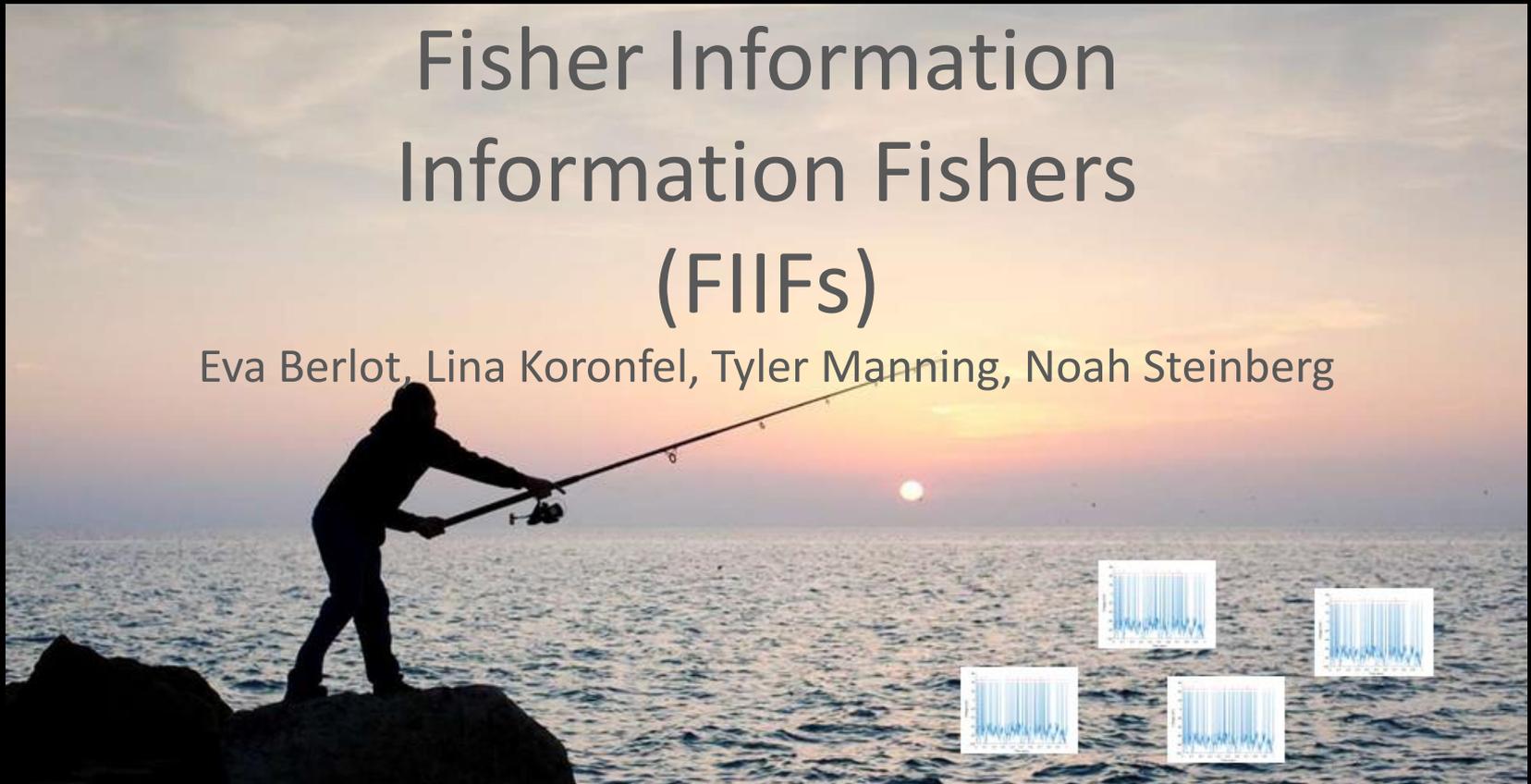




Analyzing the Effect of Noise Correlations on Decoding Neuronal Recording

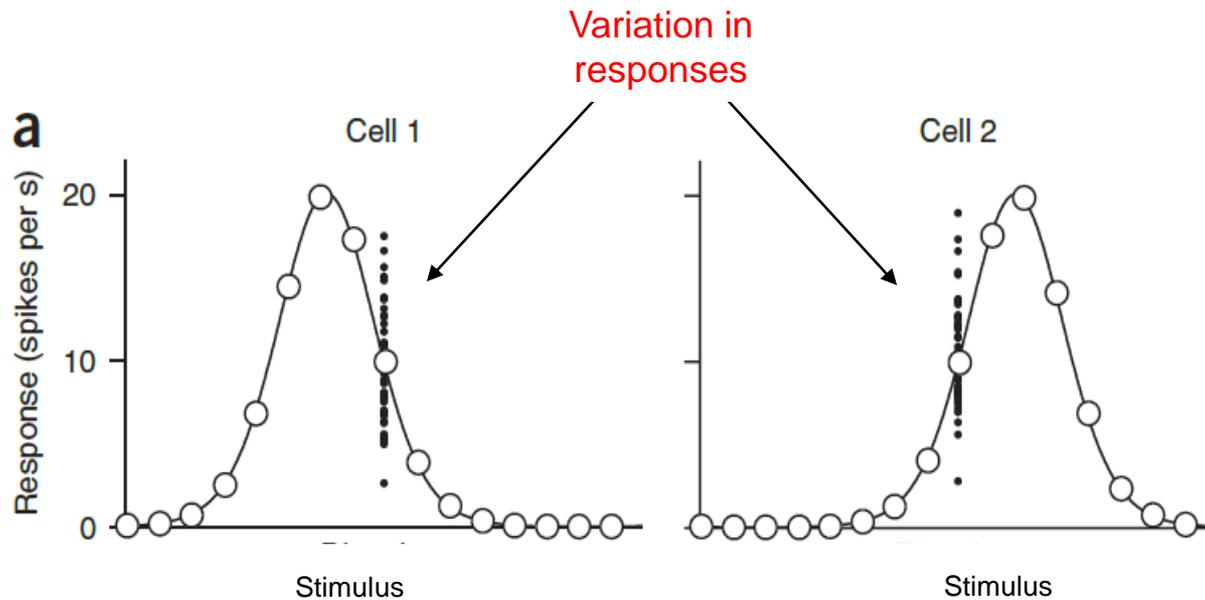
Fisher Information Information Fishers (FIIFs)

