Lecture 3:
Modelling Insect Olfaction

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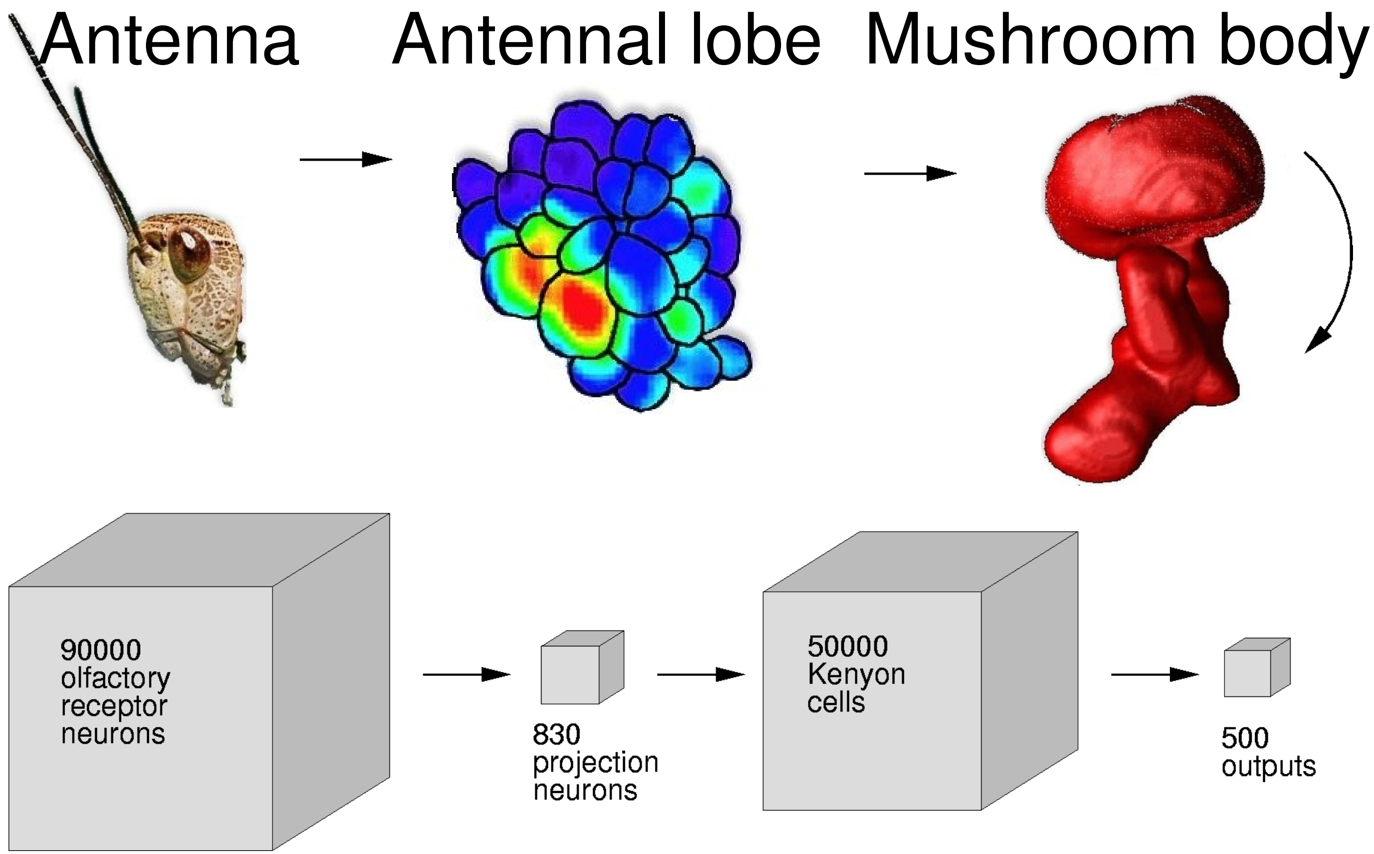
Why olfaction of insects?

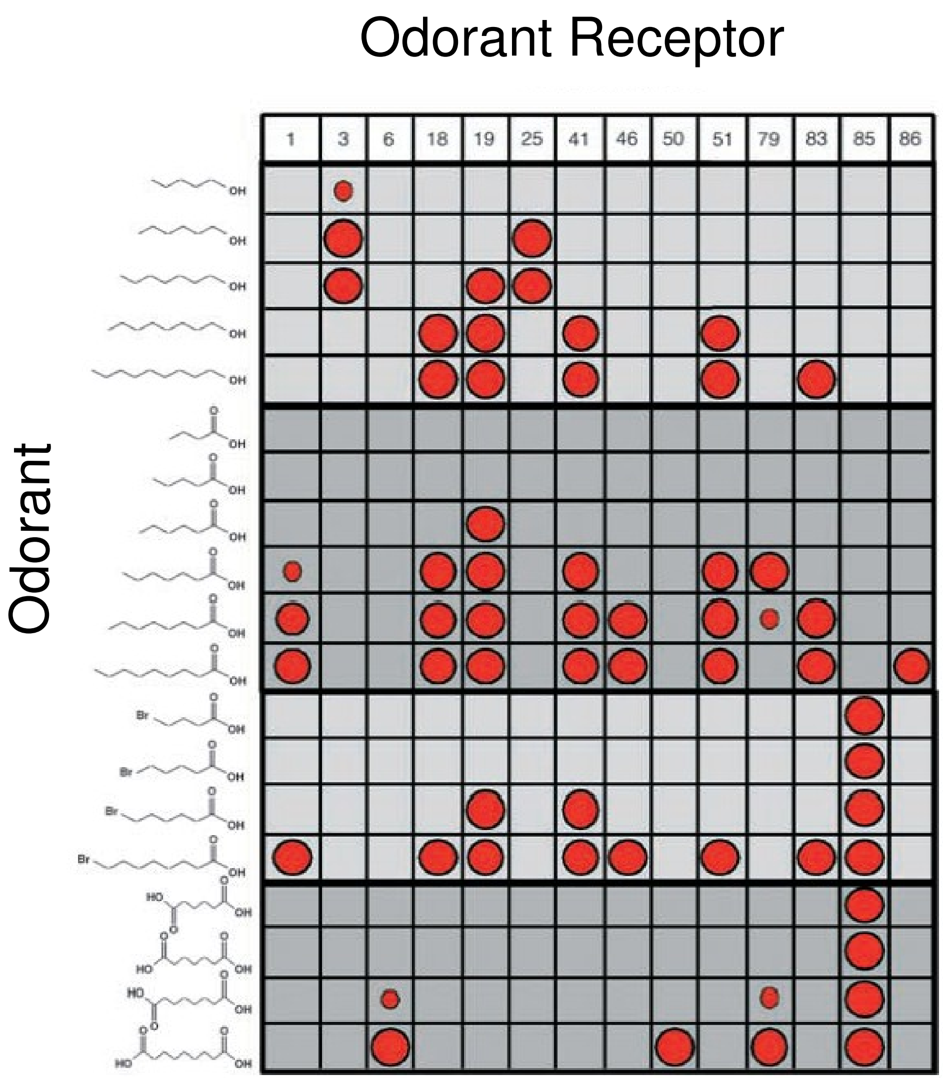
- Biological sensory systems have an amazing performance
- Insect olfaction is a good model to understand sensory processing
  - The systems are comparably small and experimentally accessible
  - Structure is very similar across species
  - Many recent advances (Nobel prize 2004)

Main olfactory pathway anatomy



Box volume ~ number of cells

Olfactory Receptors



Odors evoke different, but overlapping patterns of receptor activity

From Linda Buck: Nobel lecture

Early processing

- Each olfactory receptor neuron expresses **one** receptor type
- All olfactory receptor neurons of the same type converge onto **the same** glomerulus
- Projection neurons receive inputs from **one** glomerulus

Odors are encoded as overlapping patterns of projection neuron activity.

In Richard Axel's words

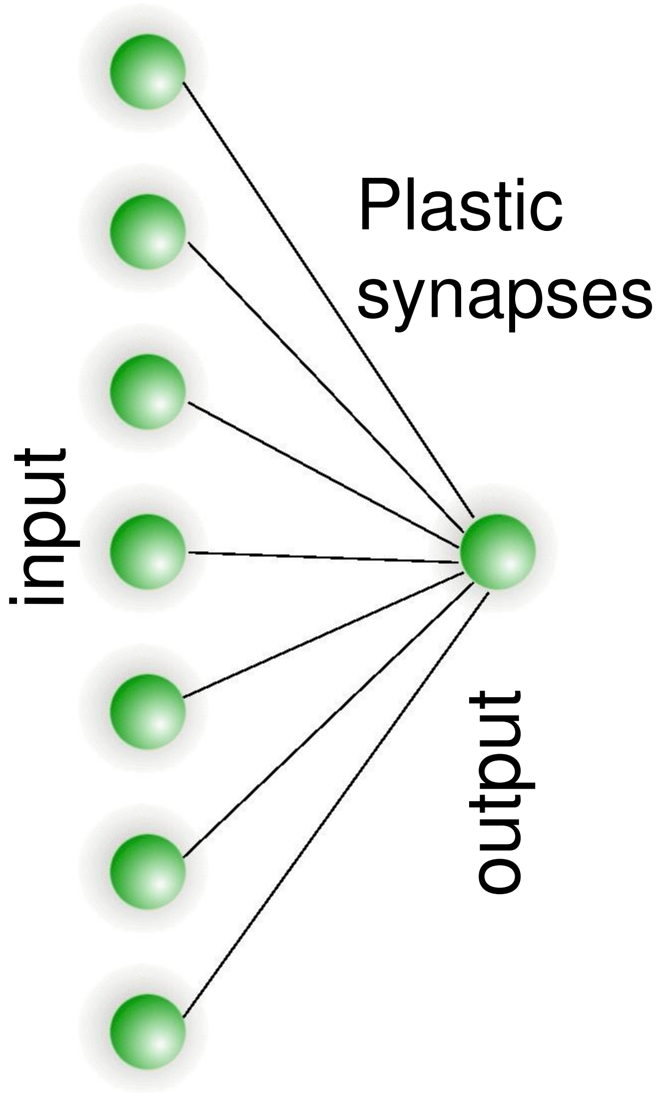
“The elucidation of an olfactory map […] leaves us with a different order of problems. Though we may look at these odor-evoked images with our brains and recognize a spatial pattern as unique and can readily associate the pattern with a particular stimulus, the brain does not have eyes. “

Richard Axel, Nobel lecture

In other words:

The algorithm of olfactory information processing remains to be found.

