Multiobjective Optimization Algorithms

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Single Objective Optimization

Inputs

- Search space: Set of all feasible solutions,

$$\mathcal{X}$$

- Objective function: Quality criterium

$$f : \mathcal{X} \rightarrow \mathbb{R}$$

Goal

Find the best solution according to the criterium

$$x^\star = \text{argmax } f$$

But, sometime, the set of all best solutions, good approximation of the best solution, good 'robust' solution...

Context

Black box Scenario

We have only $\{(x_0, f(x_0)), (x_1, f(x_1)), \dots\}$ given by an "oracle"
No information is either not available or needed on the definition of objective function

- Objective function given by a computation, or a simulation
- Objective function can be irregular, non differentiable, non continous, etc.
- (Very) large search space for discrete case (combinatorial optimization), *i.e.* NP-complete problems
- Continuous problem, mixt optimization problem

Real-world applications

Typical applications

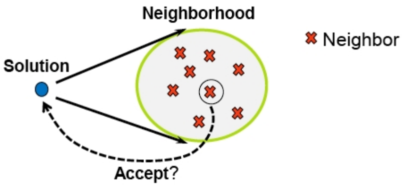
- Large combinatorial problems:
  Scheduling problems, planing problems, DOE,
  "mathematical" problems (Firing Squad Synchronization Pb.), etc.
- Calibration of models:
  Physic world $\Rightarrow$ Model(params) $\Rightarrow$ Simulator(params)
  $$\text{Model(Params)} = \operatorname{argmin}_M \mathrm{Error}(\mathit{Data}, M)$$
- Shape optimization:
  Design (shape, parameters of design)
  using a model and a numerical simulator

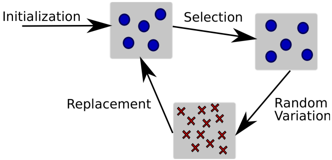
Search algorithms

Principle

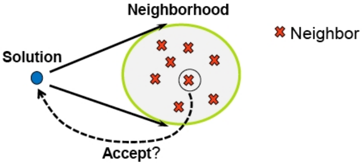
Enumeration of the search space

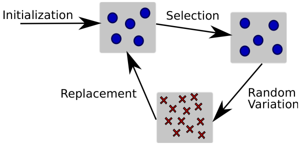
- A lot of ways to enumerate the search space
- Using random sampling: Monte Carlo technics
- Local search technics:





Search algorithms





- **Single solution-based**: Hill-climbing technics, Simulated-annealing, tabu search, Iterative Local Search, etc.
- **Population solution-based**: Genetic algorithm, Genetic programming, ant colony algorithm, etc.

Design components are well-known

- Probability to decrease,
- Memory of path, of sub-space
- Diversity of population, etc.

Research question: Parameters tuning

- One Evolutionary Algorithm key point:
  Exploitation / Exploration tradeoff
- One main practical difficulty:
  Choose operators, design components, value of parameters, representation of solutions
- Parameters setting (Lobo et al. 2007):
  - Off-line before the run: *parameter tuning*,
  - On-line during the run: *parameter control*.

One practical and theoretical question

How to combine correctly the design components according to the problem (in distributed environment...) ?

Research question: Expensive optimization

- Objective function based on a simulation:
  Expensive computation time
- One main practical difficulty:
  With few computation evaluation, choose operators, design components, value of parameters, ...
- Two main approaches:
  - Approximate objective function: *surrogate model*,
  - Parallel computation: *distributed computing*.

One practical and theoretical question

How to combine correctly the design components
with low computational budget
according to the problem in distributed environment... ?

How to solve a multi-criterium problem

Think about the decision problem!

