#### Advanced Optimization Lecture/Exercise 5: Critically Looking at Data

#### December 18, 2019 Master AIC Université Paris-Saclay, Orsay, France

Anne Auger INRIA Saclay – Ile-de-France

1--in

Dimo Brockhoff INRIA Saclay – Ile-de-France 2) RM-MEDA: A regularity model-based multiobjective estimation of distribution algorithm. Gaetano, Francesco

- 3) A universal catalyst for first-order optimization. Simon, Wafa
- 5) Efficient optimization of many objectives by approximationguided evolution. Gérémy
- 6) A Mean-Variance Optimization Algorithm. Ramine, Gaspard
- 8) Population Size Adaptation for the CMA-ES Based on the Estimation Accuracy of the Natural Gradient. Florian, Théo
- 9) CMA-ES with Optimal Covariance Update and Storage Complexity. Eric, Clément
- 10) Challenges of Convex Quadratic Bi-Objective Benchmark Problems Ghassen, Moez
- 11) A modified ABC algorithm approach for power system harmonic estimation problems Ansaar

2) RM-MEDA: A regularity model-based multiobjective estimation of distribution algorithm. Gaetano, Francesco
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too many students for one afternoon! New: 10 minutes talk + 10 minutes questions hm. Ramine, Gaspard IA-ES Based on the ient. Florian, Théo date and Storage

Complexity. Eric, Clement

10) Challenges of Convex Quadratic Bi-Objective Benchmark Problems Ghassen, Moez

11) A modified ABC algorithm approach for power system harmonic estimation problems Ansaar

#### **Organization Oral Exams**

old	Wednesday,	new	
1pm – 1:30pm	Ansaar	Ansaar	1pm – 1:25pm
1:30pm – 2pm	Simon	Simon	1:25pm – 1:50pm
2pm – 2:30pm	Wafa	Wafa	1:50pm – 2:15pm
2:30pm – 3pm	Théo	Théo	2:15pm – 2:40pm
3pm – 3:30pm	Florian	Florian	2:40pm – 3:05pm
3:30pm – 4pm	Gérémy	Gérémy	3:05pm – 3:30pm
break		Francesco	3:30pm – 3:55pm
4:30pm – 5pm	Francesco	Gaetano	3:55pm – 4:20pm
5pm – 5:30pm	Gaetano		break
5:30pm – 6pm	Eric	Eric	4:35pm – 5pm
6pm – 6:30pm	Clément	Clément	5pm – 5:25pm
6:30pm – 7pm		Ramine	5:25pm – 5:50pm
7pm – 7:30pm		Gaspard	5:50pm – 6:15pm
7:30pm – 8pm		Ghassen	6:15pm – 6:40pm
		Moez	6:40pm – 7:05pm

#### **Course Overview**

	Date		Торіс
1	Wed, 27.11.2019	Dimo	Randomized Algorithms for Discrete Problems
2	Wed, 4.12.2019	Dimo	Exercise: The Travelling Salesperson Problem
3	Wed, 11.12.2019	Dimo	Evolutionary Multiobjective Optimization I
4	Mon, 16.12.2019	Dimo	Evolutionary Multiobjective Optimization II
5	Wed, 18.12.2019	Dimo	Looking at Data
	Vacation		
6	Wed, 8.1.2020 (morning!)	Anne	Continuous Optimization I
7	Wed, 22.1.2020 (morning!)	Anne	Continuous Optimization II
	Wed, 5.2.2020		oral presentations (individual time slots)

# why?

- novelty
- repeatability
- applicability

#### A Possible Way to Learn Science...

- ...is to look at how others do it ③
- ...is to critically ask whether what others are doing is the right thing
- ...is to get your hands dirty and tackle a difficult open question yourself (most time consuming part probably)
- is to actively review papers

### Paper Review: "Dynamic Search in Fireworks Algorithm"

#### **Dynamic Search in Fireworks Algorithm**

- Read Sec. V
  - Sec. V.B less important
  - read rather only until V.A and look at the results
- Do not care about what the algorithms are actually doing
- Questions:
  - What is well done in the experimental comparison?
  - What can be improved?
  - What shall be done and is not done?
  - Concretely: Mark in Tables I and II what you find remarkable

wrt. repeatability, interpretability, clarity, ...

