MNS Project 2: Learning of Grid Cells

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BCCN

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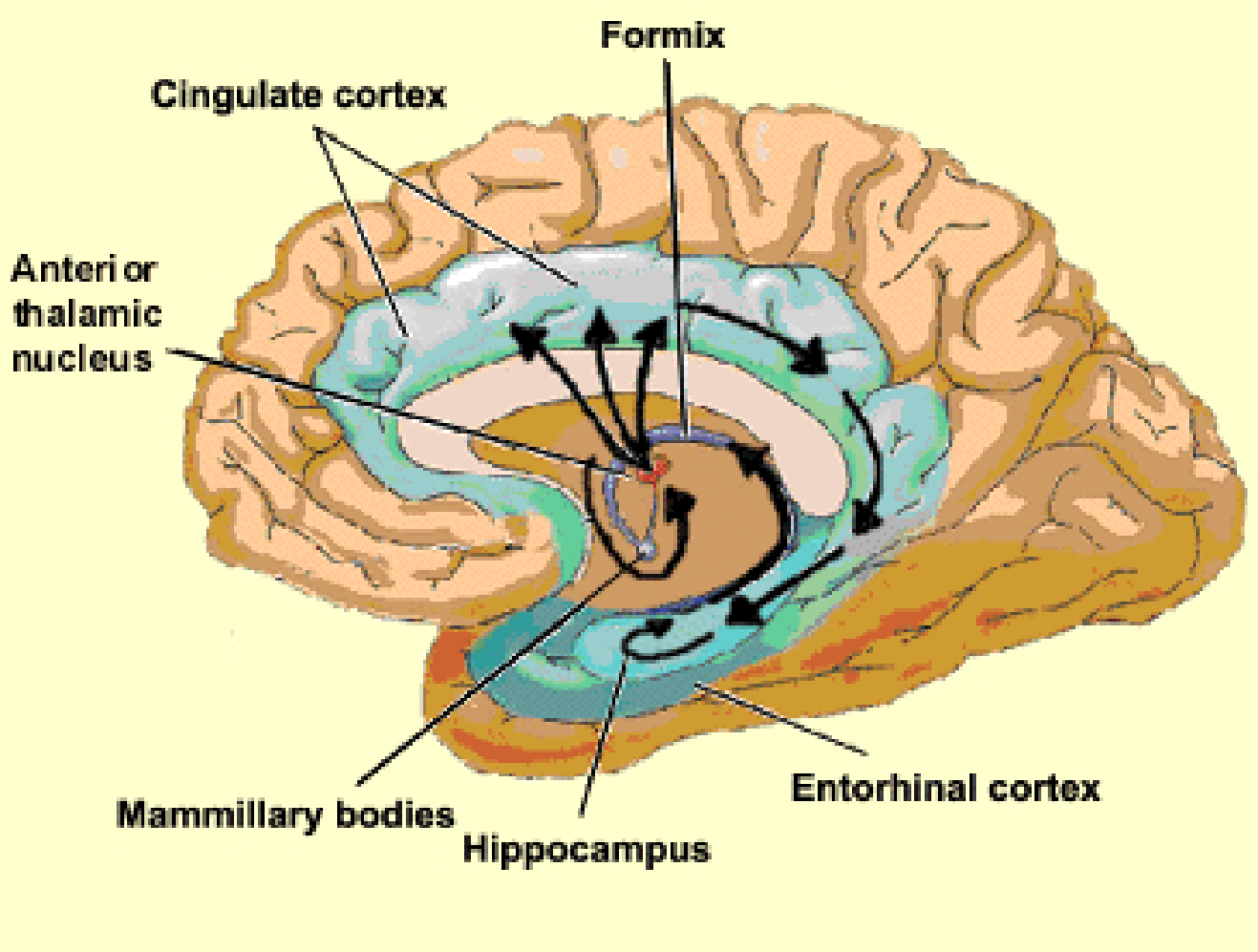
Structure

- Introduction
- Modelling details
- Results

Introduction



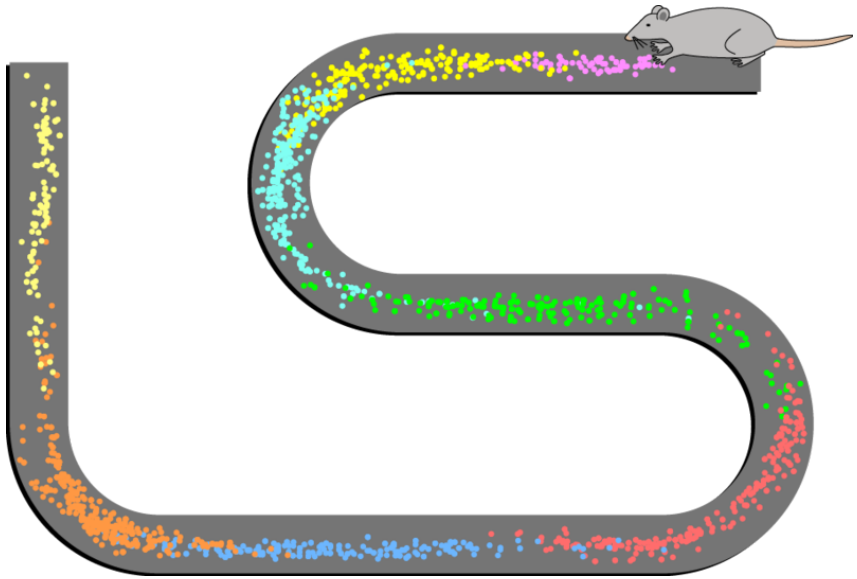
In Hippocampus and the medial enthorhinal cortex (mEC) various types of neurons have been found that encode an animals spacial location.

Cells encoding spacial location

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

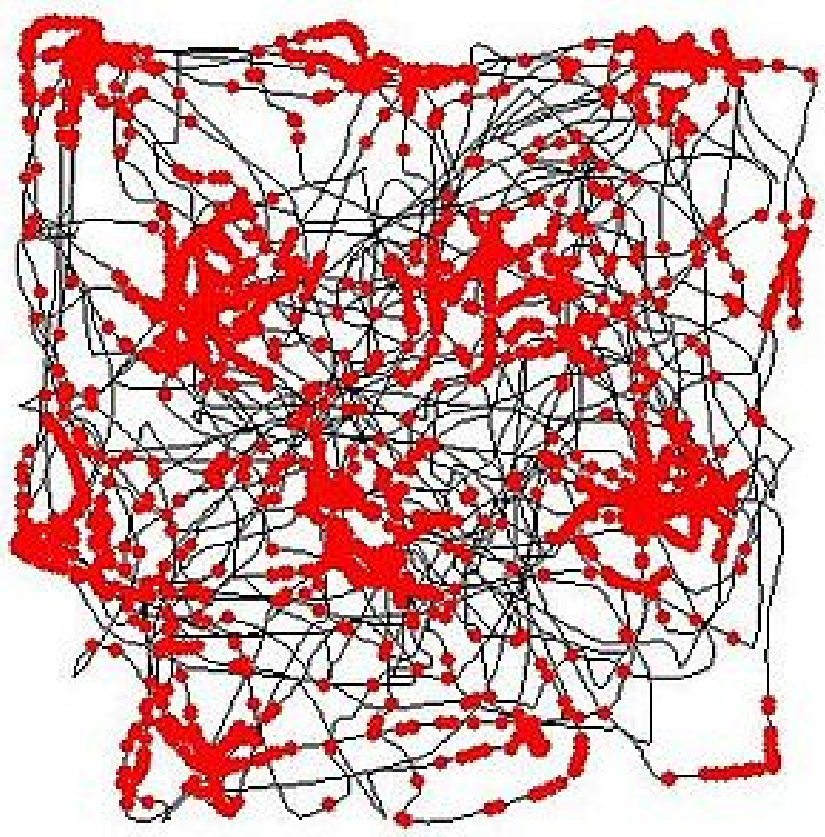
Properties of place cells

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



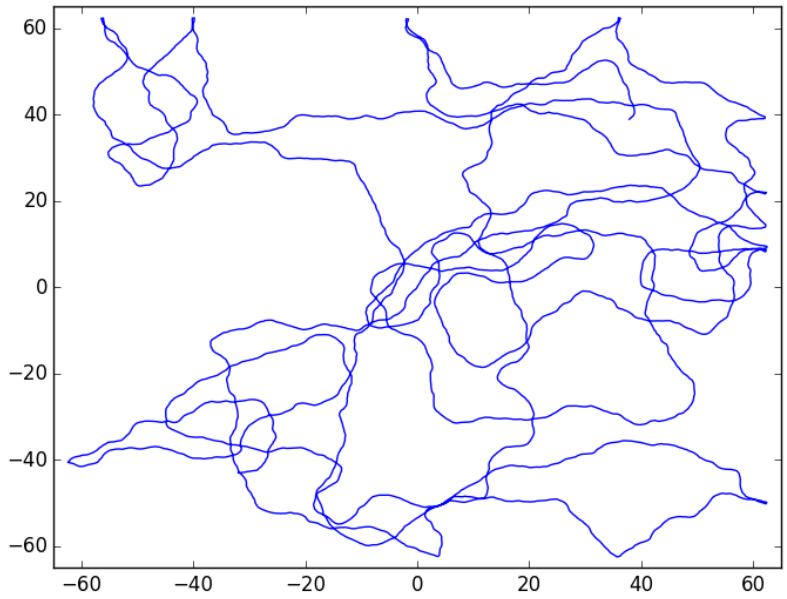
Properties of grid cells

- 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.

