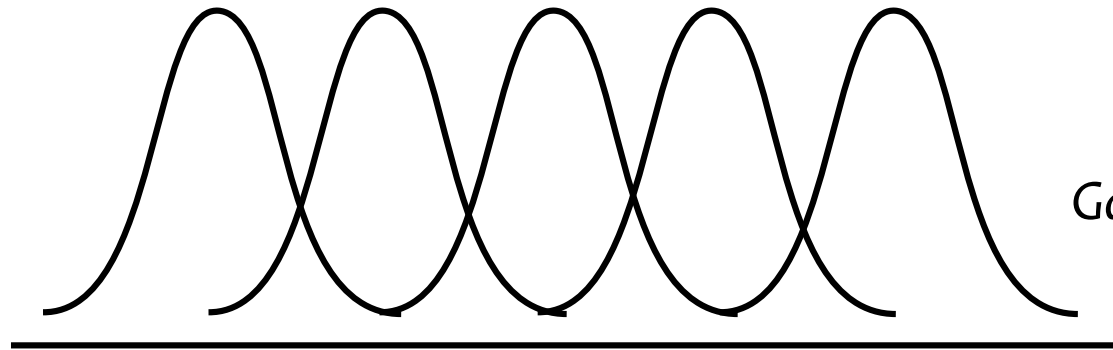


CP and neural coding

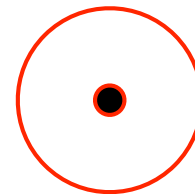
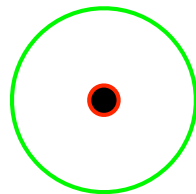
Before
training



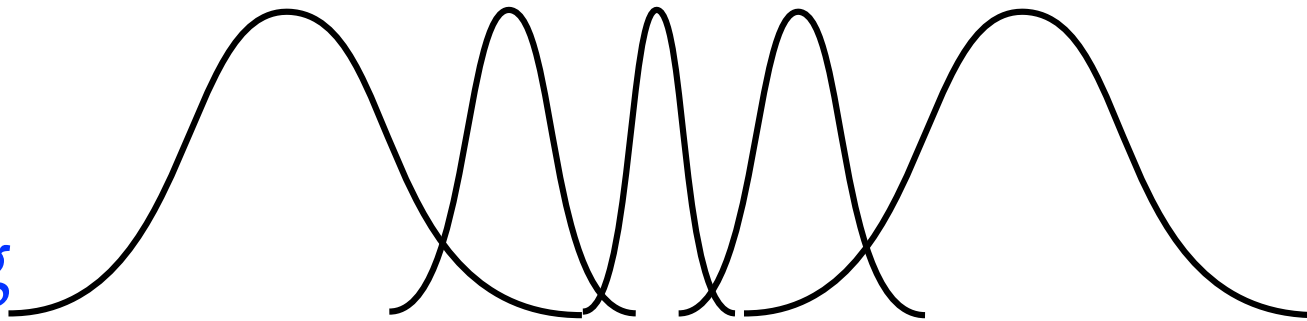
Gaussian tuning curves

parameter X

Categories



After
training

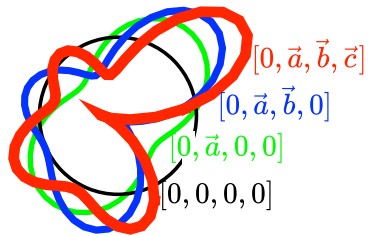


parameter X

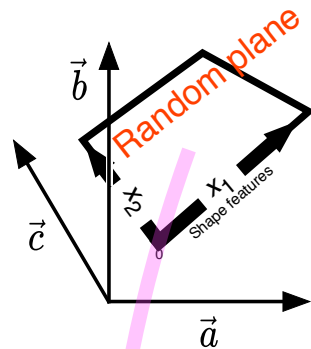
CP and “acquired distinctiveness”

- As subjects learn categories, their ability to discriminate fine differences near the category boundary improves
 - Called **acquired distinctiveness**
- But most studies have used **hard boundaries**, which don't really exist in natural categories!
- With a hard boundary, only features that cross the boundary are informative at all—but that isn't realistic

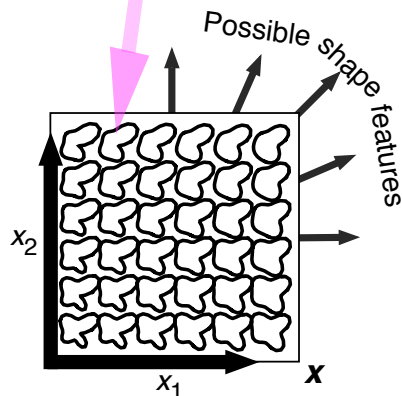
A modern CP experiment (Feldman, 2020)



