Neuroeconomics:
From The Failures of Expected Utility to the Neurobiology of Choice

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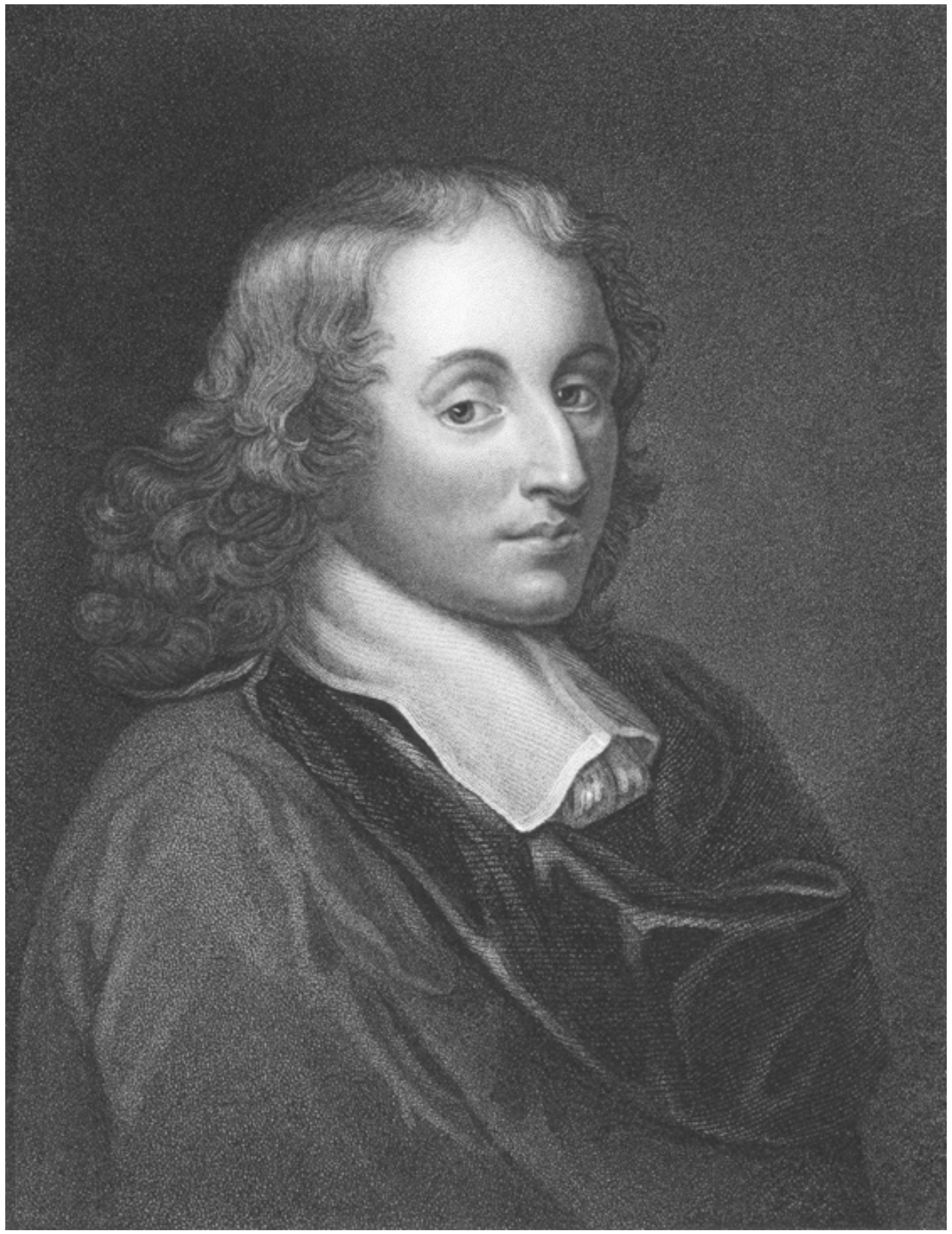
From Neurons to Nations

Blaise Pascal



Genius:

Expected Value Theory

	Probability	x Value	= Expected Value
#1	0.5	100	50
#2	1.0	45	45

Pascal's Wager

	If God Exists (Prob × Value)	+	If God Doesn't Exist (Prob × Value)	=	Exp. Value
Believe in God	$>0 \times \infty$	+	$\geq 0 \times 0$	=	∞
Do not Believe in God	$>0 \times -\infty$	+	$\geq 0 \times 0$	=	$-\infty$

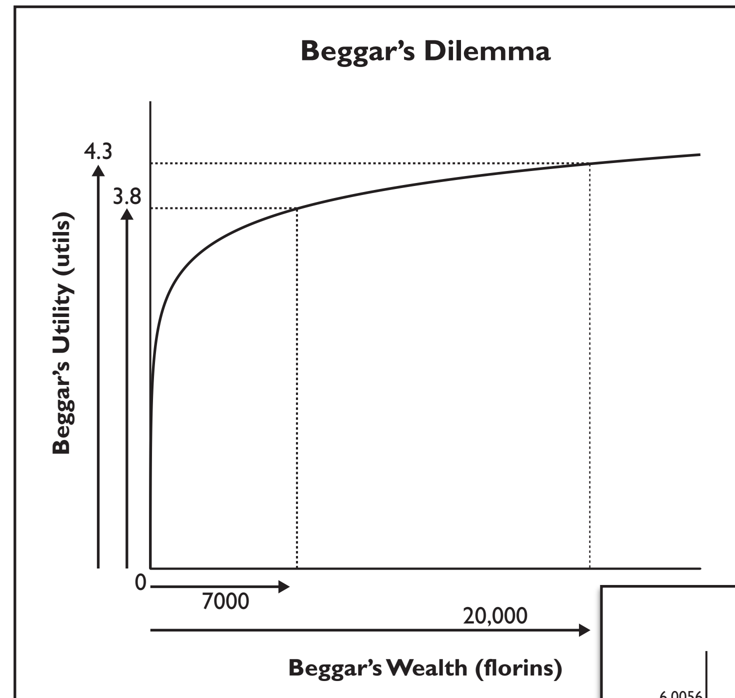
Problem:

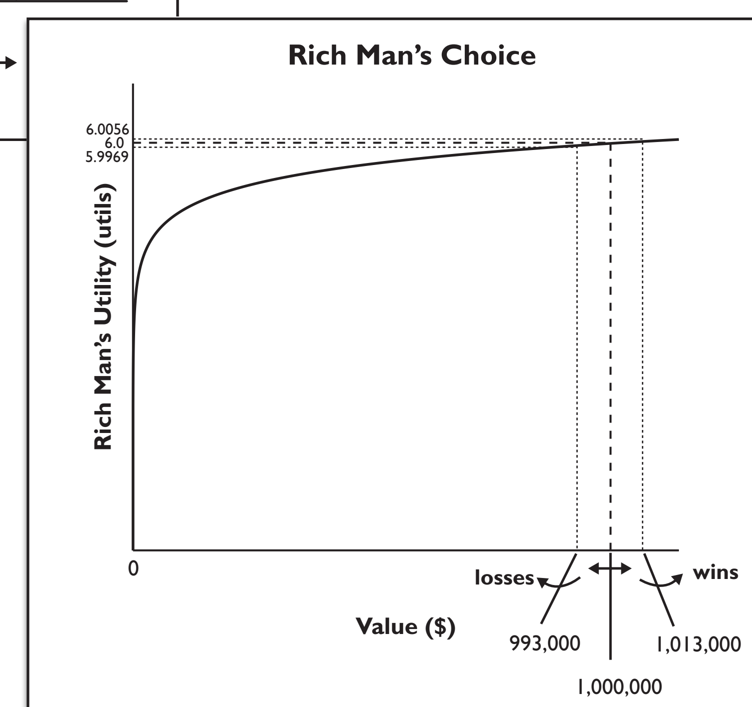
The Beggar's Dilemma

Daniel Bernoulli

Genius:

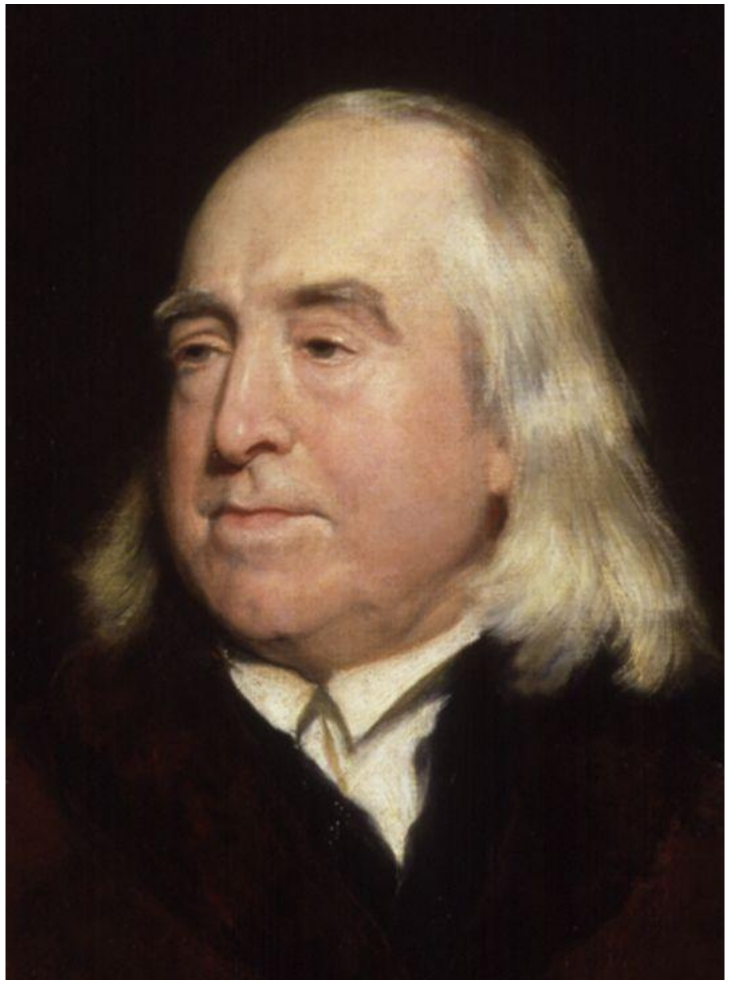
Expected ***Utility*** Theory





Problem: Bentham, Pareto, Samuelson

Jeremy Bentham

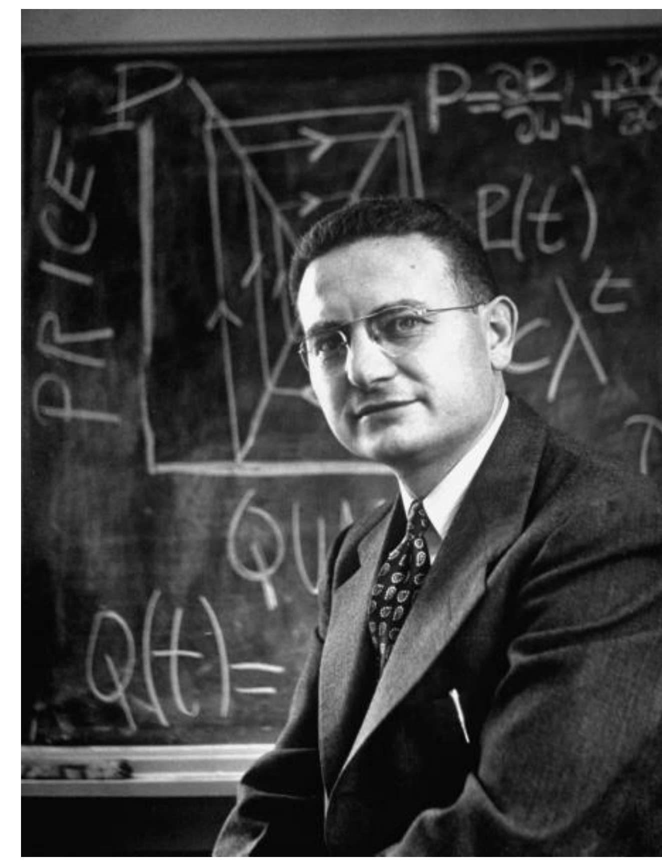


The Calculus of Utility

Vilfredo Pareto

The Intrinsic Arbitrariness of Utility

Paul Samuelson

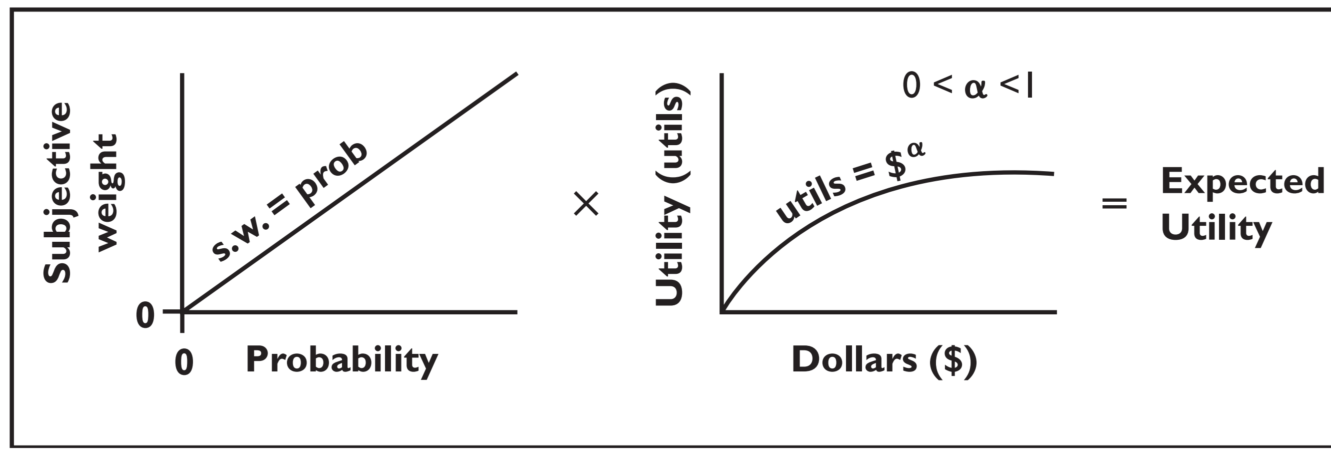


Ordinal Objective Utility

John von Neumann   Oskar Morgenstern

Genius:

Modern
Expected ***Utility*** Theory



Critical Advantages:

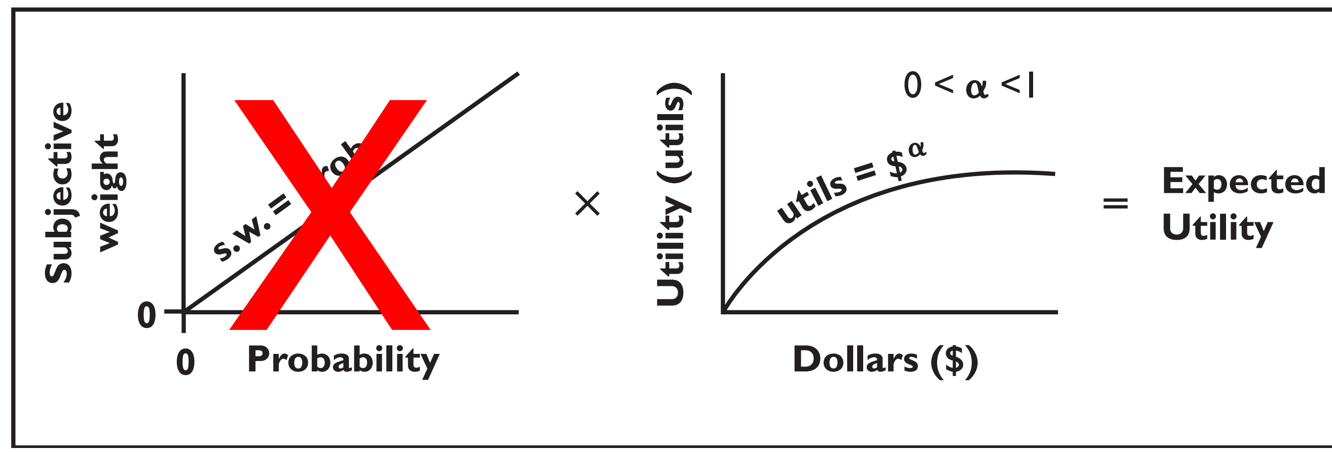
- Precise
- Compact
- **Normative** (people make sense)

Problem:

Maurice Allais

Maurice Allais

People Do Not Obey EU all the time

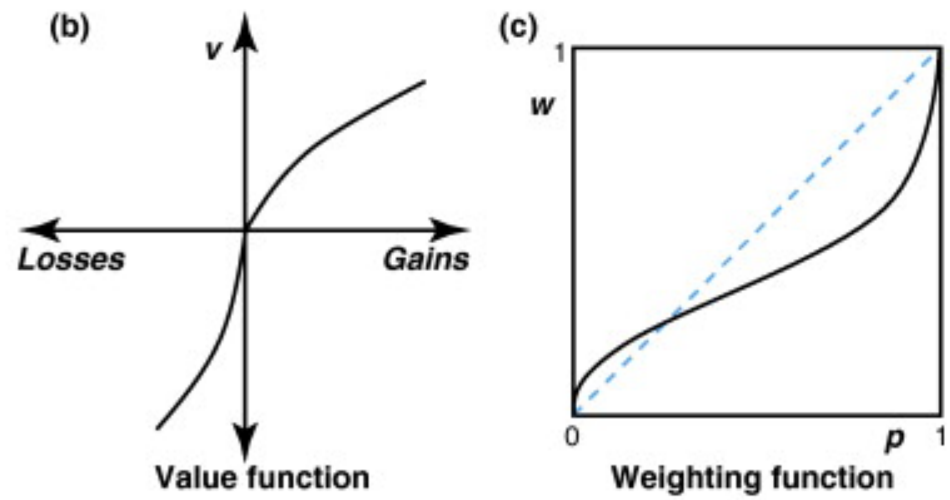


Critical Questions:

- How to Predict People?
- Are People Dumb?
- **Why?**

Amos Tversky   Danny Kahneman

Prospect Theory



Critical Advantages:

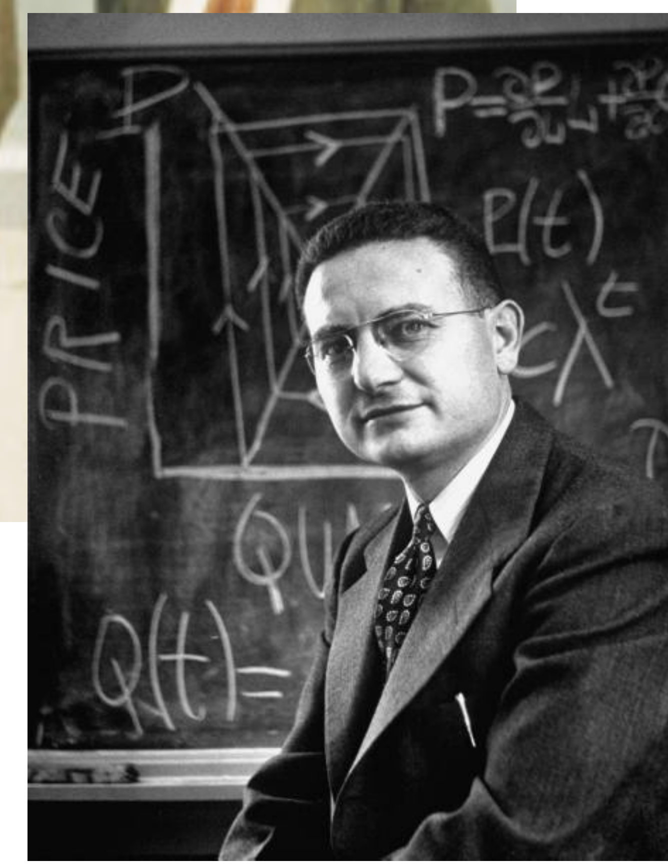
- Predictive

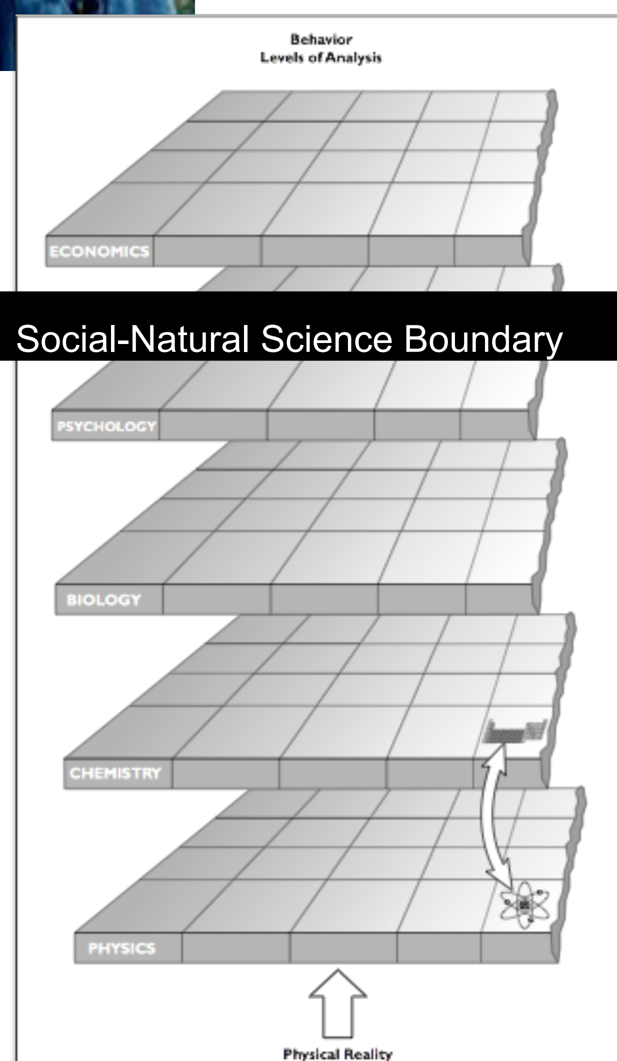
Critical Disadvantages:

