M2 AIC - Optimization

Indicator-Based Evolutionary Algorithm - IEBA

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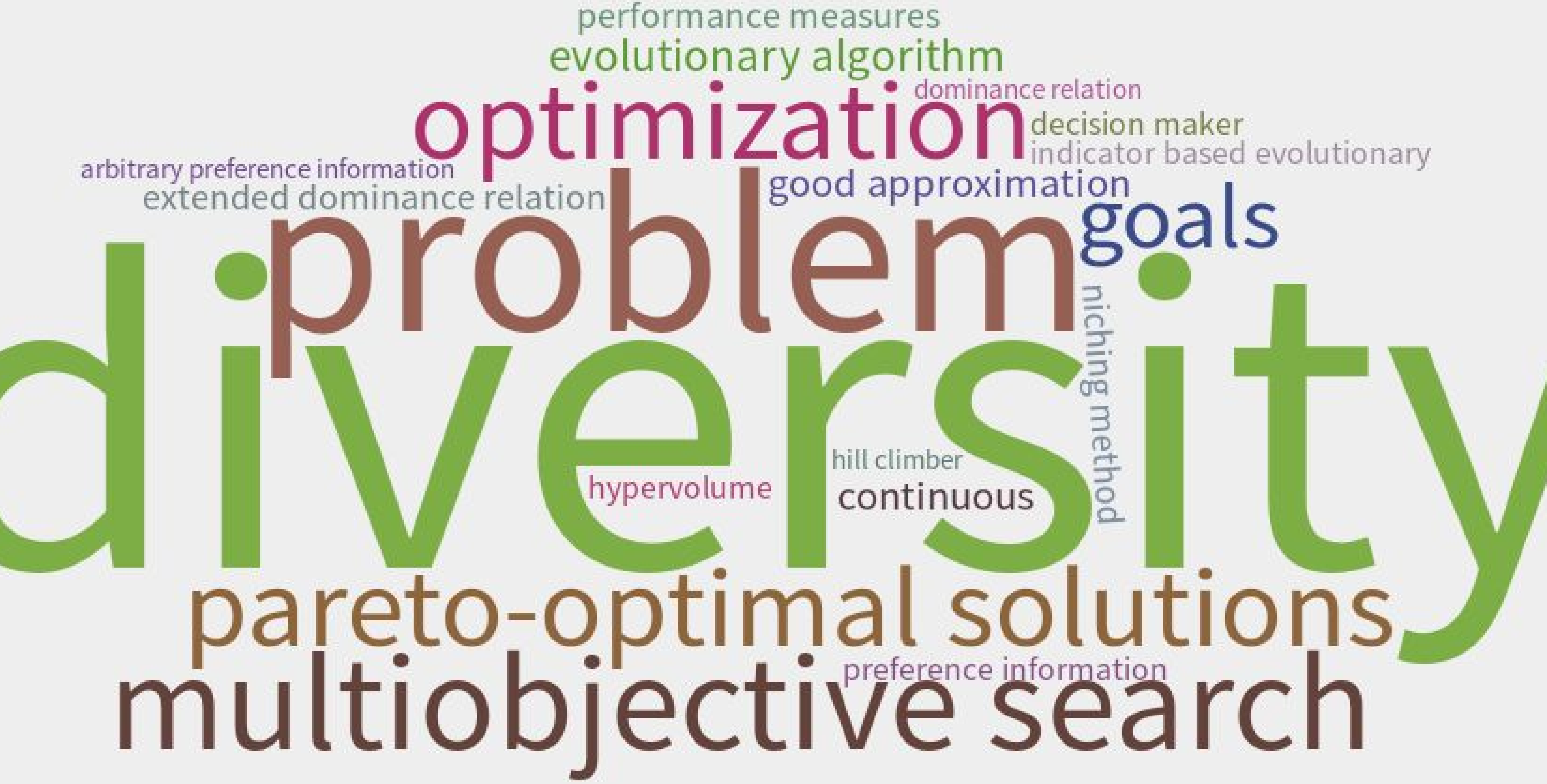
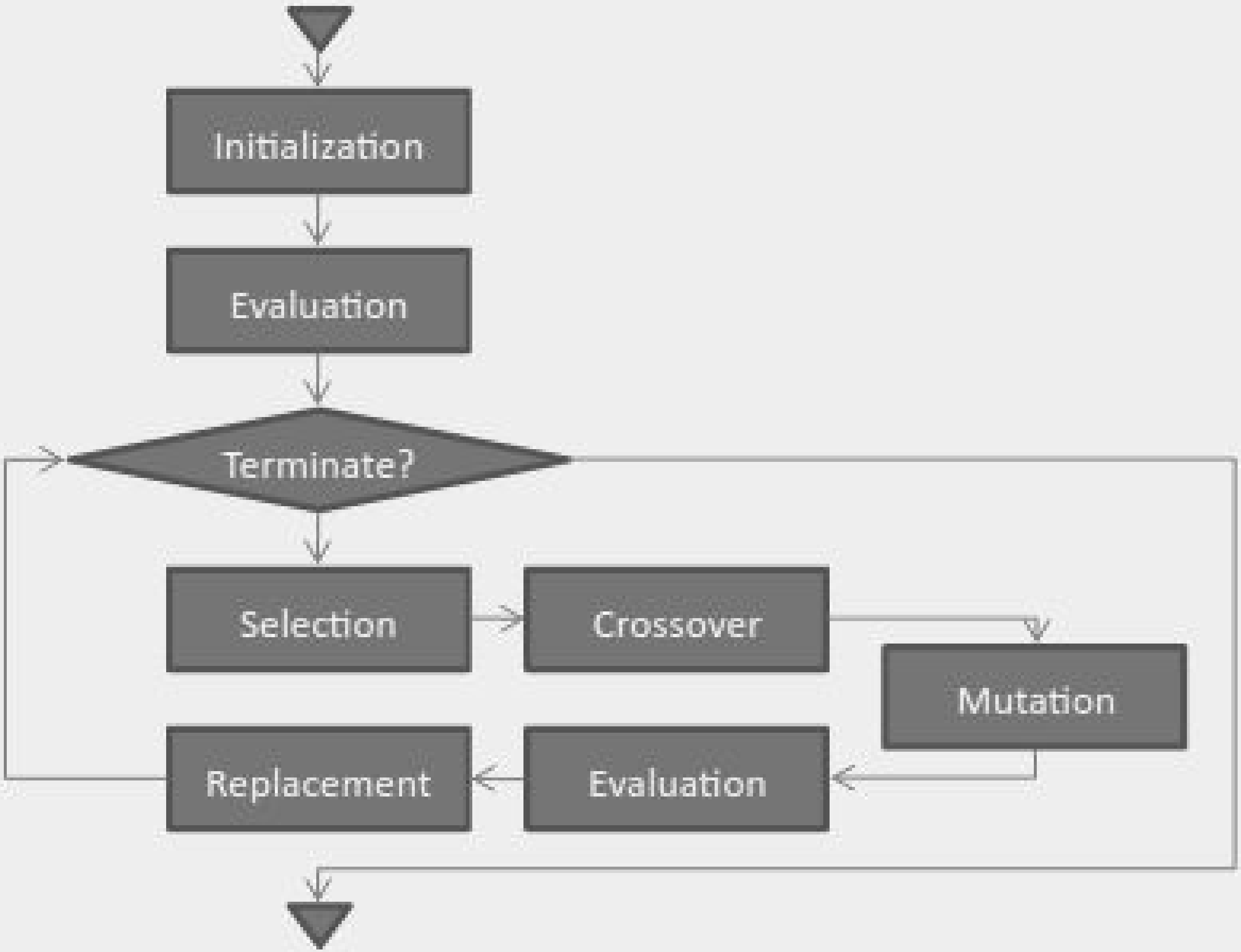
Plan

- Introduction : Multiobjective Optimisation & EA
- MOEA’s
- Adaptative IBEA
- IEBA’s steps (Implementation)
- Test & Results
- Comparaison
- Conclusion


performance measures
evolutionary algorithm
dominance relation
optimization
decision maker
indicator based evolutionary
arbitrary preference information
extended dominance relation
good approximation
goals
problem
diversity
niching method
hill climber
hypervolume
continuous
pareto-optimal solutions
preference information
multiobjective search

