

## Week 6 answers

### 1 Video 1

*Draw example spike patterns and sketch the results of how different methods to estimate the firing rate. Give examples of how changing the parameters of the firing rate estimates (e.g. bandwidth/bin-size) affects the estimates.*

Key points to notice: using too narrow a bandwidth makes sparse, low-firing-rate spikes look like little bursts. Using too broad a bandwidth smears out quick bursts.

### 2 Video 3

e.g. rods work well in low-light, cannot give colour information, and are rare in the fovea. Cones work well in strong light, give color information, and are predominant in the fovea.

### 3 Video 4

*Draw the simple-cell equivalent of week6-video4-slide6 (Text-fig 4 from Hubel and Wiesel, J Physiol, 1962)*

Complex cells differ from simple cells in that they are invariant to small translations of the bar, as in week6-video4-slide6, panel H. Thus, a simple cell is much **more** sensitive to small translations of the bar, firing alot for some bar locations, and far less for other bar locations. Draw a model of how complex cell selectivity might emerge from inputs from simple-cells.

*Draw a model of how complex cell selectivity might emerge from inputs from simple-cells.*

To obtain phase invariance (or invariance in small shifts to the bar) in a complex cell, we could consider a complex cell as taking inputs from many simple cells, where each simple cell responds to the same orientation of the bar, but slightly different shifts of the bar.

## 4 Video 5

In a Kohonen map, write down the value of  $C$  that keeps the weight vectors of unit length. The Kohonen map update rule is,

$$\mathbf{w}_i(t+1) = \frac{1}{C}(\mathbf{w}_i(t) + \alpha \mathbf{x}(t)) \quad (1)$$

where we only update the weights of the most active neuron,  $i$  (i.e. the neuron for which  $\mathbf{w}_i$  is closest to  $\mathbf{x}(t)$ ). We want,

$$1 = \|\mathbf{w}_i(t+1)\| \quad (2)$$

$$1 = \frac{1}{C} \|\mathbf{w}_i(t) + \alpha \mathbf{x}(t)\| \quad (3)$$

$$C = \|\mathbf{w}_i(t) + \alpha \mathbf{x}(t)\| \quad (4)$$

where  $\|\mathbf{a}\|$  is the length of the vector,  $\mathbf{a}$ .

*What happens in a Kohonen map if we keep giving the same input?*

First things first, each update only updates one neuron, the most active neuron (i.e. the neuron for which  $\mathbf{w}_i$  is closest to  $\mathbf{x}$ ). And the update makes  $\mathbf{w}_i(t+1)$  closer to  $\mathbf{x}$ . So next time round, the same neuron is also going to be closer. Eventually,  $\mathbf{w}_i$  will converge to the direction of  $\mathbf{x}$ , but with unit norm. To see this, we can consider steady-state, when the weights have stopped changing and  $\mathbf{w}(t) = \mathbf{w}(t+1) = \mathbf{w}$ ,

$$\mathbf{w} = \frac{1}{C}(\mathbf{w} + \alpha \mathbf{x}) \quad (5)$$

This holds only when  $\mathbf{w} = \mathbf{x} / \|\mathbf{x}\|$ ,

$$\mathbf{x} / \|\mathbf{x}\| = \frac{1}{C}(\mathbf{x} / \|\mathbf{x}\| + \alpha \mathbf{x}) \quad (6)$$

$$\mathbf{x} / \|\mathbf{x}\| = \frac{1}{C}(1 / \|\mathbf{x}\| + \alpha) \mathbf{x} \quad (7)$$

so,

$$C = \|\mathbf{x}\| (1 / \|\mathbf{x}\| + \alpha) = 1 + \alpha / \|\mathbf{x}\|. \quad (8)$$