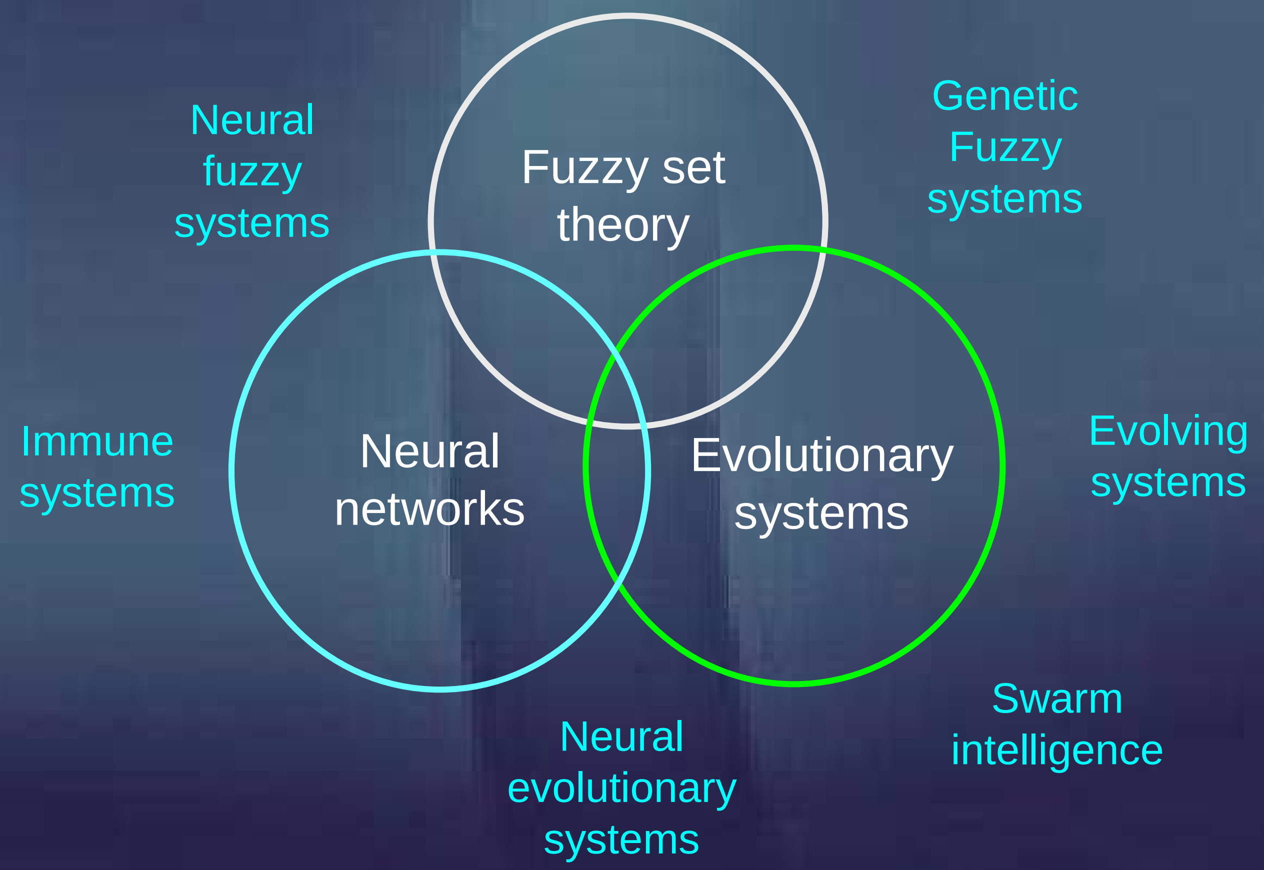
13 Fuzzy Systems and Computational Intelligence

Fuzzy Systems Engineering
Toward Human-Centric Computing

Contents

13.1 Computational intelligence

Computational Intelligence

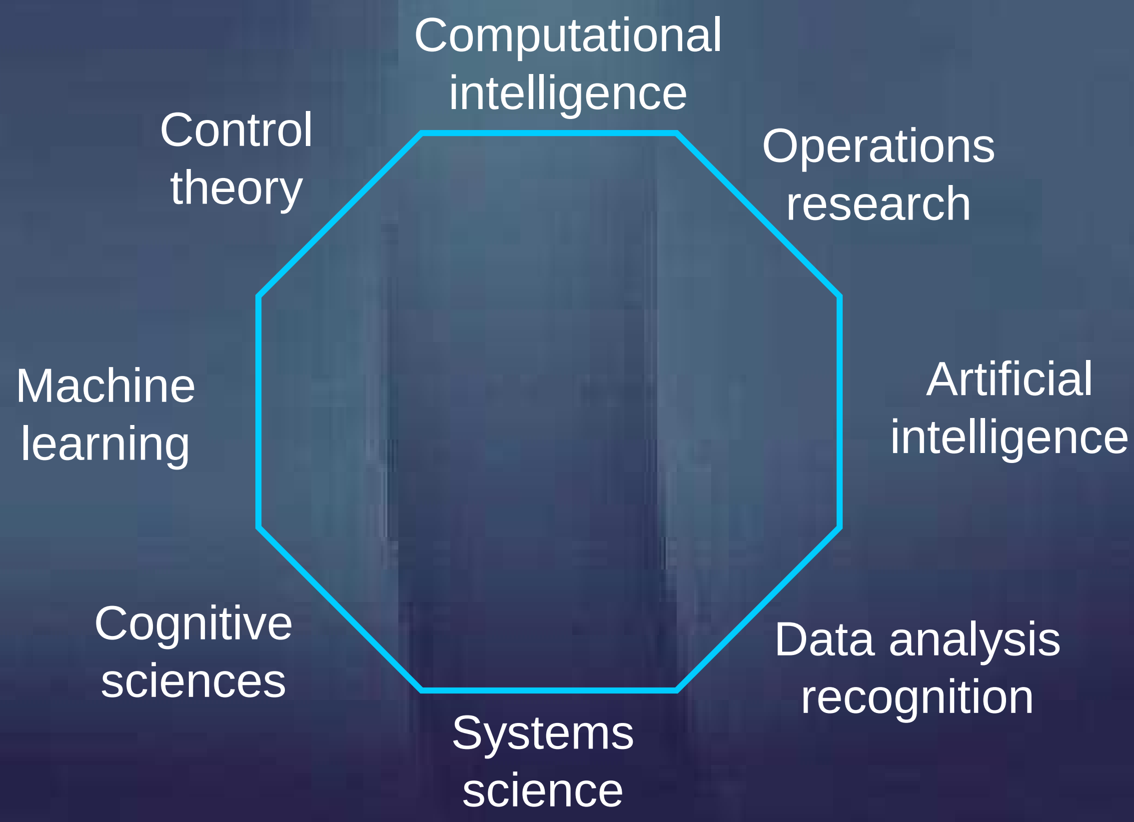


Computational intelligence

- Data processing systems with capabilities of (Bezdek, 1992/1994)
  - pattern recognition
  - adaptive
  - fault tolerance
  - performance approximates human performance
  - no use of explicit knowledge
- Framework to design and analyze intelligent systems (Duch, 2007)
  - autonomy
  - learning
  - reasoning

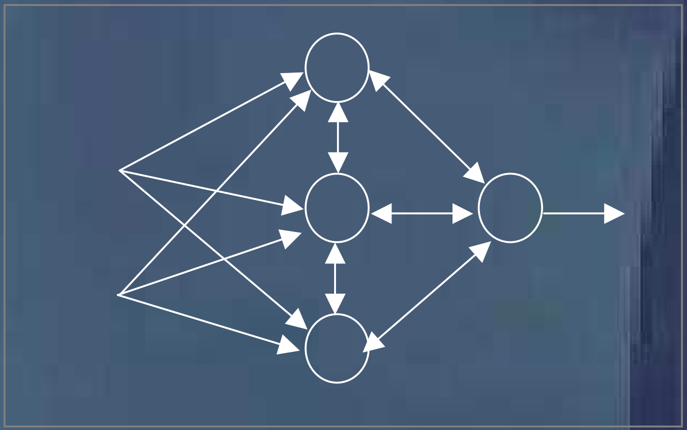
- Computing systems able to (Eberhart, 1996)
  - learn
  - deal with new situations using
    - reasoning
    - generalization
    - association
    - abstraction
    - discovering
- Computational intelligence
  - largely human-centered
  - forms of artificial and synthetic intelligence
  - collaboration man-machine

Intelligent Systems

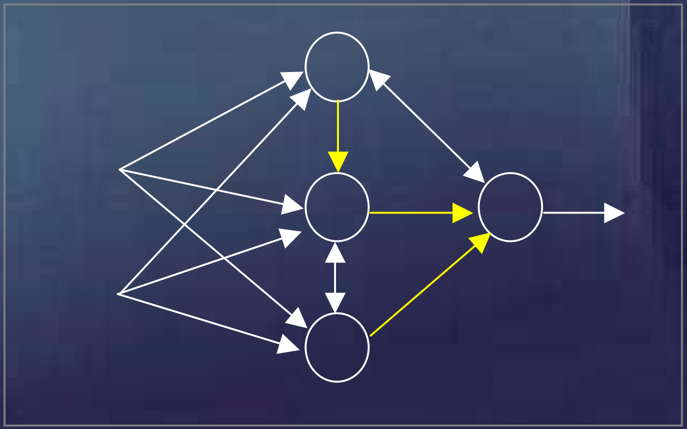


13.2 Recurrent neurofuzzy systems

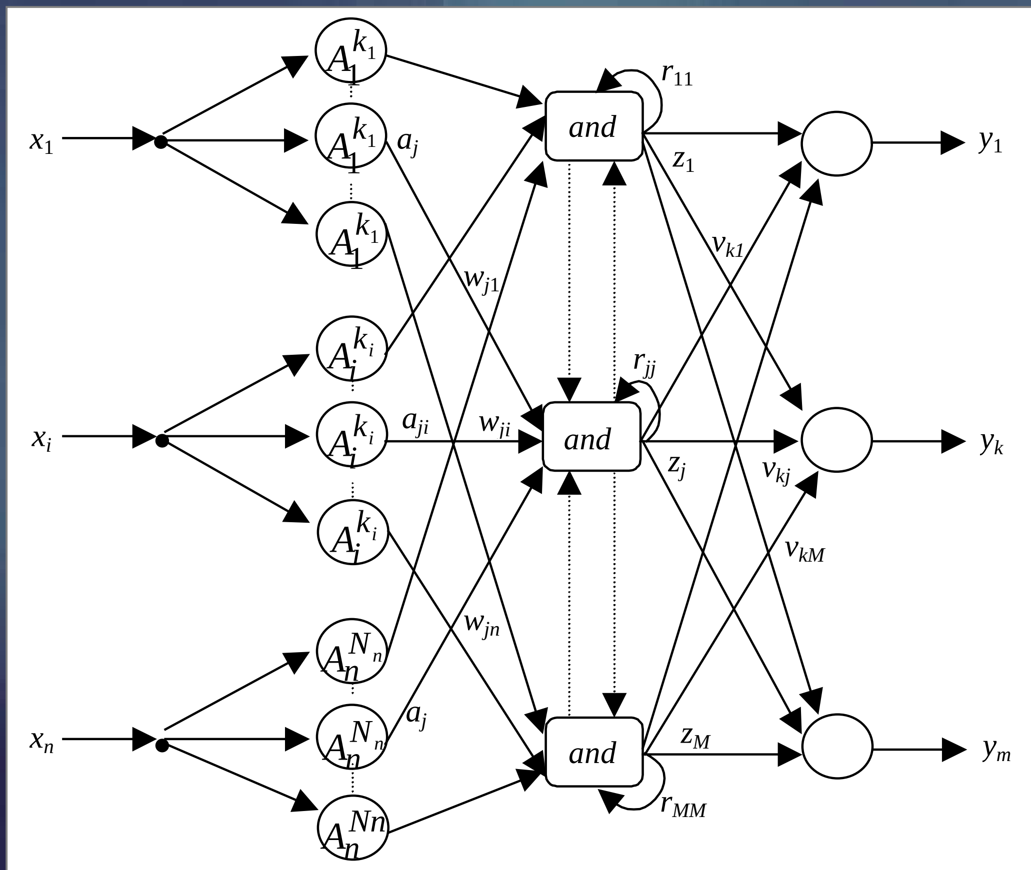
- Globally recurrent
  - – full feedback connections



