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Choice variability and suboptimality in uncertain environments

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Making decisions under uncertainty, from perceptual judgments to reward-guided choices, requires combining multiple pieces of decision-relevant information — a cognitive process modeled as statistical inference. In such conditions, human and animal decisions exhibit a large suboptimal variability whose origin and structure remains poorly understood. This variability is usually hypothesized as noise at the periphery of inferential processes, namely sensory noise in perceptual tasks and stochastic exploration in reward-guided learning, or as suboptimal biases in inference per se. Here we outline a theoretical framework aiming at characterizing the origin and structure of choice variability in uncertain environments, with an emphasis on the computational imprecision of inferential processes usually overlooked in the literature. We indicate how to modify existing computational models and behavioral paradigms to dissociate computational imprecisions from suboptimal biases in inference. Computational imprecisions have critical consequences for understanding the notion of optimality in decision-making.

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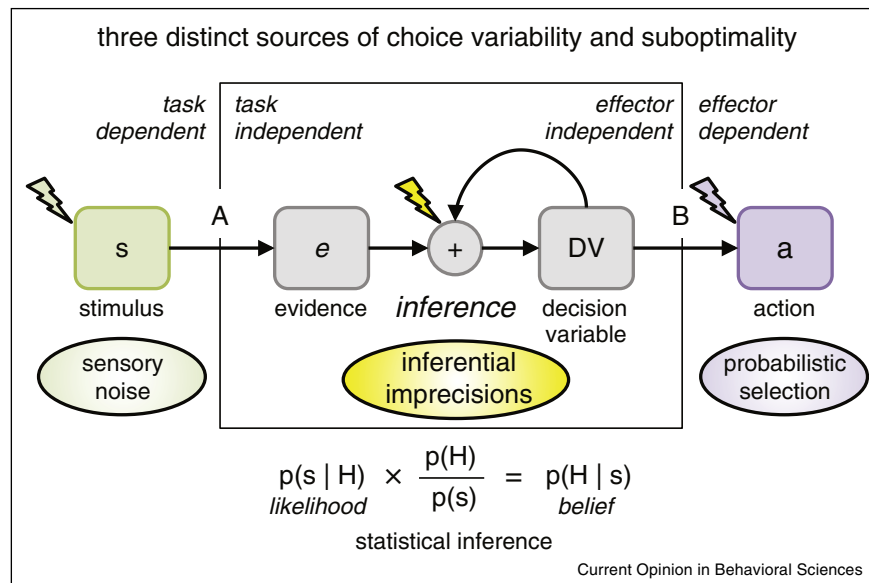## From normative to algorithmic descriptions of decision-making

In uncertain or changing environments, making decisions requires combining multiple pieces of ambiguous or conflicting information. In such conditions, human choices exhibit a suboptimal variability whose origin and structure remains poorly specified to date [1••,2•,3••]. Normative descriptions of decision-making in terms of optimal statistical inference — defined by the Bayes theorem of probabilistic inference [4] — have provided common metrics to quantify human performance in various decision problems, ranging from visual search [5] to reward-guided learning [6]. However, this approach falls short of explaining the pervasive variability and sub-optimality of human decisions and its implications in terms of cognitive and neural architecture [7].

These limitations have to do with the level of description at which Bayesian formulations are set [8,9]. Indeed, normative descriptions seek by definition to characterize the 'computational' problems that the brain tries to solve in terms of information processing. In this regard, Bayesian models of perception have been tremendously helpful in showing that humans perform inference on noisy sensory signals using contextual knowledge (or 'priors') about their environment. This computational description of brain function, inspired by the pioneering work of Helmholtz in the late 1800s, is still very influential in the field [10]. However, and despite recent attempts [11,12], this function-level description of the brain as an 'inference machine' remains inherently blind to its neurobiological implementation — that is, the 'representational' or 'algorithmic' level of description according to Marr's hierarchy. In particular, one can write virtually any departure from the Bayesian optimum as a mixture of wrong priors and probabilistic ('softmax') decision rules in an otherwise optimal inference process [7] (Figures 1–3).

