High dimensional Data visualization and clustering using Self Organizing Maps

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Overview

Overview

- About Self Organizing Maps (SOMs)
- Introduction to SOMs
  - Topology
  - Basic Algorithm
- SOMTHING Application
- Benchmark Analysis

About SOMs

What are Self Organizing Maps


Dr. Teuvo Kohonen

- Invented by Dr. Teuvo Kohonen
- Unsupervised Learning Process
- Inspired by the Human Brian
- Grid of Neurons trained by Stimuli
- Visualises High Dimensional Data as a 2D Map.

"one of the most significant inventions in computational science"

(IEEE.org 2010)

Introduction

Data Types

- Input Data Entry
  - An Item of the d-Dimensional Input Data Space
  - Represented by an Input Data Vector of Size d.
- Neuron
  - A Node in a Grid connected to a specified amount of Neighbours.
  - Containing a Weight Vector of Size d.
  - Representing any point of the d-Dimensional Input Data Space.

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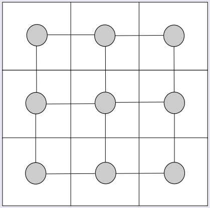
Grid Topology



Rectangular Grid

Hexagonal Grid

- Simple Implementation
- Satisfying Data Structure Preservation

- Complex Implementation
- Good Data Structure Preservation

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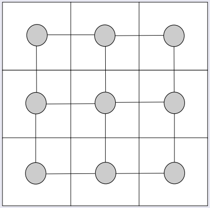
Grid Topology



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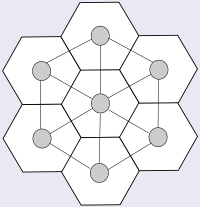

Hexagonal Grid

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- Complex Implementation
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Training

Initialisation

Step 1 Create a Grid of $n \cdot m$ Nodes (Neurons).

Step 2 Initialise Random Weight Vectors for each Neuron.

Training

Step 1 Select an Entry of the Input Data Space by Chance.

Step 2 Determine the Best Matching Unit (BMU).

Step 3 Adjust Weight Vectors of the BMU and its Neighbours inside a certain Radius r.

Step 4 Decrease the Radius r and the Learning Rate l.

Step 5 Go Back to Step 1 until Training is done.

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Example

Training Example

(a) Input Data (b) Map Training (c) Final Projection

Example

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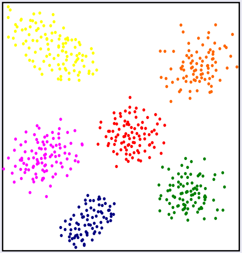

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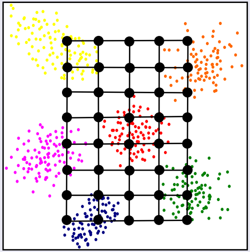
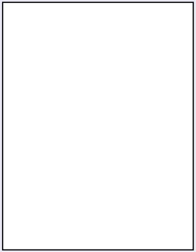


(b) Map Training



(c) Final Projection

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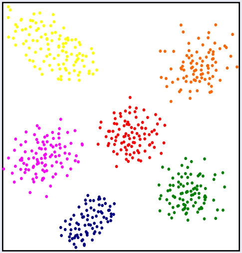

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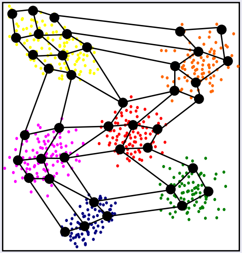

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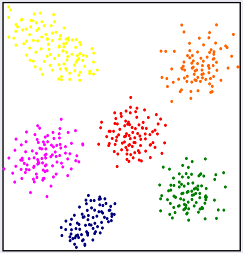

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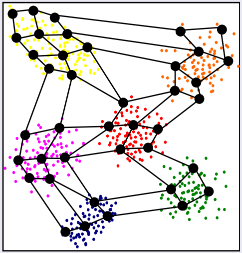

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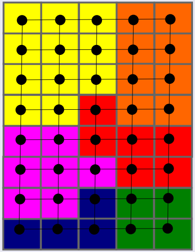