- Partially recurrent
  - – partial feedback connections



Recurrent neural fuzzy network model



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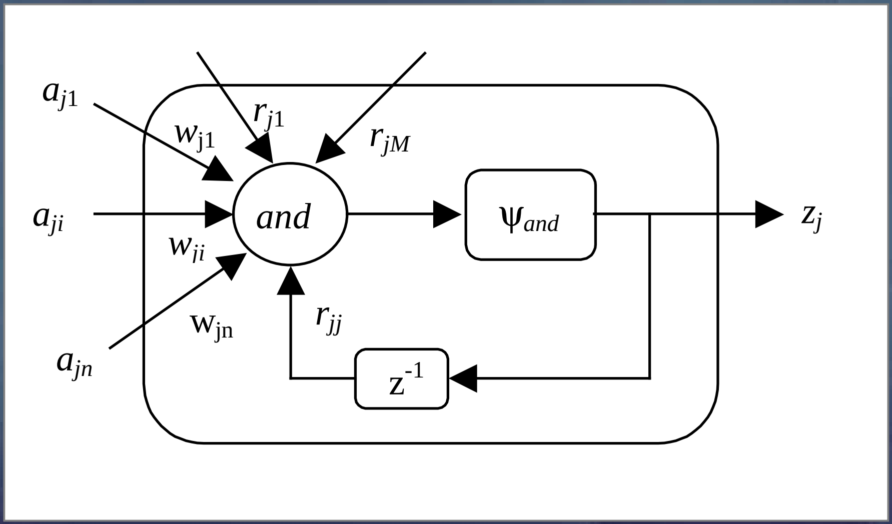
Recurrent ***and*** fuzzy neuron



$$z_j = \mathop{T}_{i=1}^{n+M} (w_{ji} \, s \, a_{ji})$$

z_j = AND($\mathbf{a}_j$;$\mathbf{w}_j$)

- Ni number of fuzzy sets that granulate the ith input
- j indexes *and* neurons; given k_i , j is found using

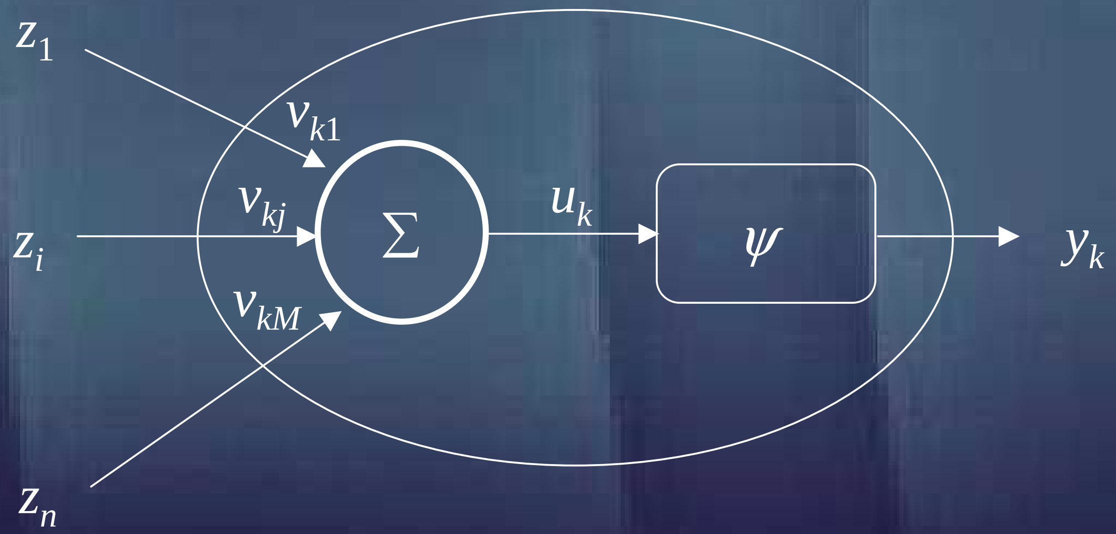
$$j = k_n + \sum_{i=2}^{M} (k_{(n-i+1)} - 1) \left(\prod_{r=1}^{i-1} N_{(n+1-r)} \right)$$

- $x_1, \ldots, x_i, \ldots, x_n$ inputs

- $a_{ji} = A_i^{k_i}(x_i)$

- w_{ji} weight between ith input and jth *and* neuron
- z_j output of the jth *and* neuron
- v_{kj} weight jth input of the kth output neuron
- r_{jl} feedback connection of the lth input of the jth *and* neuron
- $\mathrm{y}_{\mathrm{k}} = \psi(u_k)$ output kth neuron of the output layer

Output layer neuron



$$y = \psi(u_k) = \psi\left(\sum_{j=1}^{M} v_{kj} z_j\right)$$

Learning algorithm

procedure NET-LEARNING (**x**, **y**) **returns** a network

input:data **x**, **y**
local: fuzzy sets
t, *s*: triangular norms
ε: threshold

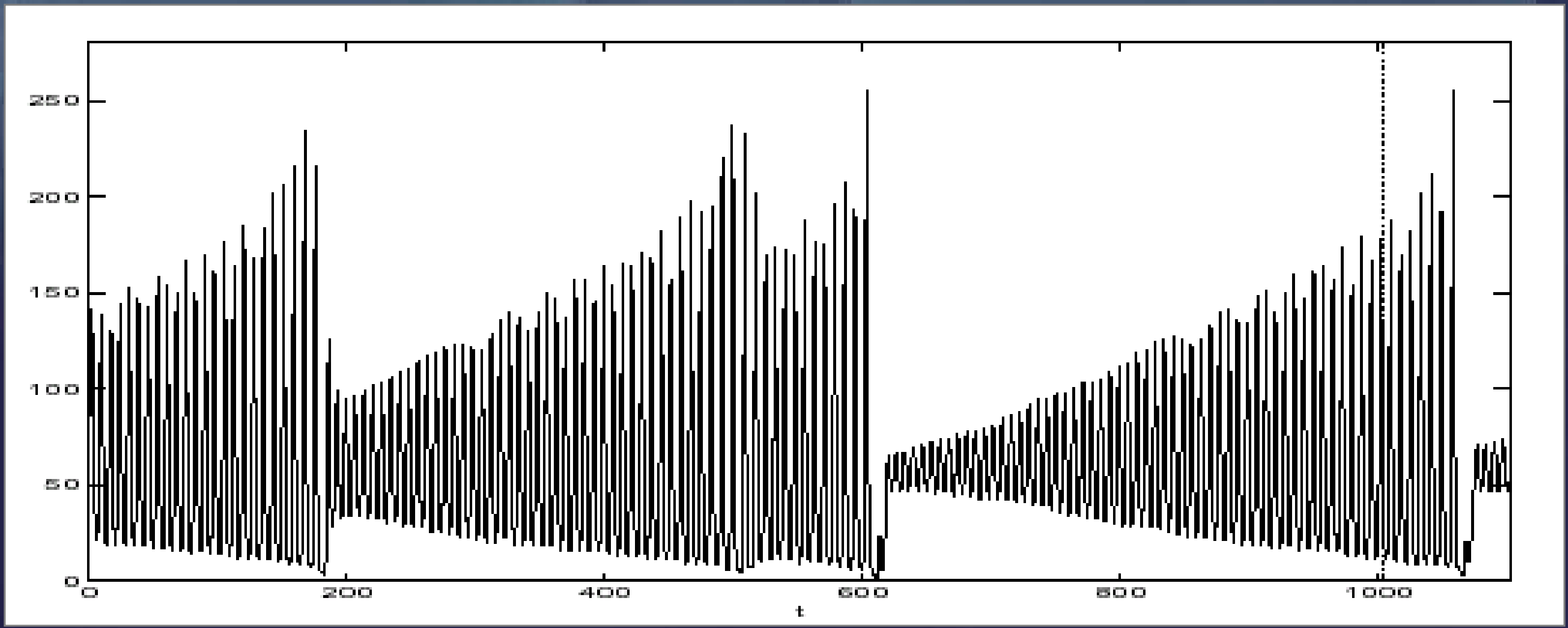
GENERATE-MEMBERSHIP-FUNCTIONS
INITIALIZE-NETWORK-WEIGHTS

until stop criteria $\leq \varepsilon$ **do**
choose and input-output pair *x* and *y* of the data set
ACTIVE-AND-NEURONS
ENCODING
UPDATE-WEIGHTS
return a network

