Lecture 2: Genetic Algorithms Introduction

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Biological Evolution Process

"Natural Selection" + "Genetic Inheritance"

Basic Idea of Principle of Natural Selection

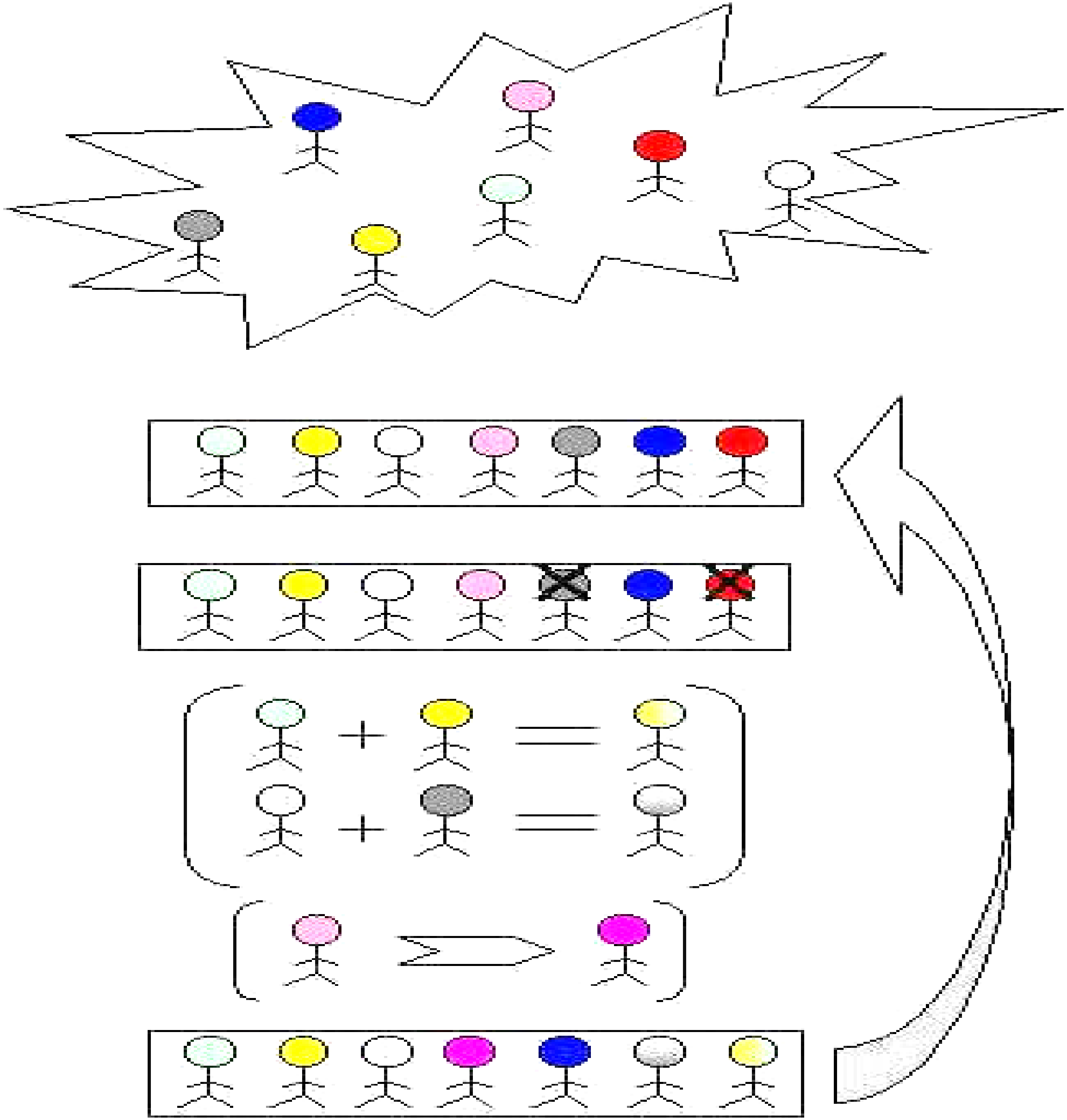
"Select The Best, Discard The Rest"

