PLACE FIELDS AND HEAD DIRECTION CELL ANALYSES

ADRIEN PEYRACHE

12TH ANNUAL CANADIAN NEUROSCIENCE MEETING
NEURAL SIGNAL AND IMAGE PROCESSING:
QUANTITATIVE ANALYSIS OF NEURAL ACTIVITY

ADRIEN.PEYRACHE@MCGILL.CA | @APEYRACHE
PEYRACHELAB.COM| GITHUB.COM/PEYRACHELAB

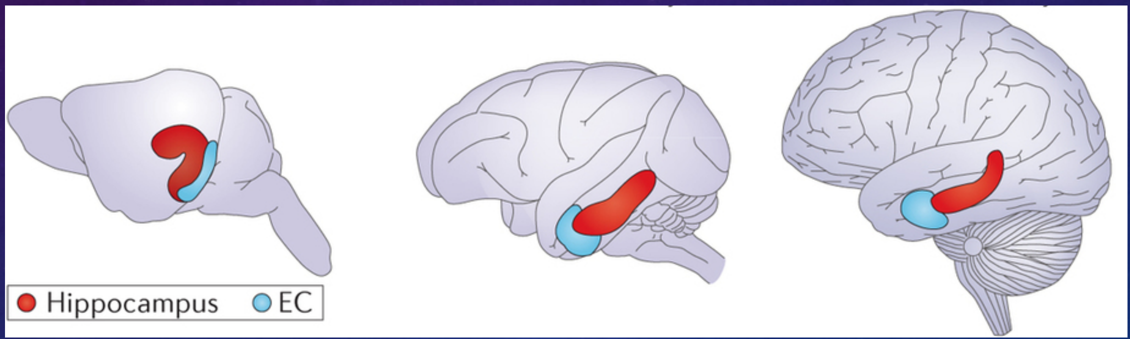
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital
McGill

~10^7 neurons | ~1000 maps | ~0.01 Watts

https://www.youtube.com/watch?v=VQNxdkXf_E4

NAVIGATION CAPABILITIES DEPEND ON THE HIPPOCAMPUS (& ASSOCIATED STRUCTURES)

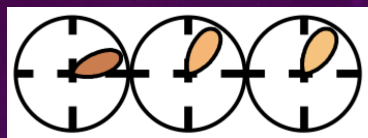
O'Keefe and Nadel, 1978



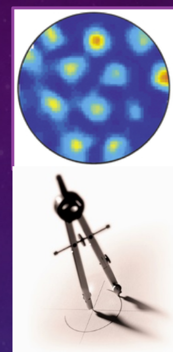
Strange et al., Nat Rev Neuro, 2014

What is the neuronal support for this cognitive process?

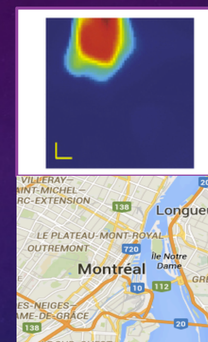
Head-direction cells



Grid cells

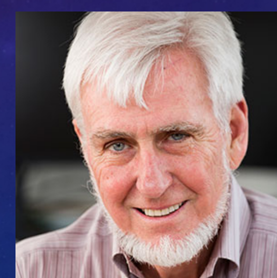


Place cells



James Ranck & Jeff Taube

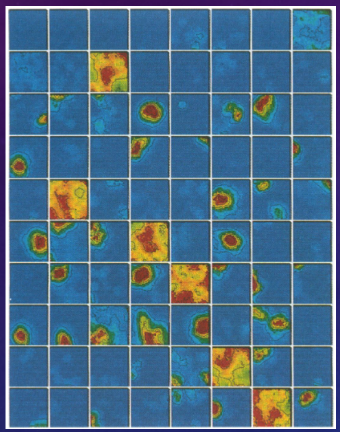
May-Britt and Edvard Moser



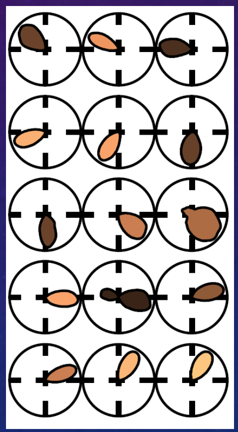
John O'Keefe

How to compute the tuning curves?
How can we measure the strength of encoding?

LARGE ENSEMBLE RECORDINGS



Wilson & McNaughton, Science, 1993



Peyrache et al., Nat Neuro, 2015

Can we decode a signal from a population of neurons?
What do we learn from studying these neuronal ensembles during sleep?

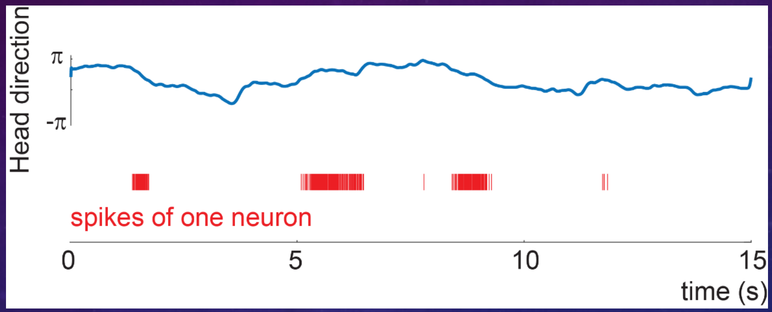
OUTLINE

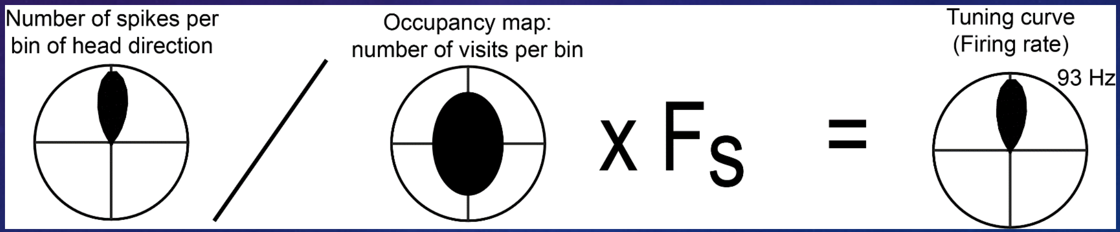
- **Tuning curves:** How to relate spiking to a parameter of the experiment?
- **Information measures:** Quantifying the strength of neuronal encoding.
- **Pairwise correlation:** Unraveling the coordination of neuronal activity
- **Decoding***:* Reading-out the 'neuronal code'.

OUTLINE

- **Tuning curves:** How to relate spiking to a parameter of the experiment?
- **Information measures:** Quantifying the strength of neuronal encoding.
- **Pairwise correlation:** Unraveling the coordination of neuronal activity
- **Decoding*:*** Reading-out the 'neuronal code'.

ESTIMATING THE TUNING CURVES



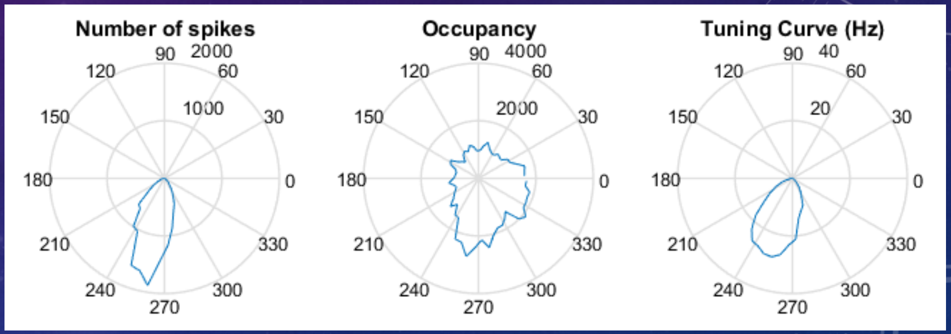


Sampling frequency

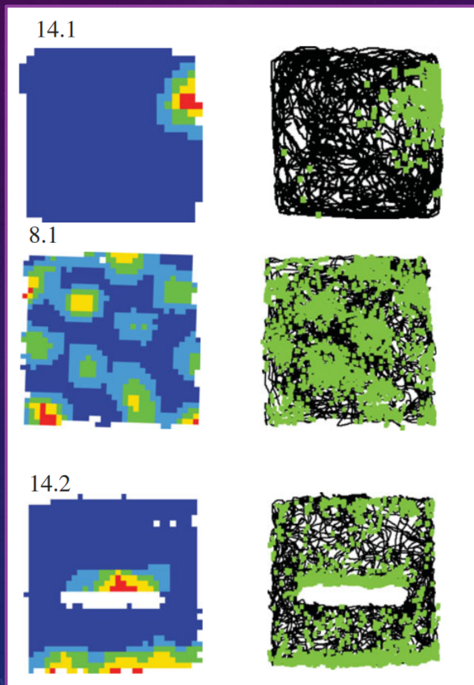
ESTIMATING THE TUNING CURVES

Run NeuroData_HDTuningCurves.m

```
%6 degree bins
da = pi/30;
angBins = [da/2:da:2*pi-da/2];

%Occupancy
histAng = hist(ang(:,2),angBins);

%Number of spikes per bin
spkPerAng = hist(spk(:,2),angBins);

%Tuning Curve
hdTuning = spkPerAng./histAng * Fs;
```



