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GECCO 2022 tutorial on benchmarking multiobjective optimizers 2.0

Dimo Brockhoff, Tea Tutar

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GECCO 2022 Tutorial on Benchmarking Multiobjective Optimizers 2.0

Dimo Brockhoff
dimo.brockhoff@inria.fr

Tea Tušar
tea.tusar@ijs.si



INSTITUT
POLYTECHNIQUE
DE PARIS



Jožef Stefan Institute

The final slides are available at
<http://www.cmap.polytechnique.fr/~dimo.brockhoff/>

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Overview

Our plan

Discuss history, present and future of multiobjective benchmarking

With respect to different topics

performance assessment / methodology

test functions

Finally, recommendations on good algorithms

Disclaimer

This is not an introductory tutorial to multiobjective optimization!

We assume you know basic definitions like

Objective function

Pareto dominance/Pareto front/Pareto set

Ideal/Nadir points

Disclaimer II

We only consider continuous search spaces

Disclaimer II

We only consider continuous search spaces

We only consider unconstrained problems

Disclaimer II

We only consider continuous search spaces

We only consider unconstrained problems

What we present is highly subjective & selective

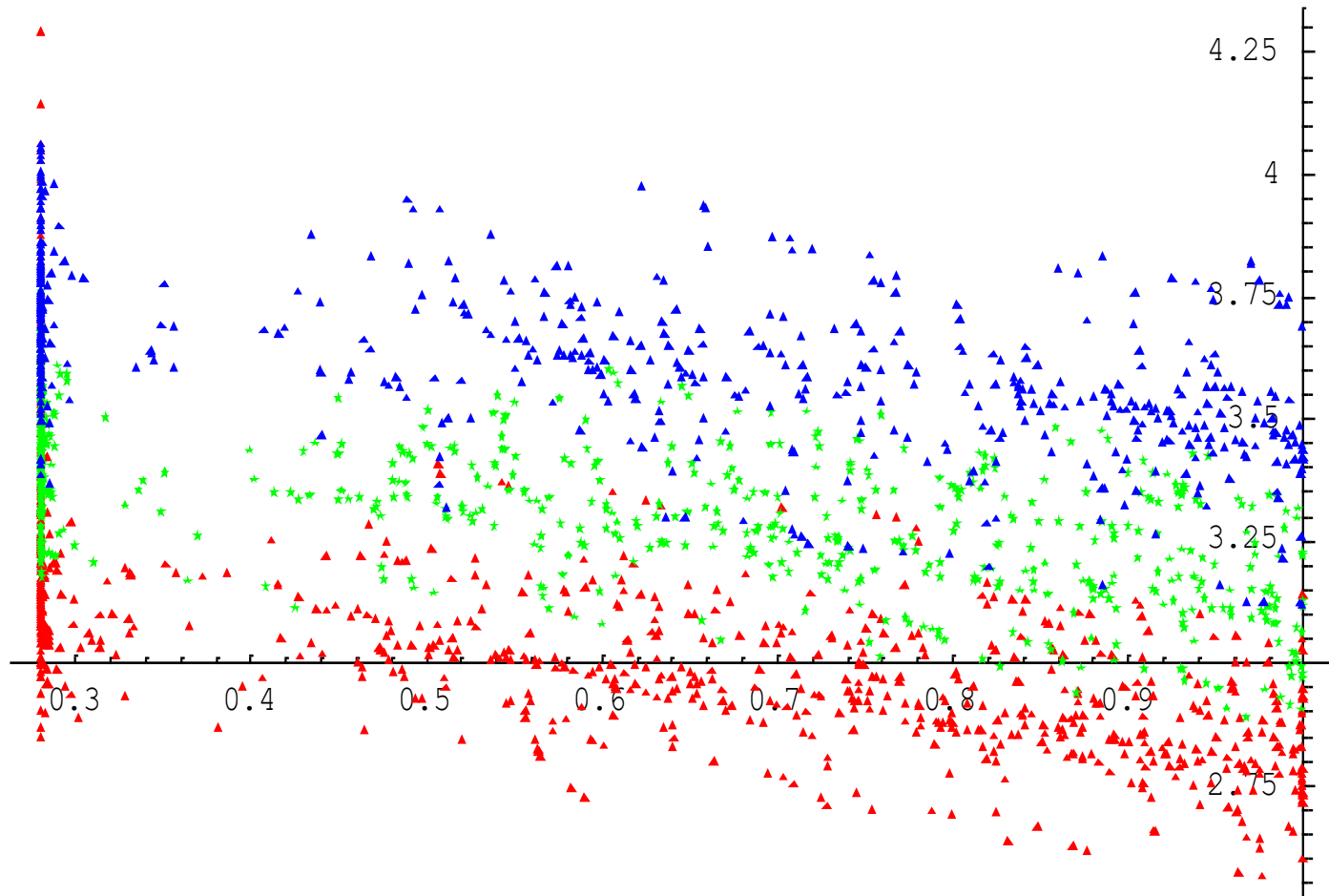
- how important do we find each milestone?
- use version numbering and branches
- what have we learned from the past?

- ① Performance Assessment
- ② Test Problems and Their Visualizations
- ③ Recommendations from Numerical Results

v0.0.1alpha

In The Early Beginnings...

... multiobjective EAs were mainly compared visually:



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

v0.1 beta

Tables

Problem	MOCSA				NSGA2			
	$\langle d \rangle$	S	GD	ER	$\langle d \rangle$	S	GD	ER
ZDT1	0.0404	0.0055	0.0000	0	0.0270	0.0156	0.0011	0.04
ZDT2	0.0404	0.0082	0.0000	0	0.0292	0.0146	0.0212	0.02
ZDT3	0.0438	0.0148	0.0001	0	0.0329	0.0201	0.0020	0.02
ZDT4	0.0404	0.0097	0.0000	0	0.0328	0.0159	0.0006	0.02
ZDT6	0.0327	0.0150	0.0000	0	0.0216	0.0119	0.0000	0
DTLZ1	0.1114	0.0068	0.0000	0	0.0615	0.0319	0.0000	0
DTLZ2	0.2319	0.0646	0.0021	0.02	0.1361	0.0683	0.0020	0.04
DTLZ3	0.2770	0.0225	0.0000	0	0.1139	0.0739	0.0000	0
DTLZ4	0.2478	0.0424	0.0009	0	0.1630	0.0898	0.0019	0.02
DTLZ5	0.0487	0.0059	0.0000	0	0.0309	0.0176	0.0610	0.06
DTLZ6	0.0484	0.0156	0.0000	0	0.0306	0.0135	0.0000	0
DTLZ7	0.2897	0.0510	0.0011	0.04	0.1880	0.1322	0.0071	0.22

arXiv, 2012

Tables

Table 4: Influence of different κ values on the performance of the cone-MOEA on test problems Deb52, ZDT1, and DTLZ2 with three and four objective functions. Median (M) and standard deviation (SD) over 30 independent runs are shown. Intermediate values for κ seem to yield reasonably good performance values for all metrics. A more appropriate study is required in order to formally characterize the effect of this parameter.

Metric		κ ; Deb52										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
γ	M	0.0006	0.0006	0.0005	0.0006	0.0005	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
	SD	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	0.0001	0.0001
Δ	M	0.6766	0.6813	0.5244	0.2991	0.2552	0.2432	0.2648	0.2892	0.3147	0.3194	0.3199
	SD	0.0004	0.0021	0.0025	0.0027	0.0034	0.0039	0.0017	0.0019	0.0016	0.0042	0.0066
HV	M	0.2735	0.2779	0.2794	0.2802	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806
	SD	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$
H	M	19.00	51.00	74.00	93.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00
	SD	$< 10^{-4}$	$< 10^{-4}$	0.2537	0.3457	0.4842	$< 10^{-4}$	$< 10^{-4}$	$< 10^{-4}$	0.1826	0.1826	0.1826

Metric		κ ; ZDT1										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
γ	M	0.0103	0.0069	0.0055	0.0059	0.0074	0.0040	0.0042	0.0051	0.0053	0.0050	0.0038
	SD	0.0072	0.0038	0.0057	0.0047	0.0049	0.0042	0.0060	0.0058	0.0040	0.0050	0.0034
Δ	M	0.3046	0.5543	0.3678	0.2084	0.1818	0.1812	0.1898	0.1937	0.1934	0.1956	0.1891
	SD	0.0122	0.0607	0.0480	0.0408	0.0235	0.0220	0.0234	0.0251	0.0240	0.0232	0.0155
HV	M	0.8435	0.8561	0.8602	0.8607	0.8598	0.8652	0.8650	0.8636	0.8633	0.8638	0.8657
	SD	0.0115	0.0066	0.0094	0.0079	0.0082	0.0069	0.0099	0.0096	0.0066	0.0083	0.0057
H	M	37.00	63.00	84.50	98.00	100.00	101.00	101.00	101.00	101.00	101.00	101.00
	SD	0.6397	5.7211	2.8730	5.0901	3.8201	5.467	0.8584	0.9371	0.9377	1.3515	0.7112

Metric		κ ; DTLZ2 (m = 3)										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
γ	M	0.0062	0.0069	0.0072	0.0070	0.0074	0.0079	0.0074	0.0076	0.0074	0.0078	0.0072
	SD	0.0002	0.0013	0.0015	0.0013	0.0012	0.0014	0.0010	0.0019	0.0007	0.0014	0.0009
Δ	M	0.0503	0.6066	0.3029	0.2411	0.2386	0.2308	0.2274	0.2175	0.2079	0.2173	0.1982
	SD	0.0041	0.0422	0.0357	0.0302	0.0264	0.0219	0.0316	0.0275	0.0306	0.0295	0.0239
HV	M	0.6731	0.7149	0.7383	0.7435	0.7458	0.7469	0.7467	0.7469	0.7470	0.7470	0.7471
	SD	0.0066	0.0042	0.0023	0.0012	0.0007	0.0006	0.0005	0.0005	0.0005	0.0005	0.0003
H	M	21.00	69.00	88.00	93.00	94.50	95.00	95.00	95.00	95.00	95.00	94.00
	SD	1.3047	3.1639	2.8367	2.0424	1.7750	1.9464	2.2894	2.0197	1.5643	2.2614	1.7100

Metric		κ ; DTLZ2 (m = 4)										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
γ	M	0.0001	0.0311	0.0385	0.0312	0.0449	0.0404	0.0445	0.0488	0.0590	0.0489	0.0534
	SD	0.0001	0.0198	0.0218	0.0239	0.0283	0.0240	0.0369	0.0281	0.0284	0.0241	0.0304
Δ	M	0.1390	0.4700	0.3602	0.3296	0.3299	0.3429	0.3377	0.3258	0.3253	0.3304	0.3319
	SD	0.1173	0.0304	0.0307	0.0226	0.0255	0.0263	0.0187	0.0262	0.0210	0.0254	0.0259
H	M	14.00	79.50	90.00	92.00	95.00	96.00	95.50	97.00	98.00	95.50	97.00
	SD	1.9815	4.9642	4.8476	4.2372	4.6307	4.2129	5.8530	5.0496	4.5945	4.6233	4.3423

Table 7: Problemwise comparison of the algorithms on the four performance metrics used, for problems Deb52, Pol and the ZDT family. The values reported represent the mean and standard error obtained for each combination of algorithm, problem and performance metric.

Problem	Metric	NSGA-II	ϵ -MOEA	cone-MOEA	C-NSGA-II	SPEA2	NSGA-IP
Deb52	γ	0.58±7e-3	0.56±3e-3	0.56±2e-3	0.58±1e-2	0.55±7e-3	0.55±6e-3
	Δ	0.53±8e-3	0.99±6e-4	0.32±3e-4	0.33±6e-3	0.20±3e-3	0.41±8e-3
	HV	0.99±7e-5	0.99±6e-5	0.99±0	0.99±1e-4	0.99±3e-5	0.99±7e-5
	CS	0.02±7e-4	0.03±10e-4	0.03±8e-4	0.02±8e-4	0.03±9e-4	0.02±8e-4
Pol	γ	0.20±2e-2	0.13±6e-4	0.19±2e-2	0.19±9e-3	0.15±2e-3	0.16±2e-3
	Δ	0.58±1e-2	0.98±9e-4	0.29±6e-3	0.38±7e-3	0.24±3e-3	0.36±8e-3
	HV	1.00±1e-5	1.00±5e-6	1.00±4e-6	1.00±3e-5	1.00±4e-6	1.00±8e-6
	CS	0.04±1e-3	0.04±1e-3	0.04±2e-3	0.04±10e-4	0.06±1e-3	0.05±1e-3
Zdt1	γ	0.16±2e-2	0.30±3e-2	0.23±3e-2	0.18±2e-2	0.30±2e-2	0.19±2e-2
	Δ	0.79±1e-2	0.70±4e-3	0.37±6e-3	0.50±8e-3	0.29±7e-3	0.56±1e-2
	HV	0.99±10e-4	0.98±2e-3	0.98±2e-3	0.98±9e-4	0.98±1e-3	0.98±1e-3
	CS	0.33±2e-2	0.20±3e-2	0.27±3e-2	0.30±2e-2	0.15±2e-2	0.27±2e-2
Zdt2	γ	0.43±9e-3	0.65±8e-3	0.30±4e-3	0.80±1e-2	0.41±8e-3	0.41±8e-3
	Δ	0.76±1e-2	0.56±3e-3	0.38±4e-3	0.50±7e-3	0.28±4e-3	0.58±1e-2
	HV	0.99±1e-4	0.99±7e-5	0.99±4e-5	0.98±1e-4	0.99±8e-5	0.99±9e-5
	CS	0.07±3e-3	0.07±3e-3	0.07±3e-3	0.07±3e-3	0.07±3e-3	0.07±3e-3
Zdt3	γ	0.16±2e-2	0.67±1e-2	0.67±1e-2	0.67±1e-2	0.67±1e-2	0.67±1e-2
	Δ	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3
	HV	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3	0.98±2e-3
	CS	0.41±3e-2	0.41±3e-2	0.41±3e-2	0.41±3e-2	0.41±3e-2	0.41±3e-2
Zdt4	γ	0.27±2e-2	0.27±2e-2	0.27±2e-2	0.27±2e-2	0.27±2e-2	0.27±2e-2
	Δ	0.61±9e-3	0.61±9e-3	0.61±9e-3	0.61±9e-3	0.61±9e-3	0.61±9e-3
	HV	0.84±9e-3	0.84±9e-3	0.84±9e-3	0.84±9e-3	0.84±9e-3	0.84±9e-3
	CS	0.73±3e-2	0.73±3e-2	0.73±3e-2	0.73±3e-2	0.73±3e-2	0.73±3e-2
Zdt6	γ	0.06±3e-2	0.06±3e-2	0.06±3e-2	0.06±3e-2	0.06±3e-2	0.06±3e-2
	Δ	0.52±1e-2	0.52±1e-2	0.52±1e-2	0.52±1e-2	0.52±1e-2	0.52±1e-2
	HV	0.96±1e-2	0.96±1e-2	0.96±1e-2	0.96±1e-2	0.96±1e-2	0.96±1e-2
	CS	0.18±2e-2	0.18±2e-2	0.18±2e-2	0.18±2e-2	0.18±2e-2	0.18±2e-2

Table 8: Problemwise comparison of the algorithms on the four performance metrics used, for the DTLZ family. The values reported represent the mean and standard error obtained for each combination of algorithm, problem and performance metric.

Problem	Metric	NSGA-II	ϵ -MOEA	cone-MOEA	C-NSGA-II	SPEA2	NSGA-IP
Dtlz1	γ	0.23±7e-3	0.13±1e-3	0.17±2e-2	0.39±1e-2	0.18±2e-3	0.17±2e-3
	Δ	0.34±3e-3	0.12±2e-3	0.05±1e-2	0.20±2e-2	0.08±1e-3	0.34±4e-3
	HV	0.95±6e-4	0.92±4e-4	0.95±2e-4	0.96±5e-4	0.97±1e-4	0.96±5e-4
	CS	0.02±8e-4	0.01±9e-4	0.03±1e-3	0.00±5e-4	0.02±1e-3	0.02±10e-4
Dtlz2	γ	0.62±10e-3	0.70±7e-3	0.42±4e-3	0.75±1e-2	0.55±8e-3	0.48±6e-3
	Δ	0.81±10e-3	0.42±4e-3	0.42±6e-3	0.29±5e-3	0.16±3e-3	0.83±9e-3
	HV	0.89±9e-4	0.92±4e-4	0.94±1e-4	0.93±4e-4	0.89±9e-4	0.89±9e-4
	CS	0.03±1e-3	0.02±8e-4	0.06±2e-3	0.01±6e-4	0.03±1e-3	0.04±1e-3
Dtlz3	γ	0.35±2e-2	0.25±1e-2	0.42±3e-2	0.50±3e-2	0.32±2e-2	0.26±1e-2
	Δ	0.33±9e-3	0.19±1e-2	0.29±2e-2	0.22±3e-2	0.15±2e-2	0.34±8e-3
	HV	0.90±10e-4	0.91±2e-2	0.91±1e-2	0.91±1e-3	0.93±3e-4	0.90±9e-4
	CS	0.02±1e-3	0.03±2e-3	0.04±2e-3	0.00±5e-4	0.02±2e-3	0.02±2e-3
Dtlz4	γ	0.32±8e-3	0.41±2e-2	0.53±3e-2	0.34±1e-2	0.33±1e-2	0.30±3e-3
	Δ	0.67±2e-2	0.37±3e-2	0.43±2e-2	0.36±4e-2	0.22±3e-2	0.66±8e-3
	HV	0.88±1e-2	0.86±2e-2	0.86±2e-2	0.84±2e-2	0.87±2e-2	0.90±7e-4
	CS	0.04±2e-3	0.02±1e-3	0.03±2e-3	0.02±2e-3	0.03±2e-3	0.03±1e-3
Dtlz5	γ	0.14±2e-3	0.26±3e-3	0.56±3e-2	0.22±5e-3	0.15±2e-3	0.13±1e-3
	Δ	0.74±2e-2	0.78±5e-3	0.83±9e-3	0.43±6e-3	0.26±4e-3	0.61±1e-2
	HV	0.99±1e-4	0.99±7e-5	0.98±3e-5	0.98±1e-4	0.99±4e-5	0.99±1e-4
	CS	0.06±2e-3	0.02±1e-3	0.03±1e-3	0.03±1e-3	0.05±2e-3	0.07±2e-3
Dtlz9	γ	0.84±8e-3	0.94±3e-3	0.83±3e-3	0.83±5e-3	0.84±7e-3	0.84±8e-3
	Δ	0.62±5e-3	0.71±1e-2	0.52±6e-3	0.44±7e-3	0.77±7e-3	0.90±5e-3
	HV	0.99±9e-5	0.99±9e-5	0.99±9e-5	0.99±9e-5	0.99±9e-5	0.99±9e-5
	CS	0.11±8e-3	0.51±1e-2	0.34±7e-3	0.23±8e-3	0.24±8e-3	0.13±7e-3

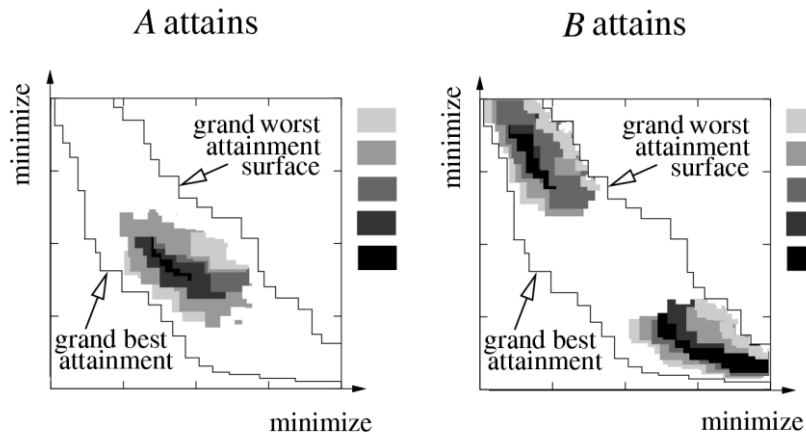
Numbers have their value.
But not *only* tables, please!

v1.0

v1.0: Two Approaches for Empirical Studies

Attainment function approach

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



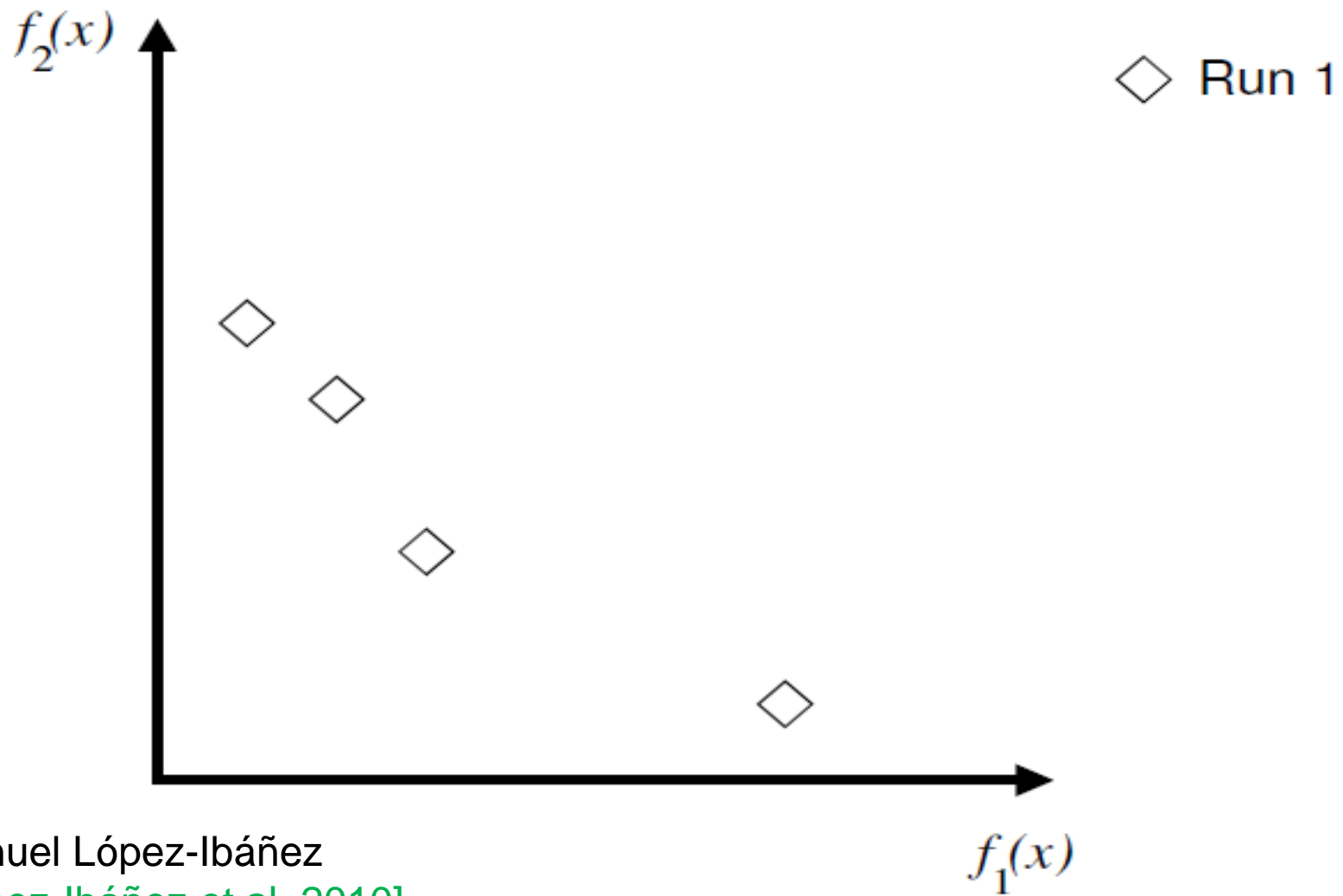
Quality indicator approach

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

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

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

Empirical Attainment Functions

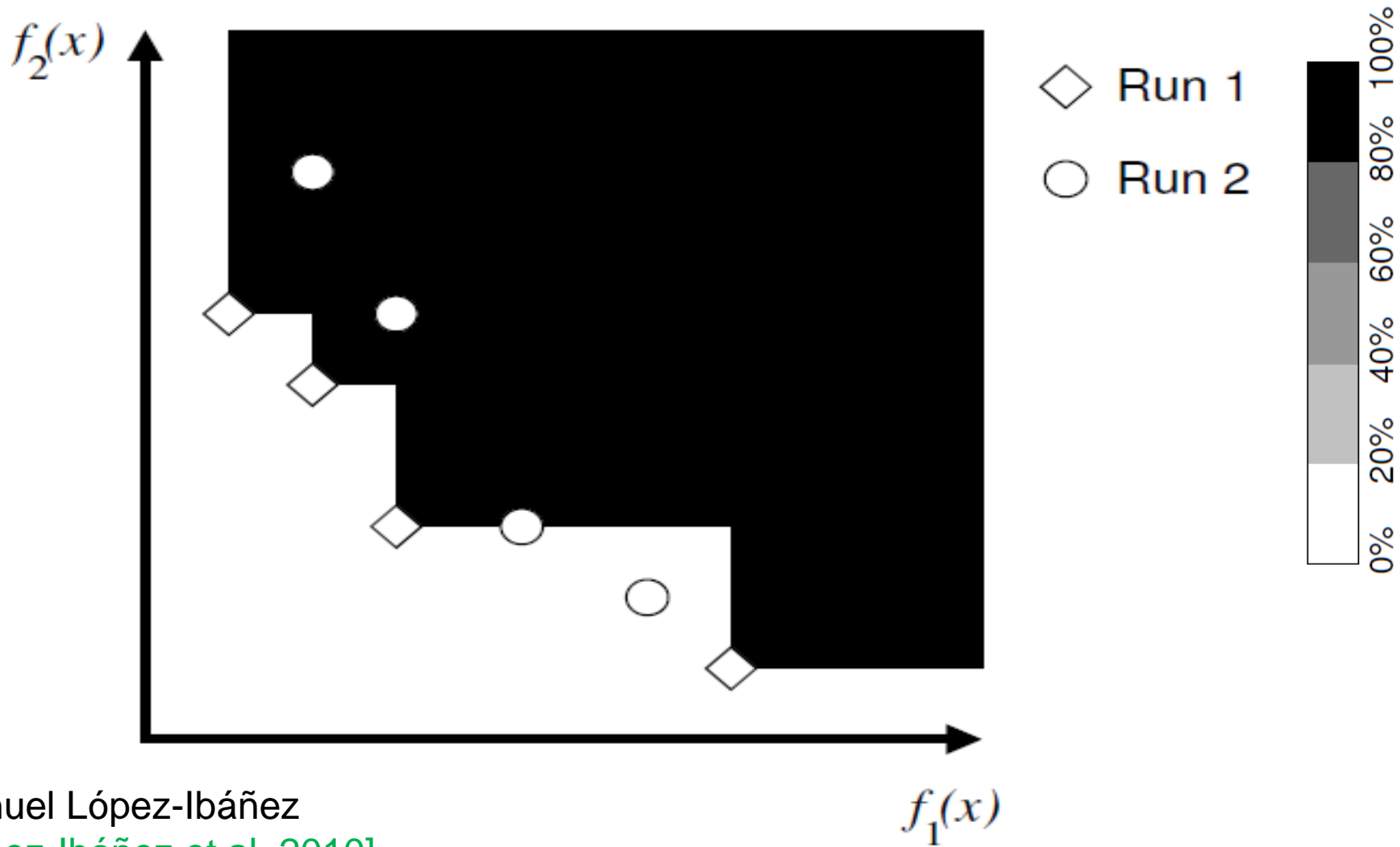


Empirical Attainment Functions



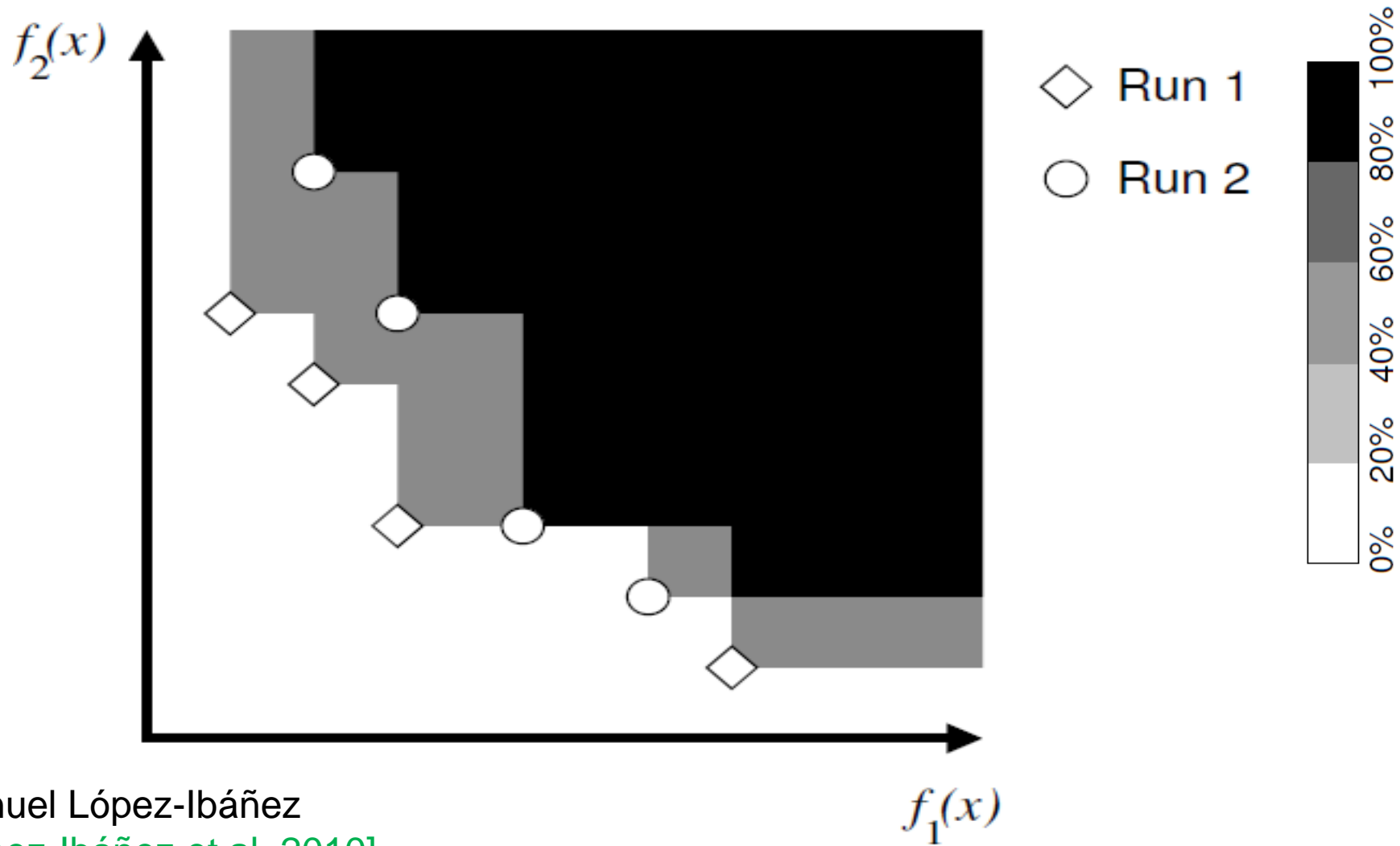
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Empirical Attainment Functions