A classical pattern recognition solution

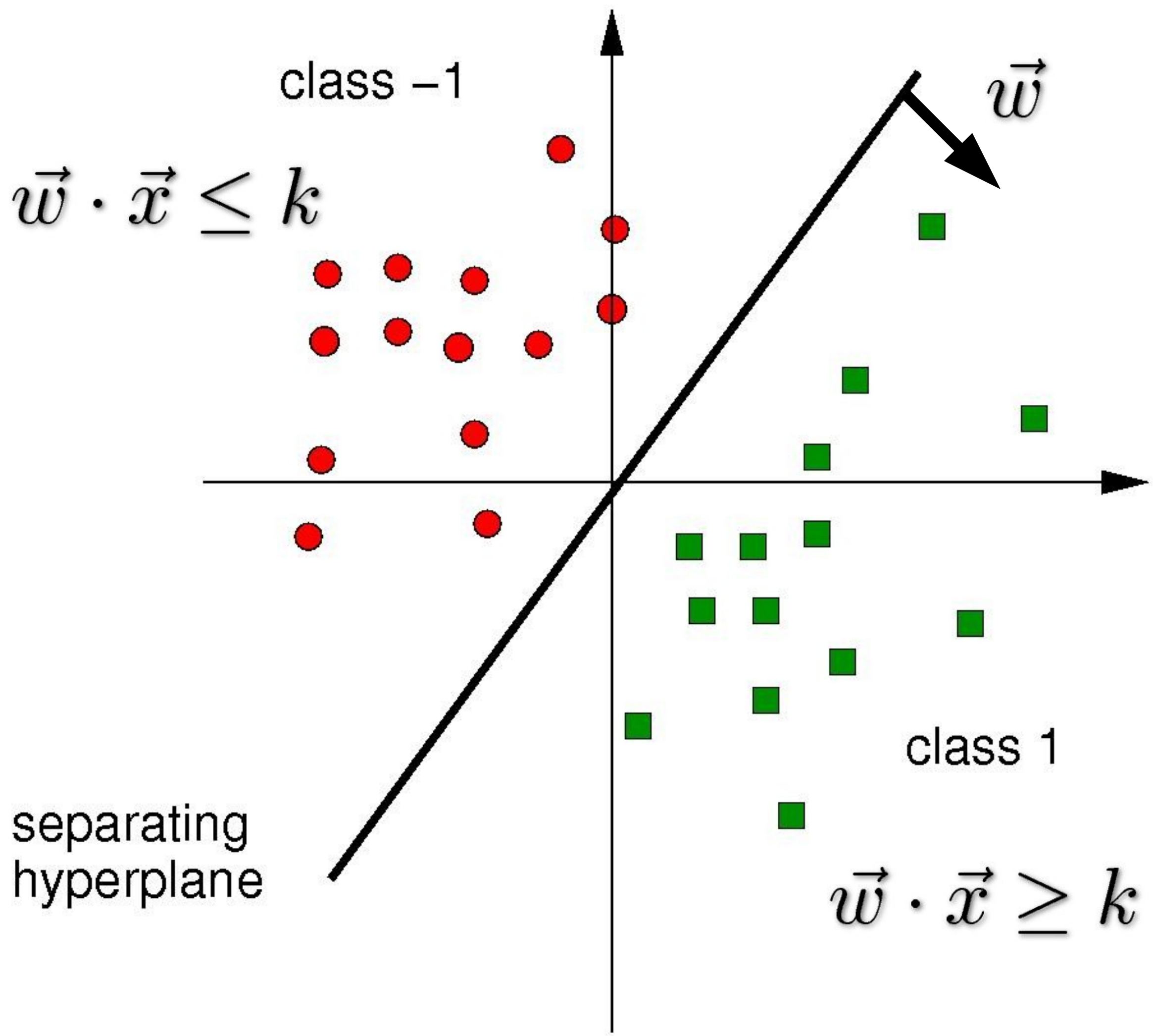


A simple perceptron rule:

Train A to respond to odor X (call it class 1)
… and hope that A does not respond to *any other odor*

(call it class -1)

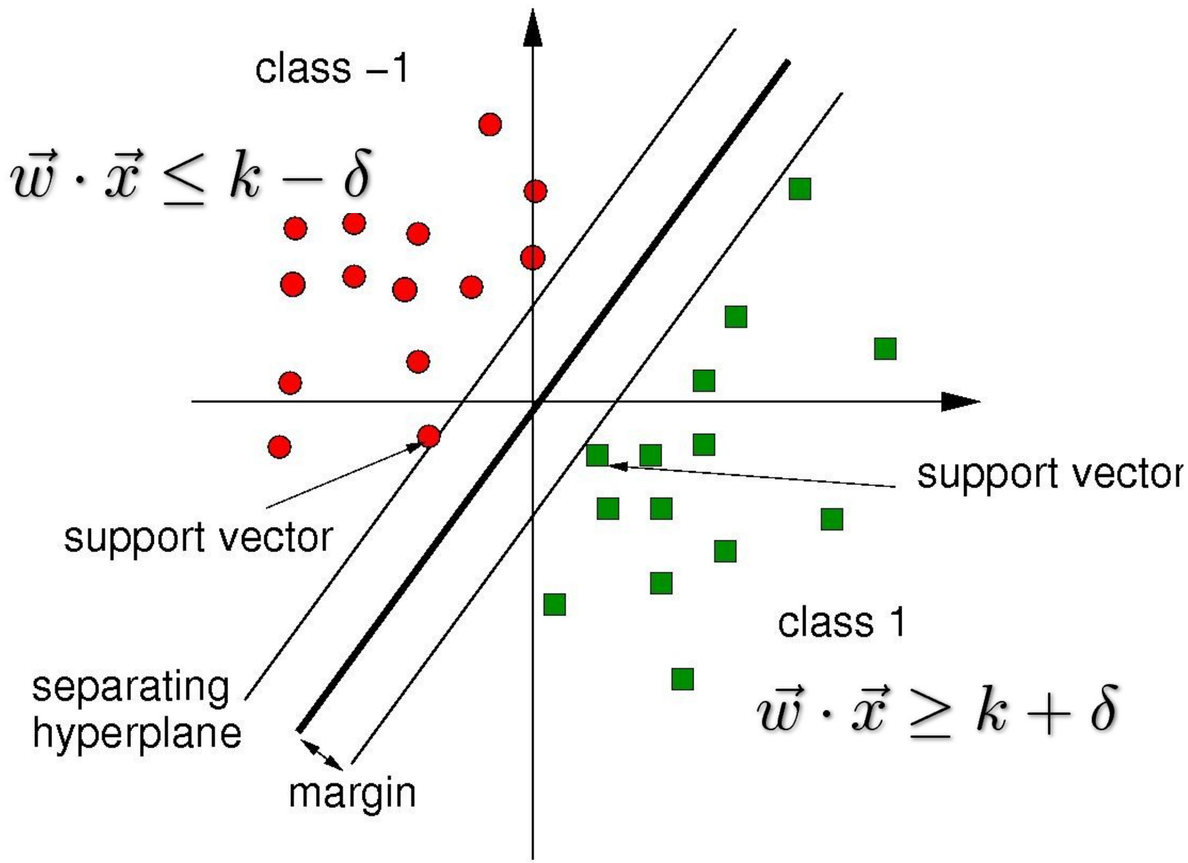
The perceptron is a linear classifier



The hyperplane is adjusted through the training and Hebbian learning

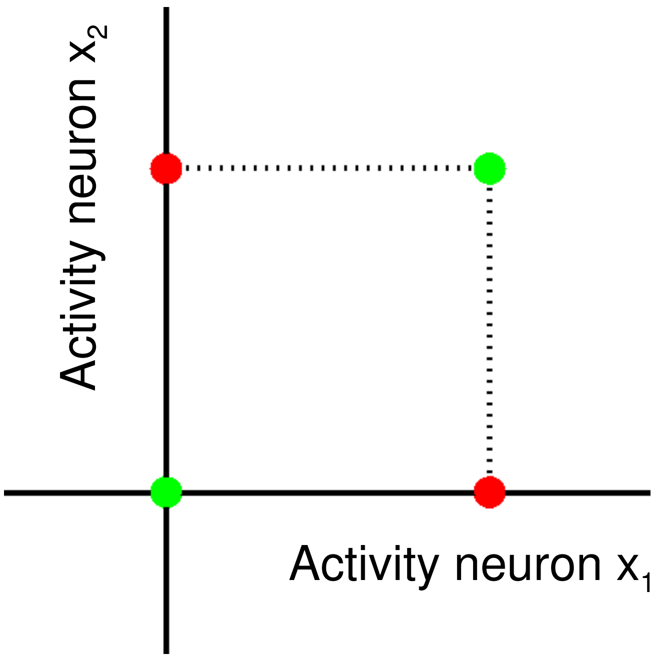
Support Vector Machines (SVM)

Cortes and Vapnik 1992,95: Support vector machine:



Here the hyperplane is adjusted to maximise the margin

Linear Classification can fail



There is no line that can separate green from red.

