Decoding the retina with the first wave of spikes

Geoffrey Portelli, John M. Barrett, Evelyne Sernagor, Pierre Kornprobst

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Geoffrey Portelli [(1)] - John Barrett [(2)] - Evelyne Sernagor [(2)] - Pierre Kornprobst [(1)]

[(1)] Neuromathcomp Project Team, Inria Sophia Antipolis Méditerranée, France
[(2)] Institute of Neuroscience, Medical School, Newcastle University, Newcastle UK

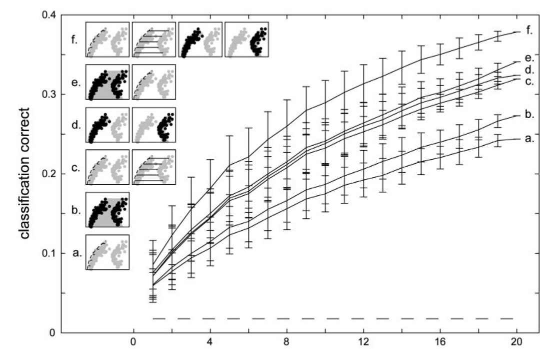
Contact : geoffrey.portelli@inria.fr

Context & motivation

► MEA & decoding tasks to decipher the neural code

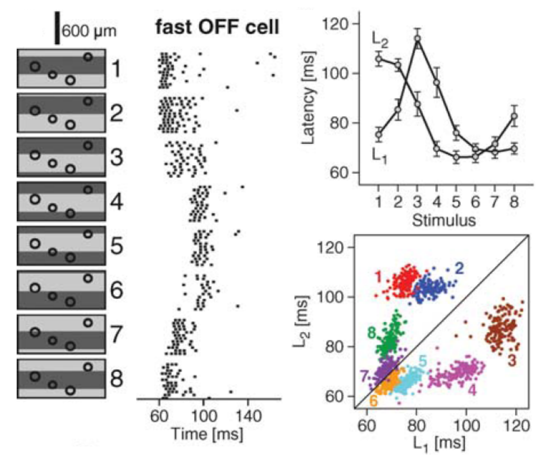
"Classification performance improves with the number of neurons and with the complexity of the used response features."

Greschner et al., 2006
MEA, turtle retina.



"Some ganglion cells can encode the spatial structure of a briefly presented image in the relative timing of their first spikes."

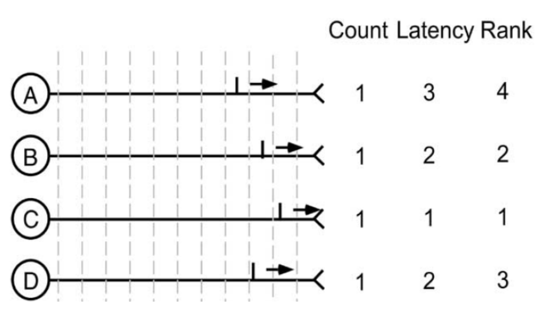
Gollisch and Meister, 2008
MEA, salamander retina



► Rank order coding hypothesis

"Neurons A-D emit spikes at different times. By using a count code, corresponding to a population rate code, there are only 4+1 states of the system. If the latency of each spike can be determined with a millisecond precision, there are 4^{10} possible states. Finally with a rank code, there are 4! possible sates."

Thorpe et al., 2001
Psychophysics



► Goal

Can the first wave of spikes be used in a decoding task ?

