



HAIS 2010: 5<sup>th</sup> International Conference on Hybrid Artificial Intelligence Systems

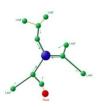
Authors Juan F. De Paz, Sara Rodríguez, Ana Gil, Juan M. Corchado and Pastora Vega





#### Contents

- Introduction
- Clustering techniques
- ESODTNN (Enhanced Self Organized Dynamic Tree Neural Network)
- Results
- Conclusions







#### Introduction

- Methods
  - Minimizing objective functions, Hierarchical, probabilistic-based models, Artificial Neural Network
- Establish the number of clusters beforehand or set the number once the algorithm has been completed
- The networks typically require a previous adaptation phase for the neurons.
- Enhanced Self Organized Dynamic Tree neural network (ESODTNN)
  - Eliminates the expansion phase
  - Uses algorithms to detect low density zones and graph theory procedures in order to establish a connection between elements.
  - Allows to revise the clustering process using hierarchical methods





#### Clustering techniques

- Hierarchical methods such as dendrograms do not require a number of clusters up front since they use a graphical representation to determine the number.
- Partition based methods:
  - Number of clusters up front.
    - The k-means algorithm presents problems with atypical points.
    - The PAM method resolves this problem by assigning an existing element as the centroid





#### Clustering techniques

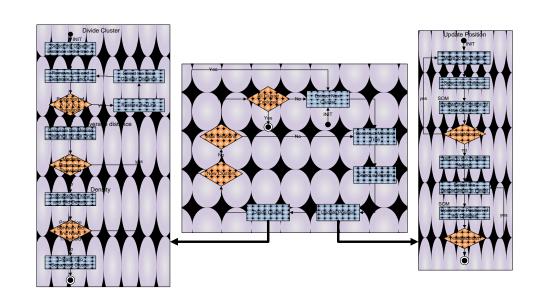
- Neural network based on mesh. Options
  - Self-organized Kohonen maps (SOM)
  - Neural Gas (NG)
  - Growing Cell Structure (GCS). The degree of proximity are set beforehand.
  - Enhanced self-organizing incremental neural network (ESOINN) doesn't establish the degree of proximity
- It is necessary to adjust the neurons to the surface for the data that needs to be grouped





- Interconnection Algorithm
- Update Algorithm
  - Neighbour Function
  - SOM
- Division algorithm
  - Average distance
  - Density

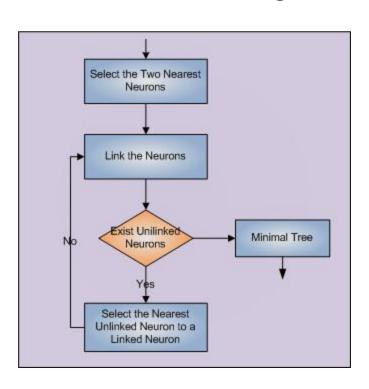
the ESODTNN does not distinguish between the original data and the neurons—during the initial training phase. It eliminates the expansion phase for a NG to adjust to the surface.

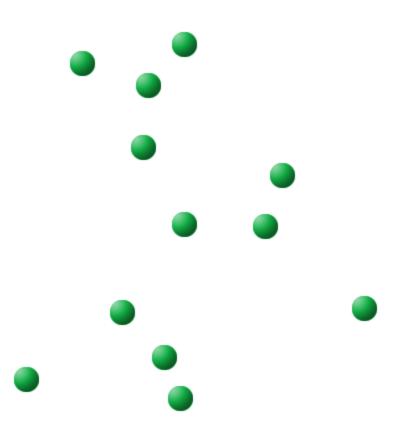






Interconnection Algorithm







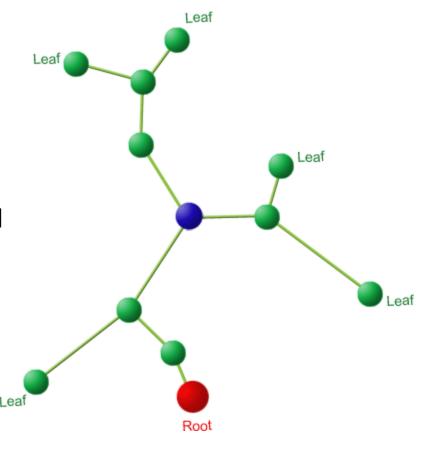


- Density
  - Distance from tree  $f^A(C,D) = \sum_{i,j} d_{ij}$  where  $c_{ij} = 1$ ,  $c_{ij} \in C$ ,  $d_{ij} \in D$
  - Distance between neurons in the tree  $f^T(D) = \sum_{i,j} d_{ij}, d_{ij} \in D$
  - Calculate the final density  $f^{D}(C,D) = f^{T}(D)/f^{A}(C,D)$ 
    - D is the distance matrix
    - C is the interconnection matrix