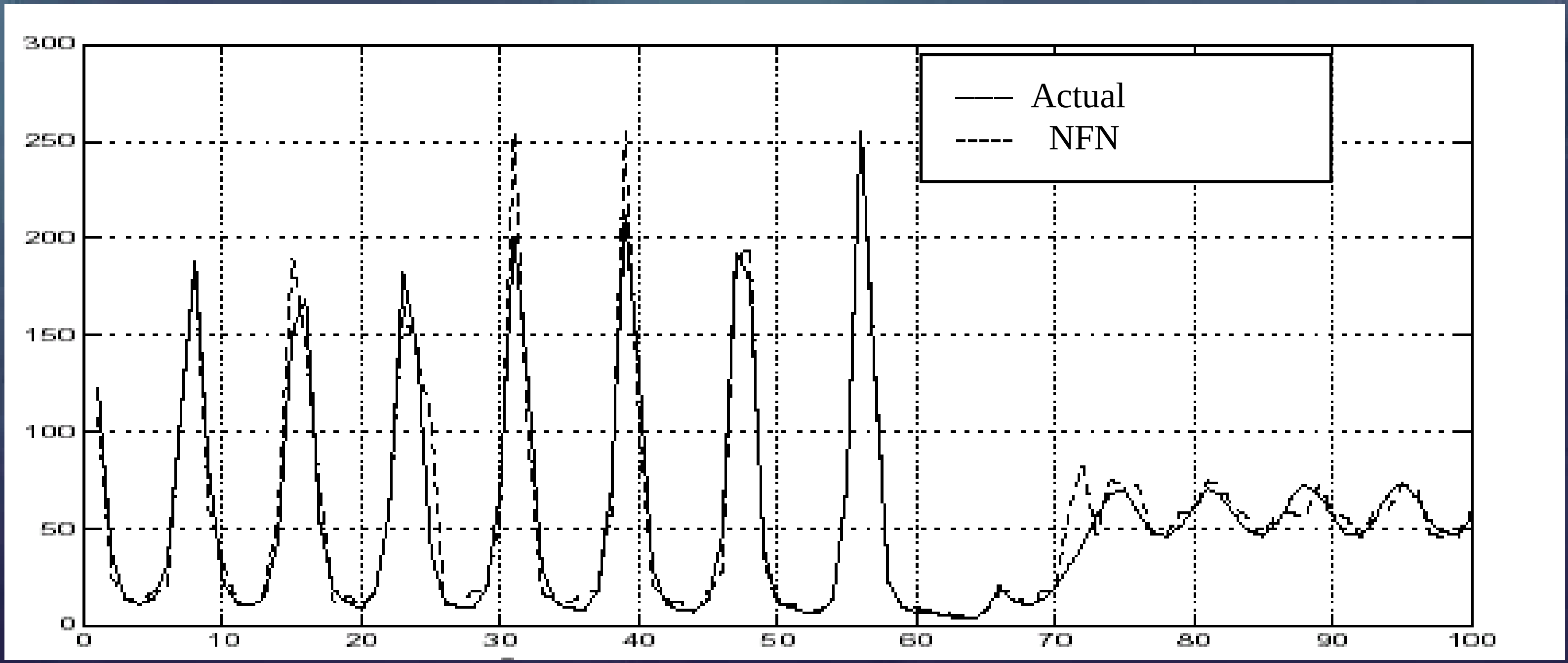
Example

Chaotic NH3 laser time series data

- first 1000 samples for learning
- predict next 100 steps



100 steps ahead prediction



Normalized squared forecasting errors (NSE) NH3 laser time series

Model	1 step ahead	100 steps ahead
FIR	0.0230	0.0551
NFN	0.0139	0.0306

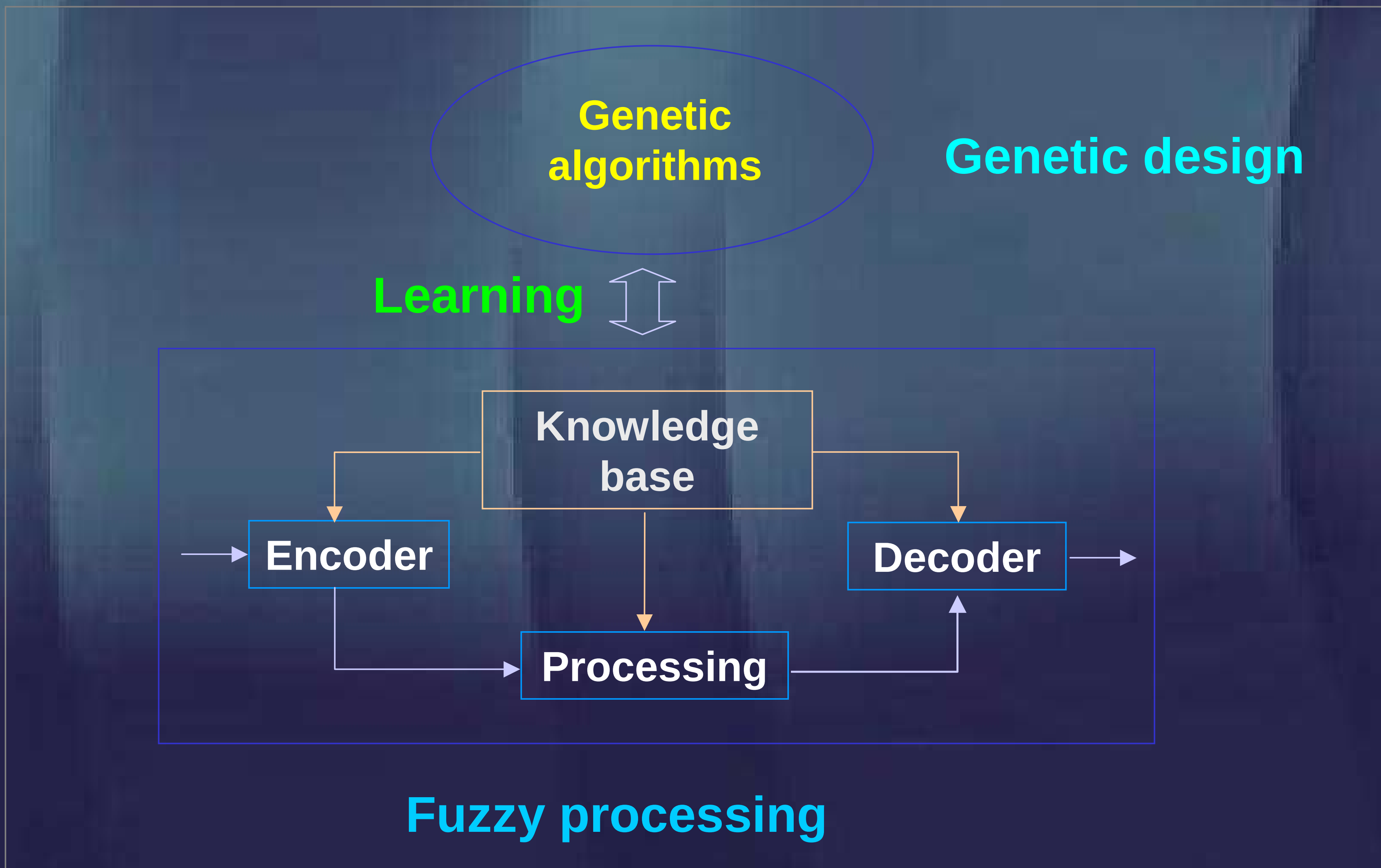
$$NSE = \frac{1}{\sigma^2 N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

13.3 Genetic fuzzy systems

Genetic fuzzy systems

- GFS is an approach to design fuzzy models and systems
- GFS = fuzzy system + learning using genetic algorithm
- Learning of models structure and parameters
  - rule base
  - fuzzy rules
  - membership functions
  - operators
  - inference procedures

Genetic Fuzzy Systems

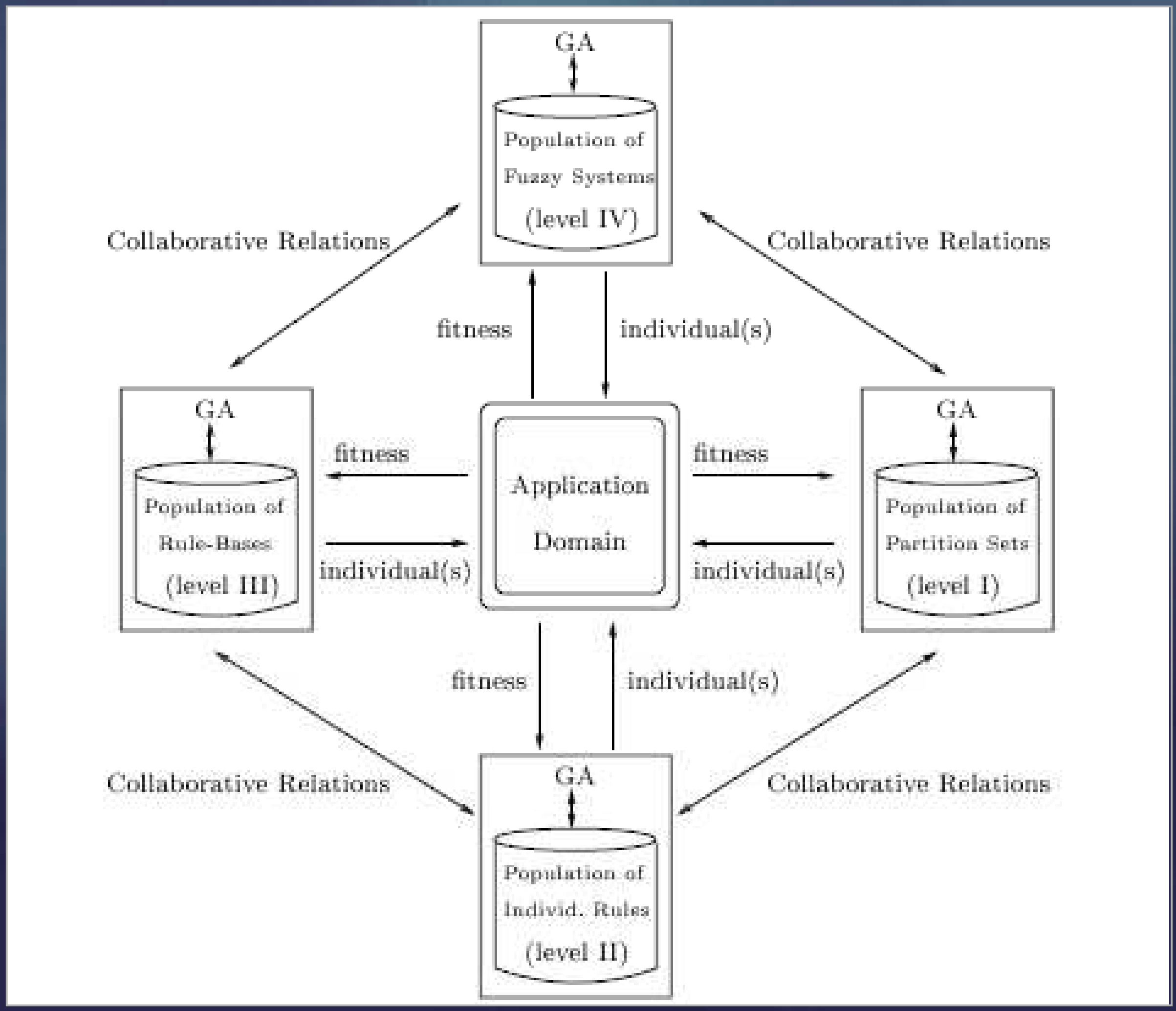


13.4 Coevolutionary hierarchical genetic fuzzy system

Coevolution

- Considers interactions between population members
- Populations hierarchically structured
- Hierarchy levels associated with partial solutions of the problem
  - individuals of different populations keep collaborative relations
  - collaboration depends on the fitness of the individuals
  - hierarchical levels:
    - I : membership functions
    - II : fuzzy rules
    - III: rule bases
    - IV: fuzzy systems (models)