- Bulky
- No Why

Behavioral

Traditional





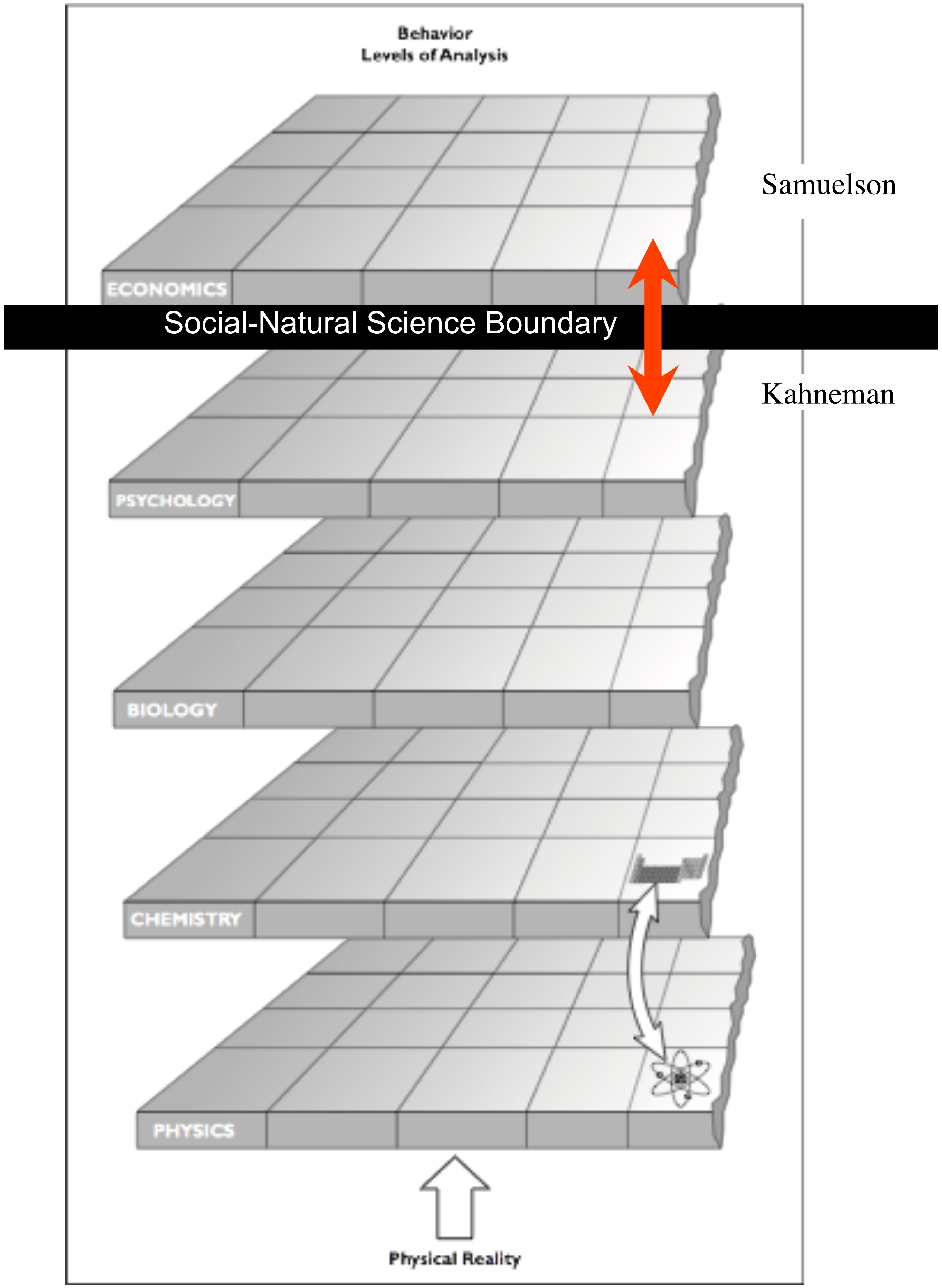
Social-Natural Science Boundary

Economics vs. Psychology

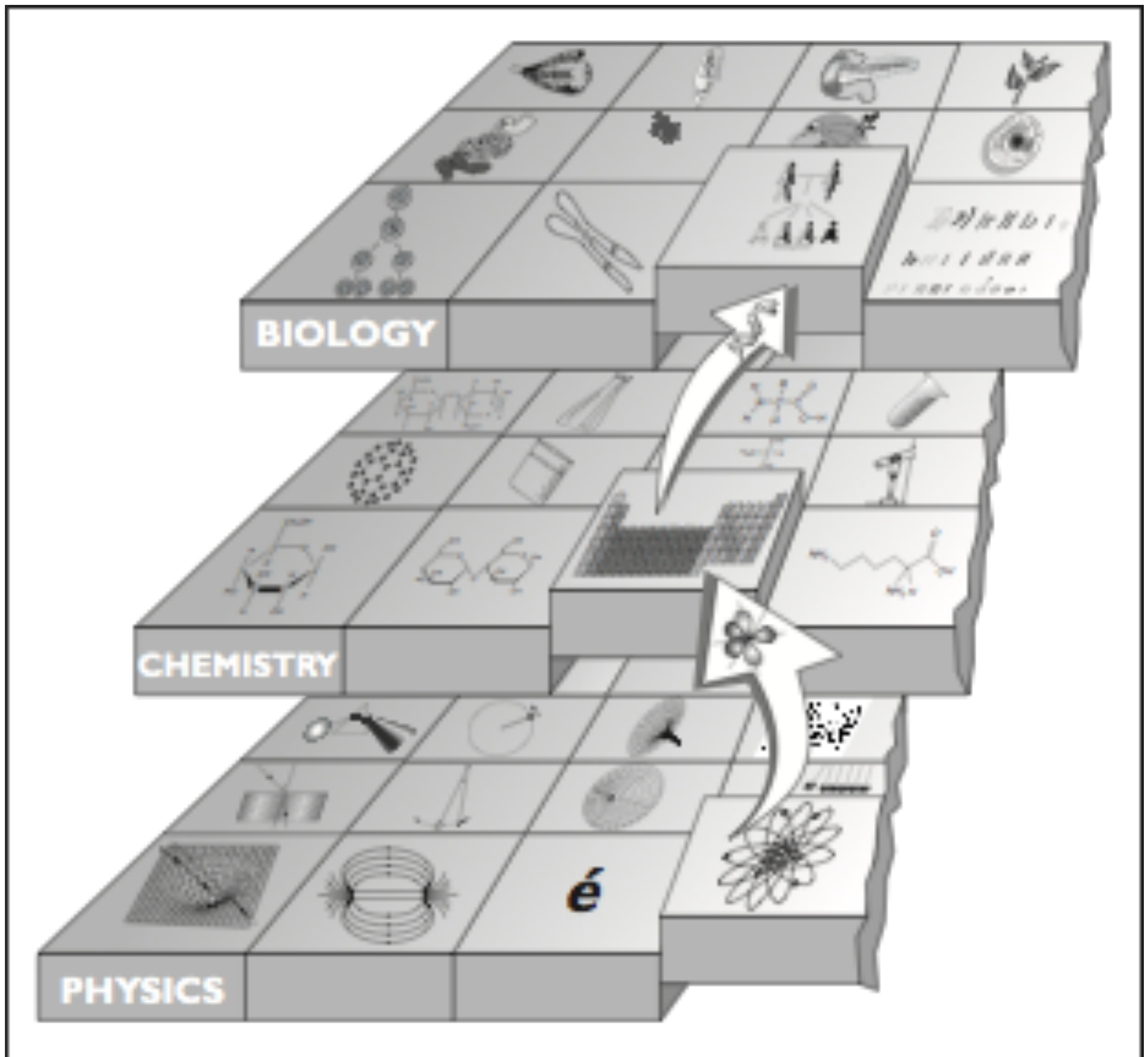
Behavioral

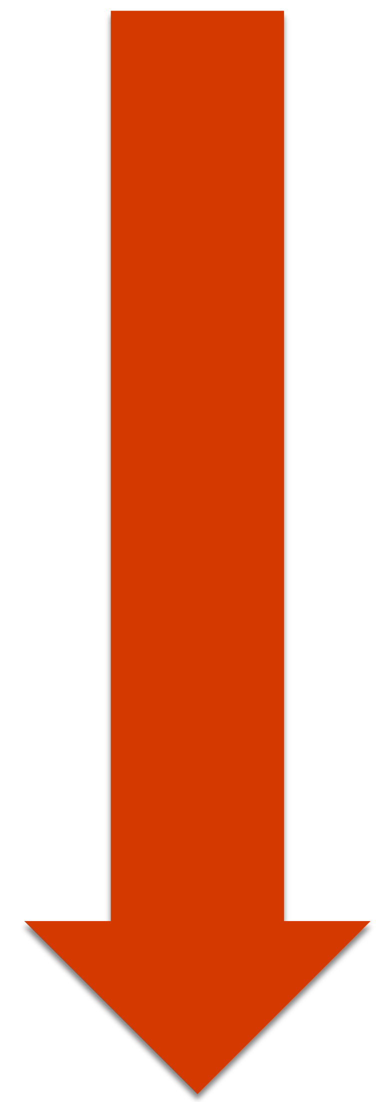
Traditional

The Reductive Levels Of Decision Science

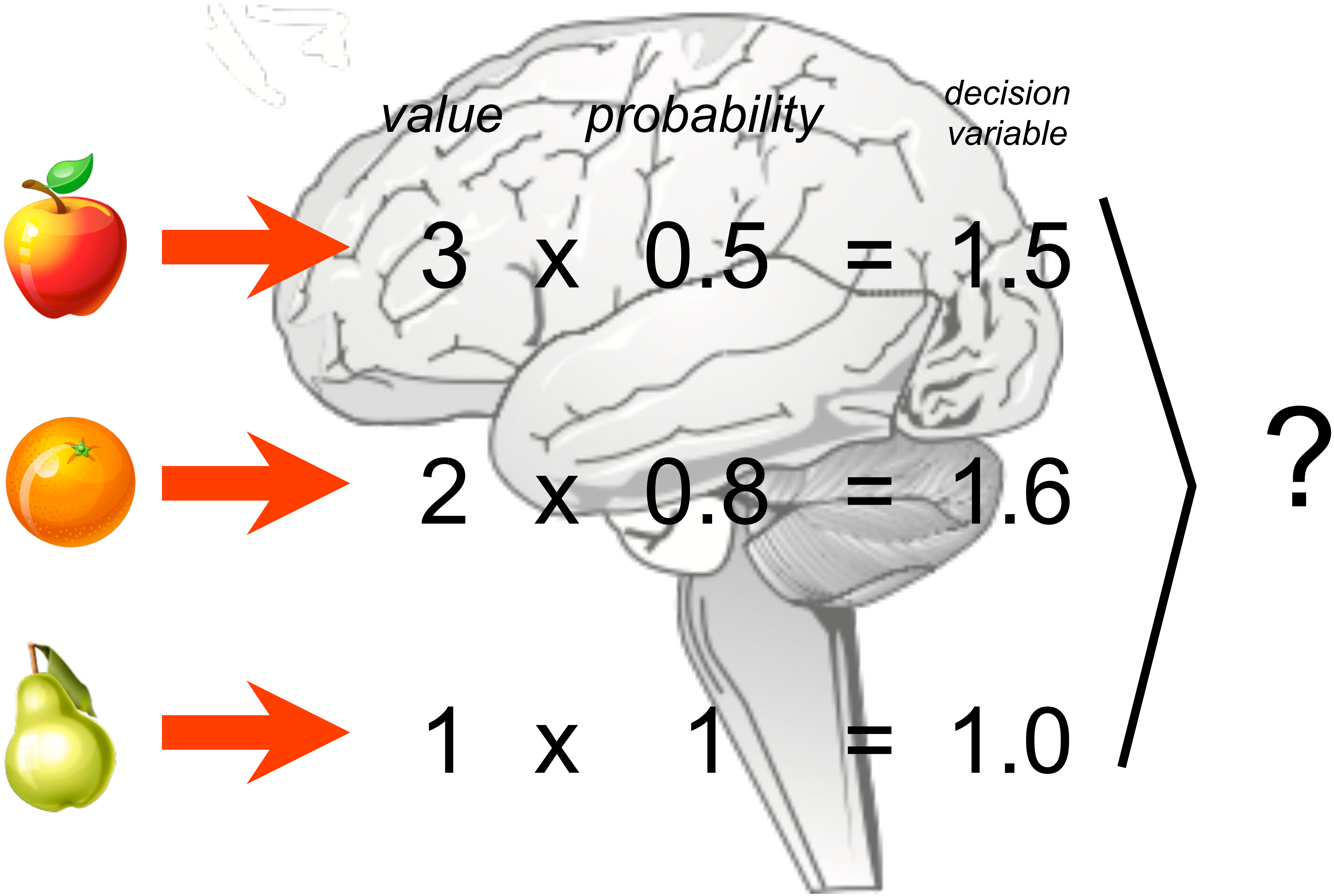


The Central Goal of Neuroeconomics *(for me)* was/is Interdisciplinary Fusion

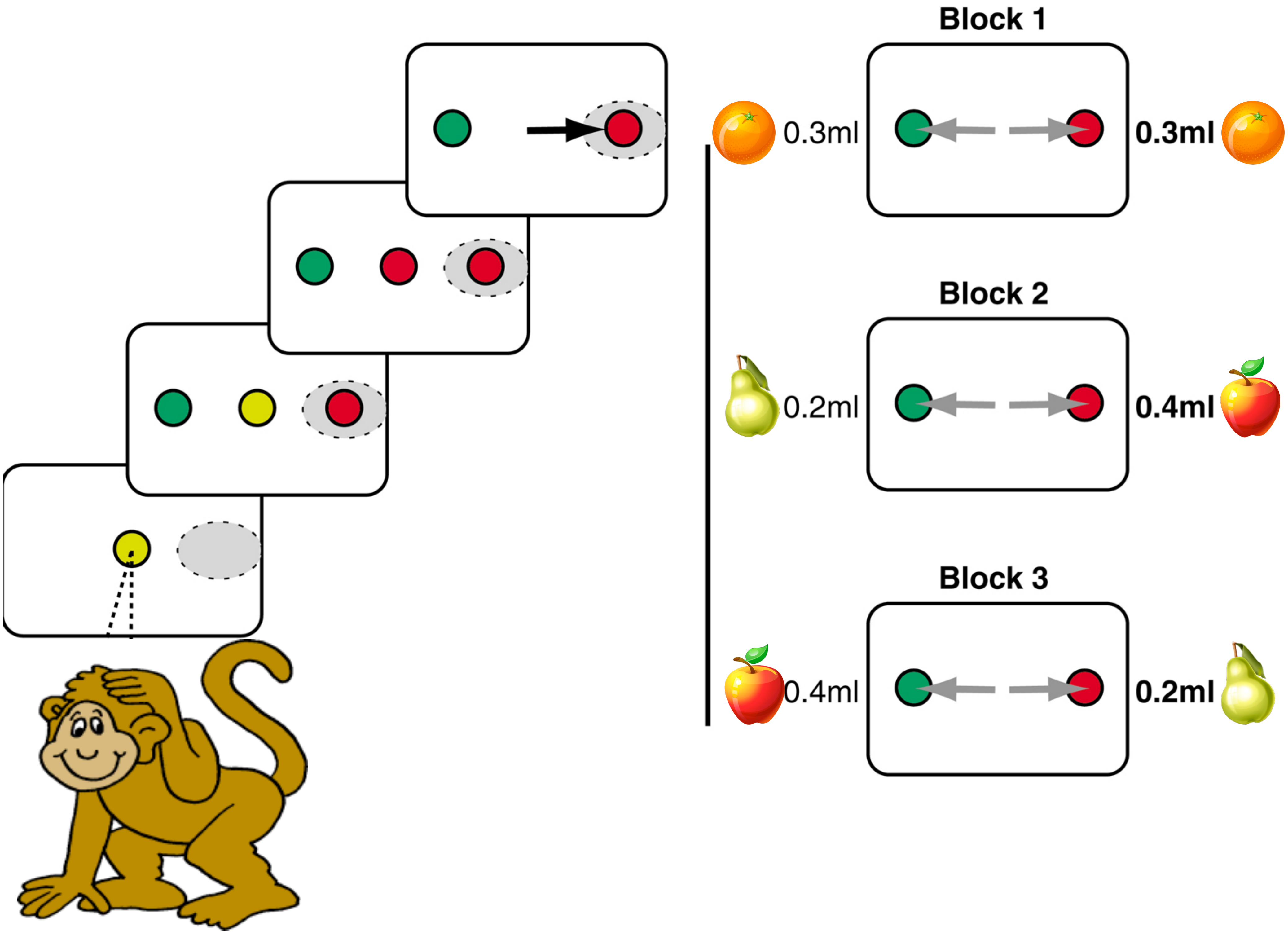




How Can We Combine These?

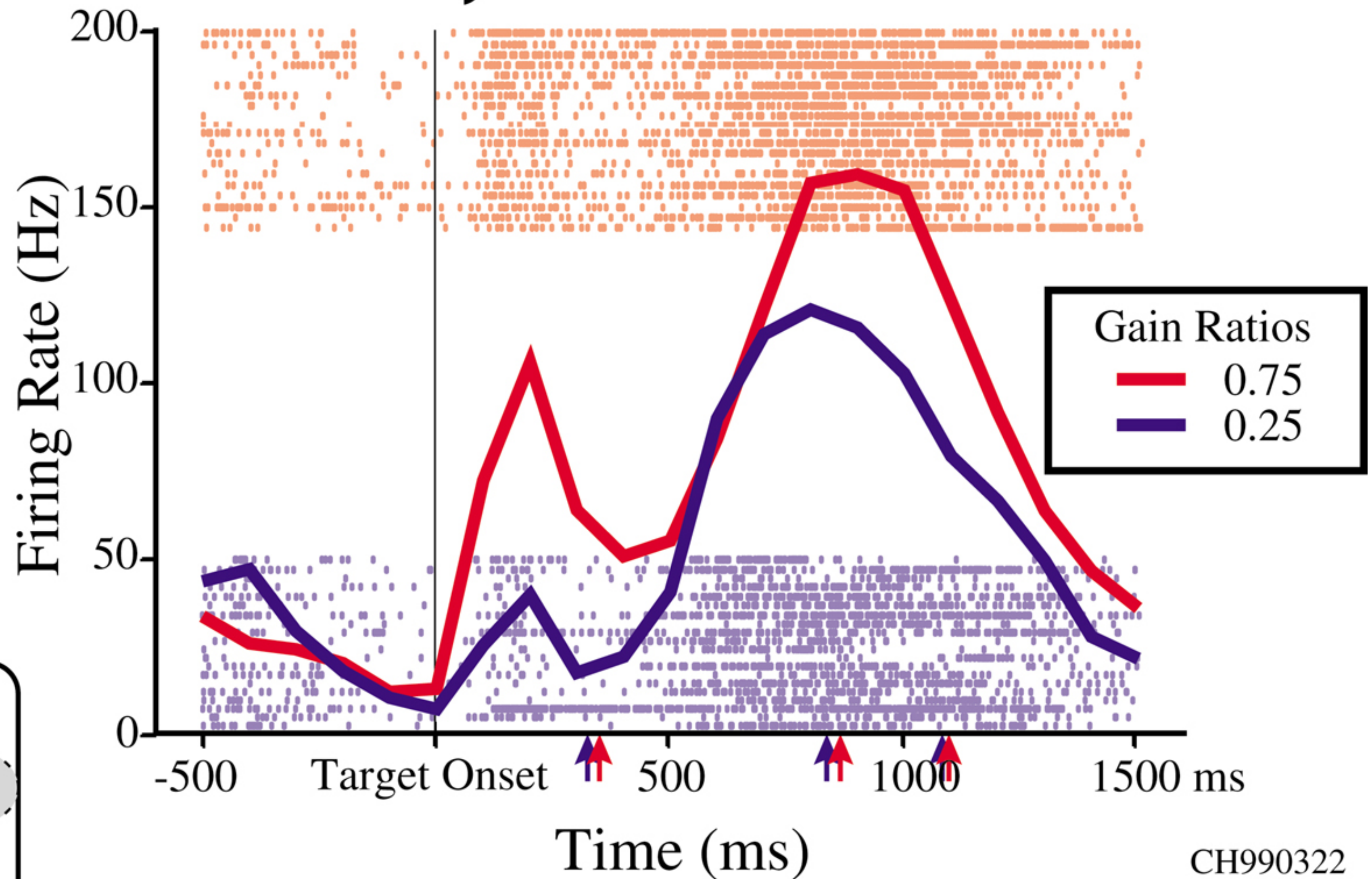


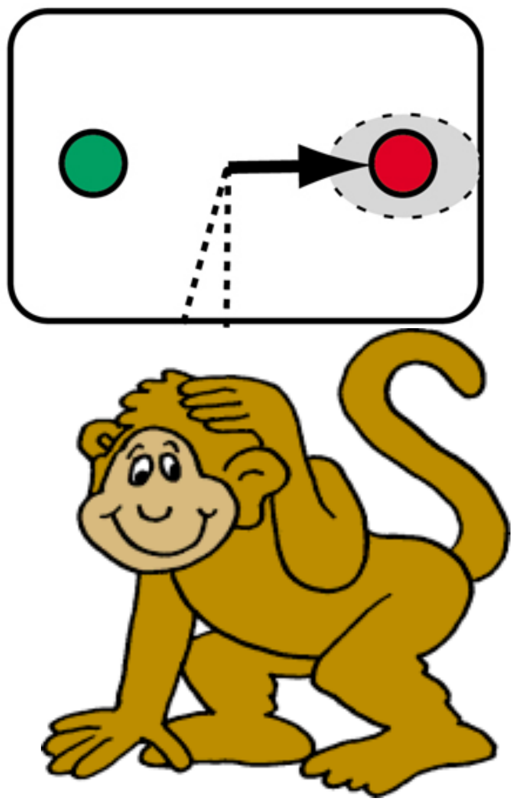
So What Happens When We Vary Value?



