A Gentle Introduction to Genetic Algorithms with Python and DEAP

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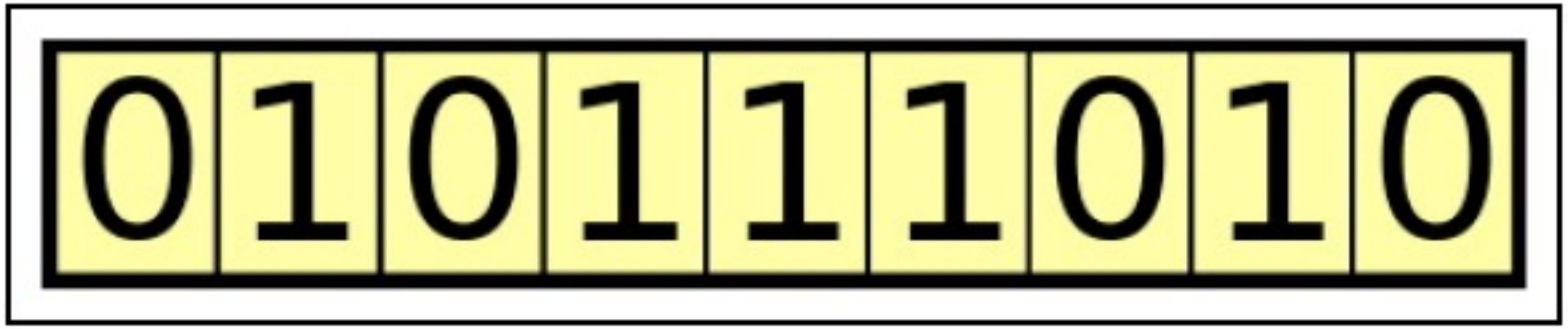
Darwinian Evolution

- Variation
- Inheritance
- Selection

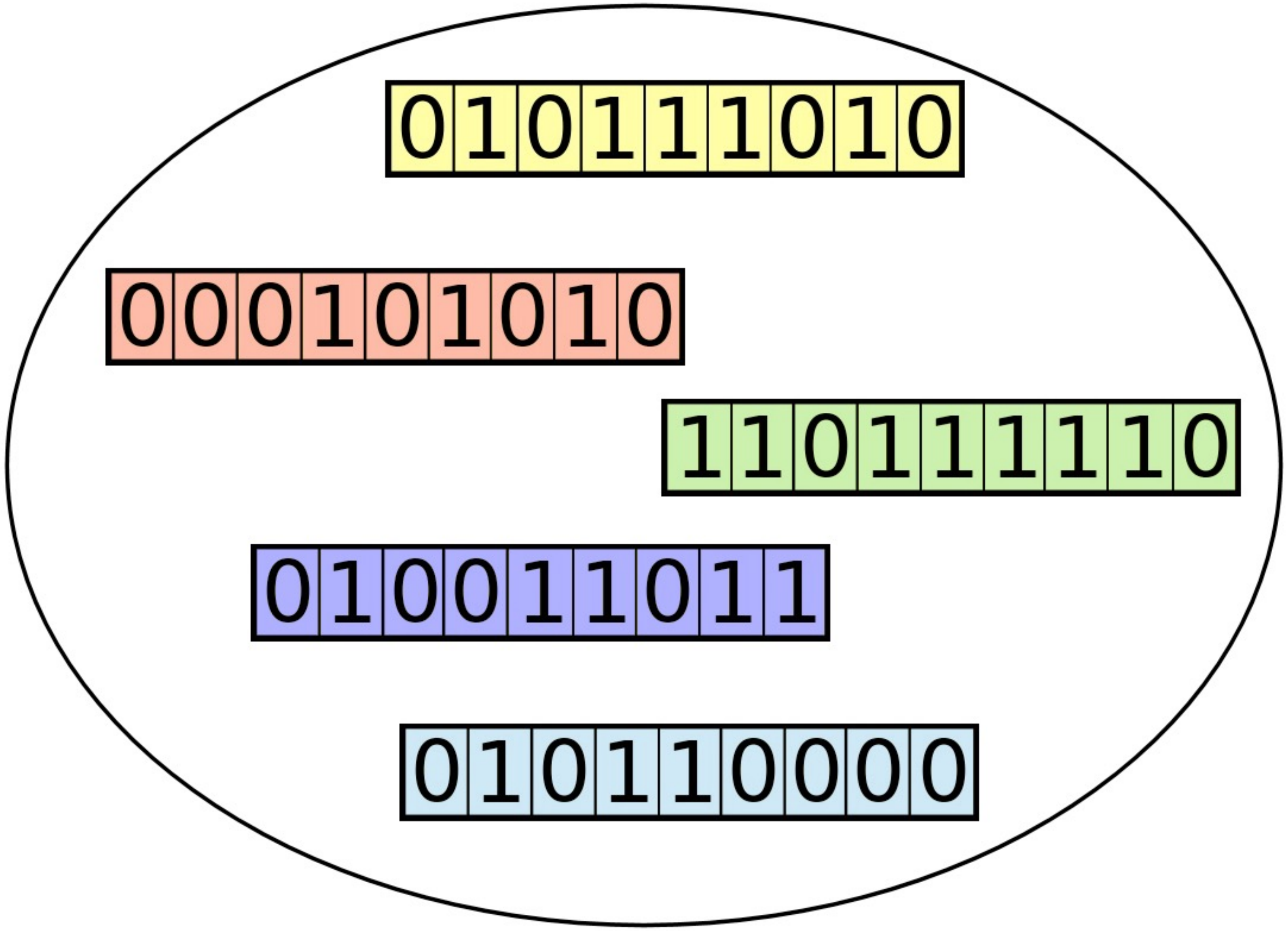
Genotype

- Each individual is represented by a chromosome representing a collection of genes.

