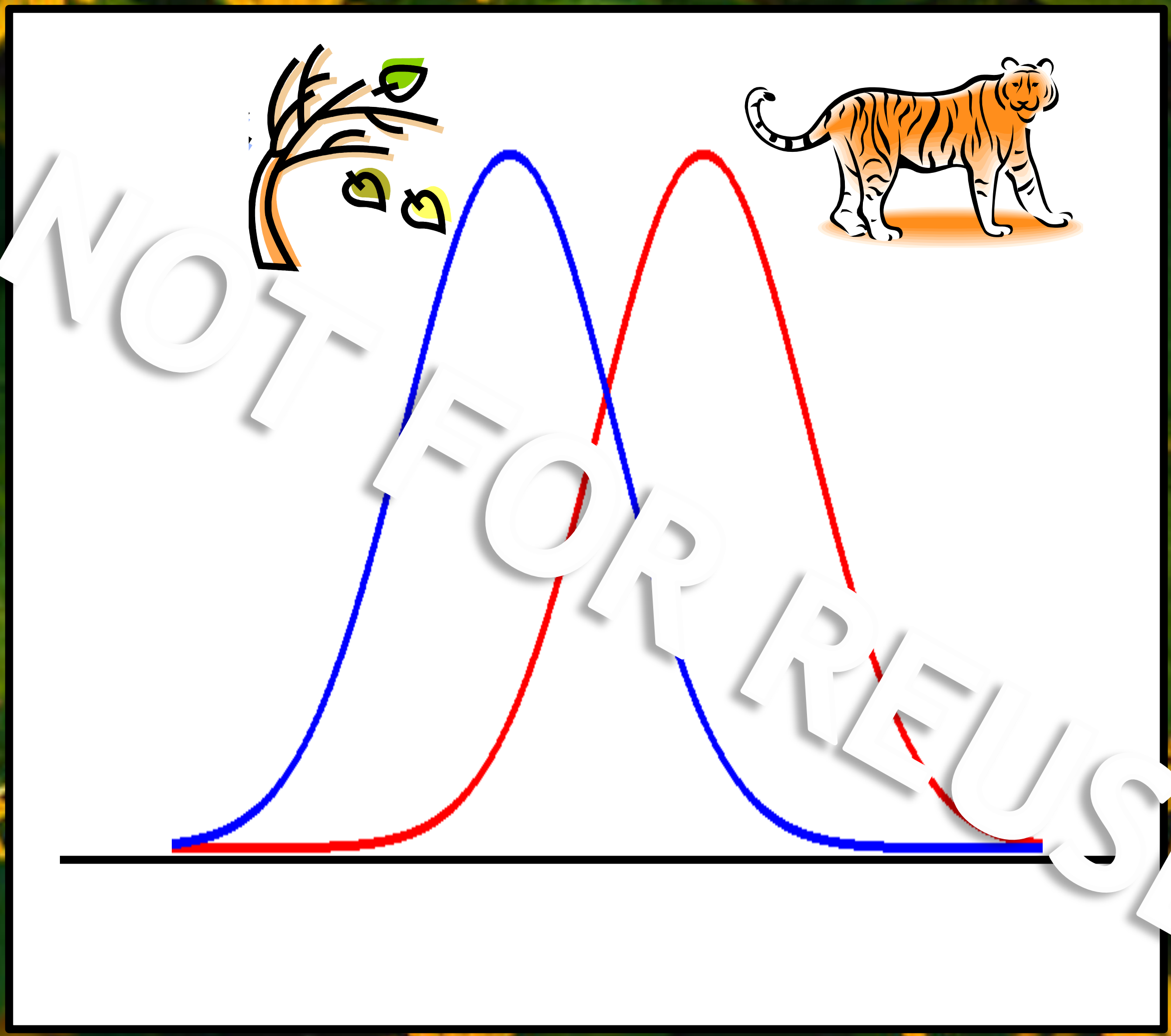
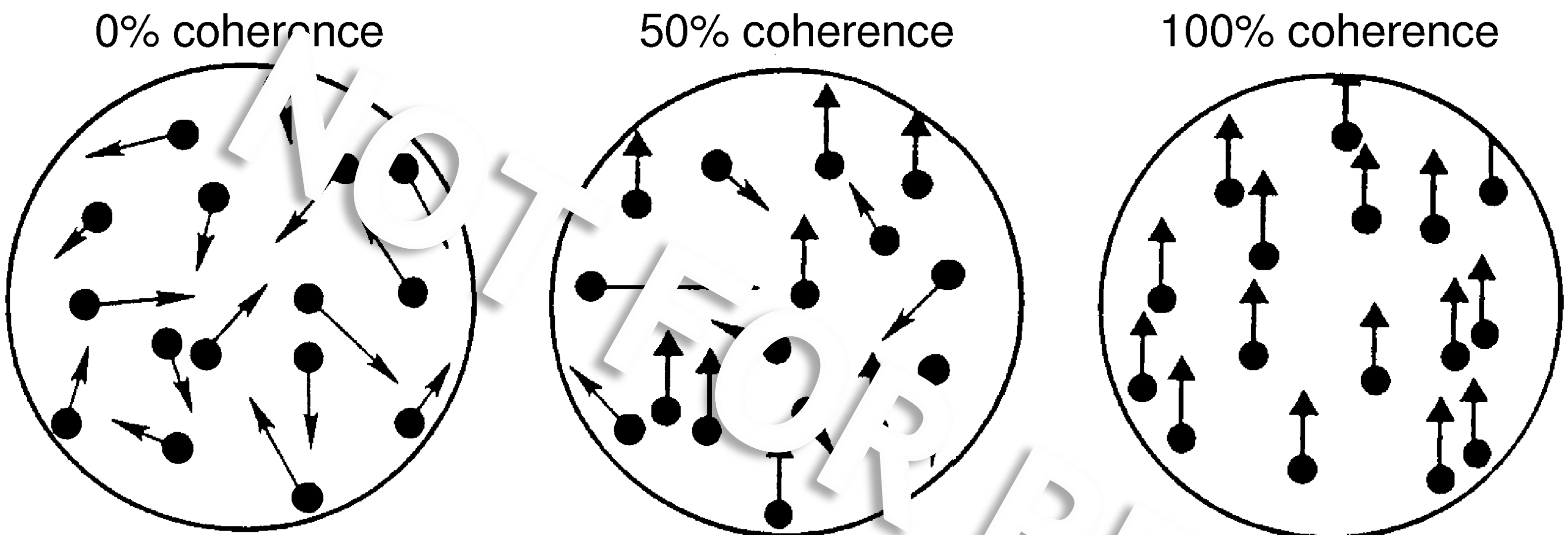
# Decoding

How well can we learn what the stimulus is by looking at the neural responses?

