SNE Talk

Hi, my name is Brenden Eum, and today I’m going to be talking about Attentional Choice Biases in Losses, an aDDM Puzzle. This is joint work with Stephen Gonzalez at Stanford and Antonio Rangel at Caltech.

Every day, we make dozens of value-based decisions, whether that be going to the grocery store and deciding what cereal to buy, choosing which restaurant to go for lunch, or even something as simple as asking whether you want an apple or a banana with breakfast.

Now one way to study how we make these types of decisions is to bring people into the lab and ask them to make a choice between two snack food items on the screen, all the while keeping track of the location of their gaze as they make their decision. What this allows us to do is to peer into the choice process guiding peoples’ decisions and ask how visual attention is influencing their choices.

There are some ways to see how visual attention is driving choice behavior without the need for models. You can look for net fixation bias, where people are more likely to choose the option they spend more time looking at. And you can look for last fixation bias, where people are significantly more likely to choose the last thing that they look at. Now note that in the absence of an attentional bias, how long someone looks at something or what they last looked at should have no effect on their choices. Instead what we see are robust attentional effects across multiple different types of decisions, whether that be choices between food items, choices between monetary gambles, and even social choices as well.

One way to model the effects of attention on choice is to use the attentional drift diffusion model, which we’ll call the aDDM. It’s an evidence accumulation process where evidence at time t is equal to evidence at time t minus one, plus some drift and some noise. This White Gaussian noise is parameterized by variance sigma squared. The evidence process initializes at a bias starting point, b. And the drift at any given point in time depends on where the decision-maker is currently looking. So drift is equal to a drift rate parameter, d, times the value difference between the left and the right option, but where we discount the value of the nonfixated option by an attentional parameter, theta, which is bounded between 0 and 1. So if you’re looking left, we’ll discount the value of the right option, and if you’re looking right, we’ll discount the value of the left. Lastly, the aDDM is agnostic to modeling the fixation process, which means we’re taking fixations as given. That process is going to look something like this, where evidence initializes at a point close to 0 and will evolve towards one of two decision boundaries indicating a choice for left or right. Now as long as the values of the two options are somewhat close to each other, as you fixate left, this process will trend towards the upper boundary. Similarly, as you look right, the process will trend downwards. Eventually, the process hits a boundary and stops, indicating what choice was made and how long it took to make that choice.

The nice thing about the aDDM is that it generates a set of testable predictions. First, we can look for evidence of attentional bias by looking at the size of parameter theta. In a meta-analysis of 20 studies by Bhatnagar and Orquin in 2022, they found that the average value of the attentional parameter is roughly 0.53. In other words, people discount the value of nonfixated option down to about half of its original value during this value comparison process. The aDDM is also capable of explaining this net fixation bias and last fixation bias that we talked about earlier.

But in most of the studies up till now, we’ve been focusing on choices between foods that people want to eat or on lotteries with positive outcomes. In other words, we’ve been asking “Which of these things do you WANT?” and then we’ve been presenting people with options that they actually DO want. But what happens if people HAVE to make a choice between things that they DON’T want?

For instance, imagine I pull out a box of Harry Potter jelly beans. And to be mean, I ask you to pick between Earthworm and Earwax.

In this scenario, what does the aDDM look like? Suppose you value both Earthworm and Earwax as -1 and you have an attentional parameter between 0 and 1. Well since the values of the options are negative, and we’re discounting nonfixated options, then as you look at earthworm, your accumulator should be pushed towards earwax, and as you look at earwax, your accumulator should be pushed towards earthworm, until eventually you make a choice.

So if attentional discounting persists in choices between losses, or in other words if theta is bounded between 0 and 1, then fixating on one option should push the value of the other option up towards 0. In other words, the nonfixated option should seem BETTER than it actually is.

Now what does this mean for the attentional choice biases that we talked about before?

Well now… they should FLIP. So you should be less likely to choose the thing you spent more time looking at, and you should be less likely to choose the last thing that you last looked at. But is this what we actually see in people’s behavior?

To answer this, we ran two eye-tracking studies involving binary choices between lotteries. In study one (we’ll call this the dot study), we had 35 subjects complete 400 trials, 200 in a gain condition, and 200 in a loss condition. In the gain condition, subjects saw two circles on the left and right sides of the screen. Inside each circle was 100 dots, either green or white. Green represents the probability of gaining $10, white represents the probability of gaining nothing. Subjects were free to take as long they liked to make their choice, and we kept track of where they were looking during their decision. The loss condition was similar to the gain condition, only now the green dots are switched to red, indicating the probability of losing $10. And the probability of gaining or losing was uniformly drawn between 45 and 55%.

Ok, let me show you the attentional choice biases in the dot study first. From here on out, red represents data from the loss condition, and green represents data from the gain condition. Recall that previous studies already found that people are more likely to choose the thing that they looked at more and more likely to choose the last thing that they looked at. We see that here too. But remember, the aDDM with attentional discounting predicts that these attentional choice biases should flip in choices between negatively valued options.

We don’t observe that. Notice that in the loss condition, people are STILL more likely to choose the thing they spent more time looking at and the last thing that they looked at.

But it’s possible that subjects were counting the number of GREEN dots in the gain trials and counting the number of WHITE dots in the loss trials, in which case this essentially reduces to a comparison of two positive counts. So to make sure that subjects weren’t doing this, we ran a second study.

