Lateral organization & neural codes

How do neural populations represent information?

Working assumptions:

Lateral organization involves a population of neurons representing features at the same level of abstraction

Receptive fields organized along a topographically mapped dimension with overlapping selectivities

Decoding — inferring world property from spikes— requires extracting information from the population

Neural Implementations of Bayesian Inference

Lecture notes adapted from Alexandre Pouget
http://cms.unige.ch/neurosciences/recherche/

Zemel, R. S., Dayan, P., & Pouget, A. (1998). Probabilistic interpretation of population codes Neural Computation, 10(2), 403–430.

Ma, W. J., Beck, J. M., Latham, P. E., & Pouget, A. (2006). Bayesian inference with probabilistic population codes. Nature Neuroscience, 9(11), 1432–1438. doi:10.1038/nn1790

Probabilistic brains: knowns and unknowns (2013.) Pouget, A., Beck, J., Ma, W.J., Latham, P. Nature Neuroscience 16:1170-1178.

Perceptual encoding:

learning to represent world properties in terms of firing patterns

Perceptual decoding:

interpretation of encoded pattern by subsequent neural processes

Poisson noise

Imagine the following process: we bin time into small intervals, δt. Then, for each interval, we toss a coin with probability, P(head) =p. If we get a head, we record a spike. This is the Bernoulli process of PS#1.

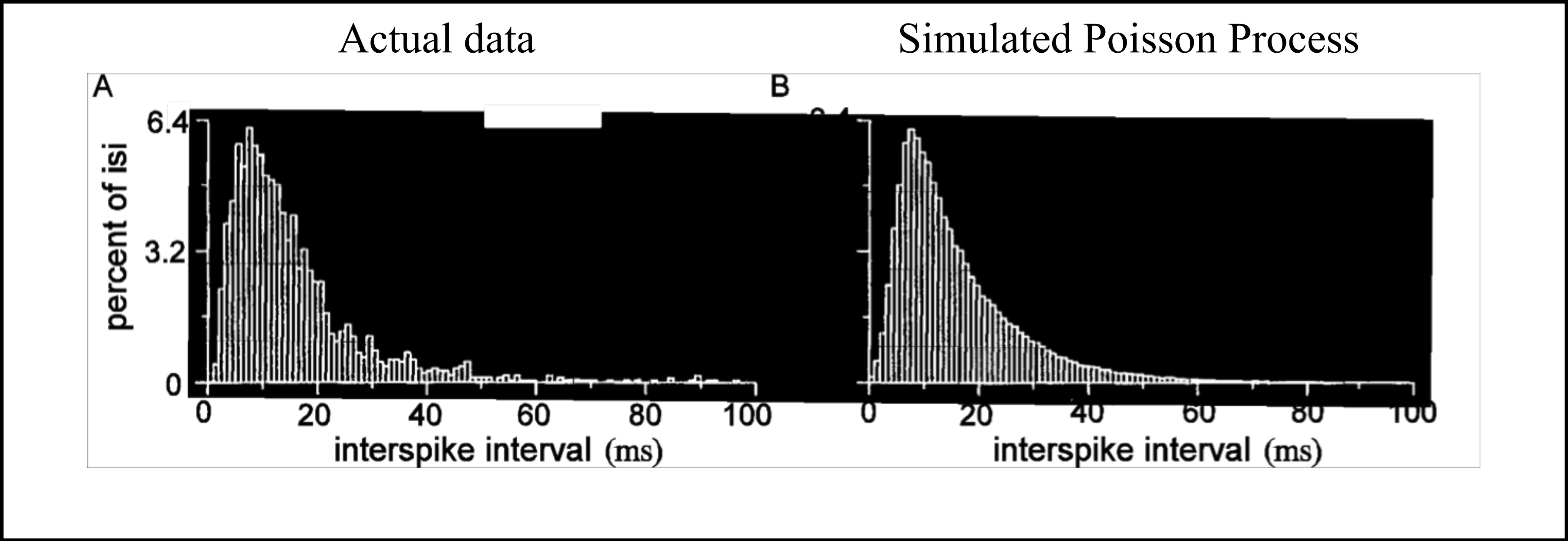
For small p, the number of spikes per second follows a Poisson distribution with mean $p/\delta t$ spikes/second (e.g., $p=0.01$, $\delta t=1$ms, mean=10 spikes/sec).

