Evolutionary Search

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Announcements

- This week's mailing list topic: think of a real-world problem where we could apply an optimization search
  - You may not repeat someone else's answer!
  - What are the states?
  - What are the actions?
  - What is the objective function?
- Read Chapter 6 in *AI: A Modern Approach* for next time

Announcements

- If you choose to do a paper instead of a programming project, 6 pages is a *minimum*… you may write more if you feel that there is too much material (but please no more than 10)
  - Keep in mind each group will only have 15 minutes to present on the last week
  - The presentations don't have to go into as much detail as the paper, though

Homework #1 Clarifications

- For problem 1, part b, your heuristics are for the 2-letter change problem, and *don't have* to be admissible
  - But do think about if they are or aren't, and explain
- Even though "hill-climbing" and "beam" searches are *local* strategies (and often used for complete searching), you can still use them to solve partial search problems like the graph in problem 2

Homework #1 Clarifications

- For problem 3, let's say you have the initial state **ABC**, and are doing standard HC… what are the neighbors you need to consider?

BC, AC, AB, ABCD, ABCE, ABCF

- So to do hill-climbing, you will generate all these states, score them all, and choose the best one (since we are maximizing the objective function)

Genetic Algorithms

- So far the optimization strategies we've discussed search for a *single* solution, one state at a time within a neighborhood
- Genetic algorithms (GAs) are a unique search approach that maintains a population of states, or individuals, which *evolves*
  - Also called evolutionary search

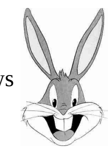
Evolutionary Analogy

- Consider a population of rabbits: some individuals are faster and smarter than others
- Slower, dumber rabbits are likely to be caught and eaten by foxes
- Fast, smart rabbits survive to do what rabbits to best: *make more rabbits!!*

7

Evolutionary Analogy

- The rabbits that survive breed with each other to generate offspring, which starts to mix up their genetic material
  - Fast rabbits might breed with fast rabbits
  - Fast rabbits with slow rabbits
  - Smart with not-so-smart, etc…
- Furthermore, nature occasionally throws in a "wild hare" because genes can mutate



8

Evolutionary Analogy

- In this analogy, an individual rabbit represents a solution to the problem (*i.e.* a single point in the state space)
  - The state description is its DNA, if you will
- The foxes represent the problem constraints
  - Solutions that do well are likely to survive
- What we need to create are notions of natural selection, reproduction, and mutation

9

Core Elements of GAs

- For selection, we use a fitness function to rank the individuals of the population
- For reproduction, we define a crossover operator which takes state descriptions of individuals and combines them to create new ones
  - What advantages does this present over local search?
- For mutation, we can merely choose individuals in the population and alter part of its state

10

Genetic Algorithm Example

```
POP = initialPopulation       // build a new population
repeat {                      // with every generation
   NEW_POP = empty
   for I = 1 to POP_SIZE {
        X = fit individual     // natural selection
        Y = fit individual
        CHILD = crossover(X,Y) // reproduction
        if small random probability then
                mutate(CHILD)   // mutation
        add CHILD to NEW_POP
   }
   POP = NEW_POP
} until solution found or enough time elapsed
return most fit individual in POP
```

11

Genetic Algorithm Example

- The previous algorithm completely replaces the population for each new generation… but we can allow individuals from older generations to live on
- Reproduction here is only between two parents (as in nature), but we can allow for more!!
- The population size also is fixed… but we can have this vary from one generation to the next

12

Genetic Algorithm Example

- *Basically, there is no one GA, we can devise many variants of these 3 principles for nearly any problem!!*
- Chapters 7 & 8 in *How to Solve It: Modern Heuristics* have a very thorough presentation of how to design genetic algorithms for particular problems

Selection

- Selection (either to reproduce or live on) from one generation to the next relies on the *fitness function*
- We can usually think of the fitness function as being a *heuristic*, or the *objective function*
- We want to apply pressure that good solutions survive and bad solutions die
  - Too much and we converge to sub-optimal solutions
  - Too little and we don't make much progress

