Programa de doctorado interuniversitario en Tecnologías de la Información

Curso: Técnicas de Computación Flexible

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Genetic Algorithms: Basic notions and some advanced topics

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Genetic Algorithms:
Basic notions and some advanced topics

SESSIONS

a. Introduction to genetic algorithms

b. Advanced topics

- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

Session b. Genetic Algorithms: Advanced topics

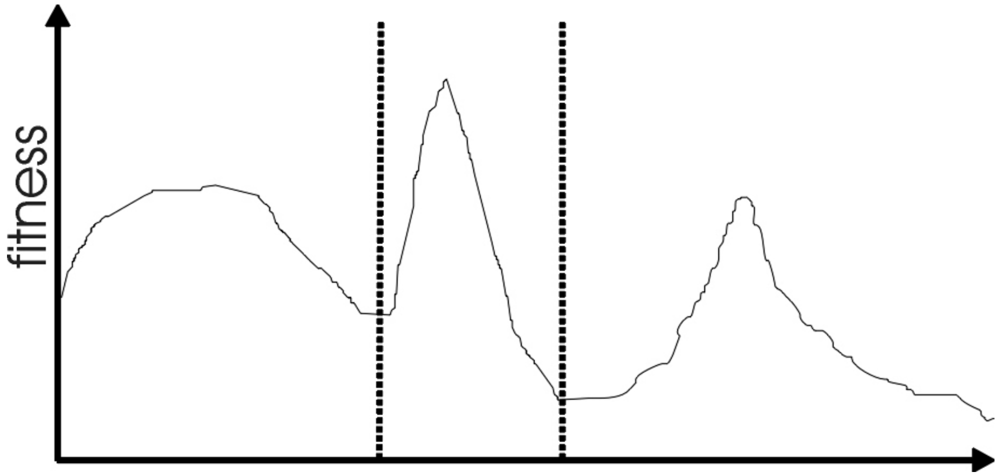
- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

1. MULTIMODAL PROBLEMS AND MULTIPLE SOLUTIOSN

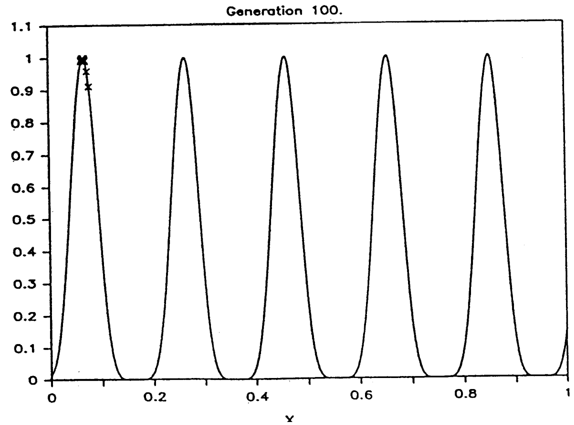
- MULTIMODAL PROBLEMS
- EVOLUTION IN MULTIMODAL PROBLEMS
- NICHING GENETIC ALGORITHMS

Multimodal problems

- **There are a lot of interesting problems with multiple optima.**



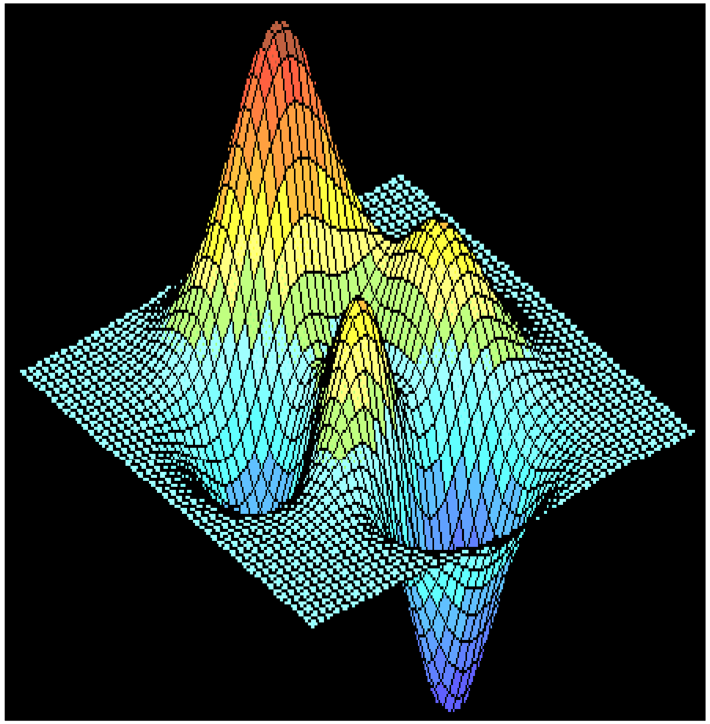
- **In some problems we want to obtain a set of multiple solutions.**

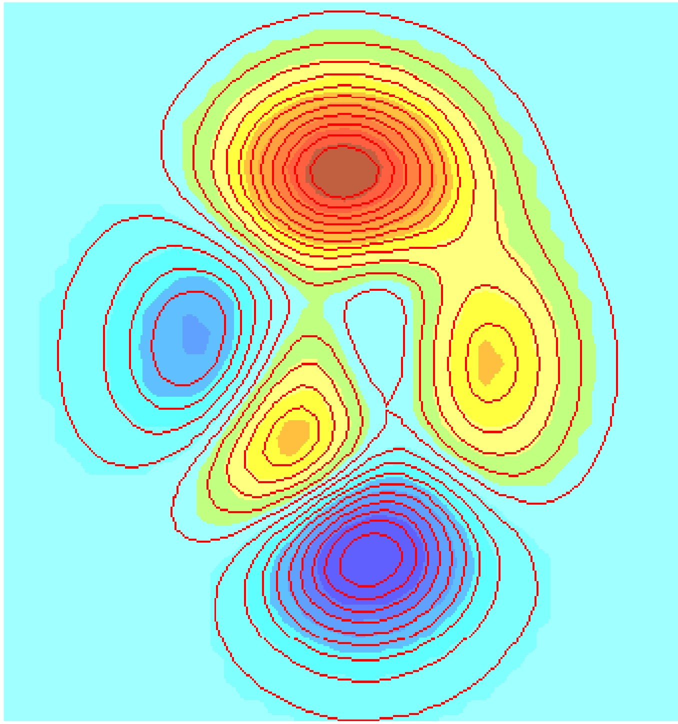


Evolution in Multimodal problems

- **Example: Max z= f(x,y)**

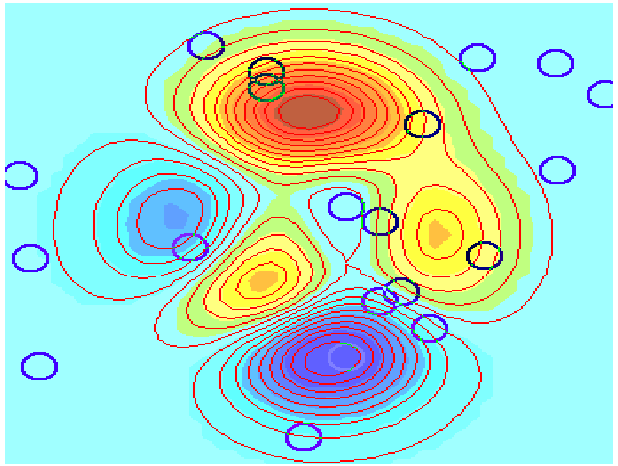
z = f(x, y) = 3*(1-x)^2*exp(-(x^2) - (y+1)^2) - 10*(x/5 - x^3 - y^5)*exp(-x^2-y^2) - 1/3*exp(-(x+1)^2 - y^2).



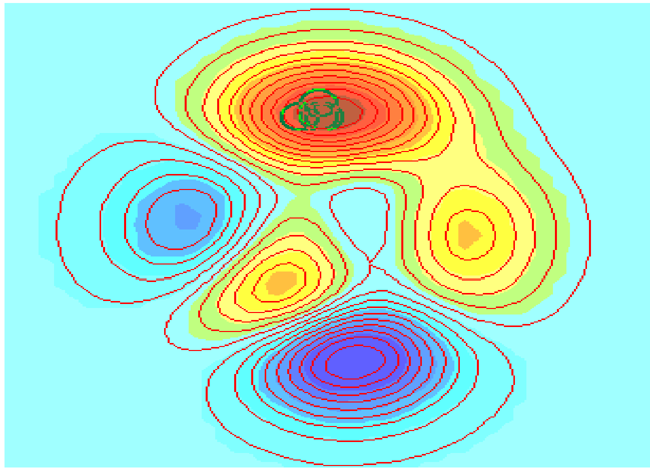


Evolution in Multimodal problems

- Initial population: random choice
- The evolutionary process converges towards a region: **genetic drift.**



Initial Population (Gen 0)



After 10 generations

Question: How to work if we can to obtain solutions in different regions?

Niching genetic algorithms

The “niching” concept is introduced for obtaining multiple solutions.

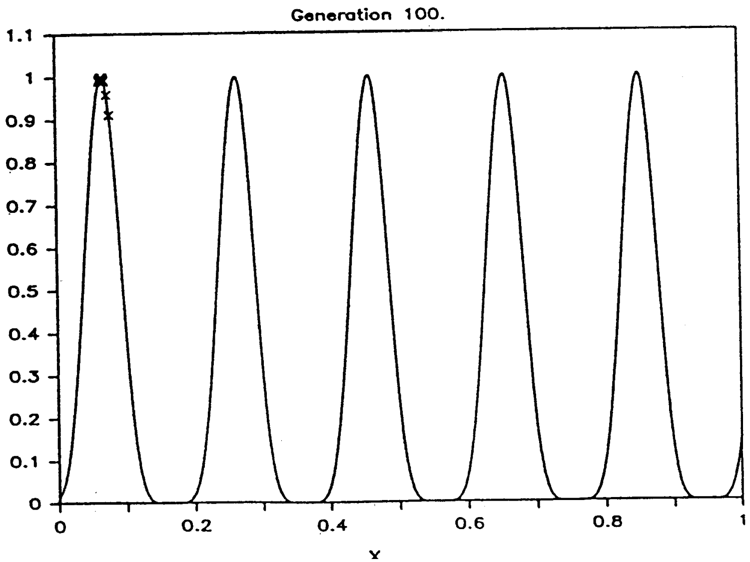
The niching genetic algorithms evolve towards different regions (niches) getting different optima (one per region).

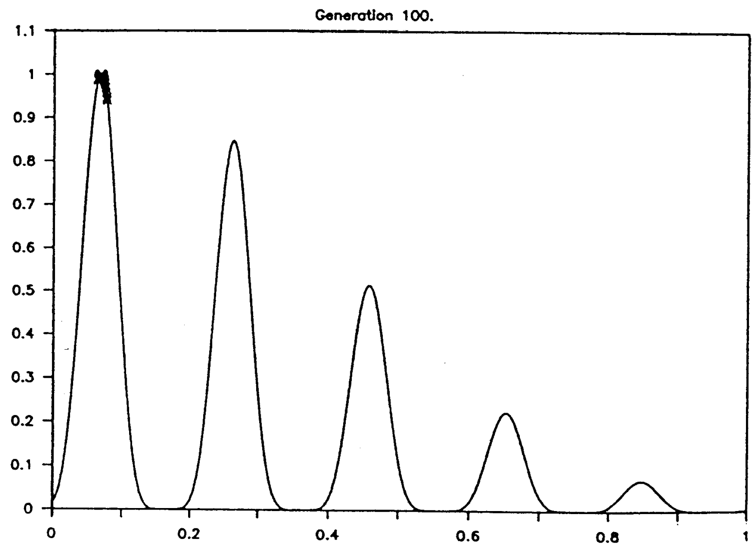
The following contribution presents a review of the classical models:

B. Sareni, L. Krähenbühk, Fitness Sharing and Niching Methods Revisited. IEEE Transactions on Evolutionary Computation, Vol. 2, No. 3, Septiembre 1998, 97-106.

http://sci2s.ugr.es/docencia/index.php (link course)

Niching genetic algorithms





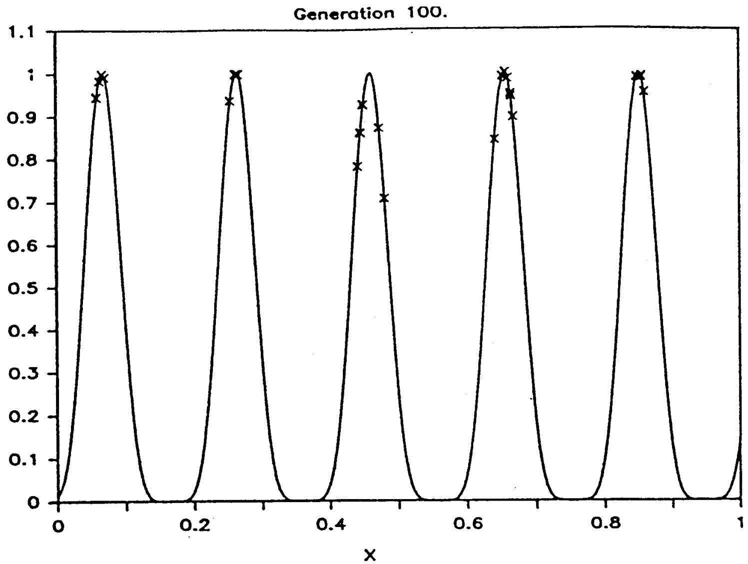
Various global optima
Evolution without niches and mutation

Various local optima
Evolution without niches and mutation

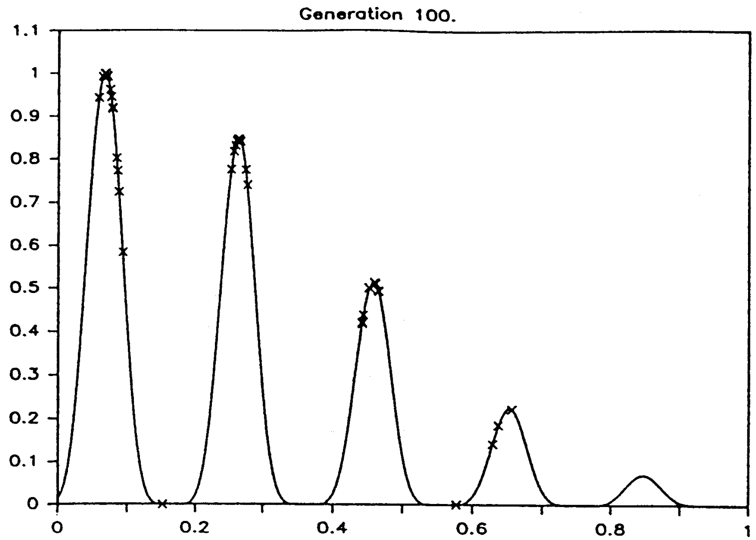
We have a convergence toward an optimum (genetic drift)

Proposal: Niching genetic algorithms for getting multiple solutions

Niching genetic algorithms



Various global optima
Evolution with niches and without mutation



Various local optima
Evolution with niches and without mutation

We have a convergence towards different optima

Niching genetic algorithms

There are four different groups into which niching techniques can be divided:

1. **Fitness sharing**
2. **Crowding**
3. **Clearing** **(very good behaviour)**
4. **Species competition**

Pétrowski, A. (1996). A clearing procedure as a niching method for genetic algorithms. In Proc. IEEE International conference on evolutionary computation. Japan. Pp. 798-803.