1. Define decision variables
2. Define objective functions (criteria)
3. Define your goal: *a priori*, or *a posteriori*
4. Use an (optimization) algorithm
5. Analyze the result

A priori goal

A priori decision

Decision maker knows what he/she wants before optimization

Weighted sum

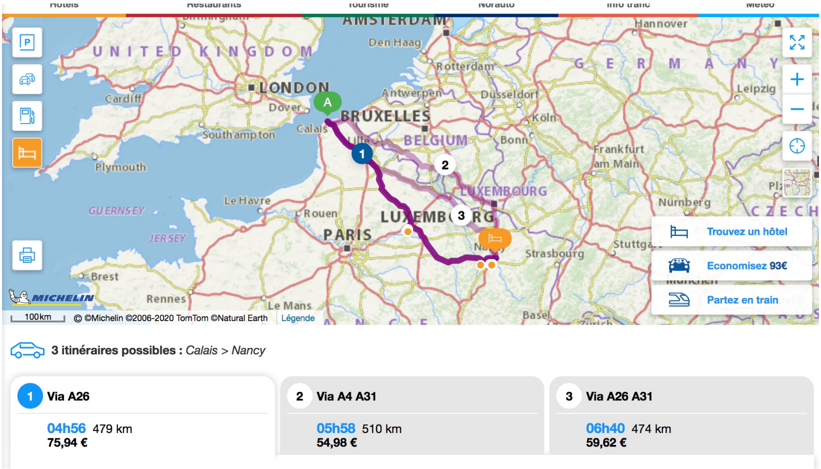
$$f_\lambda(x) = \lambda_1 f_1(x) + \ldots + \lambda_m f_m(x)$$

with $\lambda_i > 0$

- Basic model
- Often used technique
- Convert a multiobjective problem into a single-objective problem
- The definition, and the interpretation are not always straitforward

Small example

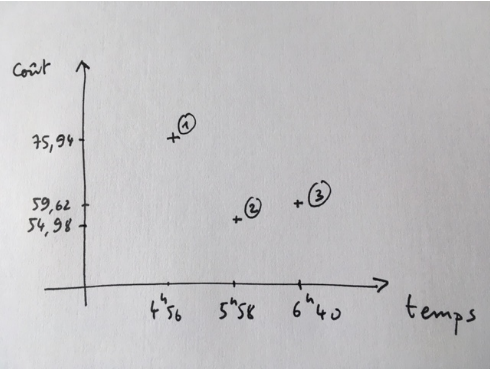
Road trip between Calais and Nancy



Which one is better ?

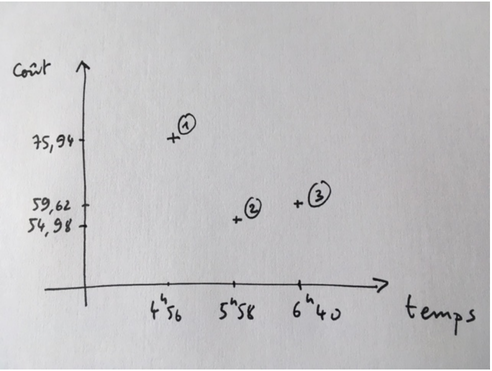
Small example

Road trip between Calais and Nancy



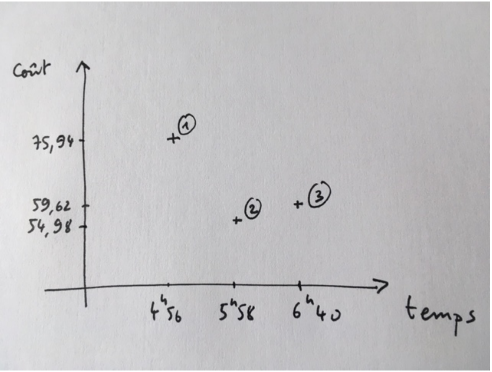
Small example

Road trip between Calais and Nancy



- According to time objective, 1 is better
- According to cost objective, 2 is better
- But, 2 is better than 3 for both objectives.

