

BISC

The Berkeley Initiative in Soft Computing

Electrical Engineering and Computer Sciences Department



Neuro-Fuzzy-Evolutionary Computing (NeF-ECom)

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Outline

- BISC Decision Support System
- Neuro-Fuzzy-Evolutionary Computing: NeF-ECom
 - Multi-Criteria Decision Analysis with Uncertain and Incomplete Information
- Application Areas
 - ASIS







OBJECTIVES

Develop soft-computing-based techniques for decision analysis

- Tools to assist decision-makers in assessing the consequences of decision made in an environment of imprecision, uncertainty, and partial truth and providing a systematic risk analysis;
- Tools to assist decision-makers answer "What if Questions", examine numerous alternatives very quickly and find the value of the inputs to achieve a desired level of output;
- Tools to be used with human interaction and feedback to achieve a capability to learn and adapt through time;



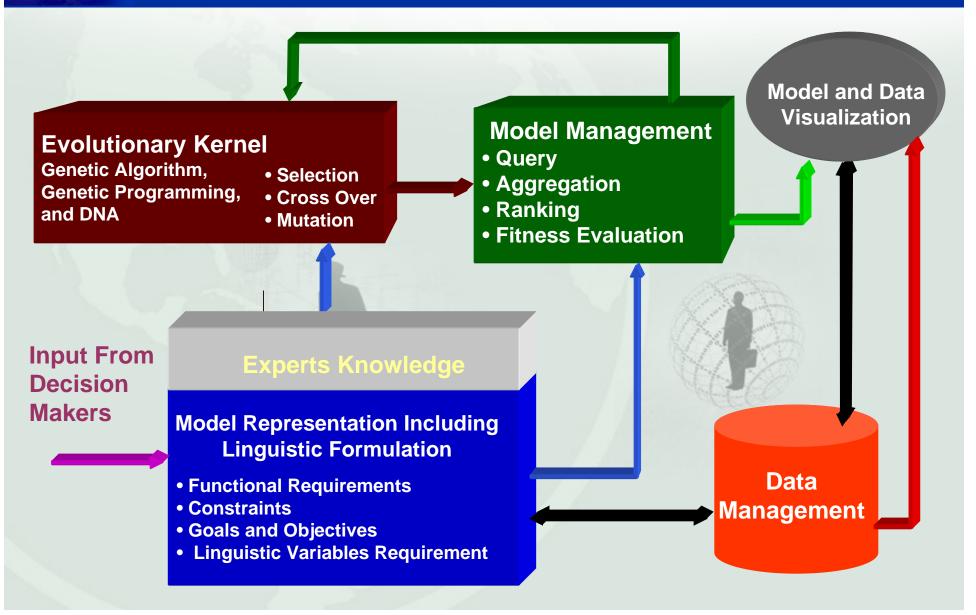
DECISION ENVIRONMENT

- Information (Can be uncertain)
- Granular (Scale and Precision)
- Query (Can be imprecise)
- Measure (Similarity)
- Aggregation (Can be fuzzy)
- Ranking (Provide Alternatives)
- Optimization (Multi-Objective & Multi-Criteria)





BISC DSS: Components and Structure



Query (Request): Q

$$Q = f(v_1\{(\mu_1, \mu_2, ...), w_1\}, v_2\{(\mu_1, \mu_2, ...), w_2\},...)$$

 v_i : Variables

 μ_i : Degree in which ν_i belong to a certain grade

 W_i : Preferences

- find if such query exists → degree of match → rank
- → decision (i.e. resource allocation)
- compare queries → rank → decision (task allocation)
- Use Fuzzy Min-Max with degree of preferences

Objective function: Cost Function/ Fitness Function

$$J = \sum_{k} \left[\frac{\sum_{i=1}^{n} \left(f(v_{i}\{(\mu_{1}, \mu_{2}, ...), w_{i}\}) \right) \hat{f}(v_{i}\{(\mu_{1}, \mu_{2}, ...), w_{i}\})}{\sum_{i=1}^{n} \left(f(v_{i}\{(\mu_{1}, \mu_{2}, ...), w_{i}\}) \hat{f}(v_{i}\{(\mu_{1}, \mu_{2}, ...), w_{i}\}) \right)} \right]_{k}$$

This may involve multi-objective, multi-criteria optimization with conflict and fuzzy variables. *Therefore, use fuzzy-GA to solve the objective function*.



