

## CT-4 : Genetic Algorithm. [From Lecture]

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### Q1) Introduction to Evolutionary Computation :

Subfield of AI uses the concept of biological evolution to find optimal or near optimal solutions for a given problem.

\* Converges soln wrt 1 or 2  
optimal or near optimal soln  
of prob in tract

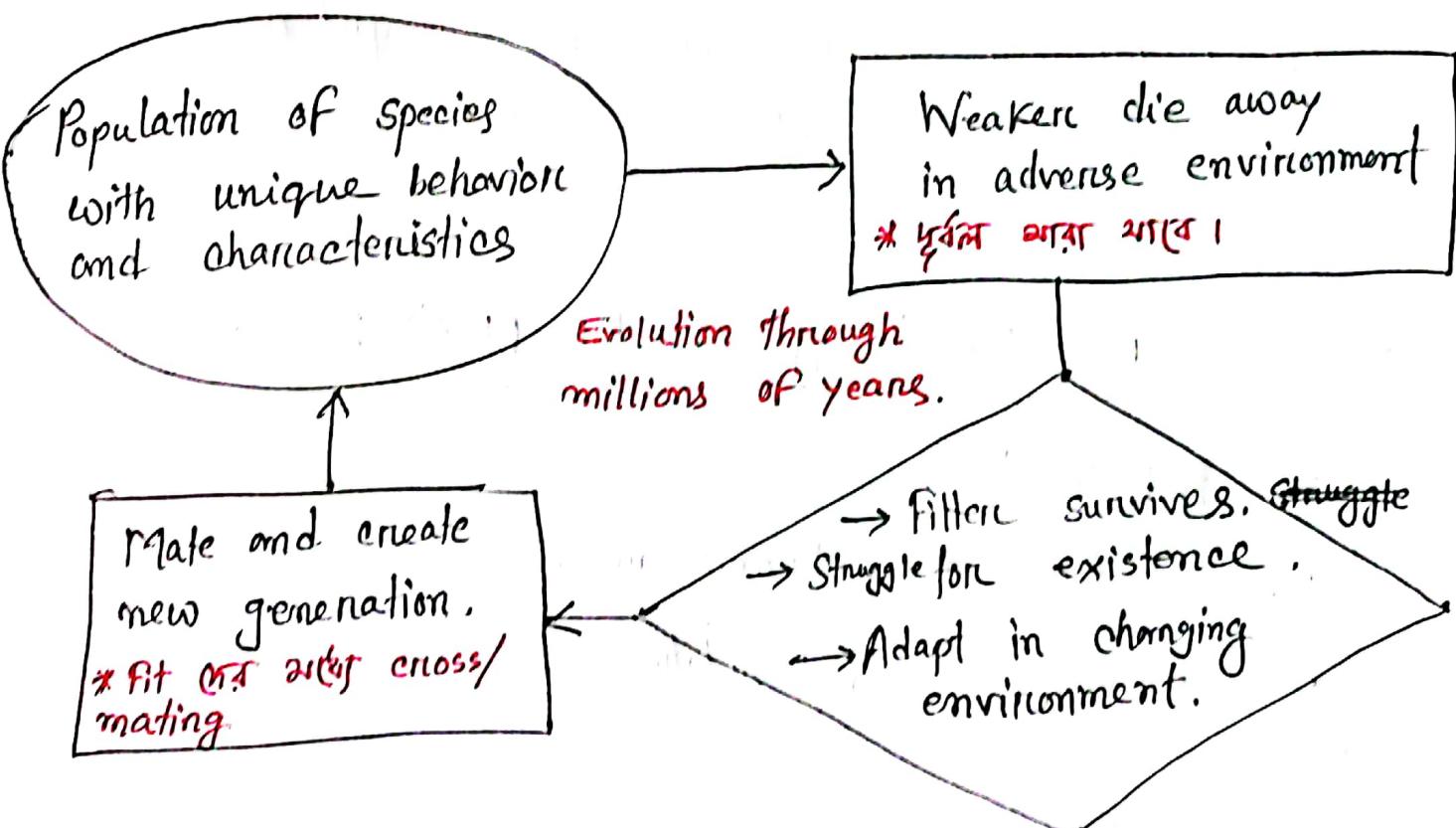


Fig: Evolution in the nature.