# Do I stay or do I go?



# Making a decision

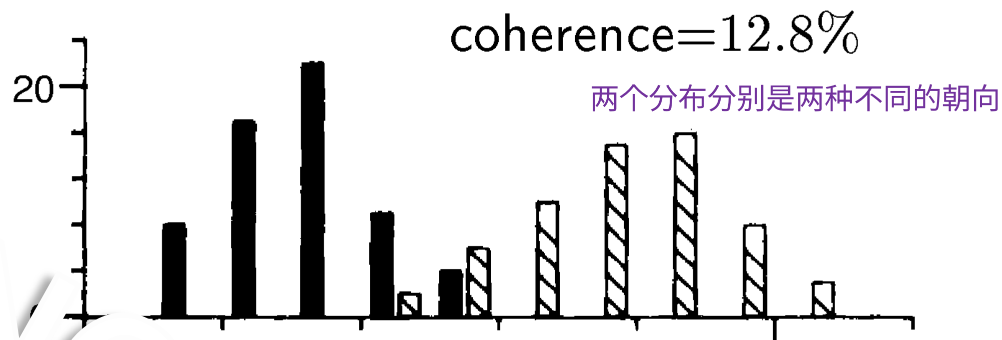


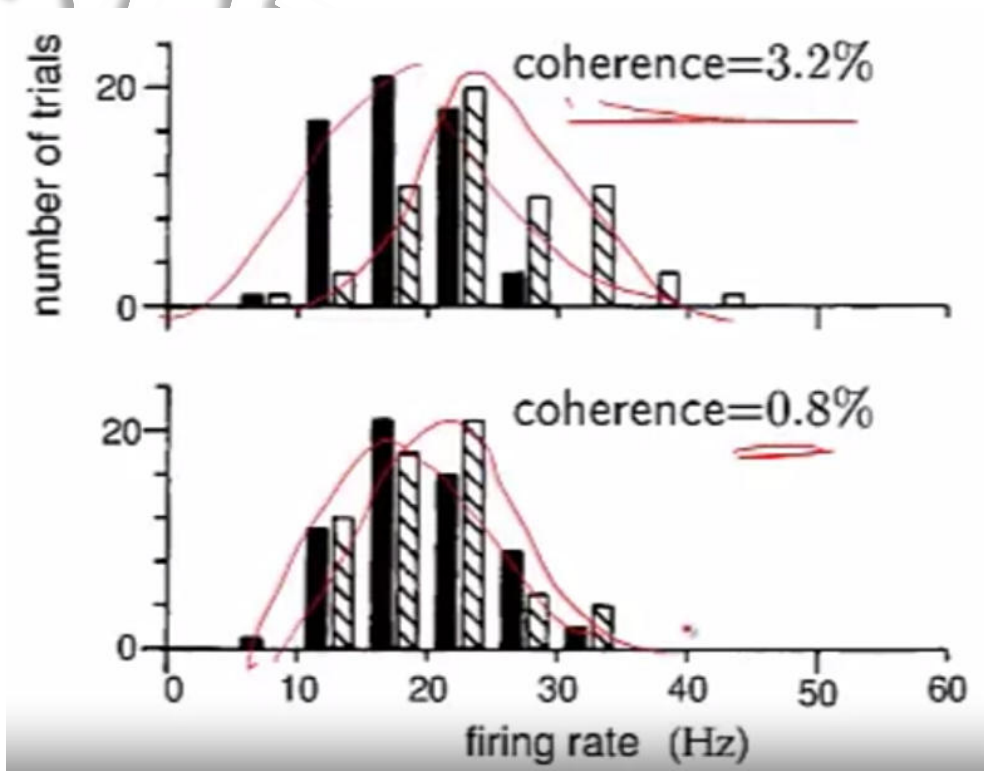



Britten et al. '92

# Predictable from neural activity?

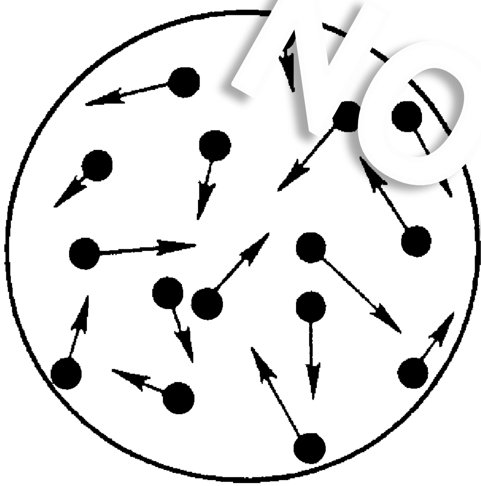
Given one sees a firing rate, one response, one trial from this neuron when trying to make a decision, how should one decode that firing rate in order to get the best guess about whether the stimulus was moving upward or downward?

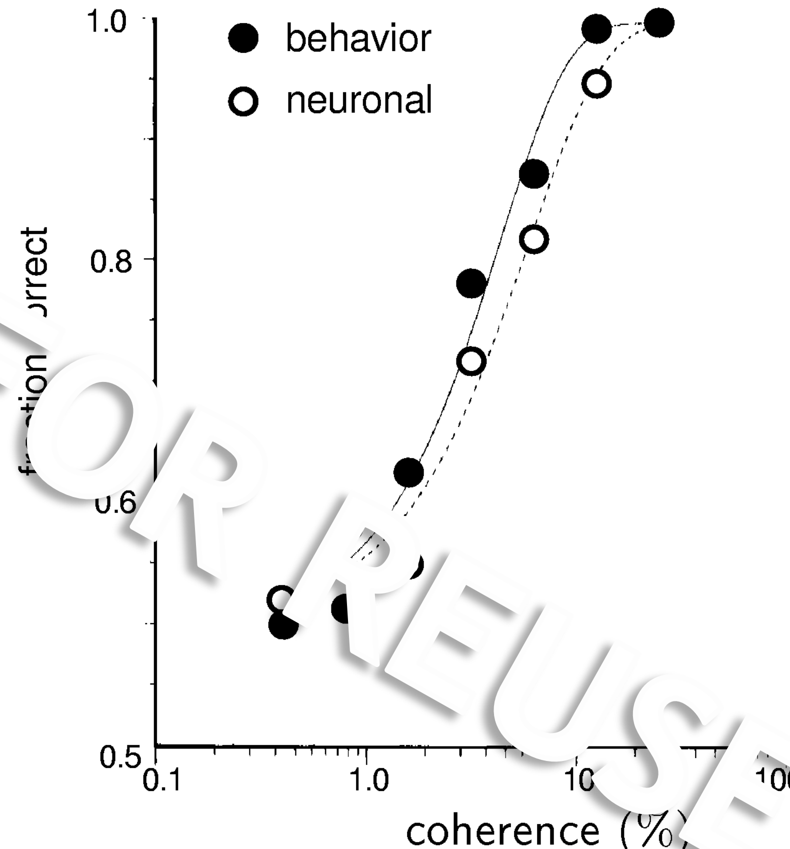



Britten et al. ‘92

# Behavioral performance



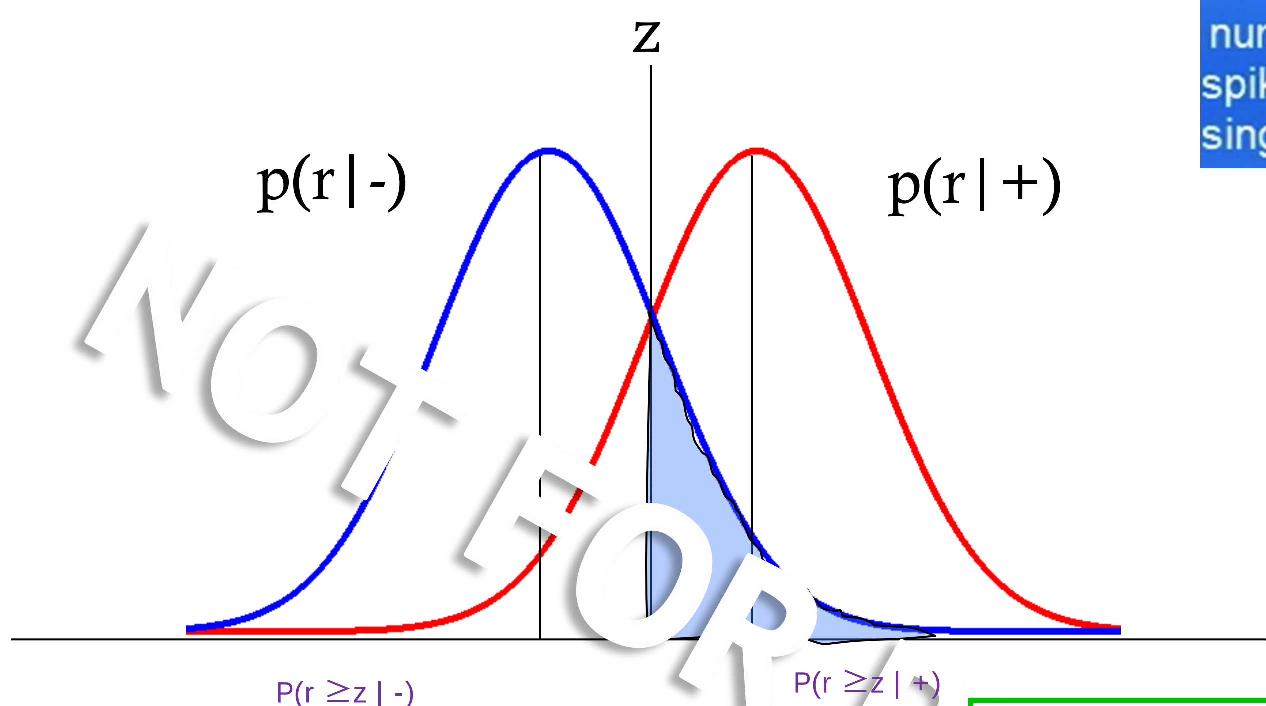





Britten et al. '92

# Signal detection theory

r is the number of spikes in a single trial!




