PLACE FIELDS AND HEAD DIRECTION CELLS ANALYSES

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11TH ANNUAL CANADIAN NEUROSCIENCE MEETING

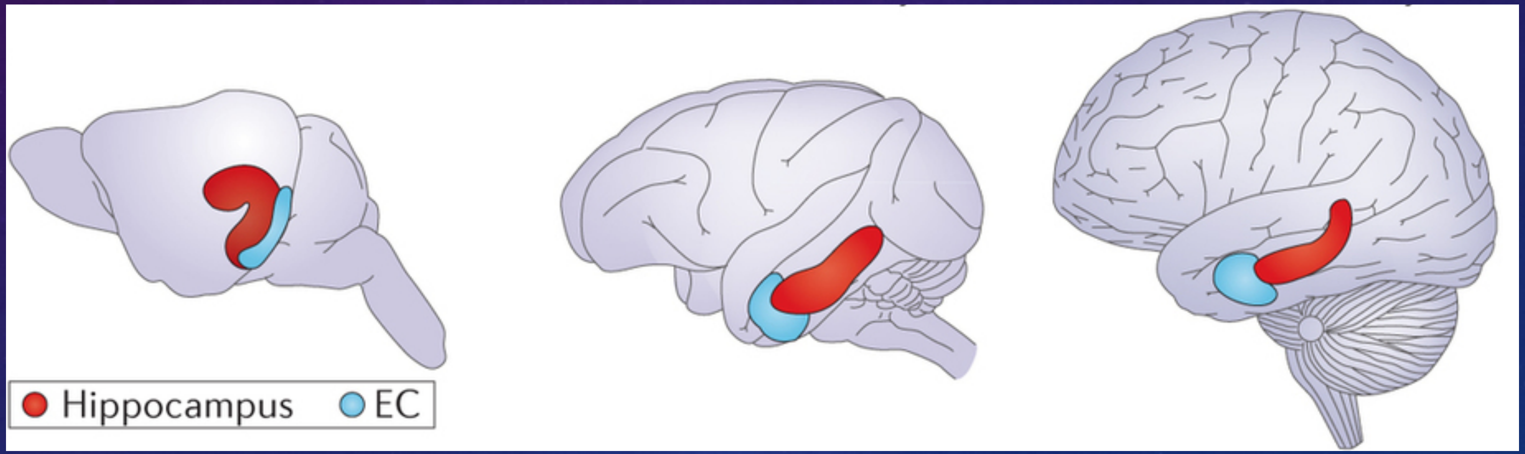
NEURAL SIGNAL AND IMAGE PROCESSING: QUANTITATIVE ANALYSIS OF NEURAL ACTIVITY

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

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

NAVIGATION CAPABILITIES DEPEND ON THE HIPPOCAMPUS (& ASSOCIATED STRUCTURES)

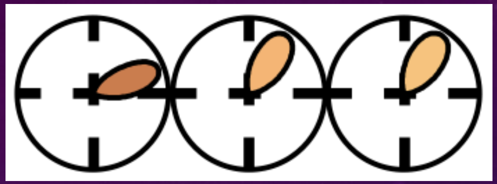
O'Keefe and Nadel, 1978



Strange et al., Nat Rev Neuro, 2014

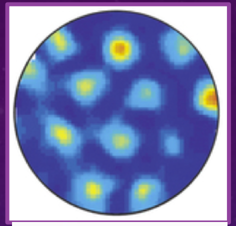
There must be a neuronal support for this cognitive process

Head-direction cells



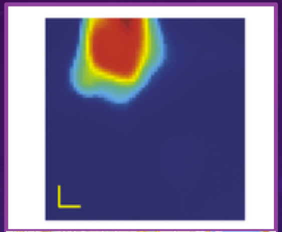
James Ranck & Jeff Taube

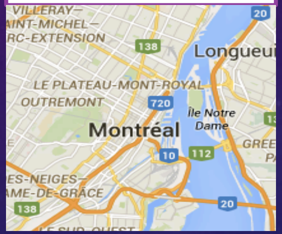
Grid cells



May-Britt and Edvard Moser

Place cells

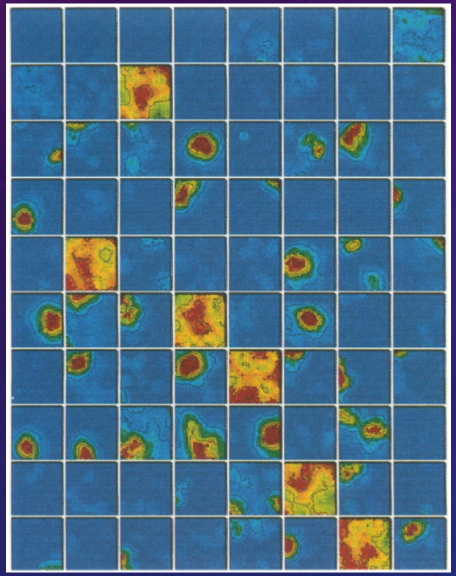




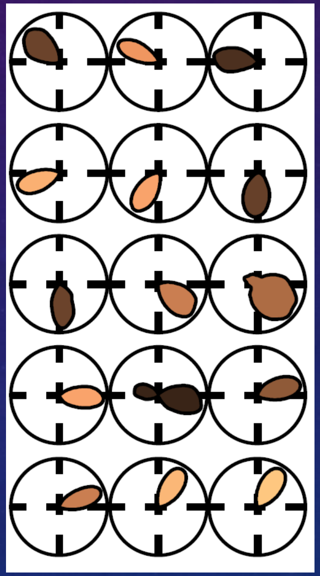
John O'Keefe

How to compute the tuning curves?
How can strength of encoding be measured?

LARGE ENSEMBLE RECORDINGS



Wilson & McNaughton, Science, 1993



Peyrache et al., Nature Neuroscience, 2015

Can we decode an information 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'.

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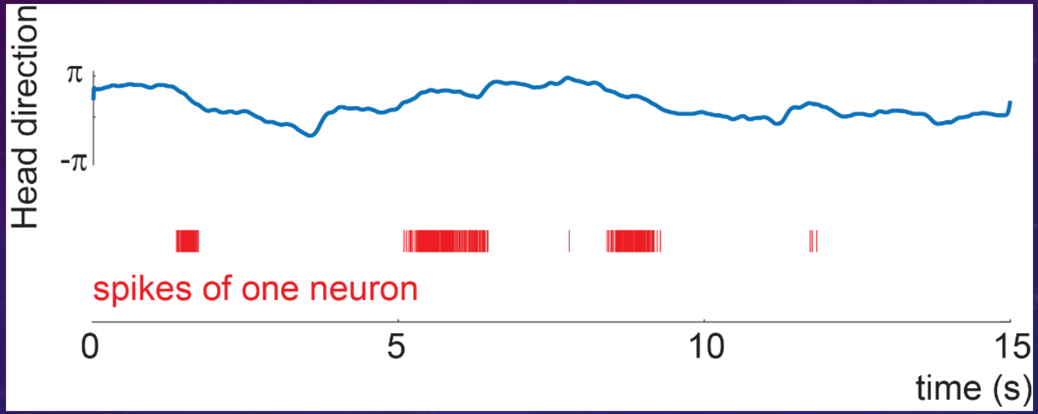
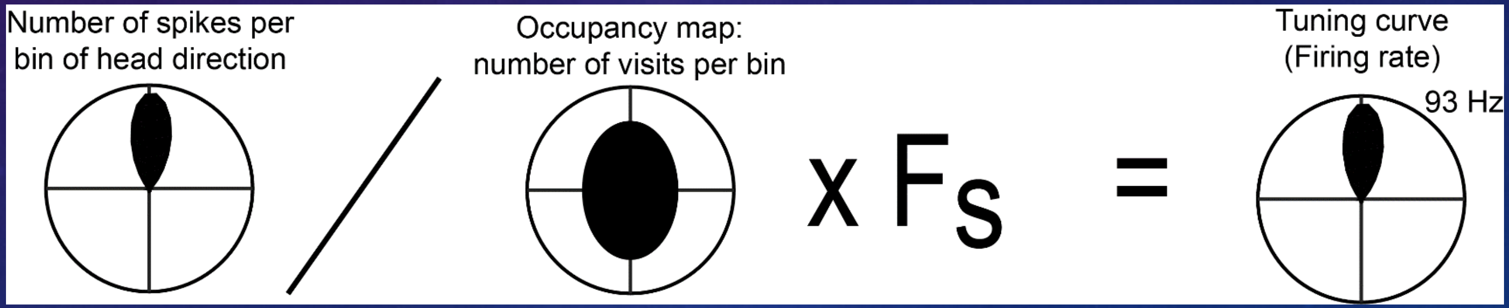
ESTIMATING THE TUNING CURVES



