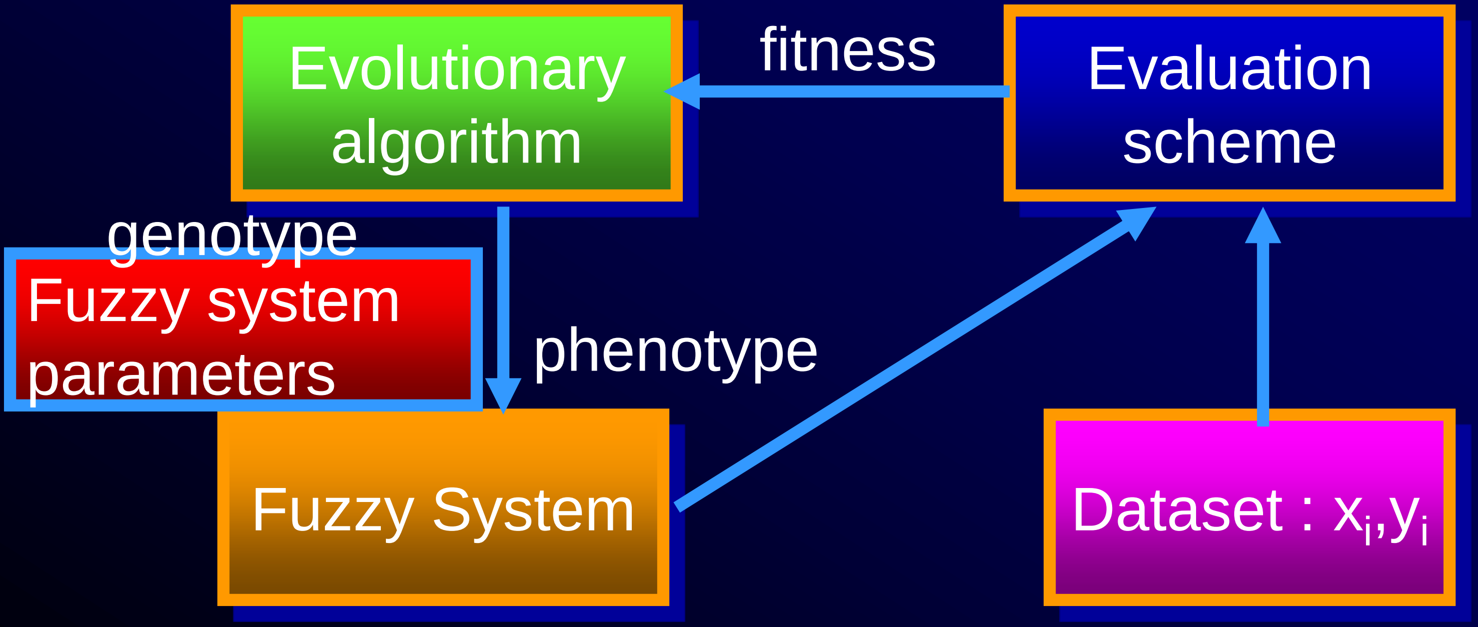
Genetic Fuzzy Systems (GFS's)

- genetic design of fuzzy systems
- automated tuning of the fuzzy knowledge base
- automated learning of the fuzzy knowledge base
- objective of tuning/learning process
    - optimizing the performance of the fuzzy system:

      e.g.: fuzzy modeling : minimizing quadratic error
      between data set and the fuzzy system outputs

      e.g : fuzzy control system: optimize the
      behavior of the plant + fuzzy controller

Genetic Fuzzy System for Data Modeling

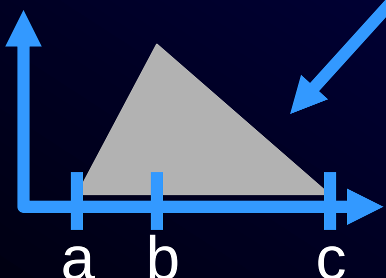


Fuzzy Systems

Knowledge Base

Database : Definition of fuzzy membership-function

Rule base: definition of fuzzy rules



If X_1 is A_1 and … and X_n is A_n then Y is B

Genetic Tuning Process

- ***tuning problems utilize an already existing rule base***
- ***tuning aims to find a set of optimal parameters for the database :***
    - ***points of membership-functions [a,b,c,d]***

      or
    - ***scaling factors for input and output variables***

Linear Scaling Functions

Chromosome for linear scaling:

- for each input x_i : two parameters a_i,b_i i=1..n
- for the output y : two parameter a_0,b_0

Genetic Algorithms:

