GECCO'2012 Tutorial on Evolutionary Multiobjective Optimization

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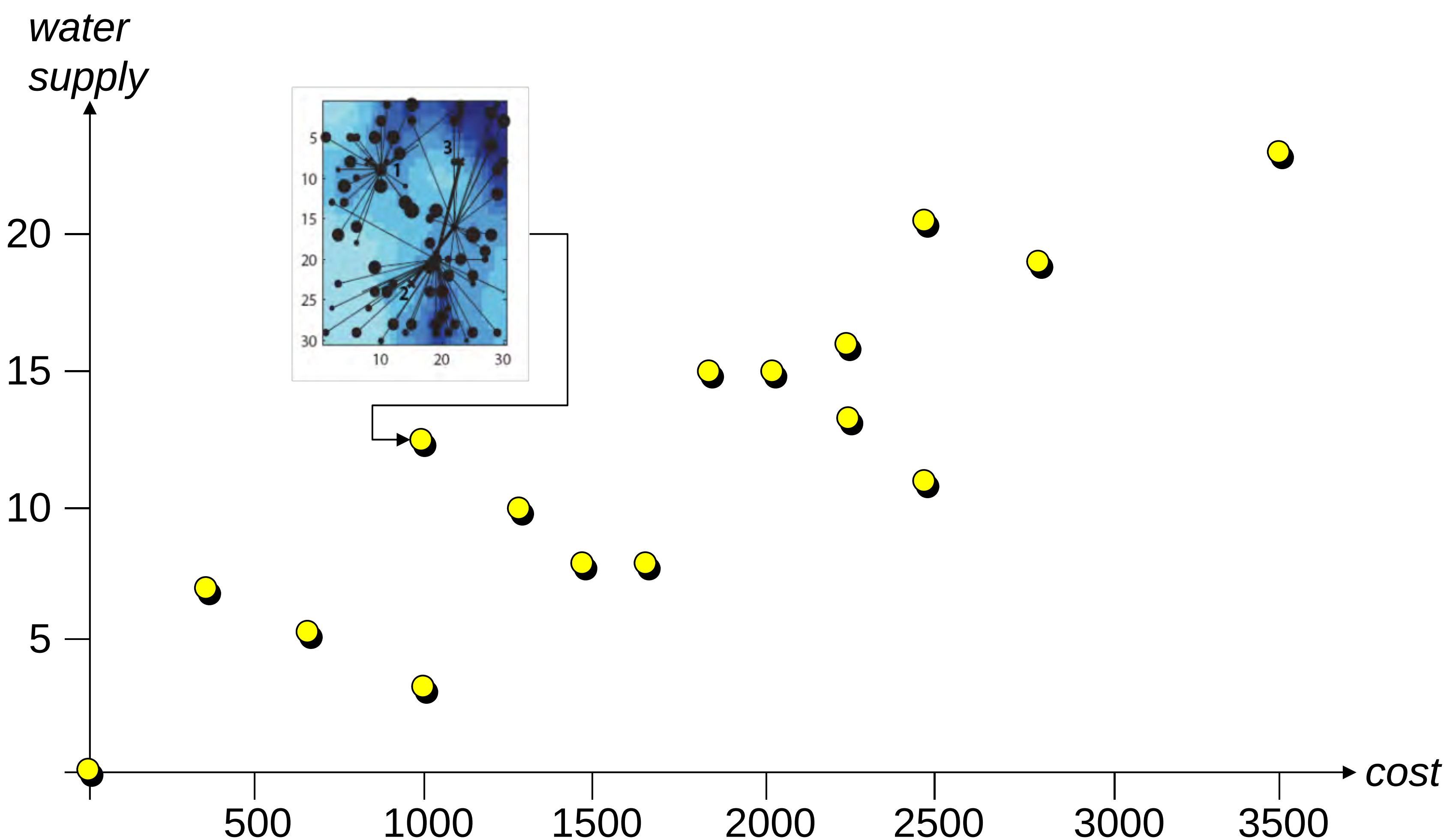
INVENTORS FOR THE DIGITAL WORLD

GECCO'12 Companion, July 7–11, 2012, Philadelphia, PA, USA.
ACM 978-1-4503-1178-6/12/07.

Principles of Multiple Criteria Decision

A hypothetical problem: all solutions plotted



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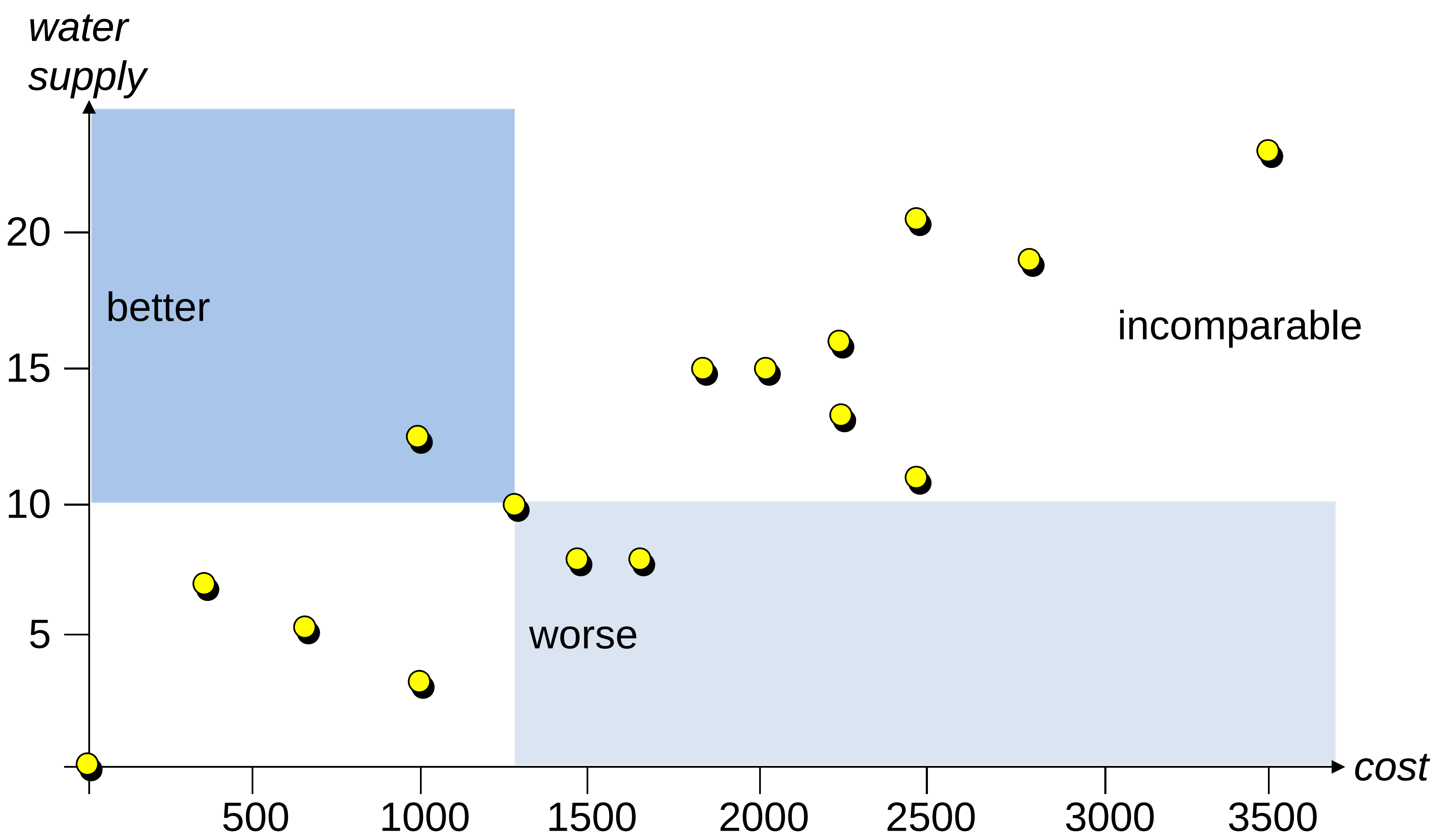
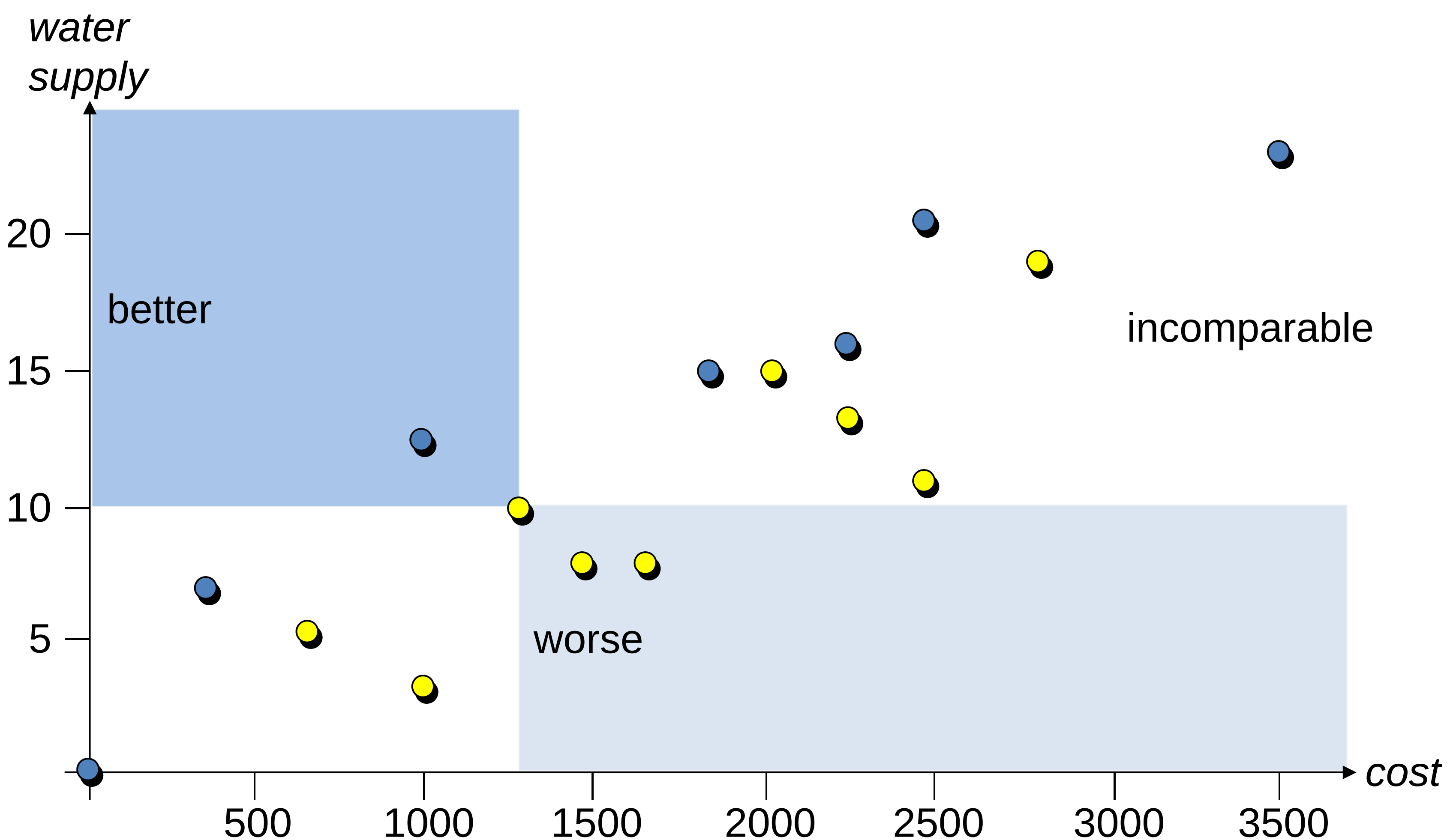


Principles of Multiple Criteria Decision

Observations: ❶ there is no single optimal solution, but
❷ some solutions (●) are better than others (●)



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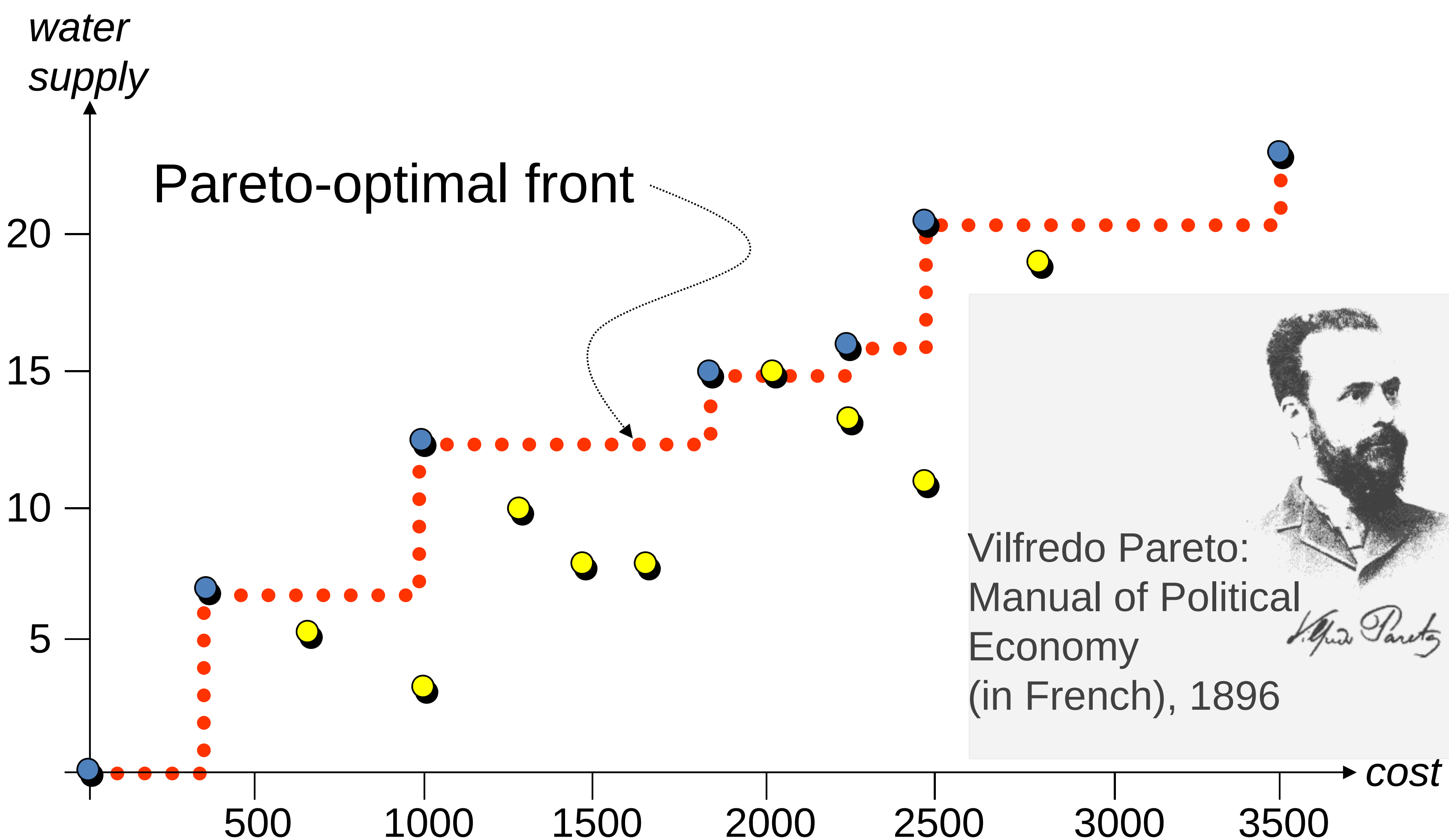

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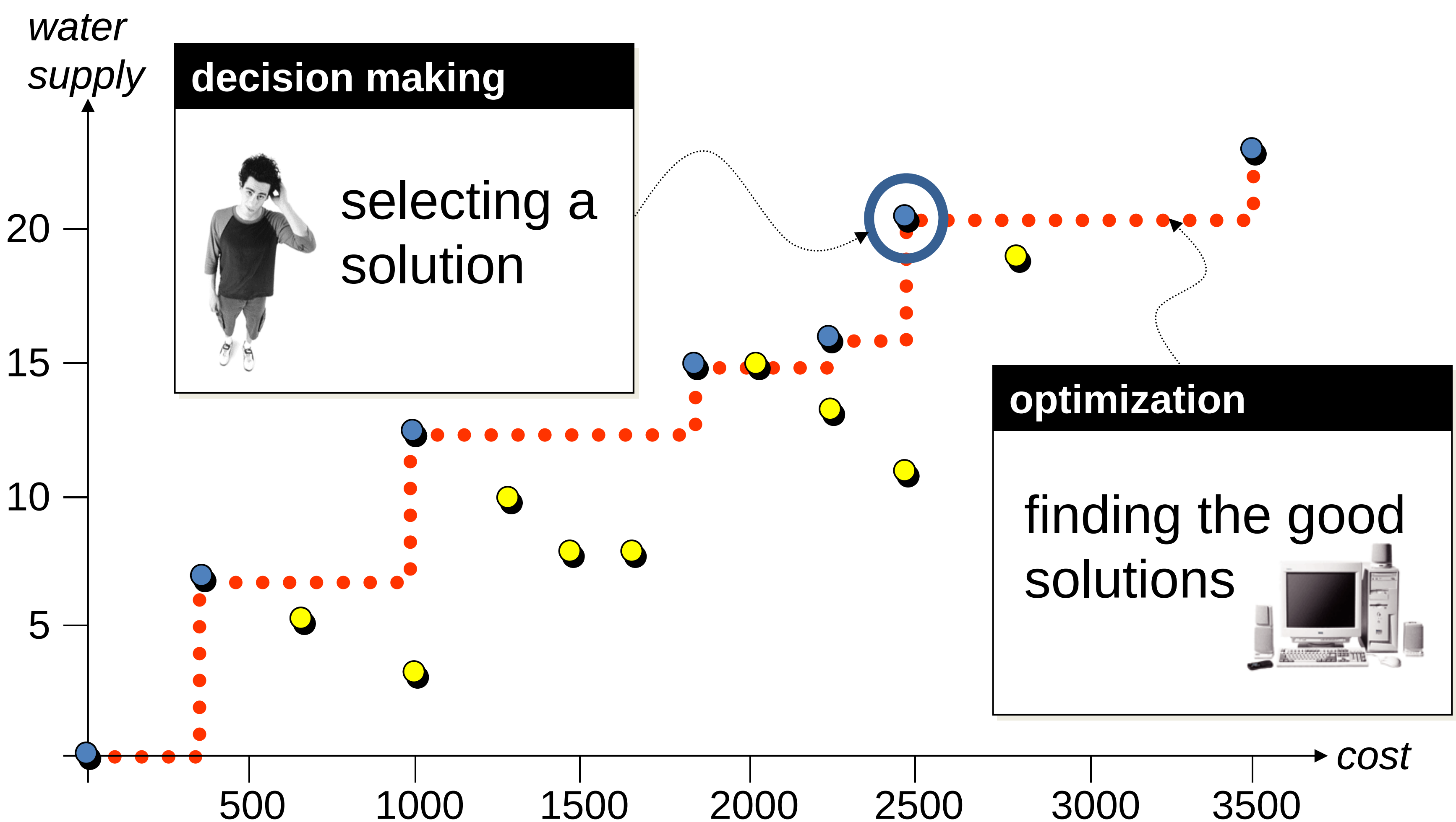
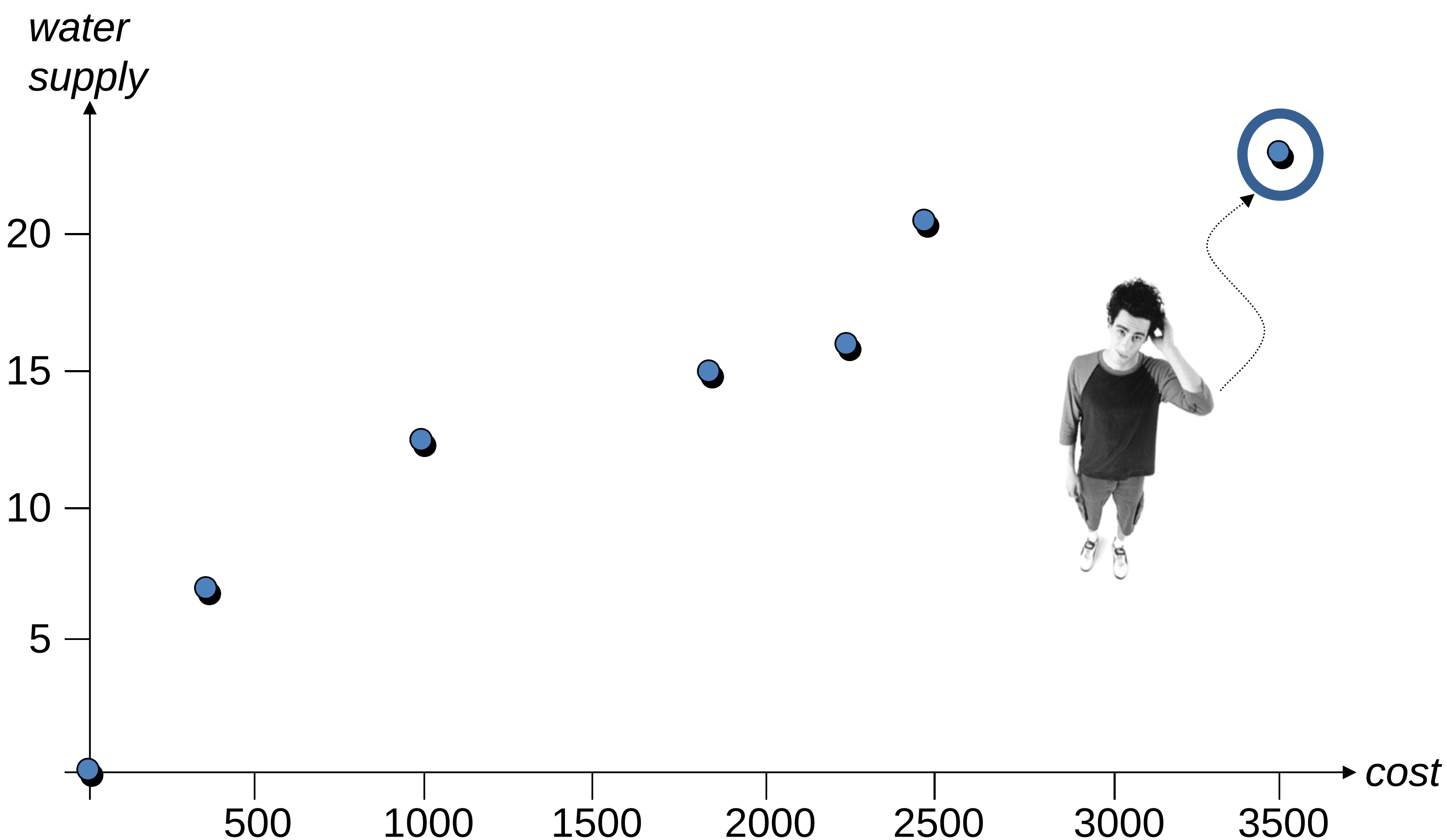


Decision Making: Selecting a Solution

Possible Approach:

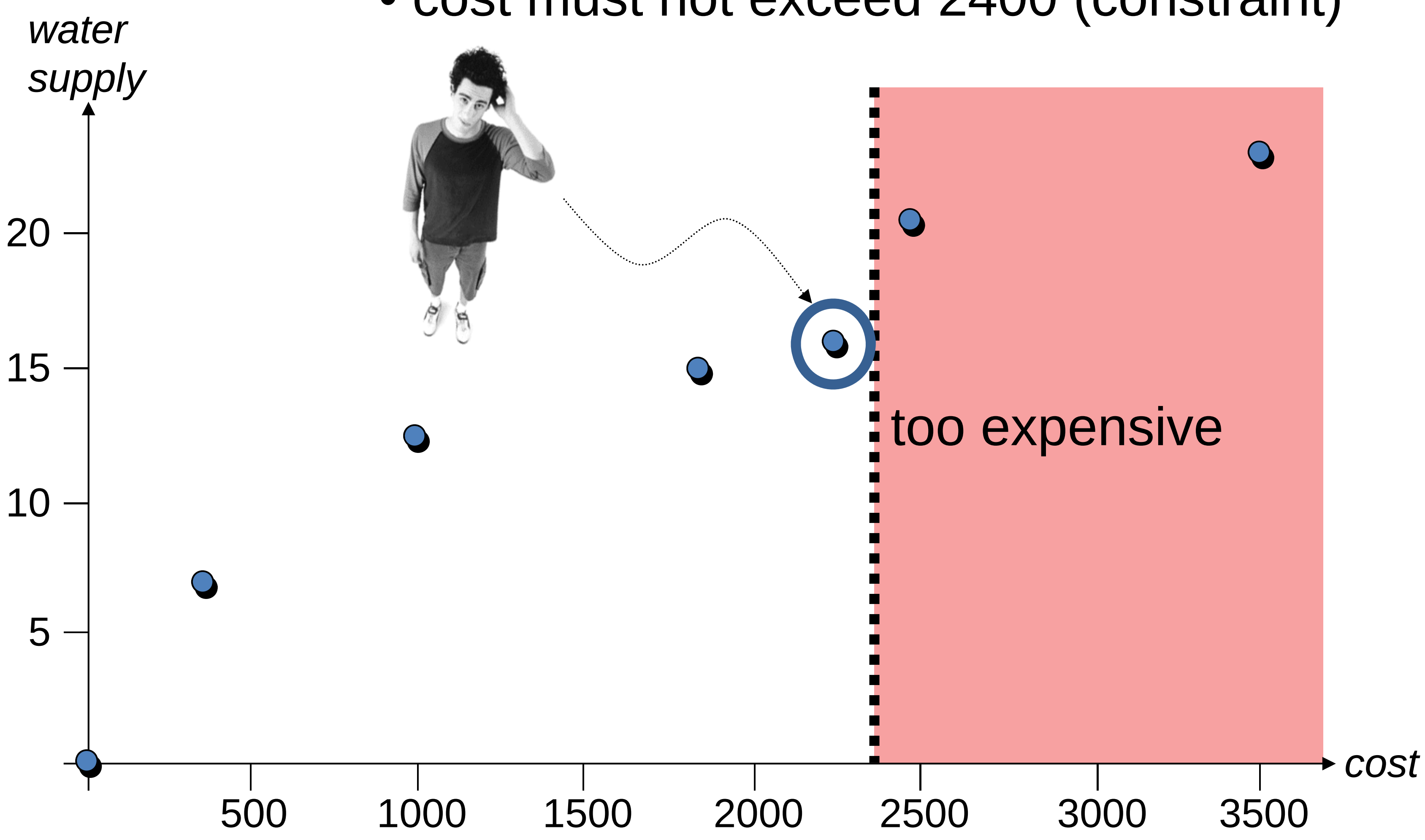
- supply more important than cost (ranking)



Decision Making: Selecting a Solution

Possible Approach:

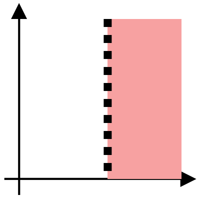
- supply more important than cost (ranking)
- cost must not exceed 2400 (constraint)



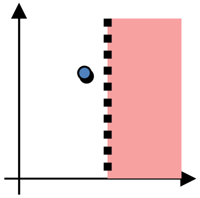
When to Make the Decision

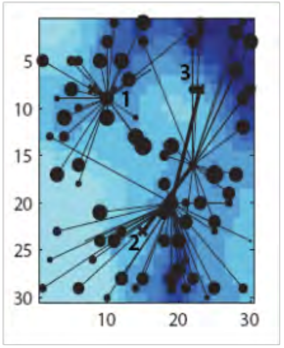
Before Optimization:

rank objectives,
define constraints,…



search for one
(blue) solution





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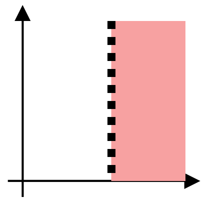

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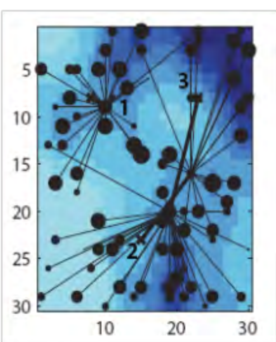

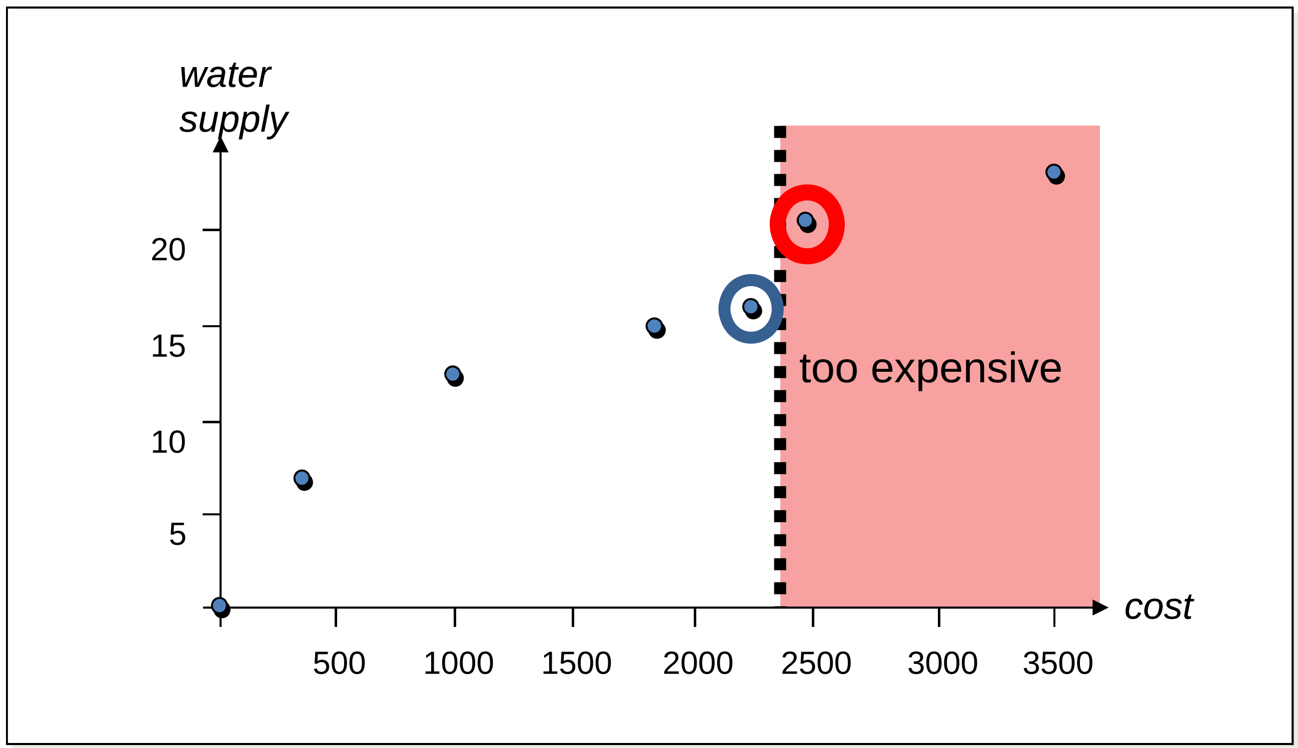

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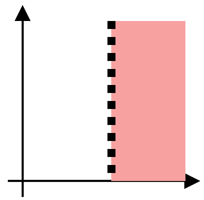

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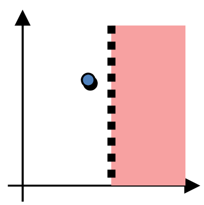
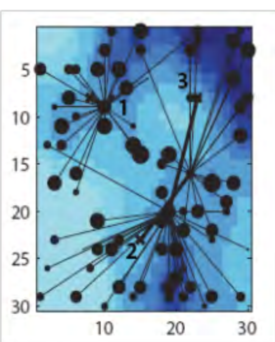
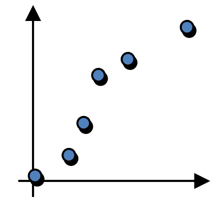


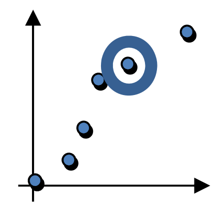


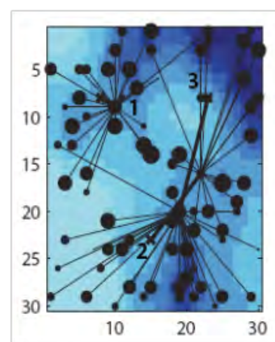
After Optimization:

search for a set of
(blue) solutions



select one solution
considering
constraints, etc.