BISC-DSS Software

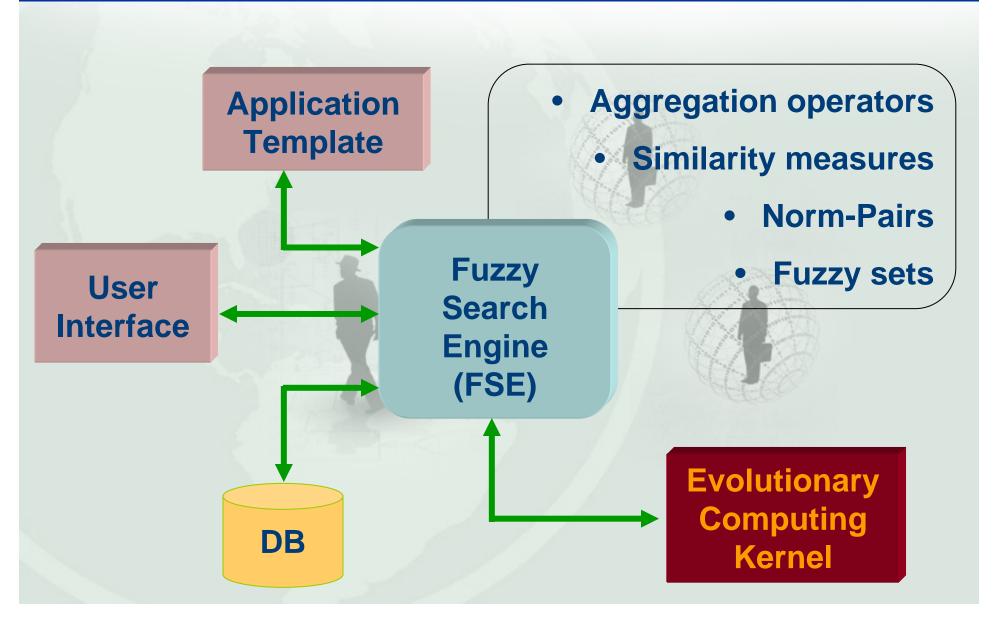
Neuro-Fuzzy-Evolutionary Computing

Multi-Criteria Decision Analysis with Uncertain and Incomplete Information



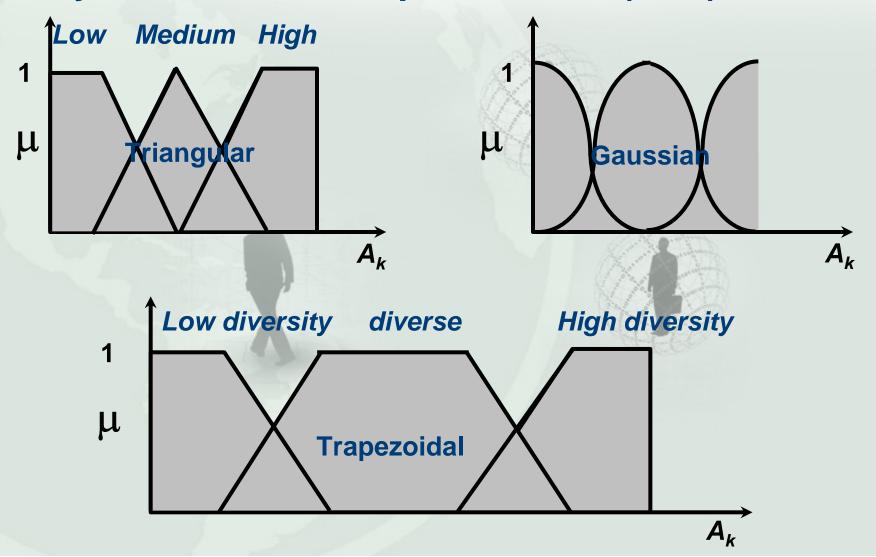


BISC – DSS Software: Architecture



Basic concepts

Fuzzy sets/ Membership Functions (MFs)



Basic concepts

Fuzzy similarity measures

Simple matching: |X I Y|

Dice:
$$2\frac{|X I Y|}{|X|+|Y|}$$

Jaccard : $\frac{|X I Y|}{|X Y Y|}$

Cosine: $\frac{|X I Y|}{|X|^{1/2} \times |Y|^{1/2}}$

Overlap: $\frac{|X I Y|}{\min(|X|,|Y|)}$

X and Y are fuzzy measures defined over the same fuzzy sets with MFs:

$$\mu_1, \mu_2, \ldots, \mu_m$$

Norm-Pair operators ∩ et ∪ (norm-conorm)

Basic concepts

Norm-Pairs

	Fuzzy AND [∩]	Fuzzy OR [∪]
MinMax	$\min(x, y)$	$\max(x, y)$
Algebraic	$x \times y$	$x + y - x \times y$
Bounded	$\max(0, x + y - 1)$	$\min(1, x + y)$
Drastic	$\int \min(x, y) if \max(x, y) = 1$	$ \begin{cases} \max(x, y) & \text{if } \min(x, y) = 1 \\ 1 & \text{else} \end{cases} $
Einstein	$(x \times y)/(2 - (x + y - x \times y))$	$(x+y)/(1+(x\times y))$ $(x+y-2\times x\times y)/(1-(x\times y))$
Hamacher	$(x \times y) / (x \times y)$	$(x+y-2\times x\times y)/$
	$(x \times y) / (x + y - x \times y)$	$/(1-(x\times y))$

x and y are MF values in [0,1].

Basic concepts

Aggregation Operators

Arithmetic Mean:
$$\frac{1}{n} \sum_{i=1}^{n} x_i$$

Geometric Mean:
$$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$$

Harmonic Mean :
$$\frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}}$$

Minimum:
$$\min(x_1, x_2, \Lambda, x_n)$$

Maximum:
$$\max(x_1, x_2, \Lambda, x_n)$$

Basic concepts

Weighted Aggregation Operators

Weighted Mean:
$$\sum_{i=1}^{n} w_i \times x_i$$

Weighted Geometric Mean:
$$\prod_{i=1}^{n} x_i^{w_i}$$
 with: $\sum_{i=1}^{n} w_i = 1$

Weighted Harmonic Mean:
$$\frac{1}{\sum_{i=1}^{n} w_i \times \frac{1}{x_i}}$$

Weighted Minimum:
$$\min_{i=1}^{n} (\max(1-w_i, x_i))$$

Weighted Maximum: $\max_{i=1}^{n} (\min(w_i, x_i))$

$$\begin{cases} \text{with: } \max_{i=1}^{n} (w_i) = 1 \\ \text{with: } \max_{i=1}^{n} (w_i) = 1 \end{cases}$$

