

GECCO 2017 Tutorial on Evolutionary Multiobjective Optimization

Dimo Brockhoff
dimobrockhoff@inria.fr

updated slides will be available at
<http://www.cmap.polytechnique.fr/~dimobrockhoff/>



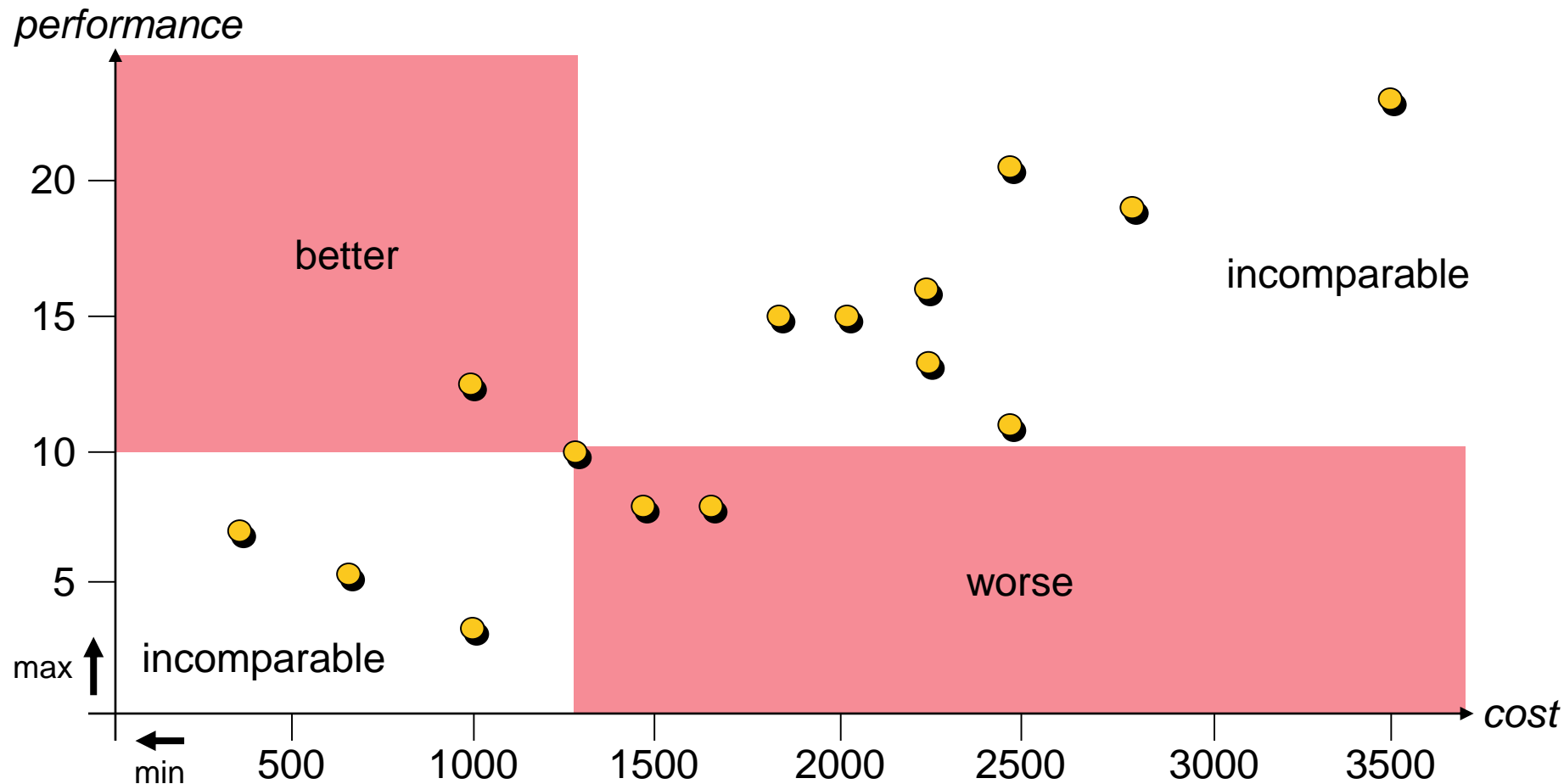
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A Brief Introduction to Multiobjective Optimization

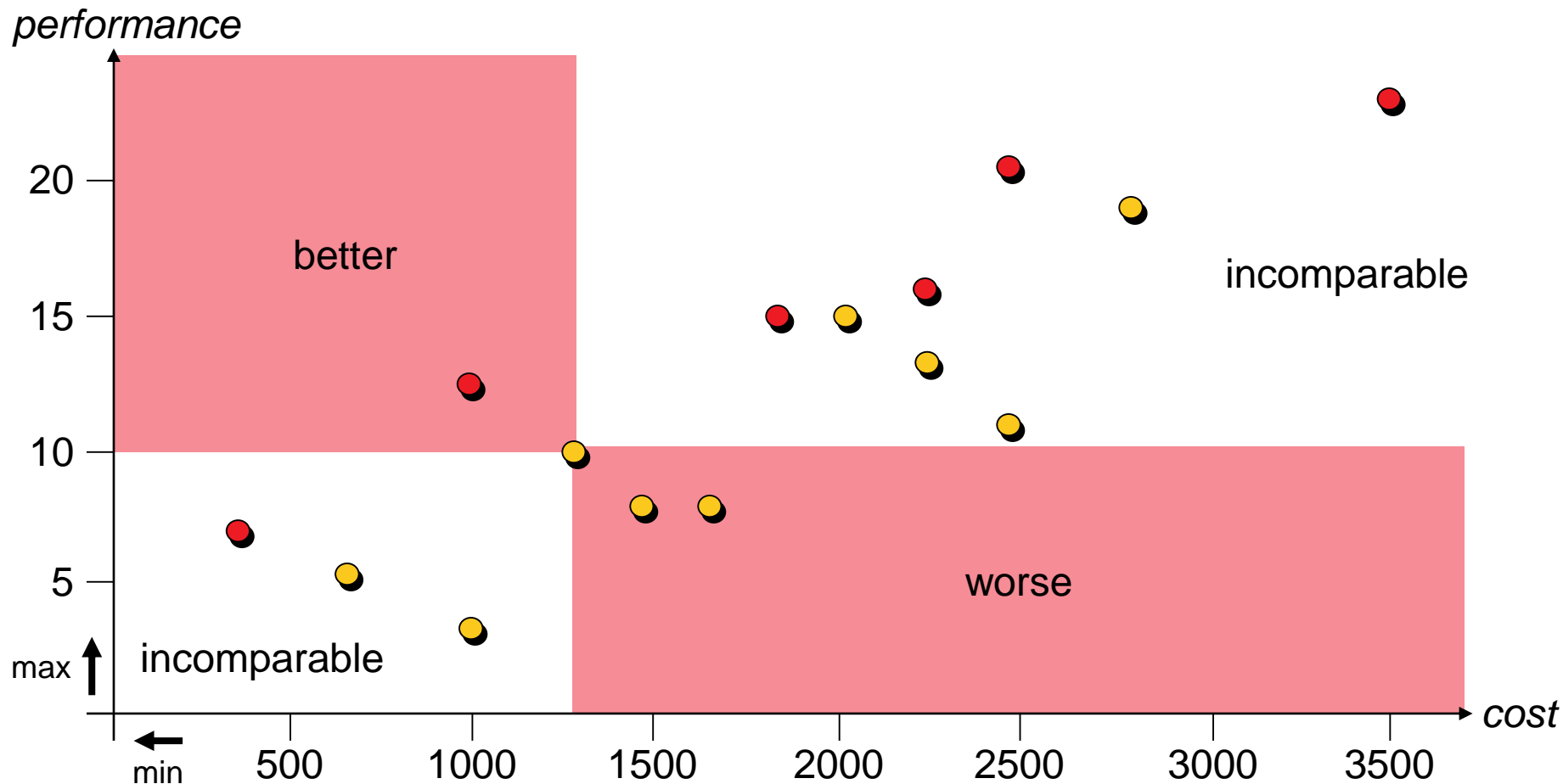
Multiobjective Optimization

Multiple objectives that have to be optimized simultaneously



A Brief Introduction to Multiobjective Optimization

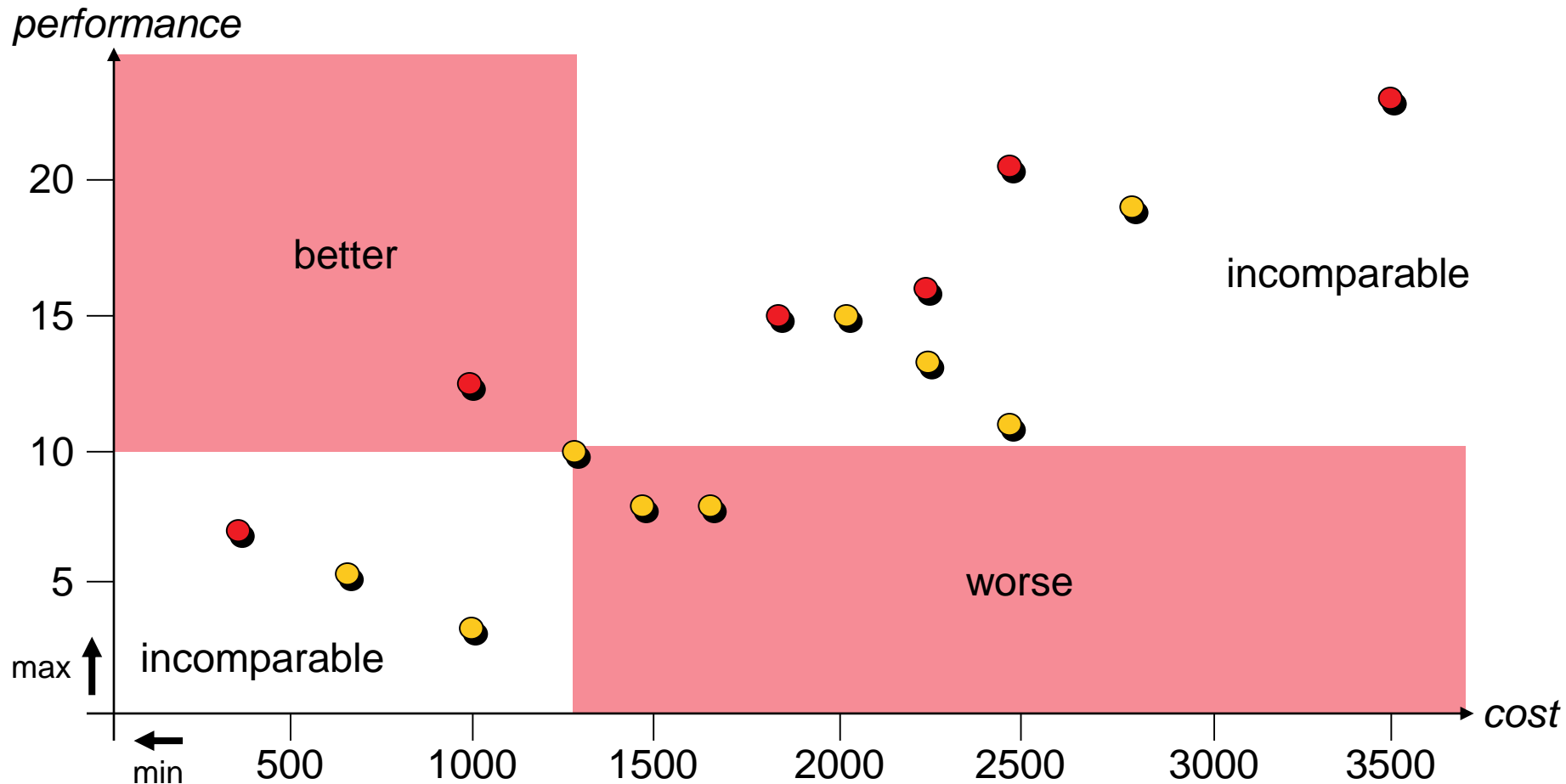
- Observations:**
- ① there is no single optimal solution, but
 - ② some solutions (●) are better than others (●)



A Brief Introduction to Multiobjective Optimization

u weakly Pareto dominates v ($u \leq_{par} v$): $\forall 1 \leq i \leq k : f_i(u) \leq f_i(v)$

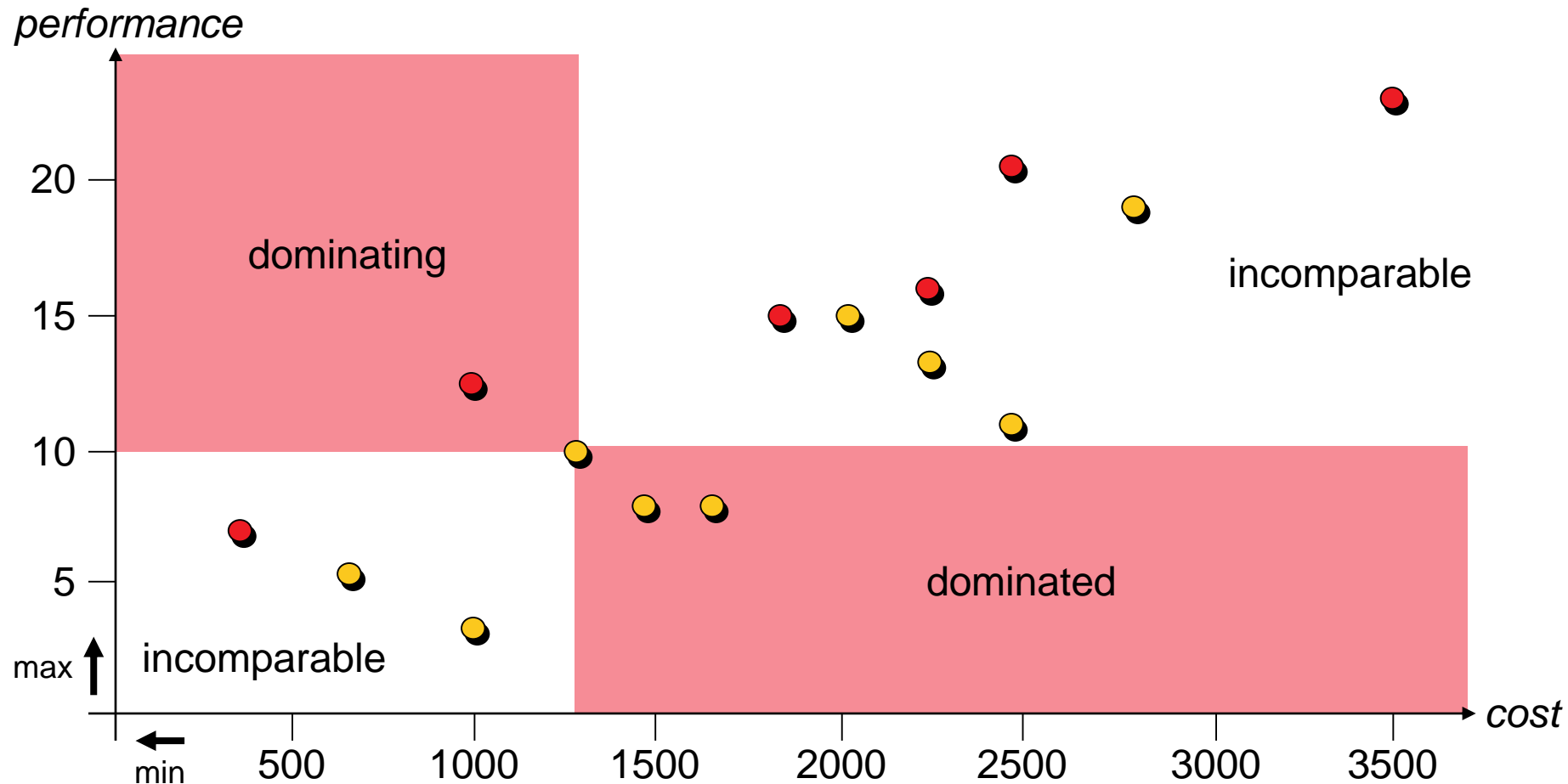
u Pareto dominates v ($u <_{par} v$): $u \leq_{par} v \wedge v \not\leq_{par} u$



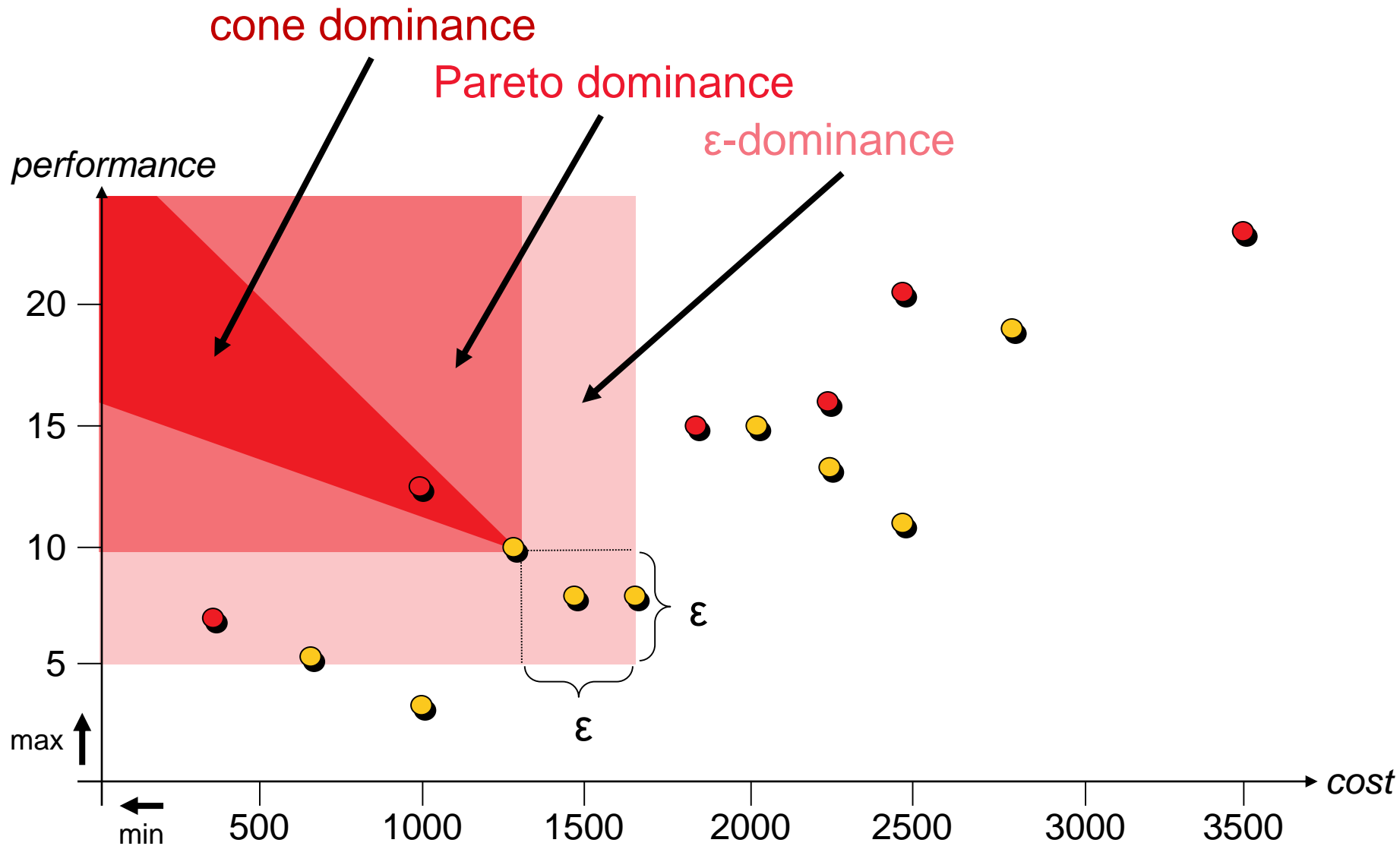
A Brief Introduction to Multiobjective Optimization

u weakly Pareto dominates v ($u \leq_{par} v$): $\forall 1 \leq i \leq k : f_i(u) \leq f_i(v)$

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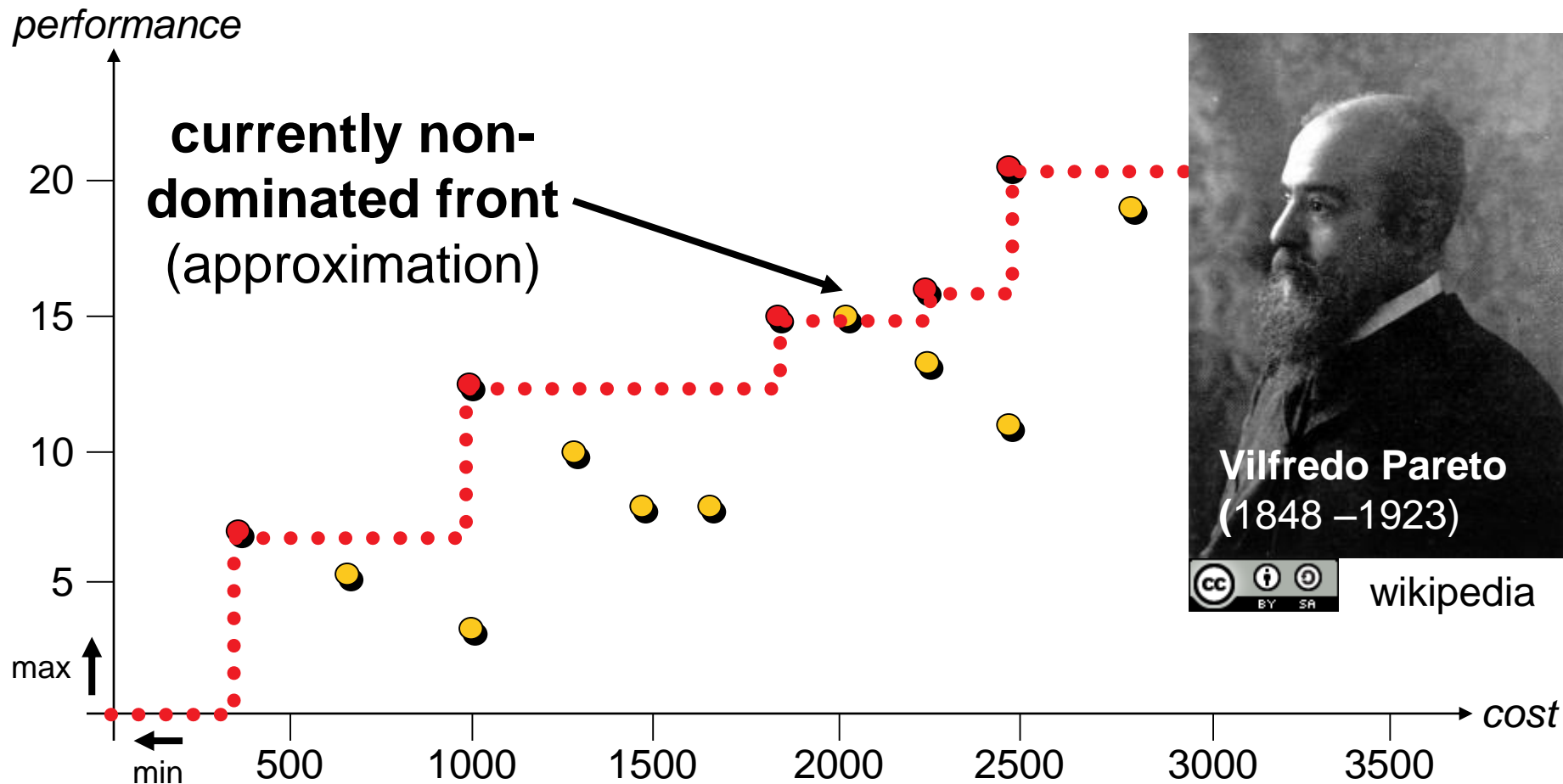
A Brief Introduction to Multiobjective Optimization



A Brief Introduction to Multiobjective Optimization

Pareto set: set of all non-dominated solutions (decision space)

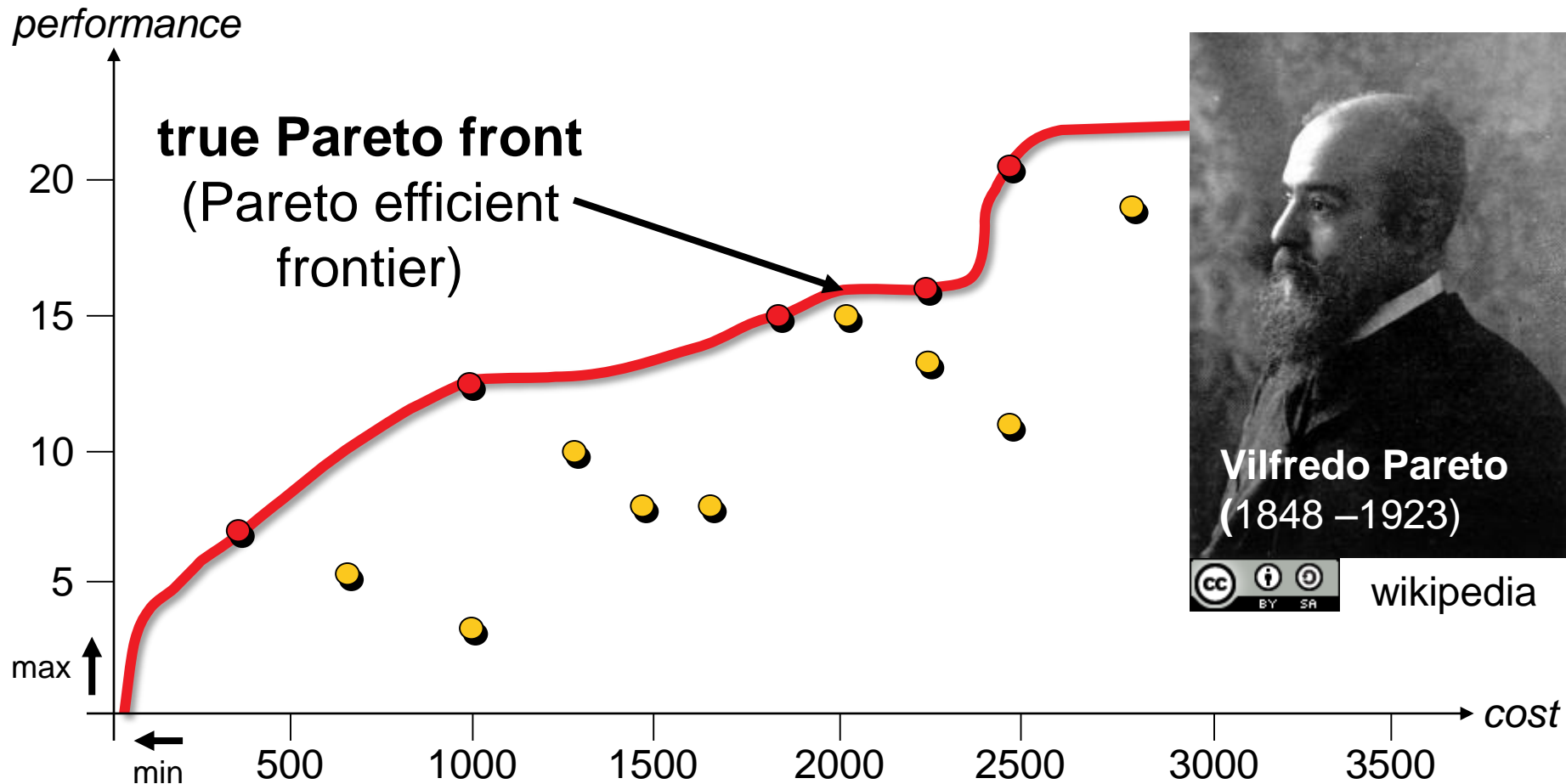
Pareto front: its image in the objective space



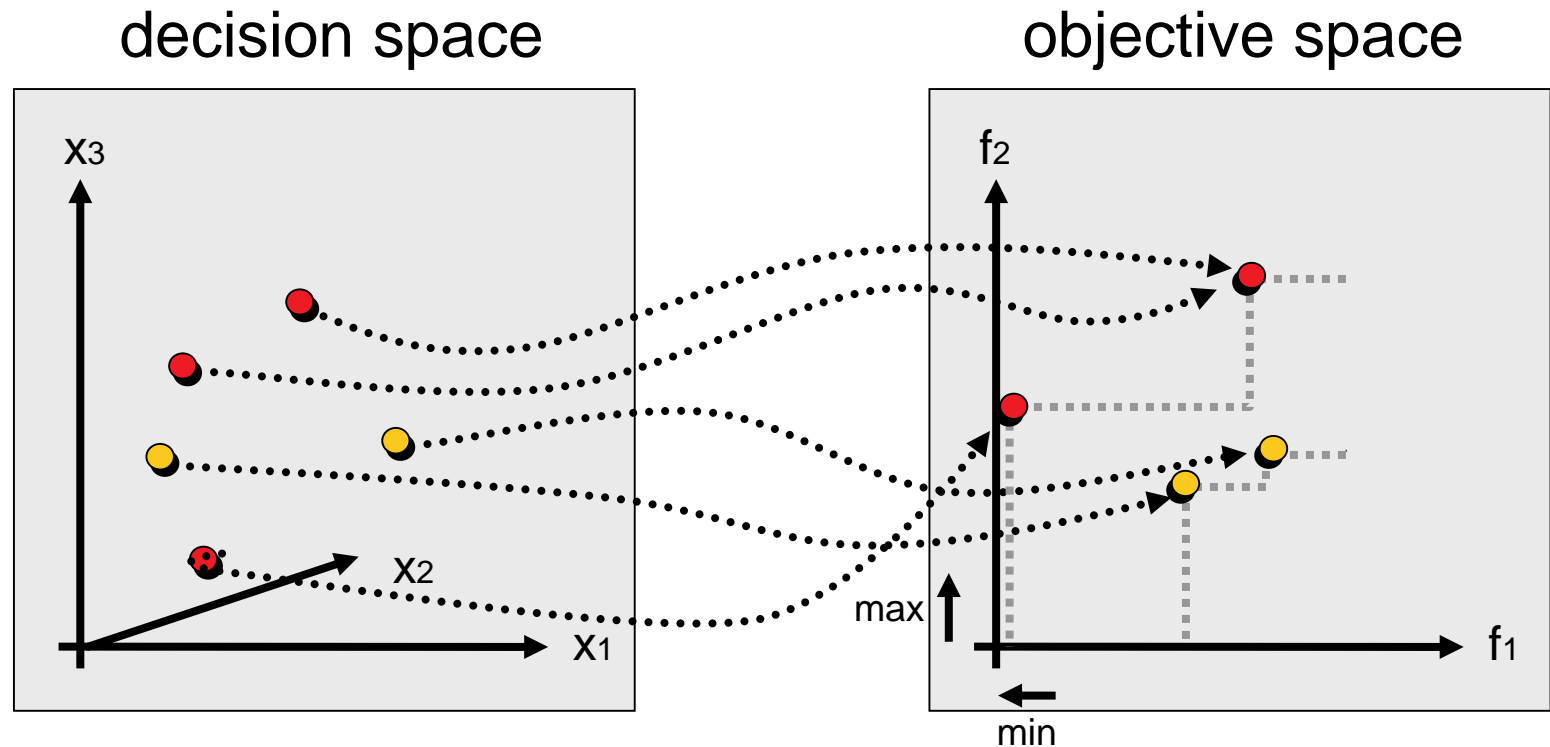
A Brief Introduction to Multiobjective Optimization

