SOM Illustrations

ELEC / COMP 602
Self-Organizing Neural Maps
(unsupervised learning)

Formation of basic (Kohonen) SOM:

\[ x = (x_1, x_2, \ldots, x_n) \in M \subseteq \mathbb{R}^n \]
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:
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synaptic weight vector (pointer)

1. Competition
   Select a pattern \( x \) randomly.
   Winning neuron
   \[ i(x) = \arg \min ||x - w_j||, j=1, \ldots, N \]
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2. Cooperation
   Winning neuron activates neurons in its neighborhood, according to a neighborhood function \( h_{j,i(x)}(t) \).
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3. **Synaptic adaptation**
   \[ w_j(t+1) = w_j(t) + a(t) \; h_{j,i(x)}(t) \; (x - w_j(t)) \]
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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
Toy example I
Weights of 10 x 10 KSOM, after learning

128 x 128 px image
6-D spectra

1-px class U

5 spectral classes
synthetic, noiseless

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KSOM

cluster boundaries

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

Weights of 10 x 10 KSOM, after learning

128 x 128 px image
6-D spectra

20 spectral classes
synthetic, noiseless

R = 1px
Q = 16 px
20-class mapping
Weights vectors (reference vectors)
of 10 x 10 KSOM, after learning
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 (auditory belt). 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: Stiles, A. Goldstein, I. B. and Gluck, C. Grochowski, B. Frisina, 1983.)

Topography preserving mapping of acoustic frequencies in the auditory cortex (2-D surface)
Clustering with SOMs

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