Discovering Consumers' Purchase Intentions Based on Mobile Search Behaviors

Mingyue Zhang, Guoqing Chen and Qiang Wei

Abstract Search activity is an essential part for gathering useful information and supporting decision making. With the exponential growth of mobile e-commerce, consumers often search for products and services that are closely relevant to the current context such as location and time. This paper studies the search behaviors of mobile consumers, which reflect their customized purchase intentions. In light of machine learning, a probabilistic generative model is proposed to discover underlying search patterns, i.e., *when to search*,*where to search* and *in what category*. Furthermore, the predicting power of the proposed model is validated on the dataset released by Alibaba, the biggest e-commerce platform in the world. Experimental results show the advantages of the proposed model over the classical content-based methods, and also illustrate the effectiveness of integrating contextual factors into modeling consumers search patterns.

Keywords Search patterns · Context-aware · Probabilistic model · Recommendation

1 Introduction

Nowadays, the Internet acts as a core information source for human worldwide, and many information gathering activities take place online [5, 10]. Search activities widely exist in daily life, from which irrelevant information is filtered and useful one is extracted to support decision making. For example, 'information retrieval' and 'database querying' are two common activities to extract relevant documents or other types of information. According to the CNNIC (China Internet Network Information Center) report, the number of search engine users in China had reached 522 million in 2014, with a growth rate of 6.7% compared to last year. In addition,

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mobile search engines also attract 429 million people and had an even higher growth rate of 17.6%. The search services have been extended to the combined presentation of pictures, applications, products and other types instead of just text and links. On one hand, search becomes an essential part for consumers to find useful information in their decision making processes. On the other hand, by keeping track of the search patterns of the consumers, online merchants can have a better understanding of the consumers' behaviors and intentions [5].

In mobile e-commerce, potential consumers search for product information before making purchasing decisions due to the overwhelming information [8, 12, 16]. Since search could reflect consumers' purchase intentions and affect their choices online [9], it is worthy of deep exploration and has attracted a lot of interest from both academia and practitioners. Moreover, as Bhatnagar & Ghose (2004) [3] indicated, consumers exhibit differences in their search patterns, i.e, time spent per search episode and search frequency, which are attributed to product categories and consumer characteristics.

In marketing practice, clickstream data are commonly used to quantify the customers' search behaviors [8, 9, 16]. Usually, the clickstream data provide information about the sequence of pages or the path viewed by the consumers as they navigate websites [18]. With the prevalence of smart mobile devices [6], the consumers' clickstream data have been enriched with various contextual information [25], such as geographical information, which poses significant new opportunities as well as challenges [13]. Some data mining techniques have been employed to extract consumers' context-aware preferences [12, 20]. However, these research efforts mostly focused on purchase records while ignoring the search activities. While purchasing indicates consumers' final preferences over different products in the same category, search is an essential reflection of their purchase intentions towards a specific category. Therefore, a more precise model is needed to capture each consumer's search behavior relating to the particular context.

In this paper, we aim to understand the mobile e-commerce consumers' potential purchase intentions by studying their search patterns. That is, because the examination and inspection of products/services come at the cost of the consumers' time and effort, search outcomes become informative about what the consumers want [12]. We start by analyzing the search history of each consumer and then examine whether there is a relationship between search activities and the contextual factors (i.e., time and location). Based on the assumption that search patterns are time and location dependent, a probabilistic generative process is proposed to model each consumer's search history, in which the latent context variable is introduced to capture the simultaneous influence from both time and location. By identifying the search patterns of the consumers, we can predict their click decisions in specific contexts and recommend the products/services with the maximum clicking probabilities of the consumers.

The remaining part of the paper is organized as follows. Section 2 reviews related research from three aspects: consumer information search, clickstream data, and context-aware preference. Section 3 presents the consumer search model and parameter estimation process. Section 4 demonstrates the experimental results on a real-world dataset and Section 5 concludes the paper.

