NUMEROS-Z: UN NUEVO ENFOQUE PARA EL ANÁLISIS DE INCERTIDUMBRE

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Motivación

- En gran medida, la ciencia y la ingeniería residen en el mundo de las mediciones y los números.

- En este mundo, una pregunta básica que surge es: ¿Cuán confiables son los números que tratamos?

- Esta pregunta desempeña un papel particularmente importante en el análisis de decisiones, la planificación, la economía, la evaluación de riesgos, el diseño y el análisis de procesos, evaluación de riesgos, predicción, anticipación, y biomedicina.

Número Z

- El concepto de un número Z está destinado a proporcionar una base para el cálculo con números que no son totalmente fiables.

- Más concretamente, un número Z, Z = (A, B), es un par ordenado de dos números difusos.
  - El primer número, A, es una restricción sobre los valores que puede tomar una variable de valor real, X.
  - El segundo número, B, es una restricción en la fiabilidad de que X es A.
  - Normalmente, A y B se describen en un lenguaje natural.

Z= (fuzzy value, fuzzy reliability)
NL NL

Número Z

- A = aproximadamente 2 millones de dólares
- B = muy probable

- A = aproximadamente 1 hora
- B = normalmente

- A = alto
  B = seguramente

Valoración Z

- Es una tripleta ordenado de la forma (X, (A, B)), donde X es una variable de valor real y (A, B) es un número-Z.

Ejemplos.

- **(desempleo el próximo año, fuerte declive, poco probable)**
- **(Edad (Robert), joven, muy probable)**
- **(Tráfico, pesado, por lo general).**

Valoración Z Condicional

Si (X, A, B) entonces (Y, C, D)

- Versión más simple

Si (X, A) entonces (Y, B, C)

- De forma equivalente,

Si (X es A) entonces (Y <u>iz</u> (B, C))

Regla Z

Información Z

En entornos reales, gran parte de la información en un entorno de incertidumbre e imprecisión puede representarse como una **colección de valoraciones Z y valoraciones Z condicionales**, a lo que se denomina **información Z.**

Ejemplos:

- Por lo general, es difícil encontrar aparcamiento cerca del campus en la madrugada => **(encontrar aparcamiento cerca del campus en la madrugada, difícil, por lo general)**
- Por lo general, Robert tarda una hora en llegar a casa del trabajo => (**tiempo de viaje del trabajo a casa, aproximadamente una hora, por lo general)**

SEMÁNTICA DE UNA REGLA Z

If X is A then Y is B => (X, Y) is A×B

If (X is A) then Y iz (B, C) => (X×Y) iz (A×B, C)

If X is A_1 then Y iz (B_1C_1)

…

If X is A_n then Y iz (B_nC_n)

(X, Y) iz ((A_1×B_1,C_1) +⋯+ (X, Y) iz (A_n×B_n,C_n))

SEMÁNTICA DE UNA REGLA Z

- (Aproximadamente 1 hora, usualmente) + (aproximadamente 45 minutos, usualmente)

- Pero, ¿Cuál es el significado del promedio de (**aproximadamente x tiempo, ?**)?

- Hay dos conceptos que desempeñan un papel esencial en la computación con números-Z, los conceptos **de restricción y de extensión**.

Concepto de restricción

- La pieza central del cálculo de los números Z es el concepto de una restricción.
- El concepto de restricción es más general que los conceptos de intervalo, conjunto, conjunto difuso, conjunto bruto (rough set) y distribución de probabilidad.

Una restricción sobre una variable X, R(X), es una respuesta a una pregunta de la forma: ¿Cuál es el valor de X?

- Ejemplos

X = 5

X es entre 3 y 7

X es pequeño

Es probable que X sea pequeño

Normalmente X es mucho más grande que aproximadamente 5.

Los veranos suelen ser fríos en San Francisco (X está implícito)

Robert es mucho más alto que la mayoría de sus amigos (X está implícito)

Concepto de restricción

Un ejemplo de un problema simple que implica el cálculo con restricciones.

- Por lo general, Robert deja su oficina alrededor de las 5 pm.
- Por lo general, Robert tarda una hora en llegar a casa del trabajo.

¿A qué hora llega Robert a casa?

Concepto de restricción

- La forma canónica de una restricción se expresa como

R (X): X es R,

Donde X es la variable restringida, R es la relación de restricción y r es una variable indexical que define la forma en que R restringe a X.

- Hay muchos tipos de restricciones.
  - Una **restricción es singular** si R es un *singleton* (uno unico elemento).
    Ejemplo. X = 5.
  - Una **restricción es no singular** si R no es un *singleton*. No singular implica incertidumbre.

Concepto de restricción

- Una **restricción es directa** si la variable restringida es X.
- Una **restricción es indirecta** si la variable restringida es de la forma F(X).
  Ejemplo.

$$R(p) = \int_b^a \mu(u)p(u)du \; es \; probable$$

Es una restricción indirecta en p.

- Los **principales tipos de restricciones** son:
  – restricciones posibilistas,
  – restricciones probabilísticas y
  – restricciones Z.

Restricciones posibilistas

R (X): X es A,

Donde A es un conjunto difuso en un espacio U, con la función de pertenencia μ_A.

- A juega el papel de la distribución de la posibilidad de X,

$$\textbf{Poss}\ (X = u) = \mu_A(u).$$

- Ejemplo

X es pequeño

Variable restringida → X

Relación de restricción (conjunto difuso) → pequeño

El conjunto borroso pequeño juega el papel de la distribución de la posibilidad en X.

Restricciones posibilistas

Leslie es más alto que Ixel =>

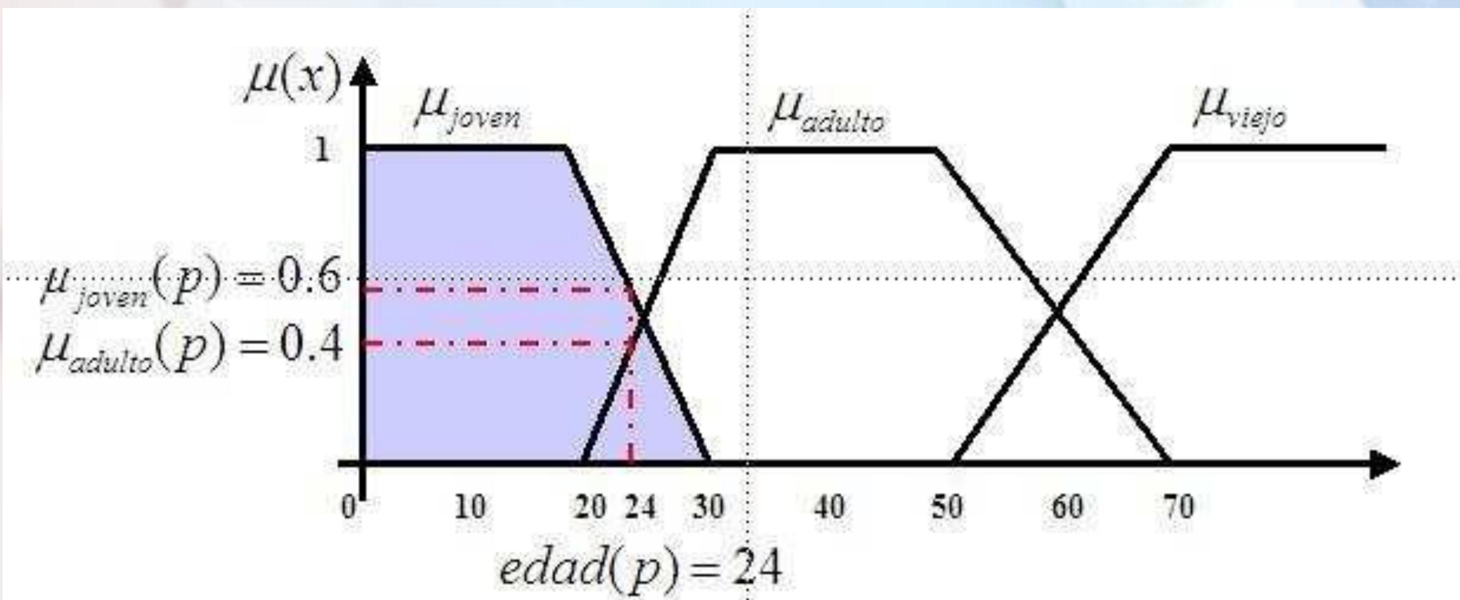
(Altura (Leslie), Altura (Ixel)) es *más alto*

↗ Variable restringida ↗ Relación de restricción (conjunto difuso)

- La relación fuzzy **más alta** es la distribución de posibilidad de ((Altura (Leslie), Altura (Ixel)).

Restricciones posibilistas

- El lenguaje natural puede ser visto como un sistema de restricciones.
- En el lenguaje natural, las restricciones son predominantemente posibilistas.



Definitivamente no adulto

Definitivamente adulto

Definitivamente no adulto

Restricciones probabilísticas

R (X): X isp p,

Donde p es la función de densidad de probabilidad de X,

$$\textbf{Prob } (u \leq X \leq u+du) = p(u)du.$$

- Ejemplo

$$X \text{ isp } \frac{1}{\sqrt{2\pi}} \exp(-(X-m)^2/2\sigma^2)$$

Variable restringida

Relación de restricción (Función de densidad de probabilidad)

Restricciones Z

- X es una variable aleatoria de valor real.
- Una restricción Z se expresa como

R (X): X iz Z,

- Donde Z es una combinación de restricciones posibilistas y probabilísticas definidas como

Z: Prob (X es A) es B,

- X iz (A, B)
- El número Z(A, B) es una restricción de X.
- X es una variable aleatoria con función de densidad de probabilidad desconocida, p.
- p se denomina función de densidad de probabilidad de X.
- La probabilidad de A puede expresarse como $\mu_A \cdot p$

Restricciones Z

- En un número Z, (A, B), B es una restricción indirecta posibilista sobre la medida de probabilidad de A.
- Más concretamente,

$\mu A \cdot p$ is B.

Esta expresión relaciona p con B.

Si X = (A, B), entonces (A, B) es una restricción directa de Z sobre X.

Ejemplos.

- Probablemente Robert es alto => Altura (Robert) es (alto, probable)
- Normalmente la temperatura es baja =>La temperatura es (baja, normalmente)
- Normalmente X es A, es una restricción Z cuando A **es un número difuso.**

P=> X isr R,

p: Robert es joven La edad (Robert) es joven

X R

COMPUTACIÓN CON NÚMEROS Z

- Juega un papel esencial para procesar la **información Z**.
- En términos generales, el cálculo con números Z implica la evaluación de una función n-ary, f, cuyos argumentos son números-Z. Por simplicidad, en lo siguiente, se supone que n es 1 ó 2.
- Ejemplos de calculo
  - (aproximadamente 1 hora, generalmente) + (aproximadamente 2 horas, muy probable
  - (pequeño, usualmente) × (aproximadamente 4, muy probable)
  - la raíz cuadrada de (alrededor de 30, probablemente)

COMBINACION DE 2 NÚMEROS Z

- Sea $X = (A_X, B_X)$ e $Y = (A_Y, B_Y)$ los números Z en el espacio de números reales.

- Sea Z una combinación de X e Y, $Z = X*Y$.

- Ejemplo.

$$Z = (A_X, B_X) * (A_Y, B_Y)$$

$$Z=X*Y.$$

•Mas precisamente,

$$(A_Z, B_Z)=(A_X, B_X) * (A_Y, B_Y)$$

•El objetivo es determiner **A_Z y B_Z.**

COMBINACION DE 2 NÚMEROS Z

$$A_Z = A_X * B_X$$

$$B_Z = \mu_{Az}\, p_Z$$

- Donde p_Z es la función de densidad de probabilidad de Z.

  Más concretamente, $p_Z = p_X\, p_Y$

- El cálculo de p_Z es simple si conocemos p_X y p_Y.
- p_X y p_Y son restricciones posibilistas.

$$\mu_{Ax} \cdot p_X \text{ is } B_X$$

$$\mu_{Ay} \cdot p_Y \text{ is } B_Y$$

Concepto de extensión

- El cálculo de p_Z requiere el uso de una versión básica del Principio de extensión
- Supongamos que Z es una función de X e Y

$$Z = f(X, Y)$$

X e Y sujetos a restricciones posibilistas

g(X) is A

h(Y) is B,

Donde A y B son conjuntos difusos.

- En esta versión del principio de extensión, Z puede expresarse como la solución del problema variacional

$$\mu_Z(w)=\sup_{u,v}(\mu_A(g(u))\wedge\mu_B(h(v)))$$

Concepto de extensión

- Aplicando esta versión del principio de extensión al cálculo de p_Z, llegamos a la siguiente definición de la combinación de dos números Z

$$(A_X, B_X) * (A_Y, B_Y) = (A_X, A_Y)\ \mu_{Ax*Ay.pz}$$

Donde μ_{pz} está dada por

$$\mu_{pz}(w) = \sup_{u,v}(\mu_{Bx}\ (\mu_{Ax} \cdot u) \wedge (\mu_{By}\ (\mu_{Ay} \cdot v)$$

Donde u, v y w toman valores en el espacio de funciones de densidad de probabilidad

Resumen

- El cálculo con números Z es un movimiento recientes con varios problemas.
  – Uno de estos problemas es la informatización de sus resultados.
  – Lo que es relevante es que una restricción es portadora de información.
- En general, la informatización se simplifica por la combinación de números Z.
- Esta presentación se centra en los fundamentos del cálculo de los números Z.
  – Las aplicaciones de los números Z están empezando a desarrollarse

The Fuzzy Cognitive Maps: History, Applications and Challengers

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Outline

- Introduction
- Theoretical Bases
- Extensions
  - Learning procedures,
  - FCM hierarchical model,
  - Dynamical FCM, etc.)
- Some Applications in different domains
  - Social systems,
  - Control systems,
  - Multiagent systems, etc.).
- Some FCM Tools
- Challengers

Introduction

•Decision makers and policy proponents face serious difficulties when approaching significant dynamic systems.

•Formulating a mathematical model may be difficult, costly, even impossible.

- •Developing the model typically requires a great deal of effort and specialized knowledge.
- •Systems involving significant feedback propagates casual influences and complicated chains may be nonlinear, in which case a quantitative model may not be possible.
- •Numerical data may be hard to come by or uncertain.

•A qualitative approach can be sufficient. If the results of this preliminary model are promising, the time and effort to pursue a quantitative model can be justified.

Introduction

•What is a “cognitive map” (CM)?

• A CM is an effort to simulate the behavior of a black box system through cause and effect relationships.

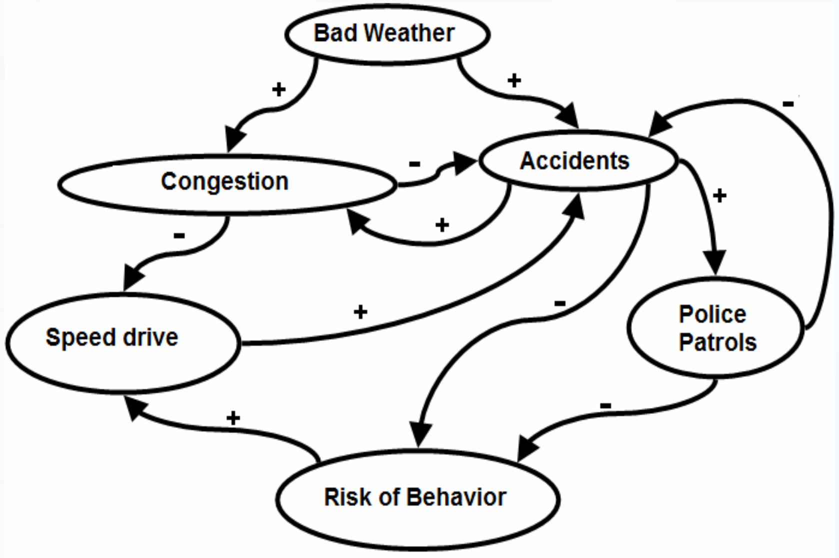
•At first, Axelord used cognitive maps as a formal way of representing social scientific knowledge and modeling decision making in social and political system.

•A CM can avoid many of the knowledge-extraction problems which are usually posed by rule based systems. This form of knowledge presentation presents problems such as:

- •Impossibility of have dynamic behavior;
- •Impossibility of have performance in real time, and so for

Introduction

- Relevant concepts in a domain are chosen. These concepts represent observable state within the domain. Variable concepts are represented by nodes in a directed graph. The value of a node reflects the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all incoming edges multiplied and the value of the originating concept at the immediately preceding state.
- Relationships: They indicate as the concepts are affected with other concepts. The graph's edges are the casual influences between the concepts.



	Bad Weather	Conges -tion	Acci- dents	Speed	Police	Behavior
Bad Weather	0	+1	+1	0	0	0
Congestion	0	0	-1	-1	0	0
Accidents	0	+1	0	0	+1	-1
Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Different representations of a Cognitive Map:

a Graph Representation and the Connection Matrix.

Introduction

•The state of a given node is obtained from the prior states of all causal nodes. These states are multiplied by the edge weight between the two nodes. The sum of these products is taken as the input to a threshold function.