Properties of a Poisson process

- The variance should be equal to the mean
- A Poisson process does not care about the past, i.e., at a given time step, the outcome of the coin toss is independent of the past ("renewal process").
- As a result, the inter-event intervals follow an exponential distribution (Caution: this is not a good marker of a Poisson process)

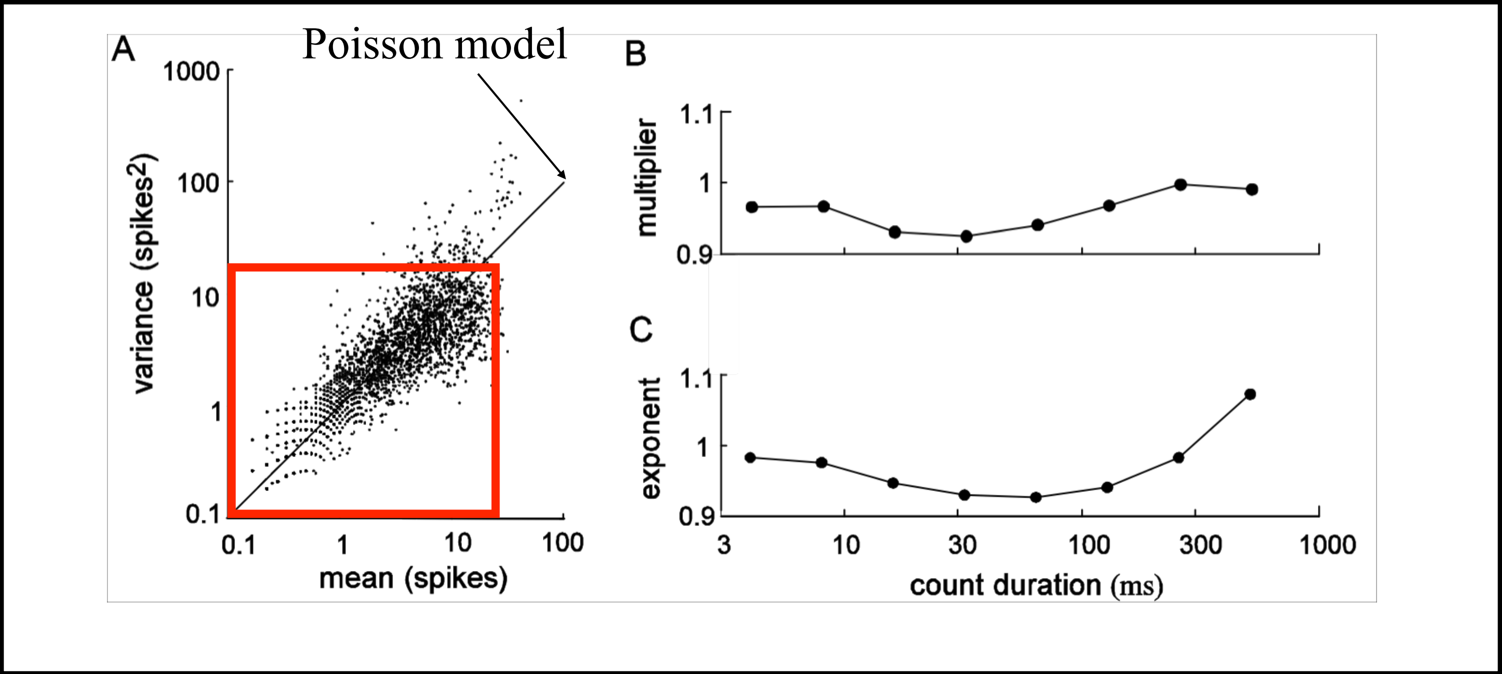
Poisson process and spiking

The inter spike interval (ISI) distribution is close to an exponential except for short intervals (refractory period) and for bursting neurons



Poisson process and spiking

The variance in the spike count is proportional to the mean but the the constant of proportionality can be higher than 1 and the variance can be an polynomial function of the mean. Log σ^2 = β Log a +log α



