Context Relevance Assessment for Recommender Systems

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ABSTRACT

Research on context aware recommender systems is taking for granted that context matters. But, often attempts to show the influence of context have failed. In this paper we consider the problem of quantitatively assessing context relevance. For this purpose we are assuming that users can imagine a situation described by a contextual feature, and judge if this feature is relevant for their decision making task. We have designed a UI suited for acquiring such information in a travel planning scenario. In fact, this interface is generic and can also be used for other domains (e.g., music). The experimental results show that it is possible to identify the contextual factors that are relevant for the given task and that the relevancy depends on the type of the place of interest to be included in the plan.

Author Keywords

Context-aware, recommender systems, user preferences.

ACM Classification Keywords

H.3.3 Information Search and Retrieval: Information Filtering.

General Terms

Algorithms, Experimentation, Human Factors.

INTRODUCTION

Recommender Systems (RSs) are tools providing suggestions for items to be of use to a user [2]. Generating good recommendations is hard because they are evaluated subjectively and the RS's knowledge about the user's current preferences is largely *uncertain*. Even worse, the user's decision is mostly influenced by contextual conditions that differ each time the decision is taken. As an illustrative example, take the two recommended routes in Figure 1 for visiting the city of Cles starting from Bolzano by car. Both of them are correct; however, they have different properties. For motor

bikers, route 1 would be a great experience as it includes the famous Mendelpass while travelers with children in the car would prefer route 2, a more comfortable, although longer route on the highway.

As this example illustrates, often a recommendation can be more relevant if its context is known. For this reason, context-aware recommender systems (CARs) are gaining more and more attention [3], and various approaches have been used to incorporate context knowledge, improving performance measures, such as: mean absolute error [4], or recall [1], or prediction accuracy [9]. However, to adapt to the context the dependency of the user preferences from the contextual conditions must be modeled. This requires to record explicit user evaluations (ratings) for items in alternative contexts, e.g., the rating for a movie after it was watched with the partner. Such data is difficult to obtain because it requires substantial user effort, since the user must provide ratings in several contextual conditions. Moreover, one can acquire such ratings and later discover that the considered contextual conditions where actually irrelevant, i.e., the ratings are not influenced, and the RS is not improved [6]. Hence, a major issue for the design of CARs is assessing the contextual factors that are worth considering. This requires to formulate informed conjectures about the influence of some data, before collecting the real data. It is a kind of active learning problem, where the relevance of the data to be acquired must be estimated to minimize the data acquisition cost [10].

The main contribution of this paper is a methodology for the quantitative assessment of the dependency of the user preferences from a candidate set of contextual factors. It is based on an interface for acquiring context relevance judgements and a data analysis method for identifying the contextual factors that are likely to influence the user decisions. This approach can be adopted after a qualitative analysis, such as a diary study, has revealed the contextual factors that are potentially relevant for a recommendation task. This methodology has been tested on a travel planning application aimed at recommending points of interests (POIs) to mobile users¹. The mobile assistant we are developing is planned to offer context-dependent recommendations for touristic POIs [5] that are updated as soon as the contextual conditions change.

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¹It is also being tested on a in car music recommendations scenario (not illustrated here for lack of space).

ACQUIRING CONTEXT RELEVANCE

In order to assess the influence of some contextual factors on the user decisions we collected data describing how users **change** their inclination to visit a POI while they imagine that a contextual condition holds. For that purpose, a large set of contextual conditions (as found in the relevant literature [11]) and a (relatively small) list of categories of POIs in Bolzano (and other nearby cities) have been incorporated in a web form (see Figure 2). POIs were aggregated into categories in order to avoid sparseness of the collected data. We defined eleven categories: castle; nature wonder; cycling and mountain biking; theater event; folk festival, arts and crafts event; church or monastery; museum; spa and pampering; music event; walking path. In the web application, the users could indicate the influence of these contextual conditions on their decision to visit POIs belonging to a randomly selected category. The influence is measured with three values: positive, negative or neutral. Three different contextual conditions (i.e., values for contextual factors) were tested in a single page while a full questionnaire consisted of five of such pages (as in Figure 2).