Coevolutionary GFS approach



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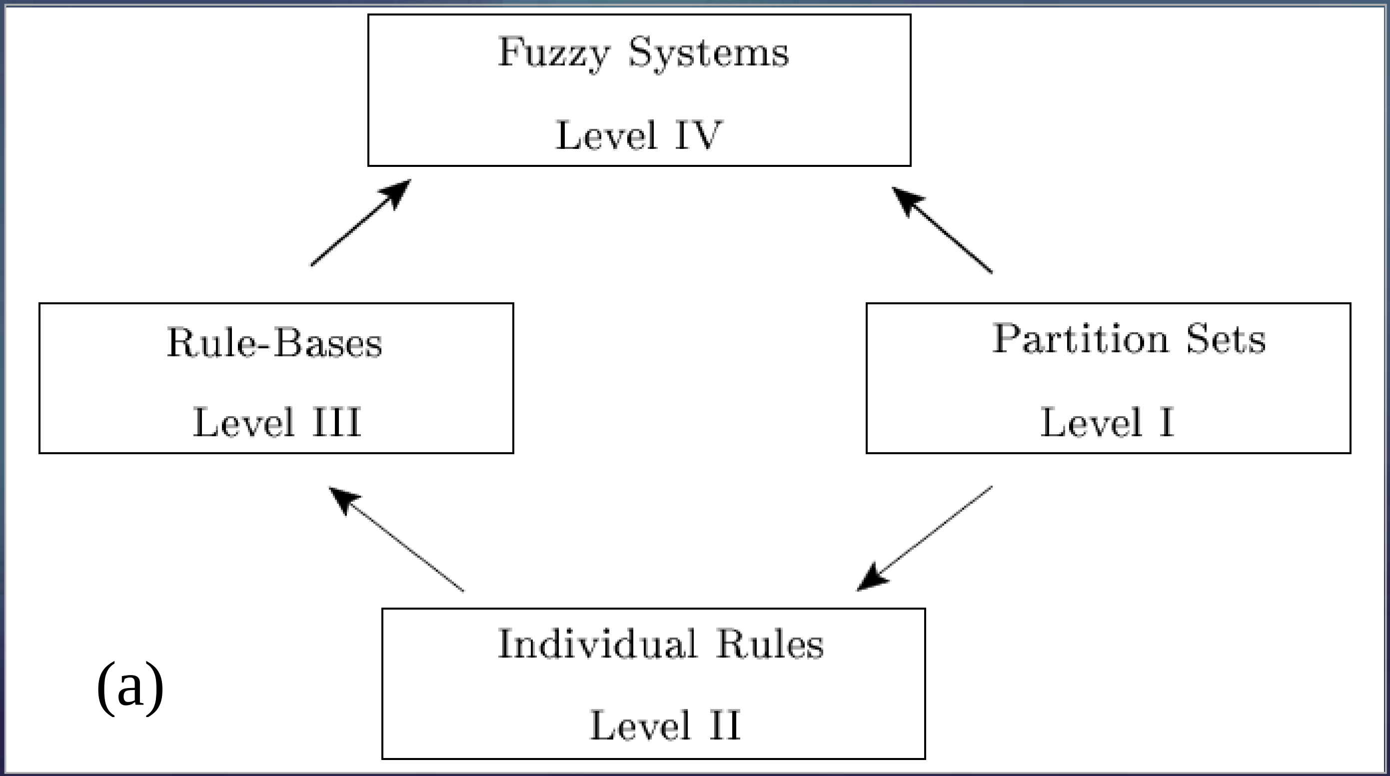
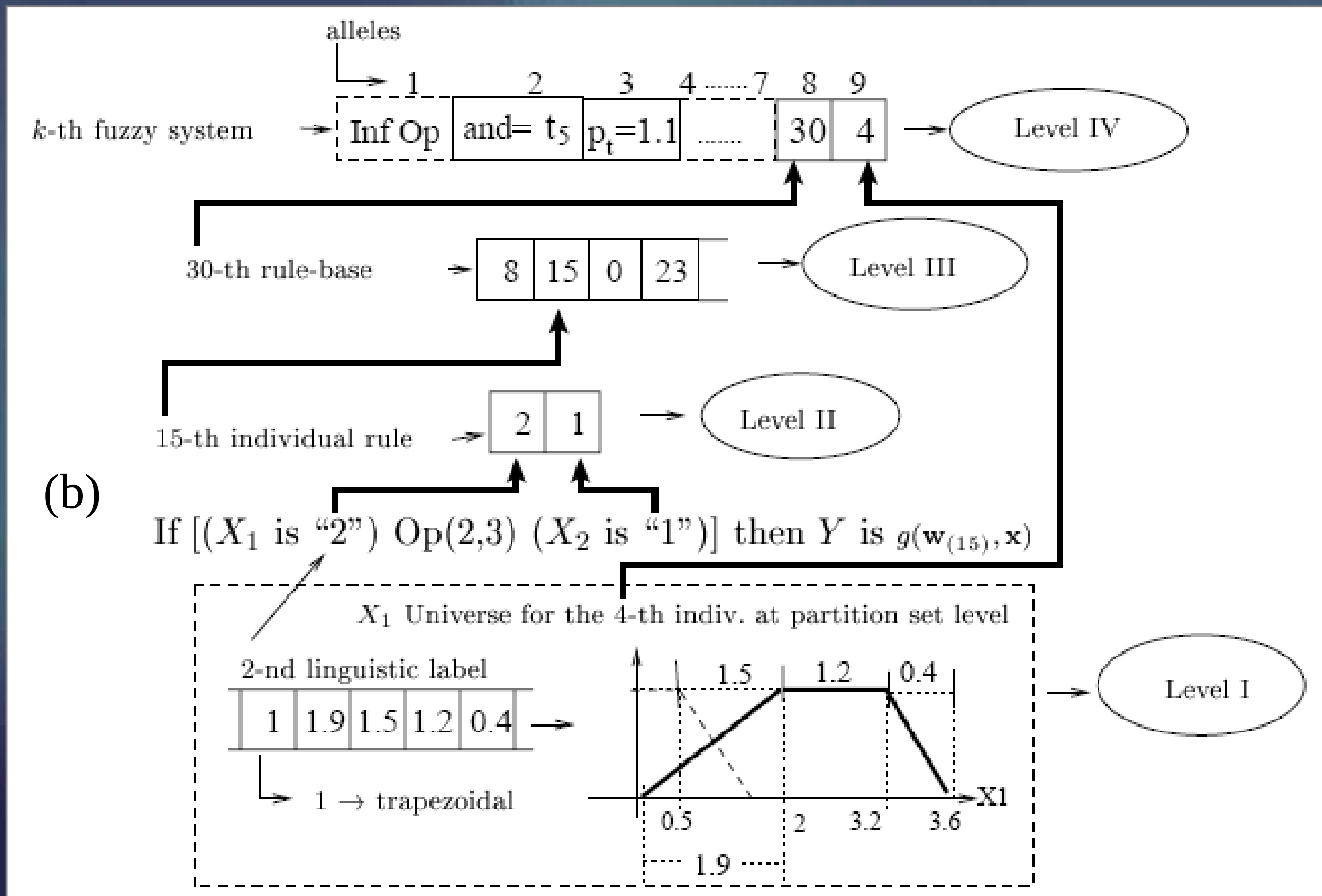
13.5 Hierarchical collaborative relations

Collaboration between species



Collaboration between individuals



R_j: **If** x_1 is A_1^j ***and*** ...***and*** x_n is A_n^j **then** y = g(w_j,**x**)

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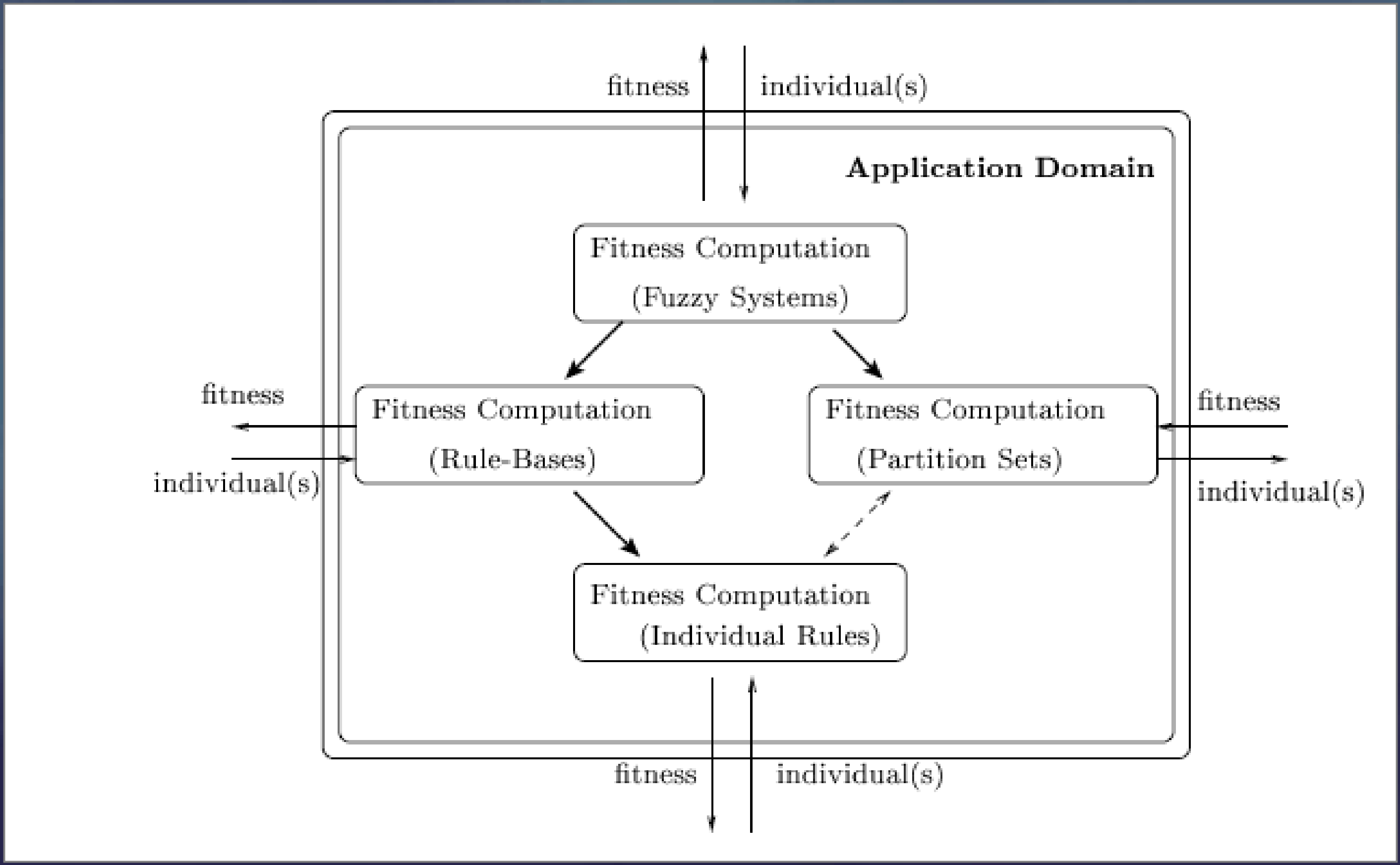
Fitness evaluation in hierarchical collaborative evolution



Example: function approximation

R_j: **If** x_1 is A_1^j ***and*** ...***and*** x_n is A_n^j **then** y = g(w_j,**x**)

