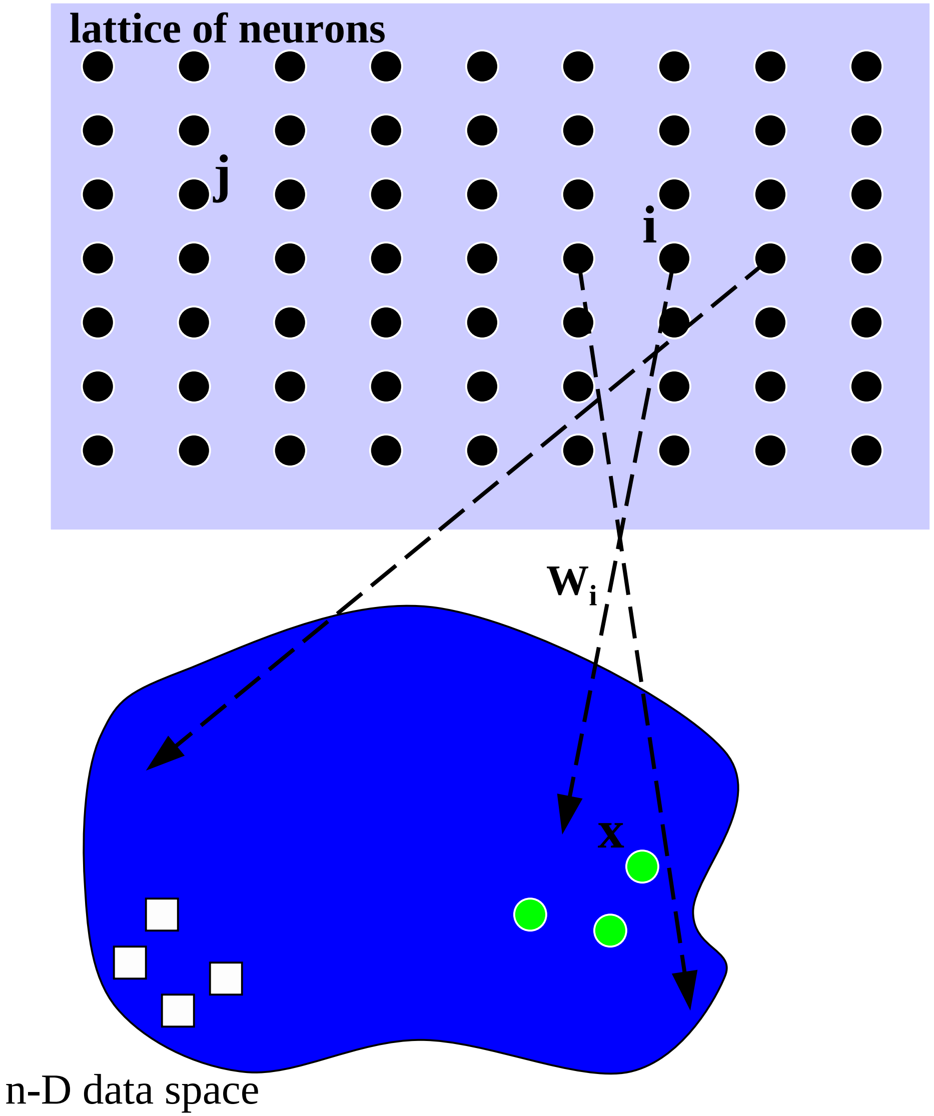
SOM Illustrations

ELEC / COMP 602

Self-Organizing Neural Maps
(unsupervised learning)



Formation of basic (Kohonen) SOM:

$x = (x1, x2, \ldots, xn) \in M \subseteq R^n$
input pattern

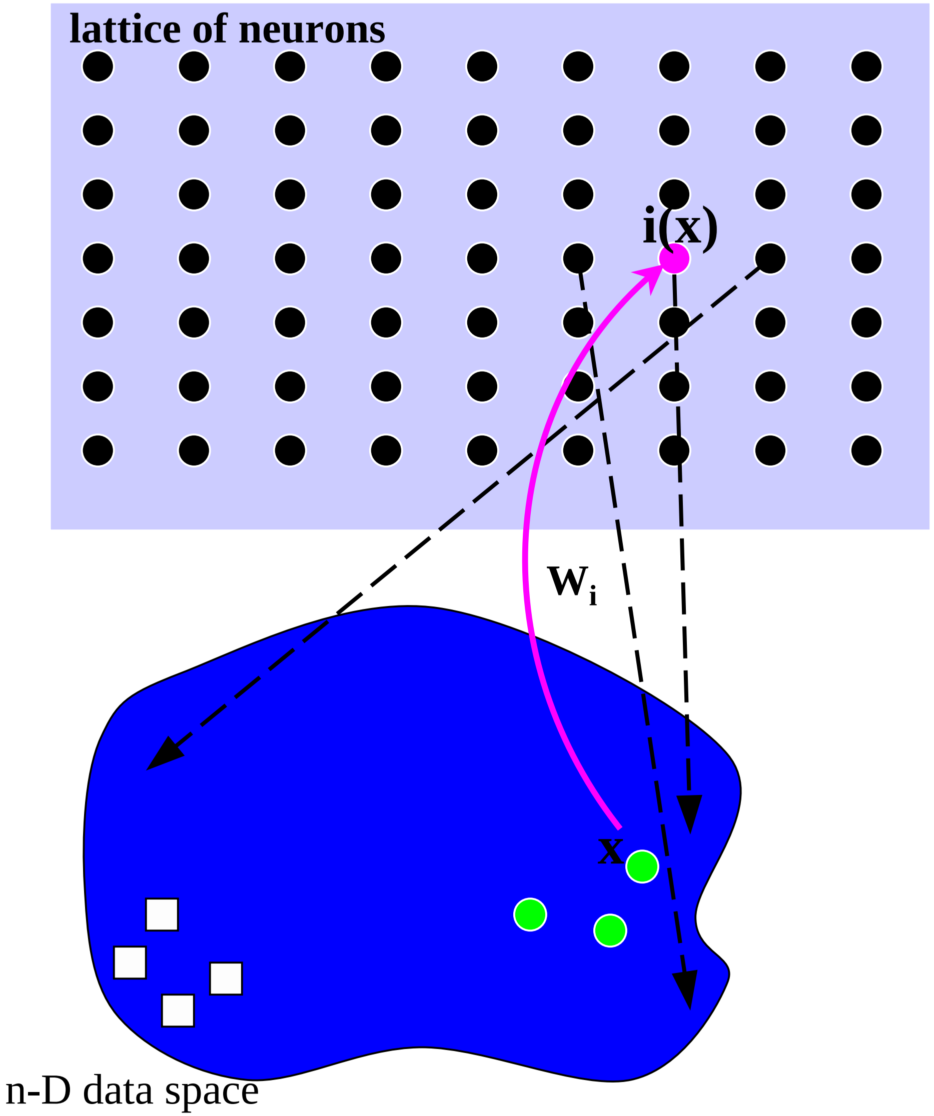
$w_j = (w_{j1}, w_{j2}, \ldots, w_{jn})$ $j=1, \ldots, N$
n-D synaptic weight vector (pointer), associated with neuron j

Weight vectors point randomly into the input data space at start.

Learning consists of cycling through the following steps many times:

Self-Organizing Neural Maps

(unsupervised learning)



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synaptic weight vector (pointer)

1. Competition

Select a pattern x randomly.

Winning neuron

$i(x) = \arg\min_j \|x - w_j\|$, j=1, … , N

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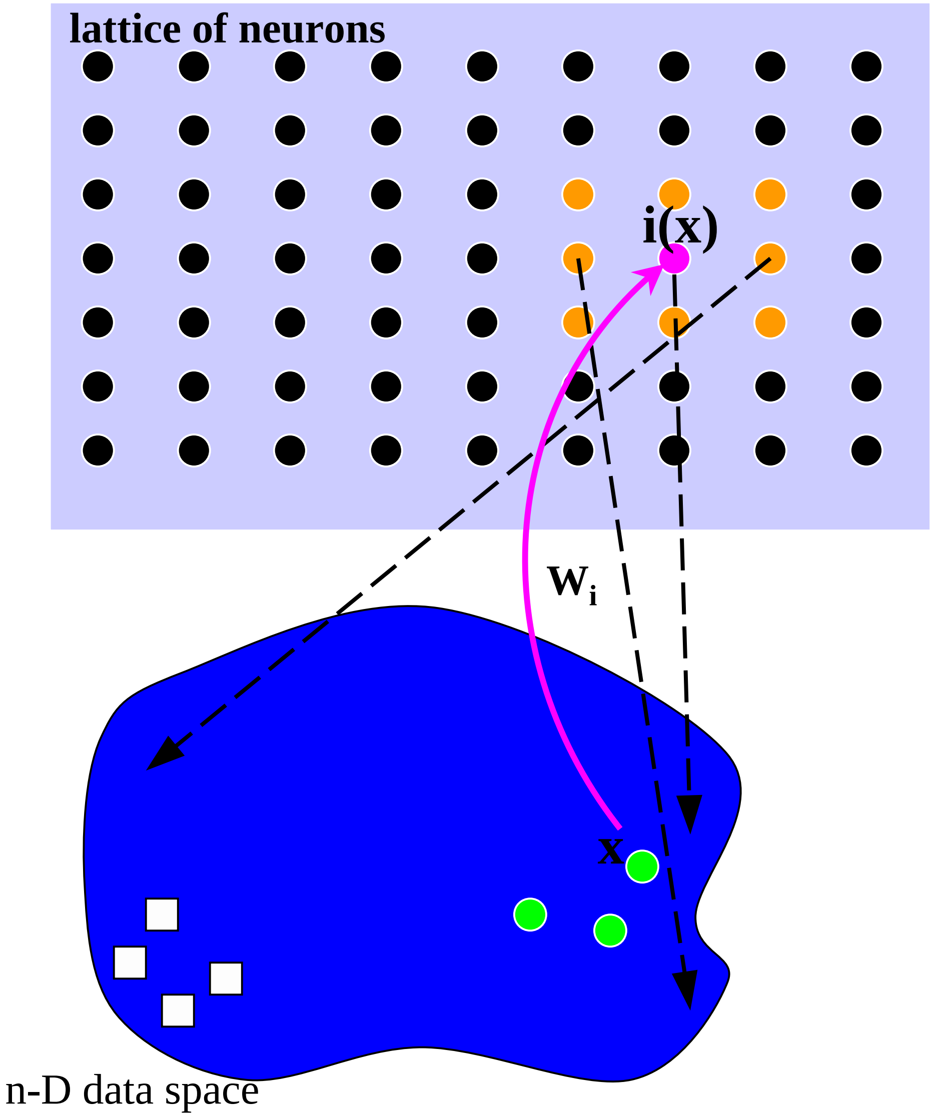