#### **Review Form**

- Short summary of what is done (3-4 sentences)
- 1-2 positive points
- 1-2 negative points (to be improved)
- Fill out the following form (from 1 (poor), over 2 (below average), 3 (average), 4 (good) till 5 (excellent)):

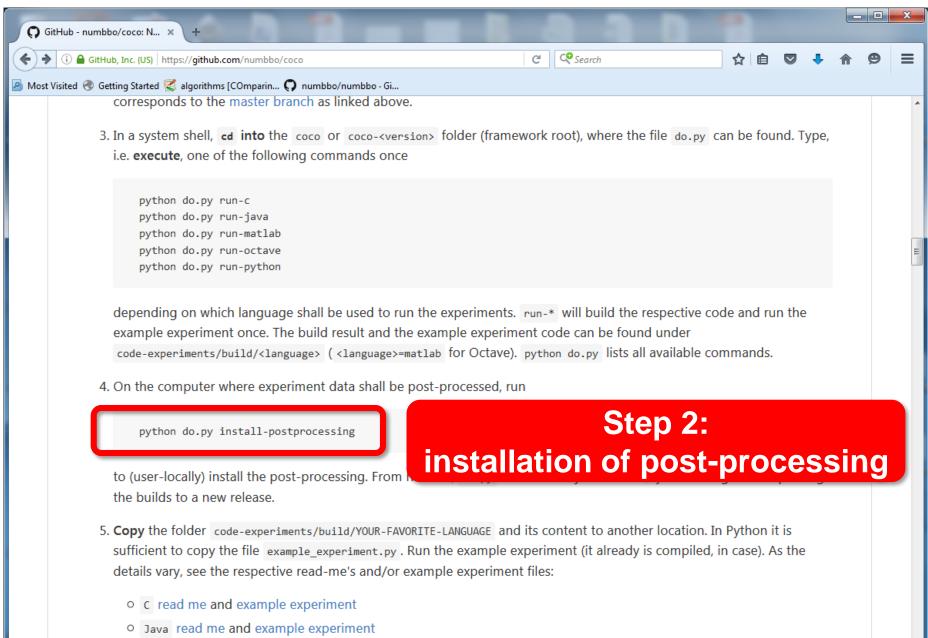
	Your evaluation (1—5)
Clarity	
Novelty	
Repeatability	
Consistency (what is promised vs. what is delivered)	
Significance	

#### **Exercise: Looking at COCO Data**

#### https://github.com/numbbo/coco

itHub - numbbo/coco: N × +			
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<> Code ① Issues 113 ⑦ Pull r	requests 2	tep 1:	
Numerical Black-Box Optimization Be		load COCO	
'			
7,902 commits	12 branches	S 25 releases	
Branch: master - New pull request			Fine file Clone or download -
<b>W</b> brockho committed on GitHub Merge pu	Ill request #1075 from numbbo/develog	oment	Lates commit askh7th on 10 lun
code-experiments	Merge pull request #1071 from the	usar/debug	2 months ago
code-postprocessing	further clean up of postprocessing	j output,	2 months ago
code-preprocessing/archive-update	Added empty last lines.		2 months ago
docs	updated reference to biobjective	3 months ago	
howtos	Update documentation-howto.mc	1	5 months ago
_		er.c when best_value is NULL. Plus s	5 months ago a year ago
<ul> <li>clang-format</li> </ul>	raising an error in bbob2009_logg	er.c when best_value is NULL. Plus s	a year ago
_	raising an error in bbob2009_logg		

