Center for Adaptive Rationality

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Conflicting conclusions about under- and overweighting of extreme values in economic and psychophysical tasks: An artefact of different modeling frameworks?

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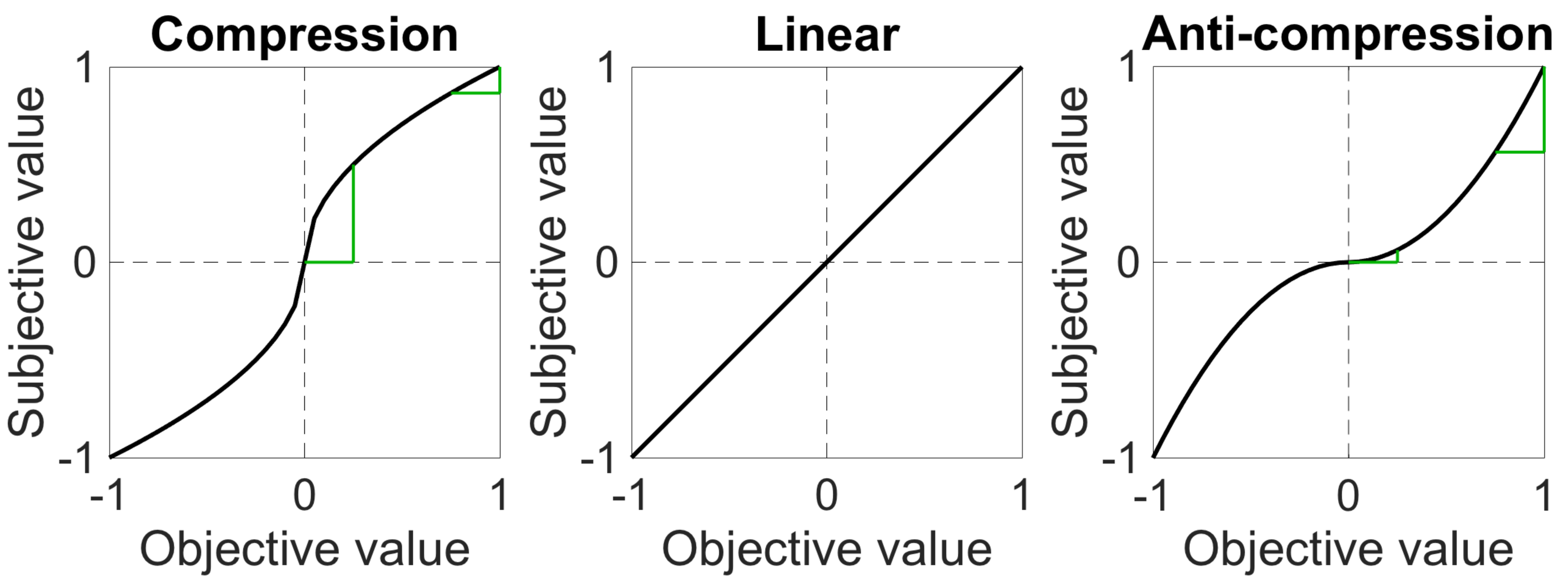
At a glance

Research question	Experiments from different research traditions came to different conclusions about over- or underweighting of extreme values in decisions from numerical samples. Is this an artefact of different modeling frameworks being used ?
Method	Reanalysis of two data sets, each with both (i) cumulative prospect theory and (ii) a selective integration model.
Key results	The two models agree in their conclusions about over- or underweighting, indicating that conflictive results patterns in previous studies are likely due to differences in stimuli and/or design features of the experiments.

Background

- Economic research commonly indicates diminished sensitivity for extreme values, indicated by a compressed (concave) value function.
- Several psychophysical studies of numerical averaging show the opposite – an overweighting of extreme values, i.e., a convex value function (e.g. Ludvig et al., 2014, Tsetsos et al., 2016, Spitzer et al., 2017, Vanunu et al., 2019).
- However, these different lines of work used different computational models, most commonly cumulative prospect theory (CPT) and selective integration (SI), respectively.
- Could the different model architectures lead to the different conclusions about the representation of extreme values?
- To test this, we reanalyzed two data sets with both models.



