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

[1] Observatório Nacional

Changing seasons

Varvite (Itu - São Paulo)

Introduction

Machine learning == > computer program with capability of automatic improvement through experience

- ~~Machine learning approaches computer program's that have the capability of automatically improve themselves through experience~~ (Michie et al., 1994; Levy, 1997; MacKay, 2005).

-> Machine learning groups: - Artificial Neural Networks (algumas refs)
- Decision trees (algumas refs)
- Statistical classifiers (algumas refs)
- Self-Organizing maps (refs)

Classifiers = use the concept of distance in the space of attributes
Euclidean = use a frase que ja esta
Mahalanobean = use a frase que ja esta

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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~~ that works as an interconnected network.

~~Objective~~ Objectives of this work

- Geofisical problem: ID of rocks from well log data
- Way to do it: Use Self-Organizing Map (Kohonen) and two statistical classifiers

- ~~Identify rocks from well log data by means of machine learning and statisticas classifiers;~~

~~Objective~~

- ~~Identify rocks from well log data by means of machine learning and statisticas classifiers;~~
- ~~Creat synthetic well log data from a model basin;~~

Objective

- ~~Identify rocks from well log data by means of machine learning and statisticas classifiers;~~
- ~~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 for a synthetic scenarium.

Methodology

ESTE SLIDE DEVE DESCER 1 !!!!!

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

ESTE SLIDE DEVE SUBIR 1 !!!!!!!

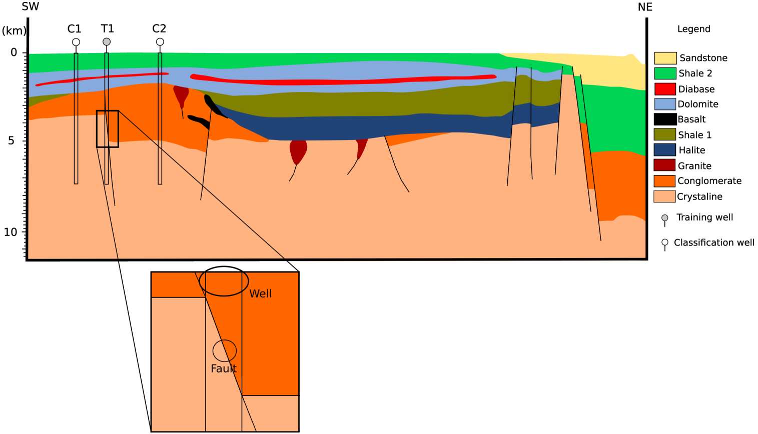

Figure : Synthetic Sedimentary Basin by Mohriak et al. (2008) T1, C1 and C2 are training and classifing wells respectively.

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

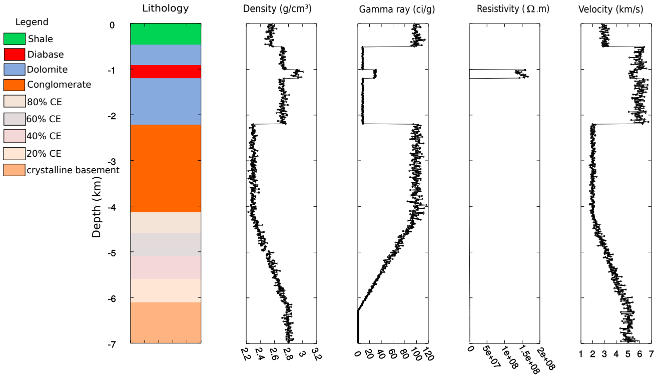

Figure : Synthetic training well T1.