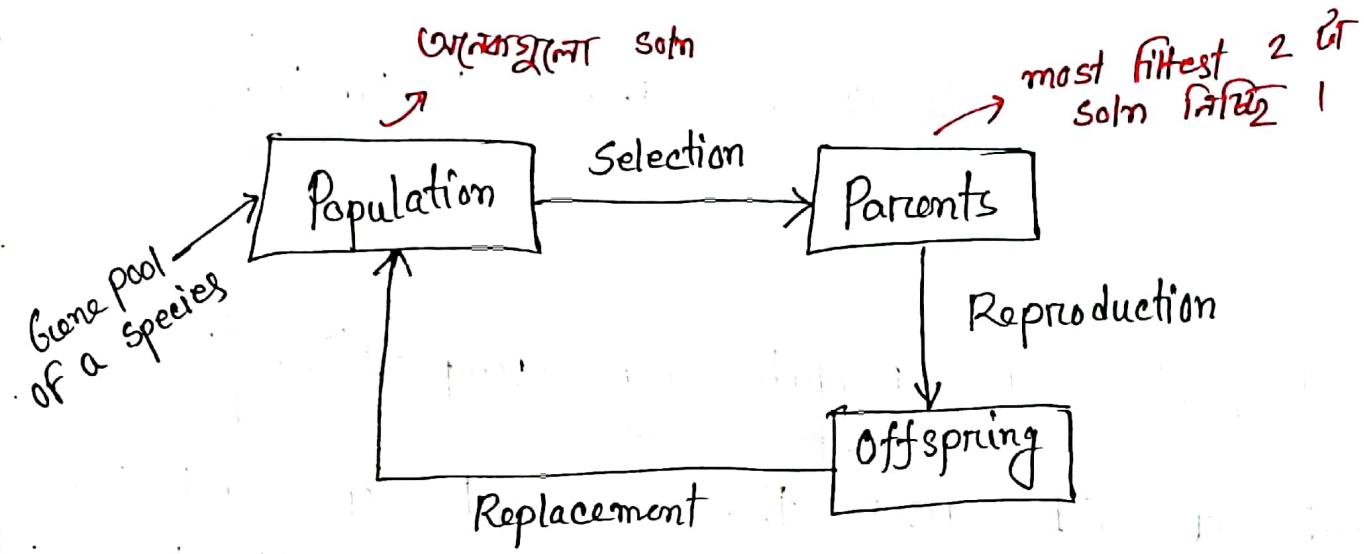


Fig: Evolutionary Computation.

\* Population, gene, chromosome etc words have different significances in computer science or genetic algorithm.

\* Steps of Evolutionary Algorithm (EA) :

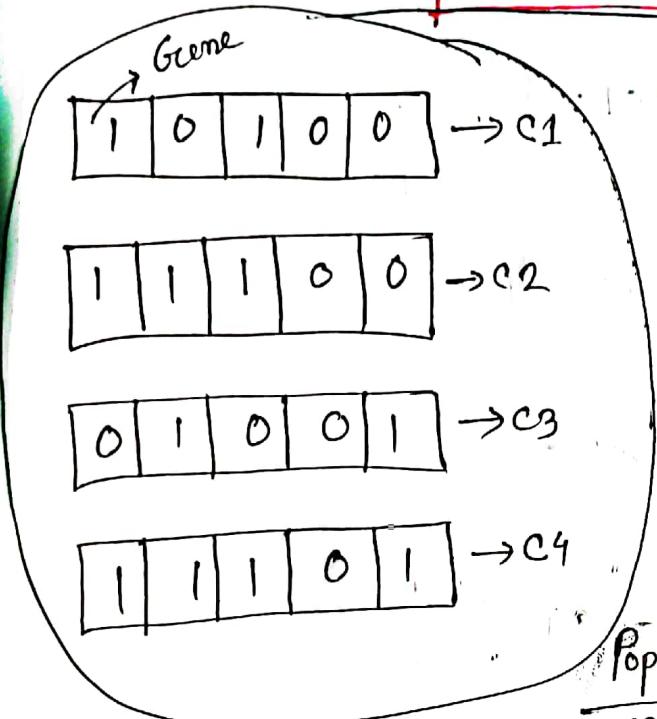
- 1. Initialization.
- 2. Selection of chromosome.
- 3. Crossover and mutation.

\* Genetic Algorithm is a kind of EA.

## What is Gene, Chromosome, Population?

①

### Initialization of Population



→ first step of EA (GCA)  
 → six parameters are set before starting the algorithm.

- ① No. of Genes per chromosome  
 ⇒ bit stream → bit string
- ② The codes value.
- ③ The size of population per generation.
- ④ Crossover probability

- ⑤ Mutation probability.
- ⑥ Termination criteria and max. no. of generations.

→ How to initialize population?  
 → What should be the population size.

\* Three most widely used encoding of gene:

- ① Binary Encoding.
- ② Real number encoding.
- ③ Permutation encoding.

## i) Binary Encoding:

# Example:  $f(x) = x^3$ ;  $0 \leq x \leq 255$   
Maximize the fn value.

$$256 = 2^8$$

8 bits.

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

 $\rightarrow c_1 - 2$

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

 $\rightarrow c_2 - 4$

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

 $\rightarrow c_3 -$

1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	---	---	---

 $\rightarrow c_4 - 255$

Population

\*  $c_4 \rightarrow$  most optimal.