Pareto dominance



- 1 and 2 are incomparable
- 1 and 3 are incomparable
- 2 is better than 3

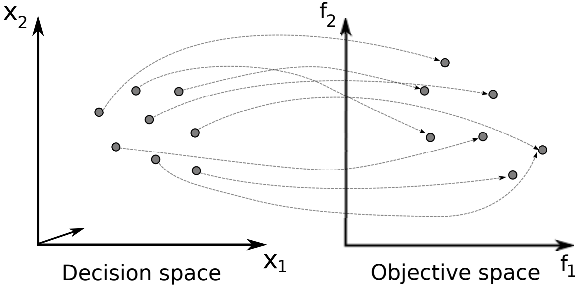
Pareto dominance

- 2 dominates 3
- 3 is dominated by 2

Multiobjective optimization

Multiobjective optimization problem

- $\mathcal{X}$: set of feasible solutions in the decision space
- $M \geqslant 2$ objective functions $f = (f_1, f_2, \dots, f_M)$ (to maximize)
- $\mathcal{Z} = f(\mathcal{X}) \subseteq \mathbb{R}^M$: set of feasible outcome vectors in the objective space

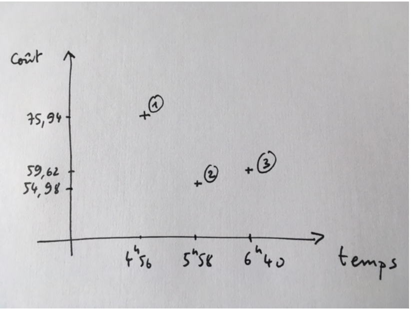


Pareto dominance definition

Pareto dominance relation (maximization)

A solution $x \in \mathcal{X}$ dominates a solution $x' \in \mathcal{X}$ $(x' \prec x)$ iff

- $\forall i \in \{1, 2, \ldots, M\}$, $f_i(x') \leqslant f_i(x)$
- $\exists j \in \{1, 2, \ldots, M\}$ such that $f_j(x') < f_j(x)$

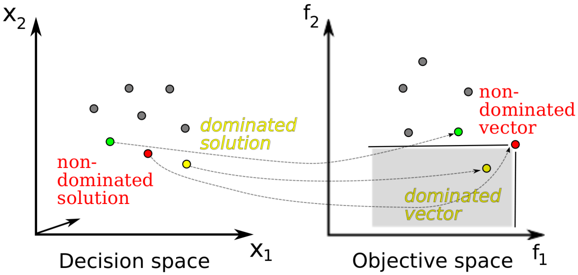


Pareto Optimale solution

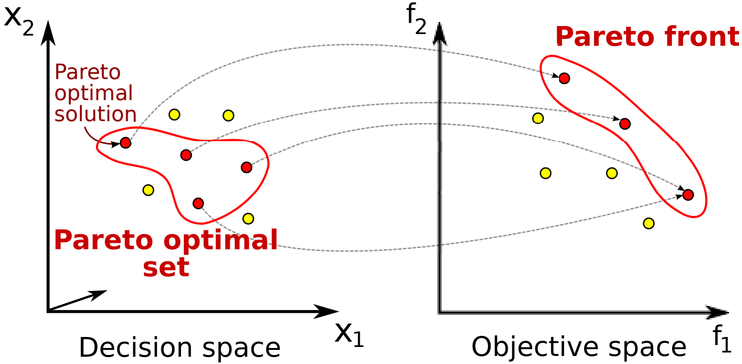
Definition: non-dominated solution

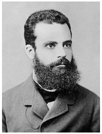
A solution $x \in \mathcal{X}$ is non-dominated (or Pareto optimal, efficient) iff

$$\forall x' \in \mathcal{X} \setminus \{x\},\ x \nprec x'$$



Pareto set, Pareto front



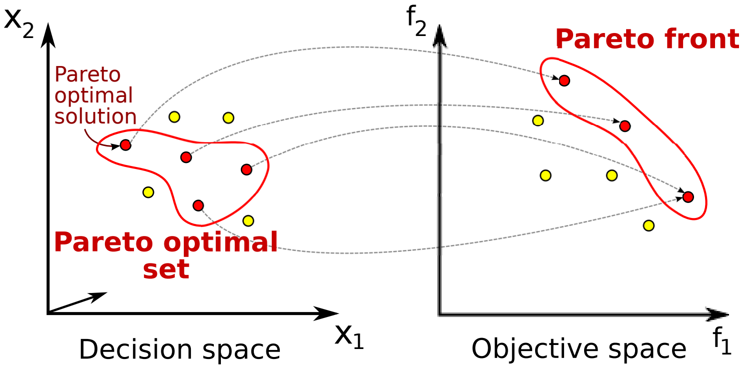


Vilfredo Pareto (1848 - 1923)
source: wikipedia

Multiobjective optimization goal

Goal

Find the Pareto Optimal Set,
or a good approximation of the Pareto Optimal Set
And not a single solution for a single aggregated objective



