Multiobjective Genetic Fuzzy Systems: Review and Future Research Directions

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In this presentation

1. Evolutionary Multiobjective Optimization

2. Multiobjective Genetic Fuzzy Systems

3. Related Issues and Future Directions

Evolutionary Multiobjective Optimization

Evolutionary multiobjective optimization (EMO) is a very active research area in evolutionary computation.

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Major Evolutionary Computation Conferences

GECCO 2006 (Seattle, USA, July 8-12)
CEC 2006 (Vancouver, Canada, July 16-21)
PPSN 2006 (Reykjavik, Iceland, September 9-13)
EMO 2007 (Sendai, Japan, March 5-8)
GECCO 2007 (London, UK, July 7-11)

Many papers are related to multiobjective optimization.
The number of EMO papers is still increasing.

Popularity of EMO Research

Most frequently cited papers published in *IEEE Transactions on Evolutionary Computation* during 1999-2007 (All TEC papers in ISI)

1. Zitzler E, Thiele L (1999) **Multiobjective evolutionary algorithms: A comparative case study and the Strength Pareto approach.** Times Cited: 312
2. Deb K et al. (2002) **A fast and elitist multiobjective genetic algorithm: NSGA-II.** Times Cited: 309
3. Clerc M, Kennedy J (2002) The particle swarm - Explosion, stability, and convergence in a multidimensional complex space. Times Cited: 162
4. Eiben AE, Hinterding R, Michalewicz Z (1999) Parameter control in evolutionary algorithms. Times Cited: 129
5. Yao X, Liu Y, Lin GM (1999) Evolutionary programming made faster. Times Cited: 112

Data from ISI Web of Science, Thomson Scientific (July 21, 2007)

Popularity of EMO Research

Most frequently cited papers published in *IEEE Transactions on Evolutionary Computation* **in the recent 5 years (2003-2007)**

1. Zitzler E et al. (2003) **Performance assessment of multiobjective optimizers: An analysis and review.** Times Cited: 66
2. Coello CAC, Pulido GT, Lechuga MS (2004) **Handling multiple objectives with particle swarm optimization.** Times Cited: 43
3. Ishibuchi H, Yoshida T, Murata T (2003) **Balance between genetic search and local search in memetic algorithms for multiobjective permutation flowshop scheduling.** Times Cited: 39
4. Lee CY, Yao X (2004) Evolutionary programming using mutations based on the Levy probability distribution. Times Cited: 37
5. Van den Bergh F, Engelbrecht AP (2004) A cooperative approach to particle swarm optimization. Times Cited: 29

Data from ISI Web of Science, Thomson Scientific (July 21, 2007)

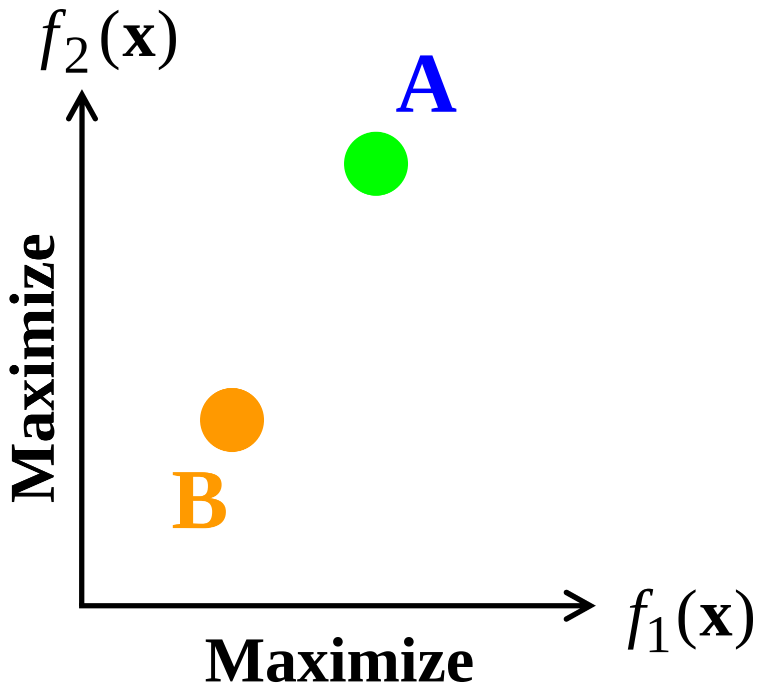
Multiobjective Optimization

Multiobjective optimization problem with *k* objectives:

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

Comparison between Two Solutions

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



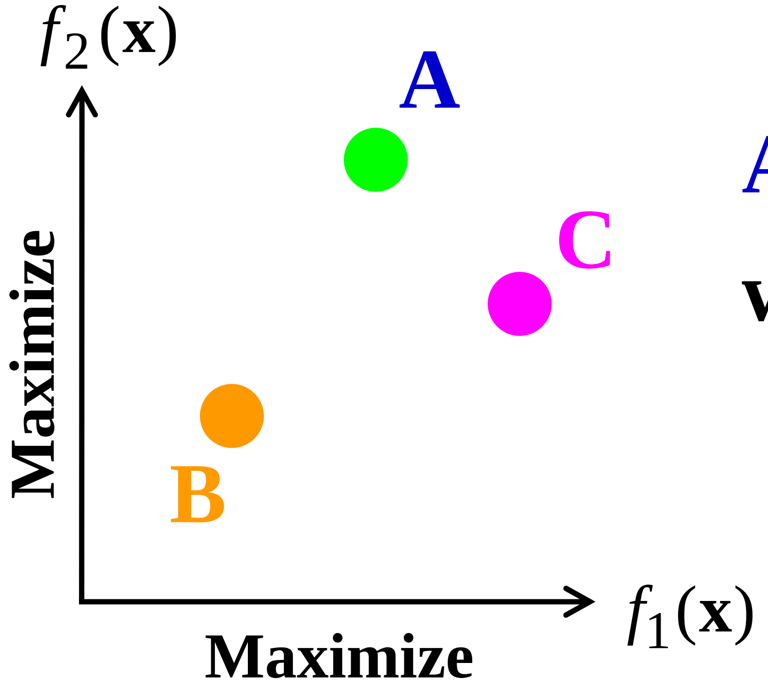
A dominates B

B is dominated by A

(A is better than B)

Comparison between Two Solutions

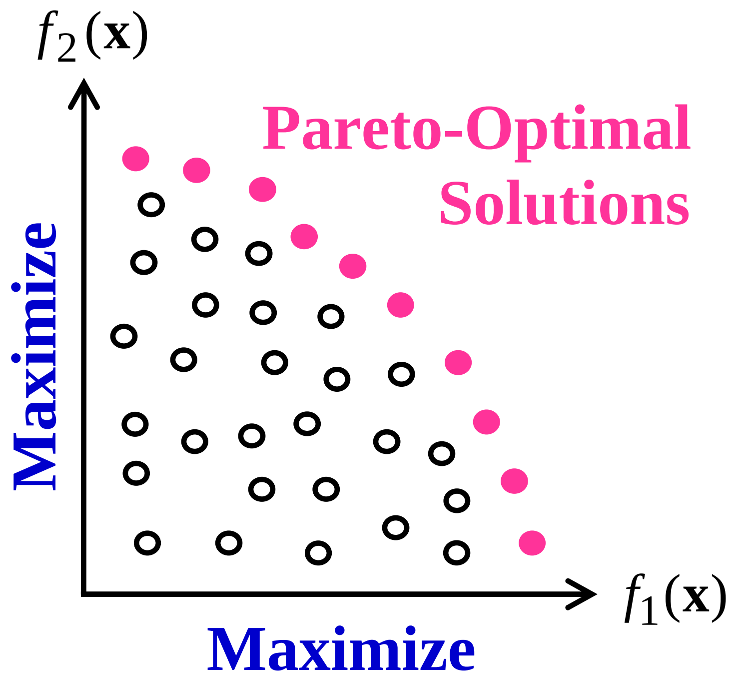
Maximize $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}),\ f_2(\mathbf{x}))$



A and C are non-dominated with each other.

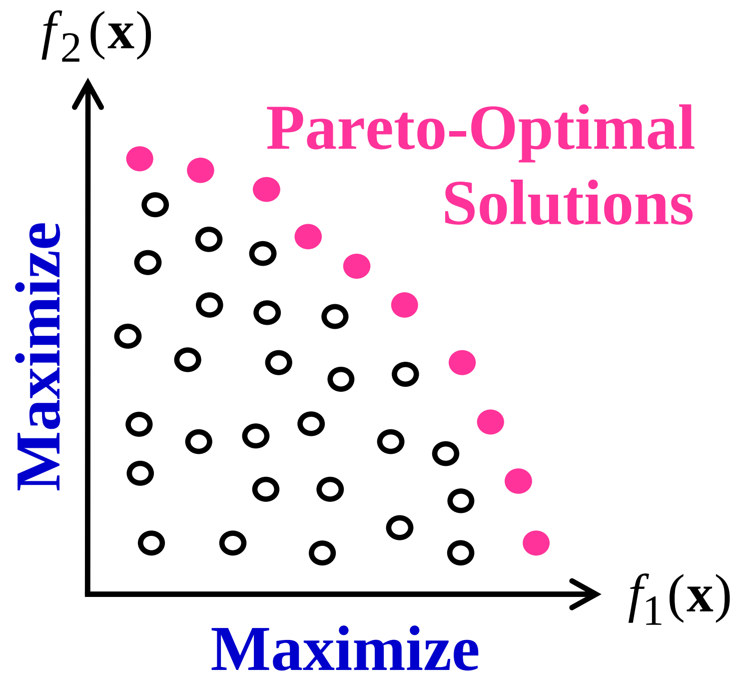
Pareto-Optimal Solutions

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



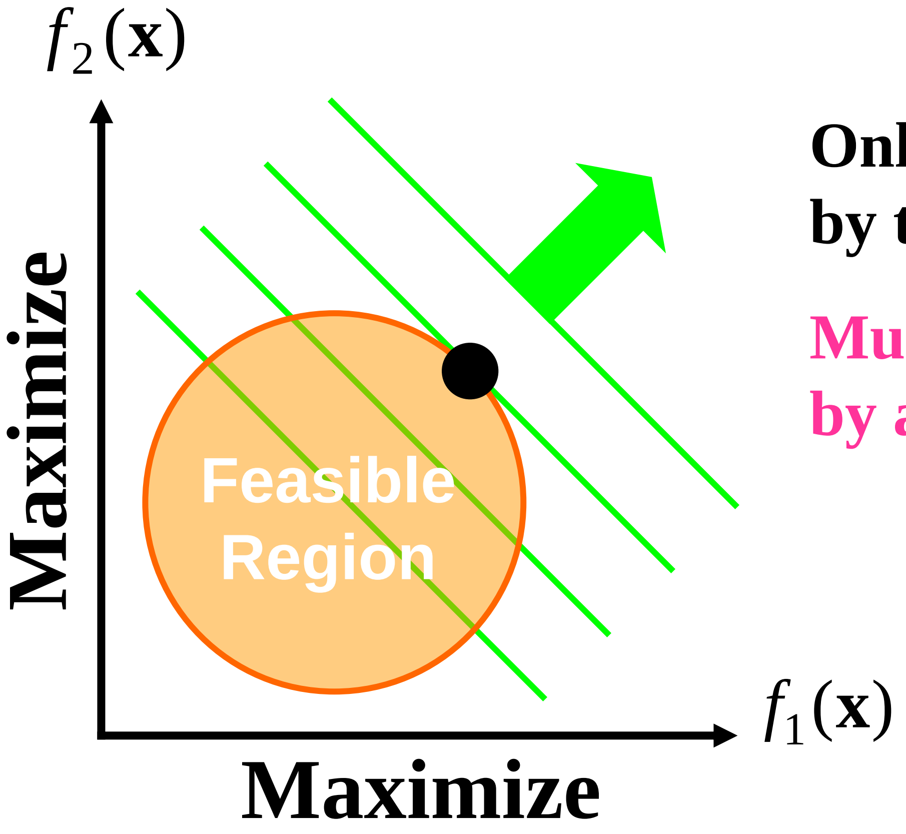
EMO Algorithm

EMO algorithms are design to efficiently search for Pareto-optimal solutions as many as possible in their single run.



Comparison: Weighted Sum Approach

Maximize $g(\mathbf{x}) = w_1 f_1(\mathbf{x}) + w_2 f_2(\mathbf{x})$

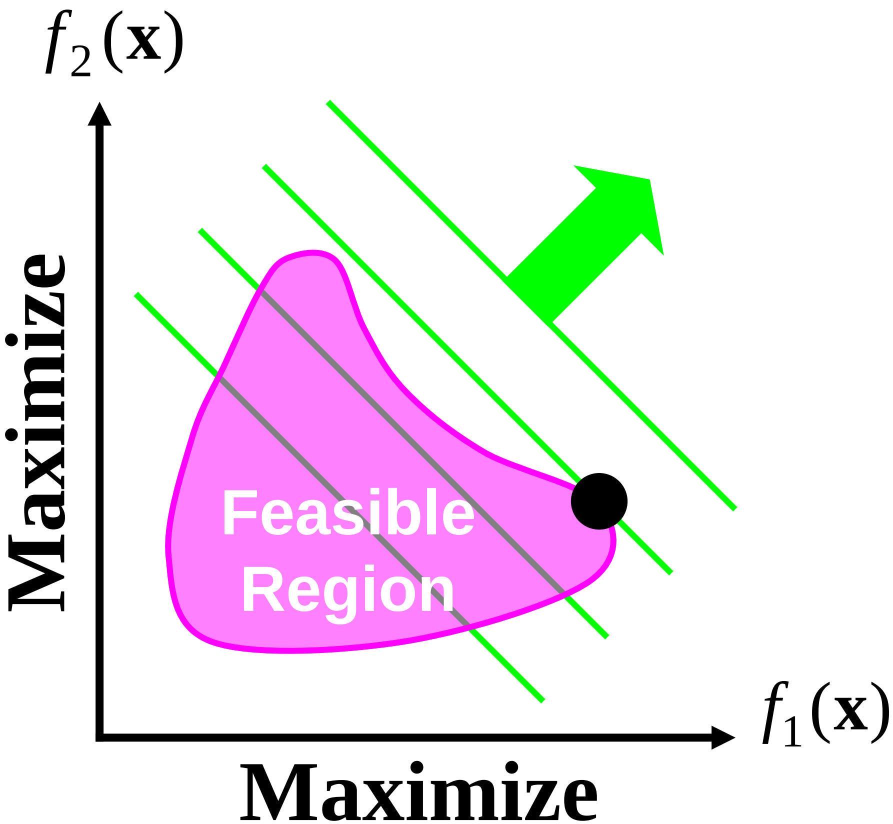


Only a single solution is obtained by the weighted sum approach.

Multiple solutions are obtained by an EMO algorithm.

Difficulties in Weighted Sum Approach

- **This approach is sensitive to the specification of the weight vector.**
- **This approach can not find any Pareto-optimal solutions in a non-convex region of the Pareto front in the objective space.**



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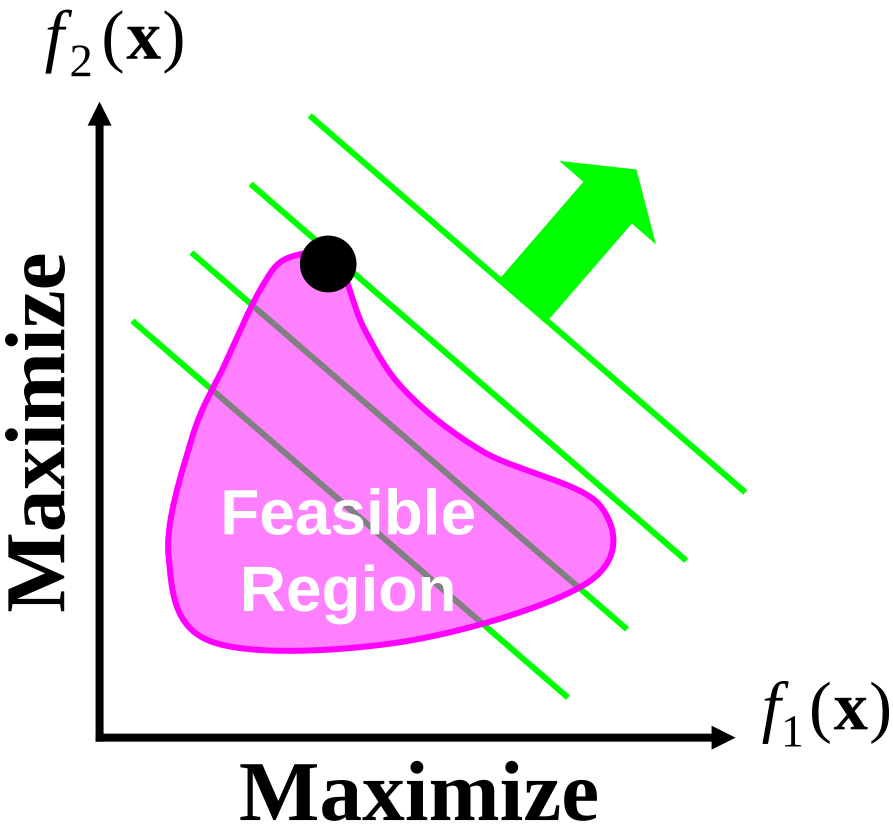

