Evolutionary Planning and Scheduling Workshop @ ICAPS 2013

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Stochastic Search Algorithms

Hypotheses

- Search space Ω
- Objective function F (to minimize)

Hill Climbing

- Randomly draw x_0 (initialization)
- Compute $F(x_0)$ (evaluation)
- Loop
  - $y = \text{Best neighbor}(x_t)$ (neighbor structure on Ω)
  - Compute $F(y)$
  - If $F(y) < F(x_t)$ $x_{t+1}=y$ (accept if improvement)

    else $x_{t+1} = x_t$

Stochastic Search Algorithms

Hypotheses

- Search space Ω
- Objective function F (to minimize)

Stochastic Hill Climbing

- Randomly draw x_0 (initialization)
- Compute $F(x_0)$ (evaluation)
- Loop
  - $y = \text{Move}(x_t)$ (stochastic variation)
  - Compute $F(y)$
  - If $F(y) < F(x_t)$ $x_{t+1} = y$ (accept if improvement)

    else $x_{t+1} = x_t$

Stochastic Search Algorithms

Hypotheses

- Search space Ω
- Objective function F (to minimize)

Stochastic Local Search

- Randomly draw x_0 (initialization)
- Compute $F(x_0)$ (evaluation)
- Loop
  - $y = Move(x_t)$ (stochastic variation)
  - Compute F(y)
  - $x_{t+1} = select(x_t, y)$ (stochastic selection)

Stochastic Search Algorithms

Hypotheses

- Search space Ω
- Objective function F (to minimize)

Stochastic Search

- Randomly draw x_0 (initialization)
- Compute $F(x_0)$ (evaluation)
- Loop
  - $y^i = Move(x_t)$, $i=1,\ldots,\lambda$ (stochastic variations)
  - Compute $F(y^i)$ $i=1,\ldots,\lambda$
  - $x_{t+1} = select(x_t, y^i, i=1,\ldots,\lambda)$ (stochastic selection)

Stochastic Search Algorithms

Hypotheses

- Search space Ω
- Objective function F (to minimize)

Evolutionary Algorithm

- Randomly draw $x_0^1, x_0^2, \ldots, x_0^\mu$ (initialization)
- Compute $F(x_0^1), F(x_0^2), \ldots, F(x_0^\mu)$ (evaluation)
- Loop
  - $y^i = \text{Move}(x_t^1, x_t^2, \ldots, x_t^\mu), i=1,\ldots,\lambda$ (stochastic variations)
  - Compute $F(y^i)$ $i=1,\ldots,\lambda$
  - $x_{t+1} = \text{select}(x_t^1, x_t^2, \ldots, x_t^\mu, y^i, i=1,\ldots,\lambda)$ (stochastic selection)

Evolutionary Algorithms

- Population-based (also distribution based)
- Any search space
- with ad hoc variation operators
  - Crossover (2 parents → offspring)
  - Mutation (1 parent → offspring)
- Any objective/constrts (very weak hypotheses)
- Very costly (number of function evaluations)
- Empirical successes
  - The second best method for any problem
  - The method of choice when everything else has failed

Evolutionary Algorithms

An alternative point of view

- Darwinian Paradigm (crude imitation of)

    Natural selection (survival of the fittest w.r.t. objective)

    +Blind variations (from parents to offspring)

    → Adaptation (i.e., optima of the objective function)

Choice of search space is crucial

Other Bio-inspired Stochastic Algorithms

- Simulated Annealing
  - Proof of convergence (83) … of no practical use
- Ant Colony Optimization
  - Mainly routing problems
- Particle Swarm Optimization
  - Mainly continuous optimization
- Differential Evolution
  - Mainly continuous optimization
- + an ever growing zoology

Evolutionary Scheduling

- Very active field, e.g., [Dahal, Tan & Cowling (eds), Springer 2007]
  - State-of-the-art performances
- Direct representation:
  - Search in schedule space
  - Strong constraints:
    - Limited variation operators
    - Repair mechanisms
- Indirect representation
  - Constraints handled by a scheduler
  - Search the input space of the scheduler
- Memetic algorithms (hybridization)
- Evolve dispatching rules

Evolutionary Planning

- Not so active
- Usually work in plan space (→ GP problem)
  - GP trees [Koza, 92; Spector, 94]
  - Linear chromosomes
    - Fixed length [Muslea 97]
    - Variable length [Morignot 05, Westerberg 02]
- Issues
  - Many invalid plans
  - Problem-dependent fitness
- Pros: can handle multiple initial states for 1 goal
- Cons: Hardly scales up
- See DaE later, hybridization working in state space

Hot Topics

- Generic Advances in Evolutionary Combinatorial Optimization
  - Multi-objective optimization
  - Complex morphogenesis
- Hybridization
  - “Classical” memetic algorithms
  - Evolving rules for (meta-)heuristics
- Use other bio-inspired algorithms/representations (see later)

Workshop Program

- 14:30 Opening
- 14:40 M. Baioletti, R. Minciarelli, F. Paolucci, V. Poggioni *Towards a new generation ACO-Based Planner*
- 15:20 X. Li, R. Y. K. Fung
  Scheduling Single-Armed Cluster Tools with Time Window Constraints Using Differential Evolution Algorithm
- 16:00 Coffee Break
- 16:30 F. Siddiqui, P. Haslum
  Local Search in the Space of Valid Plans
- 17:10 M. Khouadjia, M. Schoenauer, V. Vidal, J. Dréo, P. Savéant
  Pareto-Based Multiobjective AI Planning
- 17:50 General discussion