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Models of Choice and the TTB Heuristic

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Abstract

We examine the suitability of the Take-the-Best (TTB) heuristic (Gigerenzer, et al., 1999) as a mechanism for explaining repeated choice in experimental situations. Simulations utilizing TTB are shown to explain behavior in binary, ternary, and concurrent choice as well as previous models that were based on cost. The development of mathematical models of choice may have led us to focus on irrelevant factors rather than the kinds of information readily available to a subject. The utility of this heuristic as an explanatory tool is shown to represent a simple alternative to many current models of choice.

Introduction

Repetitive choice has been a common topic of investigation in psychology, sociology, political science, economics, and more recently, neuroscience. Fundamentally, subjects in an experiment are asked to make private choices over a number of discrete trials. They are usually provided with feedback that may either be complete or restricted in theoretically interesting ways. While the use of experimental design enables the examination of a variety of theoretical positions, the point of application extends beyond the theoretical to the actual situations in which humans are called upon to repeatedly make choices in nearly identical situations.

When humans periodically purchase products, select seats at sporting events, choose an area to fish or hunt, determine which crop to plant, or engage in any sort of behavior that requires repeatedly selecting among alternatives, they are engaging in applications of repeated choice. The ways in which humans make these choices and the information that they may (or may not) take into account is important not only for the understanding of human behavior, but for the understanding of the evolutionary processes that have shaped us and our interactions with our environments. Particular interest centers in the kinds of things actors “do” when making such decisions—given that actors have limited memories and patience, how can we understand the behaviors in which they engage when required to make a number of choices in a relatively short time?

Probability Learning

The notion of probability learning in repeated choice situations has been around since Humphreys (1939). While this perspective was clarified by Estes (1950; 1959; 1962; 1975; 1976), his “Stimulus Sampling” approach requires the estimation of parameters that cannot be directly observed; though his asymptotic predictions are consistent with many other models of choice (see Neimark and Estes 1967). Alternatives, such as those suggested by Herrnstein (1997) or Donahoe and Palmer (1994), deal with continuous time and obtained (rather than scheduled) reinforcement and will not be discussed here.

If we label scheduled reinforcement probabilities as π_1 and π_2, the general asymptotic solution for discrete-time binary choice situations is given by

$$b_1 = \frac{1-\pi_2}{1-\pi_1+1-\pi_2} = \frac{(1-\pi_1)^{-1}}{(1-\pi_1)^{-1}+(1-\pi_2)^{-1}}\ , \qquad (1)$$

where b_1 is the probability of choosing the first alternative. This solution has been derived and/or discussed by many authors (e.g., Neimark 1956; Estes 1959; Suppes and Atkinson 1960; Estes 1962; Friedman, Padilla and Gelfand 1964) and is the generally accepted asymptotic expectation for experimental situations of this type. The important question for us is whether this approach to repetitive choice deals with the processes through which humans actually make choices, or is simply a mathematically convenient summary of behavior? While mathematical convenience is important, the development of this line of thought has also led some to concentrate on the avoidance of mistakes in choice behavior and the idea that behavior change is most likely when one is shown to be wrong (e.g., Gray and Tallman 1996). Is this approach a reasonable description of the behaviors of individuals in choice situations?

Simple Contingent Choice

Table 1 shows the results of an experiment reported by Gray and Tallman (1987) along with the values expected according to Equation (1). This experiment was conducted to explore the differences between rewarding and punishing events and the data involve fixed condition repetitive choice with complete feedback. Only data involving rewarding outcomes are used here. While the equation predicts the outcomes satisfactorily, we must ask whether a focus on "mistakes" is necessarily what drives the actors behaviors?

