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Preface

Special issue on "Understanding of evolutionary optimization behavior", Part 1

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1 Introduction

The history of Evolutionary Computation has progressed from formal studies to a method-centric and framework-centric period, where many algorithms are described as methods or frameworks and their development is primarily performance-driven. We are still in a phase of optimization research where many researchers are developing "new" optimization algorithms, while not truly understanding them. With this special issue we are trying to show the importance of the move from a performance-driven community to a community in which scientific understanding is more important, in which the design of new algorithms (heuristics) becomes a science instead of an art (the future).

Understanding of optimization algorithm's behavior is a vital part that is needed for quality progress in the field of stochastic optimization algorithms. Too often (new) algorithms are setup and tuned only focusing on achieving the desired optimization goal. While this might be effective and efficient in short term, in long term this is insufficient due to the fact that this needs to be repeated for every new problem that arises. Such approach provides only minor immediate gains, instead of contributing to the progress in research on optimization algorithms. To be able to overcome this deficiency, we need to establish new standards for understanding optimization algorithm behavior, which will provide understanding of the working principles behind the stochastic optimization algorithms. This includes theoretical and empirical research, which would lead to providing insight into answering questions such as (1) why does an algorithm work for some problems but does not work for others, (2) how to explore the problem fitness landscape to gain better understanding of the algorithm's behavior, and (3) how to interconnect stochastic optimization and machine learning to improve the algorithm's behavior on new unseen problem instances.

We hope that this special issue will show why future research on optimization algorithms should not focus on (re)developing "new" algorithms, but understanding current ones and improving them according to the gained knowledge in a smarter/better way. By doing so, the community is expected to develop into one in which scientific understanding is more important. Without a doubt, this will not only lead to the development of even better, more efficient algorithms, but it will also lead to algorithms that are more easily applicable outside of the developer's lab environment. This will help researchers/users to transfer the gained knowledge from theory into the real world, or to find the algorithm that is best suited to the characteristics of a given real-world problem.

The focus of this part of the special issue is on understanding the behavior of optimization algorithms in relation to their hyper-parameters and operators. A more detailed overview is provided in the following paragraphs.

A significant issue while conceiving or parameterizing an optimization heuristic is to ensure an appropriate balance between exploitation and exploration of the search. Evolution strategies and neighborhood-based metaheuristics constitute relevant high-level frameworks that ease

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problem-solving but are often complex to configure. Moreover, according to the peculiarities of the search landscapes, their effective behavior remains difficult to grasp. In the paper *On the Use of* $(1, \lambda)$*-Evolution Strategy as Efficient Local Search Mechanism for Discrete Optimization: A Behavioral Analysis*, Tari et al. investigate the sampled walk search algorithm, a local search equivalent of the $(1,\lambda)$-evolution strategy (ES), considering that the neighborhood relation describes mutation possibilities. The main objective of this paper is to provide insights into the behavior of the $(1,\lambda)$-ES in a discrete optimization context using a fitness landscape perspective. To achieve this, the authors specifically designed experiments aiming to improve the understanding of the behavior of a strategy that offers an easy way to deal with the exploration versus exploitation dilemma. The main contribution concerns the analysis of search trajectories by evaluating and visualizing both their width (exploration) and their height (exploitation) according to landscape structures and parameter λ settings. An analysis of the best-encountered solutions by the sampled walk when correctly set is also provided to obtain insights on its behavior and highlight possible ways to improve its efficiency. Finally, the authors propose a preliminary hybridization between the sampled walk and an exploiting local search to improve the capacity to reach good-quality solutions.

The paper *Productive fitness in diversity-aware evolutionary algorithms* by Gabor is concerned with the question: Why do certain fitness functions work better than others, even when they are trying to optimize the same original objective? The second research question deals with the ideal fitness function for an evolutionary algorithm. The authors introduce the notion of productive fitness to describe an individual's effect on the evolution's overall result in future generations and argue that productive fitness—although practically not computable a priori—matches the notion of an ideal fitness for a given objective. An a posteriori approximation for productive fitness in already finished evolutionary algorithms is provided in order to evaluate various adaptations of evolutionary algorithms, focusing on the important property of diversity within the population. Empirical results show that fitness functions that happen to approximate productive fitness better also bring about evolutionary algorithms that produce better results.