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Winning neuron activates neurons in its neighborhood, according to a neighborhood function $h_{j,i(x)}(t)$.

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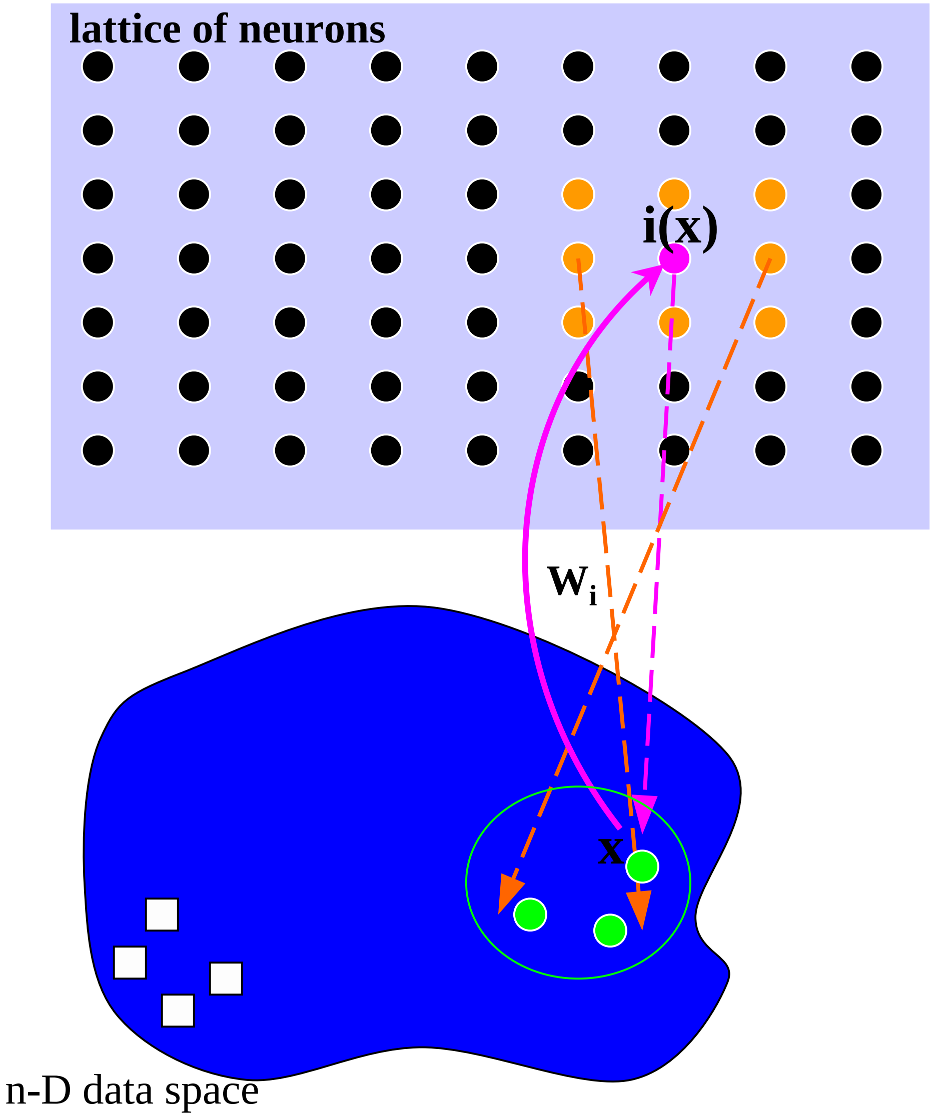

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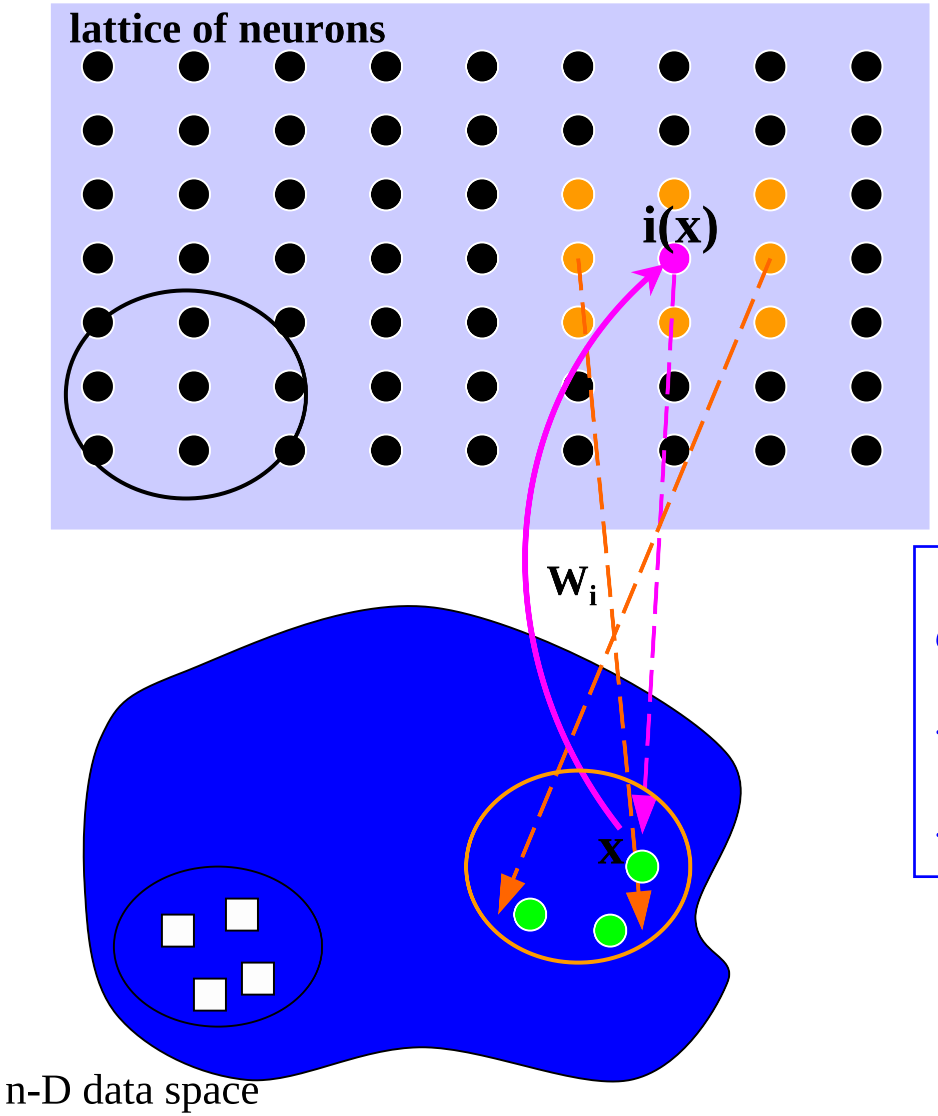
3. Synaptic adaptation

$$w_j(t+1) = w_j(t) + a(t)\, h_{j,i(x)}(t)\, (x - w_j(t))$$

Self-Organizing Neural Maps

(unsupervised learning)



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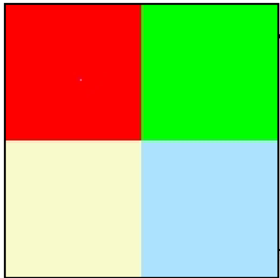
synaptic weight vector (pointer)

During learning, areas of neurons form, which collectively represent groups of similar patterns

