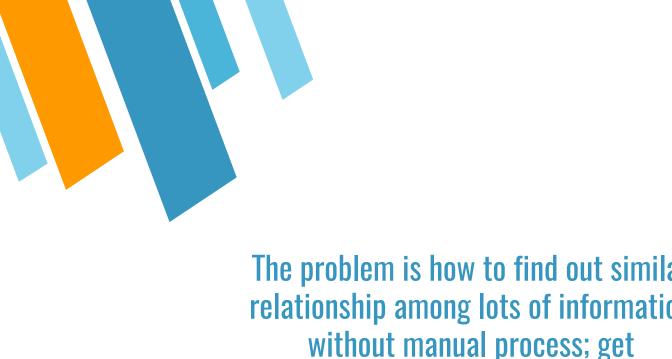
Self Organizing Map

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Overview

- » Introduction
- » Algorithm
- » Example
- » Application
- » Conclusion



The problem is how to find out similar relationship among lots of information without manual process; get information about data without knowing where to search for it and without knowing where to put the new data

Introduction [Origin]

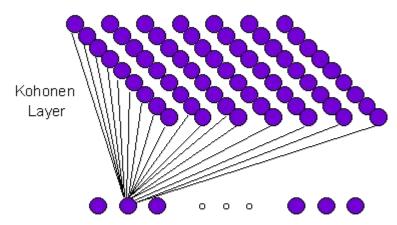
- » Introduced by C. von der Malsburg(1973), developed and refined by T.Kohonen(1982)
- » Neural Network Algorithm using unsupervised competitive learning
- » Used for organization and visualization of data
- » Neurons are arranged on a flat grid
- » No hidden layer, only input and output layer
- » Each neuron on the grid is an output neuron

Introduction [Concept]

- » Make a 2-D array and randomize it i.e. initialize weight
- » Present training data to the map and let the cells on the map compete to win(Usually Euclidean distance is used)
- » Simulate the winner i.e. updating weight matrix alongside its neighbour
- » Repeat these steps number of times
- » The final result is 2-D "weight" array

Introduction

Each Output Node is a vector of N weights



Input Layer -- Each Node a vector representing N terms.

Fig: Kohonen Network



Algorithm

- 1. Initialize weights. Set max value of R, set learning rate α
- 2. While stop condition is false repeat 3 to 8
- 3. For each input vector **x** do steps 4 to 6
- 4. For each **j** neuron, compute the Euclidean distance

$$D(j) = \sqrt{\sum_{i=1}^{n} (x_i - w_{ij})^2}$$

5. Find the index **j** such that D(j) is minimum

Algorithm

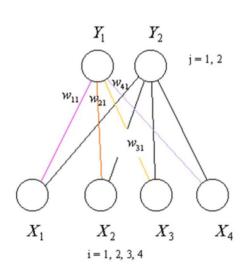
6. For all the neurons j, update the weight to the new one alongside with neighbour

$$w_{ij}(new) = w_{ij}(old) + \alpha(x_i - w_{ij}(old))$$

- 7. Update learning rate α. It is a decreasing function to limit the number of iterations
- 8. Test stop condition. Typically α so small that it is insignificant with weight update

Example[Initialize]

To make this simple, let's take a simple example with 2 neurons at output layer as shown below



Let Initial weight matrix be

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 0.2 & 0.8 \\ 0.6 & 0.4 \\ 0.5 & 0.7 \\ 0.9 & 0.3 \end{bmatrix}$$

Example[Initialize]

x1	x2	хЗ	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1

Let there be 4 input training patterns

Initial alpha be $\alpha = 0.6$

and learning rate be defined as
$$\alpha(t+1) = \frac{\alpha(t)}{2}$$

Let topological radius R = 0





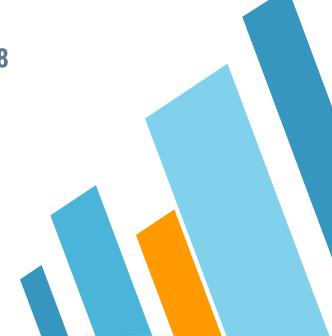
For vector <u>1100</u>(We are using Euclidean distance squared for easy mathematics)

$$D(1) = (1-0.2)^2 + (1-0.6)^2 + (0-0.5)^2 + (0-0.9)^2 = 1.86$$

$$D(2) = (1-0.8)^2 + (1-0.4)^2 + (0-0.7)^2 + (0-0.3)^2 = 0.98$$

Hence j = 2. Since R = 0, we don't consider neighbours, so we update weight for neurons.