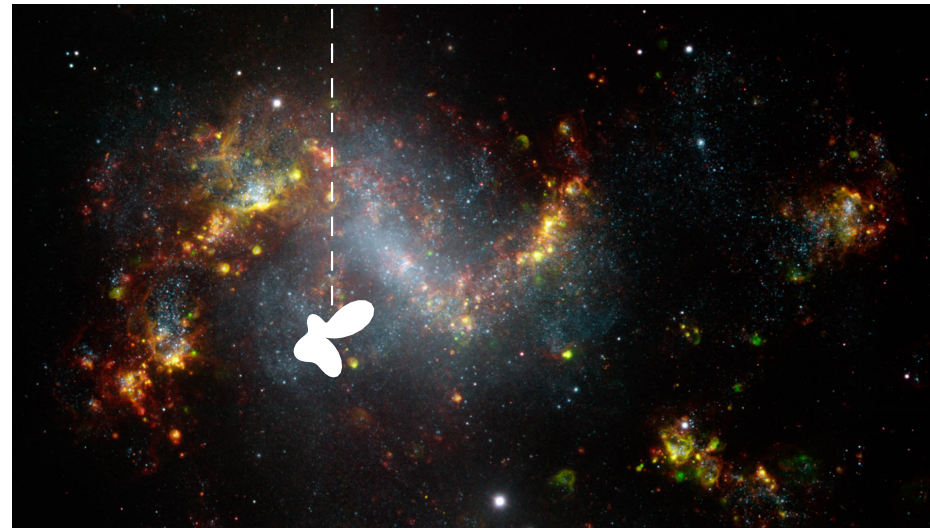
(a) Fourier shape components



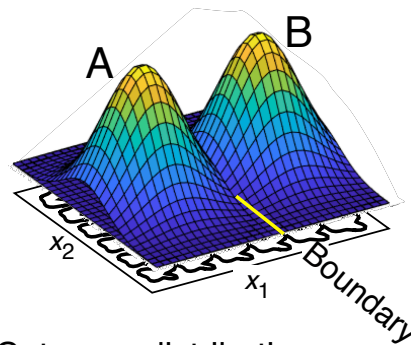
(b) Random plane through Fourier space



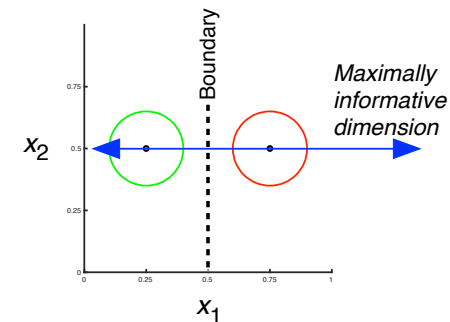
(c) Stimulus feature space



(f) Sample screen from video game task, showing shape to be classified. (Dotted line indicates motion and was not visible to subjects.)

