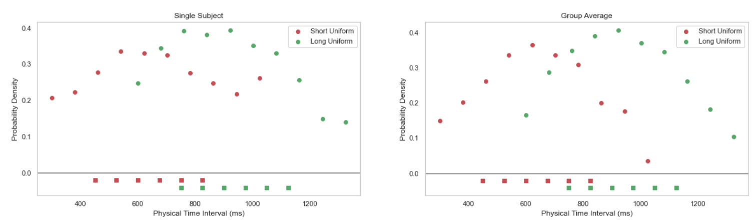
Cognitive Modelling: Final Project Part II

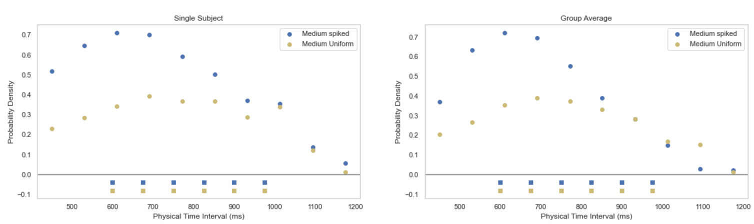
Vishal Sreenivasan (S4196392)

Jan 2020

1 Create a figure similar to Acerbi's Figure 7, based on your model's DM.



(a)



(b)

Figure 1: (a) Physical intervals (ms) vs Retrieval probabilities of Short Uniform (red points) and Long Uniform (green points) distributions. Single subject (left) and Group mean (right). (b) Physical intervals (ms) vs Retrieval probabilities of Medium Uniform (yellow points) and Medium Spiked (blue points) distributions.

The graph is created using model's inbuilt *get_retrieval_probability* for each iteration and the probabilities are stored in a DataFrame. Responses of the participants are divided in 10 equal bins as Acerbi's [1] and mean probabilities are calculated for each bin. Scatter plot is used to plot the bin data on the x-axis and it's corresponding probability on the y-axis.

2 Essay

2.1 Are there qualitative differences between the two figures? If so, what may be the cause of these differences?

Figures 1a and 1b visualizes the probability distribution of intervals based on ACT-R's declarative memory (DM). The prior(s) in ACT-R is the internal representation of information stored to compute the forthcoming inputs. Unlike Acerbi's non parametric inferred priors (Figure 2), the model exhibits tails with probabilities greater than zero and continues to form a bell shape curve in both short uniform and long uniform distributions. The highest retrieval probabilities for both the distributions does not cross 0.4 and most of the intervals vary in the range of 0.2 - 0.4. This shows that the posterior representation of the intervals almost aligns with the actual intervals with varying probabilities of 0.2 and participants form an in-build gaussian representation when the intervals are presented with equal probabilities with a peak at the mean of the distribution. This representation of prior is slightly different from Acerbi's[1] results which shows a rather pronounced peak in the mean and a few descent hills for the rest of the intervals. The reason being DM is a representation of information which depends on it's activation level. When even the ends of a distribution is presented for a number of iteration, results in a non zero retrieval probability. This can also be the result of noise inclusion during retrieval same as the motor noise before human responses.

Medium uniform and medium spiked distributions (Figure 1b) show a similar tendency as that of Acerbi's[1] for single participant. The peak of medium spiked is produced around the peaked interval. This in turn produces higher probabilities for the nearby intervals resulting in low probabilities for far away intervals [2]. The activation in DM for the peaked interval tends to become larger through time steps affecting the retrieval of nearby intervals. When the peak interval is presented for a significant number of times, the interval and it's neighbors activation in DM are increased than rest of the intervals making the retrieval probability higher. This behavior is also exhibited in Acerbi's[1] (Figure 2) where the peak is formed at the highest probable interval for spiked distribution.

2.2 At a more theoretical level, how does your model's DM compare to the priors that Acerbi derived from participants' responses?

ACT-R[3] model uses declarative memory (DM) to store the information in the form of chunks. When a chunk is added to the DM, the current time is added to it the chunk's encounter which is repeated every time for the recurrent addition of identical chunks. In order to replicate human participants, time in seconds is converted to pulses. The priors in ACT-R[3] is defined by the addition of memory and it's activation gives an estimate of the number of times a particular chunk of information is reinforced in to the memory. This works in a way human brain stores instance of information. Information retaining strength is increased every time while recalling and revisiting which in turn reduces the decay of information over time [4]. Acerbi[1] considers an ideal baysian observer for observing the priors of participants. Non parametric inference is built using continuous distribution rather than fixed set of priors producing a pronounced peak at the mean with varying probabilities for the remaining intervals. This representation cannot be shown using ACT-R due to it's growing DM. Probability of retrieval in the model is defined by the chunk's activation which in turn represents how much the chunk is being reinforced in DM whereas Acerbi's[1] results are based on noise models and loss functions. This results in a rather similar probabilities for all the equiprobable intervals with an exception of medium spiked as shown in Figure 2.

References

[1] L. Acerbi, D. M. Wolpert, and S. Vijayakumar, "Internal representations of temporal statistics and feedback calibrate motor-sensory interval timing," *PLOS Computational Biology*, vol. 8, no. 11, pp. 1–19, 11 2012. [Online]. Available: https://doi.org/10.1371/journal.pcbi.1002771

[2] N. Taatgen and H. Rijn, "Traces of times past: Representations of temporal intervals in memory," *Memory cognition*, vol. 39, pp. 1546–60, 05 2011.

[3] A. J. R., B. D., M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, "An integrated theory of the mind. psychological review," *APA PsycArticles*, 2004. [Online]. Available: ttps://doi.org/10.1037/0033-295X.111.4.1036

[4] N. Taatgen, H. Rijn, and J. Anderson, "An integrated theory of prospective time interval estimation: The role of cognition, attention, and learning," *Psychological review*, vol. 114, pp. 577–98, 08 2007.

A Figure

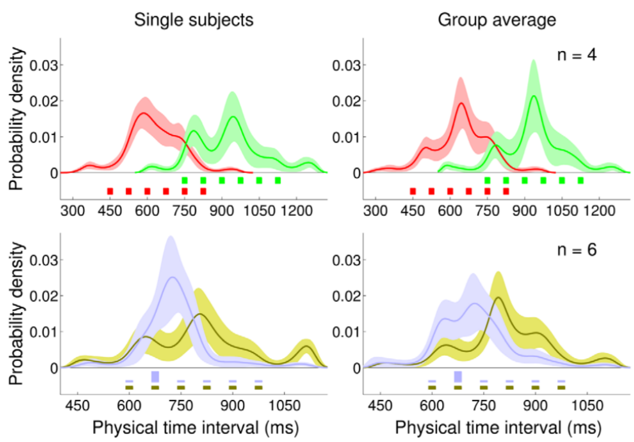


Figure 7. Nonparametrically inferred priors (Experiment 1 and 2). *Top row:* Short Uniform (red) and Long Uniform (green) blocks. *Bottom row:* Medium Uniform (light brown) and Medium Peaked (light blue) blocks. *Left column:* Nonparametrically inferred priors for representative participants. *Right column:* Average inferred priors. Shaded regions are ± 1 s.d. For comparison, the discrete experimental distributions are plotted under the inferred priors.
doi:10.1371/journal.pcbi.1002771.g007

Figure 2