\*  $c_4$  এমানো এবং  $c_3$  near optimal.

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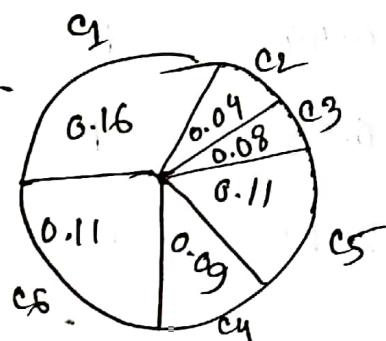
## ② Selection of Chromosome

Parent Select  
করতে

- Roulette wheel Selection \*\* }
- Rank Selection \*\*\* } 3 types.
- Tournament Selection \*\* }

### I Roulette Wheel Selection:

- Random selection of  $m$  chromosome from a big population (when fitness are not very different).



Length of circumference  $\propto$  fitness value

\* i.e. the probability of selection of a chromosome (for mating pool) is higher for larger fitness.

### 6 - Individual

\* Probability অন্তরিক্ষ এবং নতুন fitness এর পরিপন্থ  
differ হওয়ার সময়, তখন Rank selection ব্যবহার করা হবে।

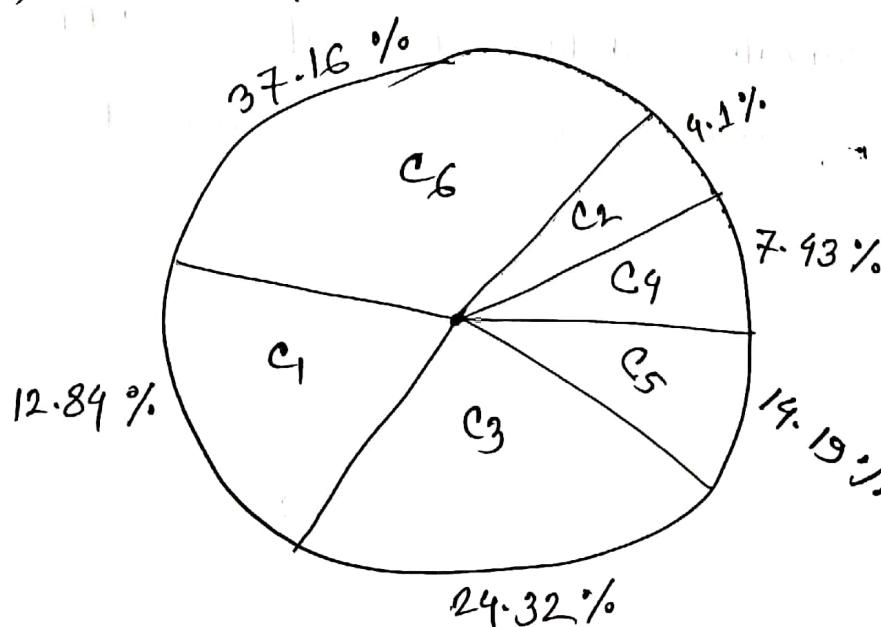
Example: Determine percentage of Roulette wheel and Actual count for 6 chromosomes with fitness values of 19, 6, 36, 11, 21, 55.

Soln:

Chromosome	Fitness, F	% of Roulette wheel	Probability P <sub>i</sub>	Expected count (P <sub>i</sub> × N <sub>total</sub> )	Actual count
C <sub>1</sub>	19	12.84 %	0.1284	0.1284 × 6 = 0.77	1
C <sub>2</sub>	6	4.1 %	0.0405	0.243	0
C <sub>3</sub>	36	24.32 %	0.2432	1.46	1
C <sub>4</sub>	11	7.43 %	0.0743	0.44	1
C <sub>5</sub>	21	14.19 %	0.1419	0.85	1
C <sub>6</sub>	55	37.16 %	0.3716	2.23	2

$$\sum F = 148$$

$$C_1 \text{ is } P_1 = \frac{19}{148} = 0.1284 \quad (P_i = P_1)$$



ನಿಂದ ಸಾಮಾನ್ಯವಾಗಿರುವ ಅನುಭವ  
ಎಂದು 1  
ಇಲ್ಲಿ 2(3/12)  
0.5 ಇಲ್ಲಿ ಅನುಭವ  
23 ಆಗಿದ್ದು ಇಲ್ಲಿ 1  
ನಿಂದ 2(5/12) 1  
Just 6  
ಬಿಂಭಿಲ್ಲ 2(5/12) 1

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## Rank Selection:

# Example: Determine percentage of Roulette wheel before ranking and after ranking

$$SP [1.0, 2.0]$$

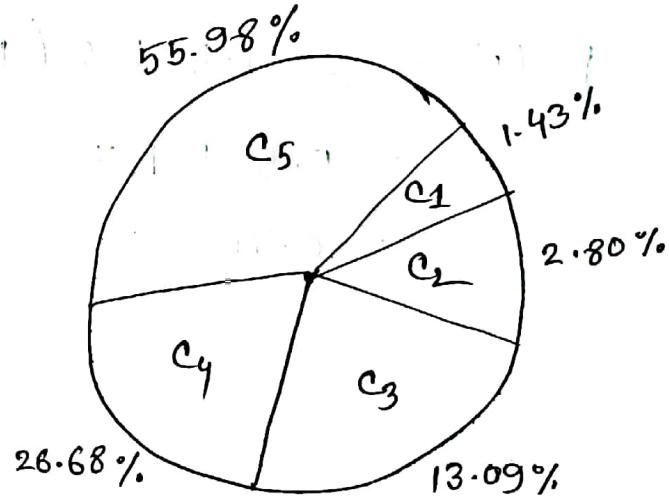
$$\frac{1.0 + 2.0}{2} = 1.5$$

Chromosome	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>
Fitness Value	0.23	0.45	2.1	4.28	8.98

Soln:

i) Before Ranking:

Chromosome	Fitness Value	% of Roulette Wheel
C <sub>1</sub>	0.23	1.43%
C <sub>2</sub>	0.45	2.80%
C <sub>3</sub>	2.1	13.09%
C <sub>4</sub>	4.28	26.68%
C <sub>5</sub>	8.98	55.98%



min as rank - 1.

ii) After ranking:

Chromosome	Fitness value	Rank	New Fitness Value	% of Roulette Wheel
C <sub>1</sub>	0.23	1	0.5	10%
C <sub>2</sub>	0.45	2	0.75	15%
C <sub>3</sub>	2.1	3	1	20%
C <sub>4</sub>	4.28	4	1.25	25%
C <sub>5</sub>	8.98	5	1.5	30%