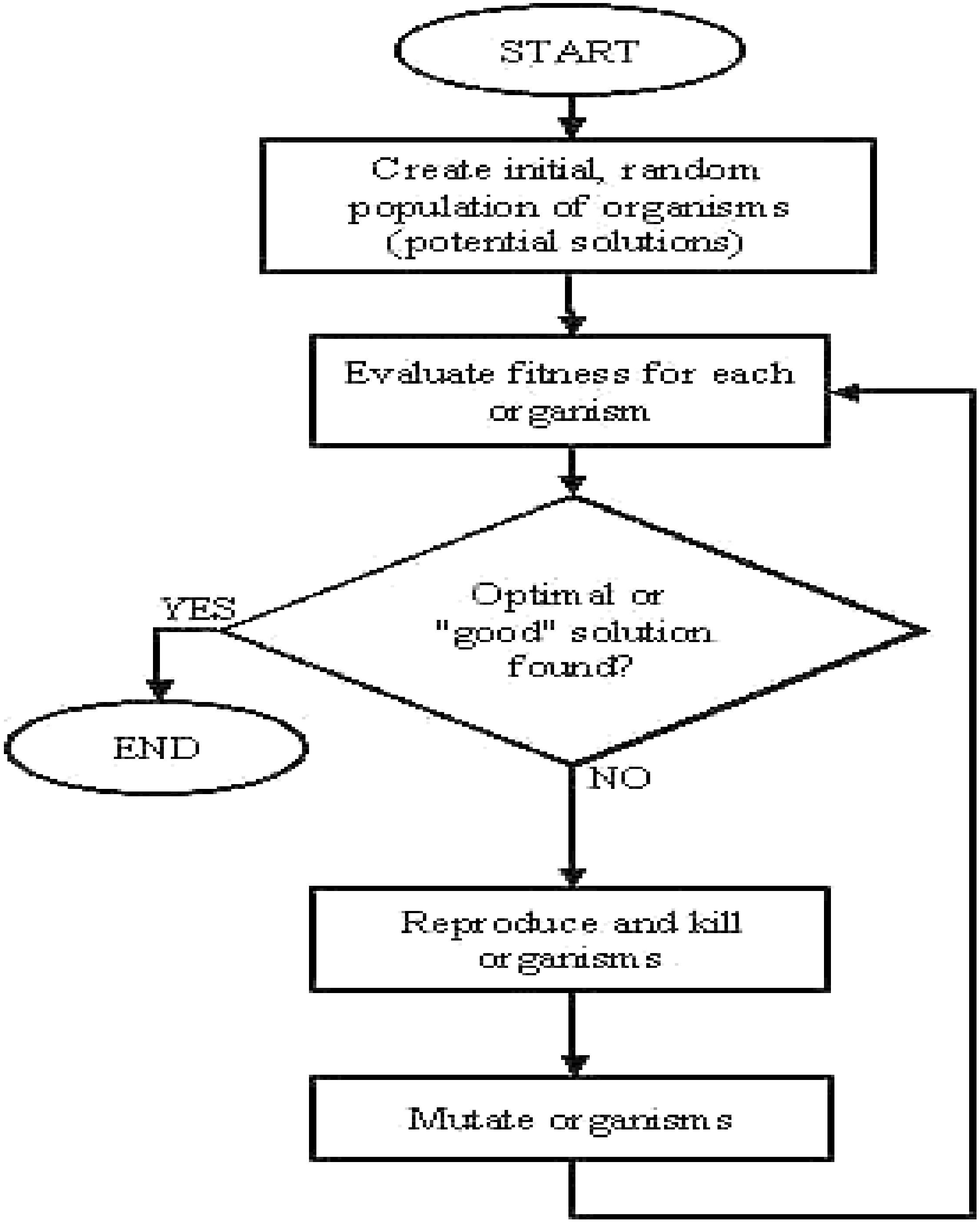
Remember

- An individual is characterized by a set of parameters: Genes
- The genes are joined into a string: Chromosome

