Neural networks for variable star classification

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- Supervised classification

Multi-Layer Perceptron (MLP)
"Neural Networks for Pattern Recognition" by C. Bishop

- Unsupervised learning and detection

Self-Organizing Map (SOM)
"Self-organizing maps" by T. Kohonen

- Bayesian methods for learning algorithms

"Information Theory, Inference and Learning Algorithms"
by D. MacKay

Multi-Layered Perceptrons for supervised classification

• **Training set** - a library of classified lightcurves.
datasets from Hipparcos, OGLE etc
Archive integration

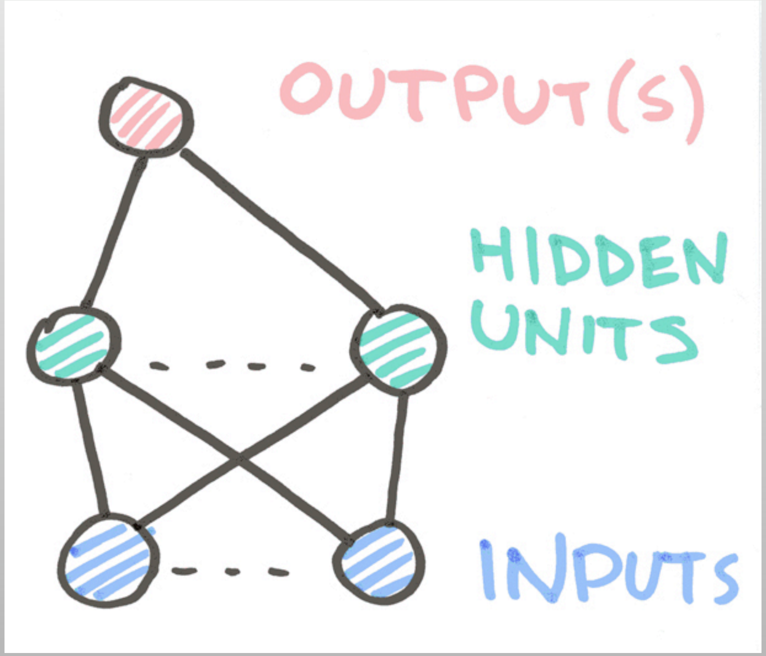
• **Feature extraction** - lightcurves need to be parameterized
Tools for spectral analysis of sparsely sampled data

• **P(C|x)** - probability that the variability class is *C* given measured features *x*
Find **P(C|x)** - nonlinear function in many dimensions
Neural Networks can approximate this mapping

Multi-Layered Perceptrons for supervised classification

Feed Forward Networks

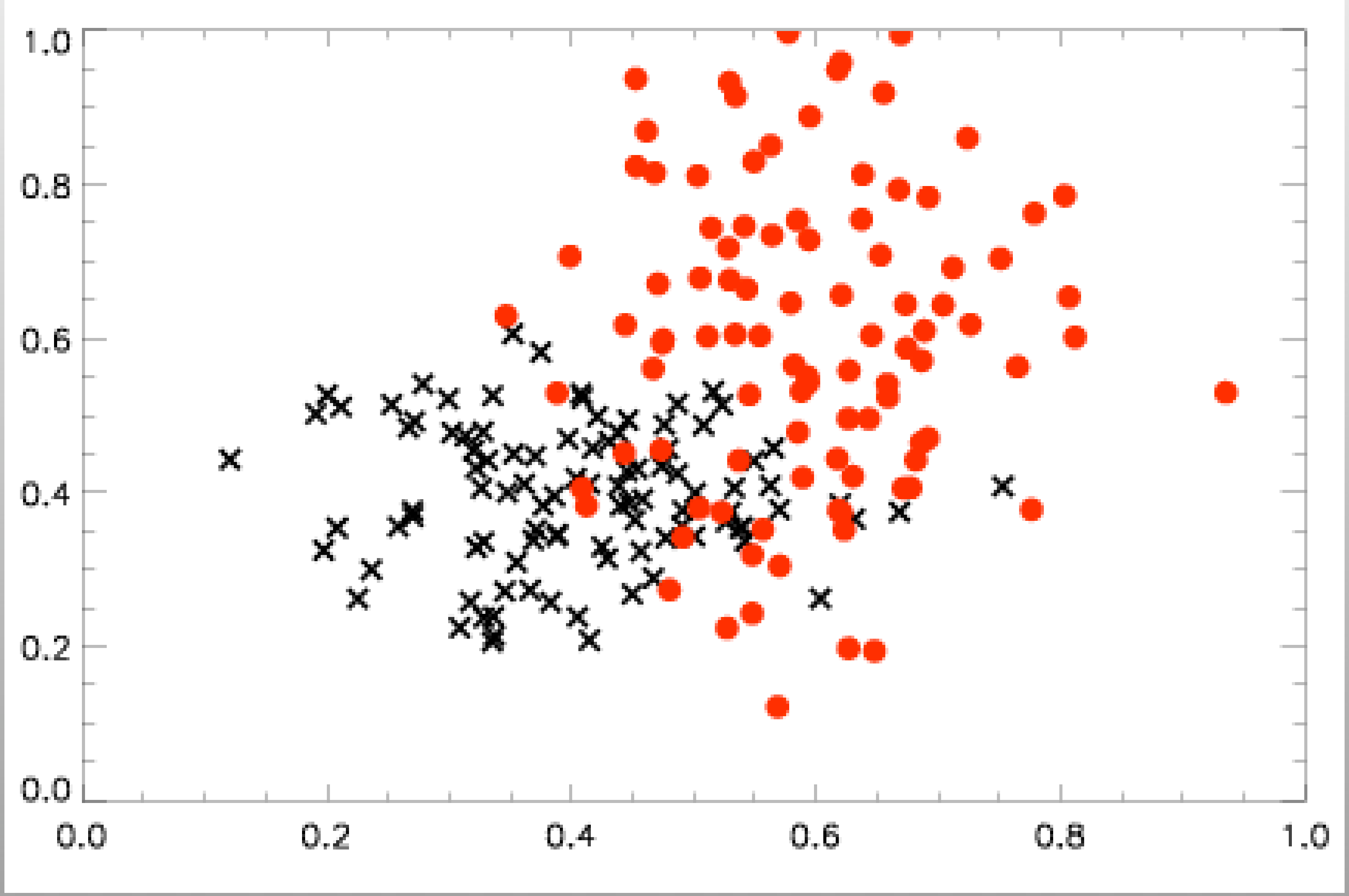
- Each connection has a *weight* assigned
- Network can have several *layers* of hidden (processing) units (neurons)
- Each neuron receives a *weighted sum* of values from the lower layer
- Each neuron then sends this linear sum transformed with a nonlinear *activation function*
- The output is calculated and can be compared to the *target*



