

Continuous Cellular Automata and Gene Evolution

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Agenda

- 01 Introduction
- 02 Method
- 03 Modeling & Result
- 04 Demo



Introduction

- **Continuous cellular automata (CCA)** is a form of artificial life. It was derived from Conway's Game of Life by making everything smooth, continuous and generalized. These digital creatures show lifelike features like self-organization, self-repair, bilateral and radial symmetries, locomotive dynamics, and sometimes chaotic nature.
- In 2020, further extension of CCA led to more emergent phenomena, like interesting 3D/4D patterns, self-replication, pattern emission, self-boundary/individuality, aggregated patterns, polymorphism, intercommunicating colonies, etc.
- **Gene evolution** is the process by which a gene changes in structure and sequence over time. Genetic algorithm is a search heuristic method that imitates genetic evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.



Research Directions

- Artificial Life
- Artificial Intelligence
- Theoretical Biology
- Computer Science
- Mathematics & Physics
- Digital Art



Method

The process of Continuous Cellular Automata:

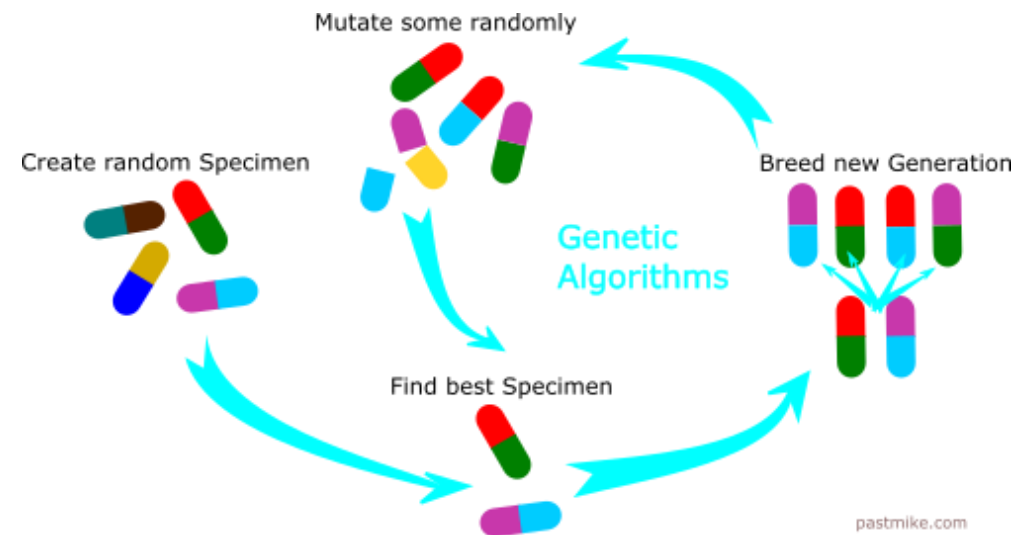
1. Take a 2D array (world A) of real values between 0 and 1, initialize with an initial pattern A0.
2. Every cell A0 interacts with its eight neighbours, which are the cells that are horizontally, vertically, or diagonally adjacent. At each step in time, the following transitions occur:
3. Any live cell with fewer than two live neighbours dies, as if by underpopulation.
4. Any live cell with two or three live neighbours lives on to the next generation.
5. Any live cell with more than three live neighbours dies, as if by overpopulation.
6. Any dead cell with exactly three live neighbours becomes a live cell, as if by reproduction.
7. Repeat steps 2-7 for each time-step.



Method

Five phases are considered in a genetic algorithm:

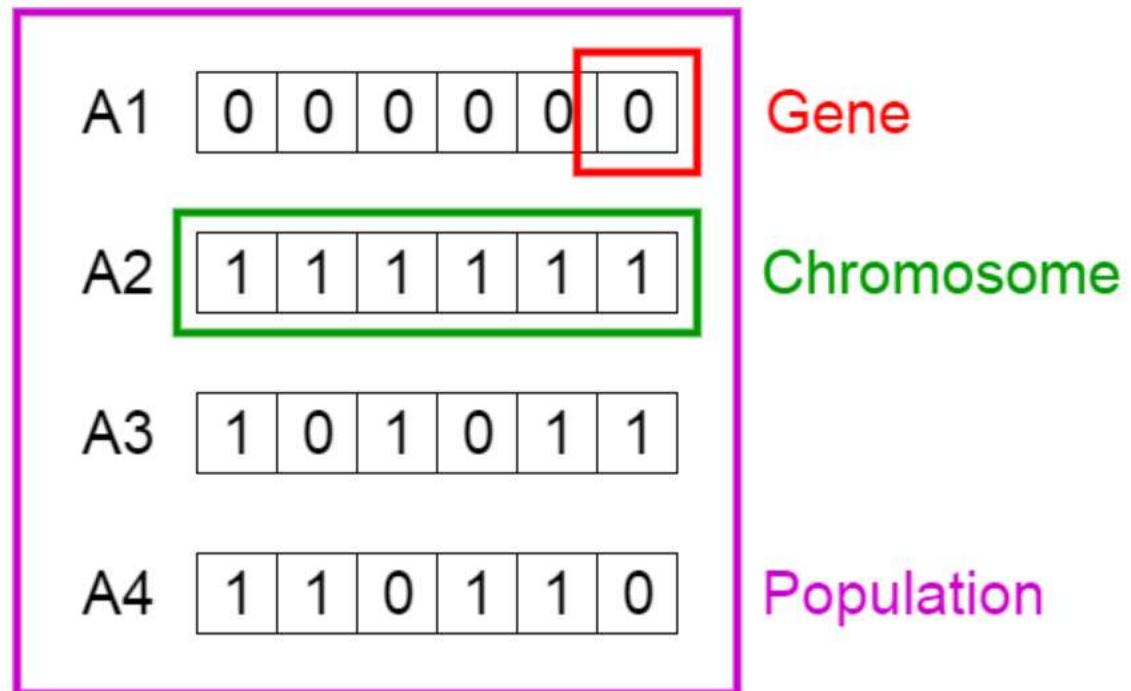
1. Initial population
2. Fitness function
3. Selection
4. Crossover
5. Mutation