- neighborhood preserving, adaptive vector quantizer
- ***nonlinear*** mapping of the n-D input space to a low-D lattice
- measure of dissimilarities is expressed by the difference of the weights

Biological analogs:
- tonotopic maps in auditory cortex
- retinotopic maps in the visual cortex

128 x 128 px image
6-D spectra

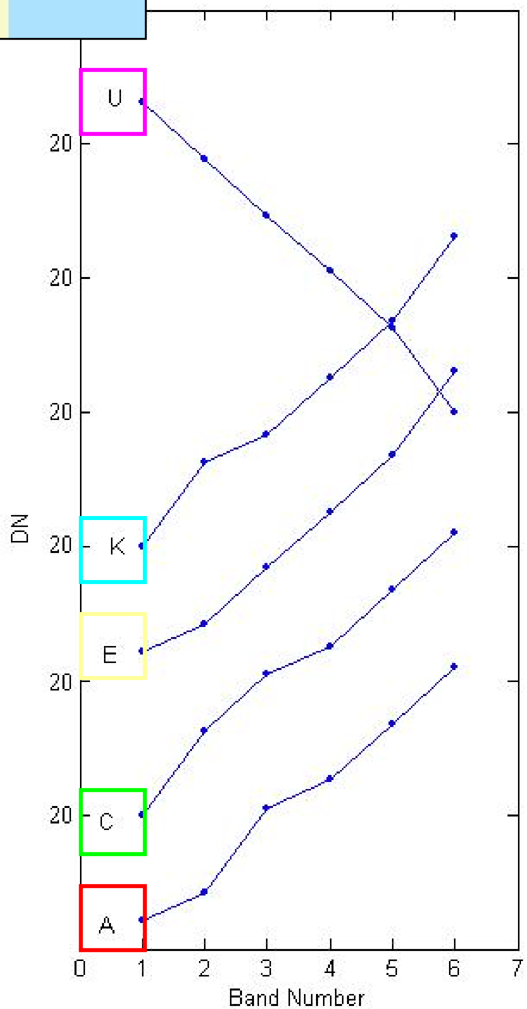


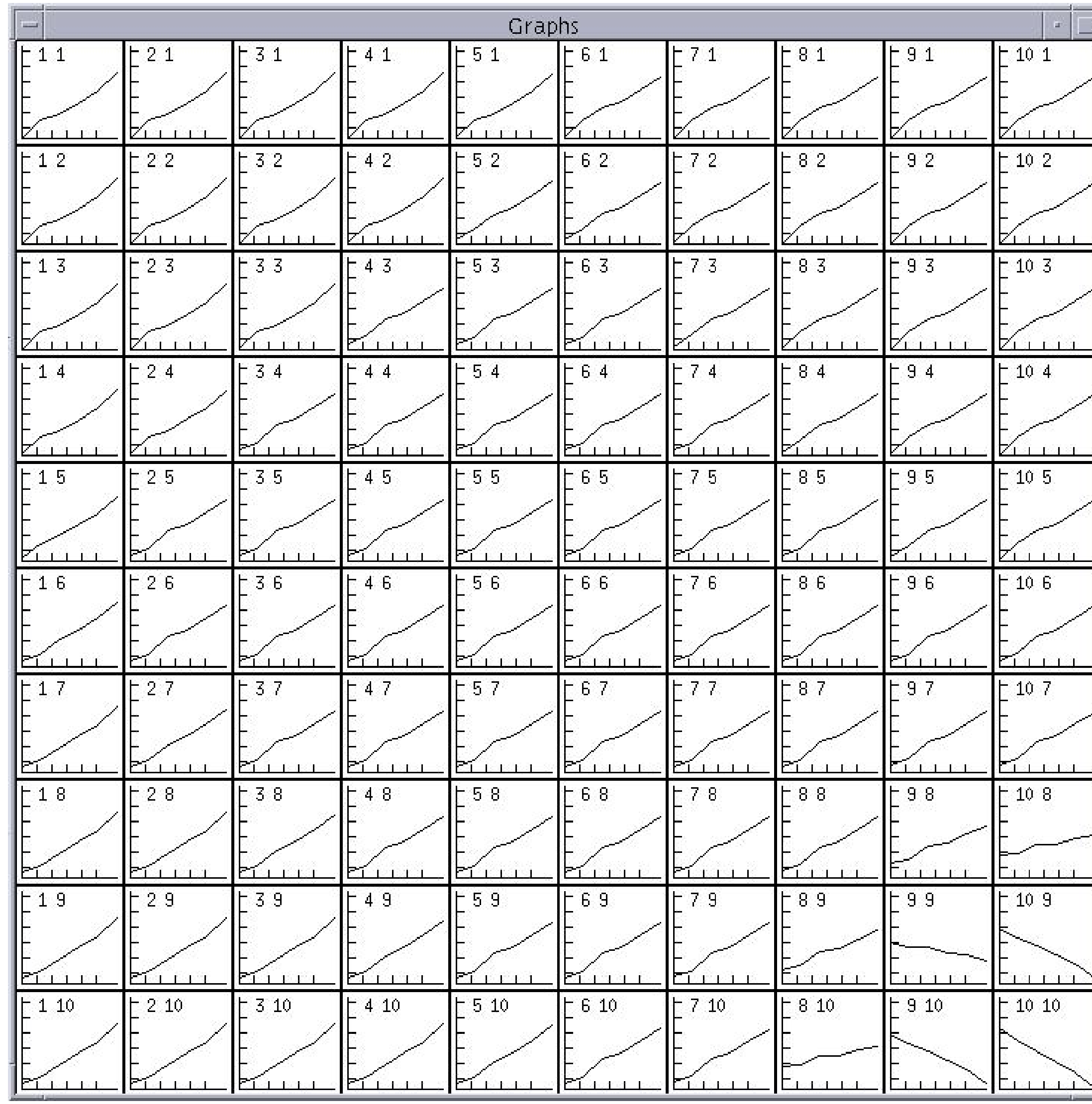
1-px class U

Toy example I

Weights of 10 x 10 KSOM, after learning

5 spectral classes
synthetic, noiseless

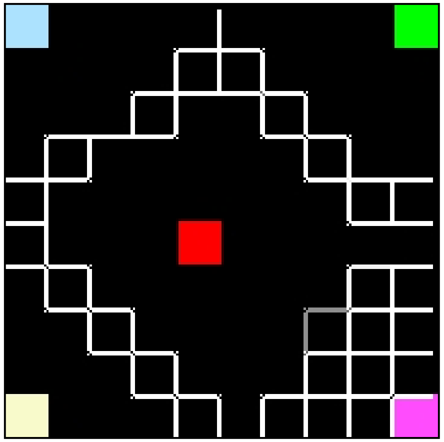


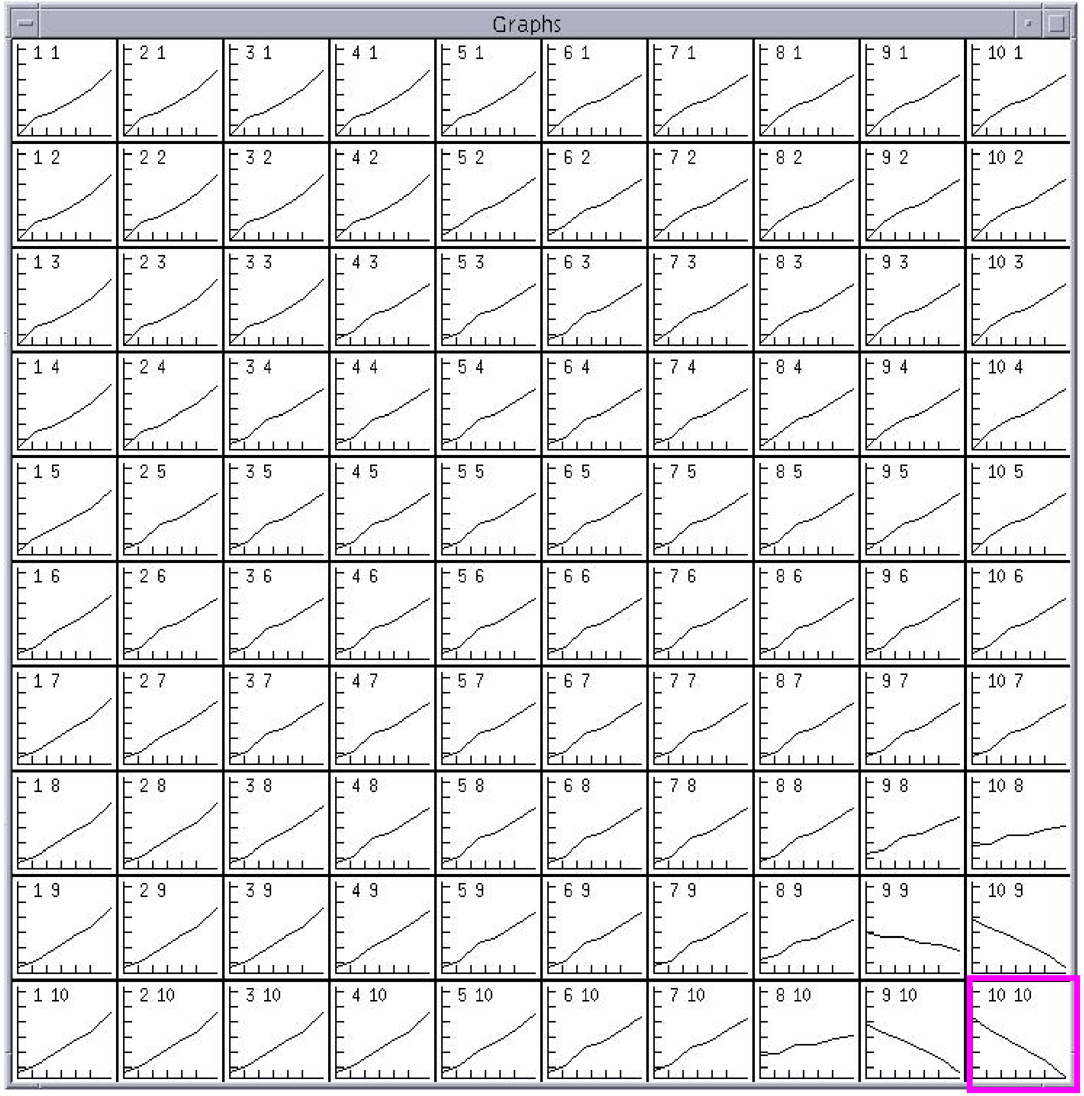


KSOM

5-class mapping
Weights vectors (reference vectors) of 10 x 10 KSOM, after learning

