Road map presentation

Neuroeconomics in Economics: the Case of Response Times

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A brief history of neuroeconomics

- 2000s:
  - let's put people in the brain scanner and make them do various tasks; which brain areas activate more when they do X vs Y?
  - zero impact on economics

- 2010s:
  - there is some other (cheap) data that we could use: response times (RT), eye-tracking
  - economists become interested
- 2020s:
  - the brain is actually a rational decision-maker functioning under resourse and time constraints
  - ???

Preferences

Definition 1.B.2: A function $u: X \to \mathbb{R}$ is a *utility function representing preference relation* $\succsim$ if, for all $x, y \in X$,

$$x \succsim y \Leftrightarrow u(x) \geq u(y).$$

Proposition 1.B.2: A preference relation $\succsim$ can be represented by a utility function only if it is rational.

MWG

Choices are not consistent

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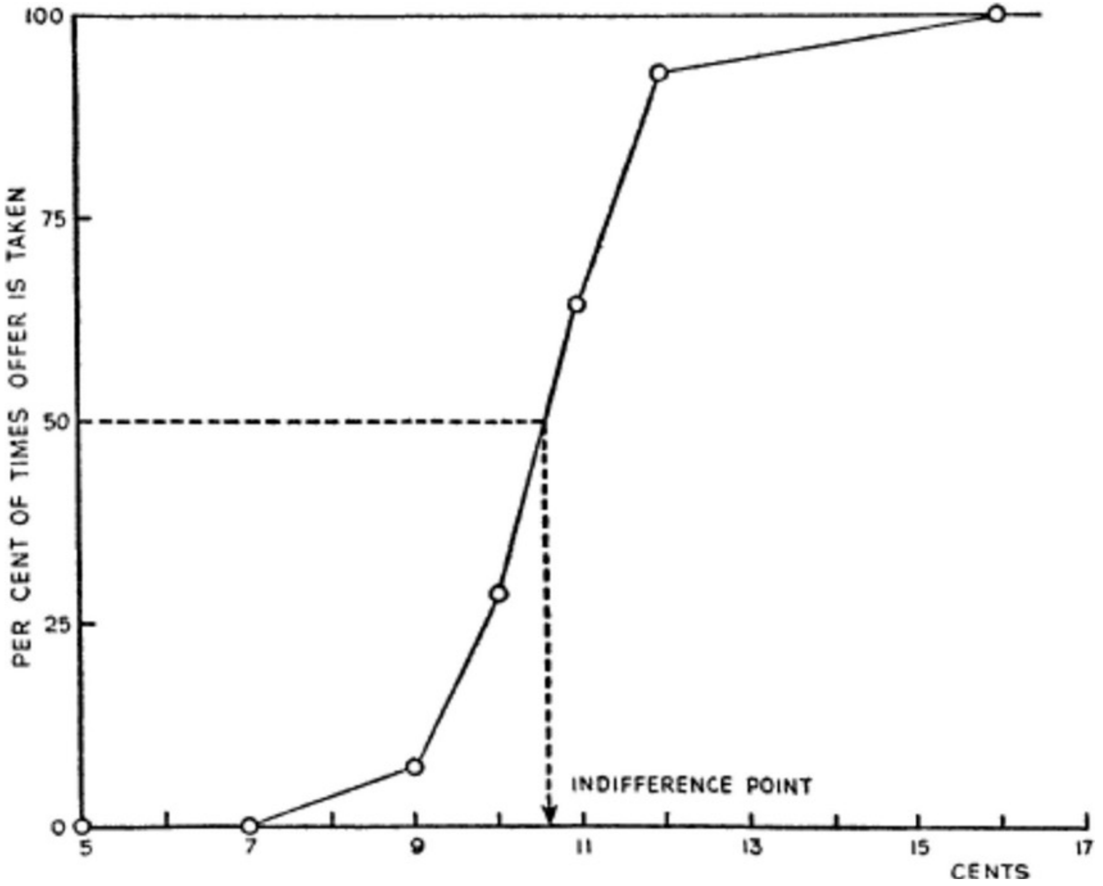


Mosteller and Nogee (1951, JPE)

Random utility

RUMs:
Luce (1959)
Block and Marschak (1960)
Marschak (1960)
Ben-Akiva and Lerman (1985)
Overview: McFadden (2001)

$$U_{ijt} = x_{jt}\beta_i + \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt}$$

$$\mathbb{P}\left(y_{it} = j | \cdot ; \theta_2\right) = \frac{exp\left\{\delta_{jt} + \left(p_{jt} \;\; x_{jt}\right) \Pi D_i\right\}}{\sum_{r=0}^{J} exp\left\{\delta_{rt} + \left(p_{rt} \;\; x_{rt}\right) \Pi D_i\right\}}$$

Where does this come from?

$+ \varepsilon_{ijt}$

Stochastic Choice and Preferences for Randomization

Marina Agranov

California Institute of Technology

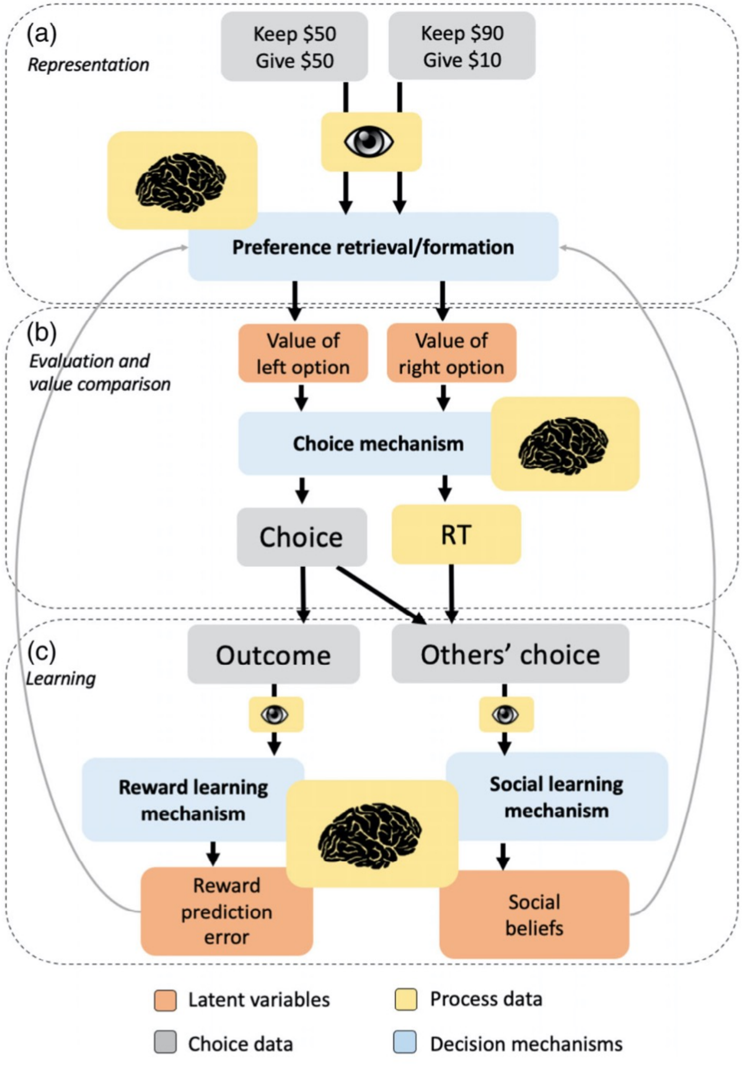
Pietro Ortoleva

Columbia University

We conduct an experiment in which subjects face the same questions repeated multiple times, with repetitions of two types: (1) following the literature, the repetitions are distant from each other; (2) in a novel treatment, the repetitions are in a row, and subjects are told that the questions will be repeated. We find that a large majority of subjects exhibit stochastic choice in both cases. We discuss the implications for models of stochastic choice.

