Multiobjectivization with NSGA-II on the Noiseless BBOB Testbed

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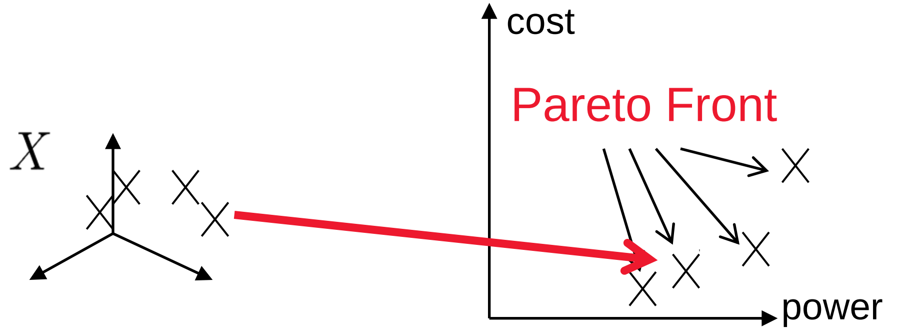
INVENTORS FOR THE DIGITAL WORLD

Overview Multiobjective Optimization

Optimizing multiple objective functions simultaneously

$$\min_{x \in X} f(x) = (f_1(x), \ldots, f_k(x)) \in \mathbb{R}^k$$



Evolutionary Multiobjective Optimization (EMO)

EMO =
randomized search heuristics
optimizing on solution **sets**

→ **“sampling”** the Pareto front
to **inform** decision maker

Multiobjectivization

Optimizing >1 Objectives Helps for Single-objective Problems ?!

Two basic ideas

- decomposition into two or more objective functions [kwc2001a]
- optimizing one or more "helper-objectives" along with original single-objective function [kwc2001a, jens2003b]

- improving performance for *combinatorial* problems reported

  e.g. TSP [kwc2001a], reducing bloat in GP [bbtz2001a,dwp2001a], job shop scheduling [jens2003b], protein structure prediction [hlk2008b]
- recently also proposed for *numerical* optimization [ssl2012a,ssl2012b]

  earlier application in parameter tuning of biological system modelling [hz2009a]
- main idea of [ssl2012a,ssl2012b]: using the distance to the closest neighbor (DCN) in the population as the second objective function; underlying idea: diversity helps especially for multimodal functions

Distance to Closest Neighbor (DCN)

WCCI 2012 IEEE World Congress on Computational Intelligence
June, 10-15, 2012 - Brisbane, Australia

IEEE CEC

Analysing the Robustness of Multiobjectivisation Parameters with Large Scale Optimisation Problems

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Abstract—**Evolutionary Algorithms (EAs) are one of the most popular strategies for solving optimisation problems. To define a configuration of an EA several components and parameters must be specified. Therefore, one of the main drawbacks of EAs is the complexity of their parameter setting. Another problem is that**

In many problems, EAs might have a tendency to converge towards local optima. The likelihood of this occurrence depends on the shape of the fitness landscape [4]. Several methods to deal with local optima stagnation have been de-

Analysing the Robustness of MultiObjectivisation Approaches Applied to Large Scale Optimisation Problems

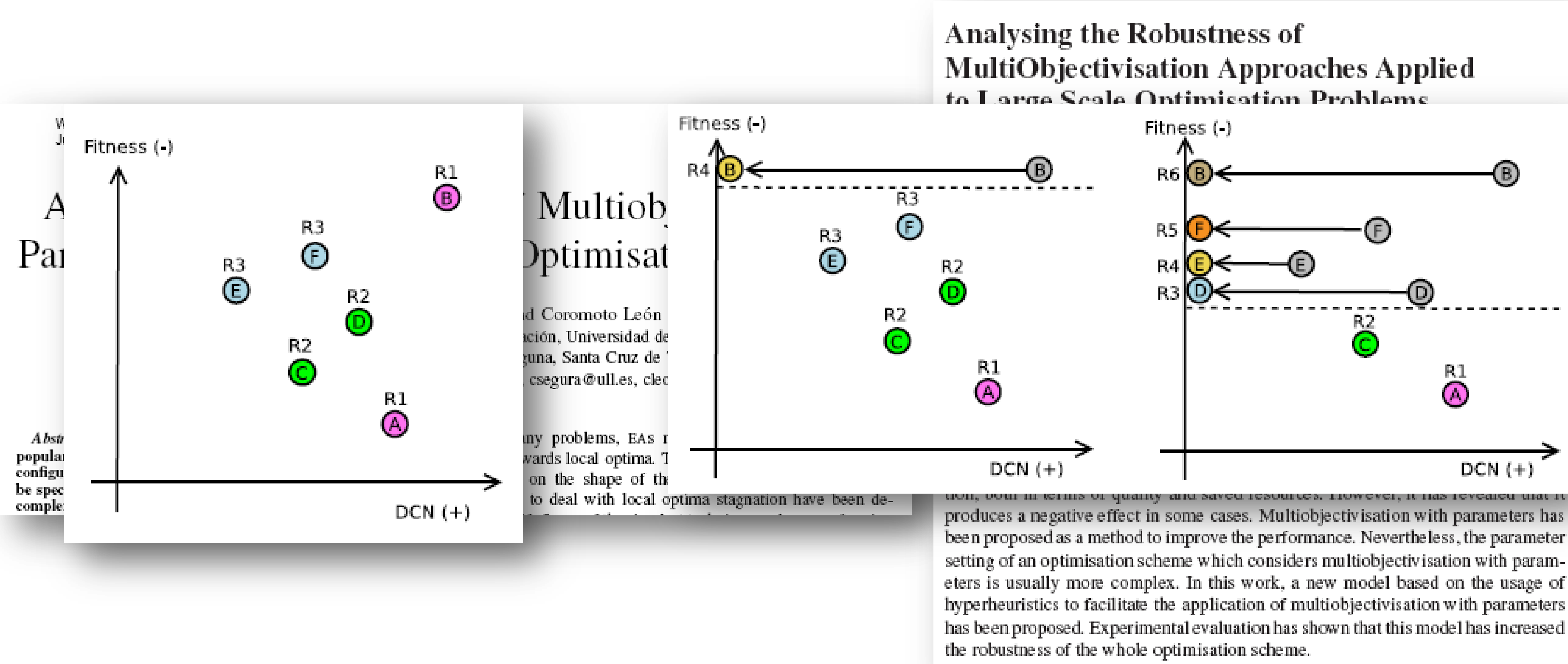
Carlos Segura, Eduardo Segredo, and Coromoto León

