Machine Learning & Neural Networks

7.- Non supervised Neural Networks: Self-organizing Maps

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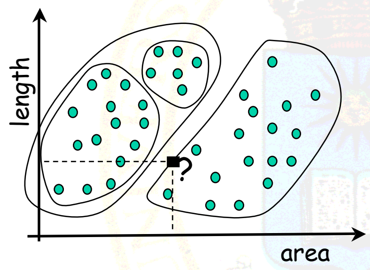
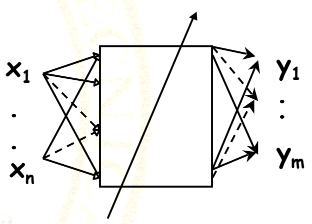
Unsupervised learning

Unsupervised learning concept



Feature space

Working structure



Clustering

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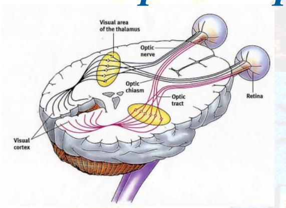
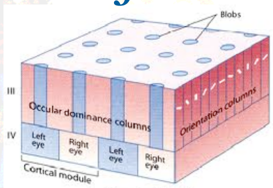
Self organizing Maps (SOM)

- ***Bio-inspired idea:***
  Similar inputs map onto neighbor outputs.





(Aus Gazzaniga et al., 1998)

- ***SOM objective:***
  Neighbor inputs map onto neighbor outputs and vice versa

$R^n \longrightarrow R^2, R^1$ **D.R. into a pattern space**

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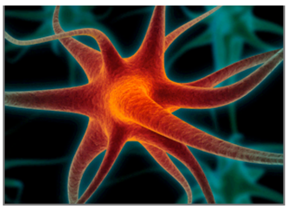
recent paper

Un método para leer el pensamiento y los sueños



(MTL por sus siglás en inglés) responden ante estímulos visuales, y se sabe que su actividad puede estar modulada por la atención. Moran Cerf y sus colegas del Instituto de Tecnología de California, en Pasadena (EE UU), han medido por primera vez en tiempo real la actividad individual de neuronas de esta región en pacientes de neurocirugía mientras les mostraban imágenes en la pantalla de un ordenador. Y han llegado a la conclusión de que **cada célula cerebral está asociada con objetos o conceptos muy específicos**.

Concretamente, en sus experimentos Cerf identificó que **cuando un voluntario estaba pensando en Marilyn Monroe, se iluminaba una neurona concreta**. Al mostrar a los voluntarios una serie de hasta cien imágenes asociadas a temas que previamente habían indicado que les interesaban, el equipo de científicos fue capaz de identificar las neuronas específicas para una amplia gama de conceptos, objetos y personajes: la Torre Eiffel, Bill Clinton, la tenista Venus Williams, el grupo Guns N'Roses... Con ellas, afirman, se podría construir **una base de datos de cada paciente que permitiera "leer la mente de los sujetos"** observando las células del cerebro que se activan en cada momento. Incluso podría utilizarse este método para grabar e interpretar los sueños de la gente, según ha propuesto Cerf.

Además, el interfaz cerebro-ordenador usado en los experimentos permitía a los individuos "pensar" en imágenes informáticas superpuestas más o menos visibles y conseguir hacer desaparecer aquellas que no les gustaban aumentando la tasa de activación de ciertas células (las que percibían a Marilyn Monroe en el experimento) a la vez que disminuían las de otras (en este caso, imágenes de Michael Jackson). Los pacientes tuvieron éxito "eliminando" una de las imágenes en un 69% de las ocasiones, mostrando cómo el cerebro humano es "capaz de controlar la dominancia de un estímulo", según Cerf.

Elena Sanz *28/10/2010* ▸ Etiquetas:cerebro, percepción, pensamiento, sueños

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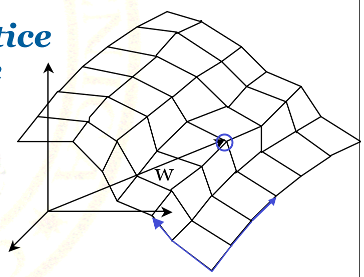
SOM working principle

- **Objective:**
  To obtain a bijective application $R^n \Leftrightarrow R^2$, such as **neighborhood in the input space ⇔ neighborhood in the output space**
- **Procedure:**
  To distribute an elastic 2D lattice into the nD input space, where the every cross represent a neuron that has:
  - a position in the input space (defined by its weights)
  - a position in the output space (defined by its coordinates in the lattice)



