Sistemas difusos evolutivos en el modelamiento de fenómenos complejos

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Agenda

- Sistemas difusos
- Modelado difuso evolutivo
- Casos de aplicación
- Discusión

“Not to be absolutely certain is, I think, one of the essential things in rationality” *Bertrand Russell*

SISTEMAS DIFUSOS

Lenguaje e incertidumbre

SI el apartamento está cerca y el arriendo es barato

ENTONCES

Podré ahorrar mucho dinero.

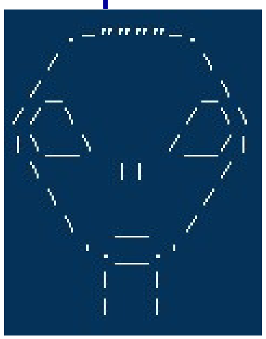
SI el apartamento está cerca y el arriendo es caro

ENTONCES

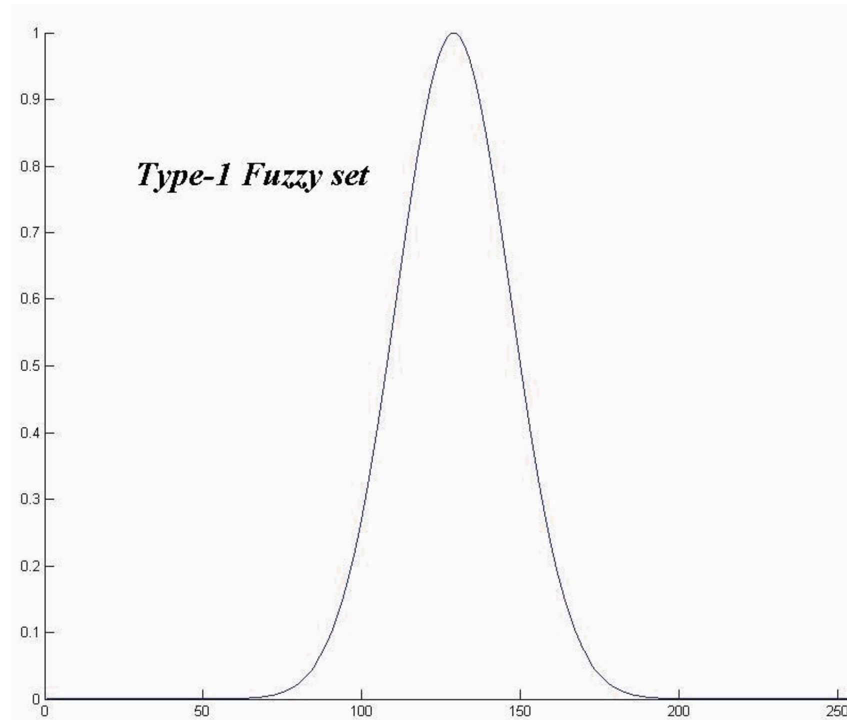
Tan solo podré ahorrar algo de dinero

Incertidumbre y conjuntos difusos

Experto



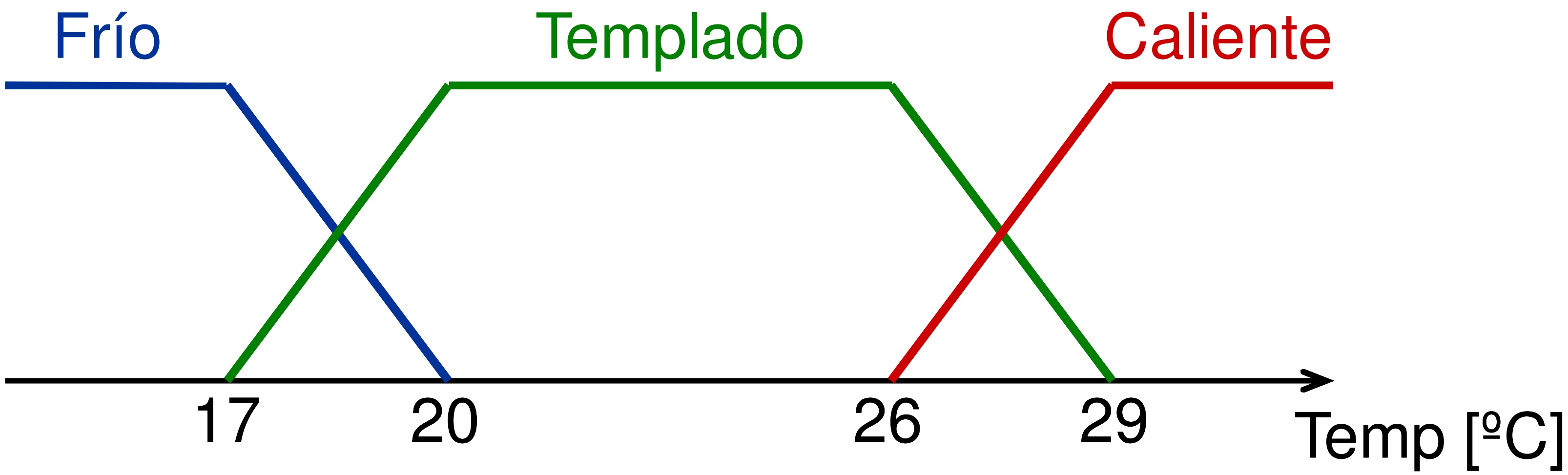
su definición
de
adecuada
(Etiqueta lingüística)



Temperatura (C)
Variable Lingüistica

Generalmente las palabras (Etiquetas lingüísticas) tienen significados difusos

Modelando la incertidumbre: variables lingüísticas y conjuntos difusos



- L.A. Zadeh, "**Fuzzy sets**", Inf. Control 8, 338-353, **1965**

Carlos A. Peña, Evolutionary Fuzzy Modelling, 2000

Incertidumbre y conjuntos difusos

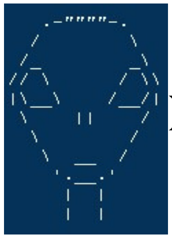
- Vaguedad = imprecisión lingüística
  e.g. El café esta medio tibio

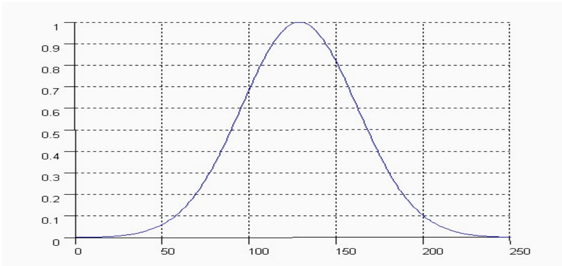
- Diversidad = imprecisión en la información
  e.g. Es probable que mañana llueva.

- Desacuerdo = conflicto o discrepancia.
  e.g. Por favor llegue temprano!