Agranov & Ortoleva (2017, JPE)

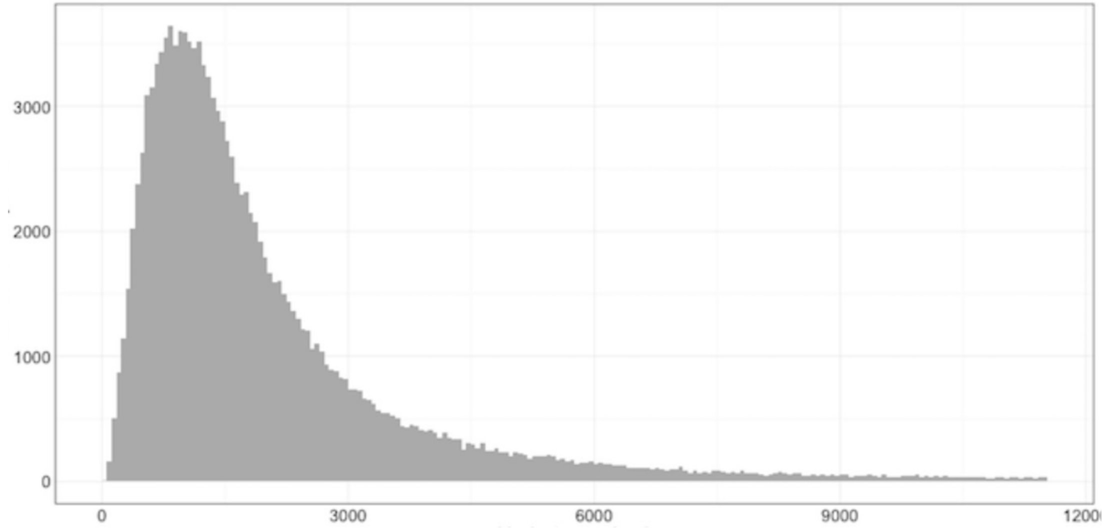
Process data



Konovalov and Ruff (2021)

Response times

- Also called decision times?
- Typically:
  - reaction time: time that take to react to a single stimulus (e.g. stop signal)
  - response time: time that take to choose between 2 or more alternatives



How to use them?

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Benefits			
Improved external validity	4.1	14	Decisions in the wild are often made under time constraints and influenced by the opportunity cost of time
Mapping the relationship between RT and performance	4.2	14	Decision makers may tailor the balance between speed and performance to the environment and to their own goals and constraints
Explicit experimental control of RT	4.3	15	Experiments without explicit time constraints may have ambiguous implicit constraints
Improved model selection, identification and parameter estimation	4.4	16	RT data provide further information about the underlying decision processes. Joint estimation of both choice and RT data improves the precision of parameter estimates in behavioral models
Classification of heterogeneous types	4.5	16	RT data can be used to classify heterogeneous subjects into more finely delineated types
RT as a proxy for other variables	4.6	16	RT can be useful as a proxy for unobserved effort and/or strength of preference

Spiliopoulos and Ortmann (2018, EE)

Instinctive or contemplative?

	L	R
T	2,−2	0,0
B	0,0	1,−1

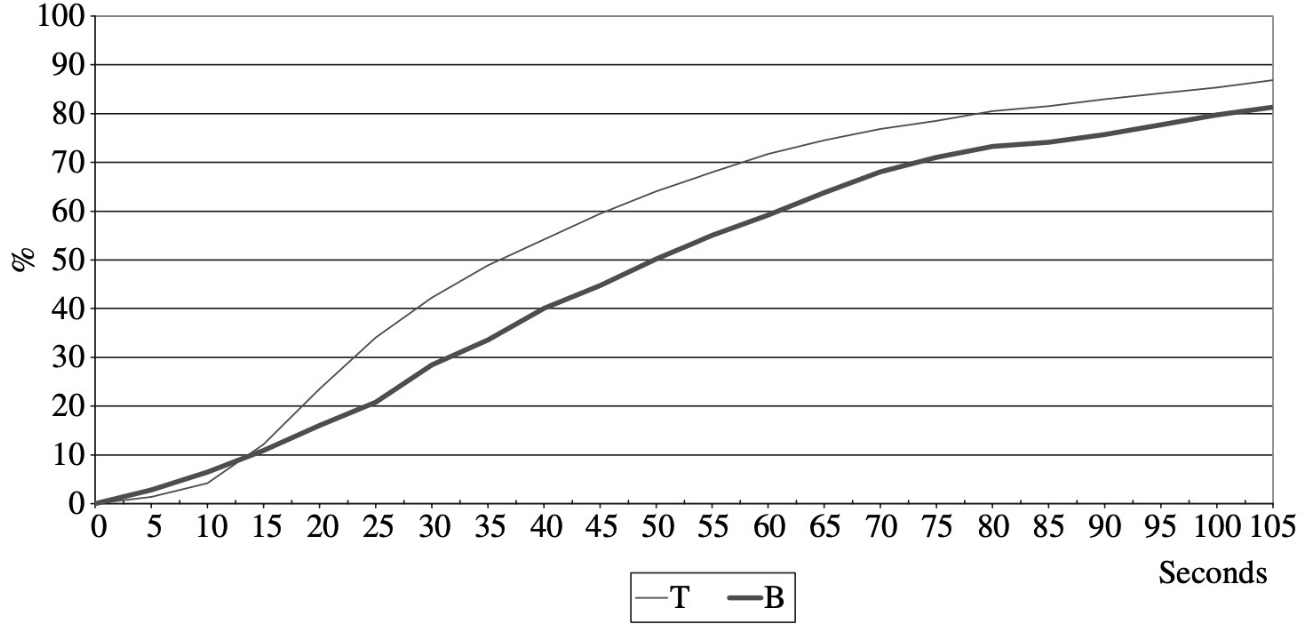

Fig. 1. *Example 1: Response Time Frequencies*

Rubinstein (2007)

Beauty contest game

		$n = 2{,}423$	0–1	2–13	14–15	16–21	22	23–32	33–34	35–49	50	51–100
		86 *sec*	11%	9%	2%	6%	4%	10%	11%	11%	16%	20%
			269	213	47	137	99	249	262	267	393	487
A	15%	126 *sec*					157 *sec*		113 *sec*			
B	49%	89 *sec*	91 *sec*	89 *sec*	84 *sec*	82 *sec*		84 *sec*		94 *sec*		
C	36%	70 *sec*									70 *sec*	70 *sec*

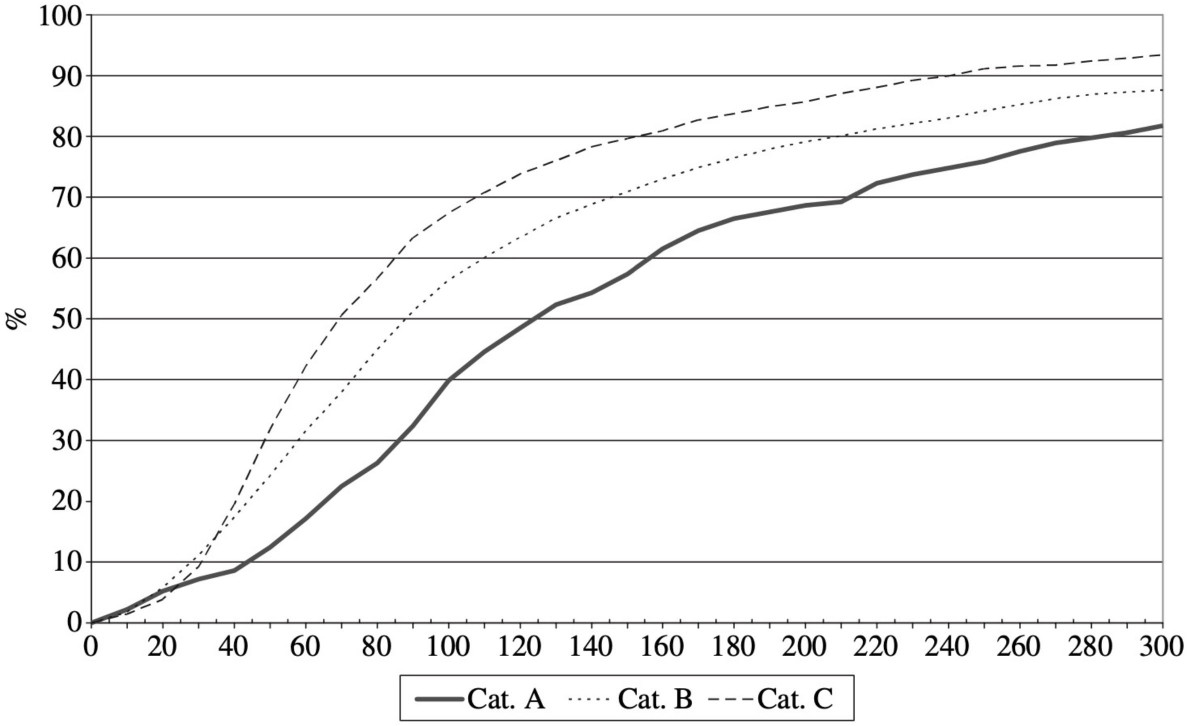

Fig. 4. *Example 4: Response Time Frequencies*

Rubinstein (2007)

What about the choice process?