- The chromosome forms the genotype
- The genotype contains all information to construct an organism: the phenotype

- Reproduction is a “dumb” process on the chromosome of the genotype
- Fitness is measured in the real world of the phenotype



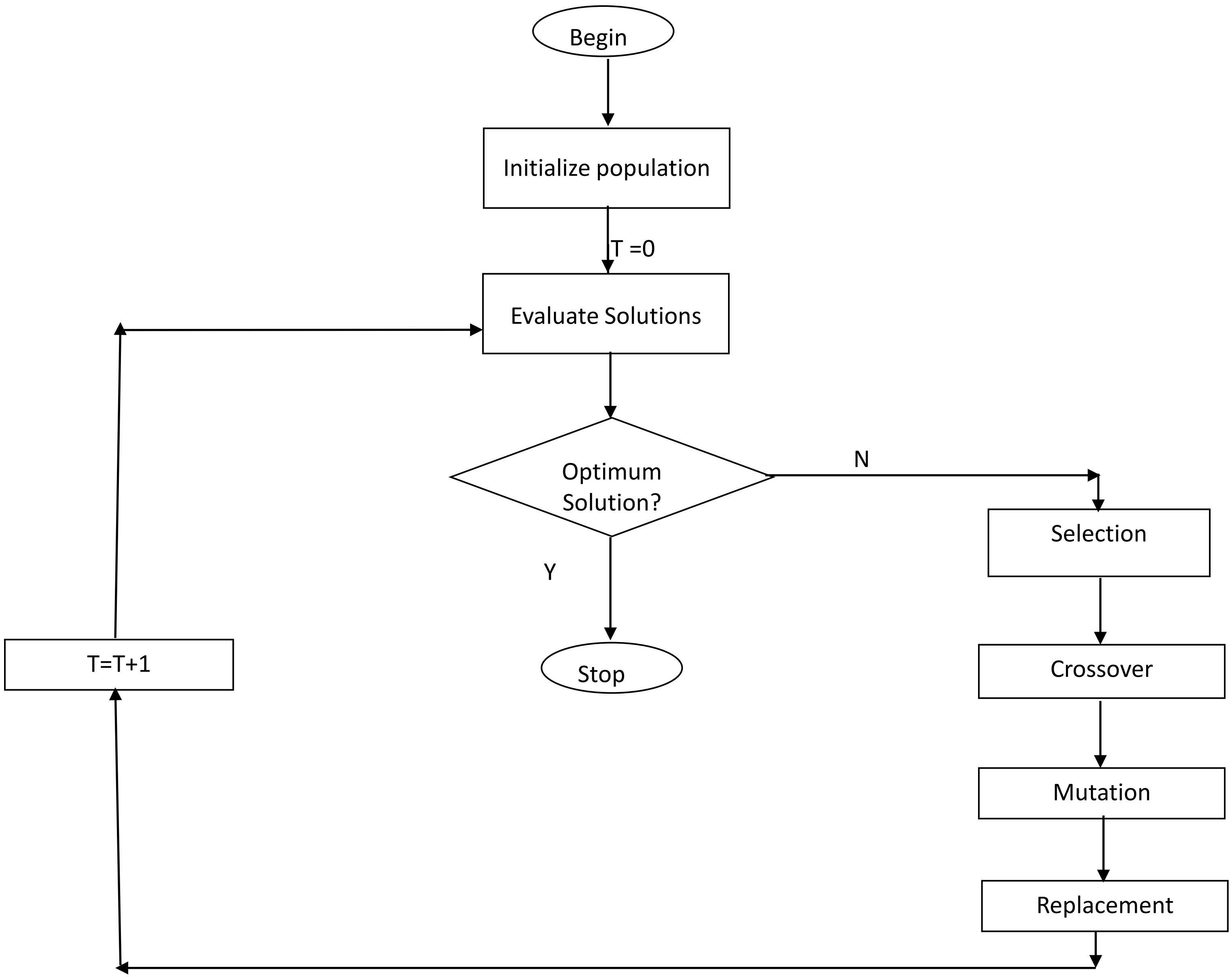

START
Create initial, random population of organisms (potential solutions)
Evaluate fitness for each organism
Optimal or "good" solution found?
YES
END
NO
Reproduce and kill organisms
Mutate organisms

What Are Genetic Algorithms (GAs)?

