Noisy Integration of Value Differences

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Sloan-Nomis Workshop
on the Cognitive Foundations of Economic Behavior

February 23, 2019

A souvenir from NY

Price	**$9**
Size	**11 ounces**

- Evaluate alternatives that differ across multiple dimensions
- We always make comparisons across available alternatives
- **Integration of separate values, differences, or "both"?**

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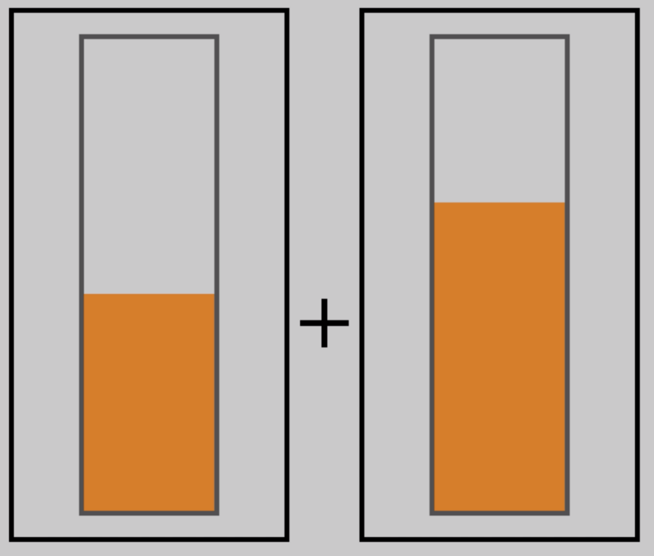
Motivation and Context

- **Noisy integration of decision information**
  - Choice across multi-dimension alternatives
  - **Averaging task**: equally relevant dimensions should be integrated with the same weight
  - Humans deviate systematically: overweight of extreme values under early noise (Spitzer, Waschke, and Summerfield 2017), robust averaging under late noise (Li et al. 2018)
- **Context effect and Violation of stochastic transitivity**
  - Commonly found in **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)
  - Stochastic transitivity violation would not occur if information was encoded in isolation