Dimension = number of neurons

Thomas Cover, 1965

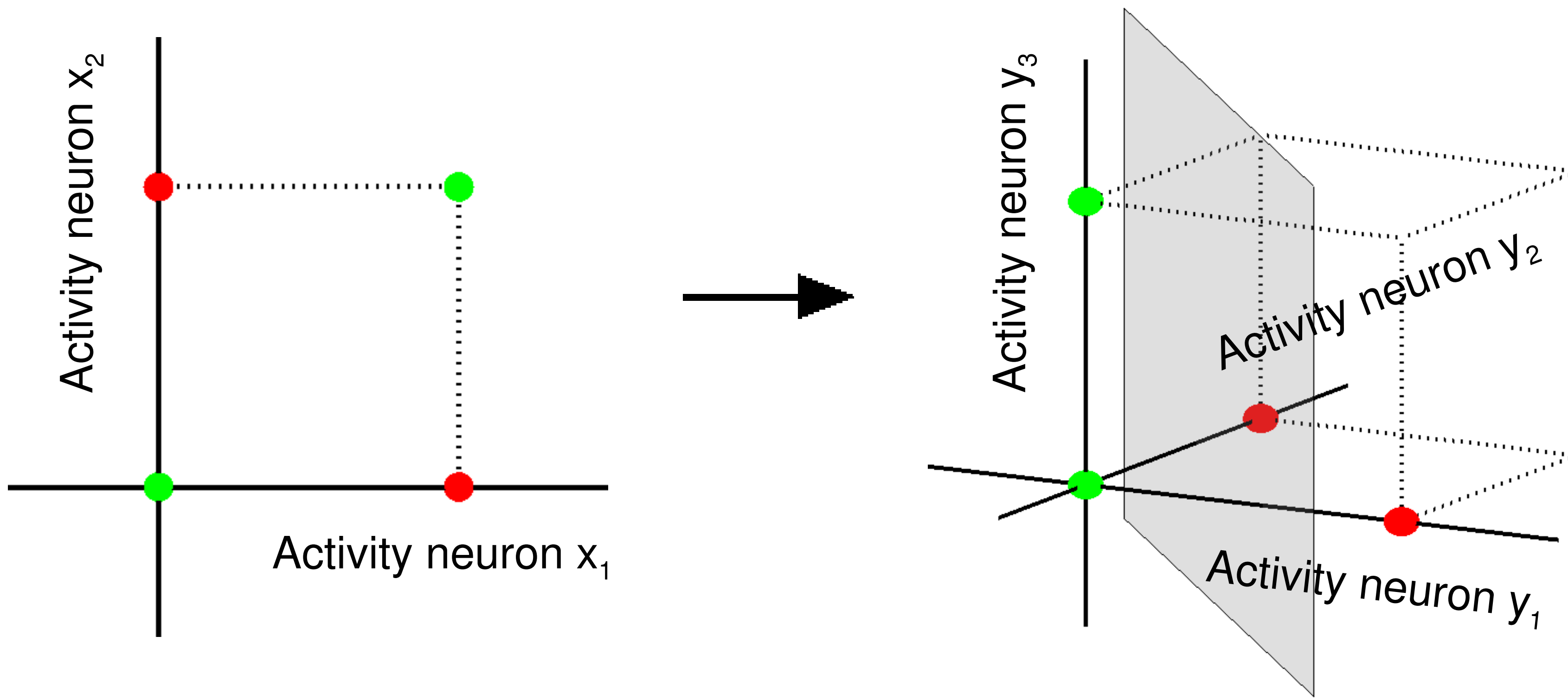
"Classification is much more probable if the input is first cast into a high-dimensional space by a non-linear transformation."

Cover, T. (1965). Geometric and statistical properties of systems of linear inequalities with applications in pattern recognition. IEEE T Elect. Comput., 14, 326.

This can be done by using a non-linear "Kernel function" instead of the scalar product $\vec{w} \cdot \vec{x}$.
When used like this it is known as the "**kernel trick**".

M. Aizerman, E. Braverman, and L. Rozonoer (1964). "Theoretical foundations of the potential function method in pattern recognition learning". Automation and Remote Control 25: 821–837

Kernel trick



Dimension = number of neurons

Typical kernels (transformations) used

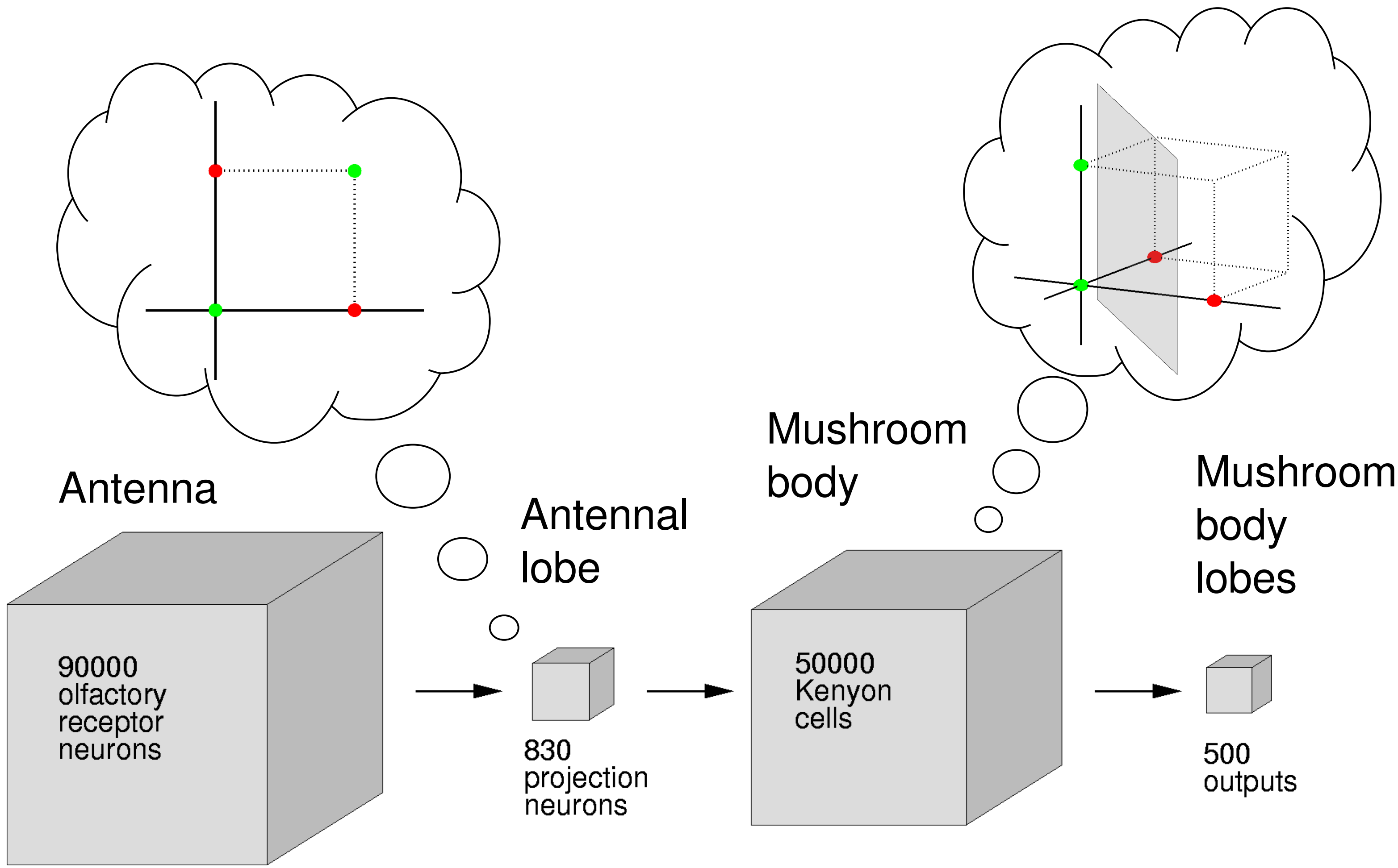
Polynomial (homogeneous): $K(\vec{w},\vec{x}) = (\vec{w}\cdot\vec{x})^j$

