

Attention and Perception in Multi-Attribute Choice Problems

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C&D Lab Meeting - Columbia University

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Multi-attribute choice

- ▶ Multi-attribute choice problems are part of everyday life
 - ▶ **Health care plans**
premium, deductible, copayment, out-of-pocket limit
 - ▶ **Elections**
Candidates may differ in several economic and social issues
 - ▶ **Pricing**
Main and ancillary good, shrouded price (taxes, shipping fees)
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- ▶ Ambiguous evidence about how the DM combines the different dimensions (both hold-up and give-away narratives coexist)
 - ▶ Different tradeoffs under full or gradual information disclosure

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Research Questions and Conjectures

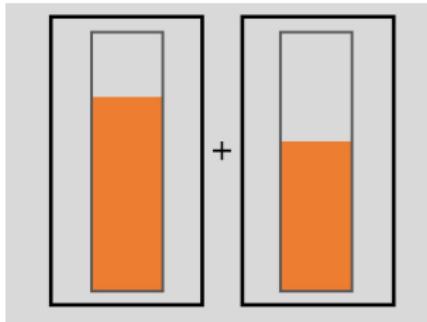
- ▶ **How does the DM integrate the attributes?**
 - ▶ Can we observe systematic behavioral patterns?
 - ▶ Violation of stochastic transitivity?
 - ▶ Range effect? Focusing or Relative thinking?
- ▶ **How does the DM collect information about attributes?**
 - ▶ What are the drivers of information collection?
 - ▶ When do “easy” choices become attention traps?
 - ▶ Does “more information” help to make better decision?

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Experimental project

- ▶ Lab experiment: binary choice between compound lotteries
- ▶ Multiple attributes represented by simple lotteries (probability of winning one point)
- ▶ Simple lotteries are displayed using bars of different length



Probability of winning is displayed using the length of the bar

Experimental project

- ▶ Lab experiment: binary choice between compound lotteries
- ▶ Multiple attributes represented by simple lotteries (probability of winning one point)
- ▶ Simple lotteries are displayed using bars of different length
- ▶ Strong link with Arthur experiment: compare results in perceptual and numerical tasks
- ▶ Introduce sequential information collection in a multi-attribute choice task
- ▶ Analyze optimality of choices under a noisy perception model

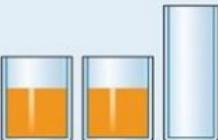
Preview of results

- ▶ Pilot experiment in CELSS lab (n=27)
- ▶ **Main task: fixed information**
 - ▶ Systematic violation of stochastic transitivity
 - ▶ Anchoring in favor of early information
 - ▶ Small differences are overweighted (range: relative thinking)
 - ▶ Choice biased in favor of frequent local winner
 - ▶ Large absolute values are overweighted (wishful thinking)
- ▶ **Two sampling tasks: endogenous information**
 - ▶ Less information is collected when options are dissimilar
 - ▶ In particular when information collection is costly
 - ▶ Heterogeneous strategies: focus on sampling or choice
 - ▶ Information collection not correlated with accuracy

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Piaget's conservation tasks

	PHASE 1	PHASE 2	PHASE 3
CONSERVATION OF LIQUID QUANTITY	 "Do they have the same amount of orange drink or a different amount?"	 "Now watch what I do" (pouring contents of one glass).	 "Now, do they have the same amount of orange drink or a different amount?"
CONSERVATION OF SOLID QUANTITY	 "Do they have the same amount of clay or a different amount?"	 "Now watch what I do" (stretching one piece of clay).	 "Now, do they have the same amount of clay or a different amount?"
CONSERVATION OF NUMBER	 "Is there the same number or a different number?"	 "Now watch what I do" (spreading one row).	 "Now, is there the same number or a different number?"

- ▶ Five years old kids systematically “fail” these tasks
- ▶ Difference in the process (evaluation), not in the goal (objective)

Piaget's conservation tasks



- ▶ Five years old kids systematically “fail” these tasks
- ▶ Funny to watch

*** Literature review and Previous results

- ▶ Tsetsos et al. (2016) “Economic irrationality is optimal during noisy decision making”
- ▶ Cognitive literature introduced mechanisms under which “choice irrationality” is a byproduct of neural computation
- ▶ **Multi-attribute choice:**
- ▶ **Range effect:**
- ▶ **Noisy encoding:**
- ▶ **Sequential information sampling:**
- ▶ **Sampling in multi-attribute choice:**

Experimental Design - Main task

- ▶ Binary choice: compound lottery L(left) vs R(ight)
- ▶ Six simple lotteries (attributes) equally likely to be selected
- ▶ Each sub-lottery is a 10-90% probability of winning one point
- ▶ Task: choose the option with the highest sum of probs. (bars)
- ▶ Timing
 - ▶ $t = 1, 2, \dots, 6$ the bars L_t and R_t are displayed simultaneously on the screen (200 ms bars + 200 ms blank)
 - ▶ $t = 7$ the sbj chooses L or R (10 sec available)
 - ▶ $t = 8$ the outcome is revealed (win/lose the round)

Experimental Design (Instructions, static trial)

- ▶ “Choose your knight and defend the castle from enemies”



Figure 1: Instructions screen: all the lotteries are visible simultaneously

Experimental Design (Instructions, sequential)

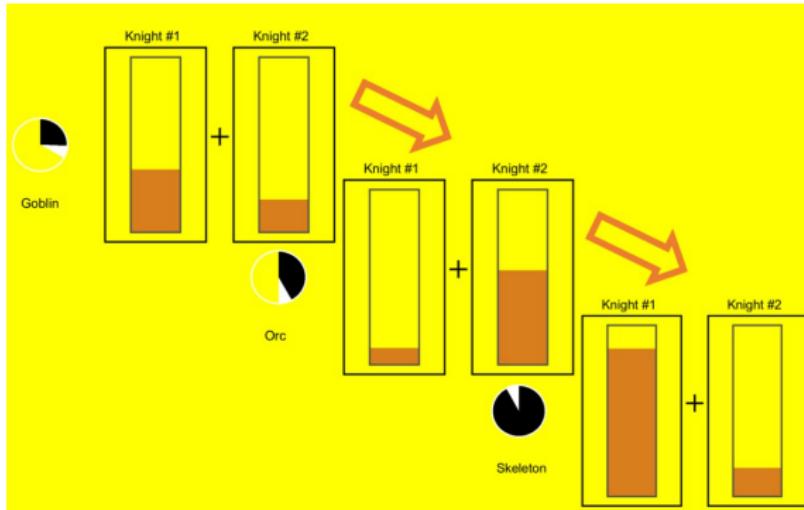
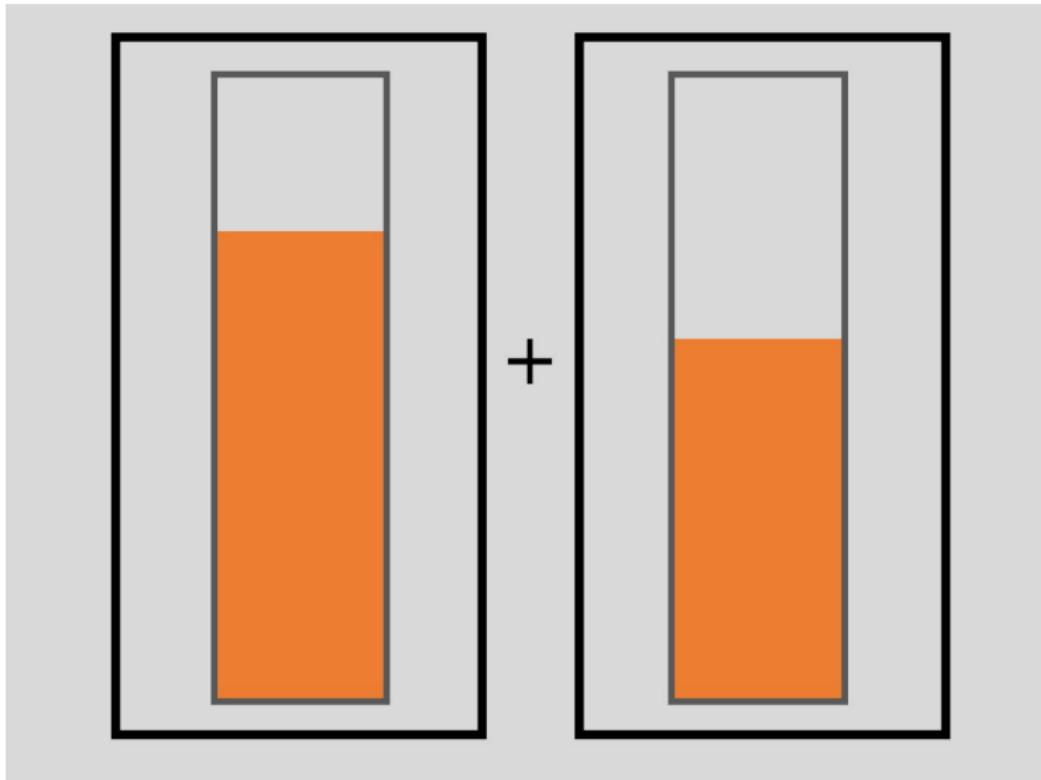