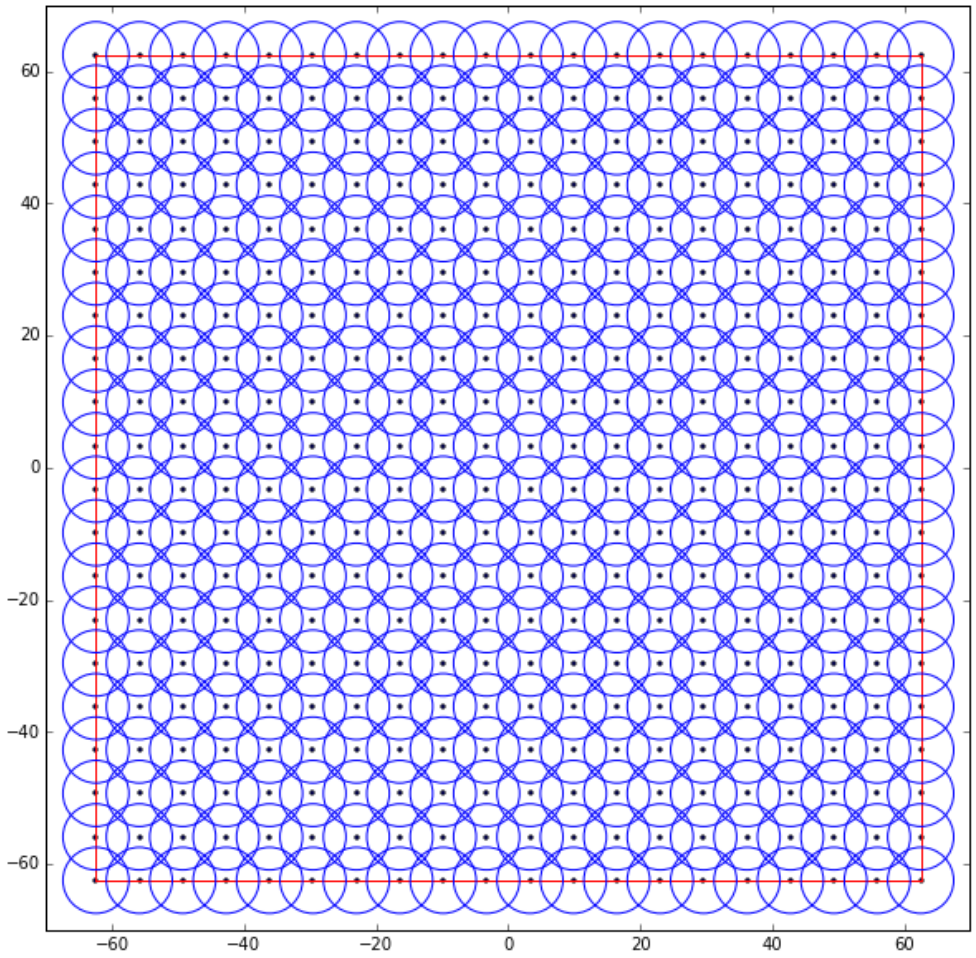


Rat trajectory

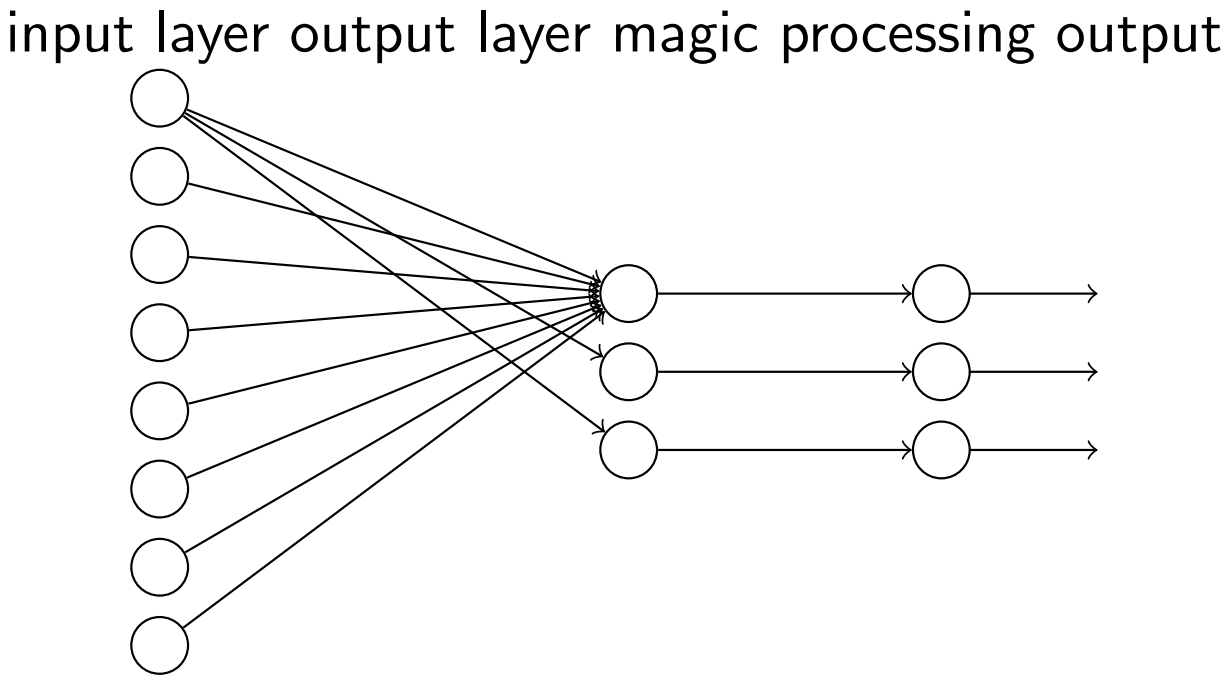
- Square environment of size 125×125 cm.
- Speed: $v = 0.4$ m/s
- Initialization with random position
- Every 10ms: chose new direction from a gaussian distribution with
  - $\mu =$ previous direction
  - $\sigma = 0.2$



