

Evolutionary Computation

Asst.Prof. Dr.Supakit Nootyaskool
IT-KMITL ©2015

1. Overview GA

Darwin's theory

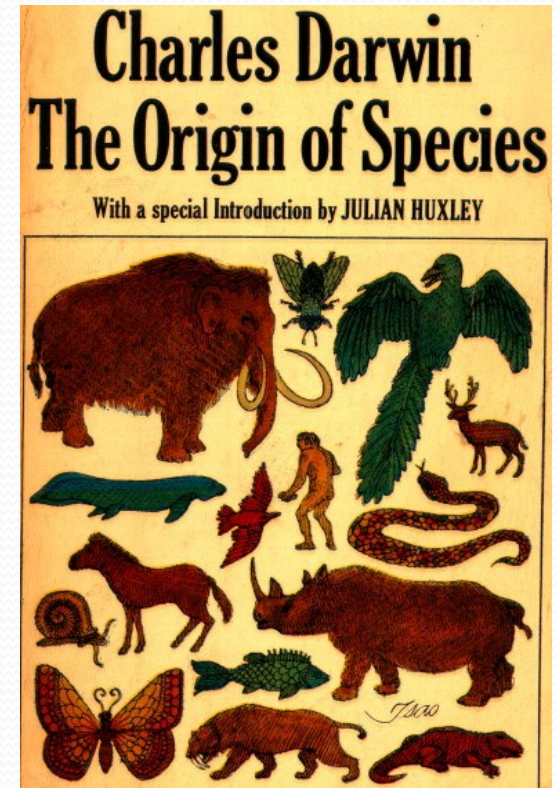
Survival

History of Evolutionary computation

Optimization

Introduction to Genetic algorithm

- Genetic algorithms are a technique to solve problems by finding an optimum solution
- GA's are a subclass of Evolutionary Computation
- GA's are based on **Charles Darwin's theory** of evolution



Introduction to Genetic algorithm

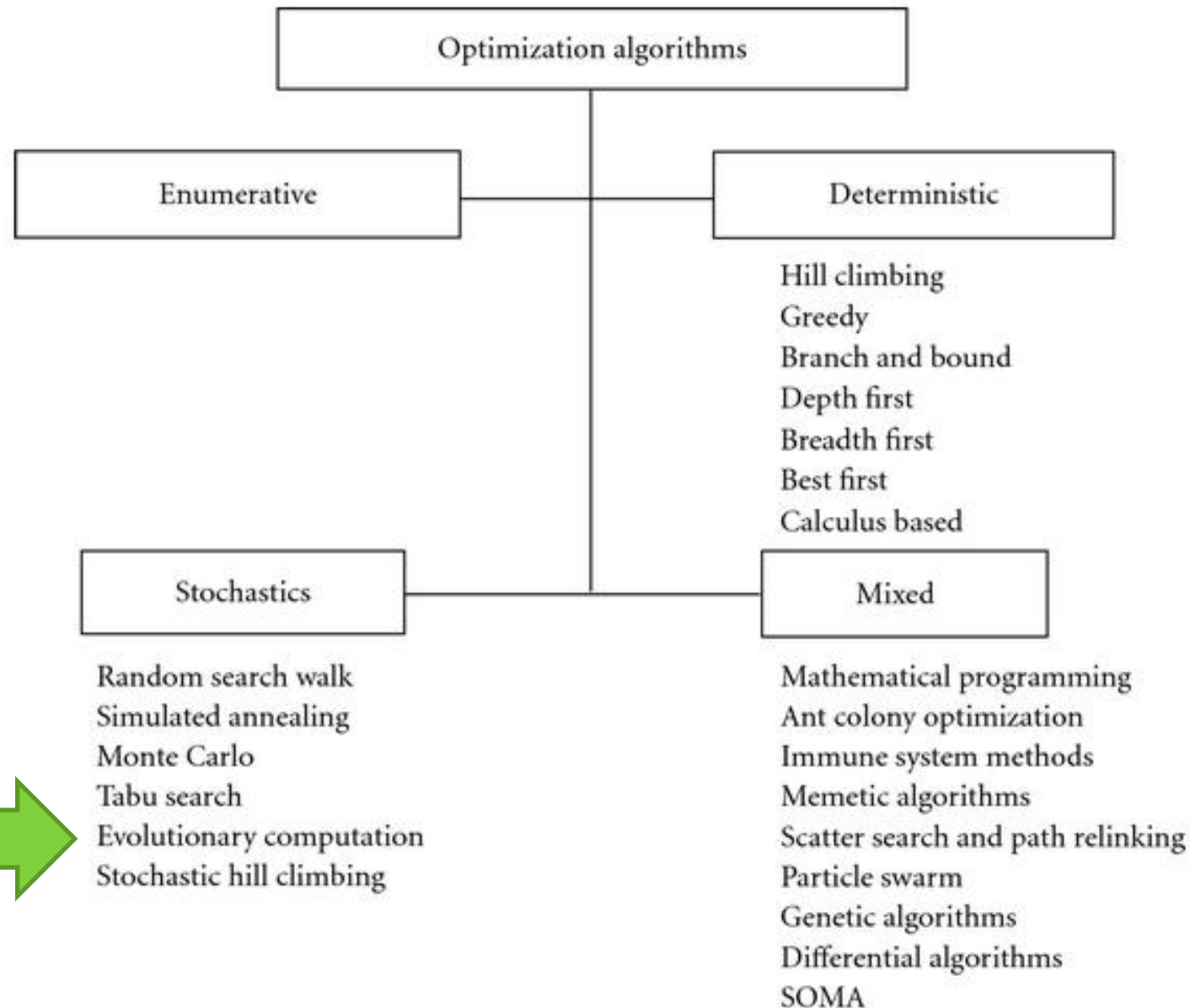
- The origin of species: “**Preservation of favorable variations and rejection of unfavorable variations.**”
- There are more individuals born than can survive by self-adapt to a different environment.
- Environment changing -> Adaptation -> Survival



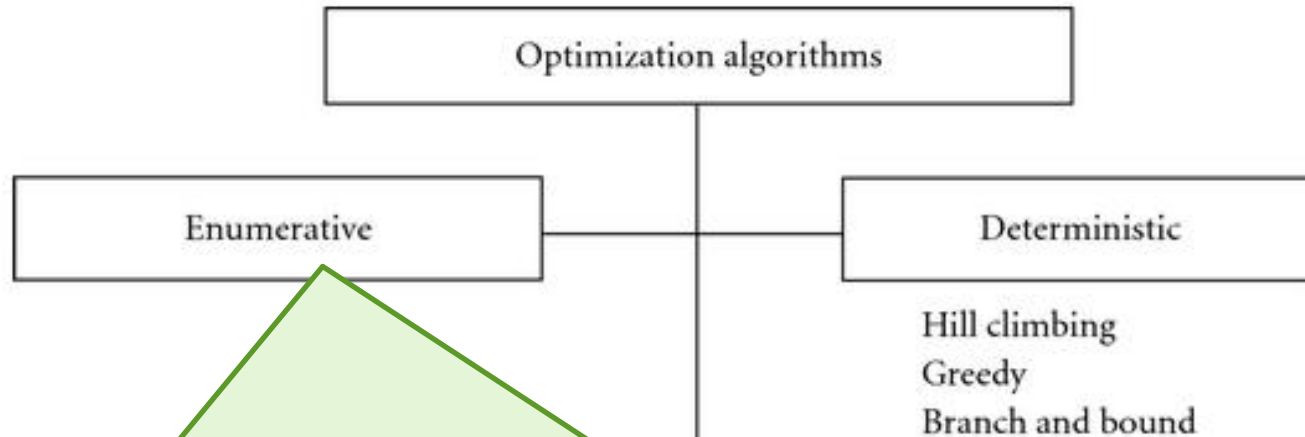
History of Evolutionary Computations

- 1948, Turing:
proposes “Genetically or evolutionary search”
- 1962, Bremermann
optimization through evolution and recombination
- 1964, Rechenberg
introduces **evolution strategies (ES)**
- 1965, L. Fogel, Owens and Walsh
introduce **evolutionary programming (EP)**
- 1975, John Holland
introduces **genetic algorithms (GA)**
- 1992, Koza
introduces **genetic programming (GP)**

Understand Optimization Algorithms



Understand Optimization Algorithm

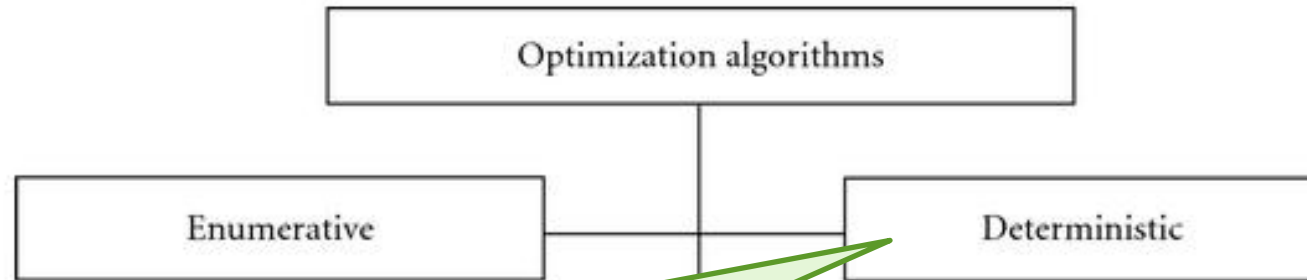


Enumeration:

The collection of items is a complete, ordered listing of all of the items in that collection. The term is commonly used in mathematics and theoretical computer science to refer to a listing of all of the elements of a set.