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Naive play and the process of choice in guessing games

Marina Agranov[1] · Andrew Caplin[2] ·
Chloe Tergiman[3]

Abstract There is growing evidence that not all experimental subjects understand their strategic environment. We introduce a "choice process" (CP) protocol that aids in identifying these subjects. This protocol elicits in an incentive compatible manner provisional choices as players internalize their decision making environment. We implement the CP protocol in the modified 2/3 guessing game and use it to pinpoint players that are naive by identifying those who make weakly dominated choices some time into the play. At all time horizons these players average close to 50. This is consistent with the assumption in Level-K theory that the least sophisticated subjects (the naive ones) play uniformly over the [1–100] action space. In contrast, sophisticated players show evidence of increased understanding as time passes. We find that the CP protocol mirrors play in multiple setups with distinct time constraints. Hence it may be worth deploying more broadly to understand the interaction between decision time and choice.

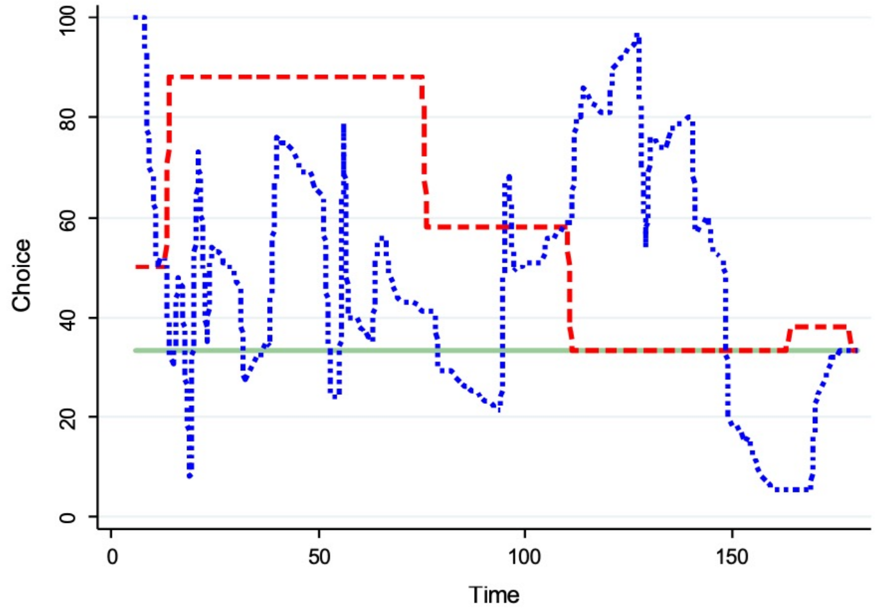

Fig. 1 Is final choice enough? Paths of choice of three subjects with the same final choice

Agranov et al. (2015, JESA)

Modified dictator game

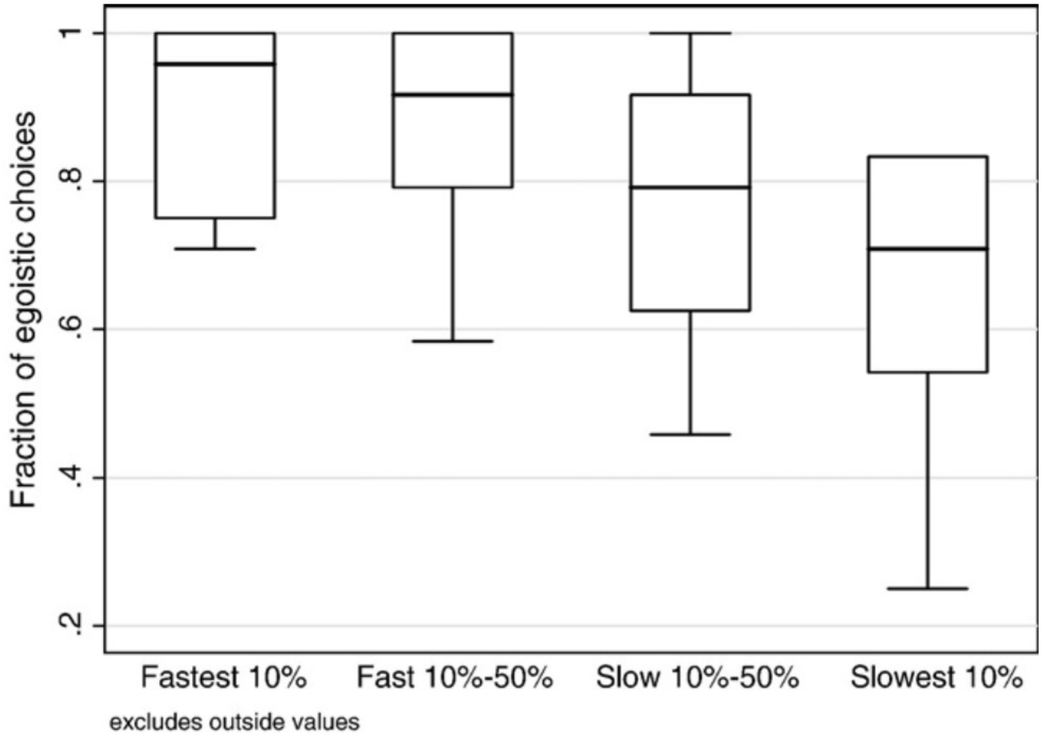

Fig. 2. Fraction of egoistic choices.

Piovesan & Wengström (2009, EL)

