Brain-machine optimization: learning objective functions by interacting with the final user

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Topics:
(machine) learning and optimization

Reactive Search Optimization

"learning on the job"

– avoiding user intervention

– internal learning loop

… suitable if single clear f(x) to optimize

but in many real-world cases… no f(x)

Multiobjective Optimization

interactive: "user in the learning/optimizing loop"

– *couple internal and external learning through systematic machine learning techniques*

Reactive search optimization

=

ON-LINE MACHINE LEARNING FOR OPTIMIZATION

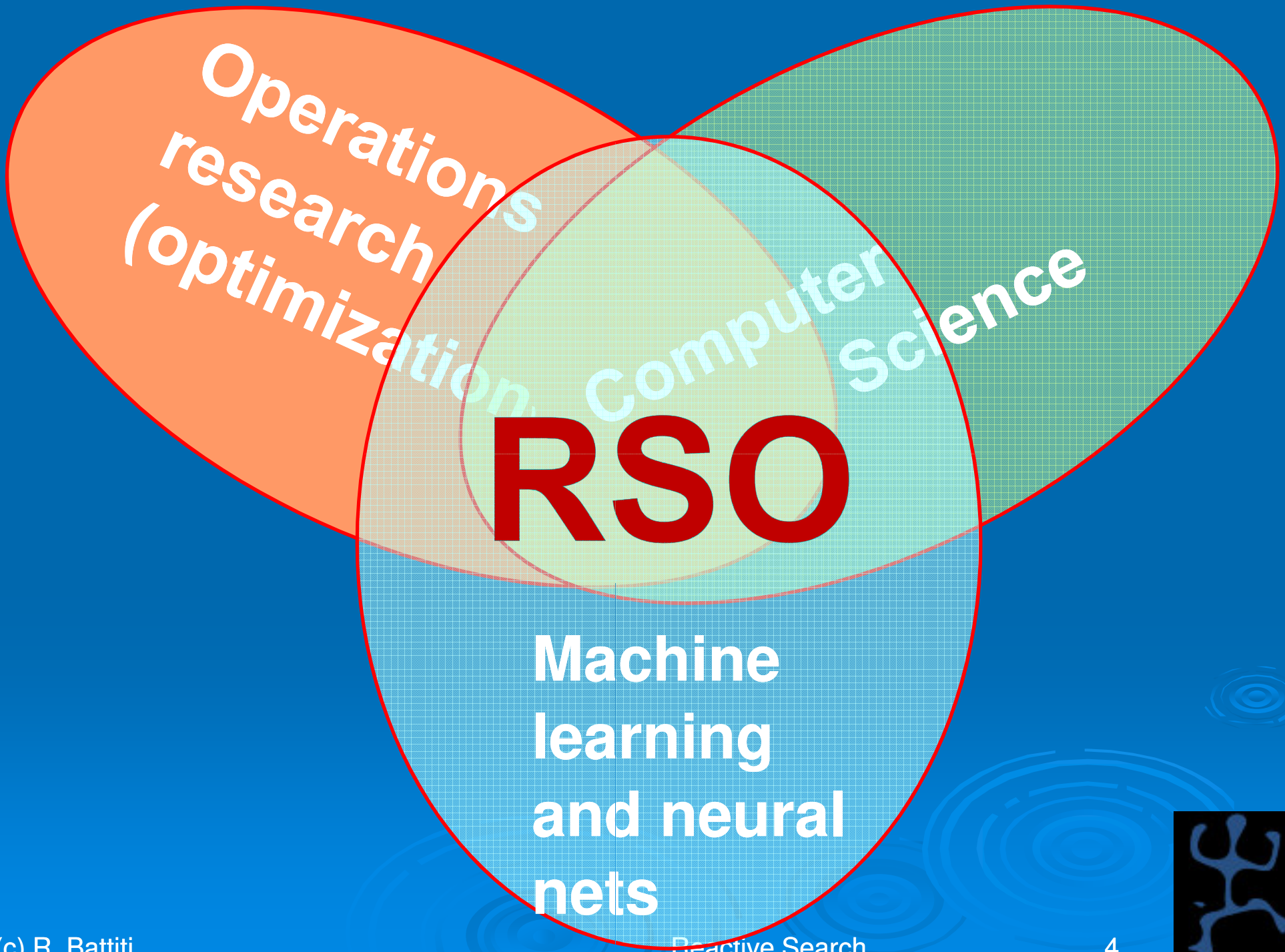
=

on-line dynamic and adaptive search

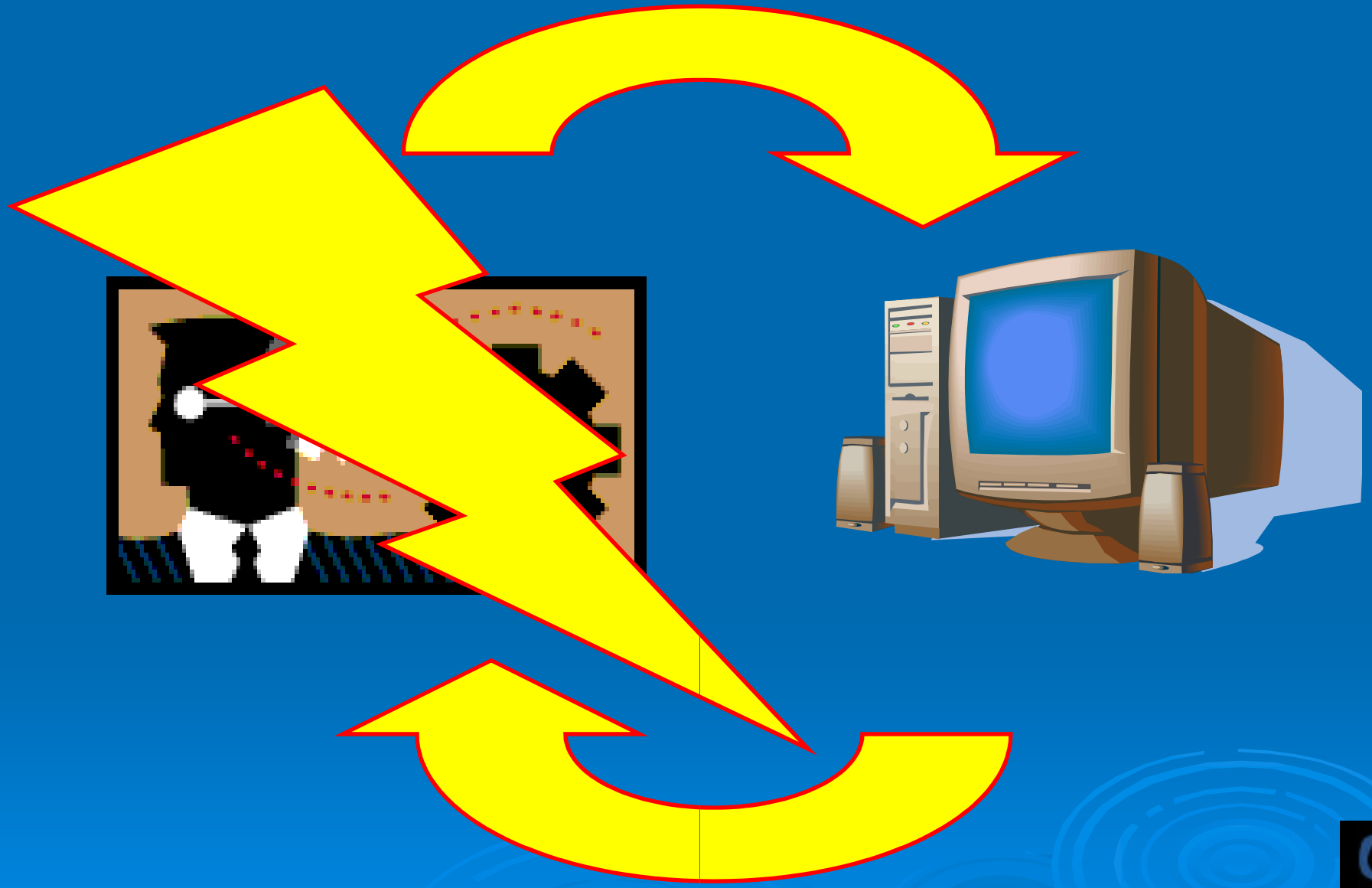
=

on-line reinforcement learning for optimization

Reactive Search: Learning on the Job


Operations research (optimization)
Computer Science
RSO
Machine learning and neural nets

The role of the user



The role of the user

- **choices and free parameters**

  Algorithm(T)

- **the user as a crucial learning component** ("trial and error")

- **Parameter tuning is a typical "learning" process** where experiments are designed, with the support of statistical estimation (parameter identification) tools.

Automated tuning through machine learning

- **Automation**. The time-consuming tuning phase is now substituted by an automated process.
- **Complete and unambiguous documentation**. The algorithm becomes self-contained: its quality can be judged independently from the designer.

Complexity is shifted
Final user → algorithm developer

On-line tuning

- Take into account:
  - Problem-dependent
  - Task-dependent
  - Local properties in configuration space (see local search), parameters are dynamically tuned based on optimization state and previous history

Reactive search optimization

- integration of sub-symbolic machine learning techniques into search heuristics. The word ***reactive*** hints at a ready response to events *during* the search through an internal online feedback loop for the *self-tuning* of critical parameters.

