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Abstract No Th K 14

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

Victor Carreira[1], Cosme Ponte[1], Rodrigo Bijani[1].

EAGE
EUROPEAN ASSOCIATION OF GEOSCIENTISTS & ENGINEERS

Observatório Nacional[1]

Changing seasons

Varvite (Itu - São Paulo)

Introduction

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Self-Organizing Map: inspired by neural cortex and based oriented graph that works as an interconnected network.

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Geophysical problem: Identify rocks from well log data by means of machine learning and statisticas classifiers;

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Geosphysical problem:	Identify rocks from well log data by means of machine learning and statisticas classifiers;
Way to solve it:	use self-organizing map (SOM) and two statistical classifers;
Strategy:	Compare the results for the three explored methods, Kohonen (SOM), euclidean and mahalanobean classifiers for a synthetic scenarium.

Synthetic Sedimentary Basin

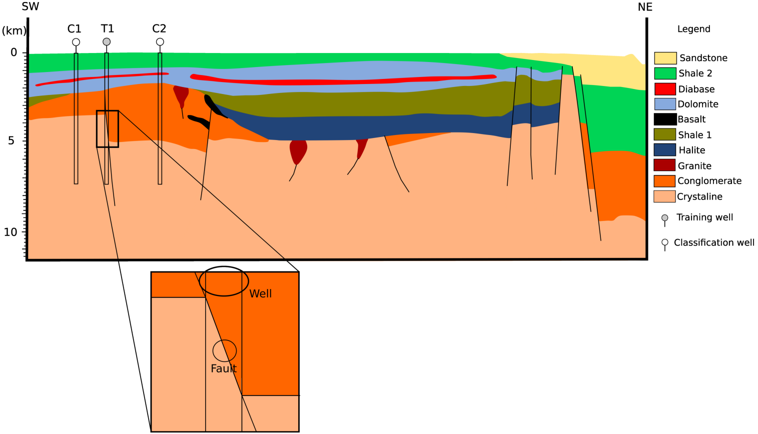

Figure : Synthetic Sedimentary Basin by Mohriak et al. (2008) T1, C1 and C2 are training and classifing wells respectively.

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

Sample rate: 0.01 observation/meter

Contamination error: 5% Radom Gaussian noise.

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

Training and Similarities

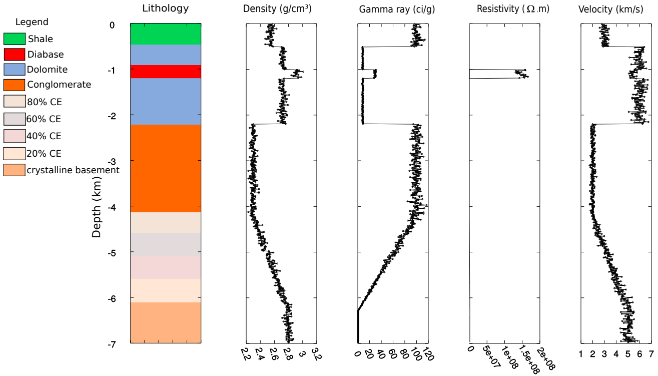

Figure : Synthetic training well T1.

Training and Similarities

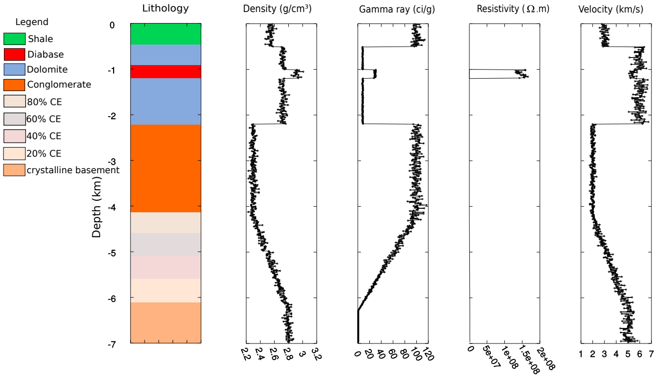

Figure : Synthetic training well T1.