Pérez, E., Herrera, F. and Hernández, C. (2003). Finding multiple solutions in job shop scheduling by niching genetic algorithms. Journal of Intelligent Manufacturing, (14) Pp. 323-341. http://sci2s.ugr.es/docencia/index.php **(link course)**

Niching genetic algorithms

- **Clearing:**

Parameters:

σ Niche radio

Kappa Number of individuals per niche (the best)

Process:

```
Order in P  from the best to the worst
for i=0 to N-1
{
     if (Fitness (P[i])>0)
     {
          NumGanadores=1
          for j=i+1 to N-1
               if (Fitness (P[j])>0) and (Distancia(P[i],P[j])<σ))
               {
                         if (NumGanadores<Kappa)
                                   NumGanadores ++
                         else
                                   Fitness(P[j])=0 (eliminated, out of the
                                             population for reproducttion)
               }
     }
}
```

1. MULTIMODAL PROBLEMS AND MULTIPLE SOLUTIOSN

Final comments

- The niching GAs allow us to obtain multiple solutions with only one run.
- The use of niching techniques is an important tool for avoiding the premature convergence to local optima.
- The niching techniques are an important tool in the design of multiobjective genetic algorithms.

Session b.
Genetic Algorithms: Advanced topics

- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

2. MULTIOBJECTIVE GENETIC ALGORITHMS

- **MULTIOBJECTIVE PROBLEMS**
- **EVOLUTION IN MULTIOBJECTIVE PROBLEMS**
- **THE ELITISM**
- **NSGAII**
- **METRICS**

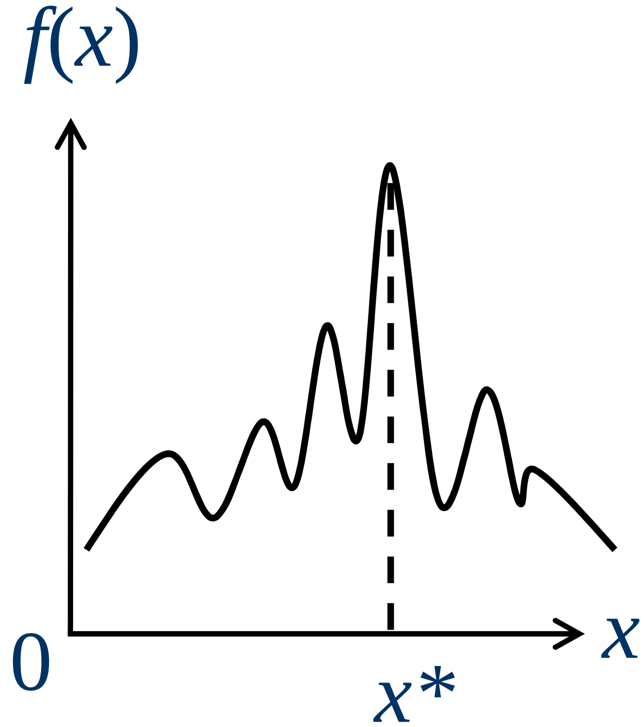
K. Deb, Multi-Objective Optimization using Evolutionary Algorithms. John Wiley & Sons, 2001.

C.A. Coello, D.A. Van Veldhuizen, G.B. Lamont, Evolutionary Algorithms for Solving Multi-Objective Problems. Kluwer Academic Pub., 2002.

Multiobjective problems

Single-objective optimization:

To find a single optimal solution x^* of a single objective function $f(x)$.



Multi-objective optimization:

To find a large number of Pareto optimal solutions with respect to multiple objective functions.

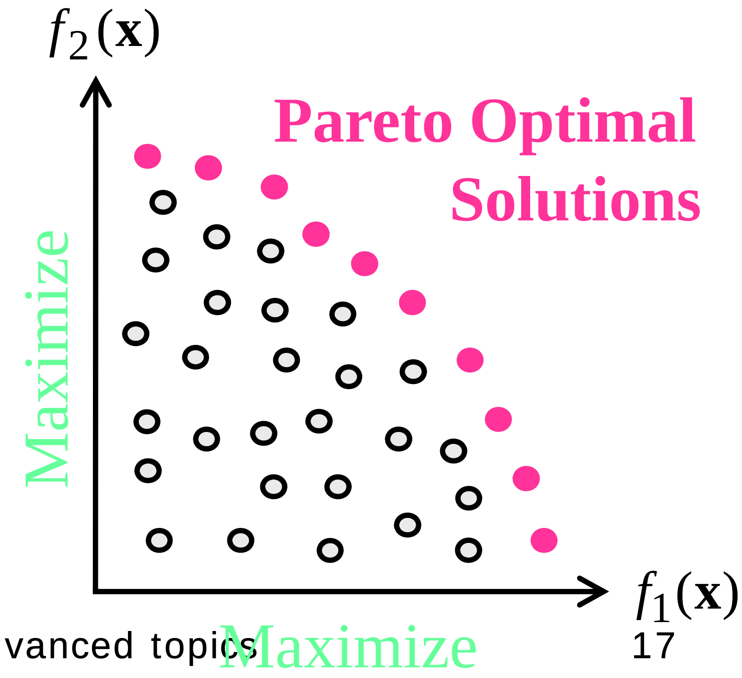
Multiobjective problems

Multiobjective Optimization Problem

$$\text{Maximize} \quad \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}),\ f_2(\mathbf{x}),\ \ldots,\ f_k(\mathbf{x}))$$

$$\text{subject to} \quad \mathbf{x} \in \mathbf{X}$$

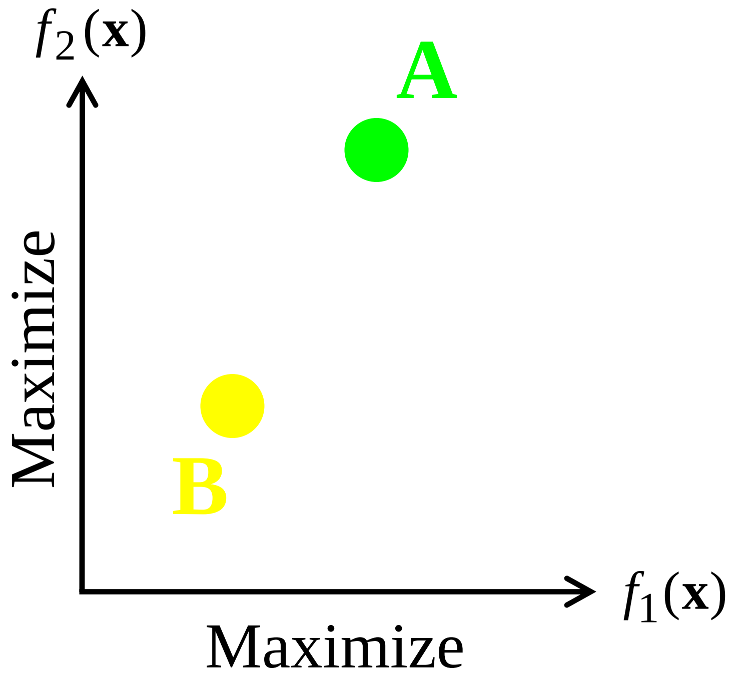
Many Pareto-optimal solutions



Multiobjective problems

Pareto Dominance

$$\text{Maximize} \quad \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}),\ f_2(\mathbf{x}))$$



A dominates B

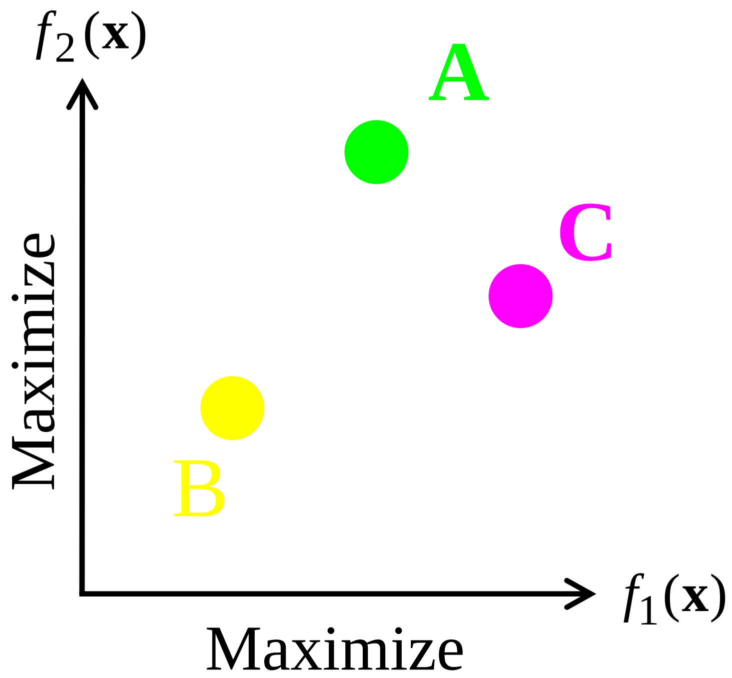
B is dominated by A

(A is better than B)

Multiobjective problems

Pareto Dominance

$$\text{Maximize} \quad \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}),\ f_2(\mathbf{x}))$$

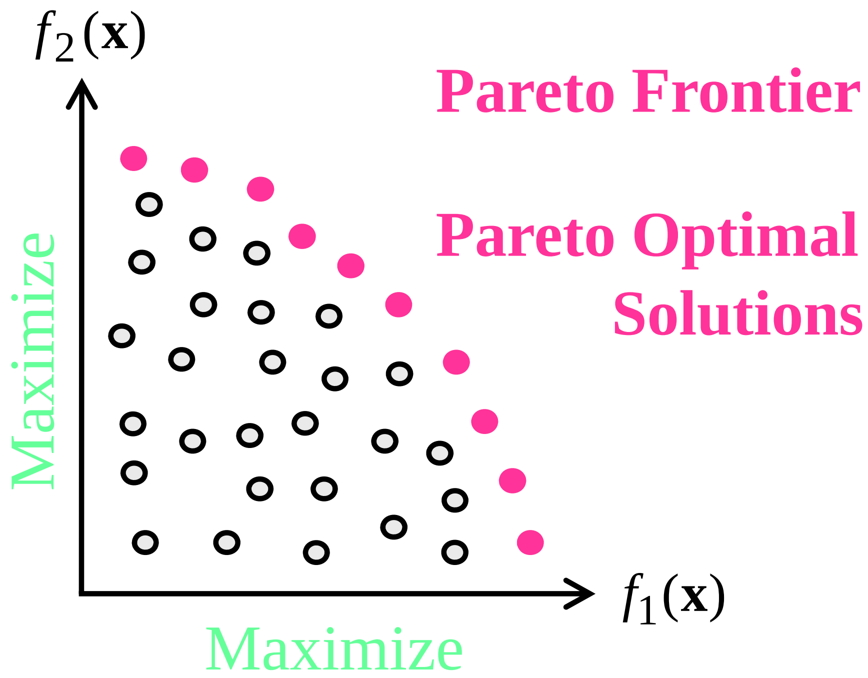


A and C are non-dominated with each other.

Multiobjective problems

Pareto Optimal Solutions

A Pareto optimal solution is a solution that is not dominated by any other solutions.

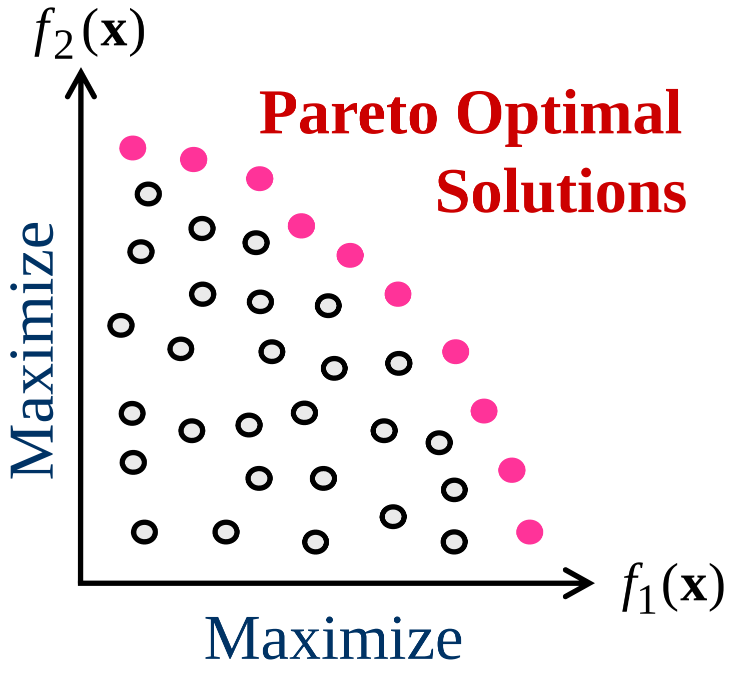


Evolution in Multiobjective problems

Two well known names:

Multiobjective genetic algorithms (MOGA)

Multiobjective evolutionary algorithms (MOEAs)



The task of MOEAs:

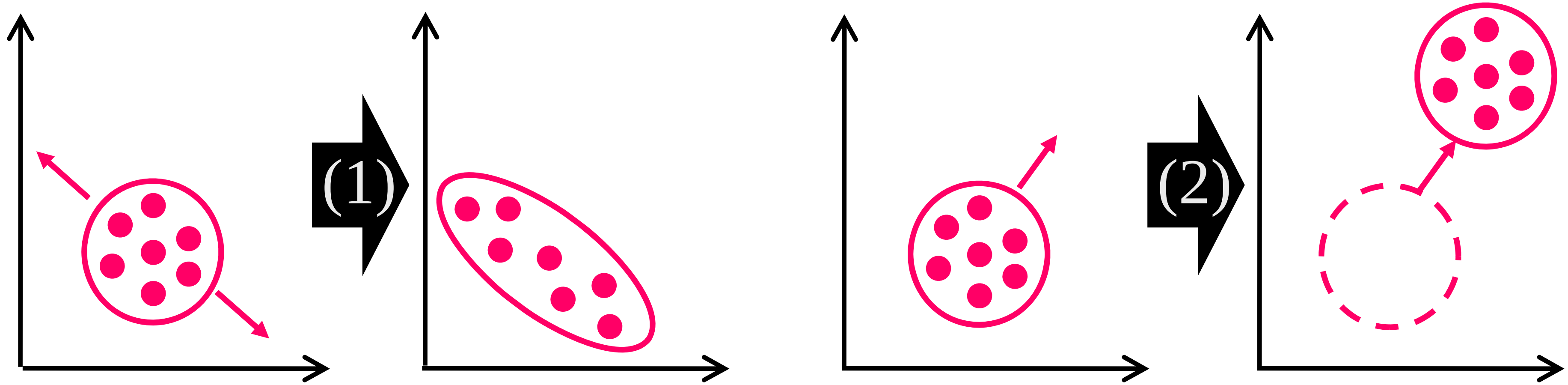
To find well-distributed (near) Pareto-optimal solutions as many as possible.

Evolution in Multiobjective problems

Two Goals in the Design of MOEAs

(1) To increase the diversity of solutions

(2) To improve the convergence on the Pareto-front



Niching, Crowding

Pareto Ranking & Elitist Strategy

Evolution in Multiobjective problems

Features:

- Evolution of a population of solutions (as classical GA).
- Application of mechanisms for mantaining the diversity and getting non-dominated solutions, as many as possible.

