5 Genetic algorithms

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Genetic algorithms are not used for everyday programmatic problems. They are called upon when traditional algorithmic approaches are insufficient for arriving at a solution to a problem in a reasonable amount of time. In other words, genetic algorithms are usually reserved for complex problems without easy solutions. If you need a sense of what some of these complex problems might be, feel free to read ahead in section 5.7 before proceeding. One interesting example, though, is protein-ligand docking and drug design. Computational biologists need to design molecules that will bind to receptors to deliver drugs. There may be no obvious algorithm for designing some particular molecule, but as you will see, sometimes genetic algorithms can provide an answer without much direction beyond a definition of the goal of a problem.

5.1 Biological background

In biology, the theory of evolution is an explanation of how genetic mutation coupled with the constraints of an environment leads to changes in organisms over time (including speciation—the creation of new species). The mechanism by which the well-adapted organisms succeed and the less well-adapted organisms fail is known as *natural selection*. Each generation of a species will include individuals with different (and sometimes new) traits that come about through genetic mutation. All individuals compete for limited resources to survive, and because there are more individuals than there are resources, some individuals must die.

An individual with a mutation that makes it better adapted for survival in its environment will have a higher probability of living and reproducing. Over time, the better-adapted individuals in an environment will have more children, and through inheritance will pass on their mutations to those children. Therefore, a mutation that benefits survival is likely to eventually proliferate amongst a population.

For example, if bacteria are being killed by a specific antibiotic, and one individual bacterium in the population has a mutation in a gene that makes it more resistant to the antibiotic, it is more likely to survive and reproduce. If the antibiotic is continually applied over time, the children who have inherited the gene for antibiotic resistance will also be more likely to reproduce and have children of their own. Eventually the whole population may gain the mutation, as continued assault by the antibiotic kills off the individuals without the mutation. The antibiotic does not cause the mutation to develop, but it does lead to the proliferation of individuals with the mutation.

Natural selection has been applied in spheres beyond biology. Social Darwinism is natural selection applied to the sphere of social theory. In computer science, genetic algorithms are a simulation of natural selection to solve computational challenges.

A genetic algorithm includes a *population* (group) of individuals known as *chromosomes*. The chromosomes, each composed of *genes* that specify their traits, are competing to solve some problem. How well a chromosome solves a problem is defined by a *fitness function*.

The genetic algorithm goes through *generations*. In each generation, the chromosomes that are more fit are more likely to be *selected* to reproduce. There is also a probability in each generation that two chromosomes will have their genes merged. This is known as *crossover*. And finally, there is the important possibility in each generation that a gene in a chromosome may *mutate* (randomly change).

After the fitness function of some individual in the population crosses some specified threshold, or the algorithm runs through some specified maximum number of generations, the best individual (the one that scored highest in the fitness function) is returned.

Genetic algorithms are not a good solution for all problems. They depend on three partially or fully *stochastic* (randomly determined) operations: selection, crossover, and mutation. Therefore, they may not find an optimal solution in a reasonable amount of time. For most problems, more deterministic algorithms exist with better guarantees. But there are problems for which no fast deterministic algorithm exists. In these cases, genetic algorithms are a good choice.

5.2 A generic genetic algorithm

Genetic algorithms are often highly specialized and tuned for a particular application. In this chapter, we will define a generic genetic algorithm that can be used with multiple problems, while not being particularly well tuned for any of them. It will include some configurable options, but the goal is to show the algorithm's fundamentals instead of its tunability.

We will start by defining an interface for the individuals that the generic algorithm can operate on. The abstract class `Chromosome` defines four essential features. A chromosome must be able to do the following:

- Determine its own fitness
- Create an instance with randomly selected genes (for use in filling the first generation)

- Implement crossover (combine itself with another of the same type to create children)—in other words, mix itself with another chromosome
- Mutate—make a small, fairly random change in itself

Here is the code for `Chromosome`, codifying these four needs.

Listing 5.1 chromosome.py

```
from __future__ import annotations
from typing import TypeVar, Tuple, Type
from abc import ABC, abstractmethod
T = TypeVar('T', bound='Chromosome') # for returning self

# Base class for all chromosomes; all methods must be overridden

class Chromosome(ABC):
    @abstractmethod

    def fitness(self) -> float:
        ...
    @classmethod

    @abstractmethod
    def random_instance(cls: Type[T]) -> T:
        ...
    @abstractmethod

    def crossover(self: T, other: T) -> Tuple[T, T]:
        ...
    @abstractmethod

    def mutate(self) -> None:
        ...
```

