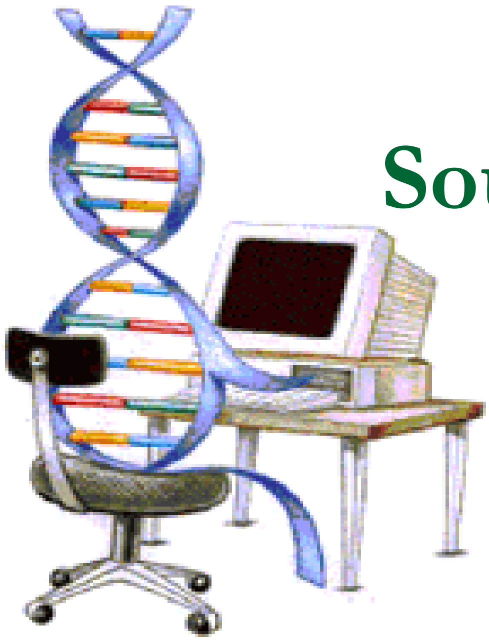
Genetic Algorithms

Prof. Dr. Md. Aminul Haque Akhand
Dept. of CSE, KUET



Source

1. Presentation of Dr. Chhavi Kashyap
2. Presentation of Dr. Son Kuswadi
3. Others

Overview

- Introduction To Genetic Algorithms (GAs)
- GA Operators and Parameters
- Application of Genetic Algorithms
- Summary

References

- D. E. Goldberg, ‘Genetic Algorithm In Search, Optimization And Machine Learning’, New York: Addison – Wesley (1989)
- John H. Holland ‘Genetic Algorithms’, Scientific American Journal, July 1992.
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- D. Whitley, et al, ‘Traveling Salesman And Sequence Scheduling: Quality Solutions Using Genetic Edge Recombination’, Handbook Of Genetic Algorithms, New York
- Jason Brownlee, “Clever Algorithms - Nature-Inspired Programming Recipes” 2011.

WEBSITES

www.iitk.ac.in/kangal www.genetic-programming.com

Introduction To Genetic Algorithms (GAs)

History Of Genetic Algorithms

- "Evolutionary Computing" was introduced in the 1960s by **I. Rechenberg**.
- John Holland wrote the first book on Genetic Algorithms 'Adaptation in Natural and Artificial Systems' in 1975.
- In 1992 **John Koza** used genetic algorithm to evolve programs to perform certain tasks. He called his method "Genetic Programming".

"It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is the most adaptable to change."

-------- Charles Darwin

(12/02/1809 – 19/04/1882)

Basic Idea Of Principle Of Natural Selection

"Select The Best, Discard The Rest"

Darwin's Principle Of Natural Selection

- IF there are organisms that reproduce, and
- IF offsprings inherit traits from their progenitors, and
- IF there is variability of traits, and
- IF the environment cannot support all members of a growing population,
- THEN those members of the population with less-adaptive traits (determined by the environment) will die out, and
- THEN those members with more-adaptive traits (determined by the environment) will thrive

The result is the evolution of species.

An Example of Natural Selection

- **Giraffes have long necks**.

Giraffes with slightly longer necks could feed on leaves of higher branches when all lower ones had been eaten off.

→ They had a better chance of survival.

→ Favorable characteristic propagated through generations of giraffes.

→ Now, evolved species has long necks.

NOTE: Longer necks may have been a deviant characteristic (mutation) initially but since it was favorable, was propagated over generations. Now an established trait.

So, some mutations are beneficial.

Evolution Through Natural Selection

Initial Population Of Animals

↓

Struggle For Existence-Survival Of the Fittest

↓

Surviving Individuals Reproduce, Propagate Favorable Characteristics

↓

Millions Of Years

↓

Evolved Species

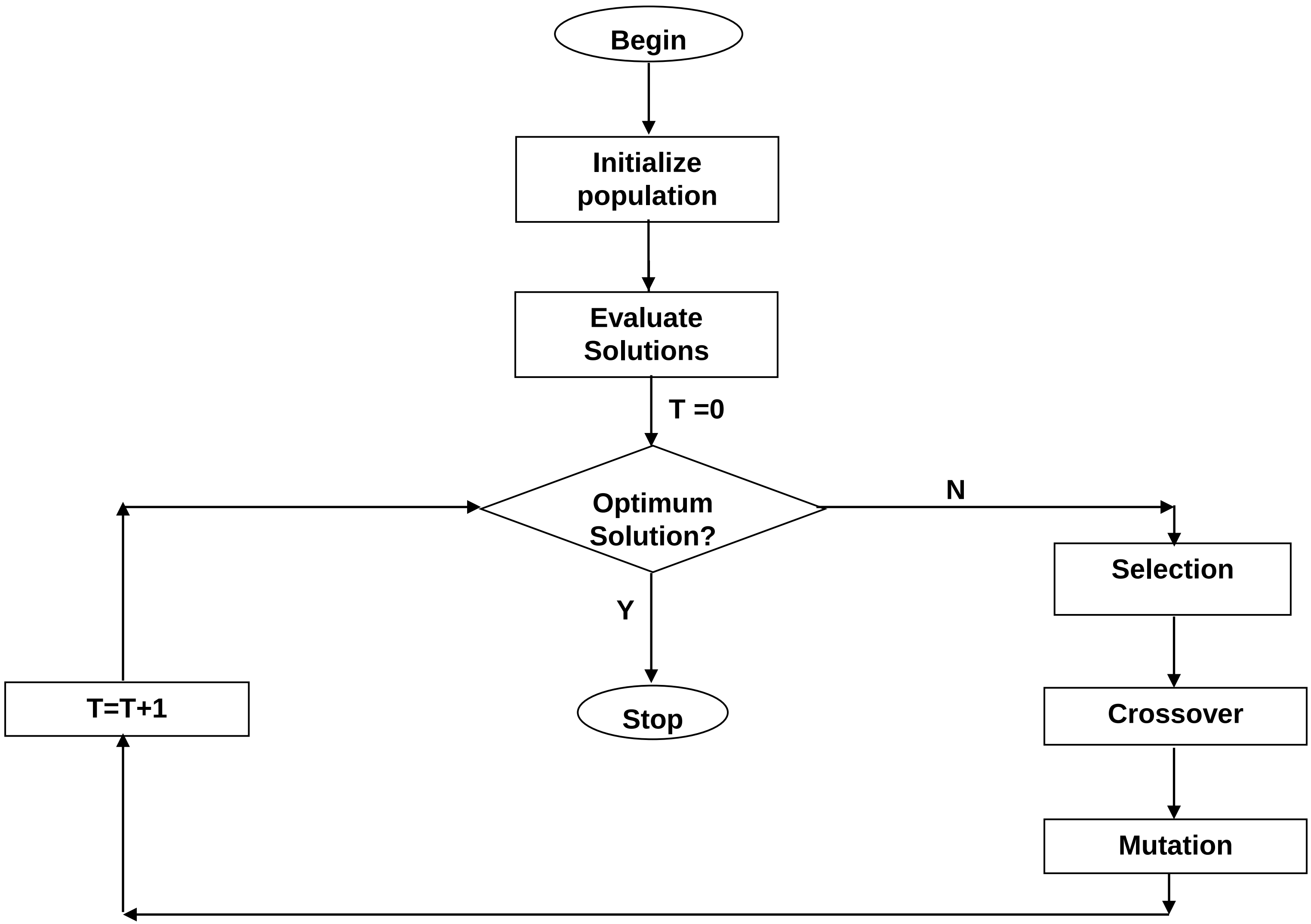
(Favorable Characteristic Now A Trait Of Species)

What Are Genetic Algorithms (GAs)?

Genetic Algorithms are *search* and *optimization* techniques based on Darwin's Principle of *Natural Selection*.

Genetic Algorithms Implement Optimization Strategies By Simulating Evolution Of Species Through Natural Selection.