Weighted Maximum:
$$\max_{i=1}^{n} (\min(w_i, x_i))$$

with:
$$\sum_{i=1}^{n} w_i = 1$$

$$with: \max_{i=1}^{n} (w_i) = 1$$

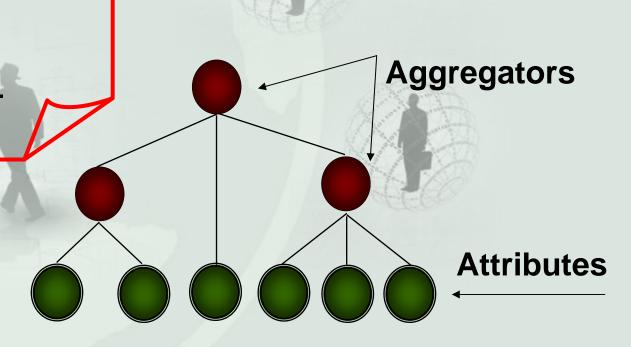


Basic concepts

Advanced Multi-Aggregator Model

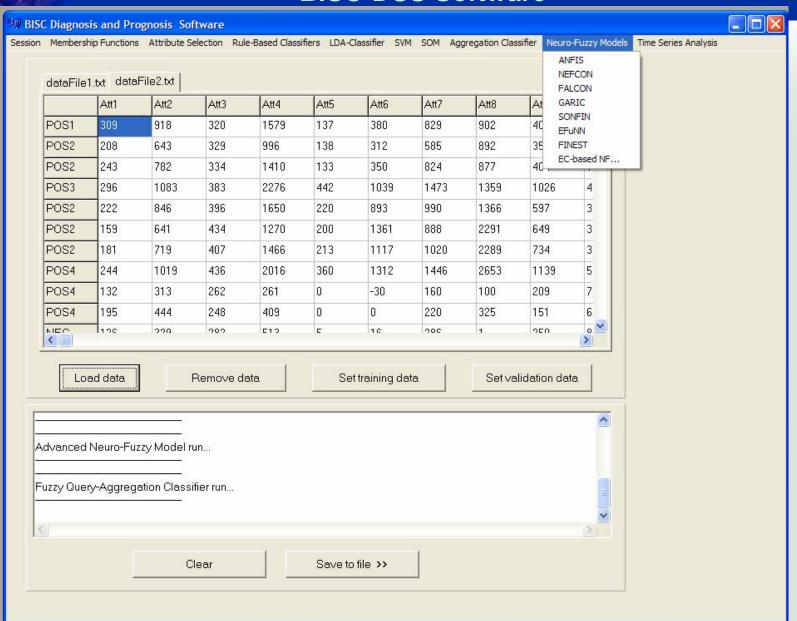
Parameters

- aggregators
- weights
- tree structure.

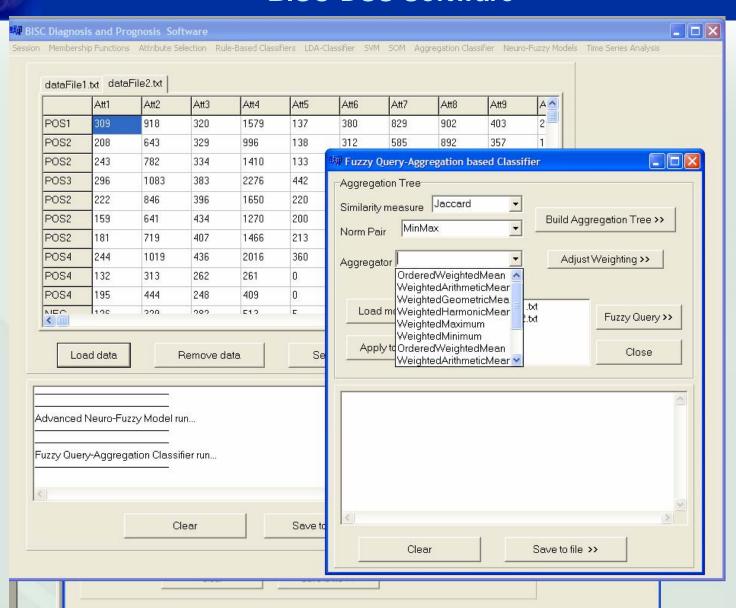


Aggregation tree

BISC-DSS Software



BISC-DSS Software





EC: Genetic Algorithms

Requirements

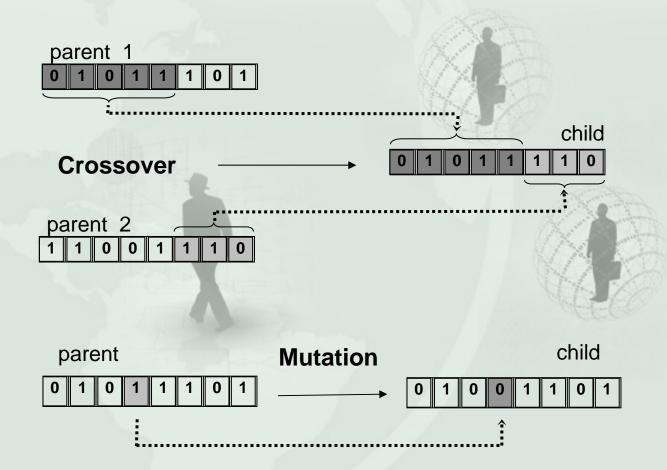
- Individual :problem representation
- Fitness function: for evaluation
- Termination criterion

Principle:

- Create randomly an initial population of individuals
- Evolve the population:
 - evaluate and select individuals
 - use them in genetic operators (crossover, mutation)
 - generate new generation
- Stop if termination criterion satisfied

EC: Genetic Algorithms

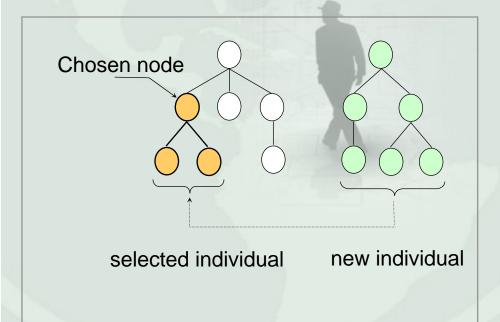
Genetic Operators





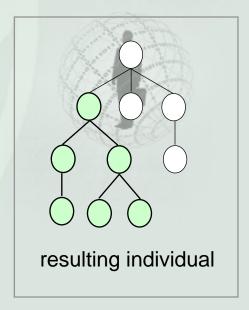
EC: Genetic Programming

- Individual = Computer program
- Most common representation : tree encoding (nodes = functions, leaves = terminals)
- Fitness function = returned value by the root node

