K

Modeling Individual Decisions from Information Search

Neha Sharma
School of Computing and Electrical Engineering, Indian Institute of Technology, Mandi, India

Varun Dutt
School of Computing and Electrical Engineering, School of Humanities and Social Sciences, Indian Institute of Technology, Mandi, India

INTRODUCTION

Nothing is more relaxing than a lunch outing on a weekend with one's family. As is the case with foodies, they like to try delicacies at several restaurants in the town before choosing a restaurant that serves dishes that agrees most to their taste buds. Trying different restaurants would help foodies to sample for information about how food tastes and then help them choose a restaurant that they most prefer. The act of making choices based upon sampled information, however, is not restricted to selecting the best restaurant in the city. Rather, it is a common way of life when making a selection out of the limited set of options (e.g., trying clothes before making a final purchase, test driving cars before buying a particular one etc.). In fact, information search by sampling before a consequential choice constitutes an integral part of Decisions from Experience (DFE) research, where the focus is on explaining human decisions based upon one's experience with sampled information. Currently, research in DFE area has focused on accounting for decision making at the aggregate level (Busemeyer &Wang, 2000; Erev, Ert, Roth, et al., 2010; Gonzalez & Dutt, 2011; Hertwig, 2011; Lejarraga, Dutt, & Gonzalez, 2012). For example, Gonzalez and Dutt (2011) suggest that computational models of DFE have explained human choice decisions after information search at the aggregate level, where models have been built and fitted to human data that is averaged over a number of participants. DFE researchers have still not focused on a computational model's ability at the individual participant level. Thus, the main aim in this article is to test how some of the best computational models of DFE that explain aggregate choices would explain the same choices at the individual participant level.

BACKGROUND

In order to study people's search and choice behaviors in the laboratory, a "sampling paradigm" has been proposed in the DFE research (Hertwig & Erev, 2009). In the sampling paradigm, people are presented with two or more options to choose between. These options are represented as blank buttons on a computer screen. People are first asked to sample as many outcomes as they wish from different button options (information search). Once people are satisfied with their sampling of the options, they decide from which option to make a single final choice for real.

In the sampling paradigm, two classes of models have been proposed and these classes include the associative learning models and cognitive heuristics (Hertwig, 2011). Among the associative learning class, human choice is conceptualized as a learning process (for example, Busemeyer & Myung, 1992; Bush & Mosteller, 1955). Learning consists in changing the propensity to select a gamble based on the experienced outcomes. Good experiences boost the propensity of choosing the gamble associated with them, and bad experiences diminish it (e.g., Barron & Erev, 2003; Denrell, 2007; Erev & Barron, 2005; March, 1996). Some of the models in this class include the Instance-Based Learning (IBL) model (Gonzalez & Dutt, 2011; Lejarraga, Dutt, & Gonzalez, 2012), value-updating model (Hertwig et al., 2006), and fractional adjustment model (March, 1996). Among all the models in the associative class, the IBL model has been shown

DOI: 10.4018/978-1-4666-5888-2.ch455

as the best performing model at the aggregate level (Gonzalez & Dutt, 2011, 2012). Thus, we choose the IBL model as a first model for evaluation in this article.

The second class of models are referred to as cognitive heuristics (Hertwig, 2011) and this class aims to describe both the process and outcome of choice as a cognitive-choice heuristic (see Brandstätter et al., 2006). A popular and very successful cognitive heuristic that focuses on outcomes obtained by participants during sampling is the Natural-Mean Heuristic (NMH) model (Hertwig & Pleskac, 2010). As per Hertwig (2011), the NMH model has two interesting properties: (a) it is well tailored to sequentially encountered outcomes; and, (b) it arrives at the same choice prediction as determining the expected-value of the options based upon sampled outcomes. Two other heuristics that have been proposed in the class of cognitive heuristics include the maximax heuristic (Hau et al., 2008) and the lexicographic heuristic (Luce & Raifa, 1957). Hau et al. (2008) and Brandstätter et al. (2006) have shown that both these heuristics seem to underperform compared to the NMH model. Furthermore, Hau et al. (2008) have also shown that a cumulative prospect theory heuristic (Tversky & Kahneman, 1992), which is another popular model in the class of cognitive heuristics, seem to perform about the same as the NMH model to account for aggregated choices. Due to these reasons, in this article, we have considered the NMH model as a second model in our evaluation.

