

MNS Project 2: Learning of Grid Cells

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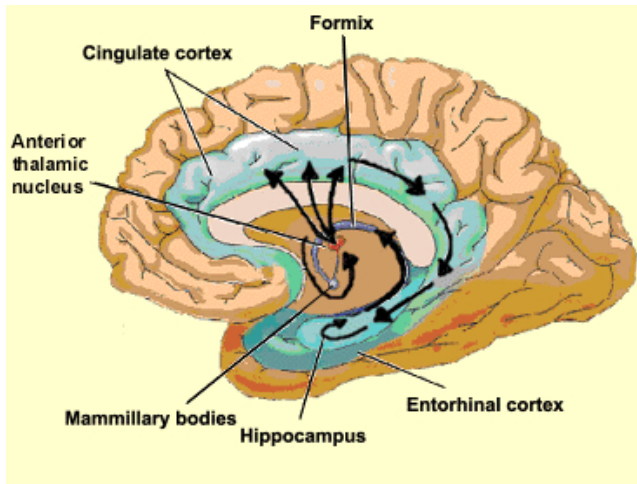
BCCN

February 9th 2016

Structure

- Introduction
- Modelling details
- Results

Introduction



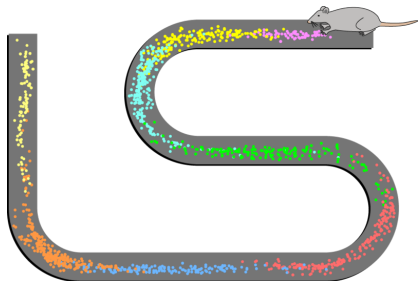
In Hippocampus and the medial enthorhinal cortex (mEC) various types of neurons have been found that encode an animals spacial location.

Cells encoding spacial location

- **Place cells**
- **Grid cells**
- **Head-direction cells**
- **Head-Grid-Conjunctive cells**

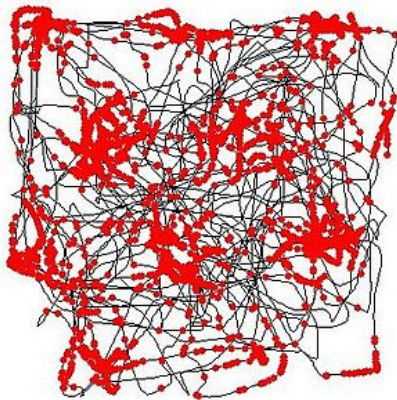
Properties of place cells

Located in hippocampus. Activated when the animal enters a specific region of the environment - the *place field*.



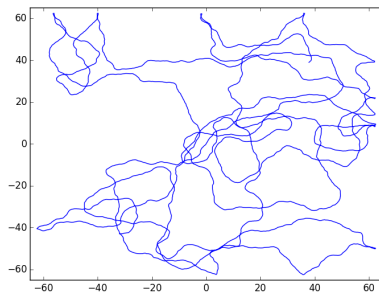
Properties of grid cells

- Located in medial enthorhinal cortex (mEC). Activated at several spacial positions. The firing map shows an equally spaced hexagonal pattern.
- Mostly independent of visual stimulus
- Different grid cells show different spacing, orientation and size of their patterns.
- Spacing from 25cm to 3m.



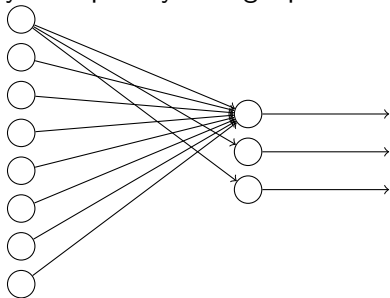
Rat trajectory

- Square environment of size 125×125 cm.
- Speed: $v = 0.4$ m/s
- Initialization with random position
- Every 10ms: chose new direction from a gaussian distribution with
 - μ = previous direction
 - $\sigma = 0.2$

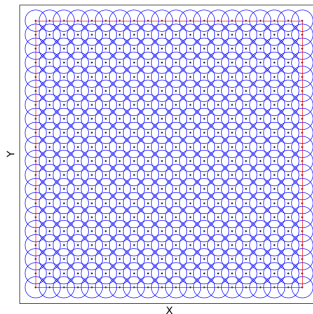
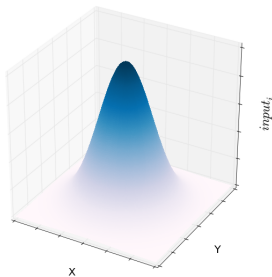
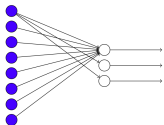