- Genetic Algorithms are ***search*** and ***optimization*** techniques based on principle of ***Biological Evolution Process***.

- 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; // Evaluate Individuals …

   While(Fitness Value != Optimal Value) // Continue Evolution …
   {
        Selection; //Natural Selection, Survival Of Fittest …

        Crossover; //Reproduction, Propagate favorable characteristics …

        Mutation;  //Mutation …

        Replacement

        Calculate Fitness Function;
   }
}
```

Nature to Computer Mapping

Nature	Computer
Environment	Problem to be optimized.
Population	Set of candidate solutions.
Individual	One candidate solution to a problem.
Fitness/Survival Degree	Quality of a solution.
Chromosome	Encoding of a Solution to another format *(For example, bit string, floating point array)*.
Gene	Part of the encoded solution.
Reproduction	Crossover
Copying errors	Mutation

Components of a GA

A problem to solve, and ...

- Encoding technique (*gene, chromosome*)
- Initialization procedure *(creation)*
- Evaluation function *(environment)*
- Selection *(reproduction, environment)*
- Genetic operators *(crossover, mutation)*
- Parameter settings *(practice and art)*

Many parameters to set

- Any GA implementation needs to decide on a number of parameters: Population size (N), mutation rate (m), crossover rate (c)
- Often these have to be “tuned” based on results obtained - no general theory to deduce good values
- Typical values might be: N = 50, m = 0.05, c = 0.9

Example 1: A Very Simple Example

- Generate a bit string for the decimal number 31.
- Traditional Technique:
  – Start by 00000 till reaching 11111
- GA Steps:
  1. Build an initial population of random individuals (chromosomes or initial solutions)
  2. Evaluate fitness of individuals
  3. Select some individuals to
     - Apply Crossover and Mutation
  4. Build next generation
  5. Go to step 2.

Example 1: GA Step 1

- Build an initial population of *random* individuals

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10100	01011	00101

- Generation 0

Example 1: GA Step 2

- Evaluate *fitness* of individuals

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10100	01011	00101
	4	20	11	5

- Fitness can be calculated as the decimal value of each bit string

Example 1: GA Step 3

- Select some individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10100	01011	00101
	4	20	11	5

- Individual with good fitness should be selected for crossover and mutation.

Example 1: GA Step 3

- Select some individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**10100**	**01011**	00101
	4	20	11	5

- Individual with good fitness should be selected for crossover and mutation.

Example 1: GA Step 3

- Select some individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**10100**	**01011**	00101

- How to apply crossover between these 2 parents?
  - Single point? Multiple point? Location?
  - It depends on your implementation parameters
  - Crossover may happen or not according to the probability of crossover

Example 1: GA Step 3 – Trial 1

- Select some individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10|100	01|011	00101
		G_{11}	G_{12}	
		10011	01100	

- Single point crossover after 2 bits (Genes)

Example 1: GA Step 3 – Trial 1

- Select some individuals to apply *crossover* and mutation

		20	11	
	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10|100	01|011	00101
	G_{14}	G_{11}	G_{12}	G_{13}
G_1	00100	10011	01100	00101
	4	19	12	5

Fitness?

Example 1: GA Step 3 – Trial 2

- Select some individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**101|00**	**010|11**	00101