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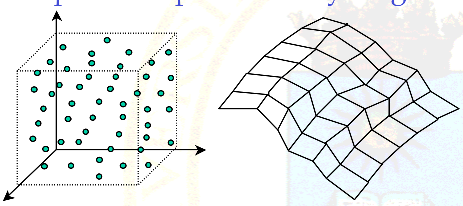
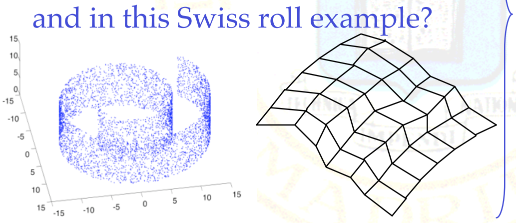
SOM: viability

is it possible in this cubic example that any two neighbor input sample are represented by neighbor neurons?



and in this Swiss roll example?



concept of **Intrinsic Dimensionality** of the data

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SOM: running and learning

Running:

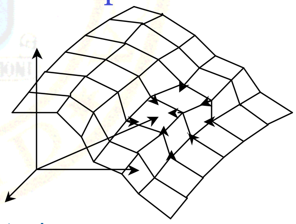
Which neuron is activated by every input data?

the neurons whose weight vector is the closest to this input data

Learning:

How are weights updated for every train input in order to fulfill the SOM objectives?

- The weights of which neurons are updated?
- How are they updated?



CVG-UPM

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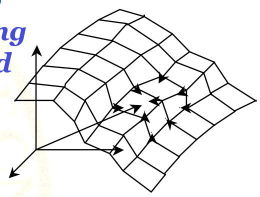
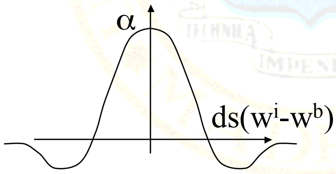
SOM: learning procedure

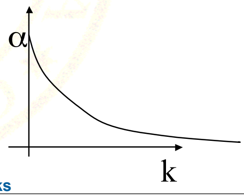
- ***The neuron whose weights are the closest to the present train sample x, called the winning neuron w^b (also the best matching unit), and its neighbors are the ones that learn (i.e. update their weights)***
- ***Learning rule:*** $\Delta_k w^i = \alpha\,(x-w^i)$

where $\alpha = \alpha(d_{os}(w^i-w^b),k)$ *is function of:*

- *the distance to the winning neuron in the output space* $d_{os}(w^i-w^b)$,
- *the training instant* k *(e.g. epoch)*

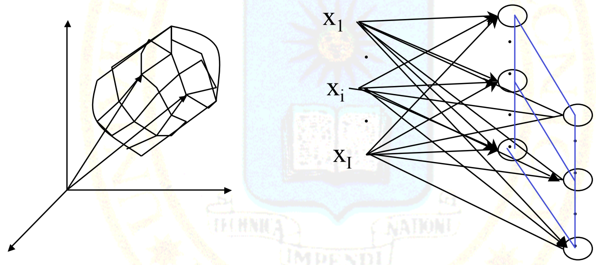






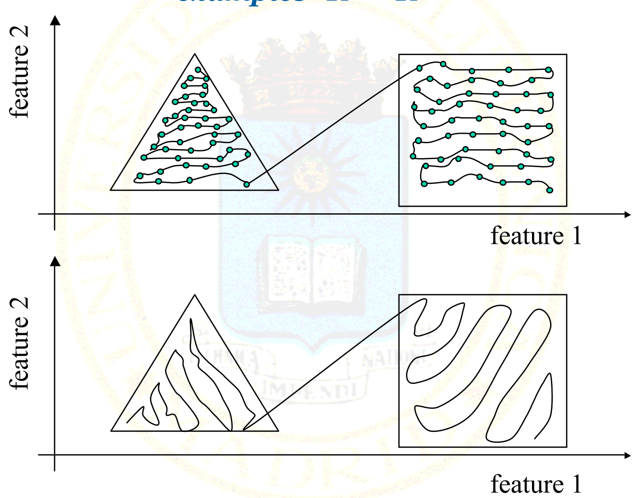
SOM: neural implementation

- Training and running imply distance calculation, that can be implemented by scalar product in a one dimensional incremented space



SOM: discussion on objective fulfillment

examples $R^2 \rightarrow R^1$



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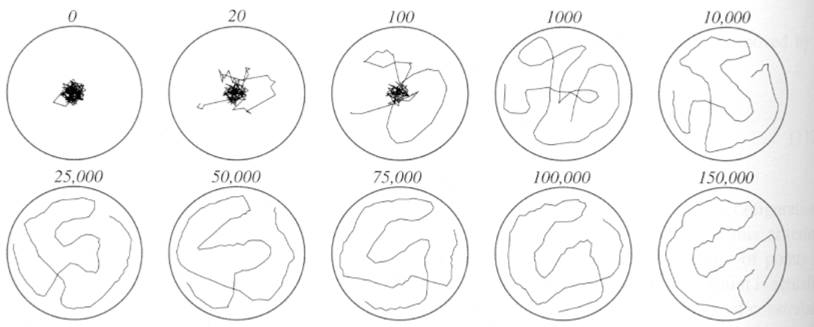
SOM: examples 1