Table 1. Results For A Test of Binary Choice (Gray and Tallman, 1987)

π_1	π_2	*N*	Mean	SE	Expected	*t*-test	Pr(>|*t*|)
0.10	0.50	9	0.361	0.027	0.357	0.14	0.890
0.37	0.50	9	0.417	0.035	0.442	-0.72	0.491
0.64	0.50	10	0.572	0.052	0.581	-0.18	0.860
0.91	0.50	9	0.822	0.045	0.847	-0.57	0.584

Recently, discussion of the manner in which humans make choices has taken a new turn. The work of Gigerenzer (Gigerenzer, et al. 1999; Gigerenzer 2006) has focused renewed attention on heuristics. Heuristics are simple rules for making choices that rely on the most basic of human abilities: those that are shared by nearly all of us. The Take-the-Best (TTB) heuristic (Gigerenzer 2006) appears to be one that might easily apply to repeated choice.

We begin by assuming that a human is faced with a binary choice situation whose structure is unknown. That means that, even given an apparent reliability of outcomes, this situation is not well understood by the actor and that whatever information becomes available must be used carefully if choices are to be successful. Given that we only assume basic skills, we can eliminate problem-solving approaches that require arithmetic or more advanced mathematics. We will assume that our actors have some memory and the ability to make rudimentary ordinal distinctions, but no more.

The information directly available to an actor is whether or not a reward occurs for a choice on a given occasion. This information provides a "cue" to the potential value of each of the alternatives. We can easily describe (or program) a simple variant on the "Take-The-Best" (TTB) heuristic that requires only the following steps:

- Step (1) retrieve the cues from short-term memory,
- Step (2) select the alternative with the higher cue value or, if neither is higher, guess.

Can a simple approach based on TTB generate the kind of asymptotic result described by equation (1)? As shown in Table 2, it can! A simulation (100 replications of samples of 100 subjects) based on the above steps generates mean values nearly identical to those expected on the basis of equation (1) and consistent with those reported in Table 1. An approach based on reward yields asymptotic outcomes identical to one thought to be based on mistakes. While both approaches are Markovian it should be clear that whether an actor's focus is on reward or on costs the asymptotic behavior generated can be identical.

Table 2. Simulation Results for Binary Choice

π_1	π_2	Mean(Sim)	SE(Sim)	E(Eq1)
0.10	0.50	0.356	0.010	0.357
0.37	0.50	0.443	0.011	0.442
0.64	0.50	0.580	0.014	0.581
0.91	0.50	0.849	0.011	0.847

A run of the simulation with sample size set to 10 (the target value in the Gray-Tallman experiment), shows no significant departure from the standard errors estimated on the basis of the observed means. The TTB model adequately explains not only the observed binary choice probabilities, but their standard errors as well.

It would be unrealistic to assume that any single approach to choice applies to all persons, even in the limited circumstances described. Informal discussions with subjects suggest that they may approach choice situations in quite a variety of ways. A few subjects, particularly those with some training in economics, business, or statistics, believe that they can increase their success rate by "maximizing" according to the way they believe the task activity to be constructed. Often they assume that a fixed probability schedule is involved, and that they can maximize their number of successes by always choosing the alternative that appears to have the highest reward probability assigned.

To the extent that these assumptions are correct, they will increase the number of rewards received, but, depending on the amount and kinds of feedback available, it can be very difficult for a subject to do any more than guess about the structure of the choice setting. In the absence of specific information about the structure of scheduled reinforcement, subjects attempting to maximize successes must act on the basis of their "beliefs" about the choice situation. If these beliefs are incorrect a subject may receive reduced rewards unless those beliefs can be changed, but the nature of the situation can make it quite difficult, if not impossible, to identify the "true" structure.

Since the TTB heuristic describes the observed data so well, it appears that most of the different kinds of experiences that actors can have in the limited duration of this choice situation have been incorporated. The success of TTB in such simple choice situations is probably due to the fact that this heuristic only utilizes information readily available to the actor and thus can be sensitive to any changes or variations in the reward schedule. It does not usually maximize success, but it's difficult to imagine how one would maximize success without knowing the underlying structure of the choice situation.