copy

TIP

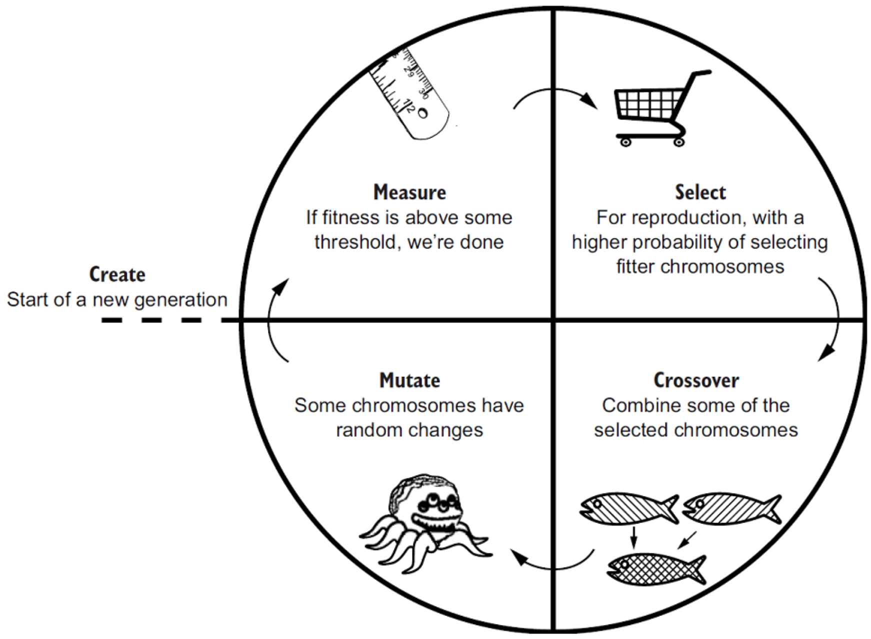
You'll notice in its constructor that the `TypeVar` `T` is bound to `Chromosome`. This means that anything that fills in a variable that is of type `T` must be an instance of a `Chromosome` or a subclass of `Chromosome`.

We will implement the algorithm itself (the code that will manipulate chromosomes) as a generic class that is open to subclassing for future specialized applications. Before we do so, though, let's revisit the description of a genetic algorithm from the beginning of the chapter, and clearly define the steps that a genetic algorithm takes:

1. Create an initial population of random chromosomes that represents the first generation of the algorithm.
2. Measure the fitness of each chromosome in this generation of the population. If any exceeds the threshold, return it and the algorithm ends.
3. Select some individuals to reproduce, with a higher probability of selecting those with the highest fitness.
4. Crossover (combine), with some probability, some of the selected chromosomes to create children that represent the population of the next generation.
5. Mutate, usually with a low probability, some of those chromosomes. The population of the new generation is now complete, and it replaces the population of the last generation.
6. Return to step 2 unless the maximum number of generations has been reached. If that is the case, return the best chromosome found so far.

This general outline of a genetic algorithm (illustrated in figure 5.1) is missing a lot of important details. How many chromosomes should be in the population? What is the threshold that stops the algorithm? How should the chromosomes be selected for reproduction? How should they be combined (crossover) and at what probability? At what probability should mutations occur? How many generations should be run?

Figure 5.1 The general outline of a genetic algorithm


Measure
If fitness is above some threshold, we're done
Select
For reproduction, with a higher probability of selecting fitter chromosomes
Create
Start of a new generation
Mutate
Some chromosomes have random changes
Crossover
Combine some of the selected chromosomes

All of these points will be configurable in our `GeneticAlgorithm` class. We will define it piece by piece so we can talk about each piece separately.

Listing 5.2 genetic_algorithm.py

```
from __future__ import annotations
from typing import TypeVar, Generic, List, Tuple, Callable
from enum import Enum
from random import choices, random
from heapq import nlargest
from statistics import mean
from chromosome import Chromosome
C = TypeVar('C', bound=Chromosome) # type of the chromosomes

class GeneticAlgorithm(Generic[C]):
    SelectionType = Enum("SelectionType", "ROULETTE TOURNAMENT")
```

copy

`GeneticAlgorithm` takes a generic type that conforms to `Chromosome`, and its name is `C`. The enum `SelectionType` is an internal type used for specifying the selection method used by the algorithm. The two most common genetic algorithm selection methods are known as *roulette-wheel selection* (sometimes called "fitness proportionate selection") and *tournament selection*. The former gives every chromosome a chance of being picked, proportionate to its fitness. In tournament selection, a certain number of random chromosomes are challenged against one another, and the one with the best fitness is selected.

Listing 5.3 genetic_algorithm.py continued

```
def __init__(self, initial_population: List[C], threshold: float, max_generations: int = 100, mutation_chance: float = 0.01,
crossover_chance: float = 0.7, selection_type: SelectionType = SelectionType.TOURNAMENT) -> None:
    self._population: List[C] = initial_population
    self._threshold: float = threshold
    self._max_generations: int = max_generations
    self._mutation_chance: float = mutation_chance
    self._crossover_chance: float = crossover_chance
    self._selection_type: GeneticAlgorithm.SelectionType = selection_type
    self._fitness_key: Callable = type(self._population[0]).fitness
```

copy

The preceding are all properties of the genetic algorithm that will be configured at the time of creation, through `__init__()`. `initial_population` is the chromosomes in the first generation of the algorithm. `threshold` is the fitness level that indicates that a solution has been found for the problem the genetic algorithm is trying to solve. `max_generations` is the maximum number of generations to run. If we have run that many generations and no solution with a fitness level beyond `threshold` has been found, the best solution that has been found will be returned. `mutation_chance` is the probability of each chromosome in each generation mutating. `crossover_chance` is the probability that two parents selected to reproduce have children that are a mixture of their genes; otherwise the children are just duplicates of the parents. Finally, `selection_type` is the type of selection method to use, as delineated by the enum `SelectionType`.

