Carola Doerr

List of Publications by Year
in descending order

103 papers	1,787 citations	430874 18 h-index	395702 33 g-index
103 all docs	103 docs citations	103 times ranked	330 citing authors

#	Article	IF	Citations
1	Black-Box Optimization Revisited: Improving Algorithm Selection Wizards Through Massive Benchmarking. IEEE Transactions on Evolutionary Computation, 2022, 26, 490-500.	10.0	13
2	Fixed-Target Runtime Analysis. Algorithmica, 2022, 84, 1762-1793.	1.3	4
3	IOHanalyzer: Detailed Performance Analyses for Iterative Optimization Heuristics. ACM Transactions on Evolutionary Learning, 2022, 2, 1-29.	3.5	20
4	MATE: A Model-Based Algorithm Tuning Engine. Lecture Notes in Computer Science, 2021, , 51-67.	1.3	0
5	Maximizing Drift is Not Optimal for Solving OneMax. Evolutionary Computation, 2021, 29, 1-20.	3.0	6
6	Nevergrad. ACM SIGEVOlution, 2021, 14, 8-15.	0.5	9
7	Blending Dynamic Programming with Monte Carlo Simulation for Bounding the Running Time of Evolutionary Algorithms. , 2021, , .		2
8	Optimal static mutation strength distributions for the (1 + Î») evolutionary algorithm on OneMax. , 2021, , .		4
9	Towards large scale automated algorithm design by integrating modular benchmarking frameworks. , 2021, , .		8
10	Leveraging benchmarking data for informed one-shot dynamic algorithm selection. , 2021, , .		3
11	OPTION. , 2021, , .		4
12	Self-Adjusting Mutation Rates with Provably Optimal Success Rules. Algorithmica, 2021, 83, 3108-3147.	1.3	13
13	Tuning as a means of assessing the benefits of new ideas in interplay with existing algorithmic modules. , 2021, , .		20
14	Towards Feature-Based Performance Regression Using Trajectory Data. Lecture Notes in Computer Science, 2021, , 601-617.	1.3	17
15	Optimal parameter choices via precise black-box analysis. Theoretical Computer Science, 2020, 801, 1-34.	0.9	35
16	Benchmarking discrete optimization heuristics with IOHprofiler. Applied Soft Computing Journal, 2020, 88, 106027.	7.2	41
17	Theory of Parameter Control for Discrete Black-Box Optimization: Provable Performance Gains Through Dynamic Parameter Choices. Natural Computing Series, 2020, , 271-321.	2.2	44
18	Variance Reduction for Better Sampling in Continuous Domains. Lecture Notes in Computer Science, 2020, , 154-168.	1.3	3

#	Article	IF	Citations
19	Exploratory Landscape Analysis is Strongly Sensitive to the Sampling Strategy. Lecture Notes in Computer Science, 2020, , 139-153.	1.3	35
20	Optimal Mutation Rates for the $$(1+lambda)$$ EA on OneMax. Lecture Notes in Computer Science, 2020, , 574-587.	1.3	8
21	Benchmarking a $$(mu +lambda)$$ Genetic Algorithm with Configurable Crossover Probability. Lecture Notes in Computer Science, 2020, , 699-713.	1.3	9
22	Dynamic control parameter choices in evolutionary computation. , 2020, , .		4
23	Integrated vs. sequential approaches for selecting and tuning CMA-ES variants. , 2020, , .		10
24	Fixed-target runtime analysis. , 2020, , .		9
25	Towards dynamic algorithm selection for numerical black-box optimization. , 2020, , .		8
26	Optimization of Chance-Constrained Submodular Functions. Proceedings of the AAAI Conference on Artificial Intelligence, 2020, 34, 1460-1467.	4.9	12
27	Mutation Rate Control in the $$(1+lambda)$$ Evolutionary Algorithm with a Self-adjusting Lower Bound. Communications in Computer and Information Science, 2020, , 305-319.	0.5	0
28	Evolving Sampling Strategies for One-Shot Optimization Tasks. Lecture Notes in Computer Science, 2020, , 111-124.	1.3	6
29	Hybridizing the 1/5-th Success Rule with Q-Learning for Controlling the Mutation Rate of an Evolutionary Algorithm. Lecture Notes in Computer Science, 2020, , 485-499.	1.3	1
30	Interpolating Local and Global Search by Controlling the Variance of Standard Bit Mutation. , 2019, , .		16
31	Bayesian performance analysis for black-box optimization benchmarking. , 2019, , .		15
32	Expressiveness and robustness of landscape features. , 2019, , .		16
33	Hyper-parameter tuning for the (1 + (<i>Î», Î»</i>)) GA. , 2019, , .		12
34	Coupling the design of benchmark with algorithm in landscape-aware solver design. , 2019, , .		4
35	Fast re-optimization via structural diversity. , 2019, , .		9
36	Offspring population size matters when comparing evolutionary algorithms with self-adjusting mutation rates. , 2019, , .		8

