Self-Organizing Maps

"Kohonen Nets"

Feature Maps

(a form of competitive learning)

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Several Different Kohonen Nets

- Linear associative memory (concept discovered at same time as that by James Anderson)

- **Self-Organizing Maps (SOMs)**
  - Similar to LVQ clustering
  - Fundamentally unsupervised
  - Supervision can be overlaid
  - Additional structure can be superimposed

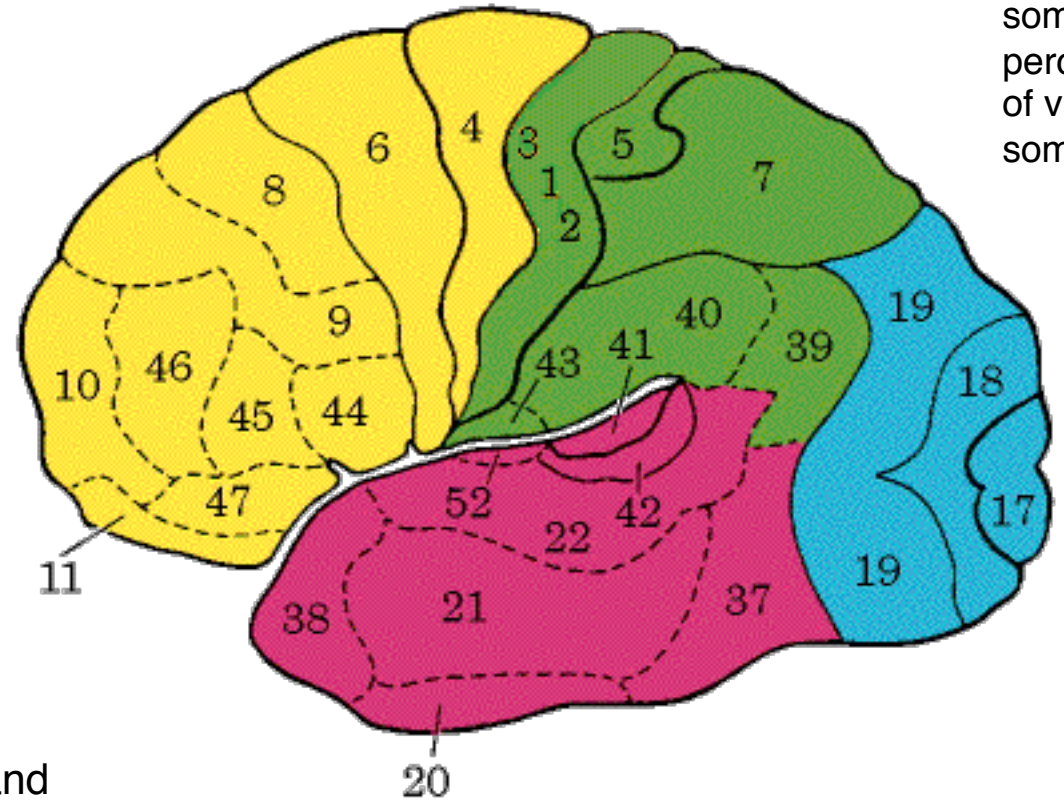
Maps in Neurobiology

- Related neural functions ***map*** onto identifiable regions of the brain
  - **retinotopic map**: vision, *superior colliculus*
  - **phonotopic map**: hearing, auditory cortex
  - **somatotopic map**: touch, somatosensory cortex

Maps in the Human Brain

Frontal Lobe
thinking, planning, and central executive functions; motor execution

Parietal Lobe
somatosensory perception ntegration of visual & somatospatial information



Occipital Lobe
visual perception and processing

Temporal Lobe
language function and auditory perception involved in long term memory and emotion

Desired Properties of Maps

- **Approximation of input space**: generally a many-one mapping of input space into weight space
- **Topology-preserving**: points close together in input space should map to points close together in weight space.
- **Density-preserving**: regions of similar density should map to regions of proportional density.

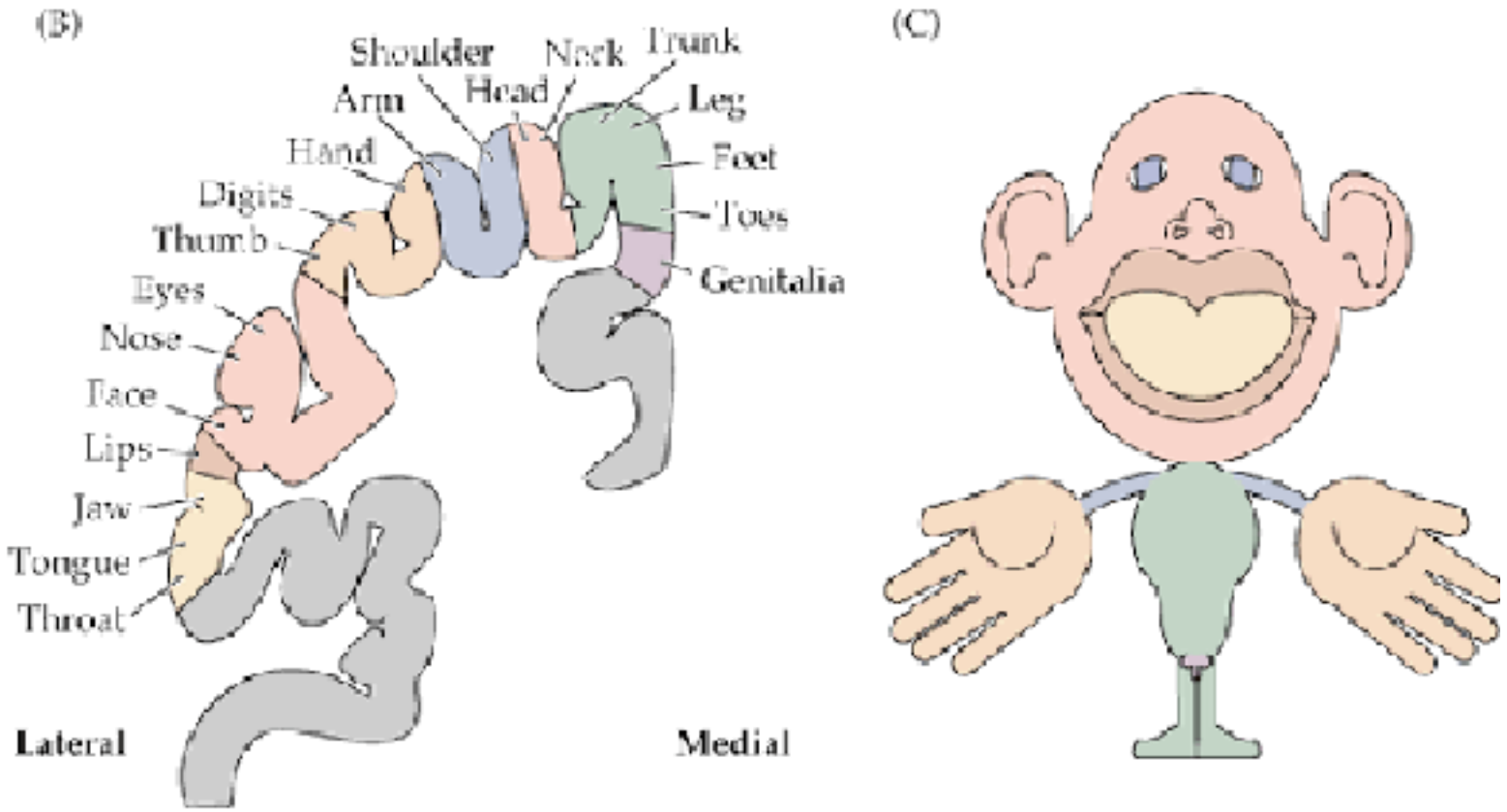
Somatotopic Map Illustration: The "Homunculus"

Cartoon map of the relationship between body surfaces and the regions of the brain that control them

(somewhat different from the original "little person inside" meaning).

Another Depiction of the Homunculus

Amount of neural real-state devoted to different sensory regions



Project: Map your own homunculus:

http://www.woodrow.org/teachers/biology/institutes/1991/homunculus.html

Procedure II: Experiment.

Your team should consist of an experimental subject (blindfolded) and an experimenter/recorder. Starting from the head and working down to the feet, measure the distance between touch receptor fields in specific parts of the right hand side of the body using the following method:

1. Spread the pins apart and press the points lightly on the skin of the subject. The subject should detect two points of contact. If he feels only one, repeat the process , moving the pins farther apart.
2. Move the 2 pins closer together, 0.5 cm at a time, until the subject will no longer be able to distinguish 2 separate pins. Measure this distance in cm. At this point, both pins are within the same receptive field of one sensory receptor, and so the 2 points cannot be identified separately.
3. Repeat this measurement 2 times in the same general area . Average these measurements, and record the mean in the data table.
4. Measure as many parts of the body as possible. See the data table for suggested areas.

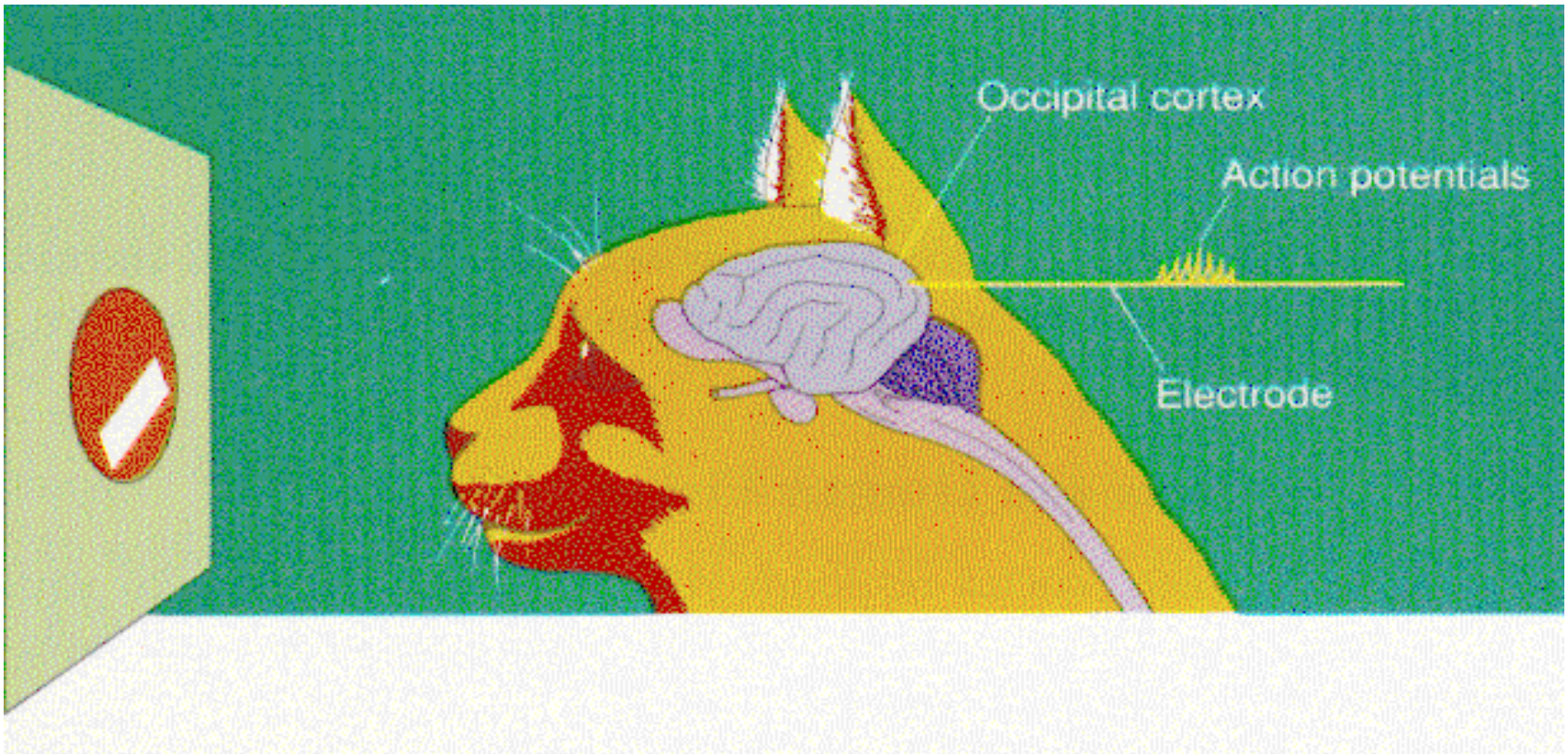
Procedure III: Calculations.

