Differentiating Changes in Population Encoding Models with Psychophysics and Neuroimaging

Jason Hays & Fabián Soto

It is now common among visual scientists to make inferences about neural population coding of stimuli from indirect measures such as those provided by neuroimaging and psychophysics. The success of such studies depends strongly on simulation work using standard population encoding models extended with decoders (in psychophysics) and measurement models (in neuroimaging).

However, not all studies are accompanied by simulation work, and those that are tend to vary widely in their assumptions about encoding, decoding, and measurement. To solve these issues, we designed a Python package (PEMGUIN) to assist computational modelling by providing simple ways to manage encoders' tuning functions, sources of noise, decoding procedures, and simulations of measurement data while also providing useful defaults.

As an example application, we tested whether it is possible to differentiate basic types of tuning changes (local and global tuning shifts, gain changes, and bandwidth narrowing see example in Fig 1) in the standard encoding/decoding model by comparing sensitivity thresholds (δ) as a function of stimulus value, external noise level, and pattern masking. We assumed optimal decoding, which allows to obtain sensitivity threshold estimates from the model using Monte Carlo simulation (see flowchart and equations in Fig 2). We were able to distinguish the tuning changes most commonly studied in the literature by using combinations of behavioral experiments.

We also show how our software can be used to model the results of corresponding neuroimaging studies (see flowchart and equations in in Fig 3).

Fig 1: Example change in tuning functions

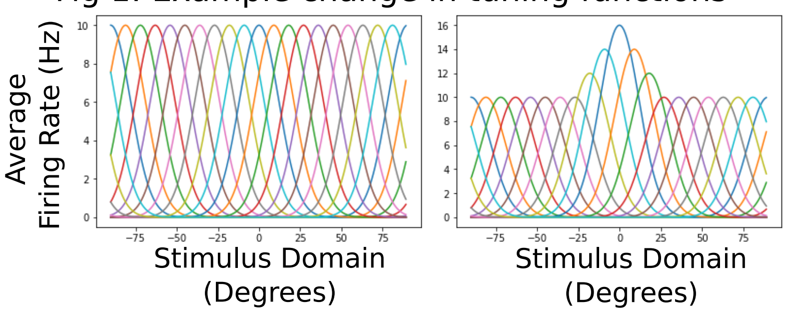
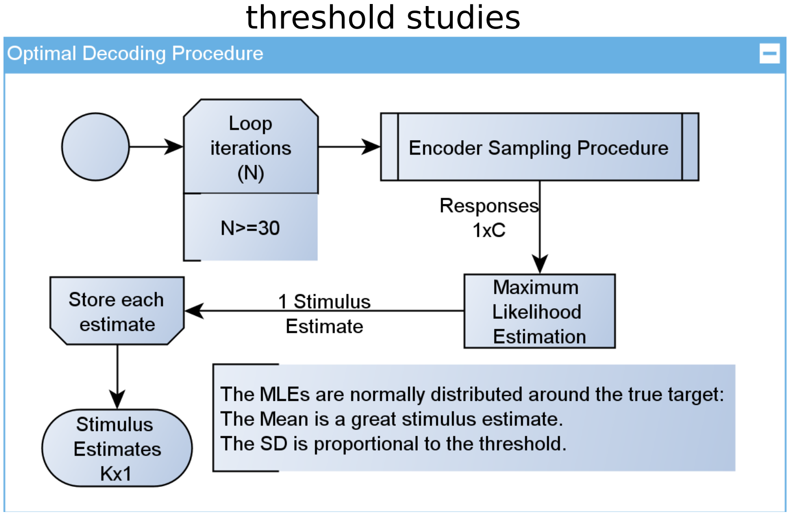


Fig 2: Procedure used to model psychophysical threshold studies



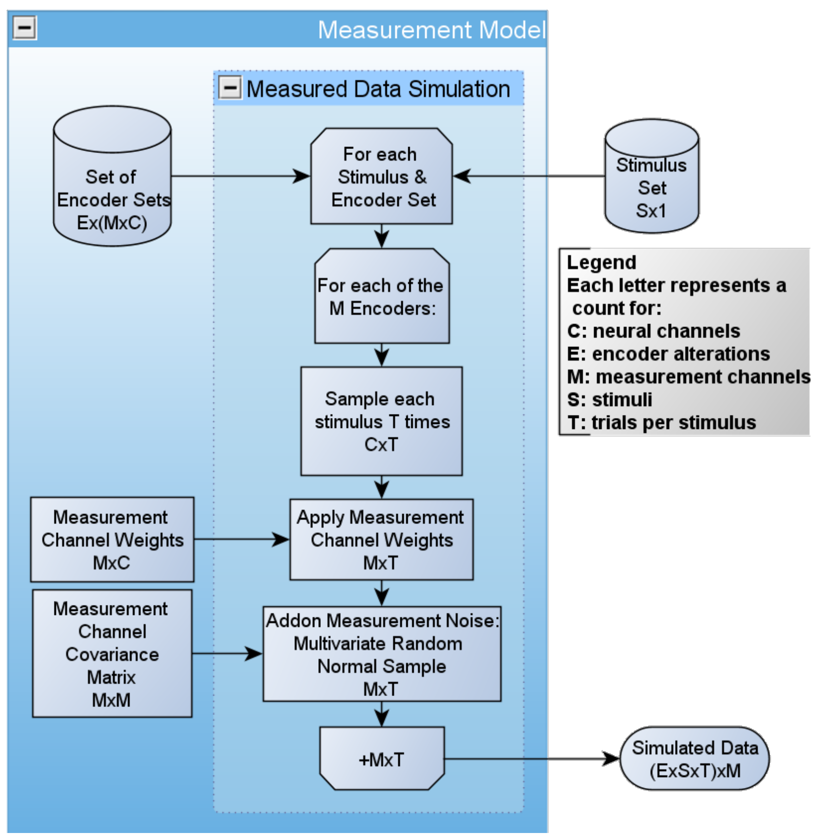
Given statistically optimal decoding,

$$d' = \frac{\delta}{\sigma_{\hat{s}}} \Rightarrow d'\sigma_{\hat{s}} = \delta,$$

where $\hat{s}$ is the stimulus estimate obtained though maximum likelihood decoding. If a distribution of $\hat{s}$ is obtained through Monte Carlo simulation, then

$$\sigma_{\hat{s}} = \sqrt{\frac{\sum_i^n (\hat{s}_i - s)^2}{n}}$$

Fig 3: Procedure used to model psychophysical threshold studies



We assume that activity in the kth measurement channel (e.g., a voxel) is a linear combination of neural responses r_i plus Gaussian measurement noise ϵ_k:

$$a_k(s) = \sum_i w_{ik} r_i + \epsilon_k,$$

where $\sum_i w_{ik} = 1$ for each measurement channel k.