Public goods game

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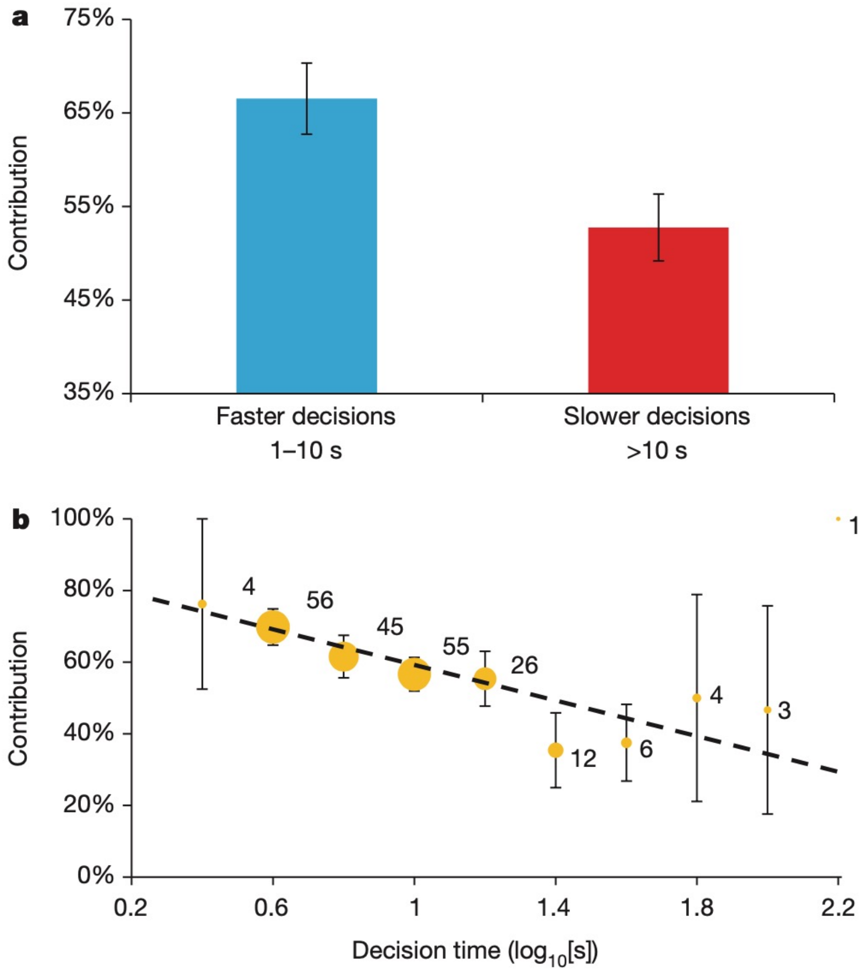
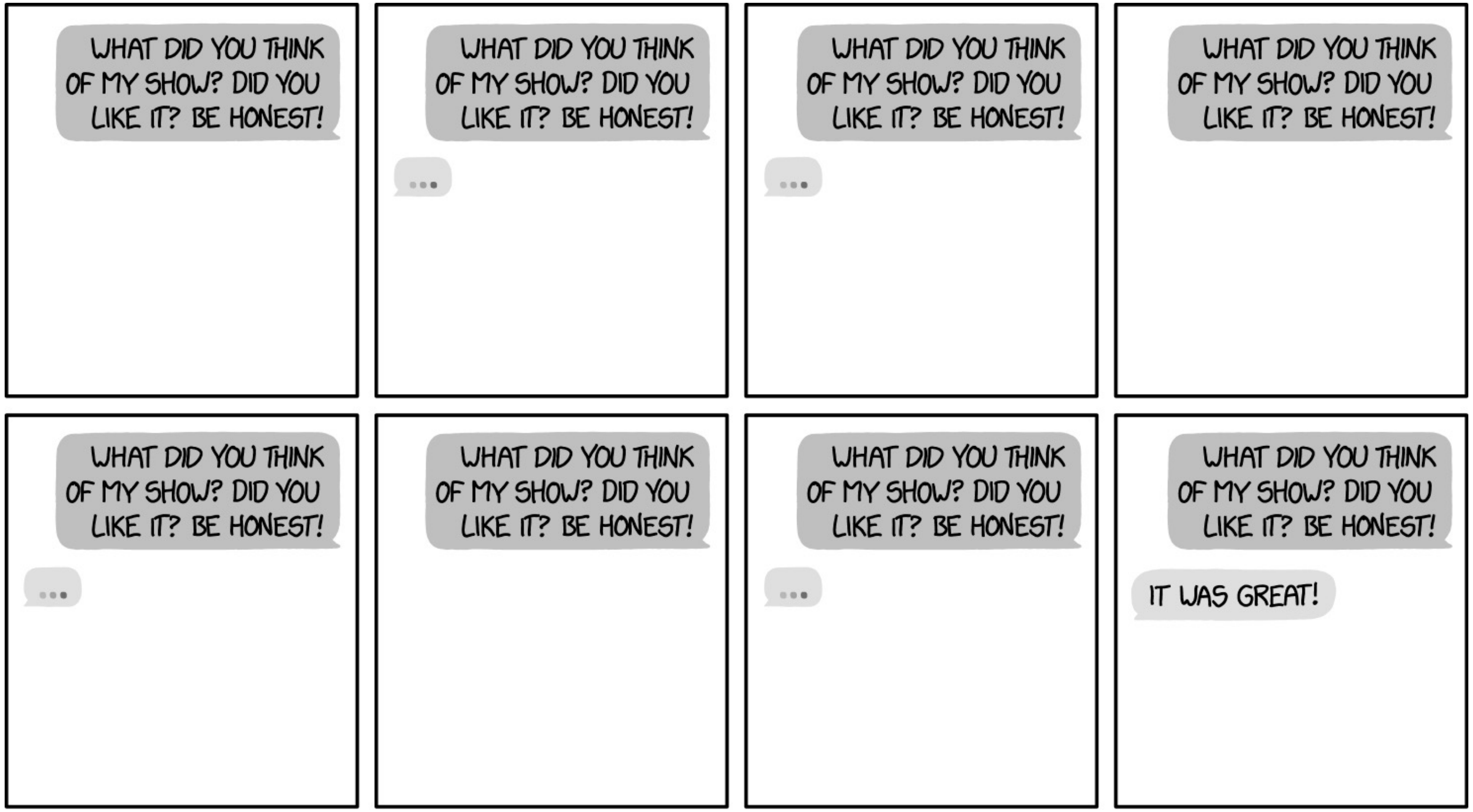


Rand et al (2012, Nature)

Response time and preferences



MY LEAST FAVORITE ASPECT OF TYPING NOTIFICATIONS

XKCD

Drift-diffusion model

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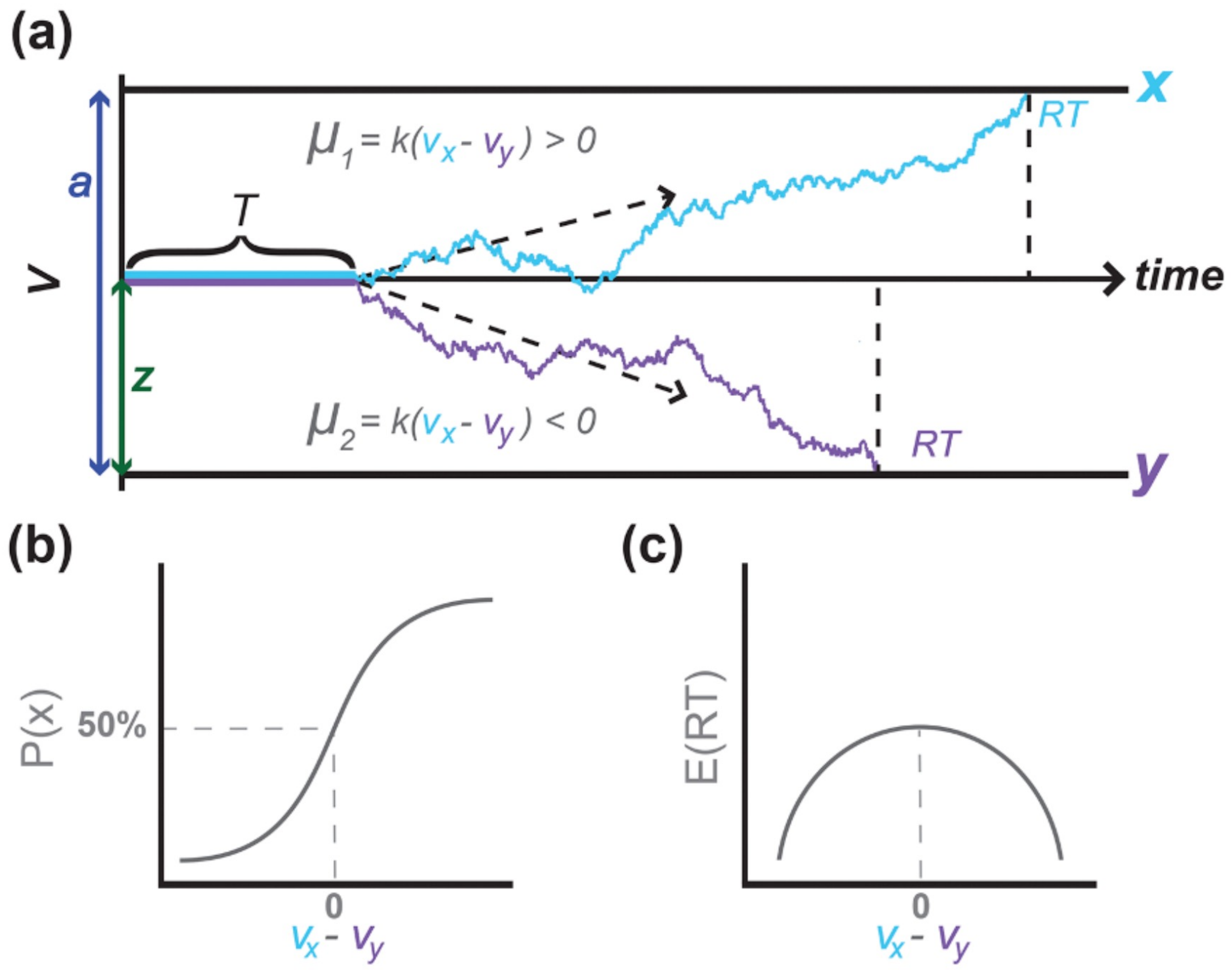