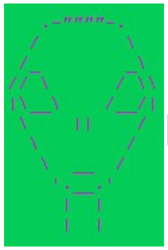
Incertidumbre y conjuntos difusos

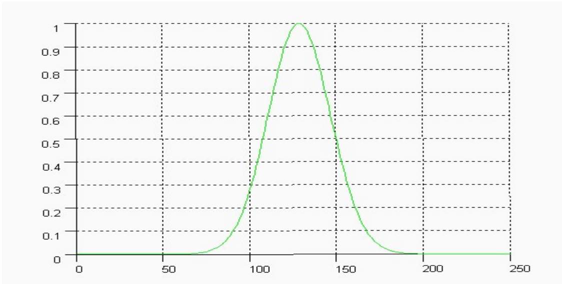
Experto (1)
adecuada



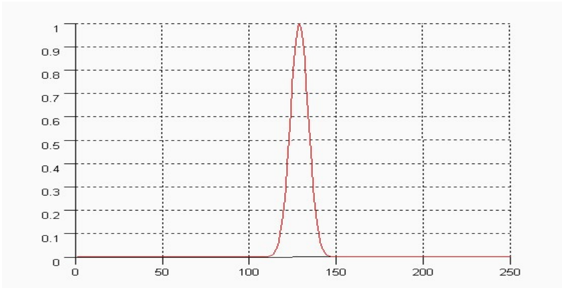


Experto (2)
adecuada

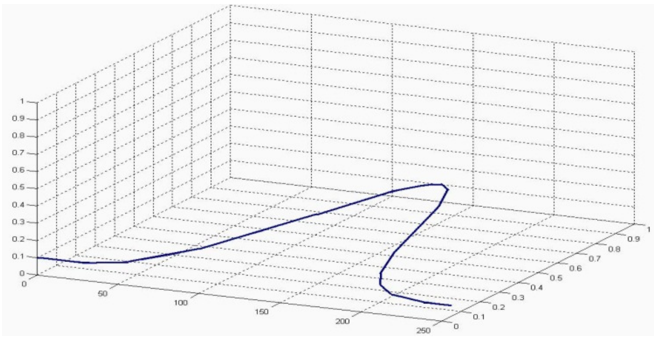




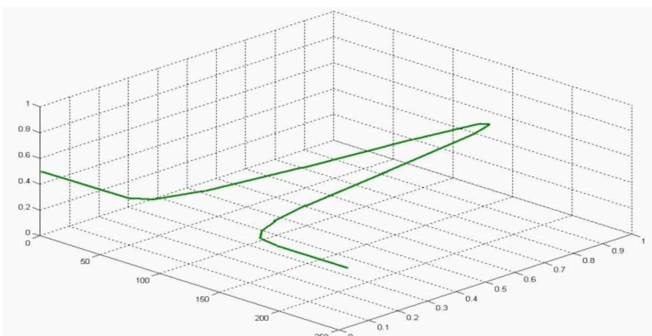
Experto (M)
adecuada



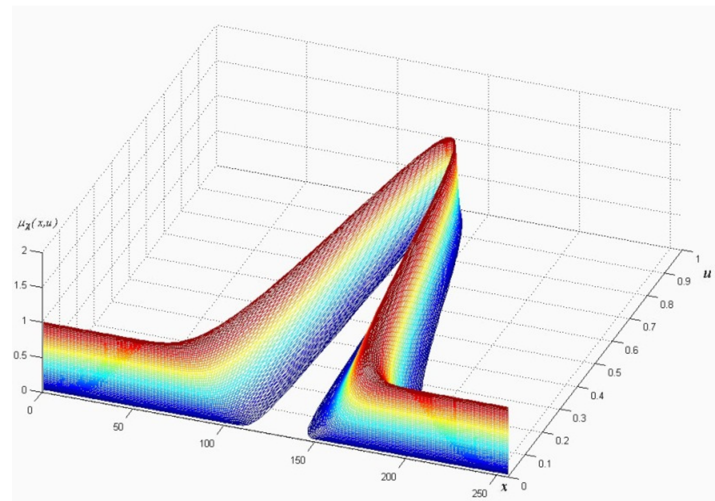
Representación de la incertidumbre

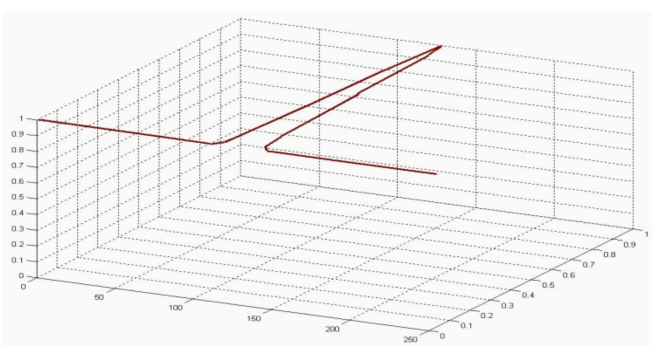


$\mu(x,u) = 0.1$



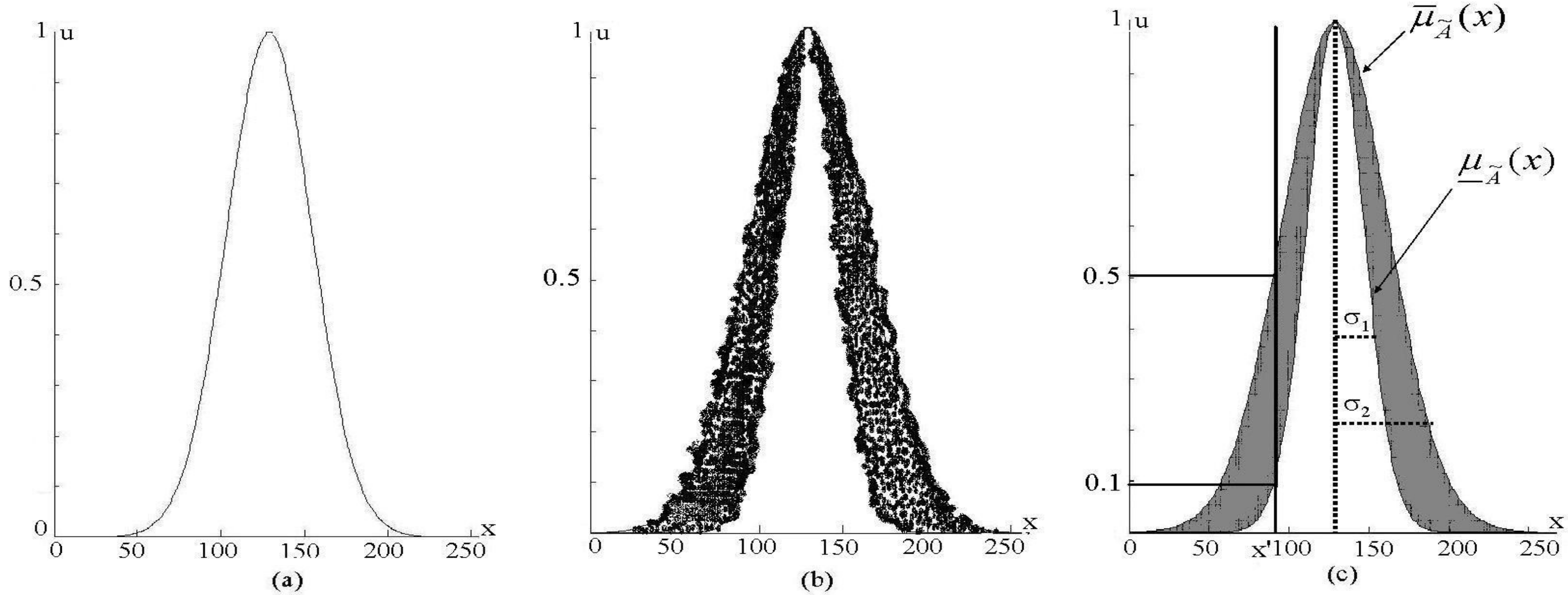
$\mu(x,u) = 0.5$





$\mu(x,u) = 1$

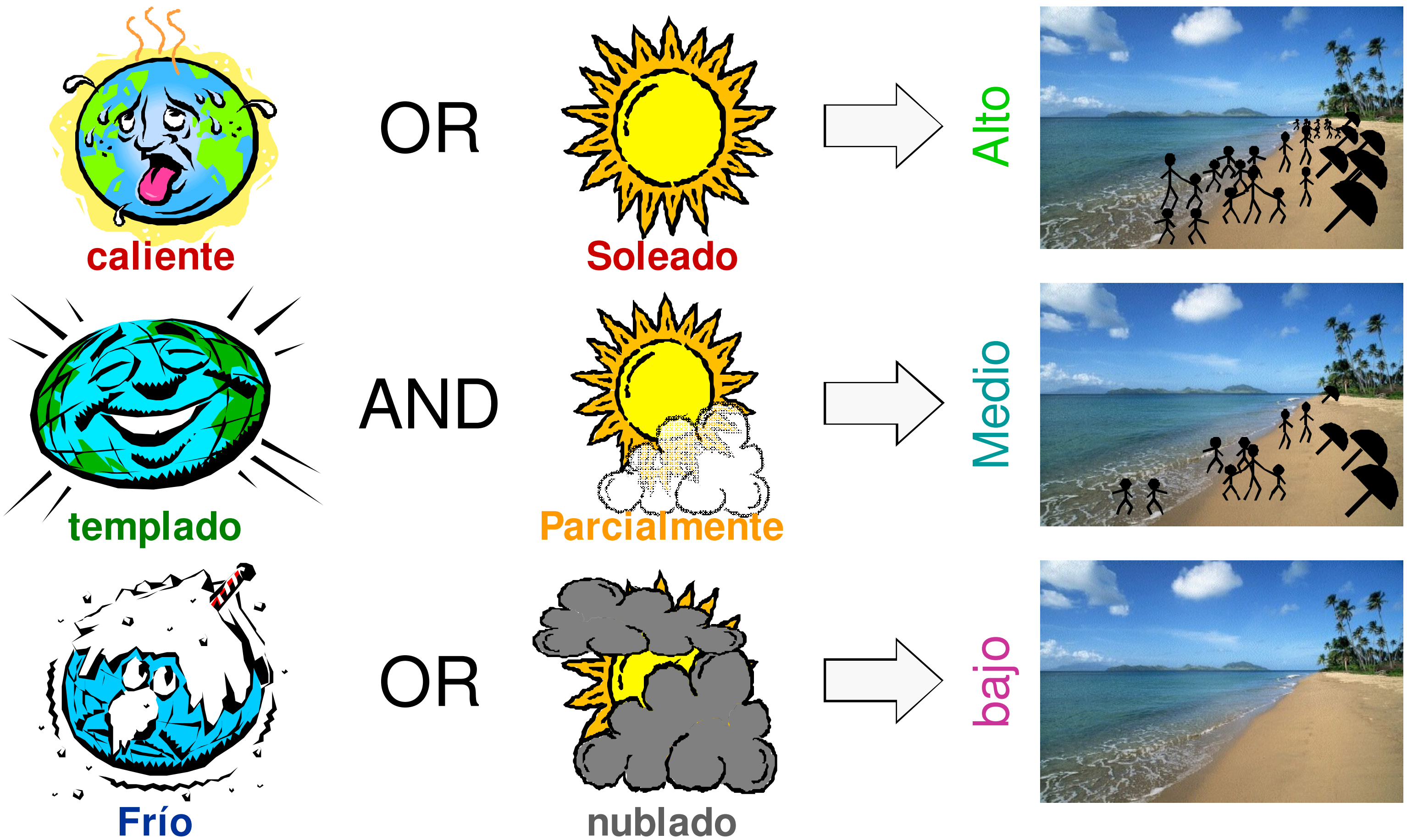
Huella de incertidumbre



a. Función de pertenencia Gaussiana
b. Incertidumbre alrededor de la función de pertenencia
c. Huella de incertidumbre

Modelando la incertidumbre: reglas difusas

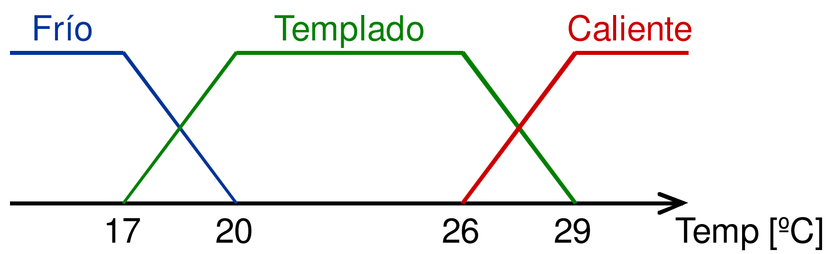
El problema de predicción de turistas.