Compressed, linear and anti-compressed subjective value weighting

Models: CPT and SI

- **Cumulative prospect theory (CPT):**
  - Value function (for gains, *x*, and losses, *y*):

$$v(x) = x^{\alpha}$$
$$v(y) = -\lambda(-y)^{\beta}$$

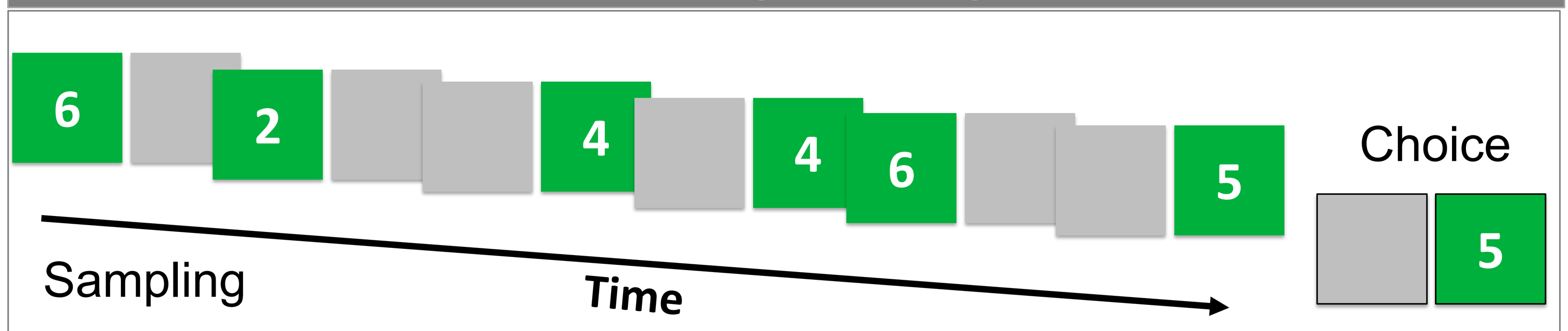
  - Probability weighting function

- **Selective integration (SI) model:**
  - Value function:

$$dv = \frac{X}{|X|} \times |X|^{k}$$

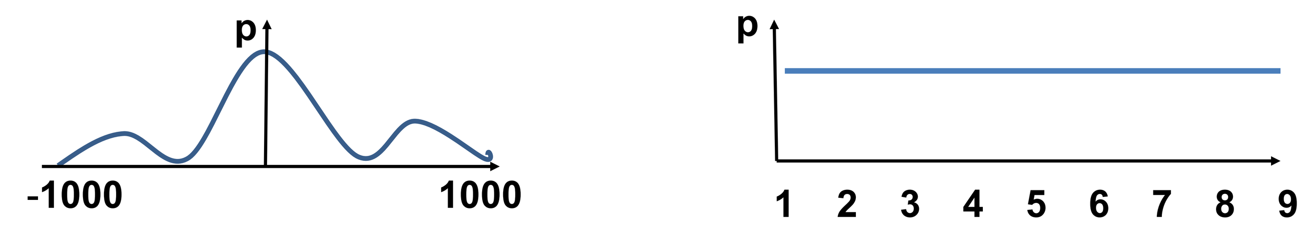
  - Sample-level decision value
  - No separate probability weighting

Sampling paradigm



Participants sample possible outcomes of two options (left and right) before making a final binary choice (e.g., Hertwig & Erev, 2009).