The preceding init method takes a long list of parameters, most of which have default values. They set up instance versions of the configurable properties we just discussed. In our examples, `_population` is initialized with a random set of chromosomes using the `Chromosome` class's `random_instance()` class method. In other words, the first generation of chromosomes is just composed of random individuals. This is a point of potential optimization for a more sophisticated genetic algorithm. Instead of starting with purely random individuals, the first generation could contain individuals that are closer to the solution, through some knowledge of the problem. This is referred to as *seeding*.

`_fitness_key` is a reference to the method we will be using throughout `GeneticAlgorithm` for calculating the fitness of a chromosome. Recall that this class needs to work with any subclass of `Chromosome`. Therefore, `_fitness_key` will differ by subclass. To get to it, we use `type()` to refer to the specific subclass of `Chromosome` that we are finding the fitness of.

Now we will examine the two selection methods that our class supports.

Listing 5.4 genetic_algorithm.py continued

```
# Use the probability distribution wheel to pick 2 parents
# Note: will not work with negative fitness results

def _pick_roulette(self, wheel: List[float]) -> Tuple[C, C]:
    return tuple(choices(self._population, weights=wheel, k=2))
```

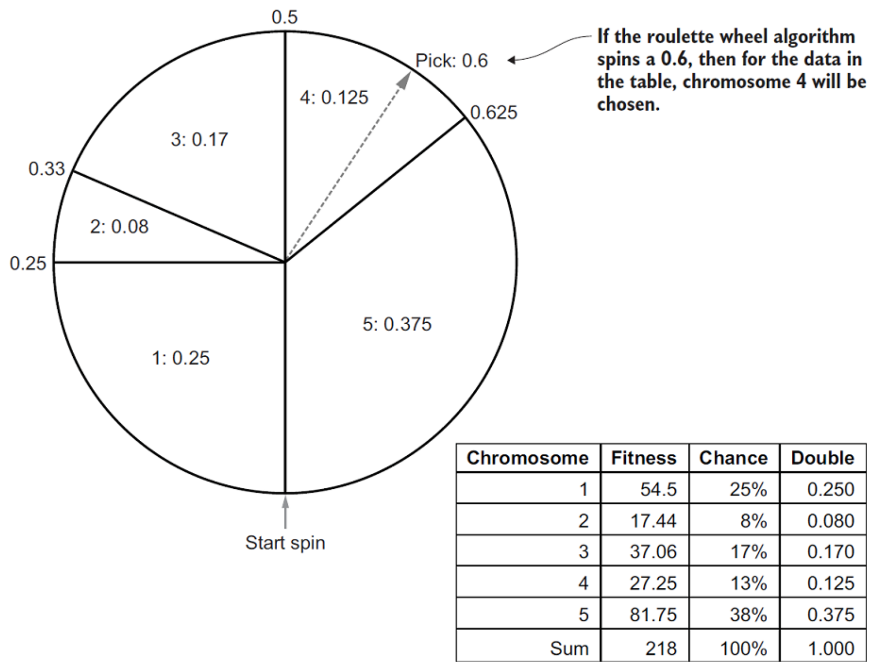
copy

Roulette-wheel selection is based on each chromosome's proportion of fitness of the sum of all fitnesses in a generation. The chromosomes with the highest fitness have a better chance of being picked. The values that represent each chromosome's fitness are provided in the parameter `wheel`. The actual picking is conveniently done by the `choices()` function from the Python standard library's `random` module. This function takes a list of things we want to pick from, an equal length list containing weights for each item in the first list, and how many items we want to pick.

If we were to implement this ourselves, we could calculate percentages of total fitness for each item (proportional fitnesses) that are represented by floating-point values between 0 and 1. A random number (`pick`) between 0 and 1 could be used to figure out which chromosome to select. The algorithm would work by decreasing `pick` by each chromosome's proportional fitness value sequentially. When `pick` crosses 0, that's the chromosome to select.

Does it make sense to you why this process results in each chromosome being pickable by its proportion? If not, think about it on pencil and paper. Consider drawing a proportional roulette wheel, as in figure 5.2.

Figure 5.2 An example of roulette-wheel selection in action


0.5
Pick: 0.6
If the roulette wheel algorithm spins a 0.6, then for the data in the table, chromosome 4 will be chosen.
4: 0.125
0.625
3: 0.17
0.33
2: 0.08
0.25
5: 0.375
1: 0.25
Start spin

Chromosome	Fitness	Chance	Double
1	54.5	25%	0.250
2	17.44	8%	0.080
3	37.06	17%	0.170
4	27.25	13%	0.125
5	81.75	38%	0.375
Sum	218	100%	1.000

The most basic form of tournament selection is simpler than roulette-wheel selection. Instead of figuring out proportions, we simply pick `k` chromosomes from the whole population at random. The two chromosomes with the best fitness out of the randomly selected bunch win.