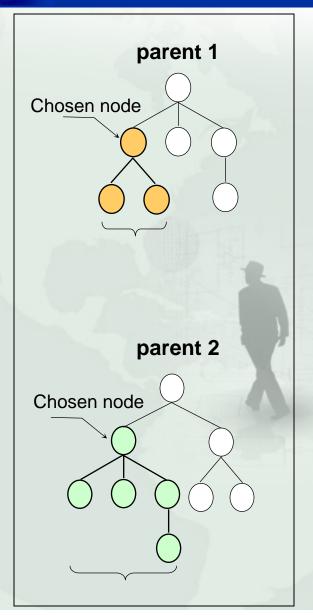


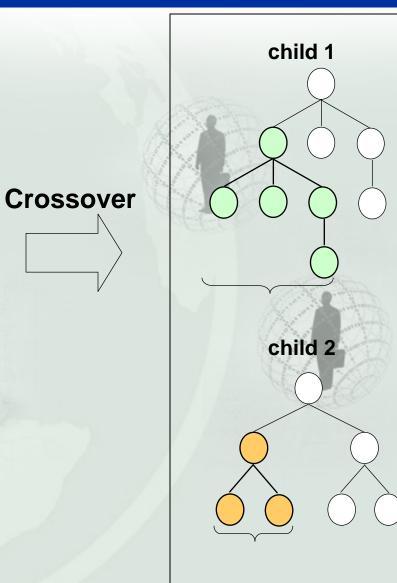
Mutation





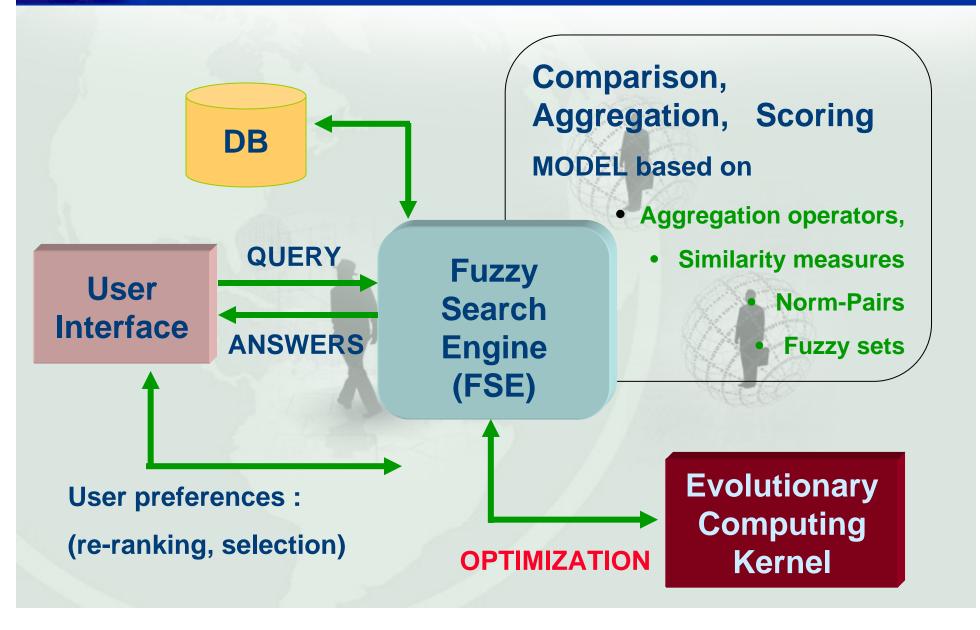
EC: Genetic Programming







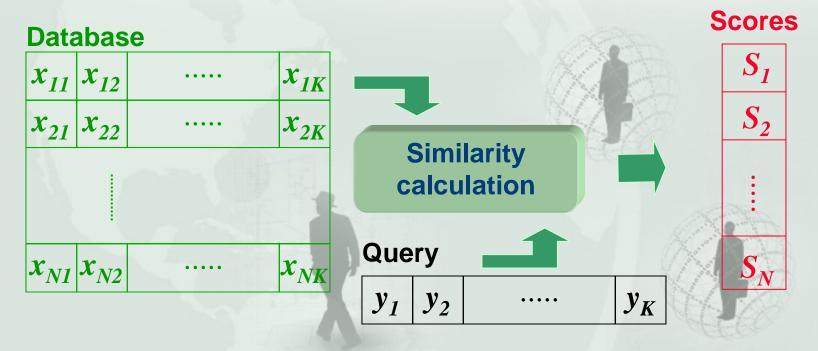
BISC-DSS: Interaction and Optimization





Multi-Criteria Decision Model (1)

Multi-Attribute Query: K attributes $A_1, A_2, ..., A_K$



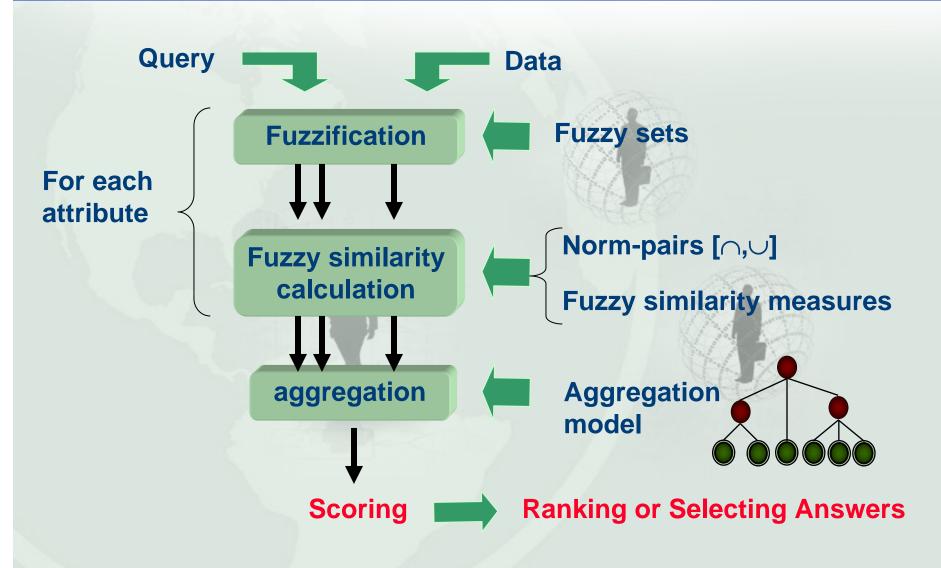
Query Answering

Ranking based (criteria: number top answers)

Selection based (criteria: threshold)



Multi-Criteria Decision Model (2)



Multi-Criteria Decision Model (3)

Data:
$$X_i = (x_{i1}, x_{i2}, ..., x_{iK}),$$
 Query: $Q = (y_1, y_2, ..., y_k)$