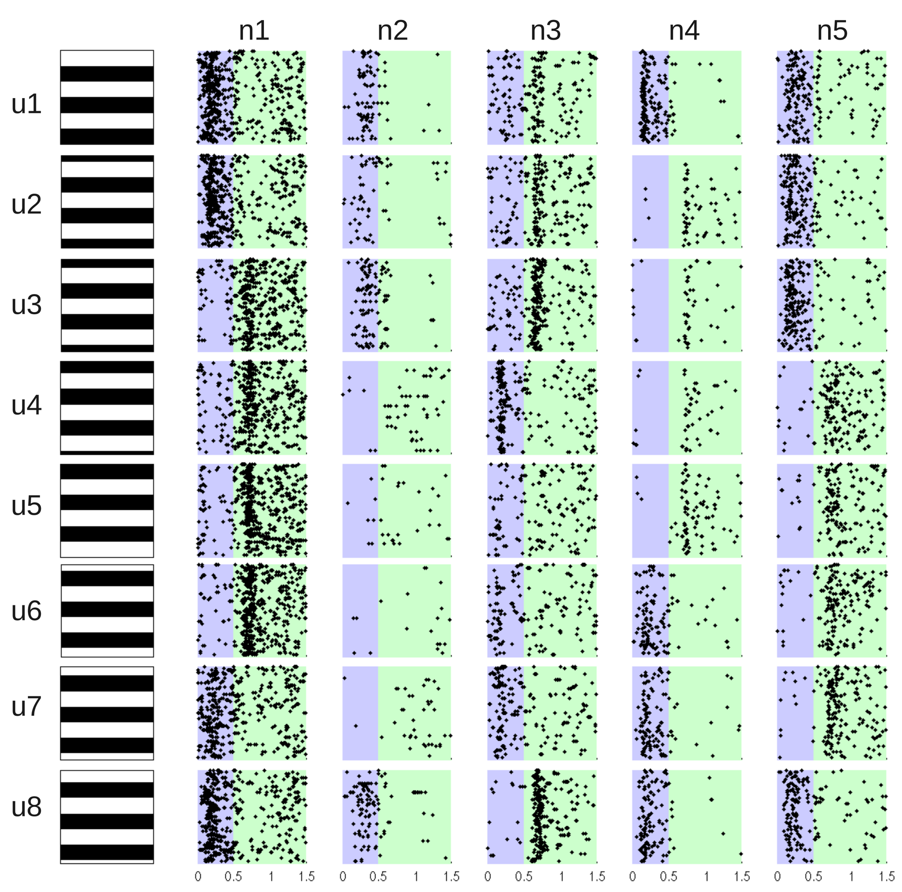
Stimulus & decoding task

► Stimulus

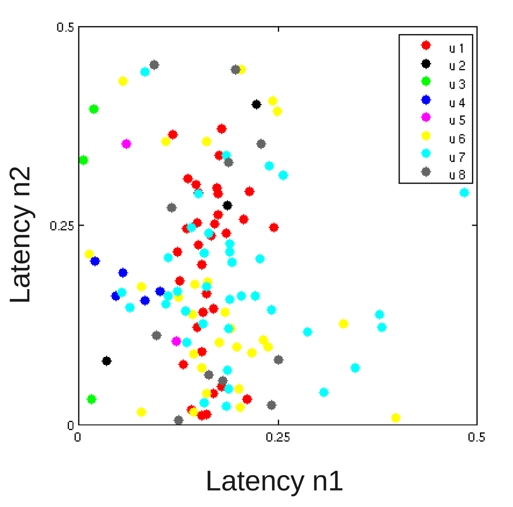
32 gratings flashed in a random order (4 spatial frequencies, 8 phases)

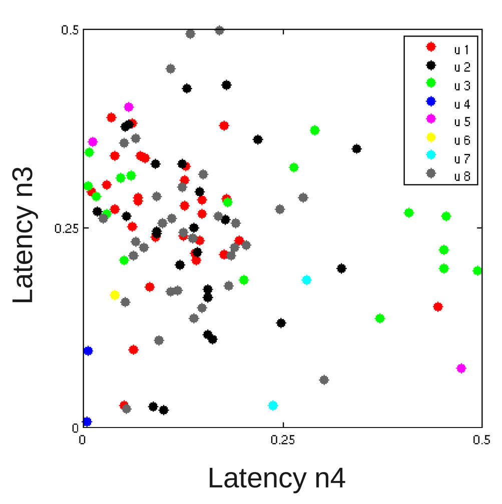
► Sample of recorded neural activity

- Onset and offset neural responses.
- Modulation of the neural responses according to the stimuli.
- Spontaneous activity.



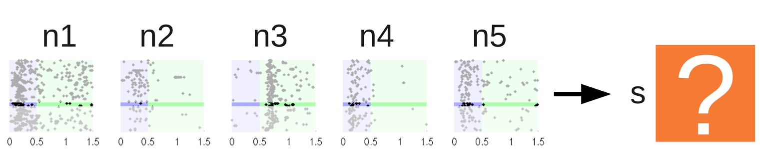
► Issues





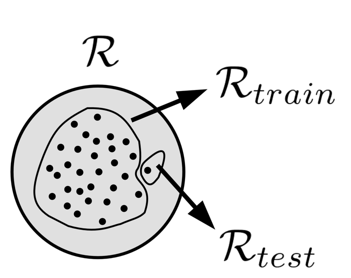
► Decoding task

Given a set of neural responses, what is the corresponding stimulus ?



