Attention and Perception in Multi-Attribute Choice Problems

Silvio Ravaioli

C&D Lab Meeting - Columbia University

November 9, 2018

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)

- 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?
  - Can “easy” choices hide attentional traps?
  - Does “more information” help to make better decision?

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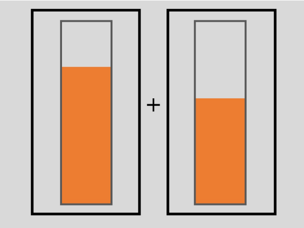
Experimental project

- 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**
  - Strong recency effect in favor of late information
  - Systematic violation of stochastic transitivity
  - Relative thinking when Δ is small, choice biased in favor of FLW
  - The effect disappears for large Δ
  - 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: careful vs reckless sampling
  - Information collection not correlated with accuracy

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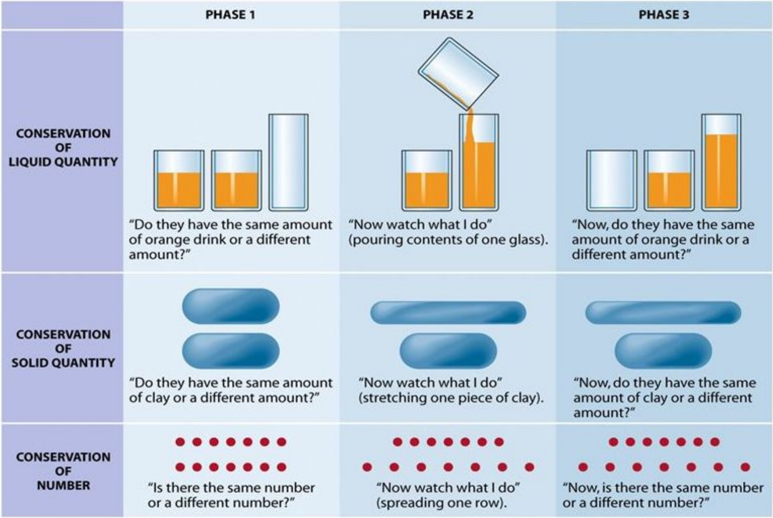
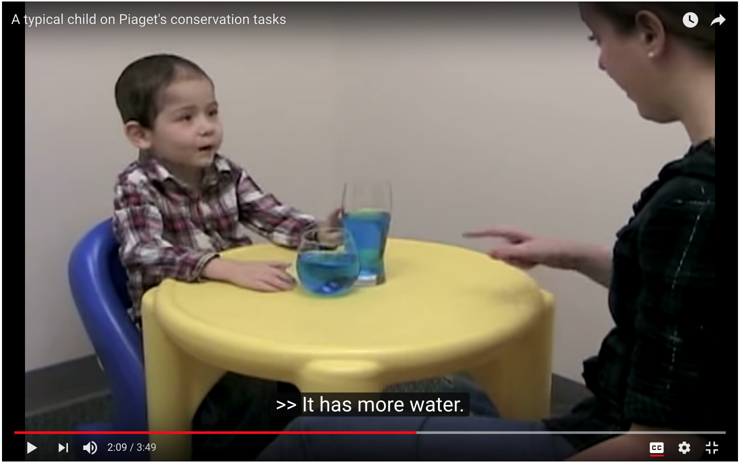
Piaget's conservation tasks



- 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 experimental results

- Tsetsos et al. (2016) “Economic irrationality is optimal during noisy decision making”
- Cognitive neurosc. literature: mechanisms under which “choice irrationality” is a byproduct of neural computation
- **Multi-attribute choice**: Andersson et al. 2016 (Focusing), Azar 2011, Somerville 2018 (Relative thinking), BGS (Salience), Gabaix and Laibson 2006 (shrouded attribute)
- **Noisy representation**: Li et al. 2017 (robust averaging), Spitzer et al. 2017 (selective overweight), Woodford 2012, Steiner and Stewart 2016, Gabaix and Laibson 2017
- **Sequential information collection**: DDM literature (Krajbich and Rangel 2011, Milosavljevic 2010), Majumdar 1990, Schmidt and Bennett 2007, Diederich and Oswald 2014

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Experimental Design - Main task

