# Computational Neuroscience
# -COMS30127-
## Lab M: Analysis of hippocampal data

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# Outline

The software developed to analyse the data and visualise it graphically can be found in the single program file called "**neuroDecode.py**". It involves some preprocessing of the data read from the input files which need to be put in a sub-folder "**data/**". The positions of each spike of every neuron are inferred by linearly interpolating between the two surrounding time-stamped positions based on the spike time. Firing-rate histograms are plotted by splitting up he experimental period into 1-second spike-trains and measuring their rates. The autocorrelograms and crosscorrelograms are symmetric and thresholded at 2 seconds but all the code is written in a general way such that all the scales used throughout can be set differently. The 2D positional firing-rate histogram discretises space across $x$ and $y$ at step $\delta_{xy} = 10$ $[cm]$ but this, again, can be set to anything in the code.

The special form of analysis performed on this data in section 6 uses the metric-space mutual information estimator introduced in Houghton [2] with one of the two metrics from [1], which are both implemented. The mutual information is estimated in terms of discrete stimuli, represented by positions falling in one of the space bins, and metric-space responses in the form of 1s spike trains elicited immediately after the position was recorded. Two types of histograms are produced. The original one maps the mutual information between the spike-train set of a neuron and a particular positional stimulus - that is the negative entropy conditioned on the stimulus, given that the total entropy is ignored by the estimator. The total $MI$ between the stimuli and the responses is calculated as well. The second type of histogram is intended to highlight the square regions which strongly influence the firing patterns of a given neuron by plotting only the above-average deviation of the conditioned mutual entropy at those spots.

The aim of this essay was to explore many different ways of measuring and expressing the relationships between spike trains as well as between spike trains and a discrete stimulus. The graphical representation is a good way to abstract the computational process to a human-readable form. But this form gives us only a relative idea of the underlying concept and the raw data used to produce it has a value of its own. This is especially the case with the $MI$ estimates which were produced using an implementation specifically tailored to this experimental data. The produced results give a much richer, but also a more complex picture of the neural process viewed as a function of physical location. The peaks in the last series of histograms indicate a strong relationship between their corresponding specimen positions and the complete structural properties of the subsequent spiking behaviour of its neurons. This is principally different to the overall position-wise firing rates plotted in section 5 and suggests further analysis of the produced numerical results. Additionally the pair-wise mutual information between neurons can be estimated too.