P_correct = P(+)·P(r ≥z | +) + P(-)·(1- P(r ≥z | +))

How many errors are you going to make?

Decoding means that we ' d like a policy that tells us if we see some value r, we can map the stimulus unto either an upper going or downward going stimulus.

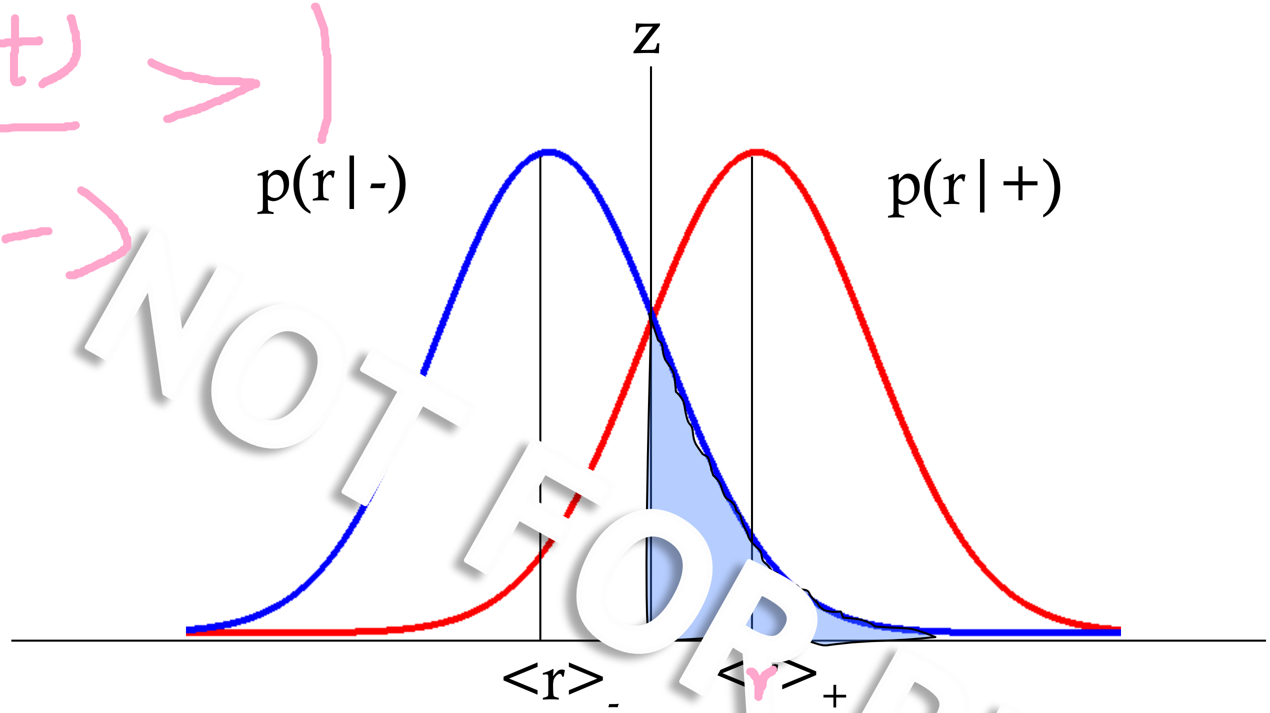
False alarms: P[ r ≥ z|-]

Good calls = P[ r ≥ z|+]

This choice of z maximizes P[correct]

# Likelihood ratio

$$\frac{p(r|+)}{p(r|-)} > 1$$



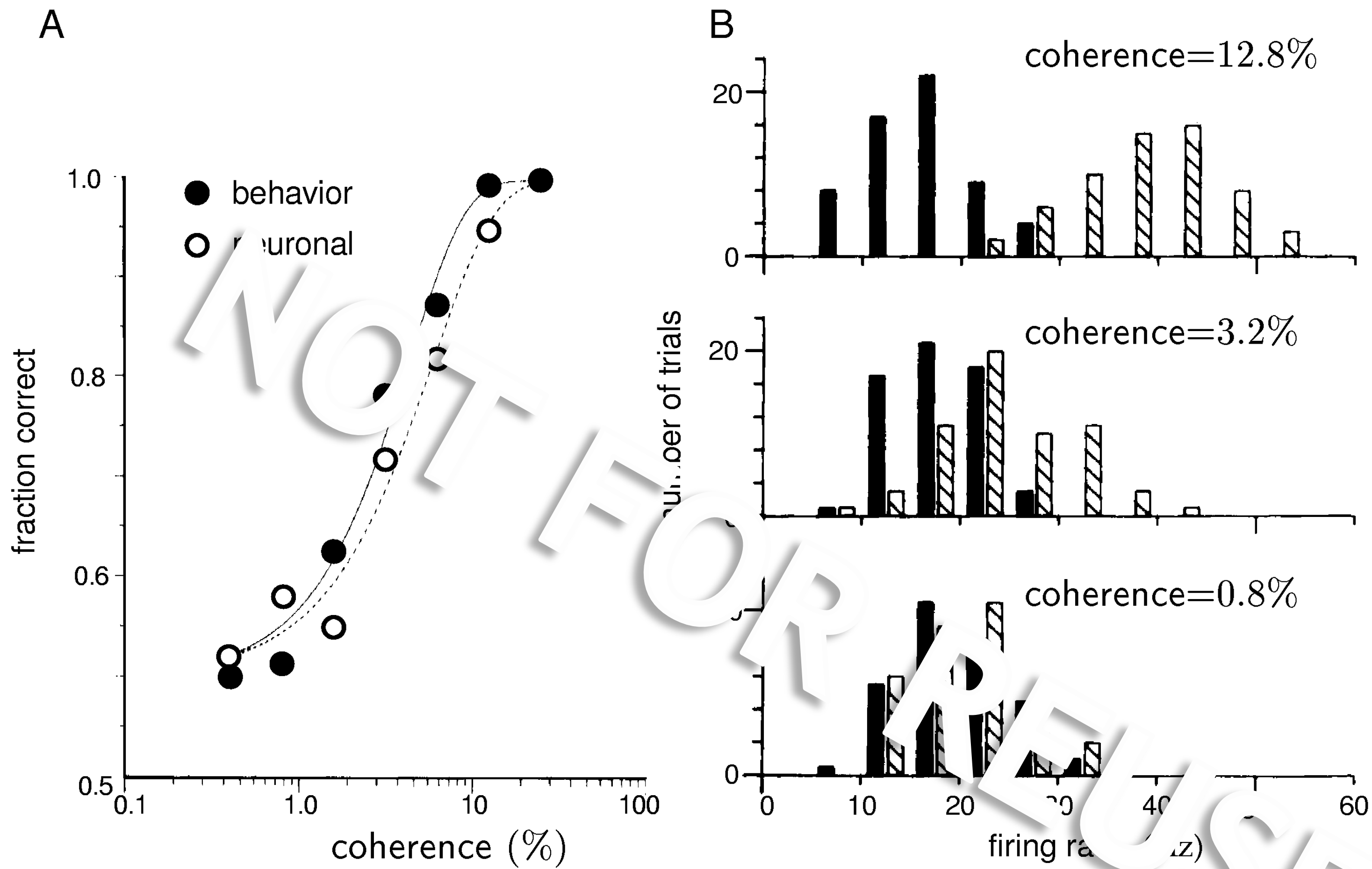



The likelihood ratio test is the most efficient statistic, in that it has the most power for a given size

