Genetic Algorithms

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Introduction

Characteristics

- Inspired in living systems
- Borrow ideas from evolution

Examples

- Genetic Algorithms
- Genetic Programming

Rui Mendes Genetic Algorithms 2 / 35

Genetic Algorithm

- Optimization algorithm
- Inspired in natural selection
- Uses a population of individuals
- Each individual encodes a solution
- There are three operators:
 - Selection
 - 2 Crossover
 - Mutation

Encoding

- Process that represents a solution in a given alphabet
- There are several encodings, e.g.:
 - binary
 - integer
 - real numbers
 - permutations
- Usually, they are linear sequences of values (chromossomes composed of genes)

Rui Mendes 4/35

Creating new solutions

- The genetic operators for creating new solutions are:
 - Recombination or Crossover
 - Mutation

Crossover

- Combines several solutions
- Usually, it takes two parents and creates two offspring
- Usual methods:
 - One point crossover
 - Two point crossover
 - Uniform crossover

One point crossover

- A cutting point is randomly selected
- Each solution takes a part from each parent

Parents	Offspring
010 110	010 101
011 101	011 110

Two point crossover

- Two cutting points are randomly selected
- The central parts are exchanged

Parents	Offspring
10 11 0	10 10 0
01 10 1	01 11 1

Uniform crossover

- The value of the first parent is randomly copied to one of the offspring
- The value of the second parent is copied to the other one

Parents	Offspring
10110	00100
01101	11111

Mutation

- A position is randomly selected inside the string
- The value is randomly selected among the possible values

Before	After
10110	10010

Rui Mendes Genetic Algorithms 10 / 35

Fitness

- Quantifies the quality of a solution
- It is usually a floating point number
- In order to compare the quality of two solutions, one simply has to compare the fitness values

Rui Mendes Genetic Algorithms 11 / 35

Selection

- Process for choosing which individuals will generate offspring or will be copied into the new population
- It usually selects individuals:
 - According to their fitness;
 - By partial or total ordering of the solutions
 - ▶ By stochastic choice of the individuals according to their fitness

Rui Mendes Genetic Algorithms 12/35

Fitness proportionate selection

- The probability of selecting an individual is proportional to their fitness
- If it is a maximization problem, the probability of selecting an individual is $p_i = \frac{f_i}{\sum_i f_i}$

13 / 35

Selection by ordering

- If using total ordering, the individuals are ranked according to their fitness and the top n individuals are chosen
- In a partial ordering, several individuals are chosen at random and they are ordered (it's called *tournament selection*)

Genetic Algorithm outline

- Initialize the population
- While not finished
 - Choose individuals
 - Apply genetic operators
 - Insert offspring into the next population

Generational scheme

- A new population is created in each iteration
- Parents are chosen from the current population
- Offspring are inserted into the new population
- The old population is discarded

Generational scheme

- Initialize population
- While not finished
 - Evaluate individuals
 - While the new population is not complete
 - Select two individuals
 - 2 Apply genetic operators
 - Insert offspring into the new population

Steady state scheme

- There are not generations
- Several individuals are randomly chosen for the tournament
- The best individuals produce offspring using the genetic operators
- The offspring substitute the worse individuals

Steady state scheme

- Initialize population
- While not finished
 - Choose 4 individuals
 - 2 Rank the individuals
 - Apply genetic operators to the best 2 individuals
 - The offspring substitute the worst 2 individuals

Representations

- There can be several solution representations
- Each representation has several advantages and disadvantages
- There are several possibilities:
 - Integer
 - Real
 - Ordered

Integer representation

• Each individual is a sequence of integers, e.g.,

- Crossover operators defined thus far can be used
- There can be new crossover and mutation operators