Experimental Design

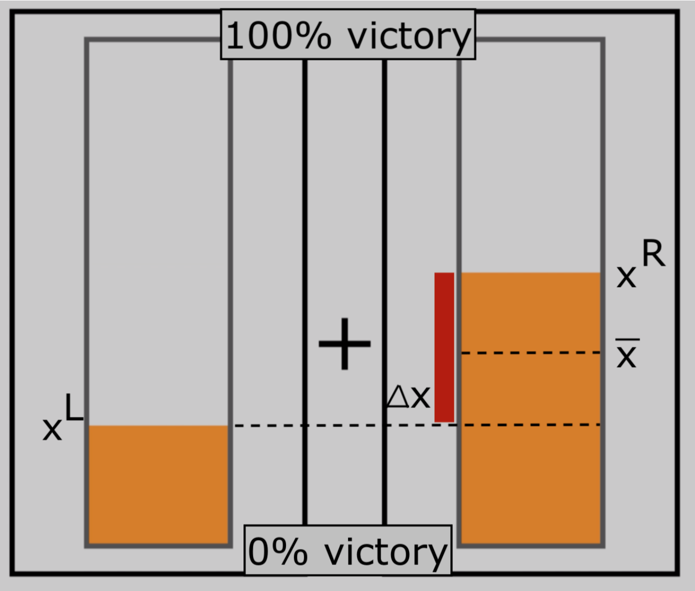


Experimental Design

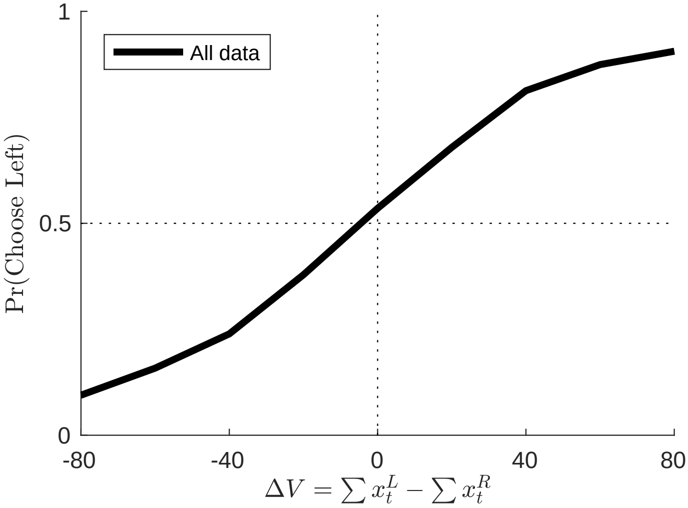
- **Binary choice**: compound lottery L(eft) vs R(ight)
- Six simple lotteries (dimensions) equally likely to be selected
- Each sub-lottery is a 10-90% probability of winning one point

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

Experimental Design

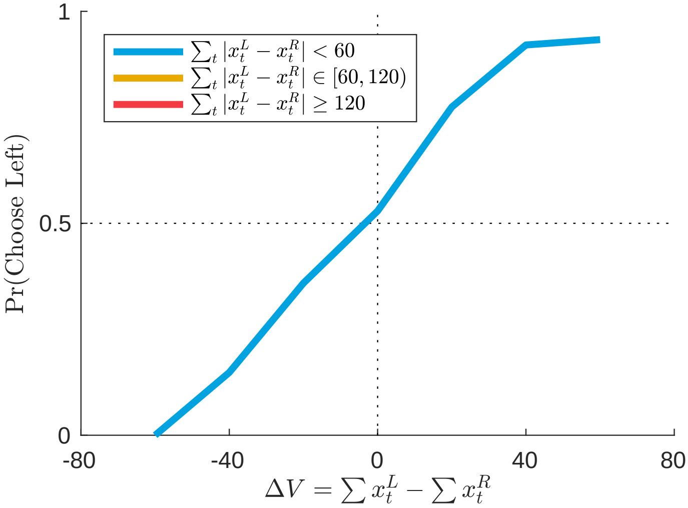


Result 0. Randomness



Choice probability in trials with different difficulty

Result 1. Similarity improves Accuracy



Choice probability, after controlling for similarity

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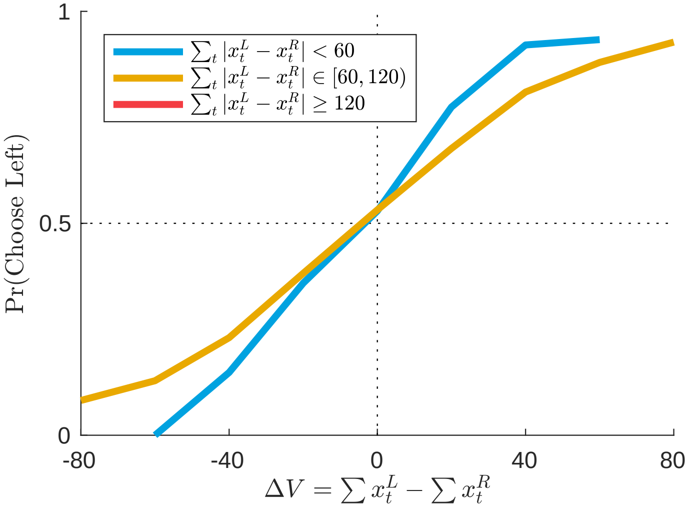