1. The number recorded for each body part represents the distance between each sensory receptor field, so the distance measured is inversely proportional to the cortical area dedicated to that body part. That is: the closer the receptor fields, the larger the area on the cortex. To calculate the inverses, divide each mean into the number 1. For example: Distance = 0.25 cm. 1/0.25 cm divides out to be 4.0. Calculate the inverses for each body part and record on the data sheet.
2. Draw a proportional picture of the homunculus on graph paper. If the inverse is 4.0, then the body part occupies 4 boxes on the graph paper, approximating the normal body shape. To enlarge the scale, for example, just multiply all values by the enlarging factor. For example, to make the drawing 5 times larger, multiply the inverses by 5.

Derivation of SOM

- Consider a spatial “field” of neurons.
- Each neuron has an **on-center, off-surround** type of behavior
  - It’s response is high to an input that occurs close by, low otherwise.
- When a stimulus is presented, neurons “compete” by **mutual lateral inhibition**.
- The winner **and neurons in the neighborhood** have their weights strengthened in the direction (in weight space) of the stimulus.
- Neurons tend to learn to respond to sets of similar stimulii.

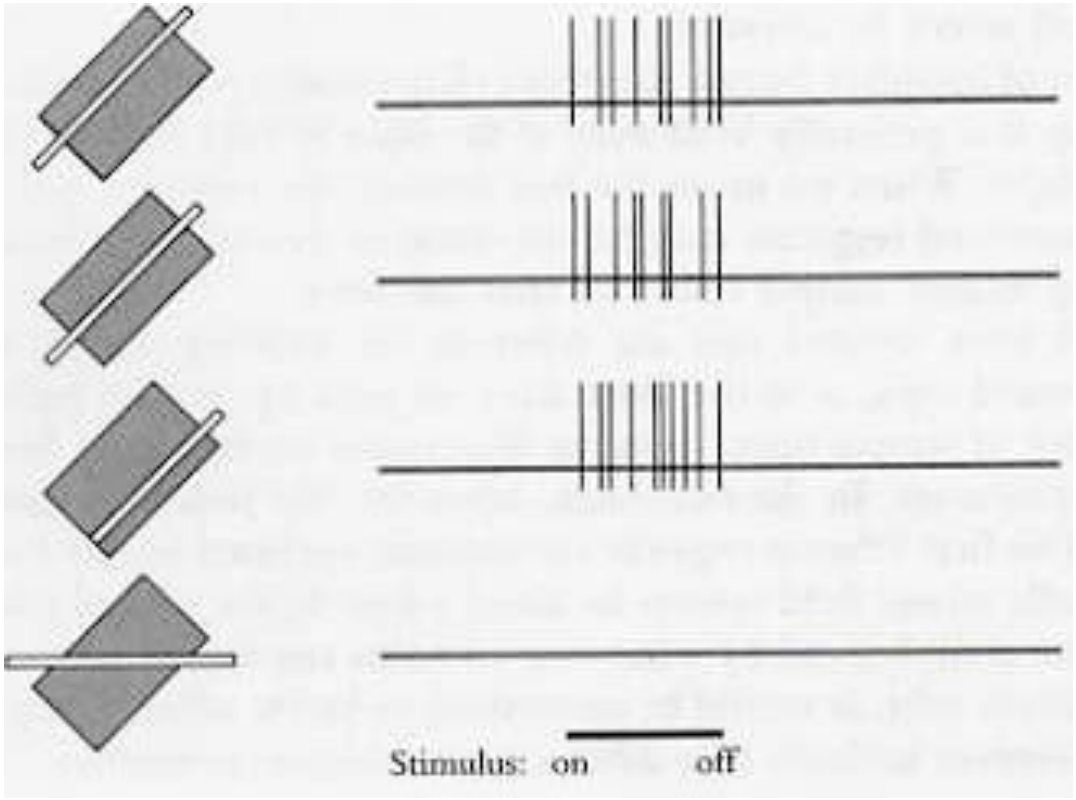
On-Center, Off-Surround: Hubel and Wiesel Experiments (1958)



Hubel and Wiesel Findings (1958)

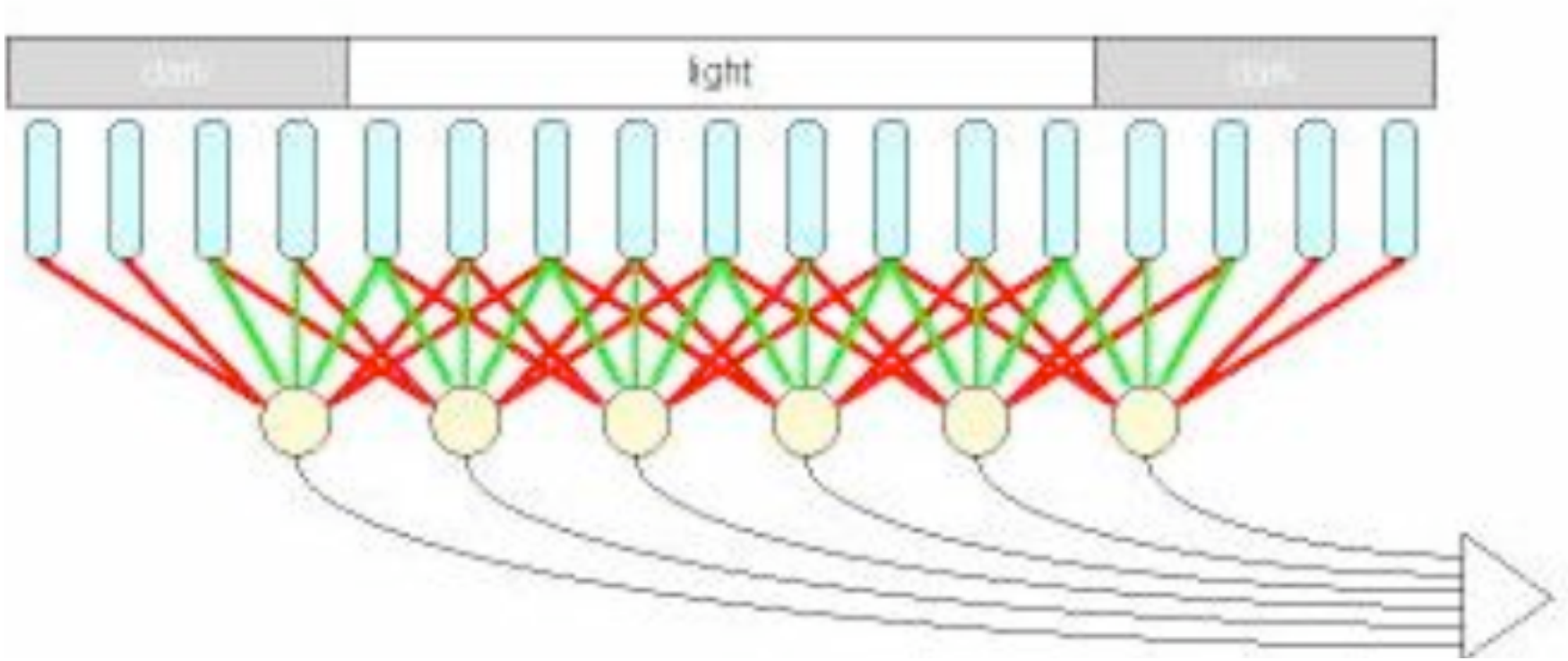
- Simple cells in the visual cortex respond to specific **angular orientations** of light bars.
- Complex cells respond to specific orientation and **direction of motion**.
- End-stopped cells respond to specific orientation, motion, and **length**.

Complex Cell Response
(orientation and motion)



Hubel's book on-line:
http://neuro.med.harvard.edu/site/dh/bcontex.htm

Receptor arrays **with lateral inhibition** ≈ "competition"



The neurons have mutually inhibitory interconnections.
The strongest responder will suppress the others.

Self-Organizing Map Modeling

Competitve: update weight vectors in a ***neighborhood*** of the winning neuron.

Kohonen Rule: $${}_i\mathbf{w}(q) = {}_i\mathbf{w}(q-1) + \alpha(\mathbf{p}(q) - {}_i\mathbf{w}(q-1))$$

$$i \in N_{i^*}(d)$$

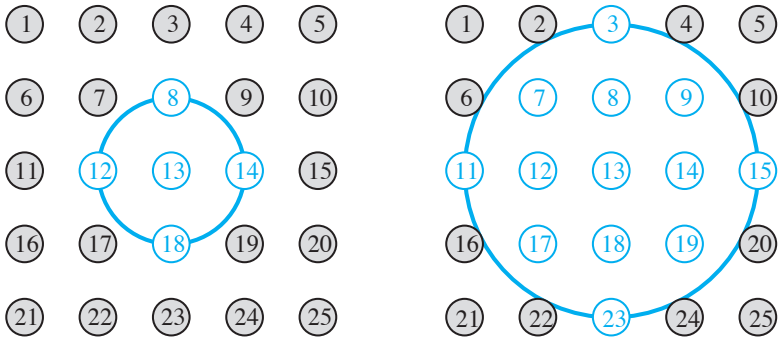
$${}_i\mathbf{w}(q) = (1-\alpha){}_i\mathbf{w}(q-1) + \alpha\mathbf{p}(q)$$

$$N_i(d) = \{j, \mathrm{d}_{i,j} \le d\}$$

$$N_{13}(1) = \{8, 12, 13, 14, 18\}$$

$$N_{13}(2) = \{3, 7, 8, 9, 11, 12, 13, 14, 15, 17, 18, 19, 23\}$$

Two possible neighborhoods of neuron 13



$N_{13}(1)$ $N_{13}(2)$

SOM Annealing Behavior

- As training progresses:
  - the learning rate is gradually reduced
  - the size of the neighborhood is gradually reduced
- Neighborhood can be based on
  - Euclidean distance, or
  - Superimposed structure

Kohonen Learning Algorithm

- Repeatedly present input vectors until resources exceeded:
  - At each vector presentation do the following:
    - Find the node *k* whose weight vector is closest to the current input vector.
    - Train node *k* and all nodes in some neighborhood of *k*.
    - Decrease the learning rate slightly.
    - After every *M* cycles, decrease the size of the neighborhood.

"Superimposed Dimensionality" of SOM

- In a general SOM, an n-dimensional grid, can be ***overlaid*** with the neurons as nodes.
- The edges connecting the neurons ***constrain the neighborhood*** *for* ***updating*** (rather than using Euclidean distance).
- Only nodes a specified ***graphical diameter on the grid*** away (not Euclidean) are in the neighborhood.

Uses of "Imposed Dimensionality" in Data Analysis

- Data points may have an *unknown, but often large,* **underlying dimensionality**, e.g. the underlying phenomenon or process that has several dimensions of attributes (such as color dimensions, various size or rate dimensions, etc.)

- By training a network with an ***imposed*** grid with a given dimensionality, the relationships among the data may become visualizable, especially if the imposed number of dimensions is small.

Uses of "Imposed Dimensionality" in Data Analysis

- In other words, training the map "organizes" the data according to similarity in each dimension.