- For example, each chromosome can be represented by a binary string, where each bit represents a single gene.



Population



Fitness Function

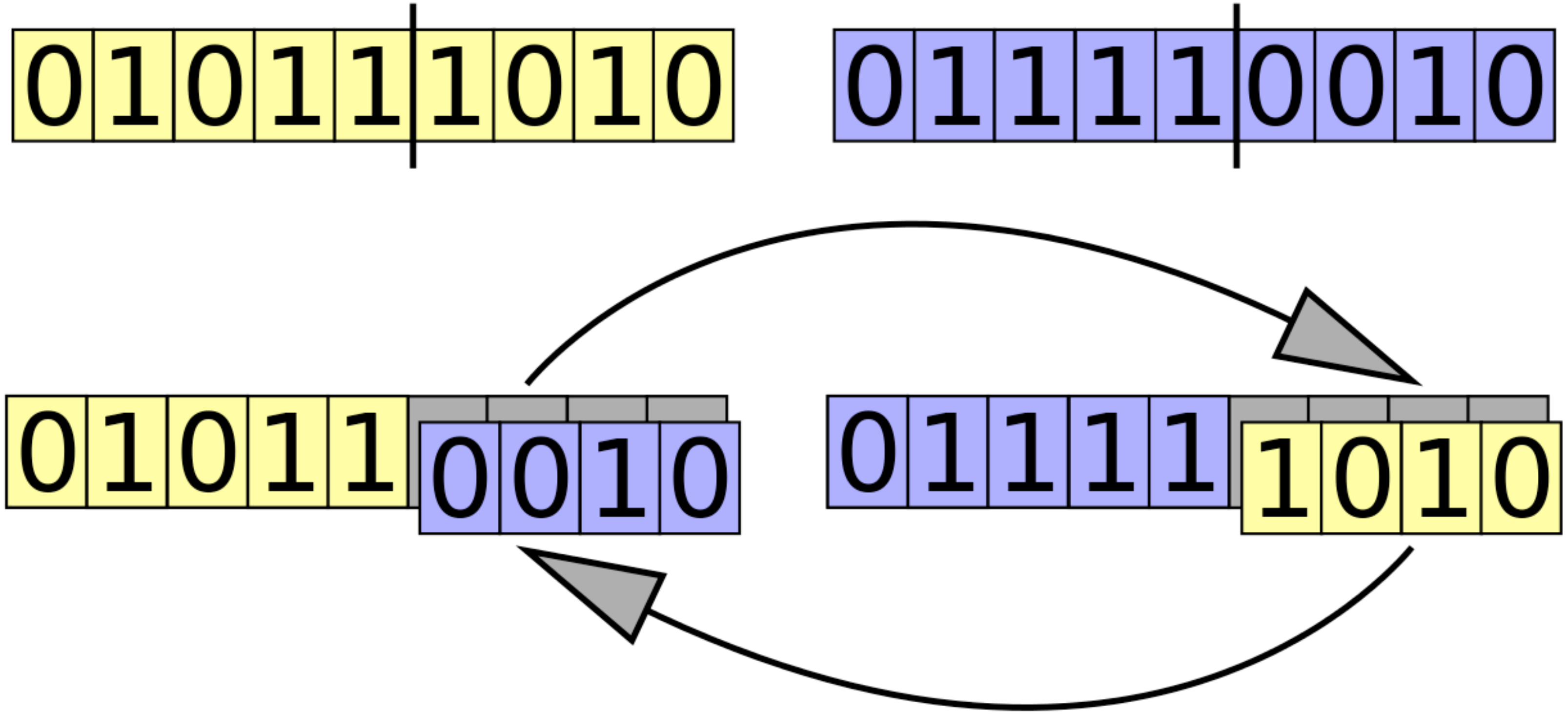
- The function we want to optimize or the problem we want to solve.
- Individuals score higher are more likely to be selected and reproduce.

Selection

- Following the calculation of the fitness score, individuals will be selected based on specific methods to reproduce and create their offspring to form the next generation.