EXAMPLE OF SPATIAL TUNING CURVES



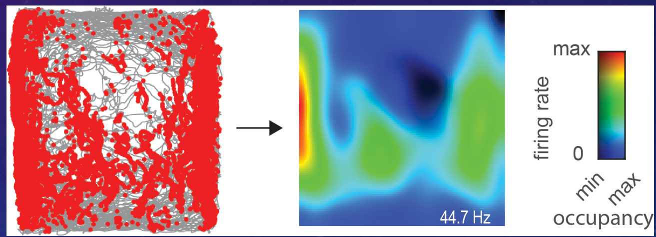
Place cell

Grid cell

Border cell

Hartley et al., *Phil Trans Roy Soc B,* 2017

Displaying occupancy



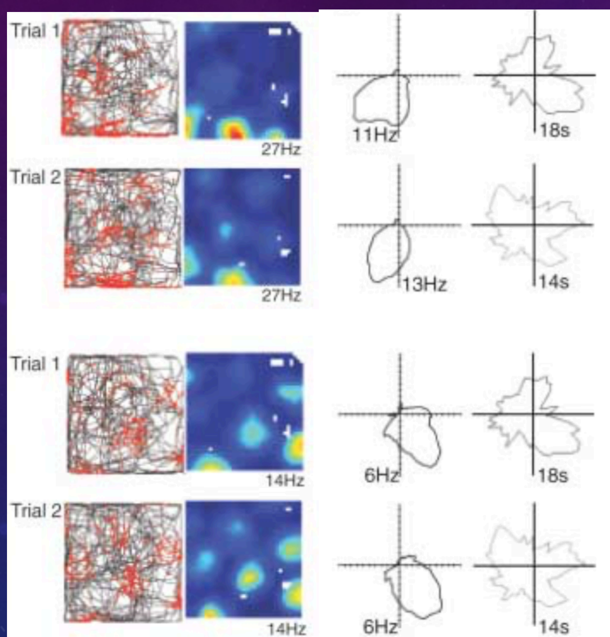
QUALITY OF THE TUNING CURVE

Criteria for quality of a tuning curve:

- Peak Firing rate (At least 1 Hz)
- Number of “fields” (HD cells, place cells)
- Stability: Correlation of the tuning curves in 1st and 2nd halves of recording
- Spatial information

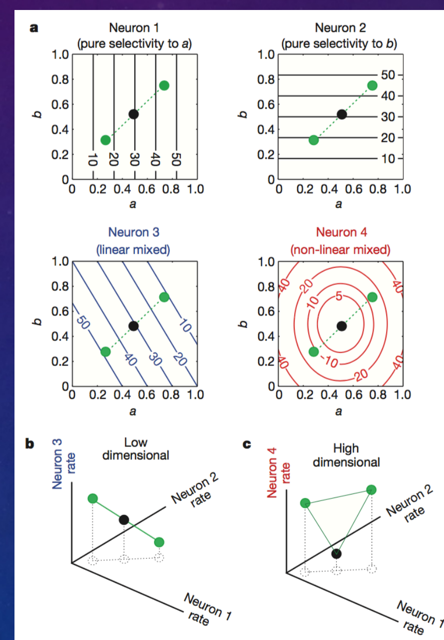
PITFALLS:
A TUNING CURVE DOES NOT TELL YOU EVERYTHING

Conjunctive cells



Sargolini et al., *Science*, 2007

Mixed selectivity
(non linear combination of features)



Rigotti et al., *Nature*, 2013

OUTLINE

- **Tuning curves:** How to relate spiking to a parameter of the experiment?
- **Information measures:** Quantifying the strength of neuronal encoding.
- **Pairwise correlation:** Unraveling the coordination of neuronal activity
- **Decoding***:* Reading-out the ‘neuronal code’.

INFORMATION

- ***Information*** is a measure of how many different messages can be transmitted. **Information rate** quantifies how many messages are transmitted per unit of time.
- If Alice sends messages to Bob, we can measure how well the two communicate by estimating the ***mutual information*** between Alice's and Bob's states.
  (the maximum mutual information is the ***capacity*** of a channel).
- Mutual information is a measure of statistical dependence between two variables, without assuming any *a priori* distribution of the samples (unlike correlation for Gaussian-distributed variables).

MUTUAL INFORMATION

- Information conveyed by X is $H_X = -\sum_x p(x) \log p(x)$

- The mutual information *MI* between X and Y is the information conveyed by Y (H_Y) *minus* the information conveyed by Y knowing X ($H_{Y|X}$, *conditional entropy*)

MI = H_Y - $H_{Y|X}$

$$MI = \sum_{x,y} p(x;y) \log\left(\frac{p(x;y)}{p(x)p(y)}\right)$$

- If we know everything about Y just by knowing X ($H_{Y|X}$=0) then *MI* = H_Y.

- If X and Y are statistically independent, then knowing X does not decrease the condition entropy ($H_{Y|X}$=H_Y), therefore *MI* = 0

CASE OF A PLACE CELL

A neuron that fires constantly in the right half:

The neuron is in two equally probable states:
P_R = P(active) = ½
P_L = P(silent) = ½

$I = -P_R \log P_R - P_L \log P_L = \log(2) = 1$ bit

A message conveying one bit of information is a code that reliably inform about one in two states.

Whenever the cell fires one spike, it transmits with absolute certainty the location of the animal.

The neuron transmits R bit per second and one bit per spike of spatial information.

In reality, a neuron has a graded firing rate and occupancy is inhomogeneous…

INFORMATION FROM A SINGLE NEURON

Mutual Information between spike train ***S*** and location ***x*** (Skaggs, 1993):

$$MI = \sum_{x,S} p(S|x)p(x)\, log_2\left(\frac{p(S|x)}{p(S)}\right)$$

$p(S = 1|x) \sim \lambda(x)\Delta t$ — *λ(x):* firing rate as a function of x: tuning curve
Δt: time bin. Valid for *Δt<<1* (resolution of a single spike)

$p(S = 1) = \lambda_0 \Delta t$ — Probability of a spike per time unit: average firing rate

$p(x)$ — Occupancy map

INFORMATION FROM A SINGLE NEURON

Mutual information between spike train and location (Skaggs, 1993):

$$I = \sum_x \lambda(x) log_2 \frac{\lambda(x)}{\lambda_0} p(x)$$

Firing rate in bin x

Average firing rate

Occupancy map

I is expressed in *bit/sec* (we got rid of the *Δt* term)

$I_{spk} = \frac{I}{\lambda_0}$ is the information per spike (*bit per spike*)