•In this way, we define the activation level of a concept:

$A_i^{new} = S(\sum nj=1\ A_j^{new}\ E_{ji}) + A_i^{old}$

•There are different threshold functions: bivalent, trivalent, and logistic signal.

$$S_i(x_i) = 0, x_i \leq 0$$
$$S_i(x_i) = 1, x_i > 0$$

Bivalent

$$S_i(x_i) = -1, x_i \leq -0.5$$
$$S_i(x_i) = 0, -0.5 < x_i < 0.5$$
$$S_i(x_i) = 1, x_i \geq 0.5$$

Trivalent

$$S_i(x_i) = \frac{1}{1 + e^{-cx_i}}$$

Logistic signal

Introduction

•A discrete time simulation is performed by iteratively applying the summation and threshold process to the state vector of the graph.

•The simulation halts if an equilibrium state is reached.

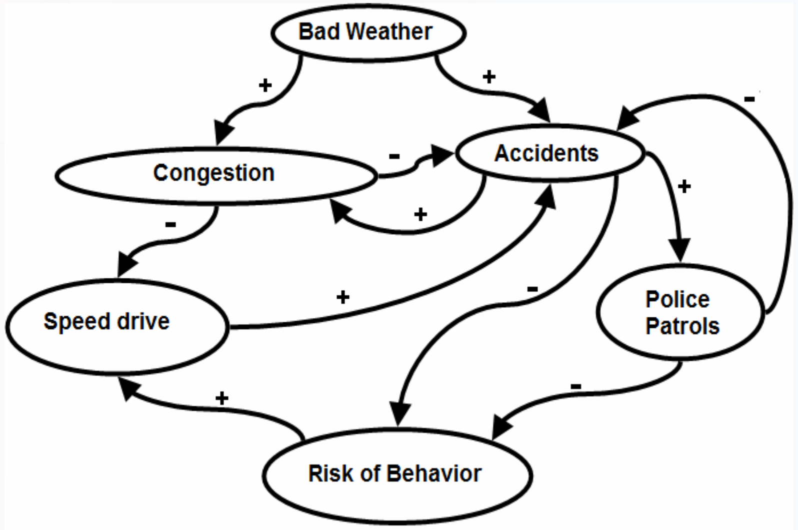
•The execution of a CM follows the following algorithm:

1 - To obtain an initial state C (0)

2- While the system does not converge

a- To calculate the present state by means of $C_m(i+1) = S\left[\sum_{k=1}^{N} w_{m,k} \cdot C_k(i)\right]$

b- to go to step 2



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Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Accidents(i+1)= S[1 * BadWeather(i) -1 * Congestion(i) +1 * Speed drive (i) -1 * Police Patrols(i)]

Theoretical Bases

Theoretical Bases

Fuzzy Cognitive Maps (FCM)

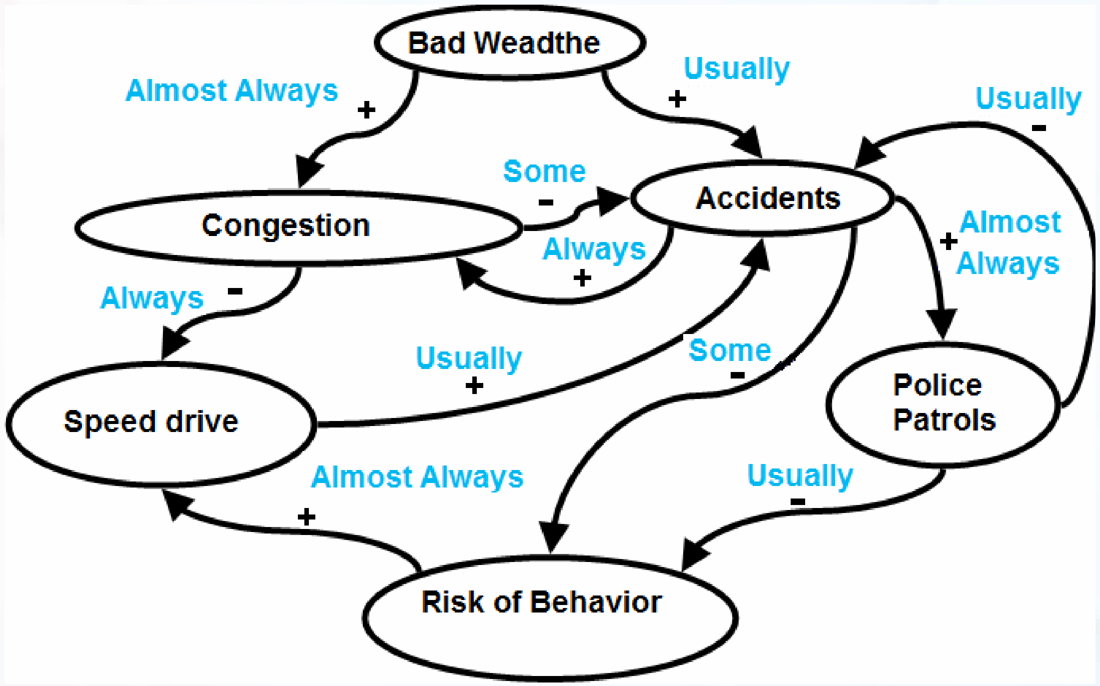
•They are proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns.

•They are the fusion of the advances of the Fuzzy Logic, Artificial Neural Networks and Cognitive Maps theories. FCMs combine the robust properties of fuzzy logic and neural networks.

•FCMs represent knowledge in a symbolic manner and relate states, processes, policies, events, values and inputs in an analogous manner.

•The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets, the causal relationships between the concepts can be fuzzy implications, or the threshold function applied to the weighted sums can be fuzzy in nature.

Theoretical Bases



Efect over the i concept vía causal relationship

$$I_l(C_i, C_j) = \min\{w_{p,p+1} : (p, p+1) \in (i, k_1^l, k_2^l, \ldots, k_n^l, j)\}$$

Total Efect

$$\mathrm{T}(\mathrm{C_i}, \mathrm{C_j}) = \max \mathrm{I_l}(\mathrm{C_i}, \mathrm{C_j})$$

Theoretical Bases

$$P = \{\text{some} \le \text{usually} \le \text{always}\}$$

$$I_1(C_1, C_5) = \min\{\text{always}, \text{usually}\} = \text{usually}$$

$$I_2(C_1, C_5) = \min\{\text{usually}, \text{some}, \text{some}\} = \text{some}$$

$$T(C_1, C_5) = \max\{I_1, I_2, I_3\} = \max\{\text{usually}, \text{some}\} = \text{usually}$$

Some Extensions

Some Extensions

1. Parallel FCMs
2. The second one focuses on the design of learning algorithms
3. FCM based on random neural networks.
4. FCM Hierarchical System
5. Rule Based Fuzzy Cognitive Map

Extensions

- There are two main approaches to develop Fuzzy Cognitive Maps
  - Deductive modeling (i.e., they use an expert knowledge from the domain of application)
  - Inductive modeling (i.e., they use learning algorithms to establish FCMs from historical data) .

- *Deductive modeling* is based on expert knowledge from the area of application.
  - Models are developed manually based on best knowledge with a group of experts.
  - This approach usually consists of the following three steps:

  1. Identification of key domain issues or concepts.
  2. Identification of causal relations among these concepts.
  3. Estimation of causal relations strengths.

- *Inductive modeling.* Automated and semi-automated approaches designed for learning FCM connection matrix, and their strength (weights) based on historical data.
  - In this case, the expert knowledge is substituted by a set of historical data and a computational procedure

Deductive modeling

•The development of a FCM often occurs within a group context. An expert draws a FCM according to his experience. The assumption is that combining incomplete, conflict opinions of different experts may cancel out the effect of oversight, ignorance and prejudice.

•The group matrix (E^G) could be computed as:

$E^G_{ji} = \max_t \{E^t_{ji}\}$ or $E^G_{ji} = \sum_{t=1}^{NE} b_t E^t_{ji}$ $\forall$ t=1 to number of experts (NE).

Where E^t_{ji} is the opinion of the expert *t* about the causal relationship among C_j and C_i, and b_i is the expert's opinion credibility weight.

•In a distributed system, a FCM is constructed for each subsystem. Then all FCM are combined in one augmented matrix E for the whole system.

$$E = \begin{bmatrix} E_1 & 0 & 0 & 0 \\ 0 & E_2 & 0 & 0 \\ 0 & 0 & E_3 & 0 \\ 0 & 0 & 0 & E_4 \end{bmatrix}$$

•Using Historical Data

$$M = \{D_1, D_2, \ldots, D_m\} = \{[d_1^{\,1}, d_1^{\,2}, \ldots, d_1^{\,n}], [d_2^{\,1}, d_2^{\,2}, \ldots, d_2^{\,n}], \ldots, [d_m^{\,1}, d_m^{\,2}, \ldots, d_m^{\,n}]\}$$

$$W_{ji}^{t} = W_{ji}^{t-1} + \eta \cdot \left(\frac{\Delta d_j^{t} \cdot \Delta d_i^{t}}{\Delta^+ d_j^{t} \cdot \Delta^+ d_i^{t}} \right)$$

where

$$\Delta d_j^t = d_j^t - d_j^{t-1}$$
$$\Delta d_i^t = d_i^t - d_i^{t-1}$$
$$\Delta^+ d_j^t = d_j^t + d_j^{t-1}$$
$$\Delta^+ d_i^t = d_i^t + d_i^{t-1}$$

Learning Algorithms

- The main goal of learning in FCMs is to determine the values of the weights of the FCM that produce a desired behavior of the system.
- In general, two main learning paradigms are used: adaptive, and evolutionary algorithms
- The adaptive algorithms are often based on the idea borrowed from the theory of artificial neural networks that is called the differential Hebbian learning law.
  - The general idea is: if two neurons on the opposite side of a connection are activated simultaneously, then the weight of that connection is increased; else they are activated asynchronously, then the weight is decreased.
  - The idea of Hebbian learning has been adapted by Kosko to FCMs.

$$w_{ij}(t+1) = w_{ij}(t) + \gamma(t)\left[\Delta a_i \Delta a_j - w_{ij}(t)\right]$$

- The coefficient: $\gamma(t) = 0.1[1 - t/1]q$ changes over time. The constant parameter q should ensure that the value of the weight does not fall beyond [-1, 1]
- Let us notice that important features of equation:
  - The learned weights depend on the temporal order of raw data,
  - the change in activation of cause concept (with subscript i) is assumed as a necessary requirement of the change of the respective weight

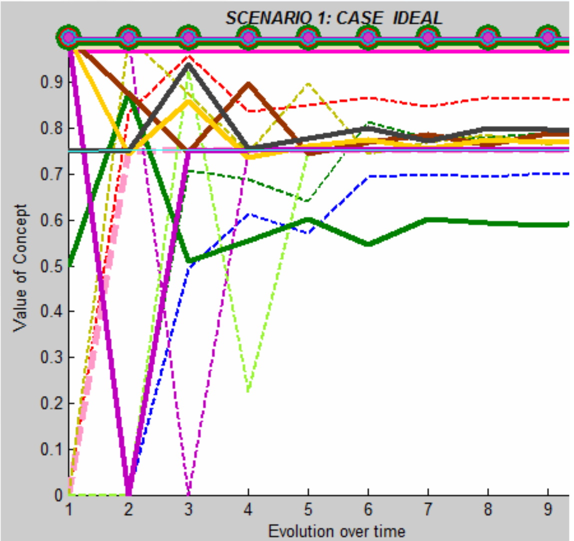
Learning Algorithms

- The evolutionary learning approach: the initially random weights of FCM stored in W are optimized by the iterative evolutionary process.
- In this case, the relationships between concepts learned during the evolution depend on the applied fitness function designed by an expert for the considered task.

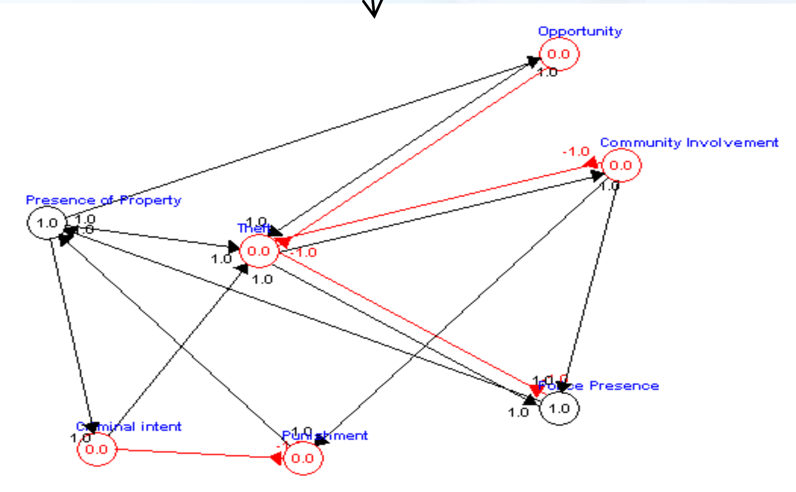
Learning Module (GA)

	Bad Weather	Conges-tion	Acci-dents	Speed	Police	Behavior
Bad Weather	0	+1	+1	0	0	0
Congestion	0	0	-1	-1	0	0
Accidents	0	+1	0	0	+1	-1
Speed	0	0	+1	0	0	0
Police	0	0	-1	0	0	-1
Behavior	0	0	0	+1	0	0

Connection Matrix



Input Data



Candidate FCM

Learning Algorithms

Some other approaches:

1. **The Balanced Differential Algorithm to learn FCMs from data.**
2. **Backpropagation learning procedure to enable the gradual learning of symbolic representations**
3. **Parallel Genetic Learning of Fuzzy Cognitive Maps**
4. **Multi-Objective Evolutionary Fuzzy Cognitive Maps for Decision Support**
5. **Fuzzy Cognitive Maps Learning through Swarm Intelligence (The Particle Swarm Optimization Algorithm)**

The desired behavior of the system is characterized by values of the output concepts that lie within prespecified bounds, determined by the experts.

The user is interested in restricting the values of these output concepts in strict bounds, which are crucial for the proper operation of the modeled system.

Thus, the main goal is to detect a weight matrix W that leads the FCM to a steady state at which, the output concepts lie in their corresponding bounds.

The latter is attained by imposing constraints on the potential values assumed by weights.

Learning Algorithms

To do this, the following objective function is considered :

$$F(W) = \sum_{t=1}^{m} H(Q_{out_t}^{min}) \left| Q_{out_t}^{min} \right| + \sum_{t=1}^{m} H(Q_{out_t}^{max}) \left| Q_{out_t}^{max} \right|$$

Where H is the well–known Heaviside function, i.e. H(x) = 0, if x < 0, and H(x) = 1 otherwise; $Q_{out_t}^{min} = A_{out_t}^{min} - A_{out_t}$ and A_{out_t} are the steady state values of the output concepts that are obtained using the weight matrix W.

•Obviously, the global minimizers of the objective function F are weight matrices that lead the FCM to a desired steady state.

•The application of PSO for the minimization of the objective function F, starts with an initialization phase, where a swarm of weight matrices is generated randomly, and it is evaluated using F.

•Then, $V_i(t + 1) = X_i(t) + V_i(t) + c(P_g(t) - X_i(t))$ and $X_i(t + 1) = X_i(t) + V_i(t + 1)$ are used to evolve the swarm.

Assume g to be the index of the particle that attained either the best position of the whole swarm.

•When a weight configuration that globally minimizes F is reached, the algorithm stops.

Rule Based Fuzzy Cognitive Map

•It is proposed as an evolution of Fuzzy Causal Maps (FCM) that allow a more complete representation of cognition, since relations other than monotonic causality are made possible.

•It presents a method to implement Fuzzy Causal Relationship.

•It consists of nodes (representing concepts), and fuzzy rule bases (which relate and link concepts). Each concept contains several membership functions.

"If the *variable 1 (input* variable) has *feature A Then the variable 2 (output variable)* has *feature B.*

•Any kind of relation that can be represented by fuzzy rules is allowed: opposition, similarity, implication, traditional fuzzy reasoning, etc.

•The concept can be represented either by a crisp or fuzzy value.

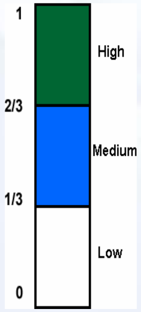
•The set of rules obviously depend on the amount of membership functions and intended meaning.

Rule Based Fuzzy Cognitive Map

•Other FCM have been recently proposed based on adjusting functions . The relationships are established using an adjustment function based on rules

•For instance, it is assumed that the state of the concepts in a modeled system can be located in three zones :

- ✓A concept has a *high state* (between 2/3 and 1) when it works correctly and contributes substantially with the functioning of the modeled system.
- ✓A concept has a *medium state* (between 1/3 and 2/3) when its functioning must be validated and its contributions to the systems' functioning is not so substantial, and so on.



•The relationship values are taken from the following table:

The following rules could be built under these three states

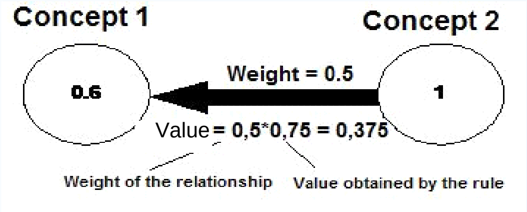
- ✓If the preceding concept is **High** and the consequent one is also **High** then the relationship is **Complete^{+}**(1.0).
- ✓If the preceding concept is **High** and the consequent one is **Medium** then the relationship is **High^{+}** (0.75).