Working Mechanism Of GAs



Simple Genetic Algorithm

```
Simple_Genetic_Algorithm()
      {
      Initialize the Population;
      Calculate Fitness Function;

      While(Fitness Value != Optimal Value)
            {
            Selection;//Natural Selection, Survival
  Of Fittest
            Crossover;//Reproduction, Propagate
  favorable characteristics


            Mutation;//Mutation
            Calculate Fitness Function;
            }
      }
```

Nature to Computer Mapping

Nature	Computer
Population	Set of solutions.
Individual	Solution to a problem.
Fitness	Quality of a solution.
Chromosome	Encoding for a Solution.
Gene	Part of the encoding of a solution.
Reproduction	Crossover

GA Operators and Parameters

Encoding

*The process of representing the solution in the form of a **string** that conveys the necessary information.*

- Just as in a chromosome, each gene controls a particular characteristic of the individual, similarly, each bit in the string represents a characteristic of the solution.

Encoding Methods

- **Binary Encoding –** Most common method of encoding. Chromosomes are strings of 1s and 0s and each position in the chromosome represents a particular characteristic of the problem.

Chromosome A	101100101100101011100101
Chromosome B	111111100000110000011111

Encoding Methods (contd.)

- **Permutation Encoding –** Useful in ordering problems such as the Traveling Salesman Problem (TSP). Example. In TSP, every chromosome is a string of numbers, each of which represents a city to be visited.

Chromosome A	1 5 3 2 6 4 7 9 8
Chromosome B	8 5 6 7 2 3 1 4 9

Encoding Methods (contd.)

- **Value Encoding –** Used in problems where complicated values, such as real numbers, are used and where binary encoding would not suffice.

  Good for some problems, but *often necessary to develop some specific crossover and mutation techniques for these chromosomes.*

Chromosome A	1.235 5.323 0.454 2.321 2.454
Chromosome B	(left), (back), (left), (right), (forward)

Fitness Function

A fitness function quantifies the optimality of a solution (chromosome) so that that particular solution may be ranked against all the other solutions.

- A fitness value is assigned to each solution depending on how close it actually is to solving the problem.
- Ideal fitness function correlates closely to goal + quickly computable.
- Example. In TSP, f(x) is sum of distances between the cities in solution. The lesser the value, the fitter the solution is.

Recombination

The process that determines which solutions are to be preserved and allowed to reproduce and which ones deserve to die out.

- The primary objective of the recombination operator is to emphasize the good solutions and eliminate the bad solutions in a population, while keeping the population size constant.
- “Selects The Best, Discards The Rest”.
- “Recombination” is different from “Reproduction”.

Recombination

- Identify the good solutions in a population.
- Make multiple copies of the good solutions.
- Eliminate bad solutions from the population so that multiple copies of good solutions can be placed in the population.

Roulette Wheel Selection

- Each current string in the population has a slot assigned to it which is in proportion to it's fitness.

- We spin the weighted *roulette wheel* thus defined *n* times (where *n* is the total number of solutions).

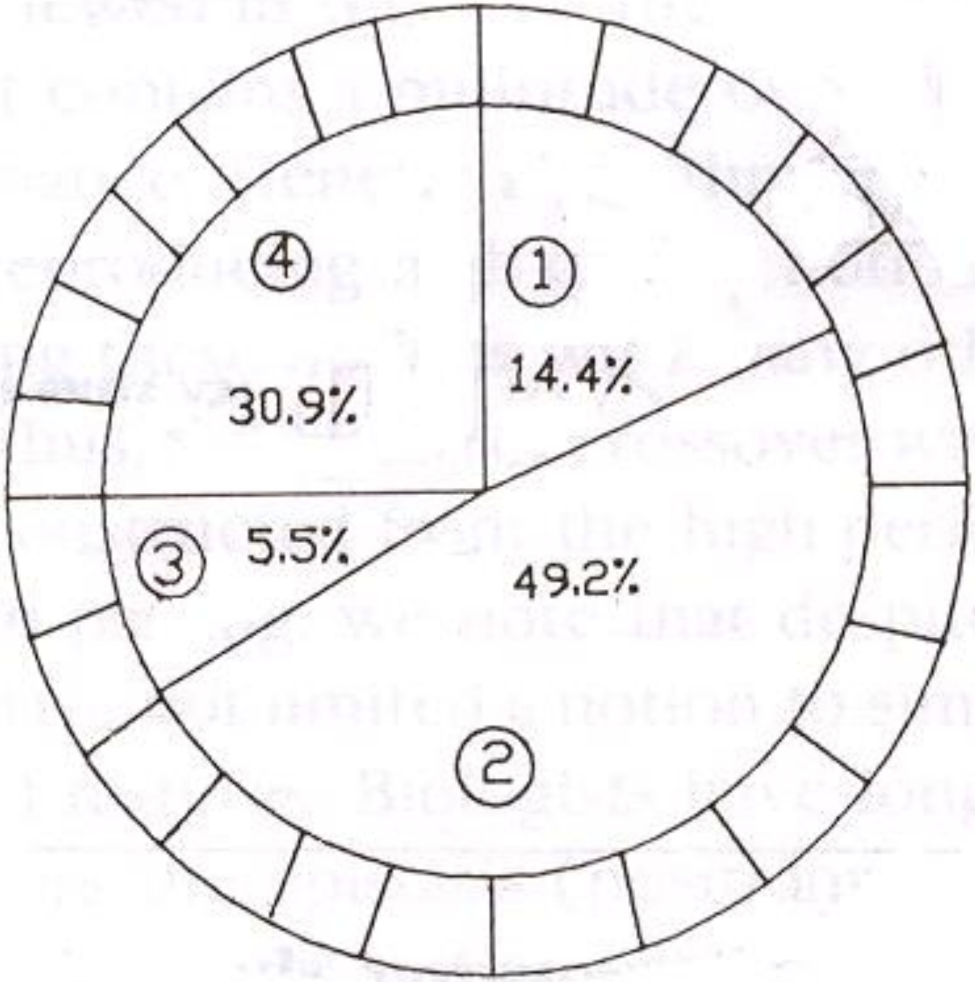
- Each time Roulette Wheel stops, the string corresponding to that slot is created.

Strings that are fitter are assigned a larger slot and hence have a better chance of appearing in the new population.

Example Of Roulette Wheel Selection

No.	String	Fitness	% Of Total
1	01101	169	14.4
2	11000	576	49.2
3	01000	64	5.5
4	10011	361	30.9
Total		1170	100.0

Roulette Wheel For Example



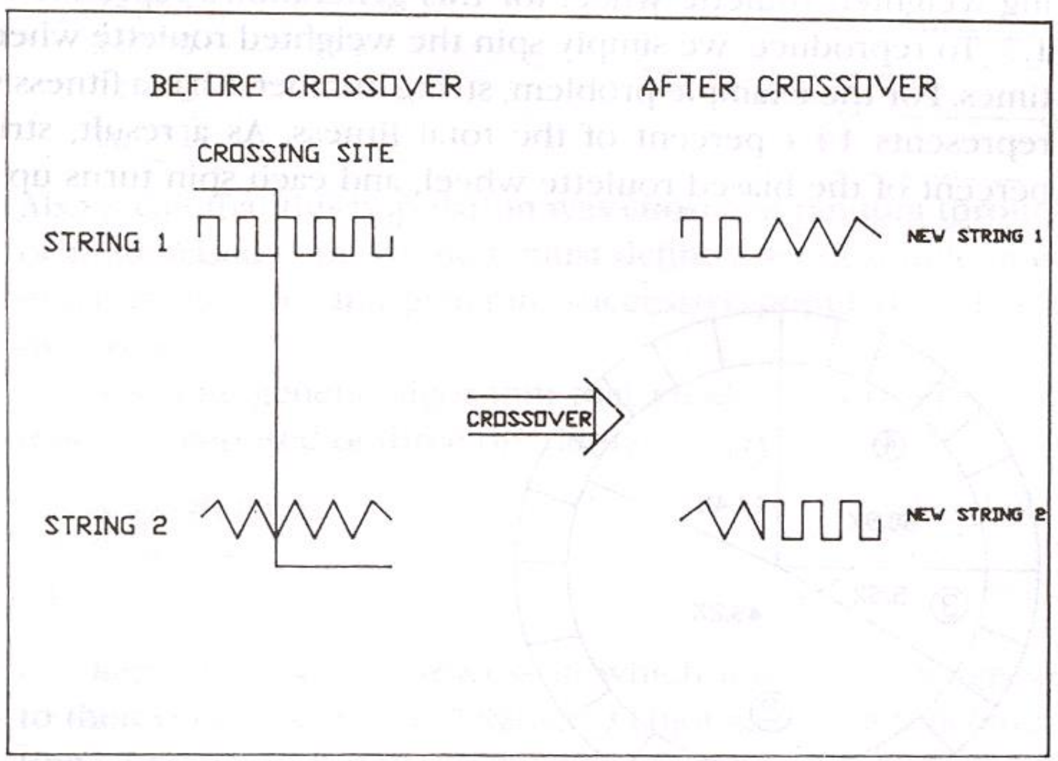
Crossover

It is the process in which two chromosomes (strings) combine their genetic material (bits) to produce a new offspring which possesses both their characteristics.

