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# Skip or Stay: Users' Behavior in Dealing with Onsite Information Interaction Crowd-Bias

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## ABSTRACT

Mobile devices and the internet of things blend our virtual online behavior with our actions in the real-world. The physical context creates numerous external factors that play a role in the user's online interactions, thus creating new external biases in the collected information interaction logs. Our general aim is to improve our understanding of onsite users' behavior, which allow us to create better online and onsite contextual suggestion systems. We focus on the cultural heritage domain and have collected onsite users' information interaction logs of visits in a museum. This prompts the question: How to understand users' behavior in order to be able to predict their onsite behaviors? Our main findings are the following: First, users behave differently in different onsite contextual situations. Second, there is a significant dependency between users' onsite behaviors and other users, who are interacting with next point of interests (POIs). Third, we have proposed a contextual Skip-Or-Stay behavior classifier based on four different pairwise contextual features that significantly improves a defined baseline based on all the considered evaluation metrics. Fourth, we have analyzed the importance of different contexts in the Skip-or-Stay behavior predictions.

**Categories and Subject Descriptors:** H.3.3 [Information Storage and Retrieval]: Information Search and Retrieval—*Query formulation, Search process, Selection process*

**Keywords:** Behavioral dynamics; Bias; Internet of things; Onsite logs

## 1. INTRODUCTION

The last years witnessed the emergence of interests in understanding users' onsite behavior in different domains like tourists [2, 6] and cultural heritage [3]. To this aim, they become interested in logging users' onsite information interactions. However, due to many external noises and biases in the onsite information interaction logs, understanding users' behavior is challenging and difficult. Existence of onsite biases in onsite logs prompts the questions: how users behave

in existence of external factors in physical spaces? Is it possible to predict users' behaviors using contextual information in the existence of onsite biases?

In the search domain, biases in query logs have been studied for a long time [1, 4]. For example, eye tracking studies for understanding how users interact with search results show a position rank bias in users click behavior, in which users tend to click on the top of the ranked list rather than the bottom [1]. Trust bias is another online bias, which is studied for using clickthrough data as implicit feedback [4]. Biases have also been studied in user click models, helping to better understand users' behavior [5].

Although users' online behaviors in interacting with search engines are well studied, there are a few studies on users' onsite behavior. Some of the biases in users' onsite information interactions are studied in [3], which found a "walk-through" position bias in users' onsite behaviors. Walk-through position bias is users' tendency in visiting point of interests one after the other, based on proximity in the real world, from check-in to check-out stations, even though users are free to visit any POI at any order. However, this users' tendency to visit POIs in a particular order is affected by other external factors leading to further, new biases in onsite information interaction logs. Specifically, as there are other visitors the next POI might be busy by another user, which leads to creation of a crowd-bias in onsite logs.

Existence of a user crowd in the physical space leads to two different users' onsite behaviors, namely, skip or stay. As it is shown in Figure 1, assume  $user_a$  is interacting with POI2 and  $user_b$  is interacting with POI3. Then, what would happen if  $user_a$  wants to see another POI, but the next POI (i.e., POI3) is busy? *Skip behavior* is the case that  $user_a$  skips the POI3 and prefers to visit another POI. *Stay behavior* is the case that  $user_a$  waits until  $user_b$  is satisfied by interacting with the POI3 and leaves the POI.

In this paper, we study users' behavior in dealing with the crowd-bias, and how their behaviors affected in different contexts. In fact, our main aim is to study the question: *How do users behave in the presence of a crowd of users in the physical space?* Specifically, we answer the following research questions:

1. *How does the context of an onsite session affect on users' behavior?*
2. *Is the Skip-Or-Stay behavior of users dependent on characteristics of users interacting with the next POI? Is it possible to effectively predict Skip-Or-Stay behavior using contextual information?*

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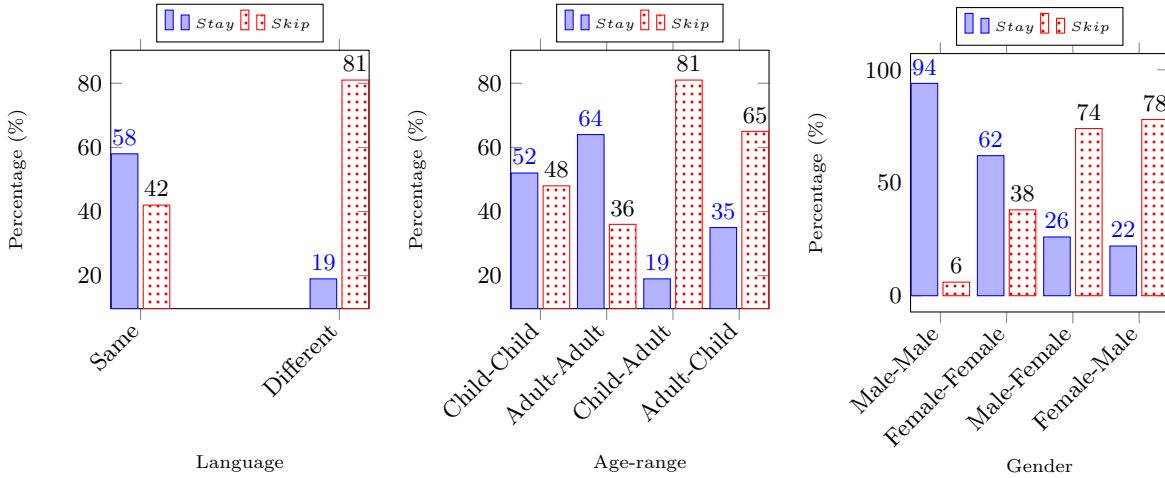