We observe that [8] already tried to estimate the impact of contextual conditions on the user evaluations by asking the user to imagine a given contextual condition. They have shown that this method must be used with care as users rate differently in real and supposed contexts. When the context is just supposed there is a tendency of the users to exaggerate its importance. In fact, in our case we are trying to measure only if a contextual factor has an influence (positive or negative) on the user's decisions and not the real value of the user's ratings. For instance, we want to understand if the proximity to a POI is influential, and not how the rating for a precise POI changes as a function of the user proximity. Moreover, as it is shown later, our statistical approach can predict to what extent that a context factor does influence the user. So, considering only conditions with high influence we can reduce significantly the number of false positives. Hence, our method is proposed as a tool for selecting potentially relevant contextual factors; while the true evaluations/ratings of the items under alternative contextual conditions can be acquired in a classical way by asking the users to rate items when they are really experienced in a contextual condition (the next step of our future work).

Figure 1. Comparison of different Routes from Bolzano to Cles.

Figure 2. Web survey tool.

33 participants (mostly from our computer science faculty) took part in the web survey. Overall, they gave 1524 responses. In a single response to one of the questions shown in Figure 2, the user evaluates the influence of one contextual condition on his decision to visit an item of the given category. For the specification of the context, the factors and conditions presented in Table 1 were applied in a randomized way: for each question a category is drawn at random along with a value (condition) for a context factor. This sampling has been implemented such that a uniform distribution over the possible categories and context conditions is achieved. A different sampling is also applicable if a prior distribution is known.

ANALYSIS

With the web survey we aimed at finding indications about which context factors influences user decisions whether to visit or not a POI. As no information about the relationships between response variable and context was available, parametric tests such as χ^2 were not applicable. Therefore, a non-parametric statistical analysis seemed to be more appropriate: The web survey delivered samples for the distribution

$$P(I|T, C_1, \dots, C_N) = \frac{P(I, T, C_1, \dots, C_N)}{P(T, C_1, \dots, C_N)} \approx \left(\prod_{i=1}^N \frac{P(I|T, C_i)}{P(I|T)} \right) \cdot P(I|T)$$

where I (Influence) is the response variable, taking one of the three values: positive, negative, or neutral. T is the POI category, and the $C_1, \dots, C_N$ are the context factors that (may or may not) influence the user decision. The probabilities $P(I|T, C_i)$ model the influence of the context factors on the user's decision. The knowledge of $P(I|T, C_i)$ can drive the acquisition of context-dependent ratings for the context factors that have a large probability to increase or de-

Context Factor	Conditions	Context Factor	Conditions	Context Factor	Conditions	Context Factor	Conditions
budget	budget traveler high spender price for quality	crowdedness	not crowded crowded empty	companion	with girl-/boy-friend with family with children	season	spring summer autumn winter
time of the day	morning time afternoon night time	travel goal	health care cultural experience scenic/landscape education	weather	alone with friends snowing clear sky sunny	transport	public transport no means of transport bicycle car
day of the week	weekend working day		hedonistic/fun social event religion	mood	rainy cloudy happy active sad	temperature	warm cold hot
distance to POI	near by far away		activity/sport visiting friends business			time available	half day more than a day one day
knowledge	new to city citizen of the city						
about about area	returning visitor						

Table 1. Context factors and conditions used in the web survey

crease the user evaluation for the items in a given category T . Hence, it is interesting to understand which C_i have impact on I , or in other words, which C_i explain I better than other context factors.

Statistical Methodology

The spread of a categorical variable $X = \{x_1, \dots, x_n\}$ can be measured by looking at the entropy of the random variable [7]. If $P(X = x_i) = \pi_i$, the entropy of X is:

$$H(X) = - \sum_{1 \leq i \leq n} \pi_i \cdot \log \pi_i$$

This measure of the spread can be used to estimate the association of two variables X_1 and X_2 , i.e., how well one variable explains the other. In the considered tourist recommendation scenario, X_1 is the variable *Inclination of the user to visit an item*, while X_2 is a context factor of the current situation which may have an influence on the user's decision, e.g. *the current weather condition*. Informally, this influence is strong if the knowledge about the weather reduces the spread of X_1 , and it is weak if the spread of X_1 remains unchanged even if one knows the weather. Therefore, the difference between the spread of X_1 and the expected spread of $(X_1|X_2)$ is a measure for the association of X_1 and X_2 . As the spread of $(X_1|X_2)$ should not be larger than that of X_1 alone we can normalize the difference to the interval $[0, 1]$ by:

$$U = \frac{H(X_1) - H(X_1|X_2)}{H(X_1)}$$

U is 1 if the spread of $(X_1|X_2)$ is zero. This occurs if for each value of X_2 the value X_1 is certain (i.e. X_1 is a deterministic function of X_2). U is zero, however, if X_2 does not have any influence on X_1 , in which case the spread of $(X_1|X_2)$ is not different from that of X_1 . Using entropy to measure spread, we get the following formula:

$$U = - \frac{\sum_{1 \leq i \leq k} \sum_{1 \leq j \leq l} \pi_{i,j} \cdot \log \left(\frac{\pi_{i,j}}{\pi_{i,\bullet} \pi_{\bullet,j}} \right)}{\sum_{1 \leq j \leq l} \pi_{\bullet,j} \cdot \log \pi_{\bullet,j}}$$

where, $\pi_{i,j} = P(X_1 = x_i, X_2 = y_j)$. X_1 and X_2 are categorical variables with $X_1 = \{x_1, \dots, x_k\}$ and $X_2 = \{y_1, \dots, y_l\}$. $\pi_{i,\bullet} = \sum_{1 \leq j \leq l} \pi_{i,j}$ and $\pi_{\bullet,j} = \sum_{1 \leq i \leq k} \pi_{i,j}$.

We note that U is the mutual information of X_1 and X_2 normalized to the $[0, 1]$ interval.

Results

Given this definition, U can be used to measure how well I (the influence) can be predicted if C_i (a context factor) is known. Therefore, in order to understand which contextual factors are more important in predicting whether the user will change his inclination to visit a POI, we have computed U for all factors and POI categories. Ordering the factors in descending value of U , one gets the results reported in the Appendix of this paper. That table indicates that there are some factors that indeed seem to be relevant for all the categories, among them *distance to the POI*, *time available*, *crowdedness*, and *knowledge of the surroundings*. Others often appear to be less relevant: *transport*, *travel goal*, *day of the week*. Finally some factors appear to have a different relevance depending on the category. For lack of space we cannot fully describe the dependencies shown in this table. In fact, there are results that may appear controversial, e.g., that "distance" is not important for cycling. But, this is explained by observing that here "distance" refers to "distance to the POI", which is actually less important for a cyclist than for a pedestrian.

CONCLUSIONS AND FUTURE WORK

In this paper we have illustrated a methodology and a tool for acquiring explicit users' evaluations about the relevancy of contextual factors for item selection and recommendation. Contextual information is known to impact on user decision making but often the relationship between context and decision is largely unknown and uncertain. Which contextual factor is relevant in a specific decision making situation is hard to predict and wrong assumptions may lead to unnecessary and misleading reasoning models. The proposed methodology tackles these problems and has been applied to a travel planning scenario. It has been shown that tourists' preferences are strongly influenced and vary significantly with respect to context and item category. The proposed methodology provides quantitative measures of context relevancy, complementing other qualitative approaches and results coming from consumer behavior literature [11]. The collected data are now being used in a mobile tourist assistant that pushes new recommendations to tourists when contextual conditions changes.

In conclusion, we have shown how the uncertain relationships between context and decision can be explored and measured. We are applying the proposed approach in a different decision making scenario, namely music recommendation for a group of passengers in a car, to understand to what extent the approach can be generalized to other tasks.

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APPENDIX

Ranking of context factors by their influence on the user decision to visit an place of interest.

	castle	church or monastery	cycling or mountain biking	folk festival, arts and crafts event	museum	music event	nature wonder	spa	theater event	walking
	distance knowledge of surroundings time available season day week crowdedness	distance time available mood day time transport travel goal surroundings budget day week	budget time available crowdedness season weather temperature mood surroundings time available companion distance day time budget transport temperature travel goal season mood surroundings weather distance	distance temperature knowledge of surroundings weather time available companion season budget day time crowdedness travel goal day week travel goal transport mood	distance budget knowledge of surroundings temperature time available companion weather crowdedness travel goal season day week travel goal transport mood	crowdedness day week time available mood companion distance day time budget transport temperature travel goal season knowledge of surroundings weather	distance day week temperature crowdedness season time available weather companion day time mood travel goal travel goal transport budget knowledge of surroundings	distance knowledge of surroundings crowdedness season time available weather temperature companion travel goal day time mood crowdedness budget transport day week	time available day time distance budget temperature knowledge of surroundings day week mood travel goal season crowdedness companion weather transport	distance budget temperature crowdedness knowledge of surroundings time available weather season day time mood day week transport travel goal companion