K attributes: $A_1, A_2, ..., A_K$

For each attribute A_j :

$$r_j$$
 fuzzy sets $\mu_1(Aj,.), \mu_2(A_j,.),...,\mu_{rj}(A_j,.)$
$$s_i = similarity(x_{ij}, y_i), \qquad j = 1, 2, ..., K$$

Score =
$$SIM(Q,X_i)$$
 = $Aggregation(s_1, s_2, ..., s_k)$

First Order Aggregation Model (1)

- Norm-pair: <u>Min/Max</u>
- Fuzzy similarity measure: <u>Jaccard</u>
- Aggregation operator: <u>Weighted Mean</u>

$$SIM(Q, X_i) = \sum_{j=1}^{M} w_j \times Jaccard(y_j, x_{ij}), \text{ with } \sum_{j=1}^{M} w_j = 1$$

$$Jaccard(y_{j}, x_{ij}) = \frac{|y_{j} \cap x_{ij}|}{|y_{j} \cup x_{ij}|}$$

$$y_{j} \cap x_{ij} = \left[Min(\mu_{k}(A_{j}, y_{j}), \mu_{k}(A_{j}, x_{ij}))\right]_{k=1,\dots,r_{j}}$$
$$y_{j} \cup x_{ij} = \left[Max(\mu_{k}(A_{j}, y_{j}), \mu_{k}(A_{j}, x_{ij}))\right]_{k=1,\dots,r_{j}}$$



First Order Aggregation Model (2)

Aggregation model = simple weighted aggregation operator

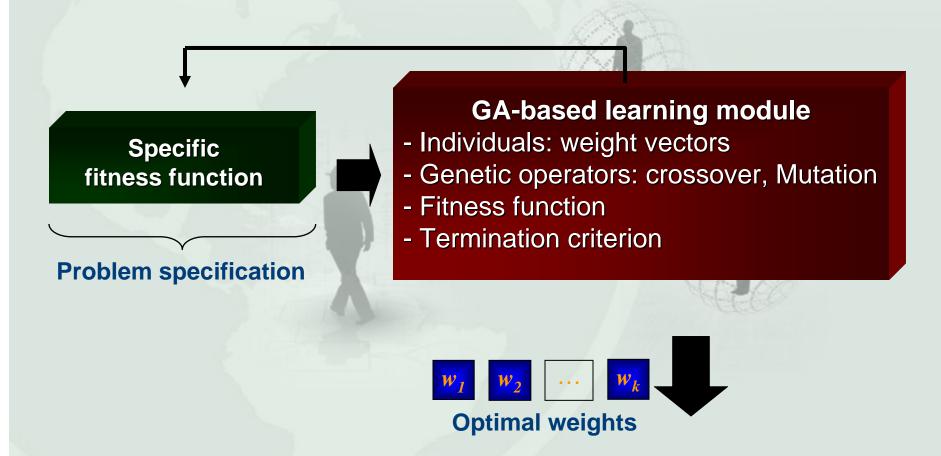
user preferences = attribute weighting
(Degree of importance of each attribute)

Aggregation model parameters = weighting vector

Optimization process: find the optimal weights Using GA.

First Order Aggregation Model (3)

Model parameters learning using GA





Advanced Multi-Aggregator Model (1)

parameters

- > similarity measures
 - >norm-pairs
- > aggregation operators
 - > weights
- > aggregation model structure

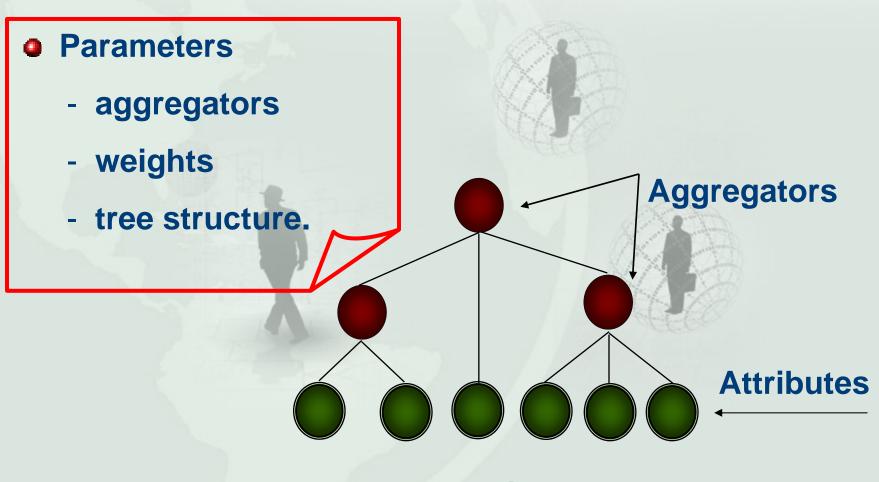


Representation of user/expert preferences



Advanced Multi-Aggregator Model (2)