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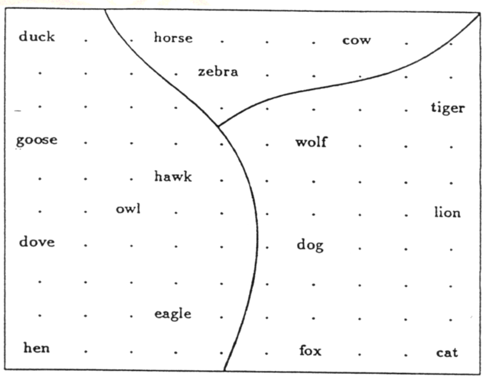
SOM: example 2

		dove	hen	duck	goose	owl	hawk	eagle	fox	dog	wolf	cat	tiger	lion	horse	zebra	cow
is	small	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0
	medium	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
	big	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
has	2 legs	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
	4 legs	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
	hair	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
	hooves	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	mane	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0
	feathers	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
likes to	hunt	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0
	run	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0
	fly	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0
	swim	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0



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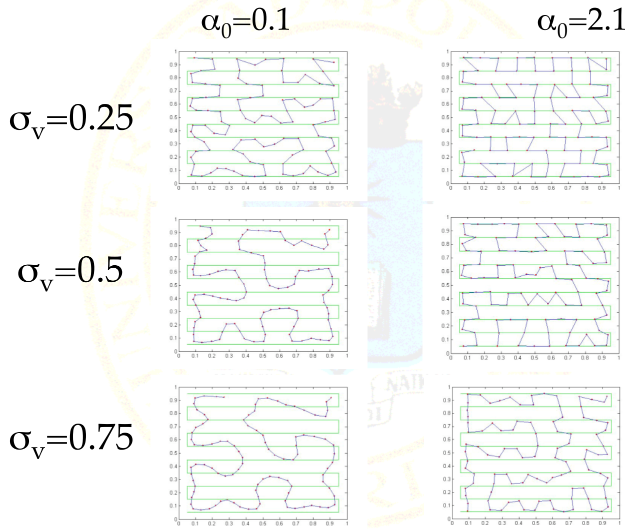
SOM results: influence of learning parameters



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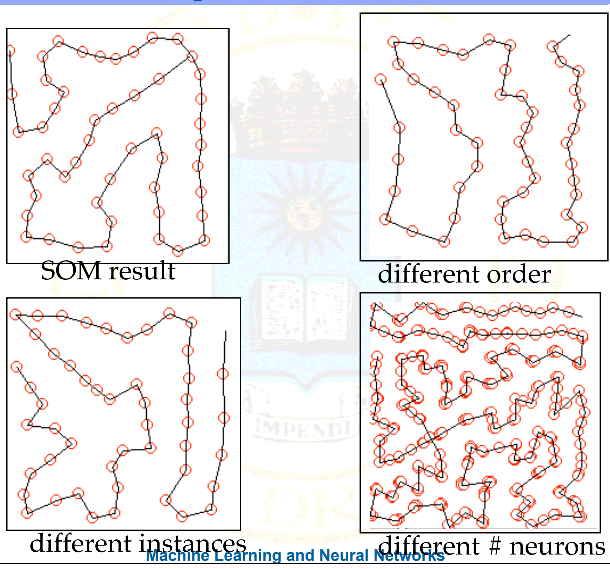
SOM: influence of training samples and # of neurons



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Matlab commands

```
som1=newsom(minmax(psom),[10 1]);
som1=train(som1,psom)

plotsom(som1.iw{1,1},som1.layers{1}.distances)

ynt=sim(som1,tsom);
yntind=vec2ind(ynt);
```