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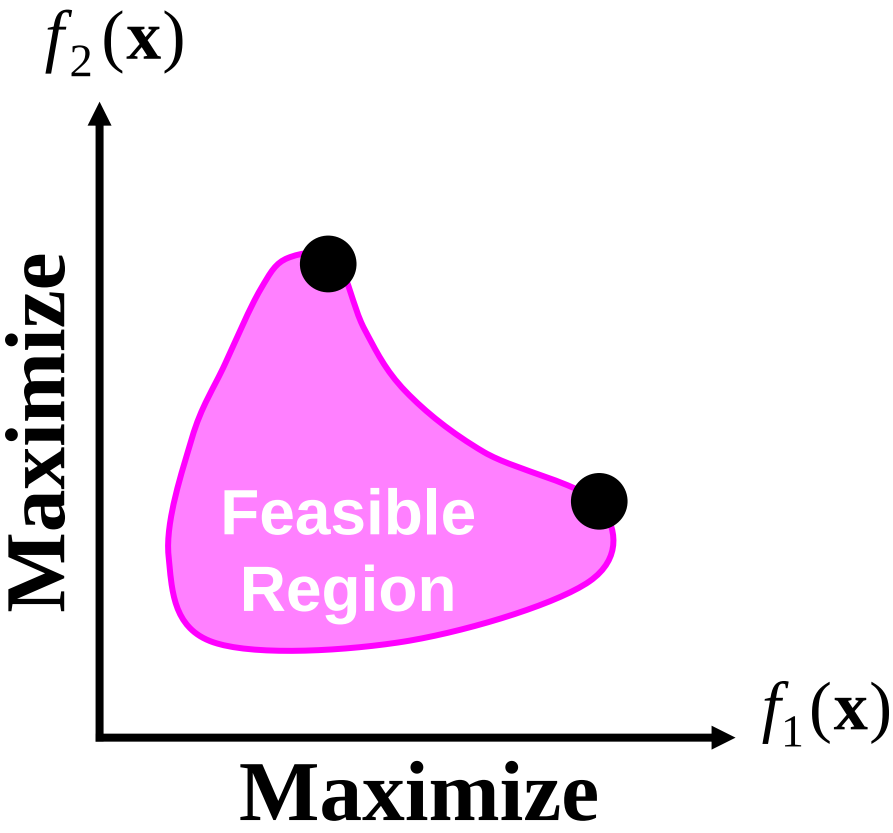
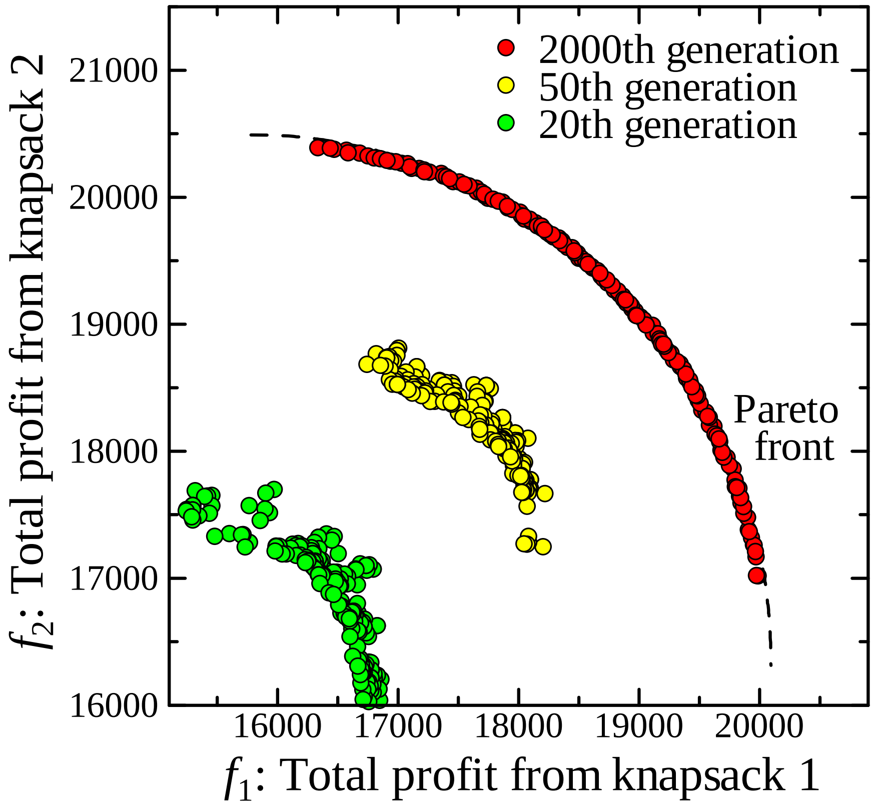
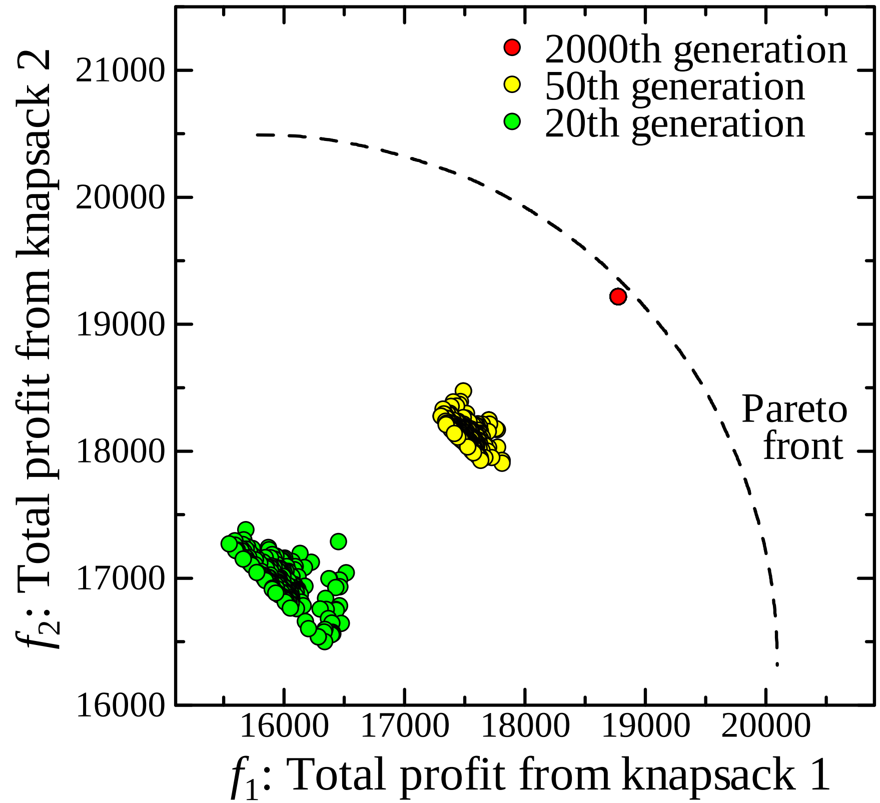


Comparison of the Two Approaches

Two-objective maximization problem



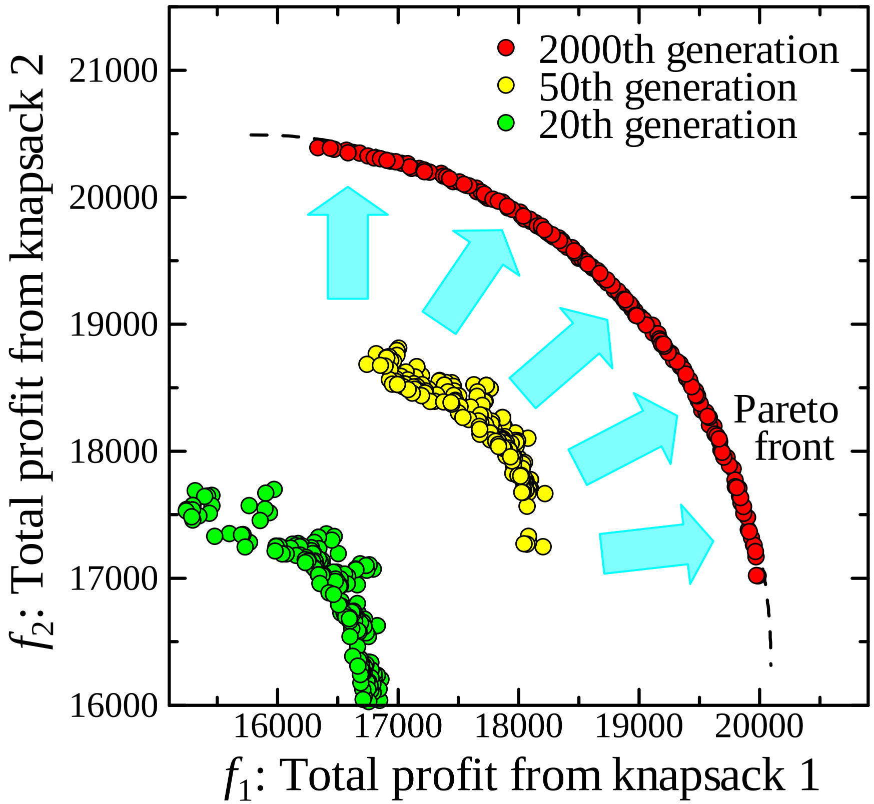
EMO Approach



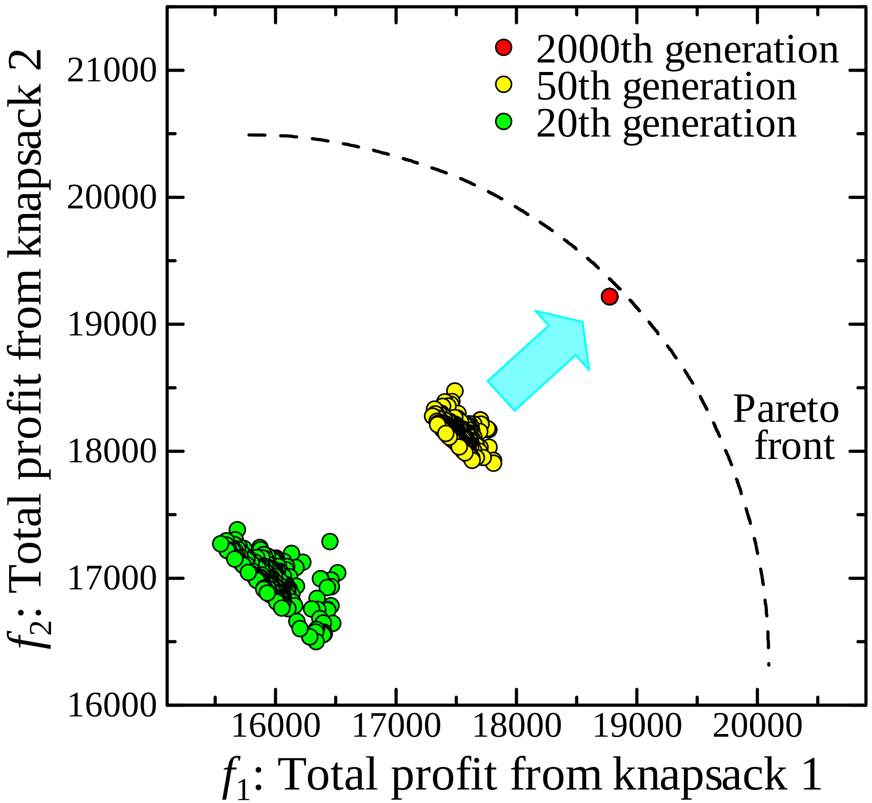
Weighted Sum Approach

Search Direction in Each Approach

Two-objective maximization problem

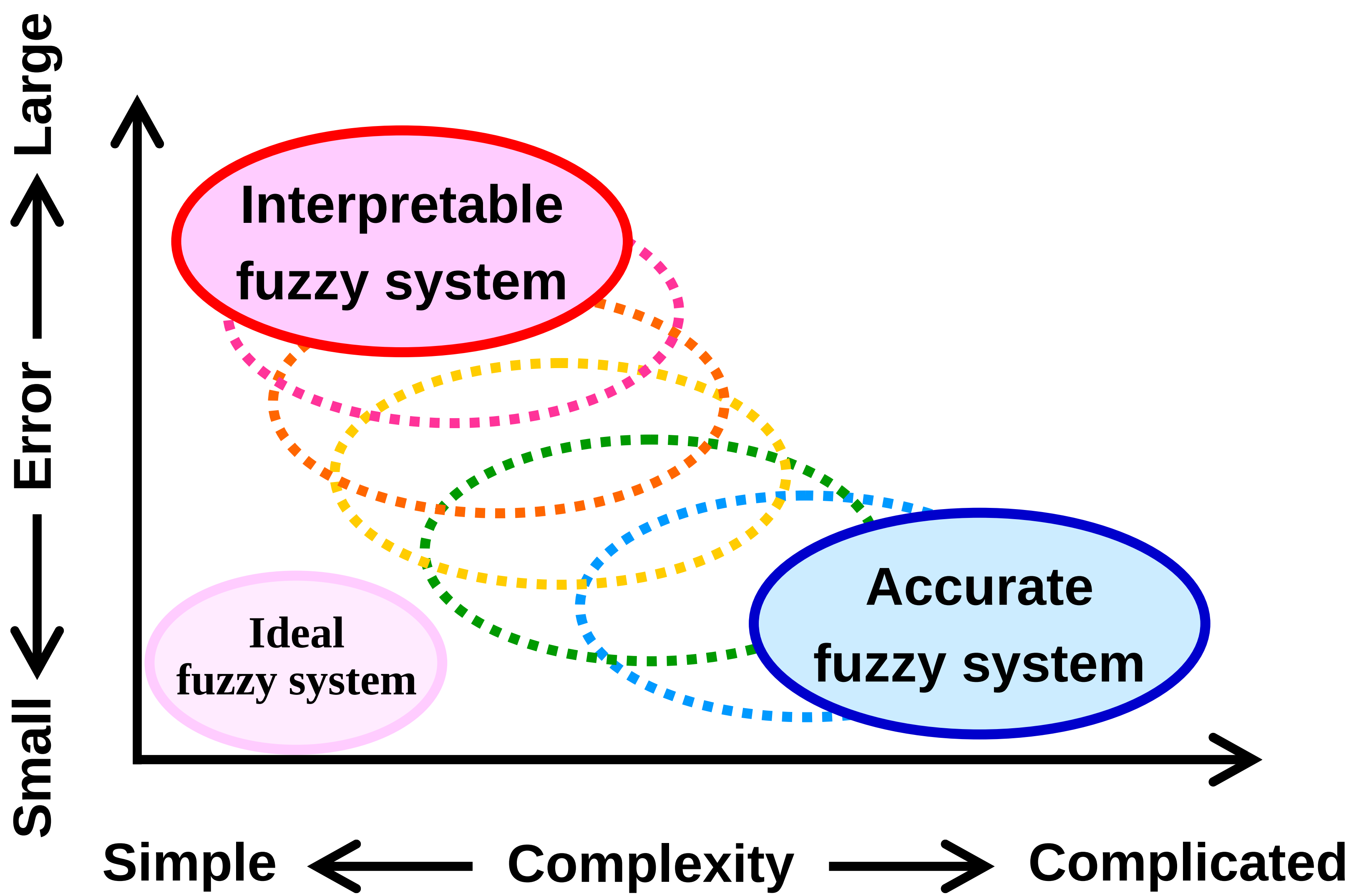


EMO Approach

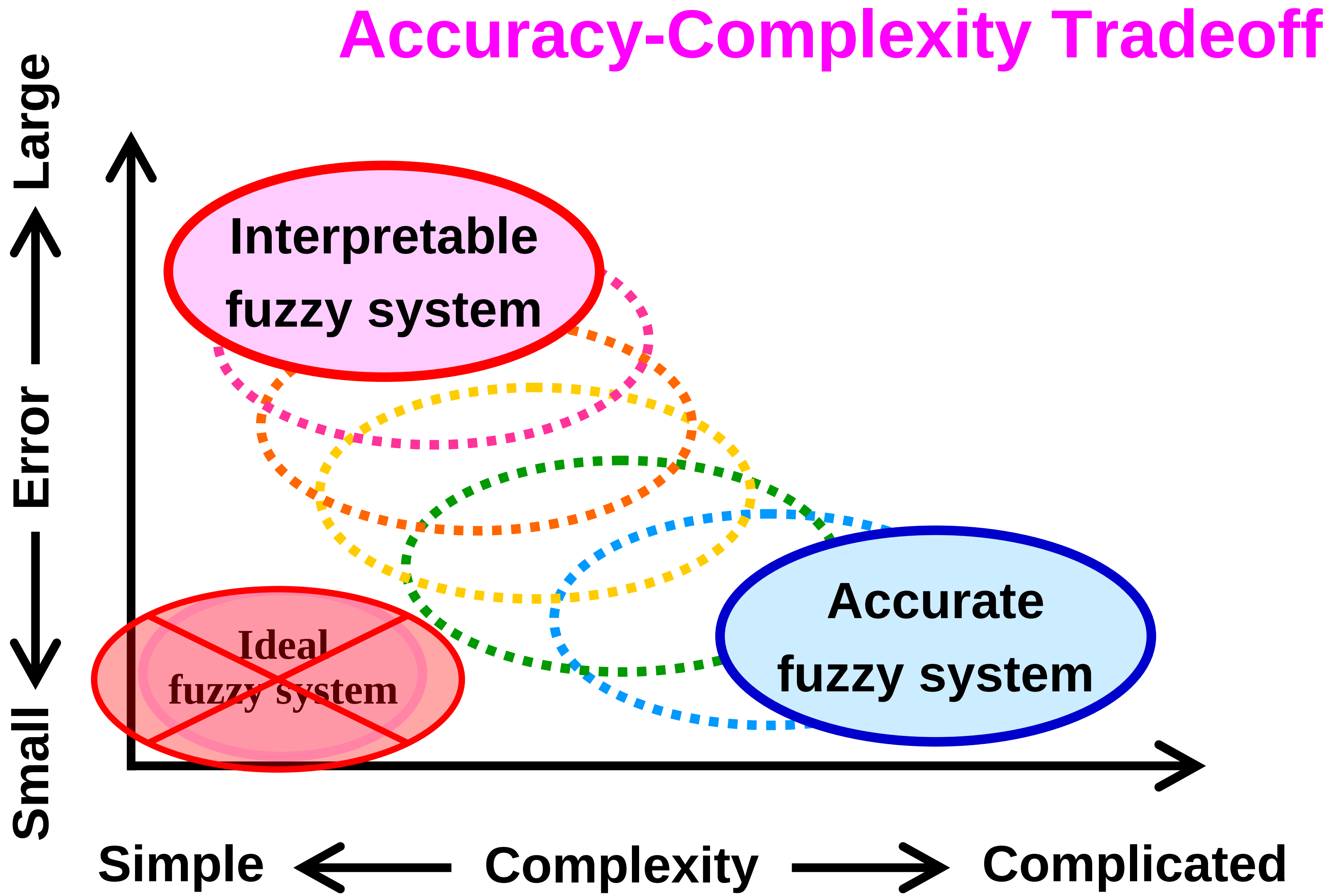


Weighted Sum Approach

Difficulties in Fuzzy System Design



Difficulties in Fuzzy System Design



Fuzzy System Research in the 1990s

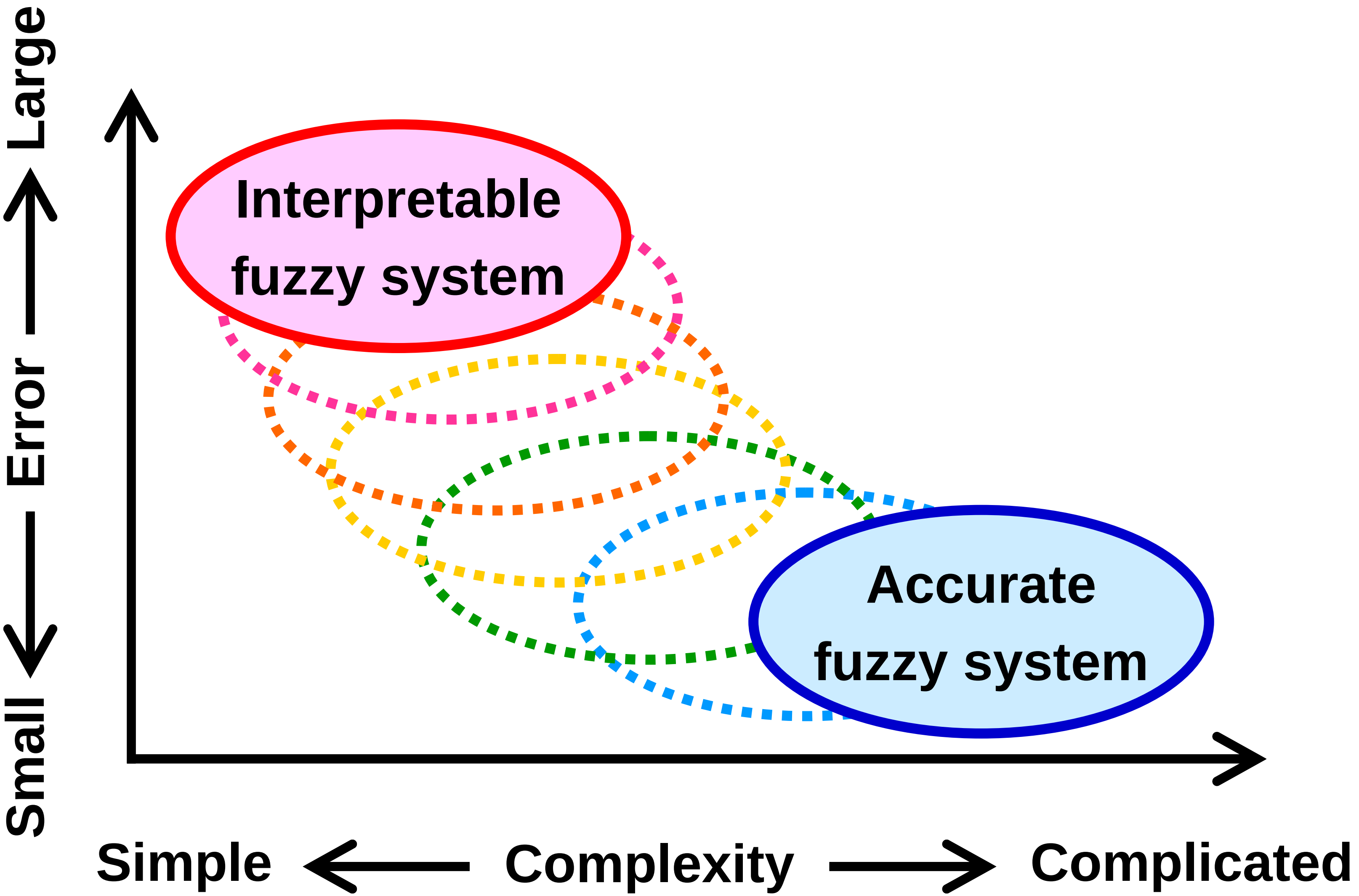
Accuracy maximization: Many studies on

- **Universal approximators of nonlinear functions**
- **Neuro-fuzzy techniques for parameter learning**
- **Genetic-fuzzy techniques for parameter and structure learning**