*Power* = probability of a false negative
*Size* = probability of a false positive

Neyman-Pearson lemma

# Neurons vs organisms

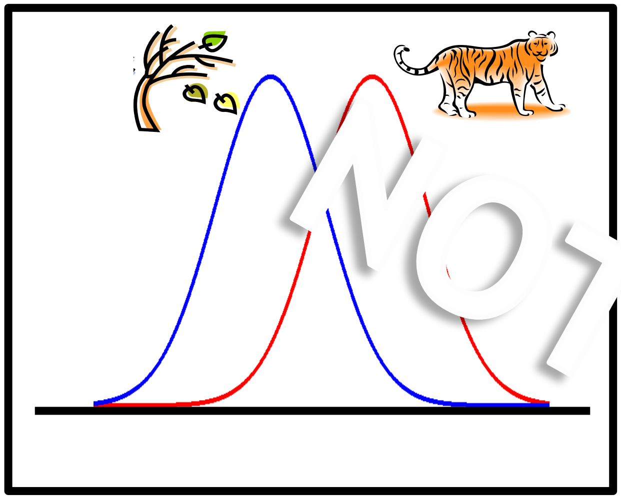



Close correspondence between neuron decoding and behavior..

So why so many neurons?

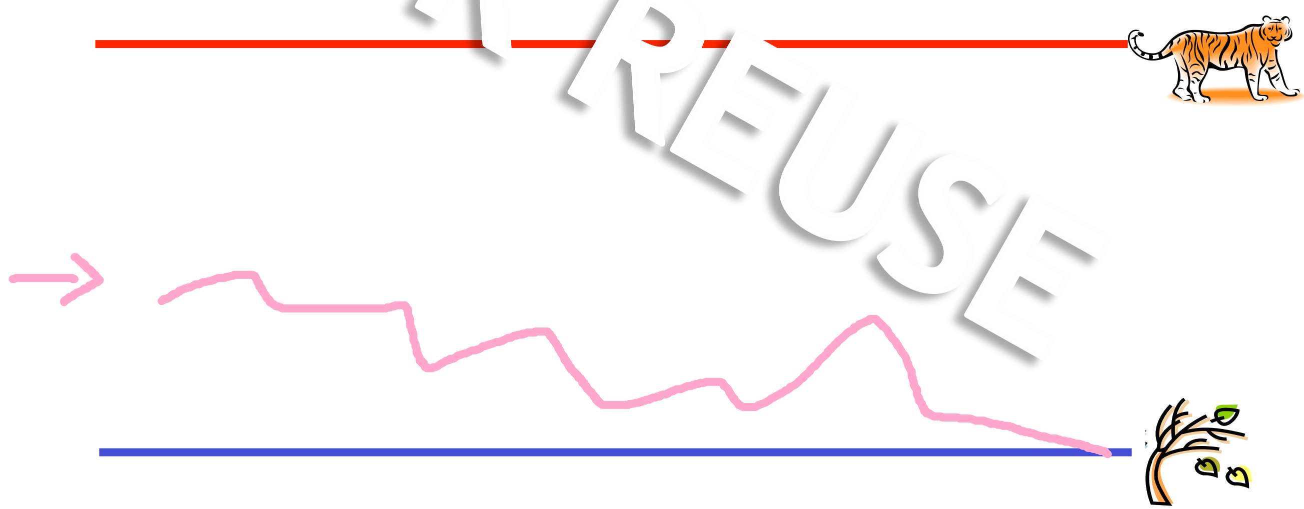
# Let's just consider for a moment

Now let's say we don't have to decide immediately…



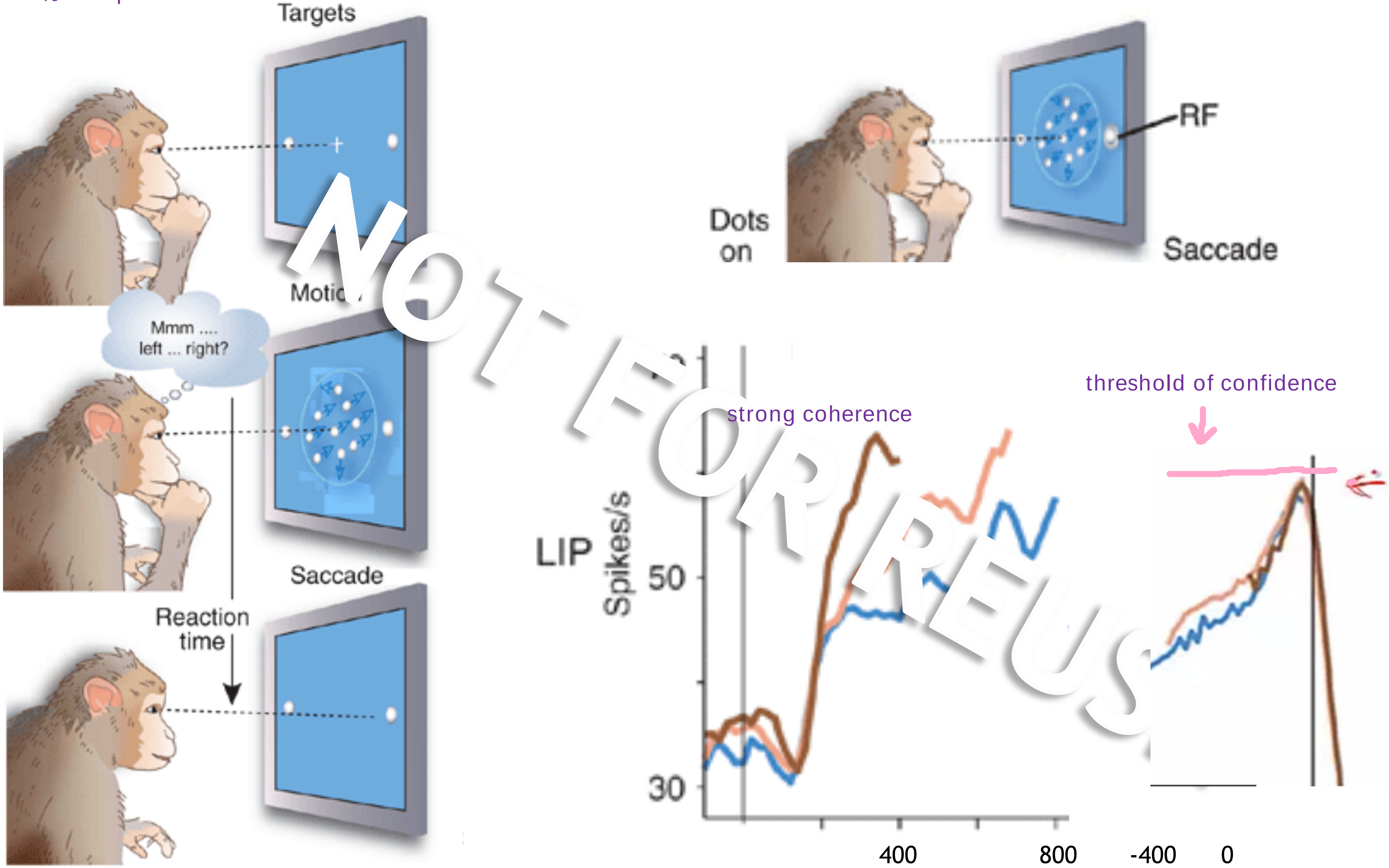
$$l(s) = \left.\frac{p(s|\text{tiger})}{p(s|\text{breeze})}\right\} < 1$$