- Average distance
  - Select the origin neuron
  - Select the neuron that connects with the neuron in a certain range
  - The average distance is calculated based on the connections

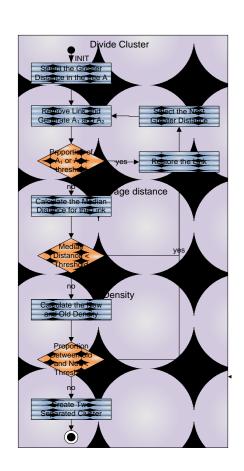






- Division algorithm
  - Select the greatest distance I
  - Remove the connection
  - If the proportion of elements for each subtree is greater than the threshold, continue
  - Calculate the average distance from the node for the tree
  - Determine if the distance from tree node and its parent is less than the average distance
  - Calculate the density of the previous tree and new trees
  - Re-establish the connection with its parent node if

$$\delta(t)/\delta(t+1) < 1/(\delta(0)/\delta(1) \cdot \rho)$$





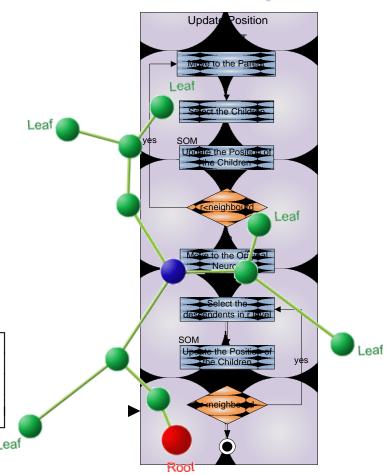


- Update Algorithm
  - Select the subtree to modify
  - The neighbouring is associated with the hierarchical in the tree
  - The magnitude of the update depends on the hierarchical and the distance

$$x_j(t+1) = x_j(t) + \eta(t) \cdot g(i,t) \cdot (x_s(t) - x_j(t))$$

$$g(i,t) = Exp \left[ -\frac{i}{N} \frac{\sqrt{(x_{j1} - x_{s1})^{2} + \dots + (x_{jn} - n_{sn})^{2}}}{\max_{i,j} \{d_{ij}\}} - \lambda \frac{i \cdot t}{\beta N} \right]$$

