

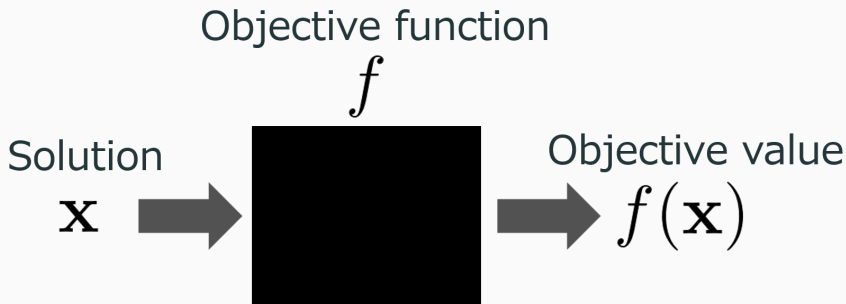
On Constructing Algorithm Portfolios in Algorithm Selection for Computationally Expensive Black-box Optimization in the Fixed-budget Setting

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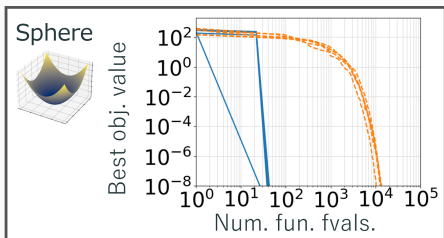
Black-box continuous optimization



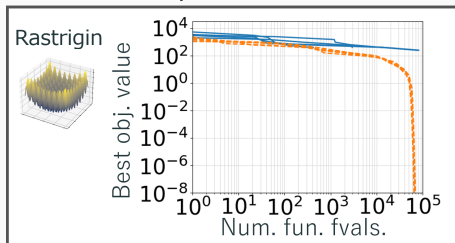
Algorithm selection problem for BBO

Best optimizer depends on the property of a problem

BFGS reaches the optimal solution about 243 times faster than **DE**



Unlike **DE**, **BFGS** cannot reach the optimal solution



- A user needs to select the most promising optimizer
 - Hand-selecting requires tedious trial-and-error

Feature-based offline algorithm selection for BBO

Training phase (on a training problem set)

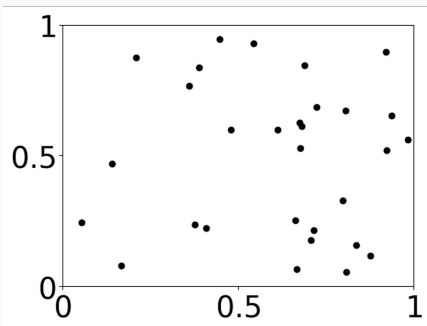
1. Generate a solution set \mathcal{X} and calculate $f(\mathcal{X})$
2. Compute features based on the pair of \mathcal{X} and $f(\mathcal{X})$
3. Train k ML models for k optimizers in a portfolio \mathcal{A}
 - \mathcal{A} : a set of k candidate optimizers ($k = 4$ in this work)

Testing phase (on a target problem)

1. Generate a solution set \mathcal{X} and calculate $f(\mathcal{X})$
2. Compute features based on the pair of \mathcal{X} and $f(\mathcal{X})$
3. Predict the performance of k optimizers by the k ML models, then select the best one

1. Generate a solution set \mathcal{X} and calculate $f(\mathcal{X})$

Generate
solutions

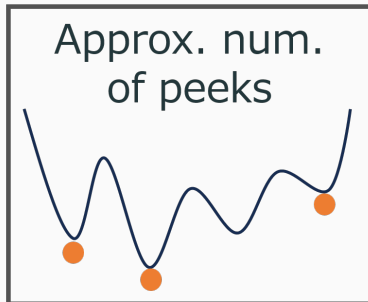
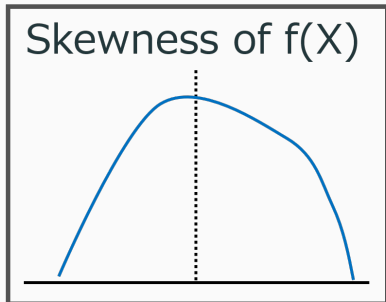