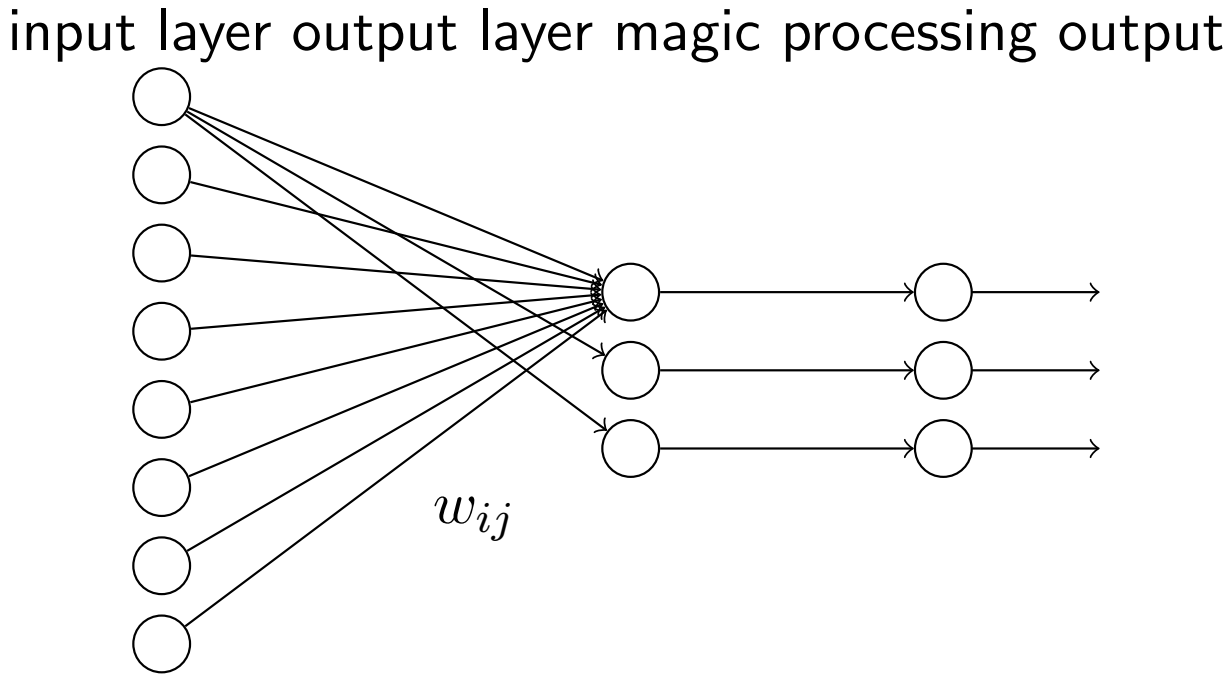
Place Cells



Model: Overview



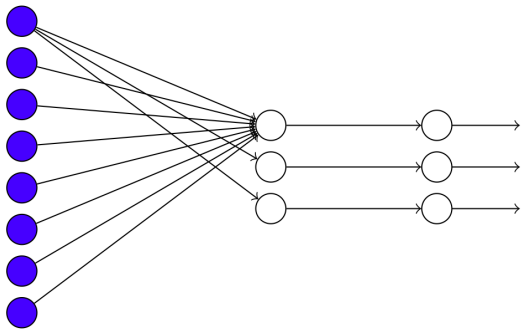
Model: Overview

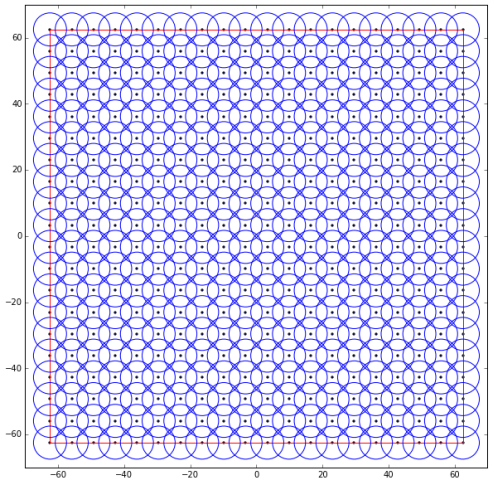


$input_i$
$i = 1, ..., 400$

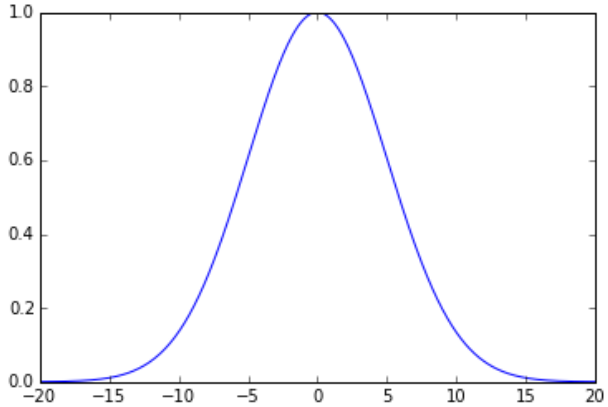
$output_j$
$j = 1, ..., 100$

Model: Input Layer

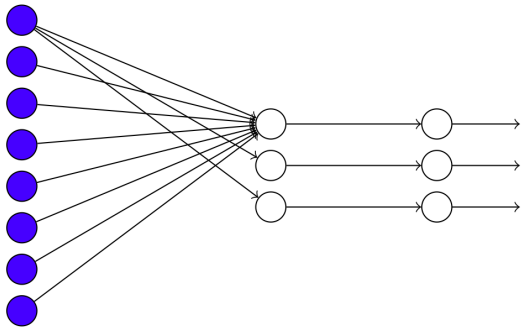


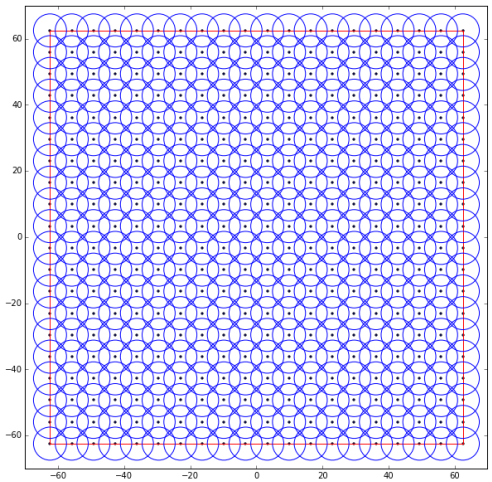


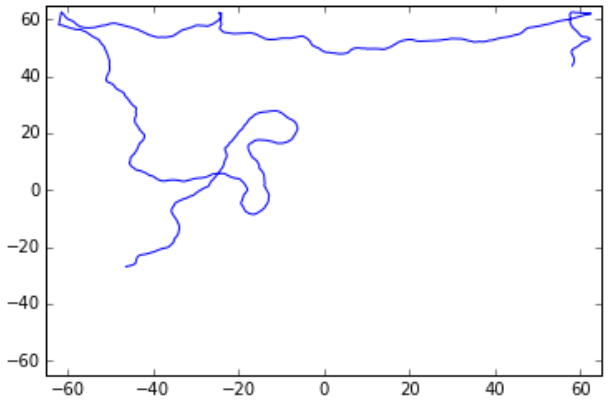
$$input_i = \exp(-\frac{||rat - center_i||^2}{50})$$

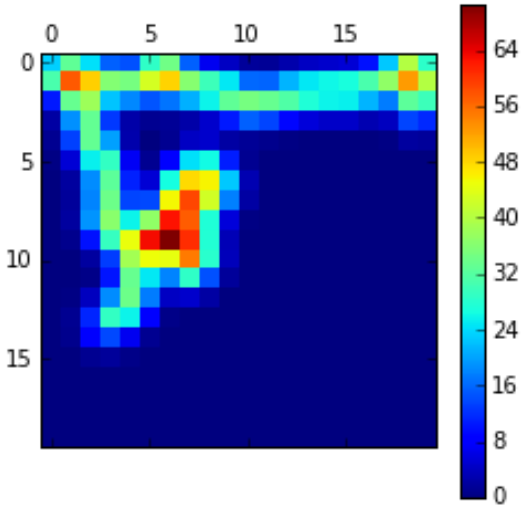


Model: Input Layer

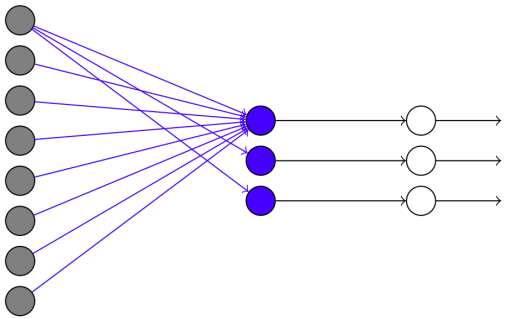








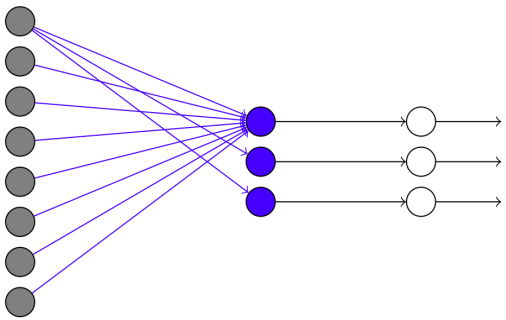
Model: Output Layer



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

$\rightarrow$ How to determine the weights w_{ij}?

Model: Output Layer

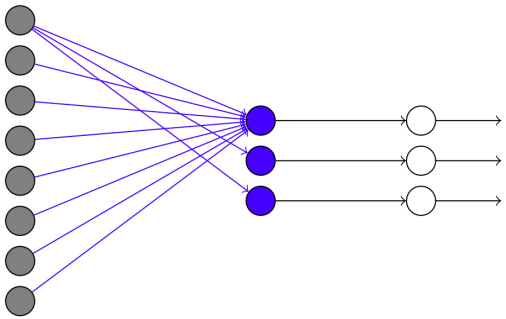


$$h_j = \sum_i w_{ij} \cdot input_i$$

$\rightarrow$ How to determine the weights w_{ij}?

$\rightarrow$ Hebbian learning dynamics

Model: Output Layer



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

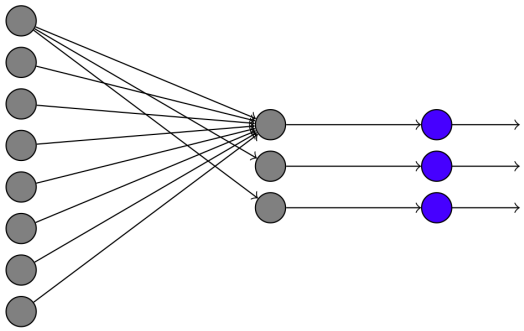
$\rightarrow$ How to determine the weights w_{ij}?

$\rightarrow$ Hebbian learning dynamics

'Fire together, wire together'

$\rightarrow$ Details on that in 2 slides

Model: Processing



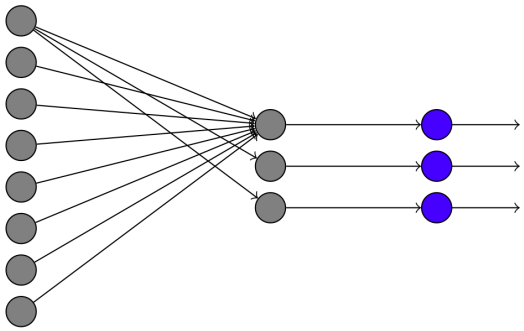
$$h_j(t) = \sum_i w_{ij} \cdot input_i(t)$$

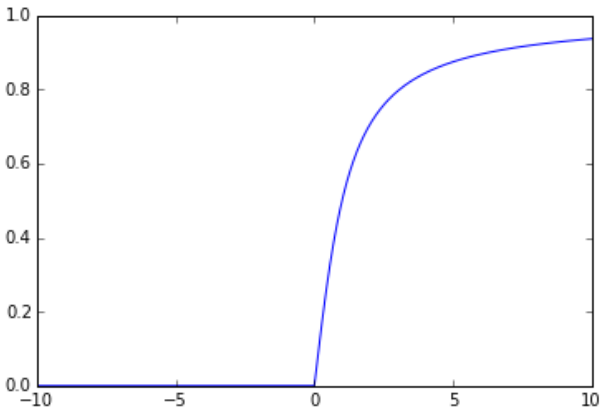
$\rightarrow$ adaptation dynamics:

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

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

Model: Processing





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

$\rightarrow$ adaptation dynamics:

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

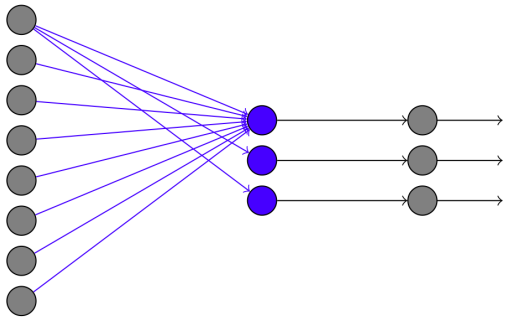
$$\tau^- \frac{d}{dt} r_j^-(t) = r_j^-(t)$$

$\rightarrow$ 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



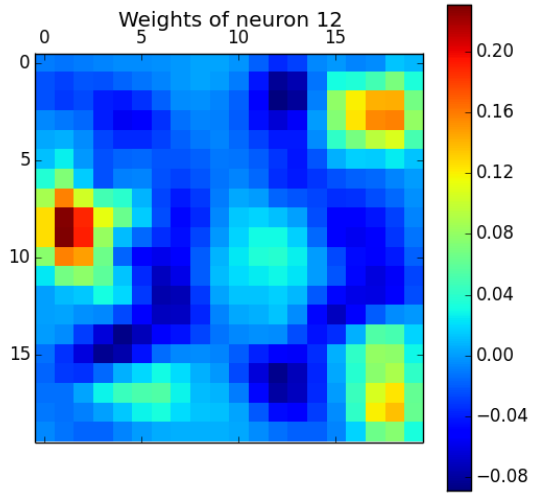
$$h_j = \sum_i w_{ij} \cdot input_i$$

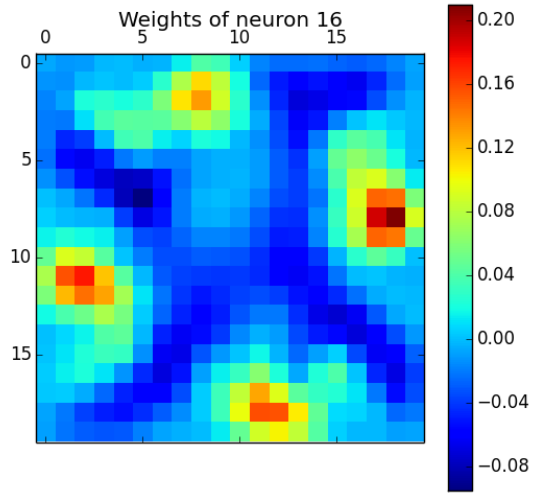
$\rightarrow$ How to determine the weights w_{ij}?

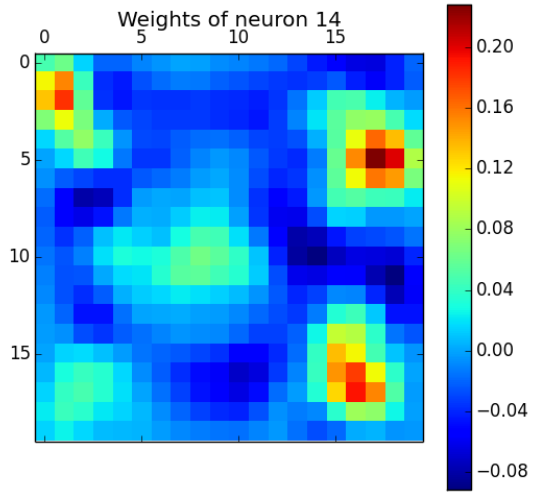
$\rightarrow$ Hebbian learning dynamics

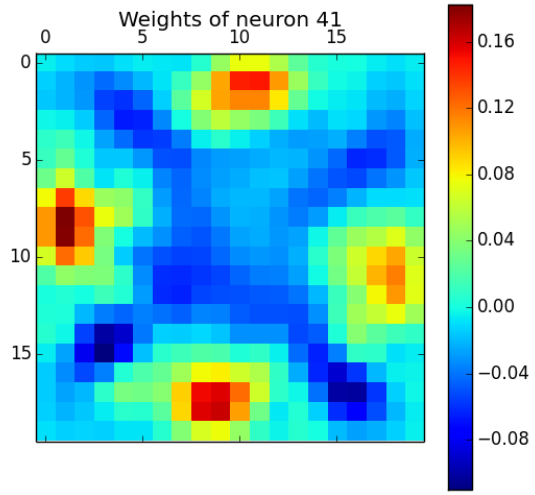
$$w_{ij}(t + \Delta) = w_{ij}(t) + \epsilon(input_i(t) \cdot output_j - \sum_s input_i(s) \cdot \sum_s output_j(s))$$

