

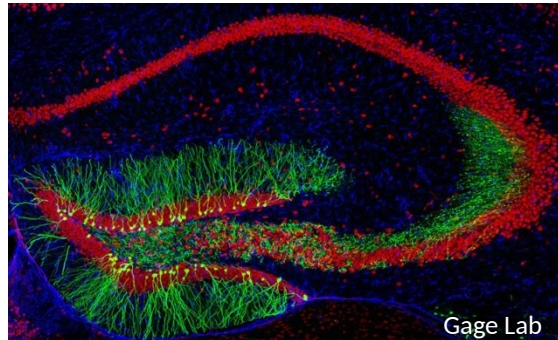
Internal representation of hippocampal neuronal population span a time-distance continuum

Alessandro Torcini

CY Cergy Paris Université - LPTM , Cergy-Pontoise

Hippocampus as a processor

Raw spatio-temporal data



Processed information



Space

Place Cells
Grid/border cells
Head direction cells

Context

Lateral Entorhinal Cortex

Timing

Theta rhythm
Speed cells

Place



Duration

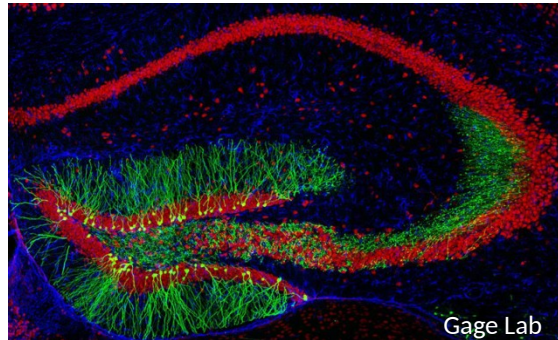


Distance



Processing information in Hippocampus

Raw spatio-temporal data



Processed information



Space
Place Cells
Grid/border cells
Head direction cells

Context
LEC

Timing
Theta rhythm
Speed cells

Bittner et al 2015
Milstein et al 2015

Place



Duration

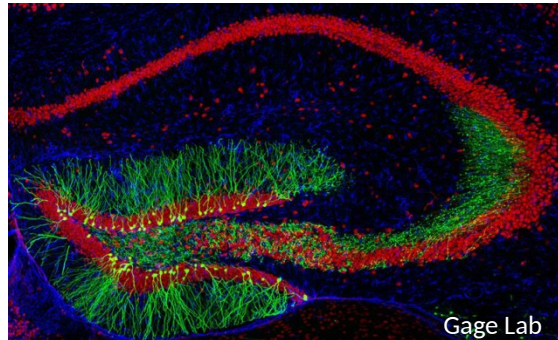


Distance



Hippocampus as a processor

Raw spatio-temporal data



Processed information



Place



Duration



Distance

Space

Grid/border cells
Head direction cells

Context

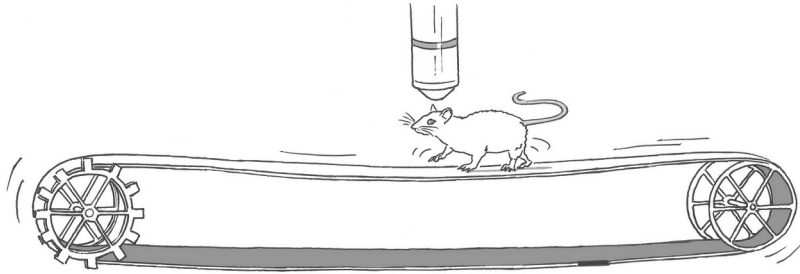
LEC

Timing

Theta rhythm is fundamental
Speed cells

Internally Generated Cell Assembly Sequences in the Rat Hippocampus
Pastalkova, Itskov, Amarasingham & Buzsáki, Science (2008)

New paradigm with spontaneous behavior



Headfixed mouse on a treadmill

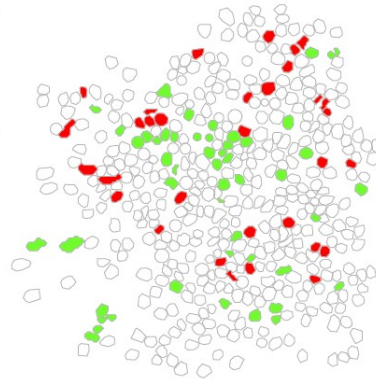
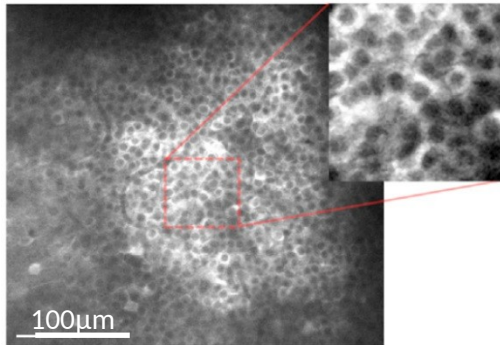
Minimize external information and constraints

- Non motorized
- No task, no reward
- No cues, experiment in the dark
- Neither water nor food deprivation
- N=7 mice

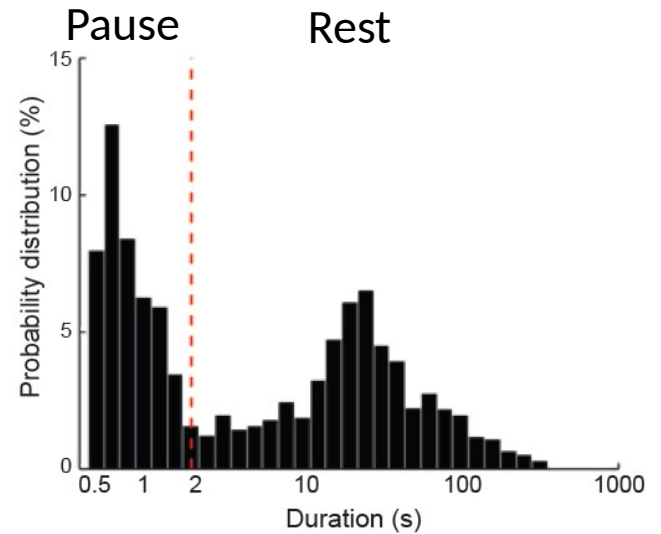
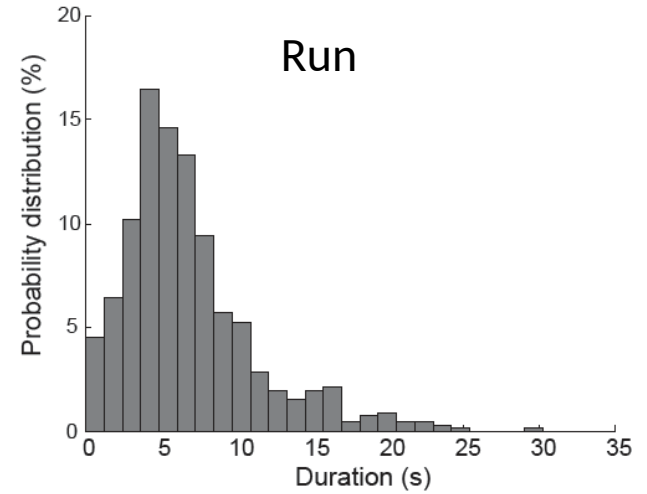
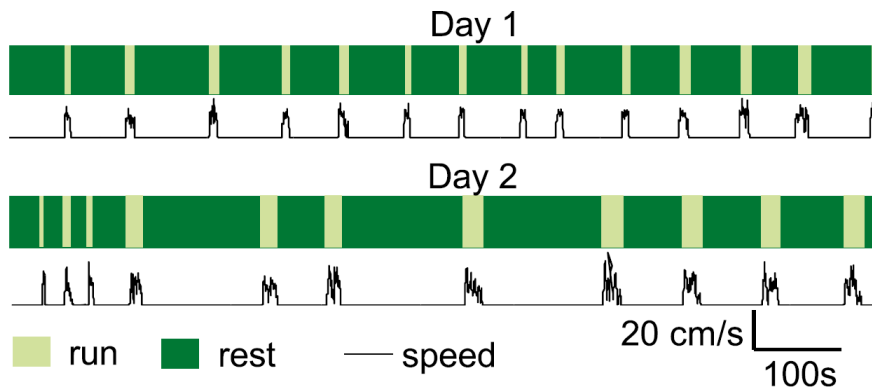
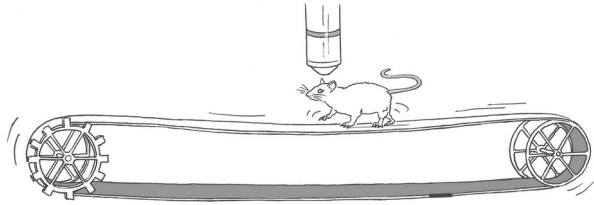
Large-scale calcium imaging

- Chronic implantation of
- cranial window
- $400 \times 400 \mu\text{m}^2$ field of view
- 140 ± 47 active neurons over 1000
- 39 ± 11 % activated during run
- 34 imaging sessions of 20/30 min
- 2 consecutive days sessions