Eva Berlot, Lina Koronfel, Tyler Manning, Noah Steinberg



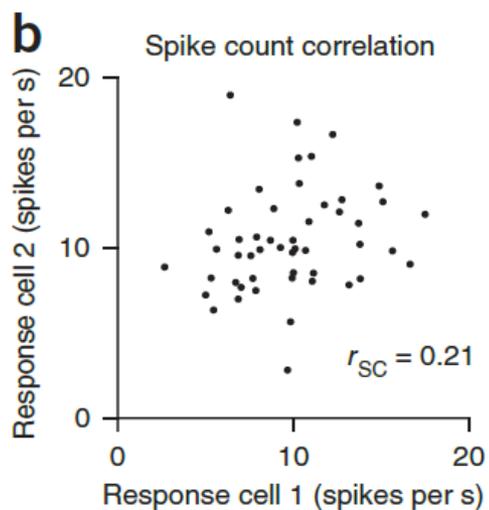
Phenomenon

Trial-to-trial variability in neuronal response to the same stimulus



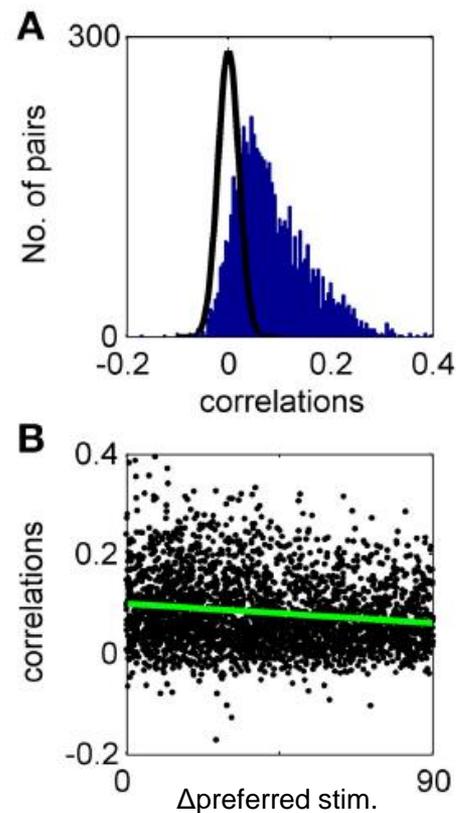
Phenomenon

Pair-wise noise correlation to the same stimulus



Cohen and Kohn, 2011

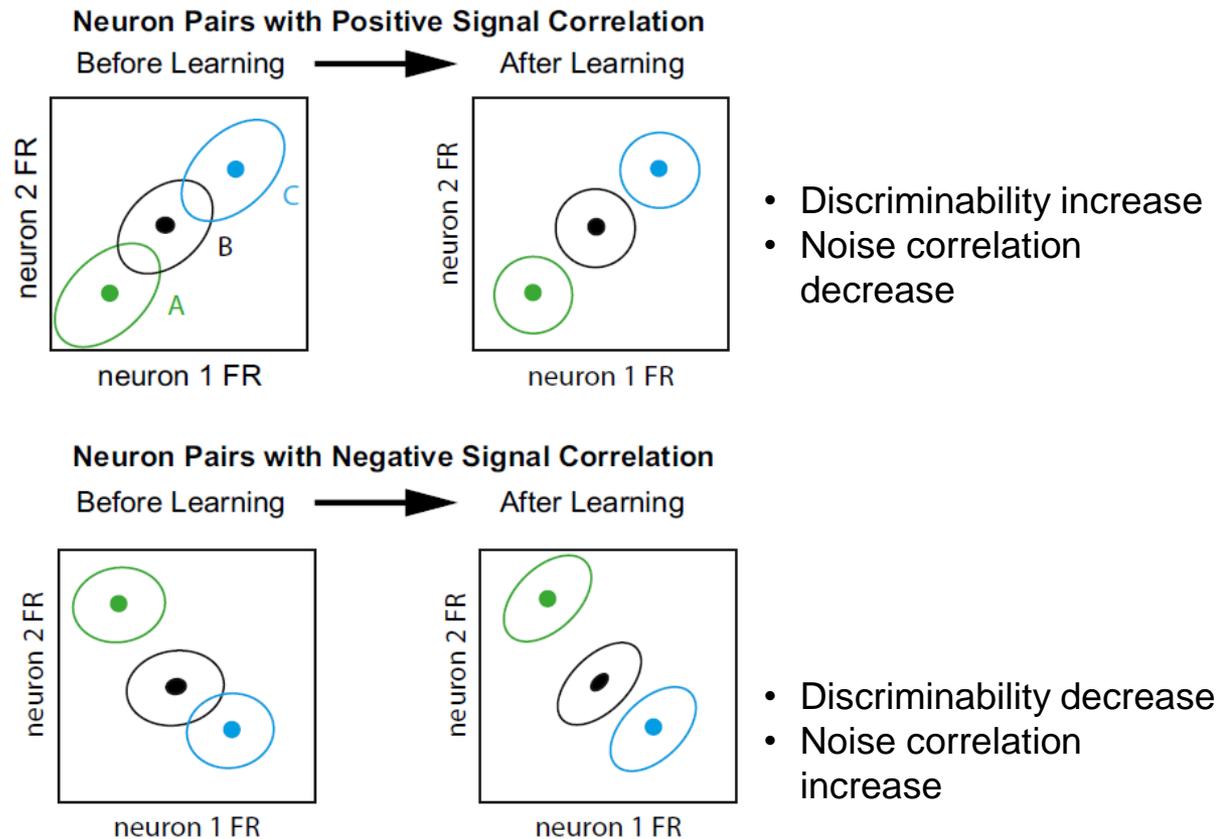
Distribution of pair-wise noise correlations



Mendels and Shamir, 2018

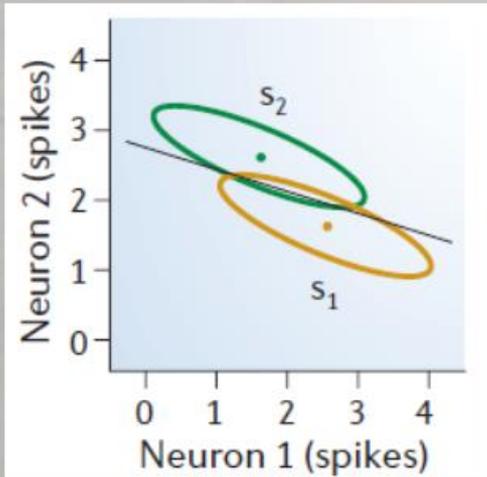
Background

Extracting information from noise correlations in auditory cortex in songbirds

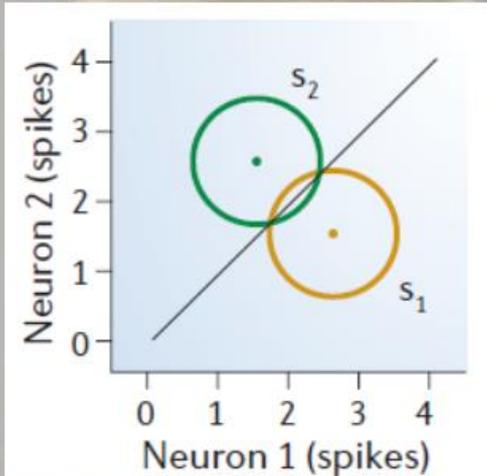


Objective / goal / question

To Correlate...



Or Not To Correlate...



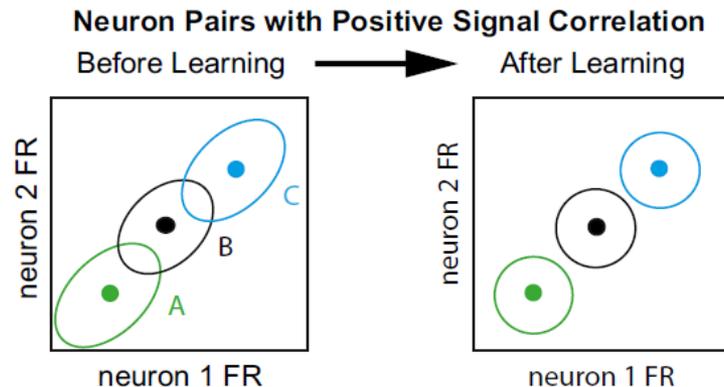
Averbeck, Lathan, &
Pouget, 2006

Objective / goal / question

How do changes in the structure of noise correlation of a neural population affect the efficiency of sensory encoding?

Hypotheses

- Predictions:
 - Subpopulations with more negative noise correlations will have more precise stimulus encoding
 - Fewer neurons needed to reach same level encoding precision (fisher information) [decoding]



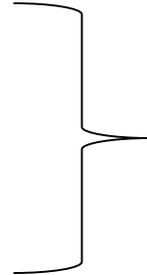
Selected Toolkit: Leaky Integrate and Fire (LIF) Neurons

- Why is this the appropriate toolkit?
 - Biologically plausible spike count generator
 - Ability to modulate sources of noise individually
 - Easy link between tuning & noise

Parameters and variables

- Leaky Integrate and Fire (LIF) Neurons

- $T = .02$ seconds
- $V_{\text{thresh}} = -0.05$ V
- $V_{\text{RMP}} = -0.07$ V
- $V_{\text{AHP}} = -0.08$ V
- ...