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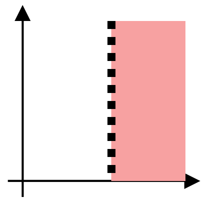

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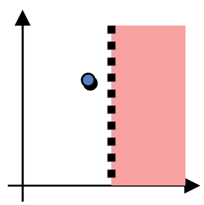

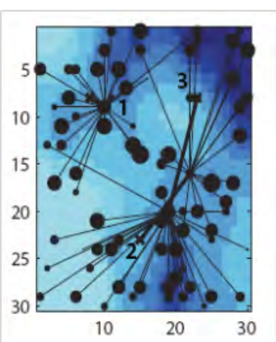

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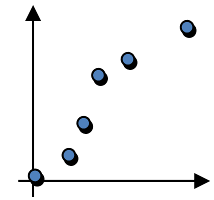

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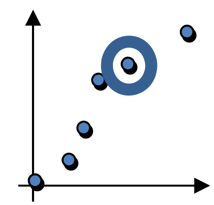


Focus: learning about a problem

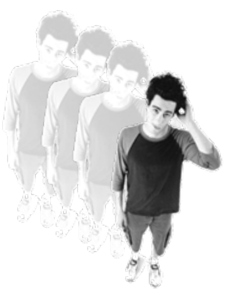
- trade-off surface
- interactions among criteria
- structural information

Multiple Criteria Decision Making (MCDM)

Definition: MCDM

MCDM can be defined as the study of methods and procedures by which concerns about multiple conflicting criteria can be formally incorporated into the management planning process

International Society on Multiple Criteria Decision Making



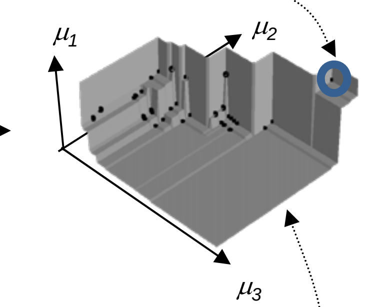
model

trade-off surface

$$\min_x \left[\mu_1(x), \mu_2(x), \ldots, \mu_n(x)\right]^T$$
$$s.t.$$
$$g(x) \le 0$$
$$h(x) = 0$$
$$x_l \le x \le x_u$$

decision making

(exact) optimization



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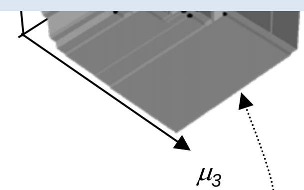
objectives: non-linear, noisy, uncertain, expensive (integrated simulations), non-differentiable

problem: many objectives, huge search spaces, many constraints

$g(x) \leq 0$
$h(x) = 0$
$x_l \leq x \leq x_u$

(ex~~a~~ct) optimization



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(integrated si

$g(x) \leq 0$
$h(x) = 0$
$x_l \leq x \leq x_u$

(~~exact~~) optim

Black box optimization

$$x \in X \longrightarrow \boxed{f} \longrightarrow (f_1(x), \ldots, f_k(x))$$

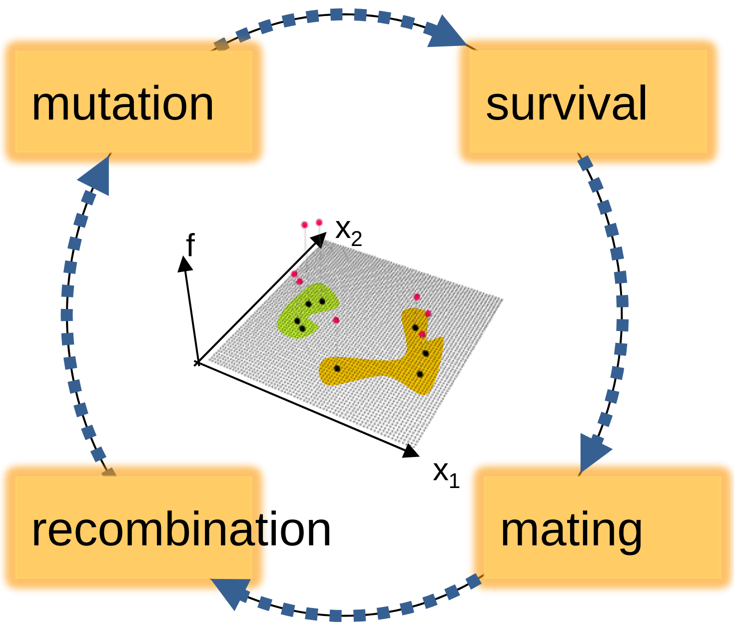
only mild assumptions

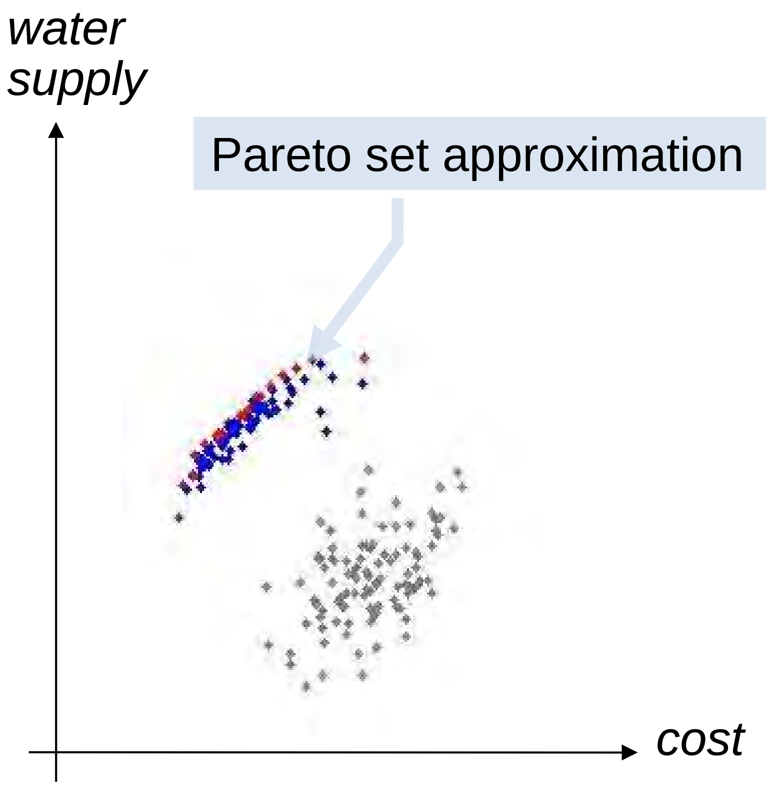
Evolutionary Multiobjective Optimization

Definition: EMO

EMO = **evolutionary algorithms** / randomized search algorithms

- applied to multiple criteria decision making (in general)
- used to approximate the Pareto-optimal set (mainly)

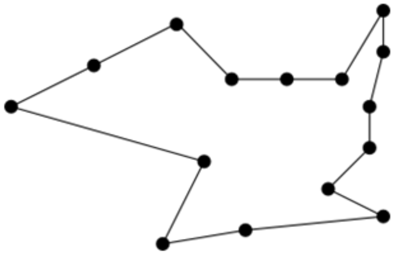




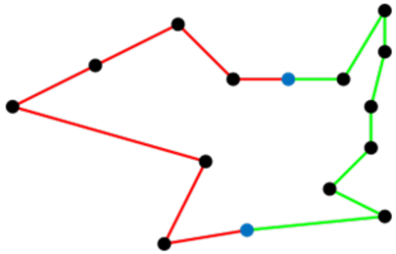
Multiobjectivization

Some problems are easier to solve in a multiobjective scenario

example: TSP
[Knowles et al. 2001]



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



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

Multiobjectivization

by addition of new "helper objectives" [Jensen 2004]

job-shop scheduling [Jensen 2004], frame structural design [Greiner et al. 2007], theoretical (runtime) analyses [Brockhoff et al. 2009]

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], theoretical (runtime) analyses [Handl et al. 2008b]

Innovization

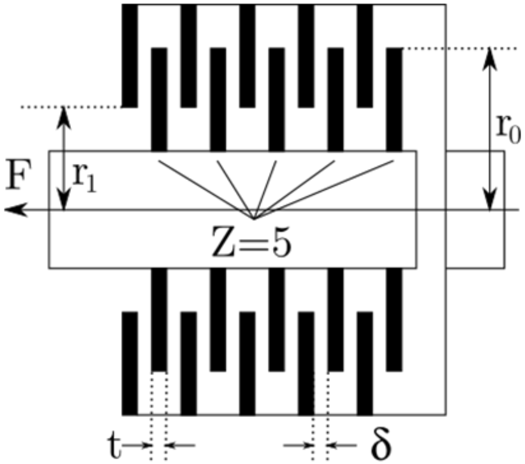
Often innovative design principles among solutions are found

example:

clutch brake design

[Deb and Srinivasan 2006]

min. mass +
stopping time



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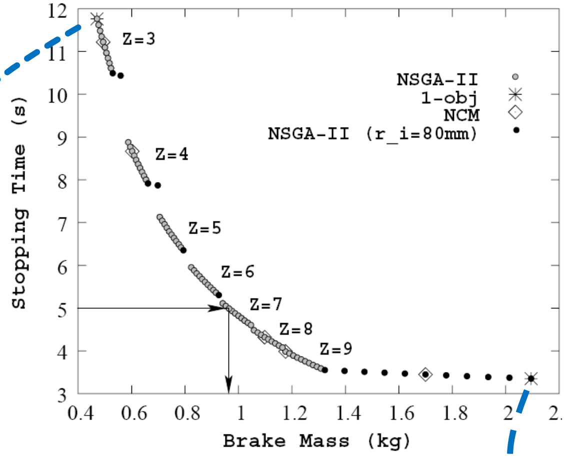
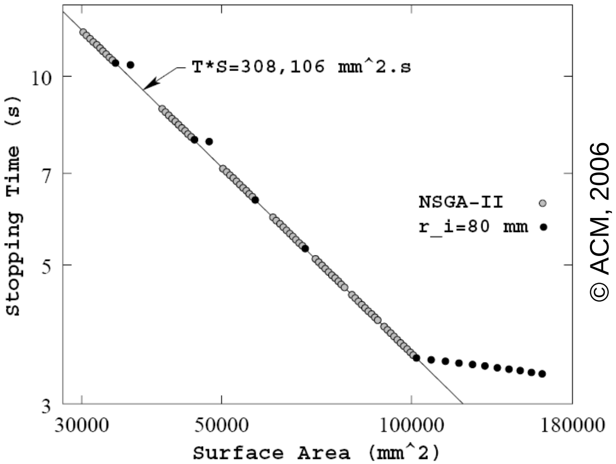




Solution	x_1	x_2	x_3	x_4	x_5	f_1	f_2
Min. f_1	70	90	1.5	1000	3	0.4704	11.7617
Min. f_2	80	110	1.5	1000	9	2.0948	3.3505

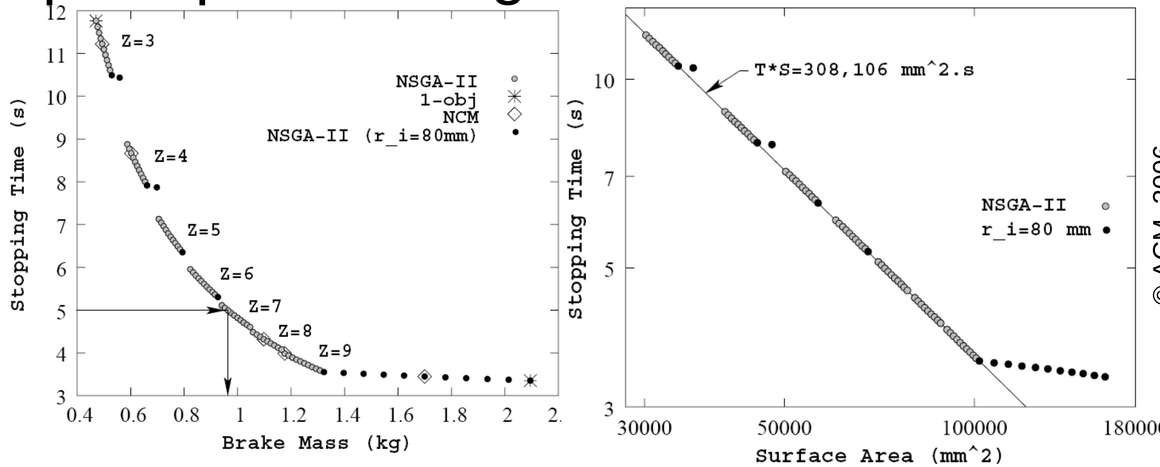
Innovization

Often innovative design principles among solutions are found

example:

clutch brake design

[Deb and Srinivasan 2006]



Innovization [Deb and Srinivasan 2006]

= using machine learning techniques to find new and innovative design principles among solution sets

= learning about a multiobjective optimization problem

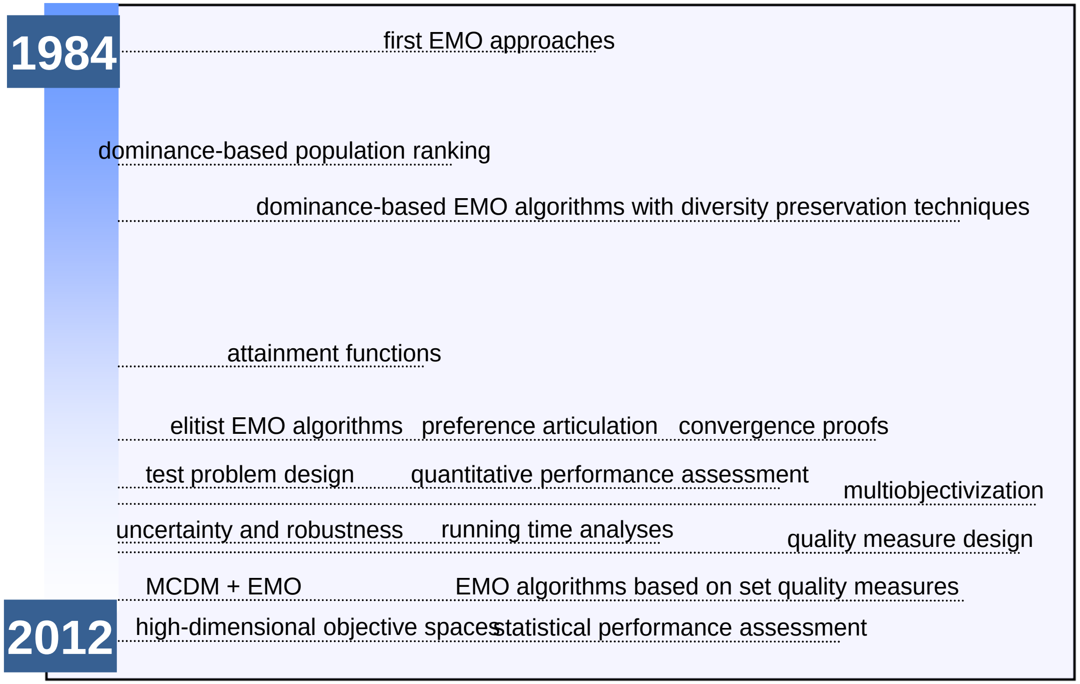
Other examples:

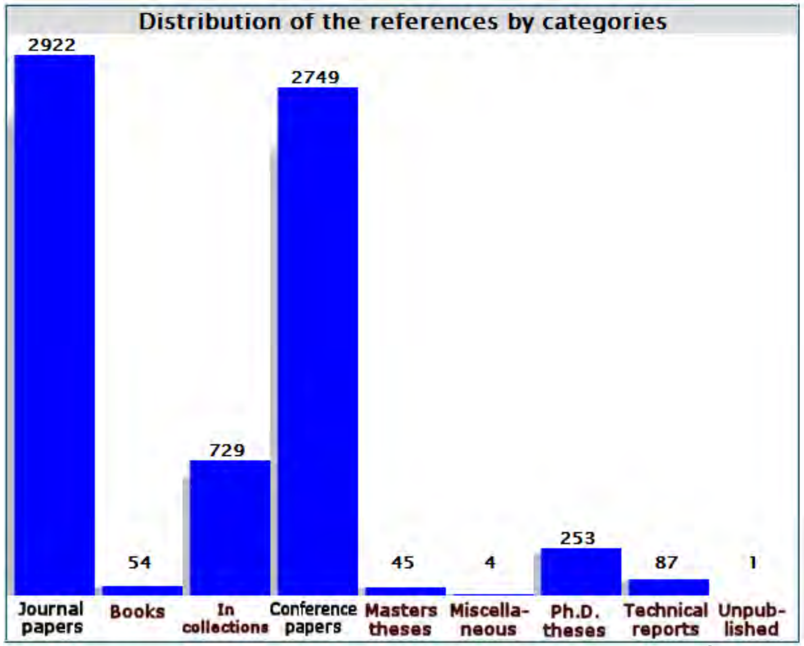
- SOM for supersonic wing design [Obayashi and Sasaki 2003]
- biclustering for processor design and KP [Ulrich et al. 2007]

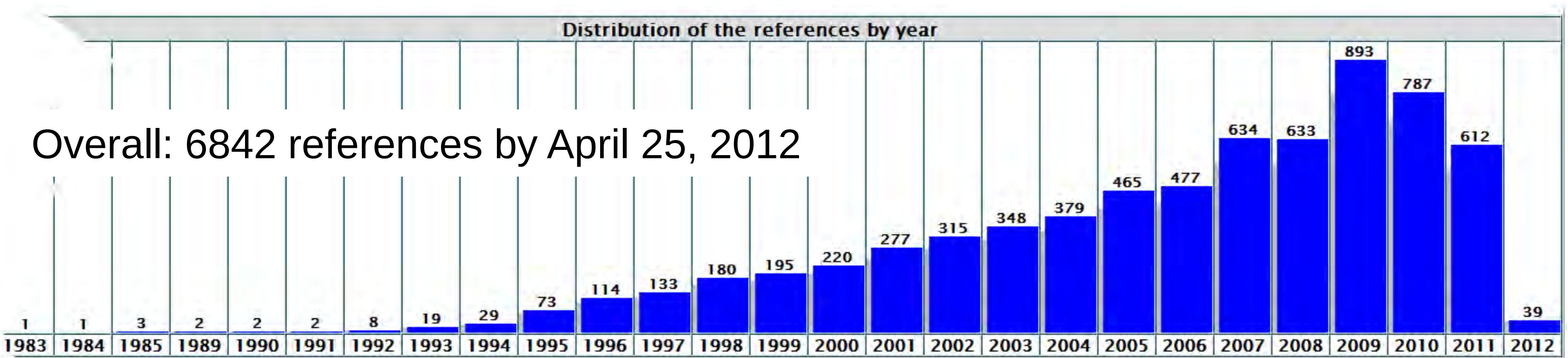
The History of EMO At A Glance

1984	first EMO approaches
	dominance-based population ranking
1990	dominance-based EMO algorithms with diversity preservation techniques
1995	attainment functions
	elitist EMO algorithms; preference articulation; convergence proofs
2000	test problem design; quantitative performance assessment; multiobjectivization
	uncertainty and robustness; running time analyses; quality measure design
	MCDM + EMO; quality indicator based EMO algorithms
2010	many-objective optimization; statistical performance assessment

The History of EMO At A Glance





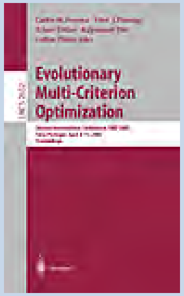
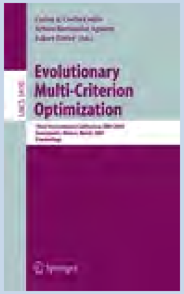
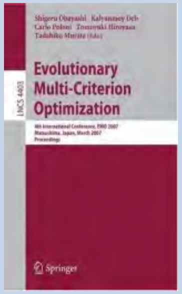
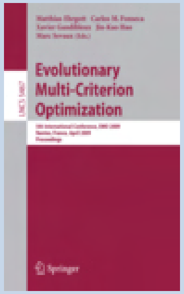
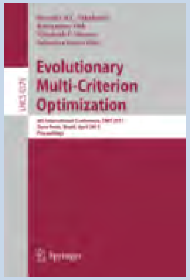


Overall: 6842 references by April 25, 2012

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

The EMO Community

The EMO conference series:

EMO2001	EMO2003	EMO2005	EMO2007	EMO2009	EMO2011	EMO2013
Zurich	Faro	Guanajuato	Matsushima	Nantes	Ouro Peto	Sheffield
Switzerland	Portugal	Mexico	Japan	France	Brazil	UK
						
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Many further activities:

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

Overview

The Big Picture

Basic Principles of Multiobjective Optimization

- algorithm design principles and concepts
- performance assessment

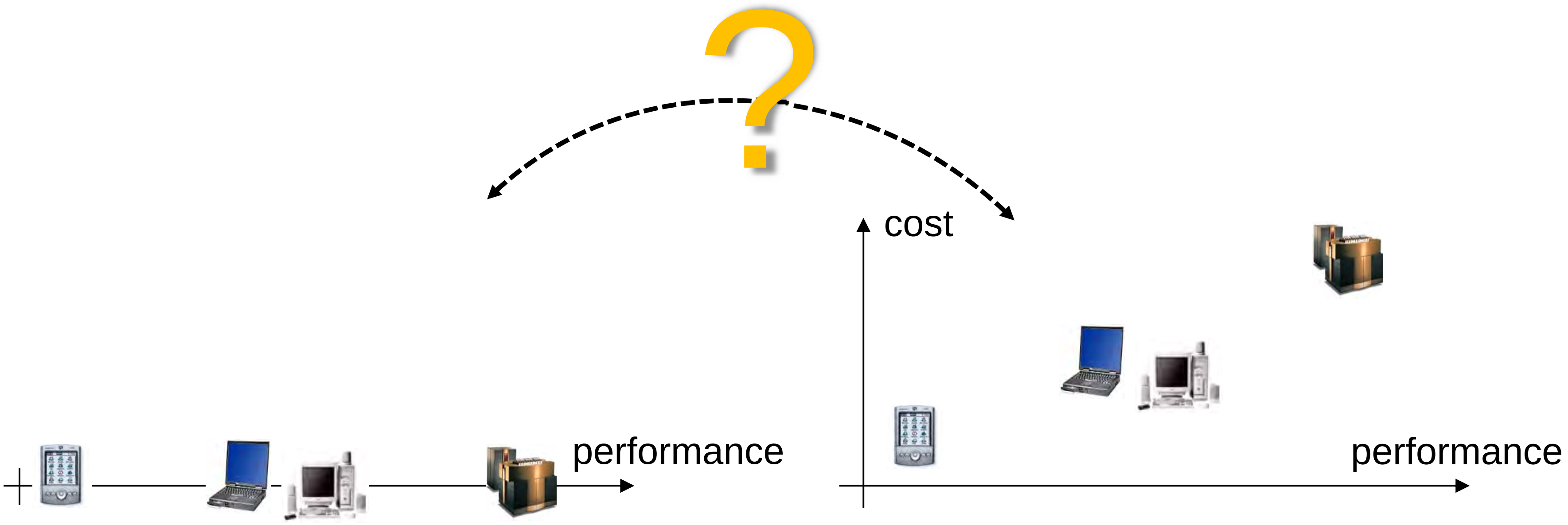
Selected Advanced Concepts

- indicator-based EMO
- preference articulation

A Few Examples From Practice

Starting Point

What makes evolutionary multiobjective optimization different from single-objective optimization?



single objective **multiple objectives**

A General (Multiobjective) Optimization

A multiobjective optimization problem: $(X, Z, \mathbf{f}, \mathbf{g}, \leq)$

$$
\begin{array}{rl}
X & \text{search / parameter / decision space} \\
Z = \mathbb{R}^n & \text{objective space} \\
\mathbf{f} = (f_1, \ldots, f_n) & \text{vector-valued objective function with} \\
 & f_i : X \mapsto \mathbb{R} \\
\mathbf{g} = (g_1, \ldots, g_m) & \text{vector-valued constraint function with} \\
 & g_i : X \mapsto \mathbb{R} \\
\leq \subseteq Z \times Z & \text{binary relation on objective space}
\end{array}
$$

Goal: find decision vector(s) $\mathbf{a} \in X$ such that

❶ for all $1 \leq i \leq m : g_i(\mathbf{a}) \leq 0$ and

❷ for all $\mathbf{b} \in X : \mathbf{f}(\mathbf{b}) \leq \mathbf{f}(\mathbf{a}) \Rightarrow \mathbf{f}(\mathbf{a}) \leq \mathbf{f}(\mathbf{b})$

