Neural mechanisms of risky decisions

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Funding: CRCNS

Decision-making under risk

Chose one of few possible actions/products: difficult

- One factors that makes decision making difficult is uncertainty about the outcome of action: ***risk***

Examples:

i) Should we organize BBQ (rain or sunny)? probability

ii) Lotteries:

A. (100 with p .5, 0 with p .5) Vs. B. (50 with p=1)

Two questions:

1. How to make good decisions: *normative theory*

2. How do we actually make decisions: *process theory*

From normative theory (economics) to descriptive (psychology)

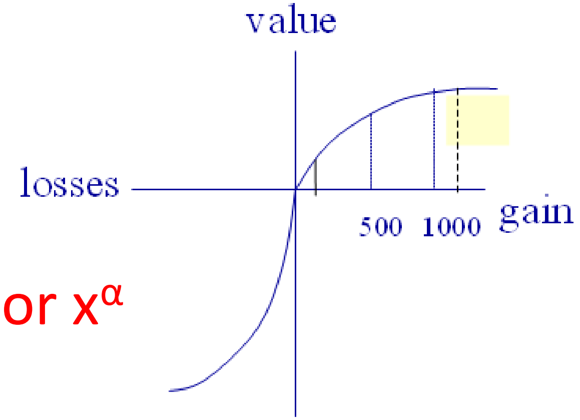
- EV-Maximization: $\sum_i p_i\, x_i$

Gives best outcome if repeated. But:

i) **A**:(100 with p. 5,   0 with p. 5) Vs. **B**. (40 with p=1)

Most people prefer **B**: *risk aversion*

Expected-utility (EU) theory:$\sum_i p_i u(x_i$



Bernoulli's solution: subjective value u(x) =Log (x) or x^α

Even this is not obeyed:

ii) (1000 with p=.001, 0 with p=.999); B (1 with p=1)

Most people prefer A.   Risk seeking

Prospect Theory *(Tversky & Kahaneman)*

CPT

$$CPT(Gamble) = \sum_i \pi(p_i) \cdot v(x_i)$$

Process theory: neuroeconomics

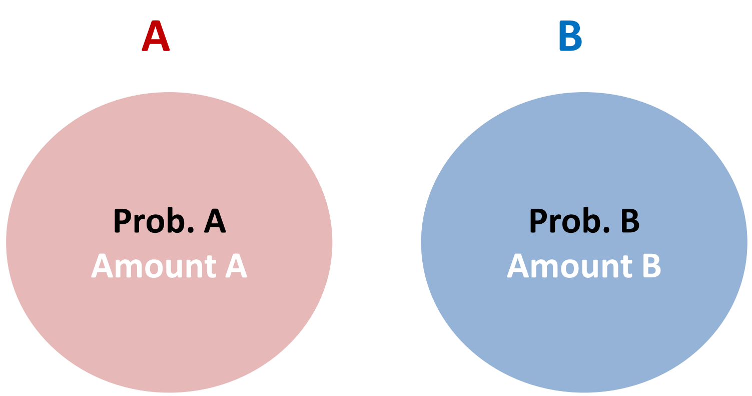
How does the brain make risky decisions?

Working assumption: animals evolved to optimize reward

Our Questions:

1. How do we represent probabilities and amounts?
2. How to we combine them to generate a value/utility?

do we process within an alternative or compare attributes?



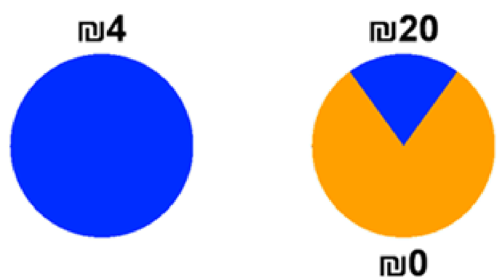
Process theory: neuroeconomics

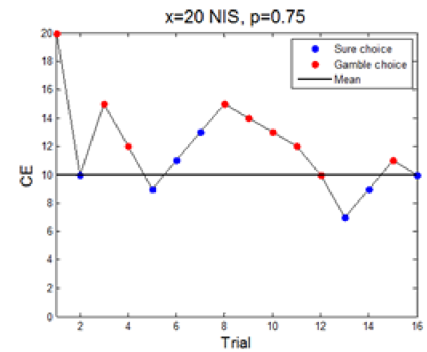
Methods:

1. Risky choice experiments with humans (eye-tracking to follow the dynamic process that builds preference)
2. Computational models
3. Physiological recordings in monkeys

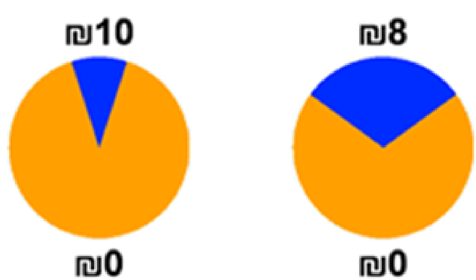
TAU Study: behavioral humans

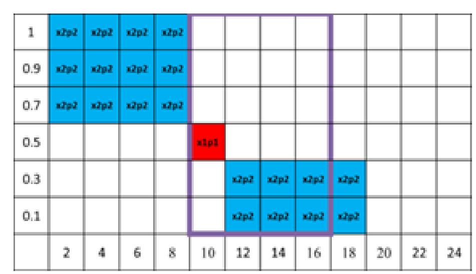
Certainty-Equivalent





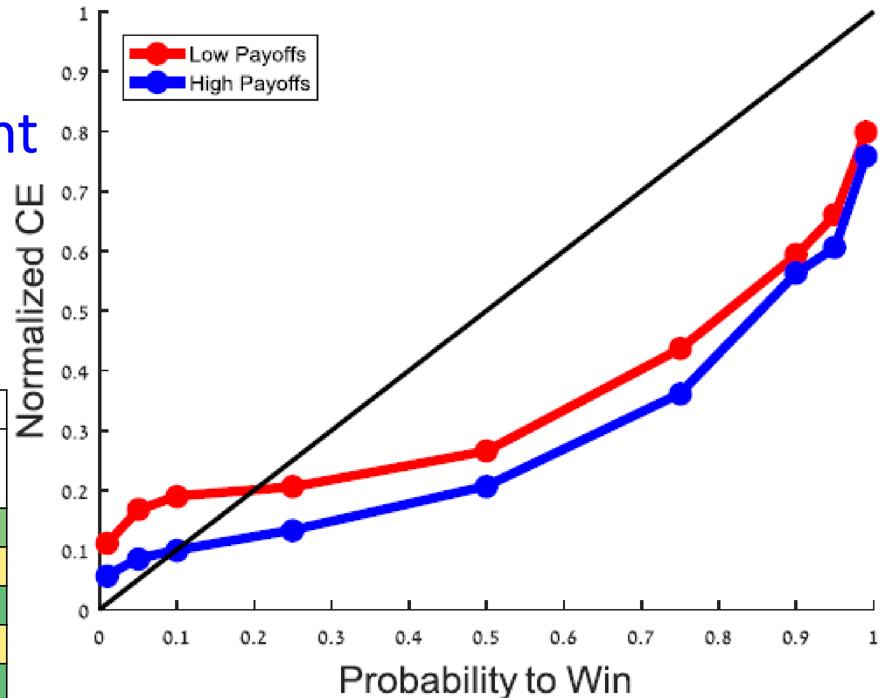
Lotteries on grid





Results: risk aversion

- Sensitive to EV, but shows risk aversion which increase with amount
- Model comparison:



