Multi-stage sequential sampling models: A framework for binary choice options Part 1

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Overview

- Part 1
  - Motivation – 3 Examples
  - Basic assumptions of sequential sampling models (as used here)
  - Multi-stage sequential sampling models
  - Time and order schedules
- Part 2
  - Implementation
  - Predictions
  - Impact of attention time distribution
  - Impact of attribute order
- Part 3
  - Applications

Example 1

A Multistage Attention-Switching Model Account for Payoff Effects on Perceptual Decision Tasks With Manipulated Processing Order

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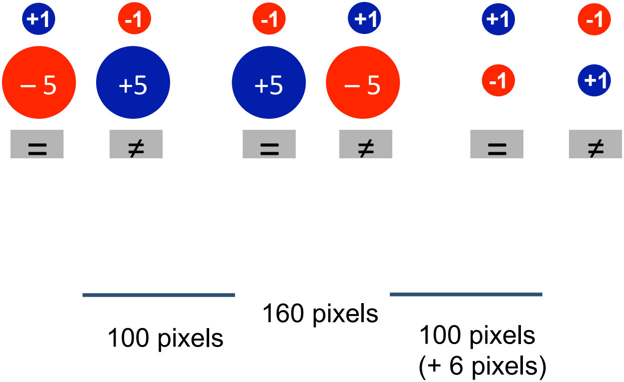
Payoffs may affect choice frequencies in perceptual decision tasks. Several studies investigating this effect have shown that sequential sampling models account for choice probability and choice response times when applying different payoffs. Typically, payoffs are presented *before* the stimuli. Here, 2 variations of this setup are added. In a second condition, payoffs are presented *after* the stimuli, and in a third condition, payoffs and stimuli are presented *simultaneously*. A multistage sequential sampling model is shown to account for the manipulated processing orders. It assumes separate accumulation processes for both the payoffs and the perceptual stimuli. Attention switches from one subprocess to the other, and payoffs and perceptual stimuli are processed serially. Depending on the processing order, the multistage model (also known as the multiattribute attention switching model) predicts a rich pattern of choice-probability/choice-response times, including both fast correct and fast incorrect responses with the same fixed set of parameter values. For comparison, predictions of single-stage models with respect to processing orders are discussed.

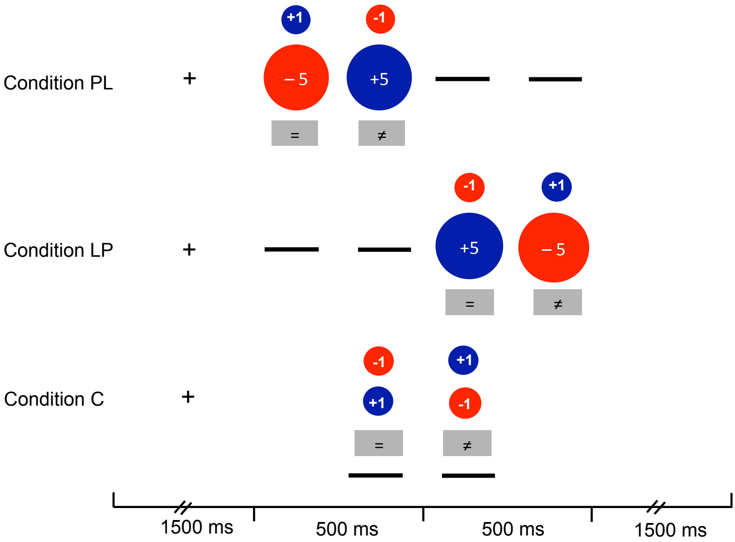
Decision, 2016

Payoffs and discrimination



Diederich & Busemeyer (2006); Diederich (2008); with time constraints

Time line and stimulus order



Example 2

Frames, Biases, and Rational Decision-Making in the Human Brain

Benedetto De Martino, **Dharshan Kumaran**, **Ben Seymour**, and **Raymond J. Dolan**

Abstract

Human choices are remarkably susceptible to the manner in which options are presented. This so-called "framing effect" represents a striking violation of standard economic accounts of human rationality, although its underlying neurobiology is not understood. We found that the framing effect was specifically associated with amygdala activity, suggesting a key role for an emotional system in mediating decision biases. Moreover, across individuals, orbital and medial prefrontal cortex activity predicted a reduced susceptibility to the framing effect. This finding highlights the importance of incorporating emotional processes within models of human choice and suggests how the brain may modulate the effect of these biasing influences to approximate rationality.