The paper *On the Class of Hybrid Adaptive Evolutionary Algorithms (chavela)* by Gómez and León proposes and studies, both from a theoretical and an experimental point of view, the class of hybrid adaptive evolutionary algorithms (called chavela), that is, the class of evolutionary algorithms that evolves every individual of the population by selecting genetic operators according to a kind of chaotic competition mechanism. In this way, the authors show that (parallel) hill-climbing algorithms may be considered as belonging to the chavela class. Moreover, they develop several replacement mechanism versions (including generational, steady, and hill-climbing like) for the chavela class, and present a formal characterization of the chavela class in terms of Markov kernels. Finally, the paper establishes convergence properties and analyzes the behavior of chavela on well-known optimization functions.

The purpose of the paper *A framework for designing of genetic operators automatically based on gene expression programming and differential evolution* by Jiang et al. is not to design high-performance algorithms, but to provide a new perspective to algorithm design and a reference scheme for machine algorithm design. In particular, the authors propose an evolutionary algorithm framework based on the automatic design of genetic operators. This design scheme can reduce the manual examination and analysis of a large amount of data, thus greatly reducing the burden of designers. In the first step, gene expression programming and the differential evolution are used together for the automatic and adaptive design of genetic operators. This hybrid method is able to automatically generate operators from the space of genetic operators. Moreover, it will choose the appropriate operator suited for the evolutionary algorithm. In the second step, the designed operator is introduced into a typical evolutionary algorithm to verify its performance. The results show that the newly designed genetic operator is superior to, or at least equivalent to, some existing evolutionary variations for a set of classical benchmark functions. In this way, the machine can automatically design more adaptive algorithms.

Different evolutionary algorithms (EAs) proposed in the literature generally have their characteristic behavior, which impacts on their performance in solving a considered problem. The choice of an appropriate evolutionary algorithm is difficult when given a problem. A common characteristic among EAs is the high computational cost to execute them. An alternative to reduce the computational cost of EAs is to implement them to run in parallel computing environments. In the Island Model (IM), the population is divided into sub-populations called islands, which are connected to each other. They evolve in parallel through their own EAs. Periodically, the islands exchange solutions through the migration process, which involves an additional operation for the IM search process. In a hybrid IM, different EAs are applied in different islands. The paper *An Island Model based on Stigmergy to solve optimization problems* by Duarte et al. proposes a hybrid IM called Stigmergy Island Model (Stgm-IM), inspired by the natural phenomenon of stigmergy that occurs in groups of some social species. By stigmergy, the group agents organize themselves and cooperate with each other through indirect communication. In Stgm-IM the connections between islands and the distribution of solutions between them occurs dynamically and adaptively, according to the level of attractiveness of their EAs in solving the problem at hand. The Stgm-IM was evaluated regarding its evolutionary behavior and its performance, delivering the expected results.

Artificial Bee Colony (ABC) is a population-based optimization algorithm that mimics the foraging behavior of honeybees. The paper *Absolute versus stochastic stability of the artificial bee colony in synchronous and sequential modes* by Kessentini and Naâs focuses on ABC stability to improve its parameter setting. Only two previous studies investigated the ABC stability—due to its complexity—and ignored the coupling between bees. Instead, the authors of this paper model the algorithm by a matrix iterative process, taking into consideration the coupling. The necessary conditions for absolute and stochastic (first and second-order) stability are derived, distinguishing between the synchronous and the sequential update mode of solutions. These criteria report on the ranges for setting the uniform distributions of the ABC algorithm. The stability regions are displayed graphically to facilitate their investigation. Finally, some supporting simulations were carried out on ABC and other algorithms on test functions in different search space dimensions and twenty real-world problems. Six considered ABC variants tested the derived and state-of-the-art criteria in sequential and synchronous update modes. The overall results show that stochastic stability proffers ABC competitiveness. The absolute stability (under the quasi-deterministic assumption) leads to head always toward employed bees, which restricts the exploitation. The two update modes may alter the ABC performance only slightly or drastically, depending on the problem, with no evidence for the supremacy of one of them.