Methodologies of interest for Reactive Search include machine learning and statistics, in particular reinforcement learning, active or query learning, transfer learning, neural networks

www.reactive-search.org

RSO context

f(x) is given (either analytically or as a black box)

the emphasis is on learning local models and using them while optimizing (*no additional knowledge from DM required*)

… but in some cases f(x) to optimize is not given, modeling user preferences is a crucial issue

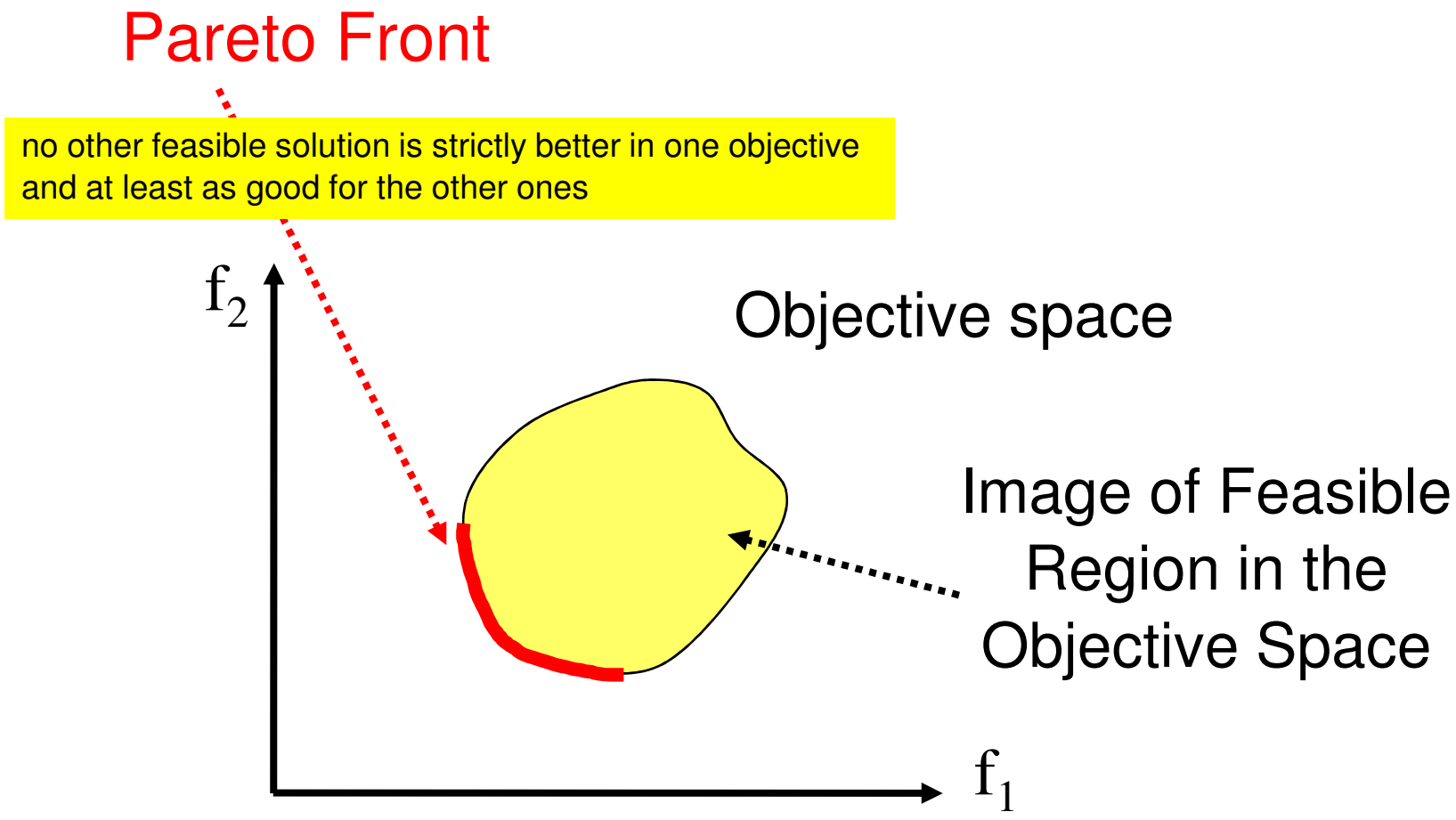
Try asking a decision maker:
"give me the f(x) that you are optimizing"

Moltiobjective optimization

intermediate (classical) case:
some criteria are given $f_1(x)$ $f_2(x)$ … $f_k(x)$
but are not easily combined into a single f(x)

…provide efficient vector solutions $(f_1,\ldots,f_k)$
leave to the user the possibility to decide
(and to learn about possibilities and “real” objectives, even if not formalized)

Efficient frontier: an example



Preference information

- Critical task: identify the best solution for the DM from the efficient frontier

- Based on the DM preference information usage:
  - *A priori* MOO methods
  - *A posteriori* MOO methods
  - *Interactive* MOO methods (IM)

A priori methods

- Assumptions about preference information before optimization process
- DM specifies preference on the objectives a priori
- Drawbacks:
  - Very difficult task for DM
  - DM often does not know before how realistic his expectations are (no learning possiblities)