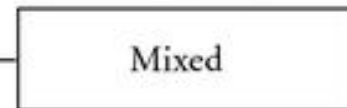
Differential algorithms
SOMA

Understand Optimization Algorithm



Deterministic optimization is a system in which no randomness. A deterministic model produces the same output from a given starting condition or initial state.

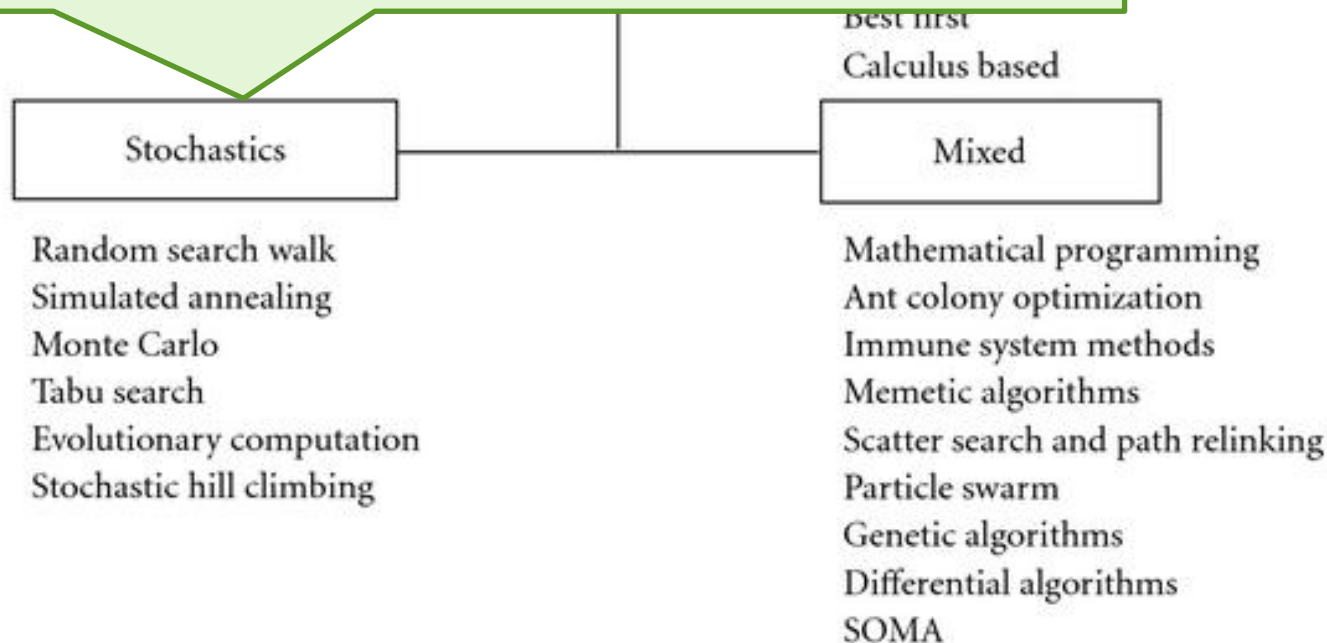
Hill climbing
Greedy
Branch and bound
Depth first
Breadth first
Best first
Calculus based



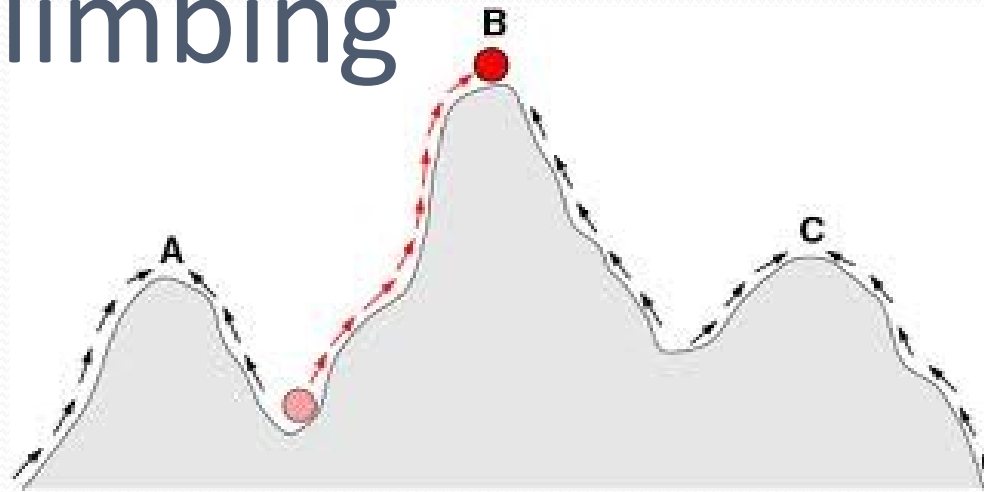
Mathematical programming
Ant colony optimization
Immune system methods
Memetic algorithms
Scatter search and path relinking
Particle swarm
Genetic algorithms
Differential algorithms
SOMA

Understand Optimization Algorithm

Stochastic optimization are optimization methods that generate and use random variables.

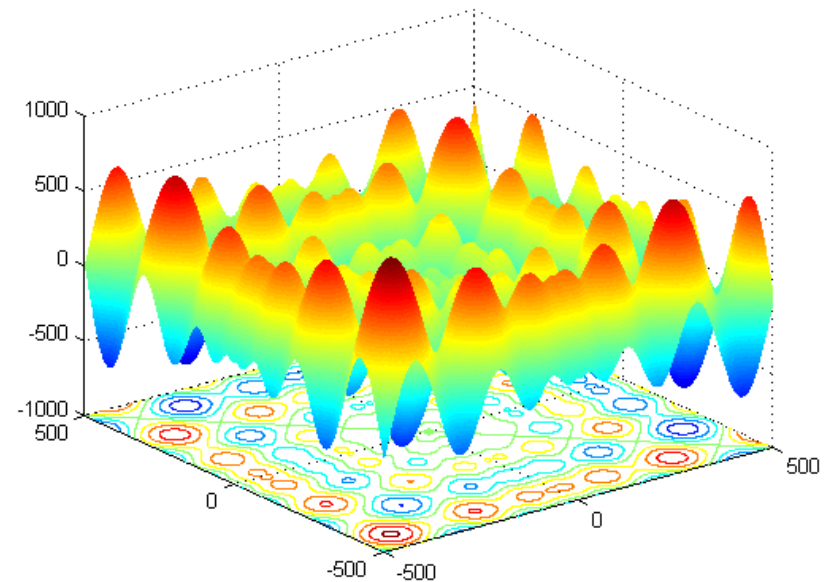
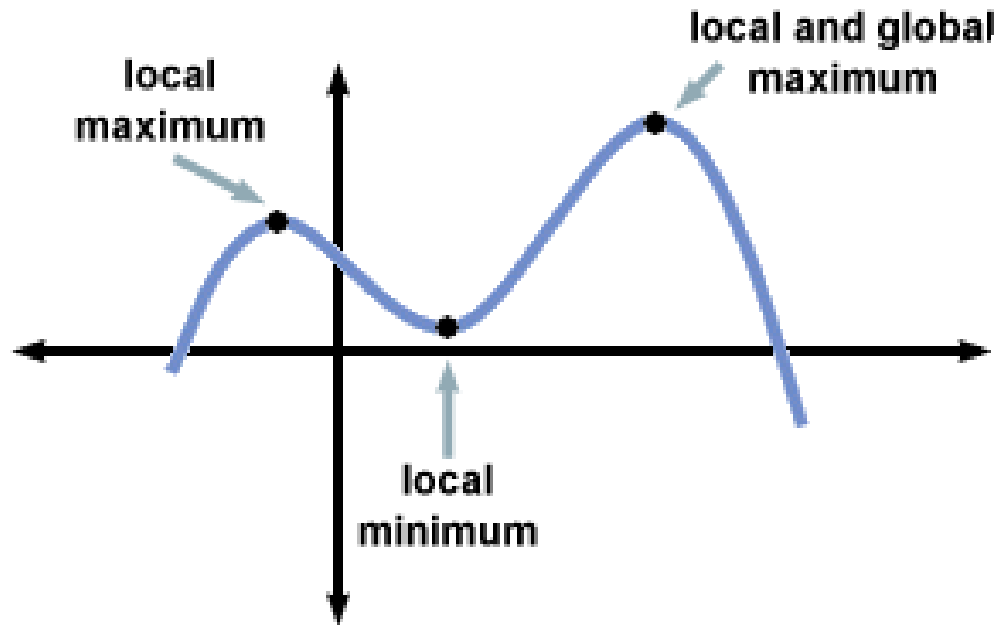


Hill Climbing



- The strategy of the Hill Climbing is iterate the process of select a neighbor for a candidate solution and only accept it if it results in an improvement. The strategy was proposed to address the limitations of deterministic hill climbing techniques that were likely to **get stuck in local optima** due to their greedy acceptance of neighboring moves.