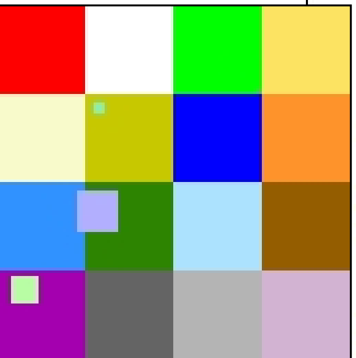
cluster boundaries

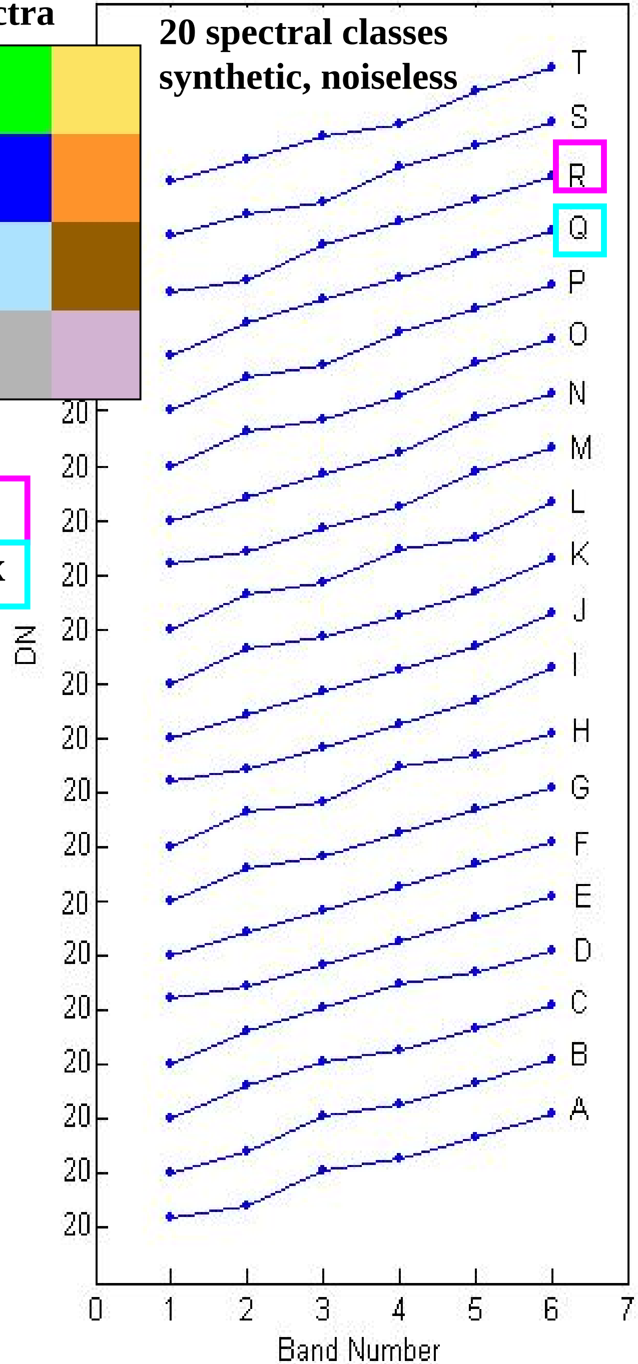




Toy example II

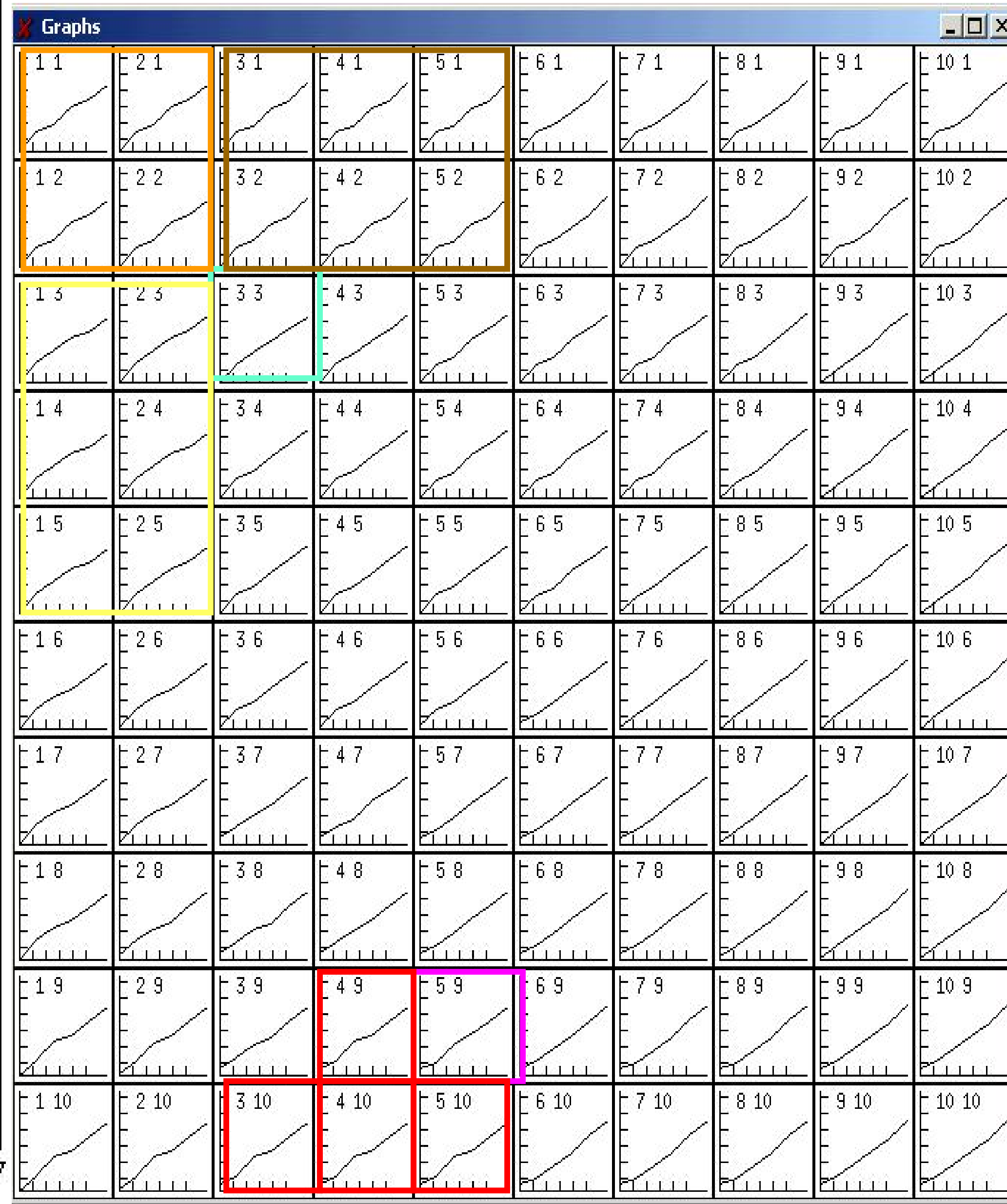
128 x 128 px image
6-D spectra





R = 1px
Q =16 px

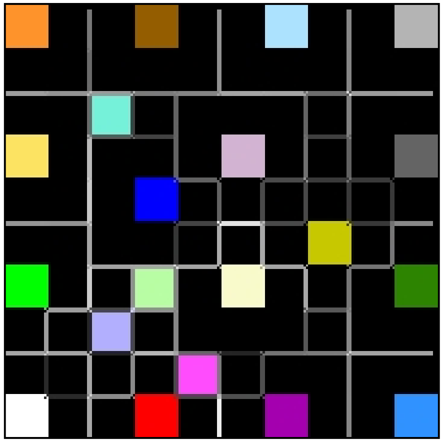
Weights of 10 x 10 KSOM, after learning

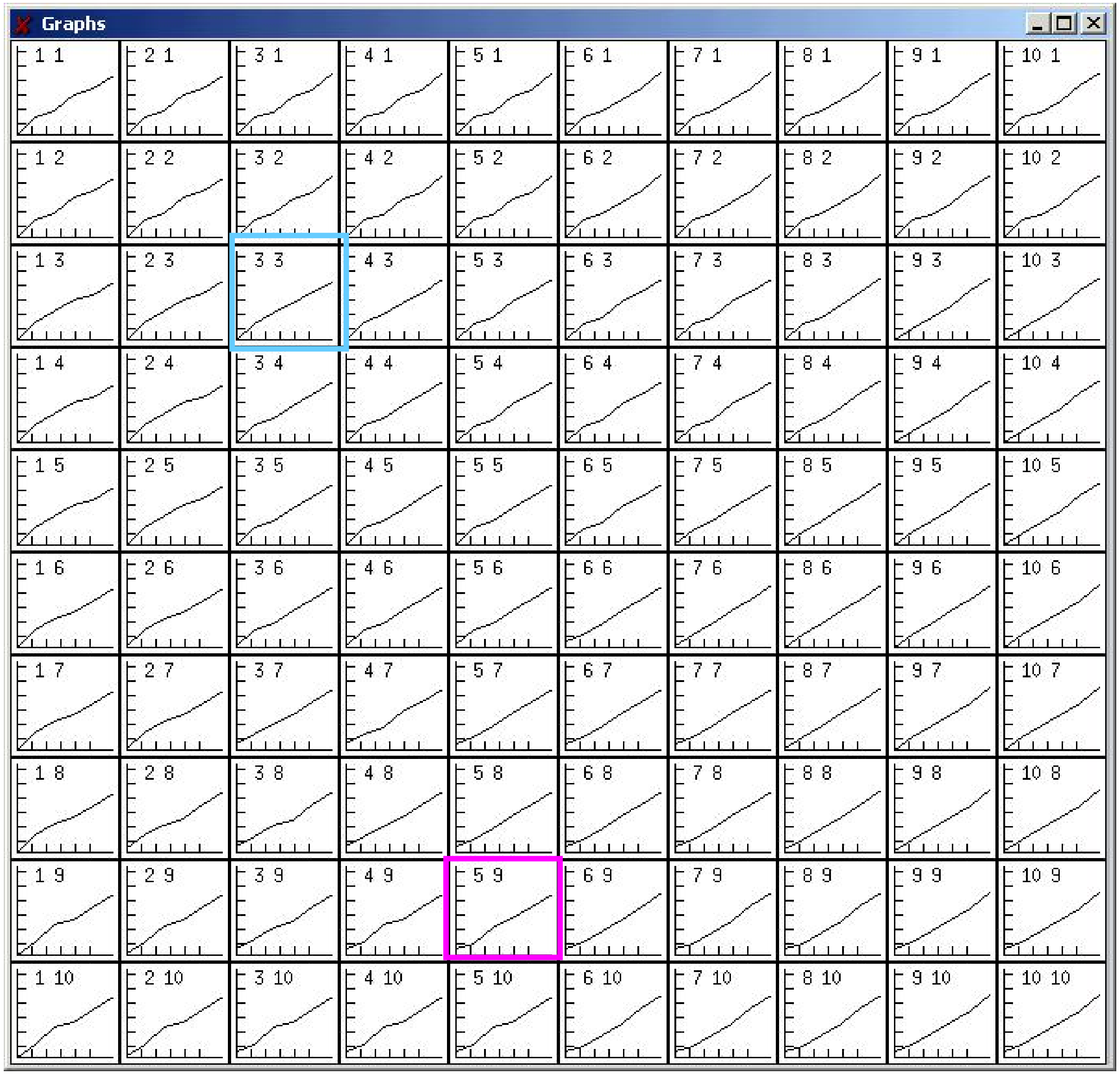


KSOM

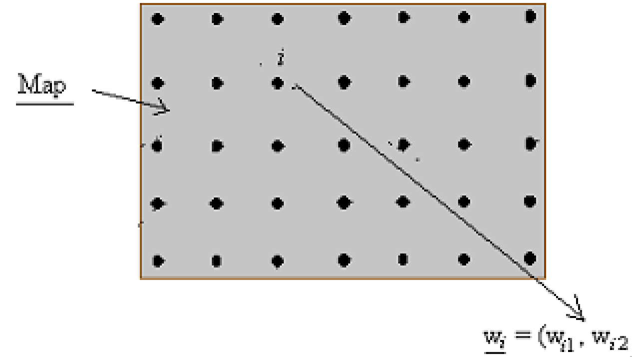
20-class mapping
Weights vectors (reference vectors) of 10 x 10 KSOM, after learning

