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EECS 491 – Problem Set 4
MODEL/SOLUTIONS
[COMMENTS BY MSB]

4.1 Name that algorithm

a) Hill climbing
b) ----------------
c) Stochastic hill climbing (OR "FIRST-CHOICE" HILL CLIMBING)
d) A random point selection algorithm, where a successor can be the same point as previously or a mutation of that point – there is no preference for more or less fit points
AKA RANDOM WALK

4.2 Of genetics and genetic algorithms

Genotype: The genetic constitution of an individual organism (http://www.news.cornell.edu/Chronicle/99/1.28.99/genomics/Glossary.html)

Phenotype: The observable characteristics of an individual (http://www.bwhct.nhs.uk/clinicalgenetics/glossary.htm)

In reference to genetic algorithms, the genotype would describe the complete information about a given individual in a population, whereas the phenotype would describe the observable result of that genotype.

4.3 Fitness functions for genetic algorithms

1. Elevator control: minimize the amount of time the elevator takes to respond to requests, both for people waiting for the elevator as well as those inside the elevator.

2. Stop lights: maximize the amount of traffic that moves through the intersection, while making sure traffic doesn't get too backed up in any direction.

4.4 Precise formulation for class scheduling CSP

A scheduled class consists of three variables:

1. Professor (a subset of all professors)
2. Time slot
3. Room

Constraints (assuming each class only needs to be offered once, and that time slots do not overlap)

1. Each class can only be offered by one of the professors that can teach that class
2. That class cannot occupy the same room as another class in the same time slot
3. The professor for that class cannot teach another class in the same time slot

4.5 Cryptarithmetic

Constraints: (I have eliminated the X_3 variable since it is identical with F)

$O + O = R + 10 \cdot X_1$

$X_1 + W + W = U + 10 \cdot X_2$

$X_2 + T + T = O + 10 \cdot F$

Distinct-Values(F, T, W, R, O)

$F > 0$

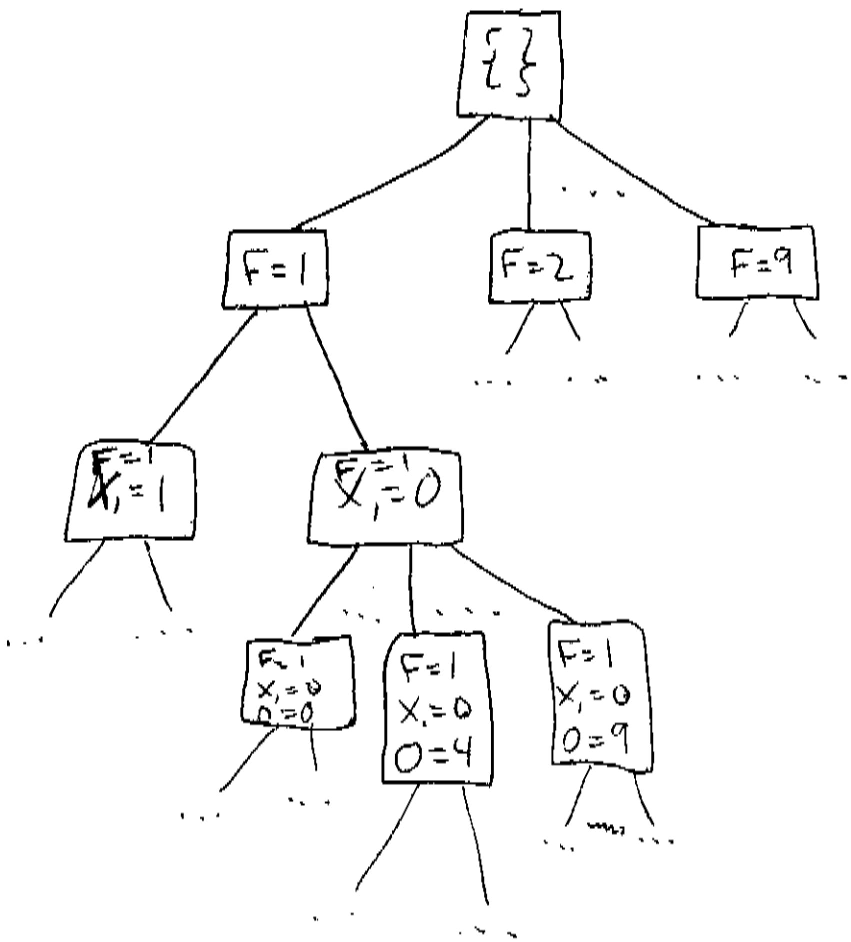
Steps (see also forward-checking table below):