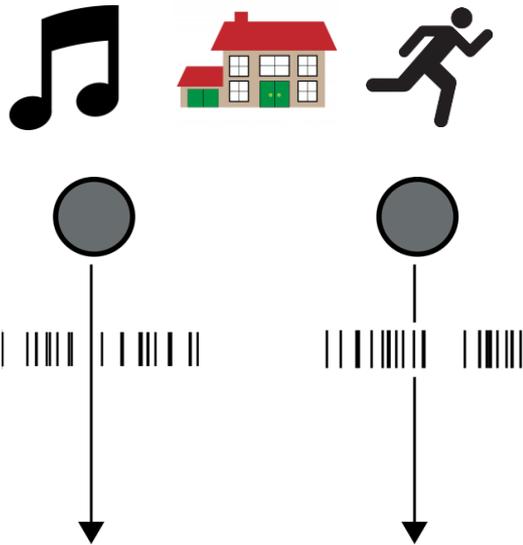


Biophysical Parameters

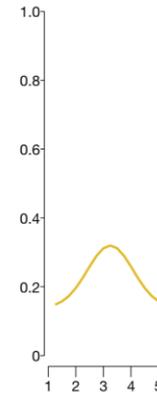
Wang and Wang, 2006

- Two gains for individual noise distributions
- Excitability of neuronal population
- Number of Neurons (250 -1000)
- Number of Stimuli (17)

Model schematic / equations

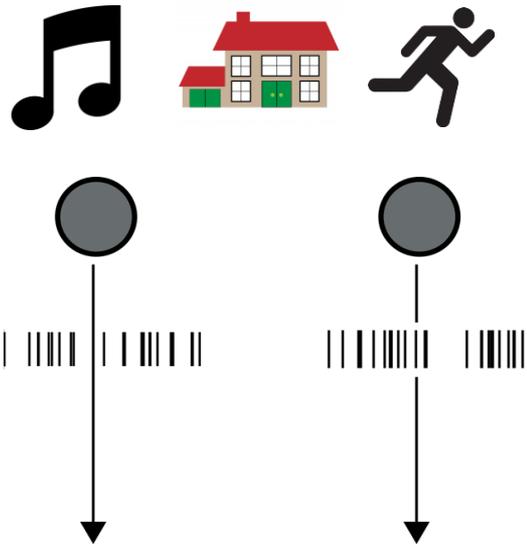


$$f_{tun}(s) = a * \exp\left(-\frac{(s - \mu)^2}{b}\right) + c$$



● Sensory Input

Model schematic / equations



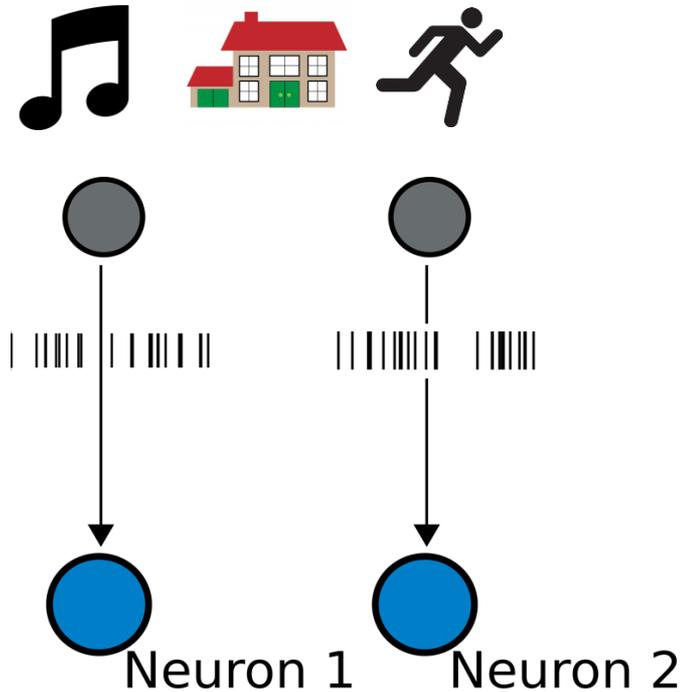
$$f_{tun}(s) = a * \exp\left(-\frac{(s - \mu)^2}{b}\right) + c$$