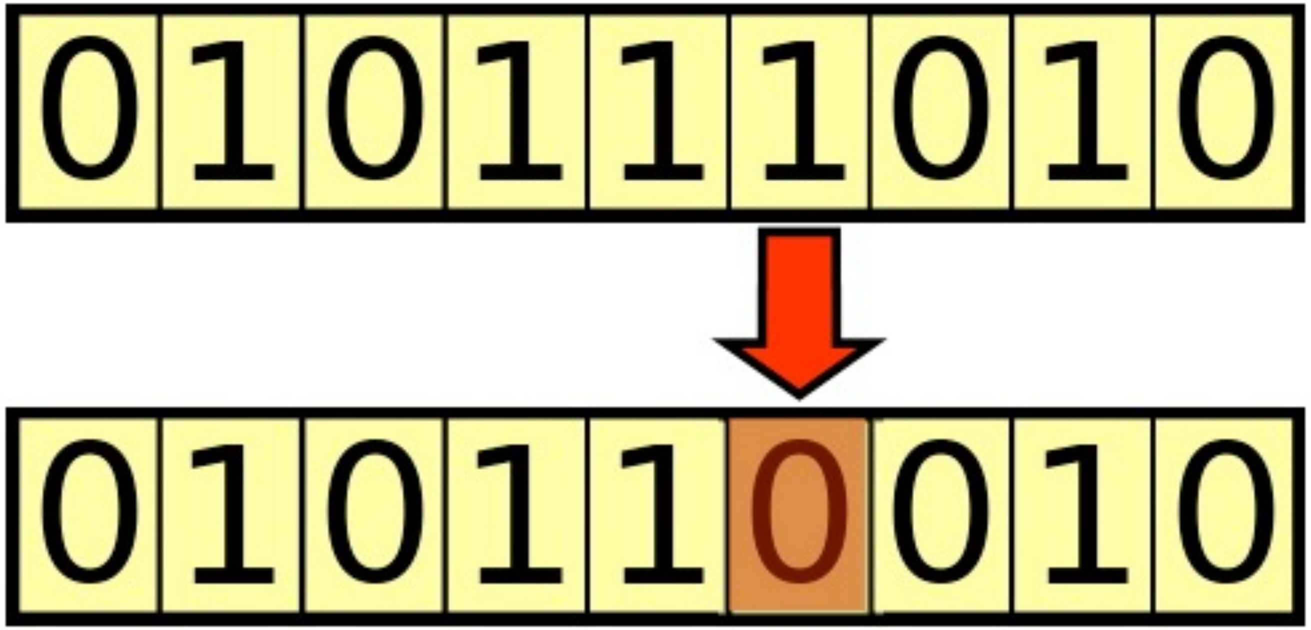
Crossover

- Chromosome exchange process

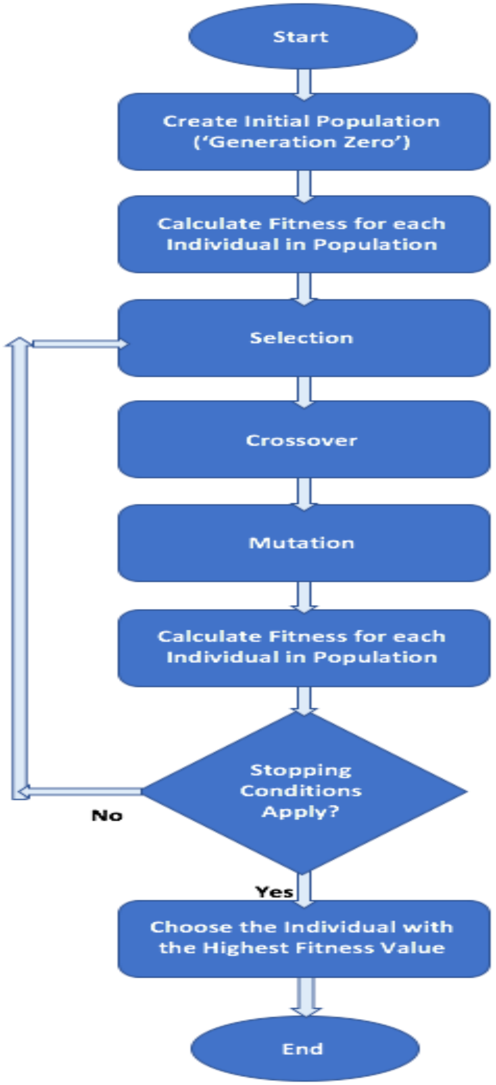


Mutation

- Introduce new patterns to the chromosomes



Basic Flow of Genetic Algorithm



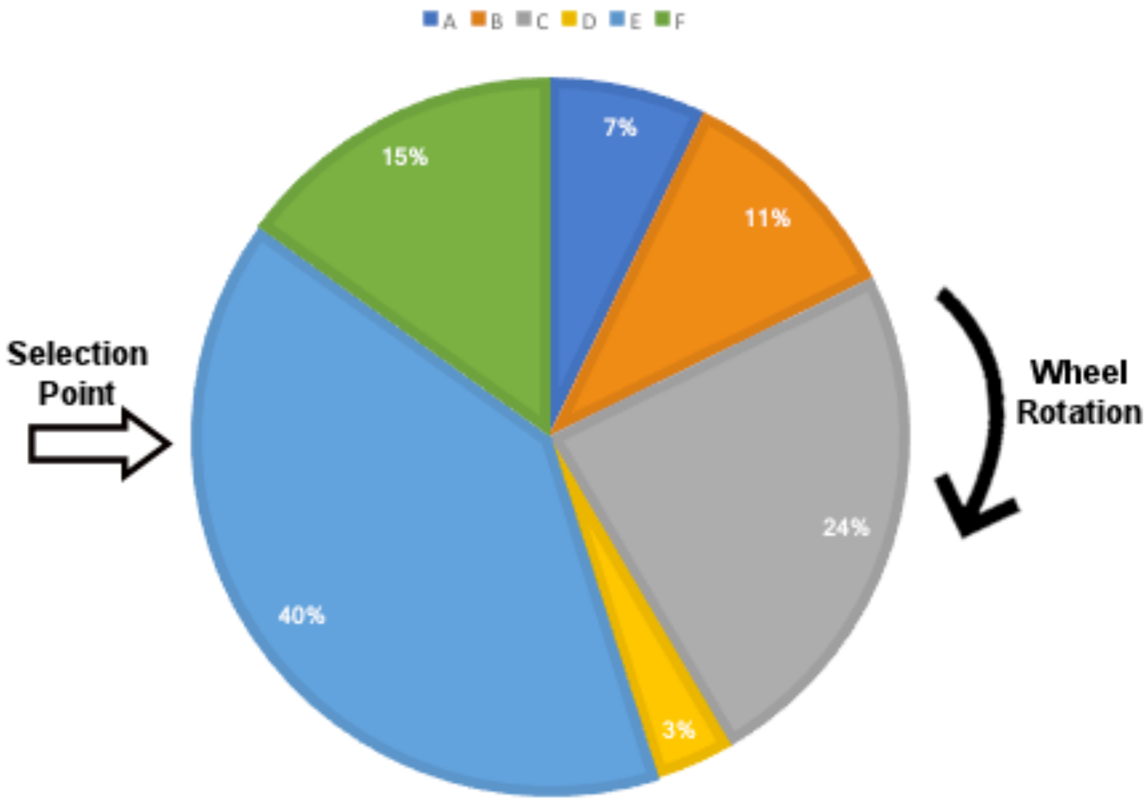
Stopping Conditions

- Time eclipsed
- CPU time/memory and associated cost
- Solution > preset threshold

