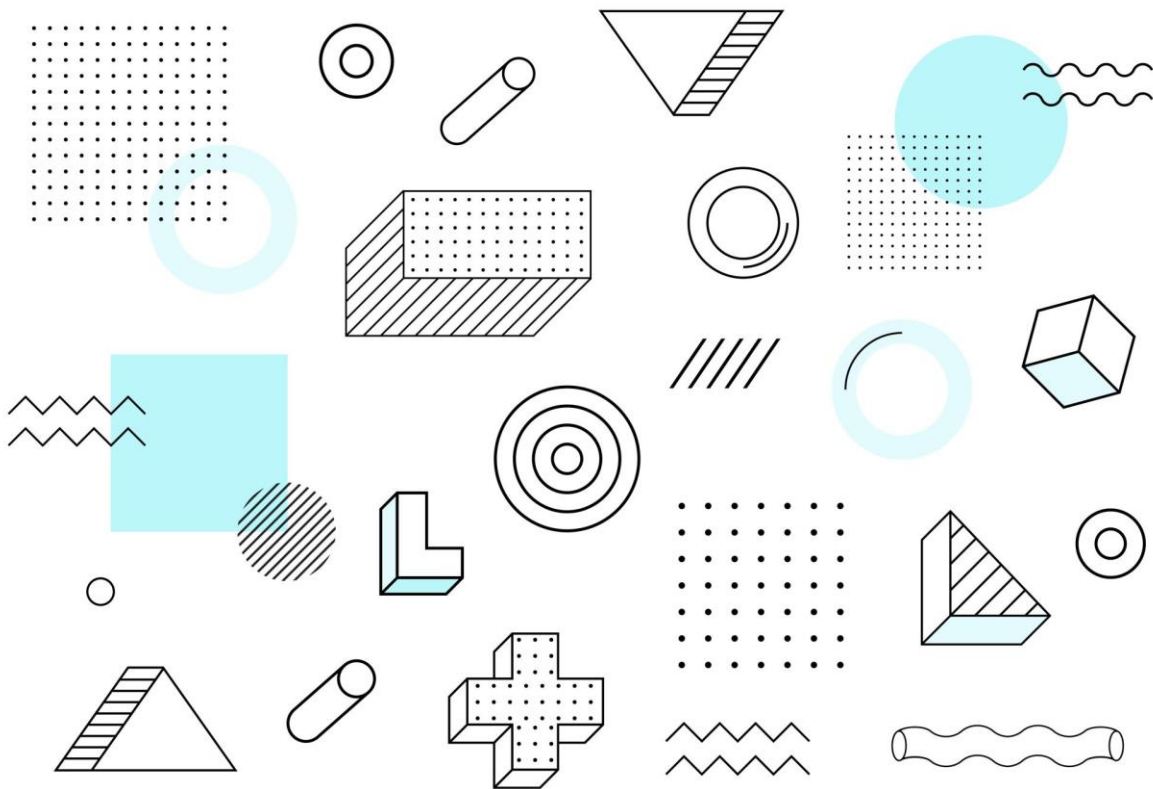




# Planning Techniques for Robotics

## Lab 03 – Genetic Algorithm (Practical)

**Eng. Yousef Elbaroudy**

2025/2026

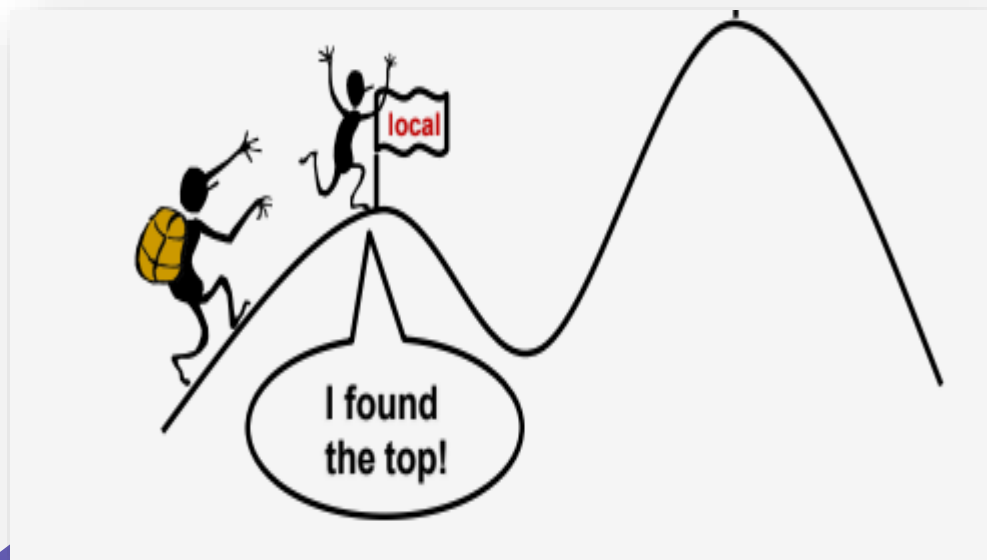
# GUIDELINES

- ❖ **You don't need to memorize what will be mentioned. Instead, try to understand**
- ❖ **Each PowerPoint Presentation will be available as PDF file on Google Drive Folder of the Course**

# Genetic Algorithm (Recap)



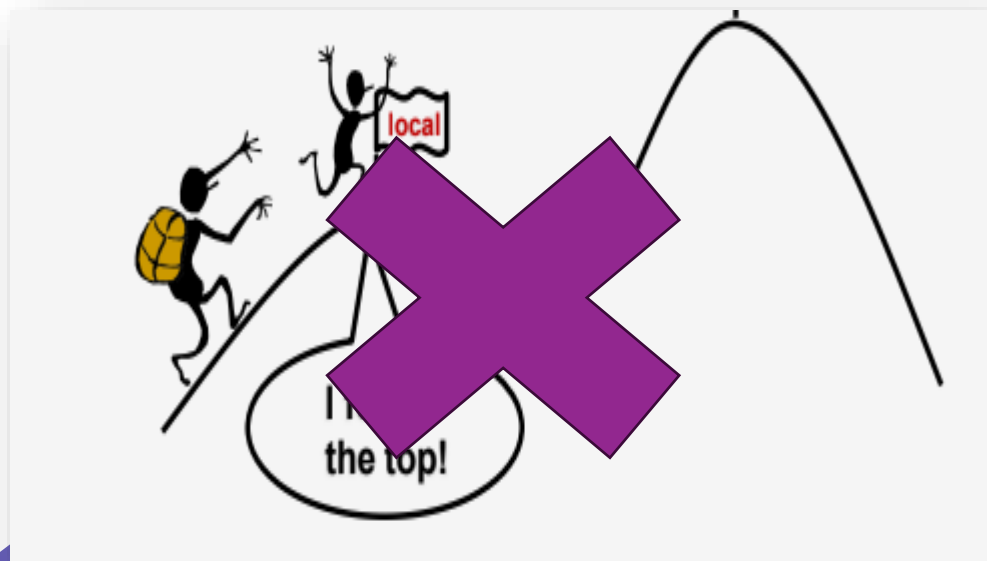
**Genetic Algorithm (GA)** is a method for **solving optimization and search problems** by mimicking the process of **natural evolution**. It's especially useful when the search space is huge, complex, or poorly understood.



# Genetic Algorithm (Recap)



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# Genetic Algorithm (Recap)