Figure 2: In the main task the lotteries are displayed sequentially

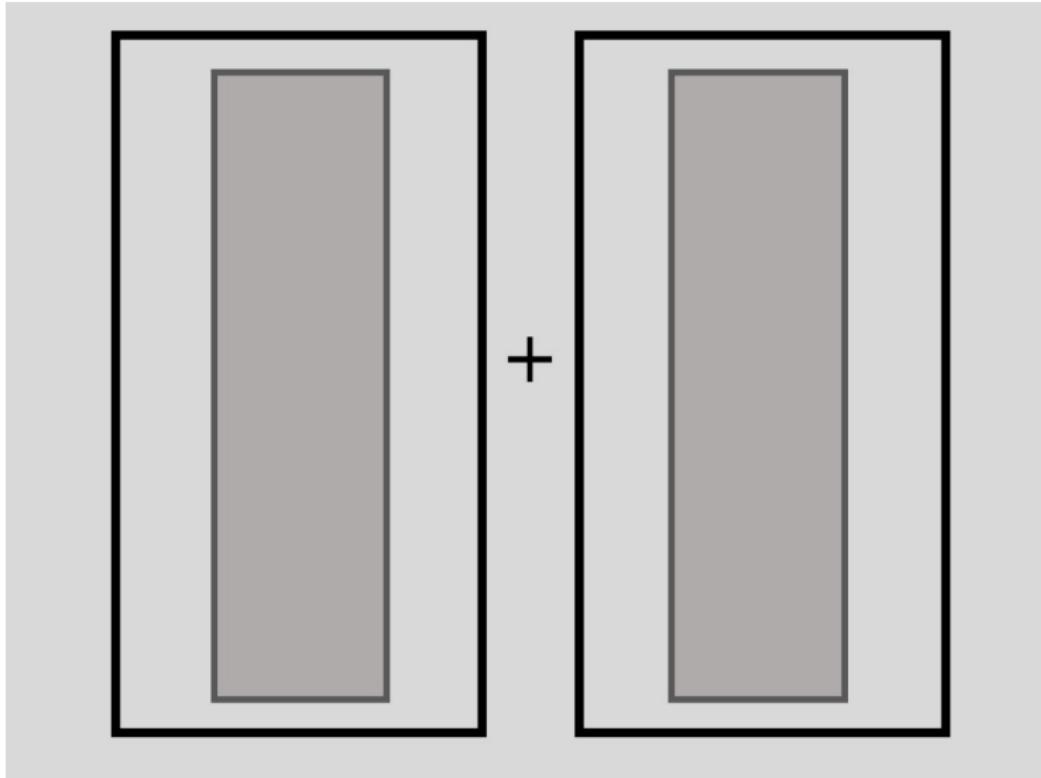
- ▶ Extensive instructions and practice trials
- ▶ Practice trials are repeated until the sbj achieves 80% accuracy
- ▶ 318 trials divided into 4 blocks

Experimental Design (t=5, bars)



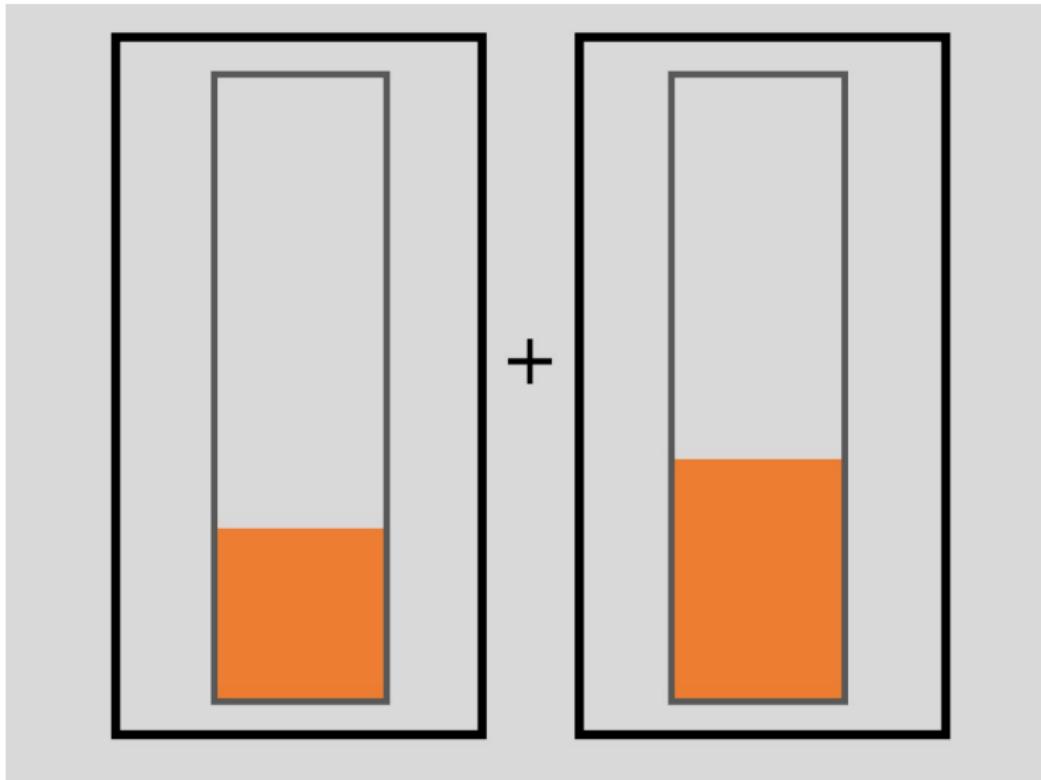
Lotteries L_5 and R_5 (200 ms)

Experimental Design ($t=5.5$, blank bars)