- If we pick 2 for F, eventually this will backtrack, since no value of T, O, and X_2 allows for F to be 2. This is true for any other value greater than 1 that we pick for F.
- Pick F = 1
- Pick for X_1 next, since by the most-constrained variable heuristic, since there are only two choices for X_1 (we could have picked X_2 instead, which has only the same number of choices).
- Set $X_1 = 0$
- We pick for O next, which using forward checking up to this point can only be {0, 2, 3, 4}. Using the least-constraining variable heuristic, we choose O = 4 since this leaves more options for W and U than 2 does; 0 leaves no options for R, and 3 forces R = T = 6, which means one of those has no values).
- Set O = 4
- We pick for W next. Using forward-checking, we see that W = 0 or W = 2 leaves no legal values for U.
- Pick W = 3;
- At this point, forward-checking shows us that the only remaining legal values are U = 6, R = 8, $X_2 = 0$, and T = 7.
- So our solution is: TWO = 734, FOUR = 1468; F = 1, O = 4, U = 6, R = 8, T = 7, W = 3

Forward checking (legend: <u>**variable picked**</u>, **variable changed**, unaffected variable, value not taken):

F	X_1	O	W	U	R	X_2	T
<u>**1**</u>	0-1	0,2-9	0,2-9	0,2-9	0,2,4,6,8	0-1	**5-9**
	<u>**0**</u>	**0,2-4**	0,2-9	**0,2,4,6,8**	0,2,4,6,8	0-1	5-9
		<u>2</u>	0,3	0,8	4	0	6
		<u>**4**</u>	**0,2,3**	**0,2,6**	**8**	**0**	**7**
			<u>**3**</u>	**6**	8	0	7

Min-conflicts would work on this problem, though it would not be ideal. Min-conflicts works best when, as the book states, solutions are densely distributed through the state space. This problem may have a few different solutions, but they are relatively few given the size of the state space.



CHECK:

  734
+ 734

 1468 ✓

IT TURNS OUT THERE IS ANOTHER SOLUTION:

  765
+ 765

 1530

4.6 Genetic Algorithms

Results, with purely roulette selection:
Using a population of 20 with 30 generations
We get a best fit of x=0.39 with a fitness value of 6.16868669074921

Results, using crossover:
Using a population of 20 with 30 generations
We get a best fit of x=0.39 with a fitness value of 6.16868669074921

Both algorithms seem to give the correct result about the same number of times – above is a typical example of the output.

Interestingly, the initial population size seems to have much more to do with the chance of success than the number of generations. The above results only used 30 generations with a population of 20. However, using a population of 10, even for 1000 generations, seemed less likely to produce the optimal result for either algorithm.

[CODE SUPPRESSED.]

4.7 8-queens

Method	T_0	Cooling Factor	Avg. Evaluations	Failures
Random Restart	n/a	n/a	1629	n/a
Simulated Annealing	30	0.998	2511	2
Simulated Annealing	100	0.9	834	5

Note: the average evaluations for simulated annealing does not count the evaluations for a failure condition, since those raised the average significantly (around 370,000 evaluations per failure with the first simulated annealing run).

[CODE SUPPRESSED.]