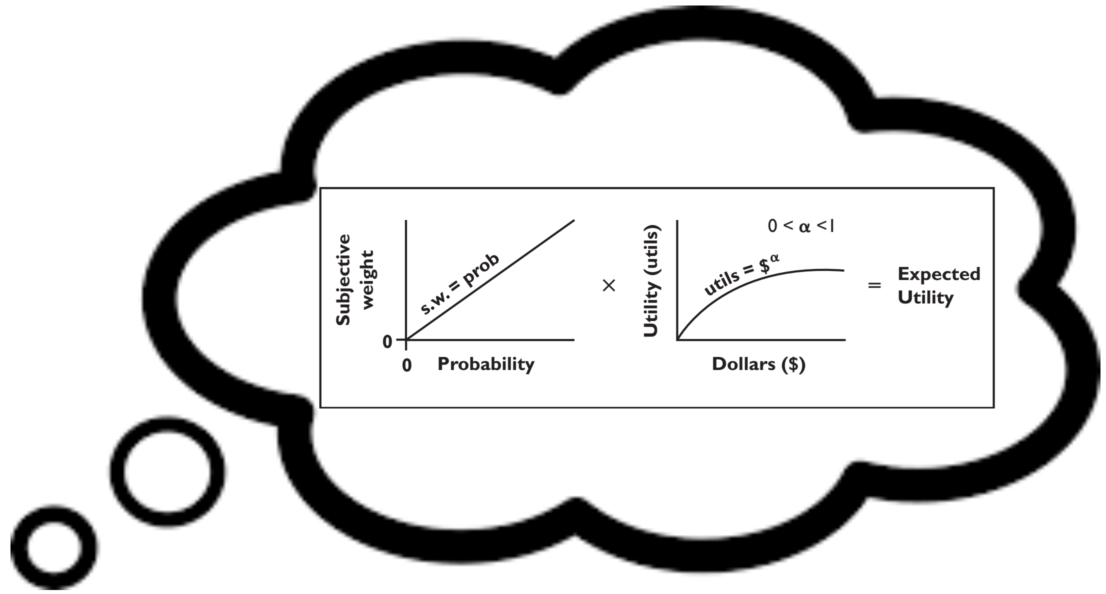
Platt and Glimcher, 1999

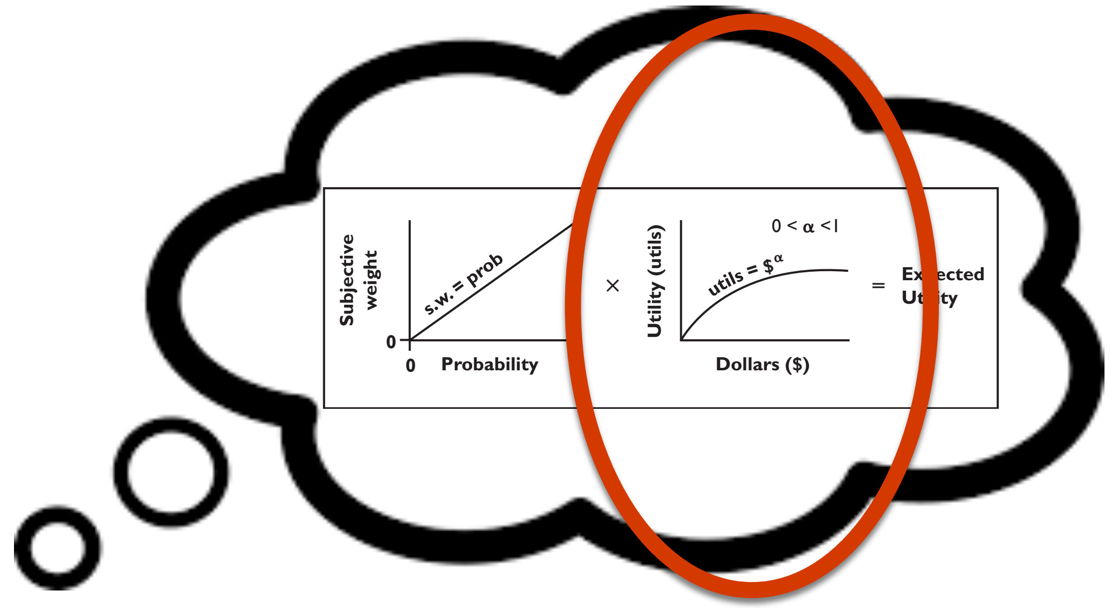
Same Movement, Different Values

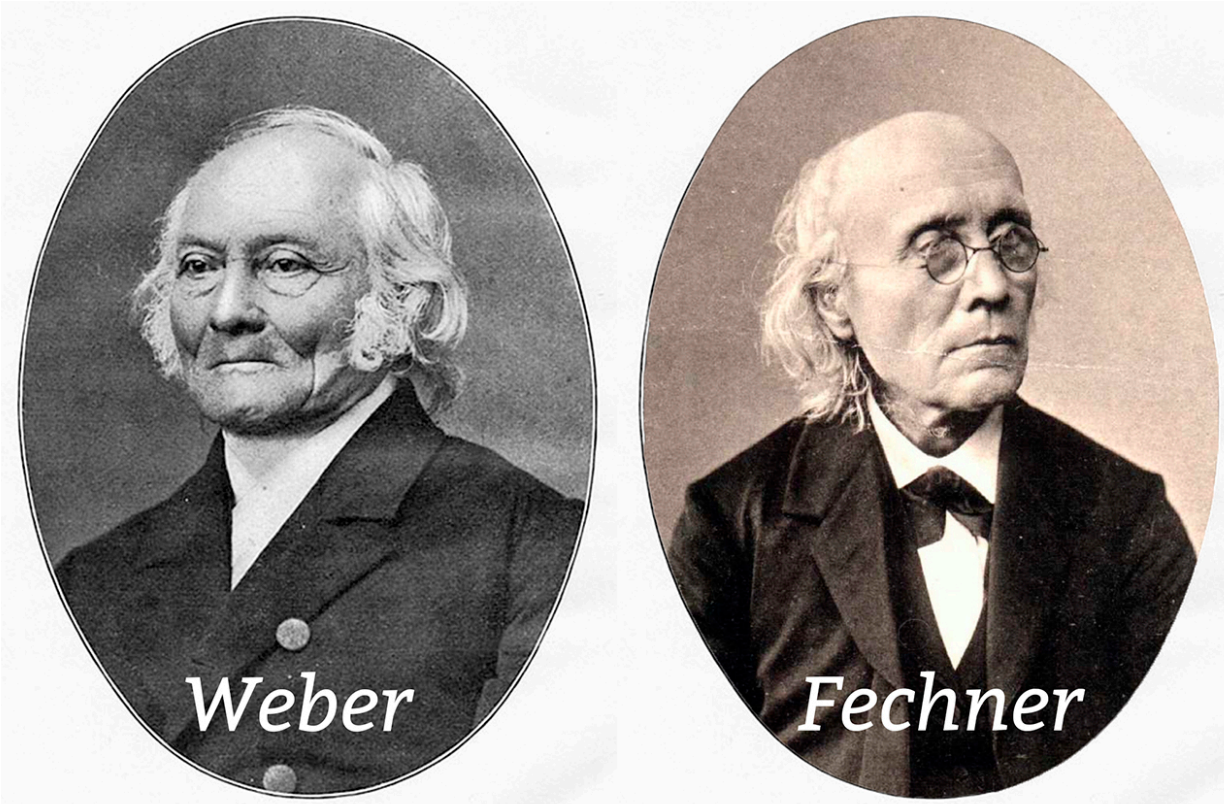


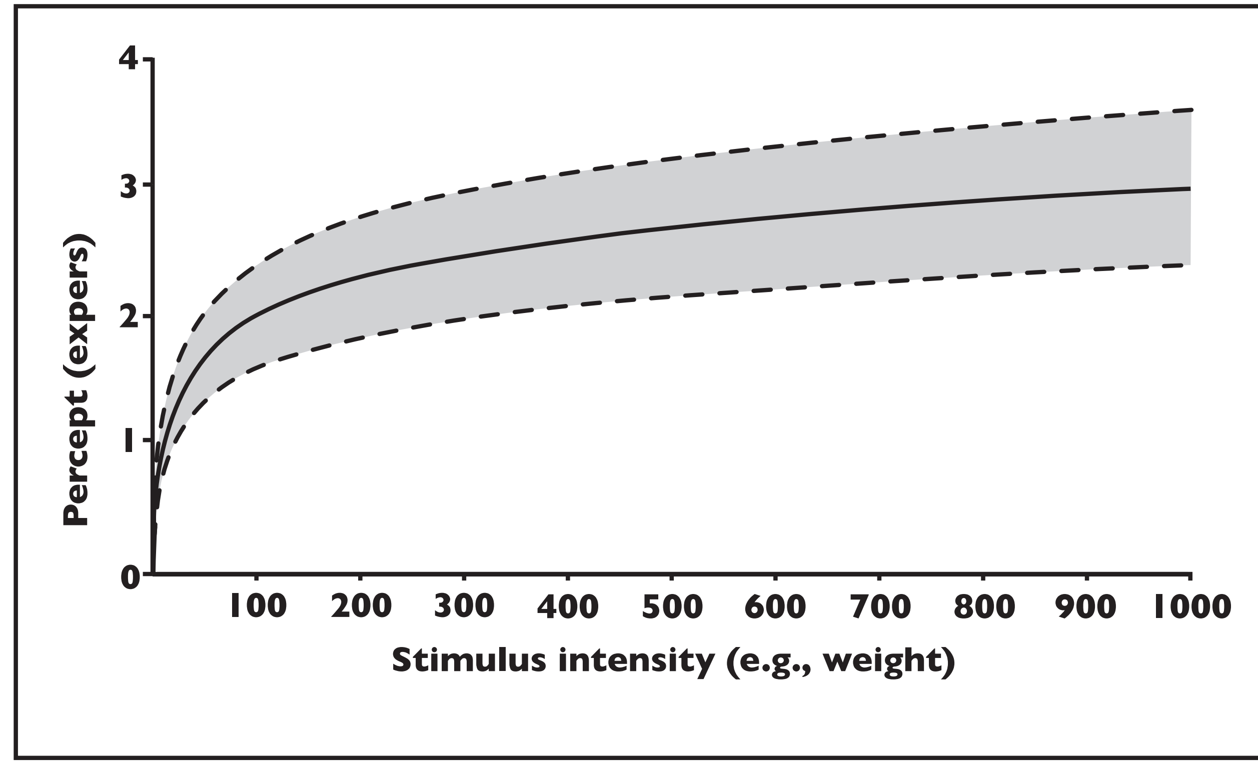


Large Reward Expectation
Small Reward Expectation


Subjective weight
s.w. = prob
0
0
Probability
×
Utility (utils)
0 < α < 1
utils = $^α
Dollars ($)
=
Expected Utility

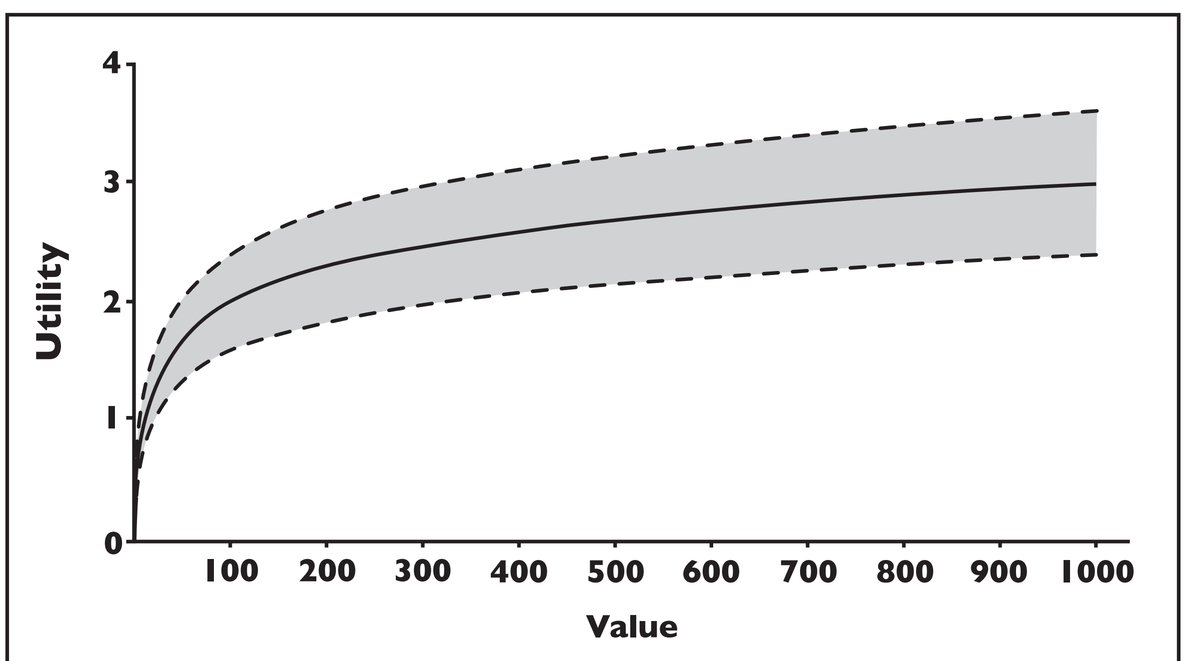

Subjective weight
s.w. = prob
0
0
Probability
×
Utility (utils)
0 < α < I
utils = $^α
Dollars ($)
=



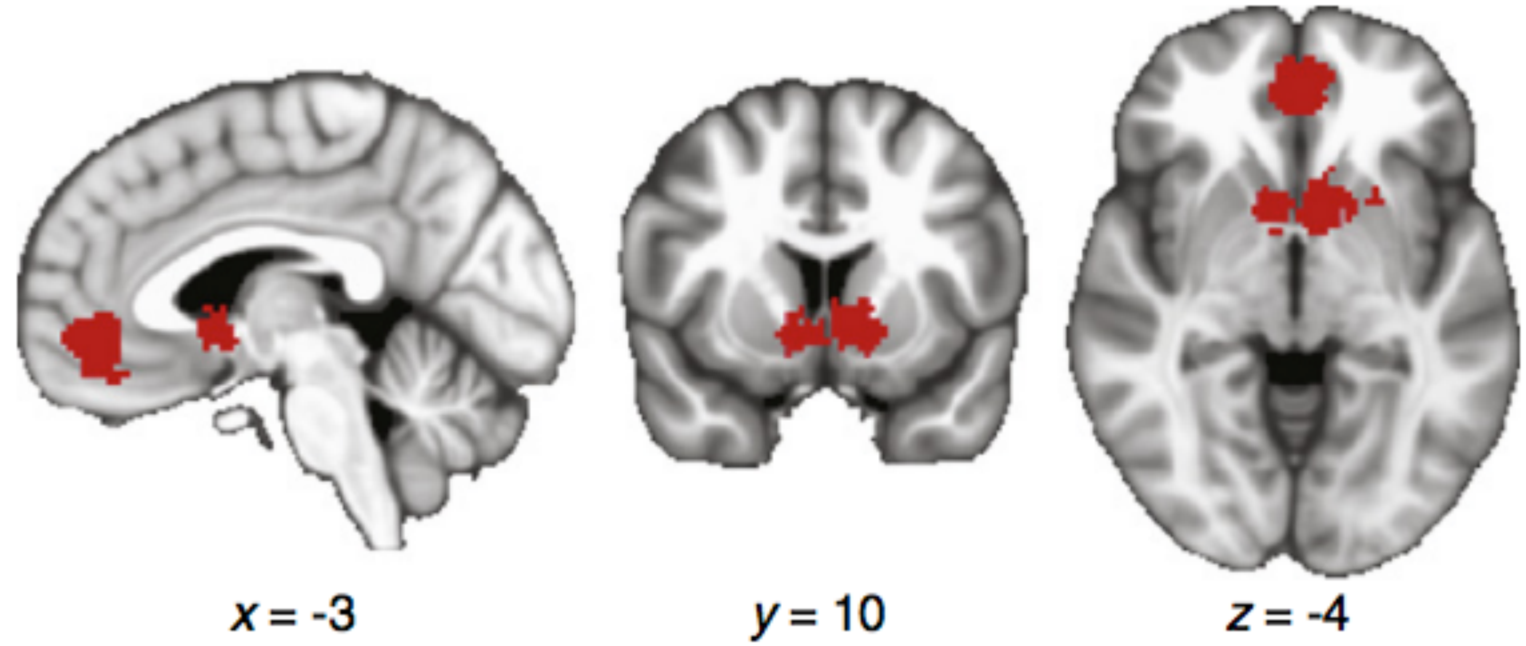


Daniel McFadden

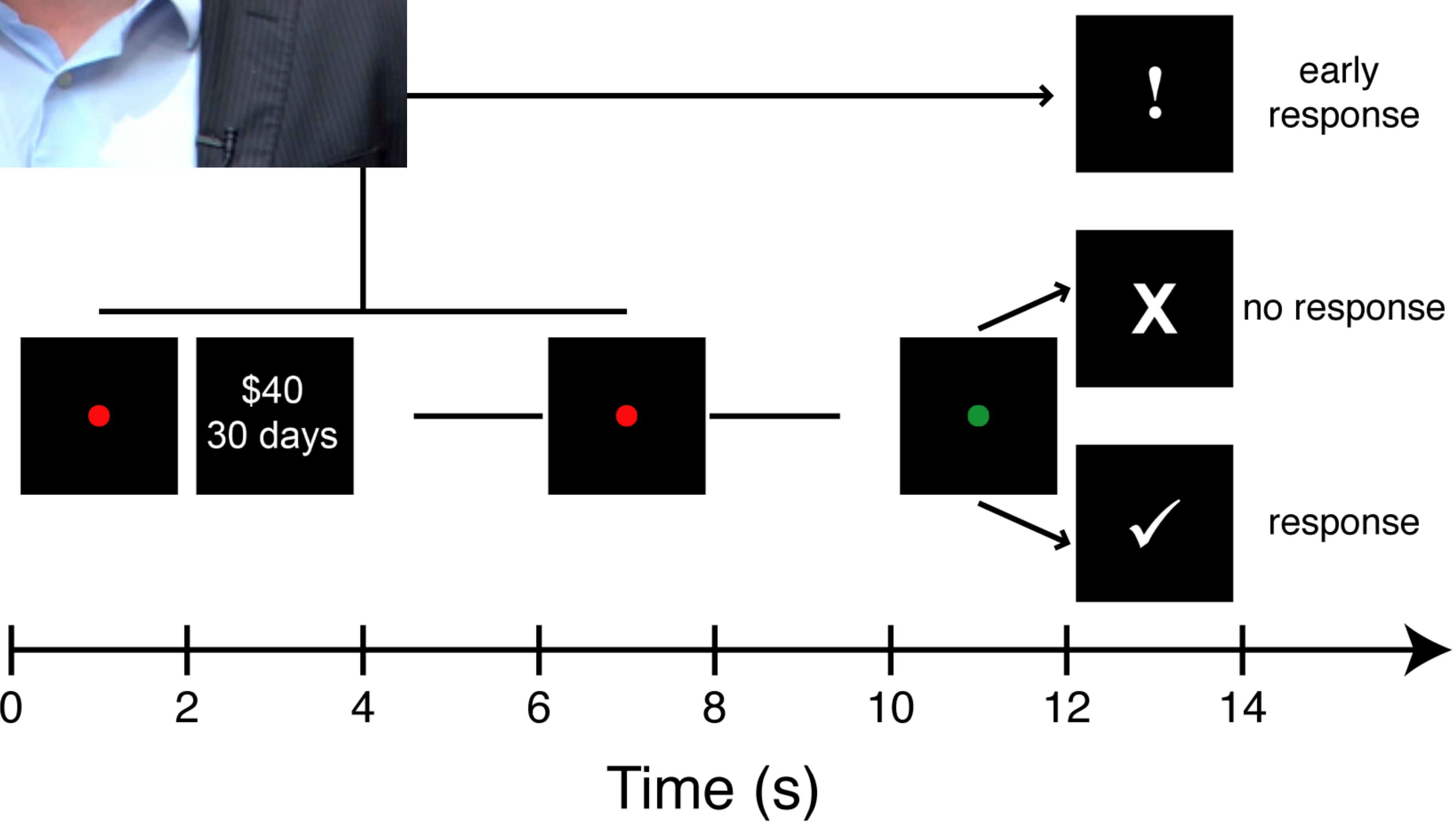
Random Utility Theory



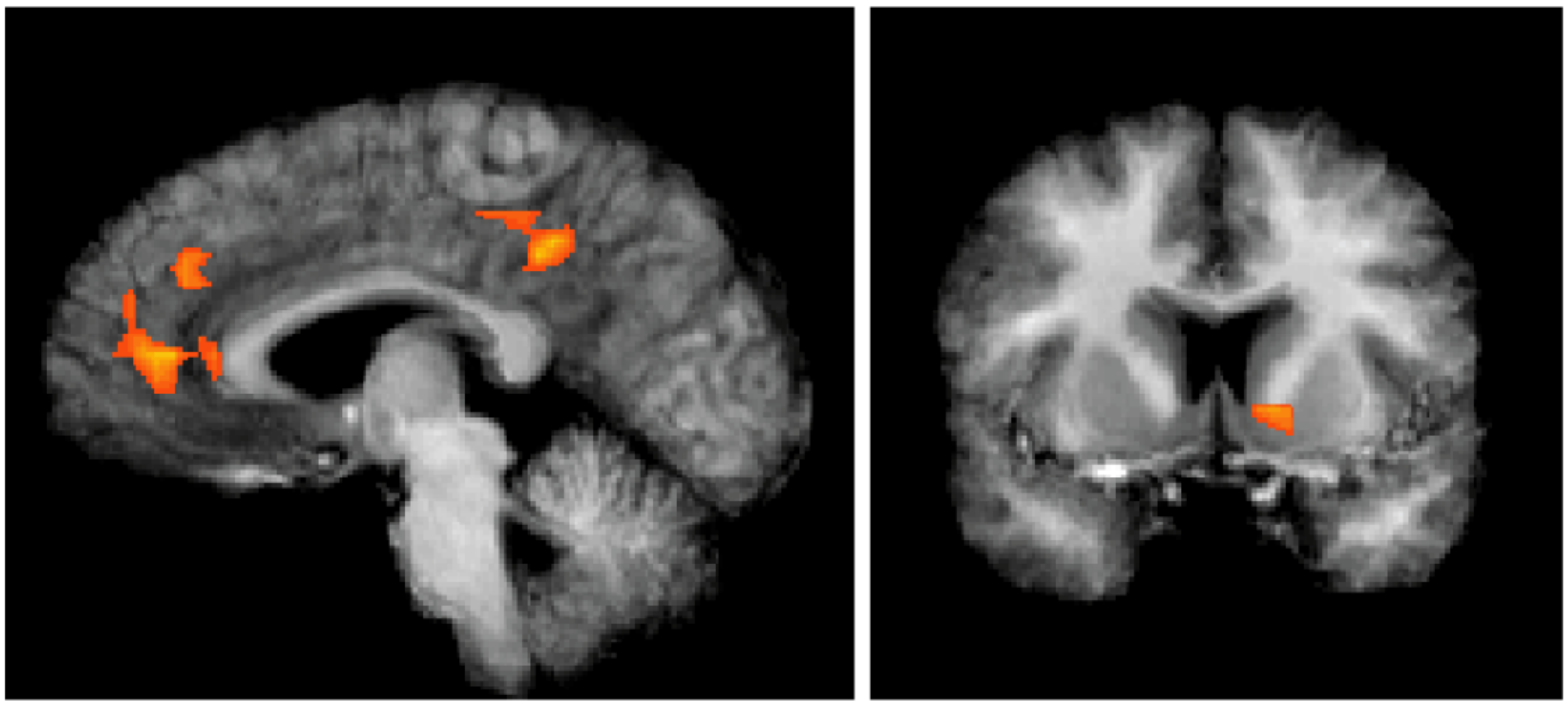
Knutson, Delgado and Elliott



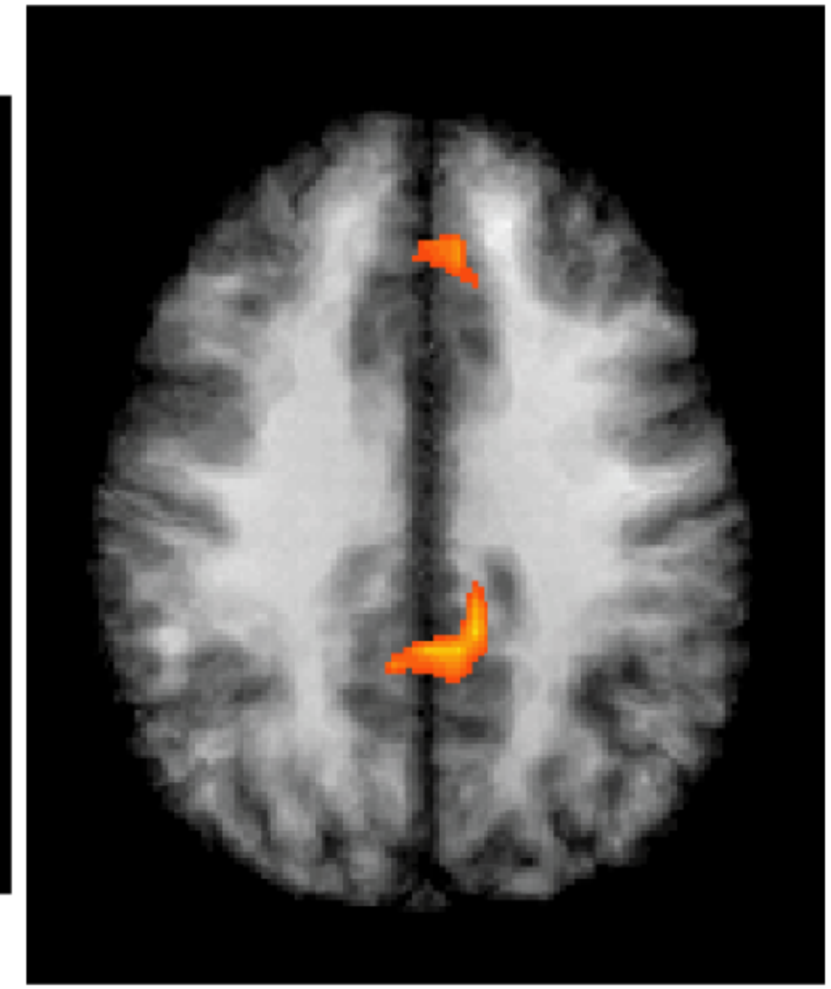
Joe Kable


early response
!
X
no response
$40
30 days
response
0
2
4
6
8
10
12
14
Time (s)

Correlation with Subjective Value

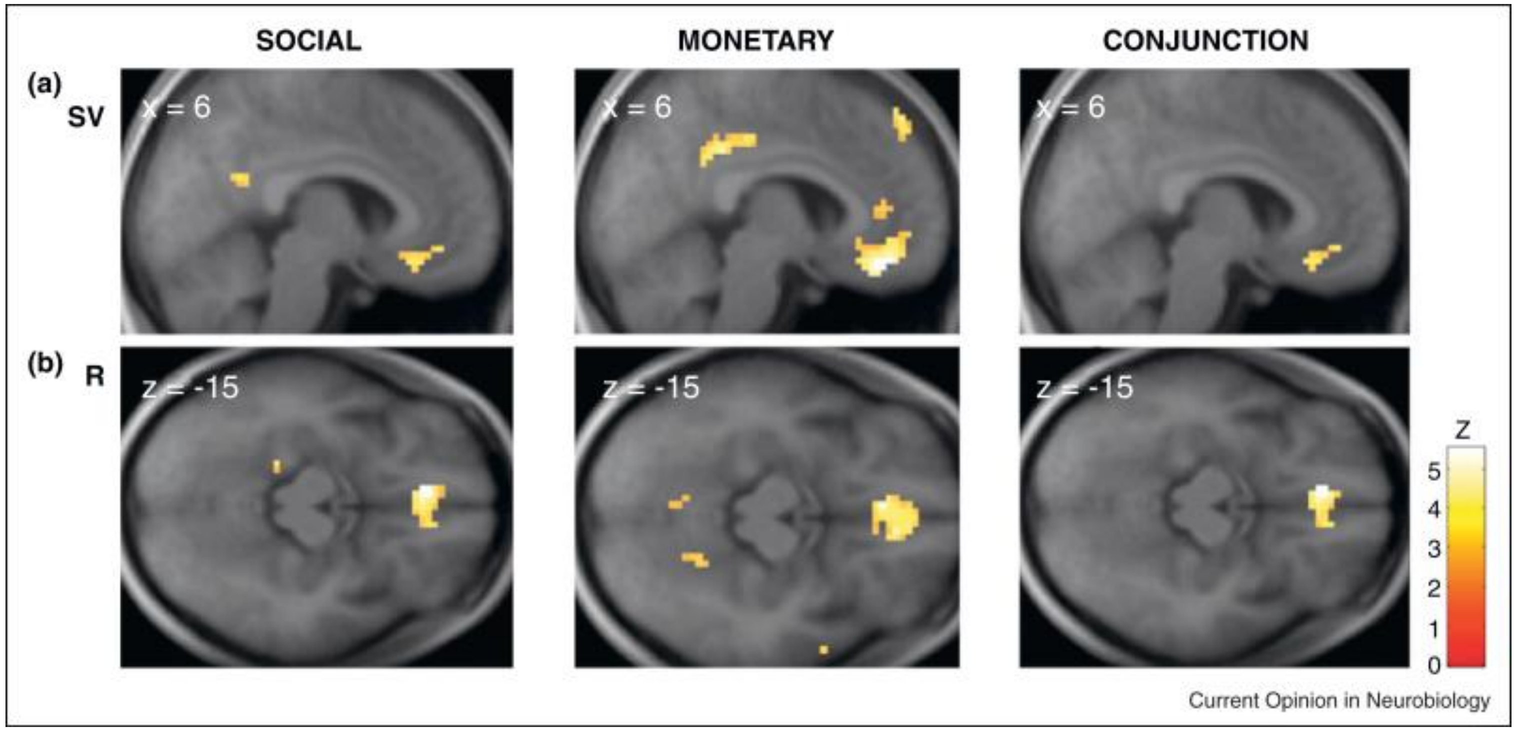


Random effect (n=10), TRs 4-6



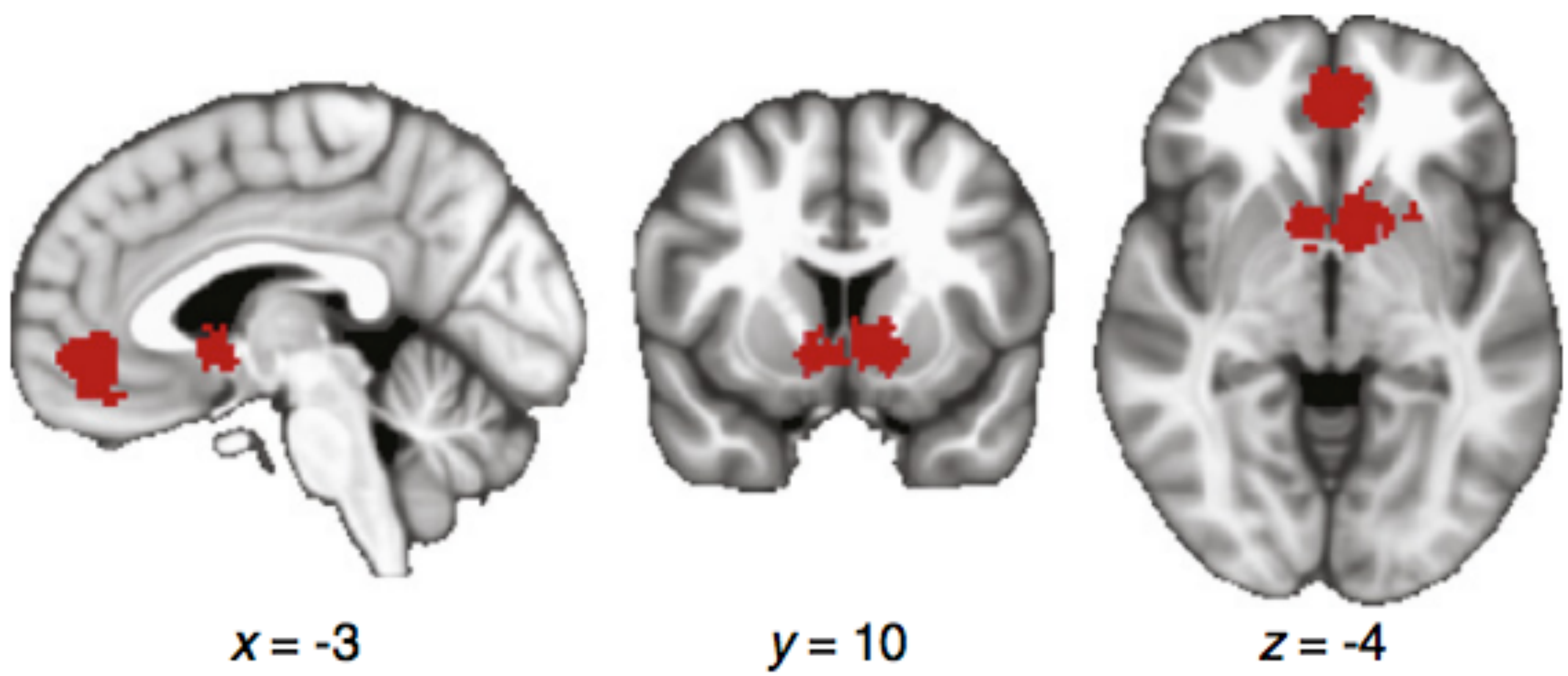
p<.005
(uncorrected)

p<.05,
(corrected, FDR)

