Abstract No Th K 14

A Comparison of Machine Learning Processes for Classification of Rock Units Using Well Log Data

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[1] Observatório Nacional

Changing seasons

Varvite (Itu - São Paulo)

Introduction

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- Classification techniques uses distances attributes (Michel and Deza, 2016).
- Euclidean classifier calculates a centroid in the space of attributes.
- Mahalanobis classifier takes into consideration the shape of attributes space.
- A Self Organizing Map (SOM) is inspired by neural cortex (Kohonen, 1989) and based oriented graph (Haykin, 1999) working as an interconnected network.

Objective

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- Creat synthetic well log data from a model basin;
- Compare the results for the three explored methods, Kohonen (SOM), an euclidean and a mahalanobean classifiers

Methodology

Compare the results

Uses C1 and C2 to make predictions using SOM and the classifiers

Uses T1 well data to train the Kohonen (SOM) and make the statistical of classifiers

Generates the hypothesis model

Synthetic Sedimentary Basin

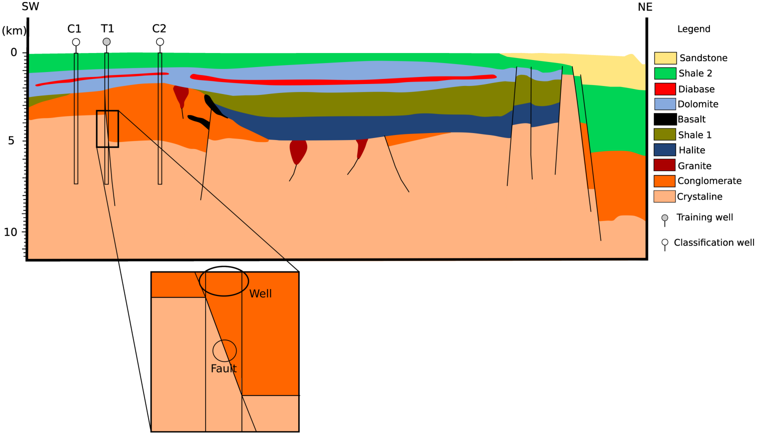


Figure : Synthetic Sedimentary Basin by Mohriak et al. (2008) T1, C1 and C2 are training and classifing wells respectively.

Synthetic Sedimentary Basin

Table : Physical properties and rock types.

Rock	Density (g/cm^3)	Gamma ray (Ci/g)	Resistivity ($\Omega.m$)	Velocity (Km/s)
Conglomerate	2.30	100.0	6000	2
Shale	2.55	100.0	1000	3
Dolomite	2.72	8.30	3.5×10^3	6
Diabase	2.91	30.0	15×10^7	5.5
Crystalline	2.80	0.7	1.3×10^6	5

- The sample rate for the well data is 0.01 observation/meter with contamination of 5% Gaussian noise.

Training and Similarities

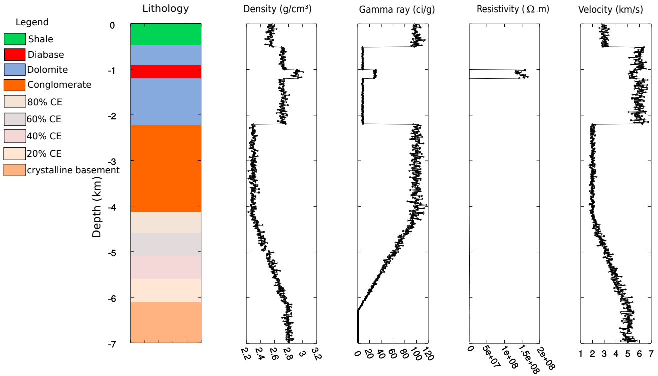
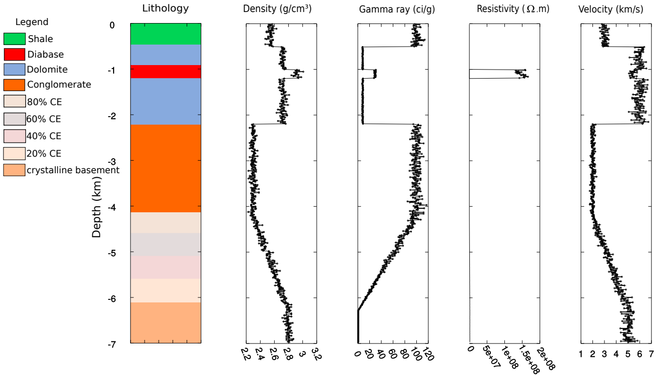


Figure : Synthetic training well T1.