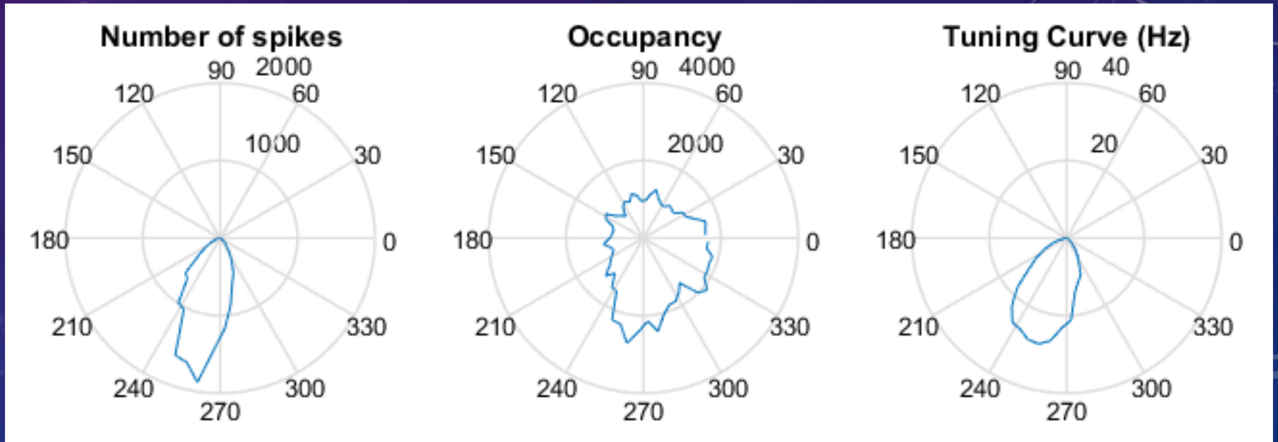


Sampling frequency

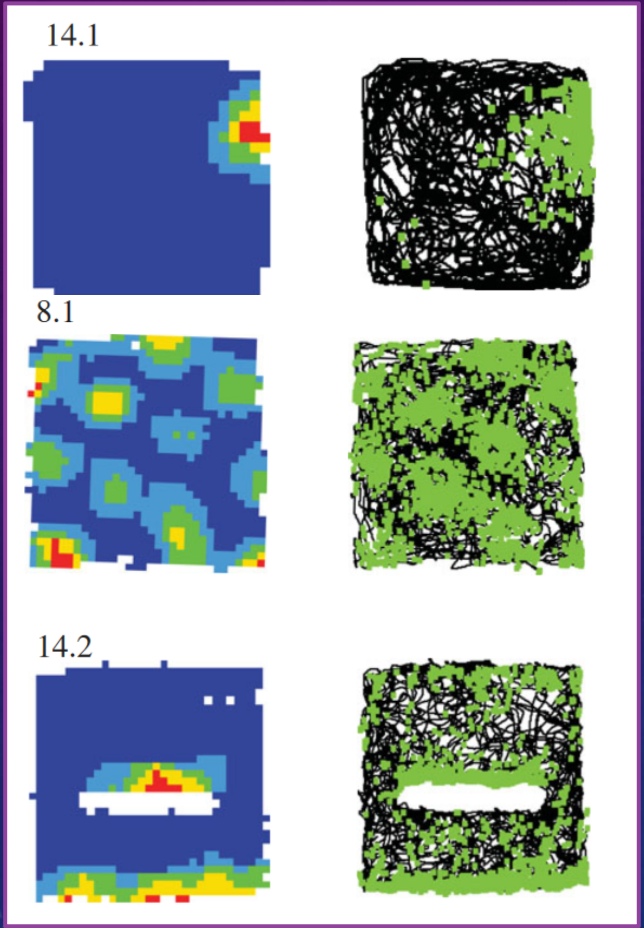
ESTIMATING THE TUNING CURVES

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



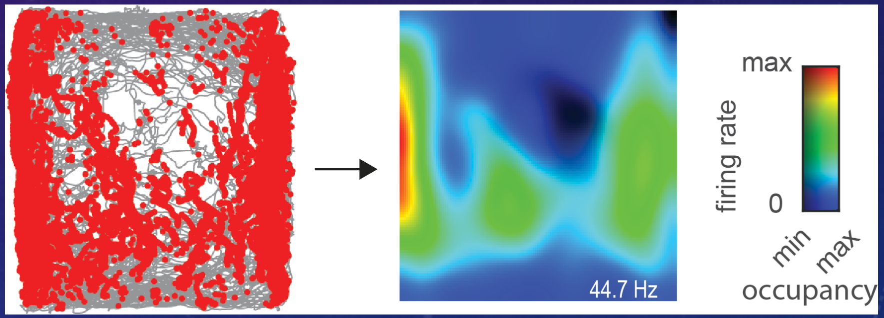
Place cell

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 1^{st} and 2^{nd} halves of recording
- Spatial information

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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)

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

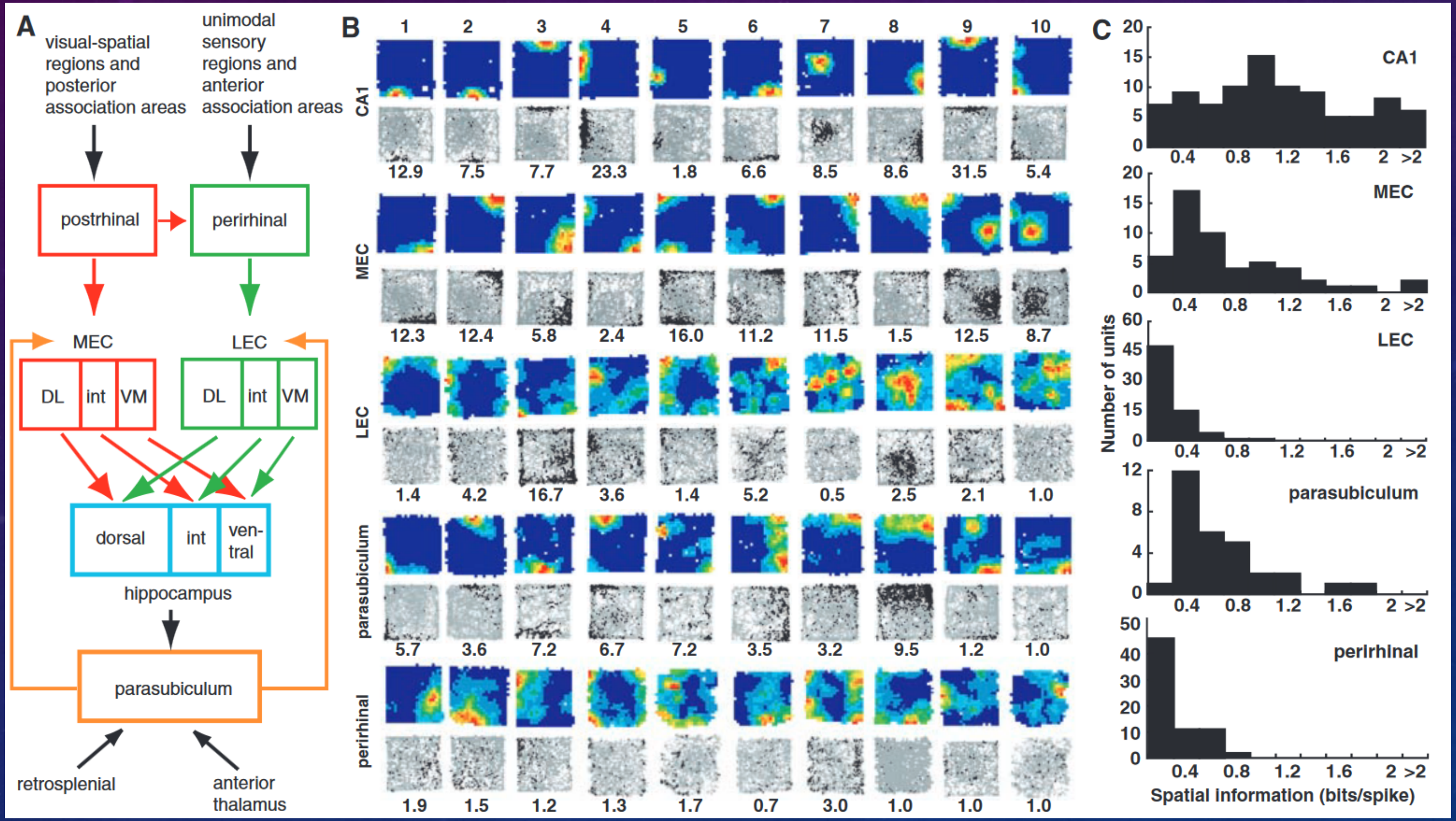
INFORMATION FROM A SINGLE NEURON

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

Run NeuroData_HDInformation.m

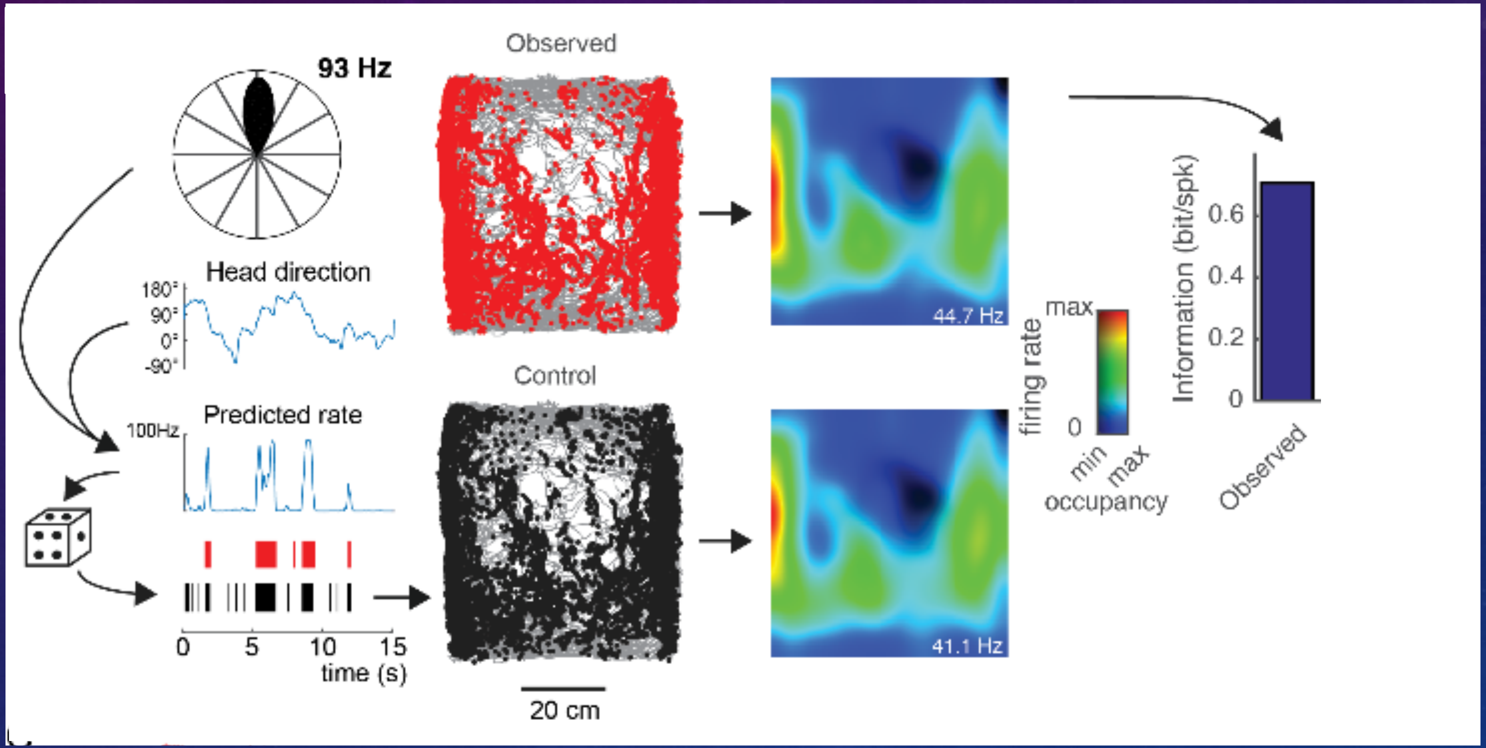
```
% probability of occupancy:
Px = histAng./sum(histAng);

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
Ispk = I/fr;
```

