Genetic Algorithms

Chapter 4.1.4

Introduction to Genetic Algorithms

- Inspired by natural evolution:

  Living things *evolved* into more successful organisms
  - offspring exhibit some traits of each parent
  - hereditary traits are determined by genes
  - genetic instructions are contained in chromosomes
  - chromosomes are strands of DNA
  - DNA is composed of base pairs (A,C,G,T), when in meaningful combinations, encode hereditary traits

Introduction to Genetic Algorithms

- Mechanisms of evolutionary change:
  - **Crossover**: the random exchange 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/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

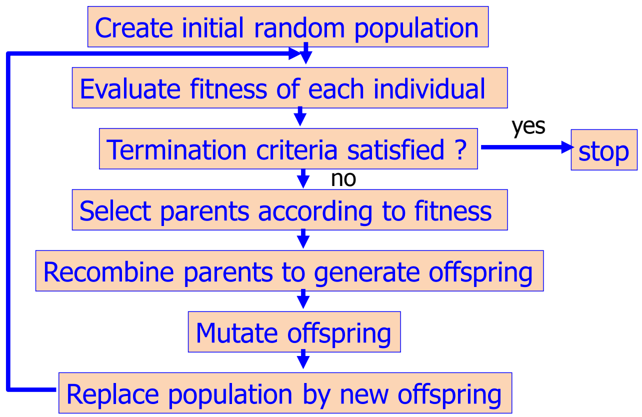
Introduction to Genetic Algorithms

- 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 **Hill-Climbing** or **Randomized Beam Search**

Representation of Individuals

- Some problems have solutions that can be represented as a vector of values:
  - e.g., satisfiability problem (SAT):
    determine if a statement in propositional logic is satisfiable
    $(P_1 \wedge P_2) \vee (P_1 \wedge \neg P_3) \vee (P_1 \wedge \neg P_4) \vee (\neg P_3 \wedge \neg P_4)$
    - each element corresponds with a proposition having a truth 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
- Some problems have solutions that can be represented as a permutation of values:
  - e.g., traveling salesperson problem (TSP)

Genetic Algorithm



Genetic Algorithm (1 version*)

1. Let $\boldsymbol{s} = \{s_1, \ldots, s_N\}$ be the current population
2. Let $p[i] = f(s_i)/\sum f(s_j)$ be the fitness probabilities
3. for $k = 1$; $k < N$; k += 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 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 prob.
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
- Concerns:
  - size of the initial population
    - experimentally determined for problem
  - diversity of the initial population (genetic diversity)
    - a common issue resulting from the lack of diversity is premature convergence to 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 by some **fitness measure** that corresponds with the quality of the individual solutions
- For example, given individual i:
  - classification: $(correct(i))^2$
  - TSP: $1/distance(i)$
  - SAT: $\#ofTermsSatisfied(i)$
  - walking animation: *subjective rating*

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

- **Proportional Fitness Selection**
  - each individual is selected proportionally to their fitness score
  - even the worst individual has a chance to survive
  - this 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*) / ∑ *Fitness for all individuals

Selection Techniques

Proportional selection example:

- Given the following fitness values for population:
- **Sum the Fitness**

  5 + 20 + 11 + 8 + 6 = 50
- **Determine probabilities**

  ***Fitness*(*i*) / 50**

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

Selection Techniques

- **Tournament Selection**
  - randomly select two individuals and the one with the highest rank goes on and reproduces
  - cares only about the one with the higher rank, not the spread between the two fitness scores
  - puts an upper and lower bound on the chances that any individual has to reproduce for the next generation equal to $(2s - 2r + 1) / s^2$
    - s is the size of the population
    - r is the rank of the "winning" individual
  - can be generalized to select best of *n* individuals

Selection Techniques

Tournament selection example:

- Given the following population and fitness:
- **Select B and D**
- **B wins**
- **Probability:**

  $(2s - 2r + 1) / s^2$

Individual	Fitness	Prob.
A	5	1/25 = 4%
B	20	9/25 = 36%
C	11	7/25 = 28%
D	8	5/25 = 20%
E	6	3/25 = 12%

B: s=5, r=1   **D**: s=5, r=3

Selection Techniques

- **Crowding**

  a potential problem associated with the 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

Alteration: Producing New Individuals

- Alteration is used to produce new individuals
- **Crossover** for vector representations:
  - pick one or more pairs of individuals as parents and randomly swap their segments
  - also known as "***cut and splice***"
- Parameters:
  - crossover rate
  - number of crossover points
  - positions of the crossover points

Alteration: Producing New Individuals

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

    1101 + 001000 and 0001 + 101101

Alteration: 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

Alteration: Producing New Individuals

- Alteration is used to produce 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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Genetic Algorithms Applications

Genetic Algorithms as Search

- **Problem of Local Maxima**

  individuals get stuck at pretty good but not optimal solutions
  - any small mutation gives worse fitness
  - crossover can help them 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 back-propagation neural networks

Summary

- Easy to apply to a wide range of problems
  - optimizations like TSP
  - inductive concept learning
  - scheduling
  - layout
- The results can be very good on some problems, and rather poor on others
- GA is very slow if only mutation is used; crossover makes the algorithm significantly faster