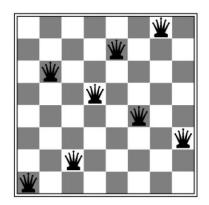


Local Search

Try to iteratively improve a small number of solutions

- Avoid space problems entirely: maintain only one a finite number of solution candidates
 Perhaps only one!
- Repeatedly tweak those candidates in the hopes of arriving at a solution.
 How do we tweak the solutions?

Example: 8 Queens



Find an arrangements of queens such that no queen attacks another

8 Queens Heuristic

				¥		18	12	14	13	13	12	14	1
		Ŵ				14	16	13	15	12	14	12	1
						14	12	18	13	15	12	14	1
	Ŵ					15	14	14	Ŵ	13	16	13	1
			¥			¥	14	17	15	Ŵ	14	16	1
2					Ŵ	17	⊻	16	18	15	Ŵ	15	V
l	<u>k</u>					18	14	Ŵ	15	15	14	Ŵ	1
						14	14	13	17	12	14	12	18

h: number of pairs of queens that attack each other

Local Beam Search

- 1. Randomly generate *k* initial states
- 2. Generate successors for each of them
- 3. If any successor is a goal, then return it and exit
- 4. Otherwise put all successors into queue, and sort queue.
- 5. Remove all but the *k* best nodes from the queue, and go to step 2
- How is this different than doing k random restarts?
- Can also have the stochastic variation, where the k nodes kept are chosen with some weighted probability based on heuristic value

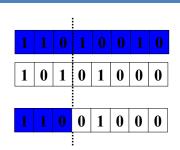
Genetic Algorithm

- Parallel hill climbing
- Candidate successors generated by crossover and mutation
- Actual successors then selected based on fitness

GA Steps

- □ Initialize population of size *N*
- □ Repeat *N* times:
 - Randomly select two "parents" from population, with probability proportional to fitness
 - Construct "child" by crossing over parents
 - Apply mutation with small probability

Crossing Over



- Randomly select crossover point.
- Child is same as parent1 up to crossover point, parent2 after that.

Genetic Algorithm: Your turn!

- You'll need a sheet of paper and a pencil
 - Write down four random numbers, x₁, x₂, x₃, and x₄.
 - Each number should be between [1, 9].
 - Seriously. They need to be random!
- □ You are our initial population!

Genetic Algorithm: Fitness

Compute your fitness:

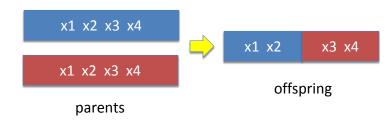
$$f = \left| 6x_1^2 x_2^2 + 18x_1^2 x_4 - 70x_1^2 - 21x_2^2 x_3 - 63x_3 x_4 + 245x_3 + 24x_2^2 + 72x_4 - 280 \right|$$

□ (In our case, *small* fitnesses are good.)

http://april.eecs.umich.edu/fitness.html

Genetic Algorithm: Reproduction

- Who has low fitnesses?
- Sexual reproduction (without mutation) by crossing (x1,x2) with (x3,x4)

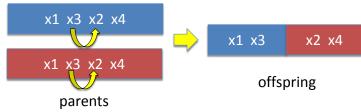


Changing the genetic representation

Our fitness function can be factored like this:

$$\left|(2x_1^2 - 7x_3 + 8)(3x_2^2 + 9x_4 - 35)\right|$$

What does this tell us about what our genetic representation should be?



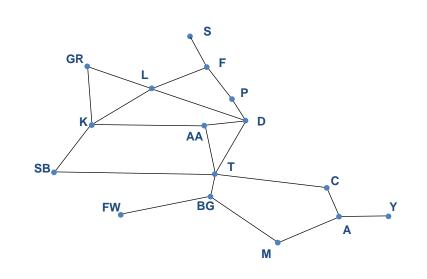
Adding Mutation

We can randomly flip bits too...