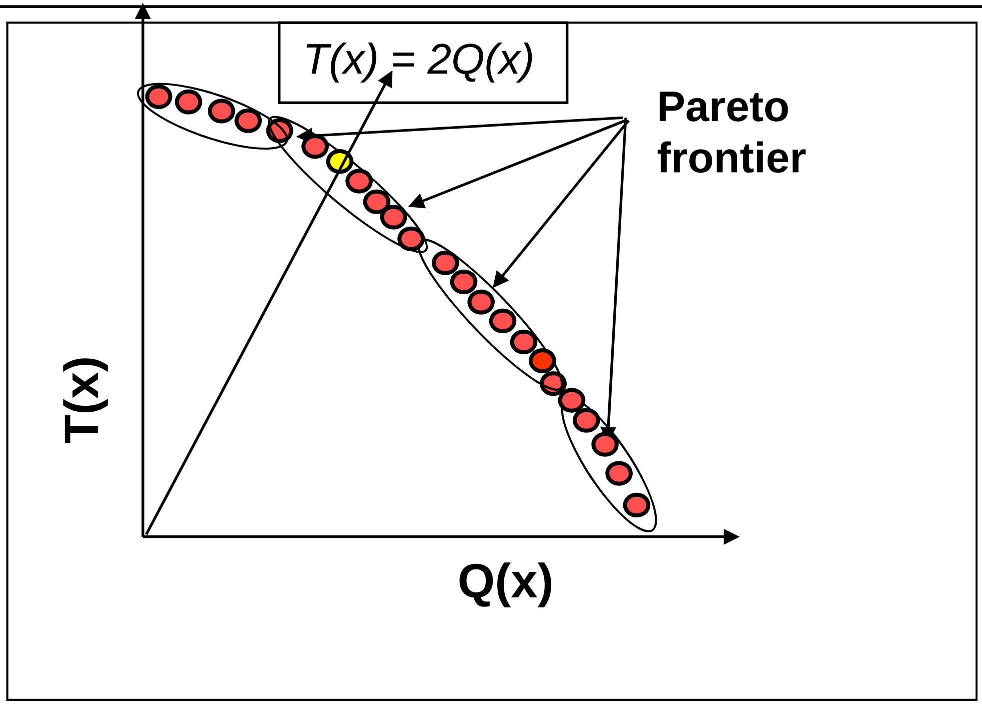
- Two kind of classical models:
  - **Aggregation of the objectives**
  - **Models that use a multicriteria trade-off for getting a pareto frontier (a set of non-dominated solutions)**

Evolution in Multiobjective problems

Aggregated fitness function focuses on one tradeoff point in frontier

Example: *[Max Q(x), Max T(x)]*

- *given that T(x) is twice as important as Q(x), i.e.: T(x) = 2Q(x)*



The line: T(x) = 2Q(y) corresponds to the Weight Vector W: [1 , 2], when we use the scalar fitness function F:

F = W * [Q(x), T(X)]
F = [1, 2] * [Q(x), T(X)]
F = Q(x) + 2*T(x)

Evolution in Multiobjective problems

MOEAs with weights

- VOW-GA: Variable Objective Weighting GA
  (*Hajela & Lin 1992*)
- RW-GA: Random Weights GA
  (*Ishibuchi & Murata, 1998*)

Evolution in Multiobjective problems

MOEAs generating the pareto frontier (first generation)

- MOGA: Multi-objective Optimization GA

  C.M. Fonseca, P.J. Fleming, Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization. S. Forrest (Ed.), Proc. 5th Int. Conf. on Genetic Algorithms, Morgan Kaufmann, 1993, 416-423.

- NPGA: Niched Pareto GA

  J. Horn, N. Nafpliotis. Multiobjective Optimization Using the Niched Pareto Genetic Algorithms. IlliGAL Report 93005, University of Illinois, Urbana, Champaign, July 1993.

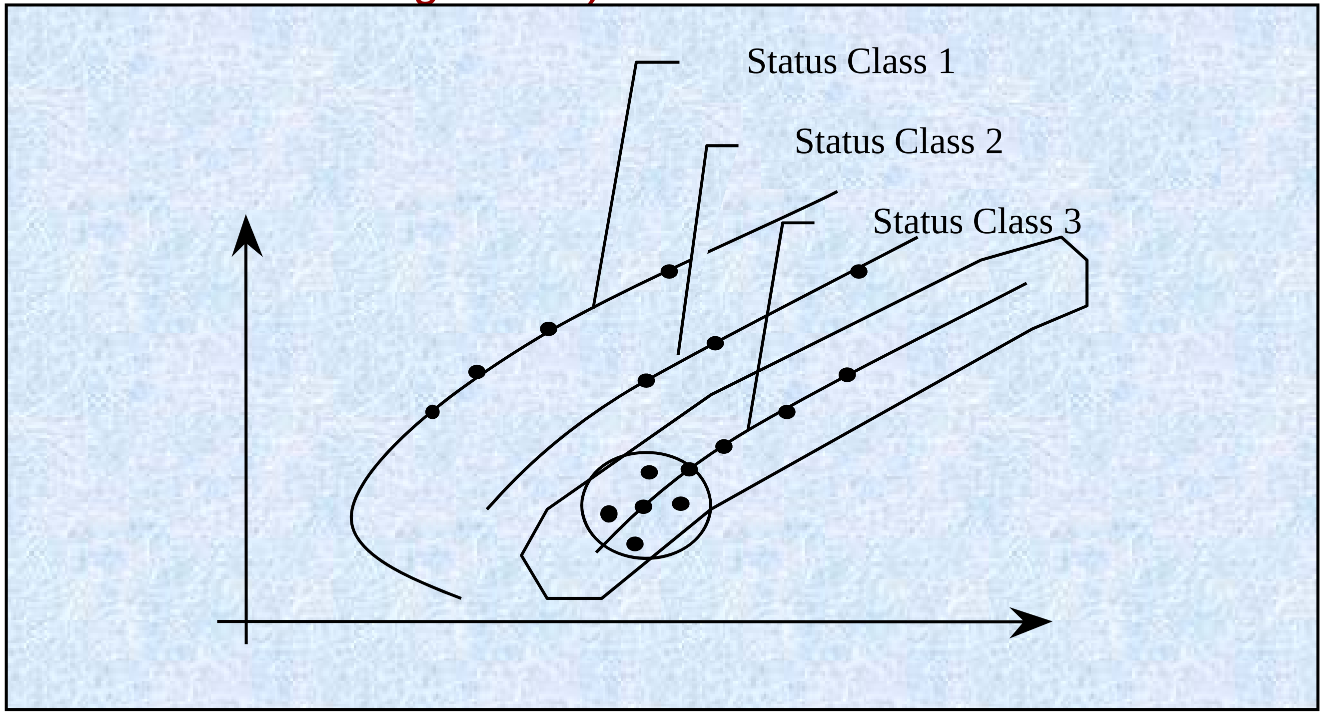
- NSGA: Non-dominated Sorting GA

  N. Srinivas, K. Deb, Multiobjetive Optimization Using Nondominated Sorting in Genetic Algorithms. Evolutionary Computation 2 (1995) 221-248.

http://sci2s.ugr.es/docencia/index.php **(link course)**

Evolution in Multiobjective problems

- MOGA: Multi-objective Optimization GA
  (*Fonseca & Fleming 1993*)



C.M. Fonseca, P.J. Fleming, Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization. S. Forrest (Ed.), Proc. 5th Int. Conf. on Genetic Algorithms, Morgan Kaufmann, 1993, 416-423.

Evolution in Multiobjective problems

Basic Ideas in EMO Algorithm Design

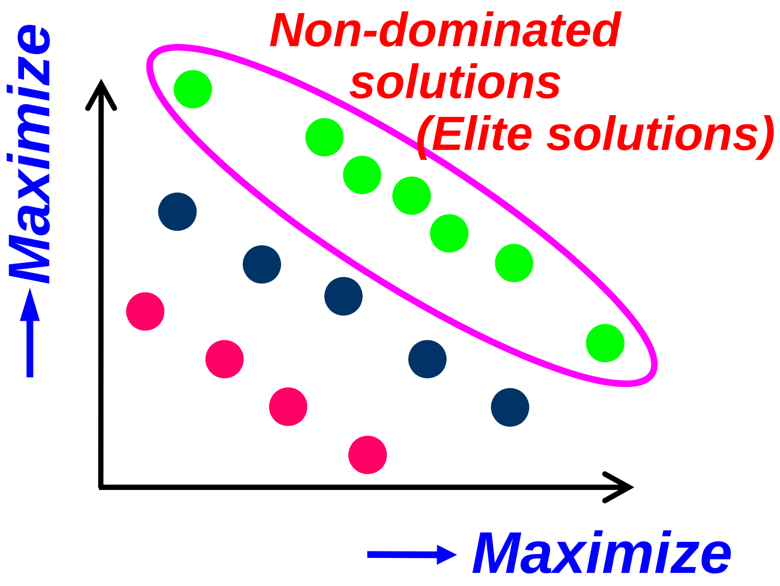
Recently developed well-known EMO algorithms such as NSGA-II and SPEA have some common features:

(1) Pareto Dominance

Converge to the Pareto front

(2) Crowding

Diversity maintenance



(3) Elitist Strategy

Non-dominated solutions are handled as elite solutions.

The Elitims: Second generation of MOEAs

Elitism as an external population (elite set): SPEA Model

Elitism in the population: NSGA II Model

The Elitism: Second generation of MOEAs

- STRENGTH PARETO EVOLUTIONARY ALGORITHMS (SPEA) (Zitzler, Thiele, 1998)

Elite set: Elitism as an external population

Zitzler, E., Thiele, L. (1998a) An evolutionary algorithm for multiobjective optimization: The strength Pareto Approach. Technical Report 43, Zürich, Switzerland: Computer Engineering and Networks Laboratory (TIK), Swiss Federal Institute of Technology (ETH).

E. Zitzler, L. Thiele. Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach. IEEE Transactions on Evolutionary Computation 3:4 (1999) 257-217.

http://sci2s.ugr.es/docencia/index.php **(link course)**

The Elitism: Second generation of MOEAs

E. Zitzler, K. Deb, L. Thiele. Comparison of Multiobjetive Evolutionary Algorithms: Empirical Results. Evolutionary Computation 8:2 (2000) 173-195.

http://sci2s.ugr.es/docencia/index.php (link course)

- Comparison between NSGA and SPEA: The best is SPEA.
- Comparing NSGA + Elitims and SPEA: Equal behaviour.

The Elitism: Second generation of MOEAs

SPEA2: Revised version of SPEA.

Eckart Zitzler, Marco Laumanns, Lothar Thiele: **SPEA2: Improving the Strength Pareto Evolutionary Algorithm.**
Zürich, TIK Report Nr. 103, Computer Engineering and Networks Lab (TIK), Swiss Federal Institute of Technology (ETH) Zurich, May, 2001.

Eckart Zitzler
http://www.tik.ee.ethz.ch/~zitzler/

Source code
http://www.tik.ee.ethz.ch/%7ezitzler/testdata.html#source

Eckart Zitzler

PISA

A Platform and Programming Language Independent Interface for Search Algorithms

http://www.tik.ee.ethz.ch/pisa/

The Elitism: Second generation of MOEAs

Elitism in the population.
NSGA-II: Considered the best

Nondominated Sorting Genetic Algorithm II

K. Deb, A. Pratap, S. Agarwal and T. Meyarivan. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6:2 (2002) 182-197.

http://sci2s.ugr.es/docencia/index.php **(link course)**

Niching approach: crowding instead of sharing.

Selection comparing parents and offspring.

Highly efficient algorithm.

It was proposed by K. Deb and his students in 2000.

NSGA

NS-GA: Non-dominated Sorting GA (*Srinivas & Deb, 1995*)

- **Before selection is applied, the population is ranked on the basis of non-domination, and all non-dominated individuals are classified into *one pool*.**
- **Each individual in the pool is assigned the same pseudo-fitness value (proportional to the population size) and has an equal chance of being considered.**
- **To maintain population diversity, these classified individuals are shared with the rest of the population by using their pseudo fitness values.**
- **After sharing, these individuals are recorded, and then temporarily ignored to identify the second pool of non-dominated individuals.**
- **These individuals were assigned a lower pseudo-fitness value than the members in the first pool.**
- **The process continues until the entire population is classified into pools.**
- **The population is then reproduced utilizing the pseudo-fitness values.**

- **NSGA suffers from overall performance issues and are** very dependent to the value of the sharing factor.

NSGA-II

Some problems:

- **When we use a high number of objectives (five or more) it has exploratory problems (as all the remaining MOEAs).**

- **It has a better behaviour with real coding than with binary coding.**

NSGA-II

Kalyanmoy Deb
http://www.iitk.ac.in/kangal/

The IEEE TEC paper describing NSGA-II for multi-objective optimization is judged as the FAST-BREAKING PAPER IN ENGINEERING by Web of Science (ESI) in February 2004

Software Developed at KanGAL
http://www.iitk.ac.in/kangal/codes.shtml

- Multi-objective NSGA-II code in C
  - Original Implementation (for Windows and Linux): NSGA-II in C (Real + Binary + Constraint Handling)
  - New (10 April 2005) (for Linux only): NSGA-II in C (Real + Binary + Constraint Handling)
  - Revision 1.1 (10 May 2005) (for Linux only): NSGA-II in C (Real + Binary + Constraint Handling)
  - Revision 1.1 (10 June 2005) (for Linux only): NSGA-II in C with gnuplot (Real + Binary + Constraint Handling)

Metrics

Given 2 non-dominated sets X' y X'', the function *C* provides us a dominance degree between them in [0,1]:

$$\boldsymbol{C(X',X'') :=}$$

$$|\{a'' \in X'';\ \exists\ a' \in X' : a' \preceq a''\}|\ /\ |X''|$$

C(X',X'') measures the dominance degree of X' over X''.

Clearly C(X',X'') ≠ C(X'',X').

Metrics

- M_1
Distance to the Optimal pareto

$$M_1(X') = \frac{1}{|X'|} \sum_{a' \in X'} \min\left\{ \| a' - \overline{a} \|_H ; \overline{a} \in \overline{X} \right\}$$

$$M_1^*(X') = \frac{1}{|X'|} \sum_{p' \in X'} \min\left\{ \| p' - \overline{p} \| ; \overline{p} \in \overline{Y} \right\}$$

- M_2
Distribution of Non-dominated Solutions

$$M_2(X') = \frac{1}{|X'-1|} \sum_{a' \in X'} \left| \left\{ b' \in X' ; \| a' - b' \| > \sigma \right\} \right|$$

Equal on the objectives

- M_3
Extension of the frontier

$$M_3(X') = \sqrt{\sum_{i=1}^{m} \max\left\{ \| a'_i - b'_i \|_H ; a', b' \in X' \right\}}$$

$$M_3^*(Y') = \sqrt{\sum_{i=1}^{n} \max\left\{ \| p'_i - q'_i \| ; p', q' \in Y' \right\}}$$

Hot Issues in EMO Research

Utilization of Decision Maker's Preference

- *Preference is incorporated into EMO algorithms.*
- *Interactive EMO approaches seem to be promising.*

Handling of Many Objectives by EMO Algorithms

- *Pareto dominance-based algorithms do not work well.*
- *More selection pressure is needed.*

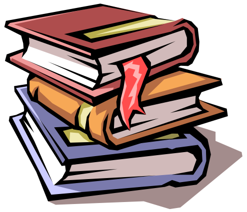
Hybridization with Local Search

- *Hybridization often improves the performance of EMO.*
- *Balance between local and genetic search is important.*

Design of New EMO Algorithms

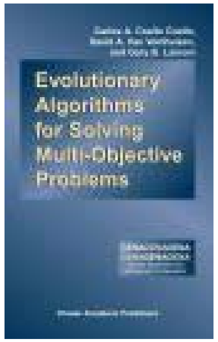
- *Indicator-based EMO algorithms*
- *Scalarizing function-based EMO algorithms*
- *Use of other search methods such as PSO, ACO and DE.*

Learning more on MOEAs

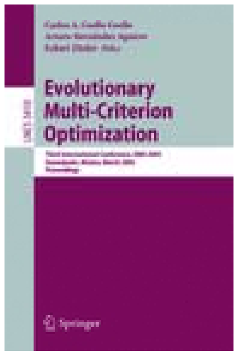


EMOO repository:

http://delta.cs.cinvestav.mx/~ccoello/EMOO



C.A. Coello, D.A. Van Veldhuizen, G.B. Lamont, Evolutionary Algorithms for Solving Multi-Objective Problems. Kluwer Academic Pub., 2002.