Abstract Multiobjectivisation transforms a mono-objective problem in a multi-objective one. The main aim of multiobjectivisation is to avoid stagnation in local optima, by changing the landscape of the original fitness function. In this contribution, an analysis of different multiobjectivisation approaches has been performed. It has been carried out with a set of scalable mono-objective benchmark problems. The experimental evaluation has demonstrated the advantages of multiobjectivisation, both in terms of quality and saved resources. However, it has revealed that it produces a negative effect in some cases. Multiobjectivisation with parameters has been proposed as a method to improve the performance. Nevertheless, the parameter setting of an optimisation scheme which considers multiobjectivisation with parameters is usually more complex. In this work, a new model based on the usage of hyperheuristics to facilitate the application of multiobjectivisation with parameters has been proposed. Experimental evaluation has shown that this model has increased the robustness of the whole optimisation scheme.

- main idea of [ssl2012a,ssl2012b]: using the distance to the closest neighbor (DCN) in the population as the second objective function; "reduce tendency to converge towards local optima"
- tested on large-scale (500D) problems

but: scaling with dimension can be investigated also in low dim.

Distance to Closest Neighbor (DCN)



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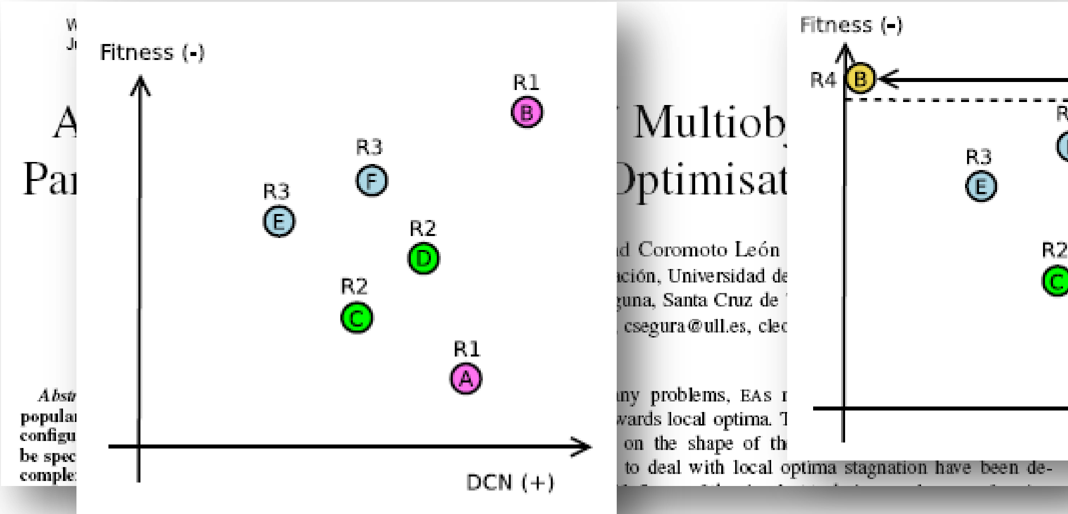
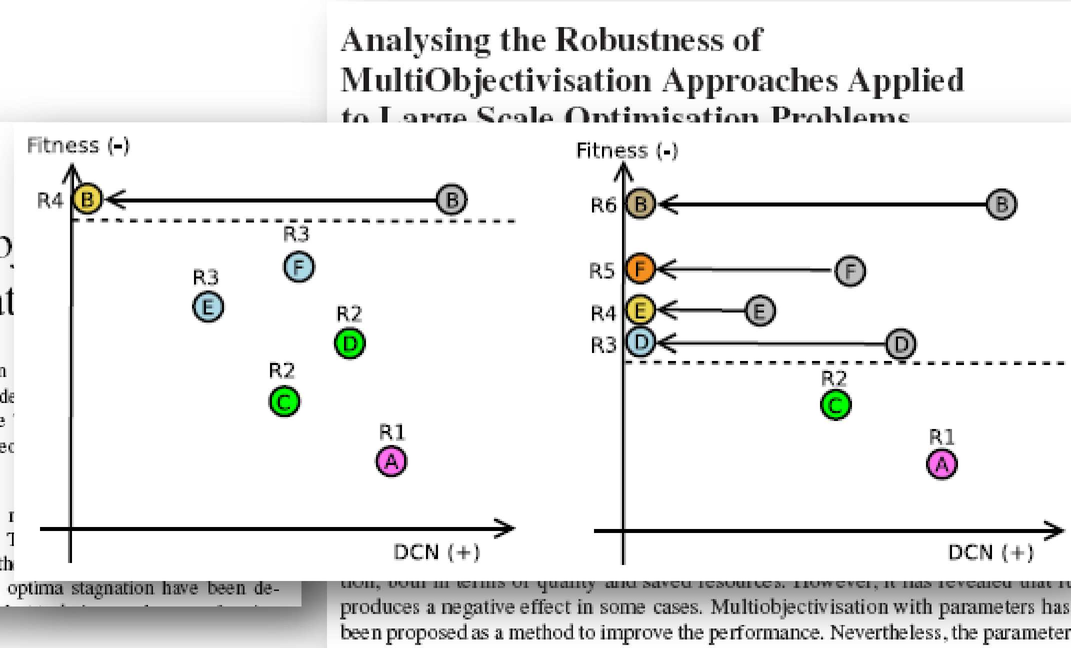