#	Article	IF	Citations
37	Online selection of CMA-ES variants. , 2019, , .		16
38	Maximizing drift is not optimal for solving OneMax. , 2019, , .		10
39	Making a case for (Hyper-)parameter tuning as benchmark problems. , 2019, , .		8
40	Fixed-target runtime analysis of the (1 + 1) EA with resampling. , 2019, , .		2
41	Dynamic parameter choices in evolutionary computation. , 2019, , .		1
42	Adaptive landscape analysis. , 2019, , .		17
43	Illustrating the trade-off between time, quality, and success probability in heuristic search. , 2019, , .		0
44	Self-adjusting mutation rates with provably optimal success rules. , 2019, , .		29
45	Benchmarking discrete optimization heuristics with IOHprofiler. , 2019, , .		6
46	Preface to the Special Issue on Theory of Genetic and Evolutionary Computation. Algorithmica, 2019, 81, 589-592.	1.3	1
47	The query complexity of a permutation-based variant of Mastermind. Discrete Applied Mathematics, 2019, 260, 28-50.	0.9	15
48	Solving Problems with Unknown Solution Length at Almost No Extra Cost. Algorithmica, 2019, 81, 703-748.	1.3	9
49	The $$(1+1)$$ (1 + 1) Elitist Black-Box Complexity of LeadingOnes. Algorithmica, 2018, 80, 1579-1603.	1.3	9
50	Optimal Static and Self-Adjusting Parameter Choices for the $$(1+(lambda ,lambda))$$ (1 + (Î» , Î»)) Genetic Algorithm. Algorithmica, 2018, 80, 1658-1709.	1.3	96
51	Static and Self-Adjusting Mutation Strengths for Multi-valued Decision Variables. Algorithmica, 2018, 80, 1732-1768.	1.3	39
52	Towards a theory-guided benchmarking suite for discrete black-box optimization heuristics. , 2018, , .		15
53	Discrepancy-based evolutionary diversity optimization. , 2018, , .		36
54	Simple on-the-fly parameter selection mechanisms for two classical discrete black-box optimization benchmark problems. , 2018, , .		26

#	Article	IF	Citations
55	A Simple Proof for the Usefulness of Crossover in Black-Box Optimization. Lecture Notes in Computer Science, 2018, , 29-41.	1.3	20
56	Compiling a benchmarking test-suite for combinatorial black-box optimization. , 2018, , .		3
57	Dynamic parameter choices in evolutionary computation. , 2018, , .		2
58	Towards an Adaptive CMA-ES Configurator. Lecture Notes in Computer Science, 2018, , 54-65.	1.3	13
59	Sensitivity of Parameter Control Mechanisms with Respect to Their Initialization. Lecture Notes in Computer Science, 2018, , 360-372.	1.3	7
60	Preface to the Special Issue on Theory of Genetic and Evolutionary Computation. Algorithmica, 2017, 78, 558-560.	1.3	0
61	Introducing Elitist Black-Box Models: When Does Elitist Behavior Weaken the Performance of Evolutionary Algorithms?. Evolutionary Computation, 2017, 25, 587-606.	3.0	14
62	OneMax in Black-Box Models with Several Restrictions. Algorithmica, 2017, 78, 610-640.	1.3	8
63	Unknown solution length problems with no asymptotically optimal run time. , 2017, , .		8
64	Non-static parameter choices in evolutionary computation. , 2017, , .		4
65	Rumor spreading in random evolving graphs. Random Structures and Algorithms, 2016, 48, 290-312.	1.1	21
66	Women@GECCO 2016 Chairs' Welcome. , 2016, , .		0
67	The Impact of Random Initialization on the Runtime of Randomized Search Heuristics. Algorithmica, 2016, 75, 529-553.	1.3	25
68	Playing Mastermind With Many Colors. Journal of the ACM, 2016, 63, 1-23.	2.2	16
69	Theory for Non-Theoreticians. , 2016, , .		0
70	The (1+1) Elitist Black-Box Complexity of LeadingOnes. , 2016, , .		4
71	Simple and optimal randomized fault-tolerant rumor spreading. Distributed Computing, 2016, 29, 89-104.	0.8	2
72	Provably Optimal Self-adjusting Step Sizes for Multi-valued Decision Variables. Lecture Notes in Computer Science, 2016, , 782-791.	1.3	8