Training and Similarities



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- Four divisions describes the normal fault by decreasing the amount of conglomerate in comparison to crystalline basement.

Training and Similarities

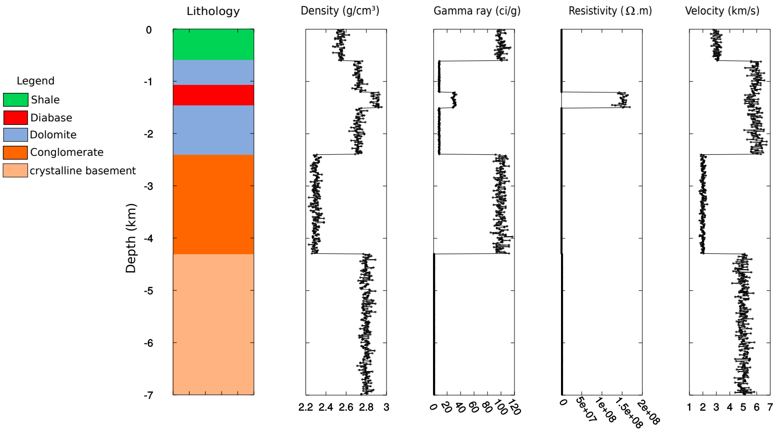

Figure : Classification well C1

Training and Similarities

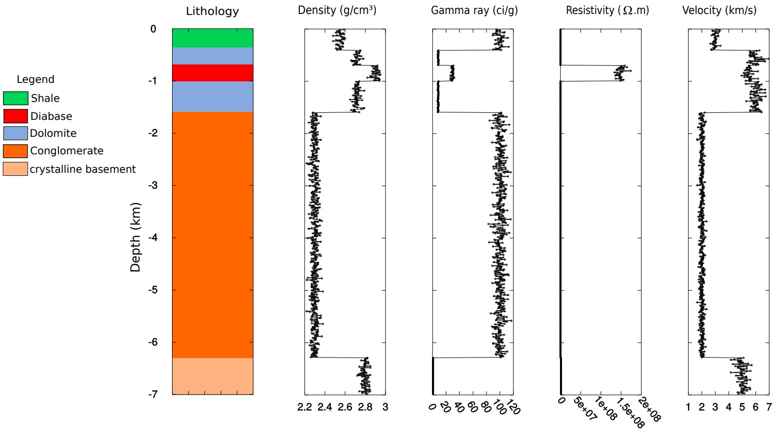

Figure : Classification well C2

Euclidean Classifier

Definition

$$Ed_i = \|\mathbf{X} - \bar{\mathbf{X}}_i\|_2$$

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$\mathbf{X}$, input vector

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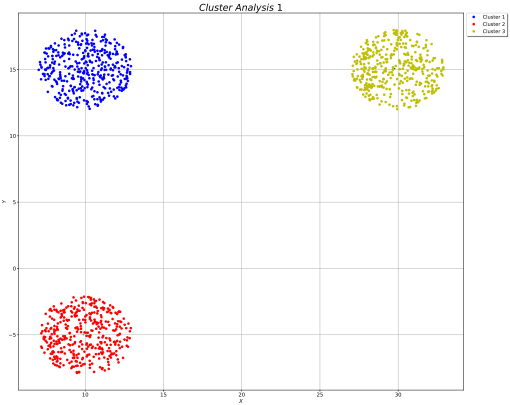
Euclidean Classifier