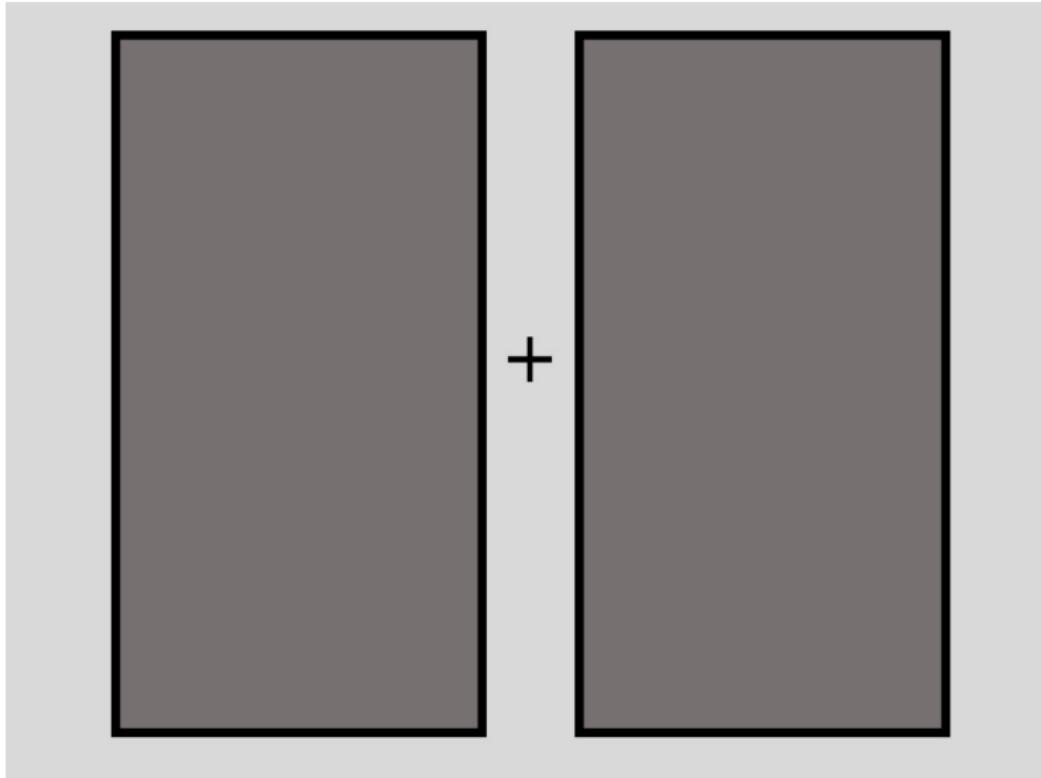
Placeholders and blank bars (200 ms)

Experimental Design (t=6, bars)



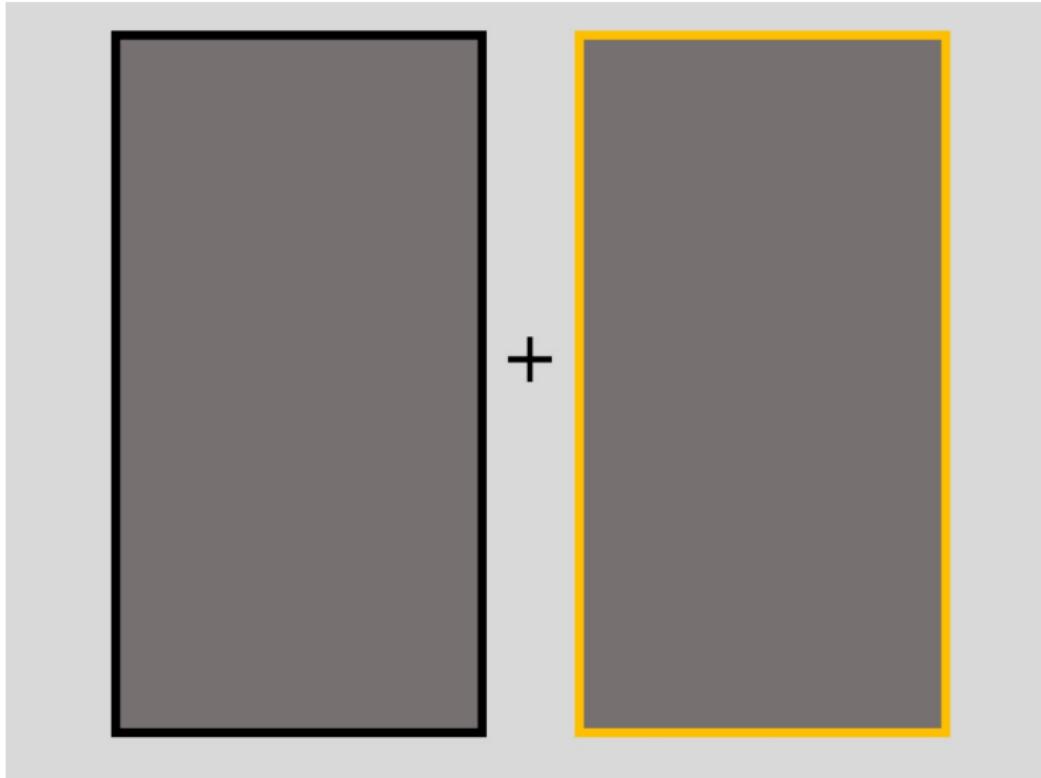
Lotteries L_6 and R_6 (200 ms)

Experimental Design (t=7, Choice screen)



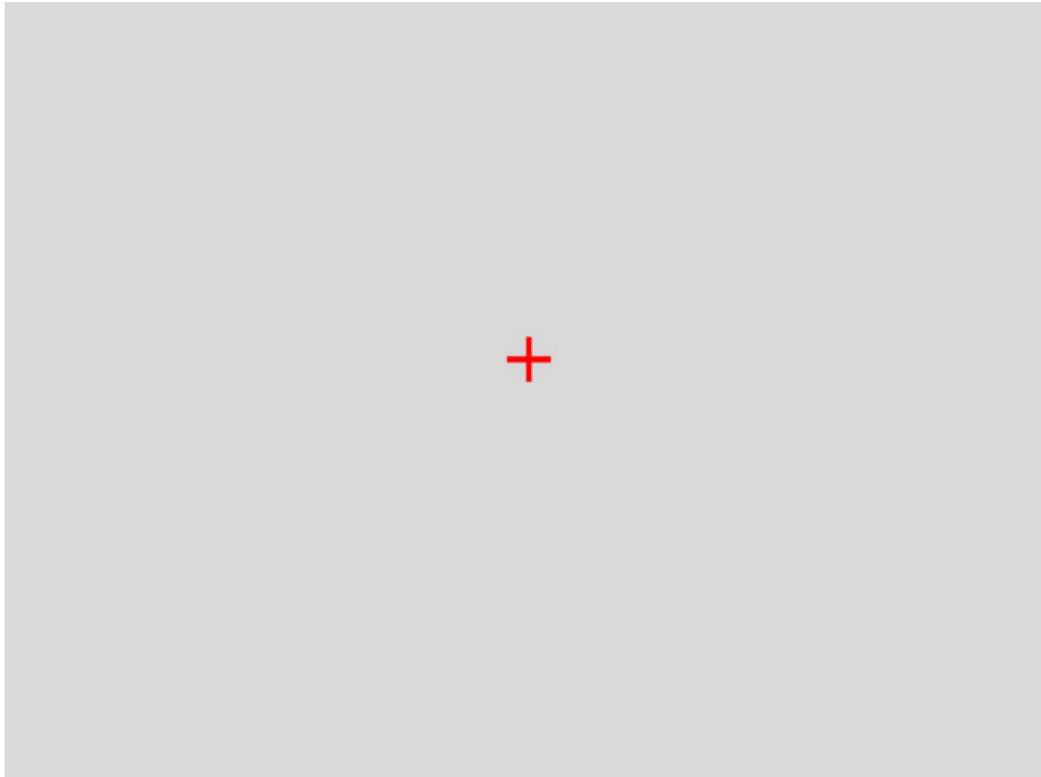
Choice screen (press F or J to select the option)

Experimental Design ($t=7$, Choice)



The subject chooses option R(ight).

Experimental Design (t=8, Outcome)



Green/red fixation cross indicates the outcome.

Average accuracy ranges between 60% and 87%

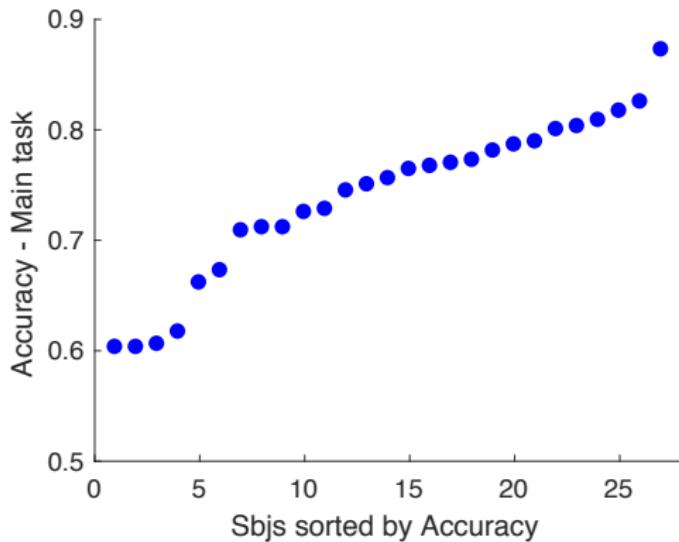


Figure 3: Accuracy in the main task [trials containing one best option].

