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Optimization by Building and Using Probabilistic Models 2004

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1 Introduction

Genetic and evolutionary algorithms (GEAs) [1–4] evolve a population of candidate solutions to a given optimization problem using two basic operators: (1) selection and (2) variation. Selection introduces a pressure toward high-quality solutions, whereas variation ensures exploration of the space of all potential solutions. Two variation operators are common in current genetic and evolutionary computation (GEC): (1) crossover, and (2) mutation. Crossover creates new candidate solutions by combining bits and pieces of promising solutions, whereas mutation introduces slight perturbations to promising solutions to explore their immediate neighborhood. However, fixed, problem independent variation operators often fail to effectively exploit important features of high-quality solutions obtained by selection. One way to make variation operators more powerful and flexible is to replace traditional variation of GEAs by the following two steps:

1. Build a probabilistic model of the selected promising solutions, and
2. sample the built model to generate a new population of candidate solutions.

Algorithms based on this principle are called probabilistic model-building genetic algorithms (PMBGAs) [5], estimation of distribution algorithms (EDAs) [6], or iterated density estimation algorithms (IDEAs) [7]. PMBGAs successfully solve problems that were intractable using previous generation of genetic and evolutionary algorithms.

The purpose of this workshop is to present and discuss

- recent advances in PMBGAs,
- new theoretical and empirical results,
- applications of PMBGAs, and
- promising directions for future PMBGA research.

Contributions to this workshop include different avenues of cutting edge PMBGA research. Mühlenbein and Höns investigate theoretical and empirical aspects of EDAs in general, and a special structure learning algorithm used in LFDA [8] in particular. Bosman and de Jong present an interesting work on designing EDAs for evolving computer programs using grammar transformations. Ocenasek and Pelikan analyze scalability of the mixed Bayesian optimization algorithm and show that PMBGAs can be effectively parallelized yielding speedups proportional to the problem size. Sastry, Goldberg, and Pelikan present two efficiency enhancement techniques for PMBGAs—a competent mutation operator, and an evaluation-relaxation technique based on an internal probabilistic fitness model—and show that significant speed-up can be obtained using the proposed techniques. Finally, Pelikan discusses existing theory and efficiency enhancement techniques for the Bayesian optimization algorithm (BOA) and its hierarchical extension, the hierarchical BOA (hBOA). The combination of papers presented at this workshop not only captures many important facets of PMBGA research, but also brings forth a number of interesting and challenging topics for future research.

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