Missouri Estimation of Distribution Algorithms

Purpose
- Combine prior models with a problem-specific distance metric to solve new problem instances with increased speed, accuracy, reliability.
- Focus on hBOA algorithm and additively decomposable functions, although the approach can be generalized to other MDOs and other problem classes.
- Extend previous work to mainly demonstrate that
  - Previous MDO runs on smaller problems can be used to bias runs on larger problems.
  - Previous MDO runs for one problem class can be used to bias runs for another problem class.

Hierarchical Bayesian optimization algorithm, hBOA
- Models allow hBOA to learn and use problem structure.
- To build models, hBOA uses Bayesian metrics that combine the current population and prior knowledge (via prior distribution of structures and parameters).

Basic idea of the approach
- Outline of the approach
  1. Define distances between problem variables.
  2. Mine probabilistic models from previous runs for model regularities with respect to distances.
  3. Use obtained information to bias model building when solving new problem instances.
- Apply approach to hBOA and additively decomposable functions (ADFs)
  - Distance metric developed for ADFs, but other metrics can be used.
  - Bias incorporated by modifying prior probabilities of network structures when building the models.
  - Strength of bias can be controlled using a parameter $\kappa > 0$.

Background
- Model-directed optimizers (MDOs), such as estimation of distribution algorithms, learn and use models to solve difficult optimization problems scalably and reliably.
- MDOs often provide more than the solution; they provide a set of models that reveal information about the problem. Why not use that information in future runs?

Distance metric for ADFs
- ADF
  $$f(X_1, \ldots, X_n) = \sum_{i=1}^{m} f_i(S_i)$$
  ($S_i$ are subsets of variables. ($f_i$) are arbitrary functions.)
- Create a graph for ADF with one node per variable by connecting variables that are in the same subproblem.
- Number of edges along shortest path between two nodes defines their distance; for disconnected variables the distance is equal to the number of variables.
- Can use other distance metrics (e.g. QAP and scheduling).

Selected results
- Problem classes:
  - Nearest-neighbor NK landscapes.
  - Spin glasses (2D and 3D).
  - MAXSAT for transformed graph coloring.
  - Minimum vertex cover for random graphs.
- Use bias from smaller problems on bigger problems (compare to the bias from problems of the same size)
  - NK landscapes
  - MVC
  - Spin glass (2D)

- Use bias from another problem class
  - NK landscapes
  - MVC (easier)
  - MVC (harder)

- Summary of results (many results omitted here)
  - Significant speedups obtained in all test cases.
  - Bias based on runs on smaller problems and other problem classes yields significant speedups as well.
  - This proves flexibility, practicality and potential of the approach.
  - Approach can be adapted to other MDOs (LTGA, ECGA, DSMGA, ...).

More information
  http://medal-lab.org/files/2012007.pdf

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