Demo Applets

- /cs/cs152/kohonen/ demo1, demo2, demo3
- Legend:
  - black = input data point (random over a 2-D region; 2-dimensional data)
  - red = neuron in winner neighborhood; learns by Kohonen rule
  - blue = other neuron
- Learning rate and neighborhood both decrease with time; demo speeds up over time.

Competition Code

```
// compete finds the neuron with weights closest to the input.
// It sets winpoint to the indices of that neuron.

  public void compete(Input input)
    {
    // initialize min with an distance to an arbitrary neuron
    winpoint = 0;
    double min = neuron[winpoint].distance(input);

    // find the min distance among all neurons

    for( int point = 0; point < points; point++ )
      {
      double dist = neuron[point].distance(input);
      if( min > dist )
        {
        min = dist;              // update the min distance
        winpoint = point;
        }
      }
    }
```

Competition Code

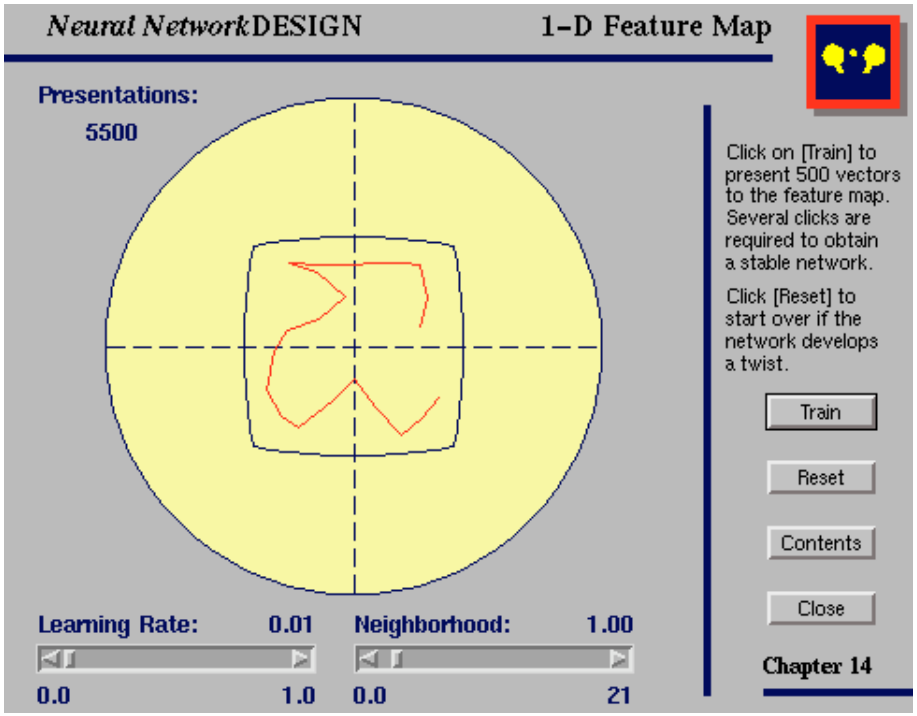
```
// learn updates all neurons within current neighborhood
// by applying the Kohonen learning rule against the current
// input.

  public void learn(Input input, double learningRate)
    {
    for( int point = 0; point < points; point++ )
      {
      if( inWinnersNeighborhood(point) )
        {
        neuron[point].learn(input, learningRate);
        }
      }
    }
```

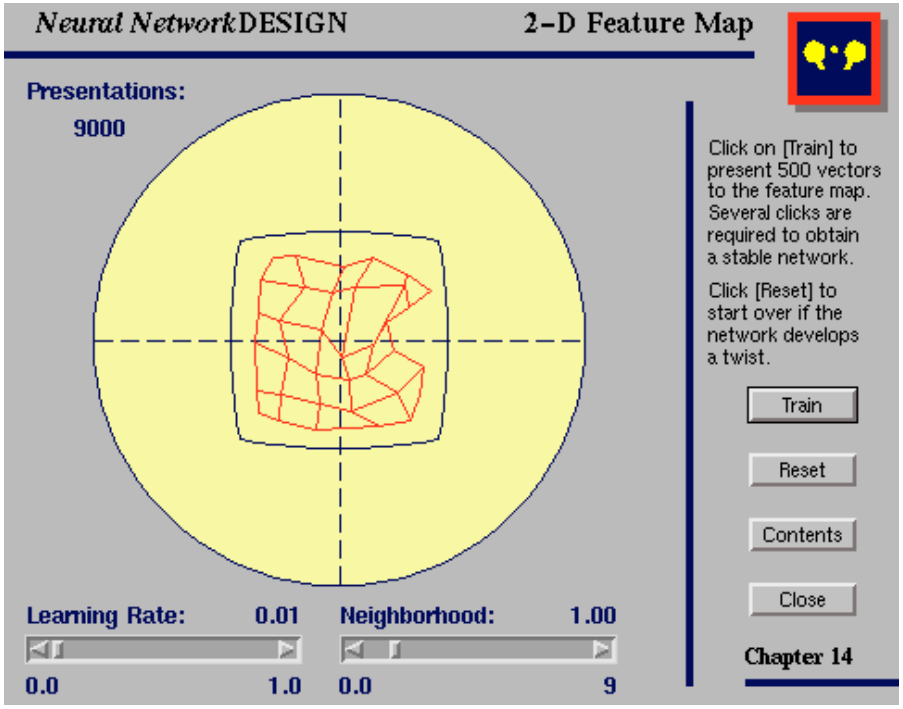
Similar matlab demos

Same input spaces, different imposed dimensions

1D

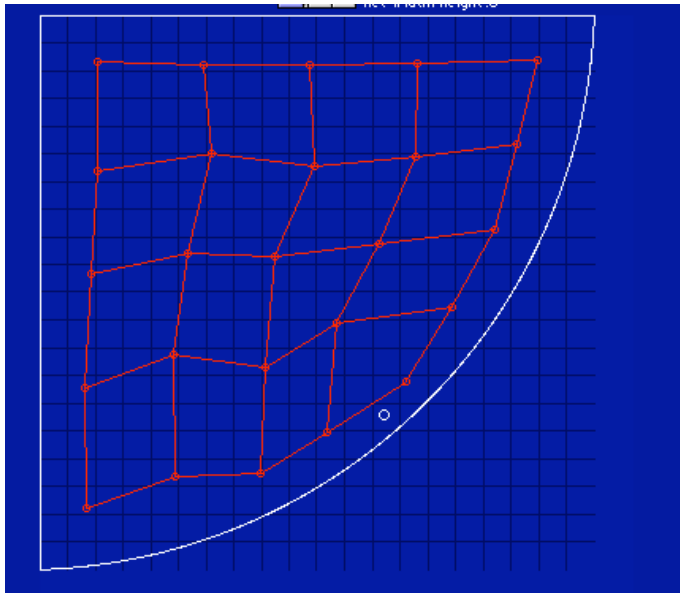


2D



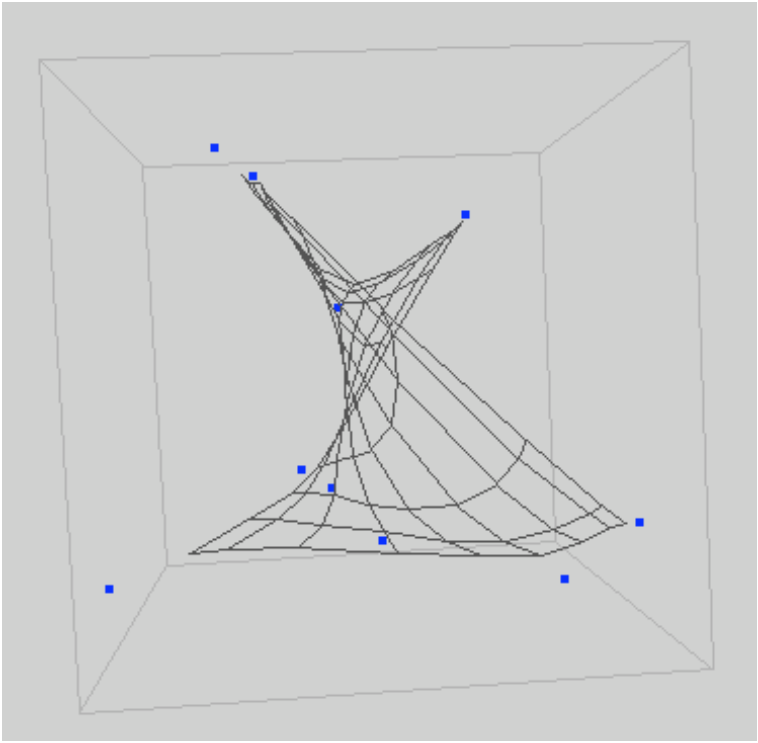
The grid adjusts to represent the data distribution

- Non-rectangular data distribution



http://www.patol.com/java/fill/index.html

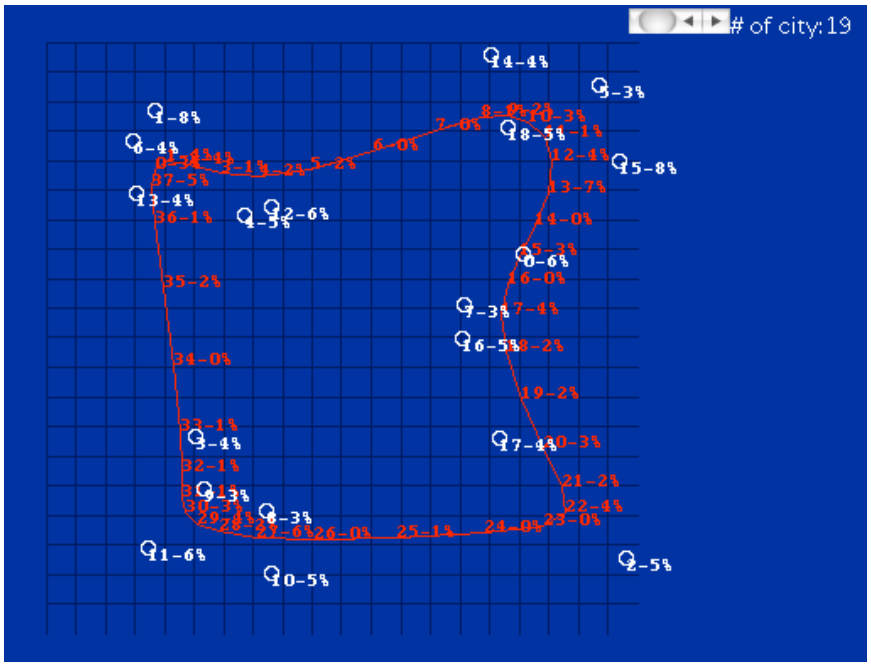
3D data to 2D Grid



http://rfhs8012.fh-regensburg.de/~saj39122/jfroehl/diplom/e-index.html

Heuristic Solutions to the TSP

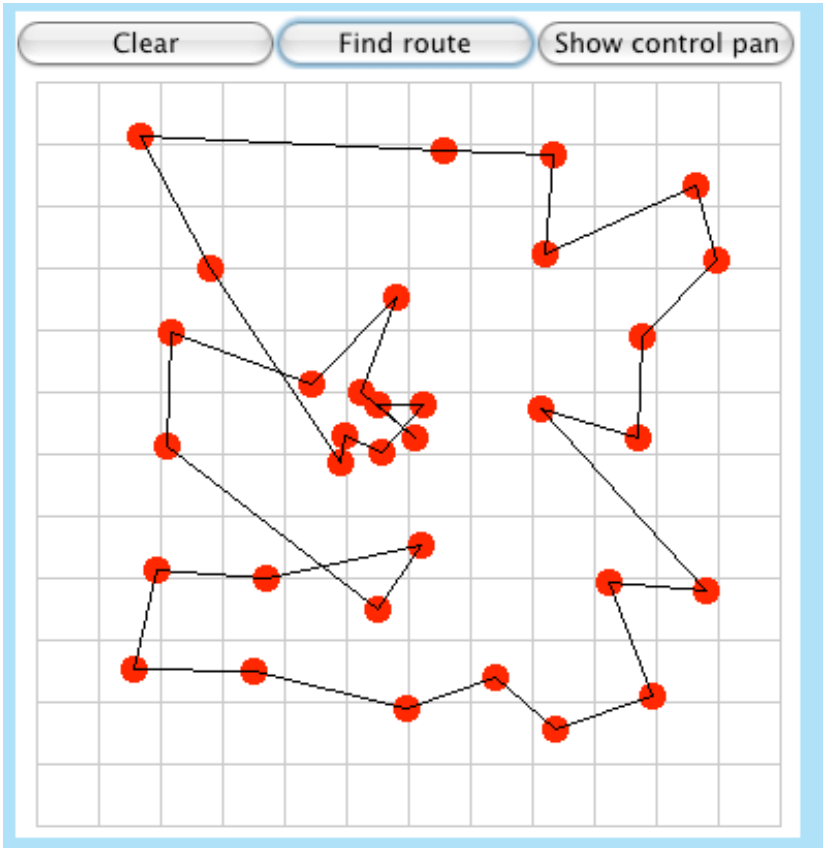
- Finding a heuristic (not necessarily optimal) solution to the Euclidean Traveling Salesperson Problem using Kohonen net
- "Elastic net" approach