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

Training and Similarities

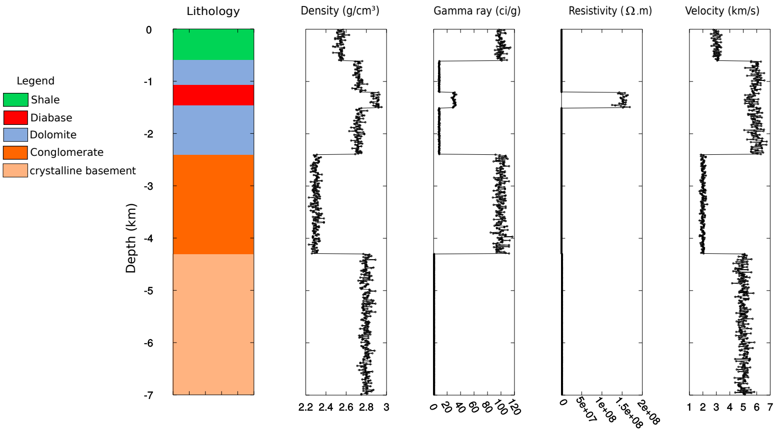

Figure : Classification well C1

Training and Similarities

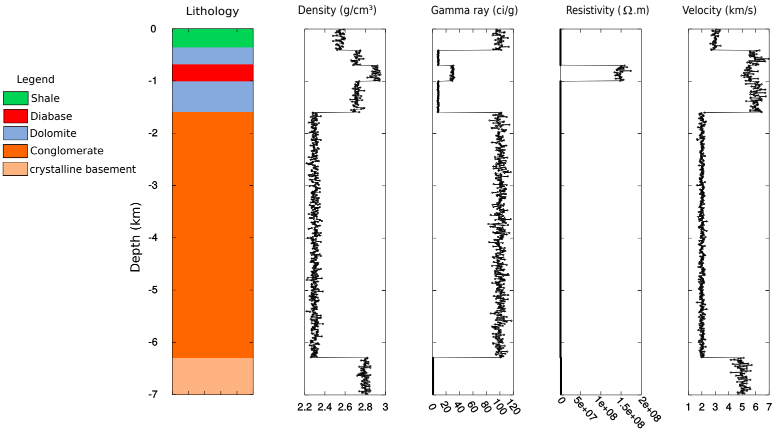

Figure : Classification well C2

Euclidean Classifier

Definition

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

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$\mathbf{X}$, input vector (attribute data)

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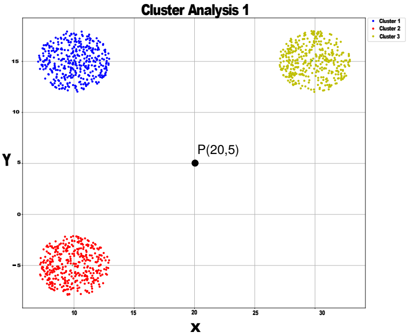
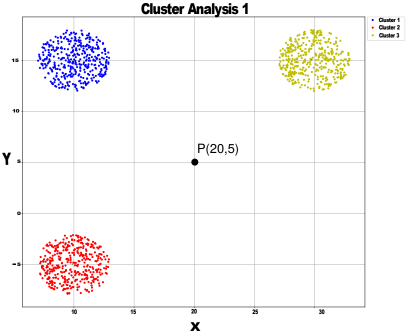


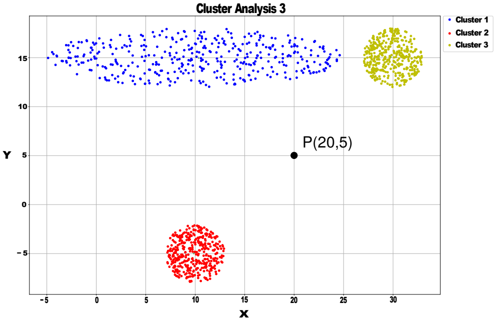
- All centroid are equidistant

Euclidean Classifier



- All centroid are equidistant
- $P(20, 5)$ could be a member of all groups from a euclidean point of view

