Assignment 2: Decoding from neural populations

Neural Computation 2019/20

16th November 2019

Practical info

Due: 4pm Friday 22 November, 2019

We may not be able to provide full feedback on assignments submitted after this date.

Organize your answers according to the questions; don't merge them. Plots should include axis labels and units. Some answers may require units as well. You will find that some questions are quite open-ended. In order to receive full marks for those you will need to do more than running a simulation and making a plot. Instead, you should justify your choices, and substantiate your explanations and claims, for instance by doing additional simulations or mathematical analysis. Just writing down all you can think of is discouraged, and incorrect claims can reduce marks. It should not be necessary to consult scientific literature, but if you do use additional literature, cite it. Add your code as an appendix to allow the marker identify problems, but note this can not replace an answer to a question. We will examine code as far as possible, but will be unlikely to trace back every bug.

For policies on late submissions, see the School Late coursework \& extension website:

`https://bit.ly/1Jy2YyV`

Please note that the University has very strict guidelines on plagiarism, which apply for all marked coursework. You should not copy results, code or text from others. For information, please consult the School Academic misconduct website:

`https://bit.ly/2PTUH3A`

Submit using the submit system:

`http://computing.help.inf.ed.ac.uk/submit`

Population codes and estimators

In this assignment we analyse the population coding model of the cricket wind receptors. This model is described in the Dayan and Abbott book (Chapter 3.3) and in Salinas and Abbott (1994; J Comp Neurosci 1:89-107). In this model there are 4 neurons, each with sensitivity to a different wind direction.

The tuning curves f_i for neuron $i = 1 \ldots 4$ as a function of the wind direction θ is modelled as

$$f_i(\theta) = a[\cos(\theta - \phi_i)]_+$$

where the preferred angle of neuron i is given by $\phi_i = \frac{\pi}{4} + \frac{2\pi i}{N}$, $a$is the maximum firing rate with $a = 40$Hz, and with notation $[x]_+ = \max(x, 0)$.

We consider two models for the number of spikes r_i emitted by the neuron in 1 second:

1. Gaussian noise:

$$r_i = f_i(\theta) + \sigma\eta_i$$

where η_i are independent Gaussian random variables with zero mean and unit standard deviation. The factor σ then determines the standard deviation of the noise, which we take to be $\sigma = 10$Hz

2. Poisson noise:

$$r_i = \text{Poisson}(f_i(\theta))$$

where the rate $f_i(\theta)$ drives a Poisson process.

Question 1: Implement a simulation of both models. Plot how each neuron responds, on average, to the different directions θ, and plot the response variability as a function of θ. Explain how the two models differ, and why. (5 marks)

Question 2: Implement a population vector decoder for activity simulated with both models. Plot the average estimated direction, and the trial-to-trial variability (the variance) as a function of the encoded angle. Describe and interpret your results. Again, analyse how the models differ, and why. (10 marks)

Question 3: Consider the Fisher Information for the two models (no extensive simulations required). How does it relate to the results you obtained in question 2? (5 marks)

Question 4: Another possible model is to assume that

$$r_i = [a\cos(\theta - \phi_i) + \sigma\eta_i]_+$$

Why is this more realistic than the Gaussian noise model? How does this change affect the decoding performance (no simulation required)? (5 marks)

Practical details

Python (numpy and matplotlib) or Matlab/Scilab are both fine for this assignment, as is any other language. You will find that you need a large number of trials to estimate variability. Therefore, efficient coding of some parts is worthwhile. Finally, because the noise models used here differ from Salinas and Abbott, the results will not look identical to theirs.