Method

Five phases are considered in a genetic algorithm:

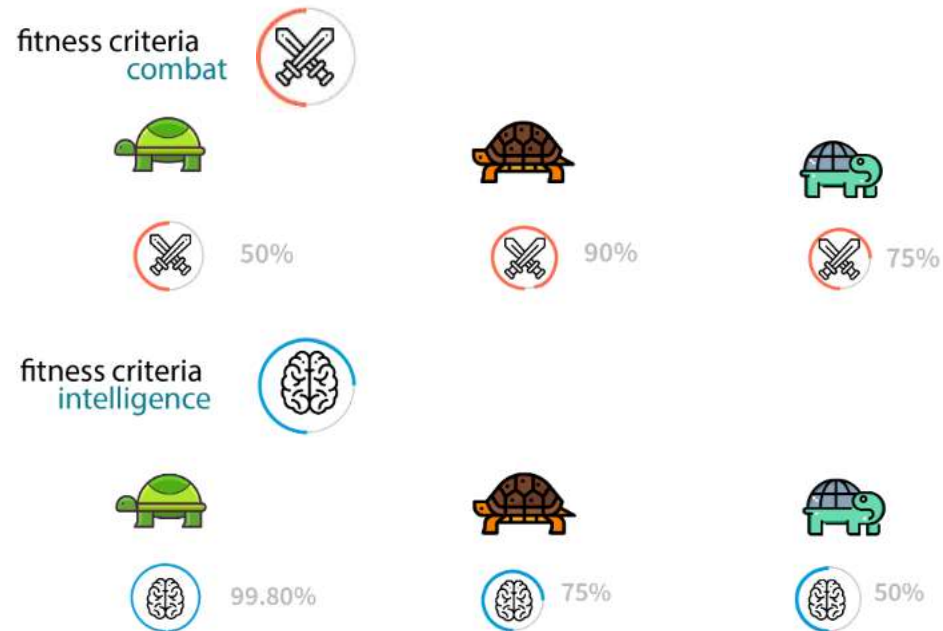
1. **Initial population**
2. Fitness function
3. Selection
4. Crossover
5. Mutation



Method

Five phases are considered in a genetic algorithm:

1. Initial population
- 2. Fitness function**
3. Selection
4. Crossover
5. Mutation

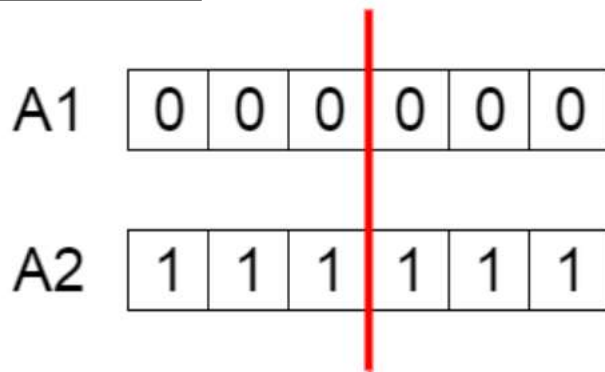


Method

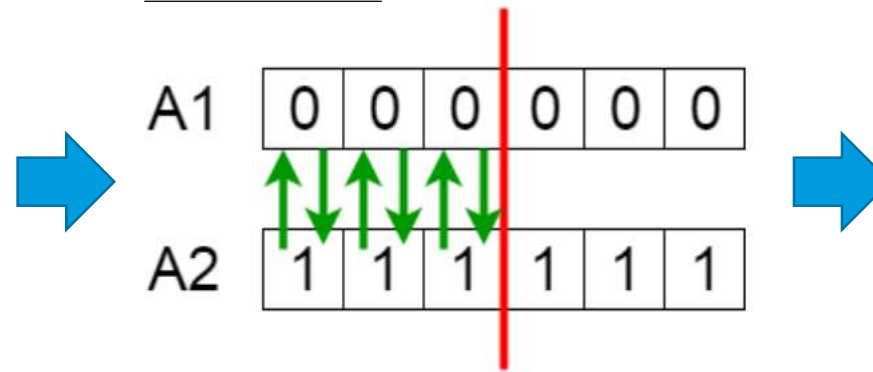
Five phases are considered in a genetic algorithm:

1. Initial population
2. Fitness function
3. **Selection**
4. **Crossover**
5. Mutation

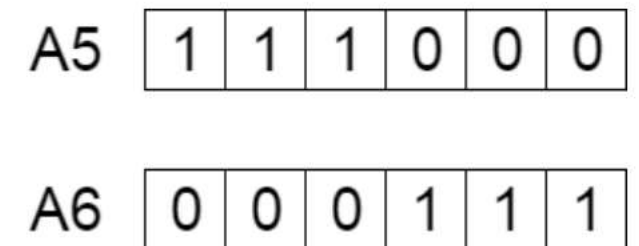
Selection



Crossover



New offspring



Method

Five phases are considered in a genetic algorithm:

1. Initial population
2. Fitness function
3. Selection
4. Crossover
5. **Mutation**

Before Mutation

A5

1	1	1	0	0	0
---	---	---	---	---	---

After Mutation

A5

1	1	0	1	1	0
---	---	---	---	---	---

Mutation: Before and After



Modeling & Result - Continuous Cellular Automata

Step-1: define the neighbours

```
def alive(x,i,j):  
    if(i>=0):  
        if(i<=n-1):  
            if(j>=0):  
                if(j<=m-1):  
                    return x[i,j]  
  
    if(i<0):  
        return 0  
    if(j<0):  
        return 0  
    if(i>n-1):  
        return 0  
    if(j>m-1):  
        return 0
```

For Example: A0 = Array(3X5)

0	0	0	0	0	0	0
0						0
0		1	1	1		0
0						0
0						0
0	0	0	0	0	0	0



Modeling & Result - Continuous Cellular Automata

```
def play(x,n,m):
    #x2=np.zeros((11,11))
    #n,m=x.shape[0],x.shape[1]
    for i in range(n):
        for j in range(m):
            s = alive(x,i+1,j)+alive(x,i+1,j+1)+alive(x,i+1,j-1)
                +alive(x,i,j-1)+alive(x,i,j+1)
                +alive(x,i-1,j)+alive(x,i-1,j-1)+alive(x,i-1,j+1)
            s = int(s)
            x2[i,j] = s

    for i in range(n):
        for j in range(m):
            if(x[i,j]==1):
                if(x2[i,j]!=2):
                    if(x2[i,j]!=3):
                        x[i,j]=0

    for i in range(n):
        for j in range(m):
            if(x[i,j]==0):
                if(x2[i,j]==3):
                    x[i,j]=1
    return(x)
```

Step-2

0	0	0	0	0	0	0
0						0
0		1	1	1		0
0						0
0						0
0	0	0	0	0	0	0

0	0	0	0	0	0	0
0	1	2	3	2	1	0
0	1	1	2	1	1	0
0	1	2	3	2	1	0
0						0
0	0	0	0	0	0	0

Step-3

0	0	0	0	0	0	0
0						0
0		0	1	0		0
0						0
0						0
0	0	0	0	0	0	0

Step-4

0	0	0	0	0	0	0
0			1			0
0		0	1	0		0
0			1			0
0						0
0	0	0	0	0	0	0



Modeling & Result - Continuous Cellular Automata

- Results:

```
for i in range(10):  
    print("Generation: ",i)  
    print(x)  
    x=play(x,n,m)
```

Generation: 0

```
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0.]  
 [0. 0. 1. 1. 1. 1. 1. 1. 1. 0. 0. 0.]  
 [0. 0. 0. 1. 1. 1. 1. 1. 1. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Generation: 1

```
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.]  
 [0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.]  
 [0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Generation: 2

```
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0.]  
 [0. 0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 0.]  
 [0. 1. 1. 1. 0. 0. 0. 1. 1. 1. 0. 0.]  
 [0. 0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 0.]  
 [0. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Generation: 3

```
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.]  
 [0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0.]  
 [0. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 0.]  
 [0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0.]  
 [0. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Generation: 4

```
[[0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]  
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]  
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]  
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]  
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]]
```