- Binary choice: compound lottery L(eft) 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
  - $t = 1, 2, \ldots, 6$ 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”

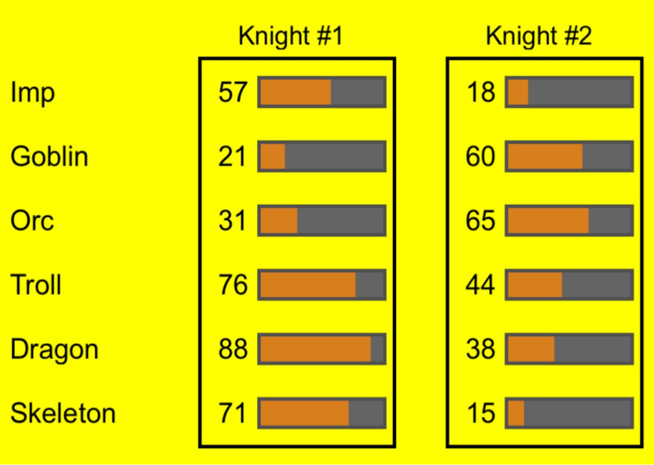


Figure 1: Instructions screen: all the lotteries are visible simultaneously

Experimental Design (Instructions, sequential)

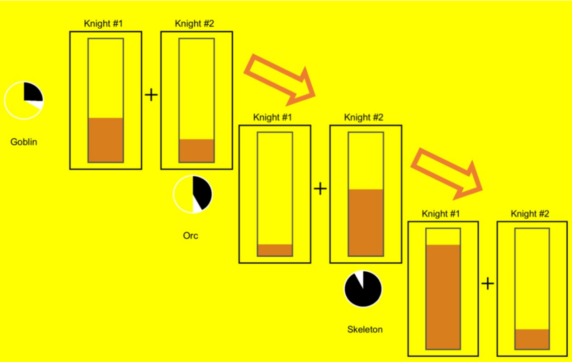
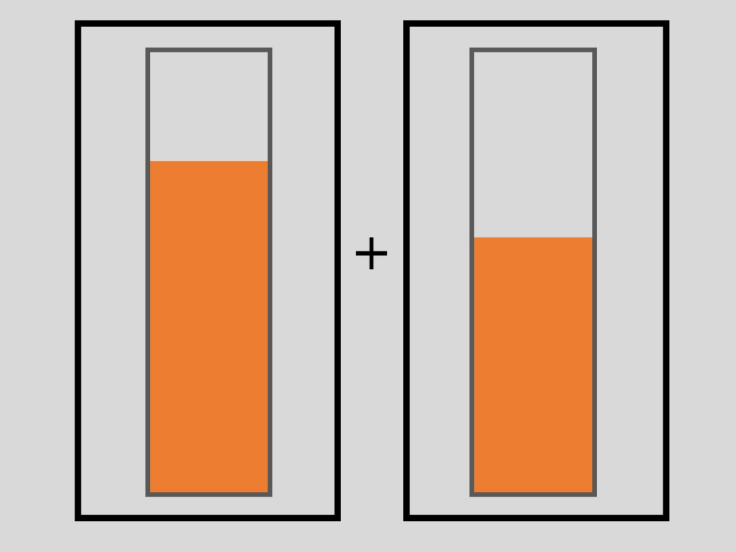


Figure 2: In the main task the lotteries are displayed sequentially

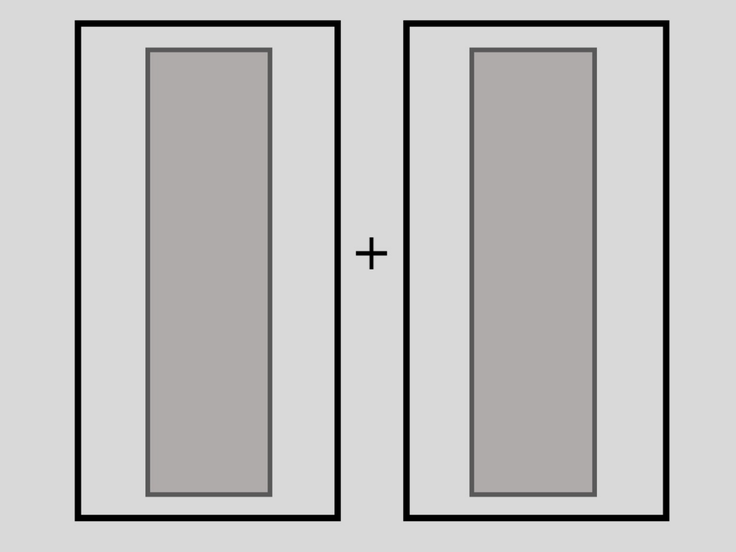
- Extensive instructions and practice trials
- Practice trials are repeated until the sbj achieves 80% accuracy
- 318 trials divided into 4 blocks

