A simple two parameter distribution for modelling neuronal activity and capturing neuronal association

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Abstract

Recent developments in electrophysiological technology have lead to an increase in the size of electrophysiological datasets. Consequently, there is a requirement for new analysis techniques that can make use of these new datasets, while remaining easy to use in practice. In this work, we fit the Conway-Maxwell-binomial distribution to spiking data read from a mouse exposed to visual stimuli.

1 Introduction

Motivate by pointing out how much computational power it can require to calculate nth order correlations.

Point out that we don't necessarily need to measure correlations anyway.

2 Results

3 Discussion

4 Data

Details from data cortex lab here.

4.1 Experimental protocol

5 Methods

Details about all kinds of things here.

5.1 Binning data

We converted the spike times for each cell into spike counts by putting the spike times into time bins of a given 'width' (in seconds). We used time bins of 1ms, 5ms, and 10ms. We used different time bin widths to assess the impact of choosing a bin width.

5.2 Number of *active* neurons

To count the number of active neurons in each neuronal ensemble, we split the time interval for each trial into bins of a given width. We counted the number of spikes fired by each cell in each bin. If a cell fired *at least* one spike in a given bin, we regarded that cell as active in that bin. We recorded the number of active cells in every bin, and we recorded each cell's individual spike counts.

It should be noted that when we used a bin width of 1ms, the maximum number of spikes in any bin was 1. For the wider time bins, some bins had spike counts greater than 1. Consequently when using a bin width of 1ms, the number of active neurons and the total spike count of a given bin were identical. But for wider bin widths, the total spike count was greater than the number of active neurons.

So for the 1ms bin width, the activity of a neuron and the number of spikes fired by that neuron in any bin can be modelled as a Bernoulli variable. But for wider time

bins, only the activity can be modelled in this way.

5.3 Moving windows for measurements

When taking measurements (e.g. moving average over the number of active neurons) or fitting distributions (eg. the beta binomial distribution) we slid a window containing a certain number of bins across the data, and made our measurements at each window position. For example, when analysing 1ms bin data, we used a window containing 100 bins, and we slid the window across the time interval for each trial moving 10 bins at a time. So that for 2560ms of data, we made 246 measurements.

For the 5ms bin width data, we used windows containing 40 bins, and slid the window 2 bins at a time when taking measurements.

For the 10ms bin width data, we used windows containing 40 bins, and slid the window 1 bin at a time when taking measurements.

By continuing to use windows containing 40 bins, we retained statistical power but sacrificed the number of measurements taken.

5.4 Fano factor

5.5 Probability Distributions suitable for modelling ensemble activty

5.5.1 Binomial distribution

5.5.2 Beta-binomial distribution

5.5.3 Conway-Maxwell-binomial distribution

5.6 Goodness-of-fit

5.7 Spike count correlations

6 Discussion

Point out that the Conway-Maxwell-binomial distribution could be used to measure activity and association without having to sort the voltage traces into spikes. That

does defeat the purpose slightly, however.

References

[1] Patricia M. E. Altham, *Two Generalizations of the Binomial Distribution*. Journal of the Royal Statistical Society 27, 162-167, (1978)

[2] Mark M Churchland, Byron M Yu, John P Cunningham, Leo P Sugrue, Marlene R Cohen, Greg S Corrado, William T Newsome, Andrew M Clark, Paymon Hosseini, Benjamin B Scott, David C Bradley, Matthew A Smith, Adam Kohn, J Anthony Movshon, Katherine M Armstrong, Tirin Moore, Steve W Chang, Lawrence H Snyder, Stephen G Lisberger, Nicholas J Priebe, Ian M Finn, David Ferster, Stephen I Ryu, Gopal Santhanam, Maneesh Sahani, Krishna V Shenoy, *Stimulus onset quenches neural variability: A widespread cortical phenomenon.* Nature Neuroscience 13, 369-378, (2010)

[3] Fraser Daly, Robert E. Gaunt, *The Conway-Maxwell-Poisson distribution: Distributional theory and approximation.* ALEA 13, 635-658, (2016)

[4] Joseph B. Kadane, *Sums of Possibly Associated Bernoulli Variables: The Conway–Maxwell-Binomial Distribution.* Bayesian Analysis 11, 403-420, (2016)

[5] Joseph B. Kadane, Galit Shmueli, Thomas P. Minka, Sharad Borle, Peter Boatwright, *Conjugate Analysis of the Conway-Maxwell-Poisson Distribution.* Bayesian Analysis 1, (2006)

[6] R. L. Prentice, *Binary Regression Using an Extended Beta-Binomial Distribution, With Discussion of Correlation Induced by Covariate Measurement Errors.* Journal of American Statistical Association 81, 321-327, (1986)

[7] Galit Shmueli, Thomas P. Minka, Joseph B. Kadane, Sharad Borle, Peter Boatwright, *A useful distribution for fitting discrete data: revival of the Conway–Maxwell–Poisson distribution.* Applied Statistics 54, 127-142, (2005)

[8] Joseph S. Verducci, Michael E. Mack, Morris H. DeGroot, *Estimating multiple rater agreement for a rare diagnosis.* Journal of Multivariate Analysis 27, 512-535, (1988)