How Can Recommender Systems Help People Learn While Choosing?

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Abstract. Support for learning while choosing is a relatively unexplored approach to choice support that takes into account the fact that most everyday choices are strongly influenced by what people have learned while making previous similar choices. In this paper we use a driving scenario as an example for discussing how recommender systems can help people acquire experience and knowledge that enables them to improve their choices over time.

1 Introduction

Within computer science, many approaches to supporting choice and decision making have been developed (see, e.g., [1,2] for recent syntheses), but one strategy has been almost entirely neglected: Given that many choices that people make are faced repeatedly, it makes sense not only to help a person make the choice that they are currently facing but also to learn how to make such choices better over time.

In this paper, we consider how recommender systems can be used to support decision making. Specifically, our approach is built upon the Aspect and Arcade models intro- duced in [1].[1] The Aspect model distinguishes six choice patterns; in this context the most relevant is "trial and error". Similarly, the Arcade model introduces six basic sup- port strategies, but choice recommendations are covered in particular by two of them: "advise about processing" and "evaluate on behalf of the chooser". The novelty of our approach stems from the fact that using recommendations to support future choices is atypical, as they are usually provided to help with a specific choice.

[1] The Aspect and Arcade models are being presented in the first talk of the workshop, so we assume everyone will have become familiar with them before the poster session.

2 Example Scenario

Drivers are constantly making choices [3,4,5], concerning not only the driving itself but also the use of the growing number of devices available inside the car. We consider two types of choices: (1) whether to enable or disable adaptive cruise control (ACC), that is, automatically adjusting the car's speed to maintain a safe distance from the ve- hicle in front; and (2) which secondary tasks are feasible while ACC is enabled. We are currently designing a user study of this scenario using a driving simulator, which will allow us to experiment with different ways of supporting learning while choosing via recommendations as well as via other Arcade strategies.

3 Questions About Support in This Scenario

The trial and error choice pattern [1] involves trying out several options and learning from the experience. One question is how to decide which options to try out and in what order—a question addressed in the recommendation field by critiquing-based recom- menders [6]. The answer depends on the chosen exploration strategy. It should be noted that such strategies normally imply a tradeoff between exploration and exploitation. We will ignore for now the exploitation aspect, in effect considering the cost of trying out an option to be negligible. (The strategies that will be explored in the user study will take exploitation into account.)

With respect to the secondary task, the system's recommendations can support a conservative strategy, such as starting with the easiest option and gradually increasing the difficulty (yet without compromising driving safety). This makes sense because performing secondary tasks requires diverting some attention from the act of driving; starting with a difficult option might put the driver in a hazardous situation.
In the case of ACC, a relatively conservative exploration strategy would be to recommend trying it out in a situation in which 50% of drivers would feel comfortable. Based on the feedback received from the driver (or from the car's sensors) the difficulty of the situations can be adjusted to match the driver's abilities.

Another question that arises with the trial and error pattern concerns the consequences that the driver should pay attention to. For the decision of whether to enable ACC or not, the system could draw the driver's attention to particular consequences, such as how relaxed she feels or how much she is able to maintain focus while the car takes over some of the driving workload. Concerning the secondary tasks, the system could recommend attending to consequences such as lane deviation (i.e. the car's move- ment outside a given lane due to an erroneous action on the steering wheel, usually due to the driver's inattention), distance to nearby cars, or possible feeling of insecurity.

The results of the planned user study will yield some empirical results about the effectiveness of recommendation strategies such as those sketched above.

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