Model: Overview

input layer output layer magic processing output

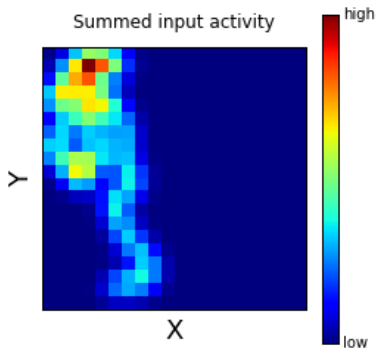
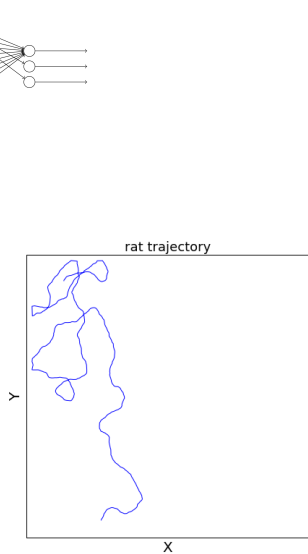


Model: Input Layer

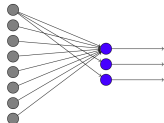


$$input_i = \exp\left(-\frac{\|rat_pos - center_i\|^2}{50}\right)$$

Model: Input Layer

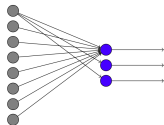


Model: Output Layer



$$h_j = \sum_i w_{ij} \cdot input_i$$

Model: Output Layer



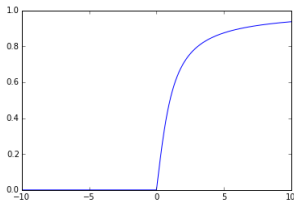
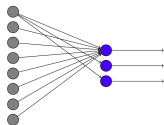
$$h_j(t) = \sum_i w_{ij} \cdot input_i(t)$$

→ adaptation dynamics:

$$\tau^+ \frac{d}{dt} r_j^+ = h_j(t) - r_j^+(t) - r_j^-(t)$$

$$\tau^- \frac{d}{dt} r_j^-(t) = r_j^-(t)$$

Model: Output Layer



$$h_j(t) = \sum_i w_{ij} \cdot input_i(t)$$

→ adaptation dynamics:

$$\tau^+ \frac{d}{dt} r_j^+ = h_j(t) - r_j^+(t) - r_j^-(t)$$

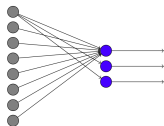
$$\tau^- \frac{d}{dt} r_j^-(t) = r_j^-(t)$$

→ output:

$$output_j(t) = \frac{2}{\pi} \arctan(g \cdot (r_j^+(t) - \mu)) \cdot \theta(r_j^+(t) - \mu)$$

g - gain, μ - threshold

Model: Weight Updates



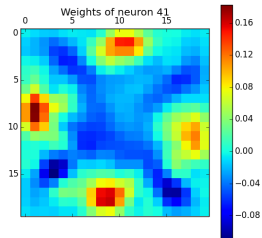
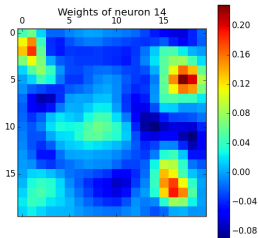
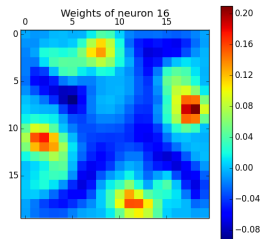
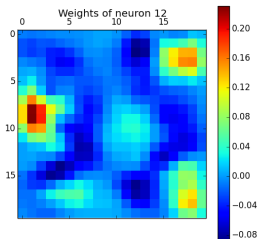
$$h_j = \sum_i w_{ij} \cdot input_i$$

→ How to determine
the weights w_{ij} ?

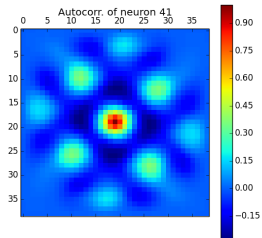
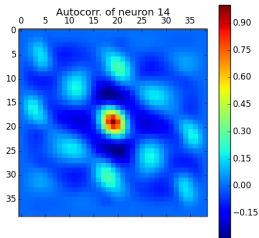
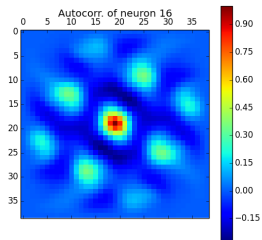
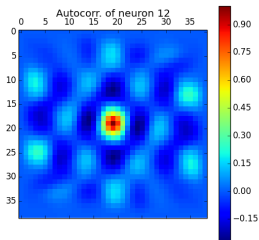
→ Hebbian learning dynamics

$$w_{ij}(t + \Delta) = w_{ij}(t) + \epsilon(input_i(t) \cdot output_j - \sum_s input_i(s) \cdot \sum_s output_j(s))$$

