Maximum-entropy analysis of multi-neuron firing patterns in primate V1 reveals stimulus-contingent patterns

Ifije E. Ohiorhenuan, Jonathan D. Victor

Department of Neurology and Neuroscience, Weill Medical College, Cornell University, New York

Introduction

The activity of pairs of neurons in V1 are correlated over a few tens of milliseconds. However, the implications of these correlations on the higher-order structure of cortical networks is not known.

In the retina, maximum entropy (MaxEnt) techniques have demonstrated that the structure of multi-neuron firing patterns can be accounted for by interactions between pairs of neurons (Schneidman et al. 2006 and Shlens et al. 2006).

Here, we implement a similar maximum entropy analysis of multi-neuron firing patterns from tetrode recordings in V1 of the anesthetized macaque.

Summary and Conclusions

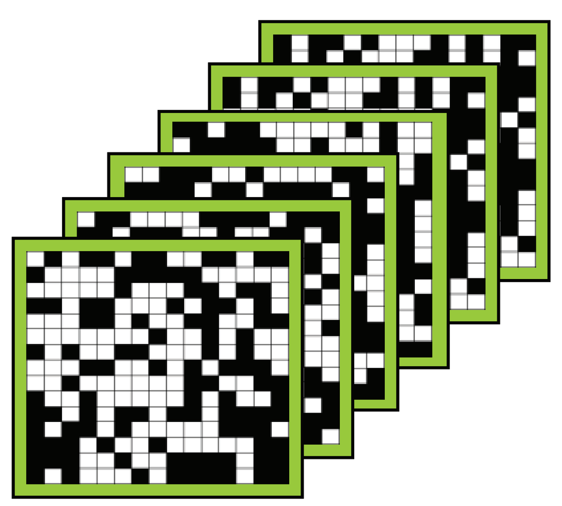
In contrast to the retina, we find that nearly half of the neuronal clusters exhibited significant higher-than-second-order interactions, indicating that cortical circuits can manifest complex patterns of population activity.

To determine whether these findings could be accounted for by stimulus driving, we condition models on informative pixels. For some clusters, higher order interactions are enhanced by specific stimulus configurations.

This suggests that V1 neurons can be flexibly and rapidly organized into stimulus-dependent groups.

References
Schneidman et al., Nature 2006
Schneidman et al., Phys. Rev. Lett. 2003
Shlens et al., J.Neuroscience 2006
Kennel et al., Neural Comp. 2005

Methods

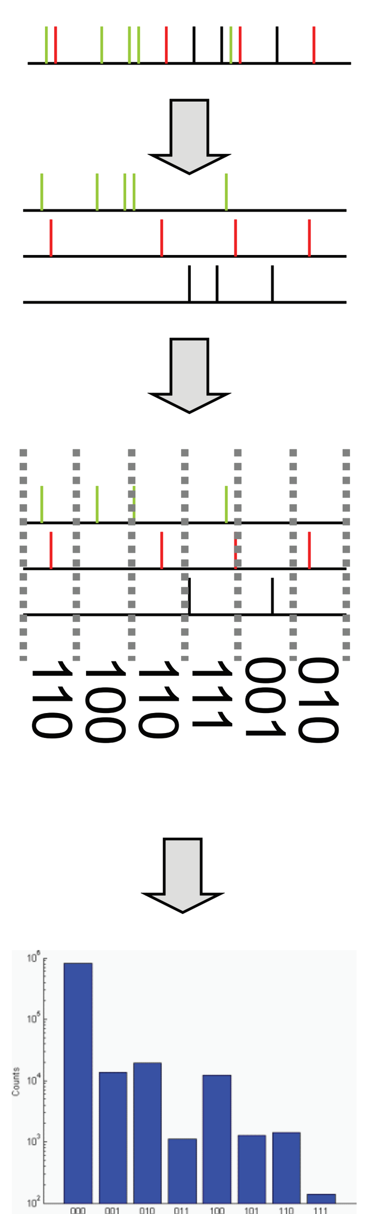


6 macaques under sufentanil/propofol anesthesia and vecuronium paralysis.