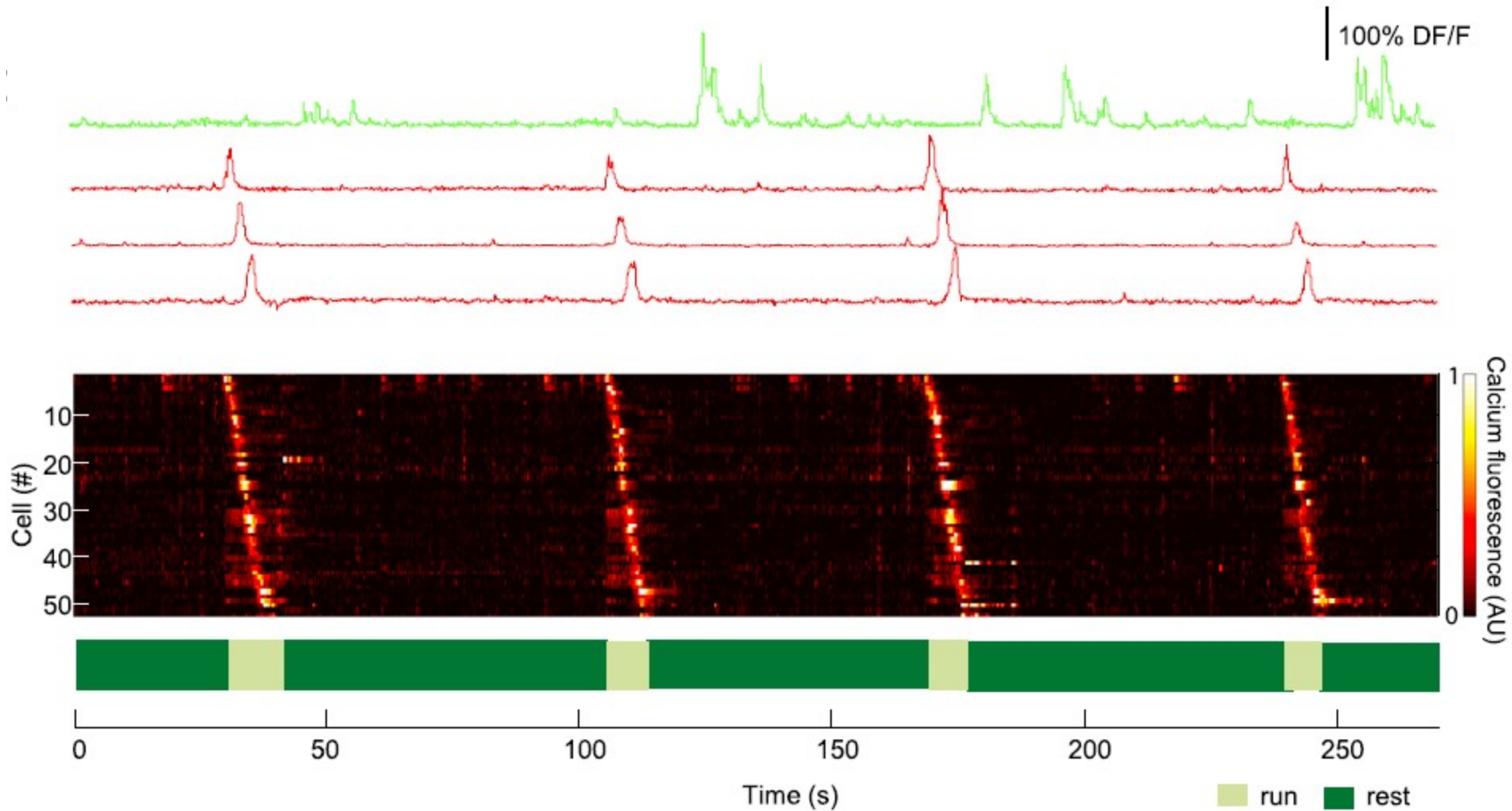
CA1 pyramidal cell layer



Spontaneous behavior

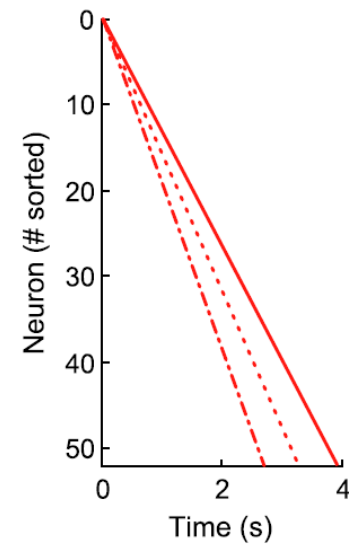
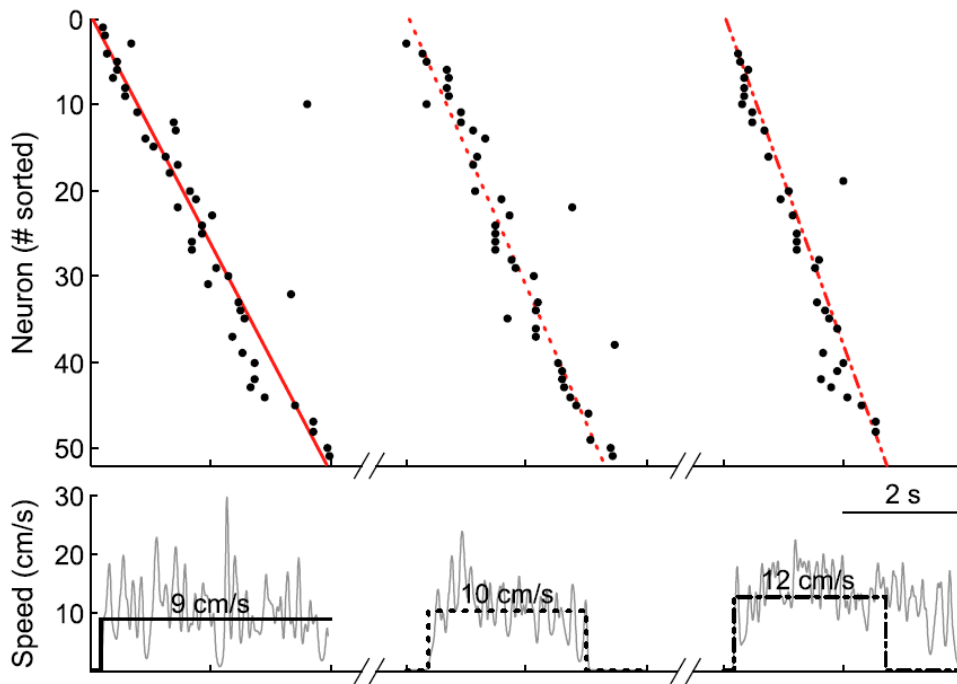


Sequences in the absence of task

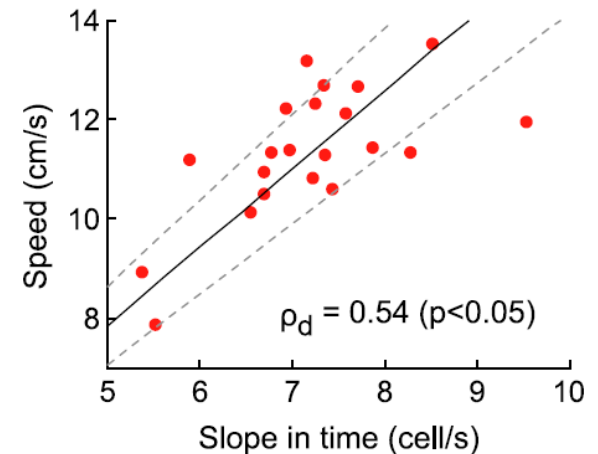


Internally Recurring Hippocampal Sequences as a Population Template of Spatiotemporal Information
Villette*, Malvache*, Tressard, Dupuy & Cossart, Neuron (2015)

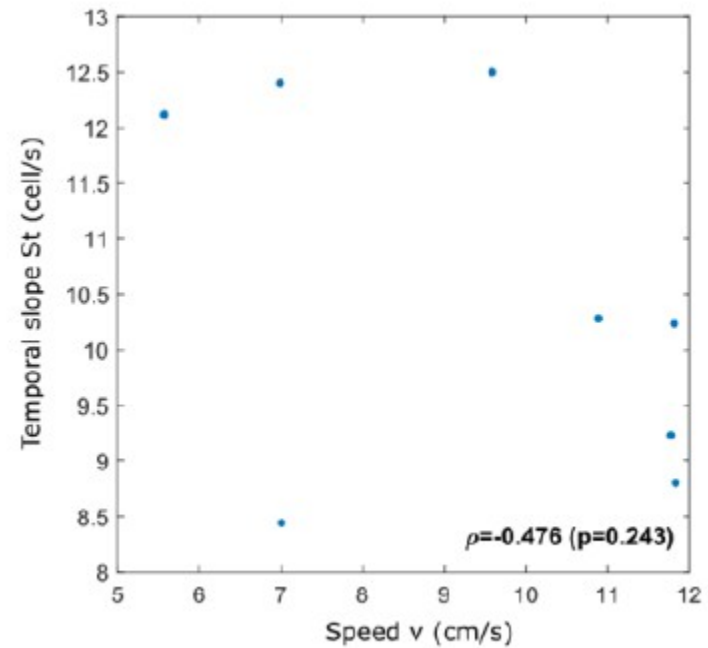
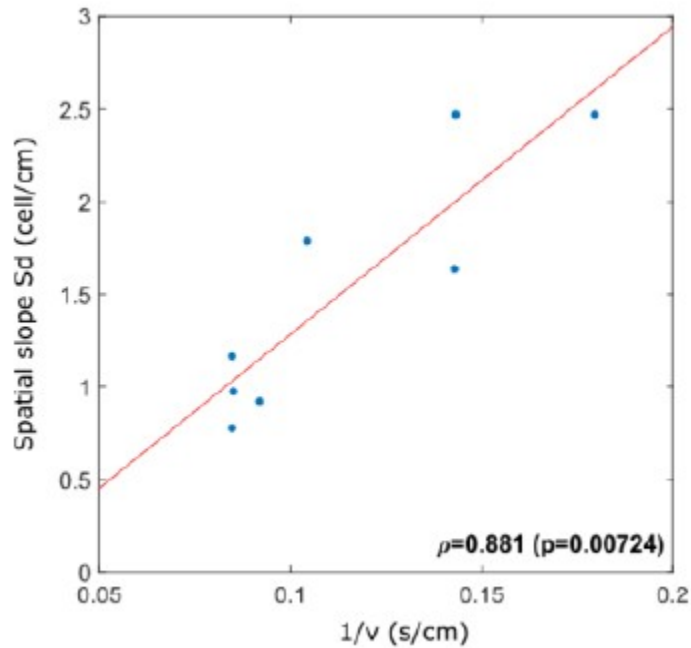
Sequence dynamics vs mouse speed



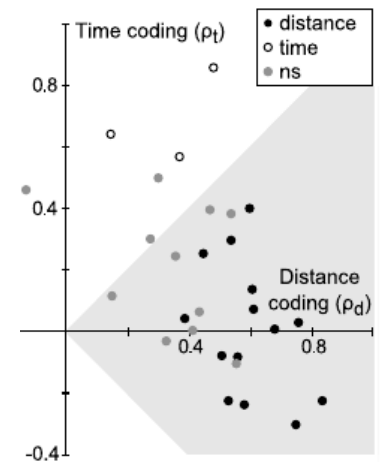
In this session, the **temporal slope** of the firing sequences is proportional to the **mouse speed**: neurons encode for **run distance**