red points = neurons,
red lines = overlay
circles = cities
neurons travel toward cities

http://www.patol.com/java/TSP/index.html

This approach to the TSP is neither optimal nor particularly fast, just "interesting"



http://eple.hib.no/~hib00ssl/TSPKohonen.html

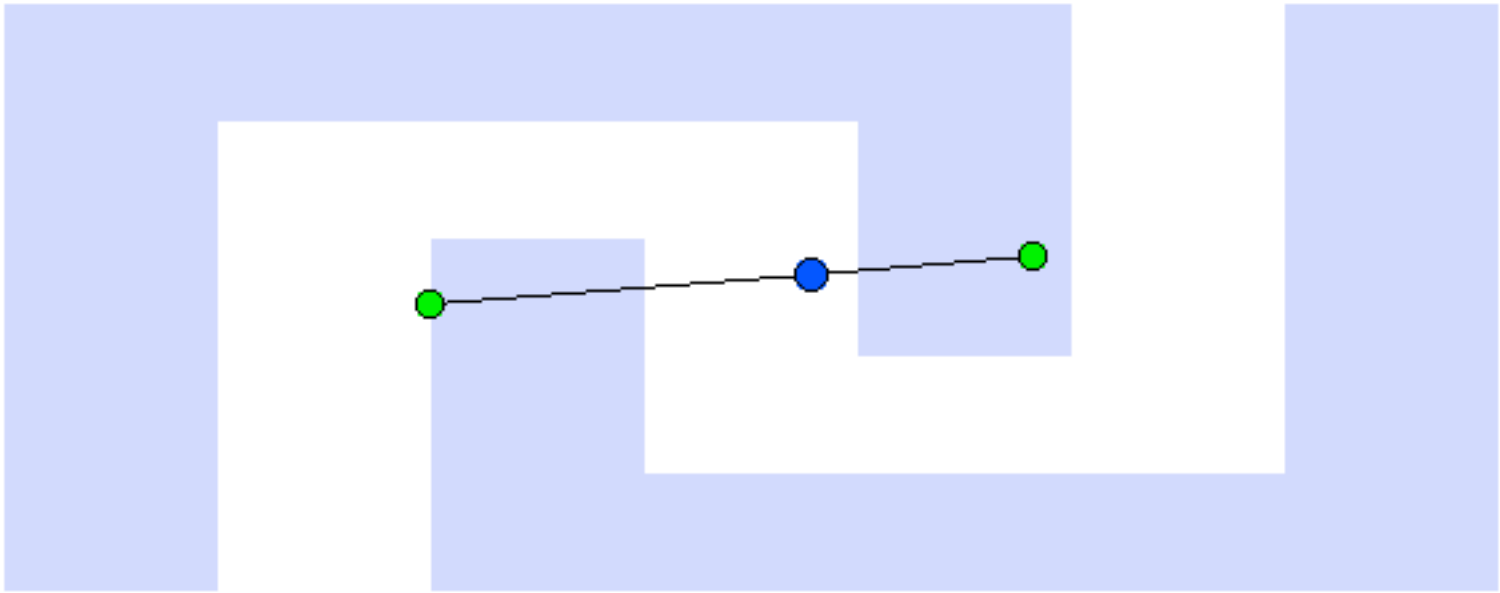
Related Demo on the Web

http://www.sund.de/netze/applets/gng/full/GNG_0.html

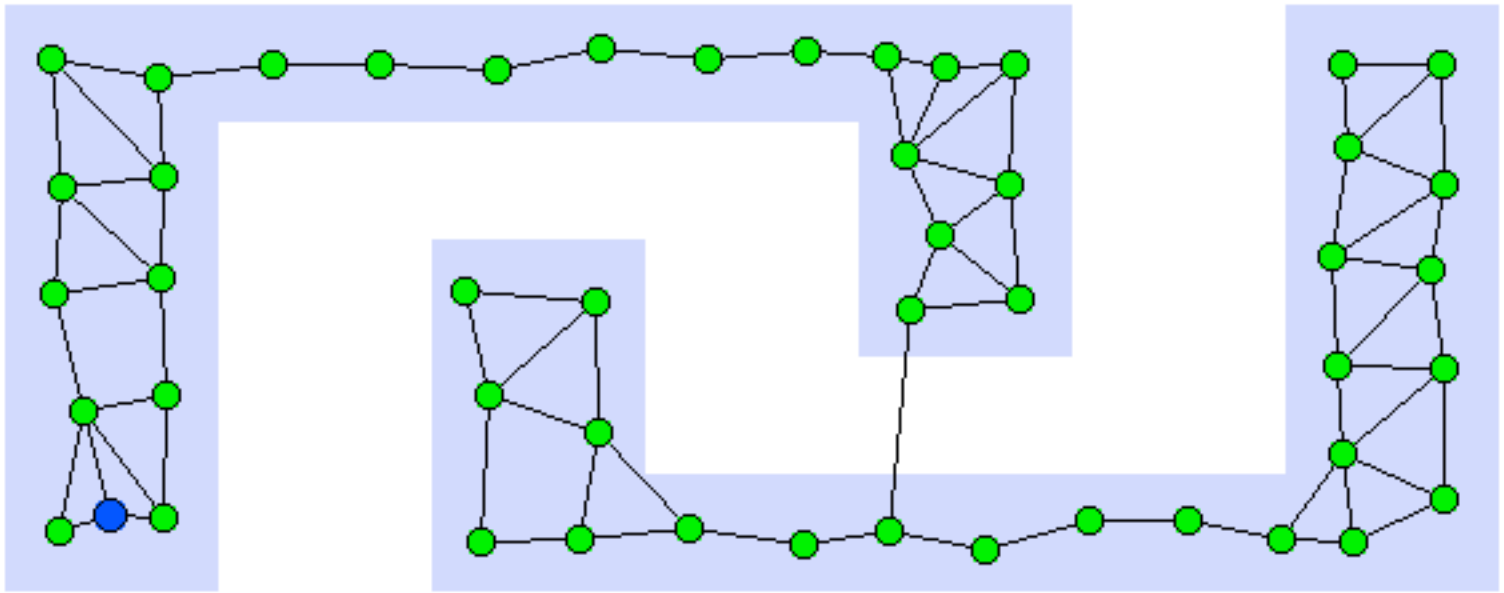
- Eight competitive models in one applet, including:
  - Kohonen
  - Neural Gas
  - Growing Neural Gas (GNG): Number of neurons grows
- Thirteen choices of input distribution
- Worth visiting

Growing Neural Gas

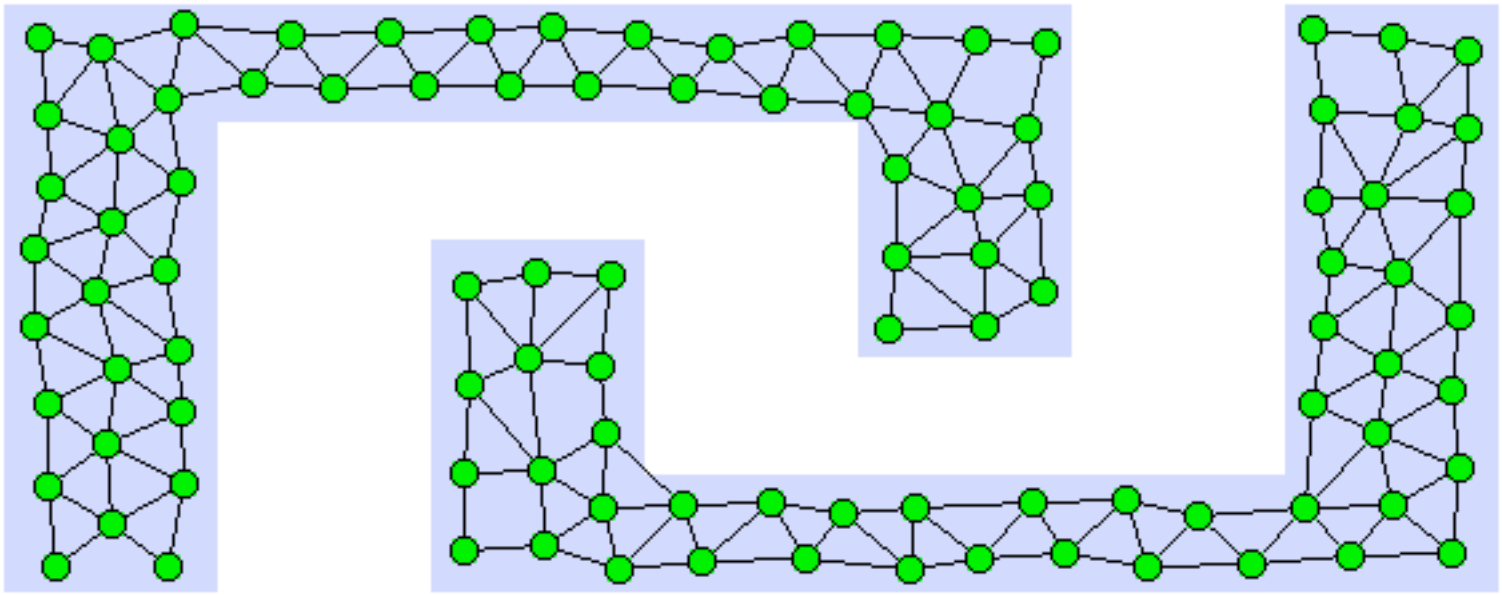
Shaded areas show data distribution.
Circles are neurons.