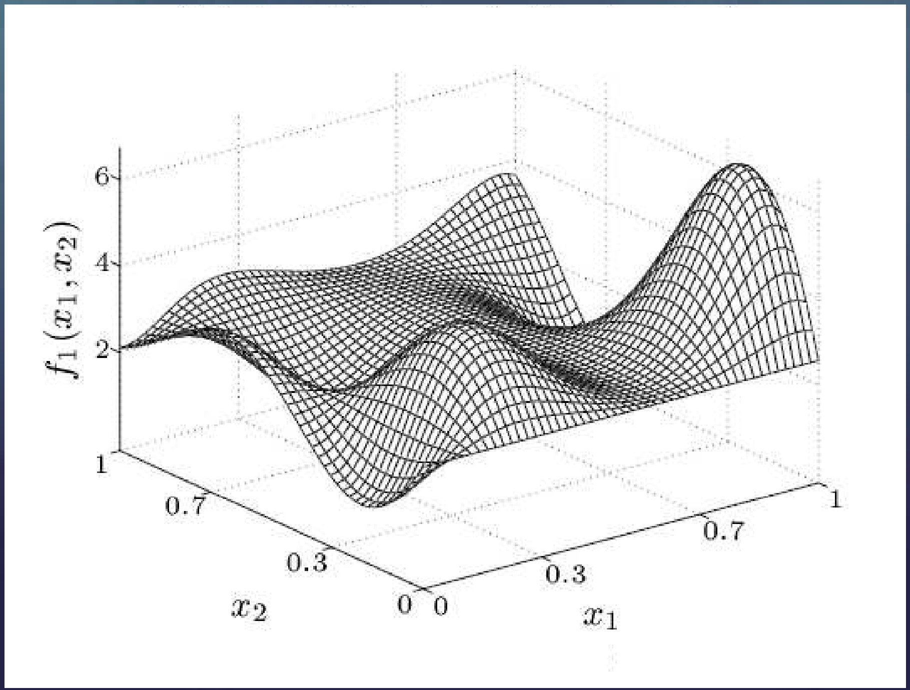
and = t-norm

$$a\,t\,b = \frac{ab}{p_t + (1 - p_t)(a + b - ab)}$$

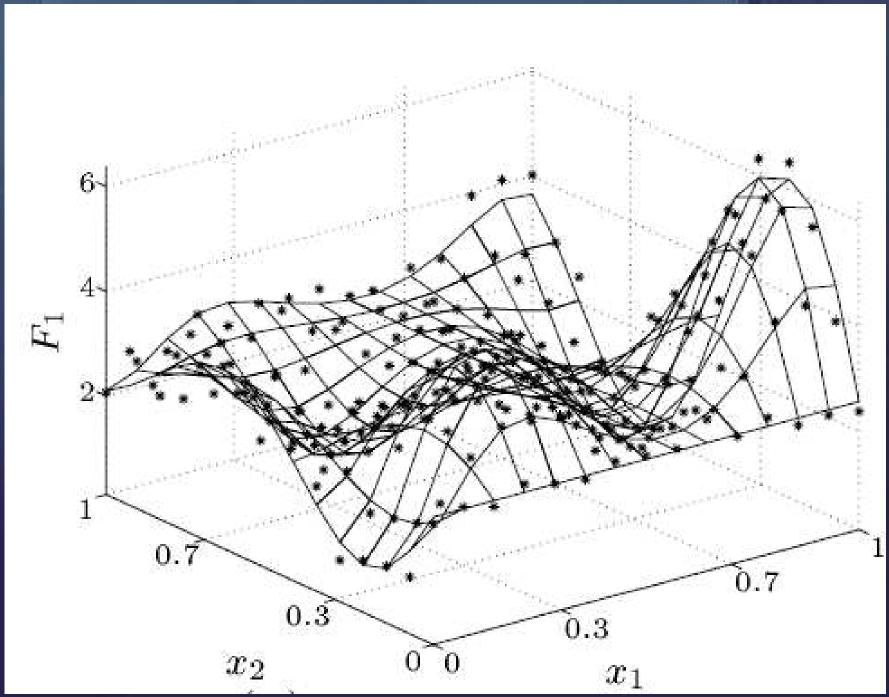
p_t : obtained by coevolution

g(w_j,**x**) : least squares + pruning

$$F_1 : \Omega \rightarrow R$$
$$F_1(x_1, x_2) = f_1(x_1, x_2) + N(m, \sigma)$$
$$f_1(x_1, x_2) = 1.9(1.35 + \exp(x_1) sin[13(x_1 - 0.6)^2 \exp(-x_2) sin(7x_2)])$$
$$\Omega = [0,1],\ m = 0,\ \sigma = 0.3$$



Original function



Training data

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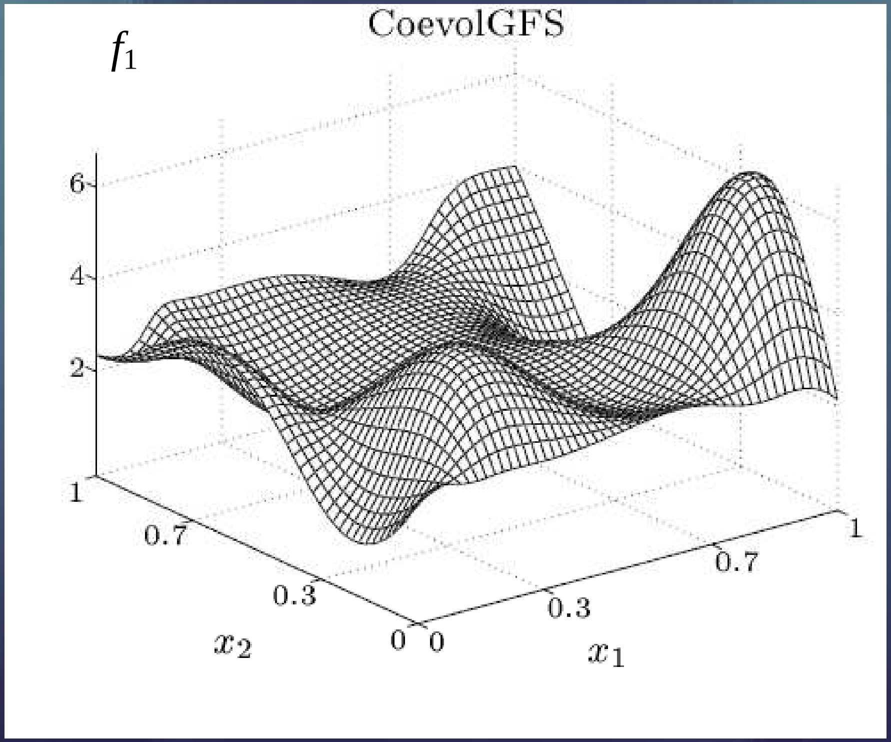
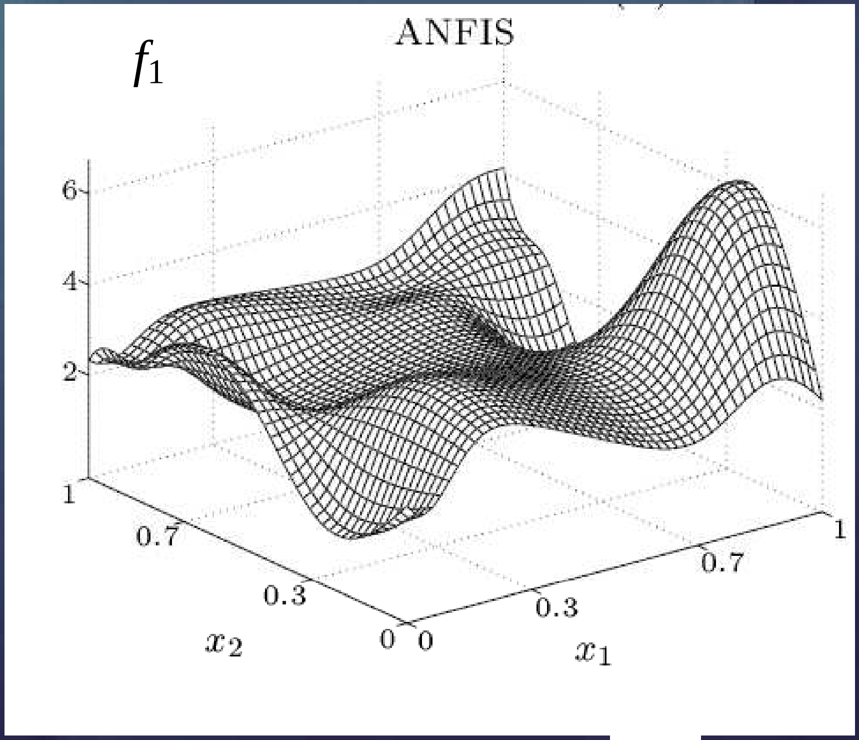
Result





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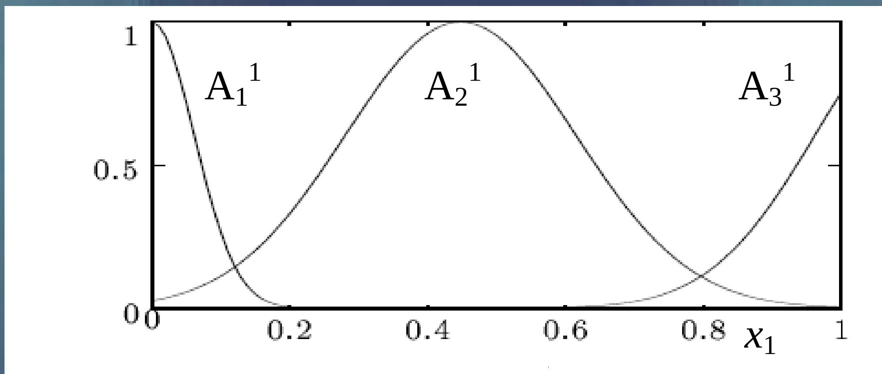
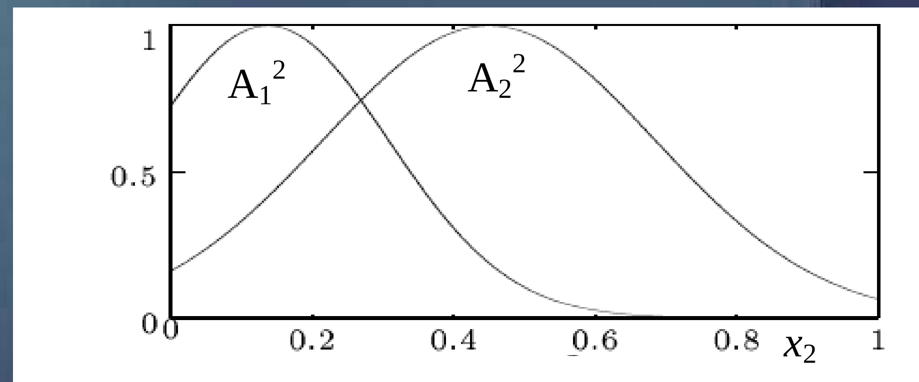
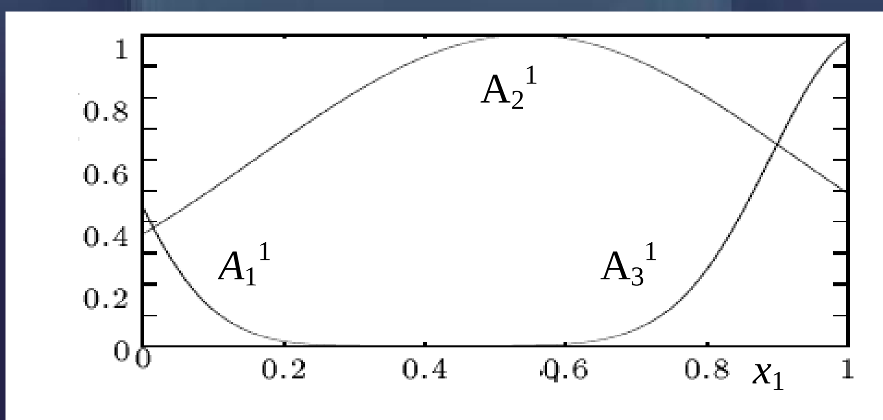
Partitions