Polynomial (inhomogeneous): $K(\vec{w},\vec{x}) = (\vec{w}\cdot\vec{x}+1)^j$

Radial Basis Function (general): $K(\vec{w},\vec{x}) = K'(\|\vec{x}-\vec{w}\|)$

Gaussian RBF: $K(\vec{w},\vec{x}) = \exp(-\gamma\,\|\vec{x}-\vec{w}\|^2)$

Hypothesis: The locust uses this idea

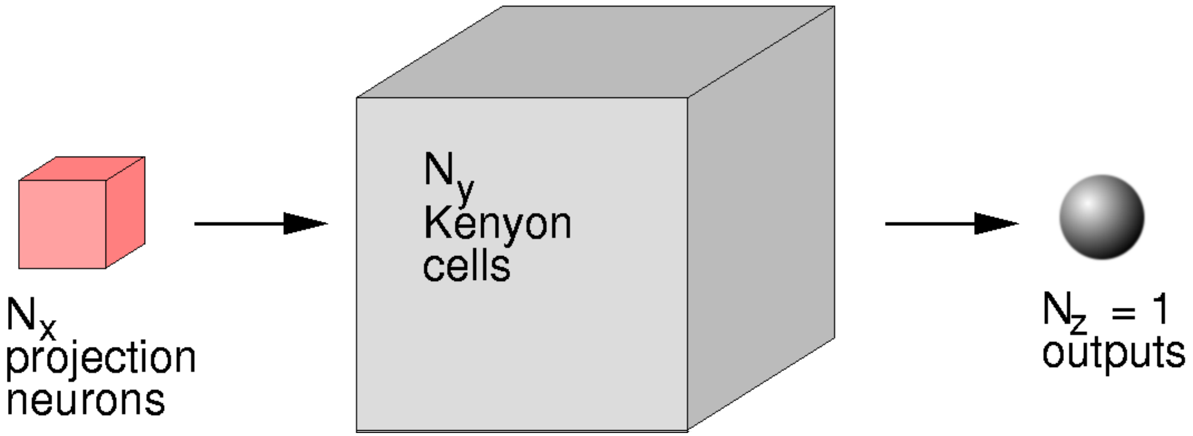


But we will use a *random kernel* (random connections)

Classify one pattern from the rest

Random input patterns

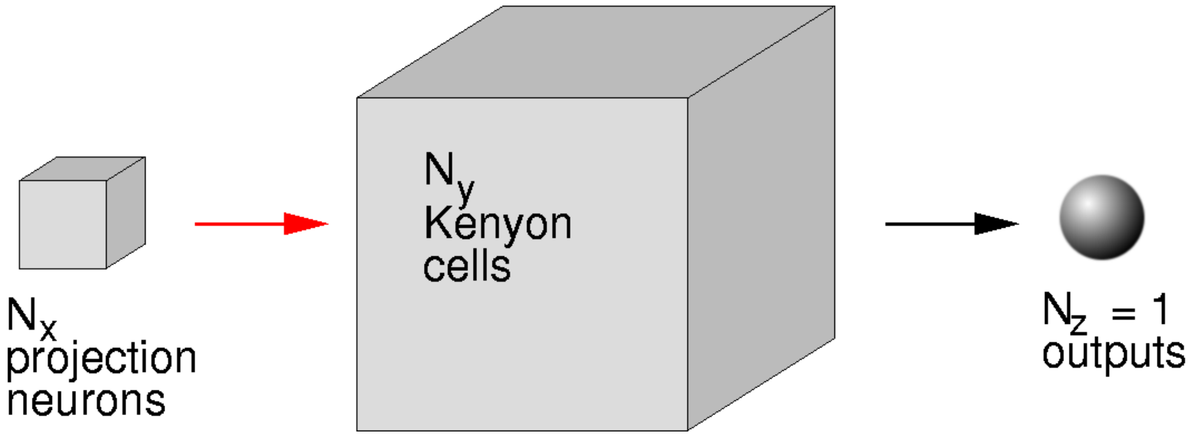
$$x_i = \begin{cases} 1 & \text{with} \quad p_x \\ 0 & \text{otherwise} \end{cases}$$



Classify one pattern from the rest

Random connections

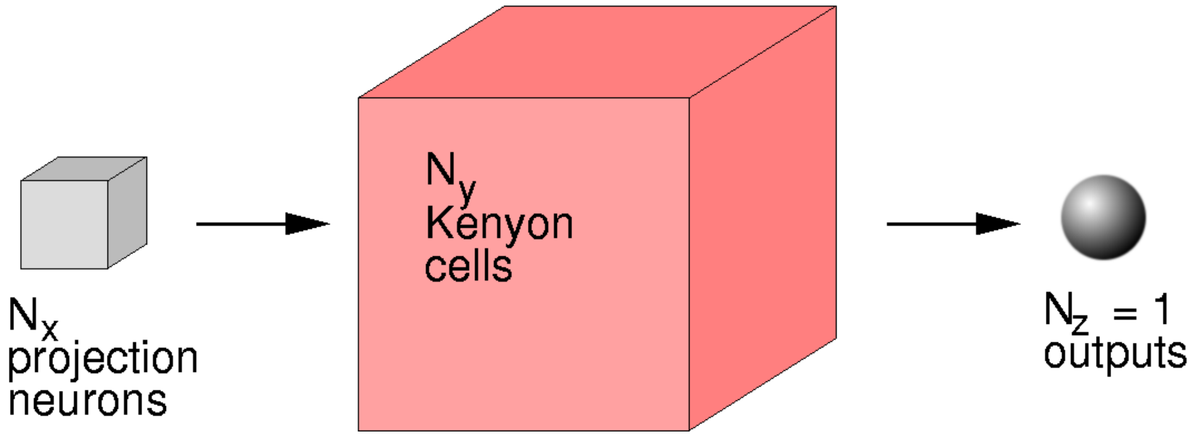
$$w_{ji} = \begin{cases} 1 & \text{with} \quad p_{y \leftarrow x} \\ 0 & \text{otherwise} \end{cases}$$



Classify one pattern from the rest

McCulloch-Pitts neurons

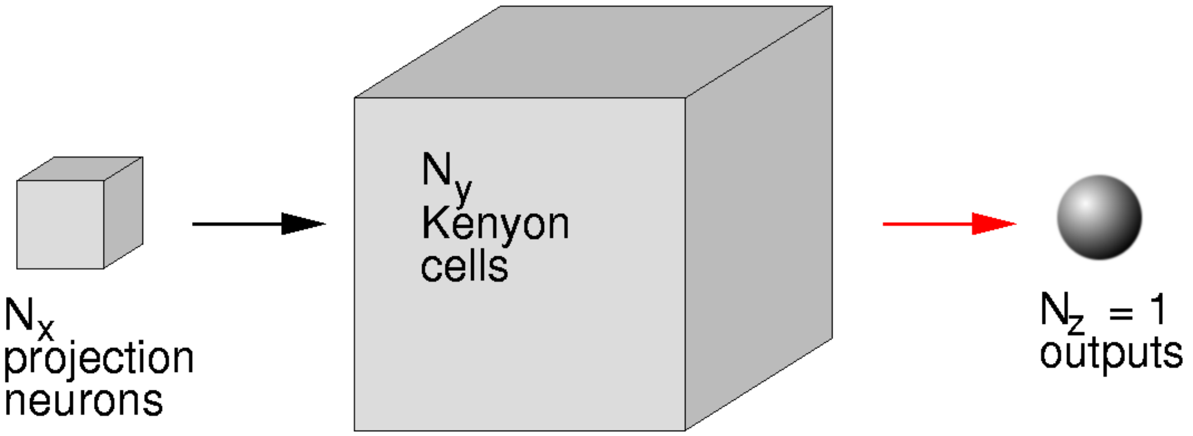
$$y_j(t) = \Theta\left(\sum_i w_{ji} x_i(t-1) - \theta \right)$$



Classify one pattern from the rest

"Hebbian" connections

$$v_{kj}(t) = \begin{cases} 1 & \text{with} \quad p_+ \quad \text{if } y_j = 1,\ z_k = 1 \\ 0 & \text{with} \quad p_- \quad \text{if } y_j = 1,\ z_k = 0 \\ v_{kj}(t-1) & \text{otherwise} \end{cases}$$

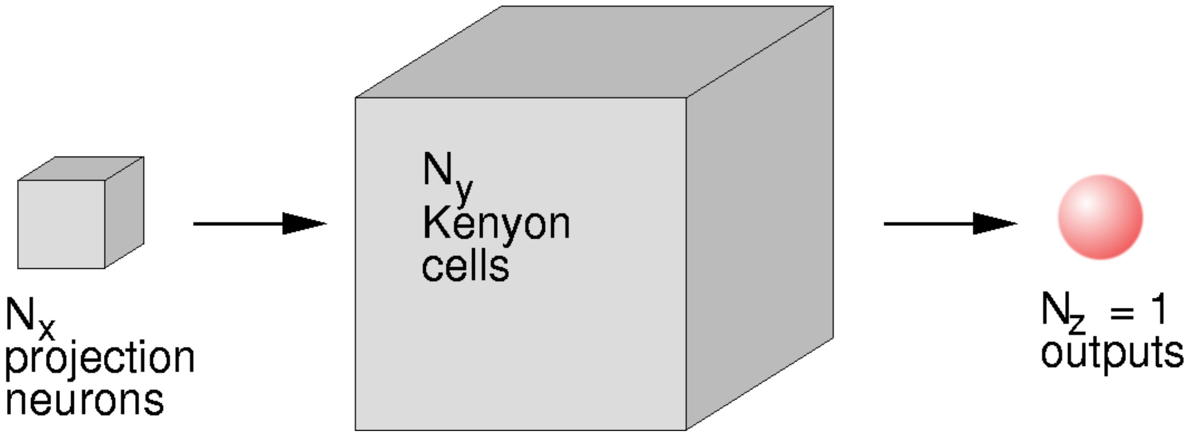


Classify one pattern from the rest

McCulloch-Pitts neuron

$$z(t) = \Theta\left(\sum_j v_{kj} y_j(t-1) - \theta \right)$$

Induce a spike for 1 trained pattern
Don't do anything for 99 others



Example calculation

Probability for a Kenyon cell to be active, given n_x=k projection neurons fire

$$P(y_i = 1 \mid n_x = k) = \sum_{l=\theta}^{k} \binom{k}{l} p_{y\leftarrow x}^{l} \,(1 - p_{y\leftarrow x})^{k-l}$$