Data sets



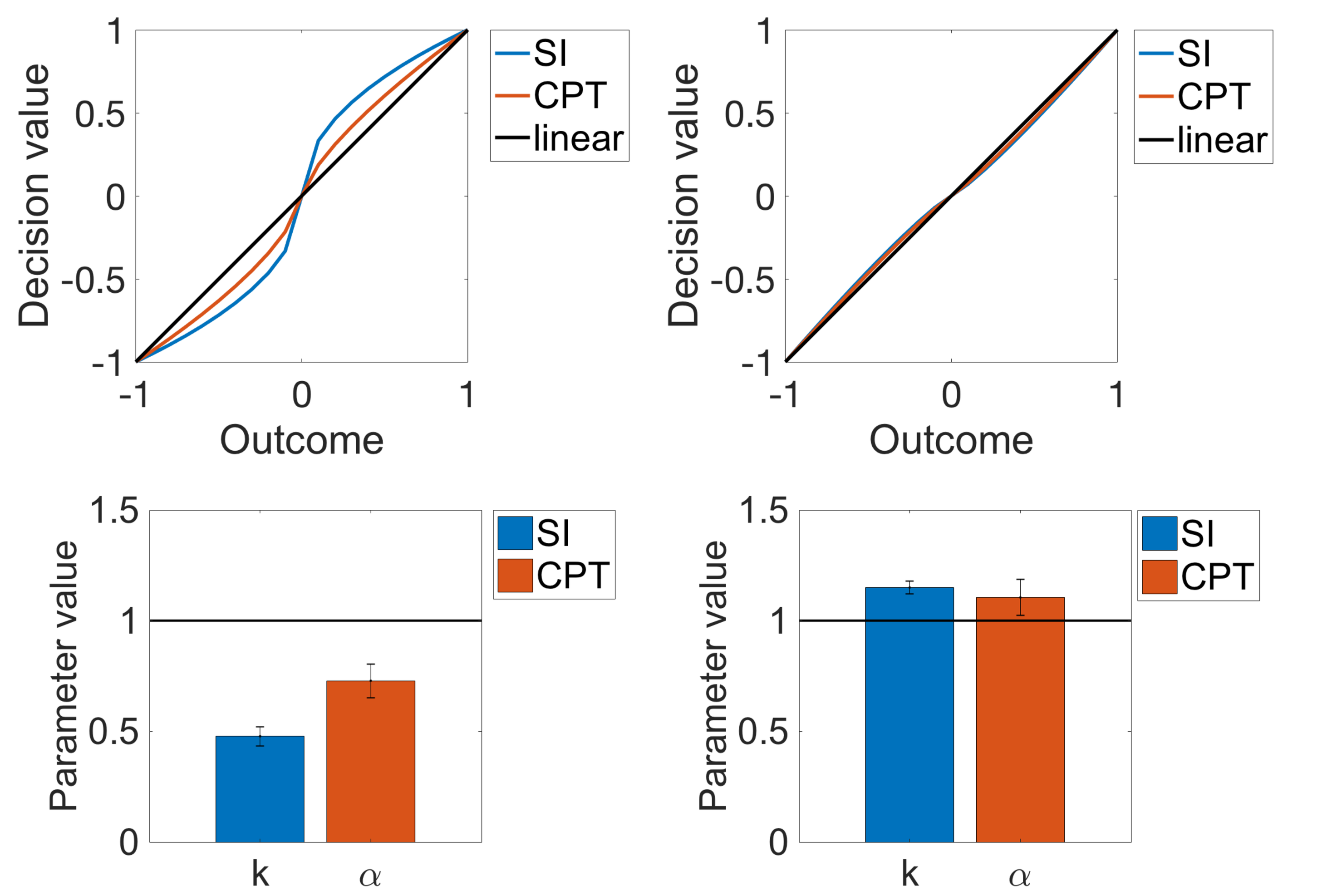
Kellen et al. (2016)
- **Gain, loss and mixed gambles**
- **Outcomes -1000 to 1000**
- **Non-uniformly distributed**

- 104 participants
- 114 trials
- 2 options with at least one two-outcome gamble
- Incentive compatible
- Active drawing and variable stopping

Appelhoff et al. (in prep)
- **Only gain gambles**
- **Outcomes integers 1 to 9**
- **Outcomes and probabilities uniformly distributed**

- 40 participants
- 100 trials
- 2 options with each 2 outcomes
- Incentive compatible
- Active vs. yoked sampling, variable vs. fixed stopping

Result



Value functions and estimated parameters for both the Kellen et al. (2016) data and the Appelhoff et al. (in prep) with both CPT (orange) and SI (blue)

Discussion

- The models agree in their predictions for the same data set.
  → The divergence is not an artefact of different models.
- Overall better fit with CPT [ΔBIC = 4.9 (Appelhoff), ΔBIC=2.6 (Kellen)] → Probability weighting in CPT might play an additional role but is not the main cause for the different distortions.
- Distortions may flexibly adapt to properties of the stimulus space (e.g., sample distribution and/or -range)

References

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