Dominant views go as far as proposing sensory noise (at the input of the decision process) to be the dominant source of choice suboptimality in perceptual tasks [13–15], whereas stochasticity in response selection (at the output of the decision process) would cause suboptimal reward-guided choices in the purpose of 'random' exploration of environmental contingencies [16,17] (see also [18,19] for a comparison between 'directed' and 'random' forms of exploration). However, the behavioral paradigms on which these claims are based cannot distinguish choice suboptimality originating from the peripheries of the decision process from computational imprecisions in inference, at the core of the decision process. This distinction requires adapting current computational models of decision-making which either make the assumption that inferential computations are performed with infinite precision (such as the updating of beliefs in probabilistic learning models, see [6]) or do not specify the origin of observed variability in the decision variable (such as random-walk drifts in sequential sampling models, see [20•]).

Figure 1

three distinct sources of choice variability and suboptimality

$$p(s \mid H) \times \frac{p(H)}{p(s)} = p(H \mid s)$$
likelihood   belief

statistical inference

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Theoretical distinction between three sources of choice variability and suboptimality. Computational description of decision-making as statistical inference: evidence from stimulus s, corresponding to the likelihood of stimulus features given possible generative hypotheses H, is accumulated across stimuli in the form of a decision variable DV, corresponding to the posterior belief of possible generative hypotheses given observed stimuli, and finally translated into an appropriate action a. Two mapping rules control: **(a)** which stimulus features are relevant for the decision, at the input of the inference process, and **(b)** the 'task set' which determines which action to take depending on the decision variable, at the output of the inference process. Three sources of variability can affect the decision process: (1) sensory noise during the processing of decision-relevant stimulus features (green), (2) probabilistic action selection in the purpose of exploration (purple), and (3) imperfections in inference (yellow). Sensory noise is stimulus-dependent but task-independent, whereas inferential imperfections should depend on the complexity of the inference process (e.g., the number of possible generative hypotheses to choose from). Probabilistic action selection, in contrast to inferential imperfections, is independent from the number of inference steps performed (i.e., the number of presented stimuli minus one) to reach a decision.

Modifying theory and practice to quantify inferential imprecisions

At the theoretical level, identifying the origin of choice suboptimality requires to compare human or animal choice accuracy to the statistical optimum — defined in terms of noise-free probabilistic inference. In this framework, statistical optimality is defined as a fixed upper *bound* on choice accuracy, and choice suboptimality as departures from statistically optimal behavior. At the practical level, however, it is often impossible to dissociate the impact of inferential imprecisions on choice suboptimality from 'peripheral' variability (at the sensory and/or response selection stages) in classical behavioral paradigms.

To measure inferential imprecisions in decision-making separately from sensory variability, one needs to distinguish the decision space in which inference is performed from the relevant sensory feature(s) of the presented samples (whose sensory discriminability is known on the basis of past literature or can be measured empirically). In practice, one can use a non-linear mapping between sensory features and decision categories, or compare conditions using identical stimuli but different numbers of decision categories. In such conditions, one can estimate the predicted impact of inferential imprecisions on choice variability, independently from sensory variability. To distinguish inferential imprecisions from variability in response selection (e.g., a probabilistic 'softmax' selection rule), one also needs an experimental condition where random exploration is neither necessary nor useful. This is by definition the case in perceptual categorization tasks where subjects are observers of the environment — that is, stimuli act as cues about a hidden state of the environment, not as outcomes of previous actions. Reward-guided learning tasks, which rely heavily on exploration, can be modified to include a condition where random exploration is useless — for example, by providing 'counter-factual' feedback from unchosen alternatives simultaneously with feedback from the chosen action [21,22]. Indeed, in this condition, the decision-maker is provided with current values of both chosen and unchosen alternatives, and has thus no incentive for random exploration of unchosen alternatives [16]. Selective modifications of classical protocols used to study human perceptual and reward-guided decisions can therefore be made to distinguish between sources of variability at the sensory, inference and response selection stages.