SPATIAL INFORMATION ACROSS BRAIN AREAS



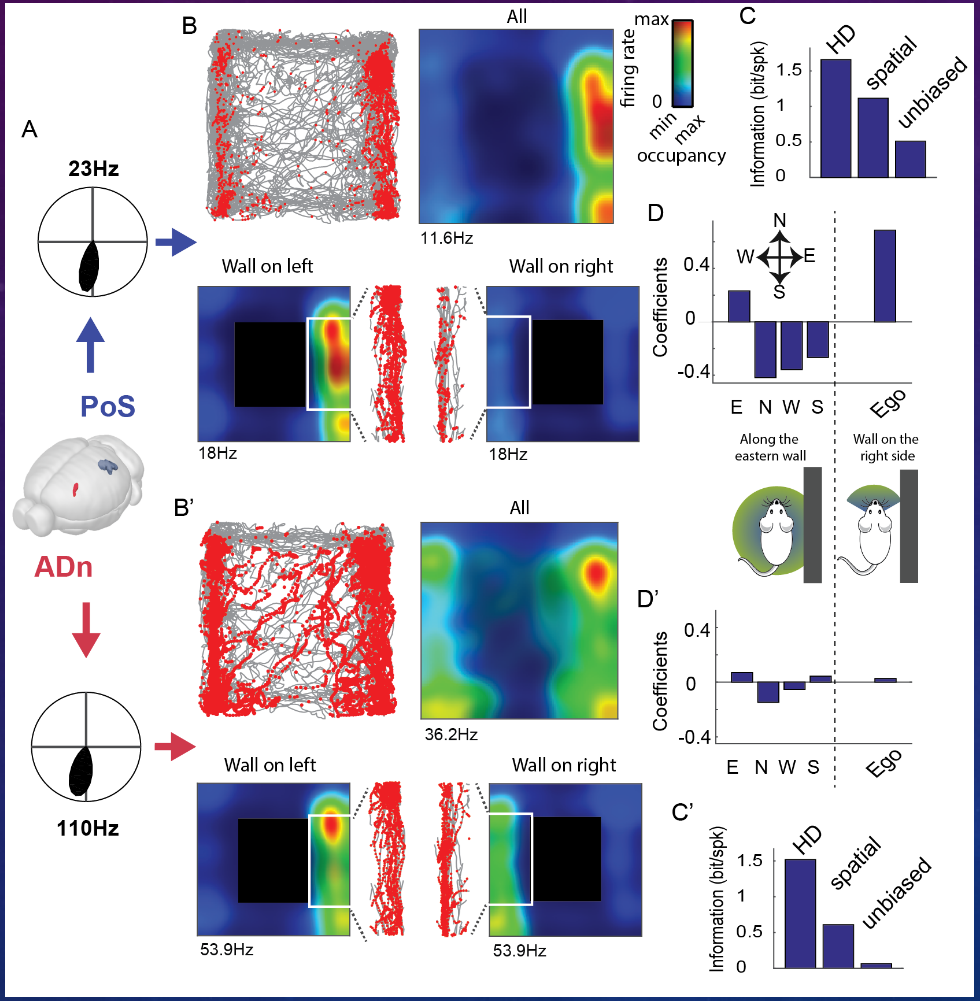
Hargreaves et al., *Science*, 2004

RELATIONSHIP BETWEEN HD AND SPATIAL INFO



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

INTEGRATING ALLOCENTRIC AND EGOCENTRIC INFO



In the Post-Subiculum:
HD cell fires more along one the wall.
Integration with 'egocentric' information

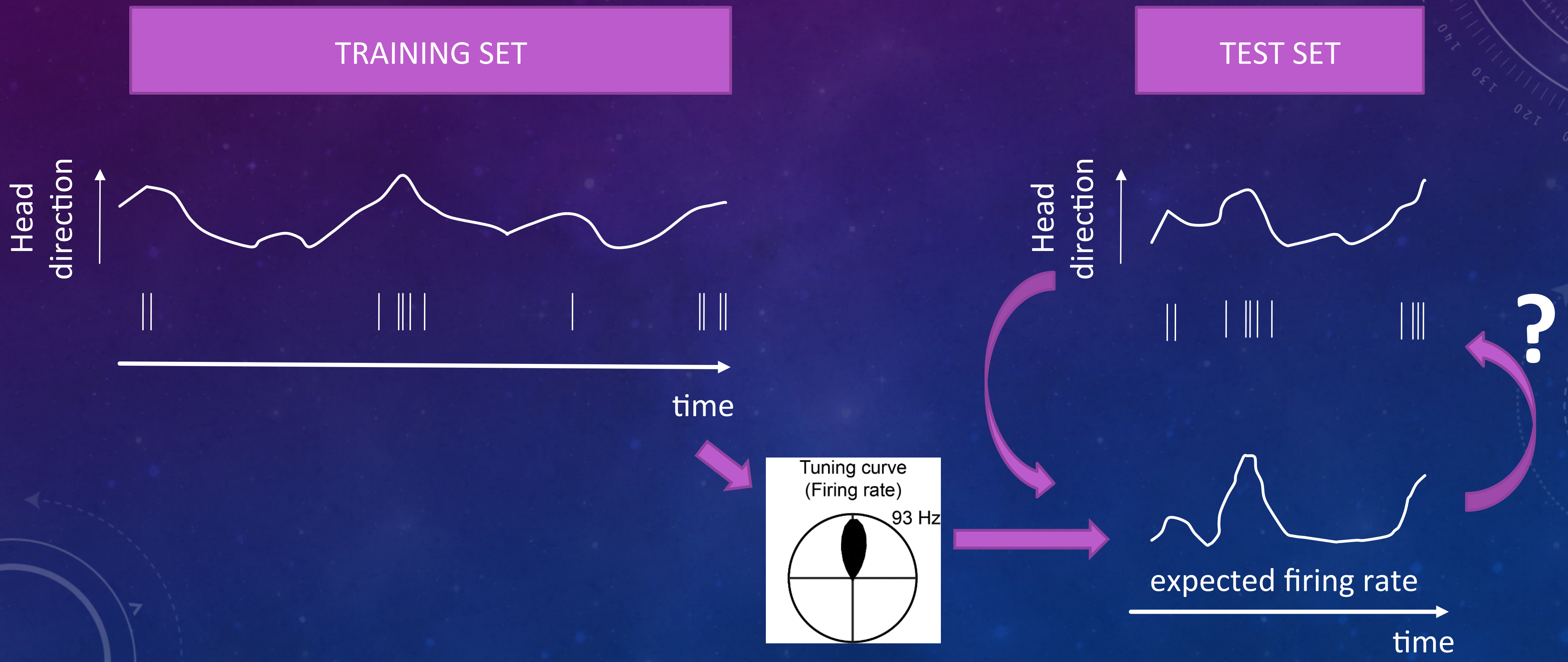
In the antero-dorsal nucleus:
HD cell fire along the walls parallel to the preferred direction

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)

$$L = L_f - L_0$$

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

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

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.

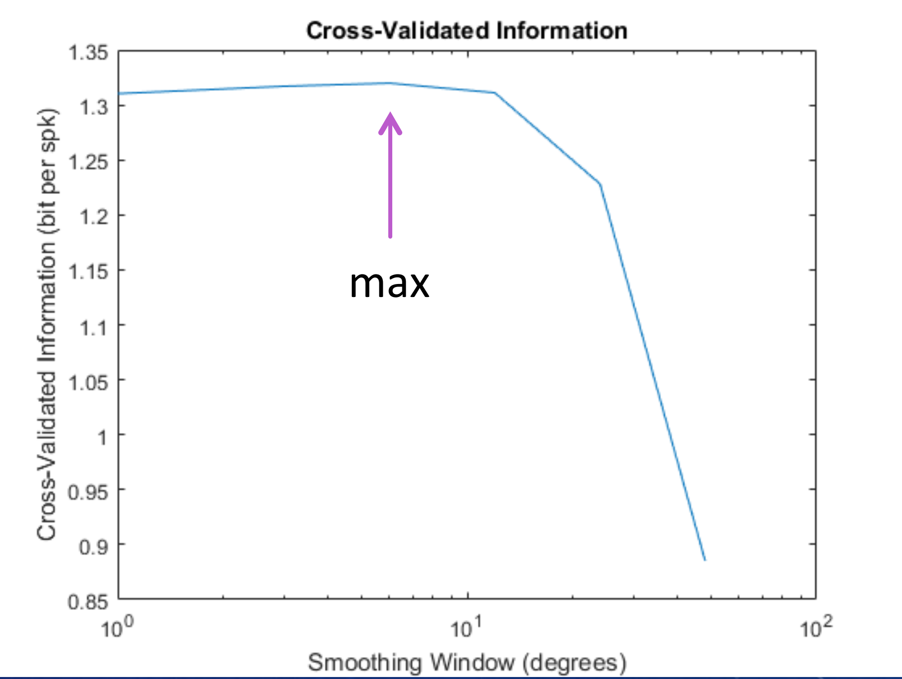
We can use cross-validation to optimize the resolution of the tuning curve

CROSS-VALIDATED INFORMATION MEASURE

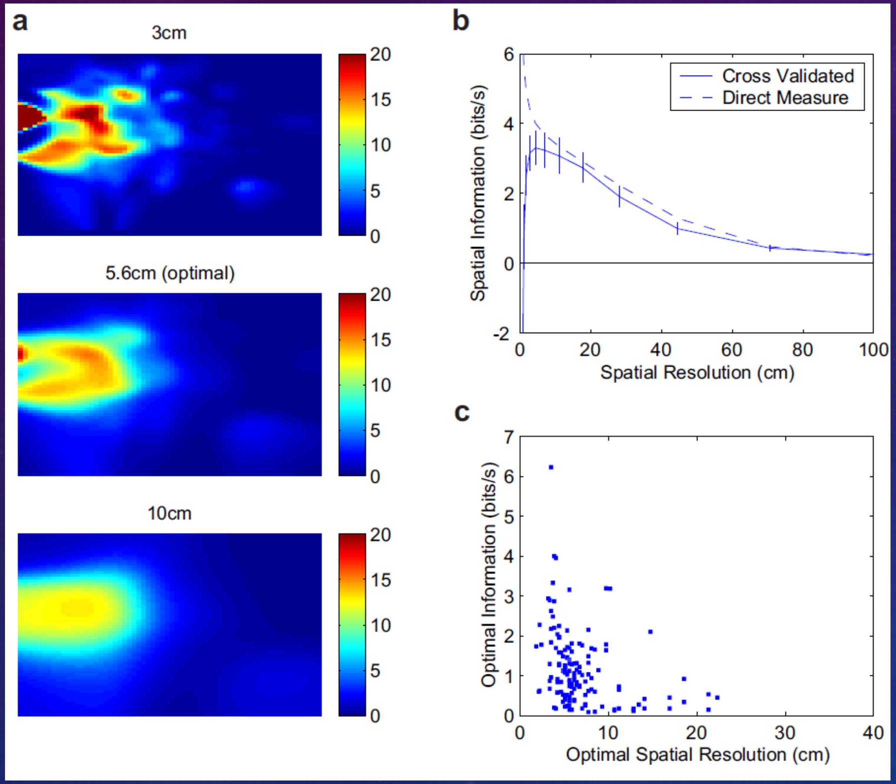
Run NeuroData_HDInformation_Xval_SmoothSearch.m

