Why Explanations Matter ? A Study on Explanations in Context based Recommendations.

Abstract

In this paper, we explore two research questions on explanations in context based recommender systems. In the first study, we explore user perceptions about the reason a recommendation was made when no explanation is given. In the second study, to understand whether explanations for context based recommendation are helpful to users a between-subject experiment (n=191) is conducted. User checking-in motivation derived from their check-in data at various locations is the context used in the study. Our study shows that explanations do help in positively impacting user intent to use the system, as well as on the transparency of the system. Results also show that in absence of explanations, majority of users perceive that the recommendations are based on proximity, other customer recommendations, and their own search history.

1 Introduction

Explanation of a recommendation provides information about the reason why a particular recommendation was made to the user. Many recommender systems follow a black-box approach and do not provide any logic how the particular recommendation was generated. Systems that have complex algorithms may find it difficult to explain the reason behind the recommendations. But explanations have been shown to make recommendations more attractive and personal. Good explanations in recommender systems explain clearly how the system i.e. make the system transparent, they positively impact users trust and confidence on the systems thus helping them make decisions faster (Herlocker, Konstan, and Riedl 2000; Tintarev 2007). Much of the research on explanations in recommender systems are primarily based on systems that apply collaborative filtering or content based algorithms.While importance of explanations in the field of context based intelligent systems(Lim, Dey, and Avrahami 2009) has been explored, to the best of our knowledge we are unaware of any paper that examines explanation in context aware recommender systems. In intelligent systems also the context of motivation based on checking-in behcvaiour is an unexplored area. In this paper we focus on explanations on context based recommender systems. The recommender system we use in this study is a location based recommender system (LBRS) that makes Point of Interests (POI) recommendation based on the context of user check-in motivations. In this study we make two contributions: First, we explore the question if no explanations are given in the LBRS recommendations, does the user correctly identify the logic behind the recommendation given to him and what are the perceptions user have regarding the reason a recommendation was made. Second, we investigate whether explanations of recommendations made in context of user check-in motivation increase the transparency of the system. Influence of transparency on perceived usefulness and intention to use the recommendations is also examined. We conducted a between-subject experiment to validate our hypothesis and our results show that motivation based explanation of recommendations does positively impact transparency of the recommendations.

1.1 Context Based Recommender Systems

In recommender systems research, context is defined as any information or conditions that can influence the perception of the usefulness of an item for a user(Chen et al. 2013). Presently, there is a clear trend towards usage of context-aware recommendation systems as they integrate contextual data like time, location, mood, emotions, companion, purpose etc. (Adomavicius and Tuzhilin 2011) and among the different contexts, location based recommendations systems are most popular because of easy availability of users location data.

In this study we use the context of user checking-in motivation. (Yavuz and Toker 2014) have studied check-in behavior of consumers and motivations for sharing their location online. Motivation has been used by pass studies to understand participation in virtual communities, internet usage, and television watching (Conway and Rubin 1991; Papacharissi and Rubin 2000; Dholakia, Bagozzi, and Pearo 2004). In this paper we follow an approach (Vakeel and Ray 2016) that refines the final set of recommendations on the basis of user check-in motivations. User and locations check-in motivations profile is created using a classification framework that classifies an user motivation for checking-in into seven categories(Yavuz and Toker 2014). To infer user check-in motivation profile the classification framework is used on user past check-ins and comments at different locations.

2 Experiment I: Perceived Explanation

Explanations help user understand why a particular recommendation was made to him/ her. This develops user trust in the system and makes him understand that the recommendation is tailored to his/ her situation. But, when no explanation is accompanied with the recommendation, the user may make an assumption why the recommendation was made to him. In such a situation user might consider the recommender system to be a black box and assume that the recommendation was made on some logic like past behavior, present behavior, his community etc. In such cases, if the user assumption is not found to be valid that might lead to a understanding of the system that is erroneous. This gap in the understanding and evaluation of the recommender system will create distrust for the system and may lead the customer to switch to a better recommender system with an explanation. To understand user perceptions about why the recommendation was made we conducted an experiment.

The experiment was conducted to test the following research questions:

1) What happens when no explanation is attached to the recommendation made? Do users assume or they do not require any explanation.
2) If they assume a logic in case of no explanation, what are the different reasons they think for the proposed recommendation.

A scenario was presented to the respondents participating in the study such that no explanation was accompanied with the recommendation. Followed by the recommendation there was a text question that asked the respondents "Why do you think this recommendation was made to you?". The respondents had to answer by writing points why they think the above recommendation was made to them.