Calculate
objective values

	$f(x)$	x_1	x_2
1	37.9	0.78	0.133
2	70.6	0.949	0.646
3	-34.1	0.858	0.15
4	56.8	0.889	0.827
5	-78.2	0.275	0.159
6	-35.3	0.594	0.529
7	-12.5	0.261	0.698

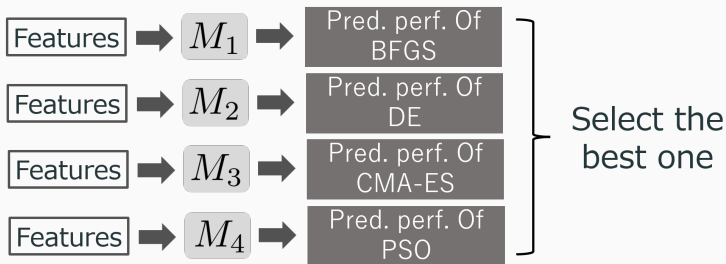
2. Compute features based on \mathcal{X} and $f(\mathcal{X})$

- Exploratory Landscape Analysis (ELA) [Mersmann 11]
 - Input: the pair of \mathcal{X} and $f(\mathcal{X})$
 - Output: a set of numerical features of a problem



3. Predict the performance of k optimizers by the k ML models, then select the best one

E.g., a portfolio $\mathcal{A} = \{ \text{BFGS, DE, CMA-ES, PSO} \}$



- The system selects a promising optimizer without:
 - any user interaction
 - actually running the k optimizers on a real-world problem

Contribution: Suggestion for constructing portfolios

- We focus on computationally expensive optimization
 - Some real-world problems require a long computation time to evaluate a solution x by expensive computer simulations
 - The max. number of fevals. (MaxFE) should be small
- Algorithm selection for compu. expensive opt.
 - has not been studied well
 - A few previous studies did it, but the setup was incorrect
- We point out two issues in existing approaches

Issue1: Most studies did not correctly count fevals

- **XFE**: fevals used for generating the solution set \mathcal{X}
 - A selection system requires **XFE** to calculate $f(\mathcal{X})$
- **OFE**: fevals used for a selected optimizer
 - E.g., the max. fevals of CMA-ES is **OFE**
- **MaxFE**: the max. fevals for the whole system
 - Correct: **MaxFE** = **XFE** + **OFE**
- However, most previous studies ignored **XFE**
 - Incorrect: **MaxFE** = **XFE** + **OFE**
- This leads to an overestimation of the performance
 - Correct: the selected optimizer can use only **OFE**
 - **XFE** should be small because a large **XFE** leads a small **OFE**
 - Incorrect: the selected optimizer can use **MaxFE**
 - **XFE** can be large as possible (**XFE** >> **MaxFE** in some work)

Our approach for the issue1

$$\text{MaxFE} = \text{XFE} + \text{OFE}$$

Issue2: Previous studies considered **MaxFE** instead of **OFE** when constructing algorithm portfolios

- **OFE**: fevals used for a selected optimizer
- **MaxFE**: max. fevals for the whole system
- How to construct a portfolio in previous studies
 - Run many optimizers on training problems until **MaxFE**
 - Select k optimizers based on their performance at **MaxFE**
- But, an optimizer can use only **OFE**, not **MaxFE**
 - Suppose: **MaxFE= 1 000** and **OFE= 500**
 - The portfolio consists of good optimizers at **1 000** fevals
 - But, they are unlikely to perform well at **500** fevals
- This gap can make the effectiveness of portfolio poor

Our approach for the issue2

Construct algorithm portfolios based on the performance of optimizers at **OFE**,
not at **MaxFE**

Experimental setup

- The COCO platform [Hansen 21]
 - The 24 bbob functions with $n \in \{2, 3, 5, 10\}$
 - Portfolios were constructed based on the benchmarking data of 244 optimizers in the COCO archive
 - Local search method for subset selection was used
- Settings for algorithm selection systems
 - flacco [Kerschke 19] was used for feature computation
 - MaxFE was set to $100 \times n$ (n : dimension)
 - The first study to set MaxFE below $100 \times n$ *actually*
 - Random forest regressor was used

Nikolaus Hansen, Anne Auger, Raymond Ros, Olaf Mersmann, Tea Tušar, Dimo Brockhoff: COCO: a platform for comparing continuous optimizers in a black-box setting. *Optim. Methods Softw.* 36(1): 114-144 (2021)

Pascal Kerschke and Heike Trautmann. 2019. Comprehensive Feature-Based Landscape Analysis of Continuous and Constrained Optimization Problems Using the R-package flacco. In *Applications in Statistical Computing – From Music Data Analysis to Industrial Quality Improvement*. Springer, 93-123.