# 1 Firing positions

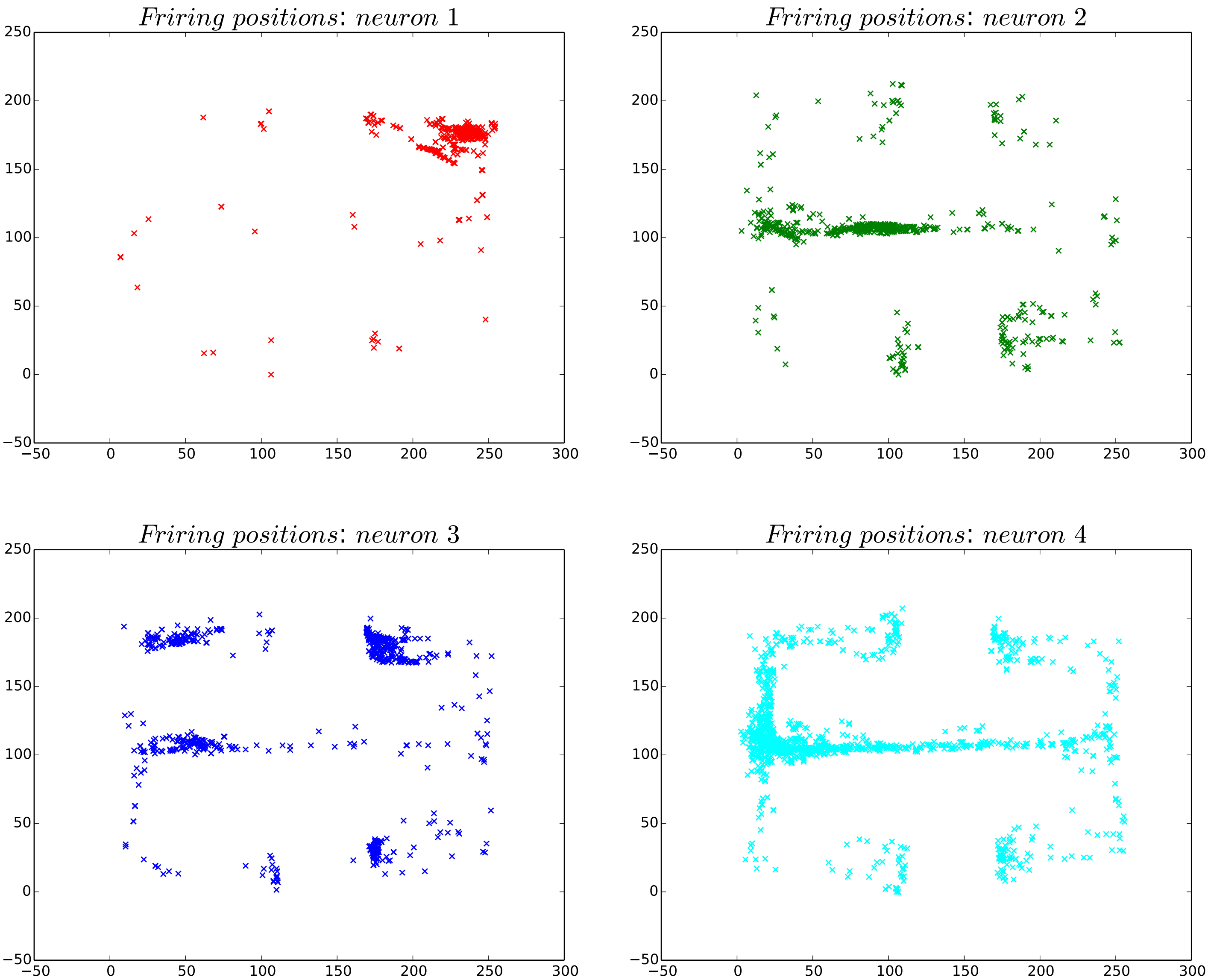


Figure 2: Firing positions of each of the four neurons. The two axis are scaled to the limits of the sampled data but the metrics are kept the same.

