Relevance, uncertainty, and expectations affect categorization

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Abstract

Auditory categorization, e.g. identifying a song in a noisy environment, is difficult. After all, only some sounds that we hear may be relevant and part of the song. Thus, we need to appropriately weight and integrate over the different sounds that we hear. Simultaneously, we also need to constantly account for our internal sensory noise. Lastly, early verses in a song generally predict latter verses, making our ability to learn over time crucial to accurate decision-making. Despite this complexity underlying categorization, previous papers have usually studied the effects of relevance, sensory noise, and expectations in separation. Here, we test how these different factors combine to affect our decisions by formalizing multi-tone sound categorization as a Bayesian model and testing it with new behavioral experiments. We find that participants are sensitive to relevance and that the history of categories affects their expectations. However, there is substantial diversity amongst participants both in their measure of relevance and in their expectations. Thus, our model reveals participant-specific tone-by-tone estimates of relevance, sensory noise, and expectations, giving us variables to understand how the brain categorizes.

Keywords: Decision-making; Auditory; Categorization; Stimulus relevance; Uncertainty; Bayesian models

Introduction

Intrinsic to perceptual decision-making is uncertainty (Vilares et al., 2012). One source of uncertainty, usually termed "sensory noise", stems from fluctuations in the neural representation of sensory information (Barthelmé & Mamassian, 2009). A second source of uncertainty is identifying stimuli that are relevant to a decision from other concurrent irrelevant stimuli, especially if the relevant and irrelevant stimuli have similar characteristics (Anders et al., 2017). A third type of uncertainty is "decision specific". For example, when categorizing continuous stimuli into different discrete categories, we frequently encounter stimuli that have ambiguous category membership (Gifford, Cohen & Stocker, 2014). Thus, perceptual decision-making in everyday scenarios necessitates a successful accounting of multiple, often coincidental sources of uncertainty. Although the effect of each of these types of uncertainties has been studied in isolation, the manner in which

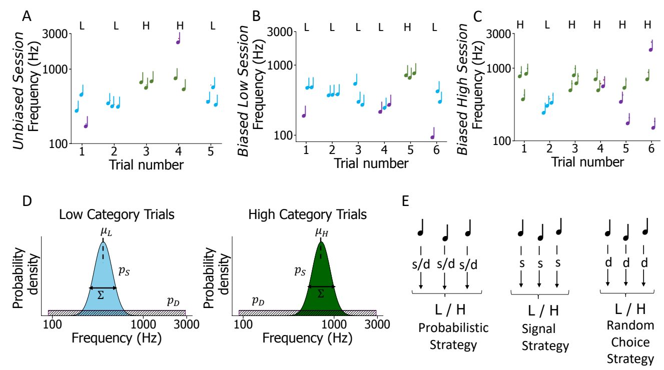

Figure 1: Examples of trial sequences from (A) *unbiased*, (B) *biased low*, and (C) *biased high* sessions. Each trial has three tone bursts denoted by notes: signal notes from the low-frequency Gaussian (blue), signal notes from the high-frequency Gaussian (green), and distractor notes from the uniform distribution (purple). (D) Signal and distractor probability distributions for each category. (E) Schematic of the Bayesian strategies. Probabilistic strategy: every tone burst is probabilistically considered either 'signal' or 'distractor'. Signal strategy: all tone bursts are considered 'signals'. Random Choice strategy: all tone bursts are considered 'distractors'. s: signal; d: distractor, L: low category, H: high category.

they interact to inform our decisions has yet to be tested. Here, we used auditory categorization (Russ, Lee & Cohen, 2007) as an illustration of human perceptual decision-making to probe whether and how these uncertainties cumulatively shape behavior.

Experimental Design

Human subjects performed a two-alternative forced choice task and categorized trial sequences of three tone bursts as 'low' or 'high'. Each tone burst could be 'signal' (i.e., relevant to the categorical decision) or 'distractor' (i.e., irrelevant to the categorical decision). In a given trial, each tone burst could probabilistically either be a signal with p_S=0.7 or a distractor p_D=0.3 (Figs.1A-C). For low- (high-) category trials, we drew signal tone bursts from the low-frequency (high-frequency) Gaussian, and distractor tone bursts from a uniform distribution (Fig.1D). Further, our experiment was divided into three

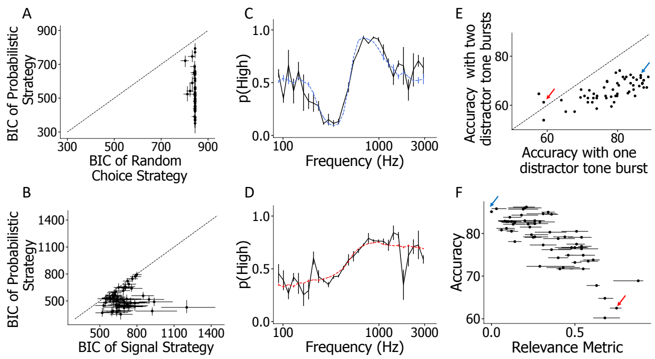

Figure 2: (A) BIC scores for Probabilistic vs. Random Choice strategy for all 56 subjects (smaller value is better). (B) Same for BIC scores for Probabilistic vs. Signal strategy. (C,D) Psychometric curves (black) and Bayesian model fits (red; dark blue) for 2 example subjects whose accuracies were 85.1% and 64.8%, respectively. (E) Categorization accuracy for trials with two versus one distractor tone burst. (F) On a subject-by-subject basis, accuracy is plotted against their corresponding relevance metric. Subjects from (C,D) are noted using arrows in (E,F). Error bars: 95% confidence.