$$\eta(t) = Exp \left| -4 \sqrt{\frac{t}{\beta N}} \right|$$



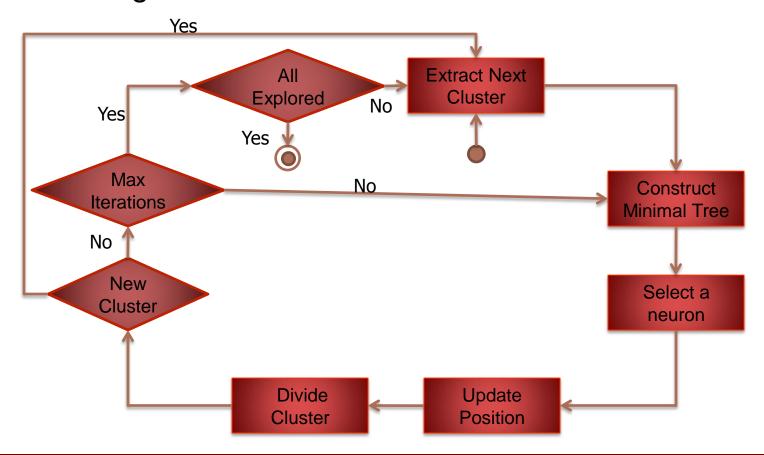


12



# ESODTNN (Enhanced Self Organized Dynamic Tree Neural Network)

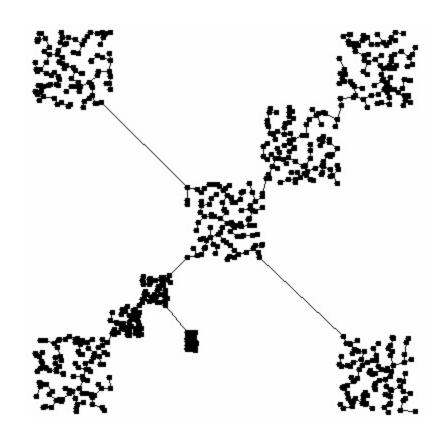
Cluster Algorithm



Introduction Clustering techniques ESODTNN Results & Conclusions



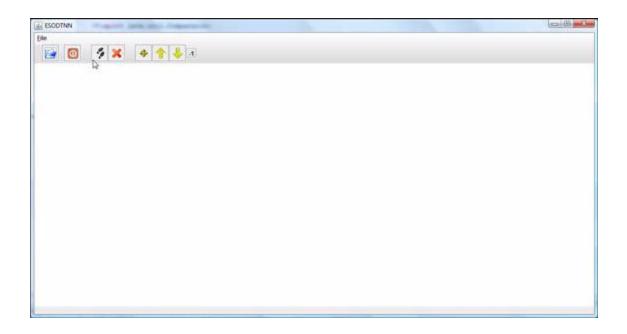




Introduction Clustering techniques ESODTNN Results & Conclusions





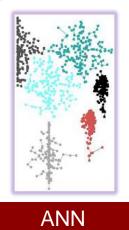


Introduction Clustering techniques ESODTNN Results & Conclusions



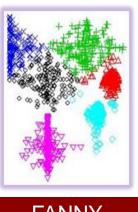


#### Results





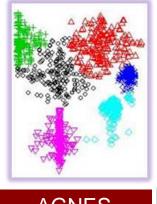


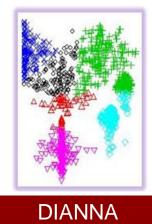


PAM

Dendrogram

**FANNY** 







**AGNES** 

**CLARA** 

Introduction

**Clustering techniques** 

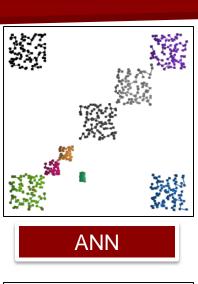
**ESODTNN** 

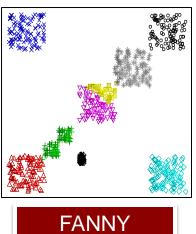
**Results & Conclusions** 

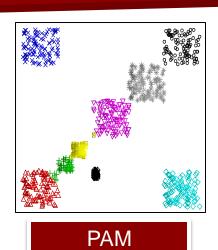


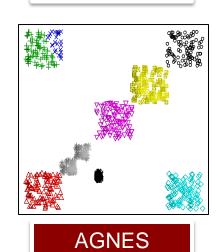


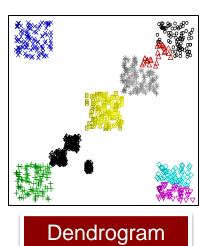
#### Results

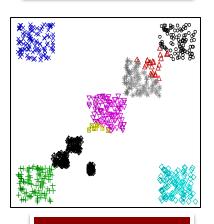












DIANNA





#### Results

- UC Irvine Machine Learning Repository. Wine
  - ESODTNN: 91,01%
  - PAM: 90,45%
  - Dendrogram: 93,26%
  - Agnes: 33.71%
  - Diana: 71.35%

17





#### Conclusions

- The neural network is more adept at detecting the different forms.
- It eliminates the expansion phase
- We have detected several deficiencies in the case of elements that are distributed along very close parallel lines.
- Occasionally, the ESODTNN is incapable of calculating the correct cut-off point for dividing clusters and the results must be interpreted according to the distances from the cut-off points and the changes in density.





HAIS 2010: 5<sup>th</sup> International Conference on Hybrid Artificial Intelligence Systems

Authors Juan F. De Paz, Sara Rodríguez, Ana Gil, Juan M. Corchado and Pastora Vega