- ▶ Accuracy (unobserved) \neq Score (observed performance)
- ▶ Unrewarded task, but motivated subject pool

Accuracy depends on difficulty of the trial

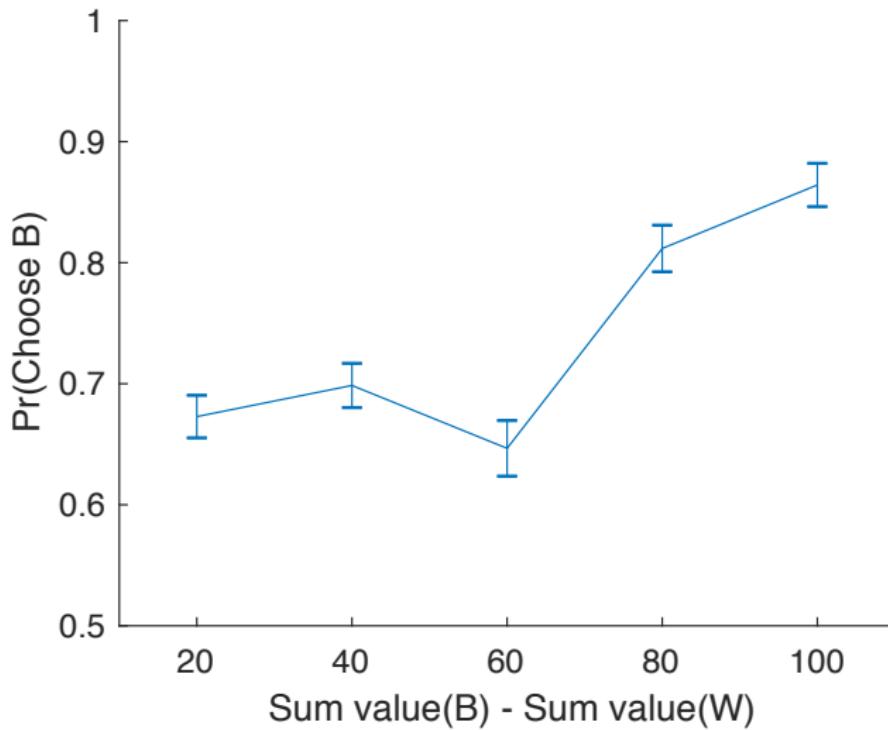


Figure 4: Performance under different levels of difficulty
Average probability and SE.

Experimental Design (Stimuli: Cycle trials)

- ▶ Three types of trials: Cycle, Increment, and Standard trials
- ▶ **Cycle trials**
- ▶ We generate triplets of lotteries (A,B,C) with the same sum
- ▶ Values are distributed asymmetrically to create frequent local winners (FLW)
 - ▶ $a_t > b_t$ 4 out of 6 times
 - ▶ $b_t > c_t$ 4 out of 6 times
 - ▶ $c_t > a_t$ 4 out of 6 times
- ▶ Each pair {A,B}, {B,C}, {C,A} is presented three times
- ▶ We have 8 different triplets generated in this way

Violation of stochastic transitivity (1)

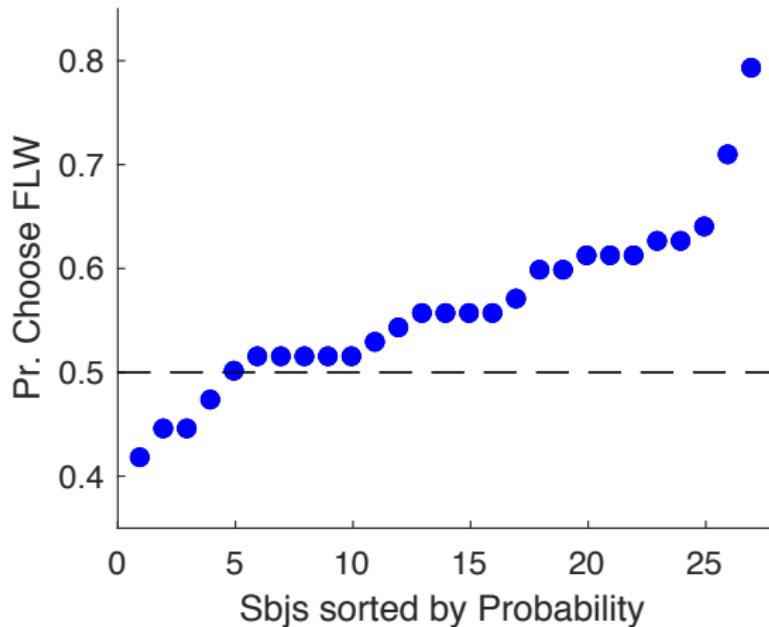


Figure 5: Probability of choosing the FLW option.

Sbj sorted by prob. 22/27 sbjs have probs >0.5.

Mean 0.5602, SE 0.0156, p-value <0.001 (H_0 : prob = 0.5)

Violation of stochastic transitivity (2)

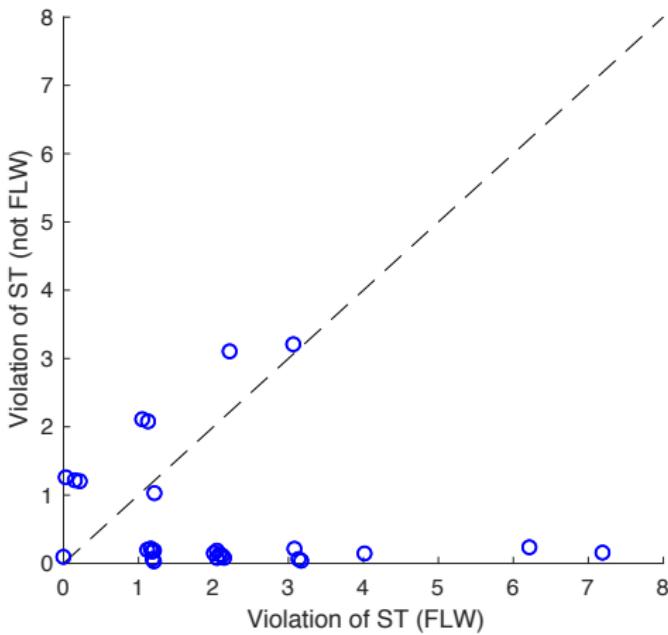


Figure 6: Number of stochastic violations in each direction (out of 8 cycles).
X-axis indicates how many times $\Pr(A|AB), \Pr(B|BC), \Pr(C|CA) > 0.5$;
Y-axis indicates how many times $\Pr(A|AB), \Pr(B|BC), \Pr(C|CA) < 0.5$.
X-axis: mean 1.93, SE 0.32. Y-axis: mean 0.51, SE 0.18 (H_0 : both = 1)

Experimental Design (Stimuli: Increment trials)

- ▶ Three types of trials: Cycle, Increment, and Standard trials
- ▶ **Increment trials**
- ▶ Same starting triplet of lotteries as in the cycle trials
- ▶ For each pair, add an asymmetric 3 points increment
 - ▶ In trial {A+,B}, A+ has the highest sum and is FLW
 - ▶ In trial {A,B+}, B+ has the highest sum but is not FLW
- ▶ Repeat this for each triplet (8 times) and for each pair (three pairs in each triplet)

Advantage of the frequent local winner (FLW) (1)