We have not yet learned to incorporate "beliefs" into experimental designs in any general way. This is probably because underlying "beliefs" may represent hidden aspects of cultural experience that we are often unable (or unwilling) to measure. While it may be difficult to develop ways of understanding aspects of culture not associated with easily measurable experience or training, that does not mean that these are not additional factors affecting choice. As the kinds of choices we ask our subjects to make become increasingly realistic, the importance of cultural background is likely to increase.

Choice with Multiple Alternatives

While most studies of choice have concentrated on the binary structure (e.g. Gray and Tallman 1987; Suppes and Atkinson 1960; Herrnstein 1997), the range of ways in which humans can approach choice situations expands with the number of alternatives available. Since humans make many choices in multi-alternative situations, we must ask whether TTB can also account for behavior in these settings?

A simple version of TTB can be applied to multi-alternative situations through a minor revision of the steps involved:

- Step (1) retrieve the *n* cues from short-term memory,
- Step (2) select the alternative with the highest cue value; if two or more alternatives have equally high cue values, guess between them, or; if all cue values are equal, guess among them all.

The conventional expectation for multiple-alternatives is a simple extension of the binary model given by

$$b_i = \frac{(1-\pi_i)^{-1}}{\sum_{j=1}^{j=R}(1-\pi_j)^{-1}}, \qquad (2)$$

where R is the number of available alternatives. This estimation formula assumes that actors guess between alternatives tied on their cue values as specified in the revised steps. Table 3 illustrates the outcomes of two three-alternative experiments by Gray and Tallman (unpublished). These data were gathered to examine aspects of "cost-equalization" in choice situations with multiple alternatives: subjects were asked to individually select between alternatives in a situation with fixed probabilities of success. These experimental situations used a randomized order in the presentation of alternatives on each trial, thus forcing subjects to attend carefully and eliminating associations between presentation order and reward probability.

Table 3. Outcomes of Two Three-Alternative Choice Situations (Gray and Tallman, unpublished)

Study (N)	π_i	Mean(Obs)	E(Mean)	T^2	F	Pr(>F)
I (23)	0.82	0.610	0.644	2.74	1.31	0.291
I (23)	0.41	0.199	0.197			
I (23)	0.27	0.191	0.159			
II (27)	0.55	0.437	0.462	1.70	0.82	0.453
II (27)	0.27	0.298	0.285			
II (27)	0.18	0.265	0.253			

A simulation of this variant of TTB applied to three-alternative choice situations reproduces the means expected by equation (2). The variability of the human actors is somewhat greater than that expected on the basis of the simulation. Since there are more ways a multi-alternative choice situation can be structured, it is reasonable that greater variability would occur, though the means do not significantly differ from the expectations by multivariate test.

Concurrent Choice

If we return to a binary choice situation in which subjects are provided with information regarding the outcomes of both possible actions, we have a situation referred to by Friedman, Padilla, and Gelfand (1964) as a "Choice Between Bets." While there are a number of situations in which more than one outcome can be reinforced, the most common examples are gambling games in which several behavioral choices can be simultaneously rewarded.

The asymptotic choice probabilities in the binary situation are estimated by

$$b_1 = \frac{\pi_1(1-\pi_2)}{\pi_1(1-\pi_2)+\pi_2(1-\pi_1)} = \frac{\pi_1(1-\pi_1)^{-1}}{\pi_1(1-\pi_1)^{-1}+\pi_2(1-\pi_2)^{-1}}, \tag{3}$$

as noted by Friedman, et al. (1964) and Gray and Tallman (1984). Fits to data obtained by Friedman, et al. (1964) are shown in Table 4.

A form of TTB that uses no more than the information directly available can successfully describe these results. Since there are two items of information, one for the outcome of the choice actually made and another for the one not made, we need only modify the steps of our simulation heuristic as follows:

- Step (1) retrieve the two cues from short-term memory,
- Step (2) begin with the choice made—if one alternative has a higher cue value proceed to step 3, otherwise examine the remaining cue value and then proceed to step 3,
- Step (3) select the alternative with the higher cue value or, if neither is higher, guess.