After analyzing the responses(n=84) the following observations were made regarding the two research question stated earlier. First, even if no explanation are given along with the recommendation, majority (84.52%) of the users assume that the recommender system is a black box, but it is not random, the system recommendation is based on some logic. Secondly, since this logic is not shown in the form of explanation, users try to understand why a particular recommendation was made by creating their own version of the plausible reason behind the recommendation. Their logic is based on assumptions created through their experience with various recommender systems in field of online shopping, movies, music, books, dating, social network etc. Thirdly, the most cited reason for a particular recommendation were not monetary but related to the context of the search like proximity,other customer recommendations, their own search history etc. Lastly, users assumed multiple reasons while doing information processing to come to a decision why a recommendation was made. The number of reasons can be as high as three or four.Our results indicate that in the absence of explanations, users are biased towards explanations that they have experienced earlier in popular recommendations systems like Foursquare (proximity), Netflix (other users recommendation), Google (search history) etc.

Reason	Count
Proximity of the restaurant	18
Other Users Recommendation	14
User Search history	13
Visited Similar Restaurants in past	12
Marketing by Restaurant	8
Food Quality and Cuisine type	6
Similarity based on Friends	6
Popularity	5
Artificial Intelligence	5
Social Media	5
Others (time, accompanied by, occasion, price)	5
No reason	13

Table 1: Perceived Explanations provided by Users

3 Experimental II: Study for Explanations

User while visiting POI has specific goals such that it satisfies their motivation .In this study our objective is to understand whether explanations for POI recommendation based on user motivation for checking-in improve the transparency of the system. The algorthim designed for making The POI recommendation was based on the motivation profile given in (Yavuz and Toker 2014) as mentined in section 1.1. We created a conceptual model based on the relatedness between the variables explanation, transparency,perceived usefulness and intention to use. Please see Figure 1 for the conceptual model. Hypothesis stated below were developed based on the model.

Transparency is user "understanding of why a particular recommendation was made" (Sinha and Swearingen 2002). Transparency helps users to identify why a recommendation has been made rather than shot in the dark (Sinha and Swearingen 2002). Motivation based explanation for POI recommendation help users understand why the recommendation was made and hence adding transparency to the LBRS.

H1: Explanation using user *motivation* for visiting POI will lead to *transparency in LBRS*.

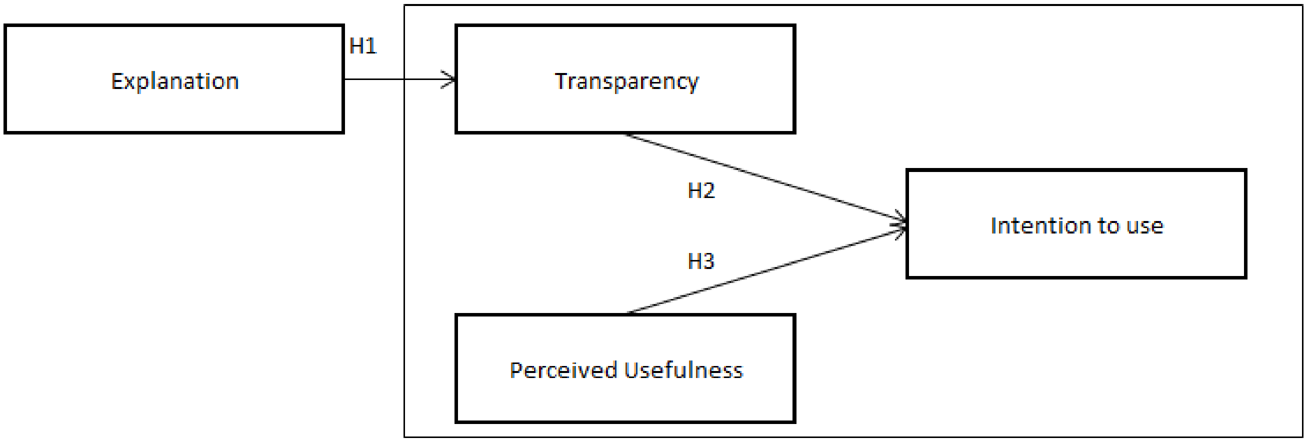

Figure 1. Conceptual Model

If users understand the reason why POI was recommended to them, it builds the trust such that they can accept the recommendations made by the system (Cramer et al. 2008). This will lead to repeat usage because users know that the system's algorithm understands them and takes their interests into consideration. This also imbibes increased confidence in the user regarding the mechanism used in the POI recommendation (Sinha and Swearingen 2002). If the user knows that the system understands the mental model of the user then user can adjust to the recommendations made by the system. On the contrary, if the user does not understand why a POI was recommended to him/her by the system, it may make the system seem unreliable thus decreasing the intent to use in future.