Selection

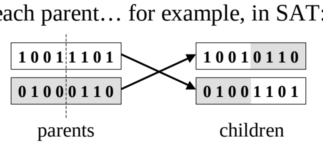
- Deterministic selection
  1. Rank all the individuals using the fitness function and choose the best *k* to survive
  2. Replace the rest with offspring
  - Can lead fast convergence (and local optima)
- Stochastic selection
  - Instead of selecting the best *k*, we could select each individual in proportion to its relative fitness to the population
  - Slower to converge, but could lose good solutions

Selection

- Tournament selection
  1. For each individual *i*, create a subset *q* of the population by random selection
  2. Assign a point to *i* for each individual in *q* that it "beats" (is less fit than itself)
  3. Rebuild the population based not on fitness scores, but the points accumulated in the tournament
  - As the size of *q* increases, though, it becomes more like deterministic selection

Reproduction

- The unique thing about GAs is the ability of solutions to *inherit* properties from other solutions in the population
- The basic way to perform a crossover operation is to splice together parts of the state description from each parent… for example, in SAT:

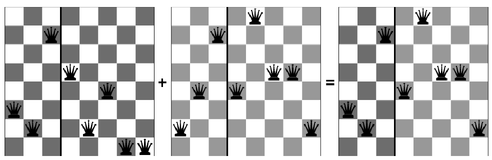


Reproduction

- There are many different ways to choose crossover point(s) for reproduction:
  - **Single-point**: choose the center, or some "optimal" point in the state description… take the first half of one parent, the second half of the other
  - **Random**: choose the split point randomly (or proportional to the parents' fitness scores)
  - ***n*-point**: make not 1 split point, but *n* different ones
  - **Uniform**: choose each element of the state description independently, at random (or proportional to fitness)

Reproduction for 8-Queens

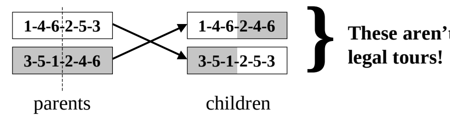
- For the 8-queens problem, we could choose a crossover point with the same number of queens on either side
- What else could we do?



19

Reproduction for TSP

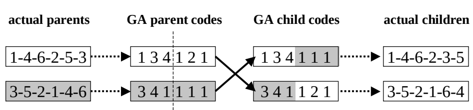
- For TSP, our individuals are *n*-city tours (*e.g.* 1-4-6-2-5-3 or 3-5-1-2-4-6 for 6 cities)
- Can we do a simple point-crossover like we could for SAT and 8-Queens?



20

Reproduction for TSP

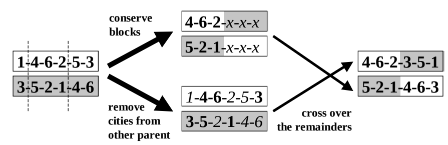
- One option is to have an ordered master queue of all the cities in the problem: *e.g.* 1,2,3,4,5,6
- Each individual, then, is a code that corresponds to "dequeuing instructions" from this master queue
  - Numbers in the code are the relative position of the appropriate city left in the queue
  - These codes can then be mated with point-crossovers



21

Reproduction for TSP

- We can try something even simpler to try and conserve information from both parents
  - Pick an block of contiguous cities in the tour to pass from one parent to a child
  - Remove all the cities in block from the other parent
  - Add the remaining cities to the child in their preserved order, after the other block



22

Mutation

- There are also a variety of ways to mutate individuals in the population
- The first question to consider it *who* to mutate
  - Alter the most fit? Least fit? Random?
  - Mutate children only, or surviving parents as well?
  - How many to mutate?
- The second question is *how* to mutate
  - Totally arbitrarily?
  - Mutate to a better neighbor?