$$p(k|s) = \frac{(g_{fr} * f_{tun}(s))^k * \exp(-g_{fr} * f_{tun}(s))}{k!}$$

$$S(t) = \sum_k \delta(t - \tau_j^k)$$

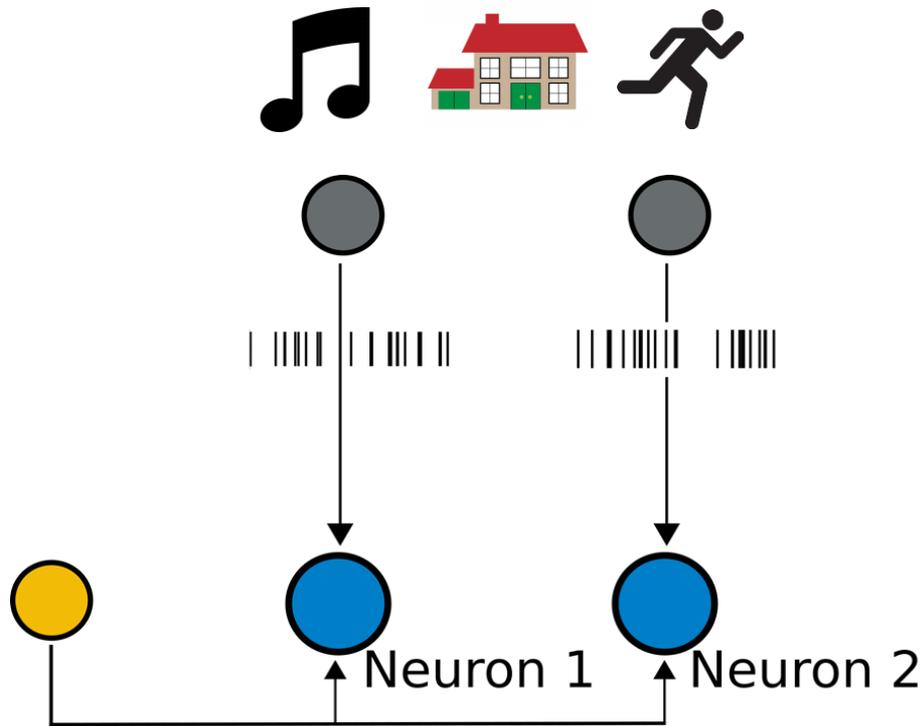
● Sensory Input

Model schematic / equations



- Sensory Input
- Output Neurons

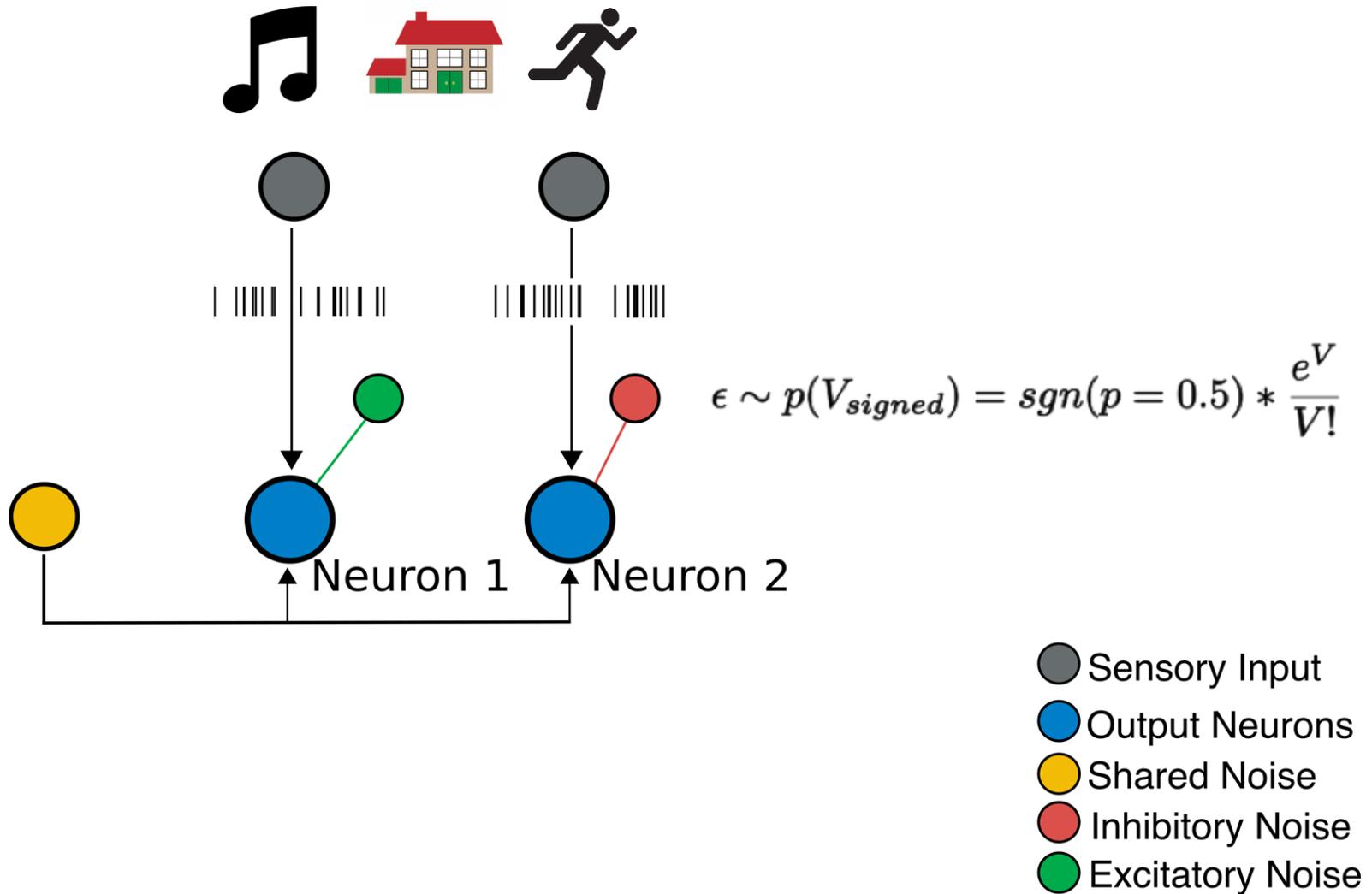
Model schematic / equations



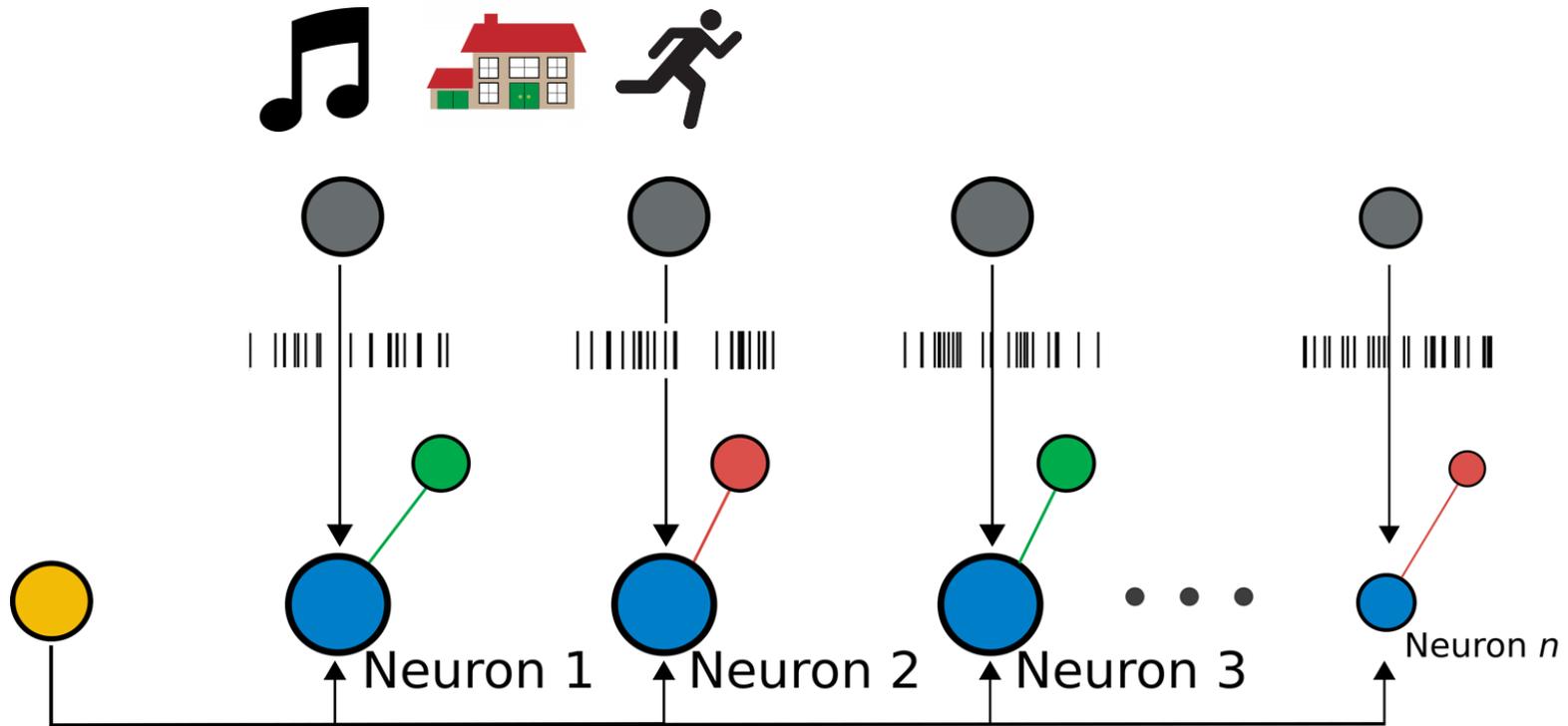
$$\eta \sim p(V_{shared}) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\eta^2}{2\pi}\right)$$

