An Information Attention-Integration Puzzle

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Sloan-Nomis Workshop
on the Cognitive Foundations of Economic Behavior

February 23, 2019

Introduction

- Evaluate alternatives that differ across multiple dimensions
- We always make comparisons across available alternatives!

Customer Rating	(2)	(4)
Price	$23.00	$8.89
Size	14 ounce	11 ounces

- How should a *noisy perception* model include comparison?
- Explicit comparison largely explains heterogeneous accuracy and biases in a simple perceptual task.

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Motivation /1 - Noisy integration

- Choice across multi-dimension alternatives
- Equally relevant dimensions should be integrated with the same weight (averaging task)
- **Humans deviate systematically**: overweight of extreme values under early noise (Spitzer, Waschke, and Summerfield 2017), robust averaging under late noise (Li et al. 2018)
- Information is integrated in isolation based on the distance from expectation

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Motivation /2 - Stochastic transitivity

- Field and experimental evidence of violation of stochastic transitivity: $a \succ b \succ c \succ a \qquad Pr(a|\{a, b\}) > 0.5$
- Commonly found for **trinary choices** when a decoy is introduced (Huber et al 1982, Heat and Chatterjee 1995)
- But also with **binary choices**, if they have multiple dimensions (Tsetsos et al. 2016)
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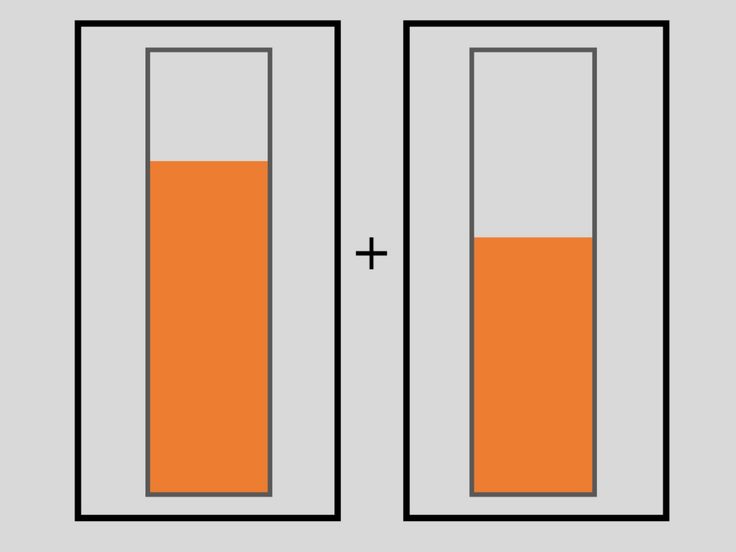
Experimental Design



6 pair of bars are shown in rapid sequence.

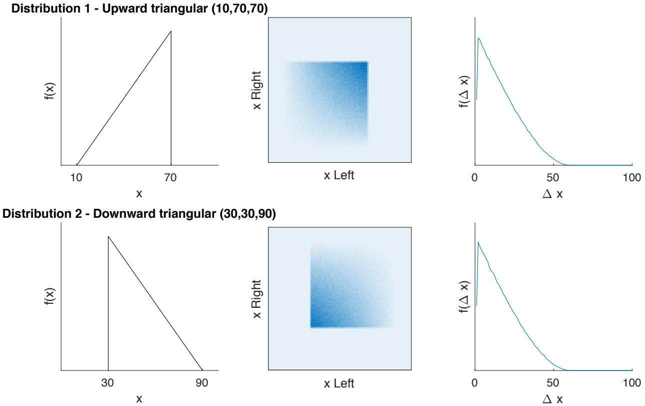
Experimental Design

- **Binary choice**: compound lottery L(eft) vs R(ight)
- Six simple lotteries (dimensions) equally likely to be selected
- Each sub-lottery is a 10-90% probability of winning one point

- Lab experiment at CELSS: n=37 participants
- 800 trials in a session ($\sim$ 75 min), including 2 extra tasks
- Incentive: collect number of points across the experiment
- Payment: (# points - 300) $\cdot$ 20 ¢ Avg. payment $24.20

