Decision making and the brain

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Lecture outline

I. fMRI modeling – How to model BOLD response

II. From behavior -- 決策的行為科學研究

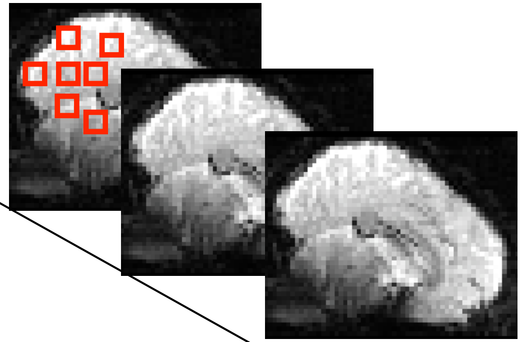
- 如何量測‘價值’？
- 決策行為的理論模型和實驗

III. Linking brain and choice behavior -- 決策的神經科學研究

- 價值 (value) 和大腦
- 價值、決策在大腦：決策的神經生物學模型

General approach: Univariate analysis

- Each voxel in the brain is analyzed *separately*



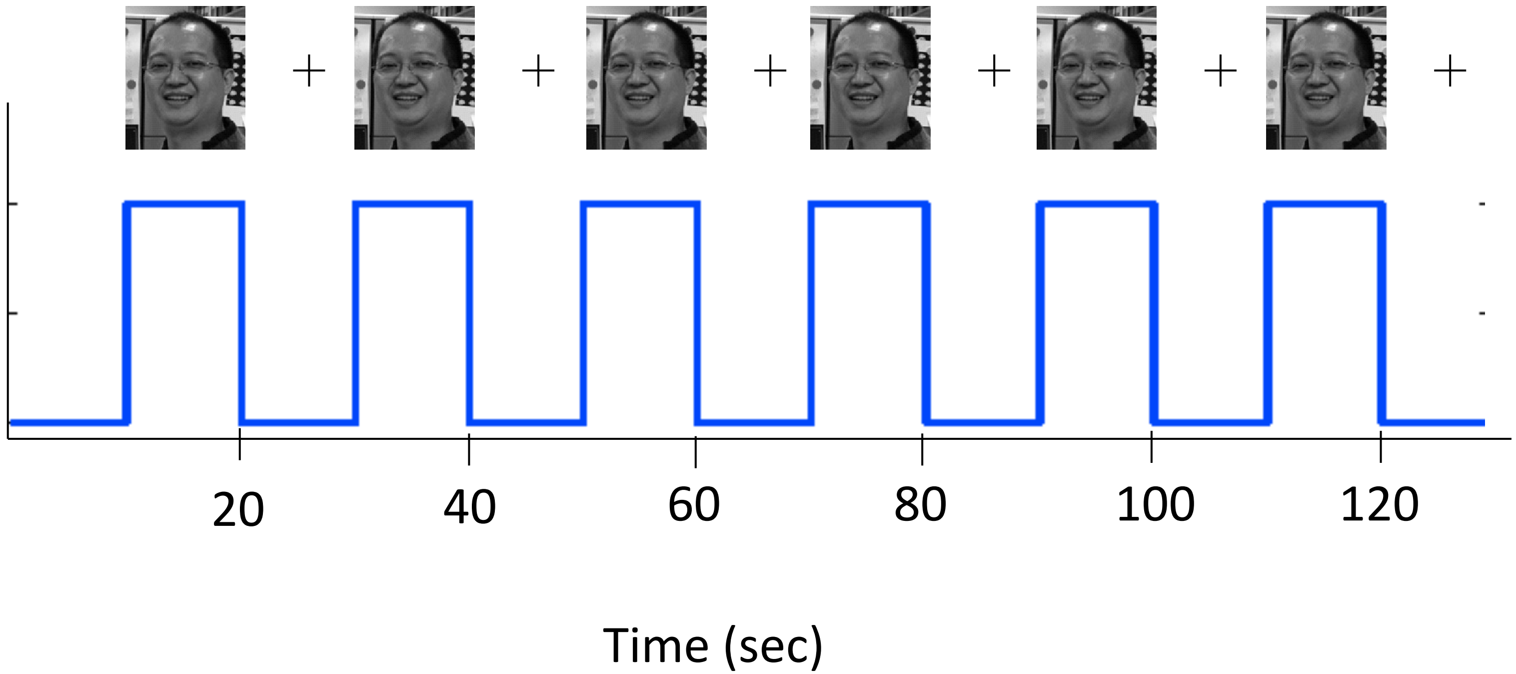
- Each voxel presents a time-series data

...

Time

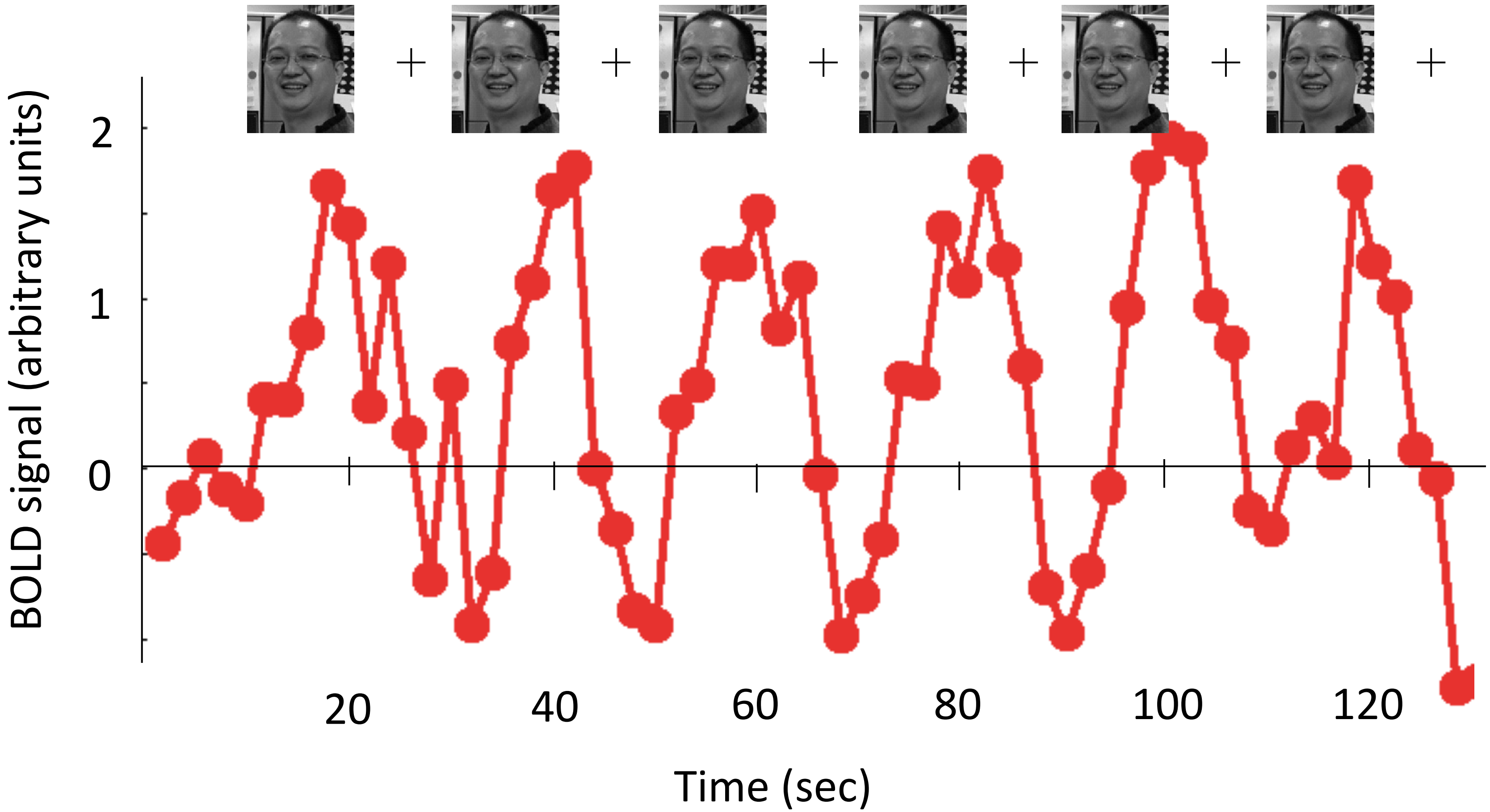
Time-series data

- Suppose you have the following experiment



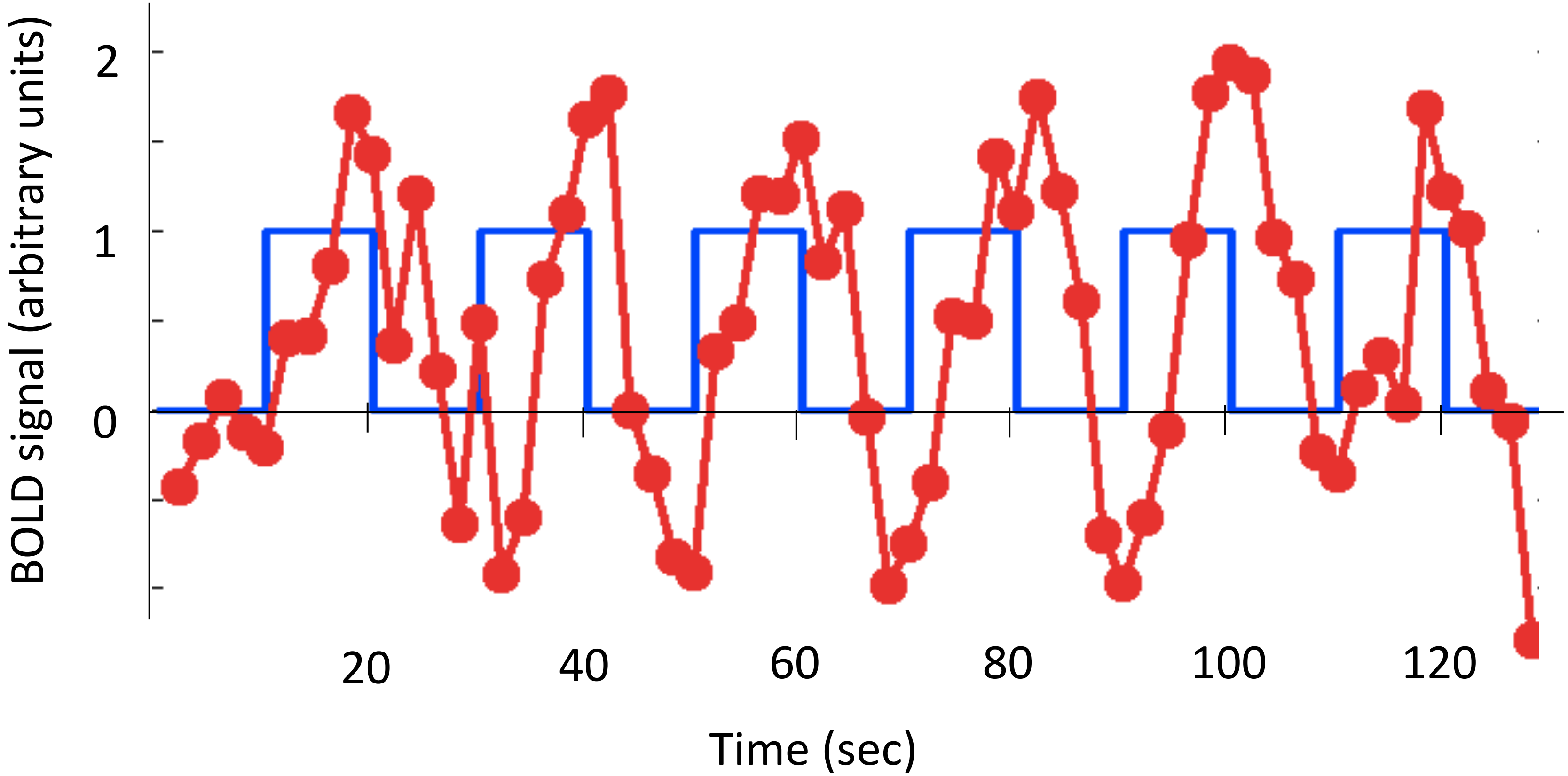
Time-series data

- This is the data – BOLD response – you get (from a single voxel)



