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Multi-attribute, multi-alternative models of choice: Choice, reaction time, and process tracing ☆

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ABSTRACT

The first aim of this research is to compare computational models of multi-alternative, multi-attribute choice when attribute values are explicit. The choice predictions of utility (standard random utility & weighted valuation), heuristic (elimination-by-aspects, lexicographic, & maximum attribute value), and dynamic (multi-alternative decision field theory, MDFT, & a version of the multi-attribute linear ballistic accumulator, MLBA) models are contrasted on both preferential and risky choice data. Using both maximum likelihood and cross-validation fit measures on choice data, the utility and dynamic models are preferred over the heuristic models for risky choice, with a slight overall advantage for the MLBA for preferential choice. The response time predictions of these models (except the MDFT) are then tested. Although the MLBA accurately predicts response time distributions, it only weakly accounts for stimulus-level differences. The other models completely fail to account for stimulus-level differences. Process tracing measures, i.e., eye and mouse tracking, were also collected. None of the qualitative predictions of the models are completely supported by that data. These results suggest that the models may not appropriately represent the interaction of attention and preference formation. To overcome this potential shortcoming, the second aim of this research is to test preference-formation assumptions, independently of attention, by developing the models of attentional sampling (MAS) model family which incorporates the empirical gaze patterns into a sequential sampling framework. An MAS variant that includes attribute values, but only updates the currently viewed alternative and does not contrast values across alternatives, performs well in both experiments. Overall, the results support the dynamic models, but point to the need to incorporate a framework that more accurately reflects the relationship between attention and the preference-formation process.

1. Introduction

People are often asked to choose from a set of alternatives, each of which varies across multiple attributes or features, for example, choosing which of three apartments to rent based on location, condition, kitchen, and size. Modelers of such

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multi-attribute, multi-alternative decisions have made a variety of assumptions about the processes underlying choice, including how people gather and use information. Early models assumed decisions are made based on the calculation of valuation or utility (e.g., Rieskamp, Busemeyer, & Mellers, 2006; Thurstone, 1927; Train, 2003). To allow for rapid decisions based on a subset of the information, later models assumed choices were driven by heuristics (e.g., Gigerenzer & Goldstein, 1996; Hogarth & Karelaia, 2007; Shah & Oppenheimer, 2008). More recently, models have incorporated dynamic processes in which information is integrated over time until some threshold condition is met, triggering the choice (Pleskac, Diederich, & Wallsten, 2015). Many of these models have been extended from simple binary choice to multi-attribute, multi-alternative decision making, and can incorporate both subjective valuation of alternatives and the allocation of attention to different attributes of the alternatives.

The first aim of this research is to compare computational models of multi-alternative, multi-attribute choice when the stimulus attributes are explicit and novel to participants. This comparison is designed to be more comprehensive than previous work, by comparing a broad set of models on both preferential and risky choice data using choice, response time, and attentional measures. By explicit attributes, we mean that the value of each attribute for each alternative is presented separately, as in the previous apartment example, as opposed to, for example, selecting among a set of pictures of snack foods. By novel attributes, we mean that participants begin the task without prior knowledge or opinions about the alternatives. We compare utility and heuristic models with representatives of the relatively new class of dynamic models.

The models are compared in two experimental paradigms: preferential and risky choice. In the preferential choice task, participants select from three apartments that vary on four attributes. In the risky choice task, participants select from three gambles, each with three probabilistic outcomes. In both tasks, the information is presented in a grid with alternatives presented as rows and attributes as columns. A similar stimulus format has been used in previous research including the collection of process tracing measures (e.g., Kwak, Payne, Cohen, & Huettel, 2015; Payne, Bettman, & Johnson, 1988; Venkatraman, Payne, & Huettel, 2014).

To provide a wide-ranging assessment, three basic classes of models are contrasted. Here each model is briefly described. The model details are provided in Appendix A. All of the models were selected as reasonable strategies that a participant might employ when faced with a choice between multiple alternatives with explicit, multiple attributes presented in a grid.

The first class of models calculates a utility for each alternative based on a weighted combination of the attribute values plus noise. Choice is determined by the probability that an alternative's utility is greater than those of the other alternatives. These utilities are calculated independently, that is, they are not influenced by the other alternatives. The standard random utility model (SRU; Rieskamp et al., 2006) and weighted valuation model (WV; Kahneman & Tversky, 1979) are used in preferential and risky choice, respectively.

The second class of models assumes that choice is driven by heuristics, allowing a choice to be determined without performing demanding computations. In contrast to the previous class of models, a choice may be made without considering all of the available information. An extensive set of heuristics have been developed (e.g., Shah & Oppenheimer, 2008). Here we examine three heuristics: elimination by aspects (EBA; Tversky, 1972), the lexicographic heuristic (LEX; Fishburn, 1974), and the maximum attribute value heuristic (MV; similar, in this scenario, to the maximax criterion). EBA is a process of sequential elimination. An attribute is randomly selected, with the probability of selection based on the importance of the attribute. Any alternative with a low value for that attribute is eliminated. The process continues until only one alternative remains. The LEX heuristic also steps through attributes, but seeks a dominating alternative. The MV heuristic makes the very simple, but reasonable, assumption that the alternative with the maximum attribute value is selected. A minimax heuristic, in which the alternative with the maximum worst alternative is selected, was also tried, but, because it performed significantly worse than MV, will not be discussed further.

The third class of models assumes information is accumulated and integrated over time until a threshold is reached. These dynamic choice, sequential sampling models are typically implemented as noisy diffusion processes. Examples include the leaky competing accumulator model (LCA; Usher & McClelland, 2004), decision field theory (DFT; Busemeyer & Townsend, 1993), and the linear ballistic accumulator (LBA; Brown & Heathcote, 2008). Here we consider versions of the LBA and DFT models that have been adapted to multi-alternative and multi-attribute paradigms: the multi-attribute linear ballistic accumulator (MLBA; Trueblood, Brown, & Heathcote, 2014) and the multi-alternative decision field theory (MDFT; Roe, Busemeyer, & Townsend, 2001). To date, the MLBA has only been applied to preferential choice stimuli with two attributes. This model is adapted to risky choice and stimuli with more than two attributes.

Because both preferential and risky choice are considered and because different stimuli are used than in the past, both the MDFT and MLBA formulations were adapted to the current paradigms. In particular, in the current versions of both the MDFT and the MLBA, attentional weighting is based on prospect theory (Tversky & Kahneman, 1992) and in the current version of the MLBA subjective valuation is also based on prospect theory. Details are provided in Appendix A.

Because, in many studies, not all of the models under consideration make response time predictions, most prior work involving the comparison of dynamic models only considers choice performance, not response time. For example, Berkowitsch, Scheibehenne, and Rieskamp (2014) compared the MDFT to utility models in a preferential choice task. Newell and Lee (2011) compared a sequential sampling model to a rational model and a set of heuristic models in a categorization task. Scheibehenne, Rieskamp, and González-Vallejo (2009) compared the DFT to the proportional difference model (Gonzalez-Vallejo, 2002) in a risky choice task. Trueblood et al. (2014) compared the MDFT and MLBA choice predictions for inference and perceptual experiments. Fiedler and Glöckner (2012) compared the DFT to a parallel constraint