- Local minima / Local maxima (Local solution)
- Global minimum / Global maximum (Optimum solution)



2. Evolutionary Computation Technique

An example GA on peaks function

3. Background of GA

Biological background

Genotype

Phenotype

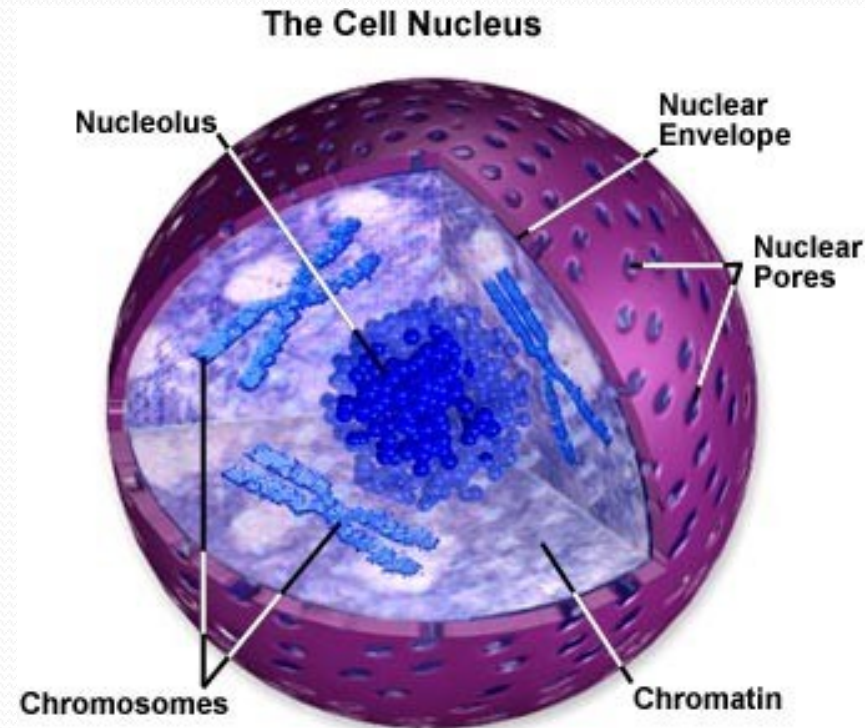
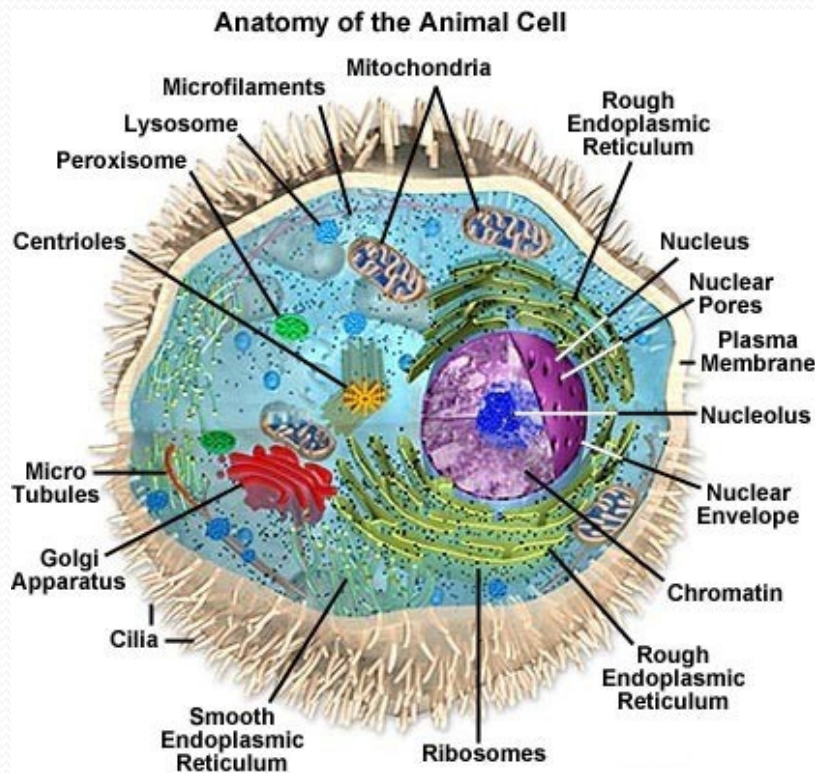
Crossover & Mutation

Selection

Chromosome representation

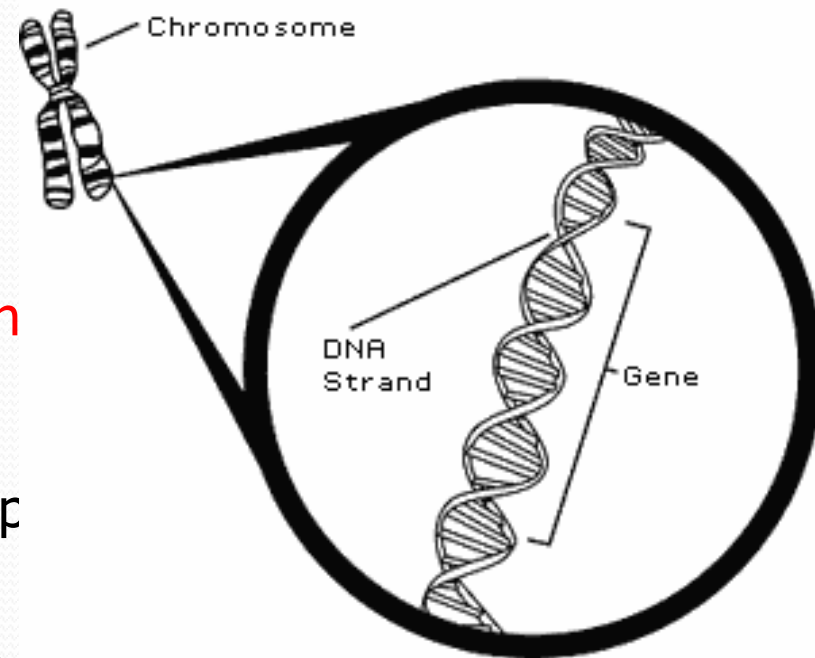
Biological background (1)

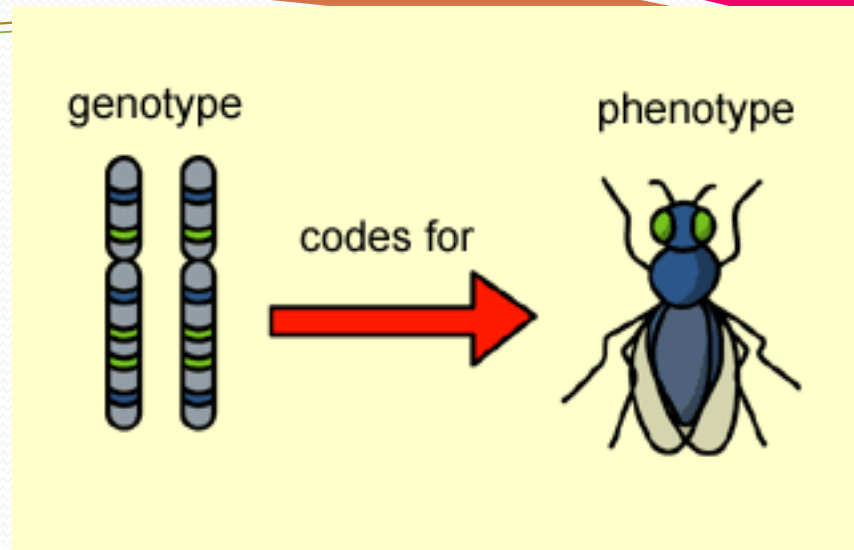
- Every animal cell is a complex of many small “factories” working together
- The center of this all is the **cell nucleus**
- The **nucleus** contains the genetic information



Biological background (2)

- **Genetic information** is stored in the **chromosomes**
- Each chromosome is build of **DNA**
- Chromosomes in humans form pairs
- There are **23 pairs**
- The chromosome is divided in parts: **gen**
- **Genes code** for properties
- The possibilities of the genes for one prop is called: **allele**
- Every gene has an unique position on the chromosome: locus