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



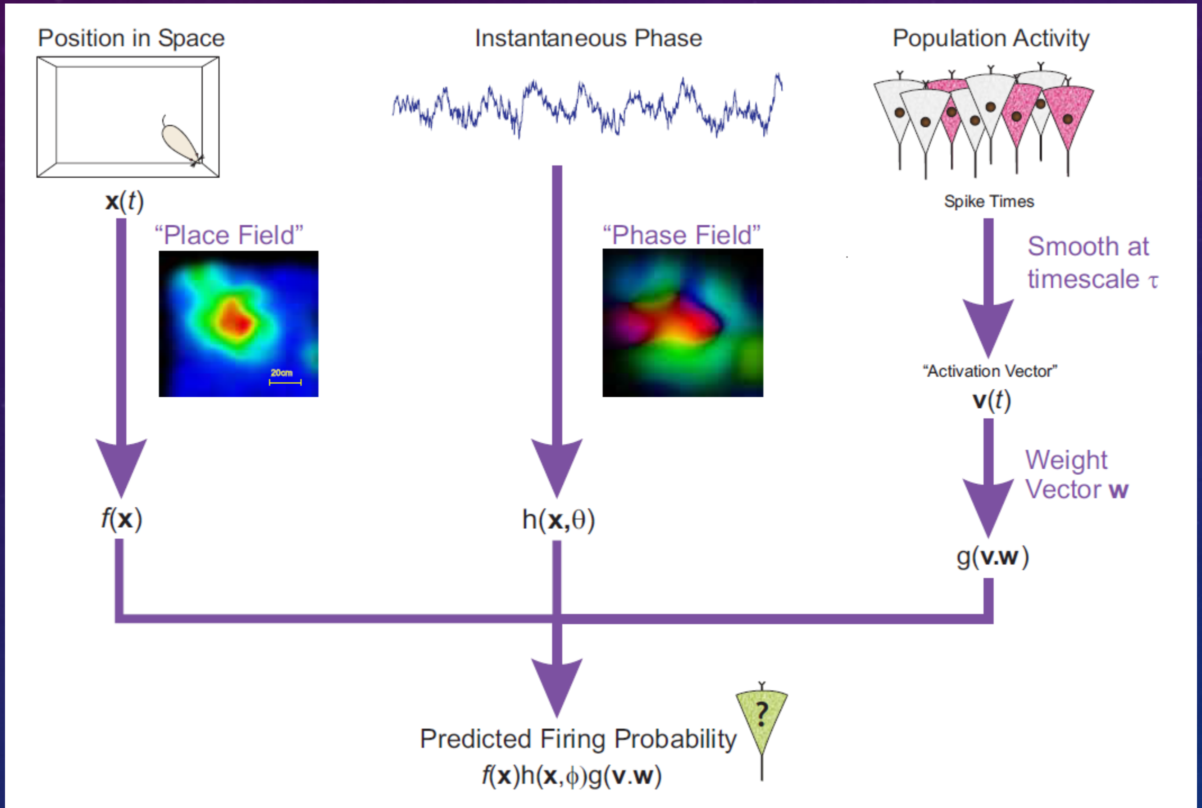
CROSS-VALIDATED INFORMATION MEASURE



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

Cross-validation allows to find the optimal spatial resolution of place cells (~4-5 cms)

CROSS-VALIDATED INFORMATION MEASURE



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

Other features can be used to build the predicted intensity function

OUTLINE

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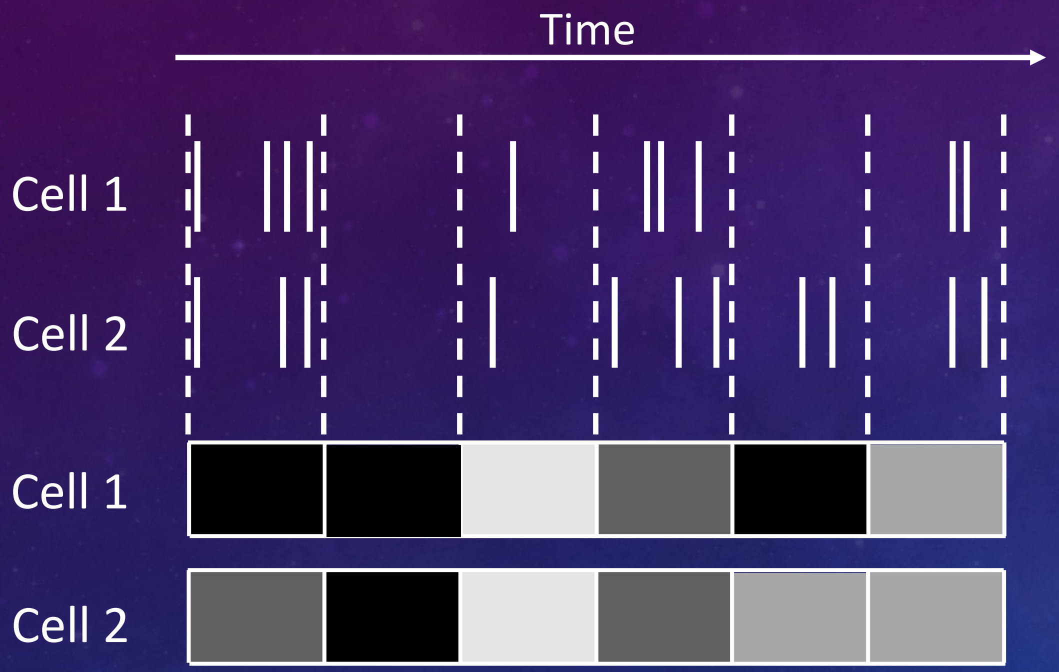
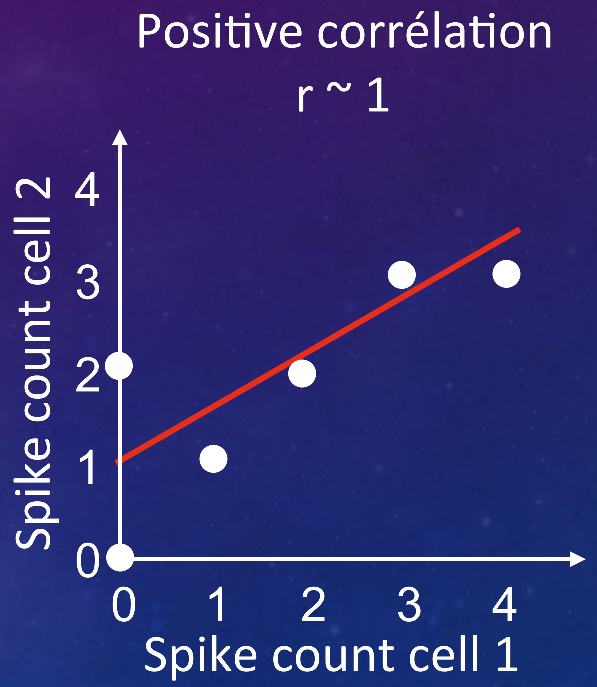
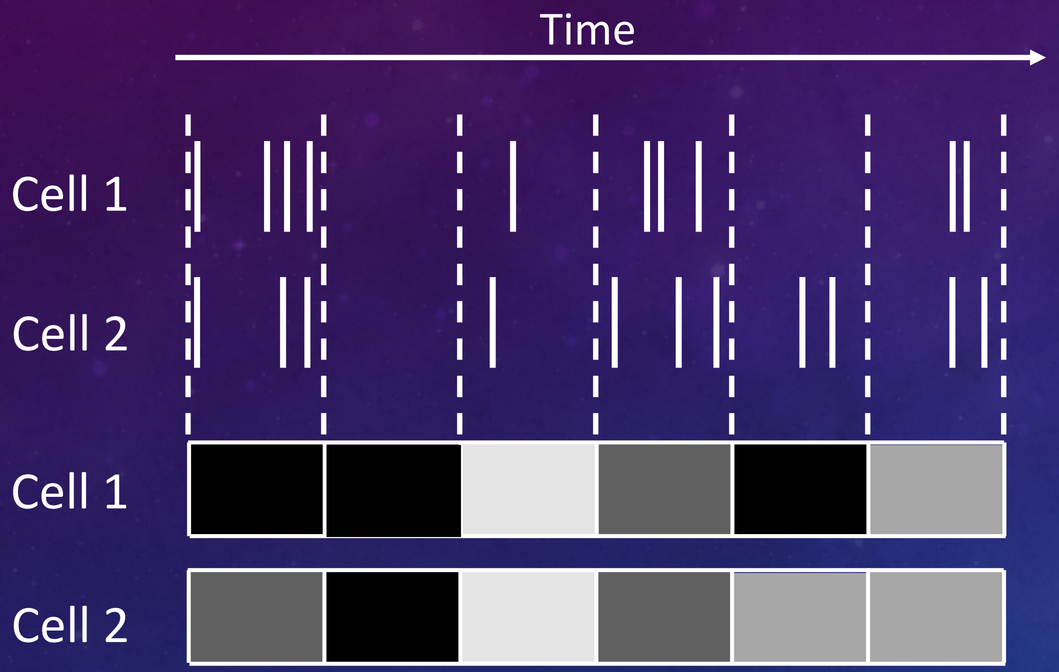
- **Decoding***:* Reading-out the 'neuronal code'.