Growing Neural Gas



Growing Neural Gas

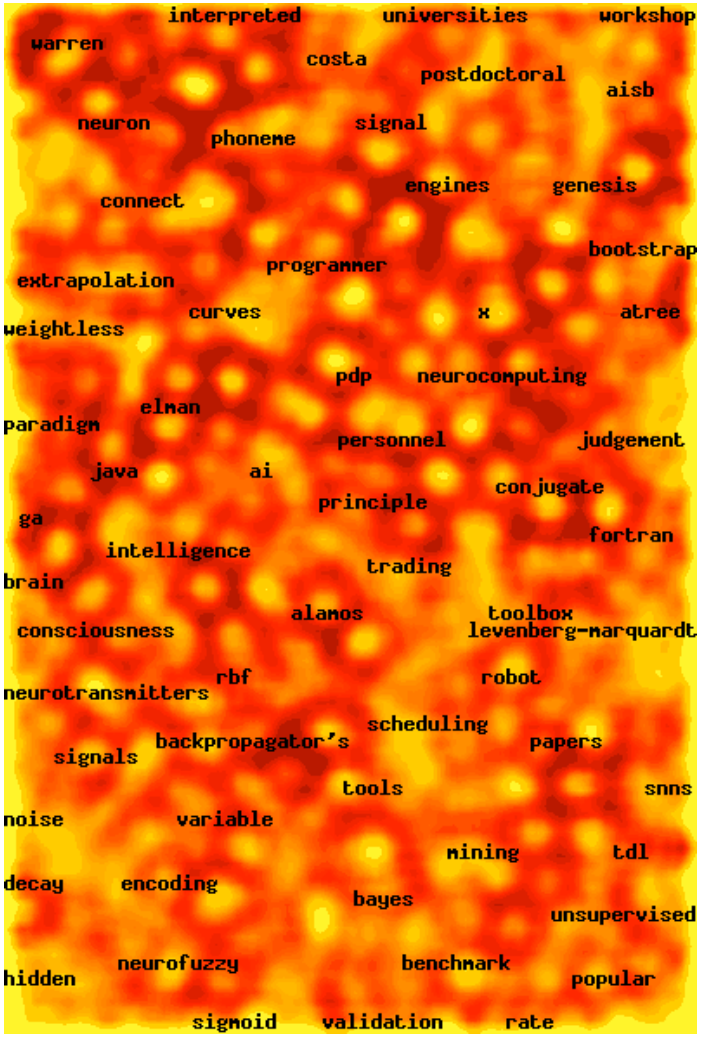


Unsupervised Applications of SOMs

- Discovering similarities in data (clustering)
- Data-mining
- KDD (Knowledge Discovery in Databases)

WEBSOM: Classifying news messages by terms occurring within

(seehttp://websom.hut.fi/websom/comp.ai.neural-nets-new/html/root.html)

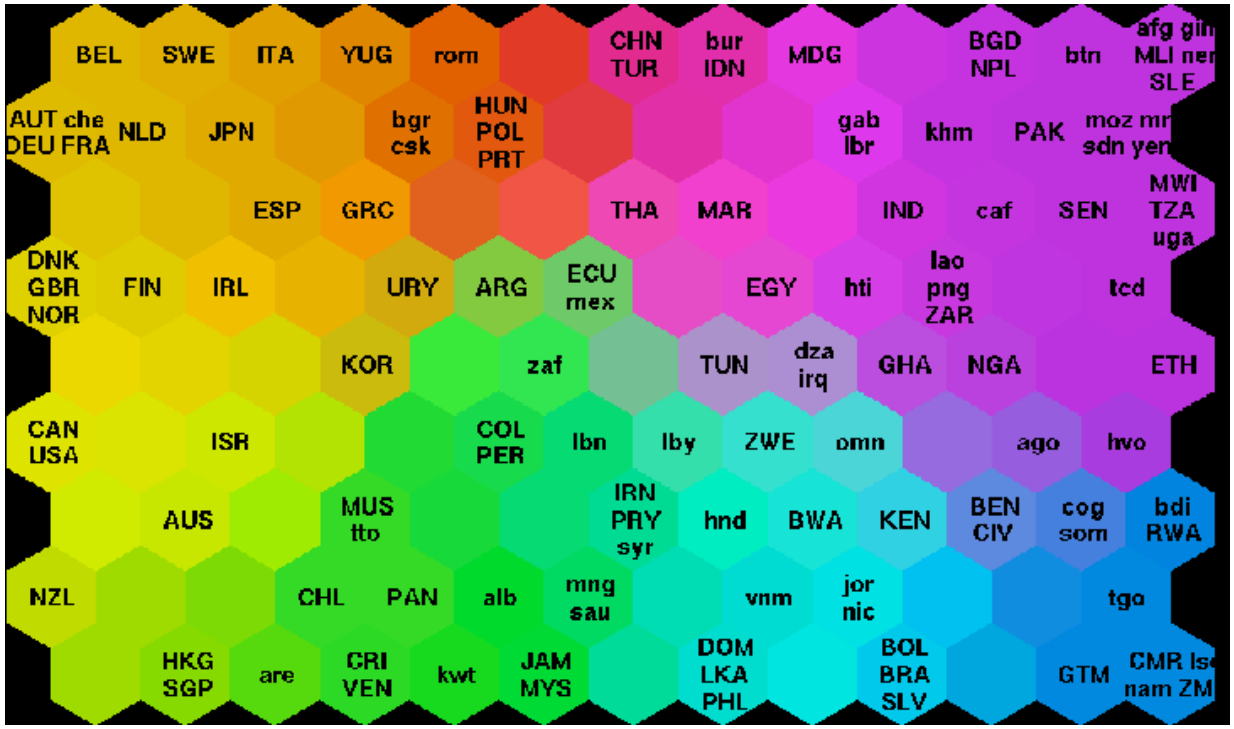


Automatically generated labels and examples of titles in which the labels have occurred

ai - SubSymbolic AI :-O
aisb - AISB and ECCS 1997 - Call for Registrations
alamos - Graduate Research Assistantship in Los Alamos National Laboratory
atree - Atree 3.0 EK mirror sites
backpropagator's - Backpropagator's review, by Donald R. Tveter
bayes - nn and stat decisions for med: Bayes vs neorotic nets
benchmark - Benchmark data for signal processing
bootstrap - Bootstrapping vs. Bayesian
brain - Brain usage Was:Re: Function of sleep
conjugate - Moller's Scaled conjugate gradienconnect - Direct Connect Problems
consciousness - electromagnetics, brain waves and consciousness
costa - New paper available "The Application of Fuzzy Logic in
curves - Predicting Learning Curves (Ph.D. thesis, online)
decay - weight decay
elman - Elman (or Edelman?) nn, references please.
encoding - Question on Encoding Input Data
engines - IC ENGINES & NEURAL NETS
extrapolation - Generalization (Interpolation & Extrapolation)
fortran - Neural Net Fortran Code
ga - GA for learning in ANN
genesis - GENESIS 2.0
hidden - Hidden layer heuristics
intelligence - Commercial Intelligence?
interpreted - Lisp is not an interpreted language
java - NN in Java?

Example: Classifying World Poverty from a 39-dimension indicator

(http://www.cis.hut.fi/research/som-research/worldmap.html)



The colors were automatically assigned after 2-D clustering using a Kohonen map.

Map Interpretation

The same ordered display can be used for illustrating the **clustering density** in different regions of the data space. The density of the reference vectors of an organized map will reflect the density of the input samples.

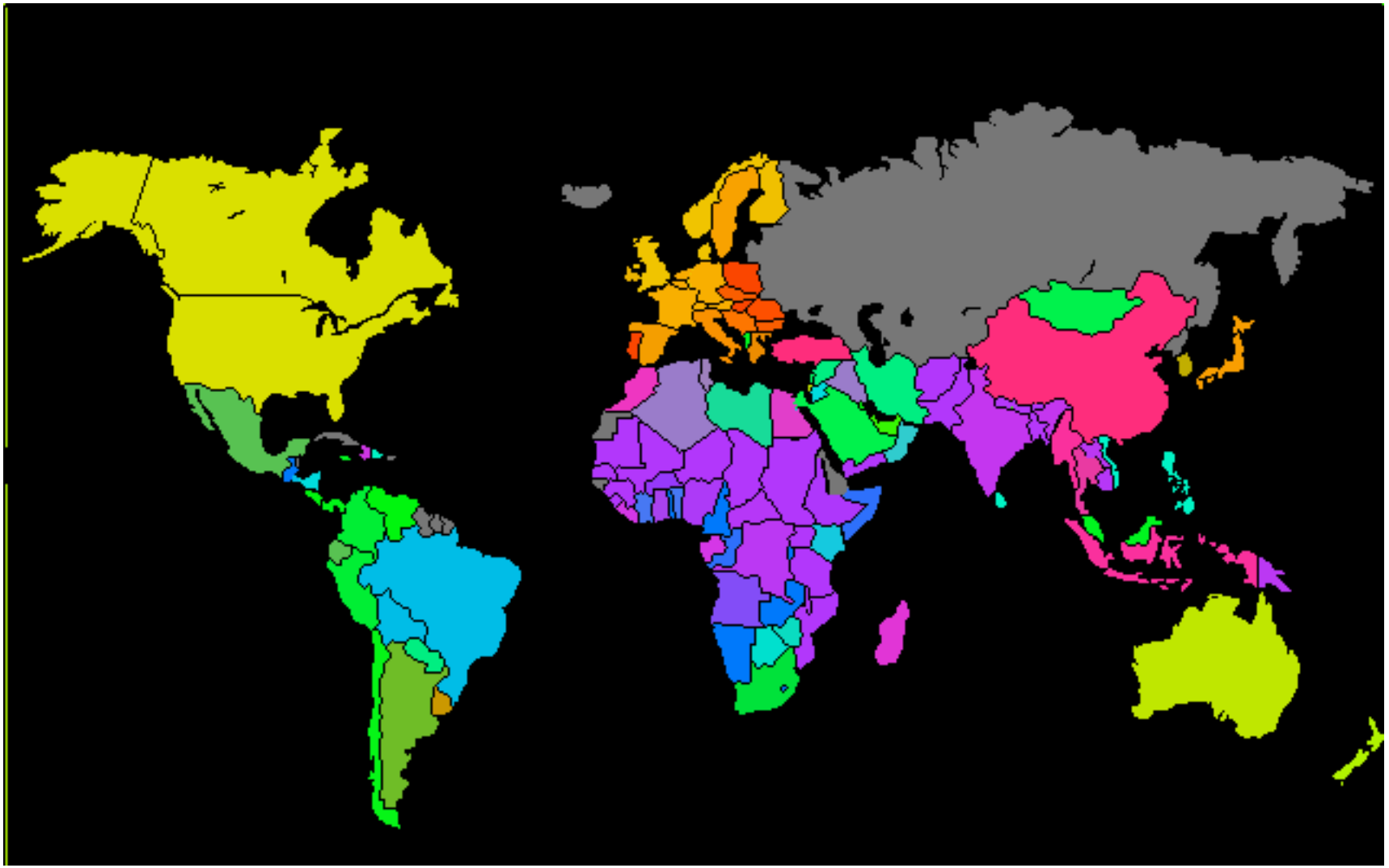
In clustered areas the **reference vector**s will be close to each other, and in the empty space between the clusters they will be more sparse. Thus, the cluster structure in the data set can be brought visible by displaying the distances between reference vectors of neighboring units.

Outliers

In measurement data there may exist **outliers**, data items lying very far from the main body of the data. The outliers may result, for instance, from measurement errors or typing errors made while inserting the statistics into a data base. In such cases it would be desirable that the outliers would not affect the result of the analysis. This is indeed the case for map displays generated by the SOM algorithm: **each outlier affects only one map unit and its neighborhood**, while the rest of the display may still be used for inspecting the rest of the data. Furthermore, the **outliers can be easily detected based on the clustering display**: the input space is, by definition, very sparsely populated near the outliers. **If desired, the outliers can then be discarded and the analysis can be continued with the rest of the data set.**

It is also possible that the outliers are not erroneous but that some data items really are strikingly different from the rest. In any case the map display reveals the outliers, whereby they can either be discarded or paid special attention to.

