The Art of Choice: Exploring the Complexities of Human Decision-Making

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Abstract

Decision scientists across various disciplines, including economics, psychology, and management, have been striving for centuries to develop a choice model that can accurately predict and describe behavior while being easy to apply and generalize. However, a major obstacle in this research program is the unobservable nature of the physical processes that guide decision-making.

To address this challenge, decision scientists have either relied on axioms that capture normative features of choice or sought mathematical frameworks that best describe empirically observed behavior. In the past century, detailed models have been constructed from the first principles of how humans and animals should make decisions. However, in recent decades, psychologists and behavioral economists have gathered data that contradicts the predictions made by these economic models. As a result, highly descriptive models have been developed that can predict people's or animal's choices which do not provide insights about why people make the choices that they do. These models are particularly limited in explaining why a decision-maker might choose an option that is not in their best interest.

In the last two decades, neurobiologists have collaborated with economists and psychologists to create new models that incorporate our understanding of how the nervous system operates. This interdisciplinary field, known as Neuroeconomics, presents a promising opportunity to transform our comprehension of decision-making behavior in humans and animals. Emerging neuroeconomic models combine the essential neurobiological representation properties with decision-theoretic analyses to offer a holistic approach. This biologically and behaviorally motivated approach is potentially offering a biological basis for normative theories and providing new insights into longstanding theoretical puzzles.

Machine learning has also become an increasingly popular approach for studying and predicting human decision-making behavior. By leveraging the power of large-scale data analysis and computational modeling, researchers are able to gain insights into the underlying mechanisms of human decision-making and develop predictive models that can accurately predict choices made by individuals. One of the main advantages of using machine learning for human decision-making research is the ability to capture complex patterns in data that may not be apparent using traditional statistical methods, but it is unclear to what extent it can enhance predictions obtained from current theories. The main obstacle is the scarcity of data, as human behavior is noisy and requires large sample sizes to be accurately captured by standard machine learning methods. Furthermore, to be useful in real-world applications, machine learning models need to be interpretable, transparent, and grounded in robust theoretical frameworks.

1 Introduction - A Brief History of Human Decision-Making

The study of human decision-making originated from the works of prominent mathematicians and economists such as Blaise Pascal, Daniel Bernoulli, Adam Smith, and David Ricardo. These intellectuals sought to explain patterns in human behavior based on first principles. Their primary focus was on understanding the "why" behind people's choices from a mathematical and theoretical perspective. Historically, it had been widely accepted among scholars and philosophers that people make choices with the goal of maximizing a certain value, whether it be monetary gain, love, or something else. Pascal was among those who postulated that individuals strive to increase their expected value over time. Expected value is the average long-run objective value of an option or offer. It is calculated by multiplying the probability of each possible outcome by the gain or loss associated with that outcome. A fair coinflip that pays $2 on heads and $0 on tails has an expected value of $1.

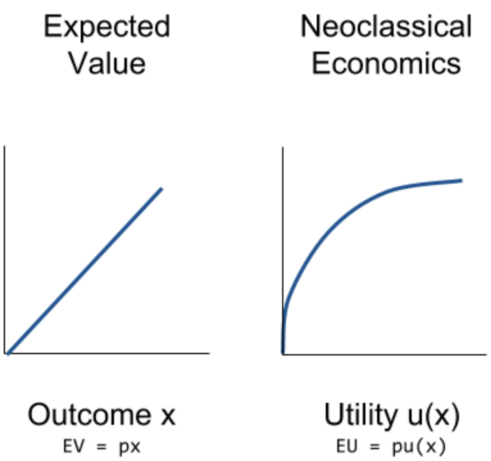

Figure 1: Expected Value vs Expected Utility Theory [https://kevinbinz.com]

However, in the 18th century, the observation that humans often sacrifice higher expected value to avoid risk largely disproved this conjecture. Mathematicians concluded that human decision-making is not just about maximizing expected value but a more subjective notion of accumulation, called expected utility. Expected Utility is the average long-run subjective value of an option or offer. It is calculated by first transforming the gains and losses associated with each possible outcome into a subjective form, for example, by taking the logarithm of the amount and multiplying them by the associated probabilities. In the first half of the 20th century, there was an effort to identify the set of all reasonable algorithms for maximization under this assumption. One critical insight was that well-organized patterns of choice must be transitive, which means that if a person prefers Manga over Marvel and Marvel over DC, then they simply cannot prefer DC over Manga. If they do then it can be proven that their choices cannot achieve any goal. No stable maximization (or utility) function can ever be used to describe or justify the intransitive choice.

