Games and Economic Behavior 82 (2013) 52–65

Contents lists available at SciVerse ScienceDirect

Games and Economic Behavior

www.elsevier.com/locate/geb

Evaluating case-based decision theory: Predicting empirical patterns of human classification learning

Andreas Duus Pape [a,*], Kenneth J. Kurtz [b]

[a] *Economics Department, Binghamton University, PO Box 6000, Binghamton, NY 13902, United States*
[b] *Psychology Department, Binghamton University, PO Box 6000, Binghamton, NY 13902, United States*

ARTICLE INFO

Article history:
Received 6 January 2012
Available online 2 July 2013

JEL classification:
D83
C63
C88

Keywords:
Case-based decision theory
Human cognition
Learning
Agent-based computational economics
Psychology
Cognitive science

ABSTRACT

We introduce a computer program which calculates an agent's optimal behavior according to case-based decision theory (Gilboa and Schmeidler, 1995) and use it to test CBDT against a benchmark set of problems from the psychological literature on human classification learning (Shepard et al., 1961). This allows us to evaluate the efficacy of CBDT as an account of human decision-making on this set of problems.

We find: (1) The choice behavior of this program (and therefore case-based decision theory) correctly predicts the empirically observed relative difficulty of problems and speed of learning in human data. (2) 'Similarity' (how CBDT decision makers extrapolate from memory) is decreasing in vector distance, consistent with evidence in psychology (Shepard, 1987). (3) The best-fitting parameters suggest humans aspire to an 80–85% success rate, and humans may increase their aspiration level during the experiment. (4) Average similarity is rejected in favor of additive similarity.

1. Introduction

We present a computational implementation of case-based decision theory (Gilboa and Schmeidler, 1995) called the case-based software agent or CBSA. CBSA is a computer program that calculates an agent's optimal behavior according to case-based decision theory for an arbitrary problem. Like expected utility theory, case-based decision theory is a mathematical model of choice under uncertainty. Case-based decision theory has the following primitives: A set of *problems* or circumstances that the agent faces; a set of *actions* that the agent can choose in response to these problems; and a set of *results* which occur when an action is applied to a problem. Together, a problem, action, and result triplet is called a *case*, and can be thought of as one complete learning experience. The agent has a finite set of cases, called a *memory*, which it consults when making new decisions.

The case-based software agent is a *software agent*, i.e. "an encapsulated piece of software that includes data together with behavioral methods that act on these data (Tesfatsion, 2006)." CBSA computes choice data consistent with an instance of CBDT for an arbitrary choice problem or game, provided that the problem is well-defined and sufficiently bounded (see Section 3). To examine CBSA's relationship with human learning, we chose to generate data for a set of problems from the psychological literature on human classification learning starting with Shepard et al. (1961). In these problems, human decision makers classify objects described by vectors of characteristics, such as color and shape, and are rewarded when they classify the objects correctly. The data include variables such as probability of error over time, which allows one to

* Corresponding author. Fax: +1 607 777 2681.
E-mail addresses: apape@binghamton.edu (A.D. Pape), kkurtz@binghamton.edu (K.J. Kurtz).

0899-8256/$ – see front matter
http://dx.doi.org/10.1016/j.geb.2013.06.010

observe relative difficulty and speed of problem-solving/learning. We generate simulated choice data that is both consistent with case-based decision theory and directly comparable to human data collected on the same set of problems.

This is the first instance of simulating nuanced choice data implied by an economic decision theory that can be brought to existing human choice data from psychology. Behavioral economics is typically characterized by applying insights from psychology to economics via a mathematical model, sometimes with modification, which is then tested using economic statistical methodologies on economic data (e.g. Laibson, 1997; Fudenberg and Levine, 2006). This paper does the reverse: it tests a decision theory from economics using psychological methods and data.

In the framework of case-based decision theory, the effects of actions on new problems are extrapolated from memory by evaluating the *similarity* between problems. The extrapolation from problems in CBDT is similar to generalization from stimuli in psychology. The study of generalization in psychology has lead to a remarkably specific empirical estimate of the functional form of similarity among humans (Shepard, 1987). We test this form with CBSA and find empirical support.