Evolutionary Multi-Criterion Optimization
Third Int. Conf, EMO 2005, Guanajuato, Mexico, March 9-11, 2005, Proceedings
Series: Lecture Notes in Computer Science, Vol. 3410
Coello Carlos A.; Hernández, Arturo; Zitzler, Eckart (Eds.) 2005, XVI, 912 p.,

C.A. Coello

Basic lectures on MOEA

Basic Lectures: http://sci2s.ugr.es/docencia/index.php (link course)

C.A. Coello. Evolutionary Multiobjective Optimization: Current and Future Challenges. Benitez, O. Cordon, F. Hoffmann, and R. Roy (Eds.), Advances in Soft Computing---Engineering, Design and Manufacturing. Springer-Verlag, September, 2003, pp. 243 - 256.

E. Zitzler, L. Thiele, M. Laumanns, C.M. Fonseca, and V. Grunert da Fonseca. Performance Assessment of Multiobjective Optimizers: An Analysis and Review. IEEE Transactions on Evolutionary Computation 7:2, April, 2003, pp. 117 - 132.

K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6:2, April, 2002, pp. 182 - 197.

M. Laumanns, L. Thiele, K. Deb, and E. Zitzler. Combining Convergence and Diversity in Evolutionary Multi-objective Optimization. Evolutionary Computation 10:3, Fall, 2002, pp. 263 - 282.

K. Deb, L. Thiele, M. Laumanns, and E. Zitzler. Scalable Test Problems for Evolutionary Multiobjective Optimization. In A. Abraham, L. Jain, and R. Goldberg (Eds.), Evolutionary Multiobjective Optimization. Theoretical Advances and Applications. Springer, USA, 2005, pp. 105 - 145.

BOOKS:

K. Deb, Multi-Objective Optimization using Evolutionary Algorithms. John Wiley & Sons, 2001.

C.A. Coello, D.A. Van Veldhuizen, G.B. Lamont, Evolutionary Algorithms for Solving Multi-Objective Problems. Kluwer Academic Pub., 2007 (second edition).

MOEA Software Links

SPEA

http://www.tik.ee.ethz.ch/%7ezitzler/testdata.html#source

NSGAII

http://www.iitk.ac.in/kangal/codes.shtml

MOMHLib++

Open source Multiple-Objective MetaHeuristics Library in C++

http://www-idss.cs.put.poznan.pl/~jaszkiewicz/MOMHLib/

At present the library includes the following methods:

- Pareto simulated annealing (PSA) PSA's home page,
- Serafini's multiple objective simulated annealing (SMOSA)[4][5],
- Ulungu's et al. multiple objective simulated annealing (MOSA) [7],
- Pareto memetic algorithm [8],
- multiple objective genetic local search (MOGLS) MOGLS's home page,
- Ishibuchi's and Murata's multiple objective genetic local search (IMMOGLS) [3],
- multiple objective multiple start local search (MOMSLS),
- non-dominated sorting genetic algorithm (NSGA) [6] and controlled NSGA II [1],
- Strength Pareto Evolutionary Algorithm [9].

EMOO-Software link: http://www.lania.mx/~ccoello/EMOO/EMOOsoftware.html

2. MULTIOBJECTIVE GENETIC ALGORITHMS

Final comments

- The MOEAs are one of the more important/active research areas in Evolutionary Computation.

- They have a high applicability, being a very important tool for tackling multiobjective optimization problems.

- It is a consolidated area but also an open area for research and development of new algorithms (incorporating preferences, dinamic functions, constraints, scalability on the number of objectives, trade-off efficiency and effectiveness in complex problemx, paralelims, ...) and also for applications.

Session b.
Genetic Algorithms: Advanced topics

- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

3. MEMETIC ALGORITHMS

- **WHAT IS A MEMETIC ALGORITHM?**
- **WHY HYBRID EAs?**
- **BASIC CONCEPTS**
- **RECENT STUDIES**

- **David W. Corne, Marco Dorigo, Fred Glover (Eds.), New Ideas in Optimization, McGraw Hill, 1999. Part Four: Memetic Algorithms**

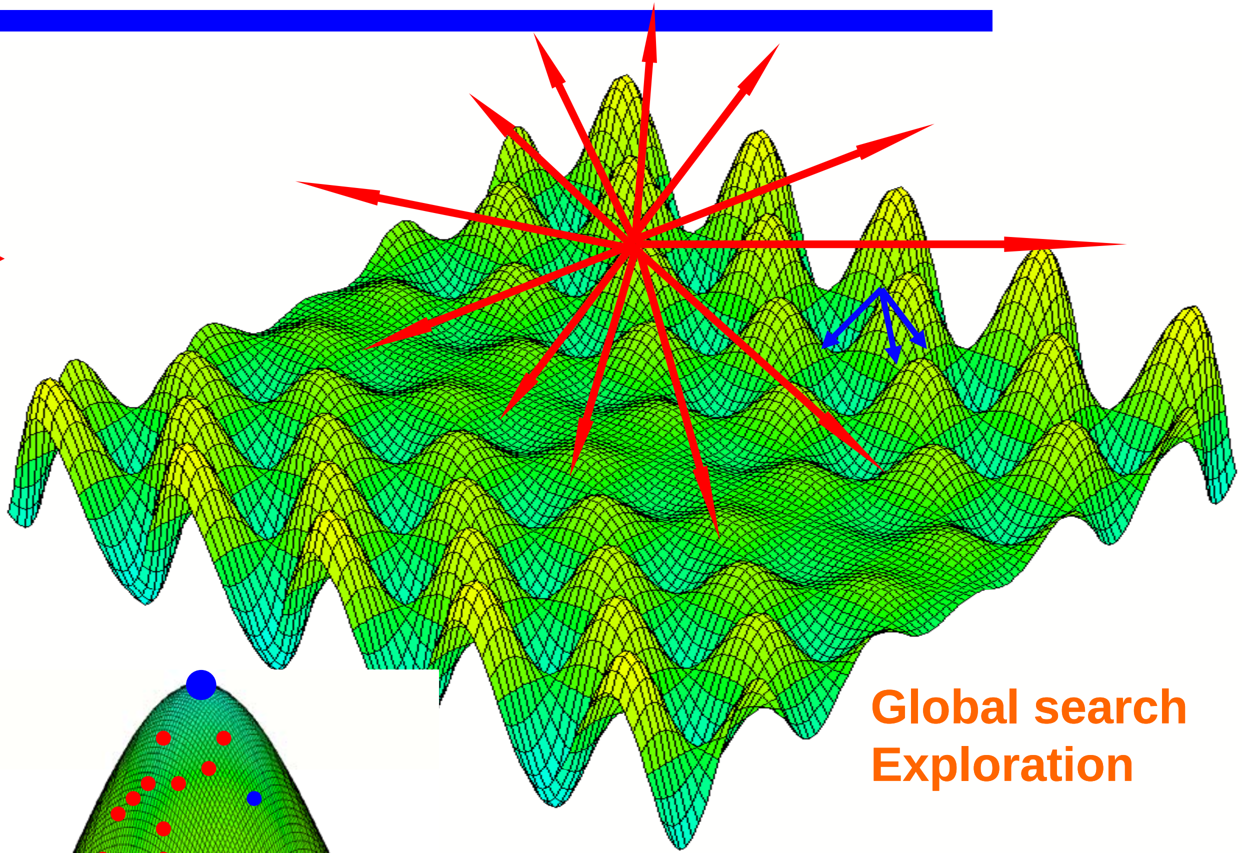
What is a memetic algorithm?

Algorithm based on the evolution of populations that use the knowledge on the problem in the search process (usually, the knowledge is in the form of local search algorithms acting on the population individuals).

Why this hybrid model?

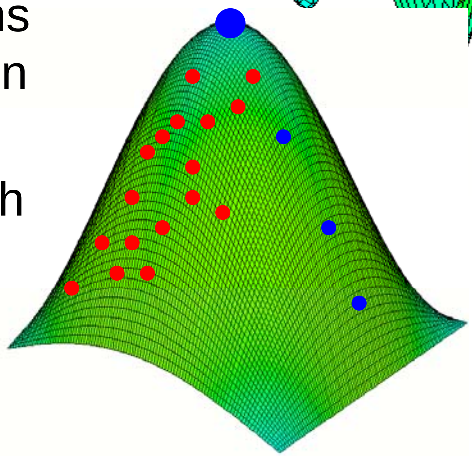
Why this hybrid model?

- Evolutionary algorithms have good exploratory features
- Local search have bad exploratory features



Global search
Exploration

- Evolutionary algorithms have not high exploitation features
- Local search have high exploitation features

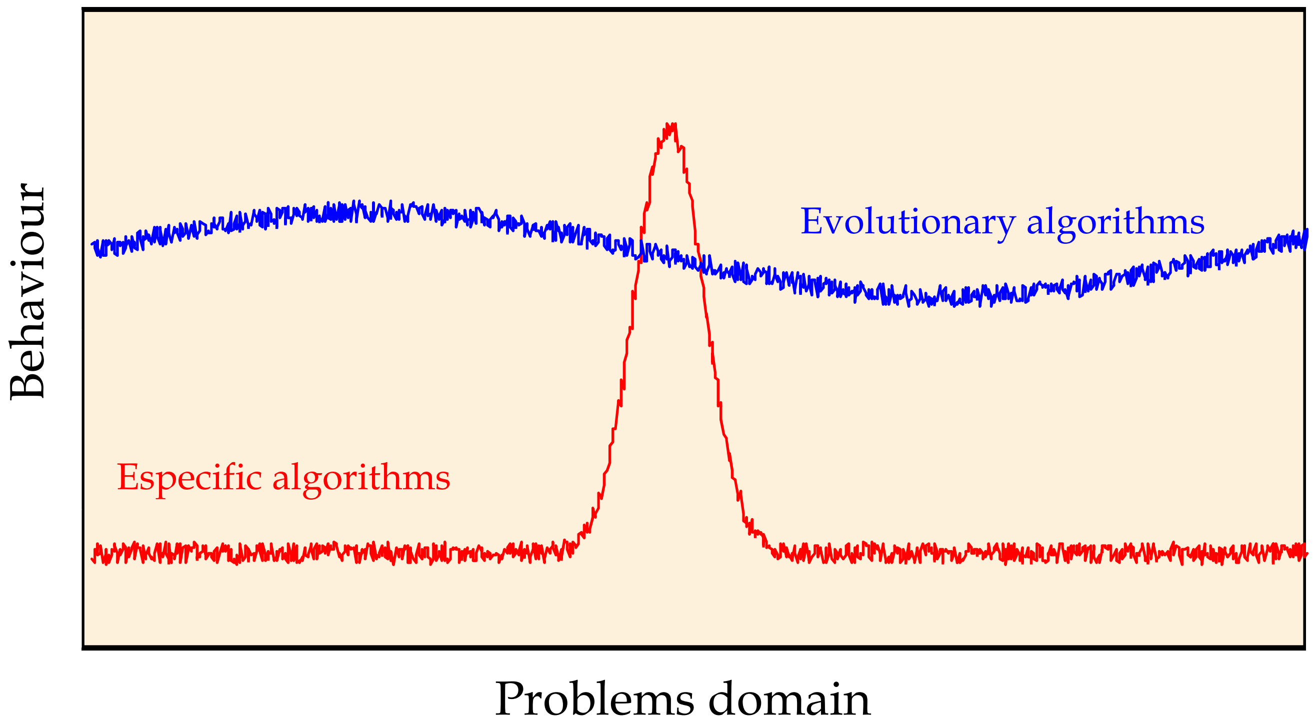


Local search
Exploitation

Why this hybrid model?

The limits of the EAs

On the behaviour of EAs



Why this hybrid model?

No Free Lunch Theorem (1995):

"...for any algorithm, any elevated performance over one class of problems is exactly paid for in performance over another class.“ Wolpert and Macready (1997)

$$\sum_{f} E(\vec{c} / f, m, a) = \sum_{f} E(\vec{c} / f, m, b)$$

David. H. Wolpert

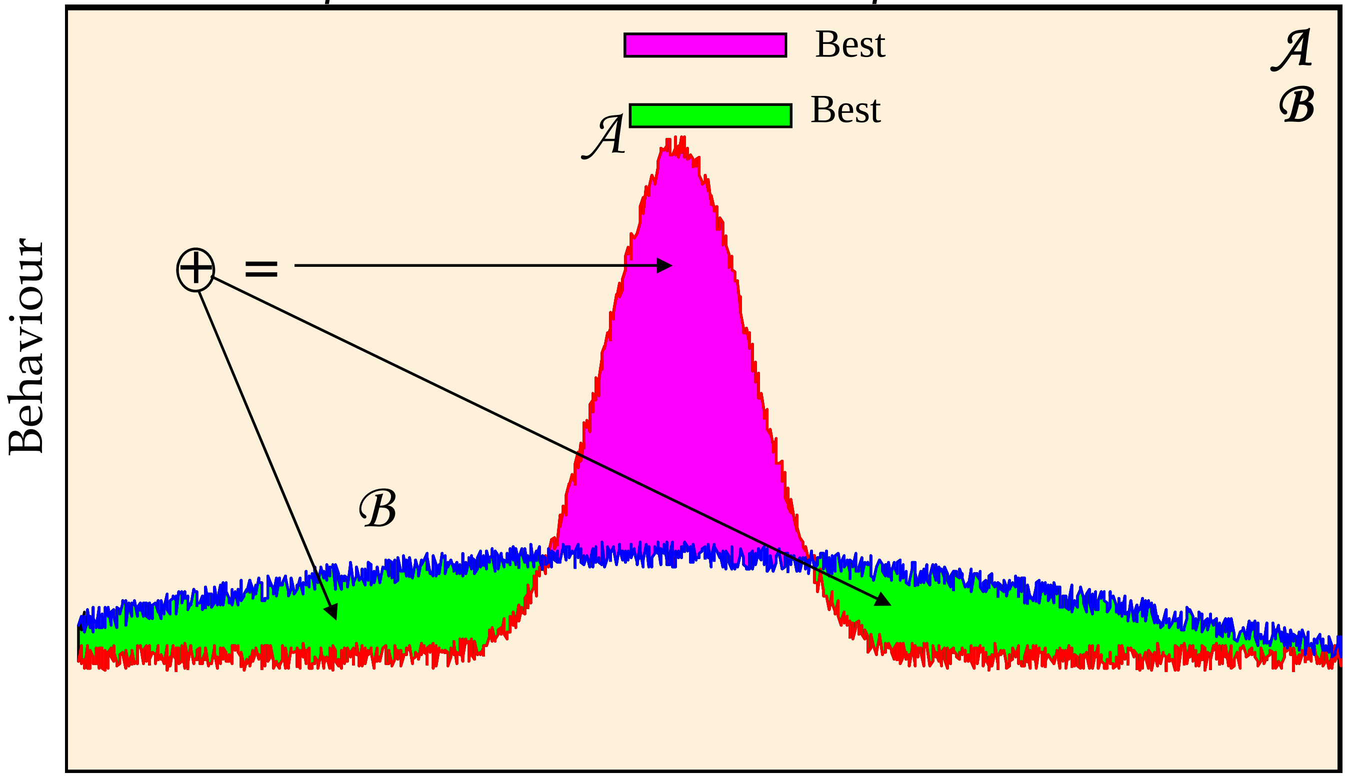
William G. Macready

No free lunch theorems for optimization
Wolpert, D.H.; Macready, W.G.;
Evolutionary Computation, IEEE Transactions on 1:1, April 1997, 67 – 82

Why this hybrid model?