Euclidean Classifier



- Blue cluster still have the same centroid

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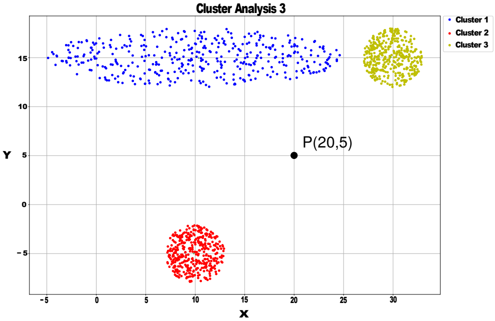

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- Problematic to define which cluster point $(20, 5)$ should be member of

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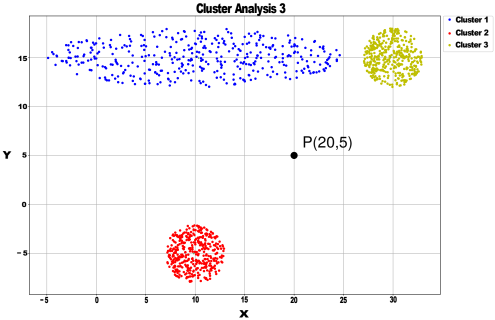

- Blue cluster still have the same centroid
- Problematic to define which cluster point $(20, 5)$ should be member of
- How could we handle this problem?

Mahalanobis Classifier

Definition

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

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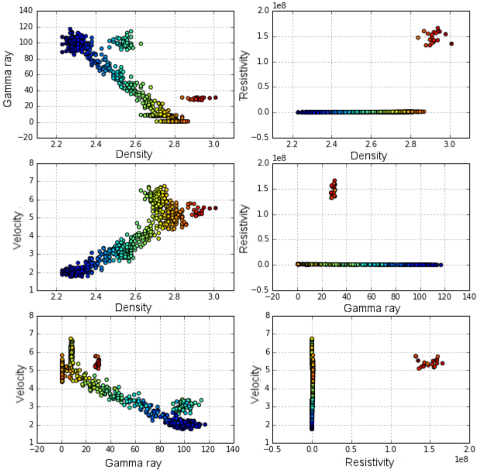
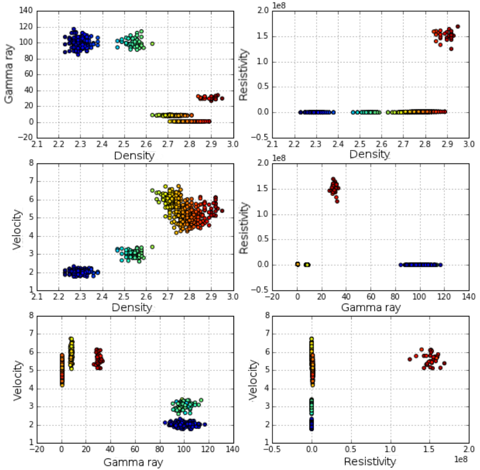
$\mathbf{C}_i$, covariance matrix

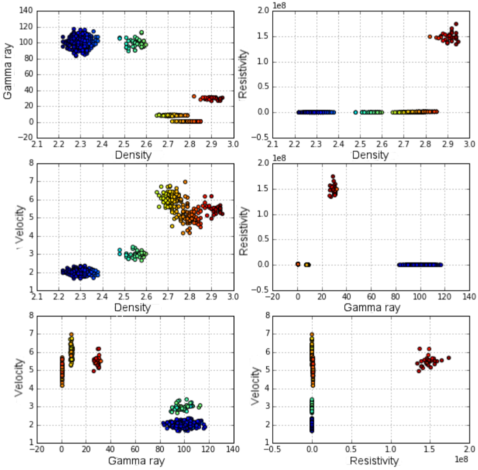
Clusters and Space of Attributes - T1 well