# 2 Firing-rate histograms

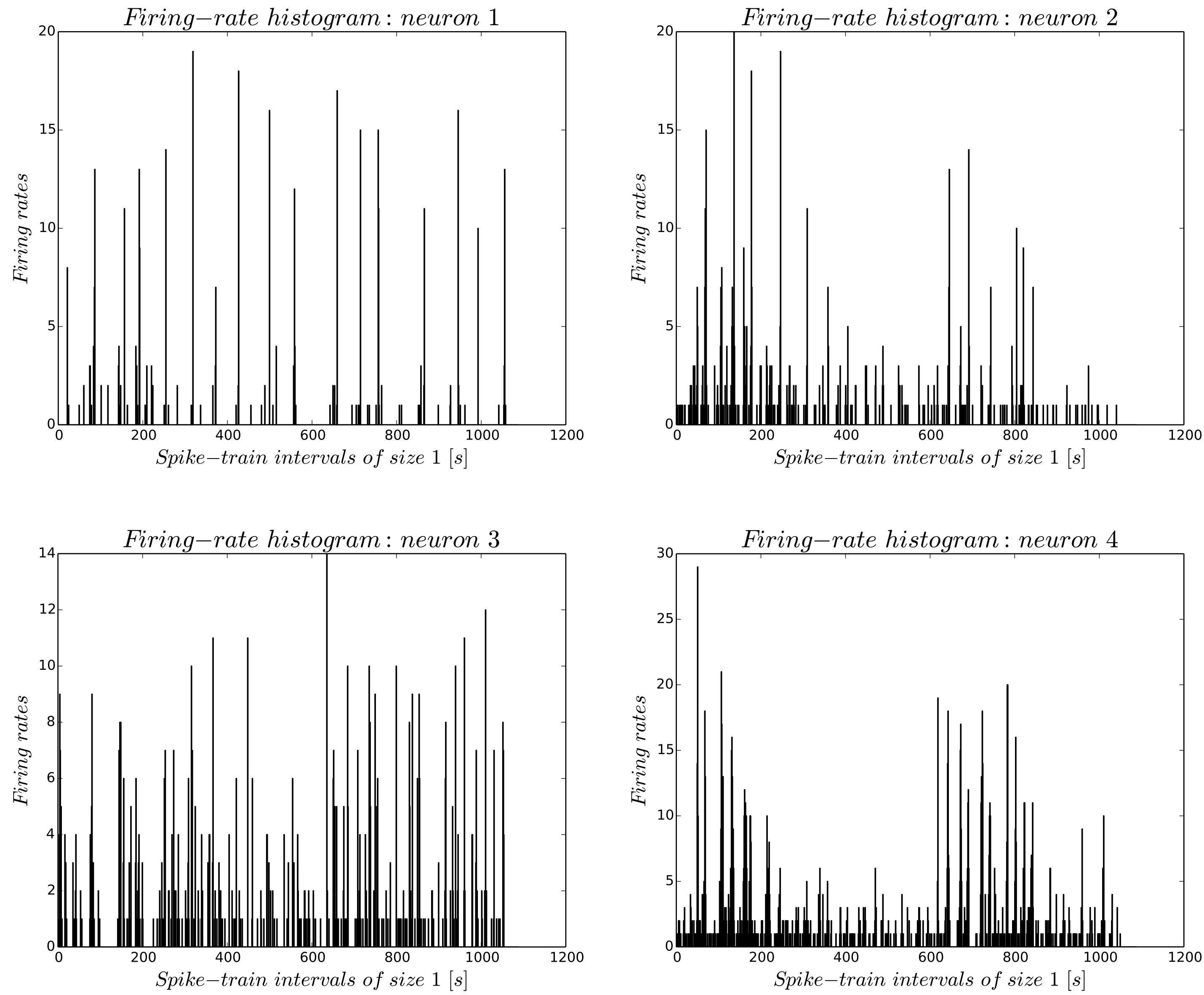


Figure 4: The firing rates in each 1s spike-train interval over the recorded spike-time data period for the four neurons.