Value	Linguistic Variable
1.00	Complete^{+}
0.75	High^{+}
0.50	Medium^{+}
0.25	Low^{+}
0.00	Null
-0.25	Low^{-}
-0.50	Medium^{-}
-0.75	High^{-}
-1.00	Complete^{-}

Rule Based Fuzzy Cognitive Map

•These rules would be used to determine all the relationships between the different concepts, but each one would have a weight defined by the experts that could vary from relationship to relationship.

•For example, if we take the relationship between Concept 1 and Concept 2, and it is assumed that Concept 2 has a High state and that Concept 1 has a Medium state, then the relationship resulting from the rules would yield a high^{+} value (that is, 0.75). This value is multiplied by the weight of the relationship and if we assume that the weight of this relationship is 0.5, then the final result of the relationship would be 0.375.



•The fuzzy rule for each interconnection is evaluated using fuzzy reasoning and the inferred fuzzy weight is defuzzified using the Center of Gravity defuzzification method

FCM based on random neural networks

•FCM based on the random neural network model called the Random Fuzzy Cognitive Map (RFCM).

•This model is based on the probability of activation of the neurons/concepts in the network.

•To calculate the state of a neuron on the RFCM (the probability of activation of a given concept C_j), the following expression is used:

$$q(j) = \min\left\{\lambda^+(j), \max\left\{r(j), \lambda^-(j)\right\}\right\}$$

where $\lambda^+(j) = \max_{i=1,n}\left\{\min\left\{q(i), W^+(i,j)\right\}\right\}$ $\lambda^-(j) = \max_{i=1,n}\left\{\min\left\{q(i), W^-(i,j)\right\}\right\}$

In addition, the fire rate is $r(j) = \max_{i=1,n}\left\{W^+(i,j), W^-(i,j)\right\}$

•The general procedure of the RFCM is the following:

1. Design the configuration of the FCM.
2. Call the Initialization phase
3. Call the Simulation phase

FCM based on random neural networks

•The RFCM can be used like an associative memory. In this way, when we present a pattern to the network, the network will iterate until generate an output close to the information keeps.

•The input is an initial state S_0= {$s_{1, \ldots}$, s_n}, such as $q^0(1)=s_1$, …, $q^0(n)=s_1$ and $s_i \in [0, 1]$ (set of initial values of the concepts ($S_0=Q^0$)).

•The output Q^m={$q^m(1)$, …, $q^m(n)$}is the prediction of the RFCM such as *m* is the number of the iteration when the system converge.

•During this phase, the RFCM is trained with a reinforced learning procedure.

$$W_{ij}^t = W_{ij}^{t-1} + \eta\left(\Delta q_i^t \Delta q_j^t\right)$$

where Δq_i^t is the change in the i^{th} concept's activation value among iterations *t* and *t-1*.

•The algorithm of this phase is:

1. Read input state Q^0
2. Until system convergence
   Calculate q(i)
   Update W^t

Some Applications in different domains

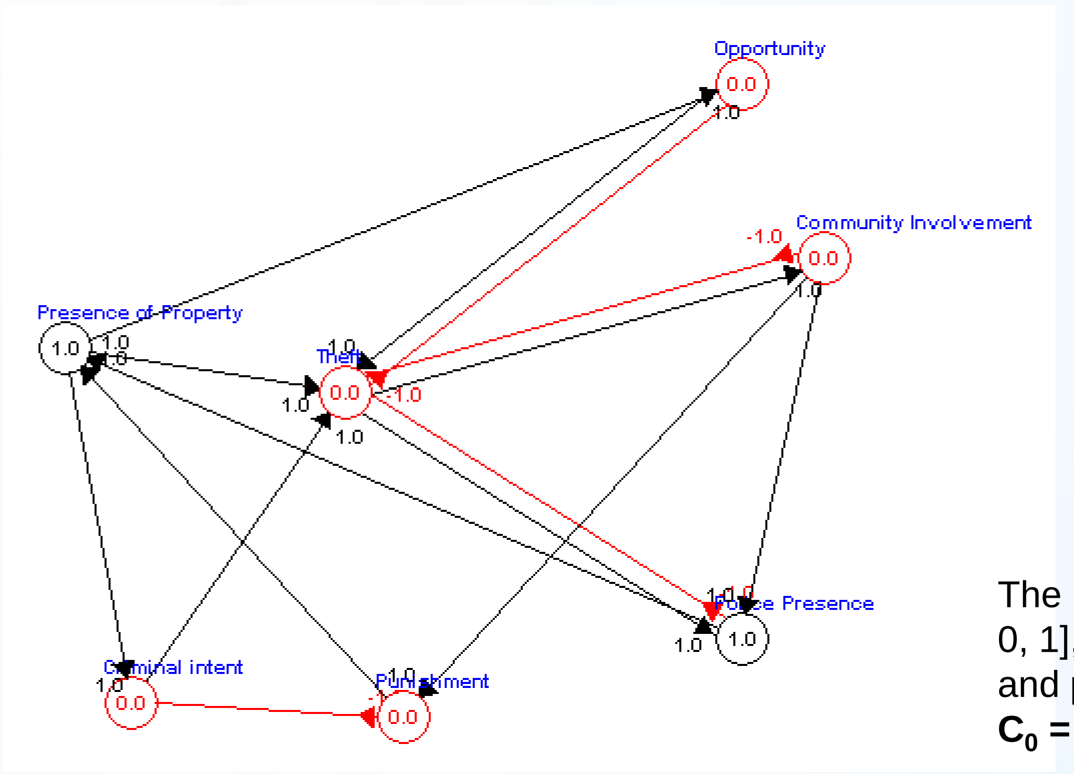
Some Applications in different domains

•FCMs have gradually emerged as a powerful modelling and simulation technique applicable to numerous research and application fields: administrative sciences, game theory, information analysis, popular political developments, electrical circuits analysis, cooperative man–machines, distributed group-decision support, etc.

1. FCMs have been used to model and support a plant control system, to model the supervisor of a control system or of manufacturing systems, etc.
2. FCMs have been used in multiagents system to represent different types of knowledge in a group of agents, to support the building of group consensus,
3. FCM has been used to structure virtual worlds that change with time .
4. In business FCMs can be used for product planning
5. In computer assisted learning FCMs enable computers to check, whether students understand their lessons

Social Systems

This map attempts to model property theft in a community.



C_0 = (0, 0, 1, 0, 0, 1, 0)

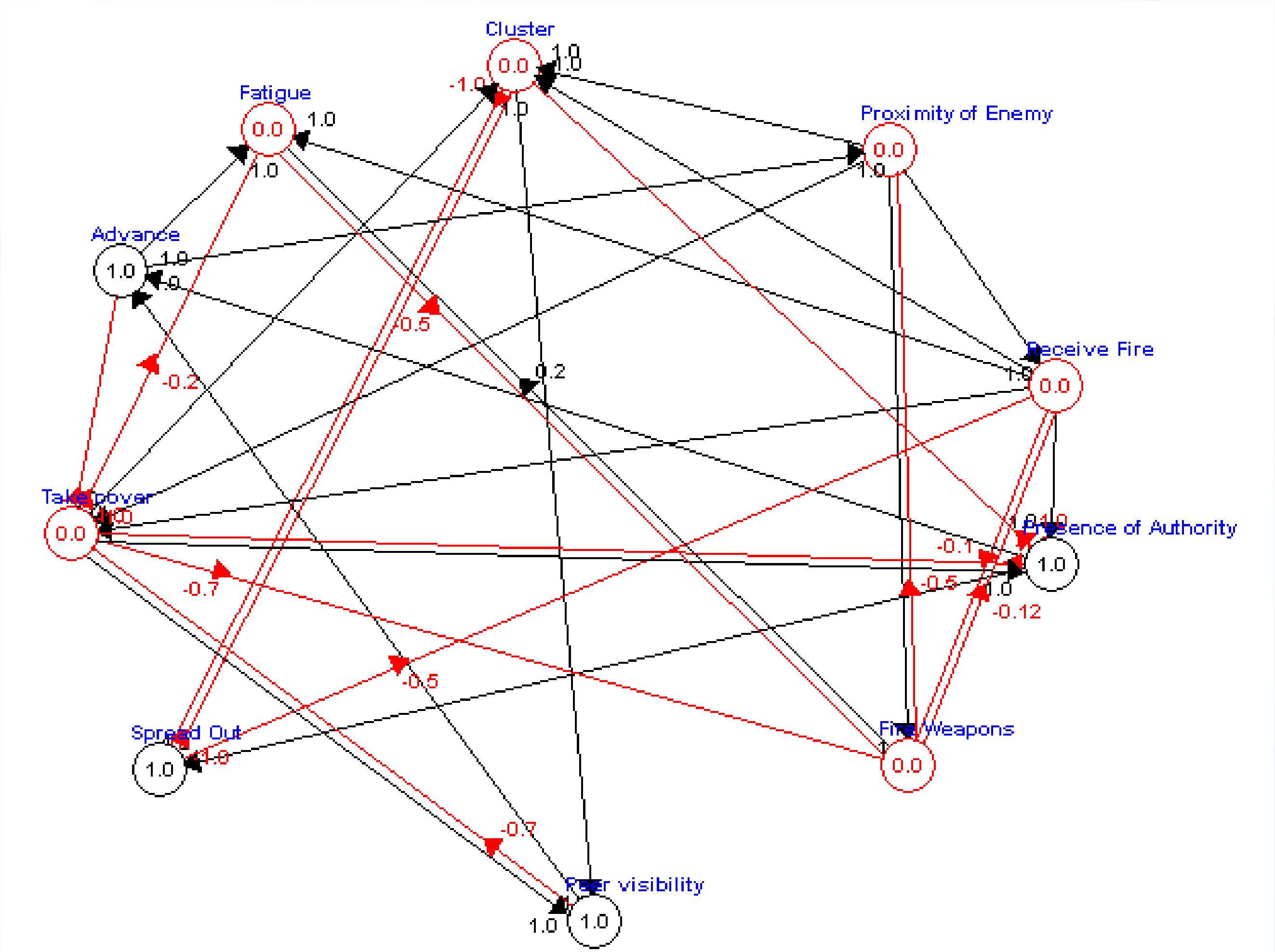
We then obtain the discrete time series

C_0 = (0, 0, 1, 0, 0, 1, 0)
C_1 = (1, 0, 0, 0, 1, 1, 0)
C_2 = (1, 0, 0, 0, 1, 0, 1)
C_3 = (0, 1, 1, 0, 0, 0, 1)
C_4 = (0, 1, 1, 1, 0, 1, 0)
C_5 = (1, 0, 1, 1, 0, 1, 0)
C_6 = (1, 0, 0, 0, 0, 1, 1)
C_7 = (0, 1, 1, 0, 1, 0, 1)

The range of allowable state values is now [-1, 0, 1], i.e., we can have negative, indifferent, and positive concept activation.
C_0 = (-1, -1, 1, -1, -1, 1, -1)
…
C_6 = (1, -1, -1, -1, 0, 1, 1)
C_7 = (0, 1, 0, -1, 1, -1, 1)
C_8 = (-1, 1, 1, 1, 0, -1, -1)
C_9 = (0, -1, 0, 1, -1, 1, -1)

Virtual Worlds

An FCM modeling a squad of soldiers in combat.



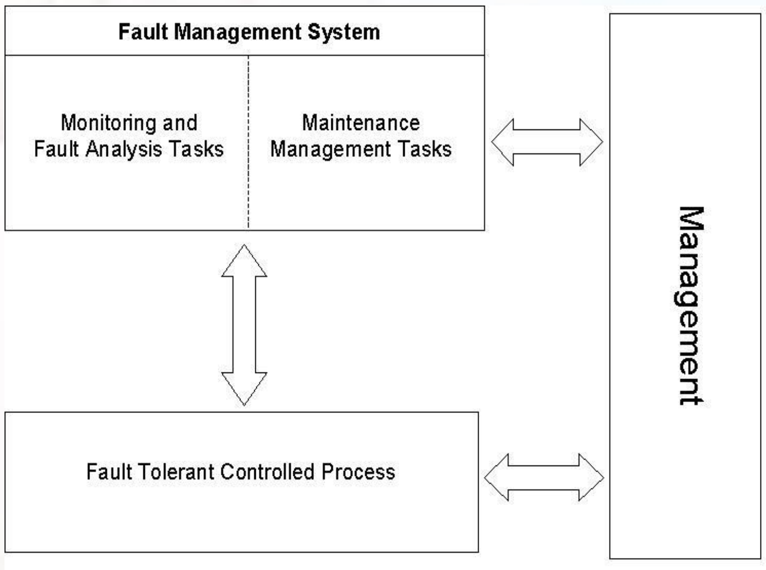
Jose Aguilar

From the initial state vector
C0 = (0, 0, 0, 1, 0, 1, 1, 0, 1, 0)

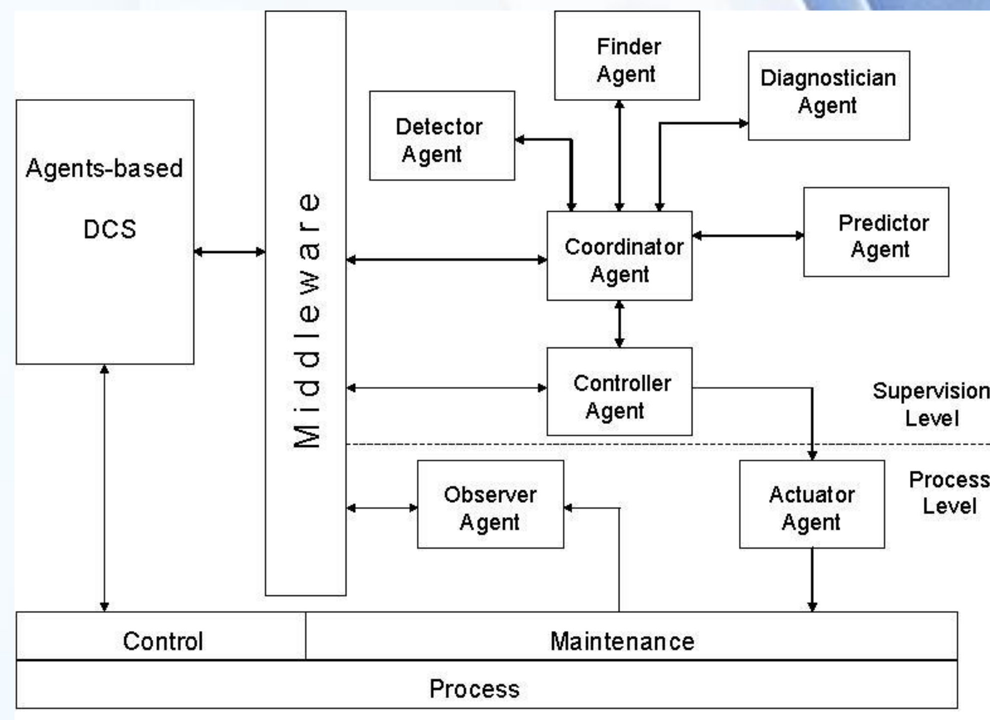
That is, the squad advancing in good order under the control of the squad leader, and no external influences, we reach the five step limit cycle

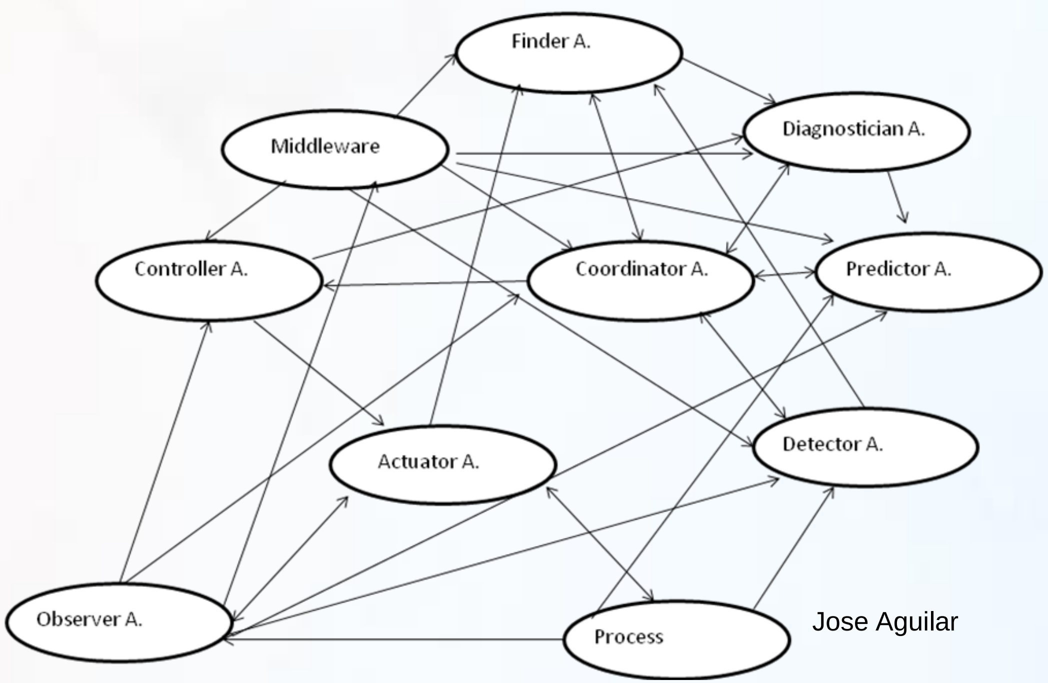
C7 = (1, 1, 1, 1, 0, 1, 0, 1, 0, 1)
C8 = (1, 0, 1, 1, 0, 1, 0, 1, 1, 0)
C9 = (1, 1, 0, 1, 0, 1, 0, 0, 1, 1)
C10 = (0, 1, 1, 0, 1, 1, 0, 0, 1, 1)
C11 = (1, 1, 1, 1, 1, 0, 0, 1, 1, 1)

