Boulder Theoretical Biophysics summer school: Introduction to neuroscience and information theory

Lecturer:

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Lecture 3: Maximum entropy and efficient coding in single neurons



intensity

The efficient coding hypothesis, brief history:

- Claude Shannon (1948) A Mathematical Theory of Communication
- Fred Attneave (1954) Some informational aspects of visual perception
- Horace Barlow (1961) Possible principles underlying the transformation of sensory messages
- Are sensory systems optimized for information transmission?

Recall: info theory basics

- Stimulus s drawn from P(s);
- \Rightarrow neural response y, P(y|s)
- Mutual information:

$$I = \int ds dy P(s, y) \log_2 \left(\frac{P(s, y)}{P(s)P(y)} \right)$$

=
$$\int ds P(s) \int dy P(y|s) \log_2 \left(\frac{P(y|s)}{P(y)} \right)$$

=
$$-\int dy P(y) \log_2 P(y) + \int ds P(s) \int dy P(y|s) \log_2 P(y|s)$$

- 1 bit of information reduces the uncertainty about the stimulus by a factor 2.
- n bits of information reduce the uncertainty about the stimulus by a factor 2^n
- Linear Gaussian channel y = s + z where s is Gaussian with variance S^2 , z is a Gaussian noise with variance N^2 :

$$I = \frac{1}{2}\log_2\left(1 + \frac{S^2}{N^2}\right)$$

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- \Rightarrow neural response y, P(y|s)
- Mutual information:

$$I = \int ds dy P(s, y) \log_2 \left(\frac{P(s, y)}{P(s)P(y)} \right)$$

= $\int ds P(s) \int du P(s) \operatorname{Old}_2 \left(\frac{P(y)}{P(y)} \right)$
= $\int ds P(s) \int du P(s) \operatorname{Old}_2 \left(\frac{P(y)}{P(y)} \right)$
= $\int ds P(y) \log_2 P(y) + \int ds P(s) \int dy P(y|s) \log_2 P(y|s)$
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Histogram equalization:

For discrete variables, the **uniform** distribution has the maximum entropy.





Histogram equalization:

$$p[r] = \frac{1}{r_{\max}}$$
$$|f(s + \Delta s) - f(s)|/r_{\max} = p[s]\Delta s$$
$$\frac{df}{ds} = r_{\max}p[s]$$

$$f(s) = r_{\max} \int_{s_{\min}}^{s} ds' \, p[s']$$

Histogram equalization:

 $p[r] = \frac{1}{r_{\max}}$

$|f(s + \Delta s) - f(s)|/r_{max} = p[s]\Delta s$ **chalkboard interlude** $\frac{df}{ds} = r_{max}p[s]$

$$f(s) = r_{\max} \int_{s_{\min}}^{s} ds' \, p[s']$$

Evidence for entropy maximization in the fly:



Evidence for entropy maximization in the fly:



Adaptive rescaling in the fly H1 neuron:

Brenner et al 2000 (H1 neuron, visual system of the blowfly)



Responses to stimuli with 2x standard deviation change are nearly identical:



Signal and noise in the two stim conditions:



Adaptive rescaling to fast varying inputs:



Rescaling maximizes information transmission:



Optimal filter: whitening

• Optimize mutual information:

$$I = \frac{1}{2} \int \frac{d\omega}{2\pi} \log_2 \left(1 + \frac{|\tilde{K}(\omega)|^2 S(\omega)}{N(\omega)} \right)$$

subject to constraint

$$\int d\omega |\tilde{K}(\omega)|^2 S(\omega) = \text{constant}$$

• Solution

$$|\tilde{K}(\omega)|^2 S(\omega) = [A - N(\omega)]_+$$

• Whitening (water-filling analogy)



Whitening in the LGN (Dan et al 1996)

• Natural stimuli



• White-noise stimuli

A lightning fast introduction to channel coding:

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chalkboard interlude