D. E. Rumelhart, J. L. McClelland and the PDP Research Group: ***Parallel Distributed Processing,*** **MIT Press (1986).**

D. E. Goldberg: ***Genetic Algorithms in Search, Optimization and Machine Learning,*** **Addison-Wesley (1989).**

Research Direction in the 1990s



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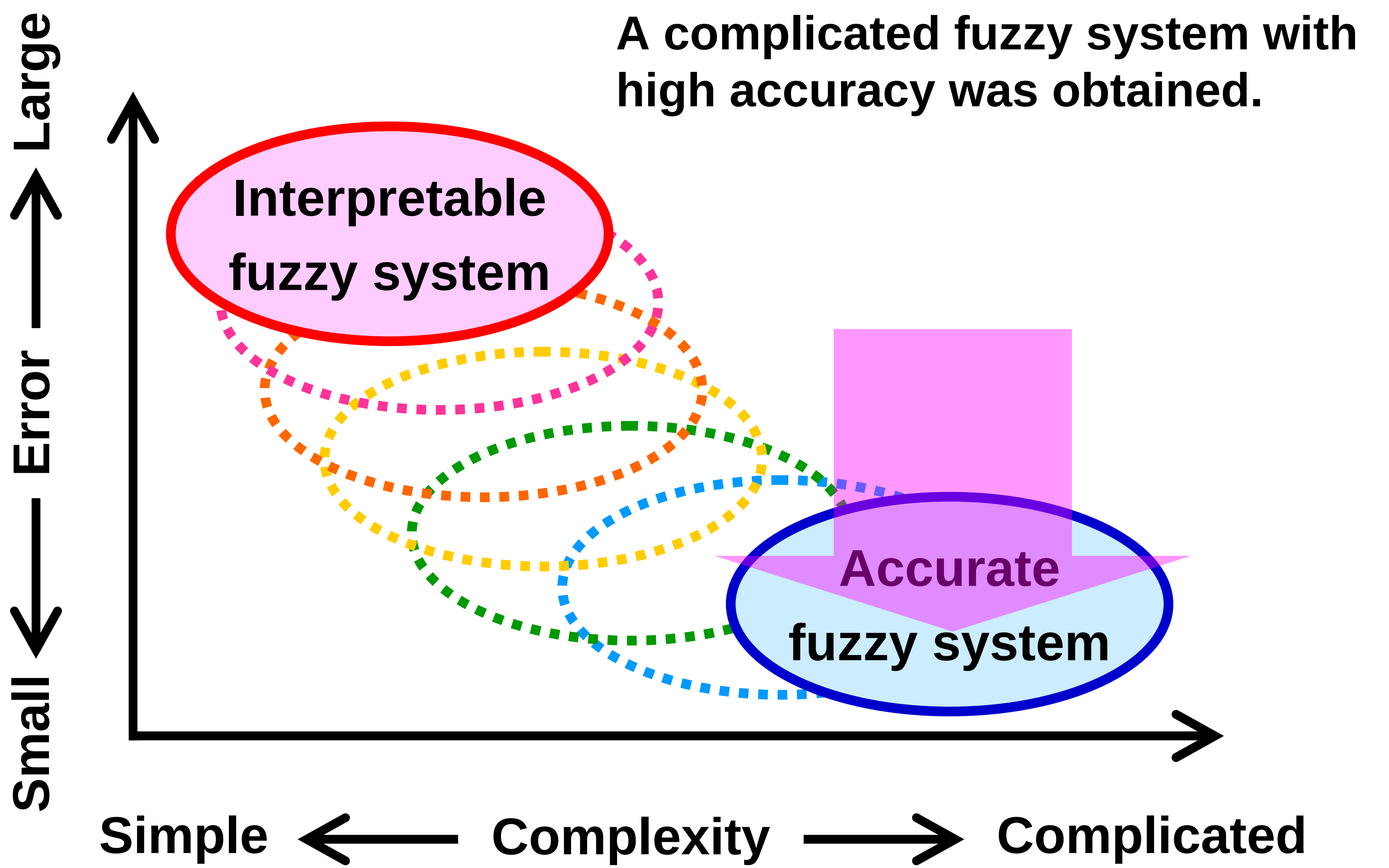

Difficulty in Accuracy Maximization

Error minimization ⇨ **Overfitting to training data**

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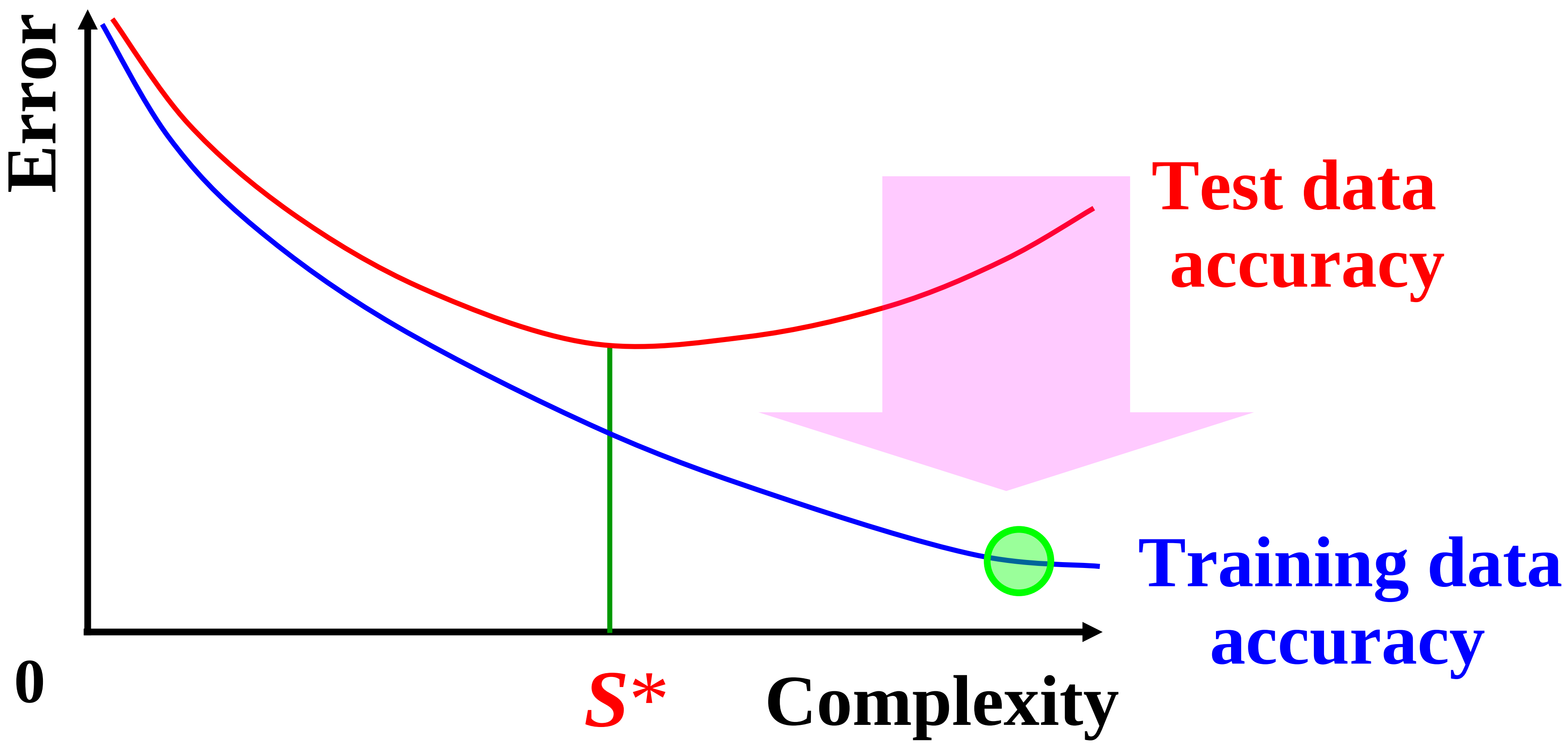

Fuzzy System Research in Late 1990s

Search for a good accuracy-complexity tradeoff

Basic Idea

To combine the error minimization and the complexity minimization into a single scalar objective function

Fuzzy System Research in Late 1990s

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To combine the error minimization and the complexity minimization into a single scalar objective function

Example: Combination of the average error rate and the number of fuzzy rules

Example of a scalar objective function: Weighted sum

$$f(S) = w_1 \cdot f_{\text{Error}}(S) + w_2 \cdot f_{\text{Complexity}}(S)$$

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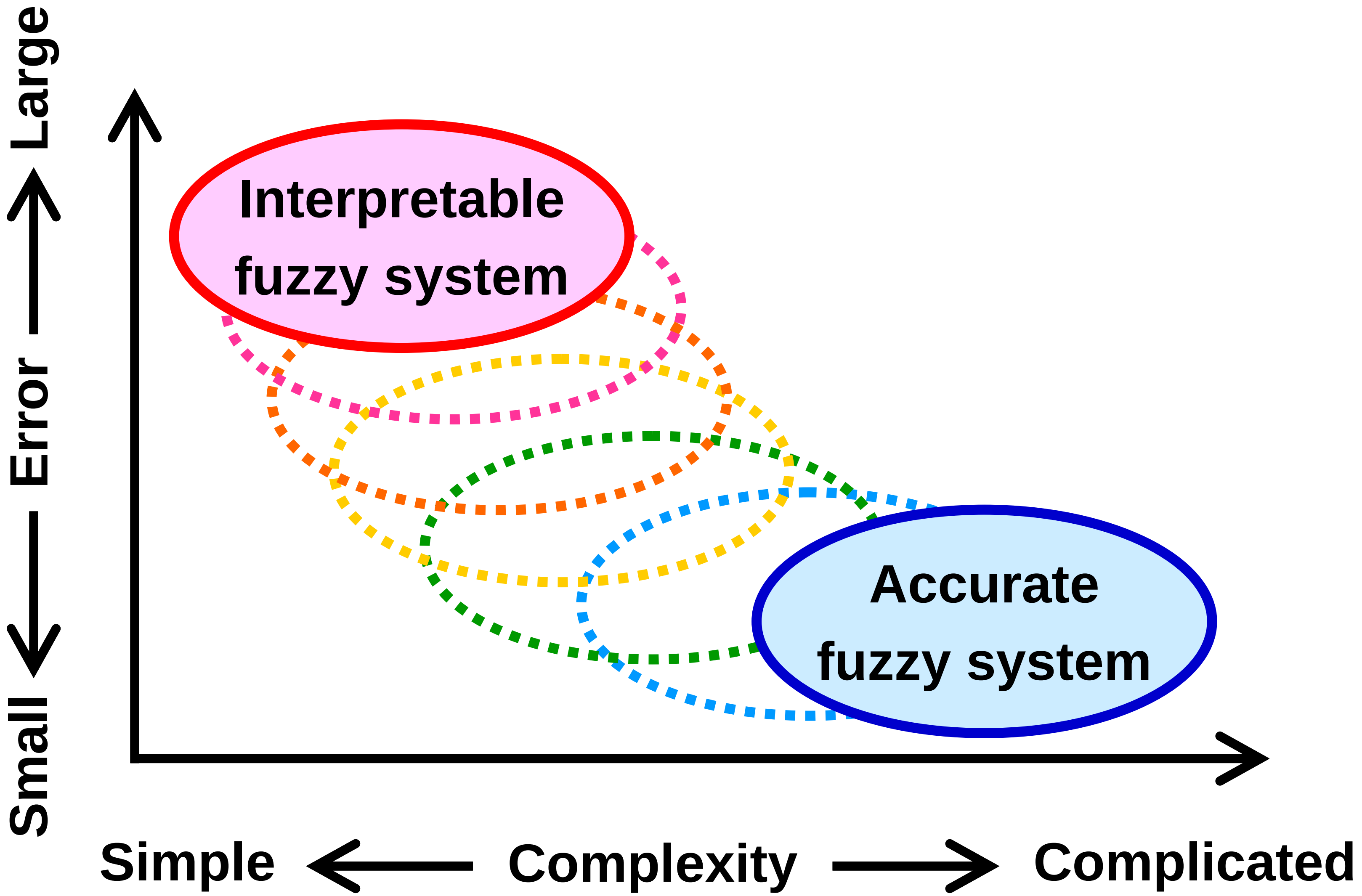
Example: Combination of the average error rate and the number of fuzzy rules

V. N. Vapnik: *Statistical Learning Theory,* Wiley (1998).

Research Direction in Late 1990s



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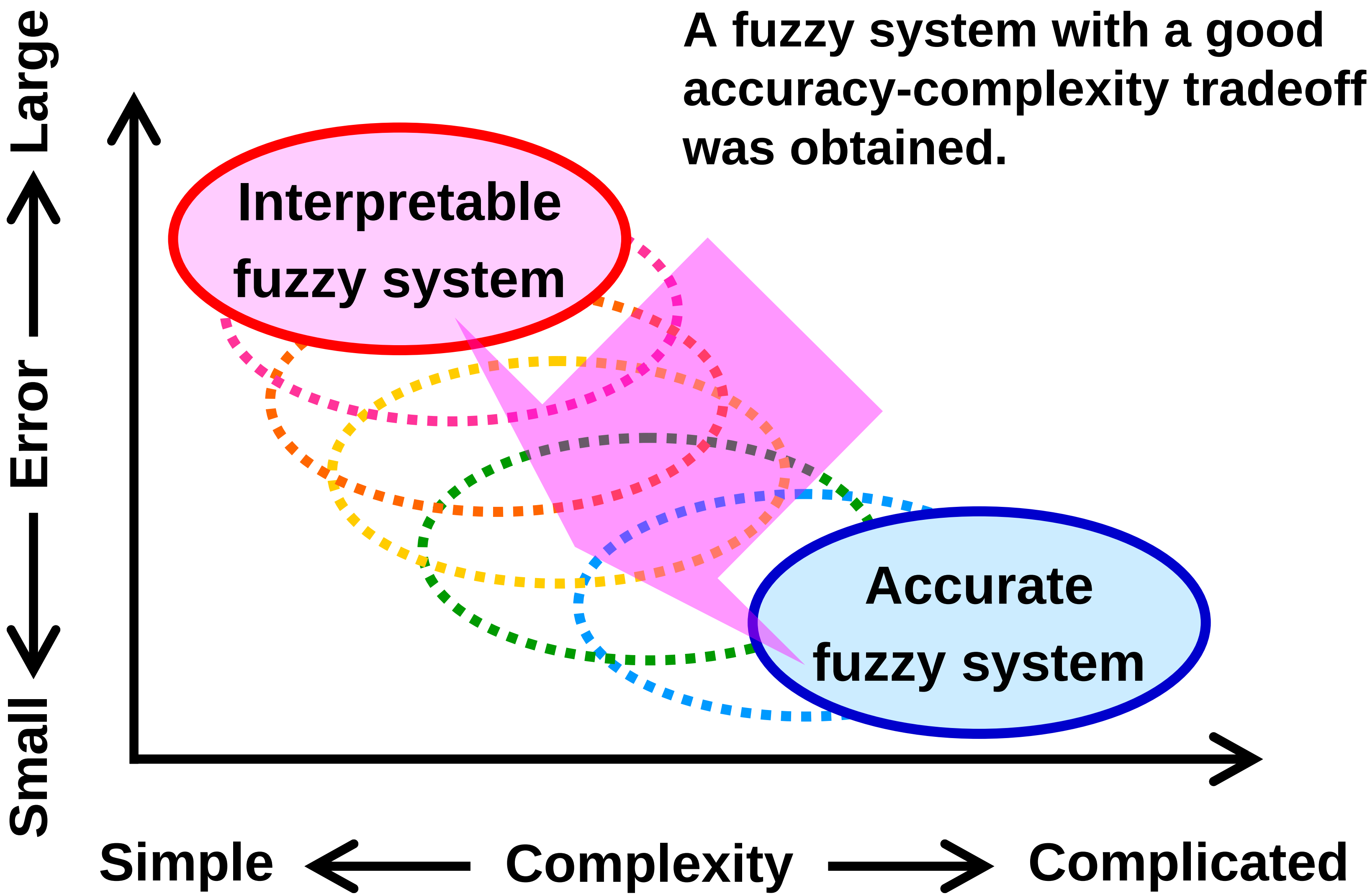