Setting:

- 10^6D funevals (no restarts)
- uniform mutation
- population size 5
- later: different threshold + hyperheuristic

but: not compared to any other single-objective algorithm

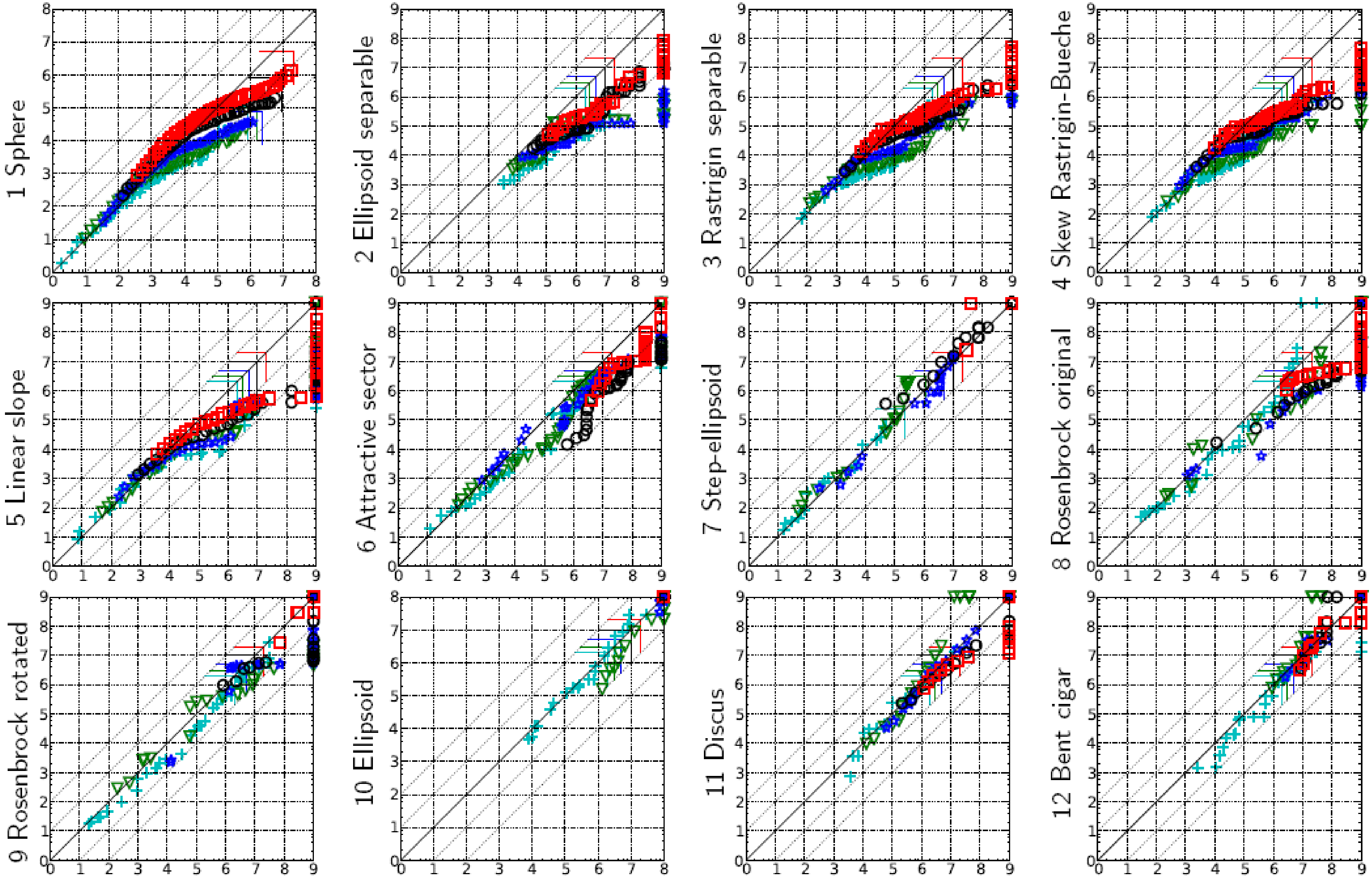
- main idea of [ssl2012 … neighbor (DCN) in t… …on; "reduce tendency to…
- tested on large-scal…

The Algorithm(s) Tested on BBOB-2013

NSGA-II

- non-dominated sorting + crowding distance
- population size 8
- based on C implementation of Kalyanmoy Deb et al.
- standard SBX crossover, p_c=1
- 10^6D funevals
- two mutation operators: uniform in [-5, 5] (**`UM`**) and polynomial mutation (η = 100) (**`PM`**)
- both variants with DCN (**`DCN`**) and without (**`zero`**)

Results 1: Impact of Multiobjectivization



U-zero (x axis) vs. U-DCN (y axis) [fixed targets]