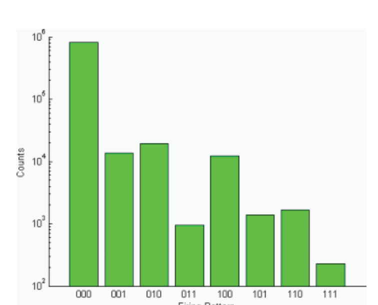
Tetrode recordings of V1 - 19 different sites with 3-5 simultaneously recorded single units. 14 triplets, 3 quadruplets, 2 quintuplets, 64 neurons in total.

Binary m-sequence modulated checkerboard stimulus. 67.6 Hz frame rate. (14.8 ms frame length). 8-16 repeats of 60.6 s stimulus and its contrast inverse (16-32 mins of data).

Spikes are sorted and spike trains binned into 14.8 ms bins.



Spike sorting prevents detection of multiple spike that are within a 1.2 ms lock-out window.
This leads to a systematic underestimate of multi-neuron spiking events within a 14.8 ms bin.
Correction assumes that within a bin all possible assortments of k spikes into n slots are equally likely but only $\binom{n}{k}$ are observable.

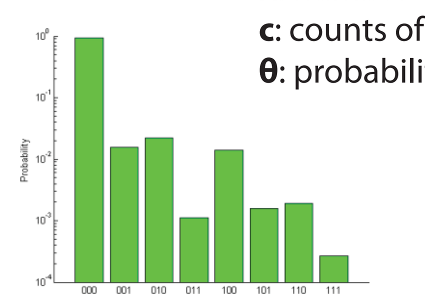


Since a range of probability distributions could have generated the observed firing counts, we use Markov Chain Monte Carlo simulations to sample from the *a posteriori* distribution under different Dirichlet priors (β = 0, 0.5, 1).

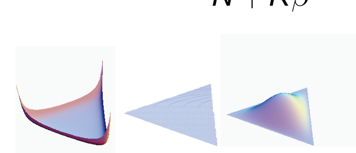
Because the *a posteriori* distributions were not significantly different under the various priors, we present only the analysis from the naive estimate, β = 0.

Sampling from the *a posteriori* distributions generates confidence intervals for model fits.

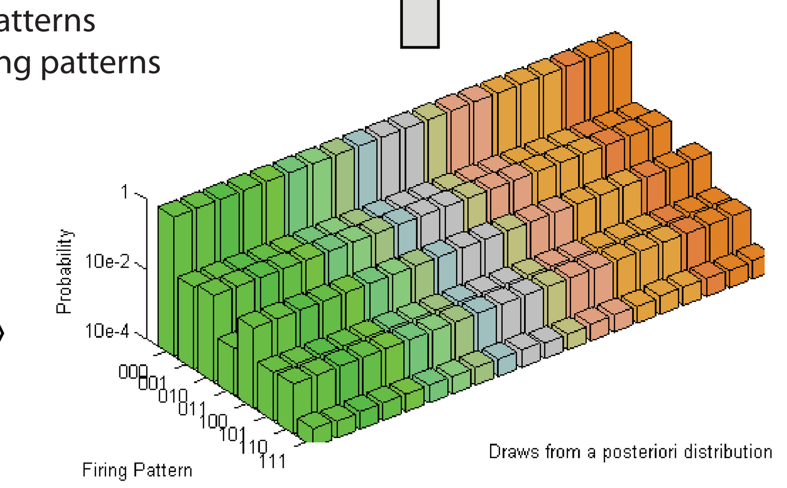
K: number of different firing patterns
c: counts of firing patterns
θ: probability of firing patterns