Cherrypicked final weights

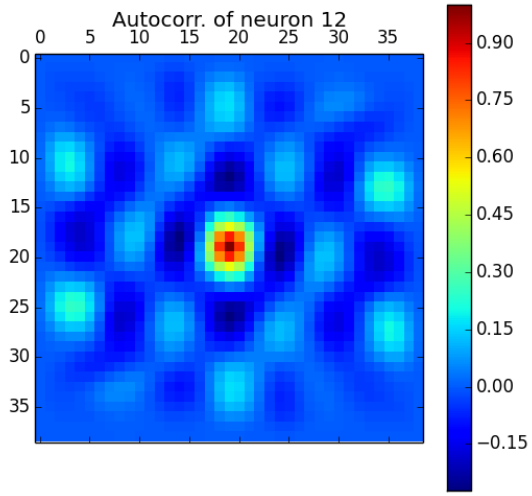


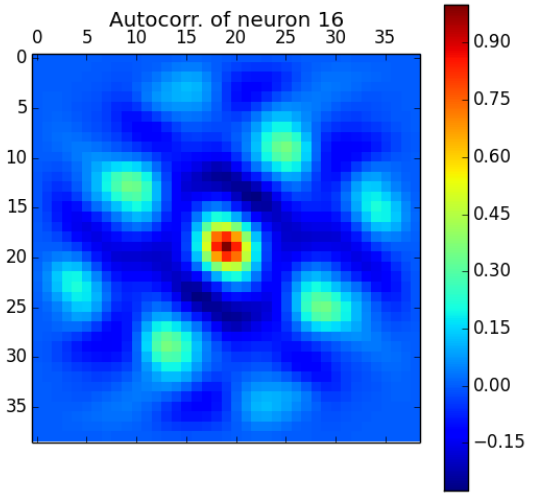


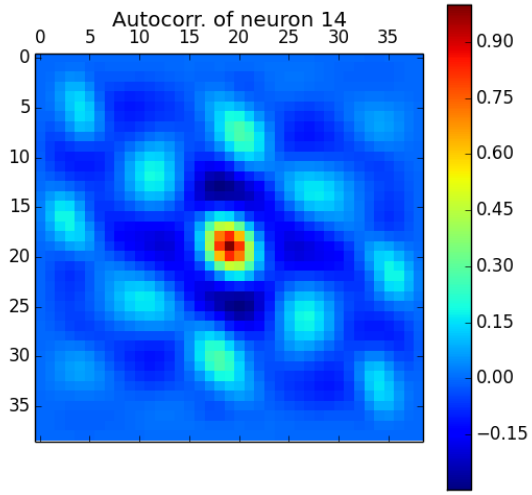


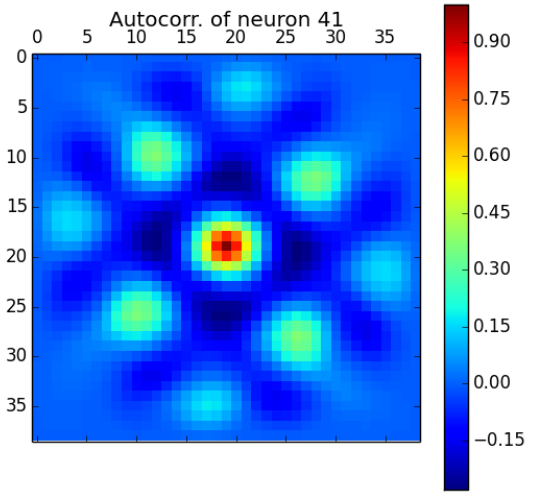


Cherrypicked final autocorrelations

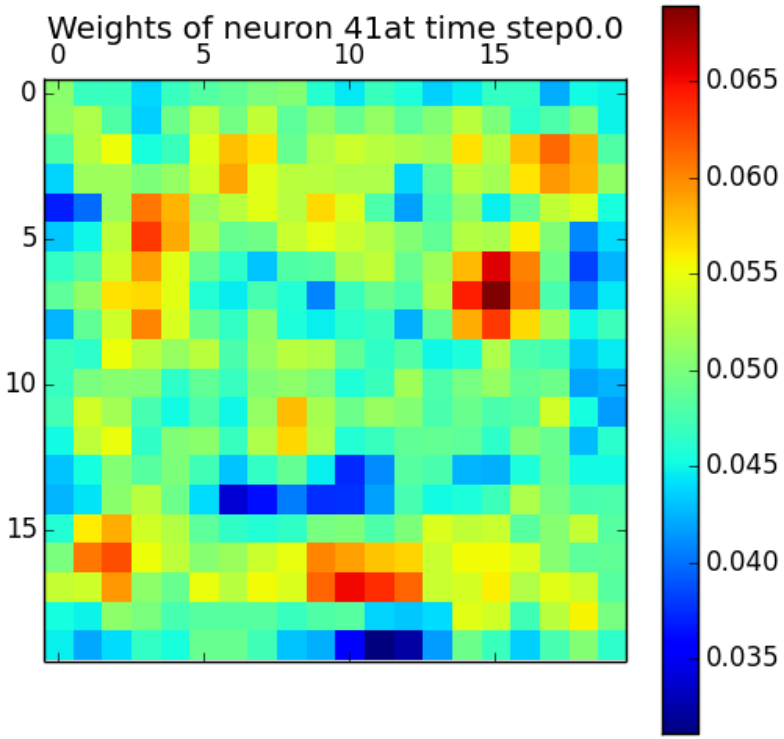


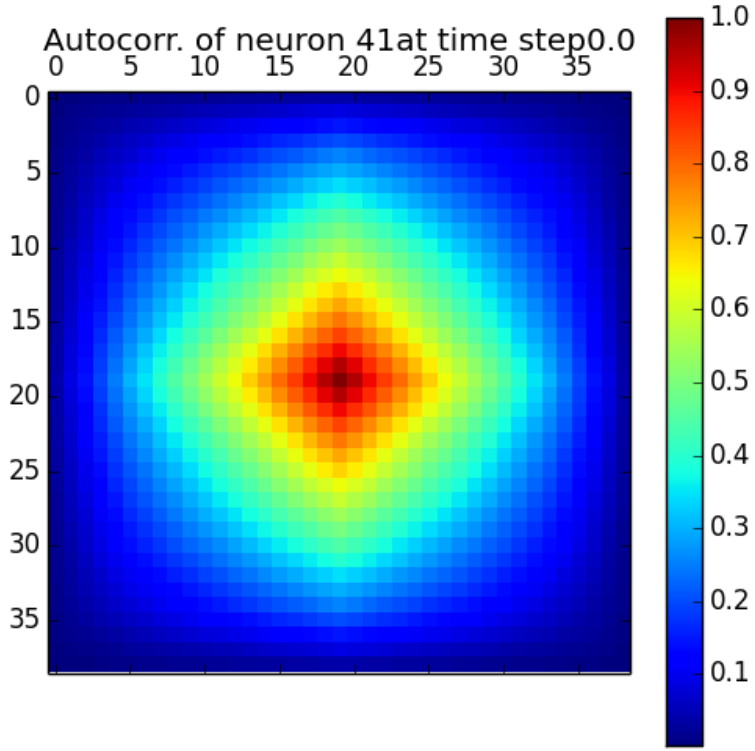






Time evolution of weights for a neuron





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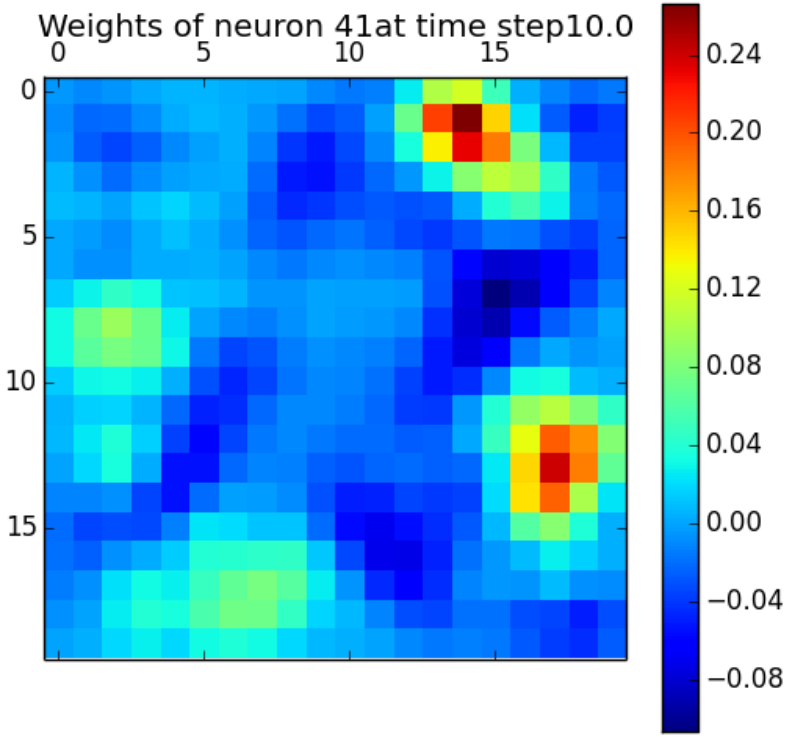

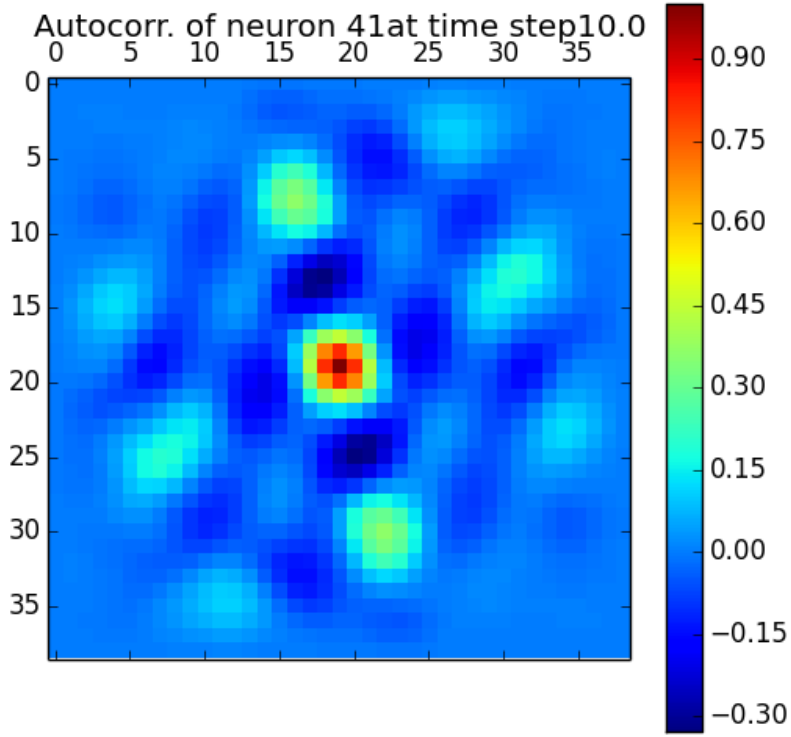

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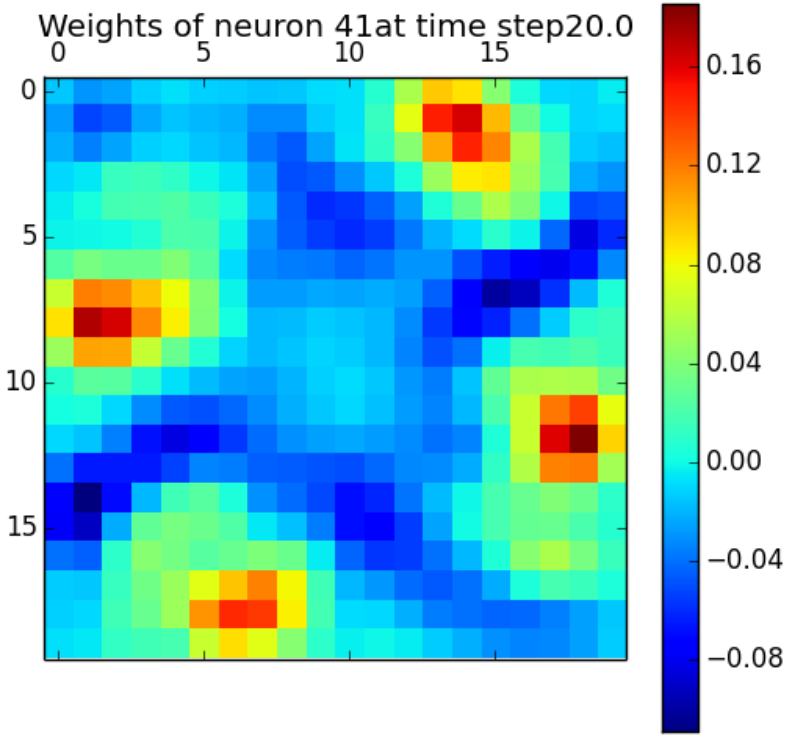