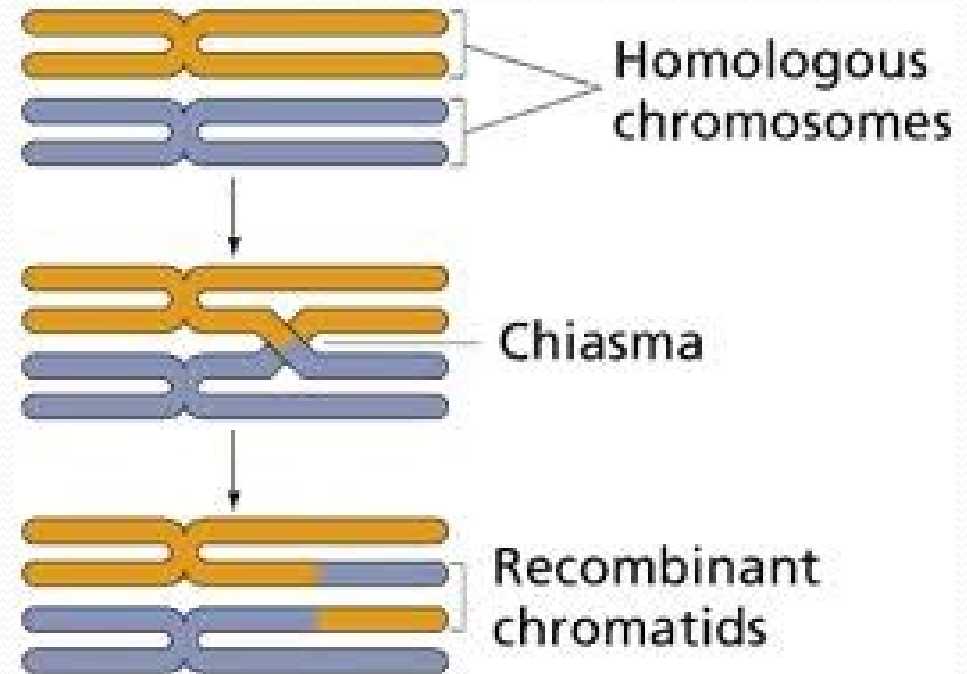




- DNA → Chromosome → Gene
- **Genotype, DNA inside** is the observable in level of gene or chromosome inside individual.
- **Phenotype** is the observable characteristics of an individual.

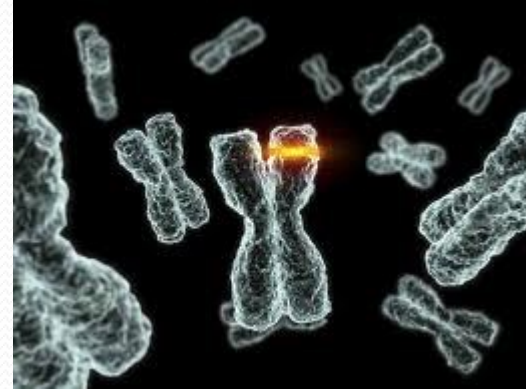
Sexual Recombination

- GA called **Crossover**
- Crossover is the primary operator to introduce diversity in population



Asexual

- GA called **Mutation**
- Crossover is the second operator to introduce diversity in population



Genetic Selection techniques

- Uniform selection
- Roulette wheel selection
- Tournament selection
- Random selection

Genetic Selection techniques

- Uniform selection
- Roulette wheel selection
- Tournament selection

Uniform selection: is the selection by using same pattern.

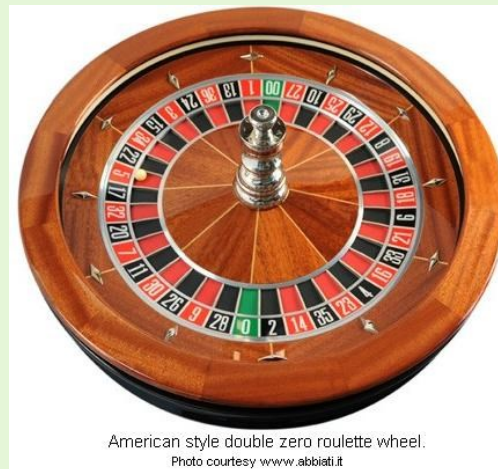
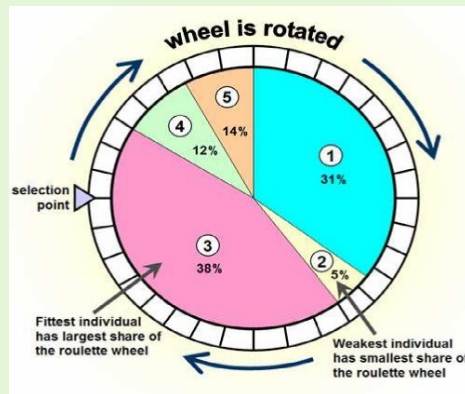
Example:

select: 1 5 8 9 10 23 45

Genetic Selection techniques

- Uniform selection
- Roulette wheel selection
- Tournament selection

Roulette selection: is random selection applying concept of roulette board.

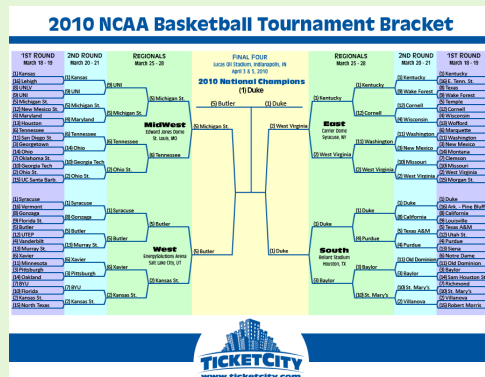


American style double zero roulette wheel.
Photo courtesy www.abbiati.it

Genetic Selection techniques

- Uniform selection
- Roulette wheel selection
- Tournament selection
- Random selection

Tournament selection: is the selection by comparing each pair of population. In each pair, the selection may select a population by randomness.



Genetic **Selection** techniques

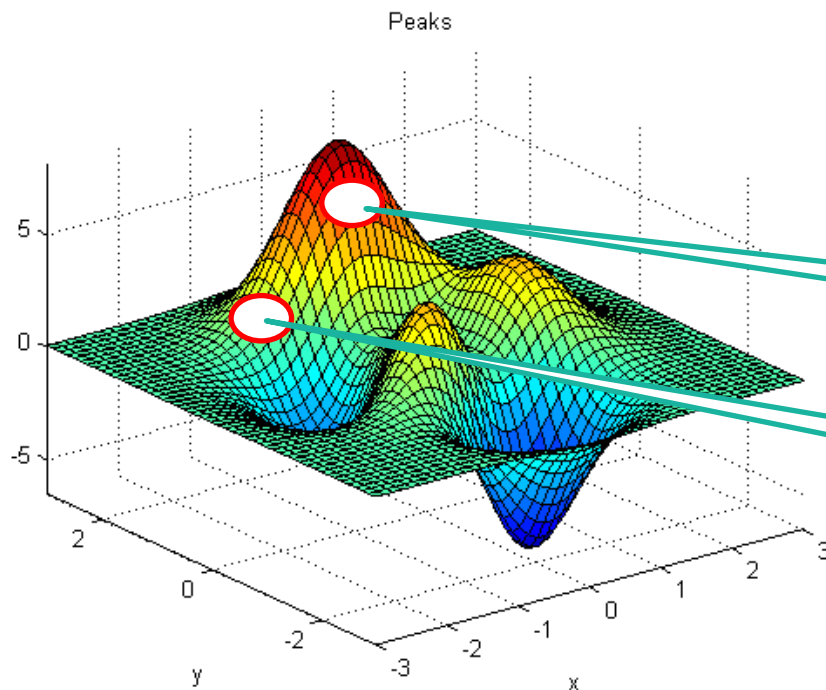
- Uniform selection
- Roulette wheel selection
- Tournament selection
- Random selection

Random selection is the randomness selecting.

Example:	C-code	srand(), rand()
	Excel	random

Fitness value

- Fitness value is a value of quality to measure result of solving a problem.



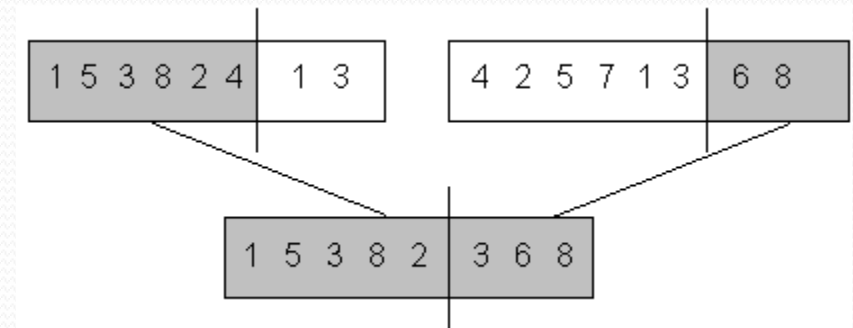
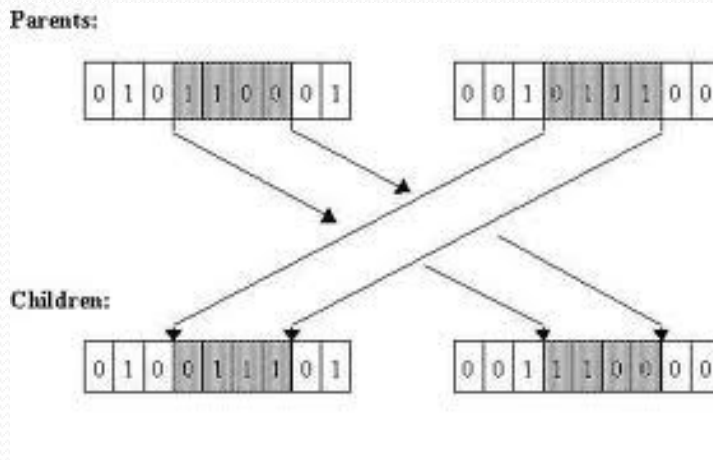
PA has high fitness value then PB.