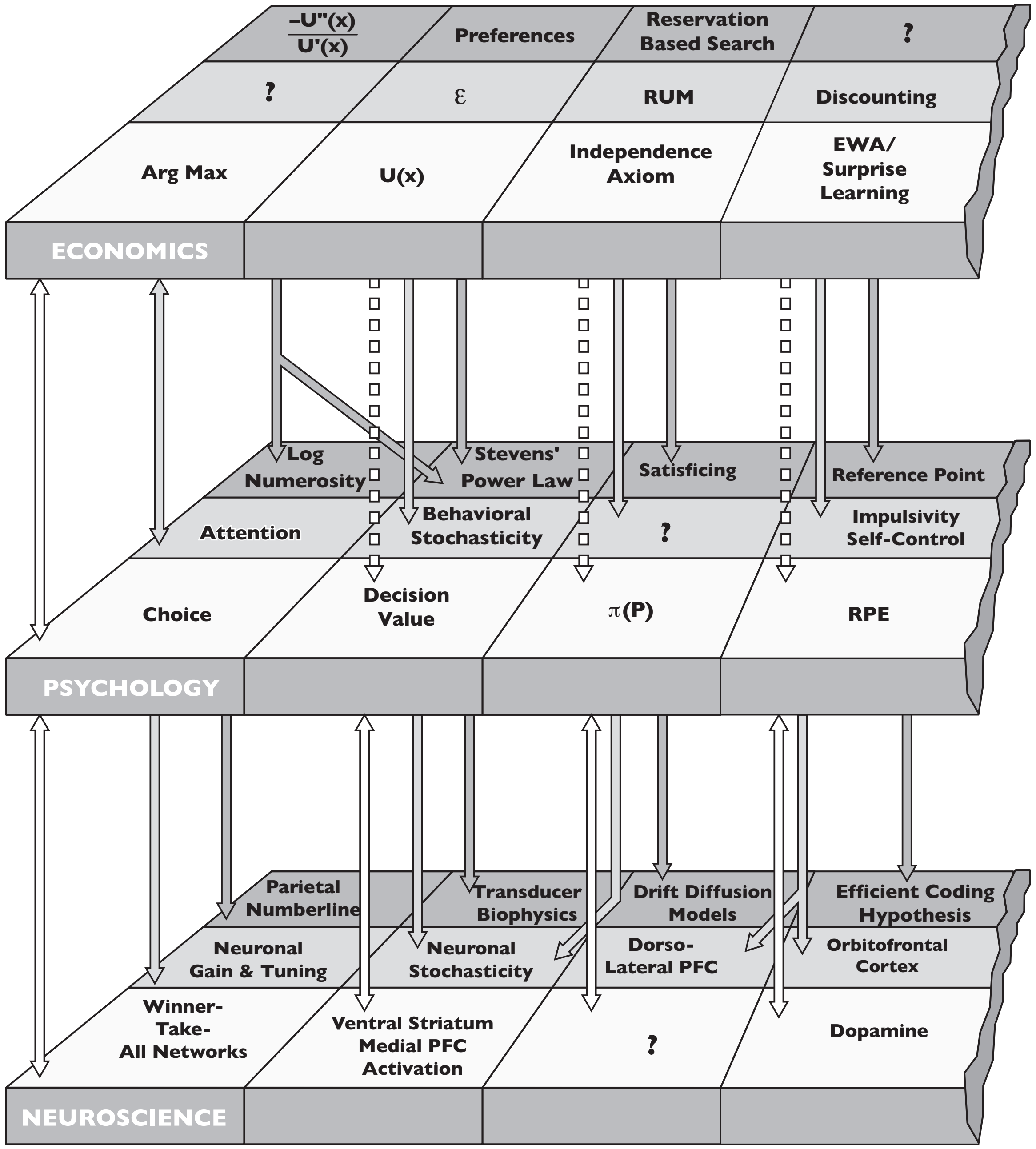


Levy and Glimcher

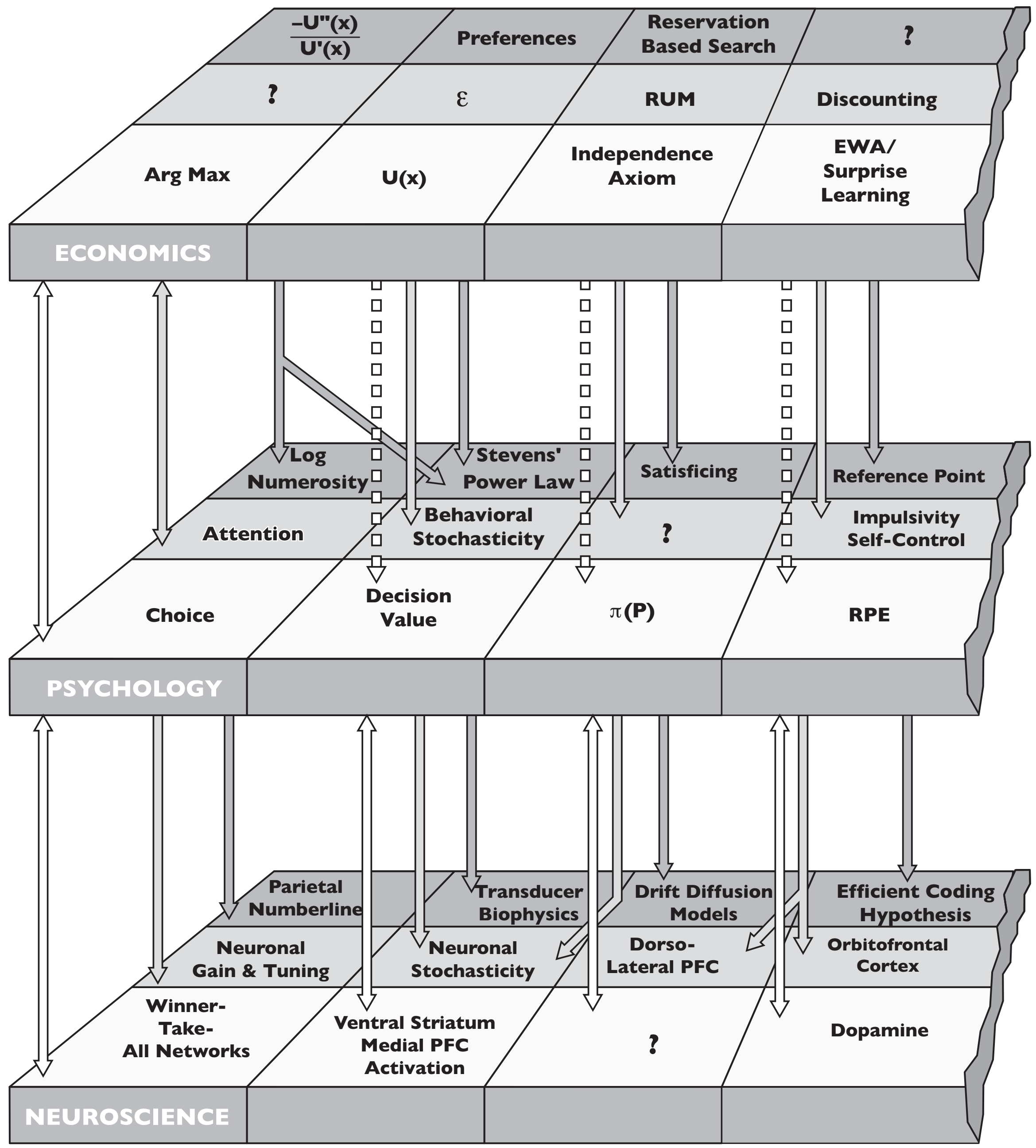
Bartra, McGuire and Kable



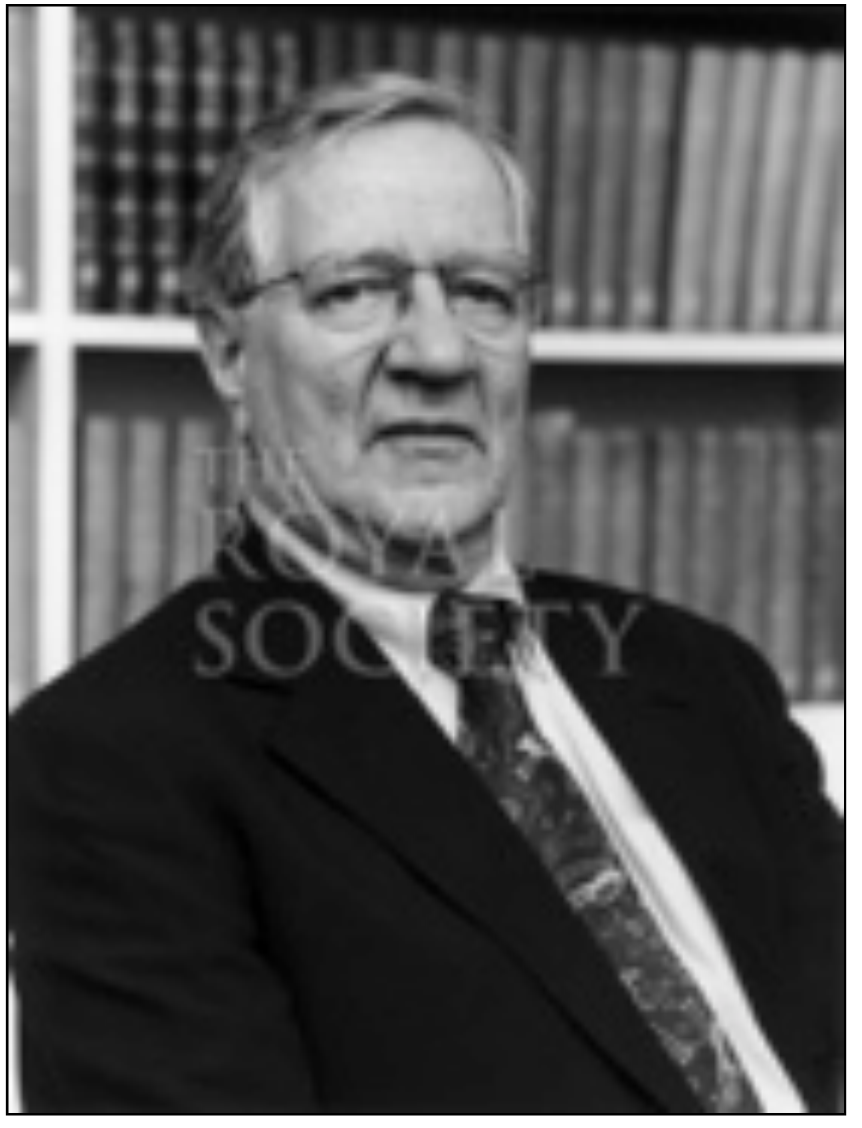
Up to this point:



When?


–U"(x) / U'(x)
Preferences
Reservation Based Search
?
?
ε
RUM
Discounting
Arg Max
U(x)
Independence Axiom
EWA/ Surprise Learning
ECONOMICS
Log Numerosity
Stevens' Power Law
Satisficing
Reference Point
Attention
Behavioral Stochasticity
?
Impulsivity Self-Control
Choice
Decision Value
π(P)
RPE
PSYCHOLOGY
Parietal Numberline
Transducer Biophysics
Drift Diffusion Models
Efficient Coding Hypothesis
Neuronal Gain & Tuning
Neuronal Stochasticity
Dorso-Lateral PFC
Orbitofrontal Cortex
Winner-Take-All Networks
Ventral Striatum Medial PFC Activation
?
Dopamine
NEUROSCIENCE

An Image

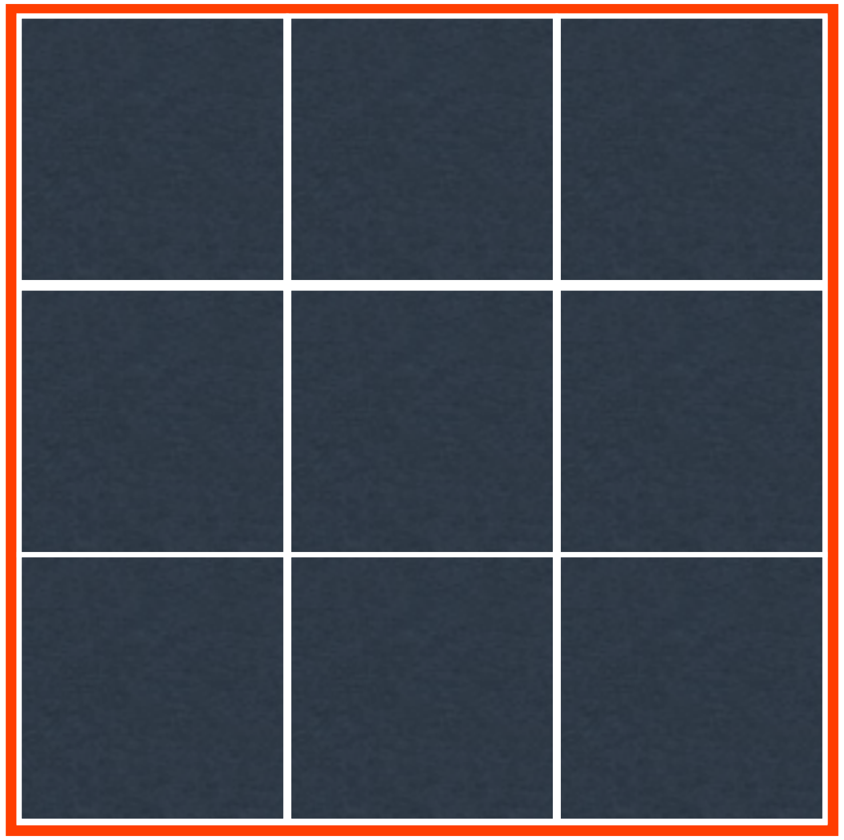


Horace Barlow

An Image

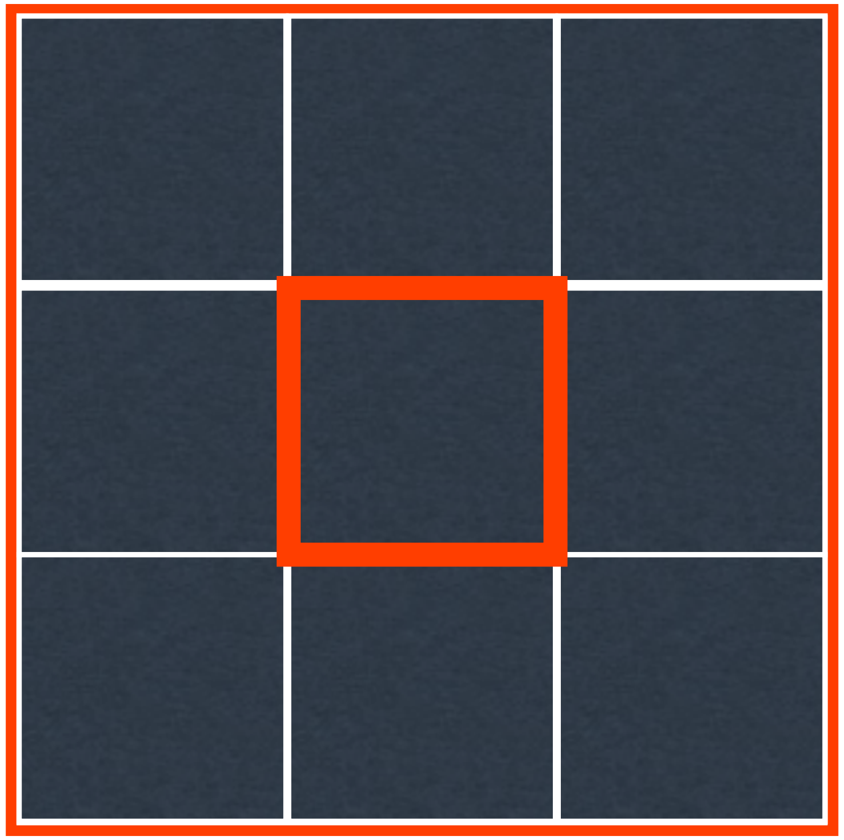
Horace Barlow

9 Pixels



Probability Pixel is Black: Conditional on Adjacent Pixel Being Black: 0.75

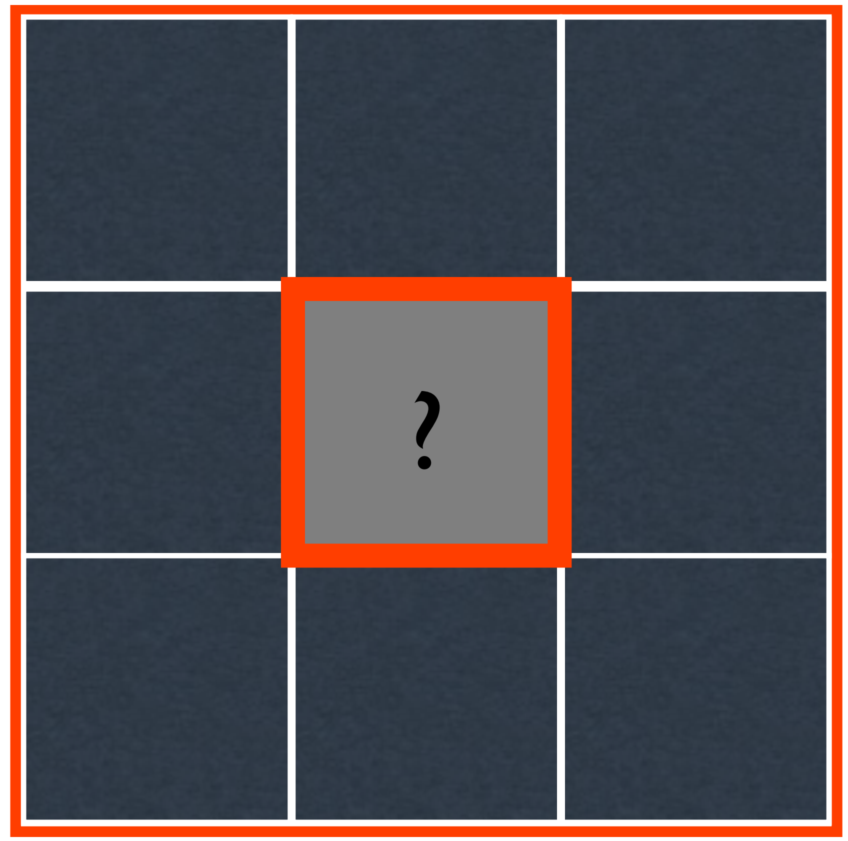
9 Pixels



Black = 10spikes
While = 0 Spikes

90 Spikes Total

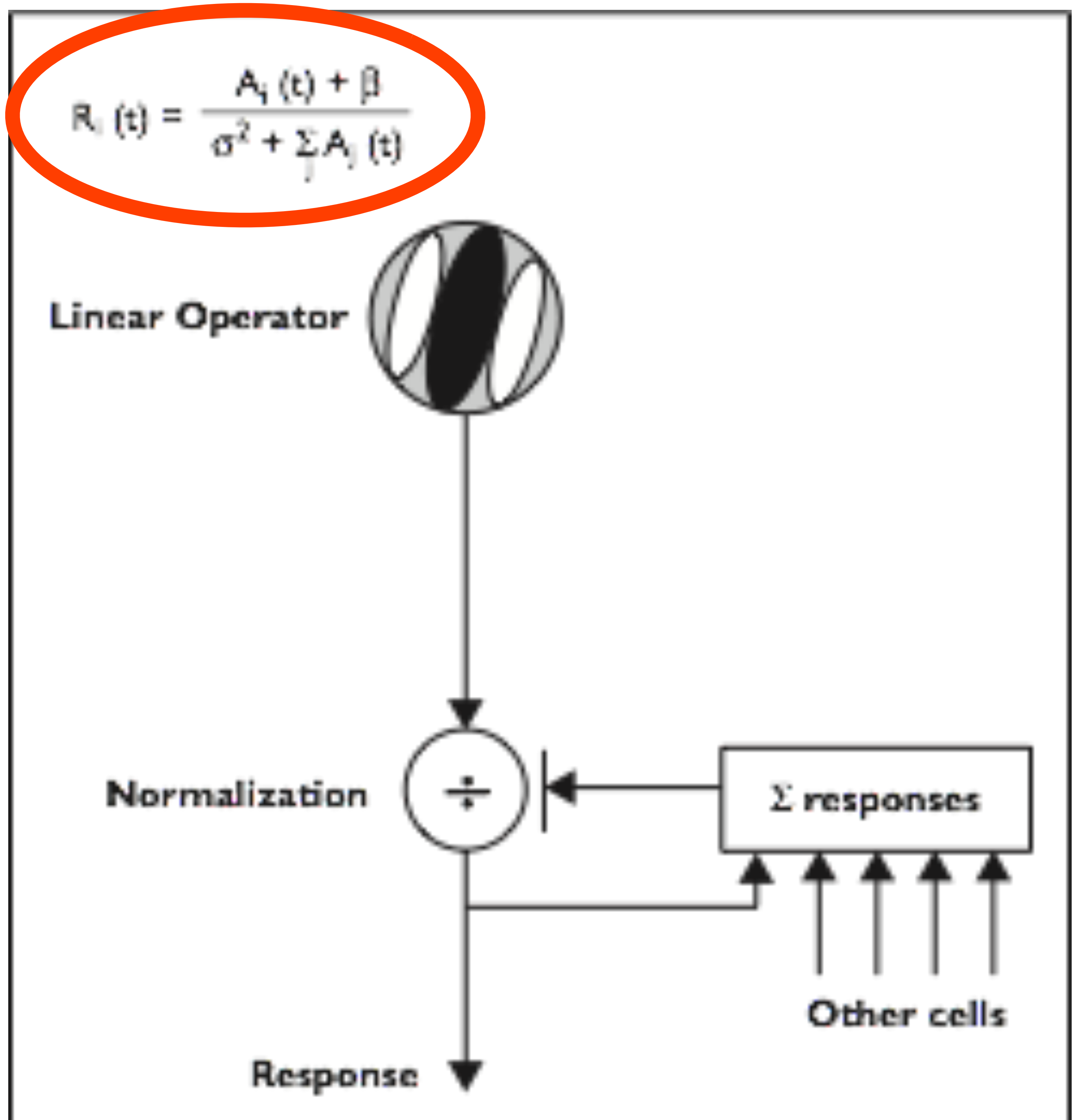
9 Pixels



Conditional on these 8 pixels being black the ex ante probability of the center being black is ~ 1.