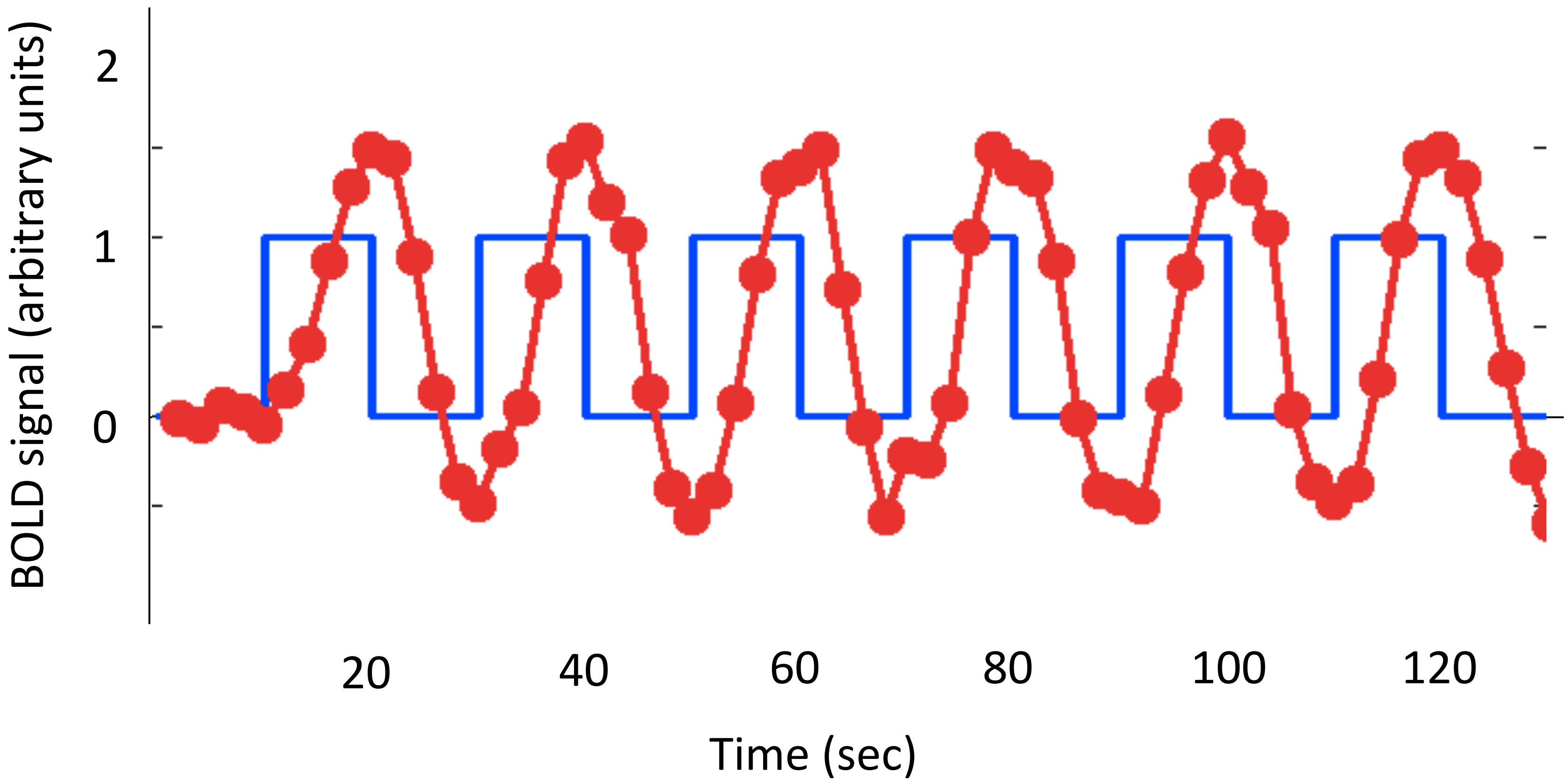
Time-series data

- When you compare prediction (based on your design) and data, you realize that there is somewhat a match, but not close



Time-series data

- What about this one? Which aspect of the comparison is the same, which aspect might be different?

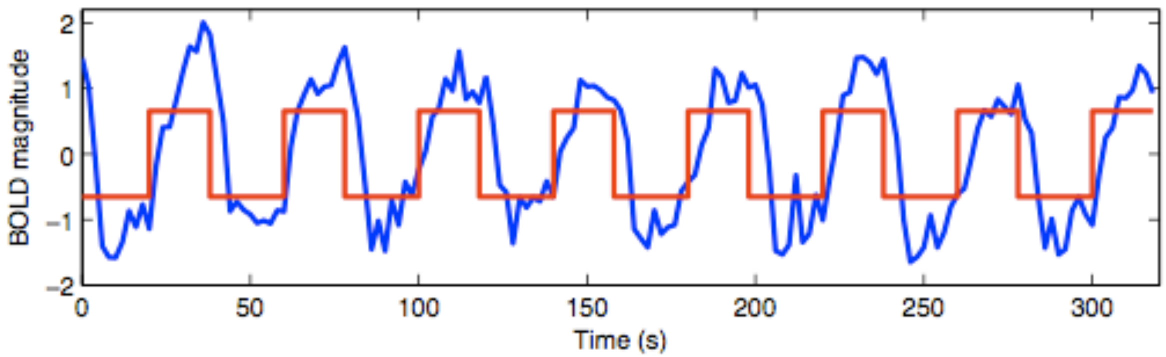


Neural activity and BOLD signal

Model BOLD signal as a transformation of neural activity

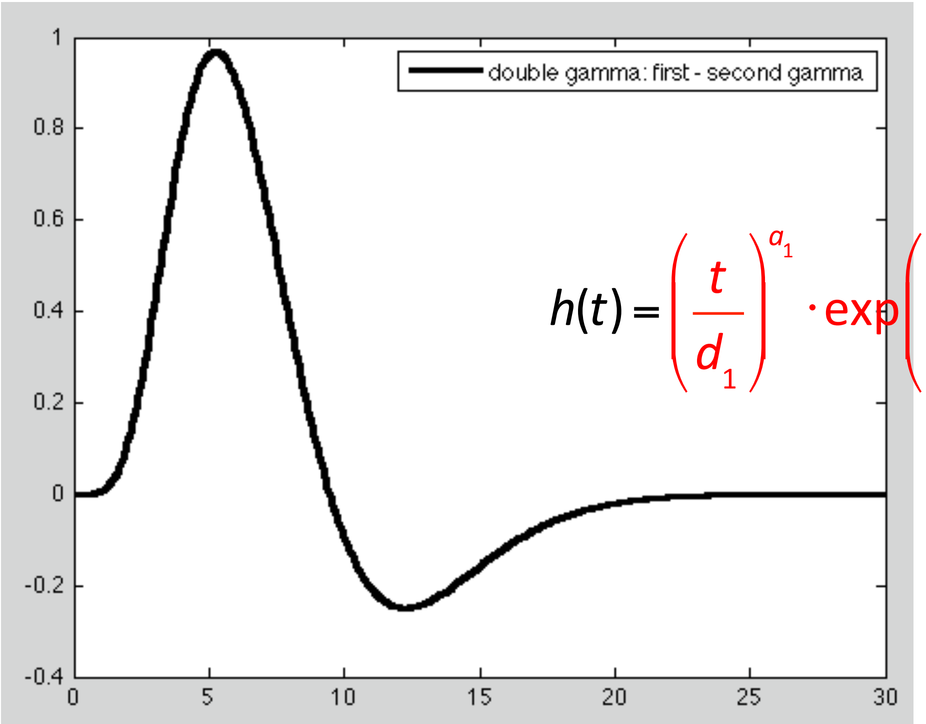
$$x \xrightarrow{f(x)} \text{BOLD}$$

(neural activity)



The hemodynamic response function (HRF)

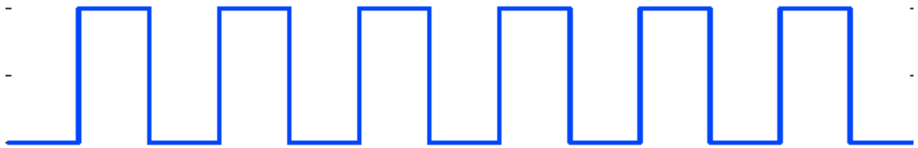
The HRF captures the relation between neural activity and BOLD response



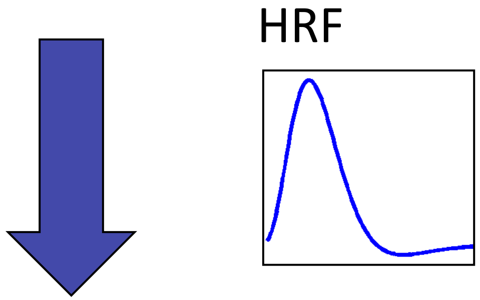
$$h(t) = \left(\frac{t}{d_1}\right)^{a_1} \cdot \exp\left(-\frac{t-d_1}{b_1}\right) - c \cdot \left(\frac{t}{d_2}\right)^{a_2} \cdot \exp\left(-\frac{t-d_2}{b_2}\right)$$