Figure 2: Impact of a sample of different contextual information on onsite users' behavior.

given explicitly at the physical environment. Then, we consider pairwise context of pairs of users as context in our study. For example, if gender of  $user_a$  is "male", and gender of  $user_b$ , who is interacting with the next POI is "female", the pairwise gender context is  $\langle Male, Female \rangle$ .

In this study, languages can be either "English" or "Dutch", age-range is either "Adult" or "Child", and perspectives are "Lowlands", "Egypt" or "Rome". As shown in Figure 2, each pair of users having different pairwise context, generally behave differently in staying or skipping the next busy POI.

Figure 2 shows pairwise contexts having a same language prefer to stay, however, users tend to skip the busy POI taken by a user speaking a different language. As another example, adults generally prefer to skip a POI taken by a child, however, they tend to stay if the next POI is taken by an adult. Interestingly, users prefer to gently skip a POI that is taken by a user having an opposite gender. On the other hand, users tend to stay at the POI in the case the next POI taken by another user having a same gender. To conclude, there are variety of onsite Skip-Or-Stay behaviors in different pairwise contexts, which seems very helpful in discriminating stay behavior from the skip behavior.

#### 4. SKIP-OR-STAY BEHAVIOR PREDICTION

This section answers our second research question: *Is the Skip-Or-Stay behavior of users dependent on characteristics of users interacting with the next POI? Is it possible to effectively predict Skip-Or-Stay behavior using contextual information?*

We first detail how we classify users' Skip-Or-Stay behavior in the given pairwise context based on the pair of users. To this aim, we have used Logistic classifier, in which variable  $c = 1$  indicates Stay behavior and  $c = 0$  is the skip behavior. Specifically,  $P_\theta(c = 1|u_a, u_b, p)$  is the probability of user  $u_a$  to stay at the next POI  $p$  and wait till the user  $u_b$  leave the POI, where  $\theta$  is unknown parameters that are learned using maximum likelihood estimation (MLE) based on the train set.

Let  $U$  be a set of onsite users and  $P$  be a set of POIs available in the physical environment. Given the class label  $l$  for behaviors of user  $u_a$  while next POI is busy by user  $u_b$

in the train set, the likelihood  $L$  of the train set is as follows:

$$L = \prod_{i=1}^{|U|} \prod_{j=1}^{|U|} \prod_{k=1}^{|P|} P_\theta(c = 1|u_i, u_j, p_k)^l P_\theta(c = 0|u_i, u_j, p_k)^{1-l},$$

in which we assume class labels  $l$  are generated independently and  $i \neq j$ . We model  $P_\theta(c = 1|u_i, u_j, p_k)$  by logistic function on a linear combination of features. Then, we optimize the unknown parameters  $\theta$  by maximizing the following log likelihood function:

$$\theta^* = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{|U|} \sum_{j=1}^{|U|} \sum_{k=1}^{|P|} (l) \log P_\theta(c = 1|u_i, u_j, p_k) + (1-l) \log P_\theta(c = 0|u_i, u_j, p_k).$$

To test the Skip-Or-Stay classification, in order to avoid overfitting, we have done 5-fold cross-validation, in which we leave one fold out as a test set and keep the rest as a train set. We repeat the process for all the 5 folds and report the average of the evaluation metrics. In this experiment, Precision of skip class (i.e.,  $P(\text{Skip})$  in Table 1), Precision of stay class (i.e.,  $P(\text{Stay})$ ), *Accuracy* and *F1* are considered as evaluation metrics.

In order to test our proposed onsite user behavior classifier using pairwise context, we have defined a user behavior classifier using pointwise context as a baseline. Pointwise context is the explicit contexts given by users onsite. The only difference of the baseline with the proposed Skip-Or-Stay classifier is considering independency of users' behavior to the user interacting with the next POI.