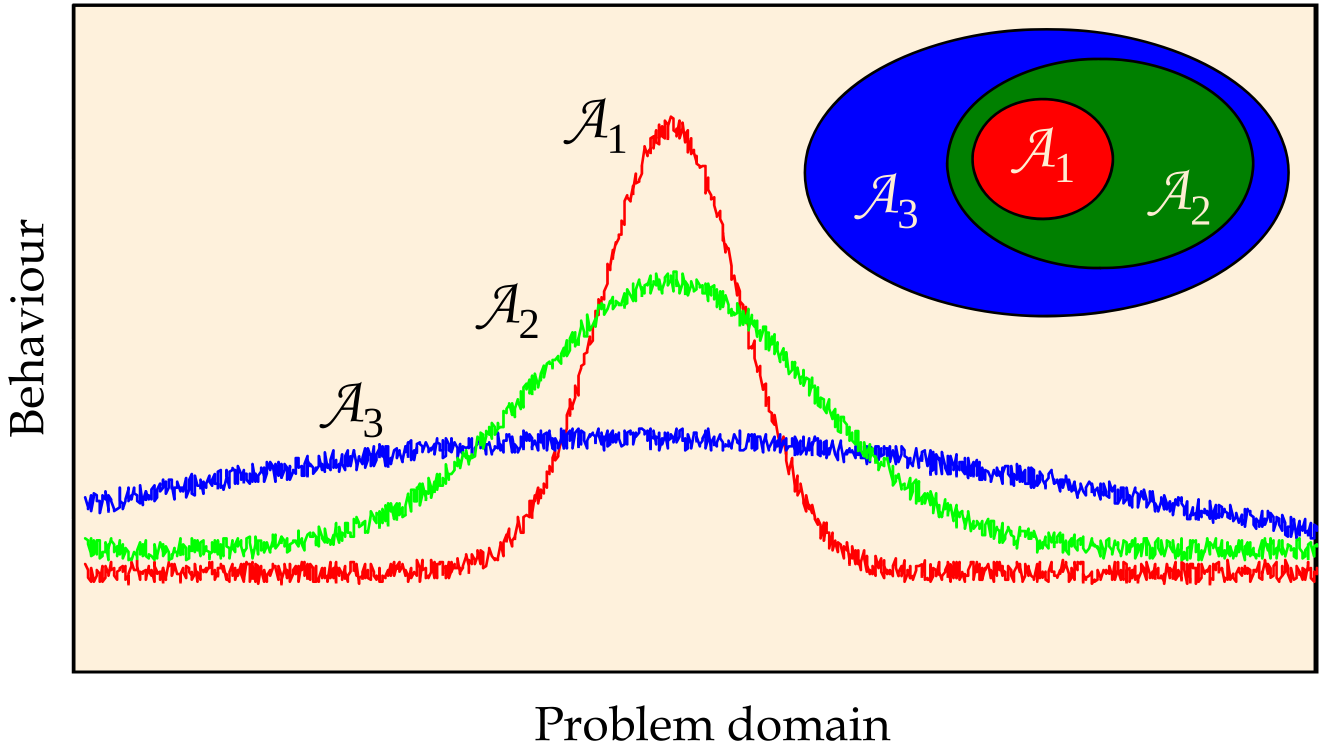
Implications of NFL (I)

$$\sum_f E(\vec{c}\,/\,f, m, a) = \sum_f E(\vec{c}\,/\,f, m, b)$$



Why this hybrid model?

Implications of NFL (II): The winner only in a particular domain



Why this hybrid model?

We consider five knowledge degrees on the problem:

1. Perfect knowledge
2. **Partial knowledge**
3. Low knowledge
4. Very low knowledge
5. **None knowledge** **(NFL)**

The results of NFL theorem are critics when we compare situations (2) and (5).

Why this hybrid model?

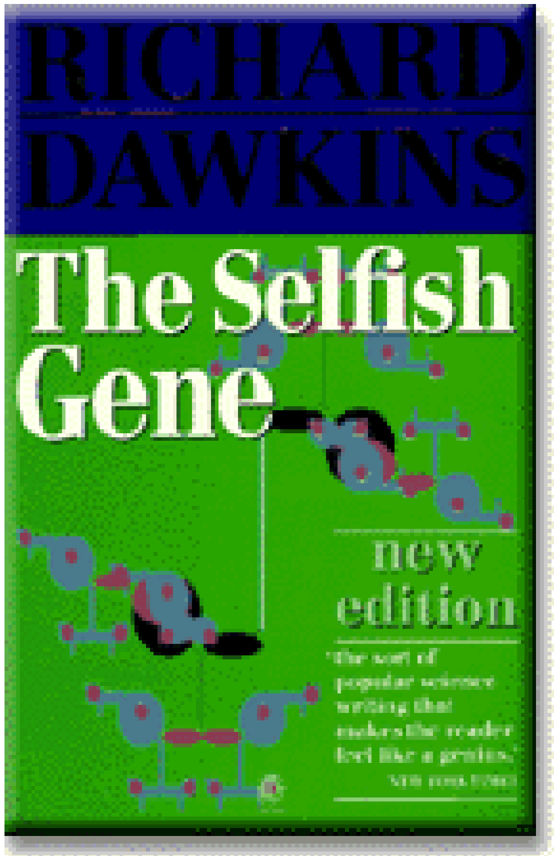
The EAs can improve their behaviour with knowledge incorporation:

Memetic Algorithms

Memetic Algoriths: Basic concepts

- The Memetic Algorithms (MAs) are constructed on the notion of *meme.*
- Meaning: Imitation unit, analogy to a gen but in the context of “cultural evolution”.
- The term was introduced by por Richard Dawkins in the book “The Selfish Gene” (University Press, 1976)

Memetic Algoriths: Basic concepts



«Examples of memes are tunes, ideas, catch-phrases, clothes fashions, ways of making pots or of building arches. Just as genes propagate themselves in the gene pool by leaping from body to body via sperms or eggs, so memes propagate themselves in the meme pool by leaping from brain to brain via a process which, in the broad sense, can be called imitation.»

R. Dawkins, 1976

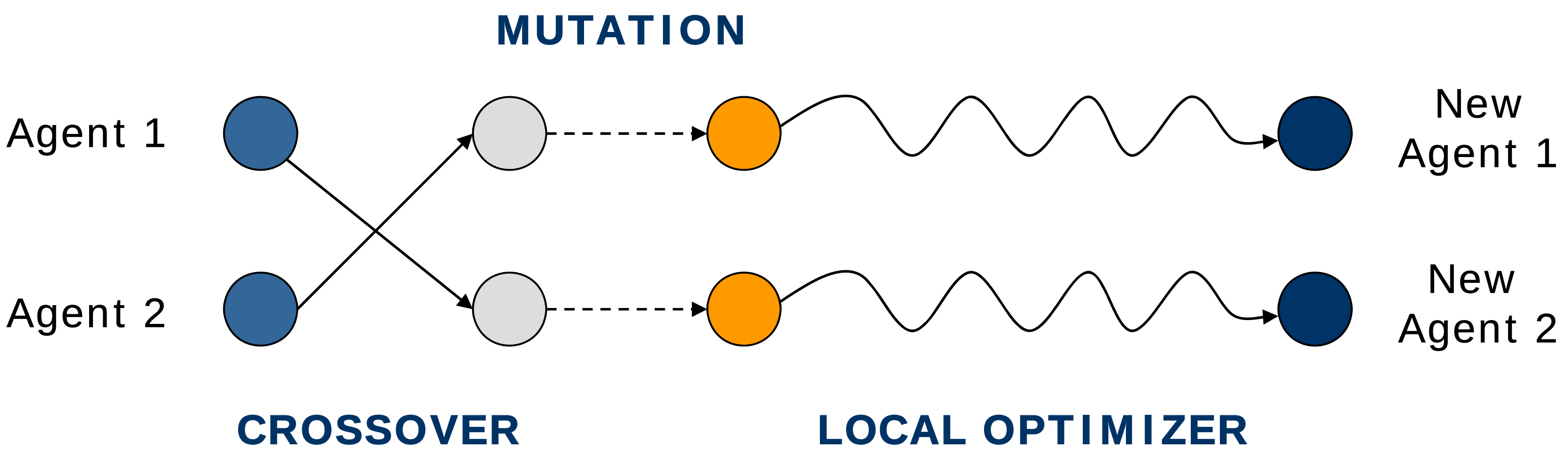
Memetic Algoriths: Basic concepts

A Memetic Algorithm is a population of agents that alternate periods of self-improvement (via local search) with periods of cooperation (via recombination), and competition (via selection).

P. Moscato, 1989

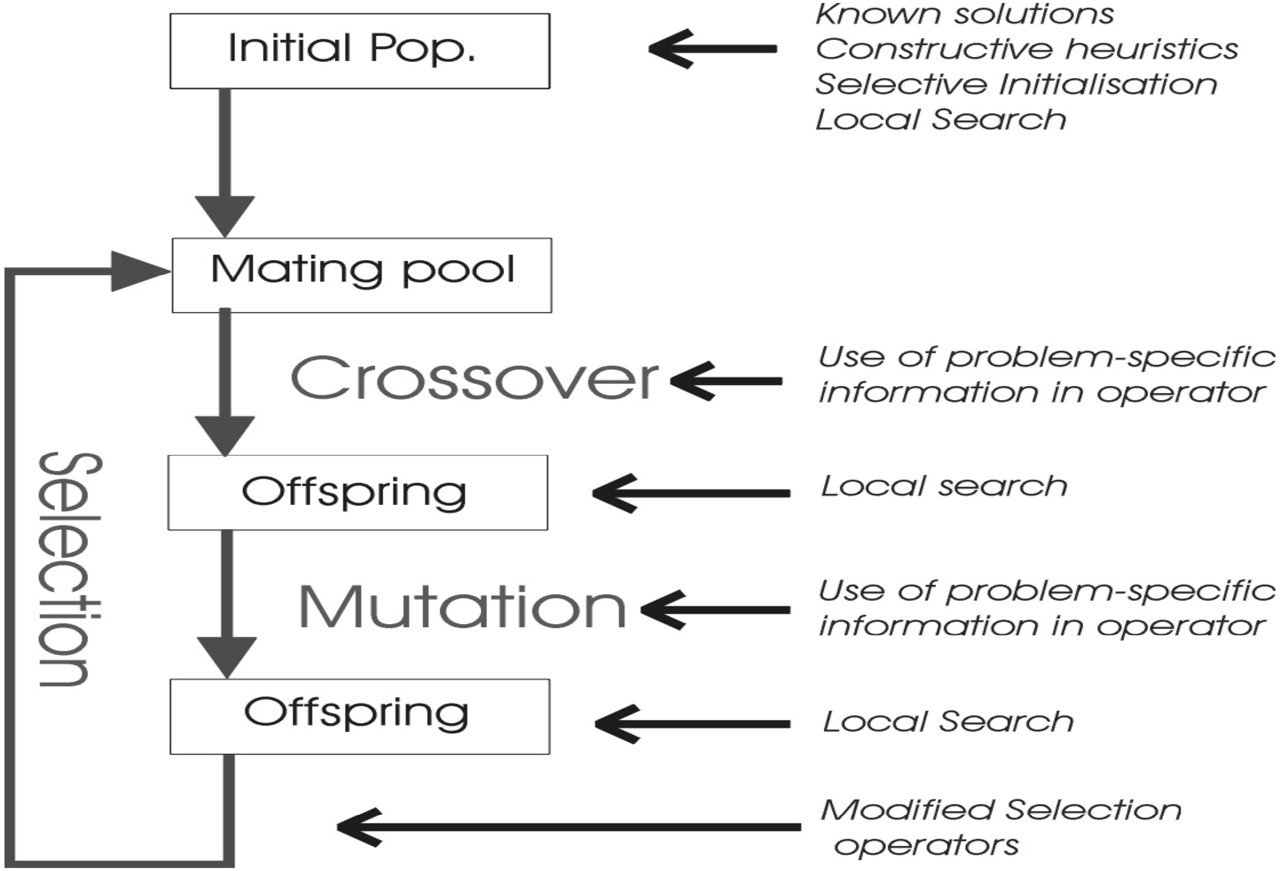
Moscato, P.A. (1989). On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms. Caltech Concurrent Computation Program Report 826, Catech, Pasadena, California.

Memetic Algorithms: Basic concepts



Memetic Algoriths: Basic concepts

Other hybridations



Memetic Algoriths: Basic concepts

Multiobjective memetic algorithms

- *M-PAES*

  M-PAES: a memetic algorithm for multiobjective optimization
  Knowles, J.D.; Corne, D.W.;
  Evolutionary Computation, 2000. Proceedings of the 2000 Congress on
  Volume 1, 16-19 July 2000 Page(s):325 - 332 vol.1

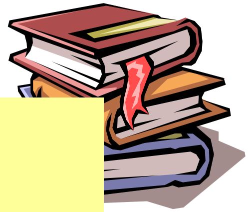
- *MOGLS*

  Genetic Local Search for Multi-Objective Combinatorial Optimization
  Andrzej Jaszkiewicz
  European Journal of Operational Research 137, 2002, 50-71.

  Balance between genetic search and local search in memetic algorithms for multiobjective permutation flowshop scheduling
  Ishibuchi, H.; Yoshida, T.; Murata, T.;
  Evolutionary Computation, IEEE Transactions on 7:2 (2003), 204 – 223

http://sci2s.ugr.es/docencia/index.php **(link course)**

Memetic Algoriths: Recent studies



N. Krasnogor and J.E. Smith.
A tutorial for competent memetic algorithms: model, taxonomy and design issues.
IEEE Transactions on Evolutionary Computation 9(5):474- 488, 2005.

Y.S. Ong and M.-H. Lim and N. Zhu and K.W. Wong.
Classification of Adaptive Memetic Algorithms: a Comparative Study
IEEE Transactions on System, Man. and Cybernetics. Part B: Cybernetics 36:1, 141-152, 2006.

J. E. Smith. Coevolving Memetic Algorithms: A Review and Progress Report. IEEE Transactions on System, Man, and Cybernetics. Part B: Cybernetics 37:1, 2007, 6-17.

IEEE TRANSACTIONS ON
SYSTEMS, MAN, AND CYBERNETICS
PART B: CYBERNETICS

Y.S. Ong, N. Krasnogor, H. Ishibuchi (Eds.)
SPECIAL ISSUE ON MEMETIC ALGORITHMS.
IEEE Transactions on System, Man. and Cybernetics. Part B: Cybernetics Vol. 37, No. 1, Feb 2007

Recent Advances in Memetic Algorithms
Studies in Fuzziness and Soft Computing, Vol. 166
Hart, William E.; Krasnogor, N.; Smith, J.E. (Eds.)
2005, X, 408 p., Hardcover
ISBN: 3-540-22904-3

3. MEMETIC ALGORITHMS

Basic Bibliography http://sci2s.ugr.es/docencia/index.php (link course)

P. Moscato, "Memetic Algorithms: A short introduction", *New Ideas in Optimization* (pp. 219-234), Corne D., Dorigo M., Glover F., McGraw-Hill-UK, 1999

P. Moscato, C. Cotta, "A Gentle Introduction to Memetic Algorithms", *Handbook of Metaheuristics*, F. Glover, G. Kochenberger (eds.), pp. 105-144, Kluwer Academic Publishers, Boston MA, 2003

P. Moscato, C. Cotta, "Una Introducción a los Algoritmos Memeticos", *Inteligencia Artificial. Revista Iberoamericana de IA, No. 19,2003, 131-148.*

W E Hart, N Krasnogor and J E Smith. "Memetic Evolutionary Algorithms", *Recent Advances in Memetic Algorithms,* Hart, William E.; Krasnogor, N.; Smith, J.E. (Eds.) 2005, 3-27.

N. Krasnogor and J.E. Smith.
A tutorial for competent memetic algorithms: model, taxonomy and design issues.
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Y.S. Ong and M.-H. Lim and N. Zhu and K.W. Wong.
Classification of Adaptive Memetic Algorithms: a Comparative Study
IEEE Transactions on System, Man. and Cybernetic 36:1, 141-152, 2006.

