Influences of temporal order in temporal reproduction

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Introduction

It is known that time estimation is influenced by history context. A well-known example is the central tendency effect, also known as Vierordt effect. Short intervals are overestimated while long intervals are underestimated. A common explanation is that time estimation is an optimal combination of a sensory temporal input D_s and the prior history D_p in a weighted manner. The weights are determined by their correspondent reliability.

 $D_e = (1 - w)D_p + wD_s$

However, this standard model does not consider the temporal order of the tested intervals and perceived volatility of the sequence. Here we showed that sequences with the same statistical properties (i.e., mean and variability) yielded different reproduction outputs, which challenges the standard model. Instead, we proposed a hierarchical model, which can predict differential behavioral results.

Experimental Design



Model prediction

The model can predict the differences among different sequential structures, which is in good agreement with the observed data.

In order to test if the temporal order and volatility matters in temporal reproduction, we asked participants (n = 15) to reproduce four interval consecutively. Critically we kept the mean and variability of the four intervals the same (M = 700 ms, SD = 294.39 ms), but they were in different temporal orders.

Figure a shows a typical trial procedure and b shows and the three patterns we tested: decelerating (DS), accelerating (AS) and random sequences (RS). There were two types of interval sets used in each pattern.

Mean Reproductions

Central tendency effects

The DSs were underestimated relative to the ASs, while the RSs were in the middle, $F(2,28) = 18.08, p < .001, \eta_g^2 = .56$. Further analysis on the first interval of the RSs showed a similar pattern, suggesting the first interval had a great impact on the mean reproduction.

Modeling

Based on the above behavioral patterns, we believe the mean reproduced interval was influenced by the first interval. We assume that the mean prior μ_e of each pattern is a weighted sum of the first

In addition to the general underestimation, the following figure shows the mean central tendency bias was larger for the DS and RS, relative to the AS condition in both interval set 1 (a) in which we have tested [400,500, 900, 1000 ms] intervals and set 2 (b) in which we have tested [400, 600, 700, 1100 ms] intervals.

Dots represent the observed data and dashed lines represent the averaged observed data across participants. Solid lines represent the predicted reproduction by the model. The Weber fractions of the sensory input and the mean prior (and associated SDs) were 0.18 ± 0.09 and 0.35 ± 0.03 respectively. The weight of the first interval was 0.195 ± 0.07 , suggesting the first interval partially yet significantly influenced the mean prior.

Conclusion

• The present study shows that in addition to the classical central tendency effect, temporal reproduction can also be influenced by (1) temporal order of the intervals, and (2) perceived volatility of the intervals. These two factors cannot be explained by the static Bayesian integration model (i.e., using only the static prior distribution).

• We proposed that the precision of the temporal sequence could be different for different temporal positions, this may well cause differential perceived ensemble mean with the same interval distributions but different temporal orders. In fact, the model showed that the first interval largely influences the mean reproduction. The model captured the variation of reproduction caused by the sequential order and volatility.

interval D_1 and the physical mean of the tested intervals (700 ms):

 $\mu_e = \alpha \cdot D_1 + 700 \cdot (1 - \alpha)$

Duration estimates often follow Weber's law. Thus, we assume that sensory variability is determined by Weber fraction wf_s and the perceived volatility of the pattern scales the sensory uncertainty. The variability (σ_i) of a given interval D_i has a multiplication factor k_j depending on the sequence type j,

$$\sigma_i^2 = k_j (w f_s \cdot D_i)^2$$

with the reproduction variance,

$$\sigma_r^2 = \frac{\sigma_i^2 \sigma_e^2}{\sigma_i^2 + \sigma_e^2}$$

We then used PyMC3 to fit the above model.

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