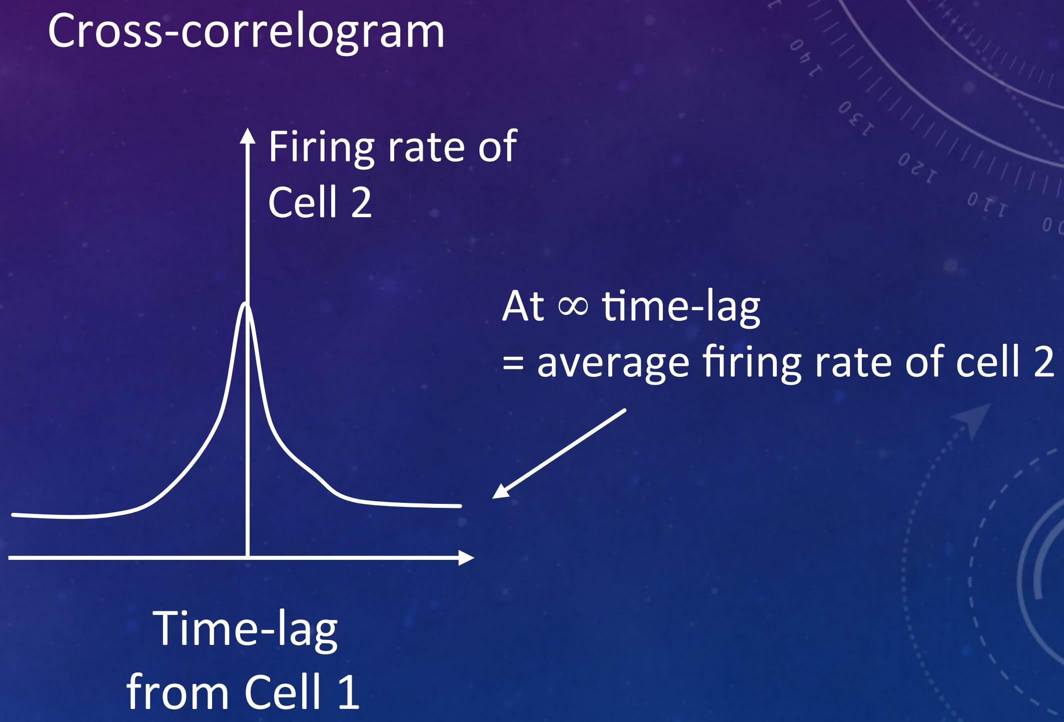
PAIRWISE CORRELATION

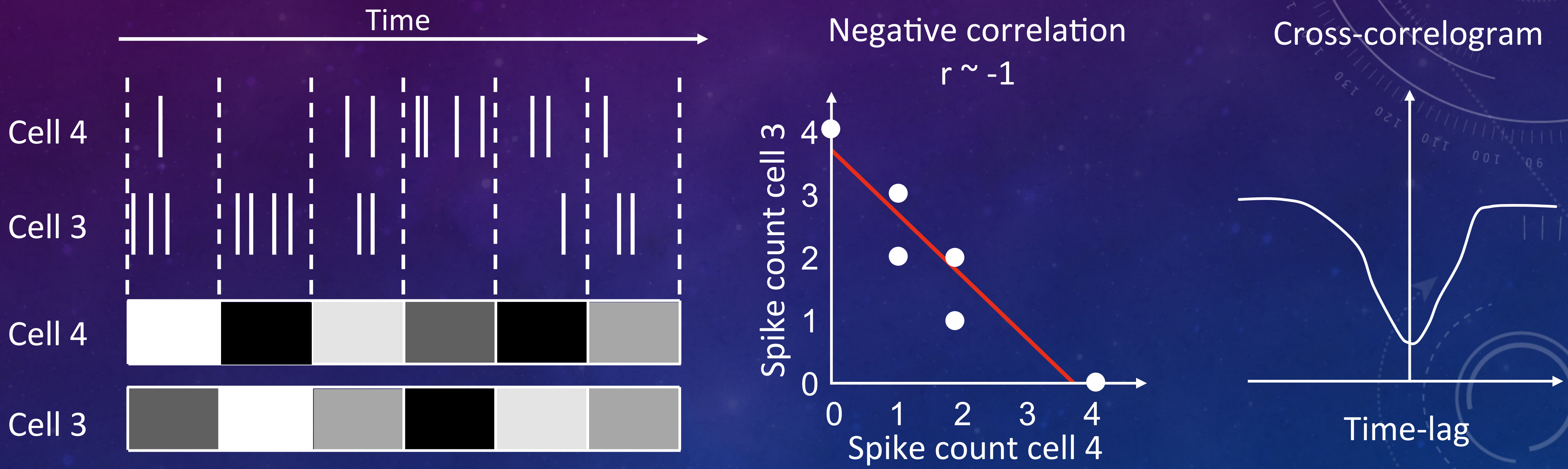


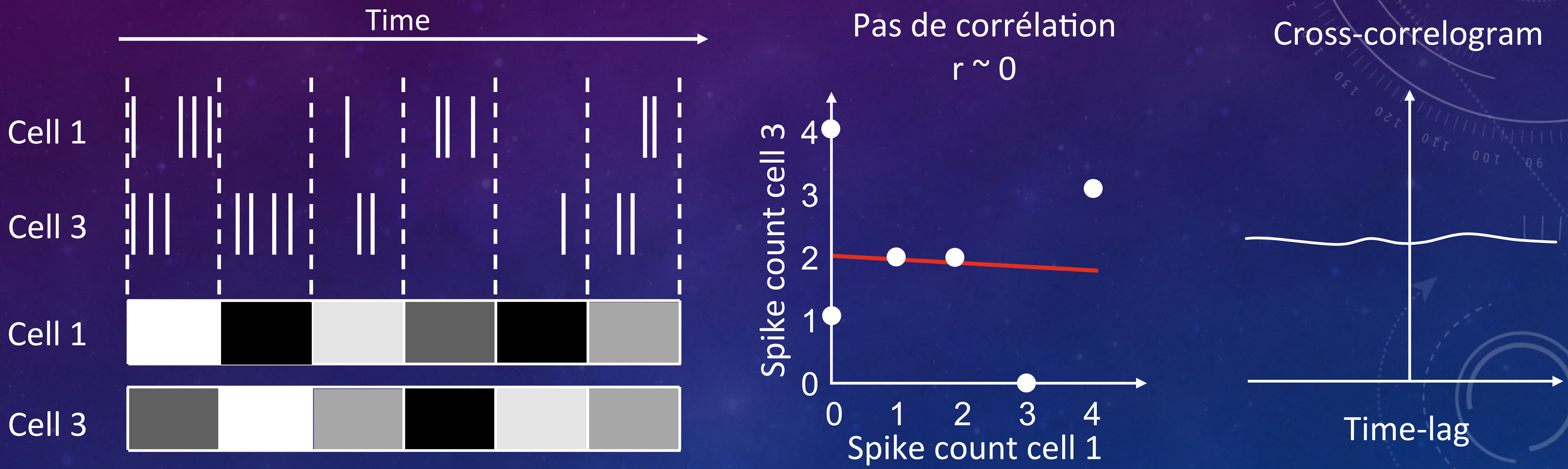


PAIRWISE CORRELATION





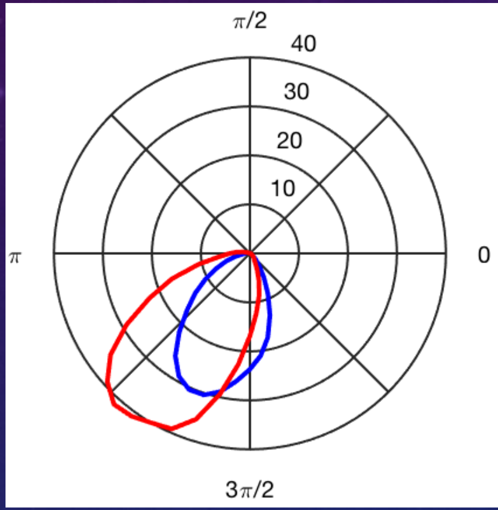

Time
Cell 4
Cell 3
Cell 4
Cell 3
Negative correlation
r ~ -1
Spike count cell 3
4
3
2
1
0
0
1
2
3
4
Spike count cell 4
Cross-correlogram
Time-lag

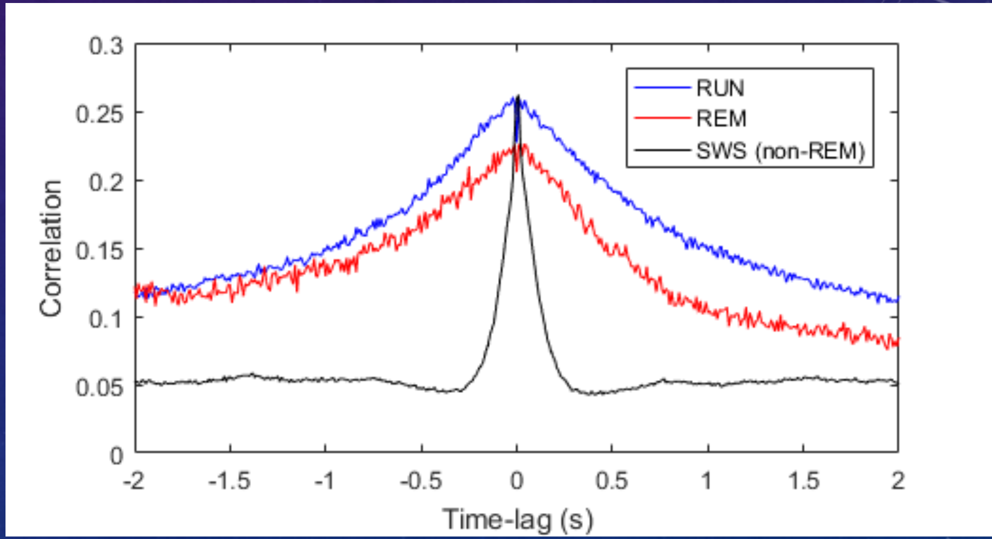

Time
Cell 1
Cell 3
Cell 1
Cell 3
Pas de corrélation
r ~ 0
Spike count cell 3
4
3
2
1
0
0
1
2
3
4
Spike count cell 1
Cross-correlogram
Time-lag

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



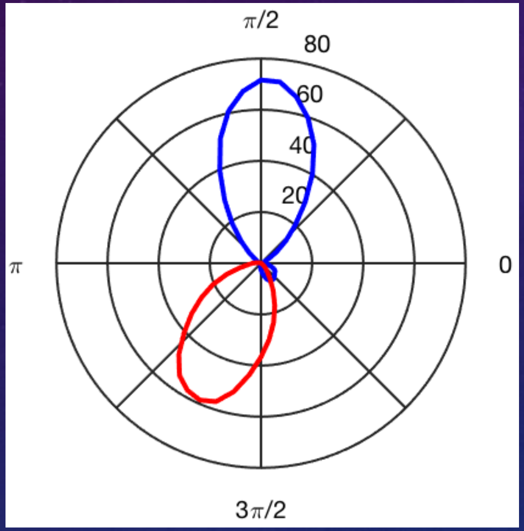


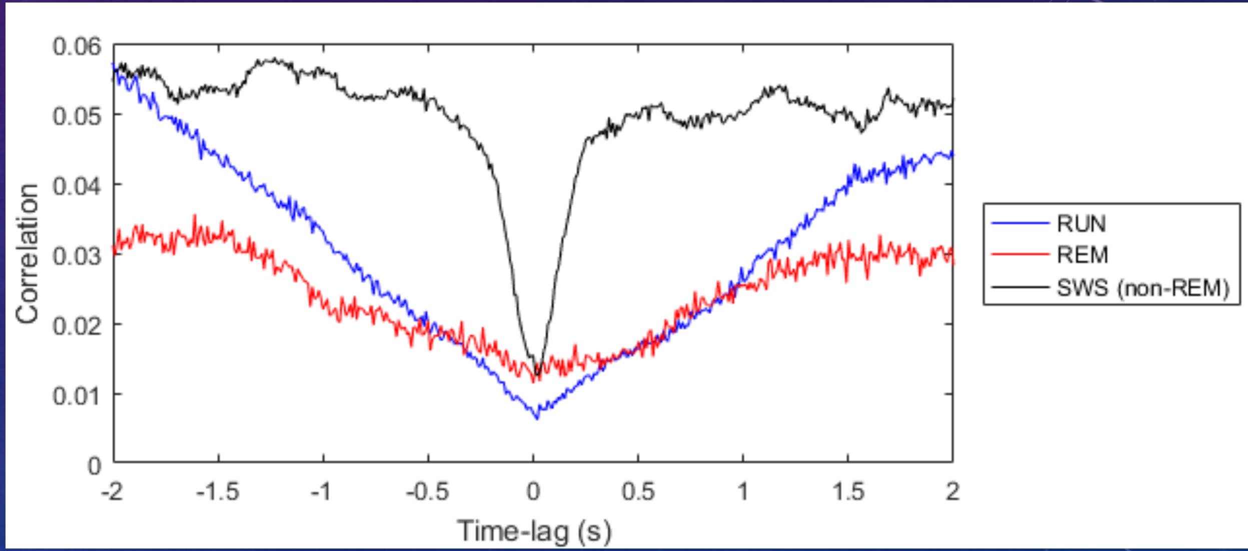
- Preserved correlation during sleep
- Same dynamics during wakefulness and REM sleep
- ‘accelerated’ dynamics during non-REN