Sequence dynamics vs mouse speed

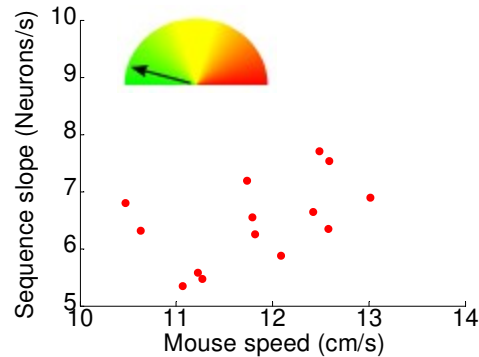
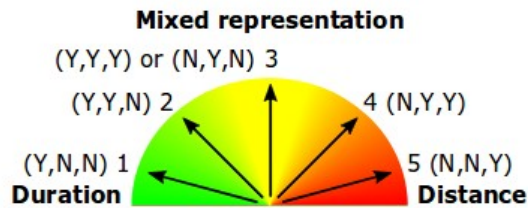


In this session, the **spatial slope** of the firing sequences is proportional to the **mouse speed**: neurons encode for the **run duration (elapsed time)**

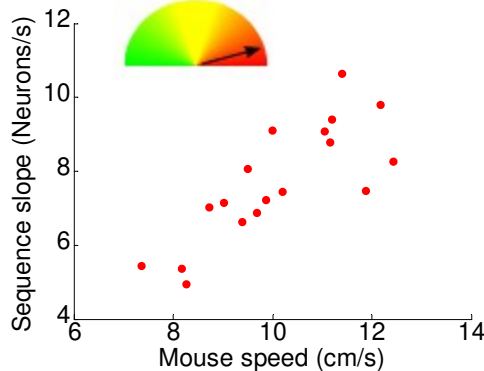
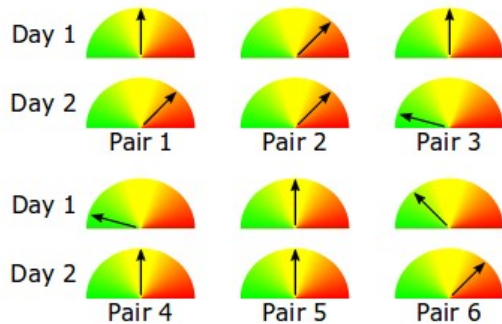


Analysis of distance and duration representation

D Tests (temporal, spatio-temporal, spatial)

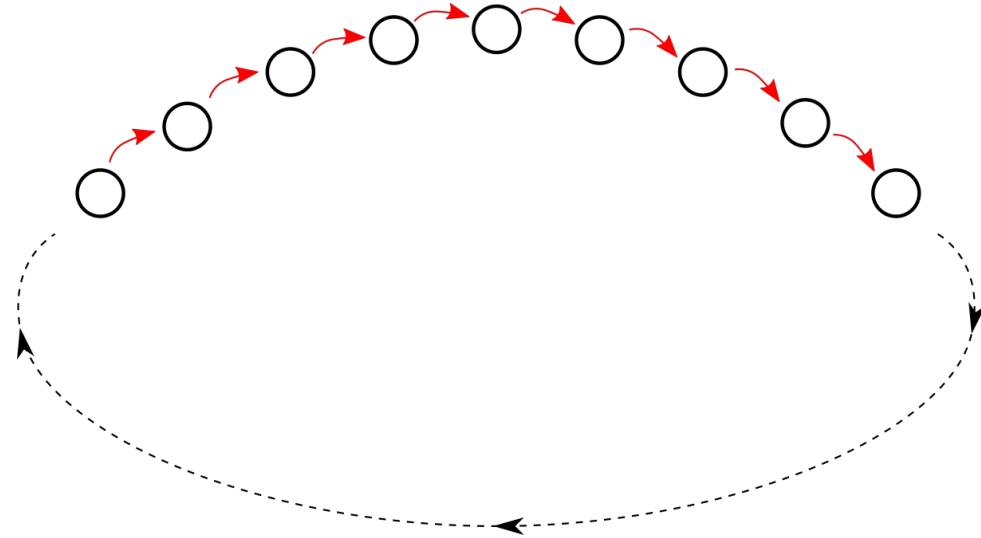
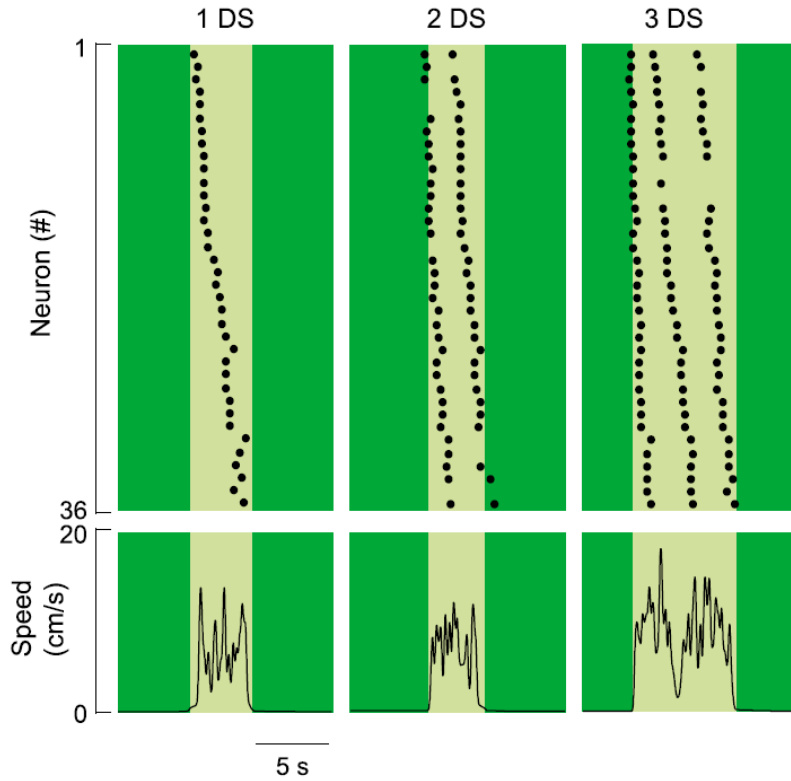


F



- Depending on the degree of correlation of the **temporal** (**spatial**) sequence slope and the **mouse speed** we have a **distance** (**duration**) representation
-
- A large part of the same neurons fires on Day 1 and Day 2, but they can modify their coding from Day 1 to Day 2
- Hippocampus can flexibly change the representation type from one day to the other

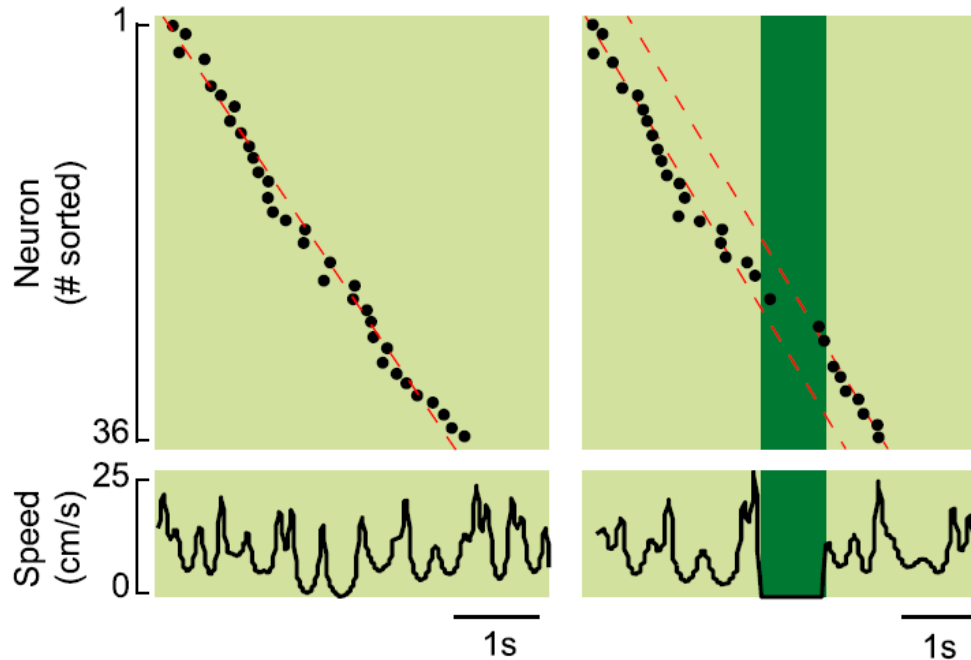
Underlying Network



Sequences reboot within continuous run episodes

Recurrent functional network with PBCs

Sequences restart after short pause



Sequences do not reboot if pause $< 2s$

Short term plasticity

Model requirements

Outputs

- Neuronal sequences generated from non sequential inputs
- Duration and distance representation

Inputs

- Time and speed.