During the 1960s, it became evident that humans didn't always conform to the predictions made by economic theories. Work by economists like Maurice Allais [Allais 1953] and psychologists like Amos Tversky and Daniel Kahneman [Kahneman and Tversky 1979] began to reveal systematic patterns of behavior that violated the predictions of the economic models. The behaviors exhibited in making choices involving risky prospects show various effects that are inconsistent with the basic principles of utility theory. In particular, people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This tendency, called the certainty effect, contributes to risk aversion in choices involving sure gains and to risk seeking in choices involving sure losses. In addition, people generally discard components that are shared by all prospects under consideration. This tendency called the isolation effect, leads to inconsistent preferences when the same choice is presented in different forms. An alternative theory of choice, called the Prospect Theory, was proposed by Kahneman and Tversky, in which value is assigned to gains and losses rather than to final assets and in which probabilities are replaced by decision weights. The value function is normally concave for gains, commonly convex for losses, and is generally steeper for losses than for gains. Decision weights are generally lower than the corresponding probabilities, except in the range of low probabilities. Overweighting of low probabilities may contribute to the attractiveness of both insurance and gambling.

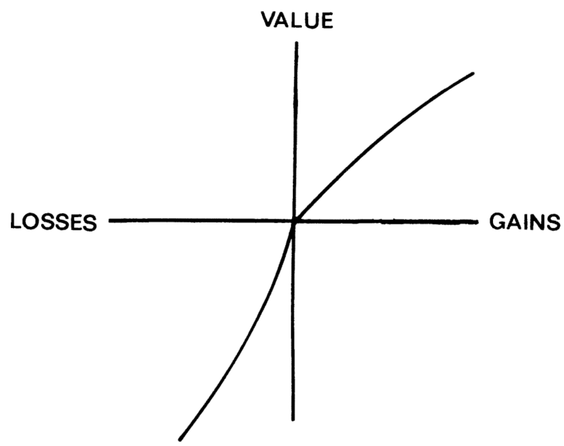

Figure 2: Prospect Theory [https://doi.org/10.2307/1914185]

Psychologist Herbert Simon proposed that these inefficiencies may have been due to cognitive or neurobiological limitations. However, while some researchers focused on developing descriptive models that could predict behavior, they provided little insight into "why" individuals displayed these seemingly self-destructive behaviors. In the early 2000s, a group of scholars from the fields of neurobiology, economics, and psychology joined forces to explore how the nervous system actually makes decisions, aiming to reconcile the tension between economic theories and observed human behavior. This interdisciplinary collaboration led to the birth of a new field called Neuroeconomics. Within this field, various models emerged, focusing on how the nervous system encodes and processes decision-related information. One of these models draws its inspiration from Horace Barlow's Efficient Coding Hypothesis. According to Barlow, building internal representations of the external world and performing computations on them is metabolically costly, so organisms should naturally trade-off completeness against metabolic cost by minimizing costly redundancies in their internal representations. Thus, the model hypothesizes that animal nervous systems are "efficient" and only devote energy to valuable computations and goals. Attneave and Barlow's proposal that neural codes in sensory systems are driven by evolution to maximize the amount of information carried by each action potential is based on Shannon's Theory of Information. This process involves two stages: first, eliminating redundancy in the incoming information, and second, adjusting the firing rate function so that more of the available range is dedicated to encoding likely inputs.