Model description

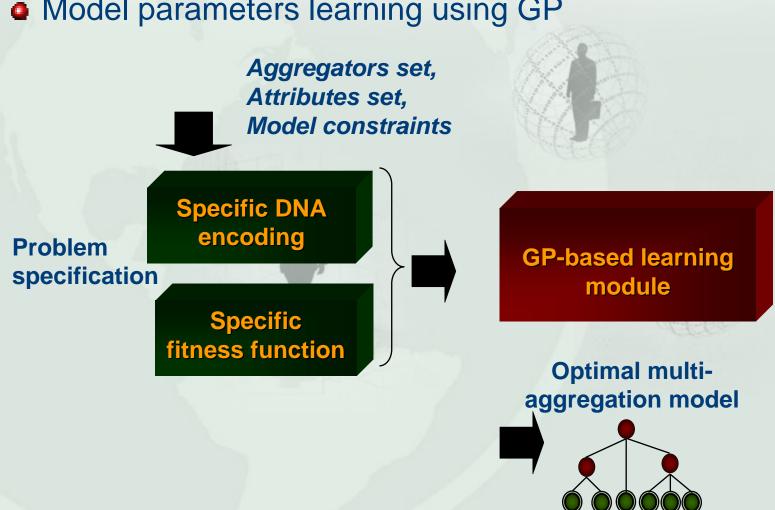


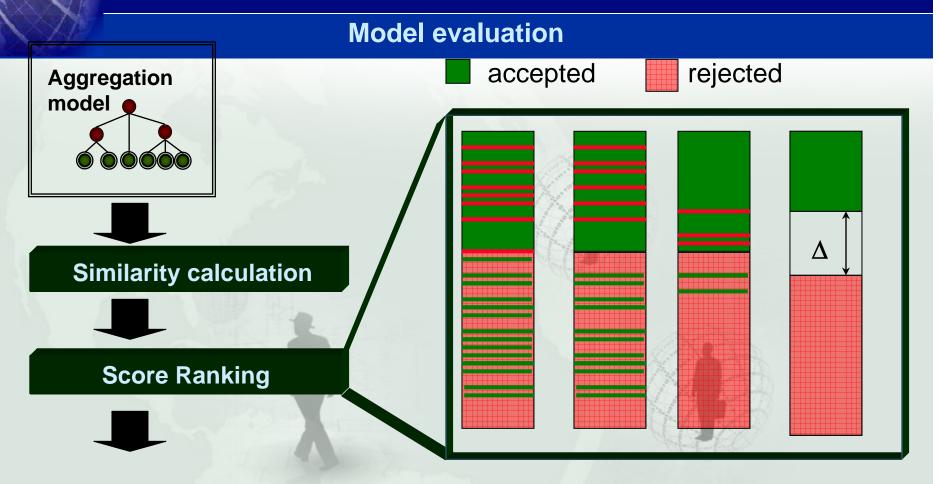
Aggregation tree



Advanced Multi-Aggregator Model (3)

Model parameters learning using GP





Fitness function combining:

- accuracy rates to <u>maximize</u>
- distance ∆ to maximize
- model structure size to minimize



Other Applications

Application

Description

Finance

 stock prices and characteristics, credit scoring, credit card ranking

Military

battlefield simulation and decision making

Medicine

diagnosis

Marketing

store and product display

electronic shopping

Internet

 provide knowledge and advice to large numbers of user

Education

university admission

Banking

fraud detection



BISC-DSS-ASIS Software

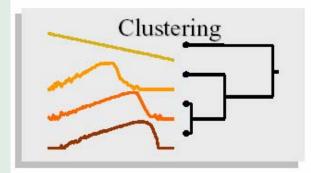
Automated Sensory Inspection System

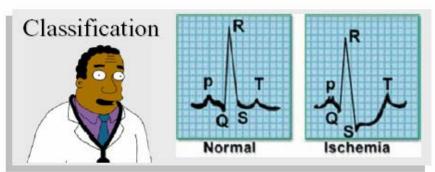


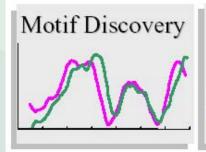


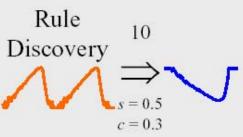
Applications

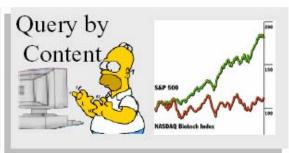
What can We Do with Time-Series?

