

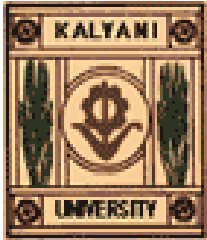
Genetic Algorithms

Anirban Mukhopadhyay

Department of Computer Science and Engineering

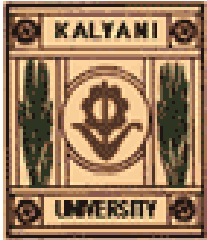
University of Kalyani

anirban@klyuniv.ac.in, www.anirbanm.in



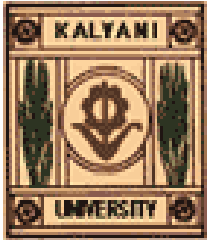
Today's Talk

- Genetic Algorithm
- Multiobjective Genetic Algorithm
- Genetic Algorithm based clustering
- Microarray Gene Expression data clustering

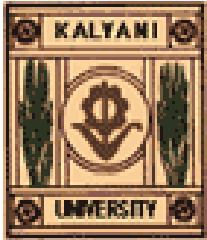


Genetic Algorithm (GA)

- Randomized search and optimization technique guided by the principle of natural genetic systems.
- Inspired by the biological evolution process
- Uses concepts of “Natural Selection”, “Genetic Inheritance” and “Survival of the Fittest” (Darwin 1859)
- Originally developed by **John Holland** (1975) and gained popularity during late 80’s.

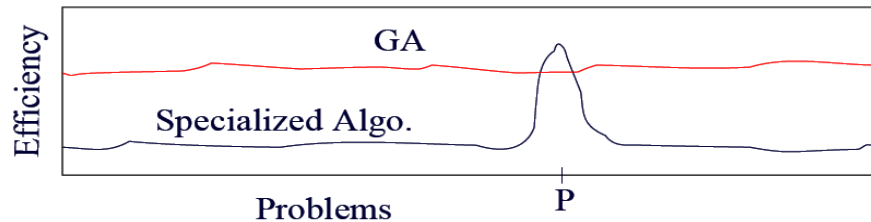


Genetic Algorithms

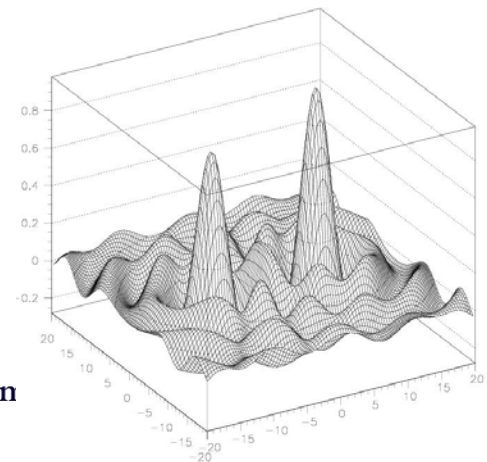


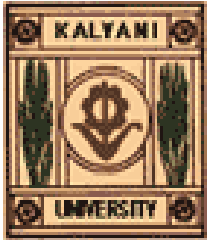
Why GA?

- Most real life problems can not be solved in polynomial amount of time using any deterministic algorithm.
- Sometimes near optimal solutions that can be generated quickly are more desirable than optimal solutions which require huge amount of time.
- When the problem can be modeled as an optimization one.
- Efficiently searches for global optima when multiple optima exist.
- Parallel implementation is easy.



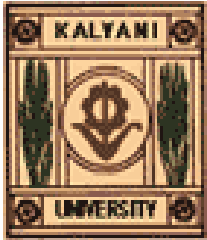
Specialized algorithms – best performance for special problems
Genetic algorithms – good performance over a wide range of problem





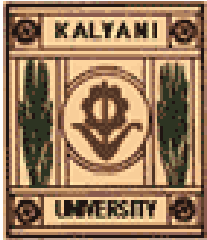
GA Features

- Evolutionary Search and Optimization Technique
- Principles of Evolution (**survival of the fittest** and **inheritance**).
- Work with **encoding** of the parameter set.
- Searches from a **population of points**.
- Uses **probabilistic transition rules**.