- *Two strings are picked from the mating pool at random to cross over.*
- *The method chosen depends on the Encoding Method.*

Crossover Methods

- **Single Point Crossover-** A random point is chosen on the individual chromosomes (strings) and the genetic material is exchanged at this point.



Crossover Methods (contd.)

- **Single Point Crossover**

Chromosome1	**11011 | 00100110110**
Chromosome 2	**11011 | 11000011110**
Offspring 1	**11011 | 11000011110**
Offspring 2	**11011 | 00100110110**

Crossover Methods (contd.)

- **Two-Point Crossover-** Two random points are chosen on the individual chromosomes (strings) and the genetic material is exchanged at these points.

Chromosome1	**11011 | 00100 | 110110**
Chromosome 2	**10101 | 11000 | 011110**
Offspring 1	**10101 | 00100 | 011110**
Offspring 2	**11011 | 11000 | 110110**

NOTE: These chromosomes are different from the last example.

Crossover Methods (contd.)

- **Uniform Crossover-** Each gene (bit) is selected randomly from one of the corresponding genes of the parent chromosomes.

Chromosome1	11011 | 00100 | 110110
Chromosome 2	10101 | 11000 | 011110
Offspring	10111 | 00000 | 110110

NOTE: Uniform Crossover yields ONLY 1 offspring.

Crossover (contd.)

- Crossover between 2 good solutions **MAY NOT ALWAYS** yield a better or as good a solution.
- Since parents are good, probability of the child being good is high.
- If offspring is not good (poor solution), it will be removed in the next iteration during “Selection”.

Elitism

Elitism is a method which copies the best chromosome to the new offspring population before crossover and mutation.

- When creating a new population by crossover or mutation the best chromosome might be lost.
- Forces GAs to retain some number of the best individuals at each generation.
- Has been found that elitism significantly improves performance.

Mutation

It is the process by which a string is deliberately changed so as to maintain diversity in the population set.

We saw in the giraffes' example, that mutations could be beneficial.

Mutation Probability- determines how often the parts of a chromosome will be mutated.

Example Of Mutation

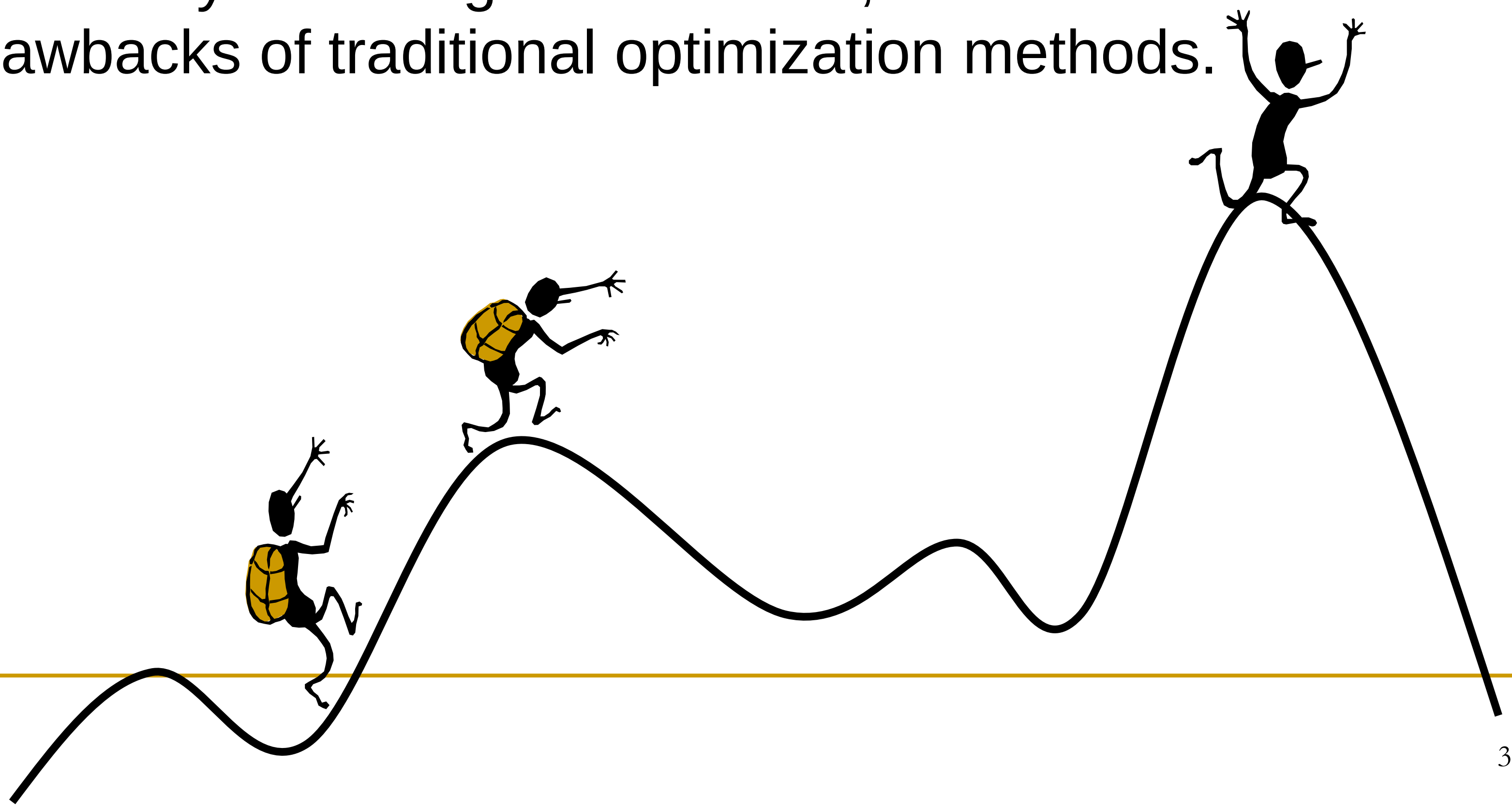
- For chromosomes using Binary Encoding, randomly selected bits are inverted.

Offspring	**11011 00100 110110**
Mutated Offspring	**11010 00100 100110**

NOTE: The number of bits to be inverted depends on the Mutation Probability.

Advantages Of GAs

- **Global Search Methods:** GAs search for the function optimum starting from a *population of points* of the function domain, not a single one. This characteristic suggests that GAs are global search methods. They can, in fact, climb many peaks in parallel, reducing the probability of finding local minima, which is one of the drawbacks of traditional optimization methods.



Advantages of GAs (contd.)

- **Blind Search Methods:** GAs only use the information about the *objective function*. They do not require knowledge of the first derivative or any other auxiliary information, allowing a number of problems to be solved without the need to formulate restrictive assumptions. For this reason, GAs are often called blind search methods.

Advantages of GAs (contd.)

- **GAs use probabilistic transition rules** during iterations, unlike the traditional methods that use fixed transition rules.

  This makes them more robust and applicable to a large range of problems.

Advantages of GAs (contd.)