A Single-Objective Optimization Problem

decision space

objective space

objective function

total order

$$(X, Z, f: X \rightarrow Z, rel \subseteq Z \times Z)$$

A Single-Objective Optimization Problem

decision space

objective space

objective function

total order

$(X, Z, f: X \rightarrow Z, rel \subseteq Z \times Z)$

$(X, prefrel)$

total preorder where

$a\ prefrel\ b \Leftrightarrow f(a)\ rel\ f(b)$

A Single-Objective Optimization Problem

Example: Leading Ones Problem

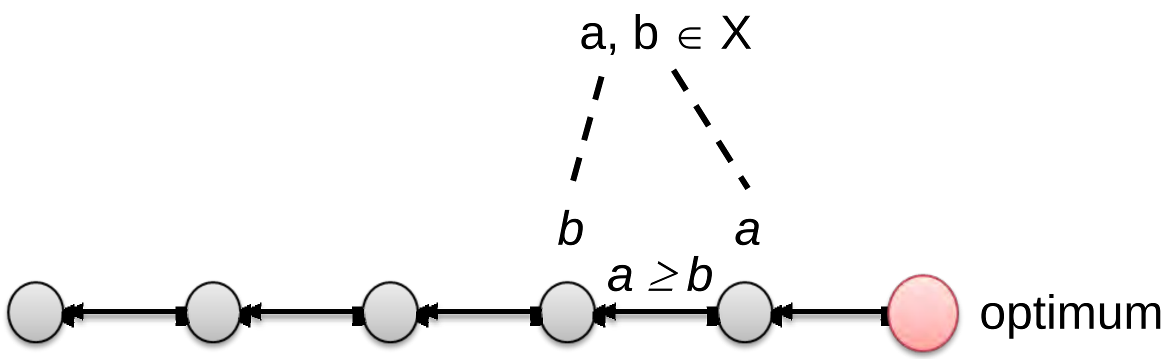
$(X, Z, f\colon X \rightarrow Z, rel \subseteq Z \times Z)$

$(X, prefrel)$

$(\{0,1\}^n, \{0,1,2,\ldots,n\}, f_{LO}, \geq)$ where $f_{LO}(a) = \sum_i \left(\prod_{j \leq i} a_j\right)$

Simple Graphical Representation

Example: $\geq$ (total order)



totally ordered

Preference Relations

decision space

objective space

objective functions

partial order

$(X, Z, f\colon X \to Z, rel \subseteq Z \times Z)$

preorder where

a prefrel b $:\Leftrightarrow$ *f(a) rel f(b)*

$(X, prefrel)$

$$(X, \preccurlyeq_{par})$$

$$a \preccurlyeq_{par} b :\Leftrightarrow f(a) \leqslant_{par} f(b)$$

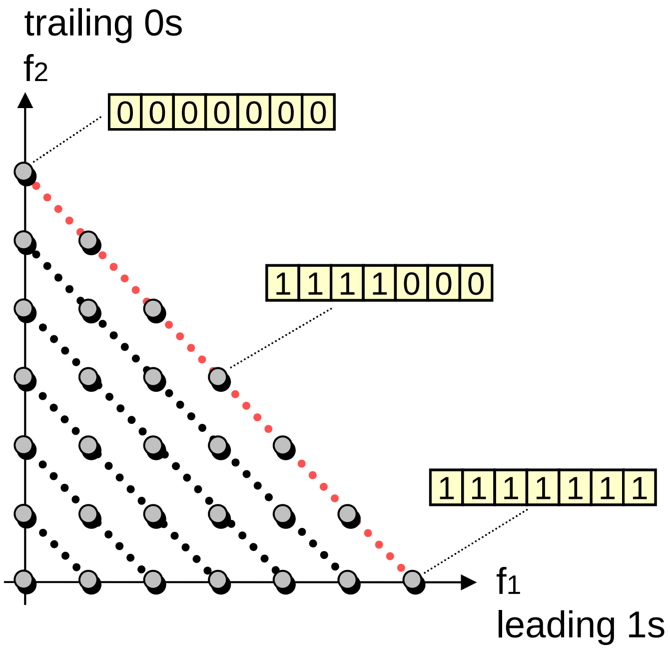
weak
Pareto dominance

A Multiobjective Optimization Problem

Example: Leading Ones Trailing Zeros Problem

(X, Z, f: X → Z, rel ⊆ Z × Z)

(X, prefrel)

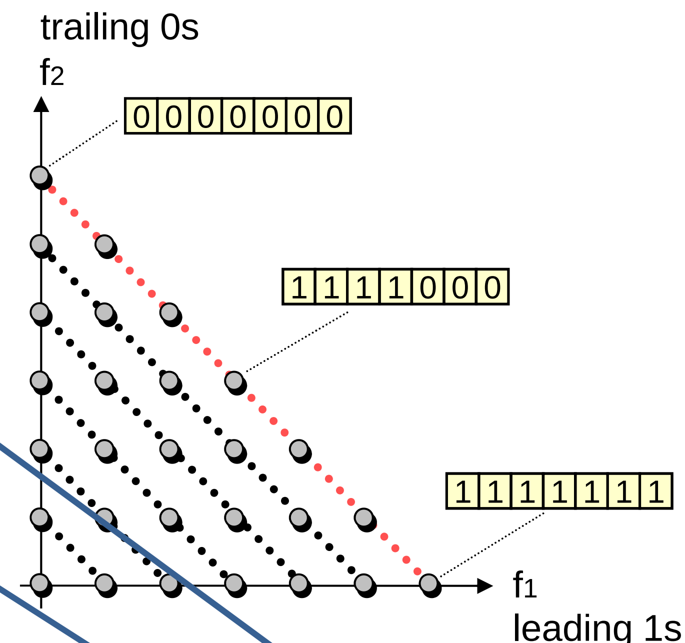


A Multiobjective Optimization Problem

Example: Leading Ones Trailing Zeros Problem

(X, Z, f: X → Z, rel ⊆ Z × Z)

(X, prefrel)



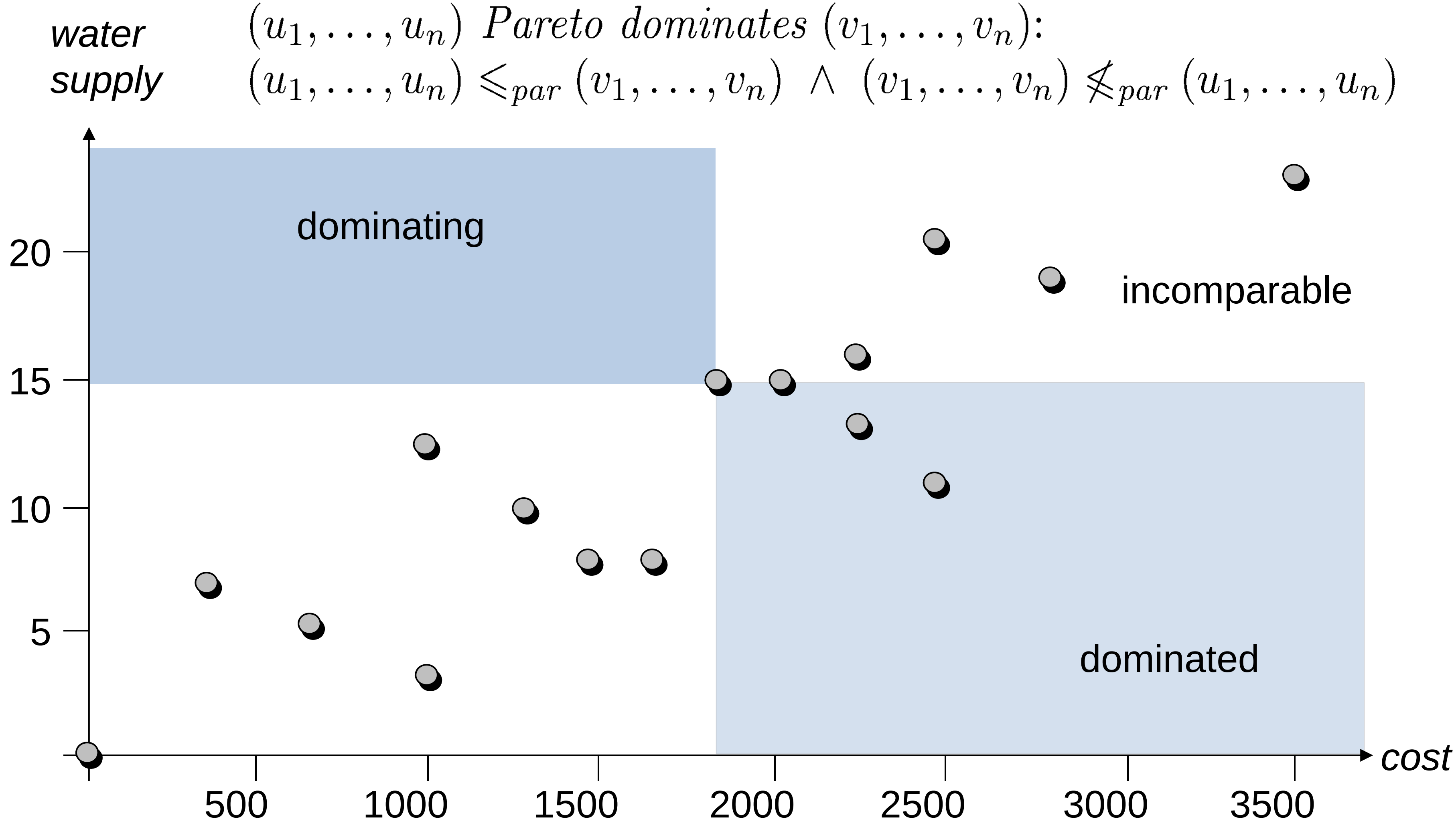
$(\{0,1\}^n, \{0,1,2,\ldots,n\} \times \{0,1,2,\ldots,n\}, (f_{LO}, f_{TZ}), \textbf{?})$

$f_{LO}(a) = \sum_i \left(\prod_{j\le i} a_j\right) \qquad f_{TZ}(a) = \sum_i \left(\prod_{j\le i}(1-a_j)\right)$

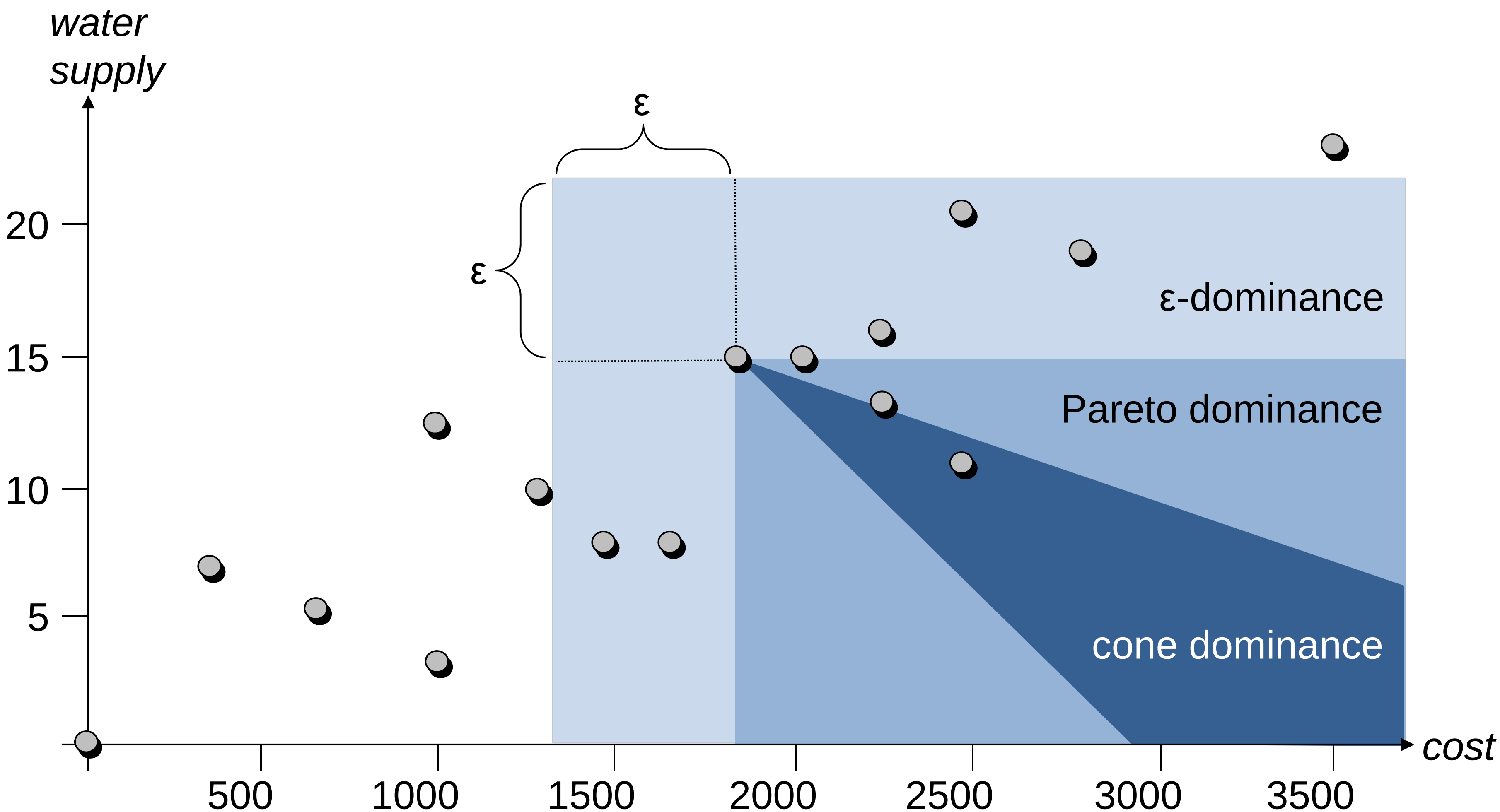
Pareto Dominance

$(u_1,\ldots,u_n)$ *weakly Pareto dominates* $(v_1,\ldots,v_n)$:
$(u_1,\ldots,u_n) \leqslant_{par} (v_1,\ldots,v_n) :\Leftrightarrow \forall 1 \leq i \leq n : u_i \leq v_i$

$(u_1,\ldots,u_n)$ *Pareto dominates* $(v_1,\ldots,v_n)$:
$(u_1,\ldots,u_n) \leqslant_{par} (v_1,\ldots,v_n) \;\wedge\; (v_1,\ldots,v_n) \not\leqslant_{par} (u_1,\ldots,u_n)$



Different Notions of Dominance



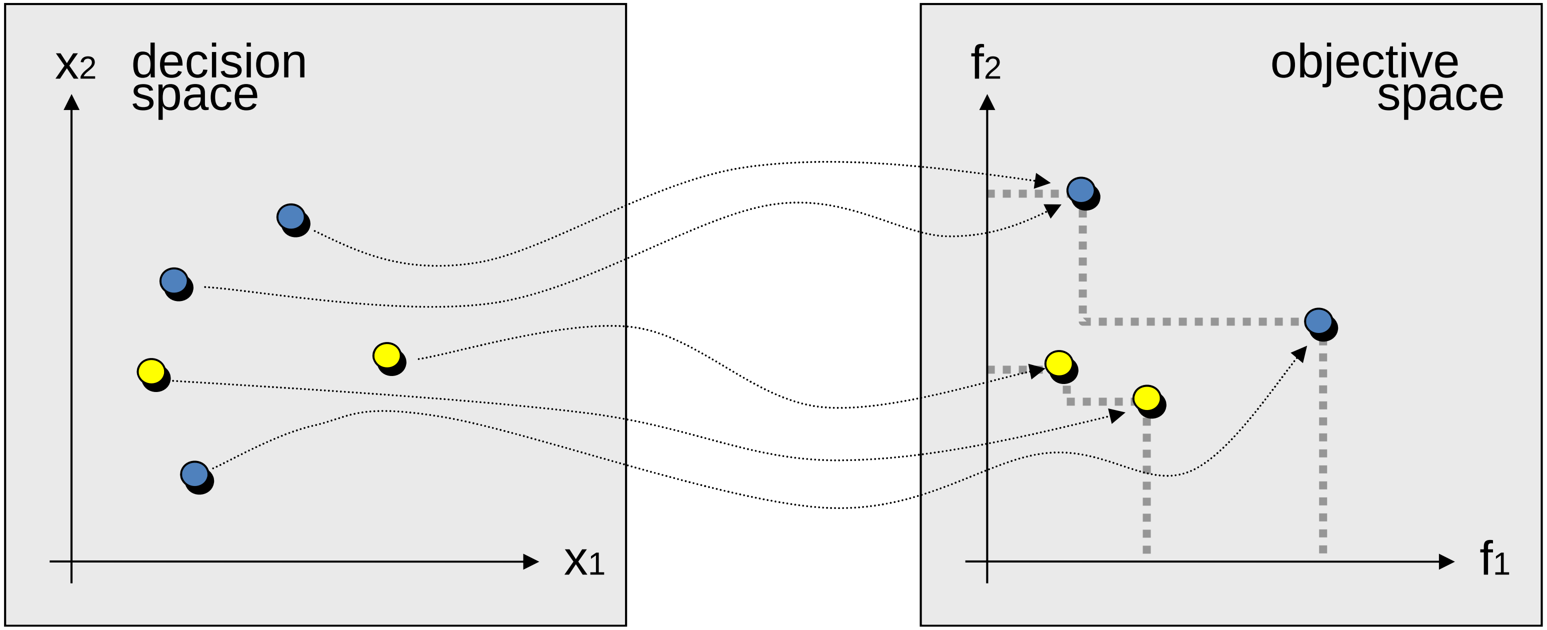
The Pareto-optimal Set

The *minimal set* of a preordered set $(Y, \leqq)$ is defined as

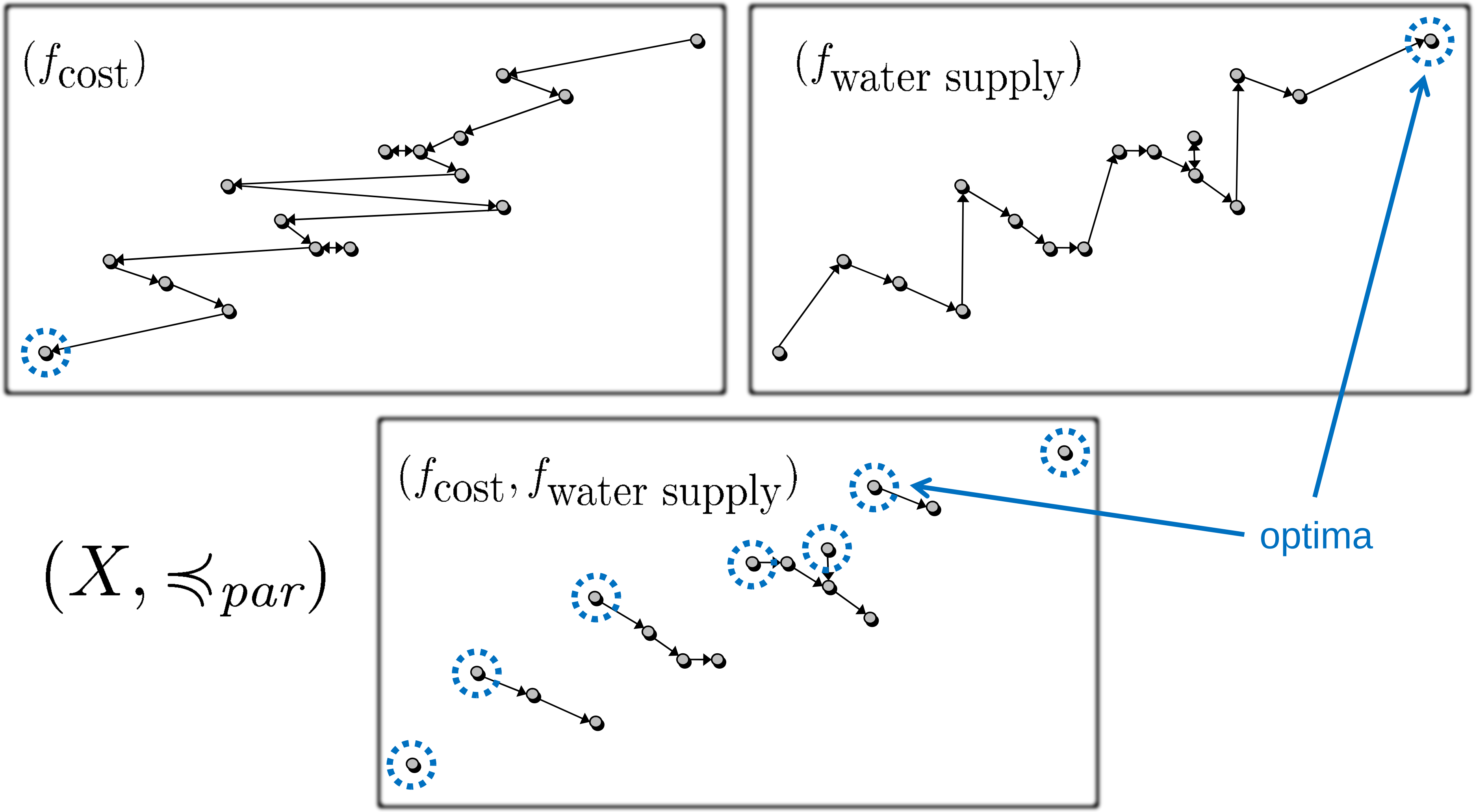
$$Min(Y, \leqq) := \{a \in Y \,|\, \forall b \in Y : b \leqq a \Rightarrow a \leqq b\}$$

Pareto-optimal set $Min(X, \preccurlyeq_{par})$ ● Pareto-optimal front

non-optimal decision vector ● non-optimal objective vector



Visualizing Preference Relations

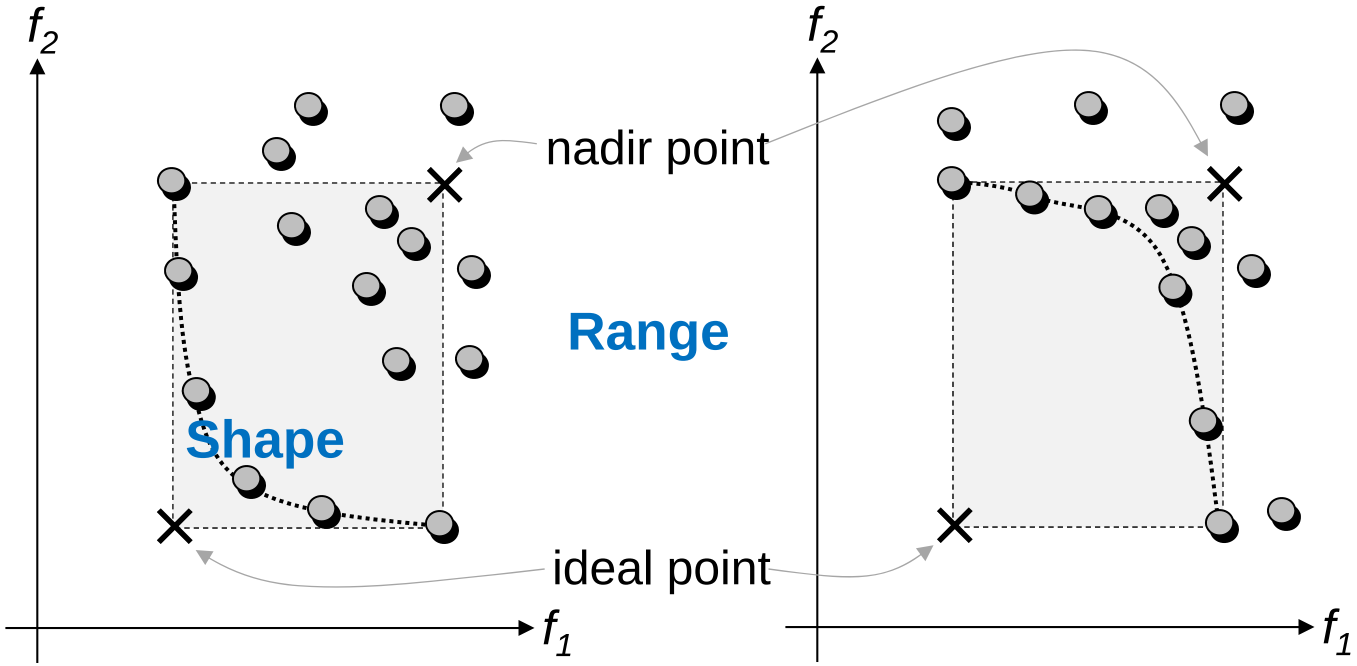


$$(X, \preceq_{par})$$

Remark: Properties of the Pareto Set

Computational complexity:
multiobjective variants can become NP- and #P-complete

Size: Pareto set can be exponential in the input length
(e.g. shortest path [Serafini 1986], MSP [Camerini et al. 1984])



Approaches To Multiobjective Optimization

A multiobjective problem is as such underspecified

…because not any Pareto-optimum is equally suited!

Additional preferences are needed to tackle the problem:

Solution-Oriented Problem Transformation:
Induce a total order on the decision space, e.g., by aggregation.

Set-Oriented Problem Transformation:
First transform problem into a set problem and then define an objective function on sets.

Preferences are needed in any case, but the latter are weaker!