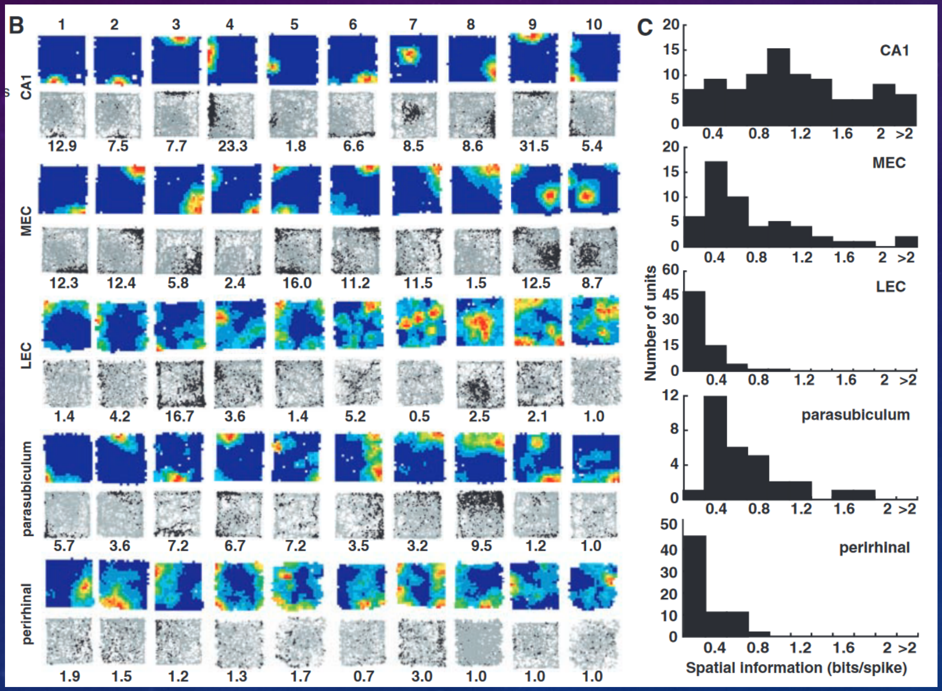
INFORMATION FROM A SINGLE NEURON

$$I = \sum_x \lambda(x) log_2 \frac{\lambda(x)}{\lambda_0} p(x)$$

Run NeuroData_HDInformation.m

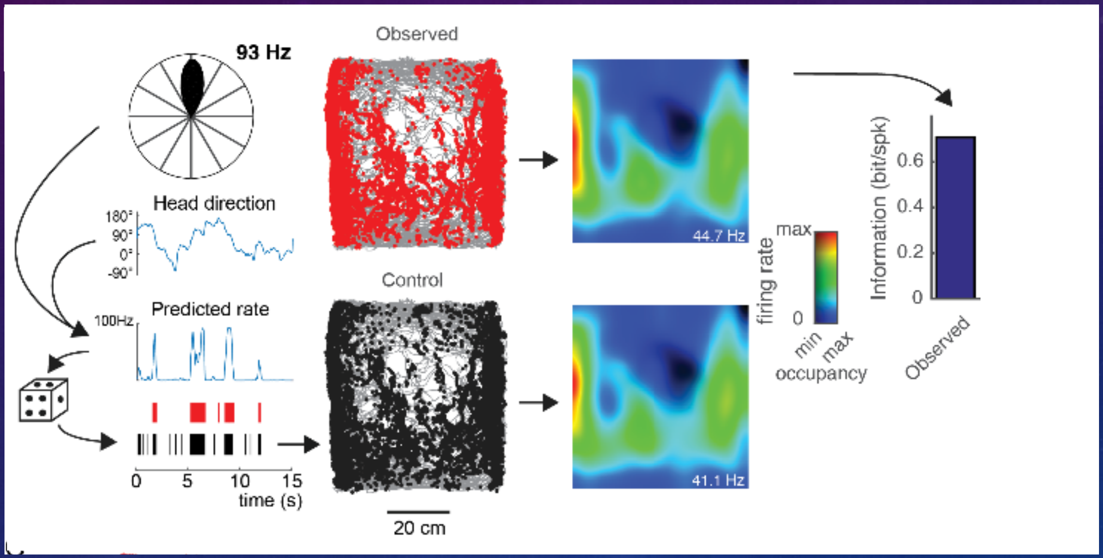
```
% probability of occupancy:
Px = histAng./sum(histAng);

logTerm = log (hdTuning/fr);
% Correct for undefined values
logTerm(hdTuning==0) = 0;

% Little trick to express a sum as a dot product
I = hdTuning * (logTerm.*Px)' ;

% Divide by firing rate to obtain information per spike
I_spk = I/fr;
```

SPATIAL INFORMATION ACROSS BRAIN AREAS



Hargreaves et al., *Science,* 2004

RELATIONSHIP BETWEEN HD AND SPATIAL INFO



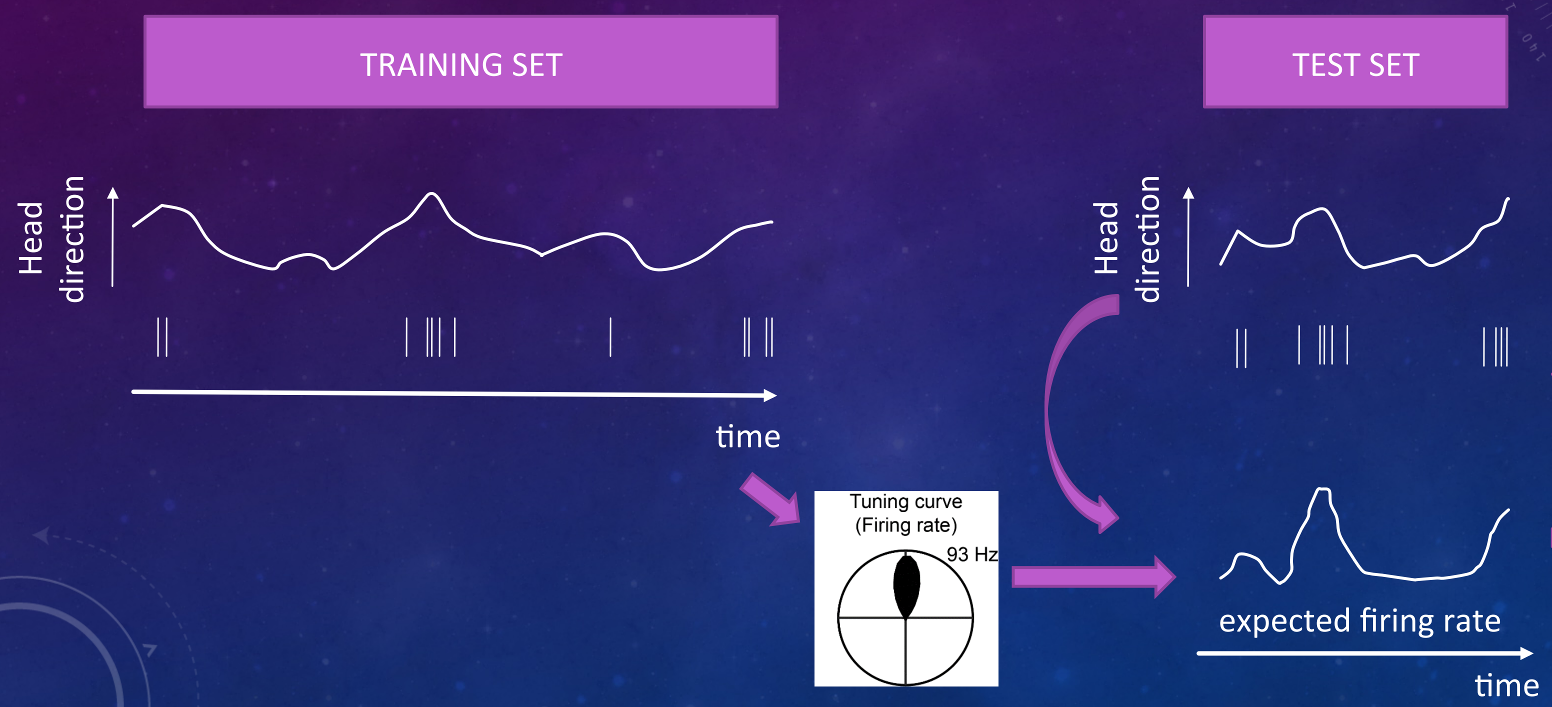
A HD cell can convey spatial information if animal's behavior is not homogeneous
(Muller et al., 1994; Burgess et al., 2005; Peyrache et al., 2017)

CAVEATS

- Information depends on bin size (the smaller the bin, the higher the information)
- Sensitive to inhomogeneous sampling

One solution: cross-validation

CROSS-VALIDATED INFORMATION MEASURE



CROSS-VALIDATED INFORMATION MEASURE

To quantify how good is the model, we compute the *Likelihood function*.

For a ***Poisson process*** of intensity (=expected rate) ***f***

$$L_f = -\int f(t)dt + \sum_s log(f(t_s))$$

The model is compared to the likelihood of a ***null model*** where the intensity function is *'flat'* (=average firing rate)

$$L = L_f - L_0$$

$$L = -\int [f(t) - \lambda_0]dt + \sum_s log\left(\frac{f(t_s)}{\lambda_0}\right)$$

Snyder and Miller, 1991
Brown et al., *J Neuro*, 1998
Harris *et al.*, *Nature*, 2003
Paninski, *Network*, 2004

CROSS-VALIDATED INFORMATION MEASURE

Test	Training

10-fold cross-validated procedure:

90% data for training, 10% for test, repeated 10 times

CROSS-VALIDATED INFORMATION MEASURE

	Test	Training

10-fold cross-validated procedure:

90% data for training, 10% for test, repeated 10 times

CROSS-VALIDATED INFORMATION MEASURE

Training	Test

10-fold cross-validated procedure:

90% data for training, 10% for test, repeated 10 times

CROSS-VALIDATED INFORMATION MEASURE

Run NeuroData_HDInformation_XVal.m

same value as previous (~1 bit per spike)

Sampling of HD is good enough &
the parameter (bins of 6 degrees) captures well the input feature.