Difficulty in Weighted Sum Approach

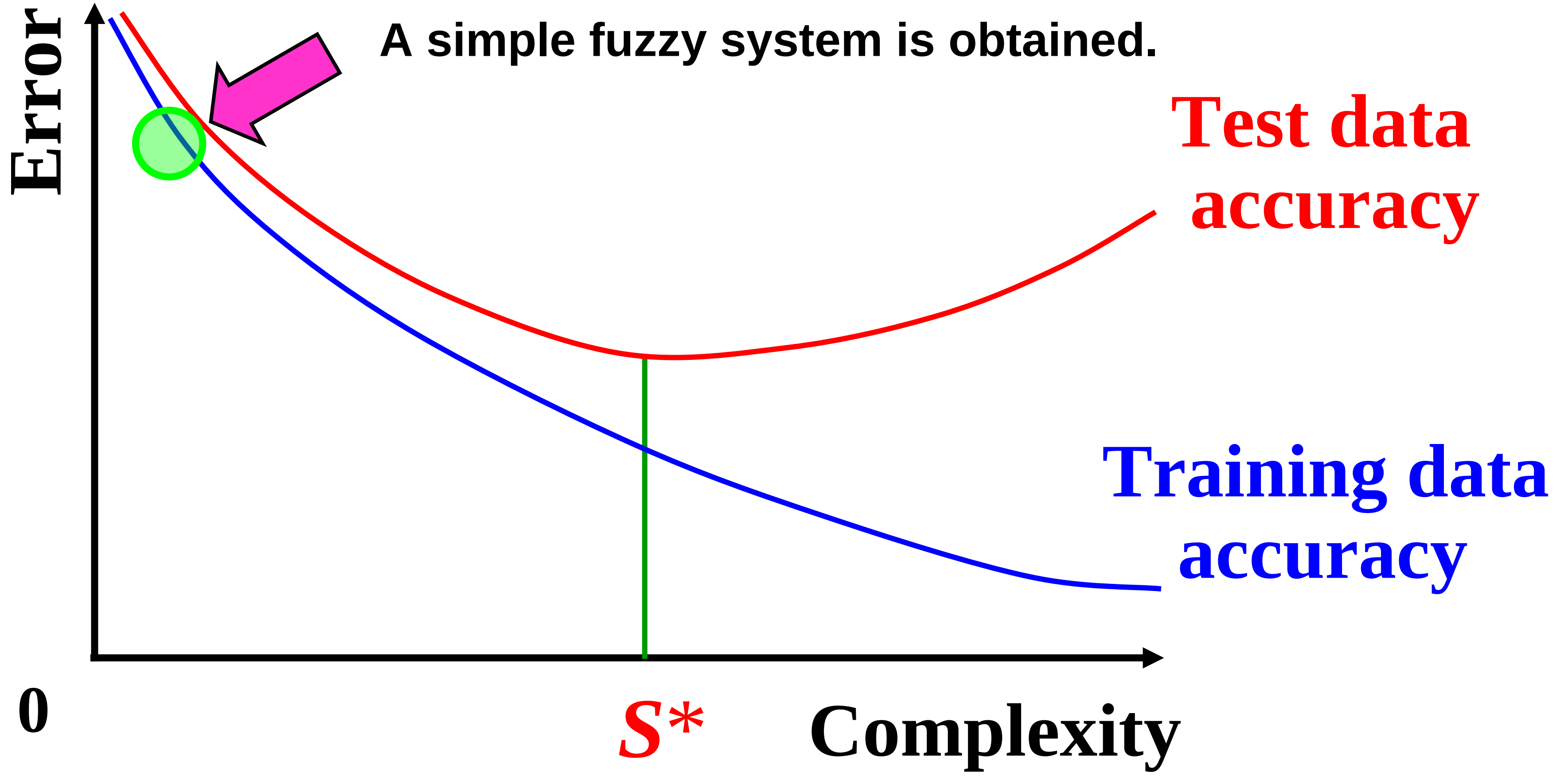
Sensitivity to the weight vector:

The obtained fuzzy system strongly depends on the specification of the weight vector.

Difficulty in Weighted Sum Approach

Minimize $w_1 \cdot Error + w_2 \cdot Complexity$

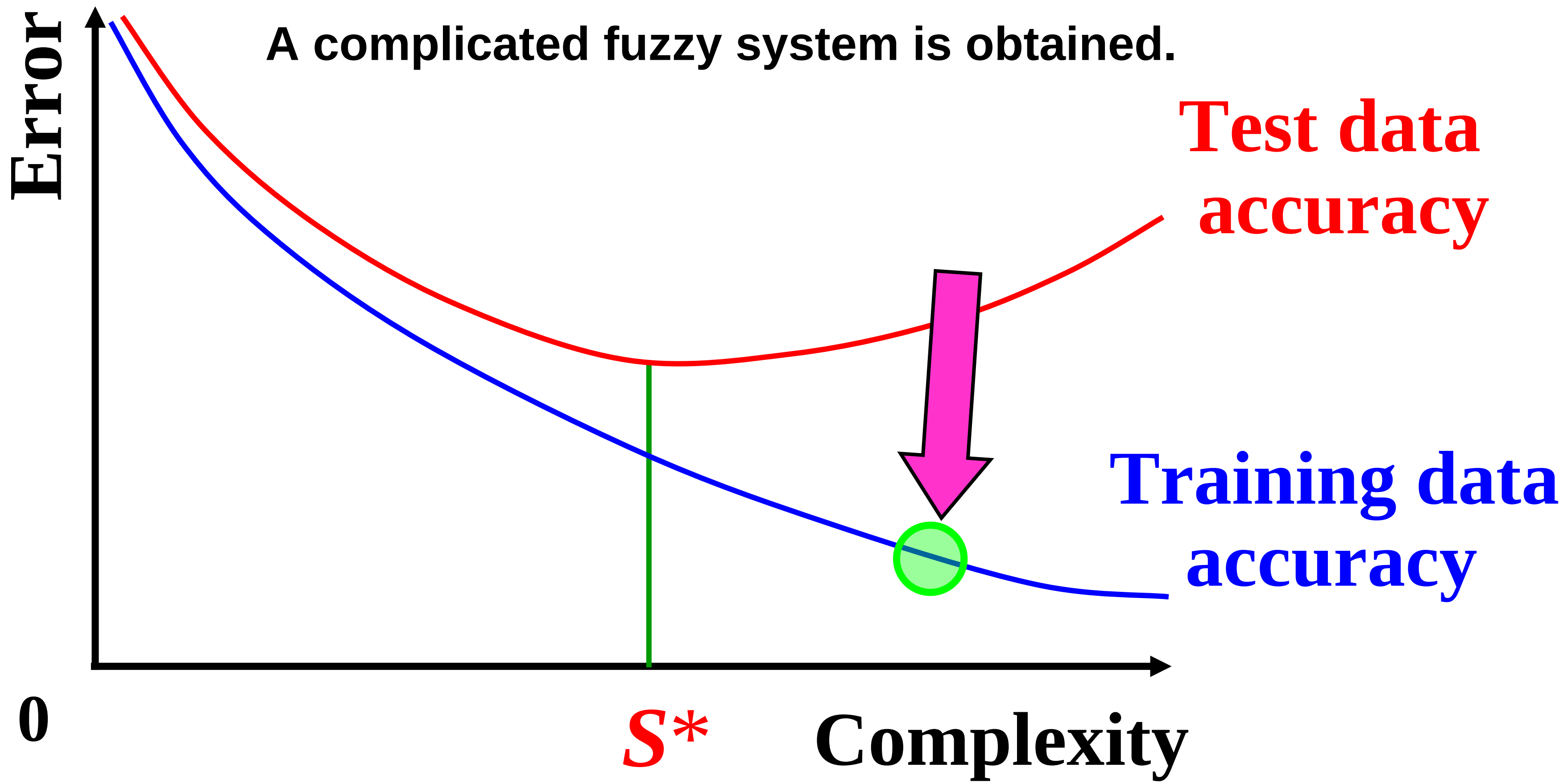
When the weight for the complexity minimization is large:



Difficulty in Weighted Sum Approach

Minimize $w_1 \cdot Error + w_2 \cdot Complexity$

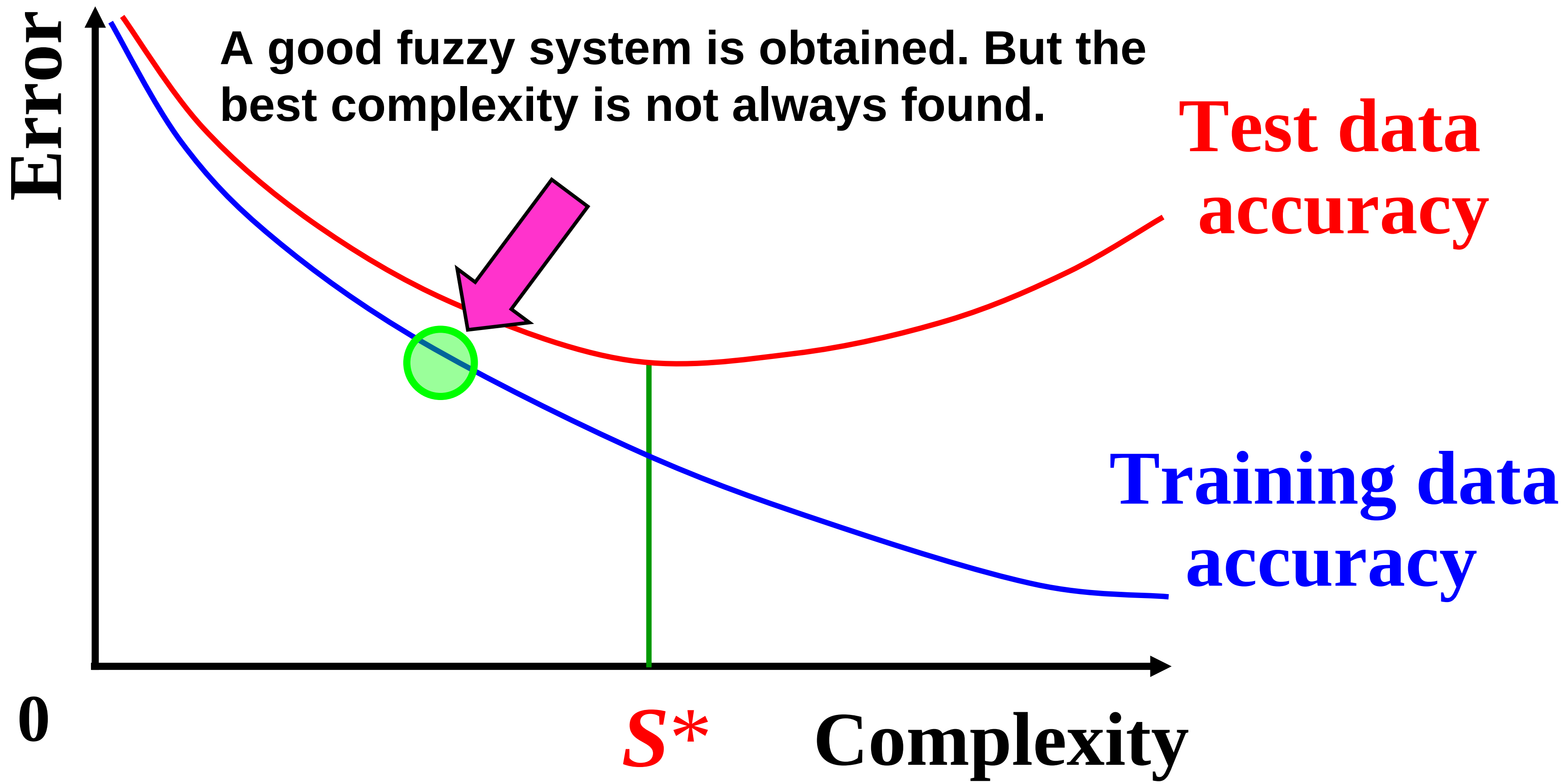
When the weight for the error minimization is large:



Difficulty in Weighted Sum Approach

Minimize $w_1 \cdot Error + w_2 \cdot Complexity$

When the two weights are appropriately specified:



Current Trend in Fuzzy System Research

Multiobjective optimization of accuracy and complexity

Basic Idea

To search for Pareto-optimal solutions with respect to the error minimization and the complexity minimization.

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Example: **Two-objective problem**

- minimize the average error rate

- minimize the number of fuzzy rules

Example of a multiobjective minimization problem

$$\text{Minimize } \{ f_{\text{Error}}(S), \ f_{\text{Complexity}}(S) \}$$

Current Trend in Fuzzy System Research

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Basic Idea

To search for Pareto-optimal solutions with respect to the error minimization and the complexity minimization.

Aggregation Approach

$$f(S) = w_1 \cdot f_{\mathrm{Error}}(S) + w_2 \cdot f_{\mathrm{Complexity}}(S)$$

Multiobjective Approach

$$\text{Minimize } \{ f_{\mathrm{Error}}(S),\ f_{\mathrm{Complexity}}(S) \}$$

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Basic Idea

To search for Pareto-optimal solutions with respect to the error minimization and the complexity minimization.

Example: **Two-objective problem**

- **minimize the average error rate**
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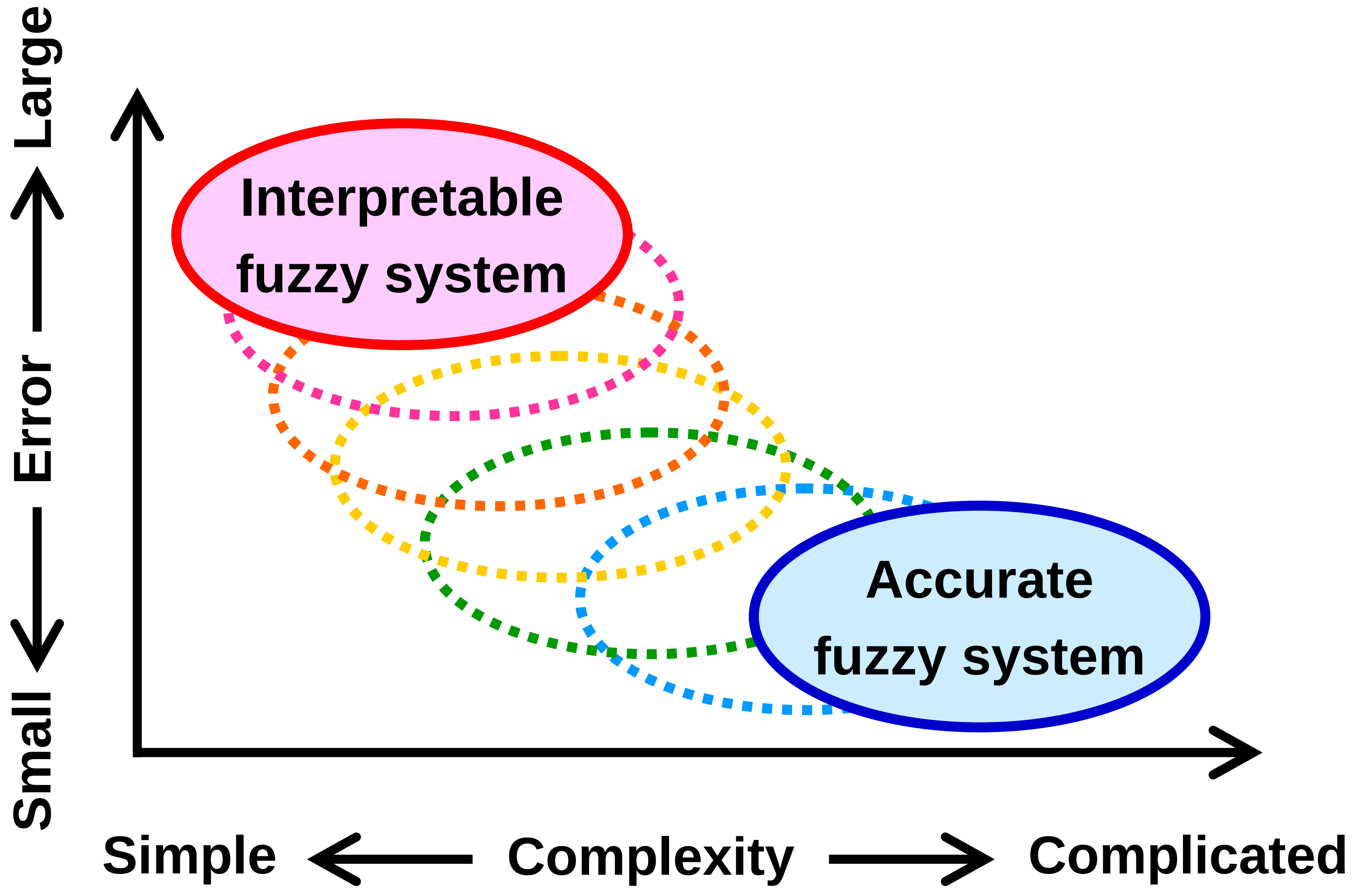
K. Deb: ***Multi-Objective Optimization using Evolutionary Algorithms,*** **Wiley (2001).**