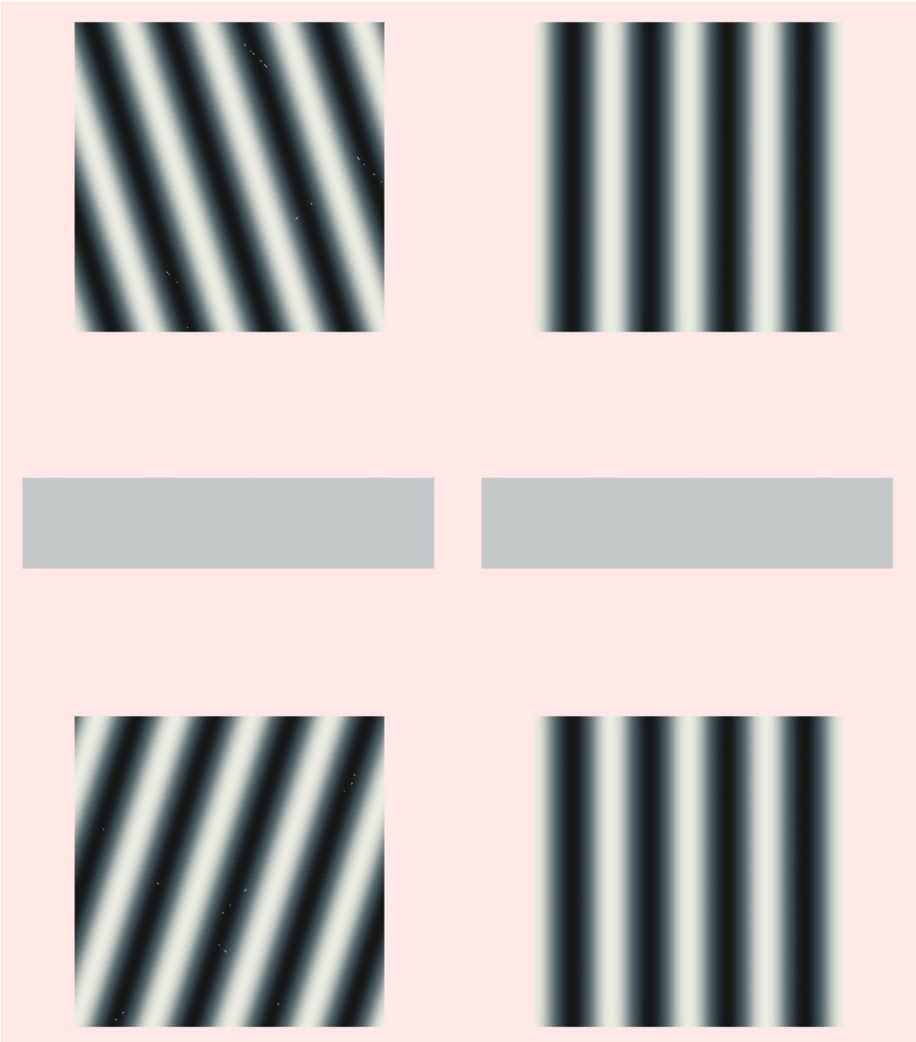
Is Poisson variability really noise?

Where could it come from?

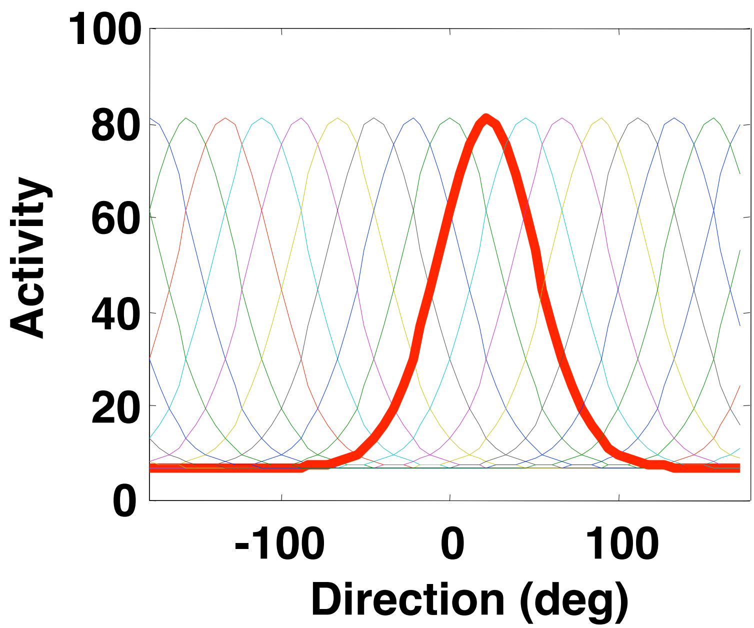
Neurons embedded in a recurrent network with sparse connectivity tend to fire with statistics close to Poisson (Van Vreeswick and Sompolinski, Brunel, Banerjee)

Could Poisson variability be useful for probabilistic computations? I.e. where knowledge of uncertainty is represented and used?