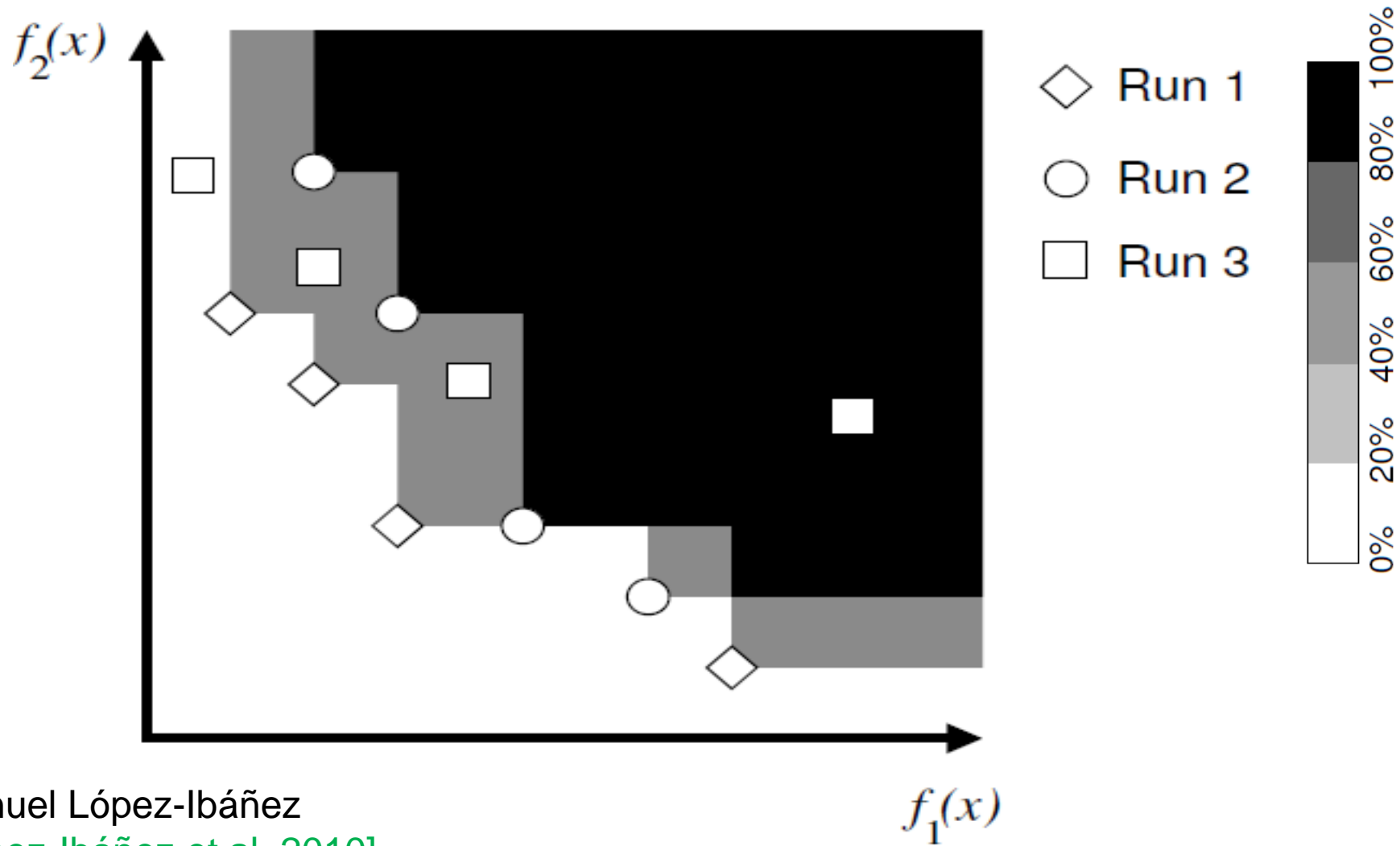
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Empirical Attainment Functions

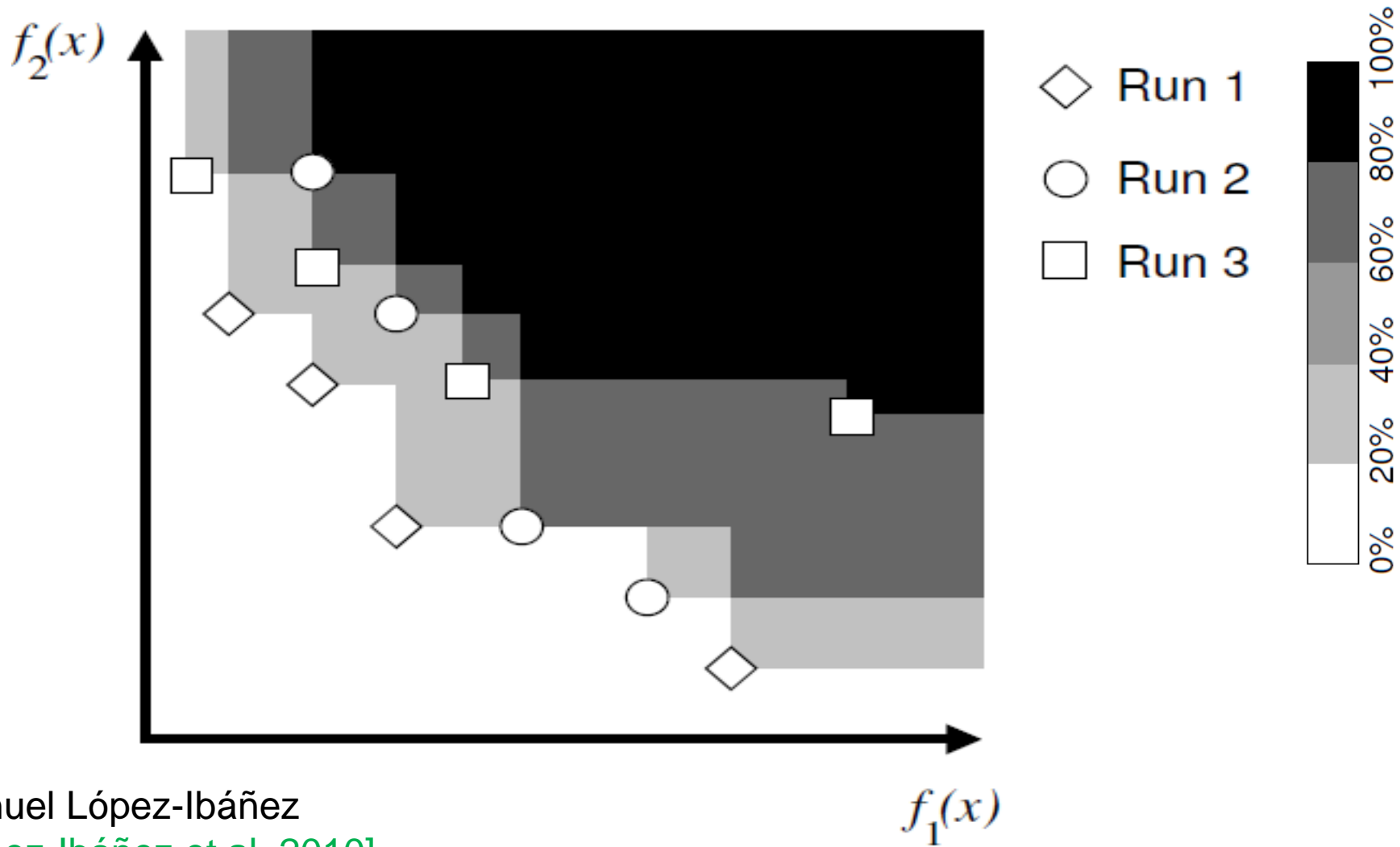


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Empirical Attainment Functions



Empirical Attainment Functions



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Empirical Attainment Functions: Definition

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

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

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

Empirical Attainment Functions: Definition

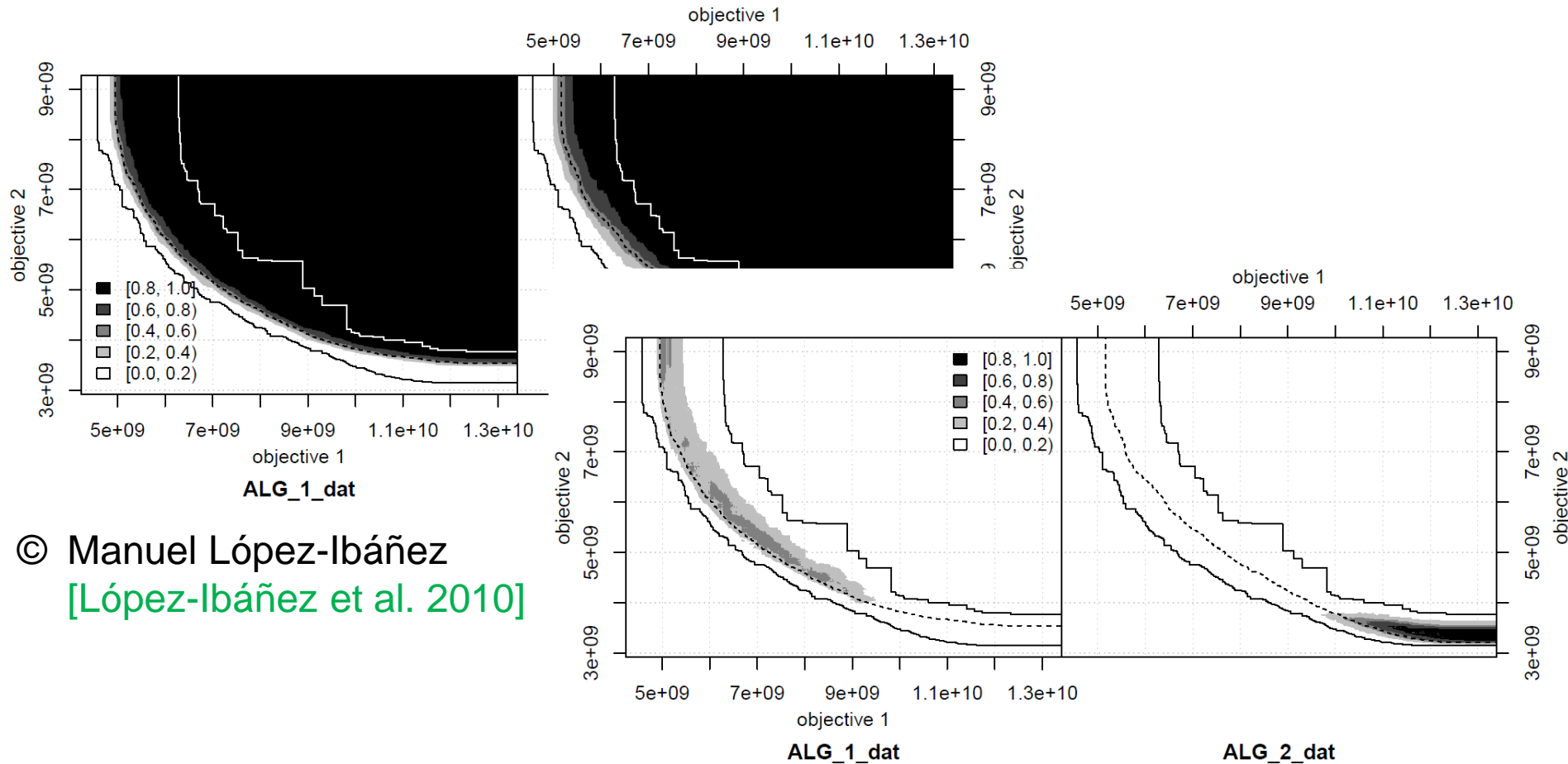
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with \preceq_T being the weak dominance relation between a solution set and an objective vector at time T .

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

Empirical Attainment Functions in Practice



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[López-Ibáñez et al. 2010]

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

Quality Indicator Approach

Idea:

transfer multiobjective problem into a set problem

define an objective function (“unary quality indicator”) on sets

use the resulting total (pre-)order (on the quality values)

Quality Indicator Approach

Idea:

transfer multiobjective problem into a set problem

define an objective function (“unary quality indicator”) on sets

use the resulting total (pre-)order (on the quality values)

Question:

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

⇒ Underlying dominance relation
should be reflected!

$$A \preceq B: \Leftrightarrow \forall b \in B \exists a \in A \ a \preceq b$$

Monotonicity and Strict Monotonicity

- Monotonicity when quality indicator does not contradict relation

$$A \preceq B \Rightarrow I(A) \geq I(B)$$

Monotonicity and Strict Monotonicity

- Monotonicity when quality indicator does not contradict relation

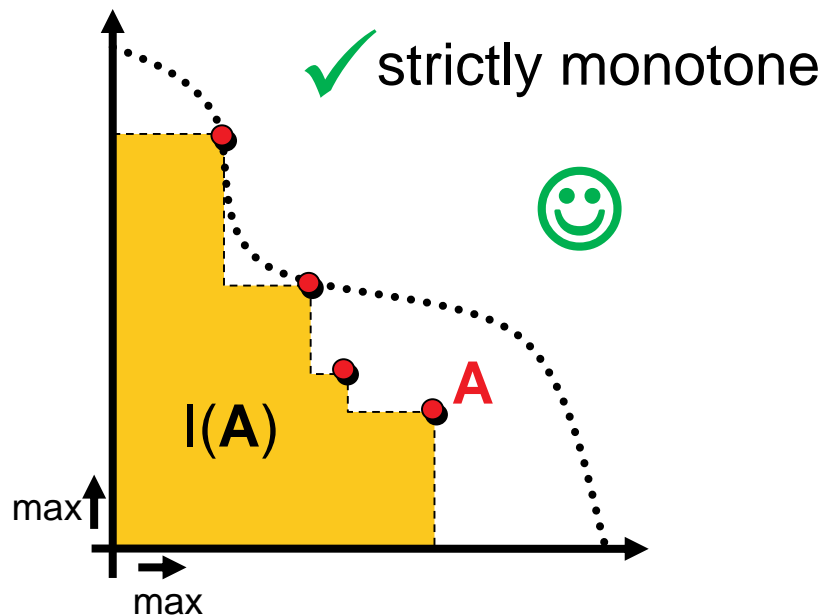
$$A \preceq B \Rightarrow I(A) \geq I(B)$$

- Strict monotonicity: better = higher indicator

$$A \preceq B \text{ and } A \neq B \Rightarrow I(A) > I(B)$$

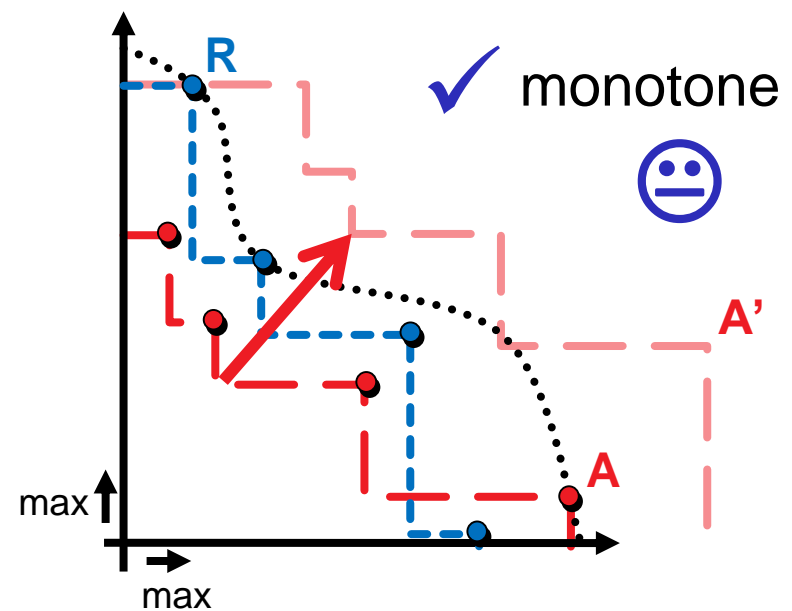
Example: Refinements Using Indicators

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



unary hypervolume indicator

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



unary epsilon indicator

v1.0.1 – v1.0.100 and counting

Performance Assessment of Multiobjective Optimizers: An Analysis and Review

Eckart Zitzler¹, Lothar Thiele¹, Marco Laumanns¹,
Carlos M. Fonseca², and Viviane Grunert da Fonseca²

¹ Computer Engineering and Networks Laboratory (TIK)
Department of Information Technology and Electrical Engineering
Swiss Federal Institute of Technology (ETH) Zurich, Switzerland
Email: {zitzler, thiele, laumanns}@tik.ee.ethz.ch

²ADEEC and ISR (Coimbra)
Faculty of Sciences and Technology
University of Algarve, Portugal
Email: cmfonsec@ualg.pt, vgrunert@csi.fct.ualg.pt

22 indicators

[Zitzler et al. 2003]

Even More Indicators...

Performance indicators in multiobjective optimization

Charles Audet^a, Jean Bignon^b, Dominique Cartier^c, Sébastien Le Digabel^a,
Ludovic Salomon^{a,1}

^a*GERAD and Département de mathématiques et génie industriel, École Polytechnique de Montréal,
C.P. 6079, Succ. Centre-ville, Montréal, Québec, H3C 3A7, Canada.*

^b*Univ. Grenoble Alpes, CNRS, Grenoble INP, G-SCOP, 38000 Grenoble, France.*

^c*Collège de Maisonneuve, 3800 Rue Sherbrooke E, Montréal, Québec, H1X 2A2, Canada.*

[Audet et al 2021]

63 indicators

Quality Evaluation of Solution Sets in Multiobjective Optimisation: A Survey

Miqing Li, and Xin Yao¹

¹CERCIA, School of Computer Science, University of Birmingham, Birmingham B15 2TT, U. K.

*Email: limitsing@gmail.com, x.yao@cs.bham.ac.uk

[Li and Yao 2019]

100 indicators

Many Indicators: What Do We Do?

Focus on indicators which are (strictly) monotone

all hypervolume-based indicators

unary epsilon indicator

R2

IGD+

Many Indicators: What Do We Do?

Focus on indicators which are (strictly) monotone

all hypervolume-based indicators

unary epsilon indicator

R2

IGD+

Why is monotonicity important?

- Pareto dominance is the lowest form of preference
- If dominance relation does not hold, we have not defined a true multiobjective problem.

v2.0

Benchmarking Multiobjective Optimizers 2.0

- With the right (strictly) monotone indicator, multiobjective optimization is not different from single-objective optimization (!)

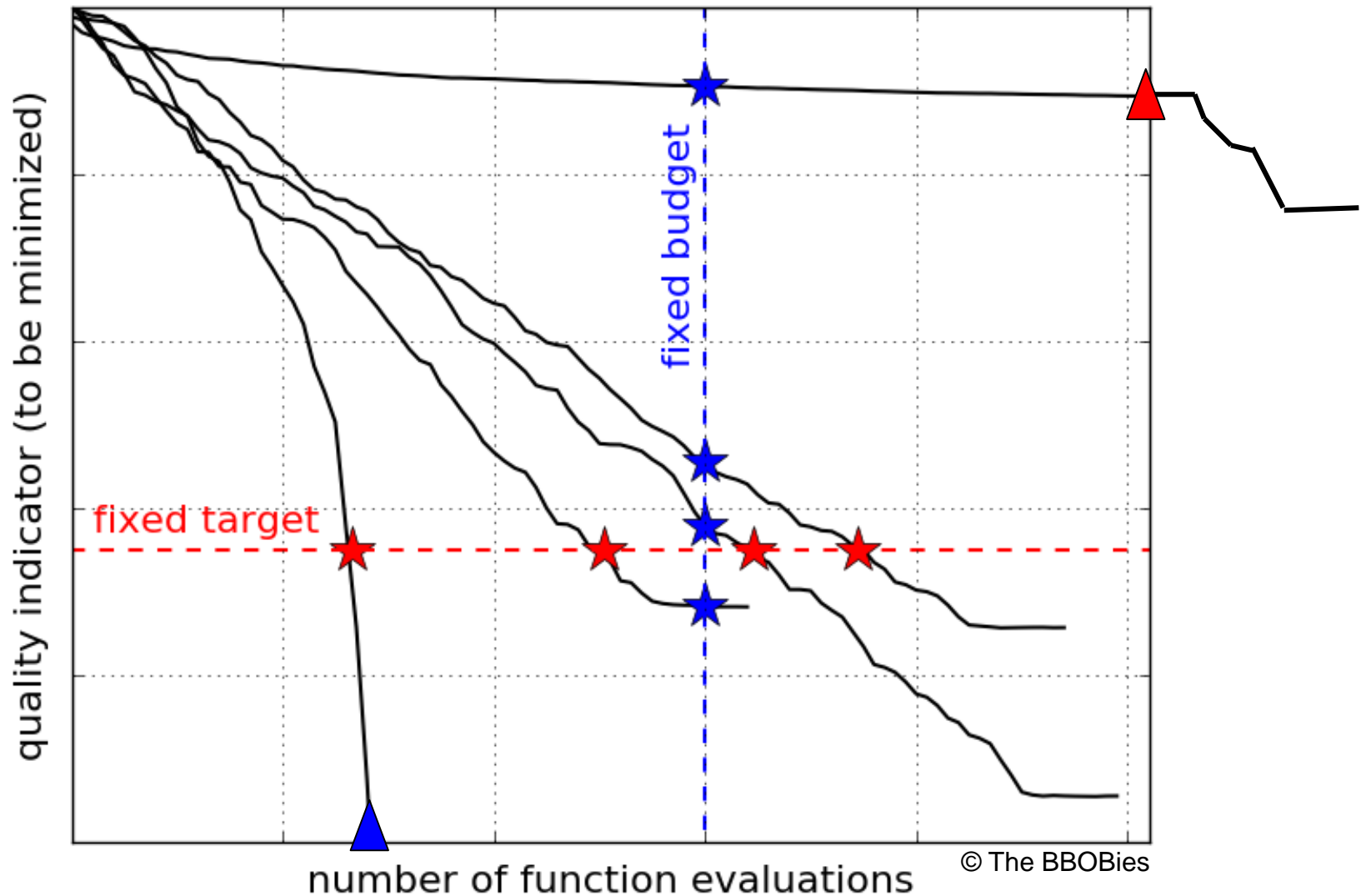
We can use our normal tools from single-objective optimization, including

- reporting of target-based runtimes
- ECDFs of runtimes, performance profiles, data profiles
- statistical tests, box plots, ...

see for example [Hansen et al. 2021]

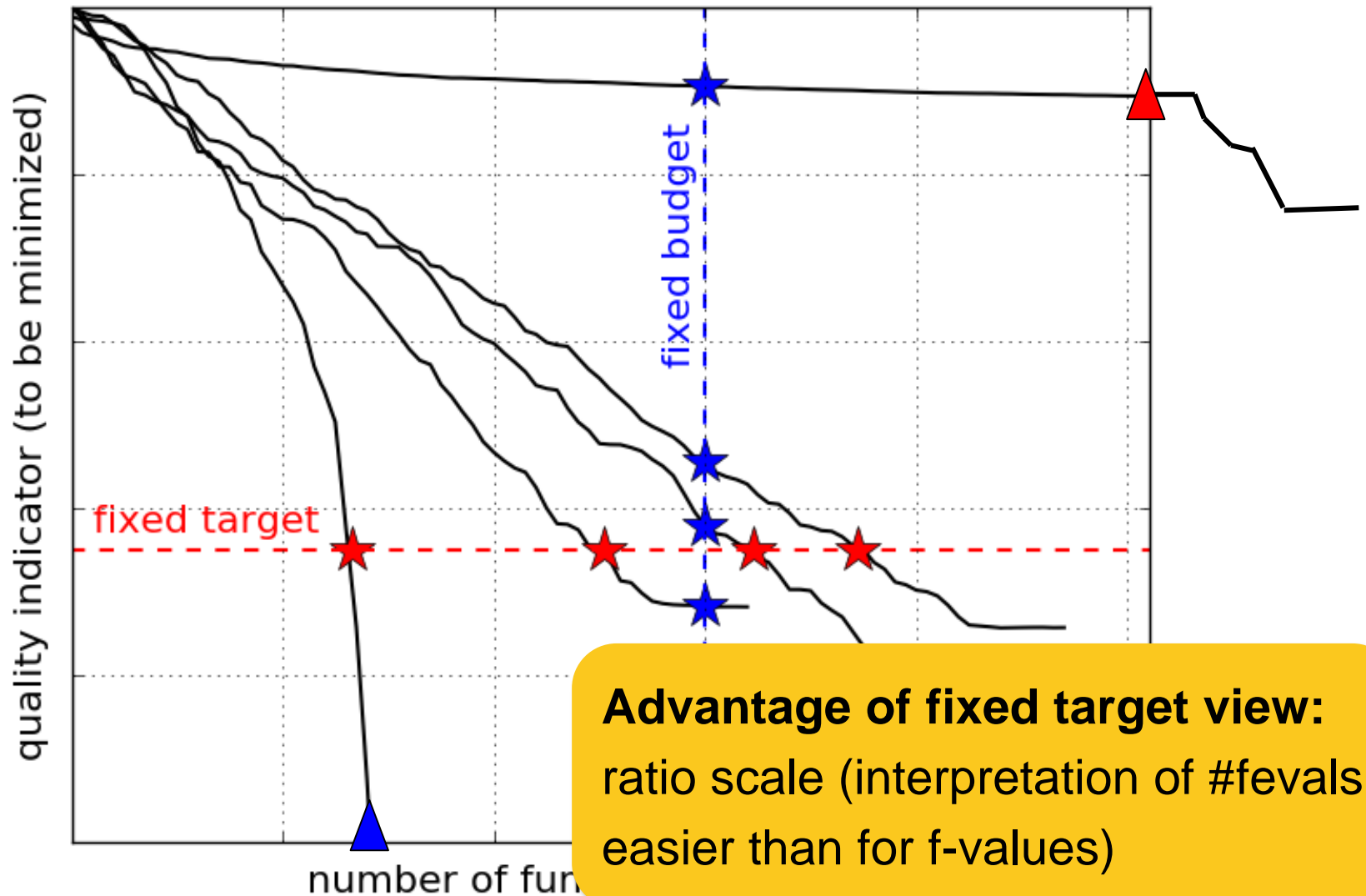
Measuring Performance Empirically

convergence graphs is all we have to start with...



