

Application of Estimation of Distribution Algorithms

(— Master thesis topic proposal for MEI and MIEET students, 2008/09 —)

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1 Research topic for Thesis

Conduct experimental research in the application of *Estimation of Distribution Algorithms* (EDAs) for solving combinatorial optimization problems. Examples might include feature subset selection, low autocorrelation binary sequences, and graph coloring, to name a few.

It is expected that the student picks one or two problems, makes a systematic experimental study with state-of-the-art EDAs, and compares the results with other (typical) problem solvers for those problems.

2 About EDAs

During the last decade, genetic algorithms (GAs) have been recasted in terms of probabilistic optimization [2, 1, 3] and this new perspective have shown to be very effective in autonomously learning a problem's structure. These new algorithms, often called Estimation of distribution algorithms (EDAs) or Probabilistic model-building genetic algorithms (PMBGAs), have many advantages over traditional GAs.

The main principle of EDAs is the recognition that a search algorithm performs induction. That is, it has to guess where to move next based on its past experiences. In the context of genetic algorithms, the population represents a collection of points that summarize the past experiences of the algorithm. Based on this set of points, the GA has to guess where to go next. The way traditional GAs typically do this guessing is by choosing another population through the actions of selection, crossover, and mutation. Unlike traditional GAs, EDAs replace the variation operators by the construction of a probabilistic model of promising solutions, and subsequent sampling from that model (or distribution). In other words, the probability distribution can be seen as a template to generate populations that are somehow similar (but different) from the best individuals in the current population.

3 Suggested timeline

- Literature survey: 1,5 month
- Experimental research: 3,5 months
- Thesis writeup: 1 month

4 Required skills

- Solid computer programming skills.
- Enjoy statistics and probabilities.
- Basic understanding of evolutionary algorithms.
- Be able to read technical papers in English.

References

- [1] Pelikan. M. *Hierarchical Bayesian Optimization Algorithms: Toward a New Generation of Evolutionary Algorithms*. Springer Verlag, 2005.
- [2] M. Pelikan, D. E. Goldberg, and F. Lobo. A survey of optimization by building and using probabilistic models. *Computational Optimization and Applications*, 21(1):5–20, 2002.
- [3] M. Pelikan, K. Sastry, and E. Cantú-Paz, editors. *Scalable Optimization via Probabilistic Modeling*, volume 33 of *Studies in Computational Intelligence*. Springer, 2006.