# 3 Autocorrelograms

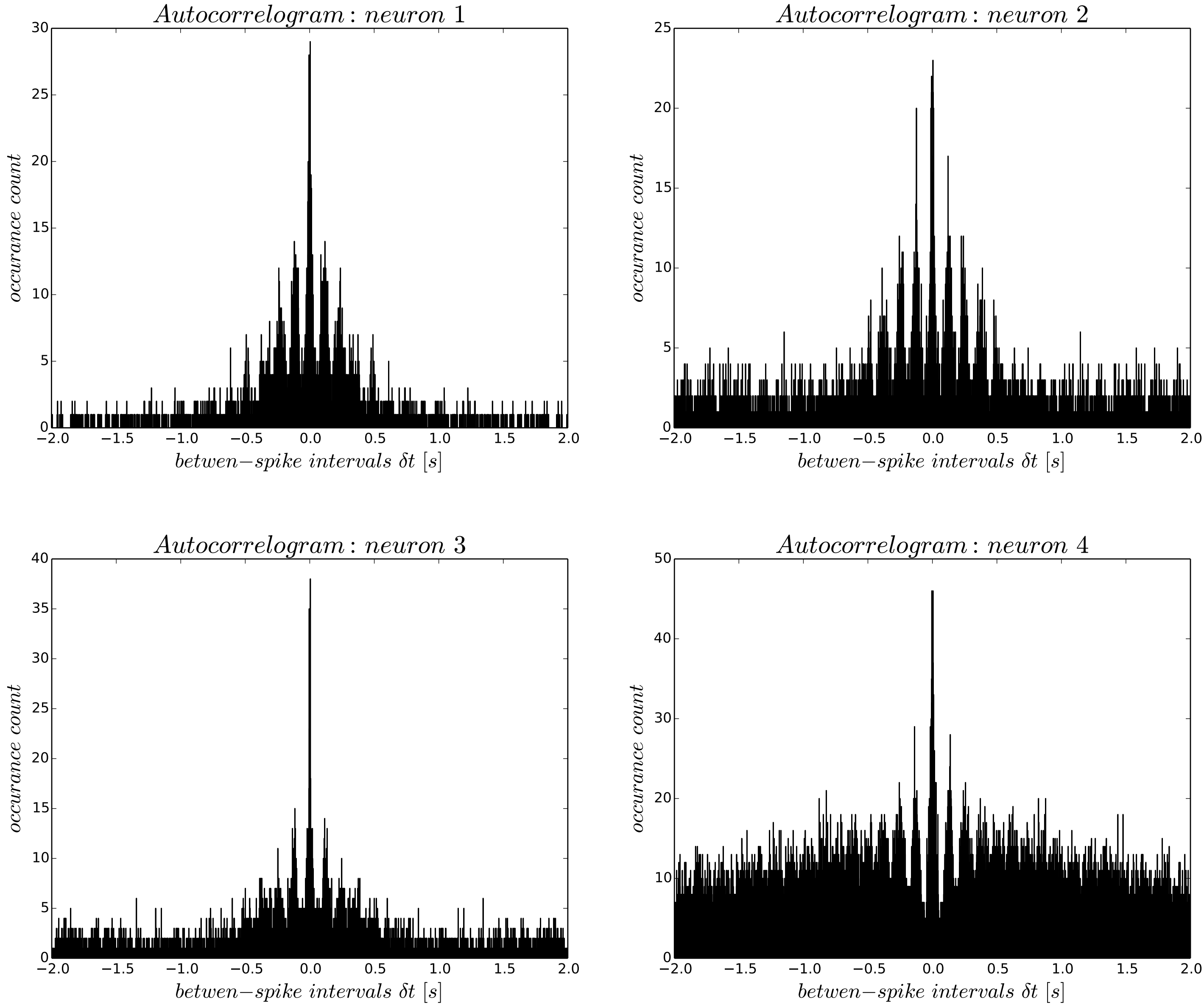


Figure 6: Autocorrelograms of the four neurons' spike-time data thresholded at $\pm 2$ $[s]$.