Pareto set: set of all non-dominated solutions (decision space)

Pareto front: its image in the objective space

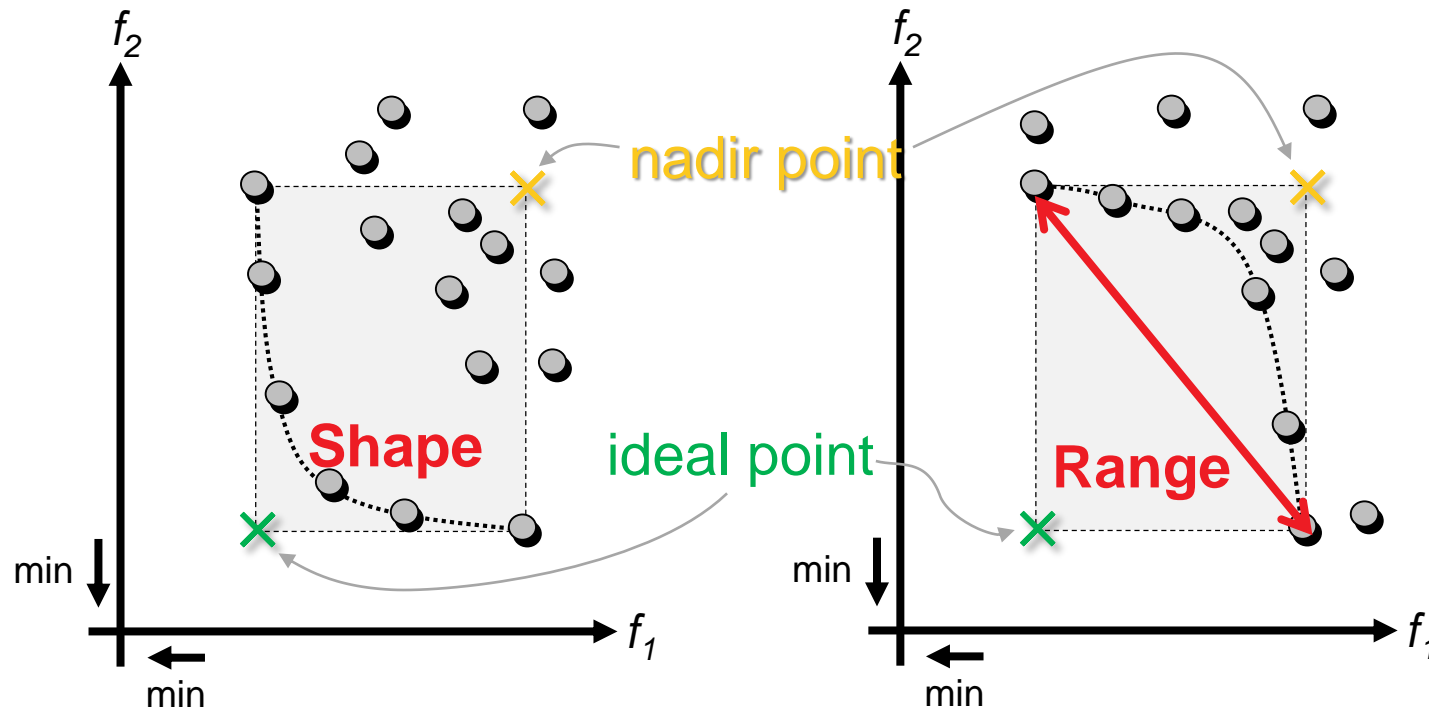


A Brief Introduction to Multiobjective Optimization



solution of Pareto-optimal set ● vector of Pareto-optimal front
non-optimal decision vector ● non-optimal objective vector

A Brief Introduction to Multiobjective Optimization

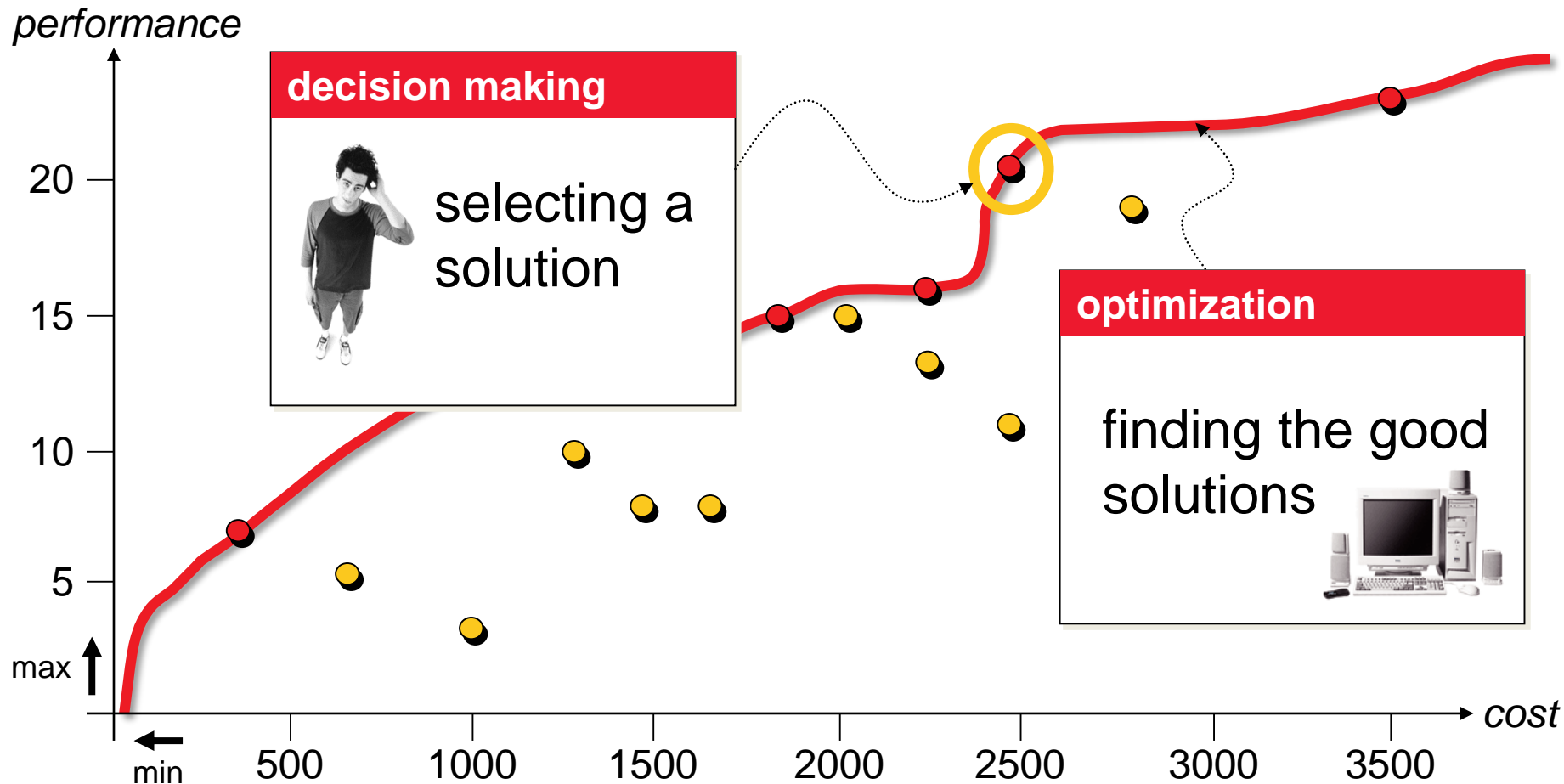


ideal point: best values
nadir point: worst values } obtained for *Pareto-optimal* points

Optimization vs. Decision Making

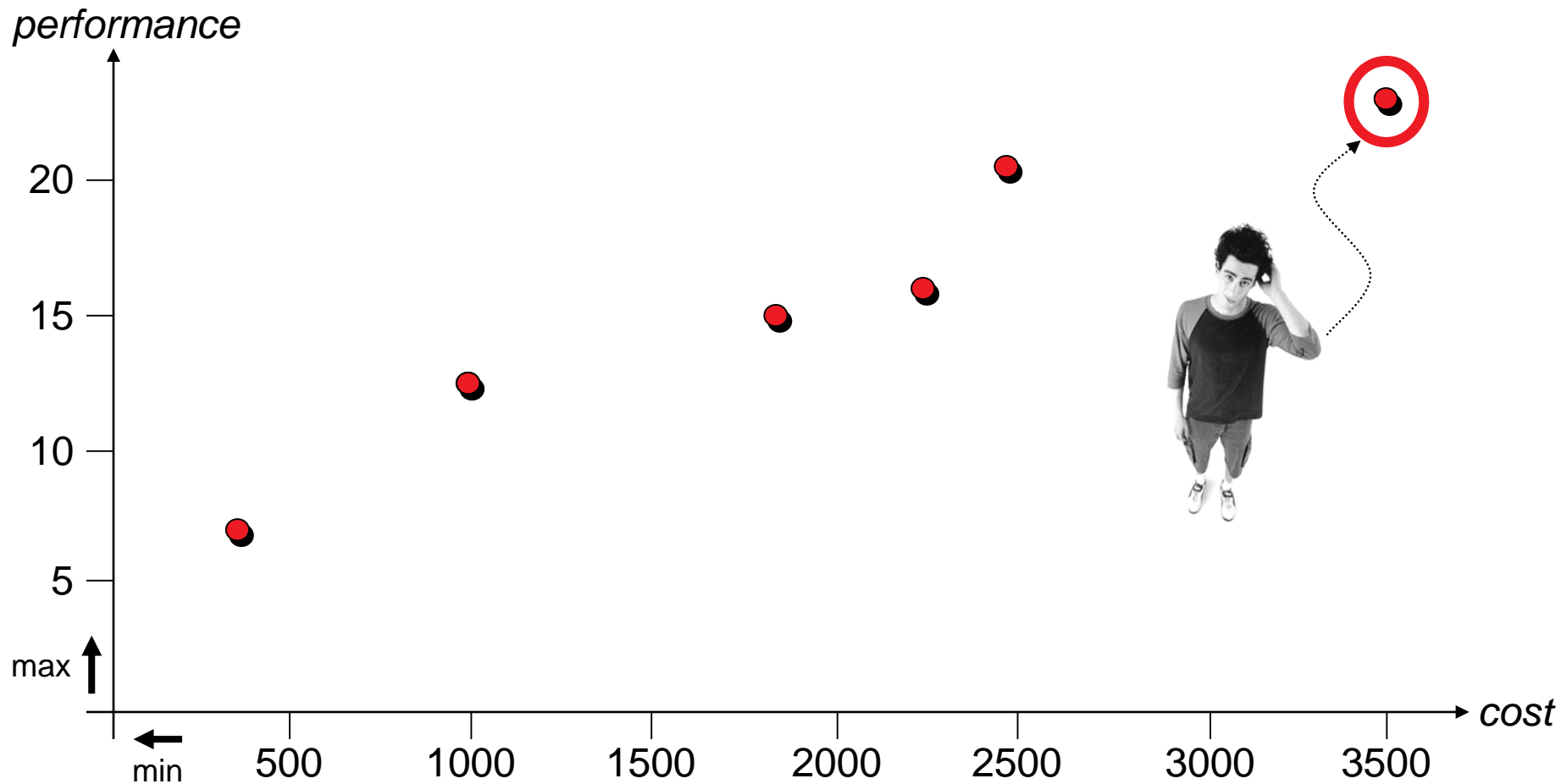
Multiobjective Optimization

combination of optimization of a set and a decision for a solution



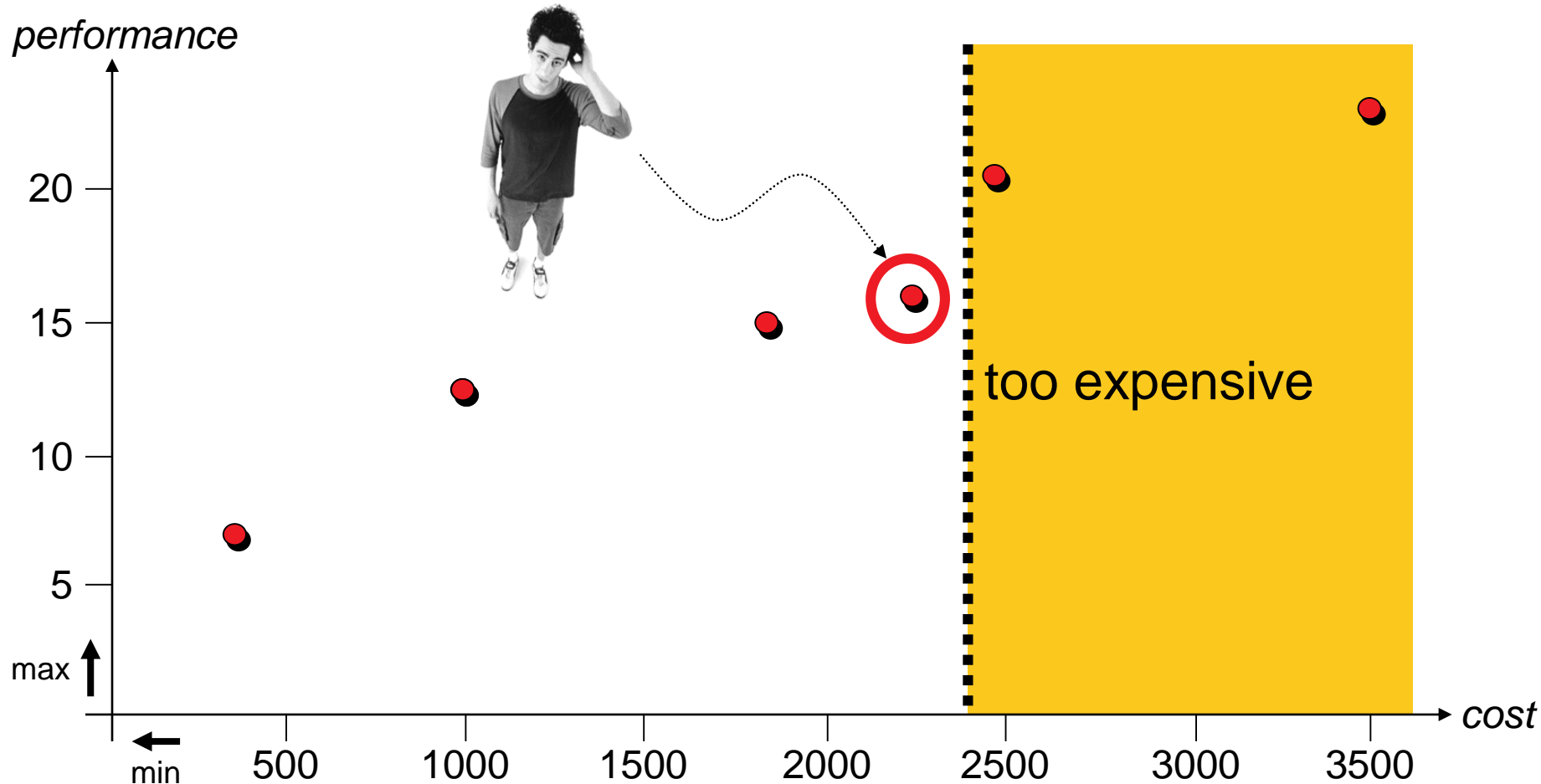
Selecting a Solution: Examples

Possible Approaches: ① **ranking:** performance more important than cost



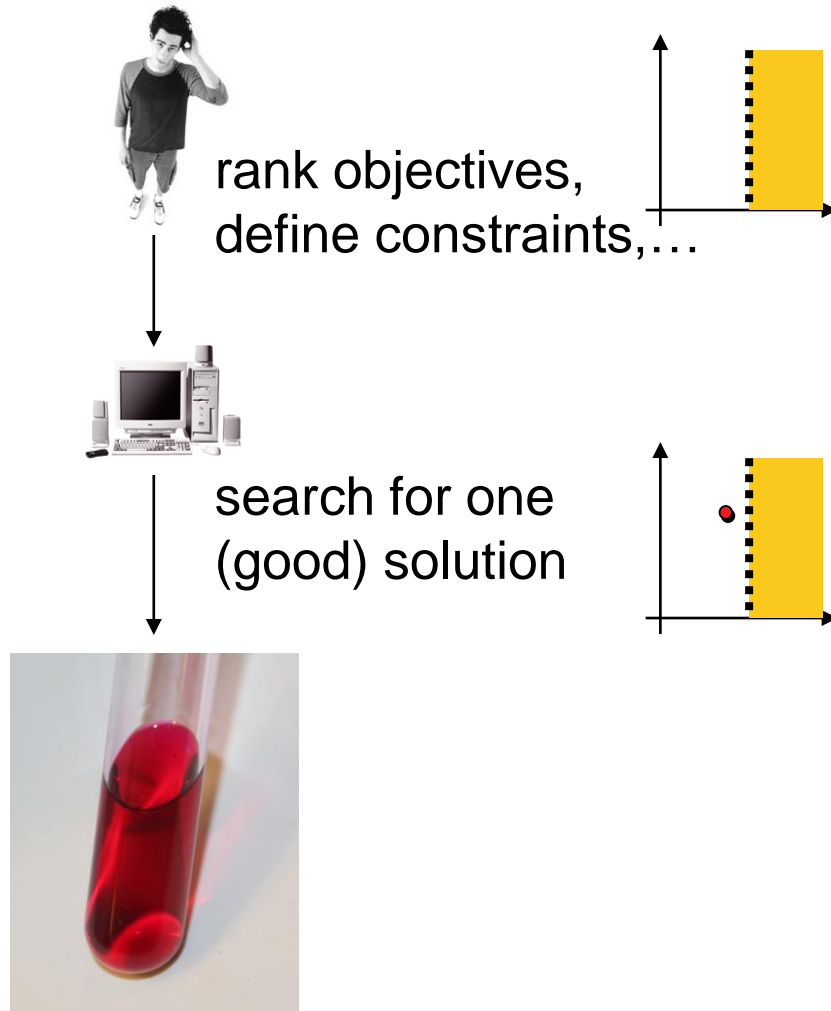
Selecting a Solution: Examples

Possible Approaches: ① ranking: performance more important than cost
② **constraints:** cost must not exceed 2400



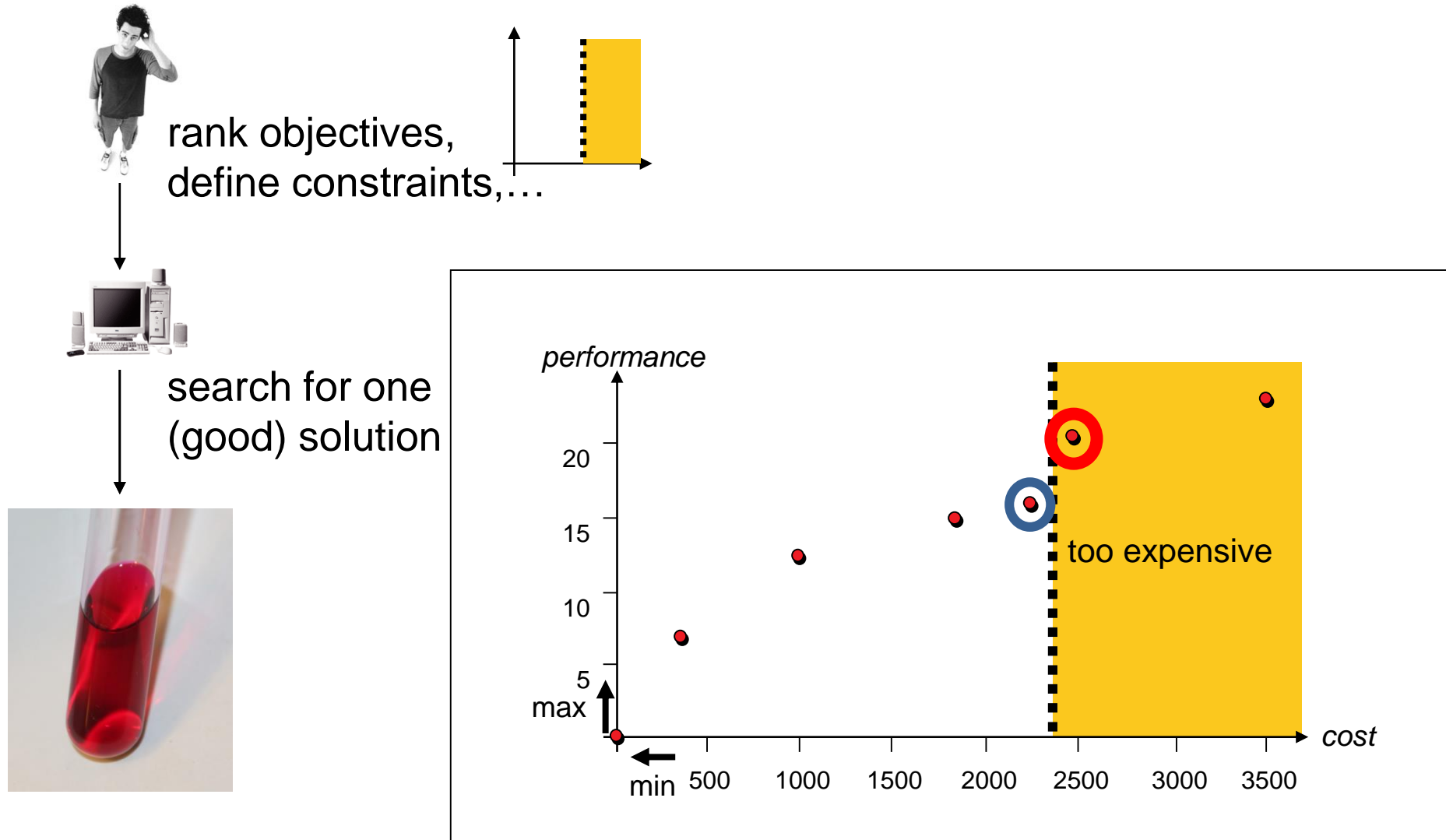
When to Make the Decision

Before Optimization:



When to Make the Decision

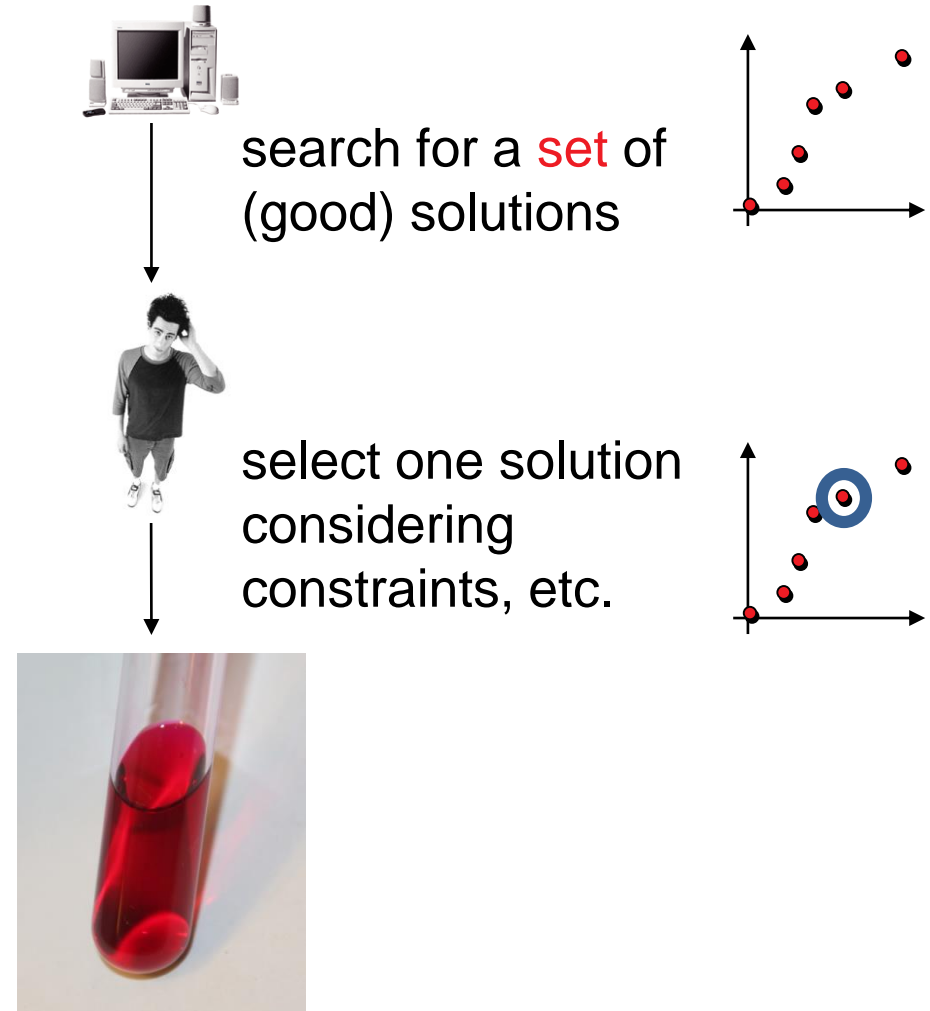
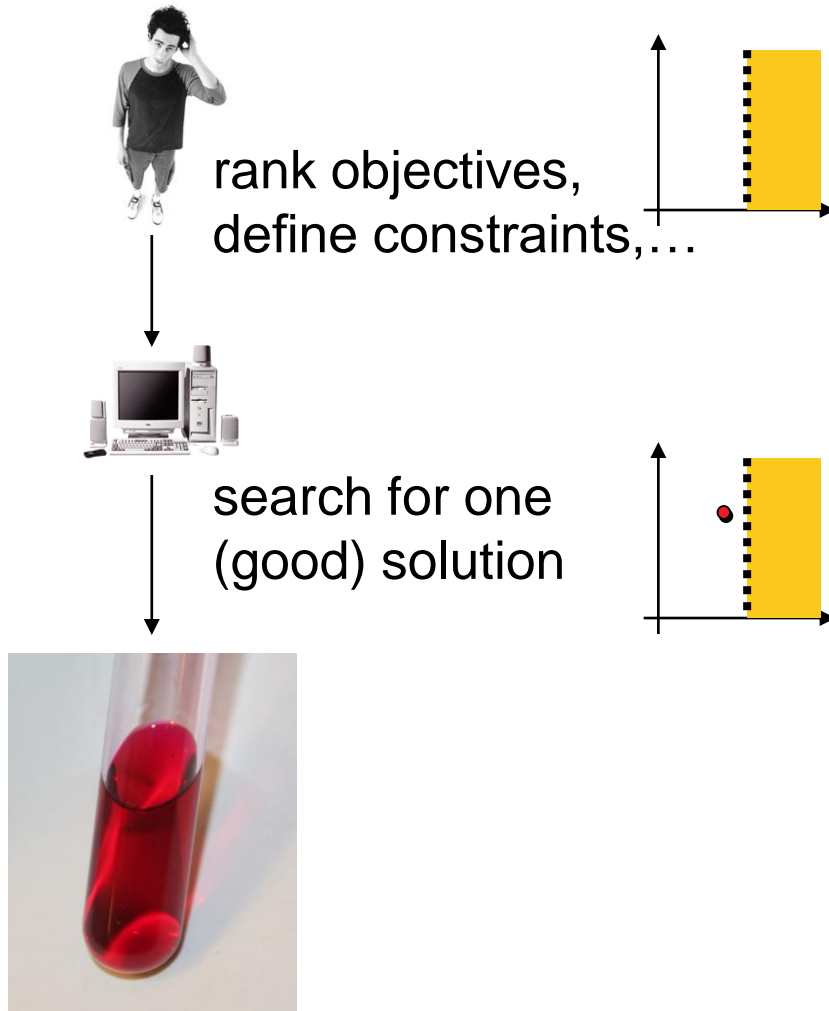
Before Optimization:



When to Make the Decision

Before Optimization:

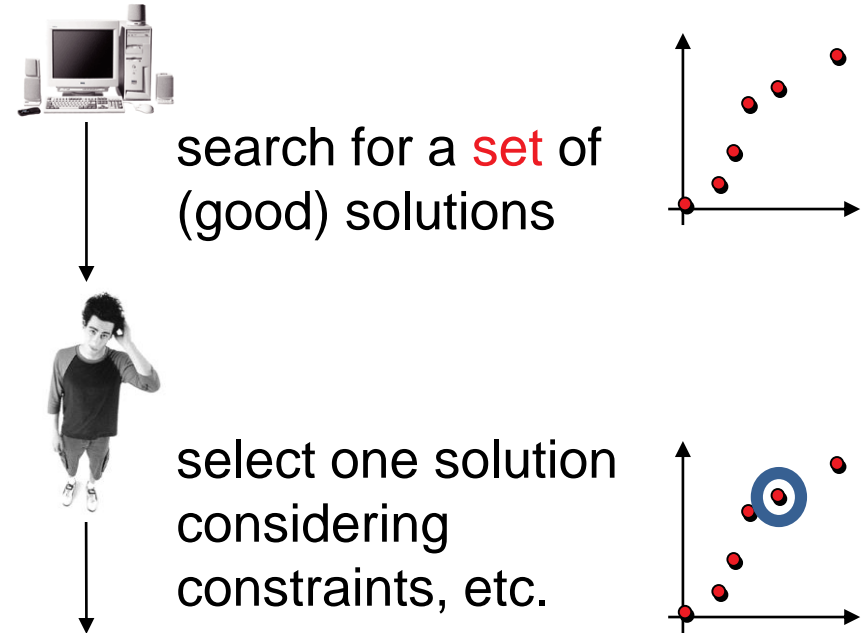
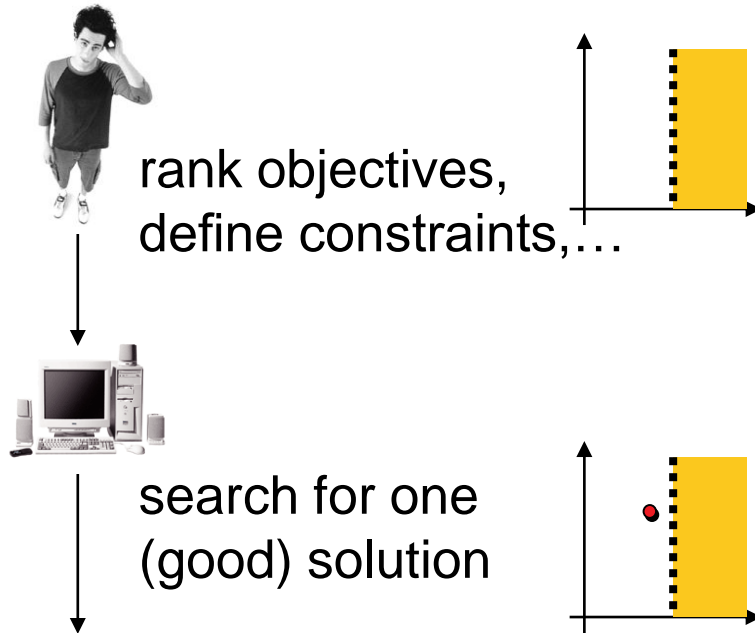
After Optimization:



When to Make the Decision

Before Optimization:

After Optimization:



Focus: learning about a problem

- trade-off surface
- interactions among criteria
- structural information
- also: interactive optimization



Two Communities...