#### https://github.com/numbbo/coco



Matlab/Octave read me and example experiment

#### https://github.com/numbbo/coco



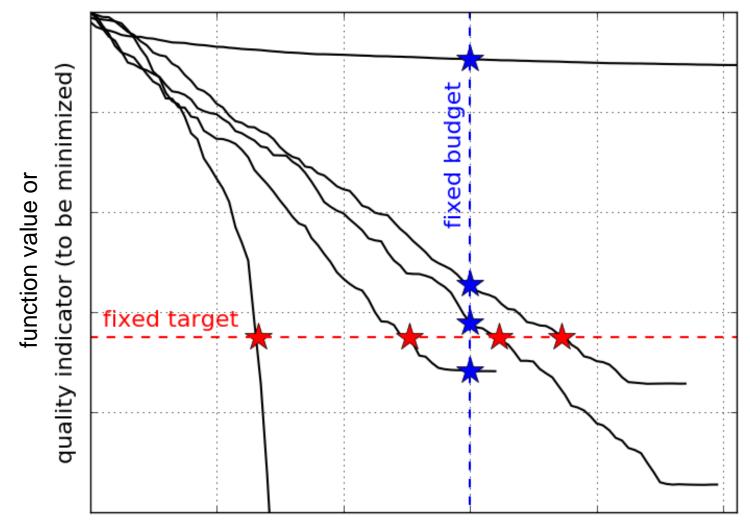
**Description by Folder** 

### Already done for you:

http://www.cmap.polytechnique.fr/
~dimo.brockhoff/advancedOptSaclay
/2019/exercises/coco-results/

### **Measuring Performance Empirically**

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

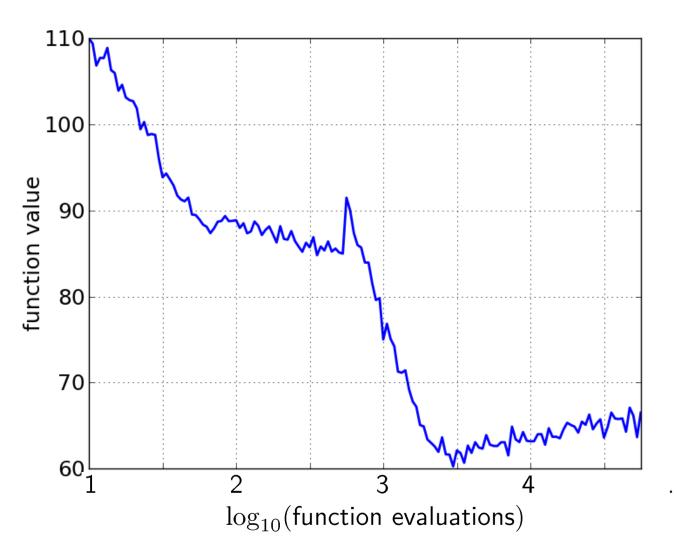


number of function evaluations

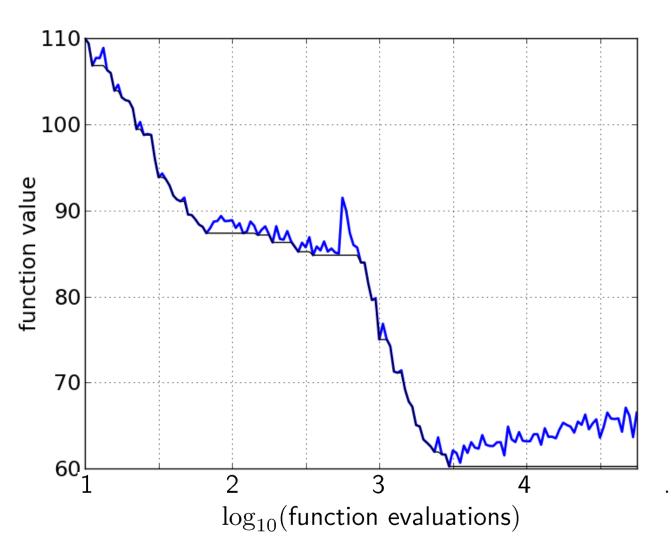
### ECDF:

### Empirical Cumulative Distribution Function of the Runtime [aka data profile]

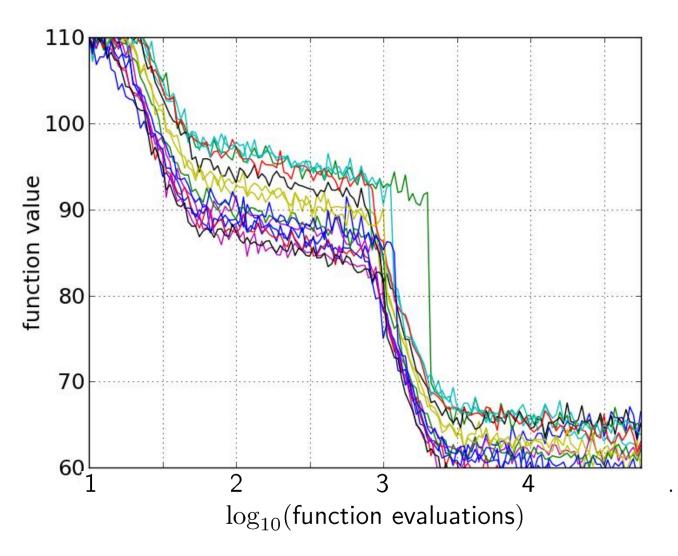
### **A Convergence Graph**



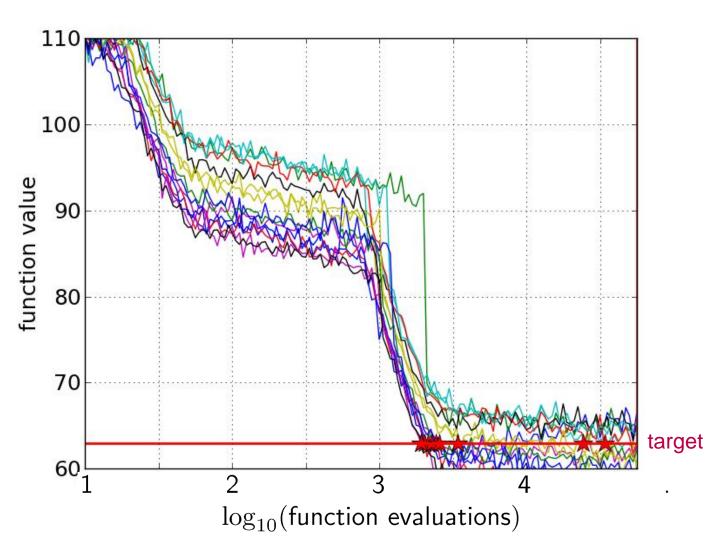
## **First Hitting Time is Monotonous**



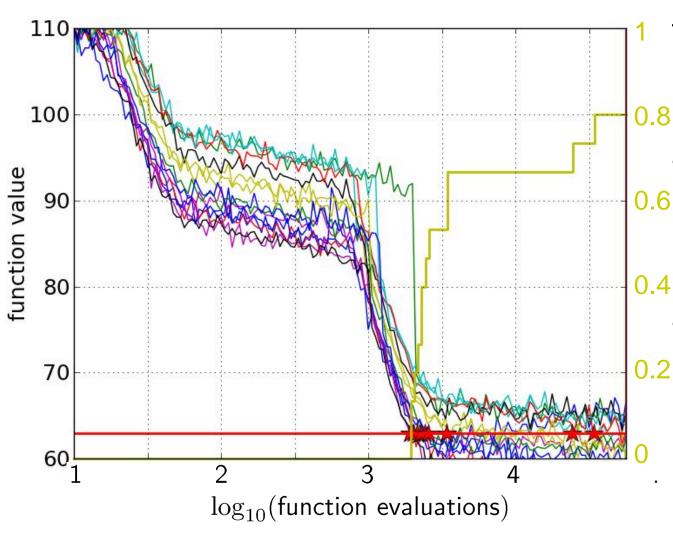