2 Related Work

This section discusses the existing work that is related to this study, consisting of three aspects: consumer information search, clickstream data, and context-aware preference.

Consumer Information Search. Consumer information search is an important part of purchase decision making [4, 8, 19], which attracts continuous attention from researchers. By using page-to-page clickstream data, Moe (2003) [16] examined in-store navigational behavior in terms of the pattern and content of pages viewed, and classified consumers into four categories according to their underlying objectives, namely, direct buying, search and deliberation, hedonic browsing, and knowledge building. This helps understand the objectives of the consumers better, thereby providing some insights into purchasing behaviors. Huang et al. (2009) [8] investigated the differences in consumer search patterns between search goods and experience goods in the online context based on clickstream data. In the empirical examination, they found the type of information that the consumers seek, and the way they search and make choices, was different for the two types of goods. Further, these differences affected the amount of time spent per page of information, the number of pages searched, the likelihood of free riding, and the relative importance of interactive mechanisms. Branco et al. (2012) [4] discussed the optimal stopping strategy for consumer search. Specially, they provided a parsimonious model of consumer search for gradual information that captured the benefits and costs of search, resulting in the optimal stopping threshold where the marginal costs outweighed the benefits. Similarly, Kim et al. (2010) [12] introduced the optimal sequential search process into a model of choice and estimated consumer information search and online demand for durable goods based on dynamic programming framework.

Clickstream Data. The widespread availability of Internet clickstream data has contributed greatly to marketing research [16], which allows both practitioners and academics to examine consumer search behaviors in a large-scale field setting. For example, Banerjee & Ghosh (2001) [2] clustered users based on a function of the longest common subsequence of their clickstreams, considering both the trajectory taken through a website and the time spent at each page. Montgomery et al. (2004) [18] used a dynamic multinomial probit model to extract information from consumers' navigation path, which is helpful in predicting their future movements. Kim et al. (2004) [11] used the clickstream data as implicit feedback to design a hybrid recommendation model, which resulted in better performance. Moe (2006) [17] proposed an empirical two-stage choice model based on clickstream data to capture observed choices for two stages: products viewed and products purchased. They found that the product attributes evaluated in Stage 1 differred from those evaluated in Stage 2. Overall, the clickstream data provided a great opportunity for researchers to dig into consumer search and purchase behaviors. Nevertheless, very little research has been conducted to describe the generative process of consumer search, especially the search behaviors in specific contexts.

Context-Aware Preference. Due to the exponential growth of mobile e-commerce, large volume of contextual information is available, which enables researchers to study the problem of personalized context-aware recommendation [13, 21, 24]. Shabib & Krogstie (2011) [21] proposed a step-by-step approach to assessing the context-aware preferences, which consists of four phases: product classification, interest matrix formation, clustering similar users and making recommendation. Zheng et al. (2010) [24] discovered useful knowledge from GPS trajectories based on users' partial location and activity annotations to provide targeted collaborative location and activity recommendations together. Specifically, they modeled the user-location-activity relations in a tensor and designed the algorithm based on regularized tensor and matrix decomposition. Liu et al. (2015) [13] considered users' check-in behavior in mobile devices to provide personalized recommendations of places, which integrated the effect of geographical factor and location based social network factor. Different from previous research, our study aims to formalize consumers' search behaviors as (*when, where, what*) patterns through a probabilistic generative model, which has better explanation ability and can be used to design appropriate recommendation strategies.

3 Consumer Search Model

3.1 Search Behavior Analysis

In the context of e-commerce, consumers commonly search for product information online before making purchase decisions [4]. Since more and more people access the Internet with their smart phone, the mobile search activities have distinctive features where contextual information can be captured by the search logs, including time and location [22, 25]. While consumers are often overwhelmed by excessive number of products in the platform, the specific category that products belong to is a good reflection of consumers' purchase intentions. In addition, the data of search log will be very sparse if each product is treated as an individual item, which may hardly be able to discover common search patterns. Therefore, we focus on the searched 'category' instead of 'product' in the following analysis. Predicting the category that consumers are most likely to click in a given timeslot and location is of great importance. If we can model a consumer's purchase intentions toward a specific category, we can recommend the appropriate products/services taking into account both his/her preferences and location information.