$$P(\mathbf{c}\,|\,\boldsymbol{\theta}) = \frac{\mathbf{c}+\beta}{N+K\beta}$$

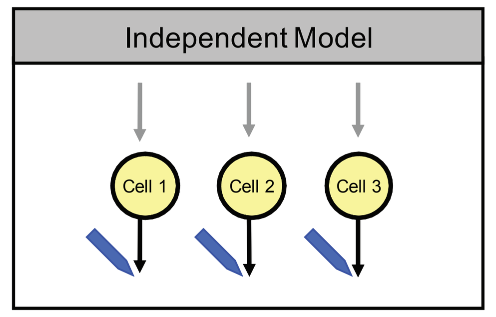


$$P_{Dir}(\boldsymbol{\theta}) \propto \prod p_{\theta}(c_i)^{\beta-1}$$

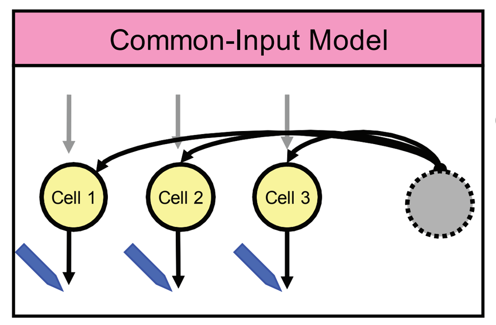


$$P_{bayes}(\boldsymbol{\theta}) = P(\mathbf{c}\,|\,\boldsymbol{\theta})P_{Dir}(\boldsymbol{\theta})$$

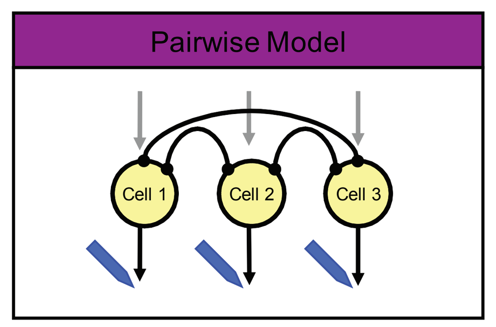
3 models:



Independent Model: Constraints on the mean firing rate of each neuron.



Common-Input Model: Constraints on the rate at which each neuron fires alone and at which it fires in participation with any ensemble.



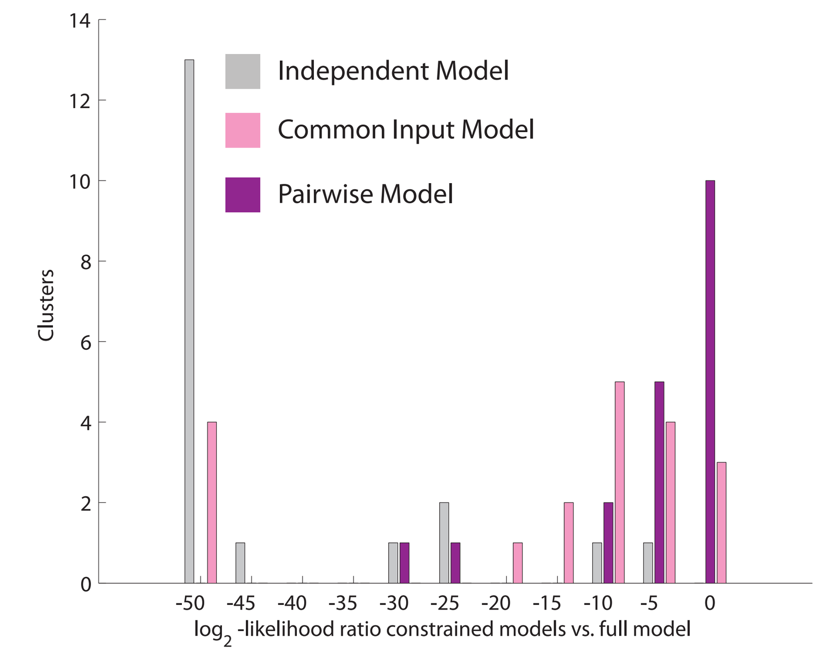
Pairwise-Constrained Model: Constraints on the mean firing rate of each neuron and the frequency of all pairwise firing events.