Probability for the number of active Kenyon cells, given …

$$P(n_y = r \mid n_x = k) = \binom{N_y}{r} P(y_i = 1 \mid n_x = k)^r \big(1 - P(y_i = 1 \mid n_x = k)\big)^{N_y - r}$$

Then the unconditioned probability is

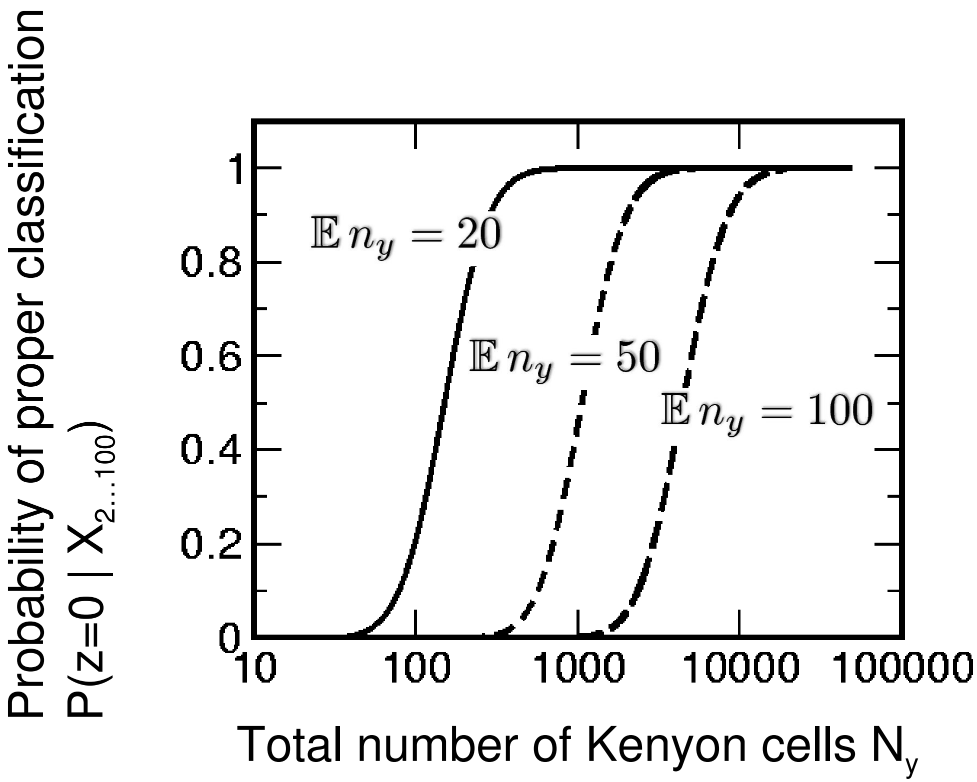
$$P(n_y = r) = \sum_k P(n_y = r \mid n_x = k)\; P(n_x = k)$$

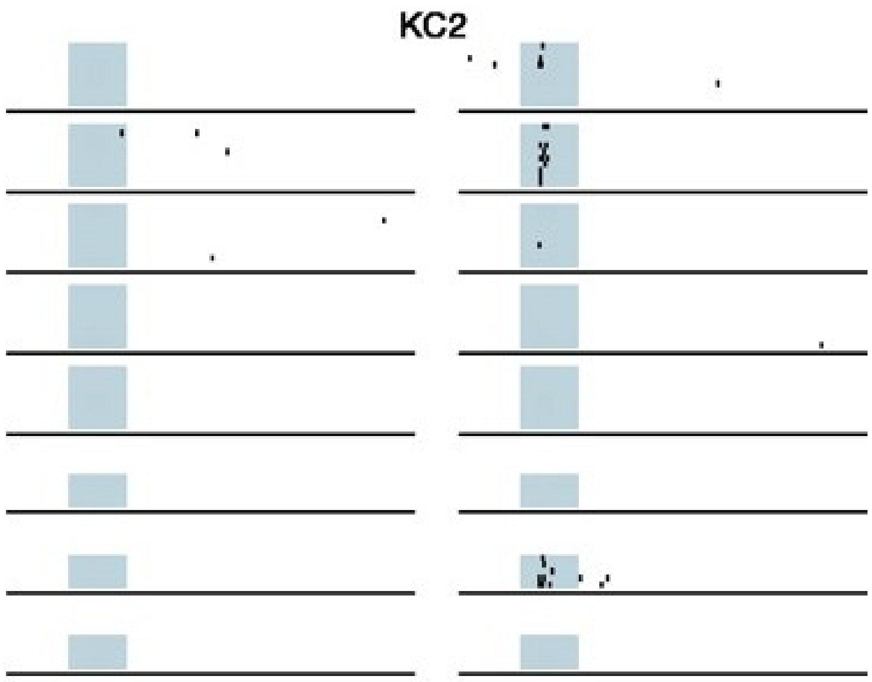
Leading (after some simplification) to

$$\mathbb{E}\, n_y = N_y\, p_x p_{y\leftarrow x}(1 - p_x p_{y\leftarrow x})$$

Example result: Classification needs sparse code

… and nature uses it!





Perez-Orive et al., Science (2002)

"Have many, but only use a few"

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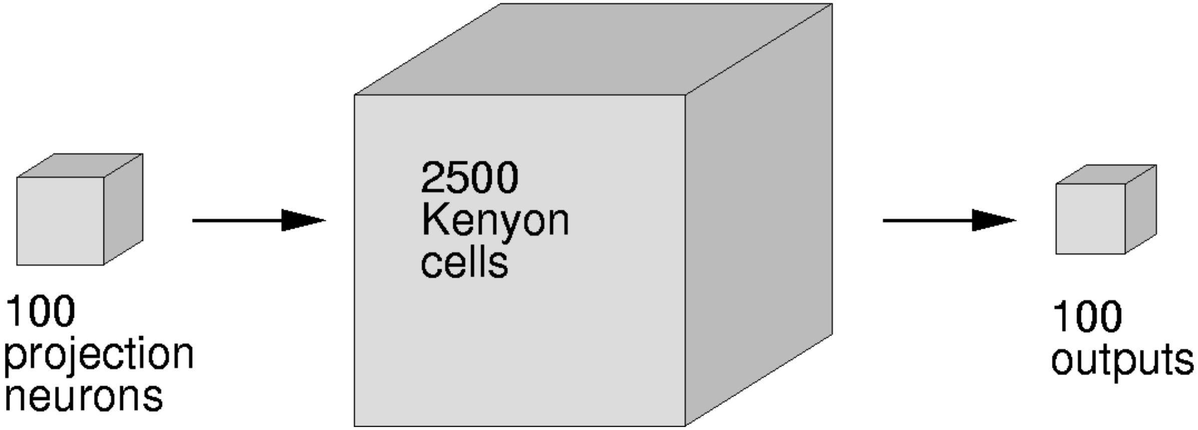
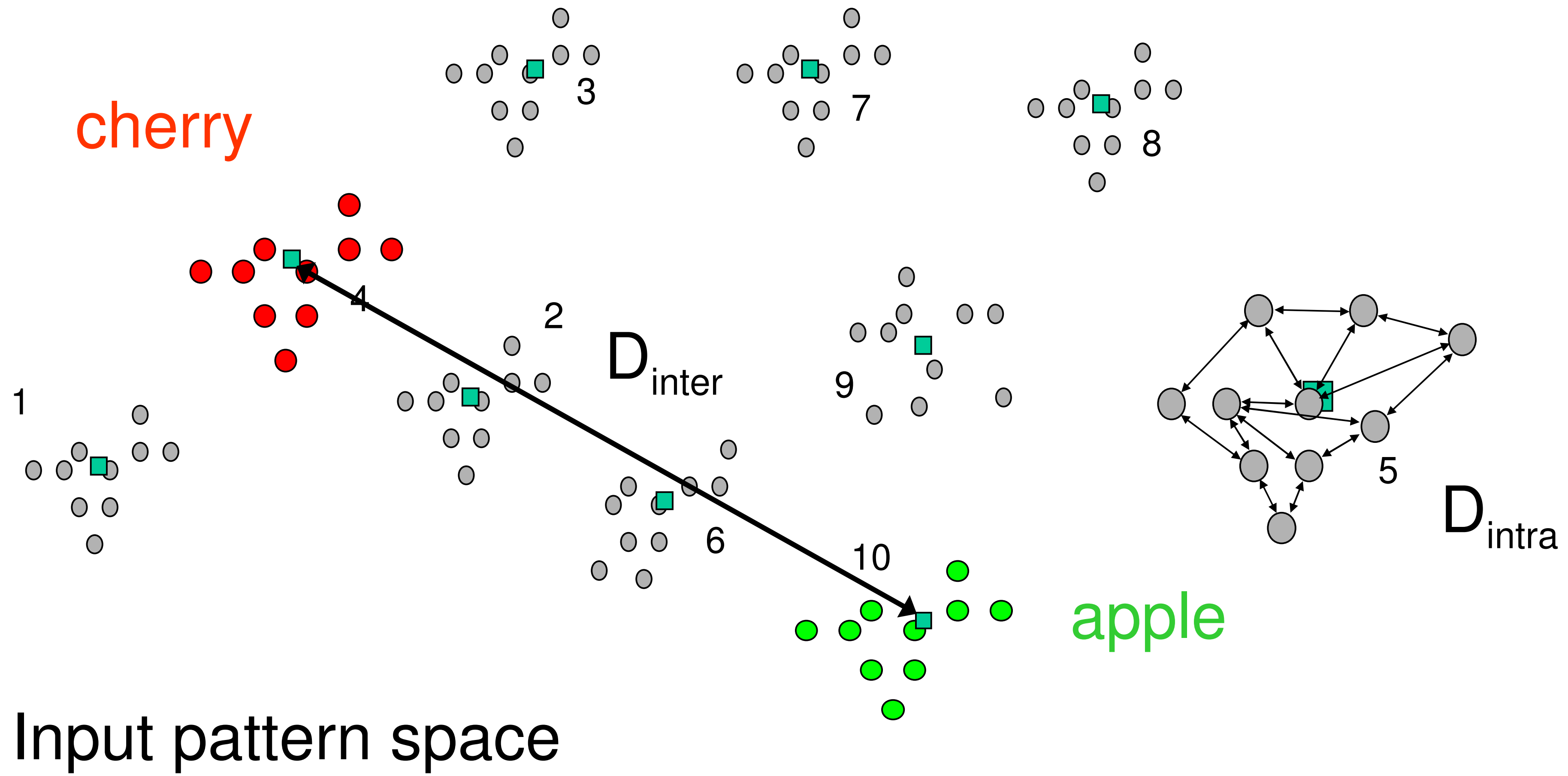
Classify classes of inputs