Training and Similarities

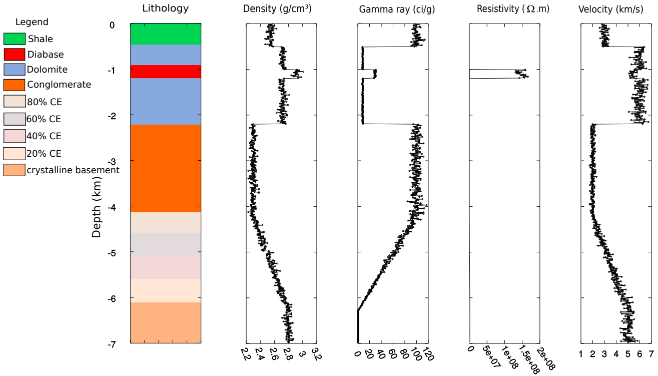

Figure : Synthetic training well T1.

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

Training and Similarities

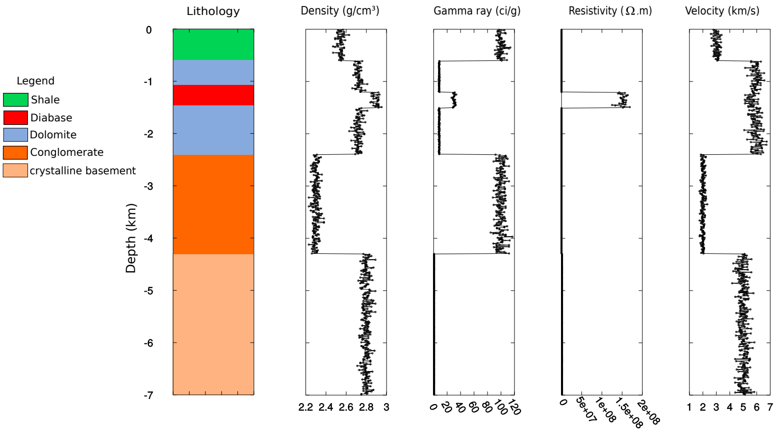

Figure : Classification well C1

Training and Similarities

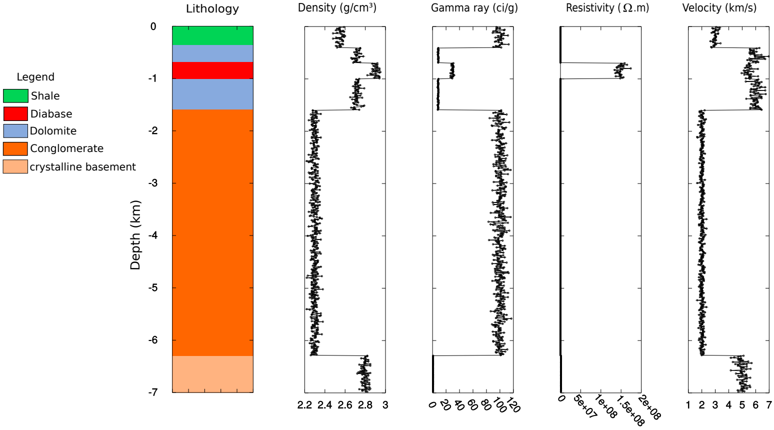

Figure : Classification well C2

Euclidean Classifier

Definition

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

Euclidean Classifier

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

Euclidean Classifier

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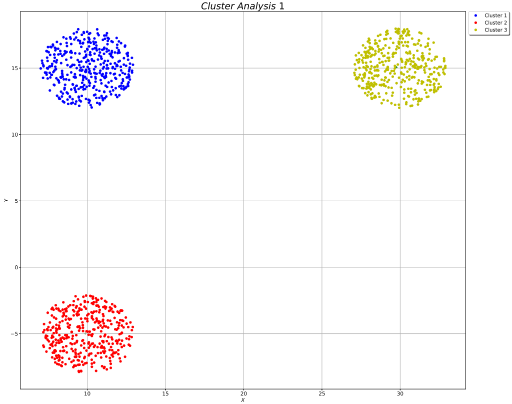
$\mathbf{X}$, input vector