Current Research Direction



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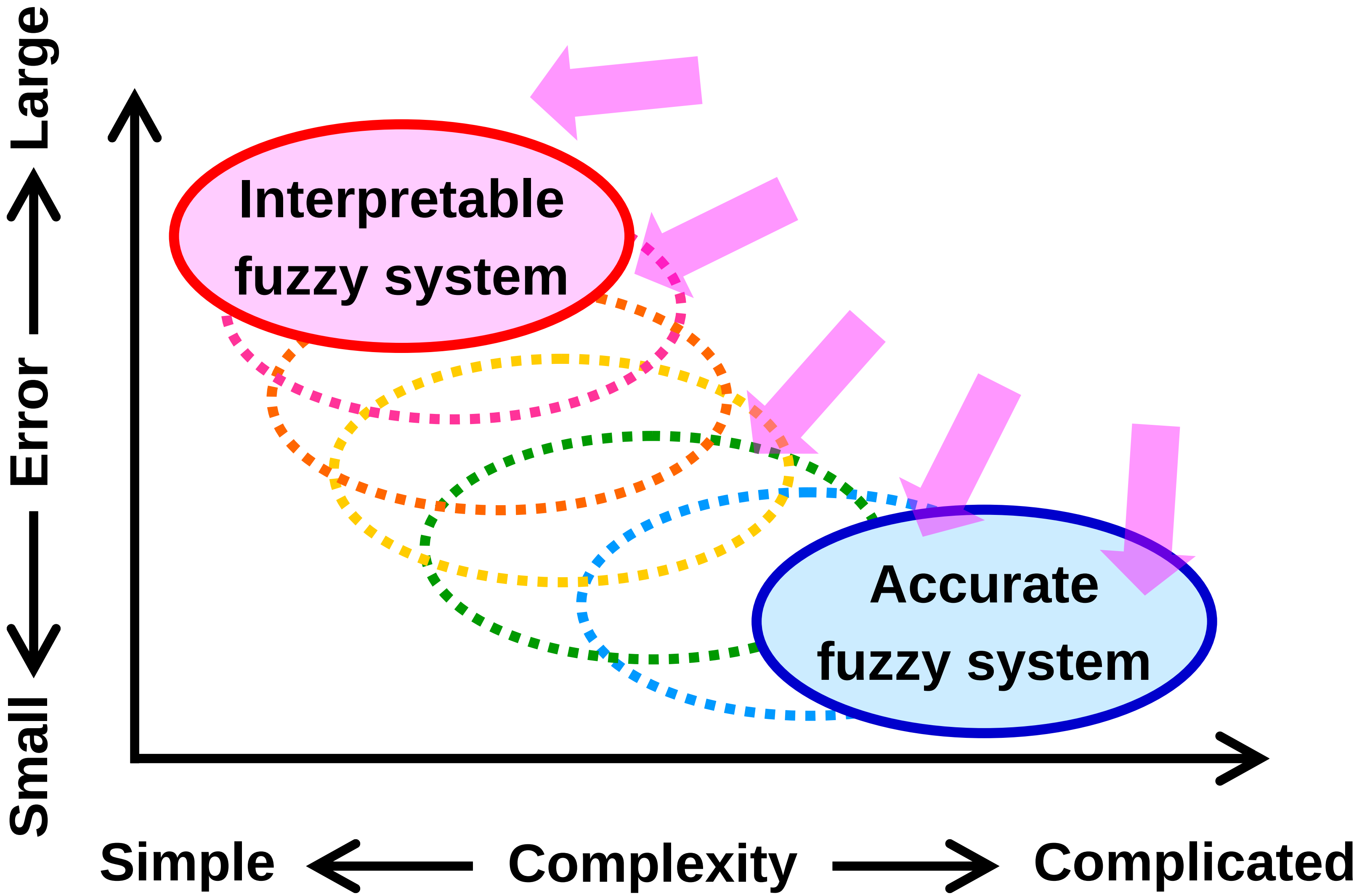
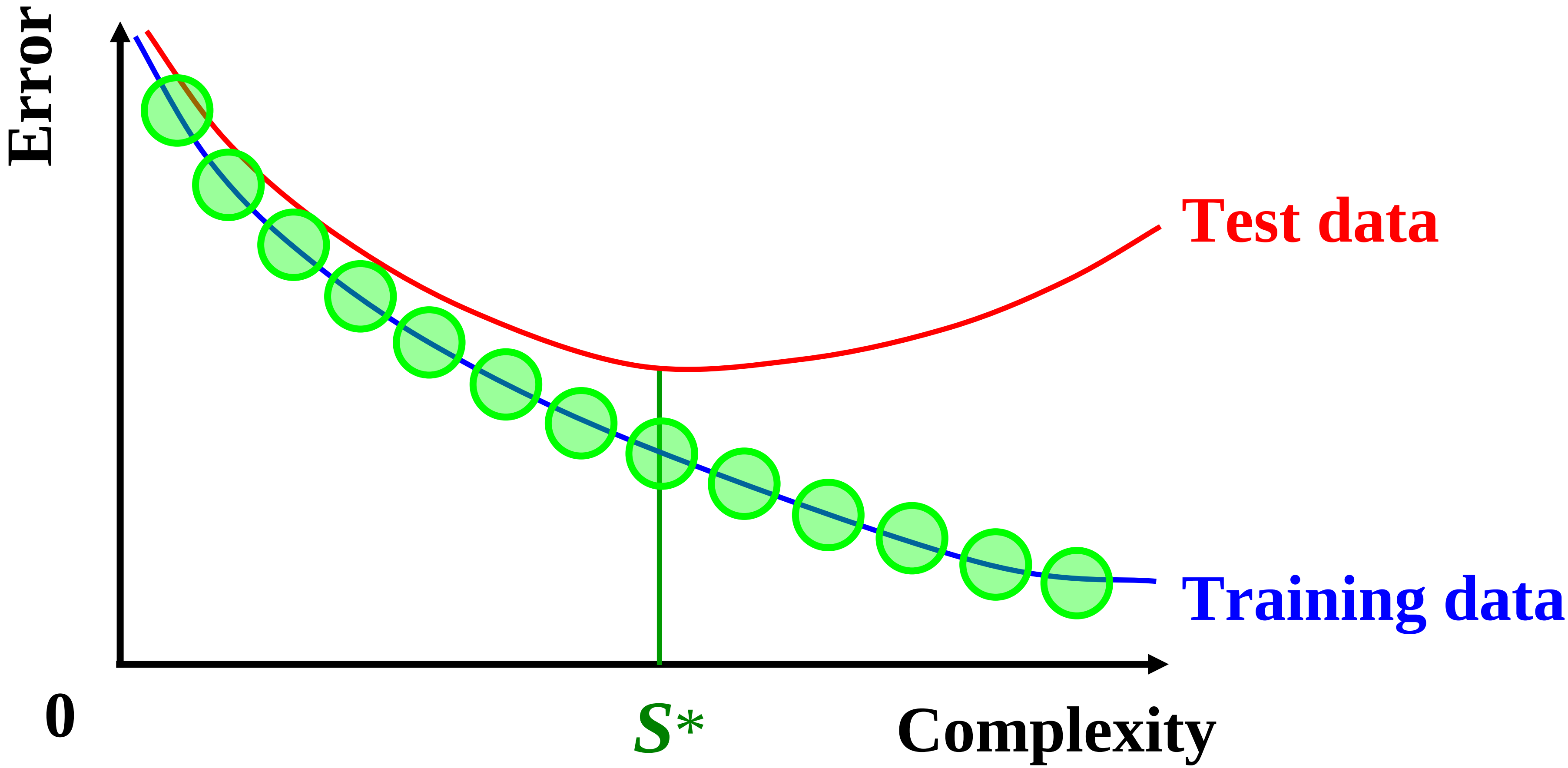


Multiobjective Approach

Many Pareto-optimal fuzzy systems can be obtained along the accuracy-complexity tradeoff surface by a single run of an EMO algorithm.



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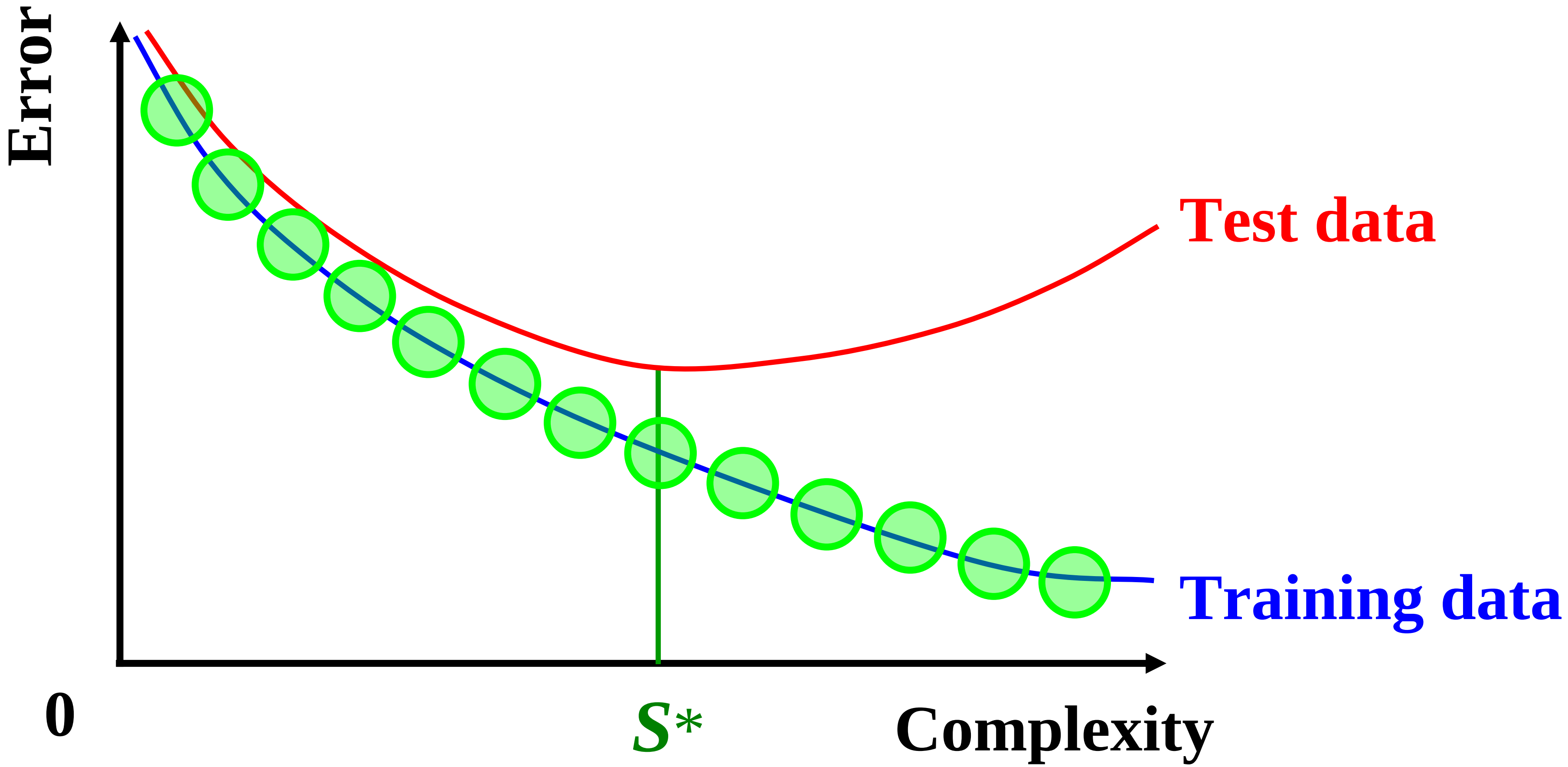

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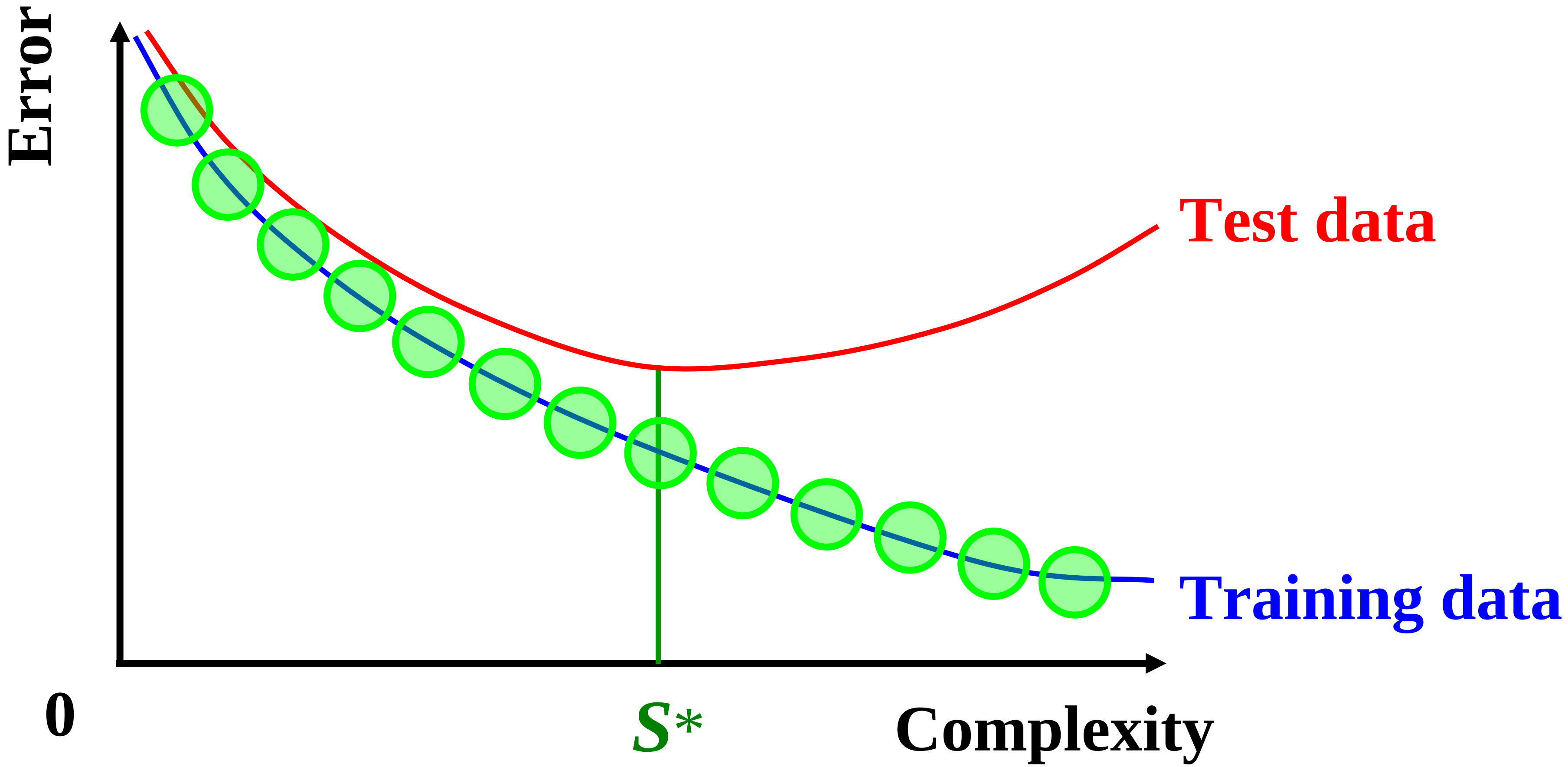


Two Multiobjective Formulations

Multiobjective Design of Fuzzy Systems

Rule set-level multiobjective optimization

Multiobjective Search for Fuzzy Rules

Rule-level multiobjective optimization

Two Multiobjective Formulations

Multiobjective Design of Fuzzy Systems

Rule set-level multiobjective optimization

Multiobjective Search for Fuzzy Rules

Rule-level multiobjective optimization

Different quality measures of fuzzy rules such as support and confidence in fuzzy data mining are simultaneously optimized.

Maximize {Confidence, Support}

Confidence maximization:

$$c(\mathbf{A}_q \Rightarrow \text{Class } h) = \frac{\sum_{p \in \text{Class } h} \mu_{\mathbf{A}_q}(\mathbf{x}_p)}{\sum_{p=1}^{m} \mu_{\mathbf{A}_q}(\mathbf{x}_p)}$$

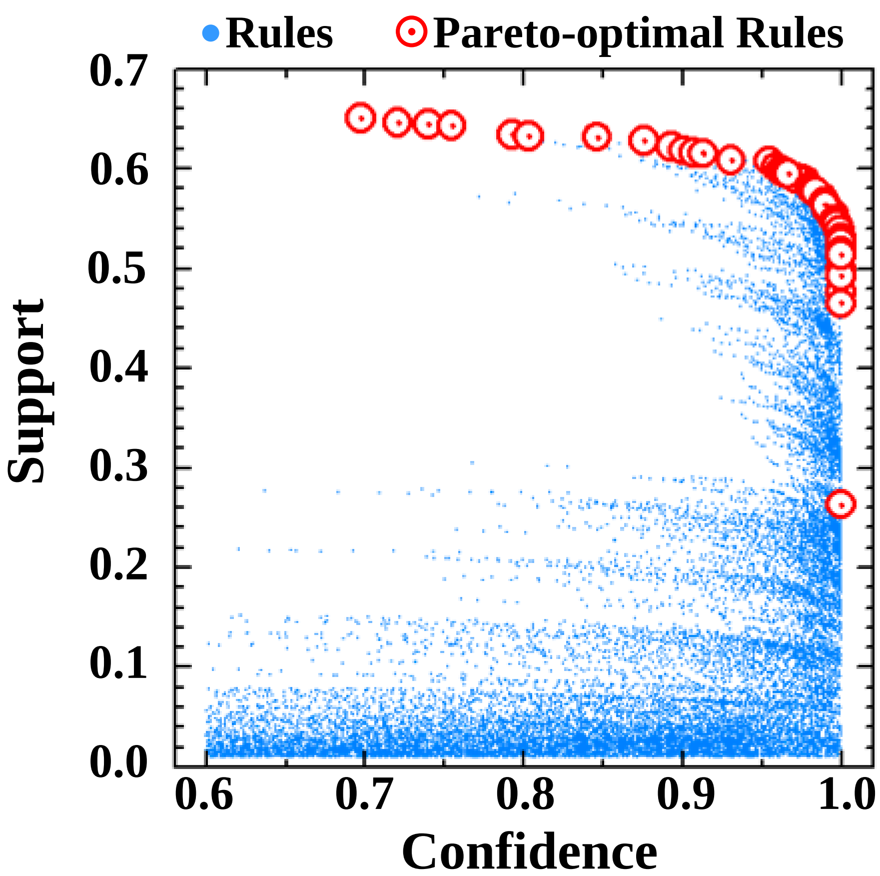
Support maximization:

$$s(\mathbf{A}_q \Rightarrow \text{Class } h) = \frac{\sum_{p \in \text{Class } h} \mu_{\mathbf{A}_q}(\mathbf{x}_p)}{m}$$

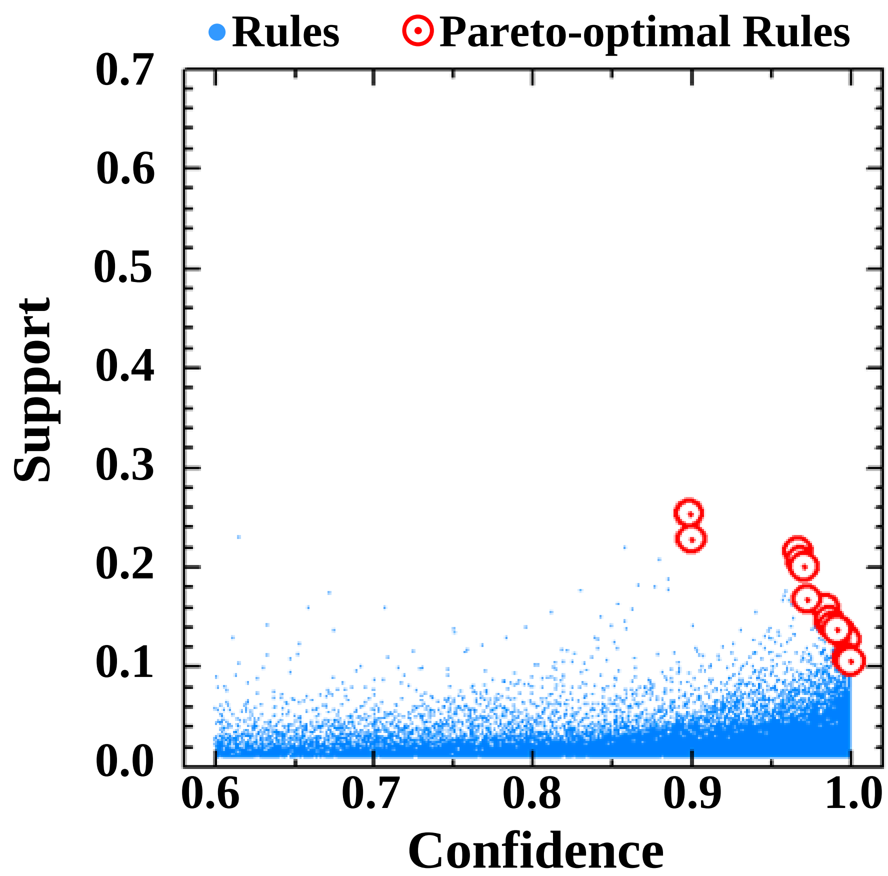
$\mu(\cdot)$: Membership function m: Number of patterns

Pareto-Optimal Fuzzy Rules

Wisconsin Breast Cancer Data Set (Breast W)