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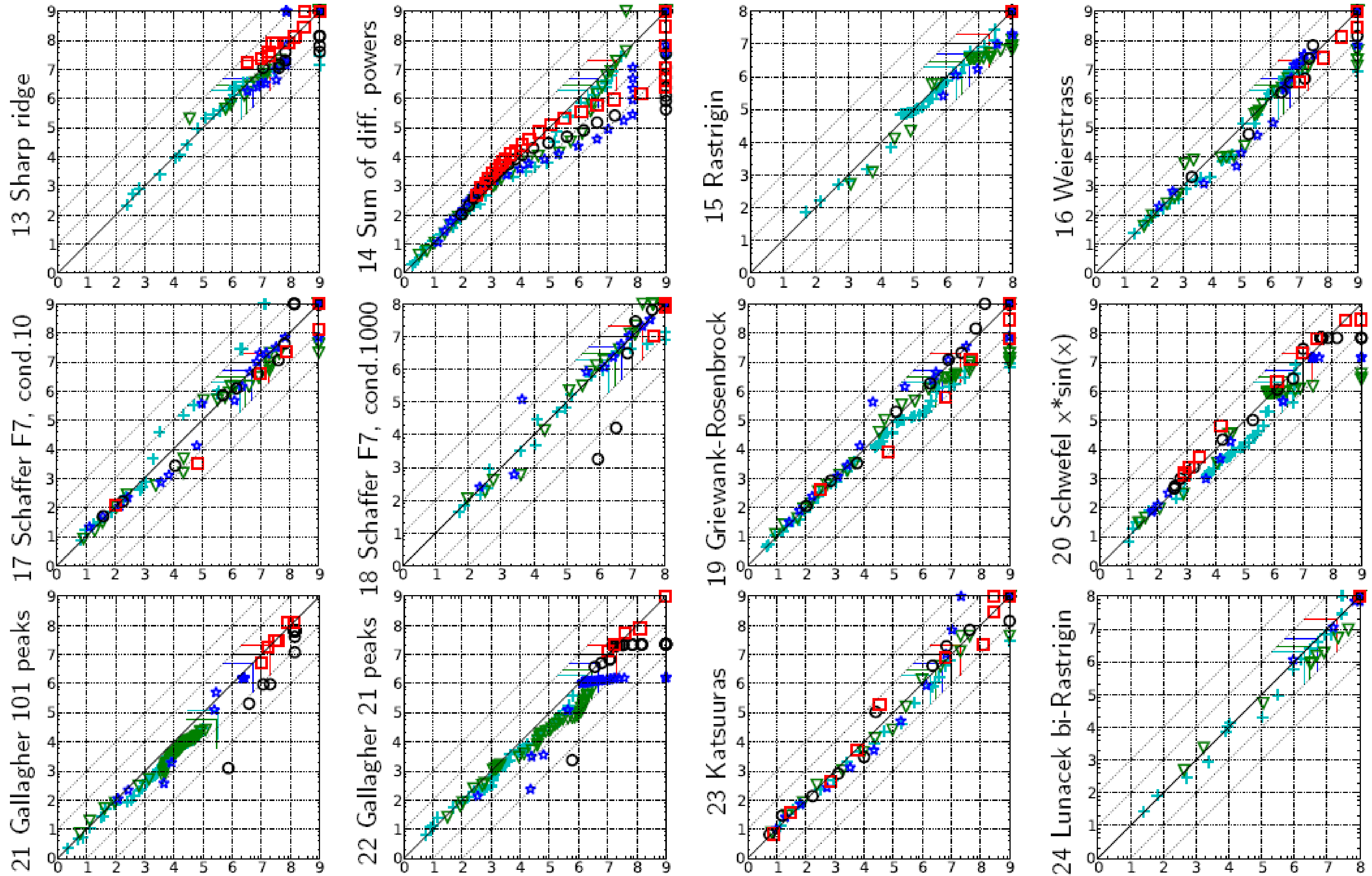

U-zero (x axis) vs. U-DCN (y axis) [fixed targets]