Challenges

- **Search space**:
  many variables, heterogeneous, dependent variables
- **Objective space**:
  many, heterogenous, expensive objective functions
- **NP-completeness**:
  deciding if a solution is Pareto optimal is difficult
- **Intractability**:
  number of Pareto optimal solutions grows exponentially with problem dimension

Methodology

Typical methodology with MO optimization

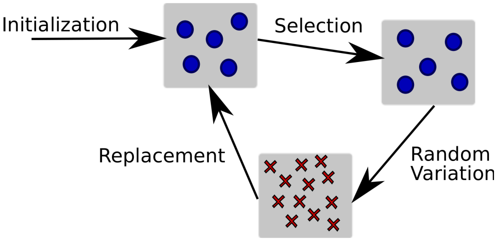
1. Define **decision variables**
2. Define all potential **objective**
3. Define **constraints** (hard/soft/objective)
4. Choose/design a relevant multiobjective **algorithm**
5. Search for an approximation of **Pareto optimal** solutions set
6. **Analyse/visualize** the solutions set

Loop between 1 to 6...

Multi-objective optimization algorithms

Population-based algorithm

A Multi-Objective (MO) algorithm is an Evolutionary Algorithm : the goal is to find a set of solutions



Evolutionary Multi-Objective (EMO) algorithm

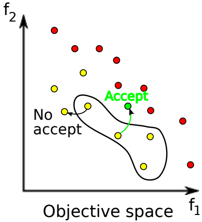
Main types of MO algorithms

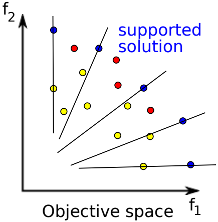
Three main classes:

(1) Pareto-based approaches: directly or indirectly focus the search on the Pareto dominance relation.
Pareto Local Search (PLS), Global SEMO, NSGA-II, etc.

(2) Indicator approaches: Progressively improvement the indicator function: IBEA, SMS-MOEA, etc.

(3) Scalar approaches: multiple scalarized aggregations of the objective functions: MOEA/D, etc.





(1) Pareto-based approaches

EMO based on dominance relation to update set of solutions (archive)

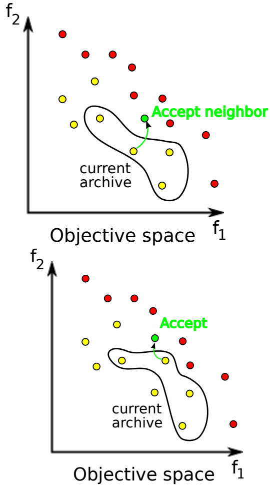
example of: Pareto Local Search (PLS)

Pick a random solution $x_0 \in X$
$A \leftarrow \{x_0\}$
repeat
  Select a non-visited $x \in A$
  Create neighbors $N(x)$ by flipping each bit of x in turns
  Flag x as visited
  $A \leftarrow$ non-dominated sol. from $A \cup N(x)$
until all-visited $\vee$ maxeval

[Paquete *et al.* 2004][8]

A Pareto-based approach: Pareto Local Search

- Archive solutions using **Dominance relation**
- Iteratively improve this archive by exploring the neighborhood



Pareto-based approaches : G-SEMO

local search:
Pareto Local Search (PLS)

Pick a random solution $x_0 \in X$
$A \leftarrow \{x_0\}$
repeat
  Select a non-visited $x \in A$
  Create $N(x)$ by flipping each bit of x in turns
  Flag x as visited
  $A \leftarrow$ non-dom. from $A \cup N(x)$
until all-visited $\vee$ maxeval