- Sensory Input
- Output Neurons
- Shared Noise

Model schematic / equations



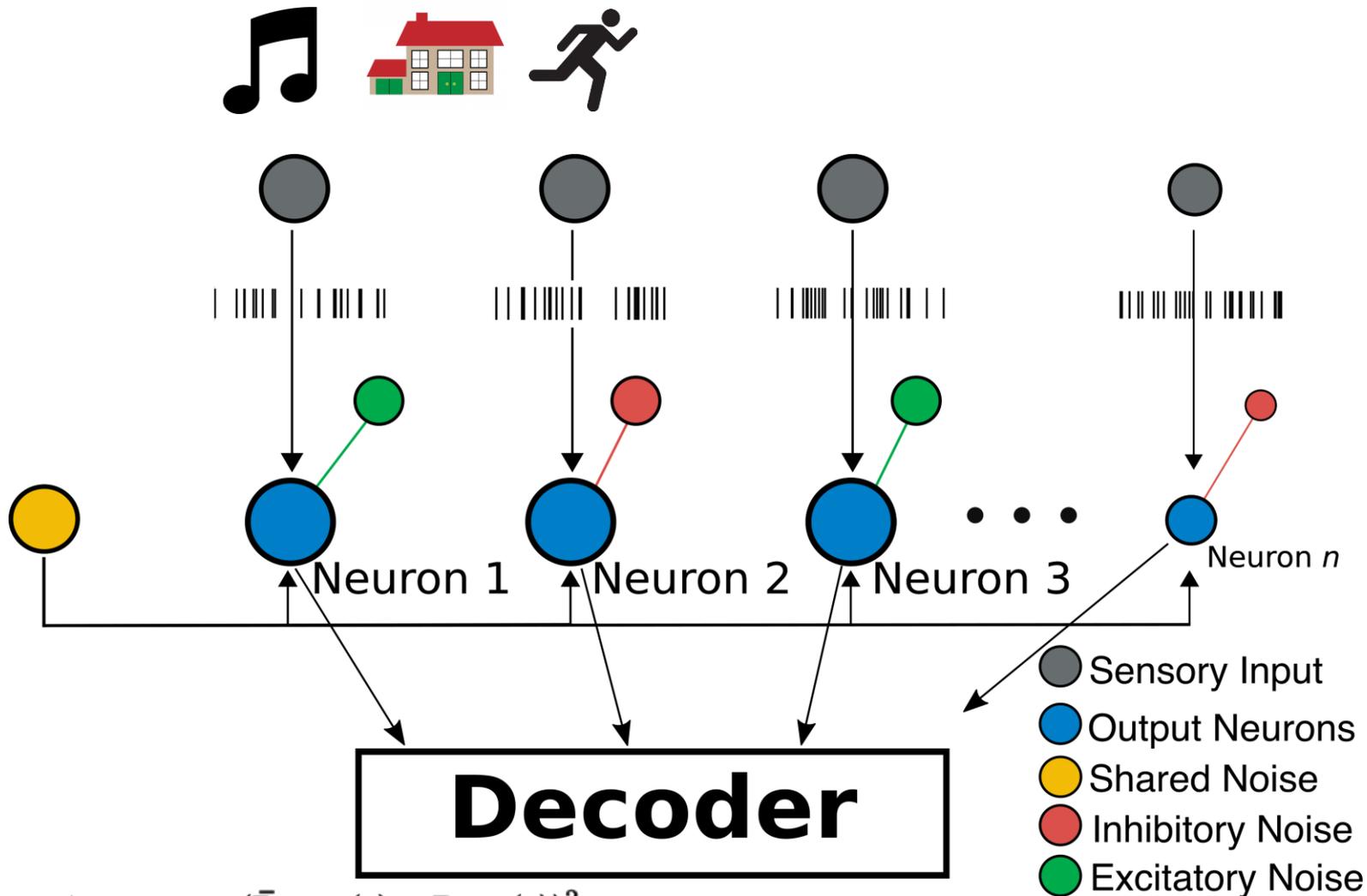
Model schematic / equations



$$C \frac{dV}{dt} = -g_{leak}(V(t) - V_{rmp}) - g_{epsc}(V(t) - V_{rmp})S(t) + g_{shared}\eta + g_{signed}\epsilon$$

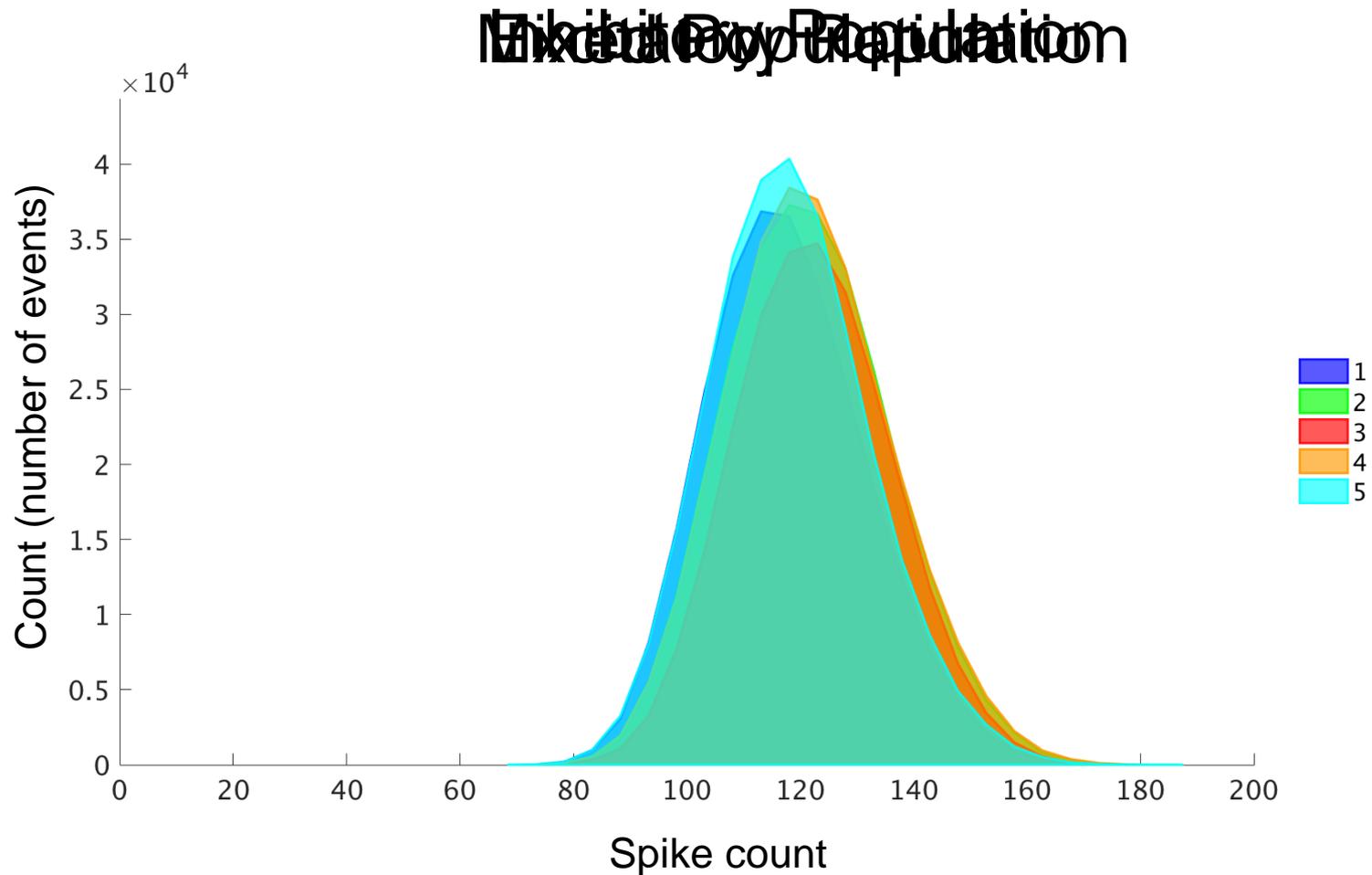
- Sensory Input
- Output Neurons
- Shared Noise
- Inhibitory Noise
- Excitatory Noise