Fault management system



MAS





Jose Aguilar

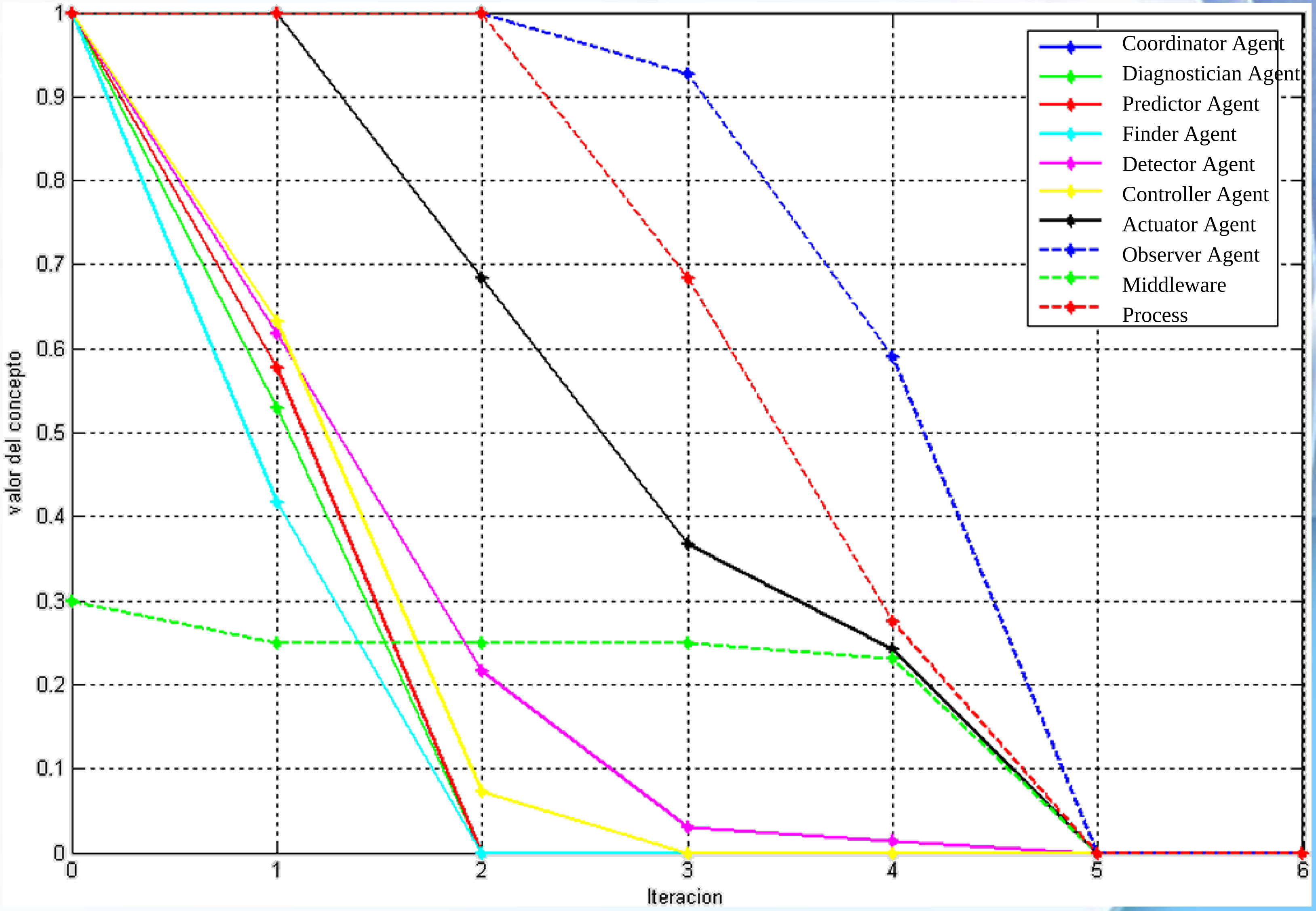
FCM

Fault management system

- If the antecedent concept is High and the consequent one is High then the relationship is complete+ (1.0)
- If the antecedent concept is High and the consequent one is Medium then the relationship is high+ (0.75)
- If the antecedent concept is High and the consequent one is low then the relationship is low+ (0.25)
- If the antecedent concept is Medium and the consequent one is High then the relationship is high+ (0.75)
- If the antecedent concept is Medium and the consequent one is Medium then the relationship is average (- 0.5)
- If the antecedent concept is Medium and the consequent one is Low then the relationship is high (- 0.75)
- If the antecedent concept is Low and the consequent one is High then the relationship is high (- 0.75)
- If the antecedent concept is Low and the consequent one is Medium then the relationship is average (- 0.5)
- If the antecedent concept is Low and the consequent one is Low then the relationship is complete (- 1.0)

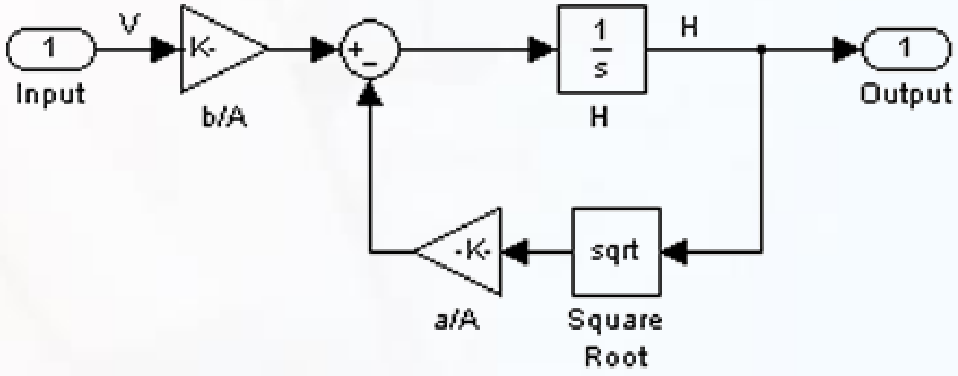
Fault management system

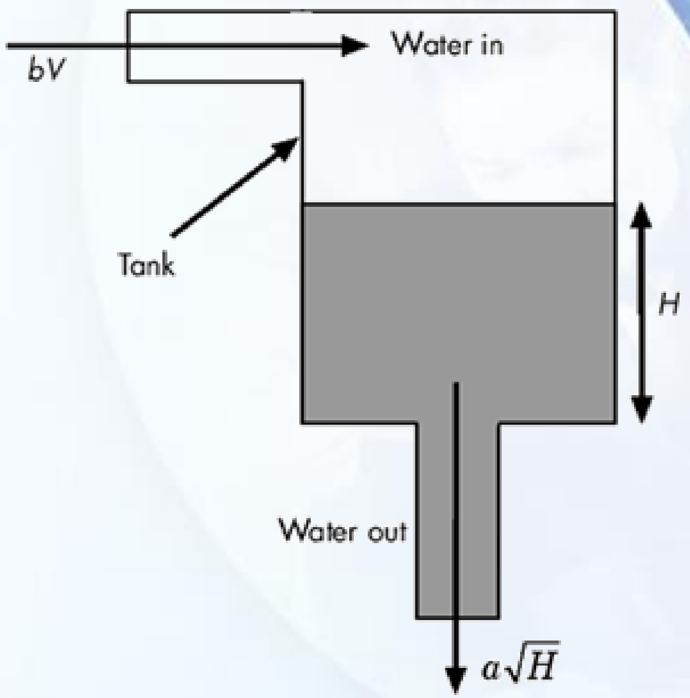
Evolution of the agents with a Middleware with value of 0.3



Dynamic Equations

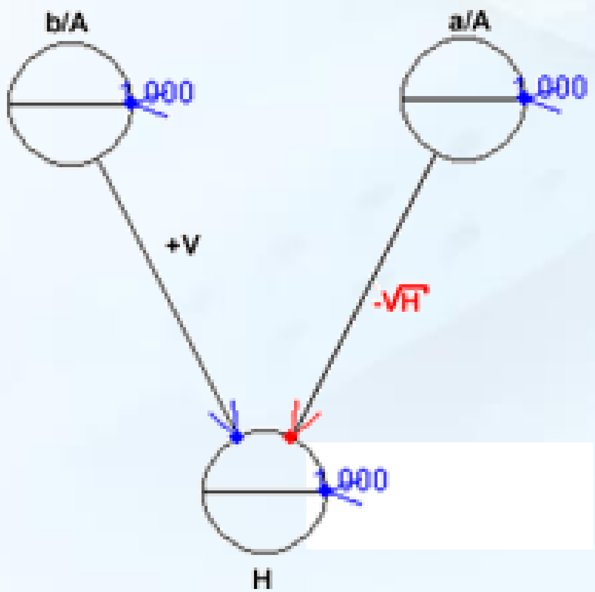
$$\frac{dVol}{dt} = A\frac{dH}{dt} = b \cdot V - a \cdot \sqrt{H}$$





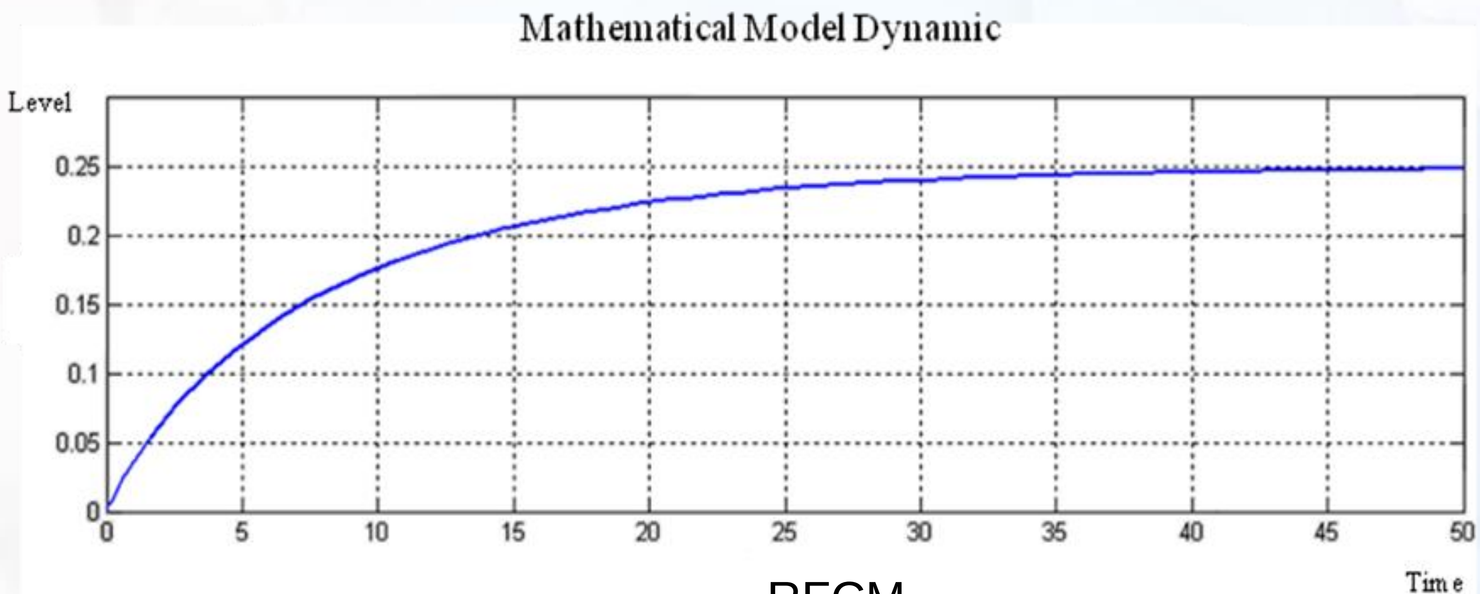
The dynamic relationships are defined of the following form:

•The relationship between the constant of input stream and the Level is given by the value of the applied voltage to pump V.
•The relationship between the constant of the exit flow and the level is given by the squared root of the value of the concept that represents the level.

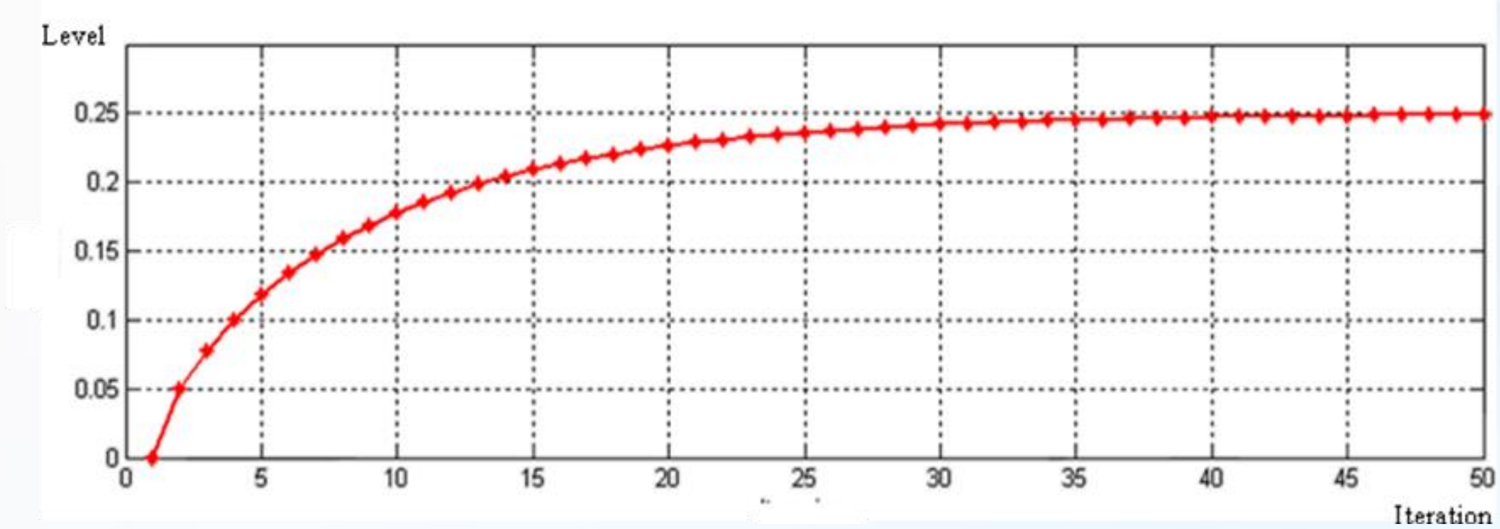


Dynamic Equations

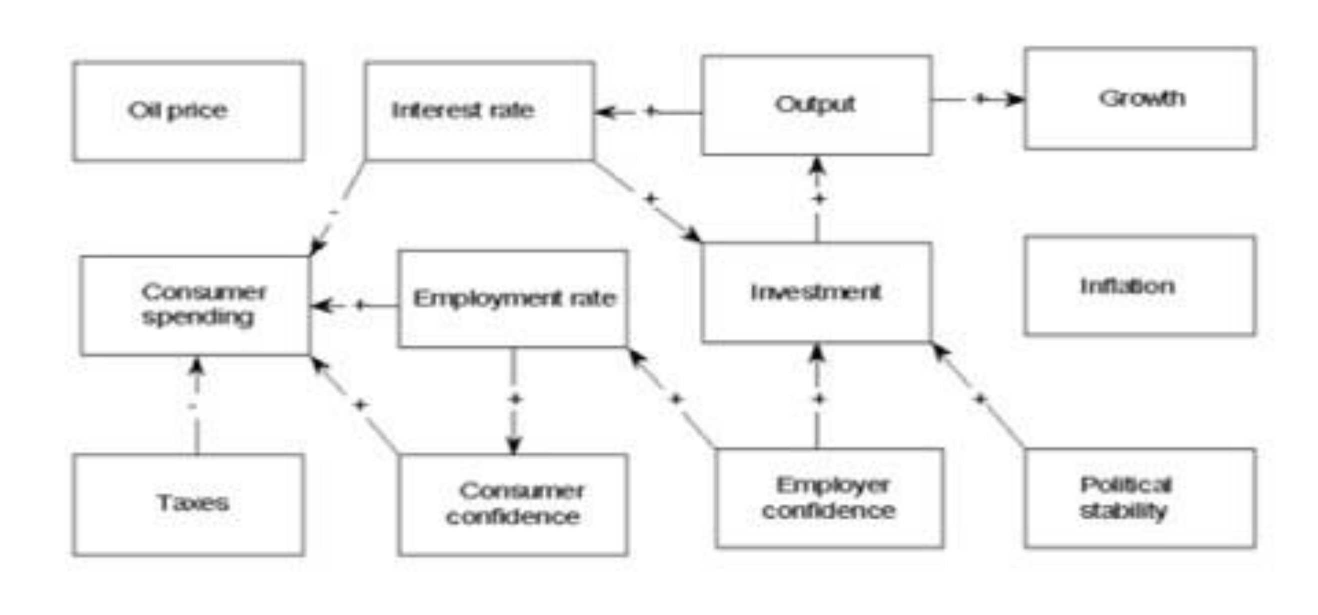
The dynamic for V= 0,2



RFCM



Challengers



The figure is incomplete, and the relationships between the factors may be wrong

The fuzzy map will grow better and better as people contribute to it!!