Listing 5.5 genetic_algorithm.py continued

```
def _pick_tournament(self, num_participants: int) -> Tuple[C, C]:
    participants: List[C] = choices(self._population, k=num_participants)
    return tuple(nlargest(2, participants, key=self._fitness_key))
```

copy

The code for `_pick_tournament()` first uses `choices()` to randomly pick `num_participants` from `_population` . Then it uses the `nlargest()` function from the the `heapq` module to find the two largest individuals by `_fitness_key` . What is the right number for `num_participants` ? Like many parameters in a genetic algorithm, trial and error may be the best way to determine it. One thing to keep in mind is that a higher number of participants in the tournament leads to less diversity in the population, because chromosomes with poor fitness are more likely to be eliminated in matchups.[11] More sophisticated forms of tournament selection may pick individuals that are not the best, but second- or third-best, based on some kind of decreasing probability model.

These two methods, `_pick_roulette()` and `_pick_tournament()` , are used for selection, which occurs during reproduction. Reproduction is implemented in `_reproduce_and_replace()` , and it also takes care of ensuring a new population of an equal number of chromosomes replaces the chromosomes in the last generation.

Listing 5.6 genetic_algorithm.py continued

```
# Replace the population with a new generation of individuals

def _reproduce_and_replace(self) -> None:
    new_population: List[C] = []
    # keep going until we've filled the new generation

    while len(new_population) < len(self._population):
        # pick the 2 parents

        if self._selection_type == GeneticAlgorithm.SelectionType.ROULETTE:
            parents: Tuple[C, C] = self._pick_roulette([x.fitness() for x in self._population])
        else:
            parents = self._pick_tournament(len(self._population) // 2)
        # potentially crossover the 2 parents

        if random() < self._crossover_chance:
            new_population.extend(parents[0].crossover(parents[1]))
        else:
            new_population.extend(parents)
    # if we had an odd number, we'll have 1 extra, so we remove it

    if len(new_population) > len(self._population):
        new_population.pop()
    self._population = new_population # replace reference
```

copy

In `_reproduce_and_replace()` , the following steps occur in broad strokes:

1. Two chromosomes, called `parents` , are selected for reproduction using one of the two selection methods. For tournament selection, we always run the tournament amongst half of the total population, but this too could be a configuration option.
2. There is `_crossover_chance` that the two parents will be combined to produce two new chromosomes, in which case they are added to `new_population` . If there are no children, the two parents are just added to `new_population` .
3. If `new_population` has as many chromosomes as `_population` , it replaces it. Otherwise, we return to step 1.

The method that implements mutation, `_mutate()` , is very simple, with the details of how to perform a mutation being left to individual chromosomes.

Listing 5.7 genetic_algorithm.py continued

```
# With _mutation_chance probability mutate each individual

def _mutate(self) -> None:
    for individual in self._population:
        if random() < self._mutation_chance:
            individual.mutate()
```

copy

We now have all of the building blocks needed to run the genetic algorithm. `run()` coordinates the measurement, reproduction (which includes selection), and mutation steps that bring the population from one generation to another. It also keeps track of the best (fittest) chromosome found at any point in the search.

Listing 5.8 genetic_algorithm.py continued

```
def run(self) -> C:
    best: C = max(self._population, key=self._fitness_key)
    for generation in range(self._max_generations):
        if best.fitness() >= self._threshold:

            return best
        print(f"Generation {generation} Best {best.fitness()} Avg {mean(map(self._fitness_key, self._population))}")
        self._reproduce_and_replace()
        self._mutate()
        highest: C = max(self._population, key=self._fitness_key)
        if highest.fitness() > best.fitness():
            best = highest

    return best
```

copy

`best` keeps track of the best chromosome found so far. The main loop executes `_max_generations` times. If any chromosome exceeds `threshold` in fitness, it is returned and the method ends. Otherwise, it calls `_reproduce_and_replace()` as well as `_mutate()` to create the next generation and run the loop again. If `_max_generations` is reached, the best chromosome found so far is returned.

5.3 A naive test

The generic genetic algorithm, `GeneticAlgorithm`, will work with any type that implements `Chromosome`. As a test, we will start by implementing a simple problem that can be easily solved using traditional methods. We will try to maximize the equation 6x – x2 + 4y – y2. In other words, what values for x and y in that equation will yield the largest number? The maximizing values can be found, using calculus, by taking partial derivatives and setting each equal to zero. The result is x = 3 and y = 2. Can our genetic algorithm reach the same result without using calculus? Let's dig in.

Listing 5.9 simple_equation.py

```python
from __future__ import annotations
from typing import Tuple, List
from chromosome import Chromosome
from genetic_algorithm import GeneticAlgorithm
from random import randrange, random
from copy import deepcopy
class SimpleEquation(Chromosome):
    def __init__(self, x: int, y: int) -> None:
        self.x: int = x
        self.y: int = y
    def fitness(self) -> float: # 6x - x^2 + 4y - y^2

        return 6 * self.x - self.x * self.x + 4 * self.y - self.y * self.y
    @classmethod

    def random_instance(cls) -> SimpleEquation:
        return SimpleEquation(randrange(100), randrange(100))
    def crossover(self, other: SimpleEquation) -> Tuple[SimpleEquation, SimpleEquation]:
        child1: SimpleEquation = deepcopy(self)
        child2: SimpleEquation = deepcopy(other)
        child1.y = other.y
        child2.y = self.y
        return child1, child2
    def mutate(self) -> None:
        if random() > 0.5: # mutate x

            if random() > 0.5:
                self.x += 1

            else:
                self.x -= 1

        else: # otherwise mutate y
            if random() > 0.5:
                self.y += 1

            else:
                self.y -= 1

    def __str__(self) -> str:
        return f"X: {self.x} Y: {self.y} Fitness: {self.fitness()}"
```