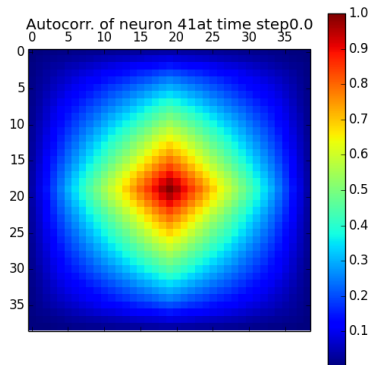
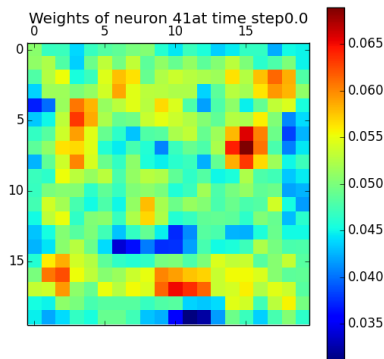
Cherrypicked final weights



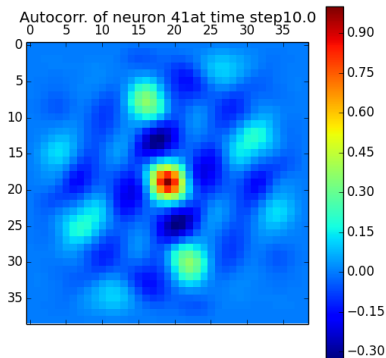
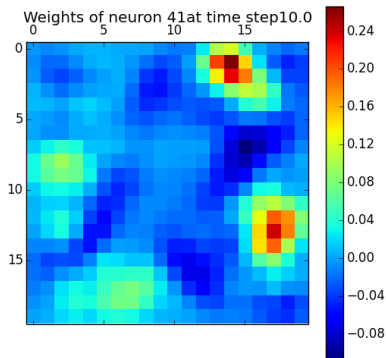
Cherrypicked final autocorrelations



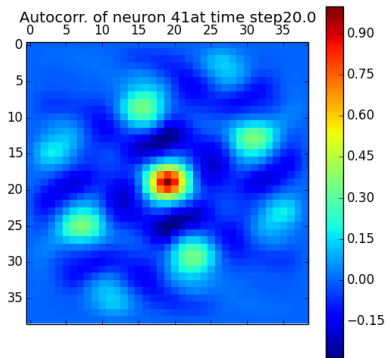
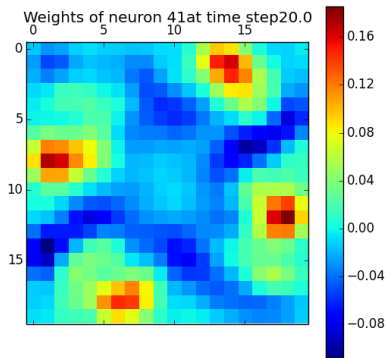
Time evolution of weights for a neuron



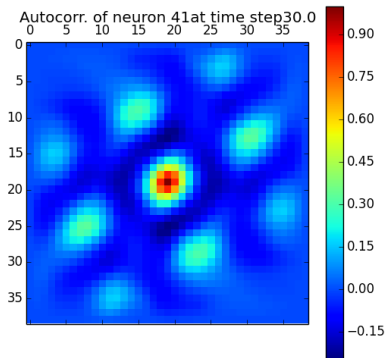
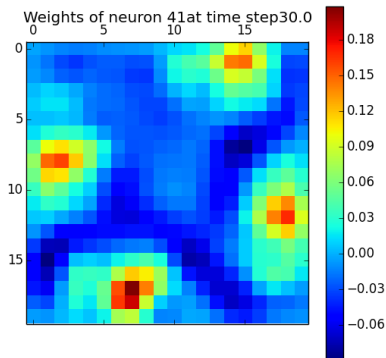
Time evolution of weights for a neuron