This modification of the TTB formulation simply makes use of an additional item of information to aid in decision-making in cases in which the first cue would require a guess. The outcome of the simulation reproducing these results also appears in Table 4.

Table 4. Simulation of a Binary Concurrent Situation (Friedman, Padilla, and Gelfand, 1964)

π_1	π_2	Mean(Obs)	Mean(Sim)	SE(Sim)	Pr(>|*t*|)	E(Eq3)
0.80	0.80	0.474	0.502	0.026	0.283	0.500
0.80	0.50	0.813	0.801	0.013	0.357	0.800
0.80	0.20	0.937	0.942	0.007	0.476	0.941
0.50	0.50	0.476	0.504	0.019	0.142	0.500
0.50	0.20	0.821	0.802	0.014	0.177	0.800
0.20	0.20	0.468	0.504	0.022	0.104	0.500
0.80	0.50	0.801	0.801	0.013	1.000	0.800

Implications

There are two major implications tied to the use of the TTB heuristic to explain repeated human choice. First, simple approaches to choice that make use only of abilities possessed by all humans (and many other organisms) are sufficient to reproduce many of the results found in studies of choice behavior. At both the theoretical and mathematical levels, the TTB heuristic describes a dynamic process that is both simple and effective.

Second, the widespread use of mathematical models to explain human choice behavior may have mislead researchers and others who were more taken by the apparent mathematical implications of such models than the simple processes that may underlie them. Detailed examination of mathematical models, especially models that are descriptively successful, may direct attention toward processes that overestimate the complexity of the dynamic approaches actors can take. Certainly we have shown that the outcomes of choice research can be more simply explained by an approach focused on reward rather than one focused on cost.

Our position should not be construed as one in opposition to mathematical descriptions of human choice behavior. Instead, we hope that we become more sensitive to the distinction between assumptions and knowledge. Each choice situation provides some level of explicit information to an actor engaged in making choices. An actor may also make a number of assumptions about the choice situation, some of which may be irrelevant and some of which may be highly relevant.

These assumptions can arise from the actor's own experience, the time involved in decision making, and the norms and constraints of the culture to which an actor has been exposed. To the extent that these assumptions are either irrelevant or are consistent with features of the true choice situation, they do no harm. If, on the other hand, the assumptions are relevant and incorrect, then they may result in a poor performance in the choice situation. Since, in the real world, feedback regarding some aspects of choice may be substantially delayed or even unavailable, it may not be possible to anticipate a problem, such as global warming has become, in time to avoid it. For choice theorists, this may simply mean that it will be difficult for an individual to assess the true probabilities of an outcome on the basis of apparently obtained reinforcement. Behavior might look like random guessing or irrational choice when, in fact, it is simply due to a lack of adequate information.

The underlying problem is one of incorporating "beliefs" in our approach to choice. Given that it may not be possible to examine the applicability of such beliefs immediately, and that the beliefs often are incorporated in cultural systems, the likelihood of mistaken choice is high. Yet, if we are correct, the simple underlying TTB heuristic can provide the most "rational" approach to choice until the additional assumptions can be verified.

For choice theorists, this may mean that the focus must shift from a desire to predict a choice alternative accurately based on sophisticated mathematical formulations to a greater understanding of the cognitive processes by which such choices are made. It may be that as we become able to identify the relevance of beliefs held by individuals that more sophisticated modeling procedures will become accurate in terms of both outcome and process. It may be that we will be able to incorporate knowledge of how to enter and appropriately weight information in such models. For the moment, however, the findings of this paper suggest that we can predict individual choice using the TTB heuristic as accurately as with more sophisticated models. The overarching message of this paper and our findings is that, in the interests of parsimony, we can use the TTB heuristic with no significant loss in accuracy over more sophisticated models and, perhaps, a clearer understanding of human approaches to choice.

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