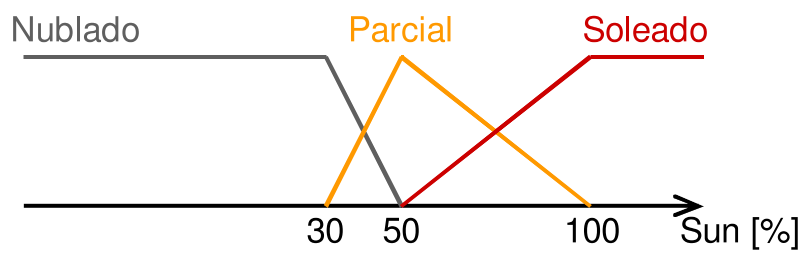


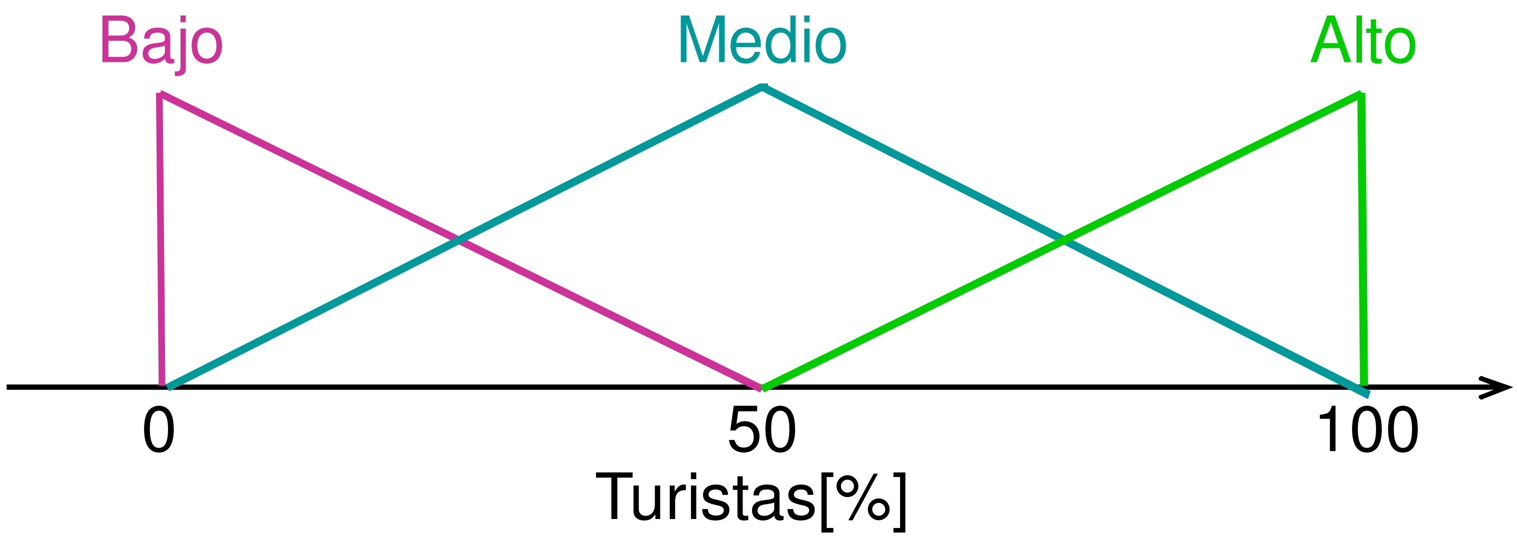
Sunshine

Carlos A. Peña, Evolutionary Fuzzy Modelling, 2000

Variables lingüísticas



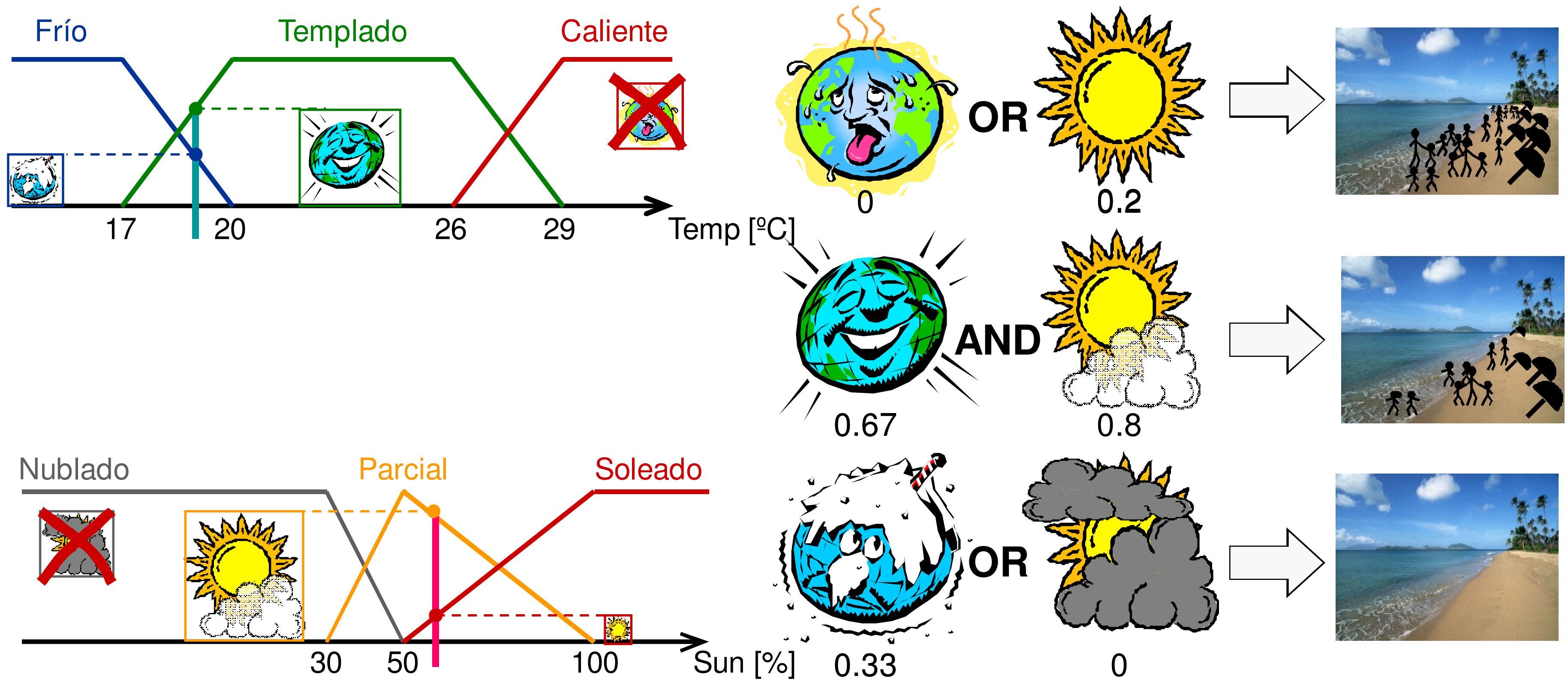




Carlos A. Peña, Evolutionary Fuzzy Modelling, 2000

Inferencia difusa

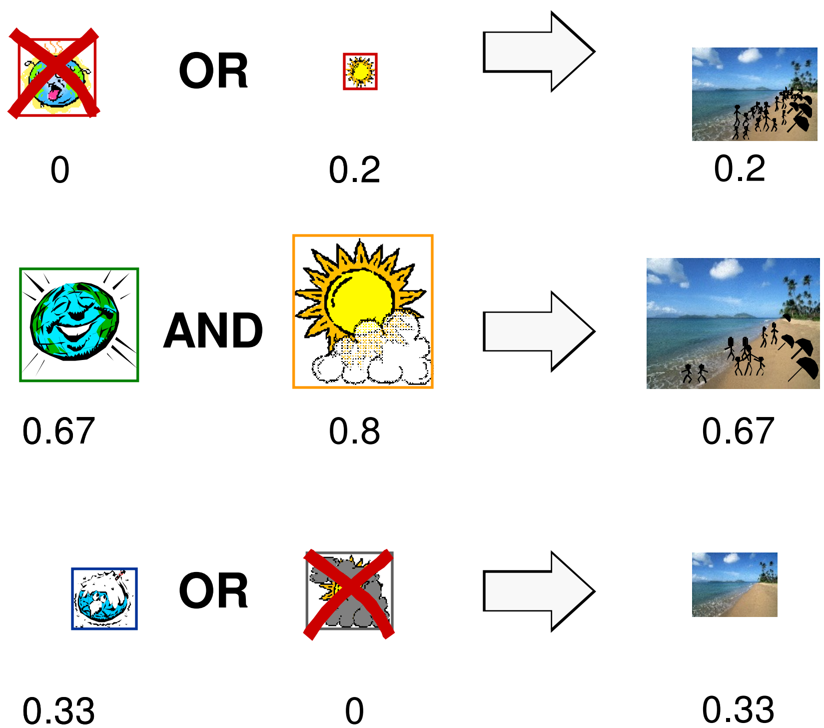
Pronóstico del clima (temperatura:19º, sol 60%)

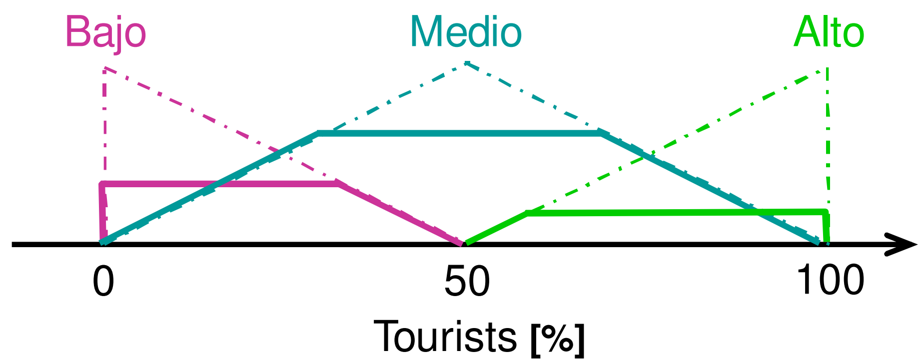


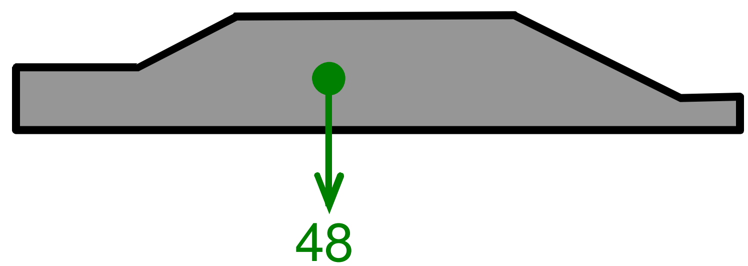
Carlos A. Peña, Evolutionary Fuzzy Modelling, 2000

Inferencia difusa

Pronóstico del clima (temperatura:19º, sol 60%)



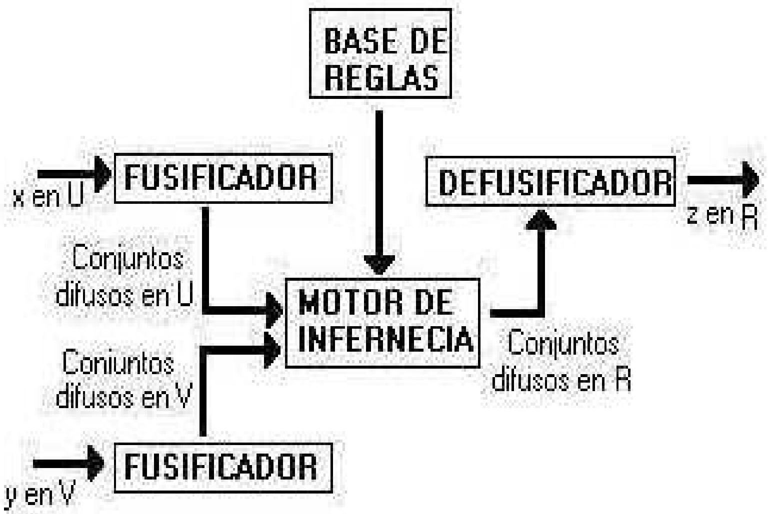


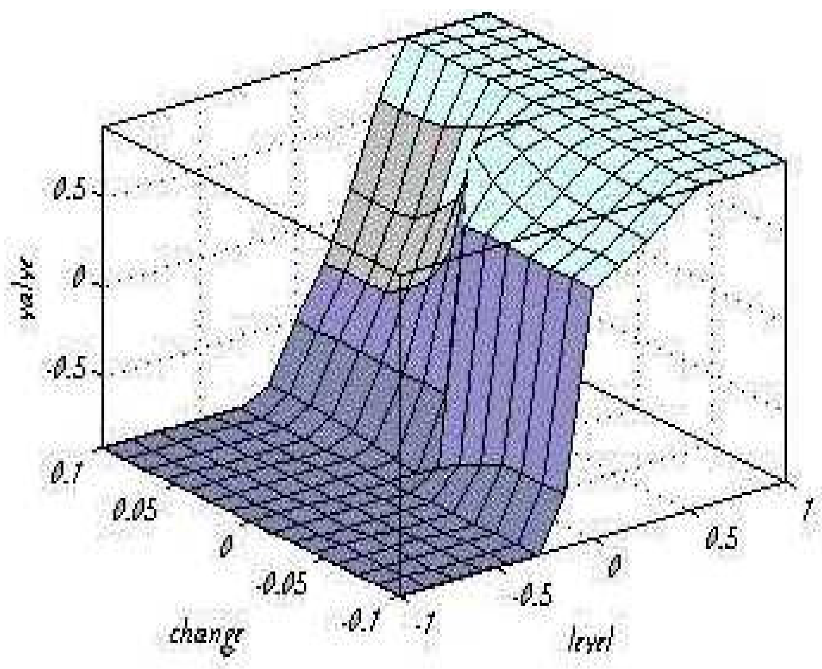


Turistas(19,60) ≈ 48

Carlos A. Peña, Evolutionary Fuzzy Modelling, 2000

Sistemas difusos





Teorema de aproximación universal

Suponga que el universo discurso de entrada U es cerrado y acotado en R^N. Entonces, para cualquier función continua g(x) en U y un valor $\varepsilon > 0$, existe un sistema difuso f(x) de la forma:

$$f(\mathbf{x}) = \frac{\sum_{l=1}^{M} y_l \left(\prod_{i=1}^{N} a_i^l \exp\left(-\frac{(x_i - x_i^l)^2}{(\sigma_i^l)^2} \right) \right)}{\sum_{l=1}^{M} \prod_{i=1}^{N} a_i^l \exp\left(-\frac{(x_i - x_i^l)^2}{(\sigma_i^l)^2} \right)}$$

Tal que :

$$\sup_{x \in U} \left| f(x) - g(x) \right| < \varepsilon$$

- L. X. Wang , *A course in fuzzy systems and control*, PTR 1996

Bases difusas

$$f(x) = \frac{\sum_{l=1}^{M} y_l \left(\prod_{i=1}^{N} \mu_{A_i^l}(x_i) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{N} \mu_{A_i^l}(x_i) \right)}$$

