Effects of Sensory Precision on Behavioral and Neuroimaging Perceptual Biases in Duration Estimation

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Abstract:

In Bayesian models of perception, the magnitude of perceptual biases towards prior expectations depends on the precision of incoming sensory information – the more precise the sensory likelihood, the weaker the bias towards the prior. Perceptual biases can be quantified behaviorally by regression to the mean effects, wherein reports are biased towards the mean of previously presented stimuli. As for many aspects of Bayesian perceptual accounts, the neural bases of regression to the mean remain unclear. Here, we investigate how sensory precision influences neural representations of duration using behavioral modelling and EEG decoding. Data simulated using a Bayesian ideal observer model shows that regression to the mean in a duration reproduction task is stronger with high, compared to low sensory precision, providing preliminary evidence that sensory precision affects regression to the mean in Bayesian observers. Using EEG, we are also investigating how sensory precision affects the accuracy of a multivariate classifier to decode stimulus context based on neural responses to the same physical stimulus. The results of these experiments will provide some of the first evidence explicitly linking these key behavioral and neural indices of Bayesian perceptual perception, providing deeper understanding of one of the most fundamental aspects of human perception.

Keywords: regression to the mean; Bayesian ideal observer model; decoding stimulus context; time perception

Introduction

Bayesian brain theories suggest that perception arises from the integration of incoming sensory information with prior knowledge about its possible causes. Under the assumption that priors and sensory likelihoods are approximated by Gaussian distributions, it is postulated that as the precision of the sensory likelihood increases, a Bayesian observer will experience weaker perceptual bias towards the prior.

In behaviour, perceptual biases towards the prior can be measured through regression to the mean effects – estimations of stimulus magnitude are biased towards the mean magnitude of previously presented stimuli. Such effects have been reported in many perceptual domains (Hollingworth, 1910), including time perception (also known as Vierordt's law), and are range specific – the same duration will be underestimated if it is longer than the mean but overestimated if shorter (Jazayeri, & Shadlen, 2010).

Neuroimaging evidence suggests that stimulus context also affects the neural response elicited by a stimulus. The same auditory pitch was found to give rise to a stronger mismatch negativity signal (MMN, elicited by violations in sequence regularity) when the underlying stimulus distribution had smaller variability (Garrido, Sahani, & Dolan, 2013). It has been also reported that sensory precision is correlated with the magnitude of the MMN response (Kraus et al.,1996).

No study to date has investigated how sensory precision influences regression to the mean in behavioural and neural responses. Focusing on the domain of time perception, we predict that human observers with low sensory precision will exhibit stronger regression towards the mean than participants with high sensory precision. As participants with low sensory precision will experience the same stimulus more differently when it is presented in different contexts, we also predict that a classifier trained on the EEG data associated with the same physical stimulus will decode stimulus context more accurately in participants with low compared to high sensory precision.

Methods

Procedure

In the EEG task and the main behavioral task participants are presented with stimuli drawn either from a range of short (5 levels between 340-626ms) or long durations (5 levels between 626-1152ms), in separate blocks of trials. During EEG recording, participants observe the stimuli passively. In the behavioral task participants reproduce the presented durations by pressing a button on a keyboard.

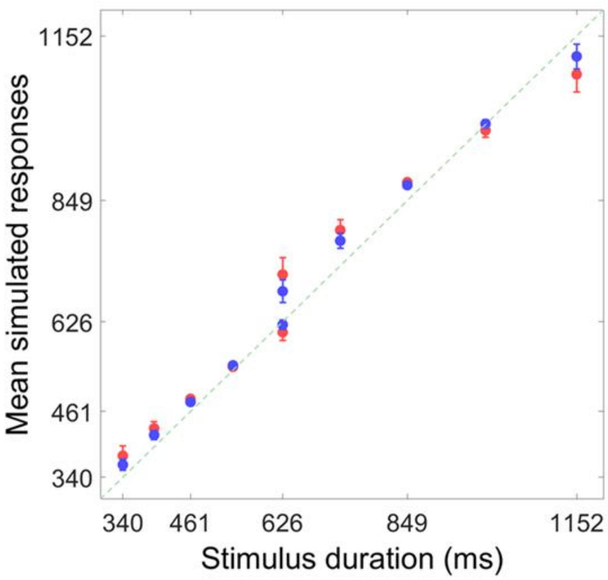

Figure 1: Results from simulations. Average responses of simulated participants with low sensory precision (red) and high sensory precision (blue).