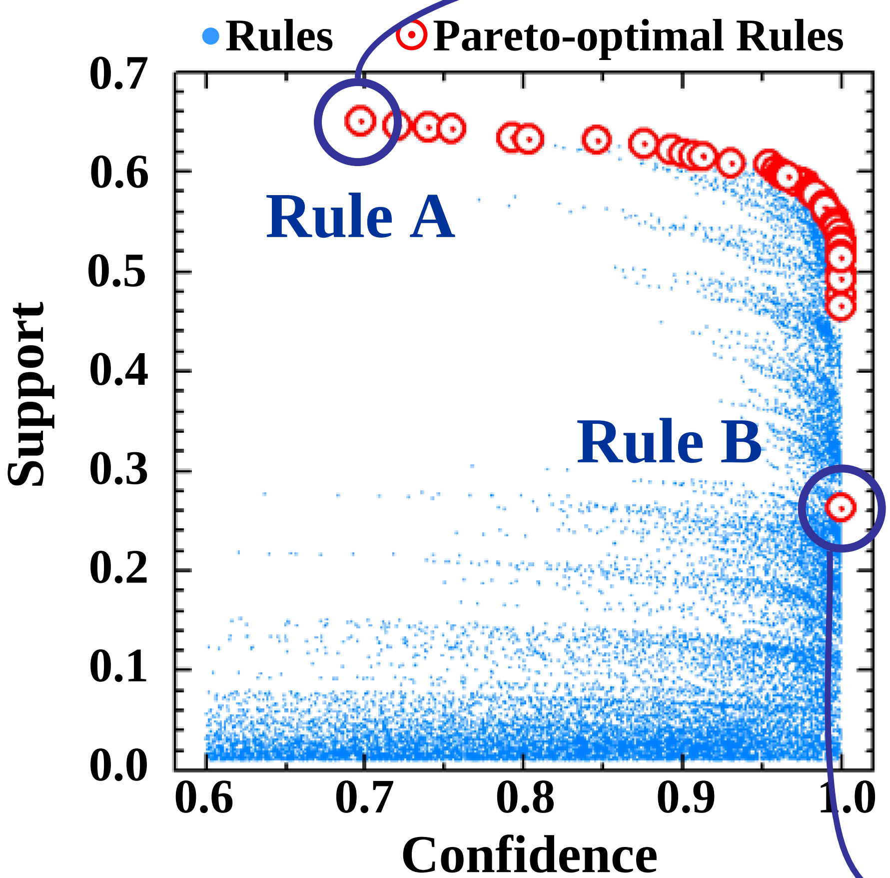
Class 1

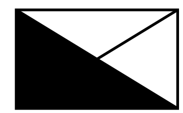


Class 2

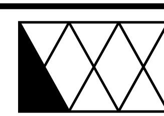
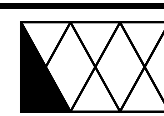
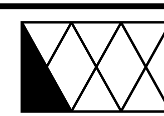
Pareto-Optimal Fuzzy Rules

Breast W



	x_1	Consequent
R_1		Class 0 (0.39)

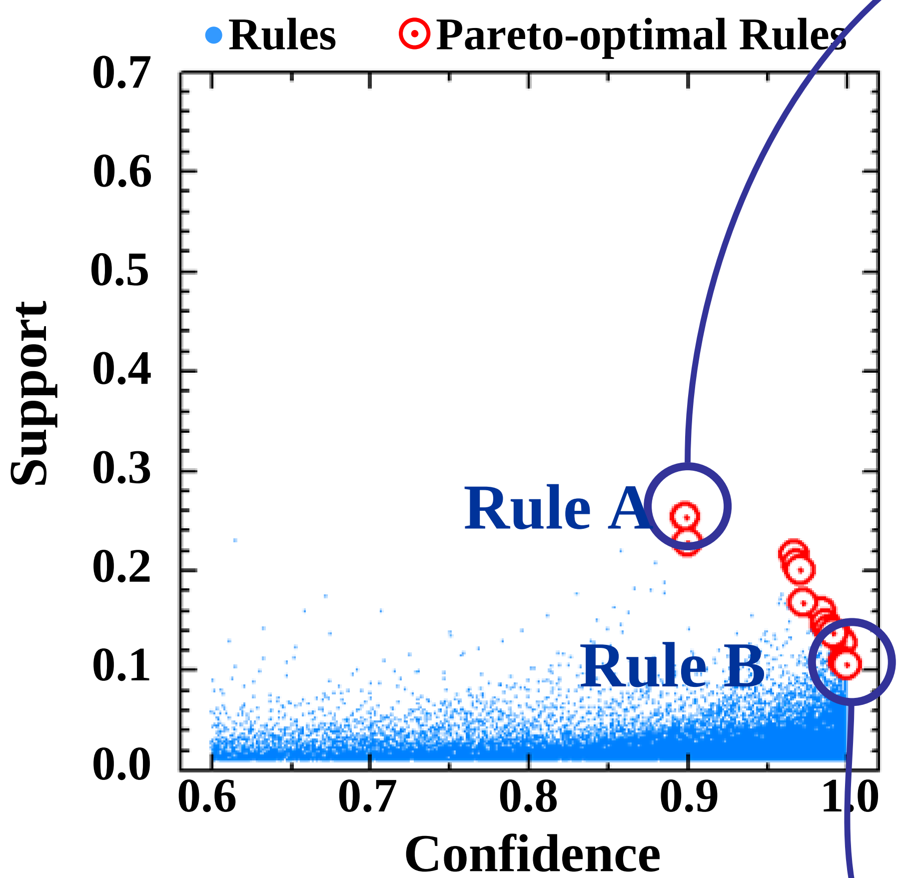
Rule A: Very General Fuzzy Rule
(confidence: 0.69, support: 0.65)

	x_1	x_2	x_3	Consequent
R_1				Class 0 (1.00)

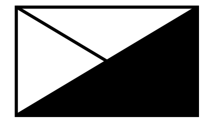
Rule B: Very Specific Fuzzy Rule
(confidence: 1.00, support: 0.25)

Pareto-Optimal Fuzzy Rules

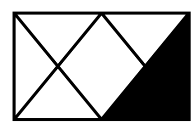
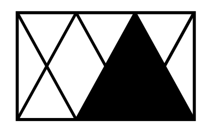
Breast W



Class 2

	x_1	Consequent
R_1		Class 1 (0.80)

Rule A: Very General Fuzzy Rule
(confidence: 0.89, support: 0.25)

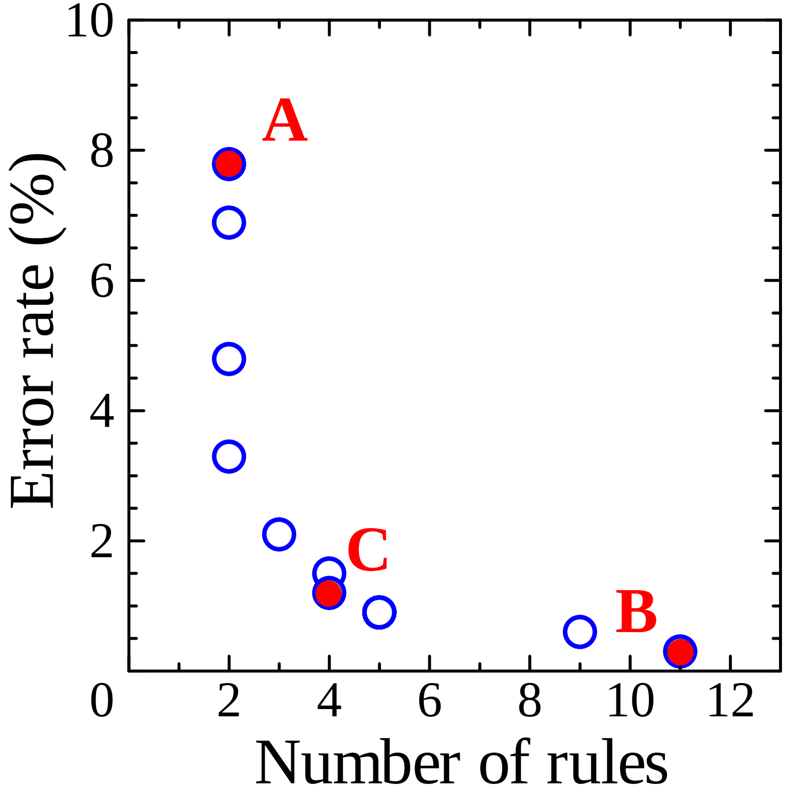
	x_1	x_2	Consequent
R_1			Class 1 (1.00)

Rule B: Specific Fuzzy Rule
(confidence: 1.00, support: 0.11)

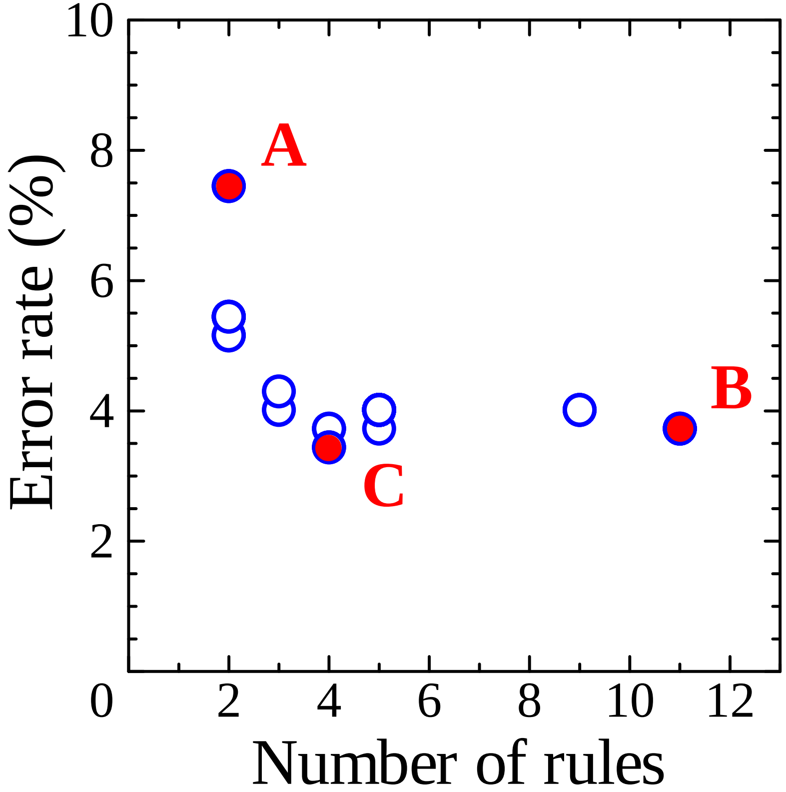
Relation between Pareto-optimal fuzzy rules and Pareto-optimal fuzzy systems

Pareto-Optimal Fuzzy Systems (Breast W)

Error Minimization and Complexity Minimization



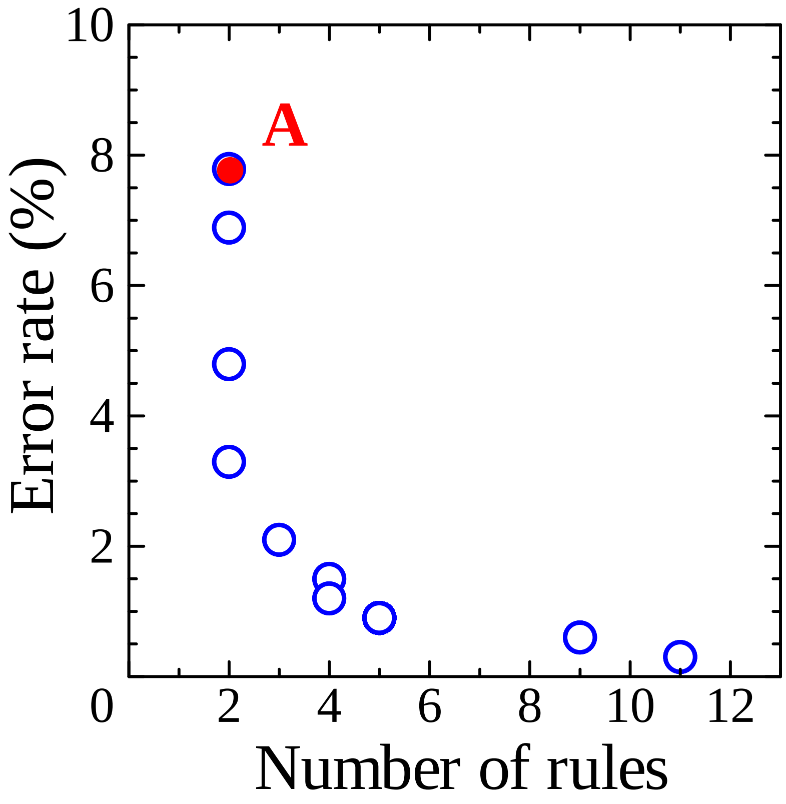
Training data accuracy



Test data accuracy

Fuzzy Rules in Simple Fuzzy System A

Fuzzy rules in a simple fuzzy system A are general rules.

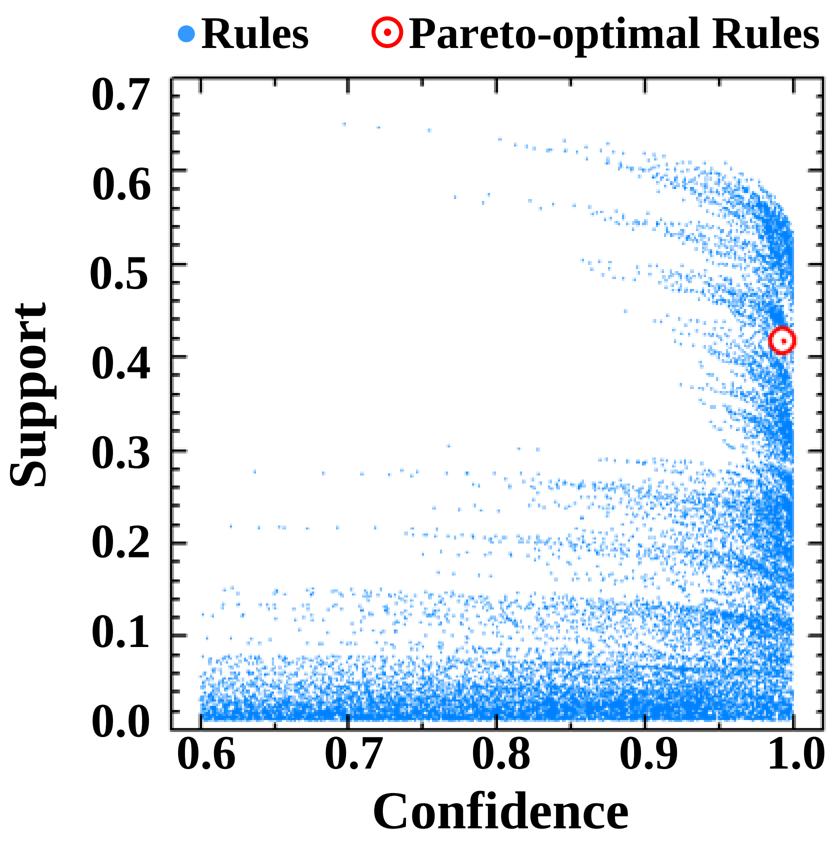


	x_1	x_2	x_3	Consequent
R_1		DC		Class 0 (0.99)
R_2	DC		DC	Class 1 (0.34)

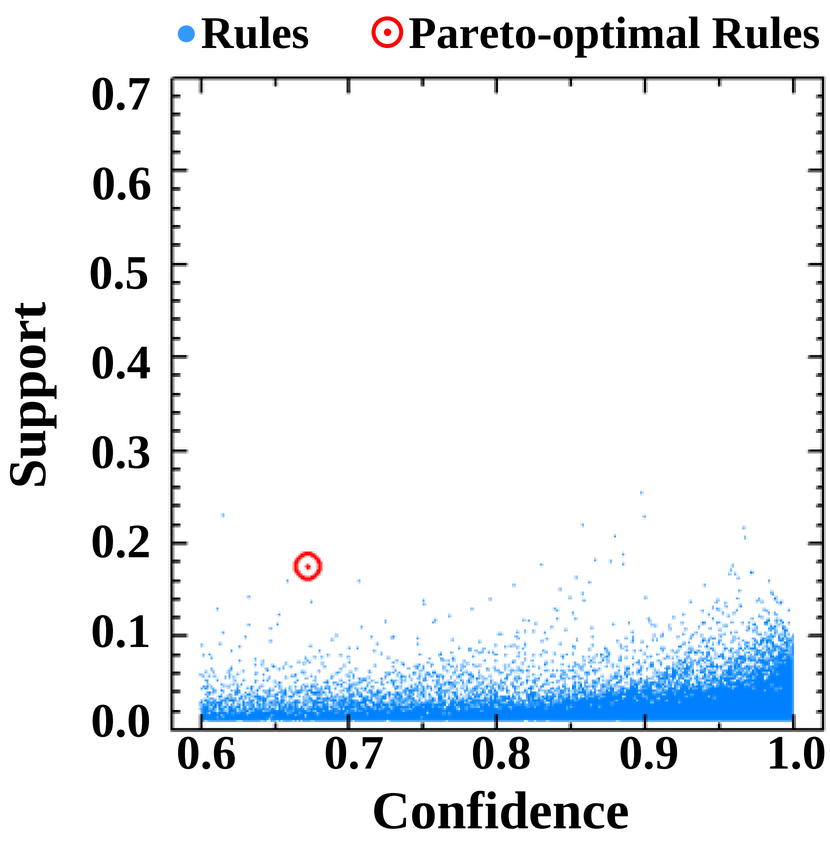
Error rate: 7.8% (training) and 7.4% (test)

Fuzzy Rules in Simple Fuzzy System A

Fuzzy rules in A are Pareto-optimal or near Pareto-optimal.



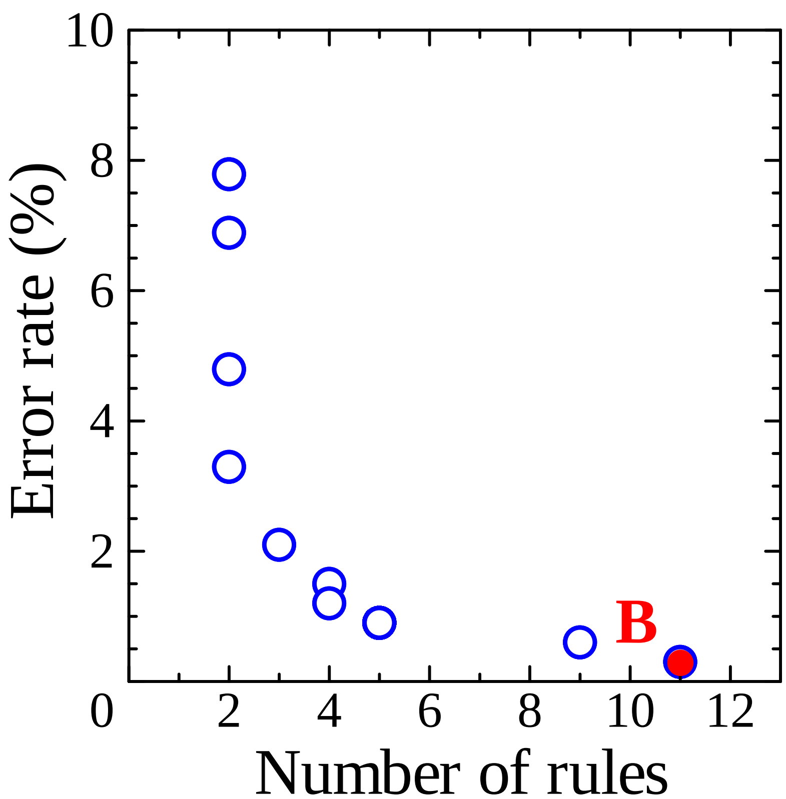
Class 1



Class 2

Rules in Complicated Fuzzy System B

Some fuzzy rules in a complicated fuzzy system B is very specific rules with narrow antecedent fuzzy sets.