To analyze the possible factors that affect mobile consumers' search patterns, the relationships between the number of clicks and contextual factors will be explored. The clickstream data were released by Alibaba.com, which will be described in detail later. Figure 1 displays the click times in a range of 24 hours and Figure 2 shows the distribution of clicks under different geographic areas. Note that locations were clustered into different geographic areas without overlap.

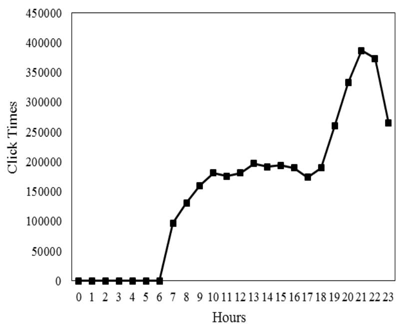


Fig. 1 Click times in different hours

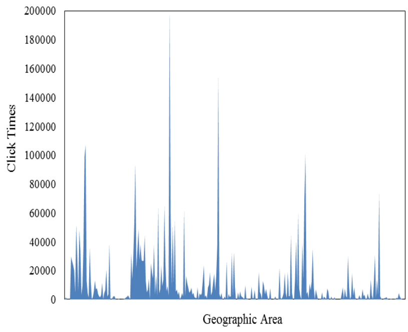


Fig. 2 Click times in different geographic areas

Here, the search events mostly occurred in the evening and reached the peak at 21:00. It can be seen that the consumers were more active in certain geographic areas, which illustrates the importance of location information. Thus, it is reasonable to assume that consumers search/click patterns are dependent on contextual factors including time and location.

Problem Definition: Suppose that we have consumers' clicking histories in mobile terminal, which reflect their search behaviors. For a consumer u, its clicking trace can be represented with a tuple (l, t, g) where a consumer u clicks category g at time t in location l. The problem is to model all the consumers' search histories and discover the patterns, in terms of *when to search, where to search*, and *in what category*. In this way, appropriate recommendation strategies can be designed so as to present the right product/service categories to right people at right time and right locations.

3.2 Generative Process

The advantage of probabilistic generative model is that it can mimic the process of a consumer's purchase behavior. Inspired by the classic topic model "Probabilistic Latent Semantic Analysis" (PLSA) [7, 15], the process of consumer search could be considered as an extension [23].

Specifically, each search is composed of particular search time, location and category, which are correlated with each other. In order to discover the common search patterns that underly these tuples, we introduce a latent factor, i.e., *shared search context* c. Thus, each value of context c is assumed to be the mixture of time, location and category, representing some common patterns among all the consumers, hence consumers' preferences towards time, location, and category are simultaneously captured by the shared search context.

For example, in the case that u wants to choose a category, he/she may choose a context according to his/her personal preference distribution, which is commonly a multinomial distribution. After that, the selected context in turn 'generates' the specific search tuple (l, t, g) following the context's generative distribution. Thus, this model simulates the process of how u picks the category g at the specific time t and location l. To simplify the analysis, we assume that these specific tuples, including time, location and category, are conditionally independent given the latent context. Therefore, the generative process for each consumer's clicked category can be summarized as follows:

– For each consumer u:
  - For each search action (l, t, g) of consumer u:

    (1) Generate a shared search context $c \sim p(c|u)$, which is a multinomial distribution;
    (2) Generate a search location $l \sim p(l|c)$ conditional on the latent context;
    (3) Generate a search timeslot $t \sim p(t|c)$ conditional on the latent context;
    (4) Generate a search category $g \sim p(g|c)$ conditional on the latent context.

