1. Equal variance model

1.2.3 Equal variance model exercise

Using a random number generator, simulate responses from 100 experiments with 3 observers each completing 50 trials containing a stimulus and 50 trials containing no stimulus. All three observers behave according to the equal variance model and have a perceptual sensitivity of $d' = 1$ but they have different response criteria: One observer is strongly biased towards 'yes'-responses, one is strongly biased towards 'no'-responses, and one is not very strongly biased towards 'yes'- or 'no'-responses.

Estimate the perceptual sensitivity for each observer and each experiment. Make a histogram of the 100 estimates of the perceptual sensitivity for each of the three observers. Are the distributions centered around the true underlying value for d' each of the three simulated data sets?

Do the same simulations for three observers that behave according to a model where $\mu_s = 1$ and $\sigma = 0.8$. Assume that you did not know that the data came from an observer for which the equal variance assumption $\sigma = 1$ does not hold and estimate d' using the equal variance model just as you did above. Make a histogram of the 100 estimates of the perceptual sensitivity for each of the three observers. Are the estimates centered around the same value for each of the three simulated data sets?

What are the implications of your results?

2. Unequal variance model

1.2.8 Unequal variance model exercise

In a confidence rating task, with four response categories, the observer can indicate her confidence as 'high' or 'low', in addition to answering 'yes' or 'no'. Using a random number generator, simulate responses from 100 experiments with one observer completing 50 trials containing a stimulus and 50 trials containing no stimulus. The observer behave according to the unequal variance model $\mu_s = 1$ and $\sigma = 0.8$.

Estimate the parameters of the model for each experiment. Also estimate the AUC. Plot the distribution of the parameters and AUC across experiments. Are the distributions of the parameters and the AUC centered around the true underlying values?

Compare your results to the equal variance model exercise in 1.2.3.

3. Psychometric function

In a 3-alternative classification task, the observer classifies speech sounds under varying sound intensities. The experiment consists of 30 experimental trials at each sound intensity. The sound intensities and the corresponding number of correct responses are shown in the table below.

Stimulus intensity, I_s (dB)	5	10	15	20	25	30
Number of correct responses	12	11	19	27	30	30

Fit the each of the three psychometric functions in Equations 1.19, 1.23 and 1.24 to the data. You can assume that the probability, P_{guess}, of guessing a correct response is $P_{guess} = \frac{1}{N_r}$ but the probability, P_{lapse}, of lapsing should be a free parameter of your model.

- Make one plot with the three psychometric functions as curves with and the response proportions as points. Estimate, by visual inspection, which of the psychometric functions fit the data better
- List the value of the negative log likelihood of the three psychometric functions. Which is lower?
- The negative log likelihood is not a good way to evaluate model fits as models with more free parameters are more flexible and will therefore provide a better fits. Akaike's Information Criterion, $AIC = 2\left(N_p - \log\left(\mathcal{L}\right)\right)$, where N_p is the number of free parameters is a better measure as it corrects for the number of free parameters. Calculate the AIC for the psychometric functions.
- List the parameter values for each of the the psychometric functions. Do they give similar estimates of the parameter values?

- Repeat all of the above steps in the case that the observer lapses once at the highest stimulus intensity level, $I_s = 30$, so that the number of correct responses is $N_c = 29$, for that level.
- Discuss your findings. Does the introduction of guessing and lapsing influence your analysis of the data?

4. Magnitude estimation

1.4.1 Magnitude estimation exercise

Although mathematically different, Fechner and Stevens' laws of perceptual intensity provide fairly good fits to perceived brightness as a function of luminance. This is because the exponent of Stevens' law is approximately $a = 0.33 < 1$ so that

$$I_p = 10 I_s^{0.33}$$

To see that this relationship might be mistaken for a logarithmic relationship, first calculate the perceived stimulus intensity, I_p, for physical intensities $I_s = 1, 2, \ldots, 10$ using Steven's law. This simulates an observer that rates the perceived intensity according to Stevens' law. Fit Fechner's law to the simulated data. Note that Fechner's law is linear with respect to I_s.

- List the parameter values for Fechner's law
- Plot the simulated data and curve showing Fechner's law

- Evaluate whether Fechner's law provides a reasonable fit by visual inspection of the simulated data and the model

For electric shock, Stevens found the exponent to be approximately $a = 3.3 > 1$. As before, calculate the perceived stimulus intensity for physical intensities $I_s = 1, 2, \ldots, 10$ using Stevens' law and fit Fechner's law to the simulated data.

- List the parameter values for Fechner's law
- Plot the simulated data and curve showing Fechner's law
- Evaluate whether Fechner's law provides a reasonable fit by visual inspection of the simulated data and the model