Selection Methods

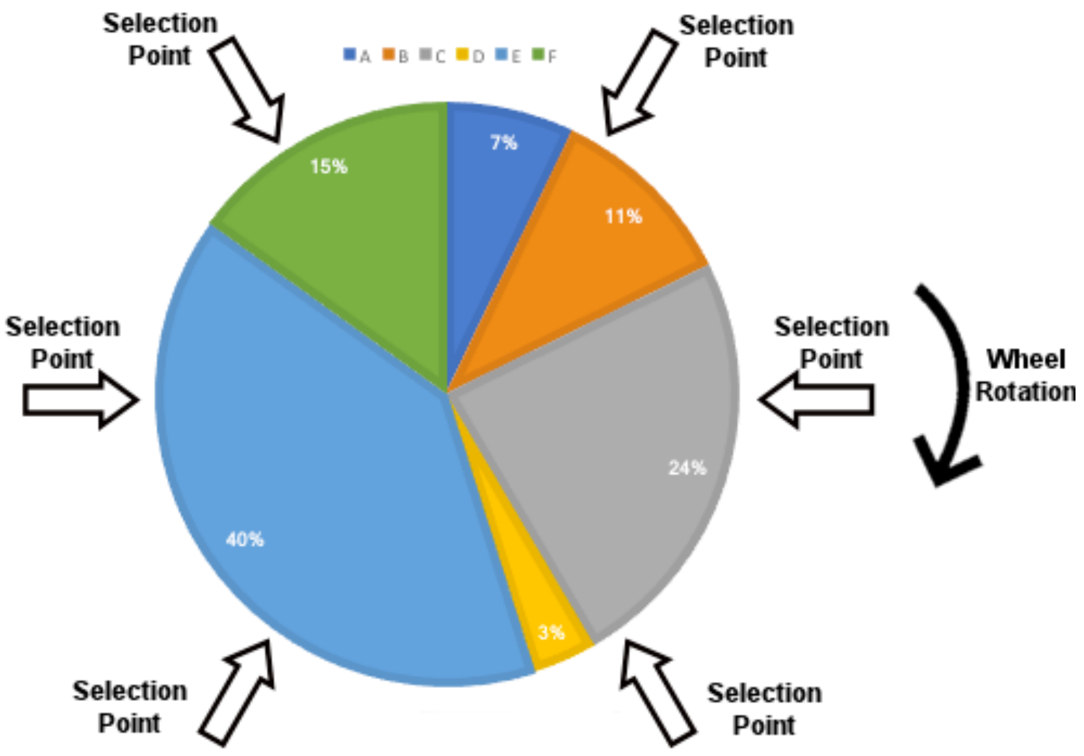
Roulette Wheel Selection (Fitness Proportionate Selection)

Individual	Fitness	Relative portion
A	8	7%
B	12	11%
C	27	24%
D	4	3%
E	45	40%
F	17	15%



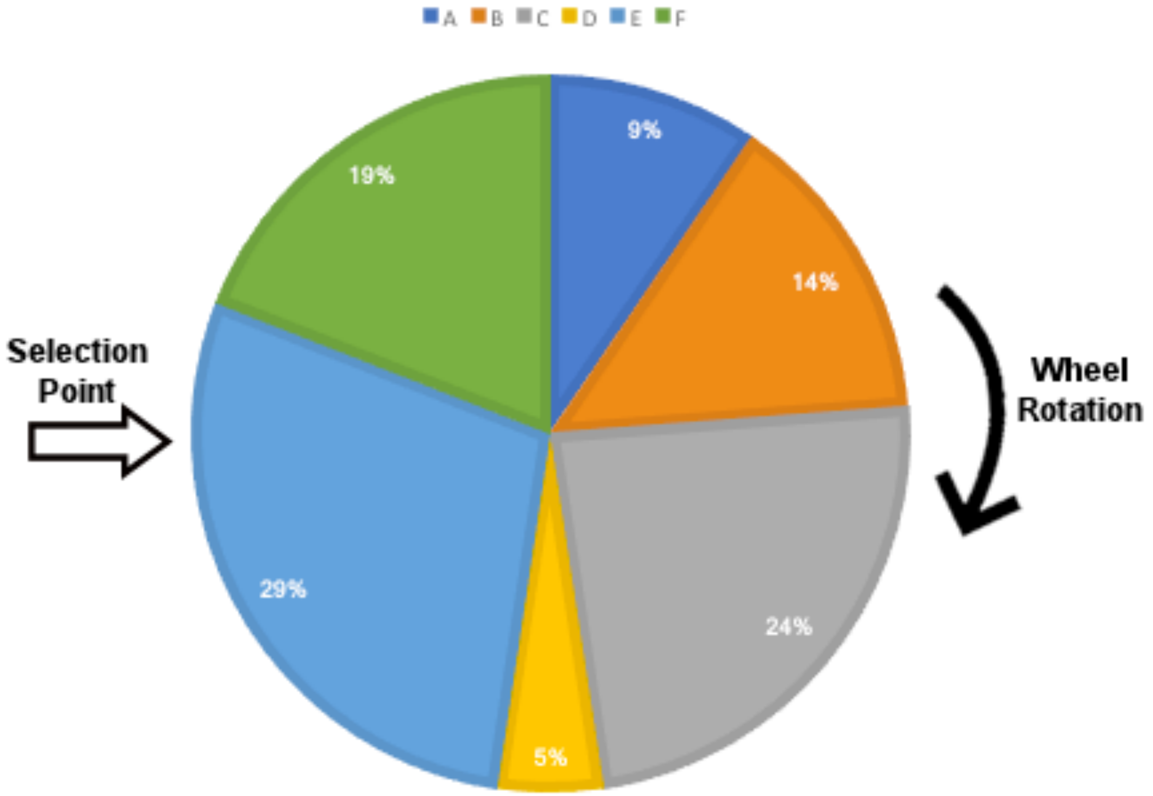
Stochastic Universal Sampling

- All individuals are chosen at the same time, offering more chances for those with lower fitness scores.



