Gain-Loss: What is the reference-point doing?

* Perceptual systems are using efficient coding (Khaw, Li, and Wooodford 2021; Heng, Woodford, and Polania 2020).
* We know that priors are adapting quickly to the distribution of observed payoffs in risky choice (Frydman and Jin 2021).
* This leads to a normalization of values which is influenced by prior beliefs.
* In Heng, Woodford, and Polania (HWP), a system of neurons with a special firing function leads to likelihoods over possible signals, conditional on a true value. These likelihoods are over the space of signals, which are positive counts (the number of neurons that fired). After the prior and likelihood are combined, we get the Bayesian posterior belief about the actual value, and use something like say… the mean to make a decision.
* In these models, the posterior beliefs are over the actual number line. We could replace that with a support for “goal-relevant” evidence… but I don’t see how that naturally comes from something like Frydman and Jin.

Decision-Weights: Progress and Next Steps



* Can clearly see some loss aversion at play here. I think it may be interesting to see how loss and risk preferences may affect decision weights.
* I can use SSE to estimate prospect theory with 2 parameters, loss and risk preference. I think this is possible, even with our unusual presentation of gambles. Average over seen samples, or transform each sample?





* Looks like early samples (2,3,4) are not weighted as heavily as late samples (-4, -3, -2; excluding the last).
* This could be from two things: (1) more compression of early than late values, or (2) a changing weight on the early vs late samples. I think only (2) makes sense with efficient coding. Re (1): If people start with uniform prior and slowly adapt to normal distribution as they see more samples from the normal, then the higher prior near the mean should bias Bayesian estimates towards the mean, i.e. compression. Re (2): If people slowly adapt to normal distribution (start from -3 to 3, then range shrinks to range in the trial), then sensitivity to more likely numbers should result in better discrimination of the samples. I would think a sequential sampling system should place more weight on the samples with better discrimination? (I need to read Mike’s paper on rational inattention when decisions take time to see if he talks about this at all).
* Regardless of which models we decide to test, teasing apart different decision weights will probably result in fitting models that end up with very similar posterior model probabilities. I’m worried we wont be able to tease them apart.



* Looks like sequential sampling is at play, though it kinda looks loss prone in some cases. Look at Pr(Play) vs Pr(Skip) at 3 seconds when avg sample was \pm 2.

Frydman and Jin: RTs are faster and choices are more accurate in low-volatility condition than high volatility. This should be captured by a change in drift rate.

* Problem: THEY ONLY COLLECT 30 "COMPARISON” TRIALS PER PARTICIPANT!!! Need more. They have a lot more non-comparison trials, but I’m hesitant to make drift rate comparisons across these because drift rate is also a function of the magnitude of the evidence. Their method of comparison trials takes care of this.
* Drift rate should be larger in low volatility than high volatility, but noise should not change.
* Reminds me a bit of the project with Trinity, but not quite the same.
* I tried fitting the DDM to Frydman Jin data, but it’s just not enough. Tried pooling subjects but need more time to figure it out since we probably need distributions of the parameters.
* Can run a version of this study using the Ella paradigm and I think it takes the decision-weights paper in an interesting direction -> can sequential sampling models pick up on nuances in behavior predicted by efficient coding?