Experimental Design (t=5, bars)



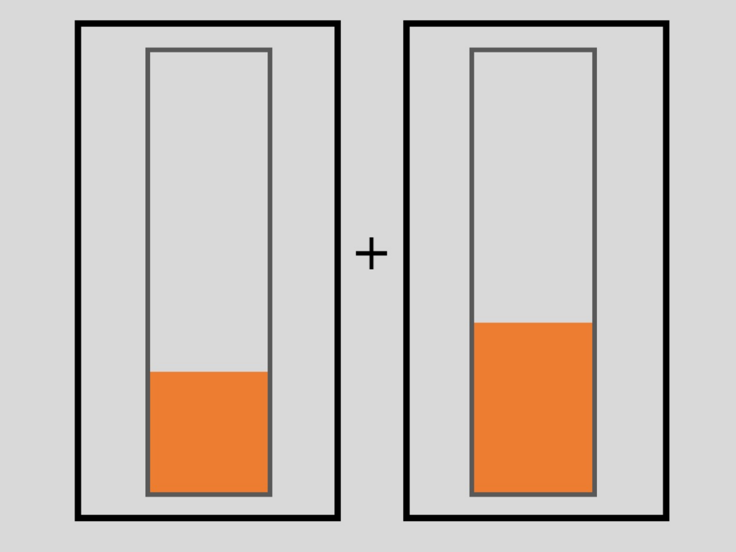
Lotteries L_5 and R_5 (200 ms)

Experimental Design (t=5.5, blank bars)



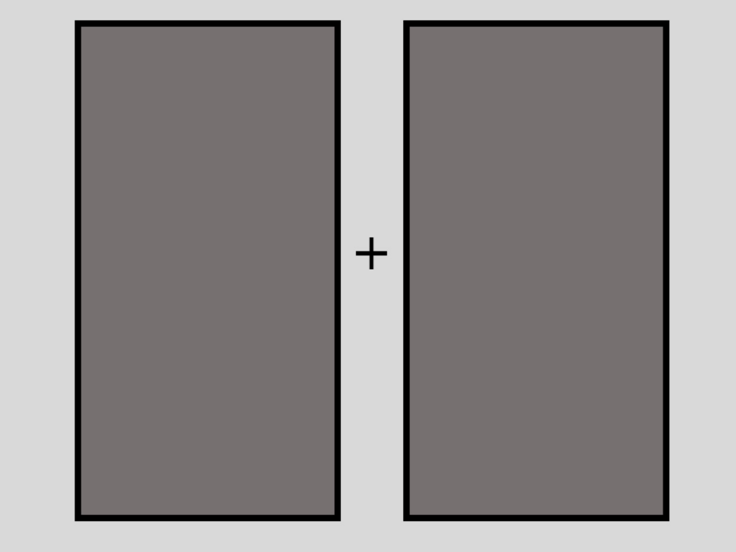
Placeholders and blank bars (200 ms)

Experimental Design (t=6, bars)