Figure 2
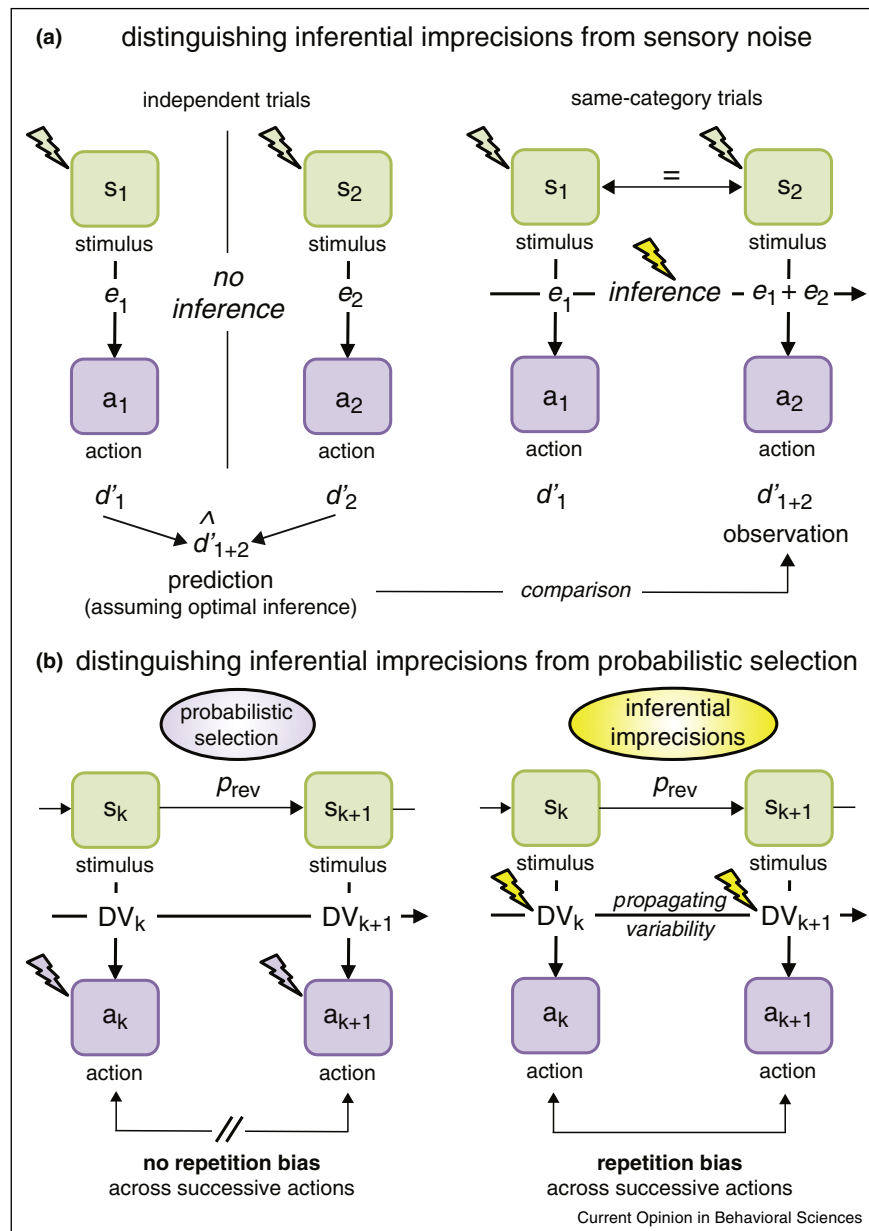
Distinguishing inferential imprecisions from other candidate sources of choice variability. **(a)** Theoretical and experimental distinction between inferential imprecisions and sensory noise. Left panel: two independent perceptual decisions. The measured perceptual sensitivity to each of the two stimuli s_1 and s_2 can be used to predict a perceptual sensitivity to the combination of s_1 and s_2, assuming noisy sensory processing followed optimal statistical inference. Right panel: two sequential perceptual decisions (on the basis of two stimuli drawn from the same perceptual category). The second decision is made on the basis of the two same stimuli — that is, results from mental inference. The measured perceptual sensitivity to the combination of s_1 and s_2 can thus be compared to the predicted estimate assuming optimal statistical inference. A discrepancy between predicted and observed perceptual sensitivities indicates the presence of inferential imprecisions during the combination of s_1 and s_2 which impacts the second decision. **(b)** Theoretical and experimental distinction between inferential imprecisions and probabilistic selection during a typical probabilistic reversal learning paradigm. Left panel: predictions from a probabilistic selection source of choice variability. Successive stimuli s_k and s_{k+1} are drawn from the same generative category, with a reversal probability p_{rev}. A probabilistic action selection policy predicts that the decision variable follows deterministically the predictions of optimal statistical inference given observed stimuli, and results in no repetition bias across successive actions. Right panel: predictions from an inferential source of choice variability. Inferential imprecisions predict that the variability on the decision variable after stimulus s_k propagates to the decision variable after stimulus s_{k+1}, and results in a repetition bias across successive actions whose magnitude scales with the extent of inferential imprecisions.