Measuring Performance Empirically

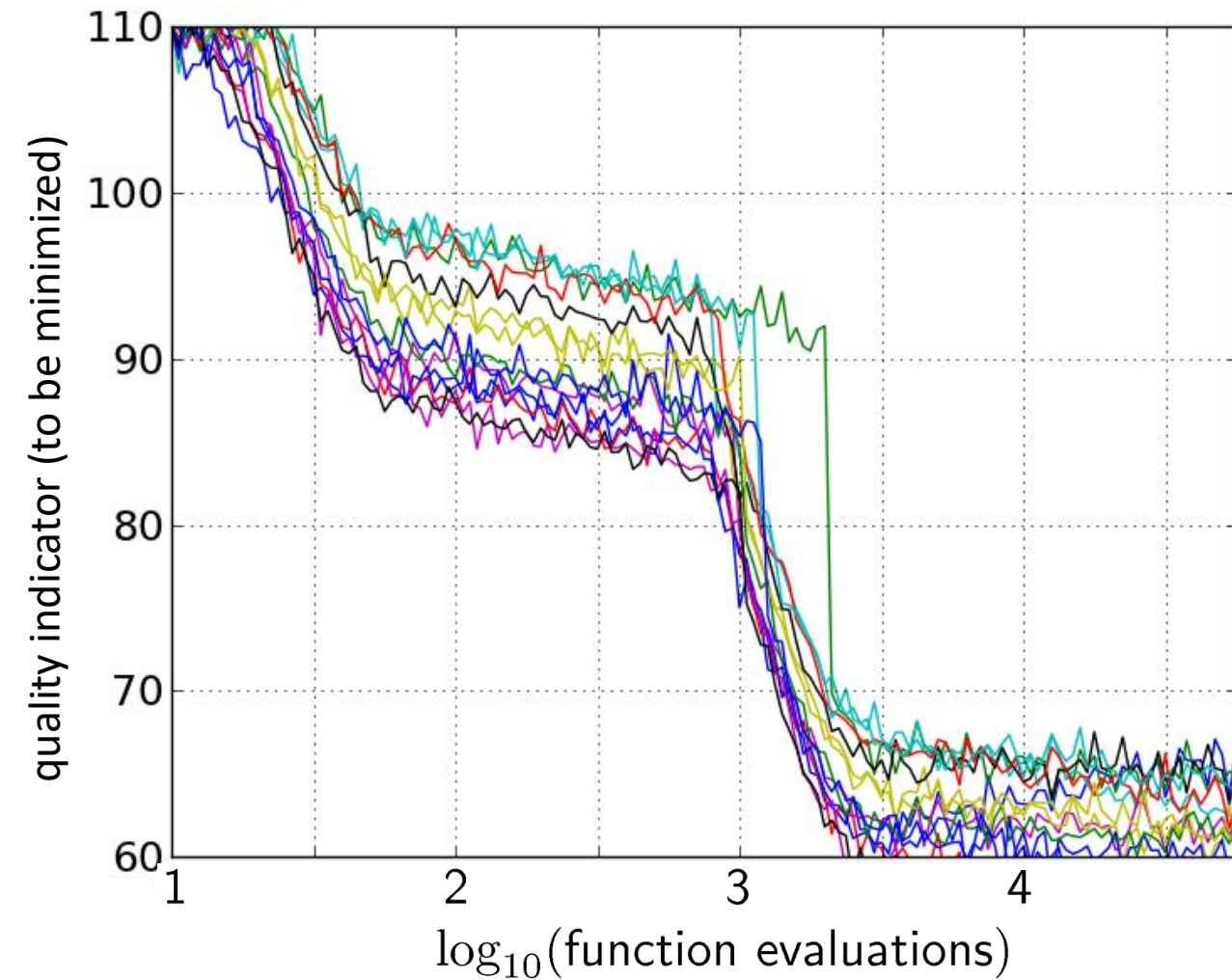
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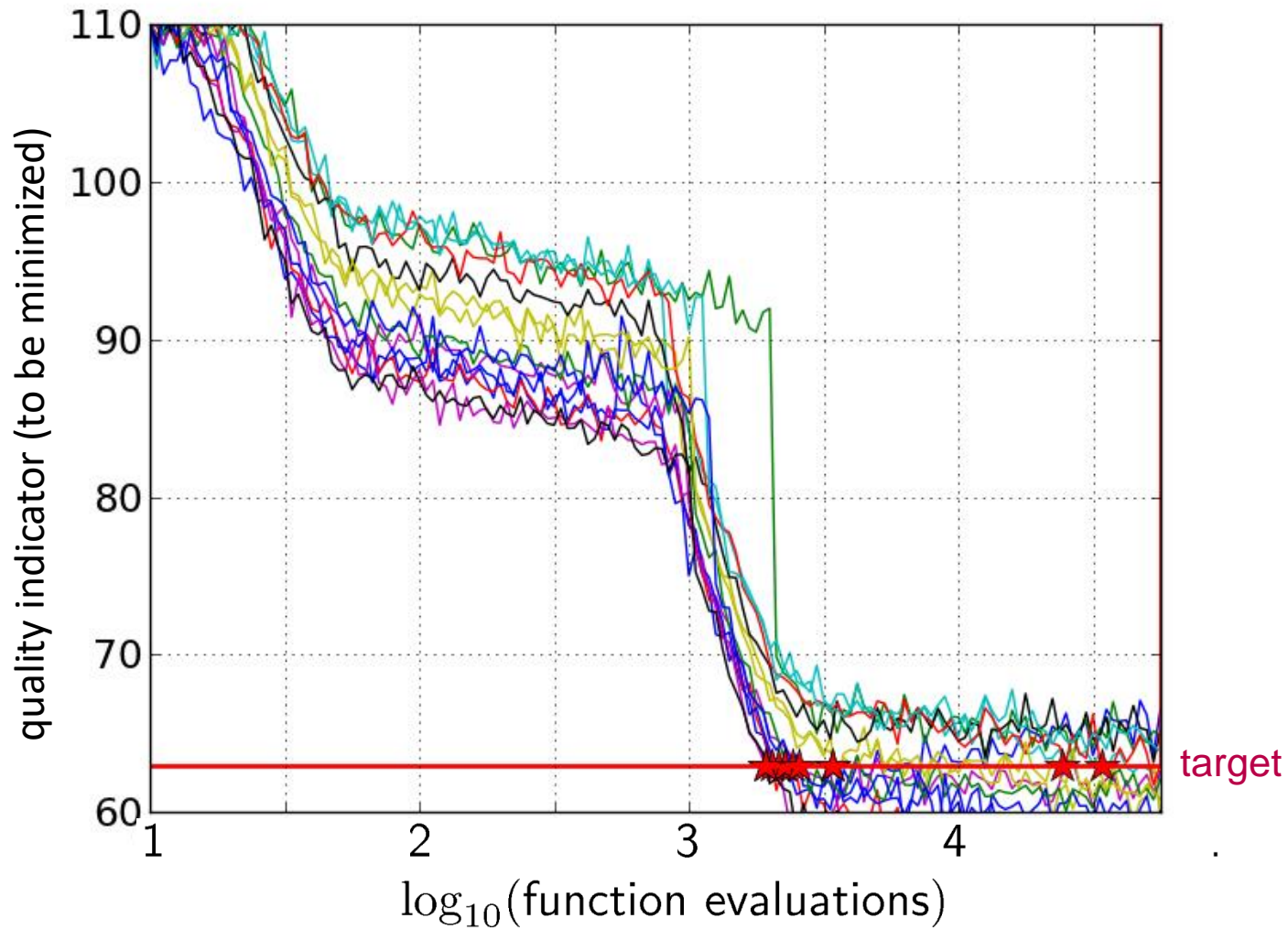
ECDF:

Empirical Cumulative Distribution Function of the
Runtime

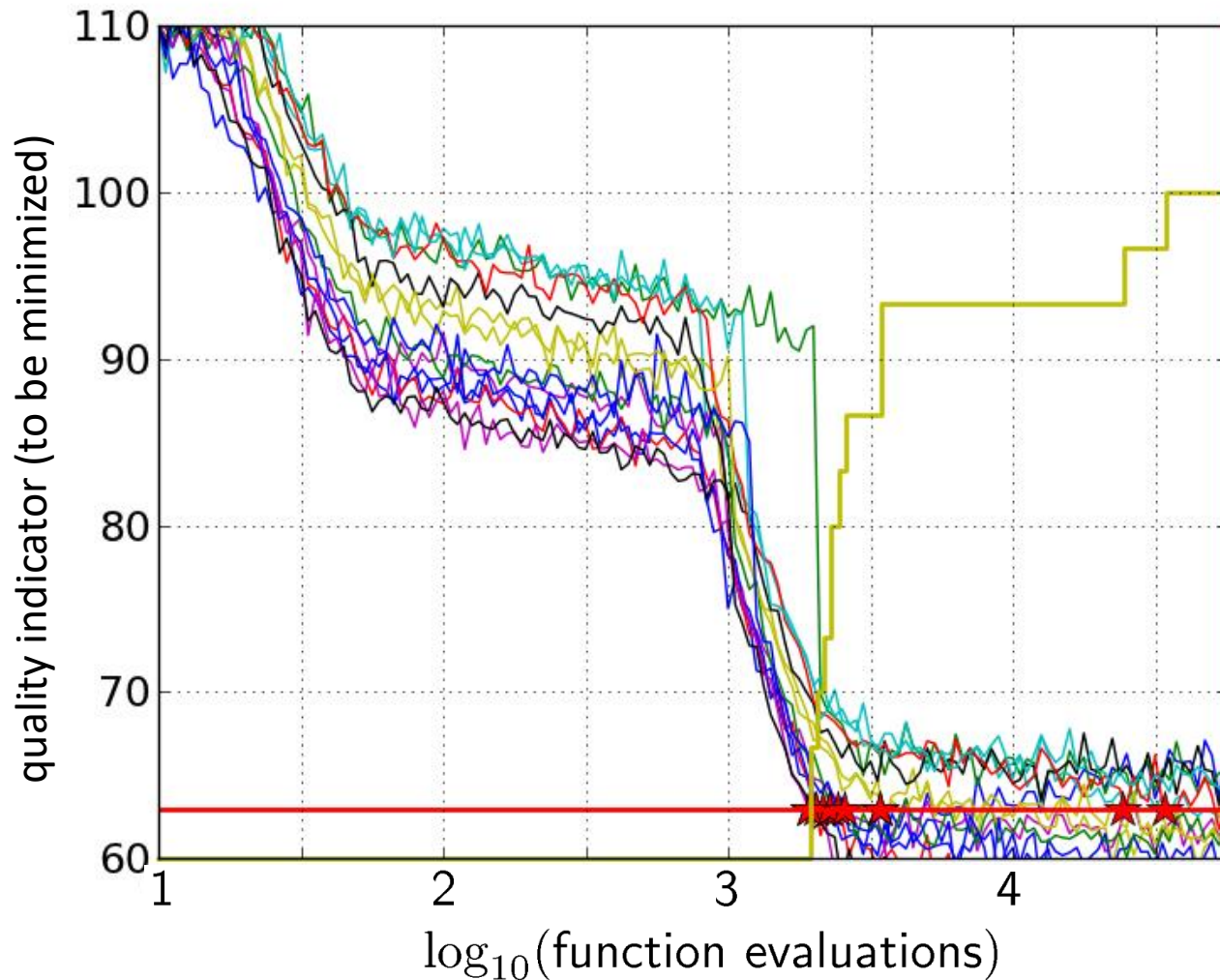
Convergence Graph of 15 Runs



15 Runs \leq 15 Runtime Data Points



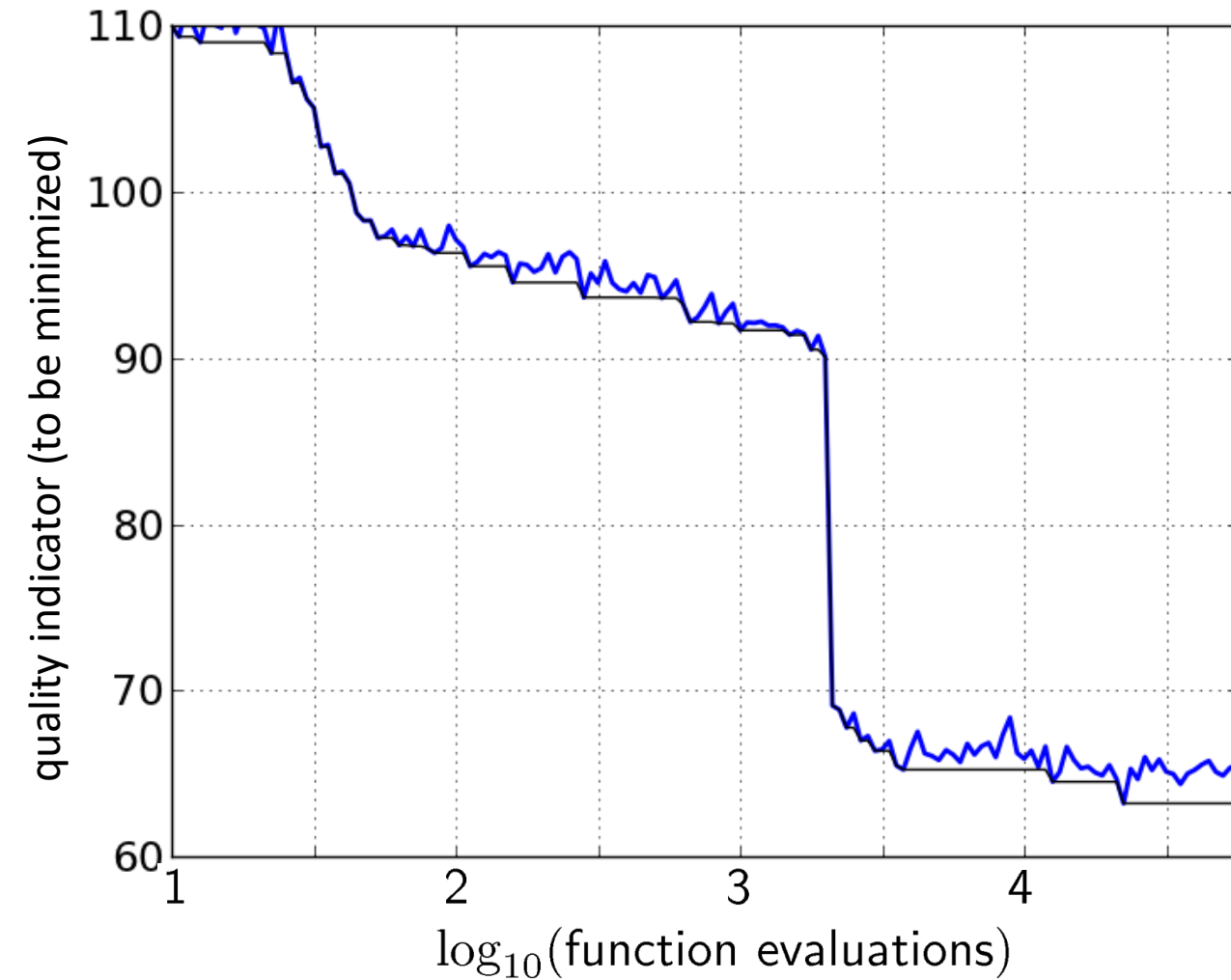
Empirical Cumulative Distribution



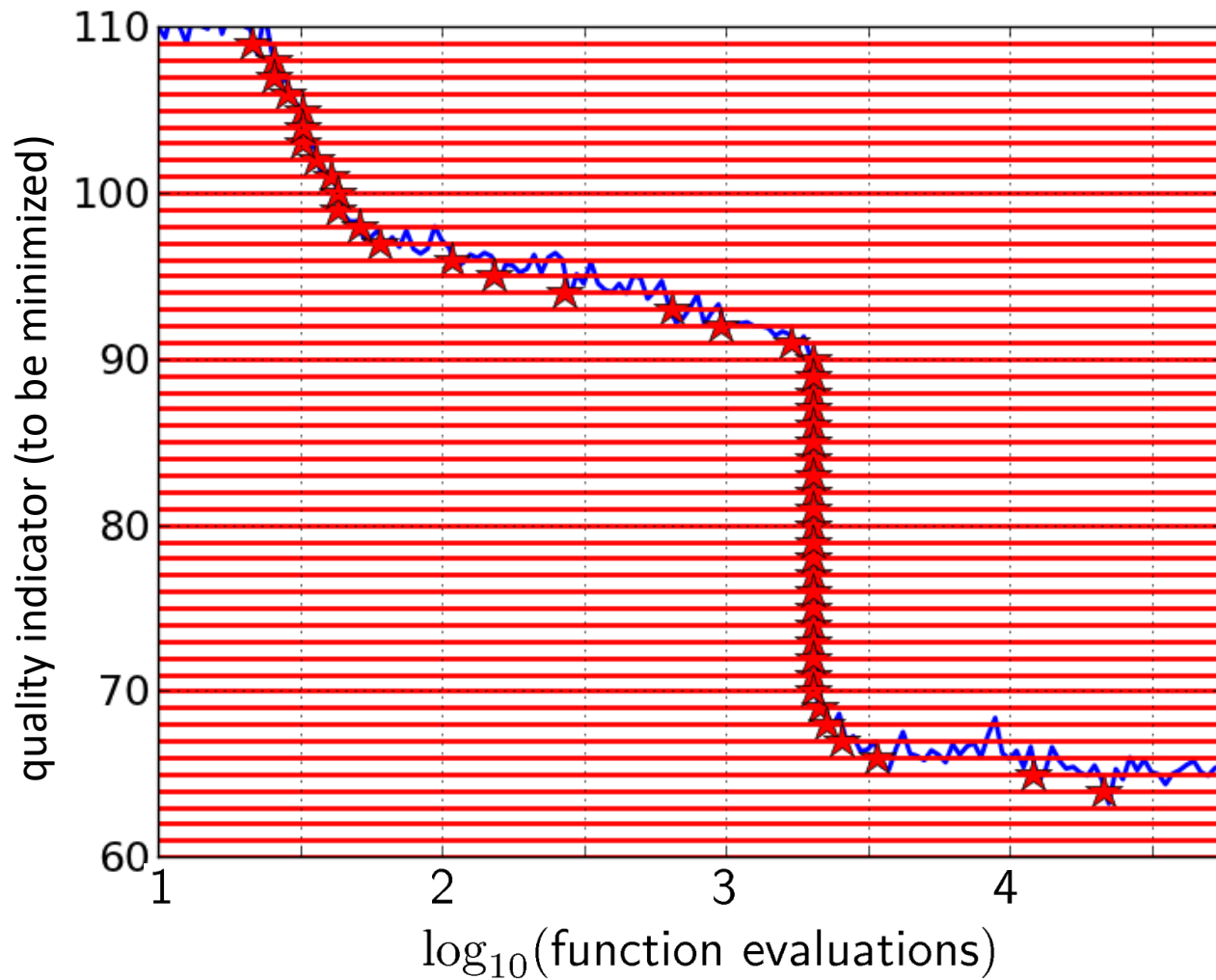
the **ECDF** of run lengths to reach the target

- has for each data point a **vertical step of constant size**
- displays for each x-value (budget) the count of observations to the left (first hitting times)