$$fit(pos) = 2 - sp + 2(sp-1) \cdot \frac{(pos-1)}{(N_{ind}-1)}$$

↙  
rank

Non linear এবং (ranking) পদ্ধতি,  $sp [1.0, N_{ind} - 1]$

$$fit(1) = 2 - 1.5 + 2(1.5-1) \cdot \frac{1-1}{5-1}$$

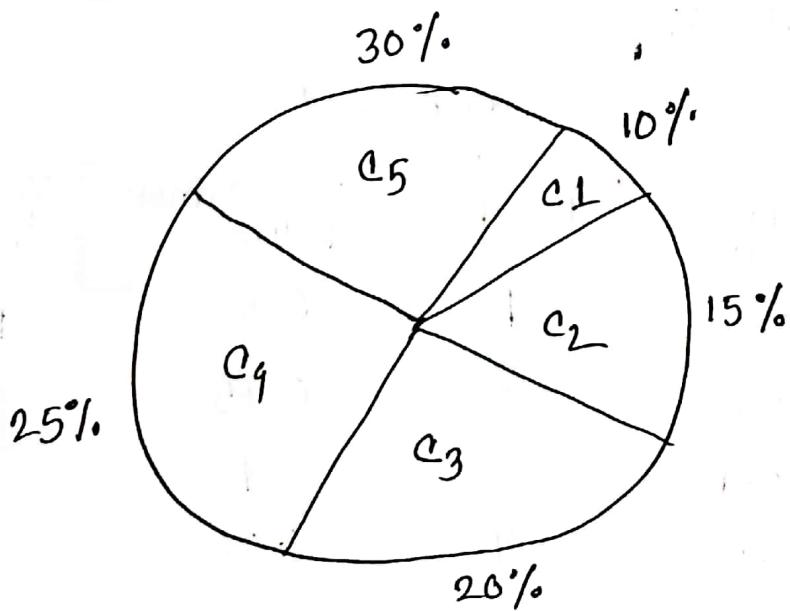
$$= 2 - 1.5 + 1 * \frac{0}{4}$$

$$= 0.5$$

$$fit(2) = 2 - 1.5 + 2(1.5-1) \cdot \frac{2-1}{5-1}$$

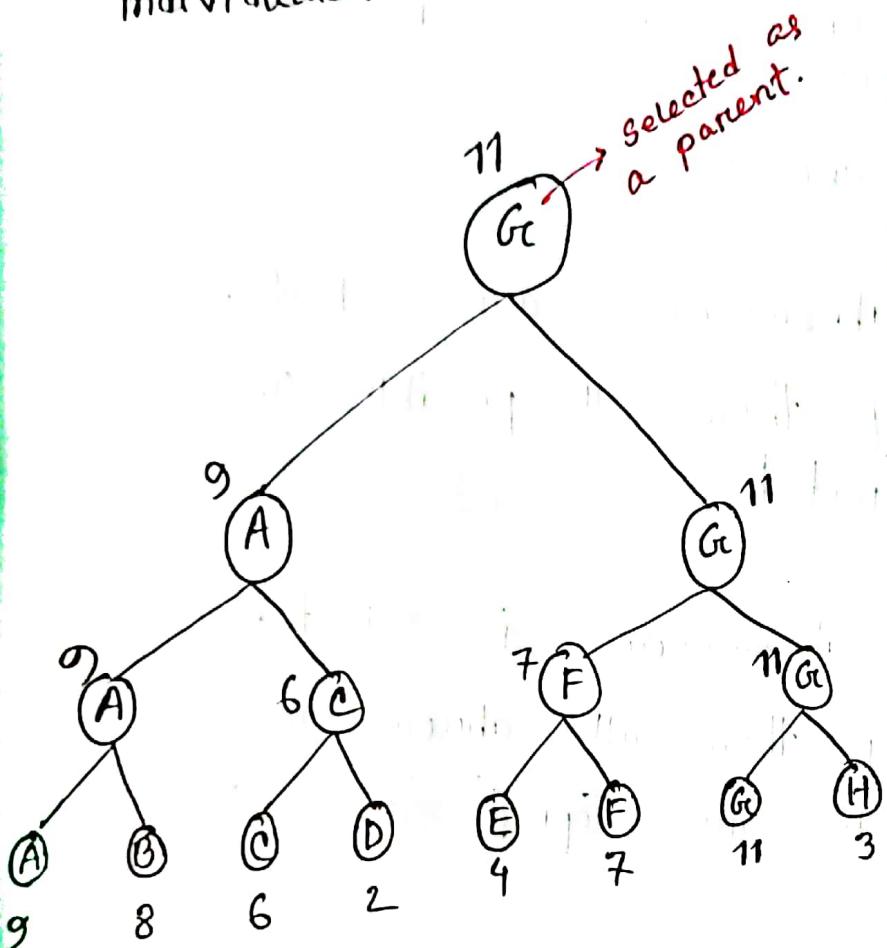
$$= 0.5 + 1 * \frac{1}{4}$$

$$= 0.75$$



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Tournament Selection : Group of  $k$  individuals randomly selected from a population of  $N$  individuals.



### Algorithm:

- ① Select  $k$  individuals from the population and perform a tournament amongst them.
- ② Select the best individual from the  $k$  individuals.
- ③ Repeat process 1 and 2 until we have the desired amount of population.

$$100 \gg 8 \\ \downarrow \\ k$$

\* यदि 4 वर्त पर्याप्त नहीं, तो टॉर्नामेंट बढ़ा  
4 वर्त पर्याप्त नहीं तो टॉर्नामेंट बढ़ा।

## Crossover & Mutation :

- \* Crossover → Generation of offspring / child.
- \* Mutation → Change characteristic of next generation.
- \* Extreme case of crossover :

\* Case-I: If all chromosomes are selected for mating then all possible offspring are generated.

\* Case-II: If no chromosome is selected for mating then all chromosomes of parents are copied for next generation.

\* Drawback of crossover: Crossover may stuck into local optima (global optima may be missed).

- \* Single-site Crossover.
- \* Two-site Crossover.
- \* Crossover Mask.