Problem Transformations and Set Problems

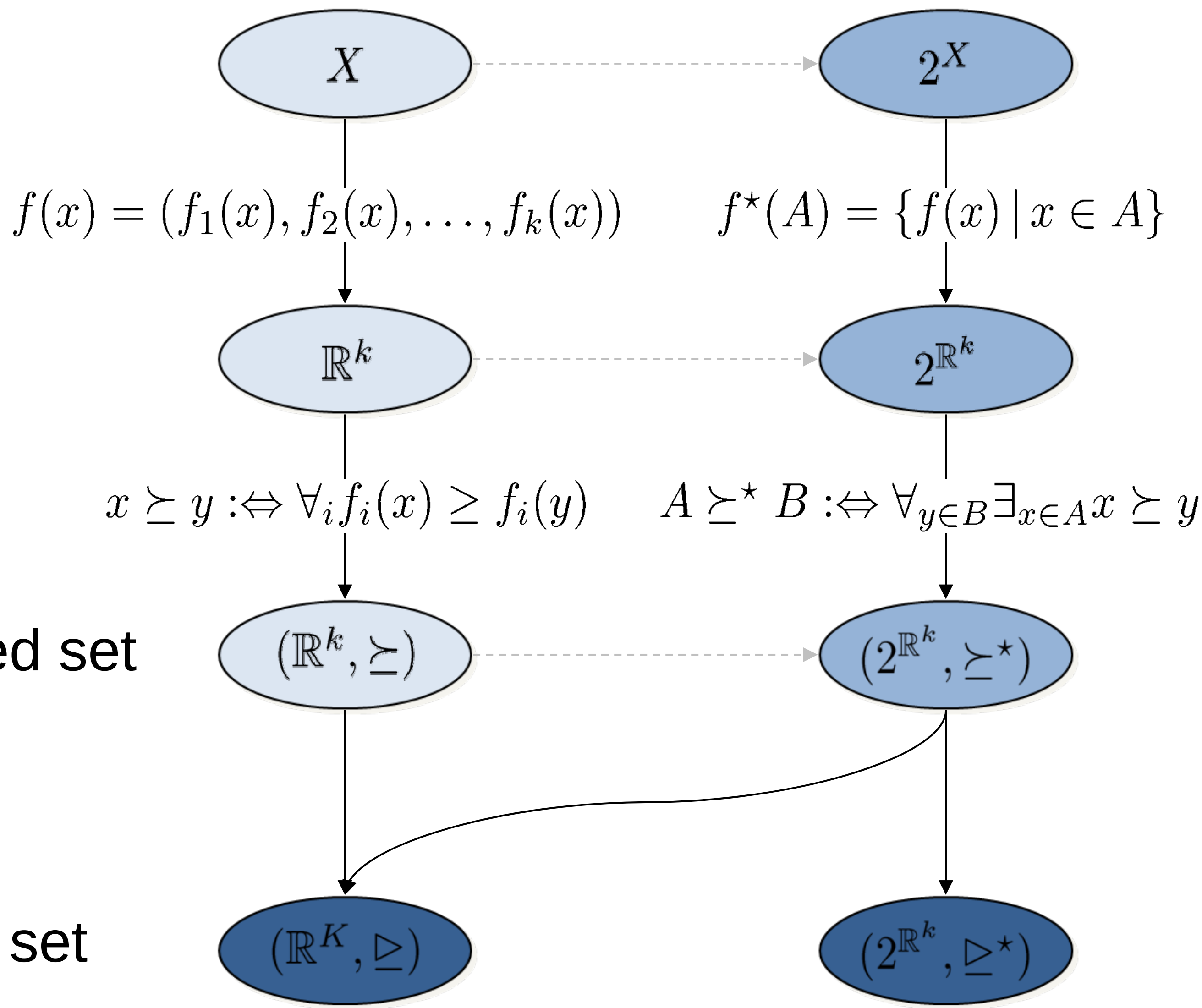
single solution problem | **set problem**

search space

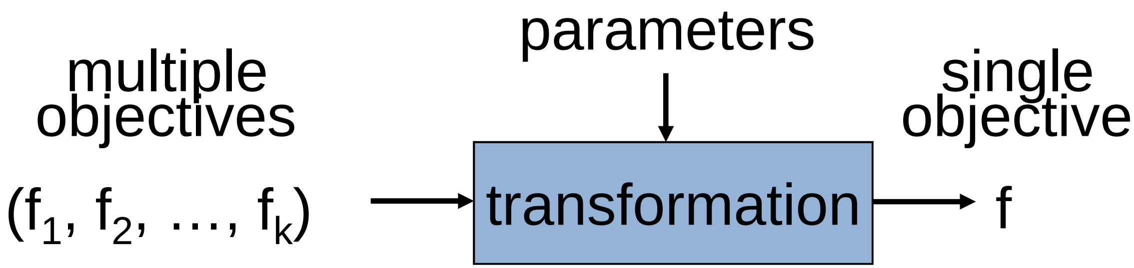
objective space

(partially) ordered set

(totally) ordered set



Solution-Oriented Problem Transformations

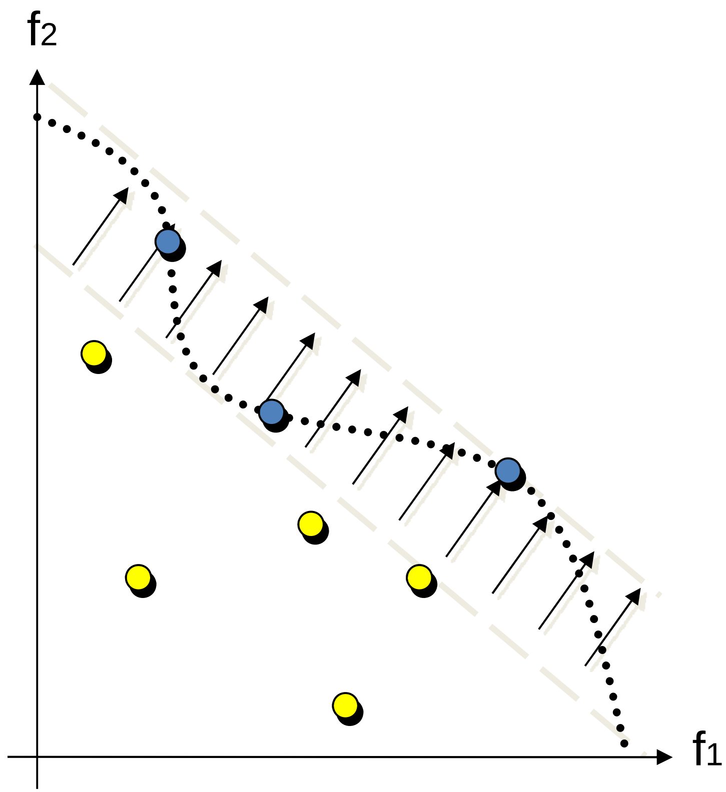


A *scalarizing function* s is a function $s : Z \mapsto \mathbb{R}$ that maps each objective vector $(u_1, \ldots, u_n) \in Z$ to a real value $s(u_1, \ldots, u_n) \in \mathbb{R}$.

Aggregation-Based Approaches

parameters

multiple objectives $(f_1, f_2, \ldots, f_k)$ → transformation → single objective f



Example: weighting approach

$(w_1, w_2, \ldots, w_k)$

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

Other example: Tchebycheff

$$y = \max w_i (u_i - z_i)$$

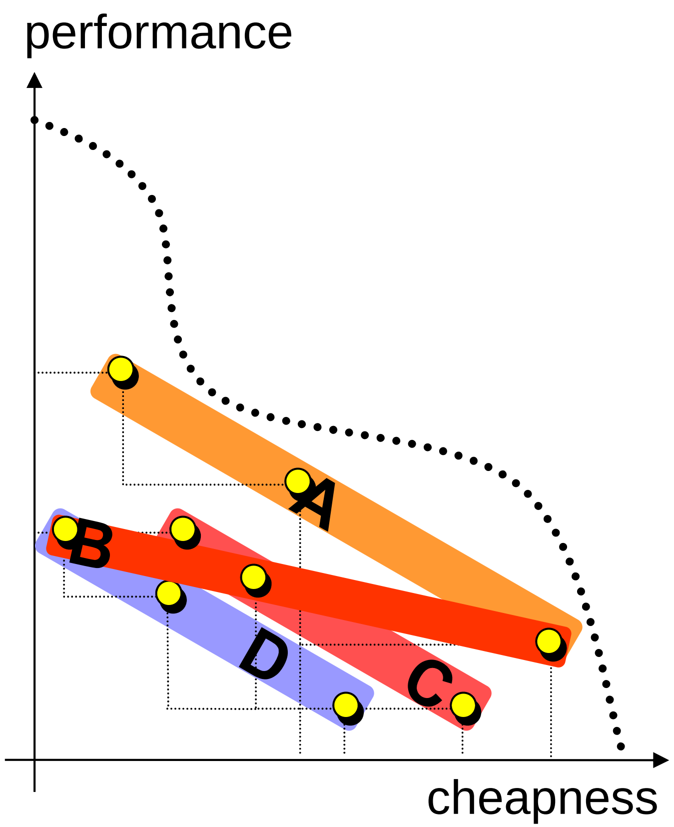
Set-Oriented Problem Transformations

For a multiobjective optimization problem $(X, Z, \mathbf{f}, \mathbf{g}, \leqslant)$, the associated *set problem* is given by $(\Psi, \Omega, F, \mathbf{G}, \preccurlyeq)$ where

- $\Psi = 2^X$ is the space of decision vector sets, i.e., the powerset of X,
- $\Omega = 2^Z$ is the space of objective vector sets, i.e., the powerset of Z,
- F is the extension of $\mathbf{f}$ to sets, i.e., $F(A) := \{\mathbf{f}(\mathbf{a}) \; : \; \mathbf{a} \in A\}$ for $A \in \Psi$,
- $\mathbf{G} = (G_1, \ldots, G_m)$ is the extension of $\mathbf{g}$ to sets, i.e., $G_i(A) := \max\{g_i(\mathbf{a}) \; : \; \mathbf{a} \in A\}$ for $1 \leq i \leq m$ and $A \in \Psi$,
- $\preccurlyeq$ extends $\leqslant$ to sets where $A \preccurlyeq B :\Leftrightarrow \forall \mathbf{b} \in B \; \exists \mathbf{a} \in A : \mathbf{a} \leqslant \mathbf{b}$.

Pareto Set Approximations

Pareto set approximation (algorithm outcome) =
set of (usually incomparable) solutions



A weakly dominates B
= not worse in all objectives and sets not equal

C dominates D
= better in at least one objective

A strictly dominates C
= better in all objectives

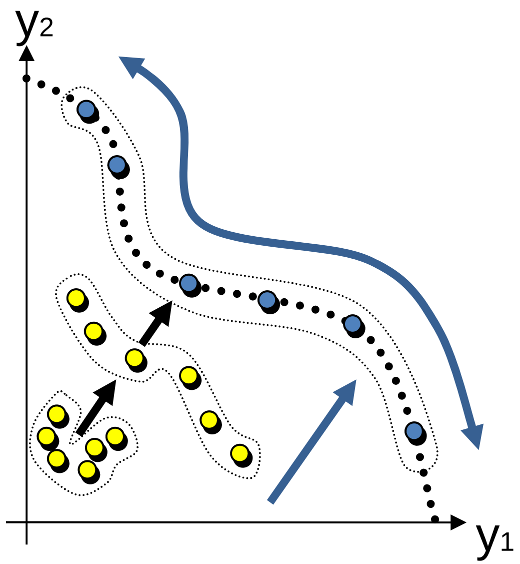
B is **incomparable** to **C**
= neither set weakly better

What Is the Optimization Goal (Total Order)?

- Find all Pareto-optimal solutions?
  - Impossible in continuous search spaces
  - How should the decision maker handle 10000 solutions?
- Find a representative subset of the Pareto set?
  - Many problems are NP-hard
  - What does representative actually mean?
- Find a good approximation of the Pareto set?
  - What is a good approximation?
  - How to formalize intuitive understanding:

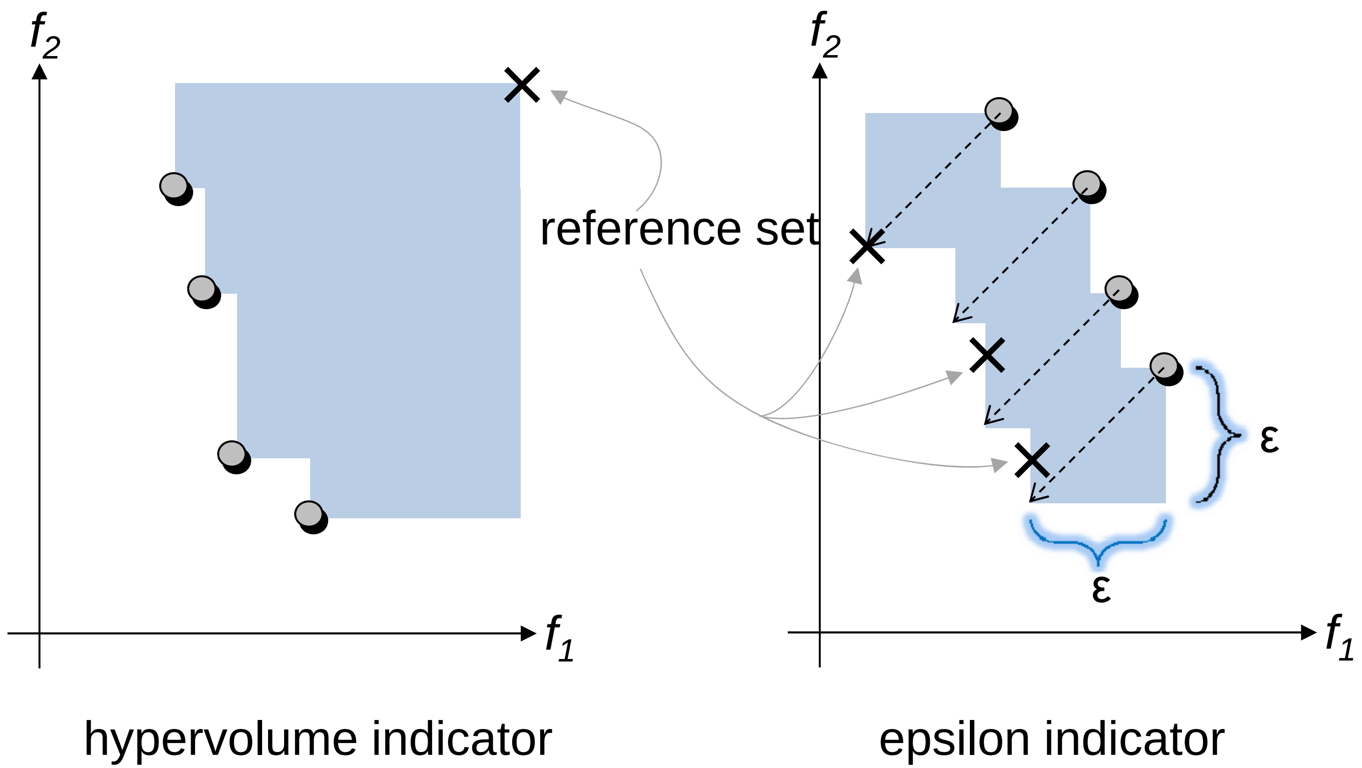
    ❶ close to the Pareto front

    ❷ well distributed



Quality of Pareto Set Approximations

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



General Remarks on Problem

Idea:

Transform a preorder into a total preorder

Methods:

- Define single-objective function based on the multiple criteria *(shown on the previous slides)*
- Define any total preorder using a relation *(not discussed before)*

Question:

Is any total preorder ok resp. are there any requirements concerning the resulting preference relation?

$\Rightarrow$ Underlying dominance relation *rel* should be reflected

Refinements and Weak Refinements

❶ $\overset{\text{ref}}{\preccurlyeq}$ **refines** a preference relation $\preccurlyeq$ iff

$$A \preccurlyeq B \wedge B \not\preccurlyeq A \Rightarrow A \overset{\text{ref}}{\preccurlyeq} B \wedge B \overset{\text{ref}}{\not\preccurlyeq} A \qquad \textit{(better} \Rightarrow \textit{better)}$$

$\Rightarrow$ fulfills requirement

❷ $\overset{\text{ref}}{\preccurlyeq}$ **weakly refines** a preference relation $\preccurlyeq$ iff

$$A \preccurlyeq B \wedge B \not\preccurlyeq A \Rightarrow A \overset{\text{ref}}{\preccurlyeq} B \qquad \textit{(better} \Rightarrow \textit{weakly better)}$$

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

…sought are total refinements…

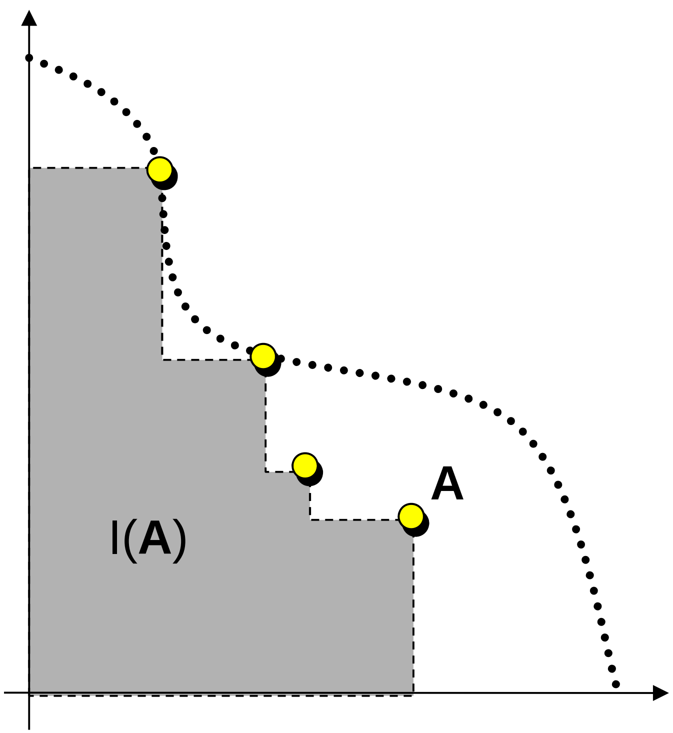
Example: Refinements Using Indicators

$$A \overset{\text{ref}}{\preccurlyeq} B :\Leftrightarrow I(A) \geq I(B)$$

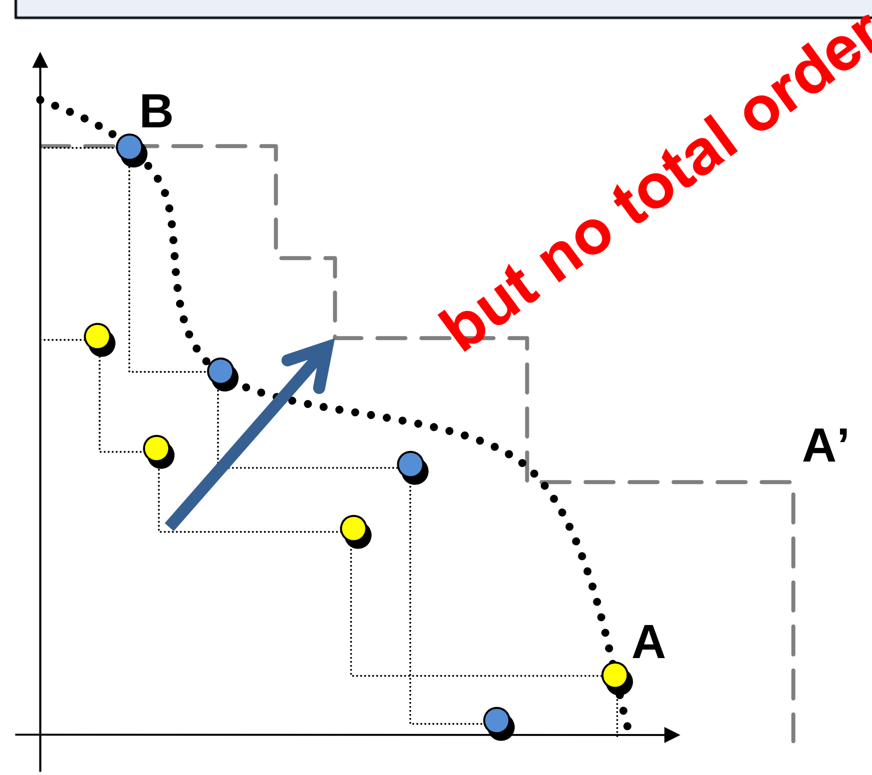
$$A \overset{\text{ref}}{\preccurlyeq} B :\Leftrightarrow I(A,B) \leq I(B,A)$$

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

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



unary hypervolume indicator



binary epsilon indicator

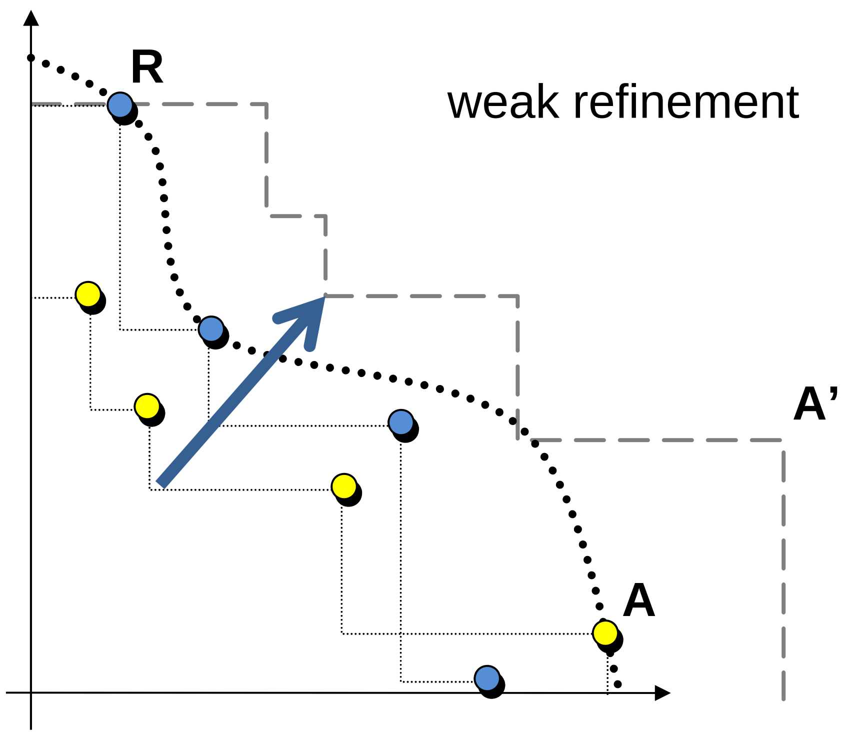
Example: Weak Refinement / No Refinement

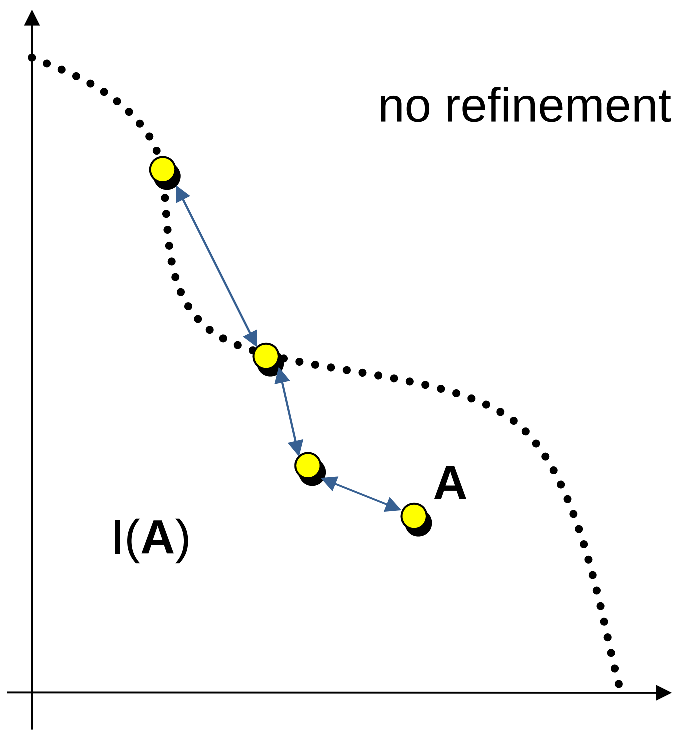
$$A \preccurlyeq^{\text{ref}} B :\Leftrightarrow I(A,R) \leq I(B,R)$$

$$A \preccurlyeq^{\text{ref}} B :\Leftrightarrow I(A) \leq I(B)$$

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

I(A) = variance of pairwise distances





unary epsilon indicator

unary diversity indicator

Overview

The Big Picture

Basic Principles of Multiobjective Optimization

- algorithm design principles and concepts
- performance assessment

Selected Advanced Concepts

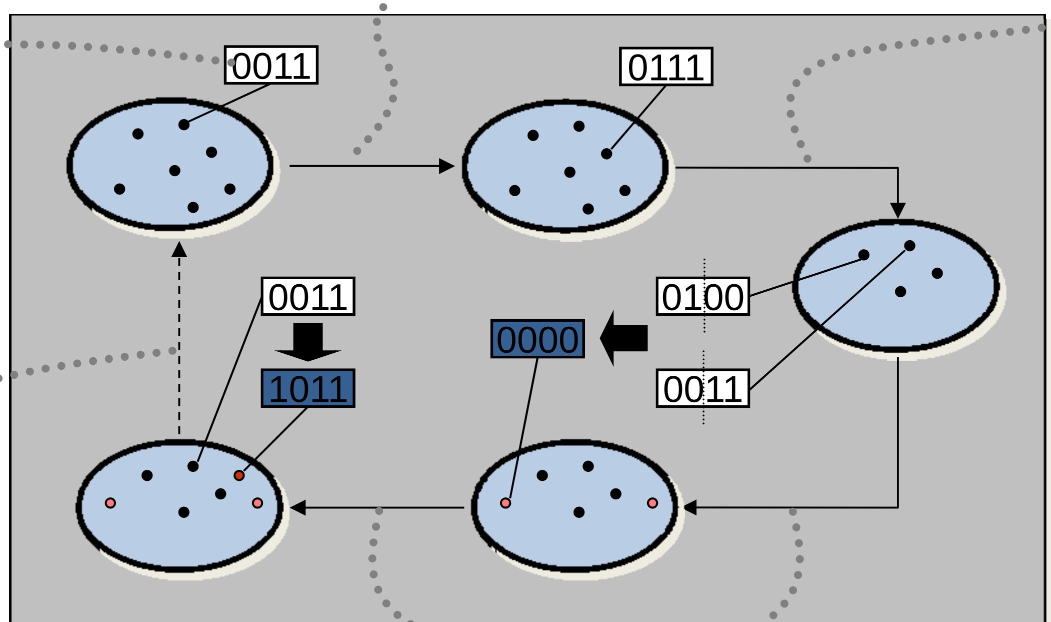
- indicator-based EMO
- preference articulation

A Few Examples From Practice

Algorithm Design: Particular Aspects

representation 1 fitness assignment mating selection

parameters



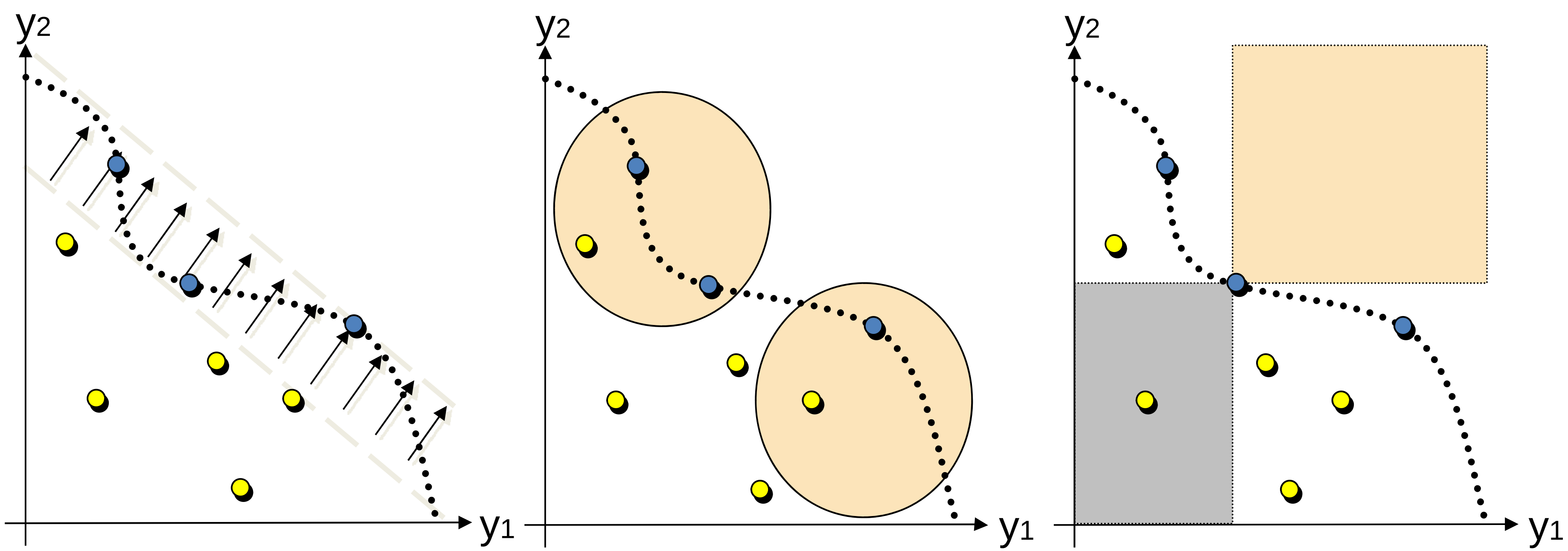
2 environmental selection 3 variation operators