- encode each parameter by k bit using Gray code
  total length = 2*(n+1)*k bit

a_0	b_0	a_1		$b_{2*(n+1)}$
100101	011111	110101	. . .	100101

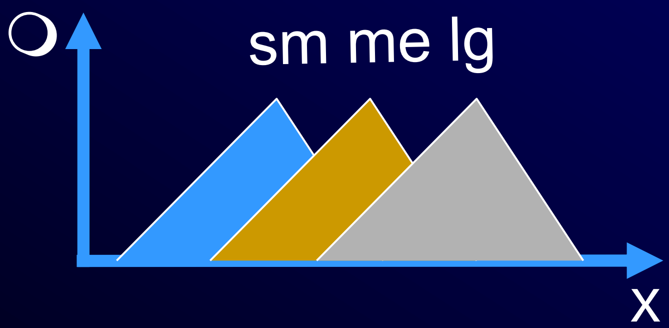
Evolutionary Strategies:

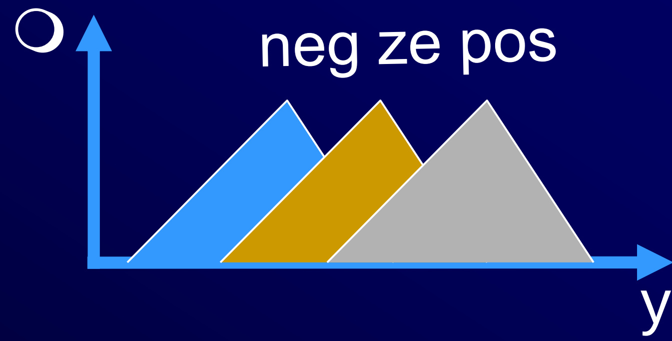
- each parameter a_i or b_i corresponds to one
  object variable x_m m : 1… 2*(n+1)

a_0	b_0	a_1		$b_{2*(n+1)}$
x_0,♦$_o$	x_1,♦$_1$	x_2,♦$_2$	. . .	x_m,♦$_m$

Descriptive Knowledge Base

- descriptive knowledge base



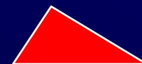


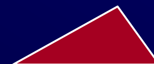
- all rules share the same global membership functions :

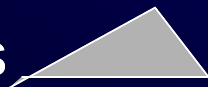
R1 : if X is sm then Y is neg
R2 : if X is me then Y is ze
R3 : if X is lg then Y is pos

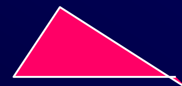
Approximate Knowledge Base

- each rule employs its own local membership function

R1 : if X is  then Y is 

R1 : if X is  then Y is 

R1 : if X is  then Y is 

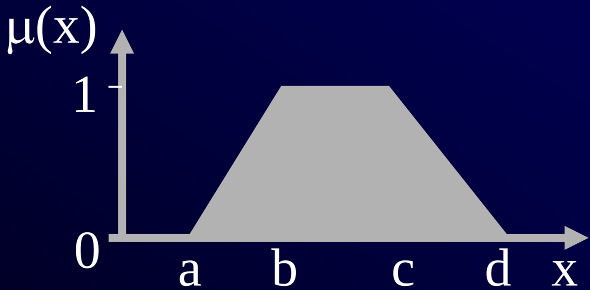
R1 : if X is  then Y is 

- tradeoff: more degrees of freedom and therefore better approximation but intuitive meaning of fuzzy sets gets lost

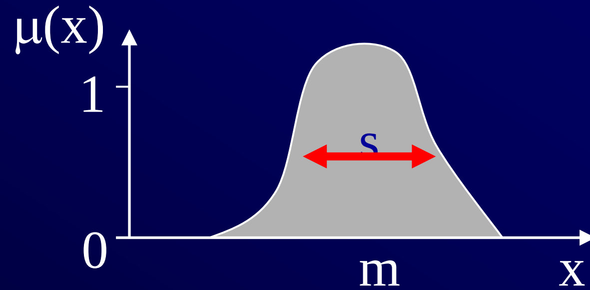
Tuning Membership Functions

- encode each fuzzy set by characteristic parameters

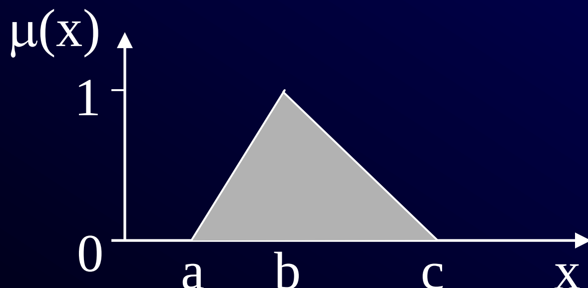
Trapezoid: <a,b,c,d>



Gaussian: N(m,s)



Triangular: <a,b,c>



x

Approximate Genetic Tuning Process

- a chromosome encodes the entire knowledge base, database and rulebase

R_i : if x_1 is A_{i1} and … x_n is A_{in} then y is B_i

encoded by the i-th segment C_i of the chromosome using triangular membership-functions (a,b,c)