Note that $p(l|c)$, $p(t|c)$ and $p(g|c)$ are also assumed to be multinomial distributions. The above Bayesian generative process can be represented as a graphical model in which a directed graph is used to describe probability distributions (see Figure 3).

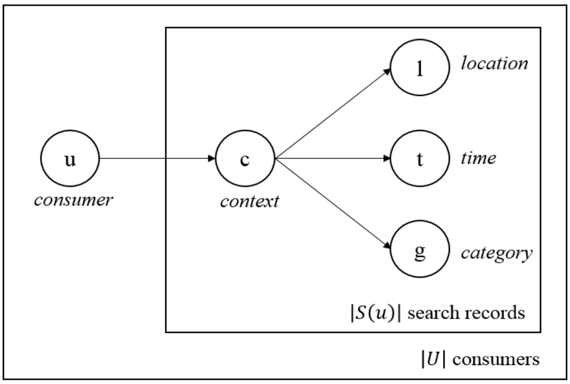


Fig. 3 A graphical representation of the probabilistic model

Thus, a consumer's search history is regarded as a sample of the following mixture model.

$$p(l, t, g|u) = \sum_c p(l, t, g|c) \cdot p(c|u) \tag{1}$$

Since l, t, g are assumed to be conditional independent with each other given the latent shared search context c, the above equation can be transformed to:

$$p(l, t, g|u) = \sum_c p(c|u) \cdot p(l|c) \cdot p(t|c) \cdot p(g|c) \tag{2}$$

The proposed model is a latent class statistical mixture model, which discovers: 1) a consumer's personal preference distribution over latent search context; 2) a category generative distribution for each latent context; 3) a consumer's preference distribution over locations/timeslots.

3.3 Parameter Estimation

To estimate parameters, the MLE (Maximum Likelihood Estimation) method is used to maximize the log likelihood of the collected search history for all consumers U that are generated by this model. The log likelihood function is given by:

$$\log p(U;\theta) = \sum_{u} \sum_{<l,t,g>\in S(u)} \{\log \sum_{c} p(c|u)\cdot p(l|c)\cdot p(t|c)\cdot p(g|c)\} \tag{3}$$

where $S(u)$ denotes the search history for consumer u; θ denotes all the parameters in the model including $p(c|u)$, $p(l|c)$, $p(t|c)$ and $p(g|c)$. Since it is difficult to directly optimize the above equation due to the log calculation being out of a summation, the EM (Expectation Maximization) algorithm is employed here to estimate these parameters.

In the **E-step**, the posterior distribution of hidden variable (i.e., context c) is computed, given the observed data and the current values of parameters according to Bayesian rule:

$$p(c|u,l,t,g) = \frac{p(c|u)\cdot p(l|c)\cdot p(t|c)\cdot p(g|c)}{\sum_{c'} p(c'|u)\cdot p(l|c')\cdot p(t|c')\cdot p(g|c')} \tag{4}$$

In the **M-step**, the new optimal values for parameters are obtained given the current settings of hidden variables calculated in E-step. By maximizing the log likelihood function, the parameters can be updated as follows:

$$p(c|u) = \frac{\sum_{<l,t,g>\in S(u)} p(c|u,l,t,g)}{\sum_{c'}\sum_{<l,t,g>\in S(u)} p(c'|u,l,t,g)} \tag{5}$$

$$p(l|c) = \frac{\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l,t,g)}{\sum_{l'}\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l',t,g)} \tag{6}$$

$$p(t|c) = \frac{\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l,t,g)}{\sum_{t'}\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l,t',g)} \tag{7}$$

$$p(g|c) = \frac{\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l,t,g)}{\sum_{g'}\sum_{u}\sum_{<l,t,g>\in S(u)} p(c|u,l,t,g')} \tag{8}$$

Table 1 Data description

# consumers	# categories	# click events	# locations
7,079	7,618	3,680,662	561,259

When implementing the EM algorithm, some intial values are randomly assigned to the parameters, then the iterations between E-step and M-step are conducted until the log likelihood gets converged.