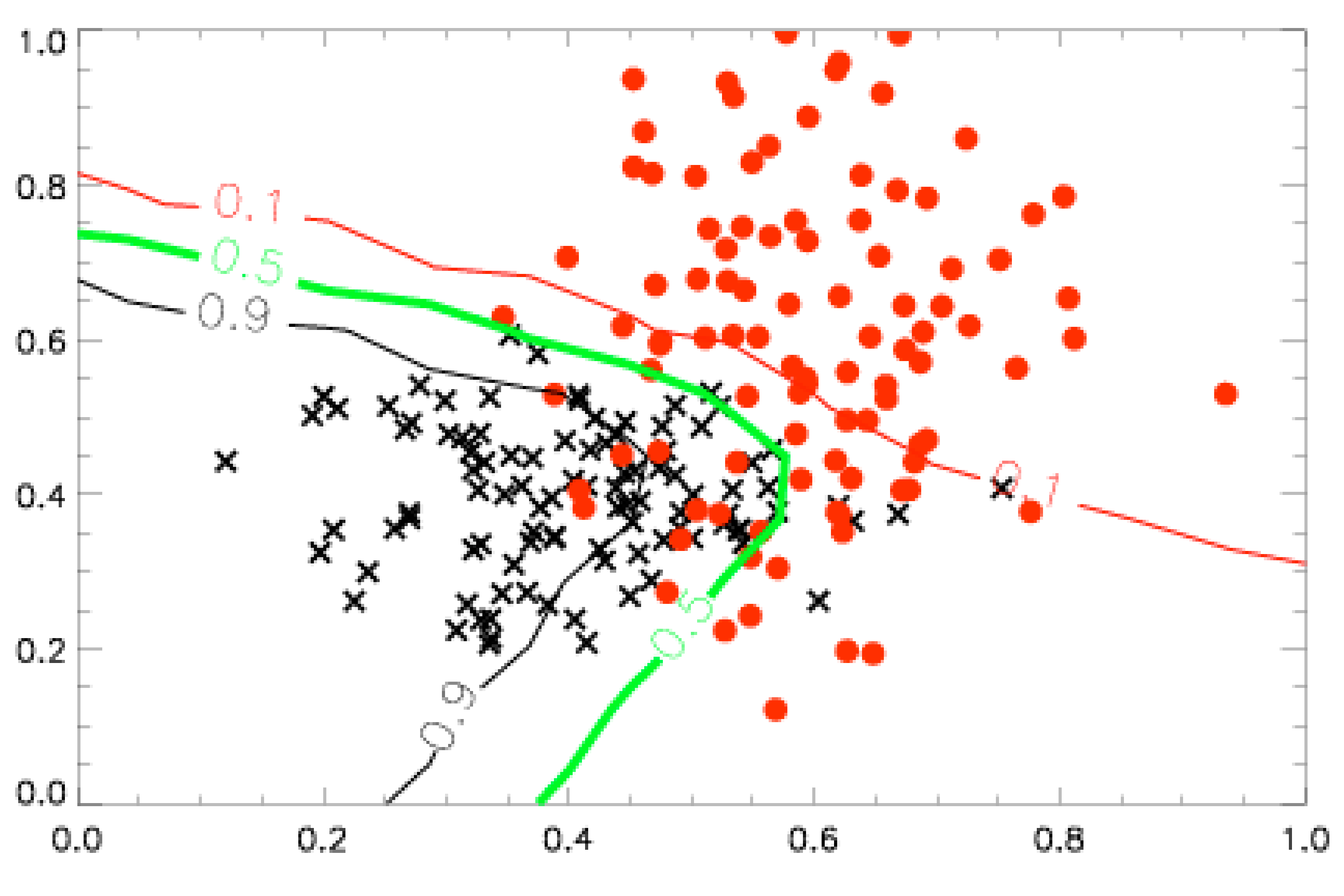
Error back-propagation

- *Error function* quantifies the difference between output and target
- Derivatives (with respect to the weights) of the error function are calculated by propagating the 'errors' from higher layers

Multi-Layered Perceptrons for supervised classification



Multi-Layered Perceptrons for supervised classification

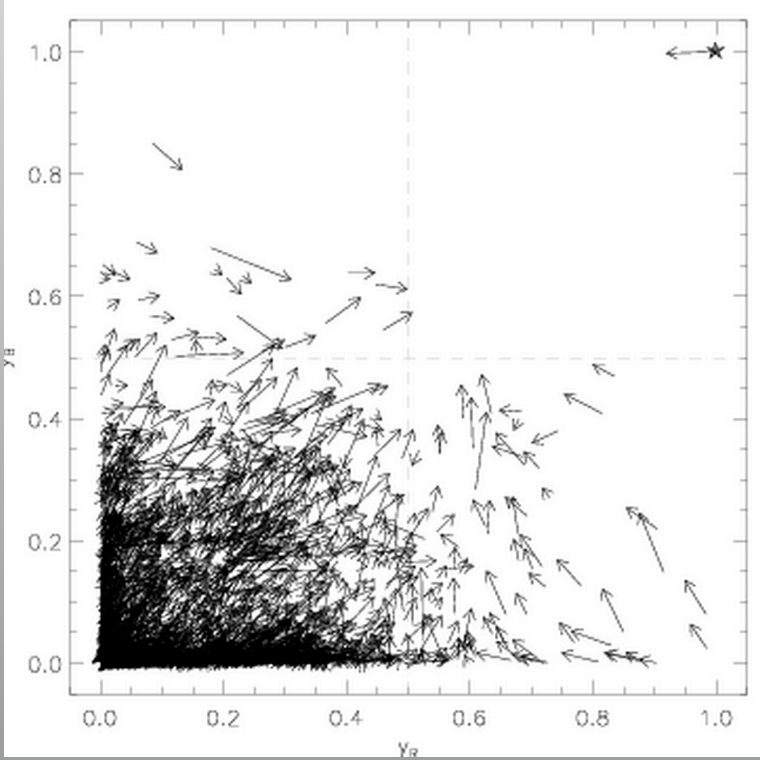


Stuttgart Neural Network Simulator

Multi-Layered Perceptrons for supervised classification

Advantages

- Distribituted processing of all available information
- Approximates complicated decision boundaries in many dimensions
- Novelty detection