H2: LBRS with *transparency* (*explanations)* for why POI was recommended will lead to higher *intent to use.*

When the user finds the system useful such that he/she is able to achieve the desired outcome, then he would want to repeatedly use the system. In this case, given an alternative because user trusts the system he would choose this POI recommendation over any other LBRS. This confidence in the system could be derived from many reasons. One such reason could be the ability to understand that on what criteria does the system makes its POI recommendations. If user observes that the customized explanation has been presented to aid the understanding of the POI recommendation, he will this it is a useful recommendation system. This usefulness will help in repeat usage of the system.

H3: *Perceived usefulness* of recommendations positively impacts *intention to use* the recommender system in selecting next POI to visit

3.1 Method

The experiment discussed in this paper had a between-subject design. The independent variable was transparency. The scenario presented to the partcipants was that of a restaurant recommendation. Two experimental scenarios were constructed: one had explanation for a transparent scenario,the other had a non-transparent condition that showed the restaurant that had no information on motivation based explanation. The other independent variable was perceived usefulness. Dependent variable included Intention to use. A LBRS of POI based on Foursquare was used for the experiment controlling for occasion, emotion, motivation and company while visiting restaurant.

The study stems from the premise that transparency using explanations influences usefulness and intent to use the LBRS. Transparency influences understanding, trust, and acceptance in different ways have been studied before(Cramer et al. 2008) . In this study, we will therefore investigate the effects of transparency and motivation by adding another layer of filtering and thus offering the users insight by stating the reasons why a particular recommendation has been made. This leads to two between-subject conditions:

- A non-transparent ('non explanation') condition with no motivation: no explanation text was offered below the recommended POI but it was mentioned that a post filtering contextual approach was applied while recommending POI the non-transparent condition showed thumbnail of the POI according to the user-profile generated using the proposed algorithm from the chosen POI and comments that the user had marked on 7-point likert scale. It did not show the reasons why recommendations were made.
- A transparent ('explanation') condition with motivation: post filtering contextual approach was applied while recommending POI and below thumbnail of the recommended POI an explanation text using motivation.The transparent ('why') condition was designed to make the criteria the system uses to recommend POI more transparent to participants. It did so by showing the motivation on which the system had based its recommendation using the post filtering as done by the proposed algorithm.

In order to check whether the transparency manipulation was successful, three seven point Likert-type scale questions were included to measure the transparency of the system in each condition with questions such as “I understand why the system recommended this place to me”. To check the realism of the POI an additional question indicating the realism of the scenarios presented was asked (Mean=3.76, SD=0.92).

3.2 Dependent Variable

Intent to use: Acceptance here is the acceptance of the system. Acceptance of the system was measured right after the participant had finished with the scenario marking transparency and usefulness. Each participant was asked to mark the intent to use the recommendation system for the POIs. The questions asked to measure intent to use were adopted from (Cramer et al. 2008) with minor modification to fit the context. Intent to Use was measured using three item scale with cronbach’s alpha 0.81. One item was reverse coded.

3.3 Procedure

Each participant participated faced all the three conditions and experiment session lasted for 30 min. Each participant’s user profile was generated to determine the motivation of the person for visiting a place. This motivation ranged from 1 to 7 (1 being social enhancement and 7 being belongingness). Table 2 presents the categories of motivations The second part after user profile generation consisted of randomly assigning one scenarios chosen from (i) non-transparent condition (‘non’) and non motivation and a transparent (‘explanation’) condition and motivation. For each scenario present the participant had to mark acceptance of recommendation and transparency of the system on 7-point likert scale.

Motivation
Social Enhancement Value
Informational Motivation
Social Motivation
Entertainment Value
Gameful experiences
Utilitarian Motivation
Belongingness

Table 2: Motivation categories

191 participants were involved in the study. Participants who did not use recommendation system were excluded from the study. In a non-transparent (‘no explanation’) condition and non motivation scenario explanation were excluded from the scenario. Participants were students from top tier business school currently pursuing their masters and under graduation. To understand the places and events taking in the city only those participants who had lived in Indore for more than 6 months were asked to participate. Participants were relatively well educated and experienced in using computers.

Demographics: Participants’ demographics and other background variables that could influence acceptance of the system were measured, including age, gender, computer experience, experience with recommender systems, level of education. One 7-point likert scale item to measure the comfort with recommender system usage was included (Mean=4.42, SD=1.491). Participants demographics were Male: 60.7%, Female: 38.2% with average age of 22.45 years.