All-but-one approach :

$\mathcal{R} = \mathcal{R}_{train} \cup \mathcal{R}_{test}$, with $|\mathcal{R}_{test}| = 1$



Methods

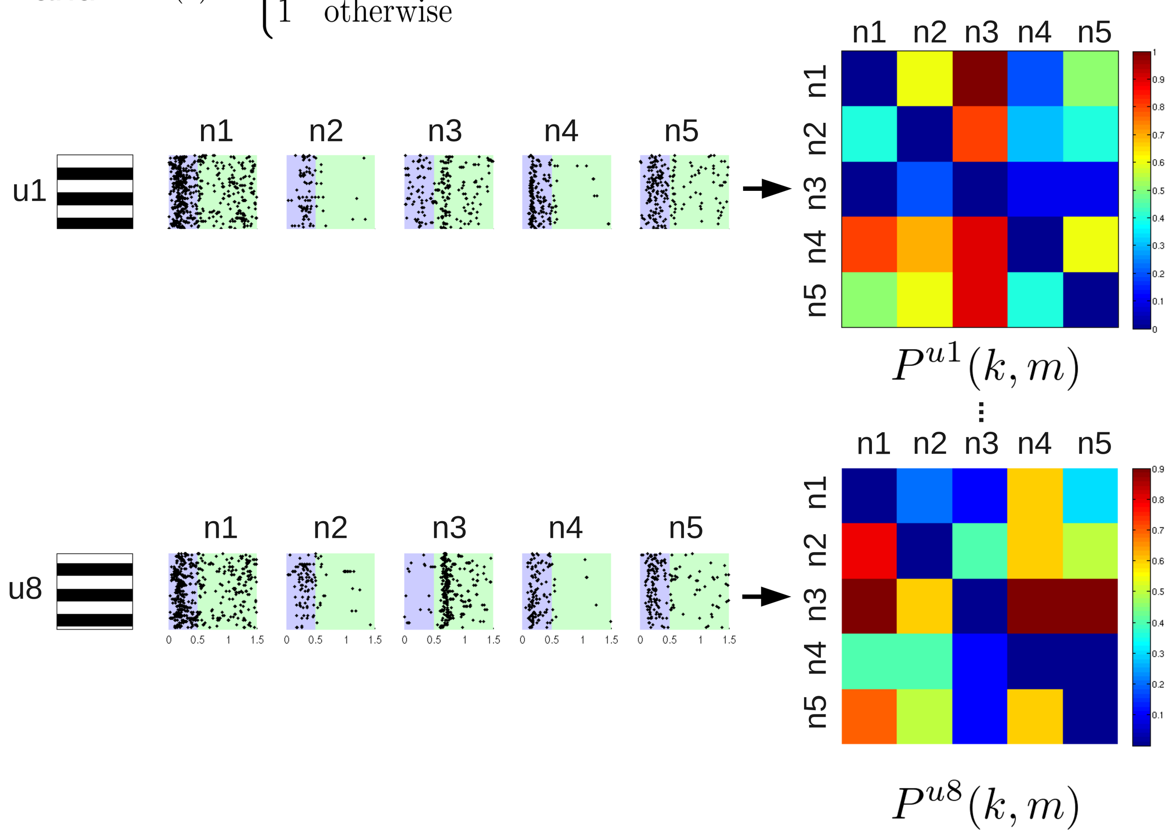
► Estimating the probabilities for each stimulus given trials in the training set $\mathcal{R}_{train}$

For an image u, and for every pair of neurons (k,m), we estimate the empirical probability that the neuron k fires before the neuron m by

$$P^u(k,m) = \frac{1}{C} \sum_{i \in \mathcal{R}_{train}} H(l_k^{u,i} - l_m^{u,i}),$$

where $l_k^{u,i}$ is the latency of neuron k, for stimulus u and trial i,

and $H(s) = \begin{cases} 0 & \text{if } s \leq 0, \\ 1 & \text{otherwise} \end{cases}$