### 15 Runs



### **15 Runs ≤ 15 Runtime Data Points**



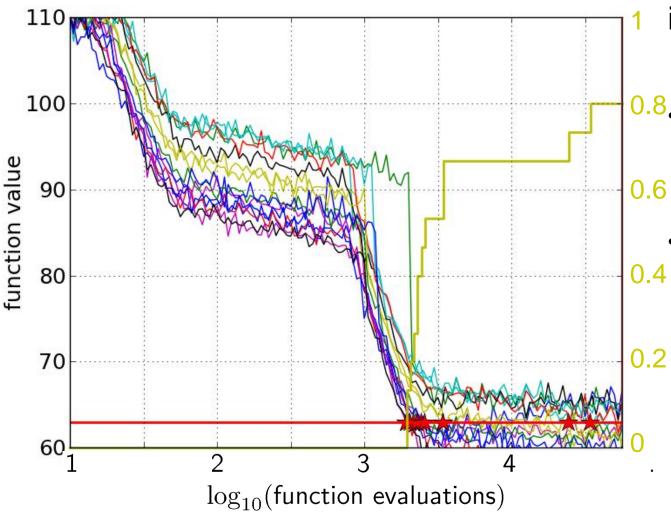
### **Empirical Cumulative Distribution**



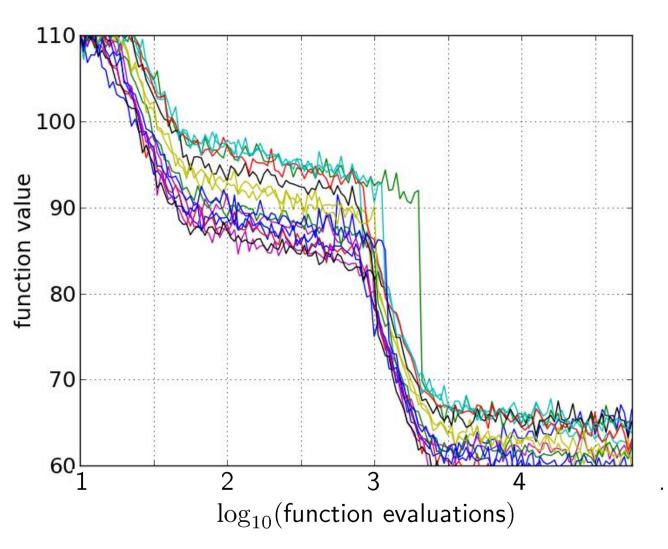
the ECDF of run lengths to reach the target

- 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)

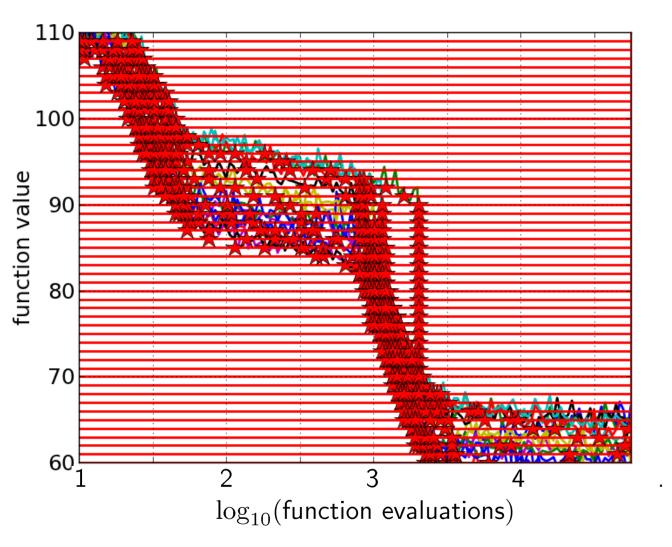
### **Empirical Cumulative Distribution**