Population B

Population A

Chromosome Representation

- Problem representation can be encoding two techniques.
 - **Binary** chromosome
 - **Real** number chromosome



Glossary--GA

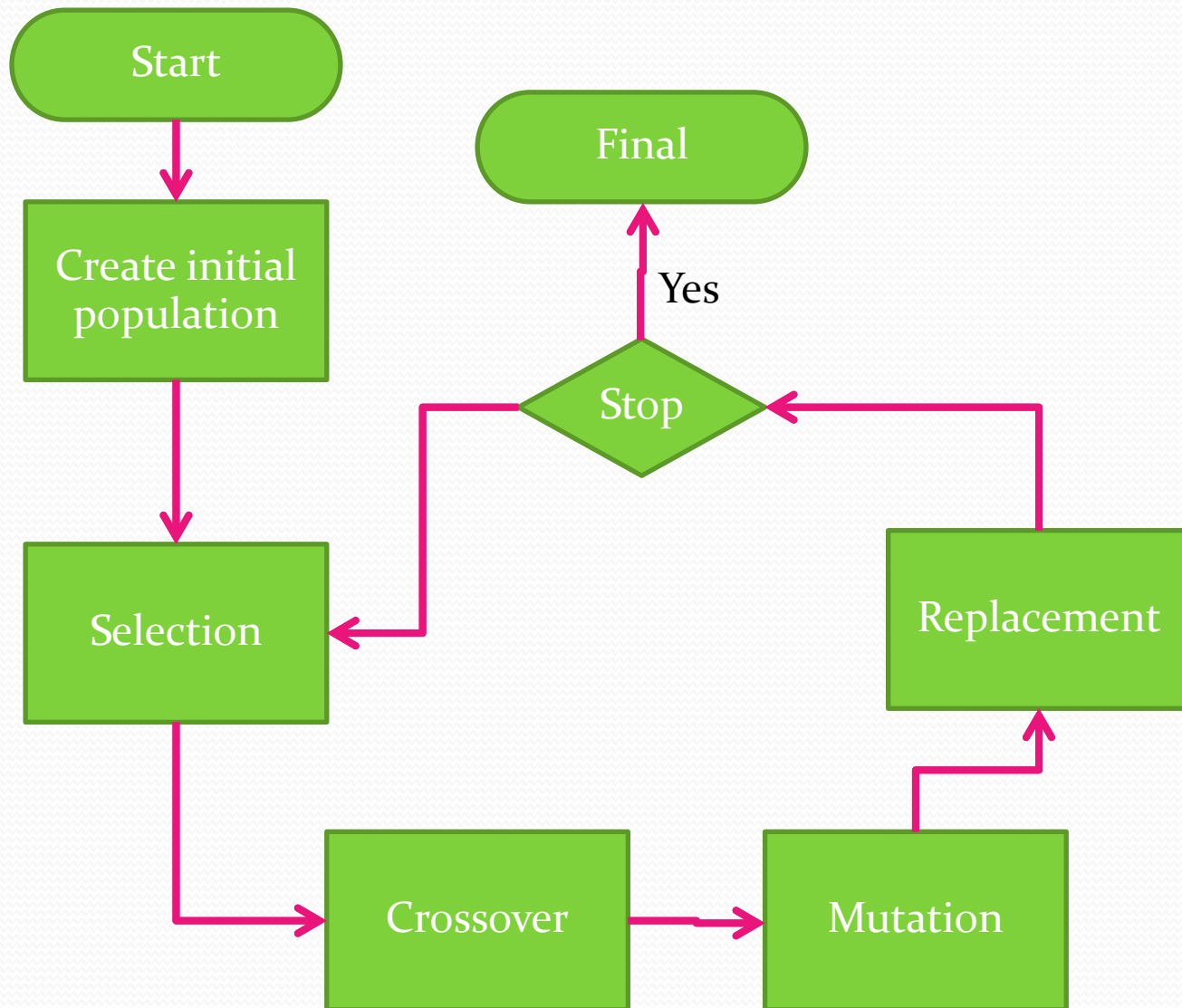
- Evolutionary Computation
 - GA
 - EC
 - EA
 - GP
 - EP
- Selection
 - Roulette wheel
 - Uniform
 - Tournament
 - Random
- Crossover (Recombination)
- Mutation
- Chromosome
 - Gene
- Phenotype $\leftarrow$ Genotype
- Fitness
- Populations
 - A population = Individual
 - Old population (Parent)
 - New population (Offspring)
- Encode Chromosome
 - Binary
 - Real
- Generation

4.Start Genetic Algorithm

Process in Flow chart

Code

GA process



Represent problem

- Problem
 - $z = x^2 + y^2$
- What is the value x, y at $z = 0$?
- Step1
 - Encode problem (Example use Binary Chromosome)

Example

$$X = 9 = 1001$$

$$Y = 3 = 0011$$

Then, a population uses two gene **1001|0011**

Create population

- Parents

P₁: 1001|0011 x=? y=? z=?

P₂: 0101|0110 x=? y=? z=?

P₃: 0011|0010 x=? y=? z=?

P₄: 1001|0011 x=? y=? z=?

P₅: 1101|0010 x=? y=? z=?

Create population

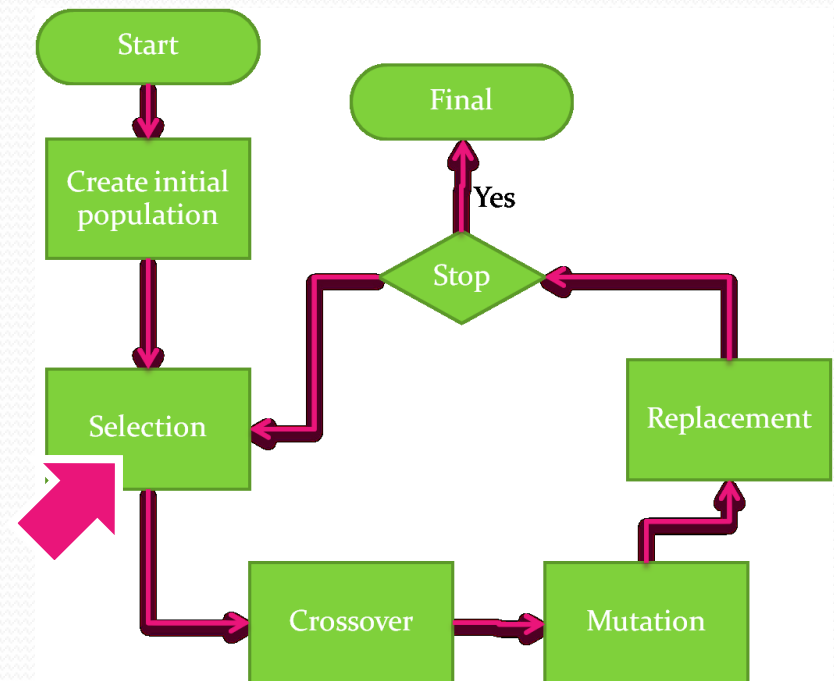
- Parents

P ₁ : 1001 0011	x=9 y=3	z=90
P ₂ : 0101 0110	x=5 y=6	z=61
P ₃ : 0011 0010	x=3 y=2	z=13
P ₄ : 1001 0011	x=9 y=3	z=90
P ₅ : 1101 0010	x=13 y=2	z=139

Which population has best fitness?

Selection

- Use roulette wheel generating 5 offspring



Selection

- Parents

P ₁ : 1001 0011	x=9 y=3	z=90
P ₂ : 0101 0110	x=5 y=6	z=61
P ₃ : 0011 0010	x=3 y=2	z=13
P ₄ : 1001 0011	x=9 y=3	z=90
P ₅ : 1101 0010	x=13 y=2	z=139
Sum	z = 393	

Which population has best fitness?

Selection

- Parents

P ₁ : 1001 0011	x=9 y=3	z=90/393
P ₂ : 0101 0110	x=5 y=6	z=61/393
P ₃ : 0011 0010	x=3 y=2	z=13/393
P ₄ : 1001 0011	x=9 y=3	z=90/393
P ₅ : 1101 0010	x=13 y=2	z=139/393
Sum	z = 393	

Which population has best fitness?