GA vs. Nature

- | | |
|---|--|
| <ul style="list-style-type: none">• A solution (phenotype) | Individual |
| <ul style="list-style-type: none">• Representation of a solution (genotype) | Chromosome |
| <ul style="list-style-type: none">• Components of the representation | Genes |
| <ul style="list-style-type: none">• Solution's quality (fitness function) | Individual's degree of ability to adopt with surrounding |
| <ul style="list-style-type: none">• Stochastic operators | Selection, Crossover (reproduction), Mutation |



Simple GA

Produce an **initial population** of individuals

Evaluate the fitness of all individuals

While termination condition not met **do**

select fitter individuals for reproduction

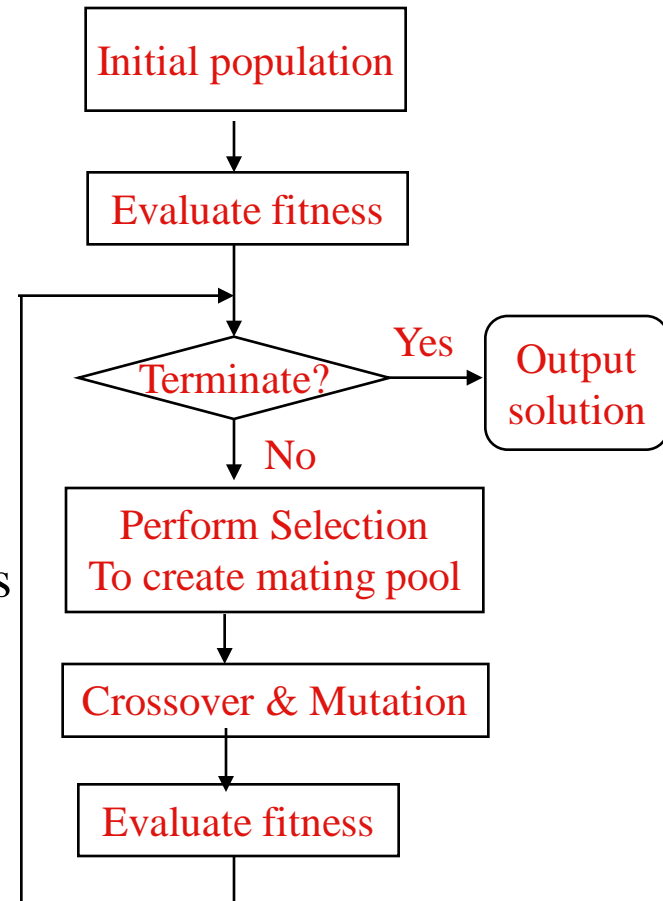
Recombine (crossover) between individuals

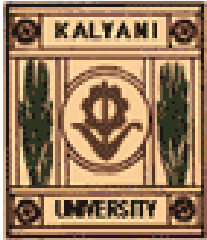
Mutate individuals

Evaluate the fitness of the modified individuals

Generate a new population

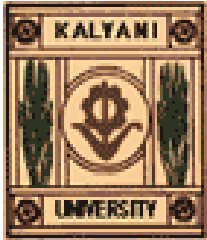
End while





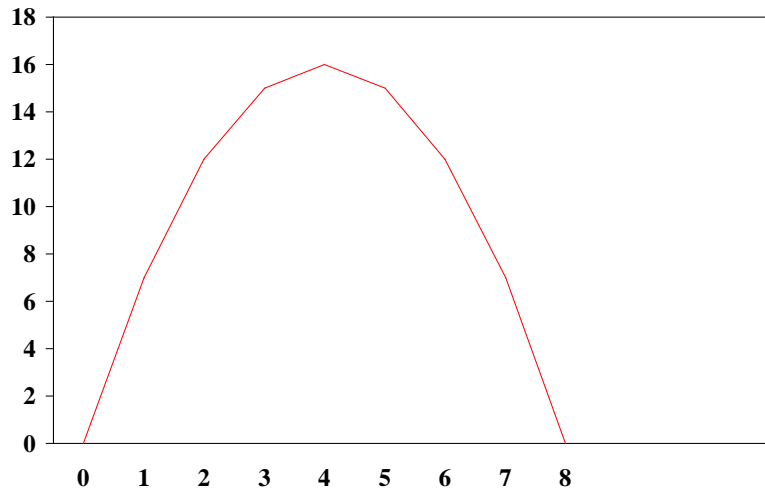
Encoding and Population

- **Chromosome encodes a solution in the search space**
 - Usually as strings of 0's and 1's
 - If l is the string length, number of different chromosomes (or strings) is 2^l
- **Population**
 - A set of chromosomes in a generation
 - Population size is usually constant
 - Common practice is to choose the initial population randomly.