Random value mutation

$$21237 \rightarrow 25237$$

Next element mutation

$$2\;1\;2\;3\;7\rightarrow2\;\textcolor{red}{2}\;2\;3\;7$$

Real representation

• Each individual is a sequence of real numbers, e.g.,

$$2.3 - 7.4 1.9 0.1$$

- There are specific crossover operators:
 - Arithmetic crossover
 - Linear crossover
 - ▶ Blend crossover
- And mutation operators:
 - Uniform mutation
 - ► Gaussian mutation
 - Cauchy modification

Arithmetic crossover

- ullet Given two parents, $ec{P}_1$ and $ec{P}_2$
- Create 2 solutions:

$$ec{S}_1: \lambda \cdot \vec{P}_1 + (1-\lambda) \cdot \vec{P}_2$$

$$\vec{S}_2$$
: $(1-\lambda)\cdot\vec{P}_1-\lambda\cdot\vec{P}_2$

ullet With λ usually being 0.6

Linear crossover

- ullet Given two parents, $ec{P}_1$ and $ec{P}_2$
- Create 3 solutions:

$$\vec{S}_1: 0.5 \cdot \vec{P}_1 + 0.5 \cdot \vec{P}_2$$

$$\vec{S}_2 : 1.5 \cdot \vec{P}_1 - 0.5 \cdot \vec{P}_2$$

$$\vec{S}_3: 0.5 \cdot \vec{P}_1 + 1.5 \cdot \vec{P}_2$$

• Choose the two best solutions among \vec{P}_1 , \vec{P}_2 , \vec{S}_1 , \vec{S}_2 and \vec{S}_3 to become the children

Rui Mendes Genetic Algorithms 24 / 35

Blend crossover

- Given two parents, x_1 and x_2 where $x_1 < x_2$
- Create solutions using:

$$U[x_1 - \alpha \cdot (x_2 - x_1), x_2 + \alpha \cdot (x_2 - x_1)]$$

ullet α is usually chosen to be 0.5.

25/35

Uniform mutation

- A random mutation where one or more positions are modified
- Modified positions are randomly generated within the entire range
- The modified position has no relationship with the original value
- $x_{new} = U[\min, \max]$

Random modification

- A random mutation where one or more positions are modified
- Modified positions are generated in the vicinity of the original value
- $x_{new} = x + U[-\epsilon, \epsilon]$ or
- $x_{new} = x \cdot (1 + U[-\epsilon, \epsilon])$

Gaussian mutation

- A random mutation where one or more positions are modified
- Modified positions are generated in the vicinity of the original value following the gaussian distribution
- $x_{new} = x + N(0, \sigma)$

Permutation based representations

- Each individual is a sequence of integers representing a permutation
- The integers are in the range $1, \ldots, n$ without repetitions
- Example:

• Genetic operators must preserve these constraints

Order preserving crossover

- Select a cutting position and copy the parts left of the cutting point directly to the corresponding offspring
- Copy the remaining values by using the order in the other parent
- Can also be used with two cutting points

Order preserving crossover

2 1 5 | 4 3 1 4 5 | 2 3

Partially mapped crossover

- ullet Choose random segment from the first parent P_1
- Look for values in the other parent P₂ that were not copied
- For each of these values $x \in P_2$, look at what values $y \in P_1$ that was copied in its place
- Place x in the position occupied by y in P_2 , because we know we will not put y there (because it's already in the child)

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Insertion mutation

- Choose two positions at random
- Move the second position to follow the first

Insertion mutation

$$2\ 1\ 5\ 3\ 4 \rightarrow 2\ 1\ 3\ 5\ 4$$

Swap mutation

- Choose two positions at random
- Swap their positions

Swap mutation

 $2\;1\;5\;3\;4\to 2\;3\;5\;1\;4$

Inversion mutation

- Choose two positions at random
- Invert the values between them

Inversion mutation

 $2\ 1\ 5\ 3\ 4 \rightarrow 2\ 3\ 5\ 1\ 4$

Scramble mutation

- Pick a random subset of genes
- Randomly change the position of the values between them
- The subset need not be contiguous

Scramble mutation

 $2\;1\;7\;5\;3\;6\;4\to 2\;7\;3\;6\;5\;1\;4$