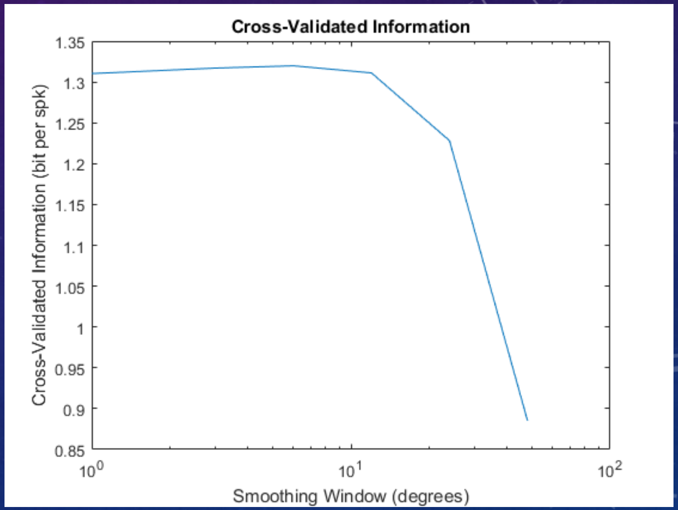
We can now use cross-validation to vary one parameter of the model,
e.g. to optimize the resolution of the tuning curve

CROSS-VALIDATED INFORMATION MEASURE

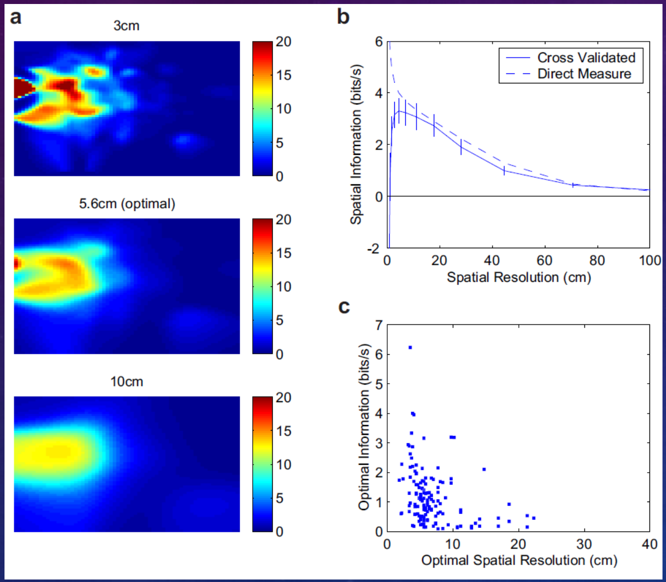
Run NeuroData_HDInformation_Xval_SmoothSearch.m

Another loop:
Tuning curve is now computed on 1-degree bins
and it is smoothed with Gaussian windows of different width.

Optimal resolution around 6 degrees



CROSS-VALIDATED INFORMATION MEASURE



Harris *et al.*, *Nature*, 2003

Cross-validation allows to find the optimal spatial resolution.

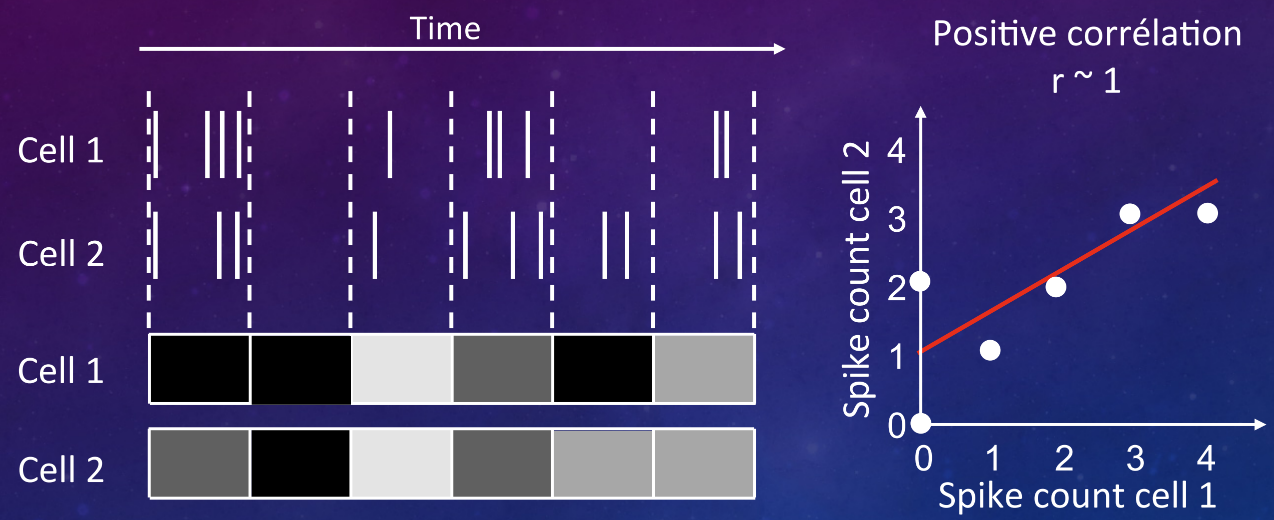
SUMMARY

- Information is a powerful measure of the mapping between the firing of neurons and internal or external states.
- It should be used carefully:
  - Information depends (in tis simplest form) on the choice of binning.
  - Whenever possible, cross-validated measures give better estimates.

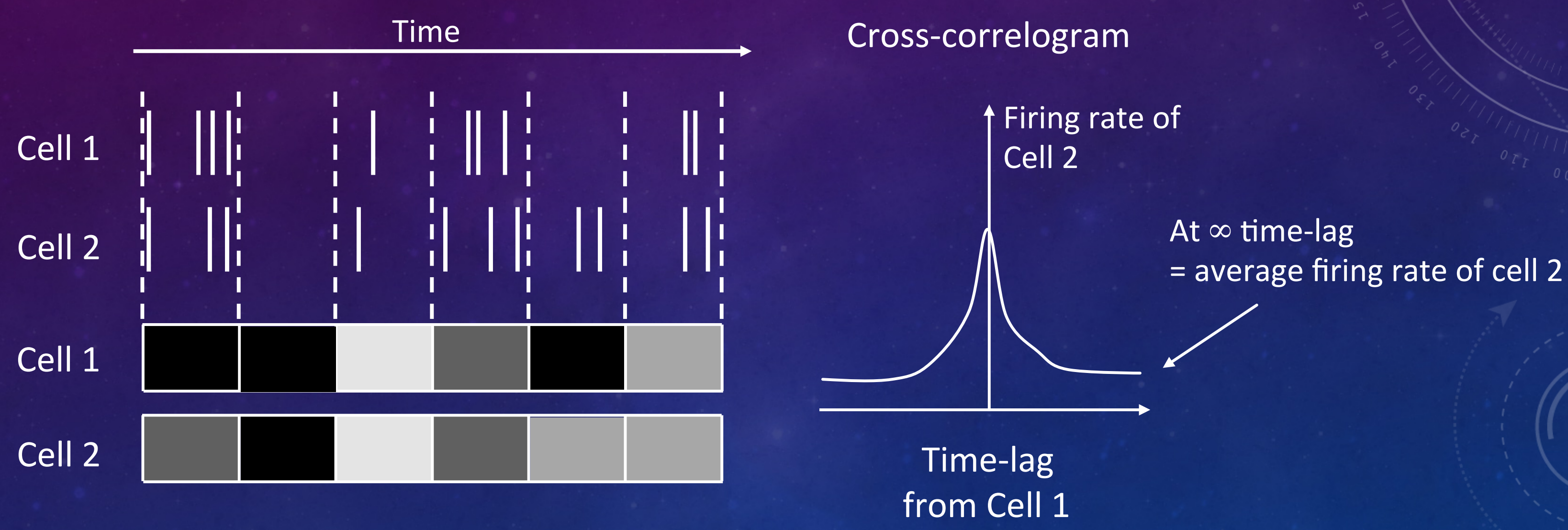
OUTLINE

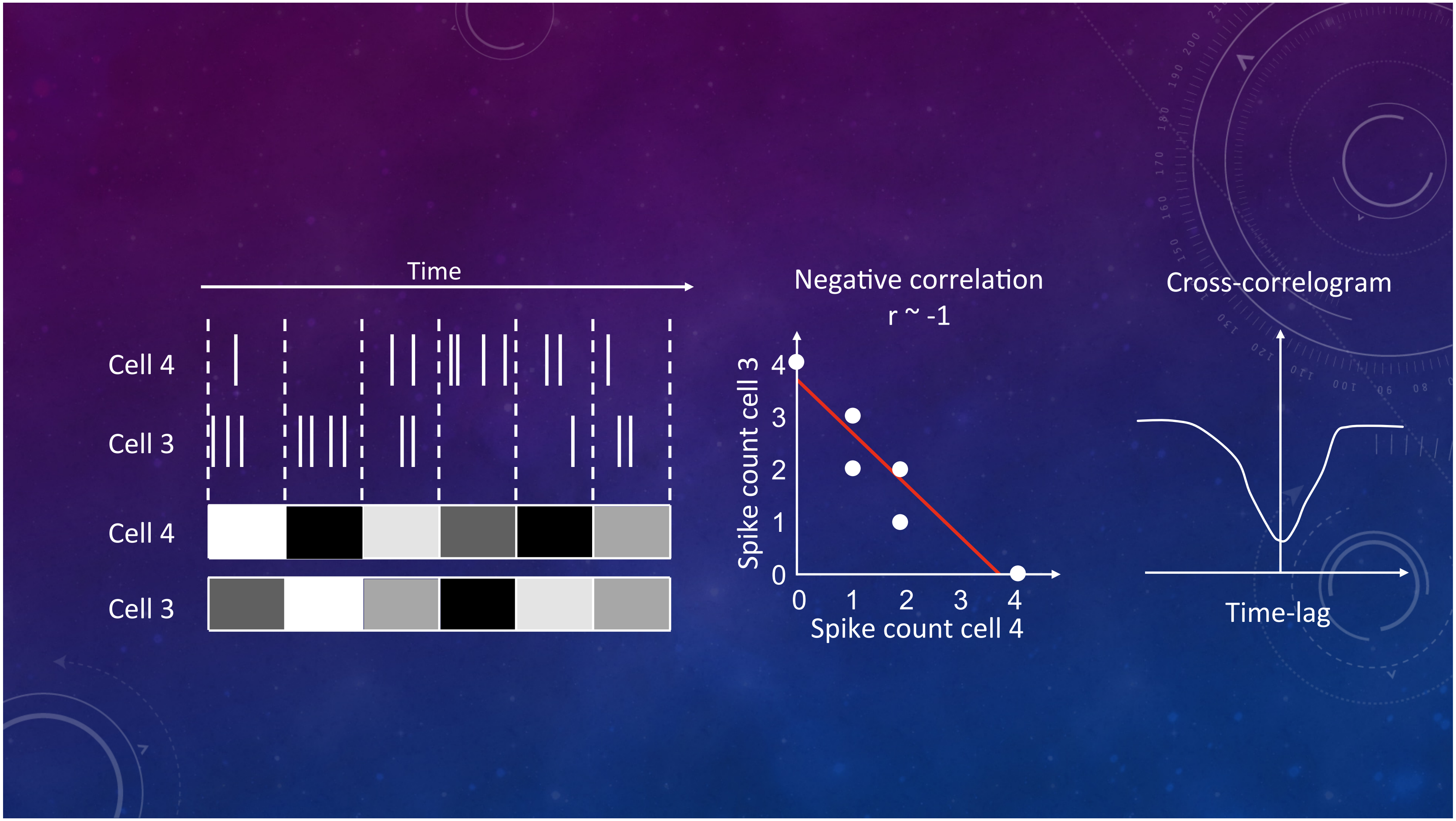
- **Tuning curves:** How to relate spiking to a parameter of the experiment?
- **Information measures:** Quantifying the strength of neuronal encoding.
- **Pairwise correlation:** Unraveling the coordination of neuronal activity
- **Decoding***:* Reading-out the 'neuronal code'.