Reconstructing A Single Run

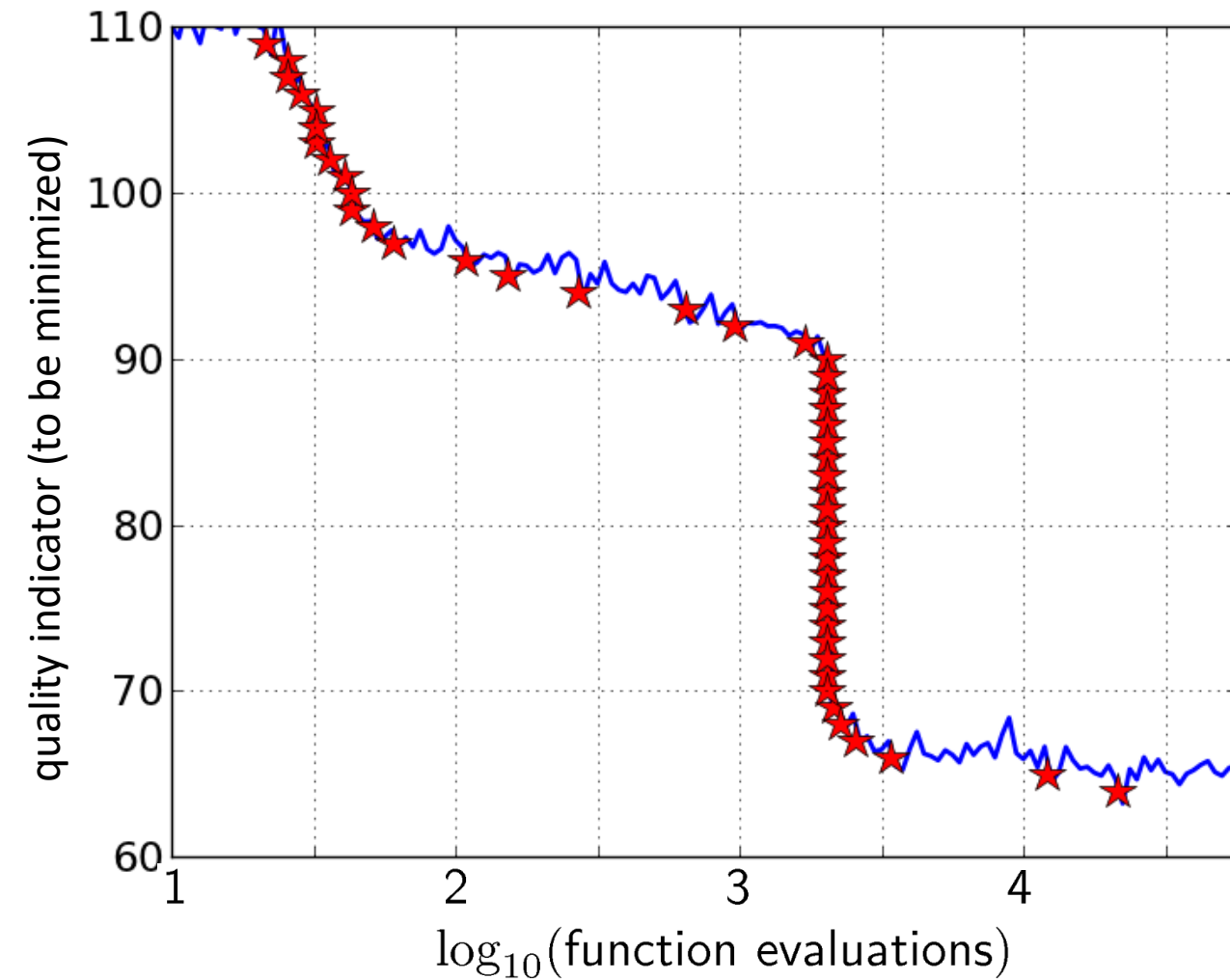


Reconstructing A Single Run

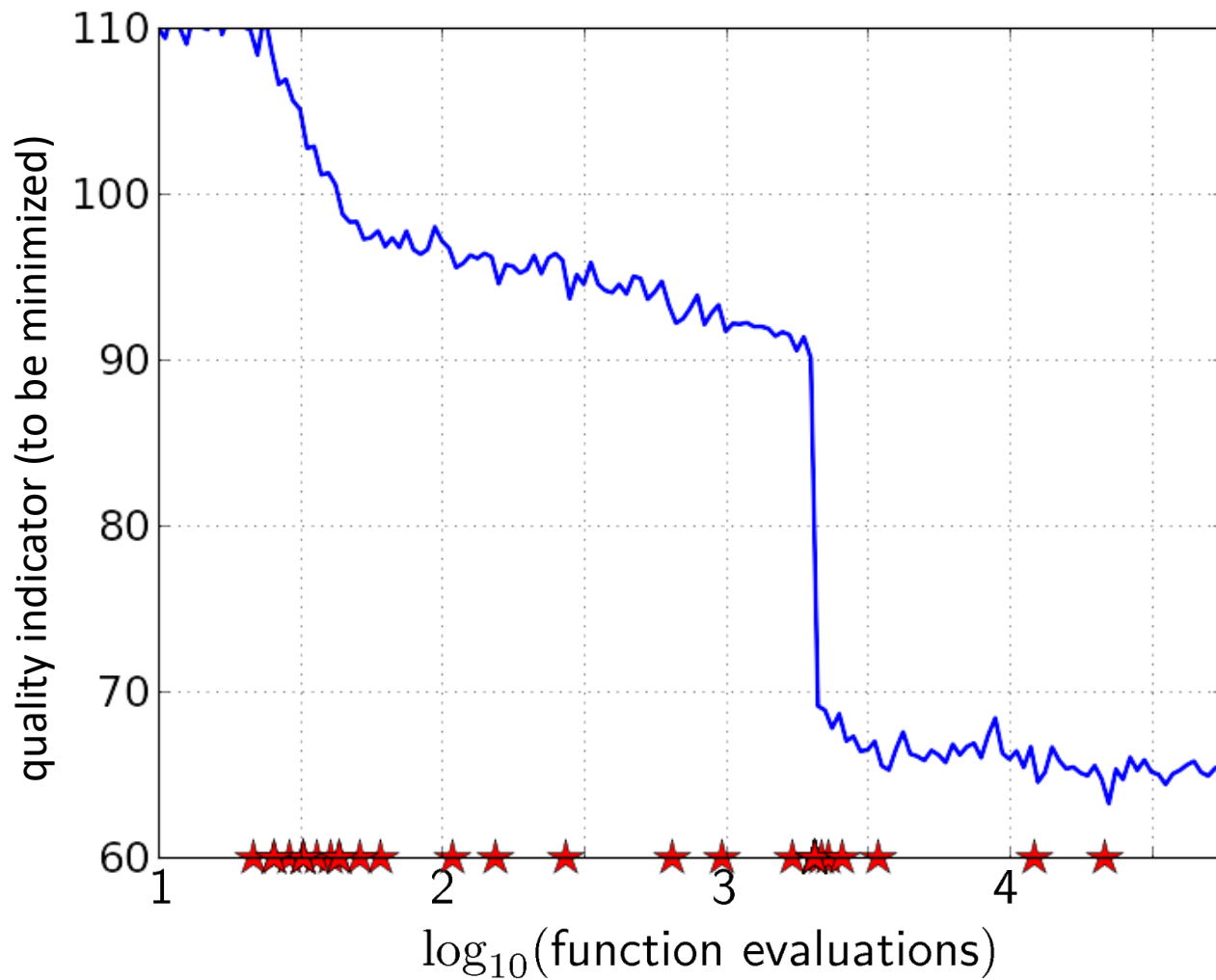


50 equally spaced targets

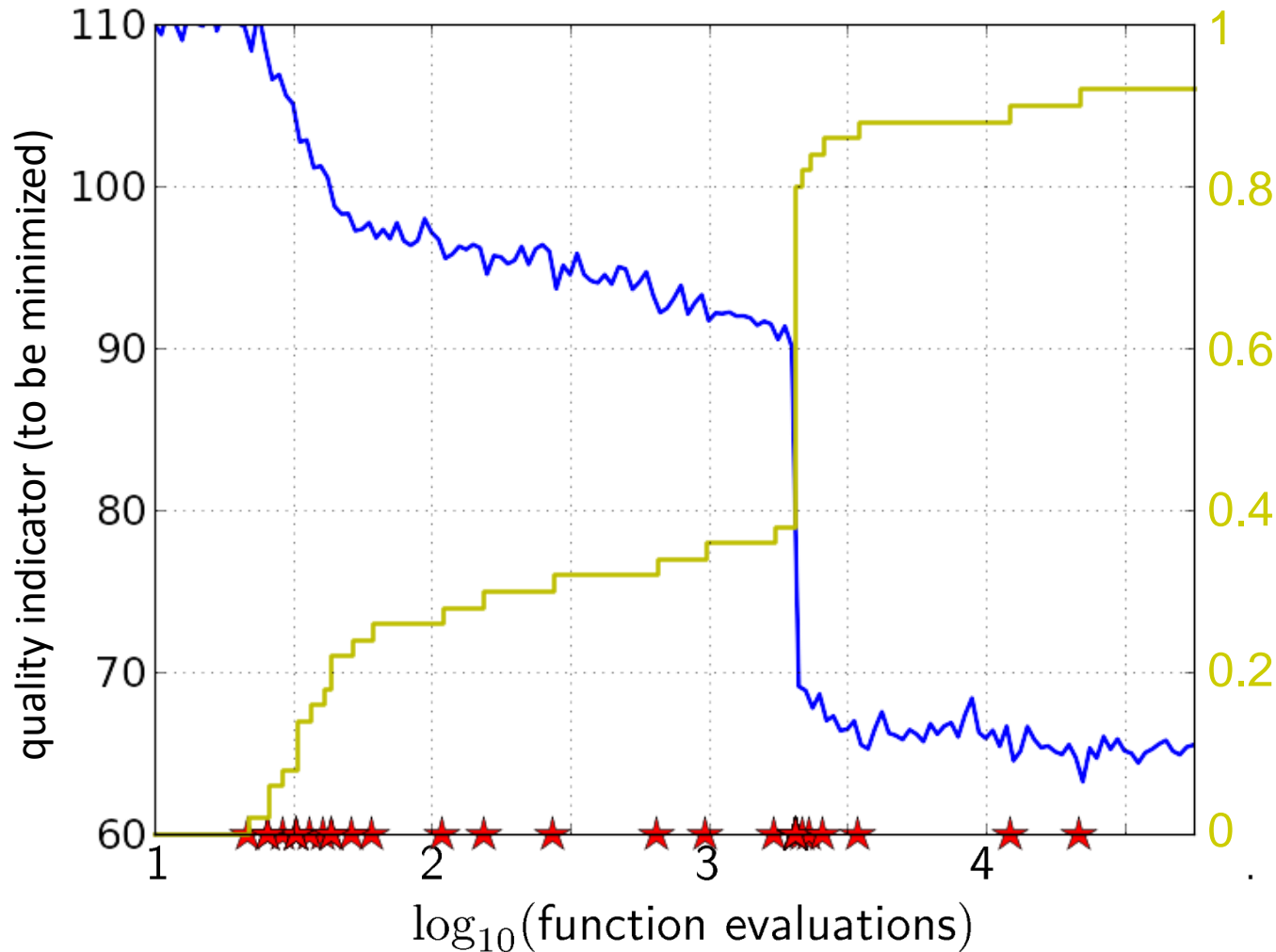
Reconstructing A Single Run



Reconstructing A Single Run

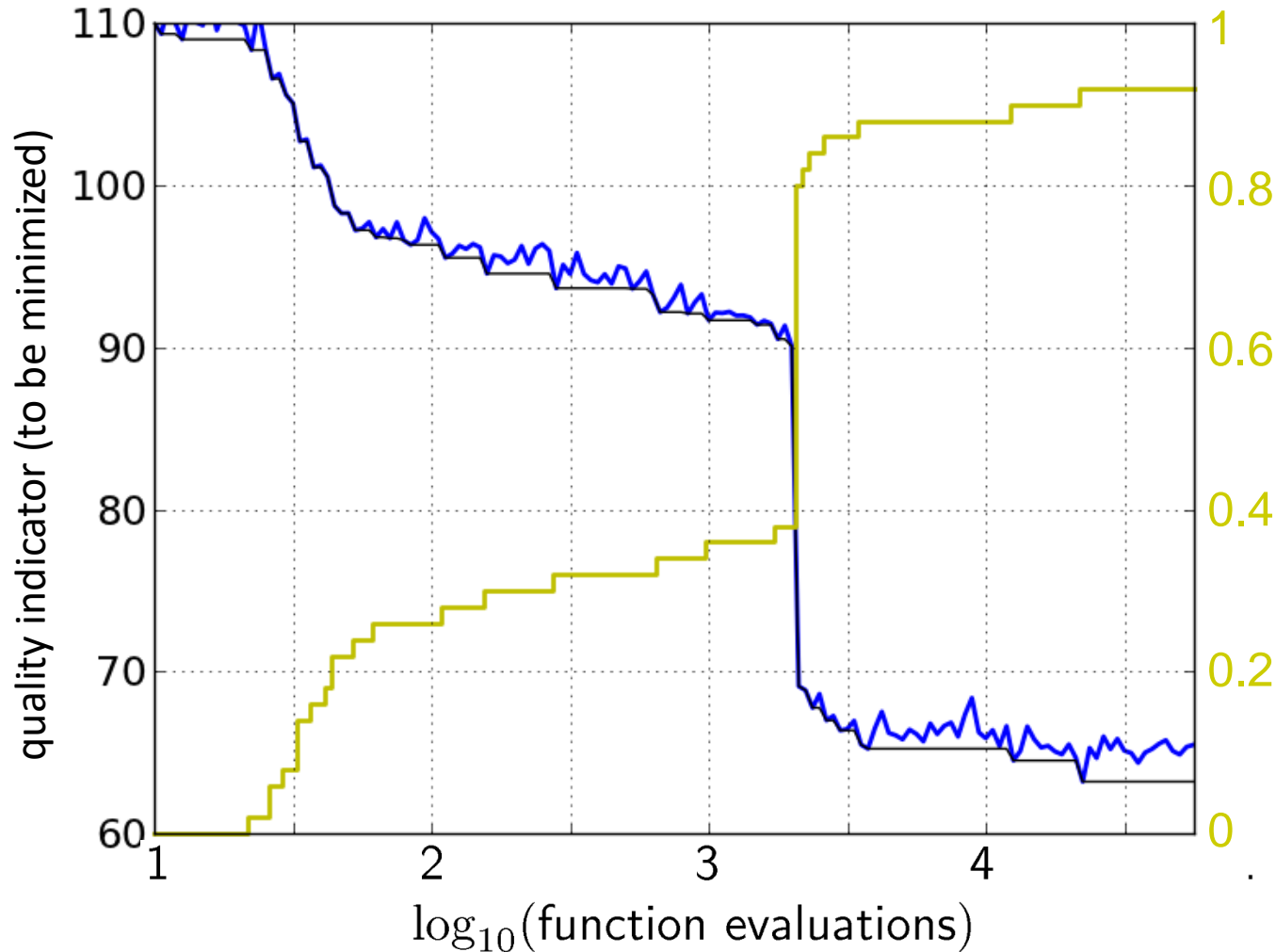


Reconstructing A Single Run



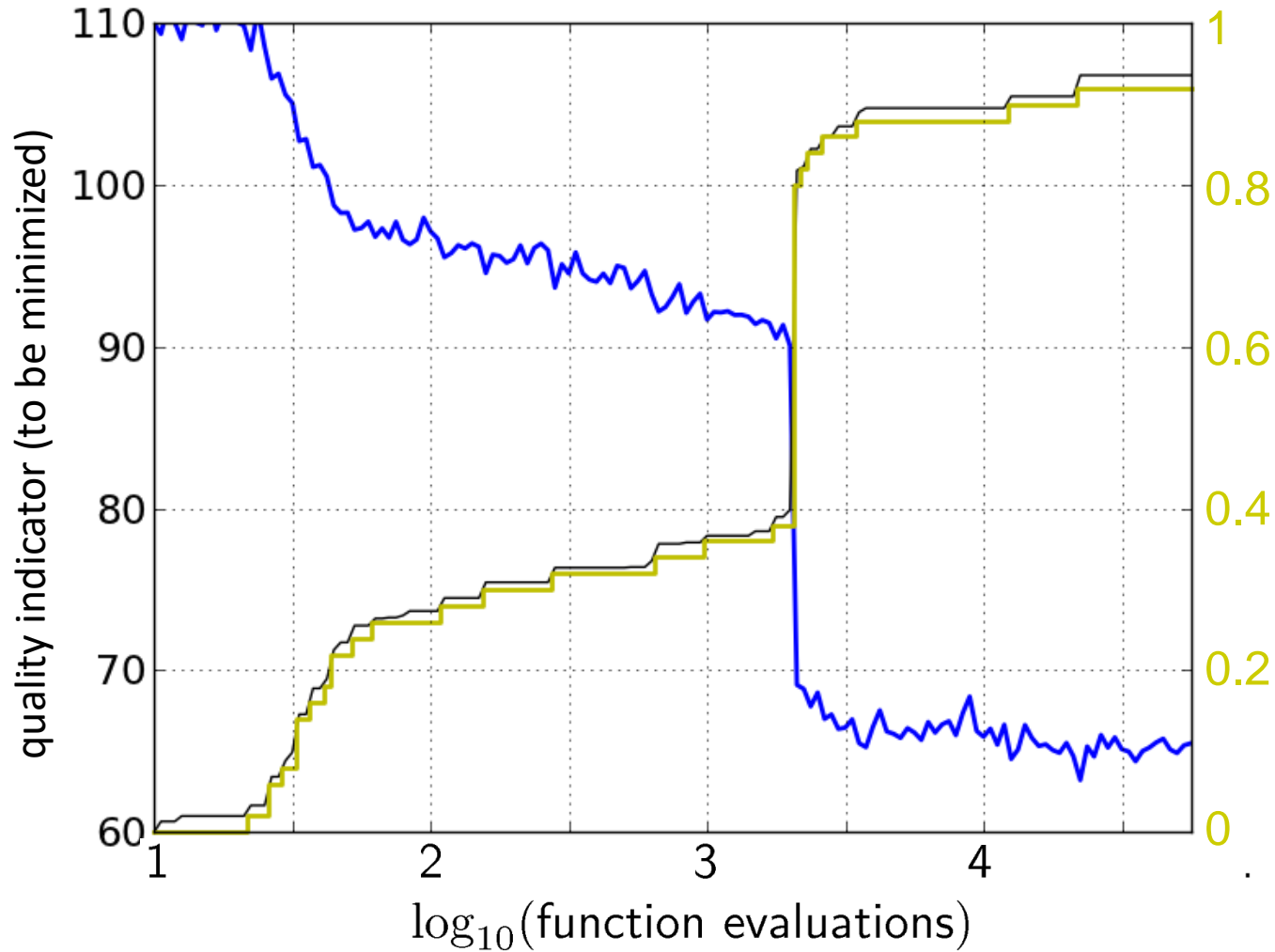
the empirical CDF makes a step for each star, is monotonous and displays for each budget the fraction of targets achieved within the budget

Reconstructing A Single Run



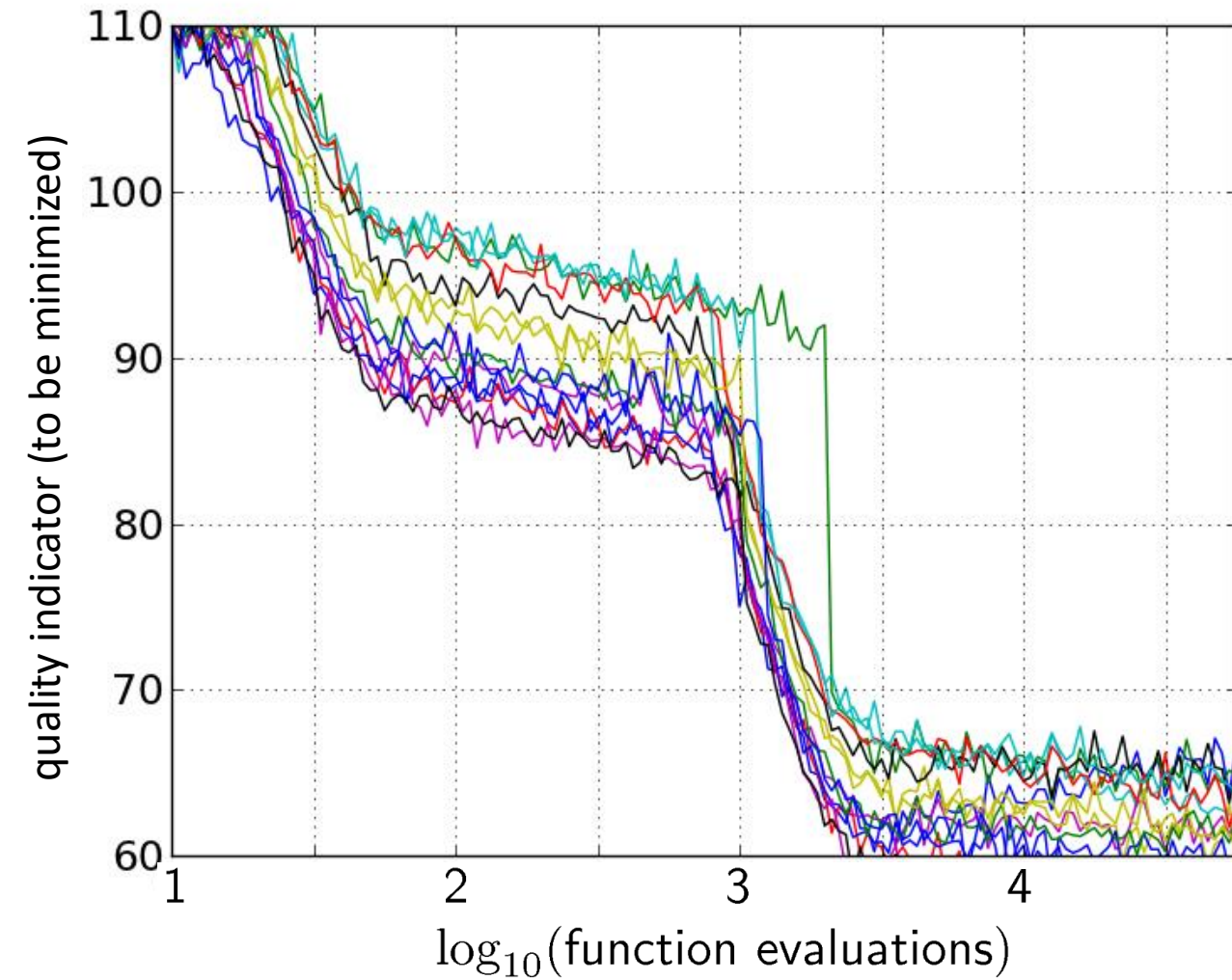
the ECDF
recovers the
monotonous
graph,
discretized and
flipped

Reconstructing A Single Run

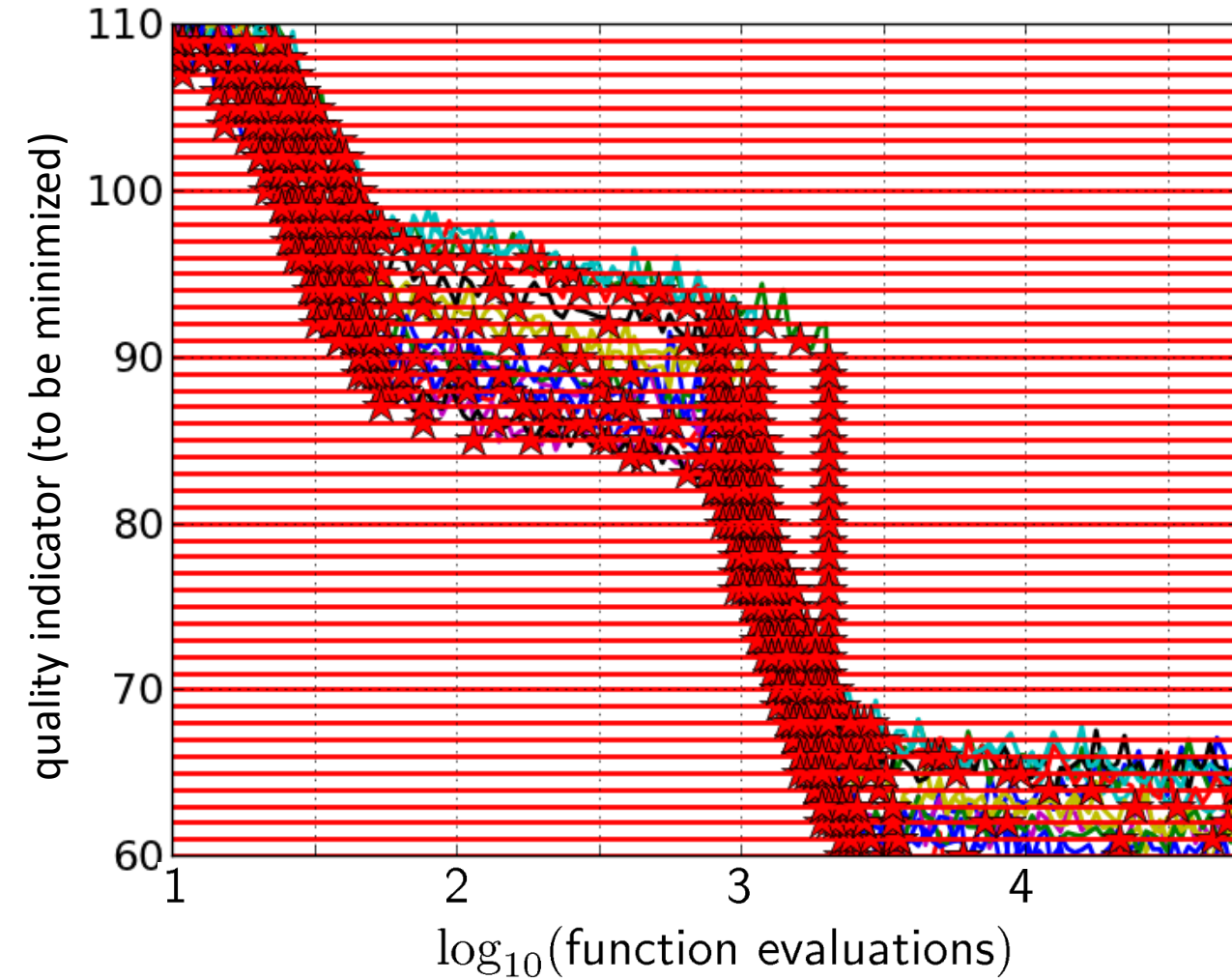


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Aggregation



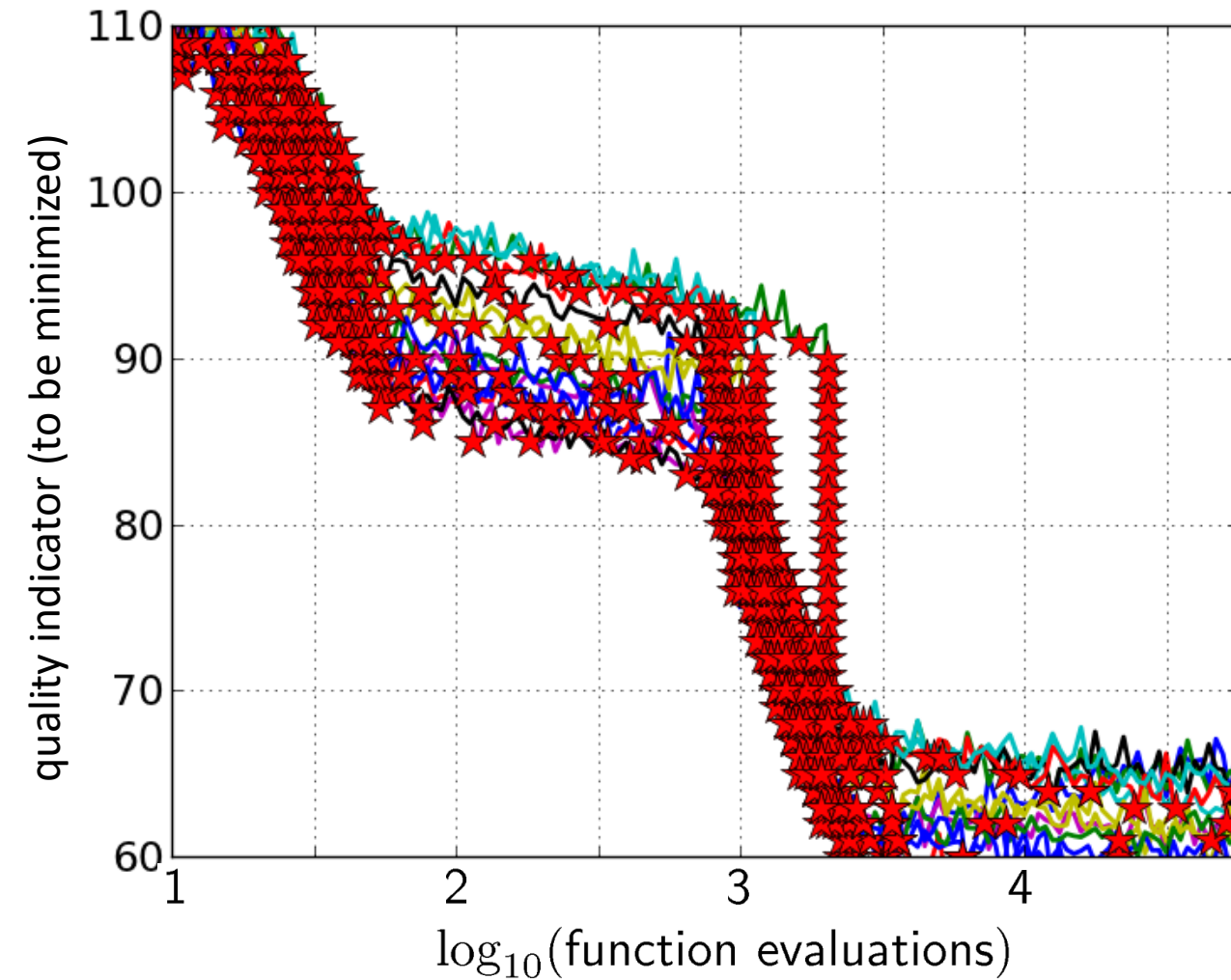
Aggregation



15 runs

50 targets

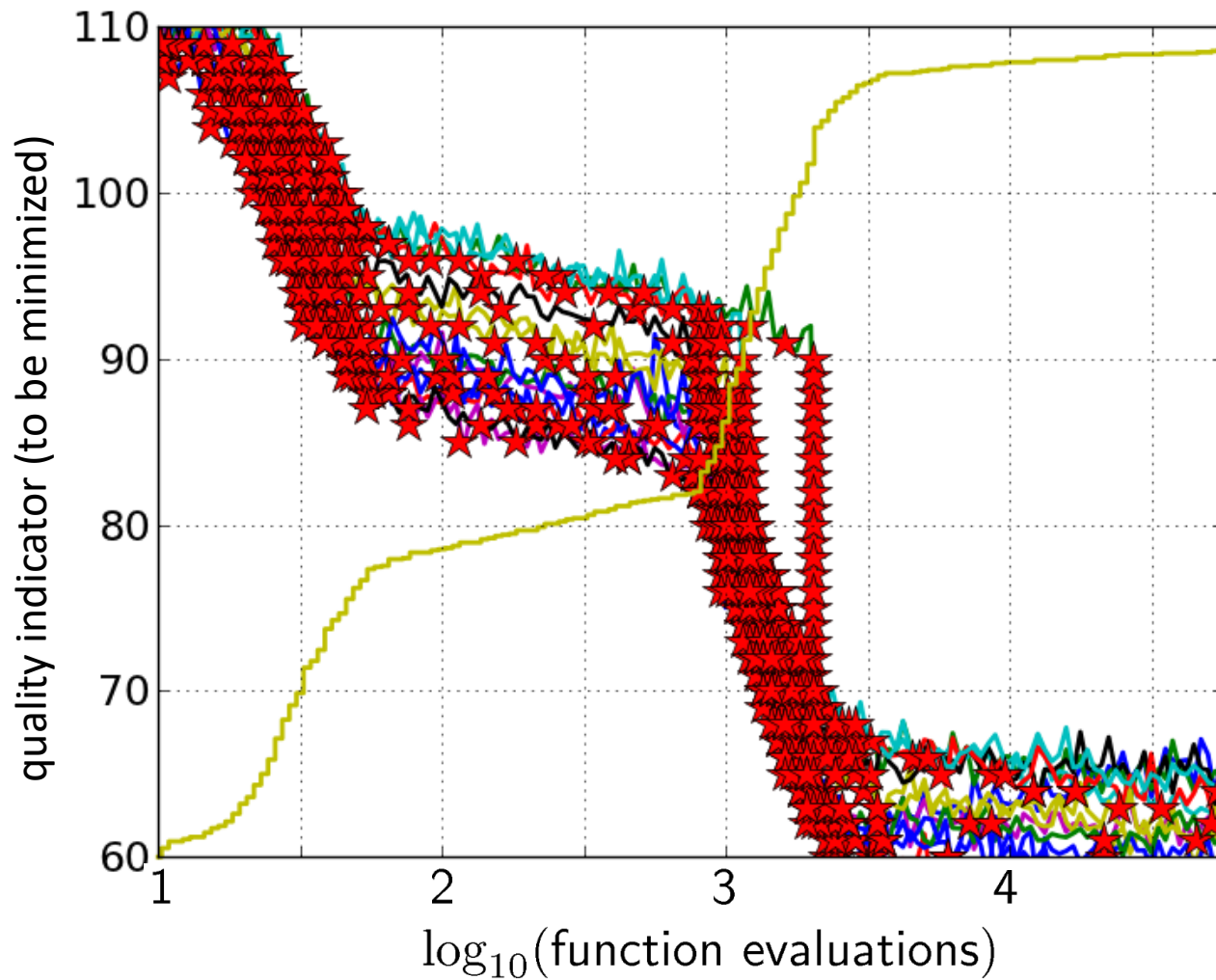
Aggregation



15 runs

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Aggregation

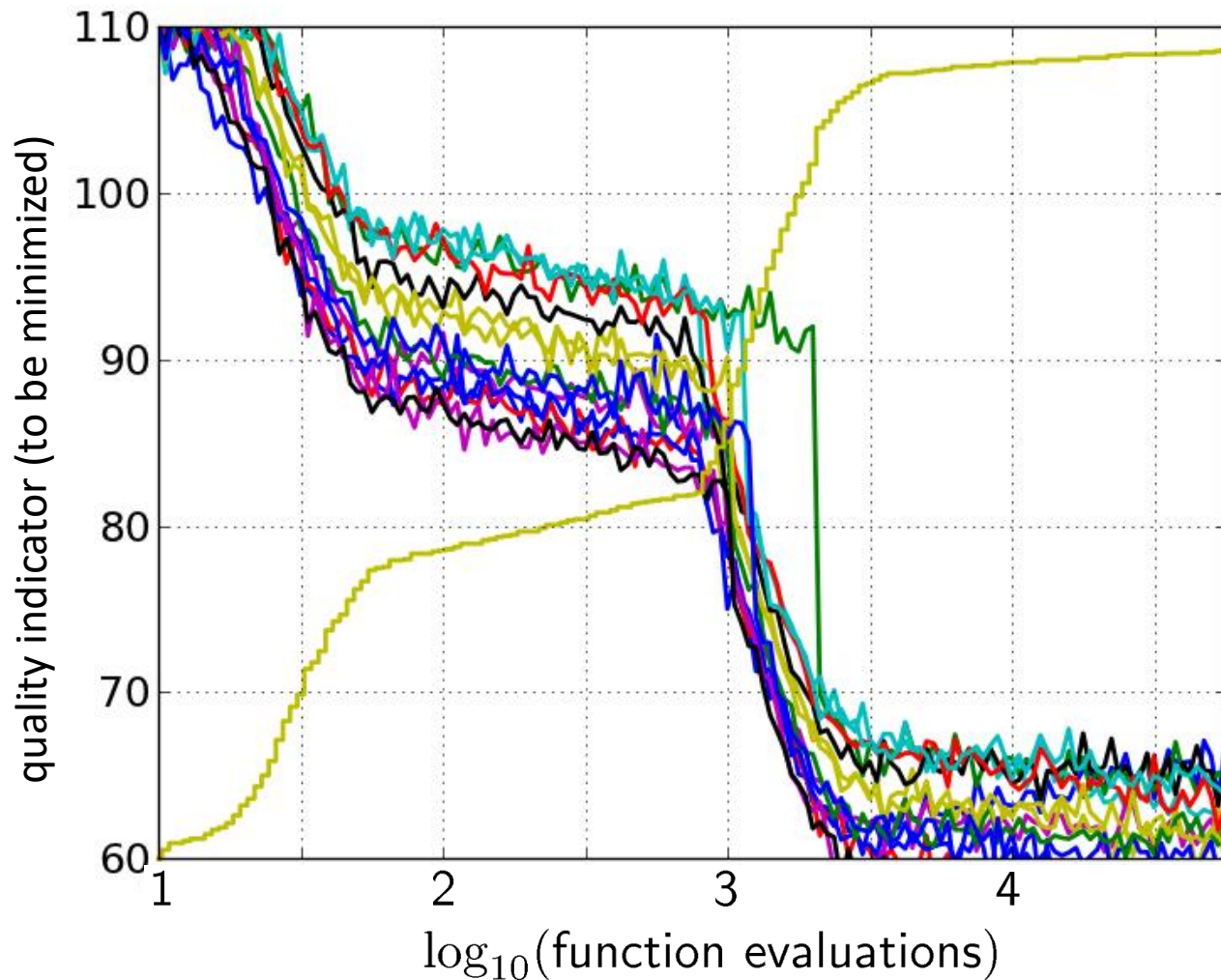


15 runs

50 targets

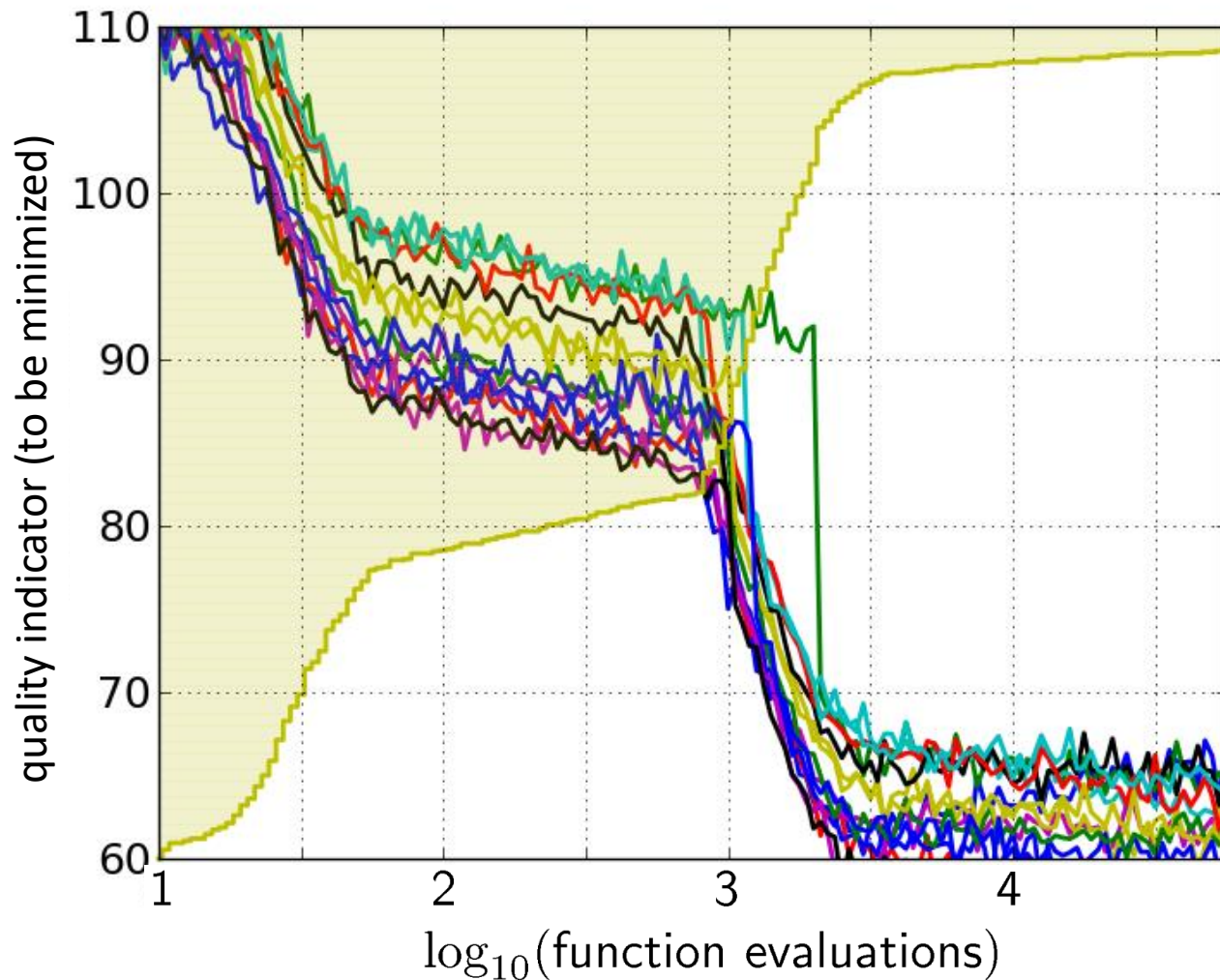
ECDF with
750 steps

Aggregation



50 targets from
15 runs
integrated in a
single graph

Interpretation



50 targets from
15 runs
integrated in a
single graph

area over the
ECDF curve

=

average log
runtime

(or geometric avg.
runtime) over all
targets (difficult and
easy) and all runs

Worth to Note

ECDF graphs

- should never aggregate over dimension

dimension is input parameter to algorithm

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- can show data of more than 1 algorithm at a time