Science, 2006

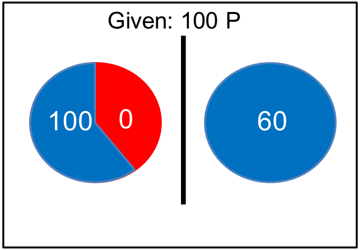
Risky choice framing

- Choice between two options
- Lotteries
- Options A is typically risk less
- Option B is risky

- **Situation 1** Outcomes are framed as **gains** (positive frame)
- **Situation 2** Outcomes are framed as **losses** (negative frame)

Gain frame

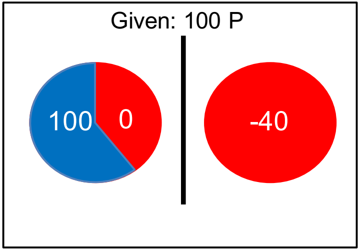
You are given 100 points



Keep

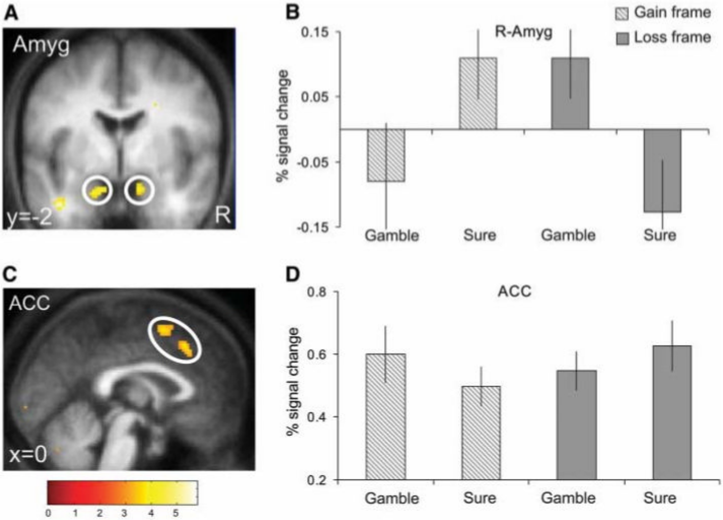
Loss frame

You are given 100 points



Lose

De Martino et al. (2006)



De Martino et al. (2006)

- Increased activation in the amygdala was associated with subjects' tendency to be risk-averse in the Gain frame and risk-seeking in the Loss frame, supporting the hypothesis that the framing effect is driven by an affect heuristic underwritten by an **emotional system**.
- When subjects' choices ran counter to their general behavioral tendency, there was enhanced activity in the ACC. This suggests an opponency between **two neural systems**, with ACC activation consistent with the detection of conflict between predominantly "**analytic**" response tendencies and a more "**emotional**" amygdala-based system.

Example 3

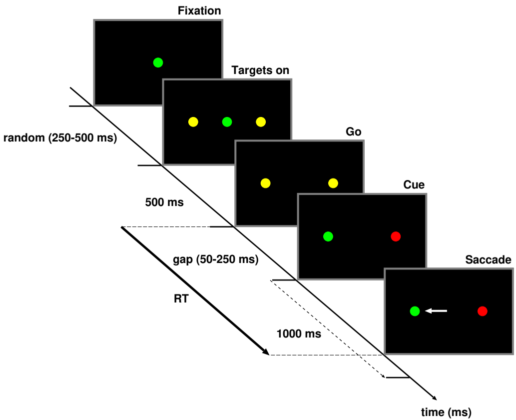
Perceptual decision making in less than 30 milliseconds

Terrence R Stanford, Swetha Shankar, Dino P Massoglia, M Gabriela Costello & Emilio Salinas

In perceptual discrimination tasks, a subject's response time is determined by both sensory and motor processes. Measuring the time consumed by the perceptual evaluation step alone is therefore complicated by factors such as motor preparation, task difficulty and speed-accuracy tradeoffs. Here we present a task design that minimizes these confounding factors and allows us to track a subject's perceptual performance with unprecedented temporal resolution. We find that monkeys can make accurate color discriminations in less than 30 ms. Furthermore, our simple task design provides a tool for elucidating how neuronal activity relates to sensory as opposed to motor processing, as demonstrated with neural data from cortical oculomotor neurons. In these cells, perceptual information acts by accelerating and decelerating the ongoing motor plans associated with correct and incorrect choices, as predicted by a race-to-threshold model, and the time course of these neural events parallels the time course of the subject's choice accuracy.