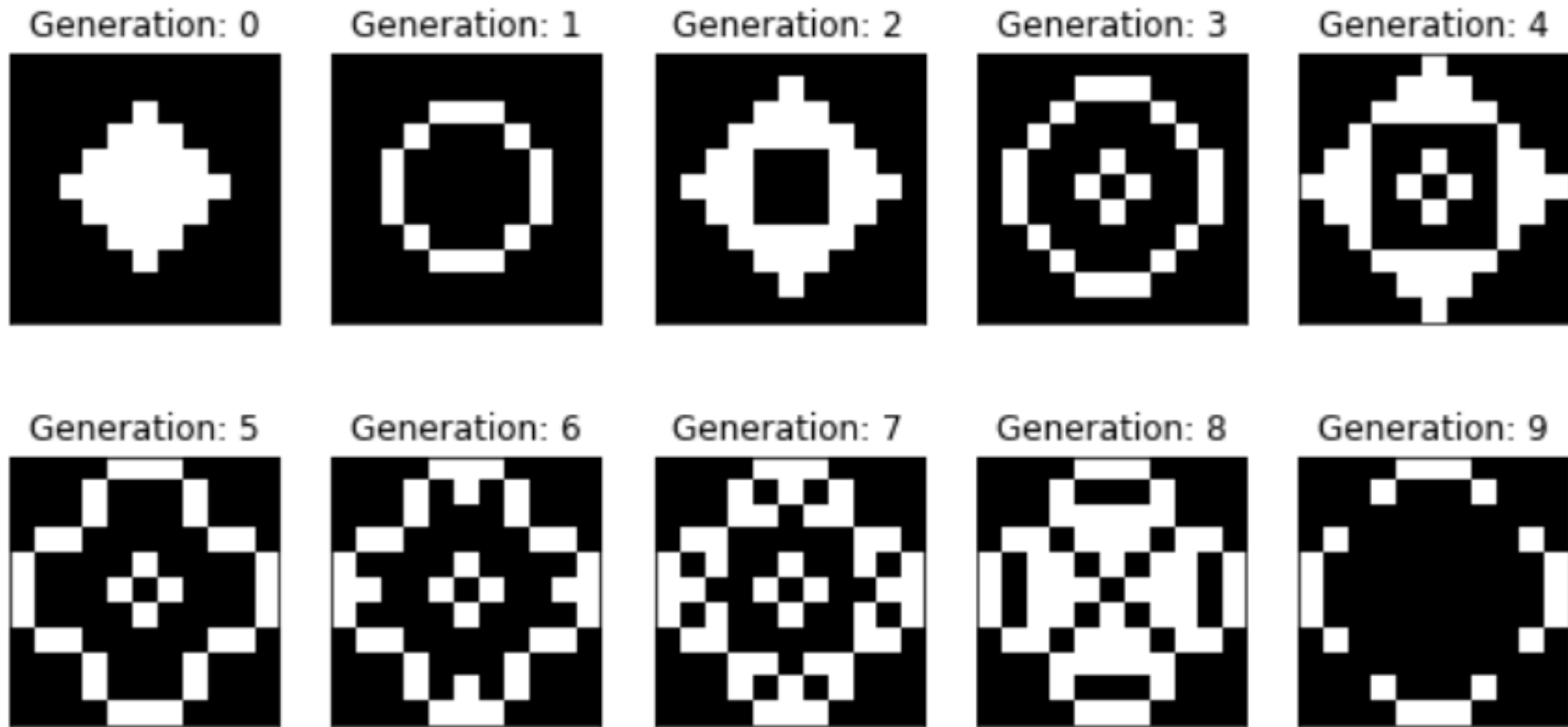
Generation: 5

```
[[0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 1.]  
 [1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 1.]  
 [1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 1.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]  
 [0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0.]]
```



Modeling & Result - Continuous Cellular Automata

- Results:



Modeling & Result - Gene Evolution

Five phases are considered in a genetic algorithm:

1. **Initial population**
2. Fitness function
3. Selection
4. Crossover
5. Mutation

```
pop = np.random.randint(2, size=(POP_SIZE, DNA_SIZE))  
pop
```

```
array([[0, 0, 0, 0, 0, 1, 0, 0, 0, 0],  
       [1, 1, 1, 0, 1, 0, 0, 0, 1, 0],  
       [1, 1, 0, 1, 1, 1, 1, 1, 0, 0],  
       [1, 0, 0, 1, 1, 1, 1, 1, 1, 0],  
       [0, 0, 1, 0, 1, 0, 1, 0, 0, 0],  
       [0, 0, 0, 0, 0, 0, 0, 1, 1, 1],  
       [0, 0, 0, 0, 1, 1, 1, 0, 0, 1],  
       [1, 0, 1, 0, 0, 1, 0, 1, 1, 0],  
       [1, 0, 0, 0, 0, 1, 1, 0, 0, 1],  
       [0, 1, 1, 0, 1, 1, 0, 1, 1, 1],  
       [0, 0, 0, 0, 0, 0, 1, 0, 1, 0],  
       _  
       _  
       _])
```

```
pop.shape
```

```
(100, 10)
```

Modeling & Result - Gene Evolution

Five phases are considered in a genetic algorithm:

1. Initial population
- 2. Fitness function**
3. Selection
4. Crossover
5. Mutation

```
def F(x):  
    return np.sin(10*x)*x + np.cos(2*x)*x
```

```
def translateDNA(pop):  
    return pop.dot(2 ** np.arange(DNA_SIZE)[::-1]) / float(2**DNA_SIZE-1) * X_BOUND[1]
```

```
F_values = F(translateDNA(pop))
```

```
F_values.min(),F_values.max()
```

```
(-9.480744870638143, 6.421816483484863)
```

```
def get_fitness(pred):  
    return pred + 1e-3 - np.min(pred)
```

```
fitness = get_fitness(F_values)
```

```
fitness.min(),fitness.max()
```

```
(0.00099999999999994458, 15.903561354123006)
```



Modeling & Result - Gene Evolution

Five phases are considered in a genetic algorithm:

1. Initial population
2. Fitness function
- 3. Selection**
4. Crossover
5. Mutation

```
def select(pop, fitness):  
    idx = np.random.choice(np.arange(POP_SIZE), size=POP_SIZE, replace=True,  
                           p=fitness/fitness.sum())  
    return pop[idx]
```

5.1 Convert the fitness value content of Array 100X1 (0~15) into probability p

5.2 According to 100 probability values p, from 0~99 (np.arange(POP_SIZE)), randomly select 100 (POP_SIZE=100), and then put it back (replace=True)



Modeling & Result - Gene Evolution

Five phases are considered in a genetic algorithm:

1. Initial population
2. Fitness function
3. Selection
- 4. Crossover**
5. Mutation

```
CROSS_RATE = 0.8
def crossover(parent, pop):
    if np.random.rand() < CROSS_RATE:
        i_ = np.random.randint(0, POP_SIZE, size=1)
        cross_points = np.random.randint(0, 2, size=DNA_SIZE).astype(np.bool)
        parent[cross_points] = pop[i_, cross_points]
    return parent
```

Randomly select n from the 10 genes in the original DNA for exchange. Cross rate is 80%.



