Genetic Algorithms

Chapter 4.1.4

Introduction to Genetic Algorithms

- Another Local Search method
- Inspired by natural evolution

  Living things *evolved* into more successful organisms

  – offspring exhibit some traits of each parent

Introduction to Genetic Algorithms

- Keep a **population of individuals** that are complete solutions (or partial solutions)
- Explore solution space by having these individuals "*interact*" and "*compete*"
  - interaction produces new individuals
  - competition eliminates weak individuals
- After multiple generations a strong individual (i.e., solution) should be found
- "**Simulated Evolution**" via a form of **Randomized Beam Search**

Introduction to Genetic Algorithms

- Mechanisms of evolutionary change:
  - **Crossover (Alteration)**: the (random) combination of 2 parents' chromosomes during reproduction resulting in

    offspring that have *some traits of each parent*

- Crossover requires genetic diversity among the parents to ensure sufficiently varied offspring

Introduction to Genetic Algorithms

- Mechanisms of evolutionary change:
  - **Mutation**: the rare occurrence of errors during the process of copying chromosomes resulting in
    - changes that are nonsensical or deadly, producing organisms that can't survive
    - changes that are beneficial, producing "stronger" organisms
    - changes that aren't harmful *or* beneficial, producing organisms that aren't improved

Introduction to Genetic Algorithms

- Mechanisms of evolutionary change:
  - **Natural selection**: the fittest survive in a competitive environment resulting in better organisms
    - individuals with better survival traits generally survive for a longer period of time
    - this provides a better chance for reproducing and passing the successful traits on to offspring
    - over many generations the species improves since better traits will out-number weaker ones

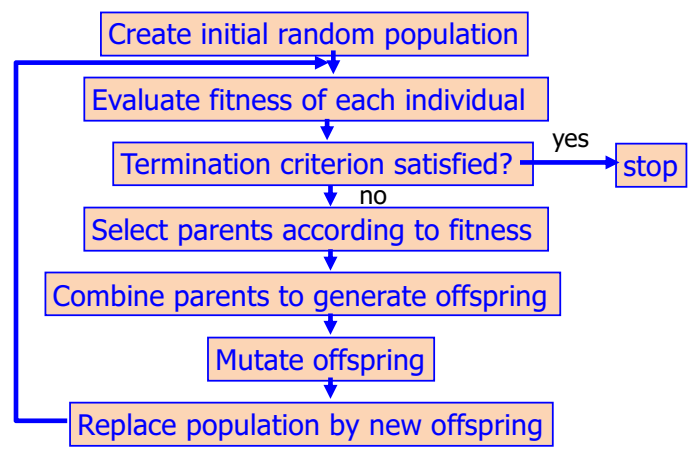
Representation of Individuals

Solutions represented as a **vector of values**

- For example: Satisfiability problem (SAT)
  - determine if a statement in propositional logic is satisfiable, for example:

    $(P_1 \vee P_2) \wedge (P_1 \vee \neg P_3) \wedge (P_1 \vee \neg P_4) \wedge (\neg P_3 \vee \neg P_4)$
  - each element corresponds to a symbol having a value of either true (i.e., 1) or false (i.e., 0)
  - vector: P_1 P_2 P_3 P_4
  - values: 1 0 1 1 ← rep. of 1 individual
- Traveling salesperson problem (TSP)
  - Tour can be represented as a sequence of cities visited

Genetic Algorithm



Genetic Algorithm (1 version*)

1. Let $\boldsymbol{s} = \{s_1, \ldots, s_N\}$ be the current population
2. Let $p[i] = f(s_i)/\text{SUM}_j f(s_j)$ be the fitness probabilities
3. for $k = 1;\ k < N;\ k \mathrel{+}= 2$
   - Parent1 = randomly pick s_i with prob. $p[i]$
   - Parent2 = randomly pick another s_j with prob. $p[j]$
   - Randomly select 1 crossover point, and swap strings of parents 1 and 2 to generate two children $t[k]$ and $t[k+1]$
4. for $k = 1;\ k \leq N;\ k{+}{+}$
   - Randomly mutate each position in $t[k]$ with a small probability
5. New generation replaces old generation: $\boldsymbol{s} = \boldsymbol{t}$

*different than in book

Initialization: Seeding the Population

- Initialization sets the beginning population of individuals from which future generations are produced
- Issues:
  - **size** of the initial population
    - experimentally determined for problem
  - **diversity** of the initial population (genetic diversity)
    - a problem resulting from *lack* of diversity is premature convergence to a non-optimal solution

Initialization: Seeding the Population

- How is a diverse initial population generated?
  - uniformly random: generate individuals randomly from a solution space with uniform distribution
  - grid initialization: choose individuals at regular "intervals" from the solution space
  - non-clustering: require individuals to be a predefined "distance" away from those already in the population
  - local optimization: use another technique (e.g. HC) to find initial population of local optima; doesn't ensure diversity but guarantees solution to be no worse than the local optima