Model schematic / equations

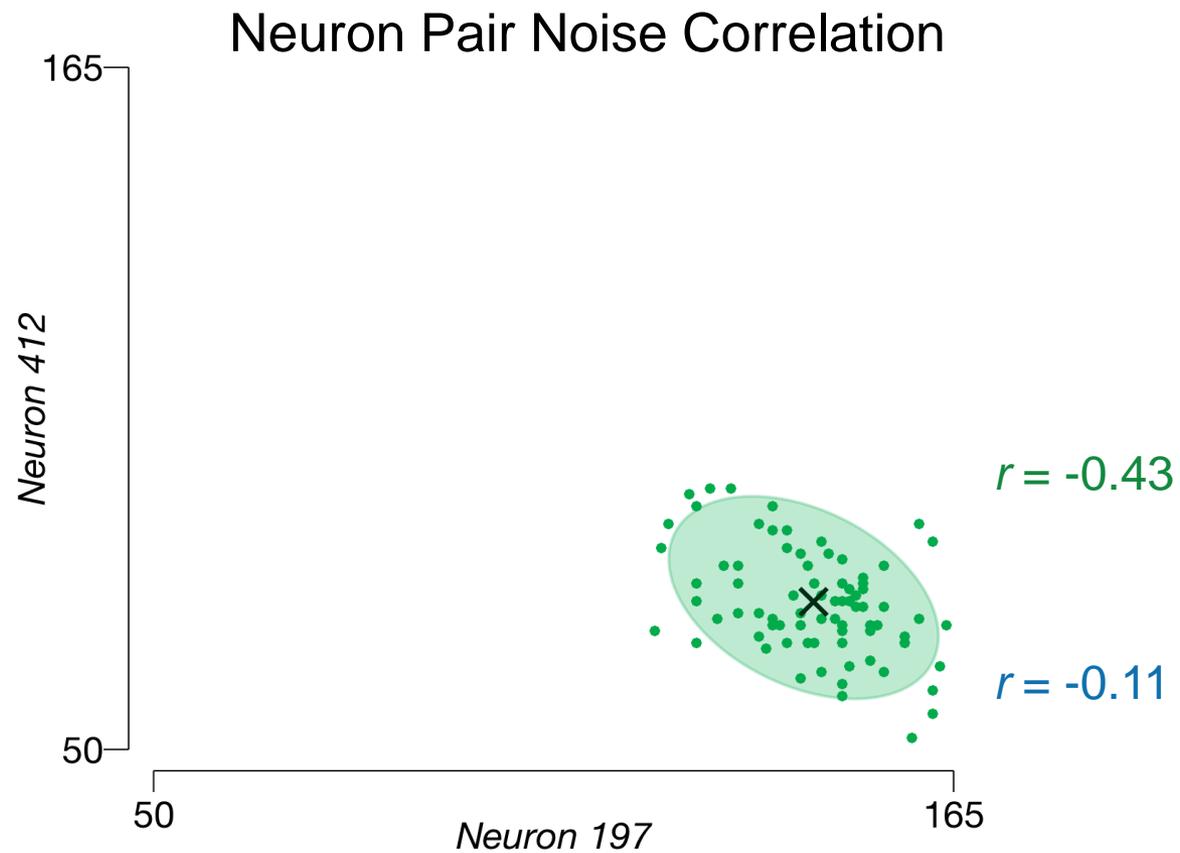


$$\hat{s} = \arg \min_s (\bar{\mathbf{R}}_{train}(s) - \mathbf{R}_{test}(s))^2$$

Model schematic / equations

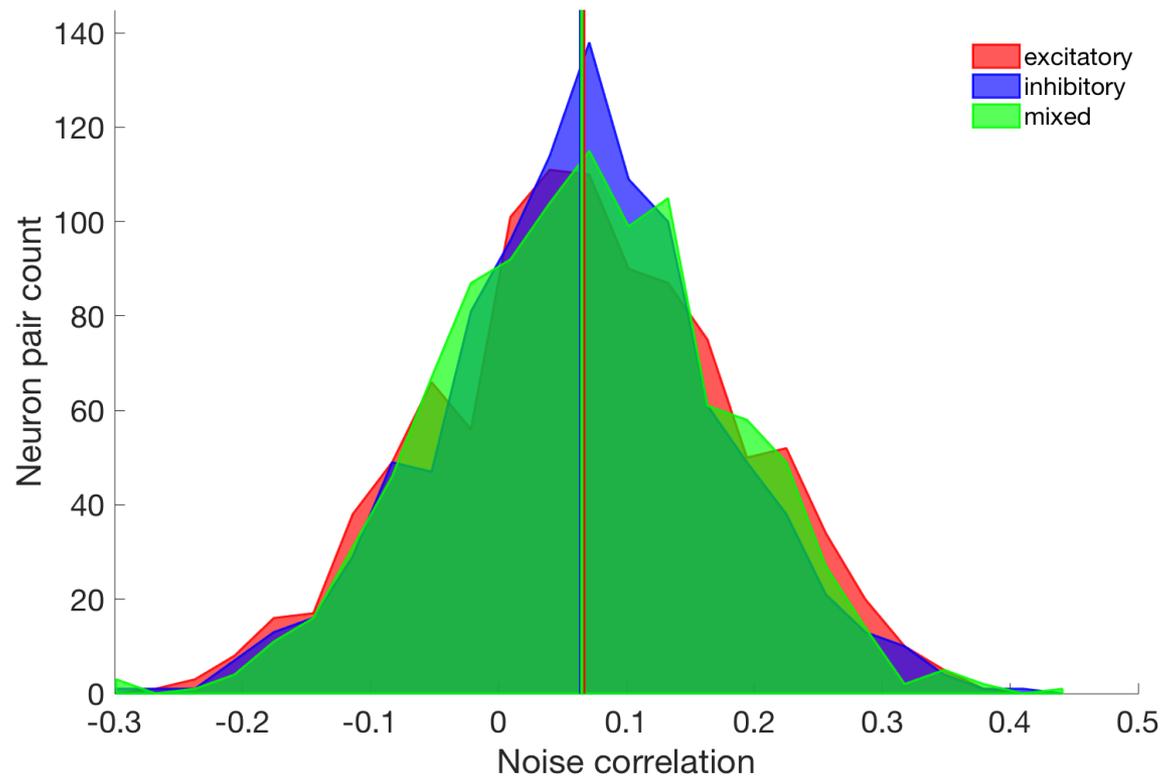


Simulations / results