[Paquete *et al.* 2004][8]

global search:
Global-Simple EMO (G-SEMO)

Pick a random solution $x_0 \in X$
$A \leftarrow \{x_0\}$
repeat
  Select $x \in A$ at random
  Create x' by flipping each bit of x with a rate $1/N$
  $A \leftarrow$ non-dom. from $A \cup \{x'\}$
until maxeval

[Laumanns *et al.* 2004][6]

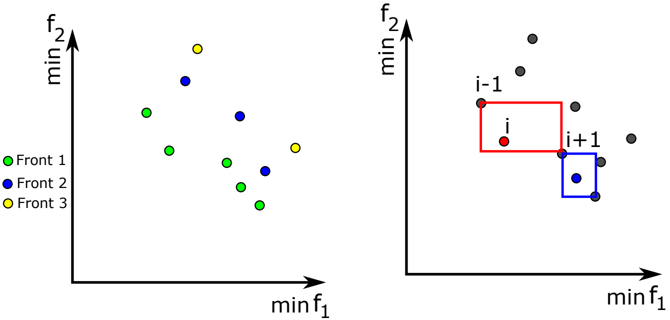
A Pareto-based approach: NSGA-II (Deb et al. 2000)

- No archive of solutions
- Classical EA based on crowding distance
- Replacement: elitist based on non-dominated sorting, and crowding distance

Evolutionary Algorithm (EA)

```
repeat
    selection(pop, children)
    random_variation(children)
    replacement(pop, children)
until stoping_criterium(pop)
```

NSGA-II: non-dominated sorting, crowding distance



- Selection:
  binary tournament using sorting, and crowding distance
- Random variation:
  crossover, mutation, etc.
- Replacement:
  elitist based on non-dominated sorting, and crowding distance

NSGA-II: non-dominated sorting, crowding distance

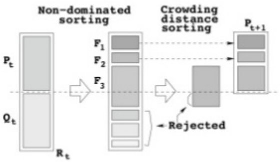


Figure: Non-dominated Selection [Deb et al. 2000]

+

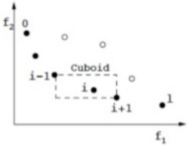


Figure: Crowding distance [Deb et al. 2000]

- Selection:
  binary tournament using sorting, and crowding distance
- Random variation:
  crossover, mutation, etc.
- Replacement:
  elitist based on non-dominated sorting, and crowding distance

(2) Indicator-based approches

Single objective optimization at population level :

- Associate one indicator (scalar value) to each population
- Optimization of this indicator

Possible indicators: hypervolume, epsilon-indicator, etc.

SMS-MOEA: $\mathcal{S}$ metric selection-MOEA

[Beume *et al.* 2007][1]

$P \leftarrow$ initialization()
repeat
  $q \leftarrow$ Generate(P)
  $P \leftarrow$ Reduce($P \cup \{q\}$)
until maxeval

Generate

Use random variation (mutation, etc.) to create one candidate solution

Reduction

Remove the worst solution according to non-dominated sorting, and $\mathcal{S}$ metric

Algorithm 2. Reduce(Q)

1: $\{\mathcal{R}_1, \ldots, \mathcal{R}_v\} \leftarrow$ fast-nondominated-sort(Q) /* all v fronts of Q */
2: $r \leftarrow \mathrm{argmin}_{s \in \mathcal{R}_v}[\Delta_{\mathcal{S}}(s, \mathcal{R}_v)]$ /* $s \in \mathcal{R}_v$ with lowest $\Delta_{\mathcal{S}}(s, \mathcal{R}_v)$ */
3: **return** $(Q \backslash \{r\})$ /* eliminate detected element */

A $\mathcal{S}$-metric is an indicateur such hypervolume

IBEA: Indicator-Based Evolutionary algorithm

[Zitzler *et al.* 2004][10]

$P \leftarrow$ initialization()
repeat
  $P^{'} \leftarrow$ selection(P)
  $Q \leftarrow$ random_variation($P^{'}$)
  Evaluation of Q
  $P \leftarrow$ replacement(P, Q)
until maxeval

