Stated preferences in the digital age: an incremental design to assist recommender systems

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Extended Abstract

Mobile platforms constantly improve their functionalities, offering users a wide set of items along with services that facilitate the selection process. Recommender systems (RS) track the interaction of users with items or transfer information from like-minded users with the objective to construct a behavioural model for each user. Typical applications in transport are personalized route RS in multimodal networks [1,2]

Recommender systems collect information through direct (e.g. rating) and indirect (e.g. purchase) channels. Discrete choice models have been estimated with Revealed Preferences (RP) and Stated Preferences (SP) to gain a better understanding of user behaviour. In the literature, there is evidence that users are better at comparison queries than they are at quantitative queries [2], although the latter are the most prevalent metrics in RS practice. The accuracy of recommendations depends both on the *quantity* and the *diversity* of the accumulated information. RP-based recommendations may offer quantity but they suffer from overfitting, because most individuals are characterized by habituation in their choices. SP-based recommendations, while offering this diversity, suffer from their static-in-time nature.

SPs can be dynamic-in-content and there are several examples of customized and interactive survey tools that allow adaptation and personalization [3,4]. This gives the researcher the opportunity to trade-off between the realism of customization and the endogeneity it might induce. However, all the SPs lack this dynamic element when it comes to their lifespan. They are either single surveys, or they are repeated in a limited manner for longitudinal surveys. As a result, there is an upper bound on the number of observations that can be collected from an individual and a constraint in observing the effect of time in preference changes.

Nevertheless, the lifespan of SP tools can be indefinitely extended after their integration with digital services. Individuals that use mobile applications or services, typically fill in some demographic information as part of the registration process. For as long as the user engages with the mobile service, incremental information can be collected through questions or even hypothetical choice situations. Methodologically we introduce the concept of an *incremental SP survey,* which can be outlined as a mobile-service-delivered SP with ongoing learning capabilities and an indefinite

number of choice tasks. The term incremental reflects the incremental adaptation of the attribute levels and the incremental preference learning.

Irrespective of the element of recommendation, an incremental SP presents several opportunities. First of all, it offers the potential for increased observations per user as well as increased number of respondents compared to traditional sample-based surveys. Moreover, there is less risk when offline statistical designs are flawed, because the choice situations will be adapted accordingly online. The direct link with the user's account facilitates personalization and strengthens its commercial value. This, in turn, may support additional features such as dynamic pricing or assortment optimization. Finally, there is a possibility that an incremental SP will reduce the fatigue effect by distributing the choice tasks in time, or even extract fatigue information from user-device interaction metrics.

The process of tuning this adapted version of SP tools for recommender systems can have several challenges: Design of the registration stage, re-contacting frequency, feedback about the improvement of recommendations, situational awareness etc. For example, varying the time, location or exogenous factors (e.g. weather or traffic conditions) at the point of re-contacting will allow the service provider to capture contextual parameters that are significant for users' choice, and hence, for recommendations.

In this paper, we explore two basic dimensions for an incremental design that assists recommendations: initial beliefs and sequence of choice tasks. We build on existing studies that use SP data and Bayesian learning methods to update preference parameters and incrementally improve the predictive capability of RS. In particular, we estimate aggregate and class-specific parameters and this knowledge is transferred as preference priors to individual respondents. Then parameters are updated sequentially after each choice situation with importance sampling. The trace of the learning curve, expressed as the difference in log-likelihood with and without the update, will vary depending on the starting point and the sequence of choice tasks. The objective of this study is to identify structural rules for optimal incremental designs through a set of attribute diversification strategies.

We use a choice experiment that has been designed to elicit the preferences of electric vehicle (EV) drivers for out-of-home recharging alternatives. The context of the choice is an early reservation for a midday charging event and the main attributes that the respondents trade-off in this experiment are charging price, walking time from charging station to destination, charging duration and a charging induced schedule delay. The activity background of the charging choices is semi-customized based on a set of demographics and preliminary analysis. The final sample size consists of 118 individuals and, considering that each of them responded to nine choice situations, this corresponds to 1062 observations.   While the users are interested on their daily travel and activities, EVs have an impact on the power grid and recommendations from a charging service provider will have both environmental and economical motives.

Examples of metrics that are used for diversification in the sequence of choice tasks are: the Hamming distance, numbers of attributes with extreme levels and the dispersion of standard deviation. It is expected that a "quick scan" of the extremes in the utility space will lead to an accelerated learning. This comparative analysis provides empirical evidence of the incremental increases in log-likelihood for different numerical representations of this “quick scan”. As a second step, the long-term taste tracking, or the ability to detect taste shifts with the same metrics is evaluated with simulated scenarios.

A limitation of the study is that the results are based on a regular SP with fixed level of attributes. Nevertheless, the methodological framework on rearranging the choice tasks works as an approximation of the suggested incremental SP. The results will provide significant insights towards two directions: the advancement of traditional SP methods in a fast-moving digital environment and their integration with recommender systems that become more and more essential for an individual to cope with constant information bombardment. They will also produce useful guidelines for an application development as a future research step.

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