So Why Waste Spikes

Heeger Normalization



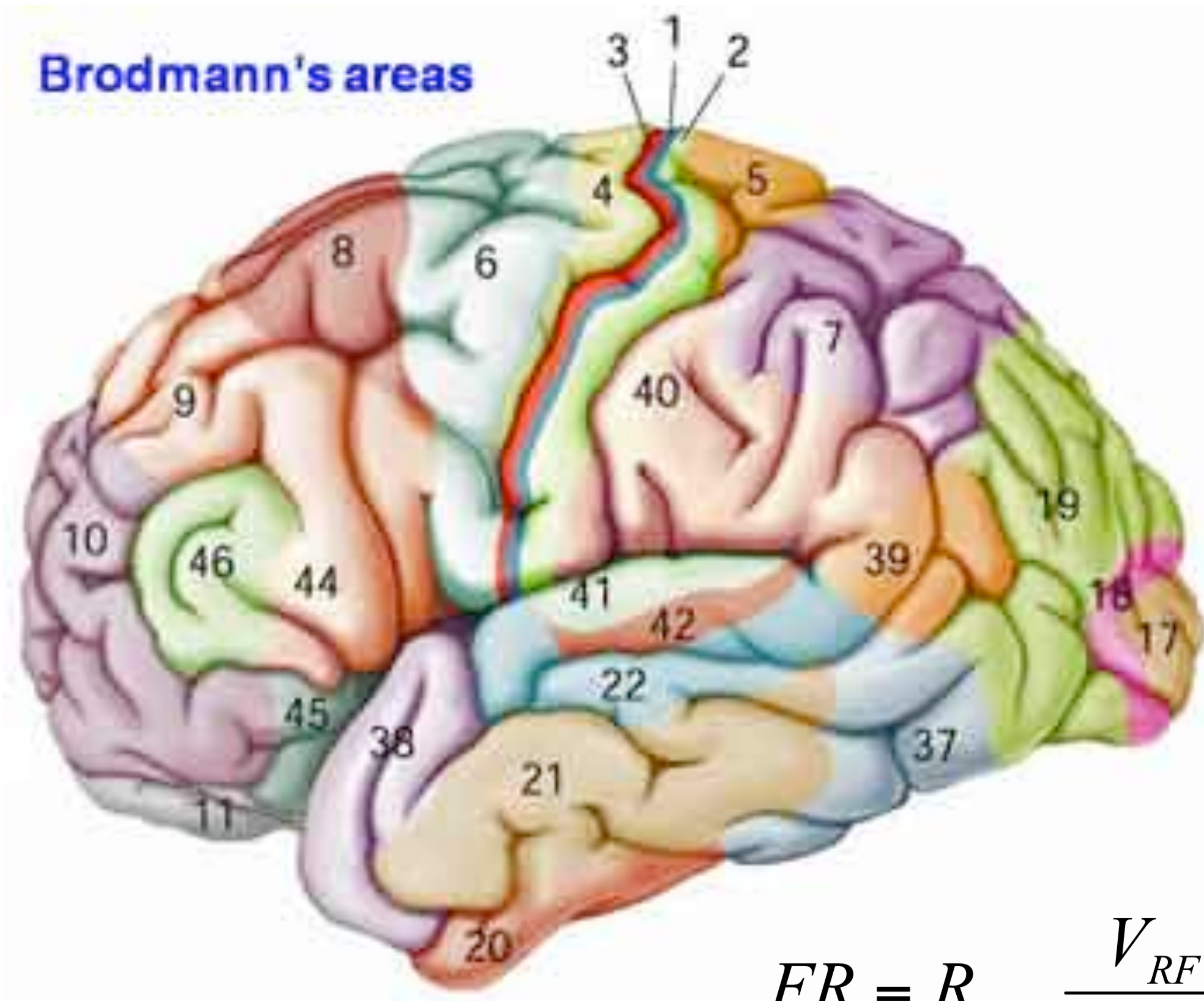
Adapted from Heeger, 1993

Eero Simoncelli and Co. Showed That:

For any given pixel to pixel correlation structure there is a set of w_i's such that the minimum number of spikes is used per bit of information

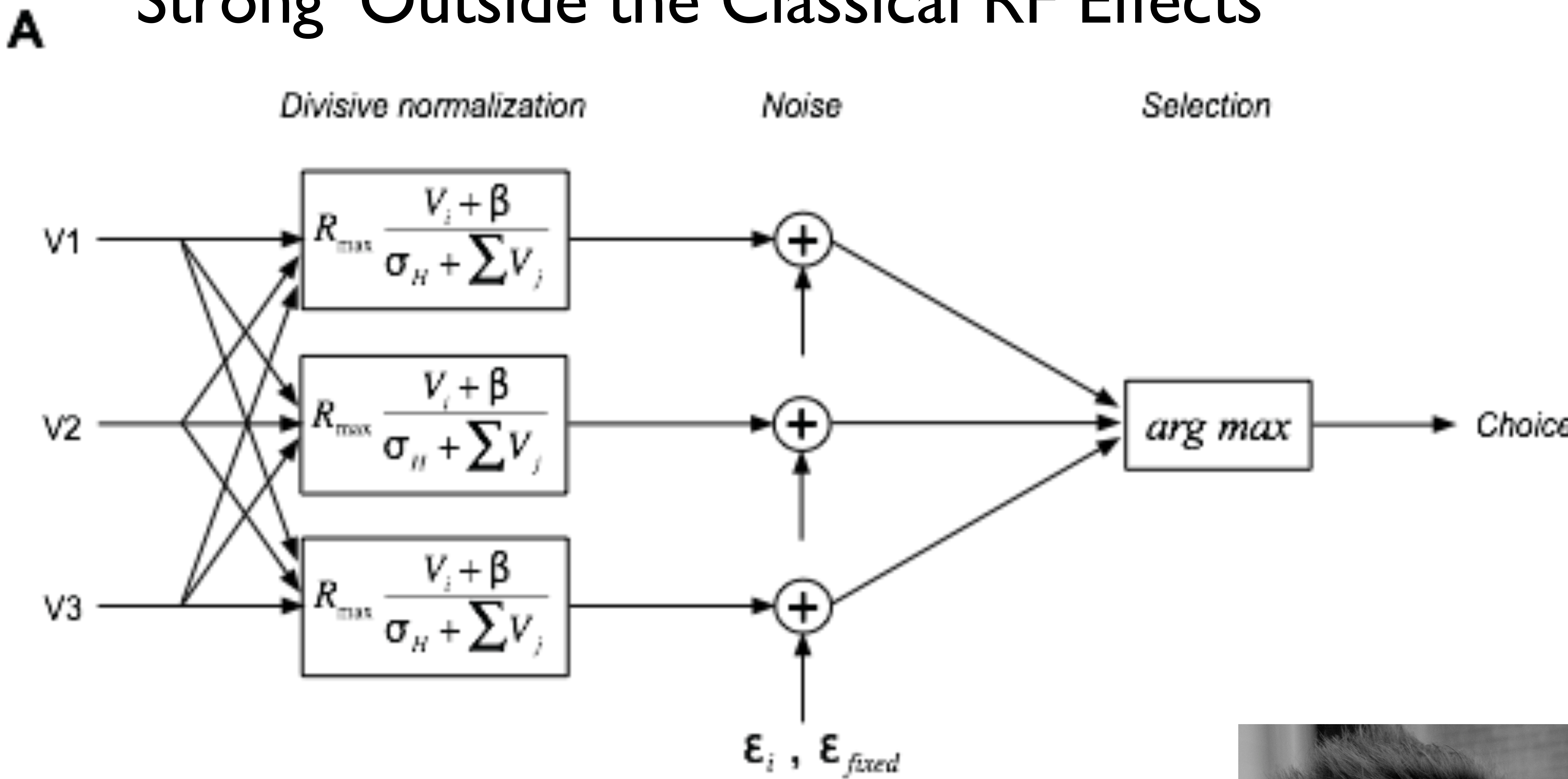
$$FR = R_{\max} \frac{V_{RF} + \beta}{\sigma^2 + \sum_j V_j w_j}$$

This is a form of decorrelation

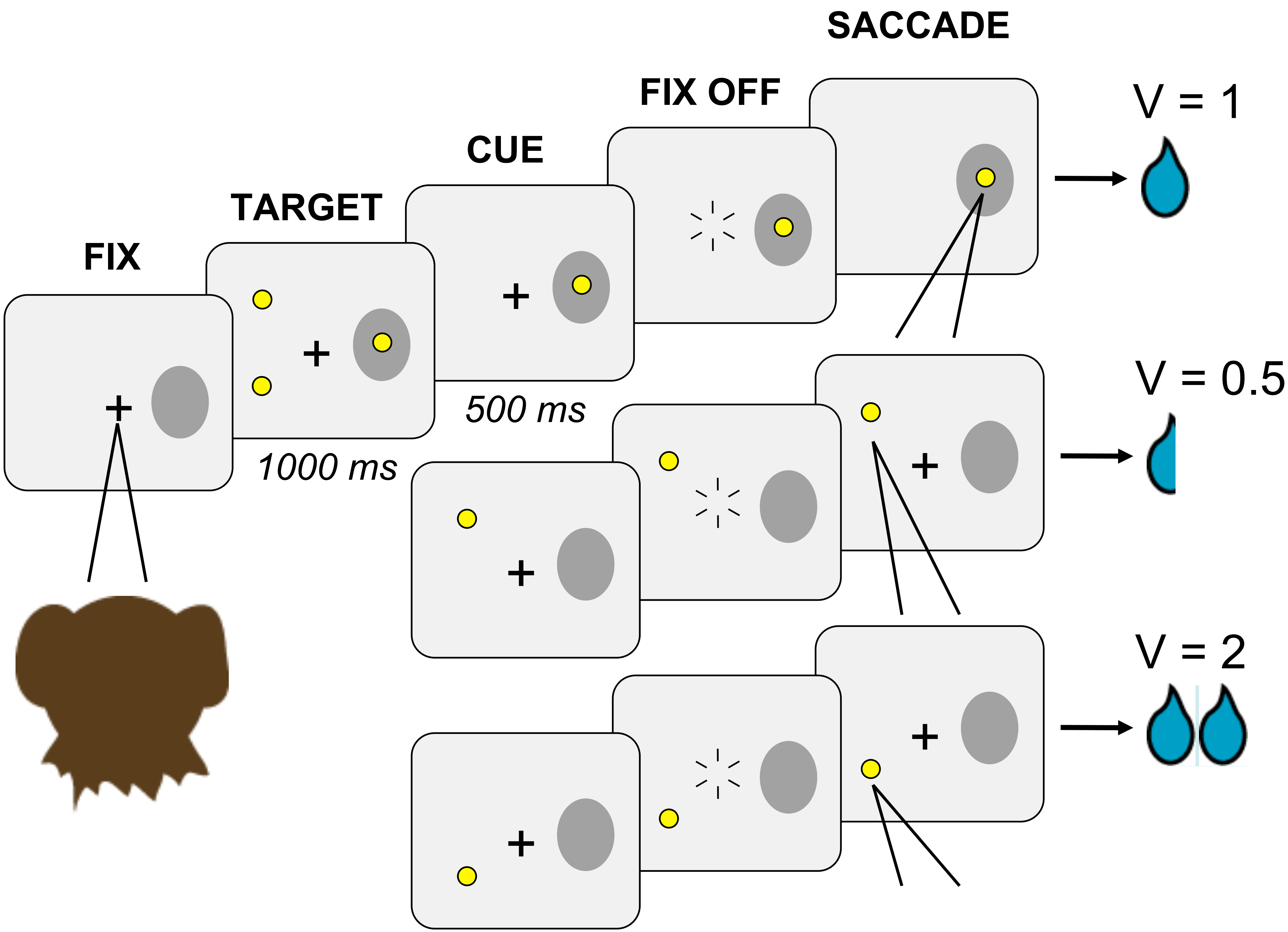


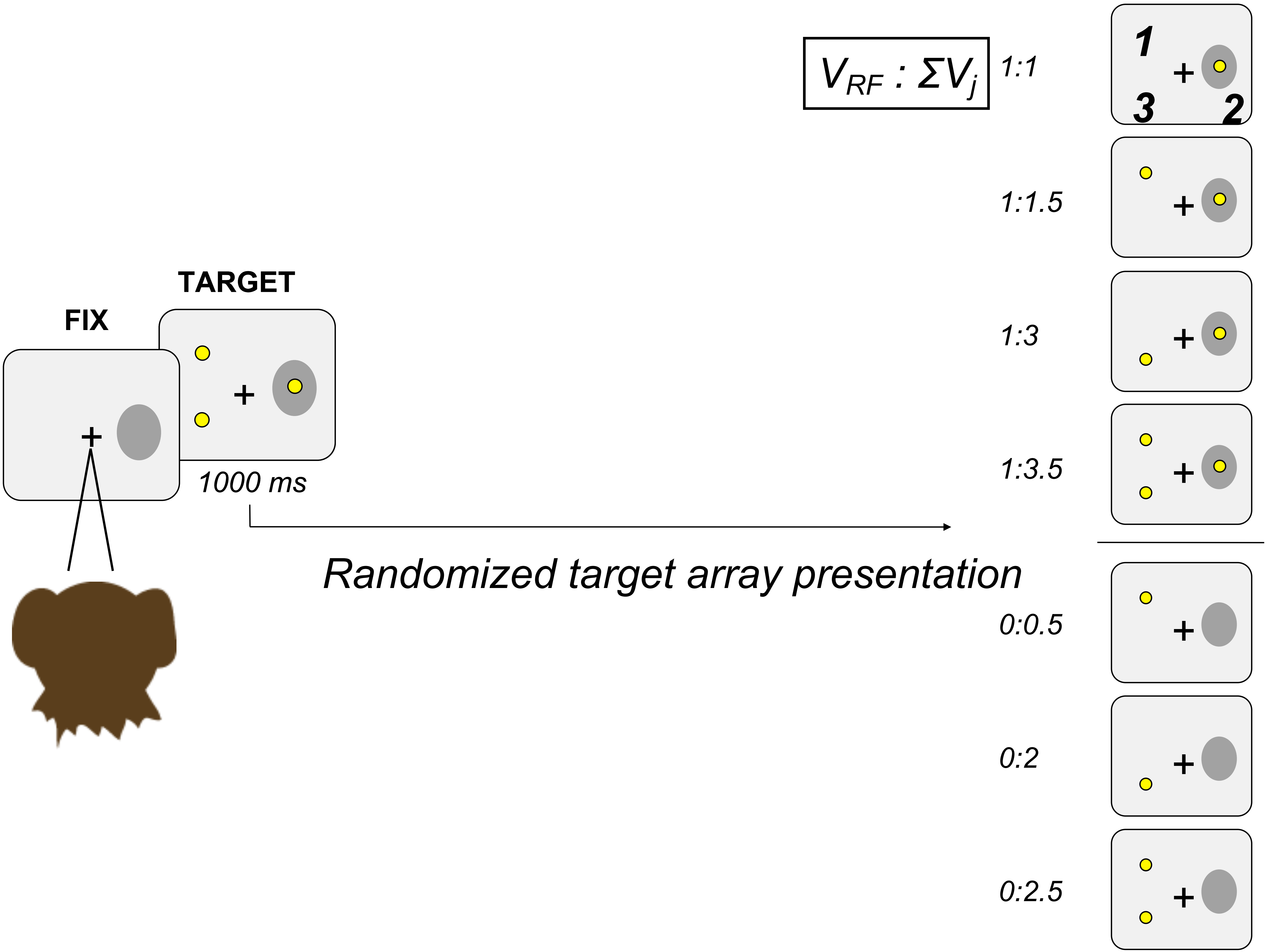
$$FR = R_{\max} \frac{V_{RF} + \beta}{\sigma^2 + \sum_j V_j}$$

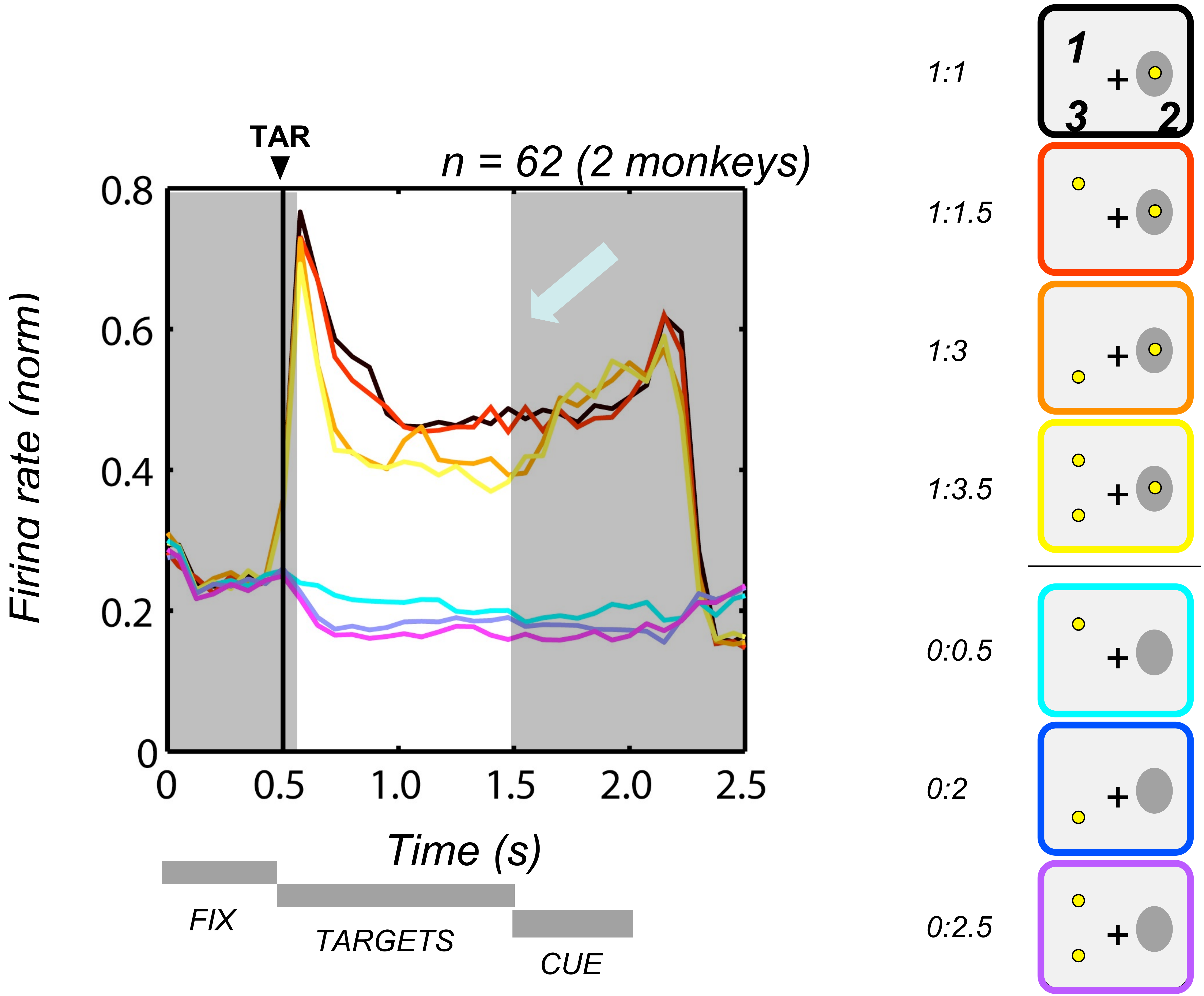
These Kinds of Networks Yield Strong 'Outside the Classical RF Effects'



Is There Evidence of Normalization in Choice-Related Circuits?

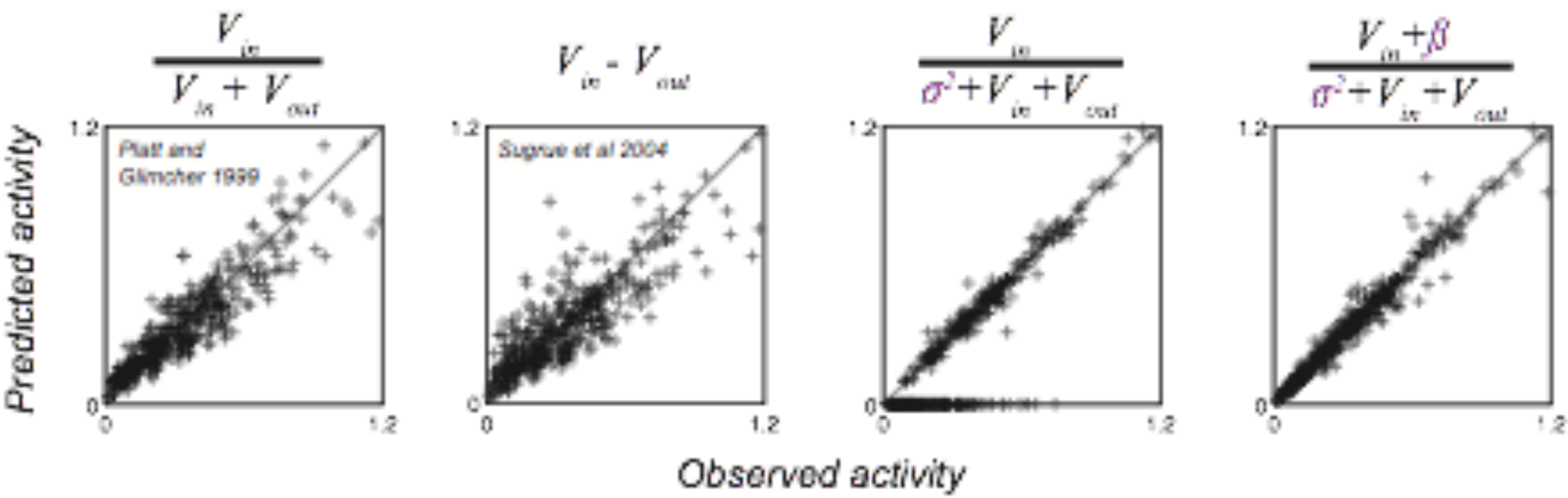

SACCADE
FIX OFF
CUE
TARGET
FIX
1000 ms
500 ms
V = 1
V = 0.5
V = 2


$V_{RF} : \Sigma V_j$
1:1
1
2
3
1:1.5
1:3
1:3.5
TARGET
FIX
1000 ms
Randomized target array presentation
0:0.5
0:2
0:2.5



TAR
n = 62 (2 monkeys)
Firing rate (norm)
0.8
0.6
0.4
0.2
0
0
0.5
1.0
1.5
2.0
2.5
Time (s)
FIX
TARGETS
CUE
1:1
1
3
2
1:1.5
1:3
1:3.5
0:0.5
0:2
0:2.5

Comparing Models Across the Dataset



Platt & Glimcher

Sugrue, Corrado & Newsome

Heeger

Heeger & Reynolds

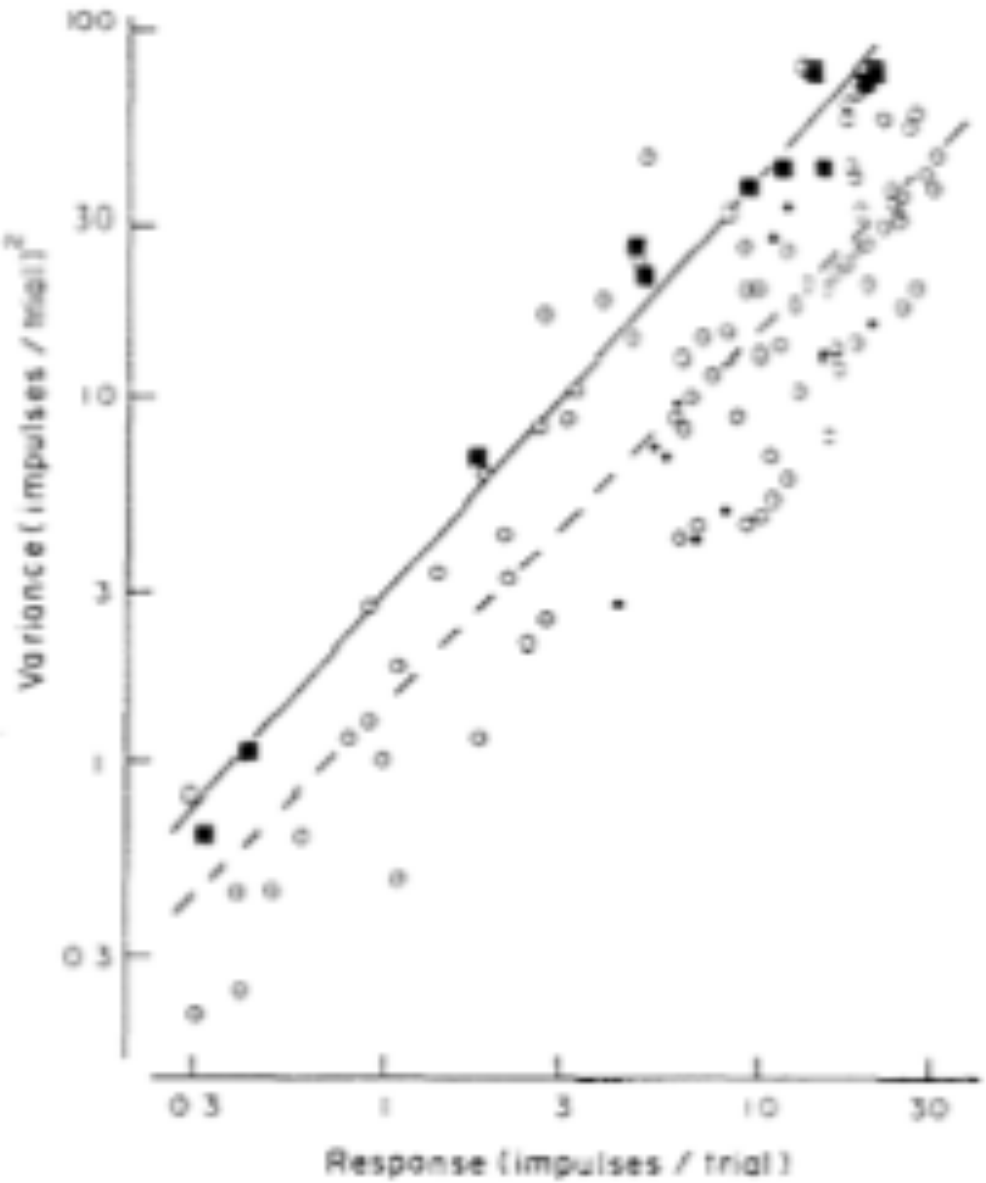
If There is Normalization, Would it Influence Choice Behavior?