Selection

- Parents

P₁: 1001|0011

x=9 y=3

z=0.229

P₂: 0101|0110

x=5 y=6

z=0.1552

P₃: 0011|0010

x=3 y=2

z=0.033

P₄: 1001|0011

x=9 y=3

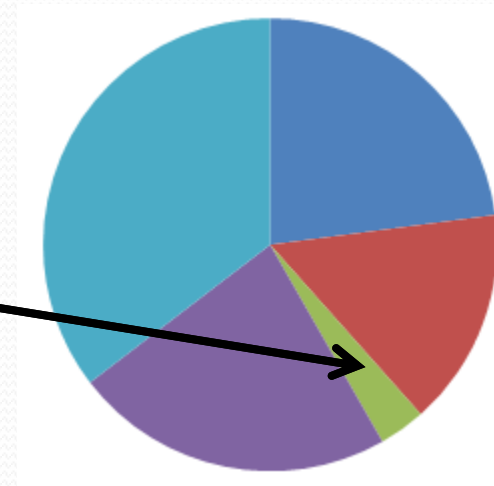
z=0.229

P₅: 1101|0010

x=13 y=2

z=0.353

Sum z = 393



Selection

- Parents

P₁: 1001|0011

x=9 y=3

z=0.229

P₂: 0101|0110

x=5 y=6

z=0.1552

P₃: 0011|0010

x=3 y=2

z=0.033

P₄: 1001|0011

x=9 y=3

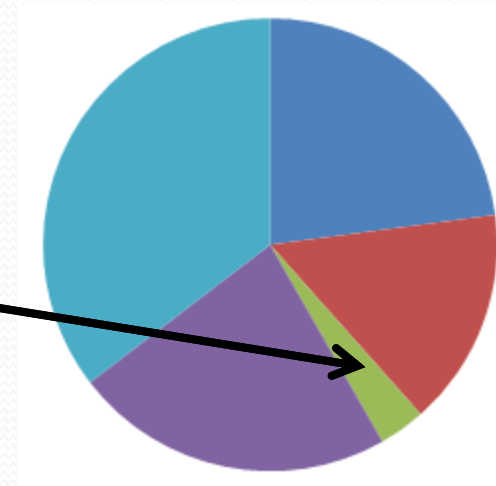
z=0.229

P₅: 1101|0010

x=13 y=2

z=0.353

Sum z = 393



Selection

- Parents

P₁: 1001|0011

x=9 y=3

z=1-0.229

P₂: 0101|0110

x=5 y=6

z=1-0.1552

P₃: 0011|0010

x=3 y=2

z=1-0.033

P₄: 1001|0011

x=9 y=3

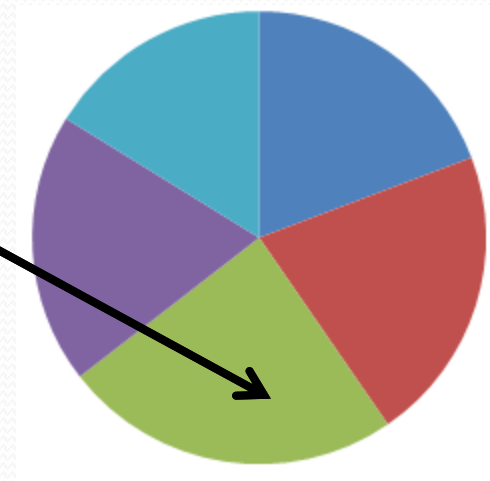
z=1-0.229

P₅: 1101|0010

x=13 y=2

z=1-0.353

Sum z = 393



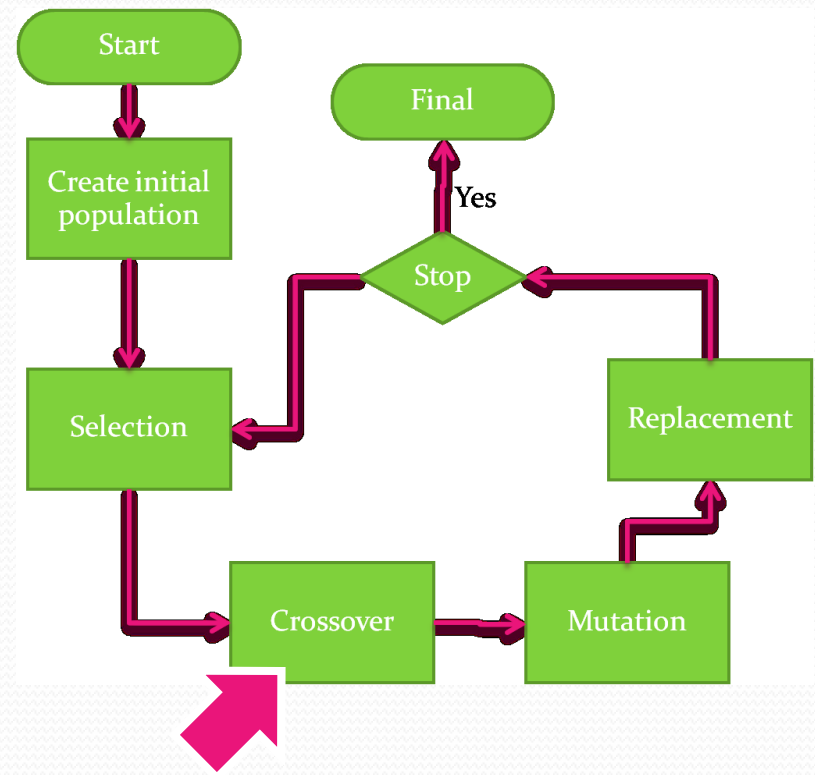
Selection

- Offspring

P6: 0011 0010	x=3 y=2	z=1-0.033
P7: 0101 0110	x=5 y=6	z=1-0.1552
P8: 0011 0010	x=3 y=2	z=1-0.033
P9: 1001 0011	x=9 y=3	z=1-0.229
P10: 0101 0110	x=5 y=6	z=1-0.1552

Crossover

- Crossover techniques
 - One point
 - Two point
 - N-point



Crossover

- Select P6 and P10 by random control with Crossover Probability

P6: 0011|0010 x=3 y=2

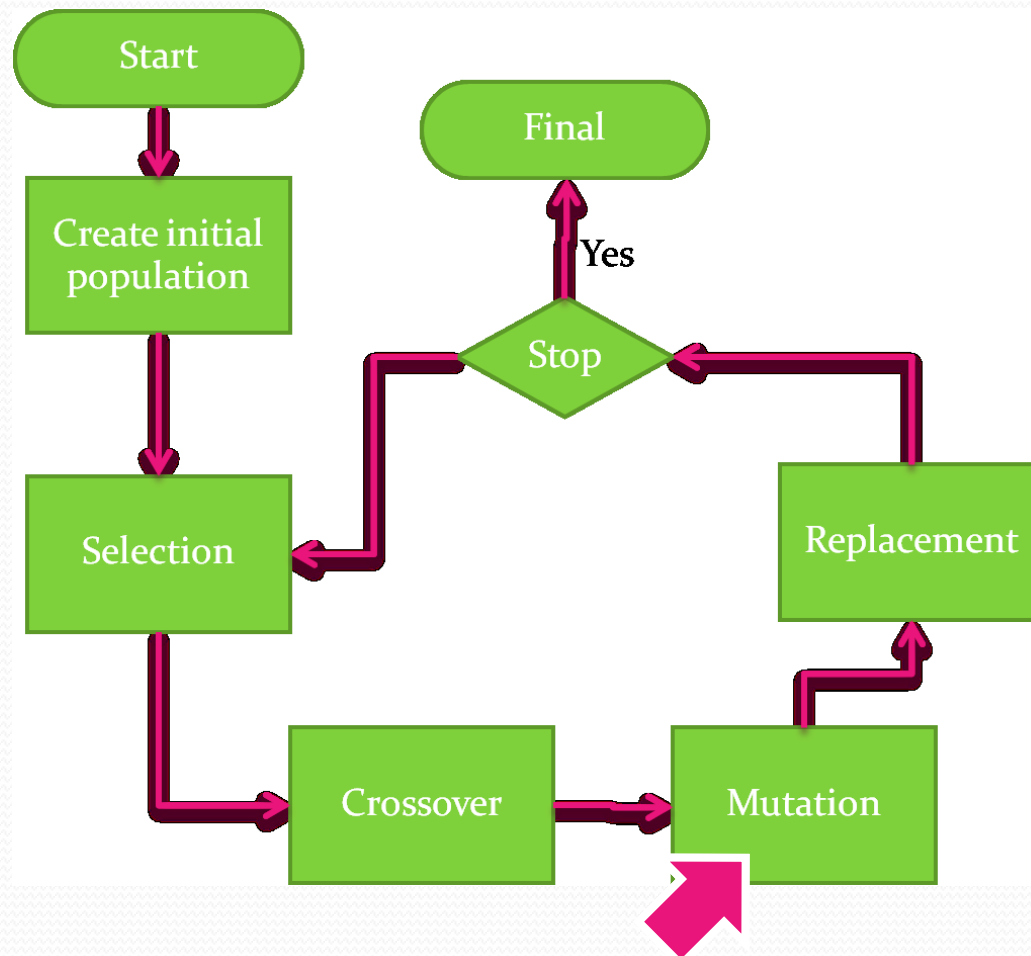
P10: 0101|0110 x=5 y=6

- Random select gene to swap

P6: 0111|0110 x=? y=? z=?