Evolutionary Algorithms

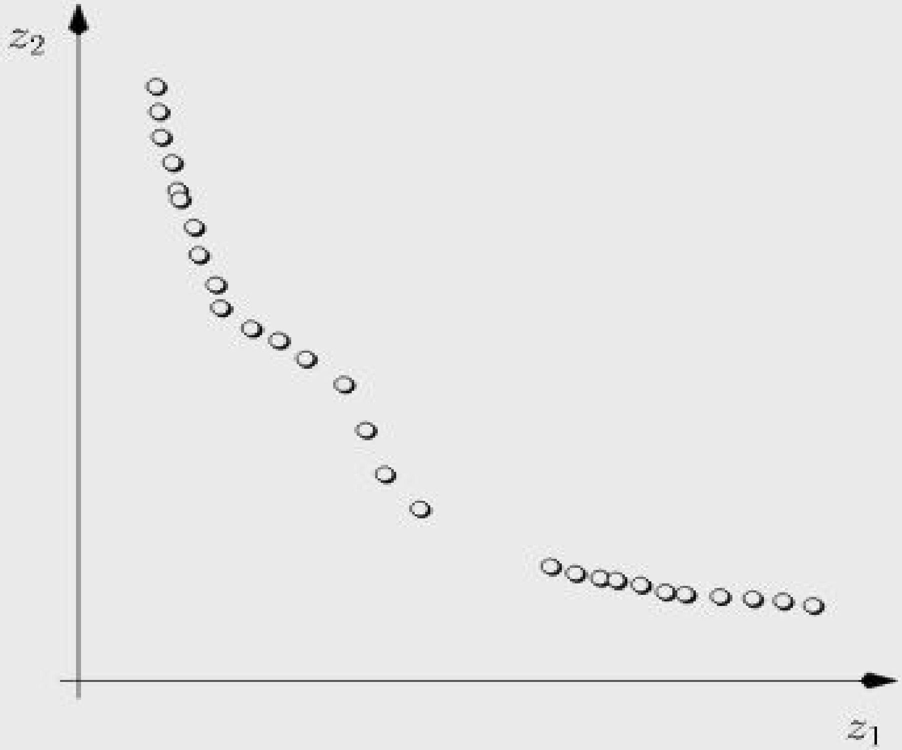


EA for Multiobjective optimization

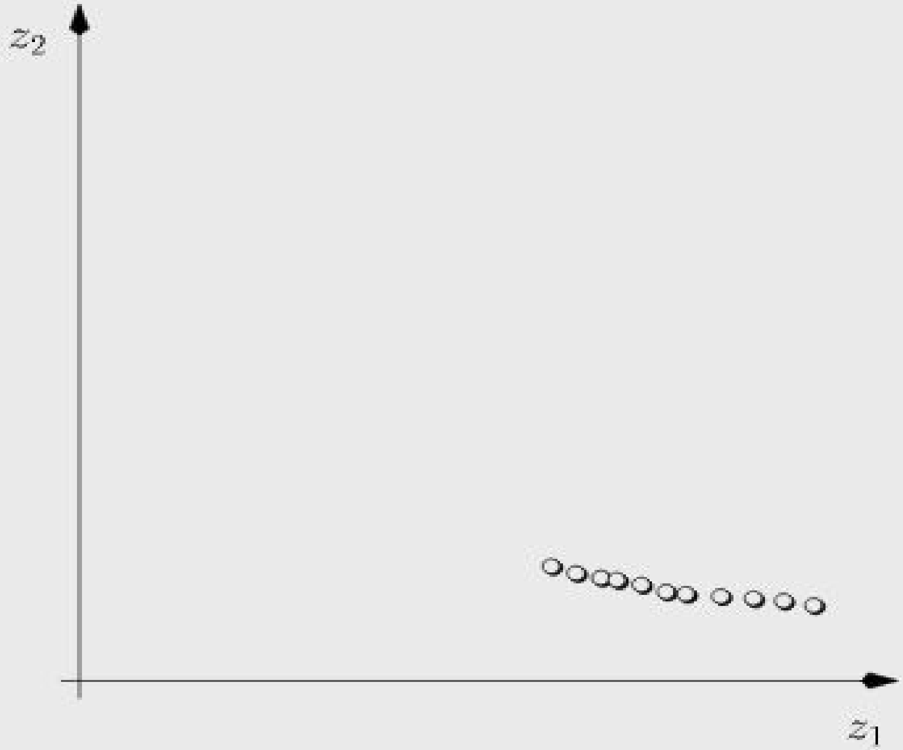
Evolutionary Algorithms (EAs) have earned popularity in solving MOPs thanks to two reasons:

(1) EAs are able to find multiple non-dominated solutions, which portrays a trade-off among objectives, in a single simulation run.

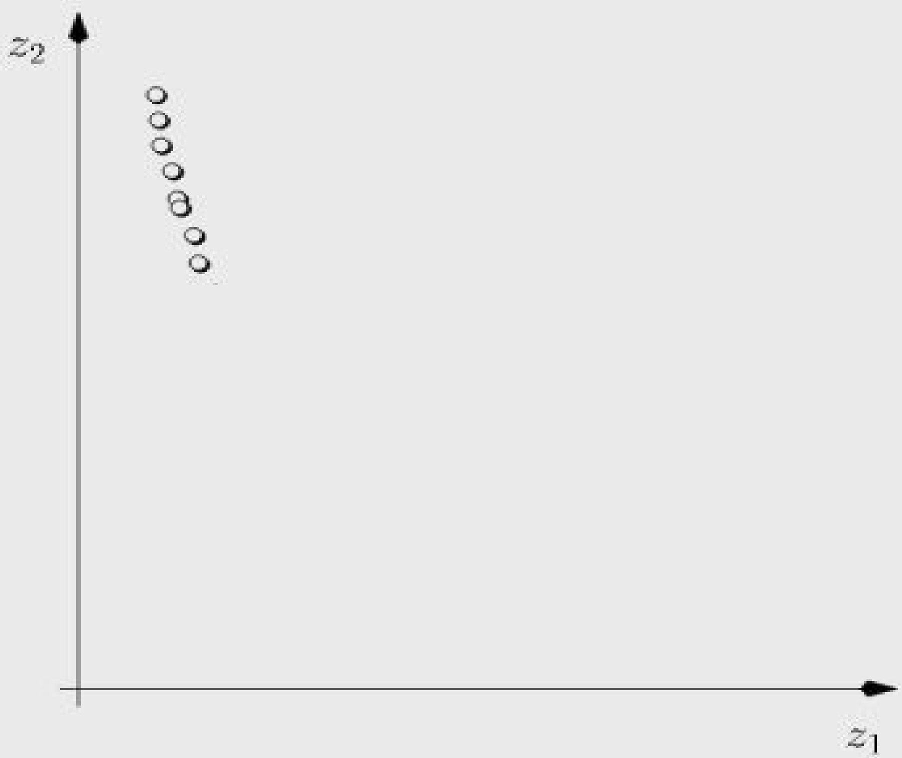
(2) EAs are insensitive to the shape of the objective functions such as nonconvexity, discontinuity, multimodality, non-uniformity of the search space,