To fit the models, we seek the joint firing distributions that are consistent with the specified constraints, but are otherwise as unstructured as possible – i.e. that maximize the entropy (*H*) of the distribution.

$$H(P) = -\sum_{i=1}^{K} p(\theta_i)\log_2 p(\theta_i)$$

Support: GM7739 and NEI1TEO7138 (IEO) 2RO1EY9314 (JDV)

Results



Cross validated models: MaxEnt models vs. the Complete Empirical Model (where all possible interactions are accounted for). After 1 minute of data, the Pairwise Model is effectively indistinguishable from the full model for 11 of 19 sites.

To evaluate the models we compare the likelihood of generating the data under the different models. We calculate the log-likelihood ratios between models (perfect fit = 0). These can be computed from firing pattern probability distributions, via the K-L distance.

K-L distance

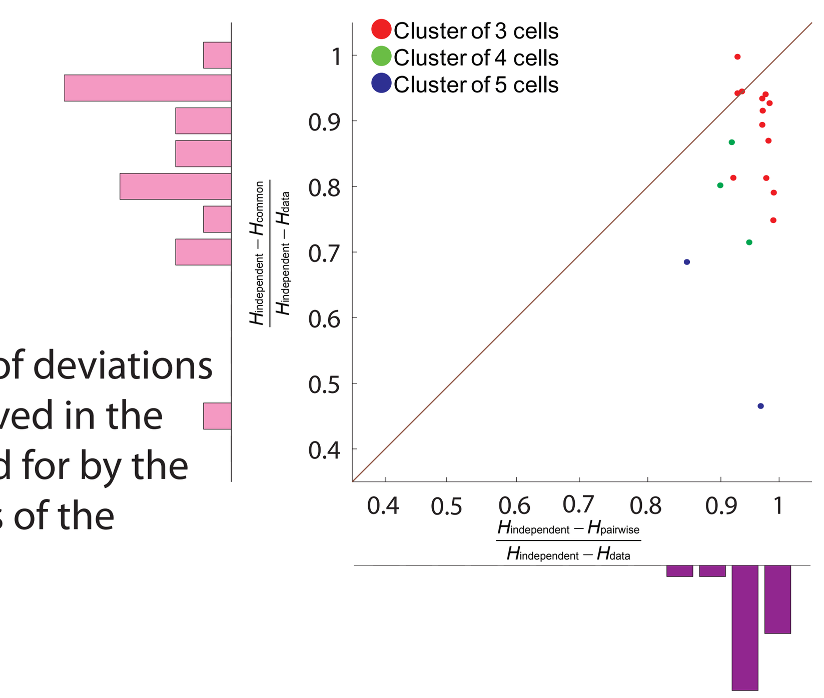
$$D_{KL}(P\,||\,Q) = \sum p_i \log_2\left(\frac{p_i}{q_i}\right)$$

Likelihood ratio

$$LR = 2^{-n\Delta\tau^{-1}\left(D_{KL}(P||Q_{Model\,2}) - D_{KL}(P||Q_{Model\,1})\right)}$$

