REPORT

Paper: Experiential values are underweighted in decisions involving symbolic options

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Introduction

Introduction to the replication study:

The study of decision-making processes has been a fascinating field of research, particularly in understanding how individuals weigh the different values of options presented to them. In recent years, researchers have noticed a phenomenon called "description-experience gap," where individuals tend to undervalue the experiential options compared to their same value symbolic(descriptive) options. This phenomenon has significant implications for various domains, including consumer behavior, public policy, and healthcare decision-making. In this context, a group of researchers conducted an experiment to investigate the effect of experiential value neglect and proposed potential reasons for the same.

The experimental approach will involve two phases, namely the learning phase (LE) and the evaluation and selection phase (ES), where participants will be presented with fixed pairs of options in the LE phase and tested with new pairs in the ES phase, which include choices between experiential (E) and symbolic (S) options. The options in the LE phase were represented by shapes, and the participants were provided with partial feedback about their expected values. In the ES phase, the options were represented by pie charts, with varying levels of experiential and symbolic values. In our replication experiment, we had 2 E-option pairs(4 E options) in the L phase. Each of these pairs were shown 20 times in front of participants in the LE phase. In the ES phase, each E option was shown against each S option(7 S options total) once without feedback.

Motivation for the extension study:

The motivation for the extension study is to investigate a possible explanation for the phenomenon of experiential value neglect, which was not fully explored in the previous study. The dual process model hypothesis presented in the paper was inconclusive, and the neglect could be due to either lower precision or higher memory retrieval costs associated with experiential options.

To address this issue, the extension study aims to examine whether higher memory retrieval costs are responsible for the experiential value neglect. This will involve testing participants' choices between experiential and symbolic options in a learning phase and a testing phase. By doing so, the study hopes to gain a better understanding of how individuals make decisions when experiential and symbolic options are present.

Overall, the extension study aims to provide further insight into the possible causes of experiential value neglect and contribute to a better understanding of decision-making processes in situations where experiential and symbolic options are present.

Methods

We first calculated the sample probability of winning for each E-option (using data from every candidate) against every S-option. We then scattered the P(win) values of every E-option(4 E-options) against 7 different S-options with varying P(win). Then we had to fit the sigmoid c/(1+exp(ax+b)) curve to the scatter plot of every E-option. For sigmoid and later linear fitting, we have used the curve fit routine from *scipy*. As extra work, we had to define the sigmoid nature mentioned above in the code to pass as a parameter to the scipy's routine. The routine fits the curve to the data points and returns the [c, a, b]. These returned values define the exact nature of the graph and are of interest to us. Once the fit is done for every E-option graph, we also find the indifference point by getting the value of x which produces the value of y to be 0.5 through the fitted sigmoid curve. Indifference point is the point in the curve where there is a 50% chance of choosing any of the two options. This is done using the inverse function of the fit sigmoid: $x=g(y) = a * \ln(c / y - 1) + b$. These indifference points indicate the estimated P(win) inferred for each E option in the ES phase.

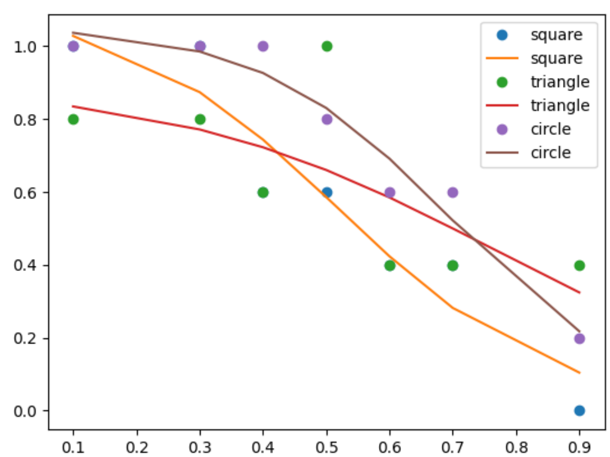
Once we got the indifference points for every phase of our experiment, namely LE, and ES, we fitted a linear curve individually to every phase's indifference data points. This plot compares the estimated P(win)% of an E option(Y - axis) from the indifference points against the actual P(win) of each E option (X - axis) . We used the same curve fit module from *scipy* for this task.

For plotting, we used the matplotlib library and pandas and numpy for data processing.

