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Acronyms

AAC Automated Algorithm Configuration.

ABS Anti-lock Braking System.

AE Autoencoder.

AS Algorithm Selection.

ASP Algorithm Selection Problem.

AUC Area Under the Curve.

BBO Black-Box Optimization.

BBOB Black-Box Optimization Benchmarking.

BEV Battery Electric Vehicle.

BH Benjamini-Hochberg.

BIW Body-in-White.

BO Bayesian Optimization.

CASH Combined Algorithm Selection and Hyperparameter Optimization.

CMA-ES Covariance Matrix Adaptation Evolutionary Strategy.

COCO Comparing Continuous Optimizers.

DE Differential Evolution.

DoE Design of Experiments.

EA Evolutionary Algorithm.

ECDF Empirical Cumulative Distribution Functions.

EGO Efficient Global Optimization.

EI Expected Improvement.

ELA Exploratory Landscape Analysis.

EMNA Estimation of Multivariate Normal Algorithm.

ES Evolutionary Strategy.

EuroNCAP European New Car Assessment Programme.

FE Finite Element.

GP Genetic Programming.

GPR Gaussian Process Regression.

HEBO Heteroscedastic Evolutionary Bayesian Optimization.

HPO Hyperparameter Optimization.

ICoFiS Information Content of Fitness Sequences.

IOH Iterative Optimization Heuristic.

irace Iterated Racing.

ISA Instance Space Analysis.

KL Kullback–Leibler.

KPCA-BO Kernel Principal Component Analysis assisted Bayesian Optimization.

KS Kolmogorov-Smirnov.

LCB Lower Confidence Bound.

LHS Latin Hypercube Sampling.

MA-BBOB Many-Affine Black-Box Optimization Benchmarking.

MELS Modified Extensible Lattice Sequence.

MIP-EGO Mixed-Integer Parallel Efficient Global Optimization.

ML Machine Learning.

ModCMA Modular Covariance Matrix Adaptation Evolutionary Strategy.

ModDE Modular Differential Evolution.

MSE Mean Squared Error.

MWU Mann-Whitney U.

NBC Nearest Better Clustering.

nDCG normalized Discounted Cumulative Gain.

NN Neural Network.

PCA Principal Component Analysis.

PCA-BO Principal Component Analysis assisted Bayesian Optimization.

PI Probability of Improvement.

PSO Particle Swarm Optimization.

RBF Radial Basis Function.

RCobyla Constrained Optimization by Linear Approximation with Random Restart.

ReLU Rectified Linear Unit.

RF Random Forest.

RGF Randomly Generated Function.

rMC reduced Multiple Channel.

RS Random Search.

RSM Response Surface Method.

SAASBO Sparse Axis-Aligned Subspace Bayesian Optimization.

SBS Single Best Solver.

SMAC Sequential Model-based Algorithm Configuration.

SPSA Simultaneous Perturbation Stochastic Approximation.

SRSM Successive Response Surface Method.

t-SNE t-distributed Stochastic Neighbor Embedding.

TPE Tree-structured Parzen Estimator.

TuRBO Trust Region Bayesian Optimization.

UCB Upper Confidence Bound.

UMAP Uniform Manifold Approximation Mapping.

VAE Variational Autoencoder.

VBS Virtual Best Solver.