Stochastic Local Search Variants; Planning Intro

CPSC 322 – CSPs 6

Textbook §4.8; §11.1
Lecture Overview

1 Recap

2 SLS Variants
Stochastic Local Search

- Idea: combine hill climbing (advantage: finds local maximum) with randomization (advantage: doesn’t get stuck).
- As well as uphill steps we can allow a small probability of:
  - Random steps: move to a random neighbor.
  - Random restart: reassign random values to all variables.
Runtime Distribution

- Plots runtime (or number of steps) and the proportion (or number) of the runs that are solved within that runtime.
  - note the use of a log scale on the $x$ axis
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2 SLS Variants
Variant: Greedy Descent with Min-Conflict Heuristic

This is one of the best techniques for solving CSP problems:

- At random, select one of the variables $v$ that participates in a violated constraint
- Set $v$ to one of the values that minimizes the number of unsatisfied constraints
- This can be implemented efficiently:
  - Data structure 1 stores currently violated constraints
  - Data structure 2 stores variables that are involved in violated constraints
  - Selecting the variable to change is a random draw from data structure 2
  - For each of $v$'s values $i$, count the number of constraints that would be violated if $v$ took the value $i$
  - When the new value is set:
    - add all variables that participate in newly-violated constraints
    - check all variables that participate in newly-satisfied constraints to see if they participate in any other violated constraints
Recap

Variant: Simulated Annealing

- **Annealing**: a metallurgical process where metals are hardened by being slowly cooled.
- Analogy: start with a high “temperature”: a high tendency to take random steps
- Over time, cool down: more likely to follow the gradient
- Here’s how it works:
  - Pick a variable at random and a new value at random.
  - If it is an improvement, adopt it.
  - If it isn’t an improvement, adopt it probabilistically depending on a temperature parameter, \( T \).
    - With current node \( n \) and proposed node \( n' \) we move to \( n' \) with probability \( e^{(h(n') - h(n))/T} \)
  - Temperature reduces over time, according to an annealing schedule
Tabu lists

- SLS algorithms can get stuck in plateaus (why?)
Tabu lists

- SLS algorithms can get stuck in plateaus (why?)
- To prevent cycling we can maintain a tabu list of the $k$ last nodes visited.
- Don’t visit a node that is already on the tabu list.
- If $k = 1$, we don’t allow the search to visit the same assignment twice in a row.
- This method can be expensive if $k$ is large.
Parallel Search

- **Idea**: maintain $k$ nodes instead of one.
- At every stage, update each node.
- Whenever one node is a solution, report it.
- Like $k$ restarts, but uses $k$ times the minimum number of steps.
- There’s not really any reason to use this method (why not?), but it provides a framework for talking about what follows...
Beam Search

- Like parallel search, with $k$ nodes, but you choose the $k$ best out of all of the neighbors.
- When $k = 1$, it is hill climbing.
- When $k = \infty$, it is breadth-first search.
- The value of $k$ lets us limit space and parallelism.
Stochastic Beam Search

- Like beam search, but you **probabilistically choose the $k$ nodes** at the next generation.
- The probability that a neighbor is chosen is proportional to the value of the scoring function.
  - This maintains diversity amongst the nodes.
  - The heuristic value reflects the fitness of the node.
  - Biological metaphor: like asexual reproduction, as each node gives its mutations and the fittest ones survive.
Genetic Algorithms

- Like stochastic beam search, but pairs of nodes are combined to create the offspring:
- For each generation:
  - Randomly choose pairs of nodes, with the best-scoring nodes being more likely to be chosen.
  - For each pair, perform a cross-over: form two offspring each taking different parts of their parents
  - Mutate some values
- Report best node found.
Crossover

- Given two nodes:
  \[ X_1 = a_1, X_2 = a_2, \ldots, X_m = a_m \]
  \[ X_1 = b_1, X_2 = b_2, \ldots, X_m = b_m \]

- Select \( i \) at random.

- Form two offspring:
  \[ X_1 = a_1, \ldots, X_i = a_i, X_{i+1} = b_{i+1}, \ldots, X_m = b_m \]
  \[ X_1 = b_1, \ldots, X_i = b_i, X_{i+1} = a_{i+1}, \ldots, X_m = a_m \]

- Note that this depends on an ordering of the variables.

- Many variations are possible.