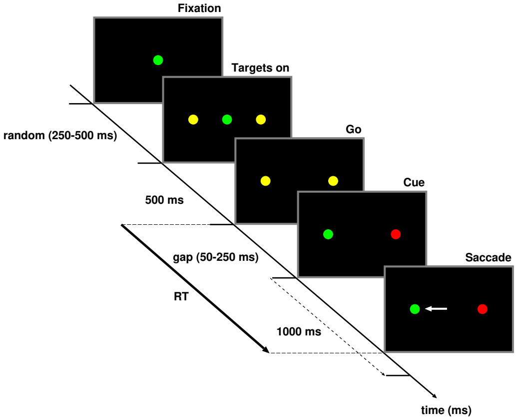
Nature Neuroscience, 2010

Timeline of events in the compelled-saccade task



- The fixation circle indicates the color of the target (green).
- The participants must initiate a saccadic response (left or right) when the fixation circle disappears (Go).
- Target and distracter colors and positions are revealed after a gap of 50 - 250 ms (Cue).

Timeline of events in the compelled-saccade task



- A trial is correct if the participant makes an eye movement to the peripheral location that matches the color of the fixation circle (green).
- Response time is defined from the offset of the fixation circle to initiating a saccade.

Ideas behind the compelled-saccadic task

- Separating perceptual decision making and motor-planning stages by always instructing the participant when to respond (go)
- Motor response is triggered first (go) $\rightarrow$ mean RT should be approximately constant
- Perceptual performance is expected to change systematically as a function of gap but motor performance is not

Remark

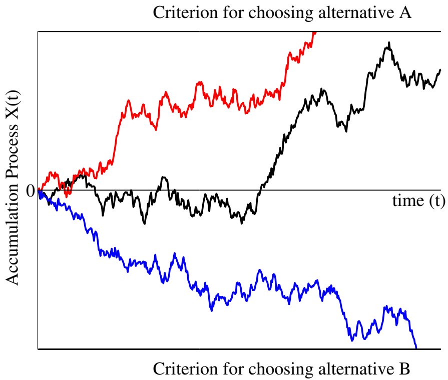
- SDT – Static description of decision process – no response times
- Sequential sampling models – dynamic extension of SDT
- Predictions of choice response times and choice frequencies

Basic assumptions

- Evidence for choosing one alternatives (option, response) over the other is continuously updated
- Example with 3 trials

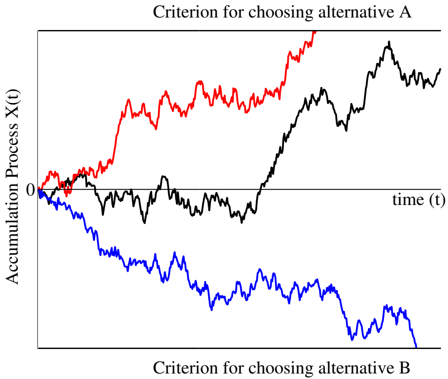
Preference accumulation process – 3 trials

Basic assumptions



- Evidence sampled continuously over time
- Random fluctuation in accumulating evidence
- $X(t)$ stochastic process
- Each trajectory represents the accumulation process for one trial

Basic assumptions – Initial state of evidence: Starting point



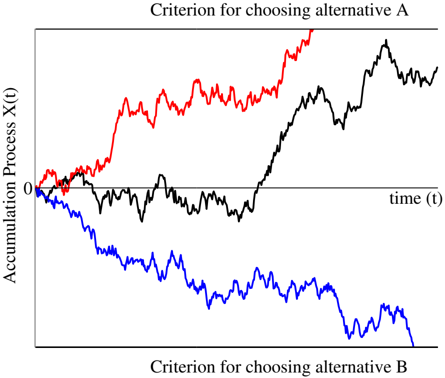
- Initial state of evidence $X(0)$

  $X(0) > 0$: favoring A

  $X(0) < 0$: favoring B

  $X(0) = 0$: neutral
- Fixed position → initial state z
- Random location → initial distribution $\mathbf{Z}$
- A priori bias