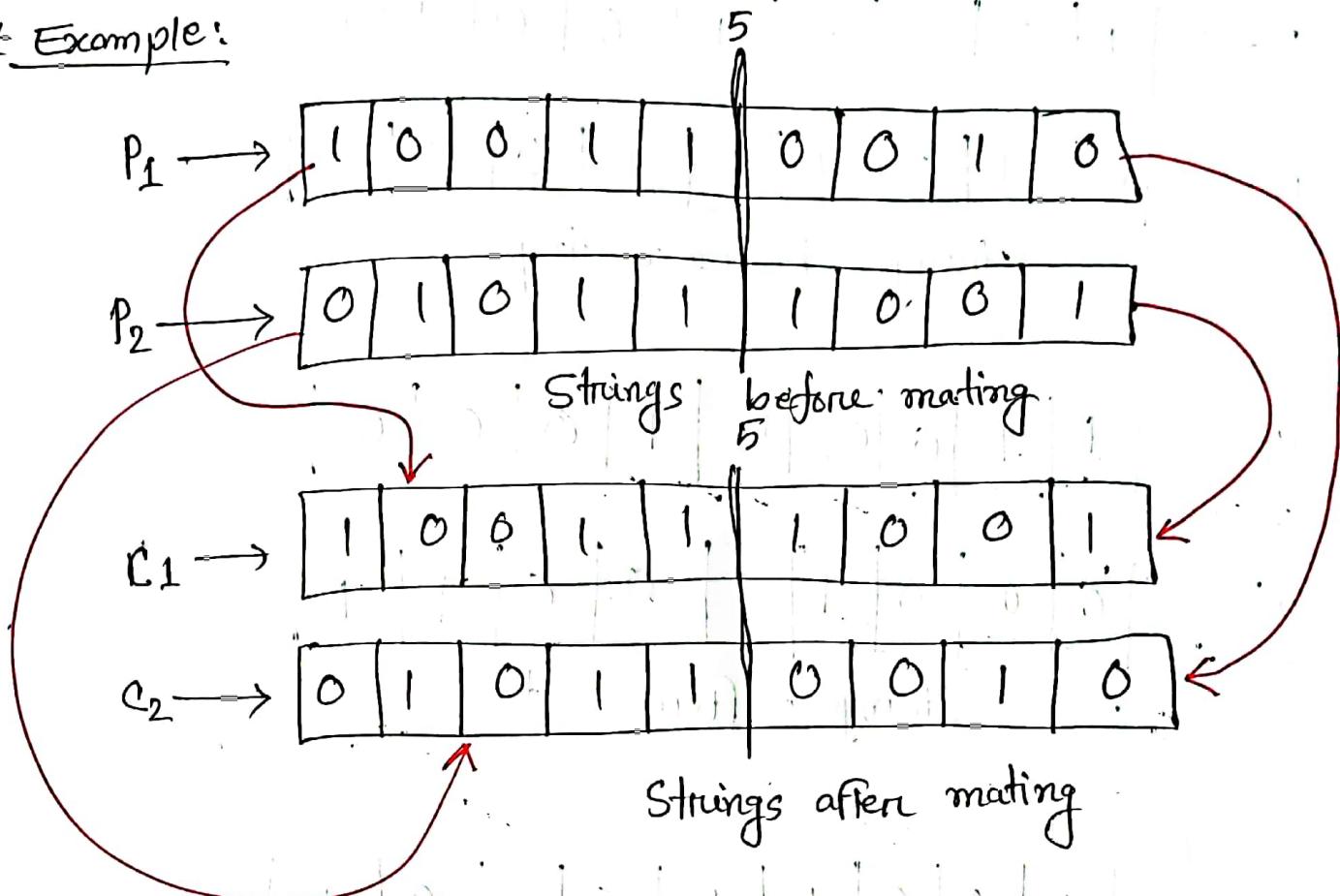
$$\begin{array}{l} P_1 \rightarrow 00 | 00 \\ P_2 \rightarrow 00 | 01 \end{array} \quad \begin{array}{l} (0) \\ (1) \end{array}$$

$$\begin{array}{l} C_1 \rightarrow 0001 \\ C_2 \rightarrow 0000 \end{array} \quad \begin{array}{l} (1) \\ (0) \end{array}$$

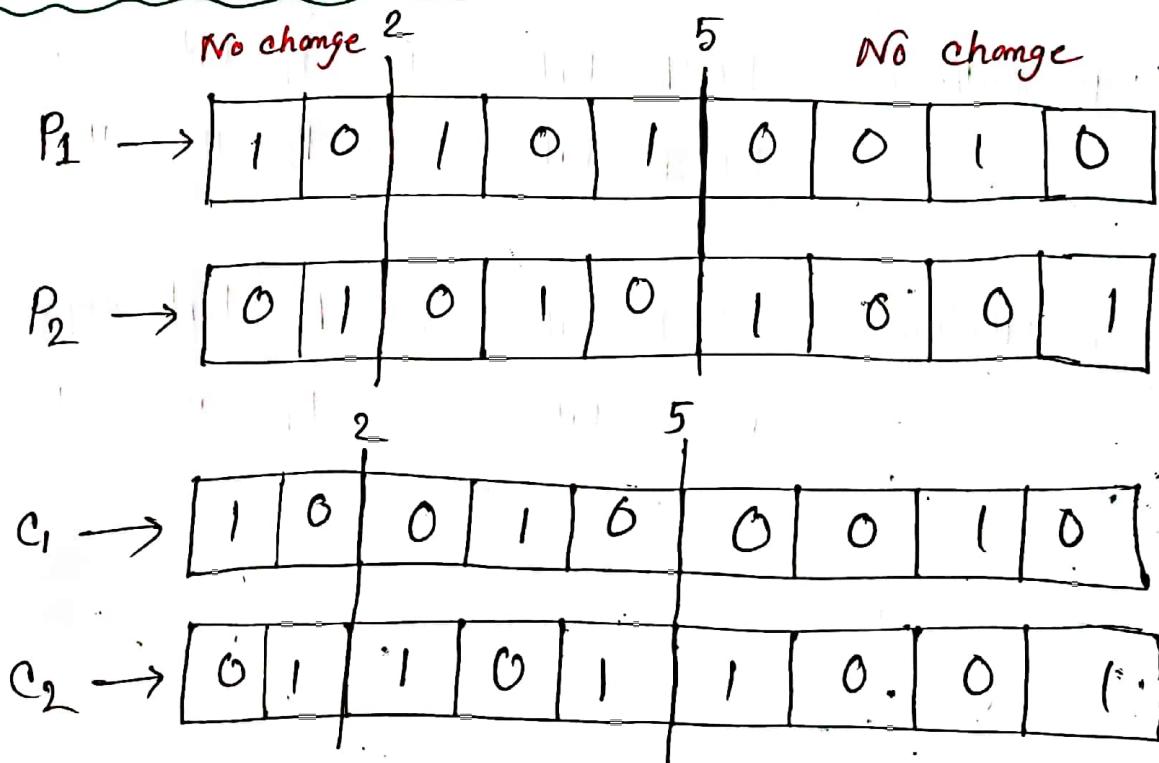
- \*  $2^3$  repeat  $2^3$  - 0 0 1 1 0 0 1 1
- \* convert 4 bit  $\Rightarrow$  max  $1111 \rightarrow 15$ .