**Genetic Algorithm (GA)** is a method for **solving optimization and search problems** by mimicking the process of **natural evolution**. It's especially useful when the search space is huge, complex, or poorly understood.

**The Genetic Algorithm (Mainly all meta-heuristic algorithms)** uses multiple climbers in parallel to find the global optimum **(a population-based algorithm)**.

GA's are useful for solving multidimensional problems containing many local maxima (or minima) in the solution space.

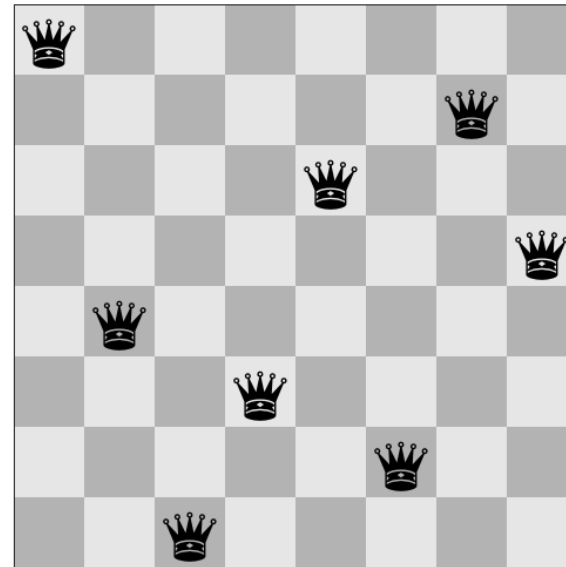
# Common Problem to Solve (Recap)

## 8-Queen Problem

placing eight chess queens on an  $8 \times 8$  chessboard so that  
no two queens threaten each other

The problem is considered a **constraint satisfaction problem**, where each queen must satisfy a set of constraints: no two queens may share the same row, column, or diagonal.