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 - introduced by Moré and Wild [Moré and Wild 2009]
 - but for multiple and absolute targets

Worth to Note

ECDF graphs

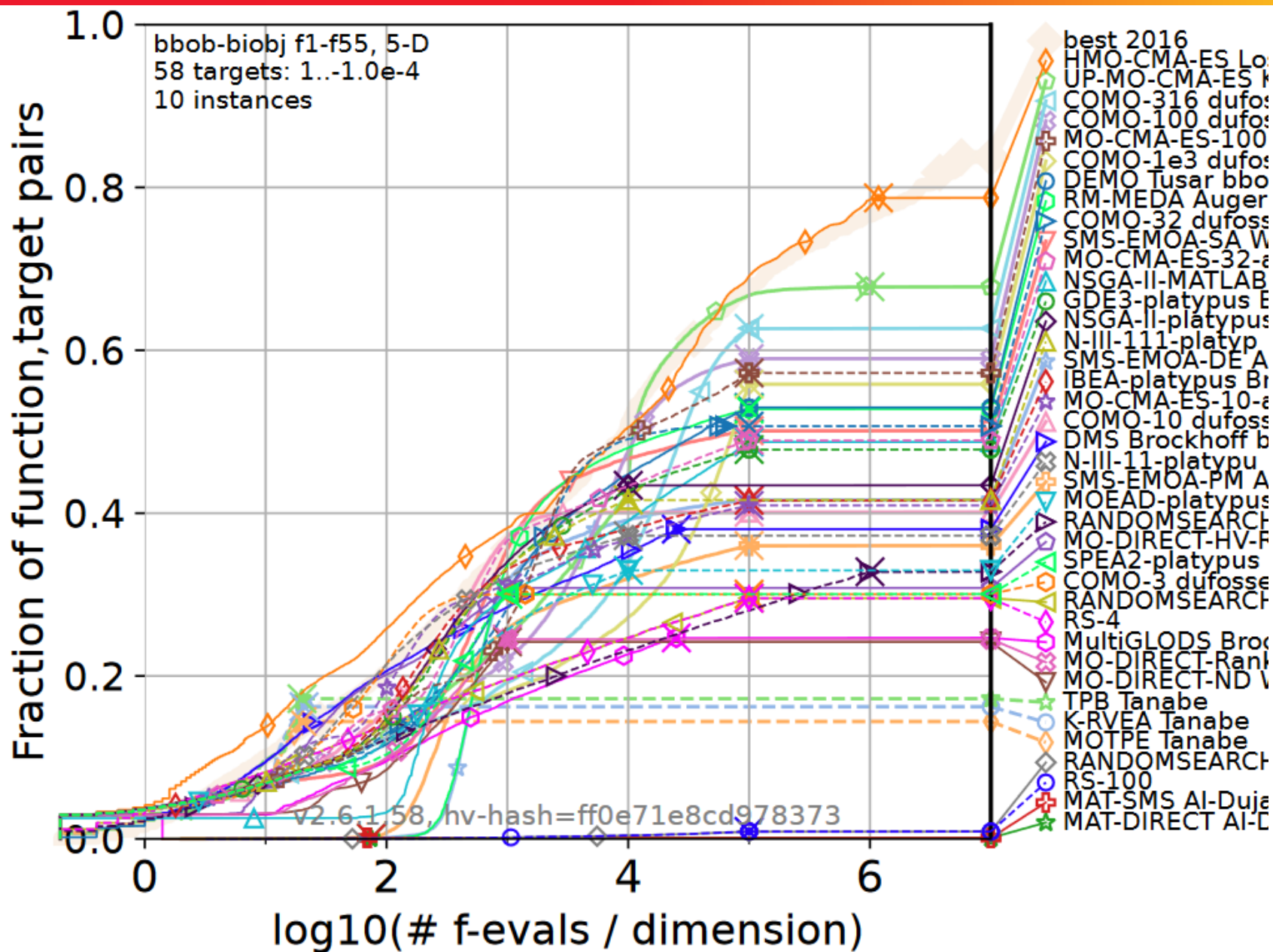
- should never aggregate over dimension

dimension is input parameter to algorithm

- but often over targets and functions
- can show data of more than 1 algorithm at a time
- are an extension of data profiles
 - introduced by Moré and Wild [Moré and Wild 2009]
 - but for multiple and absolute targets
- are COCO's main performance visualization tool

[Hansen et al. 2021] - <https://github.com/numbbo/coco>

Example ECDF (later more)



Mostly Overlooked: Scaling with Dimension

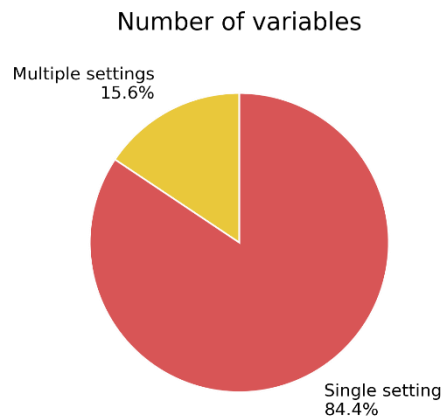
- In single-objective optimization: scaling behavior mandatory to investigate

Mostly Overlooked: Scaling with Dimension

- In single-objective optimization: scaling behavior mandatory to investigate
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 actually two dimensions: search and objective space

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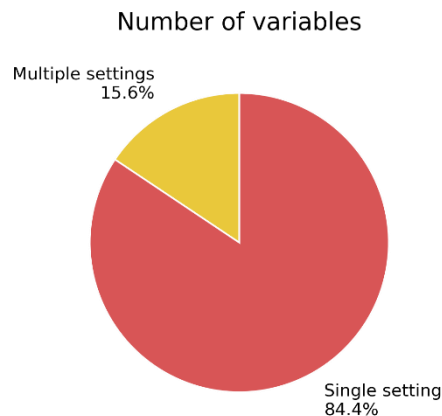
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actually two dimensions: search and objective space
but former almost never looked at right now 😞



~10 papers from EMO'21 and PPSN/GECCO/CEC'21 change dimension but 50+ papers have a “fixed” dimension

Mostly Overlooked: Scaling with Dimension

- In single-objective optimization: scaling behavior mandatory to investigate
- In multiobjective optimization:
actually two dimensions: search and objective space
but former almost never looked at right now 😞



~10 papers from EMO'21 and PPSN/GECCO/CEC'20 change dimension but 50+ papers have a “fixed” dimension

but in practice search space scalability almost more important

number of objectives often fixed

A Few General Recommendations

- always **display everything** you have
- look at **single runs**
- do each experiment **at least twice**
(= look at the *variance* of your results)

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or any indicator which is at least monotone

A Few General Recommendations

- always **display everything** you have
- look at **single runs**
- do each experiment **at least twice**
(= look at the *variance* of your results)
- as quality indicators, use hypervolume, R2, or epsilon indicator
or any indicator which is at least monotone
- see also the tutorial slides by Nikolaus Hansen on this topic
(not restricted to single-objective optimization!)

<http://www.cmap.polytechnique.fr/~nikolaus.hansen/gecco2018-experimentation-guide-slides.pdf>

Recommended Experimental Setup (w/ or w/o COCO)

1 Benchmarking Experiment

2 Choosing Algorithms for Comparison

see <https://numbbo.github.io/data-archive/>

3 Postprocessing

```
python -m cocopp resultfolder/ ALG2 ALG3
```

4 Displaying and Discussing Summary Results

5 Investigating and Discussing Complementary Results

6 Processed Data Sharing

provide html output somewhere

7 Raw Data Sharing

easy with COCO archive module & through issue tracker

- ① Performance Assessment
- ② Test Problems and Their Visualizations
- ③ Recommendations from Numerical Results

Test Problems and Their Visualizations

Introduction

Test Problems (1)

Artificial problems (continuous and unconstrained)

- v0.1:** Individual problems
- v0.2:** MOP suite (unscalable problems)
- v0.5:** ZDT suite (scalable number of variables)
- v1.0:** DTLZ suite (scalable number of variables and objectives)
- v1.2:** WFG suite
- v1.3:** Other suites with a bottom-up construction
- v1.5:** Suites of distance-based problems
- v2.0:** The bbob-biobj(-ext) suite

Test Problems and Their Visualizations

Visualization of multiobjective landscapes

Low-dimensional search spaces

Dominance ratio

Local dominance

Gradient path length

PLOT

Any-dimensional search spaces

Line cuts

Optima network

Test Problems and Their Visualizations

Test Problems (2)

Artificial problems (other)

Constrained problems

Mixed-integer problems

Real-world problems

v0.1: Individual problems

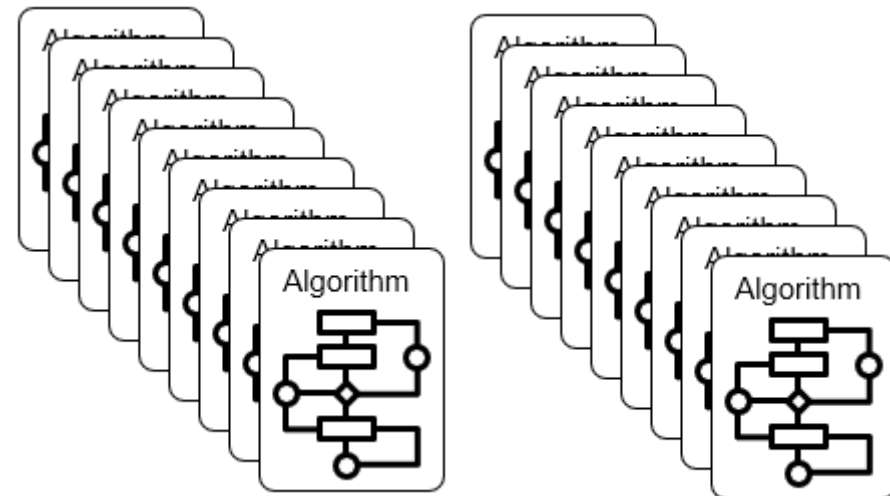
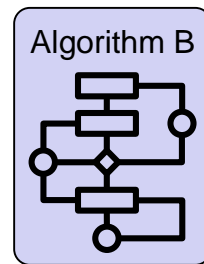
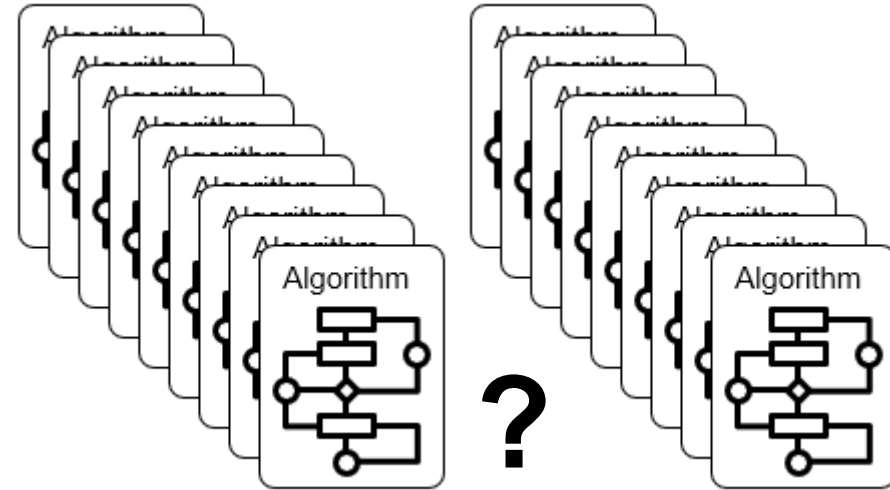
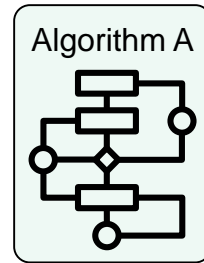
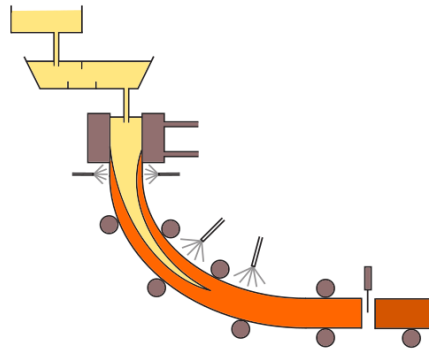
v0.2: Suites of unscalable problems

v0.5: Suites of scalable problems (number of variables)

Conclusions

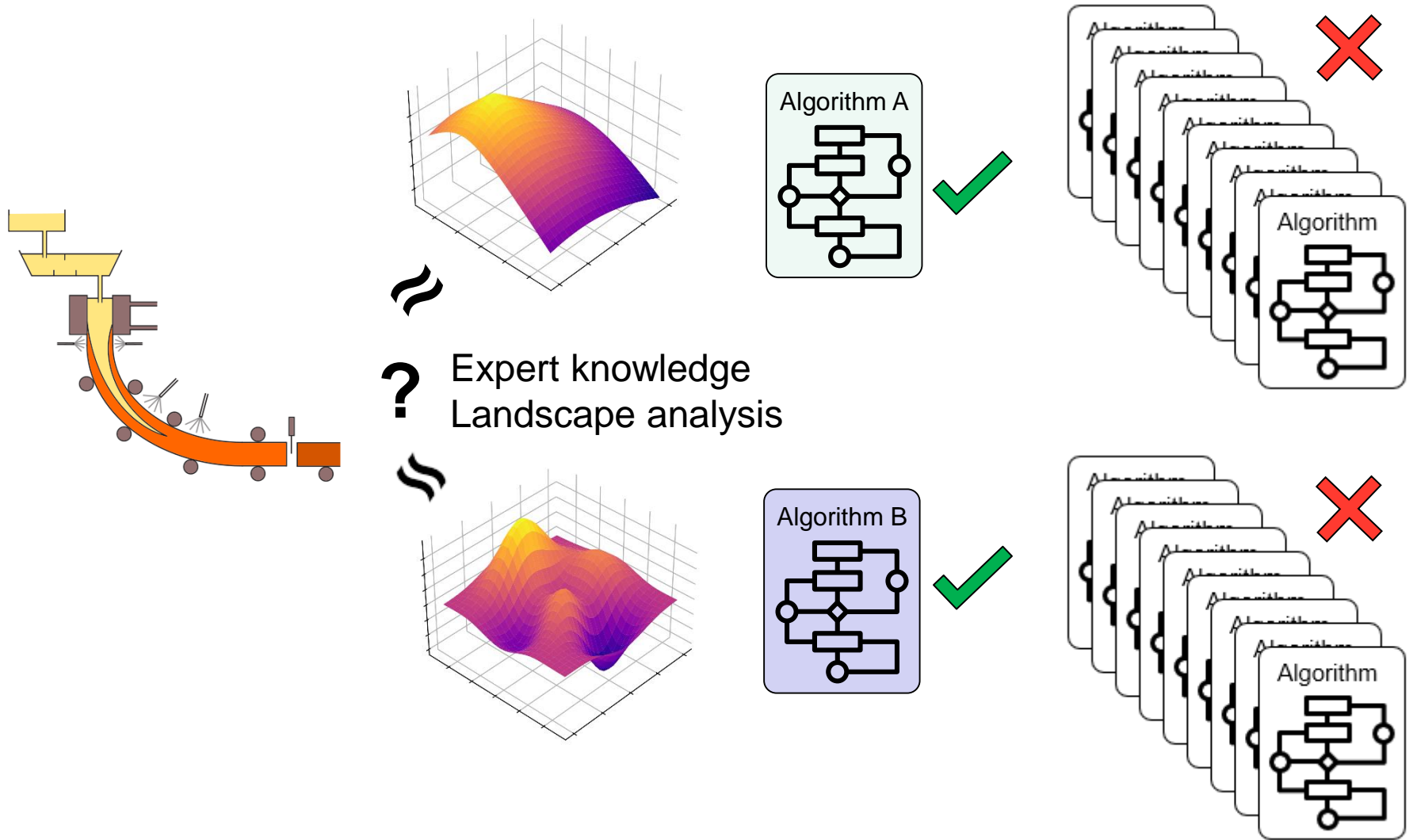
Introduction

Why use test problems?



Introduction

Why use test problems?



Desirable Characteristics of a Problem Set

[Bartz-Beielstein et al. 2020]

1. Diverse
2. Representative
3. Scalable and tunable
4. Known optima / best performance
5. [Continually updated]

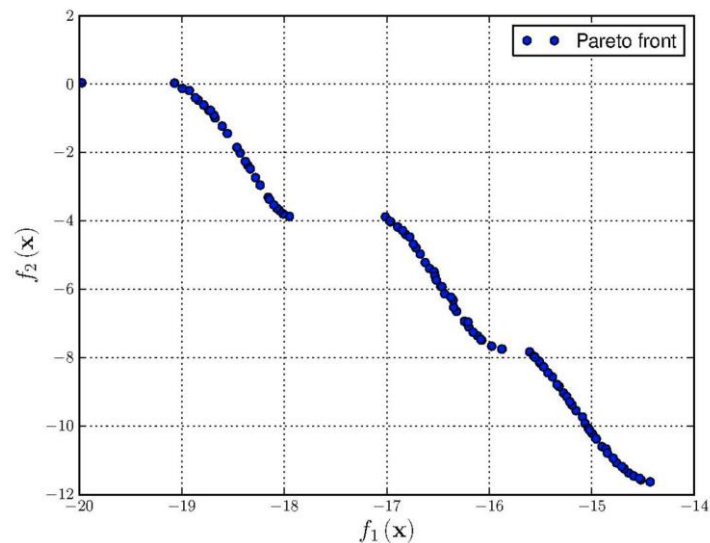
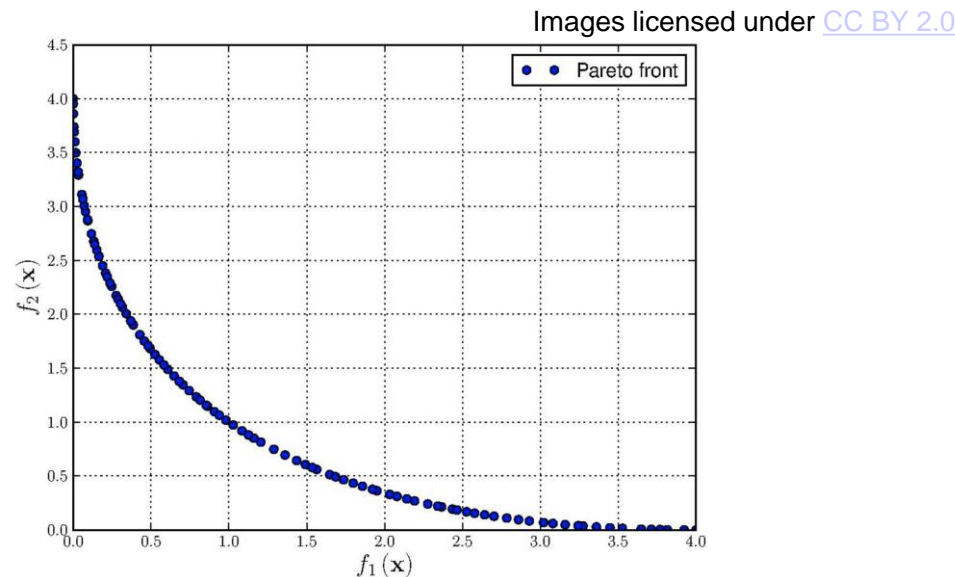
Artificial problems (continuous and unconstrained)

v0.1

Individual problems

$$\text{Minimize} = \begin{cases} f_1(x) = x^2 \\ f_2(x) = (x - 2)^2 \end{cases}$$

[Schaffer 1985]



$$\text{Minimize} = \begin{cases} f_1(\mathbf{x}) = \sum_{i=1}^2 \left[-10 \exp\left(-0.2 \sqrt{x_i^2 + x_{i+1}^2}\right) \right] \\ f_2(\mathbf{x}) = \sum_{i=1}^3 \left[|x_i|^{0.8} + 5 \sin(x_i^3) \right] \end{cases}$$

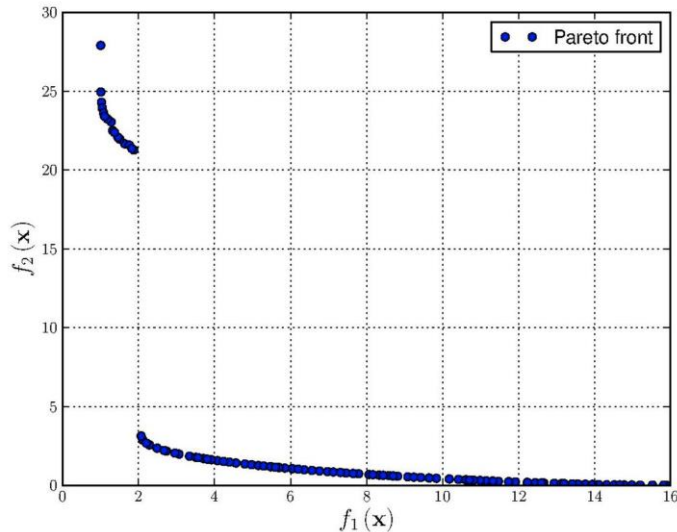
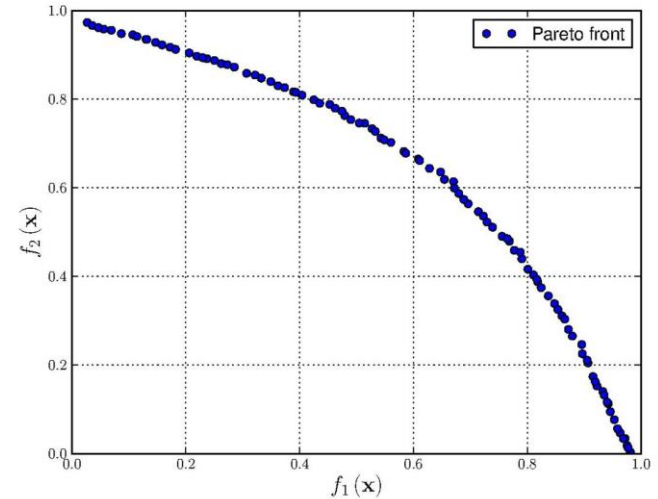
[Kursawe 1991]

Individual problems

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$$\text{Minimize} = \begin{cases} f_1(\mathbf{x}) = 1 - \exp\left[-\sum_{i=1}^n \left(x_i - \frac{1}{\sqrt{n}}\right)^2\right] \\ f_2(\mathbf{x}) = 1 - \exp\left[-\sum_{i=1}^n \left(x_i + \frac{1}{\sqrt{n}}\right)^2\right] \end{cases}$$

[Fonseca and Fleming 1995]



$$\text{Minimize} = \begin{cases} f_1(x, y) = \left[1 + (A_1 - B_1(x, y))^2 + (A_2 - B_2(x, y))^2\right] \\ f_2(x, y) = (x + 3)^2 + (y + 1)^2 \end{cases}$$

$$\text{where} = \begin{cases} A_1 = 0.5 \sin(1) - 2 \cos(1) + \sin(2) - 1.5 \cos(2) \\ A_2 = 1.5 \sin(1) - \cos(1) + 2 \sin(2) - 0.5 \cos(2) \\ B_1(x, y) = 0.5 \sin(x) - 2 \cos(x) + \sin(y) - 1.5 \cos(y) \\ B_2(x, y) = 1.5 \sin(x) - \cos(x) + 2 \sin(y) - 0.5 \cos(y) \end{cases}$$

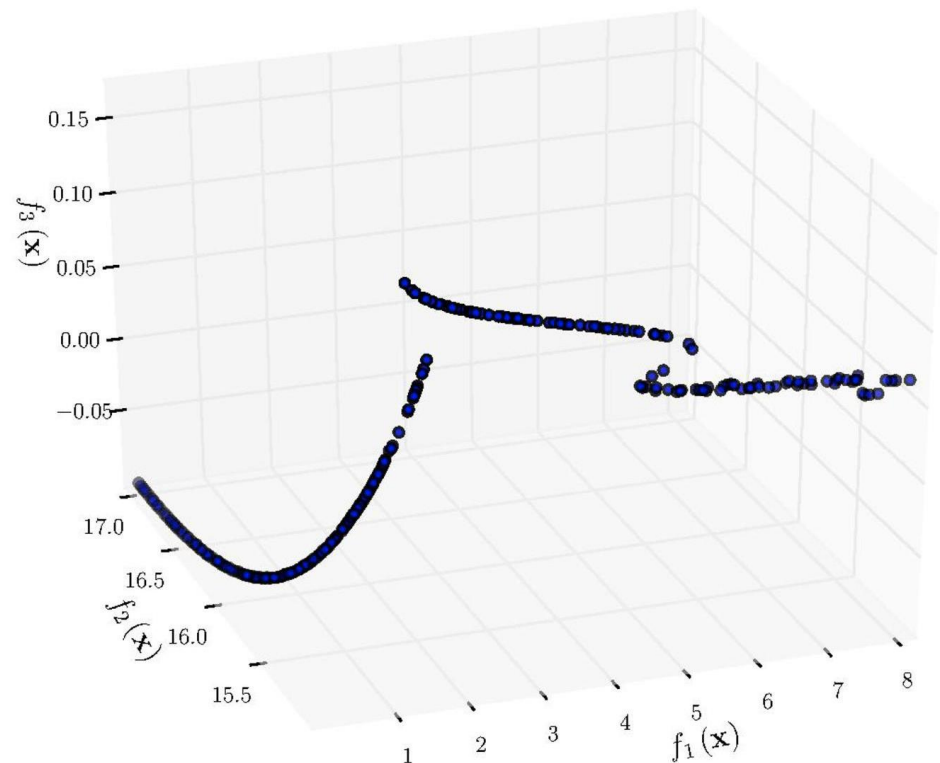
[Poloni et al. 1996]