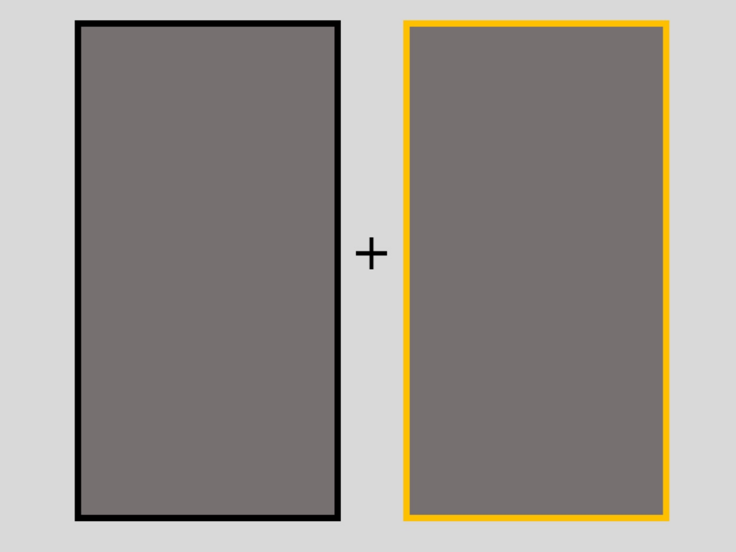
Lotteries L_6 and R_6 (200 ms)

Experimental Design (t=7, Choice screen)



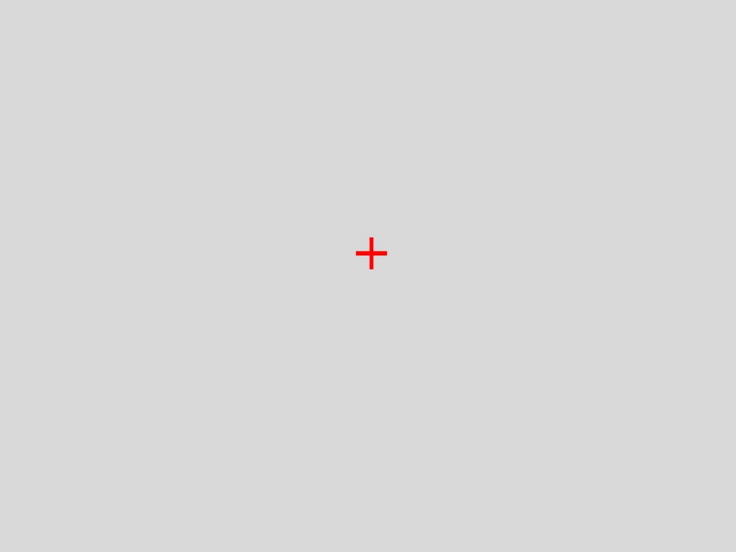
Choice screen (press F or J to select the option)

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%

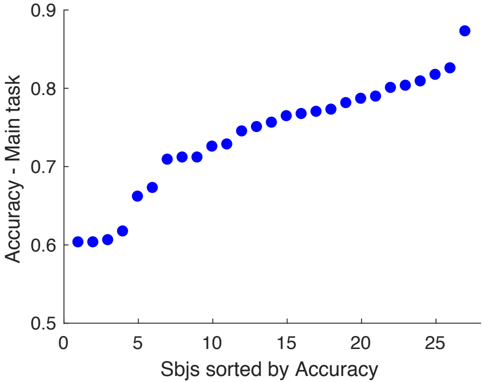


Figure 3: Accuracy in the main task [trials containing one best option].

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

Accuracy depends on difficulty of the trial

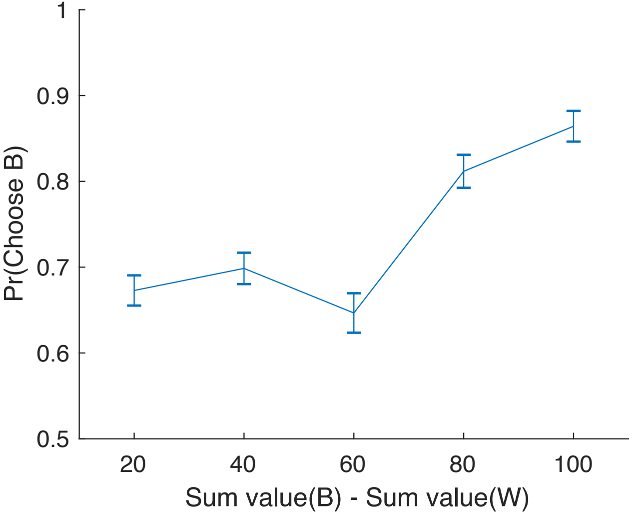


Figure 4: Performance under different levels of difficulty
Average probability and SE.