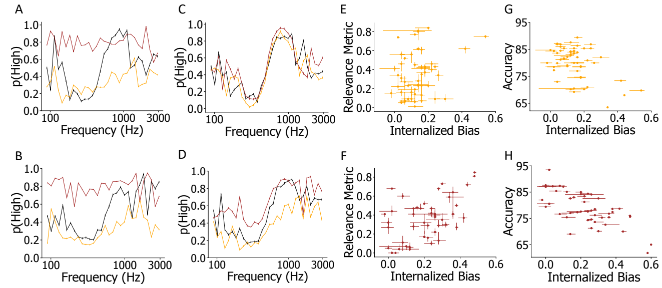

Figure 3: (A-D) Average psychometric curves computed using 20 subsampled balanced datasets for 4 example subjects in the *unbiased* (black), *biased low* (yellow), and *biased high* (brown) sessions. (E,F) For 46 subjects, internalized bias is plotted against their corresponding relevance metric and (G,H) their accuracy. Error bars: 95% confidence.

sessions: *unbiased*, *biased low*, and *biased high*. In the *unbiased* session, trials were equally likely to be drawn from either the high or low category, i.e., p_L=0.5 (Fig.1A). In the *biased low (biased high)* session, we overrepresented the corresponding distribution such that $p_L(p_H)$=0.7 (Figs.1B,C). Subjects were not cued about the change in priors.

Results and Discussion

Bayesian Framework

We hypothesized that subjects may use different strategies to solve the same categorization task, depending on their internal model of the relevance of the three tone-burst frequencies (Fig. 1E). We formalized this hypothesis with a Bayesian framework (Vilares & Kording, 2011). The first strategy (Probabilistic strategy) considers the optimal behavior of a Bayesian subject, who uses the information from all three tone bursts and determines which are signals and distractors. The model has 6 parameters (Fig. 1D): means and standard deviation of the Gaussians (μ_L, μ_H; σ), a subject's sensory noise ($\sigma_{sensory}$), the probability that a tone burst is distractor ($p_{distractor}$), and the probability that a trial's category is 'low' (p_{low}). Two other strategies, which are suboptimal, are special cases of the Probabilistic model. In the Signal strategy, all three tone bursts are assumed to be signal i.e., $p_{distractor}$=0. Conversely, in the Random Choice strategy, all tone bursts are considered to be distractor, thus a subject's choice is akin to a coin flip; this model has only 2 parameters: $\sigma_{sensory}$ and p_{low}.

Variability in subject behavior

56 subjects participated in the *unbiased* session. We found that their performance was better fit by the Probabilistic strategy compared to the Random Choice or Signal strategies (Figs. 2A,B). In other words, all subjects judged the tone-burst sequences to be a mix of signals and distractors. However, we also observed substantial inter-subject variability as seen in the psychometric curves and Probabilistic-model fits for 2 example subjects (Figs. 2C,D). Further, subjects' accuracies in trials with one distractor ranged widely from 57 - 89% and in trials with two distractors ranged from 61 - 75% (Fig. 2E). To characterize how subjects' estimates of stimulus relevance determined their accuracy, we defined a metric associated with the posterior of the Probabilistic model, the relevance metric. This metric summarizes the relevance attributed to different frequencies and is $\sim$1 if a subject considers all tone bursts as signals but $\sim$0 if they correctly identify and disregard the distractors. We found that this metric is inversely correlated with accuracy (Fig. 2F), which illustrates how relevance and uncertainty combine to shape decisions.

Next, we tested how prior information affected subjects' decisions by changing their expectations. Of the 48 subjects who completed all three sessions, 2 significantly used their priors in the *biased* sessions as seen in the shift of their psychometric curves (Figs. 3A,B). Correspondingly, out of the three strategies, their data was best fit by the Random Choice strategy. On the other hand, the data from remaining subjects were best captured by the Probabilistic strategy; these subjects were variable in the degree to which the priors affected their decisions (examples in Fig. 3C,D). We found that subject's 'internalized bias' (i.e. $2|p_{low} - 0.5|$) or in other words their 'internalized expectation' was correlated with their relevance metric. This analysis illustrates the interplay of uncertainty, relevance, and priors in decision-making. Those who successfully identified the relevant signal tone bursts and categorized accordingly were not only less biased, but also more accurate. Conversely, highly biased subjects perceived distractors as 'signals', resulting in poor accuracy.

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