Choice probability, after controlling for similarity

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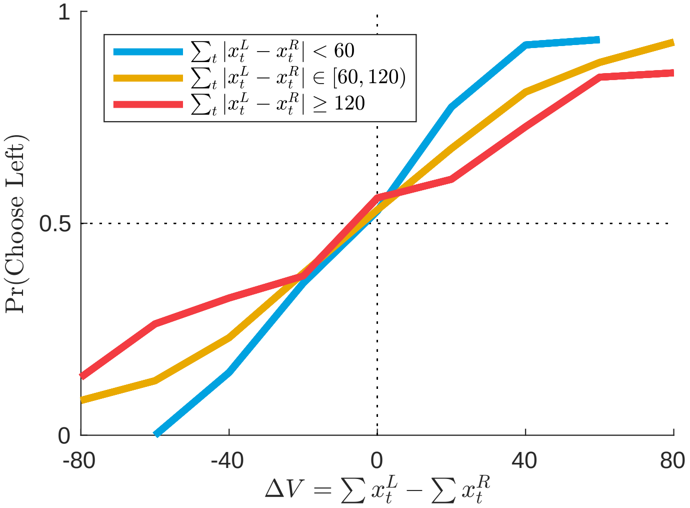
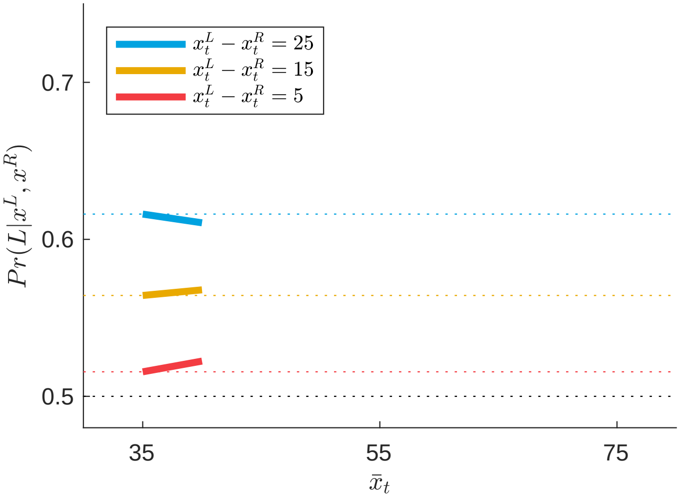


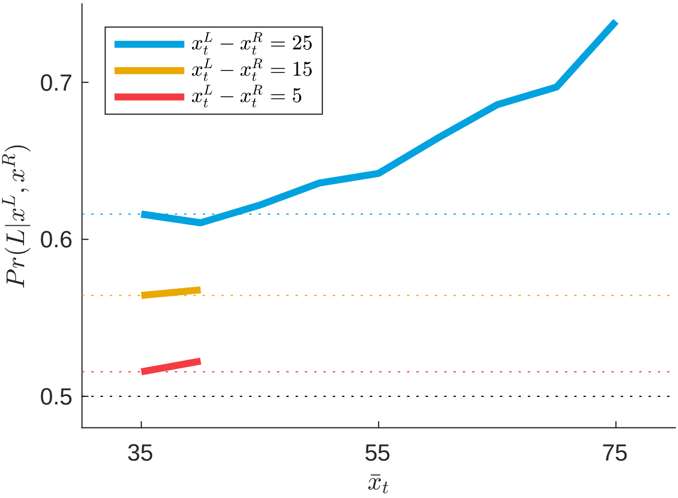
Choice probability, after controlling for similarity

Result 2. Decision Weights



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

Result 2. Decision Weights



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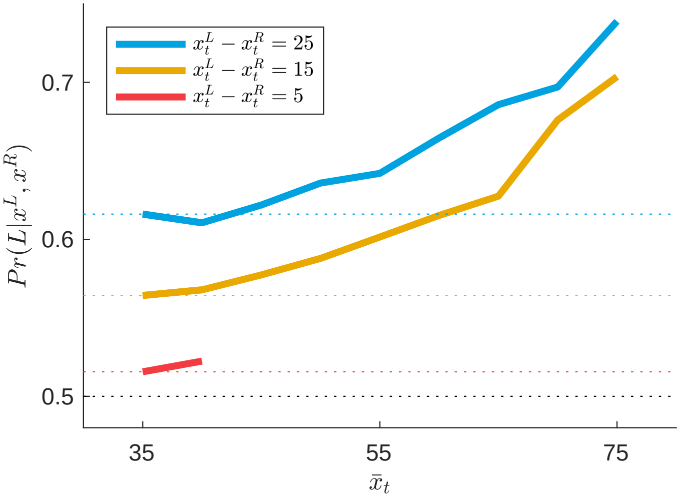