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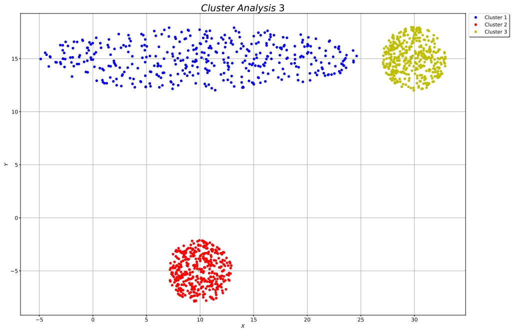

Mahalanobis Classifier

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$$Md_i = \|(\mathbf{X} - \bar{\mathbf{X}}_i)^T \mathbf{C}_i^{-1} (\mathbf{X} - \bar{\mathbf{X}}_i)\|_2$$

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$\mathbf{X}$, input vector

$\bar{\mathbf{X}}_i$, mean vector

$\mathbf{C}_i$, covariance matrix

Mahalanobis Classifier

$$\mathbf{C}_i = \frac{1}{n_i - 1} \sum_{X \in \omega_i} (\mathbf{X} - \bar{\mathbf{X}}_i)(\mathbf{X} - \bar{\mathbf{X}}_i)^T \tag{1}$$

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n_i , number of elements

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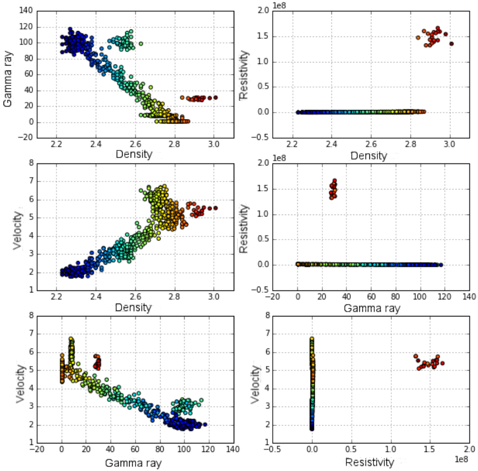
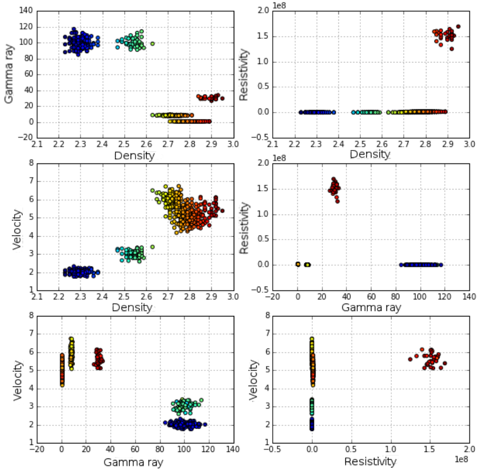
n_i , number of elements

ω_i , space of attributes

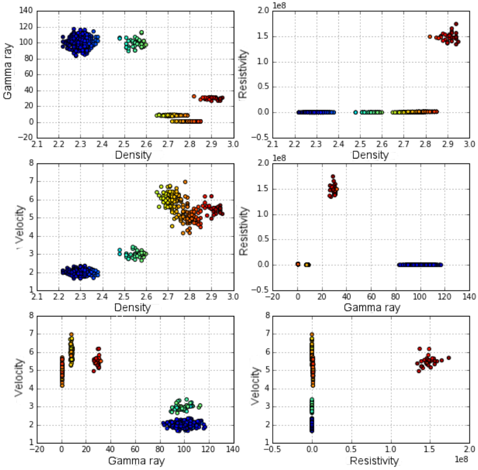
Clusters and Space of Attributes - T1 well



Clusters and Space of Attributes - C1 well

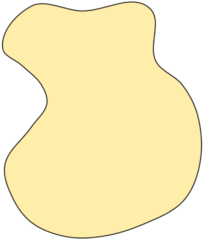


Clusters and Space of Attributes - C2 well



Kohonen - SOM

Multi-dimension space of
properties
(input)