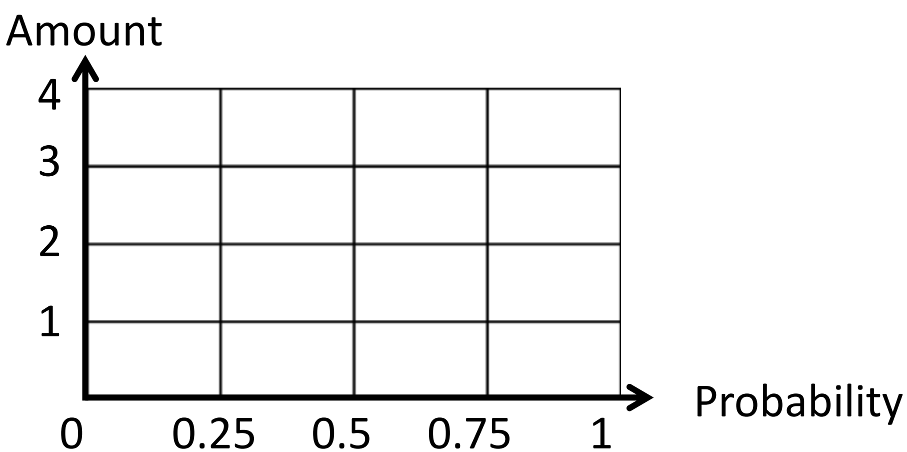
Linear, EV, EU, Prospect theory

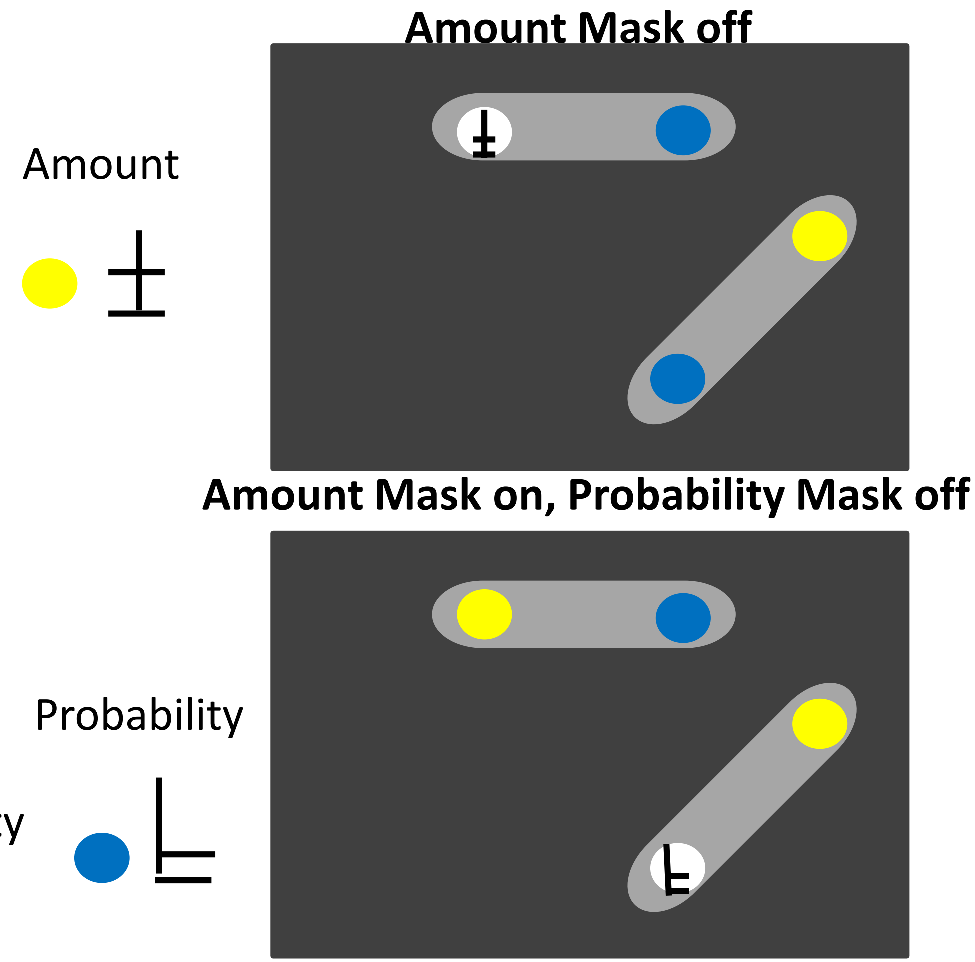
Grid BIC					Generalization: Grid to CE				
Subject	Linear Model	EV	EU	CPT2	Subject	Linear Model	EV	EU	CPT2
1	422	311	312	304	1	15	10	14	11
2	360	274	259	265	2	14	10	11	11
3	300	327	333	289	3	9	8	9	4
4	432	291	296	302	4	13	12	12	12
5	271	349	242	235	5	13	17	12	8
6	343	293	270	276	6	9	6	6	6
7	49	62	52	54	7	51	28	11	11
8	260	363	205	182	8	45	23	18	12
9	243	370	243	225	9	11	17	8	4
10	196	362	152	145	10	12	20	13	9
11	162	364	137	137	11	6	16	4	4
12	340	333	283	288	12	17	6	8	8
13	202	292	137	143	13	7	9	5	5
14	198	358	161	162	14	10	22	12	10
15	259	362	263	269	15	4	11	9	9
16	400	455	461	463	16	3	16	17	16
17	190	332	165	171	17	13	12	12	12
18	152	389	137	127	18	13	27	18	13
Group Level	283	347	231	230	Group Level	15	15	11	9

