NEUROCOMPUTATIONAL MODEL OF VALUE-BASED DECISIO-MAKING IN UNCERTAIN AND CHANGING ENVIRONMENT

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A fundamental assumption in classical economics is that reward probabilities and reward magnitudes (computational components) are integrated in optimal way, multiplicatively for deriving option values and making choices. To explain repeatedly reported systematic violation of optimal decision-making, behavioral economists have proposed prospect theory. According to that, humans do optimal integration of computational components as described in expected utility theory, but make computations based on distorted representation of reward probabilities and values (subjective valuation). Although this approach can explain human choices, it cannot dissociate sub-optimality (of computational strategy) from distortion of computational components, hence, may conclude models that fit human behavior, but are not indicative of underlying computational mechanisms. This, first, undermines the core aim of behavioral economics, that is, to understand human behavior per se, second, abridges the potential of model-based study of neural mechanisms in the brain. A recent study hypothesized an alternative additive strategy of option value derivation (model MIX) and contrasted this sub-optimal strategy with both optimal multiplicative strategy (model OPT) and subjective valuation (model DIST). Two follow-up studies manipulated reward parity via low (basic level of rewards) and high (five times larger rewards) conditions in each of gain vs loss reward representation conditions. The reward parity manipulation aimed as testing diminishing sensitivity, and gain-vs-loss manipulation aimed at checking loss aversion tendency (both are behavioral tendencies observed in behavioral economics studies).

For the original study 25 subjects with no general medical, neurological, psychiatric or addictive history were recruited. For the first and second follow-up studies 31 and 30 subjects were recruited, respectively. The experimental task of the study was one-armed bandit task. For estimating model-free parameters all models were fitted to experimental data separately for each participant by maximizing the model log-likelihood (LLH). To maximize LLH, slice sampling procedure with uniform priors was used. Then, gradient ascent starting from the best sample was used to get optimized estimates of parameters maximizing LLH. Each participant of the original study was tested in three fMRI sessions. Statistical parametric maps of local brain activations were computed in every subject using the standard general linear model.

The original study confirmed both behavioral and neural superiority of model MIX (additive strategy) over model OPT and model DIST according to Bayesian Information Criterion. Moreover, the study found model MIX is the general model of decision-making while model OPT is only a special case.of model MIX in uncertain and changing environment. The follow-up studies confirmed the main conclusion of the original study. Besides, follow-up studies did not find evidence against the normalization step of MIX model algorithm (no diminishing sensitivity); and did not find evidence supporting differential behavior in gain and loss domains (no loss aversion).

The study revealed that humans employ a sub-optimal valuation and choice algorithm in uncertain and changing environments, and found no evidence of behavioral tendencies such as diminishing sensitivity and asymmetrical risk-taking in gain and loss domains.This results contribute to the view that decision-making in environments with incomplete information may give rise to computational strategies that are not necessarily optimal in terms of normative frameworks but might ensure both behavioral flexibility and effective learning.