Colors transferred to a world map



Color Quantization Problem (discussed earlier)

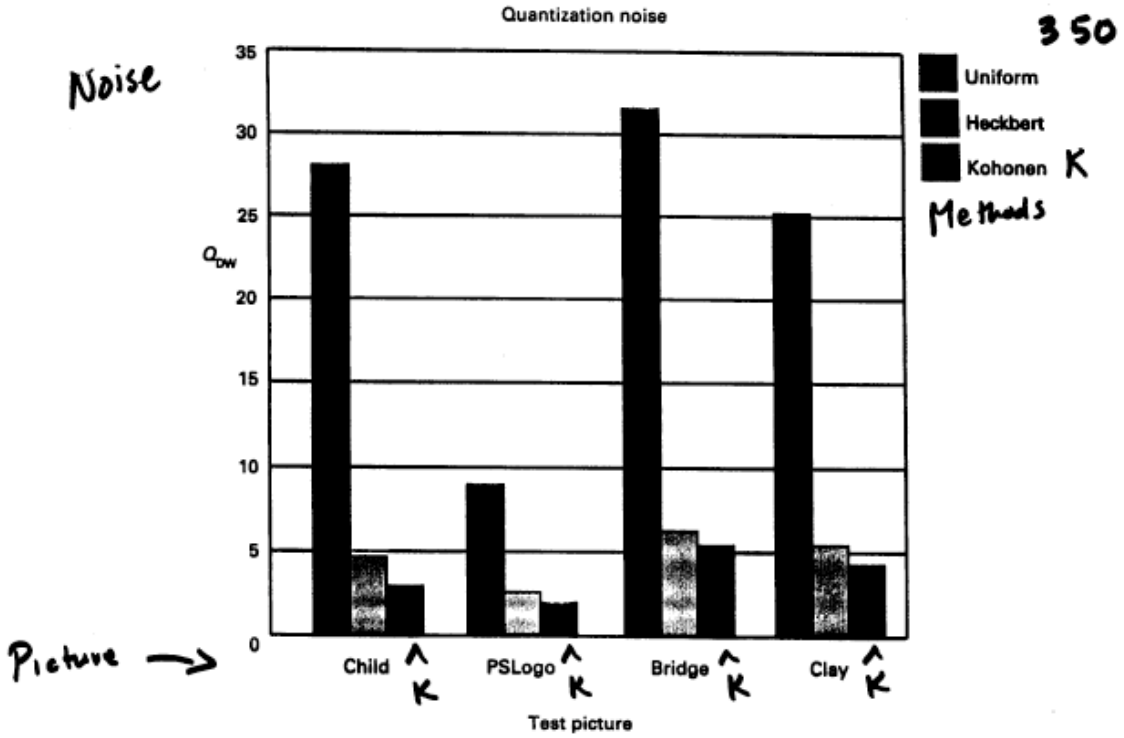


Figure 4.43 Quantization noise for different pictures and different quantization methods: uniform palette, Heckbert's algorithm and the self-organizing algorithm of Kohonen

Heckbert's median cut algorithm "Color Quantization by Dynamic Programming and Principal Analysis" by Xiaolin Wu in ACM Transactions on Graphics, Vol. 11, No. 4, October 1992, 348-372.

Animal Similarity Expt.

Table 3.4. Animal names and their attributes

		dove	hen	duck	goose	owl	hawk	eagle	fox	dog	wolf	cat	tiger	lion	horse	zebra	cow
is	small	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0
	medium	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
	big	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
has	2 legs	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
	4 legs	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
	hair	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
	hooves	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	mane	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0
	feathers	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
likes to	hunt	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0
	run	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0
	fly	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
	swim	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0

Animal Similarity Expt.

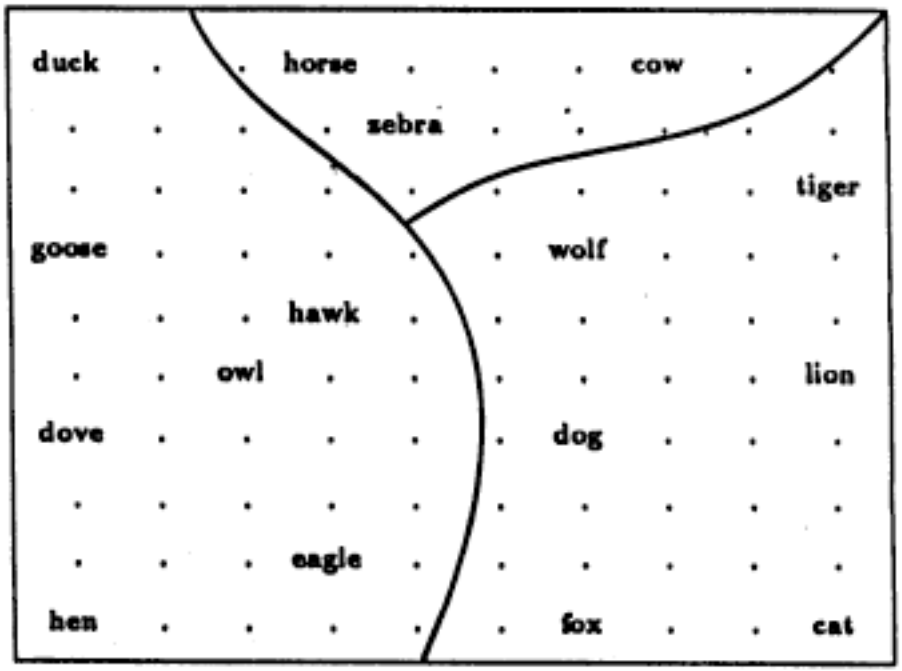


Fig. 3.22. After the network had been trained with inputs describing attribute sets from Table 3.4, the map was calibrated by the columns of Table 3.4 and labeled correspondingly. A grouping according to similarity has emerged

Semantic Map Expt.

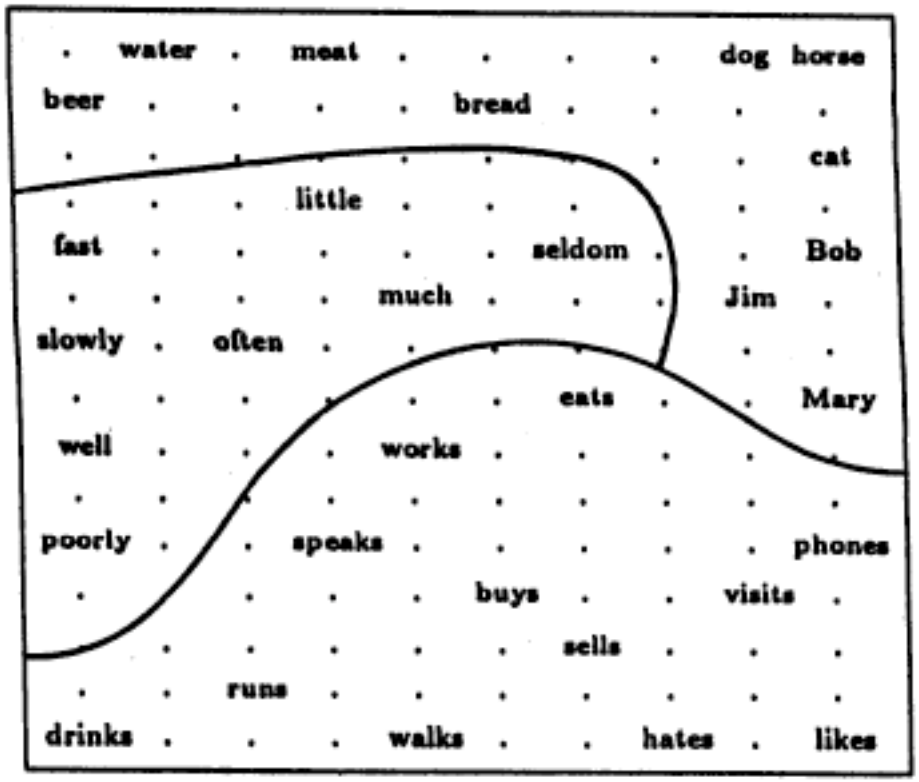


Fig. 7.11. "Semantic map" obtained on a network of 10 × 15 cells after 2000 presentations of word-context-pairs derived from 10,000 random sentences of the kind shown in Fig. 7.8. Nouns, verbs and adverbs are segregated into different domains. Within each domain a further grouping according to aspects of meaning is discernible

Tree Data Structure Expt.

- Encode a 5-dimensional tree as shown:

```
ABCDE
  F
  G
  H K L M N O P Q R
  I     S     W
  J     T     X 1 2 3 4 5 6
        U     Y
        V     Z
```

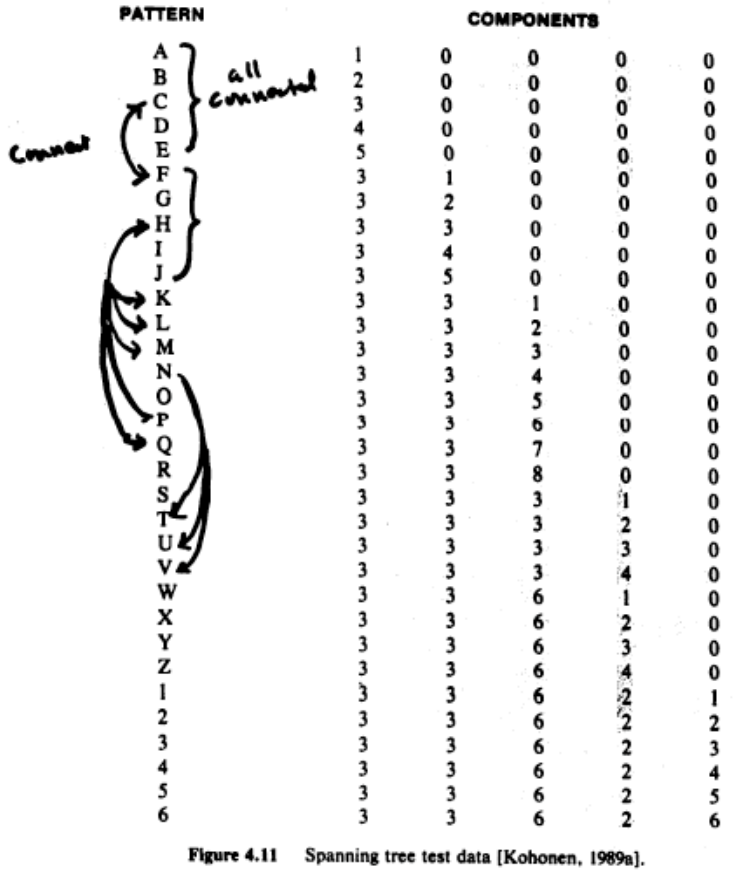


Figure 4.11 Spanning tree test data [Kohonen, 1989a].

Tree Data Structure Expt.

- Use a 2D imposed structure, with 10 x 7 neurons

- Results:

  Branches of tree tend to align in rows or columns of the array.

  5D → 2D mapping

Tree Data Structure Expt.

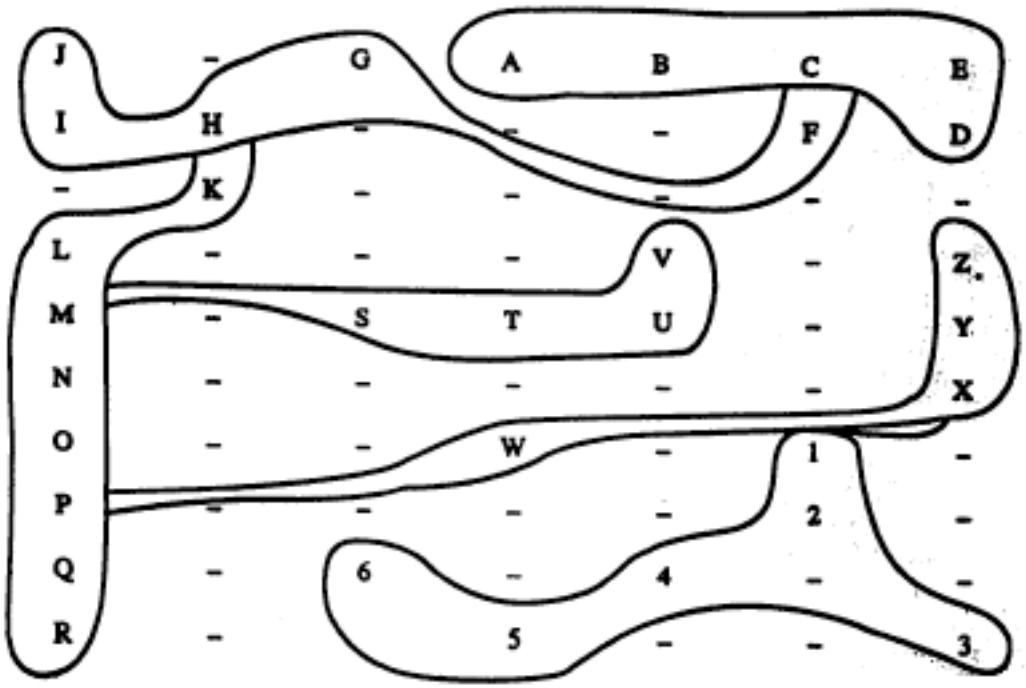


Figure 4.16 Results after another 75 iterations with $R = 0$.