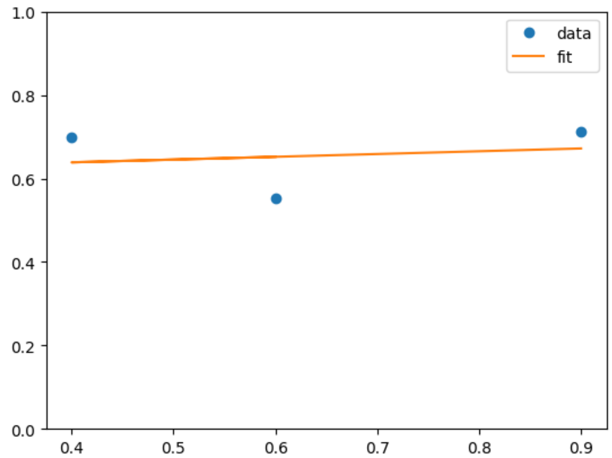
Results

Our analysis has yielded plenty of suggestive evidence to continue collecting data. We believe the results will be more accurate if more data collection is performed for modeling. More data points would also be desirable as it helps in fitting the data more accurately. It was a challenge to make the participants play a longer game(which will yield more data points) without any monetary rewards and performance bonuses.

Replication



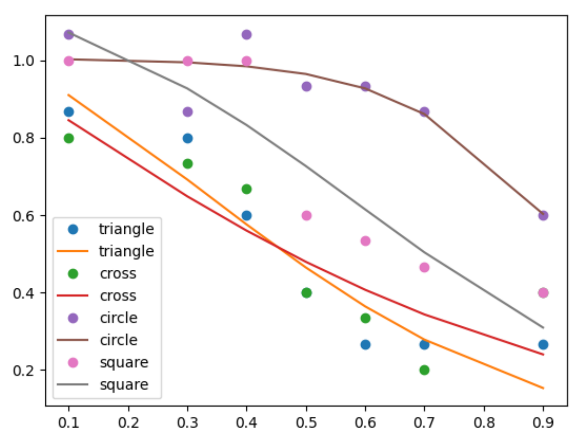
Sigmoid curve fit for replication choice data



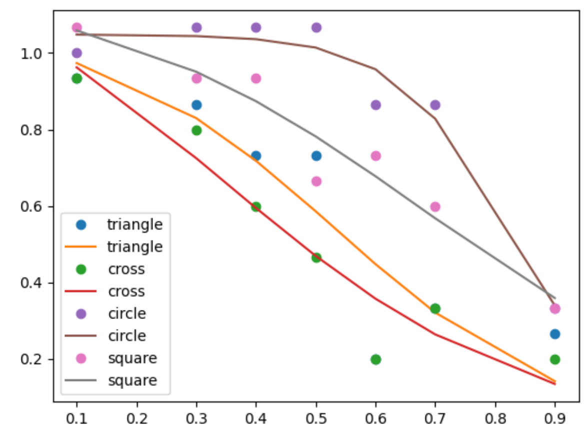
Linear fit of the indifference points obtained from the replication experiment

The results of the replication task weakly resemble the results of the original experiment. In Graph 1, we can observe the results of sigmoid fitting to our sparse datapoints. The sigmoid nature is more clearly visible for certain options than others (for example in the square option). This was to be expected when operating on such little data as sigmoids require more data to fit cleanly. The linear line of the indifference points fit also resembles the original experiment data as it has a close to 0 slope, indicating that the experiential options are indeed underweighted. The original experiment was conducted with more options, also with more trials per pair and more participants which gives clearer fits in the original experiment.