C_i	=	$(a_{i1}, b_{i1}, c_{i1}, \ldots, a_{in}, b_{in}, c_{in}, a_i, b_i, c_i,)$

each parameter may be binary or real-coded

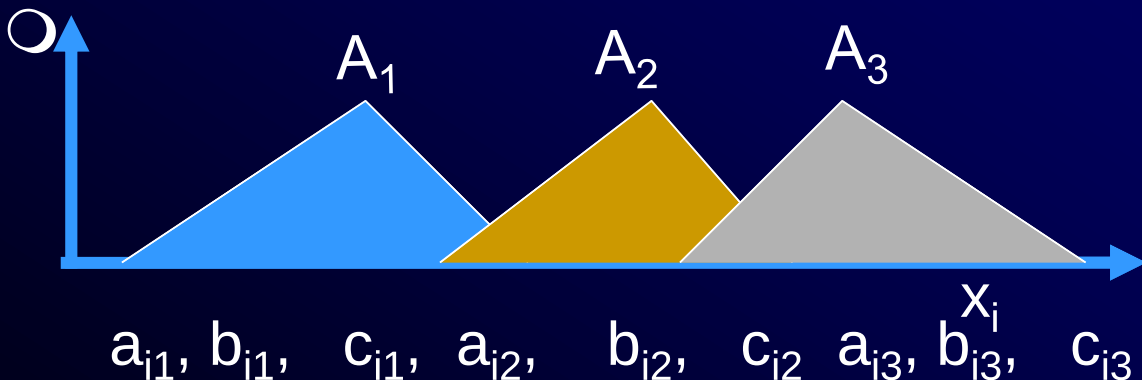
The chromosome is the concatenation of the individual segments corresponding to rules :

C_1	C_2	C_3	C_4	. . .	C_k

Descriptive Genetic Tuning Process

- the rule base already exists
- assume the i-th variable is composed of N_i terms

$$C_i = (a_{i1}, b_{i1}, c_{i1}, \ldots, a_{iN_i}, b_{iN_i}, c_{iN_i})$$

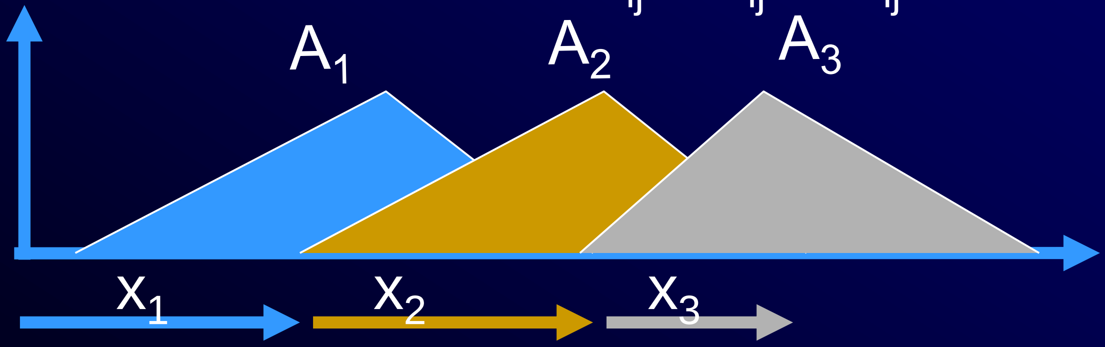


The chromosome is the concatenation of the individual segments corresponding to variables :

$C_1 \; C_2 \; C_3 \; C_4 \; \ldots \; C_k$

Descriptive Genetic Tuning

- in the previous coding scheme fuzzy sets might change their order and optimization is subject to the constraints : $a_{ij} < b_{ij} < c_{ij}$



- encode the distance among the center points of triangular fuzzy sets and choose the border points such that $\sum \Omega_i = 1$

Fitness Function for Tuning

- minimize quadratic error among training data (xi,yi) and fuzzy system output f(xi)

  $$E = \mathrm{Sum}_i \ (y_i - f(x_i))^2$$

  Fitness = 1 / E (maximize fitness)

- minimize maximal error among training data (xi,yi) and fuzzy system output f(xi)

  $$E = \max_i \ (y_i - f(x_i))^2$$

  Fitness = 1 / E (maximize fitness)

Genetic Learning Systems

- genetic learning aim to :
  - learn the fuzzy rule base

    or
  - learn the entire knowledge base

- three different approaches
  - Michigan approach : each chromosome represents a single rule
  - Pittsburgh approach : each chromosome represents an entire rule base / knowledge base
  - Iterative rule learning : each chromosome represents a single rule, but rules are injected one after the other into the knowledge base

Thanks for your attention!

That’s all.