EXAMPLE: HEAD-DIRECTION CELLS

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

Uncomment cellIx and rerun NeuroData_HDCellCorrelation

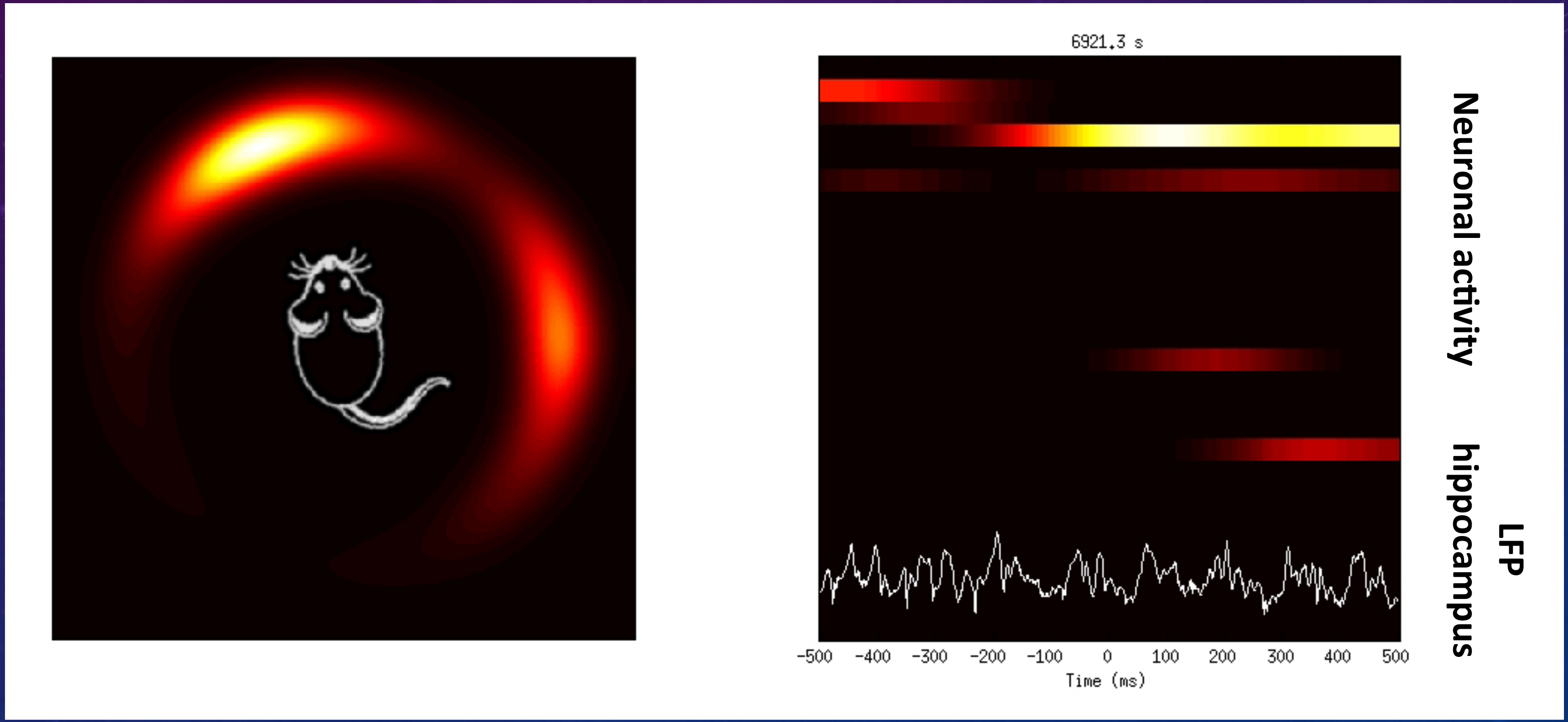




HD cells that fire for opposite direction never fire together.

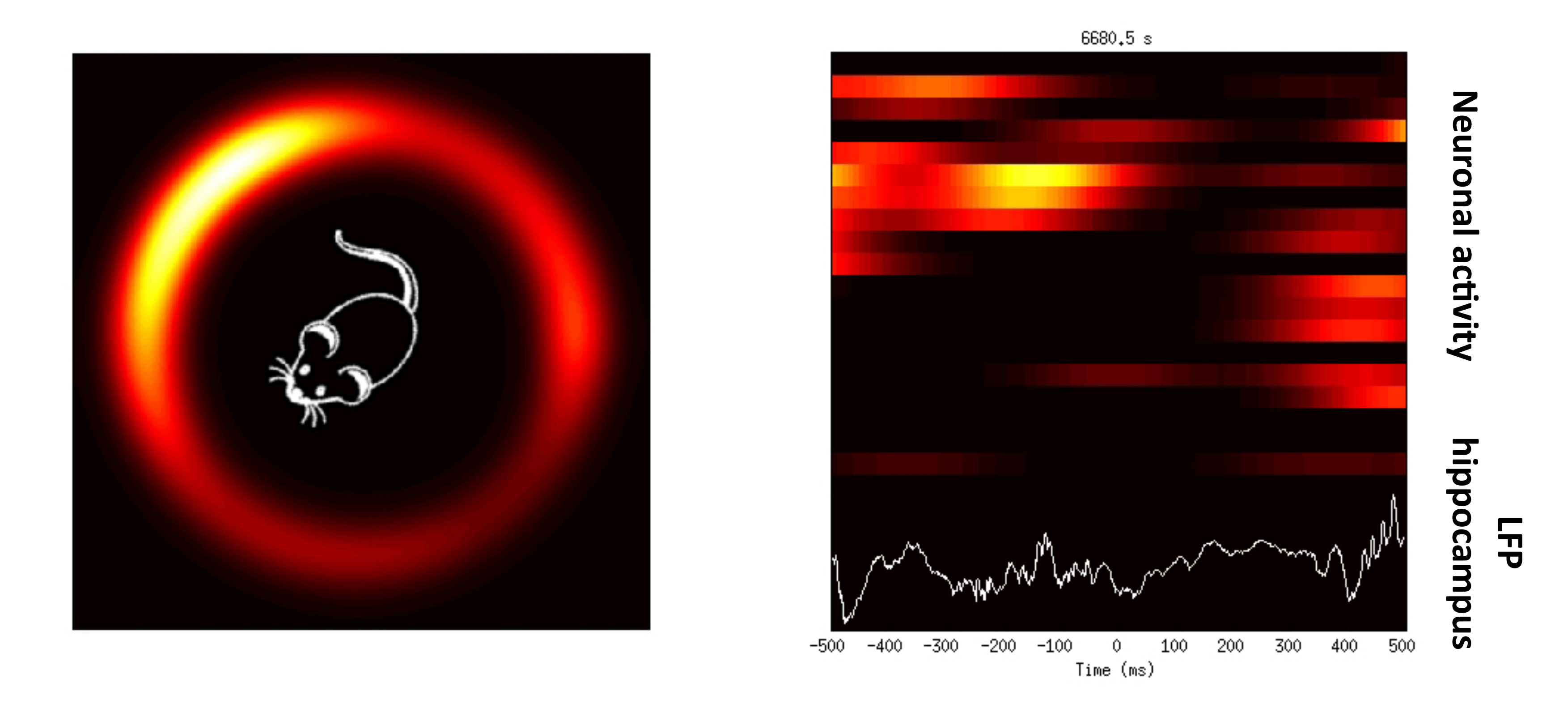
EXAMPLE: HEAD-DIRECTION CELLS

RUNNING

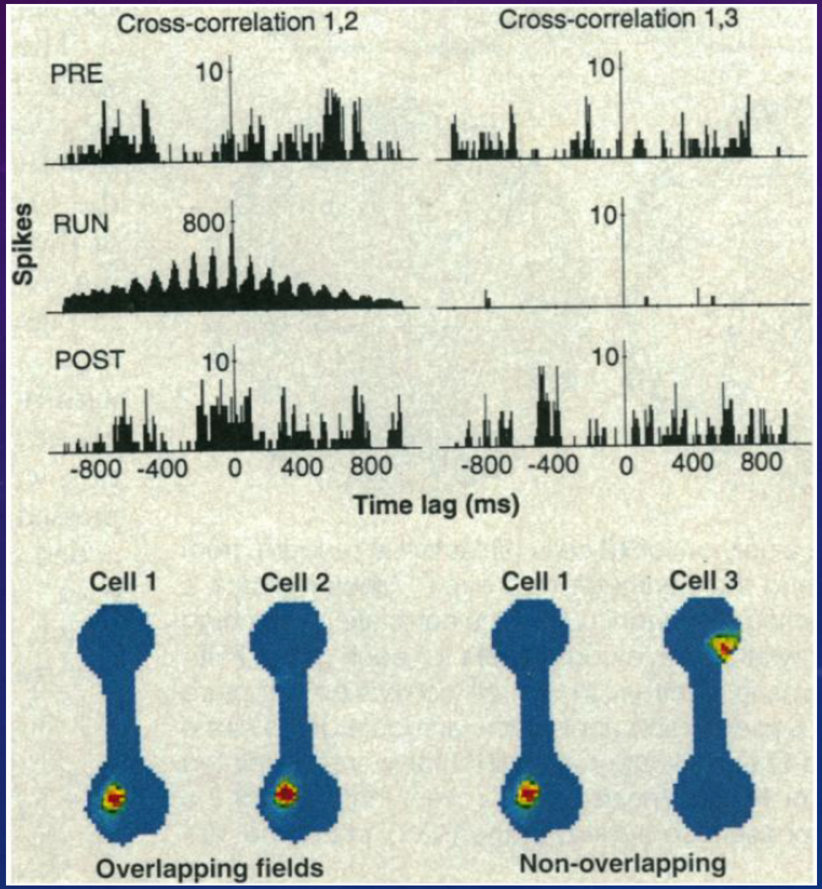


What happens when the animal is asleep?