- **GAs can be easily used in *parallel machines*-** Since in real-world design optimization problems, most computational time is spent in evaluating a solution, with multiple processors all solutions in a population can be evaluated in a distributed manner. This reduces the overall computational time substantially.

Simple Example (Goldberg98)

- **Simple problem: max x^2 over {0,1,…,31}**
- GA approach:
  - Representation: binary code, e.g. 01101 $\leftrightarrow$ 13
  - Population size: 4
  - 1-point xover, bitwise mutation
  - Roulette wheel selection
  - Random initialization
- We show one generational cycle done by hand

Selection

String no.	Initial population	x Value	Fitness $f(x) = x^2$	$Prob_i$	Expected count	Actual count
1	0 1 1 0 1	13	169	0.14	0.58	1
2	1 1 0 0 0	24	576	0.49	1.97	2
3	0 1 0 0 0	8	64	0.06	0.22	0
4	1 0 0 1 1	19	361	0.31	1.23	1
Sum			1170	1.00	4.00	4
Average			293	0.25	1.00	1
Max			576	0.49	1.97	2

Crossover

String no.	Mating pool	Crossover point	Offspring after xover	x Value	Fitness $f(x) = x^2$
1	0 1 1 0 | 1	4	0 1 1 0 0	12	144
2	1 1 0 0 | 0	4	1 1 0 0 1	25	625
2	1 1 | 0 0 0	2	1 1 0 1 1	27	729
4	1 0 | 0 1 1	2	1 0 0 0 0	16	256
Sum					1754
Average					439
Max					729

Mutation

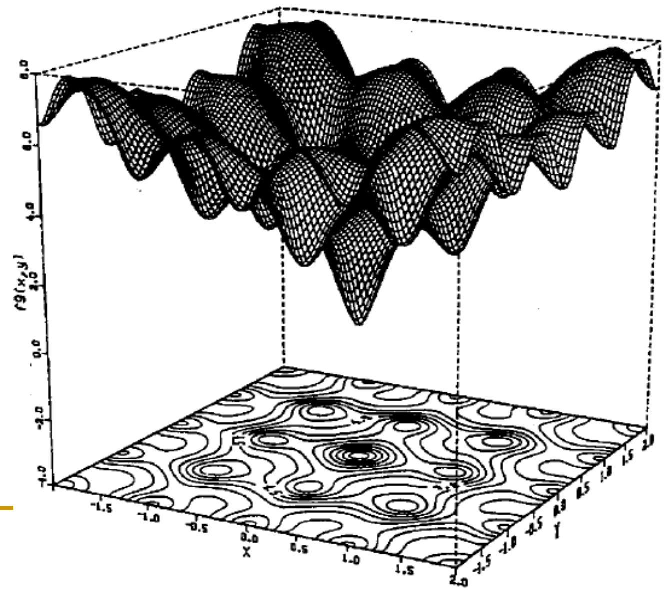
String no.	Offspring after xover	Offspring after mutation	x Value	Fitness $f(x) = x^2$
1	0 1 1 0 0	$\boxed{1}$ 1 1 0 0	26	676
2	1 1 0 0 1	1 1 0 0 1	25	625
2	1 1 0 1 1	1 1 0 1 1	27	729
4	1 0 0 0 0	1 0 $\boxed{1}$ 0 0	18	324
Sum				2354
Average				588.5
Max				729

Hard Problems

- Solution of $f(x)=x^2$ is easy to find and not realistic for GA
- Many problems occur as real valued problems, e.g. continuous parameter optimization $f : \Re^n \rightarrow \Re$
- Illustration: Ackley's function (often used in EC)

$$f(\overline{x}) = -c_1 \cdot exp\left(-c_2 \cdot \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n} \cdot \sum_{i=1}^{n} cos(c_3 \cdot x_i)\right) + c_1 + 1$$

$$c_1 = 20,\ c_2 = 0.2,\ c_3 = 2\pi$$



Genetic Algorithms To Solve The Traveling Salesman Problem (TSP)

The Problem

The **Traveling Salesman Problem** is defined as:

‘We are given a set of cities and a symmetric distance matrix that indicates the cost of travel from each city to every other city.

*The goal is to find **the shortest circular tour,** visiting every city exactly once, so as to **minimize the total travel cost**, which includes the cost of traveling from the last city back to the first city’.*

Encoding

- I represent every city with an integer .

- Consider 6 Indian cities –

  Mumbai, Nagpur , Calcutta, Delhi , Bangalore and Chennai and assign a number to each.

Mumbai	$\longrightarrow$	1
Nagpur	$\longrightarrow$	2
Calcutta	$\longrightarrow$	3
Delhi	$\longrightarrow$	4
Bangalore	$\longrightarrow$	5
Chennai	$\longrightarrow$	6

Encoding (contd.)

- Thus a path would be represented as a sequence of integers from 1 to 6.

- The path [1 2 3 4 5 6] represents a path from Mumbai to Nagpur, Nagpur to Calcutta, Calcutta to Delhi, Delhi to Bangalore, Bangalore to Chennai, and finally from Chennai to Mumbai.

- This is an example of **Permutation Encoding** as the position of the elements determines the fitness of the solution.

Fitness Function

- The fitness function will be the total cost of the tour represented by each chromosome.

- This can be calculated as the sum of the distances traversed in each travel segment.

The Lesser The Sum, The Fitter The Solution Represented By That Chromosome.

Distance/Cost Matrix For TSP

	1	2	3	4	5	6
1	0	863	1987	1407	998	1369
2	863	0	1124	1012	1049	1083
3	1987	1124	0	1461	1881	1676
4	1407	1012	1461	0	2061	2095
5	998	1049	1881	2061	0	331
6	1369	1083	1676	2095	331	0

Cost matrix for six city example.

Distances in Kilometers

Fitness Function (contd.)

- So, for a chromosome [4 1 3 2 5 6], the total cost of travel or fitness will be calculated as shown below

- Fitness = *1407* + *1987* + *1124* + *1049* + *331*+ *2095*

  = *7993 kms.*

- Since our objective is to Minimize the distance, the lesser the total distance, the fitter the solution.