Compare Original 5DTree

```
ABCDE
  F
  G
  H K L M N O P Q R
  I     S     W
  J     T     X 1 2 3 4 5 6
        U     Y
        V     Z
```

Tree Data Structure Expt. Using Hexagonal Array

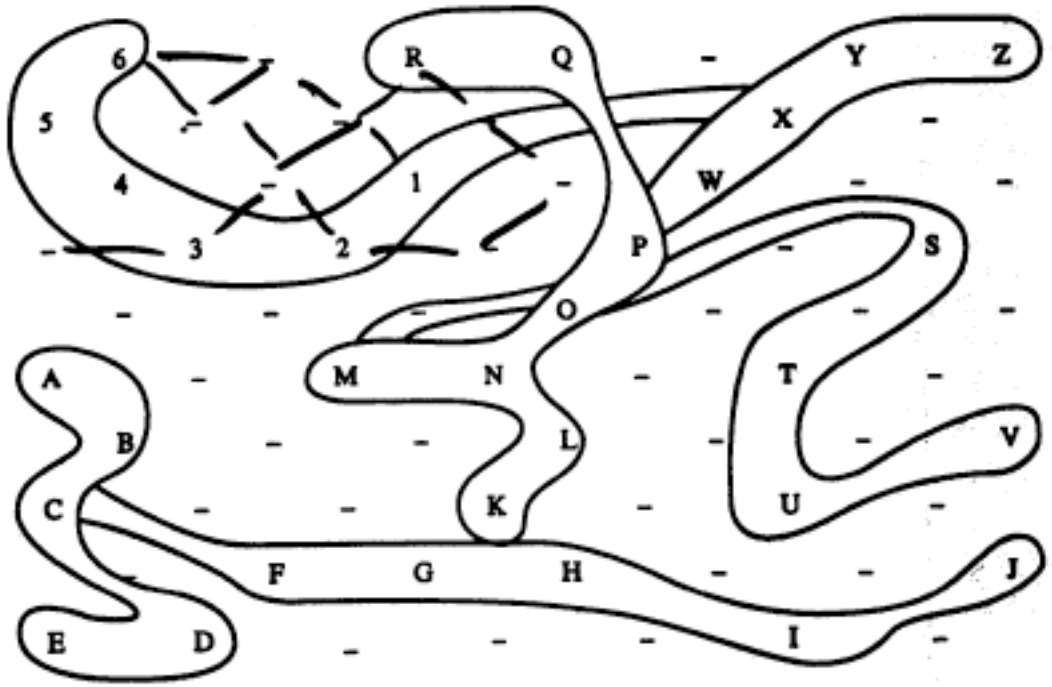


Figure 4.17 Results of spanning tree example using hexagonal array.

Compare Original 5DTree

```
ABCDE
  F
  G
  H K L M N O P Q R
  I     S     W
  J     T     X 1 2 3 4 5 6
        U     Y
        V     Z
```

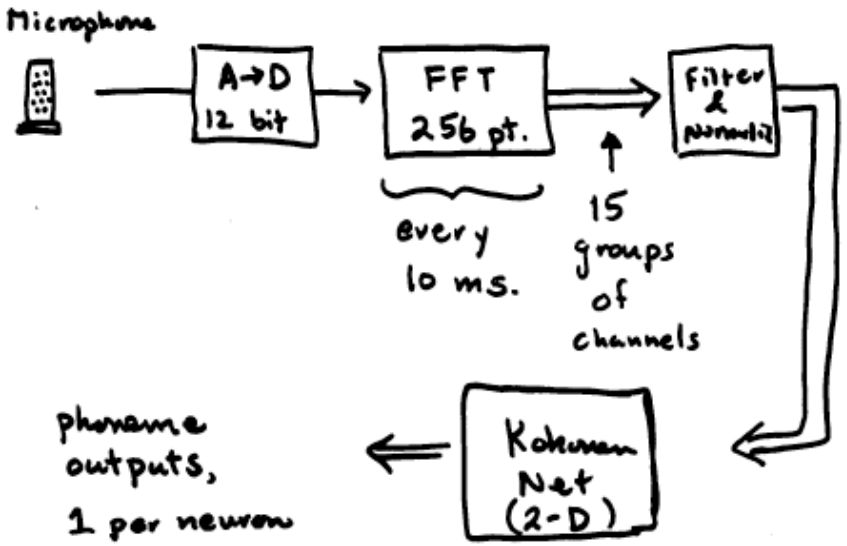
Supervised Applications of Kohonen Nets

- Most applications that can be treated with MLP's can also be treated in some way by variants of Kohonen nets.

- Example: Learning a function f:D→R is done by treating the sample space as a set of (d, r) pairs.

Phonetic Typewriter

- Objective: Spoken words →phonemes
- Languages: Finnish, Japanese
- Claimed ≥ 92% accuracy in 10 mins. of training.



Resulting Phonotopic Map

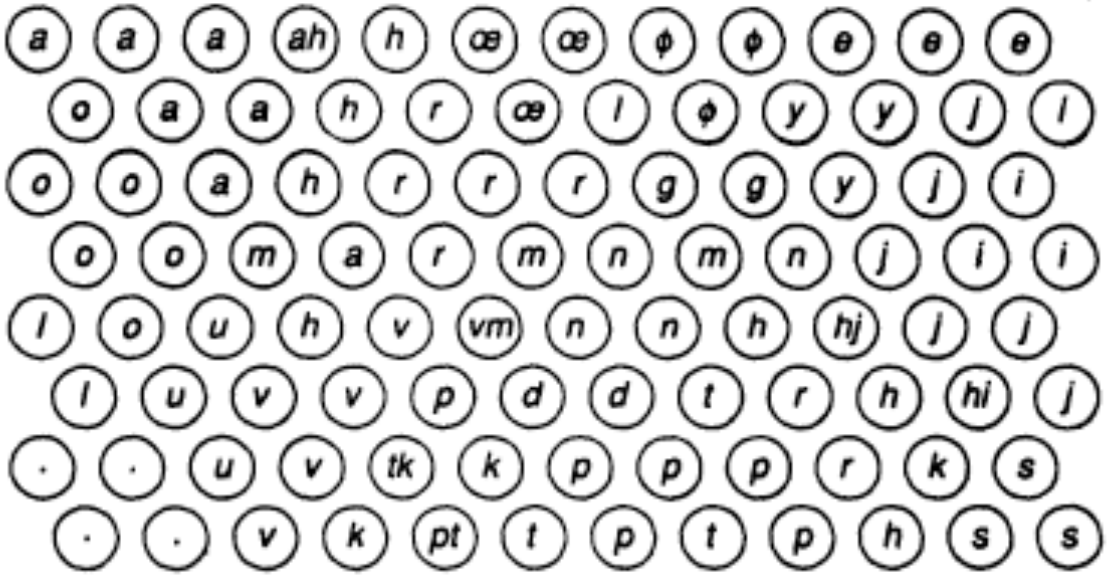


Figure 7.9 This figure is a phonotopic map with the neurons, shown as circles, and the phonemes to which they learned to respond. A double label means that the node responds to more than one phoneme. Some phonemes—such as the plosives represented by *k*, *p*, and *t*—are difficult for the network to distinguish and are most prone to misclassification by the network. *Source: Reprinted with permission from Teuvo Kohonen, "The neural phonetic typewriter."* IEEE Computer, *March 1988. ©1988 IEEE.*

Resulting Phonotopic Map

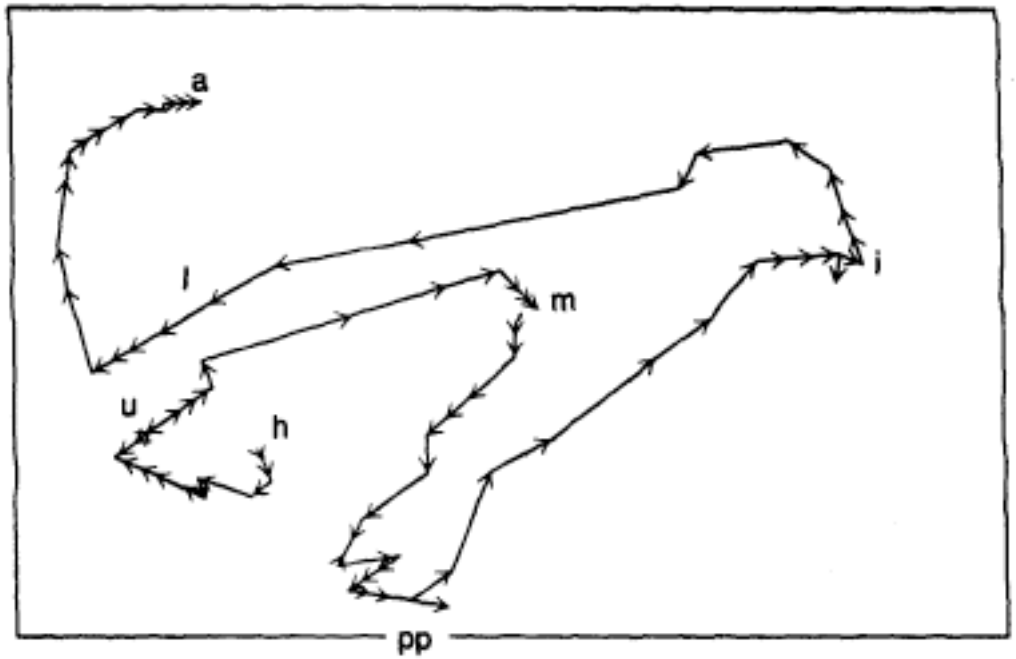


Figure 7.10 This illustration shows the sequence of responses from tl phonotopic map resulting from the spoken Finnish wo *humppila*. (Do not bother to look up the meaning of this wo in your Finnish–English dictionary: *humppila* is the name of place.) *Source: Reprinted with permission from Teuvo Kohone "The neural phonetic typewriter."* IEEE Computer, *March 198* ©*1988 IEEE.*

Function Approximation Example

- Assume 1-dimensional inputs for simplicity (not required in general).
- Represent pairs y = f(x) as (x, y).
- Learn pairs by a 2-D Kohonen net.