copy

`SimpleEquation` conforms to `Chromosome` , and, true to its name, it does so as simply as possible. The genes of a `SimpleEquation` chromosome can be thought of as `x` and `y` . The method `fitness()` evaluates `x` and `y` using the equation $6x – x^2 + 4y – y^2$. The higher the value, the more fit the individual chromosome is, according to `GeneticAlgorithm` . In the case of a random instance, `x` and `y` are initially set to be random integers between 0 and 100, so `random_instance()` does not need to do anything other than instantiate a new `SimpleEquation` with these values. To combine one `SimpleEquation` with another in `crossover()` , the `y` values of the two instances are simply swapped to create the two children. `mutate()` randomly increments or decrements `x` or `y` . And that is pretty much it.

Because `SimpleEquation` conforms to `Chromosome` , we can already plug it into `GeneticAlgorithm` .

Listing 5.10 simple_equation.py continued

```python
if __name__ == "__main__":
    initial_population: List[SimpleEquation] = [SimpleEquation.random_instance() for _ in range(20)]
    ga: GeneticAlgorithm[SimpleEquation] = GeneticAlgorithm(initial_population=initial_population, threshold=13.0,
max_generations = 100, mutation_chance = 0.1, crossover_chance = 0.7)
    result: SimpleEquation = ga.run()
    print(result)
```

copy

The parameters used here were derived through guess-and-check. You can try others. `threshold` is set to 13.0 because we already know the correct answer. When x = 3 and y = 2, the equation evaluates to 13.

If you did not previously know the answer, you might want to see the best result that could be found in a certain number of generations. In that case, you would set `threshold` to some arbitrarily large number. Remember, because genetic algorithms are stochastic, every run will be different.

Here is some sample output from a run in which the genetic algorithm solved the equation in 18 generations.

```
Generation 0 Best -349 Avg -6112.3
Generation 1 Best 4 Avg -1306.7
Generation 2 Best 9 Avg -288.25
Generation 3 Best 9 Avg -7.35
Generation 4 Best 12 Avg 7.25
Generation 5 Best 12 Avg 8.5
Generation 6 Best 12 Avg 9.65
Generation 7 Best 12 Avg 11.7
Generation 8 Best 12 Avg 11.6
X: 3 Y: 2 Fitness: 13
```

copy

As you can see, it came to the proper solution derived earlier with calculus, x = 3 and y = 2. You may also note that almost every generation, it got closer to the right answer. Take into consideration that the genetic algorithm took more computational power than other methods would have to find the solution. In the real world, such a simple maximization problem would not be a good use of a genetic algorithm. But its simple implementation at least suffices to prove that our genetic algorithm works.

5.4 SEND+MORE=MONEY revisited

In chapter 3, we solved the classic cryptarithmetic problem SEND+MORE=MONEY using a constraint-satisfaction framework. (For a refresher on what the problem is all about, please look back to the description in chapter 3.) The problem can also be solved in a reasonable amount of time using a genetic algorithm.

One of the largest difficulties in formulating a problem for a genetic algorithm solution is determining how to represent it. A convenient representation for cryptarithmetic problems is to use list indices as digits.[12] Hence, to represent the 10 possible digits (0, 1, 2, 3, 4, 5, 6, 7, 8, 9), a 10-element list is required. The characters to be searched within the problem can then be shifted around from place to place. For example, if it is suspected that the solution to a problem includes the character "E" representing the digit 4, then list[4] = "E". SEND+MORE=MONEY has 8 distinct letters (S, E, N, D, M, O, R, Y), leaving two slots in the array empty. They can be filled with spaces indicating no letter.

A chromosome that represents the SEND+MORE=MONEY problem is represented in `SendMoreMoney2`. Note how the `fitness()` method is strikingly similar to `satisfied()` from `SendMoreMoneyConstraint` in chapter 3.