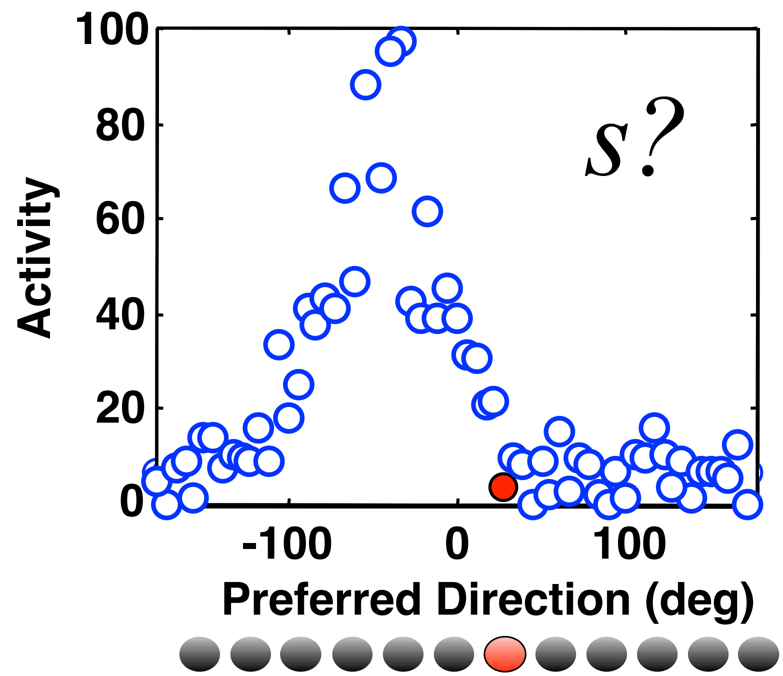
Poisson-like representations can be used for Bayesian integration of information



Population Code



Tuning Curves



Pattern of activity **(r)**

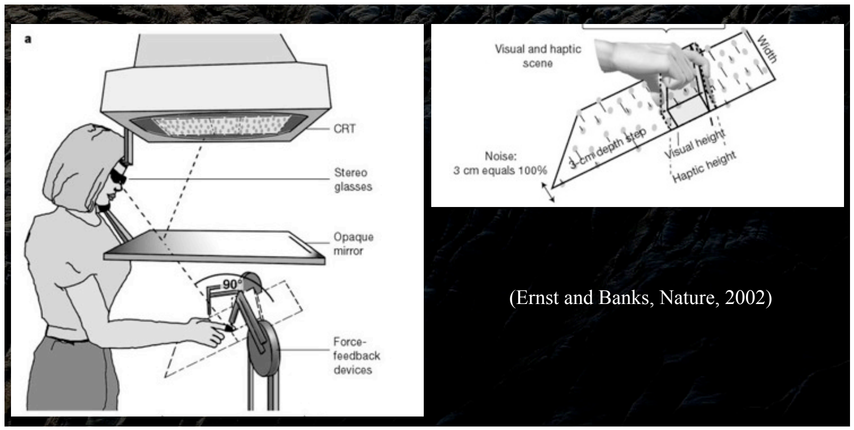
The decoding problem

Given a stimulus with unknown orientation s, what can one say about s given a vector r representing the pattern of neural activity?

Estimation theory: come up with a single value estimate from r

Bayesian approach: estimate the posterior $p(s|r)$

Advantages of a probabilistic representation



(Ernst and Banks, Nature, 2002)

Recall Ex 3 in PS #3: Derive the optimal rule for integrating two noisy measurements to estimate the mean