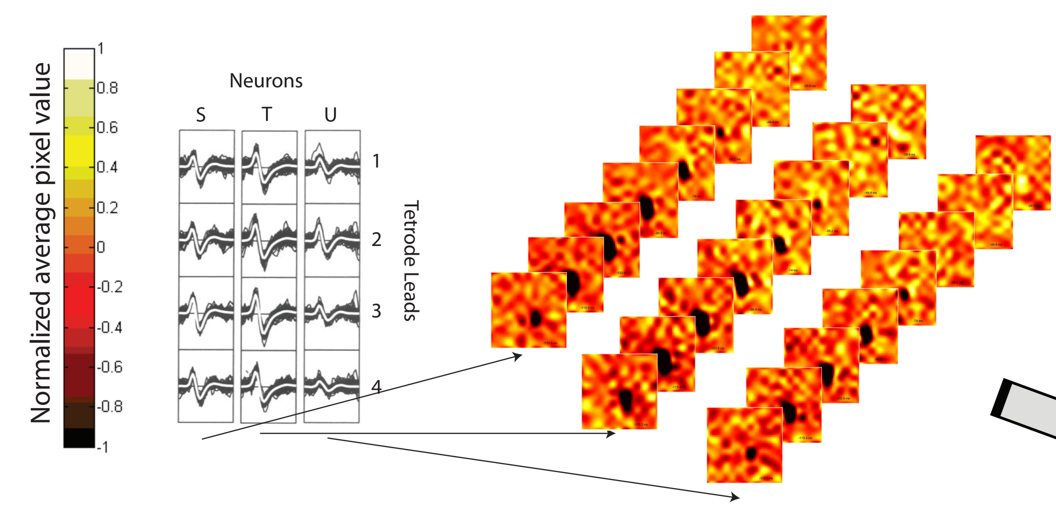
To determine the fraction of deviations from independence observed in the data that can be accounted for by the models, we calculate ratios of the connected information.

$$\frac{I_{model}}{I_{data}} = \frac{H_{independent} - H_{model}}{H_{independent} - H_{data}}$$



For the majority of clusters, both the Pairwise Model and Common-Input Model capture most of the higher order correlations observed in the data. However, the Pairwise Model (mean=0.95) captures a larger fraction of the correlations than the Common-Input Model (mean=0.85)

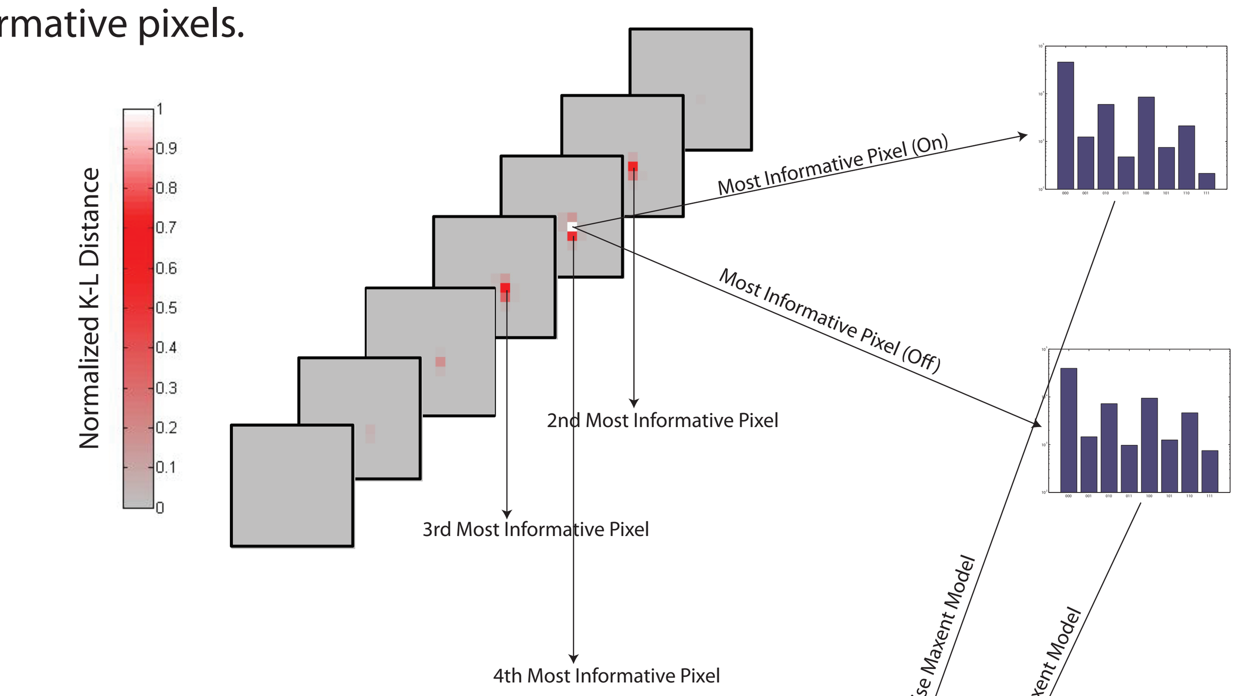
Analyzing the influence of stimulus driving