Figure 3
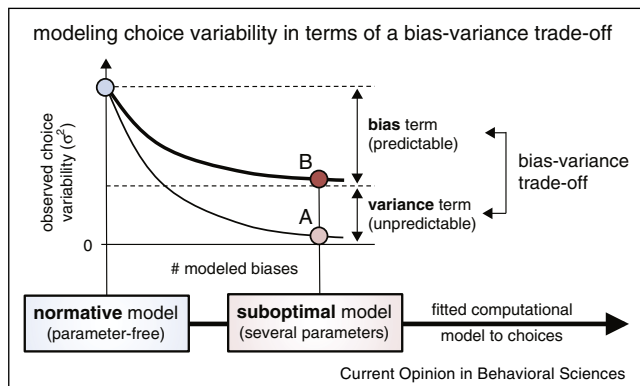
Modeling choice variability in terms of a bias-variance trade-off. The observed choice variability resulting from fits of multiple computational models to the same choice data should decrease when true underlying suboptimal biases in inference are fitted to the data — in contrast to the normative (statistically optimal) model which makes correct assumptions about the generative structure of the task. The bias-variance trade-off can be expressed in terms of the proportion of observed choice variability fitted using the normative model explained by a suboptimal model including all biases present in decision-makers. A key challenge consists in devising an experimental strategy which affords to estimate this bias-variance trade-off without having to assume explicitly all possible biases which could be present in tested decision-makers — which is unobservable in experimental conditions. Current computational models and theories predict that the variance term resulting from inferential imprecisions is negligible **(a)**. However, preliminary data from our lab [40] suggests that human choice variability during perceptual categorization is constituted of a large variance term **(b)** which amounts to about two thirds of the overall choice variability measured in this task.

In terms of computational modeling, inferential imprecisions bear a specific statistical signature on choice behavior which can be distinguished from variability in sensory processing or action selection. Indeed, inferential imprecisions produce correlated drifts of the decision variable across inference 'steps' (i.e., the combination of a current belief with new incoming information) — which should increase in spread with the number of presented samples and with the *complexity* of the inference being performed (e.g., the number of sensory dimensions relevant for the decision, or the number of possible alternatives to choose from). By contrast, the correlated drifts in the decision variable predicted by sensory noise should depend solely on the discriminability of the relevant sensory features, and not on the complexity of inference. Stochasticity in response selection, in turn, should be uncorrelated across successive decisions, and should not depend on the complexity of inference. It is therefore possible, given an appropriate protocol: (1) to design theoretical models featuring distinct (or combinations of) sources of choice suboptimality, and (2) to quantify the respective and distinct contributions of variability in sensory, inference and response selection to human and animal performance — instead of assuming a particular source of choice variability.