# 4 Crosscorrelograms

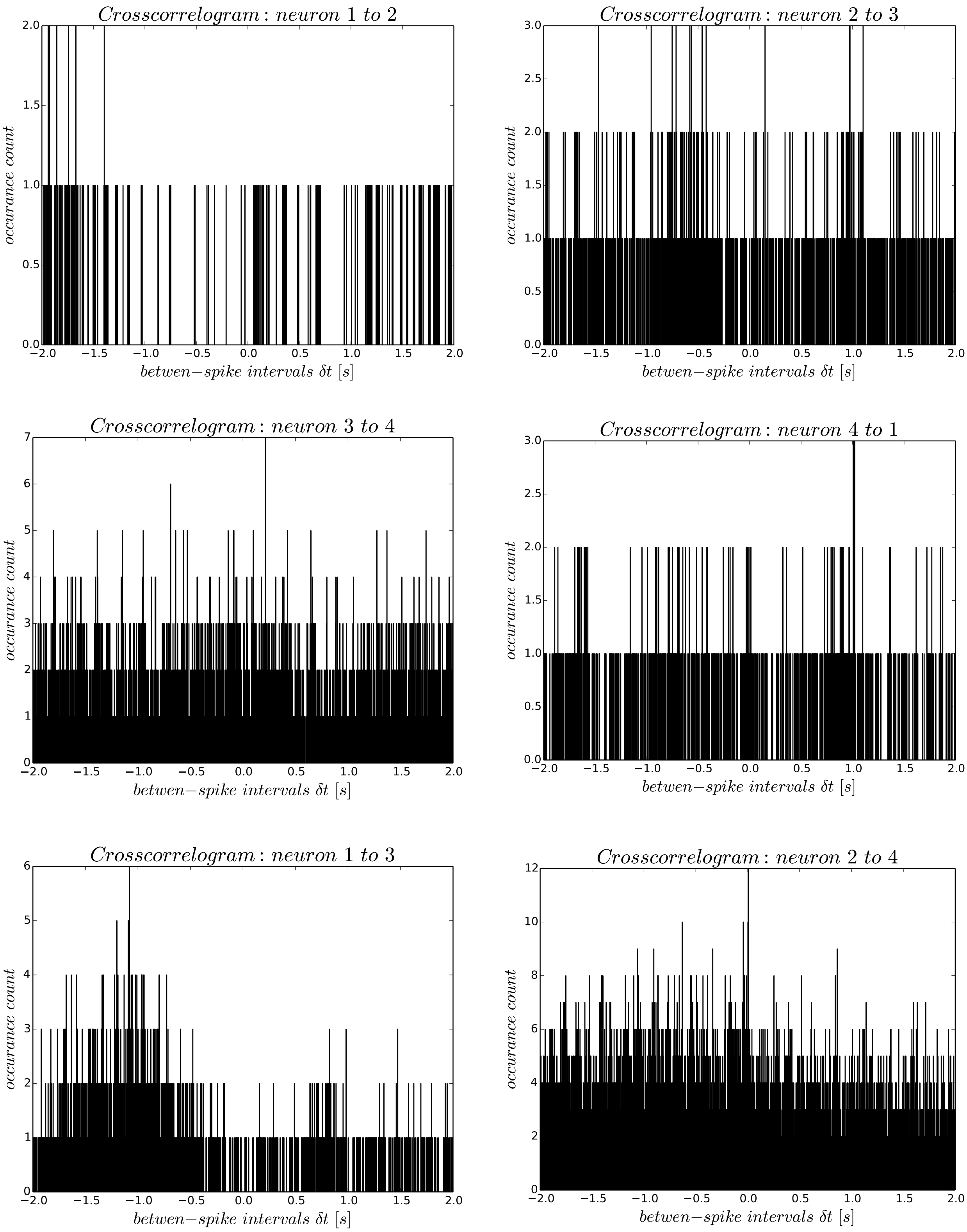


Figure 9: Pairwise crosscorrelograms on the four neurons' spike-time data thresholded at $\pm 2$ [$s$]. One direction is given here - the inverse-relation correlograms are identical but flipped horizontally.

