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Neural dynamics of affect, gist, probability, and choice

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Abstract

Recent behavioral data show that the traditional reduction of all probabilistic choices to choices among monetary gambles is inaccurate. Specifically, while decision makers tend to overweight low probabilities of obtaining any resource, the overweighting is greater when the resource is more emotionally evocative. We present a shunting nonlinear neural network that simulates the biasing effect of emotion on probabilistic choice. The network includes analogs of parts of the amygdala, orbitofrontal cortex, ventral striatum, thalamus, and anterior cingulate as well as sensory and premotor cortices. The network classifies prospective probabilistic options by means of an adaptive resonance module with vigilance selective for those attributes that are deemed most significant for the option currently being processed. The categories into which these options are placed embody significant gists of the options in a manner consistent with fuzzy trace theory.

Keywords: Decision making; Emotion; Amygdala; Orbitofrontal cortex; Adaptive resonance theory; Fuzzy trace theory

1. Introduction

One aspect of human decision making data that deviates from classical economic models is the nonlinear weighting of probabilities. Experiments on choices between explicitly described gambles show that human decision makers tend to overweight low nonzero probabilities and underweight high non-unity probabilities. Tversky and Kahneman's (1992) prospect theory includes a mathematical formulation of this nonlinear probability weighting, as shown by the S-shaped curve of Fig. 1.

Yet Tversky and Kahneman's theory tacitly assumed that specific probabilities had the same weights regardless of what resource they dealt with; for example, a certain percentage probability of saving a person's life, avoiding damage to one's house, or winning a trip to Europe in a raffle could all be reduced to the same monetary gamble. Against this simplifying assumption, there is significant evidence that the curvature of the S in Fig. 1 is different for different types of resources. For example, Rottenstreich and Hsee (2001) asked some of their participants if they would rather obtain \$50 or the kiss of their favorite movie star, and the majority (70%) preferred the money. But when the same participants were given a hypothetical choice between a 1% probability of obtaining the \$50 and a 1% probability of obtaining the kiss, the majority (65%) preferred the kiss. Rottenstreich and Hsee explained their finding by noting that the kiss was affect-rich whereas the money was affect-poor. They concluded that a low nonzero probability of obtaining an affect-rich resource is more strongly overweighted than the same low probability of obtaining an affect-poor resource, as described in Fig. 2.

The kiss-money data actually deal with curvature of the S curves only at the end closest to probability 0. Another result by Rottenstreich and Hsee (2001) indicates that affective richness also leads to sharper curvature at the end closest to probability 1. These researchers asked another set of participants how much they would be willing to pay for a 99% probability of obtaining a \$500 tuition

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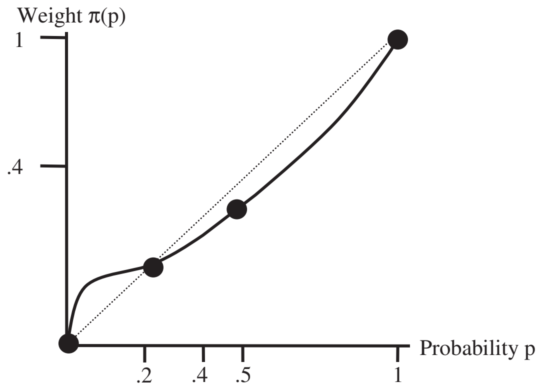

Fig. 1. Typical weighting curve from prospect theory (made continuous at 0 and 1). (Reprinted from Levine, 2011, with the permission of Springer-Verlag.).