$$P(x) = \frac{1}{1 + e^{\frac{-a\mu}{\sigma^2}}}.$$

$$E[RT] = T + \frac{a}{2\mu} tanh\left(\frac{a\mu}{2\sigma^2}\right).$$

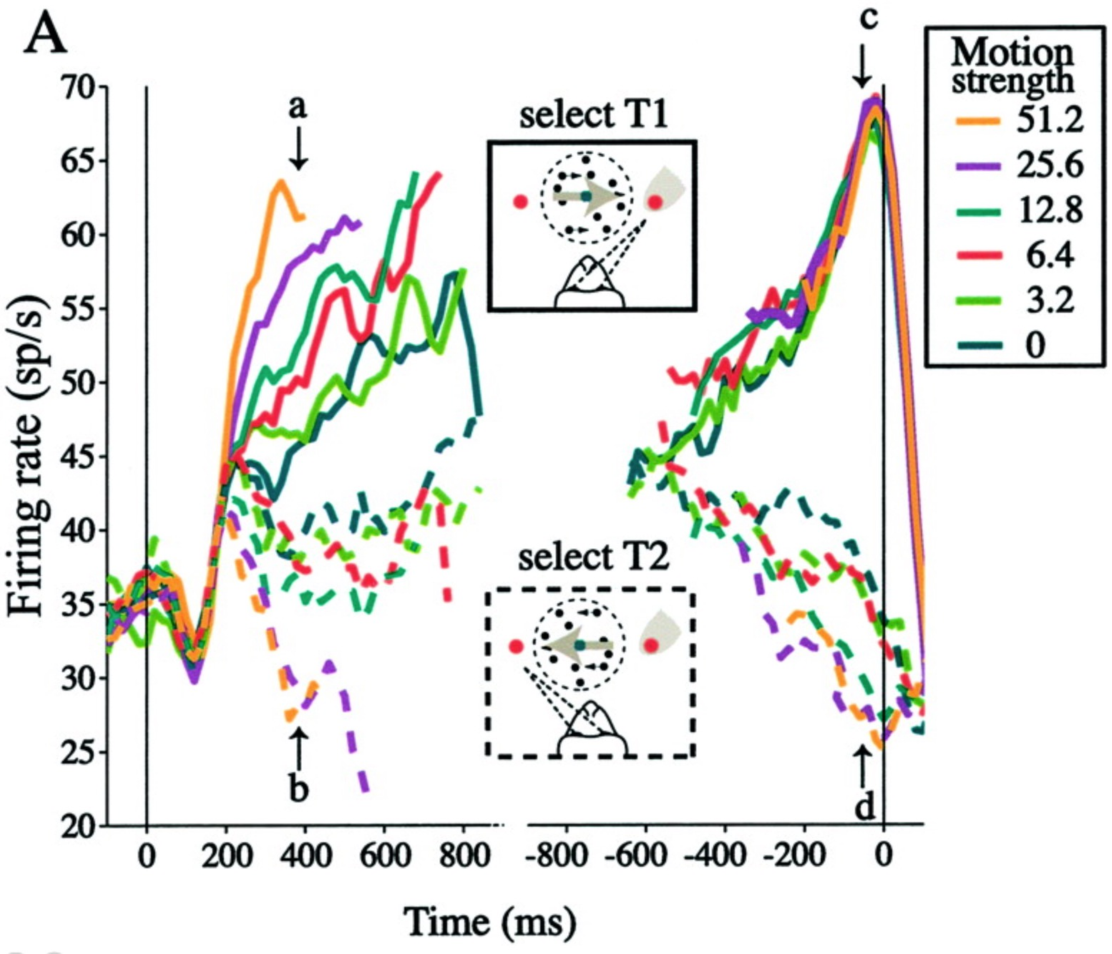
Clithero (2018)

Psychological basis

A Theory of Memory Retrieval

Roger Ratcliff
University of Toronto, Ontario, Canada

A theory of memory retrieval is developed and is shown to apply over a range of experimental paradigms. Access to memory traces is viewed in terms of a resonance metaphor. The probe item evokes the search set on the basis of probe–memory item relatedness, just as a ringing tuning fork evokes sympathetic vibrations in other tuning forks. Evidence is accumulated in parallel from each probe–memory item comparison, and each comparison is modeled by a continuous random walk process. In item recognition, the decision process is self-terminating on matching comparisons and exhaustive on nonmatching comparisons. The mathematical model produces predictions about accuracy, mean reaction time, error latency, and reaction time distributions that are in good accord with experimental data. The theory is applied to four item recognition paradigms (Sternberg, prememorized list, study–test, and continuous) and to speed–accuracy paradigms; results are found to provide a basis for comparison of these paradigms. It is noted that neural network models can be interfaced to the retrieval theory with little difficulty and that semantic memory models may benefit from such a retrieval scheme.



Ratcliff (1978)

Roitman & Shadlen (2002)

Economics!

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Speed, Accuracy, and the Optimal Timing of Choices†

By DREW FUDENBERG, PHILIPP STRACK, AND TOMASZ STRZALECKI*

We model the joint distribution of choice probabilities and decision times in binary decisions as the solution to a problem of optimal sequential sampling, where the agent is uncertain of the utility of each action and pays a constant cost per unit time for gathering information. We show that choices are more likely to be correct when the agent chooses to decide quickly, provided the agent's prior beliefs are correct. This better matches the observed correlation between decision time and choice probability than does the classical drift-diffusion model (DDM), where the agent knows the utility difference between the choices. (*JEL* C41, D11, D12, D83)

THEOREM 1: *Suppose that P has a DDM representation (α, δ, b). Then P displays increasing, decreasing, or constant accuracy if and only if $b(t)$ is increasing, decreasing, or constant respectively.*

Fudenberg et al (2018)

Slow indifference

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- **Food choice**
  - Krajbich et al. 2010, Mormann et al. 2010, Krajbich & Rangel 2011, Hare et al. 2011, De Martino et al. 2013, Krajbich et al. 2014, Polania et al. 2014, Oud et al. 2016, Enax et al. 2016, Woodford 2014, Fudenberg et al. 2019
- **Consumer choice**
  - Tyebjee 1979, Haajier et al. 2000, Srivastava & Oza 2006, Krajbich et al. 2012, Philiastides & Ratcliff 2013, Otter et al. 2018
- **Risk**
  - Busemeyer 1982, 1985; Busemeyer & Townsend 1993, Moffatt 2005, Gabaix et al. 2006, Fiedler & Glöckner 2012, Gluth et al. 2012, Hunt et al. 2012, Stewart et al. 2015
- **Uncertainty**
  - Cavanagh et al. 2014, Konovalov & Krajbich 2019
- **Intertemporal choice**
  - Chabris et al. 2009, Dai & Busemeyer 2014, Rodriguez et al. 2014
- **Social preferences**
  - Krajbich et al. 2015, Hutcherson et al. 2015, Chen & Fischbacher 2015

Deliberation or preference?