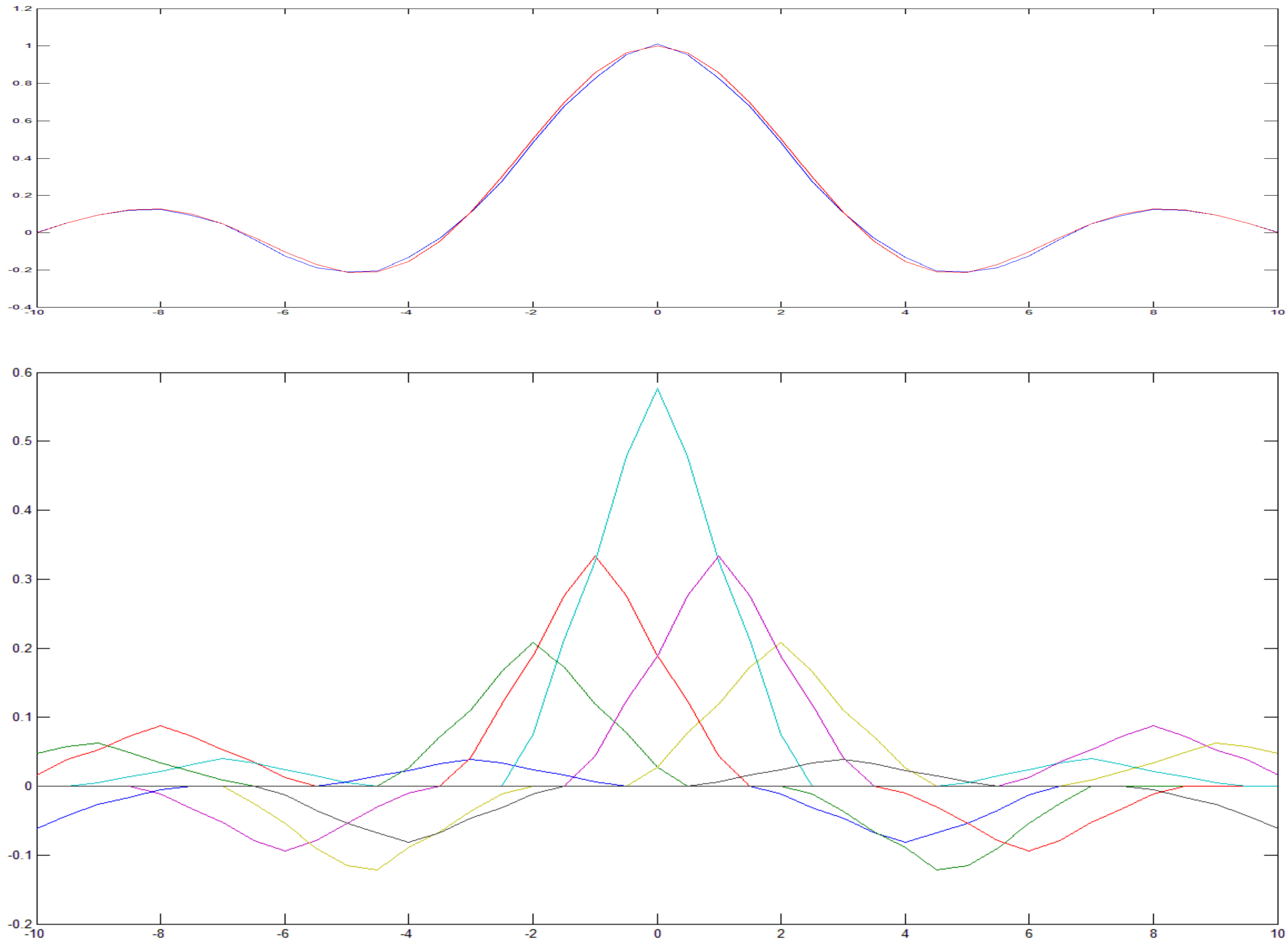
Expansión FBD

$$y(x) = f_s(x) = \sum_{l=1}^{M} y_l \cdot \phi_l(x)$$

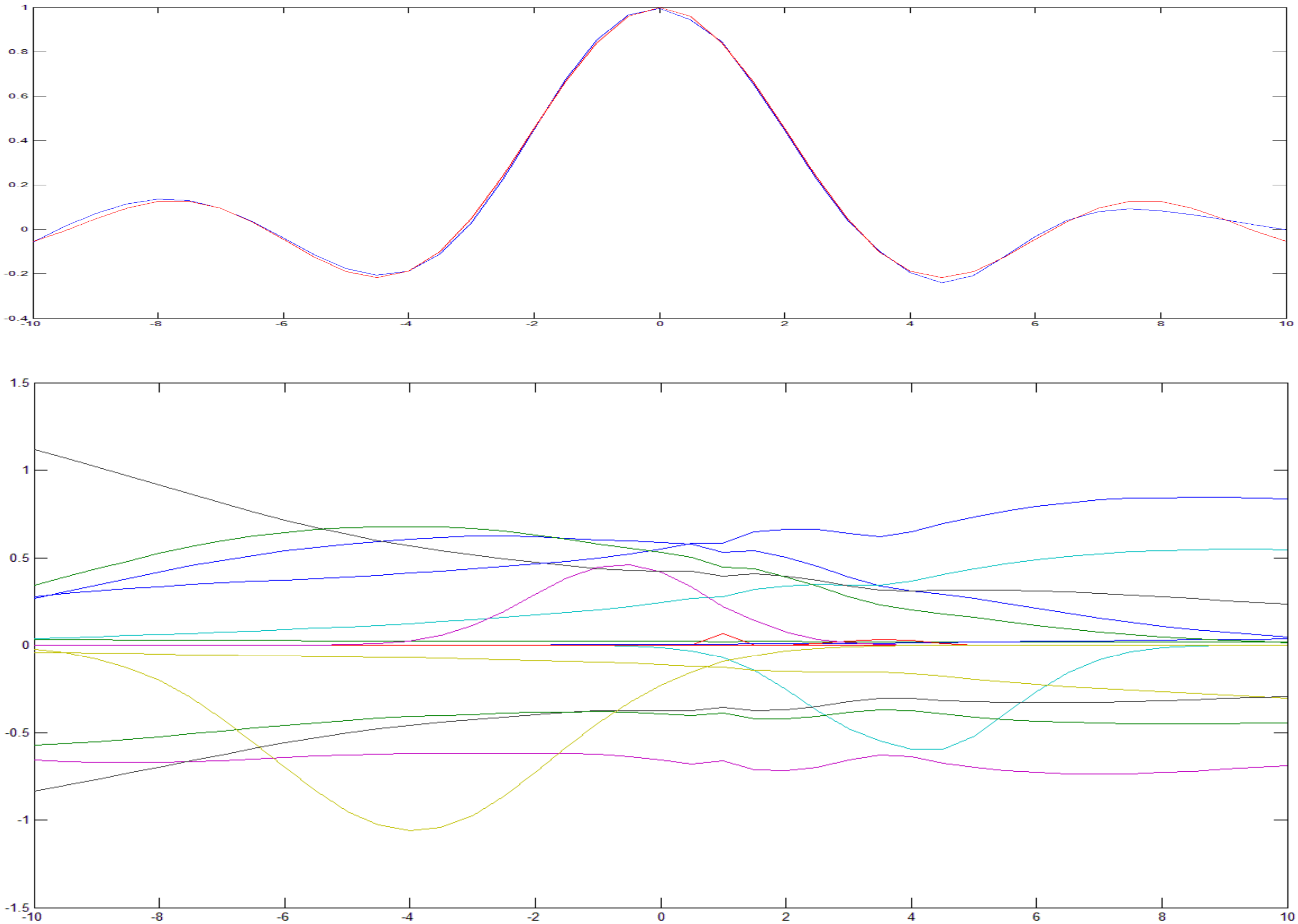
$$\phi_l(x) = \frac{\prod_{i=1}^{N} \mu_{A_i^l}(x_i)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{N} \mu_{A_i^l}(x_i) \right)}$$

Funciones de base difusa

Expansión de funciones de base difusa

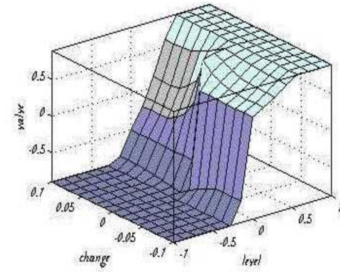


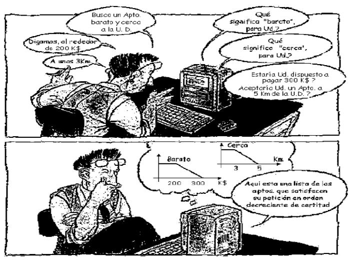
Expansión de funciones de base difusa



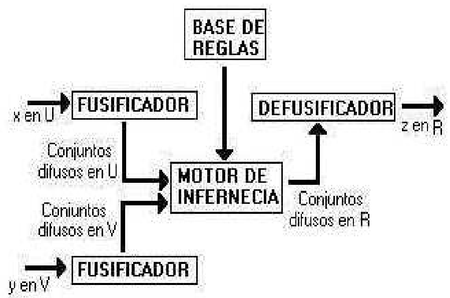
Mensaje para la casa….

Mapas
No lineales



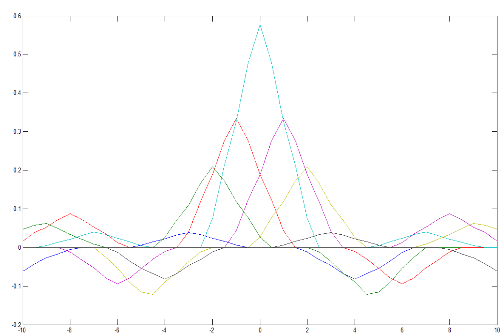


Reglas
Y
palabras



$$f(\mathbf{x}) = \frac{\sum_{l=1}^{M} y_l \left(\prod_{i=1}^{N} a_i^l \exp\left(-\frac{(x_i - x_i^l)^2}{(\sigma_i^l)^2} \right) \right)}{\sum_{l=1}^{M} \prod_{i=1}^{N} a_i^l \exp\left(-\frac{(x_i - x_i^l)^2}{(\sigma_i^l)^2} \right)}$$

Aproximador
Universal



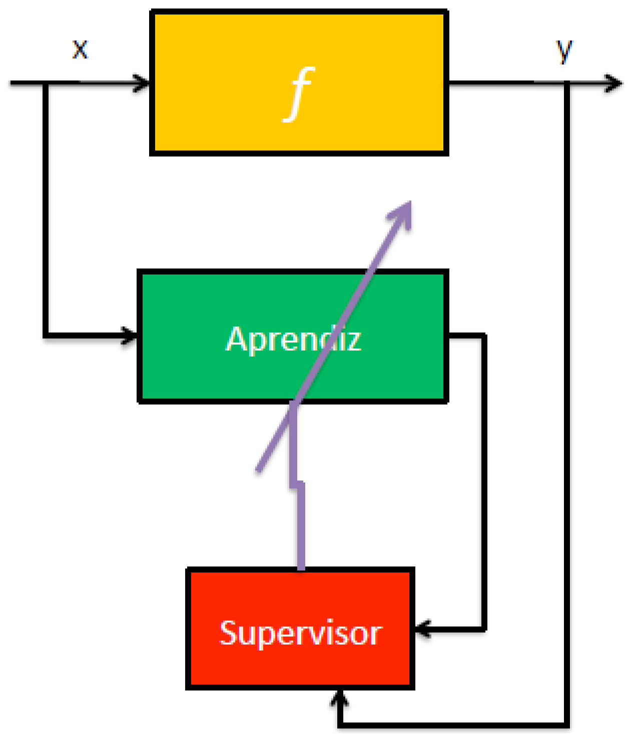
Expansión
De bases

πάντα χωρεῖ καὶ οὐδὲν μένει (*todo cambia, nada permanece)*

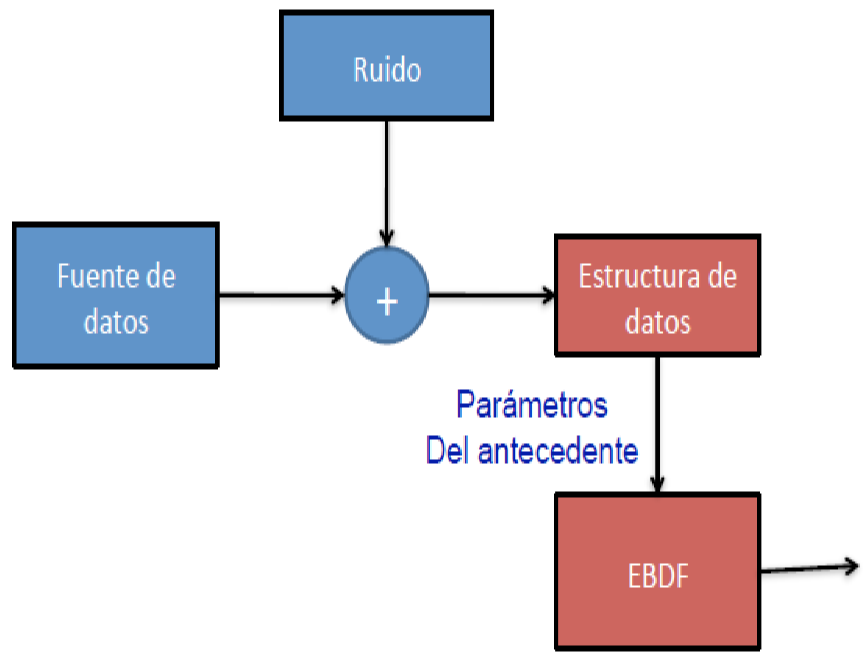
(*Heraclito*)

MODELADO DIFUSO EVOLUTIVO

Aprendizaje en sistemas difusos



Supervisado

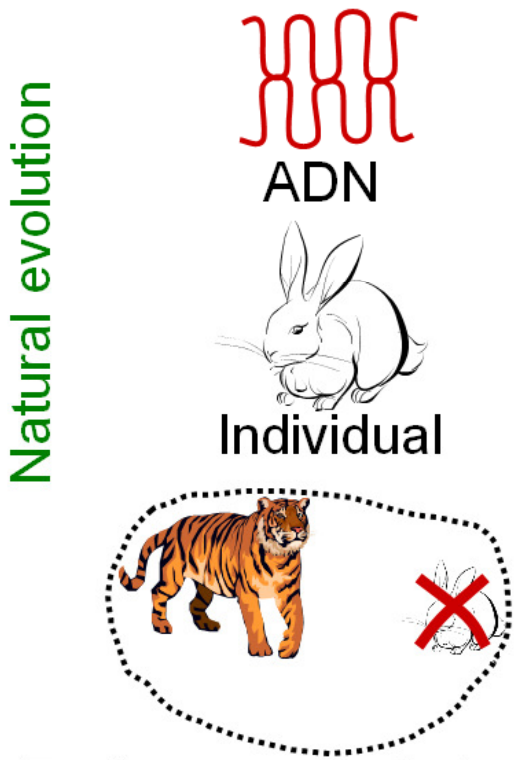


No supervisado

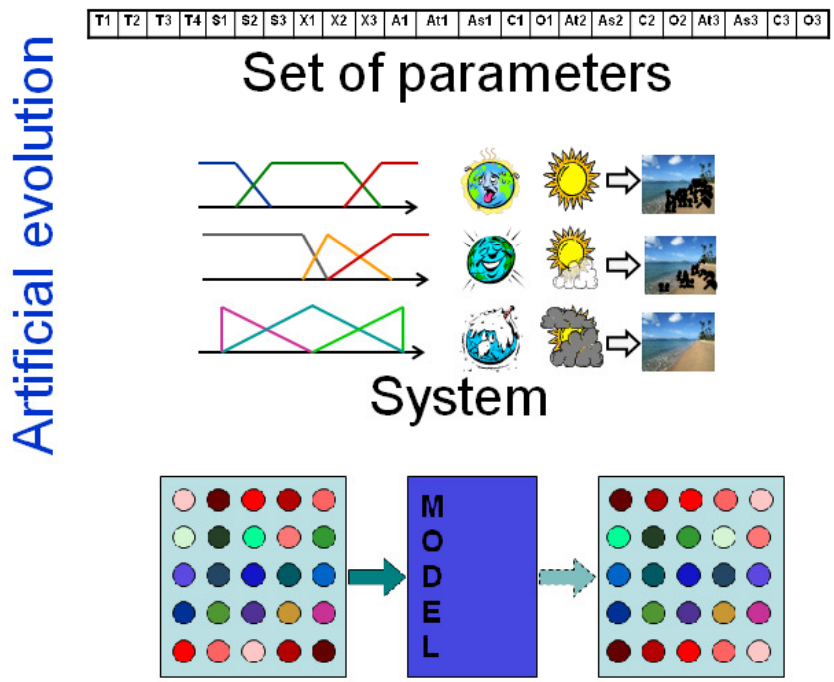
Aprendizaje en sistemas difusos

- Mínimos cuadrados
- Back-propagation
- Agrupamiento (C-means, K-means, etc)
- Mapas auto-organizados
- ….