Modeling & Result - Gene Evolution

Five phases are considered in a genetic algorithm:

1. Initial population
2. Fitness function
3. Selection
4. Crossover
- 5. Mutation**

```
MUTATION_RATE = 0.003
def mutate(child):
    for point in range(DNA_SIZE):
        if np.random.rand() < MUTATION_RATE:
            child[point] = 1 if child[point] == 0 else 0
    return child
```

Randomly take offspring (probability: 0.003) for mutation, and exchange 0 and 1 if they are taken.

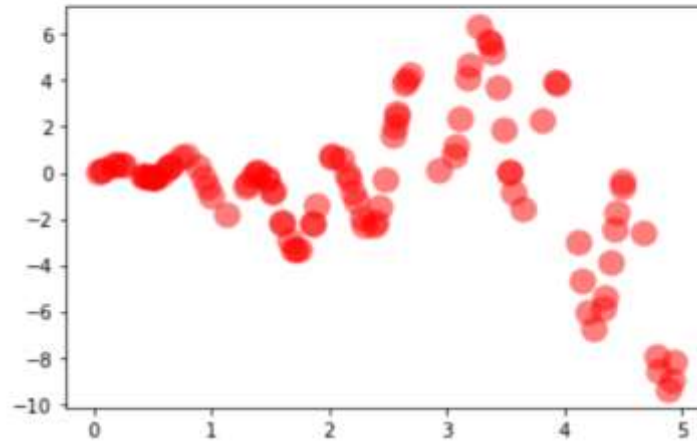


Modeling & Result - Gene Evolution

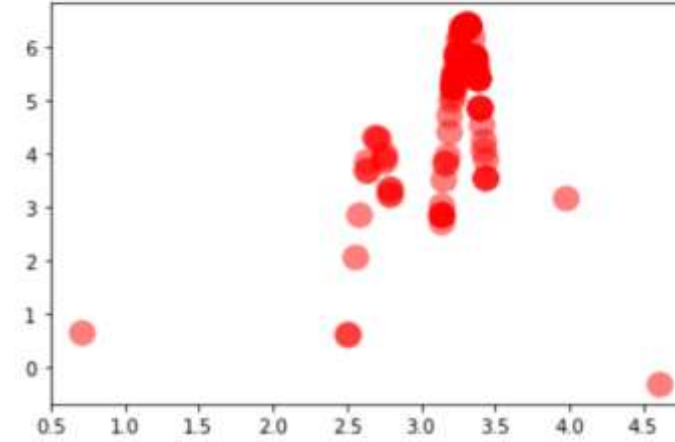
- Results:

```
def F(x):  
    return np.sin(10*x)*x + np.cos(2*x)*x
```

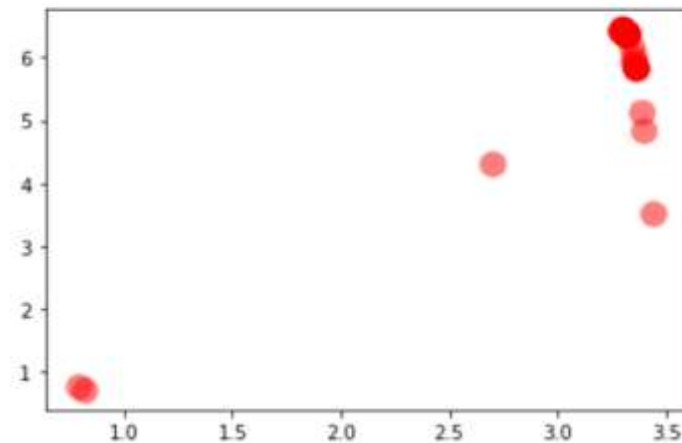
Generation: 0
Max F_values: -52.93535435940143



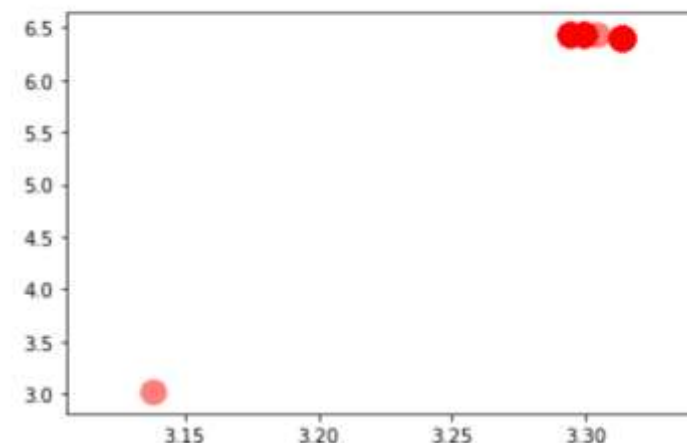
Generation: 9
Max F_values: 478.68016877484087