International Society on
Multiple Criteria Decision Making

- established field
(beginning in 1950s/1960s)
- bi-annual conferences since 1975
- background in economics, math, management and social sciences
- focus on optimization and decision making



- quite young field
(first papers in mid 1980s)
- bi-annual conference since 2001
- background in computer science, applied math and engineering
- focus on optimization algorithms

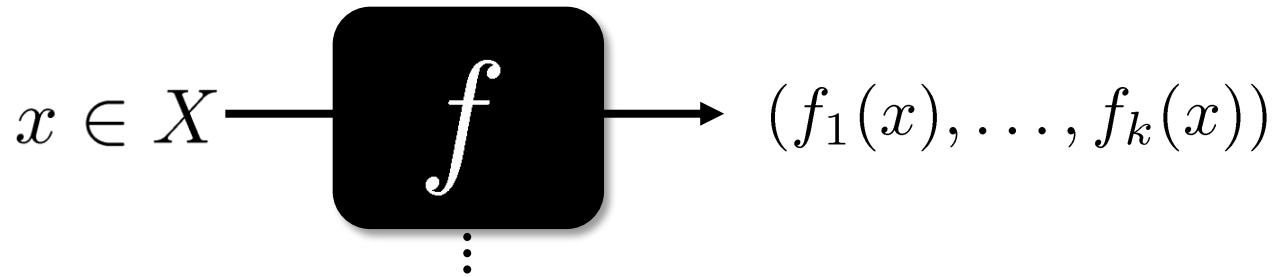
...Slowly Merge Into One



- MCDM track at EMO conference since 2009
- special sessions on EMO at the MCDM conference since 2008
- joint Dagstuhl seminars since 2004

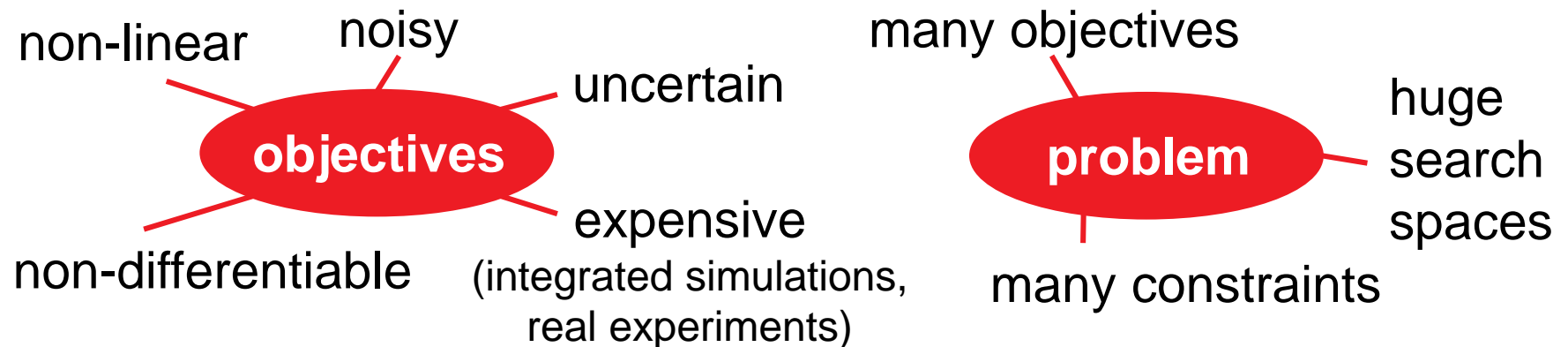
One of the Main Differences

Blackbox optimization



only mild assumptions

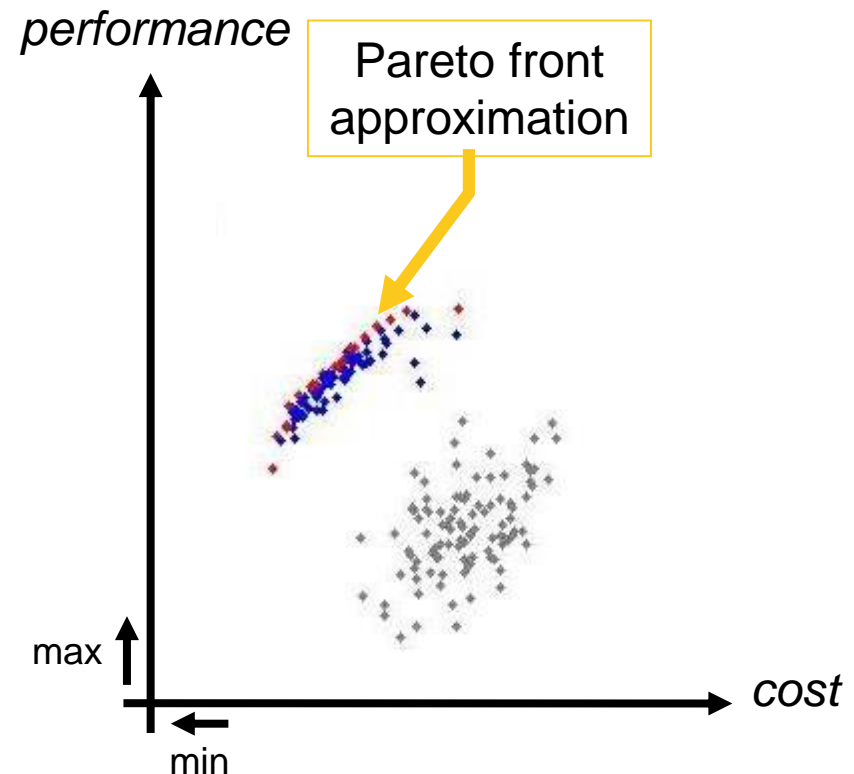
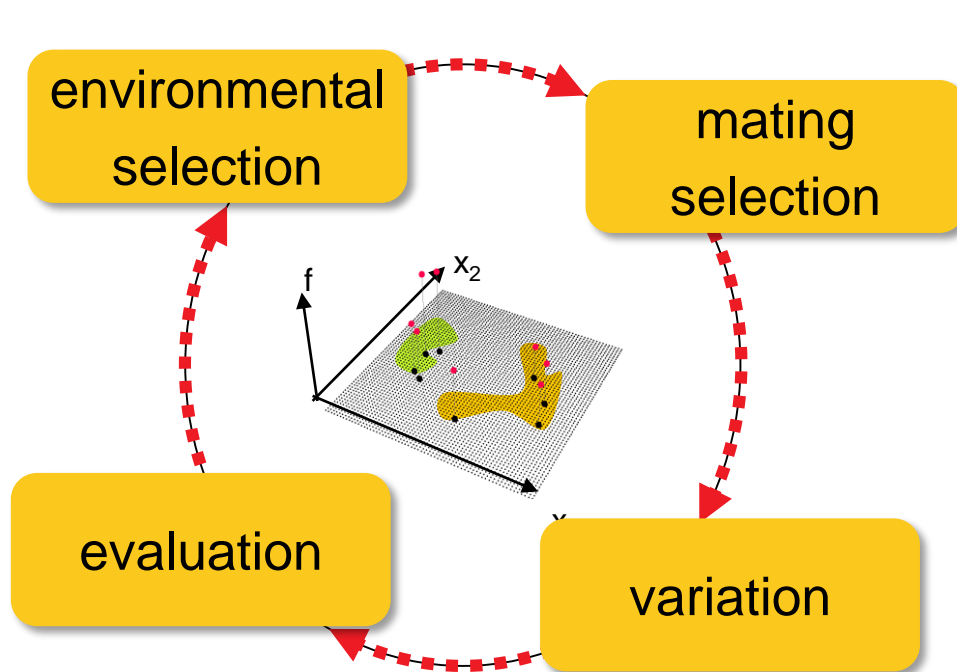
→ EMO therefore well-suited for real-world engineering problems



The Other Main Difference

Evolutionary Multiobjective Optimization

- set-based algorithms
- therefore possible to approximate the Pareto front in one run

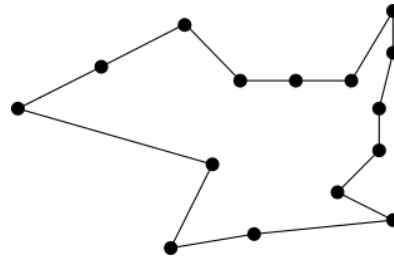


Multiobjectivization

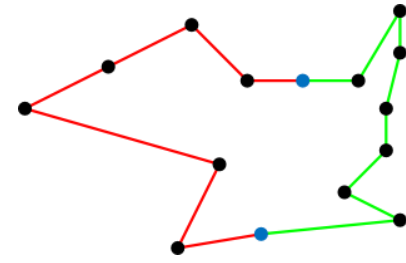
Some problems are easier to solve in a multiobjective scenario

example: TSP

[Knowles et al. 2001]



$$\pi \in S_n \rightarrow f(\pi)$$



$$\pi \in S_n \rightarrow (f_1(\pi, a, b), f_2(\pi, a, b))$$

Multiobjectivization

by **addition** of new “helper objectives” [Jensen 2004]

job-shop scheduling [Jensen 2004], frame structural design [Greiner et al. 2007], VRP [Watanabe and Sakakibara 2007], ...

by **decomposition** of the single objective

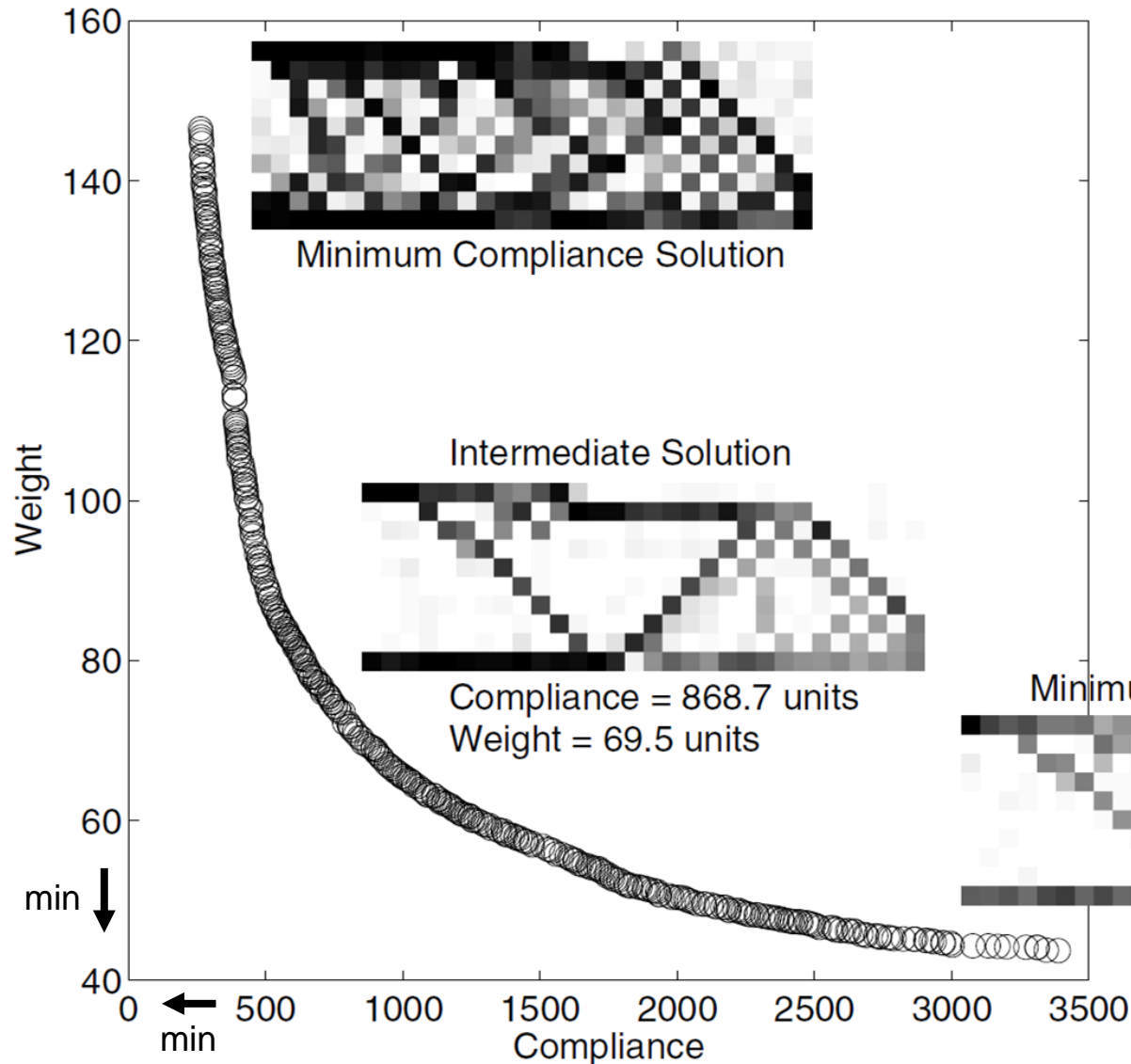
TSP [Knowles et al. 2001], minimum spanning trees [Neumann and Wegener 2006], protein structure prediction [Handl et al. 2008a], ...

also backed up by theory e.g. [Brockhoff et al. 2009, Handl et al. 2008b]

related to **constrained** and **multimodal** single-objective optimization

see also this recent overview: [Segura et al. 2013]

Often innovative design principles among solutions are found



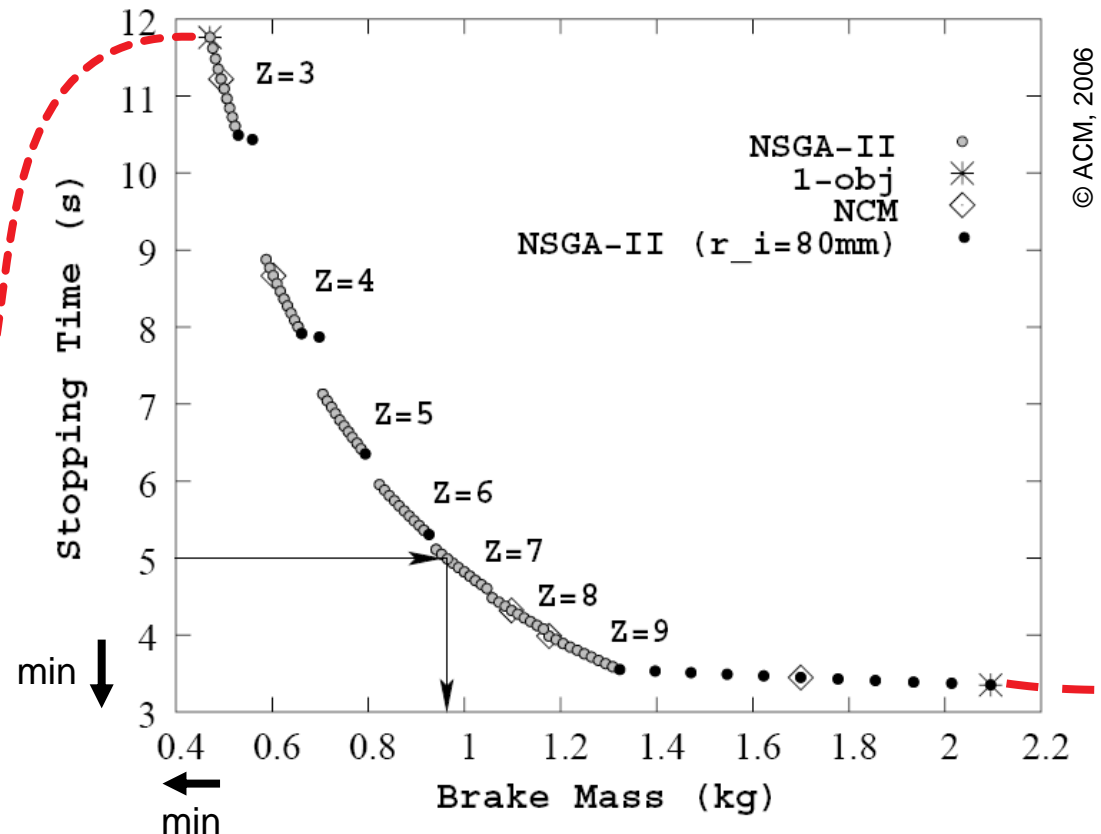
Example:
Cantilever beam
topology optimization
[Bandaru and Deb 2015]

Often innovative design principles among solutions are found

Example:

Clutch brake design

[Deb and Srinivasan 2006]



© ACM, 2006

Solution	x_1	x_2	x_3	x_4	x_5	f_1	f_2
Min. f_1	70	90	1.5	1000	3	0.4704	11.7617
Min. f_2	80	110	1.5	1000	9	2.0948	3.3505

Often innovative design principles among solutions are found

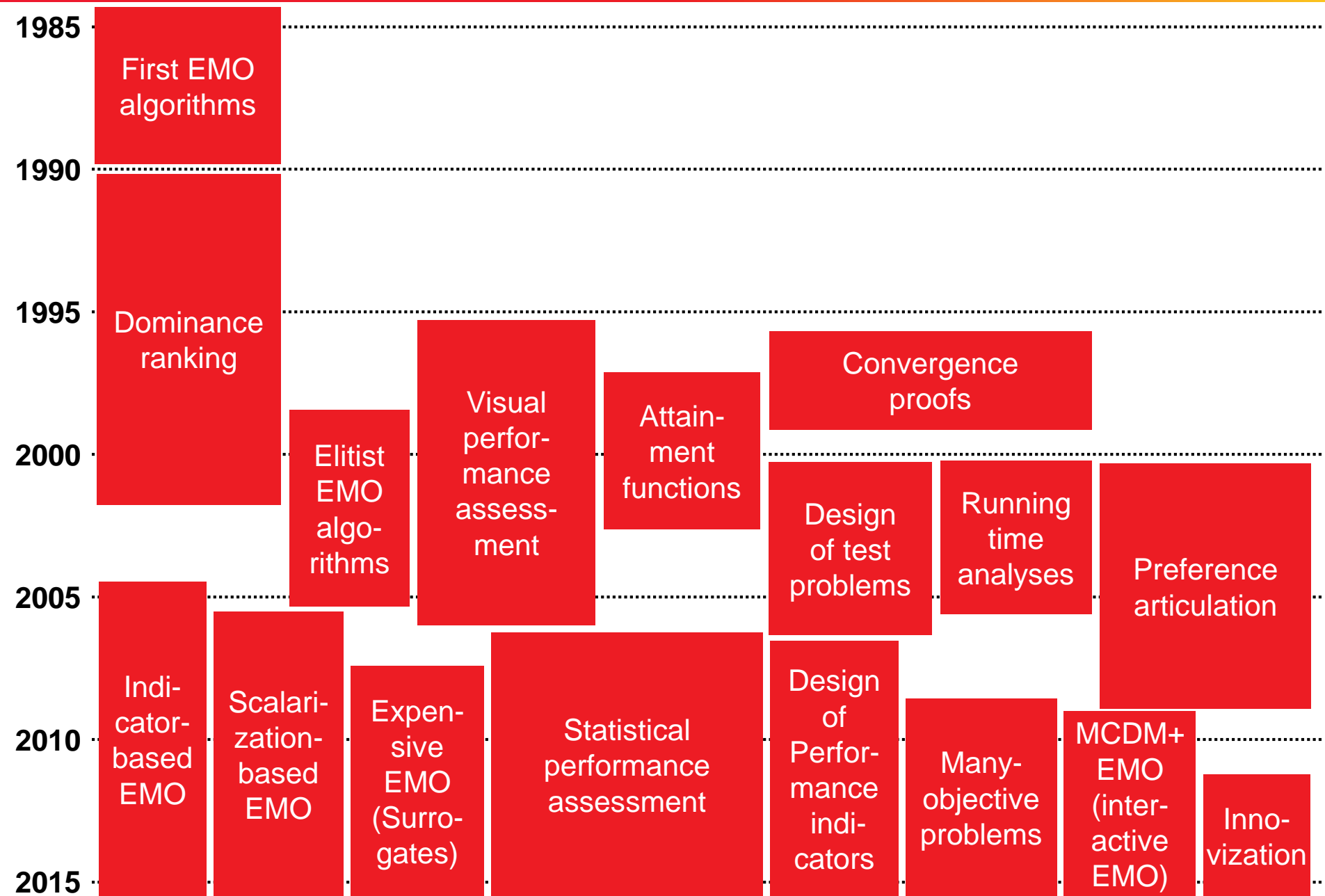
Innovization [Deb and Srinivasan 2006]

- = using machine learning techniques to find new and innovative design principles among solution sets
- = learning from/about a multi-objective optimization problem

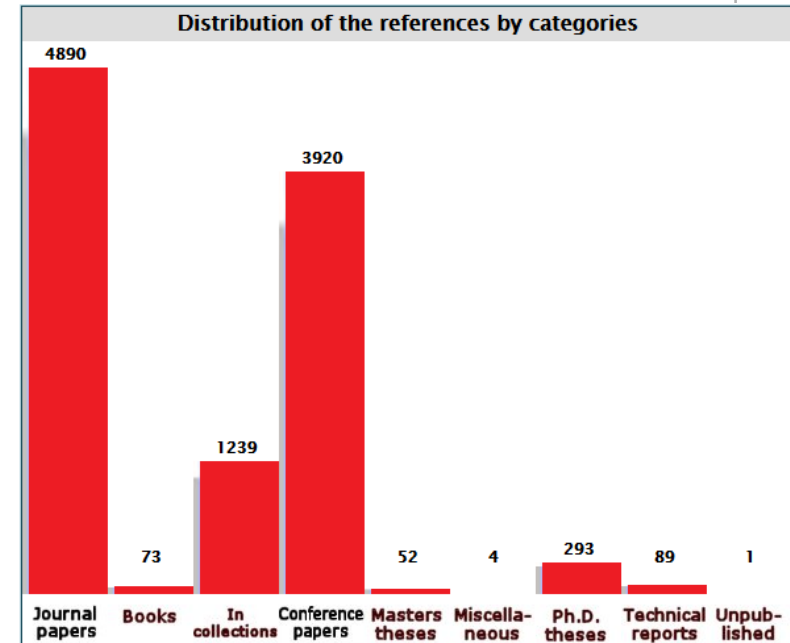
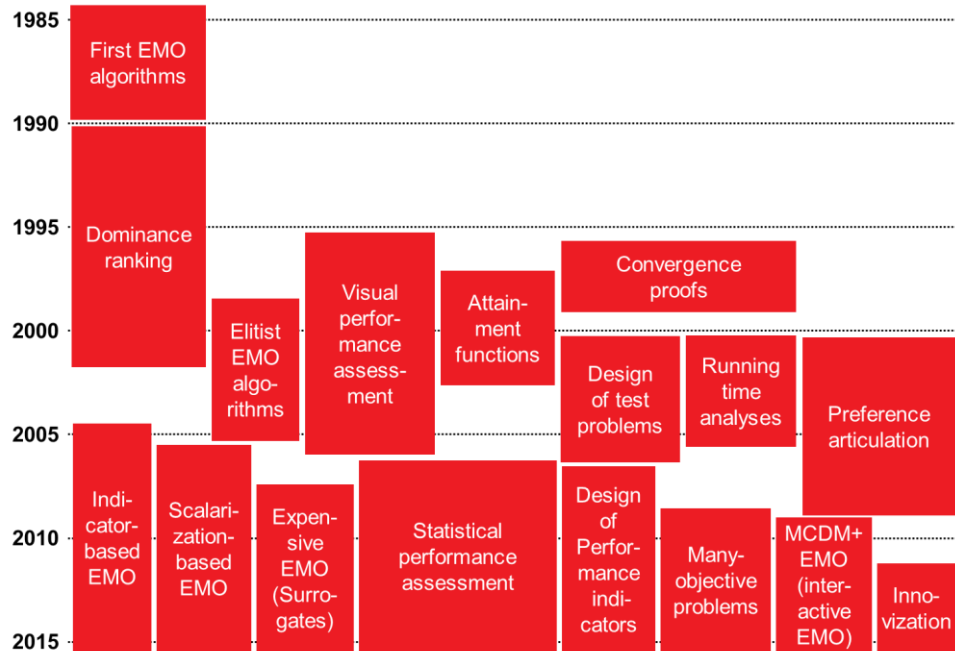
Other examples:

- SOM for supersonic wing design [Obayashi and Sasaki 2003]
- Biclustering for processor design and knapsack [Ulrich et al. 2007]
- Successful case studies in engineering
(noise barrier design, polymer extrusion, friction stir welding)
[Deb et al. 2014]

The History of EMO At A Glance

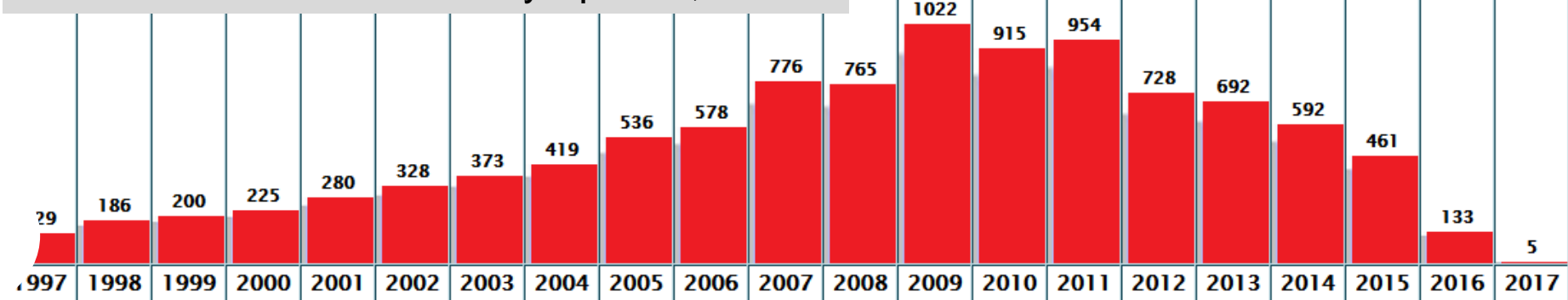


The History of EMO At A Glance



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

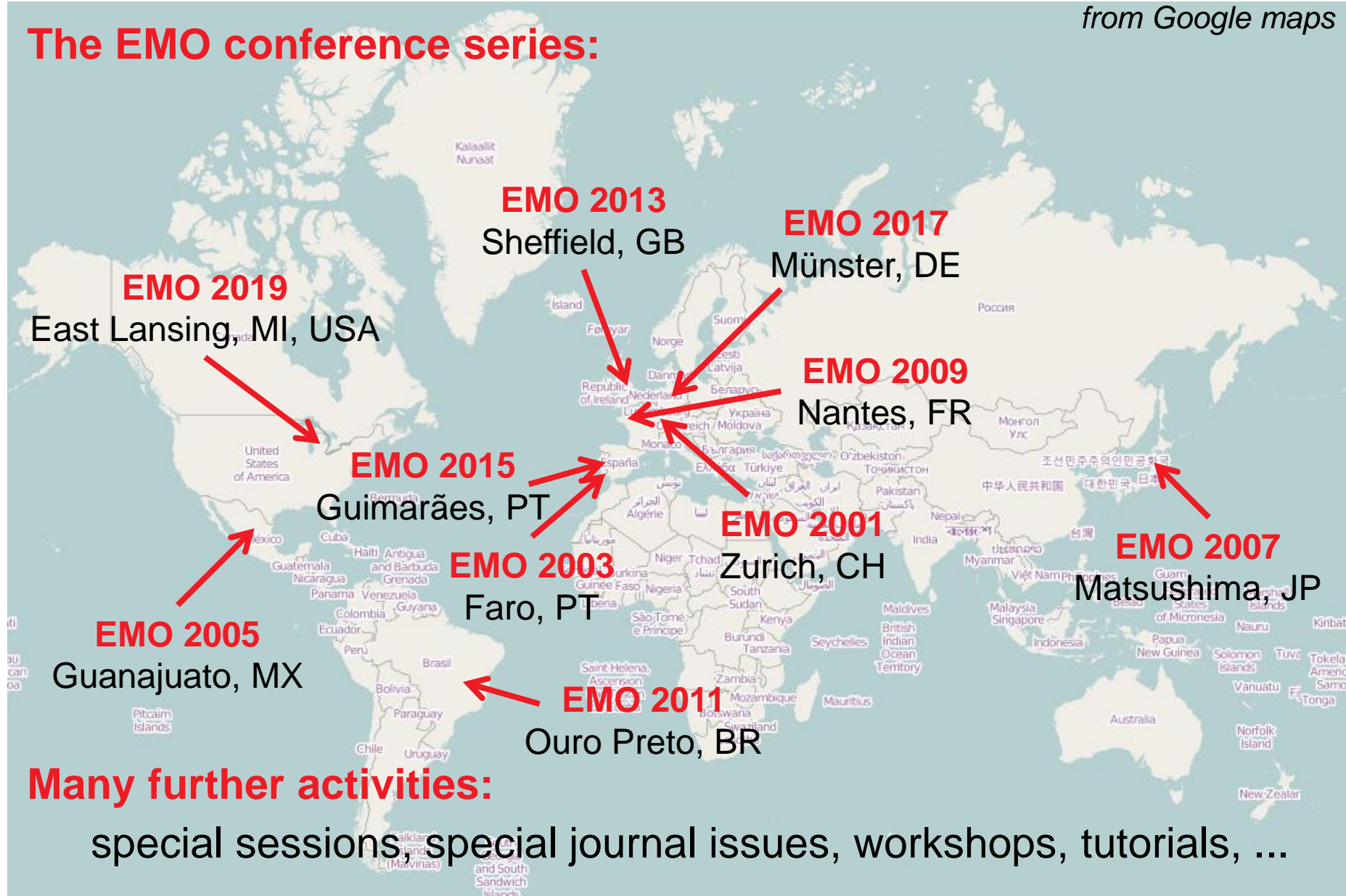
Overall: 10561 references by April 25, 2017



The EMO Community

The EMO conference series:

from Google maps



Many further activities:

special sessions, special journal issues, workshops, tutorials, ...