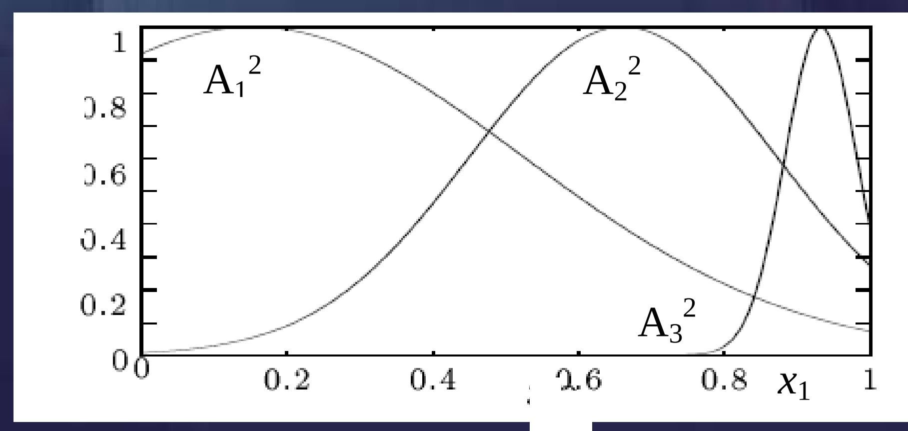
CoevolGFS





ANFIS





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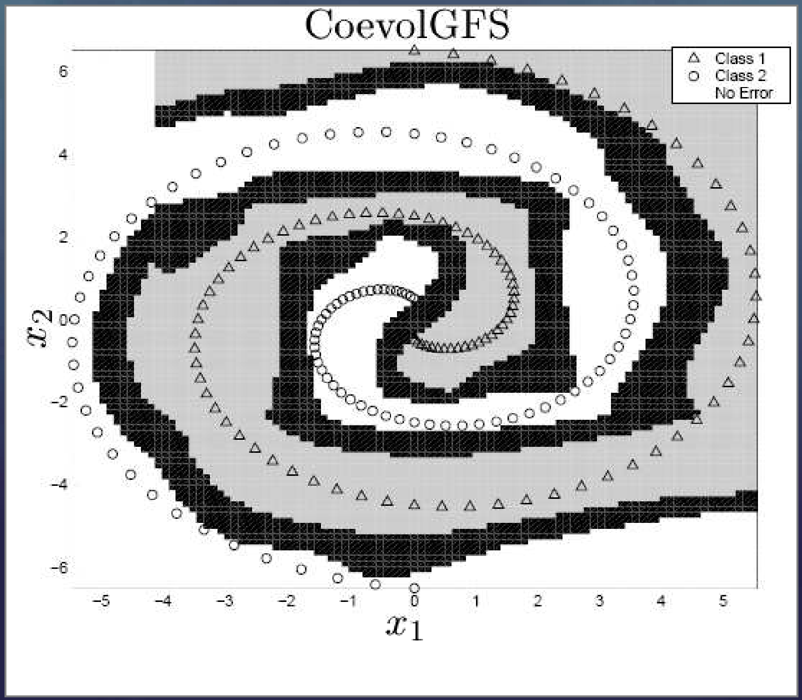
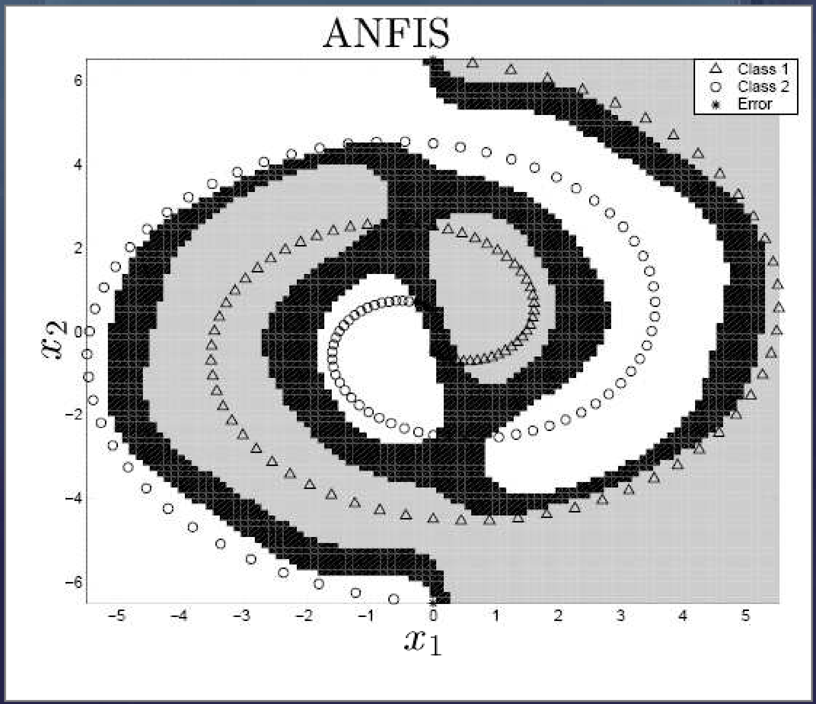
RME for function approximation example

Approach	Training RME	Test RME	Number of Rules
CoevolGFS	0.25	0.13	8
ANFIS	0.32	0.21	9

Example: classification

- Intertwined spirals





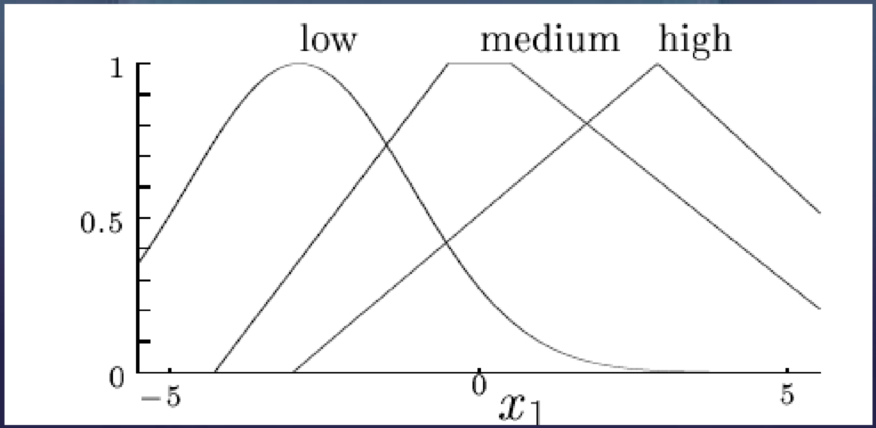
Classification rules

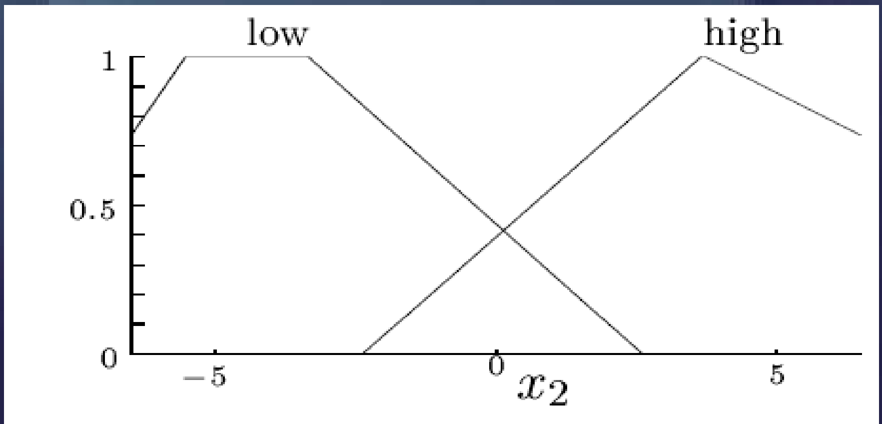
R_1 : If x_1 is low *and* x_2 is low then $y = -0.31 + 1.6x_1 - 0.26x_2 + 0.34x_1^2 + 0.17x_2^2 - 0.1x_1x_2$

R_2 : If x_1 is medium *and* x_2 is low then $y = 15.3 - 1.3x_1 + 7.7x_2 - 0.05x_1^2 + 0.84x_2^2 - 0.46x_1x_2$

R_3 : If x_1 is medium *and* x_2 *is* high then $y = -17.2 - 2.2x_1 + 7.6x_2 - 0.08x_1^2 - 0.78x_2^2 + 0.45x_1x_2$

R_2 : If x_1 is high *and* x_2 is high then $y = 1.14 + 2.0x_1 + 1.24x_2 - 0.25x_1^2 - 0.28x_2^2 - 0.34x_1x_2$





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Classification performance: Intertwined spirals

Approach	Cycles	Misclassification	Number of Rules
CoevolGFS	529	18	9
ANFIS	1000	0.21	9