$$\log l(s) < 0$$



# Accumulated evidence for accumulated evidence

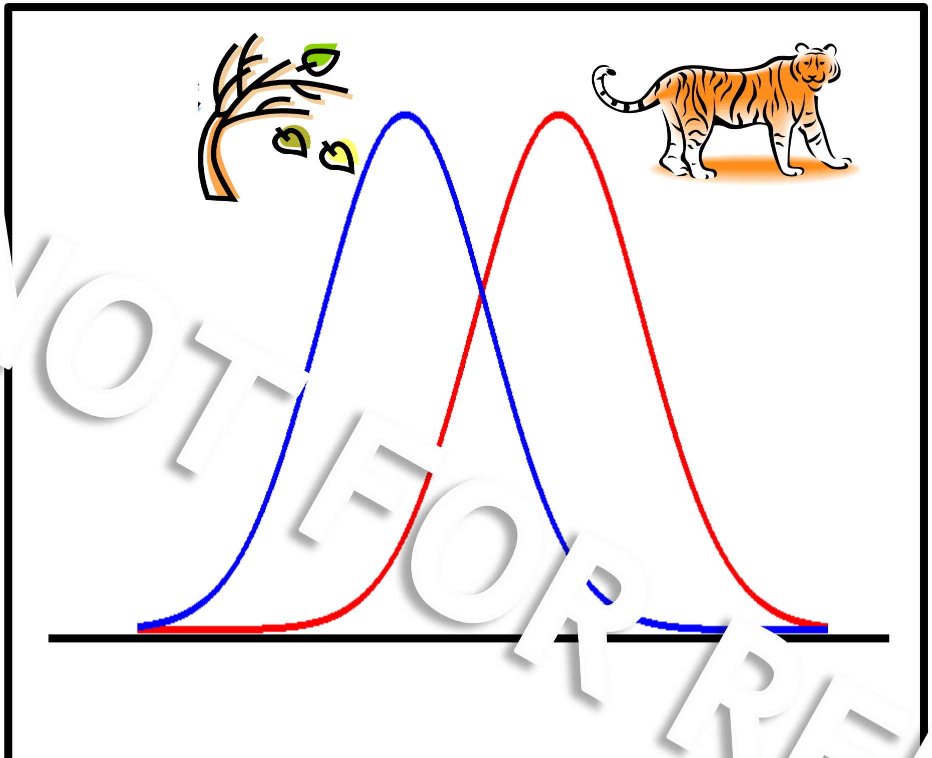
有time pressure






Kiani, Hanks & Shadlen, Nature Neuroscience (2006)

# Back to one trial: building in what we already know



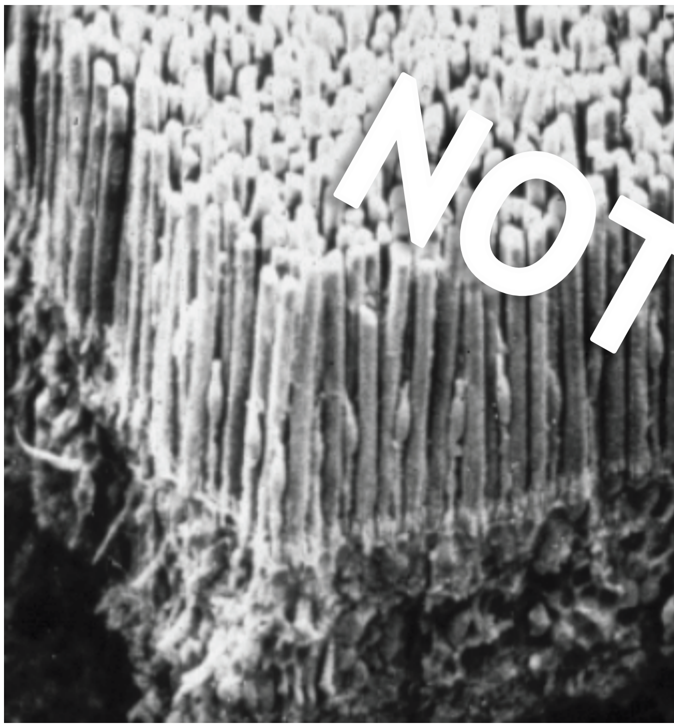


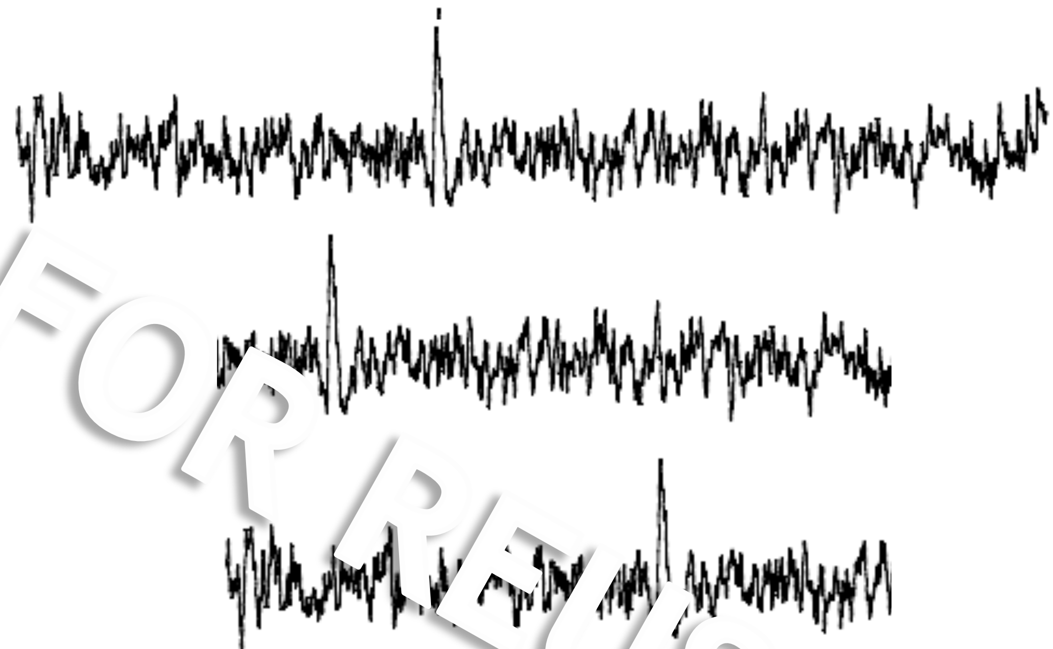
Role of *priors*:

Find z by maximizing P[correct] = p[+] b(z) + p[-](1 – a(z))