The gravitational constant G controls the balance of exploration and exploitation abilities of the Gravitational Search Algorithm (GSA). In the paper *GSA improvement via the von Neumann stability analysis*, Naâs and Kessentini analyze the GSA stability by monitoring this parameter. First, they model the iterative process by a second-order differential equation, to which the von Neumann stability criterion applies. The first and second-order stochastic stability conditions reveal a linear correlation between the gravitational constant G and the distances between solutions. Note that these distances depend on the solutions' number and the search space dimension. Therefore, the authors suggest a new law tailoring G to various search space dimensions. Supporting simulations were carried out using different update laws of the gravitational constant (e.g., exponential, log-sigmoid, linear, and chaotic) on CEC 2017 benchmark functions in different search space dimensions. The results show that the new setting leads to significantly better outcomes in high-dimensional search spaces (greater than 20). A comparison with other metaheuristics reveals that the new settings increases GSA's competitiveness. Tests on 23 real-world problems further show the merits of the proposed parameter setting strategy.

Swarm intelligence algorithms are generally stochastic, i.e., they have a random movement component. This enables them to escape from local optima and perform exploration. Exploration is required to perform a thorough inspection of the solution space. However, as the algorithm progresses, its focus needs to shift from exploration to exploitation. Exploitation helps swarm algorithms to enhance existing solutions and improves their convergence capabilities. A technique, called improved search (IS), was recently proposed to make this switch. It does so by adaptively reducing the range of random movement. The paper *Improving convergence in swarm algorithms by controlling range of random movement* by Chaudhary and Banati studies the applicability of the IS technique over different swarm algorithms employing different random distributions. Comparison results of over 30 benchmark functions show that the IS technique helps to produce better results in 78.45%. The enhanced algorithm variants produce significantly better results according to the Friedman test. Stability of the results is also tested, and it is shown that the IS technique helps in producing more stable results as compared to the basic algorithms. Hence it can be concluded that the IS technique is an efficient means to intelligently switch from exploration to exploitation in swarm algorithms. It helps to enhance the convergence capabilities of many algorithms, thus equipping them with significant efficiency improvements.

Several optimization problems in Artificial Intelligence and Machine Learning can be solved with the maximization of functions that exhibit natural diminishing return properties. One of the simplest notions of diminishing returns is submodularity. Submodular functions are particularly interesting, because they admit simple, yet non-trivial, polynomial-time approximation algorithms. In their paper *Evolutionary algorithms and submodular functions: benefits of heavy-tailed mutations*, Quinzan et al. develop suitable Evolutionary Algorithms (EAs) to tackle submodular optimization problems. They introduce a new mutation operator to this end. Moreover, they show that a simple EA with this mutation operator achieves superior performance over the state-of-the art on several real-world instances.

Learning enthusiasm-based Teaching Learning Based Optimization (LebTLBO) is a metaheuristic inspired by the classroom teaching and learning method of TLBO. In recent years, it has been used in several applications in science and engineering. All students are equally likely to get understanding from others in the fundamental TLBO and most of its versions. The main problem associated with LebTLBO is premature convergence under some conditions due to a low exploration capability. The paper *Improvement in learning enthusiasm-based TLBO algorithm with enhanced exploration and exploitation properties* by Mittal et al. proposes an improved LebTLBO algorithm that aims to achieve enhanced performance by balancing the exploration and exploitation capabilities of the conventional LebTLBO in order to improve its global performance.

Cluster analysis is an important field in pattern recognition and machine learning. The aim is to distribute a set of data patterns into groups, considering only the inner properties of those data. One of the most popular techniques for data clustering is the *k*-means algorithm, due to its simplicity and easy implementation. However, *k*-means is strongly dependent on the initial point of the search, which may lead to suboptimal solutions. In the past few decades, Evolutionary Algorithms (EAs), like Group Search Optimization (GSO), have been adapted to the context of cluster analysis, given their global search capabilities and flexibility to deal with hard optimization problems. However, due to their stochastic nature, EAs may be slower to converge in comparison to traditional clustering models. In their paper *An evaluation of k-means as a local search operator in hybrid memetic group search optimization for data clustering*, Pacifico and Ludermir propose three hybrid memetic approaches between *k*-means and GSO in order to combine the global search capabilities of GSO with the fast local search performances of *k*-means.