Categorical Decisions

Paul Masset[1] and Adam Kepecs[2]
[1]Watson School of Biological Sciences, Cold Spring Harbor Laboratory, Cold Spring Harbor, NY, USA
[2]Cold Spring Harbor Laboratory, Cold Spring Harbor, NY, USA

Definition

Categorical decision-making is the process of committing to a particular option from a discrete set of alternatives.

Detailed Description

Introduction

Studies of categorical decision-making attempt to understand behavior by probing how different features of complex and changing environments guide the selection of choices. While the parameters underlying these features often span a continuous range, the potential set of possible behavioral options is discrete. The neuroscientific study of decision-making draws heavily on the fields of psychology, economics, statistics, and ecology. Neuroscientific approaches to decision-making aim to reveal computational principles that can be mapped onto their neurobiological implementation.

There are two dominant traditions in neuroscience and psychology to study categorical decisions: perceptual and value-based decision-making. Perceptual decision-making focuses on how accurate decisions are reached by resolving perceptual uncertainty. In value-based decision-making, the stimuli themselves are not ambiguous, rather the value or utility of different options needs to be estimated based on prior experience. In both cases, the goal is to systematically manipulate different features of the environment in order to understand how they guide behavior.

Behavioral Tasks for Studying Categorical Decisions

Both traditions of decision-making have extensively used two-alternative forced choice (2AFC) task designs. 2AFC is the simplest task in which the process of a decision between alternatives can be studied. In a 2AFC task, the subject is forced to make a choice between two alternatives based on the stimulus she has experienced.

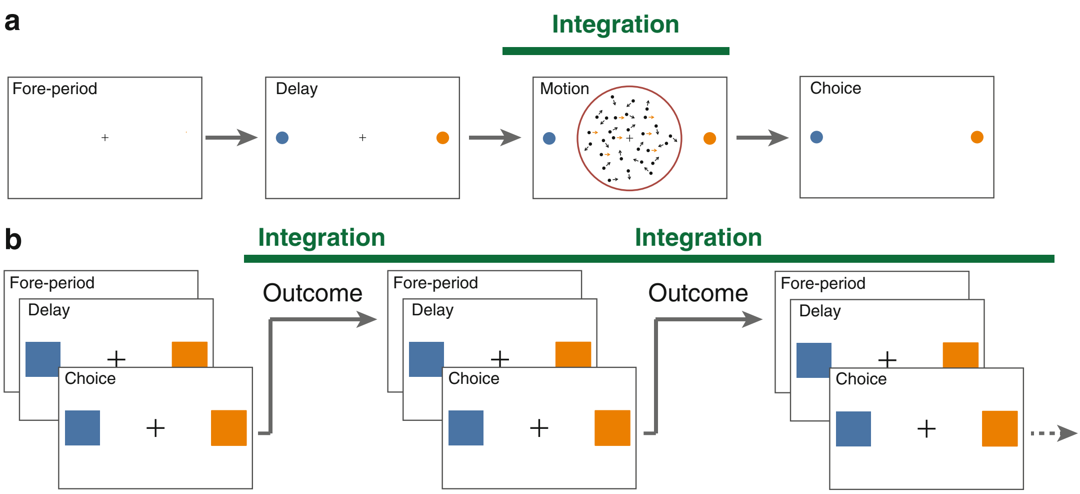
An example of a widely used perceptual decision-making task is the visual random dot task (Newsome et al. 1989; Gold and Shadlen 2007). In this task an ambiguous perceptual stimulus is instantiated by a cloud of moving dots. Subjects are asked to report whether the apparent motion is to a given direction or its opposite. A random process controls the moment-to-moment movement of individual dots. The strength of apparent motion and hence stimulus discriminability are controlled by the fraction of coherently moving dots. To perform correctly on the task, subjects need to view the stimulus over some period of time to extract the direction of coherent motion.

An example of a value-based decision-making task is the matching paradigm in which subjects have to choose between two options that differ in the probability and size of rewards (Platt and Glimcher 1999; Sugrue et al. 2004). Both reward probability and size are set by the experimenter and change across trial blocks. Here a subject has to integrate across trials (and not across time within a trial) to infer the value of the stimuli and make the correct choice (Fig. 1).

Models of Decision-Making

Computational studies of decision-making in neuroscience often focus on algorithmic descriptions of the decision process and attempt to describe both behavior and its neural correlates.