Since the board positions are discrete and the number of possible configurations is finite but large, it is also a **combinatorial problem**.





# Implementation

8-Queen Problem

# Eight Queens class (Initialize population)

```
# Represent the problem
class eight_queens:
    def __init__(self, population_size, crossover_probability, mutation_probability, num_of_generations):
        self._population_size = population_size
        self._crossover_probability = crossover_probability
        self._mutation_probability = mutation_probability
        self._num_of_generations = num_of_generations

        self._population = []
        one_individual = [0] * 8
        for i in range(self._population_size):
            copy = one_individual.copy()
            for j in range(8):
                copy[j] = random.randint(0,7)

            self._population.append(copy)
```

Columns as indices  
(i.e. queen 1 at col 0)

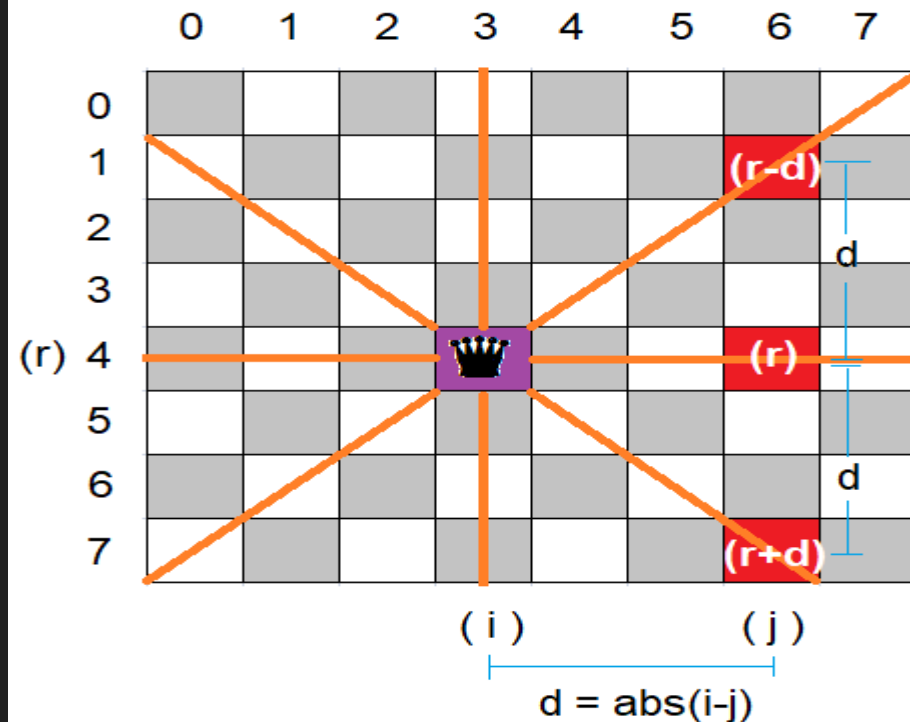
|   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|
| 5 | 0 | 4 | 1 | 7 | 2 | 6 | 3 |
|   | ♔ |   |   |   |   |   |   |
|   |   |   | ♔ |   |   |   |   |
|   |   |   |   |   | ♔ |   |   |
|   |   |   |   |   |   |   | ♔ |
|   |   | ♔ |   |   |   |   |   |
| ♔ |   |   |   |   |   |   |   |
|   |   |   |   |   |   | ♔ |   |
|   |   |   |   | ♔ |   |   |   |

Rows as elements where  
the queen exists

I will represent (encode) each individual as 8-indices as **columns**, each index will be the number of **row** which the queen exists