# 5 Positional firing-rate histograms

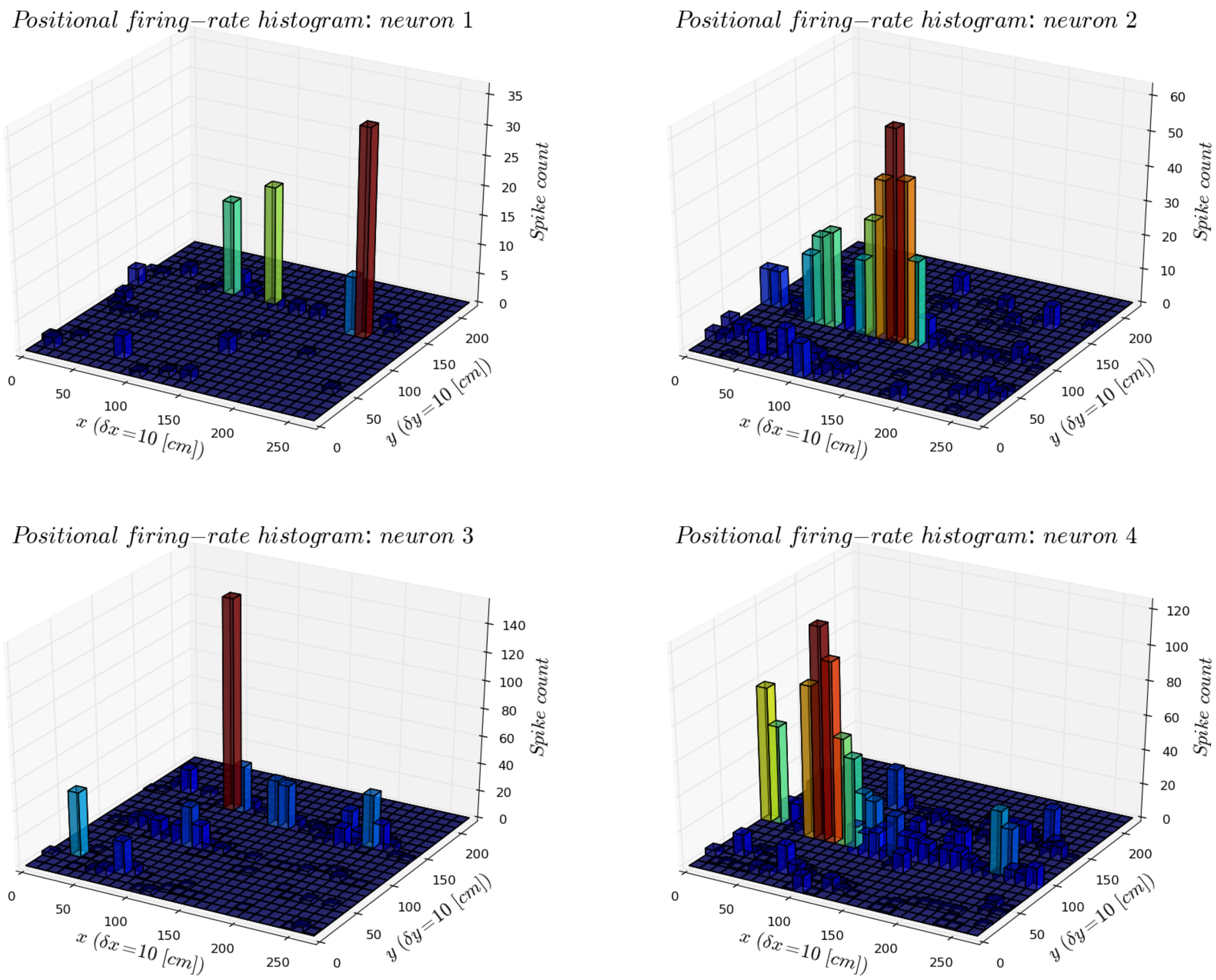


Figure 11: Position-wise fire rates histograms for each neuron. Space is discretised across $x$ and $y$ at step 10 [$cm$].