A posteriori Methods

- The Pareto optimal set (or part of it) is generated and presented to the DM who selects the most preferred among the alternatives.
- Drawbacks:
  - Generation is computationally expensive: find all the non dominated solutions!
  - Hard fo the DM the selection among a large set of alternatives
  - Presenting / displaying the alternatives to the DM

Interactive methods

- Solutions generation phases alternated to solution evaluation phases requiring user interaction
- Effective approach
  - Only a subset of the Pareto optimal set has to be generated and evaluated by the DM
  - The DM drives the search process
  - The DM gets to know the problem better (learning on the job)

Interactive methods

- Choices:
  - How information is provided to DM
  - How preference information is obtained from DM
  - How the search process is updated based on the preference information
  - How the original MOO problem is transformed into a single-objective optimization problem (scalarization process)

    e.g. optimize: $\sum w_i f_i(x)$

Interactive methods

- Assumptions:
  - DM states the decision variables, the constraints, the model, the objectives *but* he *cannot* prioritize the importance of the objectives
  - Model parameter vector (MPV): parameter vector in the MOO method capturing the preference information (e.g. weights w_i)
    - MPV defined => final solution determined
  - Value function: DM makes decisions based on an underlying (unknown) function representing the preference of the DM among the criterion vectors

Notation

- Input MOO problem

$$\begin{aligned} \text{minimize} \quad & \{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})\} \\ \text{subject to} \quad & \mathbf{x} \in S, \end{aligned}$$

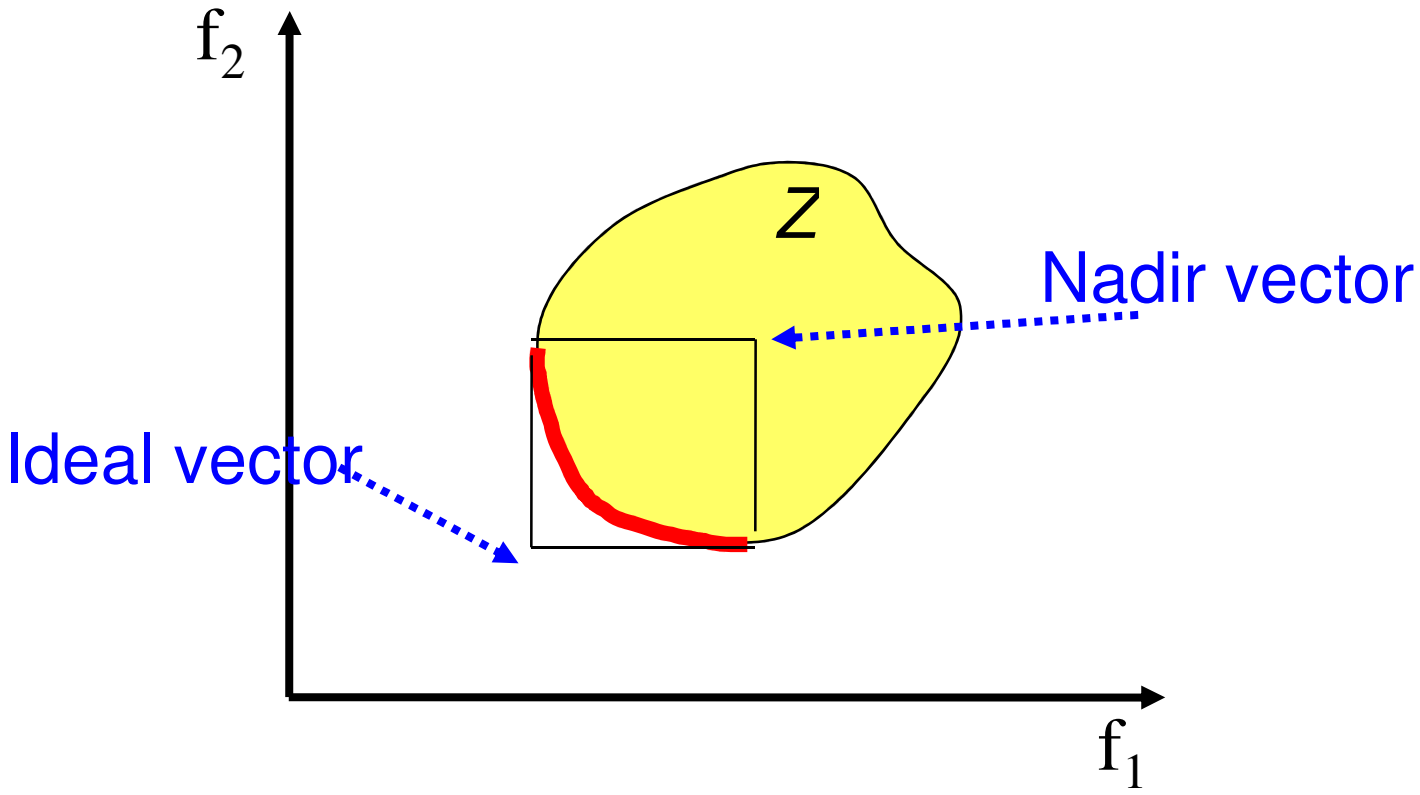
- K objective functions: $f_i \colon \mathbf{R}^n \to \mathbf{R}$