Generation: 31
Max F_values: 615.7142780895558



Generation: 49
Max F_values: 636.8499638035497

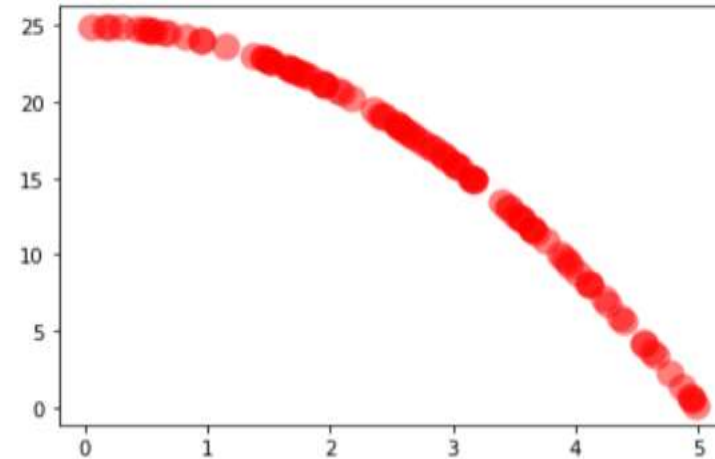


Modeling & Result - Gene Evolution

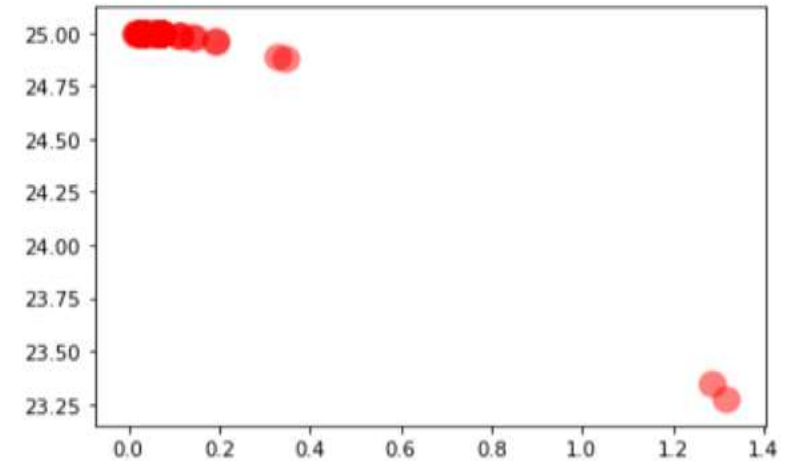
- Results:

```
def F(x): return -x**2+25
```

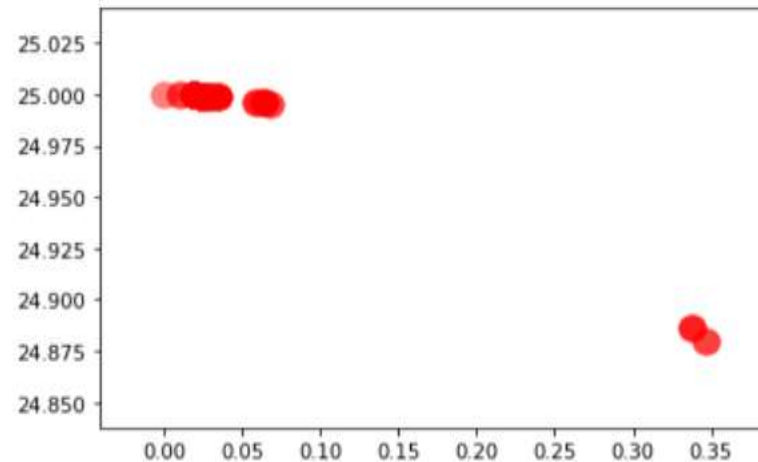
Generation: 0
Max F_values: 1617.0549024441748



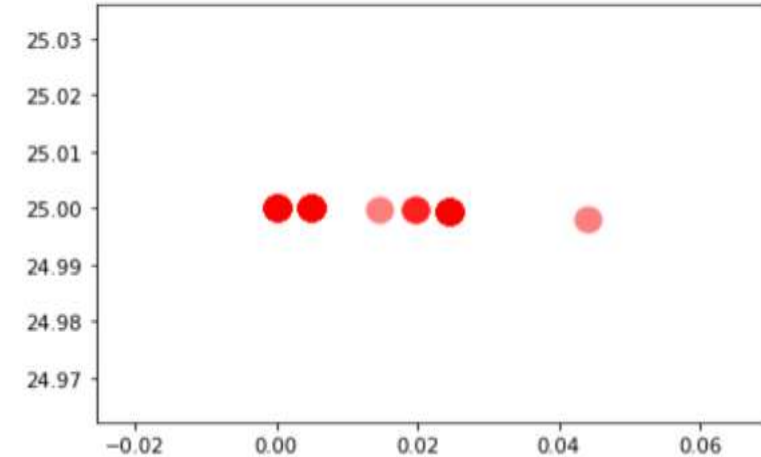
Generation: 19
Max F_values: 2496.0511366622422