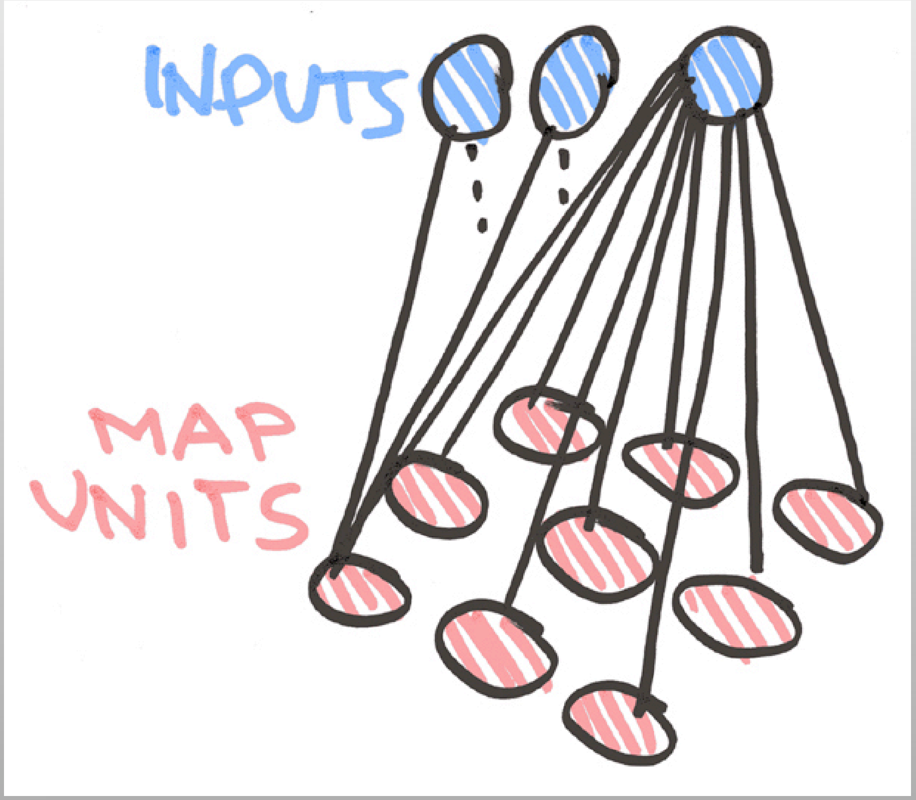
Example

- MACHO LMC data
- **5** inputs (extracted from each lightcurve)
- Identifies **1** microlensing event in the tile of **2500** lightcurves

Belokurov, Evans & Le Du 2003

Unsupervised learning with Self-Organizing Maps

Desirables
- Visualize data in more than **3** dimensions
- Preserve the topology



SOM
- The weights of each map node define a *reference vector* of the same dimensionality as the input

- The node with the smallest Euclidean distance between its reference vector and the input defines *response* of the map to the input

Unsupervised learning with Self-Organizing Maps

Learning

1. Find the *winner*
2. Update the winner to minimize the distance
3. Allow nodes in the vicinity of the winner to be updated as well (defined by the *neighborhood kernel*)
4. Kernel monotonically decreases with time