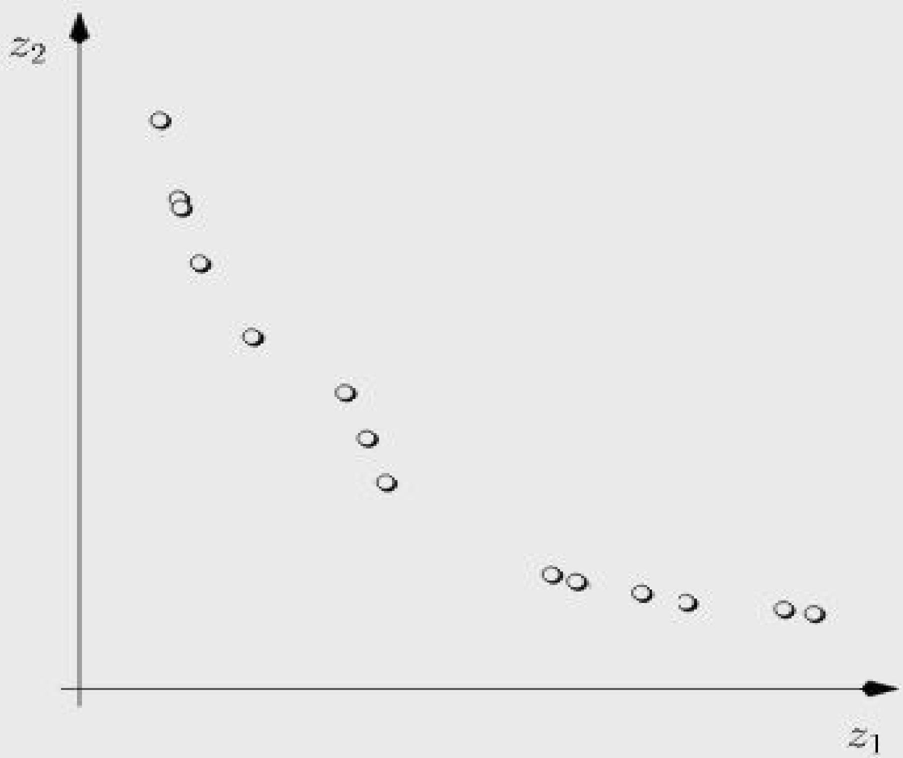
z_2
z_1



z_2
z_1



z_2
z_1



z_2
z_1

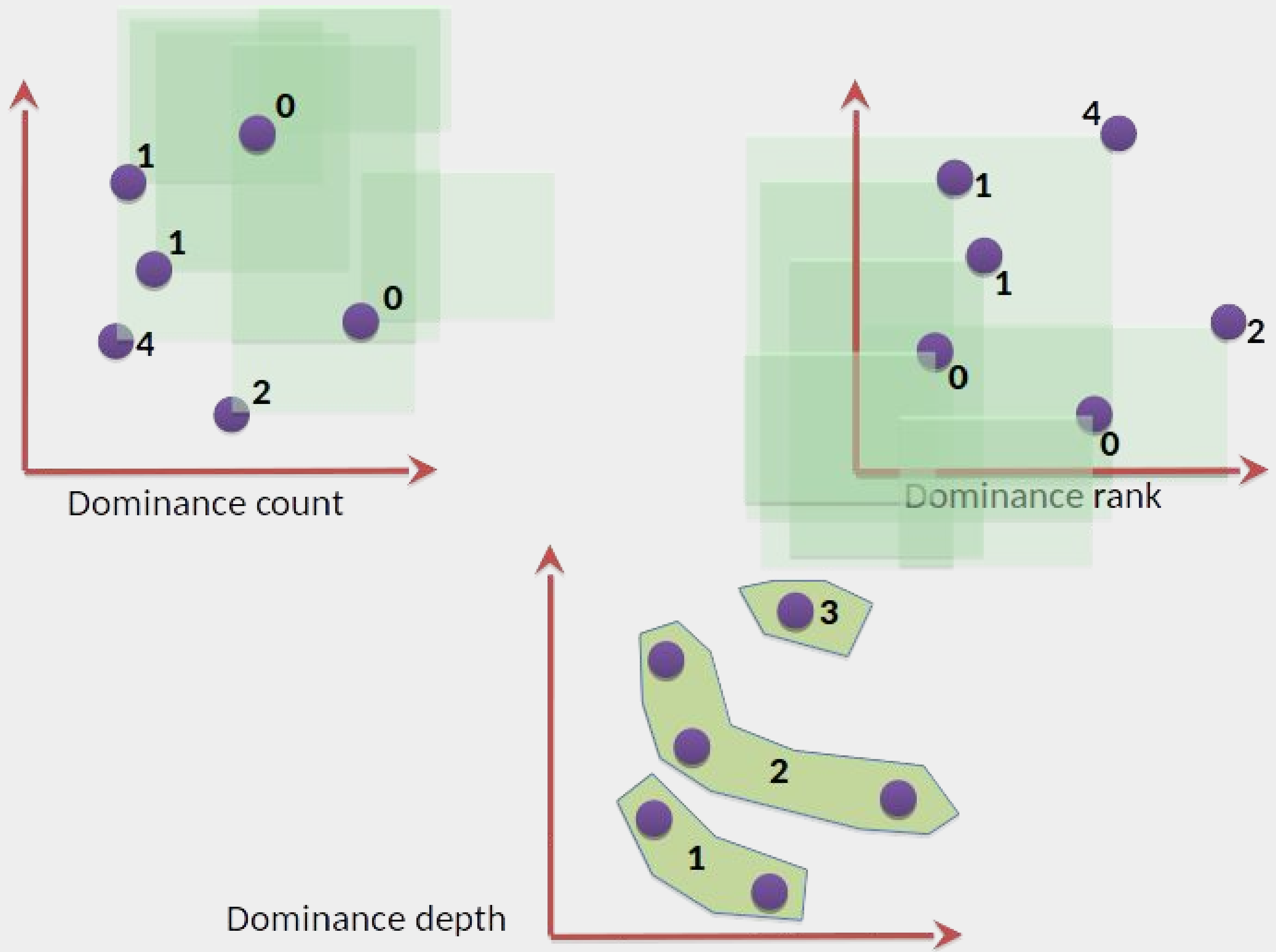
MOEA

- Solutions lie on the Pareto set
- Solutions are diverse enough

→ **Conflict**

- Need another performance measure
- Metrics : convergence,spread,both

MOEAs - Pareto-Based Ranking



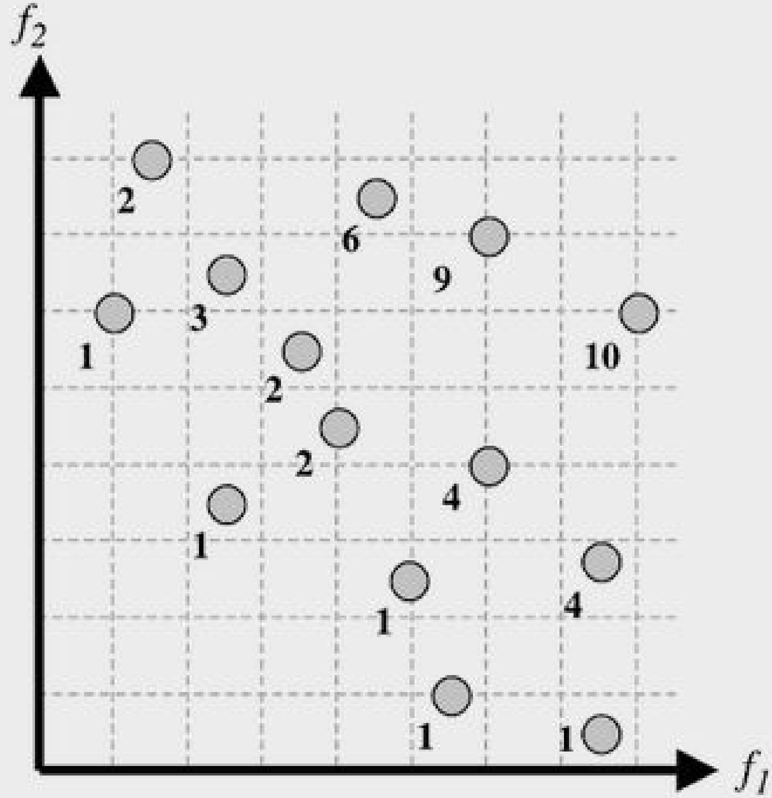
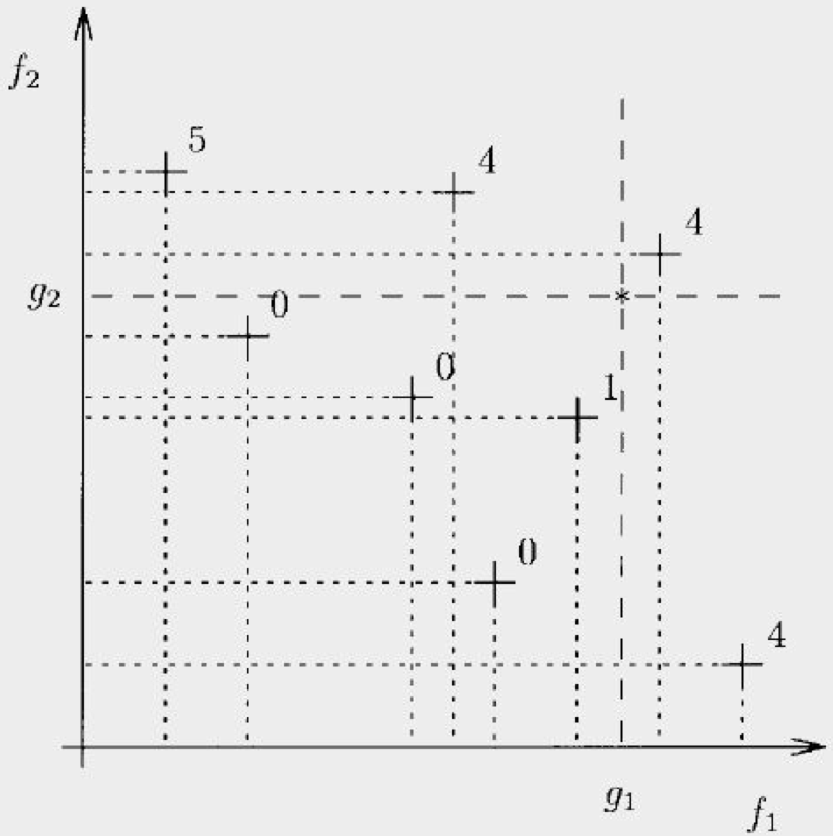
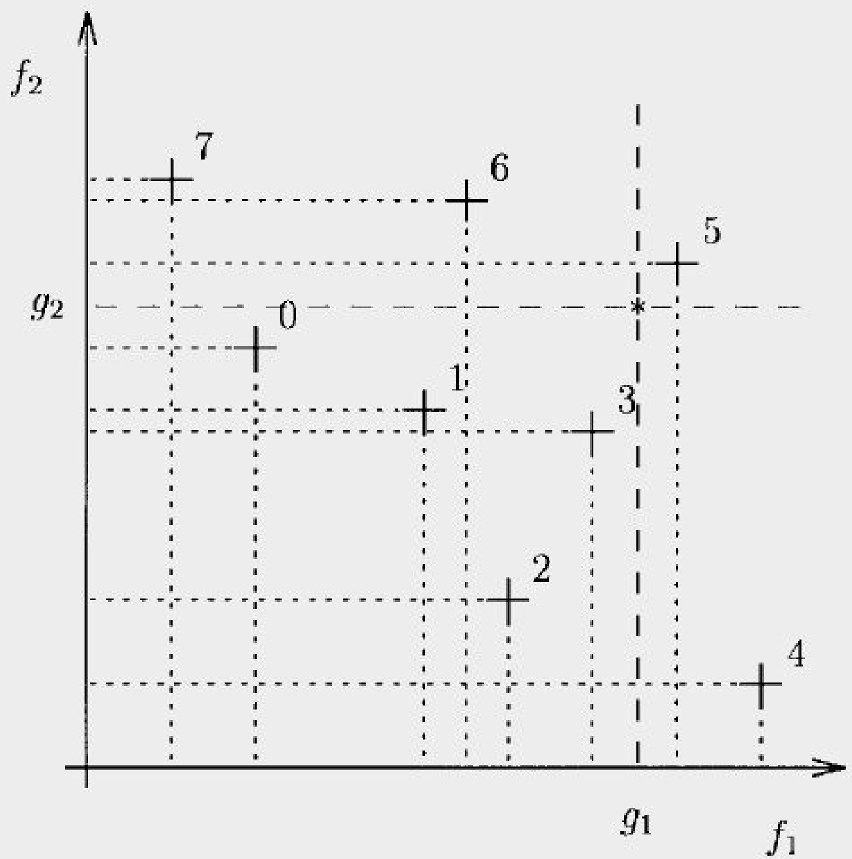


FIGURE 10.7 Illustration of fitness computation for MOGA in a biobjective minimization problem. The rank of a given individual corresponds with 1 plus the number of individuals by which it is dominated. Nondominated individuals have rank 1. The number by each individual is their rank.



-
- \- Multiobjective ranking with goal values (minimization).
- \- f(2) has the same priority as f(1)

- \- f(2) has greater priority than f(1)



Adaptative IBEA 1/3

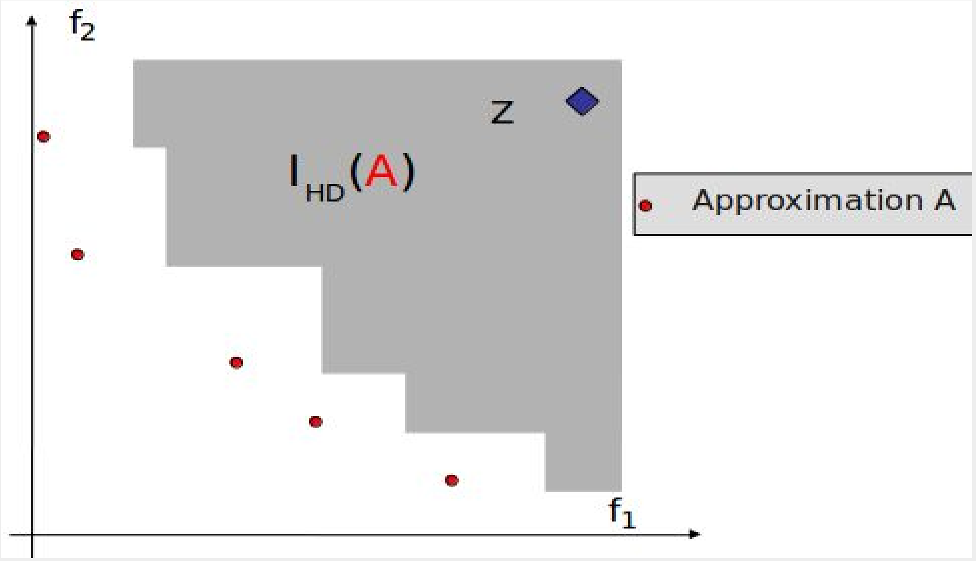
Principle

- Start from a random of initial solutions
- Use the dominance relationships based on a quality indicator for calculate the fitness
- Conclude Pareto Approximative sets

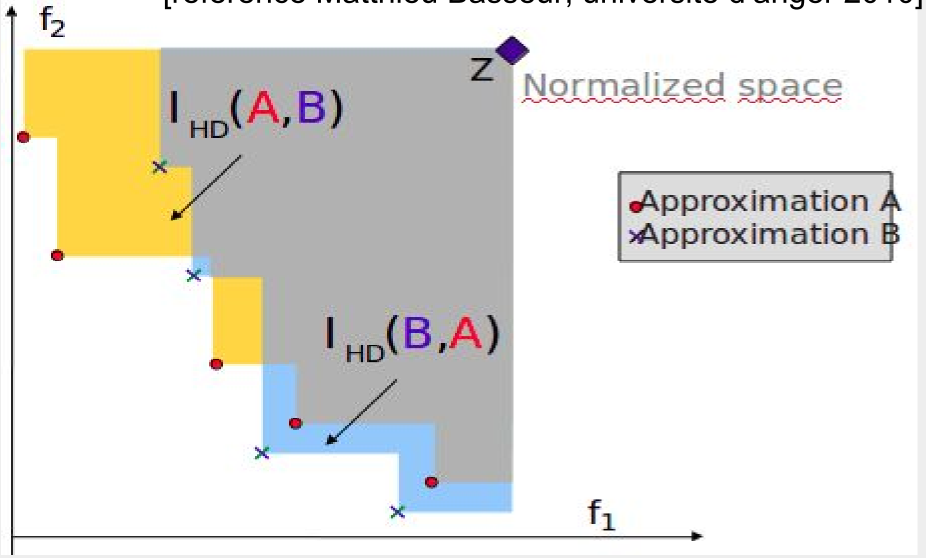
Adaptative IBEA 2/3

Hyper-Volume Indicator

- Define indicators which are able to evaluate a set of solutions and optimize them during the search.
- Binary indicator → compare 2 individuals (domination relationships)
- i(x,y) is the volume of space dominated by y and not dominated by x



[reference Matthieu Basseur, université d'anger 2010]



Adaptative IBEA 3/3

Fitness Assignment

- A Population represents a sample of the decision space and Fitness assignment try to rank the population members according to their usefulness regarding the optimal goal [Eckart Zitzler and Simon Künzli].
- Define a binary indicator which allows to compare two solutions
- Compare x against every solution in P using indicator I to compute x fitness
- loss in quality

IBEA Steps

- Step 1 - Initialization
- Step 2 - Fitness assignment
- Step 3 : Environmental selection
- Step 4 - Mating selection
- Step 5 - Variation
- Step 6 : Termination

IBEA Steps - Initialization

Population P

Alpha population size

Generate Array F = fun(P)
with two objectives to calculate
Pareto set

IBEA Steps - Fitness assignment

INPUT

population

Z

Fitness scaling factor: 0.05

- Calculate fitness values of individuals in P.
- Fitness value is calculated by using.
- HyperVolume Indicator with sub-function "indicator value(x1 , x2, reference point Z)".