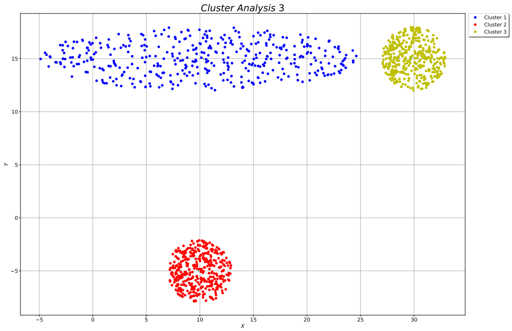
$\bar{\mathbf{X}}_i$, mean vector

Euclidean Classifier



- All centroids are equidistant
- A point in (x,y) = (0,0) could be a member of all groups from an euclidean point of view

Euclidean Classifier



- Blue cluster still have the same centroid
- Problematic to define which cluster point (0,0) 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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$\mathbf{X}$, input vector

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

$\mathbf{C}_i$, covariance matrix

Mahalanobis Classifier

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

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n_i , number of elements

Mahalanobis Classifier

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n_i , number of elements

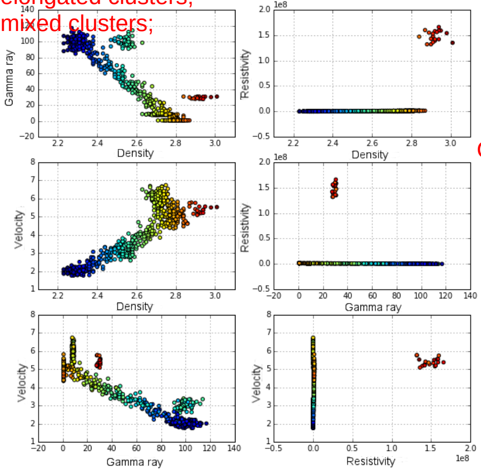
ω_i , space of attributes

ACHO QUE VC DEVERIA MOSTRAR O EXEMPLO DOS CLUSTERS ACIMA, É MAIS EXPLICATIVO! DIGA QUE O MAHALANOBIS CONSEGUE CLASSIFICAR O PONTO (0,0) MELHOR DO QUE O EUCLIDEANO NO CASO ESPECIFICO DO SEU EXEMPLO! (O QUE ACHA???)

Cluster analysis for the synthetic example: T1 well

~~Clusters and Space of Attributes - T1 well~~

- plot well log data in pairs (6 plots)
- some elongated clusters;
- some mixed clusters;

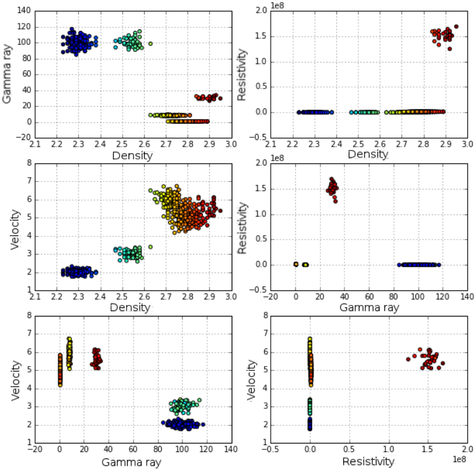


COLORBAR???

Cluster analysis for the synthetic example: C1 well

~~Clusters and Space of Attributes - C1 well~~

- well defined clusters;
- very different from the training well;



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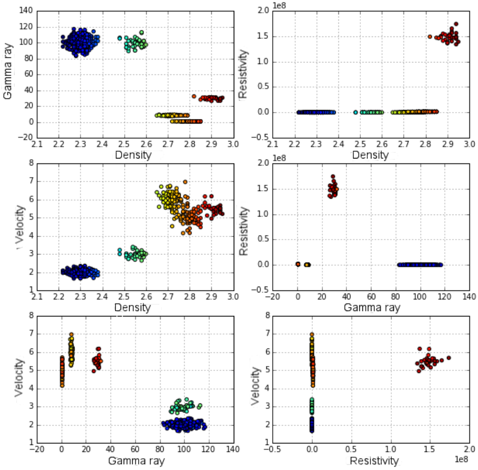
Cluster analysis for the synthetic example: C2 well

~~Clusters and Space of Attributes - C2 well~~

- similar to well C1;