Quality of learning

- Quantization error
- Distortion measure

Calibration

Set reference points with manually analyzed data

Unsupervised learning with Self-Organizing Maps

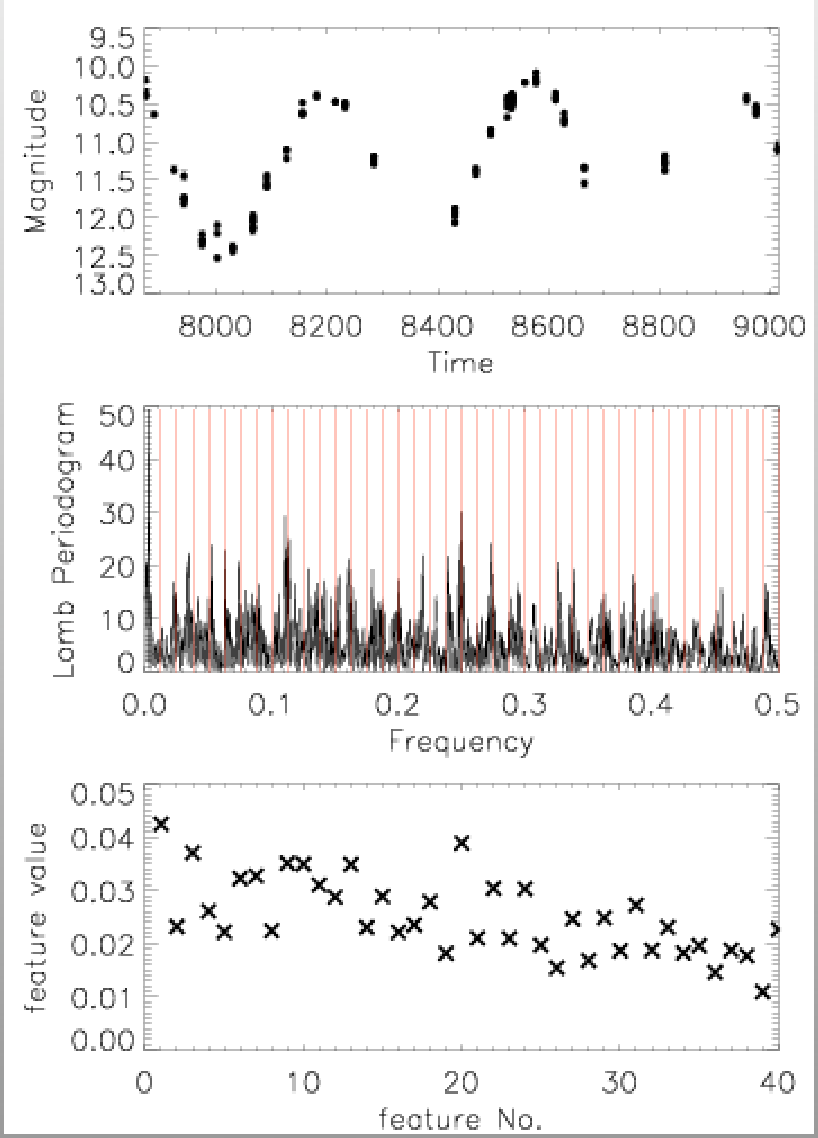
Example - Hipparcos Variables

52 input features in total

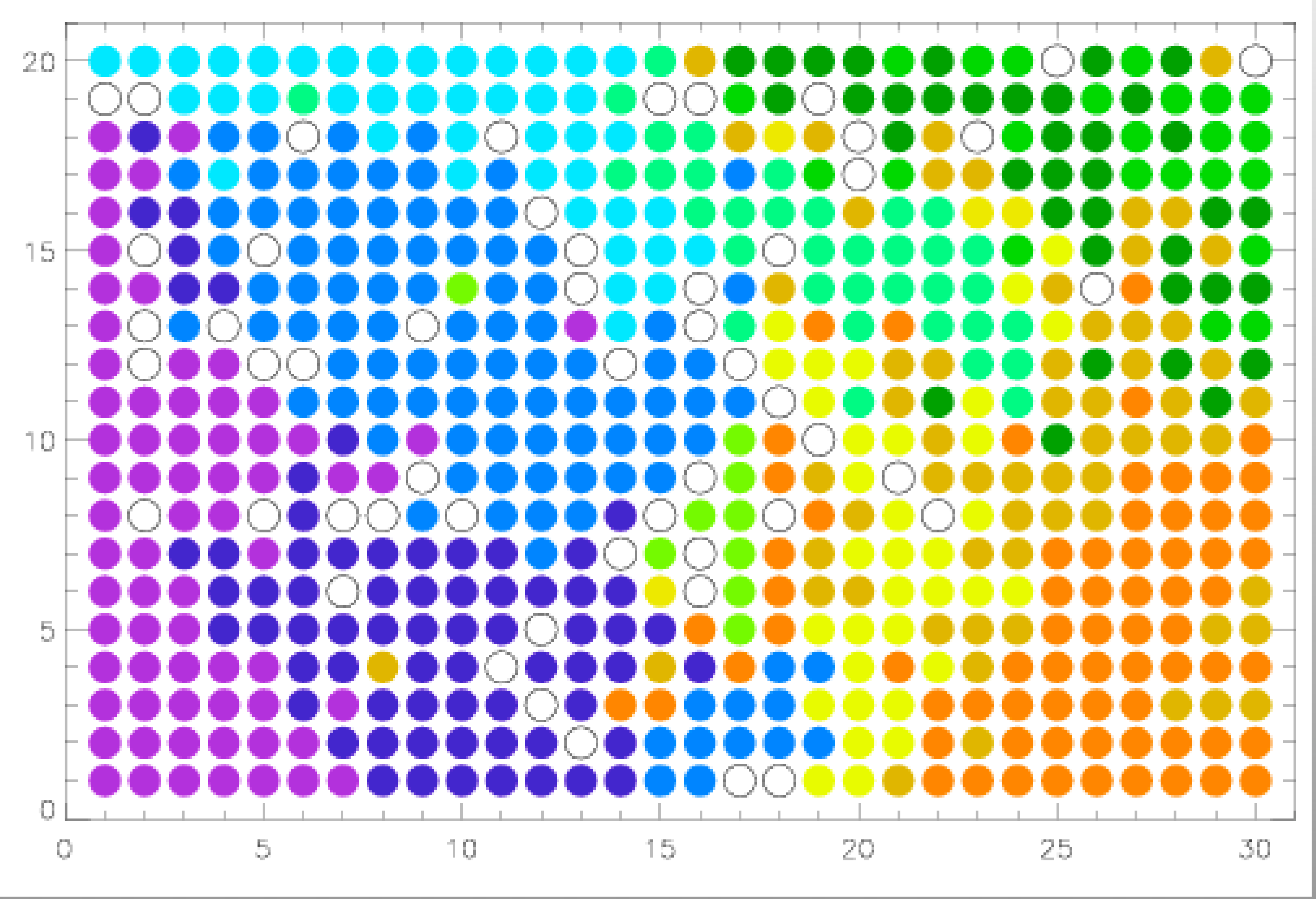
- Lomb Periodogram integrated in 40 bins and normalized
- 5,15,25,35,45,55,65,75,85,95 percentiles with median magnitude subtracted
- Ratio of magnitude above/below median
- V-I
- Color evolution?...

Dataset - more than **2500** 'solved' Hipparcos variables

Software - SOM_PAK (free)