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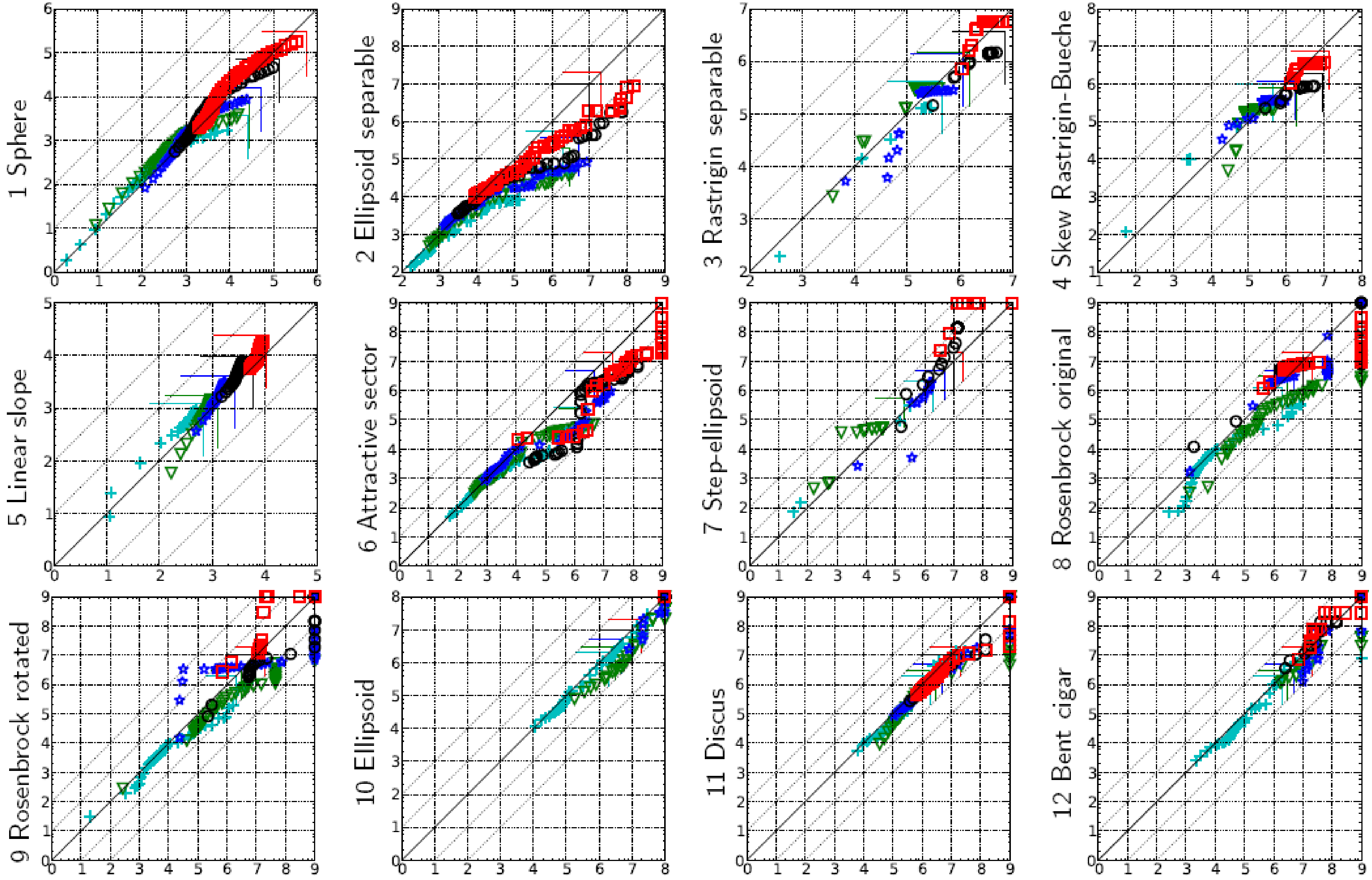
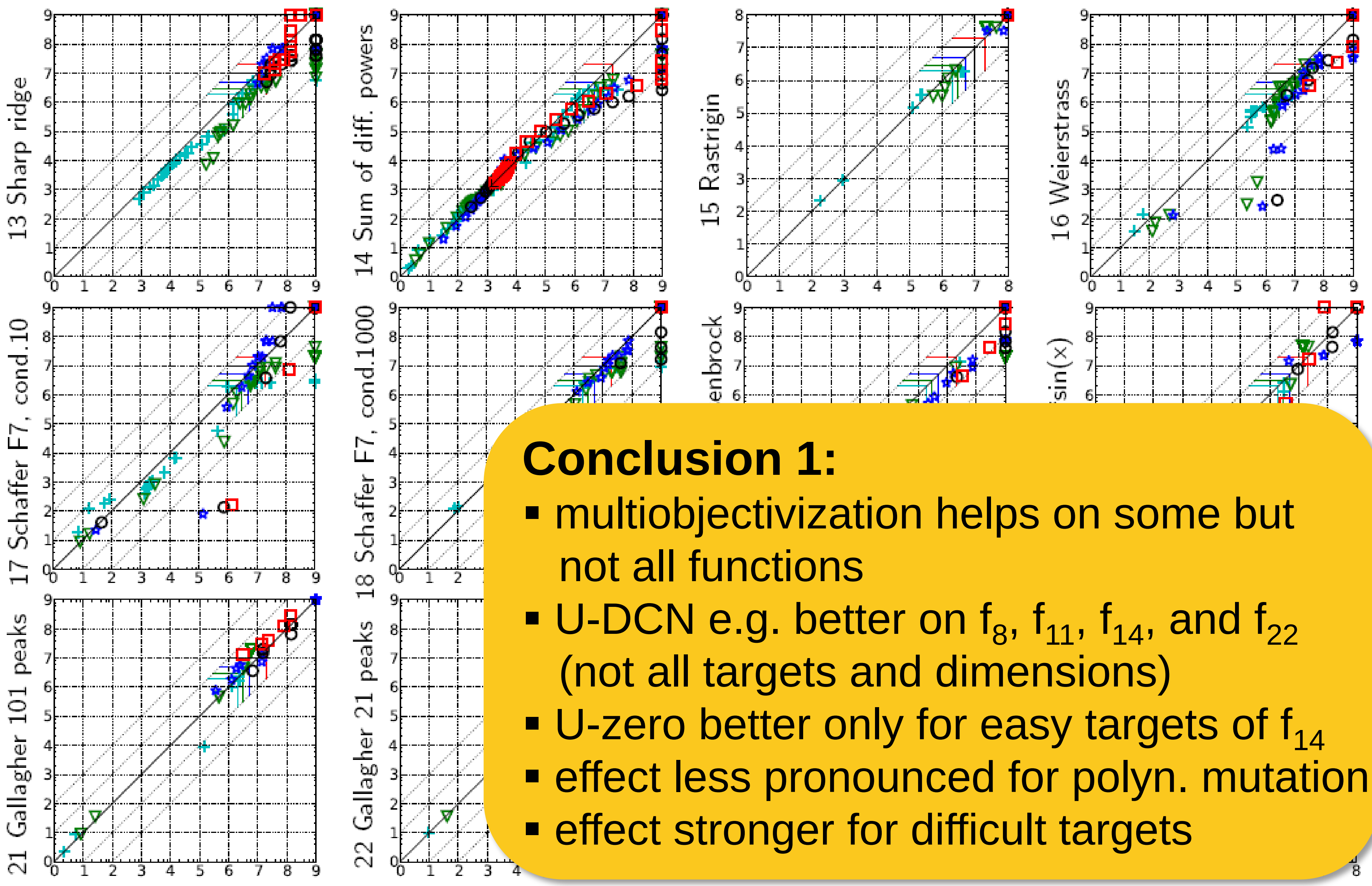