General Linear Model: Design matrix

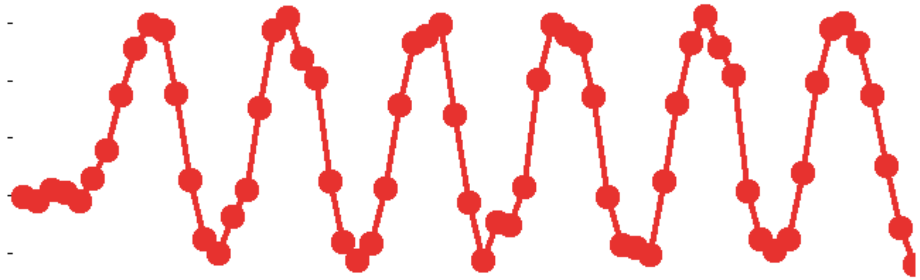
Predicted neural activity



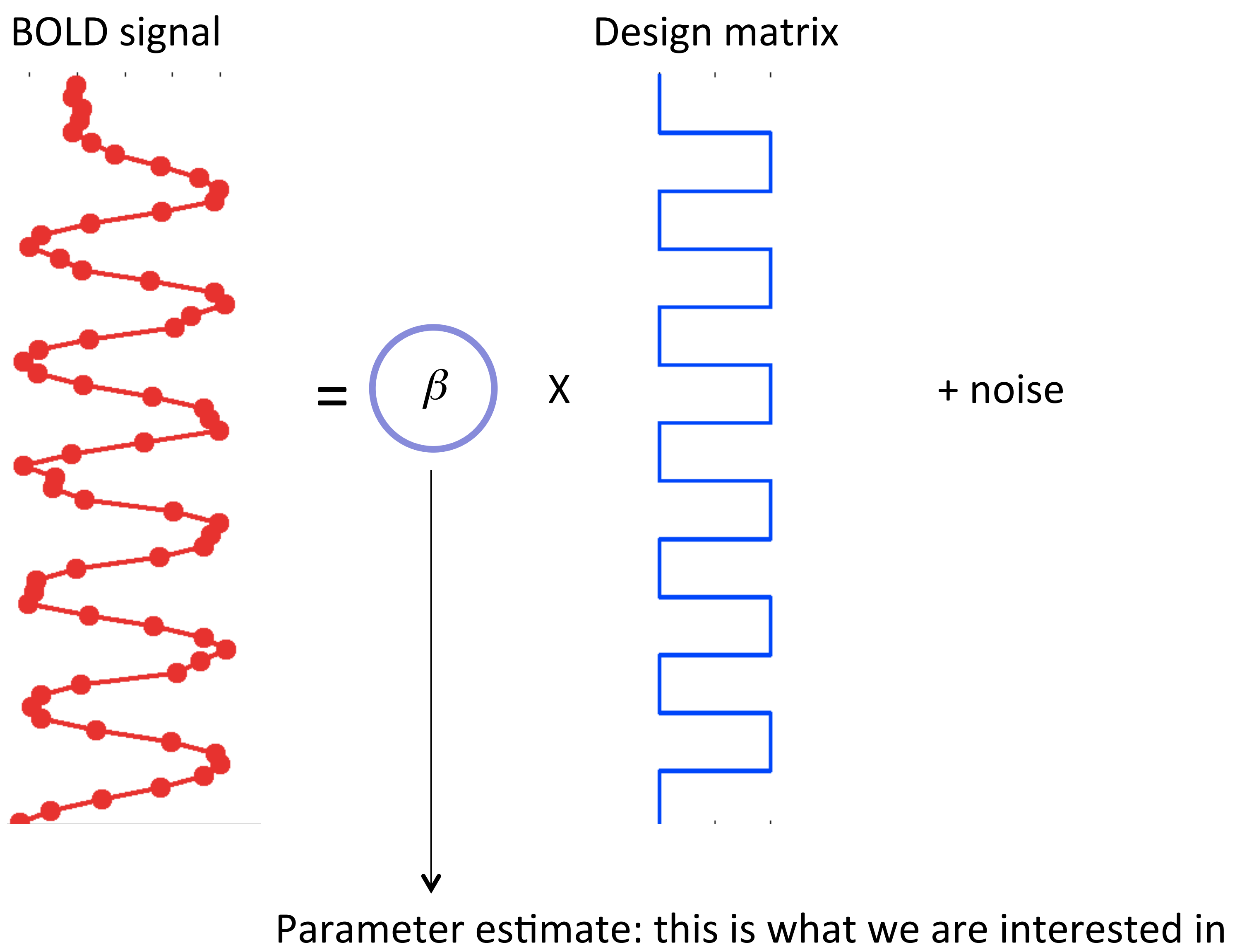
convolution



Predicted BOLD response

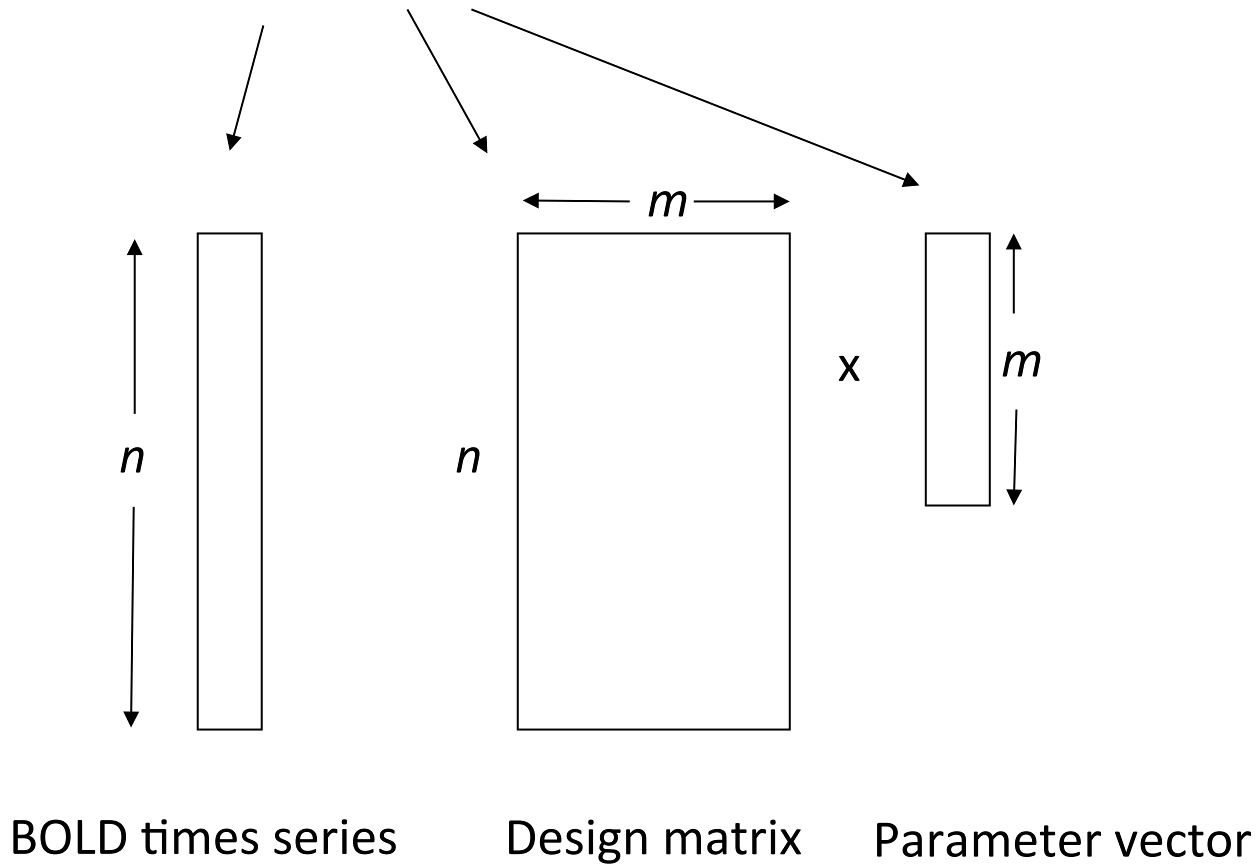


General Linear Model



General Linear Model

$$Y = X\beta + \varepsilon, \varepsilon \sim N(0, \sigma^2)$$



Decisions, decisions

Choosing a drink

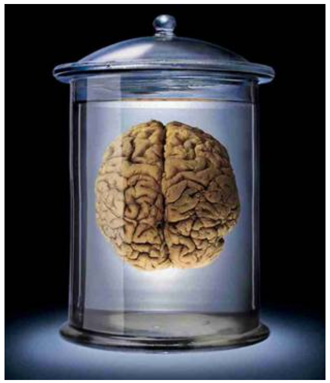
or

Who to vote for?

or

Choosing a transportation

Choosing a career



Nuclear plant or not?

Question:

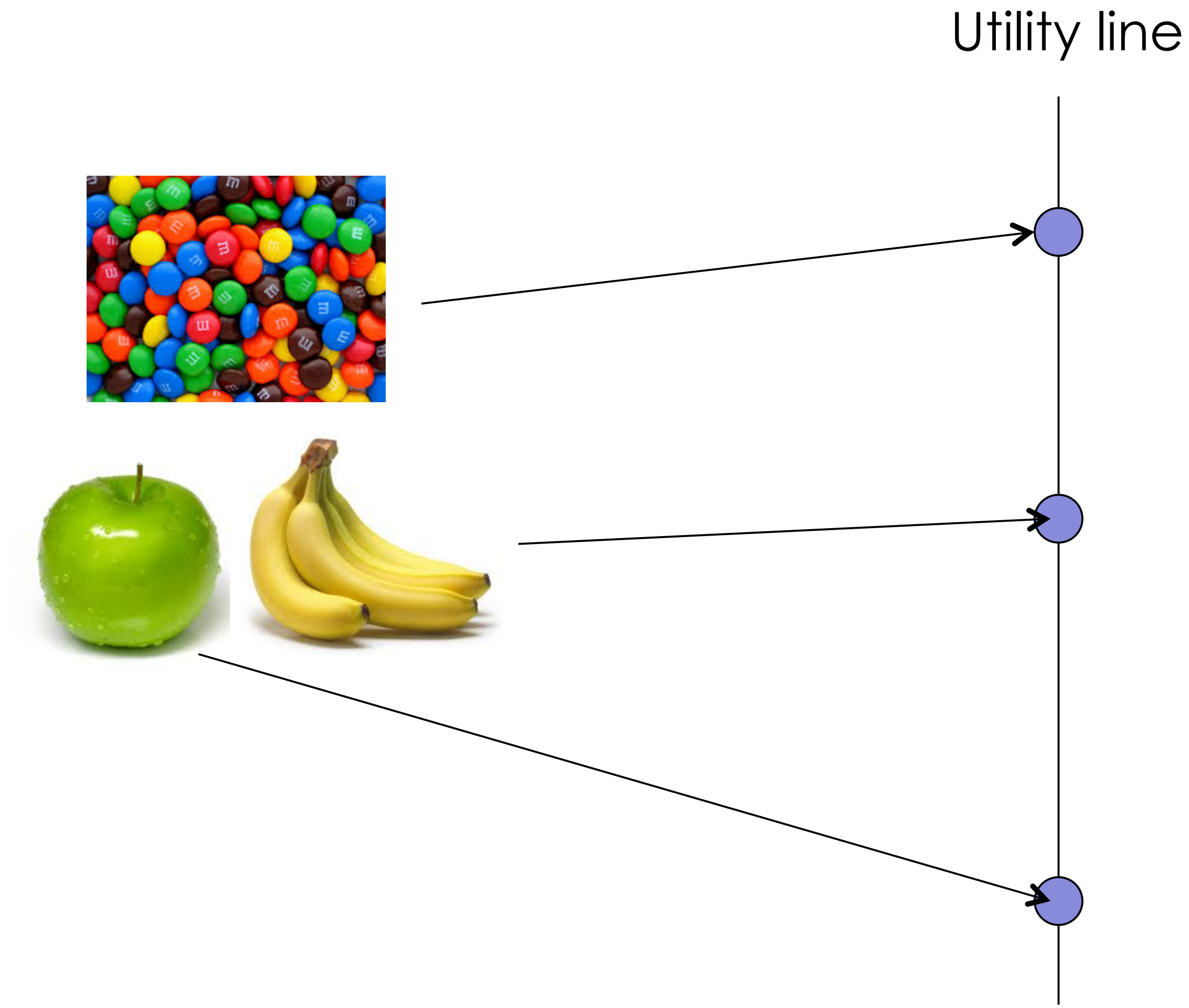
How do we study something that is not observable?

or

Preference is not observable

How do preferences represent?

Utility (效用) or value: The internal representation of one's ordering of preferences

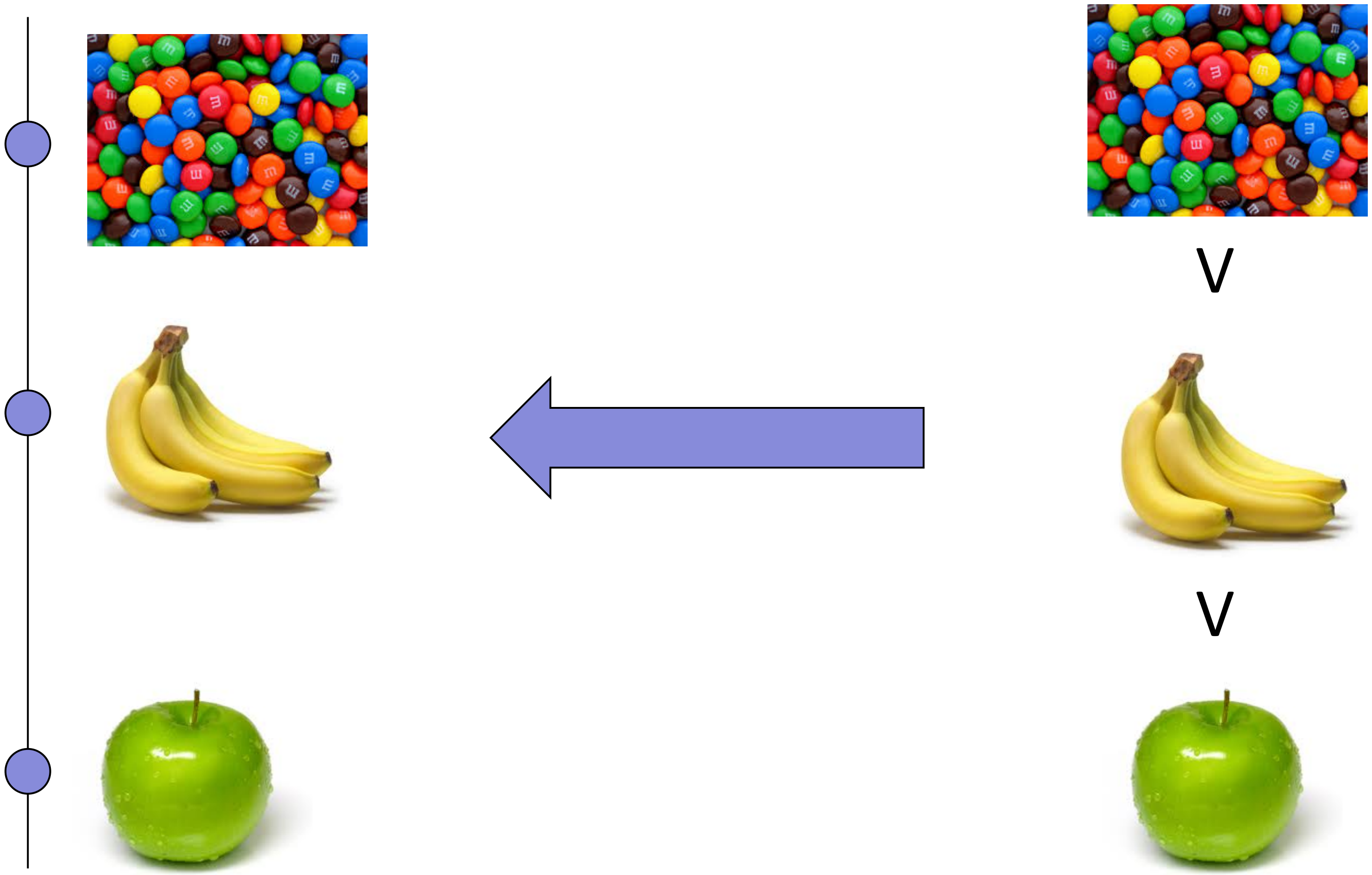


Revealed preference:

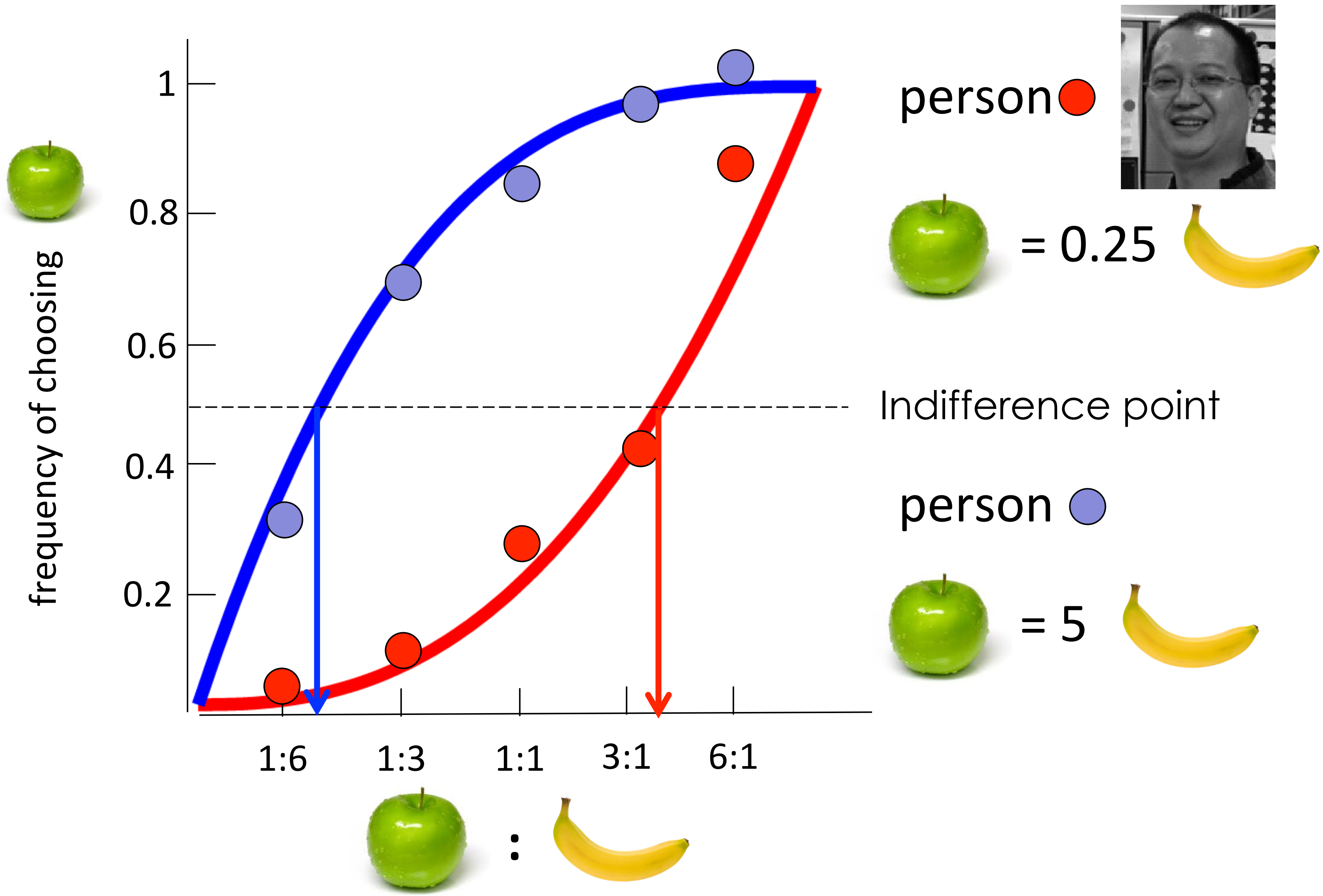
Understanding preference through choice

Not observable: utility

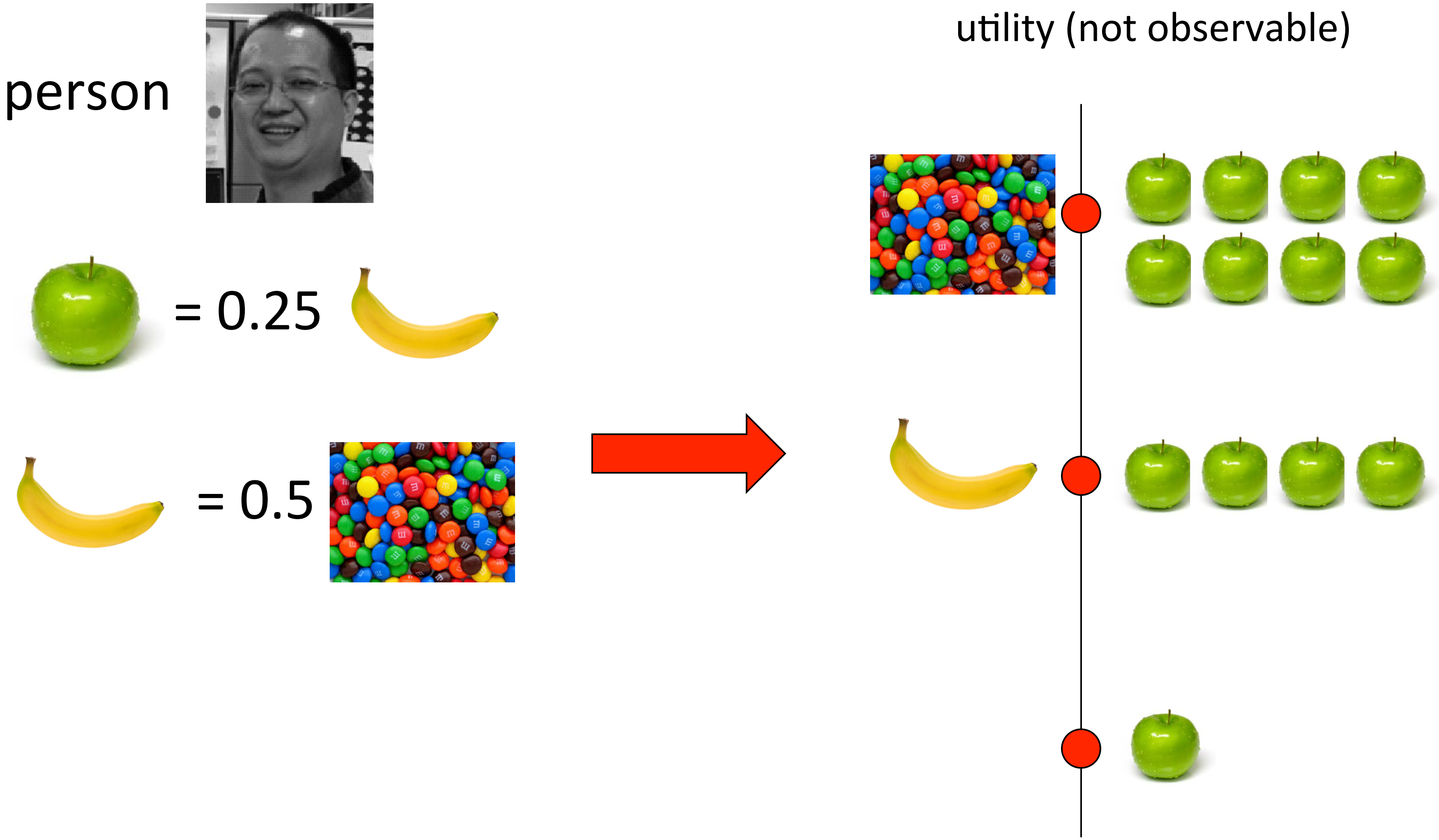
Observable: choice



How do we infer ‘utility’ through choice?



How do we infer 'utility' (subjective value) through choice?



Thought experiment

A decision-making experiment: Choose between options

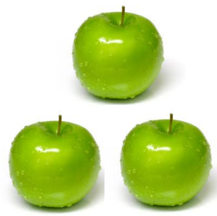
Trial 1

 or 

Trial 2

 or 

Trial 3

 or 

Thought experiment

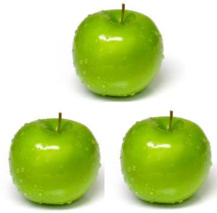
Trial 1

 or 

Trial 2

 or 

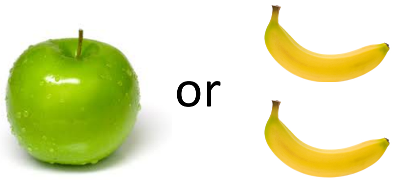
Trial 3

 or 

How do we construct the General Linear Model?

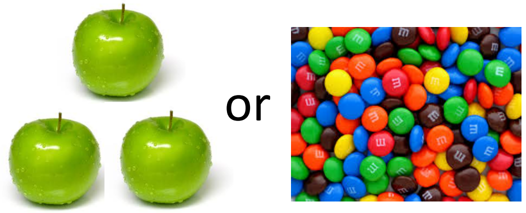
Thought experiment

Trial 1



Trial 2

Trial 3

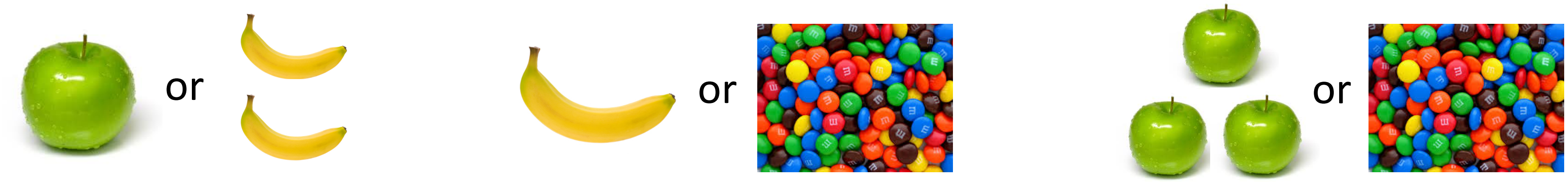


Indicator (boxcar) function

This regressor models the task effect that is consistent across trials

Thought experiment

Trial 1 | Trial 2 | Trial 3

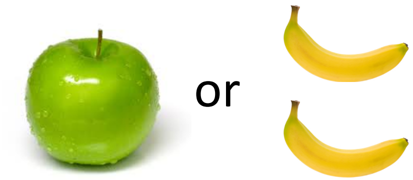


Value of the apple option

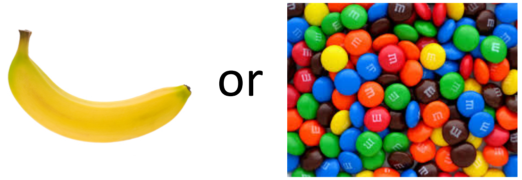
This regressor models the subjective value of the apple option

Thought experiment

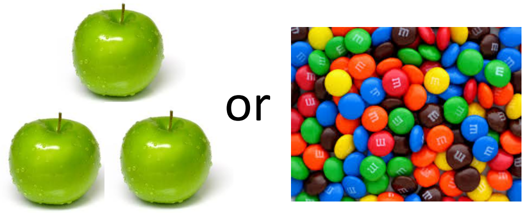
Trial 1



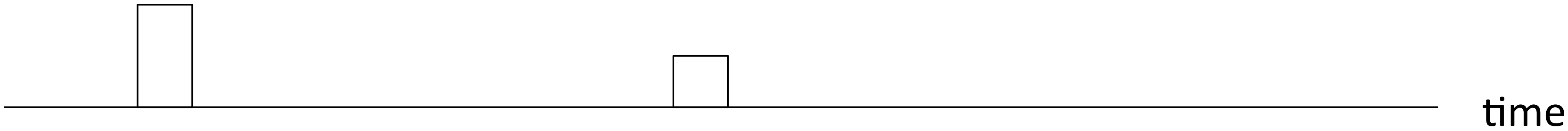
Trial 2



Trial 3



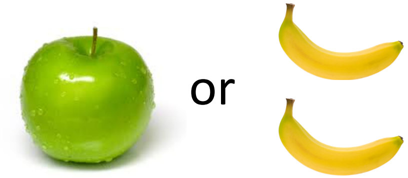
Value of the banana option (in apple units)



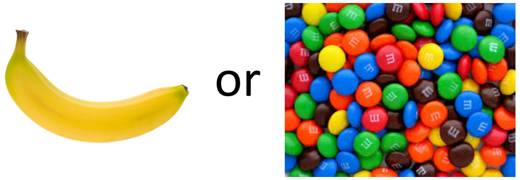
This regressor models the subjective value of the banana option in units of apple

Thought experiment

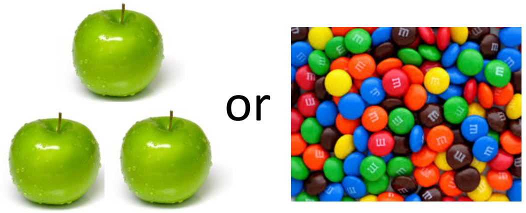
Trial 1



Trial 2



Trial 3

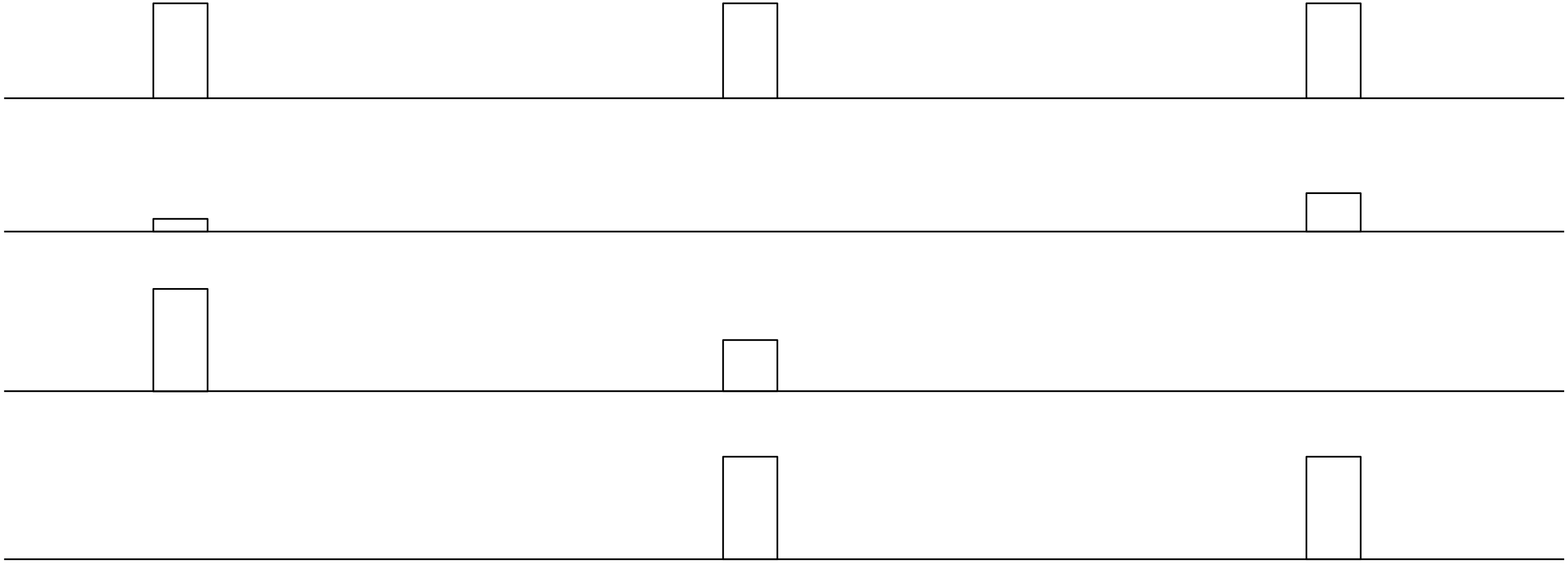


Value of the M&Ms option (in apple units)

This regressor models the subjective value of the M&Ms option in units of apple

Thought experiment

The full General Linear Model (GLM)



Decision making under risk: theory

Which lottery would  choose?