23

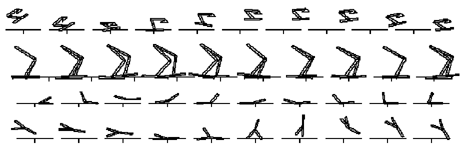
GAs and Creativity

- GAs can be thought of as a simultaneous, parallel hill-climbing search
  - The population as a whole is trying to converge to an optimal solution
- Because solutions can evolve from a variety of factors, without prodding from us as to "which direction to go" (as in local search), very novel problem solutions can be found discovered

24

GAs and Creativity

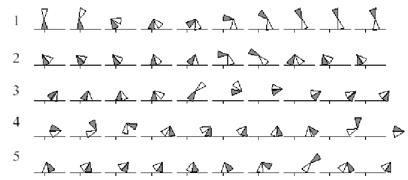
- Sensor-actuator networks (SANs) are structures that model connections between sensors and actuators (motors and muscles) in simple robots
- GAs can learn parameters for SANs that solve locomotion problems in a variety of ways



25

GAs and Creativity

- M. van de Panne, "Control Techniques For Physically-Based Animation," *Third Eurographics Workshop on Animation and Simulation*, 1994



26

GAs and Emergent Intelligence

- So far, we've talked about GAs as a search strategy for a problem solving (in which case, there is an agent conducting the GA search)
- Recall from the second lecture about *multi-agent* environments
- Now consider a GA that evolves a population of agents!! Now, our GA population is a virtual multi-agent environment

27

GAs and Emergent Intelligence

- Let's say we want to "grow" agents to predict stock market trends
- Each agent might be some statistical function that maps a stock's history to its predicted future performance:

  $(\alpha \times \textit{todaysPrice}) + (\beta \times \textit{yesterdaysPrice}) +$
  $(\gamma \times \textit{relativeValue}) + (\delta \times 1\text{-}\textit{monthStdDev}) + \ldots$

28

GAs and Emergent Intelligence

- We could maintain a population of these agents, where each agent's state ("DNA") is its set of coefficients (α, β, γ, δ, etc.)
- Now let's think about a GA for them:
  - What is our fitness function?
  - What is a good crossover?
  - How can we mutate them?

29

GAs and Emergent Intelligence

- Over time, the population should converge on a population of individuals that reflect the current stock market trends
- But will the most fit individual become a universally good stock-picker?
- Perhaps not!

30

GAs and Emergent Intelligence

- It is possible that different agents in the population specialize to aspect of the task
  - Some agents predict well for the Fortune-500 stocks
  - Others predict well for sports companies
  - Still others pick non-profits well, etc…

✱ *If there is no one universally intelligent agent in the population, perhaps we can let them all predict… or "vote" on a predictions*

31

GAs and Emergent Intelligence

- So our population of stock-pickers is a multi-agent environment… is it *cooperative* or *competitive*?

- This phenomenon is what we might refer to as emergent intelligence
  - No single agent in the environment is, taken individually, all that "intelligent"
  - Taken together, though, the entire population possesses a more global intelligence that *emerges* from its constituent agents

32

Genetic Programming

- Genetic programming is a field related to genetic algorithms (surprise!)

- Instead of maintaining and manipulating a population of strings, however, we use *expression trees*… the goal is to evolve *programs*

🗎 Section 9.5 in *Machine Learning* provides a nice overview of this (slightly more advanced) topic

33

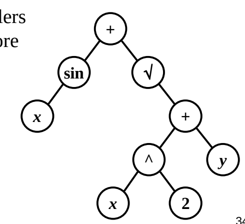
Genetic Programming

Expression trees are graphical, relational representations of functions or programs

Programming language compilers convert code to such trees before writing out machine-level instructions (CS 536)