- Reference Point Z(2,2)

OUTPUT

Fitness values of each individual
Hypervolume indicator values
Maximum absolute indicator value C

IBEA Steps - Fitness assignment

1. Scale each objective value f_i in the interval [0; 1]

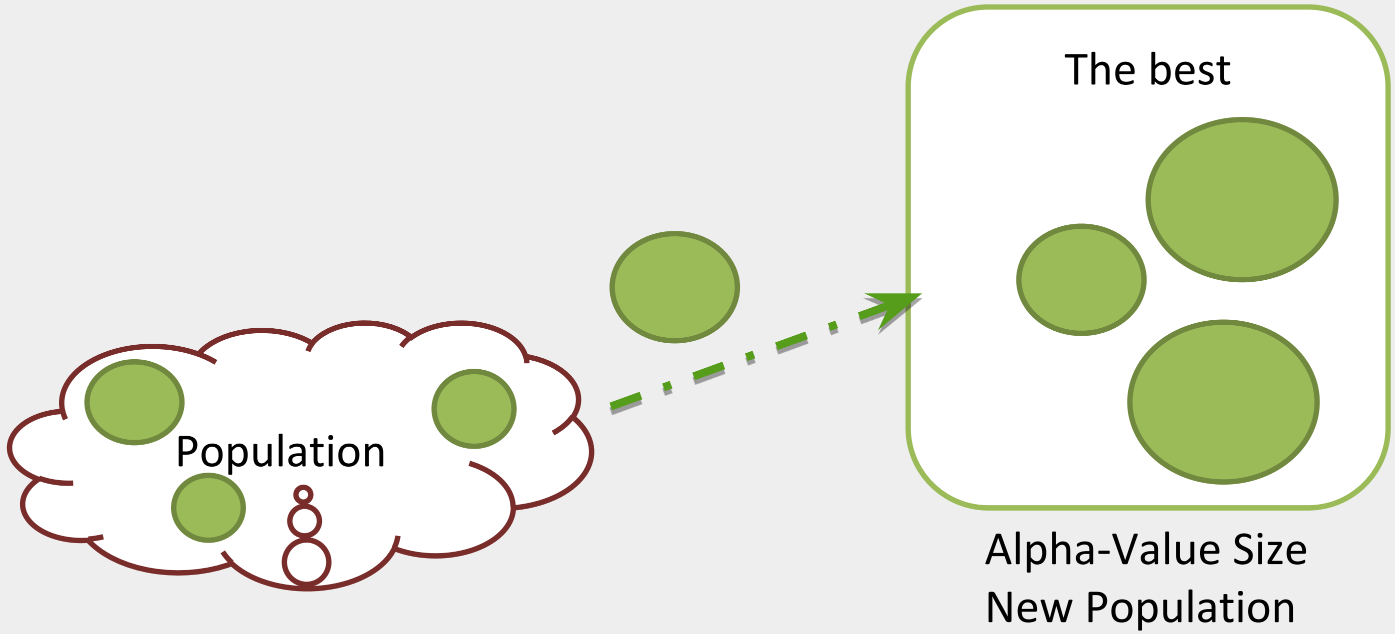
$$f_i'(x) = \frac{f_i(x) - lb_i}{ub_i - lb_i} \quad \begin{cases} lb_i = min_{x \in P} f_i(x) \\ ub_i = max_{x \in P} f_i(x) \end{cases}$$

$$F(x^1) = \sum_{x^2 \in P \ without \ x^2} -e^{-I(X^1, X^2)/(c.k)}$$

2. Sub-Function: Indicator value

IBEA Steps - Environmental selection

Remove individuals having smallest fitness value until Alpha-Value individuals chosen



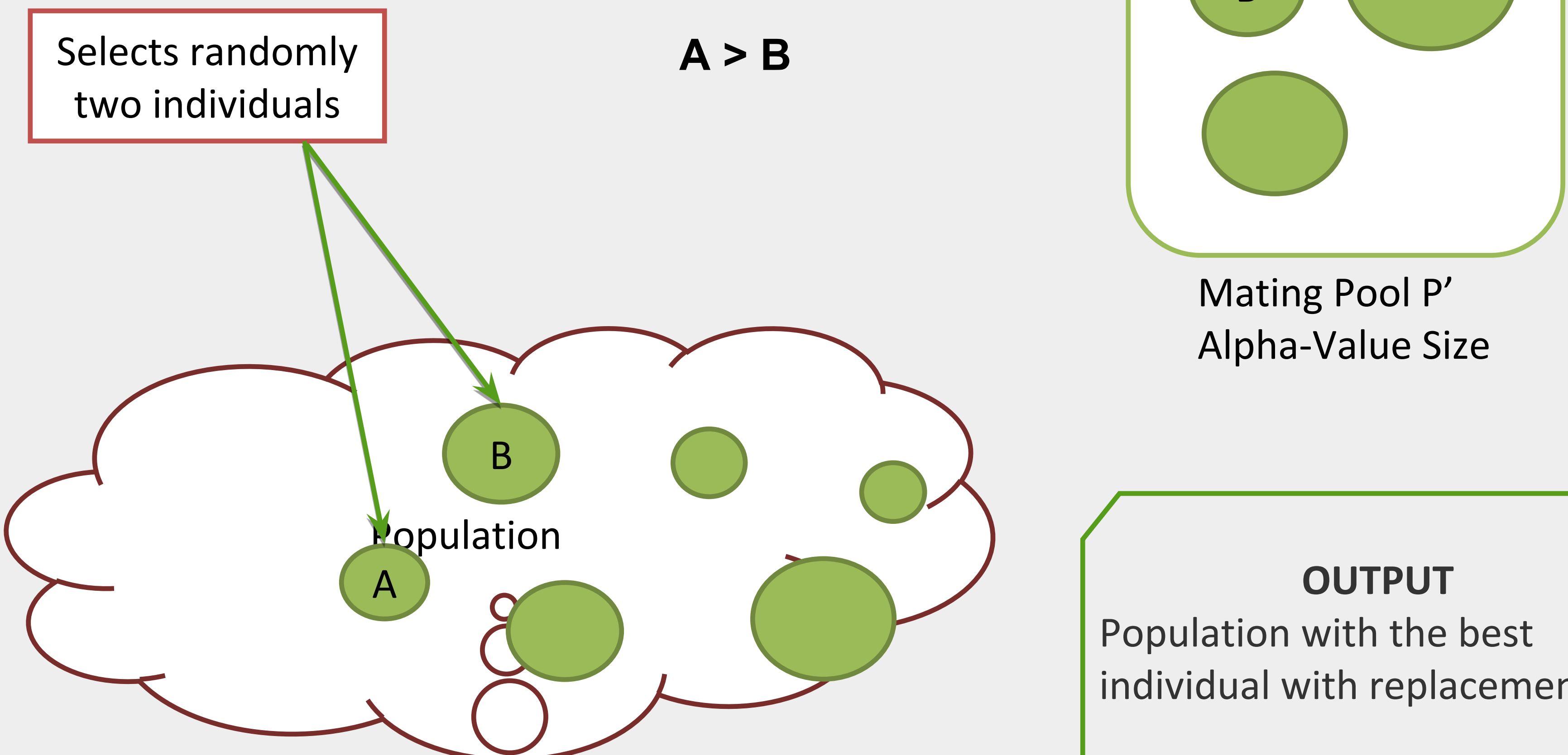
Update the fitness value of the remaining individuals for all x ∈ P:

OUTPUT

The population - the best individuals
New Fitness values
New HyperVolume indicator values