Rank-based Selection

Individual	Fitness	Rank	Relative portion
A	8	2	9%
B	12	3	14%
C	27	5	24%
D	4	1	5%
E	45	6	29%
F	17	4	19%



Fitness Scaling

- scaled fitness = a × (raw fitness) + b

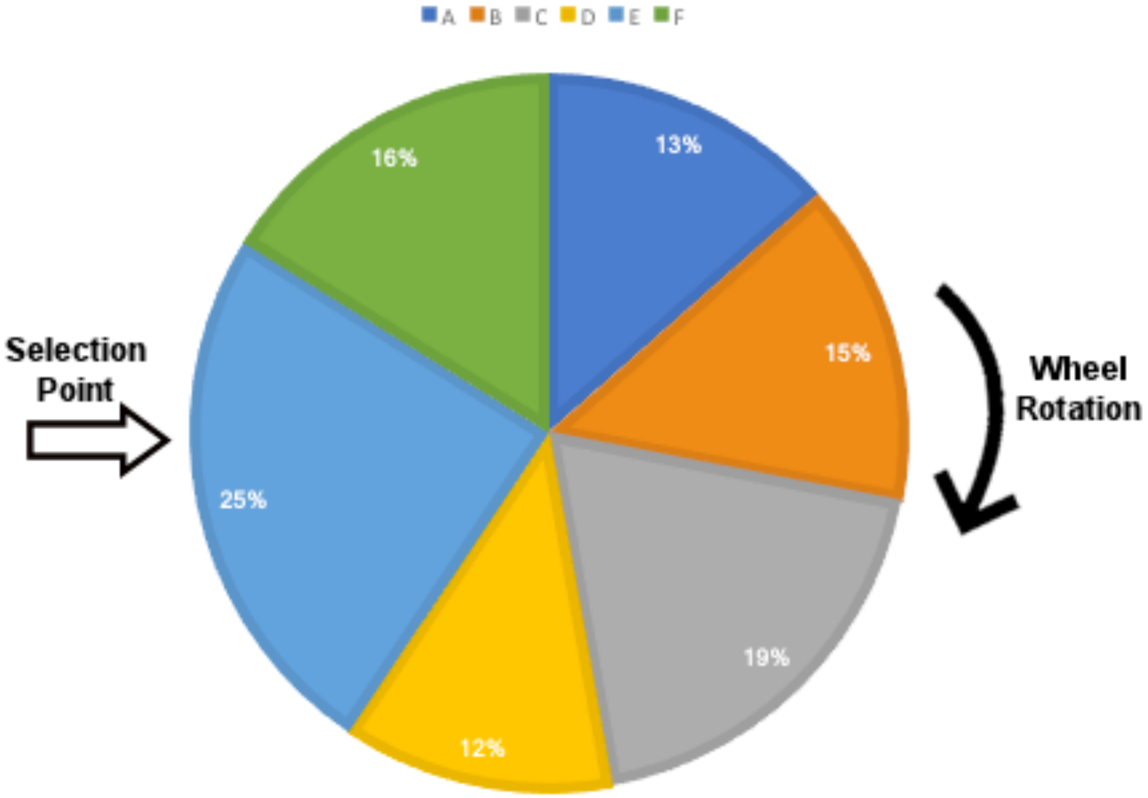
- 50 = a × 4 + b (lowest fitness value)
- 100 = a × 45 + b (highest fitness value)

- a = 1.22, b = 45.12

- scaled fitness = 1.22 × (raw fitness) + 45.12

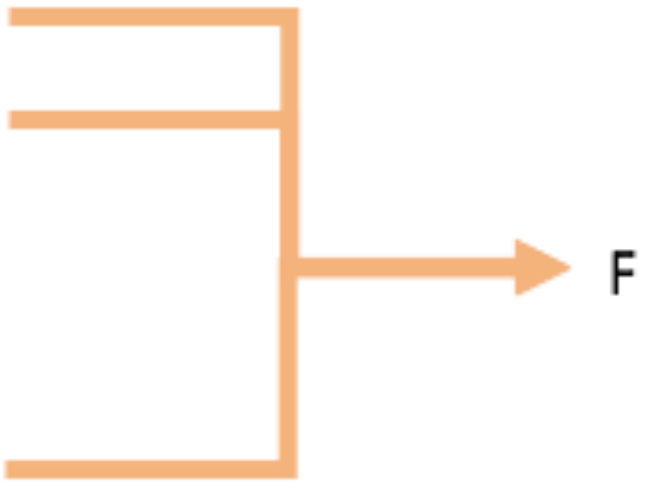
Fitness Scaling

Individual	Fitness	Scaled fitness	Relative portion
A	8	55	13%
B	12	60	15%
C	27	78	19%
D	4	50	12%
E	45	100	25%
F	17	66	16%