Models of perceptual decision-making describe how ambiguous perceptual information is processed and leads to the selection of a choice. At every instant, a subject extracts some features from the stimulus that will form the evidence that guides the decision-making process. One popular class of models that have been proposed to describe how the evidence is used is based on



Categorical Decisions, Fig. 1 (**a**) Schematic of the random dot task. Foreperiod: a fixation point appears at the center of the screen. Delay: once the subject fixates the point, the two saccade targets appear on either side of the fixation point. The trial is ready to start. Motion: the cloud of randomly moving dots appears. A subset of these dots moves coherently in the direction of one of the saccade targets. Choice: the subject makes a saccade to one of the two targets. In this paradigm, the integration of evidence occurs during the stimulus presentation. (**b**) Schematic of matching task. Foreperiod and delay: same as in (**a**). Choice: the subject makes a saccade to one of the two targets. In this paradigm, the integration of evidence occurs by integration over the previous outcome history

sequential sampling (Bogacz et al. 2006). They have been chiefly motivated by sequential probability ratio test, in which the ratio of the probability of possible alternatives is computed as evidence is accumulated. These models can be solved as a first passage time problem; a commitment to a decision occurs once the probability ratio reaches a set value. As shown in Eq. 1, the decision variable V(t) is updated by integrating the momentary evidence e(t). Once the decision variable reaches a set bound B, the corresponding alternative is chosen and the response is initiated (Eq. 2). More complex models have been developed taking into account physiological characteristics such as adaptation and the role of time in the decision process (Drugowitsch et al. 2012; Brunton et al. 2013).

Accumulation:

$$\frac{dV}{dt} = e(t) + \text{noise} \qquad (1)$$

Decision rule:

$$V(t) \geq B \qquad (2)$$

These models have been popular, as they can account for the dependence on the stimulus of both the choice and the reaction time (t_{choice} where $V(t_{choice}) = B$). They also explain the widely observed trade-off between the speed and accuracy of decisions. A lower threshold B implies that less accumulation of evidence is necessary to commit to a decision, which leads to faster reaction times at the expense of reduced accuracy. Neural recordings have revealed evidence for the existence of such accumulators in neural circuits implicated in perceptual decision-making (Gold and Shadlen 2007).

In value-based decision-making, models have used ideas from *reinforcement learning*. In a matching task, even if a full model of the task structure is not available to the subject, a reinforcement-learning algorithm can estimate the values of the stimulus features. The value of a stimulus is the subjective utility of its outcome, which needs to be estimated based on experience. There is a large class of reinforcement-learning model, but the simplest and most often used one is *temporal difference learning* (TDRL).

As shown in Eq. 3, the update rule for the value V(T) of each alternative after trial T has two terms. The first is an update term that depends only on the previous outcome history. It is a *temporal discount*, proportional (with a constant γ) to the value of the previous trial V(T − 1). The second term is the *prediction error* δ, which is proportional (with a constant α) to the difference between the outcome r(T) and the expected outcome computed from the outcome history V(T − 1). Once the value of each option is computed, the choice is made using a decision rule that optimizes the behavior according to the task contingencies. The decision rule often represents a trade-off between exploiting the currently available evidence that leads to larger reward (e.g., selecting the option with the highest value, choice = argmax(V_i)) and balancing exploitation with exploration using a probabilistic decision rule (e.g., selecting an option with a probability given by a softmax rule where $P_{Choose\ R} = e^{VR/\beta}/(e^{VR/\beta} + e^{VL/\beta})$, and β controls the trade-off between exploration and exploitation, or by a relative value rule where $P_{choice} = R = (V_R/(V_R + V_L))$) (Lee et al. 2012).

TD learning:

$$V(T) = \gamma V(T-1) + \alpha\delta(T) \tag{3}$$

$$\delta(T) = r(T) - V(T-1) \tag{4}$$

Decision rule:

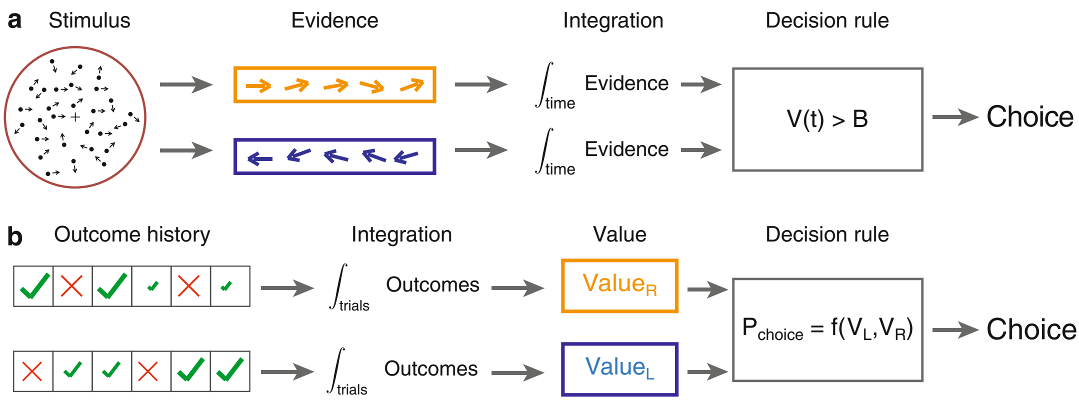
$$P_{Choice=R} = \max(V_R, V_L) \quad or \quad \frac{e^{V_R/\beta}}{e^{V_R/\beta} + e^{V_L/\beta}} \quad or \quad \frac{V_R}{V_R + V_L}$$

Despite its simplicity, this model is able to predict trial-to-trial variation in behavior in value-based decision-making tasks. For instance, an implementation of TDRL with the relative value decision rule ($P_{Choose\ R} = (V_R/(V_R + V_L))$) can account for the observation that the ratio of responses matches the ratio of inferred stimulus values (Sugrue et al. 2004). Importantly, fitting these models to behavior has enabled researchers to extract decision variables that can be mapped onto neural activity (Lee et al. 2012). For example, activity in the dopaminergic system correlates with the prediction error signal (Schultz et al. 1997), and activity in the lateral intraparietal cortex correlates with stimulus value in a matching task (Platt and Glimcher 1999; Sugrue et al. 2004).