P-zero (x axis) vs. P-DCN (y axis) [fixed targets]

Results 1: Impact of Multiobjectivization

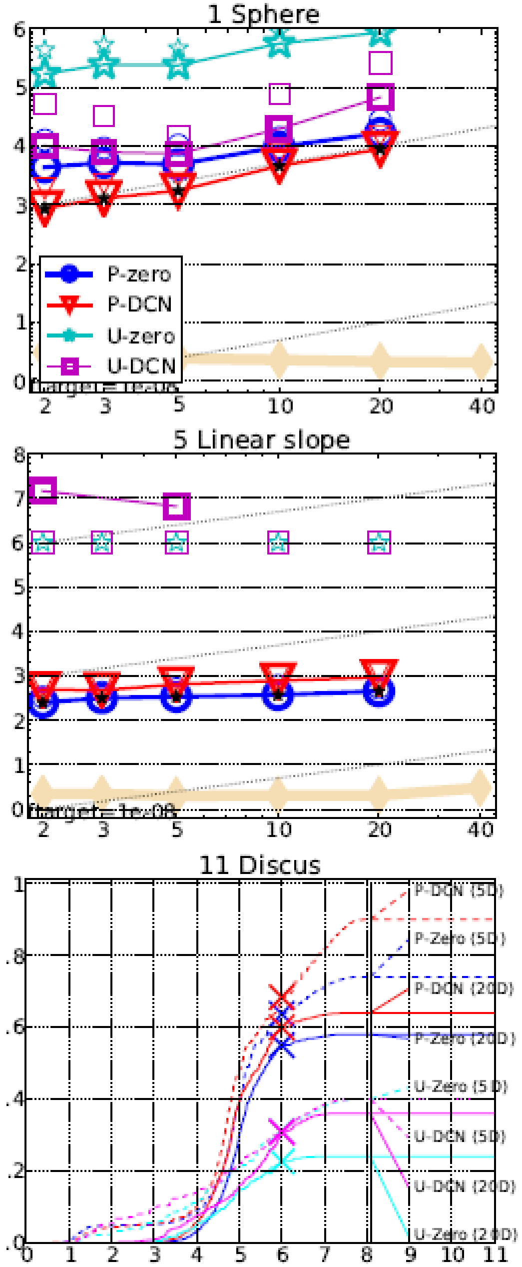


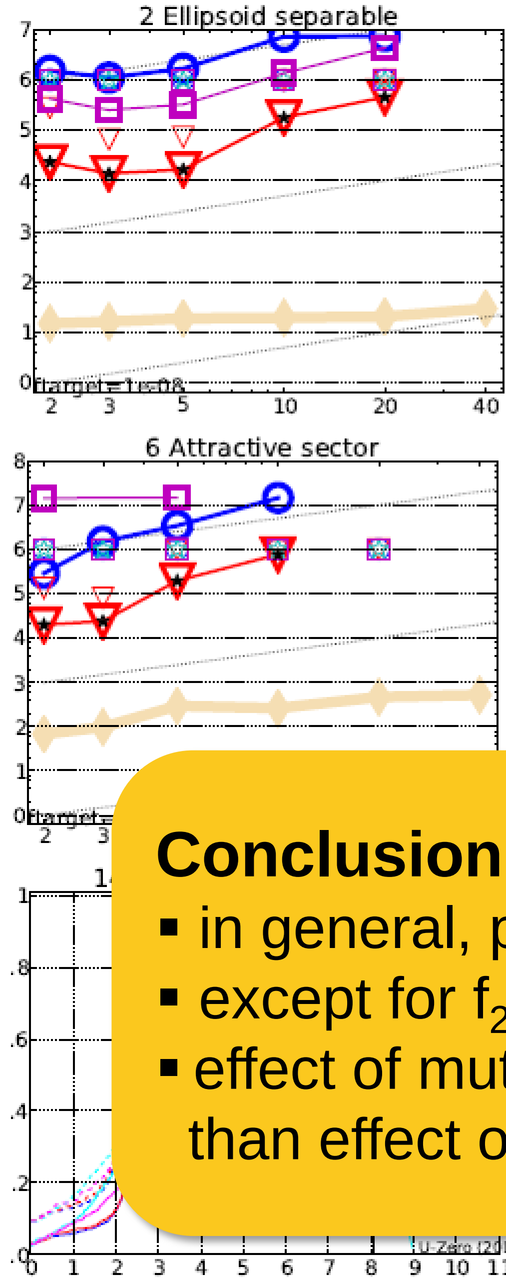
Conclusion 1:

- multiobjectivization helps on some but not all functions
- U-DCN e.g. better on f_8, f_{11}, f_{14}, and f_{22} (not all targets and dimensions)
- U-zero better only for easy targets of f_{14}
- effect less pronounced for polyn. mutation
- effect stronger for difficult targets