Generation: 67
Max F_values: 2499.32966501645



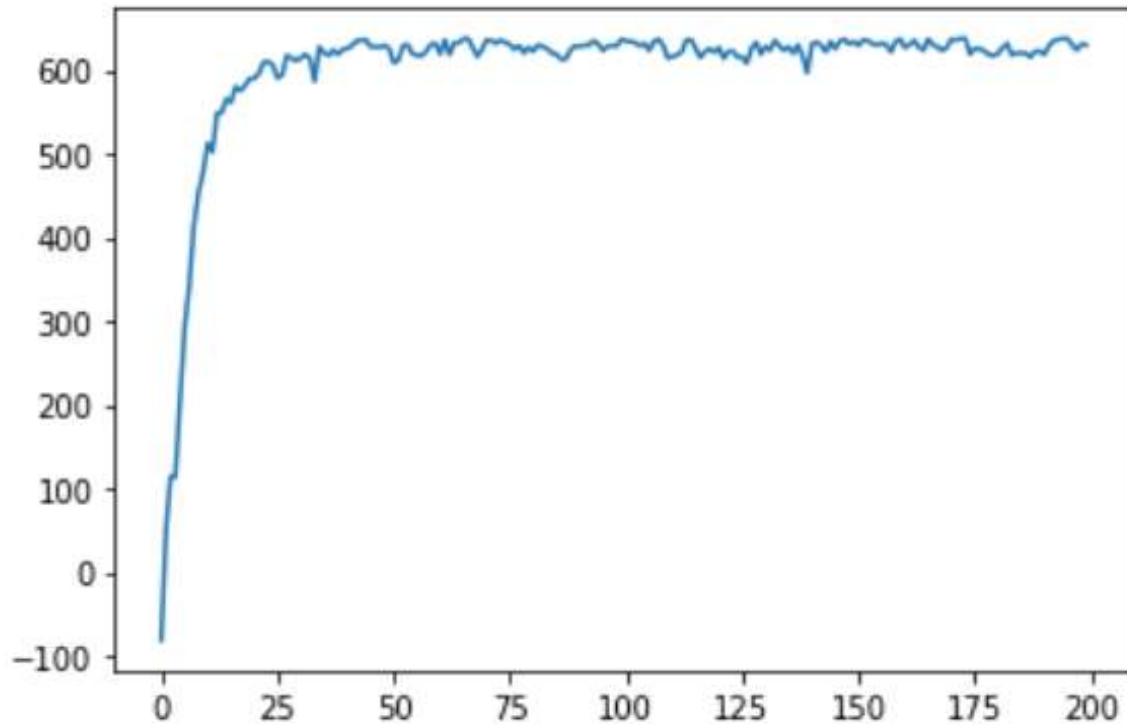
Generation: 134
Max F_values: 2499.9861924514275