4 Experiments

With the proposed consumer search model (CSM), the context-aware recommendations for mobile consumers can be implemented. In this section, the effectiveness of the CSM are demonstrated on real-world dataset, and the performances are compared with several baseline methods.

4.1 Data Description

The dataset used in the experiments is from a public data set released by Alibaba mobile recommendation challenge[1]. It contains the clickstream data in a month of 10,000 consumers on 8,898 categories which consist of 1,200,000 items. Specially, the collected records were created by smart phones instead of laptops, where location information is available. The given items mainly belong to experience goods, that is, consumers trade online and experience the service offline, such as restaurants service, hotel service and photography service. We sampled a collection of click records which reflect consumers' search behavior from the dataset, and each record was formatted as (*consumerId, categoryId, clickLocation, clickTime*). To be specific, consumers with less than 30 click records in the period were removed and the data description after preprocessing is presented in Table 1.

The dataset was split according to the timestamp of the event, that is, click records occurred in the first 26 days were treated as training set while the remaining ones were treated as test set. Then the CSM model was fitted with the training set and its performance was evaluated on test set.

4.2 Context-Aware Recommendation

Considering the effect of different contextual factors on consumers' search patterns, we can design a context-aware recommendation approach based on the CSM model. The objective of our recommendation is to present the right item category to the right people at right time and right location, hoping that the recommended category will

[1] http://tianchi.aliyun.com/competition/index.htm

be clicked by the target consumer. Therefore, given all the parameters inferred from the model, the categories can be ranked according to the probability that consumer u would click the category g at time t and location l. Formally, the key procedure for recommendation is to estimate $p(g|u, t, l)$. Based on the Bayesian rule, it can be calculated as:

$$p(g|u, t, l) = \frac{\sum_c p(c|u) \cdot p(t|c) \cdot p(l|c) \cdot p(g|c)}{\sum_{g'} \sum_c p(c|u) \cdot p(t|c) \cdot p(l|c) \cdot p(g'|c)} \tag{9}$$

In the above formula, the time is divided into 48 timeslots, which corresponds to different hours in weekends and weekdays.

(1) Baseline Methods

Several baseline recommendation methods were selected to compare with the CSM. First, since the click records in the dataset are implicit feedback from consumers, it is not feasible to directly apply collaborative filtering techniques that often use rating data. Thus, we adopted the content-based recommendation method [1] where items that were similar to consumers' click history were recommended. Second, in order to study the effectiveness of different contextual factors (i.e., time and location information), we simplified the CSM by removing the factors one by one and evaluated their recommendation performances. Concretely, CSM_time is the model without time factor and $CSM\_location$ is the model without location factor. Finally, $random$ is also served as a baseline method where item categories are randomly recommended to consumers.

(2) Evaluation Metrics

In the experiments, the click record in the test set were used as the ground truth and Mean Average Precision (MAP) at position K was applied to evaluate the performances of context-aware recommendation methods. The size of recommendation set K ranged from 5 to 15, that is, $K \in \{5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15\}$. Thus, $MAP@K$ represents the mean value of average precision at top K recommendation results over all click/search records in test set. Formally, $MAP@K = \frac{\sum_{s \in S} AP^{(s)}@K}{|S|}$ where S is the collection of records in test set and $AP^{(s)}@K$ can be computed by:

$$AP^{(s)}@K = \frac{\sum_{r=1}^{K} P(r) \times rel(r)}{N_s} \tag{10}$$

where r is the rank in the sequence of recommended categories, K is the size of recommendation set, $P(r)$ is the precision at cut-off r in the rank list, $rel(r)$ is an indicator function equaling one if the category at rank r is clicked by the target user and zero otherwise, and N_s denotes the real click count in record s which always equals to 1 in our experiment.