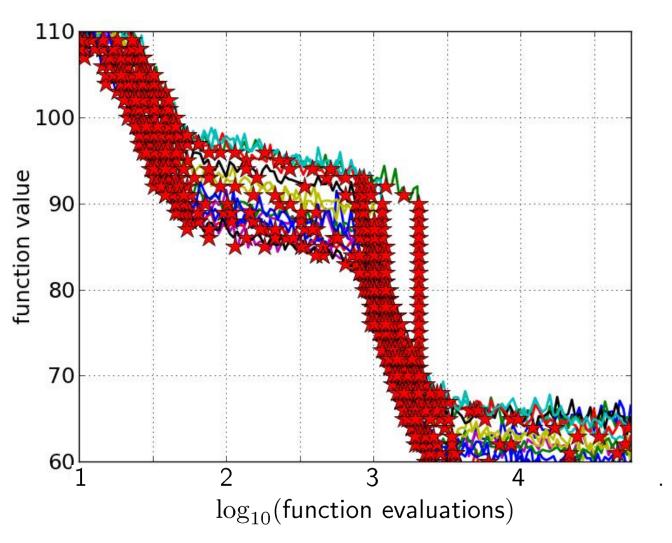
- interpretations possible:
- 0.8. 80% of the runs reached the target
   0.6 target
  - e.g. 60% of the runs need between 2000 and 4000 evaluations