Fitness Assignment: Principal Approaches

aggregation-based *weighted sum*

criterion-based *VEGA*

dominance-based *SPEA2*

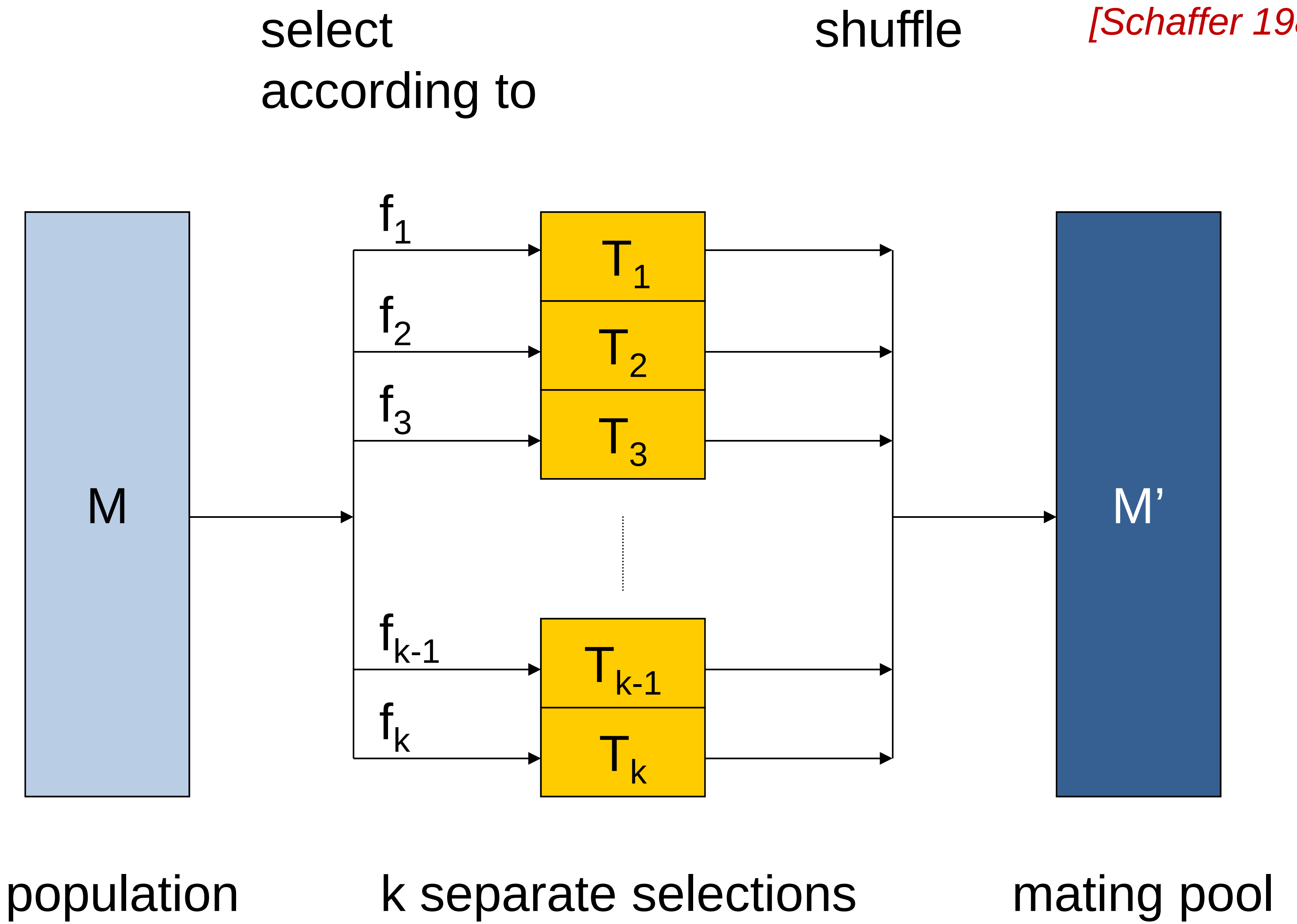


parameter-oriented
scaling-dependent

set-oriented
scaling-independent

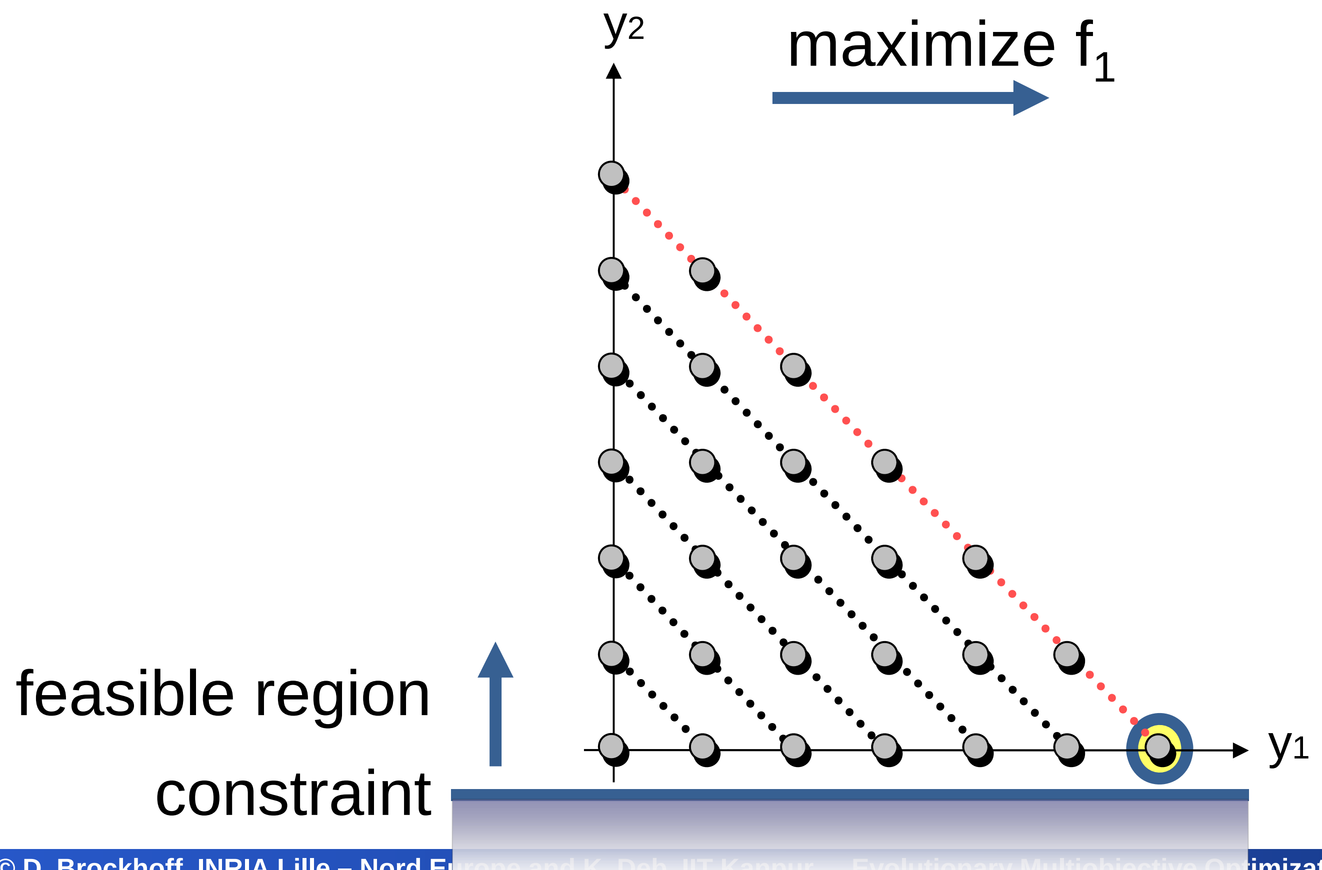
Criterion-Based Selection: VEGA

[Schaffer 1985]



Underlying concept:

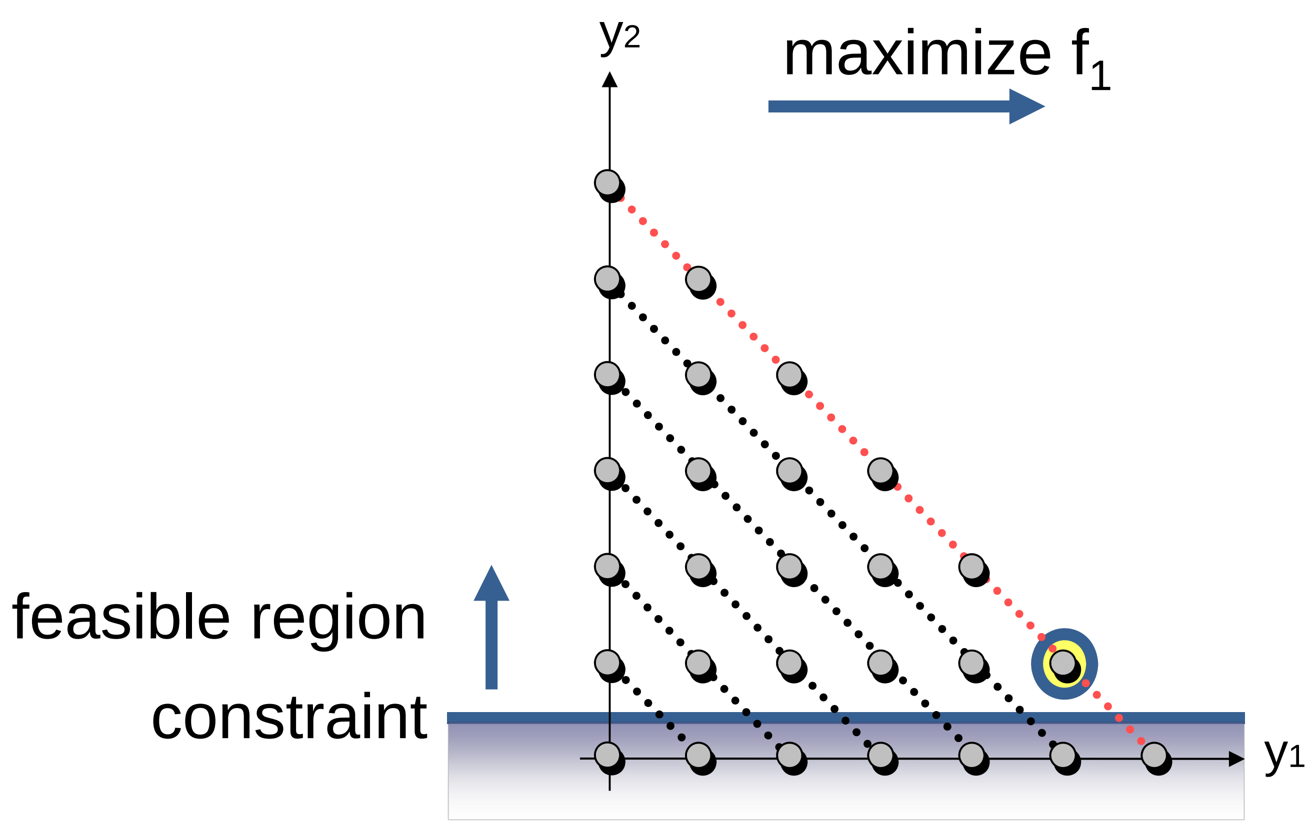
- Convert all objectives except of one into constraints
- Adaptively vary constraints



Aggregation-Based: Multistart Constraint Method

Underlying concept:

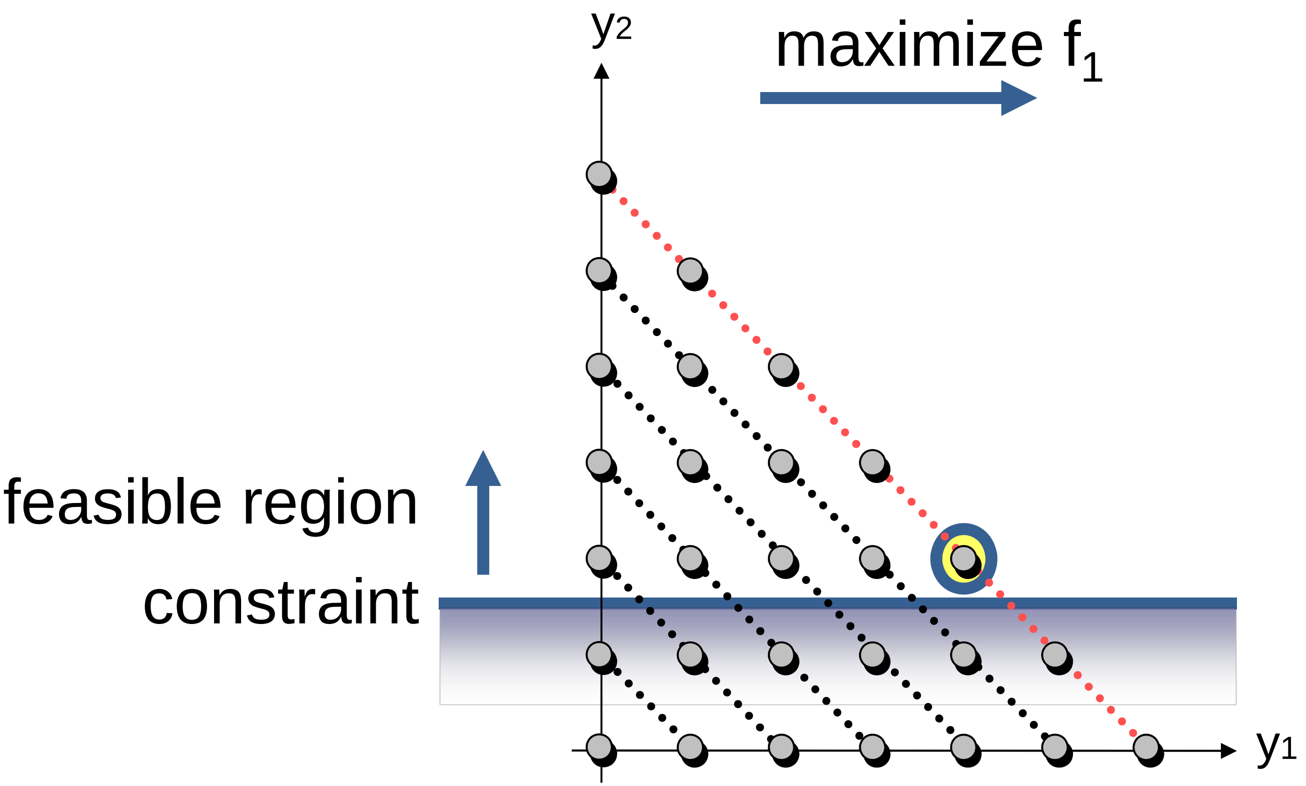
- Convert all objectives except of one into constraints
- Adaptively vary constraints



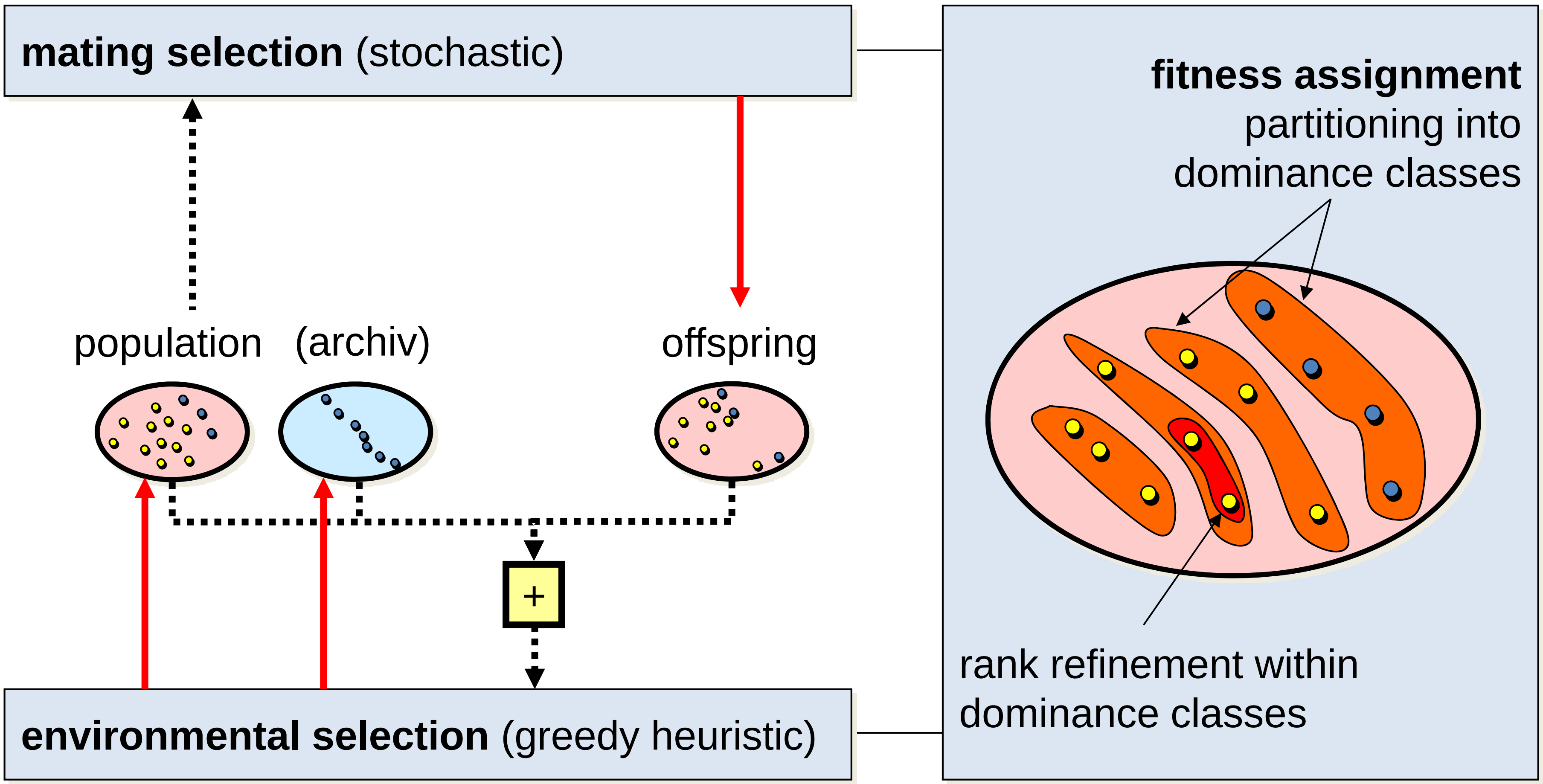
Aggregation-Based: Multistart Constraint Method

Underlying concept:

- Convert all objectives except of one into constraints
- Adaptively vary constraints



General Scheme of Dominance-Based EMO



Note: good in terms of set quality = good in terms of search?

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

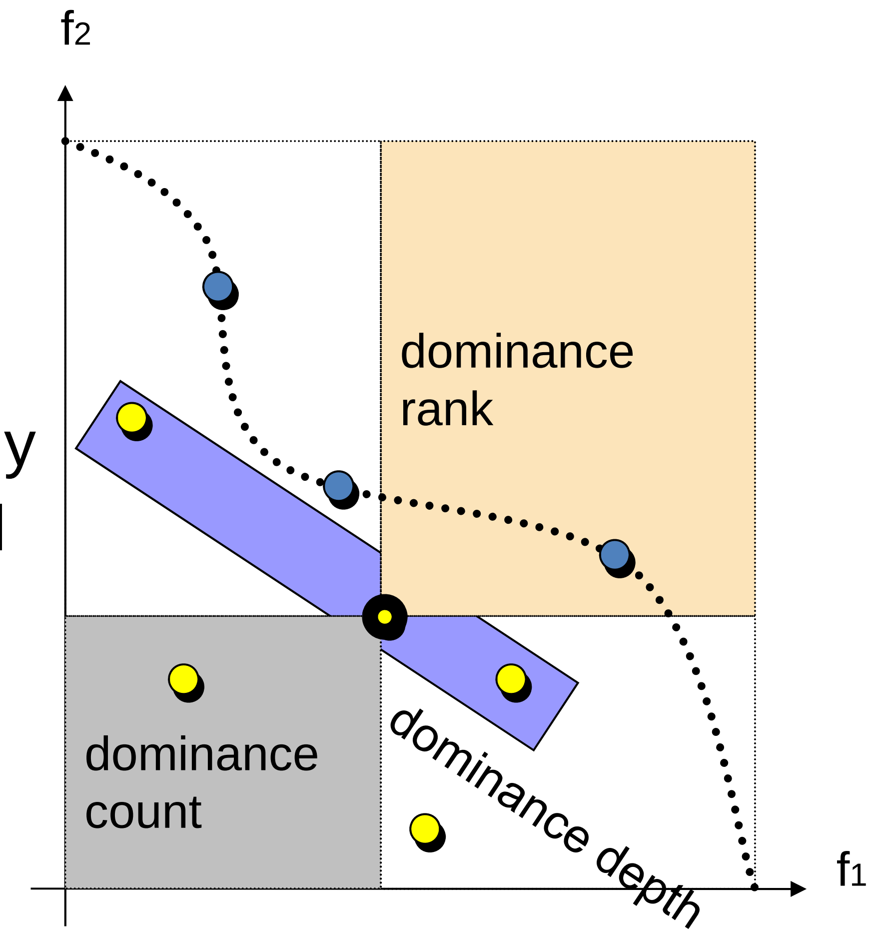
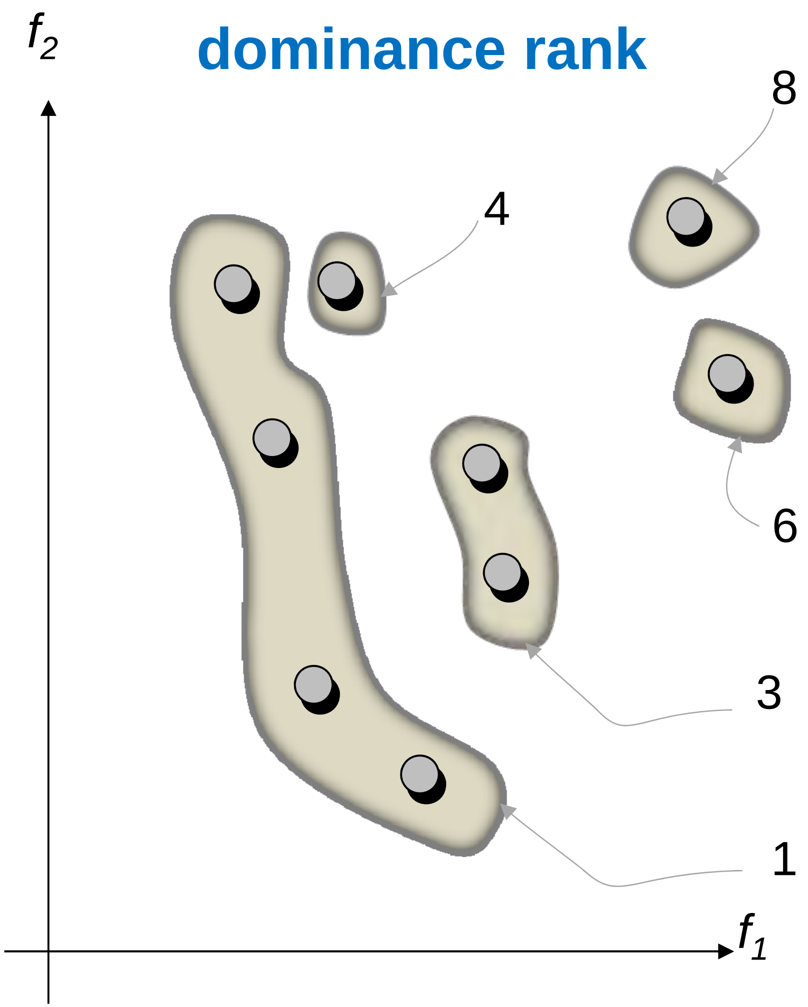
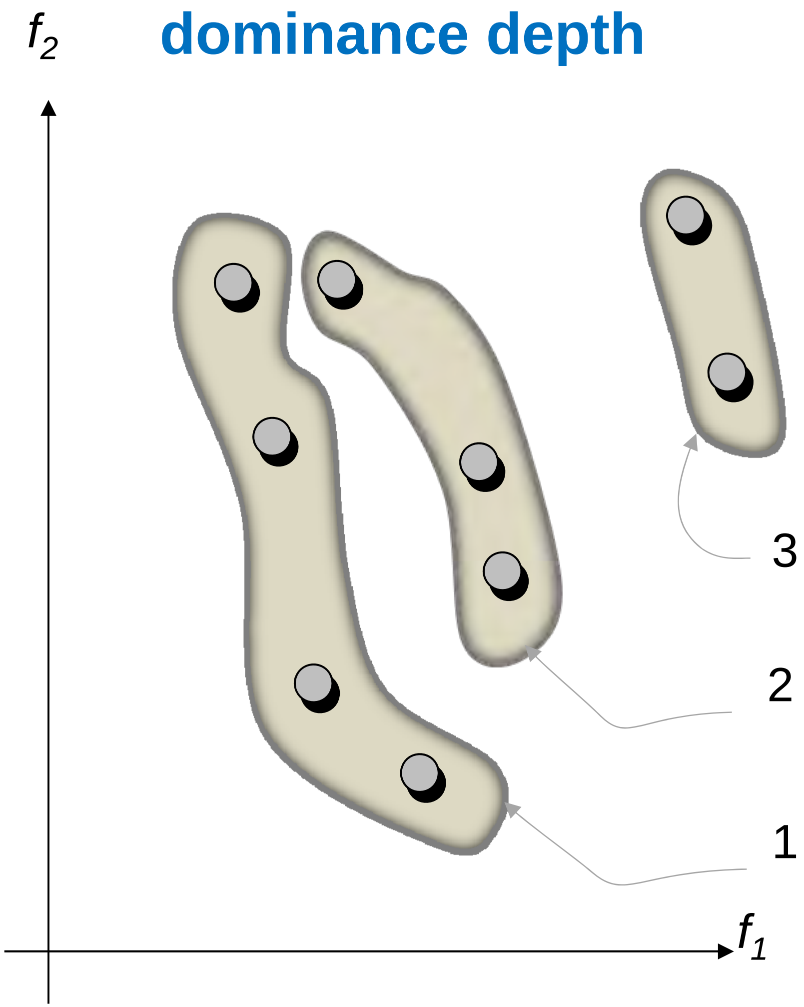


Illustration of Dominance-based Partitioning





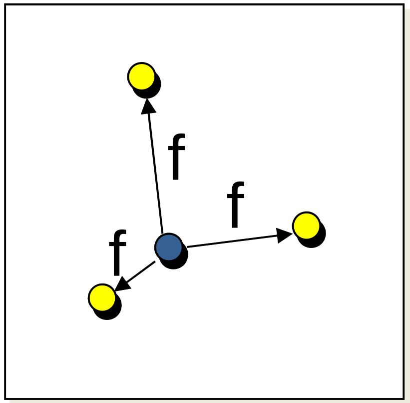
Refinement of Dominance Rankings

Goal: rank incomparable solutions within a dominance class

❶ Density information (good for search, but usually no refinements)

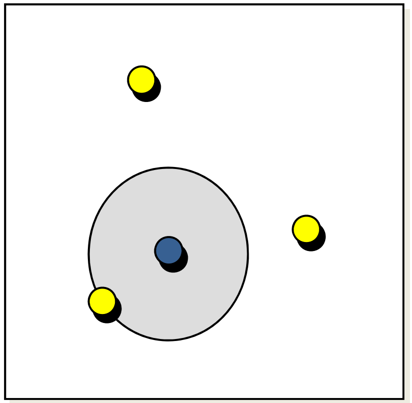
Kernel method

density =
function of the
distances



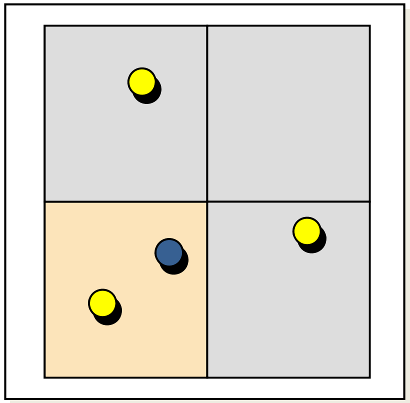
k-th nearest neighbor

density =
function of distance
to k-th neighbor



Histogram method

density =
number of elements
within box

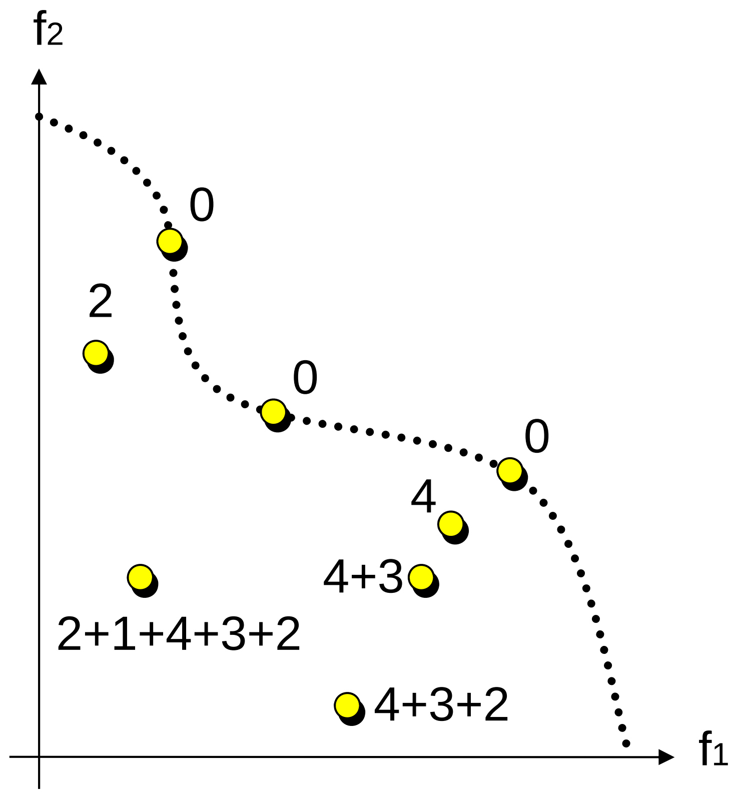


❷ Quality indicator (good for set quality): soon...

Example: SPEA2 Dominance Ranking

Basic idea: the less dominated, the fitter...