► Scoring rule applied to the test set $\mathcal{R}_{test}$

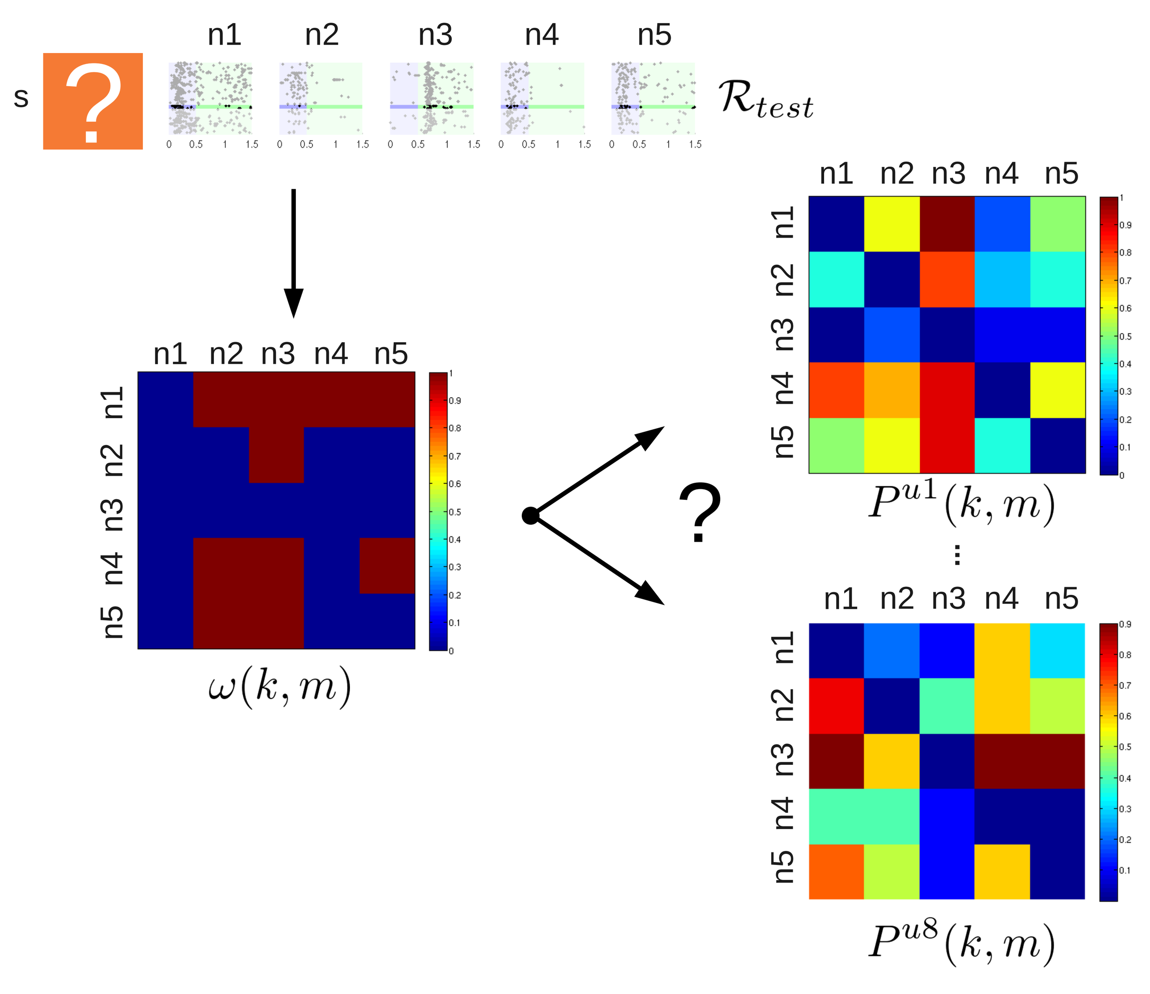
We estimate self-information which is an example of a proper scoring rule. This measure has also been called surprisal, as it represents the "surprise" of seeing the outcome (a highly improbable outcome is very surprising).

Given an outcome ω describing the rank order code, we have :

$$I^u(\omega) = -log(P^u(\omega)) = \sum_{k,m/\omega(k,m)>0} -log(P^u(k,m))$$

The identity of the unknown stimulus s is :

$$s = u^* = \text{Argmin}_u I^u(\omega)$$



► Confusion matrix and the fraction of correct prediction

Given a set of eight images, a 8x8-confusion matrix M is defined to represent the results.

Considering the *all-but-one* approach, the number of possible combination of $(\mathcal{R}_{train}, \mathcal{R}_{test})$ is $|\mathcal{R}|$.