6 portfolios constructed in this work ($k = 4$)

- **OFE**: fevals used for a selected optimizer
- **XFE**: fevals used for generating the solution set \mathcal{X}
- **MaxFE**: max. fevals for the whole system
 - **MaxFE** = **XFE** + **OFE** = $100n$ (n : dimension)
- \mathcal{A}_{\max} : based on the perf. at **MaxFE** = $100n$
 - Traditional, incorrect construction approach
- \mathcal{A}_{90} : based on the perf. at **OFE** = $90n$
 - **XFE** = $100n - 90n = 10n$
- \mathcal{A}_{85} : based on the perf. at **OFE** = $85n$
 - **XFE** = $100n - 85n = 15n$
- \mathcal{A}_{80} , \mathcal{A}_{75} , \mathcal{A}_{50} were constructed in the same way

6 portfolios constructed in this work ($k = 4$)

Surrogate-CMA-ES STEP-based mathematical DIRECT-based

\mathcal{A}_{\max} lq-CMA-ES, BIPOP-aCMA-STEP, MLSL, oMads-2N

\mathcal{A}_{90} DTS-CMA-ES_005, BrentSTEPif, DIRECT-REV, CMA-ES-2019

\mathcal{A}_{85} lq-CMA-ES, Imm-CMA-ES, STEPifeg, fmincon

\mathcal{A}_{80} lq-CMA-ES, Imm-CMA-ES, STEPifeg, fmincon

\mathcal{A}_{75} lq-CMA-ES, Imm-CMA-ES, BrentSTEPif, DIRECT-REV

\mathcal{A}_{50} lq-CMA-ES, Imm-CMA-ES, BrentSTEPrr, oMads-2N

- Left surrogate-CMA-ES is the single-best solver (SBS)
 - The best optimizer in terms of the average performance
 - Only in \mathcal{A}_{90} , the SBS is DTS-CMA-ES_005

Average rankings of 10 algorithm selection systems

- The system with \mathcal{A}_{90} performs the best
 - Importance of using the performance at OFE (not MaxFE)
 - A large OFE allows a long run of an optimizer

Portfolio	OFE	XFE	MaxFE	$n = 2$	$n = 3$	$n = 5$	$n = 10$
\mathcal{A}_{\max}	$90n$	$10n$	$100n$	5.50	5.65	5.73	5.58
\mathcal{A}_{\max}	$85n$	$15n$	$100n$	5.54	5.48	6.02	6.06
\mathcal{A}_{\max}	$80n$	$20n$	$100n$	6.21	5.10	5.35	6.15
\mathcal{A}_{\max}	$75n$	$25n$	$100n$	5.50	4.85	4.60	5.94
\mathcal{A}_{\max}	$50n$	$50n$	$100n$	5.00	5.85	6.00	5.98
\mathcal{A}_{90}	$90n$	$10n$	$100n$	4.44	4.15	4.12	3.04
\mathcal{A}_{85}	$85n$	$15n$	$100n$	4.38	4.52	5.37	4.04
\mathcal{A}_{80}	$80n$	$20n$	$100n$	5.29	5.65	5.79	4.67
\mathcal{A}_{75}	$75n$	$25n$	$100n$	5.21	5.81	4.73	5.29
\mathcal{A}_{50}	$50n$	$50n$	$100n$	7.94	7.94	7.27	8.25

Conclusion: This work focused on portfolios in algorithm selection for comput. expensive BBO

- **XFE**: fevals used for generating the solution set \mathcal{X}
- **OFE**: fevals used for a selected optimizer
- **MaxFE**: the max. fevals for the whole system
- **Two take home messages:**
 - **MaxFE** should be **XFE** + **OFE**
 - Portfolios should be constructed based on the performance of optimizers for **OFE**, not **MaxFE**
- **Future work: Improving selection systems**
 - The performance of the present system is not good