Evolución artificial
Una metáfora de la evolución natural



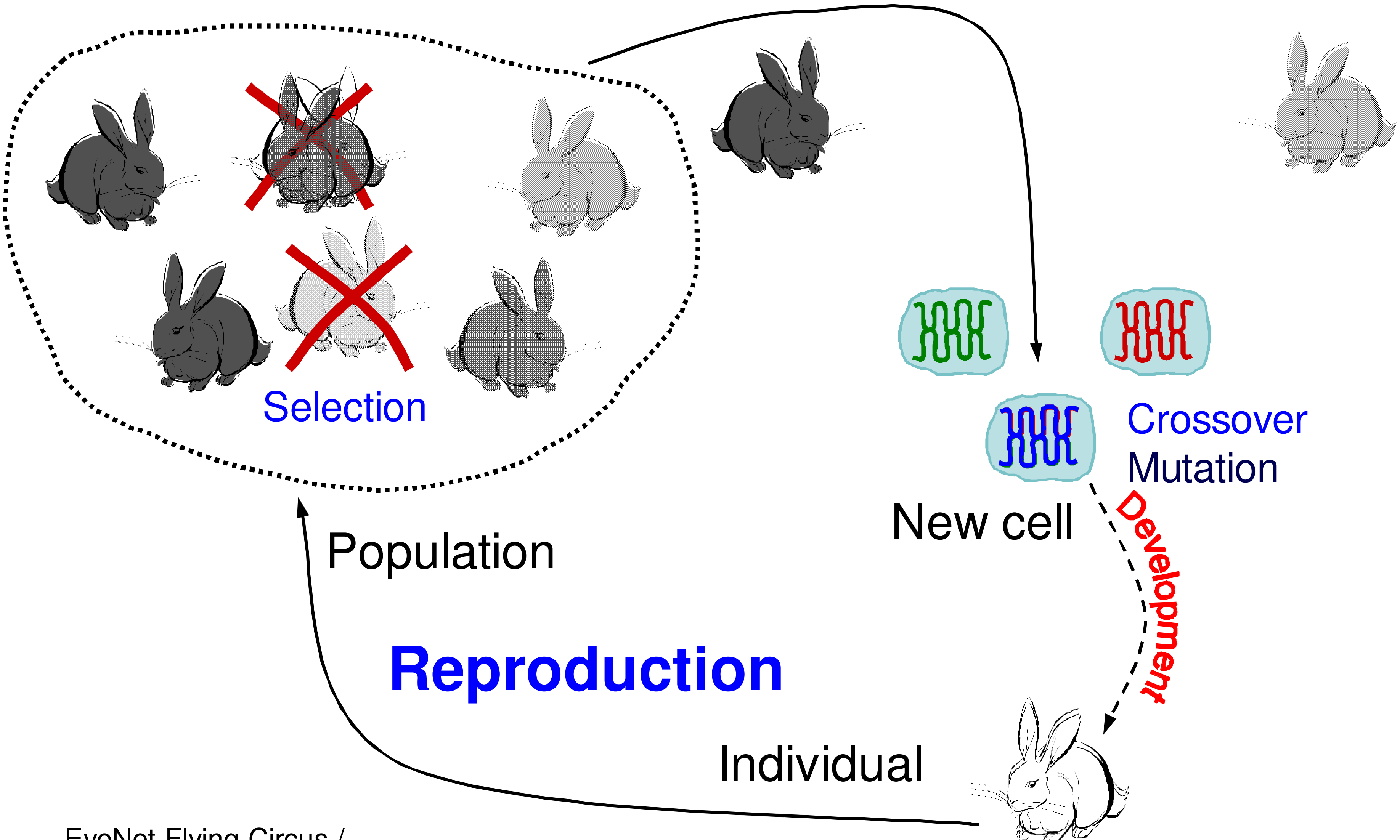
Environment = Selection



Performance = Selection

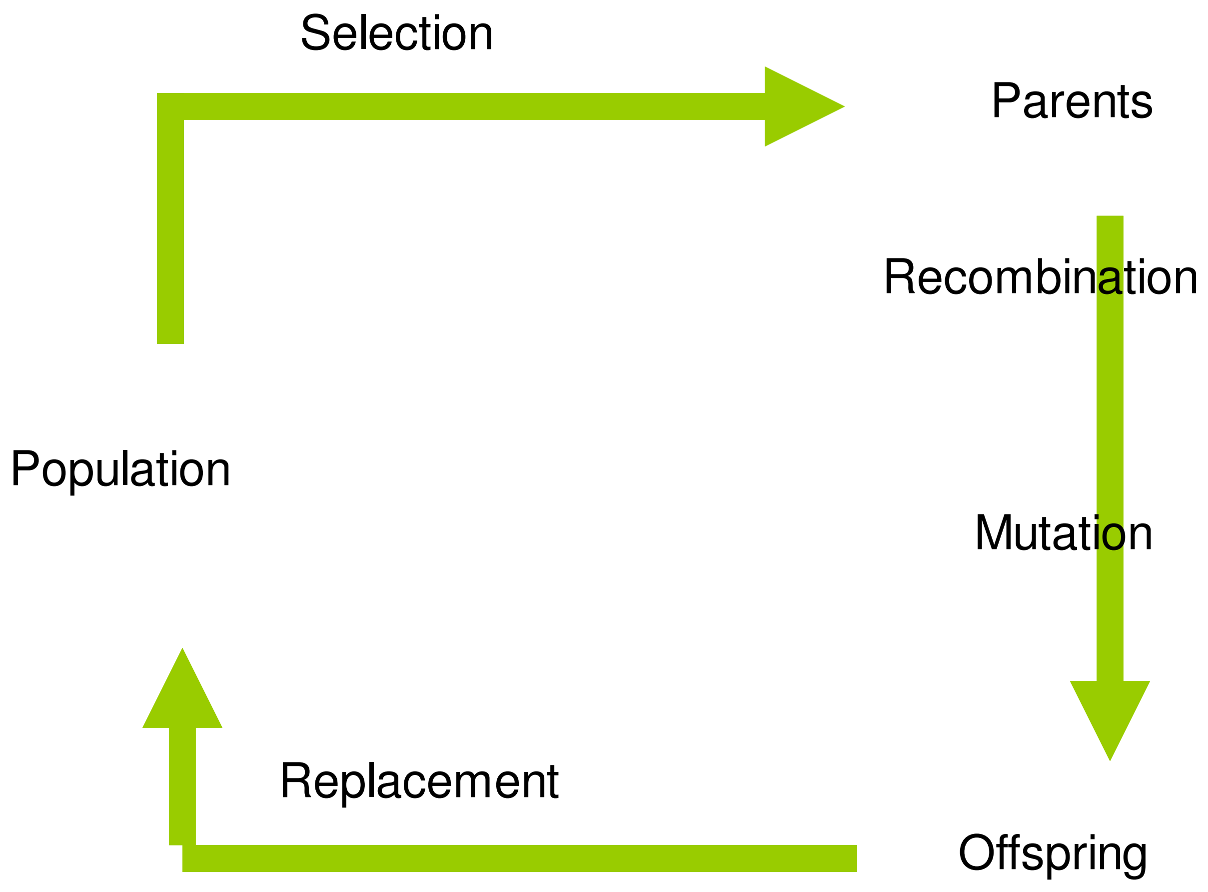
EvoNet Flying Circus /
Carlos A. Peña LSL-EPFL

Un modelo de evolución…



EvoNet Flying Circus /
Carlos A. Peña, LSL_EPFL

El ciclo evolutivo

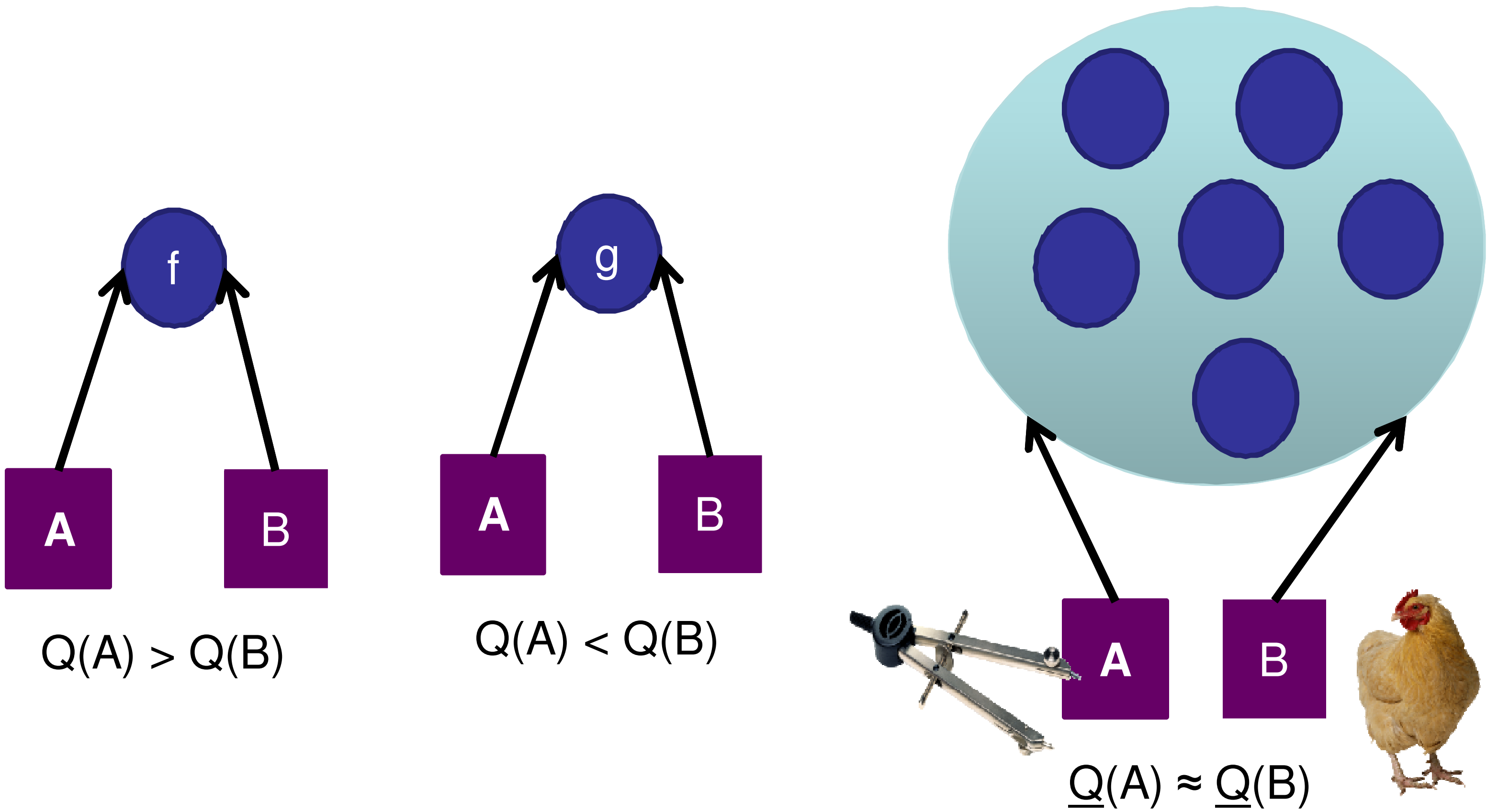


EvoNet Flying Circus /
Carlos A. Peña, LSL- EPFL

Algoritmos evolutivos (generaciones)