Option A

 20%

 80%

or

Option B

 30%

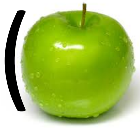
 70%

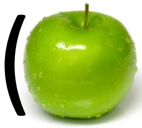
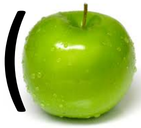
Expected Utility Theory (EUT)

Lottery A

20%

80%

8×U()×0.2+

1×U()×0.8=2.4U()

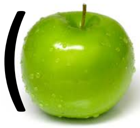
von Neumann (R)
Morgenstern (L)

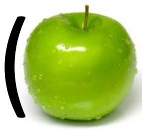
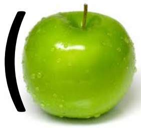
Expected Utility Theory (EUT)

Lottery B

30%

70%

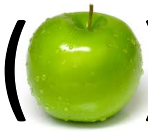
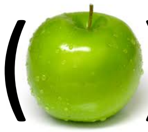
4×U()×0.3+

1×U()×0.7=1.9U()

von Neumann (R)
Morgenstern (L)

Expected Utility Theory (EUT)

Lottery A | Lottery B

2.4U() > 1.9U()

: Lottery A should be the preferred option

Does EUT predict choice well?

The Allais paradox

(.34,$2400)

(17%)

(.33,$2500)

(83%)

Maurice Allais

(1,$2400)

(82%)

(.33,$2500;.66,$2400)

(18%)

Example and data from Kahneman & Tversky (1979)

EUT cannot explain these choice patterns because …

(.34,$2400) (17%)

(.33,$2500) (83%)

Maurice Allais

would imply

$$u(\$2500).33 > u(\$2400).34$$

Example and data from Kahneman & Tversky (1979)

EUT cannot explain these choice patterns because ...

(1,$2400) (.33,$2500;.66,$2400)

(82%) (18%)

Maurice
Allais

would imply

$$u(\$2400) > u(\$2500).33 + u(\$2400).66$$

Example and data from Kahneman & Tversky (1979)

EUT predicts that

$$u(\$2500).33 > u(\$2400).34$$

Add $.66u(\$2400)$ to both sides

$$u(\$2500).33 + u(\$2400).66 > u(\$2400)$$

EUT predicts that

If you prefer

	✔
(.34,$2400)	(.33,$2500)

then you should prefer

	✔
(1,$2400)	(.33,$2500;.66,$2400)

and vice versa.

EUT predicts that

If you prefer

✔

(.34,$2400) (.33,$2500)

then you should prefer

✔

(1,$2400) (.33,$2500;.66,$2400)

and vice versa.

EUT predicts that because

(.34,$2400)

(.33,$2500)

Maurice
Allais

(.66,$2400)
Common consequence

(1,$2400)

(.33,$2500;.66,$2400)

Independence Axiom:

Adding (.66,$2400) *to both* (.34,$2400) *and* (.33,$2500) *should not alter preference*

However, people clearly do not choose as predicted by EUT

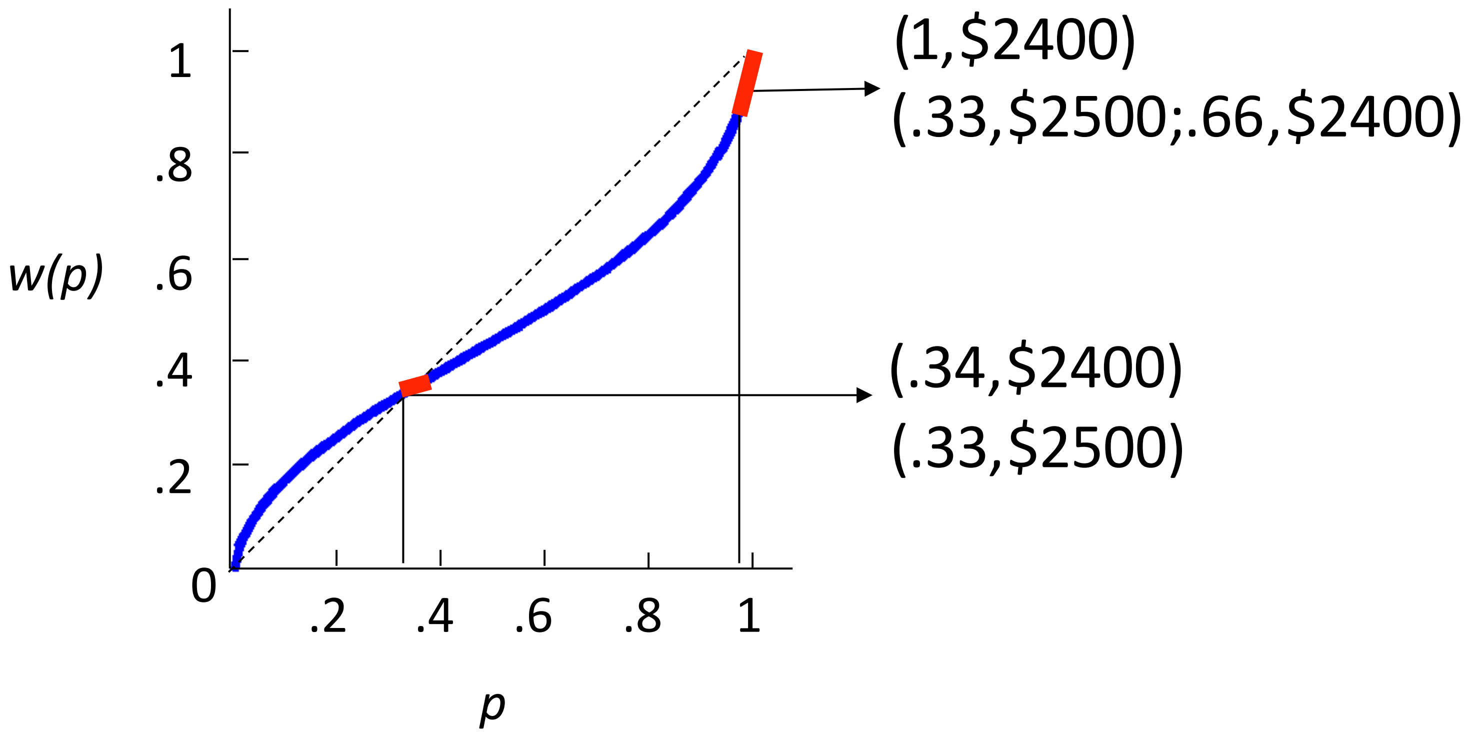
(.34,$2400)	(.33,$2500)
(17%)	**(83%)**
(1,$2400)	(.33,$2500;.66,$2400)
(82%)	(18%)

How can we interpret this result?

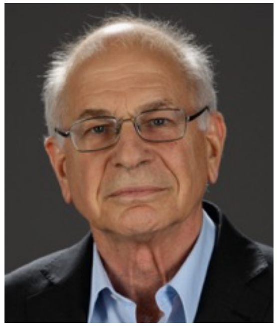
Example and data from Kahneman & Tversky (1979)

Prospect theory

People do not use probability information linearly when making decisions



A. Tversky



D. Kahneman

The probability weighting function, w(p), captures the nonlinear distortion of probability

Tversky & Kahneman (1992)

Summary: behavior and theory

- Value/utility is inherently subjective. It is not observable, but can be inferred from choice behavior

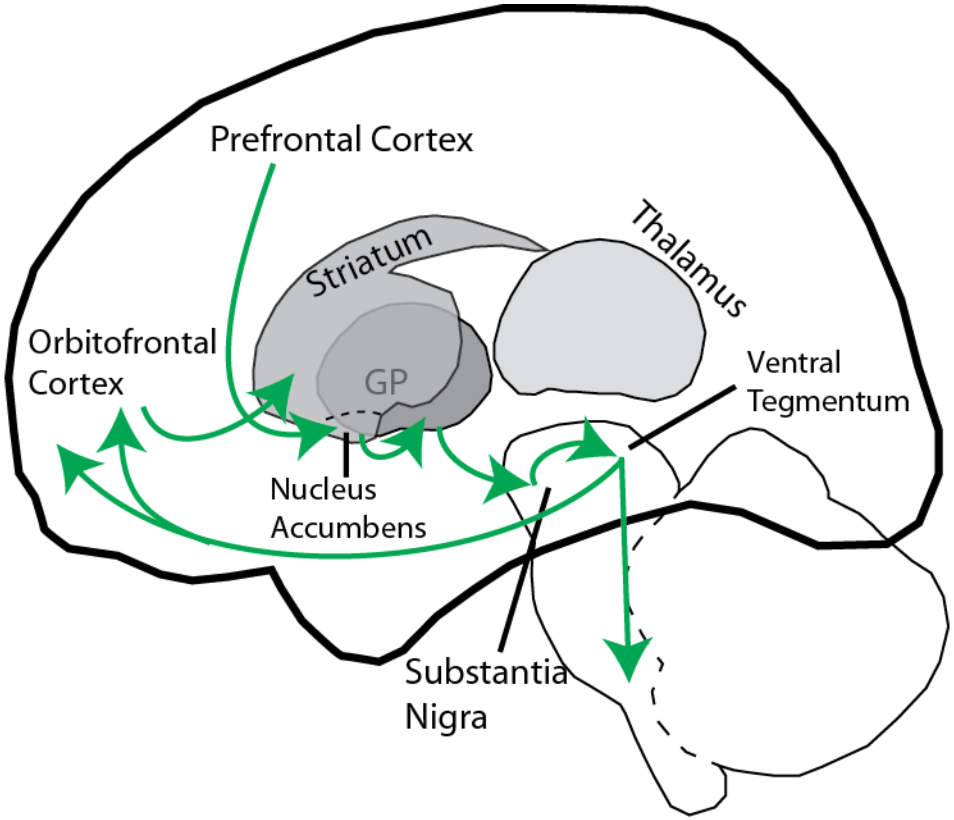
- People do not always choose as predicted by standard decision theory (EUT). Psychologists like Tversky, Kahneman, and many others had brought key insights into Understanding how and why we decide the way we are