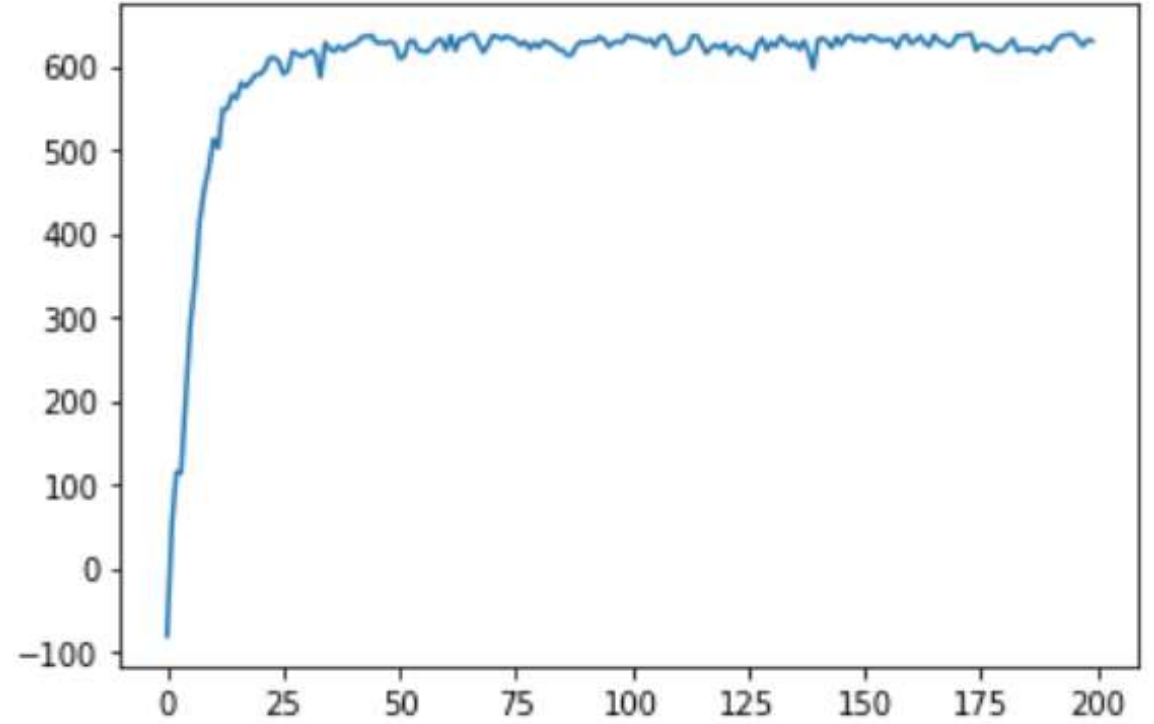
Modeling & Result - Gene Evolution

- Results:

```
def F(x):  
    return np.sin(10*x)*x + np.cos(2*x)*x
```



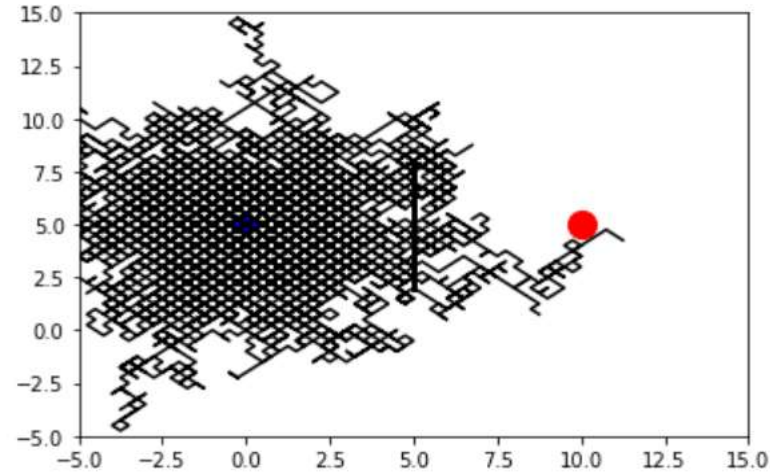
```
def F(x): return -x**2+25
```



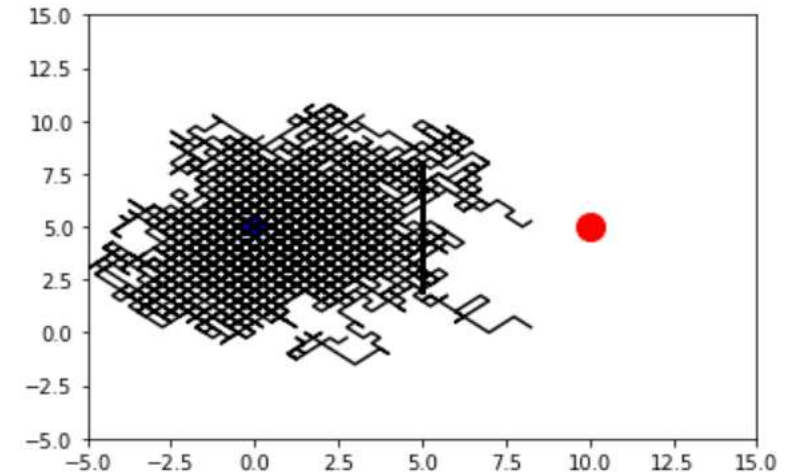
Modeling & Result - Gene Evolution

- Results:
Find the Path

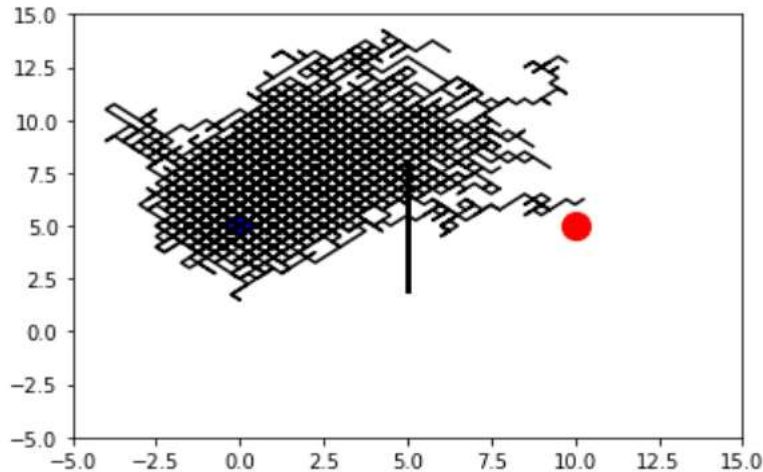
Gen: 0 | best fit: 0.02249173111529981



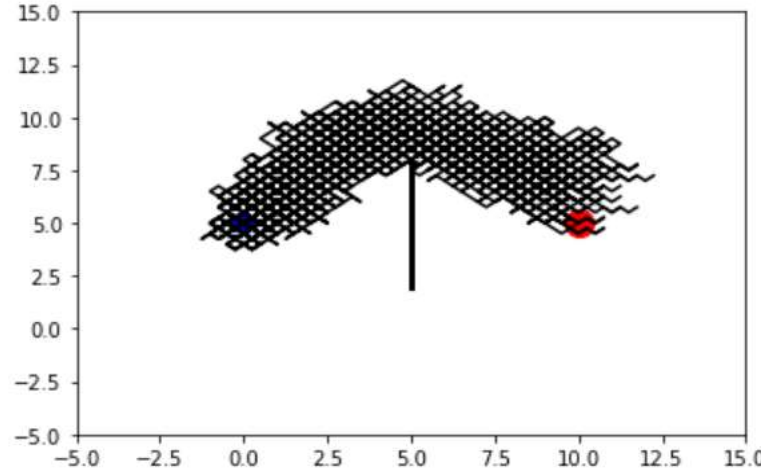
Gen: 9 | best fit: 0.021912590293173776



Gen: 31 | best fit: 0.06744963495484023



Gen: 39 | best fit: 0.3119016527346512



Gen: 99 | best fit: 0.545819714368591