Theta oscillation with varying amplitude

Network

- Excitatory neurons with global inhibition
- Recurrent excitation => *circular network*
- Short term plasticity => *synaptic facilitation and depression*

Continuous Attractor Neural Network

Circular recurrent network
+ External excitatory input

Local excitation

+ Global inhibition

→ Localized activity bump

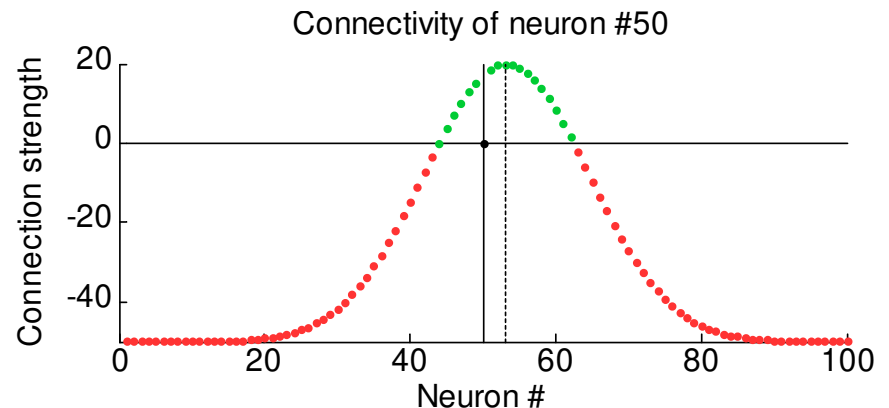
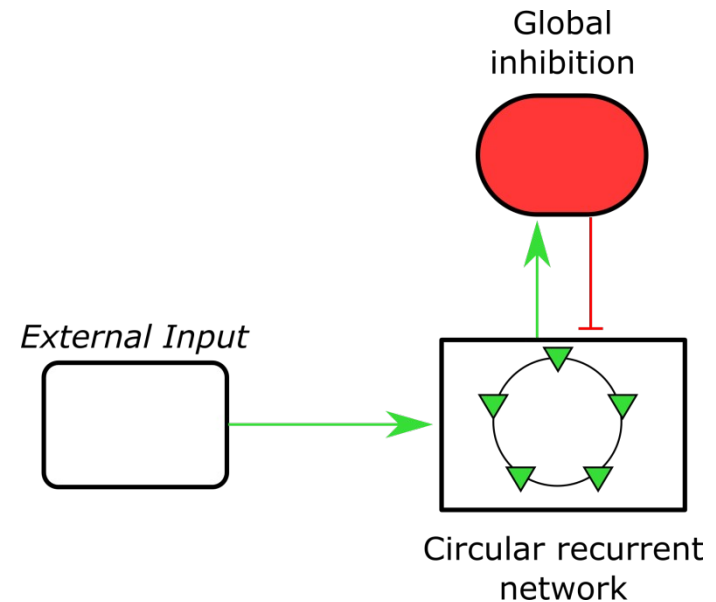
Asymmetry of local connexions δ

→ Movement of activity bump

Neuronal sequences follows always same order

$$W_{i \rightarrow j} = J_1 e^{-(i-j-\delta)^2/\sigma^2} - J_0$$

Romani & Tsodyks (2014), Wang et al (2015)



Continuous Attractor Neural Network

Firing rate model

Romani & Tsodyks (2014)

$$\tau \dot{m}(i, t) = -m(i, t) + f(I_R(i, t) + I_E(t))$$

Threshold function
↑

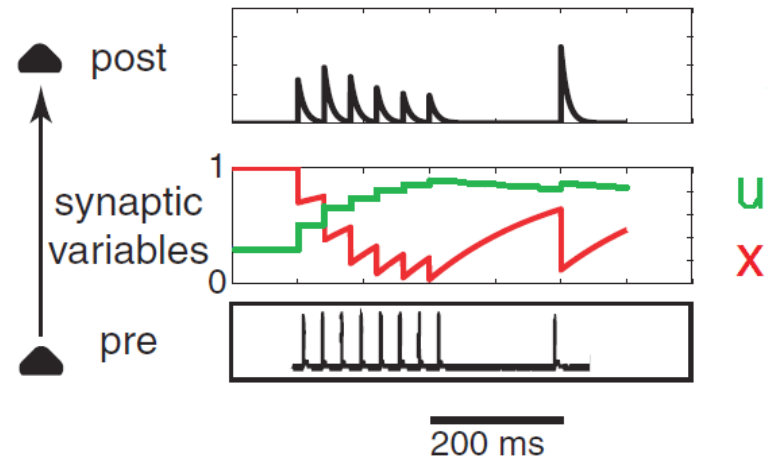
Recurrent input External input

Synaptic plasticity

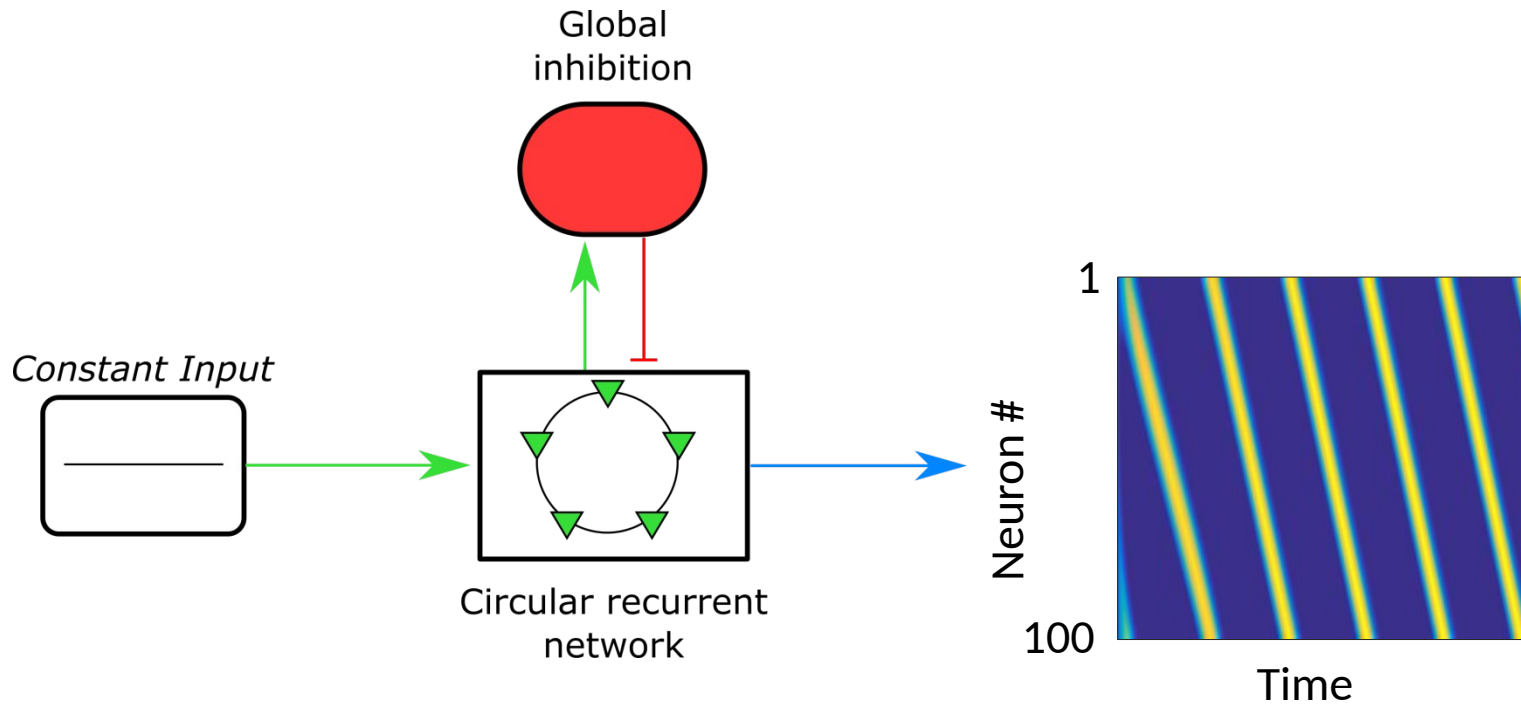
Mongillo et al (2008)

$$\frac{dx}{dt} = \frac{1-x}{\tau_D} - u x \delta(t-t_{sp})$$

$$\frac{du}{dt} = \frac{U-u}{\tau_F} + U(1-u) \delta(t-t_{sp})$$

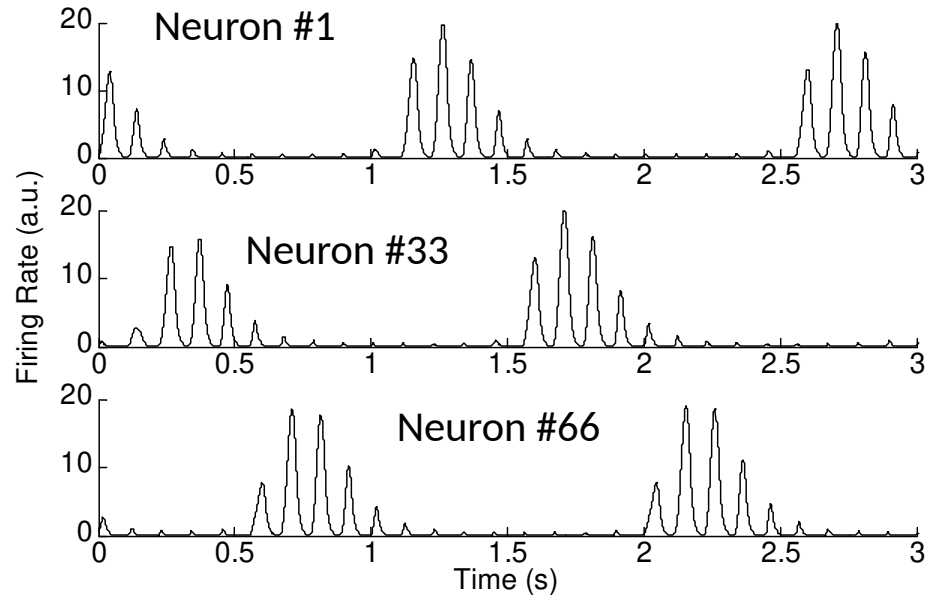
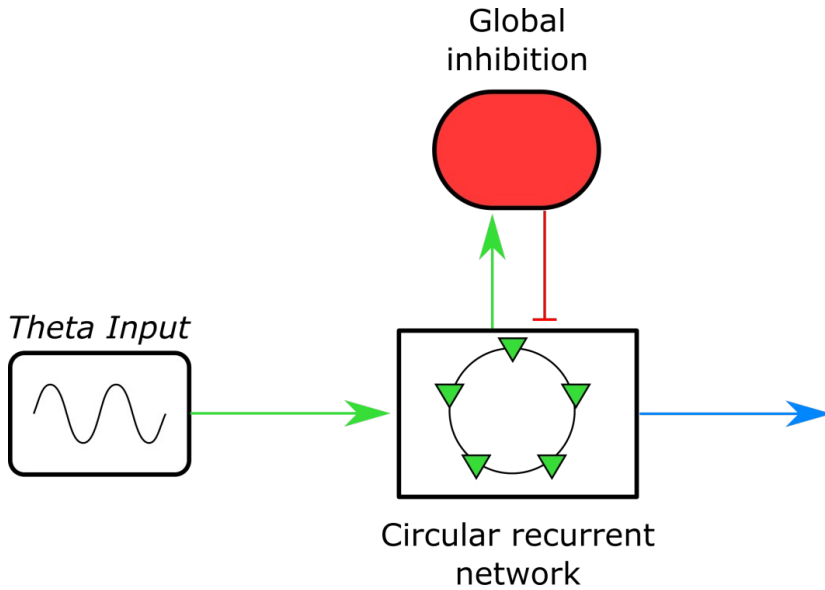