A Possible Aberration

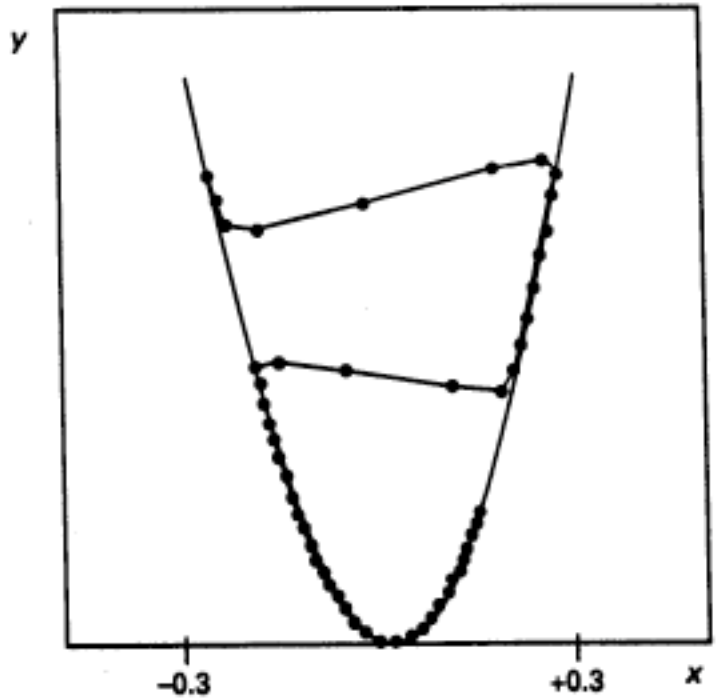


Figure 4.63 Representation of 1000 pairs of argument and function values of the function $y = 10x^2$ by two-dimensional weight vectors (dots) in a one-dimensional neural net of fifty neurons. Input argument values in $[-0.3, +0.3]$

Master-Slave Technique

- A technique known as “master-slave” can reduce the likelihood of an aberration as shown previously.
  - Select **winners** based only on x, not on the pair (x, y). The weight components corresponding to x are called the **master weights**, and others are called **slave weights.**
  - Adapt both master and slave.

No Aberration

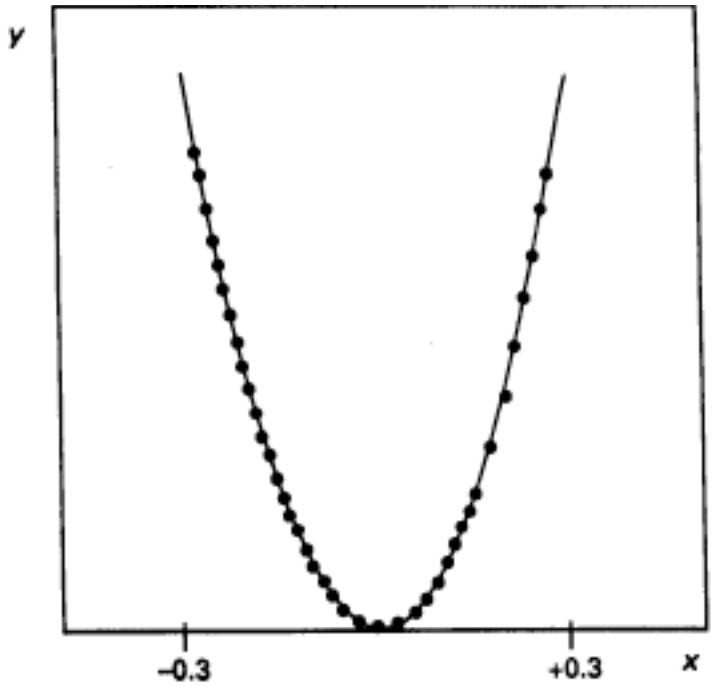


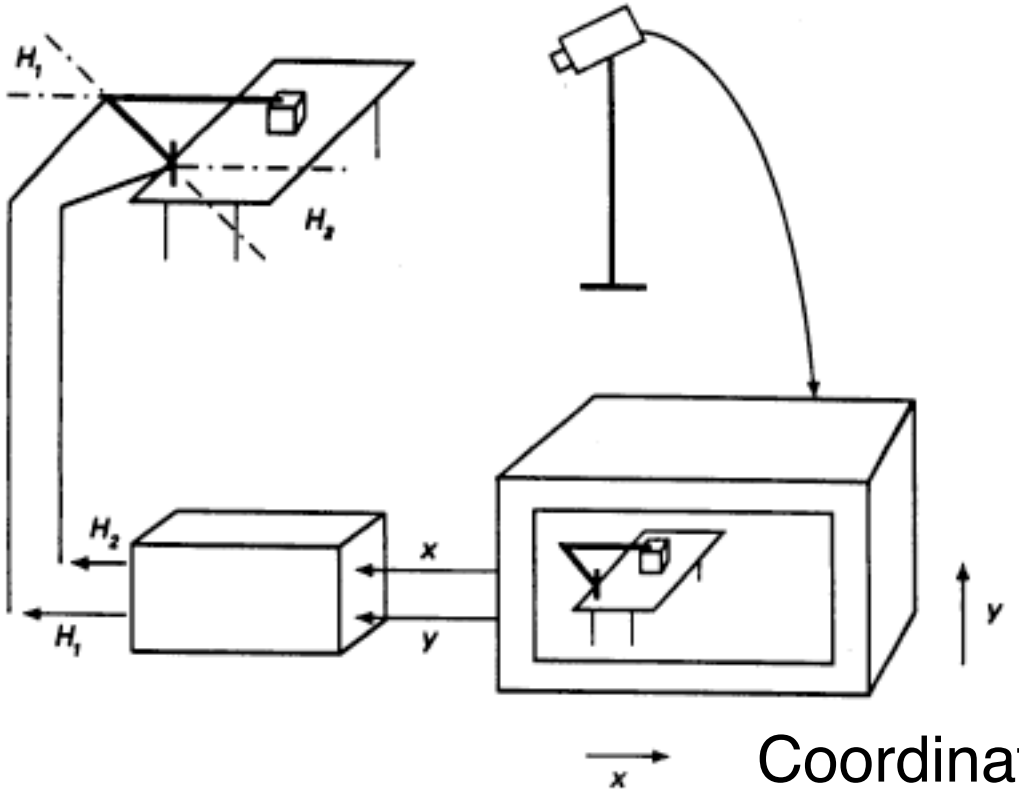
Figure 4.66 The master–slave method. The representation of 1000 pairs of argument and function values of the function $y = 10x^2$ by two-dimensional master–slave weight vectors (dots) in a one-dimensional neural net of fifty neurons. Input argument values in $[-0.3, +0.3]$

Example: Robot Hand-Eye Coordination

- Want robot to coordinate its hand with what it sees on the monitor.
- Robot arm should be able to place an object given position identified in **view**.
- The problem is how to set the arm's angles (called "inverse kinematics").

Robot Hand-Eye

Angles



Coordinates

Figure 4.68 Simple outline of robot arm control

Master-Slave

- The view is the master.
- The hand is the slave.
- Winner is determined w.r.t. the view; both view and hand are adapted.
- Example:
  - 20x20 neuron map, 2D overlay
  - 4 weights per neuron (2 for master/view and 2 for slave/angles)

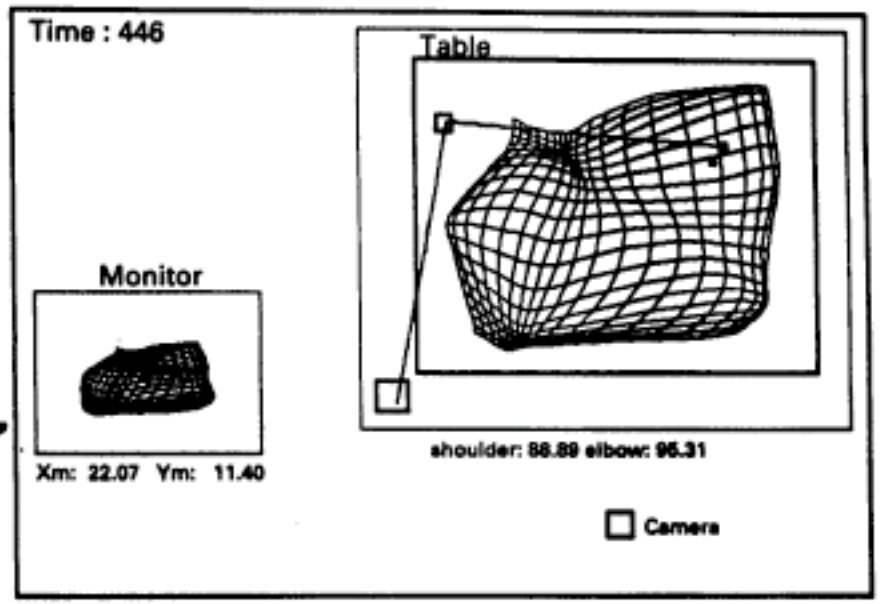


Figure 4.70 Representation of table coordinates by the two-dimensional master–slave weight vectors (dots in the right-hand figure) in a two-dimensional net of 20×20 neurons after 446 training examples. Weight vectors are connected with a line if they belong to neighbouring neurons

Positions on the monitor,

not what the monitor is seeing.

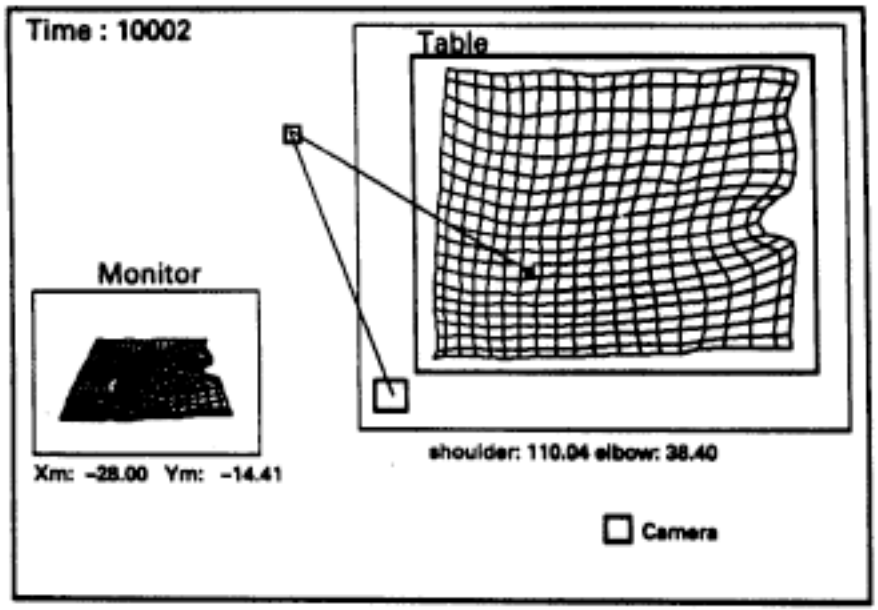
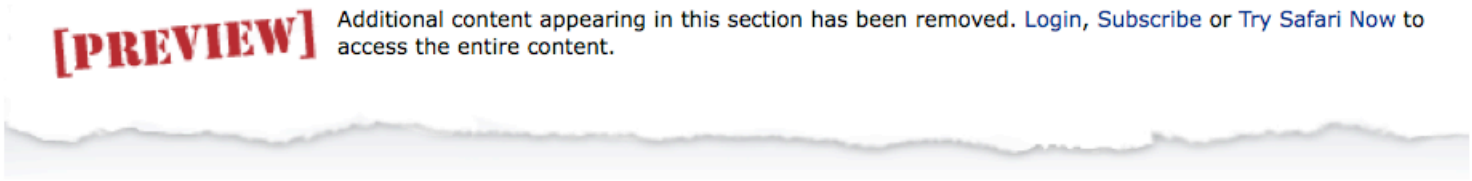


Figure 4.71 Representation of table coordinates by the two-dimensional master–slave weight vectors (dots in the right-hand figure) in a two-dimensional net of 20×20 neurons after 10 002 training examples. Weight vectors are connected with a line if they belong to neighbouring neurons

Problems Unsuitable for Kohonen Nets

- Kohonen nets work by clustering
- Nearby data points are expected to behave similarly, e.g. have similar outputs.
- Parity-like problems such as the XOR do not have this property. The would be unstable for solution by a Kohonen net.

Unexpected Encounter



The Application of SOM Network to Clustering Enterprises Based on Questionnaires*

Yan Yu[1,2], Pelian He[1], Yinghua Zhang[3], Yushan Bai[2], Zhengju Song[1], Tingting Yin[1]

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Increasing Wireless Sensor Network Lifetime through the Application of SOM Neural Networks

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