# EIGHT QUEENS CLASS (CALCULATE FITNESS METHOD)

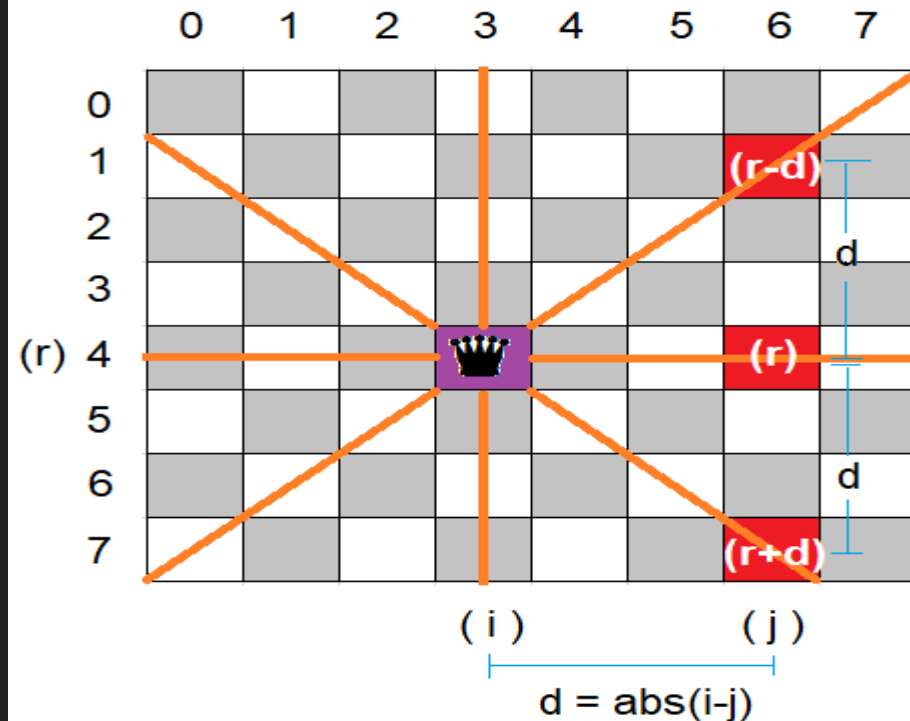
```
def __calculate_fitness(self):  
    fitness_values = []  
    for individual in self.__population:  
        penalty = 0  
        for queen in range(len(individual)):  
            for threat in range(len(individual)):  
                if queen == threat:  
                    continue  
                i = queen  
                j = threat  
                r = individual[queen]  
                d = abs(i - j)  
                if individual[threat] in [r, r-d, r+d]:  
                    penalty += 1  
            fitness_values.append(-penalty)  
    return fitness_values
```



## EIGHT QUEENS CLASS (CALCULATE FITNESS METHOD)

Each threat will be considered as penalty which is the number of mistakes

```
def __calculate_fitness(self):  
    fitness_values = []  
    for individual in self.__population:  
        penalty = 0  
        for queen in range(len(individual)):  
            for threat in range(len(individual)):  
                if queen == threat:  
                    continue  
                i = queen  
                j = threat  
                r = individual[queen]  
                d = abs(i - j)  
                if individual[threat] in [r, r-d, r+d]:  
                    penalty += 1  
            fitness_values.append(-penalty)  
    return fitness_values
```



We will multiply each penalty by -1 to indicate that refers to mistakes

# Eight Queens class (Selection Method)

To change the interval of the penalty  $\rightarrow \text{fitness} = \text{penalty} + \text{abs}(\text{minimum}) + 1$

```
def _selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

**We needed to do that to keep the best individual with highest fitness  $\rightarrow$  Maximize**

# Eight Queens class (Selection Method)

```
def __selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
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    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

Assume that we have three fitness  
[12, 7, 3]

# Eight Queens class (Selection Method)

```
def __selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
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    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

Assume that we have three fitness  
[12, 7, 3]  $\rightarrow$  [-12, -7, -3]  
After changing its interval it should be  
[1, 6, 10]

# Eight Queens class (Selection Method)

```
def __selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

Assume that we have three fitness  
[12, 7, 3]  
After changing its interval it should be  
[1, 6, 10]  
To calculate their probabilities, we  
should obtain the sum = 17

# Eight Queens class (Selection Method)

```
def __selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

Assume that we have three fitness  
[12, 7, 3]  
After changing its interval it should be  
[1, 6, 10]  
To calculate their probabilities, we  
should obtain the sum = 17  
Now divide each value on the sum  
[1/17, 6/17, 10/17] = [0.05, 0.35, 0.58]

# Eight Queens class (Selection Method)

