavior intent by the back-office system in real-time.

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