P10: 0001|0010 x=? y=? z=?

Mutation



Crossover

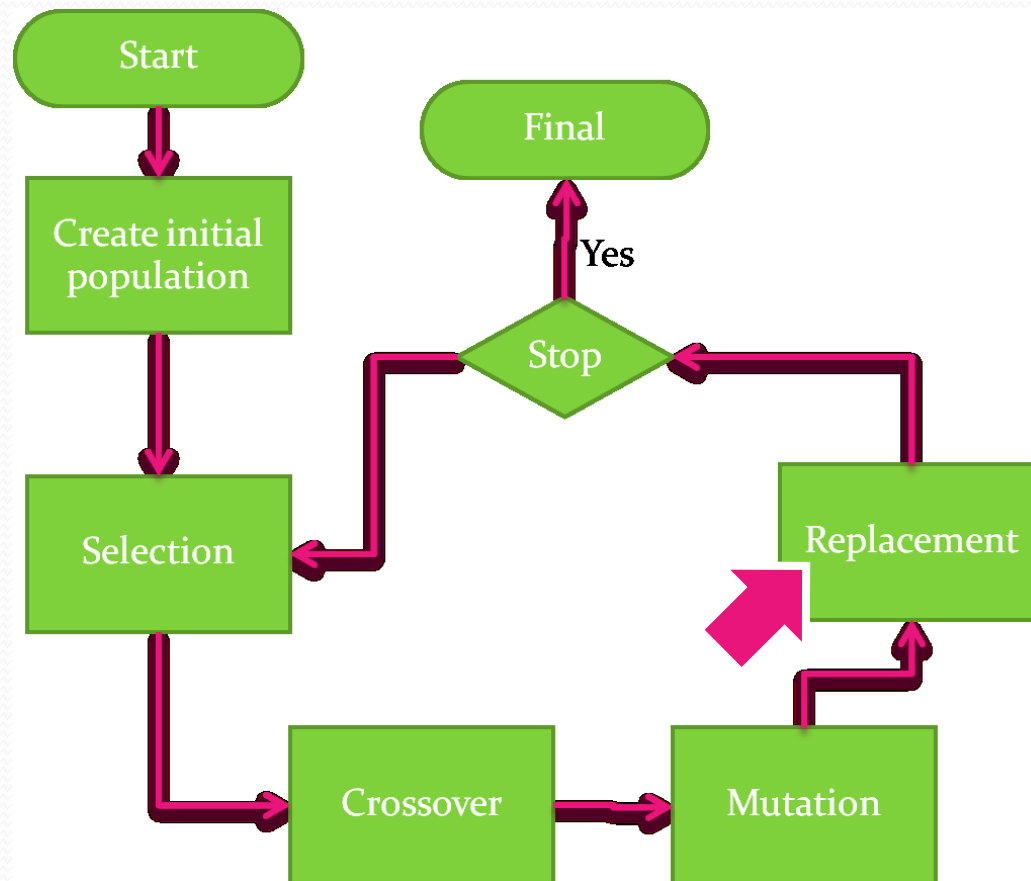
- Select P6 by random control with mutation probability (pm)

P6: 0011|0010 $x=3$ $y=2$

- Random select gene to give new value

P6: 0001|1010 $x=?$ $y=?$

Replacement



Selection

- Offspring

P6: 0011|0010 x=3 y=2 z=?

P7: 0111|0100 x=5 y=6 z=?

P8: 1011|0010 x=3 y=2 z=?

P9: 1001|0011 x=9 y=3 z=?

P10: 0111|0110 x=5 y=6 z=?



- Parents

P1: 1001|0011 x=9 y=3

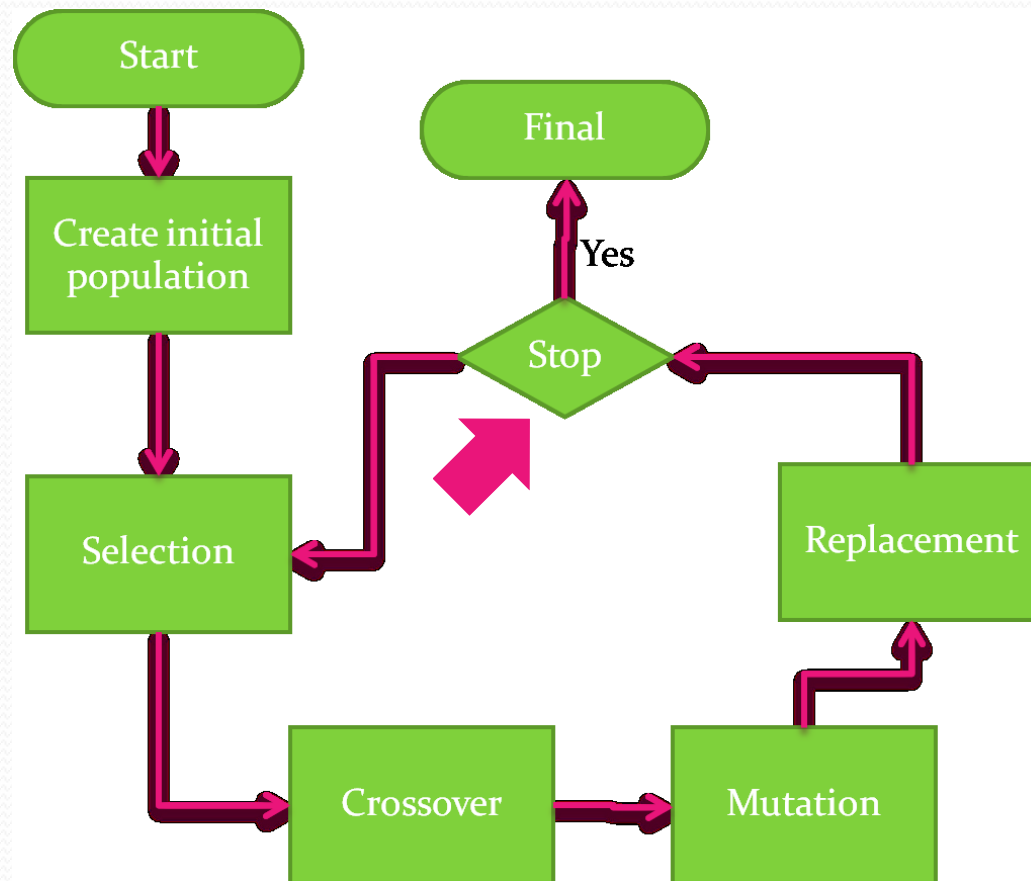
P2: 0101|0110 x=5 y=6

P3: 0011|0010 x=3 y=2

P4: 1001|0011 x=9 y=3

P5: 1101|0010 x=13 y=2

Termination?



Example GA

```
1 //Example Simple-GA
2 //Programmer: Dr.Supakit Nootyaskool
3 //Email: supakitnootyaskool@gmail.com
4 //Work: IT-KMITL
5 //Date: 2012 July 02
6 //Code status: development
7 //(c)2012
8
9
10 #include <stdio.h>
11 #include <stdlib.h>
12 #include <conio.h>
13
14 typedef struct population
15 {
16     double a,b,c;
17     double fit;
18 };
19
20 void mathfunc(population &p)
21 {
22     double fitness;
23     fitness = p.a*p.a + p.b*p.b + p.c;
24     p.fit = fitness;
25 }
26
```

```

27 void showdata(char name[10],population p)
28 {
29     printf("%s [%f,%f,%f] fit= %f\n",name,p.a,p.b,p.c,p.fit);
30 }
31
32 double random()
33 {
34     return (double) rand()/1000;
35 }
36
37 double random_0to1()
38 {
39     return (double) rand()/INT_MAX;
40 }
41
42 int main(void)
43 {
44     //parameters
45     const int maxpop = 10;
46     double pc = 0.1;
47     double pm = 0.8;
48     int maxgen = 3000;
49     int gen = 1;
50

```

```

51 //create initial population
52 population oldp[maxpop];
53 population newp[maxpop];
54 for(int i=0;i<maxpop;i++)
55 {
56     oldp[i].a = random();
57     oldp[i].b = random();
58     oldp[i].c = random();
59     mathfunc(oldp[i]);
60     showdata("oldpop",oldp[i]);
61 }
62
63 //generation cycle
64 while(1)
65 {
66     //Selection uses uniform random
67     printf("\n--SELECTION--\n");
68     for(int i=0;i<maxpop;i++)
69     {
70         newp[i] = oldp[rand()%maxpop];
71         showdata("newpop",newp[i]);
72     }
73

```

```

74 //crossover
75 printf("\n--CROSSOVER--\n");
76 for(int i=0;i<maxpop;i++)
77 {
78     int z1,z2;
79     z1 = rand()%maxpop;
80     z2 = rand()%maxpop;
81
82     if(random_0to1()<=pc)
83     {
84         double t;
85         t = newp[z1].a;
86         newp[z1].a = newp[z2].a;
87         newp[z2].a = t;
88     }
89
90     if(random_0to1()<=pc)
91     {
92         double t;
93         t = newp[z1].b;
94         newp[z1].b = newp[z2].b;
95         newp[z2].b = t;
96     }