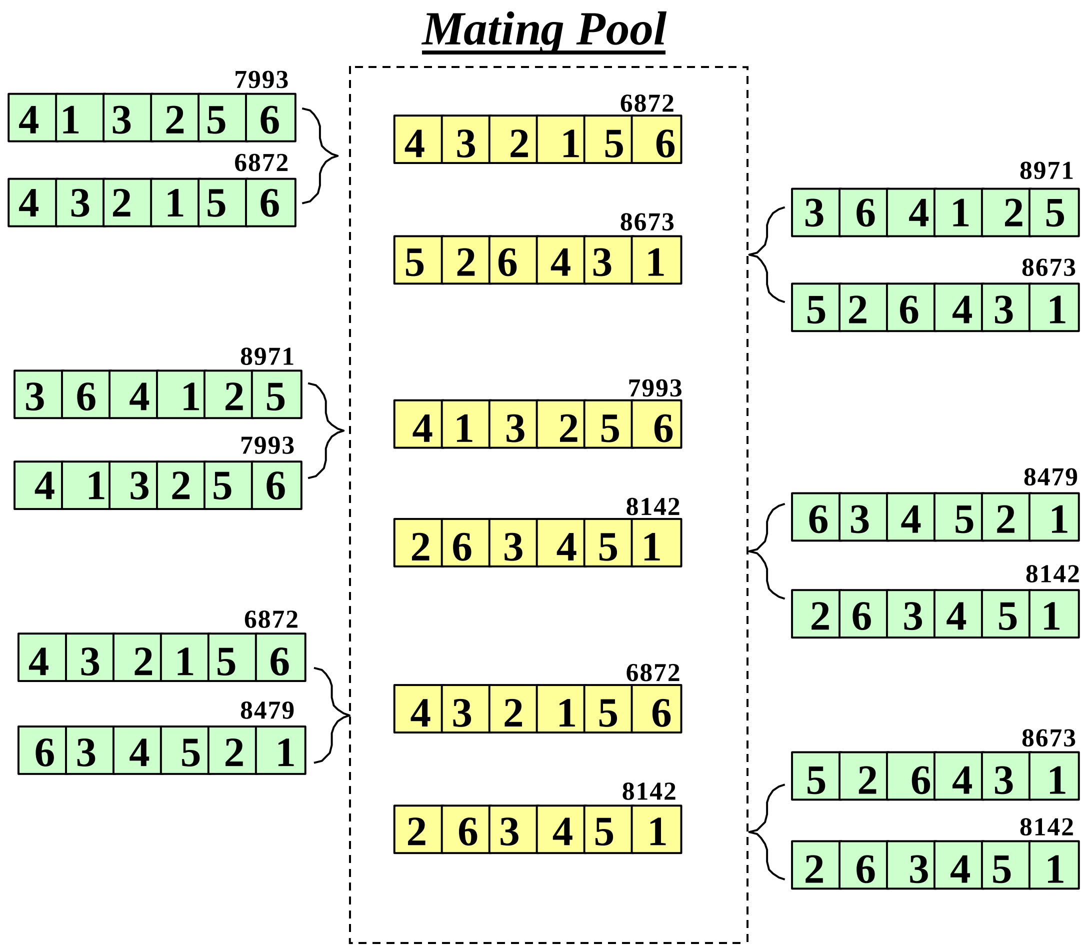
Selection Operator

May use ***Tournament Selection***.

As the name suggests *tournaments* are played between two solutions and the better solution is chosen and placed in the *mating pool.*

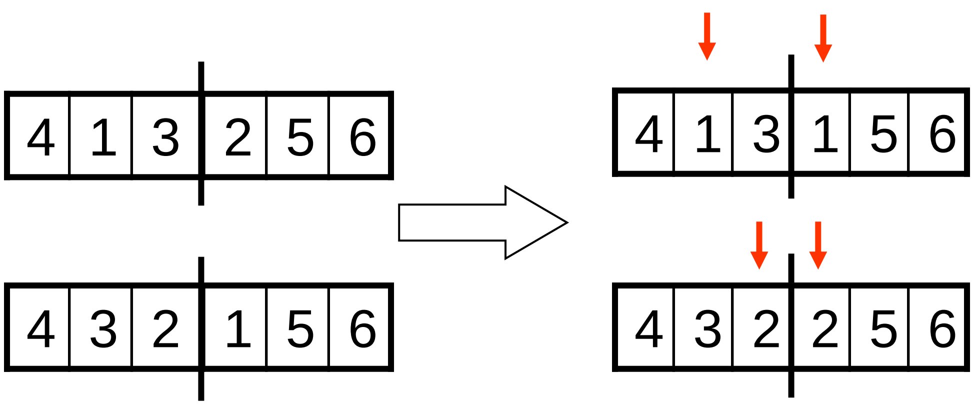
Two other solutions are picked again and another slot in the *mating pool* is filled up with the better solution.

Tournament Selection (contd.)



Why we cannot use single-point crossover:

- Single point crossover method randomly selects a crossover point in the string and swaps the substrings.
- This may produce some invalid offsprings as shown below.



Crossover Operator

- Used the *Enhanced Edge Recombination* operator (T.Starkweather, et al, *'A Comparison of Genetic Sequencing Operators,* International Conference of GAs, 1991).

- This operator is different from other genetic sequencing operators in that it emphasizes *adjacency information* instead of the order or position of items in the sequence.

- The algorithm for the Edge-Recombination Operator involves constructing an Edge Table first.

Edge Table

The *Edge Table* is an *adjacency table* that lists links *into* and *out of* a city found in the two parent sequences.

If an item is already in the edge table and we are trying to insert it again, that element of a sequence must be a *common edge* and is represented by inverting it's sign.

Finding The Edge Table

Parent 1	4	1	3	2	5	6
Parent 2	4	3	2	1	5	6

1	4	3	2	5
2	-3	5	1	
3	1	-2	4	
4	-6	1	3	
5	1	2	-6	
6	-5	-4		

Enhanced Edge Recombination Algorithm

1. Choose the initial city from one of the two parent tours. (It can be chosen randomly as according to criteria outlined in *step 4*). This is the *current city.*

2. Remove all occurrences of the *current city* from the left hand side of the edge table.(These can be found by referring to the edge-list for the *current city*).

3. If the *current city* has entries in it's edge-list, go to *step 4* otherwise go to *step 5*.

4. Determine which of the cities in the edge-list of the *current city* has the fewest entries in it's own edge-list. The city with fewest entries becomes the *current city*. In case a negative integer is present, it is given preference. Ties are broken randomly. Go to *step 2.*

5. If there are no remaining *unvisited* cities, then *stop.* Otherwise, randomly choose an *unvisited* city and go to *step 2.*

Example Of Enhanced Edge Recombination Operator

Step 1

1	4	3	2	5
2	-3	5	1	
3	1	-2	4	
4	-6	1	3	
5	1	2	-6	
6	-5	-4		

4					

Step 2

1	3	2	5
2	-3	5	1
3	1	-2	
4	-6	1	3
5	1	2	-6
6	-5		

4	6				

Example Of Enhanced Edge Recombination Operator (contd.)

Step 3

1	3	2	5
2	-3	5	1
3	1	-2	
4	1	3	
5	1	2	
6	-5		

4	6	5			

Step 4

1	3	2
2	-3	1
3	1	-2
4	1	3
5	1	2
6		

4	6	5	1		

Example Of Enhanced Edge Recombination Operator (contd.)