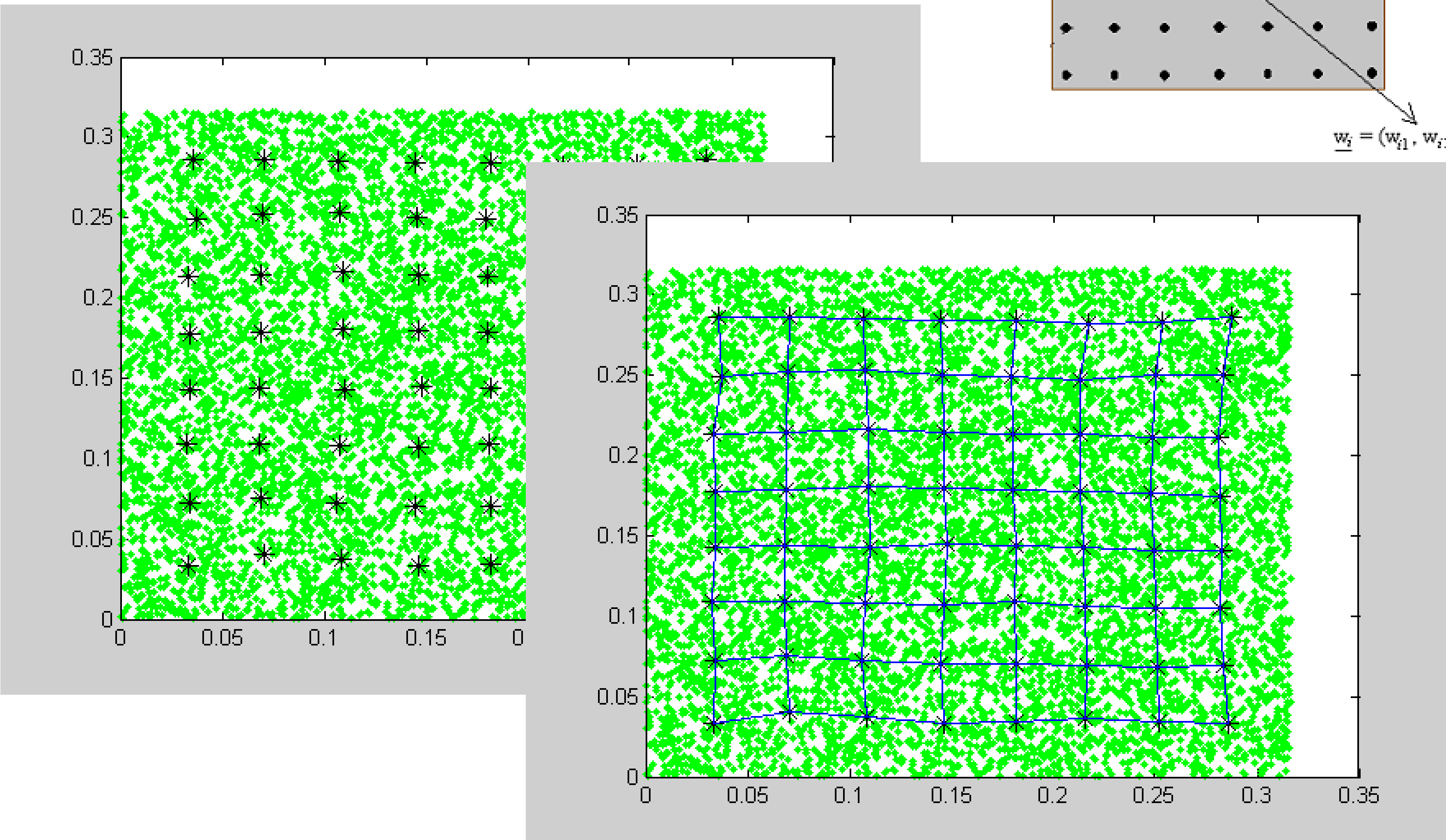
cluster boundaries



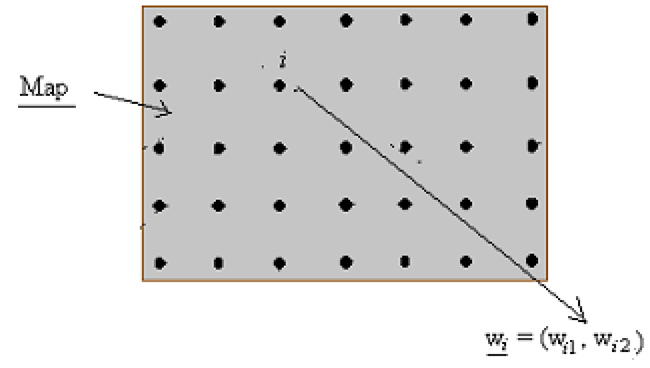


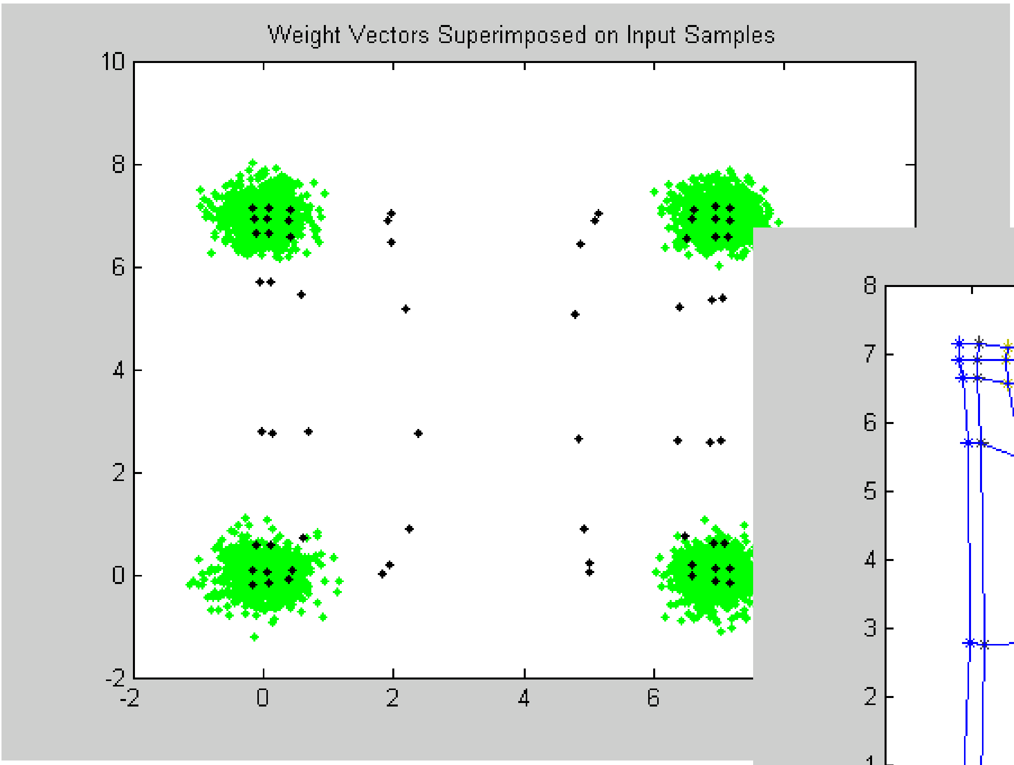
Representing weights in the input space
(1- or 2-D data)

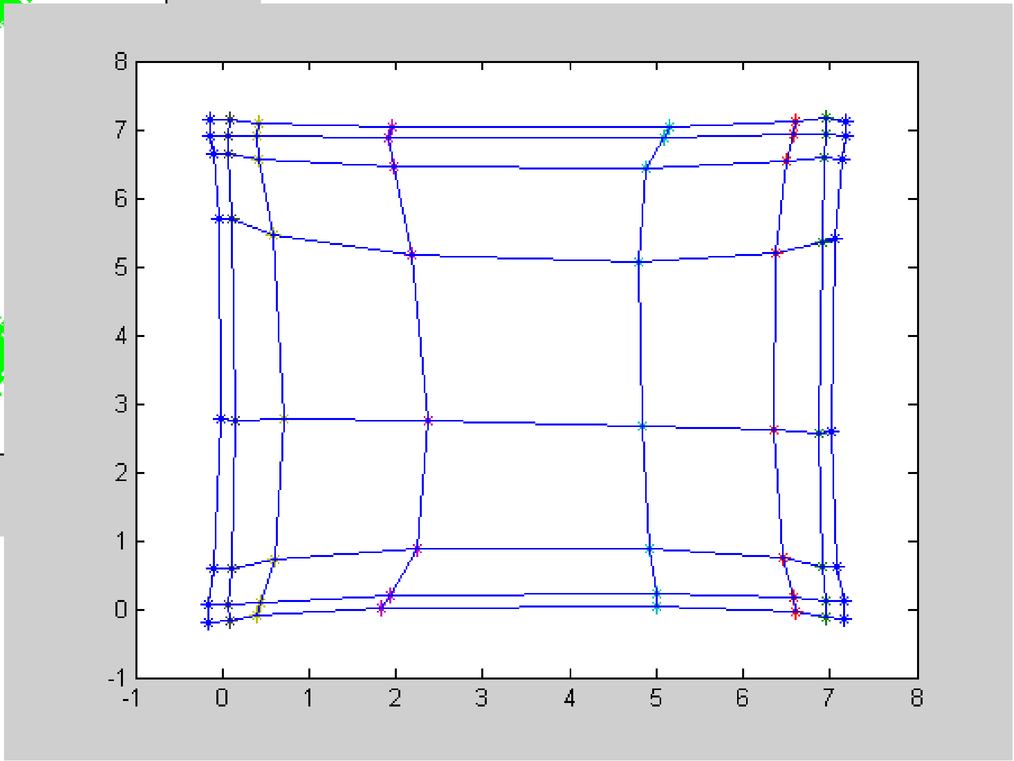




Representing weights in the input space (1- or 2-D data)







Tonotopic Map in the Brain

In the auditory cortex *tonotopic maps* are formed where the spatial order of cell responses corresponds to the acoustic frequency of tones perceived.

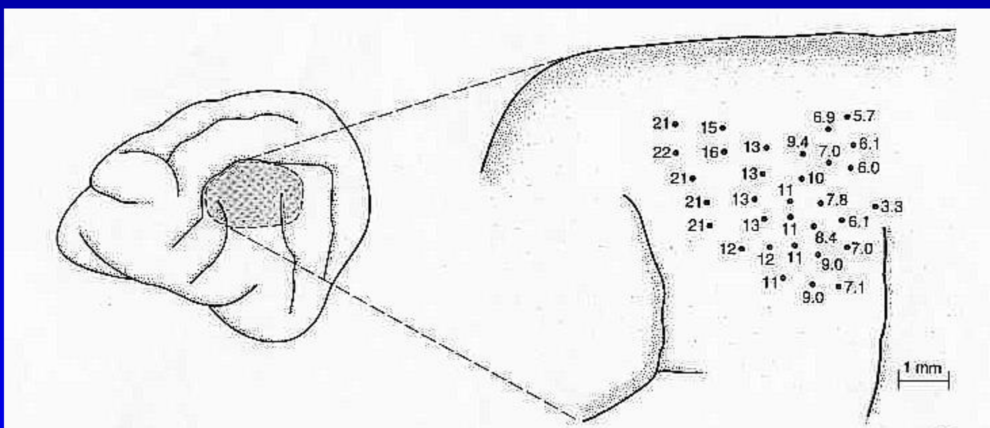