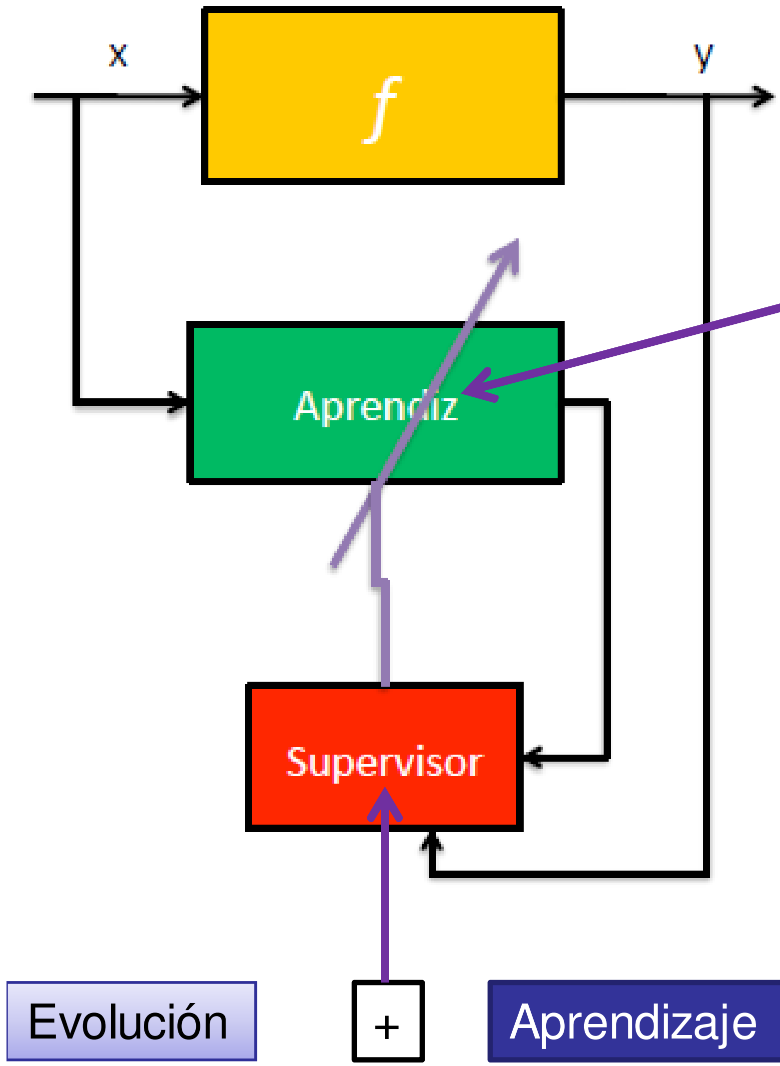
- Algoritmo genético simple
- Algoritmos co-evolutivos
- Evolución diferencial
- Algoritmo genético compacto
- Algoritmos meméticos
- Algoritmo simbióticos
- ….

No free Lunch theorem



Wolpert, D.H.; Macready, W.G., "No free lunch theorems for optimization," *Evolutionary Computation, IEEE Transactions on* , vol.1, no.1, pp.67,82, Apr 1997

Sistema difuso evolutivo



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"Experience: that most brutal of teachers. But you learn, my God do you learn."

C.S. Lewis

CASOS DE APLICACIÓN

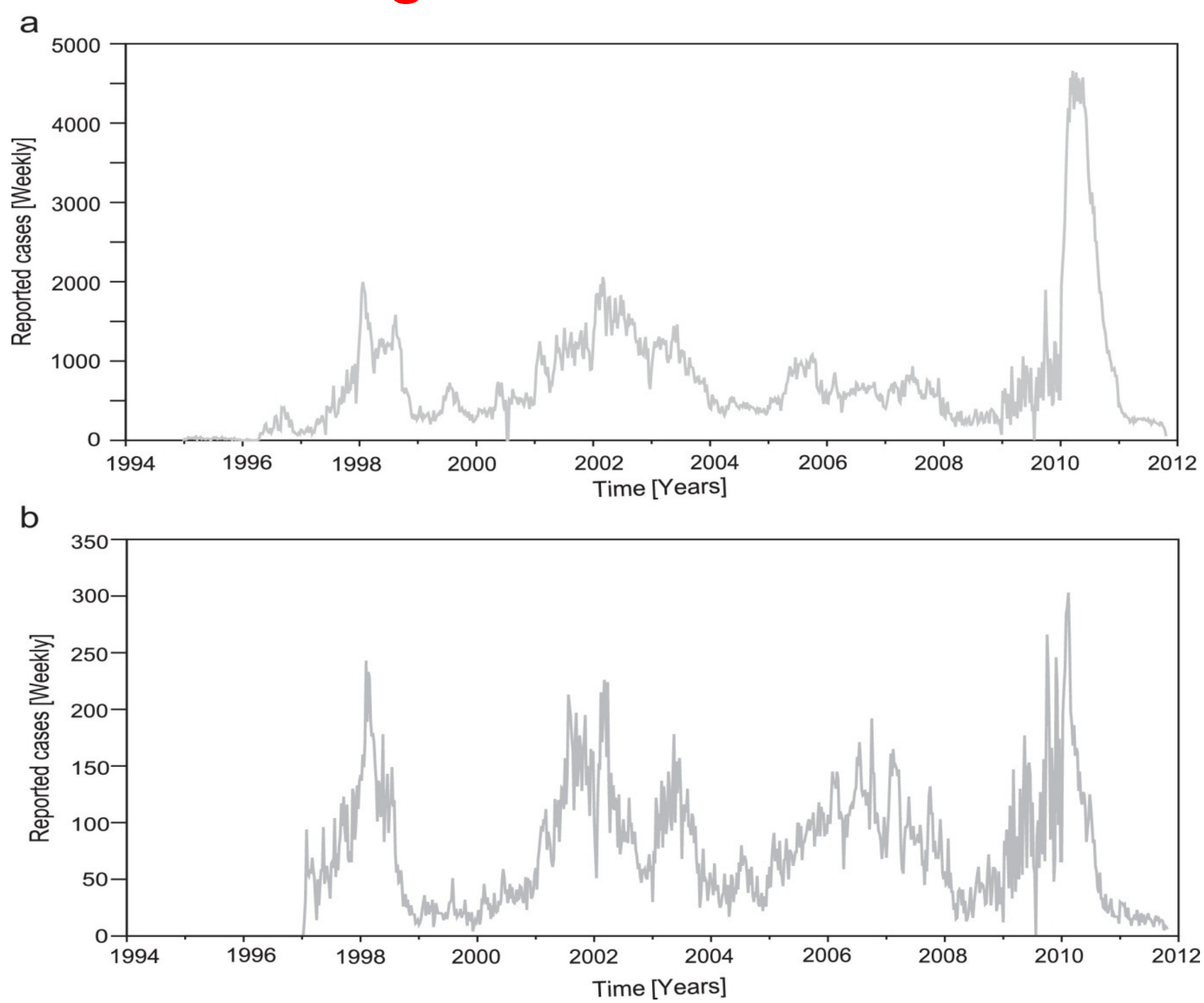
Fenómenos complejos

- Fenomenos (señales o sistemas)
- Complejos (caos, multiples escalas, fractalidad, multi-fractalidad, propiedades emergentes, auto-organización,etc)

Casos de aplicación

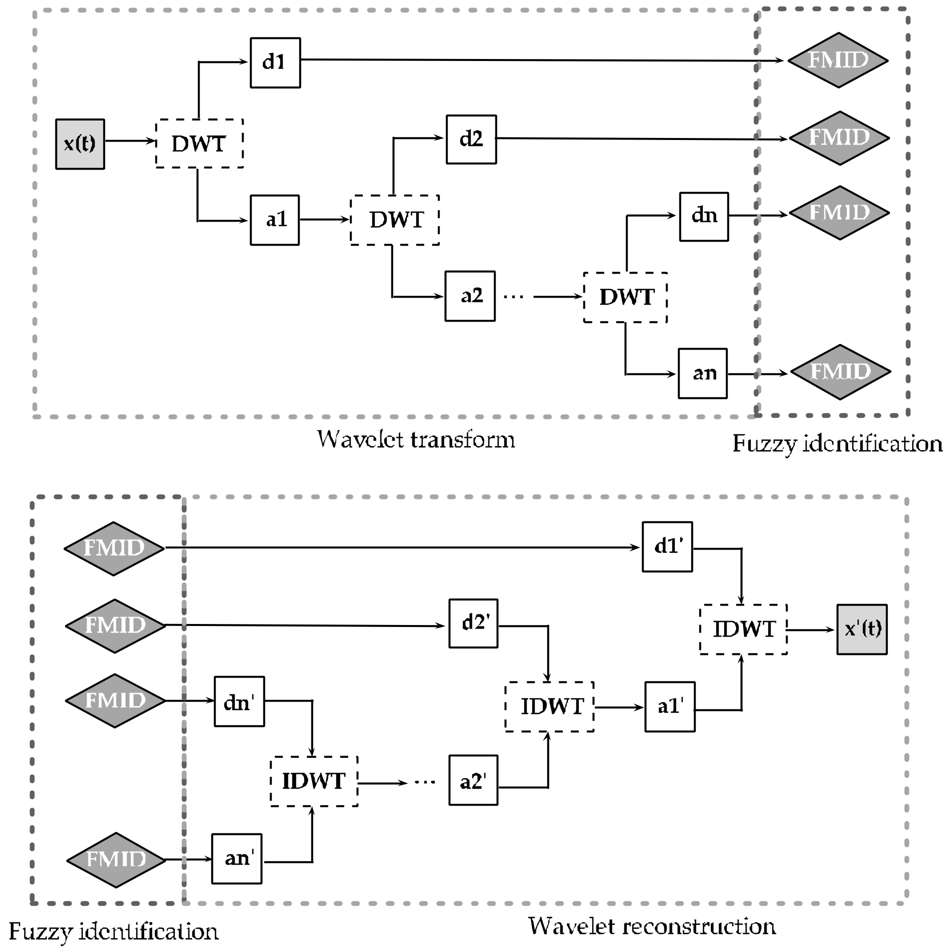
- Modelo difuso multi-escala de la epidemia de Dengue en Colombia.
- Clasificación de eventos PM10 en Bogotá DC.
- Auto-organización guiada de automatas celulares difusos.

Modelo difuso multi-escala de la epidemia de Dengue en Colombia



C. Torres, S. Barguil, M. Melgarejo, A. Olarte, *Fuzzy model identification of dengue epidemic in Colombia based on multiresolution analysis, Artificial Intelligence in Medicine*, 60,1,pp 41-51, Jan 2014

Modelo difuso multi-escala de la epidemia de Dengue en Colombia



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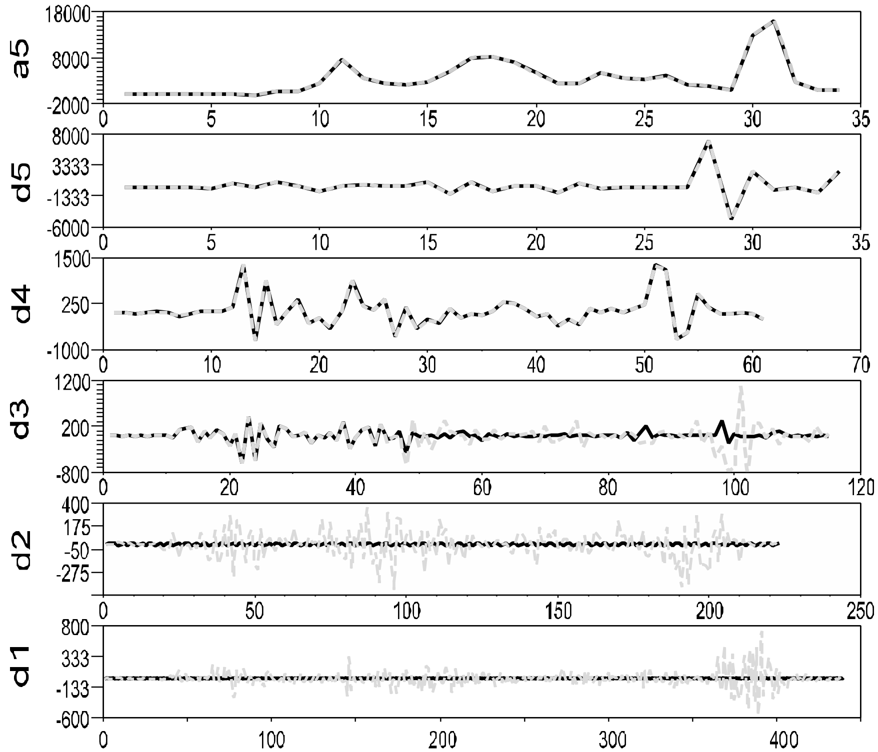