EXAMPLE: HEAD-DIRECTION CELLS

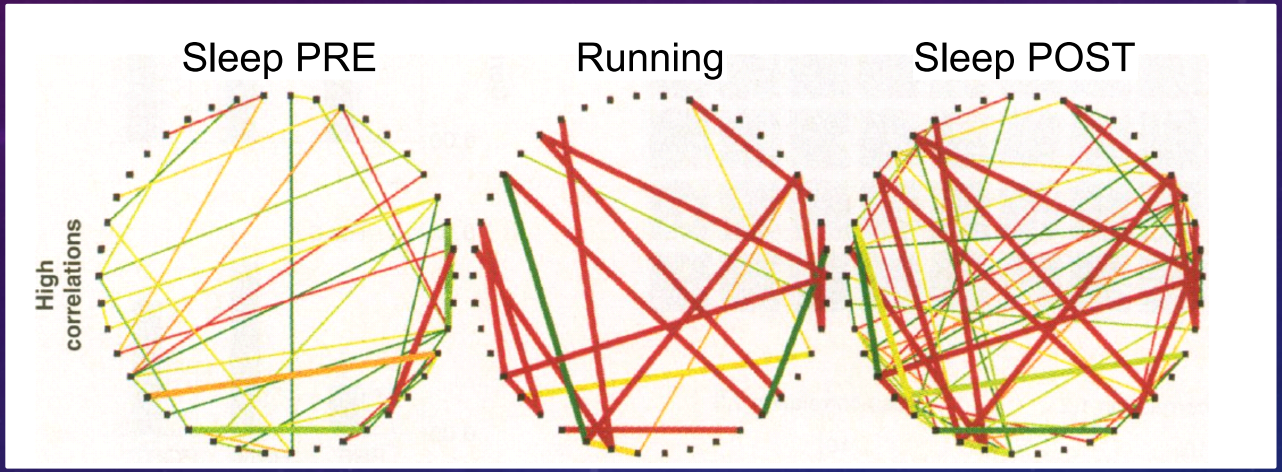


CHANGE IN CORRELATIONS WITH LEARNING



Wilson and McNaughton, *Science*, 1994

CHANGE IN CORRELATIONS WITH LEARNING



Wilson and McNaughton, *Science*, 1994

- Unlike HD cells that are ‘hard-wired’, pairwise correlations of hippocampal place cells that form during exploration are ‘reinstated’ during subsequent sleep

OUTLINE

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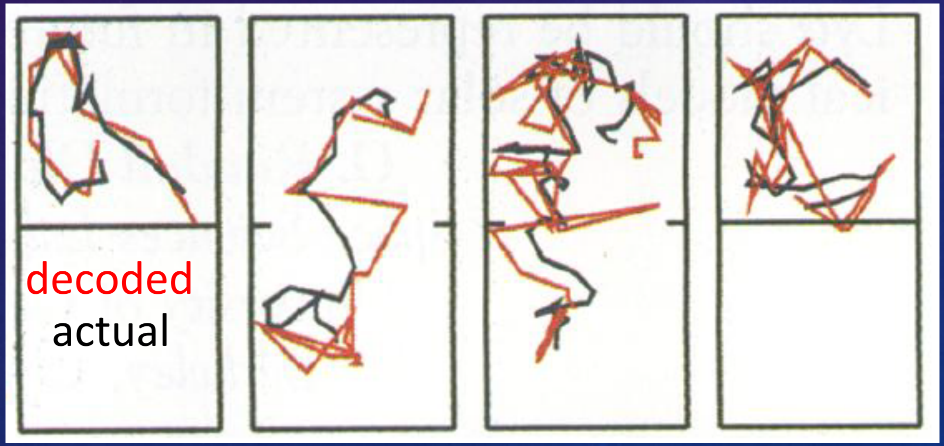
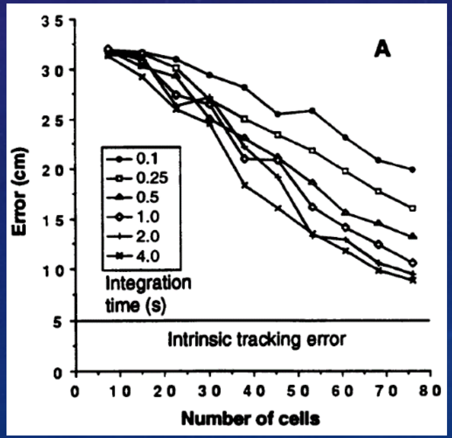
HOW TO DECODE A POPULATION CODE?

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?

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

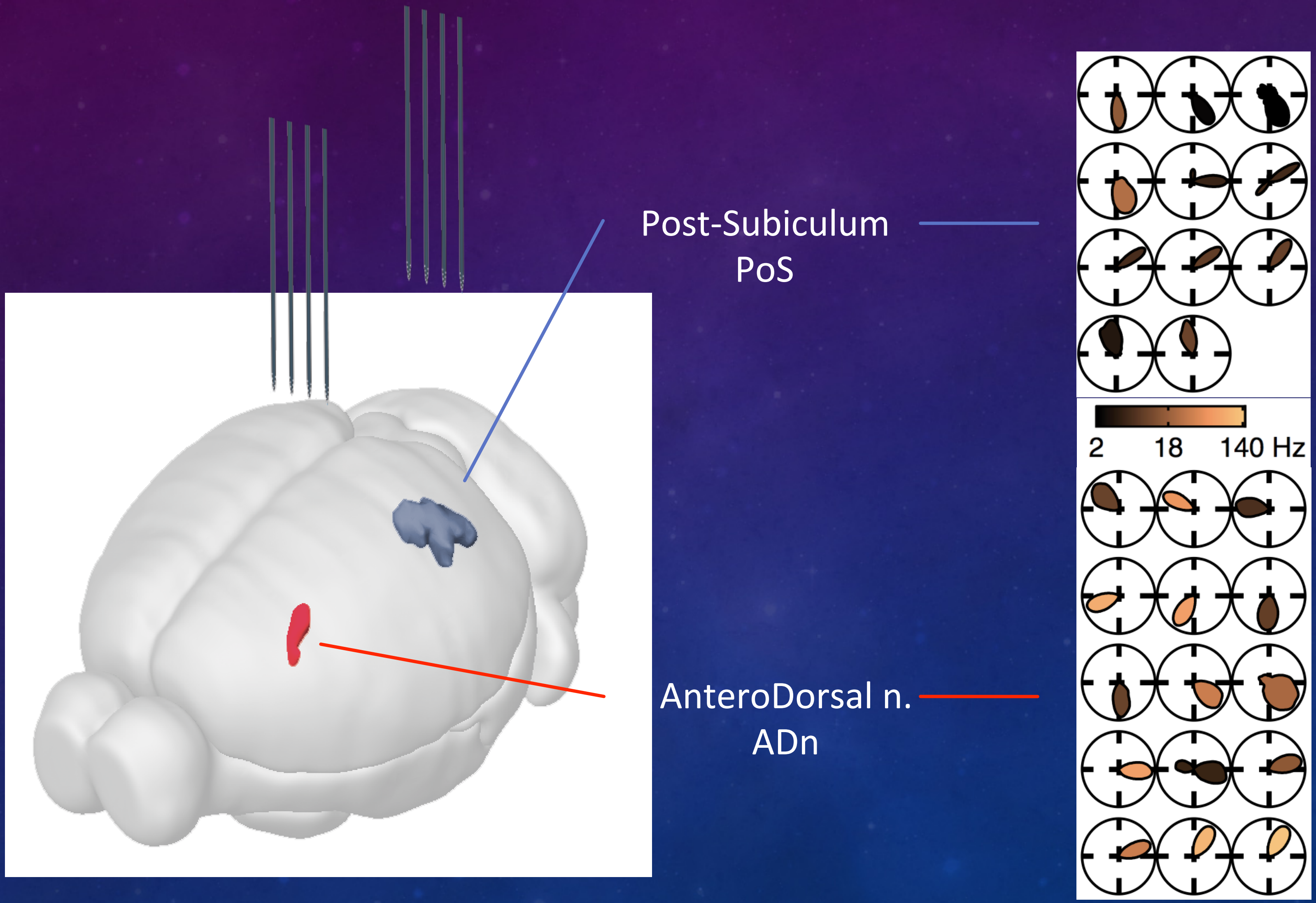
Bayes' rule:

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

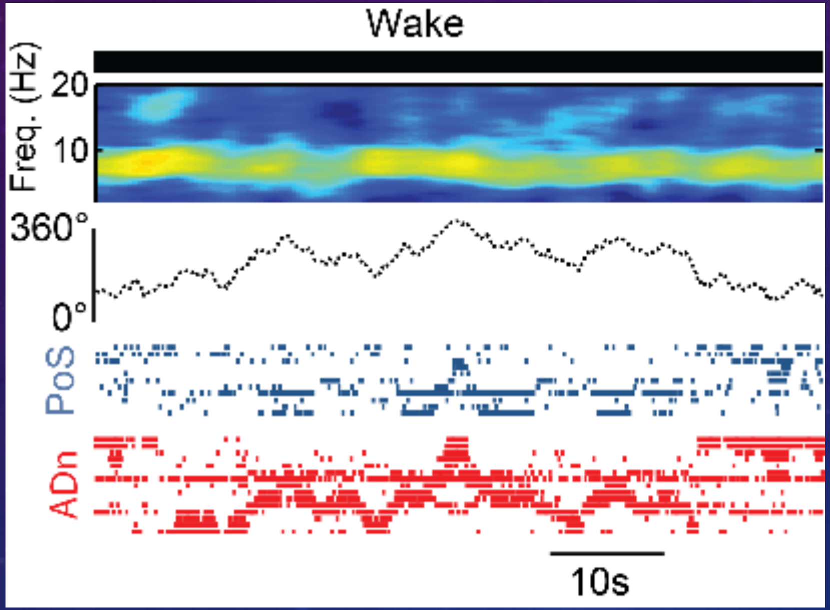
Hypothesis: neurons are independent processes.