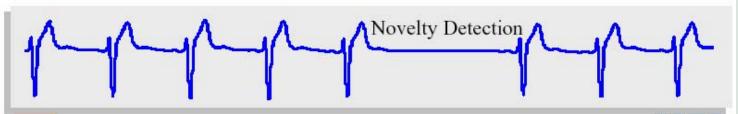




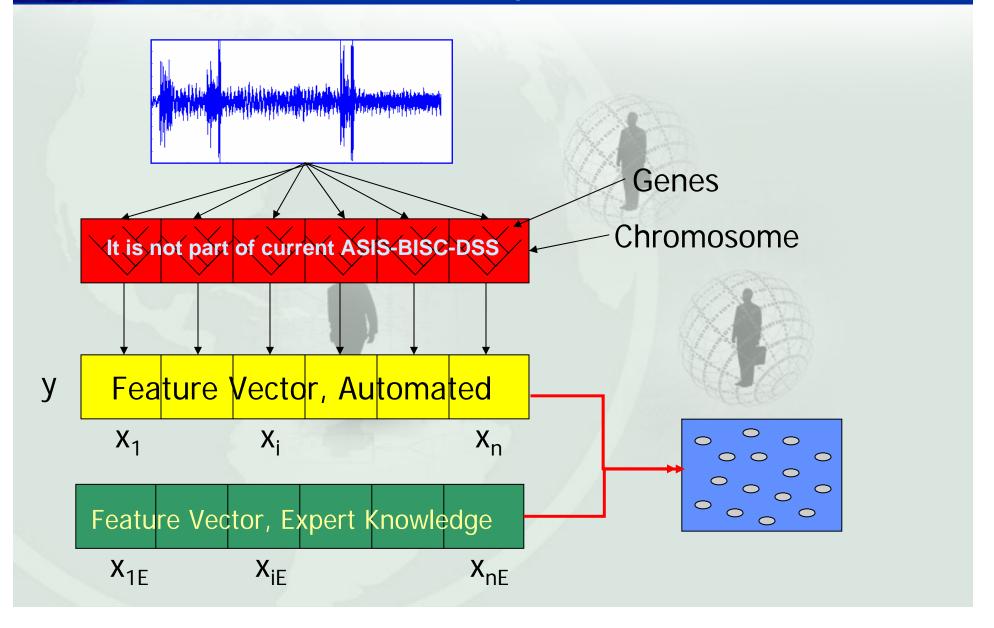








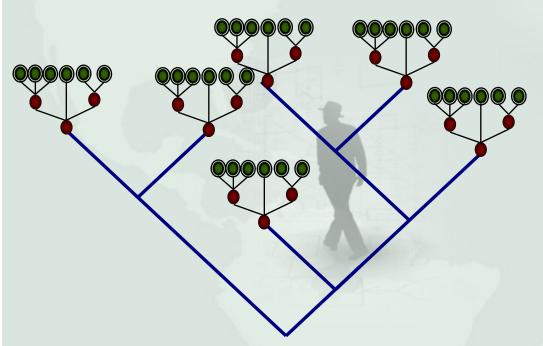
Chromosome Representation





Chromosome Representation

Fuzzy Label, Set Value, Scalar & Series Input

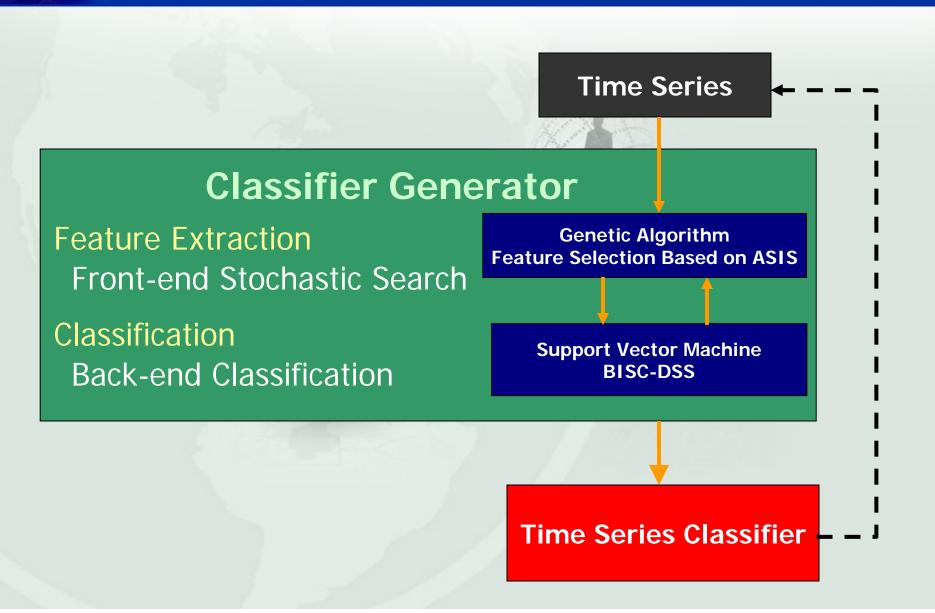


- Composed of primitive statistical, fuzzy set, aggregator, similarity, arithmetic, and signal processing operators.
- Each gene (or algorithm) is represented as a tree, accepts both scalar and series input, and outputs scalar features.
- The chromosome produces a feature vector set.