4.3 Results and Discussion

(1) Parameter Selection

Since there was a hidden variable (i.e., the latent context c) in the model, we first investigated the different recommendation performances with various values of c and chose the most appropriate parameter in the remaining experiments. Specially, the model with different number of latent contexts were trained where $c \in \{5, 10, 15, 20, 25, 30, 35, 40, 45, 50\}$ and the recommendation performances were evaluated regarding to these numbers. Figure 4 provides an illustration of the MAP at top five recommendations with different parameter settings. It is clear that the performance was best when the number of context was set to 20. Thus, we set $c = 20$ in the remaining experiments.

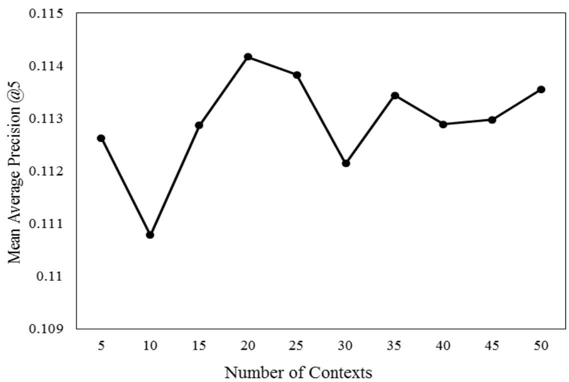
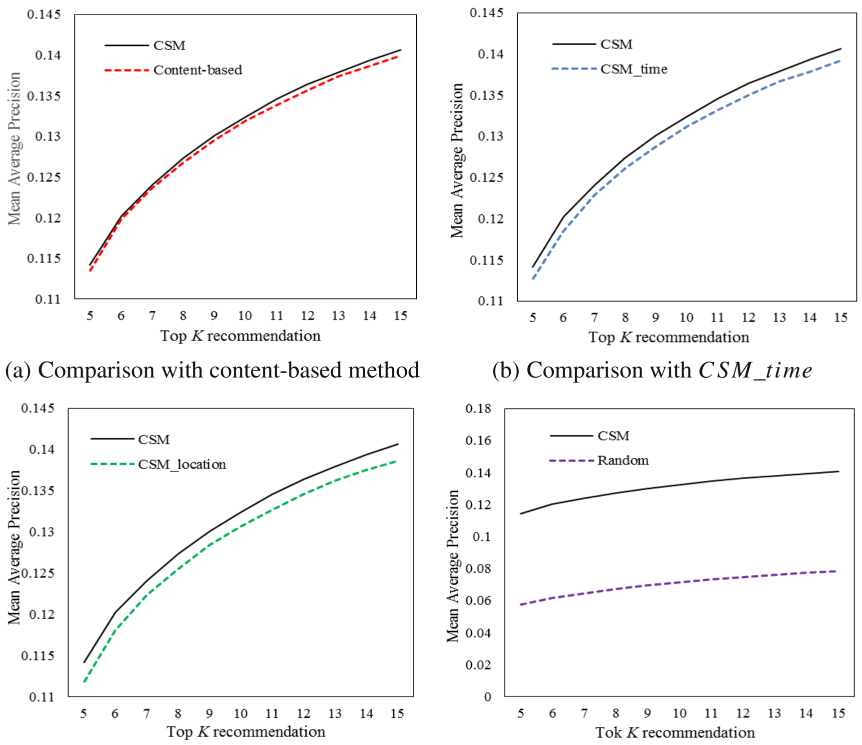


Fig. 4 Recommendation results with different parameter settings

(2) Recommendation Results

Figure 5 shows the comparing results of recommendation performances between CSM and other baseline methods. Overall, CSM outperformed other methods with different number of recommendations, indicating the advantage of proposed method. Moreover, CSM was much more explicable for consumers' search behaviors than the heuristic method (i.e., content-based method). The values of $MAP@K$ for CSM are between 0.1 to 0.2, this is because it's still a very challenging recommendation task without explict feedback, especially when the number of categories is extremely large.