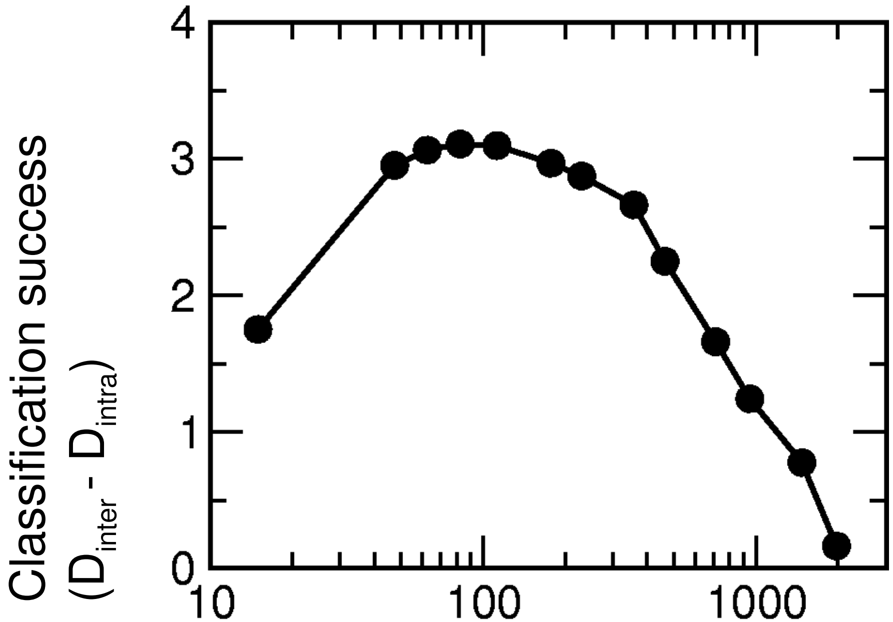
- 10 classes of inputs, 10 patterns each class
- "Winner-take-all" ouputs:
  The output neuron with the strongest input spikes
- Simulations in "*Drosophila* size"



Classes of input patterns



There are “optimal design parameters”



Number of active Kenyon cells $\mathbb{E}\, n_y$

$\exists$ Optimal $\mathbb{E}\, n_y$

of active Kenyon cells

Summary

- Random connectivity is enough for classification
- This suggests support vector machines with *random kernels* and *local*, “Hebbian” learning
- An optimal, sparse level of activity is postulated *and observed* in biology
- These systems are freely scalable & our analysis provides the parameters of choice
- These systems are extremely robust

Shortcomings

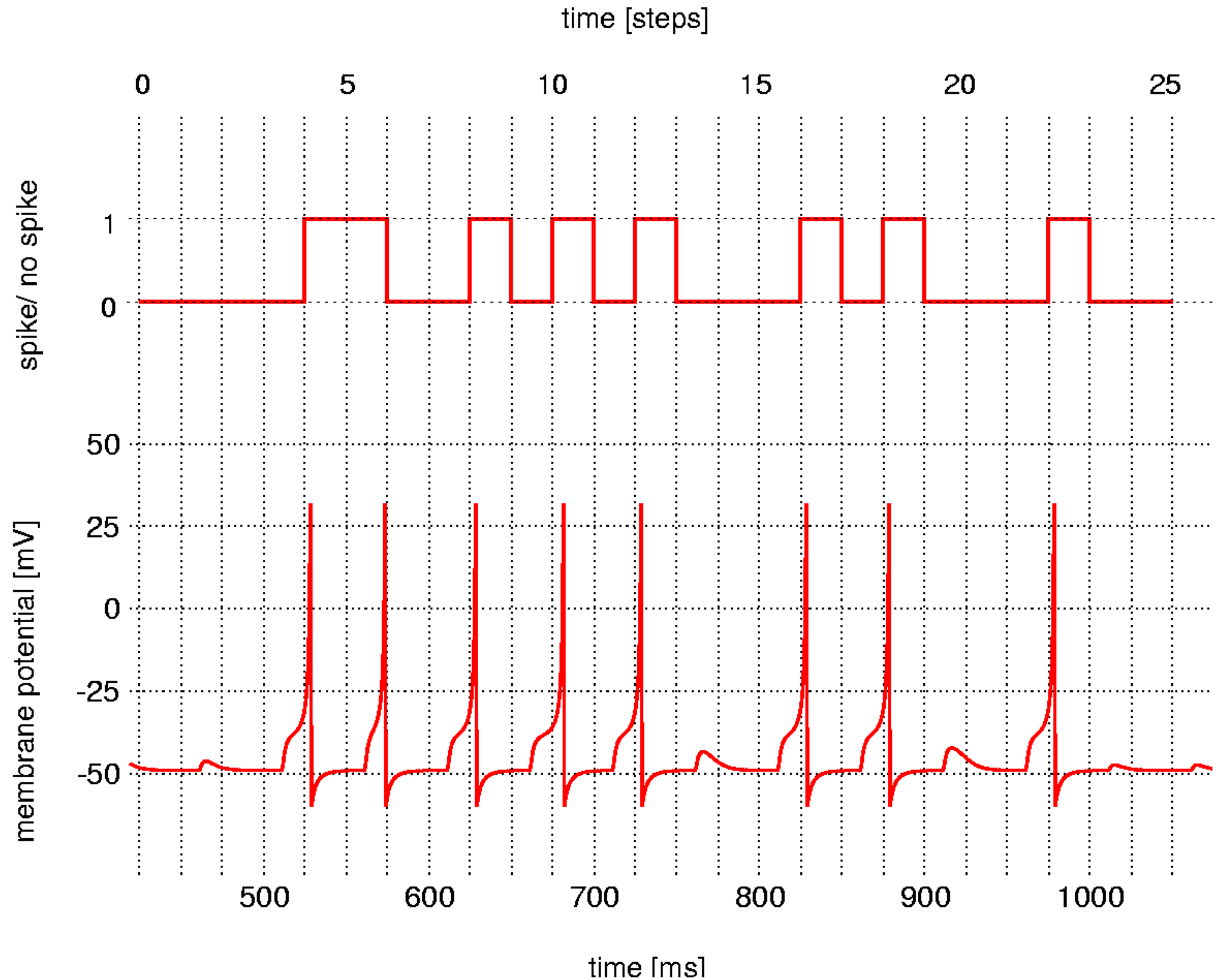
- The winner-take-all competition between output neurons has to be implemented artificially
- Gain control in the MB has to be implemented artificially

These issues can be resolved with more realistic spiking neuron models.