These models describe the computations performed during the decision-making process but not their implementation at the neuronal level. Attractor networks, neural networks composed of spiking neurons connected through synapses, have been proposed as a biologically plausible implementation of these computations (Wang 2012). These neural networks implement dynamical systems on which sensory stimuli act as perturbations. Depending on their strength, these perturbations can push the network toward different attractor states leading to a categorical decision (Fig. 2).

Open Questions and Future Directions

Decisions are, given the available evidence, not always perfect. Understanding the sources of error, the sources of noise, and uncertainty in the behavior will be essential to understanding how decisions are computed in the brain. In the two frameworks presented above, noise has distinct origins. In perceptual decision-making, the sensory perception itself can be noisy. In value-based decision-making, the external world environment can be stochastic, or the internal model of the task contingencies may be incorrect (Beck et al. 2012), leading to suboptimal behavior. Stochastic behavior, however, can also be advantageous in competitive environments so that competitors are not able to predict choice behavior. Understanding the contribution of different



Categorical Decisions, Fig. 2 (**a**) Stimulus: the stimulus is being sampled. Evidence: the relevant parameters from the stimulus are extracted to obtain the momentary evidence at a given time. Integration: the evidence is integrated over time to obtain the decision variable. Race to bound: once the decision variable reaches a predetermined bound the corresponding action is selected. (**b**) Outcome history: the subject has an internal representation of the outcome history. Integration: the outcome history is integrated over past trials to obtain a decision variable. Value computation: the value of each alternative is computed using the integrated outcome history. Decision rule: the probability of making a given choice is a function of the computed values that depends on the decision rule used

sources of noise to decisions is an exciting direction in the field.

Although reaction time is often used as a critical constraint for models of decision-making, there are multiple processes contributing to it, including non-decision time, such as the time required for movement planning. Clever behavioral manipulations can be used to separate different components of reaction time and reveal that simple discriminations can unfold in as little as 30 ms (Stanford et al. 2010).

The goal of models is to provide trial-by-trial accounts for behavioral outputs rather than just fitting averages and observed distributions of decision variables. Models, however, may be underconstrained when only using categorical choices as behavioral readouts of graded decision variables. Additional variables, such as reaction time (Gold and Shadlen 2007), confidence report (Kepecs and Mainen 2012), or changes of mind (Resulaj et al. 2009), can be used to further constrain models. Using these variables can improve trial-by-trial fits, identify different sources of noise, and help us understand the computational processes supporting decision-making.

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Cav1.1–4 "Long-Lasting" Type (L Type)

► High-Voltage-Activated Calcium Channels

Cav2.1 "Purkinje" Type (P/Q Type)

► High-Voltage-Activated Calcium Channels

Cav2.2 "Non-L Type" (N Type)

► High-Voltage-Activated Calcium Channels

Cav2.3 "Residual" Type (R Type)

► High-Voltage-Activated Calcium Channels

Cav3

► Low-Voltage-Activated Calcium Channels

CCDB

► Cell Centered Database

Cell Centered Database

Maryann E. Martone
Department of Neuroscience, University of California, San Diego, La Jolla, CA, USA

Synonyms

CCDB

Definition

The Cell Centered Database (CCDB; http://ccdb.ucsd.edu) project was launched in 2002 to provide online repository of high-resolution 3D light and electron microscopic reconstructions of cells and subcellular structures (Martone et al. 2002, 2003, 2008). The CCDB was designed to complement the structural databases of gene, protein, and tissue structure by hosting data in the dimensional range known as the "mesoscale," roughly encompassing the structures that sit between gross morphology and molecular structure, e.g., cellular networks, cellular and subcellular microdomains along with their macromolecular constituents. The study of mesoscale structures continues to present a challenge to experimentalists, because to build a comprehensive understanding of complex tissues in this dimensional range requires the ability to aggregate data obtained by multiple researchers across techniques and spatial scales.

Detailed Description

The types of imaging data stored in the CCDB are quite heterogeneous, ranging from large-scale maps of protein distributions taken by confocal (Orloff et al. 2012) microscopy to 3D reconstruction of individual cells, subcellular structures, and organelles reconstructed using electron tomography, time series of subcellular dynamics, and a growing collection of serial block face electron microscopic datasets