Step 5

1	3	2
2	-3	
3	-2	
4	3	
5	2	
6		

4	6	5	1	3	

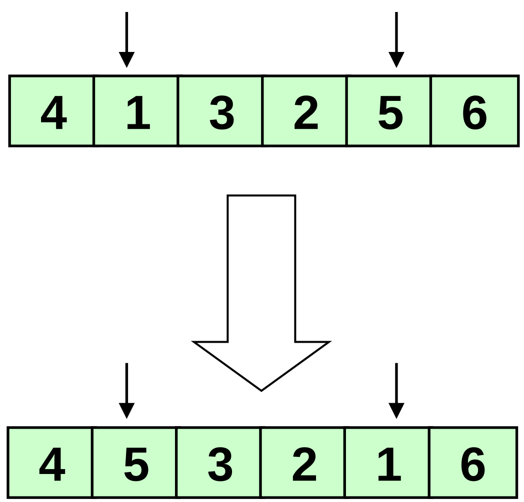
Step 6

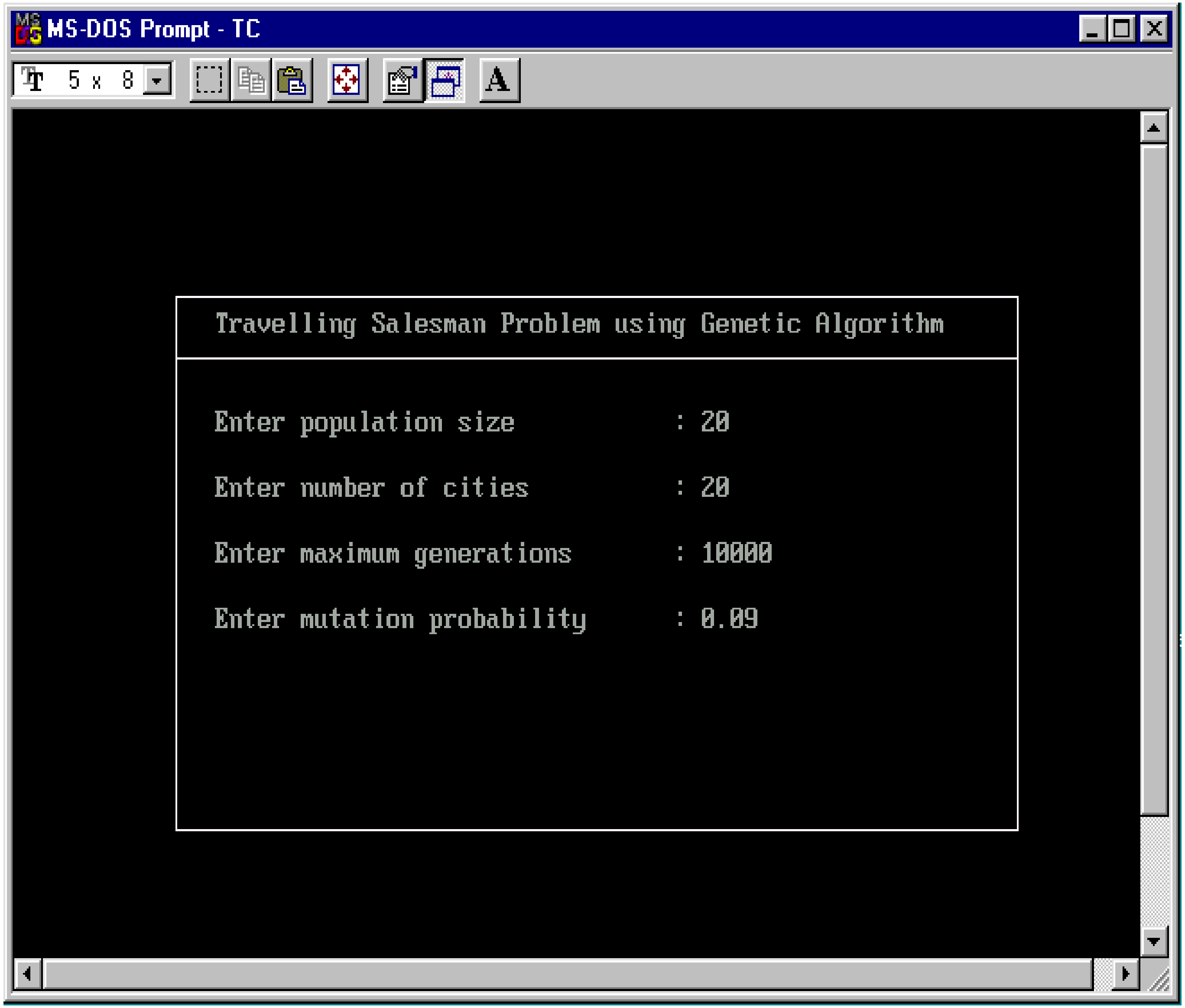
1	2
2	
3	-2
4	
5	2
6	

4	6	5	1	3	2

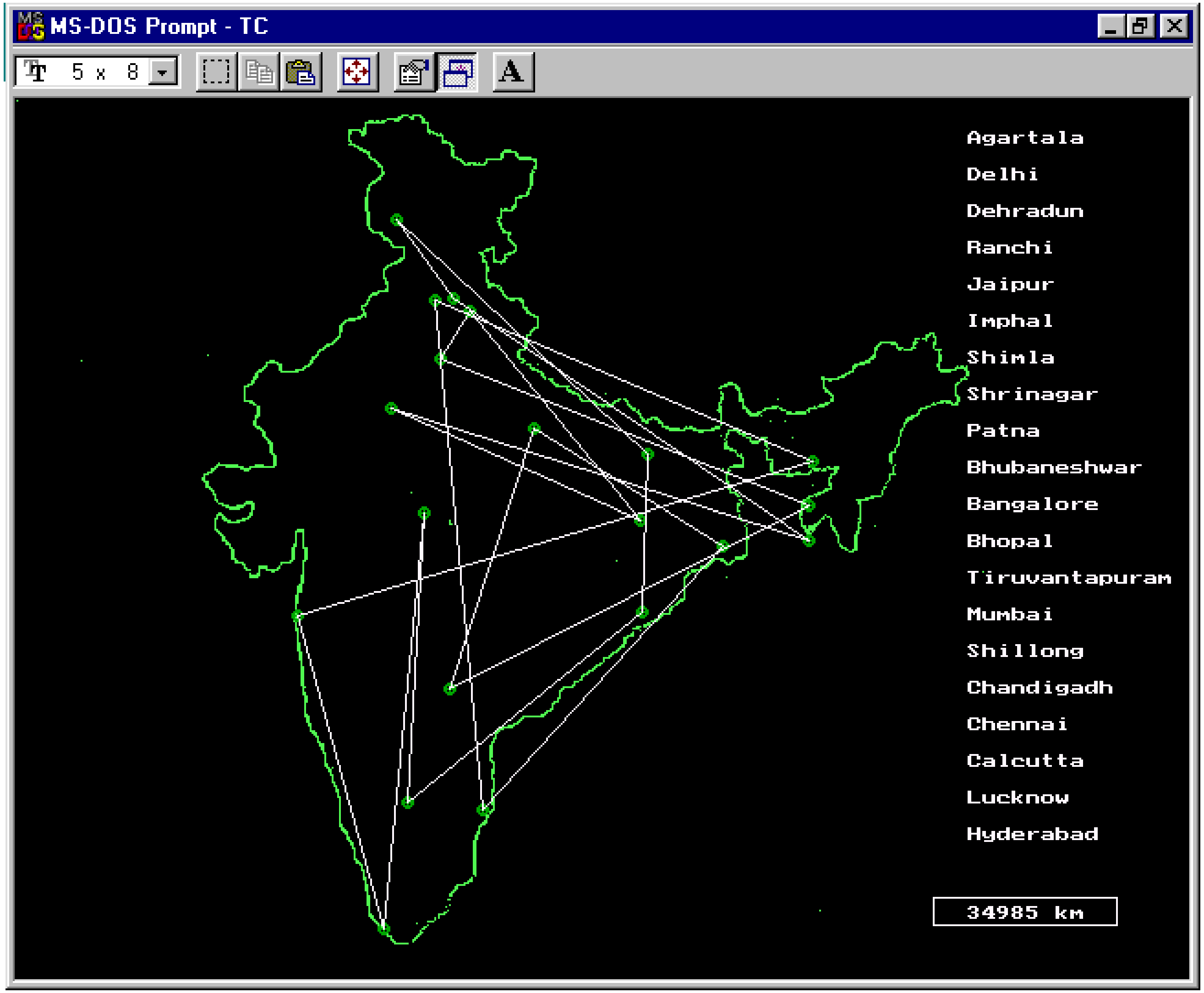
Mutation Operator

- The mutation operator induces a change in the solution, so as to maintain diversity in the population and prevent *Premature Convergence*.
- In our project, we mutate the string by randomly selecting any two cities and interchanging their positions in the solution, thus giving rise to a new tour.