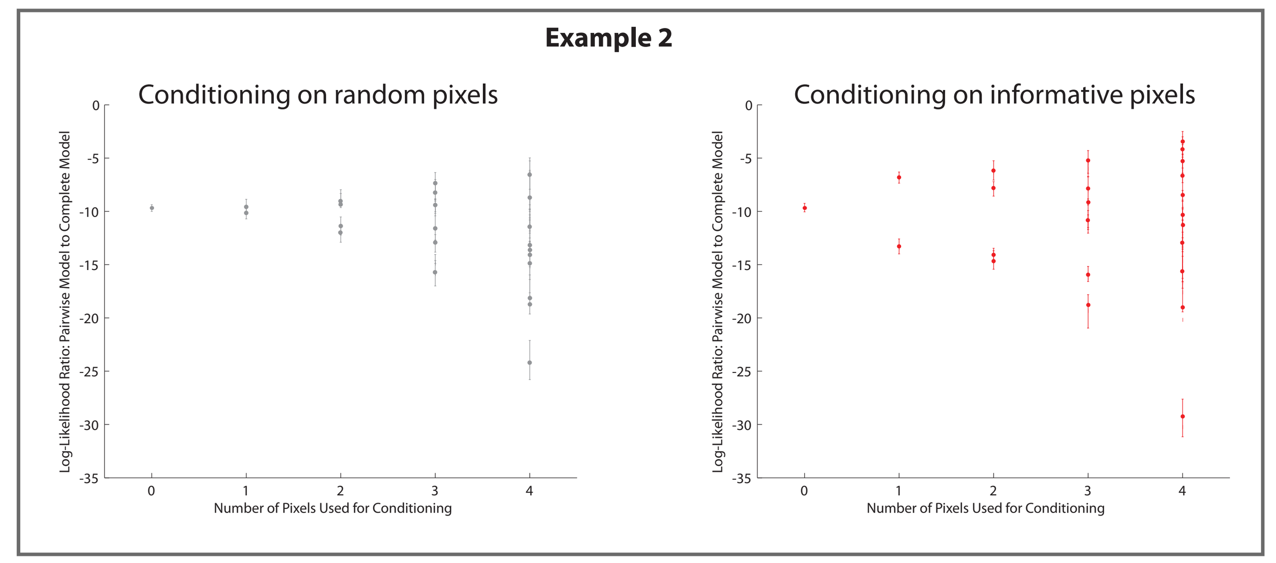


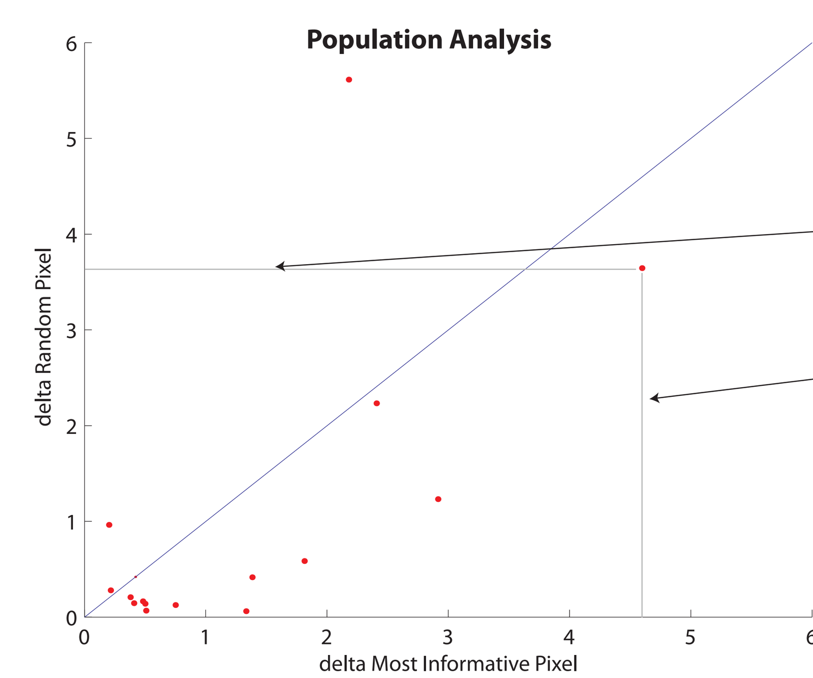
Spike triggered averaging: Clusters of neurons, simultaneously recorded from a tetrode, often have similar receptive fields.

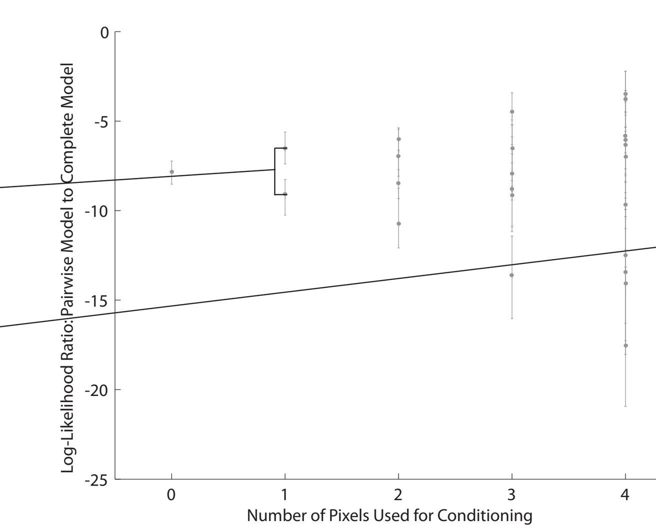
To determine which pixels most strongly modulated the response of neural clusters, we calculated the K-L distance between stimulus-triggered population responses to each of the stimulus conditions (On/Off) for each pixel, at each lag.