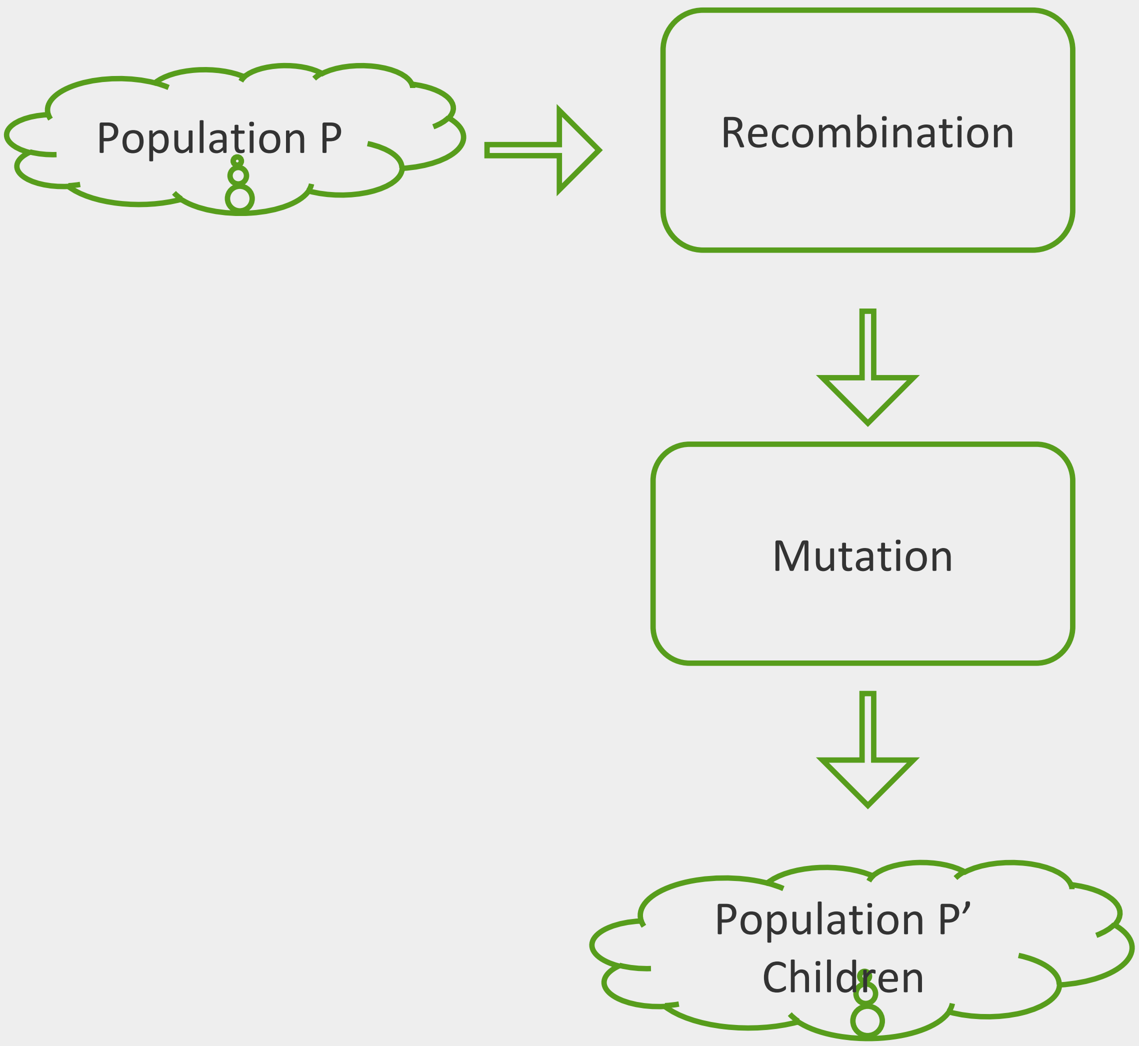
IBEA Steps - Mating selection

Selects randomly two individuals for binary tournament
Where the individual with the best fitness value is placed in the temporary mating pool P' until Alpha-Value individuals are chosen.



OUTPUT
Population with the best individual with replacements

IBEA Steps - Variation



IBEA Steps - Variation

We compared two methods

Cycle Crossover	Line Crossover
Swap Mutation	Gaussian Mutation

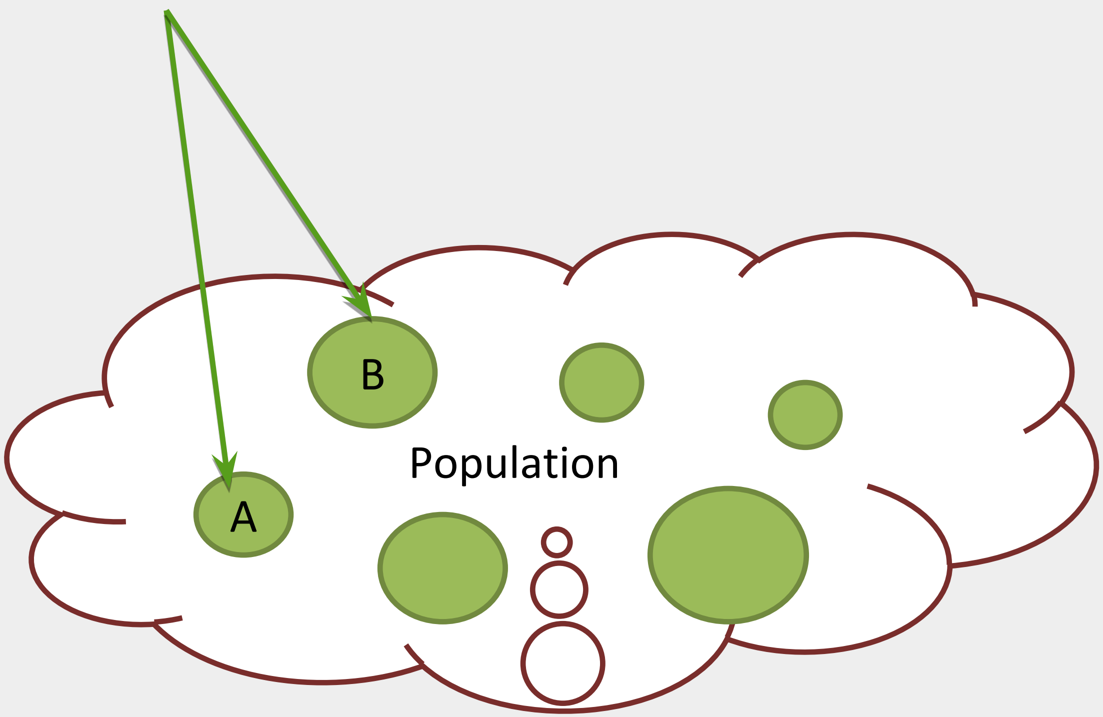
IBEA Steps - Recombinaison

Line Crossover

Selects randomly a ∈ [-0.25, 1.5]

Selects randomly two parents from P’

$$X_i^{C_i} = X_i^{P_1} * a_i + X_i^{P_2} * (1 - a_i)$$



IBEA Steps – Gaussian Mutation

INPUT

population

We add to each vector entry of the individual a randomly produced number from a Gaussian distribution with mean equal to zero.

In this case, the variance of the distribution is a parameters, which is also the case for the swapping possibility.

OUTPUT

Pchild

IBEA Steps - Termination

INPUT

population

HyperVolume indicator values

If

Max Generation counter
= Max Generation value

OR

budget < 0

else

STEP 2

Recalculate Fitness
assignment values

OUTPUT

The Pareto Set

non dominated selection

Tests & Results

Cases

Population size : α ,maximum number of generation : N ,mutation rate = μ

* Population Size:

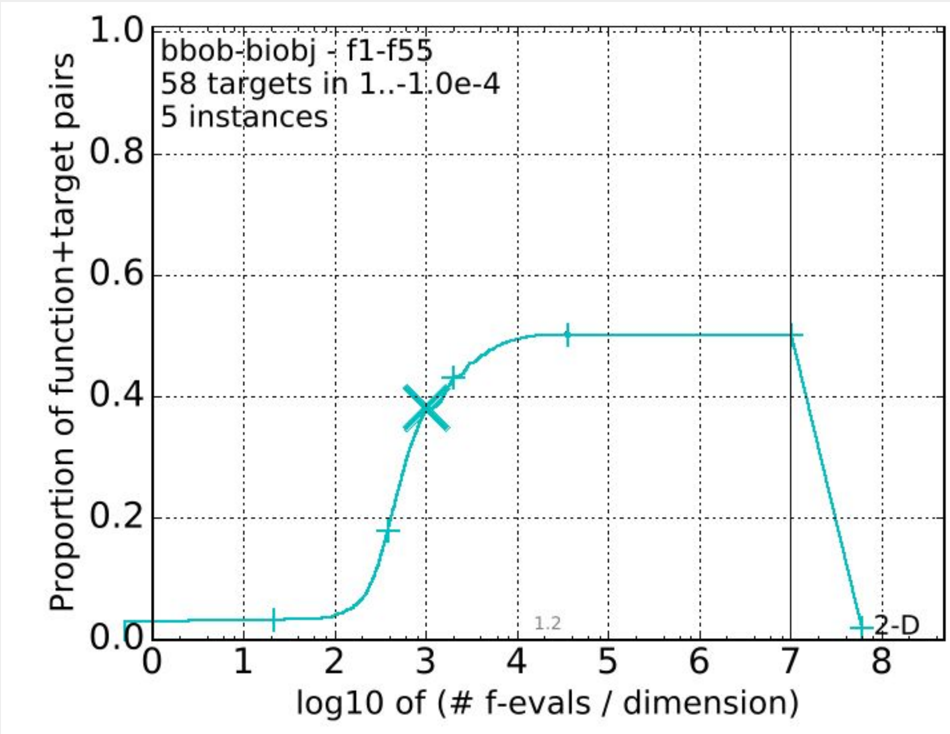
  - α=**150** , N=100 , μ=0.1
  - α=200 , N=100 , μ=0.1

* Max. Num. Generation

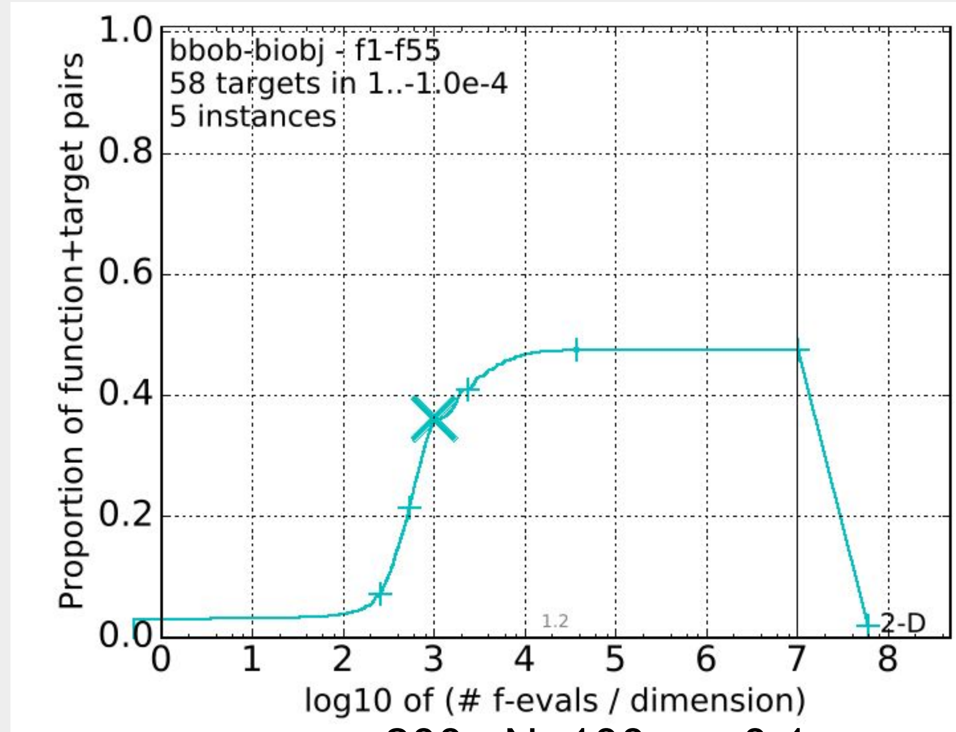
  - α=80 , N=100 , μ=0.1
  - α=80 , N=**150** , μ=0.1