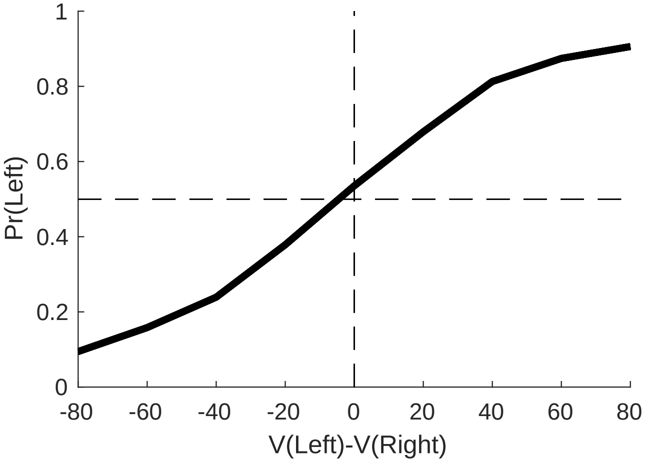
Treatments - Upward/Downward distributions

- Upward and Downward triangular distributions
  - Same range (60 pts), same mean (50 pts),
    same distribution of **differences** between two random draws
  - Different distribution and range of values (10-70 vs 30-90)



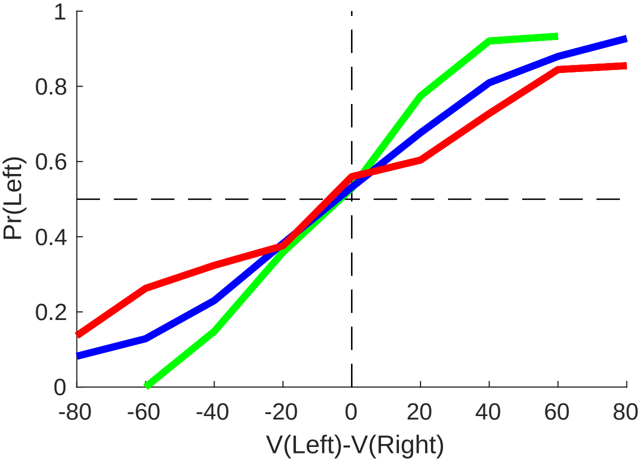
Value distributions used to generate data in the two treatments

0. Randomness



Choice probability in trials with different difficulty

1. Similarity improves accuracy



Choice probability, after controlling for similarity

1. Similarity improves accuracy

What triangle has the larger area?

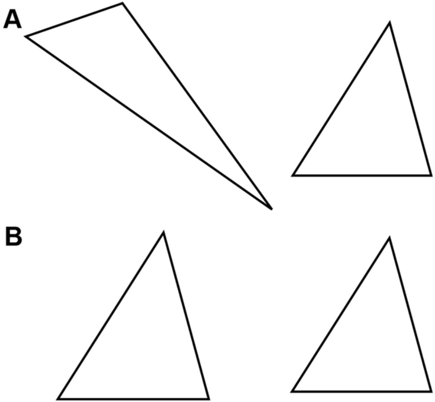
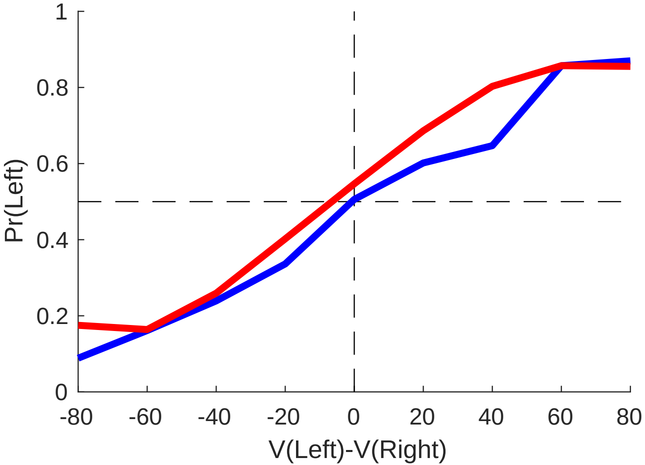


Fig. 2. Which triangle has the larger area?