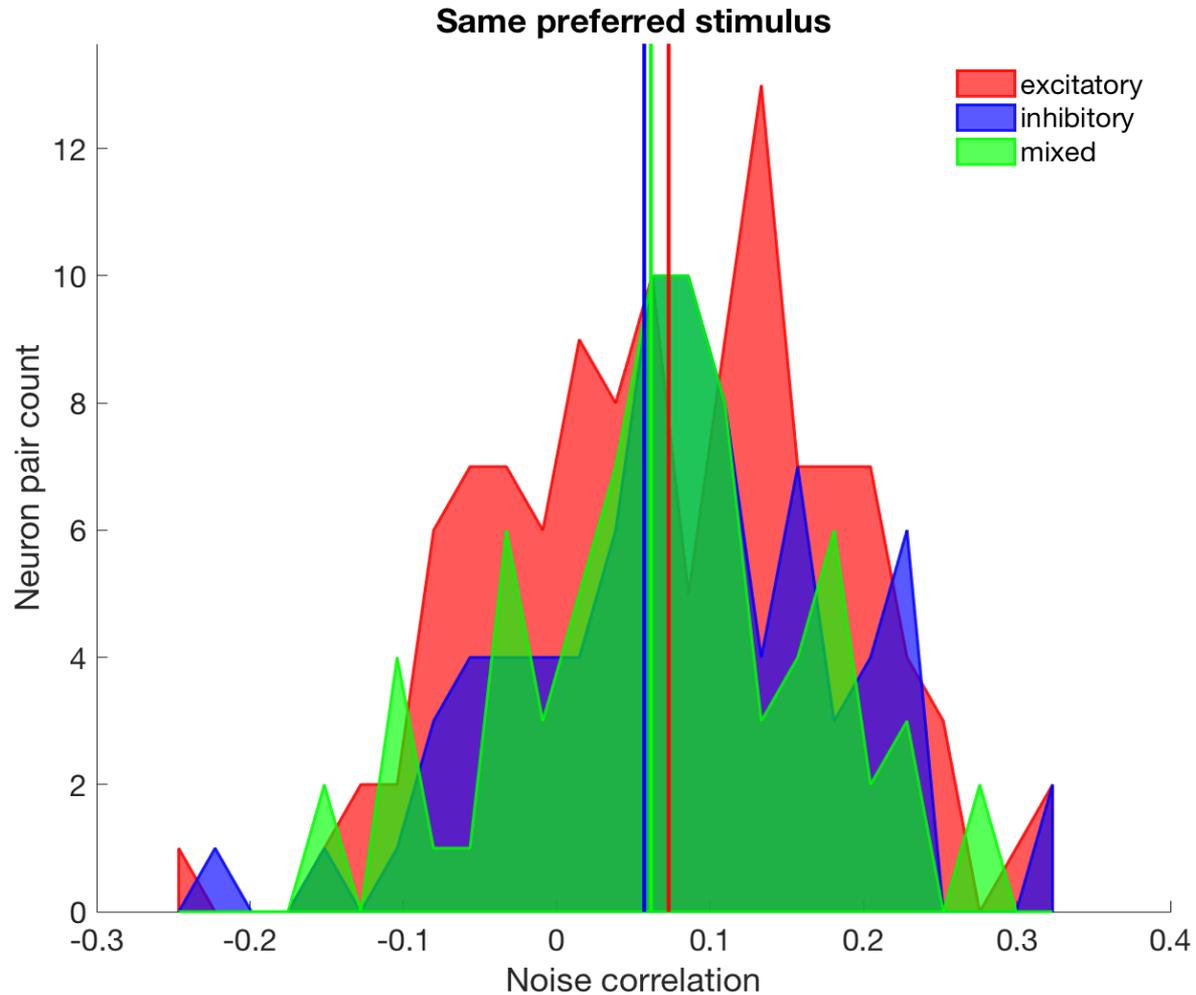


Simulations / results

Neuron Population Noise Correlation

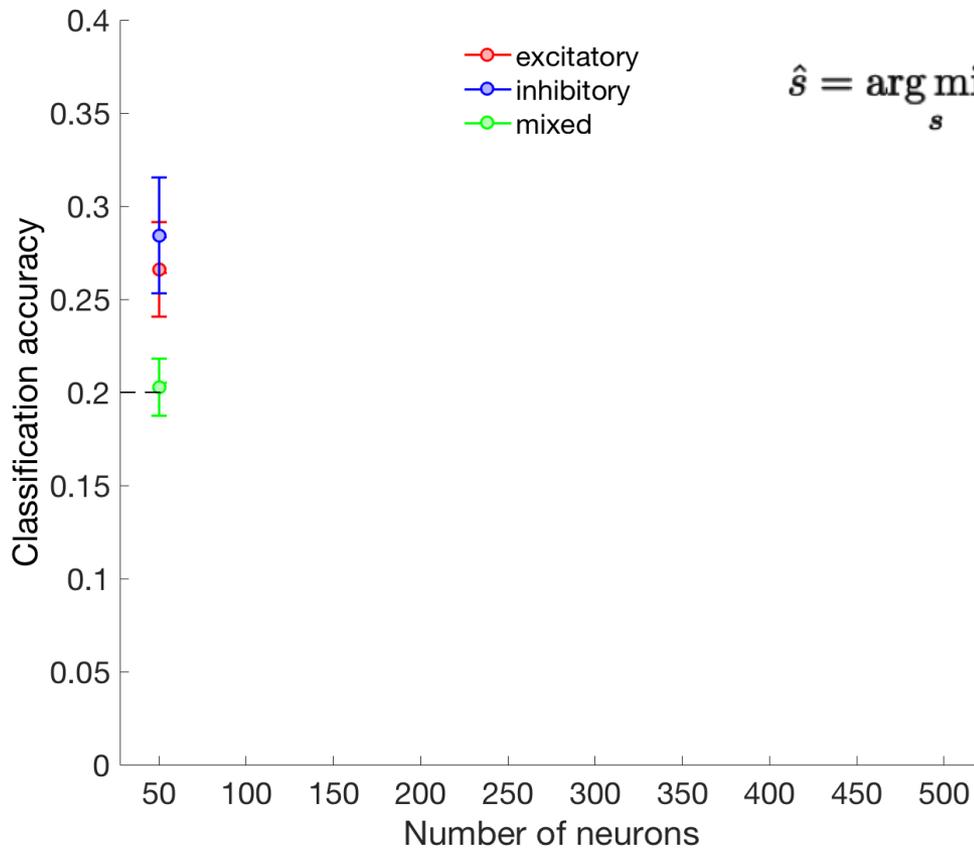


Simulations / results



Model testing re. hypotheses

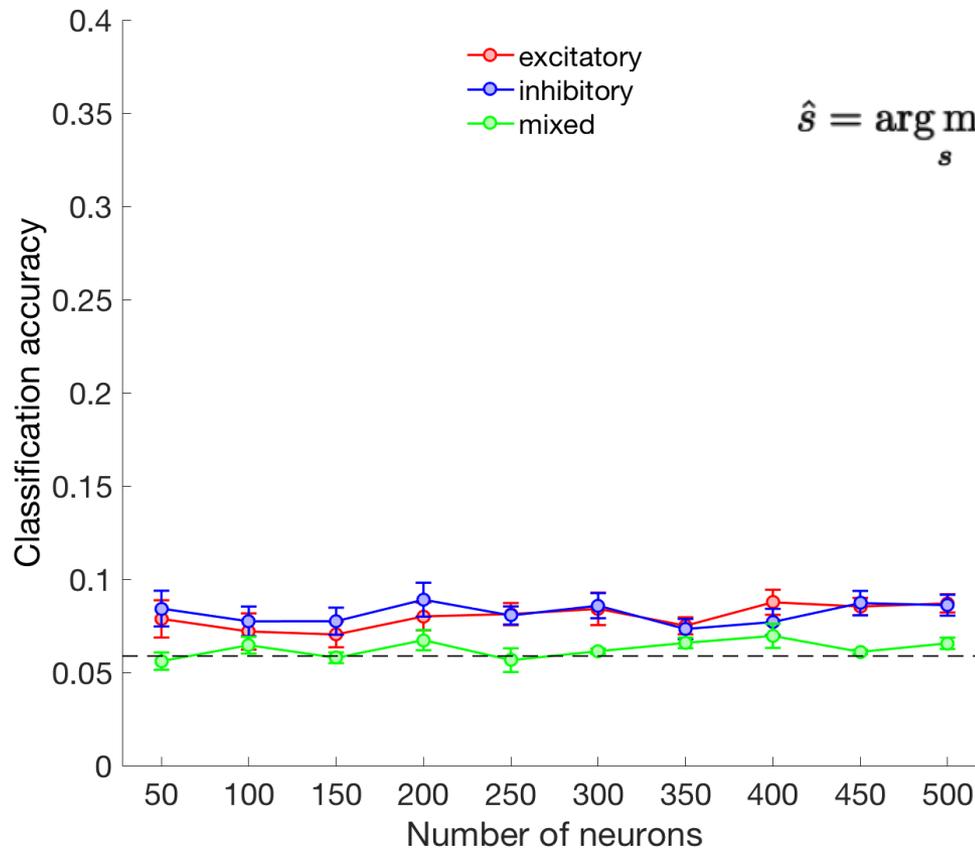
Decoding Accuracy Depending on Population