Distinguishing bias and variance terms of inferential imprecisions

Dominant psychological theories have attributed decision suboptimality to a mixture of cognitive biases and random noise. As a prime example of this dual nature of decision suboptimality, signal detection theory [23] has theorized the detection of a noisy sensory signal by human observers along two orthogonal dimensions: (1) the sensory detectability of the signal — corresponding to the quality of perceptual processing, and (2) the decision criterion used by the observer to report the signal as present — corresponding to a cognitive bias which affords to label observers as 'conservative' or 'liberal' as a function of their decision criterion. Dynamic extensions of signal detection theory offered by sequential sampling models [20•] hypothesize a similar distinction between the rate of the drifting decision particle and the level of the criterion at which a decision is taken — which controls the speed-accuracy tradeoff of the decision maker.

Similarly, inferential imprecisions can be of two forms, which can be formally distinguished in terms of the bias-variance trade-off found in estimator theory. Inferential imprecisions can be in part deterministic (i.e., the 'bias' term) and reflect fixed, systematic approximations or heuristics in the algorithms used to perform inference. In fact, recent theories postulate that most of the suboptimality of human decisions is caused by such deterministic imprecisions [1], due in part to the intractability of statistically optimal inference in environments featuring complex correlation structures [2•]. By contrast, the intrinsic stochasticity of inference imprecisions (i.e., the 'variance' term) reflects the effective precision at which inference is performed.

Fractioning observed choice suboptimality between these two forms of inferential imprecisions remains an open challenge [3••], which strongly limits the ability of computational modeling efforts to understand the origin and structure of suboptimality in human and animal decision-making. Indeed, the variability term fitted by a computational model (e.g., an additive noise spread, or a choice 'temperature') can reflect both core stochasticity in the decision-maker, but also biases not captured by the computational model. Therefore, quantifying the fraction of choice suboptimality ultimately attributable to biased computations provides a measure of the core stochasticity of mental inference — and thus of the core unpredictability of the decision-maker.

We propose that the effective precision of inference constitutes an important source of choice suboptimality in the canonical protocols used to study decision-making, from perceptual categorization (where inference is modeled by

sequential evidence accumulation, see, e.g., [20•]) to reward-guided learning (where inference is modeled by sequential probabilistic learning of action-outcome associations, see, e.g., [6]). Inference should be seen as a biologically costly computation in the decision process, which can only be performed by large populations of neurons at a limited computational precision. By assigning suboptimality to the peripheries (input or output) of the decision process, and therefore by assuming implicitly that inferential imprecisions are negligible, current computational models likely overestimate sensory noise in perceptual tasks where noisy sensory samples need to be combined and accumulated over time [14], and likely overestimate exploratory/foraging behavior in reward-guided learning tasks where reward-maximizing actions need to be taken in face of a volatile environment [6,17].

Consequences of inferential imprecisions for decision theory

Hypothesizing the existence of sizable inferential imprecisions during decision-making has far-reaching consequences regarding not only its function, but also known and pervasive cognitive biases in decision-making. First, in tasks featuring sequential decisions (such as reward-guided learning tasks), repetition biases can be seen as an overt manifestation of inferential imprecisions in the updating of the decision variable which are correlated across successive decisions. More specifically, postulating inferential imprecisions leads to a quantitative (and empirically testable) relationship between the spread of inferential imprecisions (which can be estimated by fitting it as a model parameter) and the magnitude of the repetition bias (which can be measured empirically in human choices). In practice, the repetition bias is expected to grow positively with inferential imprecisions, both within and across decision-makers.

A second important question concerns the potential function of inferential imprecisions: why have these 'errors' not been canceled through natural selection if they constrain substantially the accuracy and consistency of decision-making? In stable environments where the information is highly redundant, inferential errors are likely to be outweighed by the amount of available information and have thus a minimal impact on behavior. However, in uncertain and/or volatile environments, inferential imprecisions are not necessarily detrimental to decision accuracy. Indeed, inferring the volatility (i.e., the rate of change) of the environment using explicit, normative computations is very costly [6] and leads typically only to small improvements in obtained rewards. Inferential imprecisions can offer an implicit tracking of environmental volatility at a zero computational cost. Indeed, if the spread of inferential imprecisions scales positively with the magnitude of the performed inference step — as predicted by the pervasive 'Weber law' observed in behavior and neural activity, then the impact of inferential imprecisions on choice behavior

should grow with volatility and thus trigger more random exploration in more volatile environments (see also [24] for an 'extreme' switch to random behavior in rodents in unpredictable environments).