The Big Picture

Basic Algorithm Design Principles and Concepts

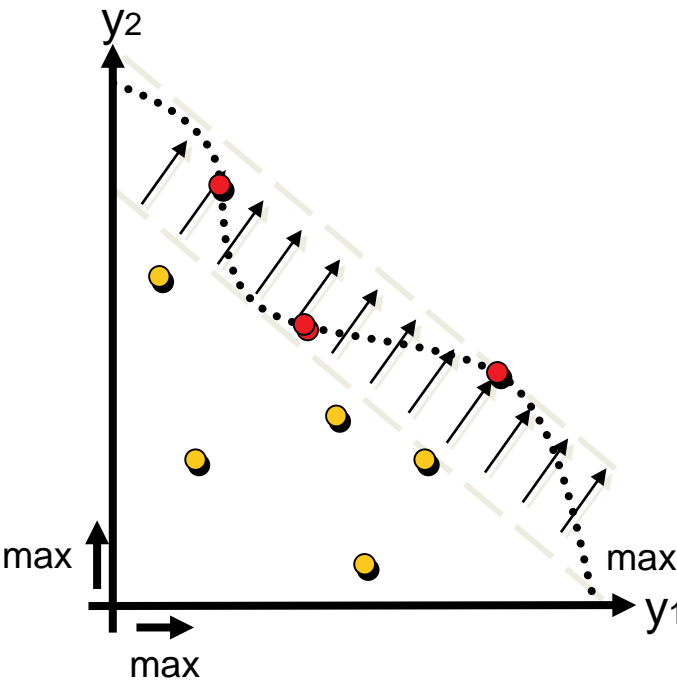
Performance Assessment and Benchmarking

Preference Articulation

Fitness Assignment: Principal Approaches

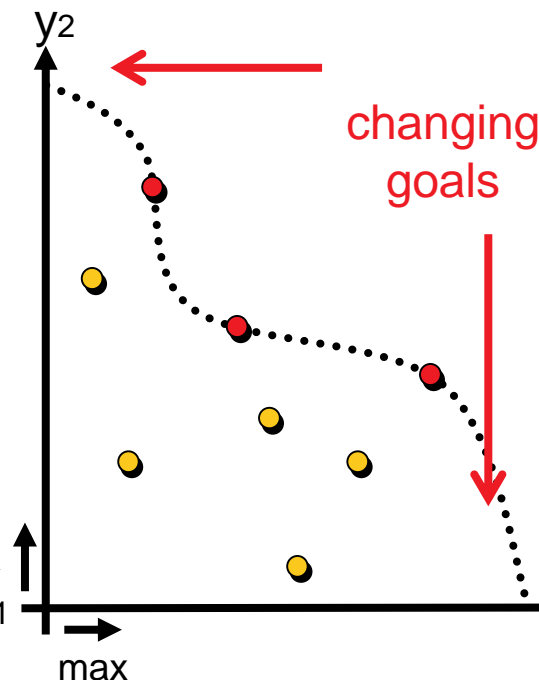
aggregation-based

*problem decomposition
(multiple single-objective
optimization problems)*



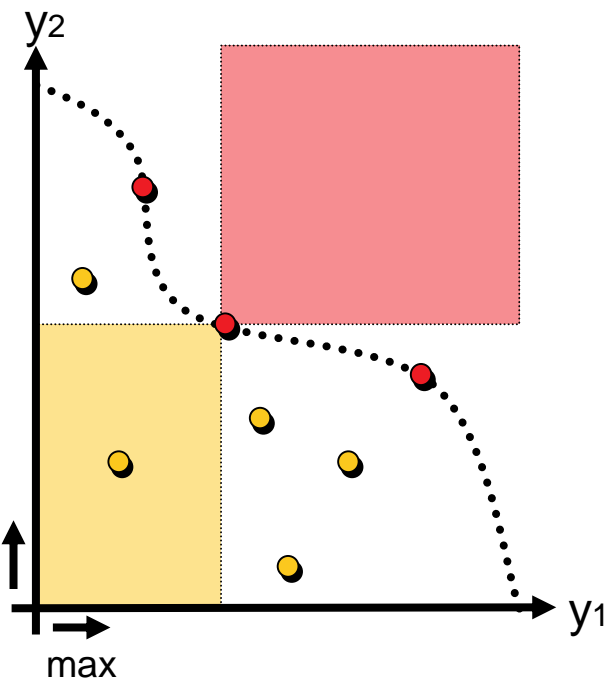
criterion-based

VEGA



dominance-based

*SPEA2, NSGA-II
"modern" EMOA*

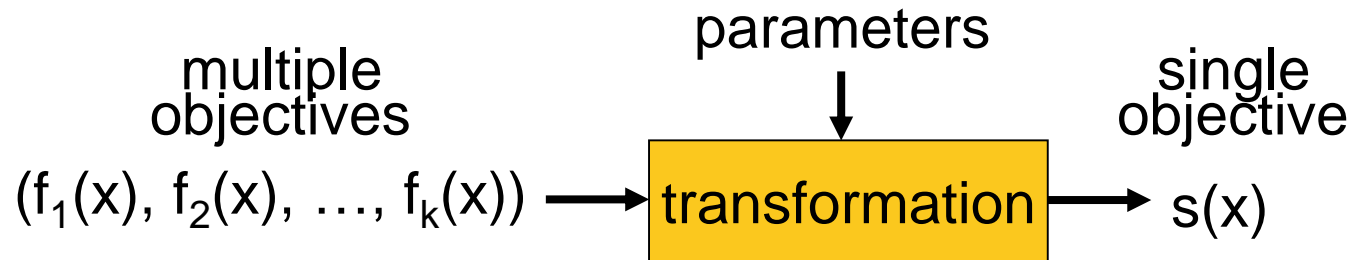


solution-oriented
scaling-dependent



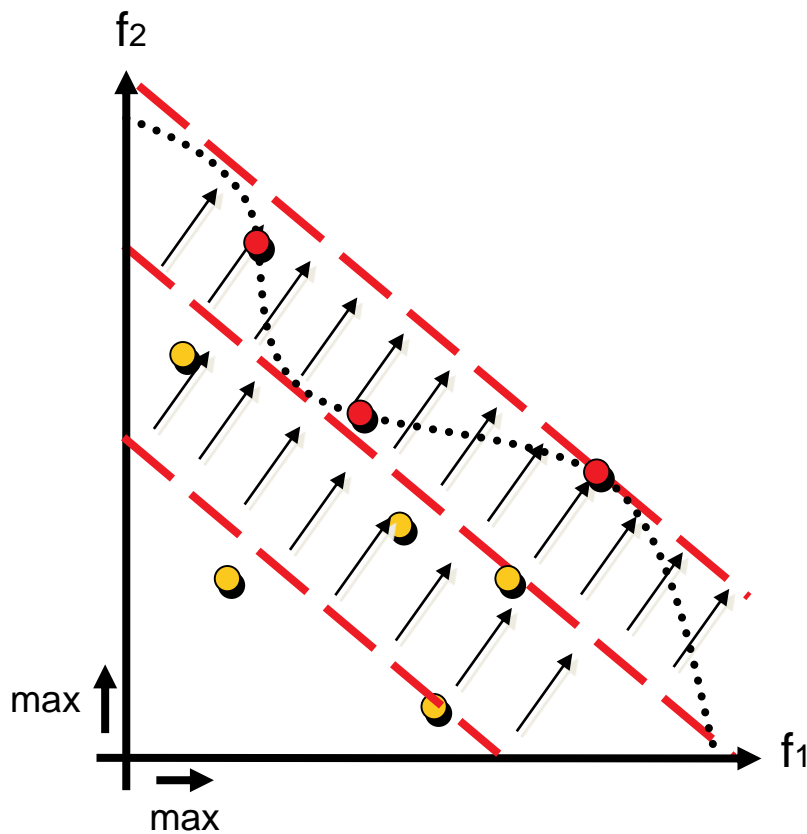
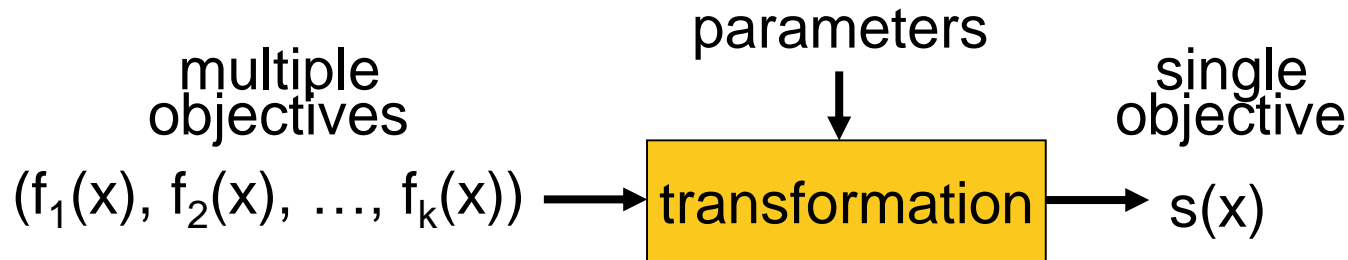
set-oriented
scaling-independent

Solution-Oriented Problem Transformations



A scalarizing function s is a function $s : Z \rightarrow \mathbb{R}$ that maps each objective vector $u = (u_1, \dots, u_n) \in Z$ to a real value $s(u) \in \mathbb{R}$

Solution-Oriented Problem Transformations



Example 1: weighted sum approach

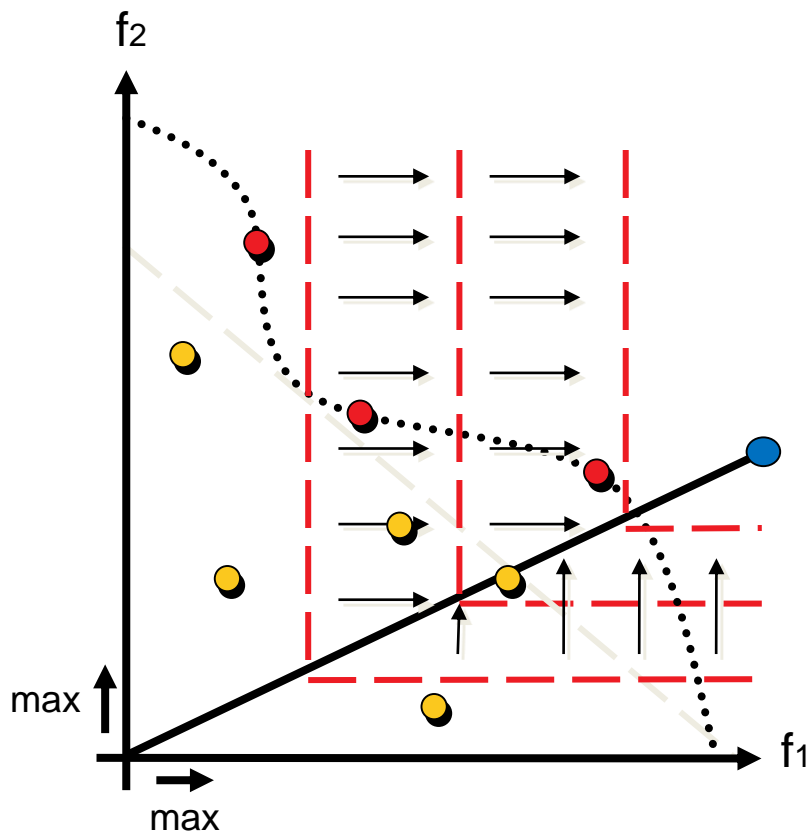
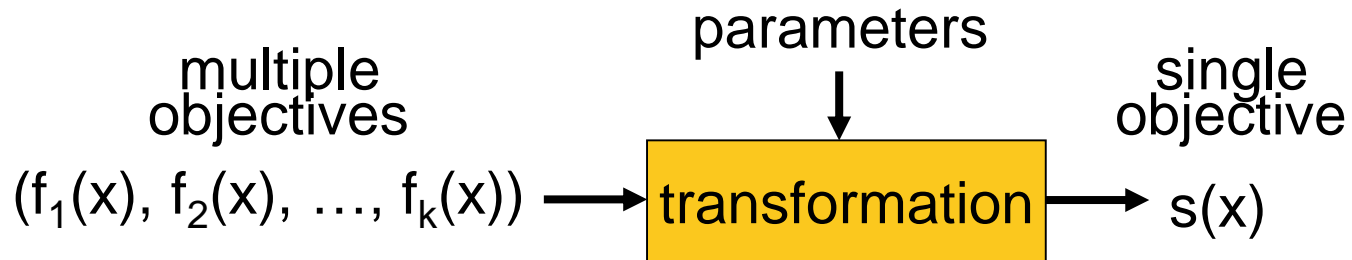
(w_1, w_2, \dots, w_k)

↓

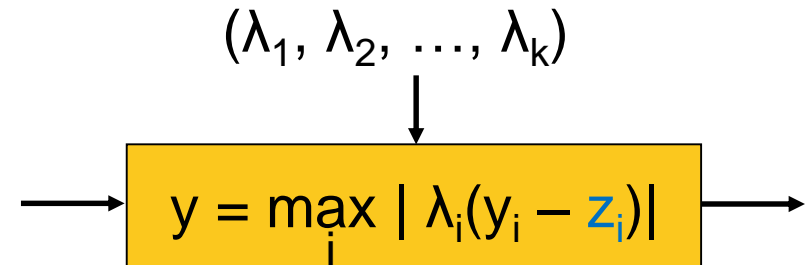
$y = w_1 y_1 + \dots + w_k y_k$

Disadvantage: not all Pareto-optimal solutions can be found if the front is not convex

Solution-Oriented Problem Transformations

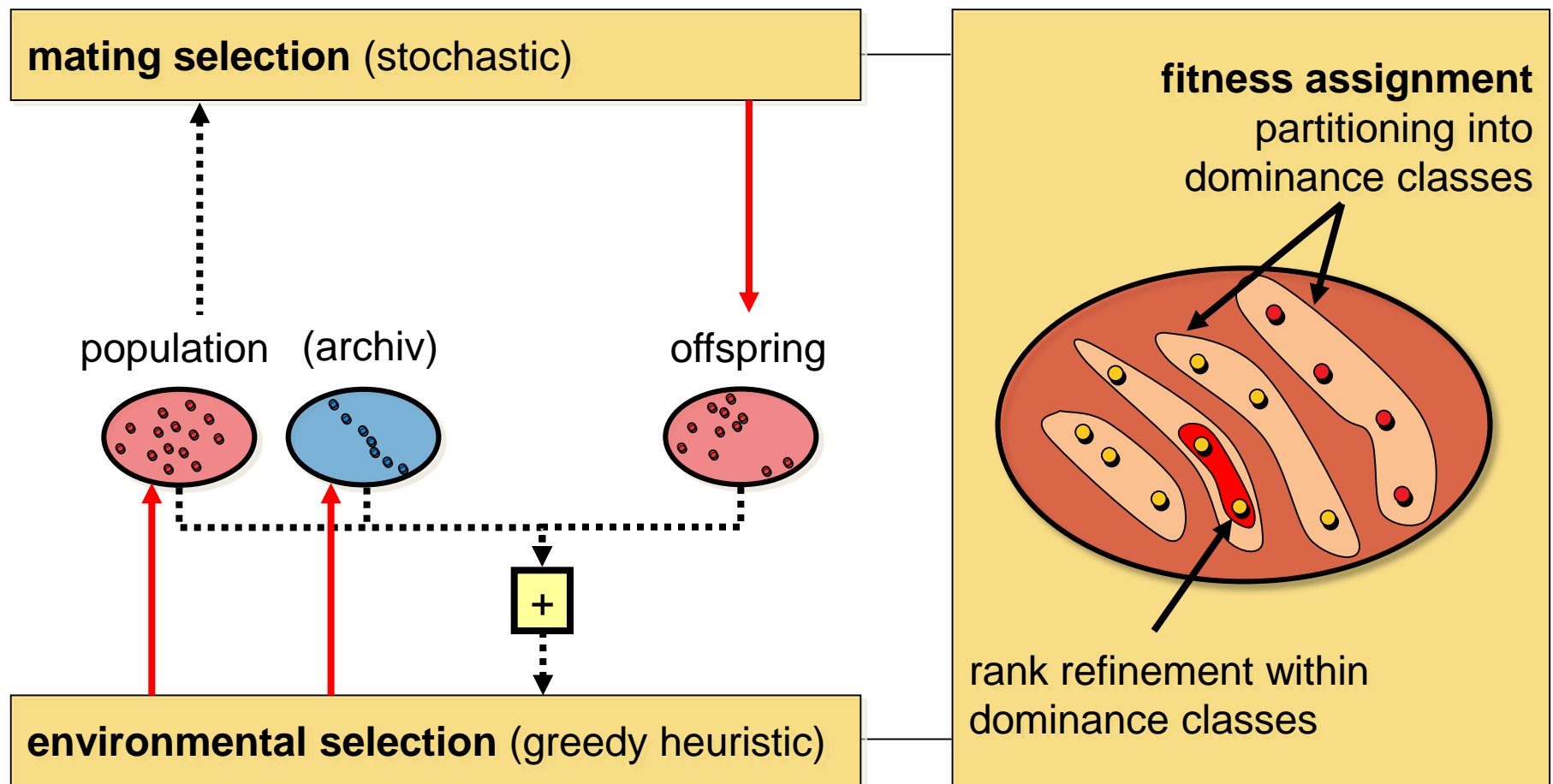


Example 2: weighted Tchebycheff



Several other scalarizing functions are known, see e.g. [\[Miettinen 1999\]](#)

General Scheme of Most Set-Oriented EMO



Ranking of the Population Using Dominance

... goes back to a proposal by David Goldberg in 1989.

... is based on pairwise comparisons of the individuals only.

- **dominance rank:** by how many individuals is an individual dominated?
MOGA, NPGA
- **dominance count:** how many individuals does an individual dominate?
SPEA, SPEA2
- **dominance depth:** at which front is an individual located?
NSGA, NSGA-II, most of the recently proposed algorithms

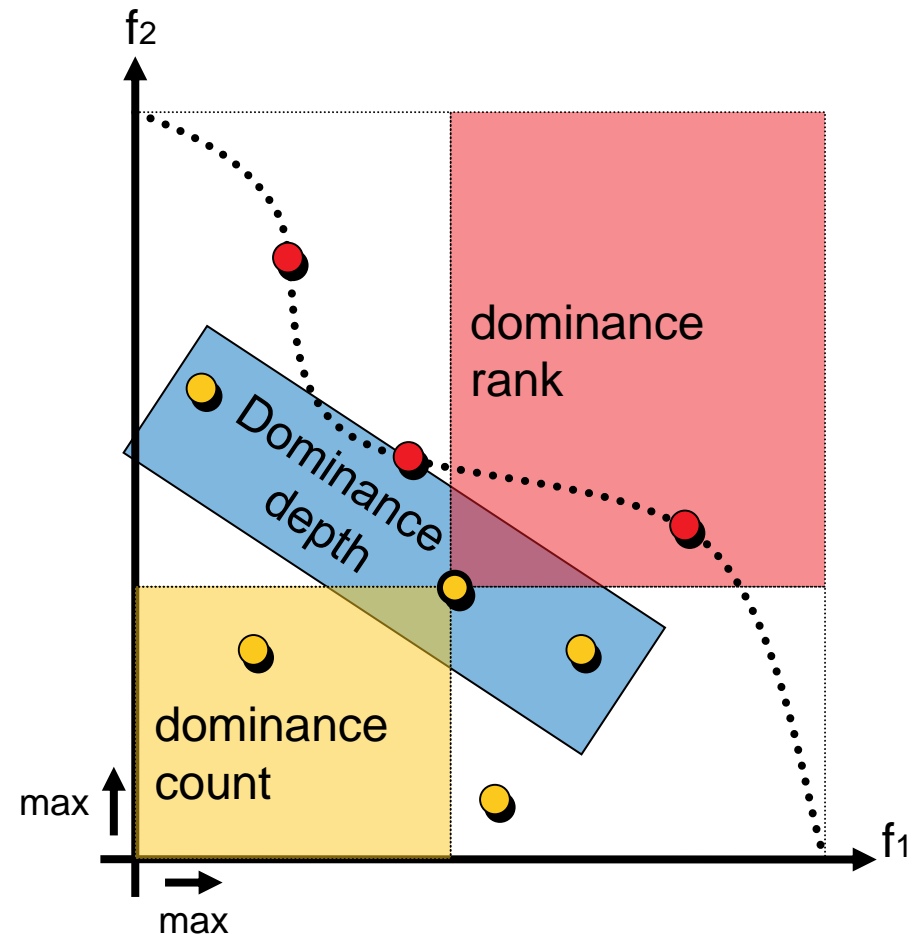
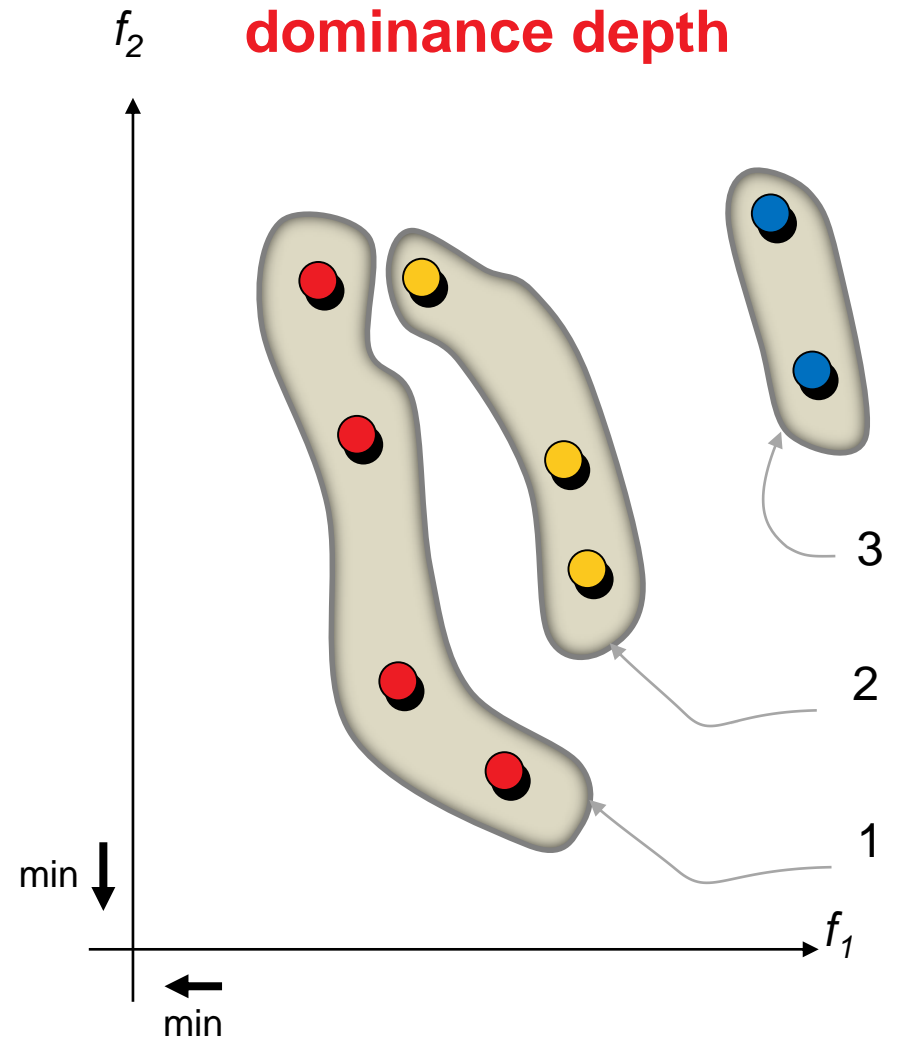
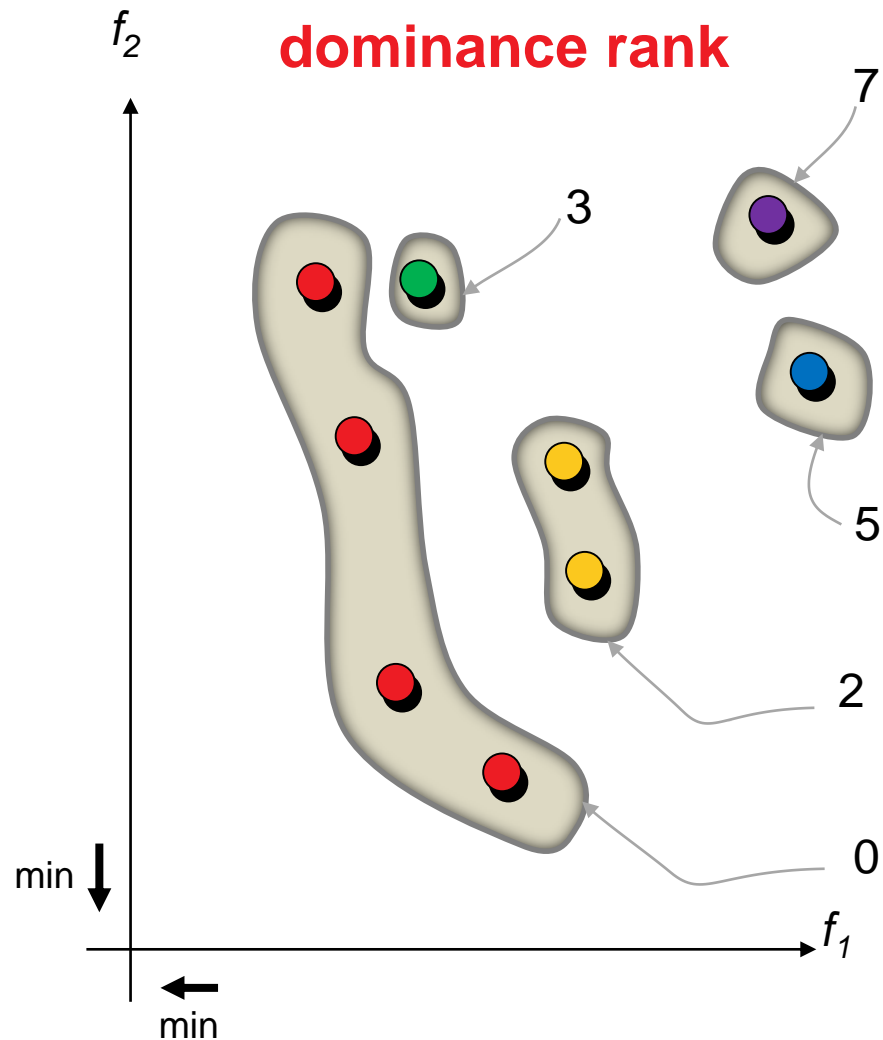


Illustration of Dominance-Based Partitioning



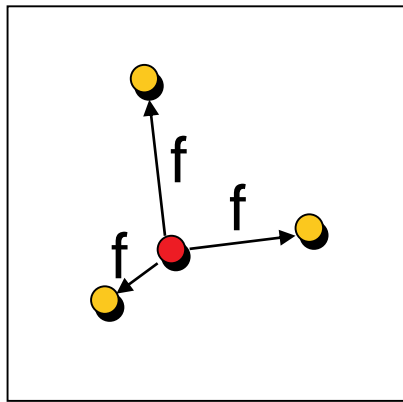
Refinement of Dominance Rankings

Goal: rank incomparable solutions within a dominance class

① Diversity information

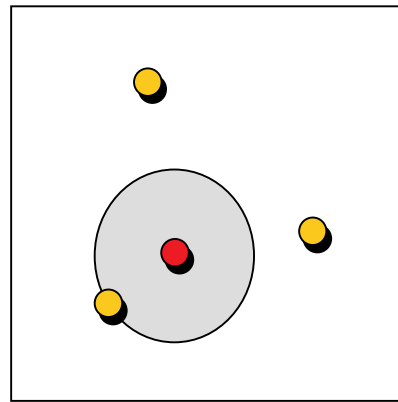
Kernel method

diversity =
function of the
distances



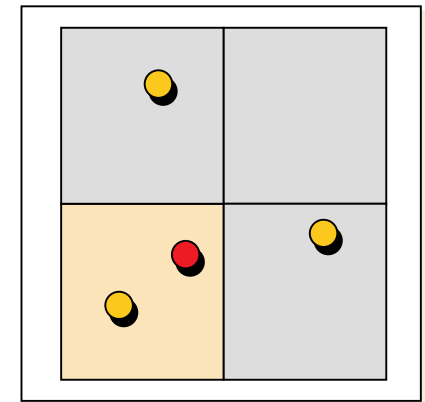
k-th nearest neighbor

diversity =
function of distance
to k-th nearest neighbor



Histogram method

diversity =
number of elements
within box(es)

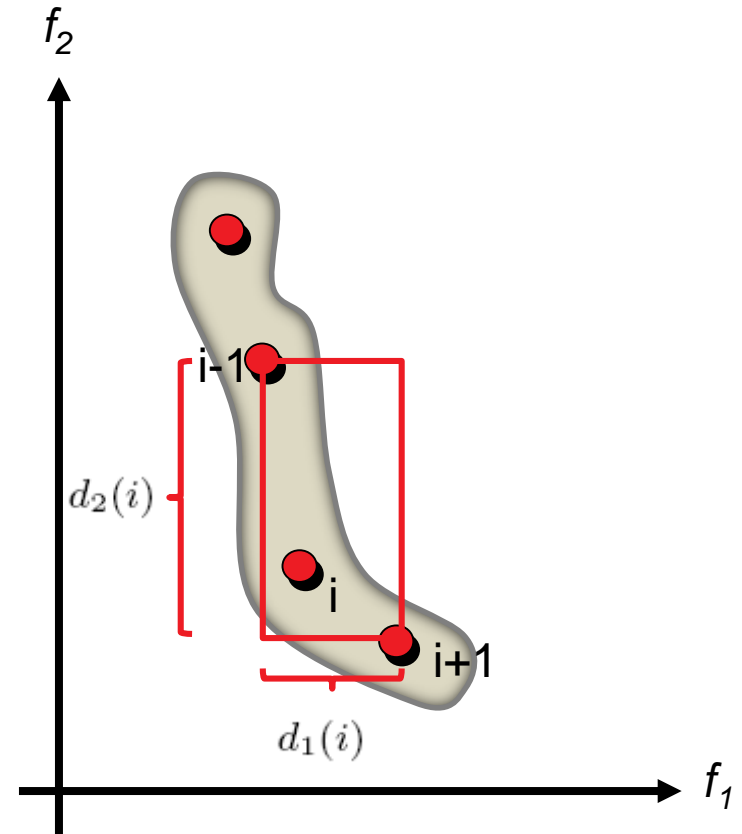


② (Contribution to a) quality indicator

Example: NSGA-II Diversity Preservation

Crowding Distance (CD)

- sort solutions with regard to each objective
- assign CD maximum value to extremal objective vectors
- compute CD based on the distance to the neighbors in each objective