- Decision variables vectors: $(x_1, x_2, \ldots, x_n)$
- Feasible region *S*

- Criterion values: $z_i = f_i(\mathbf{x}) \text{ for all } i = 1, \ldots, k$
- Image of the feasible region: $Z \ (= \mathbf{f}(S))$

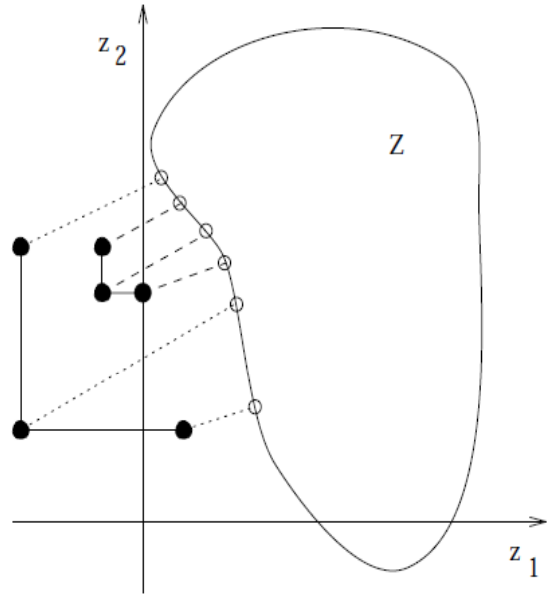
Notation

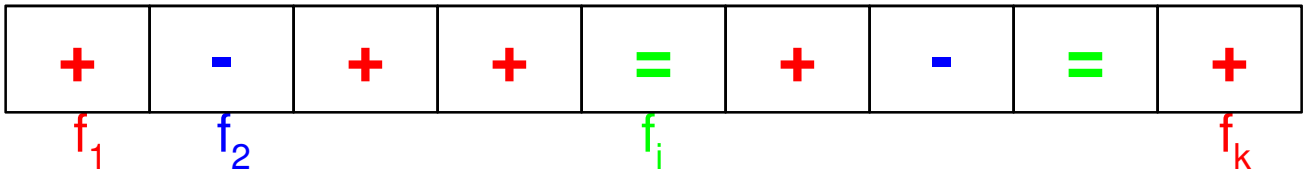
- Lower bound: ideal criterion vector $\mathbf{z}^\star \in \mathbf{R}^k$
  - Obtained by minimizing each objective individually
- Upper bound: Nadir criterion vector $\mathbf{z}^{\mathrm{nad}}$
  - (estimated) worst objective values of the Pareto Optimal solutions



Interactive methods

- Possible classification:
  - Trade-off based methods
  - Reference point methods
  - Classification based methods





- Neural network based approaches

Neural Network based approaches

- Key issue: modelling the preference information of the DM by using a Neural Network (NN)
- NN based model used to predict how much the DM appreciate a given (Pareto optimal) solution
- Two methods in the literature:
  - FFANN – Feed Forward Artificial Neural Networks procedure (Sun *et al.* 1996, 2000)
  - IMOM - Intelligent Interactive Multiobjective Optimization method (Huang *et al.* 2005)

FFANN procedure

- Iterative procedure
- NN model of the preference information structure
  - Input: criterion vector
  - Output: preference value

1. Use trained NN to determine best NN input

   max NN(f(x)) [not nec. Pareto-optimal]

2. Use trained NN to filter Pareto-optimal points to present to DM for evaluation

FFANN-2 procedure (Sun *et al.* 2000)

- At each ieration:
  - Step 1: randomly select *2P* values in the current model parameter vector space generate *2P* non-dominated criterion vectors
  - Step 2: compute the preference values for the *2P* criterion vectors using the trained NN and select the *P* vectors with highest output values
  - Step 3: present the selected P vectors to DM for evaluation. The criterion vector z_b with highest value is the best solution at current ieration. If FU is satisfied, stop