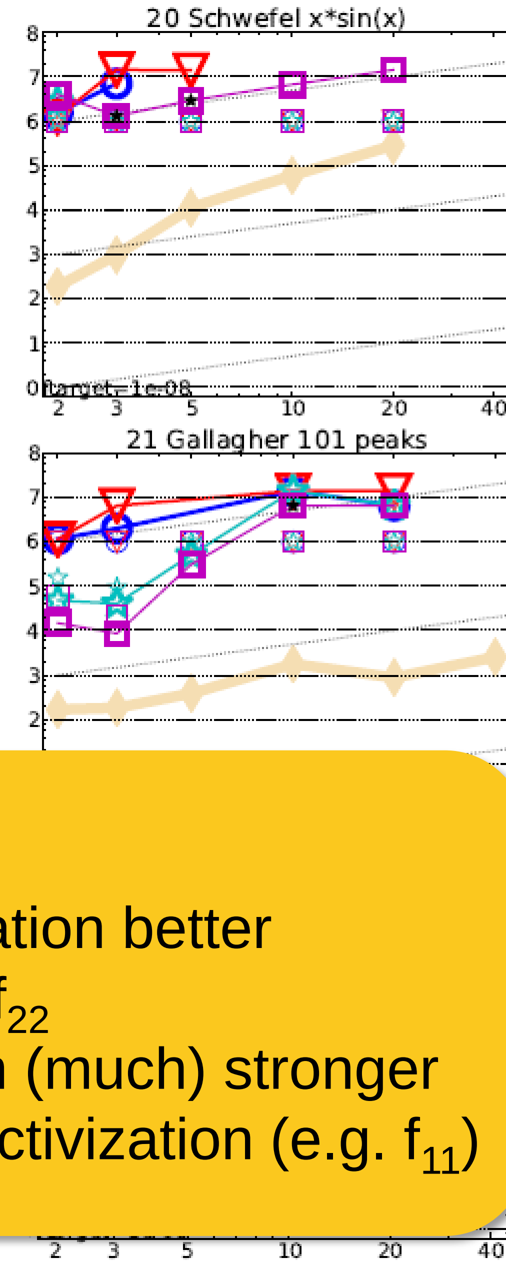
P-zero (x axis) vs. P-DCN (y axis) [fixed targets]

Results 2: Impact of Mutation





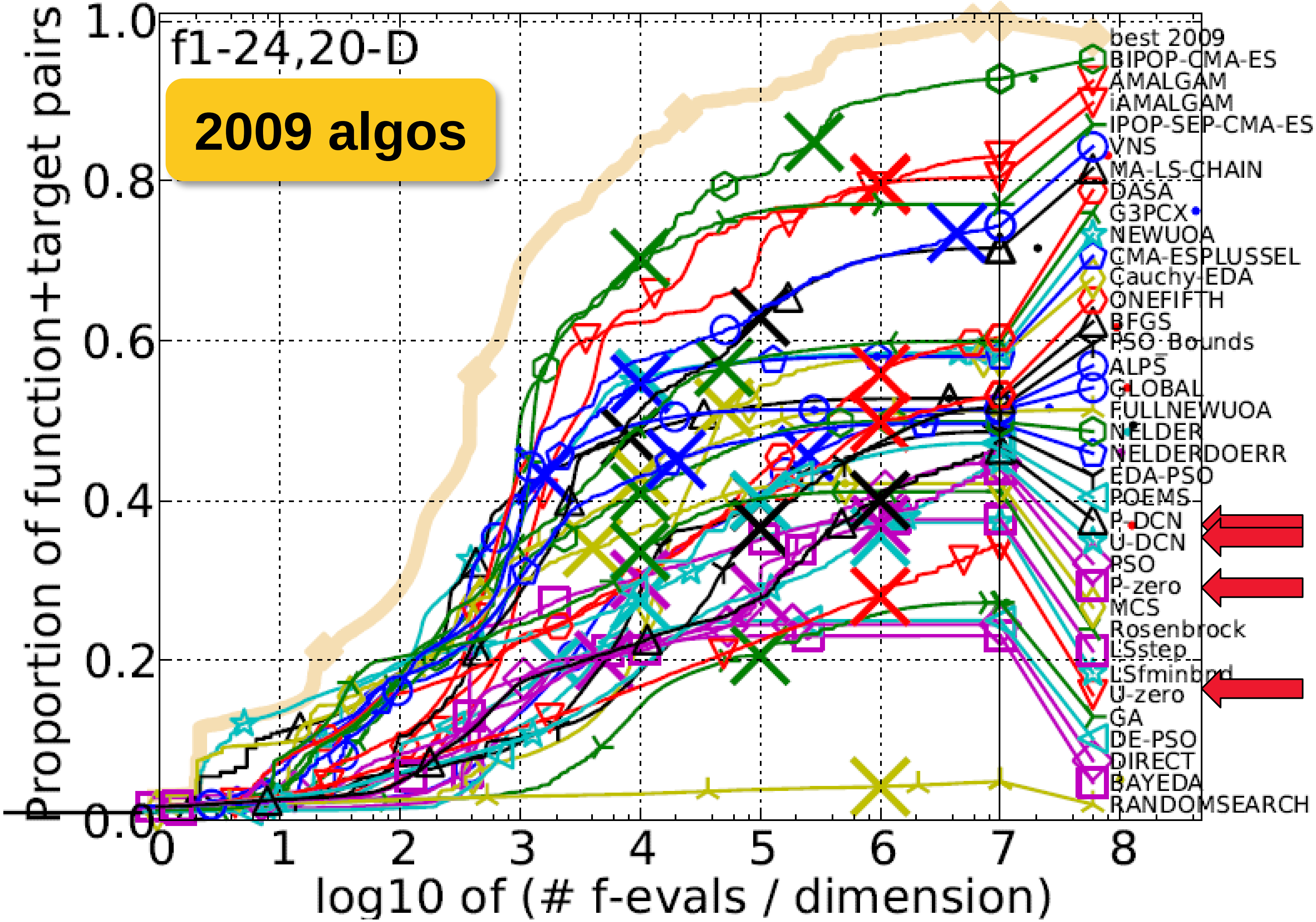
vs.