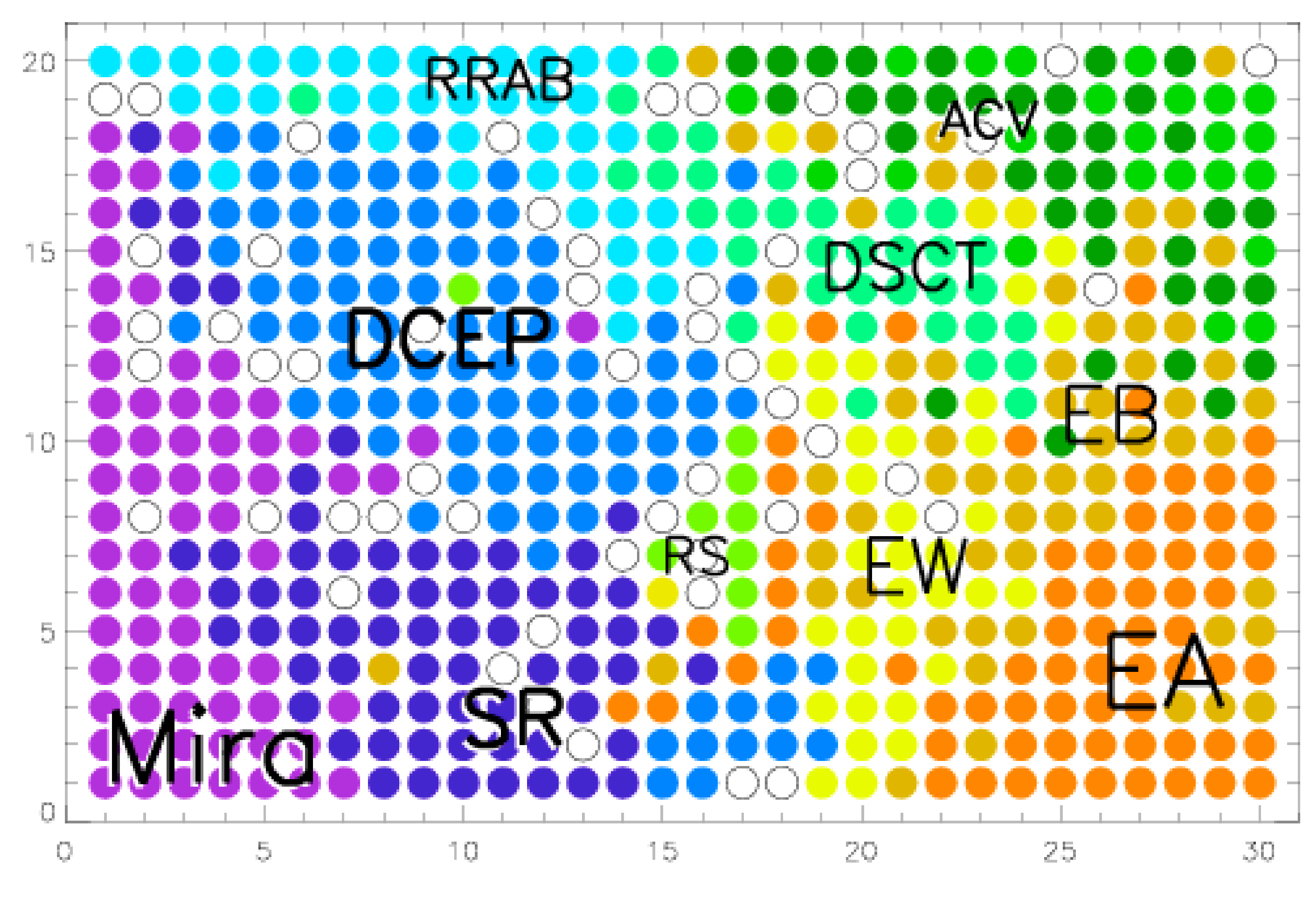


Unsupervised learning with Self-Organizing Maps



GAIA Science Alerts & Variable Star WGs

Unsupervised learning with Self-Organizing Maps



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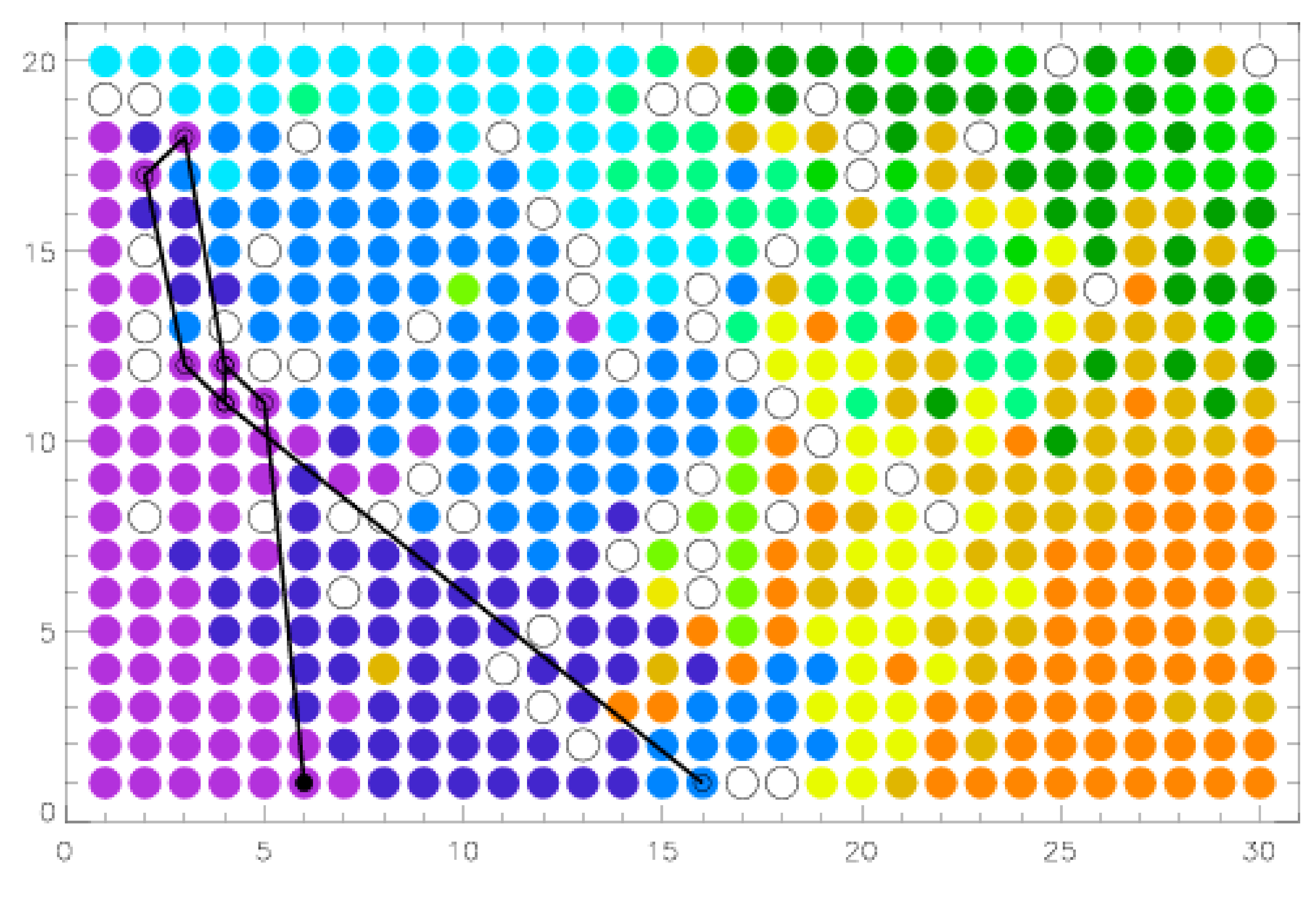
Unsupervised learning with Self-Organizing Maps