The Three Option Problem

For Neurons:

- Variance Scales with Mean
- Variance is the average **Squared** distance from the mean
- Thus as means reduce, discriminablility goes down

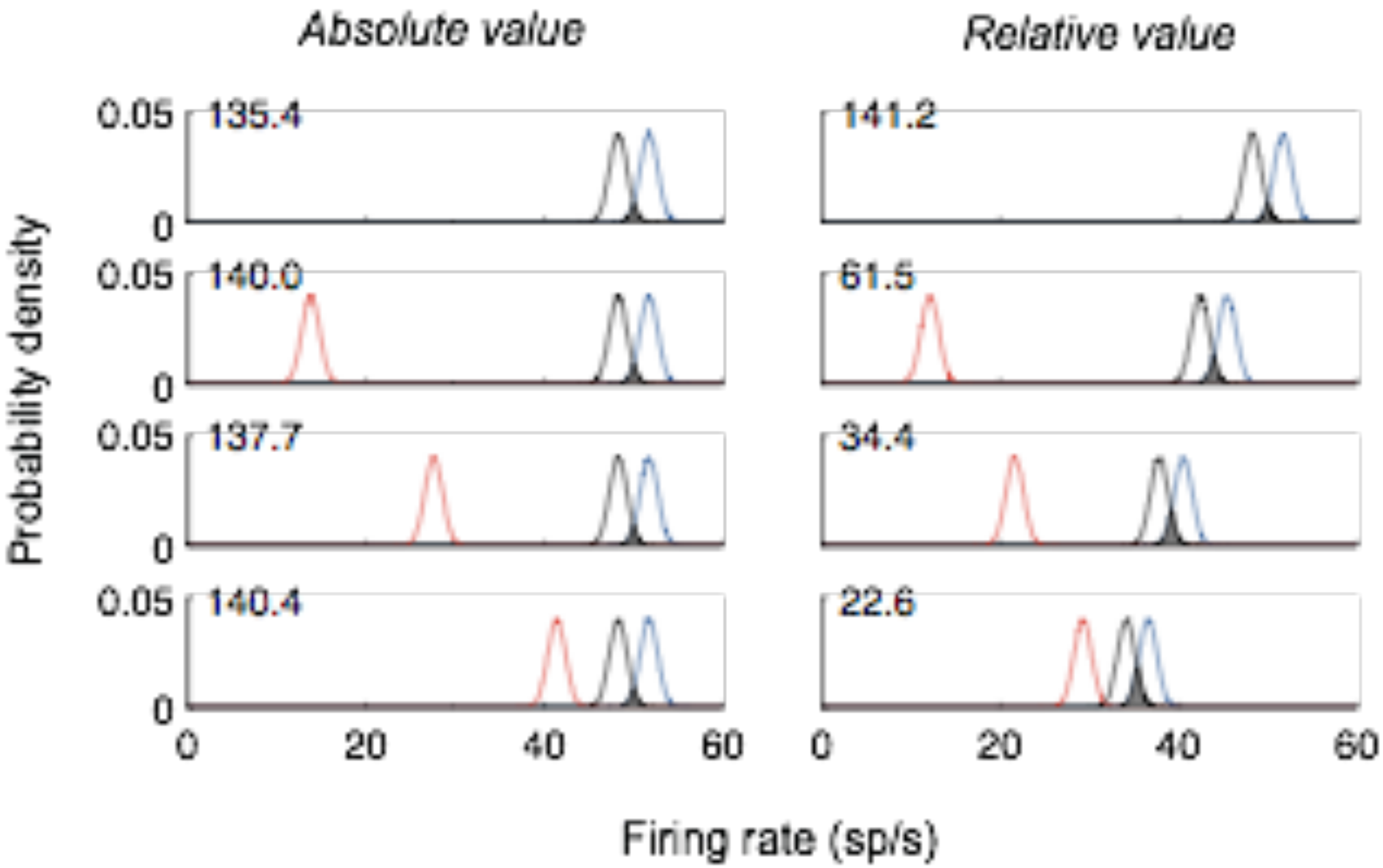
Variance



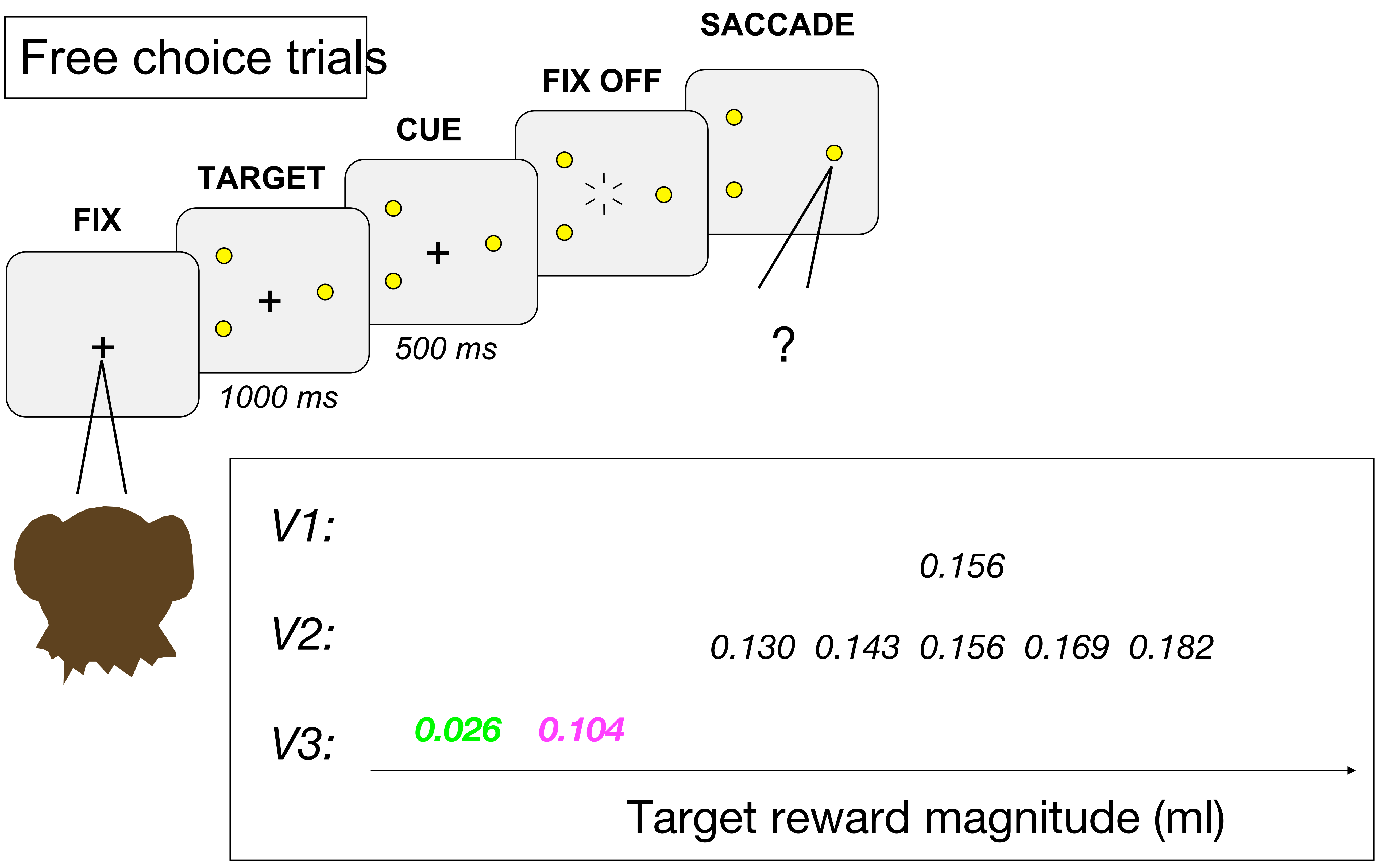
Neuronal Rate

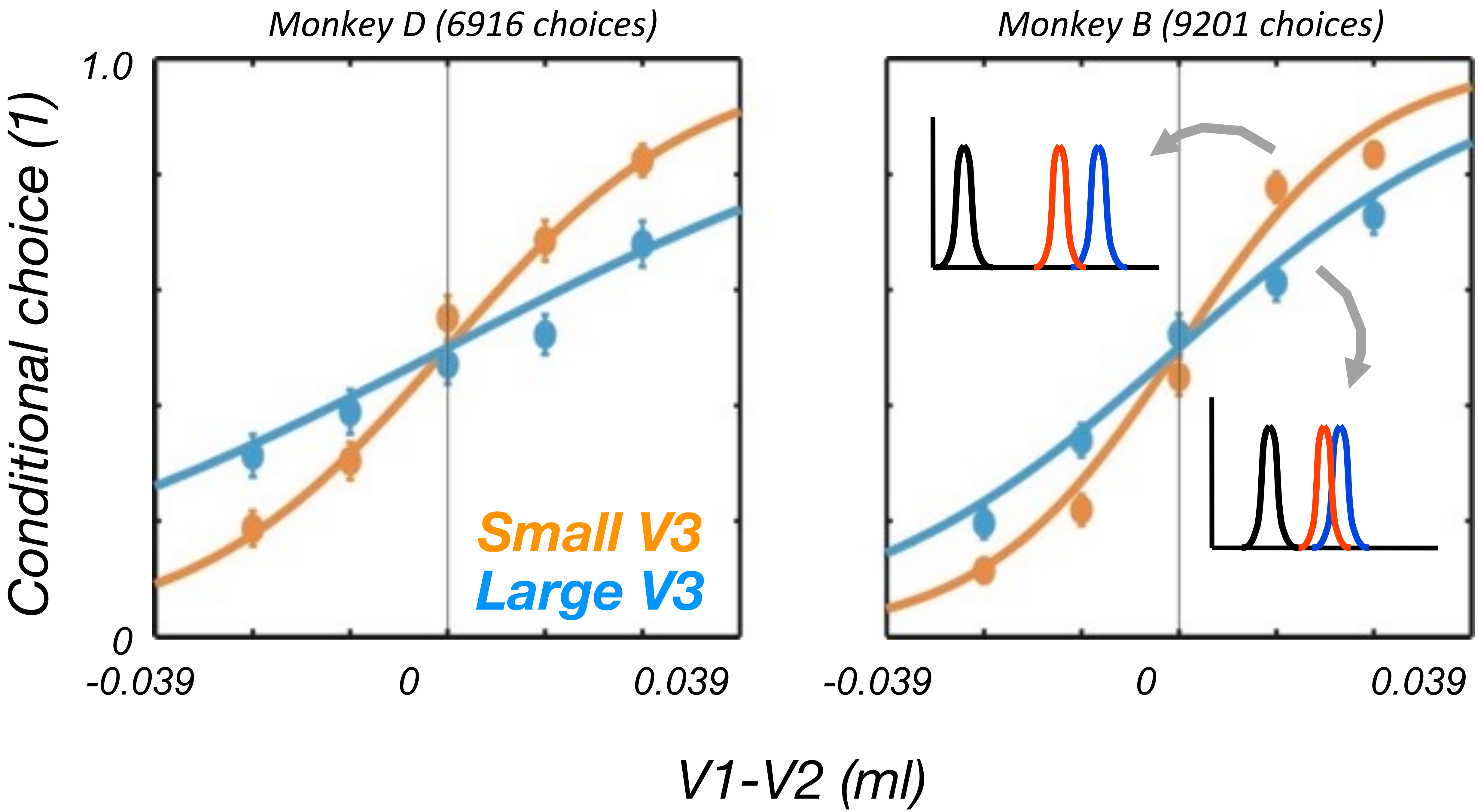
variance ~1.0-1.5 mean

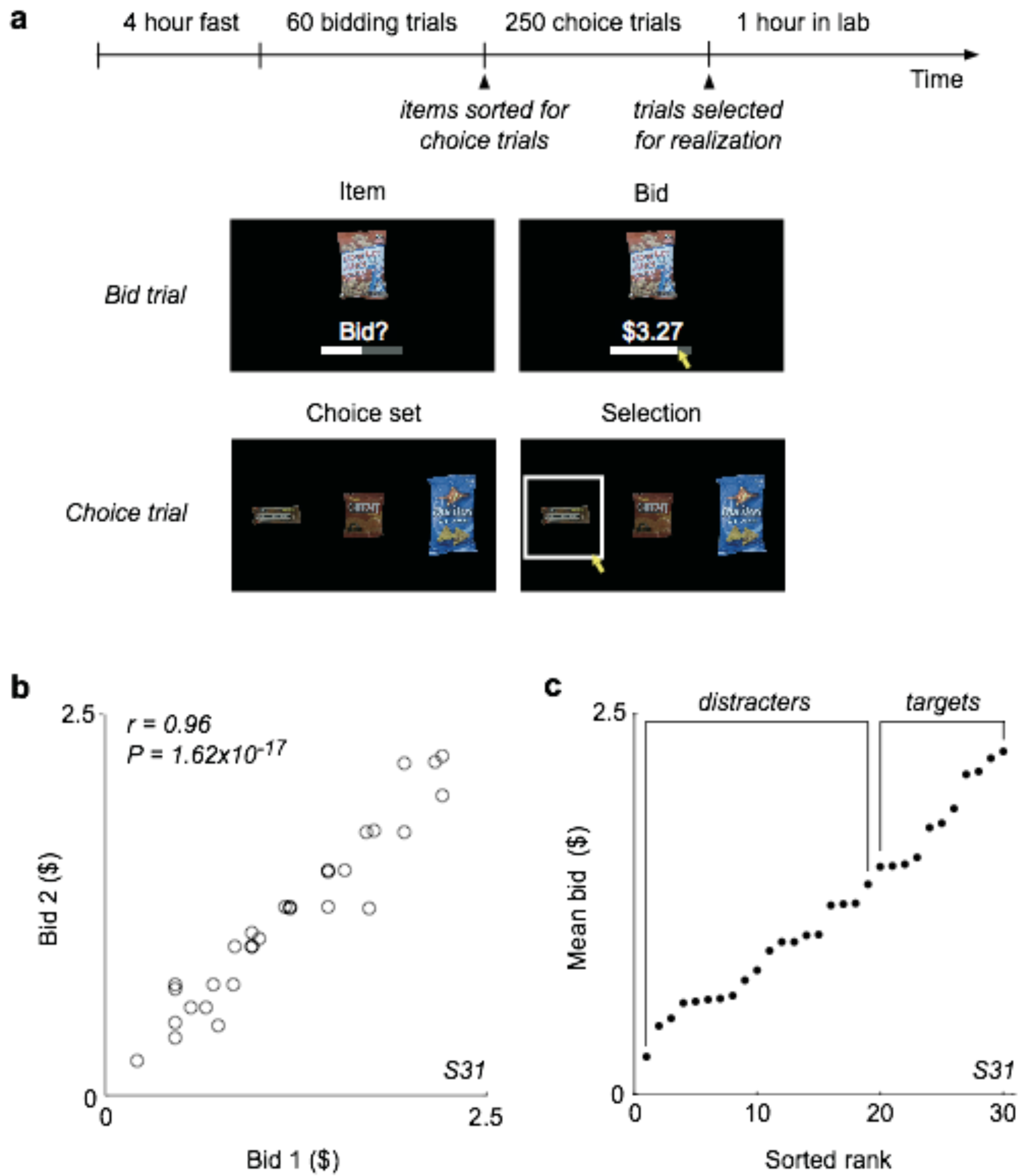
Tolhurst, Movshon and Dean, 1983



Absolute value
Relative value
Probability density
0.05
0
135.4
140.0
137.7
140.4
141.2
61.5
34.4
22.6
0
20
40
60
Firing rate (sp/s)

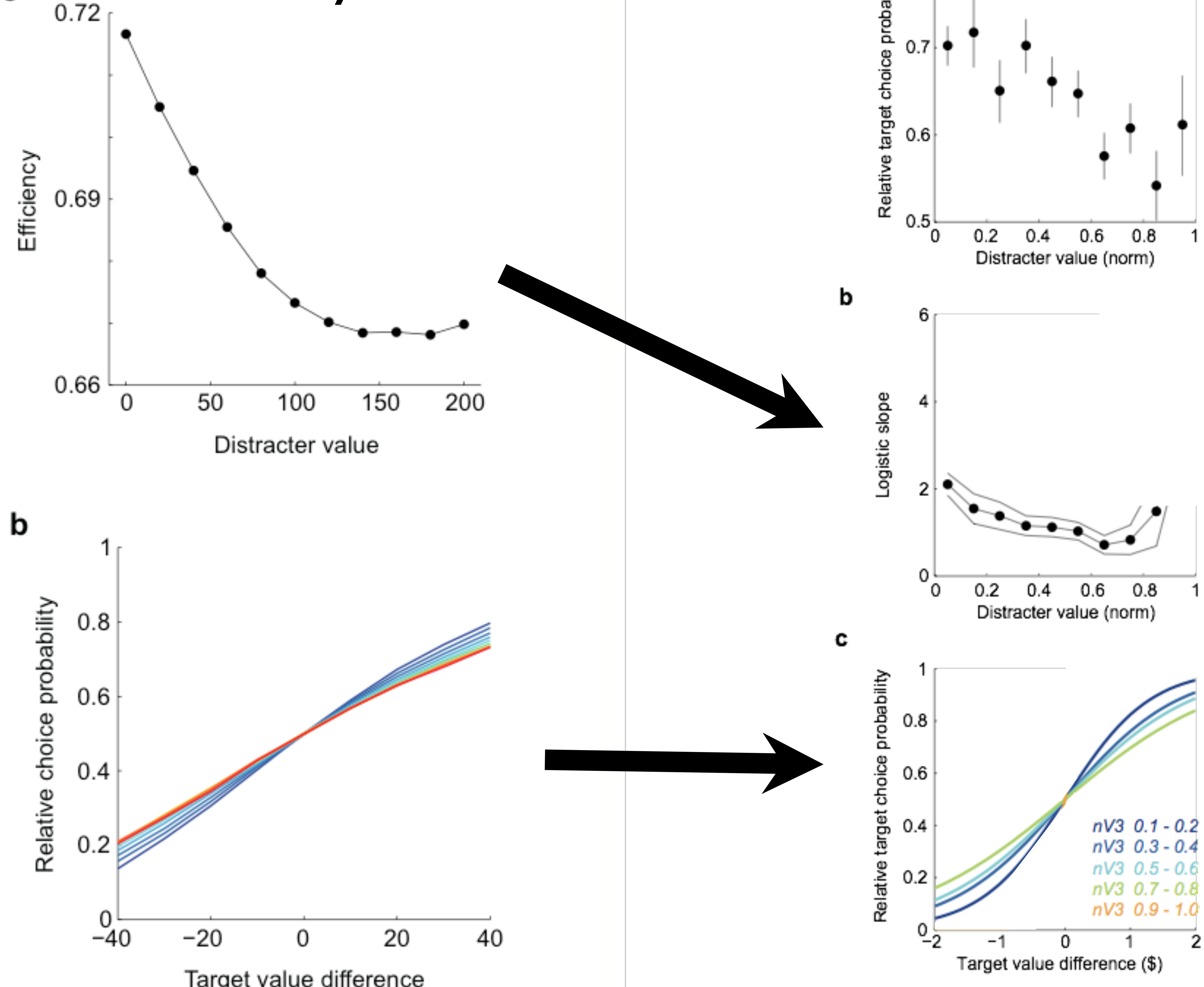

Free choice trials
FIX
TARGET
CUE
FIX OFF
SACCADE
1000 ms
500 ms
?
V1:
0.156
V2:
0.130 0.143 0.156 0.169 0.182
V3:
0.026 0.104
Target reward magnitude (ml)


Monkey D (6916 choices)
Monkey B (9201 choices)
Conditional choice (1)
1.0
0
-0.039
0
0.039
Small V3
Large V3
V1-V2 (ml)


a
4 hour fast
60 bidding trials
250 choice trials
1 hour in lab
Time
items sorted for choice trials
trials selected for realization
Item
Bid
Bid trial
Bid?
$3.27
Choice set
Selection
Choice trial
b
r = 0.96
P = 1.62x10^-17
S31
Bid 2 ($)
Bid 1 ($)
2.5
0
0
2.5
c
distracters
targets
S31
Mean bid ($)
Sorted rank
2.5
0
0
10
20
30

Theory

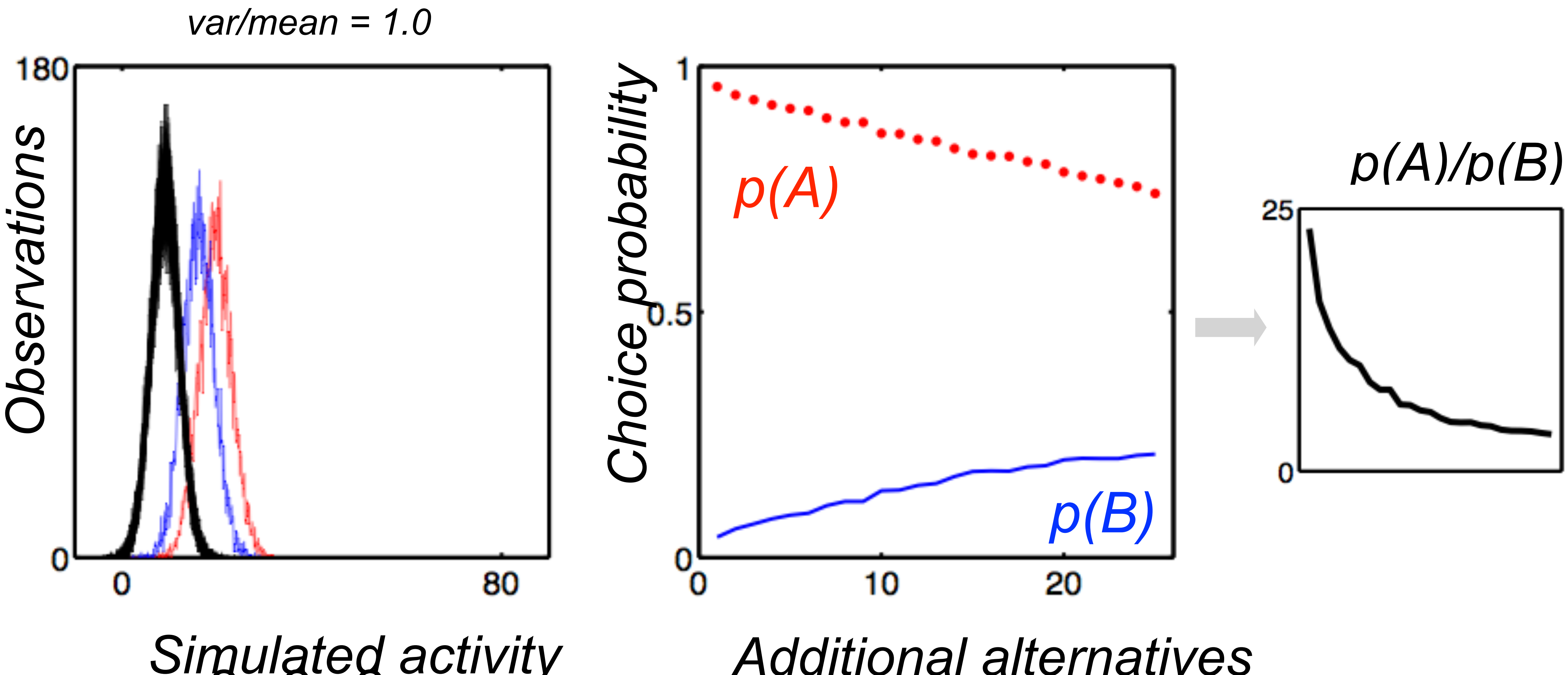
Humans



If There is Normalization, Would it Influence Choice Behavior?