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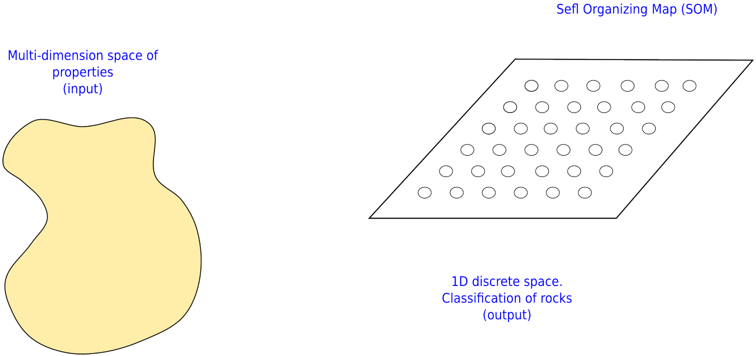
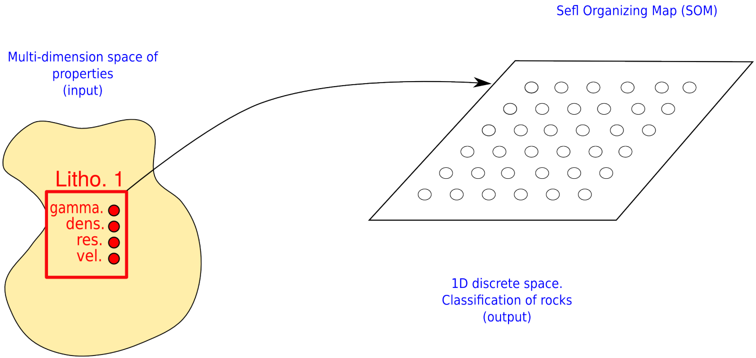

Sefl Organizing Map (SOM)
Multi-dimension space of properties (input)
1D discrete space. Classification of rocks (output)

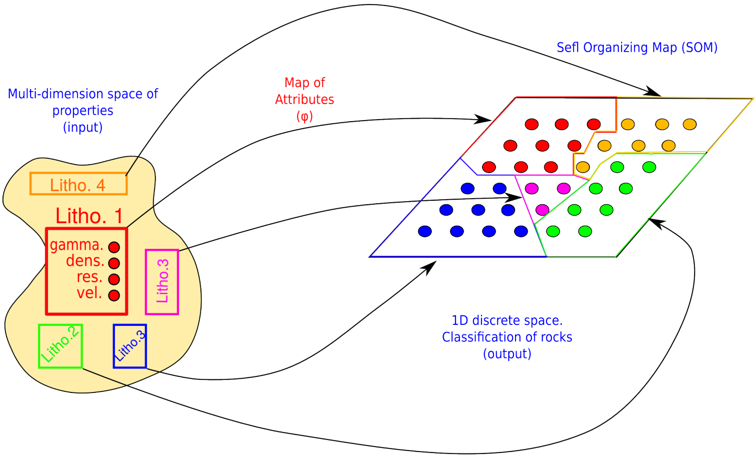
Kohonen - SOM



Lithology = F(gamma.,dens., res., vel.)