Information in the brain is conveyed by the rate at which neurons produce electrochemical impulses, called action potentials. The number of action potentials a neuron can produce is strictly bounded and the number of neurons which participate in the choice process is demonstrably finite. Therefore, the subjective value function must necessarily be bounded. Further, the mechanism for generating action potentials is imperfect and introduces noise into value representation. Neuroscientists have identified features of neural computations used by the human brain to encode decision variables for producing choices, and these computations ensure that information encoded by the nervous system is minimally redundant and maximally informative as there is a limit on the information carried by a neural signal of value. This representation relies on a utility-like construct that is directly observable and is measured in firing rates.

A significant amount of work during the 1990s examined efficient coding in the visual system using the divisive normalization equation. Divisive normalization models, a specific class of utility-like functions identified by neuroeconomists, allow agents to optimally balance the known biological costs of reducing stochasticity against the gains from more accurately representing the utility of options. Divisive normalization has been shown to predict several interesting human and animal choice behaviors and has been demonstrated to impose uniqueness on the hidden representation, making it possible to derive neurological predictions from choice and vice versa. If encoding visual images, for example, the overall brightness of the image changes over the day in a way that induces both redundancy and local correlations. Changes in pupil size both reduce this redundancy and adapt to the range of brightness that impinges on the retina. Neurons in the visual cortex encode something along the lines of Equation:

$$FR_1 = \frac{Input_1^{\alpha}}{M \ + \ \sum_i w_i Input_i^{\alpha}}$$

The classic divisive normalization equations achieve efficiency by devoting more firing rate range to more likely inputs; when the likely inputs are tightly clustered, then a sigmoidal firing rate. function centered on these likely values is efficient. When the likely inputs are more broadly distributed, then an efficient encoding function would use a more gradually sloped form. The divisive normalization functions achieve this flexibility with two key parameters, M and α. At α = 1, the function looks very much like a classical utility function. As α increases, that function takes on the characteristically sigmoidal shape of the Kahneman and Tversky value function. This suggests that the shift from a classically concave function to a sigmoid observed behaviorally is driven by changes in the distribution of the options under consideration. As the expectation point M is increased, the center of the function shifts to the right. This corresponds to a strategy that centers the firing rate function on the modal value of the input distribution.

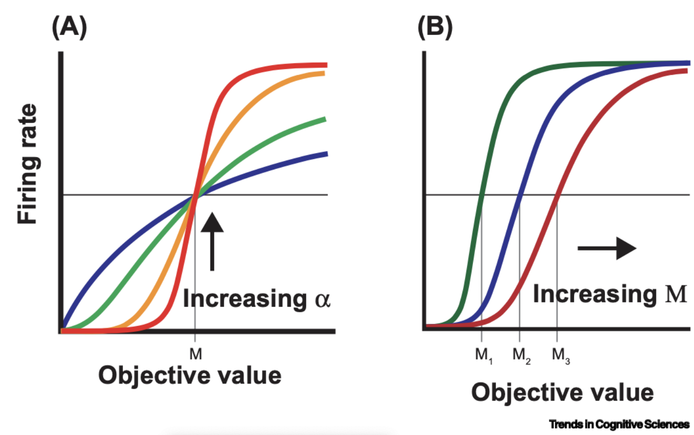

Figure 3: Divisive normalization firing rate functions

2 Choice Prediction Modeling

The second part of my paper pertains to the use of machine learning models for predicting decision-making.

2.1 CPC18: Choice Prediction Competition 2018

A recent study (Erev, Ert, Plonsky, Cohen, Cohen, 2017) has tried to address this prediction difficulty by making three observations. First, it is possible to define a single space of choice problems and a single paradigm in which 14 of the classical phenomena (including the St. Petersburg paradox, (Bernoulli, 1954), the Allais paradox, (Allais, 1953), and the Ellsberg paradox, (Ellsberg, 1961)) emerge. Second, it is possible to derive a single behavioral model that both captures all 14 classical phenomena and provides useful predictions of choice behavior in other settings that are part of the same space of problems. Specifically, the model, BEAST (acronym for Best Estimate And Sampling Tools), assumes choice is sensitive to the expected values and to four additional behavioral tendencies: (a) minimization of the probability of immediate regret, (b) a bias toward equal weighting of possible outcomes, (c) sensitivity to the payoff sign, and (d) pessimism. The third observation Erev et al. (2017) made follows from a choice prediction competition (hereinafter CPC15) in which other researchers were challenged to develop and submit models that outperform BEAST with respect to predictive power of a completely withheld dataset. The results of the competition showed that the best predictive models were variants of BEAST. Specifically, theory-free statistical learning models, as well as more traditional behavioral models such as variants of prospect theory (Kahneman and Tversky, 1979), did not predict well.