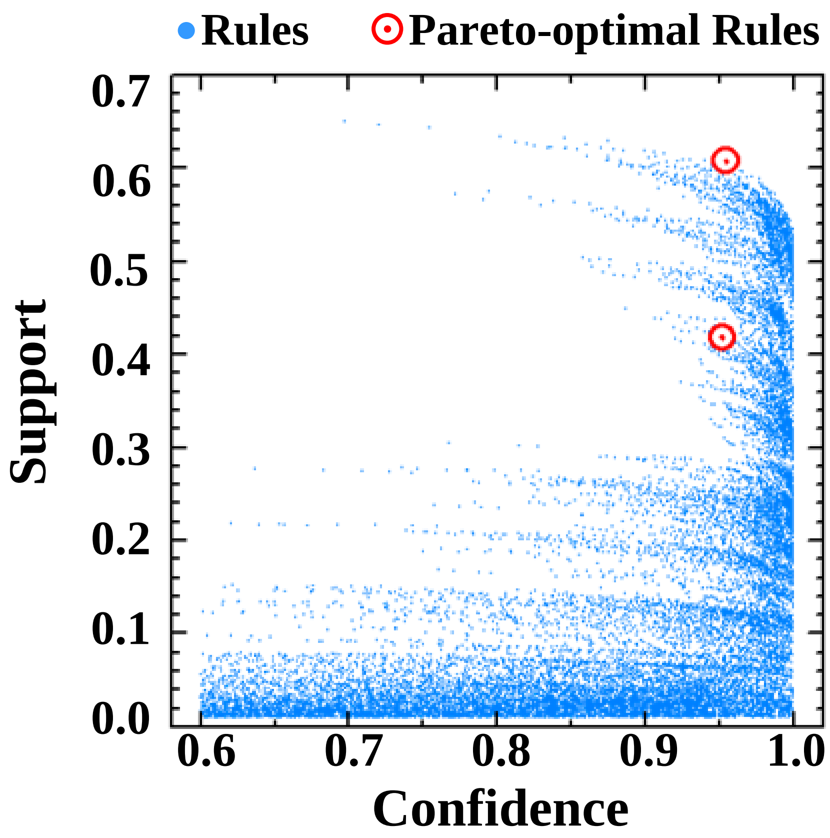


	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	Consequent
R_1	DC		DC	DC	DC		DC	DC	DC	Class 0 (0.91)
R_2	DC	DC	DC	DC	DC	DC		DC		Class 0 (0.90)
R_3	DC	DC	DC	DC		DC	DC	DC	DC	Class 1 (0.34)
R_4		DC	DC	DC	DC	DC	DC	DC	DC	Class 1 (0.93)
R_5	DC	DC	DC		DC	DC	DC	DC	DC	Class 1 (1.00)
R_6	DC	DC	DC	DC	DC	DC	DC		DC	Class 1 (0.99)
R_7	DC	DC	DC	DC	DC	DC	DC			Class 1 (0.37)
R_8		DC	DC	DC	DC	DC	DC	DC		Class 1 (0.82)
R_9	DC	DC	DC		DC	DC	DC		DC	Class 1 (0.86)
R_{10}		DC	DC	DC	DC	DC	DC	DC		Class 1 (0.98)
R_{11}		DC		DC	DC		DC	DC	DC	Class 1 (0.74)
R_{12}		DC	DC	DC		DC	DC	DC		Class 1 (0.86)

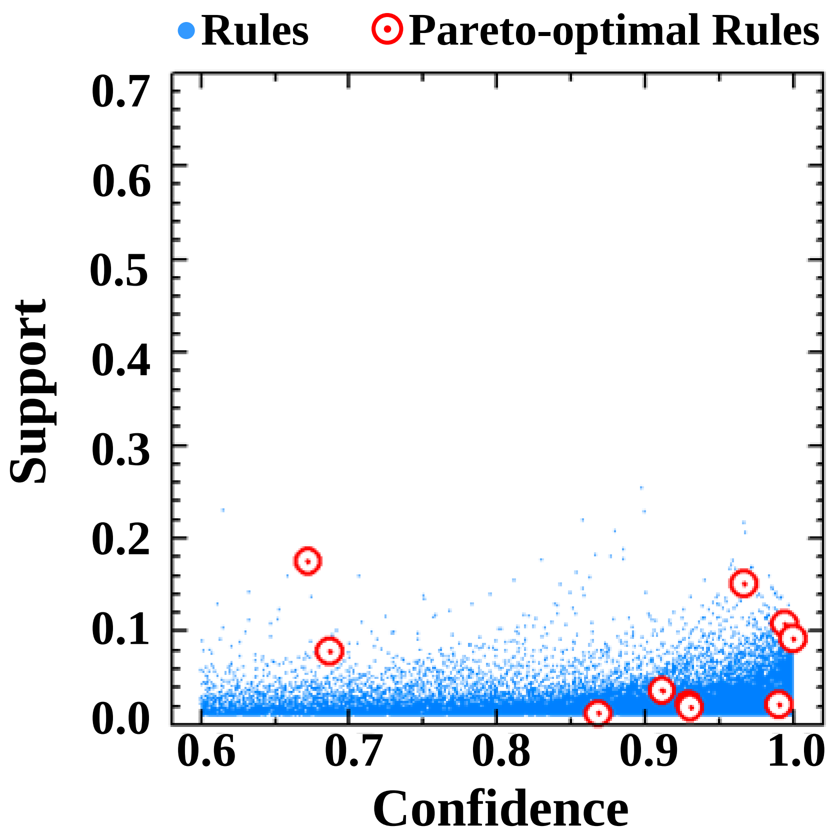
Error rate: 0.3% (training) and 3.7% (test)

Selected Rules in Rule Set B

Many fuzzy rules in B are far from the Pareto-optimal rules.



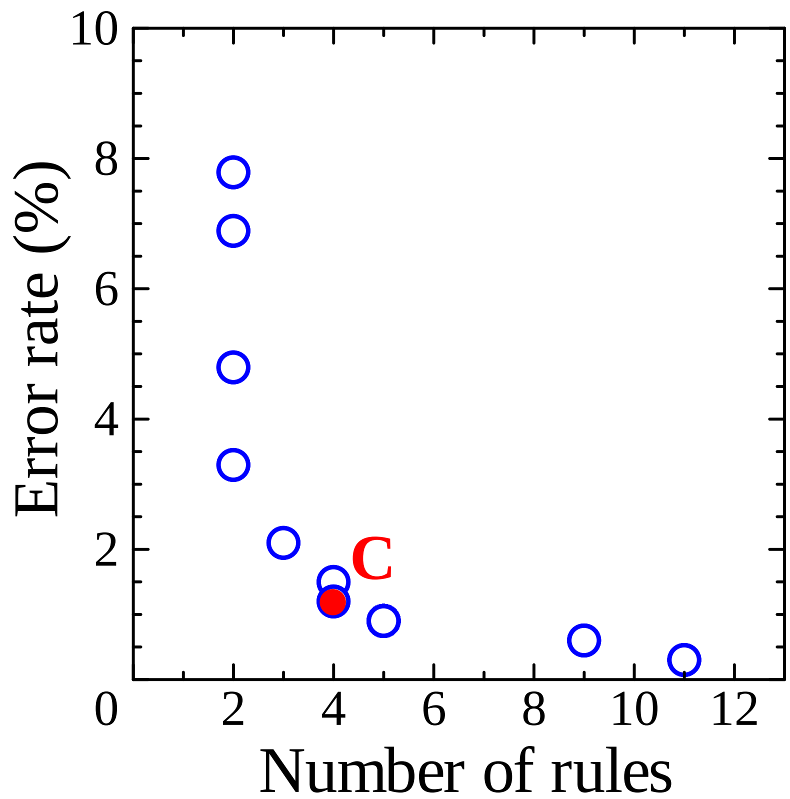
Class 1



Class 2

Fuzzy Rules in Good Fuzzy System C

Some fuzzy rules in a good fuzzy system C are specific but not very specific.

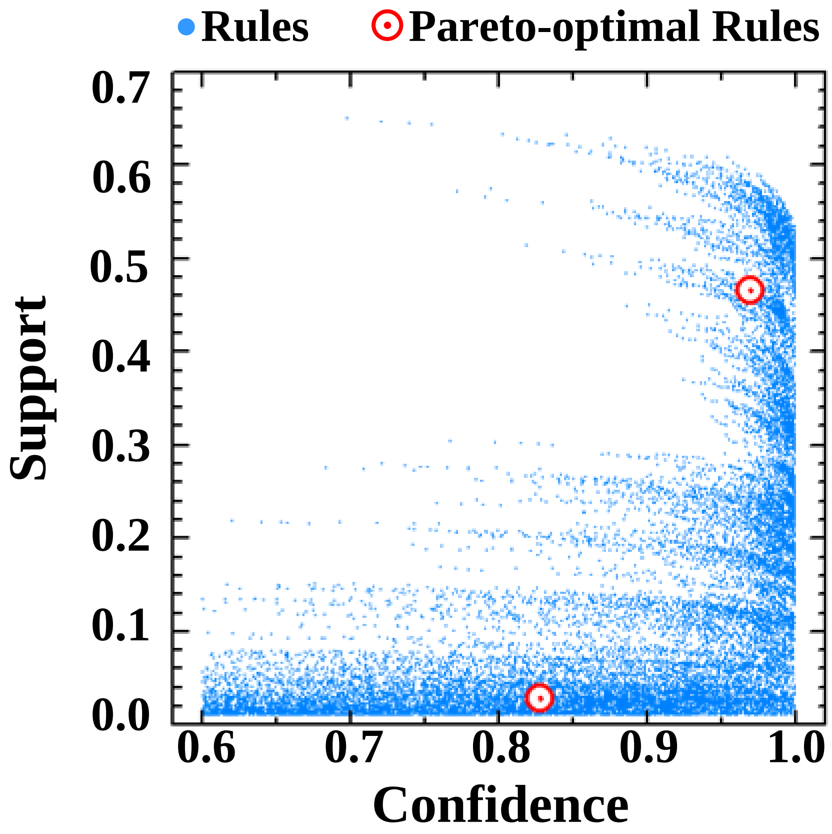


	x_1	x_2	x_3	x_5	x_6	x_7	x_8	Consequent
R_1			DC	DC	DC	DC		Class 0 (0.94)
R_2		DC			DC	DC	DC	Class 0 (0.66)
R_3	DC	DC	DC	DC		DC	DC	Class 1 (0.80)
R_4	DC	DC	DC		DC		DC	Class 1 (0.82)

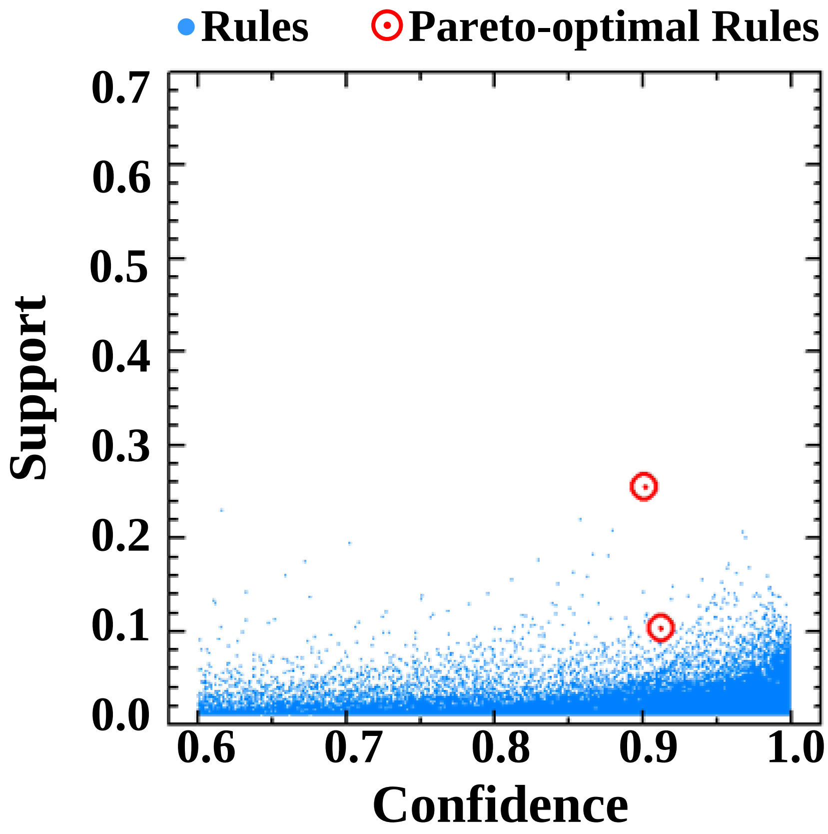
Error rate: 1.2% (training) and 3.4% (test)

Selected Rules in Rule Set C

A single fuzzy rule in B is far from the Pareto-optimal rules but the other rules are near Pareto-optimal.



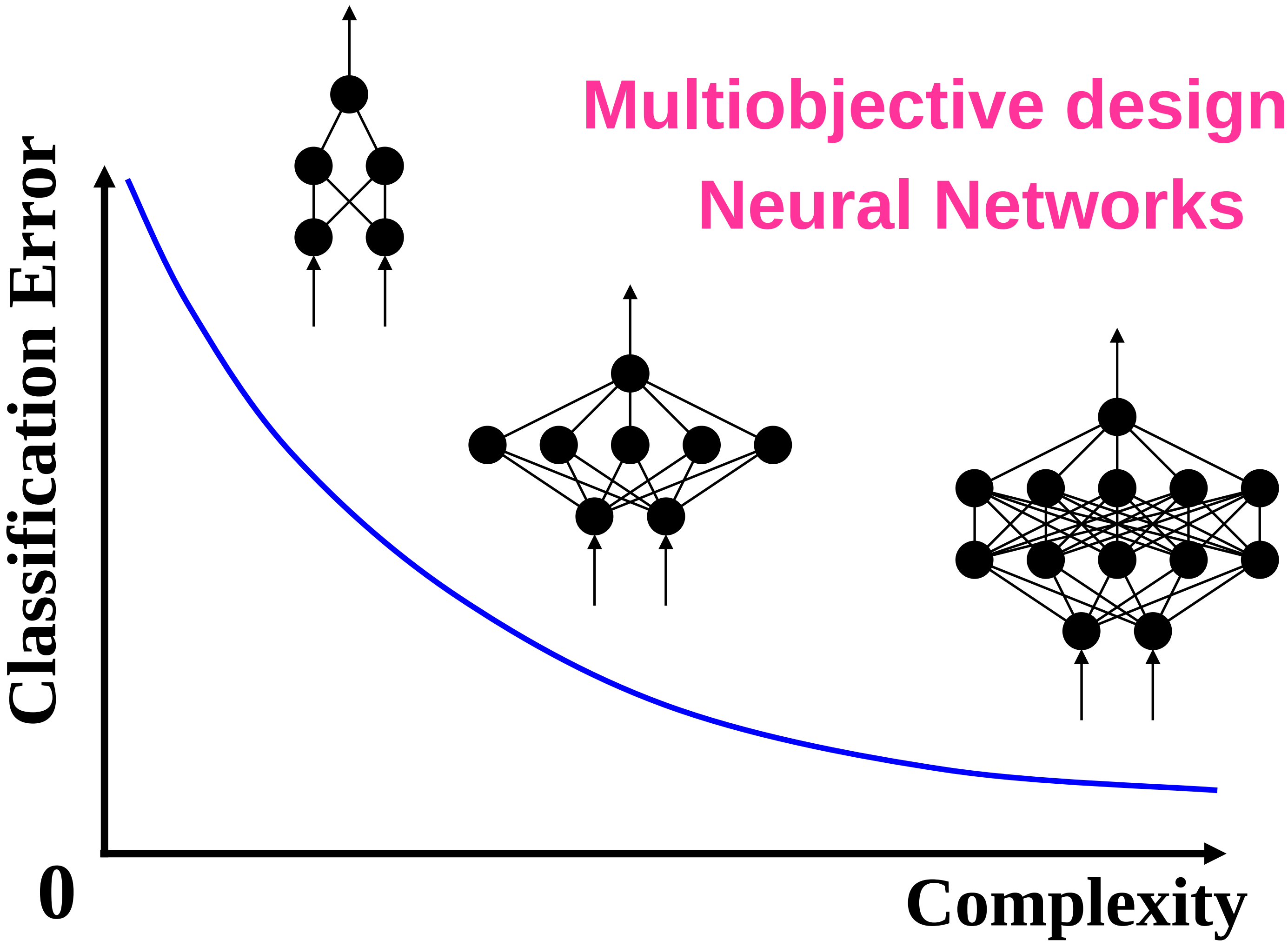
Class 1



Class 2

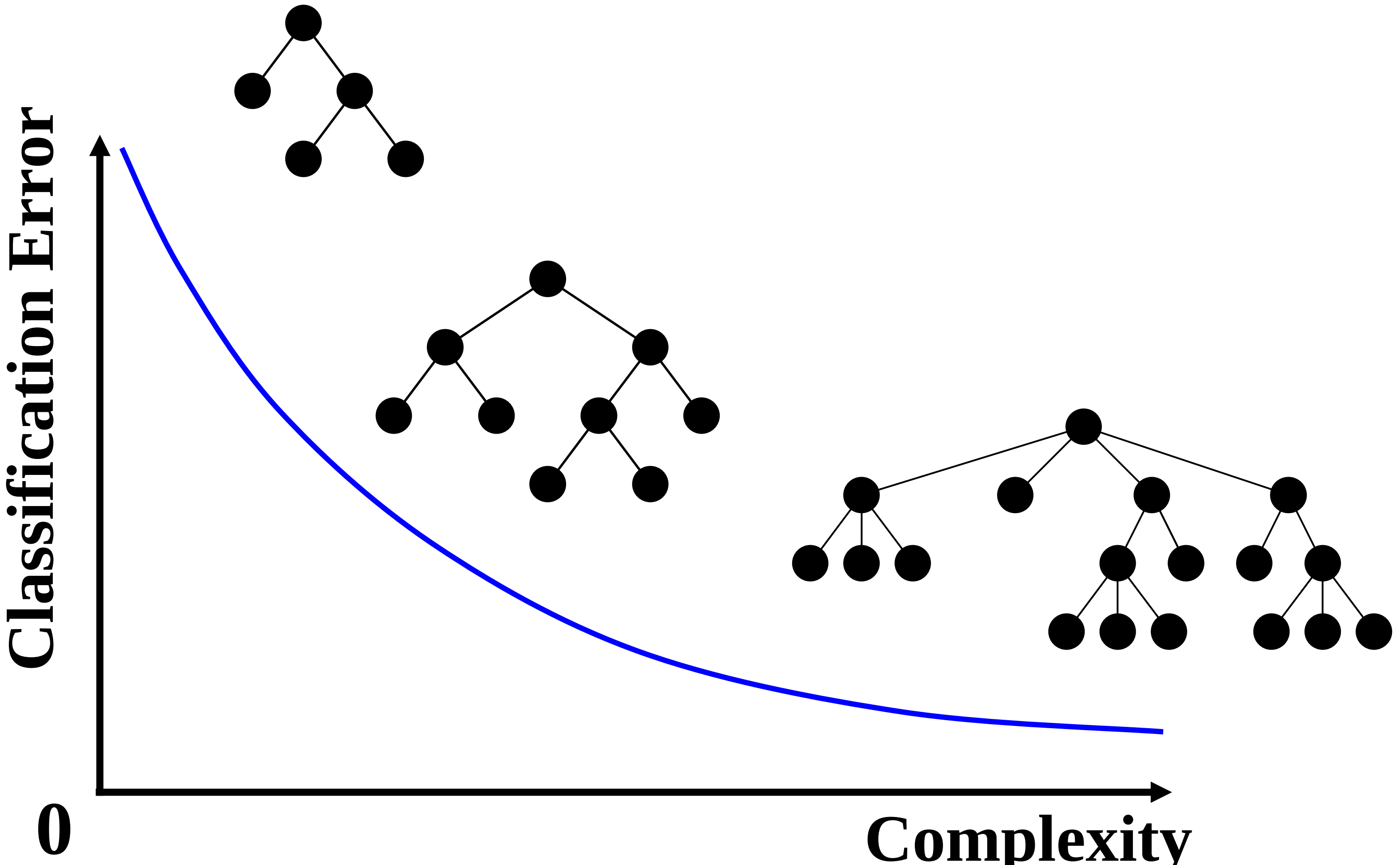
Multiobjective Machine Learning

Recently EMO algorithms were often used in other areas.