# The wind or a tiger?

Classification of noisy data: single photon responses



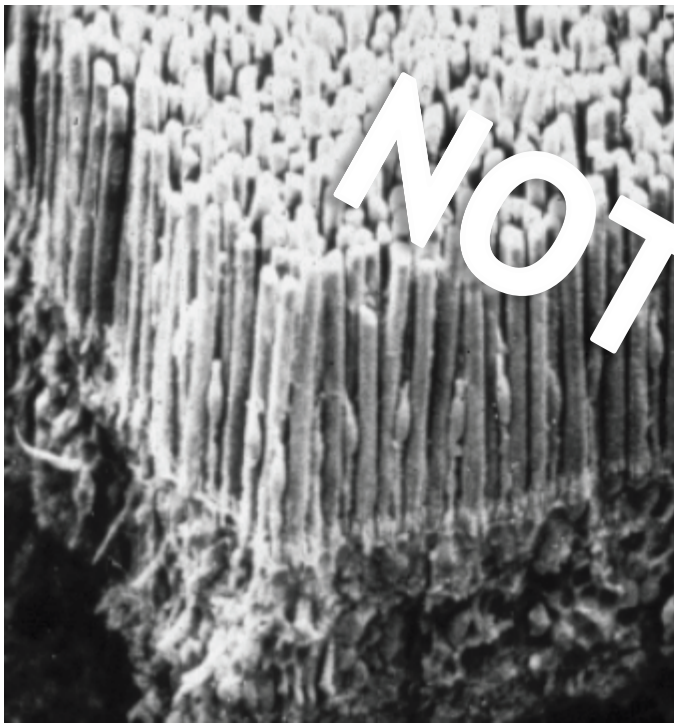


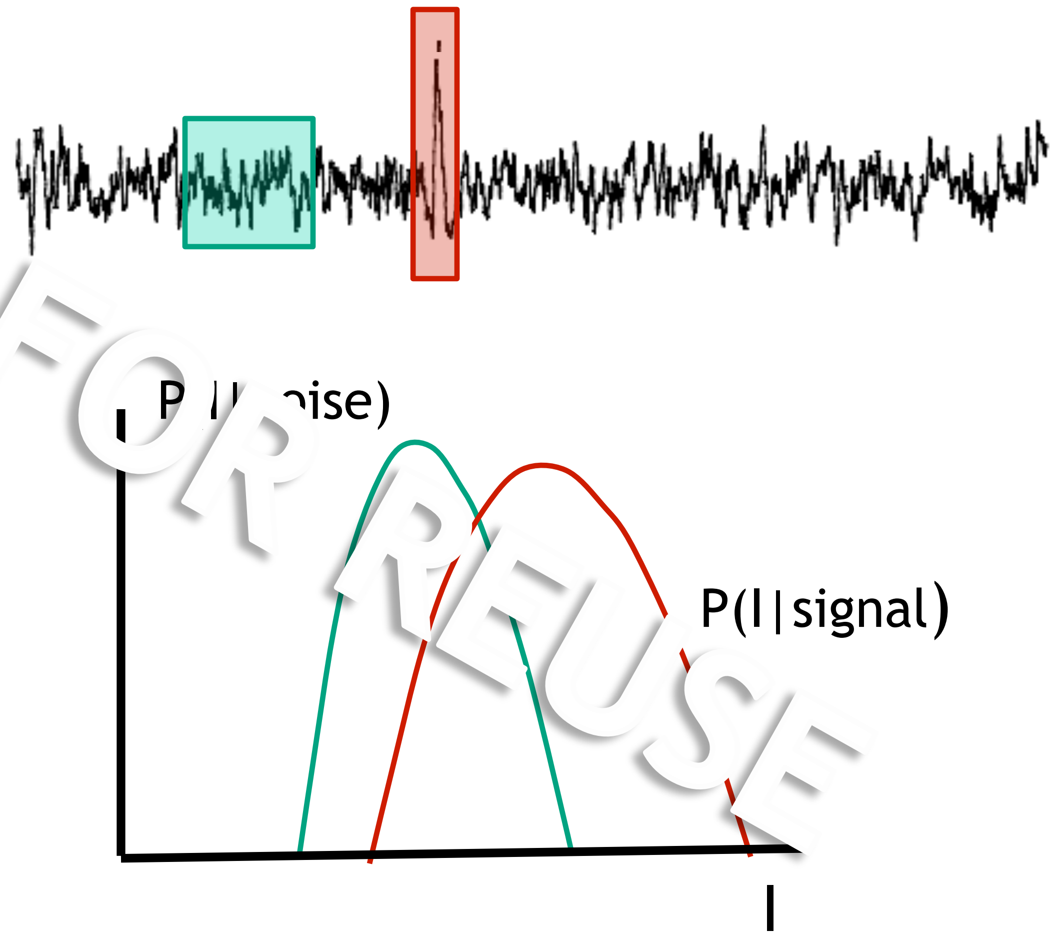


Rieke

# Nonlinear separation of signal and noise

Classification of noisy data: single photon responses



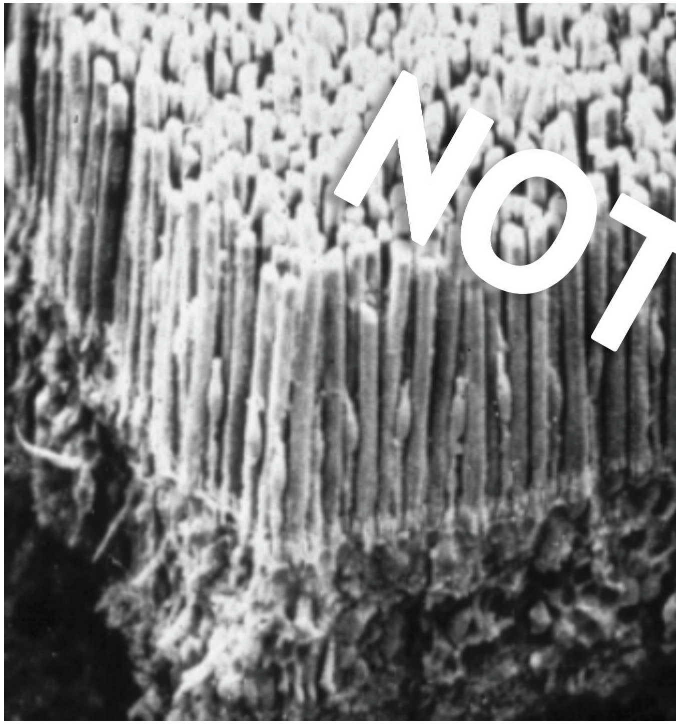


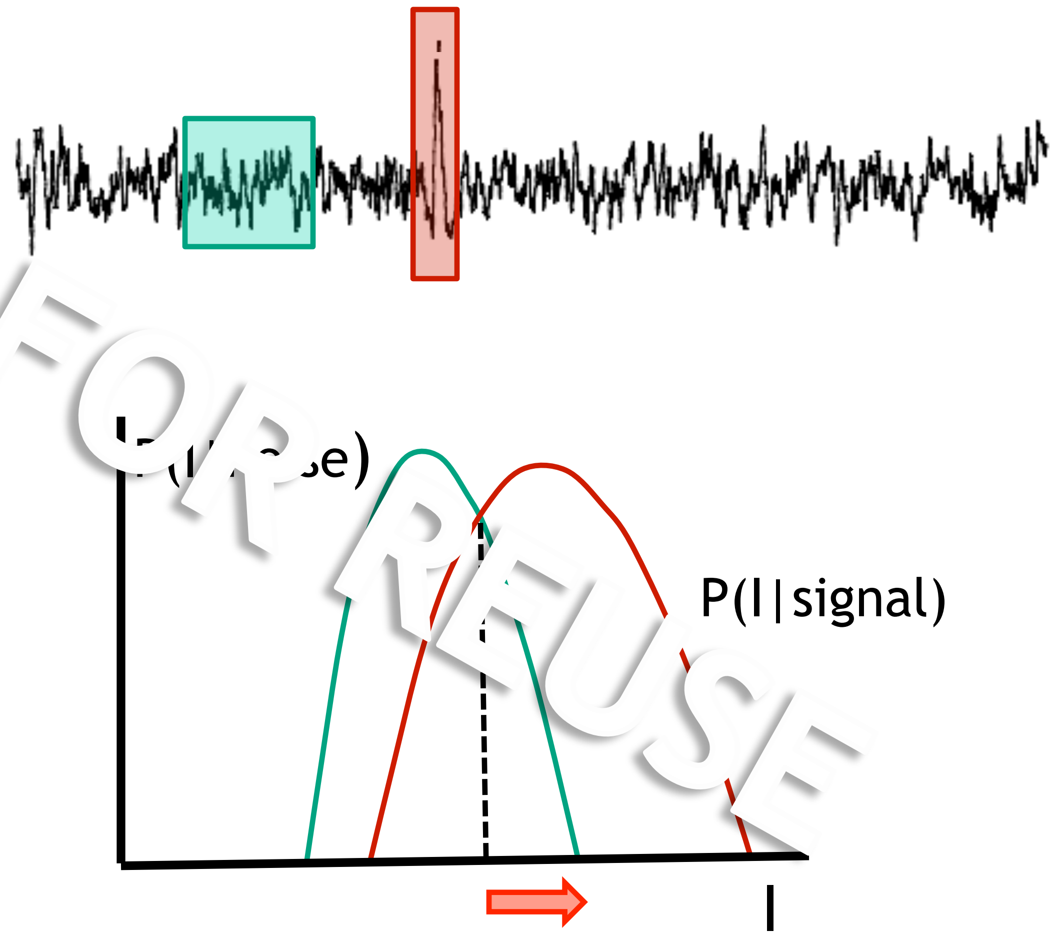



Rieke

# Nonlinear separation of signal and noise

## Classification of noisy data: single photon responses



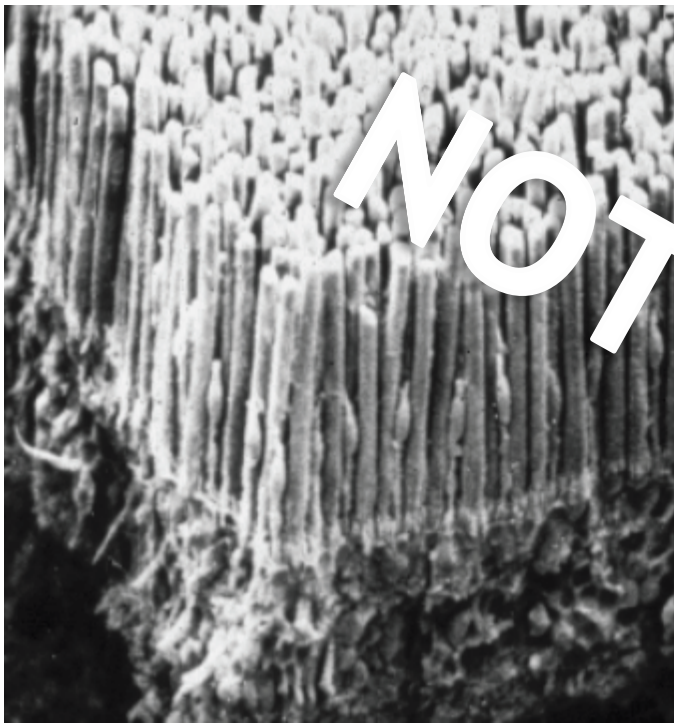