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 shown three times
- Eight different triplets generated with this procedure

Violation of stochastic transitivity (1)

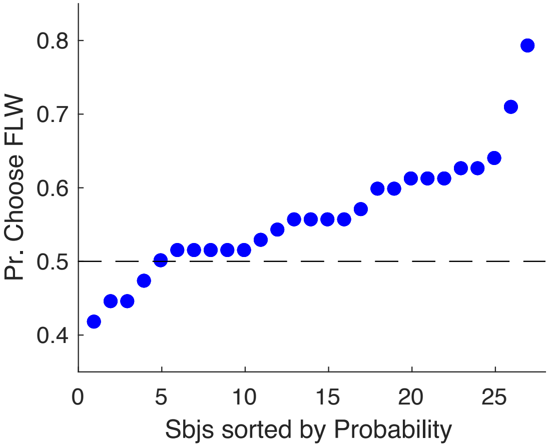


Figure 5: Probability of choosing the FLW option.
Sbjs sorted by prob. 22/27 sbjs have probs >0.5.
Mean 0.5602, SE 0.0156, p-value <0.001 (H0: prob = 0.5)

Violation of stochastic transitivity (2)

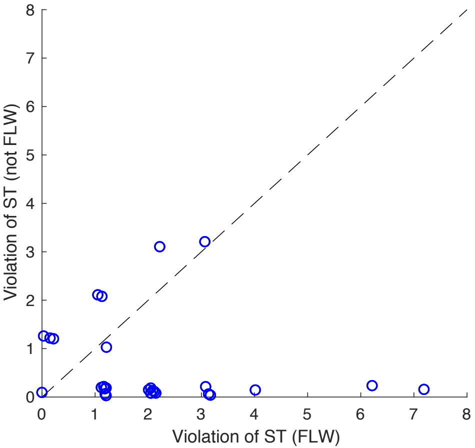


Figure 6: Number of stochastic violations in each direction (out of 8 cycles).
X-axis indicates how many times Pr(A|AB), Pr(B|BC), Pr(C|CA) >0.5;
Y-axis indicates how many times Pr(A|AB), Pr(B|BC), Pr(C|CA) <0.5.
X-axis: mean 1.93, SE 0.32. Y-axis: mean 0.51, SE 0.18 (H0: both = 1)

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)

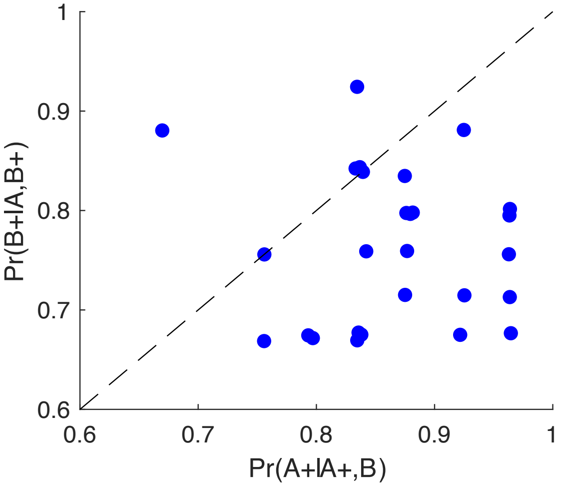


Figure 7: Increment trials: Probability of choosing the correct option when it is FLW (x-axis) and when it is not FLW (y-axis).

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)

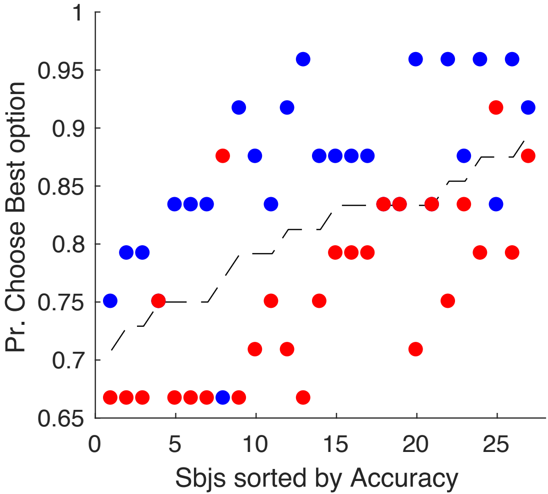


Figure 8: Increment trials: Probability of choosing the correct option when it is FLW (blue) and when it is not FLW (red).