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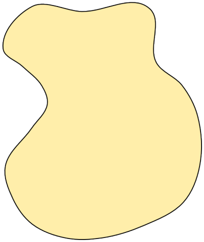
Kohonen - SOM

Multi-dimension space of properties
(input)

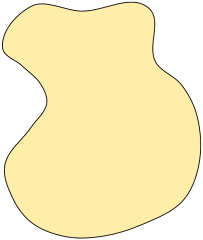


Main stages of Kohonen SOM (verificar!!!):
1) Organization
2) Synaptic adaptation (Training process)
3) Cooperation and winner neuron
4) Usage

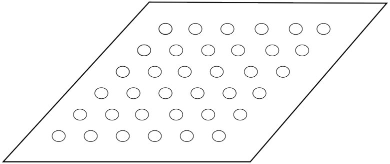
Kohonen - SOM

Destacar os estagios nos slides a que se referem!

Multi-dimension space of
properties
(input)

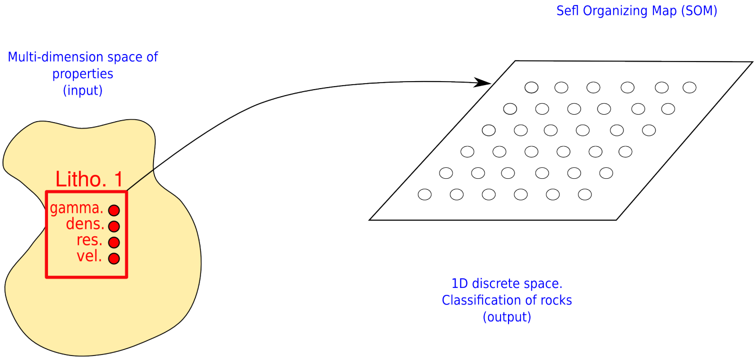


Sefl Organizing Map (SOM)



1D discrete space.
Classification of rocks
(output)

Kohonen - SOM

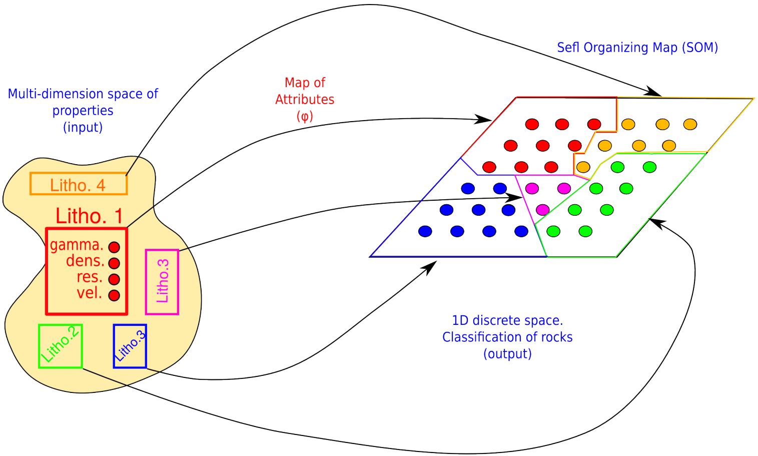


Lithology = F(gamma.,dens., res., vel.)

Kohonen - SOM

Training

FICOU BOM PACARAI !!!!!!



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

Kohonen - SOM

Organization

$$\mathbf{x} = [x_1, x_2, x_3, \ldots, x_m]^T$$

input data (attribute data)

Kohonen - SOM

Organization

$$\mathbf{x} = [x_1, x_2, x_3, ..., x_m]^T$$

$$\mathbf{w}_j = [w_{j1}, w_{j2}, w_{j3}, ..., w_{jm}]^T$$

neuron atribute matrix

Kohonen - SOM

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$$\mathbf{w}_j = [w_{j1}, w_{j2}, w_{j3}, ..., w_{jm}]^T$$

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

number of neurons

Kohonen - SOM

Cooperation and winner neuron

QUEDE O MAPA DO NEURONIO VENCEDOR?? ELE DEVERIA ESTAR NESTE SLIDE,, NAO?!