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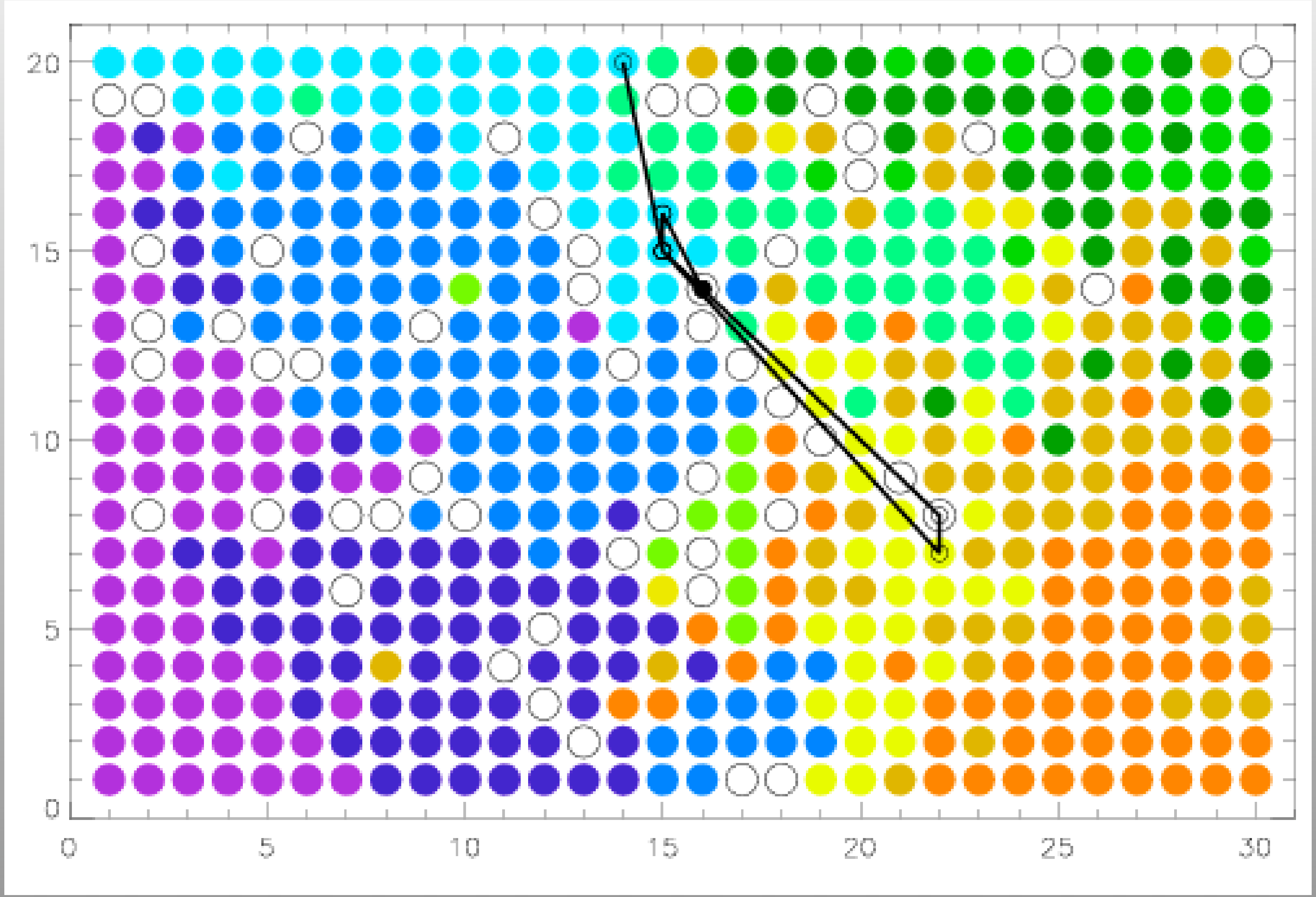

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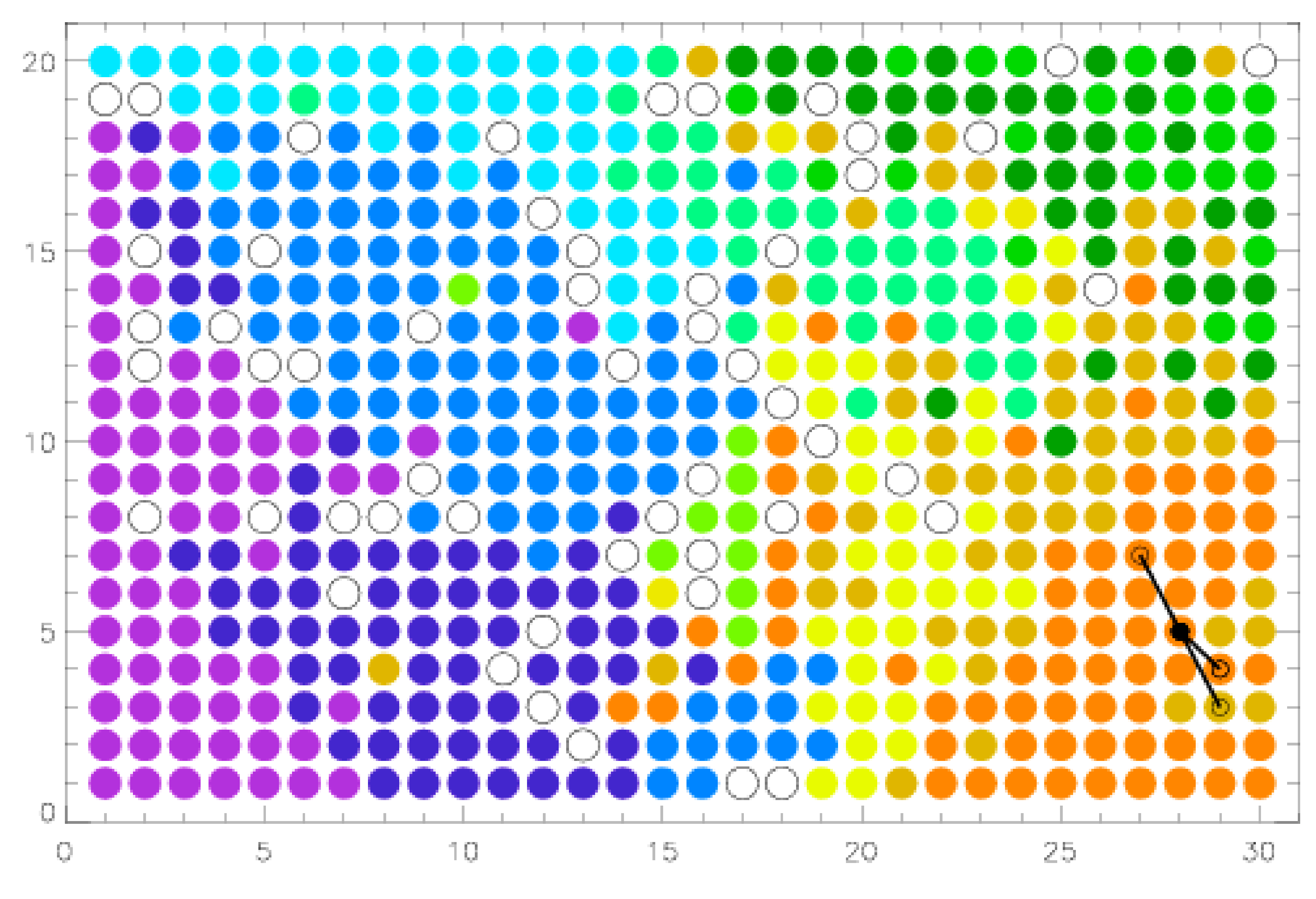