Postulating the existence of inferential imprecisions raises important questions regarding the decision-maker's knowledge of these imprecisions. Indeed, the notion of statistical optimality defined above does not consider computational constraints (such as inferential imprecisions) in the decision process. Consequently, computations considered as 'biased' in terms of statistical optimality, such as the pervasive 'recency' effect observed across tasks and species [25], can be seen as the consequence of an optimization of computations in a biological system which features sizable inferential imprecisions. Indeed, in a biological system poised with inferential imprecisions, prior beliefs become progressively less reliable over time due to propagating errors and should be down-weighted in the face of new incoming evidence — as a function of the perceived reliability of the incoming evidence. In other words, postulating inferential imprecisions requires to revisit the hypothesized suboptimal nature of cognitive biases from the perspective of a biological system with no variability in inference.

Last, if the behavioral expression of variability in inference can be dissociated from variability in sensory processing and response selection, then it should be selectively modulated by certain cognitive variables, such as executive attention and/or training. Describing inference as a biologically costly process implies that the computational precision of inference should be selectively and flexibly adapted to the cognitive demands of the environment. In practice, humans should increase the precision of inference when it is deemed necessary (in the absence of contextual information, or under high monetary incentives) and decrease it when they can rely on computationally 'cheaper' sources of information about their environment. This results in a predicted trade-off between the amount of contextual information available to the decision maker and the precision of inference being performed to make a decision. Note that such trade-off is suboptimal in information terms (where the precision of inference should always be maximized), but optimal in biological terms if inference is assumed to bear a sizable biological cost for the organism. Executive attention should be able to modulate selectively the computational precision of inference (i.e., independently of sensory discriminability or response selection variability) as a function of the cognitive resources which can be allocated to inference [26•,27]. By contrast, extensive training should influence not the precision of inference per se, but instead reduce systematic inferential imperfections (biases) resulting from approximate or wrong assumptions about the generative structure of the environment.

Behavioral versus neural measures of inferential imprecisions

Quantifying inferential imprecisions can be performed at several levels, from single-cell recordings from neurons in brain regions representing the relevant sensory features to be combined (such as motion-sensitive cells during the presentation of a random-dot kinematogram, see, e.g., [28,29]) or the decision variable [30], to the behavioral accuracy of the resulting decisions. Measuring neural variability in particular brain regions have proved difficult to relate to the psychometric accuracy of the decision maker [31] — in part due to the presence of noise correlations which complicate the interpretation of neural measures of stimulus and choice sensitivity [32••,33]. Besides, neural correlates of inferential imprecisions could reflect not only the precision of cortical representations decodable from multi-dimensional neural recordings from parietal and prefrontal regions [34,35], but also neuromodulatory influences from basal ganglia circuits (see, e.g., [36,37] in humans and [38,39] in songbirds). We argue that a *behavioral* quantification of inferential imprecisions — through a paradigm which affords to simulate optimal behavior — provides a particularly adequate method to measure the effective, function-level precision of underlying neural computations.

In other words, considering how much information is lost due to suboptimal computations provides an estimation of the effective precision of the decision process. Importantly, this effective precision sets an upper bound on the accuracy and predictability of human and animal decisions which, as we have outlined above, has important consequences in terms of its function and the existence of well-characterized cognitive biases (such as repetition biases or recency effects). Quantifying and comparing the computational precision of inference in humans and animals in a wide range of decision problems thus constitutes an important empirical and theoretical challenge for cognitive research at large in future years.

Conflict of interest statement
Nothing declared.

Acknowledgements

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- of special interest
- of outstanding interest

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