		G_{11}	G_{12}	
		10111	**01000**	

- Single point crossover after 3 bits

Example 1: GA Step 3 – Trial 2

- Select some individuals to apply *crossover* and mutation

		20	11	
	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**101|00**	**010|11**	00101
	G_{14}	G_{11}	G_{12}	G_{13}
	00100	**10111**	**01000**	00101
	4	23	8	5

Fitness?

Example 1: GA Step 3 – Trial 2

- Select some individuals to apply crossover and ***mutation***

		20	11	
	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**101|00**	**010|11**	00101
	G_{14}	G_{11}	G_{12}	G_{13}
	00100	**10111**	**01000**	00101
	4	23	8	5

- How to apply a mutation over some individual?
  - For bit strings, and according to the mutation probability of your implementation, one bit might be flipped!

Example 1: GA Step 3 – Trial 2

- Select some individuals to apply crossover and ***mutation***

	G_{01}	G_{02}	G_{03}	G_{04}
		20	11	
G_0	00100	**101|00**	**010|11**	00101

	G_{13}	G_{11}	G_{12}	G_{14}
G_1	00100	**11111**	**01000**	00101
	4	**31**	8	5

OUR OBJECTIVE!

Example 1: GA Step 3 – Trial 3

- Select some individuals to apply crossover and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**10100**	**01011**	00101

- Applying multiple point crossover!

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	**10100**	**01011**	00101

Example 1: GA Step 3 – Trial 4

- Select **ALL** individuals to apply *crossover* and mutation

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00|100	10100	01|011	00101
	4	20	11	5
Crossover	G_{11}		G_{12}	
	00011		**01100**	
	3		12	

Example 1: GA Step 3 – Trial 4

- Select **ALL** individuals to apply *crossover* and mutation

G_0	G_{01}	G_{02}	G_{03}	G_{04}
	00100	10|100	01011	00|101
	4	20	11	5
Crossover	G_{11}	G_{13}	G_{12}	G_{14}
	00011	**10101**	**01100**	**00100**
	3	21	12	4
Mutation	G_{11}	G_{13}	G_{12}	G_{14}
	00011	**11101**	**01100**	**00110**
	3	21→29	12	4→6

Example 1: GA Step 4

- Build next generation .. Full Replacement or Mix?

	G_{01}	G_{02}	G_{03}	G_{04}
G_0	00100	10100	01011	00101
	4	20	11	5
Crossover	G_{11}	G_{13}	G_{12}	G_{14}
	00011	**10101**	**01100**	**00100**
	3	21	12	4
Mutation	G_{11}	G_{13}	G_{12}	G_{14}
	00011	**11101**	**01100**	**00110**
	3	29	12	6

Example 1: GA Step 4

- Build next generation .. Mixing

	G_{02}	G_{03}	G_{11}	G_{13}
G_1	10100	01011	000|11	111|01
	20	11	3	29
	G_{02}	G_{03}	G_{21}	G_{22}
Crossover	10100	01011	00001	11111
	20	11	1	31
	G_{02}	G_{03}	G_{21}	G_{22}
Mutation	10100	11011	00000	11111
	20	27	0	**31**

OUR OBJECTIVE!

Does it really cost one iteration?

- Real world problems are not that easy.
- You could have:
  - Hundreds of individuals (chromosomes)
  - Huge search space
- You might perform thousands of iterations (have thousands of generations) before reaching your objective!

How do you encode a solution?

- Obviously this depends on the **problem**!
- GA's *often* encode solutions as fixed length "*bitstrings*" (e.g. 101110, 111111, 000101)
- Sometimes, your solutions (chromosomes) will be used in their original format (*floating point numbers* or *alphabetical strings*)

Why does crossover work?

- The idea is that crossover preserves “good bits” from different parents, combining them to produce better solutions
- The fitness may be improved or get worst after mutation
- A good scheme would therefore try to preserve “good bits” during crossover and mutation

Which problems can GAs solve?

- The solution can be encoded.
- Each gene represents some aspect of the proposed solution to the problem (the solution can be decomposed into smaller parts)
- The ability to "test" any solution and get a "score" indicating how "good" that solution is (**Fitness**).