x1	x2	х3	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1





x1	x2	х3	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1

Example[Update]

And the new updated weight matrix becomes as

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 0.2 & 0.92 \\ 0.6 & 0.76 \\ 0.5 & 0.28 \\ 0.9 & 0.12 \end{bmatrix}$$



For vector **0001**

$$D(1) = 0.66$$
, $D(2) = 2.2768$ Hence $j = 1$

$\lceil w_{11} \rceil$	w_{12}		0.08	0.92
$ w_{21} $	w_{22}		0.24 0.20	0.76
$ w_{31} $	w_{32}	_	0.20	0.28
$\lfloor w_{41} \rfloor$	w_{42}		0.96	0.12

x 1	x2	х3	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1



For vector 1000

$$D(1) = 1.8656$$
, $D(2) = 0.6768$ Hence $j = 2$

$\lceil w_{11} \rceil$	w_{12}	0.08	0.968
	w_{22}	 0.24	0.968 0.304 0.112
1	w_{32}	 0.20	0.112
$\lfloor w_{41} \rfloor$		0.96	0.048

x 1	x2	х3	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1





For vector **0011**

D(1) = 0.7056, D(2) = 2.724 Hence j = 1

$\lceil w_{11} \rceil$	w_{12}^{-}		0.032	0.968
$ w_{21} $	w_{22}		0.096 0.680	0.304
$ w_{31} $	w_{32}	_	0.680	0.112
$\lfloor w_{41} \rfloor$			[0.984]	0.048

x1	x2	х3	x4
1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1

Example[Final Stage]

Now we reduce the learning rate to $\alpha(1) = \frac{\alpha(0)}{2} = \frac{0.6}{2} = 0.3$

→ Cluster 1

After 100 iterations for all input vectors, the final weight matrix becomes

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 6.7 \times 10^{-17} & 1 \\ 2 \times 10^{-16} & 0.49 \\ 0.51 & 2.3 \times 10^{-16} \\ 1 & 1 \times 10^{-16} \end{bmatrix}$$

The matrix rounding looks like

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0.5 \\ 0.5 & 0 \\ 1 & 0 \end{bmatrix} \longrightarrow \text{Cluster 2}$$



Example[Grouping]

After we have find the weight, we calculate the cluster/group for each inputs with same Euclidean distance formula

x 1	x2	х3	х4	Cluster
1	1	0	0	2
0	0	0	1	1
1	0	0	0	2
0	0	1	1	1

Example[Testing]

Let us take a sample data **1010** and try to find out which cluster do it belong

$$D(1) = (1-0)^2 + (0-0)^2 + (1-0.5)^2 + (0-1)^2 = 2.25$$

$$D(2) = (1-1)^2 + (0-0.5)^2 + (1-0)^2 + (0-0)^2 = 1.25$$

Hence j=2 so, this test data must lie in Cluster 2

DEMO

Application

- » SOM to cluster data of IRIS Dataset
 - It is a flower dataset consisting 50
 samples from 3 species of Iris
- » Can be applied in DNA categorization
- » Can be used in OCR by clustering and verifying based on the cluster

Conclusion

- » SOM projects high-dimensional data to a 2D map
- » Projection preserves topology of data so similar data maps to nearby locations on map
- » SOM has many practical applications in pattern recognition, speech analysis, industrial and medical diagnostics, data mining
- » Large quantity of good quality representative training data required
- » Doesn't give output but cluster/group inputs



- » http://www.ai-junkie.com/ann/som/som1.html
- » [Self Organizing Map (SOM) tutorial]
 - https://www.youtube.com/watch?v=abF_FdCb50I
- » http://mnemstudio.org/neural-networks-som3.htm

THANKS!

Any questions?