Single-site Crossover (At point 5):

# Example:



Two-site Crossover (At point 2,5):



## Crossover Mask \*\*\*

$P_1 \rightarrow$ 

1	0	0	0	.	1	0	0	1	0
---	---	---	---	---	---	---	---	---	---

$P_2 \rightarrow$ 

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

Strings before mating

$C_1 \rightarrow$ 

1	.	1	0	0	1	.	1	0	0	0
---	---	---	---	---	---	---	---	---	---	---

$C_2 \rightarrow$ 

0	.	0	0	1	1	0	0	1	1
---	---	---	---	---	---	---	---	---	---

Strings after mating

Mask

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

$C_1$  generation: Mask bit  $\rightarrow 1$ ,  $P_1$  bit copy paste  
Mask bit  $\rightarrow 0$ ,  $P_2$  " " "

$C_2$  generation: Mask bit  $\rightarrow 1$ ,  $P_2$  bit copy paste  
Mask bit  $\rightarrow 0$ ,  $P_1$  " " "

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## Maximizing Function:

# Example: Maximize the function  $f(x) = x^{\sqrt{2}}$  where the range of  $x$  is  $[0, 31]$  and maximum number of generation is 3.

Soln: Step-1: Initialization.  $[32 = 2^5 \rightarrow 5 \text{ bits}]$

00000, 00001, 00010, ..., 11111

Max no. of generation = 3

Step-2: Selection (1st Generation)

Chromosome	Binary Encoding	Value of $x$	Fitness value $f(x) = x^{\sqrt{2}}$
$c_1$	00101	5	25
$c_2$	10000	16	256 <del>256</del>
$c_3$	01001	9	81
$c_4$	11100	28	784 <span style="border: 1px solid green; border-radius: 50%; padding: 2px;">784</span>

$$\sum f(x) = 1146$$

### Step-3: Crossover (2nd Generation)

Chromosome	Mating Pool	Crossover Point	Offspring after crossover	x	$f(x) = 2^x$
c <sub>1</sub>	00101	4	00100	4	16
c <sub>2</sub>	10000	4	10001	17	289
c <sub>3</sub>	011001	2	01100	12	144
c <sub>4</sub>	11100	2	11001	25	625

252205

$$\sum f(x) = 1074$$

### Mutation (3rd Generation)

Chromosome	Offspring after crossover	Offspring after mutation	x	$f(x) = 2^x$
c <sub>1</sub>	00100	00100	4	16
c <sub>2</sub>	10001	100101	21	441
c <sub>3</sub>	01100	01100	12	144
c <sub>4</sub>	11001	11011	27	729

Ans: c<sub>4</sub> → 11011 (27). [Near optimum]

$$\sum f(x) = 1330$$

## Genetic Algorithm:

- John Holland 1975.
- Random Search Algorithm.
- Achieves optimum soln of a problem with some constraints.

### \* Why GA?

- Easy to code and almost same procedure for many problems.
- Provides many solutions.
- Parallel processing can be used.