```

```

98         if(random_0to1() <= pc)
99         {
100             double t;
101             t = newp[z1].c;
102             newp[z1].c = newp[z2].c;
103             newp[z2].c = t;
104         }
105         mathfunc(newp[i]);
106         showdata("newpop", newp[i]);
107     }
108
109     //Mutation
110     printf("\n--MUTATION--\n");
111     for(int i=0; i<maxpop; i++)
112     {
113         if(random_0to1() <= pm)
114             newp[i].a = random();
115         if(random_0to1() <= pm)
116             newp[i].b = random();
117         if(random_0to1() <= pm)
118             newp[i].c = random();
119         mathfunc(newp[i]);
120         showdata("newpop", newp[i]);
121     }
122

```

```

124 //Replacement
125 population tmp[maxpop*2];
126 for(int j=0;j<maxpop;j++)
127     tmp[j] = oldp[j];
128 for(int j=0;j<maxpop;j++)
129     tmp[j+maxpop] = newp[j];
130
131
132 for(int j=0;j<maxpop*2;j++)
133 for(int i=0;i<maxpop*2-1;i++)
134 {
135     if(tmp[i].fit > tmp[i+1].fit)
136     {
137         population t;
138         t = tmp[i];
139         tmp[i] = tmp[i+1];
140         tmp[i+1] = t;
141     }
142 }
143 printf("\n--REPLACEMENT--\n");
144 for(int i=0;i<maxpop-1;i++)
145 {
146     showdata("tmp",tmp[i]);
147     oldp[i] = tmp[i]; //copy
148 }
149
150 //pause
151 printf("\n--PAUSE Gen[%d]--",gen++);
152 getch();
153 }
154 getch();
155 return 0;
156 }

```

```
oldpop [0.041000,18.467000,6.334000] fit= 347.365770
oldpop [26.500000,19.169000,15.724000] fit= 1085.424561
oldpop [11.478000,29.358000,26.962000] fit= 1020.598648
oldpop [24.464000,5.705000,28.145000] fit= 659.179321
oldpop [23.281000,16.827000,9.961000] fit= 835.113890
oldpop [0.491000,2.995000,11.942000] fit= 21.153106
oldpop [4.827000,5.436000,32.391000] fit= 85.241025
oldpop [14.604000,3.902000,0.153000] fit= 228.655420
oldpop [0.292000,12.382000,17.421000] fit= 170.820188
oldpop [18.716000,19.718000,19.895000] fit= 758.983180
```

--SELECTION--

```
newpop [14.604000,3.902000,0.153000] fit= 228.655420
newpop [4.827000,5.436000,32.391000] fit= 85.241025
newpop [26.500000,19.169000,15.724000] fit= 1085.424561
newpop [0.292000,12.382000,17.421000] fit= 170.820188
newpop [18.716000,19.718000,19.895000] fit= 758.983180
newpop [11.478000,29.358000,26.962000] fit= 1020.598648
newpop [14.604000,3.902000,0.153000] fit= 228.655420
newpop [18.716000,19.718000,19.895000] fit= 758.983180
newpop [0.491000,2.995000,11.942000] fit= 21.153106
newpop [23.281000,16.827000,9.961000] fit= 835.113890
```

--CROSSOVER--

```
newpop [14.604000,3.902000,0.153000] fit= 228.655420
newpop [18.716000,19.718000,19.895000] fit= 758.983180
newpop [26.500000,19.169000,15.724000] fit= 1085.424561
newpop [23.281000,16.827000,9.961000] fit= 835.113890
newpop [18.716000,19.718000,19.895000] fit= 758.983180
newpop [14.604000,3.902000,0.153000] fit= 228.655420
newpop [14.604000,3.902000,0.153000] fit= 228.655420
newpop [0.292000,12.382000,17.421000] fit= 170.820188
newpop [0.491000,2.995000,11.942000] fit= 21.153106
newpop [23.281000,16.827000,9.961000] fit= 835.113890
```

--MUTATION--

```
newpop [32.439000,11.323000,21.538000] fit= 1202.037050
newpop [2.082000,16.541000,31.115000] fit= 309.054405
newpop [29.658000,9.930000,2.306000] fit= 980.507864
newpop [22.386000,28.745000,19.072000] fit= 1346.480021
newpop [5.829000,15.573000,16.512000] fit= 293.007570
newpop [13.290000,18.636000,24.767000] fit= 548.691596
newpop [15.574000,12.052000,1.150000] fit= 388.950180
newpop [21.724000,3.430000,30.191000] fit= 513.888076
newpop [11.337000,12.287000,10.383000] fit= 289.880938
newpop [8.909000,9.758000,18.588000] fit= 193.176845
```

--REPLACEMENT--

```
tmp [0.491000,2.995000,11.942000] fit= 21.153106
tmp [4.827000,5.436000,32.391000] fit= 85.241025
tmp [0.292000,12.382000,17.421000] fit= 170.820188
tmp [8.909000,9.758000,18.588000] fit= 193.176845
tmp [14.604000,3.902000,0.153000] fit= 228.655420
tmp [11.337000,12.287000,10.383000] fit= 289.880938
tmp [5.829000,15.573000,16.512000] fit= 293.007570
tmp [2.082000,16.541000,31.115000] fit= 309.054405
tmp [0.041000,18.467000,6.334000] fit= 347.365770
```

--PAUSE Gen[1]--

--SELECTION--

--REPLACEMENT--

```
tmp [1.054000,0.213000,0.475000] fit= 1.631285
tmp [1.369000,0.641000,4.820000] fit= 7.105042
tmp [1.888000,1.887000,0.648000] fit= 7.773313
tmp [1.453000,2.141000,1.807000] fit= 8.502090
tmp [1.831000,1.668000,5.099000] fit= 11.233785
tmp [0.821000,2.175000,6.360000] fit= 11.764666
tmp [0.632000,1.950000,7.763000] fit= 11.964924
tmp [0.533000,2.767000,4.415000] fit= 12.355378
tmp [2.890000,1.869000,0.948000] fit= 12.793261
```

--PAUSE Gen[599]--

--SELECTION--

```
newpop [1.054000,0.213000,0.475000] fit= 1.631285
newpop [1.369000,0.641000,4.820000] fit= 7.105042
newpop [1.831000,1.668000,5.099000] fit= 11.233785
newpop [1.369000,0.641000,4.820000] fit= 7.105042
newpop [1.888000,1.887000,0.648000] fit= 7.773313
newpop [0.533000,2.767000,4.415000] fit= 12.355378
newpop [1.888000,1.887000,0.648000] fit= 7.773313
newpop [0.533000,2.767000,4.415000] fit= 12.355378
newpop [1.453000,2.141000,1.807000] fit= 8.502090
newpop [2.890000,1.869000,0.948000] fit= 12.793261
```

--CROSSOVER--

```
newpop [1.054000,0.213000,0.475000] fit= 1.631285
newpop [1.369000,0.641000,4.820000] fit= 7.105042
newpop [1.888000,1.887000,0.648000] fit= 7.773313
newpop [1.369000,0.641000,4.820000] fit= 7.105042
newpop [1.888000,1.887000,0.648000] fit= 7.773313
newpop [1.054000,0.213000,0.475000] fit= 1.631285
newpop [1.831000,1.668000,5.099000] fit= 11.233785
newpop [0.533000,2.767000,4.415000] fit= 12.355378
newpop [0.533000,2.767000,4.415000] fit= 12.355378
newpop [1.369000,0.641000,4.820000] fit= 7.105042
```

--MUTATION--

```
newpop [21.360000,25.005000,16.756000] fit= 1098.255625
newpop [6.344000,28.462000,25.972000] fit= 876.303780
newpop [2.175000,32.700000,7.145000] fit= 1081.165625
newpop [12.622000,16.545000,19.500000] fit= 452.551909
newpop [25.318000,31.141000,10.898000] fit= 1621.661005
newpop [30.084000,12.271000,2.439000] fit= 1058.063497
newpop [29.387000,23.826000,18.383000] fit= 1449.657045
newpop [27.941000,12.300000,16.524000] fit= 948.513481
newpop [20.183000,11.349000,29.143000] fit= 565.296290
newpop [15.495000,24.412000,5.393000] fit= 841.433769
```

--REPLACEMENT--

```
tmp [1.054000,0.213000,0.475000] fit= 1.631285
tmp [1.369000,0.641000,4.820000] fit= 7.105042
tmp [1.888000,1.887000,0.648000] fit= 7.773313
tmp [1.453000,2.141000,1.807000] fit= 8.502090
tmp [1.831000,1.668000,5.099000] fit= 11.233785
tmp [0.821000,2.175000,6.360000] fit= 11.764666
tmp [0.632000,1.950000,7.763000] fit= 11.964924
tmp [0.533000,2.767000,4.415000] fit= 12.355378
tmp [2.890000,1.869000,0.948000] fit= 12.793261
```

--PAUSE Gen[600]--