```
def __selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

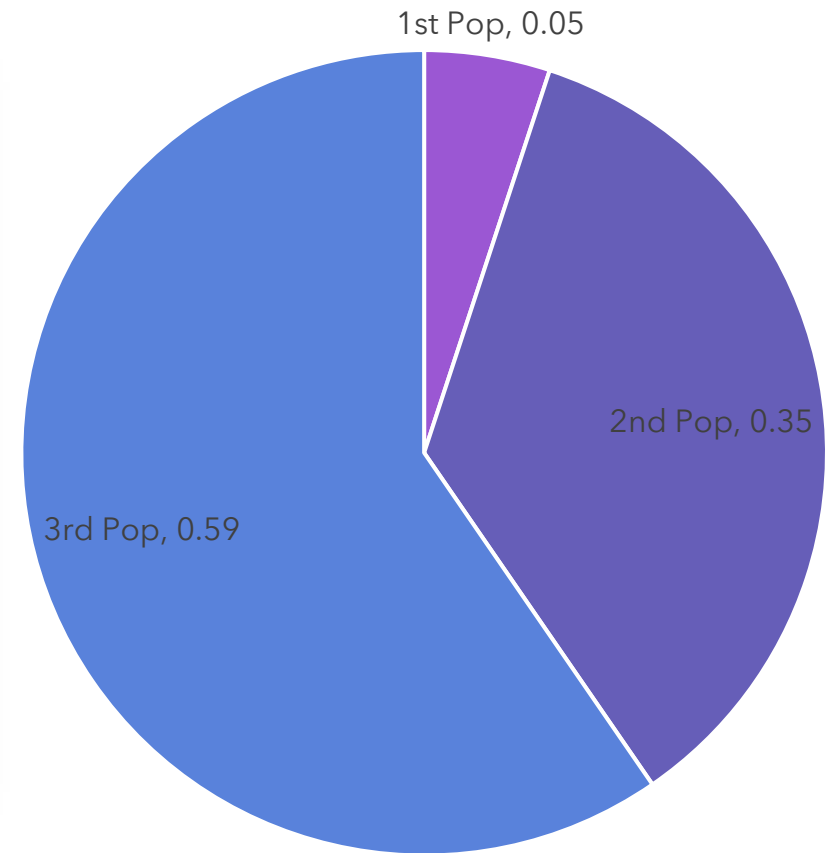
Assume that we have three fitness  
[12, 7, 3]  
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To calculate their probabilities, we  
should obtain the sum = 17  
Now divide each value on the sum  
[1/17, 6/17, 10/17] = [0.05, 0.35, 0.58]

**That's why we changed the interval,  
to keep the best fitness with highest  
probability**

# Eight Queens class (Selection Method)

## Roulette Wheel

```
def _selection(self, fitness_vals):  
    fitness_values = fitness_vals.copy()  
    minimum_fitness = abs(min(fitness_values)) + 1  
    scaled_fitness = [value + minimum_fitness for value in fitness_values]  
    sum_of_fitness = sum(scaled_fitness)  
    probabilities = [value/sum_of_fitness for value in scaled_fitness]  
  
    selected_population = random.choices(self.__population, k = self.__population_size, weights=probabilities)  
    return selected_population
```

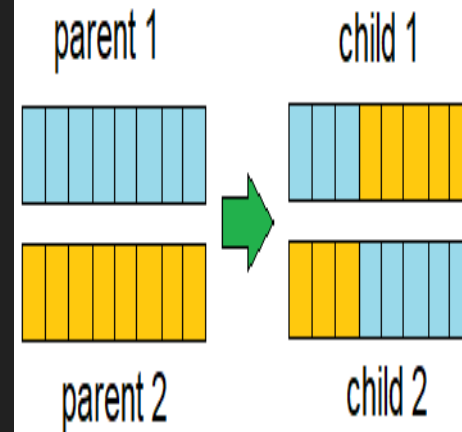


# Eight Queens class (Crossover Method)

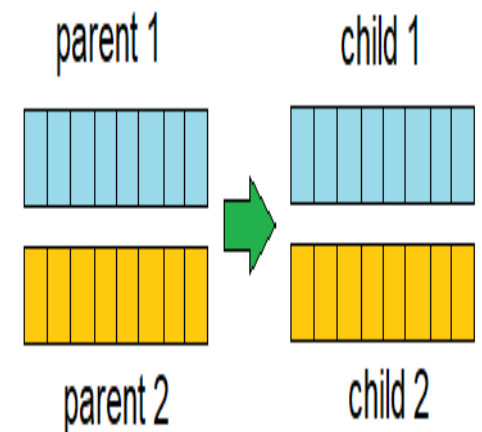
Simulating reality, there is a chance that chromosomes could crossover, and it may not then copy the genes of parents

```
def __crossover(self, parent1, parent2, probability):  
    r = random.random()  
    if r < probability:  
        middle_point = random.randint(0,7)  
        offspring1 = parent1[:middle_point] + parent2[middle_point:]  
        offspring2 = parent2[:middle_point] + parent1[middle_point:]  
    else:  
        offspring1 = parent1.copy()  
        offspring2 = parent2.copy()  
  
    return offspring1, offspring2
```