Fitness assignment

- Pairwise comparison of solutions in a population w.r.t. indicator i
- Fitness value: "loss in quality" in the population P if x was removed

$$f(x) = \sum_{x^{'} \in P \setminus \{x\}} (-e^{-i(x^{'},x)/\kappa})$$

- Often the ϵ-indicator is used

(3) Decomposition based approaches: MOEA/D

Principe

Divide the multi-objective problem
into several single-objective sub-problems

Cooperation
between different single-objective sub-problems

Original MOEA/D [9] (minimization)

/ μ sub-problems defined by μ directions */*
$(\lambda^1, \ldots, \lambda^\mu) \leftarrow$ initialization_direction()
Initialize $\forall i = 1..\mu$ $B(i)$ the neighboring sub-problems of sub-problem i
/ one solution for each sub-problem */*
$(x^1, \ldots, x^\mu) \leftarrow$ initialization_solution()
repeat
  for $i = 1..\mu$ **do**
    Select x and $x^{'}$ randomly in $\{x_j \ : \ j \in B(i)\}$
    $y \leftarrow$ mutation_crossover(x, $x^{'}$)
    for $j \in B(i)$ **do**
      if $g(y|\lambda_j, z_j^\star) < g(x_j|\lambda_j, z_j^\star)$ **then**
        $x_j \leftarrow y$
      end if
    end for
  end for
until max_eval

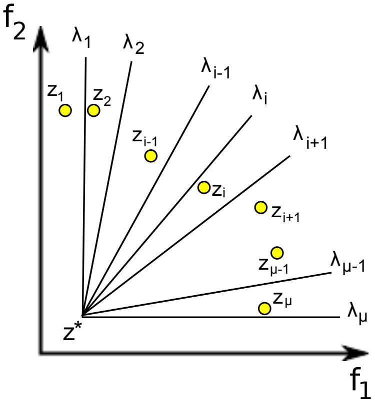
$B(i)$ is the set of the T closest neighboring sub-problems of sub-problem i
$g(\ |\lambda_i, z_i^\star)$: scalar function of sub-pb. i with λ_i direction, and $z_i^\star$ reference point

MOEA/D steady-state variant

Another MOEA/D (minimization)

/ μ sub-problems defined by μ directions */*
$(\lambda^1, \ldots, \lambda^\mu) \leftarrow$ initialization_direction()
Initialize $\forall i = 1..\mu$ $B(i)$ the neighboring sub-problems of sub-problem i
/ one solution for each sub-problem */*
$(x^1, \ldots, x^\mu) \leftarrow$ initialization_solution()
repeat
    Select i at random $\in 1..\mu$
    Select x randomly in $\{x_j \;:\; j \in B(i)\}$
    $y \leftarrow$ mutation_crossover(x_i, x)
    for $j \in B(i)$ **do**
        if $g(y|\lambda_j, z_j^\star) < g(x_j|\lambda_j, z_j^\star)$ **then**
            $x_j \leftarrow y$
        end if
    end for
until max_eval

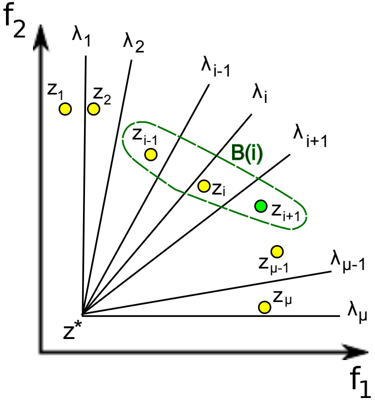
Representation of steady-state MOEA/D



Population at iteration t

- Minimization problem
- One solution x_i for each sub pb. i
- Representation of solutions in objective space: $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Scalar function g: Weighted Tchebycheff
- Neighborhood size $\sharp B(i) = T = 3$