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

i(t) distance or identity of a neuron i

NAO SERIA i (x) ao inves de i (t) ????

Kohonen - SOM

Synaptic adaption or Training process

Definition

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

Kohonen - SOM

Synaptic adaption or Training process

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$w_{i,j}(t+1)$ updated neuron attribute matrix ~~, updated attribute matrix of neurons~~

$\eta(t)$, learning rate

Kohonen - SOM

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$w_{i,j}(t+1)$, ~~updated attribute matrix of neurons~~

$\eta(t)$, learning rate

Definition

$$\eta(t) = \eta(0)(1 - \frac{t}{T})$$

T , number of training cyles

Kohonen - SOM

Synaptic adaption or Training process

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updated neuron attribute matrix

$w_{i,j}(t+1)$, ~~updated attribute matrix of neurons~~

$\eta(t)$, learning rate

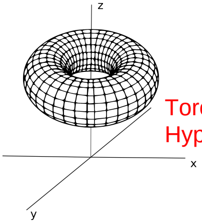
Definition

$$\eta(t) = \eta(0)(1 - \frac{t}{T})$$

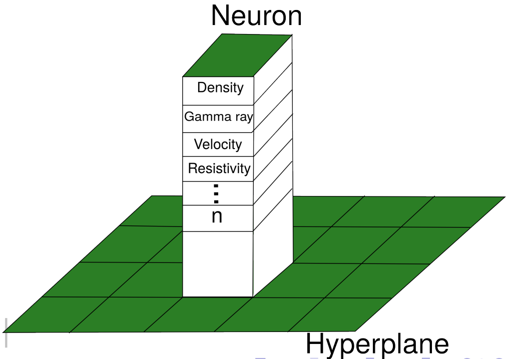
T , number of training cyles

t , number of iteractions

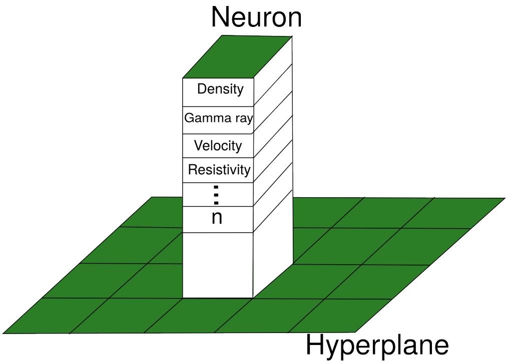
The geometry



Toroid = efficent way to connect all cells;
Hyperplane = similar to a drawer (all attribute data go here)



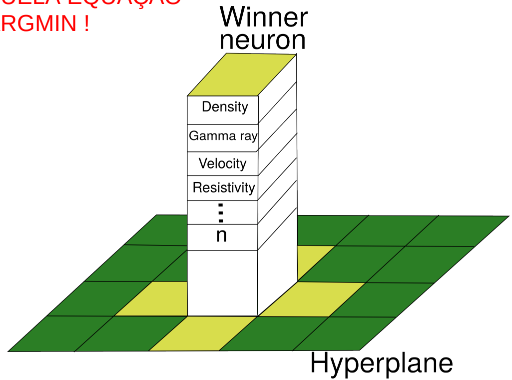
Winner neuron and neighborhood



Winner neuron and neighborhood

i(x) = argmin(bla)

AQUI ENTRA AQUELA EQUAÇÃO ESCROTA DO ARGMIN !