Individual problems

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$$\text{Minimize} = \begin{cases} f_1(x, y) = 0.5(x^2 + y^2) + \sin(x^2 + y^2) \\ f_2(x, y) = \frac{(3x-2y+4)^2}{8} + \frac{(x-y+1)^2}{27} + 15 \\ f_3(x, y) = \frac{1}{x^2+y^2+1} - 1.1 \exp(-(x^2 + y^2)) \end{cases}$$

[Viennet et al. 1996]



v0.2

MOP = Multi-Objective Problem

[Van Veldhuizen 1999]

Properties

- A collection of 7 test problems from the literature (including the 5 shown before)
- Most problems have 2 or 3 variables
- Not scalable in the number of objectives
- Many problems have optimal solutions on the boundary or middle of the search space
- Some problems are both nonseparable and multimodal
- A collection of various Pareto front geometries
- The Pareto set is hard to compute for some problems

v0.5

ZDT Suite

ZDT = Zitzler, Deb, Thiele

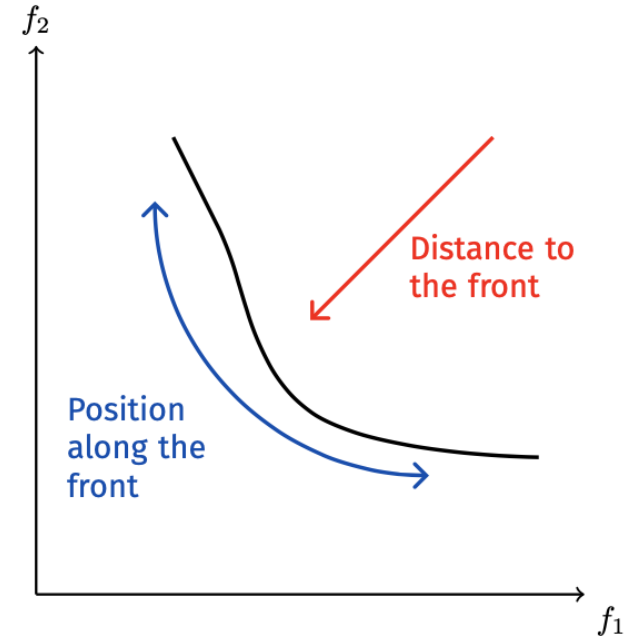
[Zitzler et al. 2000]

The same construction for all problems
(following Deb's toolkit [Deb 1999])

Given $\mathbf{x} = \{x_1, \dots, x_n\}$
Distribution f.
Minimise $f_1(\mathbf{y})$
Distance f. Front shape
 $f_2(\mathbf{y}, \mathbf{z}) = g(\mathbf{z})h(f_1(\mathbf{y}), g(\mathbf{z}))$

where $\mathbf{y} = \{x_1, \dots, x_j\}$ Position variable(s) ($j = 1$ for ZDT)

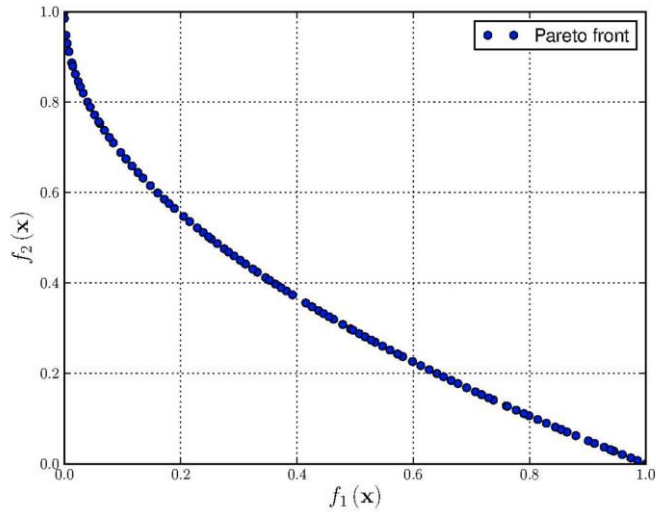
$\mathbf{z} = \{x_{j+1}, \dots, x_n\}$ Distance variables



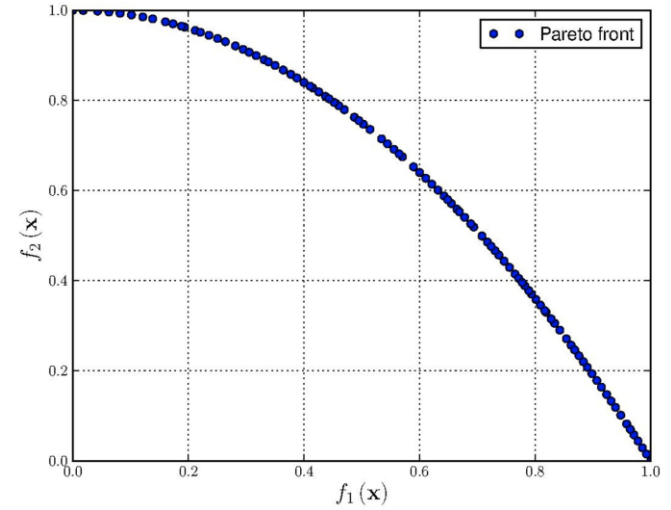
The separation of variables was done to simplify problem construction

ZDT Suite

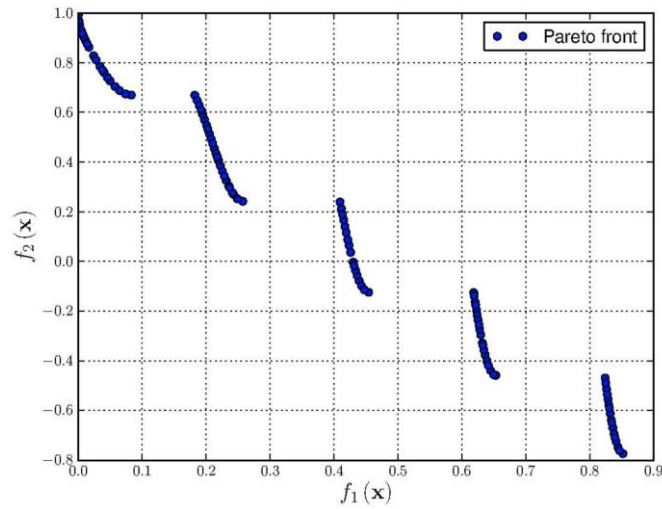
Images licensed under [CC BY 2.0](https://creativecommons.org/licenses/by/2.0/)



ZDT1



ZDT2



ZDT3

Properties

- 6 test problems, but ZDT5 is regularly omitted, because it has a binary encoding
- Scalable in the number of (distance) variables
- All problems have 2 objectives
- 4 problems have optimal solutions on the boundary and 1 in the middle of the search space
- All problems are separable (the first objective depends only on the first variable)
- Some problems are multimodal
- Convex, concave and disconnected Pareto fronts
- The Pareto sets and fronts are known

v1.0

DTLZ = Deb, Thiele, Laumanns, Zitzler

[Deb et al. 2005]

Desired Features of Test Problems

1. Have controllable difficulty to converge to the Pareto front, a widely-distributed set of Pareto-optimal solutions
2. Scalable number of variables
3. Scalable number of objectives
4. Simple to construct
5. Pareto front easy to comprehend, both the Pareto set and front known
6. Similar difficulties to those present in real-world problems

Problem Design Approaches

1. Multiple single-objective functions approach
2. Bottom-up approach
 1. Choose a Pareto front
 2. Build the objective space
 3. Construct the search space (add difficulties using the function g)
3. Constraint surface approach (for constrained problems)

Properties

- Originally 9 problems, but then 2 were dropped
- Scalable number of distance variables, $M - 1$ position variables
- Scalable number of objectives
- Objectives separable in practice (optimizing one variable at a time will yield at least one global optimum)
- Linear, concave and disconnected Pareto fronts
- The Pareto sets and fronts are known
- Most problems have the Pareto set in the middle of the search space

Note that although the suite is scalable in the number of variables, this is rarely used in benchmark studies

v1.2

WFG = Walking Fish Group

[Huband et al. 2006]

Recommendations for multiobjective test problems

1. No extremal variables
2. No medial variables
3. Scalable number of variables
4. Scalable number of objectives
5. Dissimilar variable domains
6. Dissimilar objective ranges
7. Pareto set and front known

Recommendations for multiobjective test suites

[Huband et al. 2006]

1. A few unimodal test problems to test convergence velocity relative to different Pareto optimal geometries and bias conditions
2. Cover the three core types of geometries: degenerate Pareto fronts, disconnected Pareto fronts, and disconnected Pareto sets
3. The majority of problems should be multimodal with a few deceptive problems
4. The majority of problems should be nonseparable
5. Contain problems that are both nonseparable and multimodal to be representative of real-world problems

Properties

- 9 problems constructed from a combination of shape functions and several transformations
- Scalable number of variables (2 variables are not supported for some of the problems)
- Scalable number of objectives
- Includes also nonseparable, multimodal, deceptive and biased problems
- Convex, linear, concave, mixed, disconnected and degenerate Pareto fronts
- The Pareto sets and fronts are known
- Optimal solutions do not lie on the boundary or the middle of the search space, but the Pareto set is linear for 8 of the 9 problems
- Still rely on distance and position variables

v1.3

Other Suites and Problems

Problems constructed with the bottom-up approach

[Zapotecas et al. 2019]

- IHR test suite of 5 rotated ZDT problems [Igel et al. 2007]
- LZ test suite of 9 problems with complicated Pareto sets [Li and Zhang 2009]
- SZDT test suite of 7 scalable problems with complicated Pareto sets [Saxena et al. 2011]
- Convex DTLZ problem [Deb and Jain 2014]
- Inverted DTLZ problem [Jain and Deb 2014]
- MNI test suite of 2 test problems with diverse shapes of the Pareto front [Masuda et al. 2016]
- LSMOP test suite of 9 test problems for large-scale optimization with variable dependencies [Cheng et al. 2017b]
- Minus-DTLZ and Minus-WFG test suites [Ishibuchi et al. 2017]
- MMF test problems with diverse landscapes [Yue et al. 2019]

CEC Competition Suites

Information about all CEC competitions:

https://www3.ntu.edu.sg/home/EPNSugan/index_files/cec-benchmarking.htm

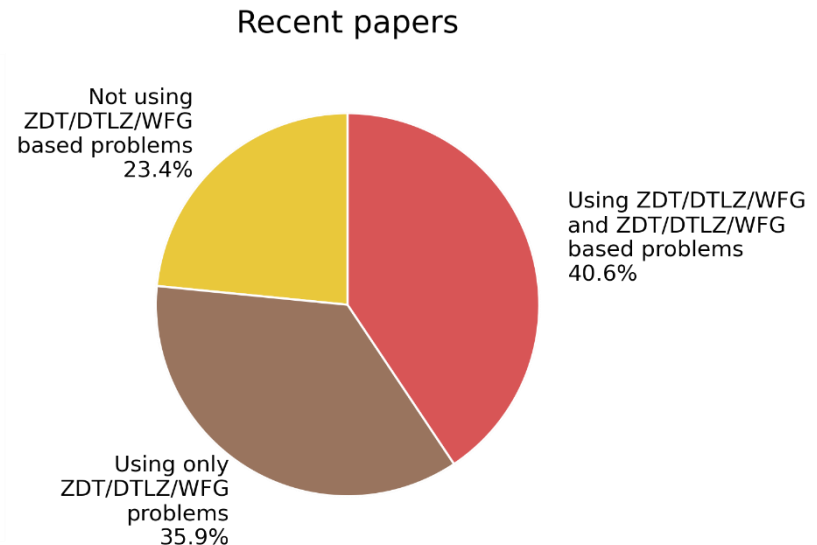
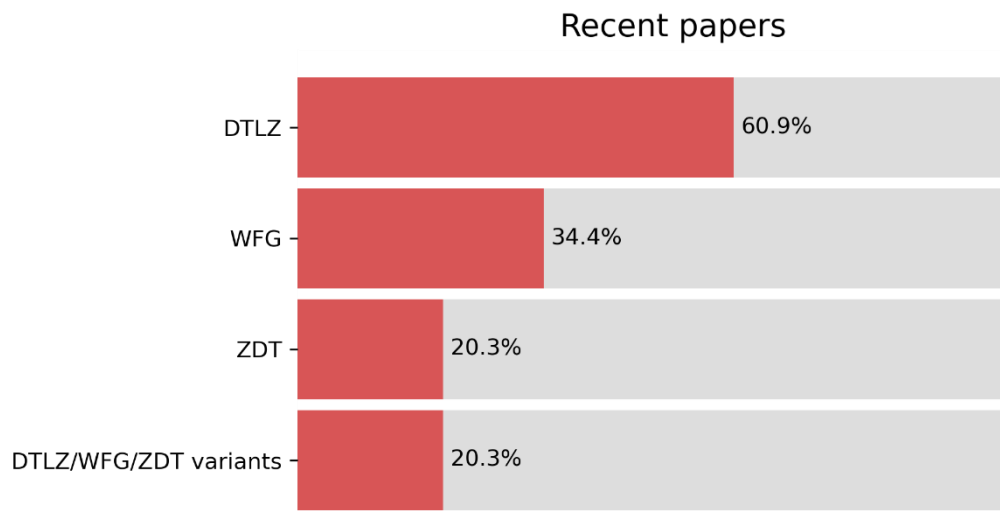
- 13 test problems for CEC 2007 [Huang et al. 2007]
 - OKA [Okabe et al. 2004], SYM-PART [Rudolph et al. 2007]
 - 4 shifted ZDT, 1 rotated ZDT
 - 2 shifted DTLZ, 1 rotated DTLZ
 - 3 WFG
- 13 test problems for CEC 2009 (UF suite) [Zhang et al. 2009]
 - 10 with complicated Pareto sets (4 from the LZ suite)
 - 2 extended rotated DTLZ
 - 1 WFG

CEC Competition Suites

- 15 test problems for CEC 2017 (MaF suite) [Cheng et al. 2017a]
 - 7 modified DTLZ problems
 - 2 distance minimization problems
 - 3 WFG problems
 - 1 SZDT problem
 - 2 LSMOP problem
- 22 test problems for CEC 2019 [Liang et al. 2019]
 - 2 SYM-PART
 - Omni-test [Deb and Tiwari 2008]
 - 19 MMF problems
- 24 test problems for CEC 2020 [Liang et al. 2020]
 - 24 MMF problems

Survey of Recent Papers

- 64 papers on unconstrained continuous multiobjective optimization from recent conferences (without application papers)
 - CEC 2020
 - GECCO 2020
 - PPSN 2020
 - EMO 2021



v1.5

Distance-Based Problems

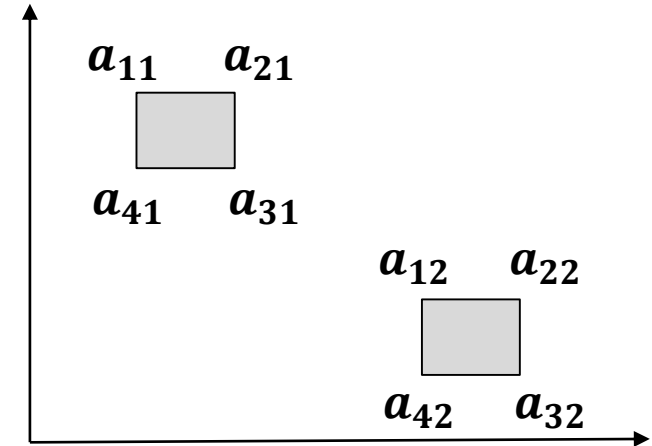
General idea

[Ishibuchi et al. 2010]

Minimize $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x}))$

$f_i(\mathbf{x}) = \min\{\text{dis}(\mathbf{x}, \mathbf{a}_{i1}), \text{dis}(\mathbf{x}, \mathbf{a}_{i2}), \dots, \text{dis}(\mathbf{x}, \mathbf{a}_{im})\}$

- 2-D test problems that are inherently visualizable
- Pareto set easy to characterize
- Scalable in the number of objectives
- Useful for visualizing the distribution of solutions
- Unlikely to be relevant for real-world problems
- Based on earlier work [Köppen et al. 2005, Rudolph et al. 2007]



Distance-Based Problems

Extensions

- High-dimensional search spaces [Masuda et al. 2014]
- Distance to lines (instead of points) [Li et al. 2014, 2018]
- Dominance resistance regions [Fieldsend 2016]
- Local Pareto fronts [Liu et al. 2018]
- Problem generator for scalable problems with various properties (local fronts, disconnected Pareto sets and fronts, dominance resistance regions, uneven ranges of objective values, varying density of solutions) [Fieldsend et al. 2019]

v2.0

Motivation

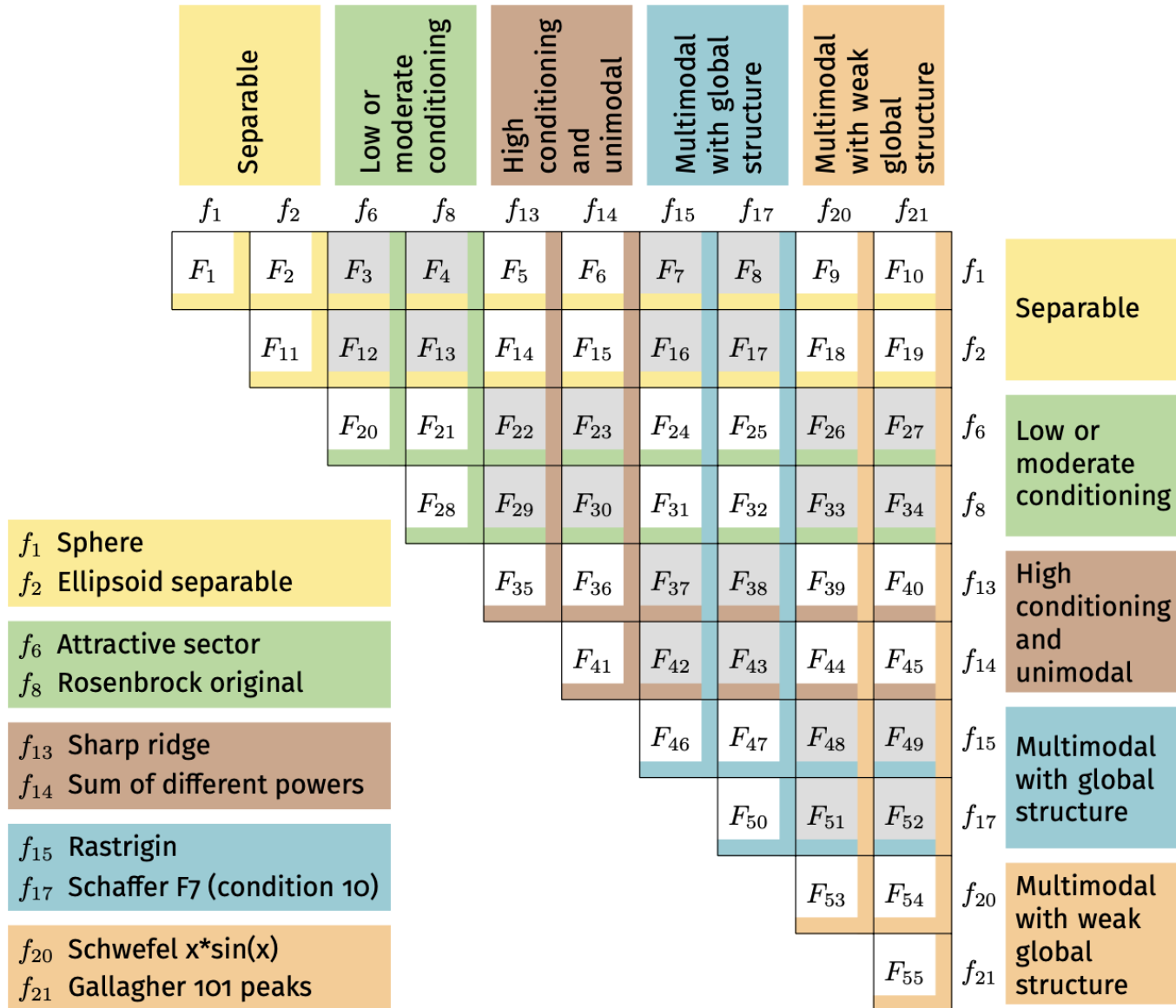
[Brockhoff et al. 2016]

- Most other suites are constructed based on the desired Pareto front properties
- Consequently, problems have artificial properties not likely to exist in real-world problems
 - Distance and position parameters (DTLZ-like problems)
 - Linear objectives (distance-based problems)
- In real-world problems each objective is a separate function
- Go back to basics – use single-objective functions for each objective
 - Idea not new [Schaffer 1985, Igel et al. 2007, Emmerich and Deutz 2007, Kerschke et al. 2016]

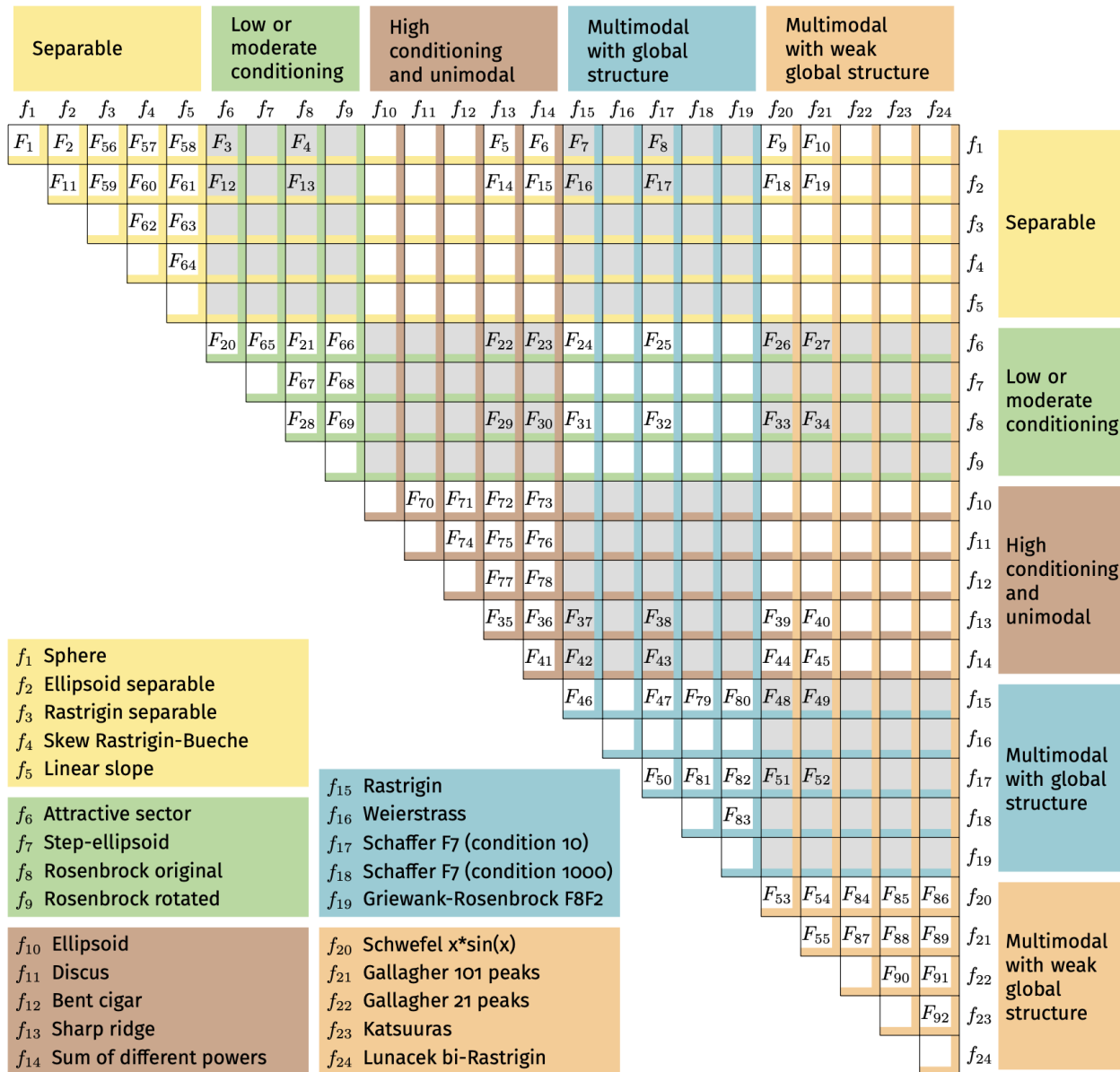
Construction

- Use the functions from the **bbob** suite
 - Well-understood
 - Scalable in the number of variables and *parametrized*
 - 24 functions categorized in 5 groups based on their properties
 - Separable
 - Low or moderate conditioning
 - High conditioning and unimodal
 - Multimodal with global structure
 - Multimodal with weak global structure
- How to avoid an explosion in the number of problems?

bbob-biobj Suite



bbob-biobj-ext Suite

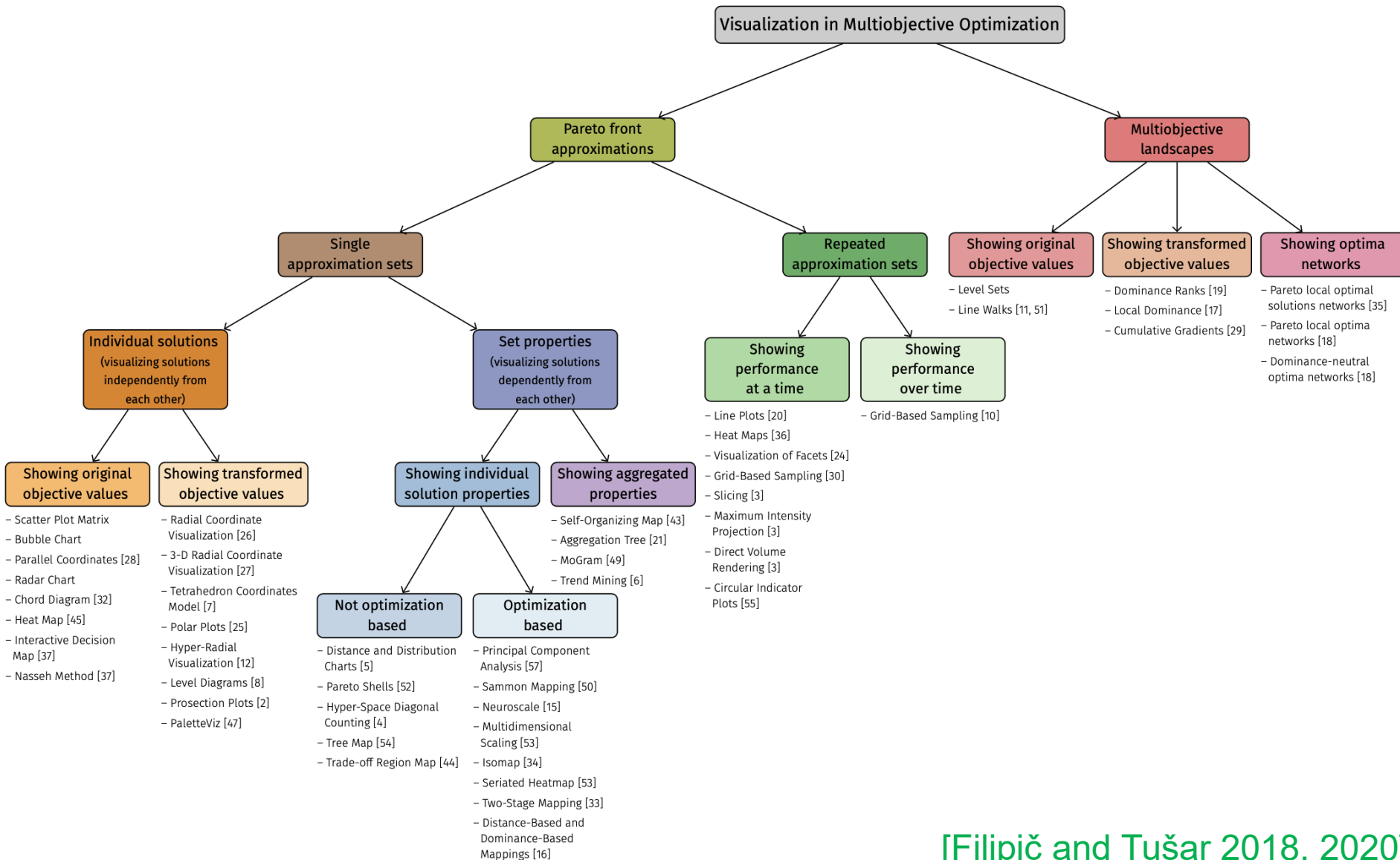


Properties

- Construction similar as in real-world problems
- Scalability in the number of variables
- Various problem properties (more diverse than existing multiobjective test suites)
- Problem instances more diverse than for the single-objective suite
- Currently limited to 2 objectives
- Unknown Pareto set and front (but known single-objective optima)
- Available approximations of the Pareto fronts (and sets for lower-dimensional problems)