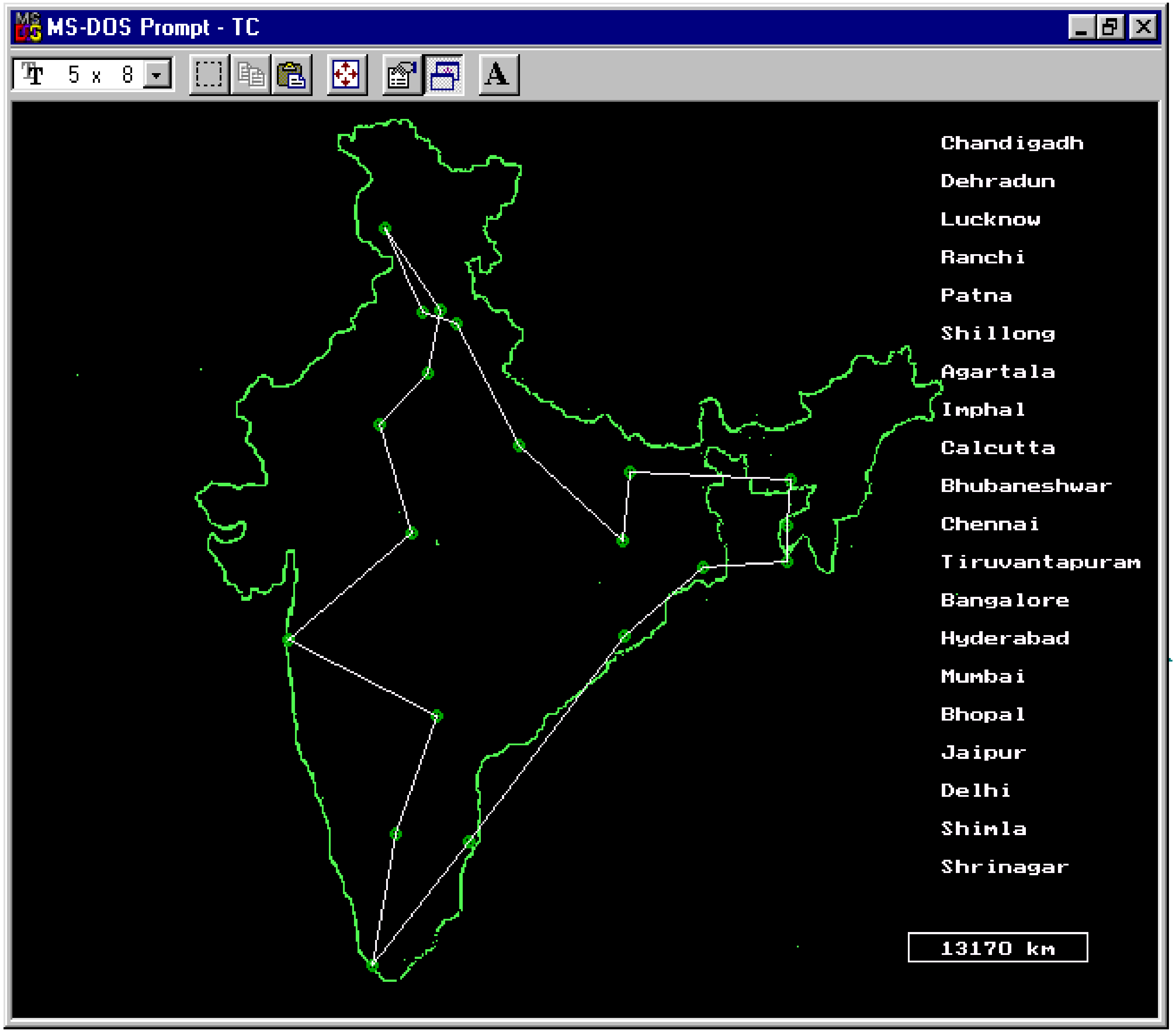




Input To Program



Initial Output For 20 cities : Distance=34985 km
Initial Population



Final Output For 20 cities : Distance=13170 km
Generation 4786

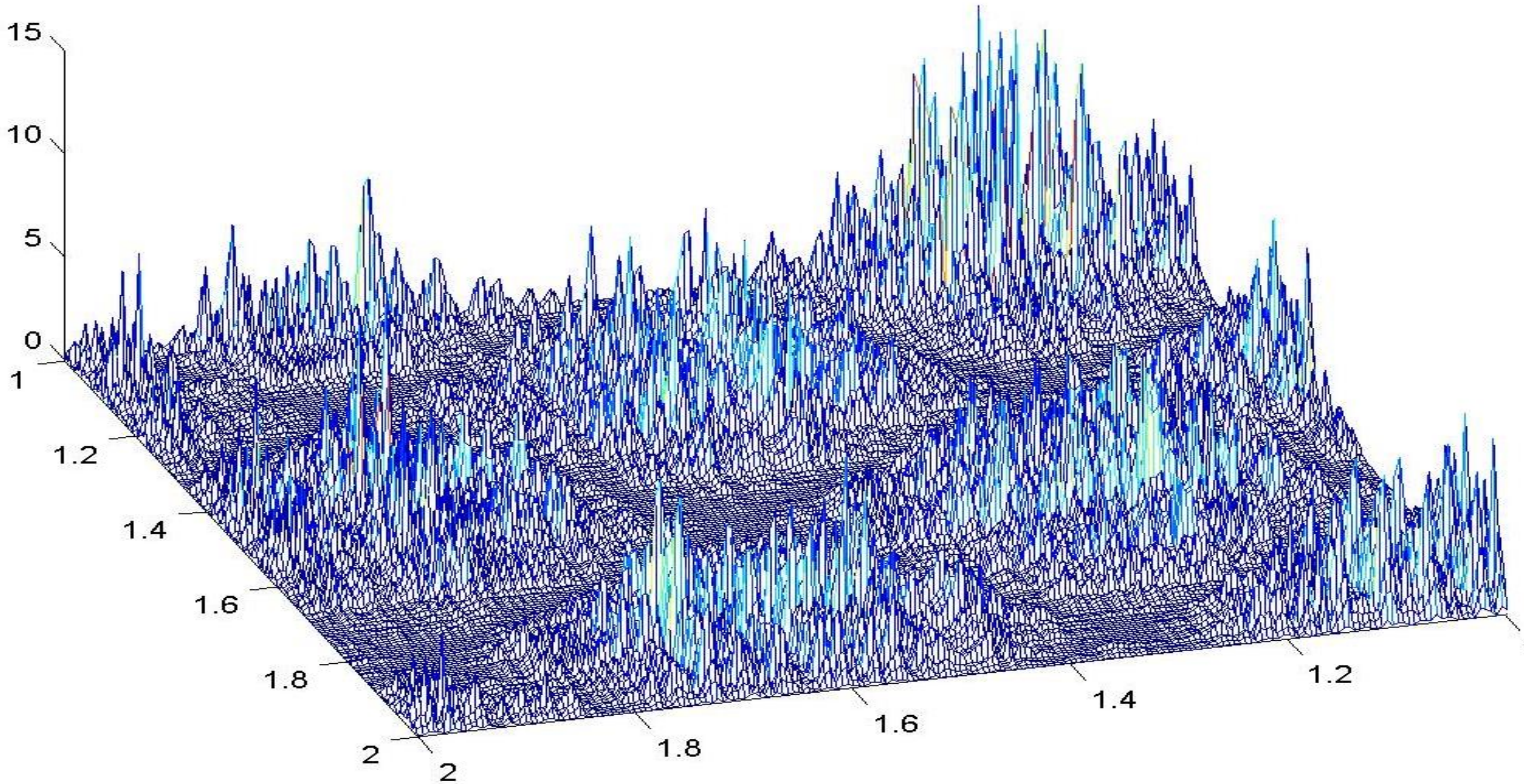
Other Typical applications:

When to use it?