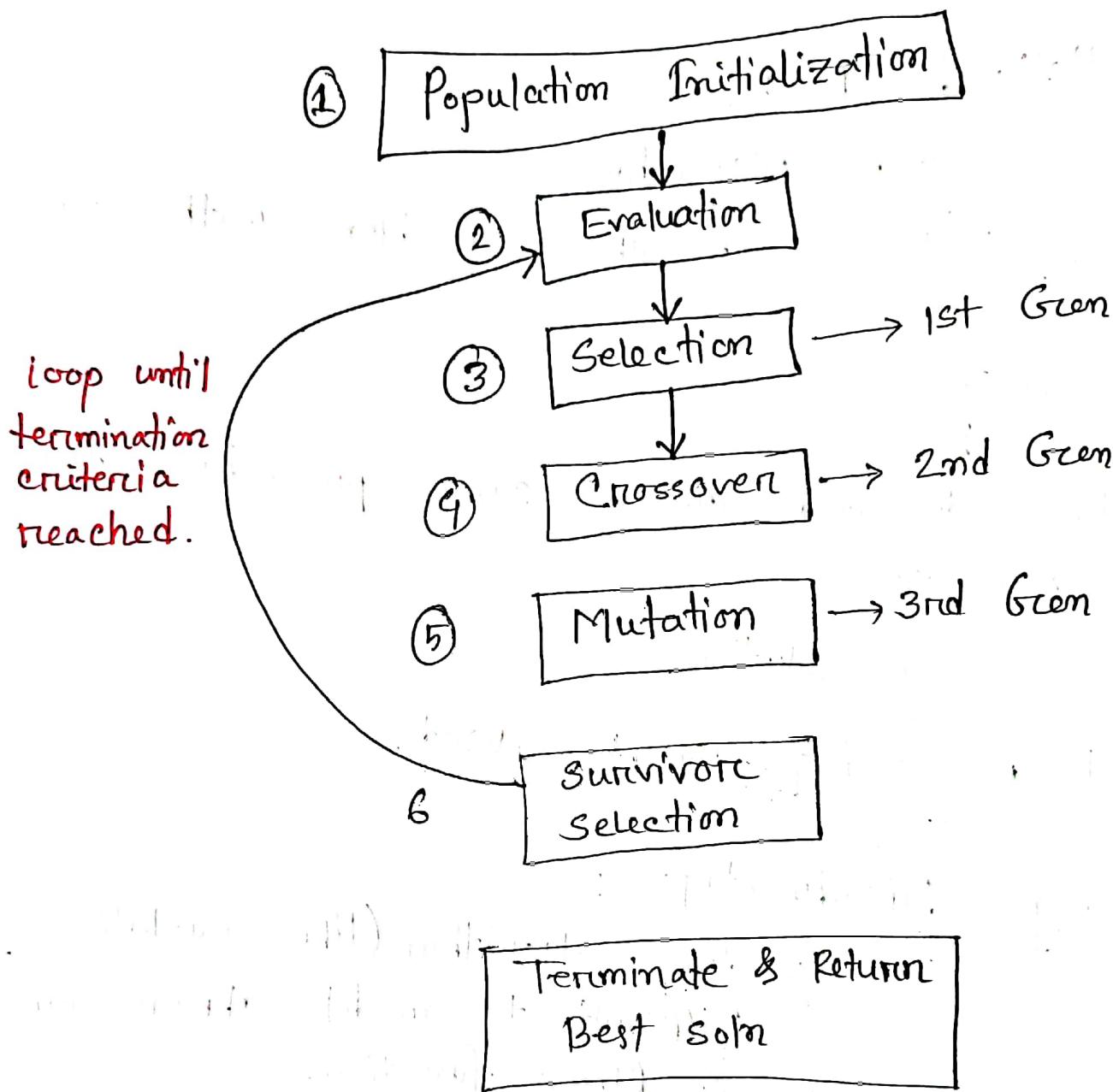
### \* Shortcomings / Disadvantages:

- Slow algorithm (like evolution).
- Difficult to model chromosome & fitness function.

### \* Termination criteria of GA:

- Maximum no. of generation.
- Diversity minimum level.
- No change in fitness level.
- Target fitness is achieved.
- Change in  $\Sigma$  fitness is very little.

Steps: 6 steps.



7b. # Genetic Algorithm example: Generate 3 chromosomes each containing 12 bits. Apply single point and two crossover. Apply mutation generating random numbers  $r \in [0,1]$  where  $r < p$ ,  $p = 1/12 = 0.0833$ .

Soln:  $c_1 \rightarrow 001\ 001\ 000\ 111$   
 $c_2 \rightarrow 101101000011$   
 $c_3 \rightarrow 110110010001$

$c_1, c_2, c_3$  (2 marks)

Single point crossover (At point 6)

$c_1 \rightarrow 001\ 001$	000111
$c_2 \rightarrow 101\ 101$	000011
6	

1.5 marks.

ch<sub>1</sub> → 001001 000011

ch<sub>2</sub> → 101101 000111

Two point crossover (2,6)

$c_1 \rightarrow 00$	1001	000111
$c_2 \rightarrow 10$	1101	000011
2      6		

1.5 marks.

ch<sub>1</sub> → 00 1101 000111

ch<sub>2</sub> → 10 1001 000011

Mutation:

Random numbers generate রোল  
হার্ড।

$C_3 \rightarrow$

1	1	0	1	1	0	0	1	0	0	0	1
0.5	0.6	0.02	0.9	0.01	0.33	0.45	0.62	0.77	0.53	0.8	0.87

+ Randomly

$C_3' \rightarrow$

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

Ans.