Principle: first assign each solution a weight (strength), then add up weights of dominating solutions



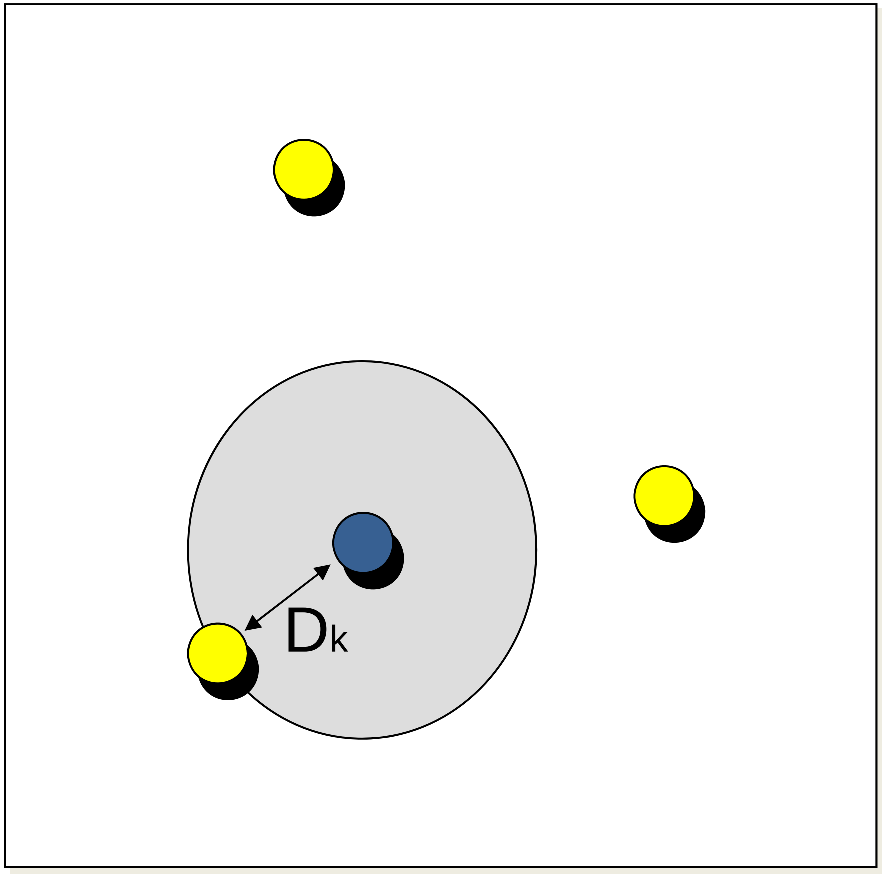
- S (strength) = #dominated solutions
- R (raw fitness) = $\sum$ strengths of dominators

Example: SPEA2 Diversity Preservation

Density Estimation

k-th nearest neighbor method:

- Fitness = R + $\underbrace{1 / (2 + D_k)}_{< 1}$
- D_k = distance to the k-th nearest individual
- Usually used: k = 2



Example: NSGA-II Diversity Preservation

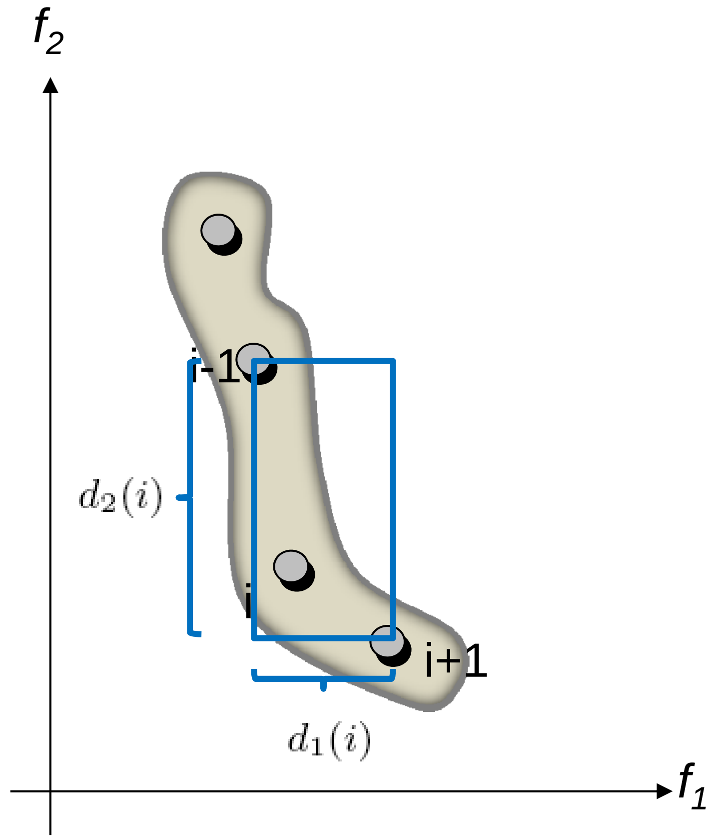
Density Estimation

crowding distance:

- sort solutions wrt. each objective

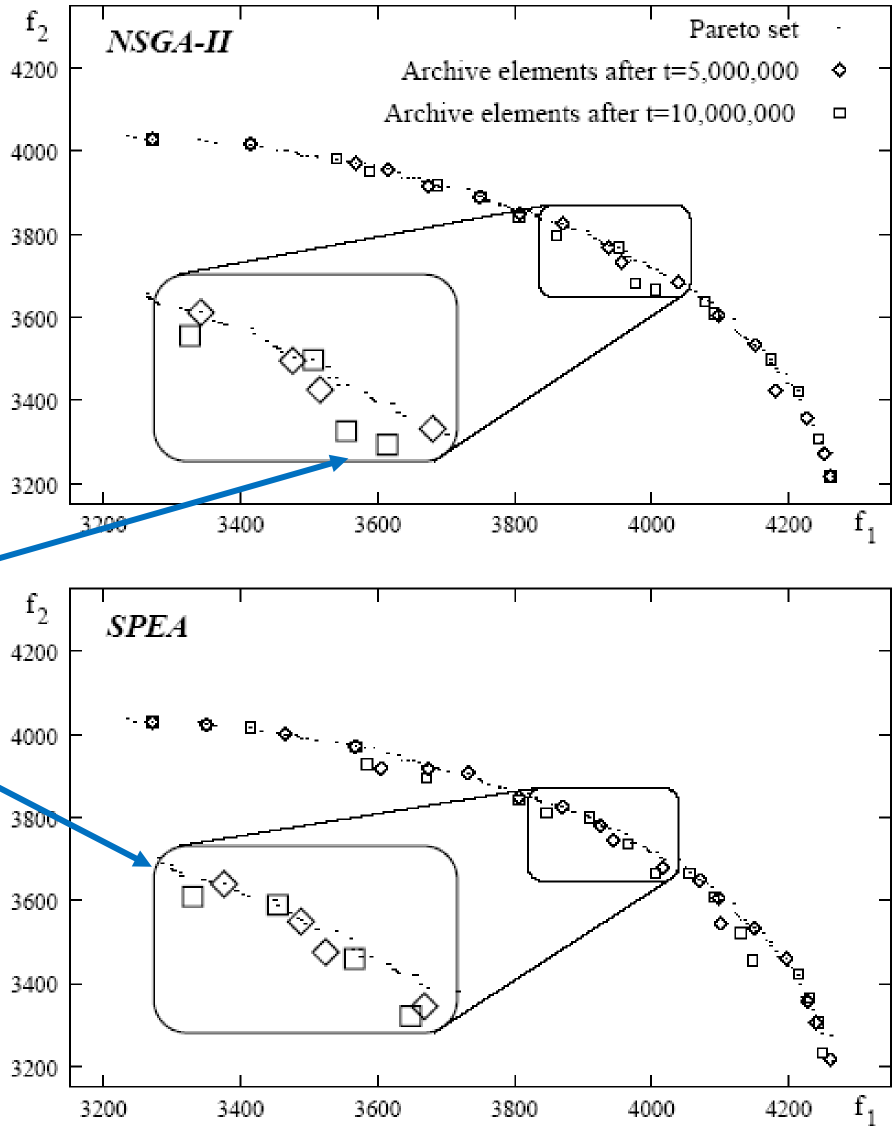
- crowding distance to neighbors:

$$d(i) - \sum_{\text{obj. } m} |f_m(i-1) - f_m(i+1)|$$



SPEA2 and NSGA-II: Cycles in Optimization

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



non-dominated solutions already found can be lost

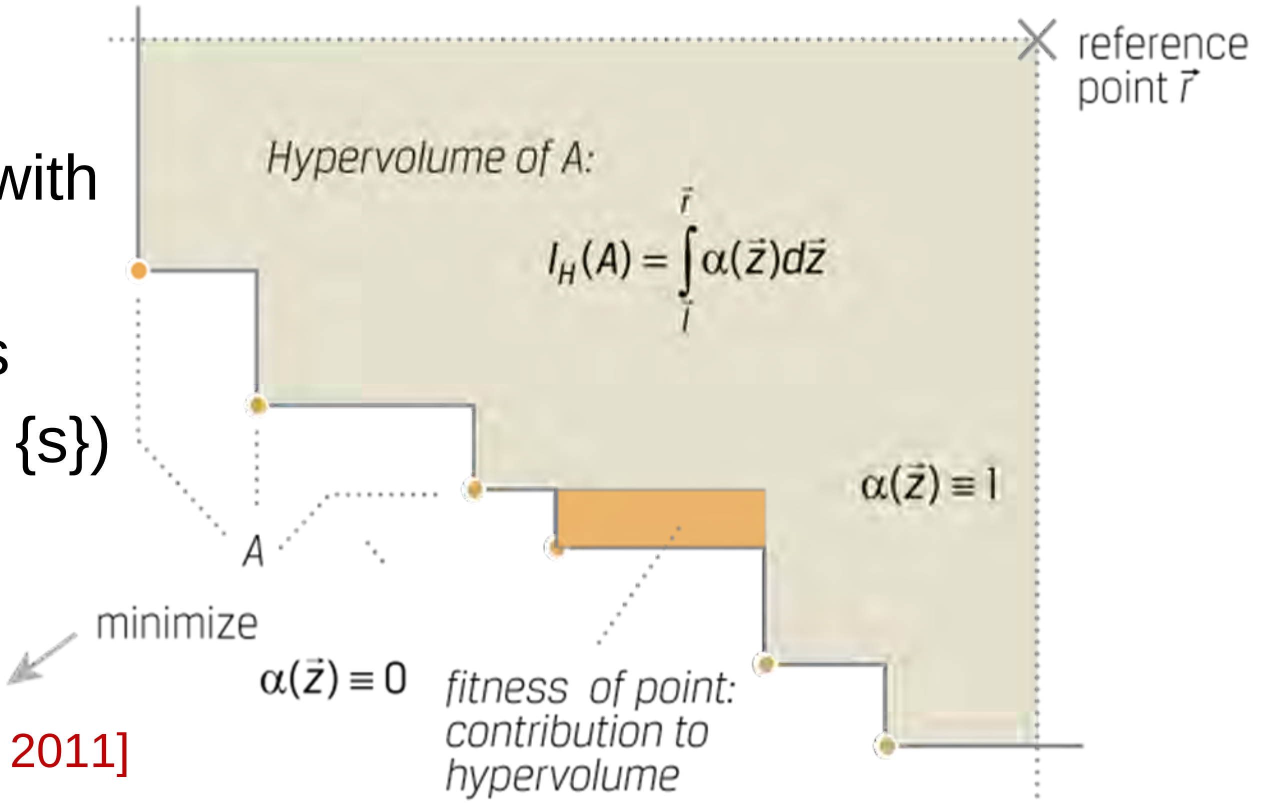
Hypervolume-Based Selection

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

use hypervolume indicator to guide the search: refinement!

Main idea

Delete solutions with the smallest hypervolume loss $d(s) = I_H(P) - I_H(P / \{s\})$ iteratively



But: can also result in cycles [Judt et al. 2011] and is expensive [Bringmann and Friedrich 2009]

Moreover: HypE [Bader and Zitzler 2011]

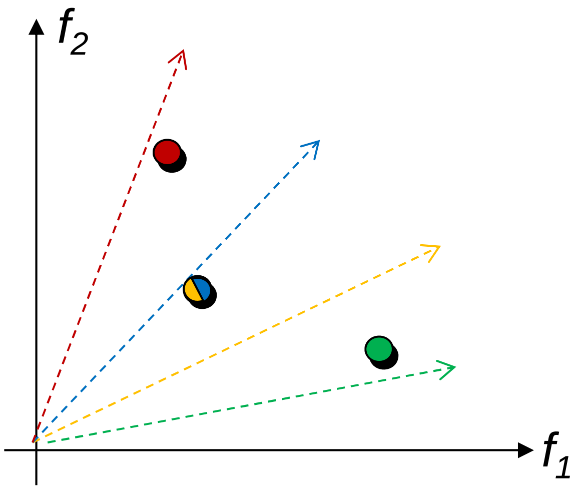
Sampling + Contribution if more than 1 solution deleted

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 only best solutions of "neighbored scalarizing function" for mating
- keep the best solutions for each scalarizing function
- use external archive for non-dominated solutions



Variation in EMO

- At first sight not different from single-objective optimization
- Most algorithm design effort on selection until now
- But: convergence to a set ≠ convergence to a point

Open Question:

- how to achieve fast convergence to a set?

Related work:

- multiobjective CMA-ES [Igel et al. 2007] [Voß et al. 2010]
- set-based variation [Bader et al. 2009]
- set-based fitness landscapes [Verel et al. 2011]

Overview

The Big Picture

Basic Principles of Multiobjective Optimization

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- performance assessment

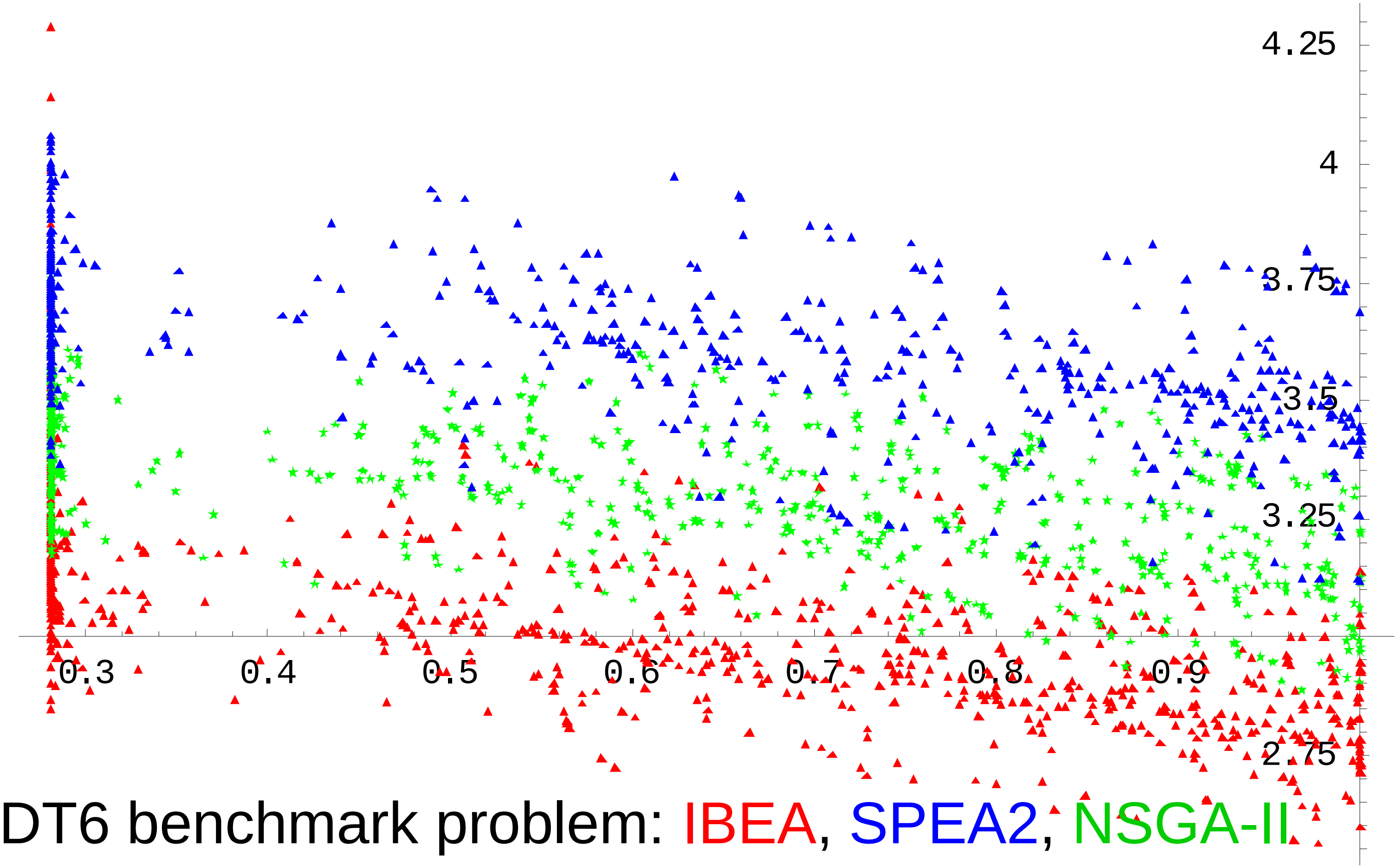
Selected Advanced Concepts

- indicator-based EMO
- preference articulation

A Few Examples From Practice

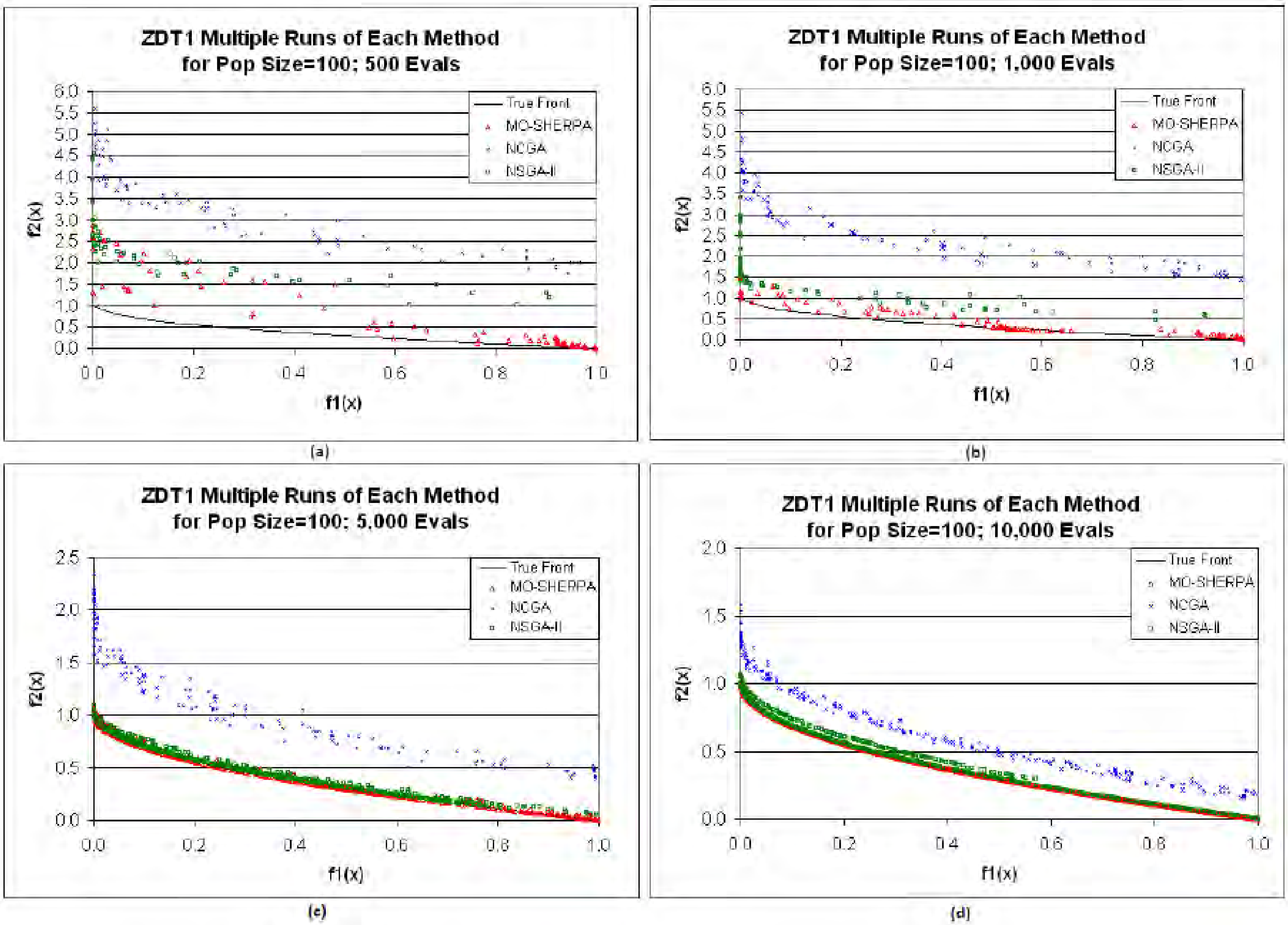
Once Upon a Time...

... multiobjective EAs were mainly compared visually:



ZDT6 benchmark problem: IBEA, SPEA2, NSGA-II

...And Even Today!



[found in a paper from 2009]

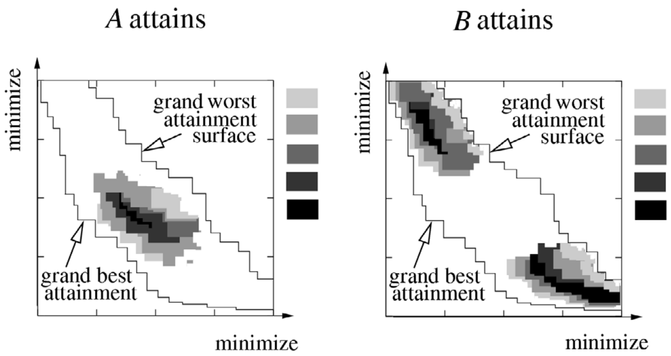
Two Approaches for Empirical Studies

Attainment function approach:

- Applies statistical tests directly to the samples of approximation sets
- Gives detailed information about how and where performance differences occur

Quality indicator approach:

- First, reduces each approximation set to a single value of quality
- Applies statistical tests to the samples of quality values

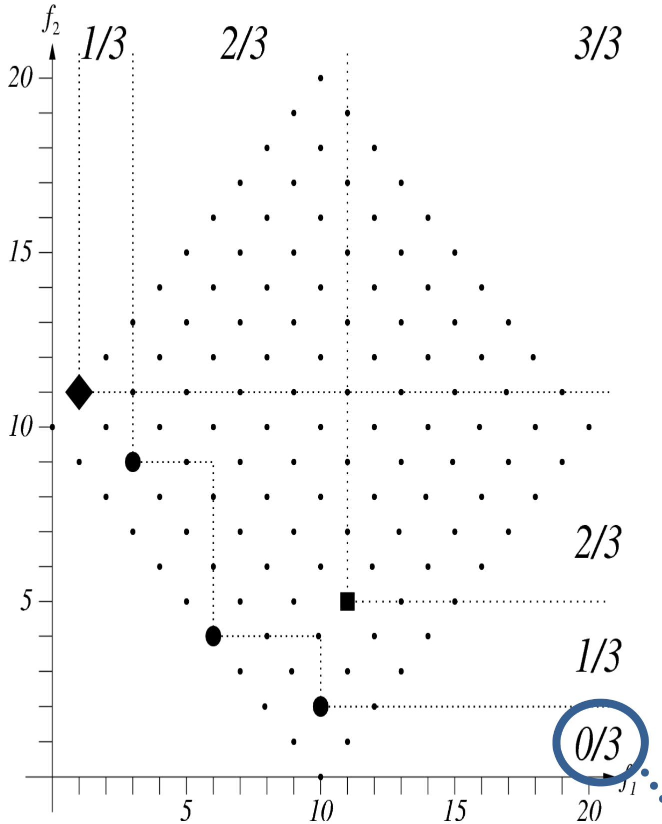


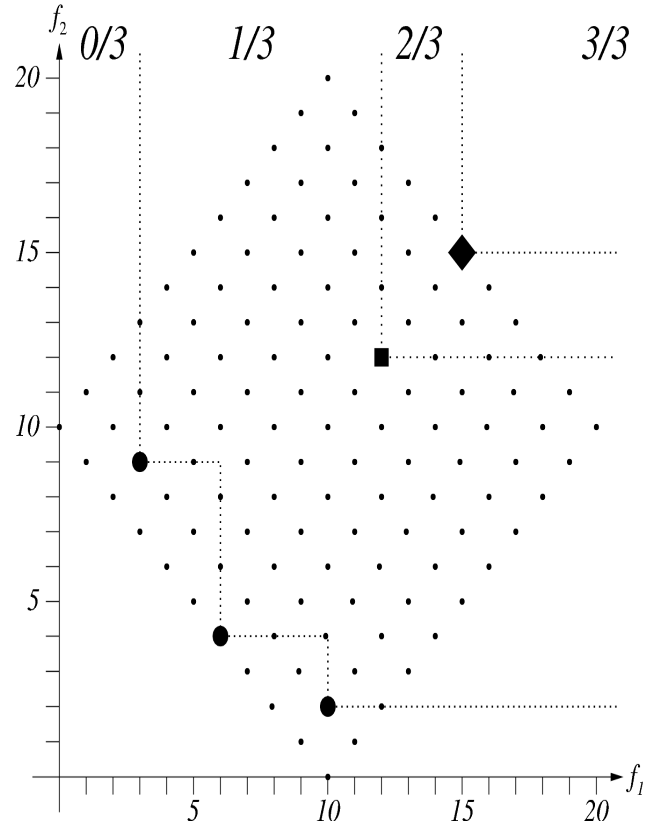
Indicator	A	B
Hypervolume indicator	6.3431	7.1924
ϵ-indicator	1.2090	0.12722
R_2 indicator	0.2434	0.1643
R_3 indicator	0.6454	0.3475

see e.g. [Zitzler et al. 2003]