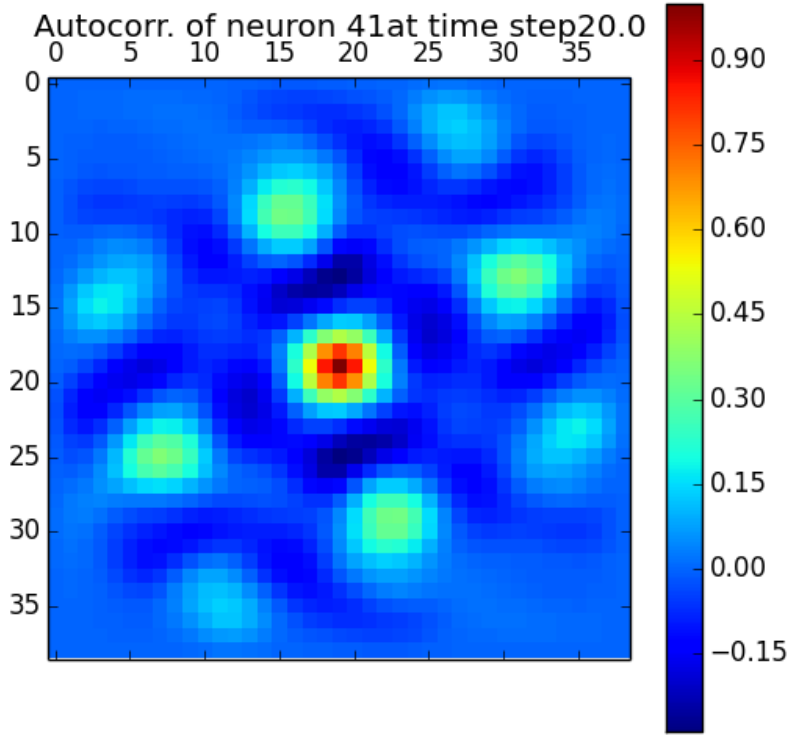

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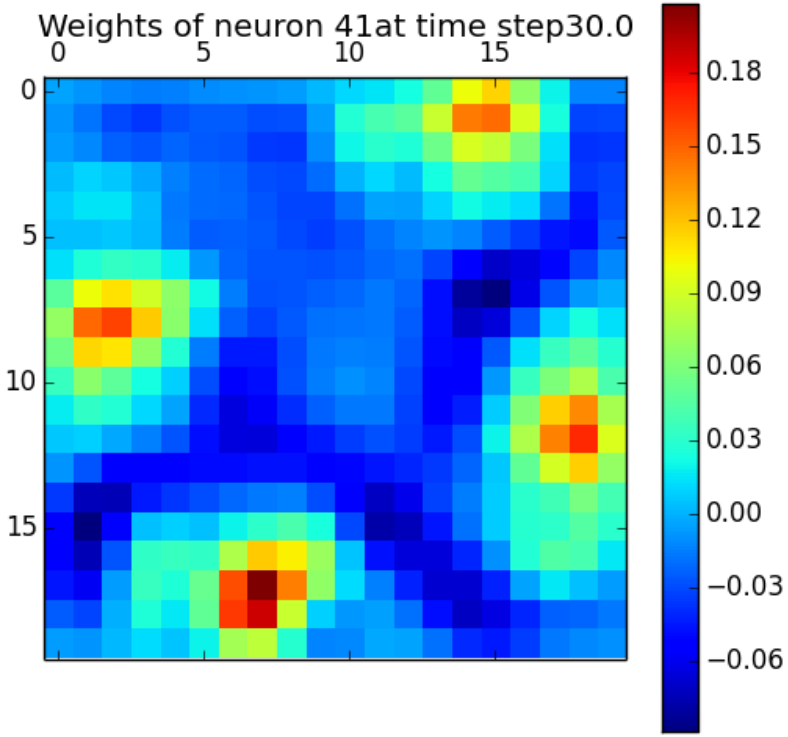

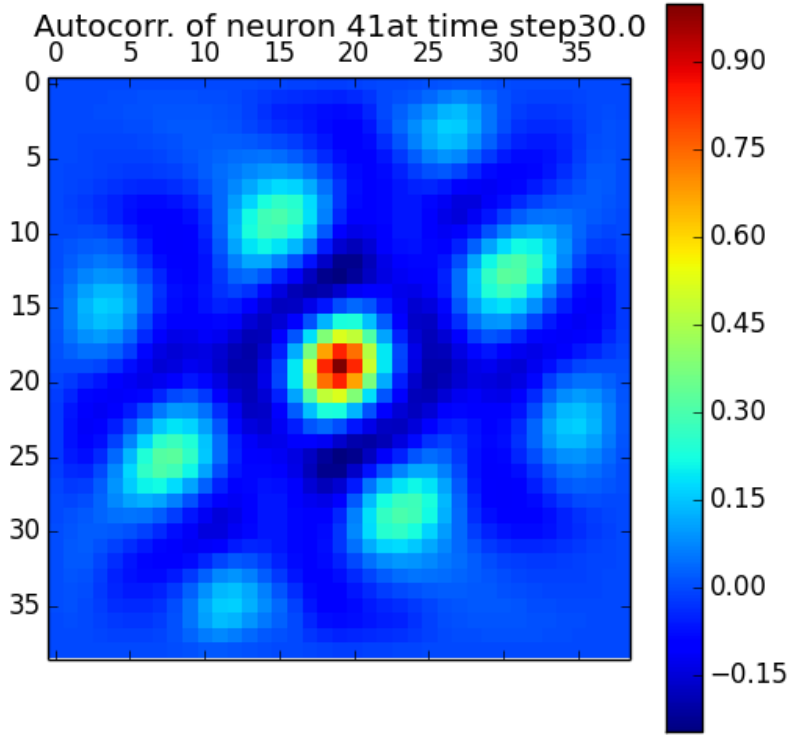

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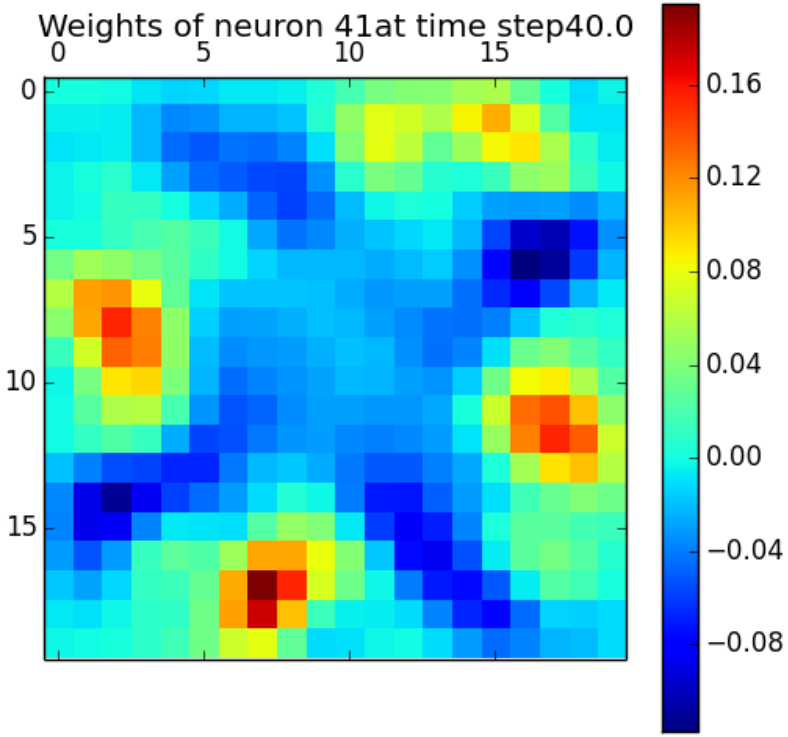
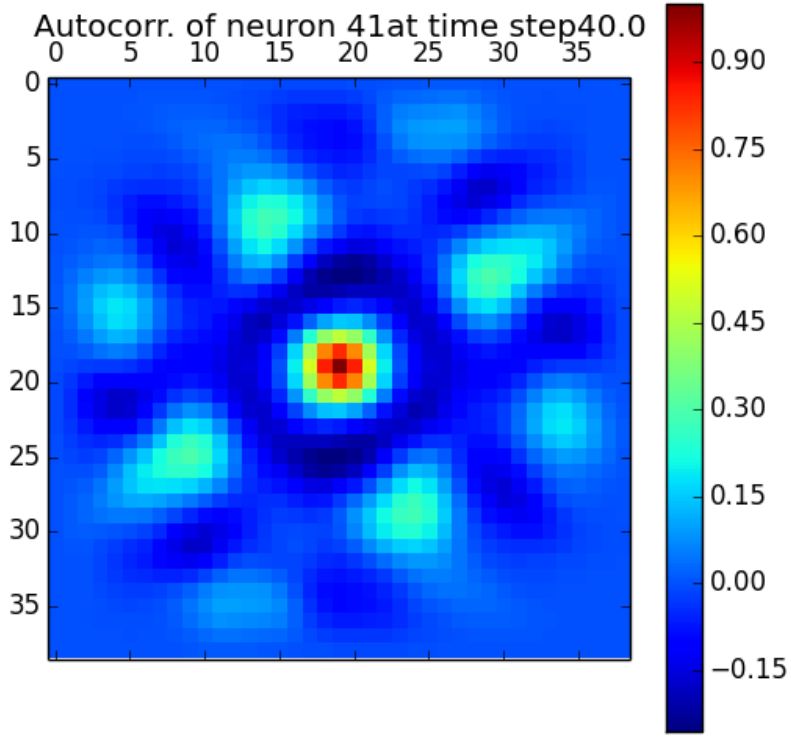
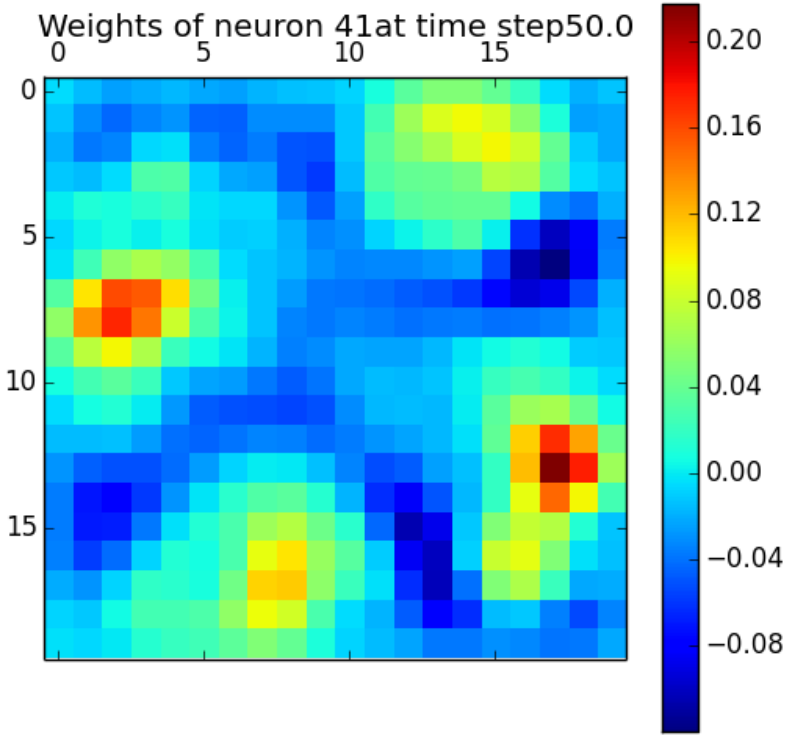
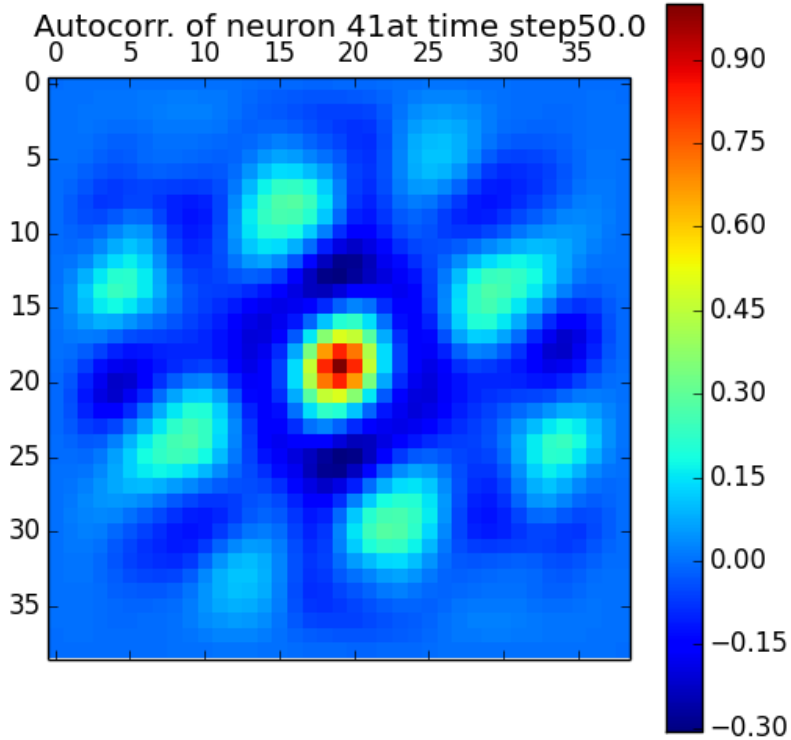