if  $r < PC$



else



# Eight Queens class (Mutation Method)

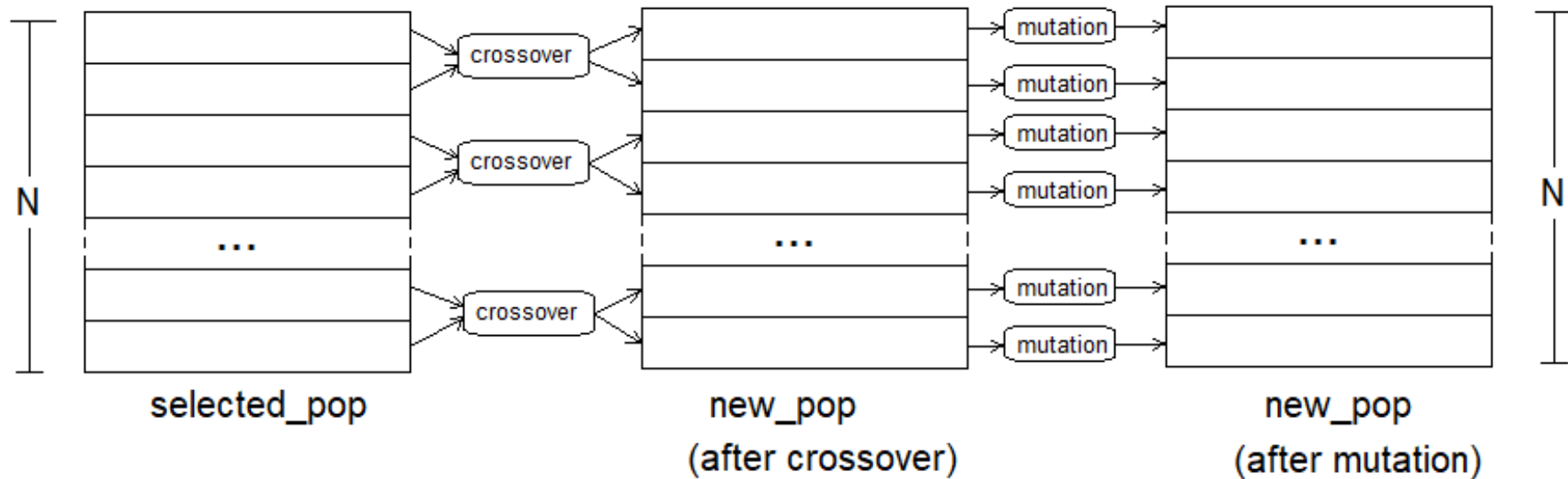
Remember that mutation happens **RARELY**  
It means that the genes could be modified

```
def __mutation(self, individual, probability):  
    ind = individual.copy()  
    r = random.random()  
    if r < probability:  
        random_neuclutide = random.randint(0,7)  
        ind[random_neuclutide] = random.randint(0,7)  
    return ind
```



## Eight Queens class (Crossover-Mutation Method)

**Every two parents should produce two childs**  
**Each child can be mutated or not**



# Eight Queens class (Crossover-Mutation Method)

```
def __crossover_mutation(self, crossover_probability, mutation_probability):
    new_population = []
    for index in range(0, self.__population_size, 2):
        child1, child2 = self.__crossover(self.__population[index], self.__population[index+1], crossover_probability)
        new_population.append(child1)
        new_population.append(child2)
    for index in range(self.__population_size):
        new_population[index] = self.__mutation(new_population[index], mutation_probability)

    self.__population = new_population.copy()
```

## Eight Queens class (Solution –putting all together- Method)

```
def solution(self):
    best_fitness_overall = None
    best_individual = None
    for generation in range(self.__num_of_generations):
        fitness_values = self.__calculate_fitness()
        index_of_best_fitness = fitness_values.index(max(fitness_values))
        best_fitness = fitness_values[index_of_best_fitness]
        if best_fitness_overall is None or best_fitness > best_fitness_overall:
            print(f"\rNo. of generation: {generation:06}    Best fitness (negative)={-best_fitness:03}", end="")
            best_individual = self.__population[index_of_best_fitness]

        if best_fitness == 0:
            print("\nFound optimal Solution")
            return best_individual

        self.__population = self.__selection(fitness_values)
        self.__crossover_mutation(self.__crossover_probability, self.__mutation_probability)

    return best_individual
```