Empirical Attainment Functions

three runs of two multiobjective optimizers

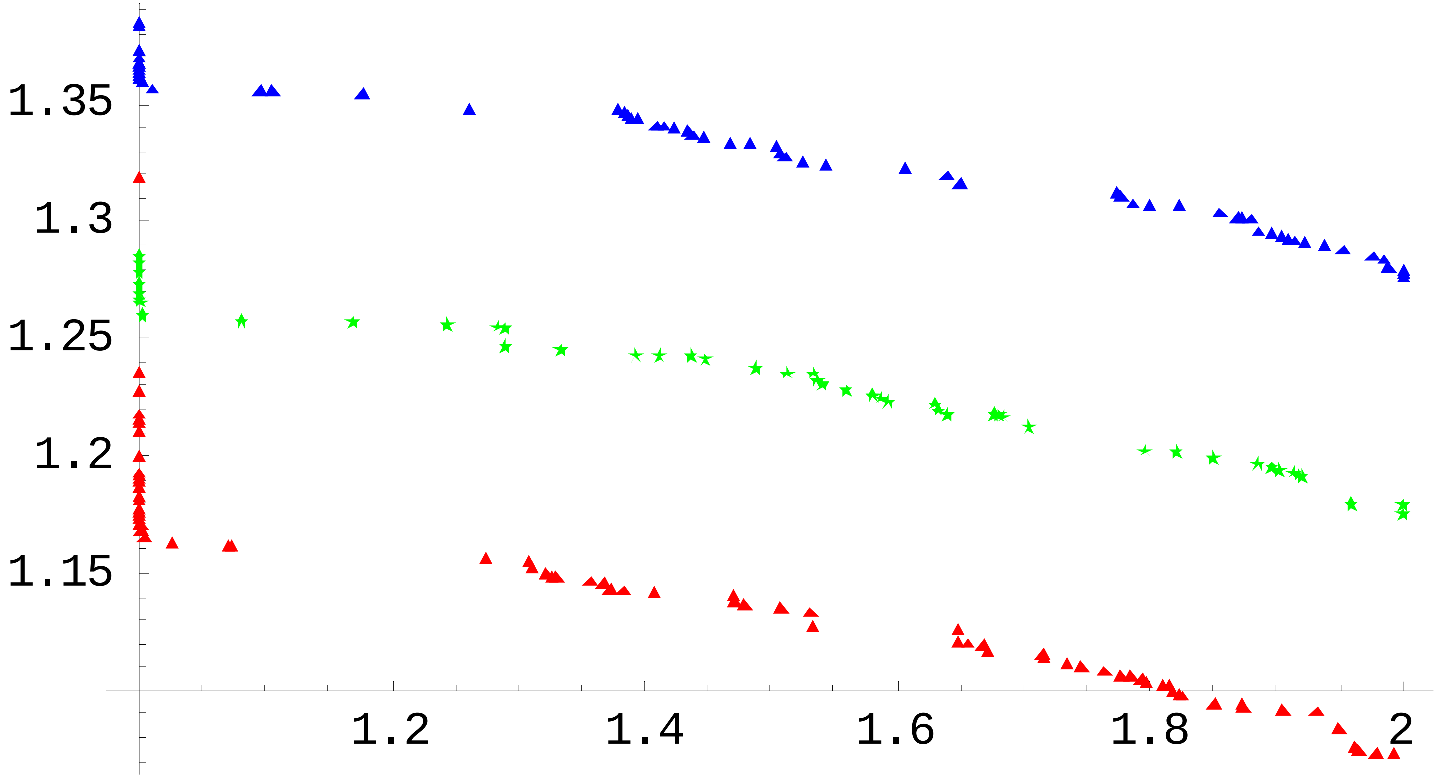




frequency of attaining regions

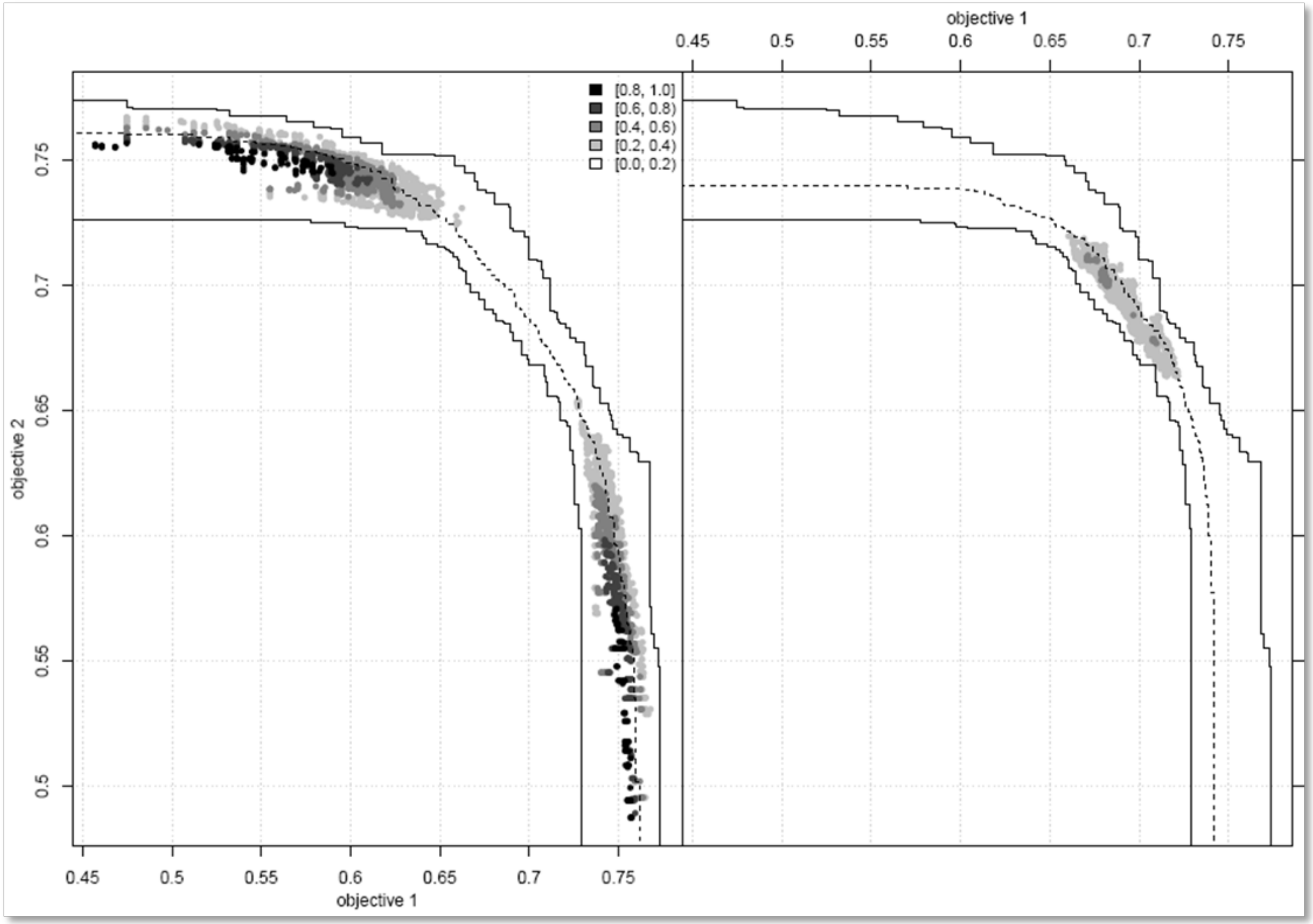
Attainment Plots

50% attainment surface for IBEA, SPEA2, NSGA2 (ZDT6)



latest implementation online at
http://eden.dei.uc.pt/~cmfonsec/software.html
see [Fonseca et al. 2011]

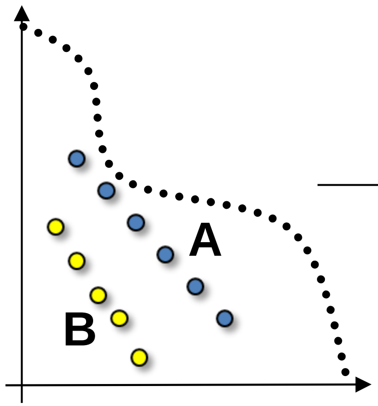
Attainment Plots



latest implementation online at
http://eden.dei.uc.pt/~cmfonsec/software.html
see [Fonseca et al. 2011]

Quality Indicator Approach

Goal: compare two Pareto set approximations A and B



	A	B
hypervolume	*432.34*	*420.13*
distance	*0.3308*	*0.4532*
diversity	*0.3637*	*0.3463*
spread	*0.3622*	*0.3601*
cardinality	*6*	*5*

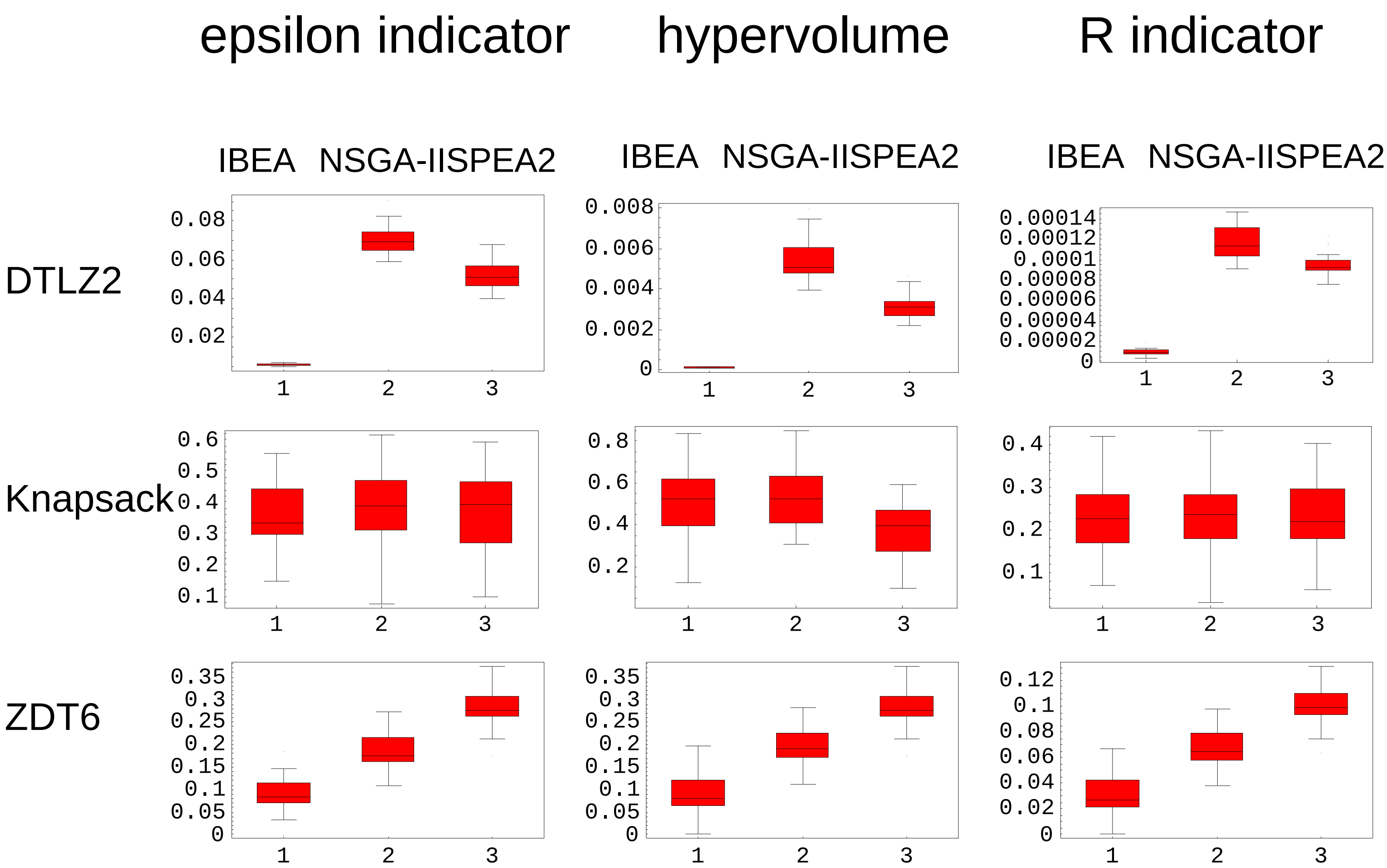
→ "**A** better"

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

$$A, B \xrightarrow{\text{quality measure}} \mathbb{R}^n \xrightarrow{\text{Boolean function}} \text{statement}$$

reduction **interpretation**

Example: Box Plots



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

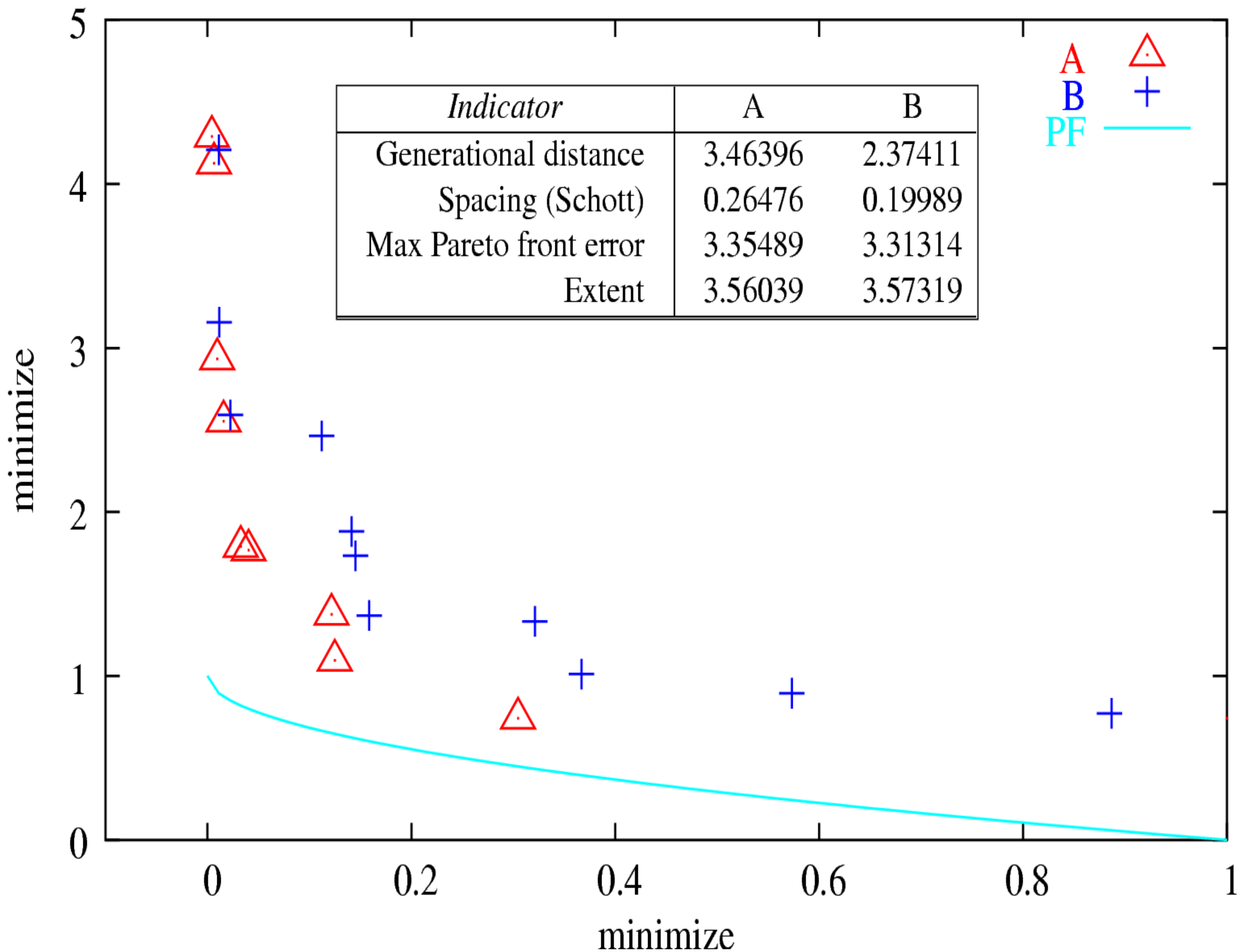
is better than →

	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

Problems With Non-Compliant Indicators



Indicator	A	B
Generational distance	3.46396	2.37411
Spacing (Schott)	0.26476	0.19989
Max Pareto front error	3.35489	3.31314
Extent	3.56039	3.57319

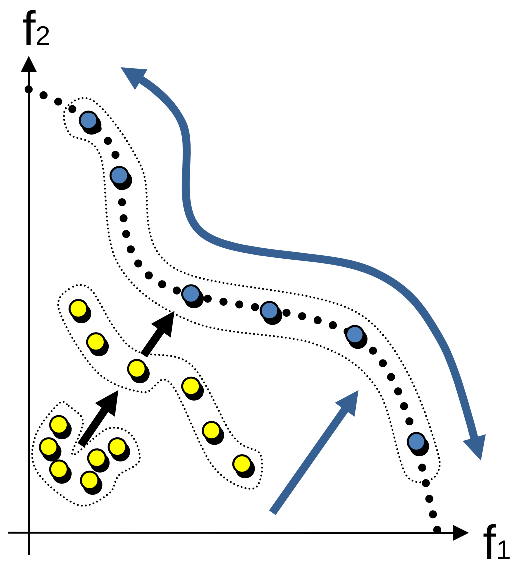
What Are Good Set Quality Measures?

There are **three aspects** [Zitzler et al. 2000]

Comparing different optimization techniques experimentally always involves the notion of performance. In the case of multiobjective optimization, the definition of quality is substantially more complex than for single-objective optimization problems, because the optimization goal itself consists of multiple objectives:

- The distance of the resulting nondominated set to the Pareto-optimal front should be minimized.
- A good (in most cases uniform) distribution of the solutions found is desirable. The assessment of this criterion might be based on a certain distance metric.
- The extent of the obtained nondominated front should be maximized, i.e., for each objective, a wide range of values should be covered by the nondominated solutions.

In the literature, some attempts can be found to formalize the above definition (or parts



Wrong! [Zitzler et al. 2003]

An infinite number of unary set measures is needed to detect in general whether A is better than B

Set Quality Indicators

Open Questions:

- how to design a good benchmark suite?
- are there other unary indicators that are (weak) refinements?
- how to achieve good indicator values?

Overview

The Big Picture

Basic Principles of Multiobjective Optimization

- algorithm design principles and concepts
- performance assessment

Selected Advanced Concepts

- indicator-based EMO
- preference articulation

A Few Examples From Practice

Indicator-Based EMO: Optimization Goal

When the goal is to maximize a unary indicator…

- we have a single-objective set problem to solve
- but what is the optimum?
- important: population size μ plays a role!

Multiobjective Problem $\xrightarrow{\text{Indicator}}$ Single-objective Problem

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

$\Longrightarrow$ 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

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

! (probably) does not hold for > 2 objectives

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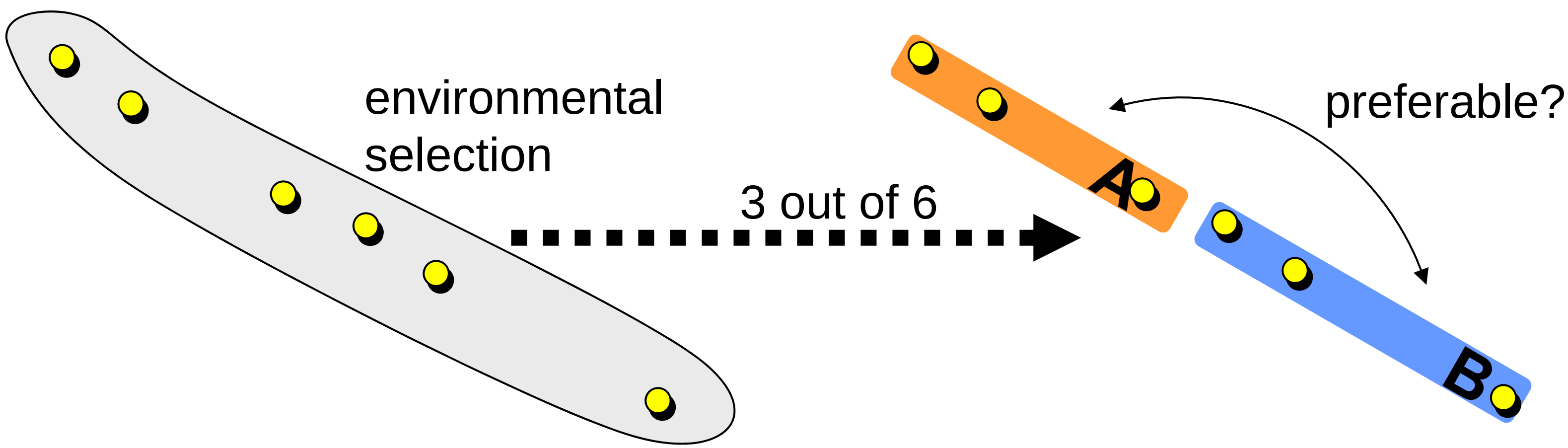
Articulating User Preferences During Search

What we thought: EMO is preference-less

> given by the DM.
>
> **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.
>
> **Decision making during search:** The DM can articulate preferences during

[Zitzler 1999]

What we learnt: EMO just uses weaker preference information

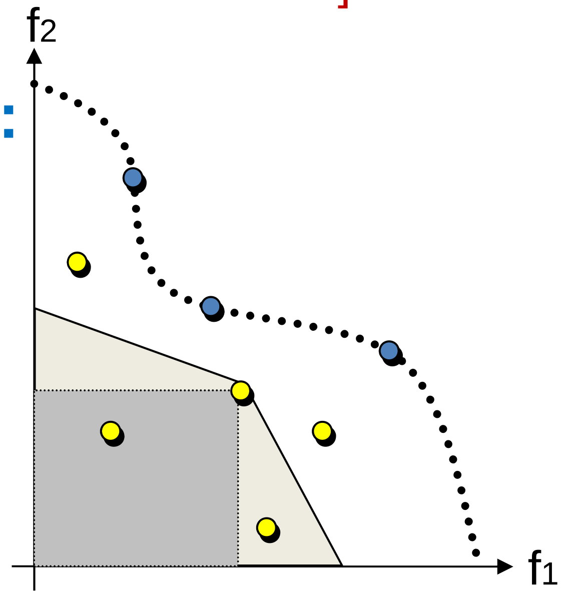


Incorporation of Preferences During Search

Nevertheless...

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

[Branke 2008], [Rachmawati and Srinivasan 2006], [Coello Coello 2000]



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

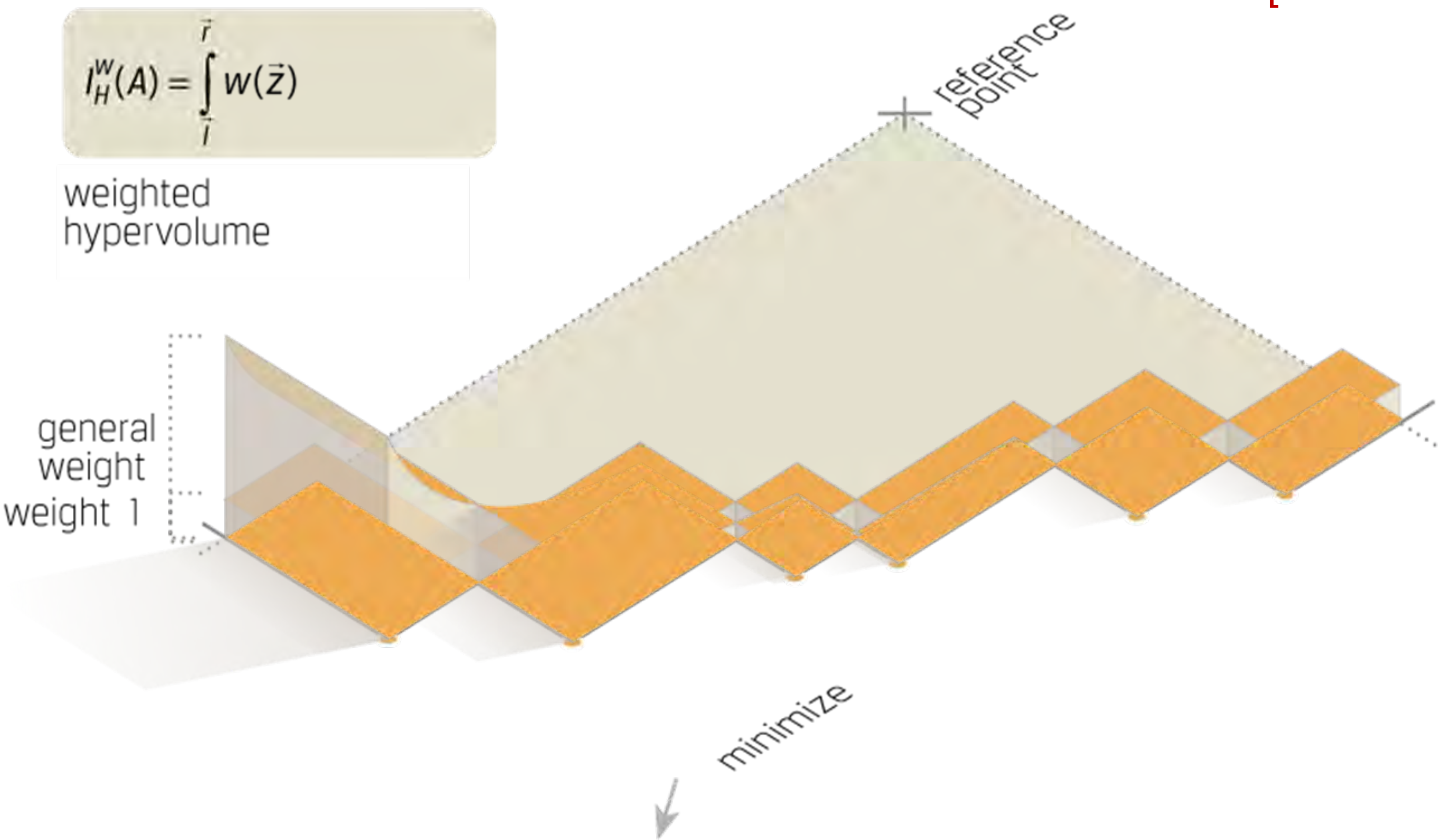
- using goals, priorities, constraints [Fonseca and Fleming 1998a,b]
- using different types of cones [Branke and Deb 2004]

❷ Use quality indicators, e.g.:

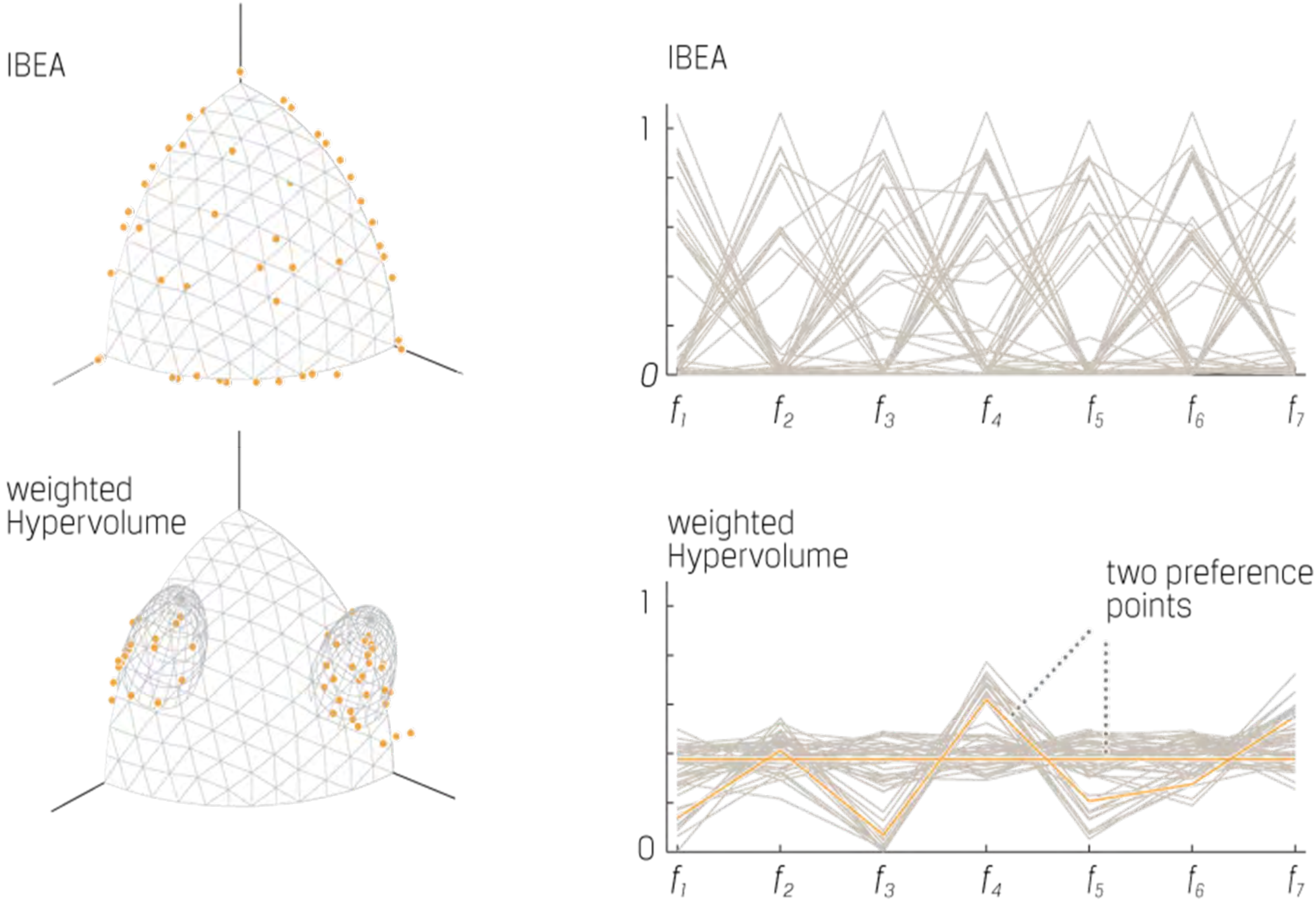
- based on reference points and directions [Deb and Sundar 2006, Deb and Kumar 2007]
- based on binary quality indicators [Zitzler and Künzli 2004]
- based on the hypervolume indicator (now) [Zitzler et al. 2007]

Example: Weighted Hypervolume Indicator

[Zitzler et al. 2007]



Weighted Hypervolume in Practice



[Auger et al. 2009b]