Encoding and Population - Example

Optimize $f(x) = x(8 - x)$, $x=[0,8]$



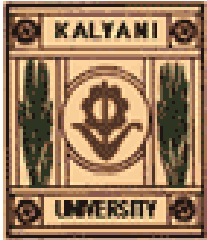
Binary String of 8 bits

0-255 \longleftrightarrow 0-8

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

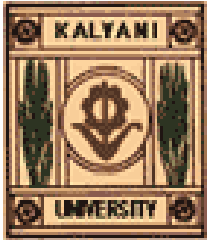
= 154

$$x = 0 + (8/255) * 154 = 4.8313$$



Fitness Evaluation

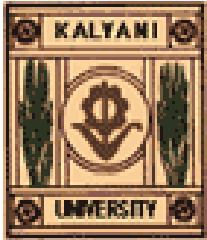
- Fitness/objective function is associated with each chromosome
- This indicates the degree of goodness of the encoded solution
- The only problem specific information (**also known as the payoff information**) that GA uses
- If minimization problem is to be solved then
 $\text{fitness} = 1/\text{objective}$.



Fitness Evaluation - Example

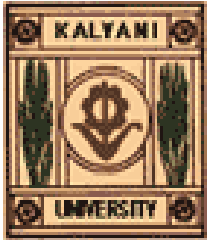
Function $f(x) = x(8-x)$

Population (size = 4)	Corresponding x	Fitness/ Objective Fn.
1 0 0 1 1 0 1 0	4.8313	15.3089
0 1 1 0 0 1 1 1	3.2313	15.4091
0 0 0 1 0 1 0 1	0.6588	4.8363
1 0 1 1 1 1 0 0	5.8980	12.3975



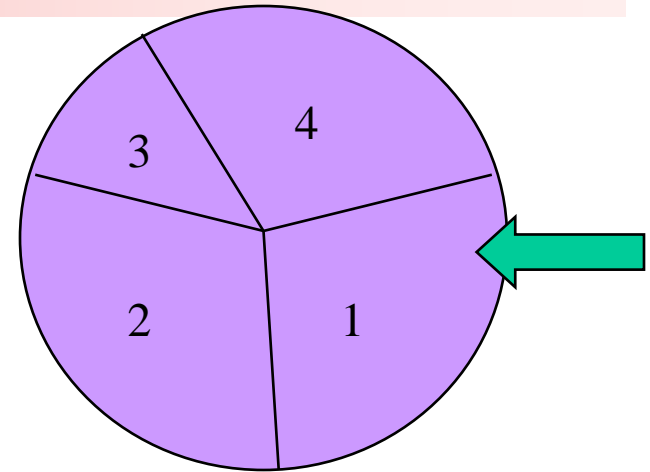
Selection

- More copies to good strings
- Fewer copies to bad string
- Proportional selection scheme
 - Number of copies taken to be directly proportional to its fitness
 - Mimics the natural selection procedure to some extent.
- **Roulette wheel selection** and **Tournament selection** are two frequently used selection procedures.



Roulette Wheel Selection - Example

Chromosome #	Fitness
1	15.3089
2	15.4091
3	4.8363
4	12.3975

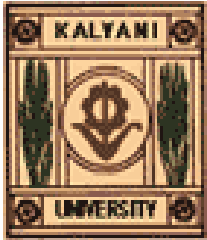


Individual i will have a probability $\frac{f(i)}{\sum_i f(i)}$ to be chosen

- Spin 1 Chromosome 2 is selected
- Spin 2 Chromosome 1 is selected
- Spin 3 Chromosome 2 is selected
- Spin 4 Chromosome 4 is selected

