

Information in the brain

We will look at two applications of information theory to the study of the brain; the first, dealt with here is calculating the information content of spike trains. This is an example of data analysis for interpreting experimental data in neuroscience. The second, infomax, is an interpretation of information processing in the brain, which may have something to tell us about how to compute with data; this will be in the next chapter.

The information content of spike trains

Neurons communicate using action potentials, discrete voltage spikes that travel from neuron to neuron. This is the main way information propagates through the brain. The action potentials, often also called spikes, are stereotypical in amplitude, so the information that they carry is represented in their timing. Spike trains are very noisy, repeated responses to the same stimulus tend to be very different; for example, in Fig. 1 there are raster plots from neurons in the auditory area of the zebra finch brain; a raster plot is a plot with a little dash for each spike. The individual trials run horizontally. As you can see there is considerable variation from trial to trial. This variability is unsurprising, the brain is made up of multiple interlocking ad hoc networks so there is likely to be considerable background noise. The question is then, how much information do spike trains carry.

An attempt to answer this question is found in Strong et al. (1998). They consider the response of the large movement sensitive ‘H1’ neurons at the back of the brain of blowfly. They recorded from these neurons for some time while the fly was shown a moving stimulus. They then discretized the spike trains, binning them into small time bins, as in Fig. 2. If the time bins are chosen small enough, this is a sequence of zeros and ones. The sequence of zeros and ones can then be split into a sequence of words

$$010001000000100 \rightarrow 01000, 10000, 00100 \quad (1)$$

These words can be considered a set of outcomes for a random variable:

$$\begin{aligned} \mathbf{w}_0 &= (0, 0, 0, 0, 0) \\ \mathbf{w}_1 &= (0, 0, 0, 0, 1) \\ \mathbf{w}_2 &= (0, 0, 0, 1, 0) \\ \mathbf{w}_3 &= (0, 0, 0, 1, 1) \end{aligned}$$

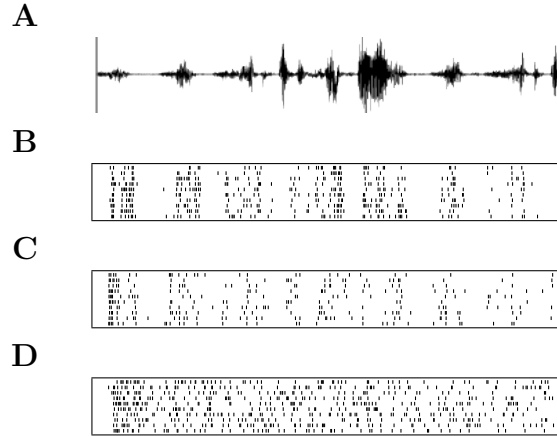


Figure 1: The response of cells in the auditory fore brain of zebra finch to a conspecific song stimulus. **A** shows the sonogram for the song; **B**, **C** and **D** show rasterplots for three responses, each one second long. For each cell there are ten trials, stacked vertically, with each horizontal line corresponding to a single trial. Each small dash is a single spike.

$$\dots \quad (2)$$

Now the idea is to calculate the mutual input between the \mathbf{w}_i s and the stimulus. To this end they recorded two cases, in the first they varied the input for some time, allowing them to calculate $H(W)$; in the second they repeated the same stimulus sequence many times, allowing them to calculate $H(W|S)$; S represents the stimulus. Taking one from the other estimates $I(W; S)$.

One question is how to decide how small to make the discretization time and how long to make the words. It is argued that the blowfly responds very quickly to attempts to swat it, so the information coming from H1 is being interpreted by other brain areas over a time scale of 30 ms. The discretization size is 3 ms. In Strong et al. (1998) they report 78 ± 5 bits per second, which, given the firing rate, equates to 1.8 ± 0.1 bits per spike.

The difficulty with this approach to the information content of spike trains is the huge number of words: with 30 ms words and 3 ms letters there are

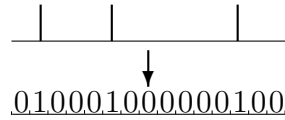


Figure 2: Discretization: the spike train is changed into a series of zeros and ones by binning then using a small time step.

$2^{10} = 1024$ words. This means that it would take a lot of data to reliably estimate the probabilities needed to calculate the mutual information. Of course, in the case of blowfly considerable amounts of data are available; the quick reaction time also makes the restriction to 30 ms words reasonable.

References

Strong, S. P., Koberle, R., van Steveninck, R. R. d. R., and Bialek, W. (1998). Entropy and information in neural spike trains. *Physical review letters*, 80(1):197.