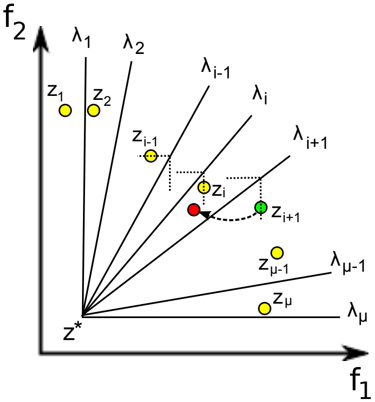
Representation of steady-state MOEA/D



From the neigh. $B(i)$ of sub-pb. i,
x_{i+1} is selected

- Minimization problem
- One solution x_i for each sub pb. i
- Representation of solutions in objective space: $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Scalar function g:
  Weighted Tchebycheff
- Neighborhood size $\sharp B(i) = T = 3$

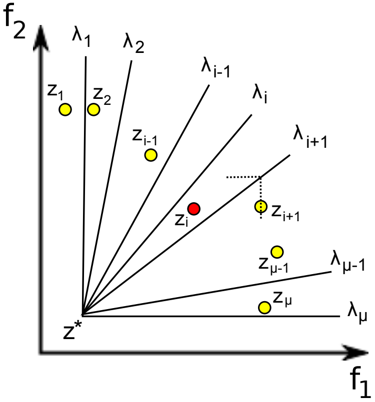
Representation of steady-state MOEA/D



The mutated solution y is created

- Minimization problem
- One solution x_i for each sub pb. i
- Representation of solutions in objective space: $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Scalar function g: Weighted Tchebycheff
- Neighborhood size $\sharp B(i) = T = 3$

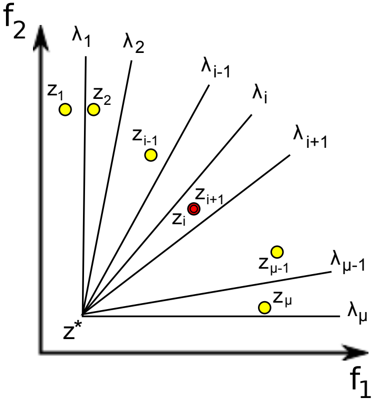
Representation of steady-state MOEA/D



According to scalar fonction,
y is worst than x_{i-1},
y is better than x_i and replaces it.

- Minimization problem
- One solution x_i for each sub pb. i
- Representation of solutions in objective space: $z_i = g(x_i|\lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Scalar function g: Weighted Tchebycheff
- Neighborhood size $\sharp B(i) = T = 3$

Representation of steady-state MOEA/D



According to scalar fonction,
y is also better than x_{i+1}
and replaces it for the next iteration.

- Minimization problem
- One solution x_i for each sub pb. i
- Representation of solutions in objective space: $z_i = g(x_i | \lambda_i, z_i^\star)$
- Same reference point for all sub-pb. $z^\star = z_1^\star = \ldots = z_\mu^\star$
- Scalar function g:
  Weighted Tchebycheff
- Neighborhood size $\sharp B(i) = T = 3$

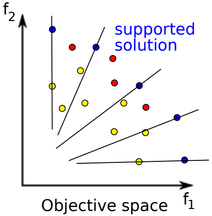
Decomposition based approaches: MOEA/D

Main issues

1. Impact of the scalar function:
   cf. Slide suivant et `ppsn2014poster-impactScalarFunction.pdf` [Derbel *et. al.*, 2014] [2]
2. Direction of search:
   cf.[Derbel *et. al.*, 2014] [3]
3. Cooperation between sub-problems:
   cf. slides Nagano: `2014-06-19-nagano-moeadxy.pdf` [Gauvain *et al.*, 2014] [7]
4. Parallelization:
   cf. algorithm of "A fine-grained message passing MOEA/D" [Derbel *et al.*, 2015] [4]
   cf. [Drouet *et al.*, 2021] [5]

Scalar approaches: scalarizing function

- multiple scalarized aggregations of the objective functions



Different aggregations

- Weighted sum:

$$g(x|\lambda) = \sum_{i=1..m} \lambda_i f_i(x)$$

- Weighted Tchebycheff:

$$g(x|\lambda, z) = \max_{i=1..m} \{\lambda_i |z_i - f_i(x)|\}$$

- ... cf. poster PPSN 2014

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