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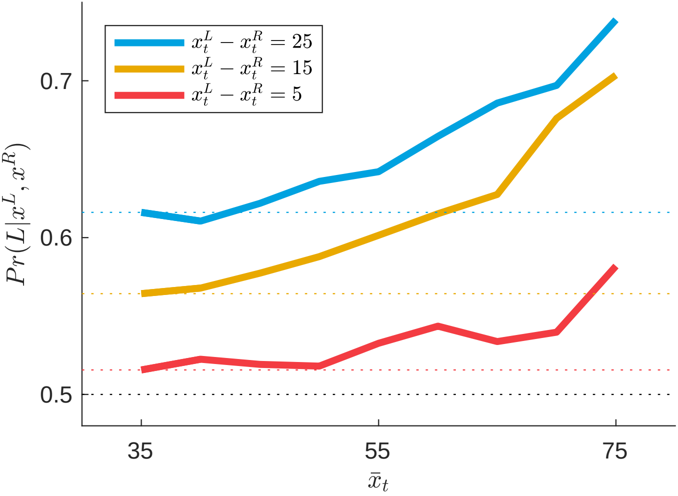
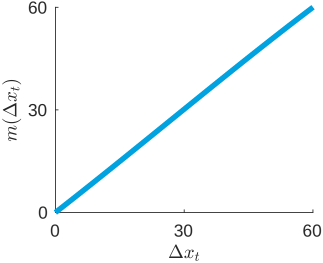


Decision weight $Pr(L|x^L, x^R)$ for different magnitudes $\bar{x}$ and differences Δx

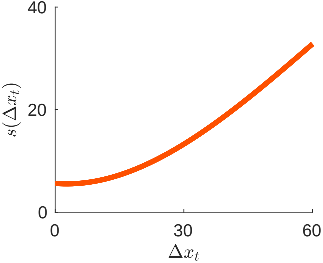
Model Selection (the last mile)

- At time $t \in 1, \ldots, 6$ two values x_t^L and x_t^R are observed
- **Mental representation of the difference** $\Delta x_t := x_t^L - x_t^R$
  - Noisy representation $\hat{\Delta x} \sim N(m(\Delta x), s(\Delta x))$
  - Transformation $m(\Delta x)$, degree 3 polynomial
  - Varying noise $s(\Delta x)$, degree 3 polynomial
- **Choice based on** $\Delta V := \sum_{t=1}^{T} \delta^{T-t} \cdot \hat{\Delta x}_t \cdot \bar{x}_t^{\alpha}$
- Focus towards higher values ("good news"): $\alpha > 0$
- Leaking memory: $\delta < 1$

Model Fit - Noisy integration of value differences



Transformation $m(\Delta x)$

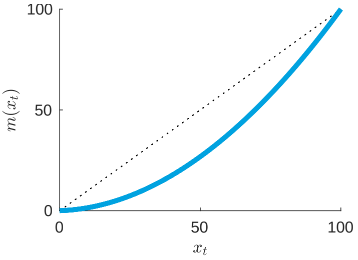


Varying noise $s(\Delta x)$

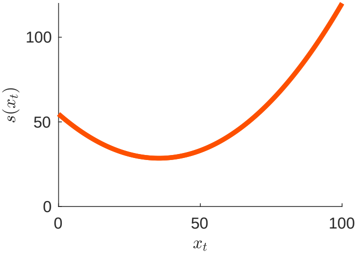
- Leaking memory $\hat{\delta} = 0.81 < 1$ (recency effect)
- High-value focusing $\hat{\alpha} = 1.19 > 0$ (magnitude effect)