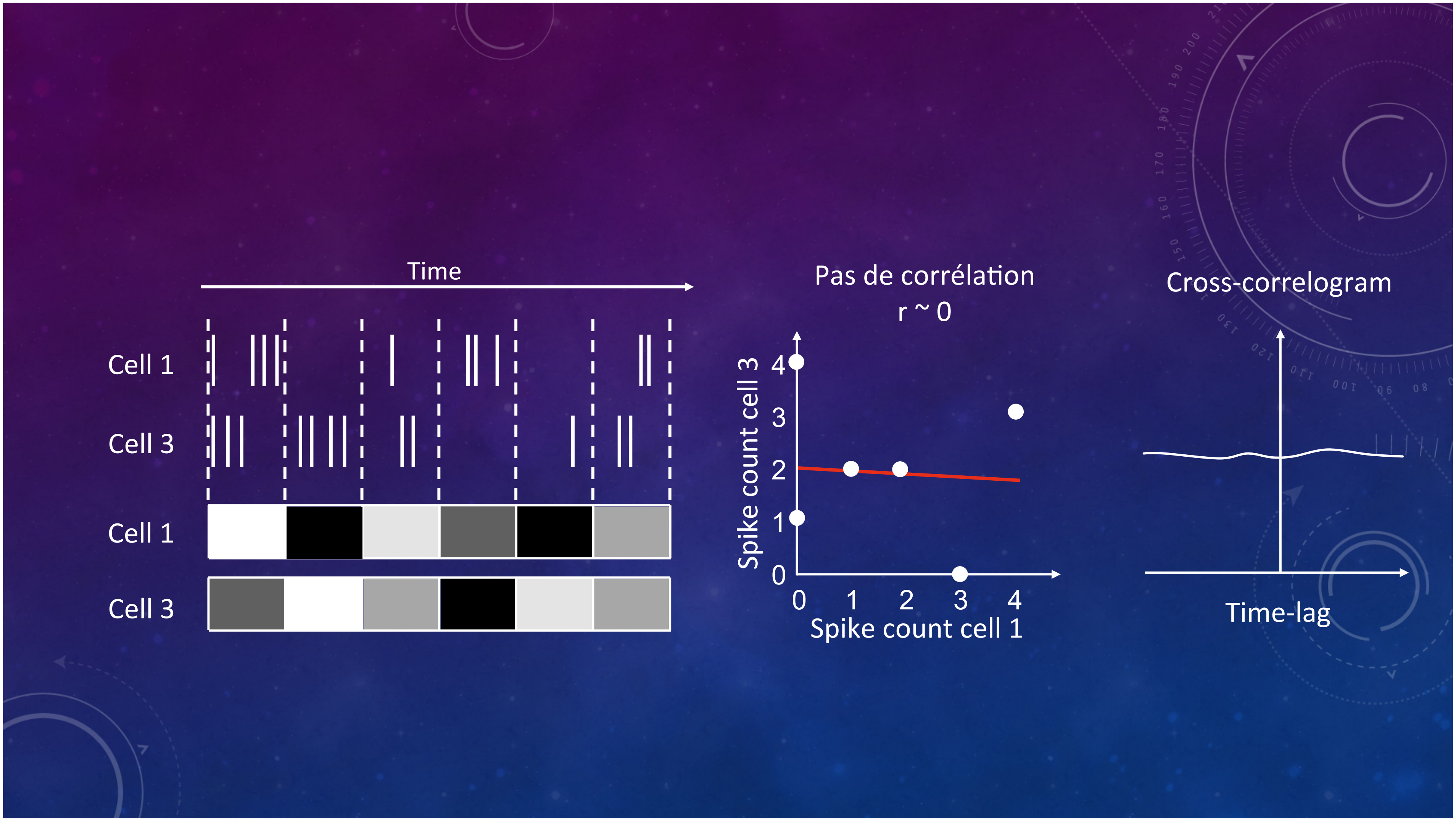
PAIRWISE CORRELATION



PAIRWISE CORRELATION



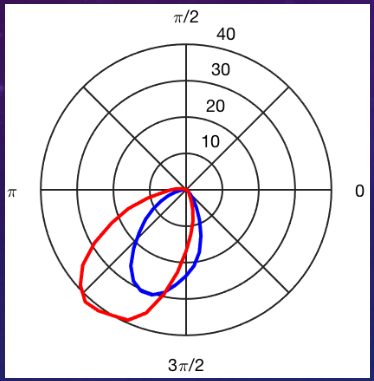

Time
Cell 4
Cell 3
Cell 4
Cell 3
Negative correlation
r ~ -1
Spike count cell 3
Spike count cell 4
0
1
2
3
4
0
1
2
3
4
Cross-correlogram
Time-lag

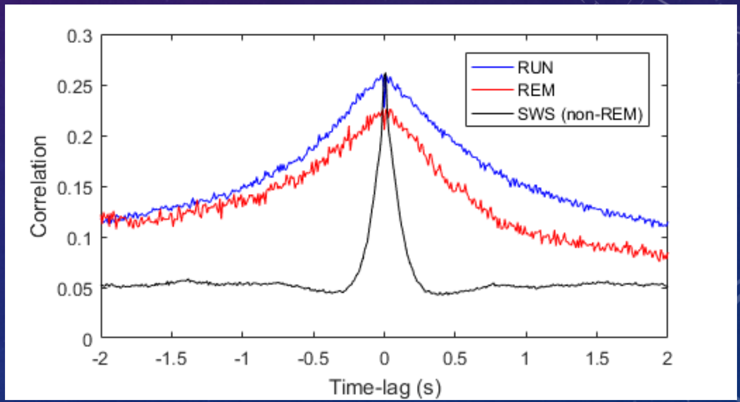

Time
Cell 1
Cell 3
Cell 1
Cell 3
Pas de corrélation
r ~ 0
Spike count cell 3
Spike count cell 1
0
1
2
3
4
Cross-correlogram
Time-lag

EXAMPLE: HEAD-DIRECTION CELLS

Let's examine the correlation between two HD cells firing for the same head-direction (cells #5 and #6)

run NeuroData_HDCellCorrelation



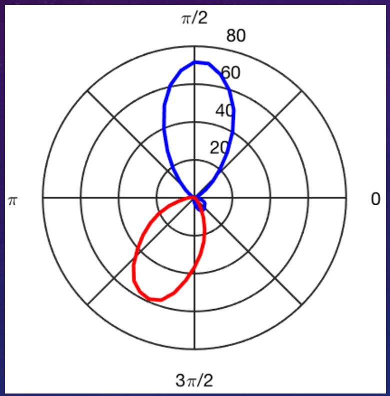


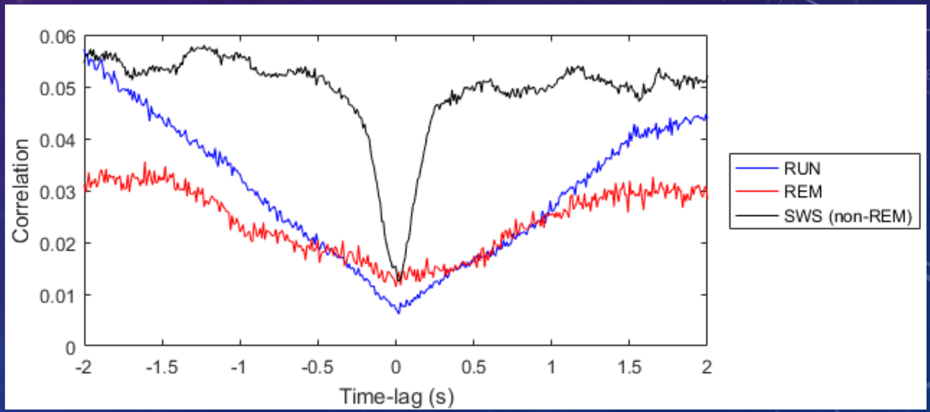
- Preserved correlation during sleep
- Same dynamics during wakefulness and REM sleep
- 'accelerated' dynamics during non-REN