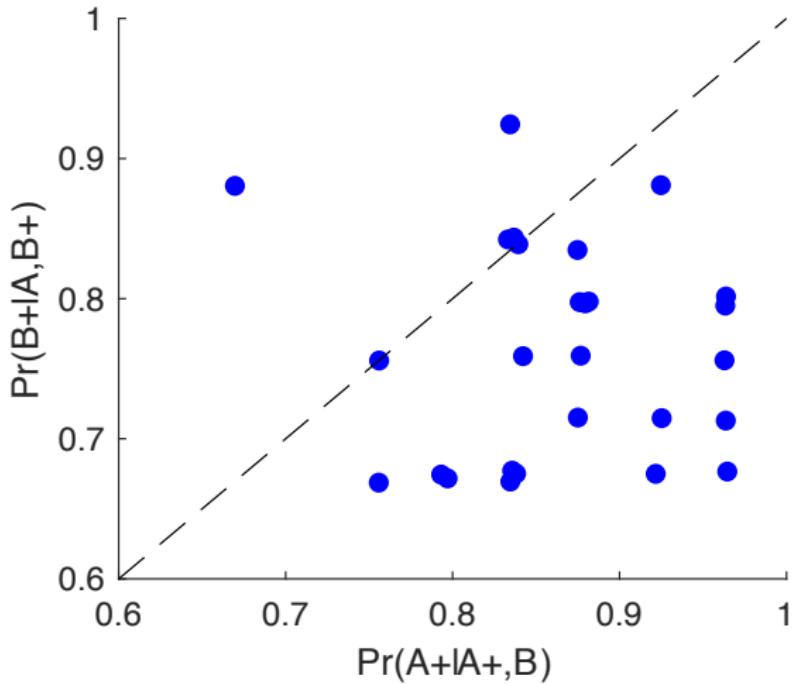


Figure 7: Increment trials: Probability of choosing the correct option when it is FLW (x-axis) and when it is not FLW (y-axis).

21/27 sbjs choose the best option more often when it is also the FLW.
Average accuracy increases from 0.76 (SE 0.015) to 0.86 (SE 0.014).

Advantage of the frequent local winner (FLW) (2)

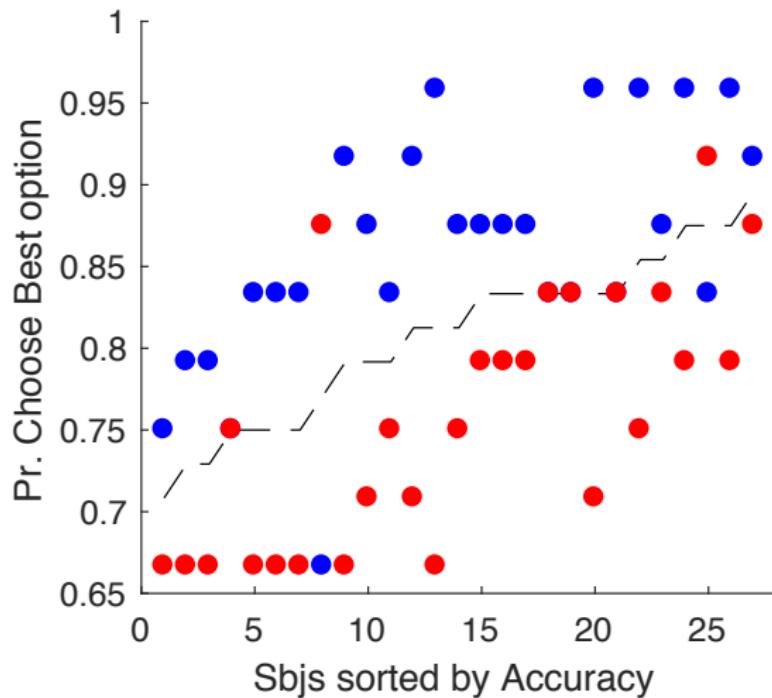


Figure 8: Increment trials: Probability of choosing the correct option when it is FLW (blue) and when it is not FLW (red).

Experimental Design (Stimuli: Standard trials)

- ▶ Three types of trials: Cycle, Increment, and Standard trials
- ▶ **Standard trials**
- ▶ Randomize trial difficulty Δ_V and FLW Δ_L
 - ▶ Difficulty $\Delta_V = \sum B_t - \sum W_t$ can be 0, 20, 40, 80, 100
 - ▶ B/W indicate the B(est) / W(orst) option
 - ▶ High Δ_V corresponds to easier trials (higher discriminability)
- ▶ FLW effect $\Delta_L = \sum_t [1(B_t > W_t) - 1(W_t > B_t)]$ can be -2, 0, +2
 - ▶ 1 is the indicator function
 - ▶ We have $\Delta_L = 2$ when the FLW has the highest sum

Anchoring in favor of early information



Figure 9: Performance under different levels of difficulty
Average choice and SE.

Small differences are overweighted

- ▶ equation and plot

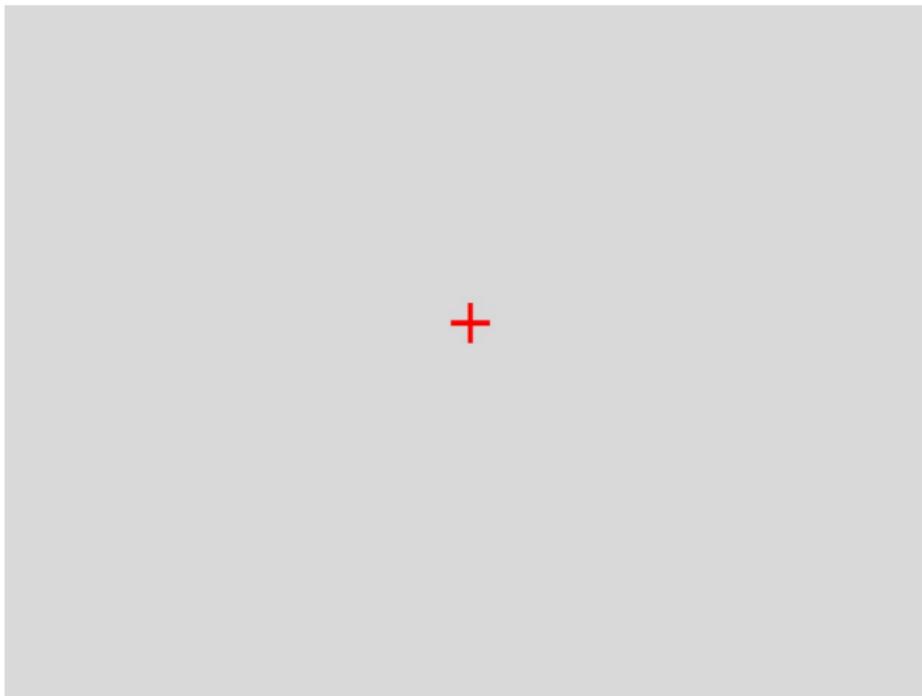


Figure 10: Performance under different levels of difficulty
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Large absolute values are overweighted

- ▶ equation and plot

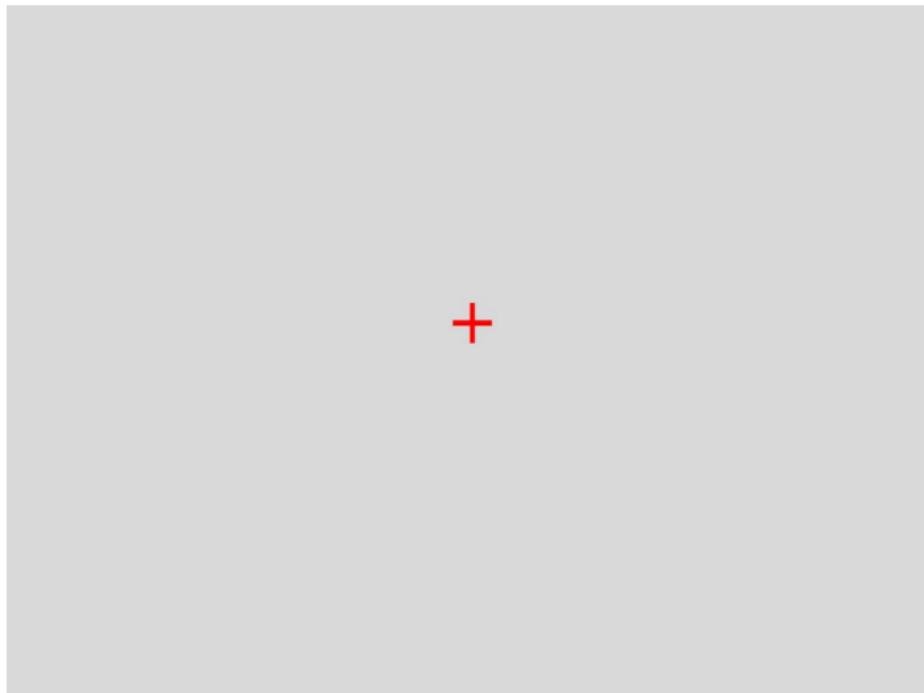


Figure 11: Performance under different levels of difficulty
Average choice and SE