As it is shown in Table 1, Skip-Or-Stay classifier using the pairwise contextual features significantly improves the baseline that gets independent pointwise contextual features as input based on all the defined evaluation metrics. In particular, the proposed Skip-Or-Stay classifier has 37% improvement in term of *Accuracy* and 59% improvement in term of *F1* over the baseline. We perform significance testing in terms of all metrics using a paired t-test, treating p-values lower than 0.05 as statistically significant.

This experiment shows that users' Skip-Or-Stay behavior is not independent on other users in the physical environment. In fact, improvement of the Skip-Or-Stay classifier,

**Table 1: Comparison of Skip-Or-Stay classification based on pairwise context and pointwise context. \* indicates a statistically significant ( $p < 0.05$ ) improvement.**

Method	P(Skip)	P(Stay)	Acc.	F1
<i>Pointwise</i>	43.41	55.76	52.73	44.77
<i>Pairwise</i>	<b>76.18</b>	<b>70.42</b>	<b>72.42</b>	<b>71.06</b>
<i>Improvement</i>	<b>75.49*</b>	<b>26.30*</b>	<b>37.34*</b>	<b>58.72*</b>

which uses pairwise contextual features created based on users’ behavior dependency on users interacting with the next POI, over the baseline is a proof for this conclusion.

## 5. CONTEXTS IMPORTANCE IN UNDERSTANDING USERS’ ONSITE BEHAVIOR

This section answers our third research question: *What is the importance of each context in understanding users’ Skip-Or-Stay behavior?*

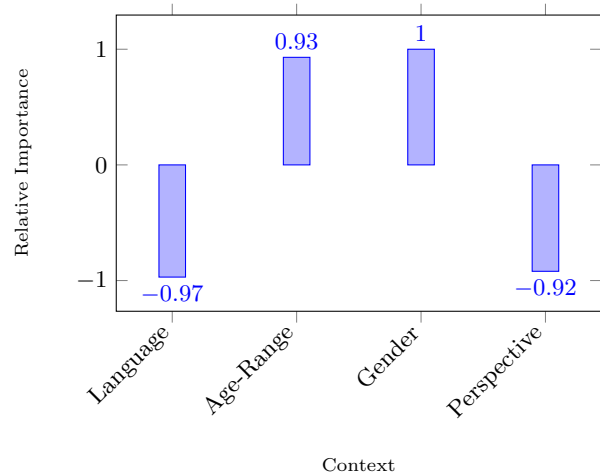
To this aim, by assuming that contextual features obtaining greater weights in the training phase of the successful logistic regression classifier are more important than other contextual features, we consider the trained weights of the contextual features in the logistic classifier as an importance indicator.

To be able to compare the weights being optimized in each fold of the 5-fold cross validation, we have normalized learned weights of the logistic classifiers in each fold and mapped weights to values between -1 and 1. Then, we average the weights over the 5 folds. As it is shown in Figure 3, pairwise age-range and gender contextual features are relatively more important in Skip-Or-Stay behavior prediction in comparison to pairwise language and chosen perspective contextual features.

To conclude, this section shows different contexts has different importance and contribution in prediction of users’ onsite behavior. Specifically, language is less important than the gender. The reason could be the ability of majority of Dutch people to fluently speak English. Therefore, it causes less limitations in users’ onsite communications and behaviors. On the other hand, age-range and gender has a considerable impact in users’ onsite behavior variance, which leads to greater weights and importance in comparison to language and chosen perspective as contextual information.

## 6. CONCLUSIONS

The main focus of this paper is to study users’ behaviors in dealing with onsite external factors that create bias in onsite information interaction logs. Specifically, we observed a crowd-bias in the onsite logs, in which the user’s tendency to visit POIs one after another is affected by other users occupying the next POI. An analysis based on more than 5,000 onsite sessions shows that different pairs of users with different pairwise contextual features behave differently in skipping the next busy POI or staying at the next busy POI till the POI becomes free. We defined four different pairwise contextual features, namely, language, age-range, gender and the chosen narrative perspective. In order to understand users’ onsite behavior and predict their behavior, we have studied dependency of users’ behaviors on other



**Figure 3: Relative importance of different contextual information on onsite users’ behavior.**

users interacting with the next POIs. The result of this study proves that user’s behavior is more predictable by a users’ behavior dependency assumption using pairwise contextual information in comparison to a Skip-Or-Stay classification based on pointwise contextual features with users’ behavior independency assumption. Moreover, a study on contexts importance in understanding users’ onsite behavior shows that different contexts contribute differently in prediction of the users’ onsite behaviors. We realized that users pairwise age-range and gender contextual features have relatively more contribution in users’ onsite behavior prediction in comparison to pairwise language and chosen perspective contextual features. As future work, we are going to investigate the effects of considering users’ onsite behavior (e.g., Skip-Or-Stay behavior) in the unseen POI recommendation model based on onsite human information interactions.

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