EXAMPLE: HEAD-DIRECTION CELLS

Let's examine cells #8 and #17 which fire at ~180º from each other

Uncomment cellIx and rerun NeuroData_HDCellCorrelation

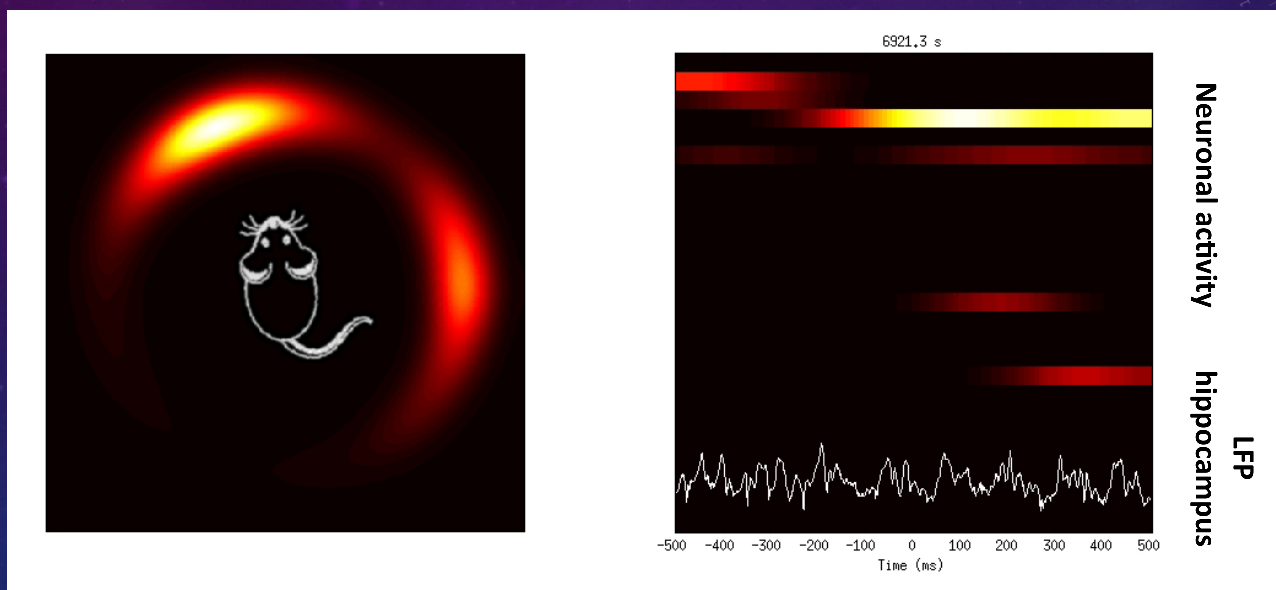




HD cells that fire for opposite direction never fire together.

EXAMPLE: HEAD-DIRECTION CELLS

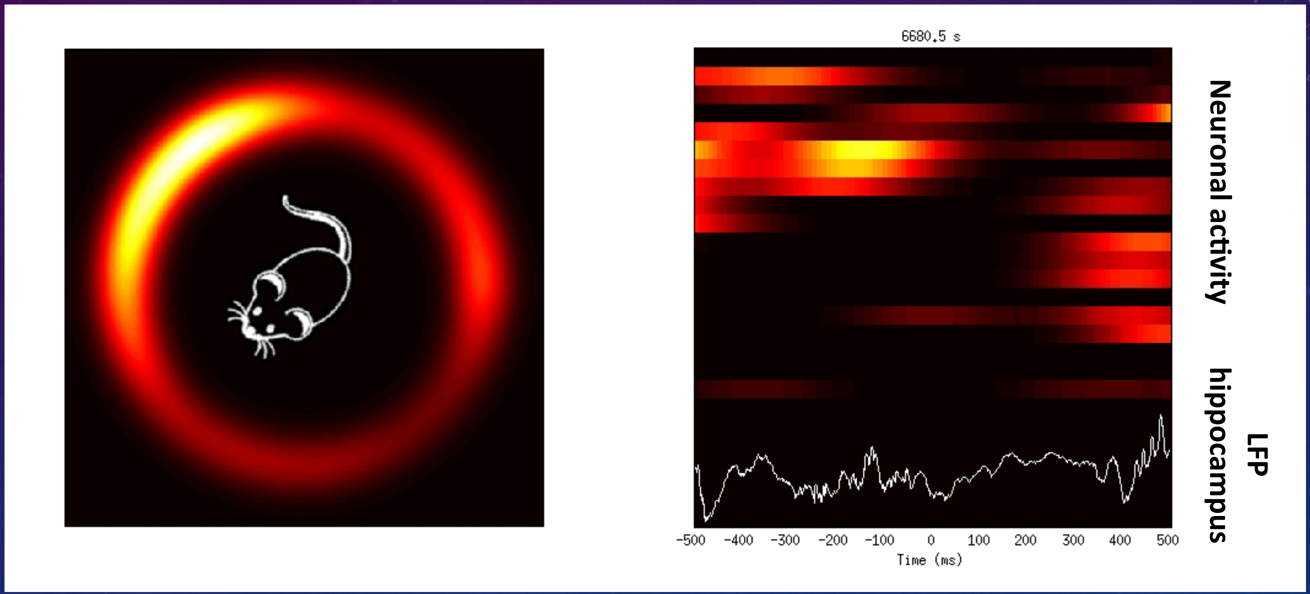
RUNNING



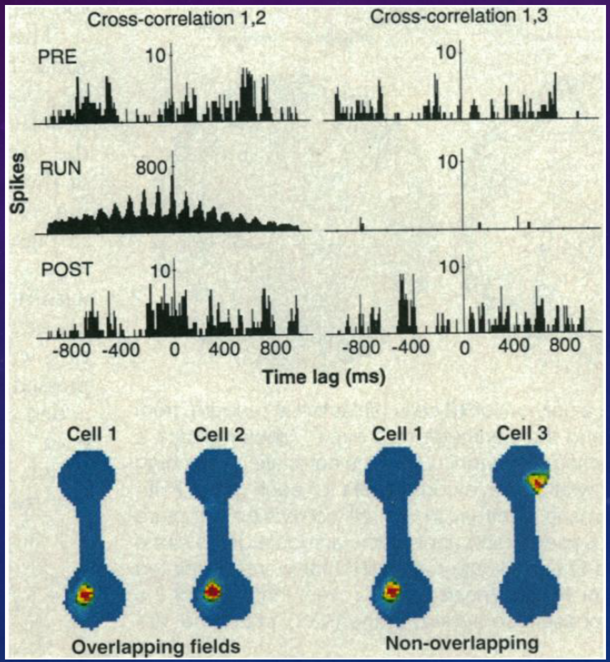
What happens when the animal is asleep?

https://www.youtube.com/watch?v=X84CZKkdkvI

EXAMPLE: HEAD-DIRECTION CELLS



CHANGE IN CORRELATIONS WITH LEARNING



Wilson and McNaughton, *Science*, 1994

SUMMARY

- Pairwise correlation is a simple, straightforward measure of how two neurons are coordinated.
- Inform on the tendency of two neurons to fire together (positive correlations) or to be mutually exclusive (negative correlations)
- Cross-Correlation is a simple indication of the typical duration of this coordination.
  (how long two neurons fire together?)
- However:
  - Depends on firing rates
    (De La Rocha, *Nature*, 2007)
  - Spike correlations results from signal (tuning curve) correlations and noise (non-specific) correlations.
    (Averbeck et al., *Nat Rev Neuro*, 2006)

OUTLINE

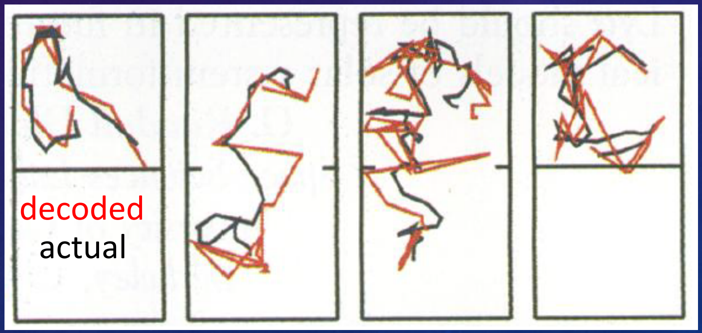
- **Tuning curves:** How to relate spiking to a parameter of the experiment?
- **Information measures:** Quantifying the strength of neuronal encoding.
- **Pairwise correlation:** Unraveling the coordination of neuronal activity
- **Decoding***:* Reading-out the 'neuronal code'.