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

Recency effect in favor of late information

- Individual fit of the logit model

$$V_L = \sum_t (L_t - R_t) \cdot \pi_t \qquad Pr(L) = \frac{1}{1 + exp(-\beta V_L)} \qquad \sum_t \pi_t = 1$$

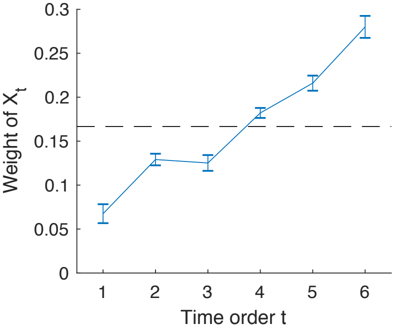


Figure 9: Relative weight of evidence collected at different time.
Mean across participants: $\pi_{first} = 0.07$ SE 0.011, $\pi_{last} = 0.28$ SE 0.013.

Range effect is not robust to the full dataset

- Individual fit of the logit model

$$V_L = \sum_t (L_t - R_t) \cdot |L_t - R_t|^{\alpha_{range}} \qquad Pr(L) = \frac{1}{1 + exp(-\beta V_L)}$$

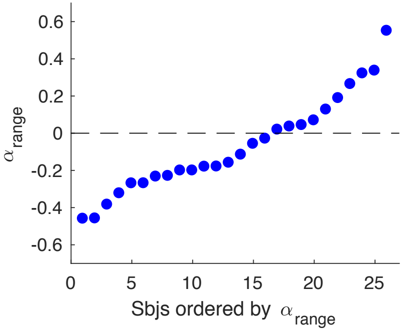


Figure 10: Distribution of the fitted parameter across participants. Mean across participants $\alpha_{range} = -0.021$, SE 0.07.

Large values are overweighted - Wishful thinking

- Individual fit of the logit model

$$V_L = \sum_t (L_t - R_t) \cdot \left(\frac{L_t + R_t}{2}\right)^{\alpha_{mean}} \qquad Pr(L) = \frac{1}{1 + exp(-\beta V_L)}$$

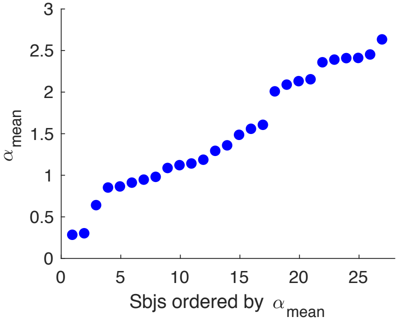


Figure 11: Distribution of the fitted parameter across participants. Mean across participants α_{mean} = 1.50, SE 0.14.

Experimental Design (Sampling tasks)

- Two similar tasks with endogenous information acquisition
- At $t = 1, 2, \ldots$ 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

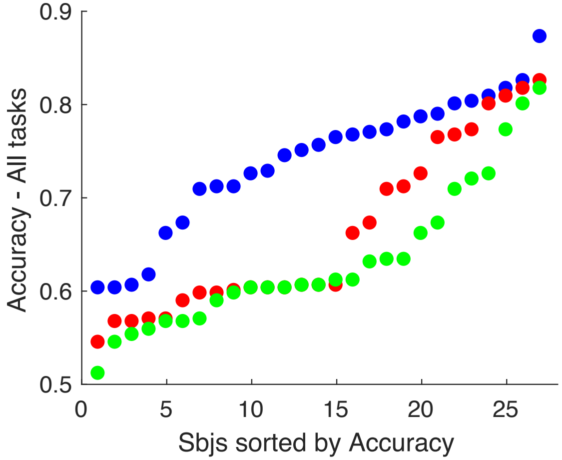


Figure 12: Accuracy in the main task (blue, range 60-87%, mean 74%), sampling-risk (red, range 54-82%, mean 66%), and sampling-freely (green, range 51-82%, mean 63%).