Clusters and Space of Attributes - C1 well

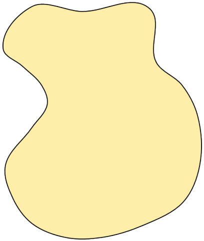


Clusters and Space of Attributes - C2 well



Kohonen - SOM

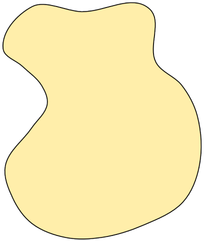
Multi-dimension space of
properties
(input)

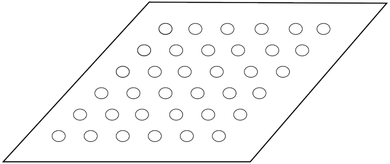


Kohonen - SOM

Sefl Organizing Map (SOM)

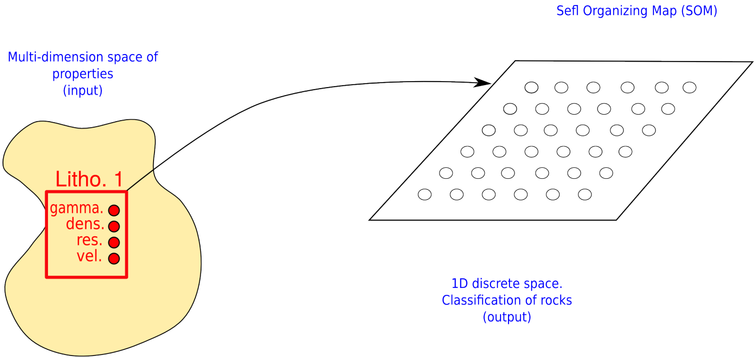
Multi-dimension space of properties (input)





1D discrete space.
Classification of rocks
(output)