Spiking neuron models

McCulloch-Pitts

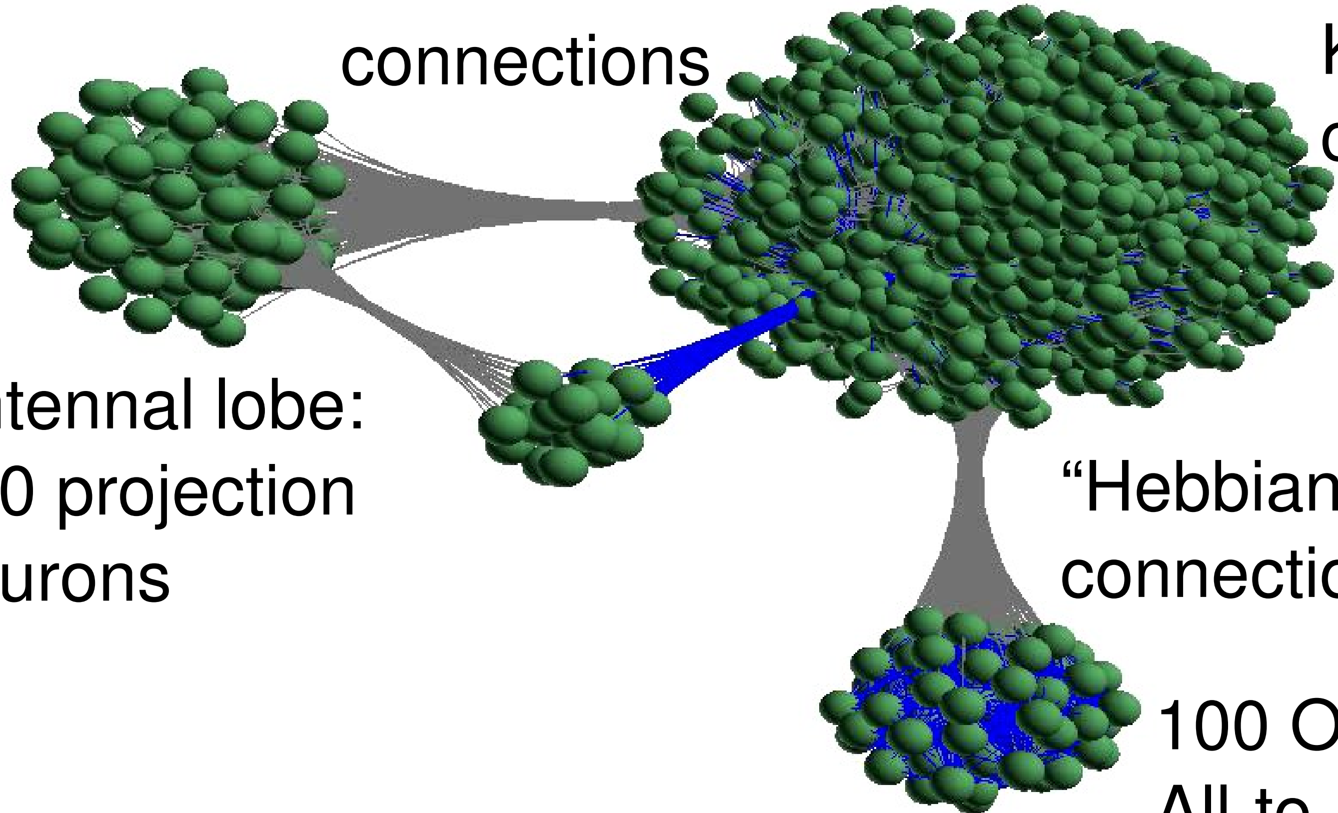
Spiking neurons



Process of recognition: Naïve locust

Random
connections

2500
Kenyon
cells



Antennal lobe:
100 projection
neurons

“Hebbian”
connections

100 Output neurons:
All-to-all inhibition

Created with neuranim
http://sourceforge.net/projects/neuranim

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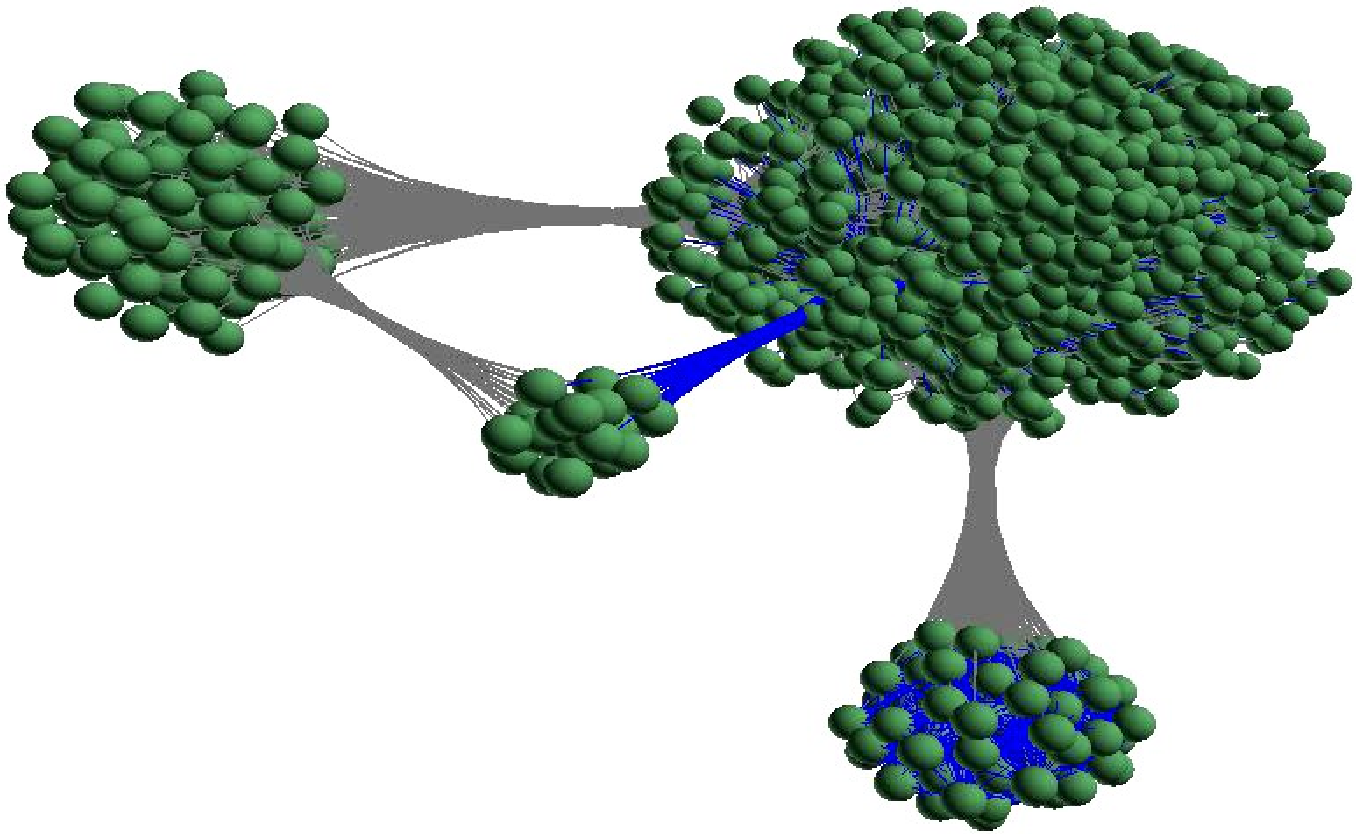
Experienced locust



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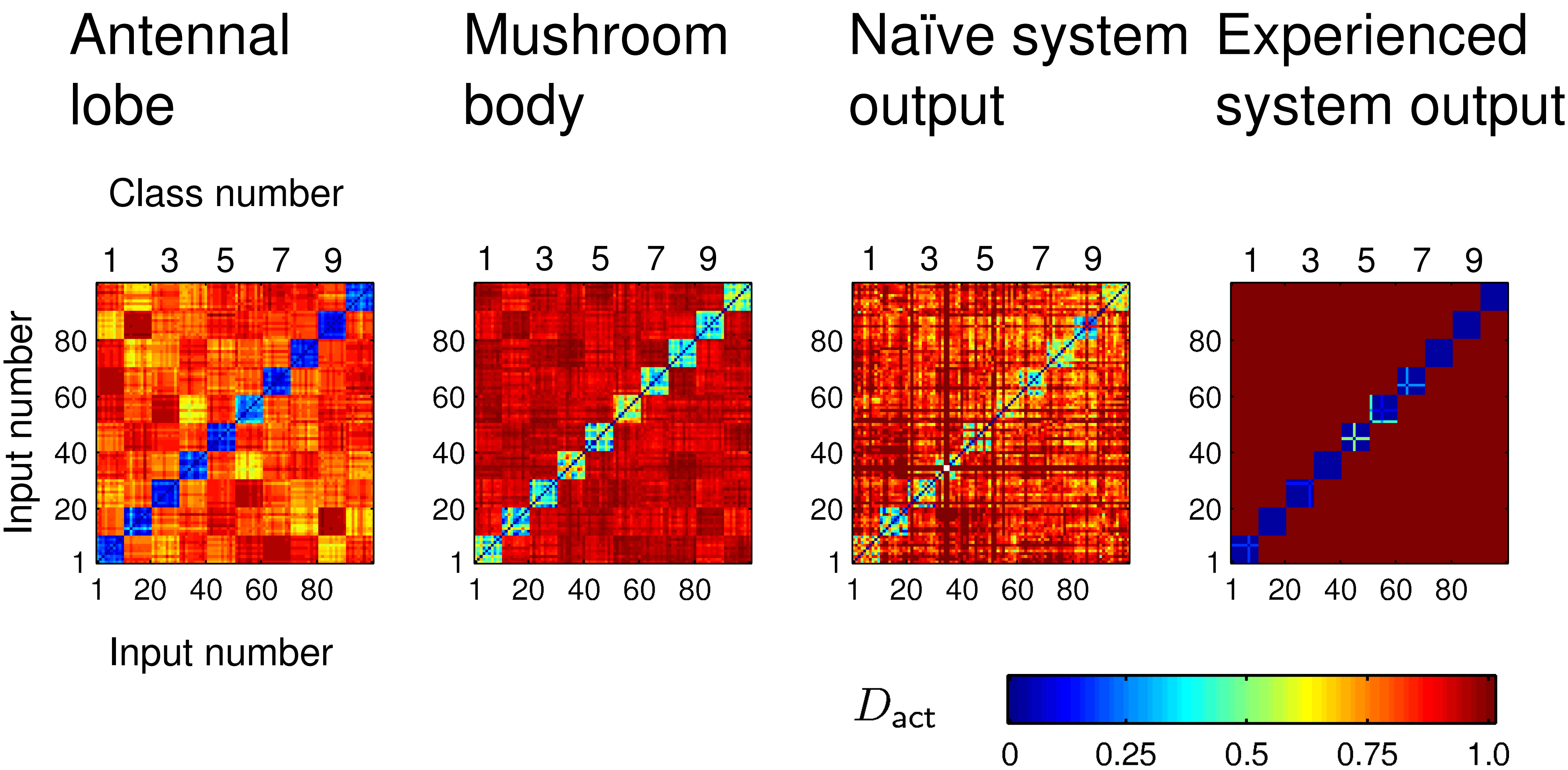
Quantitative Analysis



