

# Application of self-organizing maps in astroinformatics

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## Abstract

*The astronomy is source of big amount of data with possibility to be effectively examined by computer. For this purpose we focused on the machine learning algorithm called self-organizing maps and its use on big astronomical data. For scaling of algorithm we used well known data sets from the UCI repository and then concerned ourselves particularly with the classification of stars based on their spectral characteristics.*

*The self-organizing maps are excellent tool for clustering data in a new way. The unsupervised learning paradigm enabled us to find the groups of self-similar outliers and hidden patterns in data, hardly possible to find by eye. The algorithm shows very promising results.*

**Application of Self-Organizing Maps in Astroinformatics**

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**Problem domain**

- Clustering of stellar spectra
- Data mining
- Self-organizing maps.

**Self-organizing maps**


- Similar to real brain
- Unsupervised learning paradigm
- Self-organization

**Usage**

- Pattern recognition (sounds, photos, countries, ...)
- Reduction of dimensionality
- Visualization for high-dimensional data
- Topological ordering of data space (clustering)

**Usage**

5x5 SOM clustering results



**Topology of the map**

- Input layer
- Grid of neurons
- Connection weights

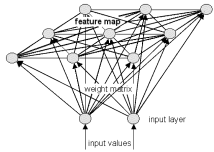


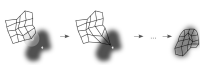
Figure: Topology of SOM

**Algorithm**

- Random initialization of weights
- Selection of random vector
- Finding of best matching unit
- Counting of neighborhood radius
- Actualization of weight to better fit to input vector

$$W_{ij}(t) = W_{ij}(t+1) + \Theta(t, i)\mathcal{L}(t)(V_j(t) - W_{ij}(t))$$

- Choose another random vector



**Data**

- Spectra of Be and normal stars from archive of the Astronomical Institute of the Academy of Sciences of the Czech Republic in Ondřejov
- Four shape depended classes
- Special class containing outliers

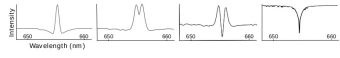


Figure: Characteristic shapes of spectra.

Application

- Wrapped more implementations together
- Sequential reading of files
- Also special boosting methods (probing algorithm)
- Parallelization (10 threads, 8x) , MapReduce, GPU

	learning rate function	time [s]
<b>Rapid Miner</b>	linear	215
<b>WEKA</b>	linear	202
<b>SOM_PAK</b>	inverse time	116
<b>SOM_PAK</b>	linear	103
<b>Our Implementation</b>	exponential	68

Table: Time comparison

Application

Figure: Association matrix of Iris data set after using exponential learning rate function.

Application

Figure: Association matrix of Iris data set after using linear learning rate function.

Application

Figure: Association matrix of Iris data set after using inverse time learning rate function.

Application

	learning rate function	q.err (iris)	q.err (stellar spectra)
<b>SOM_PAK</b>	inverse time	0.035	104.19
<b>SOM_PAK</b>	linear	0.018	86.92
<b>Our Implem.</b>	exponential	0.005	7.78

Table: Time comparison of implementations

Clustering of outliers

Figure: Four main clusters of outliers.

Clustering of outliers

Visualizations