However, Plonsky, Erev, Hazan, and Tennenholtz (2017) have since shown that a model that integrates insights from the behavioral decision research with a machine learning algorithm can provide state-of-the-art predictive performance for the CPC15 data. Specifically, the model, called Psychological Forest, employs the basic theoretical building blocks of BEAST (as well as the predictions of BEAST) as features (covariates or predictors) to be used in a supervised learning setting with a random forest algorithm (Breiman, 2001). Notice however, that Psychological Forest, unlike BEAST, was developed after the test data was already available, which makes it possible to fine tune the model to improve prediction accuracy.

2.1.1 Dataset

CPC18 contains 210 choice problems (90 test problems) for five repeated trials for a total of 1,050 datapoints (450 test datapoints). Problems in the CPC datasets required people to choose between a pair of gambles, A and B. Each gamble consisted of a collection of rewards and their associated outcome probabilities. In CPC15, gamble A was constrained to only have only two outcomes (similar to the example given in section 2). Gamble B yielded a fixed reward with probability $1 - p_L$ and the outcome of a lottery (i.e., the outcome of another explicitly described gamble) otherwise. That is, by convention in the competition problems, a lottery is defined as the outcome of a chosen gamble (occurring with probability pL) that can also yield one of multiple monetary outcomes, each with some probability. Gamble B's lottery varied by problem and was parameterized using a range of options, including the number of outcomes and the shape of the payoff distribution. In CPC18, the only difference was that some of the problems allowed gamble A to take on the more complex lottery structure of gamble B. For each problem, human participants made sequential binary choices between gamble A and B for five blocks of five trials each. The first block of each problem was assigned to a no-feedback condition, where subjects were shown only the reward they received from the gamble they selected. In contrast, during the remaining four blocks subjects were shown the reward they obtained from their selection as well as the reward they could have obtained had they selected the alternative gamble. Finally, gambles for problems assigned to an "ambiguous" condition had their outcome probabilities hidden from participants.

2.1.2 Baseline

The baseline used here is the Psychological Forest model, which integrates the theoretical insights of BEAST for what type of features are likely to be important for prediction with the power of a random forest algorithm that had been provided. Psychological Forest uses as one of its features the predictions of the original BEAST, as well as 13 hand-crafted features constructed to capture the logic underlying BEAST.

2.1.3 Models

- The first modification to the baseline is to use a single Random Forest Regressor, instead of using different models for each problem. This would help in generalization.
- The second modification is to make use of Multi-layer Perceptron with ReLU activation. Multiple networks with different depths and hidden units were analyzed.
- The third modification is to train a model on a similar dataset called Choices13K dataset and transfer the knowledge while fine-tuning for the CPC-18 dataset. This is achieved using MLP.

2.1.4 Evaluation

Prediction of the aggregated human selection frequencies (proportions between 0 and 1) is made given a 12-dimensional vector of the parameters of the two gambles and the block number. As this information is all displayed to the participant in the course of their selection, we refer to these as "raw" problem features. Prediction accuracy is measured using mean squared error (MSE).

2.1.5 Results

Model	MSE
Baseline	0.8187271422582493
Modification 1	0.8294995815734035
MLP	9.034410759679913
MLP + Modification 1	2.0638094422805295
MLP + Transfer Learning	1.518164884135073

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Github Repository `https://github.com/ShreyaSinha14468/Modeling-the-Mind`