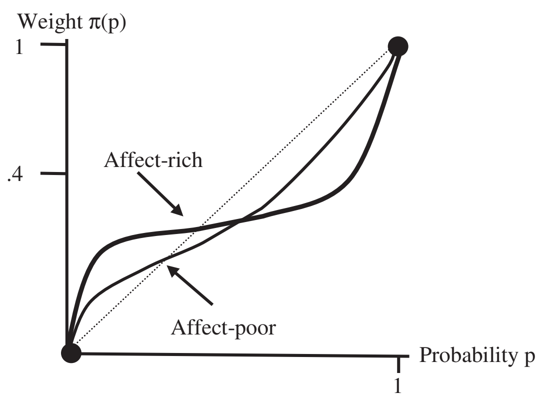

Fig. 2. Possible affect-poor and affect-rich probability weighting curves. (Adapted from Rottenstreich & Hsee, 2001, with the permission of Sage Publications.).

rebate (affect-poor) and for a 99% probability of obtaining \$500 toward a trip to European tourist destinations (affect-rich: these were American students). The median price that the participants were willing to pay for the almost-certain European trip was \$28 lower than the median they were willing to pay for the almost-certain tuition rebate, indicating that the gap between a 99% and a 100% probability was psychologically larger in the affect-rich case.

Variability in the shape of the S-curve is also supported by results of Kusev, van Schaik, Ayton, Dent, and Chater (2009) who framed equivalent probabilistic choices either as insurance purchases – for example, "(a) 1% chance of losing your luggage, which is worth £400, or (b) buying insurance at a cost of £20 to insure against the loss of your luggage" (Kusev et al., 2009, p. 1489) or as monetary gambles. When the decision was framed in an insurance context, the participants overweighted not only small probabilities but also, to a lesser degree, mid-range probabilities and even probabilities just less than 1. In prospect theory terms, that meant that their S-curves were above the 45° line for probabilities from 0 to about .8. However, this overweighting only occurred with insurance losses. For insurance-gain scenarios – for example, "(a) 1% chance of winning an insurance rebate of £400 or (b) a guaranteed insurance rebate of £20" (Kusev et al., 2009, p. 1489) – all probabilities of gains above .2 but less than 1 were underweighted.

Gonzalez and Wu (1999) fit the S-shaped curve of prospect theory to a specific mathematical function with several cognitively significant parameters. However, these researchers did not include a theory of underlying cognitive or neural processes that generate those parameters. There have been partial mappings of prospect theory to brain processes (Tom, Fox, Trepel, & Poldrack, 2007; Trepel, Fox, & Poldrack, 2005) but these mappings have not yet been integrated into a quantitative model.

Our goal is to develop a neurocognitive theory that can account for characteristic human distortions of probability processing. As part of this theoretical process, we develop and simulate a brain-based neural network model of the Rottenstreich and Hsee (2001) data on probability weighting with affect-rich and affect-poor resources. Our model does not generate an explicit probability weighting curve, but instead treats probabilities as one attribute of complex stimuli that are processed as a whole. The model incorporates elements of several existing theories that have been utilized in the simulation of other cognitive data: the adaptive resonance theory of categorization (Carpenter & Grossberg, 1987); the gated dipole theory of affective contrasts (Grossberg & Gutowski, 1987); and the fuzzy trace theory of memory (Reyna & Brainerd, 2008; Reyna, Lloyd, & Brainerd, 2003). The model also incorporates roles for different prefrontal and limbic regions that are compatible with fMRI results on emotionally influenced decision making (DeMartino, Kumaran, Seymour, & Dolan, 2006).

2. Background and structure of the model

2.1. Fuzzy emotional traces

One of the clues to understanding nonlinear probability weights arises from *fuzzy trace theory* (Reyna et al., 2003). Fuzzy trace theory posits the coexistence and interaction of two distinct systems for encoding information: literal or *verbatim* encoding, and intuitive or *gist* encoding. Verbatim encoding means literal storage of facts, whereas gist encoding means storing the essential intuitive meaning or "gist" of a situation.

As Reyna et al. (2003) note, gist encoding of probabilities tends toward all-or-none representations of risk. That is, the gist encoding perceives gambles as "certainty," "no chance," or "some chance" of a particular gain or loss, and the precise probability of that gain or loss is largely neglected. For this reason, gist encoding tends to reduce the relative attractiveness of sure losses and enhance the relative attractiveness of sure gains in comparison with risky alternatives. The S-shaped function of Fig. 1 was interpreted in Levine (2011) as a nonlinear weighted average of an all-or-none step function arising from gist encoding and a linear function arising