Multiobjective Machine Learning

Multiobjective Design of Decision Trees



Multiobjective Machine Learning

EMO algorithms can be used for the multiobjective design of various intelligent systems such as

- Fuzzy Rule-Based Systems
- Multilayer Neural Networks
- RBF Networks
- Support Vector Machines
- Decision Trees
- GP Trees
- . . .
- . . .

Future Research Directions in MGFSs

Multiple objectives are usually involved in the design of any intelligent systems. So you will easily find many future research issues in this research area.

Especially, if you are using an aggregation-based method, you will be able to improve it by the EMO approach.

Aggregation Approach

$$f(S) = w_1 \cdot f_{\text{Error}}(S) + w_2 \cdot f_{\text{Complexity}}(S)$$

Multiobjective Approach

$$\text{Minimize } \{ f_{\text{Error}}(S),\ f_{\text{Complexity}}(S) \}$$

Future Research Directions in MGFSs

Formulations of the Interpretability

- The number of fuzzy rules
- The number of antecedent conditions in each rule
- The number of input variables
- The separability of adjacent antecedent fuzzy sets

Handling of Large Data Sets

- Design of efficient EMO algorithms
- Subdivision of data sets
- Parallel implementation

Development of Special-Purpose EMO Algorithms

- Handling of many objectives
- Handling of both discrete and continuous variables

Future Research Directions in MGFSs

Development of New MGFS Methods with

- Multiobjective input selection algorithm
- Multiobjective fuzzy clustering algorithm
- Multiobjective fuzzy partition algorithm
- Multiobjective rule selection algorithm
- . . .

Visualization of Pareto-Optimal Fuzzy Systems

- Visualization of a single fuzzy system
- Visualization of multiple fuzzy systems
- Visualization of accuracy-complexity tradeoff

Ensemble Classifier Design

- Search for multiple fuzzy systems with a large diversity
- Choice of ensemble members and their combination

Future Research Directions in MGFSs

Incorporation of Other Ideas into MGFS

- FUZZ-IEEE 2007 Tutorial by Alexander Gegov on Rule Base Compression in Fuzzy Systems

- . . .

- . . .

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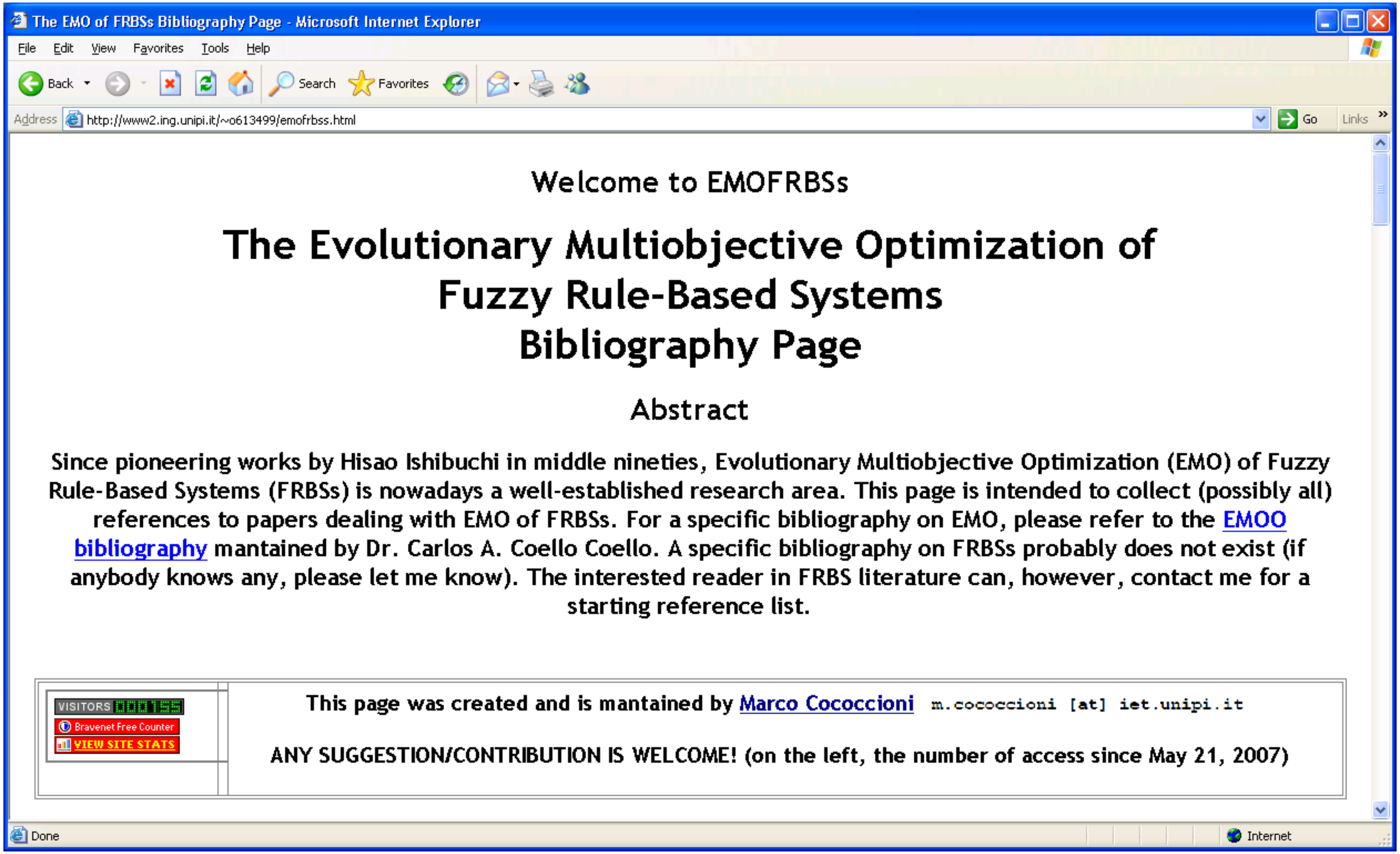
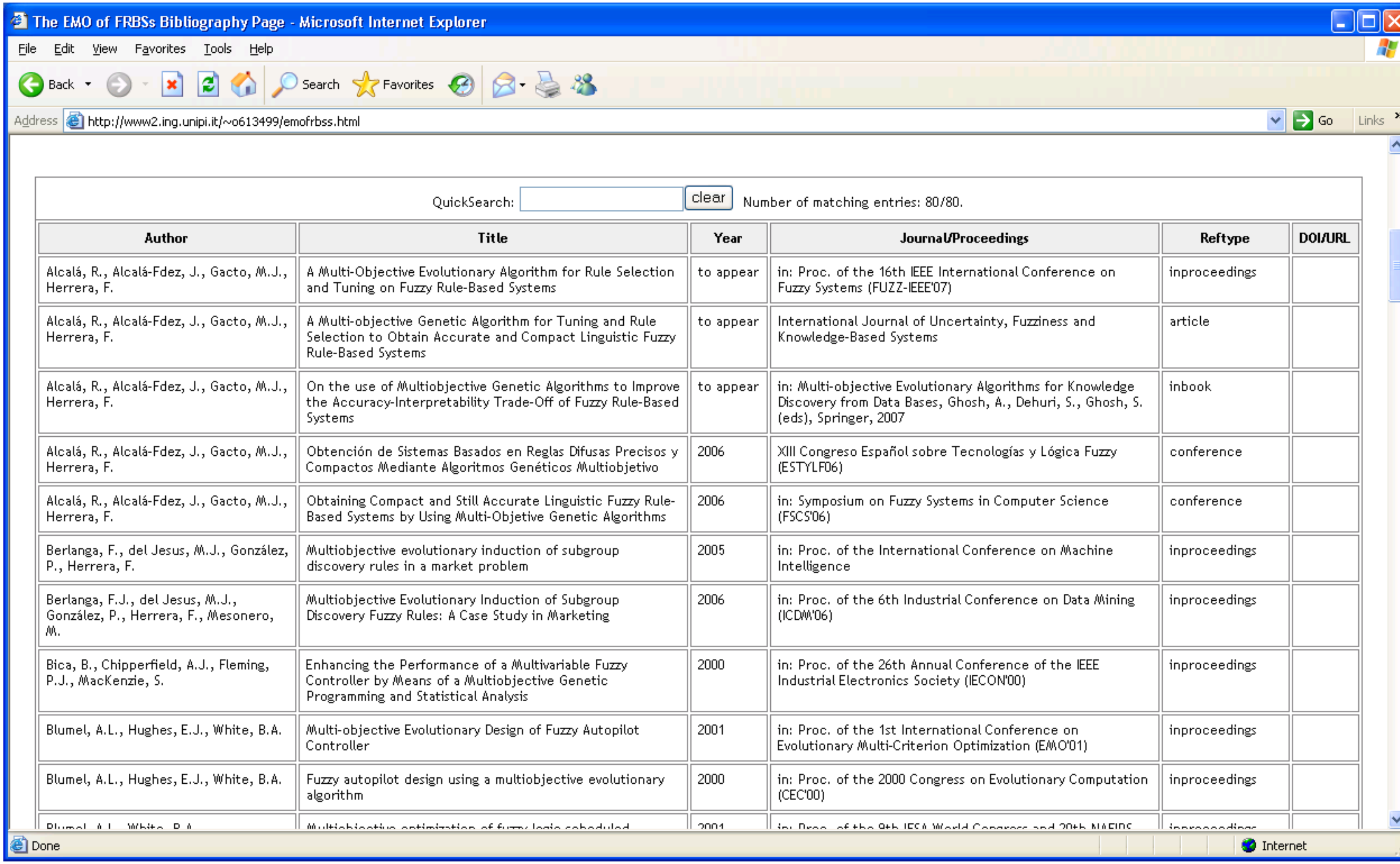
Webpage of EMOFRBSs



http://www2.ing.unipi.it/~o613499/emofrbss.html

Webpage of EMOFRBSs



The EMO of FRBSs Bibliography Page - Microsoft Internet Explorer

Address http://www2.ing.unipi.it/~o613499/emofrbss.html

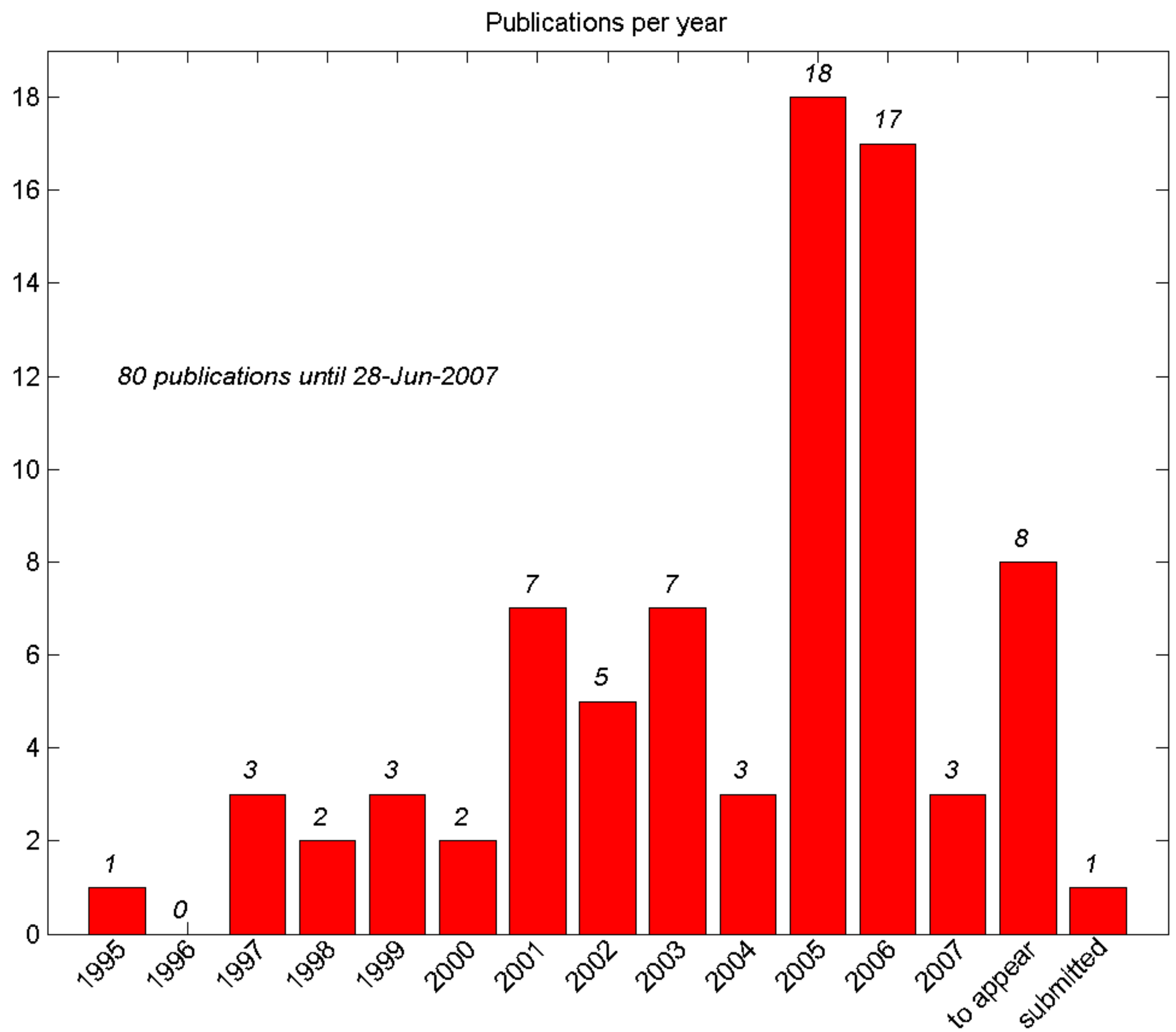
QuickSearch: clear Number of matching entries: 80/80.

Author	Title	Year	Journal/Proceedings	Reftype	DOI/URL
Alcalá, R., Alcalá-Fdez, J., Gacto, M.J., Herrera, F.	A Multi-Objective Evolutionary Algorithm for Rule Selection and Tuning on Fuzzy Rule-Based Systems	to appear	in: Proc. of the 16th IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'07)	inproceedings	
Alcalá, R., Alcalá-Fdez, J., Gacto, M.J., Herrera, F.	A Multi-objective Genetic Algorithm for Tuning and Rule Selection to Obtain Accurate and Compact Linguistic Fuzzy Rule-Based Systems	to appear	International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems	article	
Alcalá, R., Alcalá-Fdez, J., Gacto, M.J., Herrera, F.	On the use of Multiobjective Genetic Algorithms to Improve the Accuracy-Interpretability Trade-Off of Fuzzy Rule-Based Systems	to appear	in: Multi-objective Evolutionary Algorithms for Knowledge Discovery from Data Bases, Ghosh, A., Dehuri, S., Ghosh, S. (eds), Springer, 2007	inbook	
Alcalá, R., Alcalá-Fdez, J., Gacto, M.J., Herrera, F.	Obtención de Sistemas Basados en Reglas Difusas Precisos y Compactos Mediante Algoritmos Genéticos Multiobjetivo	2006	XIII Congreso Español sobre Tecnologías y Lógica Fuzzy (ESTYLF06)	conference	
Alcalá, R., Alcalá-Fdez, J., Gacto, M.J., Herrera, F.	Obtaining Compact and Still Accurate Linguistic Fuzzy Rule-Based Systems by Using Multi-Objetive Genetic Algorithms	2006	in: Symposium on Fuzzy Systems in Computer Science (FSCS'06)	conference	
Berlanga, F., del Jesus, M.J., González, P., Herrera, F.	Multiobjective evolutionary induction of subgroup discovery rules in a market problem	2005	in: Proc. of the International Conference on Machine Intelligence	inproceedings	
Berlanga, F.J., del Jesus, M.J., González, P., Herrera, F., Mesonero, M.	Multiobjective Evolutionary Induction of Subgroup Discovery Fuzzy Rules: A Case Study in Marketing	2006	in: Proc. of the 6th Industrial Conference on Data Mining (ICDM'06)	inproceedings	
Bica, B., Chipperfield, A.J., Fleming, P.J., MacKenzie, S.	Enhancing the Performance of a Multivariable Fuzzy Controller by Means of a Multiobjective Genetic Programming and Statistical Analysis	2000	in: Proc. of the 26th Annual Conference of the IEEE Industrial Electronics Society (IECON'00)	inproceedings	
Blumel, A.L., Hughes, E.J., White, B.A.	Multi-objective Evolutionary Design of Fuzzy Autopilot Controller	2001	in: Proc. of the 1st International Conference on Evolutionary Multi-Criterion Optimization (EMO'01)	inproceedings	
Blumel, A.L., Hughes, E.J., White, B.A.	Fuzzy autopilot design using a multiobjective evolutionary algorithm	2000	in: Proc. of the 2000 Congress on Evolutionary Computation (CEC'00)	inproceedings	

Done Internet

http://www2.ing.unipi.it/~o613499/emofrbss.html

List of 80 MGFSs papers



End of My Presentation

Thank you very much !