Experimental Design (Sampling tasks)

- ▶ Two similar tasks with endogenous information acquisition
- ▶ At $t = 1, 2, \dots$ the subject can choose L, choose R, or “sample”, i.e. observe another attribute (randomly drawn, with replacement)
 - ▶ **Sampling-risk:** sampling can be interrupted (geometric distribution, $p=1/6$), enforcing random choice
 - ▶ **Sampling-freely:** sample without interruptions
- ▶ Same interface, same trials used in the main task
- ▶ These tasks are more difficult (can I compare the results?)
 - ▶ Choose whether to sample
 - ▶ Imperfect information about new/old attributes

Lower accuracy in both tasks

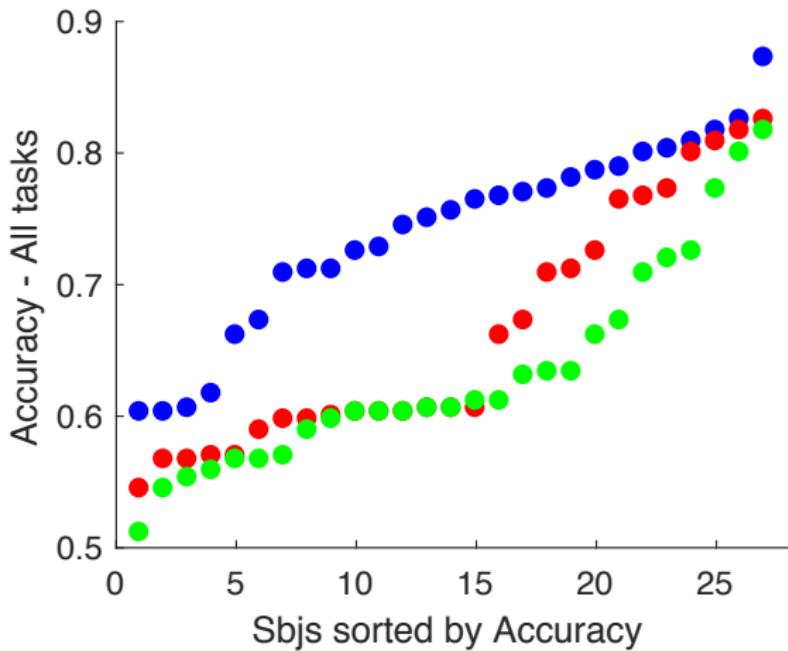


Figure 12: Accuracy in the main task (blue, range 60-87%, mean 74%), sampling-risk (red, range 54-82%, mean 66%), and sampling-freely (green, range 51-82%, mean 63%).

Accuracy depends on difficulty of the trial

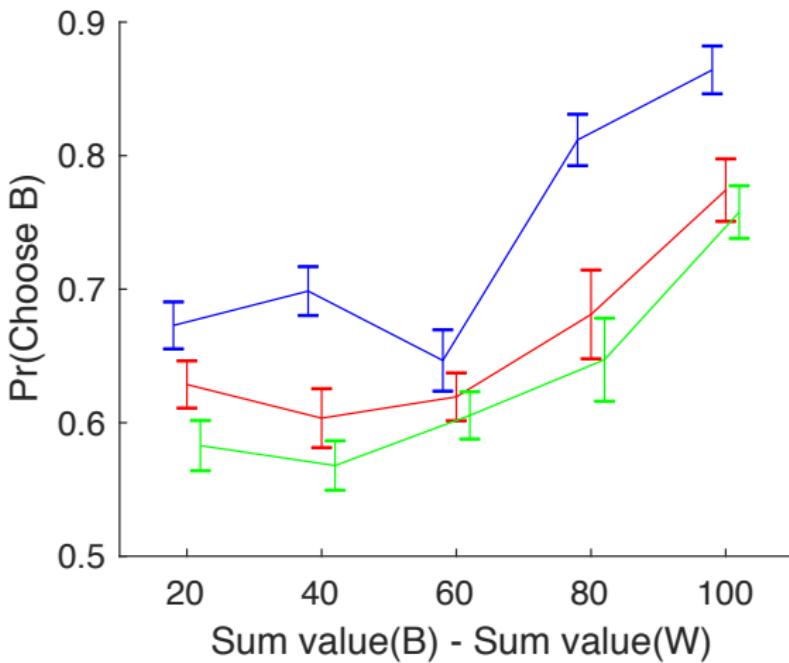


Figure 13: Accuracy under different levels of difficulty (average probability and SE). Main task (blue), sampling-risk task (red), and sampling-freely task (green).

Sampling more provides more information (duh!)

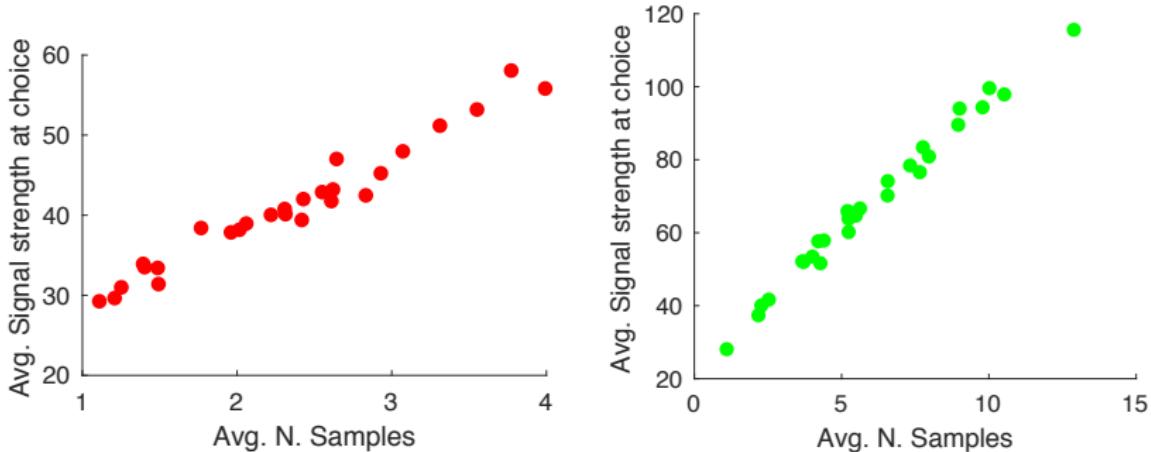


Figure 14: Joint distribution of samples collected in task 2 (left, in red) and task 3 (right, in green) and subject's accuracy in the task.

- ▶ Task 2: Avg. N. Samples ranges from 1.11 to 4 (mean 2.33)
- ▶ Task 3: Avg. N. Samples ranges from 1.14 to 13 (mean 6.12)

Sampling more does not improve accuracy!