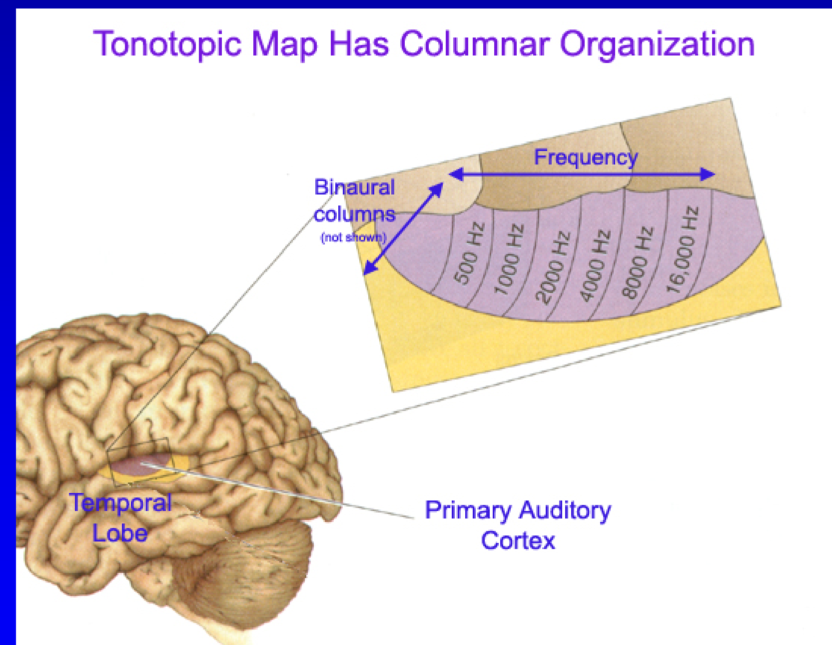
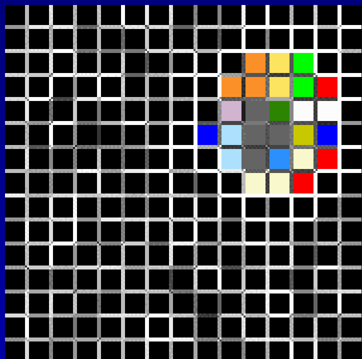


Figure 8.32
Left: The cat's brain, showing the location of the auditory receiving area (shaded). Right: A close-up of the auditory receiving area, showing the tonotopic map on the cortical surface. Each large dot represents a single neuron, and the number beside each dot represents the characteristic frequency of that neuron in thousands of Hz. (From Abeles & Goldstein, 1970, and Gulick, Gescheider, & Frisina, 1989.)