Kohonen - SOM

Training



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$$j = 1, 2, 3, \ldots, l$$

Kohonen - SOM

Cooperation and winner neuron

$$i(\mathbf{x}) = argmin_j \parallel \mathbf{x} - \mathbf{w}_j \parallel_2$$

i(t) distance or identity of a neuron i

Kohonen - SOM

Synaptic adaption or Training process

Definition

$$w_{i,j}(t+1) = w_{i,j}(t) + \eta(t)[x(t) - w_{i,j}(t)]$$

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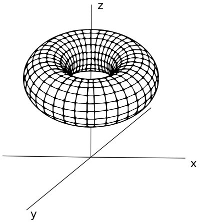
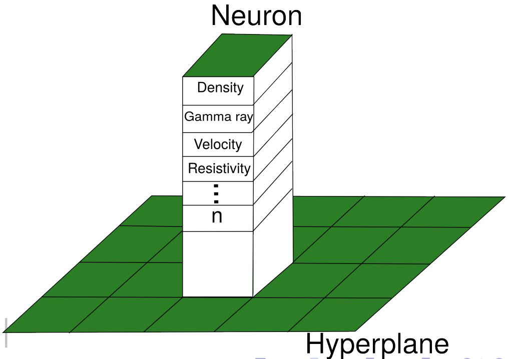
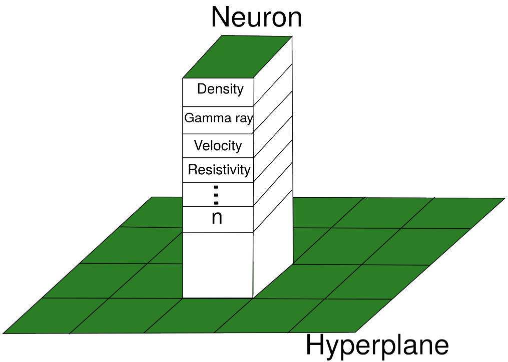
t , number of iteractions

The geometry





Winner neuron and neighborhood



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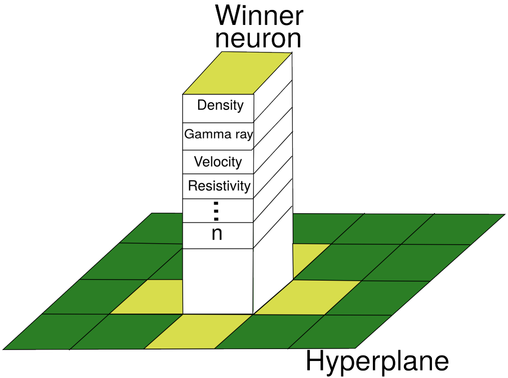
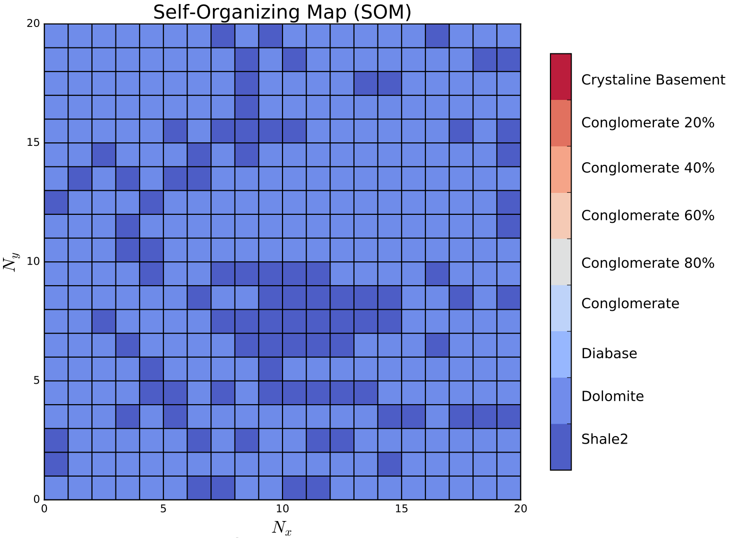