3. MEMETIC ALGORITHMS

Final comments

- The MAs exploit the available knowledge on the problem, using it embeded in the evolutionary model.
- It is very important to design the MA with a good balance between the global search (evolutionary model) and the local search. There does not exist a sistematic procedure for that.
- They show a high effectiveness in different problems.

Session b.
Genetic Algorithms:
Advanced topics

- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

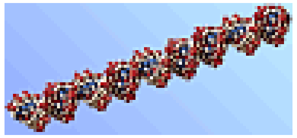
4. GENETIC LEARNING

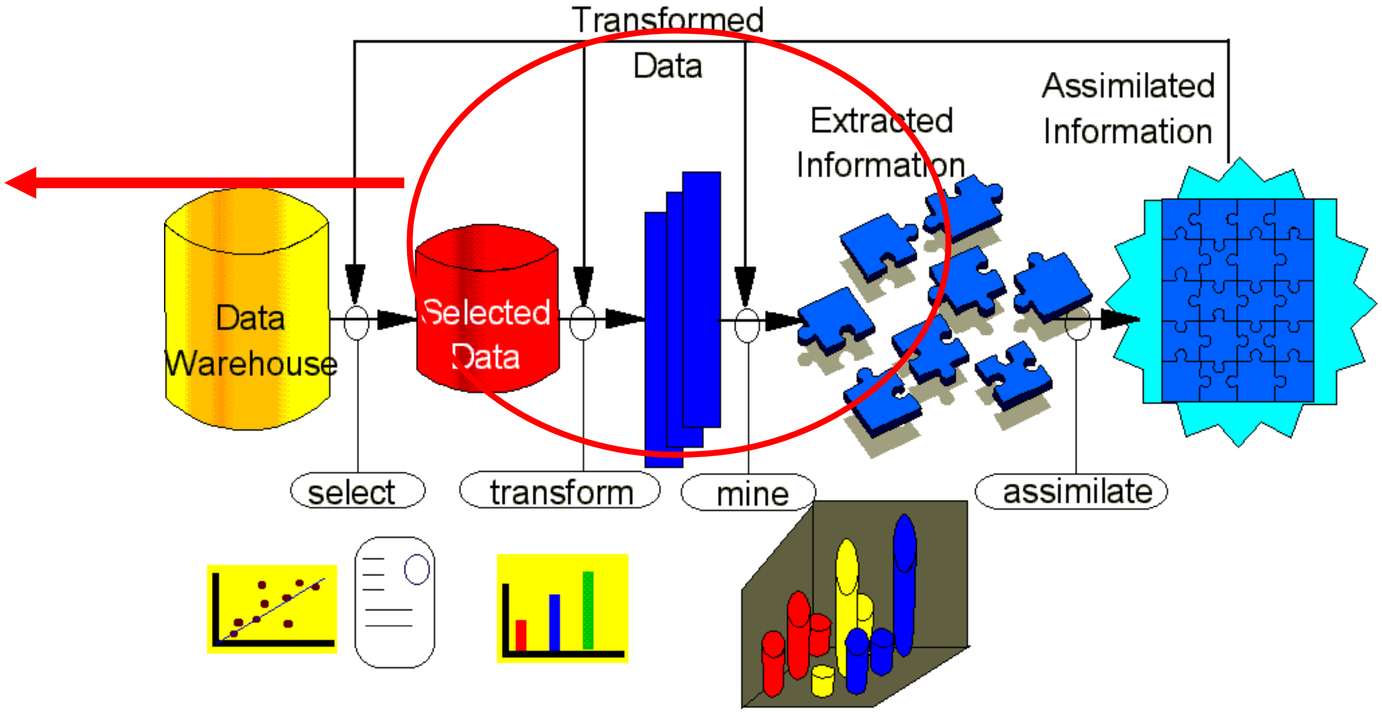
- WHY GENETIC LEARNING?
- SOME MODELS
- KEEL SOFTWARE TOOL

Why genetic learning?

The EAs were not designed as a learning paradigm.

However, a lot of learning models use optimization techniques, and EAs can be used in these optimization processes.





Why genetic learning?

We can find different ways to use Evolutionary Algorithms in knowledge extraction:

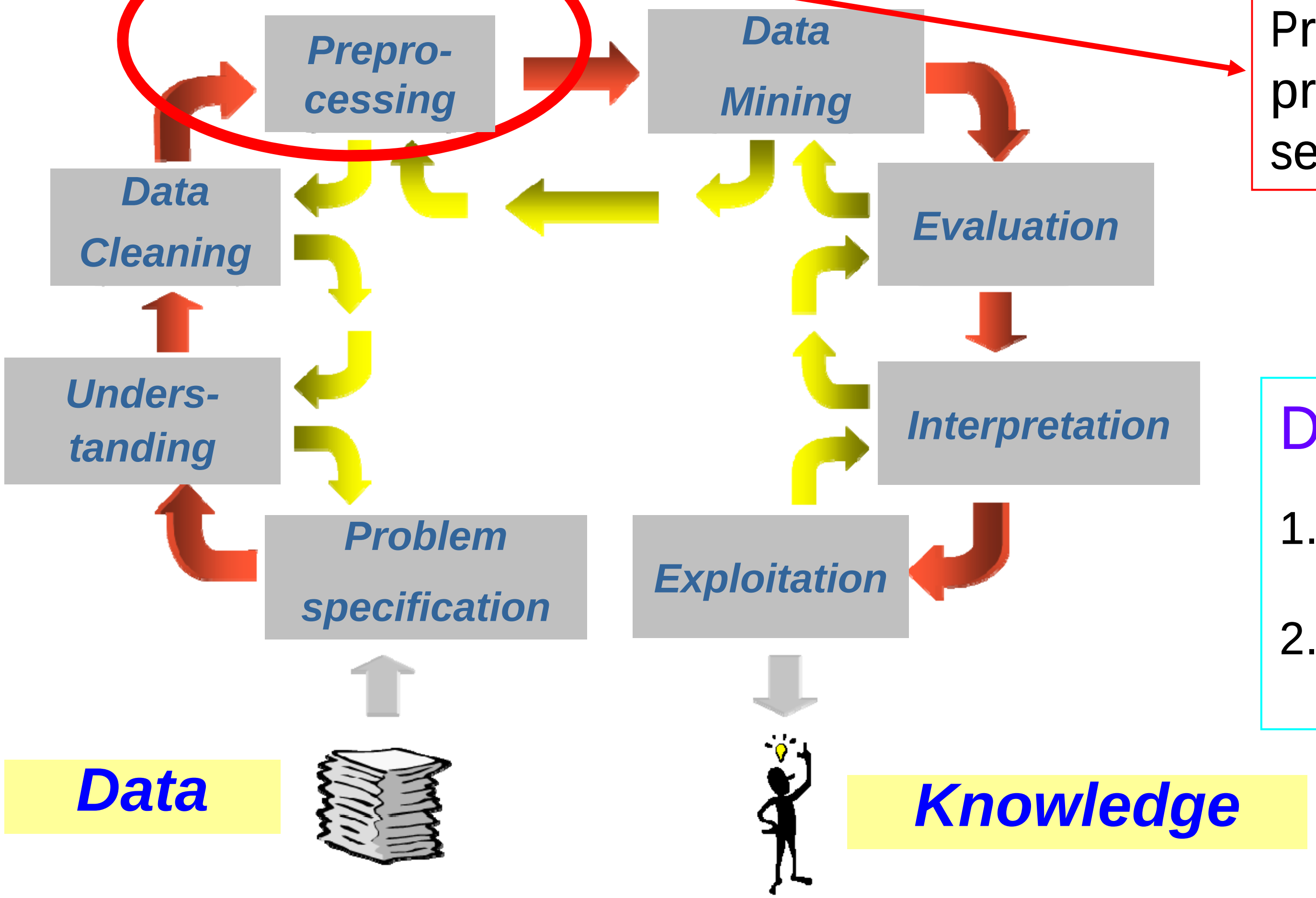
Rules genetic learning: genetic fuzzy systems, interval learning algoritms, etc.

Genetic programming in regression and classification

Hybrid evolutionary learning models: evolutionary neural networks, evolutionary instance selection, evolutionary clustering, ...

Application in different KDD steps: data redution, models extraction in Data Mining ...

Some genetic learnig models

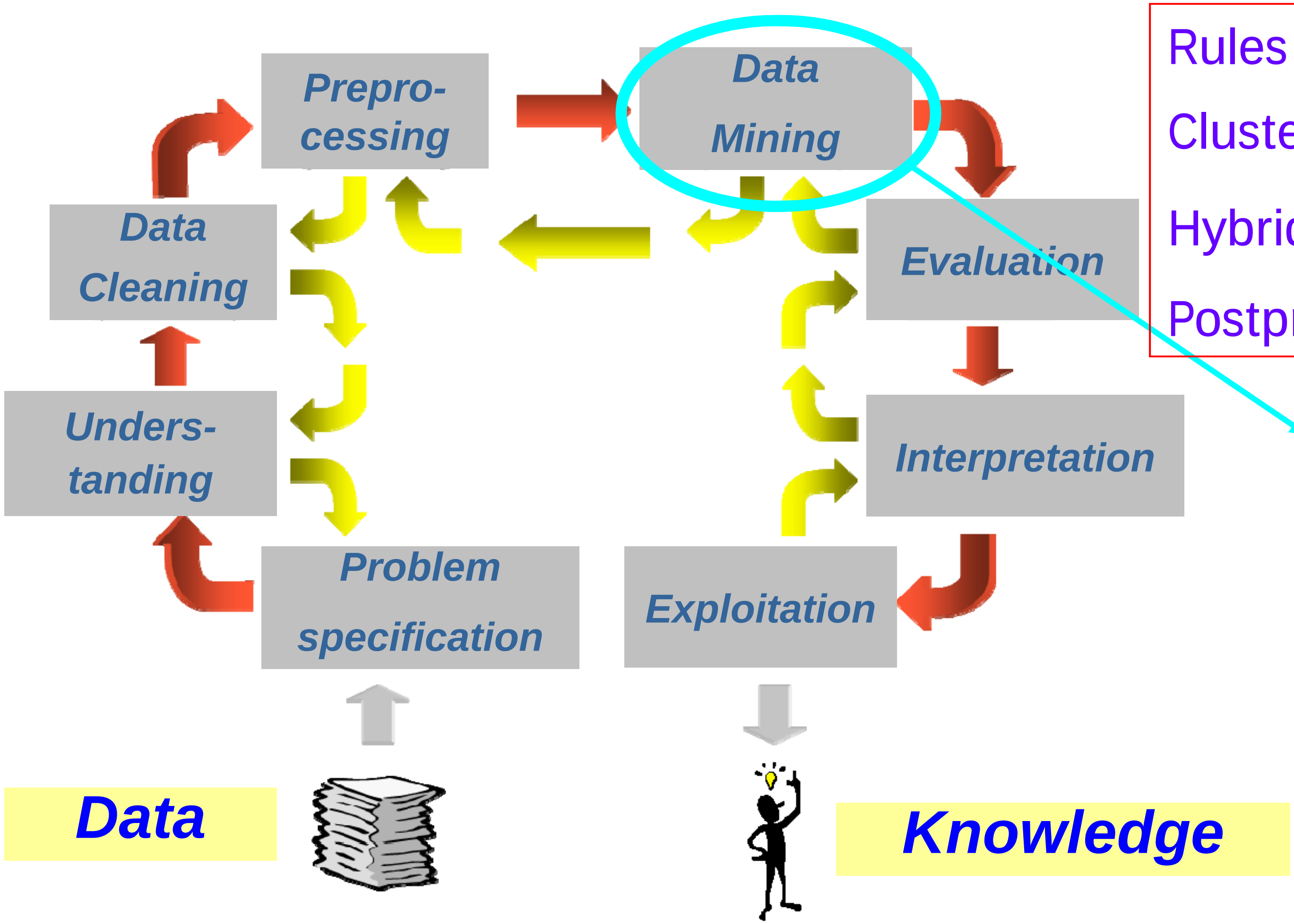


Preprocessing problems as search problems

Data Reduction

1. Feature Selection
2. Instance Selection

Some genetic learnig models



Rules extraction

Clustering

Hybrid models

Postprocesssig

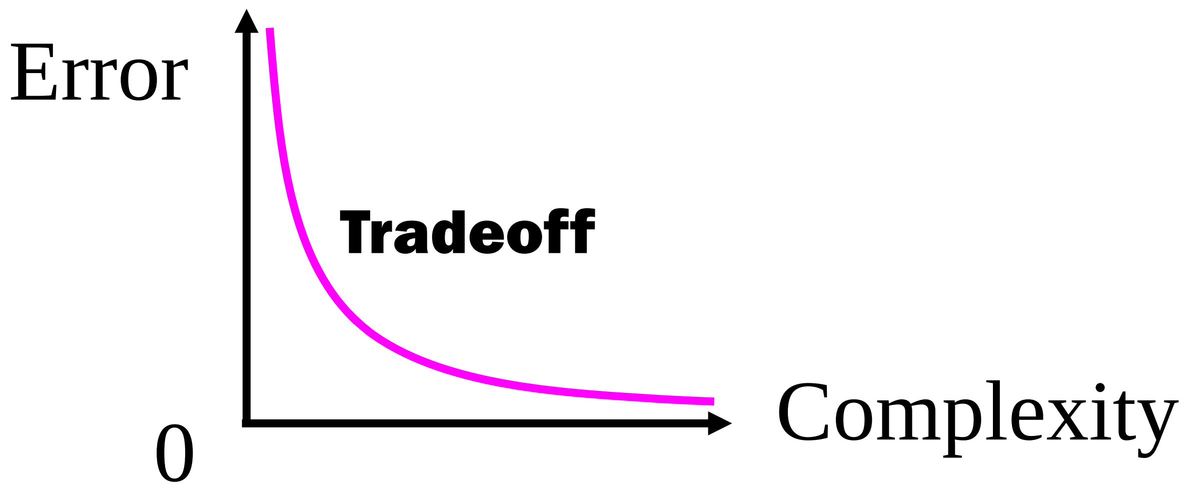
learning/ Knowledge extraction as optimization and search problems