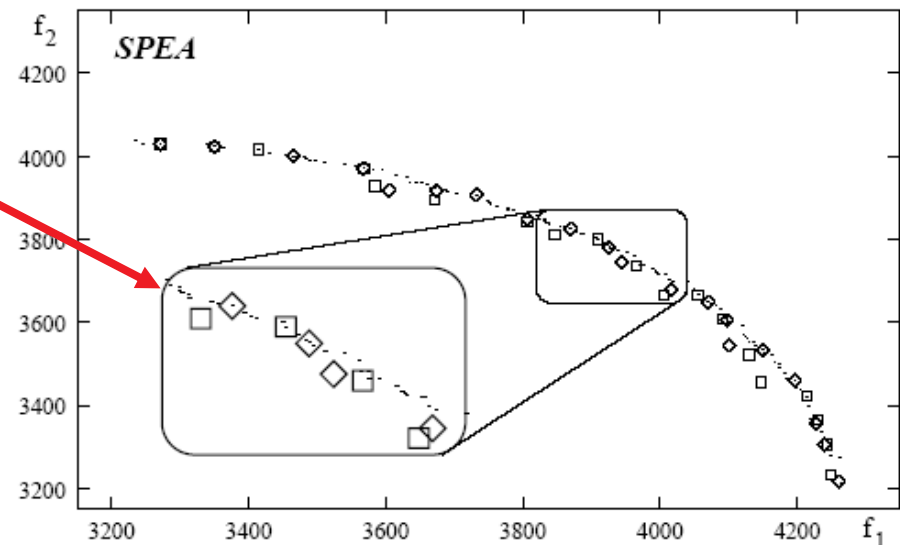
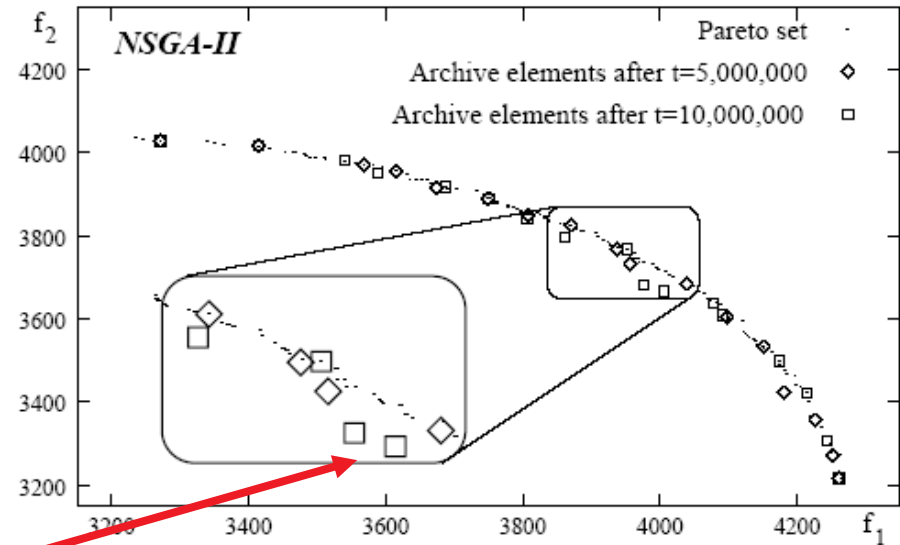


$$CD(i) = \frac{d_1(i)}{f_{1,\max} - f_{1,\min}} + \dots + \frac{d_m(i)}{f_{m,\max} - f_{m,\min}}$$

SPEA2 and NSGA-II: Deteriorative Cycles

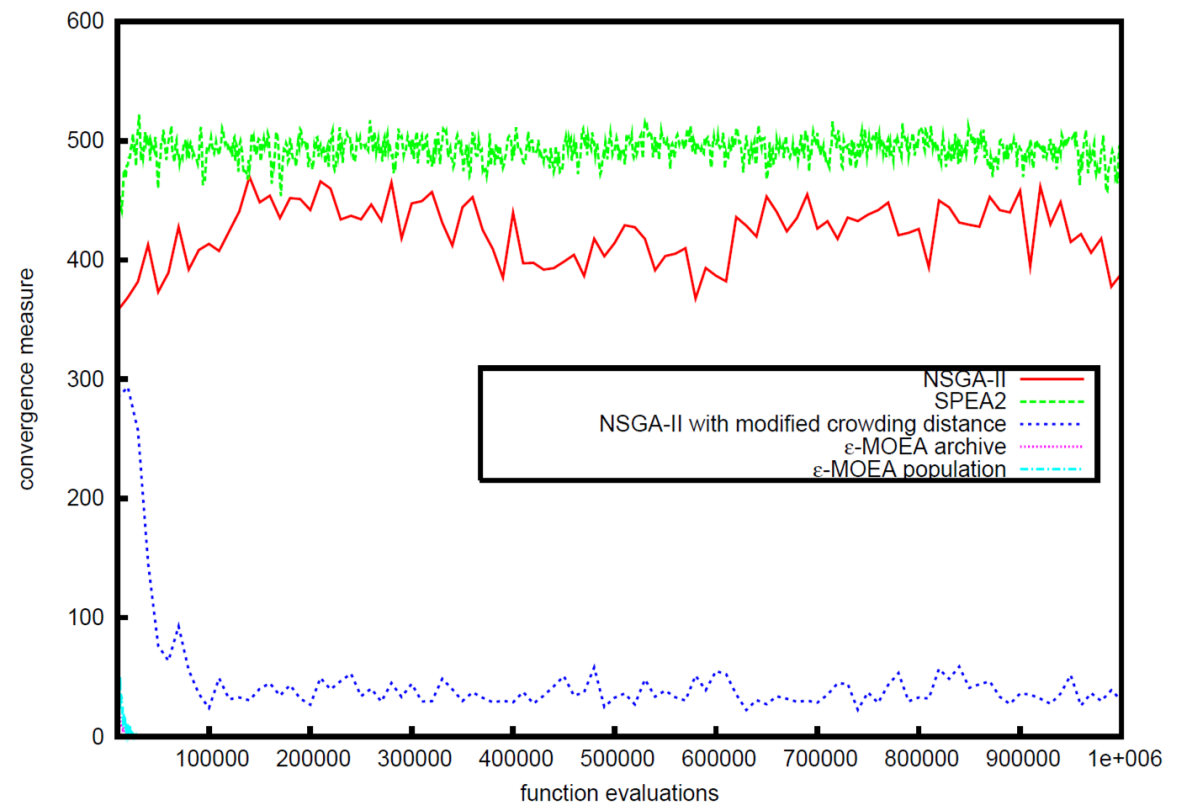
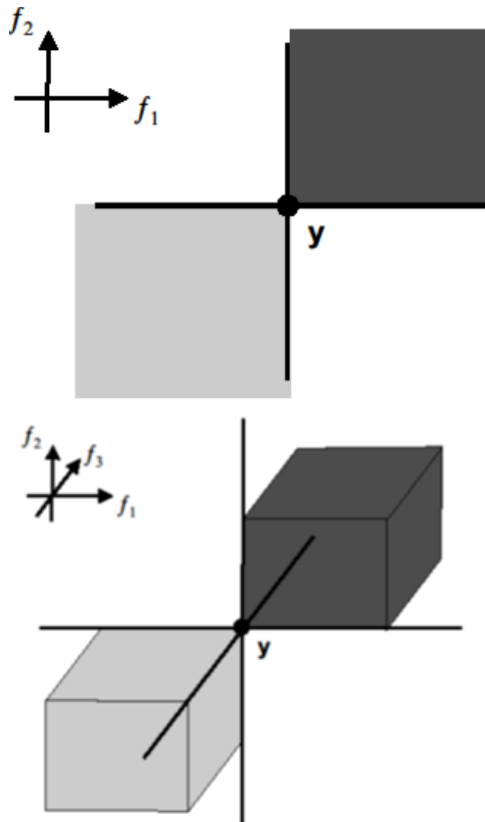
Selection in SPEA2 and NSGA-II can result in
deteriorative cycles

non-dominated
solutions already
found can be lost



Remark: Many-Objective Optimization

- high number of objectives
 - percentage of non-dominated solutions within a random sample quickly approaches 100 %
 - optimization is mainly guided by diversity criterion
 - apply secondary criterion compliant with dominance relation



Hypervolume-Based Selection

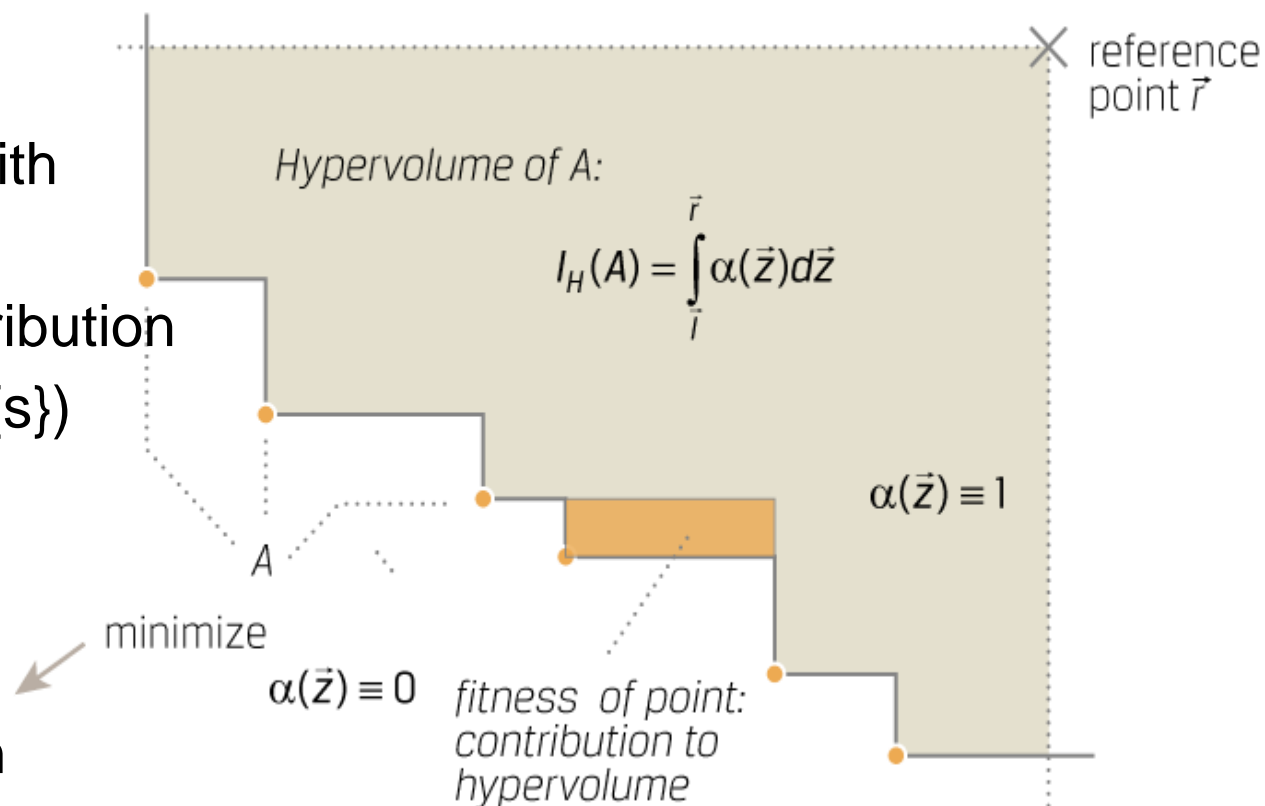
Latest Approach (SMS-EMOA, MO-CMA-ES, HypE, ...)

use hypervolume indicator to guide the search: refines dominance

Main idea

Delete solutions with the smallest hypervolume contribution

$d(s) = I_H(P) - I_H(P \setminus \{s\})$
iteratively



But: can also result in cycles if reference

point is not constant [Judt et al. 2011]

and is expensive to compute exactly [Bringmann and Friedrich 2009]

Indicator-Based Selection

- Concept can be generalized to any quality indicator

A (unary) quality indicator I is a function $I : \Psi = 2^X \mapsto \mathbb{R}$ that assigns a Pareto set approximation a real value.



- for example: R2-indicator [Brockhoff et al. 2012], [Trautmann et al. 2013], [Díaz-Manríquez et al. 2013]
- Generalizable also to contribution to larger sets
HypE [Bader and Zitzler 2011]: Hypervolume sampling + contribution if more than 1 (random) solution deleted

The Optimization Goal in Indicator-Based EMO

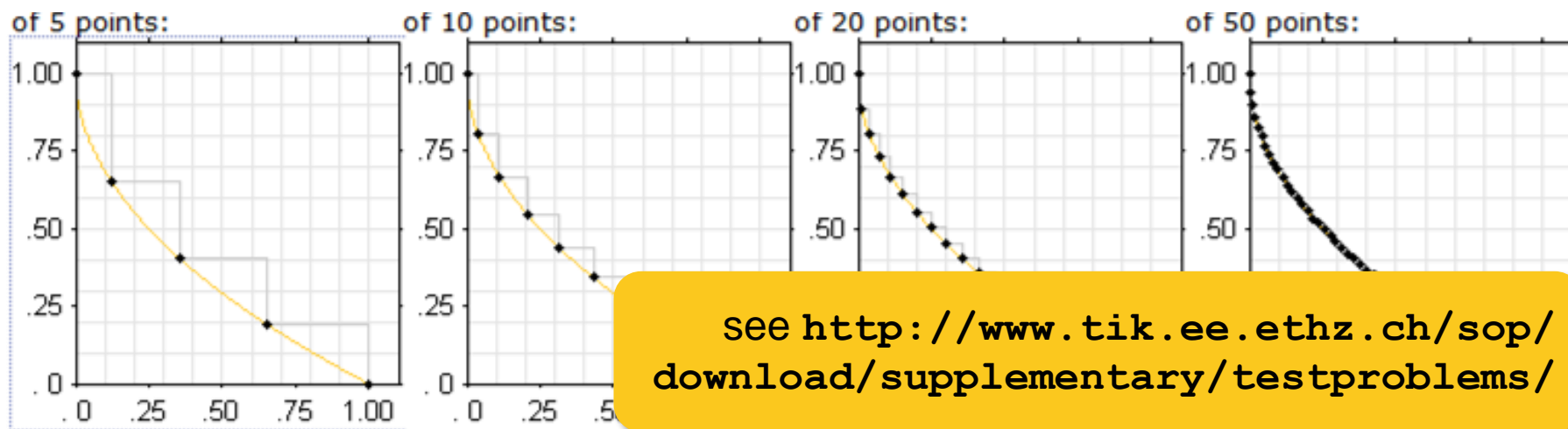
When the goal is to maximize a unary indicator...

- we have a single-objective problem on sets
- but what is the **optimum**?
- important: population size μ plays a role!

Optimal μ -Distribution:

A set of μ solutions that maximizes a certain unary indicator I among all sets of μ solutions is called **optimal μ -distribution** for I .

[Auger et al. 2009a]



Optimal μ -Distributions for the Hypervolume

Hypervolume indicator refines dominance relation

\Rightarrow most results on optimal μ -distributions for hypervolume

Optimal μ -Distributions (example results)

[Auger et al. 2009a]:

- contain equally spaced points iff front is linear
- density of points $\propto \sqrt{-f'(x)}$ with f' the slope of the front

[Friedrich et al. 2011]:

optimal μ -distributions for the
hypervolume correspond to
 ε -approximations of the front

$$\begin{array}{ll} \text{OPT} & 1 + \frac{\log(\min\{A/a, B/b\})}{n} \\ \text{HYP} & 1 + \frac{\sqrt{A/a} + \sqrt{B/b}}{n - 4} \\ \text{logHYP} & 1 + \frac{\sqrt{\log(A/a) \log(B/b)}}{n - 2} \end{array}$$

! (probably) does not hold for > 2 objectives

Open Questions:

- How do the optimal μ -distributions look like for >2 objectives?
- how to compute certain indicators quickly in practice?
 - several recent improvements for the hypervolume indicator
[Yildiz and Suri 2012], [Bringmann 2012], [Bringmann 2013]
- how to do indicator-based subset selection quickly?
 - also here several recent improvements
[Kuhn et al. 2014], [Bringmann et al. 2014], [Guerreiro et al. 2015]
- what is the best strategy for the subset selection?

further open questions on indicator-based EMO available at

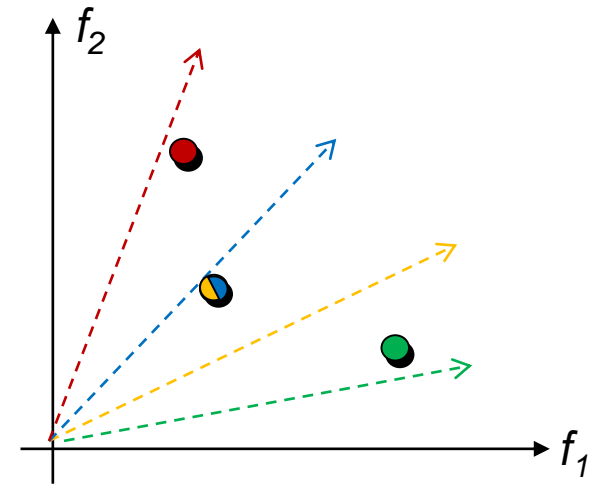
<http://simco.gforge.inria.fr/doku.php?id=openproblems>

Decomposition-Based Selection: MOEA/D

MOEA/D: Multiobjective Evolutionary Algorithm Based on Decomposition [Zhang and Li 2007]

Ideas:

- optimize N scalarizing functions in parallel
- use best solutions of neighbor subproblems for mating
- keep the best solution for each scalarizing function
- update neighbors
- use external archive for non-dominated solutions
- several variants and enhancements



Remark: Variation in EMO

- at first sight not different from single-objective optimization
- most research on selection mechanisms (until now)
- but: convergence to a set \neq convergence to a point

Open Question:

- how to achieve fast convergence to a *set*?

Related work:

- set-based gradient of the HV [Emmerich et al. 2007]
- multiobjective CMA-ES [Igel et al. 2007, Voß et al. 2010, Krause et al. 2016]
- RM-MEDA [Zhang et al. 2008]
- set-based variation [Bader et al. 2009]
- set-based fitness landscapes [Verel et al. 2011]
- offline and online configuration based on libraries of variation operators [Bezerra et al. 2015, Hadka and Reed 2013]

The Big Picture

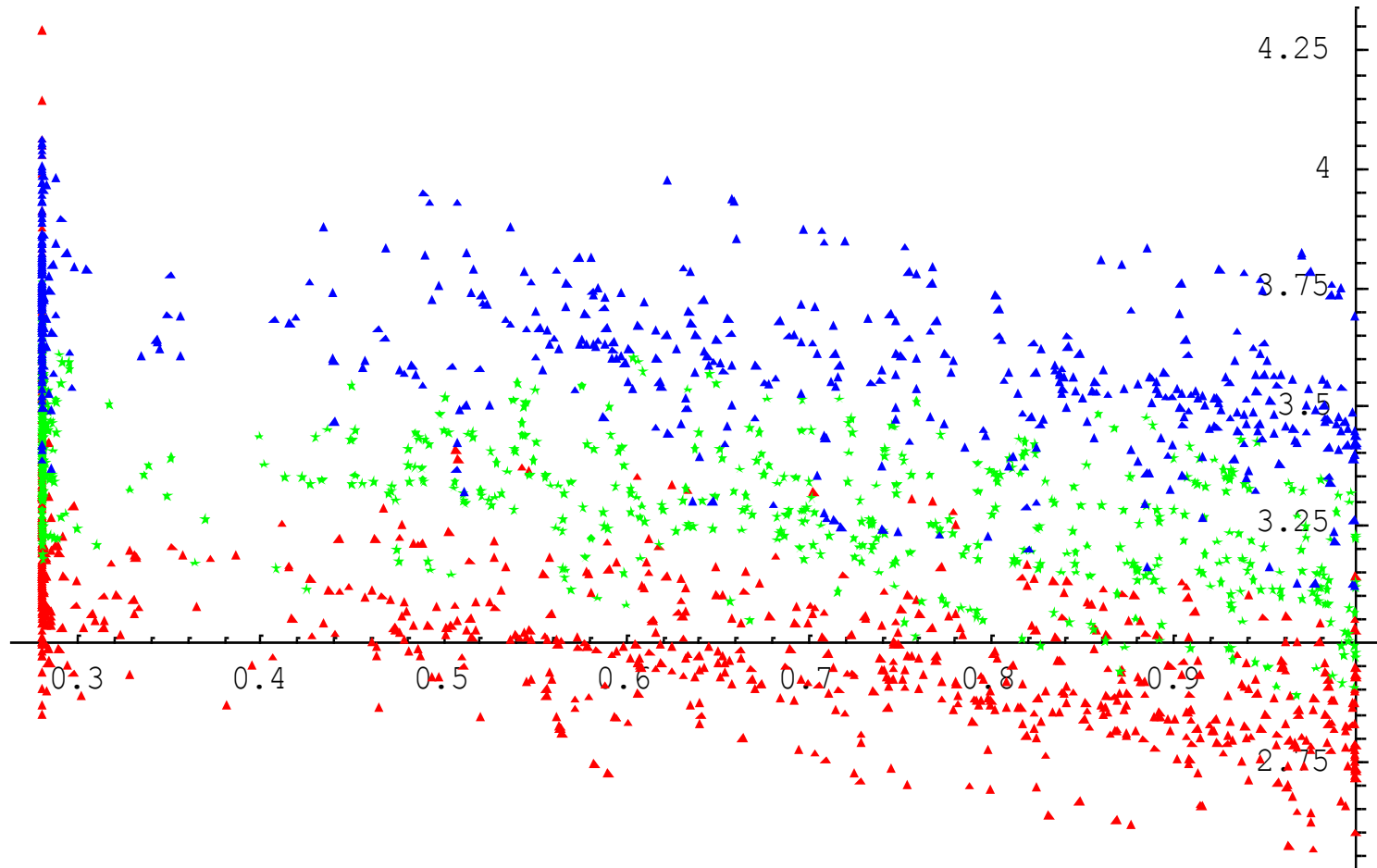
Basic Algorithm Design Principles and Concepts

Performance Assessment and Benchmarking

Preference Articulation

Once Upon a Time...

... multiobjective EAs were mainly compared visually:

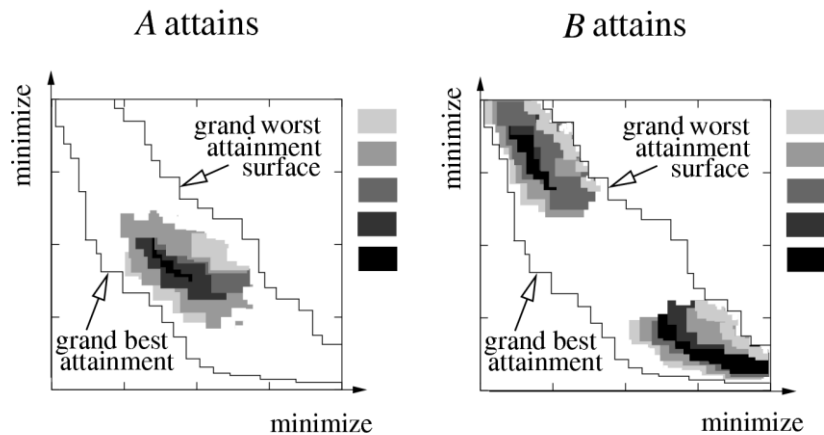


ZDT6 benchmark problem: **IBEA**, **SPEA2**, **NSGA-II**

Two Approaches for Empirical Studies

Attainment function approach

- applies statistical tests directly to the approximation set
- detailed information about how and where performance differences occur



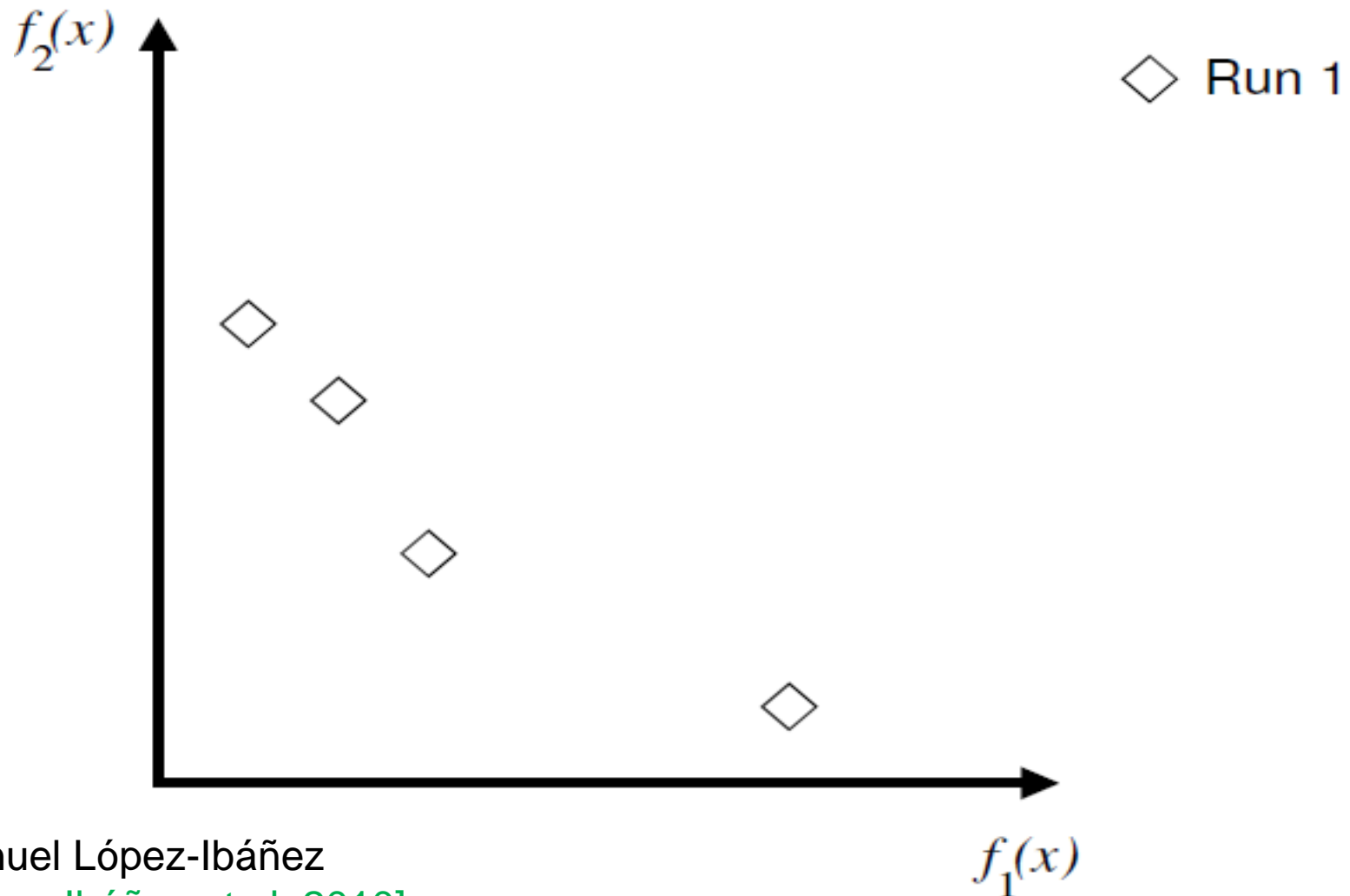
Quality indicator approach

- reduces each approximation set to a single quality value
- applies statistical tests to the quality values

<i>Indicator</i>	A	B
Hypervolume indicator	6.3431	7.1924
ϵ -indicator	1.2090	0.12722
R_2 indicator	0.2434	0.1643
R_3 indicator	0.6454	0.3475

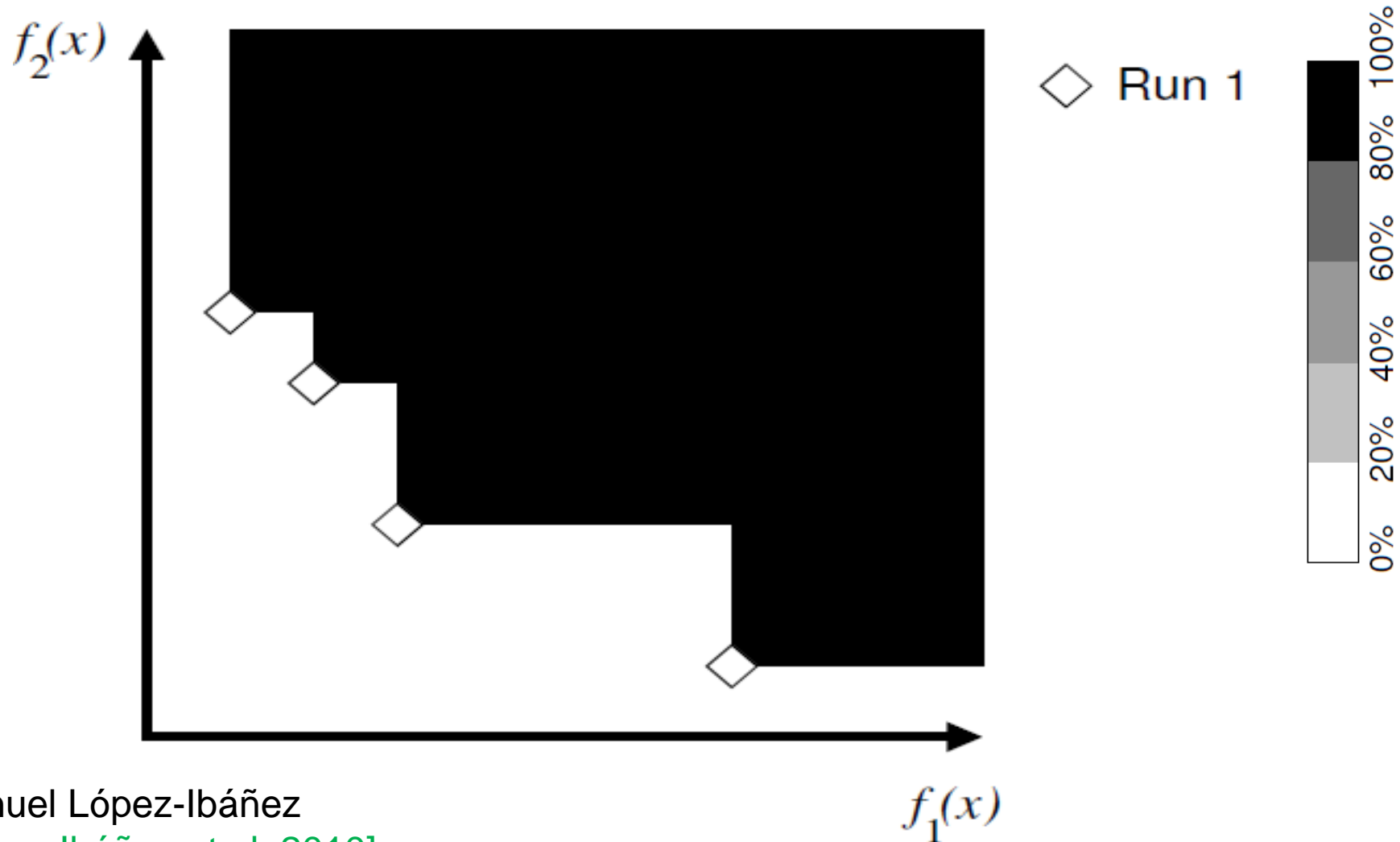
see e.g. [\[Zitzler et al. 2003\]](#)