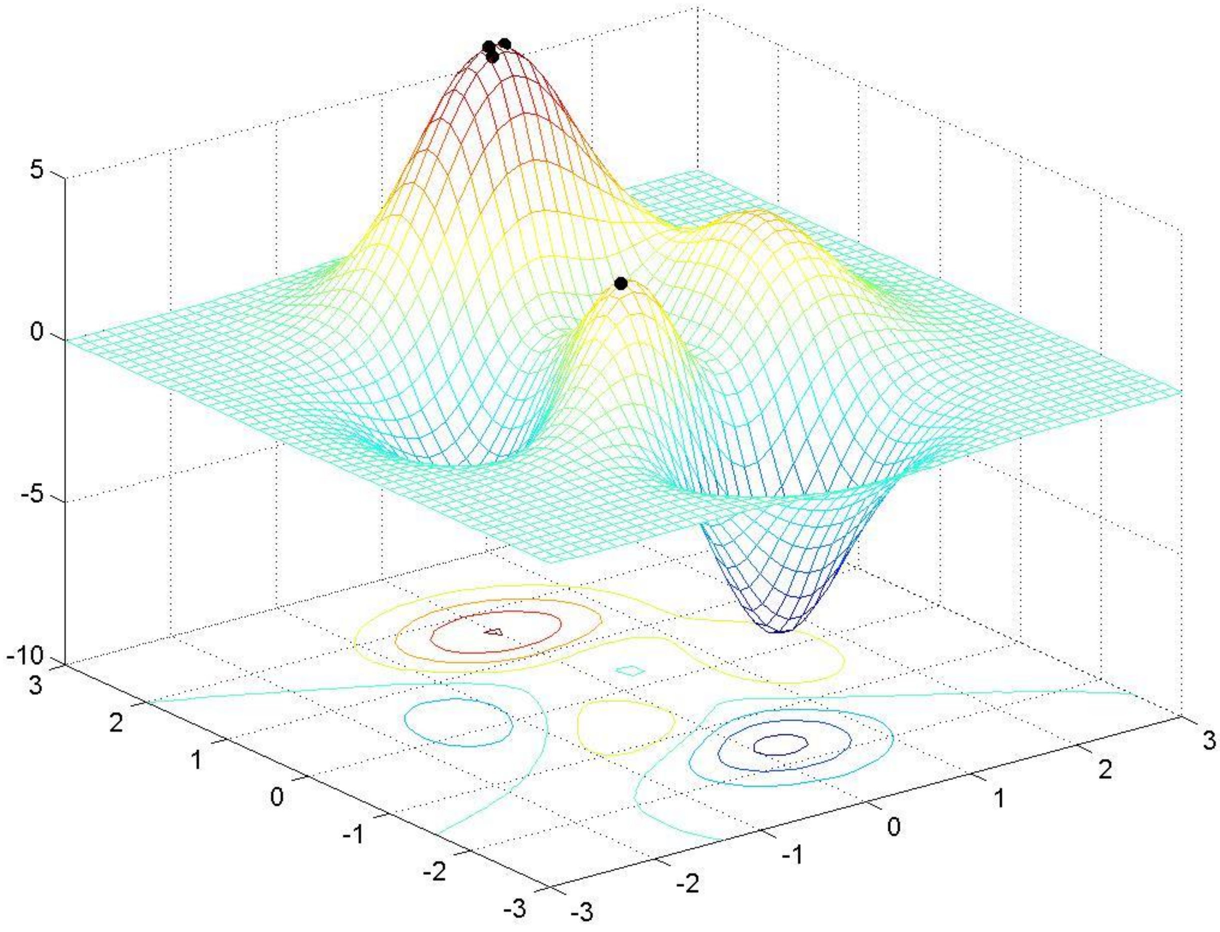
- machine learning
- timetabling, scheduling
- data mining
- robot trajectory
- etc.

- optimisation problems
- designing neural networks
- strategy planning
- evolving programs

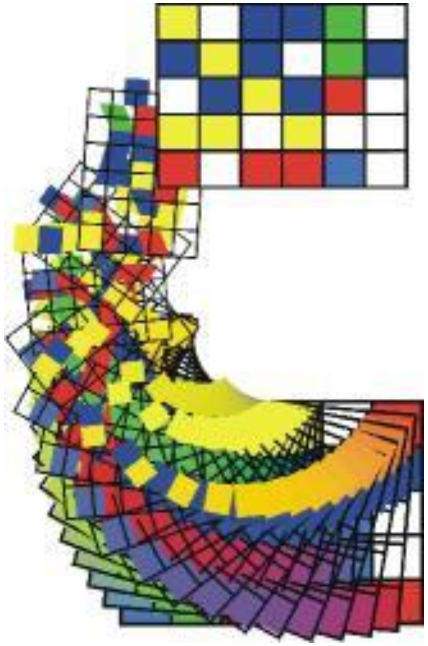
Extremes of multimodal functions



Extremes of multimodal functions



Timetabling



- Each chromosome represents a timetable
- A random population of feasible
- timetables is created
- Each timetable is evaluated according to chosen criteria
- Timetables are selected for reproduction
- Crossover and mutation operators are used to produce offspring
- The population increasingly consists of “good” timetables

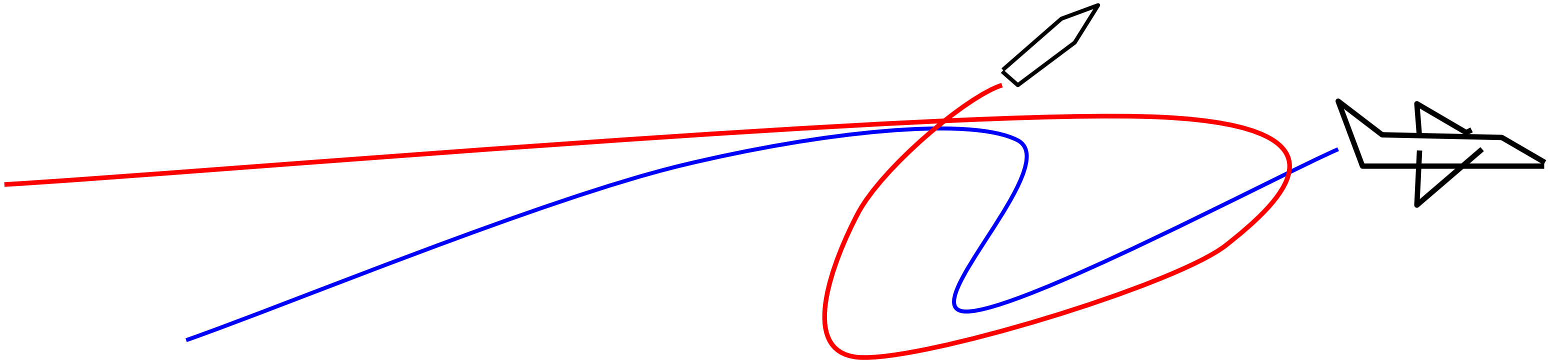
Evolution of Strategies - Game Playing

- Each chromosome represents different strategies for playing the game
- Initial population is generated randomly
- During the selection process each strategy is required to play a certain number of games against other strategies
- The strategies with the most wins are selected for reproduction
- The population increasingly consists of “good” strategies

Rule Discovery

- SAMUEL system discovers rules by which a slower but more manoeuvrable aircraft can evade a faster but less agile missile until the missile runs out of fuel
- The aircraft can sense the range, speed, heading and bearing of the missile
- Rules are of a fairly uniform sort, such as to turn left by 90 degrees if the missile parameters are lie within certain intervals

Rule Discovery

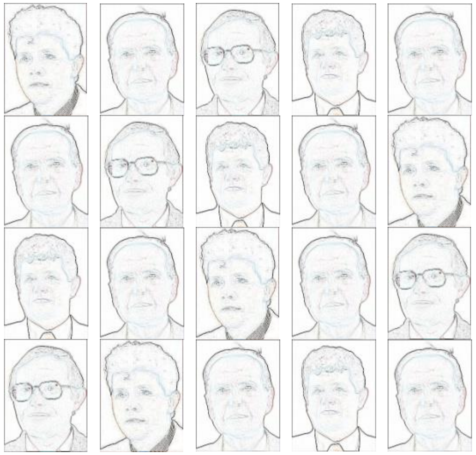


- Chromosomes are ordered sets of possible rules (if situation x occurs do action encoded within x-th gene)
- Fitness evaluation is by simulation (it is examined for how long the aircraft can evade the missile using particular set of rules)
- It takes hours to evaluate initial population !

Criminal suspect recognition

- It is easy to identify a criminal from photo but hard to describe his or her features
- It is difficult to generate even from computer library of visual features
- Idea to use genetic algorithms to help witnesses in the identification of criminal suspects

Criminal suspect recognition



Faceprints

- randomly generates 20 faces on a computer screen
- witness evaluates each face on a 10 point scale
- GA generates additional faces from 5 building blocks: eyes, mouth, nose, hair and chin (7-bit string each)
- Chromosome is a 35-bit binary string (34 billion faces)
- Witness rates successive generations with 10 point scale
- Convergence often occurs after 20 generations

Boeing 777

- The engines were designed by classical techniques with the emphasis on efficient fuel consumption
- Genetic algorithms were used to fine-tuning of some parameters of the already designed engines
- Due to their utilization at this stage the consumption of fuel has been reduced by 2,5%
- (operating cost savings cca 2 mil USD at one plane per year)

Summary

- *Genetic Algorithms* (GAs) implement optimization strategies based on simulation of the natural law of evolution of a species by *natural selection*

- The basic GA Operators are:

  Encoding

  Recombination

  Crossover

  Mutation

- GAs have been applied to a variety of function optimization problems, and have been shown to be highly effective in searching a large, poorly defined search space even in the presence of difficulties such as high-dimensionality, multi-modality, discontinuity and noise.

Questions ?