An example of fuzzy maps library http://www.ochoadeaspuru.com/fuzcogmap/software.php:

1 .Donnelly's investment rules

2. Tax cuts

3. Correction fears grip US market

4. Money - This is a map derived from alternative currency/economic proponents

FCM Hierarchical System

- Motivation
- Definition of a MCM
- MASOES
- Case Study: Wikipedia
- Experiments
- Conclusion

Motivation

- There are multiple problems that can be solved using monolayer CM. **However, there are complex cases where it is necessary to use Multilayer CM (MCM).**

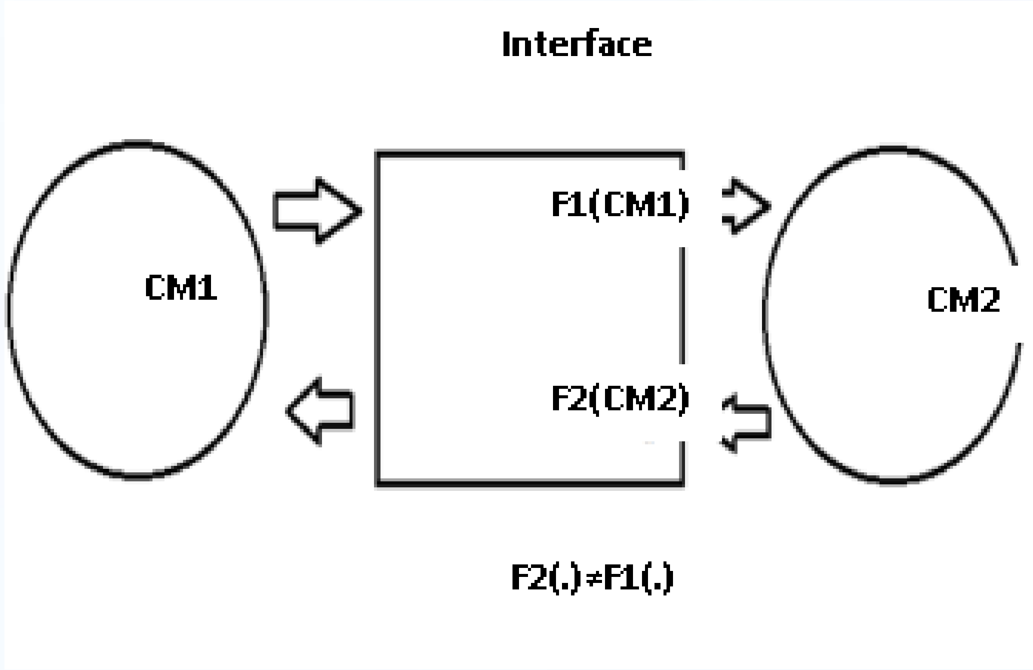
- The ability to model of a MCM is much higher, allowing characterize different aspects.

- In general, the different tools proposed to model CM, as the FCM Designer tool [16], FCModeler tool [17], the Multiagent-Causal Maps tool [18], Amit Roy [19], the FCM applet based on Python [20], etc., **do not support MCM.**

This paper presents an approach to build multilayer cognitive maps.

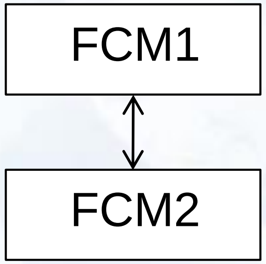
Definition of a MCM

The main aspect in the MCM is the necessity to connect the CM of the different levels, viewing them as a multilayer system, where the concepts of the layers depend on the concepts of other layers.



FCM Hierarchical System

•For the case of two levels, the macroalgorithm is:



1. Values of the concepts on lower level
2. Interface (fuzzy rules)
3. New values of upper concepts
4. If accept values of upper concepts then final decision
5. Else update concepts on lower level (Interface (fuzzy rules))

•The interface is a set of fuzzy rules. An example of the fuzzy rules:

- If value of OUT-LC1 is very high values then value of UC2 is very high.

•In the same way, we can define a set of fuzzy rules for the interface from the upper-level toward the lower-level

Definition of a MCM

Each function F_i can be defined in different ways, in order to define the communication or relationship between different CM:

- **Fuzzy rules**: they describe the relationship between the concepts of the different CM using the fuzzy sets theory.
- **Weights**: the user can assign the weights of the connections between the concepts of the different CM.
- **Mathematical Equations**: The user can define mathematical equations to describe the relationships between the concepts of the different CM.

Definition of a MCM

In a multilayer system the equation for calculating the current status of the concepts of a CM is modified, in order to integrate the function generated by the interface (F_i):

$$C_m(i+1) = S\left[\sum_{i=1}^{N} w_{m,k}\, C_k(i)\right] + F_i(m,p) \qquad (1)$$

$C_m(i+1)$ indicates the value of the concept m in the next iteration,

N indicates the number of concepts in the level where the concept m belong,

$w_{m,k}$ indicates the value of the causal relationship between the concepts C_k and C_m (they belong at the same level),

S(y) is the function used to normalize the value of the concept, and

$F_i(m, p)$ is the function of the interface of the MCM, due to the relationship between the concepts p and m in different levels (F_i can be F1 or F2).

For a given level, there is a F_i for each level to which is connected

Definition of a MCM

Main algorithm of the MCM :

1 Repeat while CM1 and CM2 not converge globally.

1.1 Repeat while CM1 not converge locally.

Calculate concepts of CM1 using eq. 1

1.2 Repeat while CM2 not converge locally.

Calculate concepts of CM2 using eq. 1

1.3 Invoke interface (F_i is recalculated).

MASOES

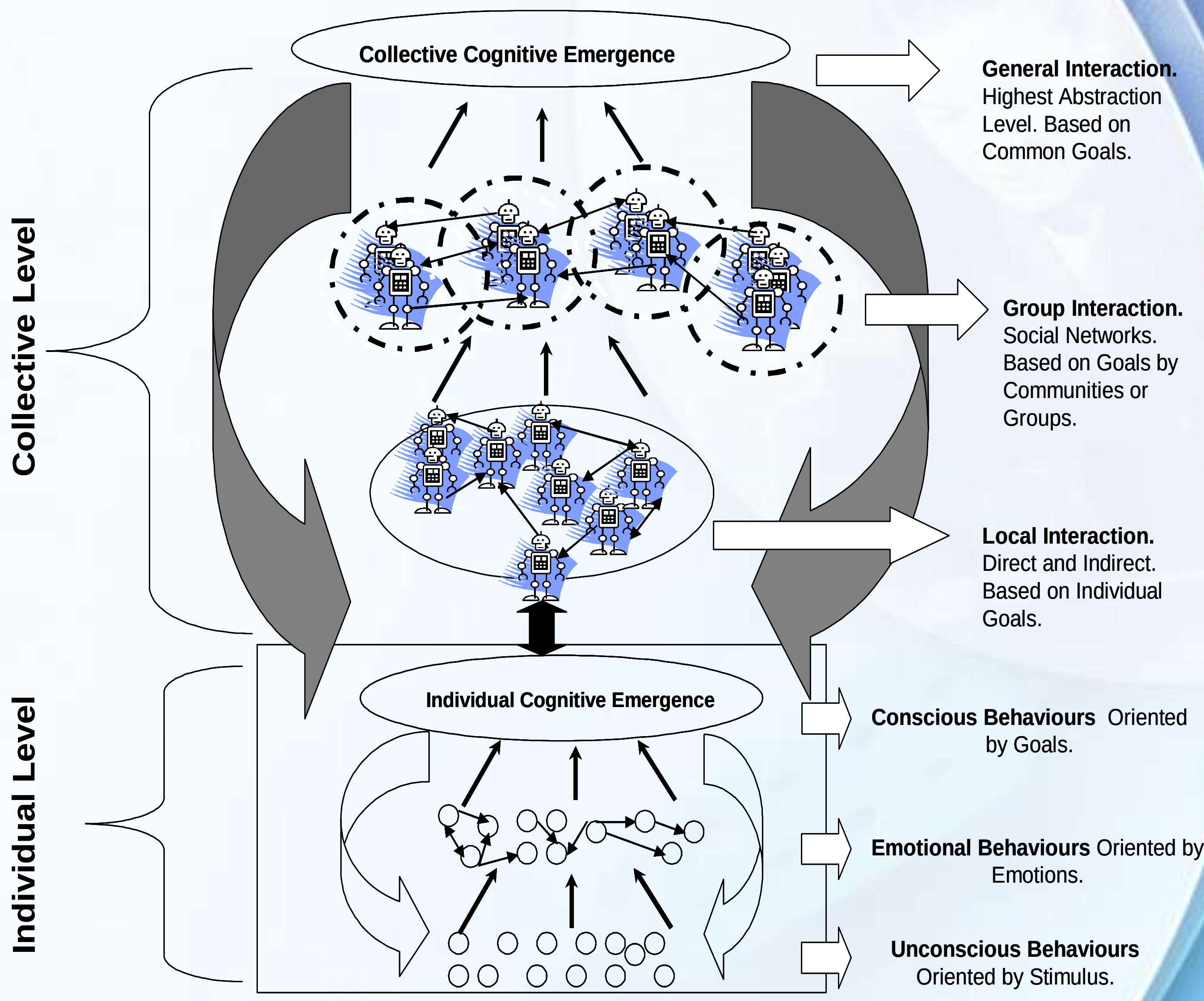
MASOES is an agent architecture for studying self-organizing and emergent systems. The architecture is divided into two levels: individual and collective.

- The **collective level** follows the next ideas: in order to generate emergent behavior, self-organization is based on a set of rules that specifies the interactions among the system's components using only local information.

- The **individual level** consists of characterizing the reactive, cognitive, emotional and social individual behaviors of each type of agent in the system. The architecture at an individual level is made up of **4 components: Reactive; Cognitive; Behavior and Social**

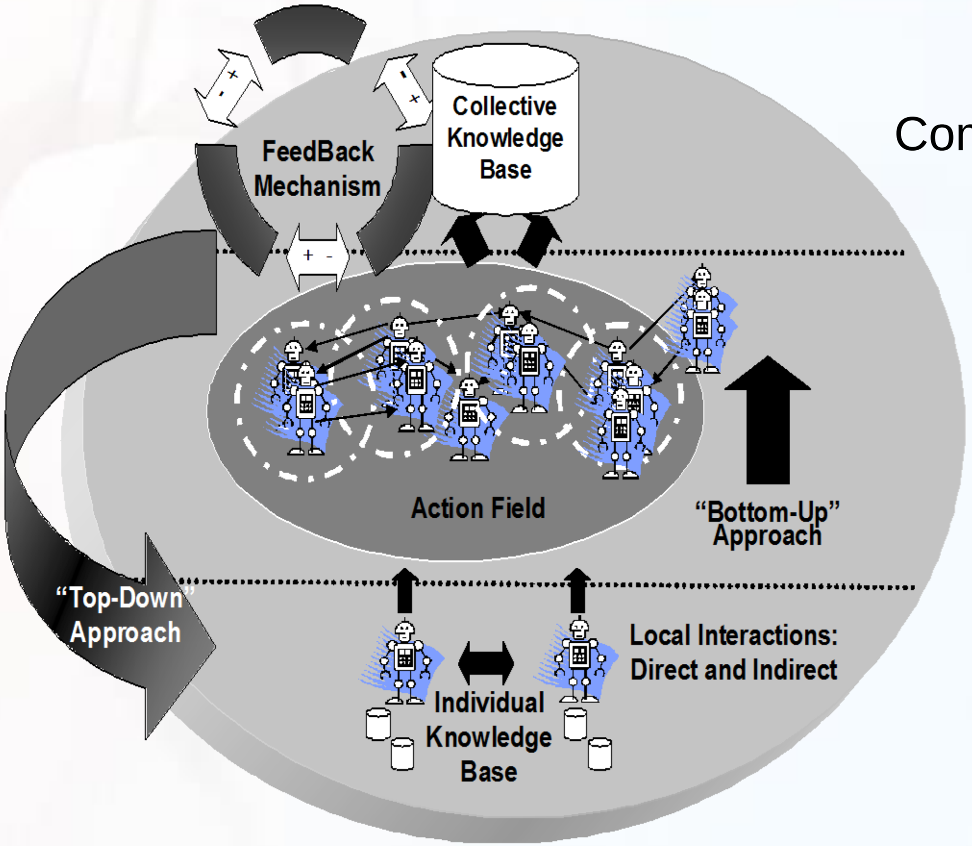
MASOES

To design a Multiagent Architecture for Self-Organizing systems i.e *systems which produces a state of a community of agents where agents' actions mutually adapt in a coherent way through behaviors that emerge from local interactions among them and from the changes that take place in the environment*

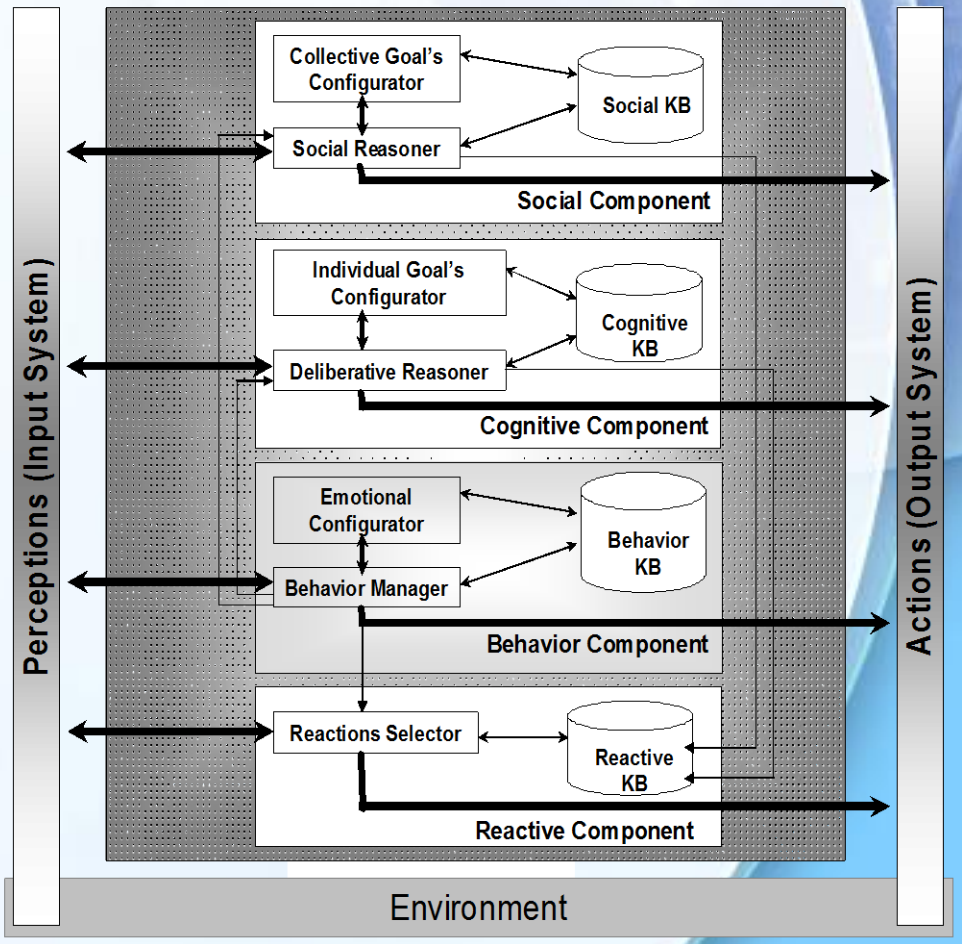


MASOES

Components at Collective Level



Components at Individual Level



MASOES

Verification method for MASOES.

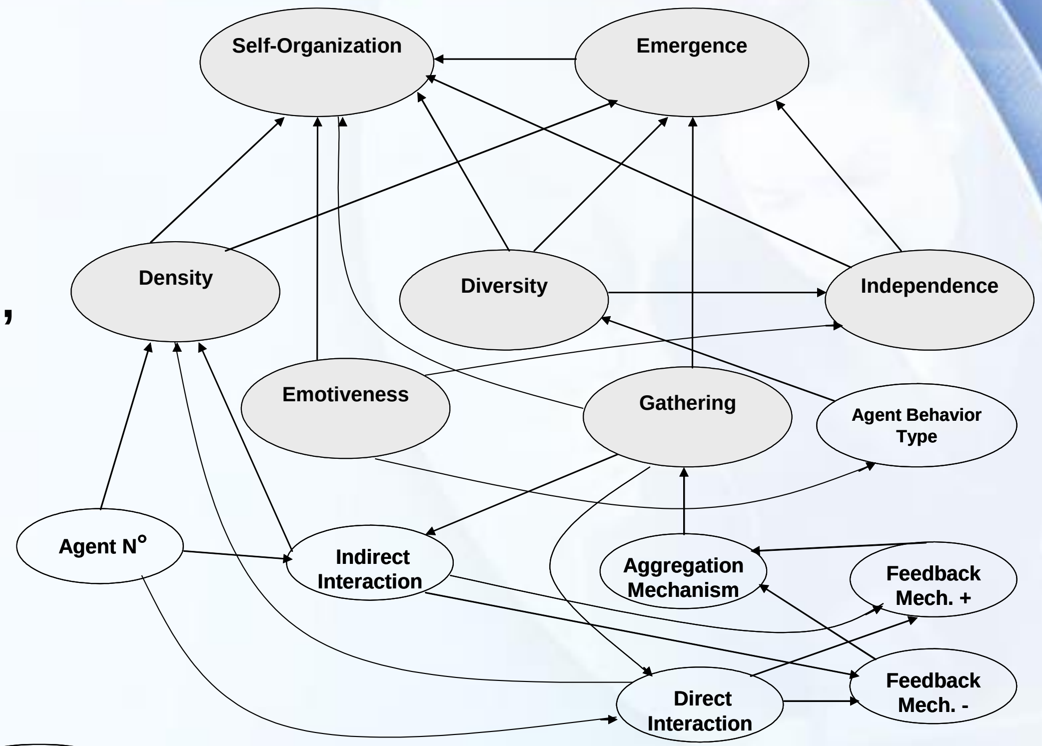
- To verify the emergent and self-organizing properties in the modeled system.