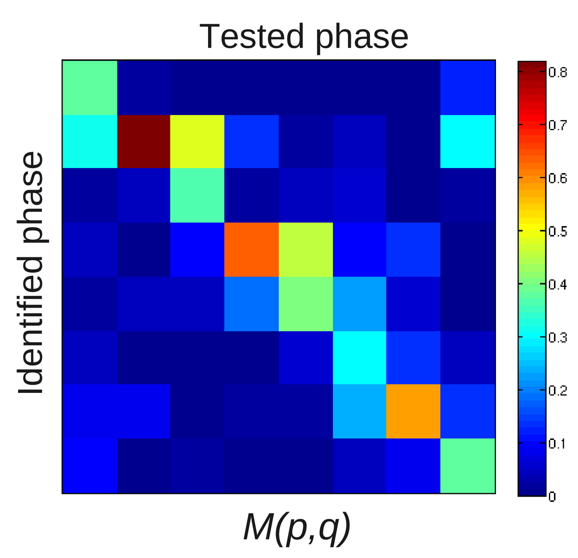
For each combination, each image is tested: If image u^p is tested and if the image u^q is identified, then the value of $M(p,q)$ is increased by one.

The fraction of correct identification is the mean of the diagonal.

Example of a confusion matrix showing the phase identification performance within 8 gratings of the lowest spatial frequency.

Here, the mean performance is equal to 0.48±0.18.

Chance level is $\frac{1}{8}$ = 0.125.

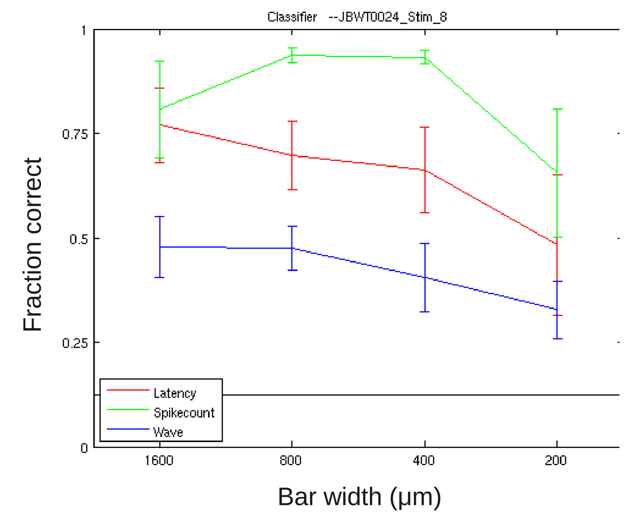


Preliminary results

Analysis was performed on responses recorded from one wild type mouse retina (age P26), using a 60-multielectrodes array (Multi-Channel System). Following spike sorting, 88 neurons were selected according to a responsive criterion inspired from Quiroga *et al*, 2007.

► Evolution of the fraction of correct identification as a function of the spatial frequency

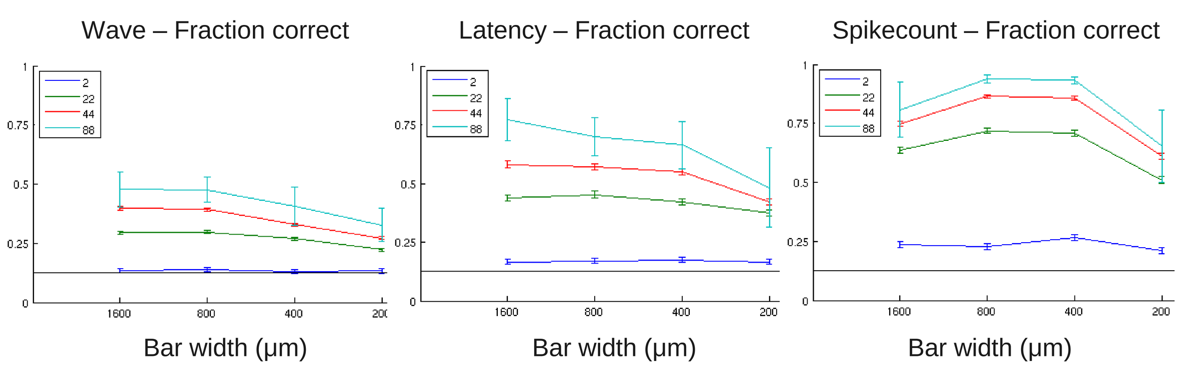
From the lowest spatial frequency (bar width of 4-fold the mean receptive field size) to the highest spatial frequency (bar width of half of the mean receptive field size) the performance of the first wave of spikes (blue) is compared to the performance of classical Bayesian classifier based on the latency (red) and on the spikecount (green).