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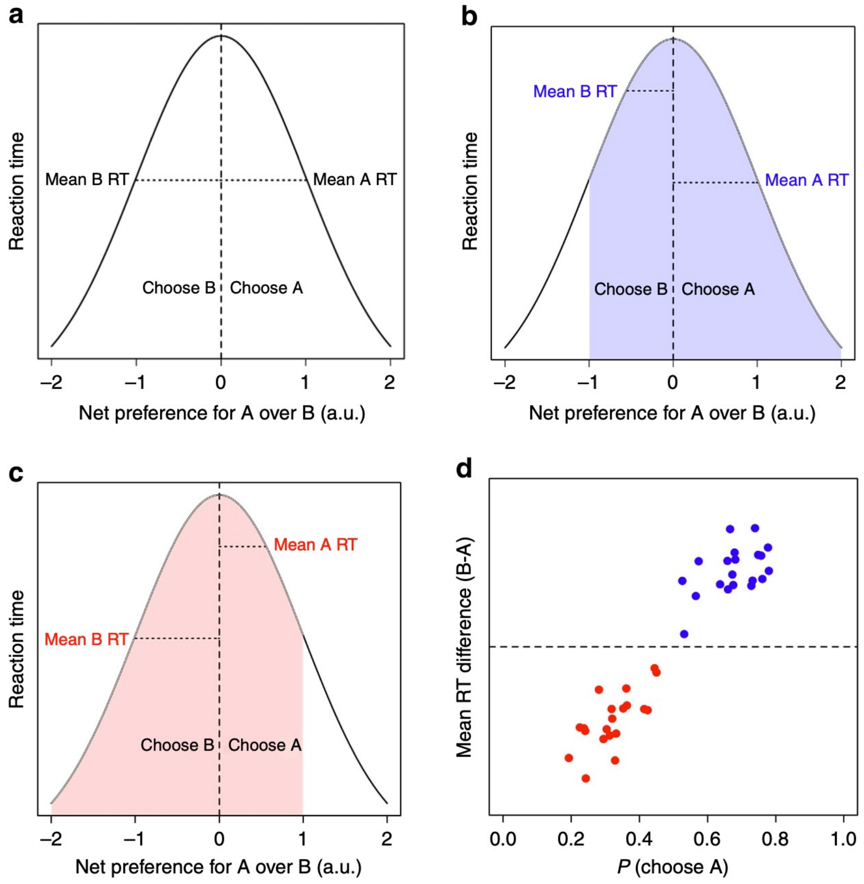
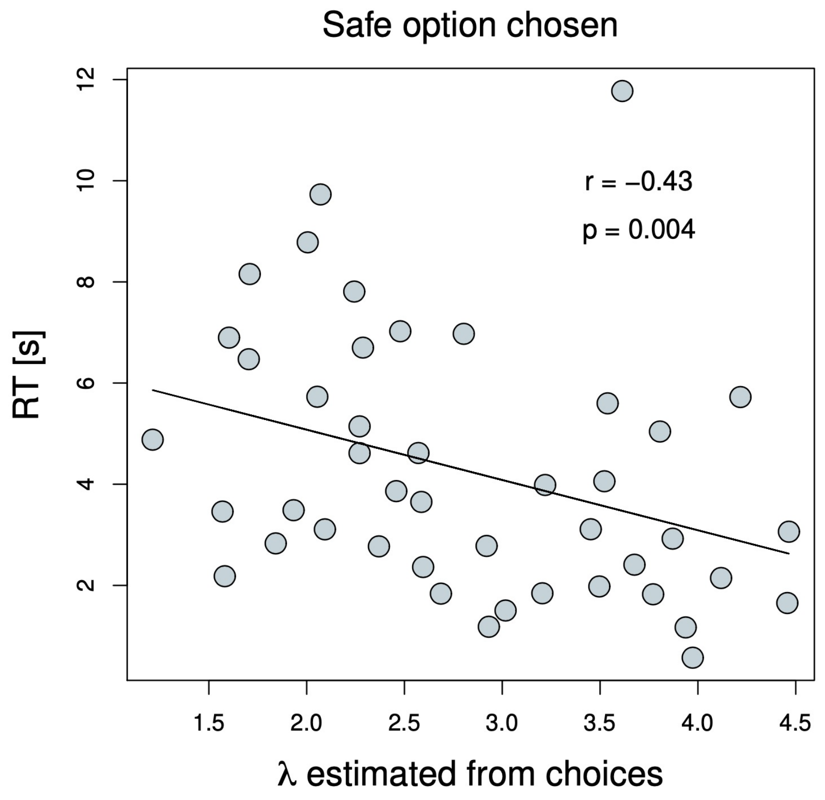


Krajbich et al (2015, Nature Comm)

Estimating preferences from RTs

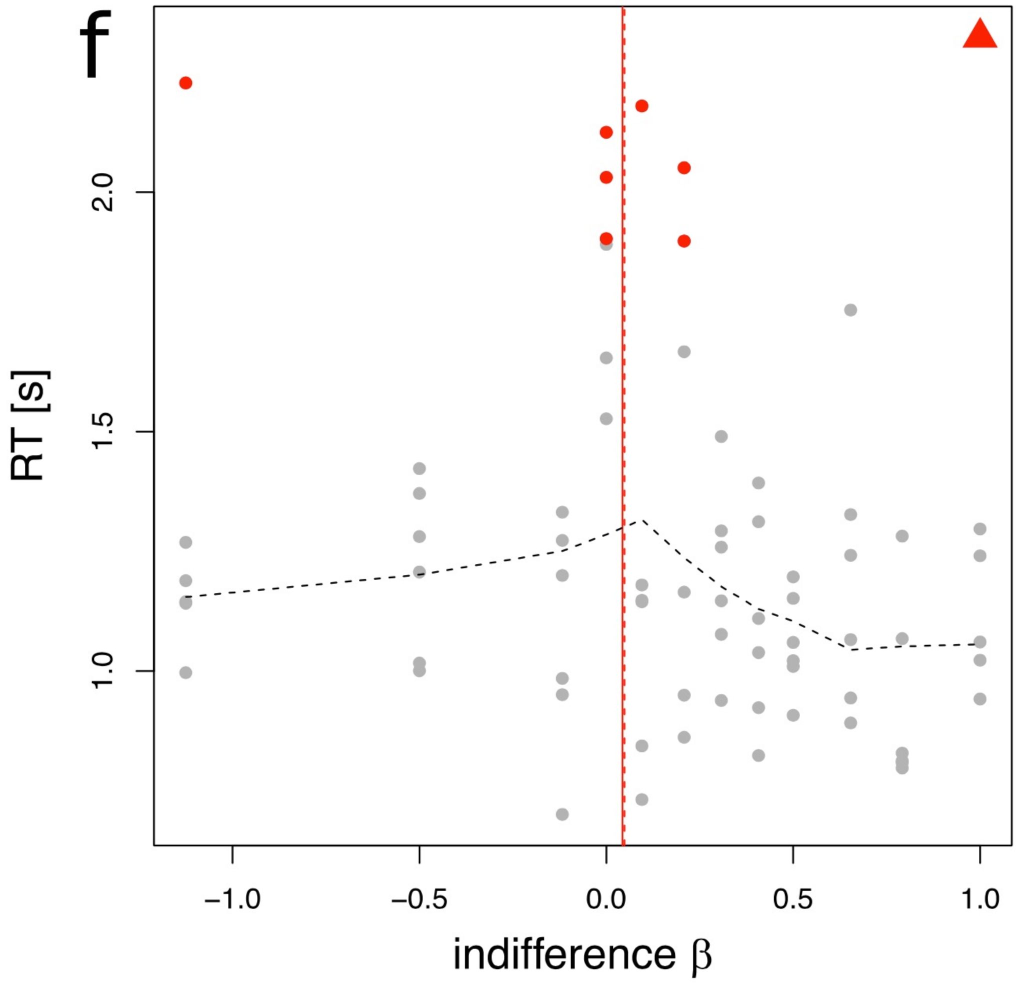
+$12
-$7.5

$0



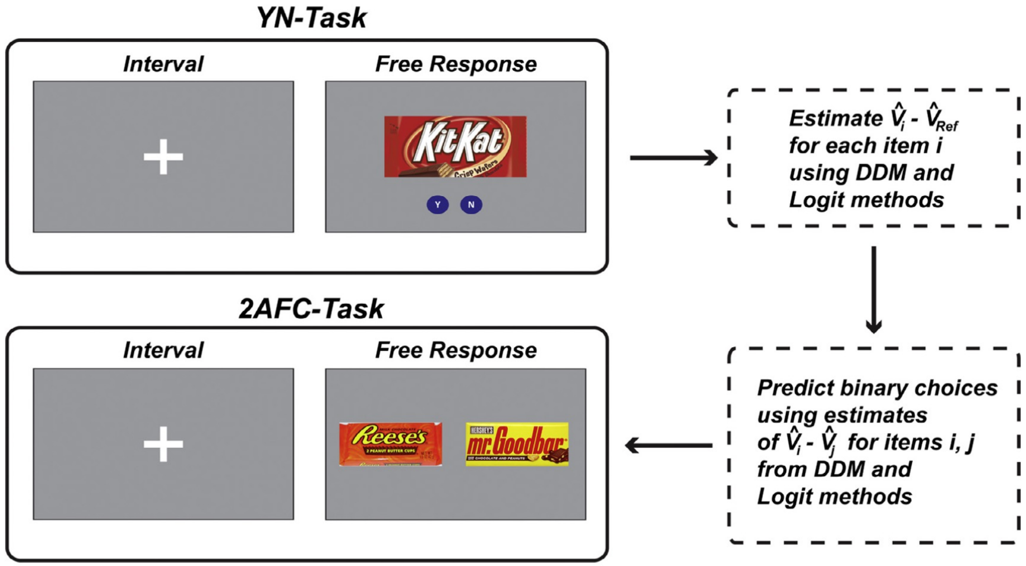
Konovalov & Krajbich (JDM, 2019)