Visualization of multiobjective landscapes

Visualization in Multiobjective Optimization



Visualization of Multiobjective Problem Landscapes

Low-dimensional search spaces

- Dominance ratio [Fonseca 1995]
- Gradient path length (inspired by gradient plots [Kerschke and Grimme 2017])
- Local dominance [Fieldsend et al. 2019]
- PLOT [Shaepfermeier et al. 2020]

Any-dimensional search spaces

- Line cuts [Brockhoff et al. 2016, Volz et al. 2019]
- Optima network [Liefoghe et al. 2018, Fieldsend and Alyahya 2019]

Various visualizations of bbob-biobj-ext problems:

<https://numbbo.github.io/bbob-biobj/>

Visualizations of bbob-biobj and other multi-objective suites using PLOT:

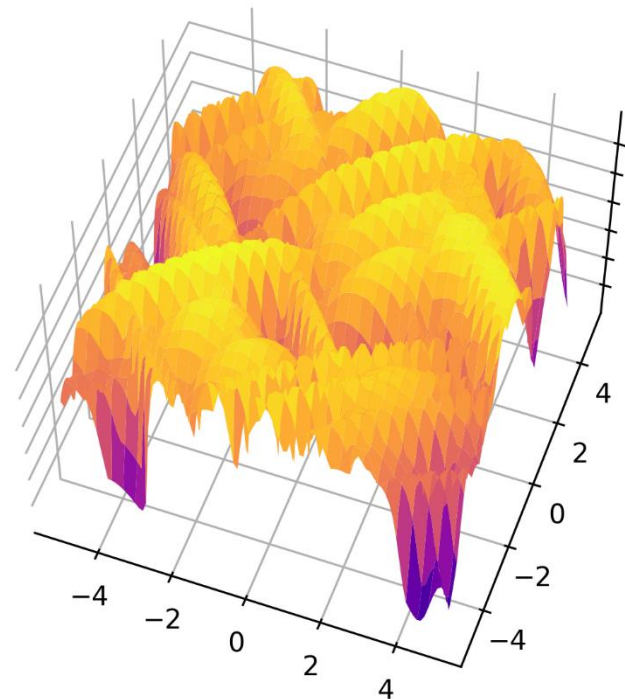
<https://schaepfermeier.shinyapps.io/moPLOT/>

Visualization of Multiobjective Problem Landscapes

Problems for demonstration

- Double sphere problem bbob-biobj $F_1 = (f_1, f_1)$, instance 1
- Sphere-Gallagher problem bbob-biobj $F_{10} = (f_1, f_{21})$, instance 1
- Double Gallagher problem bbob-biobj $F_{55} = (f_{21}, f_{21})$, instance 1

Gallagher = Gallagher's Gaussian
101-me Peaks Function

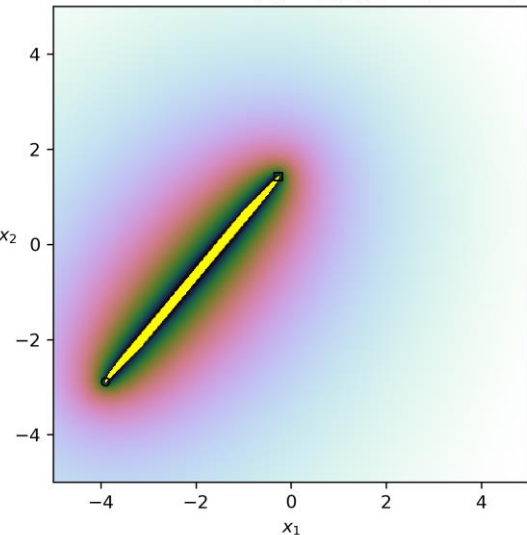


Dominance Ratio

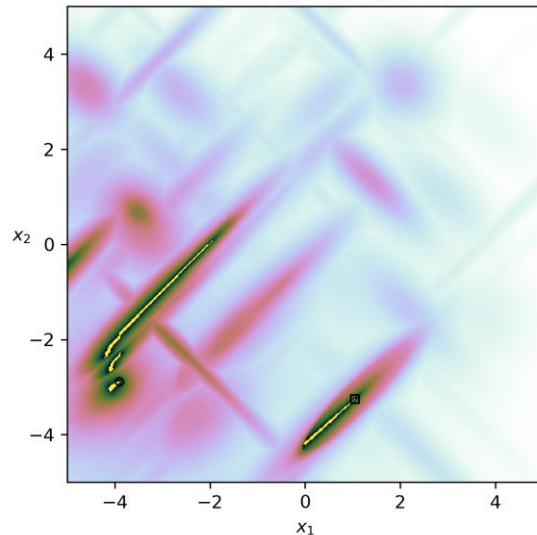
[Fonseca 1995]

- Discretized search space (501 x 501 grid)
- Dominance ratio = the ratio of grid points that dominate the current point
- All nondominated points have a ratio of zero
- Visualize dominance ratios in logarithmic scale

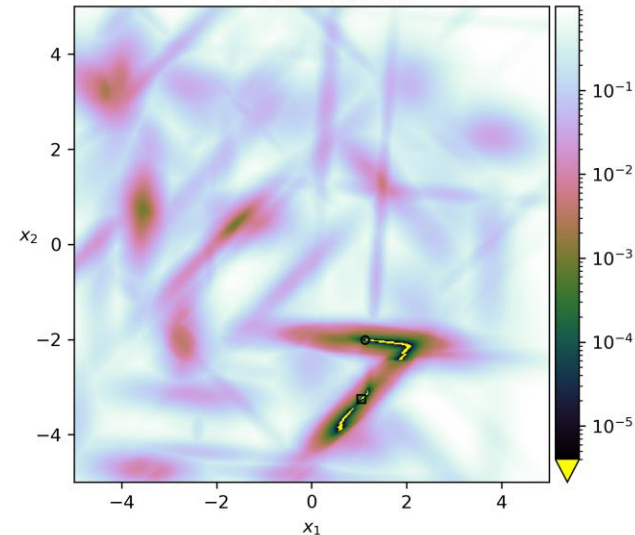
Dominance ratio ($F_1 = (f_1, f_1)$, 2-D, inst. 1)



Dominance ratio ($F_{10} = (f_1, f_{21})$, 2-D, inst. 1)



Dominance ratio ($F_{55} = (f_{21}, f_{21})$, 2-D, inst. 1)



Gradient Path Length

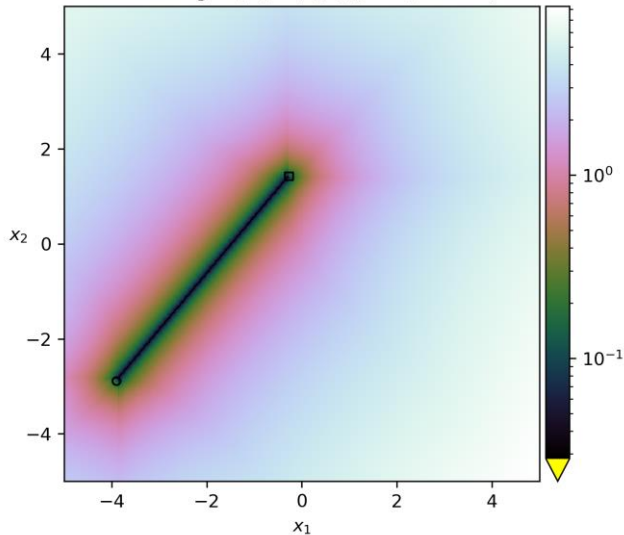
Adjusted from [Kerschke and Grimme 2017]

- Compute the **bi-objective gradient** for all grid points

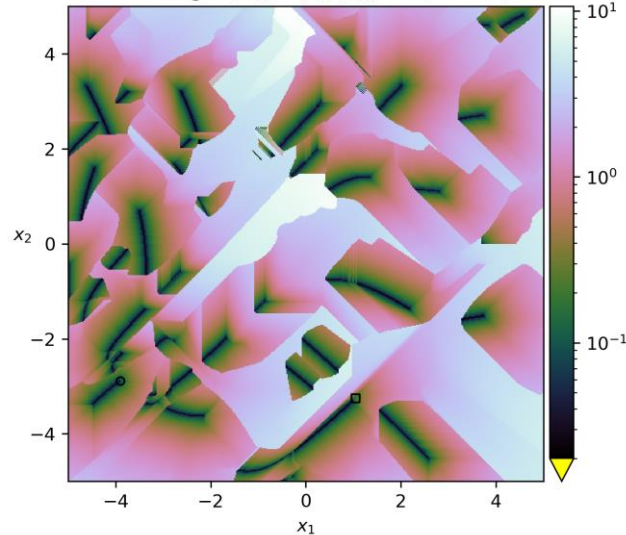
$$v = \frac{\nabla f_1(x)}{\|\nabla f_1(x)\|} + \frac{\nabla f_2(x)}{\|\nabla f_2(x)\|}$$

- From a grid point, follow the path in the direction of this gradient
- Visualize the length of the path to the local optimum

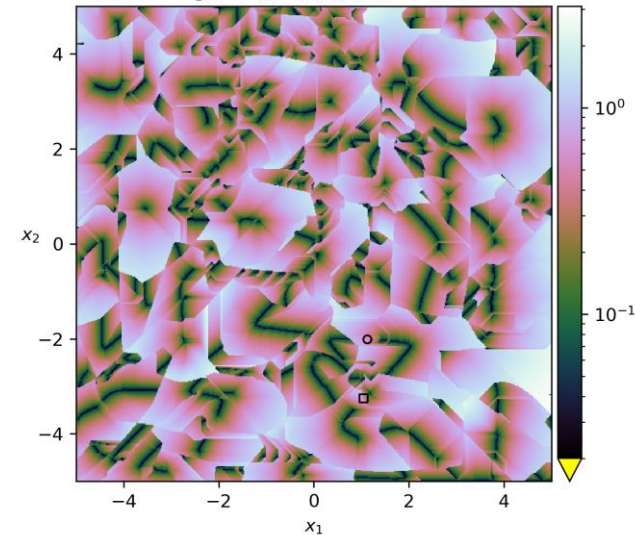
Path length ($F_1 = (f_1, f_1)$, 2-D, inst. 1)



Path length ($F_{10} = (f_1, f_{21})$, 2-D, inst. 1)



Path length ($F_{55} = (f_{21}, f_{21})$, 2-D, inst. 1)

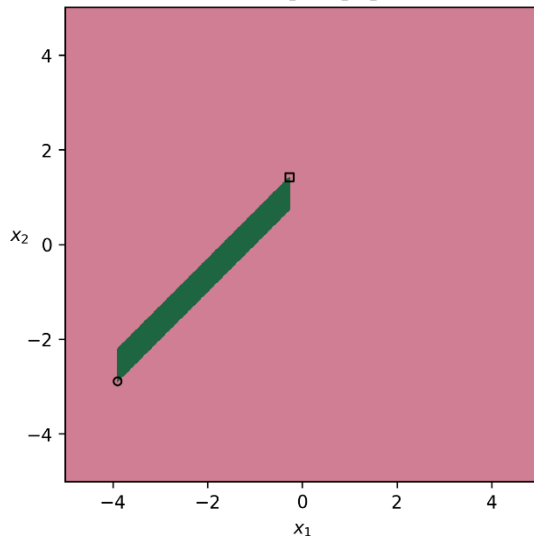


Local Dominance

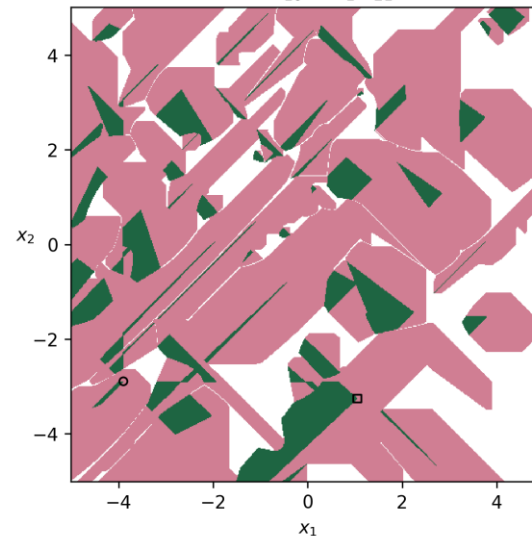
[Fieldsend et al. 2019]

- Green: Dominance-neutral local optima regions
Points that are mutually nondominated with all their 8 neighbors (not equal to Pareto sets)
- Pink: Basins of attraction
Points that are dominated by at least one neighbor and whose dominating paths lead to the same green region
- White: Boundary regions
Points whose dominating paths lead to different green regions

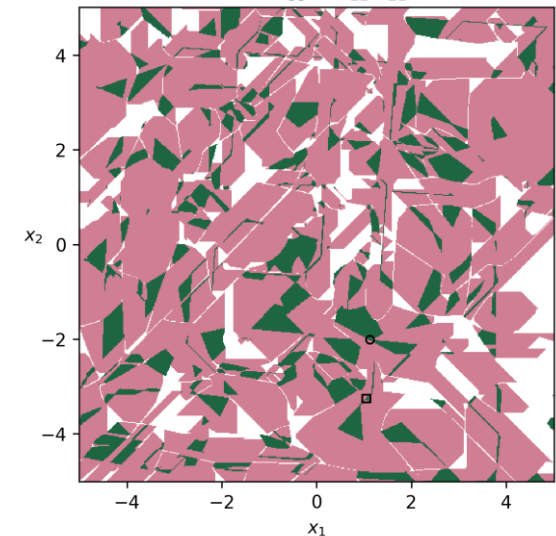
Local dominance ($F_1 = (f_1, f_1)$, 2-D, inst. 1)



Local dominance ($F_{10} = (f_1, f_{21})$, 2-D, inst. 1)

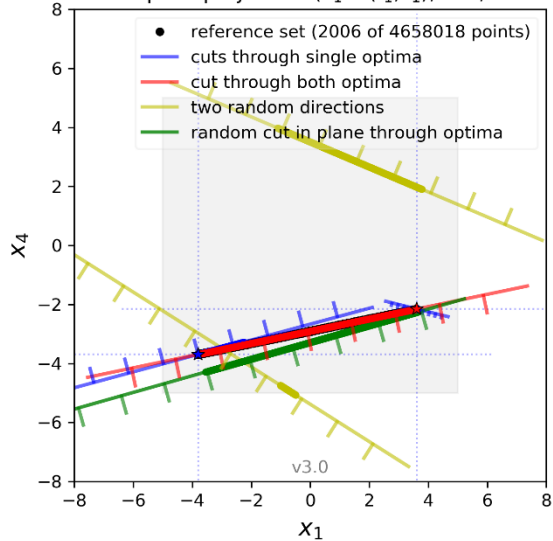


Local dominance ($F_{55} = (f_{21}, f_{21})$, 2-D, inst. 1)

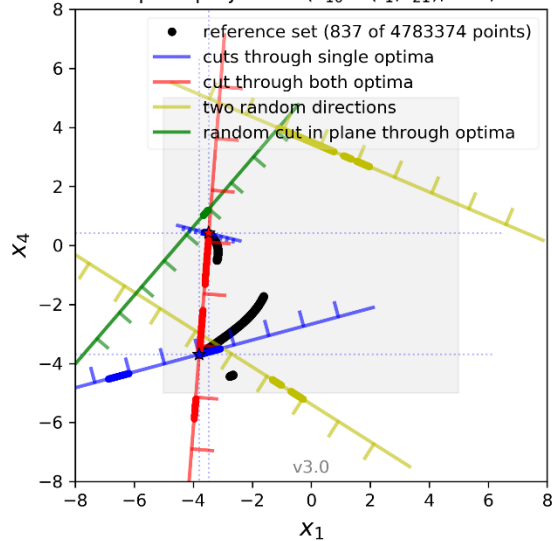


Line Cuts

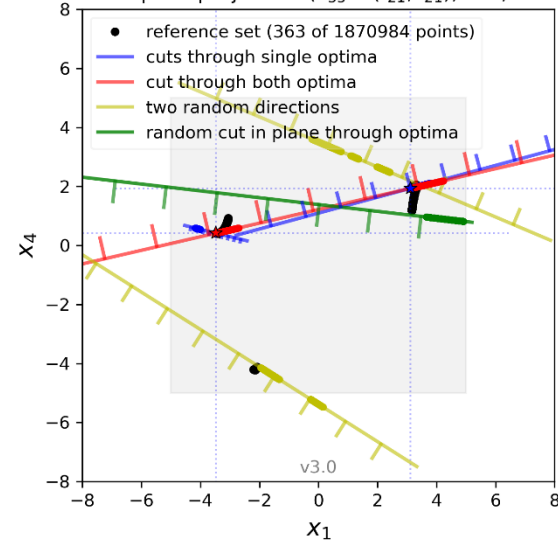
Search space projection ($F_1 = (f_1, f_1)$, 5-D, inst. 2)



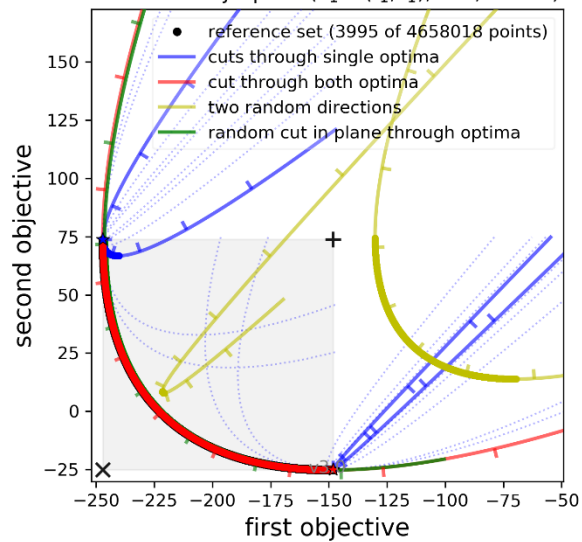
Search space projection ($F_{10} = (f_1, f_{21})$, 5-D, inst. 2)



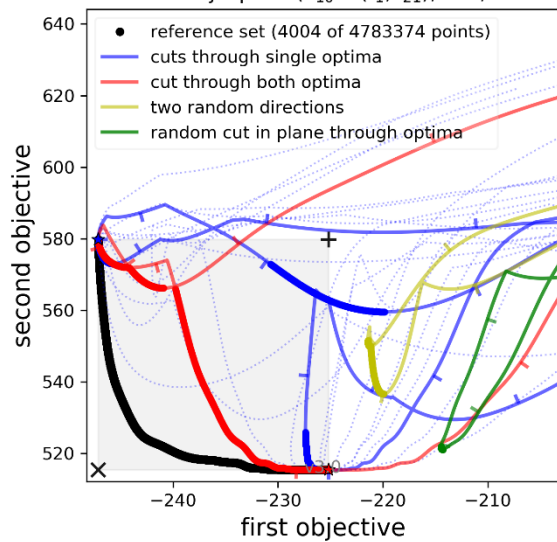
Search space projection ($F_{55} = (f_{21}, f_{21})$, 5-D, inst. 2)



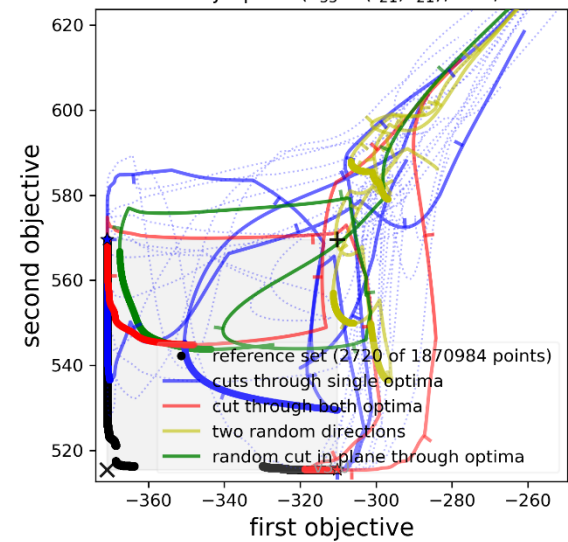
Unscaled obj. space ($F_1 = (f_1, f_1)$, 5-D, inst. 2)



Unscaled obj. space ($F_{10} = (f_1, f_{21})$, 5-D, inst. 2)



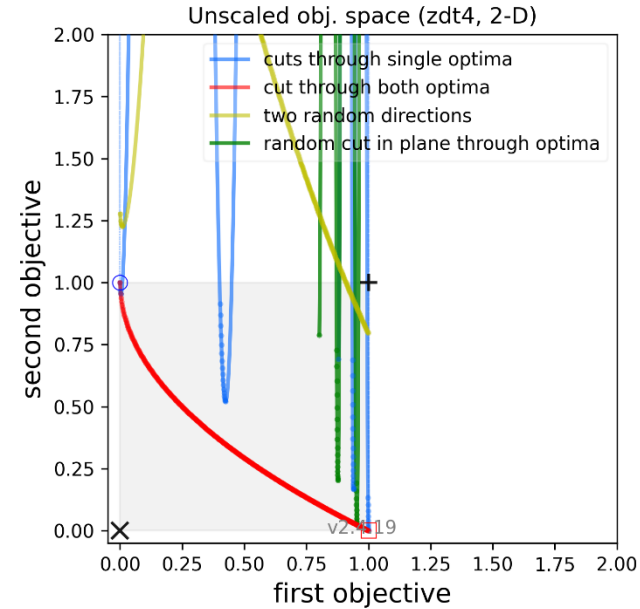
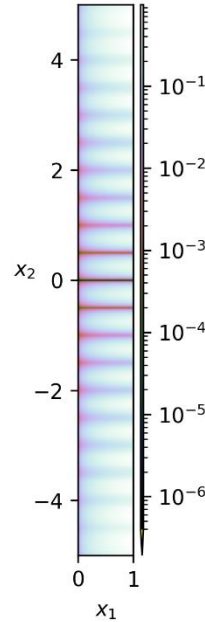
Unscaled obj. space ($F_{55} = (f_{21}, f_{21})$, 5-D, inst. 2)



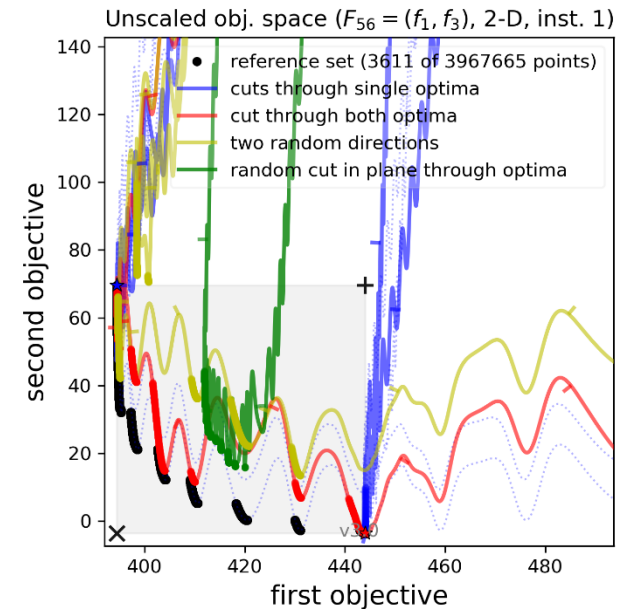
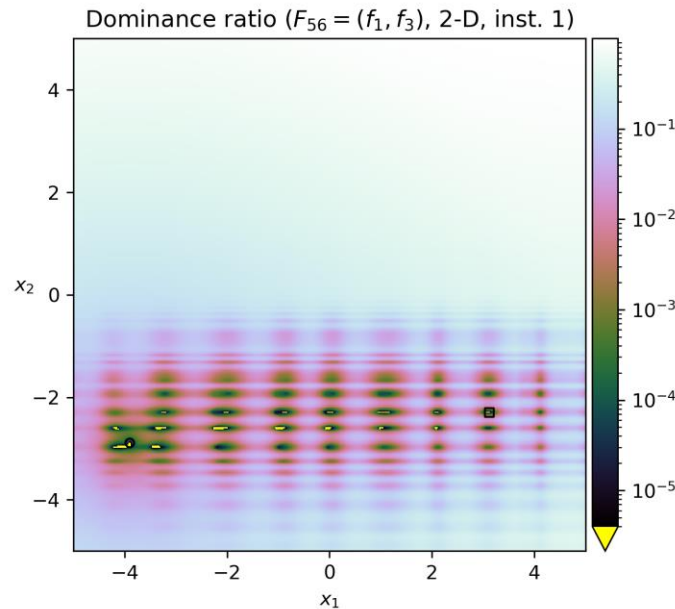
Comparison of Problem Landscapes

ZDT4

Two problems where both objectives are separable, first is unimodal and second is multimodal



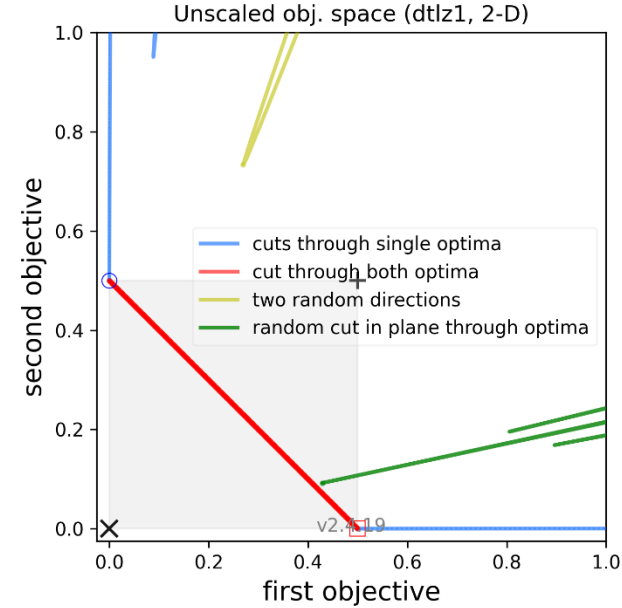
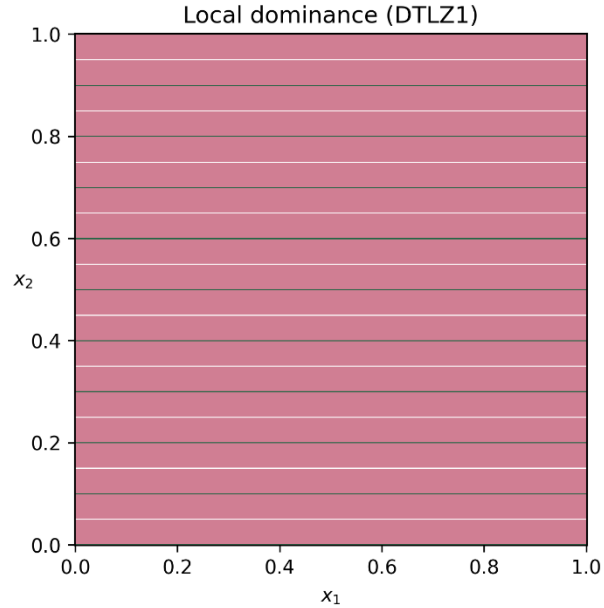
bbob-biobj-ext F_{56}
 f_1 Sphere function
 f_3 Rastrigin function