Model Fit - Noisy integration of individual values

- **Noisy representation of individual values** $\hat{x} \sim N(m(x), s(x))$
  - Transformation $m(x)$, degree 3 polynomial
  - Varying noise $s(x)$, degree 3 polynomial
- **Choice based on** $\Delta V := \sum_{t=1}^{T} \delta^{T-t} \cdot (\hat{x}_t^L - \hat{x}_t^R)$
- Worse fit of data: BIC 12,954 [>10,969 noisy integration of Δx]



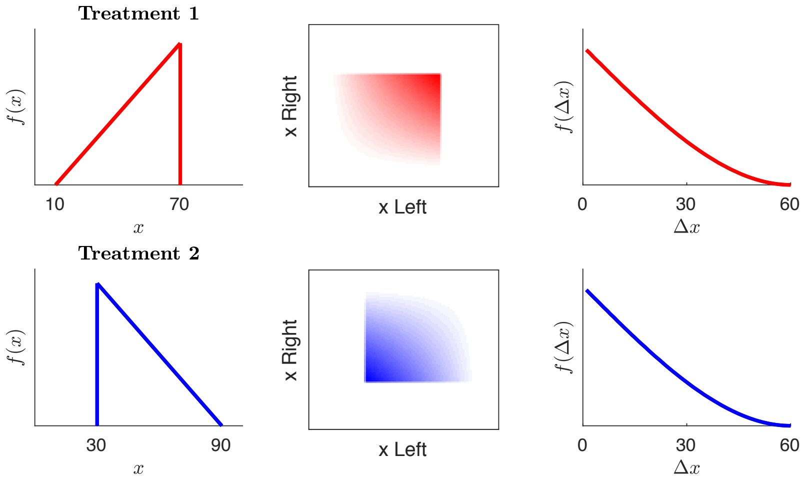
Transformation $m(x)$



Varying noise $s(x)$

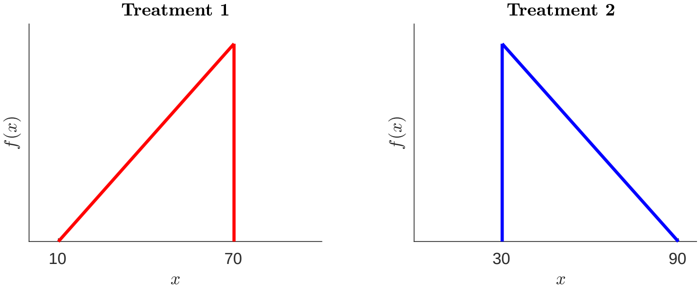
Treatments - Upward/Downward distributions

- Upward and Downward triangular distributions



Value distributions used to generate data in the two treatments

Model Fit - Separate treatments



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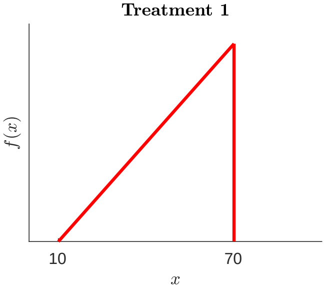
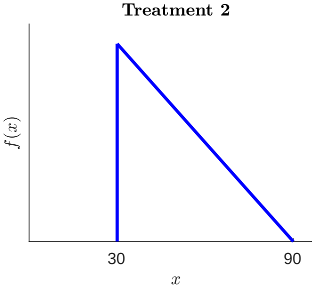
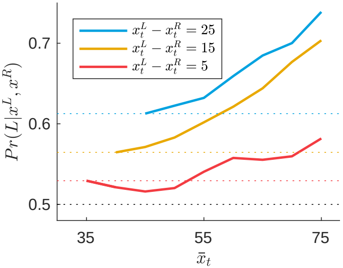
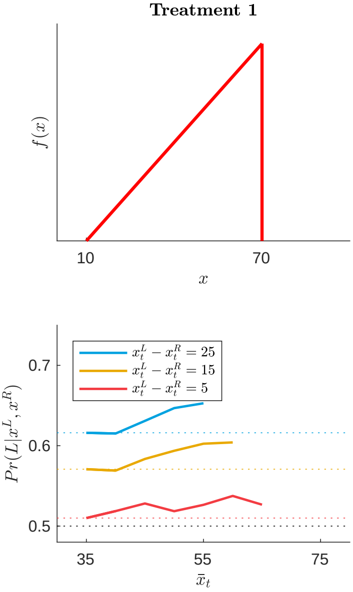