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

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


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

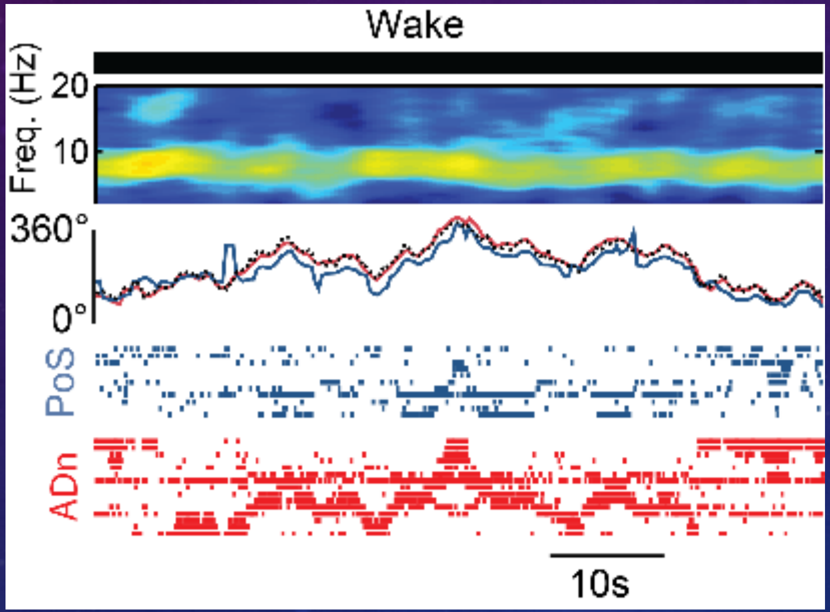
DECODING FROM HD CELL ENSEMBLES



High theta power

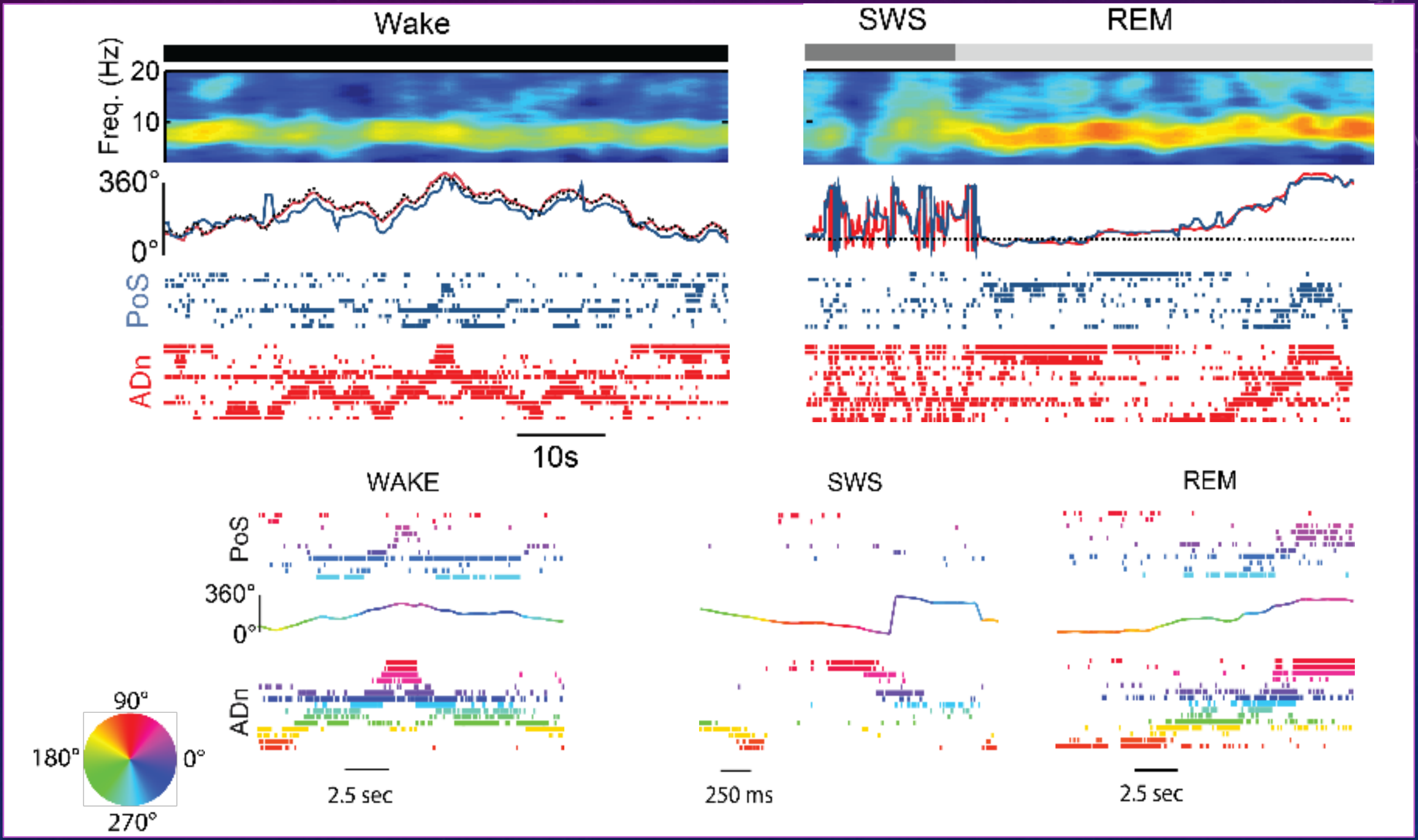
Actual head-direction

DECODING FROM HD CELL ENSEMBLES



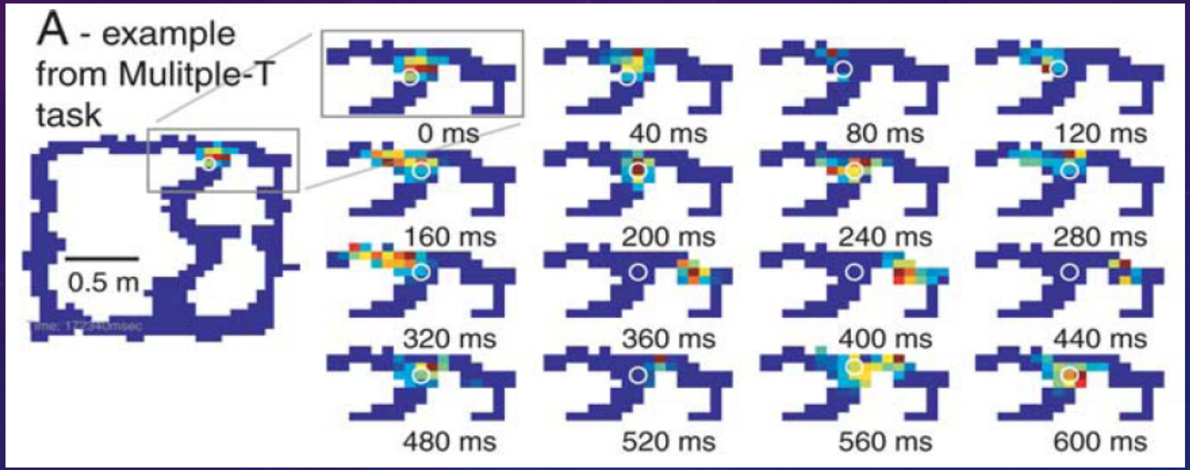
ADn Bayesian reconstruction

PoS Bayesian reconstruction



Wake
SWS
REM
Freq. (Hz)
20
10
360°
0°
PoS
ADn
10s
WAKE
SWS
REM
PoS
360°
0°
ADn
90°
180°
0°
270°
2.5 sec
250 ms
2.5 sec

IMAGINATION:
DISENGAGEMENT FROM SENSORY EXPERIENCE

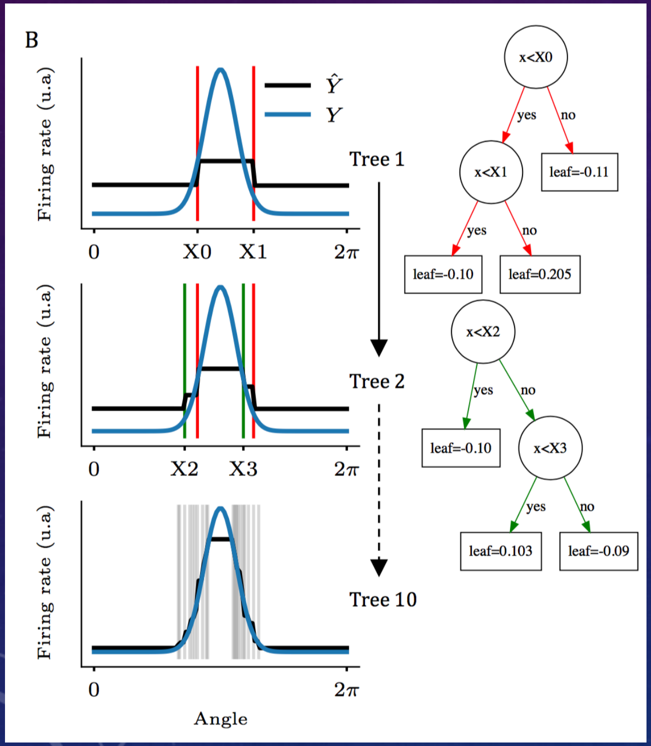


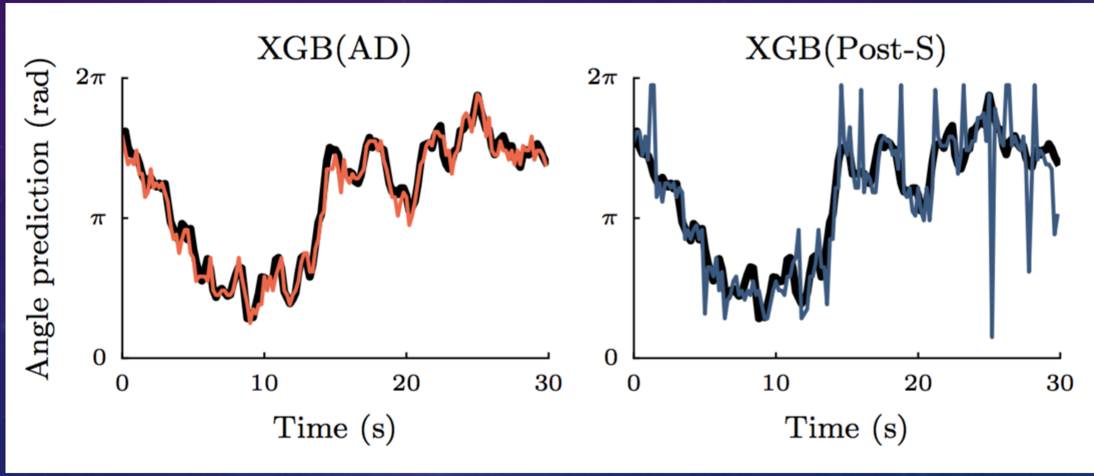
Johnson et al., *J Neuroscience*, 2007

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



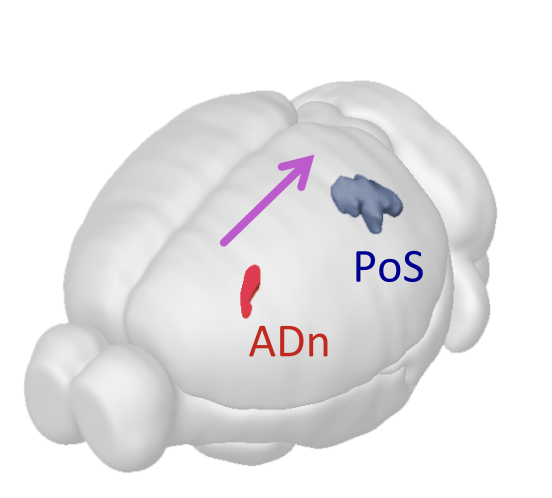


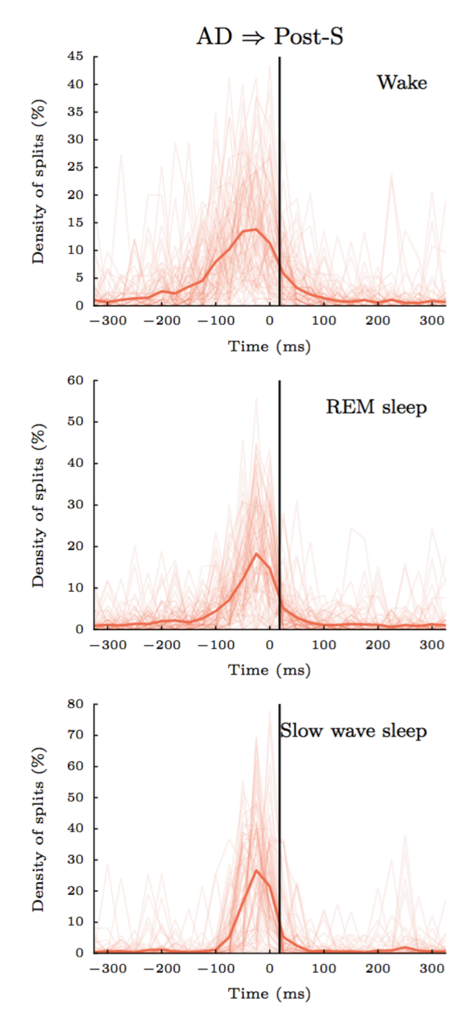
- Splits feature space to build optimal prediction
- Equals, if not outperforms Bayesian decoder, without computing tuning curve, etc.

Guillaume Viejo

Thomas Cortier

THE FUTURE OF DECODING: MACHINE LEARNING





Feature space:
ADn spikes at multiple time lags

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

Easy way to reveal invariant feed-forward information flow.
(no need to assume a *model*)

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