Empirical Attainment Functions



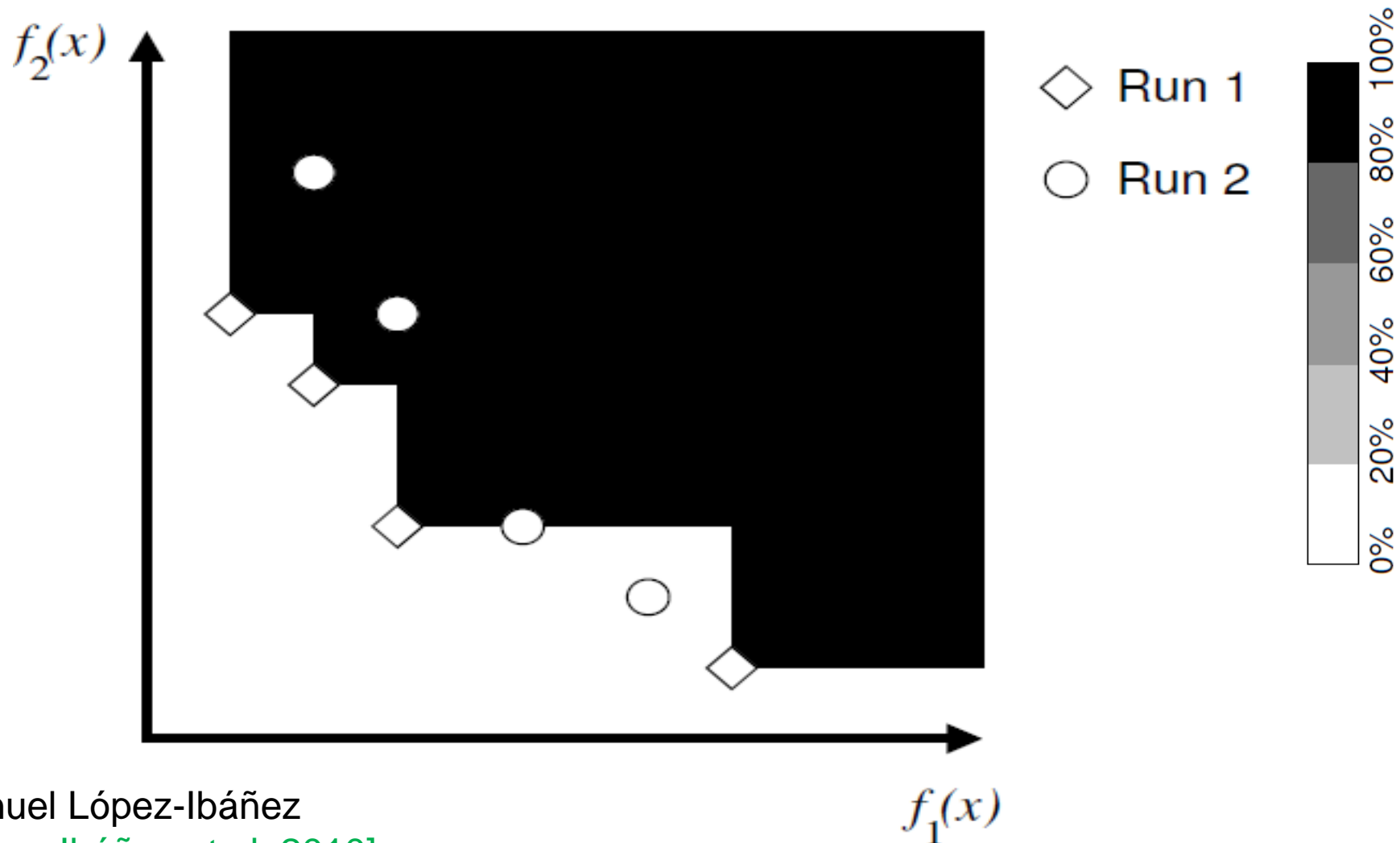
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[López-Ibáñez et al. 2010]

Empirical Attainment Functions



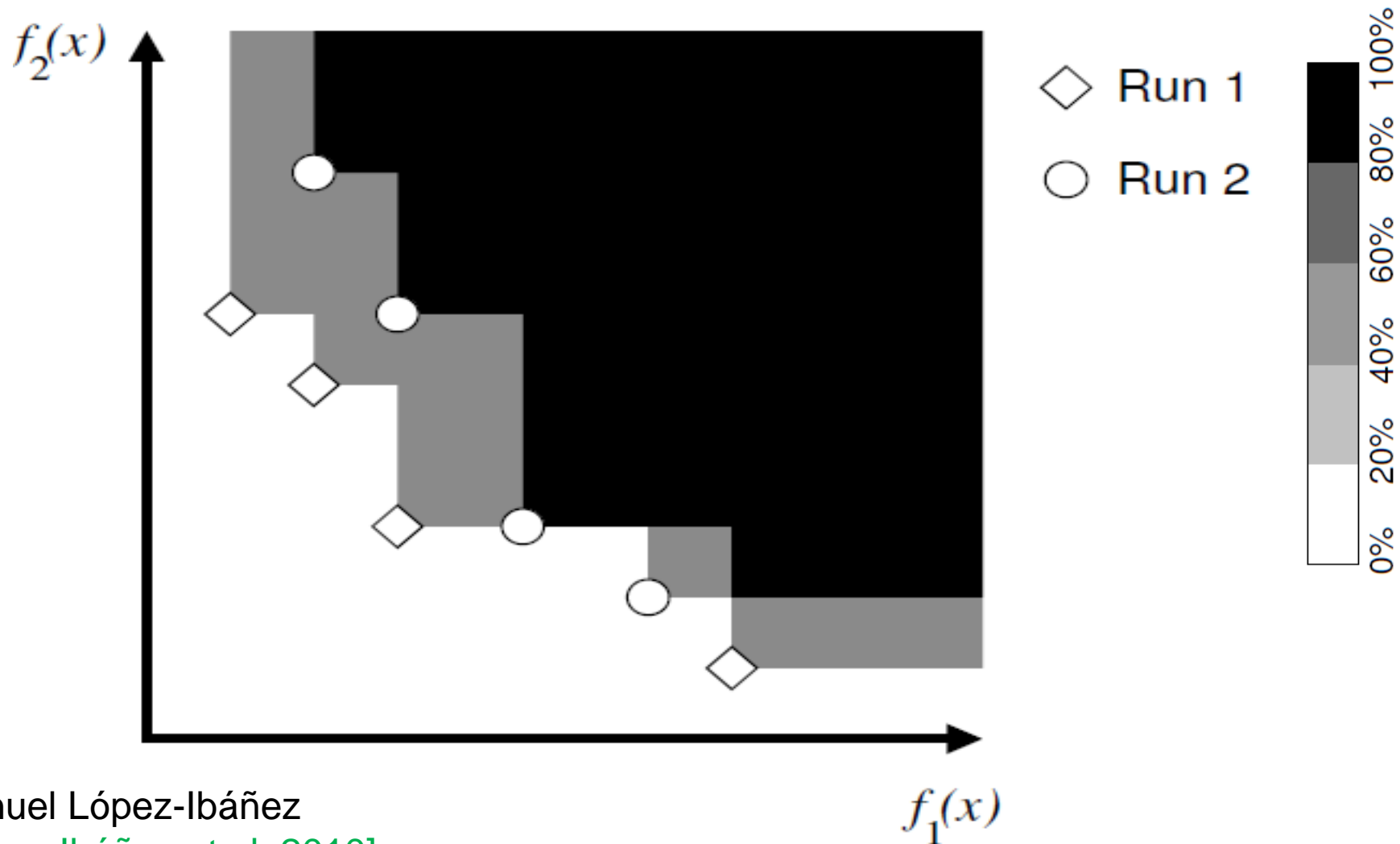
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[López-Ibáñez et al. 2010]

Empirical Attainment Functions



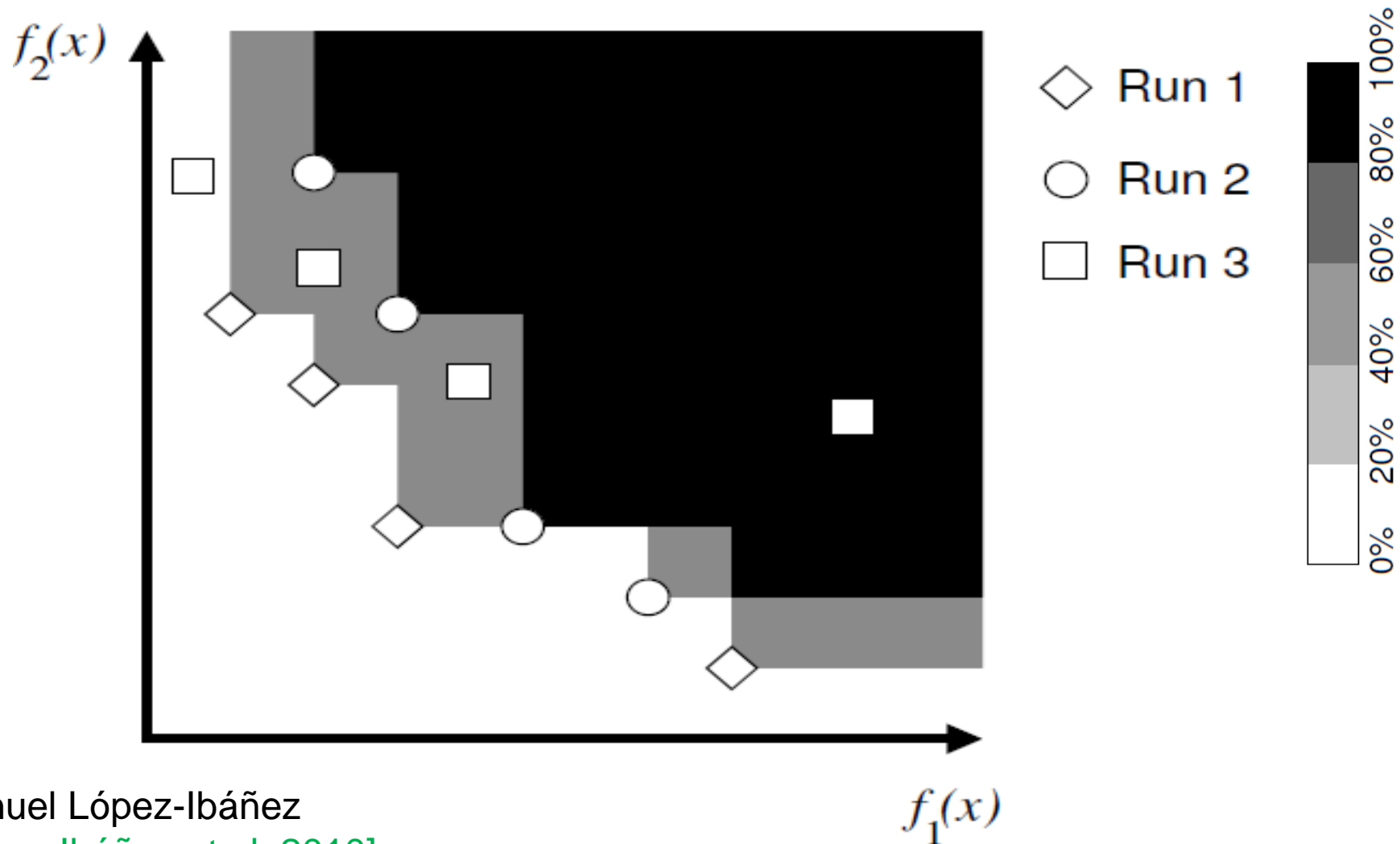
© Manuel López-Ibáñez
[López-Ibáñez et al. 2010]

Empirical Attainment Functions



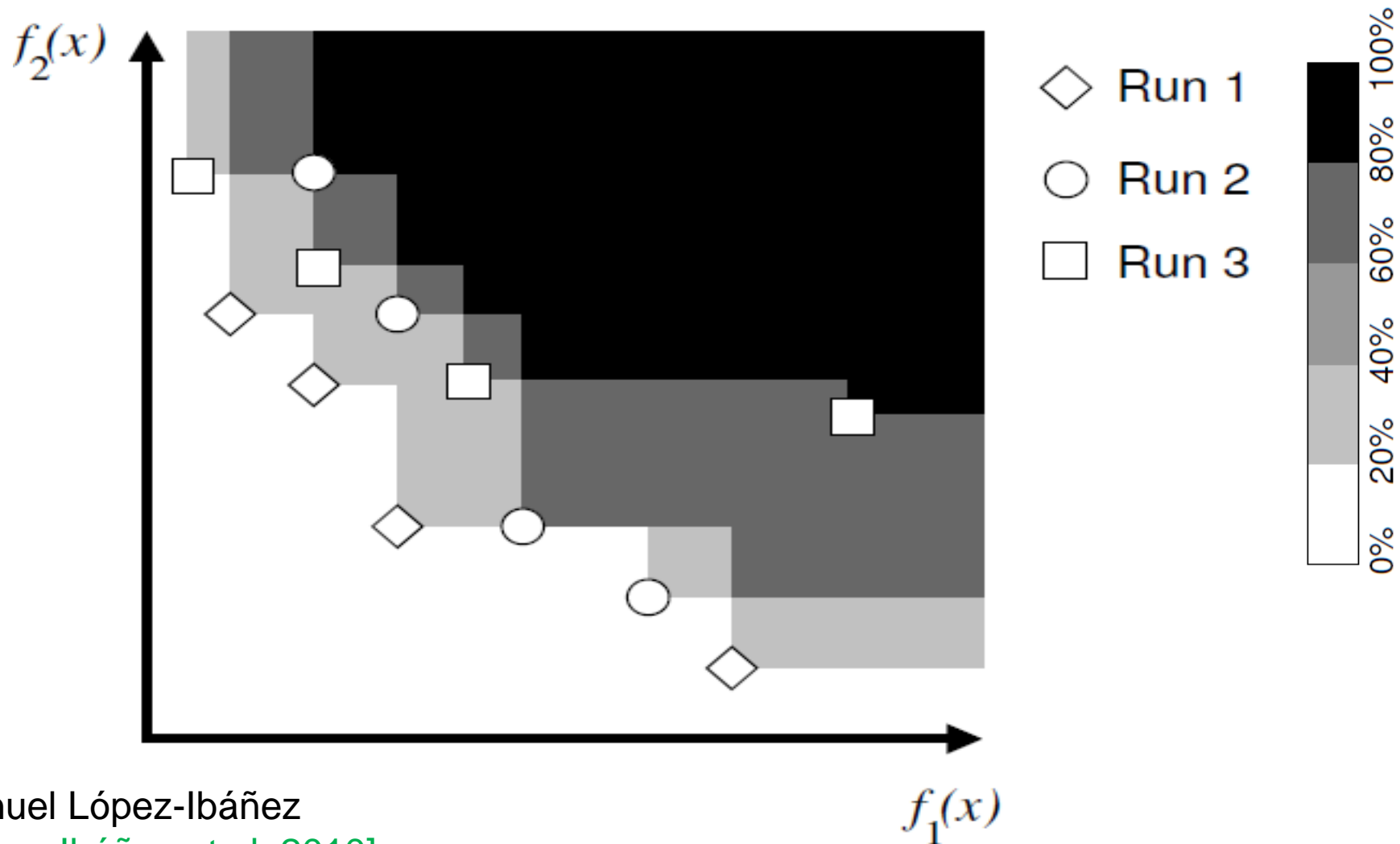
© Manuel López-Ibáñez
[López-Ibáñez et al. 2010]

Empirical Attainment Functions



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Empirical Attainment Functions



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[López-Ibáñez et al. 2010]

Empirical Attainment Functions: Definition

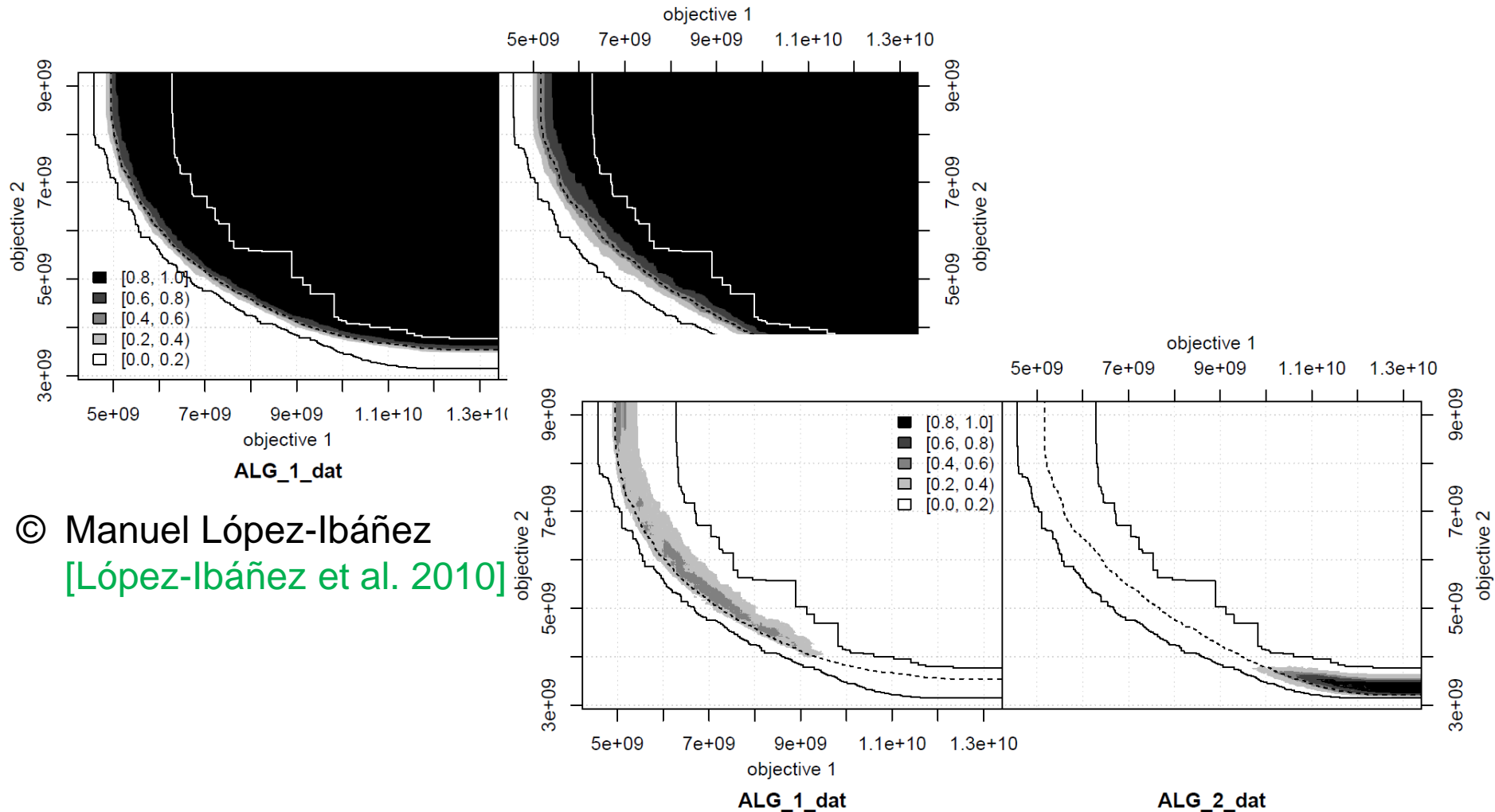
The Empirical Attainment Function $\alpha(z)$ "counts" how many solution sets \mathcal{X}_i attain or dominate a vector z at time T :

$$\alpha_T(z) = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{\{\mathcal{X}_i \preceq_T z\}}$$

with \preceq_T being the weak dominance relation between a solution set and an objective vector at time T .

Note that $\alpha_T(z)$ is the **empirical cumulative distribution function of the achieved objective function distribution at time T** in the single-objective case ("fixed budget scenario").

Empirical Attainment Functions in Practice

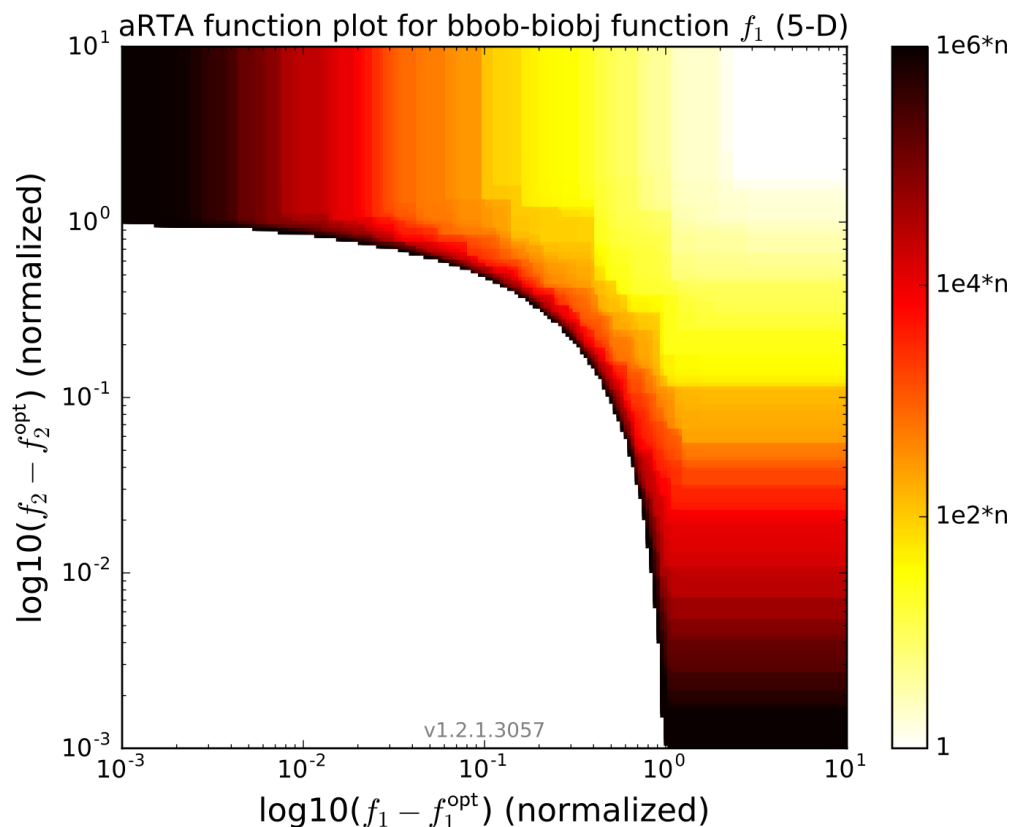


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[López-Ibáñez et al. 2010]

latest implementation online at
<http://eden.dei.uc.pt/~cmfonsec/software.html>
R package: <http://lopez-ibanez.eu/eaftools>
see also [López-Ibáñez et al. 2010, Fonseca et al. 2011]

Plotting Average Runtimes

Note: success probability can be naturally replaced by the average runtime of an artificially restarted algorithm (aRT):



code available at <http://github.com/numbbo/coco/>
see also [Brockhoff et al. 2017]

Quality Indicator Approach

Idea:

- transfer multiobjective problem into a set problem
- define an objective function (“quality indicator”) on sets
- use the resulting total (pre-)order (on the quality values)

Question:

Can any total (pre-)order be used or are there any requirements concerning the resulting preference relation?

⇒ Underlying dominance relation
should be reflected!

$$A \preceq B :\Leftrightarrow \forall_{y \in B} \exists_{x \in A} x \leq_{par} y$$

Refinements and Weak Refinements

① $\overset{\text{ref}}{\preceq}$ **refines** a preference relation \preceq iff

$$A \preceq B \wedge B \not\preceq A \Rightarrow A \overset{\text{ref}}{\preceq} B \wedge B \not\overset{\text{ref}}{\preceq} A \quad (\text{better} \Rightarrow \text{better})$$

\Rightarrow fulfills requirement

② $\overset{\text{ref}}{\preceq}$ **weakly refines** a preference relation \preceq iff

$$A \preceq B \wedge B \not\preceq A \Rightarrow A \overset{\text{ref}}{\preceq} B \quad (\text{better} \Rightarrow \text{weakly better})$$

\Rightarrow does not fulfill requirement, but $\overset{\text{ref}}{\preceq}$ does not contradict \preceq

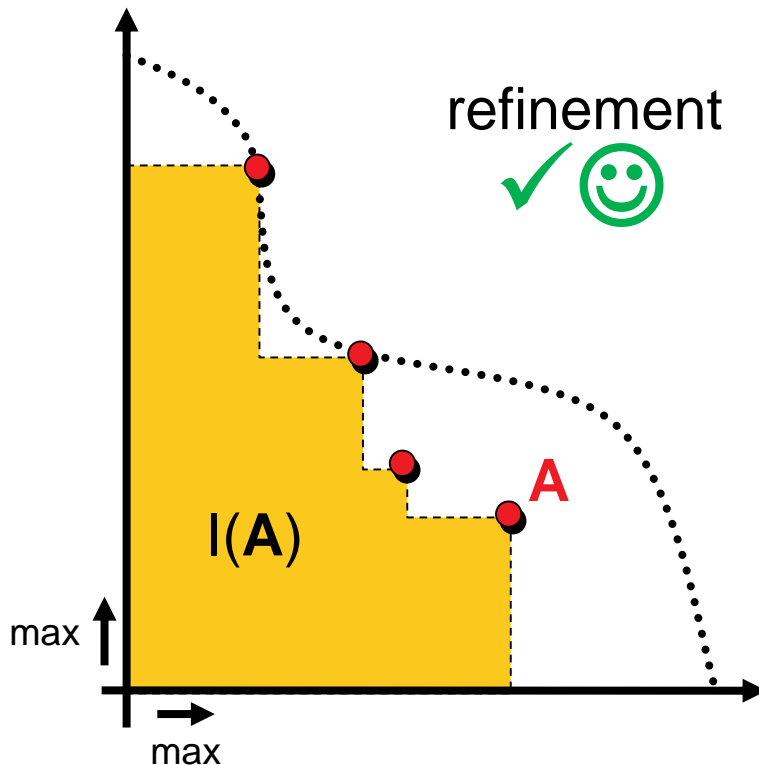
! sought are total refinements...