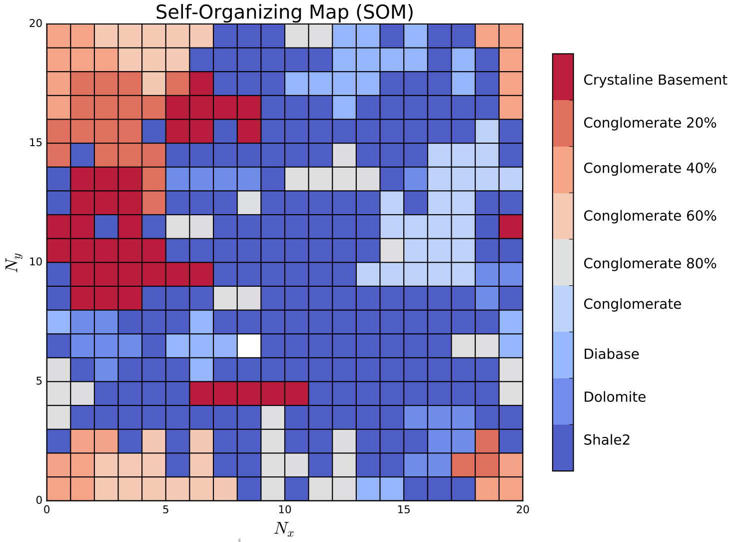
A hyperplane with 400 neurons

Epoch 5



A hyperplane with 400 neurons

Epoch 100



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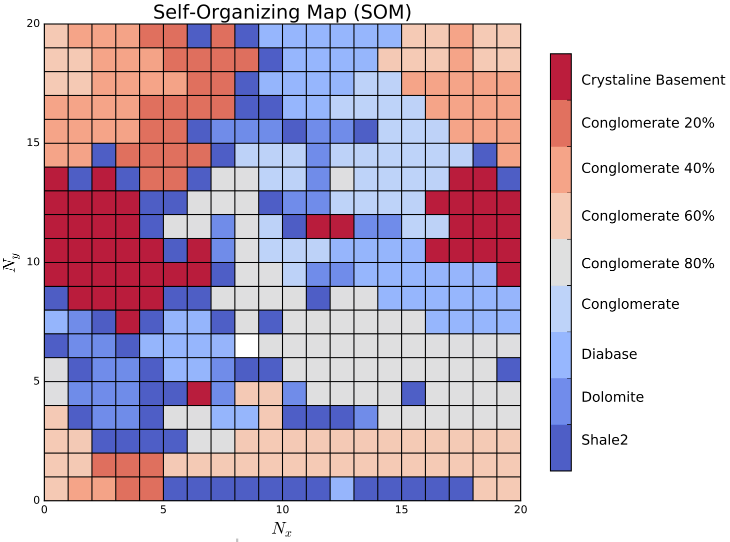


Results

Classifications C1

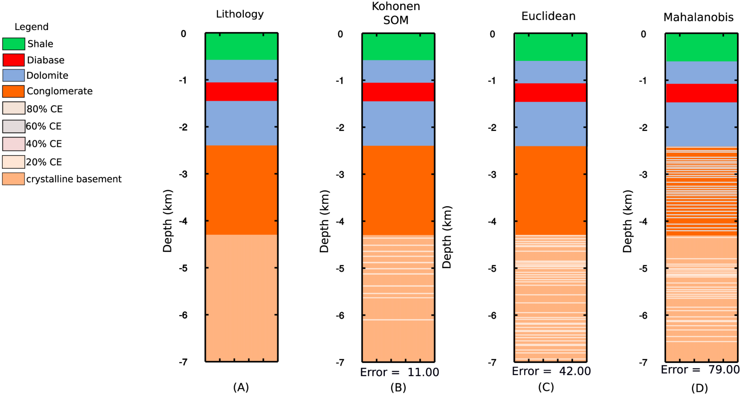
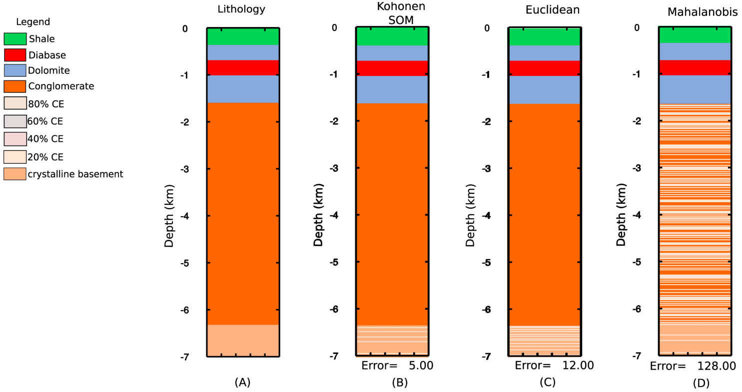


Figure : 700 data analyzed in each well

Results

Classifications C2



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- Classifiers can not perform classification of bell patterns in well data.
- Box patterns could be solved with euclidean classifier but not in mahalanobis
- Kohonen - SOM showed the bests results concerning classification of mixture of rocks or the bell pattern

Future Perspectives

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- Make more tests

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- Apply methodology on real data

References I

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Questions?

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