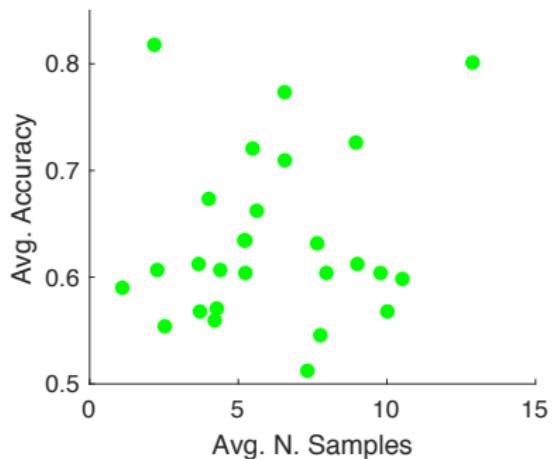
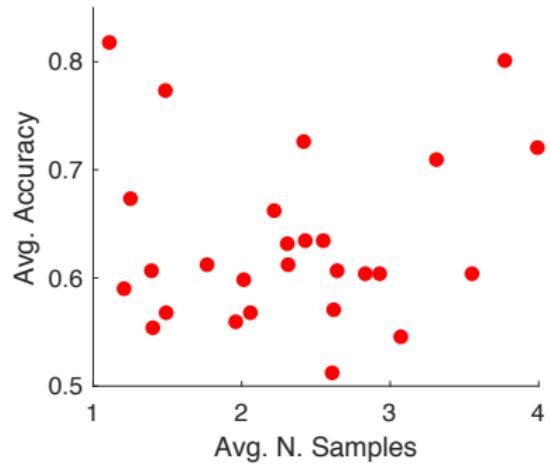


Figure 15: Distribution of samples collected in task 2 (left, in red) and task 3 (right, in green).

More information collected in difficult trials

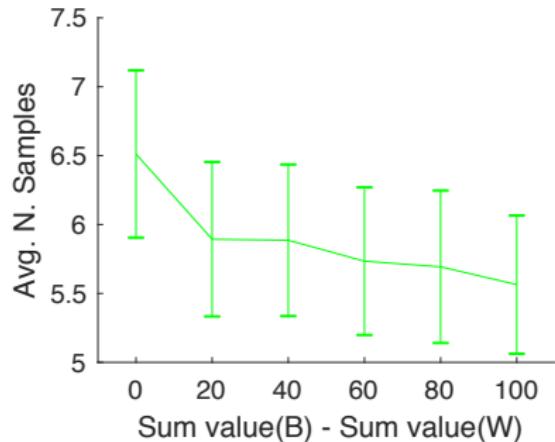
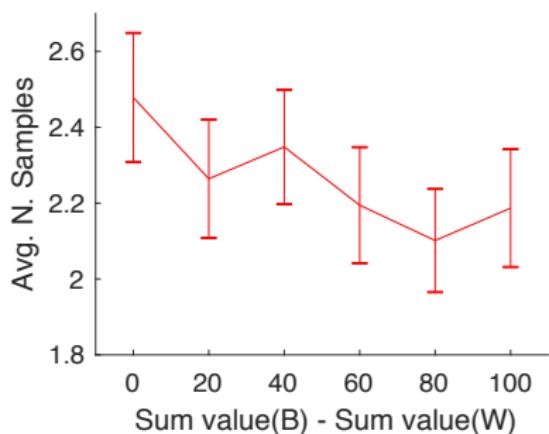


Figure 16: Number of samples under different levels of difficulty (average and SE). Note: high heterogeneity at the individual level.

Sampling strategies

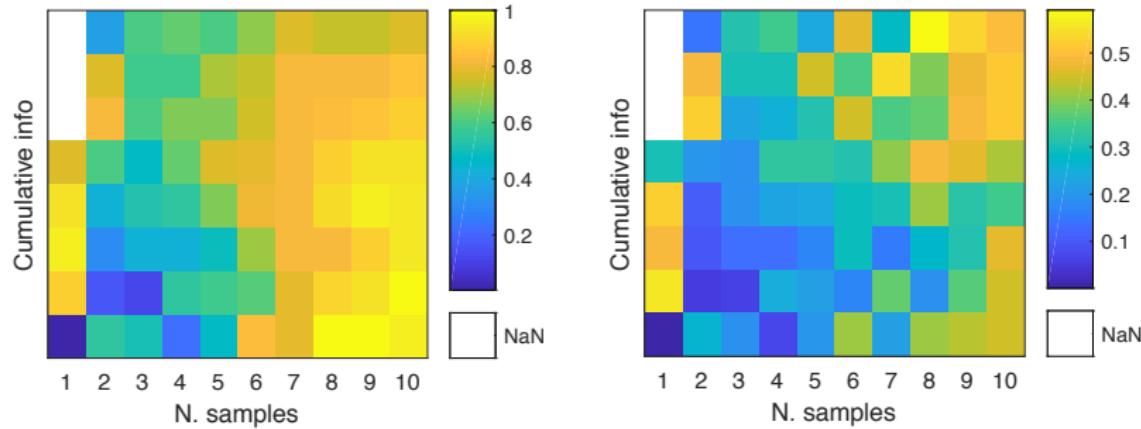


Figure 17: Probability of choosing conditional on time and information. Sampling-risk task (left) and Sampling-freely task (right). Note: high heterogeneity at the individual level.

Violation of stochastic transitivity (cycle trials 1)

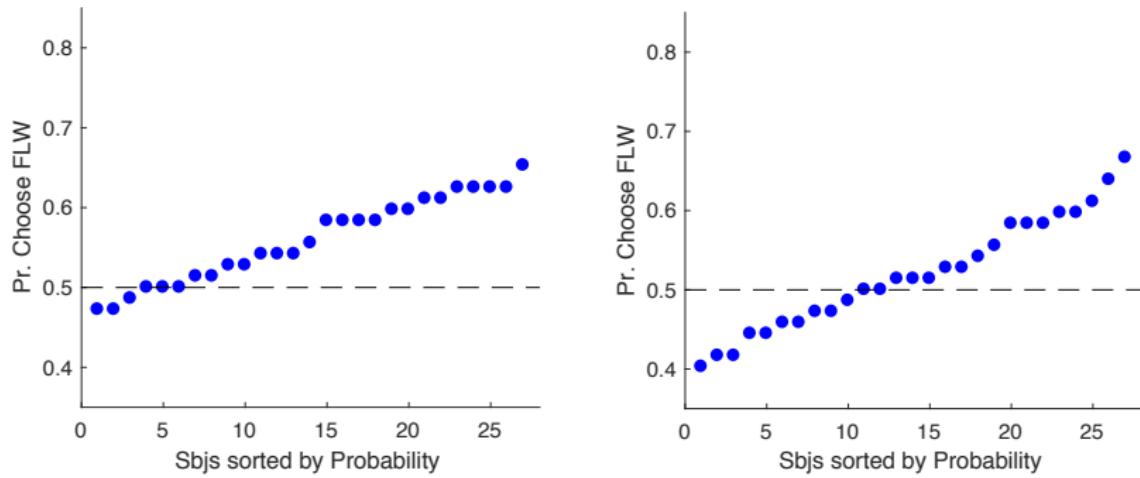


Figure 18: Prob of choosing the FLW option in task 2 (left) and 3 (right).