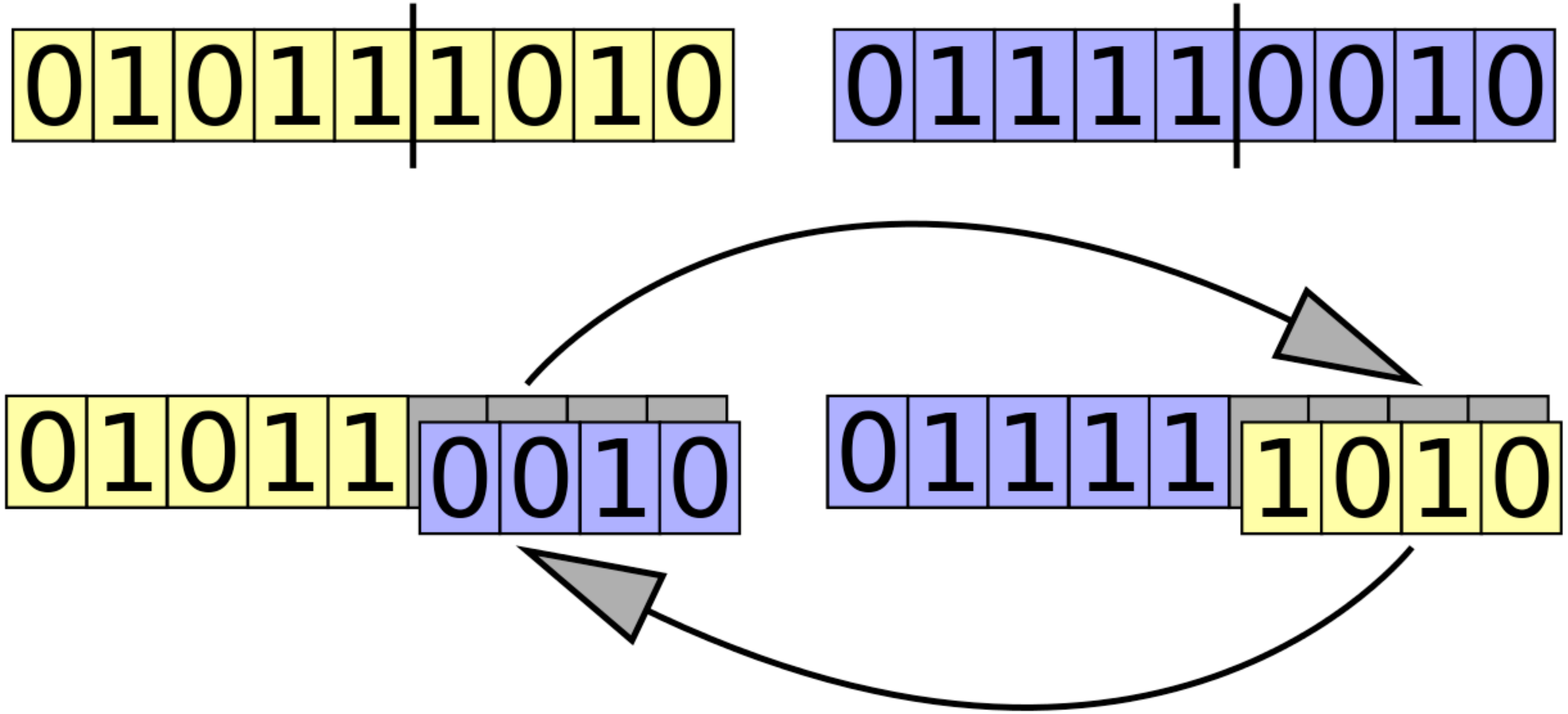
Tournament Selection

Individual	Fitness
A	8
B	12
C	27
D	4
E	45
F	17

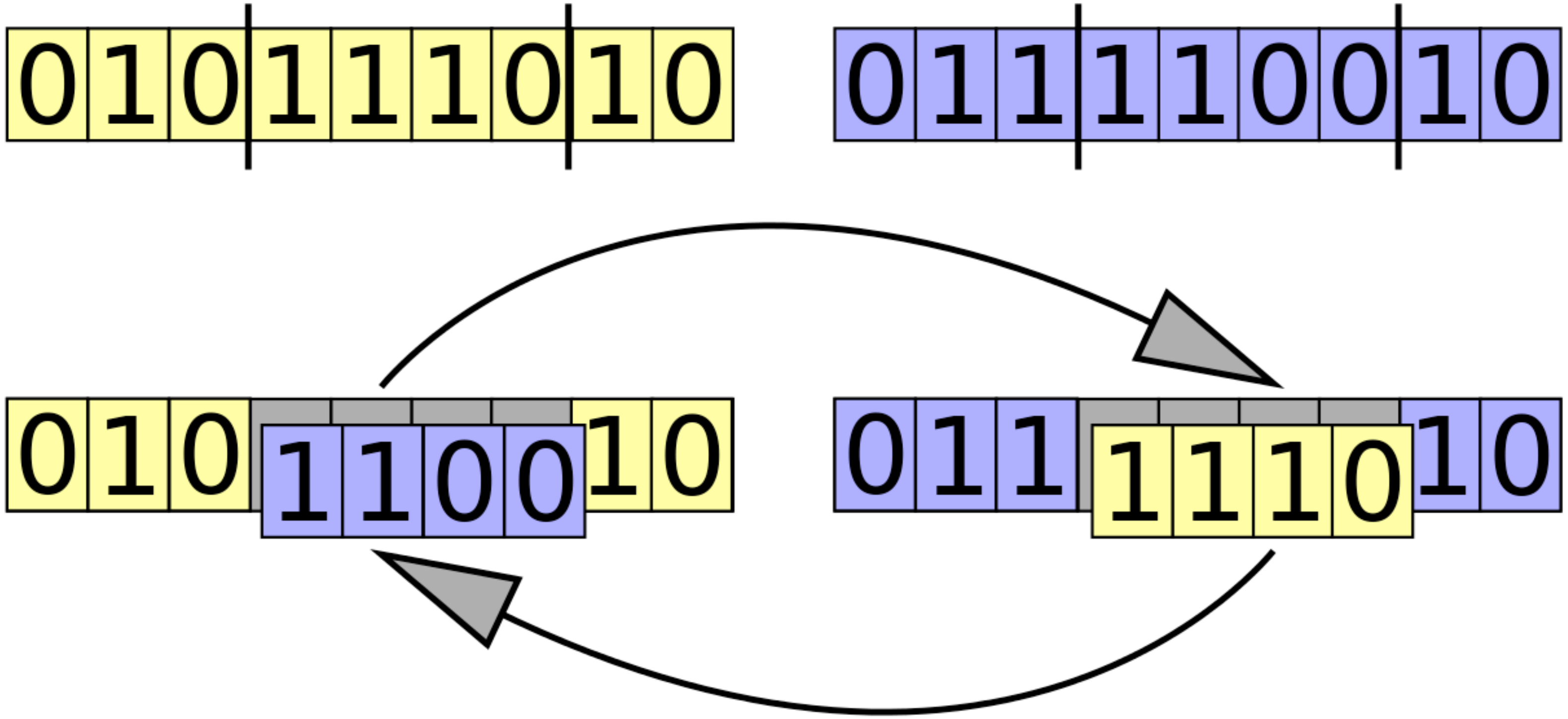


Crossover Methods

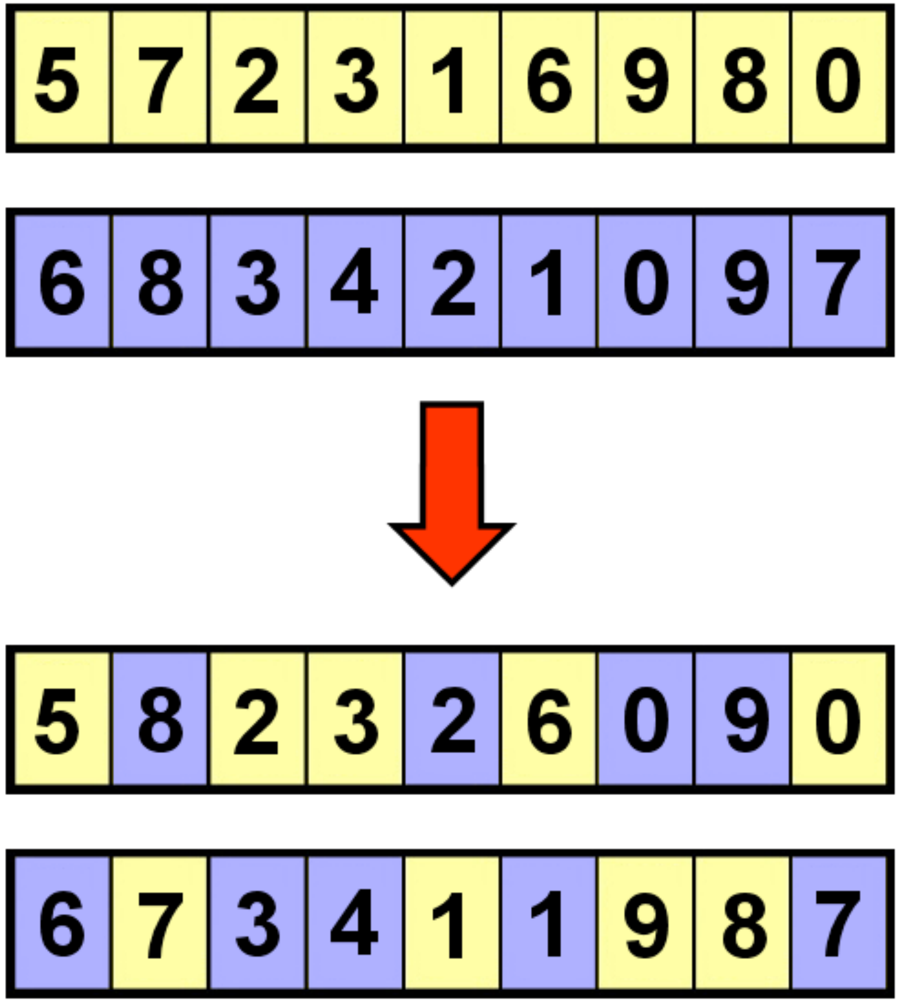
Single Point Crossover



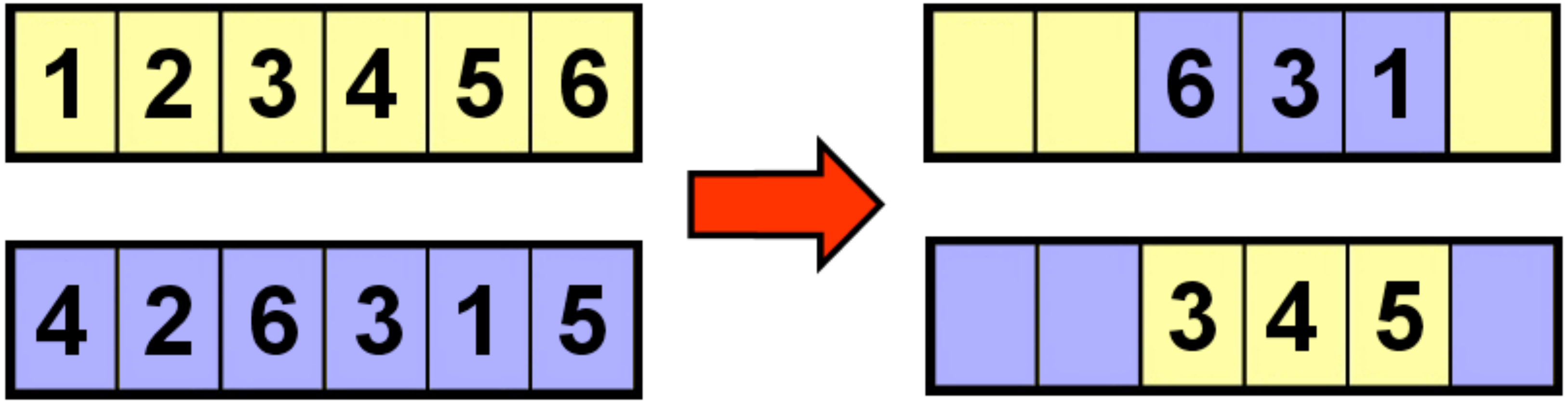
Two-Point or K-Point Crossover



Uniform Crossover

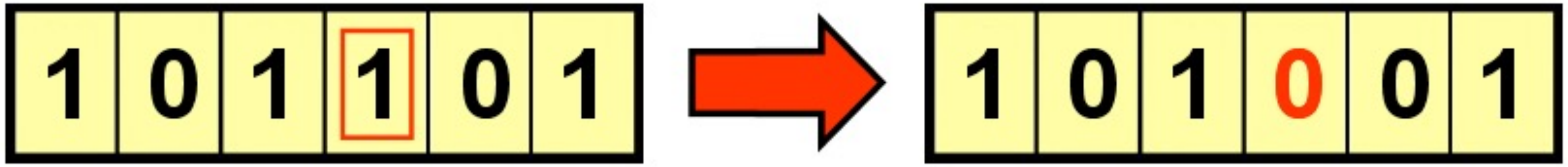


Ordered Crossover

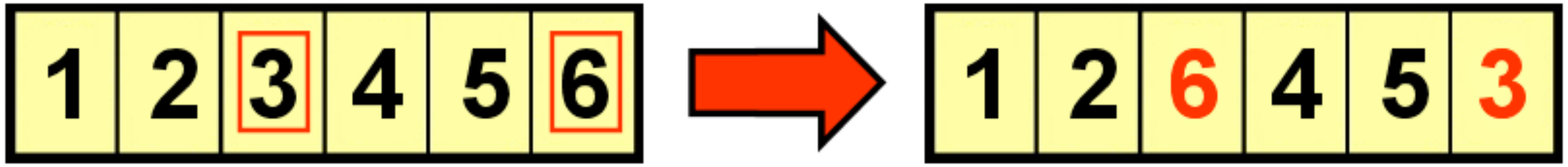


Mutation Methods

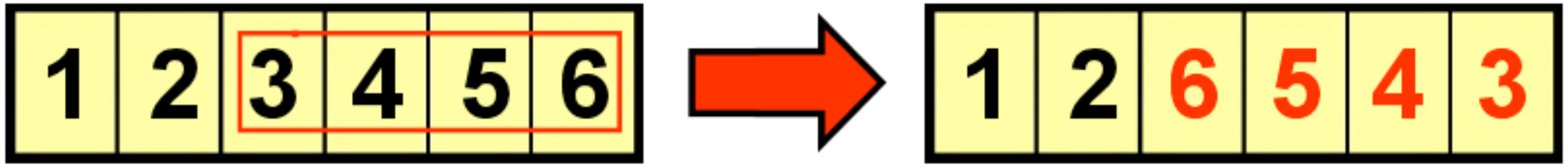
Flit Bit Mutation



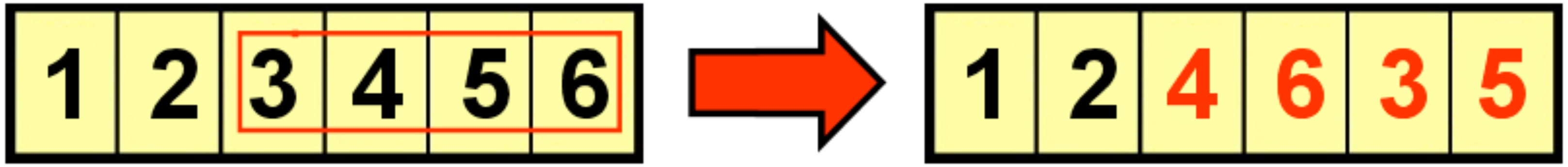
Swap Mutation



Inverse Mutation



Scramble Mutation



Elitism

- A strategy to retain the best individuals in the population of a genetic algorithm across generations.

- Purpose
  - Prevents loss of the best-found solutions.
  - Ensures consistent improvement in solution quality over time.