- EU gives a good account of risk-aversion
- PT improves the fit, and the generalization to certainty equivalents (low-p risk seeking)

Risky choice with eye-tracking

US study:
information is gaze contingent





⇒ 5x5 = 25 options
⇒ 25x25 = 625 comparisons

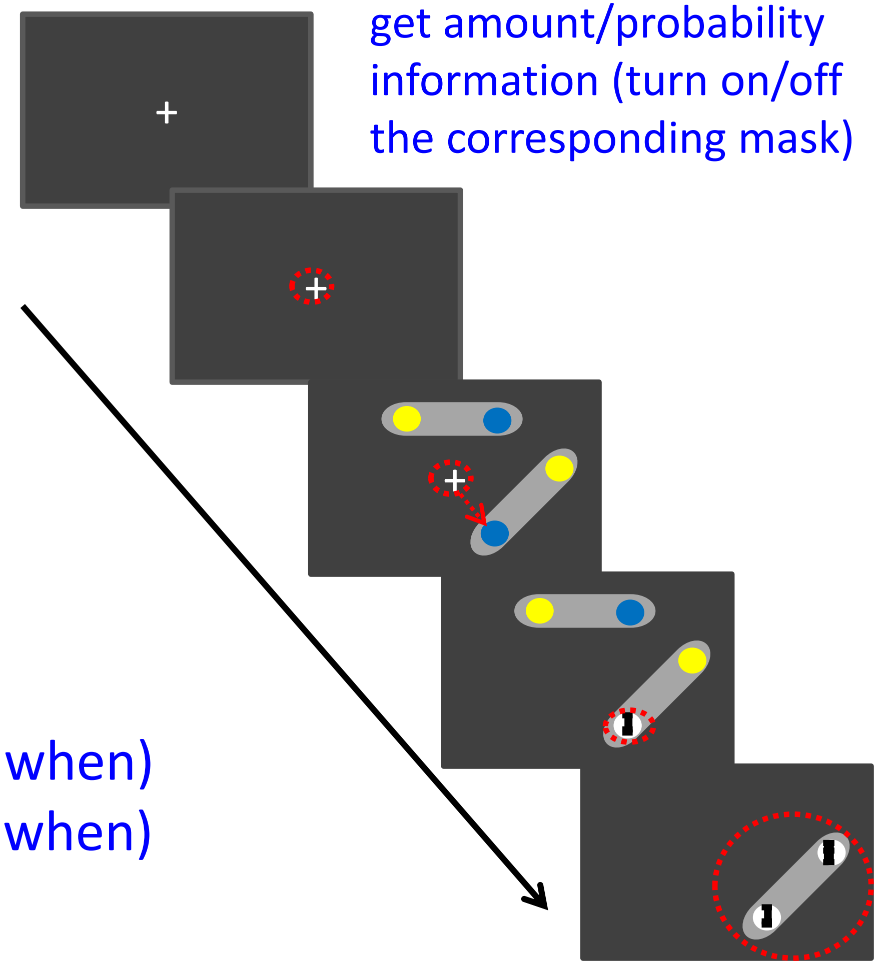
Experiment procedure

1. spatial configuration
2. eye position for whole trial: x(t), y(t)

Events (and time):