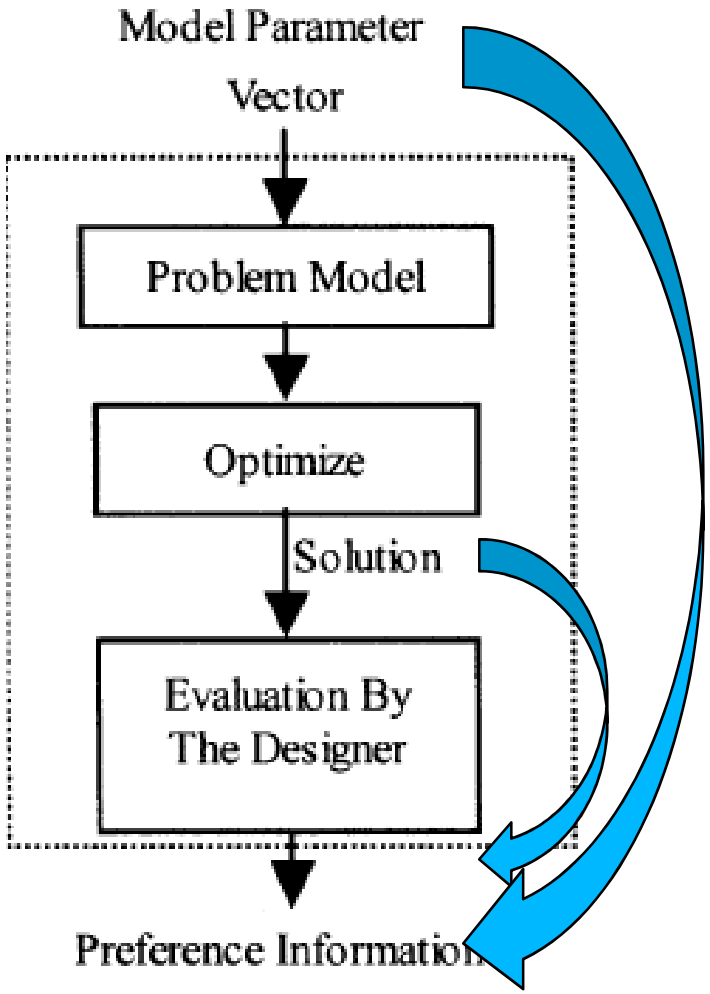
FFANN-2 procedure (Sun *et al.* 2000)

  - Step 4: train the NN with the P criterion vectors as input and the DM evaluation as the desired output
  - Step 5: based on z_b update the model parameter vector space

- NN model reduces the burden on the DM of evaluating the generated solutions
- Drawbacks: NN model cannot help in searching improved solutions

Intelligent Interactivel MO Method IMOM (Huang *et al.* 2005)

- Iterative procedure
- NN model of the preference information structure
  - Input: model parameter vector
  - Output: preference value
- At each iteration reduce the model parameter vector space based on DM preference information



IMOM (Huang *et al.* 2005)

- At each iteration:
  - Step 1: pick the best value for the model parameter vector (*mpv*) obtained at previous iteration, randomly select *P-1* values in the current model parameter vector space Ω and generate *P* pareto optimal solutions
  - Step 2: If the designer is satisfied with one on the P solutions, stop. Otherwise, DM evaluates the *P* criterion vectors

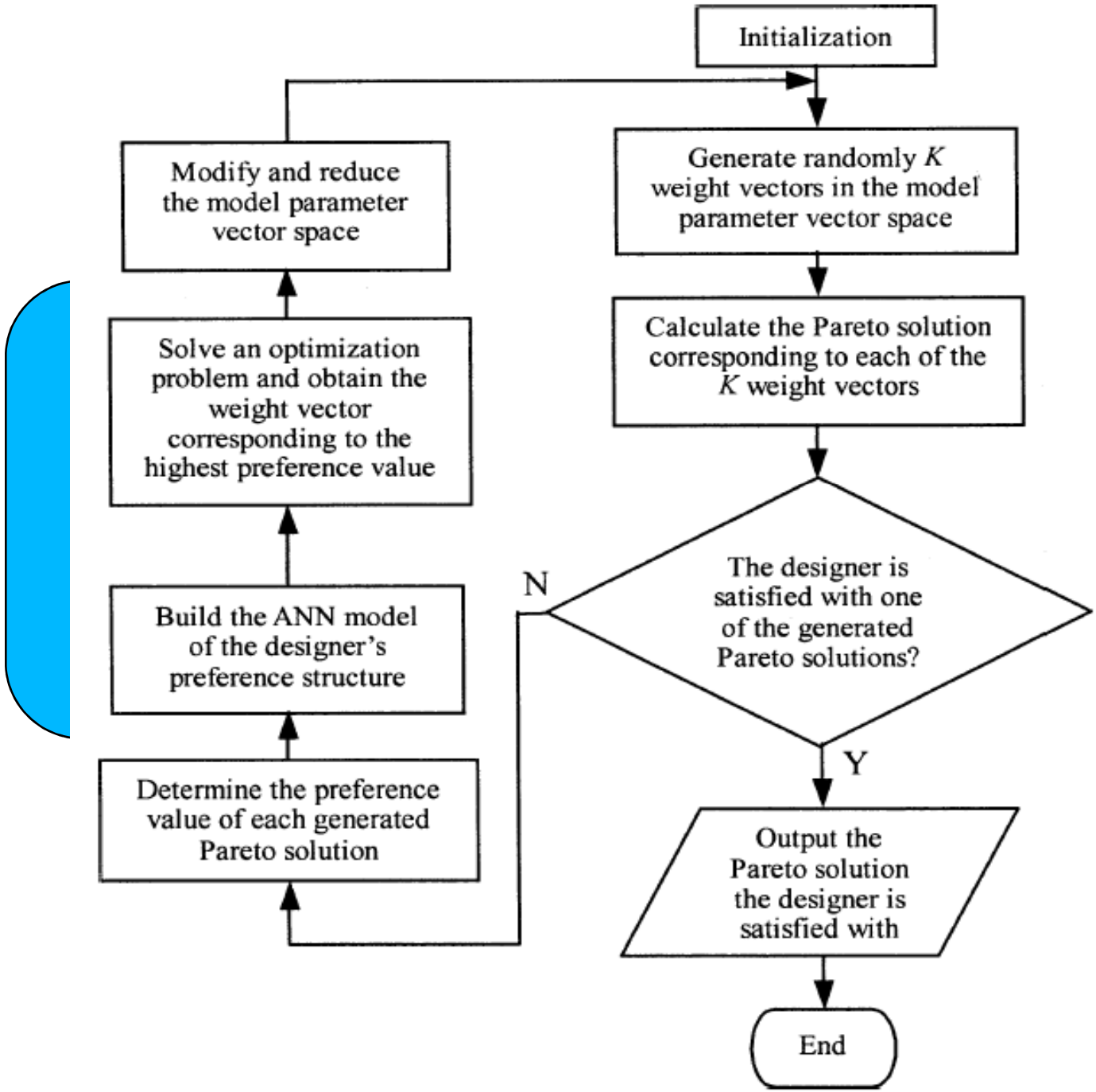
IMOM (Huang *et al.* 2005)