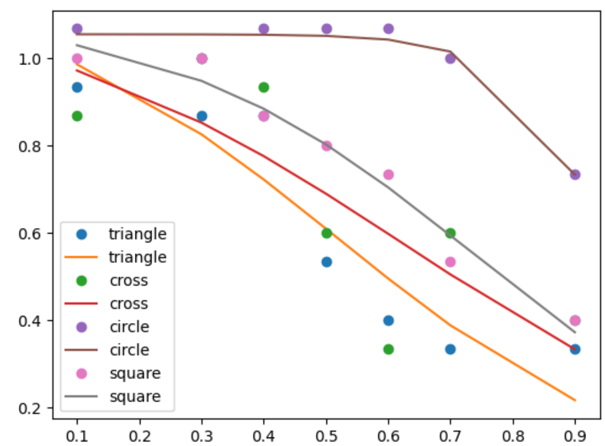
Extension



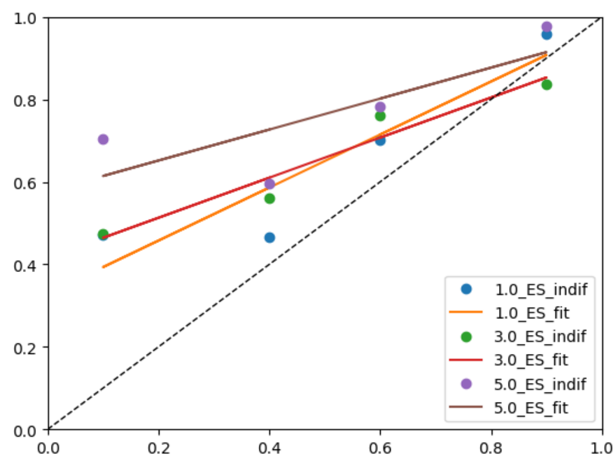
Sigmoid curve fit for difficulty 1 choice data



Sigmoid curve fit for difficulty 3 choice data



Sigmoid curve fit for difficulty 5 choice data



Linear fit of indifference points obtained for the 3 difficulty levels

In the extension experiment, the difficulty level is the number of additional clicks required to select the S option. We chose 1,3 and 5 as our difficulty levels(corresponding to 2, 4 and 6 clicks), to make sure the experiment was kept short enough to convince enough participants to play the game without any reward or monetary incentive.

Across all difficulties, the graphs are still being fit to sigmoids, increasing the difficulty seems to make the sigmoid sharper, although this cannot be said conclusively due to insufficient data.

The final regression fit graph seems to display neglect with some bias. It is unclear what may have caused this bias. Increasing the difficulty decreases the slope, while also increasing this bias. In the extension experiment, with increased difficult in the S options, we do notice that the slope overall is higher than that of the replication experiment. This does give some evidence to our hypothesis of experiential value neglect happening partially(or wholly) due to computational cost difference. It is nice to remember here that the difficulty added to the S option here doesn't impair the symbolic nature of the S option or increase uncertainty. It quite simply adds a waiting time and some mechanical effort to the S option.

This would mean that experiential value neglect could actually be evidence of rational inattention since the brain appears to be tuning the effort it puts into E options based on the difficulty level of S options. This rational inattention finds some evidence in the increasing bias value for the perceived P(win) of the E options with increasing difficulty. There doesnt seem to be sufficient evidence to validate or invalidate experiential value neglect with increasing values as only 4 indifference points have been used to fit the line. Even if S and E options are weighed equally with sufficiently difficult options, this can also be accounted to rational inattention towards the S options and so doesn't help invalidate the dual process model entirely.

Conclusions

Through our replication experiment, we were able to observe some initial evidence of experiential value neglect. We notice however that more data points and participants will be required for a better curve fit. There is an unaccounted bias term in the linear fit the source of which is unclear. We couldn't perform t-tests for the hypothesis because of the restriction in time.

Difference in the sigmoid and linear fits between the replication and the extension experiments seems to show that there is relatively lesser experiential value neglect, but this can't be validated without more data and consequent t-tests. In the extension experiment also, there is a bias in the linear fit which is unclear why.

More data collection with more participants and more S and E options will be one of the primary future plans. Additionally, t-tests have to be performed to realise the statistical significance of the obtained results.

Some other extension experiments could also be performed to test other possible hypotheses too:

1. It could be a possibility that the participants are not actually inferring the values of each E option and are only learning which option is more likely to perform better. This is a likely possibility as the participants have no idea that these E options will be compared with numeric symbolic values. This is a possible serious flaw in the assumptions of the paper and this explanation can be truly ruled out by conducting an a modified experiment. This will also promote easier generalisation for hybrid choice cues.
    a. In this new experiment, conduct the experiment twice, each time with an LE and ES phase. Choose the E option pairs to be different in the two iterations for the LE phase.
    b. In the first iteration of the experiment, give the participants partial feedback on how they are performing in the ES phase. This will help them realise what is exactly expected of them to learn for the task in the LE phase.
    c. Additionally, we can also try to find performance differences with the original experiment.
2. It is very likely(as mentioned by the authors themselves) that the cause of experiential value neglect could be associated with the uncertainity(lack of precision) of the E option with reference to the S option. This is difficult to prove or disprove as this boils down to what does it mean for an option to be experiential or symbolic. It very well maybe the case that symbolic options are values with high certainty while experiential values are values with lower certainty, thus forming a spectrum. We may also attempt to design an experiment, which helps determine the behaviours along this spectrum. We may conduct an experiment which have some E option cues which are learnt over many more trials than other E option cues. If the experiential value neglect reduces over the more trained options, it will prove the effect of uncertainty in the decision making process for hybrid choices.