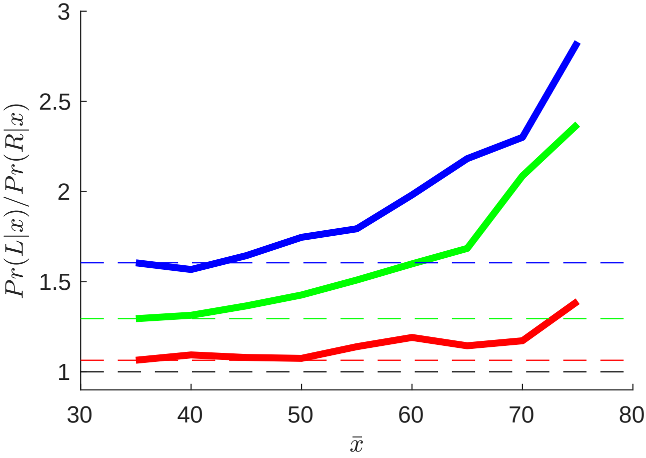
Natenzon 2019 “Random choice and learning”, figure 2.

2. Advantage of frequent local winner



Choice probability in trials with and without Frequent Local Winner

3. Monotonic decision weights

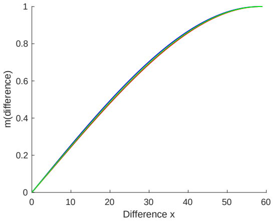


Decision weight $\frac{Pr(L|x)}{Pr(R|x)}$ for different magnitudes $\bar{x}$ and differences Δx

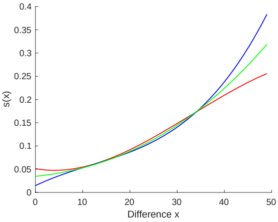
Model selection (the last mile)

- At time $t \in 1, \ldots, 6$ two values x_t^L and x_t^R are observed
- Mental representation of the difference $\Delta x := x^L - x^R$
  - Noisy representation $\hat{\Delta x} \sim N(m(\Delta x), s(\Delta x))$
  - Transducer $m(\cdot)$, degree 3 polynomial
  - Heterogeneous variance $s(\cdot)$, degree 3 polynomial
- Focus towards higher values (“good news”): $\alpha > 1$
  - Interaction with $\bar{x} = \frac{x^L + x^R}{2}$
- Leaking memory: $\delta < 1$
- Choice based on $\Delta V = \sum_t \delta^{T-t} \cdot \hat{\Delta x}_t \cdot \bar{x}_t^{\alpha}$

Model fit



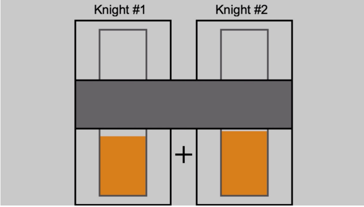
Transducer $m(\Delta x)$



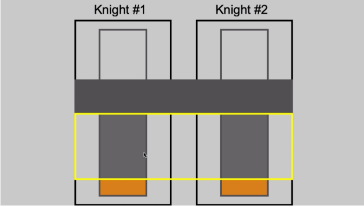
Heterogeneous variance $s(\Delta x)$

- Leaking memory $\hat{\delta} = 0.78 < 1$ (recency effect)
- High-value focusing $\hat{\alpha} = 1.42 > 1$ (directed salience)
- No “traditional” salience (comparison across treatments)

Next steps



Task 2. Part of the range is obscured by a fixed rectangle.



Task 3. The participant chooses the part of the screen to observe.

- Two additional tasks:
  - *Exogenous* information restriction: part of the screen is obscured
  - *Endogenous* information restriction: choose which part of the screen to reveal (above or below a given value)
- Early results:
  - Accuracy increases when fewer values are observed
  - *Asymmetric* directed salience: seek the best vs. avoid the worse
  - Disproportionate preference for high-range information

Challenges and questions

- Explore heterogeneity across participants
- Connect results in main and ancillary tasks
- Model comparison: model of *directed* salience

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