Constant input



Continuous sequences

Oscillatory input



Romani & Tsodyks (2014), Wang et al (2015)

Theta modulated sequences

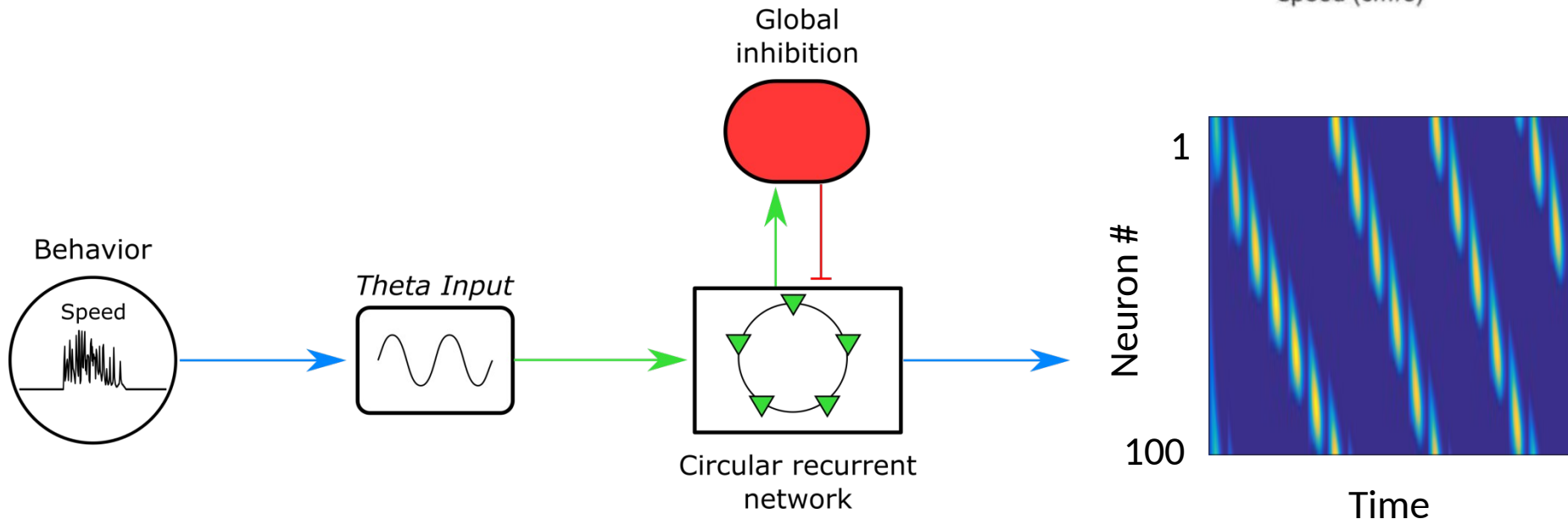
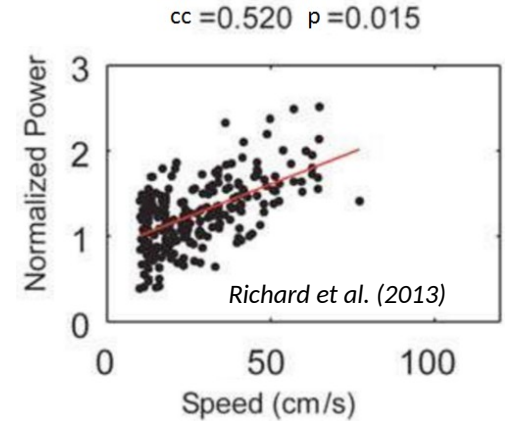
Speed-dependent input

Working hypothesis :

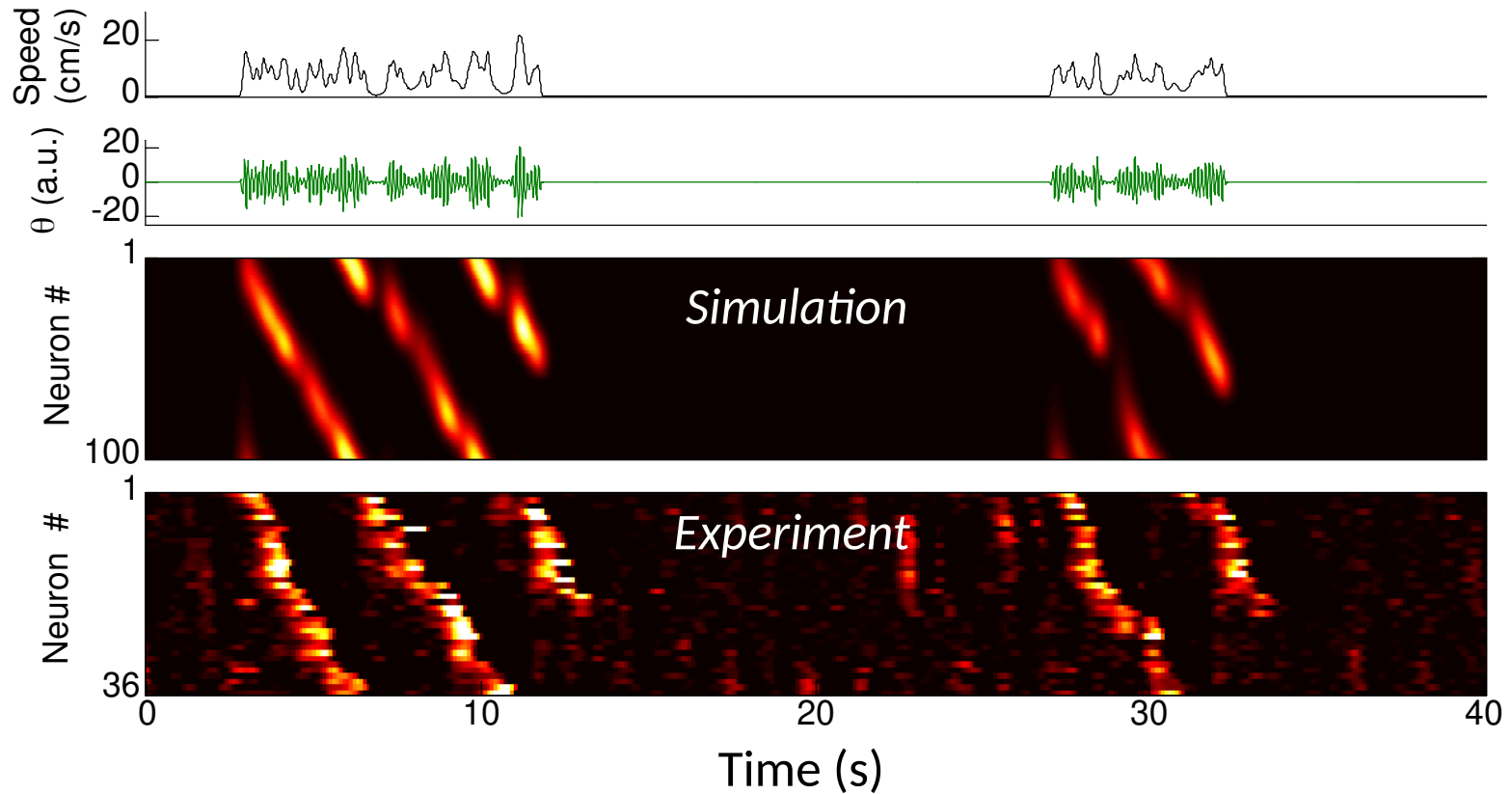
$$I_{\theta} = \alpha + \beta v$$

Linear relationship between theta amplitude and running speed

Richard et al. (2013), Fuhrmann et al. (2015), Bender et al. (2016)