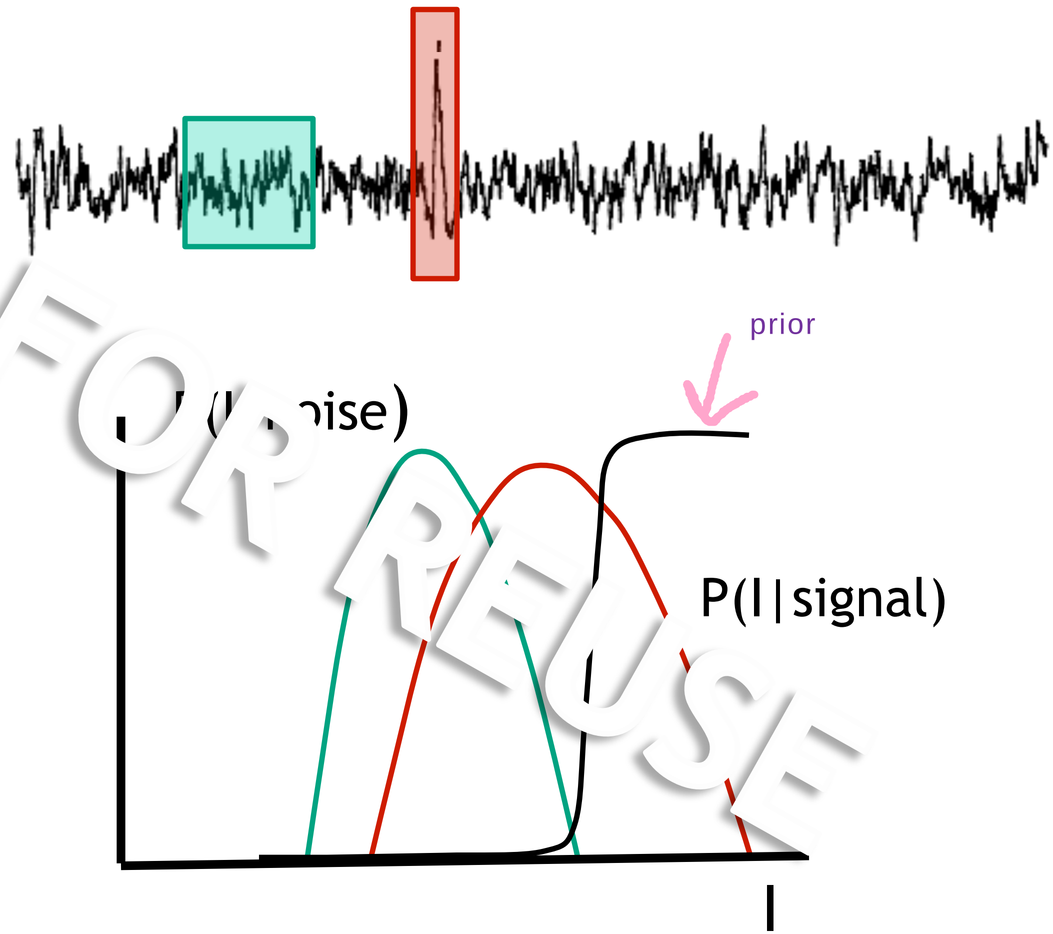



Rieke

# Nonlinear separation of signal and noise

Classification of noisy data: single photon responses





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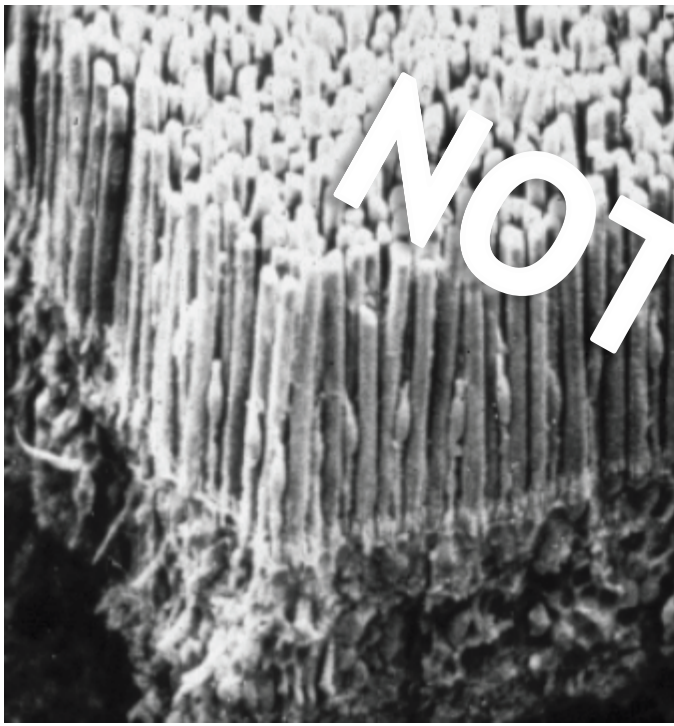
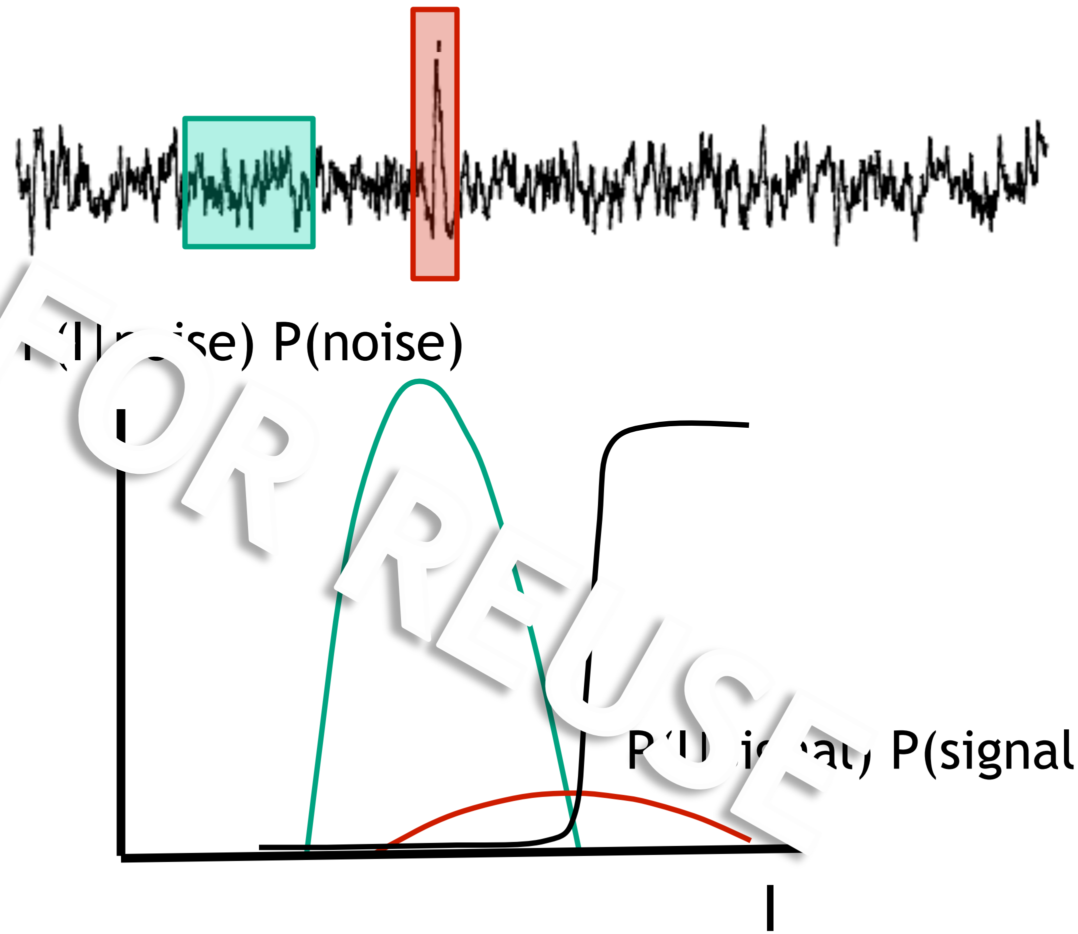
# Nonlinear separation of signal and noise

Classification of noisy data: single photon responses