Evaluation: Ranking by Fitness

- Evaluation ranks the individuals using some **fitness measure** that corresponds with the *quality* of the individual solutions
- For example, given individual i:
  - classification: $(\#\,correct(i))^2$
  - TSP: $1/tour\text{-}length(i)$
  - SAT: $\#\,ofClausesSatisfied(i)$

Selection: Finding the Fittest

- **Choose which individuals survive and possibly reproduce in the next generation**
- Selection depends on the evaluation/fitness function
  - if too dependent, then, like greedy search, a non-optimal solution may be found
  - if not dependent enough, then may not converge to a solution at all
- Nature doesn't eliminate all "unfit" genes; they usually become recessive for a long period of time, and then may mutate to something useful

Selection Techniques

- **Deterministic Selection**
  - relies on evaluation/fitness function
  - converges fast
- Two approaches:
  - next generation contains parents *and* children
    - parents are the best of the current generation
    - parents produce children, and parents survive to next generation
  - next generation contains only children
    - parents are the best of the current generation
    - parents are used to produce children
    - parents don't survive (counters early convergence)

Selection Techniques

- **Proportional Fitness Selection**
  - each individual is selected *proportionally* to their fitness score
  - even the worst individual has a chance to survive
  - helps prevent "stagnation" in the population
- Two approaches:
  - **rank selection**: individual selected with a probability proportional to its *rank* in population sorted by fitness
  - **proportional selection**: individual selected with a probability: $Fitness(individual) / \sum Fitness\ for\ all\ individuals$

Selection Techniques

Proportional selection example:

- Given the following fitness values for population:
- **Sum all the Fitnesses**
  $5 + 20 + 11 + 8 + 6 = 50$
- **Determine probability for each individual, *i***
  $Fitness(i) / 50$

Individual	Fitness	Prob.
A	5	10%
B	20	40%
C	11	22%
D	8	16%
E	6	12%

Selection Techniques

Crowding: a potential problem associated with Selection

- occurs when the individuals that are most-fit quickly reproduce so that a large percentage of the entire population looks very similar
- *reduces diversity* in the population
- may hinder the long-run progress of the algorithm

Crossover: Producing New Individuals

- Crossover is used to produce new individuals (i.e., children)
- **Crossover** for vector representations:
  - Pick pairs of individuals as parents and randomly swap their segments
  - also known as "***cut and splice***"
- Parameters:
  - number of crossover points
  - positions of the crossover points

Crossover: Producing New Individuals

- **1-point Crossover**
  - pick a dividing point in the parents' vectors and swap their segments
- Example
  - given parents: 1101101101 and 0001001000
  - crossover point: after the 4th digit
  - children produced are:

    1101 + 001000 and 0001 + 101101

Crossover: Producing New Individuals

- **N-point Crossover**
  - generalization of 1-point crossover
  - pick *n* dividing points in the parents' vectors and splice together alternating segments
- **Uniform Crossover**
  - the value of each element of the vector is randomly chosen from the values in the corresponding elements of the two parents
- Techniques also exist for permutation representations

Producing New Individuals

- **Mutation**
  - randomly change an individual
  - e.g. TSP: two-swap, two-interchange
  - e.g. SAT: bit flip
- Parameters:
  - mutation rate
  - size of the mutation

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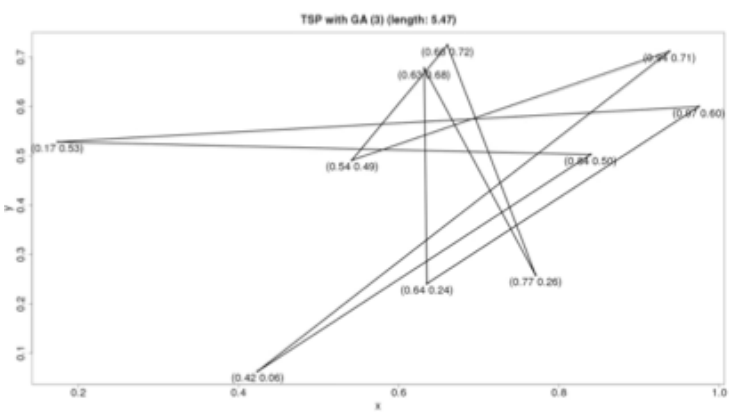
GA Solving TSP



Genetic Algorithm Applications

Genetic Algorithms as Search

The Problem of Local Maxima

Individuals get stuck at pretty good, but not optimal, solutions

- any small mutation gives worse fitness
- crossover can help get out of a local maximum
- mutation is a random process, so it is possible that we may have a sudden large mutation to get these individuals out of this situation

Genetic Algorithms as Search

- GA is a kind of hill-climbing search
- Very similar to a randomized beam search
- One significant difference between GAs and HC is that, it is generally a good idea in GAs to "fill the local maxima up with individuals"
- Overall, GAs have less problems with local maxima than HC or neural networks

Summary

- Easy to apply to a wide range of problems
  - Optimization problems such as TSP
  - inductive concept learning
  - scheduling
  - Layout
- Results can be very good on some problems and poor on others
- GA is very slow if only mutation is used; crossover makes the algorithm significantly faster