

Genetic Algorithms

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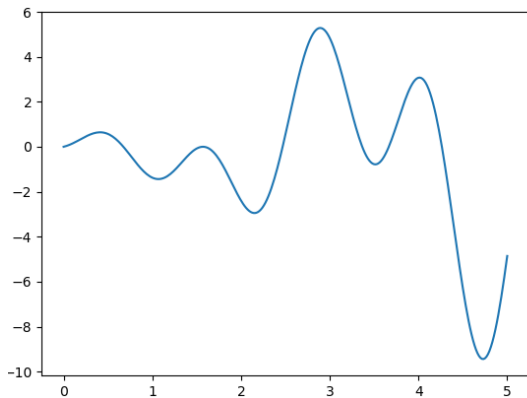
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A Working Example

Find x that maximize the following function?

$$f(x) = x \sin(5x) + x \cos(2x)$$



Initialize random population

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pop = np.random.randint(2, size=(POP_SIZE, CHROMOSOME_SIZE))
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- The CHROMOSOME_SIZE will be chosen such that the precision of the solution is up to certain value.
- For instance, what is the float point precision of the solution that we need from 0 to 5?

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- To **decode the entire population** at once:

```
def Decode(pop):  
    return pop.dot(2 ** np.arange(CHROMOSOME_SIZE)[::-1]) * X_MAX / float(2**(CHROMOSOME_SIZE-1))
```

Reproduction

```
def reproduction(pop, fitness):    # nature selection wrt pop's fitness
    idx = np.random.choice(np.arange(POP_SIZE), size=POP_SIZE, replace=True,
                           p=fitness/fitness.sum())
    return pop[idx]
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- `np.random.choice` can take a probability `p` of associated with each individual in the population `pop`
- A roulette wheel selection in just a single line.

Crossover

```
def crossover(parent1, parent2):    # mating process (genes crossover)
    if np.random.rand() < CROSS_RATE:
        cross_over_site = np.random.randint(0, CHROMOSOME_SIZE) # choose crossover site
        child1 = np.concatenate((parent1[0:cross_over_site],parent2[cross_over_site:]))
        child2 = np.concatenate((parent2[0:cross_over_site],parent1[cross_over_site:]))
    else:
        child1, child2 = parent1, parent2
    return child1, child2
```

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- Mating between two parents parent1 and parent1 if the probability is less than the CROSS_RATE
- Single point crossover.
- Two offsprings are generated.

Mutation

```
def mutate(child):  
    for point in range(CHROMOSOME_SIZE):  
        if np.random.rand() < MUTATION_RATE:  
            child[point] = 1 - child[point]  
    return child
```

- Each bit can be mutated (i.e., flipped) with probability `MUTATION_RATE`
- Single point crossover.
- Two offsprings are generated.

Main Loop

- Below is the main operations done by a simple GA
- Mating the first half of the population with the second half.

```
pop = reproduction(pop, fitness)
pop = np.random.permutation(pop)
i = 0
while i < len(pop)//2 :
    parent1 = pop[i]
    parent2 = pop[-(i+1)]
    child1, child2 = crossover(parent1, parent2)
    child1 = mutate(child1)
    child2 = mutate(child2)
    pop[i] = child1
    pop[-i] = child2
    i+=1
```

References

- Goldenberg, D.E., 1989. Genetic algorithms in search, optimization and machine learning.
- Michalewicz, Z., 2013. Genetic algorithms + data structures= evolution programs. Springer Science & Business Media

Thank
You!



Questions 