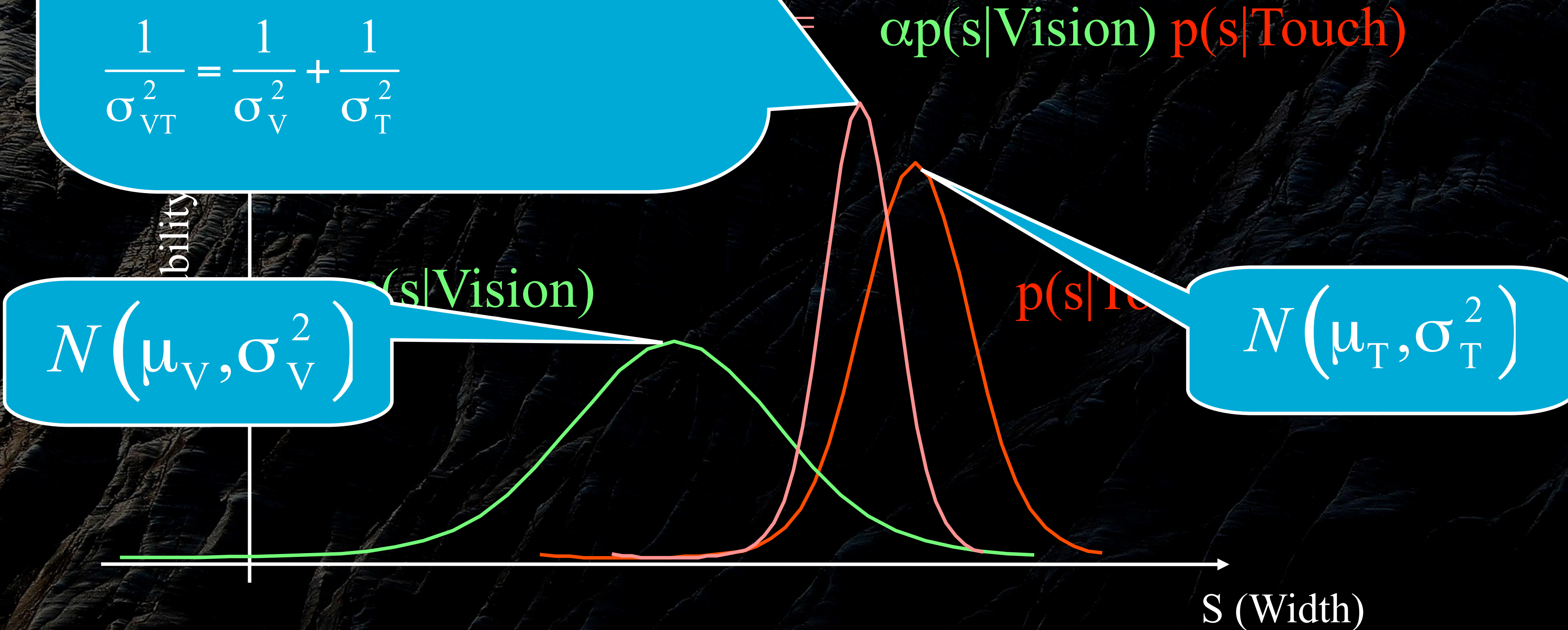
$$\mu = \frac{r_1}{r_1 + r_2}\mu_1 + \frac{r_2}{r_1 + r_2}\mu_2$$

Cue integration

$$N\left(\mu_{VT},\sigma_{VT}^2\right)$$

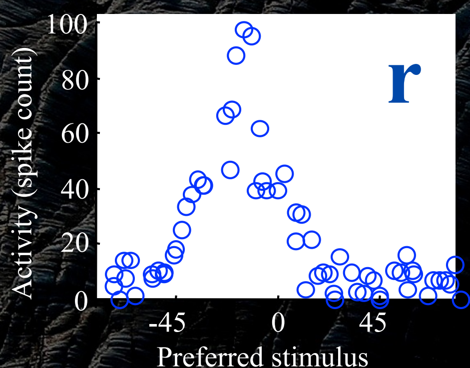
$$\mu_{VT}=\frac{\sigma_T^2}{\sigma_V^2+\sigma_T^2}\mu_V+\frac{\sigma_V^2}{\sigma_V^2+\sigma_T^2}\mu_T$$