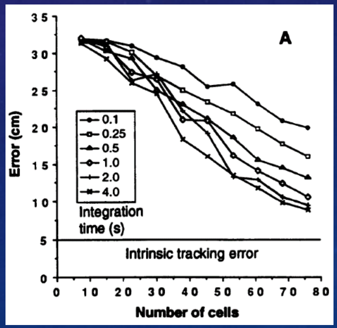
HOW TO DECODE A POPULATION CODE?

Linear models: what is the probability of encoding the value *X* knowing the firing rates *r* of an ensemble of *N* neurons?

$$P(X(t)) \propto \sum_{i=1}^{N} \omega_i r_i(t)$$

Decoding of animal's position





Wilson and McNaughton, *Science*, 1993

NON-LINEAR DECODERS: BAYESIAN

Tuning curve:
f(X), the firing rate in the condition X (stimulus, position, etc.)

The question is, can we decode *X* by reading *n* (the number of spikes), that is $P(X|n)$?

Hypothesis: neurons are Poisson processes.
How many spikes in a window of *t* seconds?

$$P(n \mid X) = \frac{(t.f(X))^n}{n!} \exp^{-t.f(X)}$$

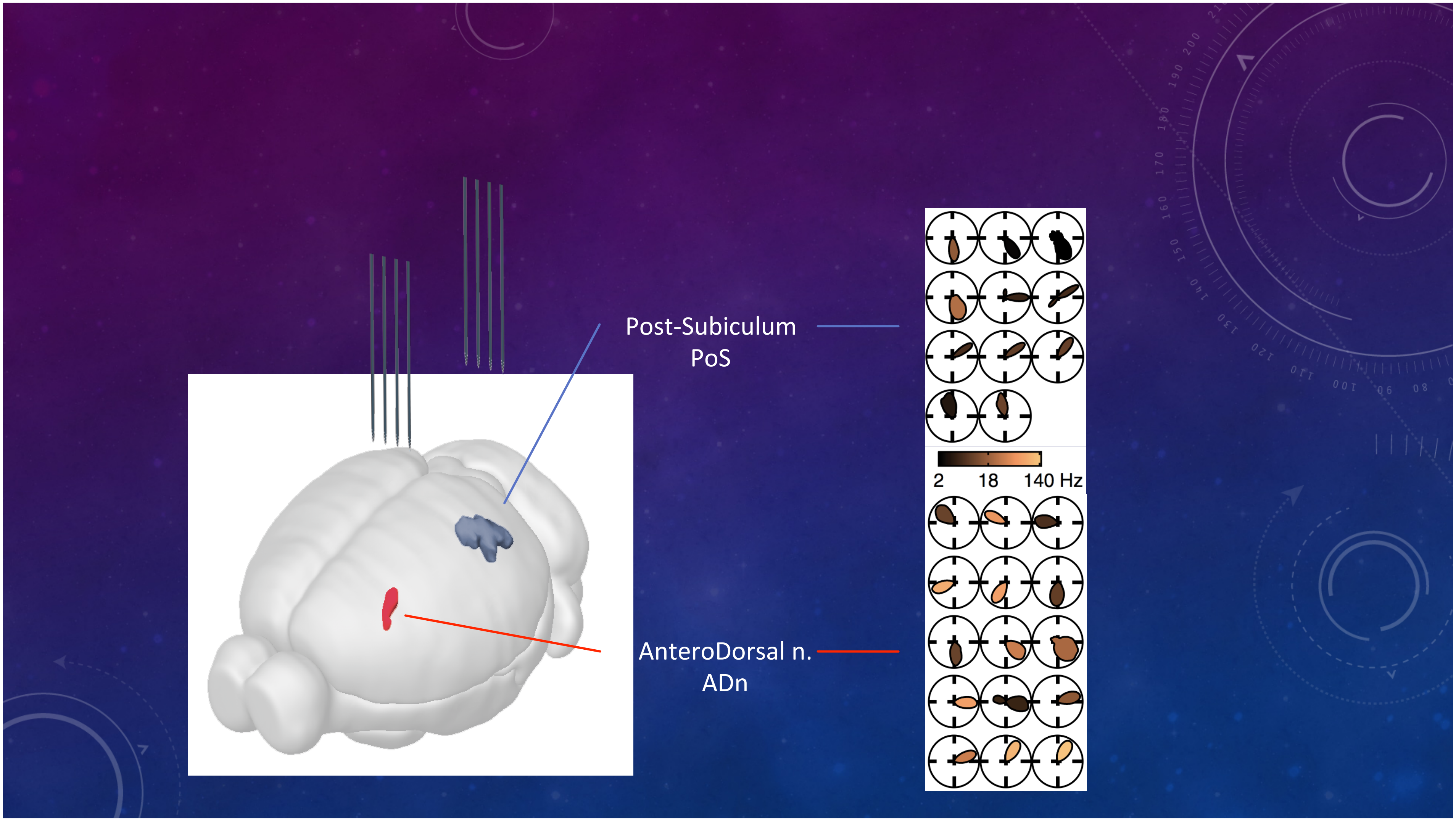
Bayes' rule:

$$P(X \mid n) = P(n \mid X).P(X) / P(n) = C.P(n \mid x)$$

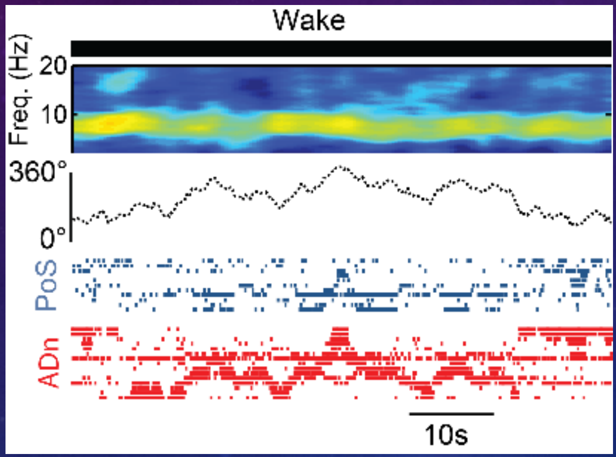
Hypothesis: neurons are independent processes.