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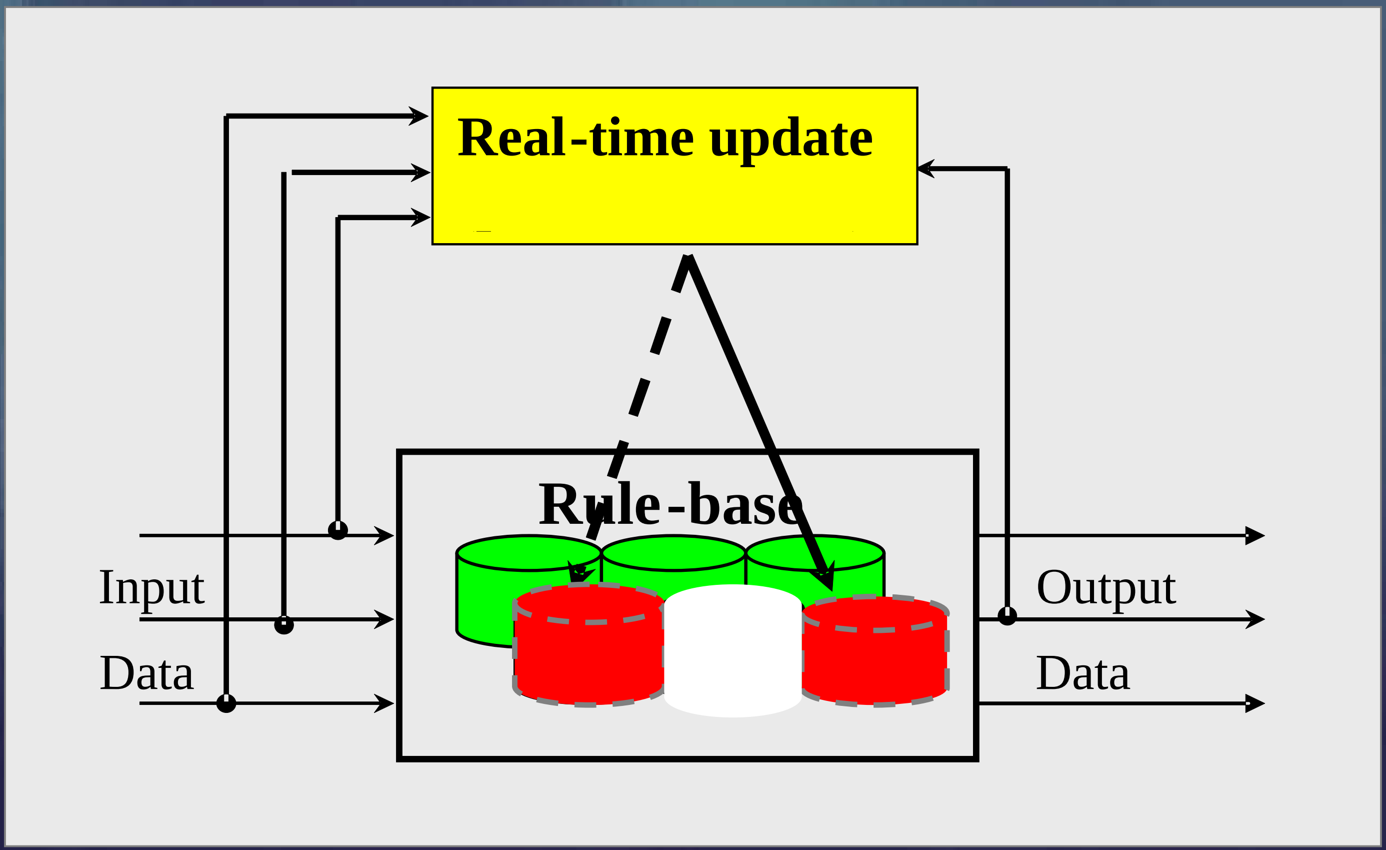
13.6 Evolving fuzzy systems

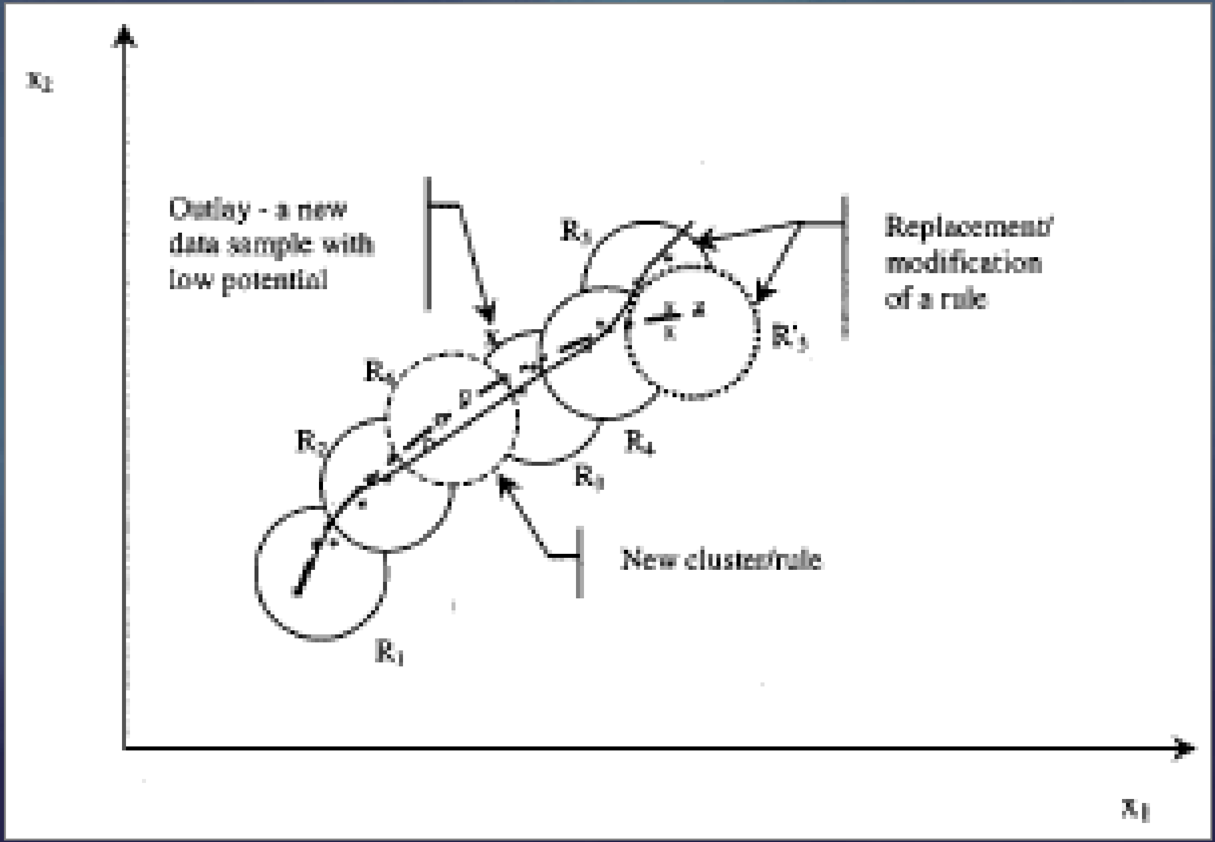
Evolving fuzzy systems

- Evolving systems: an approach to develop adaptive fuzzy models
- Evolving modeling targets nonstationary process and systems
- Main properties
  - inherit new knowledge
  - gradual changes
  - life-long learning
  - self organization of the system structure
  - complements GFS approach
  - may act online

Rule base evolution



Recursive clustering



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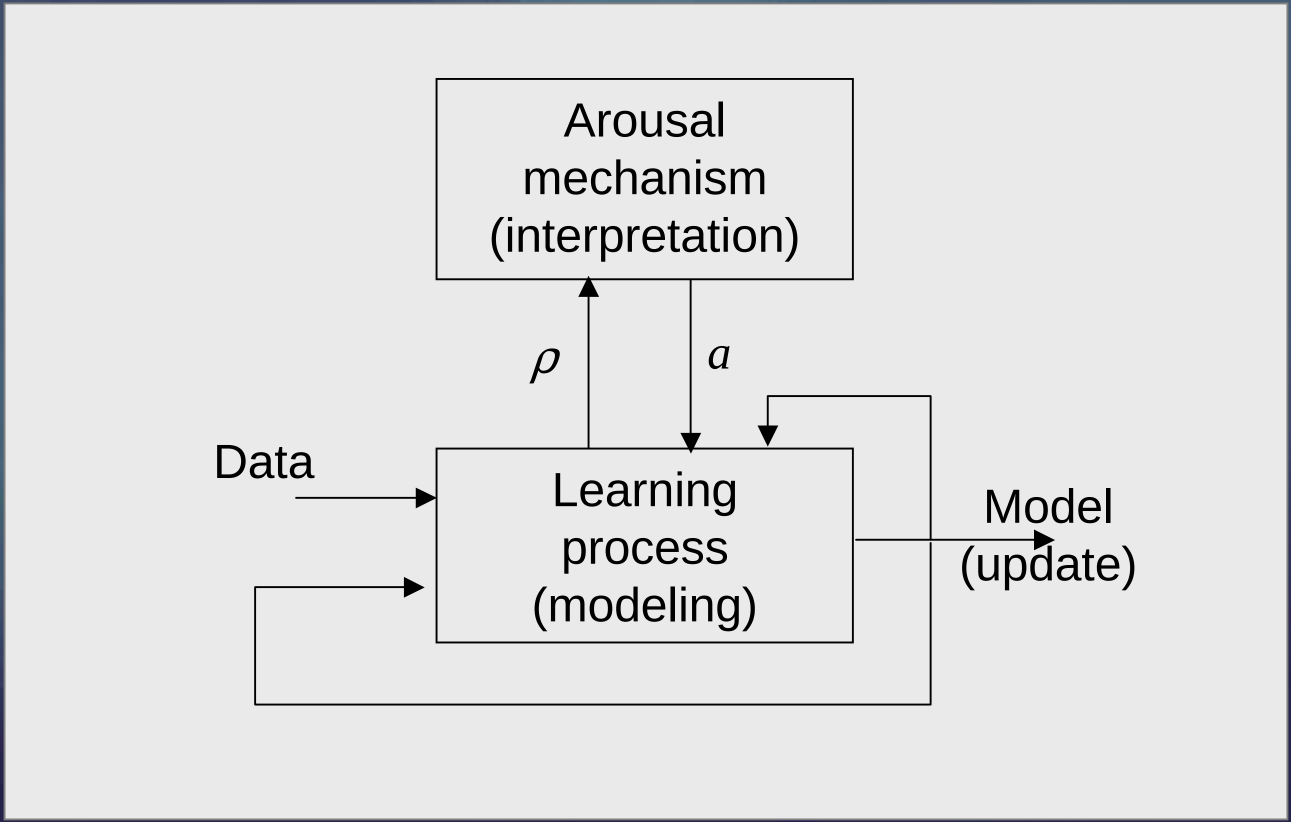
Participatory learning



(Details in Chapter 14)