# Eight Queens class (Display grid method)

**This method only to simulate the final solution**

```
def display_grid(self, sol):
    lst = ["  "] * 8
    representation = []
    for i in range(8):
        representation.append(lst.copy())

    for col in range(len(sol)):
        representation[sol[col]][col] = " Q "

    row_line = "+" + ('---+' * 8)
    for row in representation:
        print(row_line)
        print("|" + "|".join(cell for cell in row) + "|")
    print(row_line)
```

# TESTING

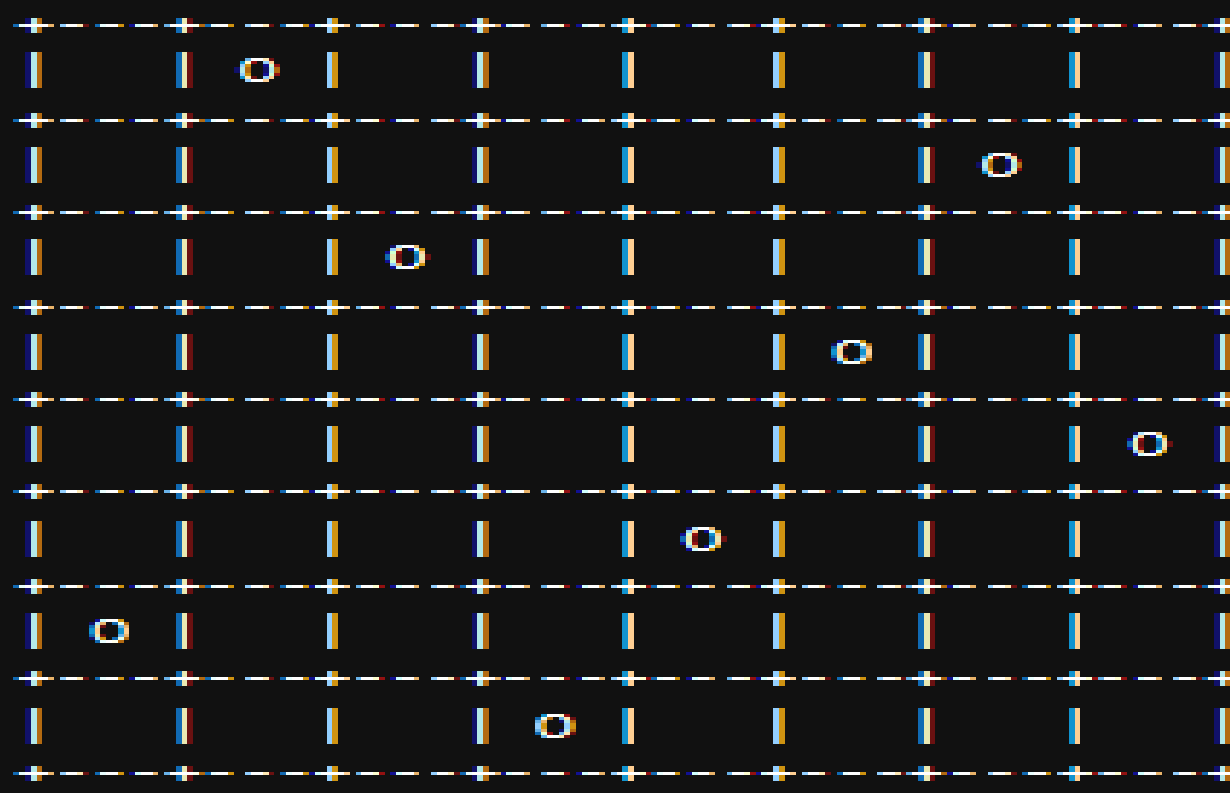
```
my_problem = eight_queens(population_size=6, crossover_probability=0.68, mutation_probability=0.1, num_of_generations=10000)
sol = my_problem.solution()
print(sol)
```

```
No. of generation: 000120    Best fitness (negative)=000
Found optimal Solution
[6, 0, 2, 7, 5, 3, 1, 4]
```

Let's see if it is true answer ?