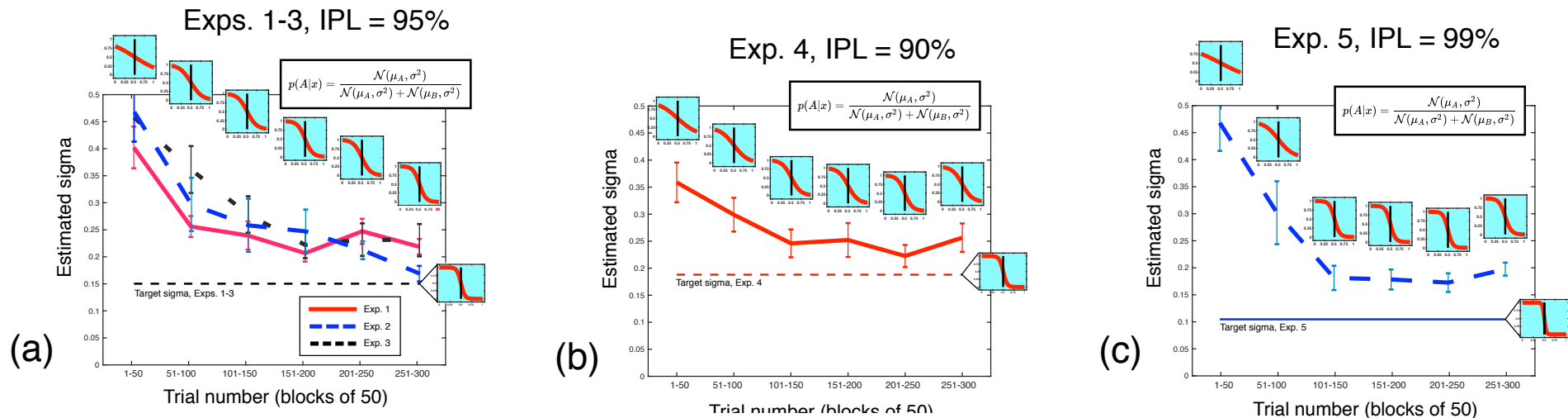


(d) Category distributions



(e) Contour plot of category distributions

Categorization results

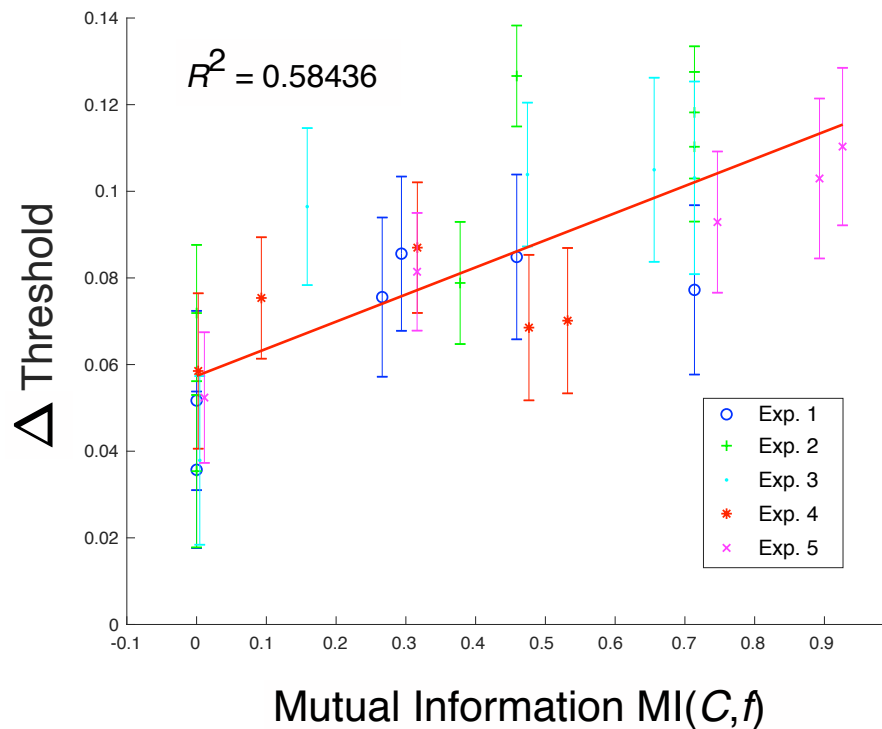


As training progresses, the classification curve gets more and more **step-like**