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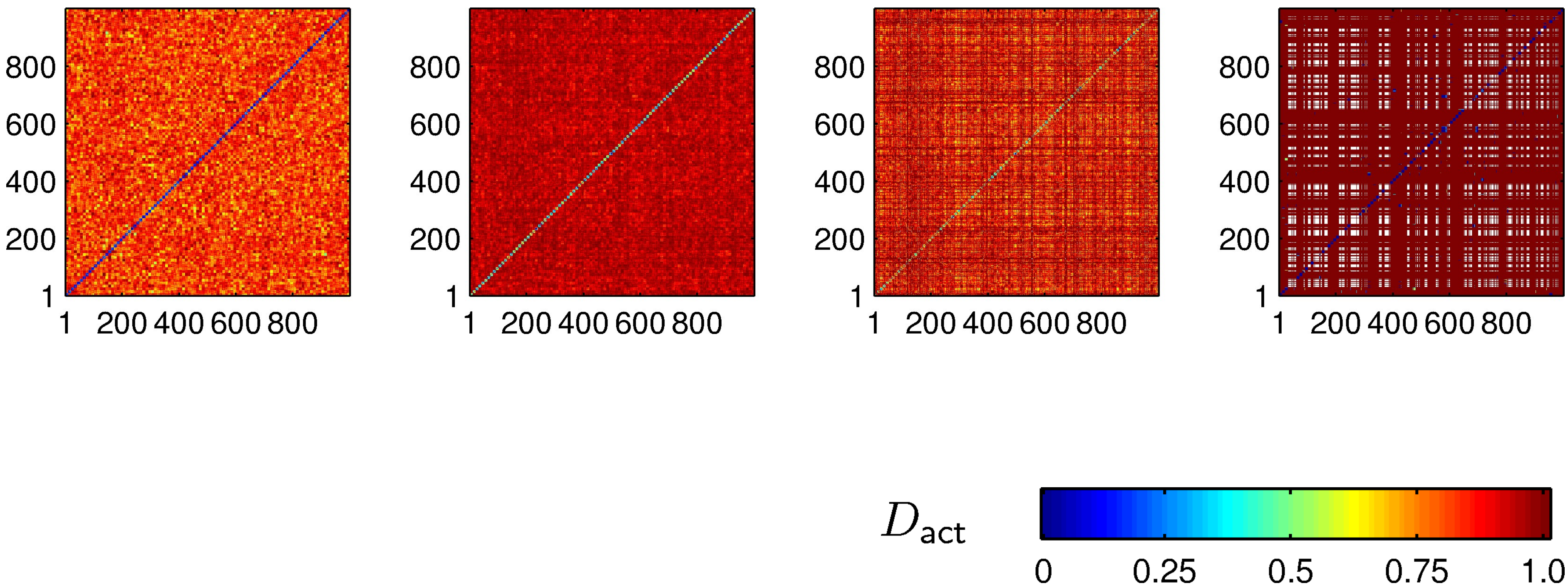
Quantitative Analysis

Antennal lobe

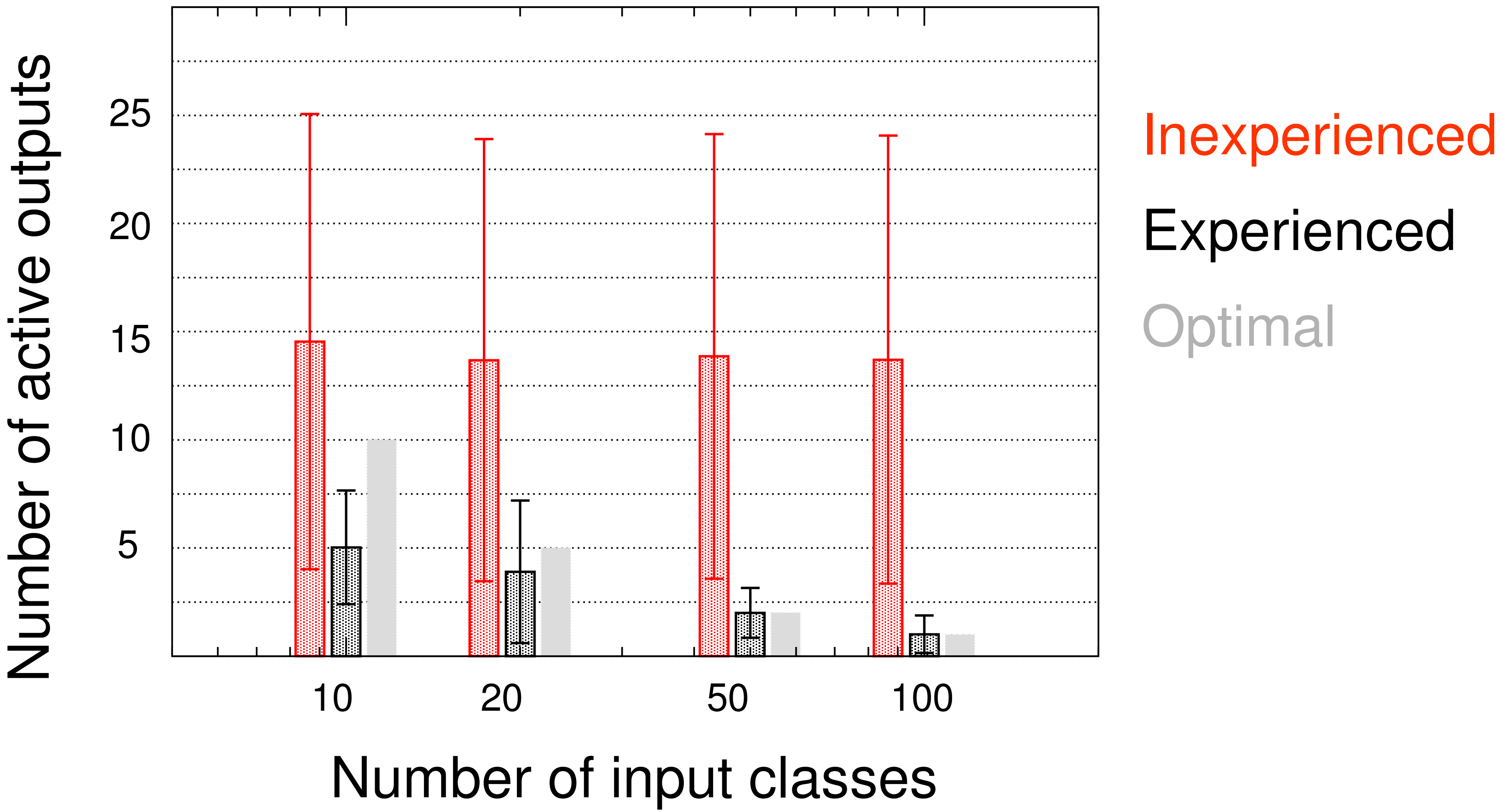
Mushroom body

Naïve system output

Experienced system output



Automatic detection of input set structure



Summary

- More realistic biophysical models demonstrate that the system can *self-organize* to recognize odors
- The system detects *the structure of the input pattern set* autonomously

Future directions

- Apply the McCulloch-Pitts/ spiking neuron "random SVM" to pattern classification problems (OCR, …)
  Huerta R & Nowotny T, Fast and robust learning by reinforcement signals: explorations in the insect brain, Neural Comput., in press
- Use of non-linear dynamics for *information preprocessing* in the antennal lobe
- Use of lateral excitation in the mushroom body to generalize to classification of *sequences*
- Feed-forward inhibition/ gain control
  Nowotny et al., in preparation

Future directions

- Reward systems and associative learning
- Other sensory input to mushroom bodies/ multimodal associations
- Implementations on massively parallel hardware
  Nowotny T, Muezzinoglu KM & Huerta R, Biomimetic classification on parallel hardware: Implementations in Nvidia¨ CUDA™, submitted