Time evolution of weights for a neuron





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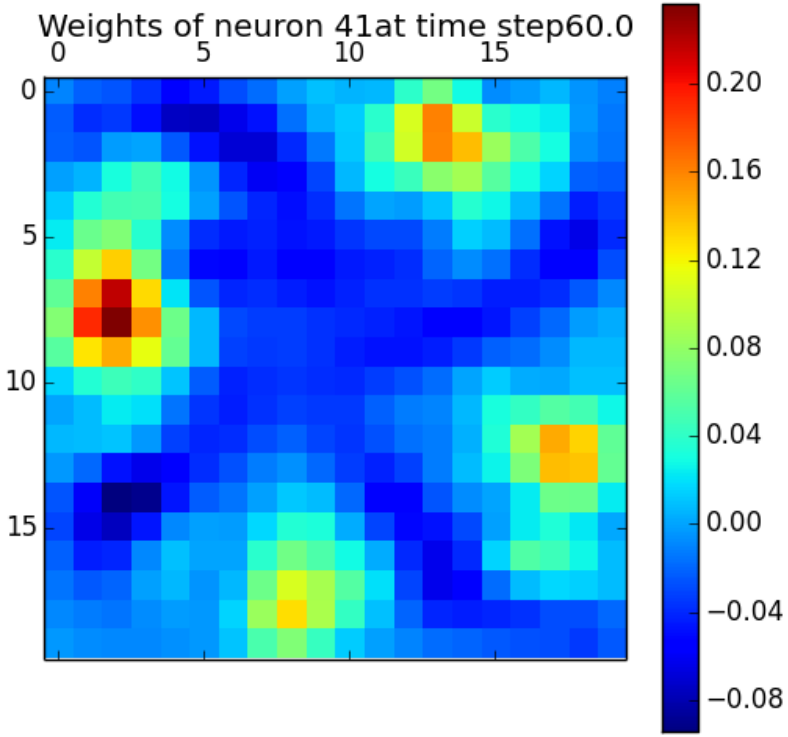

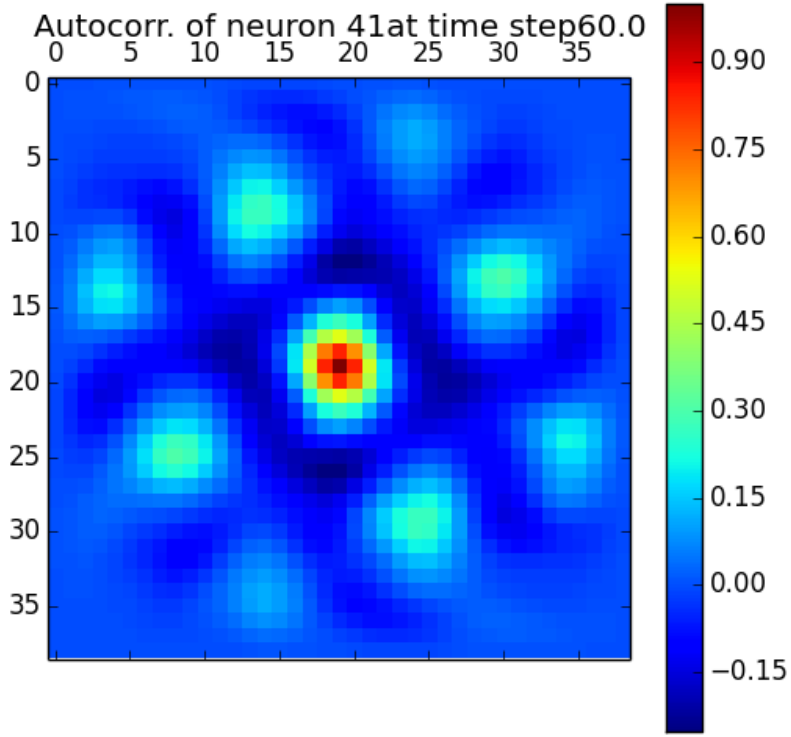

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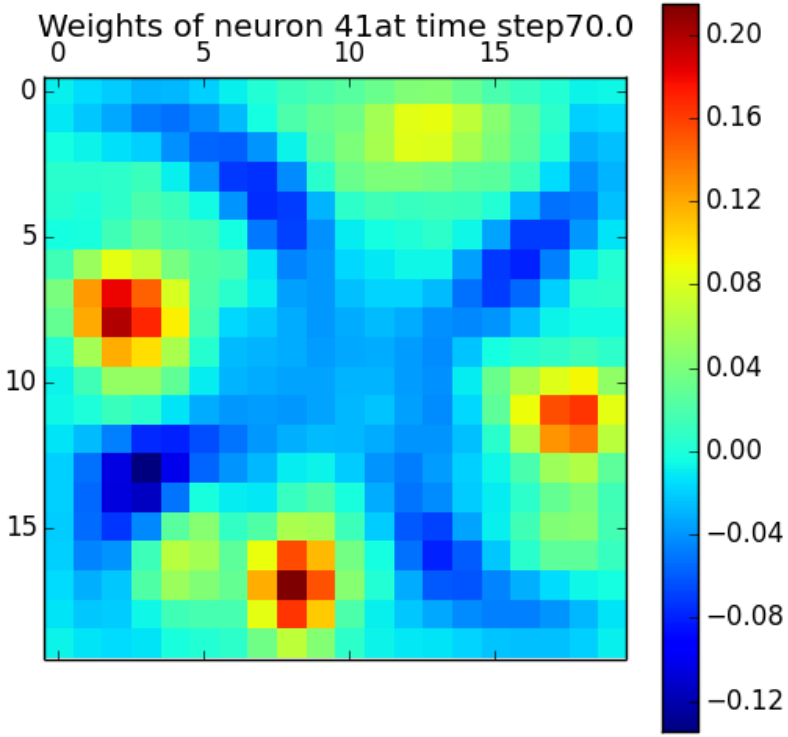