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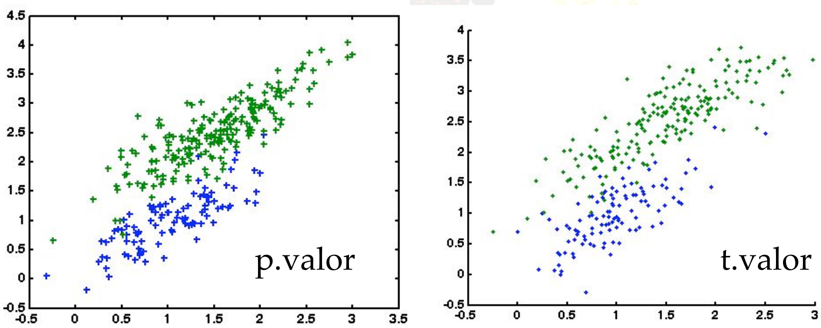
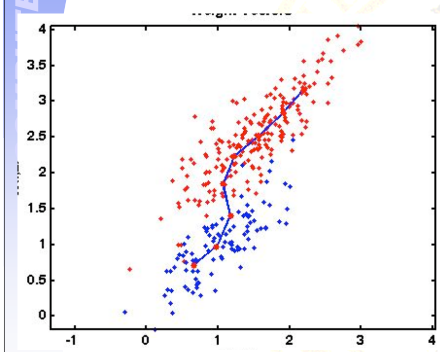
Example 7.1: SOM as classifier

load datos_D2_C2



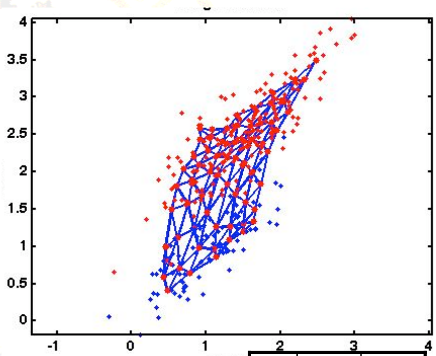
Solution example 7.1

SOM 8x1



	C1	C2
C1	100	11
C2	7	182

SOM 8x8



	C1	C2
C1	101	6
C2	6	187

Exercise 7.1: SOM as classifier

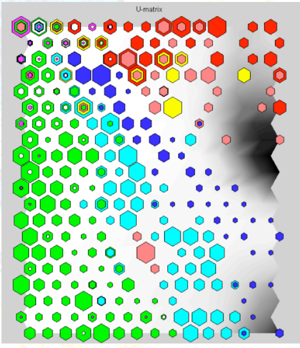
Using the data of the previous example:

Discuss the influence of the following factors (plot the results and quantify the test error and the training error):

1. # of training samples
2. # order of the training samples
3. # of neurons
4. # of epoches

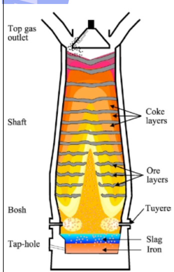
SOM example: Transfos state

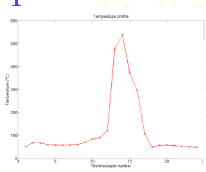
- 5D input: % de H_2 , CH_4 C_2H_2 C_2H_4 C_2H_6
- 2D U-matrix output
- Supervised manual semantic



SOM example: temperature profile classification for pig iron control

24D input

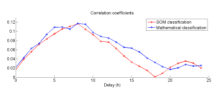


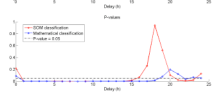


10x10 output map

manual labeling into 3 classes

95% confidence for pig iron temperature prediction (8h)

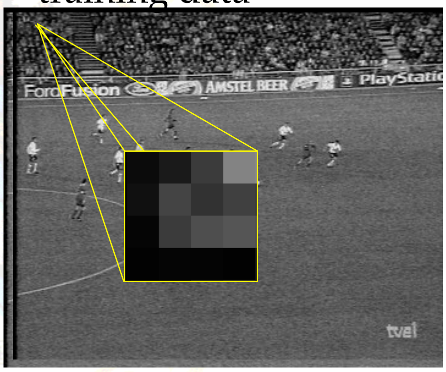




SOM example: video compression ...

original sequence

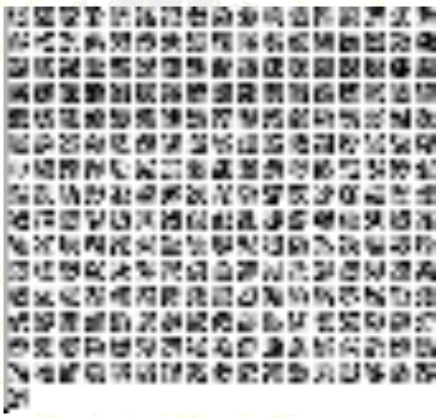
training data



- 1D output map
- 256 neurons

... SOM example: video compression ...

Training: weights update



… SOM example: video compression

Testing

√MSE=13,47

compression factor: 1:16
bits/pixel: 0.5
H=0.4375

SOM: concerns and limitations

- ***Concerns:***
  - output map dimension?
  - # of neurons?
  - learning rate? neighborhood?
  - order of the training samples?
- ***Limitations:***
  - neighbor inputs may activate distant neurons
  - distant inputs may activate neighbor neurons