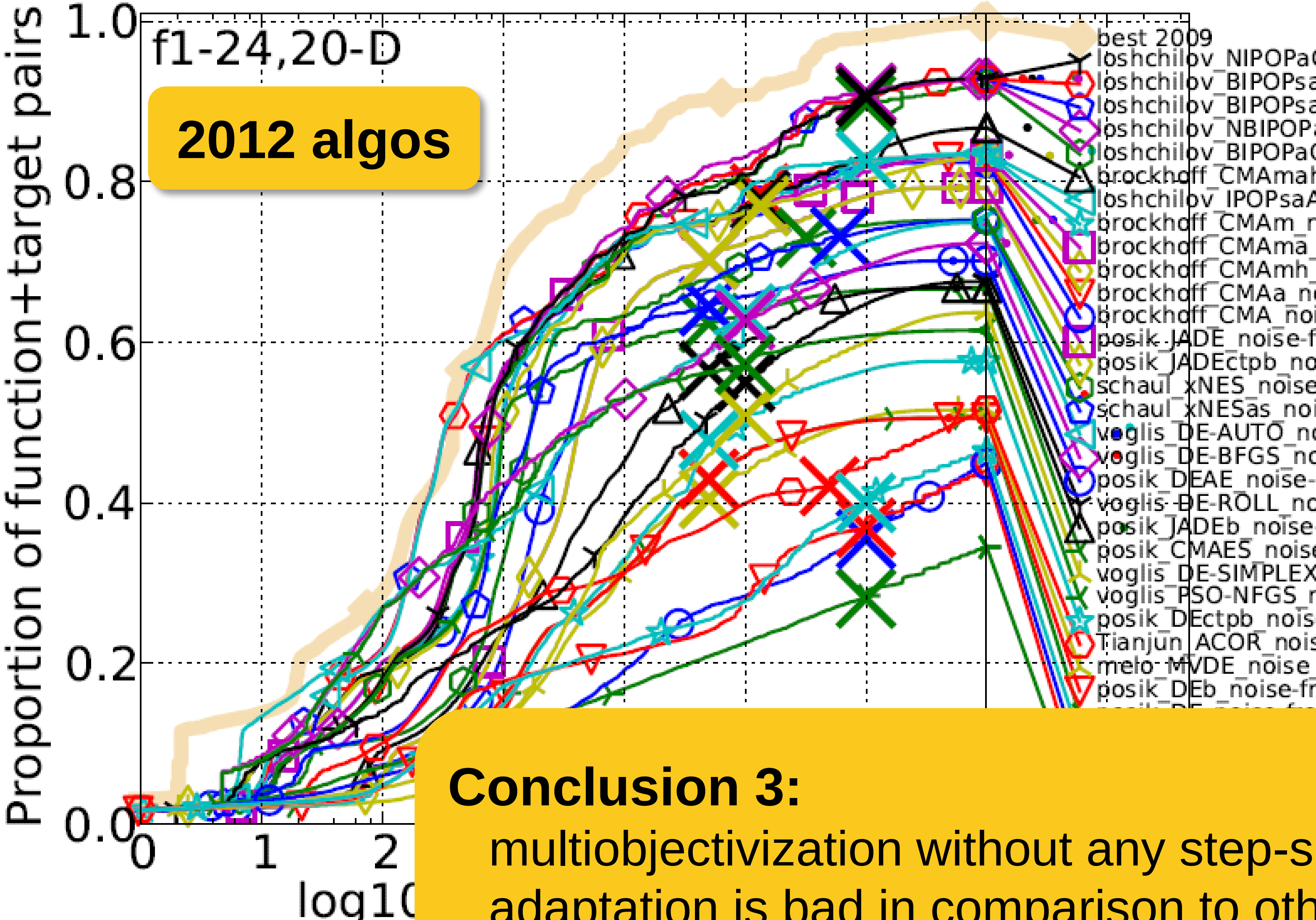
Conclusion 2:

- in general, polyn. mutation better
- except for f_{20}, f_{21}, and f_{22}
- effect of mutation often (much) stronger than effect of multiobjectivization (e.g. f_{11})

Results 3: Competitiveness wrt. 2009 Algorithms



comparison with all 2009 algos: typically ≈100x slower than best



2012 algos

Conclusion 3:

multiobjectivization without any step-size adaptation is bad in comparison to other state-of-the-art single-objective optimizers

comparison with a

Conclusions

- tested NSGA-II with DCN as second objective on BBOB-2013
- impact of multiobjectivization visible
- stronger effect due to other parameters such as mutation (no adaptive step size)
- effect seems stronger if algorithm performance is better (tested with a R2-EMOA variant with BLX-alpha crossover and non-uniform mutation)
- multiobjectivization helps most on multimodal functions but less/not on simple ones

our idea was neither to benchmark a "killer algorithm" nor to prove a bad performance of the DCN-approach but rather to show that it is important to invest time in the "right" design choices

questions?