- For this, MASOES uses concepts such as: density, diversity, independence, emotions, self-organization, emergence, among others

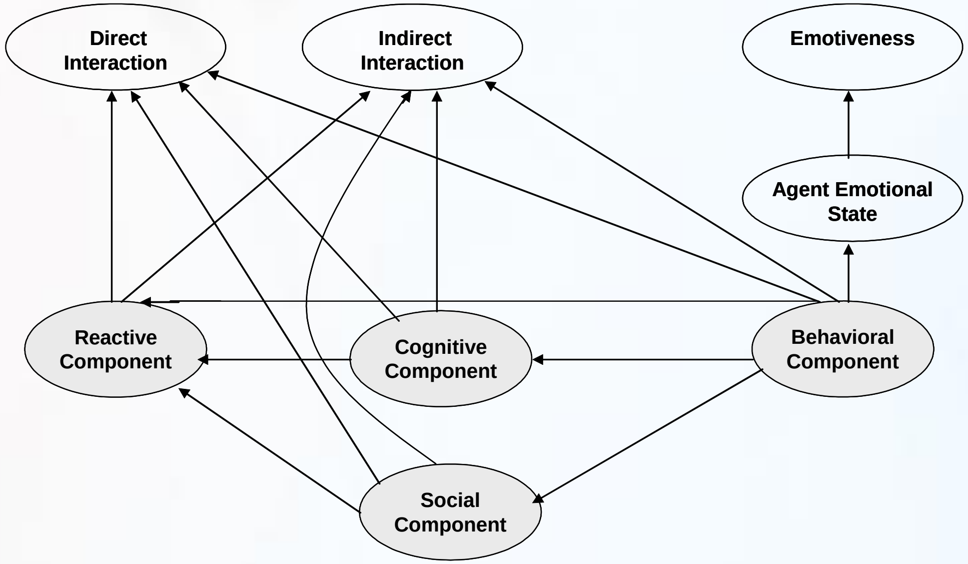
- the proposed CM for MASOES verification establishes the relationships between the architectonic concepts and those linked to self-organizing and emergent properties.

- The levels are:
  - **Level I:** composed by the self-organizing and emergent properties, representing the MASOES verification criteria,
  - **Level II:** composed by architectonic concepts of MASOES at the collective level,
  - **Level III:** composed by architectonic concepts of MASOES at the individual level.

FCM for MASOS



FCM for Concepts linked to self-organized, emerging properties



FCM for Architectonic Concepts

CASE STUDY: WIKIPEDIA

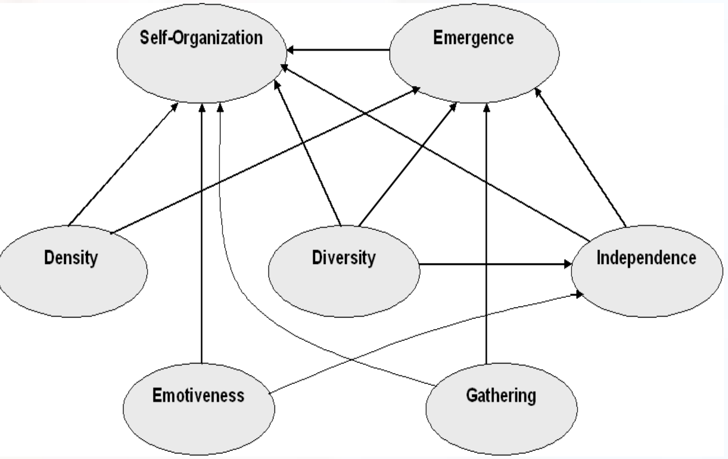
MASOES has been used to study the self-organizing and emergent properties in in the Wikipedia community. In this previous work have been used FCM tools, which support one level of CM

N. Perozo, J. Aguilar, O. Teran, H. Molina, "A Verification Method for MA-SOES, IEEE Transactions on Cybernetics, , vol.43, pp.64-76, 2013

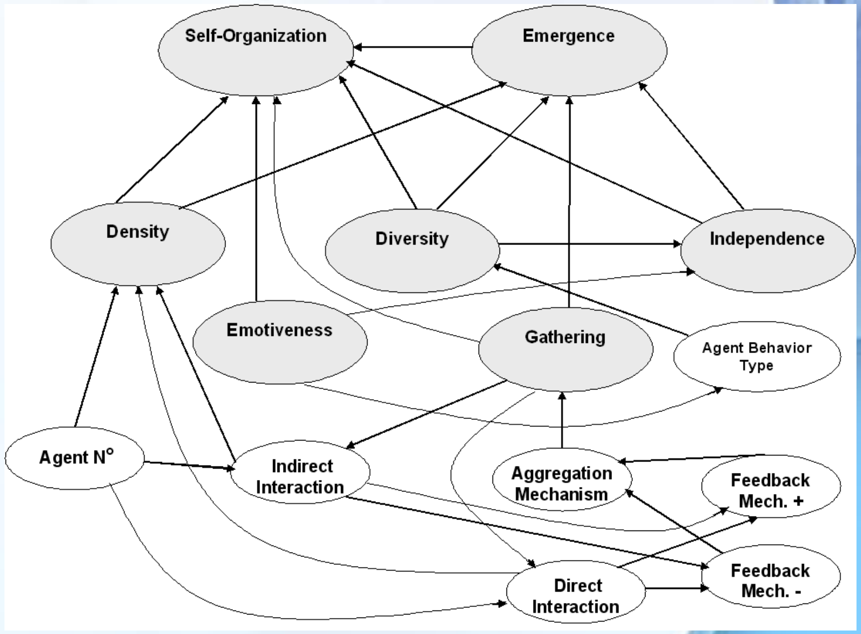
- **Self-Organization:** Wikipedia has the ability to self-organize.
- **Emergency**: It is possible the emergence of articles and rules of operation, thanks to the collective effort of people around the world.
- **Density:** In Wikipedia, each article is the result of multiple contributions of a critical mass of participants, ensuring the quality of the content.
- **Diversity:** there are different individuals involved in both the creation, revision and maintenance of content, and management of the platform that supports Wikipedia.
- **Synthesis:** The formation of social networks in Wikipedia, its rules and regulations, and the content managed with high standards, is the result of a process of aggregation and collective cleansing.
- **Independence:** Each wikipedista involved in the process of generating content in Wikipedia, initially is integrated according to their knowledge, skills, goals, and interests.
- **Emotionality:** It is measured by the satisfaction of Wikipedians according to their activities

MASOES

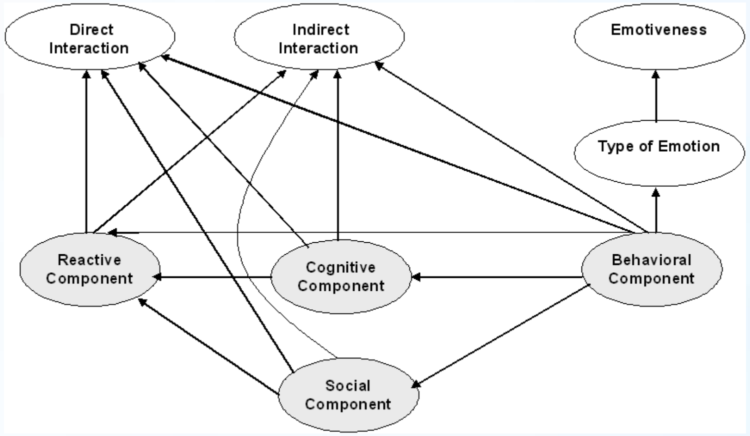
Verification method for MASOES.



Level II



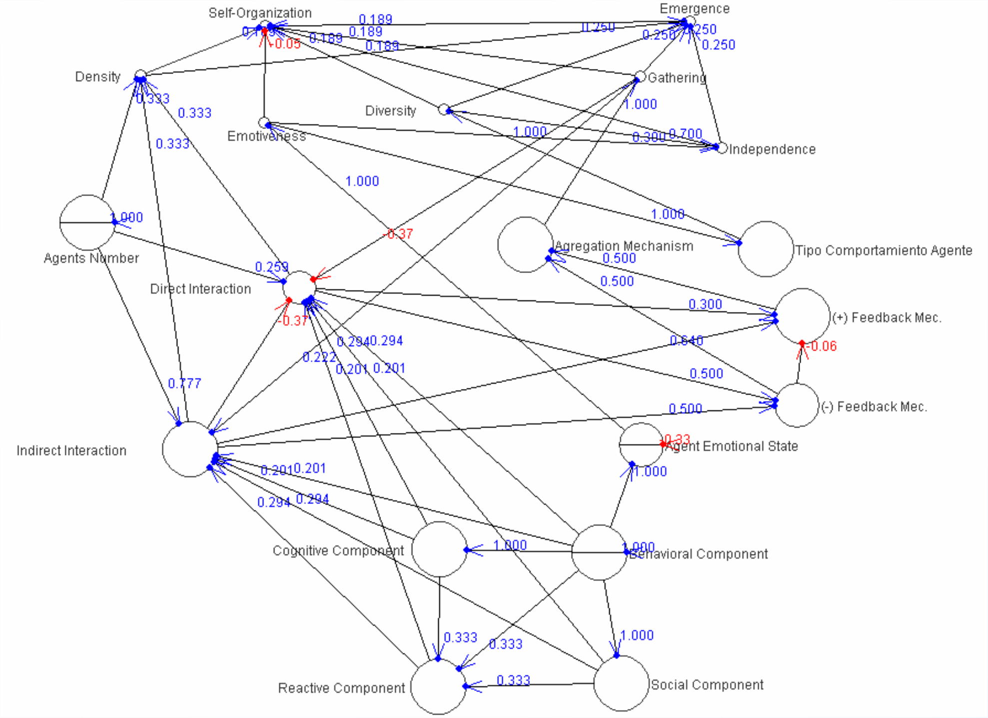
Level I



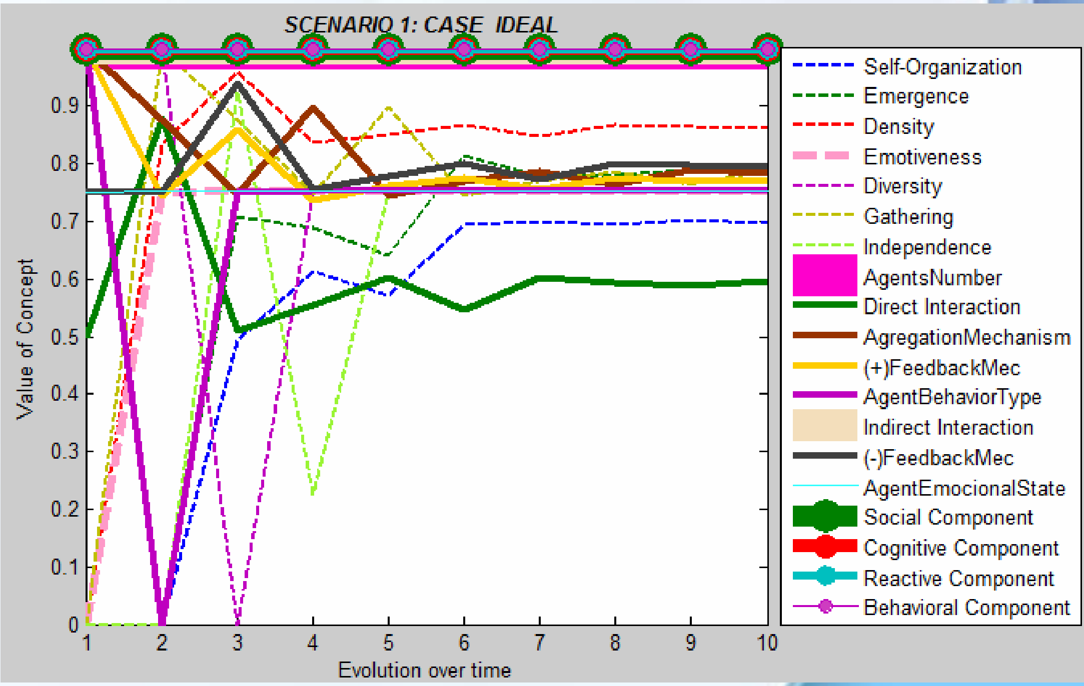
Level III

FCM for MASOS

- **Study Case: Free Software Development based on communities using the Bazaar Paradigm**



Scenario 1: Ideal Case for the LKDC

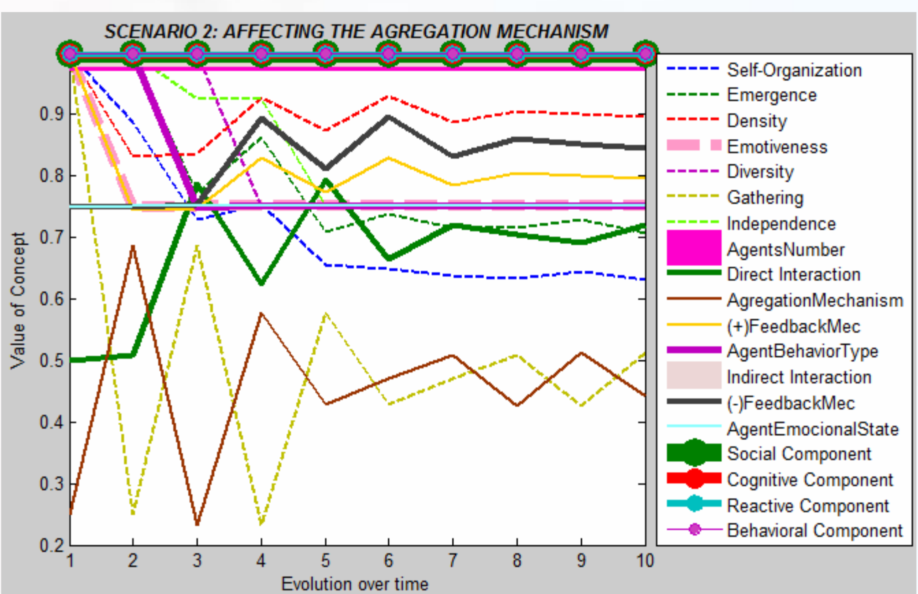


FCM for MASOS

- **Study Case: Free Software Development based on communities using the Bazaar Paradigm**

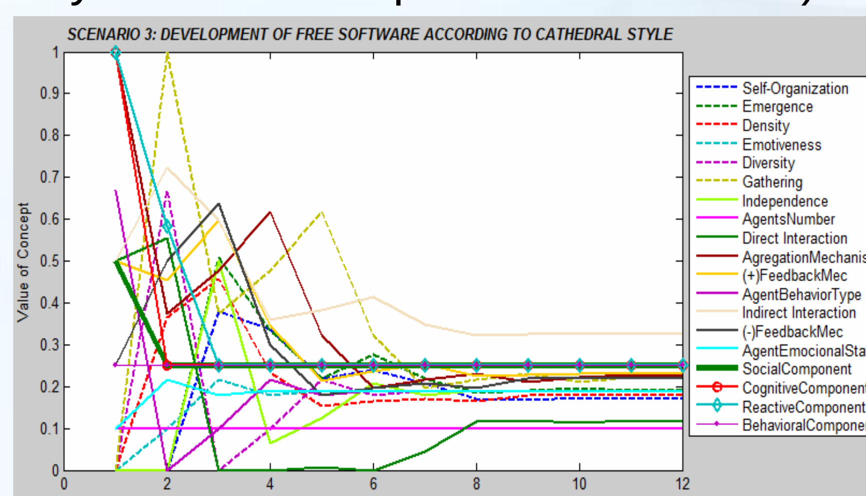
Scenario 2: Affecting the Aggregation Mechanism.

In this case, the initial value of the aggregation concept will begin in 0.25, which represents a decrease in its performance of approximately 68 % with respect to its ideal value for the LKDC.