- Step 3: train the NN model with the preference information of the DM obtained in the last several iterations
- Step 4: Obtain the best *mpv* w.r.t. the highest preference value by solving

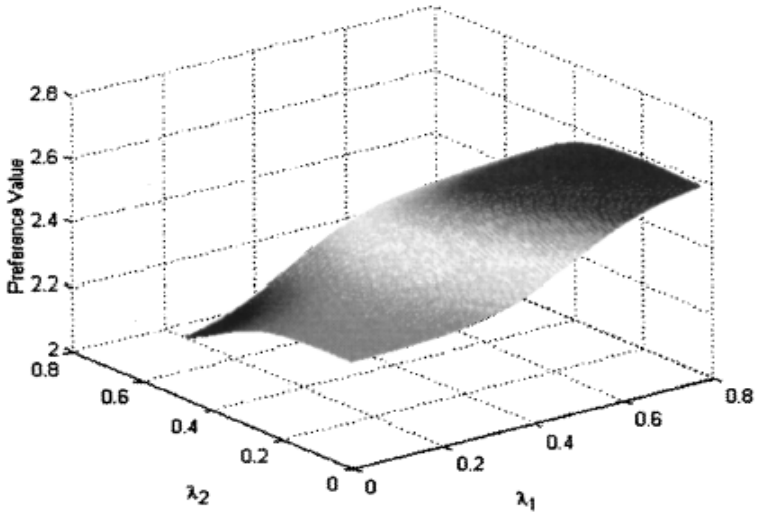
  max NN(*mpv*)

  s.t. *mpv* ϵ Ω
- Step 5: modify and reduce the model parameter vector space based on the best *mpv* obtained at step 4

IMOM (Huang *et al.* 2005)



IMOM (Huang *et al.* 2005)



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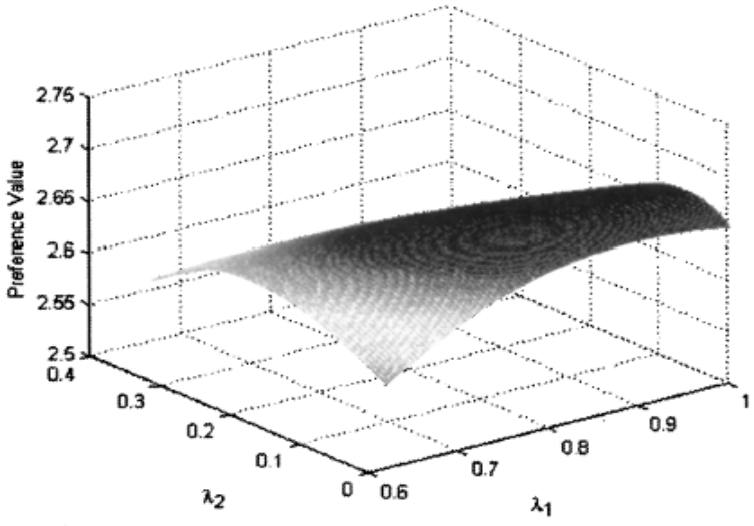