We are able to establish four key facts about CBDT and its relationship with human choice behavior in these classification learning experiments.

First, we find the choice behavior of CBSA fits two canonical experiments' worth of human choice data very well. The best-fitting benchmark model fits both the relative difficulty of these categorization problems and the speed of learning to solve these sorting problems (i.e. probability of error over time). Moreover, the best-fitting benchmark model fits human data with a mean-squared error near the leading choice models in psychology. (This is the standard that psychology uses to evaluate models of classification learning.) This consistency with human behavior should be taken as a vote of confidence in support of CBSA as an account of human decision-making.[1]

Second, we find that, consistent with research in psychology cited above (Shepard, 1987), similarity functions that are decreasing in vector distance induce the best match to human data. On the other hand, whether the distance is mapped to similarity via an inverse exponential function, versus some other decreasing function, appears to not be critical.

Third, we find the best-fitting *aspiration level*, which can be thought of as a target success rate in the classification problem, is 80–85%. This falls into the range consistent with a correctly-specified choice model.[2] We also find some evidence that agents start at a lower aspiration level, around 70%, and increase their aspiration levels during the course of the experiment in a manner consistent with Gilboa and Schmeidler (1996).

Fourth, we find that additive similarity provides a better match for human data than does average similarity.

We augment CBDT in two ways in this computational implementation. First, we provide a dynamic, endogenous similarity function following the ALCOVE model from psychology (Kruschke, 1992). A dynamic similarity function is necessary to match one of the two human data sets; the other is matched with static similarity. Second, we introduce two different models of imperfect memory: imperfect storage (stochastic 'writing to memory') and imperfect recall (stochastic 'reading from memory'). Imperfect memory brings the speed of CBSA problem mastery in line with humans: with perfect memory, CBSA learns much too fast. Moreover, it appears that imperfect recall is more important than imperfect storage, which suggests cognitive processing limitations as opposed to storage-capacity limitations.

Below, we review the relevant literature in decision theory and agent-based computational economics (Section 2); we define CBSA precisely, then show that CBSA correctly and completely implements case-based decision theory (CBDT), and therefore an instance of CBSA is an instance of CBDT (Section 3); we then introduce the psychology of human classification learning and relate it to decision theory (Section 4), including defining the two augmentations of CBDT we pursue (Sections 3.3 and 4.3). Then we present and discuss our empirical results (Section 5) and conclude with some implications for future work (Section 6).

2. Related literature

To define a decision theory in the tradition of Savage and von Neumann and Morgenstern, an agent's choice behavior is observed and, if the choice behavior follows certain axioms, then a mathematical representation of utility, beliefs, et cetera can be constructed (von Neumann and Morgenstern, 1944; Savage, 1954). In an implementation, this is turned on its head: the mathematical representation is taken as given and choice behavior is produced. The purpose is to generate choice behavior for particular problems in hopes of finding empirical patterns in choice behavior that were not be *a priori* obvious from the mathematical representation alone. These patterns, coupled with human choice data, can be used to empirically test the hypothesis that the implemented decision theory describes human behavior. We do that here.

Case-based decision theory (Gilboa and Schmeidler, 1995)—hereafter, CBDT—postulates that when an agent is confronted with a new problem, she asks herself: How similar is today's case to cases in memory? What acts were taken in those cases? What were results? She then forecasts payoffs of actions using her memory, and choses the action with the highest forecasted payoff.

[1] This is an account of human decision-making in the same sense that a representation theorem provides an account of decision-making: That is, given the observed human choice behavior, we can find an instance of CBSA which generates the same or similar choice behavior, in the same way that when an agents' choices satisfy certain axioms, we can find a utility function and similarity function that generate that agent's behavior. We have achieved behavioral predictability, but in neither case can we claim that we have uncovered the actual inner workings of the agent's mind.

[2] Unless the model is misspecified, the aspiration level must lie between 50%, which is achievable by random selection, and 100%, which is perfect classification.