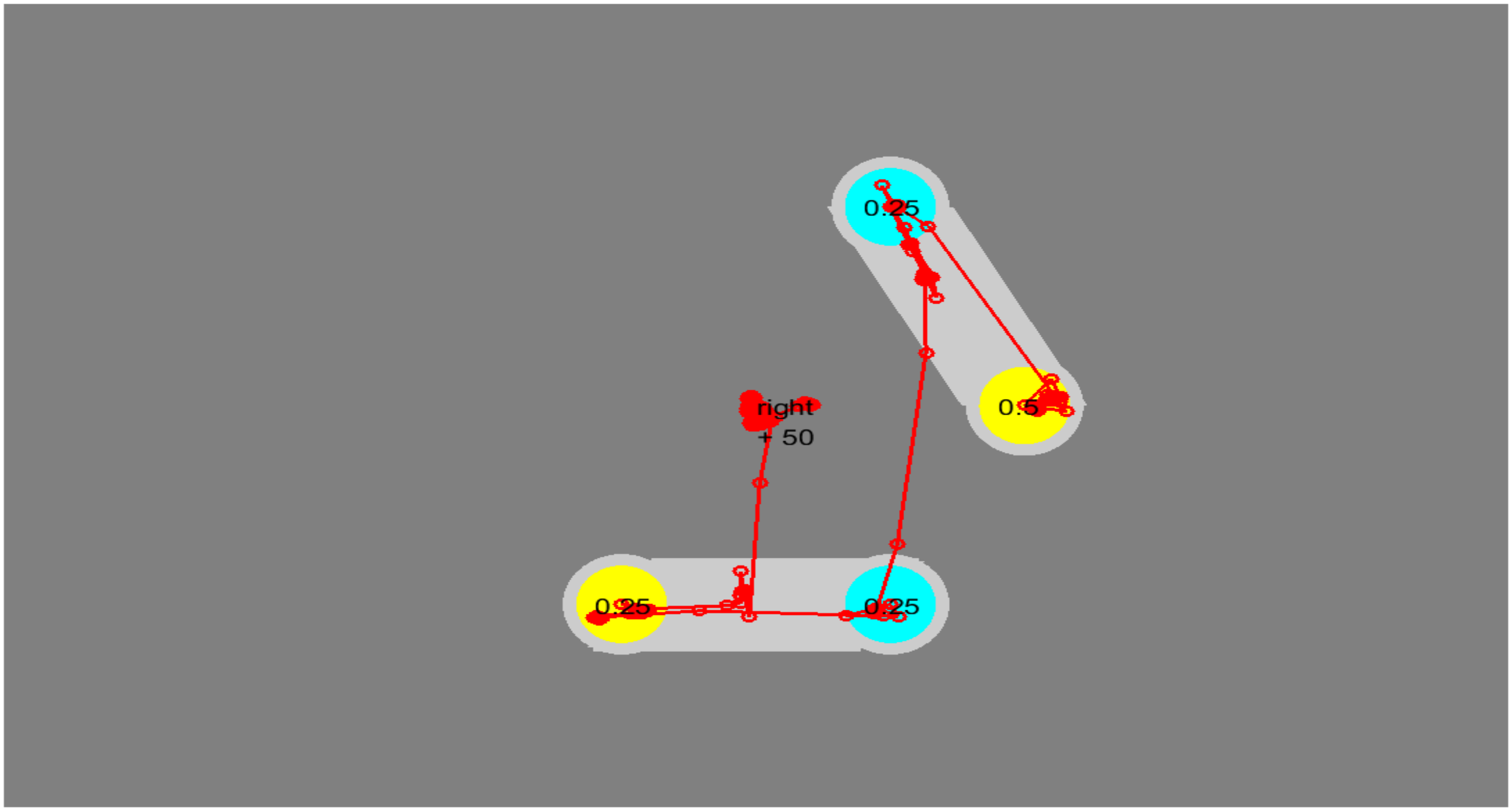
0. fixation point display (as time “0”)
1. Central fixation onset
2. Display onset
3. Mask on (which and when)
4. Mask off (which and when)
5. Button/joystick response (which and when)
6. Reward/outcome display (which and when)

Eye movement to get amount/probability information (turn on/off the corresponding mask)