Hill Climbing

- aka Gradient descent
- Requires heuristic h measuring quality of soln
- □ Algorithm:
 - Find all incremental modifications of candidate soln
 - Pick best one
 - Repeat

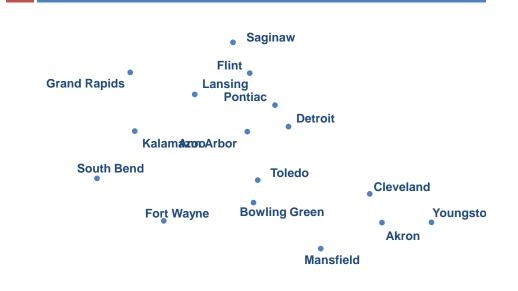
Example: Map Labeling



Example: Map Labeling



Example: Map Labeling



Example: Map Labeling



3SAT Example

$$(P_{1}\vee\neg P_{2}\vee\neg P_{3})\wedge(P_{1}\vee\neg P_{2}\vee\neg P_{4})\wedge(P_{1}\vee\neg P_{3}\vee\neg P_{4})\wedge (\neg P_{1}\vee P_{2}\vee\neg P_{3})\wedge(P_{2}\vee\neg P_{3}\vee\neg P_{4})\wedge(\neg P_{1}\vee P_{2}\vee\neg P_{4})\wedge (\neg P_{1}\vee\neg P_{2}\vee P_{3})\wedge(\neg P_{1}\vee P_{3}\vee\neg P_{4})\wedge(\neg P_{2}\vee P_{3}\vee\neg P_{4})\wedge (\neg P_{1}\vee\neg P_{2}\vee P_{4})\wedge(\neg P_{1}\vee\neg P_{3}\vee P_{4})\wedge(\neg P_{2}\vee\neg P_{3}\vee P_{4})\wedge (\neg P_{1}\vee\neg P_{2}\vee\neg P_{3}\vee P_{4})\wedge (\neg P_{1}\vee\neg P_{2}\vee\neg P_{3})$$

Q: What's a good fitness function?

GSAT

```
procedure GSAT(\phi)

for i := 1 to Max-tries

T := random truth assignment

for j := 1 to Max-flips

if T satisfies \phi then return T

else Poss-flips := set of vars that increase satisfiability most

V := a random element of Poss-flips

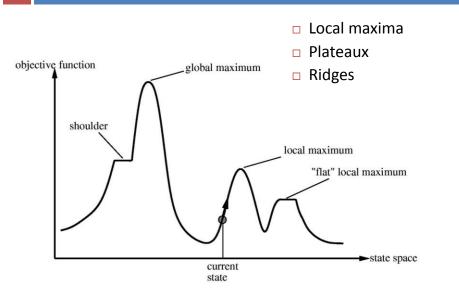
T := T with V's truth assignment flipped

end

end

return "no satisfying assignment found"
```

Hill Climbing Terrain



Hill-Climbing: 2-d Ridge

2	1	1	1	1	1	2
1	4	3	1	3	4	1
1	3	6	5	6	3	1
1	1	5	10	5	1	1
1	3	6	5	6	3	1
1	4	3	1	3	4	1
2	1	1	1	1	1	2



Stochastic Variations

- Stochastic hill climbing
 - Select among positive steps at random
 - Probability proportional to steepness
- Random restarts
 - Repeat hill climbing from randomly chosen initial state
 - Return best local maximum found
- No clear answer on how often to restart from scratch versus trying to "repair" a current candidate that's stuck or making slow progress.

Simulated Annealing

- Hill climbing, but take worse-appearing steps with some probability
 - Generate random neighbor
 - If it is an improvement, accept;
 - else accept with probability < 1</p>
 - probability decreases exponentially with the "badness" of the move, temperature
- Annealing: Decrease temperature gradually
- Stochastic Gradient Descent is similar
 - Useful for optimization with many simultaneous "soft" constraints
 - Temperature decreases as 1/T
 - Actually takes a *long* time for the temperature to get really small.

GA: Discussion

- Appealing analogy to natural selection with sexual reproduction
- Does it work?
 - Hard to characterize in general
 - Depends crucially on string rep'n of state
 - Intuition: GA maintains good "building blocks" in population
 - Not generally better than simpler stochastic local search methods

Assessing Local Search

- Key advantages
 - Very little memory
 - Can often find reasonable solutions in large or infinite (continuous) state spaces where other systematic approaches are unsuitable
- Usually incomplete and not optimal

Constraint satisfaction

Next time...