3.4 Results & Discussions

The results of hypothesis are shown in Table 2. To test the hypothesis 1, we ran one-way ANOVA to see if there is statistical difference between the transparency for POI recommendation system with explanation and without explanation. The results of H1 show that LBRS with explanations are perceived to have higher transparency (F=4.08, p=0.05) than LBRS with no explanation shown with the recommendation system.

For the Hypothesis 2 and Hypothesis 3, we ran regression with intent to use as dependent variable and transparency and perceived usefulness as the independent variable. As per H2, transparency leads to higher intention to use as shown in the result statistics of table 3. Thus, higher the transparency higher is the intent to participate because user trusts the system and also understands why a particular POI is being recommended to him/her (β=0.46, p=0.05). Lastly, as per hypothesis H3, perceived usefulness leads to increased intention to use (β=0.26, p=0.001).

Hypothesis Results		
	F statistics	**Sig**
Explanation-->Transparency	4.08 (H1)	0.05
	beta coefficient	
Transparency--> Intention to Use	0.46**	(H2)
Perceived Usefulness-->Intention to Use	0.26***	(H3)

Table 3: Hypothesis Results Note: 95% **, 99.9% ***

4 Conclusion

In this paper we examine the question why explanations matter in context based recommender systems. Through two studies, using the context of user checking-in motivation in a LBRS, we show that in absence of explanations user assume the explanations to be similar to popular recommendation systems and presence of explanations in context based recommenders increase the transparency of the system thus positively impacting user intent to use the system, as well as his perceived usefulness of the system.

References

Adomavicius, Gediminas, and Alexander Tuzhilin. 2011. ‘Context-Aware Recommender Systems’. In *Recommender Systems Handbook*, edited by Francesco Ricci, Lior Rokach, Bracha Shapira, and Paul B. Kantor, 217–53. Boston, MA: Springer US. http://link.springer.com/10.1007/978-0-387-85820-3_7.

Chen, Li, Marco de Gemmis, Alexander Felfernig, Pasquale Lops, Francesco Ricci, and Giovanni Semeraro. 2013. ‘Human Decision Making and Recommender Systems’. *ACM Transactions on Interactive Intelligent Systems* 3 (3): 1–7. doi:10.1145/2533670.2533675.

Conway, Joseph C., and Alan M. Rubin. 1991. ‘Psychological Predictors of Television Viewing Motivation’. *Communication Research* 18 (4): 443–63. doi:10.1177/009365091018004001.

Cramer, Henriette, Vanessa Evers, Satyan Ramlal, Maarten van Someren, Lloyd Rutledge, Natalia Stash, Lora Aroyo, and Bob Wielinga. 2008. ‘The Effects of Transparency on Trust in and Acceptance of a Content-Based Art Recommender’. *User Modeling and User-Adapted Interaction* 18 (5): 455–96. doi:10.1007/s11257-008-9051-3.

Dholakia, Utpal M., Richard P. Bagozzi, and Lisa Klein Pearo. 2004. ‘A Social Influence Model of Consumer Participation in Network- and Small-Group-Based Virtual Communities’. *International Journal of Research in Marketing* 21 (3): 241–63. doi:10.1016/j.ijresmar.2003.12.004.

Herlocker, Jonathan L., Joseph A. Konstan, and John Riedl. 2000. ‘Explaining Collaborative Filtering Recommendations’. In , 241–50. ACM Press. doi:10.1145/358916.358995.

Lim, Brian Y., Anind K. Dey, and Daniel Avrahami. 2009. ‘Why and Why Not Explanations Improve the Intelligibility of Context-Aware Intelligent Systems’. In , 2119. ACM Press. doi:10.1145/1518701.1519023.

Papacharissi, Zizi, and Alan M. Rubin. 2000. ‘Predictors of Internet Use’. *Journal of Broadcasting & Electronic Media* 44 (2): 175–96. doi:10.1207/s15506878jobem4402_2.

Sinha, Rashmi, and Kirsten Swearingen. 2002. ‘The Role of Transparency in Recommender Systems’. In , 830. ACM Press. doi:10.1145/506443.506619.

Tintarev, Nava. 2007. ‘Explanations of Recommendations’. In , 203. ACM Press. doi:10.1145/1297231.1297275.

Vakeel, Khadija, and Sanjog Ray. 2016. ‘A Motivation-Aware Approach for Point of Interest Recommendations’. In *Proceedings of the Workshop on Recommenders in Tourism*, 1685:24–29. Boston, MA: CEUR-WS.org.

Yavuz, Ramazan, and Aysegül Toker. 2014. ‘Location Sharing on Social Networks: Implications for Marketing’. Edited by Dr Ramendra Singh. *Marketing Intelligence & Planning* 32 (5): 567–85. doi:10.1108/MIP-05-2013-0084.