- How It Works
  - Selects top-performing individuals based on fitness.
  - Copies them unchanged into the next generation.

Introduction to DEAP

- A versatile Python library for evolutionary algorithms.
- Key Features
  - Easy to use and highly customizable.
  - Provides tools for implementing custom genetic operators.
- Installation
  - Install via pip: pip install deap

Setting Up a Genetic Algorithm with DEAP

- Importing Required Modules
  - from deap import base, creator, tools, algorithms

- Defining Fitness and Individual
  - Create fitness: creator.create("FitnessMax", base.Fitness, weights=(1.0,))
  - Define individual: creator.create("Individual", list, fitness=creator.FitnessMax)

Population Setup and Evaluation Function

- Registering Components with Toolbox
  - toolbox.register("attribute", random.randint, 0, 100)
  - toolbox.register("individual", tools.initRepeat, creator.Individual, toolbox.attribute, n=10)
  - toolbox.register("population", tools.initRepeat, list, toolbox.individual)

- Defining the Evaluation Function
  - def evalOneMax(individual): return (sum(individual),)

- Register Evaluation Function
  - toolbox.register("evaluate", evalOneMax)

Genetic Operators and Algorithm Execution

- Registering Genetic Operators
  - Selection: toolbox.register("select", tools.selTournament, tournsize=3)
  - Crossover: toolbox.register("mate", tools.cxTwoPoint)
  - Mutation: toolbox.register("mutate", tools.mutFlipBit, indpb=0.05)

- Executing the Algorithm
  - population = toolbox.population(n=300)
  - result = algorithms.eaSimple(population, toolbox, cxpb=0.5, mutpb=0.2, ngen=40, verbose=False)