Unsupervised Learning

learning with an internal goal

Clustering Networks:

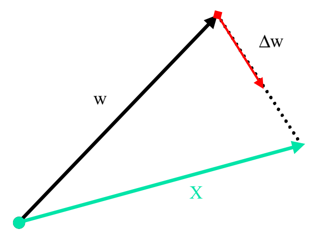
- We want networks with n input nodes, and p output nodes
- Each output node represents one of p clusters of input vectors
- An output of 1 from output node A means that the current output is in cluster A
- We will base clusters on "nearness" to a "prototype" vector for that cluster
- Note that these are "unlabeled" clusters

Kohonen self-organizing nets

- Let's start with random weight (prototype) vectors
- Let's pick out the nearest prototype to the current input
- Let's update to bring the prototype of the winning node closer to the input vector...

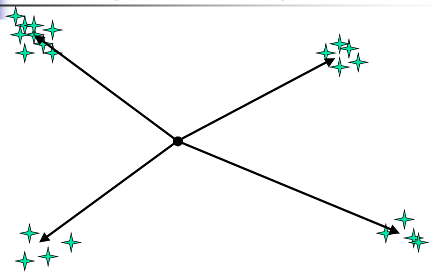
$$\vec{w}(t+1) = \vec{w}(t) + \alpha\left(\vec{x}(t) - \vec{w}(t)\right)$$

Pictorially



$$\vec{w}(t+1) = \vec{w}(t)(1-\alpha) + \alpha\,\vec{x}(t)$$

What you end up with...



Prototypes approach cluster centroids

The CounterPropagation Network

- Heicht-Nielson, 1987
- Kohonen nets divide inputs into clusters (by indirectly locating centroids).
- However, Kohonen nets don't assign associated outputs to those clusters.

Counterpropagation Nets

- Consider hooking a Kohonen layer to a layer of linear output nodes.
- Let's use the Grossberg (flywheel) learning to assign mean outputs to each cluster.

$$\vec{w}(t+1) = \vec{w}(t)(1-\alpha) + \alpha \; \vec{y}(t)$$

- Note that this network works in both directions (thus the name).

Feature Maps

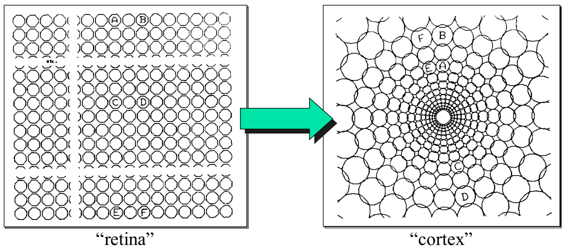
- Early in the course, we said that data compression or pre-processing was important for data interpretation
- This can be seen as reducing data in a high-dimensional pattern space to a lower-dimensional feature space

Feature extraction as data mapping

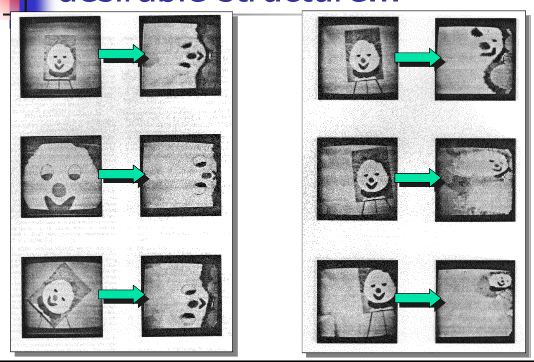
- Consider the Fourier Transform
  - Continuous time data to a finite set of frequency amplitudes
- ACT interest inventory charts
- Dimensional Analysis
- Mapping classes of images (signals) to their features

Mapping structure

- Can be important too
- Consider visual cortical mappings...



Certain mappings have desirable structure...

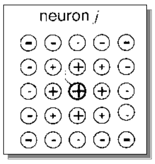


What we want in a feature map

- we want reduction of the dimensionality of the input space, but...
- we also want the preservation of the important topology of the pattern space
  - nearby patterns map to nearby sets of features
  - Can we get a network to automatically find such mappings?

Yes, we can!

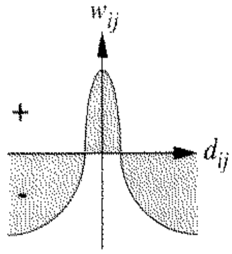
- The key is in using Kohonen learning with spatially localized weight updates
- Consider a 2-D feature map…



- Note the difference between pattern (input) space and feature (mapping or node) space

Updating

- We update nodes near the winning node with a portion of the winners update
- This can be accomplished with "on-center, off-surround" or "Mexican-hat function" connections

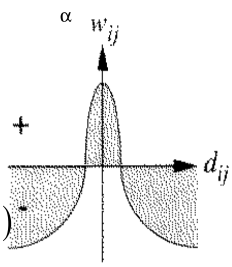


Updating: the equation

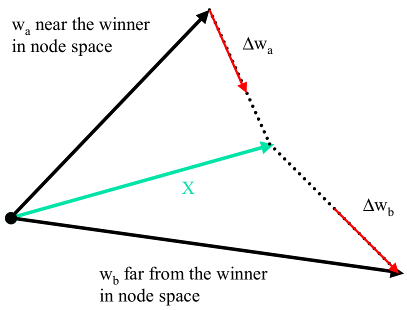
- We update nodes near the winning node with a portion of the winners update

$$(t+1) =$$

$$(t)\left(1-\alpha\left(d_{ij}\right)\right)+\alpha\ \left(d_{ij}\right)\ \overset{r}{x}(t)$$

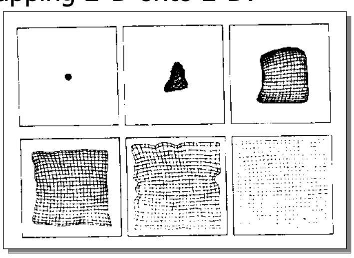


Pictorially



An Example

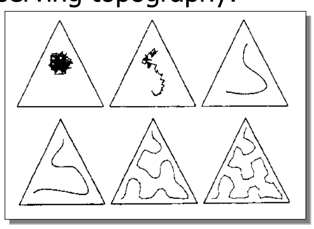
- Mapping 2-D onto 2-D:



The grid is the geography of node space, the square is the input space.

Compressing

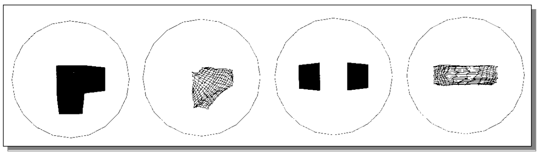
- Mapping 2-D onto 1-D, while preserving topography:



The grid is the geography of node space, the square is the input space.

Non-Uniform Inputs

- From the 2-D input space



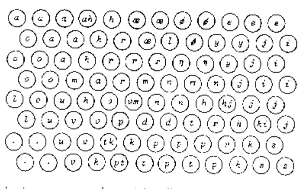
The grid is the geography of node space, the square is the input space.

A practical example

- Consider long vectors, describing "phonemes" for Norwegian
- It would be nice to map these to a 2-D "keyboard" preserving topography
- Then, a word is a path along the keyboard, and similar words have similar paths
- This improves the possibility of recogonizing patterns in the new, 2-D space…

Phoneme Map...

- That preserves input topology…



This is the node space, input space is the waveform of phonemes, represented as a 15 channel FFT.

Final Comments

- Topology-preserving maps may be very important in several application areas, including:
  - Feature Extraction
  - Clustering in reinforcement learning
  - Networks with spatially localized learning...