Basic assumptions – Increments

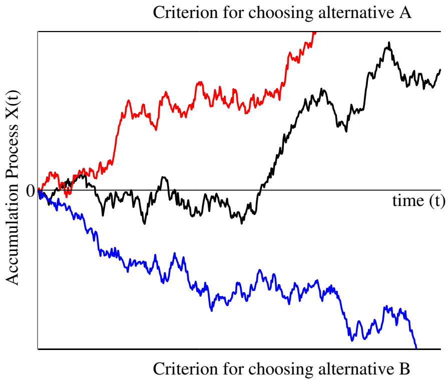


- Increments of evidence sampled at any moment in time $dX(t)$

  $dX(t) > 0$: favoring A at t

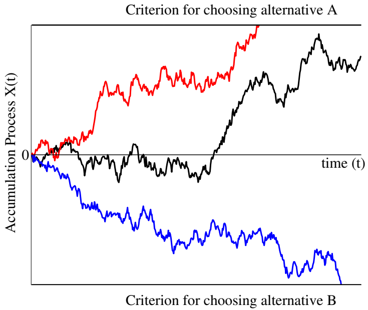
  $dX(t) < 0$: favoring B at t
- Continuous update of evidence

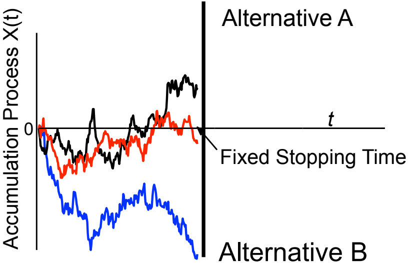
Basic assumptions – Decision criterion



- Process stops and response is initiated when a criterion is reached
- Instructions or strategies affects the criterion
- Function of time constraints

Basic assumptions – Stopping times





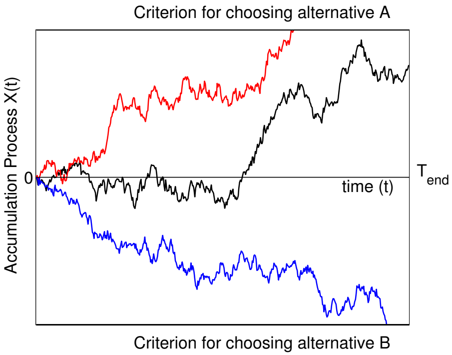
- Optional stopping time

  $X(t) = \theta_A > 0$ – choose A

  $X(t) = \theta_B < 0$ – choose B
- Internally controlled decision threshold

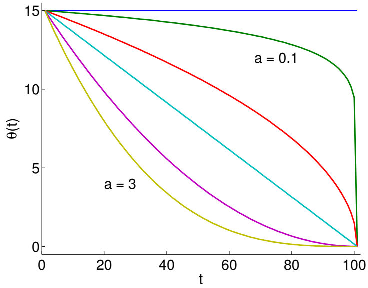
- Fixed stopping time
- Externally controlled decision threshold

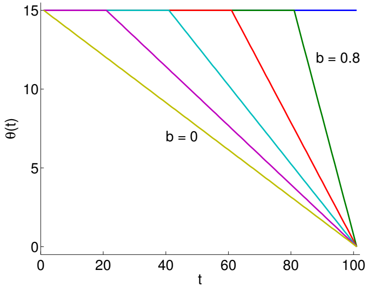
Combination of optional and fixed stopping



- Internally controlled decision threshold plus
- Externally controlled decision threshold, e.g duration of one trial, $p_0 > 0$

Variable decision boundaries





Variable decision boundaries

- $\theta_A(t) = \theta_A(0) \cdot (1 - t/T_{end})^{a_A}, \; t \in [0, T_{end}]$
- $\theta_A(t) = \theta_A(0) min(1, (1 - t/T_{end})/(1 - b)), \; t \in [0, T_{end}]$

Diederich, A. & Oswald, P. (2016). Multi-stage sequential sampling models with finite or infinite time horizon and variable boundaries. *Journal of Mathematical Psychology*, 74, 128–145

Basic assumptions – Evidence accumulation

$$X(t+h) \approx X(t) + \mu(X(t),t)h + \sigma(X(t),t)(W(t+h) - W(t))$$

- $\mu(x,t)$ is called the **drift rate** and describes the expected value of increments per unit time
- $\sigma(x,t)$ is called the **diffusion rate** and relates to the variance of the increments.
- h small time unit