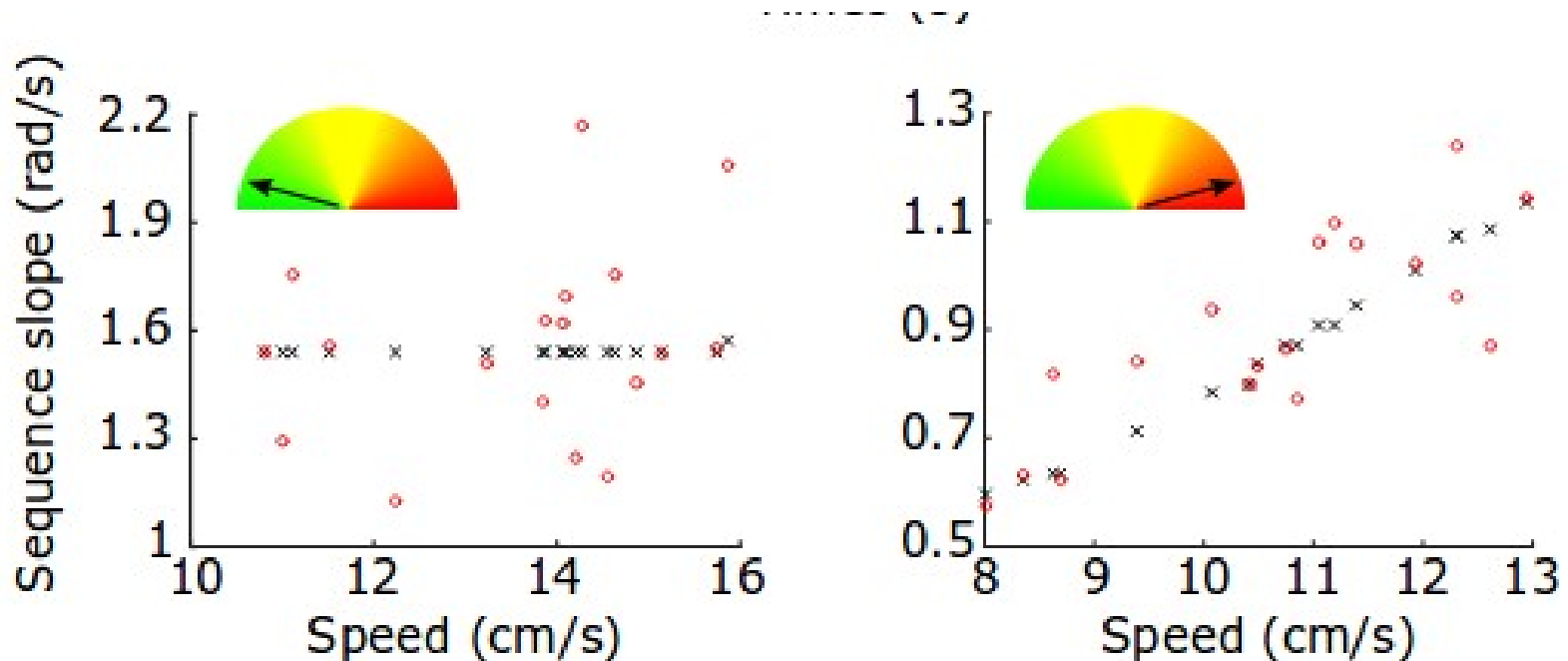
Speed-dependent input



Fitting to experimental data

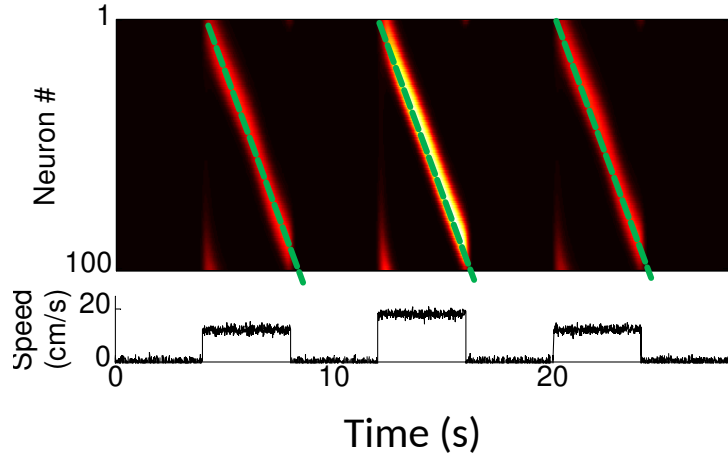
We fitted the sequence slopes obtained from our model versus mouse velocity to the experimental data to obtain the mean input power I_0 , the connectivity asymmetry Δ and the velocity gain β

c

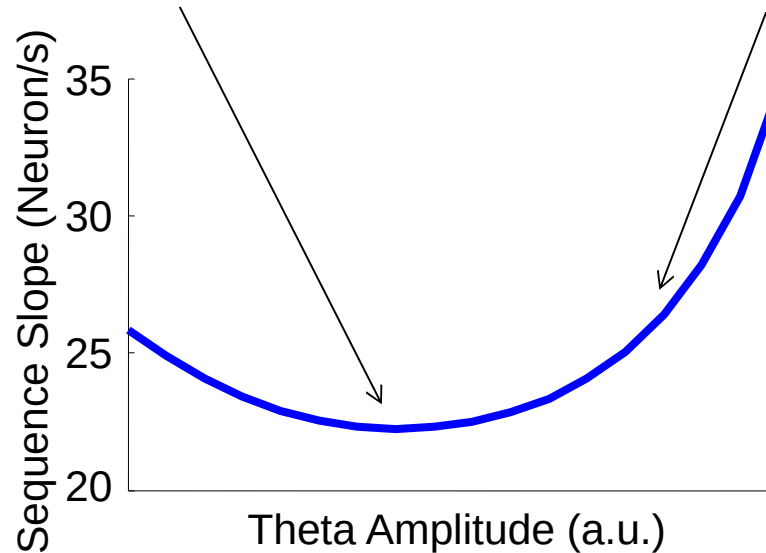
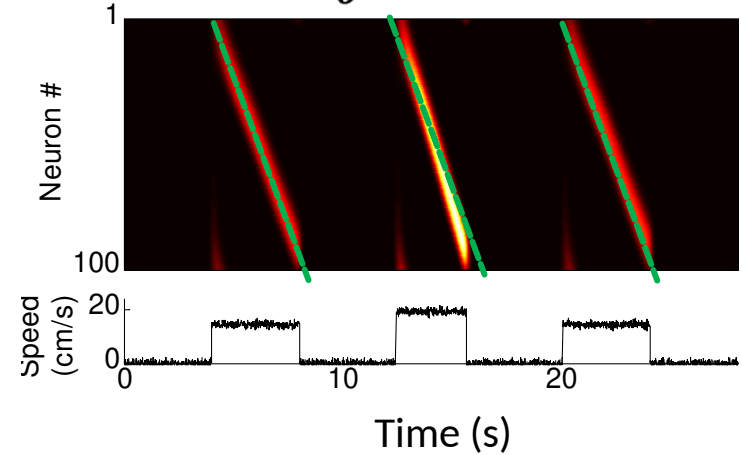


Neuronal sequences dynamics

$$I_{\theta} = v$$



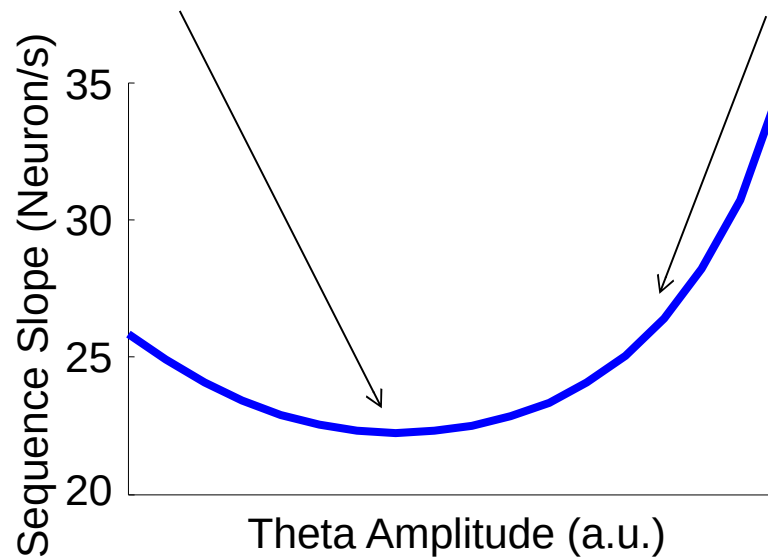
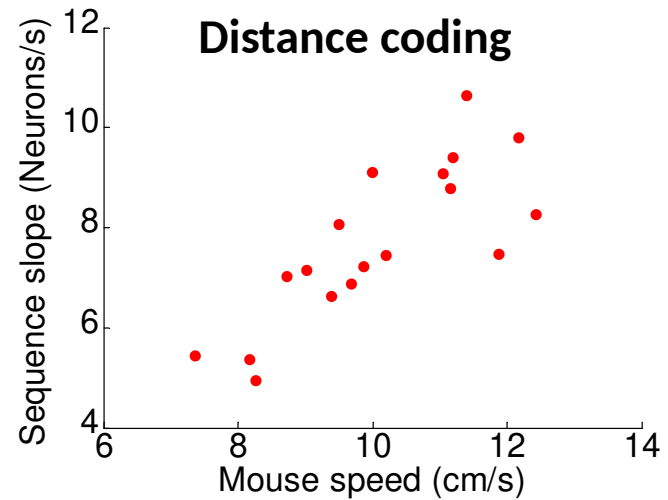
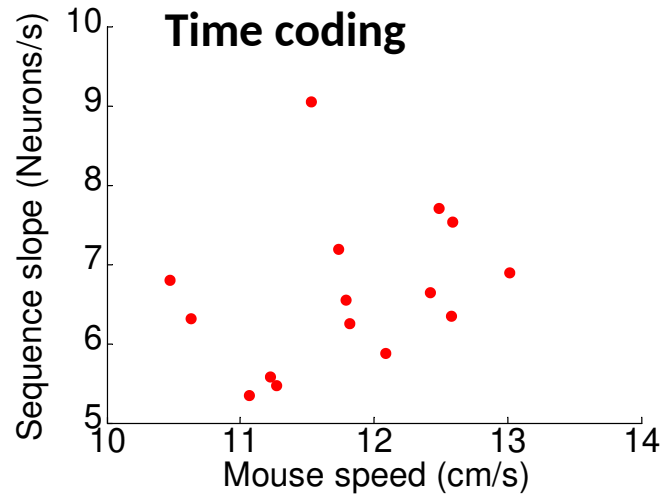
$$I_{\theta} = 1.5 v$$



Nonlinear dependence induced by short-term plasticity

Facilitation is fundamental

Spatio-temporal coding



**The same network
can display
both representations
changing Theta Amplitude**

Summary

- Experimental data suggest (functional) circular connectivity plus plasticity
- CANNs can encode both duration and distance, without modifying the network structure
- The dynamic range is sufficient for fitting the experimental data

The hippocampus is able to generate a spatiotemporal representation tuned to the task at hand

Acknowledgments



Susanne Reichinnek & Vincent Villette



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Arnaud Malvache & David Angulo Garcia



Thomas Tressard



Rosa Cossart



Fundings



Labex MME-DII

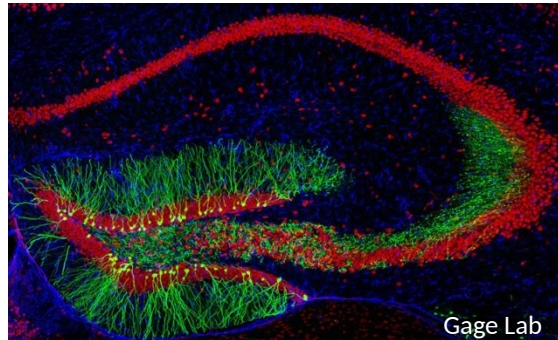
Modèles Mathématiques et Économiques de la Dynamique, de l'Incertain et des Interactions