$$\hat{s} = \arg \min_s (\bar{\mathbf{R}}_{train}(s) - \mathbf{R}_{test}(s))^2$$

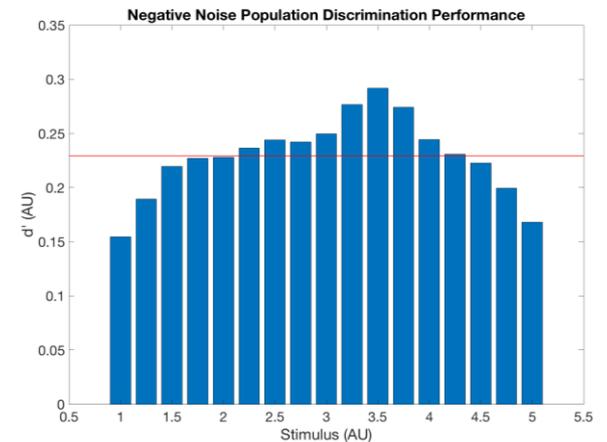
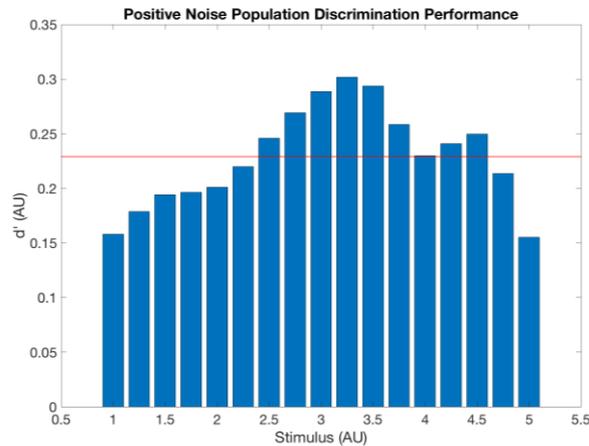
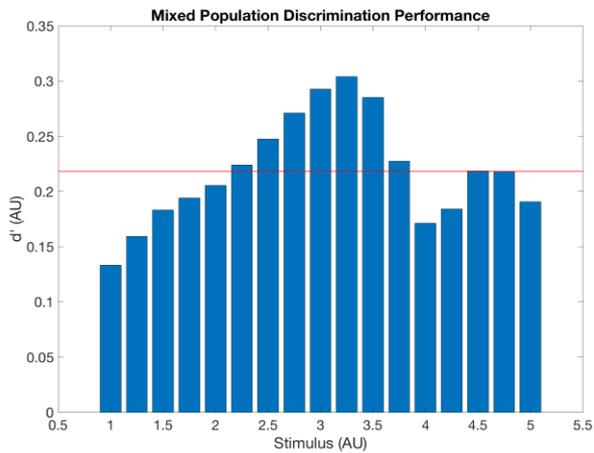
Model testing re. hypotheses

Decoding accuracy Isn't Better in Mixed Population



Model testing re. hypotheses

- Fisher information $\rightarrow d'$



$$d'_{pop}(s) = \Delta s \sqrt{FI(s)}$$

$$Fisher\ Information = FI(s) = \frac{df(s)}{ds} \Sigma(s)^{-1} \frac{df(s)}{ds}$$

Critical model evaluation

- Is this a good model?

Criteria	Our Model
Explains the data?	?
Generalizable?	✓
Provides new insight?	X
Usefulness?	?
Elegance?	✓

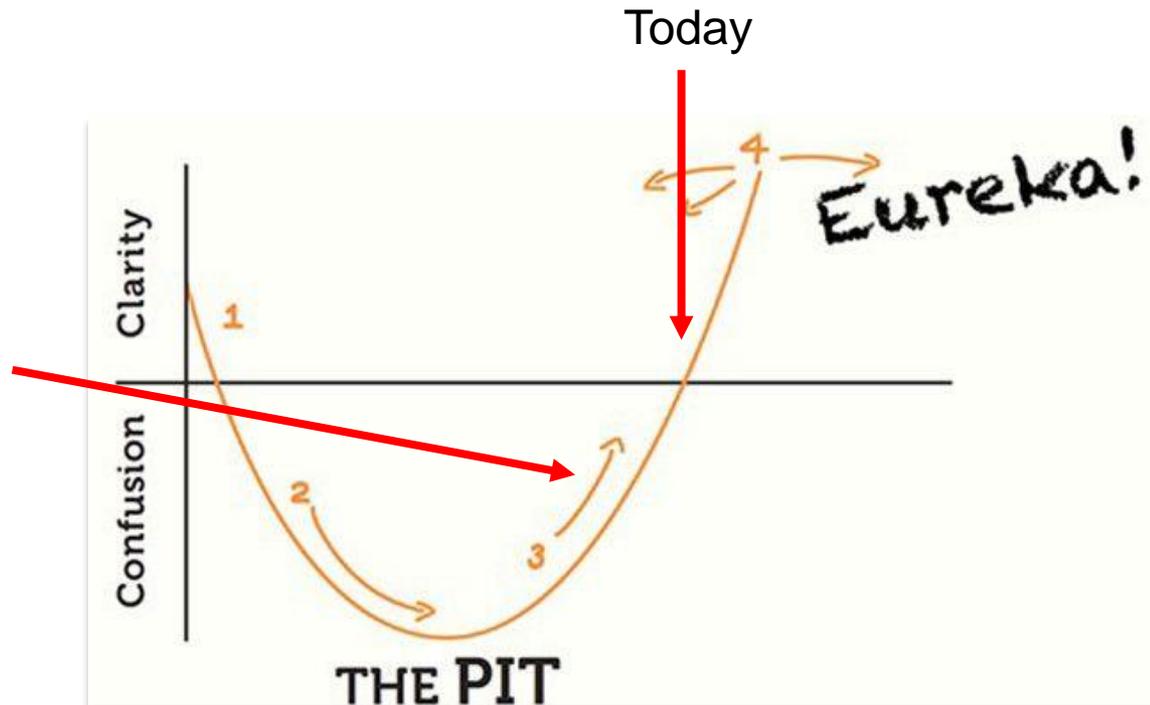


Limitations

- Steep learning curve
 - Unable to inject structured noise in a LIF population
 - No time to systematically vary signal:noise relationship

Last Night

4:23 - we're fucked
4:44 - we've paralleled, maybe not fucked yet
5:35 - oh, we back to ground 0
5:59 - maybe if we get drunk this will be easier?
6:11 - par for (TW)
7:30 - need food and drinks. Hope to sleep tonight



Summary & conclusions

- What have we learned?
 - Initial foray into modeling realistic neural networks
 - The ~~significance~~ ^{difficulty} of noise sources in neural modeling
 - Generating useful correlation structure de novo is challenging
 - Hofstadter's Law: A task always takes longer than you expect, even when you take into account Hofstadter's law

References

- Averbeck, Bruno B., Peter E. Latham, and Alexandre Pouget. “Neural Correlations, Population Coding and Computation.” *Nature Reviews Neuroscience* 7, no. 5 (May 2006): 358–66. <https://doi.org/10.1038/nrn1888>.
- Cohen, Marlene R, and Adam Kohn. “Measuring and Interpreting Neuronal Correlations.” *Nature Neuroscience* 14, no. 7 (July 2011): 811–19. <https://doi.org/10.1038/nn.2842>.
- Mendels, Or P., and Maoz Shamir. “Relating the Structure of Noise Correlations in Macaque Primary Visual Cortex to Decoder Performance.” *Frontiers in Computational Neuroscience* 12 (March 5, 2018). <https://doi.org/10.3389/fncom.2018.00012>.
- Theunissen, Frédéric E., and Julie E. Elie. “Population Code, Noise Correlations, and Memory.” *Neuron* 78, no. 2 (April 2013): 209–10. <https://doi.org/10.1016/j.neuron.2013.04.012>.