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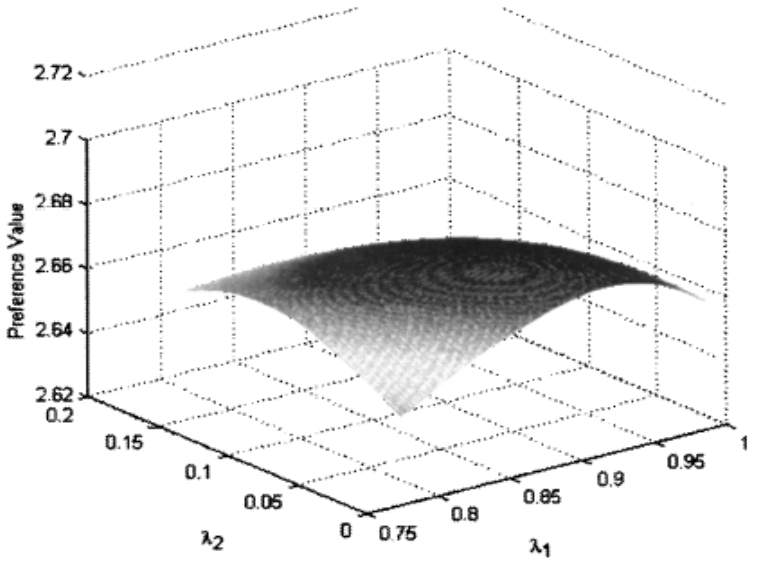
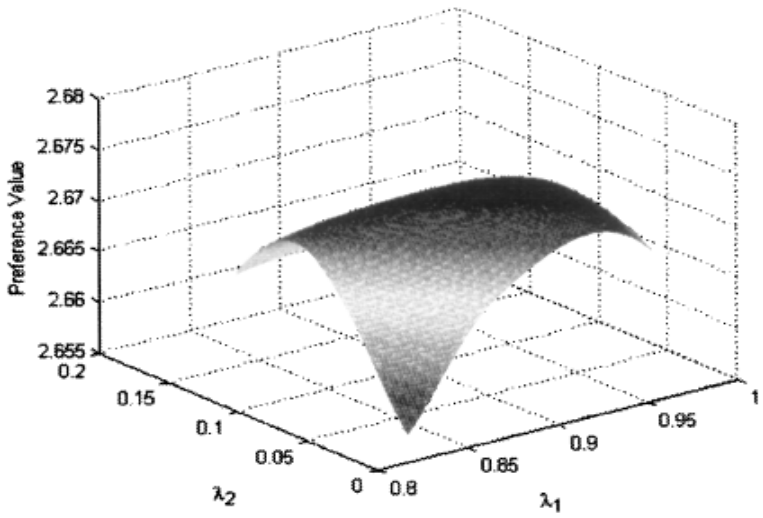


(c)



(d)

Current work: learning for multiobjective optimization

Context is the same: learning user preferences

1. Train a predictor able to reproduce user preferences
2. Use the learned predictor to guide the search in place of the user

Emphasis is different:

DM time is a scarce and costly resource It is crucial to minimize the number of queries made to the user and their complexity

Current work: learning for multiobjective optimization

Design:

- Question structure (comparison, qualitative evaluation,...)
- Way in which the predictor is updated based on the preference information obtained in an online manner
- Detect the most informative questions (**active learning**)

support vector ranking

Algorithm

- Given:
  - A set of candidate solutions $\{\mathbf{f}(\mathbf{x}_1), \ldots, \mathbf{f}(\mathbf{x}_N)\}$
  - A set of user preferences as $\mathbf{f}(\mathbf{x}_i) > \mathbf{f}(\mathbf{x}_j)$
- Learn a large margin ranking function $\mathbf{w}^T\mathbf{f}(\mathbf{x})$:

$$\min_{\mathbf{w}} ||\mathbf{w}||^2$$

- Satisfying constraints:

$$\mathbf{w}^T\mathbf{f}(\mathbf{x}_i) > \mathbf{w}^T\mathbf{f}(\mathbf{x}_j)$$

Extensions

- Soft constraints can be employed adding penalties for violatied ones
- A complex non-linear ranker can be learned by the *kernel trick*

Online support vector ranking

Algorithm

1. The ranker is trained with an initial set of user preferences
2. Ranker guided search and ranker refinement steps are alternated:
    1. the ranker guides the search emulating user preferences
    2. produced solutions are ranked by the user, and the ranker is refined adding the new constraints

Transfer learning

- The learned ranker could be used for related multiobjective optimization tasks, with same objectives but different feasible sets

PRELIMINARY CALL

Learning and Intelligent OptimizatioN
LION 4, Jan 18-22, 2010, Venice, Italy

Technical Co-Sponsorship (pending): IEEE Computational Intelligence Society, Microsoft Research, Associazione Italiana per l'Intelligenza Artificiale

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THE END