Although the performance of identification obtained with the first wave of spikes is the lowest, it is still above the chance level.

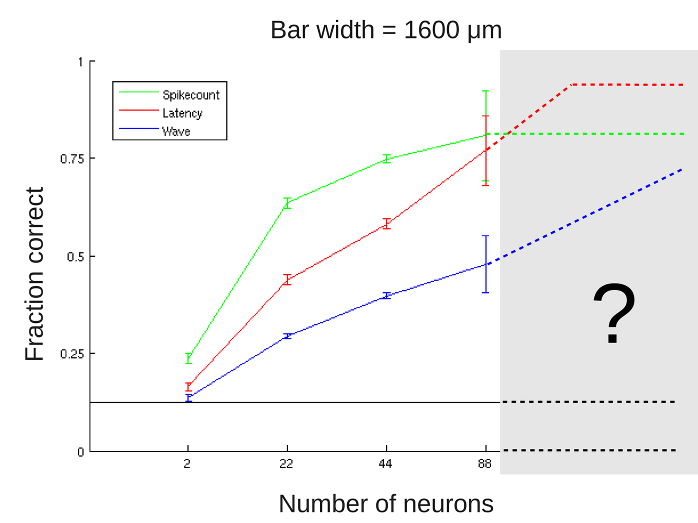
► Evolution of the fraction of correct identification as a function of the spatial frequency and the number of neurons

From the lowest spatial frequency to the highest spatial frequency the performance of the three approaches were compared depending on the number of neurons.

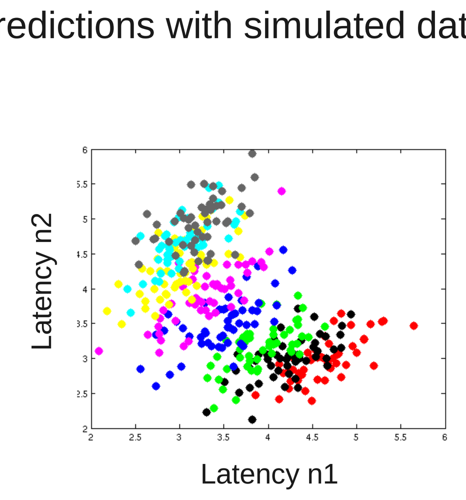


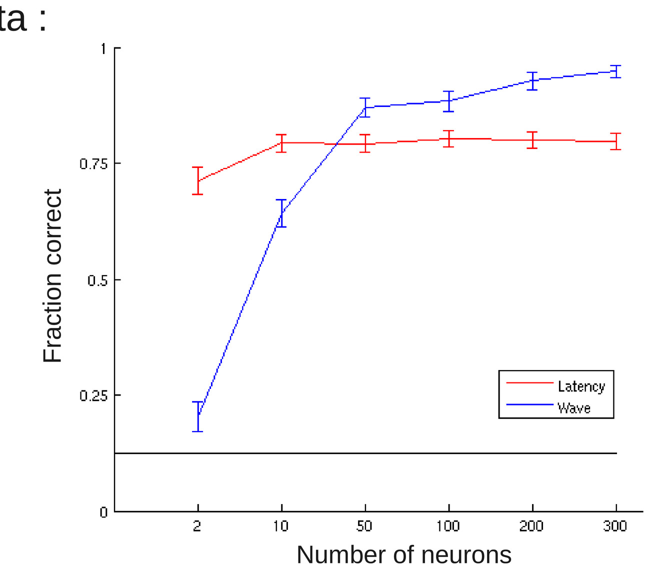
In all cases, the higher the number of neurons, the better the performances are.

► Evolution of the fraction of correct identification as a function of the number of neurons



Predictions with simulated data :





Conclusions & perspectives

► The first wave of spikes (rank order code) can be used in a decoding task.

► Refine the method to decrease the sensitivity to spontaneous neural activity.

► Take into account both stimulus onset and stimulus offset.

► Evaluate the size of the training and the testing sets, on the identification performance.

► Current work : test this method on larger neuronal populations.

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