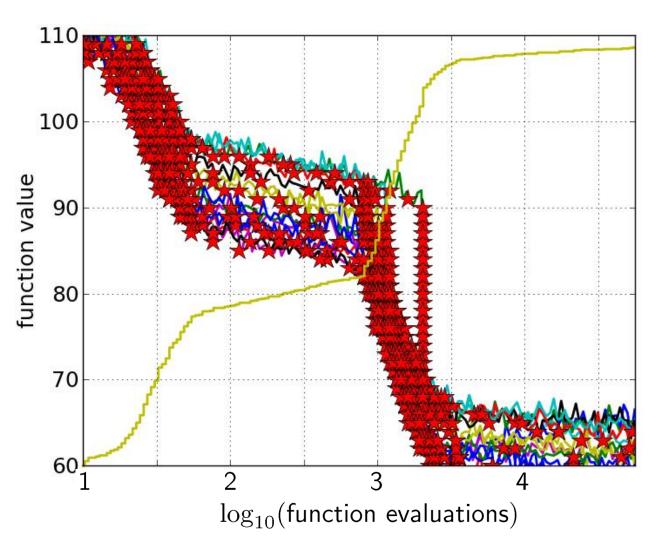
#### 15 runs



# 15 runs50 targets

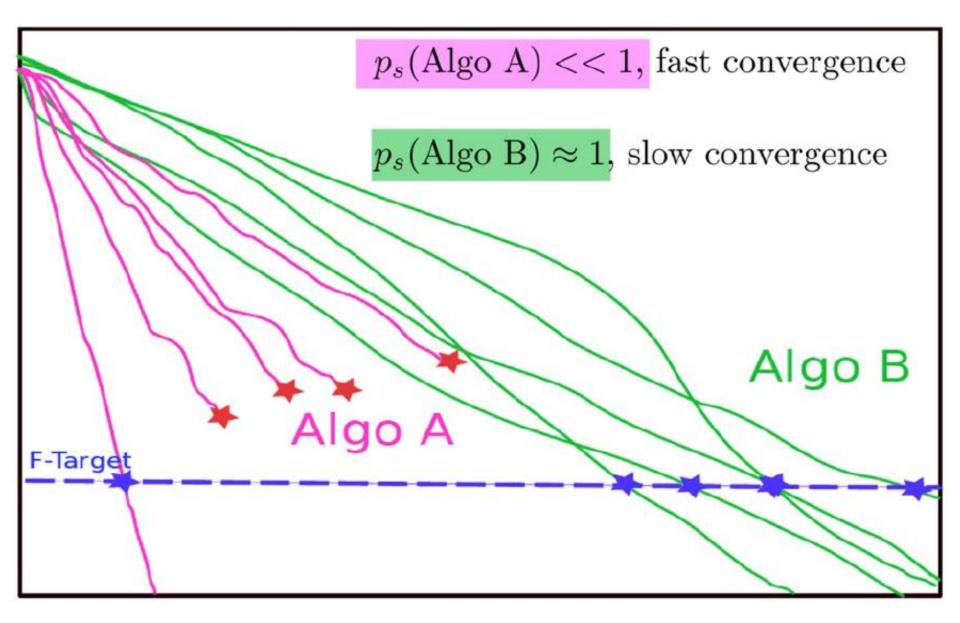


15 runs50 targets



15 runs50 targetsECDF with 750 steps

### **Fixed-target: Measuring Runtime**



### **Fixed-target: Measuring Runtime**

• Algo Restart A:



### $RT_B^r$ p<sub>s</sub>(Algo Restart B) = 1

### **Fixed-target: Measuring Runtime**

• Expected running time of the restarted algorithm:

$$E[RT^{r}] = \frac{1 - p_{s}}{p_{s}} E[RT_{unsuccessful}] + E[RT_{successful}]$$

• Estimator average running time (aRT):

$$\widehat{p_s} = \frac{\# \text{successes}}{\# \text{runs}}$$

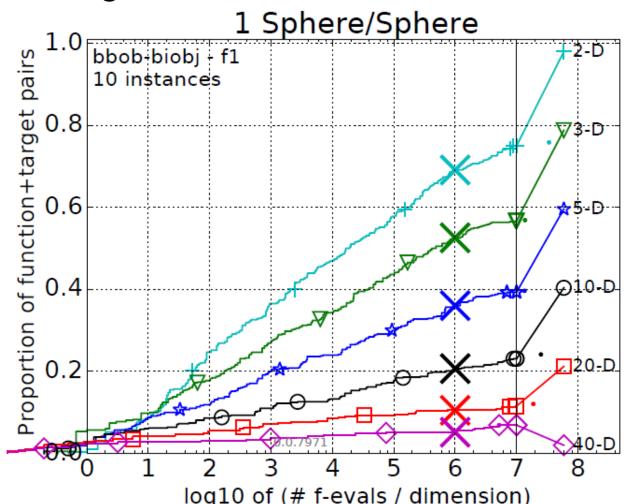
 $\widehat{RT_{unsucc}}$  = Average evals of unsuccessful runs

 $\widehat{RT_{succ}}$  = Average evals of successful runs

$$aRT = \frac{\text{total #evals}}{\text{#successes}}$$

### **ECDFs with Simulated Restarts**

What we typically plot are ECDFs of the simulated restarted algorithms:



### The single-objective BBOB functions

https://coco.gforge.inria.fr/downloads/download16.00/bbobdocfunctions.pdf

### The bbob Testbed

#### • 24 functions in 5 groups:

1 Separable Functions		4 Multi-modal functions with adequate global structure		
f1	Sphere Function	f15	Rastrigin Function	
f2	Sellipsoidal Function	f16	Weierstrass Function	
f3	Rastrigin Function	f17	Schaffers F7 Function	
f4	Büche-Rastrigin Function	f18	Schaffers F7 Functions, moderately ill-conditioned	
f5	♥Linear Slope	f19	Composite Griewank-Rosenbrock Function F8F2	
2 F	unctions with low or moderate conditioning	5 M	ulti-modal functions with weak global structure	
f6	Attractive Sector Function	f20	Schwefel Function	
f7	Step Ellipsoidal Function	f21	Gallagher's Gaussian 101-me Peaks Function	
f8	Rosenbrock Function, original	f22	Gallagher's Gaussian 21-hi Peaks Function	
f9	Rosenbrock Function, rotated	f23	Katsuura Function	
3 Functions with high conditioning and unimodal		f24	Lunacek bi-Rastrigin Function	
f10	Sellipsoidal Function			
f11	ODiscus Function			
f12	Bent Cigar Function			
f13	Sharp Ridge Function			
f14	ODifferent Powers Function			

• 6 dimensions: 2, 3, 5, 10, 20, (40 optional)

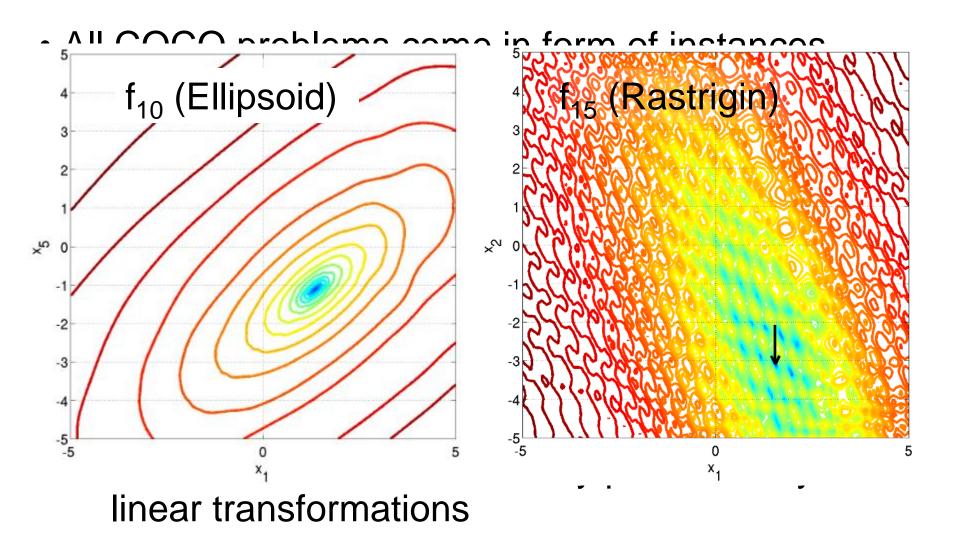
# **Notion of Instances**

- All COCO problems come in form of instances
  - e.g. as translated/rotated versions of the same function
- Prescribed instances typically change from year to year
  - avoid overfitting
  - 5 instances are always kept the same

Plus:

 the bbob functions are locally perturbed by nonlinear transformations

### **Notion of Instances**



#### **Exercise (Part 1)**

#### **Objectives:**

- investigate the performance of these 6 algorithms:
  - CMA-ES ("IPOP-CMA-ES" version)
  - CMA-ES ("BIPOP-CMA-ES" version)
  - Nelder-Mead simplex (use "NelderDoerr" version here)
  - BFGS quasi-Newton
  - Genetic Algorithm: discretization of cont. variables ("GA")
  - ONEFIFTH: (1+1)-ES with 1/5 rule
- postprocessed available here: http://www.cmap.polytechnique.fr/~dimo.brock hoff/advancedOptSaclay/2019/exercises/cocoresults/
- so now: investigate the data!

#### **Exercise (Part 2)**

#### **Objective:**

investigate the data:

- a) which algorithms are the best ones?
- b) does this depend on the dimension? Or on other things?
- c) look at single graphs: can we say something about the algorithms' invariances, e.g. wrt. rotations of the search space?
- d) what's the impact of covariance-matrix-adaptation?
- e) what do you think: are the displayed algorithms well-suited for problems with larger dimension?