Some genetic learnig models: Multiobjective learning

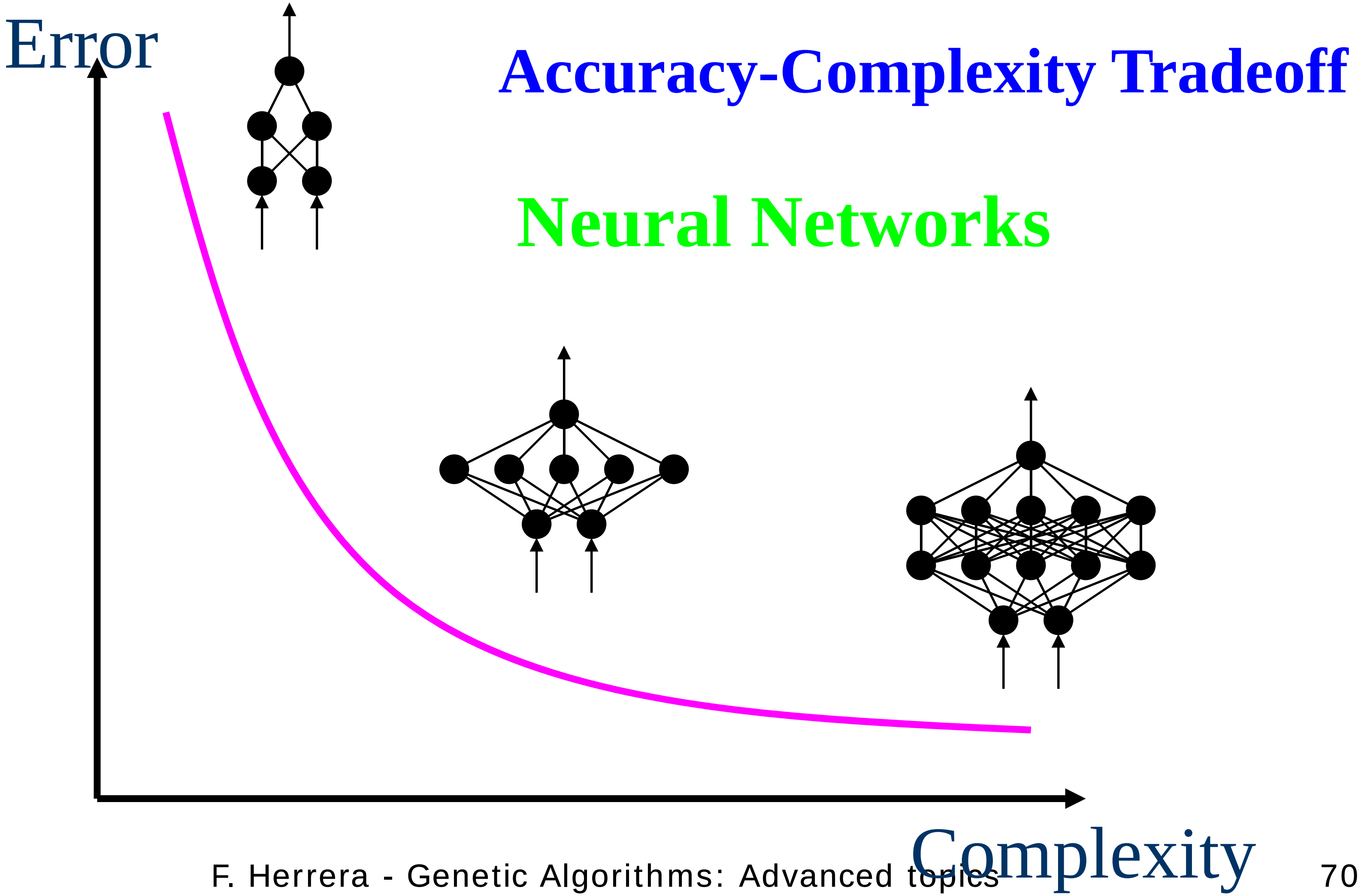
Two Goals in Knowledge Extraction

(1) **Accuracy Maximization**
(Error Minimization)

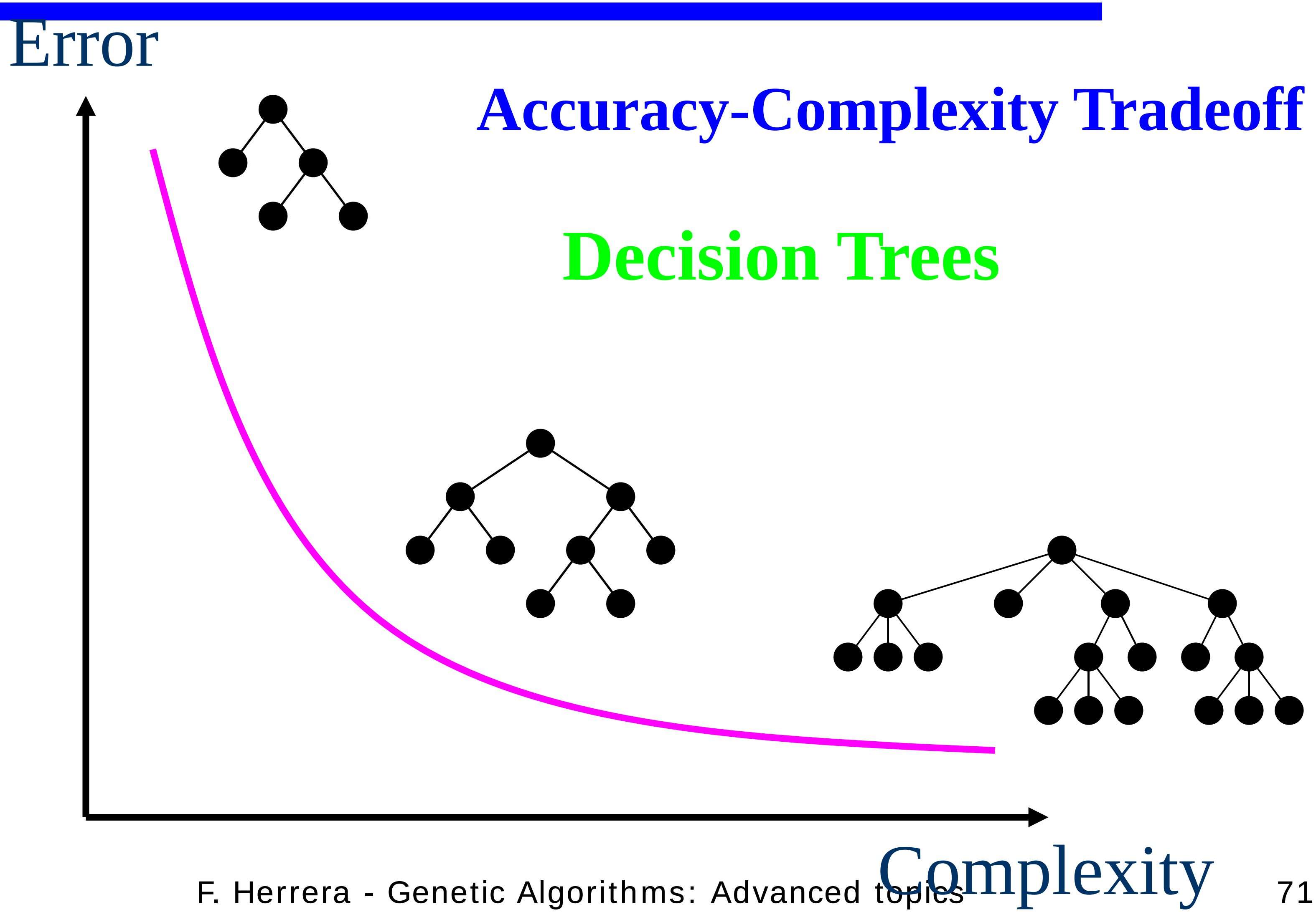
(2) **Interpretability Maximization**
(Complexity Minimization)



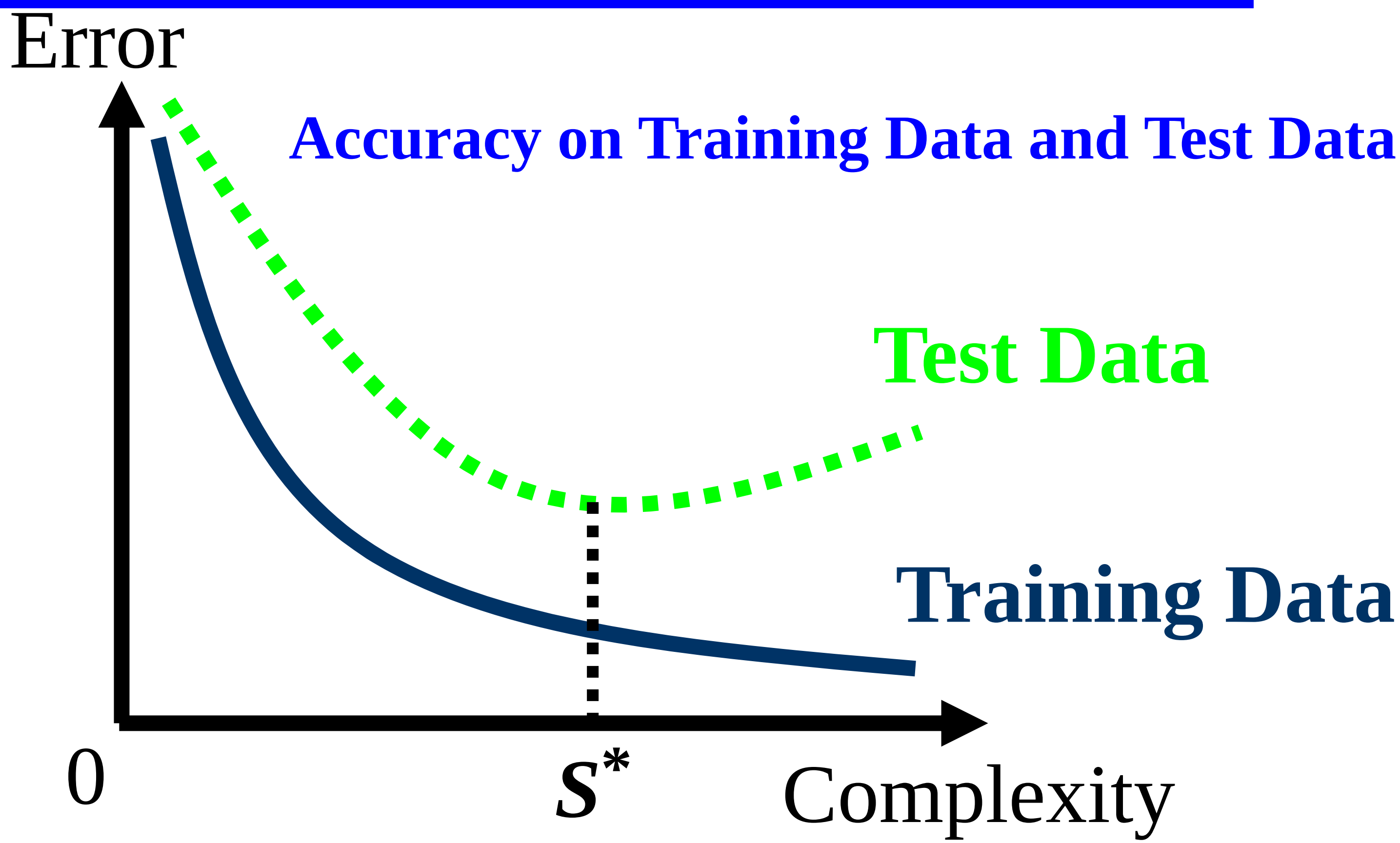
Some genetic learnig models: Multiobjective learning



Some genetic learnig models: Multiobjective learning



Some genetic learnig models: Multiobjective learning



Tradeoff between Accuracy and Complexity

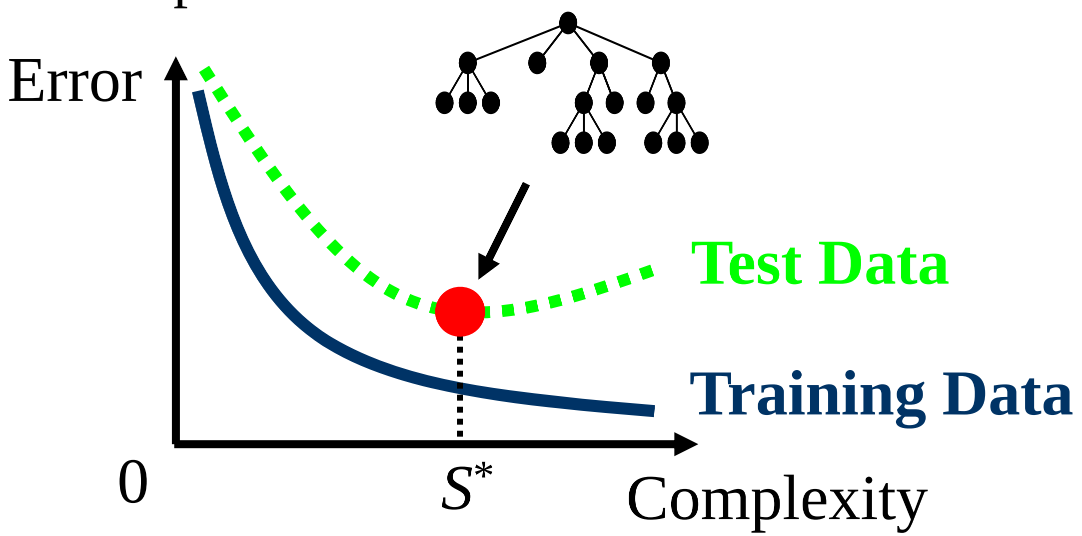
Some genetic learnig models: Multiobjective learning

Single-Objective Approach

Goal: To maximize the generalization ability.

Difficulty 1: It is very difficult to find an appropriate complexity (i.e., it is difficult to find *S**).

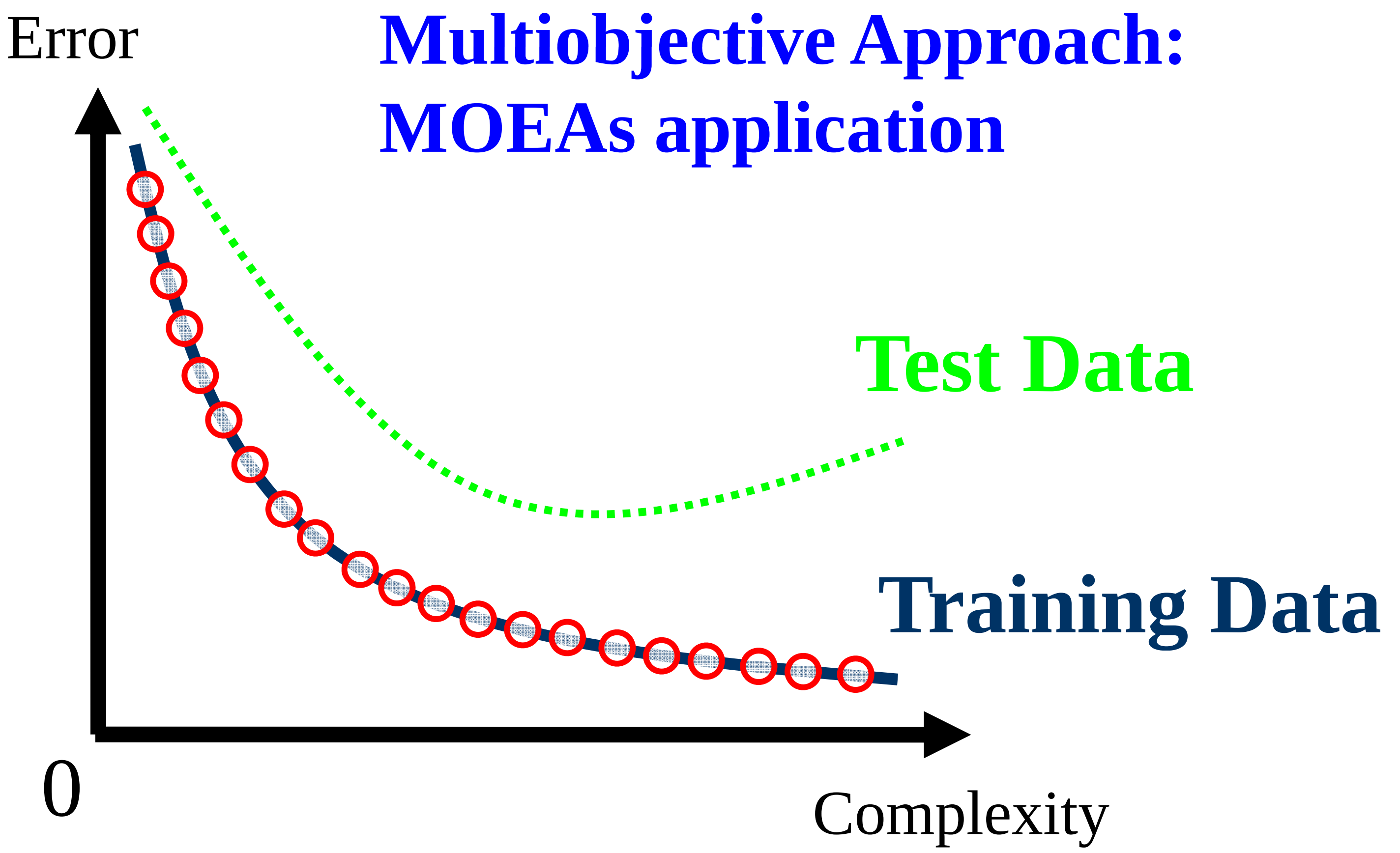
Difficulty 2: If the user thinks that the interpretability is very important, S^* may be too complicated.