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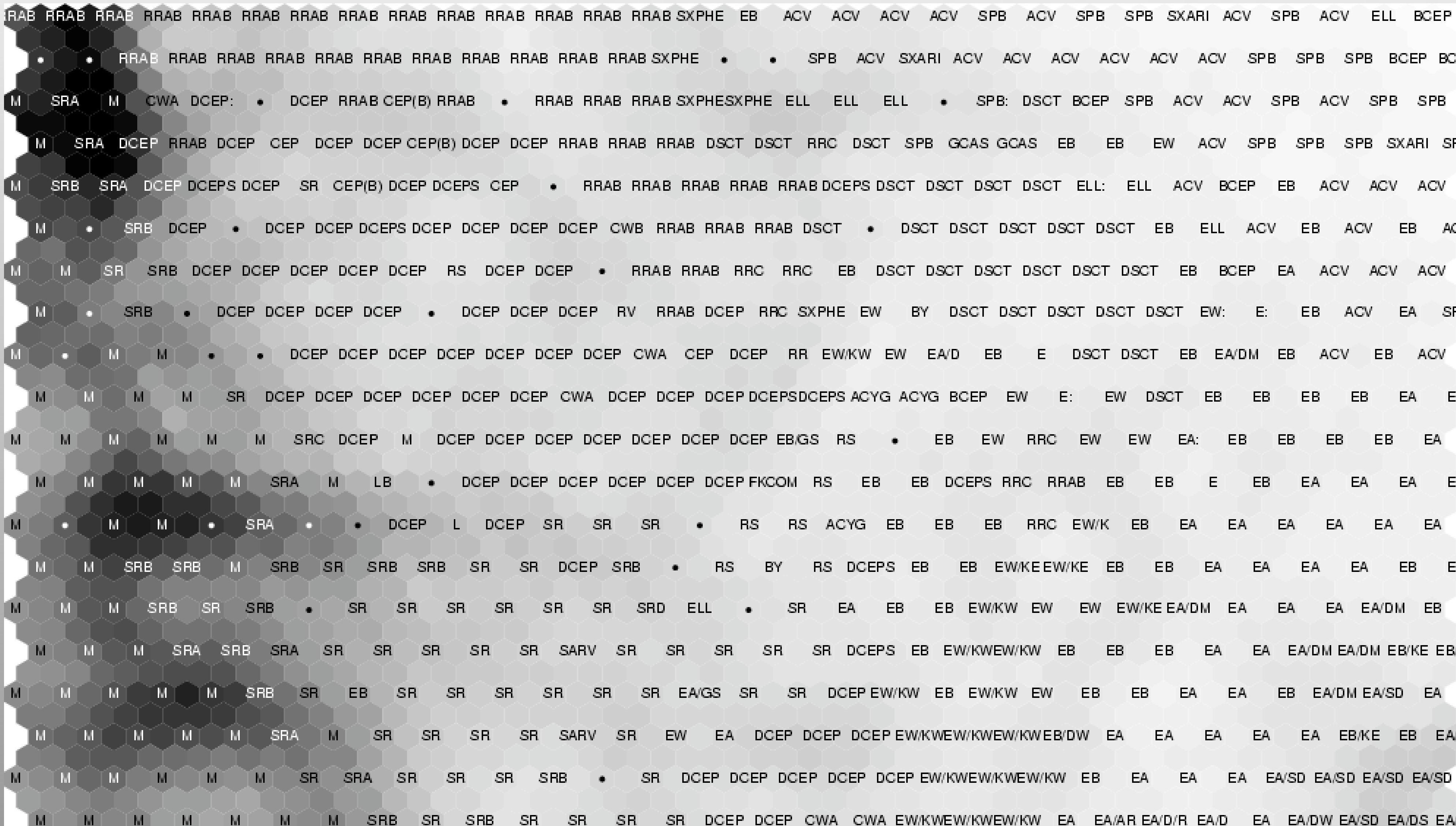