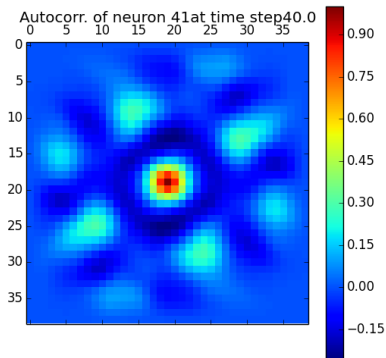
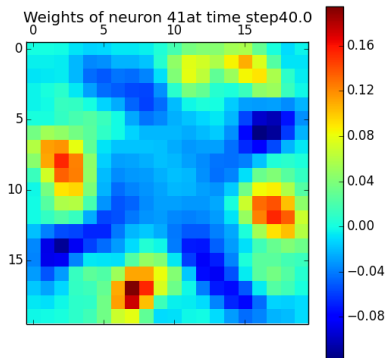
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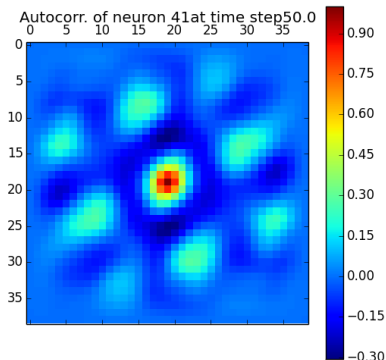
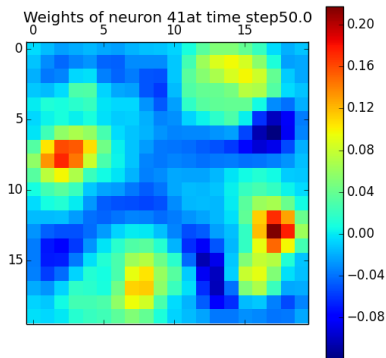
Time evolution of weights for a neuron



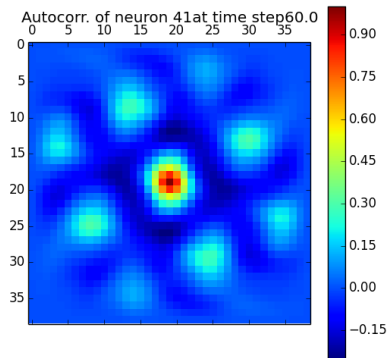
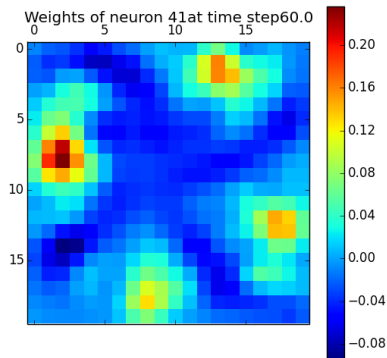
Time evolution of weights for a neuron



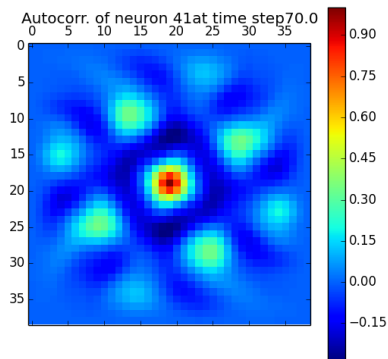
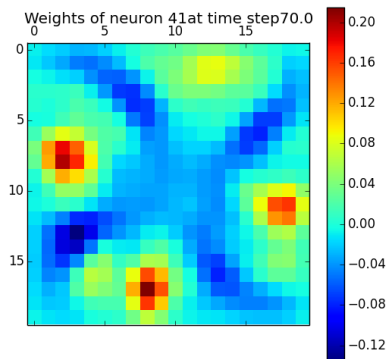
Time evolution of weights for a neuron



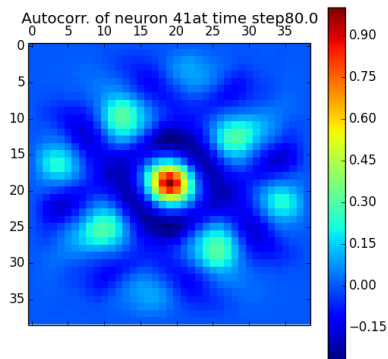
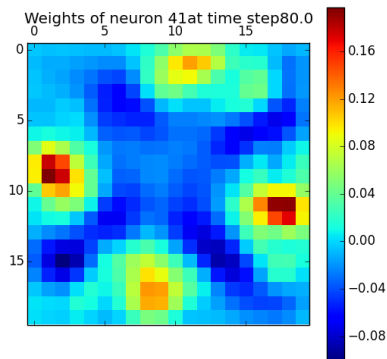
Time evolution of weights for a neuron



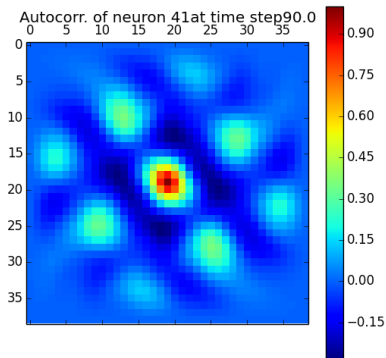
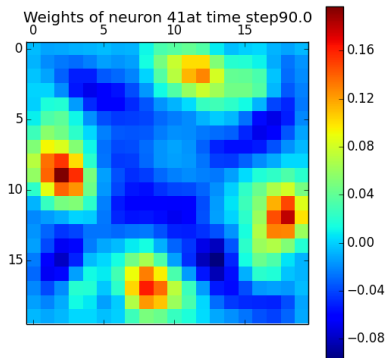
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