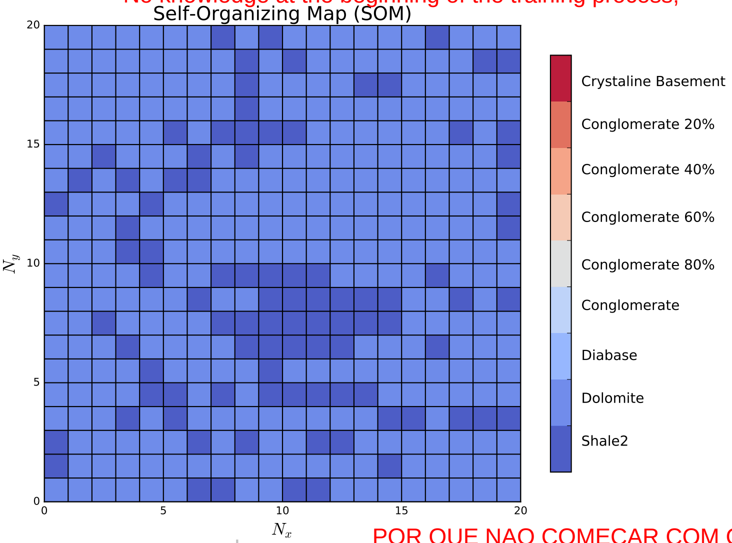


Training process for the synthetic case

~~A hyperplane with 400 neurons~~

- 400 neurons comprising the hyperplane;
- Epoch = training process (precisa definir os termos e jargões!)
- No knowledge at the beginning of the training process;

Epoch 5

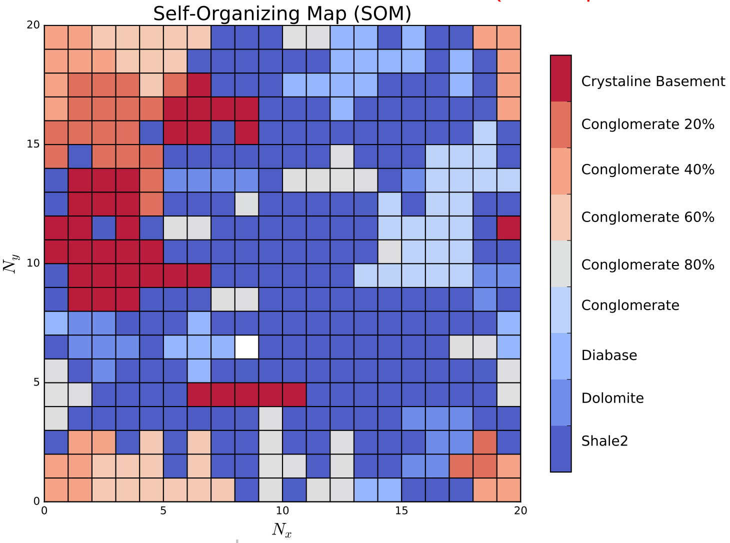


POR QUE NAO COMEÇAR COM O TABULEIRO VAZIO??? SERIA MELHOR!!!!!

A hyperplane with 400 neurons

Epoch 100

- Shale is the predominant rock at this stage!
- white neuron => not visited neuron (useless part of the cortex)



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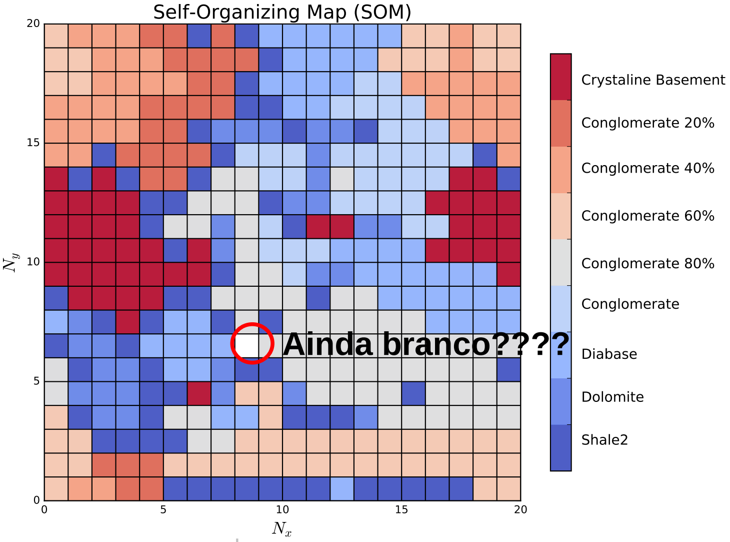
A hyperplane with 400 neurons

Epoch 1000

Final stage ===> All neurons were "trained"