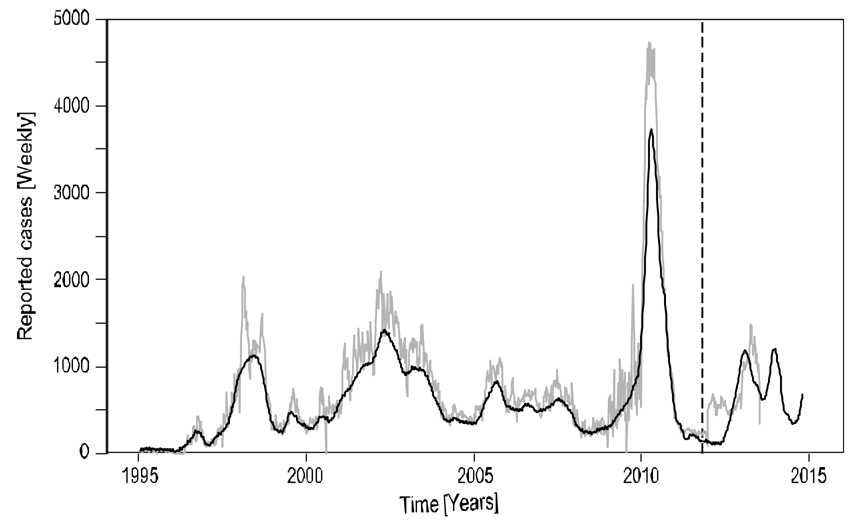

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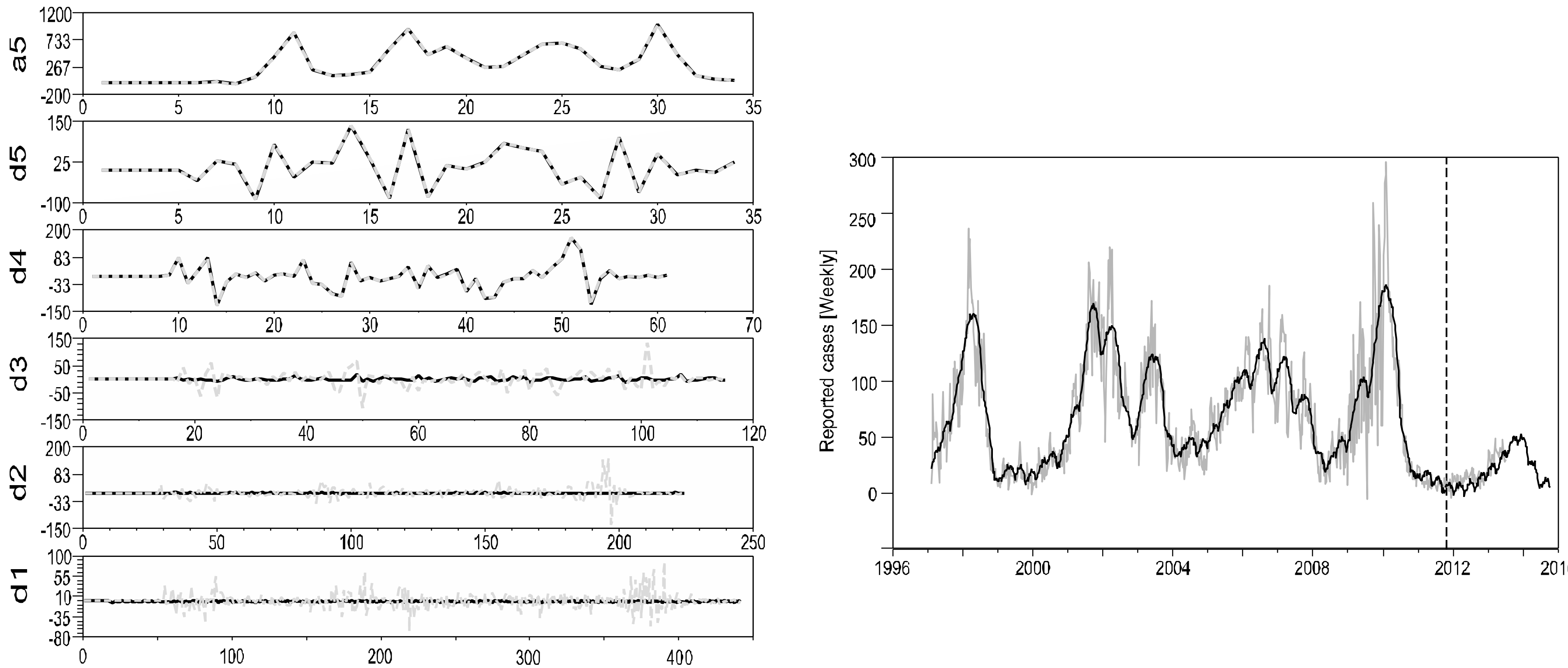
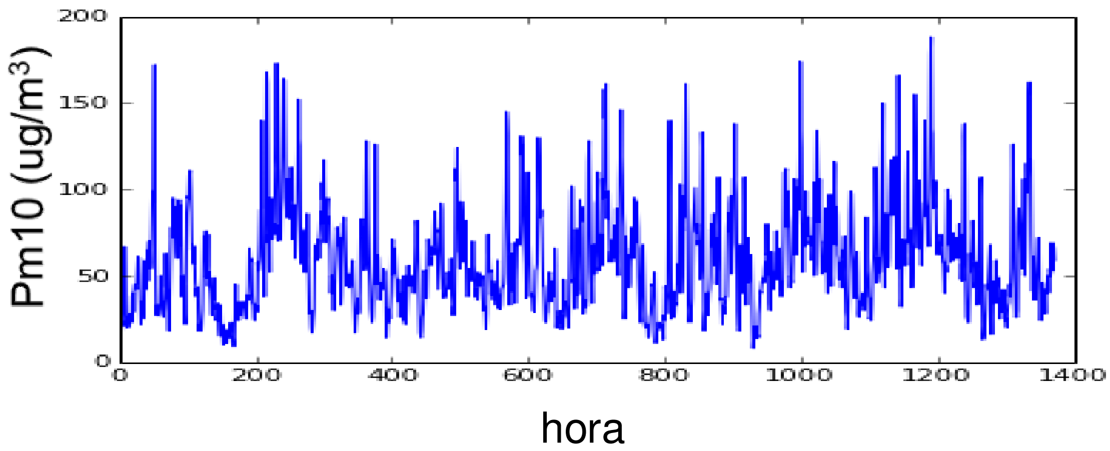
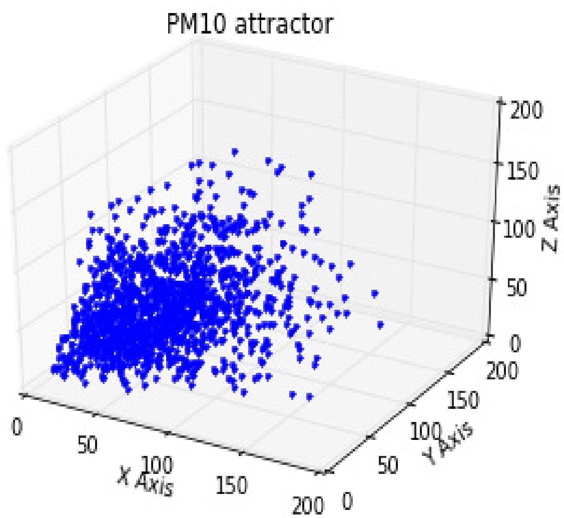


C. Torres, S. Barguil, M. Melgarejo, A. Olarte, *Fuzzy model identification of dengue epidemic in Colombia based on multiresolution analysis, Artificial Intelligence in Medicine*, 60,1,pp 41-51, Jan 2014

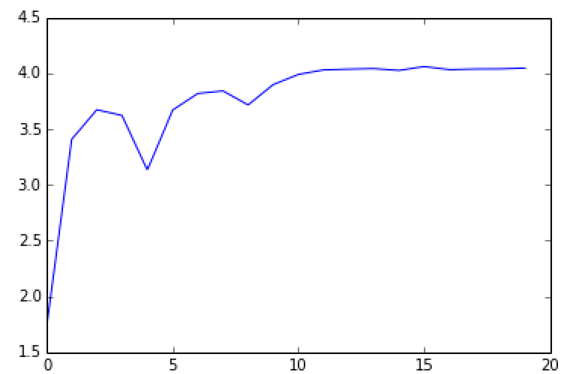
Clasificación de eventos PM10 en Bogotá DC



Reconstrucción del Atractor (Teorema de Takens)

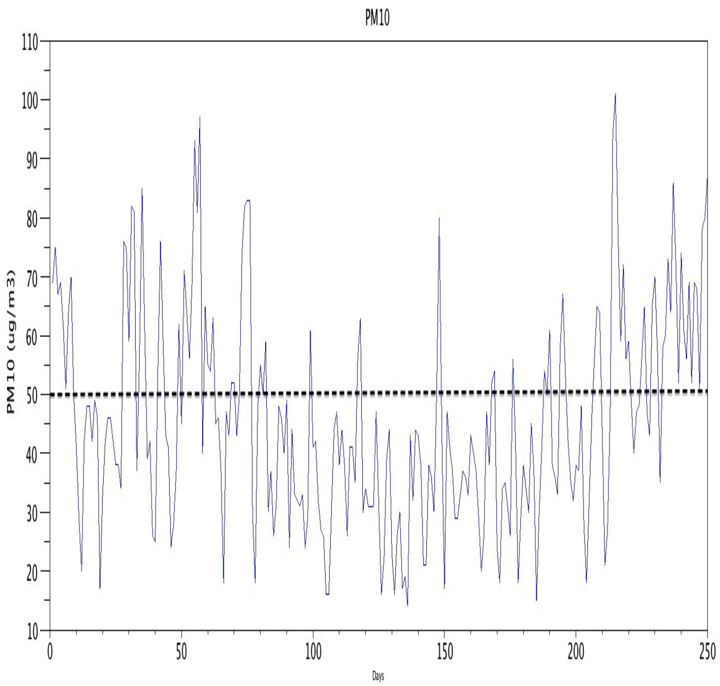


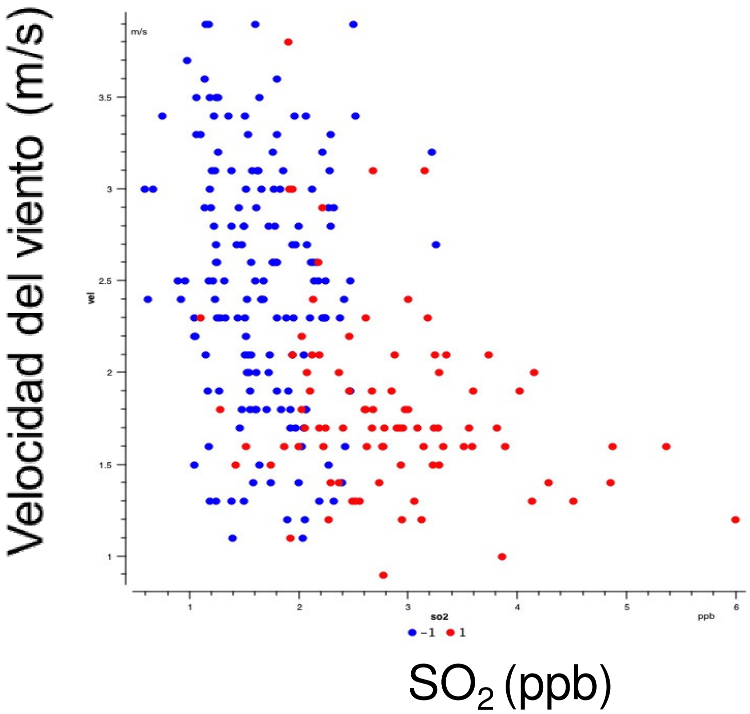
Máximo exponente de Lyapunov (Método de Rosenstein)



M. Melgarejo, N. Obregon, C. Parra, Applying Computational Intelligence to the Classification of Environmental Situations Associated to Pollution Events, *IEEE Transactions Latin America*, Dic 2014, (TBP)

Clasificación de eventos PM10 en Bogotá DC





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Clasificación de eventos PM10 en Bogotá DC