Specific processes

Wiener

$$dX(t) = \mu dt + \sigma dW(t)$$

Ornstein-Uhlenbeck Process (OUP)

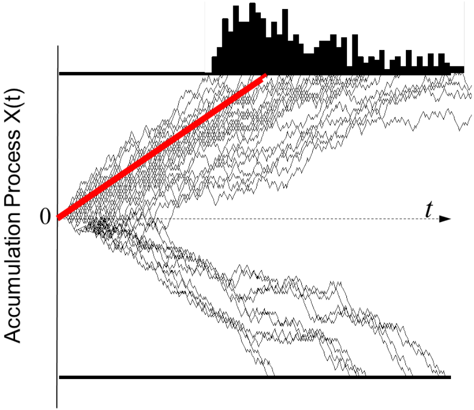
$$dX(t) = (\delta - \gamma X(t))dt + \sigma dW(t)$$

$W(t)$: standard Wiener process
γ : change in drift rate, proportional to the value of the process, causes the decay of the process depending on the state in the state space

Predictions

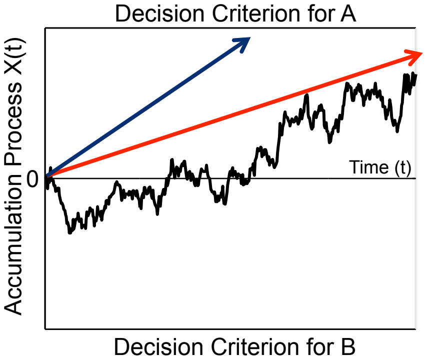
- First passage probability $\rightarrow$ choice probabilities
- First passage time $\rightarrow$ decision times

Choice probability – choice time



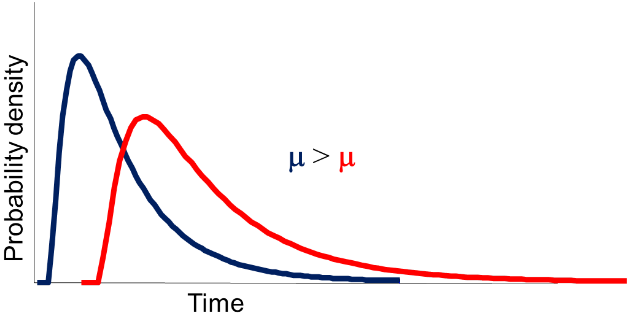
- Each trajectory = accumulation process for one trial → response frequency
- Decision time distribution
- Mean decision time - drift rate

Drift rate – most important in psychological modeling



- Stimulus difficulty (e.g., similarity) affects quality of extracted evidence
- Quality of evidence determines drift rate (mean drift, drift coefficient)
- The better the evidence the larger μ

Response time distributions



Drift rate affects shift and scale parameters, but not shape

Wiener process: Parameters and their interpretation

μ : drift rate, reflects quality of information

σ^2 : diffusion coefficient, scaling, set to 1

θ : absorbing boundary, reflects decision criterion

z : initial state, reflects bias

Specific process in psychology

Assumption:

$$RT = D + R$$

D : Decision time
R : Residual time (encoding, motor, etc)

Laming (1968), Link & Heath (1975), Ratcliff (1978), Ratcliff & Tuerlinckx (2002)

$X(t)$	Wiener process with drift $\mu(x, t) = \mu$
$\boldsymbol{\mu}$	$N(\mu, \eta^2)$
$\mathbf{Z}$	$U(\beta, \xi^2)$
$\mathbf{R}$	$U(\alpha, \gamma^2)$
θ	constant

Multi-stage decision model: Situation

Binary choices for choice alternatives with at least **two "attributes"**

- perceptual
- preferential
- inferential
- experimental setup

Attributes - examples

- different modalities (tone - light)
- consumer goods with attributes (in classic sense)
- pieces of (changing) information
- Cuing, e.g. Posner, Stroop
- System 1 and 2 in dual processes
- ...

Multi-stage decision model: Situation

Information presented **simultaneously**

- Object with different features, such as shape and size $\longrightarrow$ categorization
- Consumer choice alternatives $\longrightarrow$ preference
- ...

Information presented **sequentially**

- Trials with SOA such as in cuing experiments, multimodal stimuli
- MOUSELAB
- Eye tracking
- ...

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