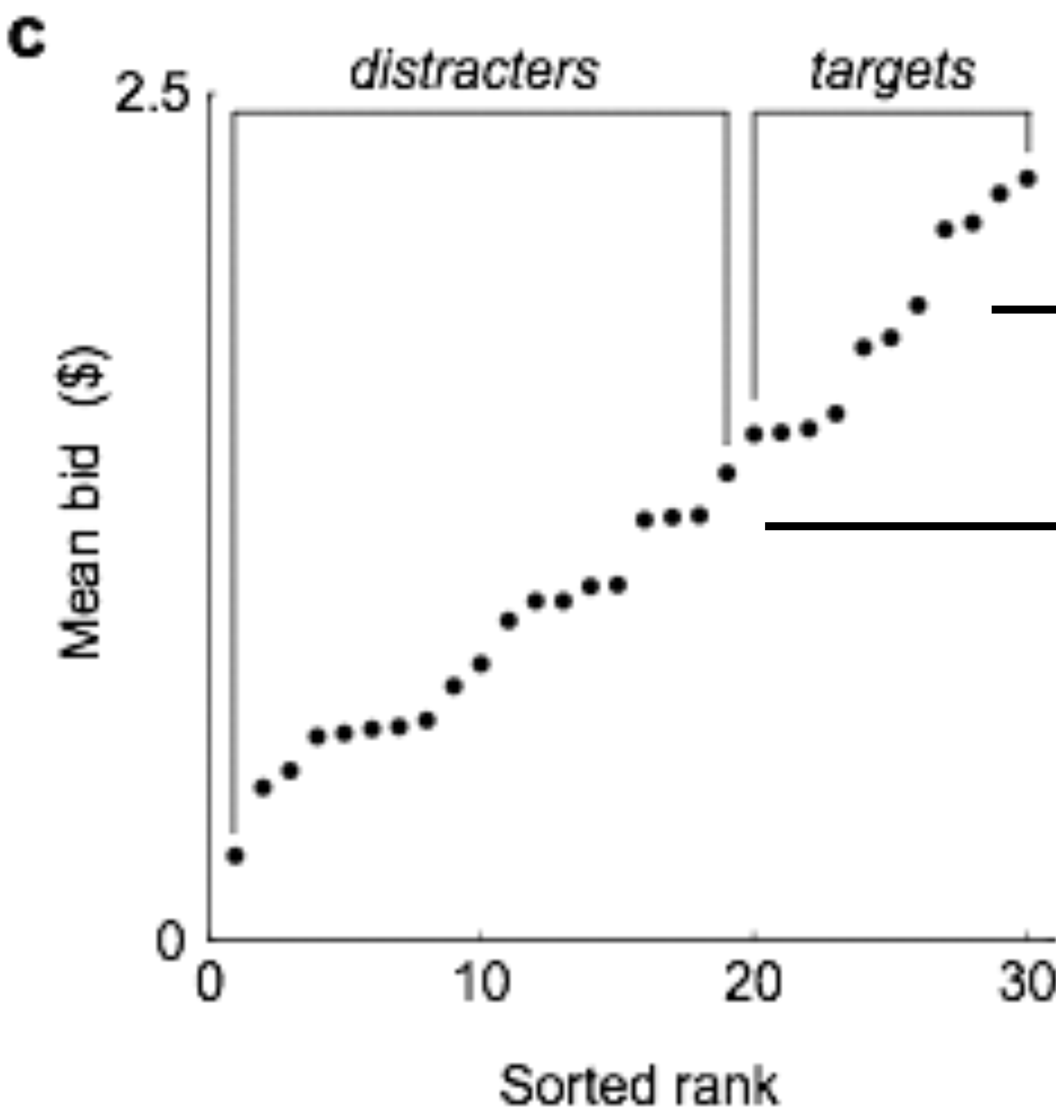
The Three Option Problem

The Multi-Option Problem
The Curse of Choice



Divisive normalization + cortical variability → choice-set effect

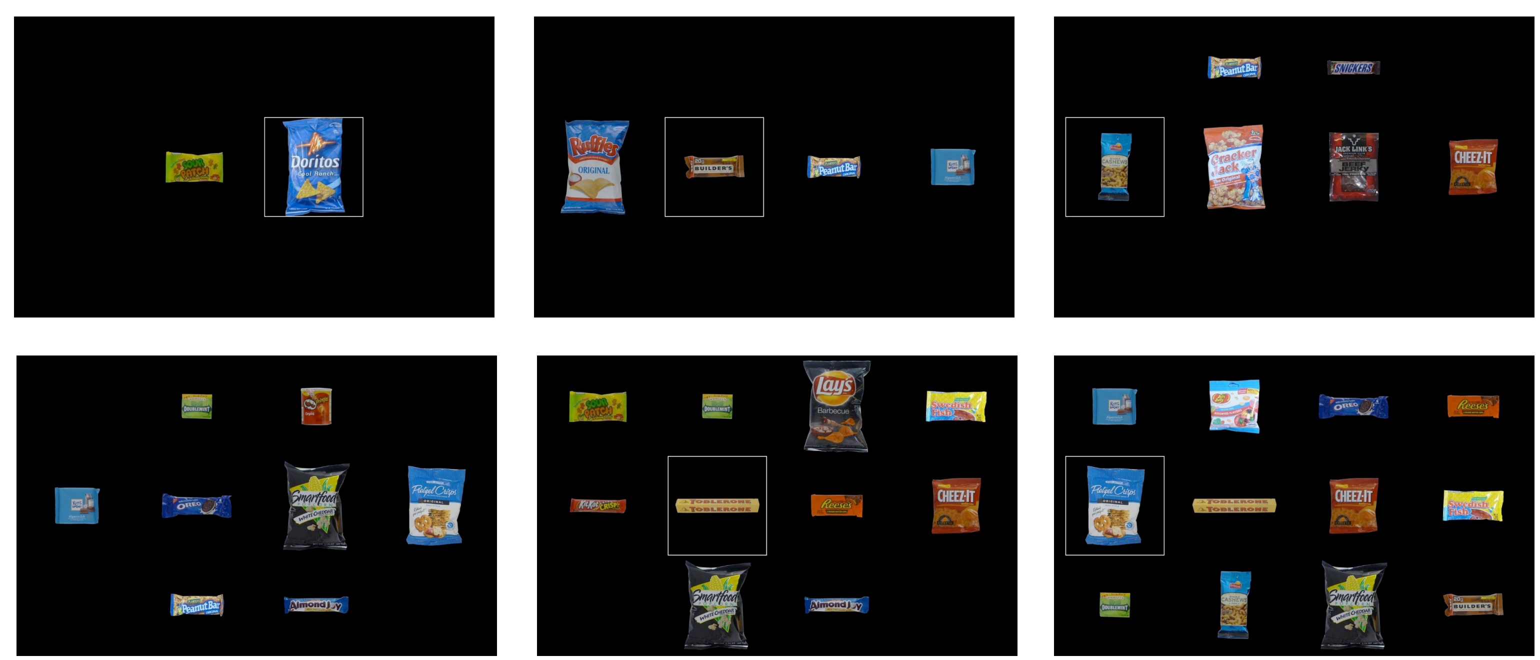
etc.



Target pairs

Distracters

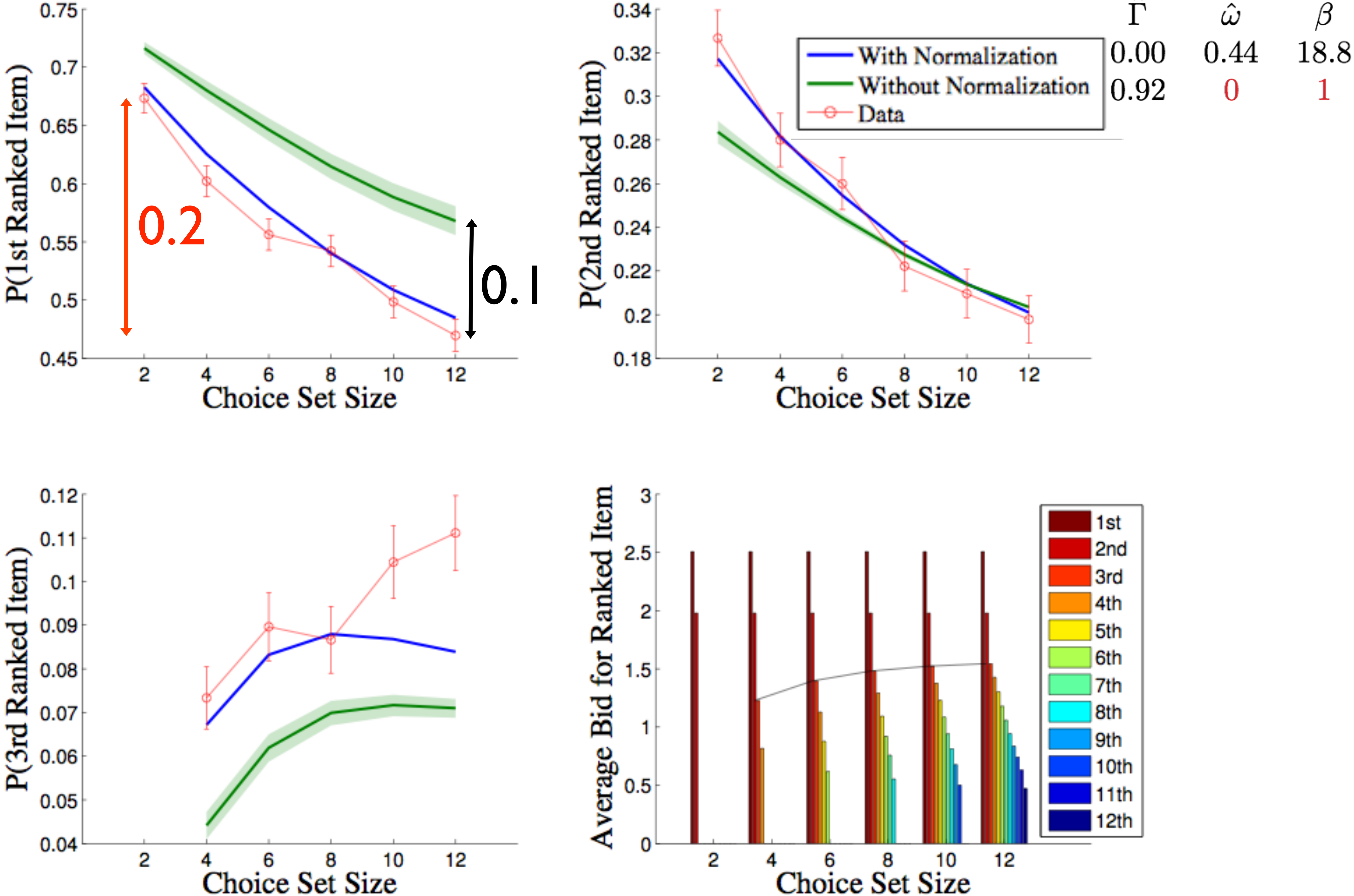
$N \in \{2, 4, 6, 8, 10, 12\}$



30 Subjects

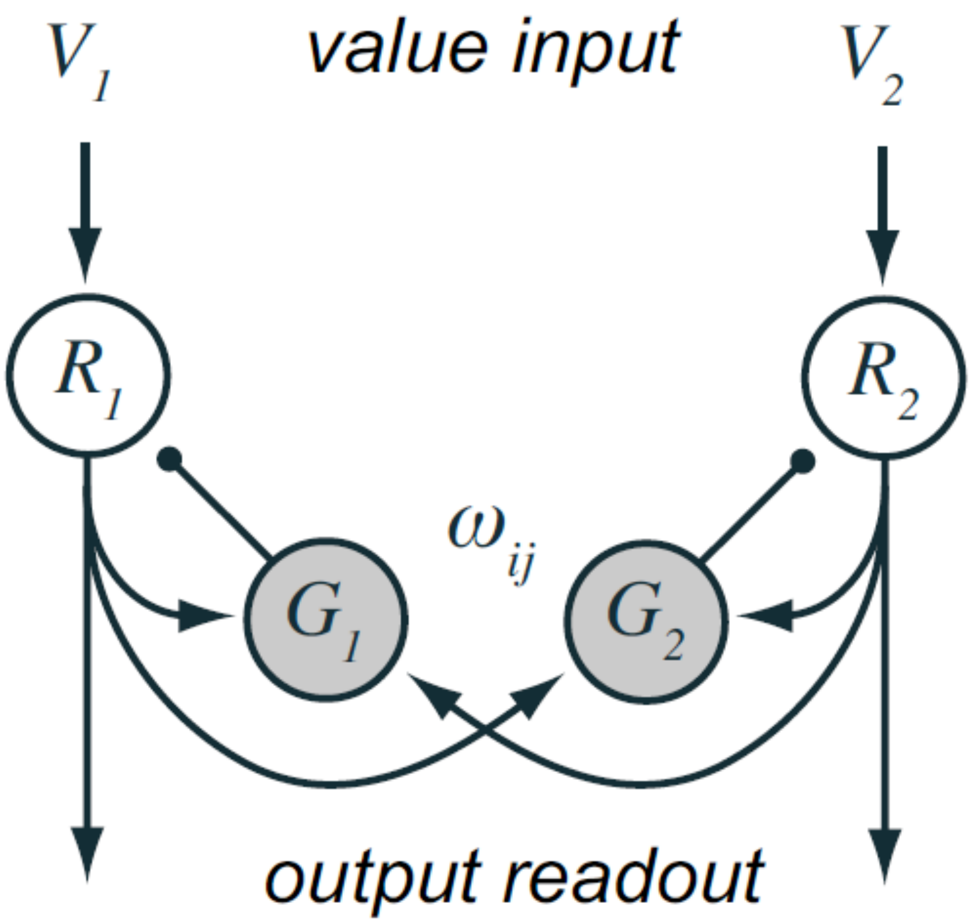
6x45 Trials Per

8100 Trials Total


P(1st Ranked Item)
P(2nd Ranked Item)
P(3rd Ranked Item)
Average Bid for Ranked Item
Choice Set Size
0.2
0.1
With Normalization
Without Normalization
Data
$\hat{\Gamma}$ $\hat{\omega}$ $\hat{\beta}$
0.00 0.44 18.8
0.92 0 1
1st
2nd
3rd
4th
5th
6th
7th
8th
9th
10th
11th
12th

But How Would A Network Implement Normalization?

What Would the Network Dynamics Be Like?

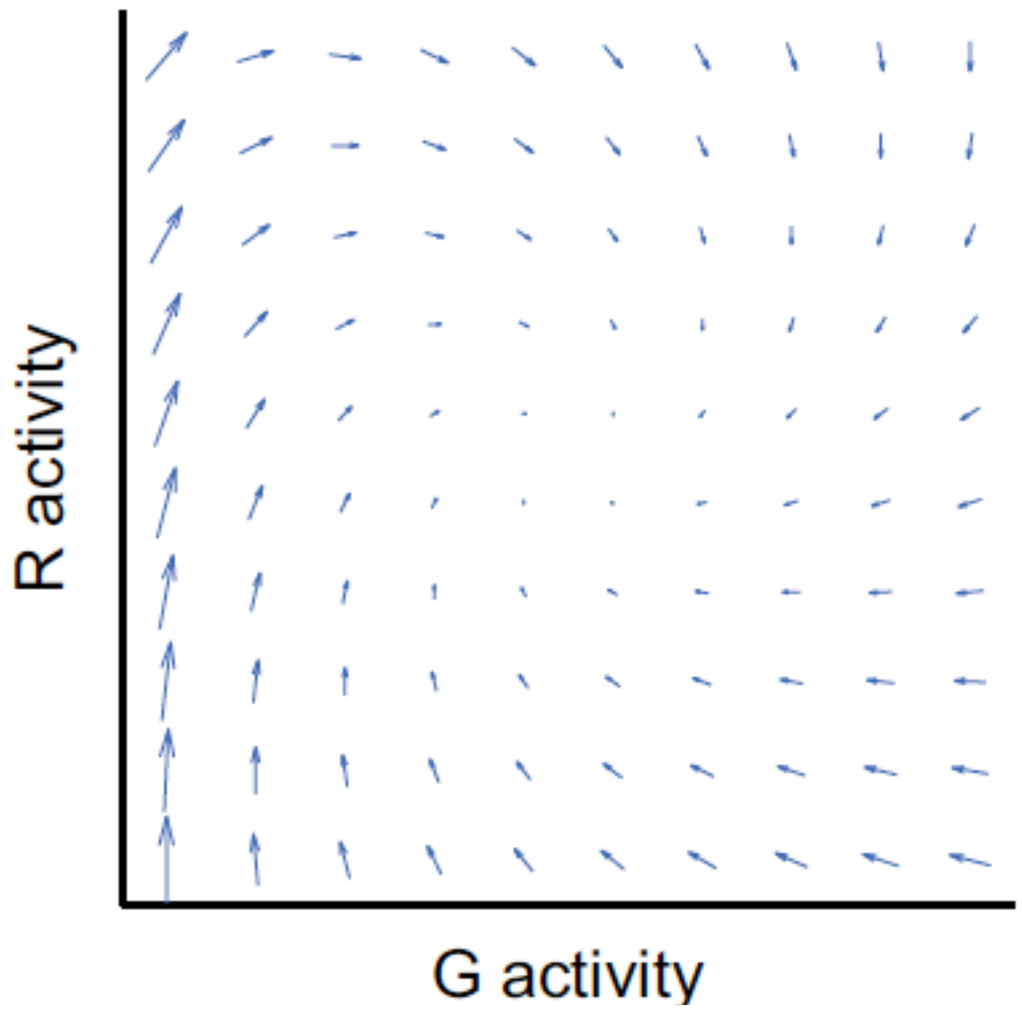


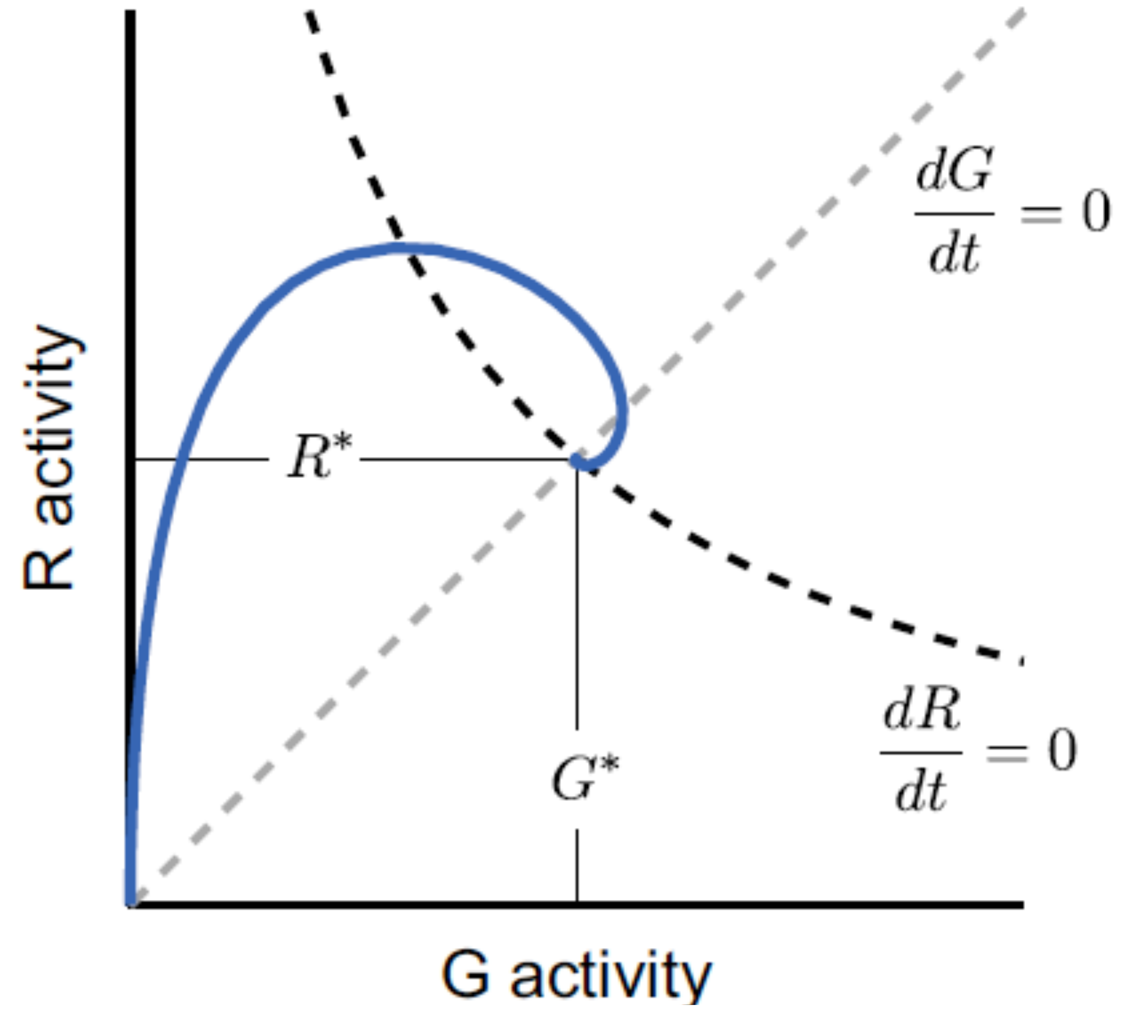
Excitatory neurons

$$\tau \frac{dR_i}{dt} = -R_i + \frac{V_i}{1 + G_i}$$

Inhibitory neurons

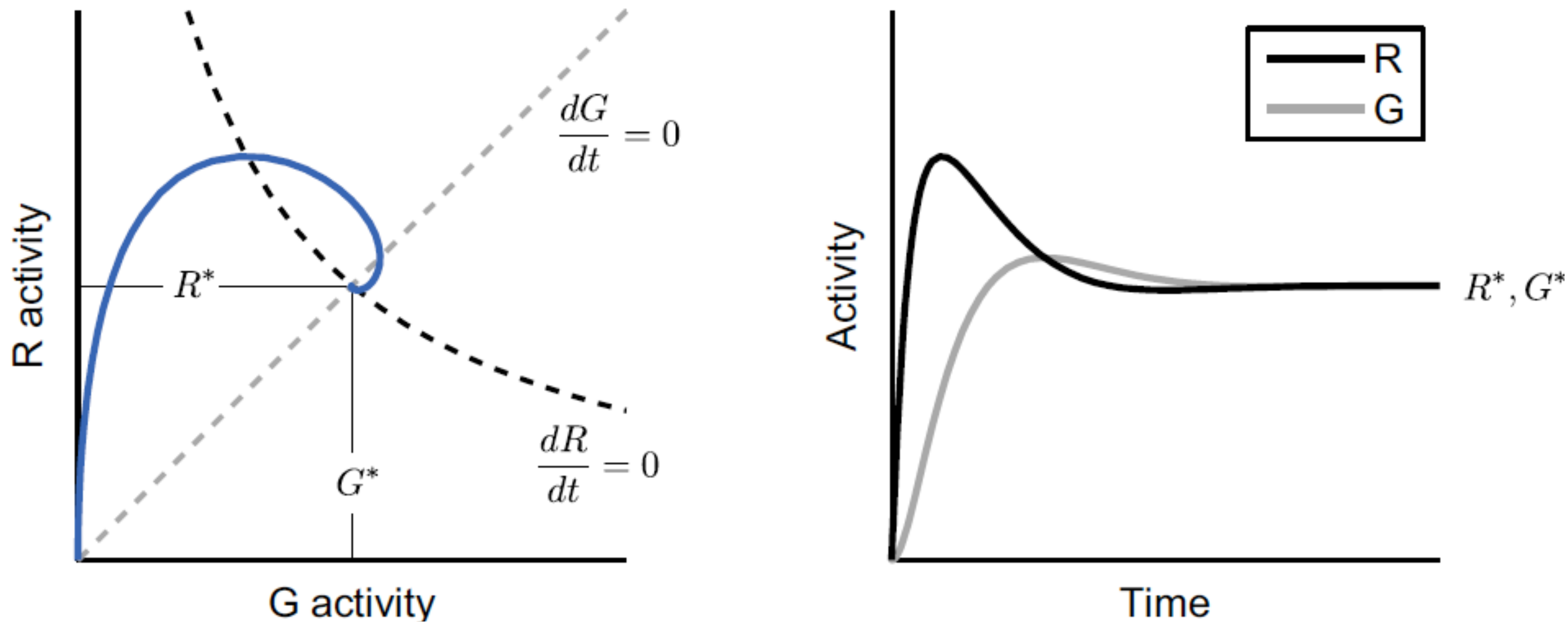
$$\tau \frac{dG_i}{dt} = -G_i + \sum_{j=1}^{N} \omega_{ij} R_j$$