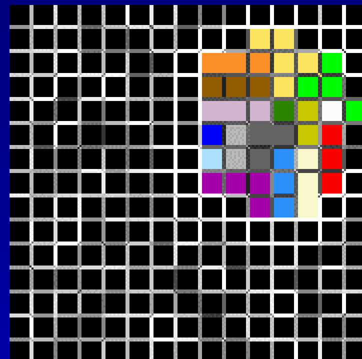


Topology preserving mapping of acoustic frequencies in the auditory cortex (2-D surface)

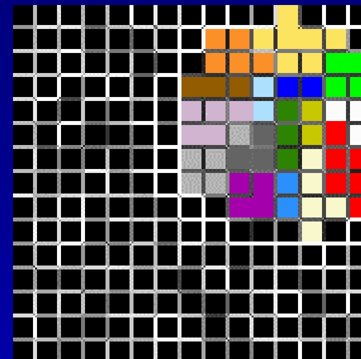
Clustering with SOMs



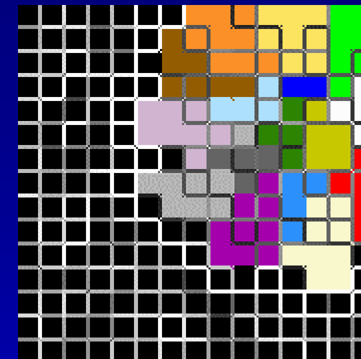
200 steps



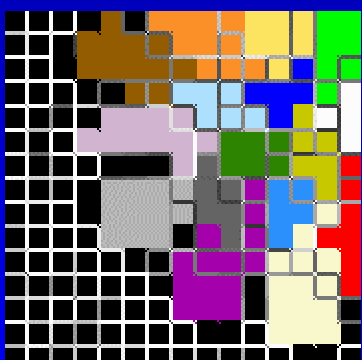
500 steps



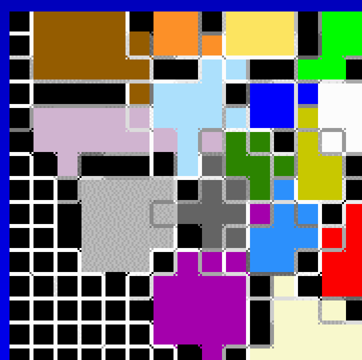
1000 steps



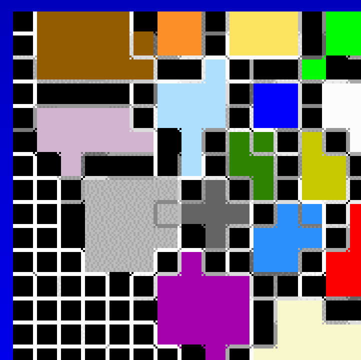
3000 steps



10000 steps

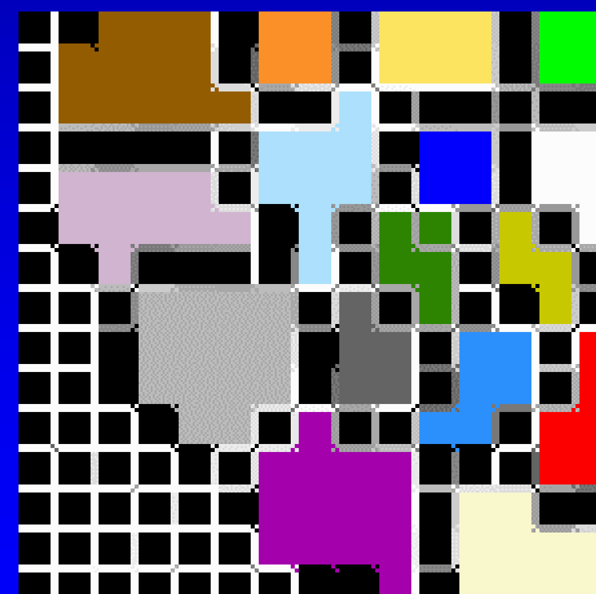


22000 steps



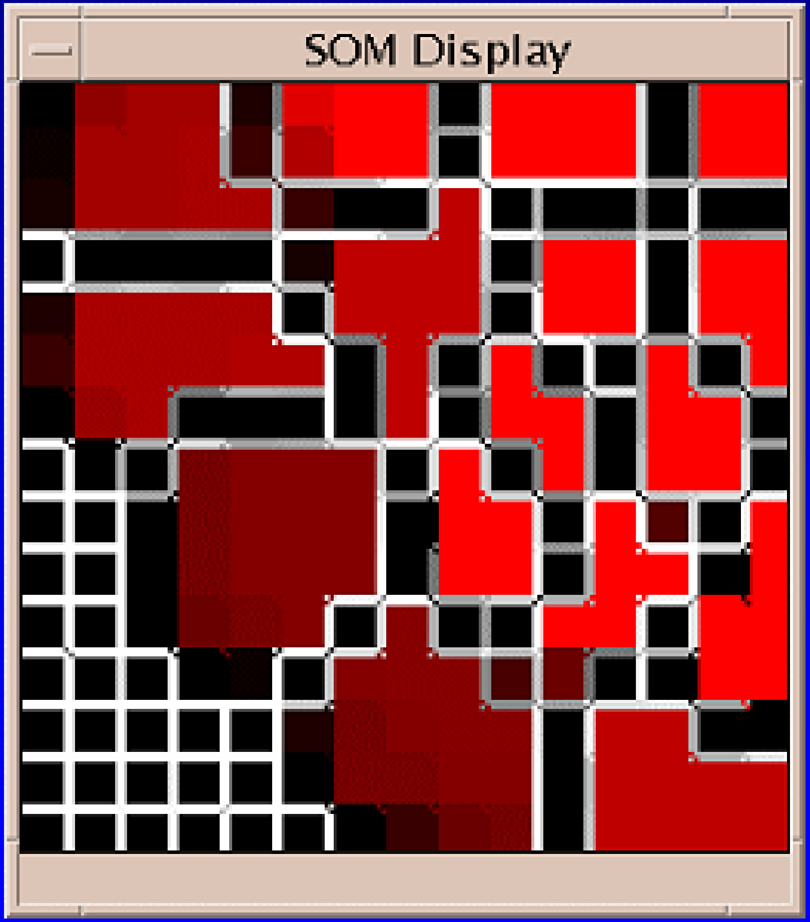
35000 steps

Source data: synthetic image
Size: 128 x 128 pixels x 6 bands = 0.2 Mb

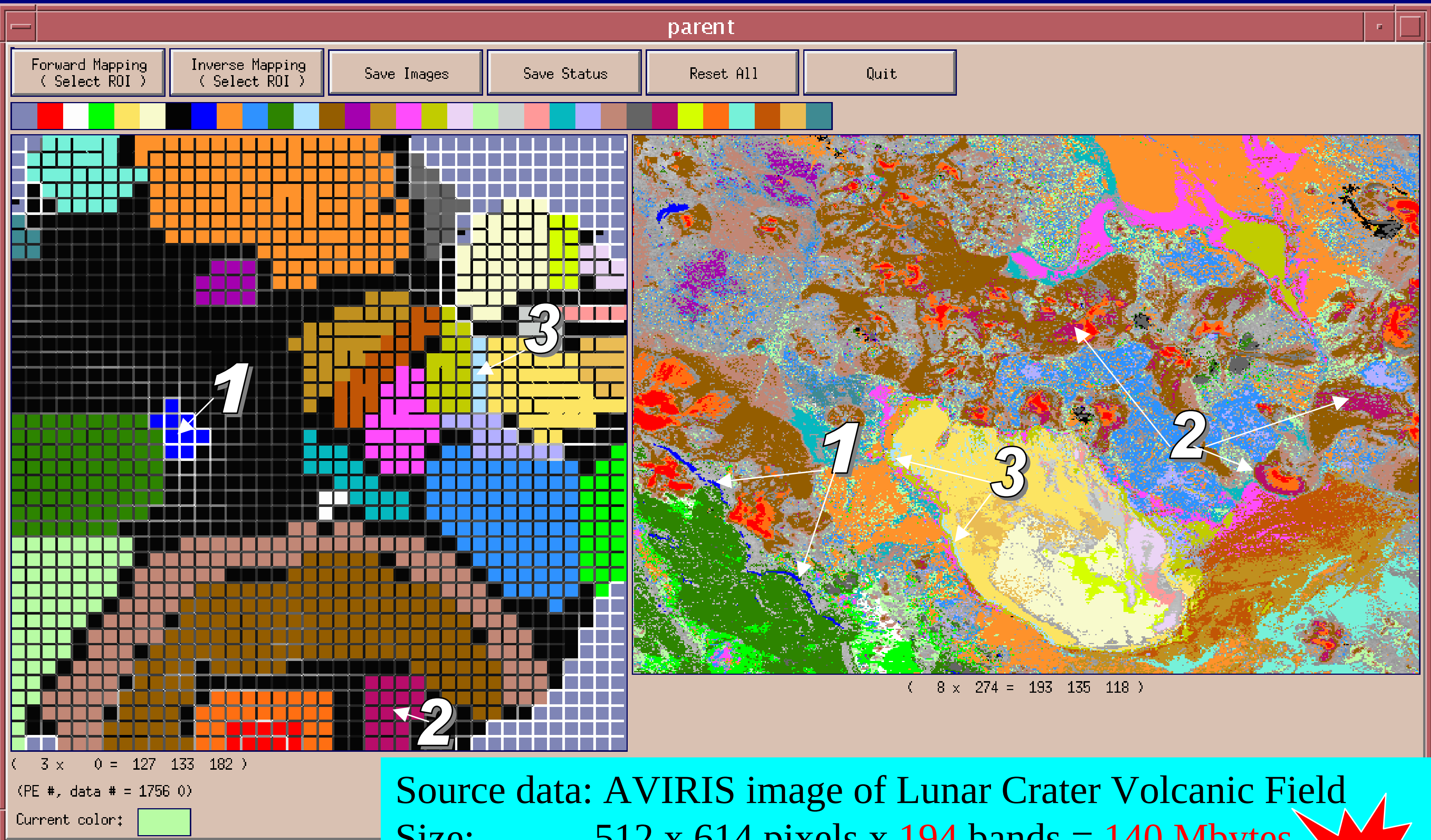


45000 steps

Capturing clusters in an SOM



