Course: Natural Computing *8 Exploratory Landscape Analysis



J. Michael Herrmann School of Informatics, University of Edinburgh

michael.herrmann@ed.ac.uk, +44 131 6 517177

- Types and applications of MHO algorithms
- Landscape analysis
- Automated algorithm selection

Domains of metaheuristic applications



Number of publications per algorithm



Hussain, Kashif et al. Metaheuristic research: A comprehensive survey. Al Review 52:4 (2019) 2191. [1]

Classification of problems

- Exploratory landscape analysis [3] →
- Classification of problems to be optimized [4, 6]
- Problem is implied by a fitness function f : X → ℝ



Level of classification

- Instances or templates (or sets) of instances (SAT, TSP, ...)
- Types of prior knowledge (see figure from [3])
- Amount of available knowledge and respective costs
- Generating or evolving of additional problem instances



O. Mersmann ea. (2010) Benchmarking evolutionary algorithms: Towards exploratory landscape analysis.

Ranking



Search in 5, 10, 20 dimensions averaged over 24 benchmark functions

O. Mersmann ea. (2010) Benchmarking evolutionary algorithms: Towards exploratory landscape analysis.

- ELA aims at finding a relation between problems (fitness functions) and algorithms based on landscape features which can be extracted by suitable methods
- There may be more direct or comprehensive ways to identify *alignement* (see NFL theorem) between algorithms and problems.

Classification of algorithms



* Solution manipulation refers to algorithm details: Best suited for classification.

** The source of inspiration may be irrelevant and is often not even unique.

*** Encoding is crucial in practical applications; this may help for re-use of algorithms.

Peres, F. and Castelli, M.: Combinatorial Optimization Problems and Metaheuristics: Review, Challenges, Design, and Development. *Applied Sciences* 11:14 (2021) 6449.

Matching of algorithms and problems

- Ideally: Alignment (see NFL theorem)
- Hyperheuristic algorithms (ibid.)
- Algorithm selection (next slides)

Decisions based on performance measures

- Resources or runtime needed for given solution quality
- Solution quality obtainable by given budget
- Robustness (stochasticity of the algorithm's search behaviour, complexity of fitness landscape, problem noise)
- Performance relative to problem class
- Time course of performance (e.g. slower for hyperheuristics)
- Deviation of fitness from estimate by a surrogate model

Algorithm selection guideline





Automated algorithm selection



Kerschke e.a.: Automated algorithm selection: Survey and perspectives. Evol. Comp. 27:1 (2019) 3-45.

Remarks: Automated algorithm selection

- Algorithm selection (AS) for portfolio selection
 - Specialised: SATzilla [7] or
 - More general: AutoFolio [2] for speed-up
 - Algorithm schedules [Lindauer 2014, 2016]
 - Machine learning: Bag of landscape features [Shirakawa & Nagao, 2016]
 - See review [Kerschke e.a., 2019]
- No clear winner: AS for AS or hyper-hyperheuristics?
- Background knowledge on problem instance or problem class can be more useful than automated AS

- moPLOT landscape explorer: Visualizing Multi-Objective Optimization Problems
- ParadisEO: Heuristic Optimization Framework (S. Cahon (2004) Paradiseo: A framework for the reusable design of parallel and distributed metaheuristics. *Journal of Heuristics* 10:3,357-380)
- irace: Automated algorithm configuration tool (M. López-Ibáñez et al. (2016) The *irace* package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives* 3, 43-58)
- IOHprofiler: Experimental platform (C. Doerr et al. (2018) IOHprofiler: A benchmarking and profiling tool for iterative optimization heuristics. arXiv:1810.05281)

- Landscape analysis is suggestive, but perhaps not easier than optimisation itself.
- Other attempts with huge numbers of features have been made.
- AAS is an advanced form of hyperheuristics.
- Evolved into automatic algorithm composition based on neural networks



Kashif Hussain, Mohd Najib Mohd Salleh, Shi Cheng, and Yuhui Shi. Metaheuristic research: a comprehensive survey. Artificial Intelligence Review, 52(4):2191–2233, 2019.



Marius Lindauer, Holger H Hoos, Frank Hutter, and Torsten Schaub. Autofolio: An automatically configured algorithm selector.

Journal of Artificial Intelligence Research, 53:745–778, 2015.



Olaf Mersmann, Bernd Bischl, Heike Trautmann, Mike Preuss, Claus Weihs, and Günter Rudolph.

Exploratory landscape analysis. In Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation, pages 829–836. ACM, 2011.



Helena Stegherr, Michael Heider, and Jörg Hähner. Classifying metaheuristics: Towards a unified multi-level classification system. *Natural Computing*, pages 1–17, 2020.



Jörg Stork, Agoston E Eiben, and Thomas Bartz-Beielstein. A new taxonomy of global optimization algorithms. *Natural Computing*, pages 1–24, 2020.



El-Ghazali Talbi.

Machine learning into metaheuristics: A survey and taxonomy. ACM Computing Surveys (CSUR), 54(6):1-32, 2021.



Lin Xu, Frank Hutter, Holger H Hoos, and Kevin Leyton-Brown. Satzilla: portfolio-based algorithm selection for sat. Journal of artificial intelligence research, 32:565–606, 2008.