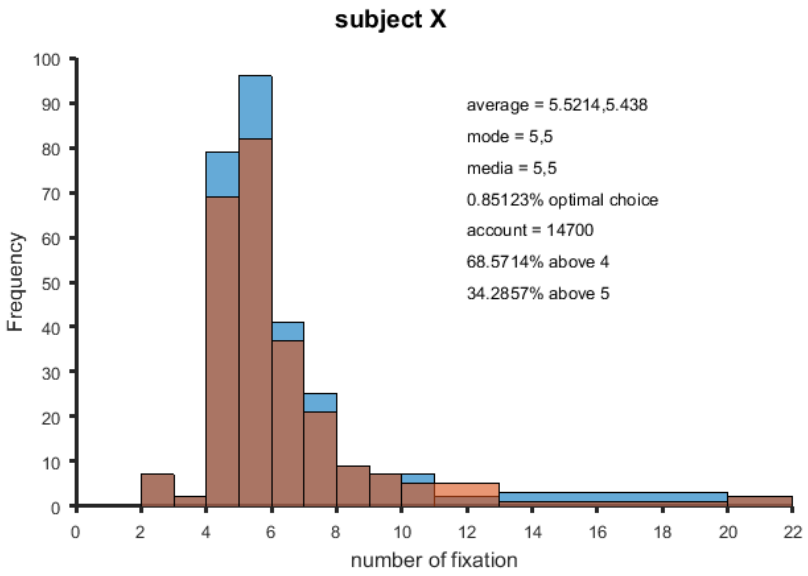


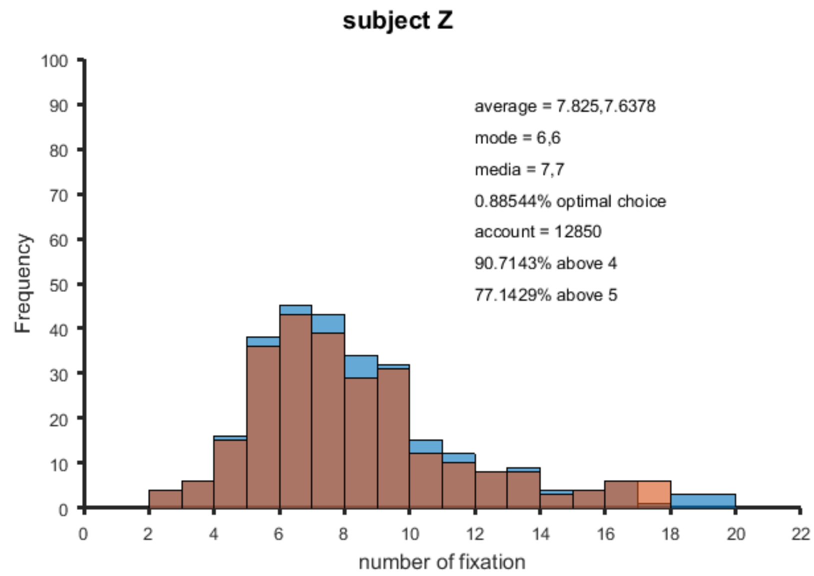
Make final decision by pressing button (human) or moving joystick (monkey)

Human behavioral data

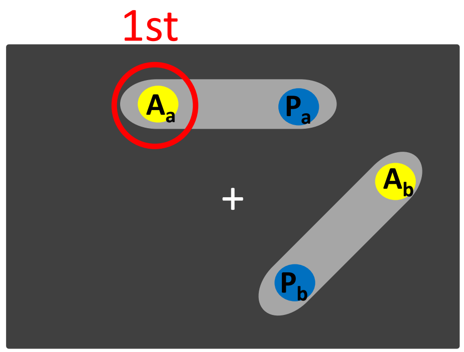


Number of fixations of attributes before choice





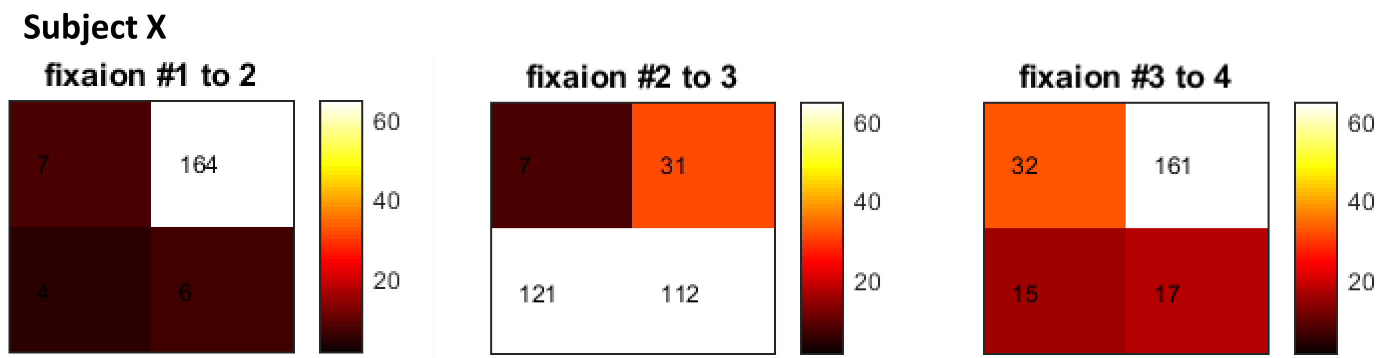
‘Within-option’ and ‘Within-Dimension’ Search Strategy