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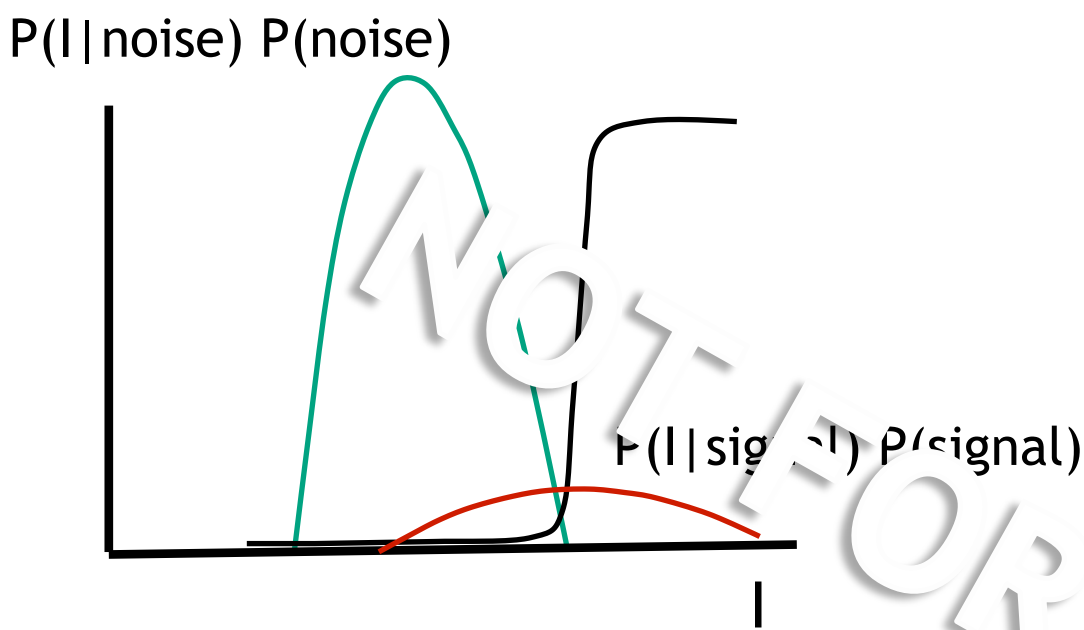
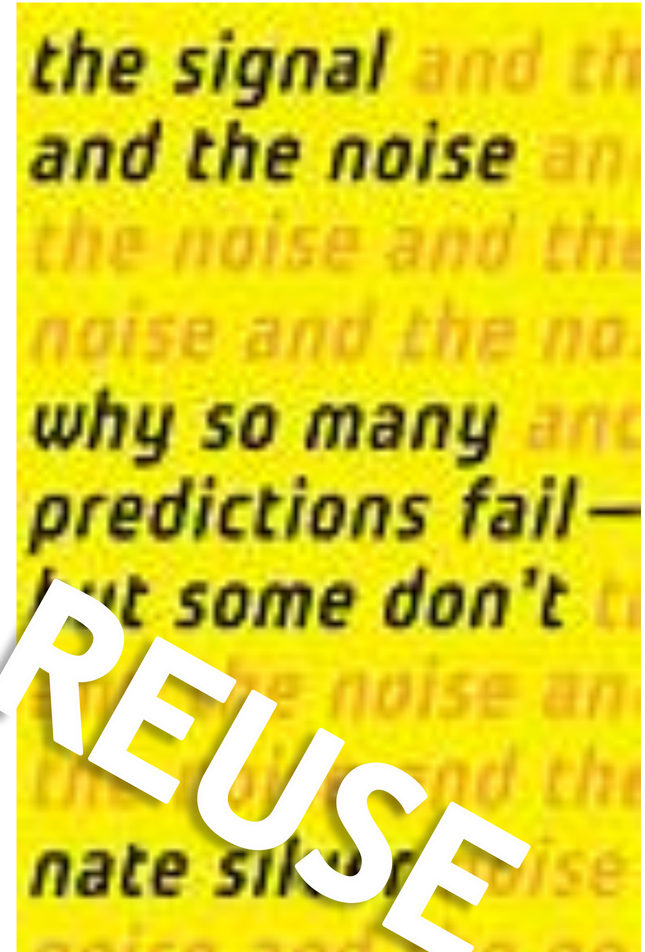
# That's prior knowledge: how about costs?



# Building in cost

penalty weight
-的重要程度

$Loss_- = L_- P[+|r]$

$Loss_+ = L_+ P[-|r]$

Cut your losses: answer + when $Loss_+ < Loss_-$

i.e. $L_+ P[-|r] < L_- P[+|r]$.

$$\frac{L_+ \, p(r|-) \, p(-)}{p(r)} < \frac{L_- \, p(r|+) \, p(+)}{p(r)}$$

Bayesian Rule

$\rightarrow$ $p[r|+]/p[r|-] > L_+ P[-] / L_- P[+]$ .