Accuracy depends on difficulty of the trial

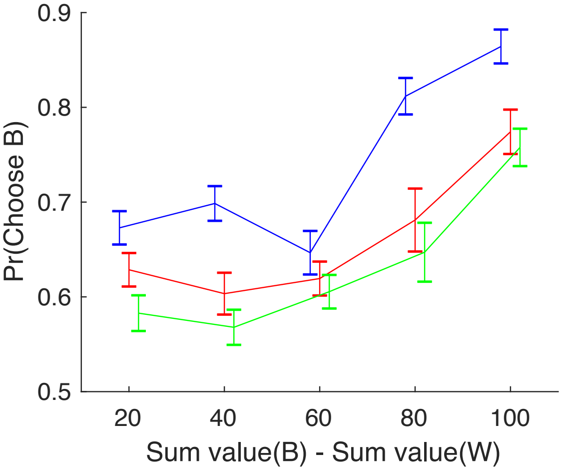


Figure 13: Accuracy under different levels of difficulty (average probability and SE). Main task (blue), sampling-risk task (red), and sampling-freely task (green).

Sampling more provides more information (duh!)

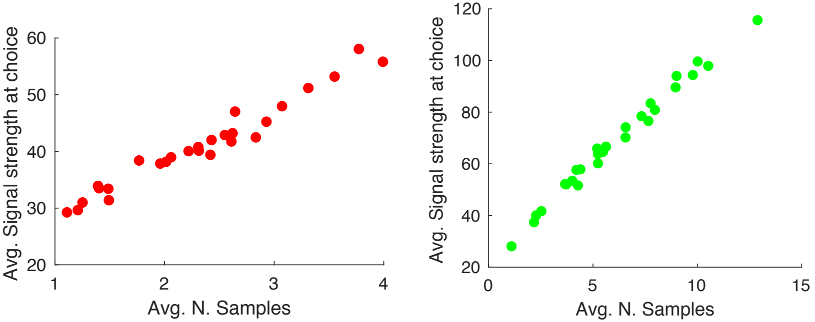


Figure 14: Joint distribution of samples collected in task 2 (left, in red) and task 3 (right, in green) and subject's accuracy in the task.

- 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!

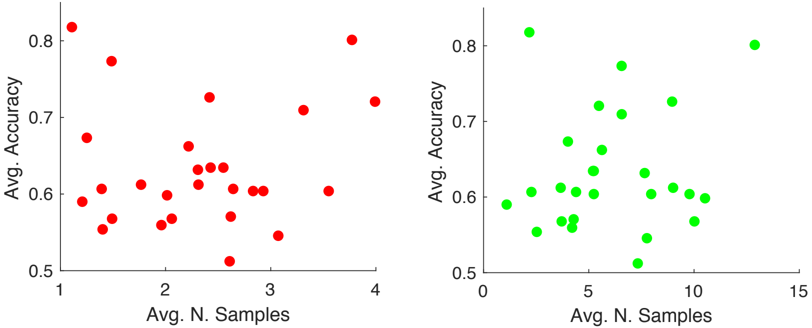


Figure 15: Distribution of samples collected in task 2 (left, in red) and task 3 (righ, in green).

More information collected in difficult trials

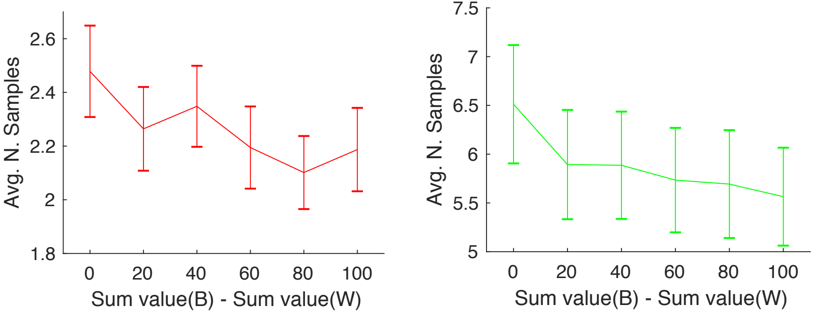


Figure 16: Number of samples under different levels of difficulty (average and SE). Note: high heterogeneity at the individual level.