[Zitzler et al. 2010]

Example: Refinements Using Indicators

$$A \stackrel{\text{ref}}{\preceq} B :\Leftrightarrow I(A) \geq I(B)$$

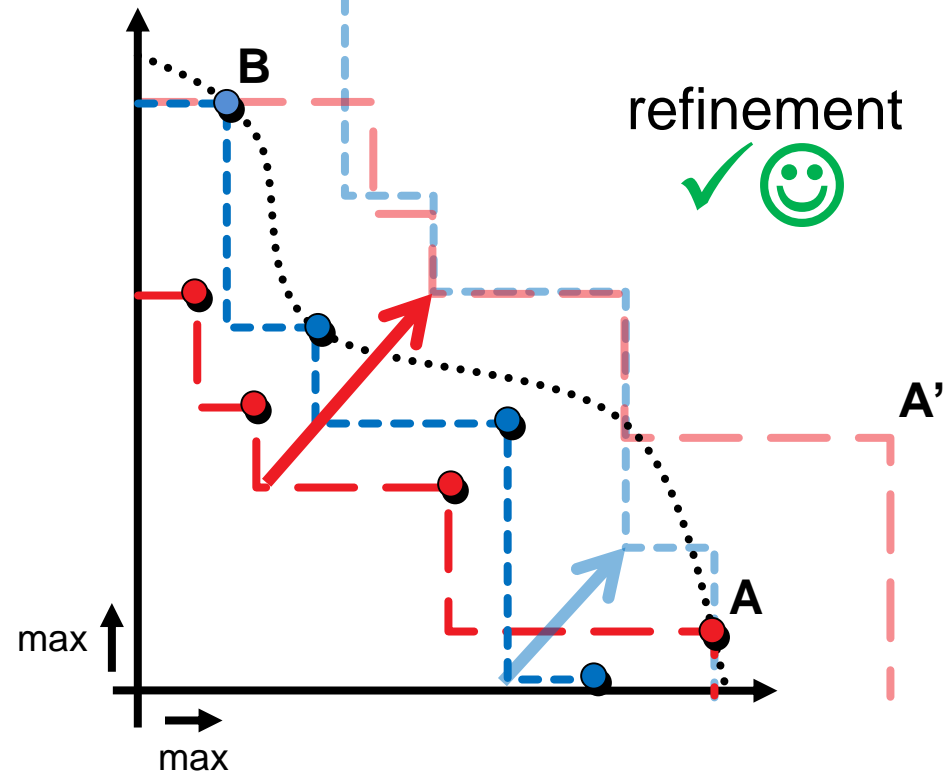
$I(A)$ = volume of the weakly dominated area in objective space



unary hypervolume indicator

$$A \stackrel{\text{ref}}{\preceq} B :\Leftrightarrow I(A,B) \leq I(B,A)$$

$I(A,B)$ = how much needs A to be moved to weakly dominate B

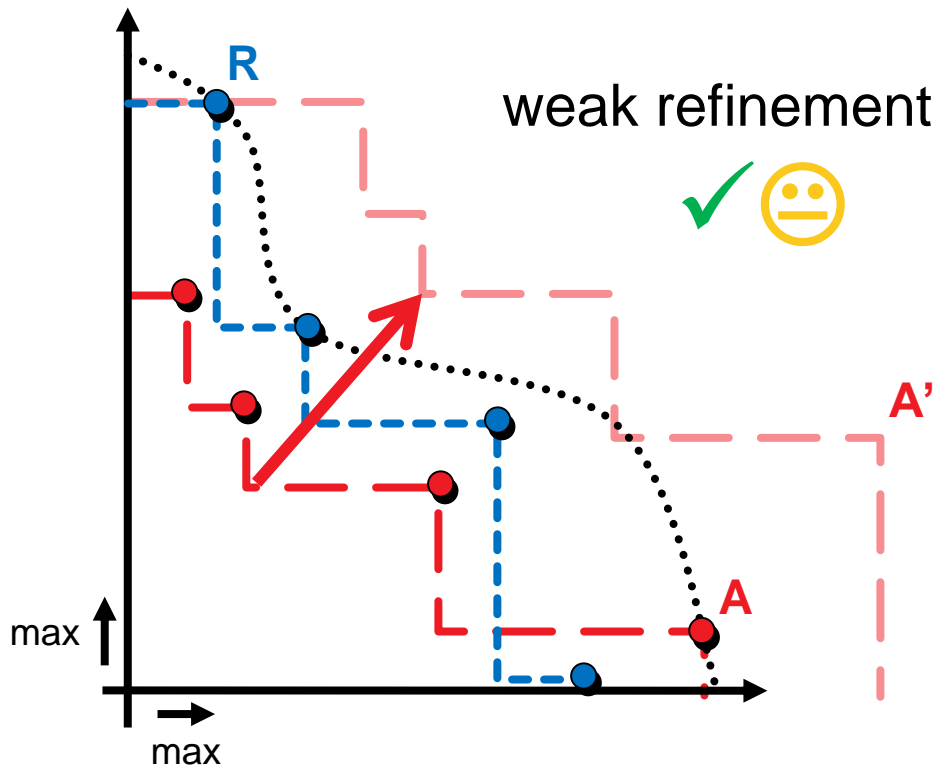


binary epsilon indicator

Example: Weak Refinement / No Refinement

$$A \stackrel{\text{ref}}{\preceq} B :\Leftrightarrow I(A, R) \leq I(B, R)$$

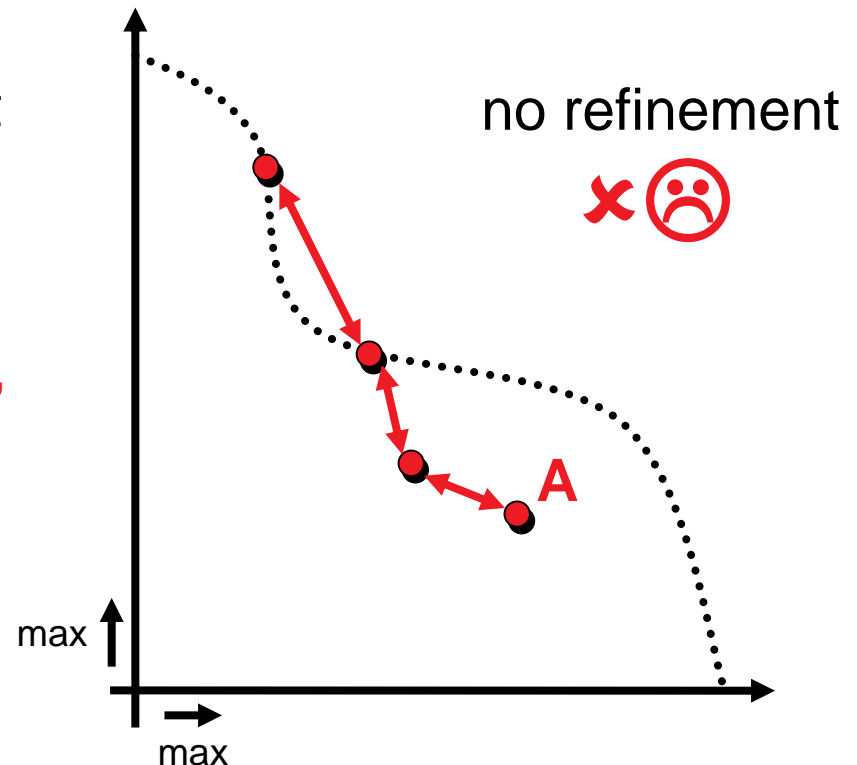
$I(A, R)$ = how much needs A to be moved to weakly dominate R



unary epsilon indicator

$$A \stackrel{\text{ref}}{\preceq} B :\Leftrightarrow I(A) \leq I(B)$$

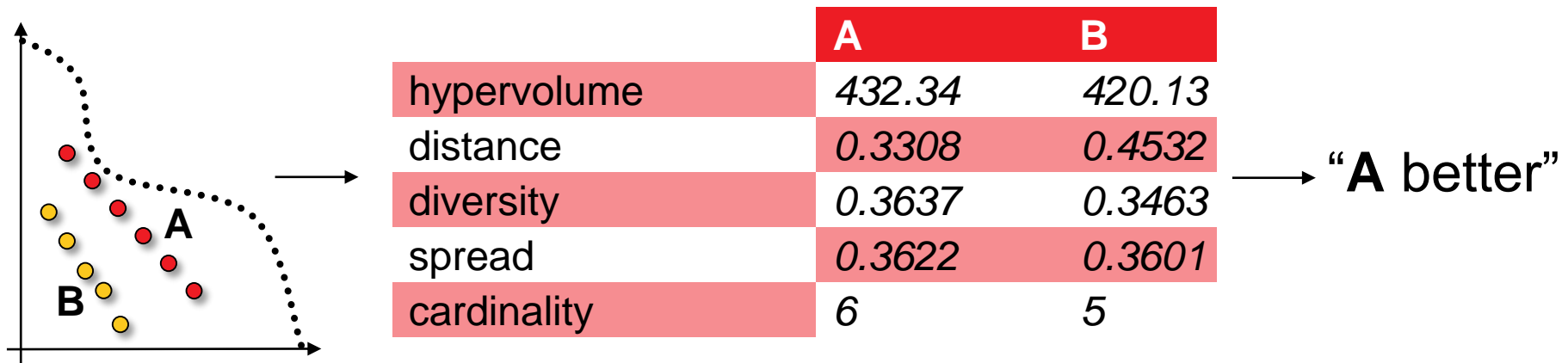
$I(A)$ = variance of pairwise distances



unary diversity indicator

Quality Indicator Approach

Goal: compare two Pareto set approximations A and B



Comparison method C = quality measure(s) + Boolean function

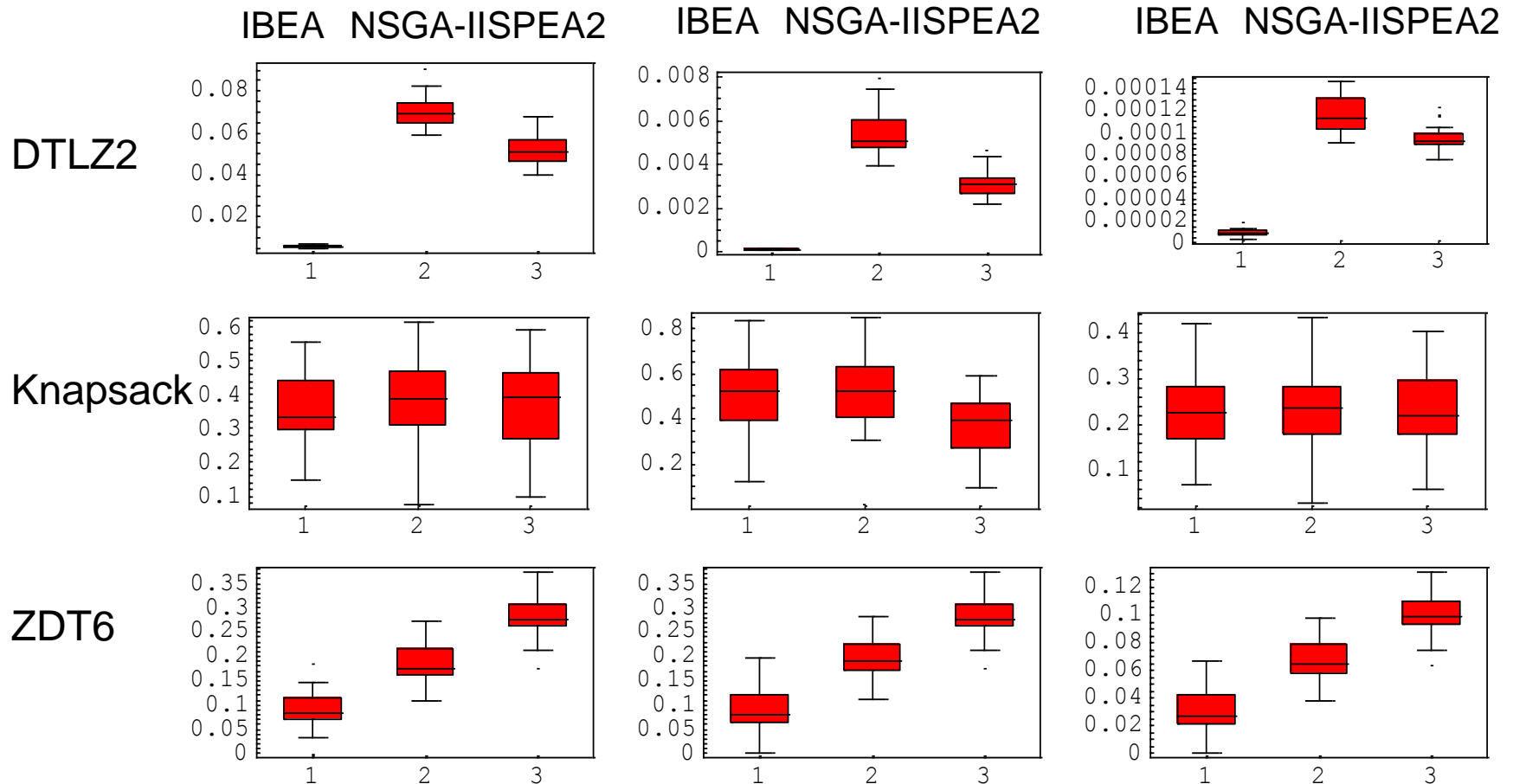


Example: Box Plots

epsilon indicator

hypervolume


R indicator



Statistical Assessment (Kruskal Test)

ZDT6 Epsilon

is better
than




	IBEA	NSGA2	SPEA2
IBEA		~0 😊	~0 😊
NSGA2	1		~0 😊
SPEA2	1	1	

Overall p-value = 6.22079e-17.
Null hypothesis rejected (alpha 0.05)

DTLZ2 R

is better
than



	IBEA	NSGA2	SPEA2
IBEA		~0 😊	~0 😊
NSGA2	1		1
SPEA2	1	~0 😊	

Overall p-value = 7.86834e-17.
Null hypothesis rejected (alpha 0.05)

Knapsack/Hypervolume: H_0 = No significance of any differences

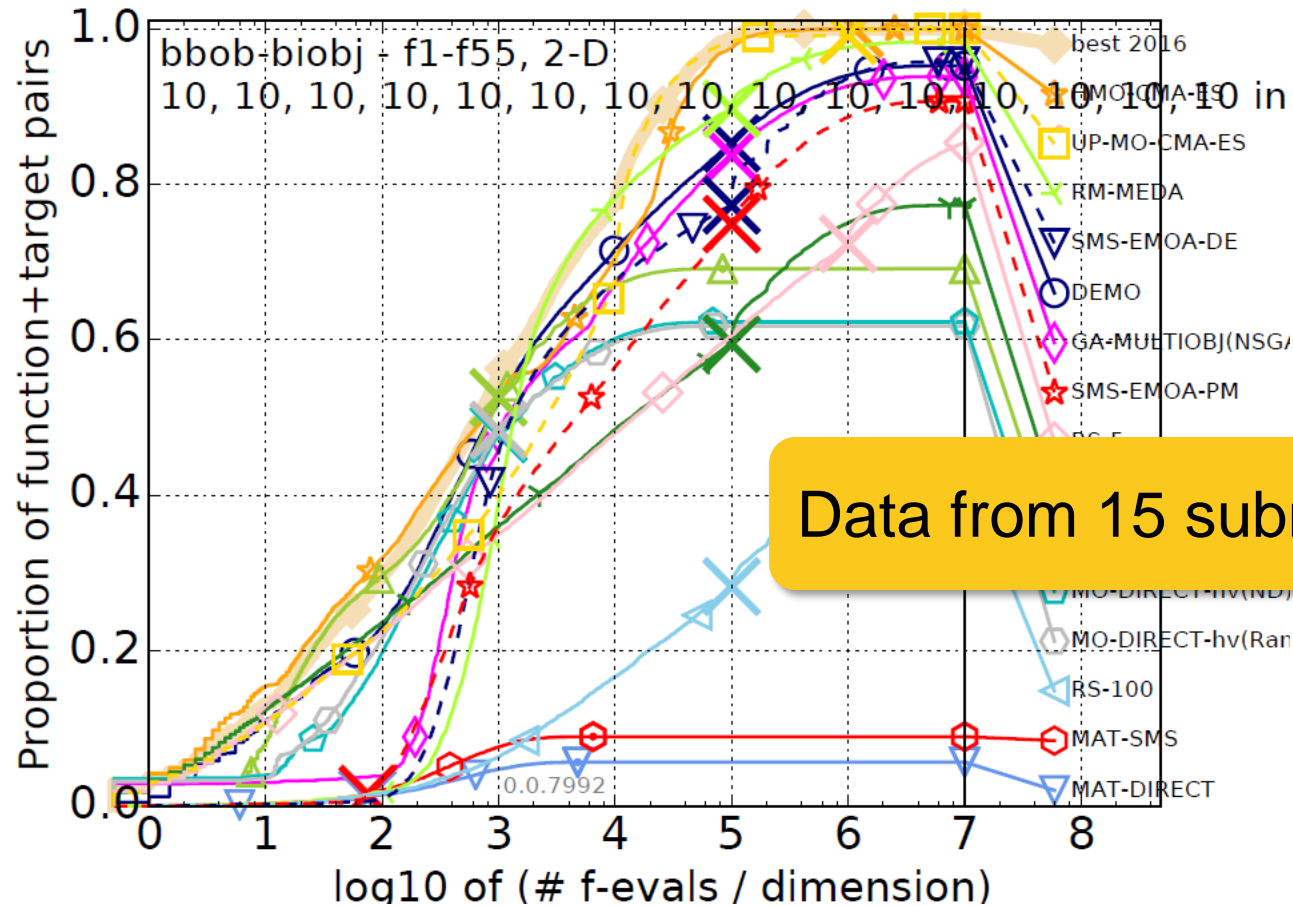
Open Questions:

- are there other unary indicators that are (weak) refinements?
- how to compute indicators efficiently (enough for practice)?
 - especially for >3 objective functions
 - and in the online/archiving case
- how to achieve good indicator values?

Automated Benchmarking

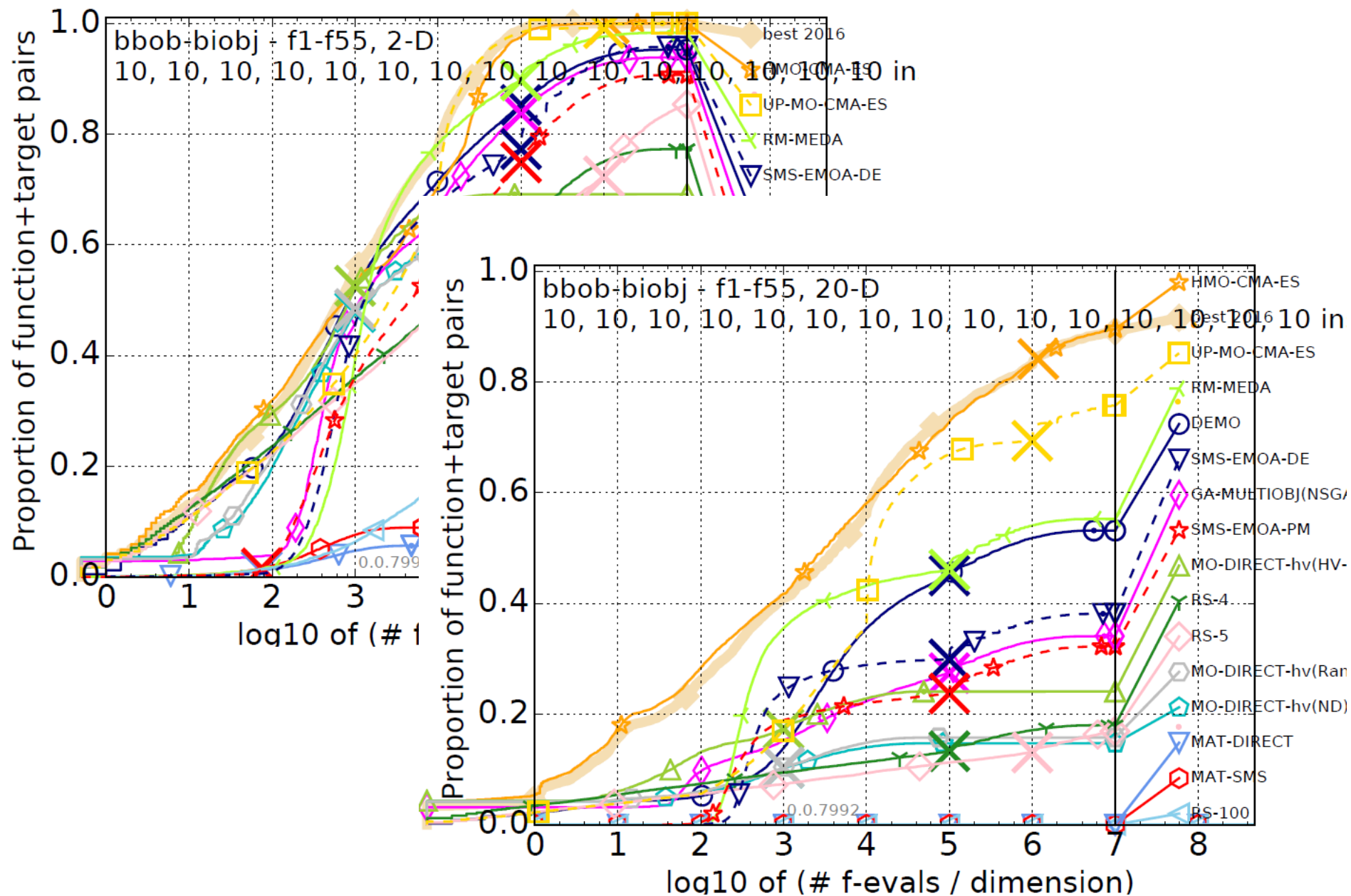
- State-of-the-art in single-objective optimization: **Blackbox Optimization Benchmarking (BBOB)** with COCO platform
<https://github.com/numbbo/coco>
- Release of a **bi-objective test suite** at BBOB-2016 workshop
- Focus on **target-based runlengths**
 - gives (nearly) anytime, interpretable results
 - defines problem=(test function instance, single-objective goal e.g. min. indicator difference to reference set, target precision)
 - reports average runtimes (aRT) to reach target precision
- COCO provides **data profiles**, **scaling plots**, scatter plots, tables, statistical tests, etc. **automatically**

Exemplary BBOB-2016 Results



Data from 15 submitted algorithms

Exemplary BBOB-2016 Results



The Big Picture

Basic Algorithm Design Principles and Concepts

Performance Assessment and Benchmarking

Preference Articulation

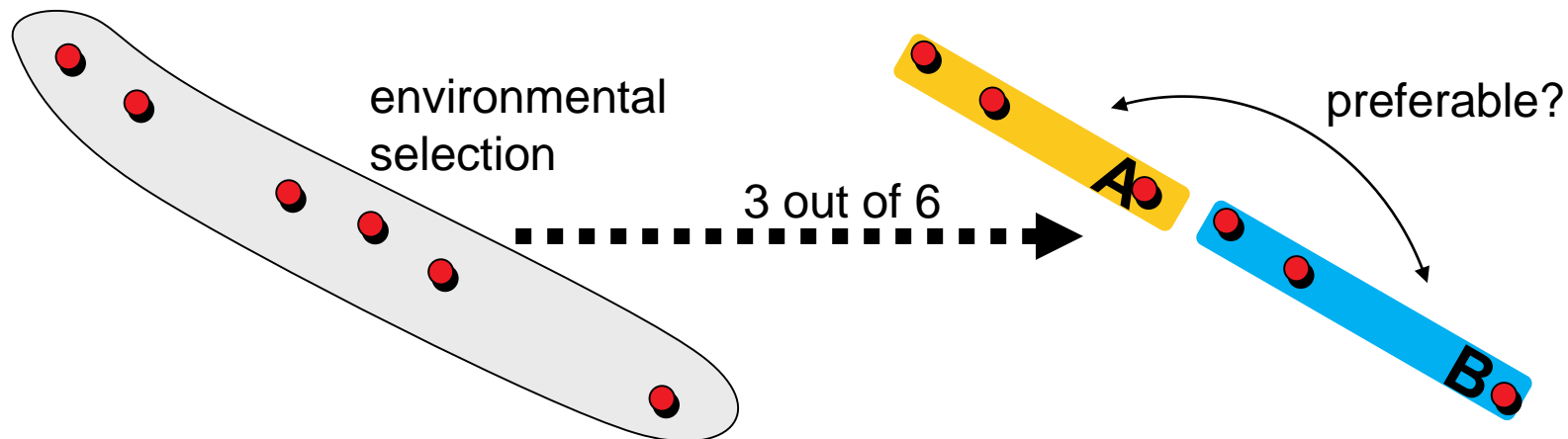
Articulating User Preferences During Search

What we thought: EMO is preference-less

Search before decision making: Optimization is performed without any preference information given. The result of the search process is a set of (ideally Pareto-optimal) candidate solutions from which the final choice is made by the DM.

[Zitzler 1999]

What we learnt: EMO just uses weaker preference information



Incorporation of Preferences During Search

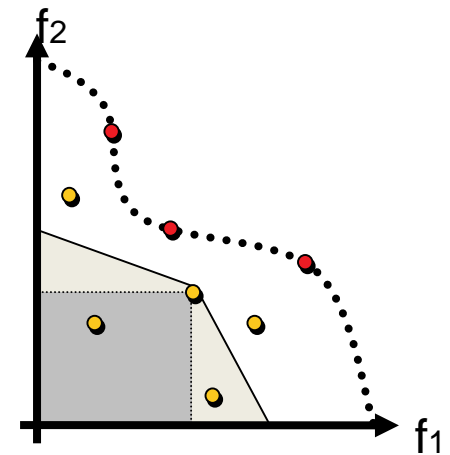
Nevertheless...

- the more (known) preferences incorporated the better
- in particular if search space is large

[Branke and Deb 2004] [Branke 2008] [Bechikh et al. 2015]

① Refine/modify dominance relation, e.g.:

- using goals, priorities, constraints
[Fonseca and Fleming 1998a,b]
- using different types of dominance cones
[Branke and Deb 2004]



② Use quality indicators, e.g.:

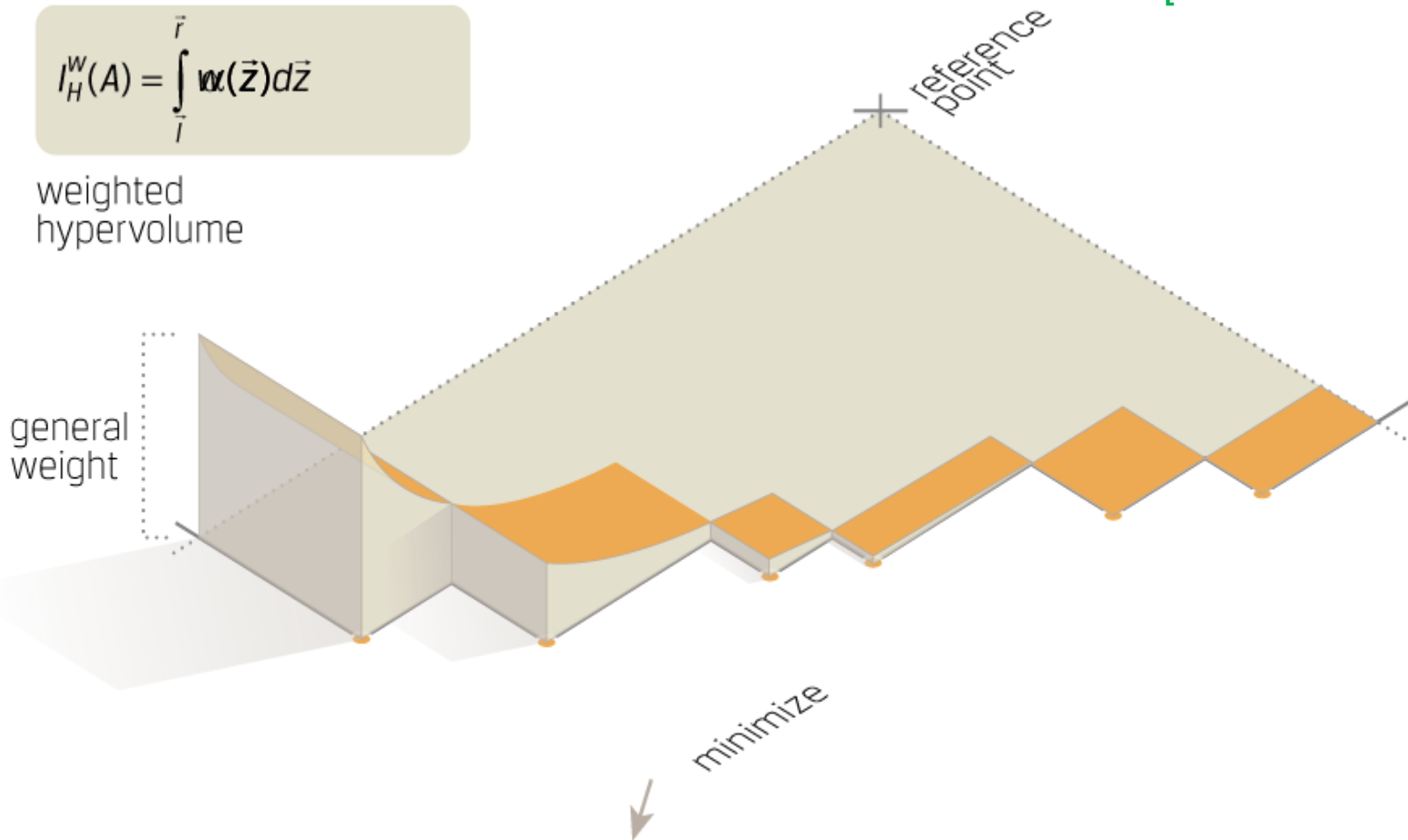
- based on reference points and directions [Deb and Sundar 2006, Deb and Kumar 2007]
- based on the hypervolume indicator
[Brockhoff et al. 2013] [Wagner and Trautmann 2010]
- based on the R2 indicator [Trautmann et al. 2013]

Example: Weighted Hypervolume Indicator

[Brockhoff et al. 2013]

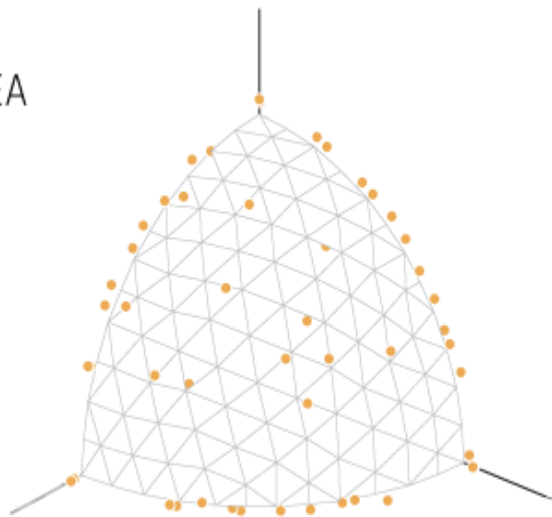
$$I_H^W(A) = \int_{\vec{l}}^{\vec{r}} w(\vec{z}) d\vec{z}$$

weighted
hypervolume

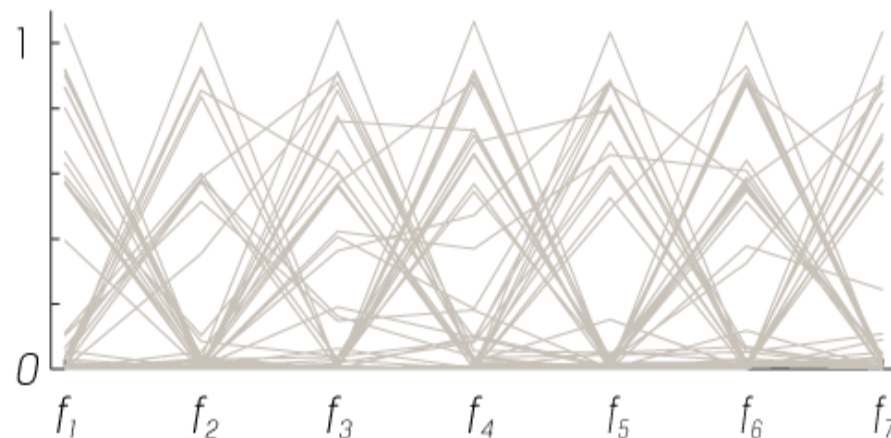


Weighted Hypervolume in Practice

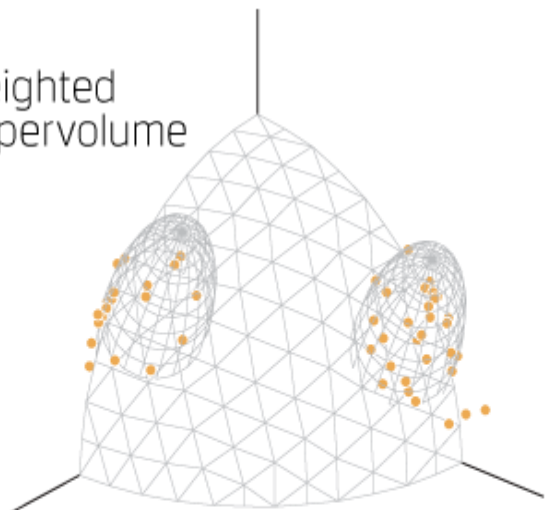
IBEA



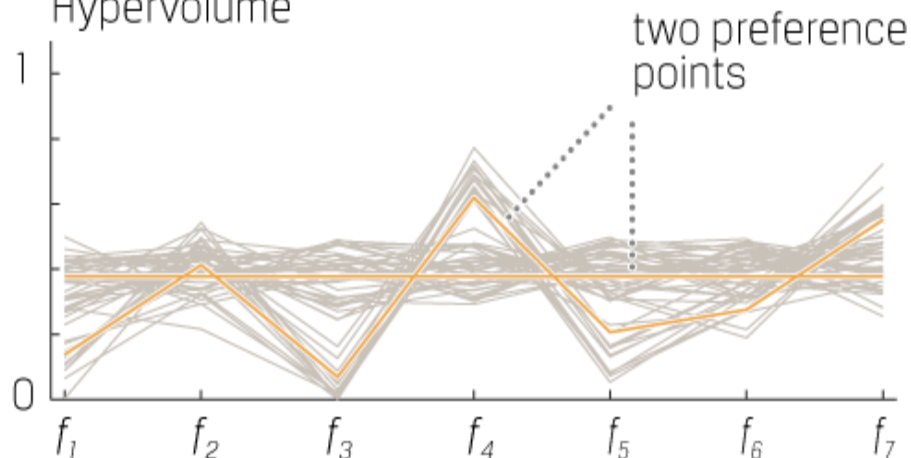
IBEA



weighted
Hypervolume



weighted
Hypervolume

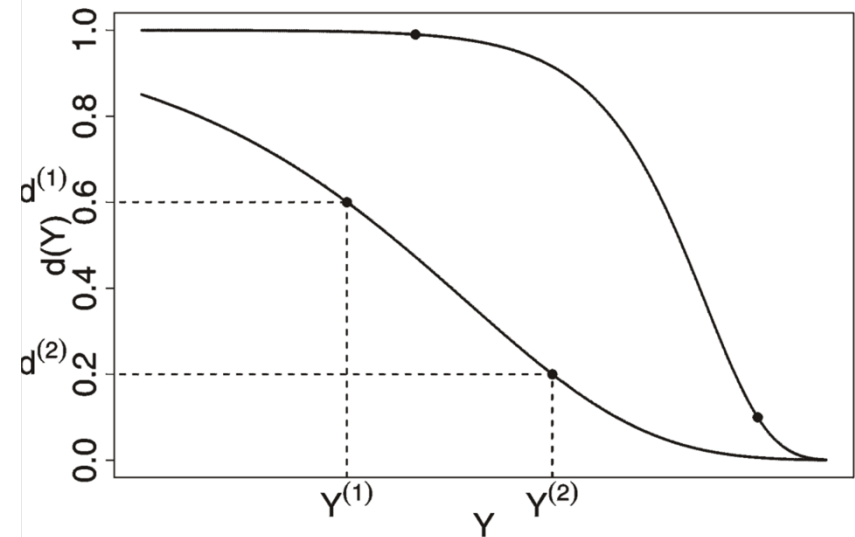
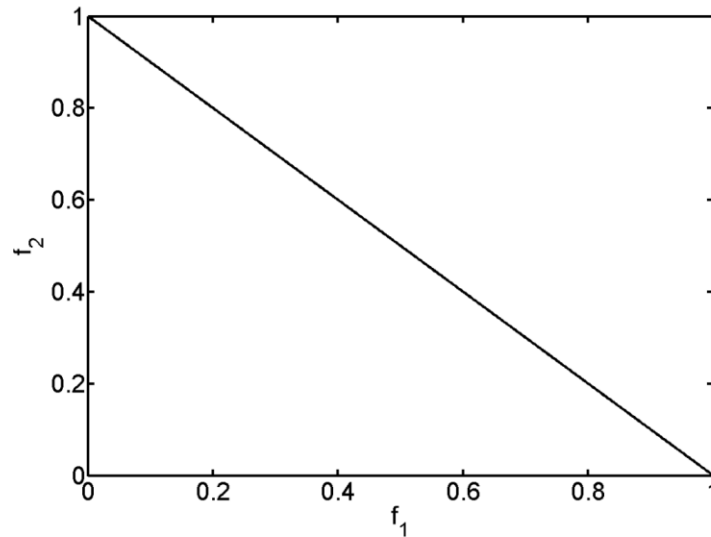