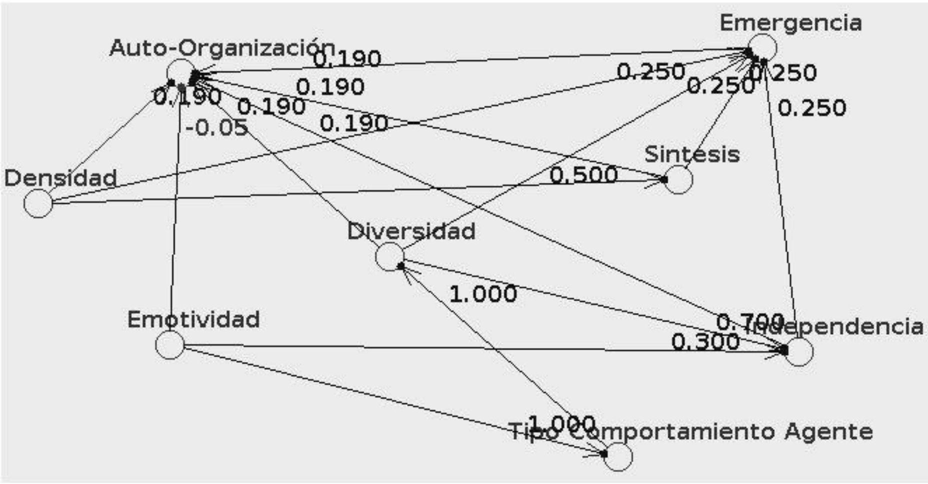
Scenario 3: Free Software Development through Cathedral Style

Number of agents 0.1 the direct interactions 0.5, and indirect 0.5. (reduced group of participants)and quality of the social component is diminished (0.5) and the emotional state (0.1) (establishment of a style of leadership and coordination)

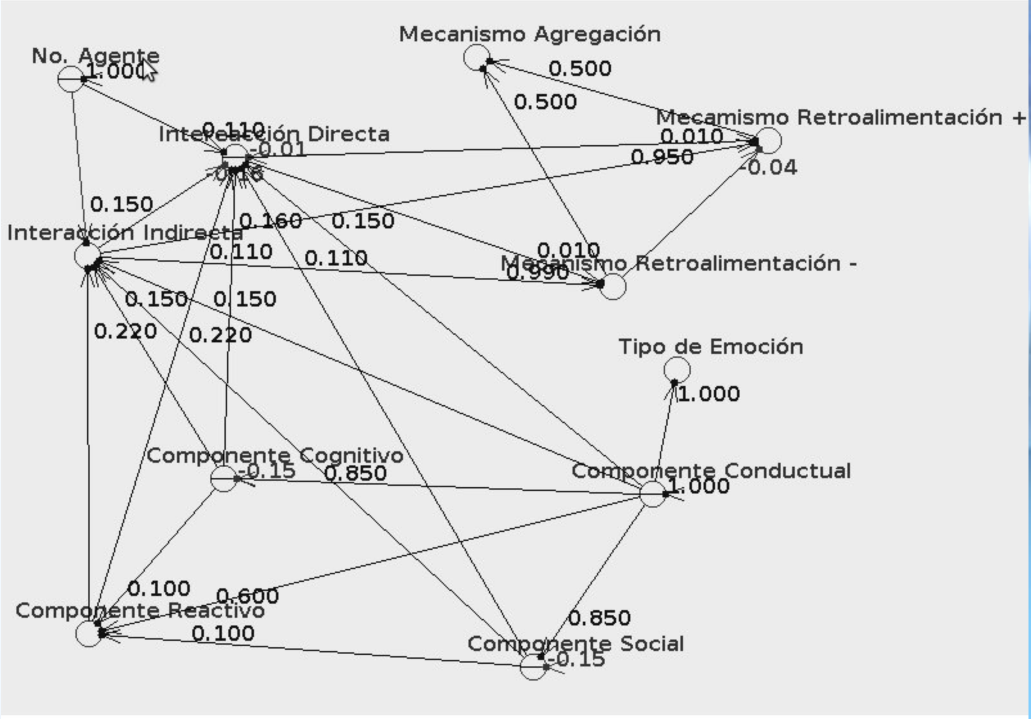


Case Study: Wikipedia

Implementation of the verification method for MASOES like MCM



CM of the Level I for Wikipedia



CM for the Levels II and III of Wikipedia

CASE STUDY: WIKIPEDIA

Implementation of the verification method for MASOES like MCM

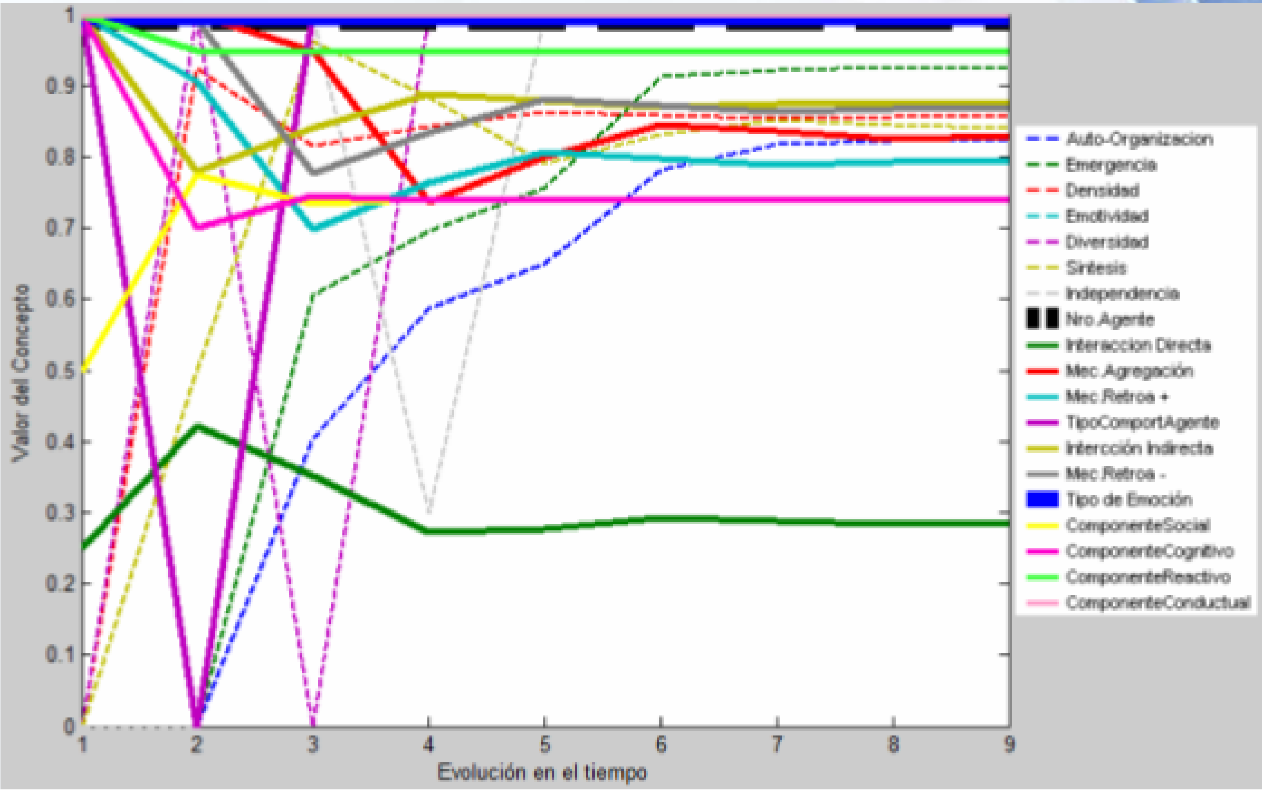
Concept of origin	weight	Concept of destination
Synthesis	0,110	Direct interaction.
Synthesis	-0,160	Indirect interaction.
Aggregation mechanism	0,500	Synthesis
Emotion Type	1,000	Emotionality
Direct interaction	0,100	Density
Indirect interaction	0,566	Density
Number agents	0,333	Density

CONNECTION WEIGHTS BETWEEN LAYERS

EXPERIMENTS

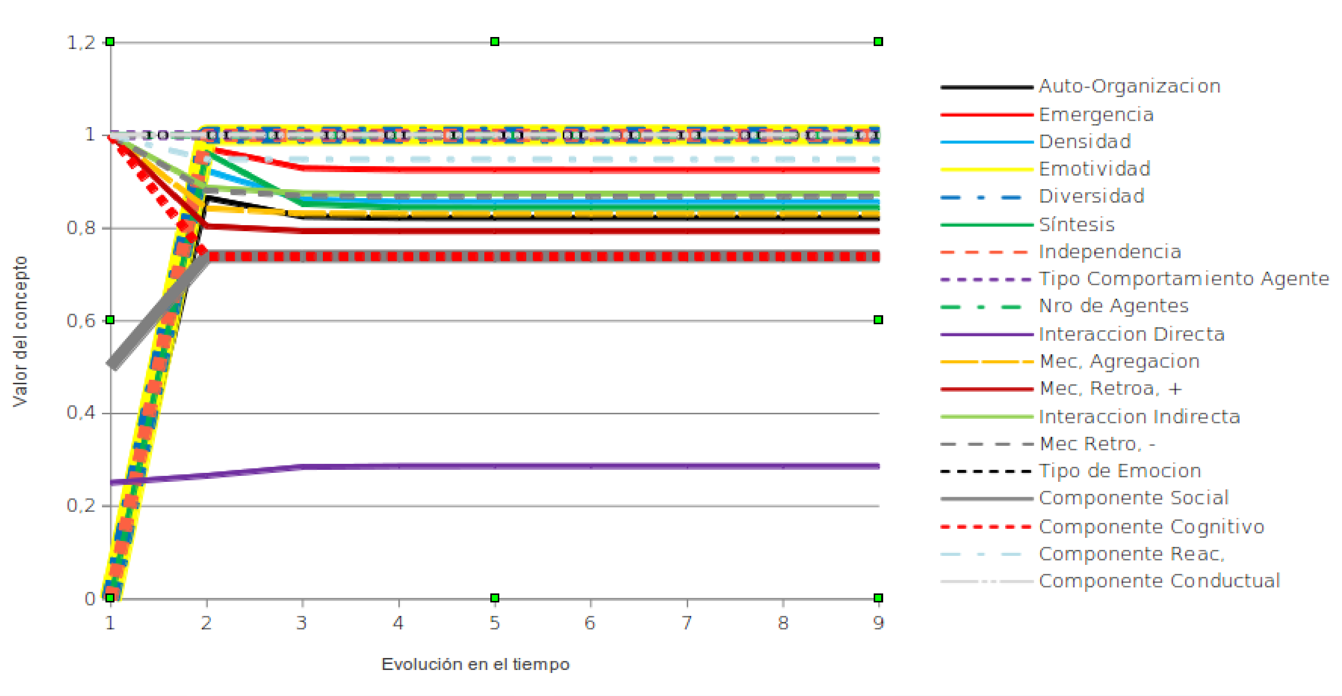
We instantiate both CM in a first scenario, which represents **the case of Wikipedia in English**, i.e., the case where almost all concepts work correctly.

For that reason, **the architectonic concepts are initialized in a high state,** in order to contribute in an important way to the self-organization and emergence.



Results obtained for Wikipedia in English, using a CM with a level

EXPERIMENTS



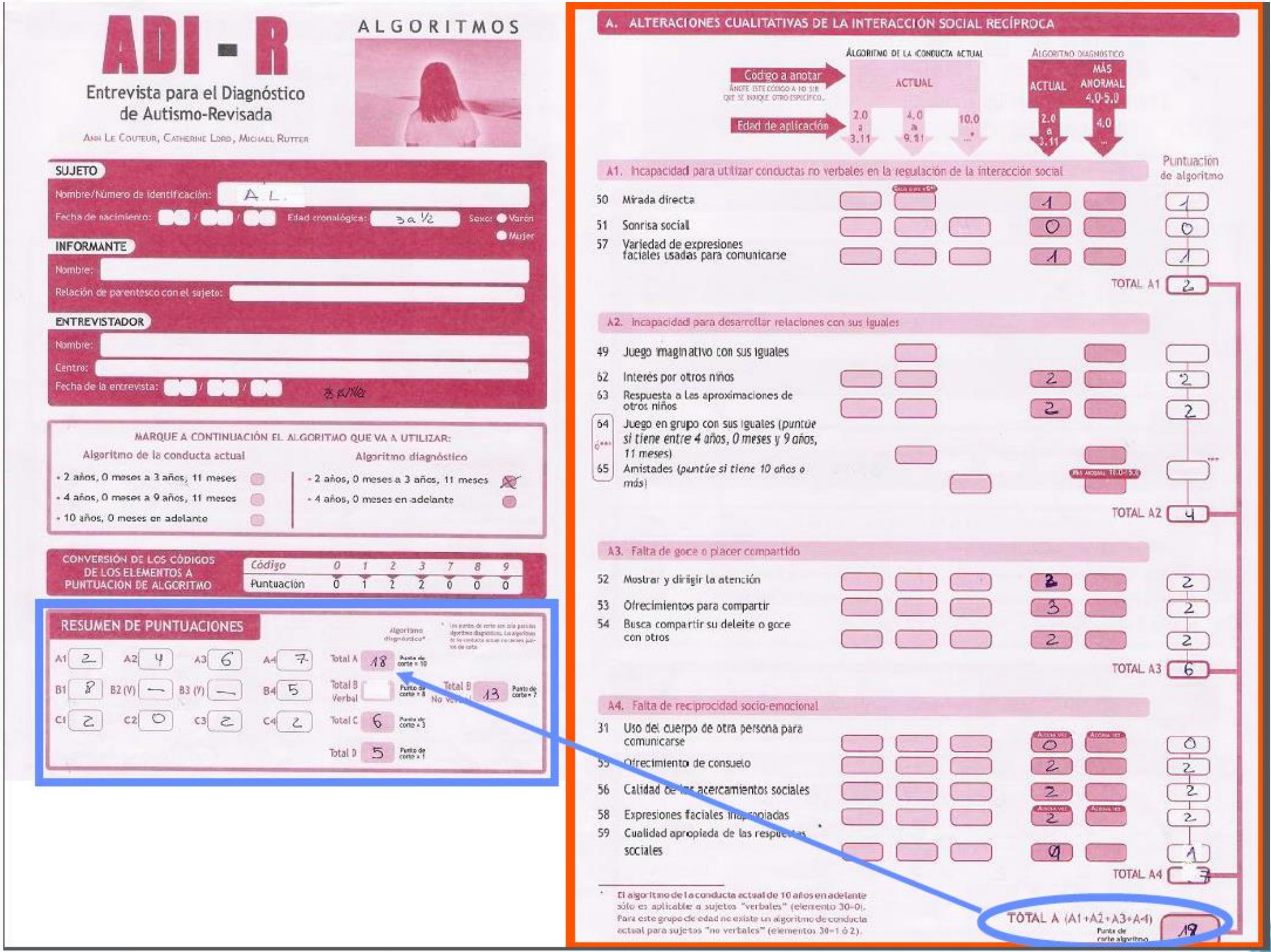
Results obtained for Wikipedia in English, using a MCM

The main differences are that

- In a map of two levels its values **are stabilized more quickly** (only 3 iterations).
- In addition, **the relationships between the concepts in different maps can be specifically defined**, which allows enriching the specification of the system under study.
- Finally, the **design of these systems (verification method of MASOES) is natural** with MCM

Modelo Cognitivo Difuso Multicapa para la Identificación de TEA y Diagnostico Autista

Instrumento ADIR



Instrumento ADOS

ADOS 2 — Algoritmos Módulo T

Identificación: JPM — Sexo: Varón ☐ Mujer ☒
Fecha de nacimiento: 02/03/2013 — Fecha de evaluación: 26/03/2015
Edad cronológica: 2 años — Examinador:

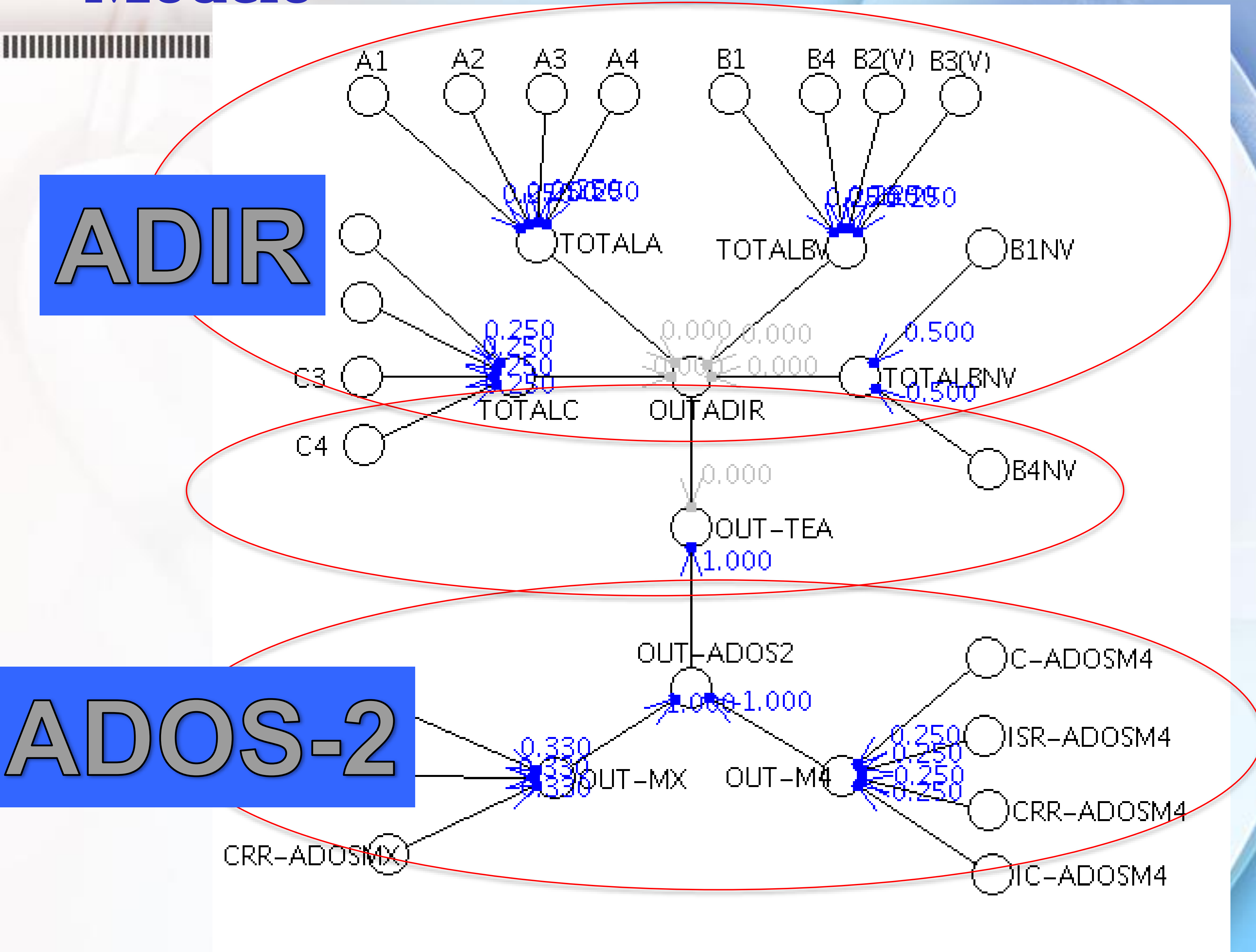
	ALGORITMO: TODOS LOS NIÑOS PEQUEÑOS/NIÑOS MAYORES CON POCAS PALABRAS O NINGUNA (Edad cronológica entre **12 y 20 meses** o edad cronológica entre **21 y 30 meses** y un código de **3 o 4** en el ítem **A1** "Nivel general de lenguaje oral no ecolálico")	ALGORITMO: NIÑOS MAYORES CON ALGUNAS PALABRAS (Edad cronológica entre **21 y 30 meses** y con un código de **0, 1 o 2** en el ítem **A1** "Nivel general de lenguaje oral no ecolálico")
Afectación social (AS)		
Comunicación		
Frecuencia de la vocalización espontánea dirigida a otros (A-2)		
Señalar (A-7)		2
Gestos (A-8)		
Interacción social recíproca		
Contacto visual inusual* (B-1)		2
Expresiones faciales dirigidas a otros (B-4)		2
Integración de la mirada y otras conductas durante las iniciaciones sociales (B-5)		1
Disfrute compartido durante la interacción (B-6)		
Respuesta al nombre (B-7)		1
Ignorar (B-8)		0
Pedir (B-9)		0
Mostrar (B-12)		
Iniciación espontánea de la atención conjunta (B-13)		0
Respuesta a la atención conjunta (B-14)		
Características de las iniciaciones sociales (B-15)		0
Cantidad de las iniciaciones sociales/familiar o cuidador (B-16b)		0
Calidad general de la relación (B-18)		0
TOTAL AS		8
Comportamiento restringido y repetitivo (CRR)		
Comportamientos restringidos y repetitivos		
Entonación de las vocalizaciones o verbalizaciones (A-3)		
Interés sensorial inusual en los materiales de juego o en las personas (D-1)		0
Movimientos de manos y dedos / postura (D-2)		0
Intereses inusualmente repetitivos o comportamientos estereotipados (D-5)		0
TOTAL CRR		0
PUNTUACIÓN TOTAL GLOBAL (AS + CRR)		8

RANGO DE PREOCUPACIÓN E IMPRESIÓN CLÍNICA

Rango de preocupación: Leve - Moderada

Impresión clínica:

Modelo


ADIR
ADOS-2
A1
A2
A3
A4
B1
B4
B2(V)
B3(V)
TOTALA
TOTALBV
B1NV
C3
C4
TOTALC
OUTADIR
TOTALBNV
B4NV
0.500
0.000
OUT-TEA
1.000
OUT-ADOS2
C-ADOSM4
ISR-ADOSM4
CRR-ADOSM4
IC-ADOSM4
OUT-MX
OUT-M4
CRR-ADOSMX
0.330
0.250

Resultados de la Simulación de los 27 Casos ADOS2 proporcionados por la Dra Catalina

ESCALA DE SEVERIDAD

NO AUTISMO			TEA		AUTISMO				
1	2	3	4	5	6	7	8	9	10

ADOS	MóduloX-AlgoritDiagnos	C	ISR	CRR	Diagnistico Experto: Dra-Cat	OUT-MCDM-ADOS	Interpretación Salida del
Caso ADOS-1	M1-NV-7años	4	15	7	Nivel Alto Sintomas	0.926	AUTISMO-10
Caso ADOS-2	M1-NV-9años	4	10	1	Nivel Moderado de Sintoma	0.578	AUTISMO-6
Caso ADOS-3	M1-V-9añosy3meses	2	7	2	Nivel Moderado de Sintoma	0.353	TEA-5
Caso ADOS-4	M3-V-12años	4	4	0	Nivel Moderado de Sintoma	0.313	AUTISMO-6
Caso ADOS-5	M1-V-3años	0	1	1	No evidencia de Sintomas	0.065	NA-1
Caso ADOS-6	M3-V-10años	5	5	1	Nivel Moderado de Sintoma	0.433	AUTISMO-7
Caso ADOS-7	M1-NV-3añosy8meses	6	14	0	Nivel Alto Sintomas	0.606	AUTISMO-6
Caso ADOS-8	M1-NV-6años	4	9	0	Nivel Bajo de Sintomas	0.516	TEA-5
Caso ADOS-9	M1-V-9años	1	7	3	Nivel Bajo de Sintomas	0.341	TEA-5
Caso ADOS-10	M2-V-11años	0	5	5	Nivel Bajo de Sintomas	0.309	AUTISMO-6
Caso ADOS-12	M1-V-5años	3	11	4	Nivel Moderado de Sintoma	0.589	AUTISMO-7
Caso ADOS-13	M1-V-9añosy3meses	0	0	1	No evidencia de Sintomas	0.041	NA-1
Caso ADOS-14	M3-V-12	5	10	5	Nivel Alto Sintomas	0.716	AUTISMO-10
Caso ADOS-15	M3-V-11años	4	4	1	Nivel Moderado de Sintoma	0.355	AUTISMO-6
Caso ADOS-16	M1-V-4años	0	0	1	No evidencia de Sintomas	0.000	NA-1
Caso ADOS-17	M1-V-3años	0	3	3	No evidencia de Sintomas	0.186	NA-2
Caso ADOS-18	M3-V-12años	2	5	0	Nivel Bajo de Sintomas	0.227	TEA-4
Caso ADOS-19	M3-V-8años	0	0	0	No evidencia de Sintomas	0.000	NA-1
Caso ADOS-20	M1-NV-6años	4	14	6	Nivel Alto Sintomas	0.866	AUTISMO-10
Caso ADOS-21	M3-V-7añps2meses	2	2	3	Nivel Bajo de Sintomas	0.280	TEA-5
Caso ADOS-22	M1-V-8añosy6meses	3	12	3	Nivel Moderado de Sintoma	0.530	AUTISMO-6
Caso ADOS-23	M3-V-11años	1	2	4	Nivel Bajo de Sintomas	0.267	TEA-4
Caso ADOS-24	M3-V-11años	5	8	5	Nivel Alto Sintomas	0.669	AUTISMO-10
Caso ADOS-25	M3-V-11añosy9meses	3	4	2	Nivel Moderado de Sintoma	0.341	AUTISMO-6
Caso ADOS-26	M2-V-8añosy7meses	1	5	4	Nivel Moderado de Sintoma	0.351	AUTISMO-6
Caso ADOS-27	M2-V-11años	0	5	5	Nivel Bajo de Sintomas	0.309	AUTISMO-6

Codigo Color:
Amarillo: Corresponde a los casos módulo 1 tomados de la doctora.
Verde: Corresponde a los casos módulo 2 tomados de la doctora
Rojo: Corresponde a los casos módulo 3 tomados de la doctora

Azul: Corresponde a los resultados de nuestro modelo
NV: Sujeto No Verbal Y V: Sujeto Verbal

Resultados de la simulación de 3 Casos diagnosticados por expertos, detallados en el artículo:

Kannappan, A., Tamilarasi, A., & Papageorgiou, E. I. (2011). Analyzing the performance of fuzzy cognitive maps with nonlinear hebbian learning algorithm in predicting autistic disorder. Expert Systems with Applications, 38(3), 1282-1292.

DA: Autista Definitivo
PA: Probable Autismo

Experto	Nosotros	Griega
0.51 = DA	0.50= AUTISMO-7	0.73= DA
0.41 = PA	0.28=TEA-4	0.37= PA
0.87 = DA	0.60=AUTISMO-8	0.659= DA

Análisis de los tres resultados:

El modelo replica o sigue de manera consistente los tres diagnósticos del experto.

Usando modelo MCHAT
(psicologos han cuestionada ese modelo)

Simulación de 40 Casos de la Base de datos usada en

Kannappan, A., Tamilarasi, A., & Papageorgiou, E. I. (2011). Analyzing the performance of fuzzy cognitive maps with nonlinear hebbian learning algorithm in predicting autistic disorder. Expert Systems with Applications, 38(3), 1282-1292.

Análisis de Resultados Griegos:

$$\text{Accuracy Percentage} = (20/23 + 10/13 + 3/4)/3 = 79.9\%$$

Tiene un ERROR de 21% en 40 casos

Análisis de resultados Nuestro:

32 Casos buenos (Están dentro del rango) indicados por la flecha verde

Accuracy Percentage: 84.2%

DA PA NA

(25/25+ 7/10 + 0/4)/3

Tiene un ERROR de 15% en 40 casos

	Salida Experto	Modelo Nuestro	
Caso1	0.73	0.722	AUTISMO-10
Caso2	0.75	0.750	AUTISMO-10
Caso3	0.76	0.722	AUTISMO-10
Caso4	0.73	0.738	AUTISMO-10
Caso5	0.72	0.729	AUTISMO-10
Caso6	0.76	0.716	AUTISMO-10
Caso7	0.75	0.733	AUTISMO-10
Caso8	0.71	0.720	AUTISMO-10
Caso9	0.70	0.712	AUTISMO-10
Caso10	0.73	0.736	AUTISMO-10
Caso11	0.75	0.731	AUTISMO-10
Caso12	0.77	0.723	AUTISMO-10
Caso13	0.76	0.722	AUTISMO-10
Caso14	0.73	0.725	AUTISMO-10
Caso15	0.77	0.731	AUTISMO-10
Caso16	0.73	0.723	AUTISMO-10
Caso17	0.72	0.713	AUTISMO-10
Caso18	0.20	0.715	AUTISMO-10
Caso19	0.70	0.736	AUTISMO-10
Caso20	0.71	0.731	AUTISMO-10
Caso21	0.33	0.331	TEA-4
Caso22	0.20	0.381	TEA-4
Caso23	0.32	0.527	AUTISMO-7
Caso24	0.20	0.479	AUTISMO-6
Caso25	0.30	0.419	TEA-5
Caso26	0.30	0.570	AUTISMO-7
Caso27	0.39	0.525	AUTISMO-7
Caso28	0.23	0.578	AUTISMO-7
Caso29	0.28	0.613	AUTISMO-8
Caso30	0.25	0.393	TEA-5
Caso31	0.22	0.695	AUTISMO-8
Caso32	0.83	0.680	AUTISMO-8
Caso33	0.57	0.738	AUTISMO-9
Caso34	0.73	0.506	AUTISMO-7
Caso35	0.61	0.690	AUTISMO-9
Caso36 Proyec	0.36	0.697	AUTISMO-8
Caso37	0.78	0.548	AUTISMO-7
Caso38	0.73	0.677	AUTISMO-8

Conclusions

- The extension of MCM is essential **to allow the use of the CM in problems where the utilization of several CM is natural to model the system.**

- Our proposal of MCM **allows the introduction of a way to follow the dynamics of systems, now through the relationships that exist between various CM,** which describe the system, in particular, through the interface that define the dynamic relationships between these various CM.

Tools based on FCMs

- **The FCModeler tool.**
  http://orion.math.iastate.edu/danwell/GET/GETFC.html

- **FCM Designer**
  http://www.ing.ula.ve/~aguilar/desarrollo-software/desarrollo-software.html

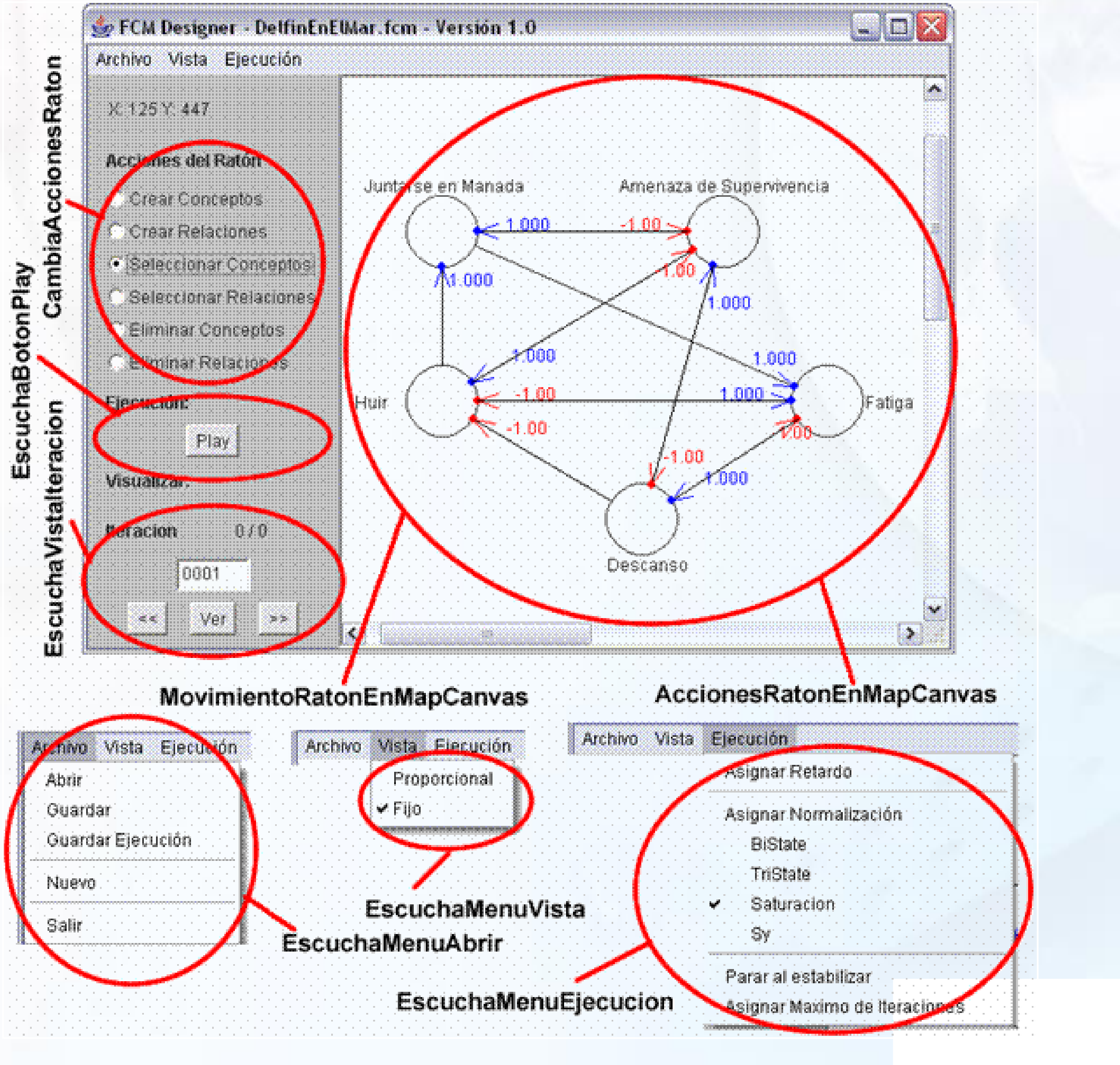
- **FCM Research Group - epapageorgiou**
  www.epapageorgiou.com/index.php/fcm-research-group

- **CARTES CAUSALES DANS LES SYSTÈMES MULTIAGENTS (Multiagent-Causal Maps.1.0)**
  http://www.damas.ift.ulaval.ca/~fabiola/recherche/

- **Amit Roy has written an FCM tool as Python CGI**.
  http://www.artecs.net/cgi-bin/FCM.cgi

- **The fuzzy cognitive map applet.**
  http://www.ochoadeaspuru.com/fuzcogmap/software.php

FCM Designer



Conclusions

•Obviously, the success of a particular FCM model depends greatly on the selection of concept nodes and the interpretation of state vectors.

•Generally, a FCM exhibits a number of desirable properties that make it attractive:

- •Provide qualitative information about the inferences in complex dynamic models.
- •Can represent an unlimited number of reciprocal relationships.
- •Facility the modeling of dynamic, time evolving phenomena and process (it has defined learning procedure).
- •Has a high adaptability to any inference with feedback.
- • Another important characteristic is its simplicity, the result of each cycle is computed from an specific equation.
- •Most of the computations are intrinsically parallel and can be implemented on SIMD or MIMD architectures.
- •The ability to easily model uncertain systems at low cost and with adaptive behavior