#	Article	IF	Citations
73	k-Bit Mutation with Self-Adjusting k Outperforms Standard Bit Mutation. Lecture Notes in Computer Science, 2016, , 824-834.	1.3	32
74	The Right Mutation Strength for Multi-Valued Decision Variables. , 2016, , .		13
75	Optimal Parameter Choices via Precise Black-Box Analysis. , 2016, , .		48
76	2014 Women@GECCO workshop. ACM SIGEVOlution, 2015, 7, 26-27.	0.5	0
77	From black-box complexity to designing new genetic algorithms. Theoretical Computer Science, 2015, 567, 87-104.	0.9	166
78	A Tight Runtime Analysis of the (1+(Î», Î»)) Genetic Algorithm on OneMax. , 2015, , .		30
79	Money for Nothing. , 2015, , .		25
80	Elitist Black-Box Models. , 2015, , .		13
81	Solving Problems with Unknown Solution Length at (Almost) No Extra Cost. , 2015, , .		7
82	Optimal Parameter Choices Through Self-Adjustment. , 2015, , .		60
83	OneMax in Black-Box Models with Several Restrictions. , 2015, , .		10
84	Unbiased Black-Box Complexities of Jump Functions. Evolutionary Computation, 2015, 23, 641-670.	3.0	12
85	The Price of Anarchy for Selfish Ring Routing is Two. ACM Transactions on Economics and Computation, 2014, 2, 1-24.	1.1	0
86	The impact of random initialization on the runtime of randomized search heuristics. , 2014, , .		8
87	Unbiased black-box complexities of jump functions. , 2014, , .		14
88	Black-box complexity. , 2014, , .		3
89	Women@GECCO 2014. , 2014, , .		0
90	The unbiased black-box complexity of partition is polynomial. Artificial Intelligence, 2014, 216, 275-286.	5.8	15

#	Article	IF	Citations
91	Playing Mastermind with Constant-Size Memory. Theory of Computing Systems, 2014, 55, 658-684.	1.1	22
92	Ranking-Based Black-Box Complexity. Algorithmica, 2014, 68, 571-609.	1.3	35
93	Calculation of Discrepancy Measures and Applications. Lecture Notes in Mathematics, 2014, , 621-678.	0.2	22
94	Computing Minimum Cycle Bases in Weighted Partial 2-Trees in Linear Time. Journal of Graph Algorithms and Applications, 2014, 18, 325-346.	0.4	1
95	Lessons from the black-box. , 2013, , .		41
96	Direction-reversing quasi-random rumor spreading with restarts. Information Processing Letters, 2013, 113, 921-926.	0.6	0
97	Black-box complexity. , 2013, , .		1
98	Constructing low star discrepancy point sets with genetic algorithms. , 2013, , .		12
99	The Query Complexity of Finding a Hidden Permutation. Lecture Notes in Computer Science, 2013, , 1-11.	1.3	13
100	A New Randomized Algorithm to Approximate the Star Discrepancy Based on Threshold Accepting. SIAM Journal on Numerical Analysis, 2012, 50, 781-807.	2.3	22
101	Multiplicative Drift Analysis. Algorithmica, 2012, 64, 673-697.	1.3	187
102	Memory-restricted black-box complexity of OneMax. Information Processing Letters, 2012, 112, 32-34.	0.6	13
103	Finding optimal volume subintervals with k points and calculating the star discrepancy are NP-hard problems. Journal of Complexity, 2009, 25, 115-127.	1.3	44