$$P(X \mid \vec{n}) = \prod_{i=1}^{N} P(X \mid n_i)$$

Brown et al., *J Neurosci*, 1998
Zhang, *J Neurophy*, 1998


Post-Subiculum
PoS
AnteroDorsal n.
ADn
2
18
140 Hz

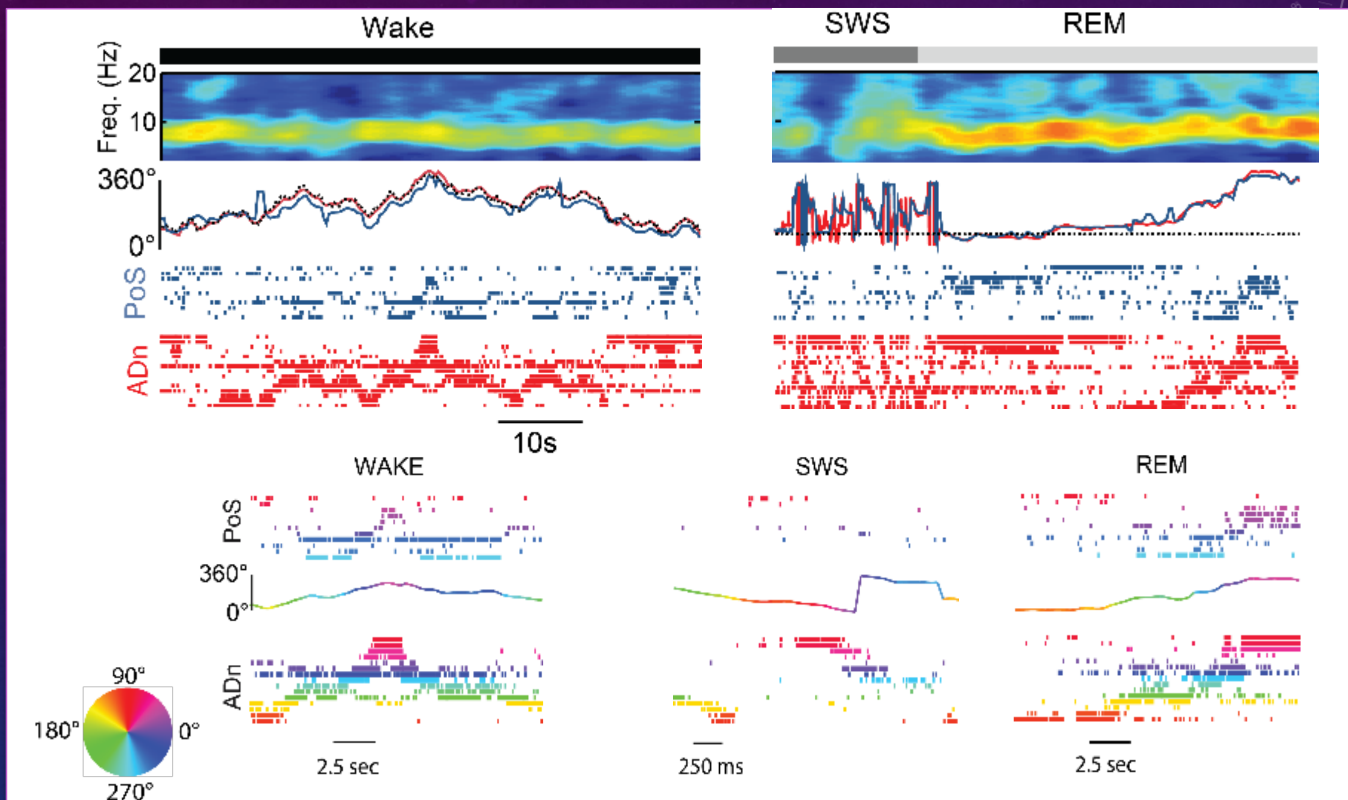
DECODING FROM HD CELL ENSEMBLES



High theta power

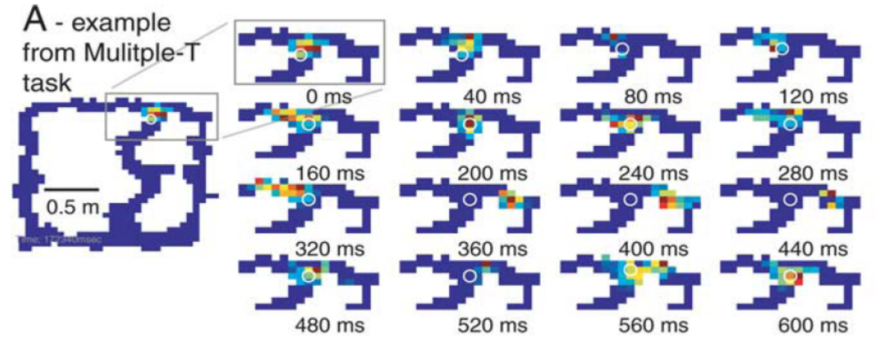
Actual head-direction

Peyrache et al., *Nat Neuro*, 2015



Peyrache et al., *Nat Neuro*, 2015

IMAGINATION:
DISENGAGEMENT FROM SENSORY EXPERIENCE

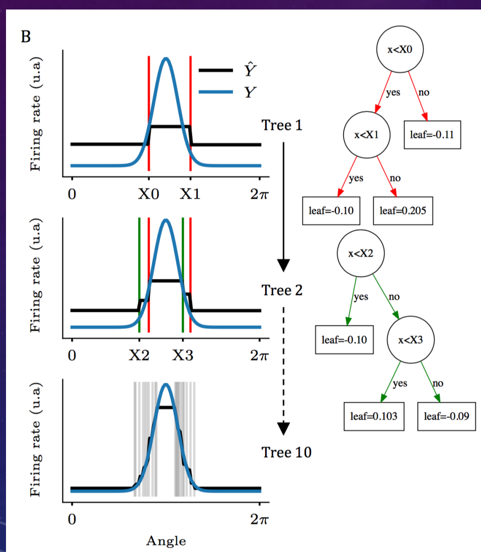


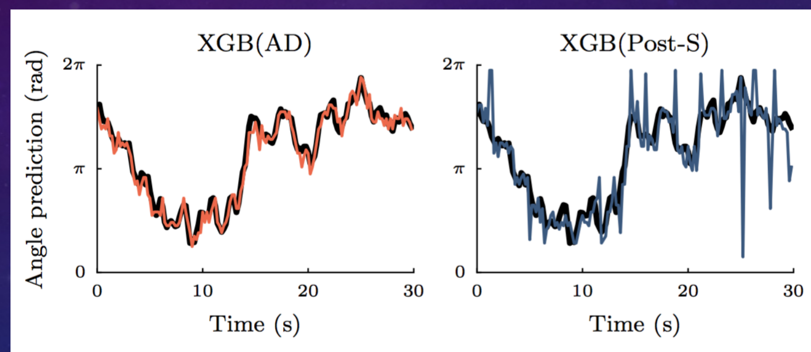
Johnson et al., *J Neuroscience*, 2007

Bayesian decoding of ensemble of hippocampal place cells reveals that when weighting options (going left or right) at the fork of the maze, **hippocampal place cells 'imagine' future routes**

THE FUTURE OF DECODING: MACHINE LEARNING

Gradient Tree Boosting



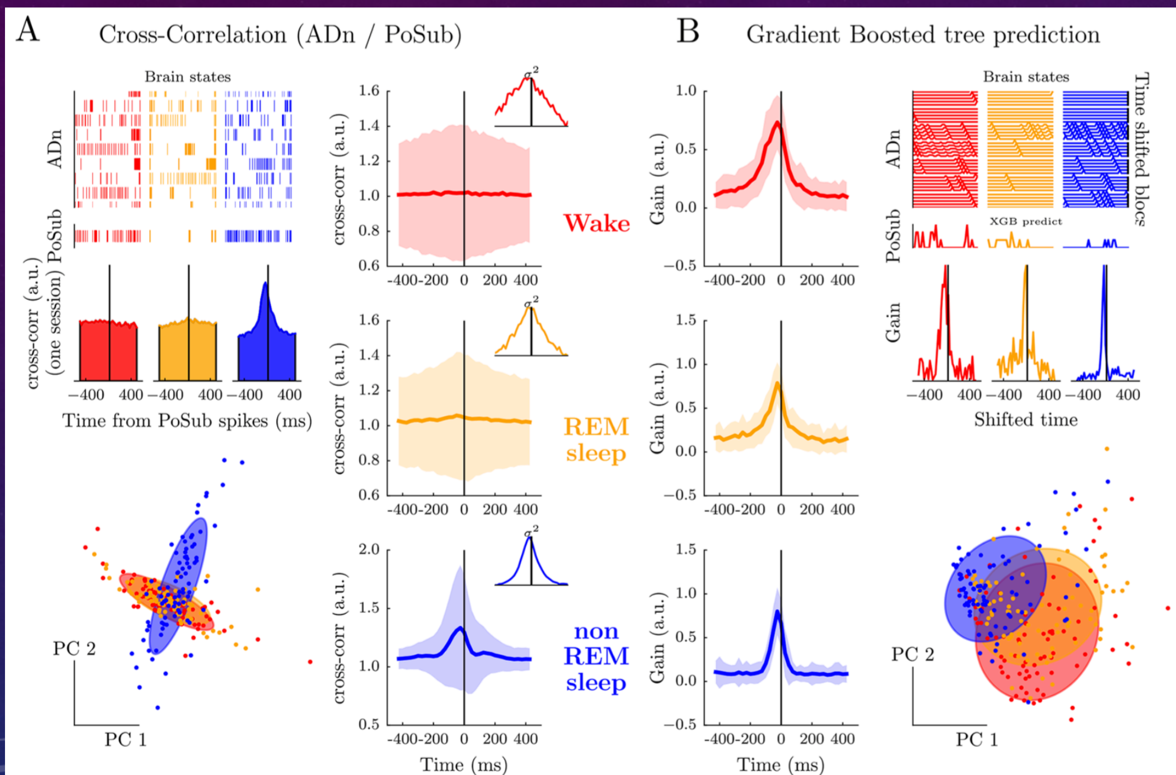


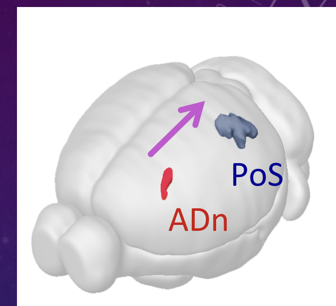
- Splits feature space to build optimal prediction
- Equals, if not outperforms Bayesian decoder, without computing tuning curve, etc.

Viejo et al., PLoS Comp Bio, 2018

Guillaume Viejo

Thomas Cortier





Feature space:
ADn spikes at multiple time lags

Gradient tree boosting ‘splits’ ADn data from previous 50-100ms to predict PoSub spiking IN ALL BRAIN STATES.

Easy way to reveal invariant feed-forward information flow.

Viejo et al., PLoS Comp Bio, 2018

DATA AVAILABLE FOR DOWNLOAD

CRCNS
Collaborative Research in Computational Neuroscience

th–1

Extracellular recordings from multi–site silicon probes in the anterior thalamus and subicular formation of freely moving mice. Contributed by Adrien Peyrache and Gyorgy Buzsáki.

About th–1
Information about the th–1 data set.

th–1 downloads at NERSC
Link for downloading th–1 data set files. Requires logging in with a CRCNS.org account. Allows batch downloading of multiple files. Details about batch downloading are given in the "Alternative Download method" section of the download page.

crcns.org/data-sets/thalamus/th-1
Github.com/PeyracheLab