* Mutation Rate

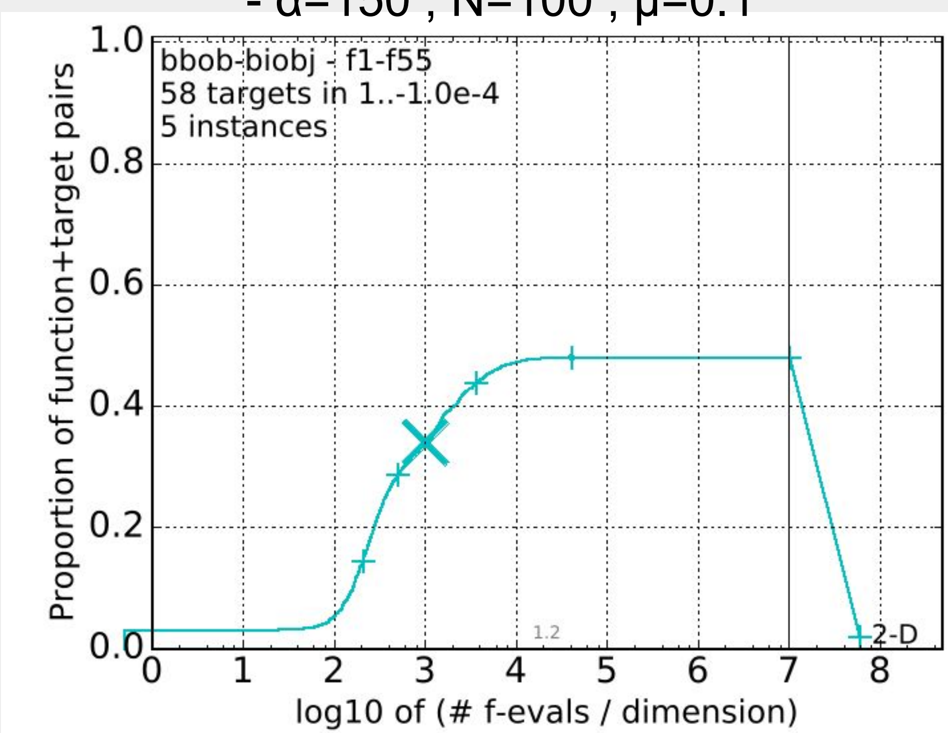
  - α=80 , N=50 , μ=0.05
  - α=80 , N=50 , μ=**0.1**



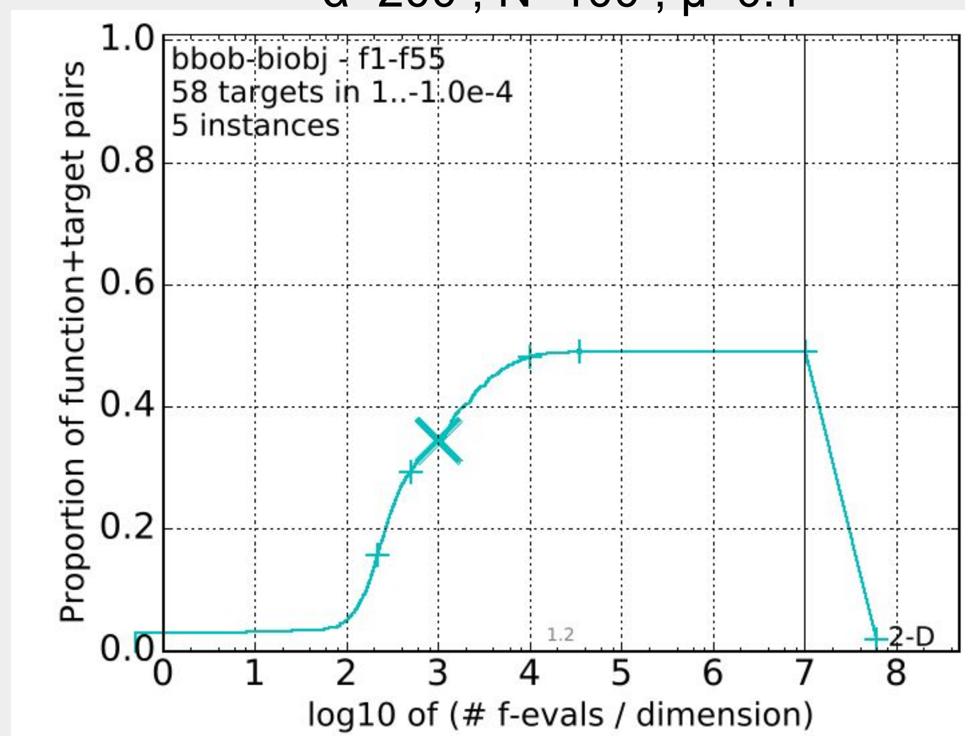
- α=150 , N=100 , μ=0.1



- α=200 , N=100 , μ=0.1



- α=80 , N=100 , μ=0.1



- α=80 , N=150 , μ=0.1

Tests & Results

Cases

Population size : α ,maximum number of generation : N ,mutation rate = μ

* Population Size:

- α=150 , N=100 , μ=0.1
- α=200 , N=100 , μ=0.1

- α=**100** , N=100 , μ=0.1
- α=80 , N=100 , μ=0.1

- α=100 , N=150 , μ=0.1

* Max. Num. Generation

- α=80 , N=100 , μ=0.1
- α=80 , N=150 , μ=0.1

* Mutation Rate

- α=80 , N=50 , μ=0.05
- α=80 , N=50 , μ=0.1

Comparison

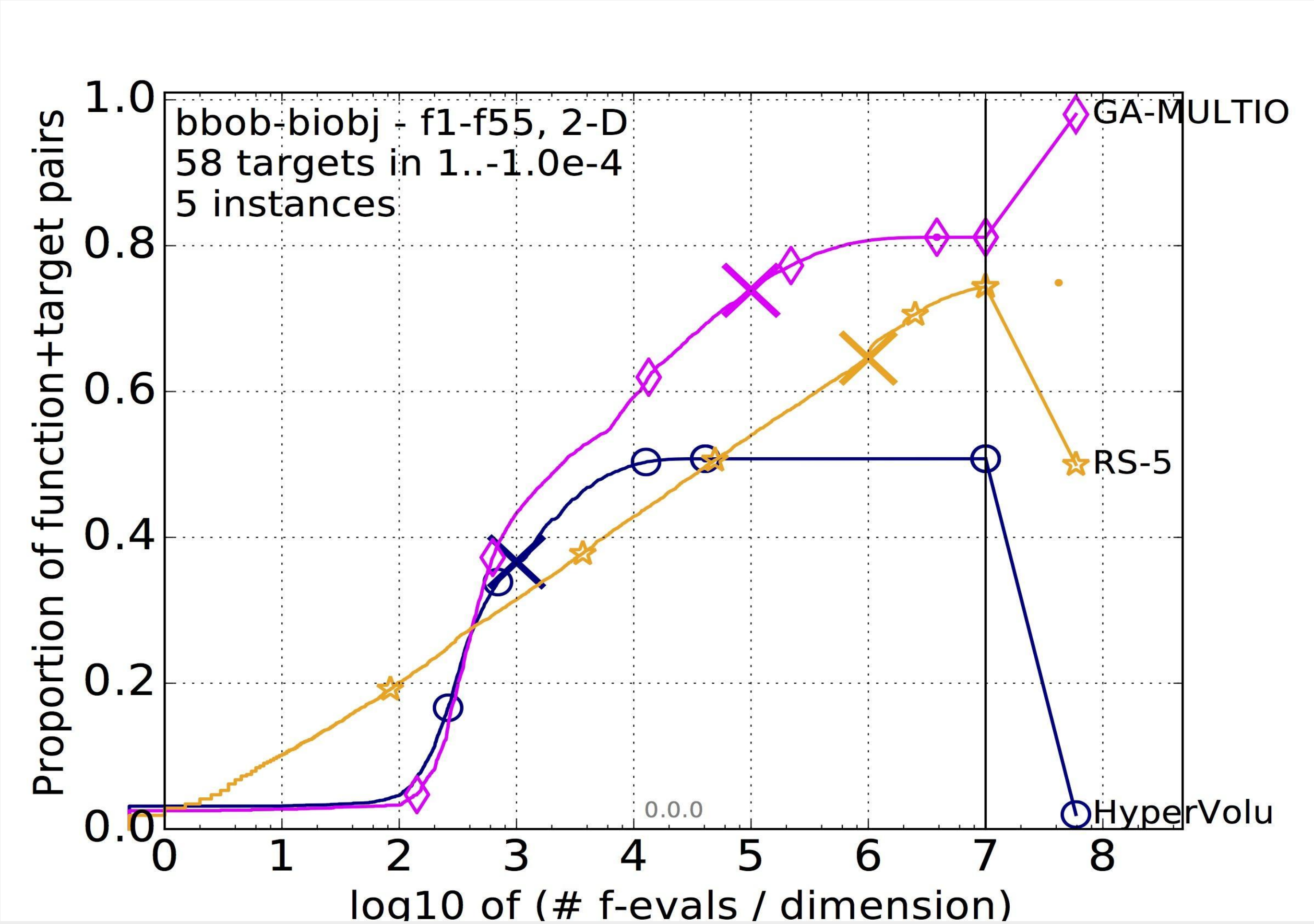
Hyper-Volume Indicator Based Evolutionary (HV IBEA) vs

- NSGA-II
- Random Search

- NSGA-II: Non-dominated Sorting Genetic Algorithm II (2002).
- Random Search: Optimization method not requiring the problem optimized gradient.
- Empirical cumulative distribution function (ECDF) - Graph:
  - Y-axis: Faction/Percentage of problems solved.
  - X-axis: Budget/Maximal runtime observed.

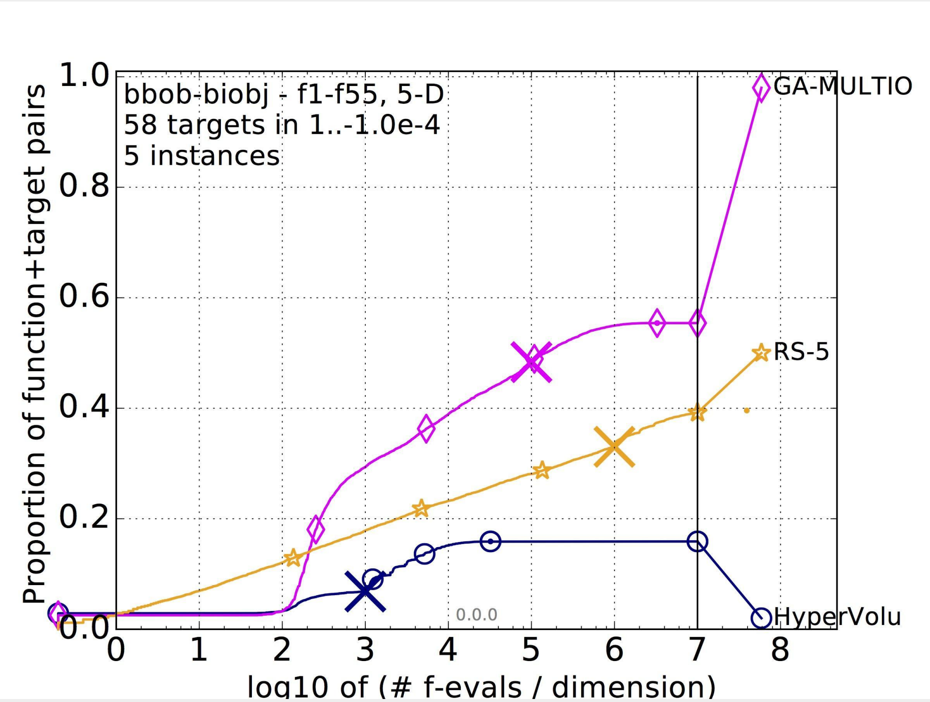
Comparison

- ECDFs per function and dimension
- - All Functions/Groups with two dimensions:

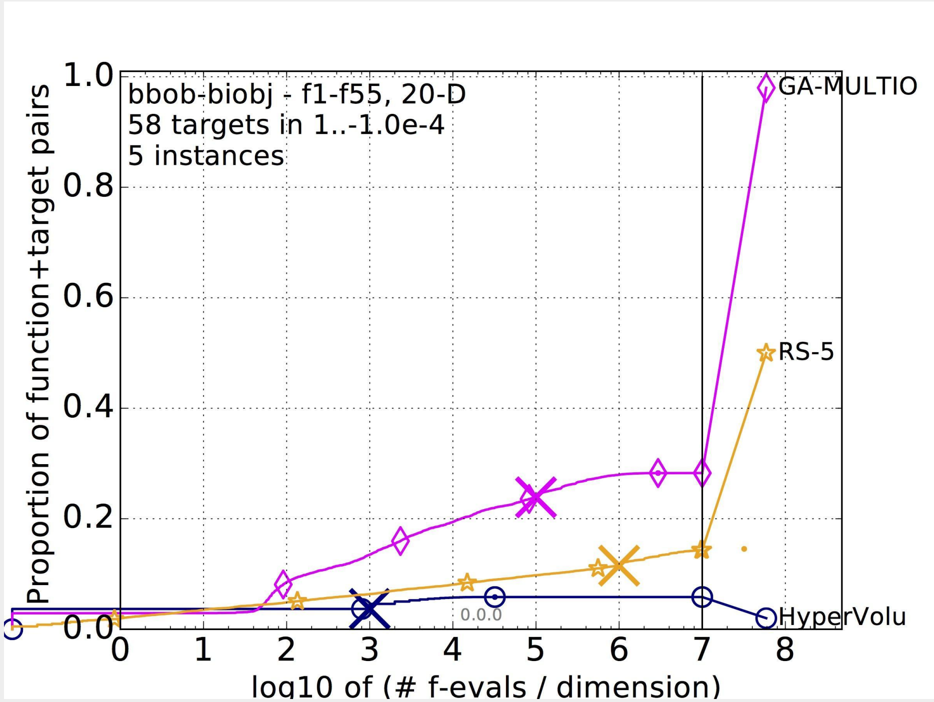


Comparison

- ECDFs per function and dimension
- - All Functions/Groups with higher dimensions:



5 Dimensions



20 Dimensions

Comparison

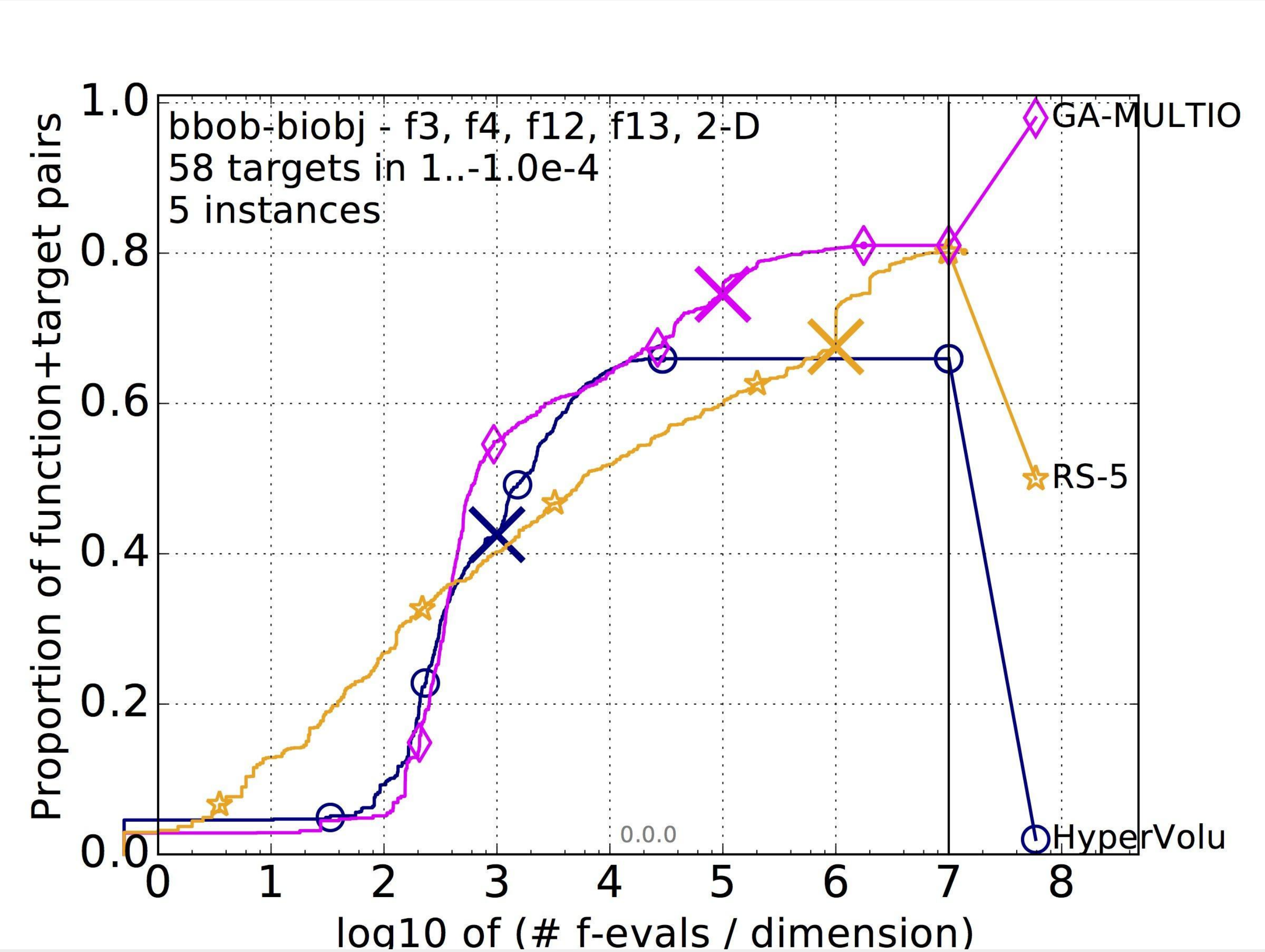
- ECDFs per function and dimension

- **- HV-IEBA:** Proportion of problems solved within 10ˆ5 - 2 Dimensions:

	Separable	Moderate	Ill-Conditioned	Multi-Modal	Weakly-Structured
Separable	≈ 0.61	≈ 0.65	≈ 0.54	≈ 0.42	≈ 0.62
Moderate		≈ 0.58	≈ 0.5	≈ 0.38	≈ 0.58
Ill-Conditioned			≈ 0.5	≈ 0.4	≈ 0.48
Multi-Modal				≈ 0.3	≈ 0.46
Weakly-Structure					≈ 0.57

Comparison

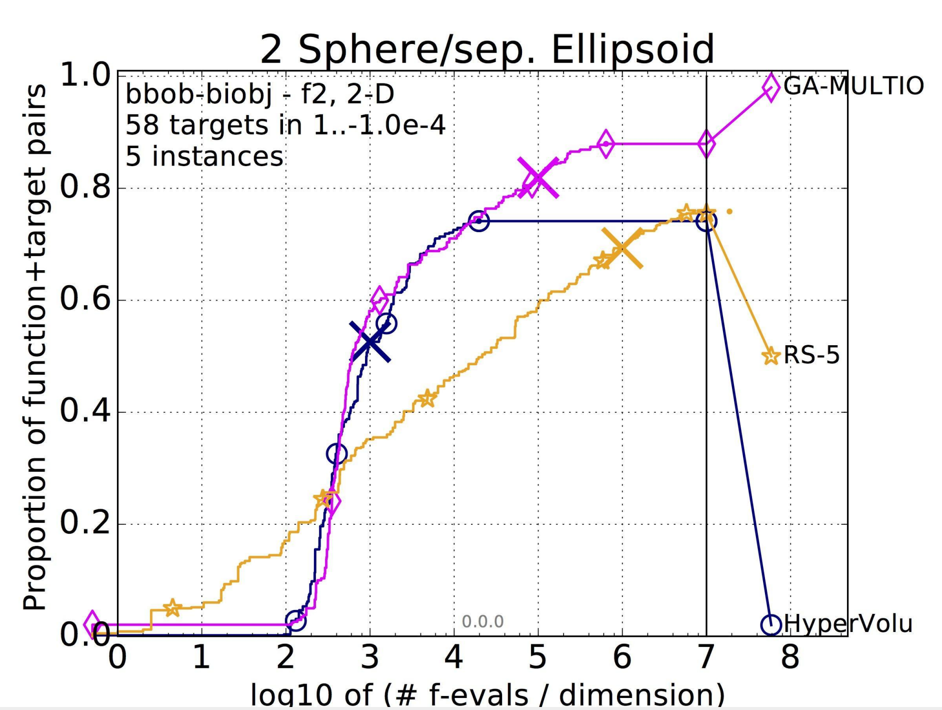
- ECDFs per function and dimension
- - Two Dimensions: Separable - Moderate Conditioning Group:



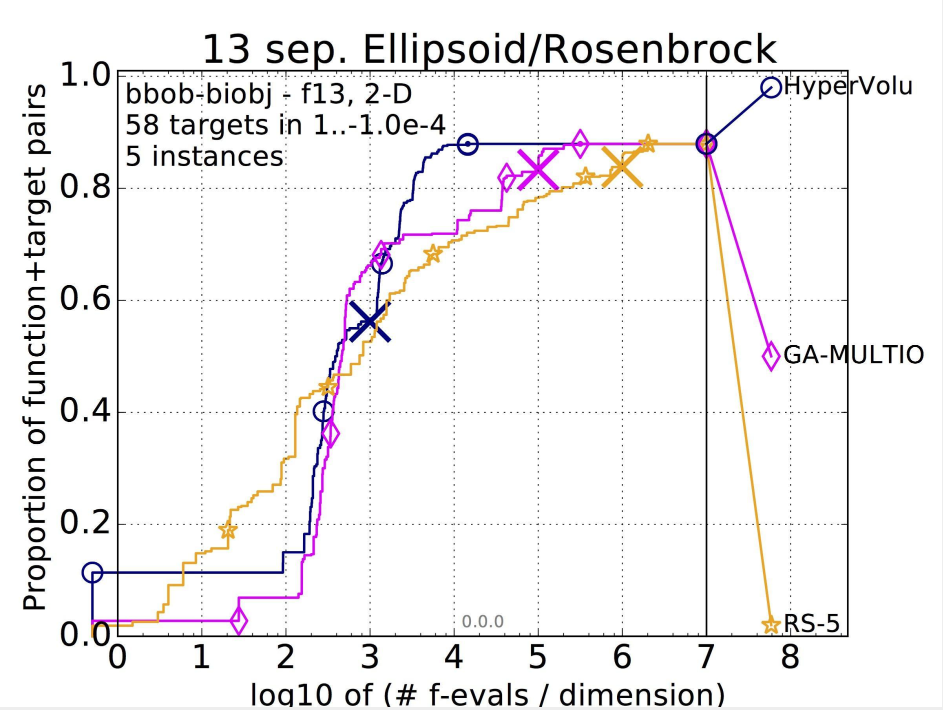
Comparison

- ECDFs per function and dimension

- - HV-IBEA has the similar levels with NSGA-II and RS: f2 and f13.