[6, 0, 2, 7, 5, 3, 1, 4]

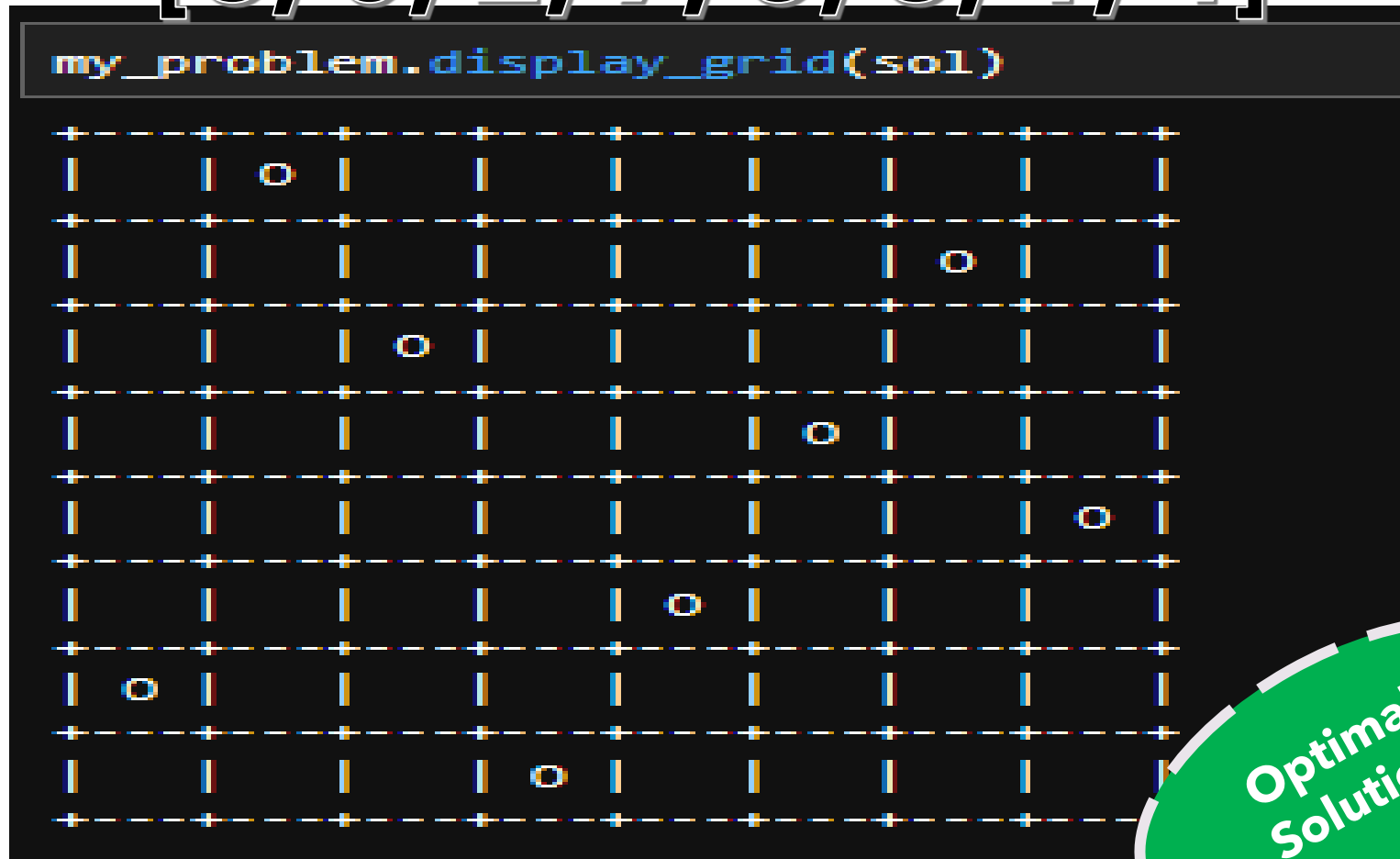
```
my_problem.display_grid(sol)
```



Let's see if it is true answer ?

[6, 0, 2, 7, 5, 3, 1, 4]

```
my_problem.display_grid(sol)
```



Optimal  
Solution

# Compare between first and last generation

## First Generation

```
[[2, 2, 3, 0, 0, 3, 7, 0], [7, 2, 0, 1, 4, 4, 7, 2], [6, 0, 5, 6, 5, 2, 4, 3], [7, 3, 6, 1, 0, 3, 0, 4], [1, 0, 7, 1, 2, 3, 2, 4], [4, 7, 2, 2, 0, 0, 5, 0]]
```

## Last Generation (Convergent)

```
[[6, 1, 7, 2, 0, 3, 7, 4], [6, 1, 7, 2, 0, 3, 7, 4], [6, 1, 5, 2, 0, 3, 7, 4], [6, 1, 7, 2, 0, 3, 7, 4], [6, 1, 7, 2, 0, 3, 7, 4], [6, 1, 7, 2, 0, 3, 7, 4]]
```



# Thank You

**Next Lab:**  
**Ant Colony Optimization**  
**(Theoretical)**