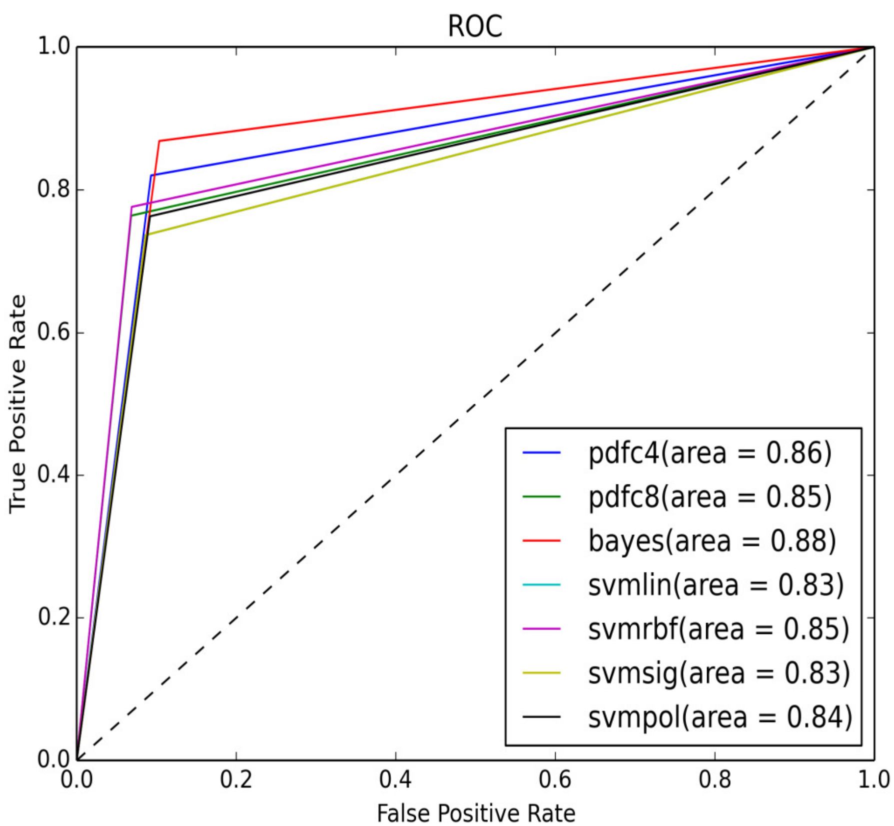
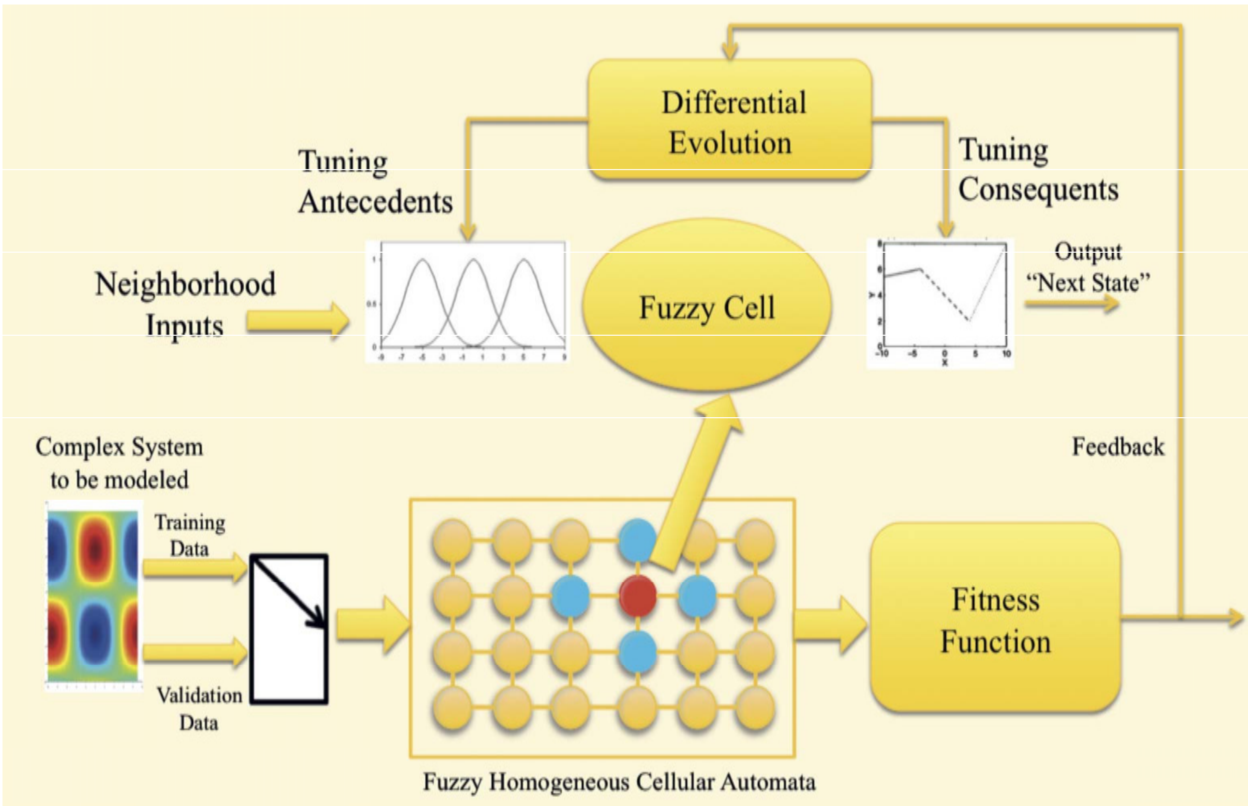


TABLA I
RESULTADOS DE LA VALIDACIÓN DE LOS CLASIFICADORES

Clasificador	Exactitud (%)	Sensibilidad (%)	Especificidad (%)
Bayes	85.63	91.1	75.31
Svmlin	86.44	93.02	74.04
Svmpol	86.41	93.16	73.69
Svmrbf	86.40	92.98	74.00
Svmsig	86.47	93.00	74.15
Pdfc4	84.16	85.10	82.81
Pdfc8	84.86	85.60	84.50

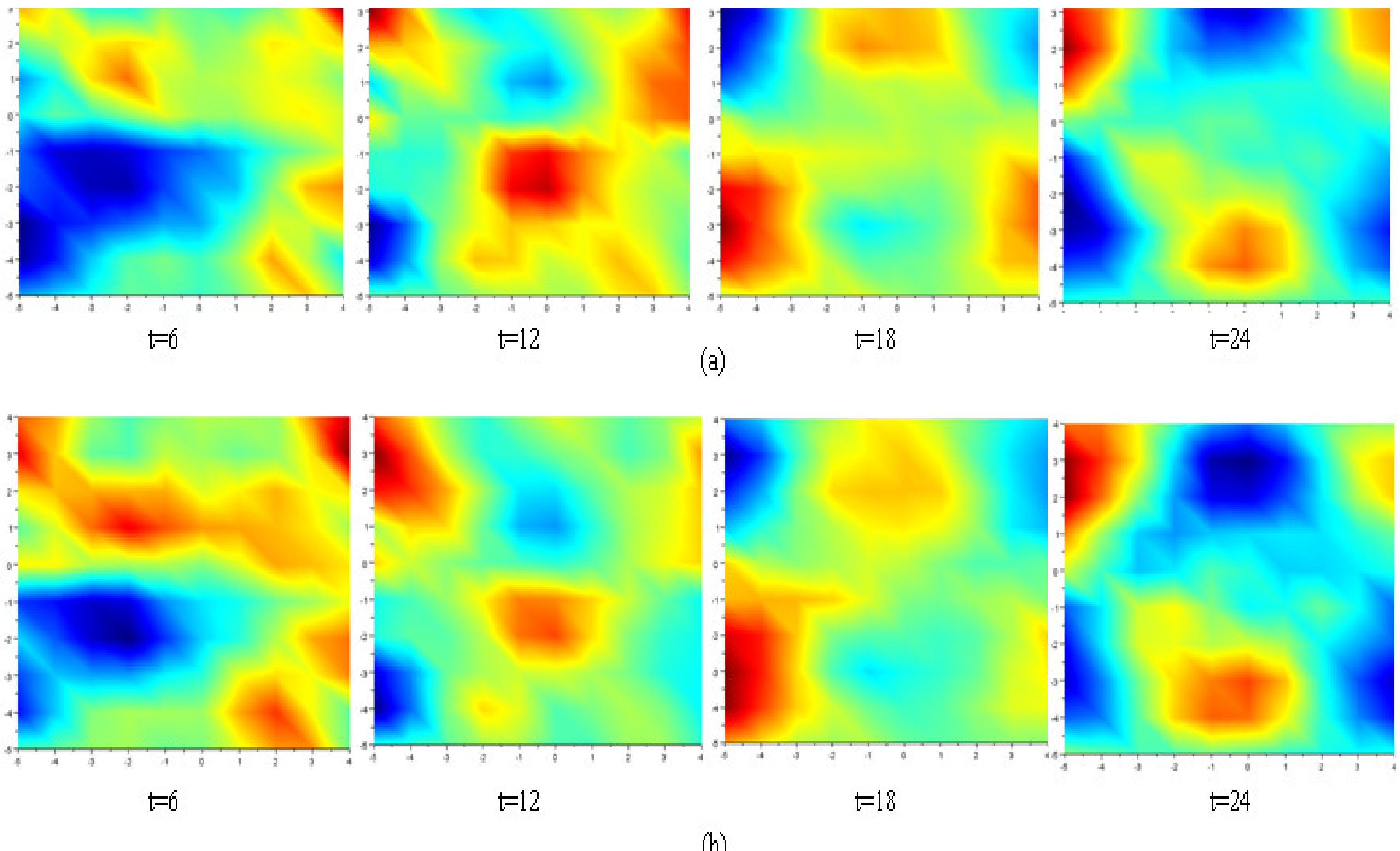
M. Melgarejo, N. Obregon, C. Parra, Applying Computational Intelligence to the Classification of Environmental Situations Associated to Pollution Events, *IEEE Transactions Latin America*, Dic 2014, (TBP)

Automatas celulares difusos (Auto-organización guiada)



Chivata, J.; Luengas, Y.; Melgarejo, M.; Obregon, N., "Complex system modeling using TSK fuzzy cellular automata and differential evolution,"*2013 IEEE International Conference on Fuzzy Systems (FUZZ),* July 2013

Automatas celulares difusos (Auto-organización guiada)



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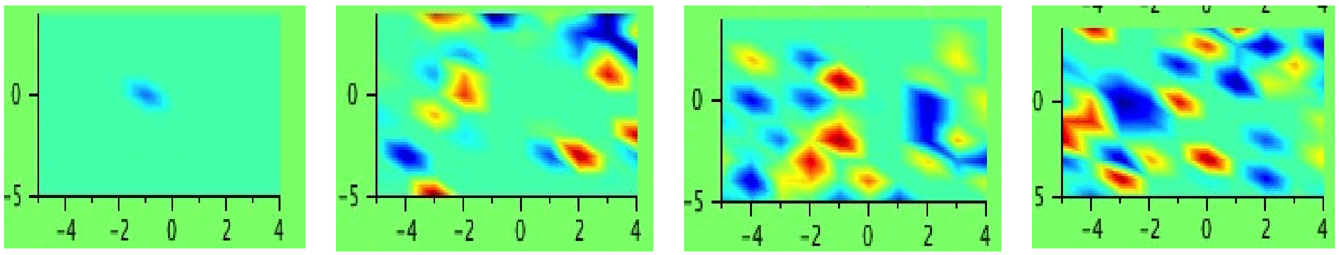

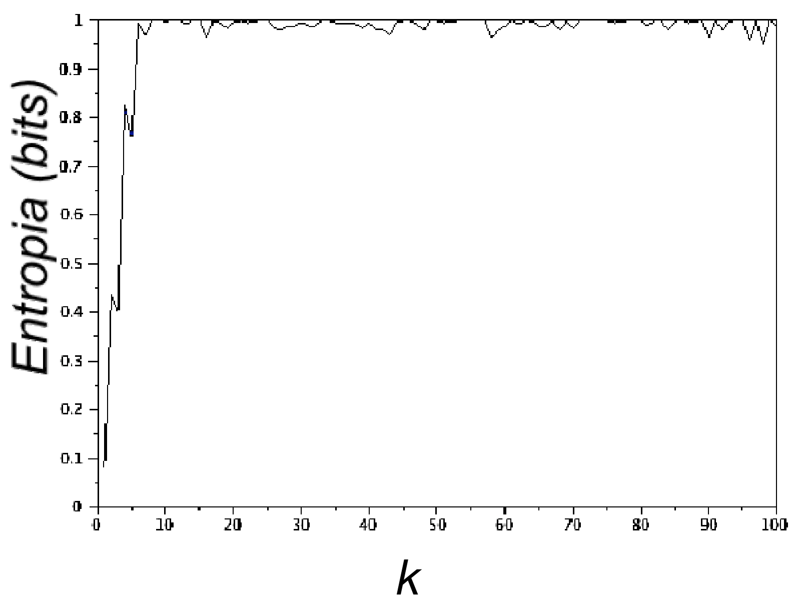

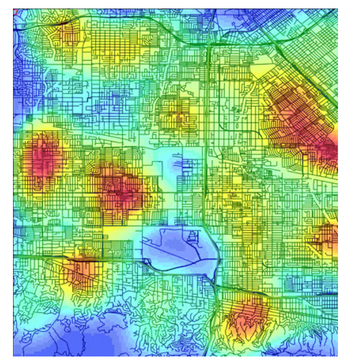

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M. Melgarejo, N. Obregon, "On the design of fuzzy cellular automata following a maximum entropy principle," *2014 IEEE Conference on Norbert Wiener in the 21st Century (21CW),* pp.1,5, 24-26 June 2014

Para finalizar…

- Modelado difuso evolutivo : una herramienta.

- Limitaciones: Teorema de aproximación universal y No Free Lunch Theorem.

- Posibilidades: conexión Micro-Macro.

Evaluando en lo Macro, diseño en lo Micro.