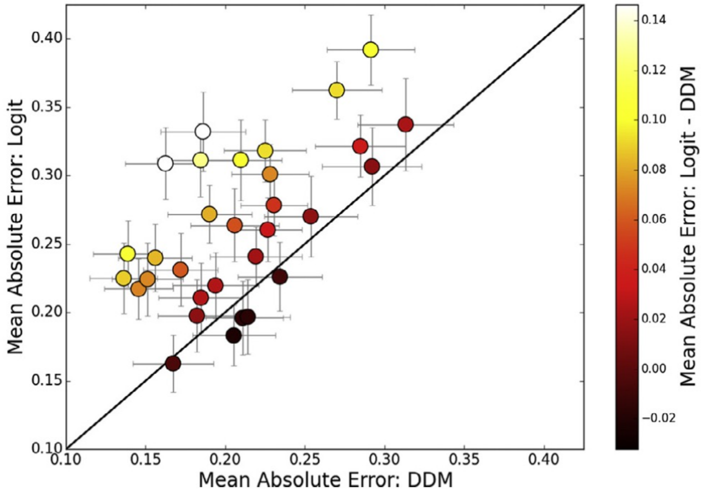
Estimating preferences from RT

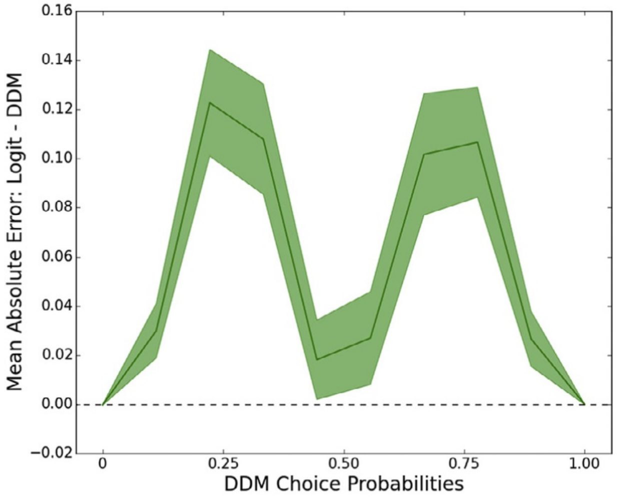


Konovalov & Krajbich (JDM, 2019)

Out-of-sample prediction







Clithero (2018, JEBO)

Estimating preferences with RTs

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Time Will Tell: Recovering Preferences When Choices Are Noisy

When choice is stochastic, revealed preference analysis often relies on random utility models. However, it is impossible to infer preferences without assumptions on the distribution of utility noise. We show that this difficulty can be overcome by using response time data. A simple condition on response time distributions ensures that choices reveal preferences without distributional assumptions. Standard models from economics and psychology generate data fulfilling this condition. Sharper results are obtained under symmetric or Fechnerian noise, where response times allow uncovering preferences or predicting choice probabilities out of sample. Application of our tools is simple and generates remarkable prediction accuracy.

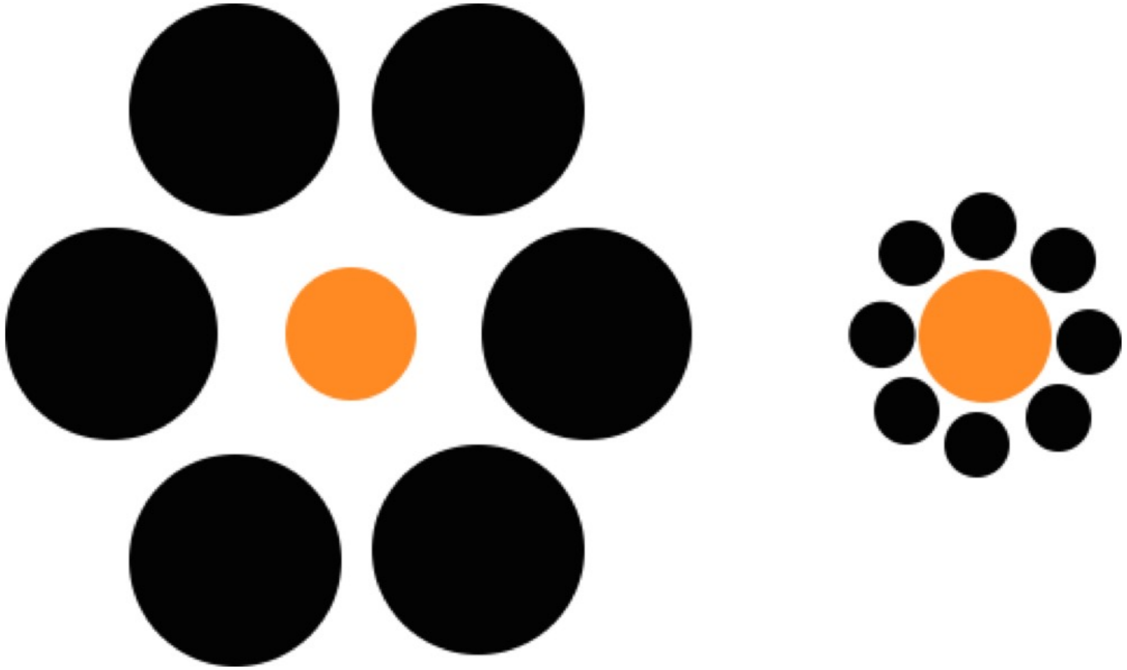
DEFINITION 2. A *random utility model* (RUM) is a pair $(u, \tilde{v})$ where $u : X \to \mathbb{R}$ is a utility function and $\tilde{v} = (\tilde{v}(x, y))_{(x,y)\in C}$ is a collection of real-valued random variables, with each $\tilde{v}(x, y)$ having a density function $g(x, y)$ on $\mathbb{R}$, fulfilling the following properties:

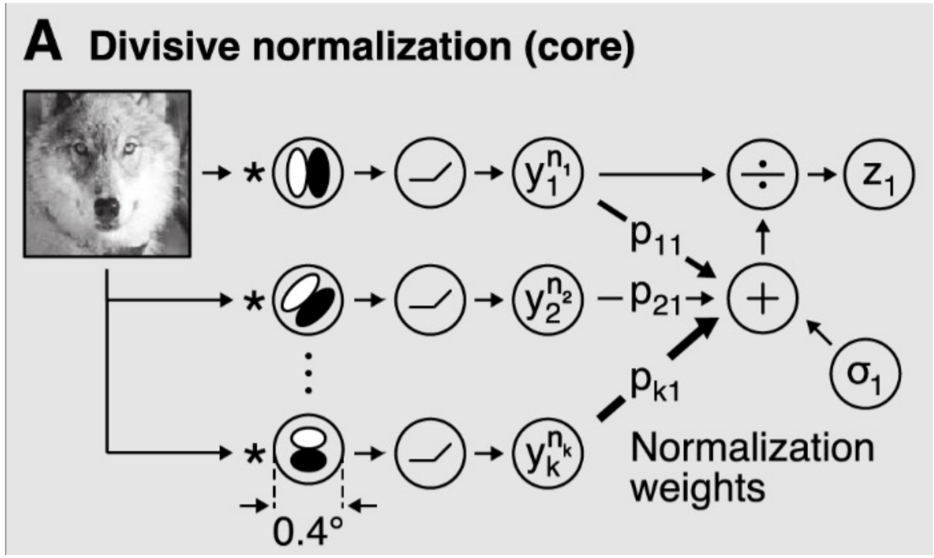
RUM.1: $\mathbb{E}[\tilde{v}(x, y)] = u(x) - u(y)$;
RUM.2: $\tilde{v}(x, y) = -\tilde{v}(y, x)$; and
RUM.3: The support of $\tilde{v}(x, y)$ is connected.

