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Editorial for the Special Issue on Automated Design and Assessment of Heuristic Search Methods

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Editorial for the Special Issue on Automated Design and Assessment of Heuristic Search Methods

Heuristic search algorithms have been successfully applied to solve many problems in practice. Their design, however, has increased in complexity as the number of parameters and choices for operators and algorithmic components is also expanding. There is clearly the need for providing the final user with automated tools to assist the tuning, design and assessment of heuristic optimisation methods. In recent years a growing number workshops and tracks has been held to address these issues. In 2010, the Parallel Problem Solving from Nature (PPSN) conference hosted two workshops, which decided to joint efforts to organise this journal special issue. The workshop “Self-Tuning, Self-Configuring and Self-Generating Search Heuristics,” distinguished three general processes in automated heuristic design: 1) tuning: the process of adjusting the algorithm’s control parameters, 2) configuring: the process of selecting and using existing algorithmic components such as search operators, construction heuristics or acceptance criteria, and 3) generating: the process of creating altogether new heuristics (or heuristic components) from the basic sub-components of previously existing methods. Machine learning, meta-modelling and multilevel search approaches can and have been applied to automate these three processes. The workshop introduced the term ‘Self-* Search’, which is now the name of a track in GECCO, which started in 2011 and is also being held this year. The other workshop “Methods for the Assessment of Computational Systems” stressed the idea that the experimental analysis of computational systems inspired by nature can be made more sound and effective by the use of appropriate experimental methods. More severe requirements have been transmitted to draw objective conclusions from computational experiments, while at the same time the design and configuration of the computational systems can be improved by profitable ways of looking into the data collected.

The quest for methods to automate the design and assessment of heuristic search methods is spawning a considerable amount of interdisciplinary research, mainly between the fields of computer science, artificial intelligence, optimization, statistics and machine learning. This special issue gathers contributions at the interface of these topics. It comprises five high quality papers that were selected after a rigorous reviewing process.

The first two articles are related to the automatic, online configuration of heuristic search methods. Adaptive memetic algorithms (Ong et al., 2006) and selective hyper-heuristics (Burke et al., 2010) have developed separately. However, they share key research issues. In particular, they need to provide adaptive mechanisms to autonomously guide the choice of operators during the search. In the case of memetic algorithms, the choice is among a set of *memes*, which are generally local search heuristics. In the case of hyper-heuristics, the choice may involve different types of heuristics, such as constructive heuristics, mutational heuristics or neighborhood moves, crossovers and local search heuristics. Both algorithmic schemes require mechanisms for assigning rewards to operators according to their past performance and select which operator to apply at each decision point according to the computed qualities. These mechanisms have been

also studied within the evolutionary computation community using the term Adaptive Operator Selection (Fialho et al., 2010).

The first paper, “Estimating Meme Fitness in Adaptive Memetic Algorithms for Combinatorial Problems” by J. Smith studies two fundamental issues when assigning credit to search operators. First, whether it is better to assign credit to a meme based on an estimate of the extreme, or the mean benefit it causes. It has been found that, when the operator choice is related to mutation in a standard evolutionary algorithm, “extremal” versions that reward occasional large jumps rather than small steady improvements, produce better results. However, in the case of memes, which by design cause local improvement, the opposite was found in this study. The second issue concerns whether the aggregation of feedback from the search process should be global or local to some part of the solution space. Results suggest that local reward schemes outperform their global counterparts in combinatorial spaces, in contrast to continuous spaces. This study therefore confirms that the performance of credit assignment mechanisms depends on both the nature of the search space and the type of search operator.

The paper “Hyper-Heuristics with Low Level Parameter Adaptation” by Z. Ren, H. Jiang, J. Xuan, and Z. Luo incorporates a search-based mechanism for adapting the parameters of the low-level heuristics in a hyper-heuristic framework. Traditionally, selective hyper-heuristics adaptively select the choice of fixed low-level heuristics. But clearly, some of these heuristics are parameterised (for example, the rate of a mutation operator). The proposed framework, then, simultaneously adapt the choice of low-level heuristics and their parameters, with improved results. It also proposes a mechanisms to separate the low-level heuristics into intensification and diversification heuristics, which helps to reduce the heuristic search space and improves efficiency.

Parameter tuning of evolutionary algorithms is attracting more and more interest. In particular, the Sequential Parameter Optimization (SPO) is an established parameter tuning framework (Bartz-Beielstein et al., 2005). It uses the available budget (e.g., number of function evaluations) sequentially. Information from the exploration of the search space guides the search by building meta models. New design points are determined based on predictions from these meta models. The meta models are refined stepwise to improve knowledge about the search space. SPO provides techniques to cope with noise and guarantees comparable confidence for search points. It collects information to learn from this tuning process, e.g., integrated exploratory data analysis and provides mechanisms both for interactive and automated tuning. The following two papers discuss essential ways to improve SPO related algorithms by embedding transformations and resampling techniques. Their results are in no way restricted to parameter tuning or SPO.

Since data from optimization runs are non-normal, transformations are tools of choice. The paper “On the Effect of Response Transformations in Sequential Parameter Optimization,” by T. Wagner and S. Wessing enhances the SPO framework by introducing transformation steps before the actual modeling. Based on design-of-experiments techniques, they analyze the effect of integrating different transformations. They demonstrate that in particular a rank transformation of the responses provides significant improvements. A deeper analysis of the resulting models and additional experiments with adaptive procedures indicate that the rank and the Box-Cox transformation are able to improve the properties of the result distributions with respect to symmetry and normality of the residuals.

The paper “Resampling Methods for Meta-Model Validation, with Recommendations for Evolutionary Computation” by B. Bischl, O. Mersmann, H. Trautmann, and C. Weihs summarizes basic resampling methods from statistics, puts them into the

context of meta-model validation and extensively discusses their advantages and disadvantages together with common pitfalls users shall avoid. Meta-model validation is then discussed as a supportive technique within evolutionary algorithms, also providing some concrete examples.

Finally, the paper “An Experimental Approach to the Comparison of Continuous Metaheuristics Based on Landscape Topology” by R. Morgan and M. Gallagher extends previous work of the authors on Max-Set of Gaussians (MSG) problem generators. Two Estimation of Distribution type Evolutionary Algorithms (EDA) with different abilities to adapt to problem properties are compared on various randomly determined ridge landscapes, which are constructed by means of a modification of the MSG generator. The article also suggests two visualization tools that shall be helpful for the experimental analysis of non-deterministic optimization algorithms: heatmaps and parameterized difference plots. After detecting typical landscapes that favor either one or the other algorithm, the authors undertake a meta-search in the problem parameter space, maximizing the performance difference of the algorithms, thereby further enhancing the algorithm-problem interaction knowledge for this case.

The guest editors wish to thank the contributing authors for their interesting submissions and the reviewers for their constructive feedback and detailed comments. We hope this special issue will promote the cross-fertilisation of ideas in assessing the performance and designing more autonomous and user-friendly heuristic search algorithms.

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