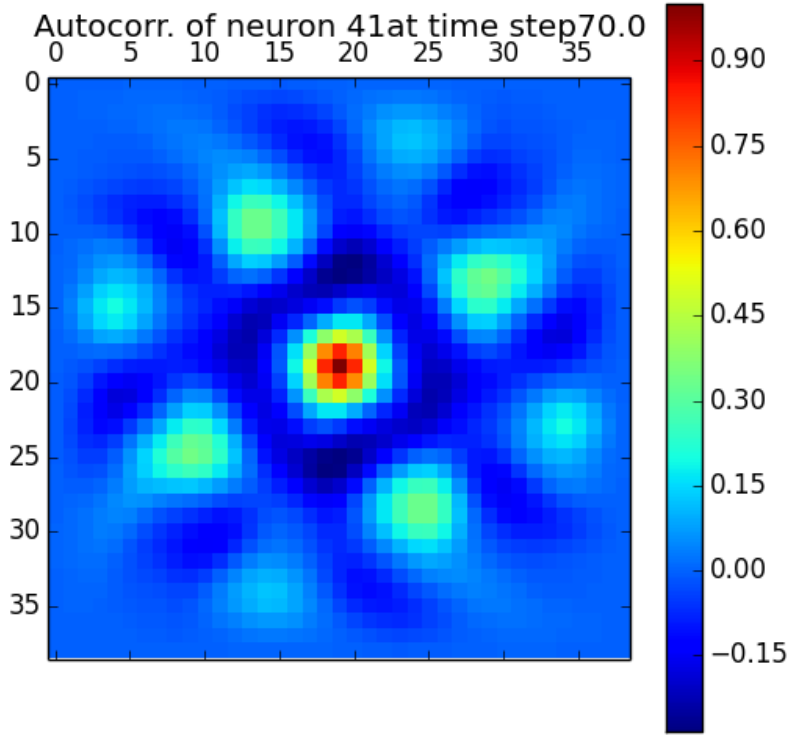

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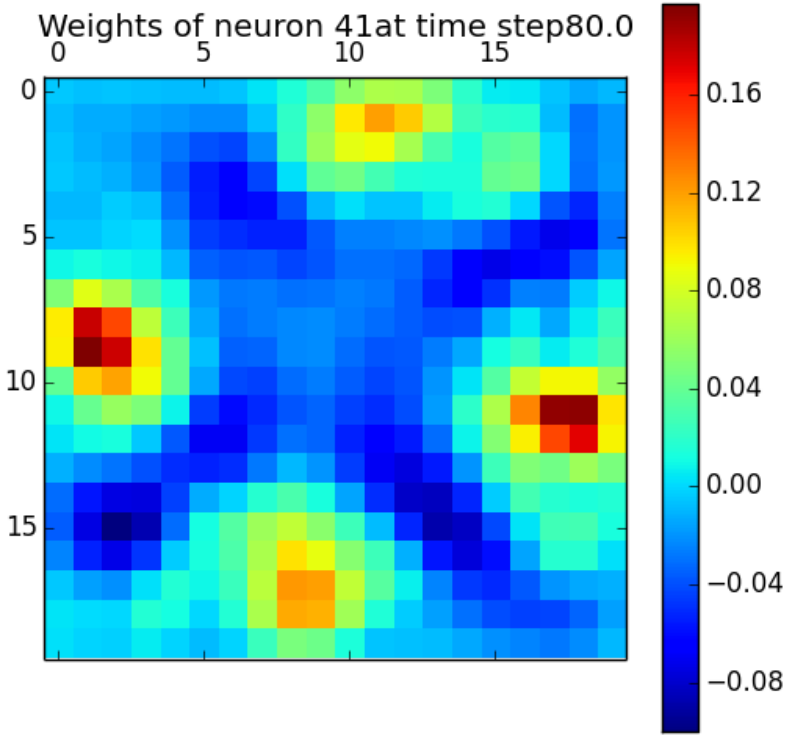

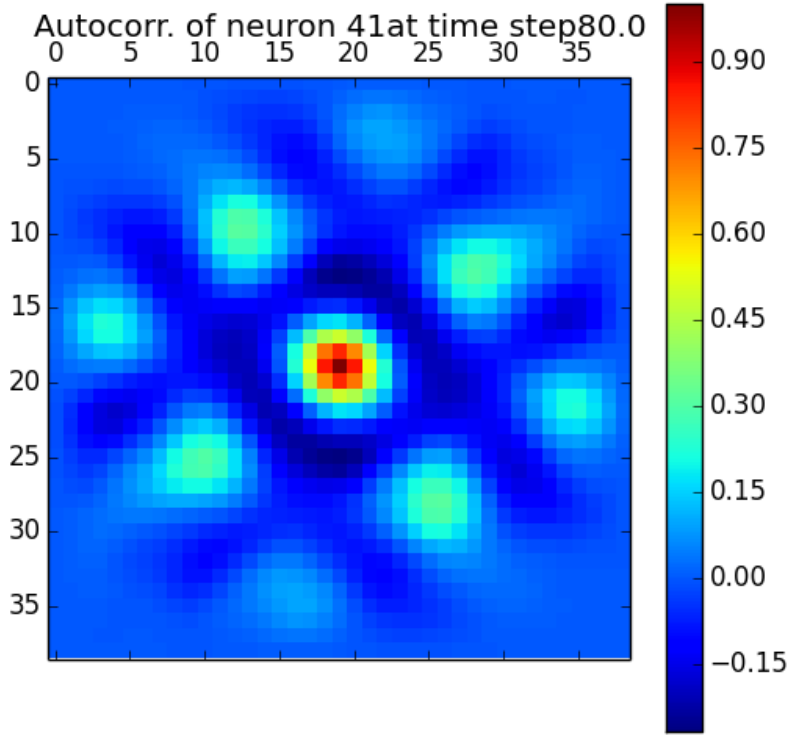

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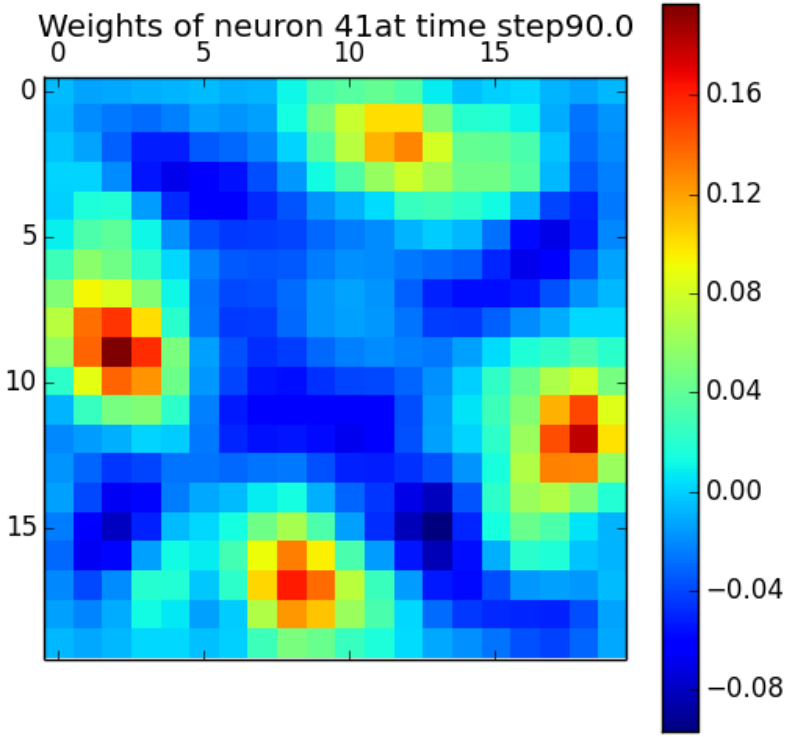

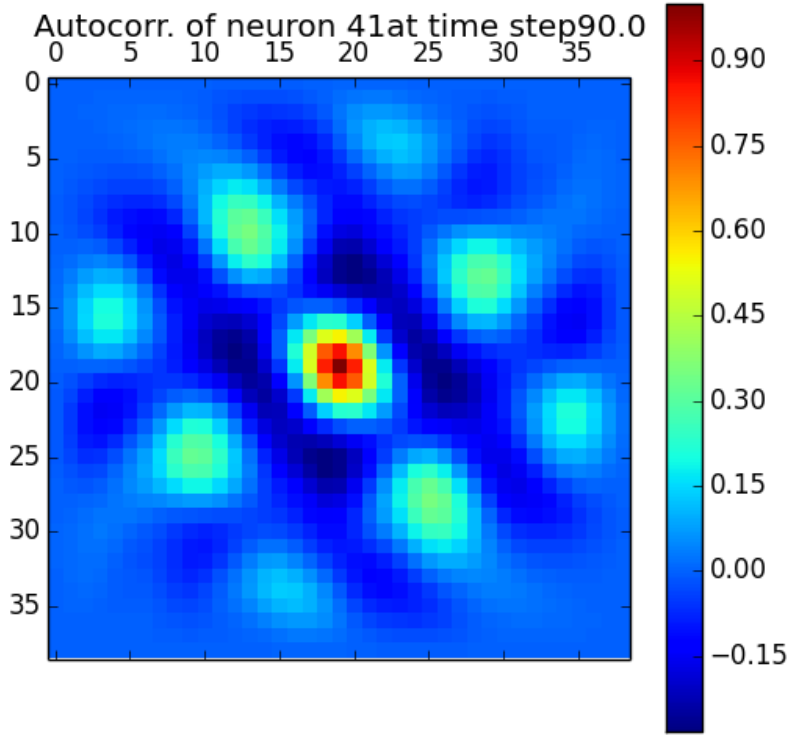

Time evolution of weights for a neuron