# 6 MI Estimation. Conditional MI histograms

## 6.1 Total position-wise conditional $MI$

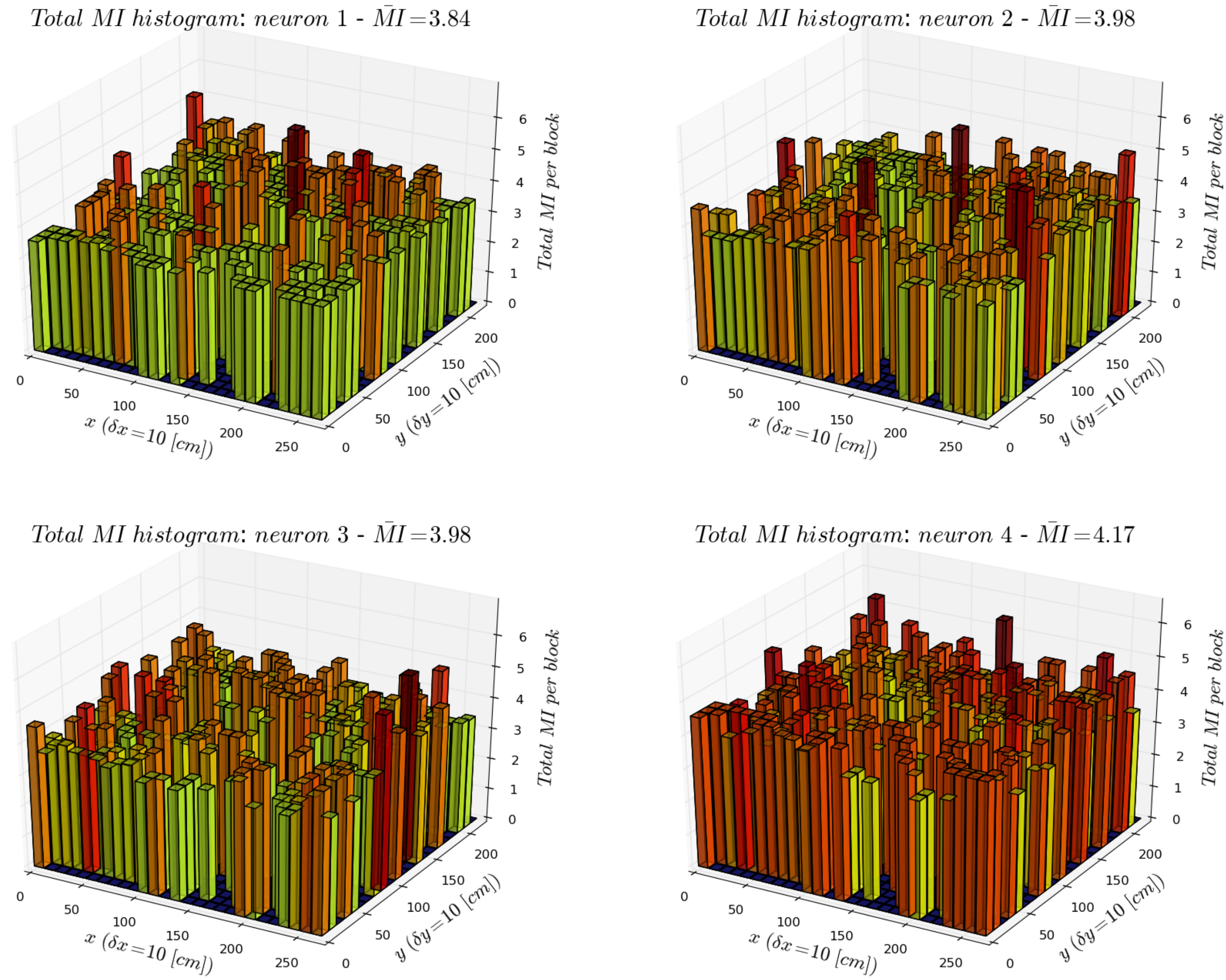


Figure 13: Position-wise conditioned $MI$ estimates for each neuron. The van Rossum distance is used with the metric-space estimator for this example. The total (average) $MI$ for each plot are given in the legends.