II. Linking behavior and neural activity

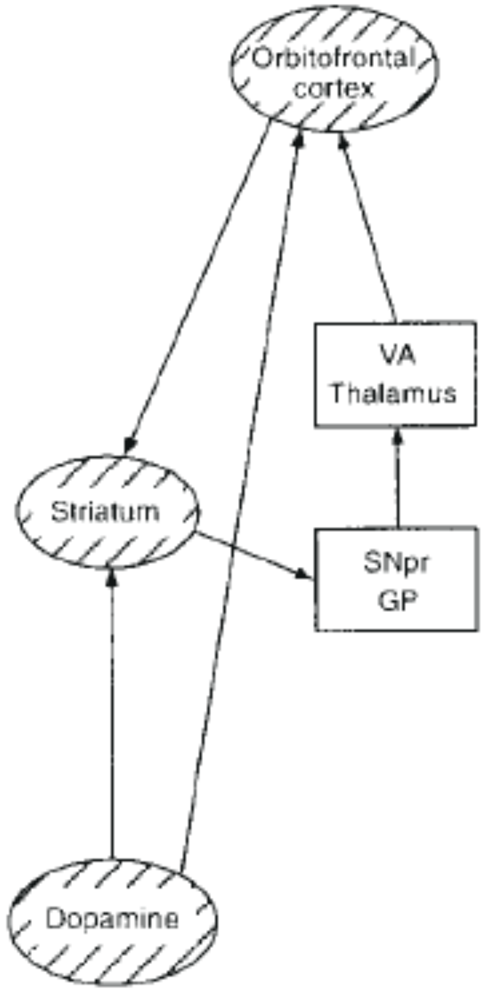
Reward circuitry in the brain

The reward circuitry

Dopamine, striatum, and orbitofrontal cortex

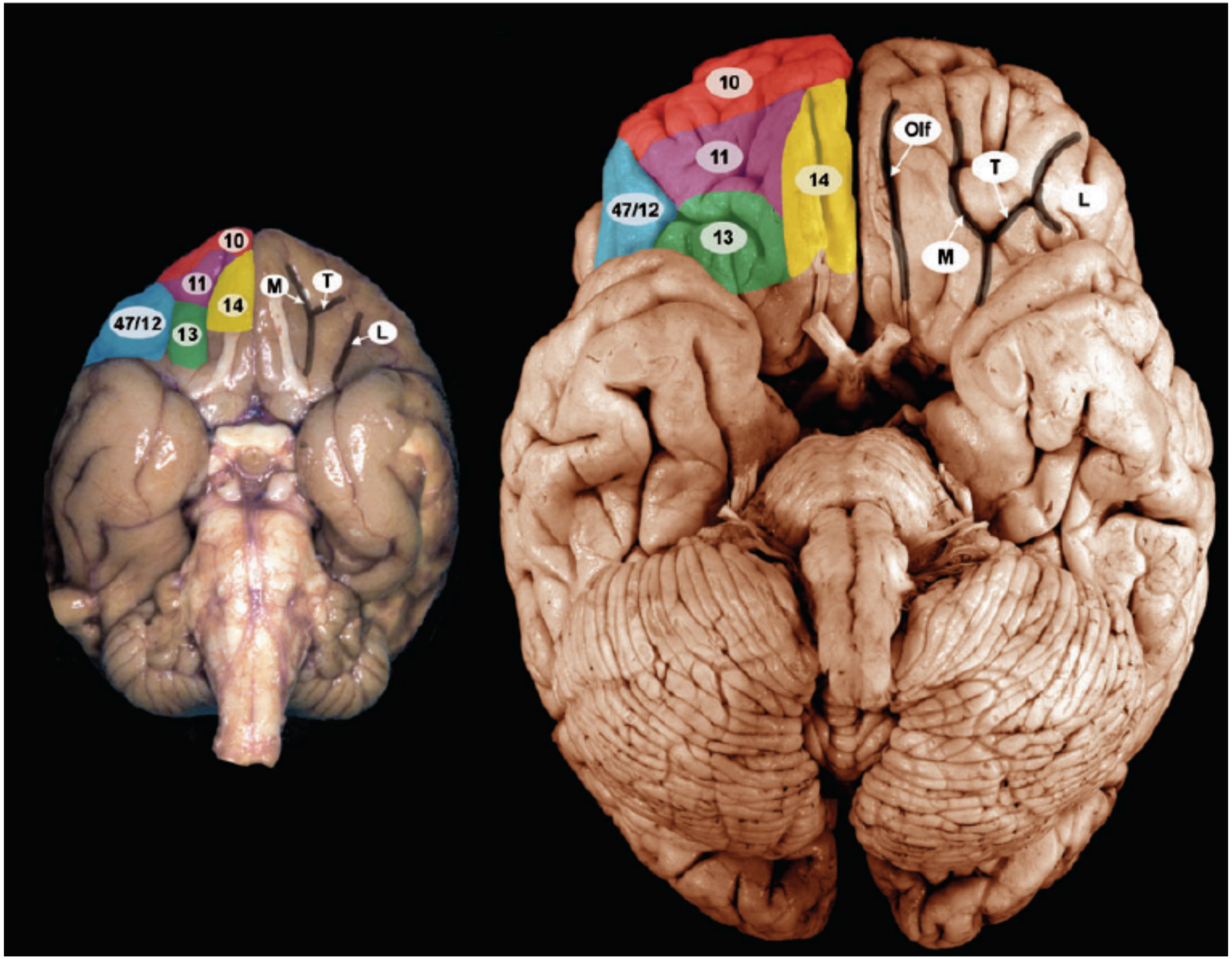


Wise (2002, Neuron)



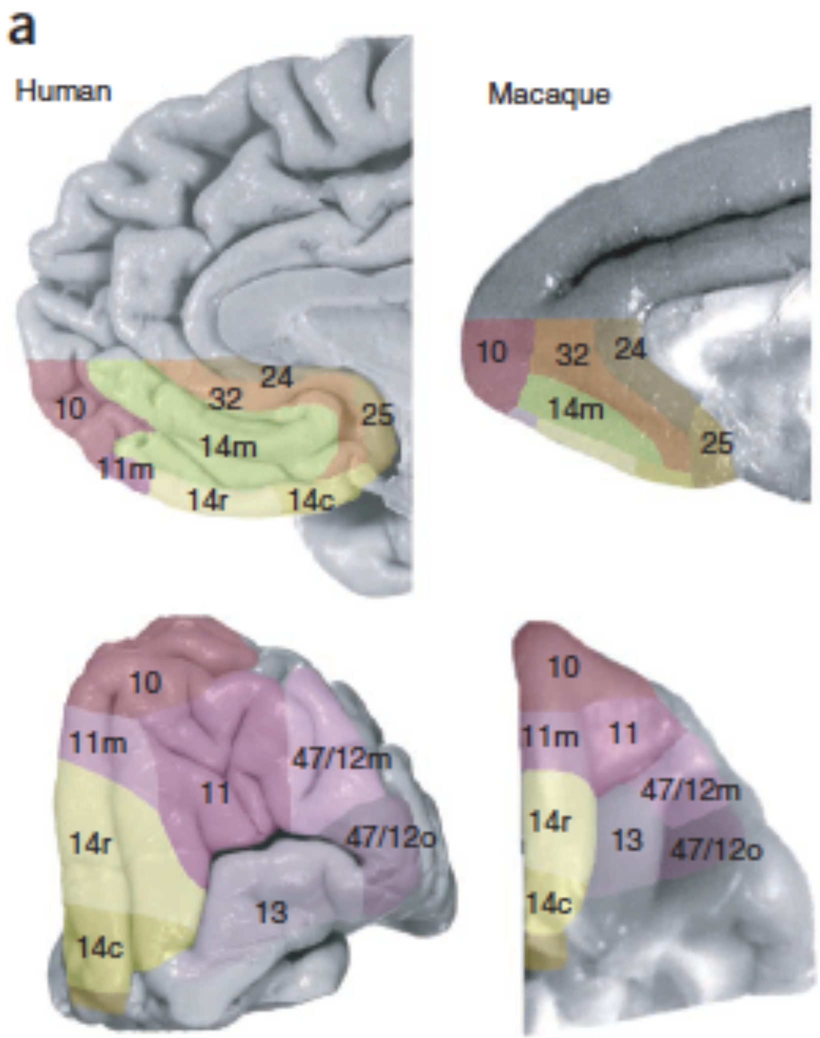
Schultz et al. (1998, Cerebral Cortex)

The orbitofrontal cortex (OFC)



Wallis (2007 ARN)

Orbitofrontal cortex (OFC)



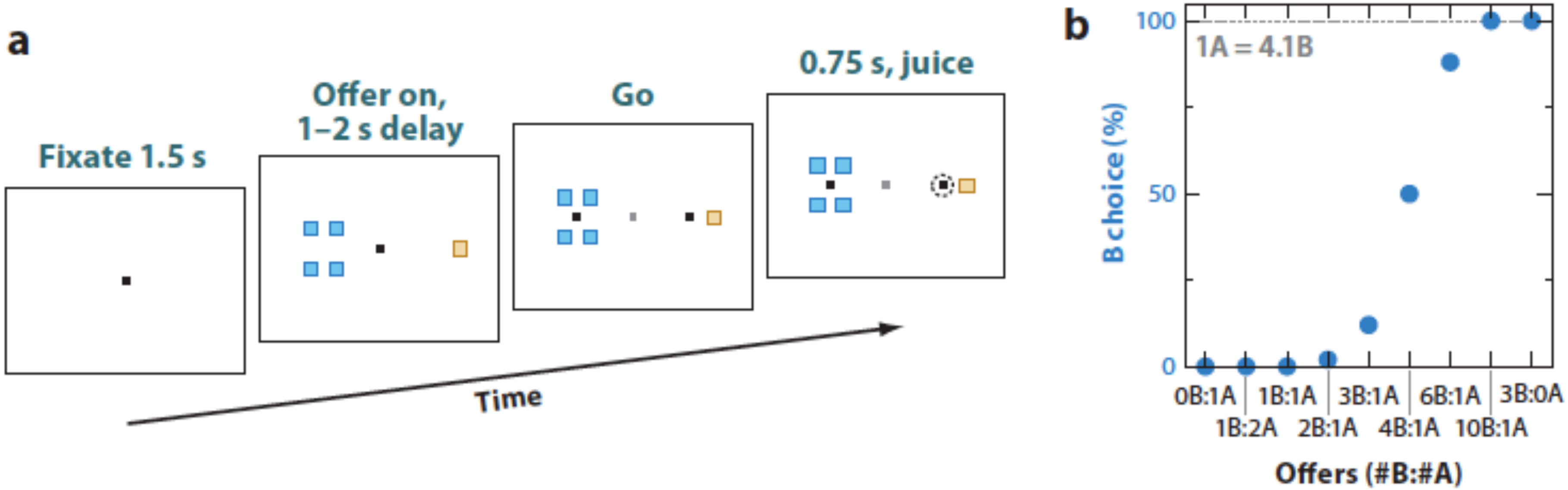
- damage leads to poor decision making (e.g. risk and/or loss seeking in financial decisions)

- damage leads to inability to properly updates stimulus value through experience (e.g. probability reversal learning)

Wallis (2012 Nat Neurosci)

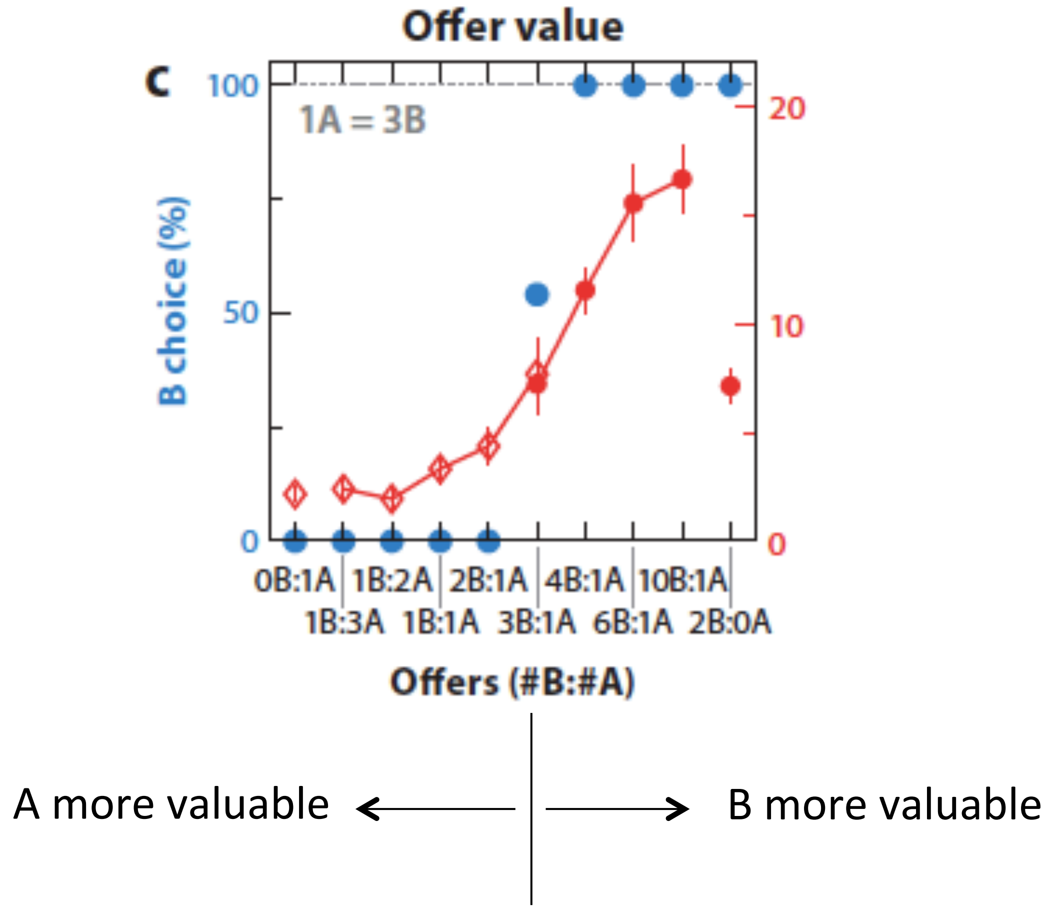
OFC represents the subjective value of rewards

An economic choice task: Animals choose between different rewards



Padoa-Schioppa (2006, Nature)

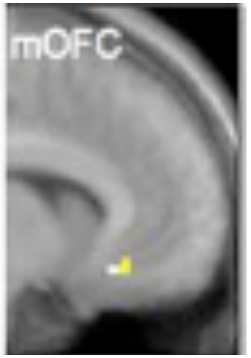
OFC represents the subjective value of rewards



Padoa-Schioppa (2006, Nature)

How does the brain compute subjective value?
Evidence from human fMRI studies

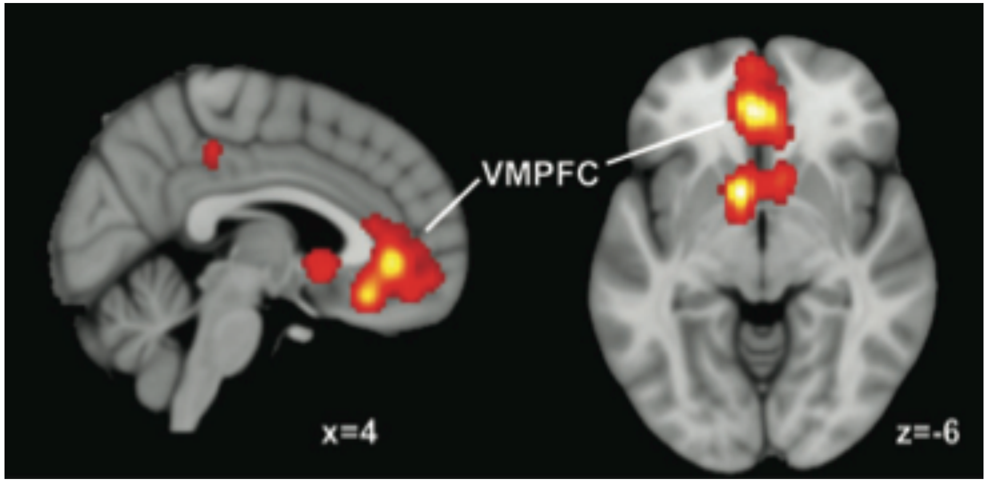
Summary: fMRI results in humans



Activity in the medial orbitofrontal cortex (mOFC) correlates with subjective value (SV)

e.g. Plassmann, O'Doherty, & Rangel (2007)

Valuation network consists of VMPFC and ventral striatum



Clithero & Rangel (2013)

Example study 1:

Self control and decision making

Self control and decision making

- An example: exercising self-control
- Hare et al. (2009, Science):

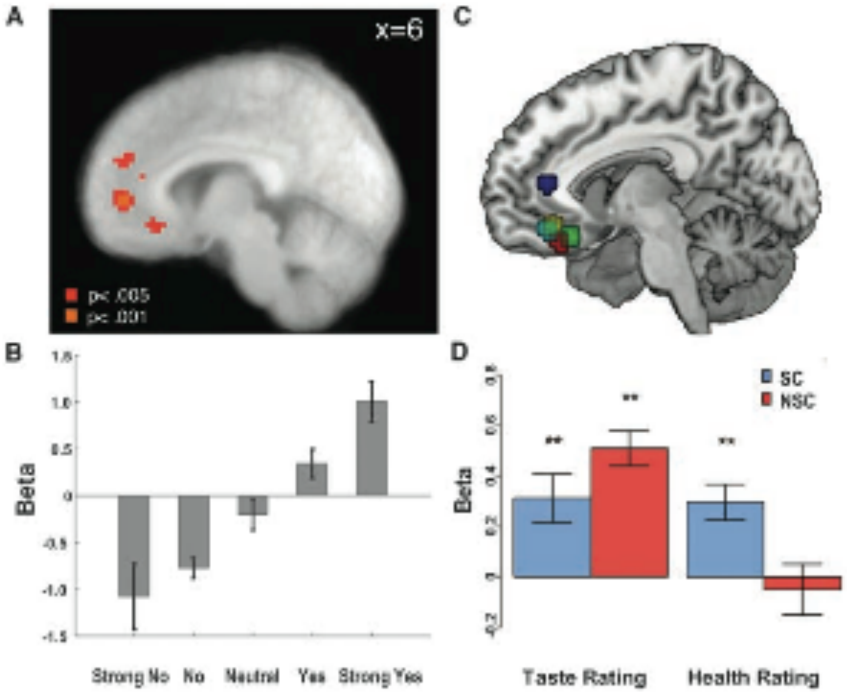
Tasty, bad for health

Or

Not tasty, good for health

The vmPFC represents subjective value

fMRI results

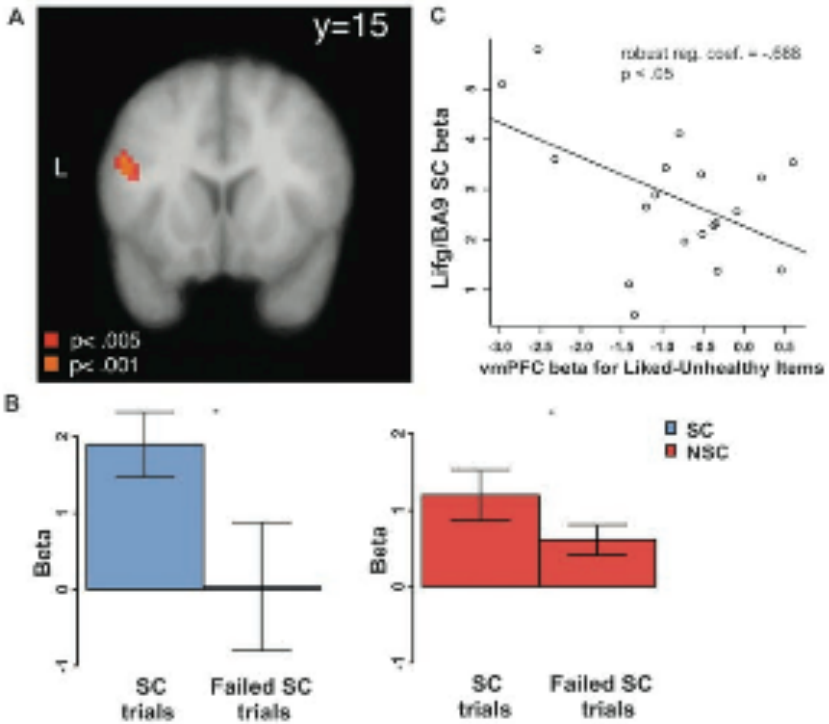


- Activity in ventro-medial prefrontal cortex (vmPFC) correlated with subjective value of food (irrespective of its taste and health)

- NSC's taste rating is more corrleated with vmPFC activity than SC's; SC's health rating is more correlated with vmPFC activity than NSC's

Hare et al. (2009, Science)

The DLPFC correlates with to self control



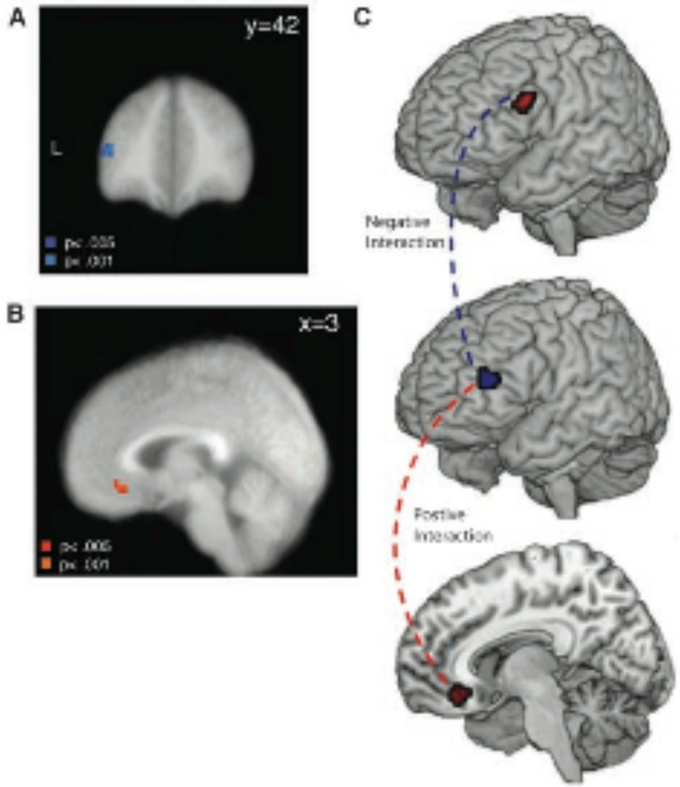
- Activity in dorsolateral prefrontal cortex (DLPFC) was greater in successful self-control trials in SC group than in NSC group

Can DLPFC be responsible for exercising self control??

Hare et al. (2009, Science)

How does the brain exercise self control?

Functional connectivity analysis



- Looking at the SC group:

Increased functional connectivity during unhealthy trials between DLPFC and IFG

Increased functional connectivity during unhealthy trials between IFG and vmPFC

Possible self-control mechanism: DLPFC exercise self-control to vmPFC through IFG

Hare et al. (2009, Science)

Example study 2:

Why do we hate losing more than we enjoy winning?
Neural basis of loss aversion

Examining loss aversion

- Option: Lottery (樂透彩券)

(贏140萬,0.5;輸100萬,0.5)?

- Task: Would you like to play this lottery? (yes or no)

Tom et al. (2007, Science)

People are loss averse

Option	Count (yes)
(贏130萬,0.5;輸100萬,0.5)	7
(贏140萬,0.5;輸100萬,0.5)	10
(贏150萬,0.5;輸100萬,0.5)	10
(贏160萬,0.5;輸100萬,0.5)	11
(贏170萬,0.5;輸100萬,0.5)	13
(贏180萬,0.5;輸100萬,0.5)	16
(贏190萬,0.5;輸100萬,0.5)	16
(贏200萬,0.5;輸100萬,0.5)	28

Tom et al. (2007, Science)

Questions

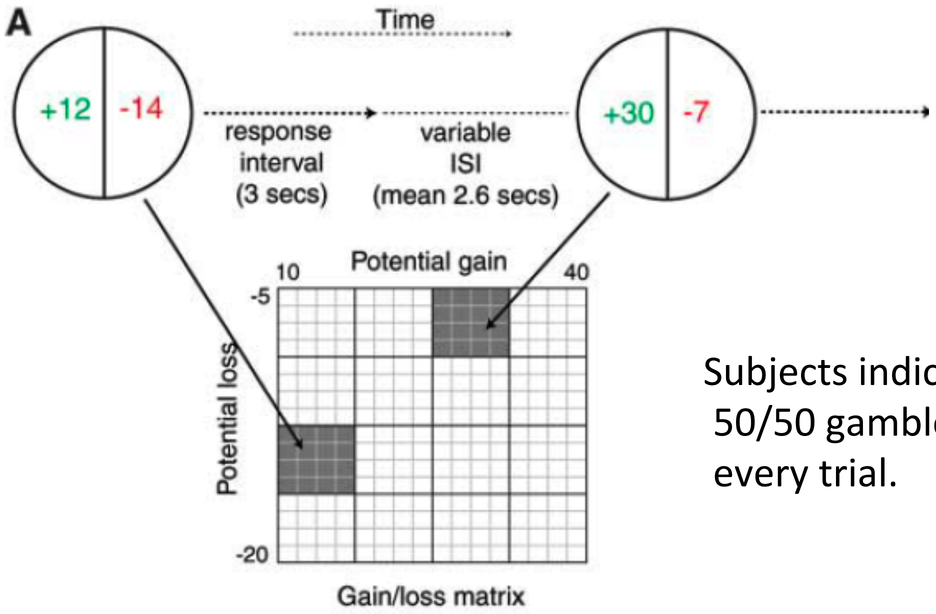
1. How does the brain represent information about gains and losses?

2. Is there any neurobiological evidence for why people are *loss averse*?

Tom et al. (2007, Science)

A gambling experiment

- Experimental design



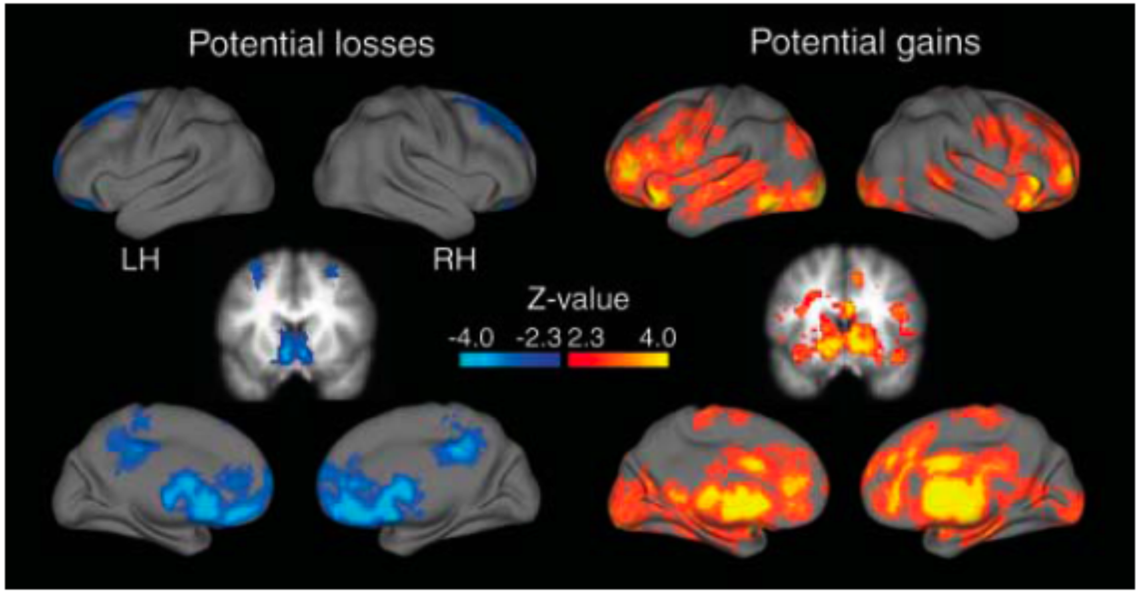
Subjects indicate whether s/he wanted to play a 50/50 gamble on either winning $x or losing $y in every trial.