[Auger et al. 2009b]

Example: Desirability Function (DF)-SMS-EMOA

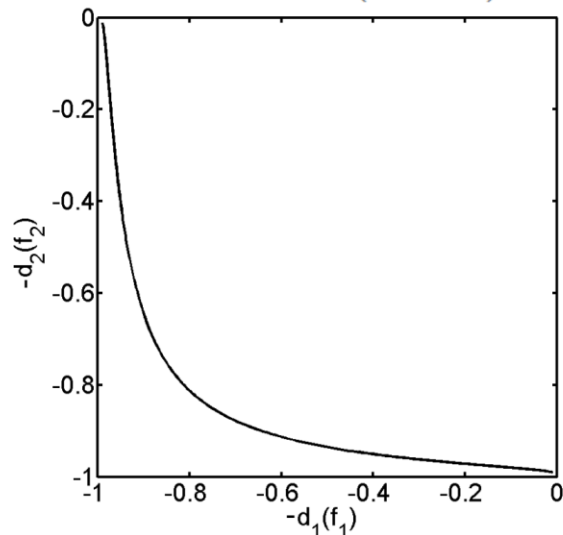
[Wagner and Trautmann 2010]

Shape of the untransformed Pareto front



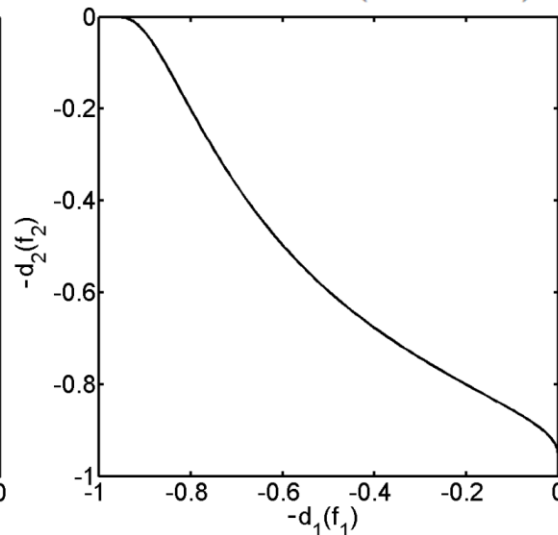
Shape of the transformed front for

identical DFs with $\begin{pmatrix} 0 & 0.99 \\ 1 & 0.01 \end{pmatrix}$



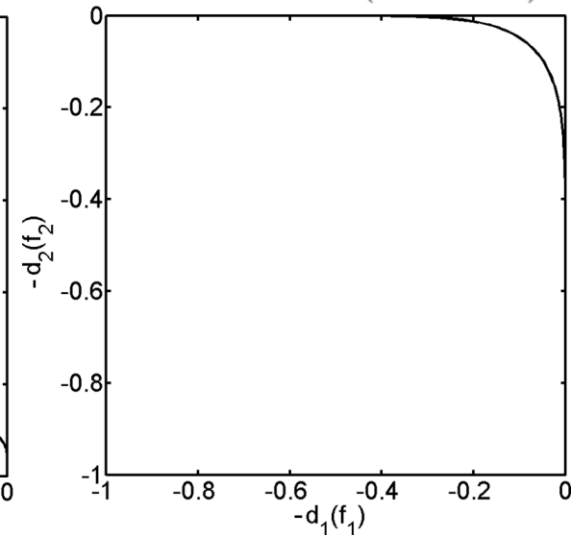
Shape of the transformed front for

identical DFs with $\begin{pmatrix} 0 & 0.99 \\ 0.75 & 0.01 \end{pmatrix}$

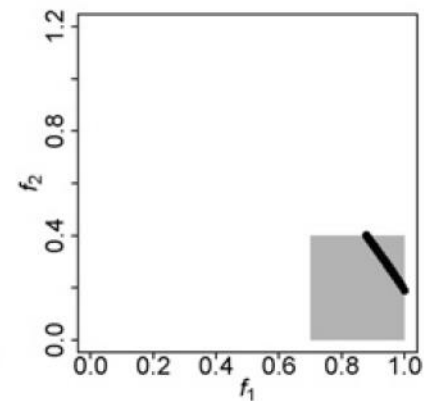
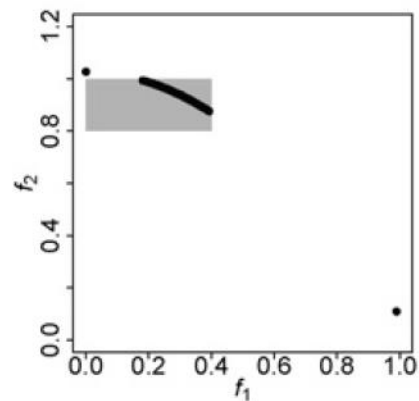
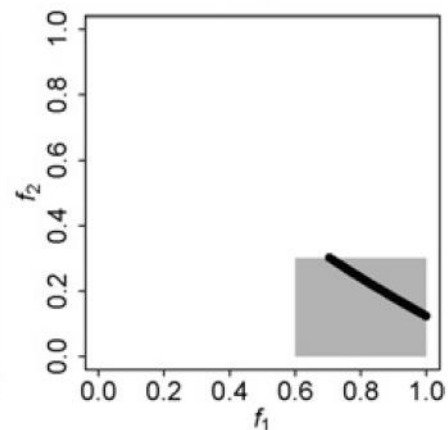
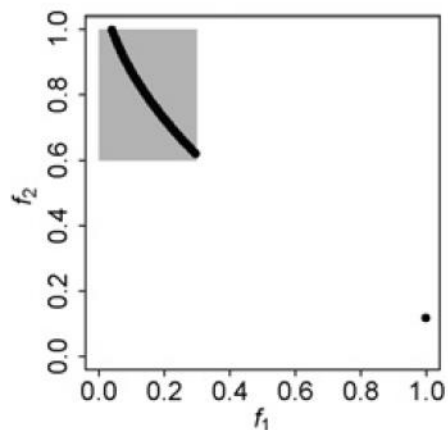
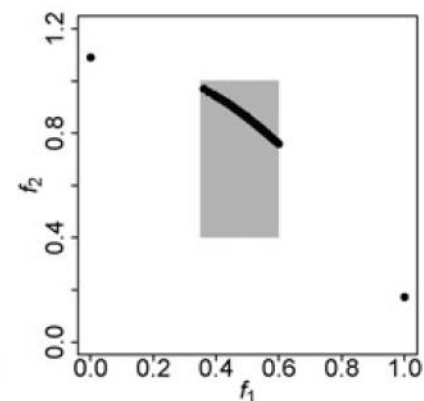
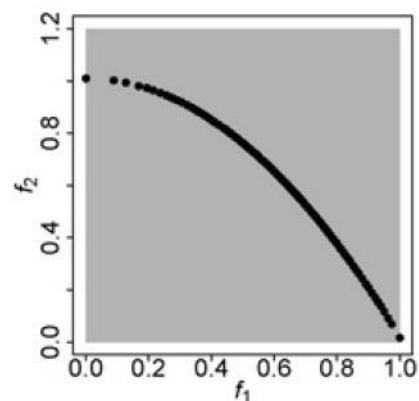
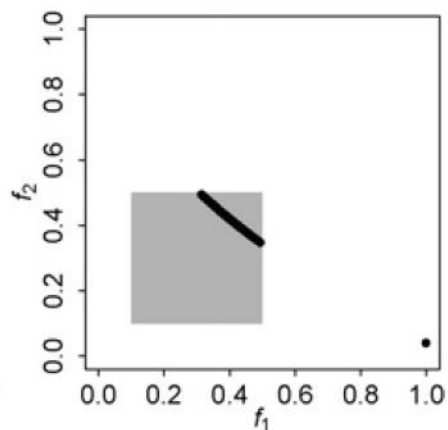
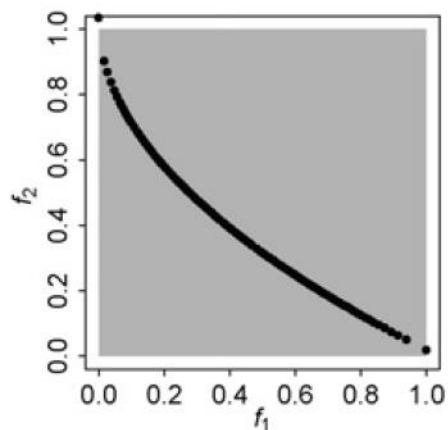


Shape of the transformed front for

identical DFs with $\begin{pmatrix} 0 & 0.99 \\ 0.55 & 0.01 \end{pmatrix}$



DF-SMS-EMOA in Practice

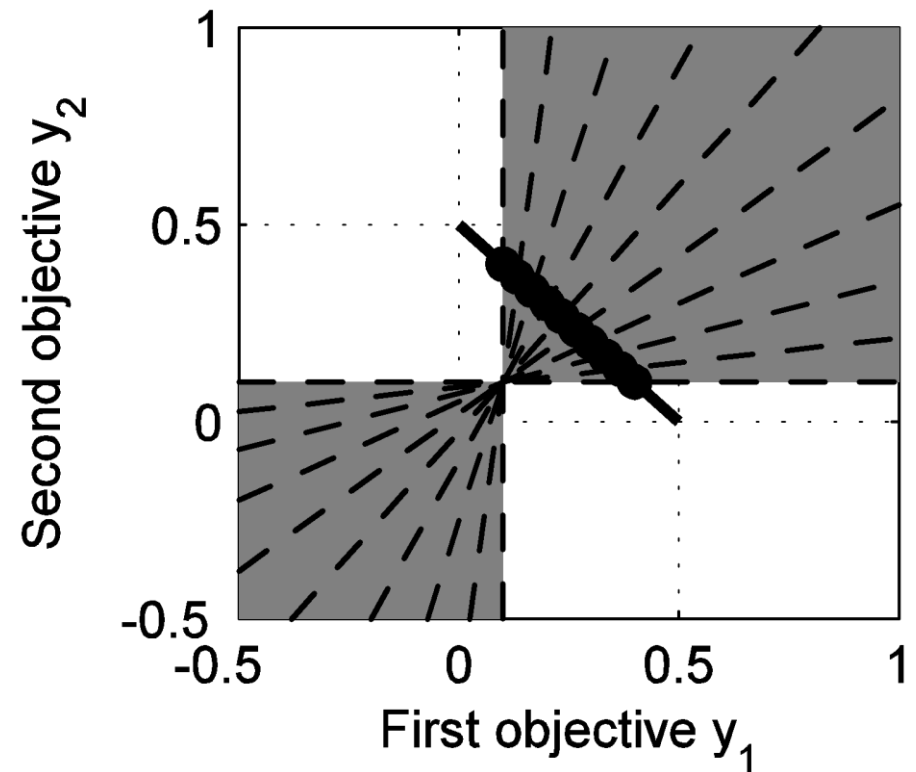
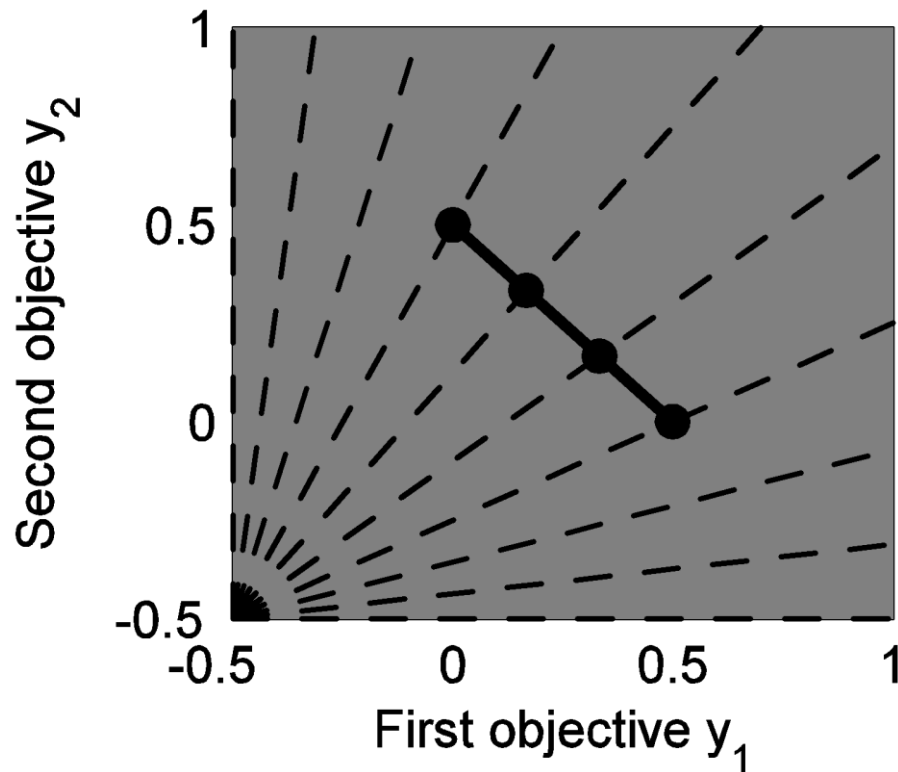


Example: R2-EMOA

Concept

Integration of preferences by varying the scalarizing functions

Position of ideal point

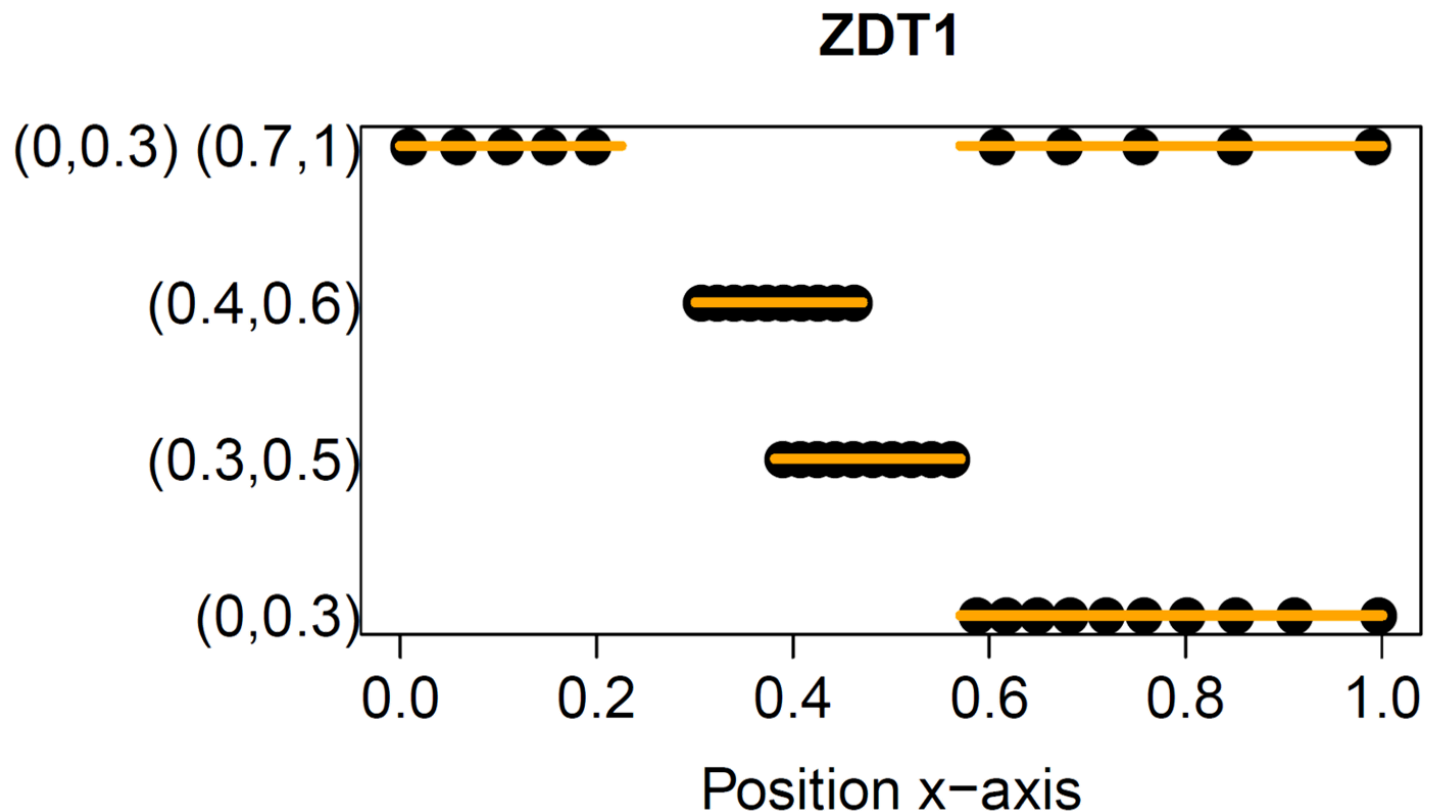


Example: R2-EMOA

Concept

Integration of preferences by varying the scalarizing functions

Restriction of the weight space



Interactive Approaches

Successive Preference Articulation = Interactive EMO

- recent interest of both EMO and MCDM community
- important in practice

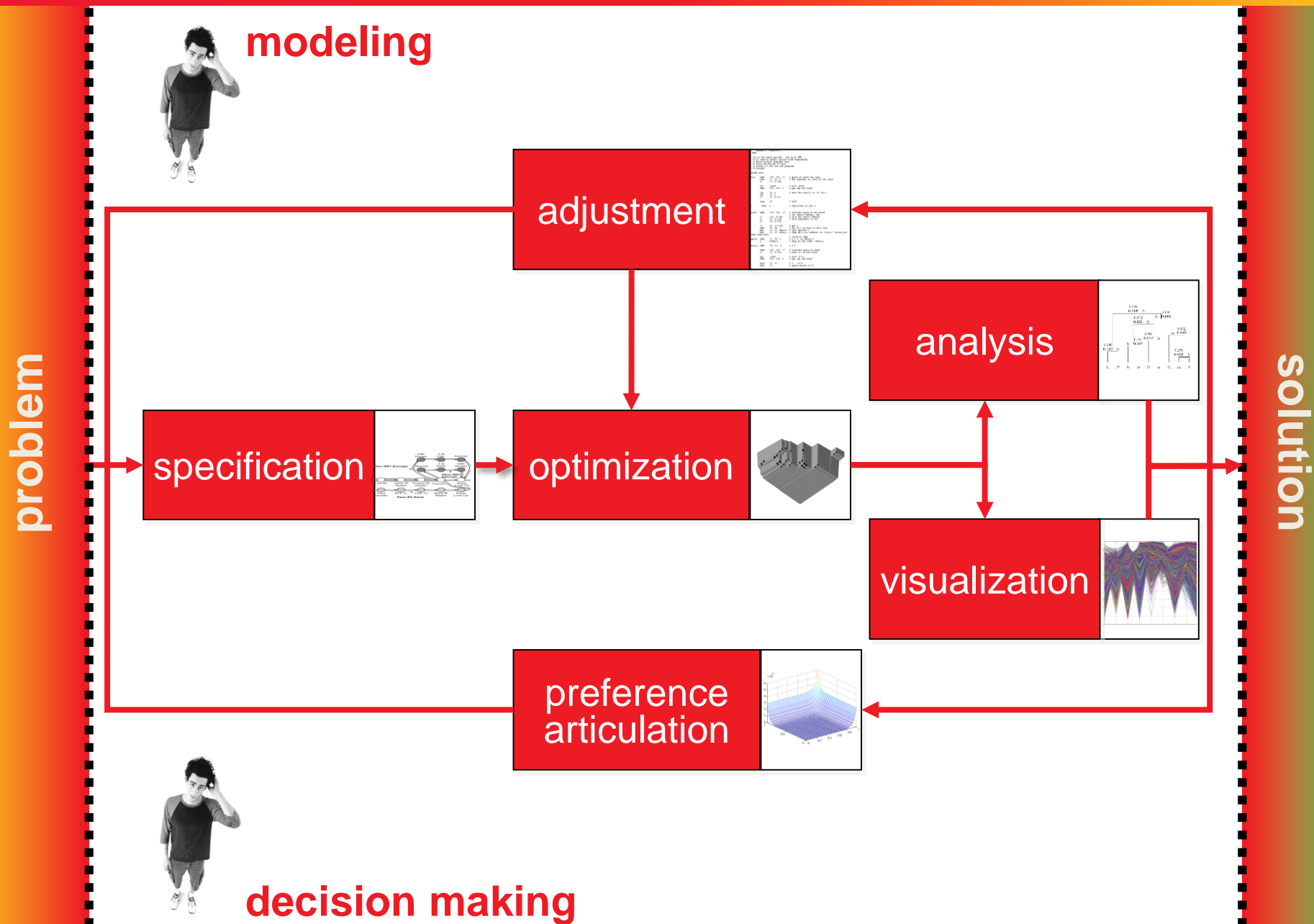
Examples

- first interactive EMO: [Tanino et al. 1993]
- good overview: [Jaszkiewicz and Branke 2008]
- more recent work: [Brockhoff et al. 2014] [Branke et al. 2014]

Issues/Open Questions

- realistic scenarios/ value functions
- evaluation of interactive algorithms [López-Ibáñez and Knowles 2015]

Conclusions: EMO as Interactive Decision Support



The EMO Community

Links:

- EMO mailing list: <https://lists.dei.uc.pt/mailman/listinfo/emo-list>
- MCDM mailing list: <http://lists.jyu.fi/mailman/listinfo/mcdm-discussion>
- EMO bibliography: <http://www.lania.mx/~ccoello/EMOO/>
- EMO conference series: <http://www.dep.uminho.pt/EMO2015/>

Books:

- ***Multi-Objective Optimization using Evolutionary Algorithms***
Kalyanmoy Deb, Wiley, 2001
- ***Evolutionary Algorithms for Solving Multi Evolutionary Algorithms for Solving Multi-Objective Problems Objective Problems***, Carlos A. Coello Coello, David A. Van Veldhuizen & Gary B. Lamont, Kluwer, 2nd Ed. 2007
- **Multiobjective Optimization—Interactive and Evolutionary Approaches**, J. Branke, K. Deb, K. Miettinen, and R. Slowinski, editors, volume 5252 of *LNCS*. Springer, 2008 [(still) many open questions!]
- and more...

PISA

PISA

Principles and Documentation

PISA for Beginners

Downloads

Performance Assessment

Write and Submit a Module

Publications, Bugs, Contact & License

A Platform and Programming Language Independent Interface for Search Algorithms

Principles and Documentation

What is PISA? How does PISA work? What is useful?

PISA for Beginners

The first steps in order to use PISA

Downloads

Download Selectors, Downloaders

Crucial Bugfix

A severe bug in the hypervolume calculation of the **IBEA variator** has been found, please redownload the module if your version is older



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ALGORITHMS

PROBLEMS

RESOURCES

OUR TECHNIQUES ▼

Welcome to the jMetal Web Site

jMetal is ...

jMetal stands for **Metaheuristic Algorithms in Java**, and it is an object-oriented Java-based framework for multi-objective optimization with metaheuristics.

You can use it to ...

The object-oriented architecture of the framework and the included features allow you to: experiment with the provided classic and state-of-the-art techniques, develop your own algorithms, solve your optimization problem, integrate jMetal in other tools, etc.

Our motivation is ...

The motivation driving us is to provide a

Summary of features

Download from **sourceforge**

Home

Examples

Downloads

Documentation

Support

Donate



MOEA Framework

A Free and Open Source Java Framework for Multiobjective Optimization

A Framework for Innovation

The MOEA Framework is a free and open source Java library for developing and experimenting with multiobjective evolutionary algorithms (MOEAs) and other general-purpose multiobjective optimization algorithms. The MOEA Framework supports genetic algorithms, differential evolution, particle swarm optimization, genetic programming, grammatical evolution, and more. A number of algorithms are provided out-of-the-box, including NSGA-II, NSGA-III, e-MOEA, GDE3 and MOEA/D. In addition, the MOEA Framework provides the tools necessary to rapidly design, develop, execute and statistically test optimization algorithms.

Key Features

- Fast, reliable implementations of many state-of-the-art multiobjective evolutionary algorithms
- Extensible with custom algorithms, problems and operators
- Supports master-slave, island-model, and hybrid parallelization
- Modular design for constructing new optimization algorithms from existing components
- Permissive open source license
- Fully documented source code

Downloads

Current Version: 2.4
Released: Jan 02, 2015

❖ [DEMO APPLICATION](#)

❖ [COMPILED BINARIES](#)

❖ [SOURCE CODE](#)

❖ [USER MANUAL](#)

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github.com/numbbo/coco/

This repository Search

numbbo / coco

Code

Issues 115

Pull requests 1

Pulse

Graphs

Settings

Numerical Black-Box Optimization Benchmarking Framework <http://coco.gforge.inria.fr/> — Edit

7,902 commits

12 branches

25 releases

13 contributors

Branch: master











New pull request

Create new file

Upload files

Find file

Clone or download

 brockho committed on GitHub Merge pull request #1075 from numbbo/development	Latest commit 0cbb7db on 10 Jun
 code-experiments	Merge pull request #1071 from ttusar/debug a month ago
 code-postprocessing	further clean up of postprocessing output, a month ago
 code-preprocessing/archive-update	Added empty last lines. a month ago
 docs	updated reference to biobjective perf-assessment paper on arXiv in ge... 2 months ago
 howtos	Update documentation-howto.md 4 months ago
 .clang-format	raising an error in bbob2009_logger.c when best_value is NULL. Plus s... a year ago
 .hgignore	raising an error in bbob2009_logger.c when best_value is NULL. Plus s... a year ago
 AUTHORS	small correction in AUTHORS 4 months ago
 LICENSE	Added acknowledgements to external collaborators... 4 months ago

Key Features

- Fast, reliable implementations of many state-of-the-art multiobjective evolutionary algorithms
- Extensible with custom algorithms, problems and operators
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- Permissive open source license
- Fully documented source code

Using Maven? Add our [dependencies](#)
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License

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Challenging Open (Research) Directions

- from algorithms to toolkits
 - libraries of modules for each task (selection, variation, etc.)
 - problem-specific algorithm configuration/ parameter tuning
- benchmarking
 - comparison with classical approaches
 - design/selection of practically relevant problems
 - Algorithm/toolkit recommendations for practice
- integration of EMO and MCDM into one field
- interactive preference articulation and learning
- interactive problem design
- integration of problem-specific knowledge

Questions?

Additional Slides

Instructor Biography: Dima Brockhoff

Dima Brockhoff

RandOpt team
Inria Saclay - Ile-de-France
CMAP UMR 7641 École Polytechnique CNRS
Route de Saclay
91128 Palaiseau
France



After obtaining his diploma in computer science (Dipl.-Inform.) from University of Dortmund, Germany in 2005, Dima Brockhoff received his PhD (Dr. sc. ETH) from ETH Zurich, Switzerland in 2009. Between June 2009 and October 2011 he held postdoctoral research positions---first at Inria Saclay Ile-de-France in Orsay and then at Ecole Polytechnique in Palaiseau, both in France. Since November 2011, Dima has been a permanent researcher at Inria: from 2011 till 2016 with the Inria Lille - Nord Europe research center and since October 2016 with the Saclay - Ile-de-France research center, co-located with CMAP, Ecole Polytechnique. His most recent research interests are focused on evolutionary multiobjective optimization (EMO) and other (single-objective) blackbox optimization techniques, in particular with respect to benchmarking, theoretical aspects, and expensive optimization.

References

- [Auger et al. 2009a] A. Auger, J. Bader, D. Brockhoff, and E. Zitzler. Theory of the Hypervolume Indicator: Optimal μ -Distributions and the Choice of the Reference Point. In Foundations of Genetic Algorithms (FOGA 2009), pages 87–102, New York, NY, USA, 2009. ACM.
- [Auger et al. 2009b] A. Auger, J. Bader, D. Brockhoff, and E. Zitzler. Articulating User Preferences in Many-Objective Problems by Sampling the Weighted Hypervolume. In G. Raidl et al., editors, Genetic and Evolutionary Computation Conference (GECCO 2009), pages 555–562, New York, NY, USA, 2009. ACM
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