Listing 5.11 send_more_money2.py

```
from __future__ import annotations
from typing import Tuple, List
from chromosome import Chromosome
from genetic_algorithm import GeneticAlgorithm
from random import shuffle, sample
from copy import deepcopy
class SendMoreMoney2(Chromosome):
    def __init__(self, letters: List[str]) -> None:
        self.letters: List[str] = letters
    def fitness(self) -> float:
        s: int = self.letters.index("S")
        e: int = self.letters.index("E")
        n: int = self.letters.index("N")
        d: int = self.letters.index("D")
        m: int = self.letters.index("M")
        o: int = self.letters.index("O")
        r: int = self.letters.index("R")
        y: int = self.letters.index("Y")
        send: int = s * 1000 + e * 100 + n * 10 + d
        more: int = m * 1000 + o * 100 + r * 10 + e
        money: int = m * 10000 + o * 1000 + n * 100 + e * 10 + y
        difference: int = abs(money - (send + more))
        return 1 / (difference + 1)
    @classmethod

    def random_instance(cls) -> SendMoreMoney2:
        letters = ["S", "E", "N", "D", "M", "O", "R", "Y", " ", " "]
        shuffle(letters)
        return SendMoreMoney2(letters)
    def crossover(self, other: SendMoreMoney2) -> Tuple[SendMoreMoney2, SendMoreMoney2]:
        child1: SendMoreMoney2 = deepcopy(self)
        child2: SendMoreMoney2 = deepcopy(other)
        idx1, idx2 = sample(range(len(self.letters)), k=2)
        l1, l2 = child1.letters[idx1], child2.letters[idx2]
        child1.letters[child1.letters.index(l2)], child1.letters[idx2] = child1.letters[idx2], l2
        child2.letters[child2.letters.index(l1)], child2.letters[idx1] = child2.letters[idx1], l1
        return child1, child2
    def mutate(self) -> None: # swap two letters' locations

        idx1, idx2 = sample(range(len(self.letters)), k=2)
        self.letters[idx1], self.letters[idx2] = self.letters[idx2], self.letters[idx1]
    def __str__(self) -> str:
        s: int = self.letters.index("S")
        e: int = self.letters.index("E")
        n: int = self.letters.index("N")
        d: int = self.letters.index("D")
        m: int = self.letters.index("M")
        o: int = self.letters.index("O")
        r: int = self.letters.index("R")
        y: int = self.letters.index("Y")
        send: int = s * 1000 + e * 100 + n * 10 + d
        more: int = m * 1000 + o * 100 + r * 10 + e
        money: int = m * 10000 + o * 1000 + n * 100 + e * 10 + y
        difference: int = abs(money - (send + more))
        return f"{send} + {more} = {money} Difference: {difference}"
```

copy

There is, however, a major difference between `satisfied()` in chapter 3 and `fitness()` here. We return `1 / (difference + 1)`. `difference` is the absolute value of the difference between MONEY and SEND+MORE. This represents how far off the chromosome is from solving the problem. If we were trying to minimize the `fitness()` `difference` on its own would be a fine number to return. But because `GeneticAlgorithm` tries to maximize the value of `fitness()`, it needs to be flipped (so smaller values look like larger values), and that is why 1 is divided by `difference`. 1 is added to `difference` first, so that a `difference` of 0 does not yield a `fitness()` of 0 but instead of 1. Table 5.1 should help illustrate how this works.

Table 5.1 How the equation 1 / (difference + 1) yields fitnesses for maximization

difference	difference + 1	fitness (1/(difference + 1))
0	1	1
1	2	0.5

2	3	0.25
3	4	0.125

Remember, lower differences are better and higher fitnesses are better. Because this formula causes those two facts to line up, it works well. Dividing 1 by a fitness value is a simple way to convert a minimization problem into a maximization problem. It does introduce some biases, though, so it is not foolproof[13].

`random_instance()` makes use of the `shuffle()` function in the `random` module. `crossover()` selects two random indices in the `letters` lists of both chromosomes, and swaps letters so that we end up with one letter from the first chromosome in the same place in the second chromosome and vice versa. It performs these swaps in children so that placement of letters in the two children ends up being a combination of the parents. `mutate()` swaps two random locations in the `letters` list.

We can plug `SendMoreMoney2` into `GeneticAlgorithm` just as easily as we plugged in `SimpleEquation`. But be forewarned: this is a fairly tough problem, and it will take a long time to execute if the parameters are not well tweaked. And then there's still some randomness even if one gets them right! The problem may be solved in a few seconds or a few minutes. Unfortunately, that is the nature of genetic algorithms!

Listing 5.12 send_more_money2.py continued

```
if __name__ == "__main__":
    initial_population: List[SendMoreMoney2] = [SendMoreMoney2.random_instance() for _ in range(1000)]
    ga: GeneticAlgorithm[SendMoreMoney2] = GeneticAlgorithm(initial_population=initial_population, threshold=1.0,
max_generations = 1000, mutation_chance = 0.2, crossover_chance = 0.7,
selection_type=GeneticAlgorithm.SelectionType.ROULETTE)
    result: SendMoreMoney2 = ga.run()
    print(result)
```

copy

The following output is from a run that solved the problem in 3 generations using 1000 individuals in each generation (as created above). See if you can mess around with the configurable parameters of `GeneticAlgorithm` and get a similar result with fewer individuals. Does it seem to work better with roulette selection than it does with tournament selection?

```
Generation 0 Best 0.0040650406504065045 Avg 8.854014252391551e-05
Generation 1 Best 0.16666666666666666 Avg 0.001277329479413134
Generation 2 Best 0.5 Avg 0.014920889170684687
8324 + 913 = 9237 Difference: 0
```

copy

This solution indicates that SEND = 8324, MORE = 913, and MONEY = 9237. How is that possible? It looks like letters are missing from the solution. In fact, if M = 0, there are several solutions to the problem not possible in the version from chapter 2. MORE is actually 0913 here, and MONEY is 09237. The 0 is just ignored.

5.5 Optimizing List Compression

Suppose we have some information we want to compress. Suppose that it is a list of items and we do not care about the order of the items, as long as all of them are intact. What order of the items will maximize the compression ratio? Did you even know the order of the items will affect the compression ratio for most compression algorithms?