Additionally, from Figure 5(b) and Figure 5(c) we can see that the $MAP@K$ in CSM is higher than that in CSM_time and $CSM\_location$, illustrating the effectiveness of contextual factors when modeling consumers' search patterns. This also verifies the assumption that consumers' search behaviors are time and location dependent. It is worth mentioning that the improvement of CSM over $CSM\_location$ is higher than that of CSM over CSM_time, which demonstrates that location factor is more influential in mobile e-commerce environment.



(a) Comparison with content-based method (b) Comparison with CSM_time

(c) Comparison with $CSM\_location$ (d) Comparison with $random$ method

Fig. 5 Performances for top K recommendations

(3) Discussion

As mentioned above, the timeslot was set to 48 corresponding to different hours in weekdays and weekends. This partition standard is similar to that in [14] where it was applied to the retweeting time in Twitter. Unlike retweeting patterns, consumers' shopping behaviors may not be so sensitive to whether the day is weekday or weekend. Figure 6 shows the average click times in each hour on weekdays and weekends, separately in our experimental dataset. It can be found that there was no apparent difference between weekdays and weekends, which confirms our speculation.

With this observation, we re-trained the CSM with 24 timeslots and the performances of top K recommendations were shown in Table 2. It can be observed that there was some small improvements after adjusting the model, which indicates that the model can be further improved if consumers' search behaviors can be better understood.

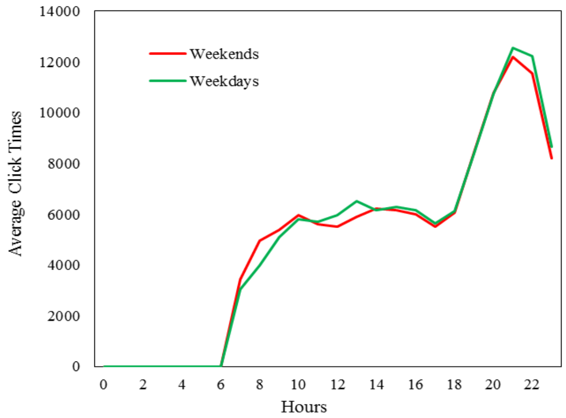


Fig. 6 Click patterns in weekdays and weekends

Table 2 $MAP@K$ for CSM with 24 timeslots

K	$Timeslots = 48$	$Timeslots = 24$	K	$Timeslots = 48$	$Timeslots = 24$
5	0.1142	0.1146	10	0.1324	0.1331
6	0.1202	0.1206	11	0.1346	0.1353
7	0.1241	0.1247	12	0.1364	0.1372
8	0.1274	0.1279	13	0.1379	0.1387
9	0.1301	0.1306	14	0.1393	0.1401

5 Conclusion

Consumer information search has long been recognized as an important procedure before consumers making purchase decisions, which reflects their purchase intentions. In this paper, we have studied the search behaviors of mobile consumers. In doing so, the click times in terms of different timeslots and geographical areas have been analyzed, where the contextual information including time and location has great influence on consumer search behaviors. Then, the problem has been formalized as to model all the consumers' search histories so as to discover underlying patterns, in terms of *when to search*, *where to search* and *in what category*. A probabilistic generative model (i.e., the consumer search model — CSM) has been developed to identify search patterns for its good explanation. In CSM, a latent variable (i.e., *shared search context*) has been introduced to capture the simultaneous effects among different factors. With the inferred parameters of the model, a context-aware recommendation method has been designed where categories are ranked according to the probability that the target consumer would click the category at a particular time and location. Real-world data experiments from Alibaba.com have revealed the advantages of our proposed method over others in related metrics.

In future explorations, the proposed model can be extended by incorporating other contextual factors, such as companions and e-retailers. Another future effort may apply the proposed method to other mobile e-commerce platforms such as the ones in western countries so as to test and find the similarities and differences in consumers' behaviors.

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