For example:

$$\mathbf{sin}(x) + \sqrt{x^2 + y}$$



34

Genetic Programming

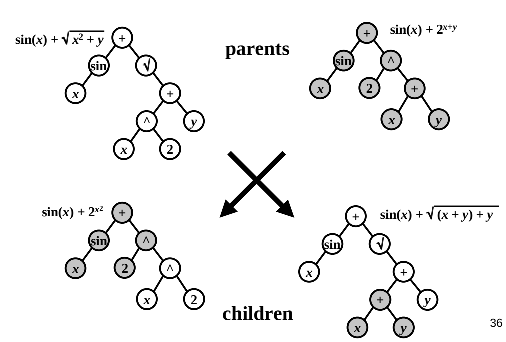
- Populations are initialized with randomized, well-formed expressions build up from:
  - Operators (e.g. +, sin, ×, etc.)
  - Terminals (x, y, 2, etc.)

- Fitness is evaluated on how well its encoded function/algorithm performs the task

- Crossover is applied by swapping subtrees in the parent expressions

35

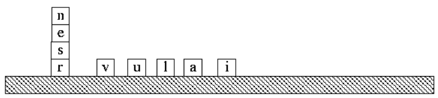
Genetic Programming



36

Genetic Programming

- J. Koza, *Genetic programming: On the programming of computers by means of natural selection*, MIT Press, 1992
- 300 random programs were initialized with primitives to solve block-stacking problems with the goal of spelling “UNIVERSAL”
- After 10 generations, a program evolved that solved all of 166 initial configurations



Views of Evolution

- The Lamarkian Theory
  - Popular in 1800s
  - An individual’s genetic makeup is altered as it learns through life experience
  - Today’s biological evidence contradicts this

Views of Evolution

- The Baldwin Effect
  - Learning has no effect on genetic makeup
  - However, ability to learn reduces the need for “hard-wired” functions
  - Therefore, individual learning allows for a more diverse gene pool (less hard-wiring) and more adaptable populations
  - Example: a new predator appears in an environment; individuals who can learn to avoid it live on, resulting in more adaptable gene pool

Last Thoughts on GAs

- Evolutionary algorithms are *simulations* of what we perceive happening in nature, but we don’t have to follow the laws of nature
  - Lamarkian GAs have been experimented with, and shown successful on some problems
- Since we get to design the framework for the simulation, there is a wide margin for creative license in the framework we create!
  - Concepts of age/gender/politics?
  - Variety of fitness functions?

Summary of Search Strategies

- Partial Search
  Look through state space for a goal from which a solution can be found
  - **Node**: state description
  - **Edge**: action that changes state at some cost
  - **Path**: sequence of actions that change from the start state to the goal state

Summary of Search Strategies

- Uninformed Search: no domain information
  - Complete/optimal if costs uniform: BFS, IDS
  - Complete/optimal with costs: UCS
  - Not complete/optimal: DFS, DLS
- Informed Search: use heuristics to guide search
  - ***g(n)***: cost from start to n
  - ***h(n)***: estimates cost from n to goal (heuristic)
  - ***f(n): g(n) + h(n)***: estimated cost of searching through n
  - Complete/optimal: A* = ***h(n)*** is admissible
  - Not complete/optimal: Greedy, A

Summary of Search Strategies

- Optimization Search
  Look through solution space for better solutions to the problem
  - **Node**: complete solution
  - **Edge**: operator changes to a new solution
  - Can stop anytime
  - Well-suited for NP-Complete problems, optimization problems

43

Summary of Search Strategies

- Local Search
  Focus on a *local* part of the search space rather than exploring it all
  - Beam search limits the list of candidate states
  - Hill-climbing follows a single path of promising successor states
  - Solution heavily dependent on the initial state
  - Can get stuck in “local optima”

44

Summary of Search Strategies

- Escaping Local Optima
  Ways to avoid the traps into which local search methods tend to fall
  - Random Restarting
  - Simulated Annealing
  - Tabu Search
- Evolutionary Search
  Unique, non-local, parallel optimization search

45