Of course, the answer will depend on the compression algorithm used. For this example, we will use the `compress()` function from the `zlib` module with its standard settings. The solution is shown here in its entirety for a list of twelve first names. If we don't run the genetic algorithm and we just run `compress()` on the twelve names in the order they were originally presented, the resulting compressed data will be 165 bytes.

Listing 5.13 list_compression.py

```
from __future__ import annotations
from typing import Tuple, List, Any
from chromosome import Chromosome
from genetic_algorithm import GeneticAlgorithm
from random import shuffle, sample
from copy import deepcopy
from zlib import compress
from sys import getsizeof
from pickle import dumps
PEOPLE: List[str] = ["Michael", "Sarah", "Joshua", "Narine", "David", "Sajid", "Melanie", "Daniel", "Wei", "Dean", "Brian",
"Murat", "Lisa"] # 165 bytes compressed

class ListCompression(Chromosome):
    def __init__(self, lst: List[Any]) -> None:
        self.lst: List[Any] = lst
    @property

    def bytes_compressed(self) -> int:
        return getsizeof(compress(dumps(self.lst)))
    def fitness(self) -> float:
        return 1 / self.bytes_compressed
    @classmethod

    def random_instance(cls) -> ListCompression:
        mylst: List[str] = deepcopy(PEOPLE)
        shuffle(mylst)
        return ListCompression(mylst)
    def crossover(self, other: ListCompression) -> Tuple[ListCompression, ListCompression]:
        child1: ListCompression = deepcopy(self)
        child2: ListCompression = deepcopy(other)
        idx1, idx2 = sample(range(len(self.lst)), k=2)
        l1, l2 = child1.lst[idx1], child2.lst[idx2]
        child1.lst[child1.lst.index(l2)], child1.lst[idx2] = child1.lst[idx2], l2
        child2.lst[child2.lst.index(l1)], child2.lst[idx1] = child2.lst[idx1], l1
        return child1, child2
    def mutate(self) -> None: # swap two locations

        idx1, idx2 = sample(range(len(self.lst)), k=2)
        self.lst[idx1], self.lst[idx2] = self.lst[idx2], self.lst[idx1]
    def __str__(self) -> str:
        return f"Order: {self.lst} Bytes: {self.bytes_compressed}"

if __name__ == "__main__":
    initial_population: List[ListCompression] = [ListCompression.random_instance() for _ in range(1000)]
    ga: GeneticAlgorithm[ListCompression] = GeneticAlgorithm(initial_population=initial_population, threshold=1.0,
max_generations = 1000, mutation_chance = 0.2, crossover_chance = 0.7,
selection_type=GeneticAlgorithm.SelectionType.TOURNAMENT)
    result: ListCompression = ga.run()
    print(result)
```

copy

Note how similar this implementation is to the implementation from SEND+MORE=MONEY immediately preceding it. The `crossover()` and `mutate()` functions are essentially the same. In both problems' solutions, we are taking a list of items and continually rearranging them and testing those rearrangements. One could write a generic superclass for both problems' solutions that would work with a wide variety of problems. Any problem that can be represented as a list of items that needs to find its optimal order, could be solved the same way. The only real point of customization for the subclasses would be their respective fitness functions.

If we run `list_compression.py` it may take a very long time to complete. This is because we don't know what constitutes the "right" answer ahead of time, unlike the prior two problems, so we have no real threshold that we are working towards. Instead, we set the number of generations and the number of individuals in each generation to an arbitrarily high number and hope for the best. What is the minimum number of bytes that rearranging the twelve names will yield in compression? Frankly, we don't know the answer to that. In my best run, using the configuration in the above solution, after 546 generations, the genetic algorithm found an order of the 12 names that yielded 159 bytes compressed.

That's only a savings of 6 bytes over the original order. That's a ~4% savings. One may say that 4% is irrelevant, but actually if this were a far larger list that would've been transferred many times over the network, that could add up. Imagine if this were a 1 megabyte list that would eventually be transferred across the Internet 10,000,000 times. If the genetic algorithm could optimize the order of the list for compression to save 4%, it would save ~40 kilobytes per transfer and ultimately 400 gigabytes in bandwidth across all transfers. That's not a huge amount, but perhaps it could be significant enough that it's worth running the algorithm once to find a near optimal order for compression.

Consider this though—we don't really know if we found the optimal order for the 12 names, let alone the hypothetical 1 megabyte list. How would we know if we did? Unless we have a deep understanding of the compression algorithm, we would have to try compressing every possible order of the list. Just for a list of 12 items, that's a fairly unfeasible 479,001,600 possible orders (12!, where ! means factorial). Using a genetic algorithm that attempts to find optimality is perhaps more feasible, even if we don't know if its ultimate solution is truly optimal.

5.6 Challenges for genetic algorithms

Genetic algorithms are not a panacea. In fact, they are not suitable for most problems. For any problem in which a fast deterministic algorithm exists, a genetic algorithm approach does not make sense. Their inherently stochastic nature makes their runtimes unpredictable. To solve this problem, they can be cut off after a certain number of generations. But then it is not clear if a truly optimal solution has been found.