THE
PARIS SEINE
INITIATIVE



Place cell microcircuit

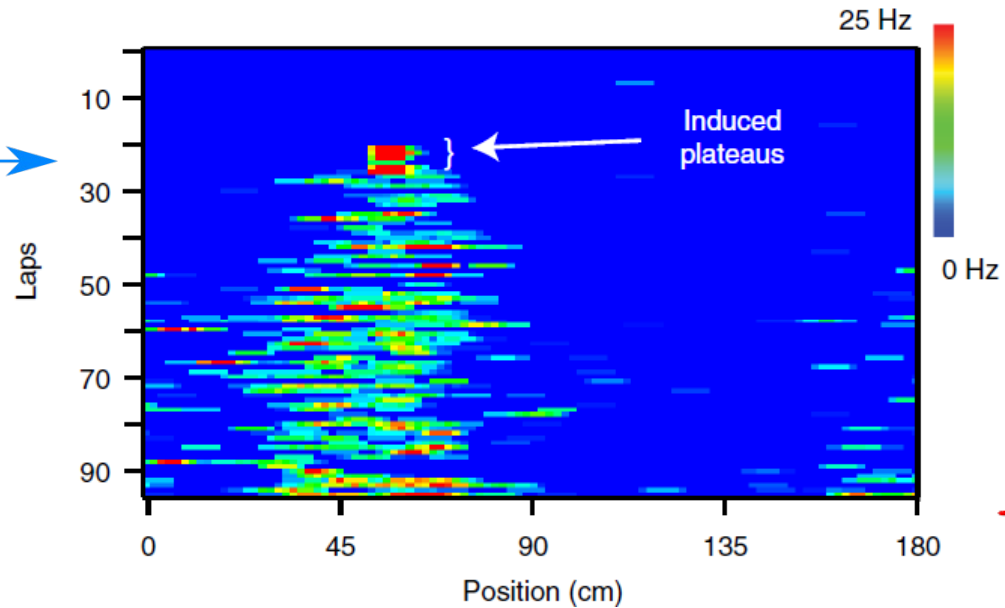
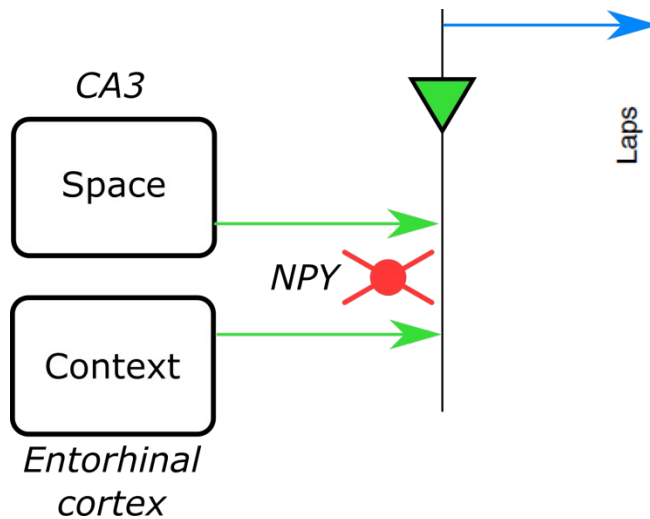
Raw spatio-temporal data



Processed information

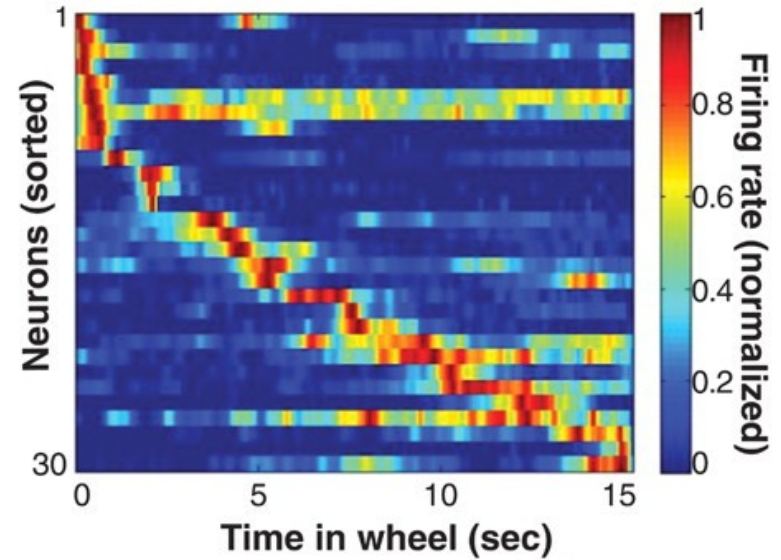
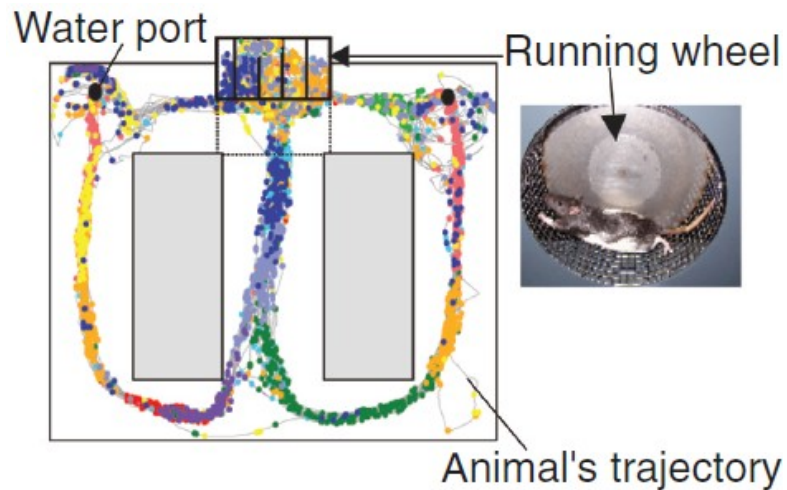


Bittner et al 2015
Milstein et al 2015



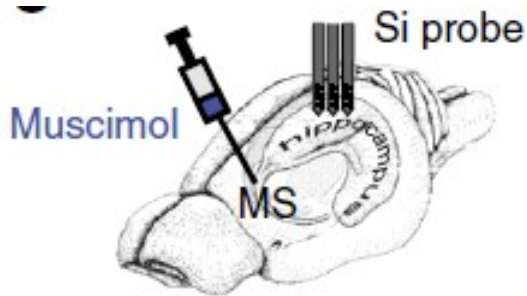
Time sequences

Time sequences in CA1 in a wheel during a delay task



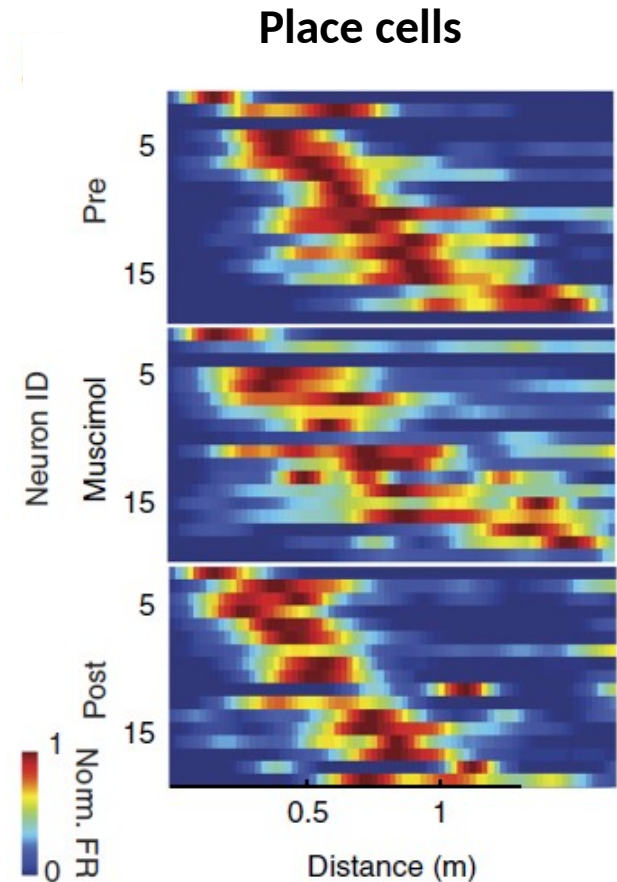
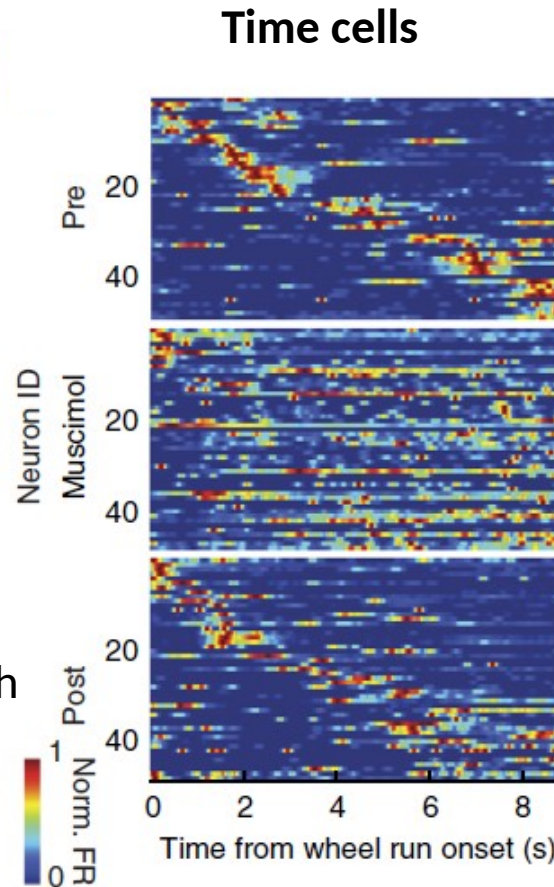
Internally Generated Cell Assembly Sequences in the Rat Hippocampus
Pastalkova, Itskov, Amarasingham & Buzsáki, Science (2008)

Different mechanisms for place cells and time cells



Medial Septum inhibition
Decreases theta power

- * Memory-dependent firing fields in the wheel are lost
- * Firing fields in the maze with sensory cues are maintained
- * Theta sequences are lost