In study 2 (we’ll call this the numeric study) we collected 26 subjects with 340 trials each, but instead of presenting lotteries as dots in a circle, we presented them numerically. We selected amounts and probabilities such that expected value always stayed between 1 and 6 dollars, and that the expected value could not be easily calculated with mental math. Aside from that change, everything else is identical to study 1.

Here's the results from the previous dot study. And this is what the attentional choice biases look like in the numeric task. Note that the biases STILL did not flip, which means that subjects are still more likely to choose the thing they spent more time looking at, and still more likely to choose the last thing that they looked at.

So so far, I’ve shown you what we predicted attentional choice biases to look like in choices between losses, then I showed you that they didn’t flip as we predicted. Next I’m going to show you how we initially fit the aDDM to these loss choices, describe why it doesn’t make intuitive sense, then propose a variation of the aDDM that does seem to comply with what we know about value signals in the brain and the choice process. Finally, I’m going to end with a short description of a puzzle in loss choices that we think warrants further research.

So in an effort to understand what might be going on in the underlying choice process, we first fit the aDDM to subjects’ data separately for the gain condition and for the loss condition. We also made one crucial change to the model, which is that we relaxed the bounds on the attentional parameter, theta. Now the drift rate parameter shrank slightly when moving from gains to losses, but otherwise the noise parameter, sigma, and the bias parameter remained relatively unchanged. Now notice though that the attentional parameter experiences a HUGE shift from gains to losses. In gains, theta falls between 0 and 1, which is great since this is what previous studies have recorded too. But in losses, theta flips to greater than 1. What does this mean? This is like amplifying the value of the nonfixated option. But if you amplify a negative value, that makes it even more negative, and thus the aDDM would predict that attention is driving your choice towards the thing that you’re looking at, which is what we see in the data.

The next thing we did was to run some simulations to see if the aDDM could qualitatively explain the observed data. First, I want show you what simulated behavior looks like if theta is bounded between 0 and 1. It turns out, it is IMPOSSIBLE to predict the LACK of an attentional choice bias flip without relaxing the bounds on the attentional parameter. But as soon as you relax the bounds on theta, you see simulated behavior qualitatively match observed behavior. So it's great that the aDDM can capture these attentional choice biases in both gains and losses once we relax the bounds on the attentional parameter, but this introduces a problem… What the heck does theta greater than one intuitively mean?!

See, up until now, my favorite interpretation of theta was inspired by this paper by Jang, Sharma and Drugowitsch in 2021. Imagine you’re choosing between an apple and a donut, and that you value apples and donuts equally. What their model says is that as you fixate on apple, you sample a more precise estimate of its value than for donut. Translating this back to the aDDM, this would result in your accumulator being pushed towards choosing apple.

But if theta is greater than one, then it’s as if we’re saying you sample a more precise estimate of the thing you’re NOT currently looking at! And I don’t think that makes a lot of sense.

So how do we move towards a more intuitive explanation of what’s going on during the choice process? Well perhaps we’ve been too focused on what’s going on with the attentional parameter, and we haven’t yet thought about what kind of evidence we are accumulating; what are those value signals? Perhaps we aren’t accumulating evidence according to just the value signal, but instead we are taking context into consideration and using range normalized value signals. In other words, we are going to normalize all values to between 0 and 1, depending on where they fall between the minimum and maximum value in a given context. Here, I’m thinking of the gain and loss conditions as separate contexts.

So that’s going to look something like this, where we take the distance FROM the minimum value in a certain context TO the value of the option, and compare that with the total range of values in a certain context. In our paradigm, this is going to normalize all values to between 0 and 1, regardless of whether they’re gains or losses, all the while preserving rank ordering.

And it turns out that plugging range normalized values into the aDDM fits the loss data better than the aDDM with an unbounded attentional parameter. It also – for the most part – brings theta estimates back into that 0 to 1 range in losses, which means we’re back to that space where theta makes intuitive sense.

Simulated behavior using the range normalized variation of the aDDM also qualitatively matches our observed data, predicting the lack of an attentional choice bias flip in losses.

So it seems that IN choices involving negative-outcome lotteries, people may be accumulating range normalized evidence instead of context-independent value samples.

But are people ALWAYS accumulating range normalized information in losses?

My hunch is no. And the reason why is there’s this paper from 2008 by Armel, Beaumel, and Rangel looking at choices between aversive food options while forcing subjects to look at each option for a certain amount of time. They found that subjects were LESS likely to choose the option that was presented for longer, which is in line with a theta between 0 and 1 and negative value signals, not range normalized information.

So I want highlight here, a puzzle about choices in losses which is that we don’t know when people switch to accumulating range normalized information. Does it have something to do, maybe, with the nature of the stimuli (whether they’re numerically presented lotteries, or they’re pictures of food, or they’re even how food smells) which causes this switch?

So in conclusion, contrary to one of the assumptions of the aDDM, we find that attention to an option still pushes choices towards that option, even in losses. The aDDM with an unbounded attentional parameter, and the aDDM with range normalized evidence, are both capable of capturing this effect, though only the latter seems to make intuitive sense. And finally, there seems to be evidence that in choices between losses, people might not always be accumulating range normalized evidence, so we’re asking if you have any ideas as to when people might switch between using range normalized value signals and context-independent value signals.

Thanks.