- ▶ Task 1: 22/27 sbj.s >0.5. Mean 0.5602, SE 0.0156, p-value <0.001
- ▶ Task 2: 21/27 sbj.s >0.5. Mean 0.5592, SE 0.0103, p-value <0.001
- ▶ Task 3: 15/27 sbj.s >0.5. Mean 0.5195, SE 0.0136, p-value 0.15

Violation of stochastic transitivity (cycle trials 2)

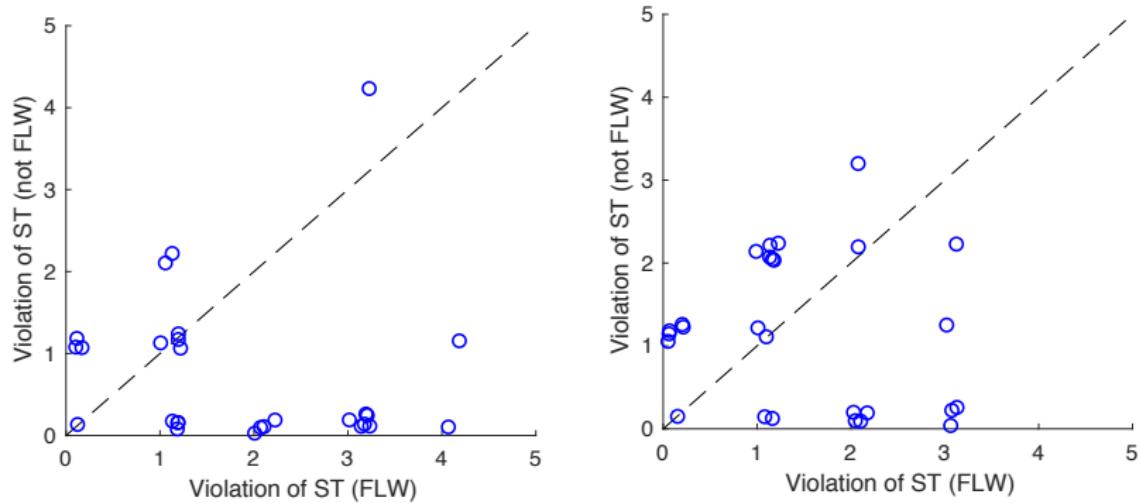


Figure 19: Number of stochastic violations in each direction.

- ▶ Task 1: X-axis: mean 1.93, SE 0.32. Y-axis: mean 0.51, SE 0.18
- ▶ Task 2: X-axis: mean 1.74, SE 0.24. Y-axis: mean 0.59, SE 0.18
- ▶ Task 3: X-axis: mean 1.37, SE 0.20. Y-axis: mean 1.00, SE 0.18

Frequent local winner (increment trials 1)

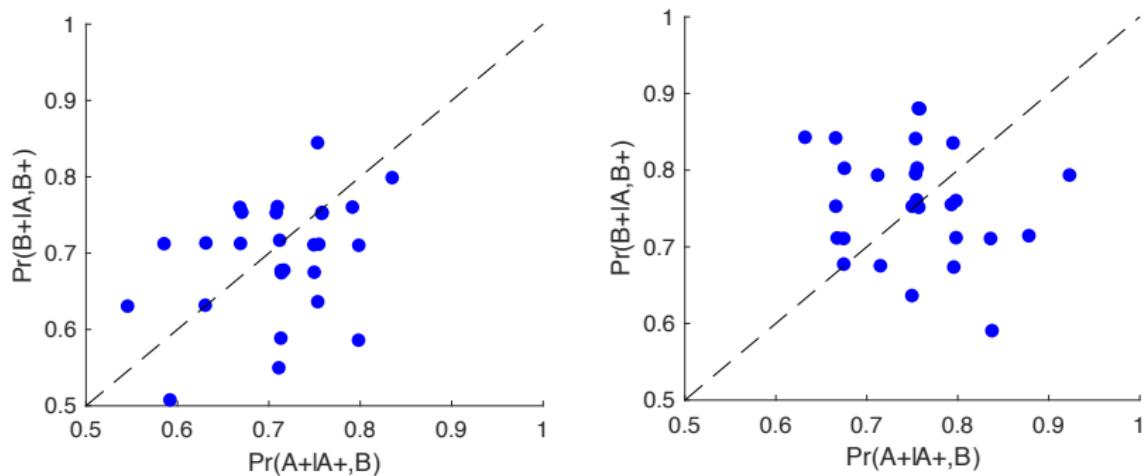


Figure 20: Increment trials: Probability of choosing the correct option when it is FLW (x-axis) and when it is not FLW (y-axis) in the sampling tasks

- ▶ Task 1: 21/27 show FLW effect, avg accuracy from 0.76 to 0.86.
- ▶ Task 2: 14/27 show FLW effect, avg accuracy from 0.69 to 0.71.
- ▶ Task 3: 10/27 show FLW effect, avg accuracy from 0.75 to 0.75.

Frequent local winner (increment trials 2)

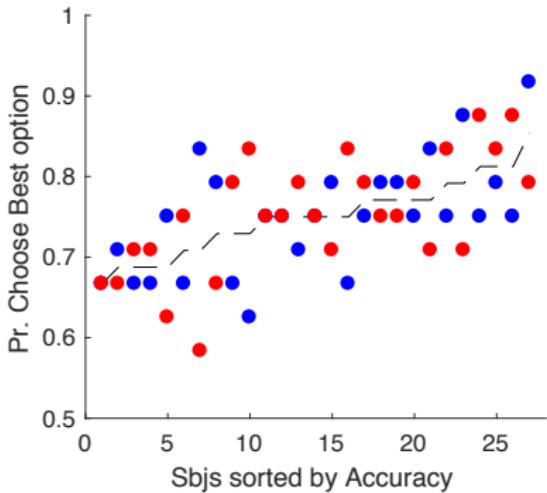
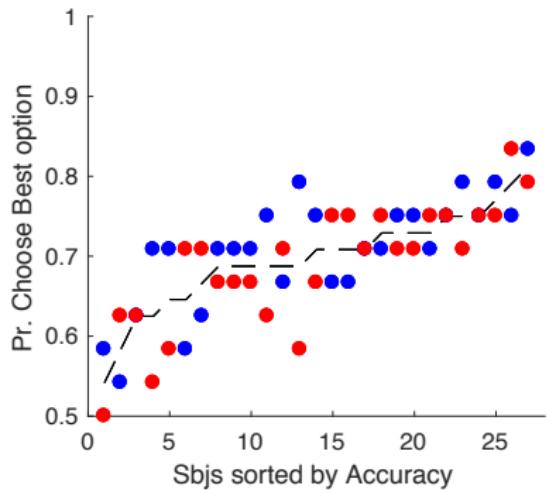


Figure 21: Increment trials: Probability of choosing the correct option when it is FLW (blue) and when it is not FLW (red) in tasks 2 (left) and 3 (right).

Large absolute values are overweighted

- ▶ equation and plot

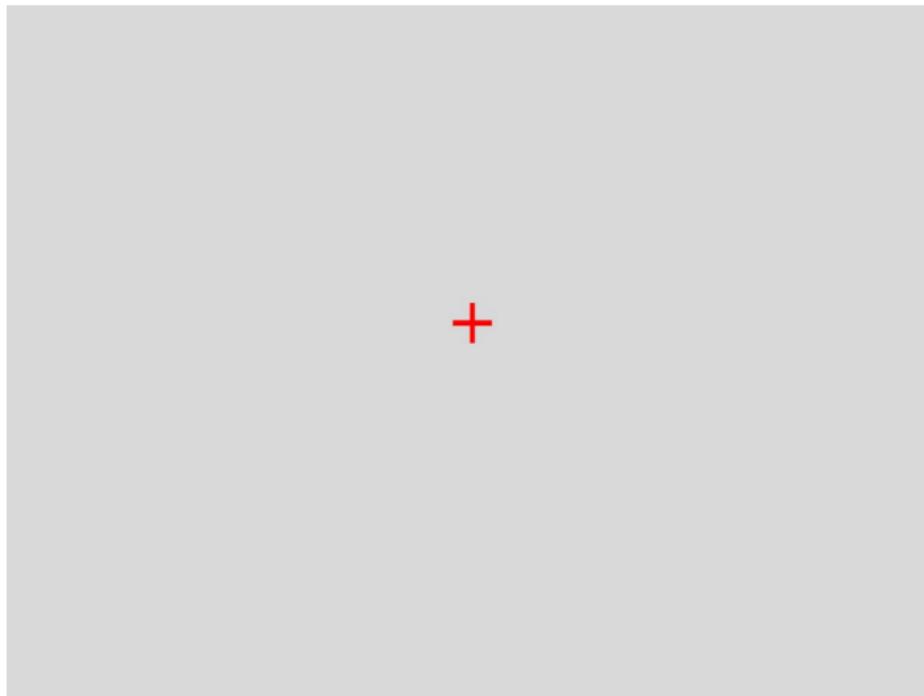


Figure 22: Performance under different levels of difficulty
Average choice and SE

Attention and Perception in Multi-Attribute Choice Problems

Silvio Ravaoli

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