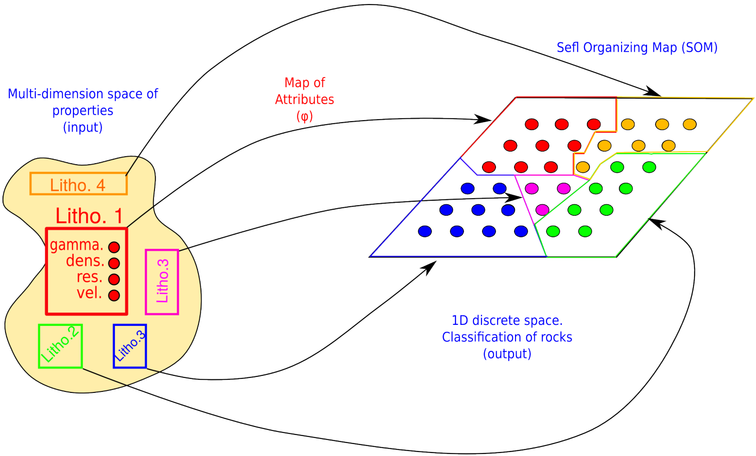
Kohonen - SOM



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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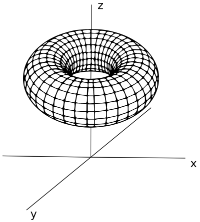
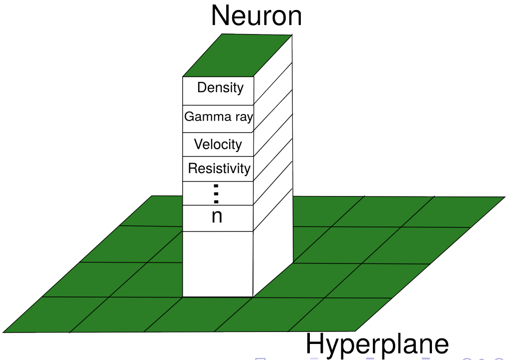
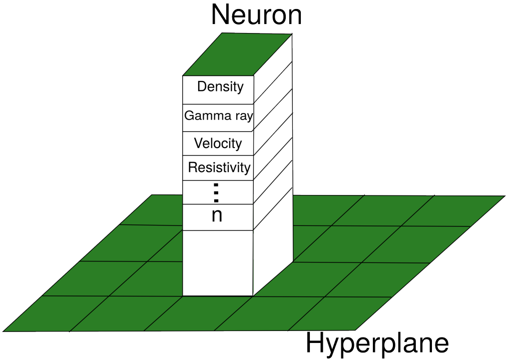
t , number of iteractions

The geometry





Winner neuron and neighborhood



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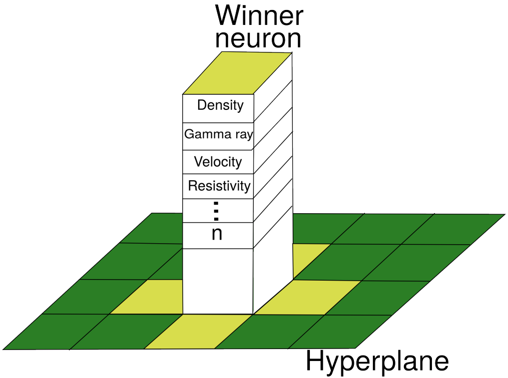
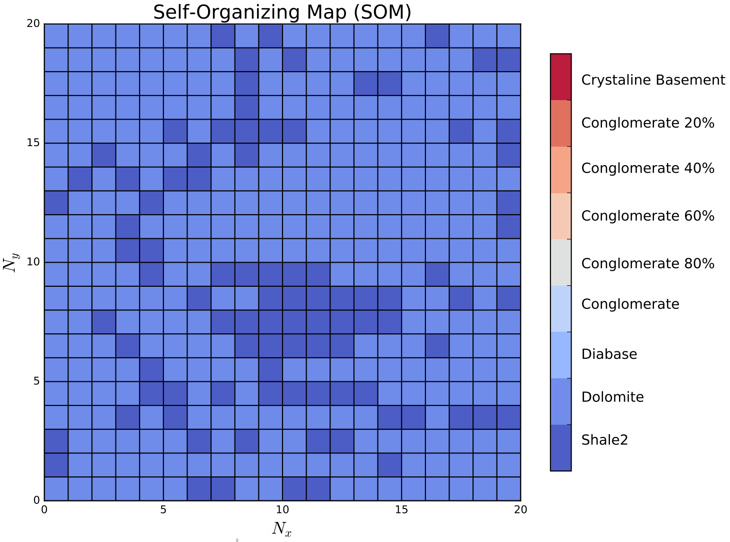