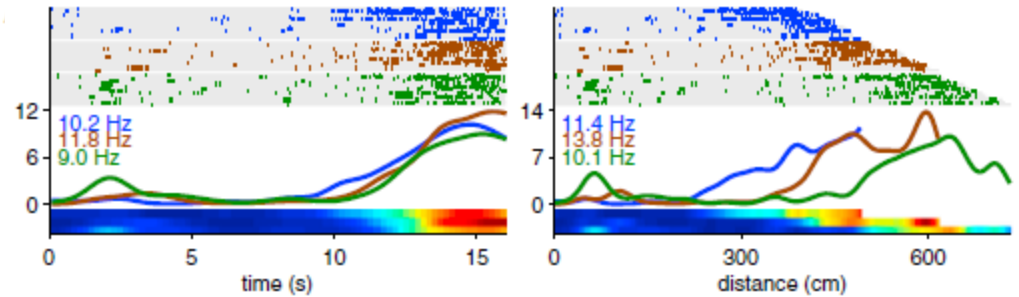
Theta sequences are essential for internally generated hippocampal firing fields. Wang, Romani, Lustig, Leonardo & Pastalkova, Nature Neuroscience (2015)

Disentangling time and distance

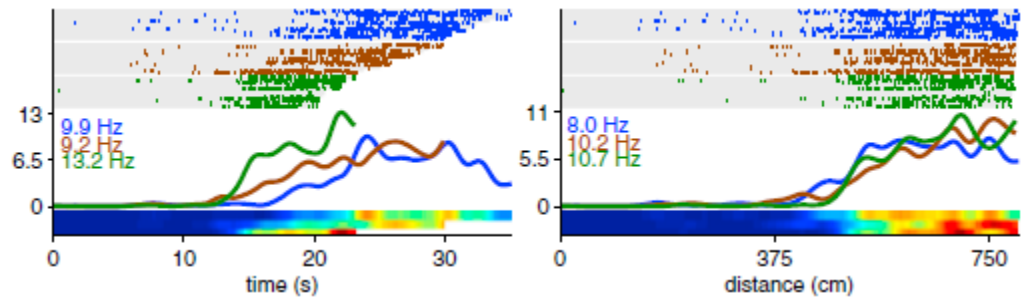
Time-fixed sessions



Treadmill with varying speed



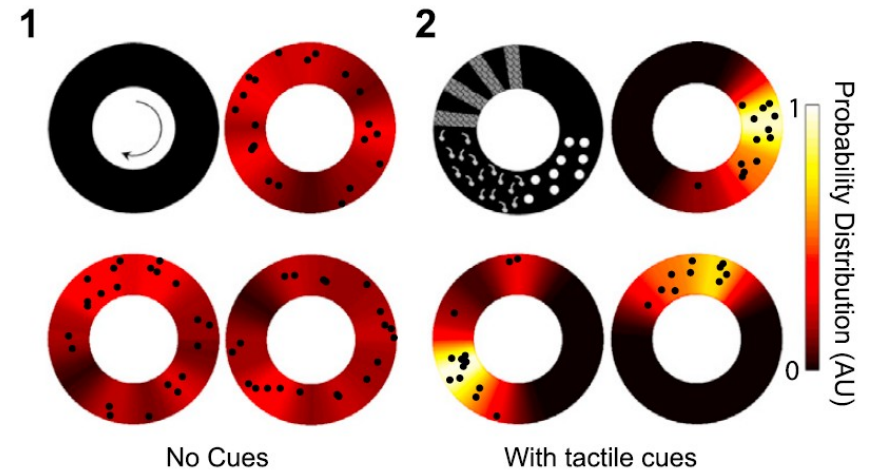
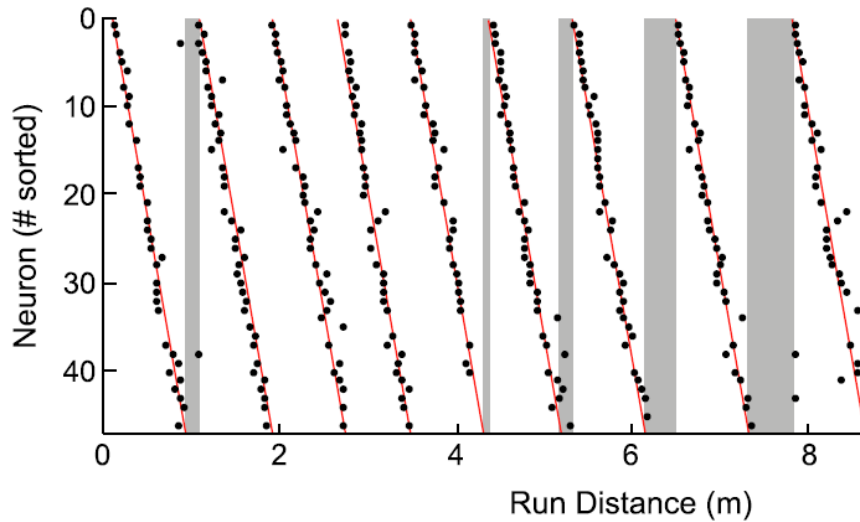
Distance-fixed sessions



Hippocampal "Time Cells": Time versus Path Integration

Kraus, Robinson, White, Eichenbaum & Hasselmo, *Neuron* (2013)

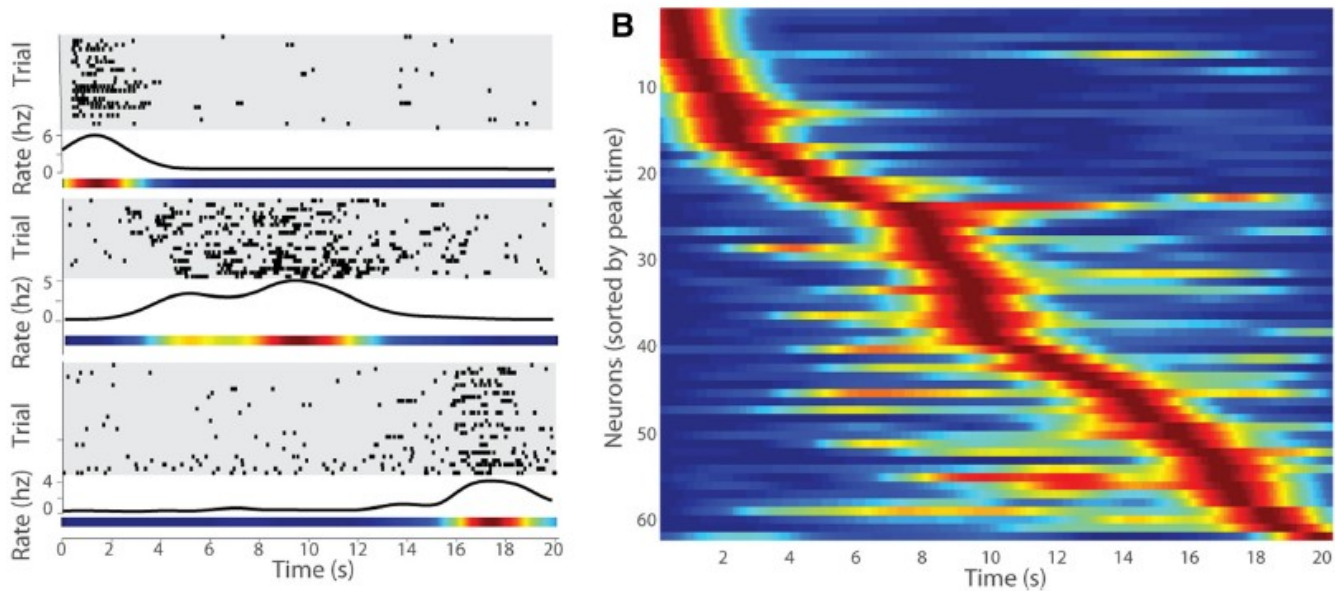
Sequence dynamics in spatial domain



Distance representation but not place cells!

Recurrent network to model CA1 ?!?

Hypothesis: CA1 reflects CA3 activity in the absence of external drive

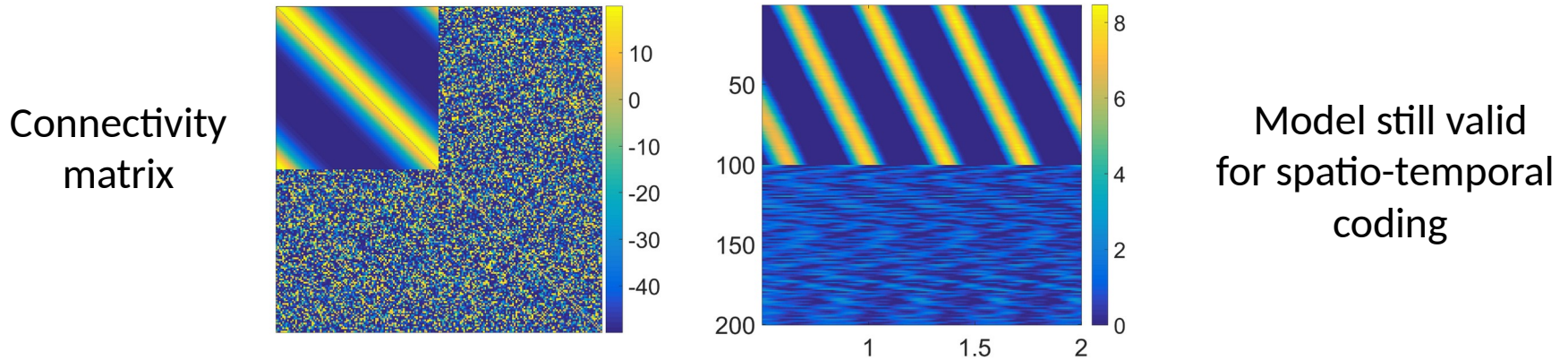


Time Cells in Hippocampal Area CA3

Salz, Tiganj, Khasnabish, Kohley, Sheehan, Howard & Eichenbaum, J. Neuro (2016)

Towards a more realistic model

Circular connectivity embedded in a random network



Connectivity in CA3 Guzman *et al* , *Science* (2016)