Tom et al. (2007, Science)

Neural representations of gains and losses

• Network of regions positively correlated with gains and negatively correlated with losses

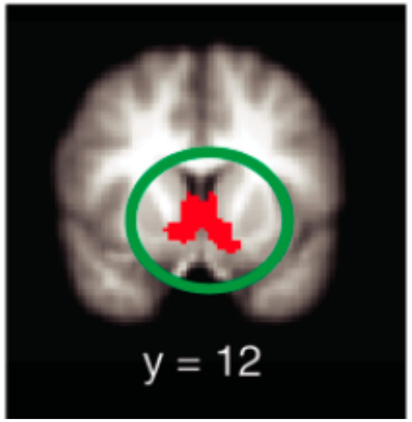
• Including ventromedial prefrontal cortex, ventral striatum, posterior cingulate cortex

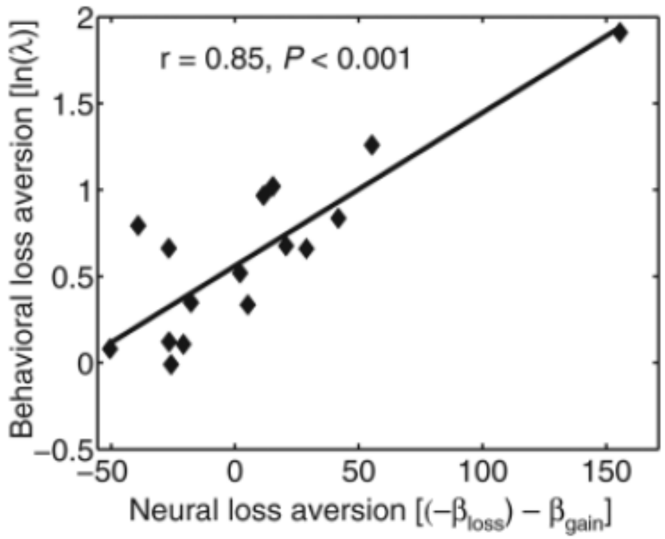


Tom et al. (2007, Science)

Ventral striaum correlates with loss aversion

• Neural measure of loss aversion in ventral striatum strongly correlated with behavioral measure of loss aversion





Suggesting that sensitivity of activity in response to losses relative to gains in this area might contribute to loss aversion observed in behavior

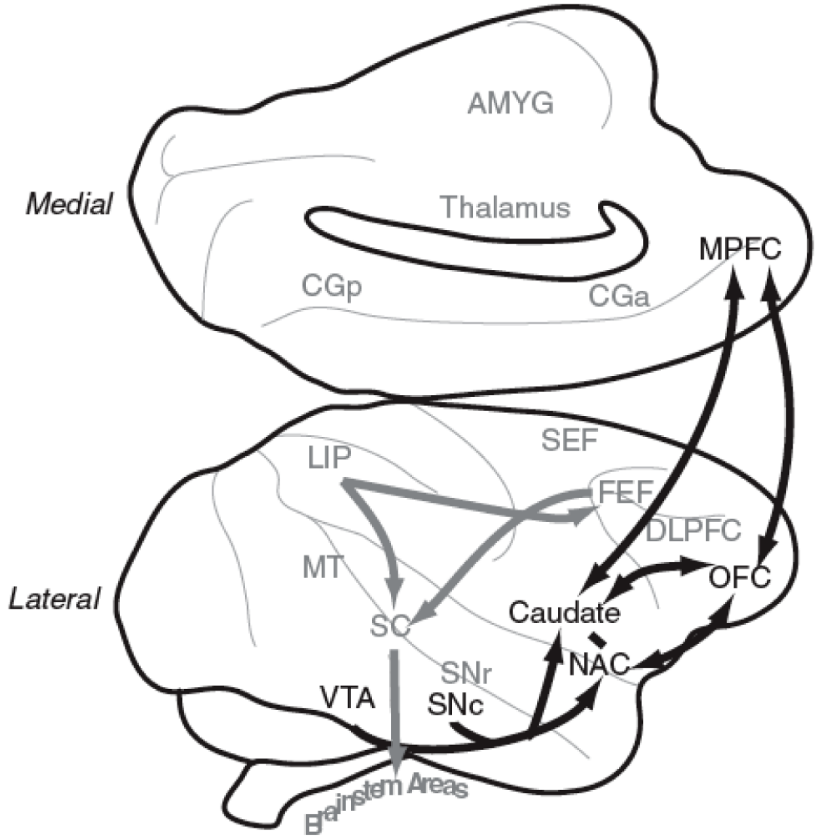
Tom et al. (2007, Science)

Value and choice in the brain:

Neurobiological models of decision-making

The Kable-Glimcher model

Stage 1: Valuation



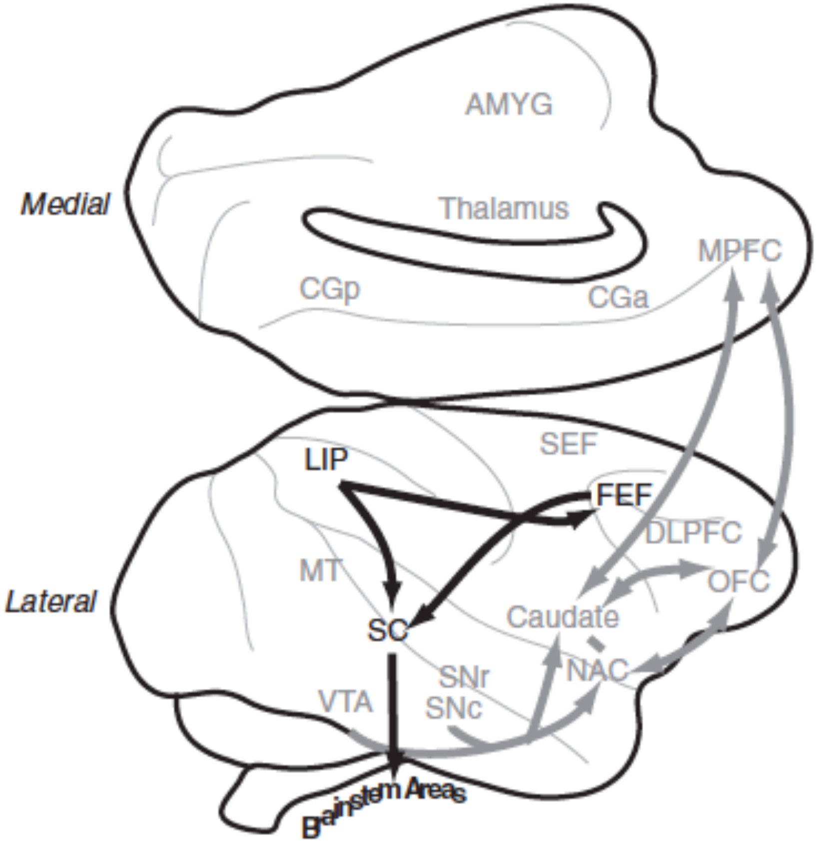
Paul Glimcher

Learning, computing, and representing the value associated with each option in the choice set

Kable & Glimcher (2009, Neuron)

The Kable-Glimcher model

Stage 2: Choice



Paul Glimcher

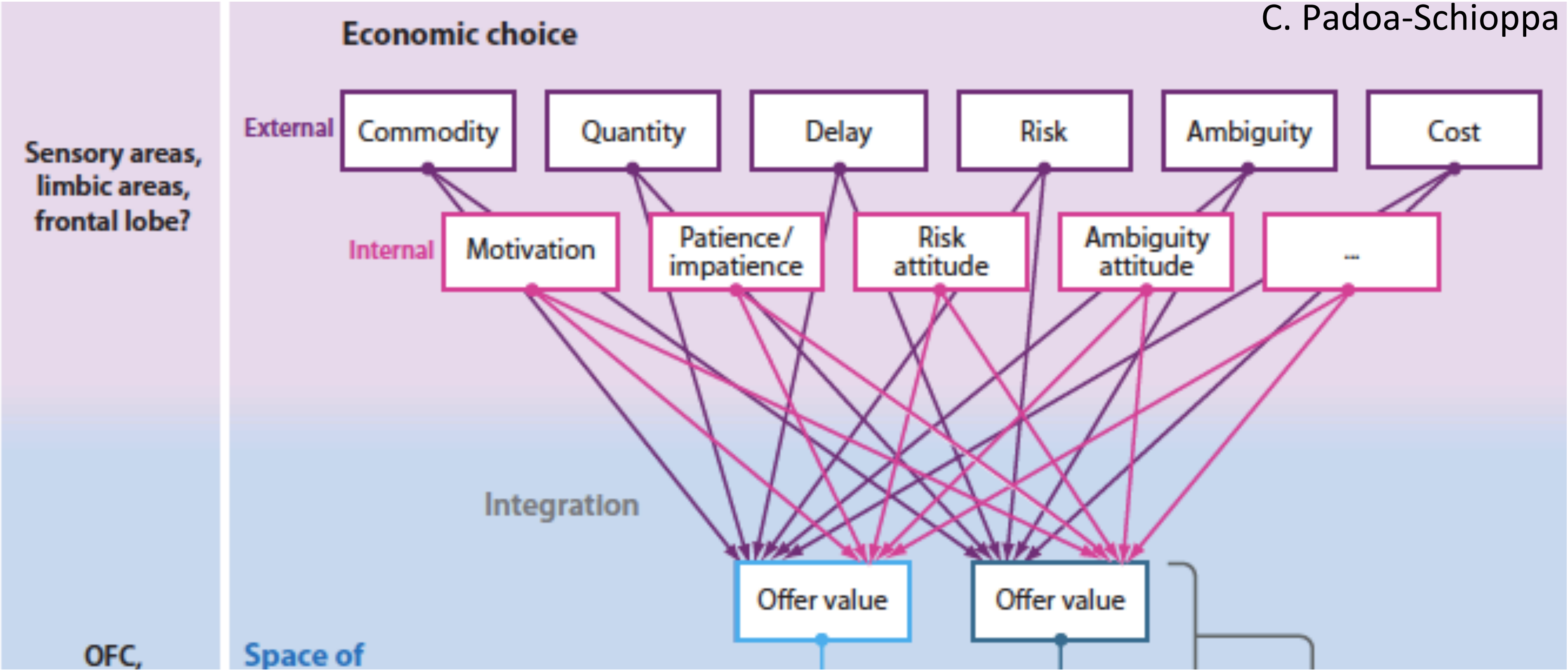
Comparing the values associated with different options through inter-neuronal competitions

Kable & Glimcher (2009, Neuron)

The Padoa-Schioppa model

1. OFC integrates different sources of information into a common value signal

C. Padoa-Schioppa

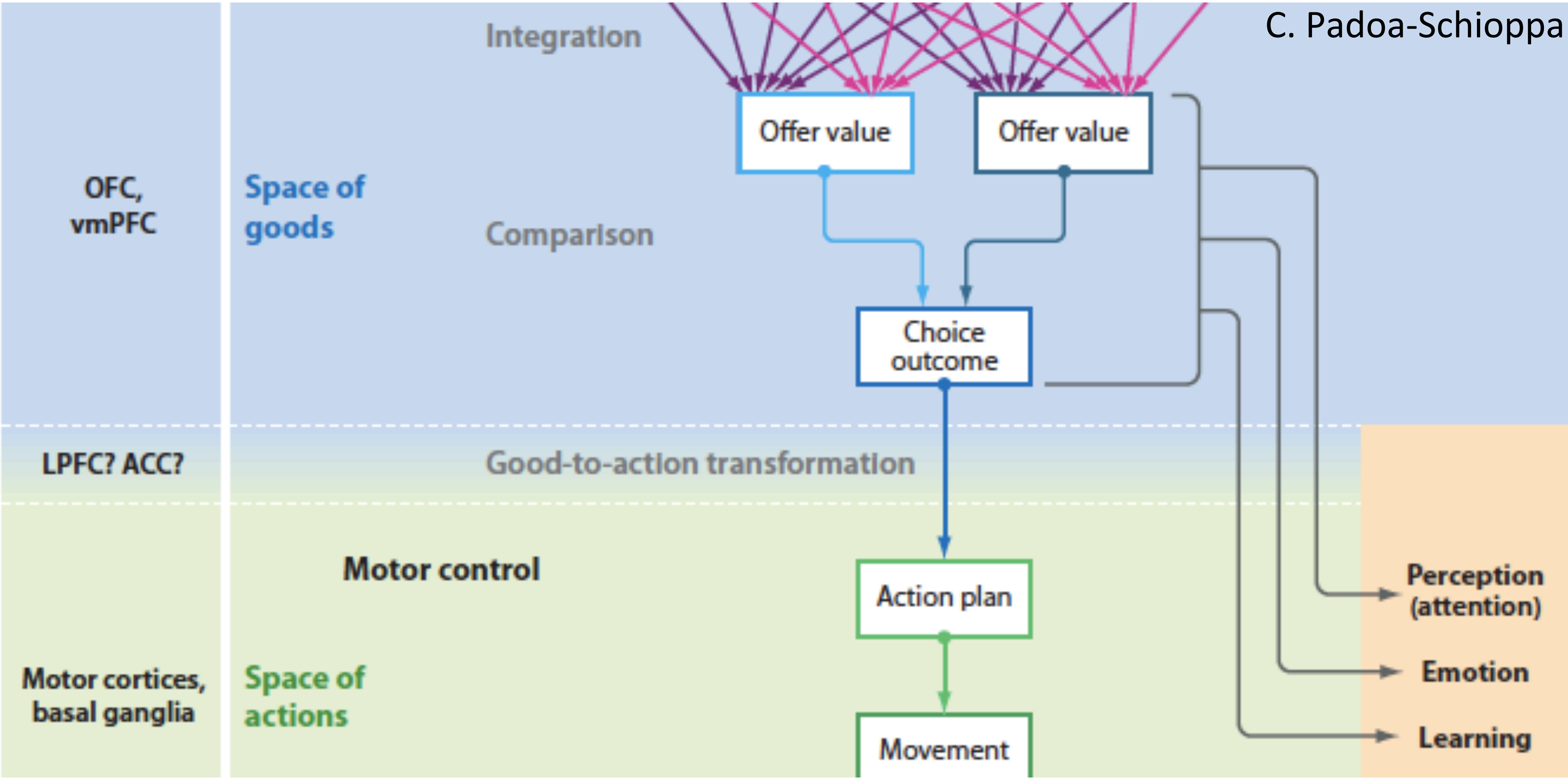


Padoa-Schioppa (2011, ARN)

The Padoa-Schioppa model

2. OFC compares values between options to make choices

C. Padoa-Schioppa



Padoa-Schioppa (2011, ARN)

Conclusions

1. Behavioral studies on decision making provide critical insights into *how* we use different sources of information when making decisions

2. Neuroscience studies on reward processing had identified the neural systems (OFC and others) involved in valuation and choice

3. Neurobiological models are derived from the confluence of insights derived from economics, psychology, and neuroscience

4. Neurobiological models on decision making provide detailed mechanistic descriptions on the decision process and offer a unique perspective looking at choice that is complementary to behavioral models