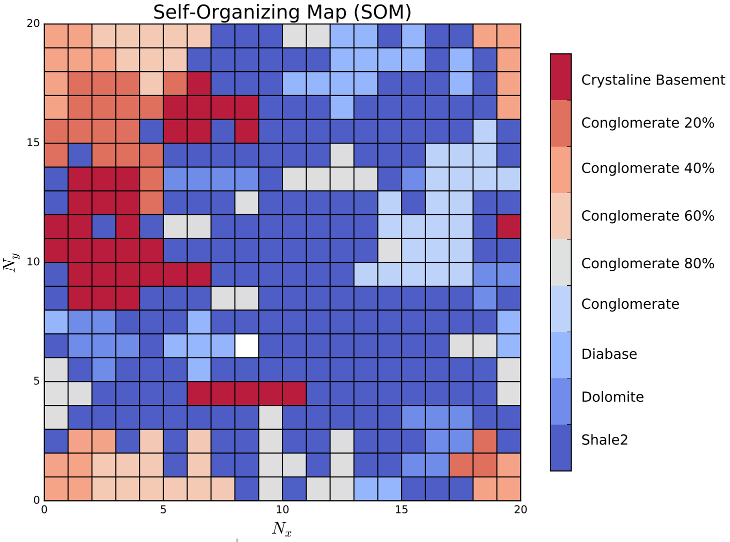
A hyperplane with 400 neurons

Epoch 5



A hyperplane with 400 neurons

Epoch 100



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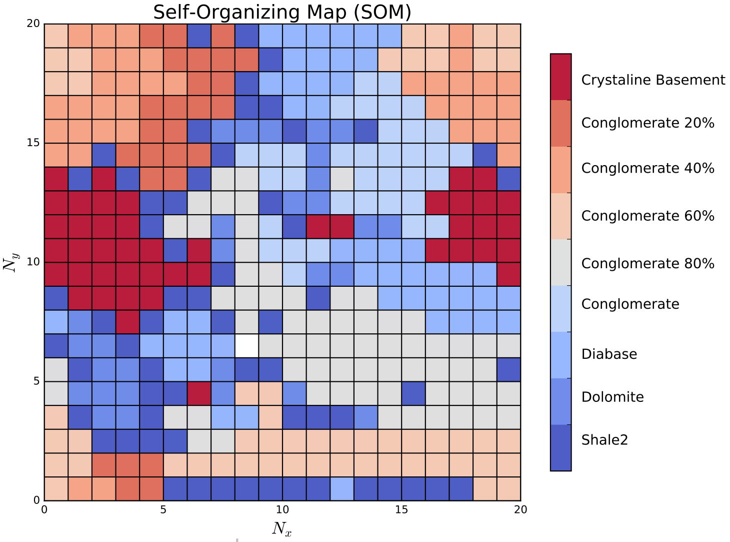
A hyperplane with 400 neurons

Epoch 1000



Results

Classifications C1

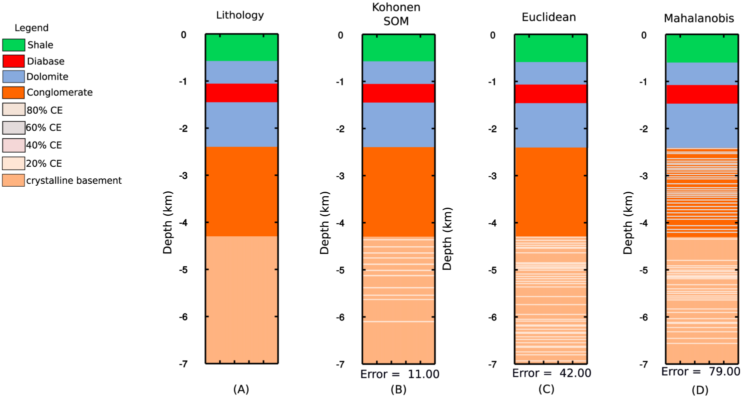
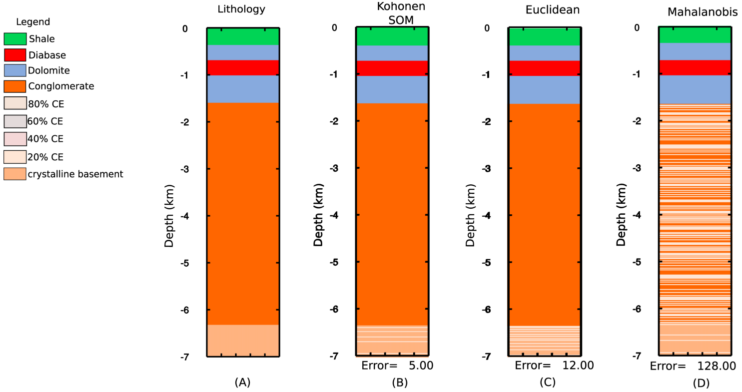


Figure : 700 data analyzed in each well

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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