$$\frac{1}{\sigma_{VT}^2}=\frac{1}{\sigma_V^2}+\frac{1}{\sigma_T^2}$$



Population codes

Standard approach: estimating



Population vector →

$\hat{s}$

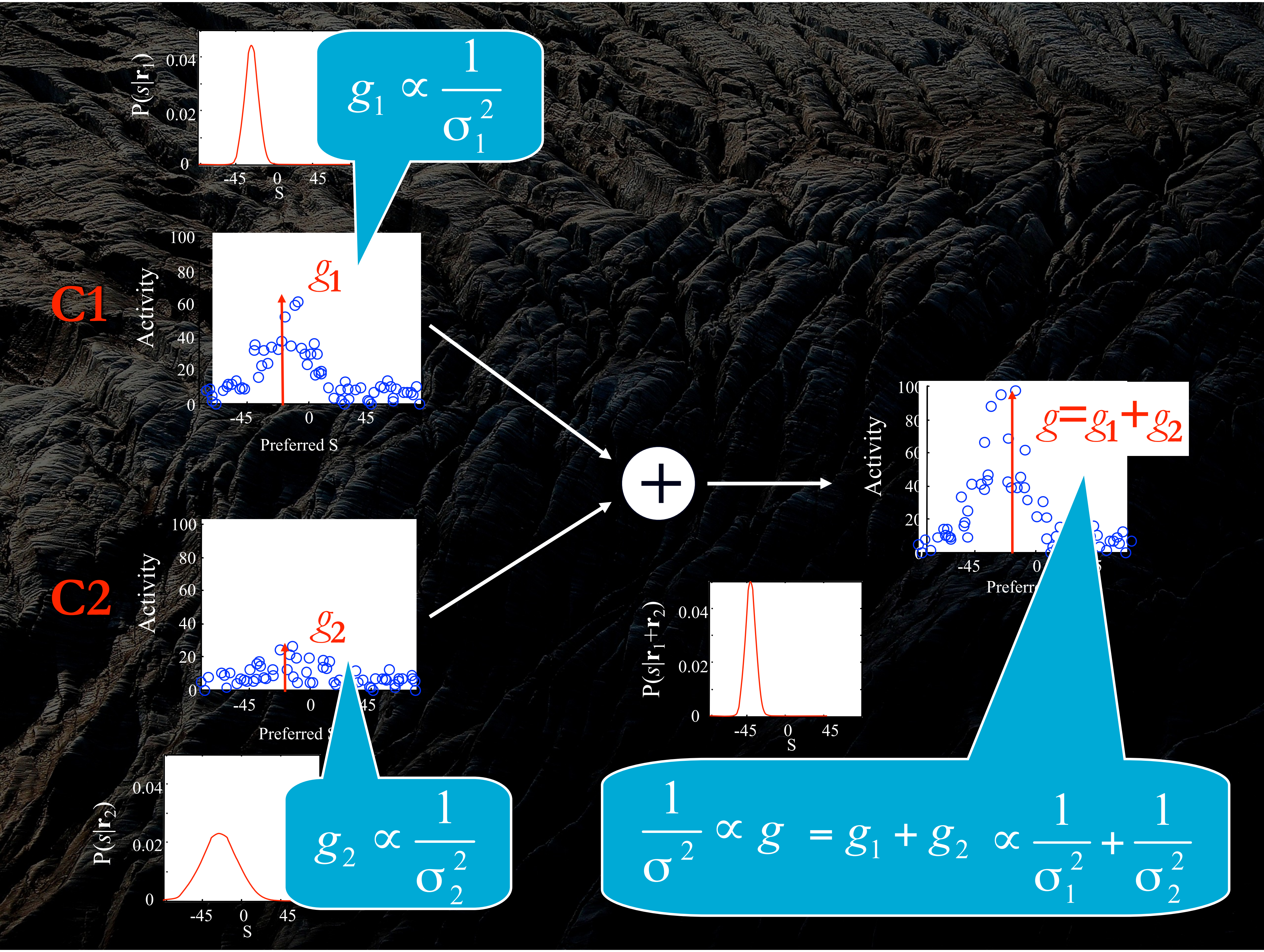
Underlying assumption: population codes encode **single values.**

Probabilistic population codes

Alternative: compute a posterior distribution, $p(s|\mathbf{r})$ from (Foldiak, 1993; Sanger 1996).

$$p(s\,|\,\mathbf{r}) \propto p(\mathbf{r}\,|\,s)$$

Variability in neural responses for a constant stimulus: *Poisson-like*



C1
C2
$g_1 \propto \frac{1}{\sigma_1^2}$
$g_2 \propto \frac{1}{\sigma_2^2}$
g_1
g_2
$g = g_1 + g_2$
$\frac{1}{\sigma^2} \propto g = g_1 + g_2 \propto \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$
$P(s|\mathbf{r}_1)$
$P(s|\mathbf{r}_2)$
$P(s|\mathbf{r}_1+\mathbf{r}_2)$
Activity
Preferred S
S