Furthermore, a very commonly used heuristic is the Primed-Sampler (PS) model (Erev, Ert, Roth, et al., 2010). The PS model depends upon the recency of sampled information and it looks back a number of samples (= k) on each option during sampling before making a final choice (Gonzalez & Dutt, 2011). A variant of the PS models is the PS model with variability (Erev, Ert, Roth, et al., 2010). In this model variant, the look-back sample size k is varied between participants and problems. The PS model with variability (referred to as the PS model hereafter for brevity) is a special case of the NMH model (as the NMH model looks back the entire sample size while deriving a choice). In the Technion Prediction Tournament (TPT; Erev, Ert, Roth, et al., 2010), which was the largest tournament involving several associative and cognitive-heuristic models, the PS model was the best baseline model for aggregated choices in the sampling paradigm. Due to this latter reason and the fact that the PS model is a specialized case of the NMH model, we consider it as the third model for our evaluation in this article.

If the IBL, NMH, and PS models are able to account for choices at the aggregate level, then one expects that they might also be able to account for choices at the individual level. However, given that there are sources of noise in both the sampling data as well as in these models, it is likely that these models are no better than random chance in explaining choices (based upon a coin-toss) at the individual level.

In this article, our main goal is to evaluate how some of the best models, which explain choice behavior at the aggregate level, perform at the individual level. In order to evaluate models at the level of an individual participant, we use the largest publically available TPT dataset in the sampling paradigm (Erev, Ert, Roth, et al., 2010). In what follows, we detail the working of the three models that we chose for our evaluation. Then, we discuss the methodology of calibrating these models at the individual participant level. Next, we present the results of models' evaluation at the individual level. Finally, we close the article by discussing the implications of our results for models of aggregate choice.

THE MODELS

In this section, we detail the working of three popular DFE models that have been used to evaluate human choices at the individual participant level.

Prime-Sampler (PS) Model

The PS model (Hertwig, 2011) employs a simple choice rule. In this model, participants are expected to take a sample of *k* draws from each option, and select the option with the highest sample mean. The exact value of *k* differs between observations (an observation is defined as a participant playing a problem in a dataset). The PS model assumes that the exact value of *k* for an observation is uniformly drawn as an integer between 1 and *N*, where *N* is a free parameter that is calibrated in the model. If the value of *k* for an observation is larger than the sample size of an option, then the *k* is restricted to that option's sample size. The final choice for each observation is determined by choosing the option with the highest sample mean based upon the last *k* draws. According to literature, the PS model has

Related Content

Hybrid Computational Intelligence
Georgios Dounias (2015). *Encyclopedia of Information Science and Technology, Third Edition (pp. 154-162).*
www.irma-international.org/chapter/hybrid-computational-intelligence/112325

Learning With Mobile Devices
Helen Cromptonand John Traxler (2018). *Encyclopedia of Information Science and Technology, Fourth Edition (pp. 6347-6360).*
www.irma-international.org/chapter/learning-with-mobile-devices/184332

Evaluation Platform for DDM Algorithms With the Usage of Non-Uniform Data Distribution Strategies
Mikoaj Markiewiczand Jakub Koperwas (2022). *International Journal of Information Technologies and Systems Approach (pp. 1-23).*
www.irma-international.org/article/evaluation-platform-for-ddm-algorithms-with-the-usage-of-non-uniform-data-distribution-strategies/290000

An Adaptive Curvelet Based Semi-Fragile Watermarking Scheme for Effective and Intelligent Tampering Classification and Recovery of Digital Images
K R. Chetanand S Nirmala (2018). *International Journal of Rough Sets and Data Analysis (pp. 69-94).*
www.irma-international.org/article/an-adaptive-curvelet-based-semi-fragile-watermarking-scheme-for-effective-and-intelligent-tampering-classification-and-recovery-of-digital-images/197381

Interpretable Image Recognition Models for Big Data With Prototypes and Uncertainty
Jingqi Wang (2023). *International Journal of Information Technologies and Systems Approach (pp. 1-15).*
www.irma-international.org/article/interpretable-image-recognition-models-for-big-data-with-prototypes-and-uncertainty/318122