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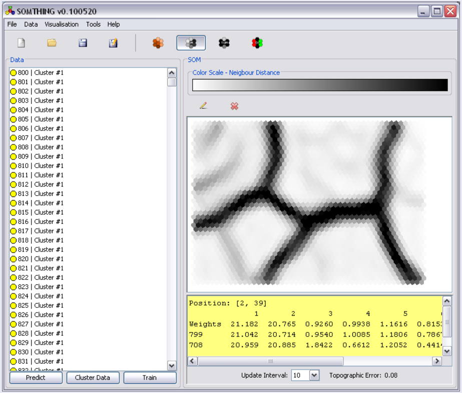
SOMTHING

SOMTHING Application



SOMTHING Application Main Window

Self
Organised
Mapping
Tool using
Hexagonal
Interlaced
Neuron
Grids

SOMTHING

Features

- SOM Visualisation Methods
  - U-Matrix
  - P-Matrix
  - U*-Matrix
  - Component Planes
  - Hit Histogram
- Clustering
  - Hierarchical Clustering
  - SOM Clustering

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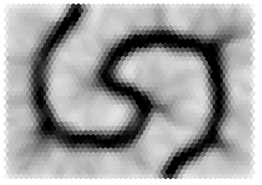
U-Matrix

U-Height = Total Euclidean Distances between a Neuron's Weight Vector to its Neighbours.



U-Matrix Visualisation

- Local Distances
- Bright Colors
  - Low U-Height
  - Similar to Neighbours
  - Cluster Centres
- Dark Colors
  - High U-Height
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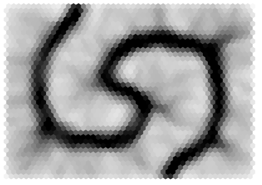

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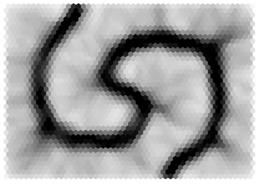

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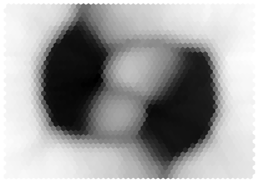

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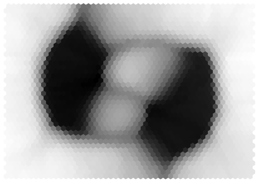

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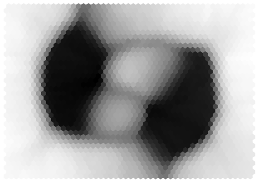

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Benchmark

Chainlink Dataset

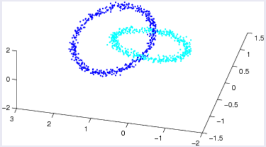


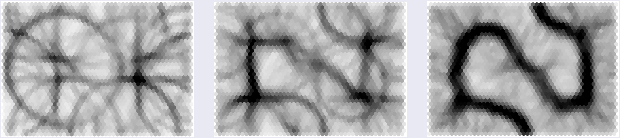
image taken from www.ifs.tuwien.ac.at

- Common Clustering Benchmark
- 2 intertwined 3D Rings
- 500 Data Points per Ring
- unsolvable with K-Means or Hierarchical Clustering

Benchmark

Learning Process

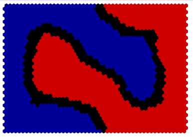
(a) Iteration 0 (b) Iteration 100 (c) Iteration 1000

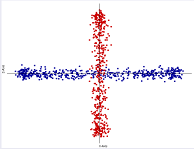


(d) Iteration 3000 (e) Iteration 4000 (f) Iteration 6000

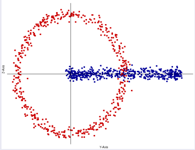
Benchmark

Results





(a) X-Z Axis



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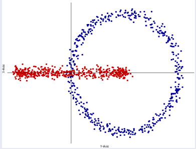


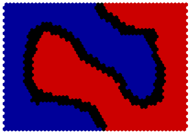
(c) Y-X Axis

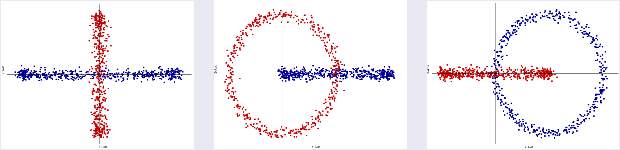
Automatic Clustering Result

Not one Sample misclassified!

Benchmark

Results





(a) X-Z Axis (b) Y-Z Axis (c) Y-X Axis

Automatic Clustering Result

Not one Sample misclassified!

Conclusion

Self Organising Maps are ...

- an unsupervised learning method
- a powerful approach to visualise very high dimensional data.
- an interesting alternative to usual Clustering Methods.

Questions?