Model Fit - Separate treatments



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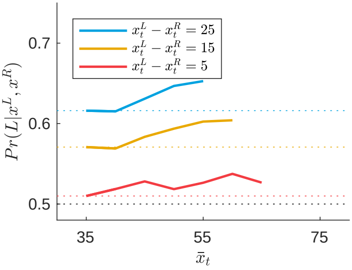

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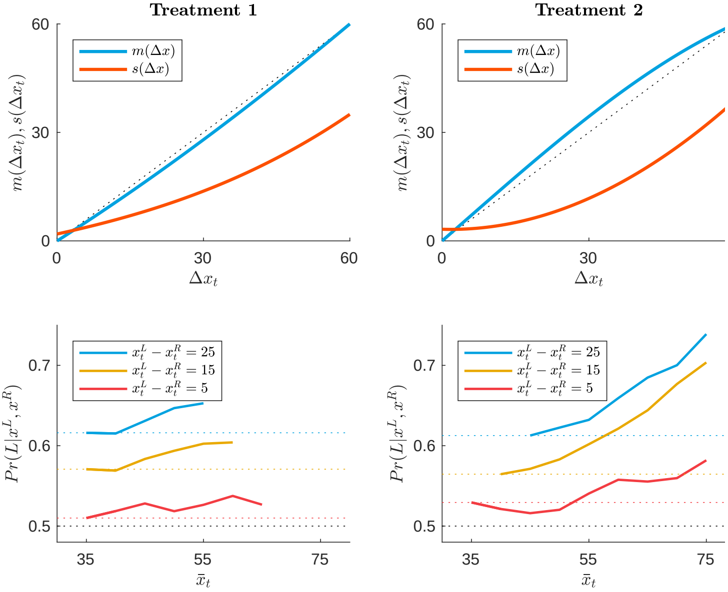

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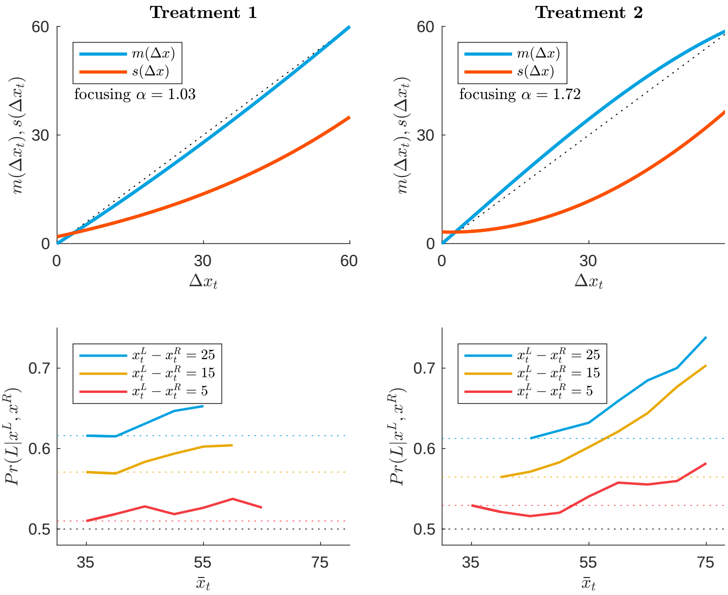

Next Steps

- Treatments: effect of different underlying distributions
- Learning during the session
- Explore individual-level heterogeneity
- Connect results in main and ancillary tasks
- Model comparison

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