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Results

Classifications C1

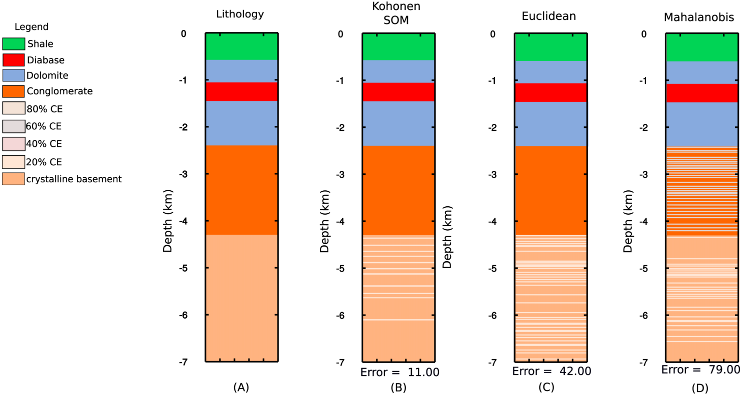

Figure : 700 data analyzed in each well

Results

Classifications C2

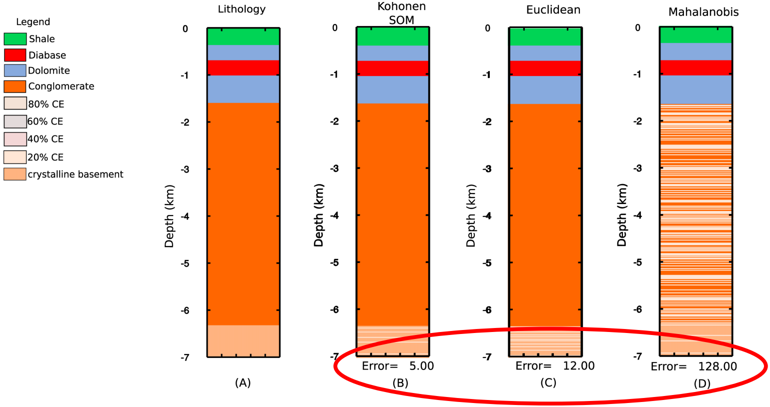

Figure : 700 data analyzed in each well

Error = colocar uma eq mostrando como calcular error.

Conclusions

- SOM algorithm overperformed the euclidean and mahalanobis classifiers with an error of 0.71%

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- The complex distribution of features on the space of properties led to an increase of errors on classifiers of 18.28% (mahalanobis) and 1.74% (euclidean)
- Classifiers ~~can~~ could not perform classification of bell patterns in well data. **(Why??? - lack of training wells?)**

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- The complex distribution of features on the space of properties led to an increase of errors on classifiers of 18.28% (mahalanobis) and 1.74% (euclidean)
- Classifiers can not perform classification of bell patterns in well data.
- Box patterns could be solved ~~with~~ by euclidean classifier but not ~~in~~ by mahalanobis

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- The complex distribution of features on the space of properties led to an increase of errors on classifiers of 18.28% (mahalanobis) and 1.74% (euclidean)
- 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 better performance ~~the bests results~~ concerning classification of mixture of rocks or the bell pattern

Future Perspectives

Future Perspectives

- Make more tests **with more Training wells;**

Future Perspectives

- Make more tests
- Apply methodology on real data (Paraná Basin, Southeast Brazil)

Create a more promising stop criterion for the training process (in development)

Verify why such a poor performance of Mahalanobis classifier
(Need mode Training data to over-perform Euclidean?)

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THANK YOU !

~~Questions?~~

SUGIRO RETIRAR ESSE SLIDE E COLOCAR APENAS UM SPECIAL THANKS PARA QUEM TE PAGA , POIS AS QUESTIONS JÁ VAO FAZER PARTE DO EVENTO, LOGO NAO PRECISA!

Author: Victor Carreira
E-mail: victorcarreira@on.br

(POE LOGO DA CAPES E O DOS 190 ANOS DO on, O QUE ACHA???)