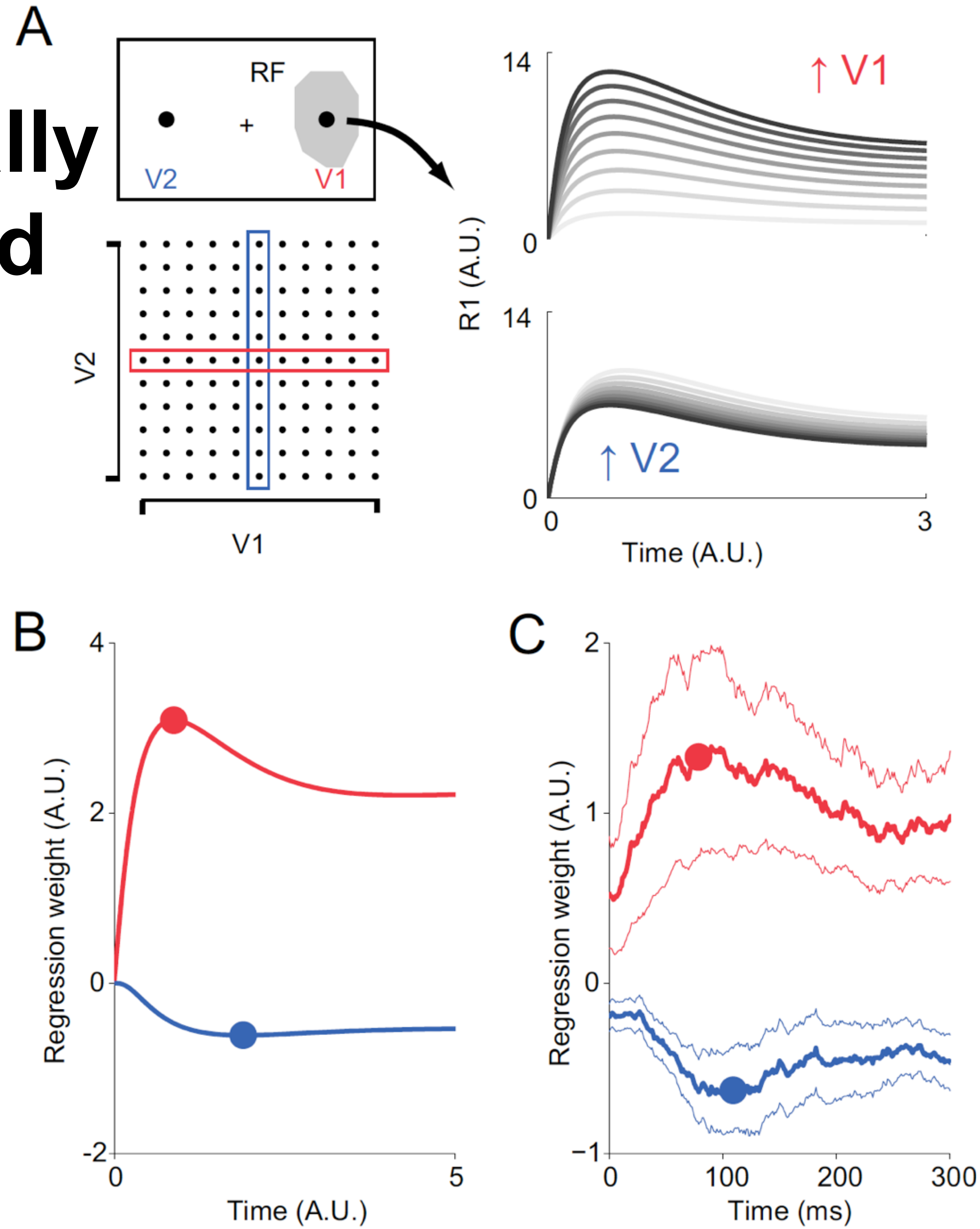


Normalization is the Unique Equilibrium State for Networks of this Kind

These Networks Have Specific Dynamics



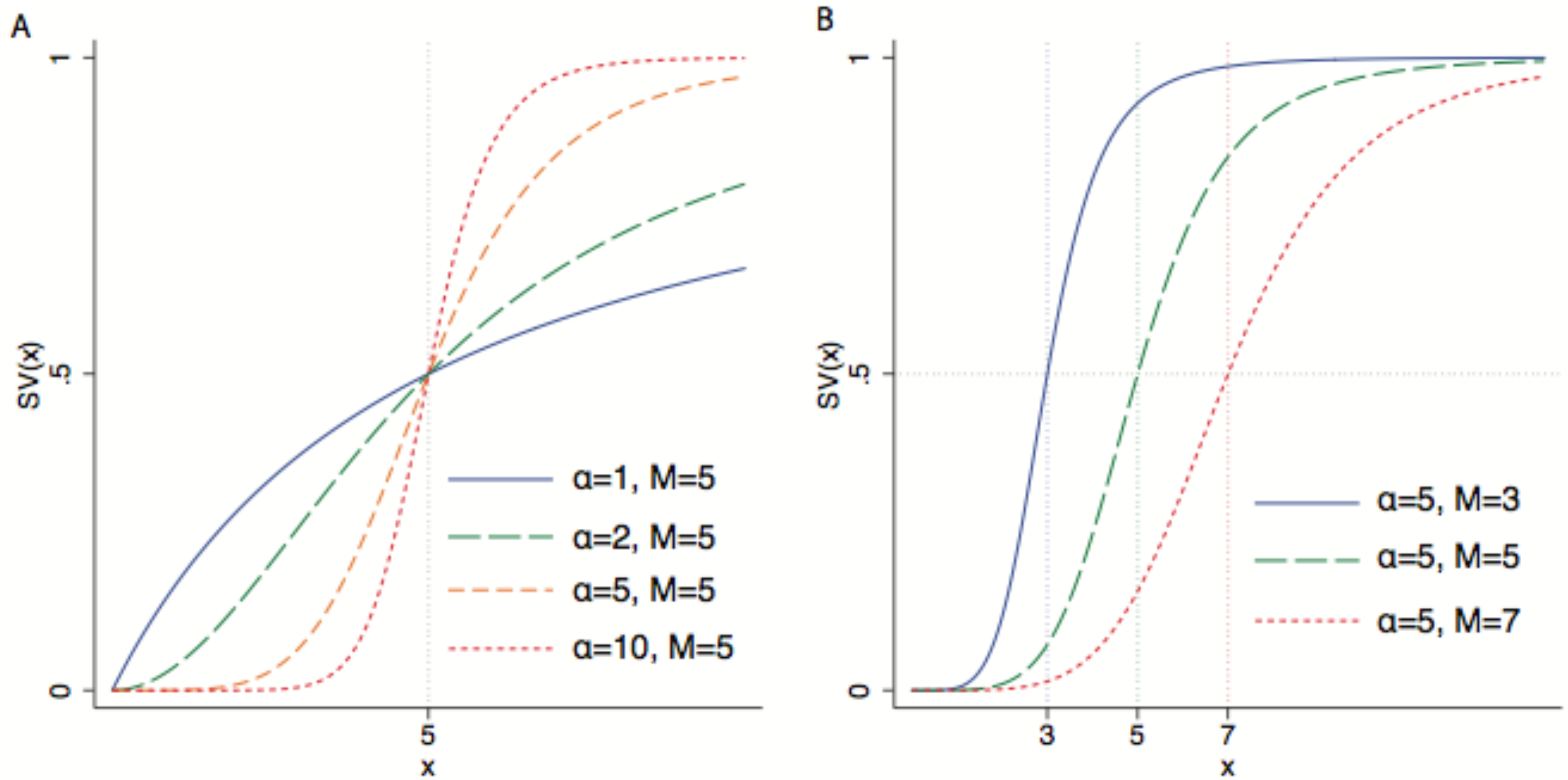
Which Actually Are Observed



If a Choice Network Used These Dynamics, How Would It Choose?

The ESVT "Value Function"

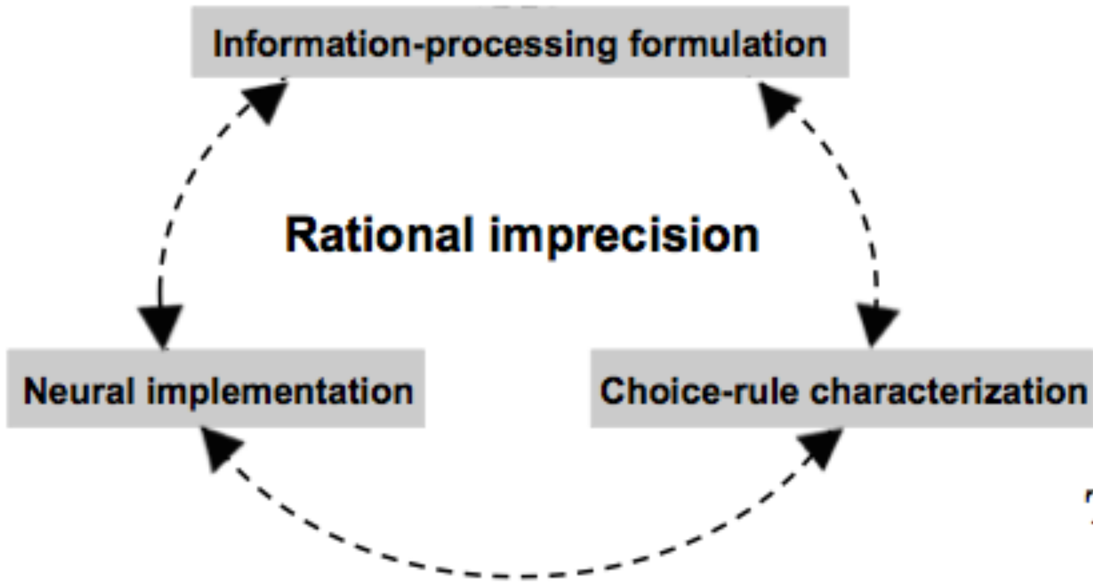
$$V(x) = \frac{x^{\alpha}}{x^{\alpha} + M_t^{\alpha}}$$



Captures:

- Reflection Effect
- Probability Distortion
- Loss Aversion
- Endowment Effect

Would It Be Normative?



Theorem 1. *For any random choice rule ρ the following are equivalent:*

1. *ρ has an information-processing formulation.*
2. *ρ has a neural-normalization implementation.*
3. *ρ has a relaxed IIA characterization.*

Definition 1. A random choice rule ρ has an **information-processing formulation** if there exist functions $v : X \to (0, \infty)$ and $F : \mathcal{A} \to (0, \infty)$ such that for all $A \in \mathcal{A}$:

$$\rho \in \arg\max_{\hat{\rho} \in \mathcal{P}} \left\{ \sum_{x \in A} \hat{\rho}(x, A) v(x) - F(A) \left(H_{\max}(A) - H(\hat{\rho}, A) \right) \right\}.$$

Definition 2. A random choice rule ρ has a **neural-normalization implementation** if there exist functions $v : X \to (0, \infty)$ and $F : \mathcal{A} \to (0, \infty)$ such that for all A in $\mathcal{A}$ and x in A:

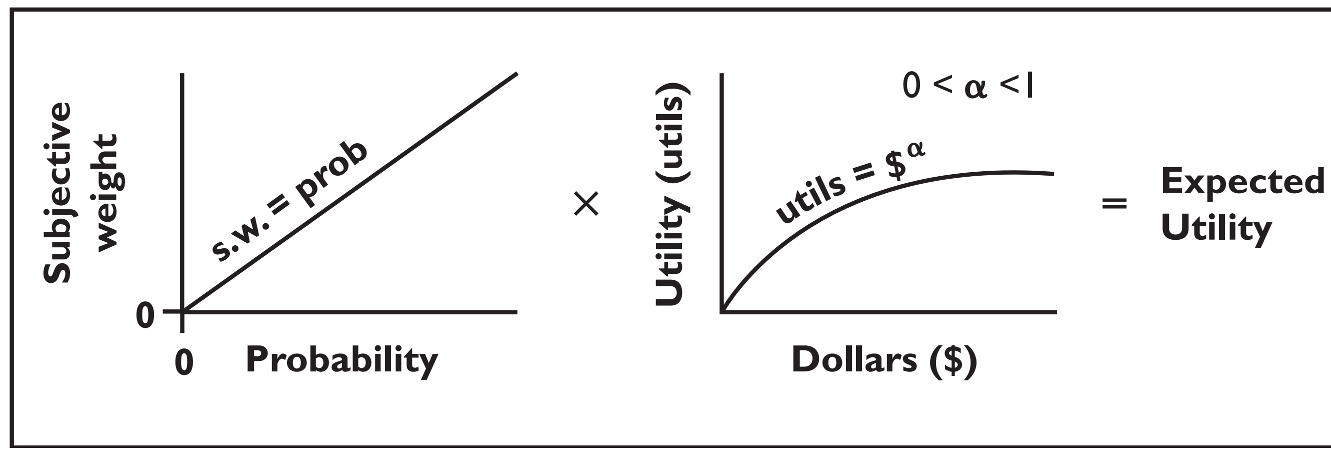
$$\rho(x, A) = \Pr\left(x = \arg\max_{y \in A} \frac{v(y)}{F(A)} + \varepsilon_y \right),$$

where the ε_y's are i.i.d. and Gumbel with location 0 and scale 1.

Definition 5. A random choice rule ρ is a **relaxed IIA** rule if there exists an admissible family of functions $\{G_A\}_{A \in \mathcal{A}}$ with respect to which ρ obeys Equation (1).

John von Neumann   Oskar Morgenstern

Modern
Expected ***Utility*** Theory



Critical Advantages:

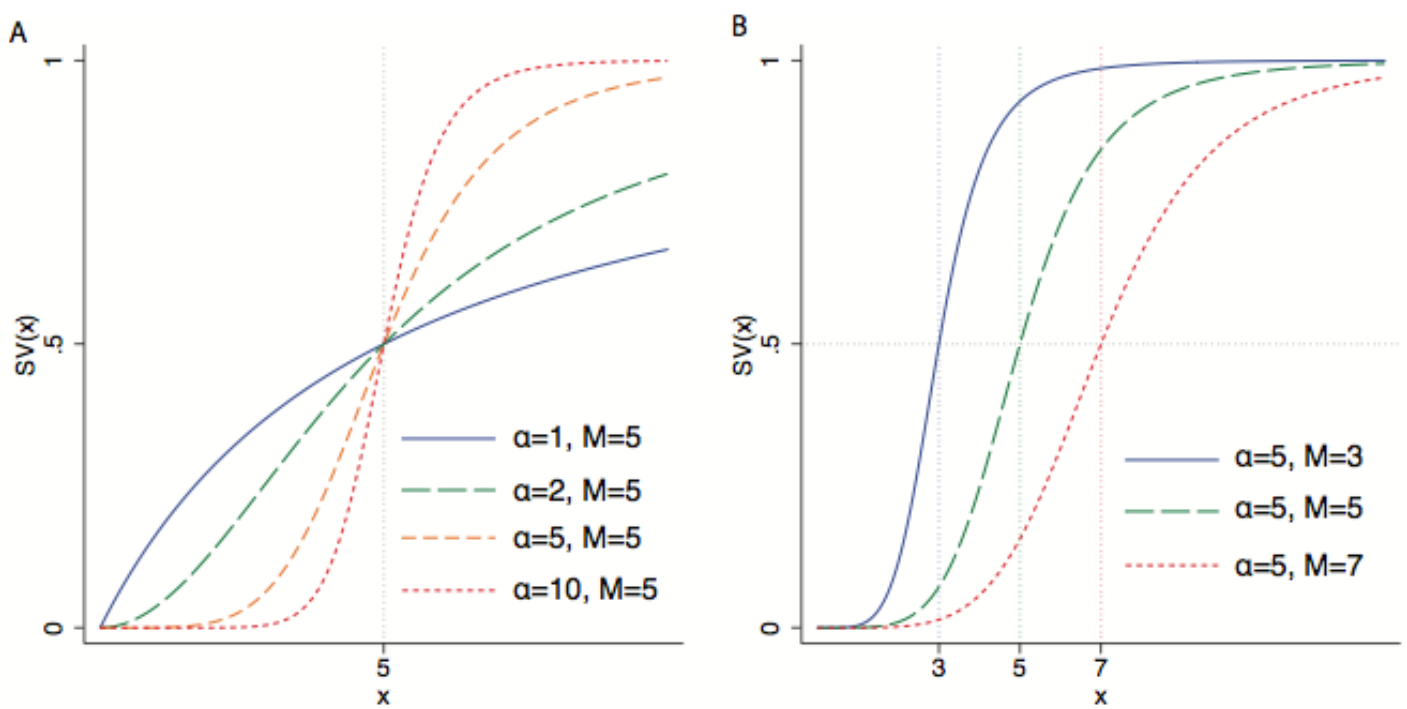
- Precise
- Compact
- **Normative** (people make sense)

Expected Subjective Value Theory

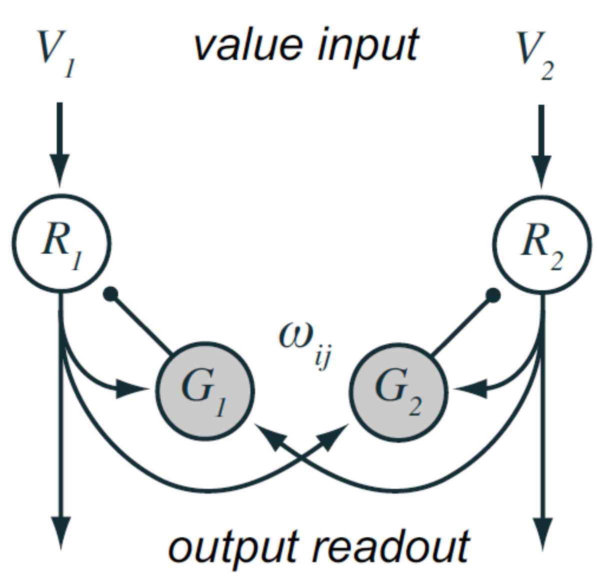
Definition 1. A random choice rule ρ has an **information-processing formulation** if there exist functions $v : X \to (0, \infty)$ and $F : \mathcal{A} \to (0, \infty)$ such that for all $A \in \mathcal{A}$:

$$\rho \in \arg\max_{\hat{\rho} \in \mathcal{P}} \left\{ \sum_{x \in A} \hat{\rho}(x, A)\, v(x) - F(A) \left(H_{\max}(A) - H(\hat{\rho}, A) \right) \right\}.$$

Economics



Psychology



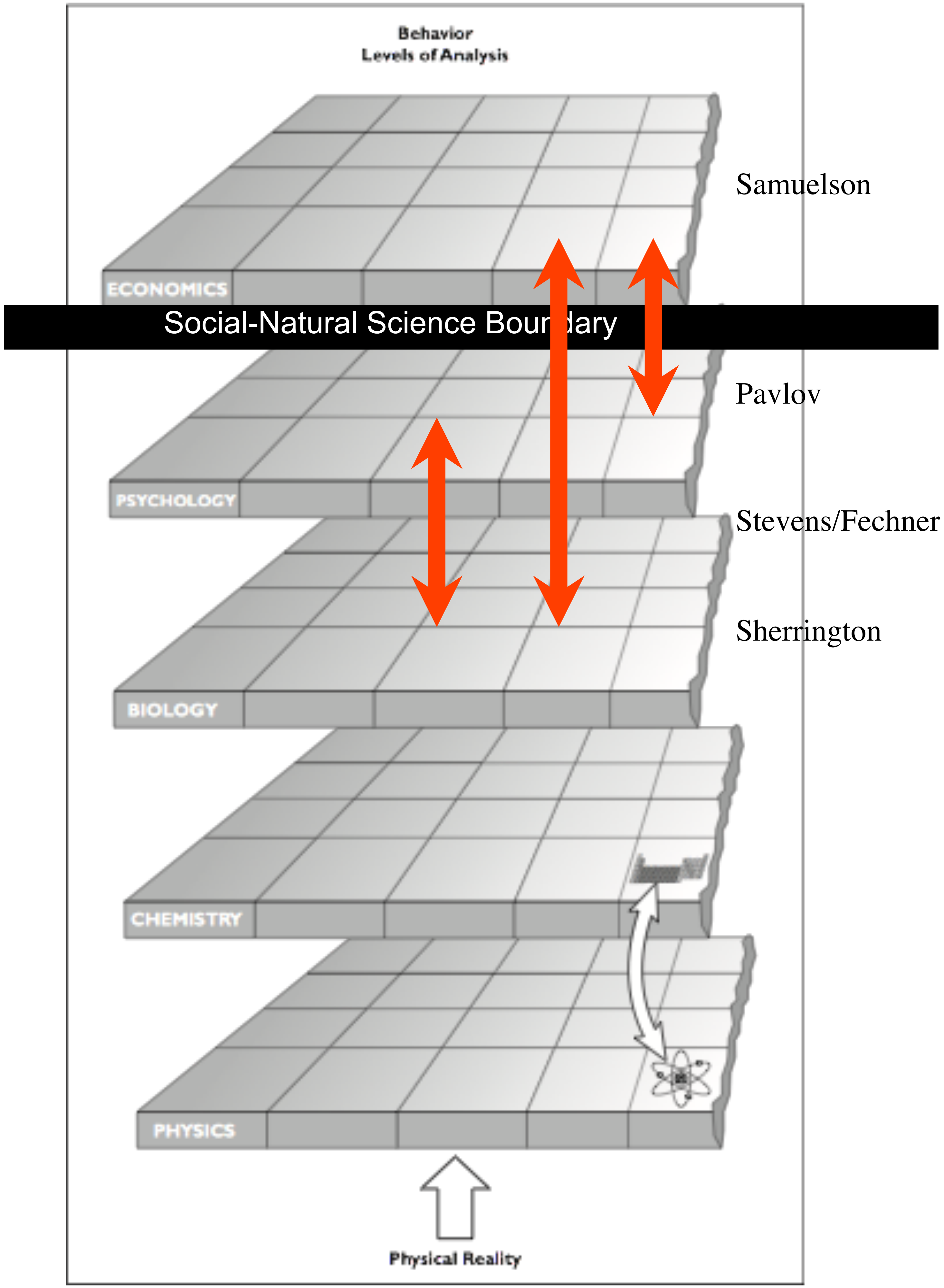
Excitatory neurons

$$\tau \frac{dR_i}{dt} = -R_i + \frac{V_i}{1 + G_i}$$

Inhibitory neurons

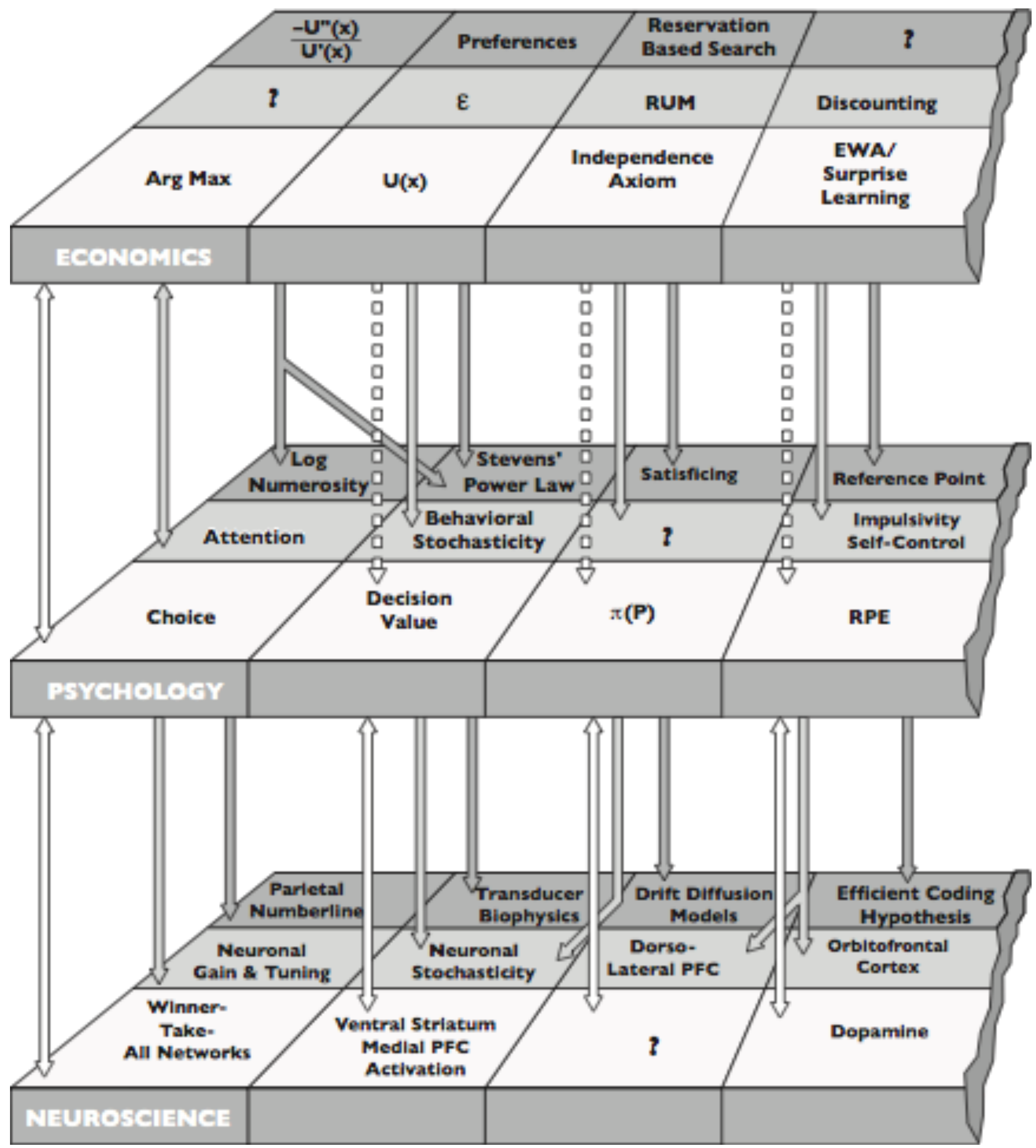
$$\tau \frac{dG_i}{dt} = -G_i + \sum_{j=1}^{N} \omega_{ij} R_j$$

Biology



Behavior
Levels of Analysis
ECONOMICS
Social-Natural Science Boundary
PSYCHOLOGY
BIOLOGY
CHEMISTRY
PHYSICS
Physical Reality
Samuelson
Pavlov
Stevens/Fechner
Sherrington

Neuroeconomics
Aligning and Refining Hard Theories



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