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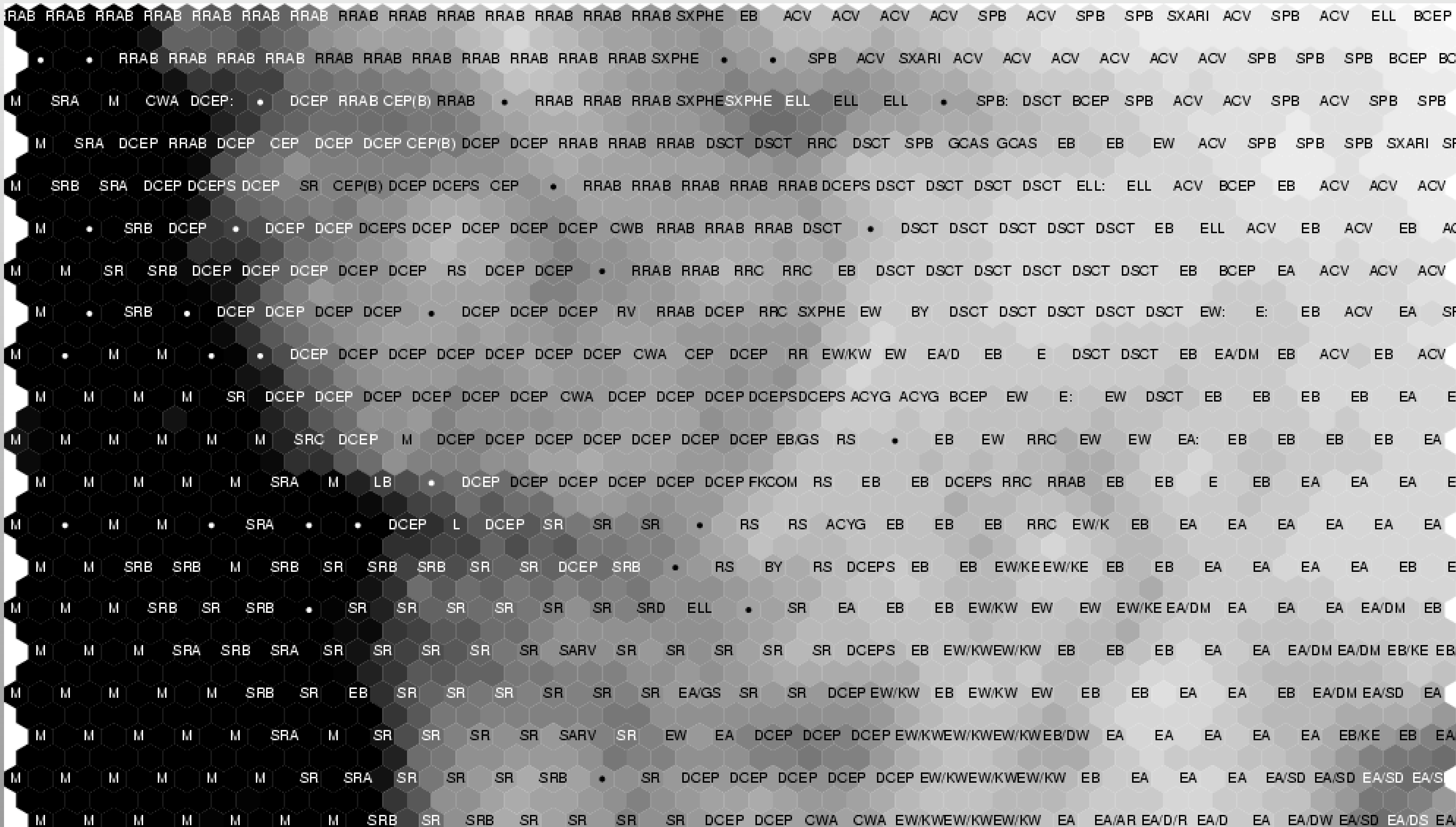

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Unsupervised learning with Self-Organizing Maps

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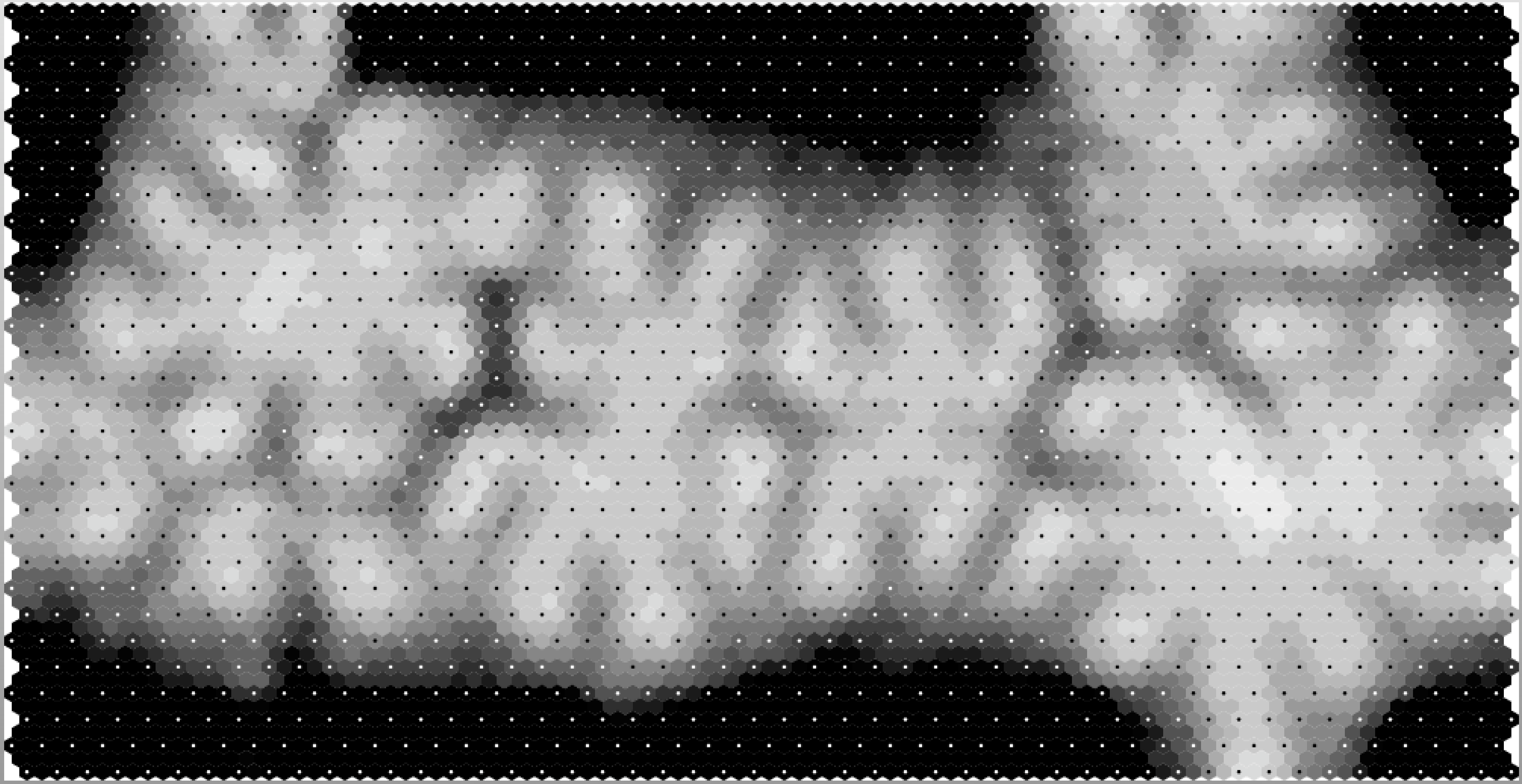
Unsupervised learning with Self-Organizing Maps

50000 variables in the POINT-AGAPE dataset



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Unsupervised learning with Self-Organizing Maps

Strategy 1
Train the map with the whole dataset available
Calibrate with known (archived) variables
Strategy 2
Train the map only with known variables
For each new lightcurve find the location on the map
Science Alerts
Novelty detection - the black spots and walls - regions with low reference vector density

Numbers on the x and y-axis do **NOT** carry any (usual) meaning. However, SOMs can be used for feature extraction and then the (x,y) positions on the map can be analysed with MLPs.