Comparison of Problem Landscapes

DTLZ1

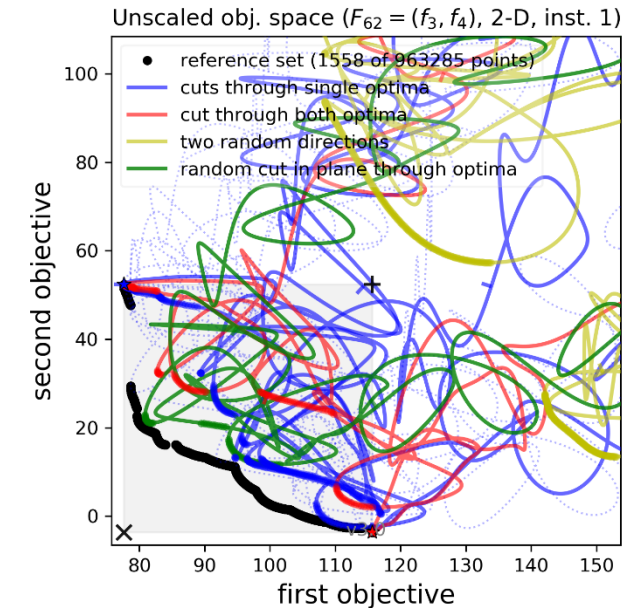
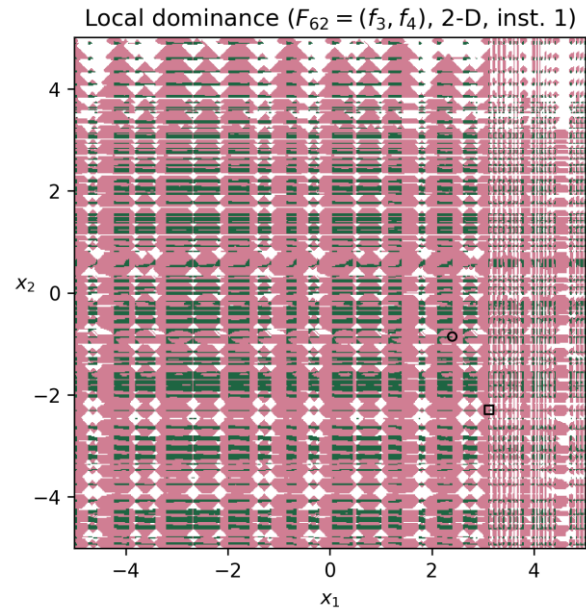
Two problems where both objectives are separable and multimodal



bbob-biobj-ext F_{62}

f_3 Rastrigin function

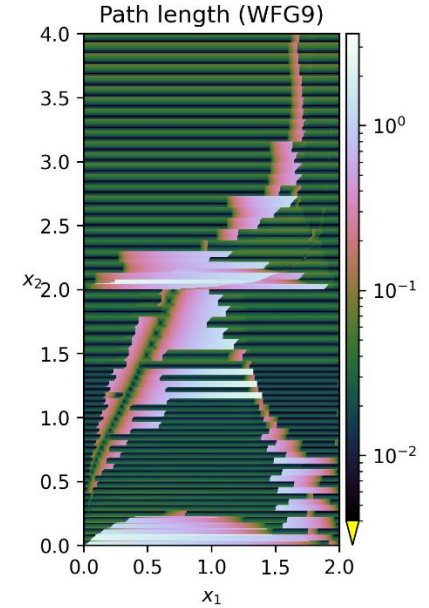
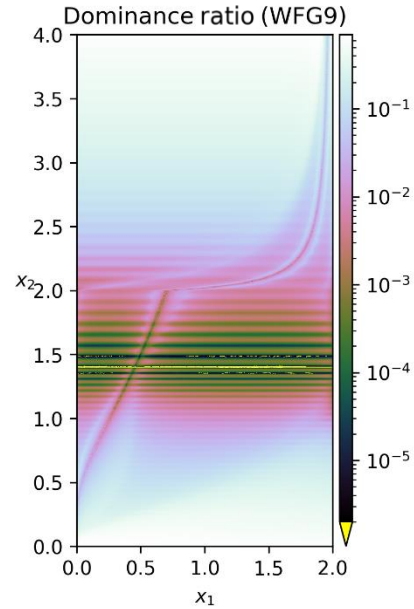
f_4 Skew Rastrigin-Bueche



Comparison of Problem Landscapes

WFG9

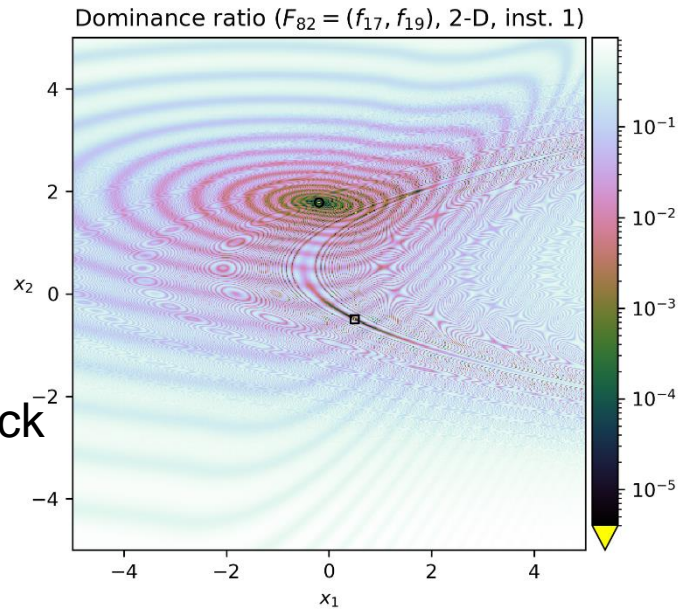
Two problems where both objectives are nonseparable and multimodal



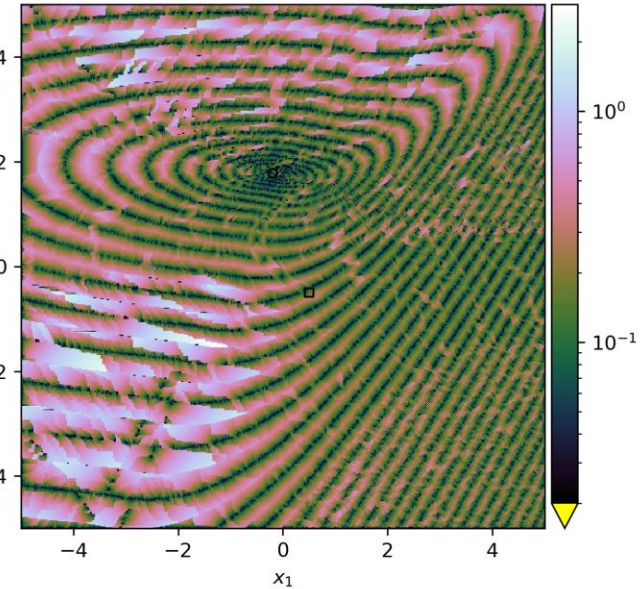
bbob-biobj-ext F_{82}

f_{17} Schaffer F7

f_{19} Griewank-Rosenbrock



Path length ($F_{82} = (f_{17}, f_{19})$, 2-D, inst. 1)



Other artificial problems

Other Artificial Problems

Suites of multiobjective problems with constraints

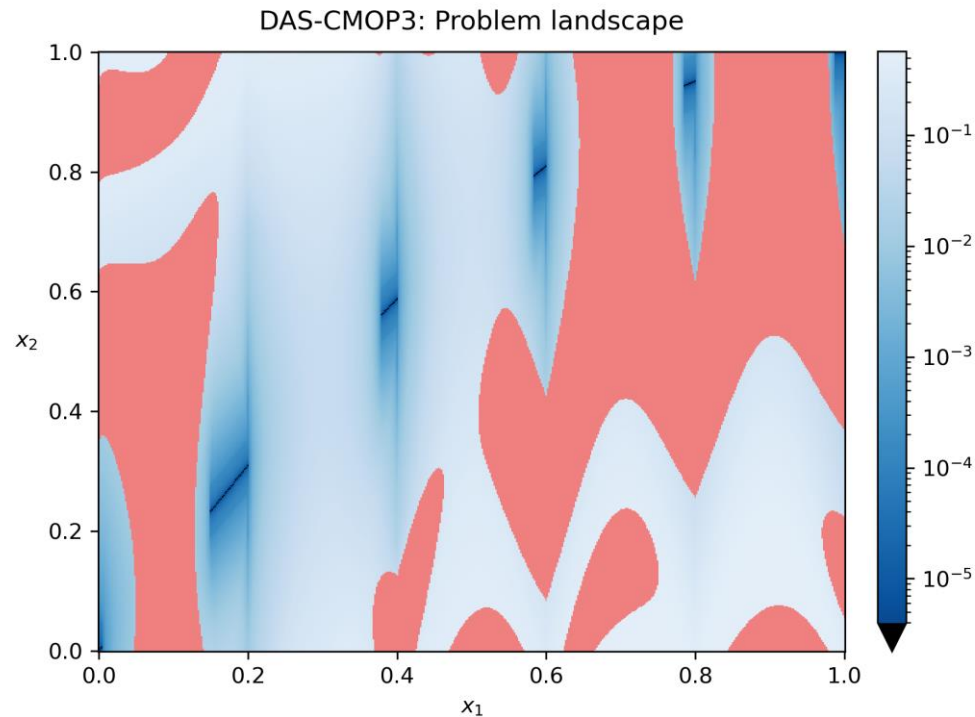
- CTP [Deb et al. 2001]
- CF [Zhang et al. 2009]
- C-DTLZ [Jain and Deb 2014]
- NCTP [Li et al. 2016]
- DC-DTLZ [Li et al. 2019]
- LIR-CMOP [Fan et al. 2019a]
- DAS-CMOP [Fan et al. 2019b]
- MW [Ma and Wang 2019]
- DOC [Liu and Wang 2019]
- Eq-DTLZ and Eq-IDTLZ [Cuate et al. 2020]
- CLSMOP [He et al. 2021]

Analysis and visualization of multiobjective problems with constraints:

<https://vodopijaaljosa.github.io/cmop-web/>

Tutorial on Multiobjective optimization in the presence of constraints:

<https://dis.ijs.si/filipic/cec2021tutorial/>

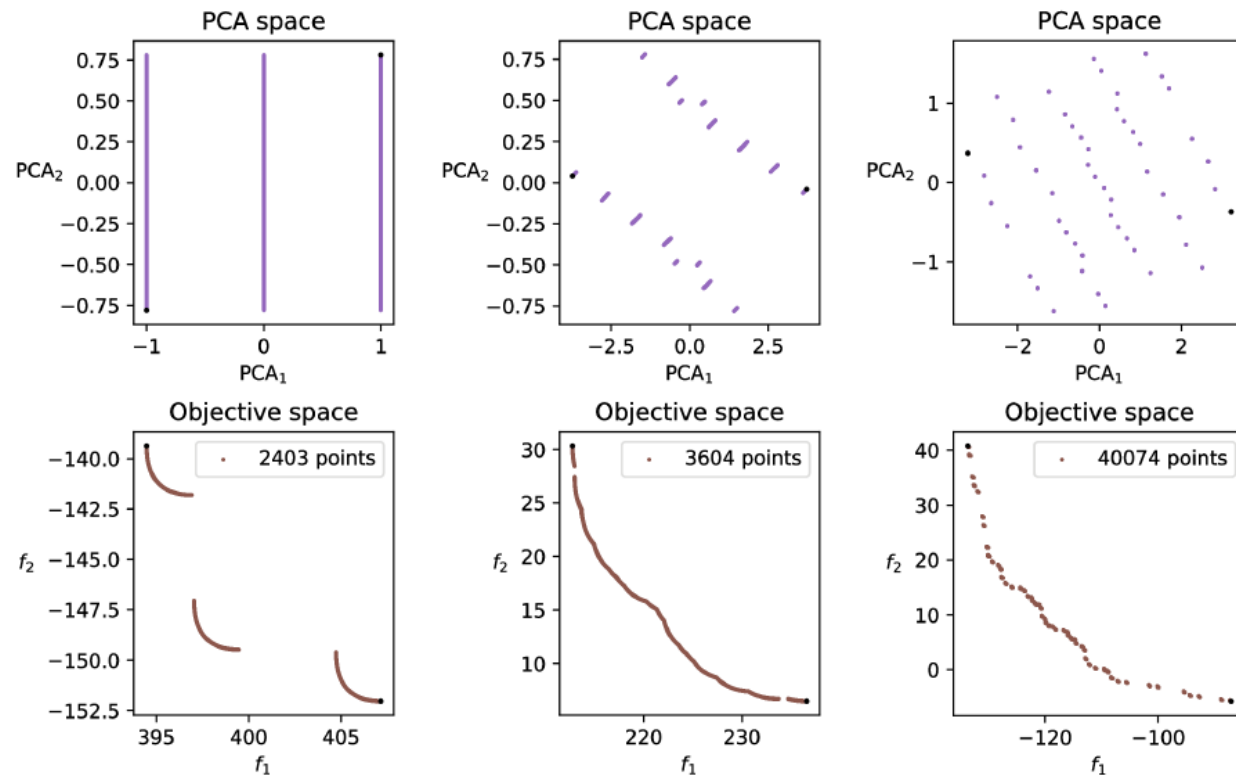


Other Artificial Problems

Suites of multiobjective mixed-integer problems

- Exeter suite of 6 problems constructed with the bottom-up approach [McClymont and Keedwell 2011]
- bbob-biobj-mixint suite of 92 bi-objective problems [Tušar et al. 2019]

Pareto set and front approximations for three different instances of the double sphere function



Real-world problems

v0.1

Real-World Problems

Individual problems

- Radar waveform design problem with a varying number of variables and 9 objectives [Hughes 2007]
- HBV problem of calibrating the HBV rainfall-runoff model with 14 variables and 4 objectives [Reed et al. 2013]
- MAZDA car structure design problem with 222 integer variables, 2 objectives and 54 constraints [Kohira et al. 2018]
- Lunar lander landing site selection problem with 2 variables, 3 objectives and 2 constraints [JSEC and JAXA 2018]
- Wind turbine design problem with 32 variables, 5 objectives and 22 constraints [JSEC 2019]

v0.2

Suites of Real-World Problems

Suites of unscalable problems

- DDMOP suite of 7 test problems with a different number of variables (5–17) and objectives (2–10) [He et al. 2020]
- Two suites of previously published problems [Tanabe and Ishibuchi 2020]
 - RE suite of 16 test problems with a different number of variables (2–7) and objectives (2–9)
 - 11 continuous, 1 integer, 4 mixed-integer
 - CRE suite of 8 test problems with constraints a different number of variables (3–7) and objectives (2–5)
 - 6 continuous, 1 integer, 1 mixed-integer
- RCM suite of 50 problems with a different number of variables (2–34), objectives (2–5) and constraints (1–29) [Kumar et al. 2021]

v0.5

Suites of Real-World Problems

Suites of scalable problems

- Heat exchanger design problem with scalable variables and 1 or 2 objectives [Daniels et al. 2018]
- Suite of 3 bi-objective TopTrumps problems in multiple dimensions and instances [Volz et al. 2019]
- Suite of 26 bi-objective MarioGAN problems in multiple dimensions and instances [Volz et al. 2019]
- Framework with scalable pathfinding problems (5 different objectives) [Weise and Mostaghim 2022]

Conclusions

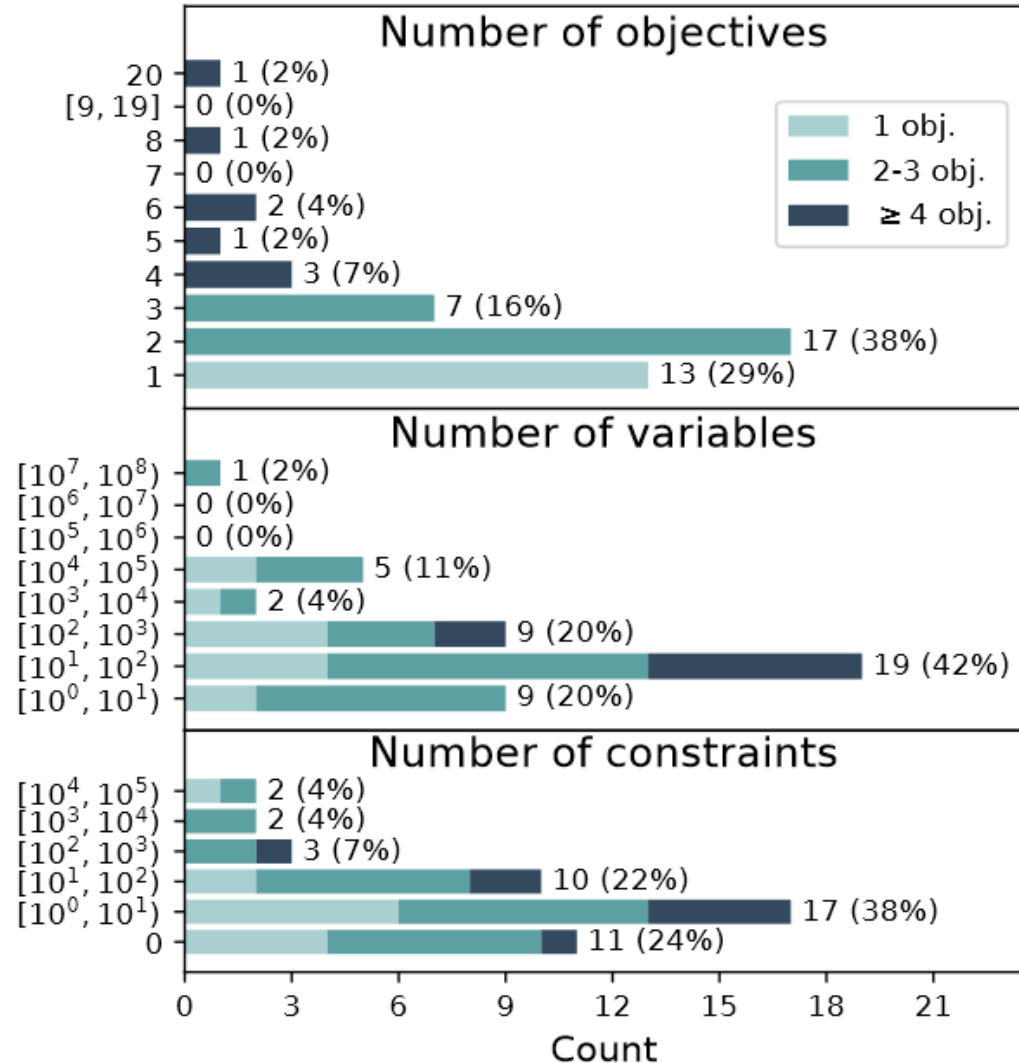
We should think about the usefulness of our research

Results of a questionnaire on the properties of real-world problems has shown their diversity [van der Blom et al. 2020]

<https://sites.google.com/view/macoda-rwp/home>

Most research is done on continuous unconstrained problems

Although the test problems are scalable, most studies use a fixed number of variables



Conclusions

Problem suites constructed with the bottom-up approach have unrealistic properties

Algorithms are overfitting to these problems (especially the overused DTLZ and WFG) [Ishibuchi et al. 2017]

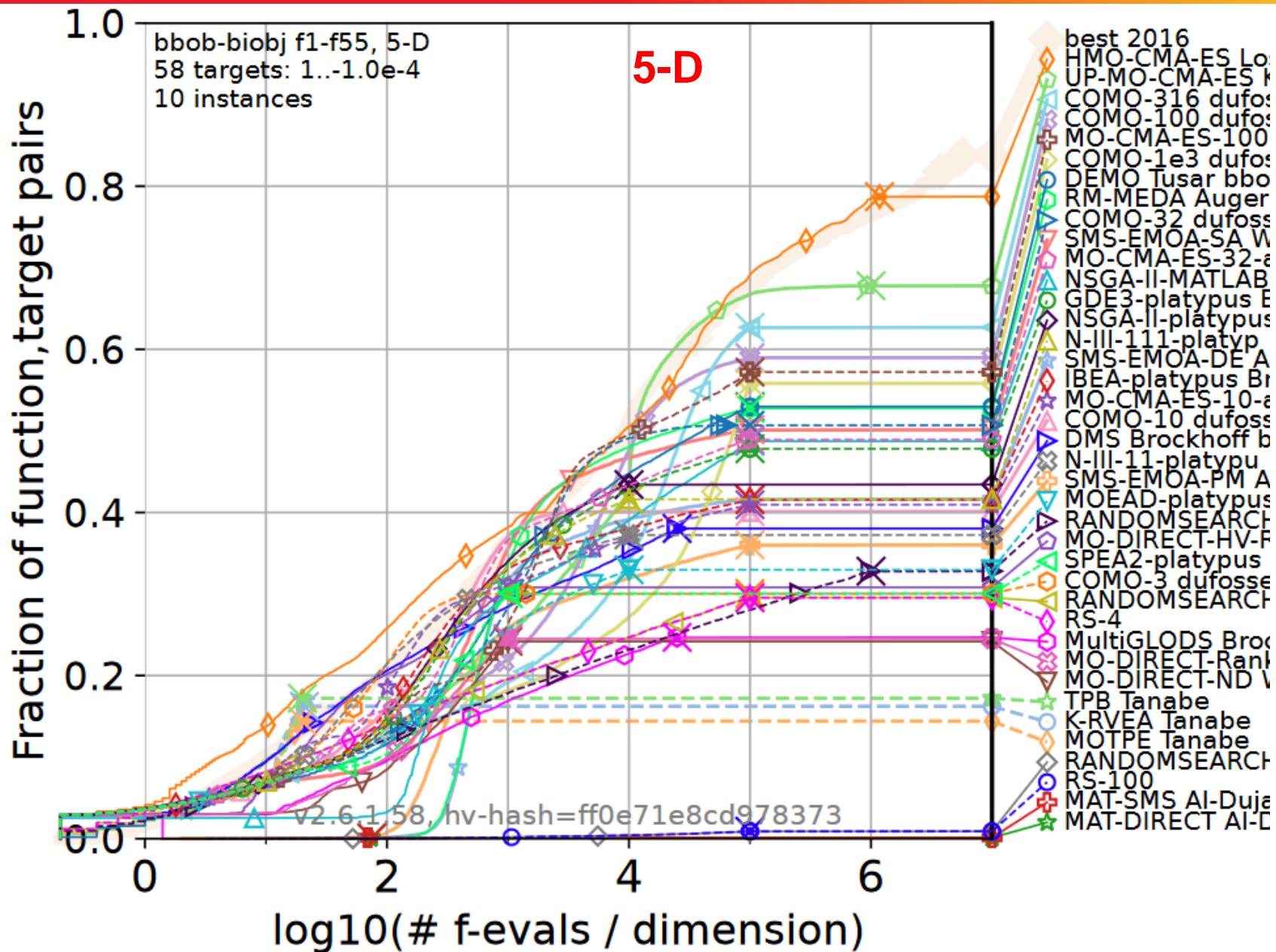
Using separate functions for the objectives looks like a step in the right direction



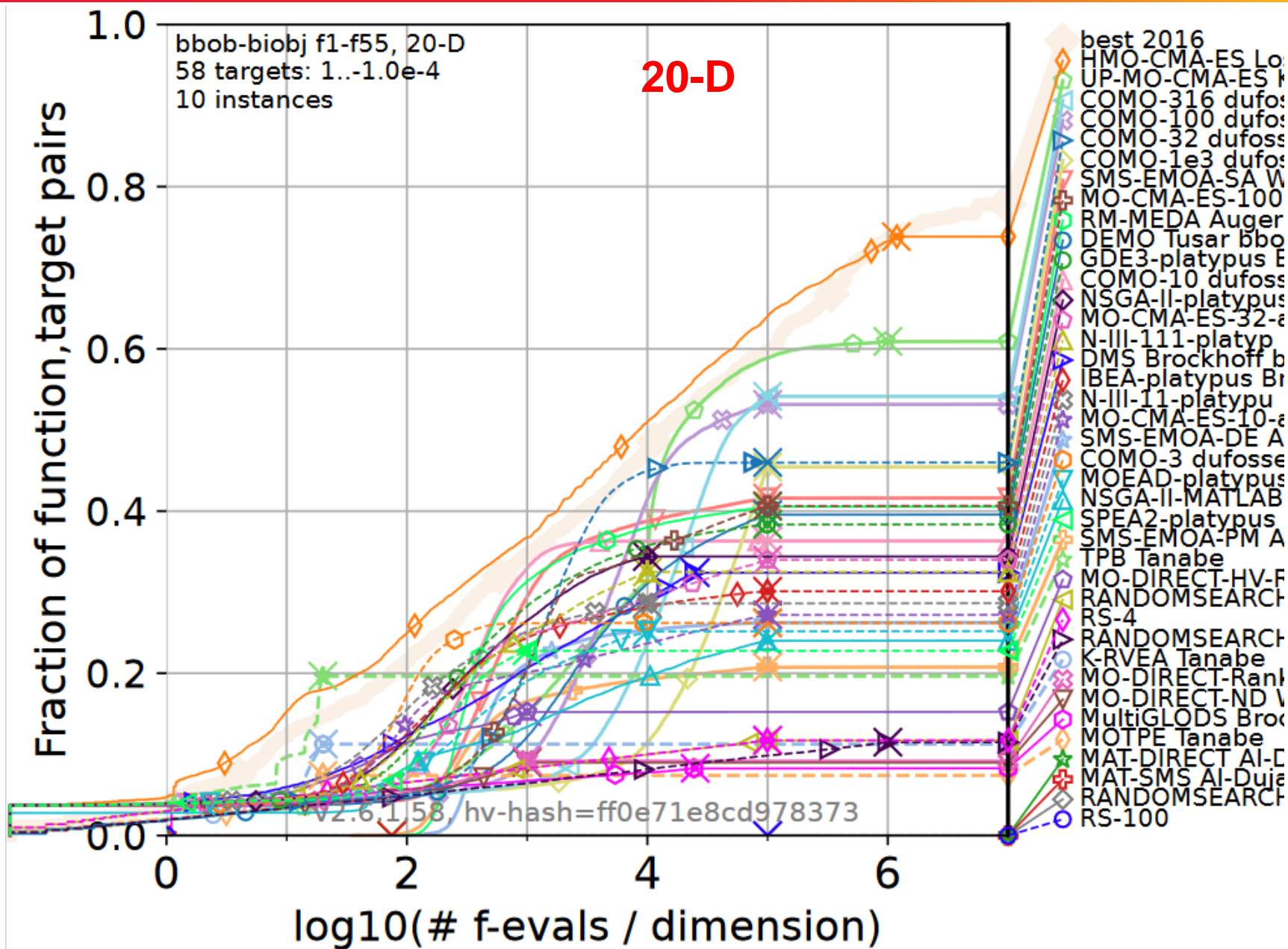
- ① Performance Assessment
- ② Test Problems and Their Visualizations
- ③ Recommendations from Numerical Results

```
python -m cocopp bbob-biobj*
```

Aggregated Results Over All 55 Functions



Aggregated Results Over All 55 Functions



Multiobjective Benchmarking 3.0?

a.k.a Challenging Open Research Directions

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- many-objective problems
problems/suites
indicators
efficient implementations

Multiobjective Benchmarking 3.0?

a.k.a Challenging Open Research Directions

- many-objective problems
 - problems/suites
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- constraints, mixed-integer, ...

Multiobjective Benchmarking 3.0?

a.k.a Challenging Open Research Directions

- many-objective problems
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 - efficient implementations
- constraints, mixed-integer, ...
- real-world benchmarking?
 - simulation crashes
 - parallelism
 - dynamic changes
 - interactive decision making
 - ...

Multiobjective Benchmarking 3.0?

a.k.a Challenging Open Research Directions

- many-objective problems
 - problems/suites
 - indicators
 - efficient implementations
- constraints, mixed-integer, ...
- real-world benchmarking?
 - simulation crashes
 - parallelism
 - dynamic changes
 - interactive decision making
 - ...
- benchmarking results from more classical approaches

Three “New Year” Resolutions

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① Show convergence graphs/ECDF

anything else than tables for fixed budget

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Thank you!

Supplementary Material

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Instructor Biography: Dimo Brockhoff

Dimo Brockhoff

RandOpt team

Inria Saclay - Ile-de-France

CMAP, CNRS, Ecole Polytechnique, IP Paris

Route de Saclay

91128 Palaiseau

France



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. After postdoctoral research positions at Inria Saclay Ile-de-France in Orsay and at Ecole Polytechnique in Palaiseau, both in France, Dimo has been a permanent researcher at Inria: from 2011 till 2016 with the Inria Lille - Nord Europe research center and since October 2016 with the Saclay - Ile-de-France research center, co-located with CMAP, Ecole Polytechnique, IP Paris. His most recent research interests are focused on evolutionary multiobjective optimization (EMO) and other (single-objective) blackbox optimization techniques, in particular with respect to benchmarking, theoretical aspects, and expensive optimization.

Instructor Biography: Tea Tušar

Tea Tušar

Computational Intelligence Group
Department of Intelligent Systems
Jožef Stefan Institute
Jamova cesta 29
1000 Ljubljana
Slovenia



Tea Tušar is a research associate at the Department of Intelligent Systems of the Jožef Stefan Institute, and an assistant professor at the Jožef Stefan International Postgraduate School, both in Ljubljana, Slovenia. After receiving the PhD degree in Information and Communication Technologies from the Jožef Stefan International Postgraduate School for her work on visualizing solution sets in multiobjective optimization, she has completed a one-year postdoctoral fellowship at Inria Lille in France where she worked on benchmarking multiobjective optimizers. Her research interests include evolutionary algorithms for singleobjective and multiobjective optimization with emphasis on visualizing and benchmarking their results and applying them to real-world problems.