Since each conditional pixel divides the data in half, we restrict the analysis to the four most informative pixels.

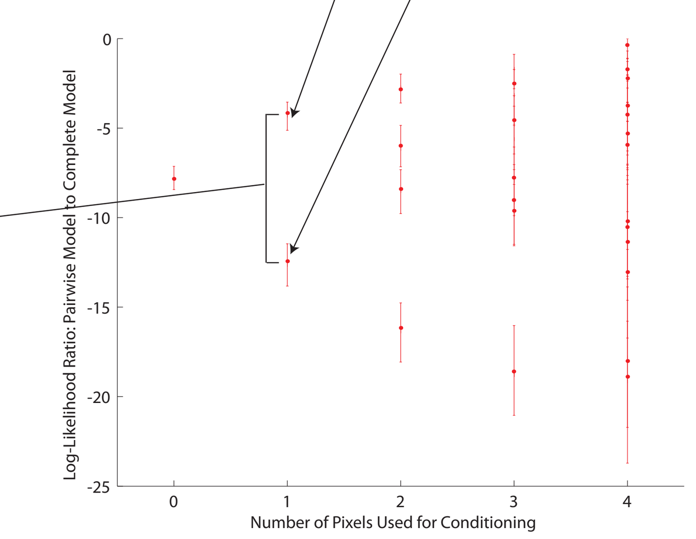








Control: Conditioning on random pixels



Conditioning on informative pixels reveals two regimes of behavior: For some pixel states the Pairwise Model is sufficient, but for others, higher order correlations persist.