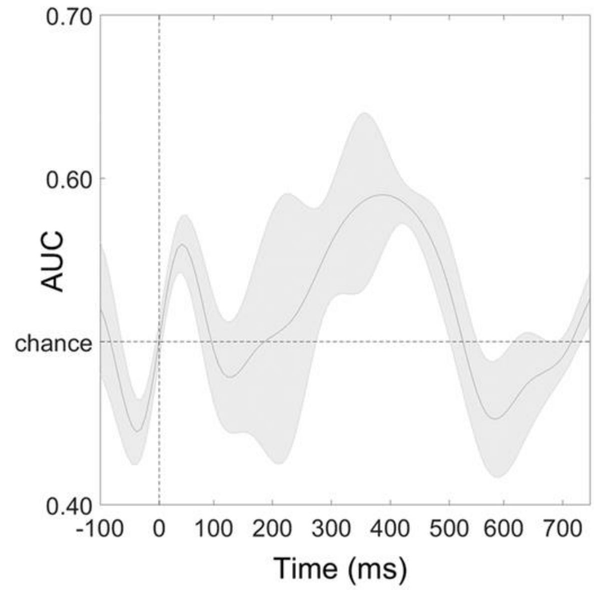

Figure 2: Classifier performance (area under the curve) across time, averaged over participants (N=4).

To estimate sensory precision, participants also complete a 2-interval forced choice (2IFC) task. Participants are presented with two durations and have to indicate which is longer or shorter in different blocks (one always being 626ms). Sensory precision is quantified as the difference from 626ms for which participants reach 75% accuracy.

Analysis

Behavioral analysis Participants will be divided into low and high sensory sensitivity groups based on their performance on the 2IFC task. We will use a Bayesian ideal observer model (Acerbi, Wolpert, & Vijayakumar, 2012) to derive a specific numerical prediction of the difference in regression to the mean we expect to find between the two groups. Regression to the mean is quantified as the difference in reproduction times of the stimulus present in both the long and short conditions: 626ms. We will also calculate the difference in the average regression to the mean effect between the two groups in the behavioural data. Then we will conduct an independent Bayesian t-test to examine whether the behavioural data support the prediction of the Bayesian observer model.

EEG analysis After pre-processing, we perform multivariate pattern analysis (MVPA; Fahrenfort et at., 2018) to decode stimulus context (long or short condition) based on the pattern of brain responses associated only with the stimulus common to the two contexts: 626ms. Classification is done using linear discriminant analysis (LDA) and classification performance is evaluated through a 10-fold cross-validation.

Preliminary results

Using the model specified by Acerbi et al. (2012), we generated behavioral responses of ten simulated participants with high sensory precision and ten simulated participants with low sensory precision. The model-generated data shows that the 626ms stimulus is overestimated when presented in the long context and underestimated when presented in the short context: Mean difference = 98.57ms (SE=1.80). The simulated data also suggests that in Bayesian observers, regression to the mean is greater with high, compared to low sensory precision – the mean difference between the two simulated groups is 59.57ms (SE=7.15). Mean model-generated responses are depicted in Figure 1.

Behavioral data collected to date (N=6) supports the overall range effect found in the simulations – the mean difference in responses to the 626ms stimulus between the long and short condition is 99.80ms (SE=11.31).

Finally, preliminary MVPA results (N=4) revealed that the classifier could distinguish stimulus context in all participants with AUC>0.6, reached during stimulus presentation. Classification performance, averaged over participants, is show in Figure 2.

Conclusions

The model-based simulations provide initial support for our prediction that sensory precision affects regression to the mean. Behavioral data collected to date successfully replicates the range effects in regression to the mean reported previously and predicted by the model. Finally, preliminary EEG data suggests that a classifier can distinguish the context in which a stimulus is presented based solely on the patterns of the EEG response generated by the same physical stimulus. Ultimately this research will improve our understanding of the neural basis of perceptual biases and help address the question of the degree to which the brain engages in (approximate) Bayesian inference.

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