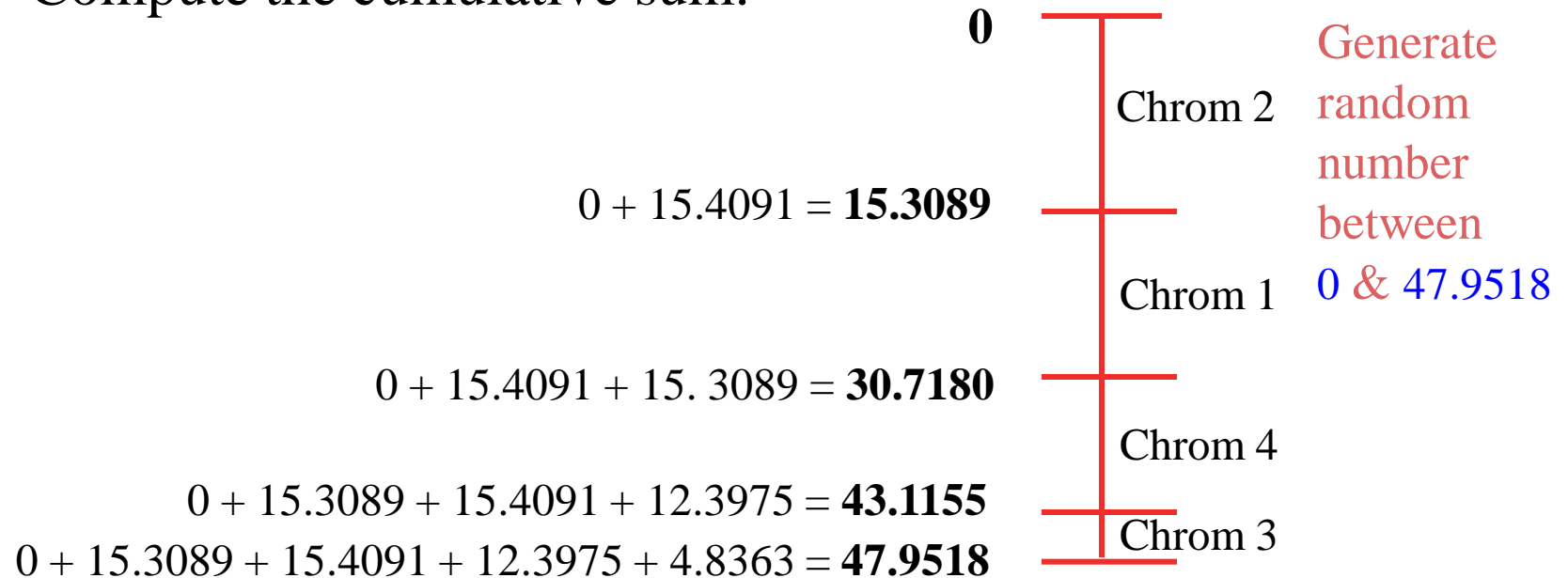
Mating
→
Pool

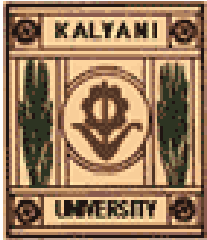
0	1	1	0	0	1	1	1
1	0	0	1	1	0	1	0
0	1	1	0	0	1	1	1
1	0	1	1	1	1	0	0



Roulette Wheel Selection - Implementation

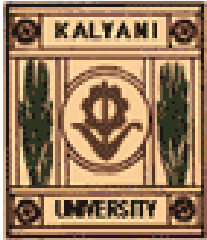
- Sort the solutions in descending order of fitness.
- Compute the cumulative sum.





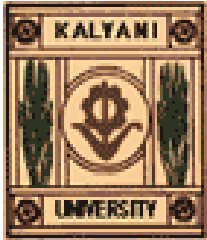
Tournament - Selection

- Repeat until mating pool is full
 - Select a set (size $<$ population size) of chromosomes randomly.
 - Copy the best chromosome among them into the mating pool.
- Usually tournament size is 2 (**binary tournament**).
- The chromosome with lowest fitness value can never be copied into the mating pool.



Crossover

- Exchange of genetic information
- It takes place between randomly selected parent chromosomes
- **Single point crossover** and **Uniform crossover** are the most commonly used schemes.
- Probabilistic operation



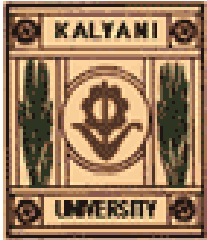
Single Point Crossover – Example

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

Here l (string length) = 8. Let k (crossover point) = 5

Offspring formed:

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



Uniform Crossover – Example

Parents:

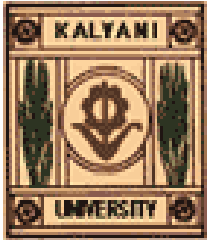
1	0	0	1	1	0	1	0
0	1	1	1	1	1	0	1

Mask:

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

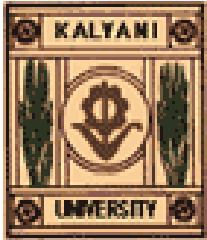
Offspring formed:

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

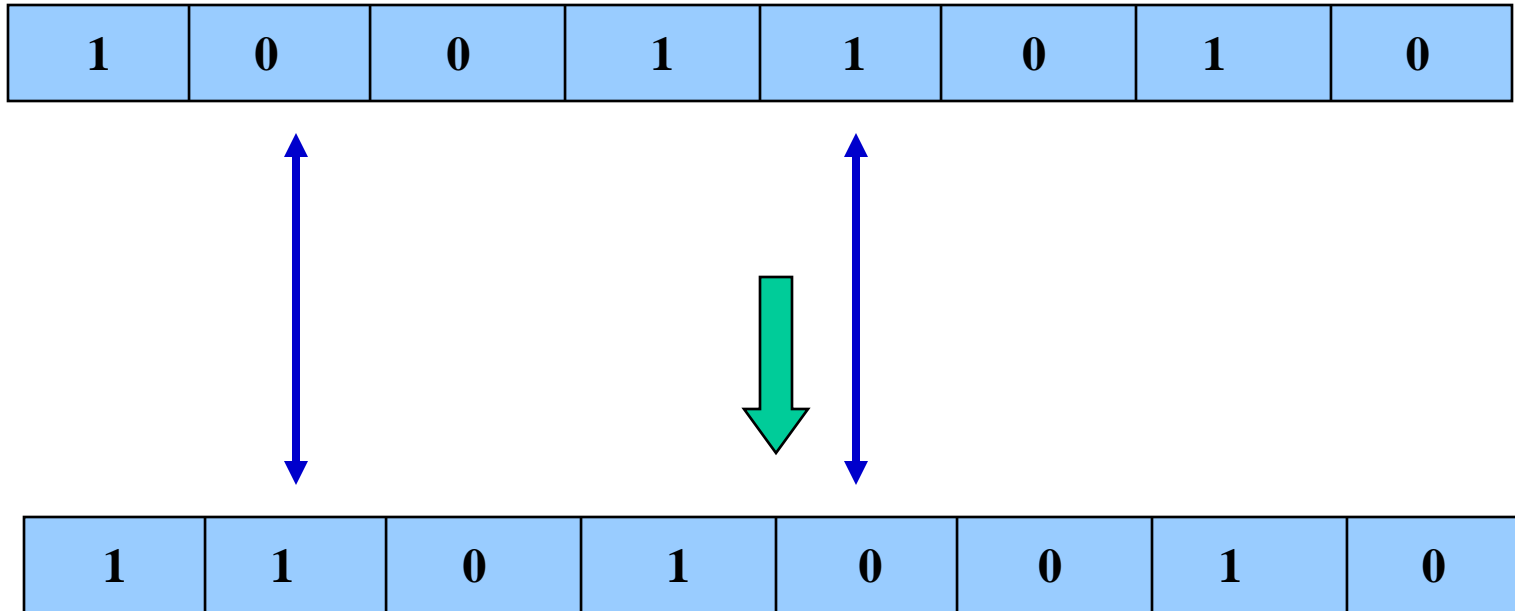


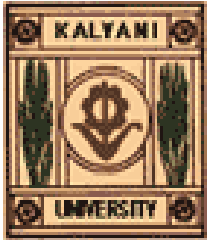
Mutation

- **Random alteration** in the genetic structure
- Introduces **genetic diversity** into the population.
- Exploration of new search areas
- Mutating a binary gene involves simple **negation of the bit**
- Mutating a real coded gene defined in a variety of ways
- Probabilistic operation



Mutation – Example



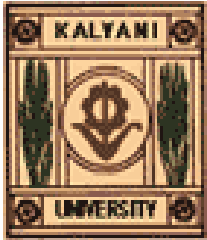


Parameters

- Population size – usually fixed
- String length – usually fixed
- Probabilities of crossover, μ_c , and mutation, μ_m

μ_c is kept high and μ_m is kept low.

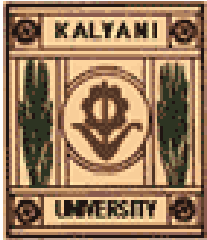
- Termination criteria
- Parameters are often manually tuned
- Sometimes may be adaptive.



Parameters – Example

For the example being considered,

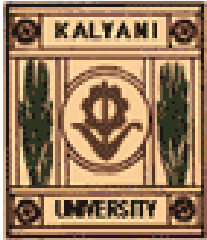
- $P = 4, l = 8$.
- But for most realistic cases P is usually chosen in the range 50-100.
- $\mu_c = [0.6-0.9]$,
- $\mu_m = [0.01-0.1]$.
- l usually depends on the required precision



Termination Criterion

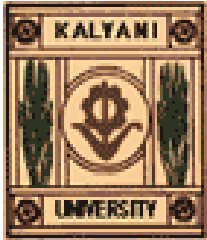
The cycle of selection, crossover and mutation are repeated for number of times until one of these occurs

- Average fitness value of a population more or less constant over several generations,
- Desired objective function value is attained by at least one string in the population,
- **Number of generations (or iterations) is greater than some threshold ----- most commonly used.**



Elitist Model of GAs

The best string seen up to the current generation is preserved in a location either inside or outside the population.



Variation of Fitness over Generation