DEFINITION 5. A *random utility model with a chronometric function* (RUM-CF) is a triple $(u, \tilde{v}, r)$ where $(u, \tilde{v})$ is a RUM and $r : \mathbb{R}_{++} \to \mathbb{R}_+$ is a continuous function that is strictly decreasing in v whenever $r(v) > 0$, with $\lim_{v\to 0} r(v) = +\infty$ and $\lim_{v\to\infty} r(v) = 0$.

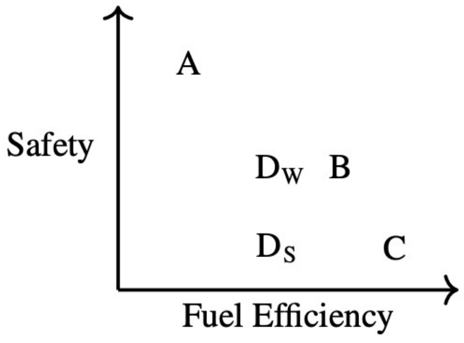
Alos-Ferrer et al (2021, JPE)

Divisive normalization





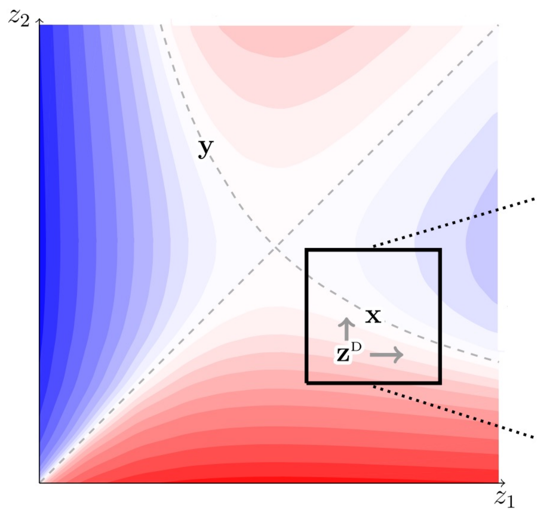
Divisive normalization



While car A may be chosen over car B in binary choice, car B may be chosen with car C in the choice set, reflecting a compromise effect, or with some car D, whether weakly (D_W) or strictly (D_S) dominated by car B, reflecting a dominance effect.

Fig. 1. Illustration of compromise and dominance effects.

$$V(\mathbf{x}; X) = \sum_{n=1}^{N} \sum_{\mathbf{y} \in X \setminus \mathbf{x}} \frac{x_n}{x_n + y_n}.$$



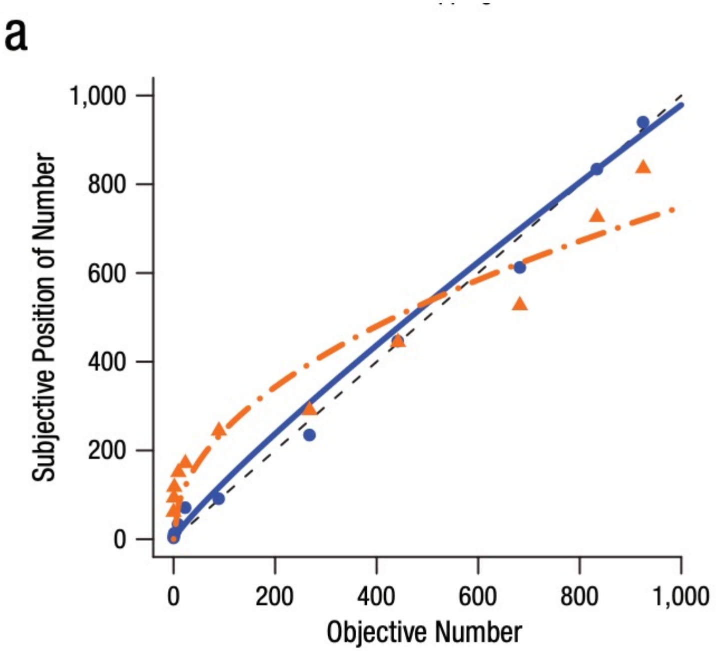
Landry and Webb (2021, JET)

Imprecise representations

University of Zurich[UZH]

Dan R. Schley and Ellen Peters
The Ohio State University

Abstract
Diminishing marginal utility (DMU) is a basic tenet of economic and psychological models of judgment and choice, but its determinants are little understood. In the research reported here, we tested whether insensitivities in valuations of dollar amounts (e.g., $40, $100) may be due to inexact mappings of symbolic numbers (i.e., "40," "100") onto mental magnitudes. In three studies, we demonstrated that inexact mappings appear to guide valuation and mediate numeracy's relations with riskless valuations (Studies 1 and 1a) and risky choices (Study 2). The results highlight the fundamental notion that individuals' valuations of $100 depend critically on how individuals perceive and map the symbolic quantity "100." This notion has implications for conceptualizations of value, risk aversion, intertemporal choice, and dual-process theories of decision making. Normative implications are also briefly discussed.



Schley and Peters (2014, Psych Science)

Numbers and risk aversion

Cognitive Imprecision and Small-Stakes Risk Aversion

MEL WIN KHAW
Duke Institute for Brain Sciences, Duke University
ZIANG LI
Department of Economics, Princeton University
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Department of Economics, Columbia University

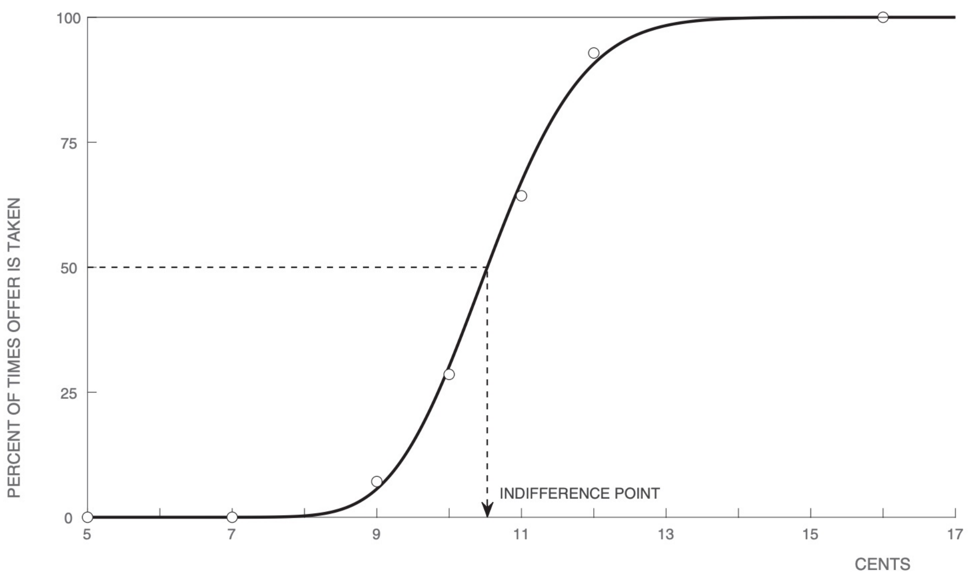
First version received May 2019*; Editorial decision April* 2020*; Accepted June* 2020 (*Eds.*)

Observed choices between risky lotteries are difficult to reconcile with expected utility maximization, both because subjects appear to be too risk averse with regard to small gambles for this to be explained by diminishing marginal utility of wealth, as stressed by Rabin (2000), and because subjects' responses involve a random element. We propose a unified explanation for both anomalies, similar to the explanation given for related phenomena in the case of perceptual judgments: they result from judgments based on imprecise (and noisy) mental representations of the decision situation. In this model, risk aversion results from a sort of perceptual bias—but one that represents an optimal decision rule, given the limitations of the mental representation of the situation. We propose a quantitative model of the noisy mental representation of simple lotteries, based on other evidence regarding numerical cognition, and test its ability to explain the choice frequencies that we observe in a laboratory experiment.

Key words: Weber's Law, random utility, prospect theory, Rabin critique

JEL Codes: C91, D03, D81, D87

$$\text{Prob}[\text{accept risky}|X,C] = \Phi\left(\frac{\log X/C - \beta^{-1}\log p^{-1}}{\sqrt{2}\nu}\right).$$



Other materials

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- Spiliopoulos and Ortmann (2018, EE)
- Clithero (2018, JEP)
- https://sites.google.com/site/arkadykonovalov/

Thank you!

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