Separable - Unimodal - 2D

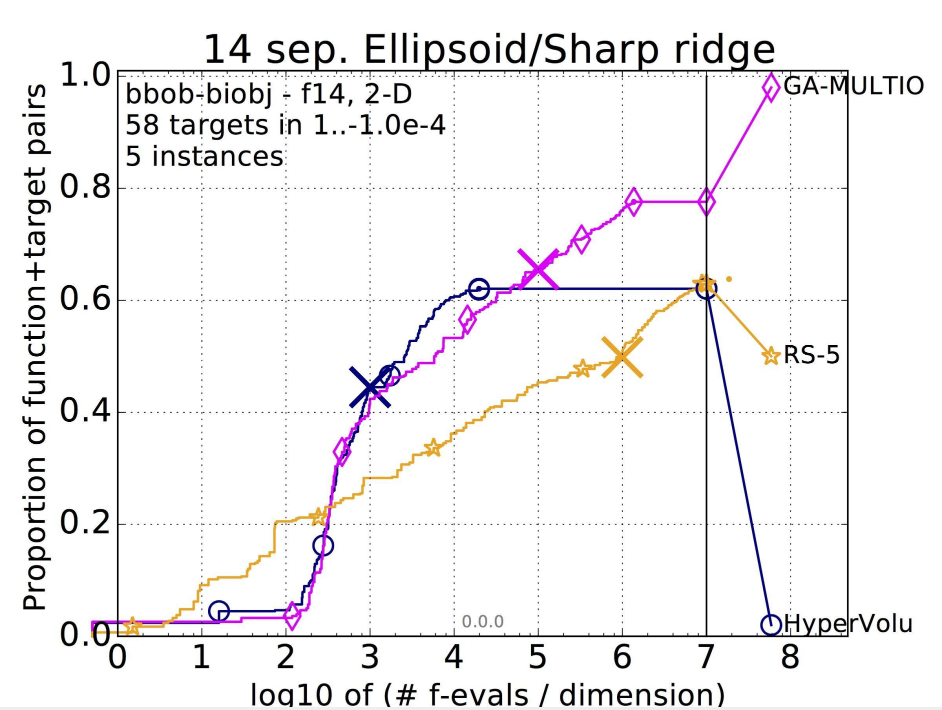


Separable - Moderate Conditioning - 2D

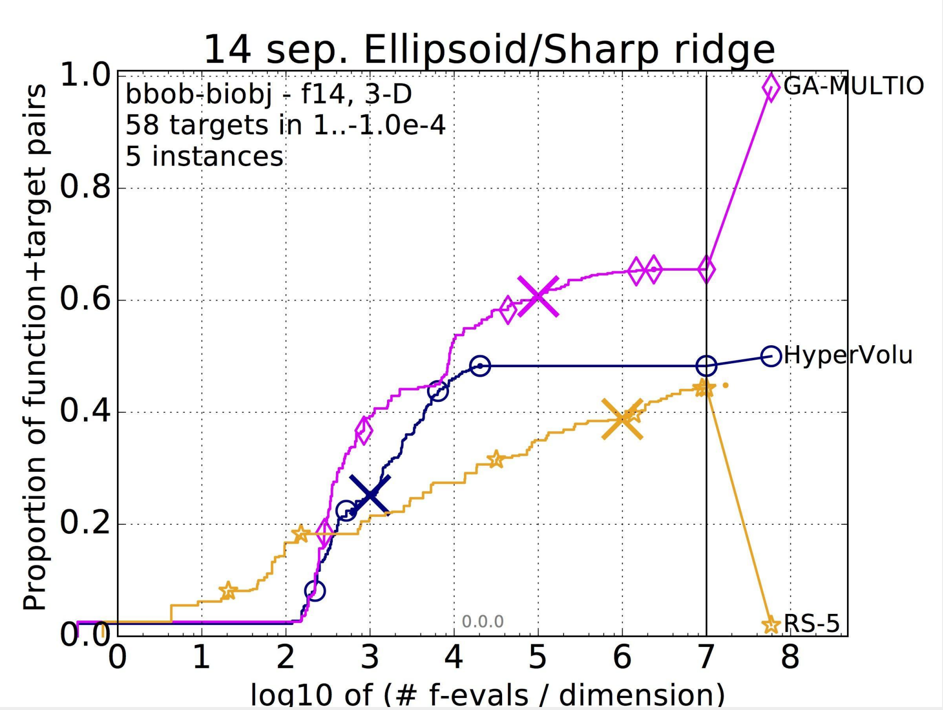
Comparison

- ECDFs per function and dimension

- HV-IBEA has the similar levels with NSGA-II and RS: f14.



Separable - Ill-Conditioned Function - 2D

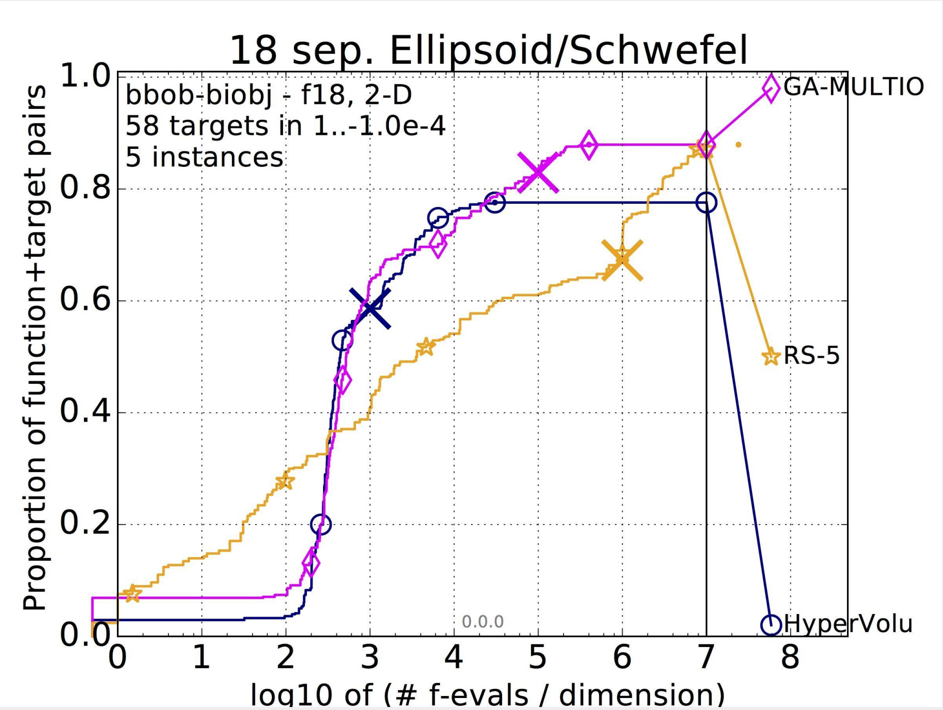


Separable - Ill-Conditioned Function - 3D

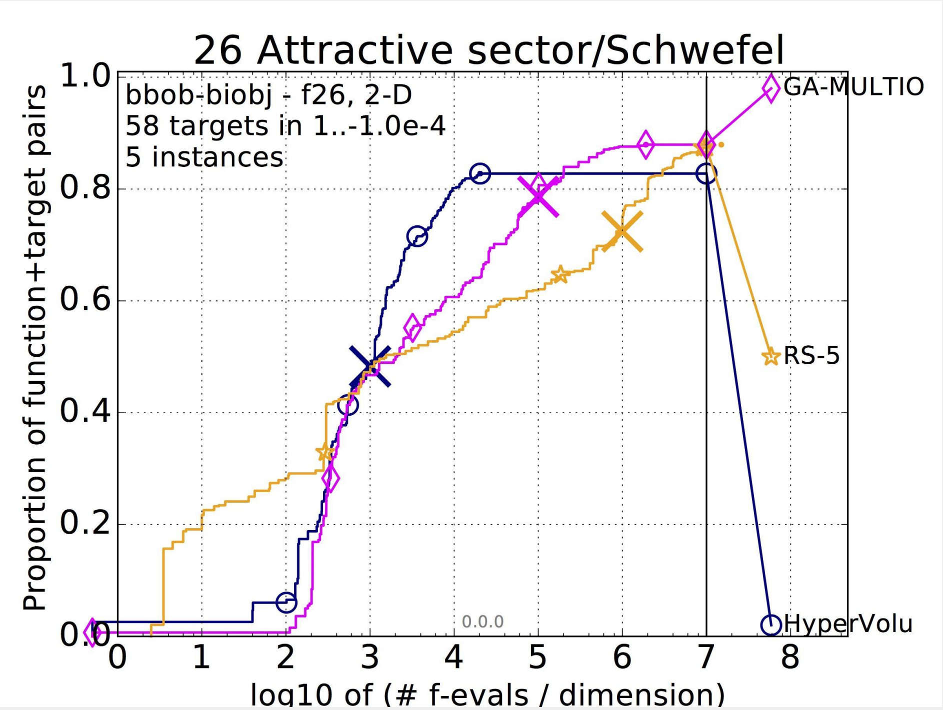
Comparison

ECDFs per function and dimension

- - HV-IBEA has the high levels: f18 and f26.



Separable - Weakly Structured - 2D



Moderate - Weakly Structured - 2D

Comparison

- NSGA-II and Random Search have the better results.
- However, in cases of Separable, Unimodal, Moderate Conditioning and Weakly Structure, HV IBEA has the remarkable proportions.

Conclusion

- The algorithm proposed define the optimization goal in term of an indicator which will be used in fitness calculation.
- The indicator used is a hyper-volume indicator : is a space volume representing the domination relationship of individuals.
- Problem with IBEA HV approach is execution time. It requires high-level computational capacity.
- The algorithm give better results when the COCO budget is very high.