- though note that it only becomes as step-like as the actual category

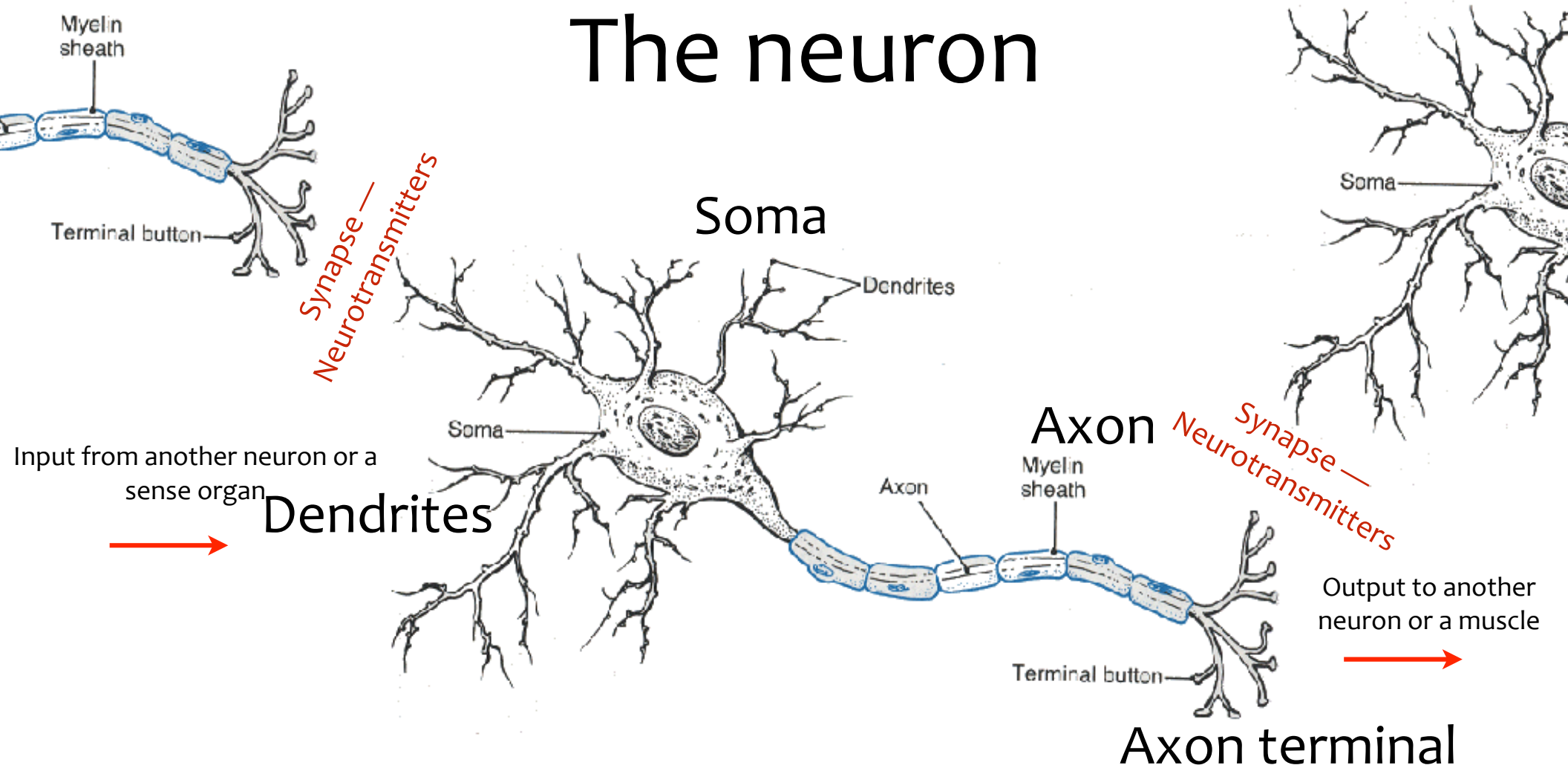
Discrimination results

Improvement in discrimination after training vs before training



Discrimination improves in proportion to how **informative** each feature is about the categories

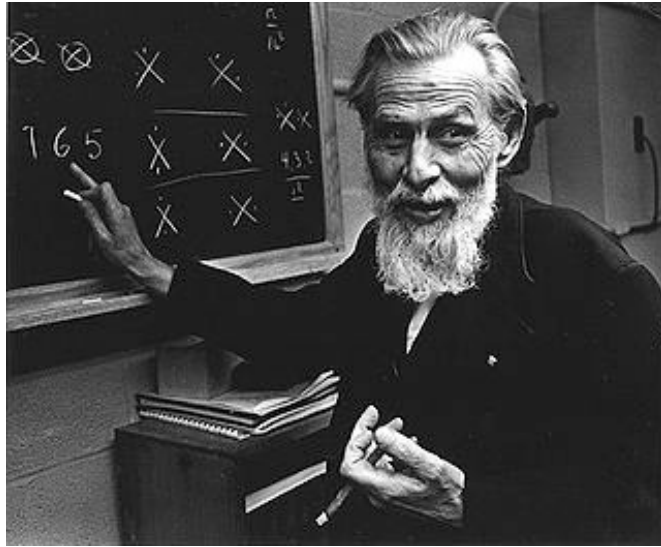
The neuron



Neuron integrates **excitation** and **inhibition** to get total net **activation**;
If activation is above threshold, it "**spikes**" (sends an **action potential** down the axon)

After firing, the neuron resets (~2 or 3msec). If it is still being stimulated over threshold, it fires again. Hence the **firing rate** indicates the level of activation.

McCulloch & Pitts: Neurons are little computing devices



Excitatory/
Inhibitory
0/1 inputs

Summation/
thresholding

0 or 1 output