## 6.2 Above-average deviation in position-wise conditional $MI$.

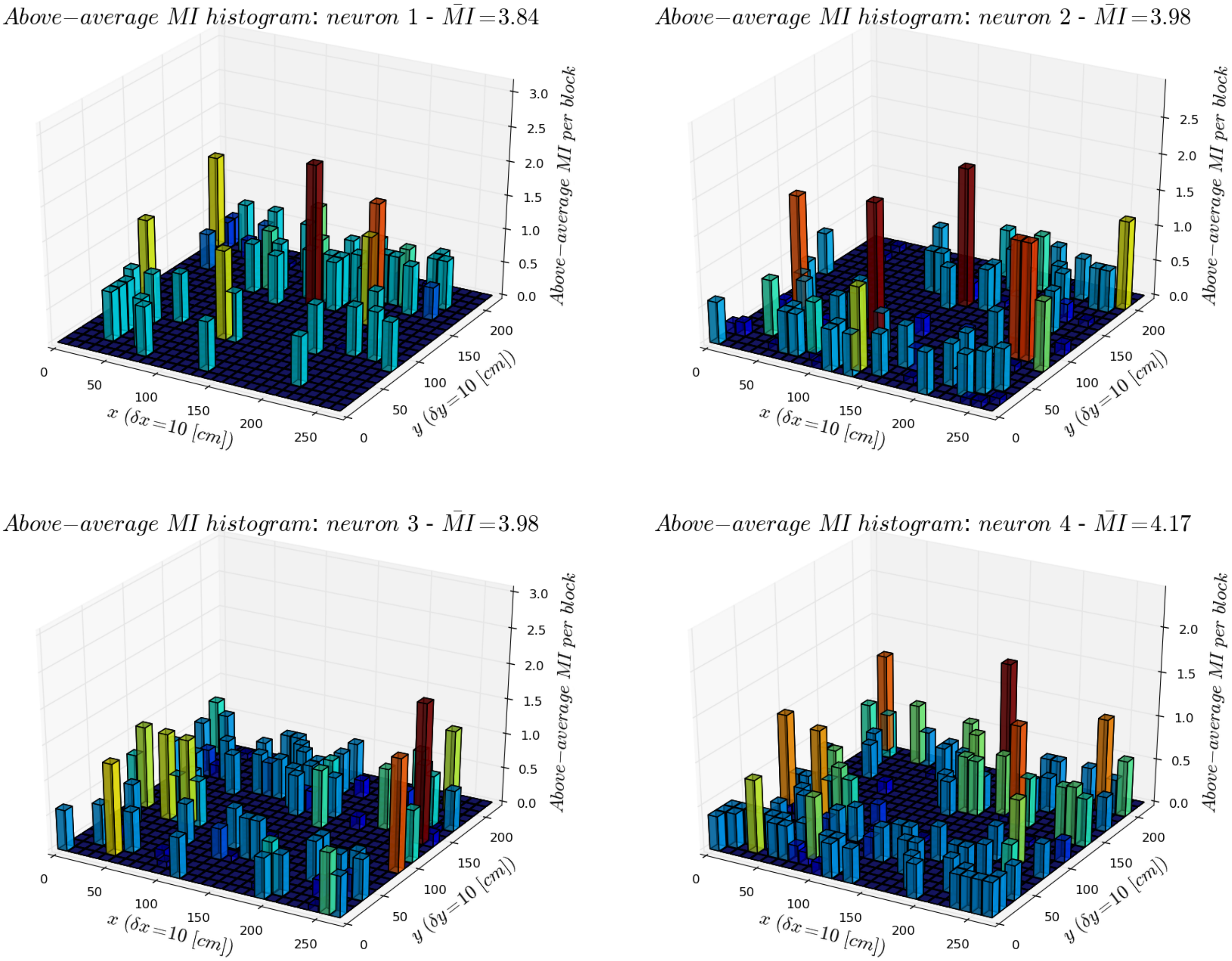


Figure 15: Above-average deviations in the position-wise conditioned $MI$ estimates for each neuron, extracted from the plots in the previous figure, highlighted to give a better picture of the most influential positional stimuli.

# References

[1] Houghton CJ, Victor JD. (2012) Measuring representational distances – the spike-train metrics approach. *"Visual population codes: toward a common multivariate framework for cell recording and functional imaging". (eds N Kriegeskorte, G Kreiman) Cambridge, MA:MIT Press*, p.391-416.

[2] Houghton CJ. (2015) Calculating mutual information for spike trains and other data with distances but no coordinates. *R. Soc. open sci.*, 2: 140391.