Sampling strategies

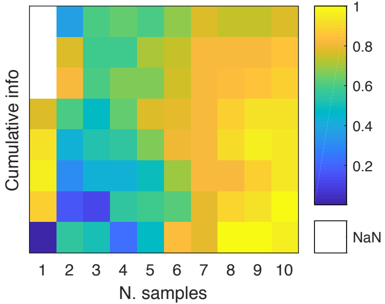


Figure 17: Probability of choosing conditional on time and information. Sampling-risk task (left) and Sampling-freely task (right). Note: high heterogeneity at the individual level.

Summary

- Multi-attribute problems (online shopping, taxes, shipping fee)
- Recency effect is striking
  - In the static task, overweight latest stimuli
  - In the sequential tasks reduces the importance of early evidence
  - and explains the lack of correlation btw sampling and accuracy
- Early observations are not very relevant in a static problem
  - but may determine a longer collection process
- Wishful thinking
  - overweight events that are positive (in absolute terms)
- Range effect (relative thinking) used for difficult choices only
- Heterogeneous sampling strategy across subjects

Attention and Perception in Multi-Attribute Choice Problems

Silvio Ravaioli

C&D Lab Meeting - Columbia University

November 9, 2018

Extra material

Violation of stochastic transitivity (cycle trials 1)

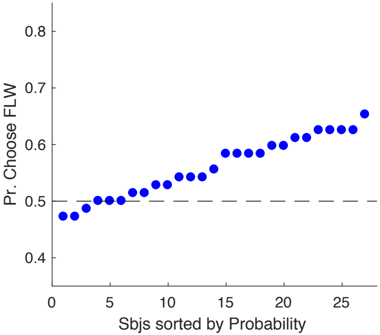


Figure 18: Prob of choosing the FLW option in task 2 (left) and 3 (right).

- 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)

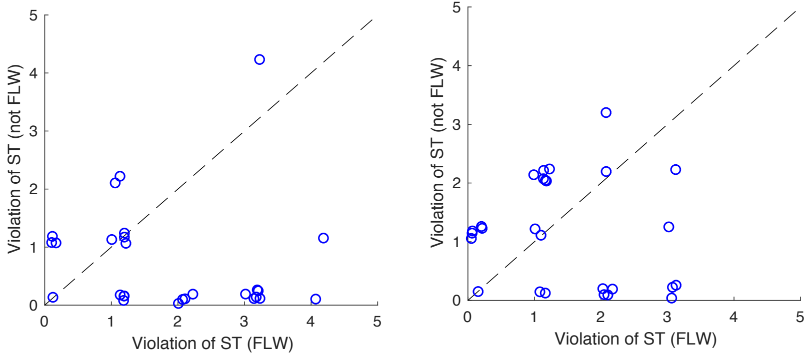


Figure 19: Number of stochastic violations in each direction.

- 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)

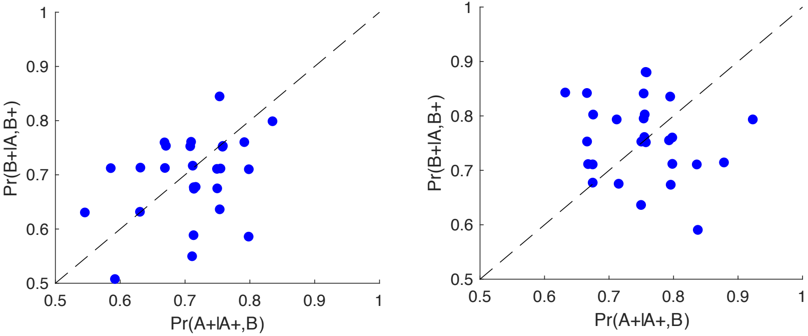


Figure 20: Increment trials: Probability of choosing the correct option when it is FLW (x-axis) and when it is not FLW (y-axis) in the sampling tasks

- 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)

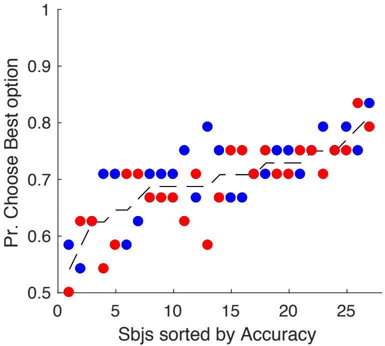


Figure 21: Increment trials: Probability of choosing the correct option when it is FLW (blue) and when it is not FLW (red) in tasks 2 (left) and 3 (right).