Steven Skiena, author of one of the most popular texts on algorithms, even went so far as to write this:

I have never encountered any problem where genetic algorithms seemed to me the right way to attack it. Further, I have never seen any computational results reported using genetic algorithms that have favorably impressed me.[14]

Skiena's view is a little extreme, but it is indicative of the fact that genetic algorithms should only be chosen when you are reasonably confident that a better solution does not exist. Another issue with genetic algorithms is determining how to represent a potential solution to a problem as a chromosome. The traditional practice is to represent most problems as binary strings (sequences of 1's and 0's, raw bits). This is often optimal in terms of space usage, and it lends itself to easy crossover functions. But most complex problems are not easily represented as divisible bit strings.

Another, more specific issue worth mentioning, is challenges related to the roulette-wheel selection method described in this chapter. Roulette-wheel selection, sometimes referred to as "fitness proportional selection," can lead to a lack of diversity in a population due to the dominance of relatively fit individuals each time selection is run. On the other hand, if fitness values are close together, roulette-wheel selection can lead to a lack of selection pressure[15]. Further, roulette-wheel selection as constructed in this chapter, does not work for problems in which fitness can be measured with negative values, as in our "Simple Equation" example.

In short, for most problems large enough to warrant using them, genetic algorithms cannot guarantee the discovery of an optimal solution in a predictable amount of time. For this reason, they are best utilized in situations that do not call for an optimal solution, but instead a "good enough" solution. They are fairly easy to implement, but tweaking their configurable parameters can take a lot of trial and error.

5.7 Real-world applications

Despite what Skiena wrote, genetic algorithms are frequently and effectively applied in a myriad of problem spaces. They are often used on hard problems that do not require perfectly optimal solutions, such as constraint-satisfaction problems too large to be solved using traditional methods. One example is complex scheduling problems.

Genetic algorithms have found many applications in computational biology. They have been used successfully for protein-ligand docking, which is a search for the configuration of a small molecule when it is bound to a receptor. This is used in pharmaceutical research and to better understand mechanisms in nature.

The Traveling Salesman Problem, which we will revisit in chapter 9, is one of the most famous problems in computer science. A traveling salesman wants to find the shortest route on a map that visits every city exactly once and brings him back to his starting location. It may sound like minimum spanning trees in chapter 4, but it is different. In the Traveling Salesman, the solution is a giant cycle that minimizes the cost to traverse it, whereas a minimum spanning tree minimizes the cost to connect every city. A person traveling a minimum spanning tree of cities may have to visit the same city twice to reach every city. Even though they sound similar, there is no reasonably timed algorithm for finding a solution to the Traveling Salesman problem for an arbitrary number of cities. Genetic algorithms have been shown to find suboptimal, but pretty good, solutions in short periods of time. The problem is widely applicable to the efficient distribution of goods. For example, dispatchers of FedEx and UPS trucks use software to solve the Traveling Salesman problem every day. Algorithms that help solve the problem can cut costs in a large variety of industries.

In computer-generated art, genetic algorithms are sometimes used to mimic photographs using stochastic methods. Imagine fifty polygons placed randomly on a screen and gradually twisted, turned, moved, resized, and changed in color until they match a photograph as closely as possible. The result looks like the work of an abstract artist, or if more angular shapes are used, a stained-glass window.

Genetic algorithms are part of a larger field called evolutionary computation. One area of evolutionary computation closely related to genetic algorithms is *genetic programming*, in which programs use the selection, crossover, and mutation operations to modify themselves to find non-obvious solutions to programming problems. Genetic programming is not a widely used technique, but imagine a future where programs write themselves.

A benefit of genetic algorithms is that they lend themselves to easy parallelization. In the most obvious form, each population can be simulated on a separate processor. In the most granular form, each individual can be mutated, crossed, and have its fitness calculated in a separate thread. There are also many possibilities in between.

5.8 Exercises

1. Add support to `GeneticAlgorithm` for an advanced form of tournament selection that may sometimes choose the second or third best chromosome, based on a diminishing probability.
2. Add a new function to the constraint-satisfaction framework from chapter 3 that solves any arbitrary `CSP` using a genetic algorithm. A possible measure of fitness is the number of constraints that are resolved by a chromosome.
3. Create a class, `BitString` , that implements `Chromosome` . Recall what a bit string is from chapter 1. Then use your new class to solve the Simple Equation problem from earlier in this chapter. How can the problem be encoded as a bit string?

[11] Artem Sokolov and Darrell Whitley, "Unbiased Tournament Selection," GECCO'05 (June 25–29, 2005, Washington, D.C., U.S.A.), http://mng.bz/S7l6.

[12] Reza Abbasian and Masoud Mazloom, "Solving Cryptarithmetic Problems Using Parallel Genetic Algorithm," 2009 Second International Conference on Computer and Electrical Engineering, http://mng.bz/RQ7V.

[13] For example, it possible that we will end up with more numbers closer to 0 than we will closer to 1 if we were to simply divide 1 by a uniform distribution of integers, which with the subtleties of how typical microprocessors interpret floating point numbers could lead to some unexpected results. An alternative way to convert a minimization problem into a maximization problem is to simply flip the sign (make them negative instead of positive). However, this will only work if our values are all positive to begin with.

[14] Steven Skiena, *The Algorithm Design Manual*, 2nd edition (Springer, 2009), p. 267

[15] A.E. Eiben and J.E. Smith, *Introduction to Evolutionary Computation*, 2nd edition (Springer, 2015), p. 80