Discovery in large hyperspectral image with SOM

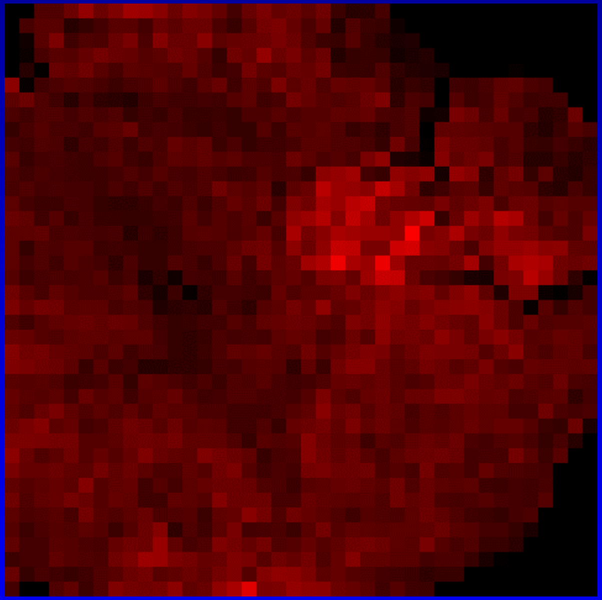


Source data: AVIRIS image of Lunar Crater Volcanic Field

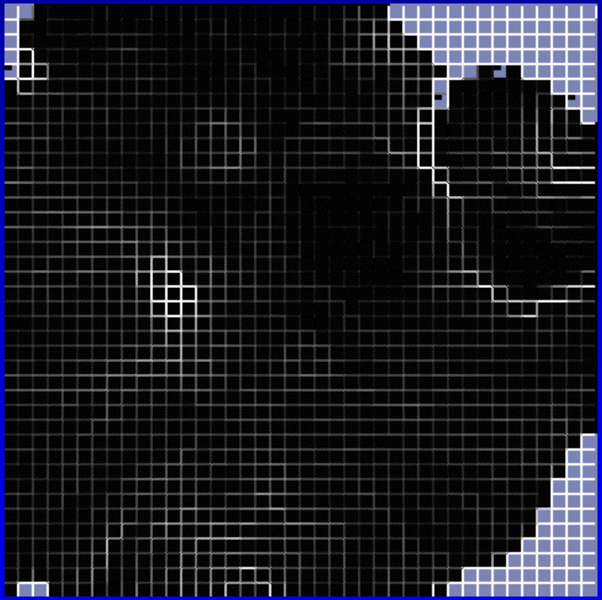
Size: 512 x 614 pixels x 194 bands = 140 Mbytes

Possible representations for SOM cluster detection
(remap HYPEREYE module)

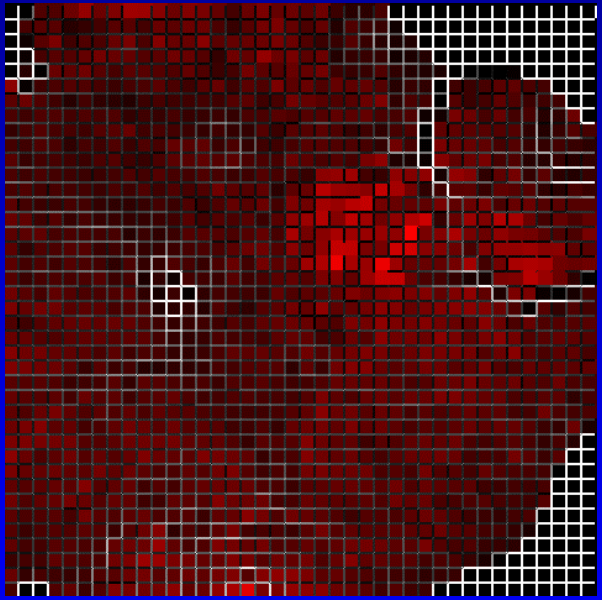
Density Map



Fence Map



Combined Density & Fence Map



Input data: AVIRIS image of Lunar Crater Volcanic Field, 512 x 614 pixels x 194 bands

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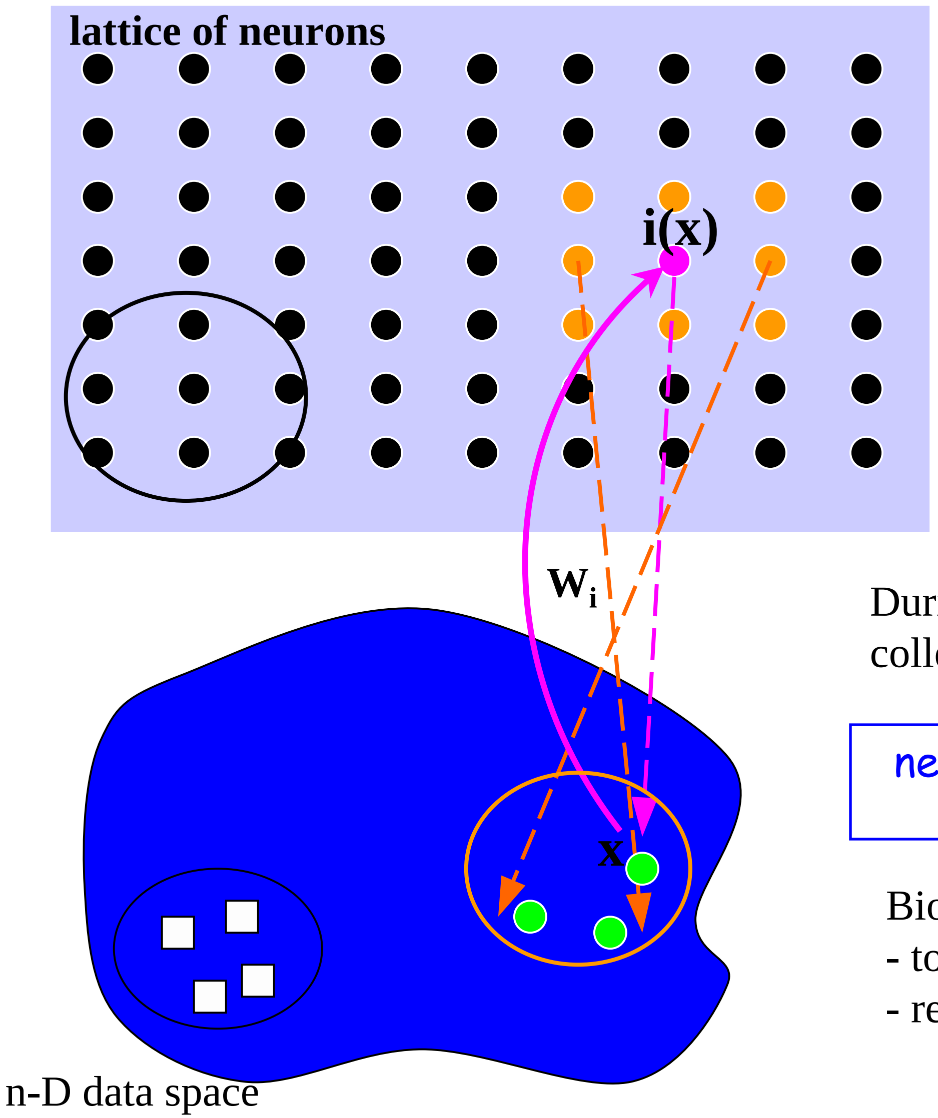
(unsupervised learning)



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