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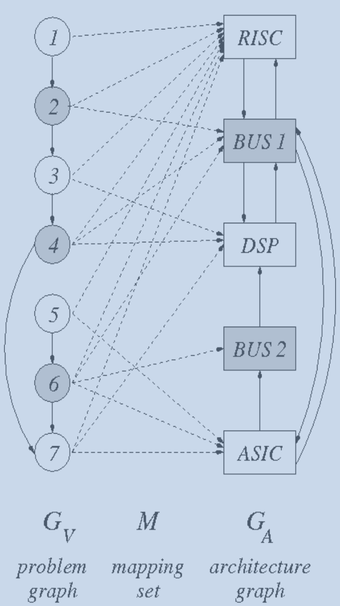
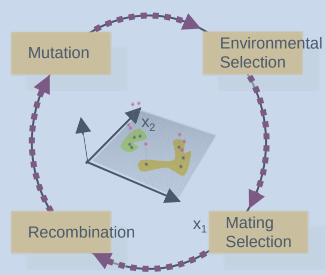
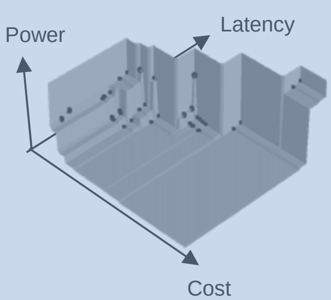
A Few Examples From Practice

Application: Design Space Exploration

Specification → Optimization → Evaluation → Implementation



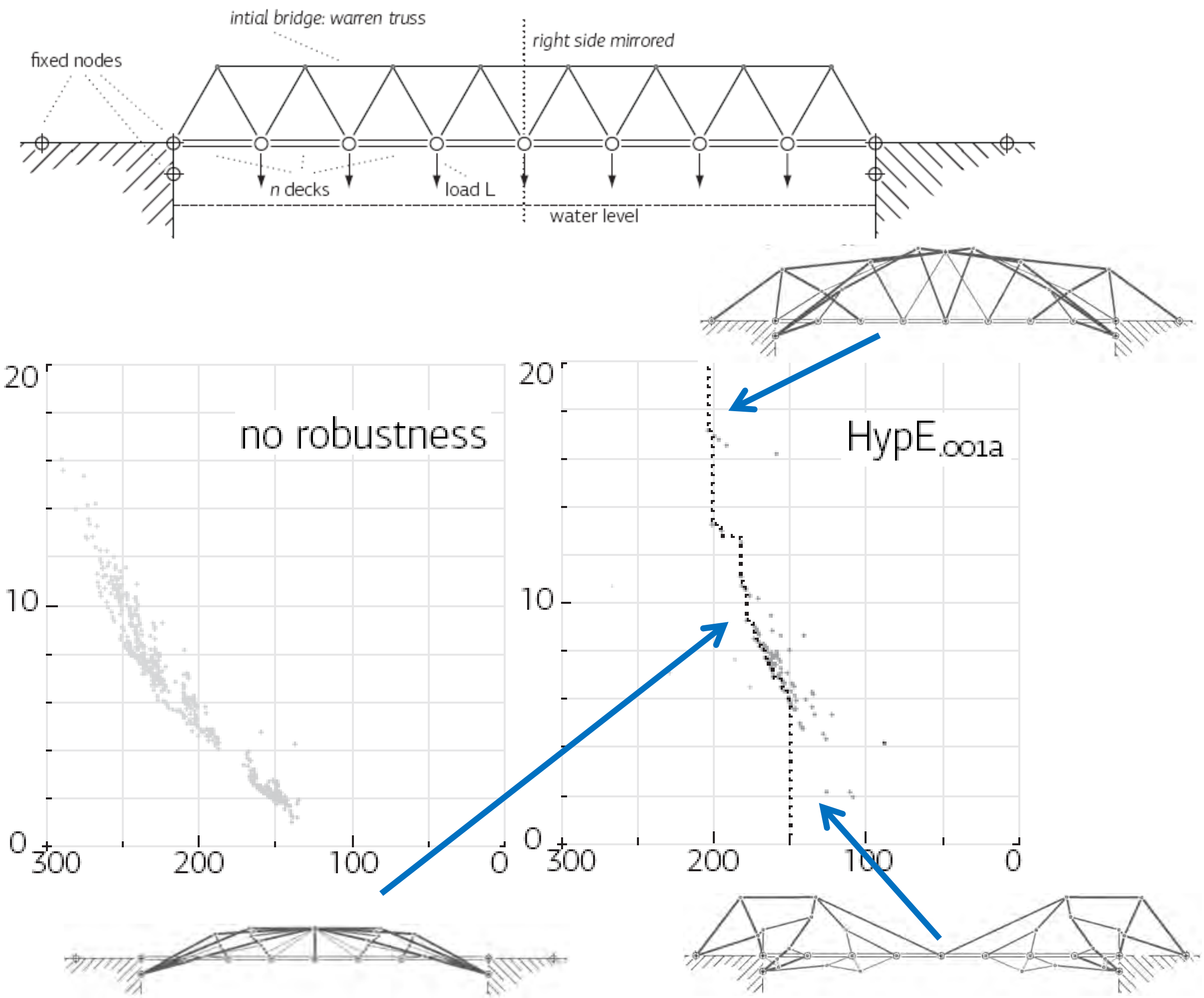




Application: Design Space Exploration

Truss Bridge Design

[Bader 2010]

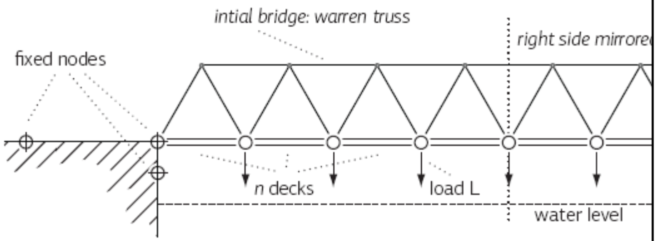


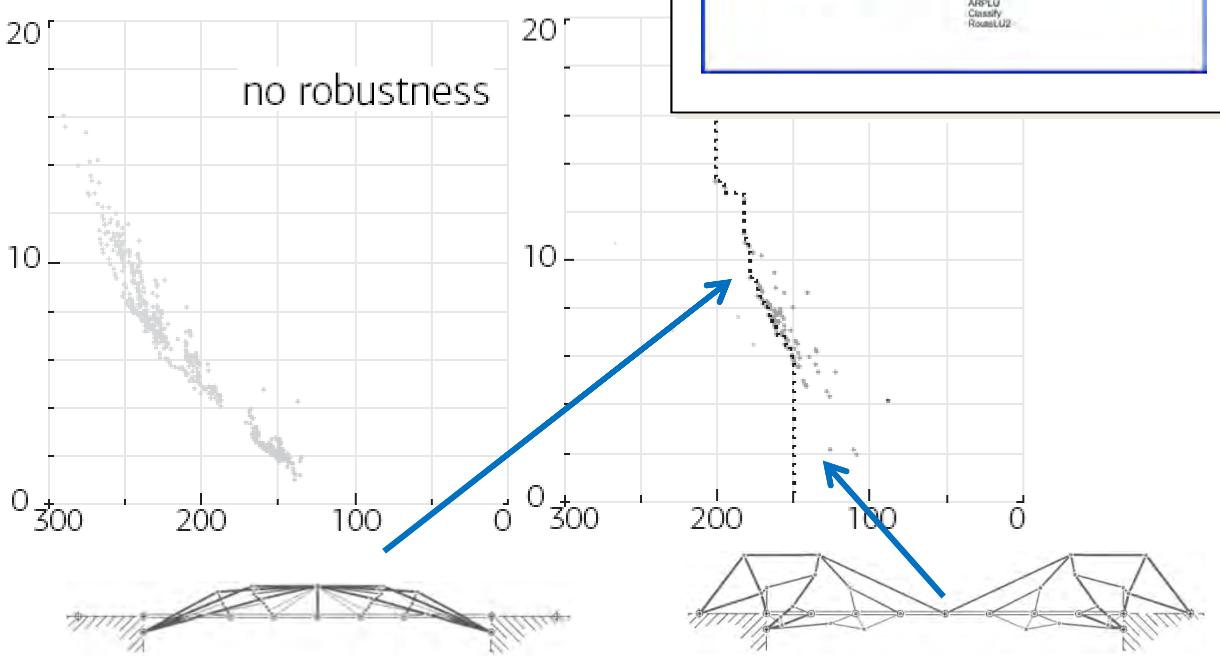
Implementation

Application: Design Space Exploration

Truss Bridge Design

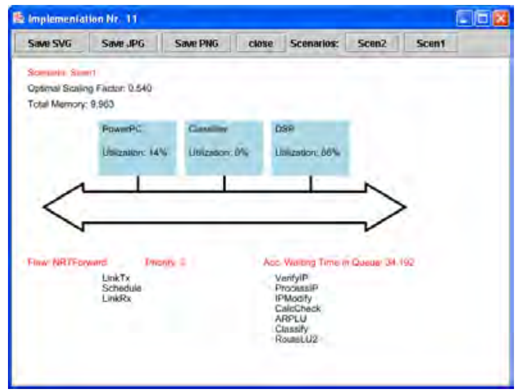
[Bader 2010]

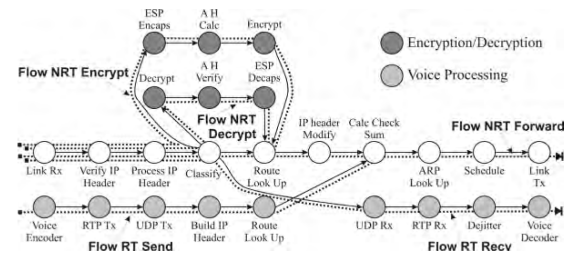


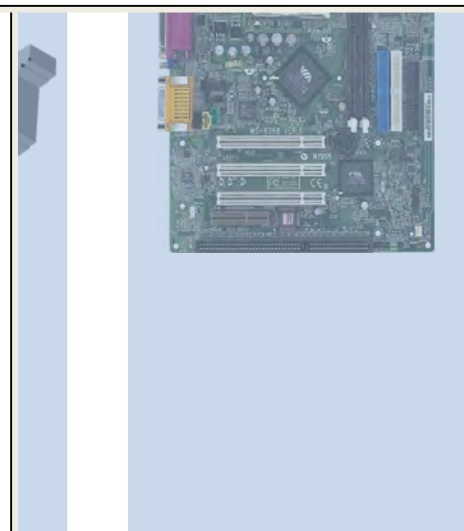


Network Processor Design

[Thiele et al. 2002]



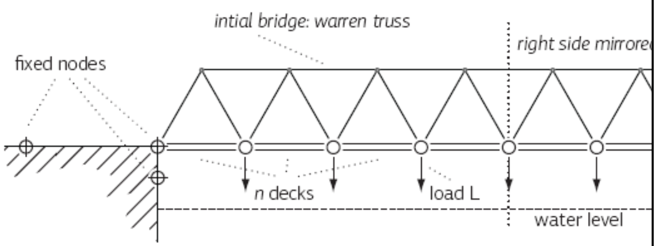


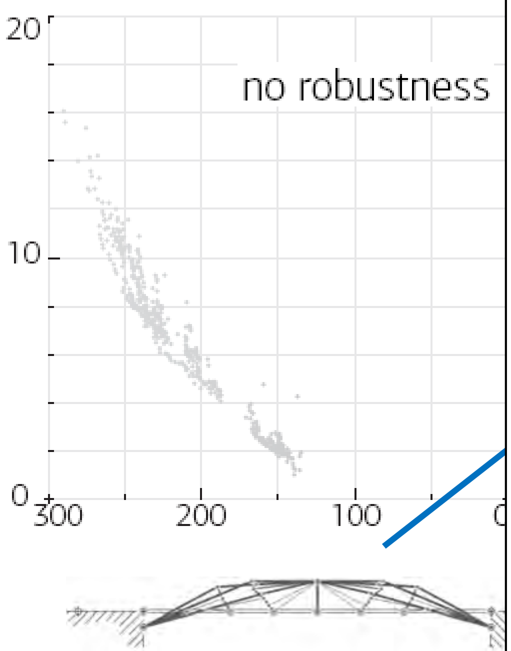


Application: Design Space Exploration

Truss Bridge Design

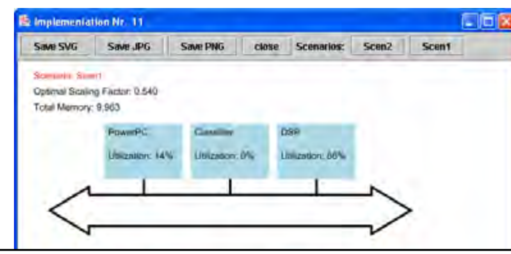
[Bader 2010]

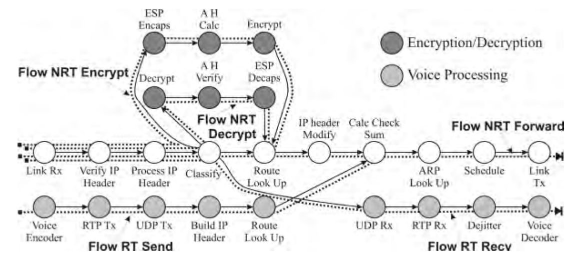




Network Processor Design

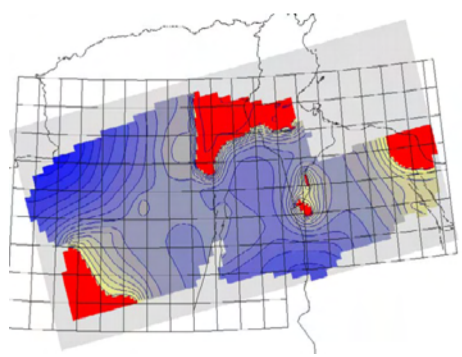
[Thiele et al. 2002]

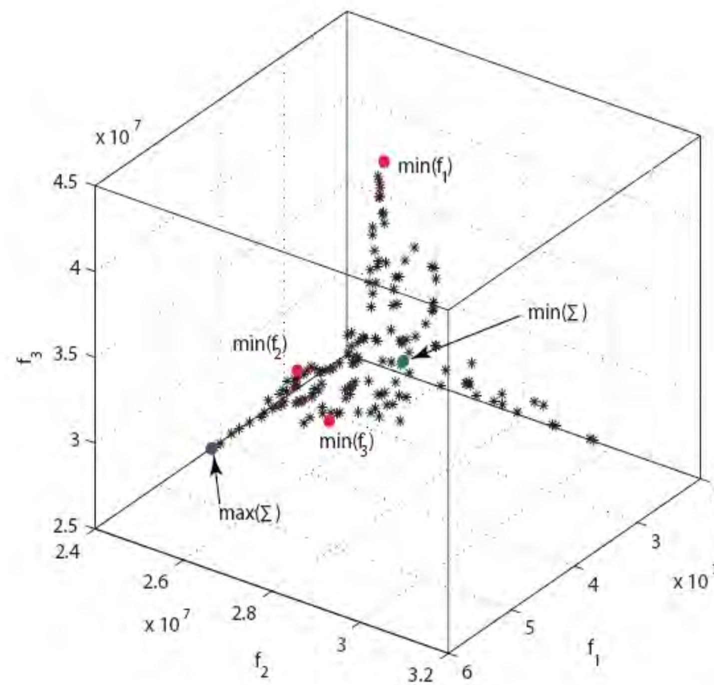




Water resource management

[Siegfried et al. 2009]



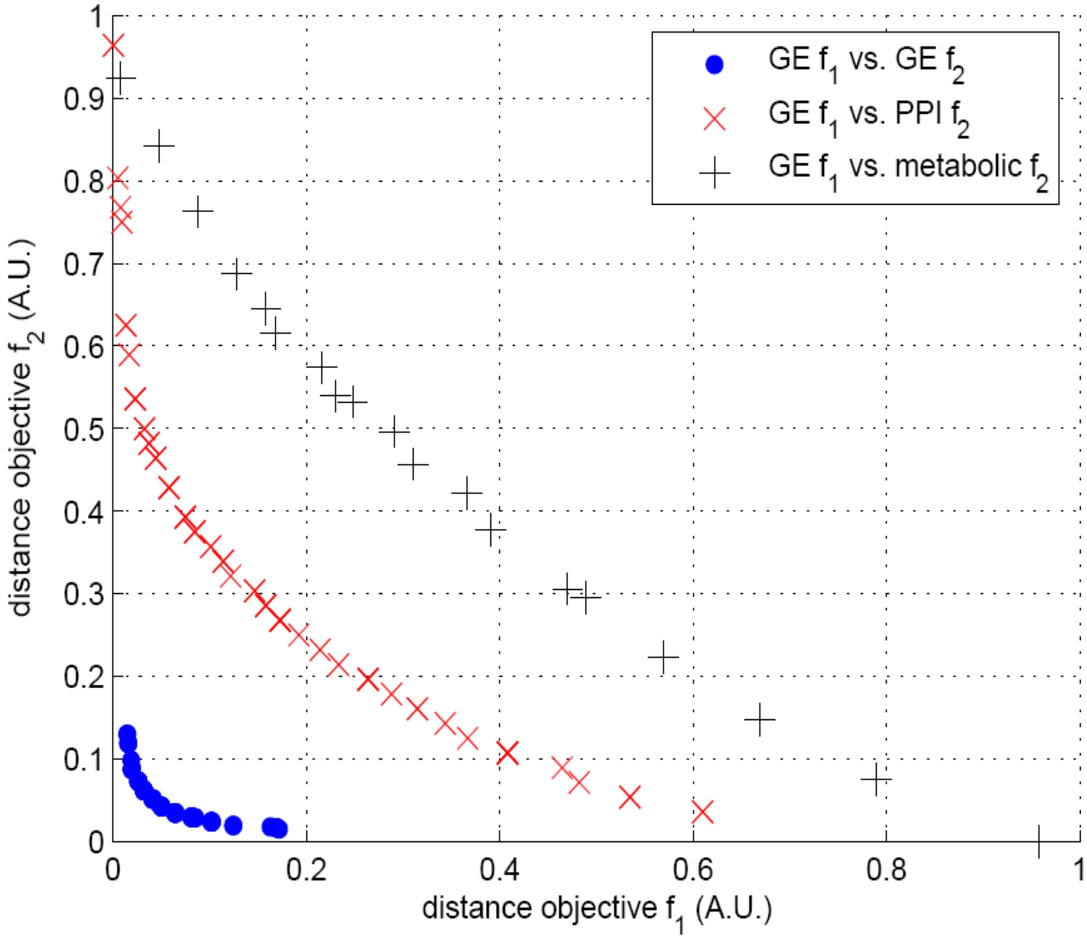


Application: Trade-Off Analysis

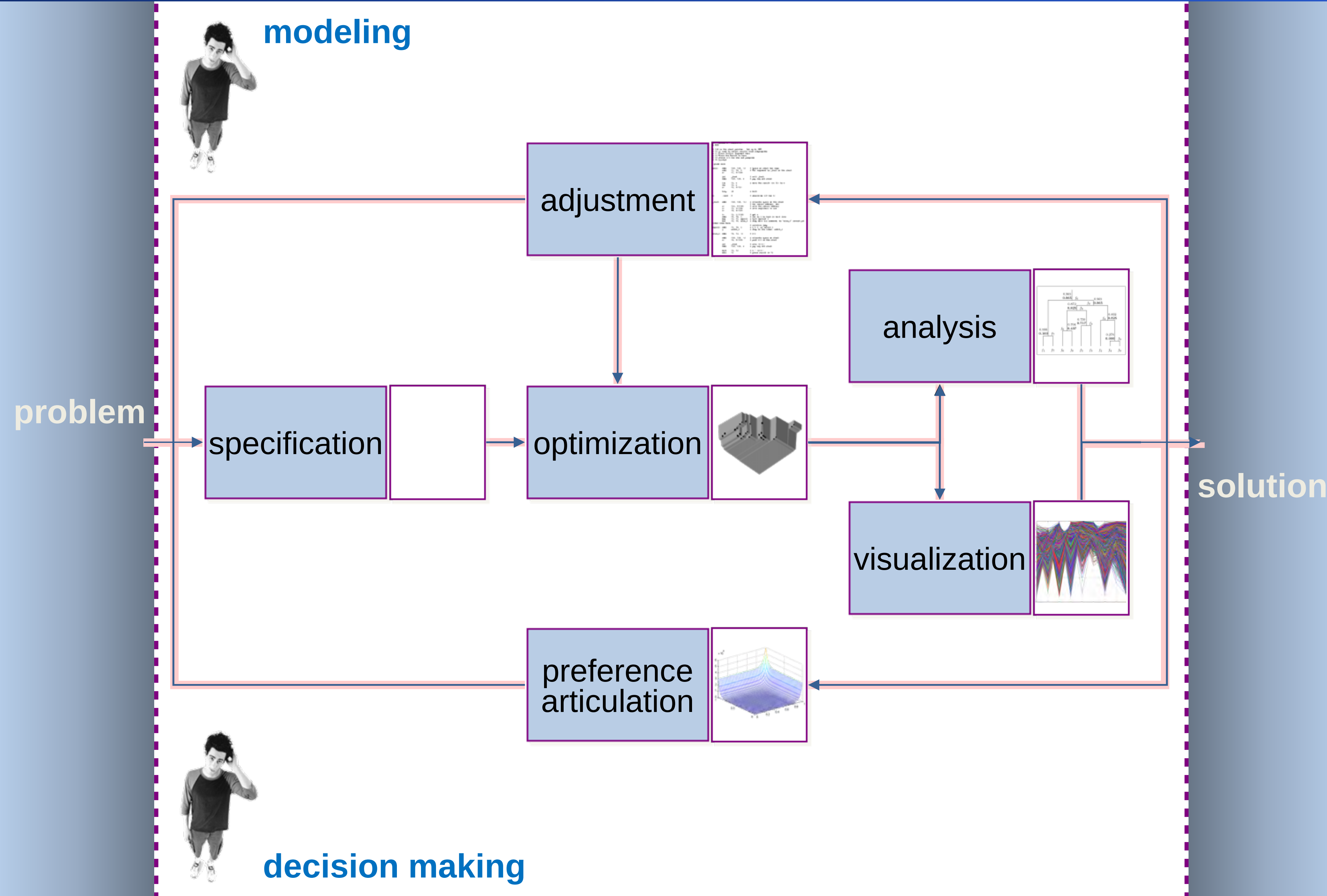
Module identification from biological data [Calonder et al. 2006]

Find group of genes wrt different data types:

- similarity of gene expression profiles
- overlap of protein interaction partners
- metabolic pathway map distances



Conclusions: EMO as Interactive Decision Support



The EMO Community

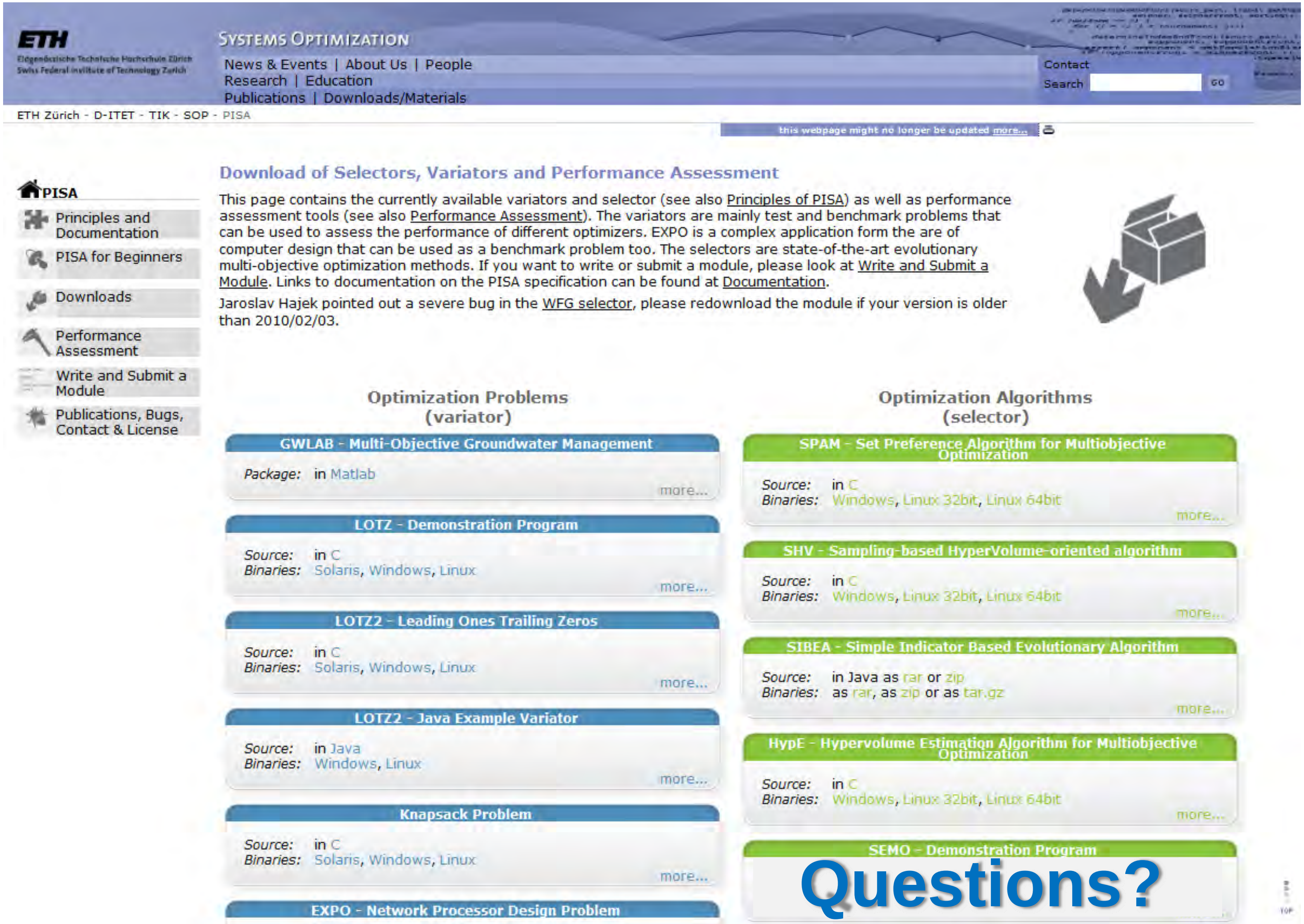
Links:

- EMO mailing list: *http://w3.ualg.pt/lists/emo-list/*
- EMO bibliography: *http://www.lania.mx/~ccoello/EMOO/*
- EMO conference series: *http://www.shef.ac.uk/emo2013/*

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 [many open questions!]
- and more…

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



Questions?

Additional Slides

Instructor Biography: Dimo Brockhoff

Dimo Brockhoff

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DOLPHIN team
Parc scientifique de la Haute Borne
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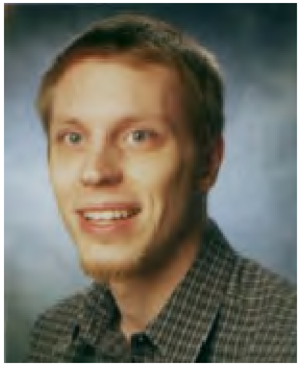

After obtaining his diploma in computer science (Dipl.-Inform.) from University of Dortmund, Germany in 2005, Dimo Brockhoff received his PhD (Dr. sc. ETH) from ETH Zurich, Switzerland in 2009. Between June 2009 and October 2011 he held postdoctoral research positions---first at INRIA Saclay Ile-de-France in Orsay and then at Ecole Polytechnique in Palaiseau, both in France. Since November 2011 he has been a junior researcher (CR2) at INRIA Lille - Nord Europe in Villeneuve d'Ascq, France . His research interests are focused on evolutionary multiobjective optimization (EMO), in particular on many-objective optimization, benchmarking, and theoretical aspects of indicator-based search.

Instructor Biography: Kalyanmoy Deb

Kalyanmoy Deb

Gurmukh and Veena Mehta Endowed Chair Professor

Department of Mechanical Engineering

Indian Institute of Technology Kanpur

Kanpur, PIN 208 016, Uttar Pradesh, India

He holds Deva Raj Chair Professor at Indian Institute of Technology Kanpur in India. He is the recipient of the prestigious MCDM Edgeworth-Pareto award by the Multiple Criterion Decision Making (MCDM) Society, one of the highest awards given in the field of multi-criterion optimization and decision making. He has also received prestigious Shanti Swarup Bhatnagar Prize in Engineering Sciences for the year 2005 from Govt. of India.

He has also received the `Thomson Citation Laureate Award' from Thompson Scientific for having highest number of citations in Computer Science during the past ten years in India. He is a fellow of Indian National Academy of Engineering (INAE), Indian National Academy of Sciences, and International Society of Genetic and Evolutionary Computation (ISGEC). He has received Fredrick Wilhelm Bessel Research award from Alexander von Humboldt Foundation in 2003. His main research interests are in the area of computational optimization, modeling and design, and evolutionary algorithms. He has written two text books on optimization and more than 240 international journal and conference research papers. He has pioneered and a leader in the field of evolutionary multi-objective optimization. He is associate editor of two major international journals and an editorial board members of five major journals.

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