Some genetic learnig models: Multiobjective learning

Goal: **To find a large number of rule sets with different accuracy-complexity tradeoffs.**

Multiobjective Approach: MOEAs application



KEEL software tool

KEEL

Knowledge Extraction based on Evolutionary Learning

http://www.keel.es/

KEEL is a software tool which allows analyzing the behaviour of evolutionary learning in the different areas of learning and preprocessing tasks, making easy to the user the management of these techniques.

J. Alcalá, et al.

KEEL: A Software Tool to Assess Evolutionary Algorithms to Data Mining Problems.

Soft Computing 13:3 (2009) 307-318, doi: 10.1007/s00500-008-0323-y

KEEL software tool

KEEL software tool

KEEL software tool

The currently available version of KEEL consists of the following function blocks:

Data Management: *This part is composed of a set of tools that can be used to build new data, export and import data in other formats to KEEL format, data edition and visualization, apply transformations and partitioning to data, etc...*

Design of Experiments (off-line module): *The aim of this part is the design of the desired experimentation over the selected data sets. It provides options for many choices: type of validation, type of learning (classification, regression, unsupervised learning), etc...*

Educational Experiments (on-line module): *With a similar structure to the previous part, allows us to design an experiment which can be step-by-step debugged in order to use this as a guideline to show the learning process of a certain model by using the platform with educational objectives.*

KEEL software tool

Shortly, we can describe the main features of KEEL.

Evolutionary algorithms are presented in predicting models, pre-processing and postprocessing

It includes data pre-processing algorithms: data transformation, discretization, instance selection and feature selection.

It has a statistical library to analyze algorithms' results: parametric and non-parametric comparisons among the algorithms.

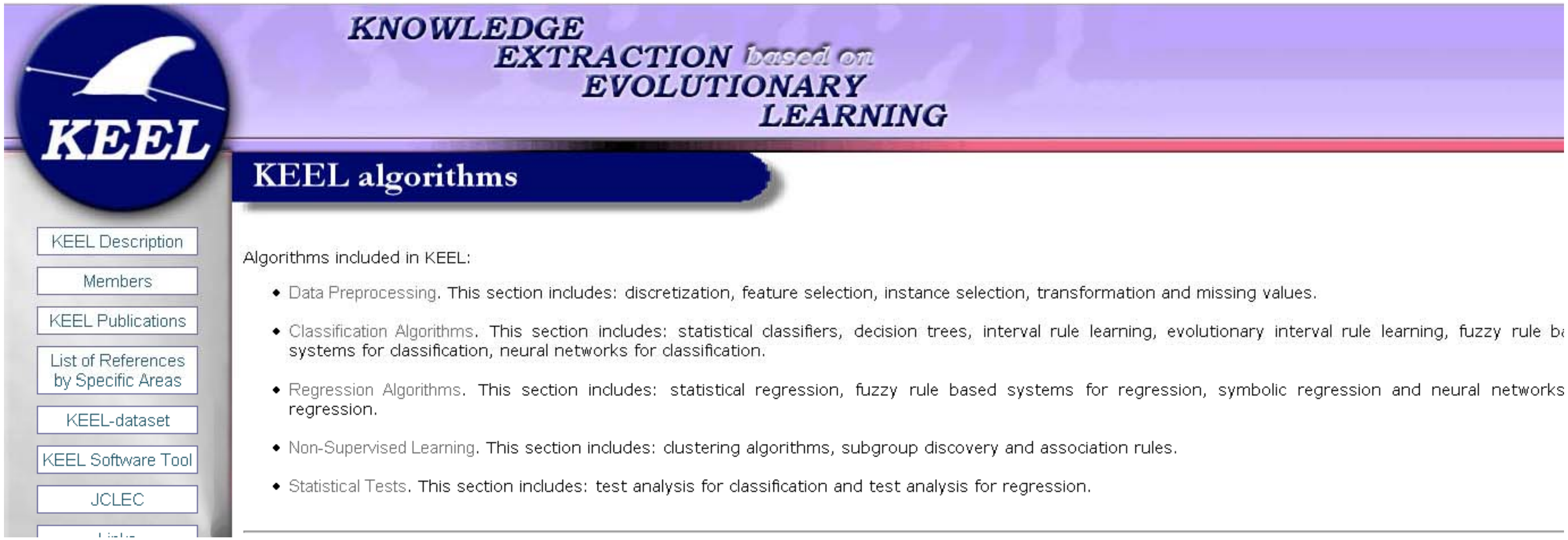
It provides an user-friendly interface, oriented to the analysis of algorithms.

The software is aimed to create experimentations containing multiple data sets and algorithms connected among themselves to obtain a result expected. Experiments are independently script-generated from the user interface for an off-line run in the same or other machines.

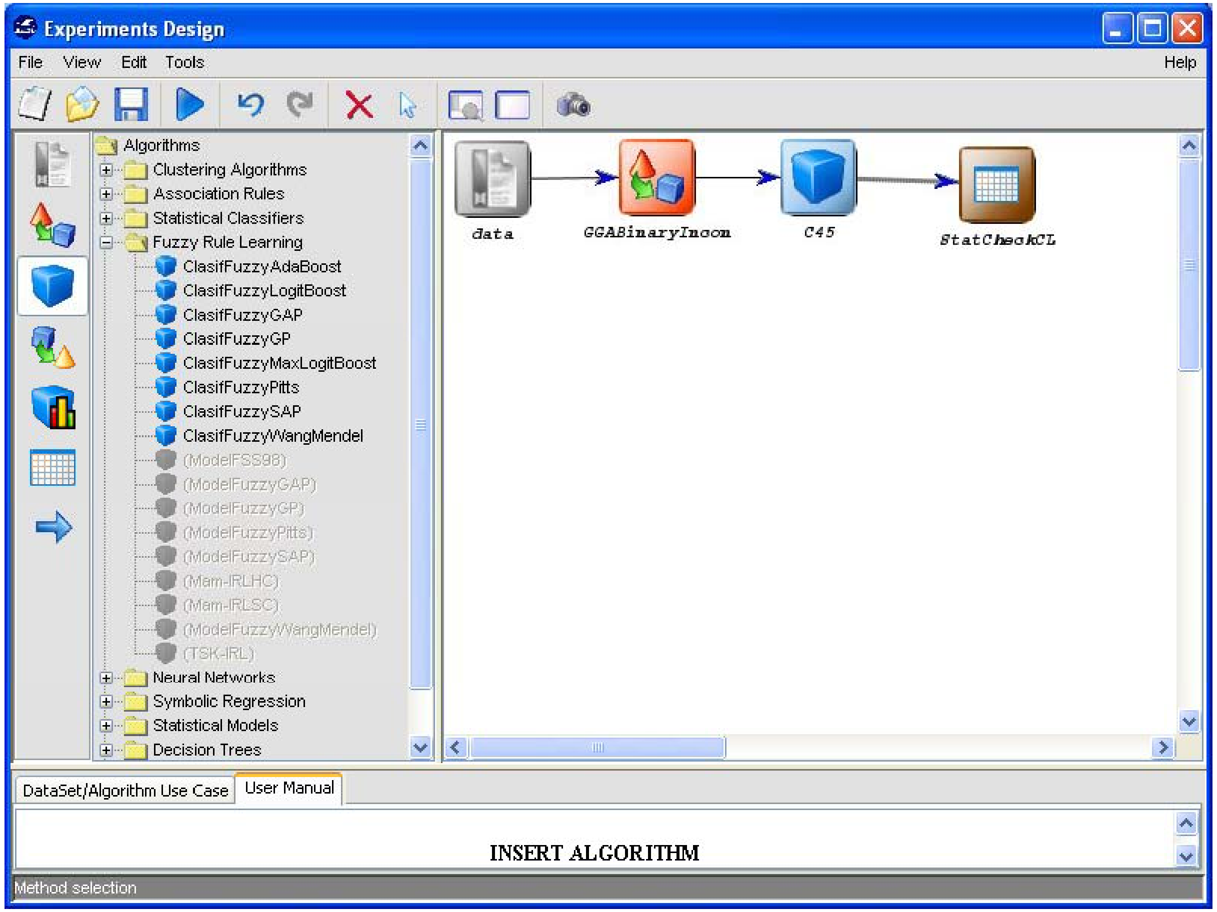
KEEL also allows to create experiments in on-line mode, aiming an educational support in order to learn the operation of the algorithms included.

KEEL software tool

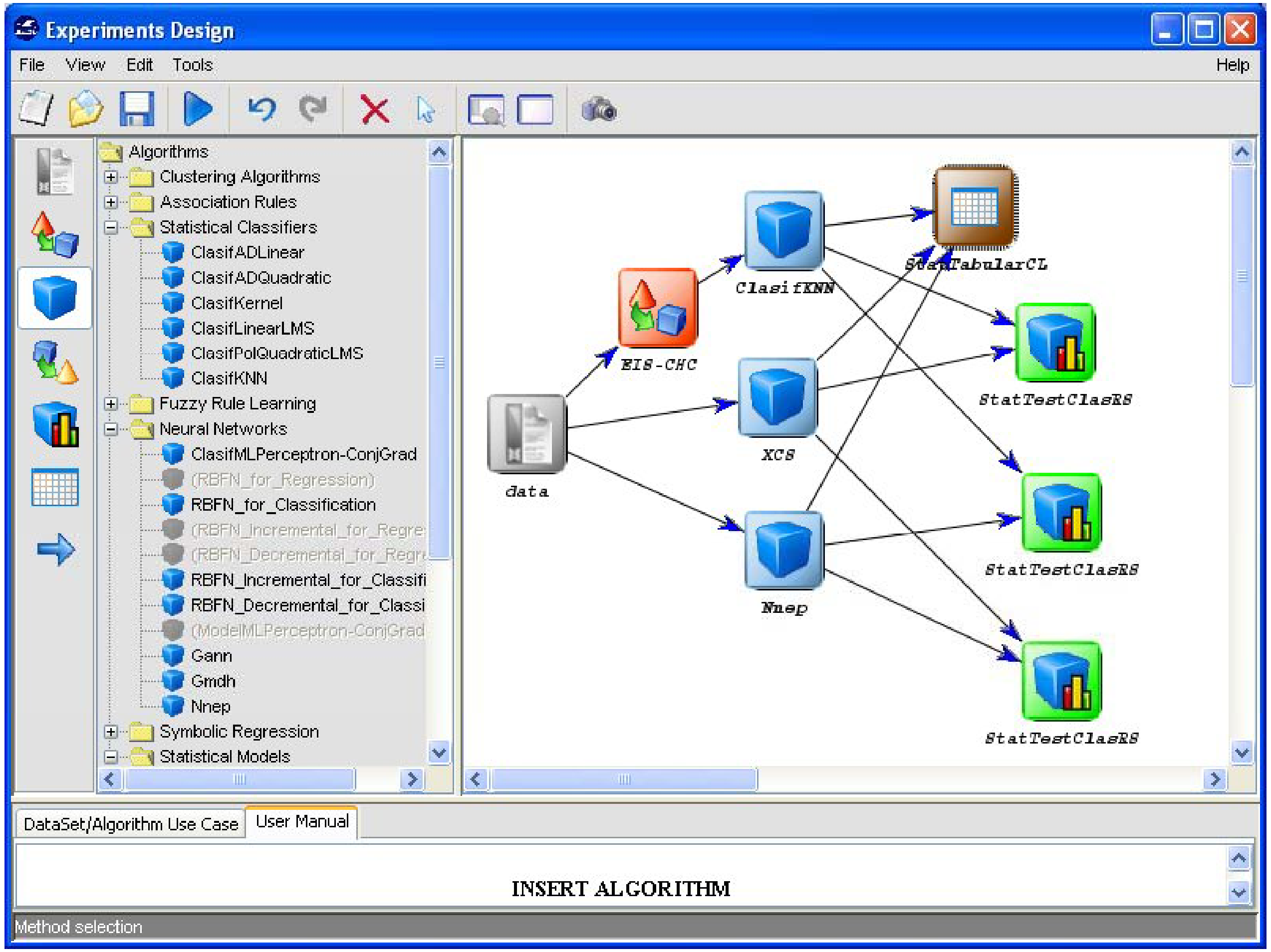
It contains a Knowledge Extraction Algorithms Library, remarking the incorporation of multiple evolutionary learning algorithms, together with classical learning approaches



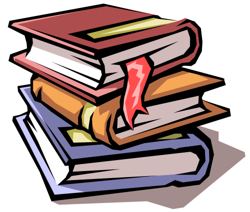
KEEL software tool



KEEL software tool



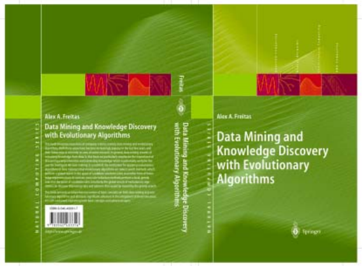
4. GENETIC LEARNING



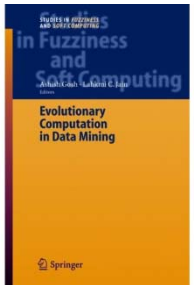
Bibliography

John J. Grefenstette (Eds.)
Genetic Algorithms for Machine Learning. Kluwer-Academic, 1993.

Sankar K. Pal and Paul P. Wang (Eds.)
Genetic Algorithms for Pattern Recognition CRC Press, 1996.

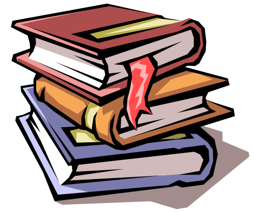


A.A. Freitas, *Data* Mining and Knowledge Discovery with Evolutionary Springer-Verlag, 2002.



A. Ghosh, L.C. Jain (Eds.), Evolutionary Computation in Data Mining. Springer-Verlag, 2005.

4. GENETIC LEARNING



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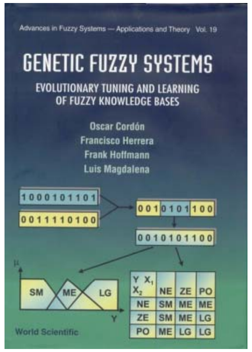
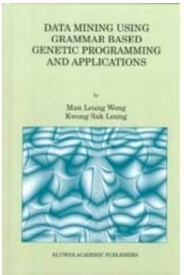
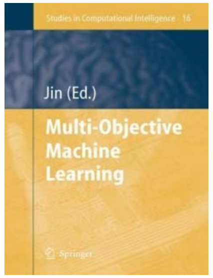


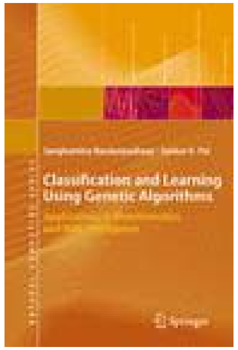
O. Cordón, F. Herrera, F. Hoffmann, L. Magdalena GENETIC FUZZY SYSTEMS. Evolutionary Tuning and Learning of Fuzzy Knowledge Bases. World Scientific, Julio 2001.



M.L. Wong, K.S. Leung, *Data Mining using Grammar Based Genetic Programming and Applications*. Kluwer Academics Publishers, 2000.



Y. Jin (Ed.) Multi-Objective Machine Learning Springer-Verlag, 2006.



S. Bandyopadhyay, S.K. Pal. Classification and Learning Using Genetic Algorithms. Springer, 2007.

4. GENETIC LEARNING

Final comments: Some new challenges

Scalability of the evolutionary algorithms for knowledge extraction in large data sets.

Distributed genetic learning.

Multiobjective genetic learning including two or more objectives: precision and intepretability measures.

Genetic Algorithms: Introduction and Advanced Topics

¡Thanks!