Functional fuzzy models

$$R_i : if\ \mathbf{x}\ is\ \mathbf{A}_i\ then\ y_i = a_{i0} + \sum_{j=1}^{n} a_{ij} x_j$$

$$A_j^i(x_j) = \exp[-k_{ij}(x_j - v_{ij})^2]$$

$$y = \sum_{i=1}^{c} w_i y_i$$

$$w_i(x) = \frac{\lambda_i(x)}{\sum_{i=1}^{c} \lambda_i(x)}$$

$$\lambda_i = A_1^i(x_1)\ t\ A_2^i(x_2)\ t \cdots t\ A_n^i(x_n)$$

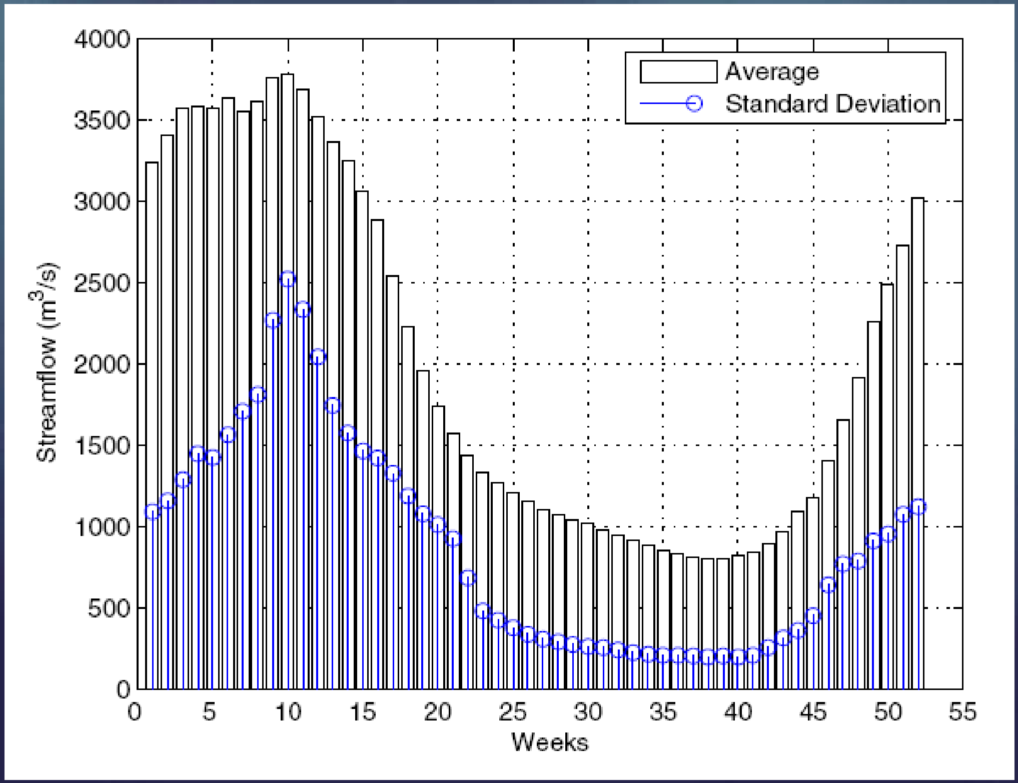
Evolving participatory learning algorithm

```
procedure EVOLVE-PARTICPATORY- LEARNING (x,y) returns an output
input : data x,y
local:    antecedent parameters
          consequent parameters

 INITIALIZE-RULES-PARAMETERS
       do forever
            read x
            PL-CLUSTERING
            UPDATE-RULE-BASE
            RUN-LEAST-SQUARES(x,y)
            COMUTE-RULE-ACTIVATION
            COMPUTE-OUTPUT
 return y
```

Example

Time series forecasting



Average weekly inflows of a power plant

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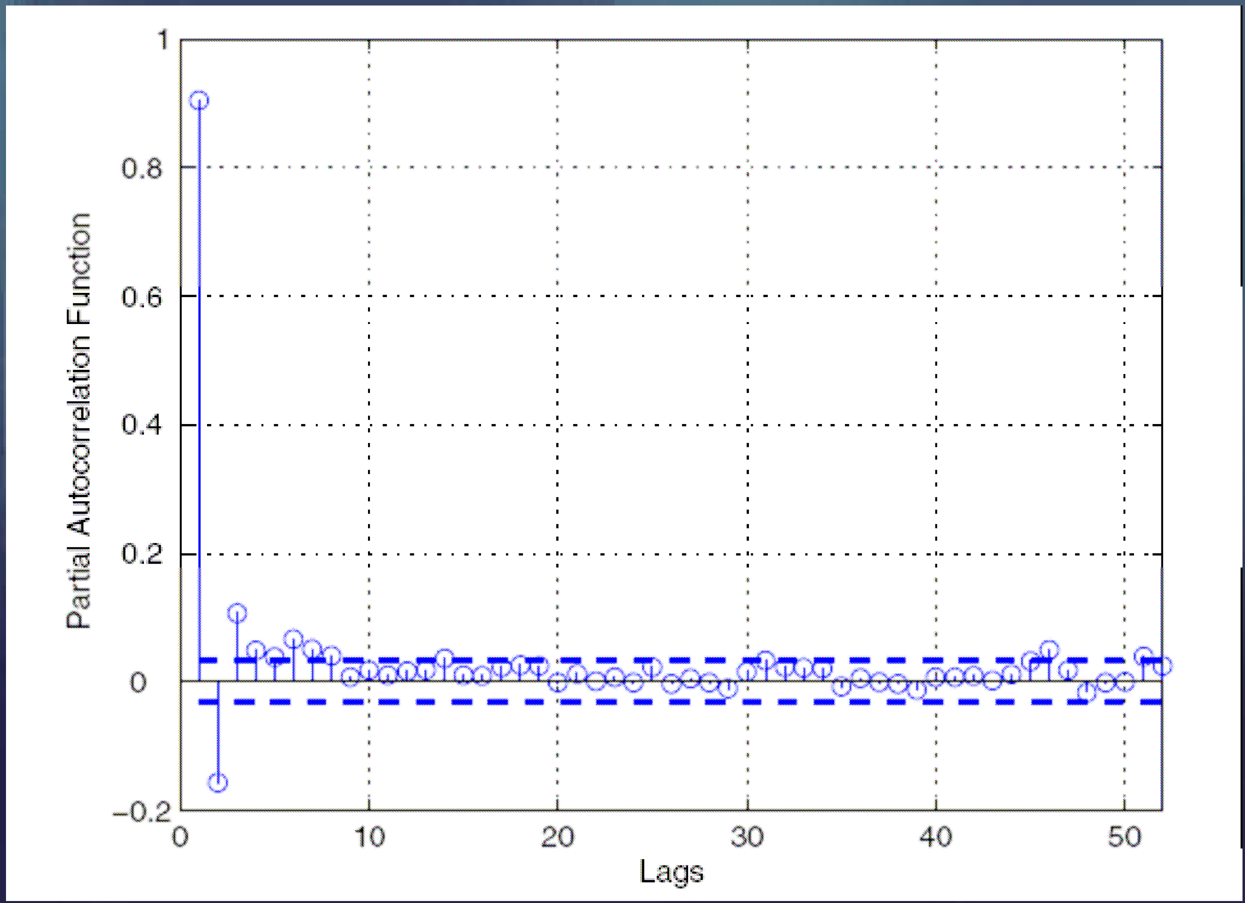
Estimated partial correlation



Performance measures

$$RMSE = \sqrt{\frac{1}{P}\sum_{k=1}^{P}(x^k - x_d^k)^2}$$

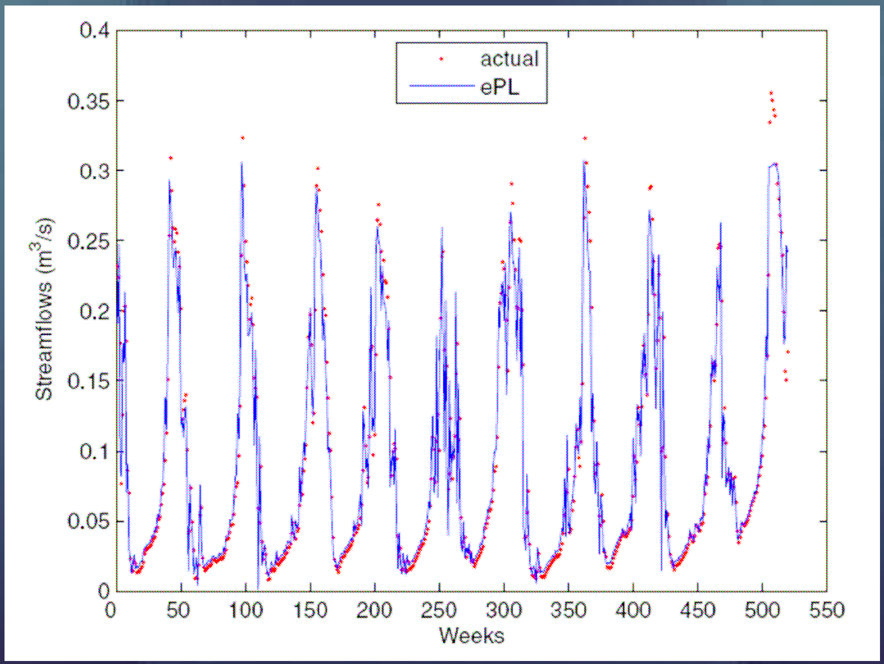
$$MRE = \frac{100}{P}\sum_{k=1}^{P}\frac{|x^k - x_d^k|}{x_d^k}$$

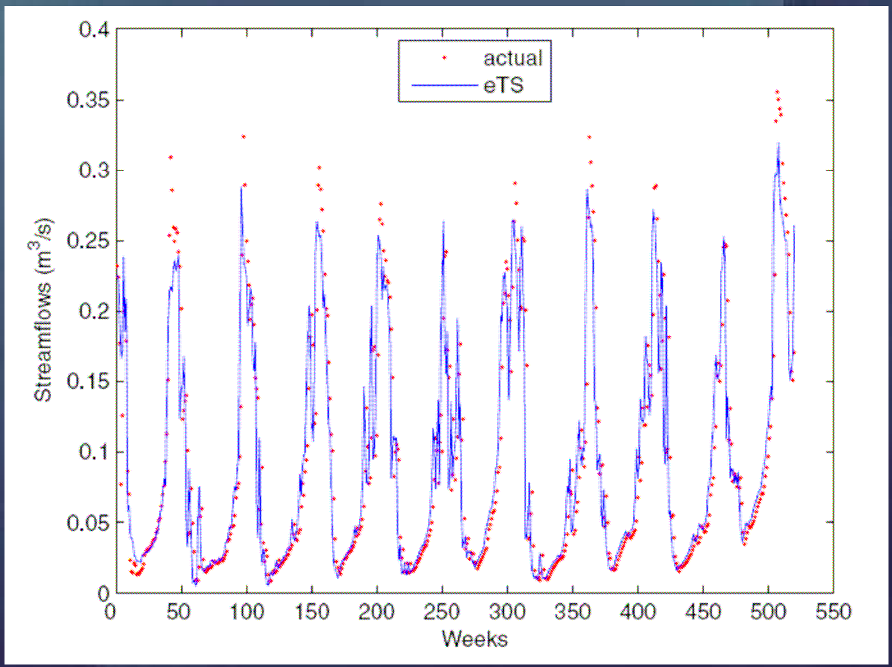
$$MAD = \frac{1}{P}\sum_{k=1}^{P}|x^k - x_d^k|$$

$$RE_{\max} = 100\max\left(\frac{|x^k - x_d^k}{x_d^k}\right)$$

$$\rho = \frac{\sum_{k=1}^{P}(x_d^k - \bar{x}_d)(x^k - \bar{x})}{\sqrt{\sum_{k=1}^{P}(x_d^k - \bar{x}_d)^2 \sum_{k=1}^{P}(x^k - \bar{x})^2}}$$

Result





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Forecasting performance average weekly inflow

Error	Models	
	ePL	eTS
RMSE (m^3/s)	378.71	545.28
MAD (%)	240.55	356.85
MRE (%)	12.54	18.42
RE_{max} (%)	75.51	111.22
ρ	0.95	0.89
Number of rules	2	2

Pedrycz and Gomide, FSE 2007