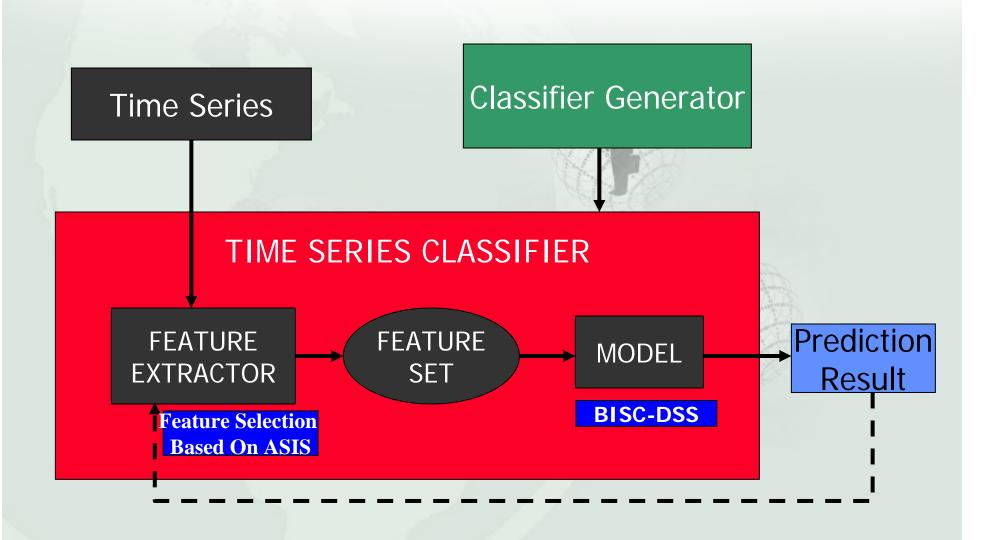
Scalar & Fuzzy Label Features



Front/Back-end Architecture

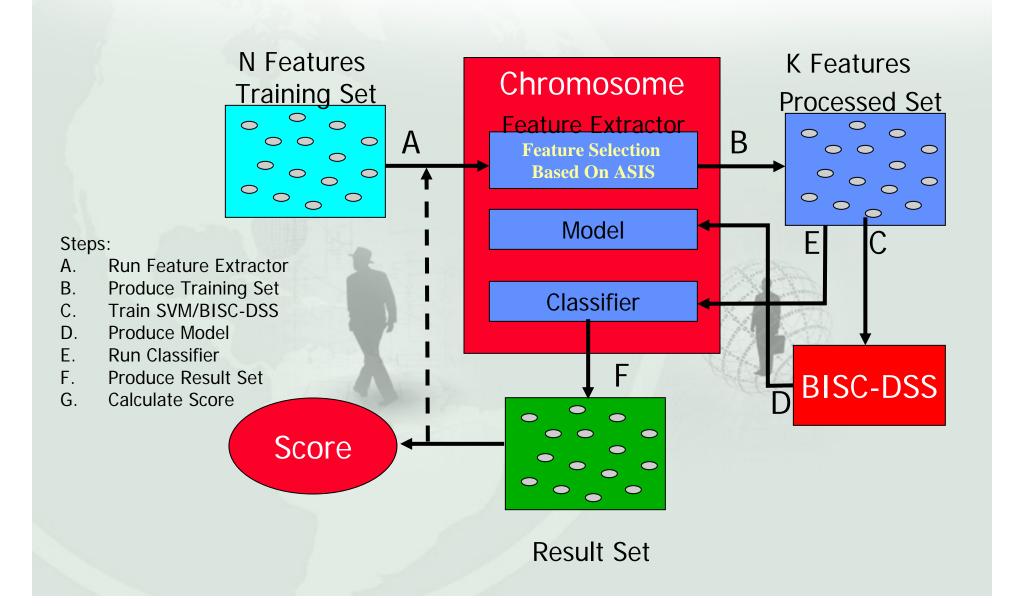


Classifier Architecture

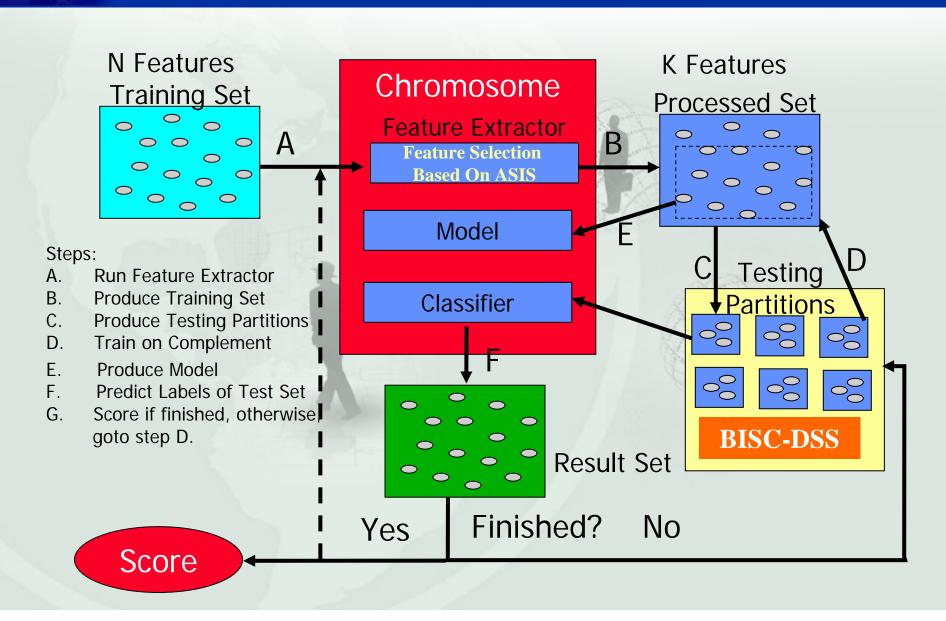


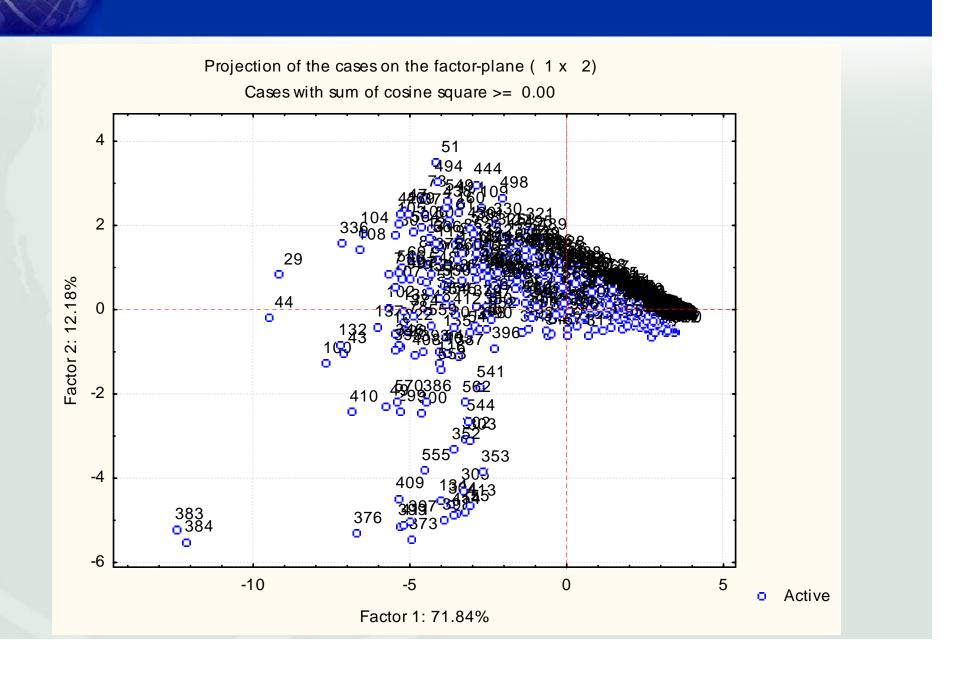


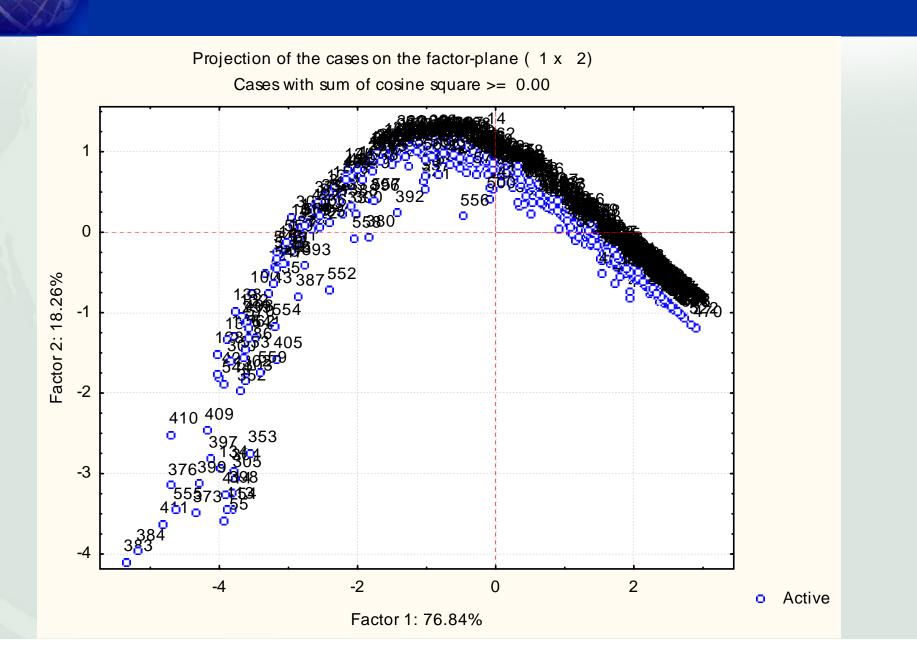
Fitness: In-sample Rate



Fitness: N-Fold Cross Valid









BISC-DSS Clustering-Based ANSIS