S	O
D	N

S: same
O: option
D: dimension
N: neither

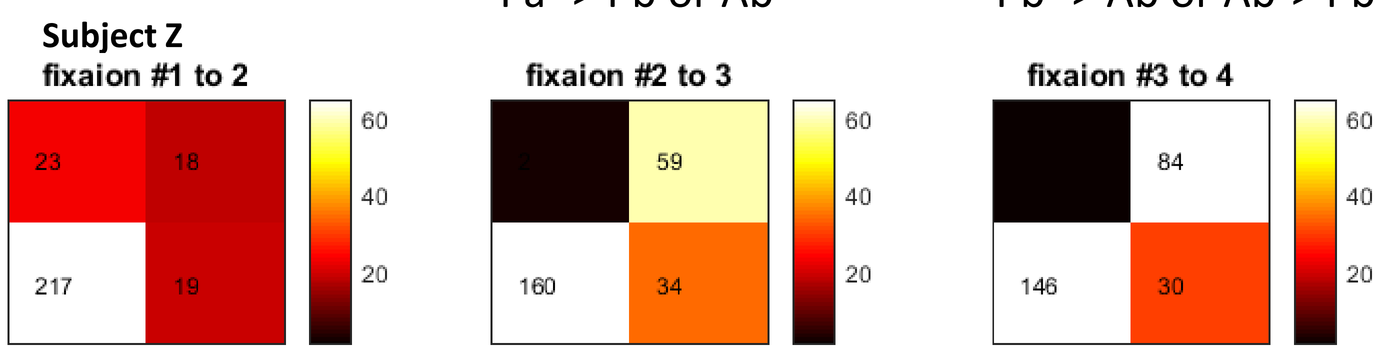
Within-option strategy



Pa -> Pb or Ab

Pb -> Ab or Ab-> Pb

Within-dimension strategy



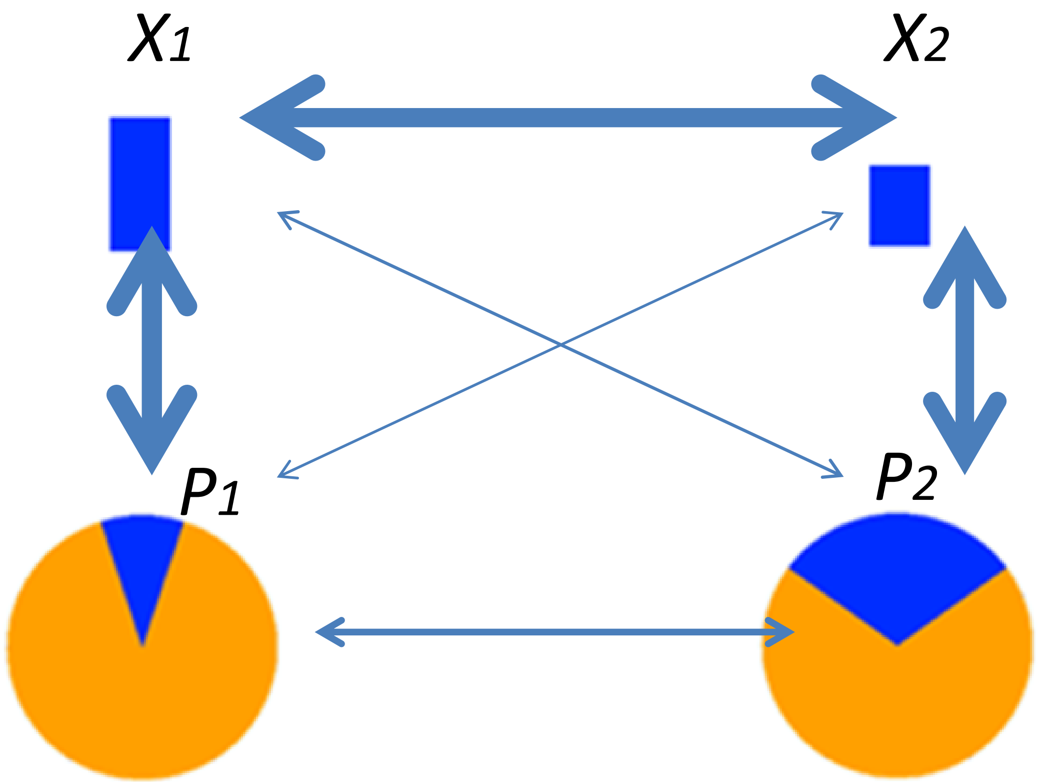
Aa -> Ab

Ab -> Aa

Aa -> Ab or Aa->Pa

TAU study: information always available

Average across fixations and S

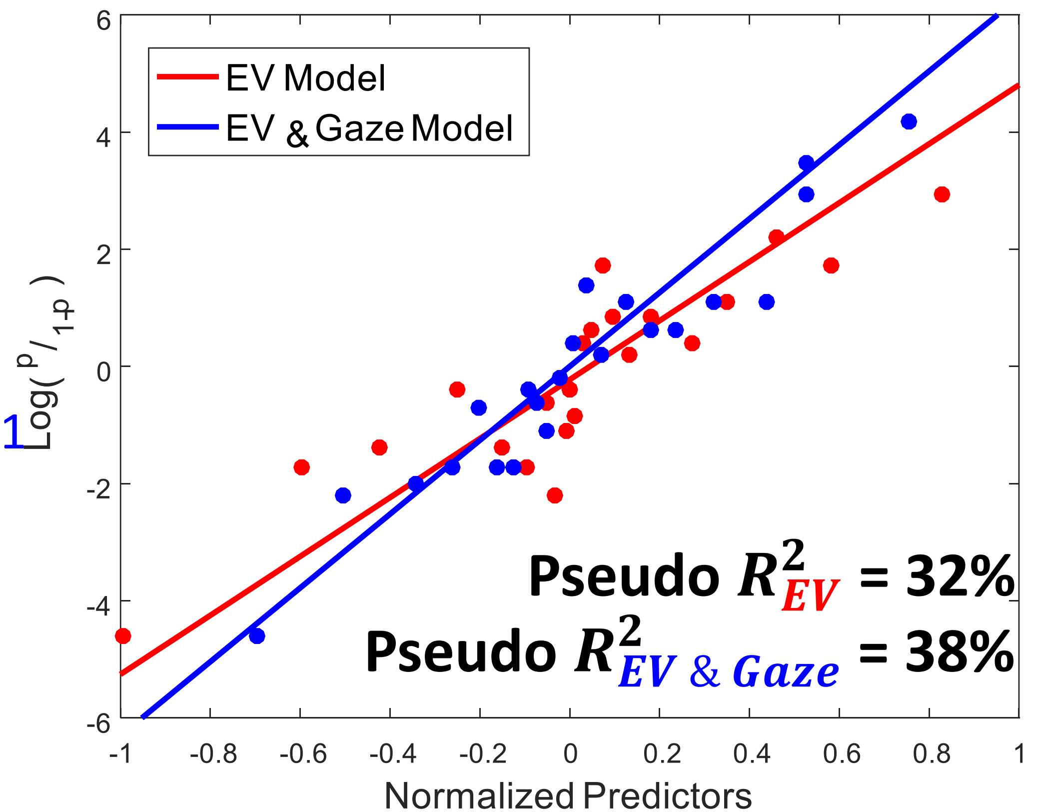


Do eye fixations help to predict choice

- Eye-movements add explanatory power that goes beyond the capabilities of the normative expected-value model.

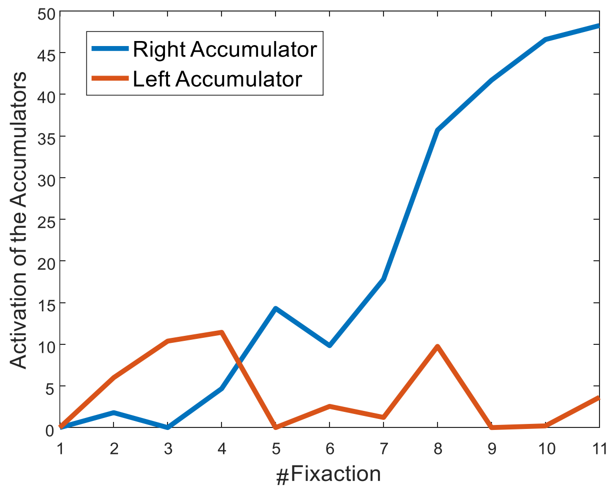
logistic regression on choice with *ΔEV* (left-right) and right options (henceforth), as well *Δtime* (left-right): $P(Left\ option) = \frac{1}{1+e^{-(\alpha+\beta_1 \Delta EV+\beta_2 \Delta time)}}$

- ΔEV coefficients - significant for all the participants
- Δtime coefficients – significant for 11 of the 15 participants
- Δtime accounted for 6% of the variance beyond EV (group level)



A neurocomputational model

Build-up of accumulators' activation across time



Model	Pseudo R^2
EV	35%
EU	39%
Model	42%

Gaze modulates the weights by which Log-v and log-P are integrated