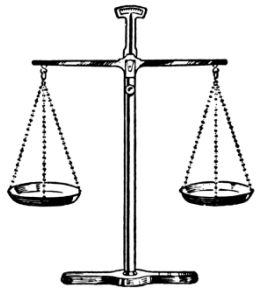


Genetic Algorithms

Genetic Algorithms - History

Originated in the fifties, but developed in the sixties by three distinct research groups:

- Pioneered by L. J. Fogel in the US
- J. H. Holland in the 1970's called his method a genetic algorithm
- I. Rechenberg and H.P. Schwefel introduced evolution strategies

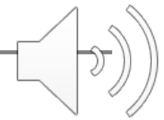
Got popular in the late 1980's

Based on ideas from Darwinian Evolution

Can be used to solve a variety of problems that are not easy to solve using other techniques

Evolution in the real world

- Each cell of a living thing contains ***chromosomes*** - strings of *DNA*
- Each chromosome contains a set of ***genes*** - blocks of DNA
- Each gene determines some aspect of the organism (like eye colour)
- A collection of genes is sometimes called a ***genotype***
- A collection of aspects (like eye colour) is sometimes called a ***phenotype***
- Reproduction involves recombination of genes from parents and then small amounts of ***mutation*** (errors) in copying
- The ***fitness*** of an organism is how much it can reproduce before it dies
- Evolution based on "survival of the fittest"



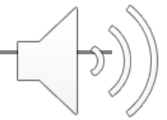
Genetic Algorithms

Generate a *set* of random solutions

Repeat

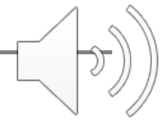
- Test each solution in the set (rank them)
- Remove some bad solutions from set
- Duplicate some good solutions
  - make small changes to some of them

Until best solution is good enough



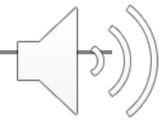
How do you encode a solution?

- Obviously this depends on the problem!
- GA's *often* encode solutions as fixed length "bitstrings" (e.g. 101110, 111111, 000101)
- Each bit represents some aspect of the proposed solution to the problem
- For GA's to work, we need to be able to "test" any string and get a "score" indicating how "good" that solution is

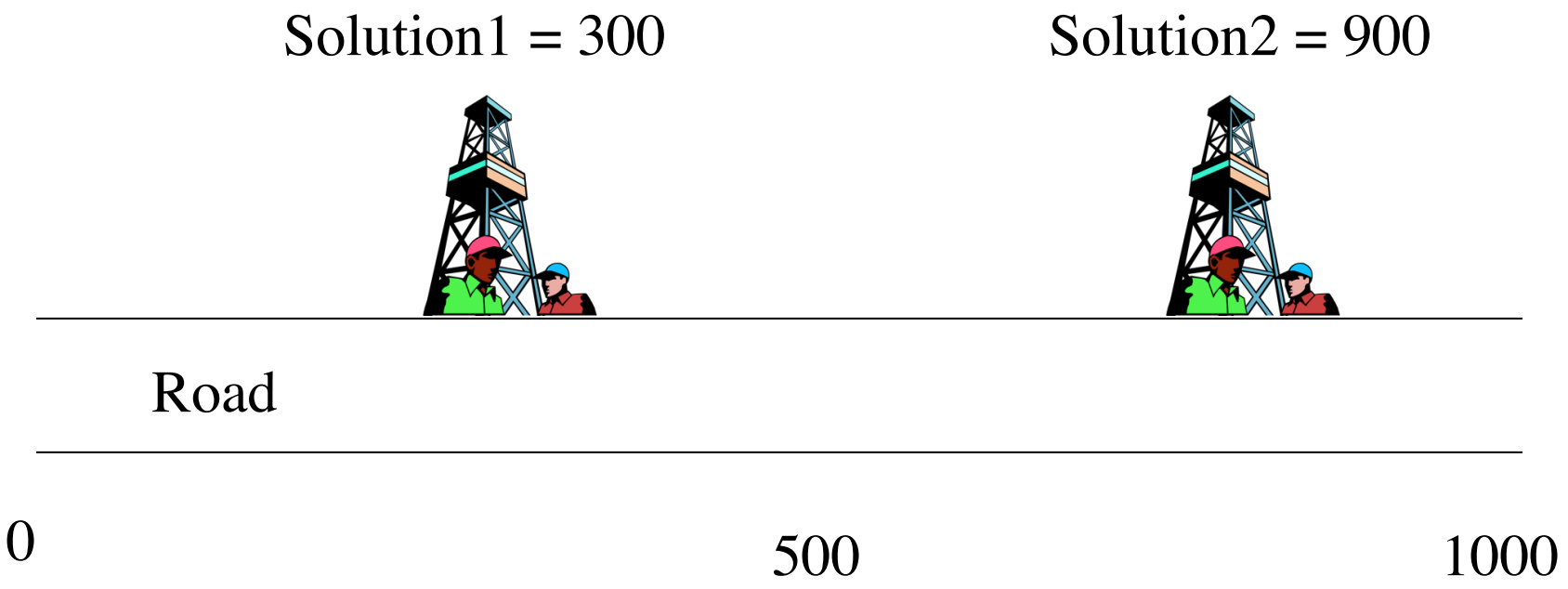


Silly Example - Drilling for Oil

- Imagine you had to drill for oil somewhere along a single 1km desert road
- Problem: choose the best place on the road that produces the most oil per day
- We could represent each solution as a position on the road
- Say, a whole number between [0..1000]

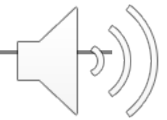


Where to drill for oil?



Digging for Oil

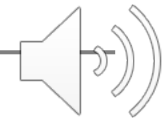
- The set of all possible solutions [0..1000] is called the *search space* or *state space*
- In this case it's just one number but it could be many numbers or symbols
- Often GA's code numbers in binary producing a bitstring representing a solution
- In our example we choose 10 bits which is enough to represent 0..1000



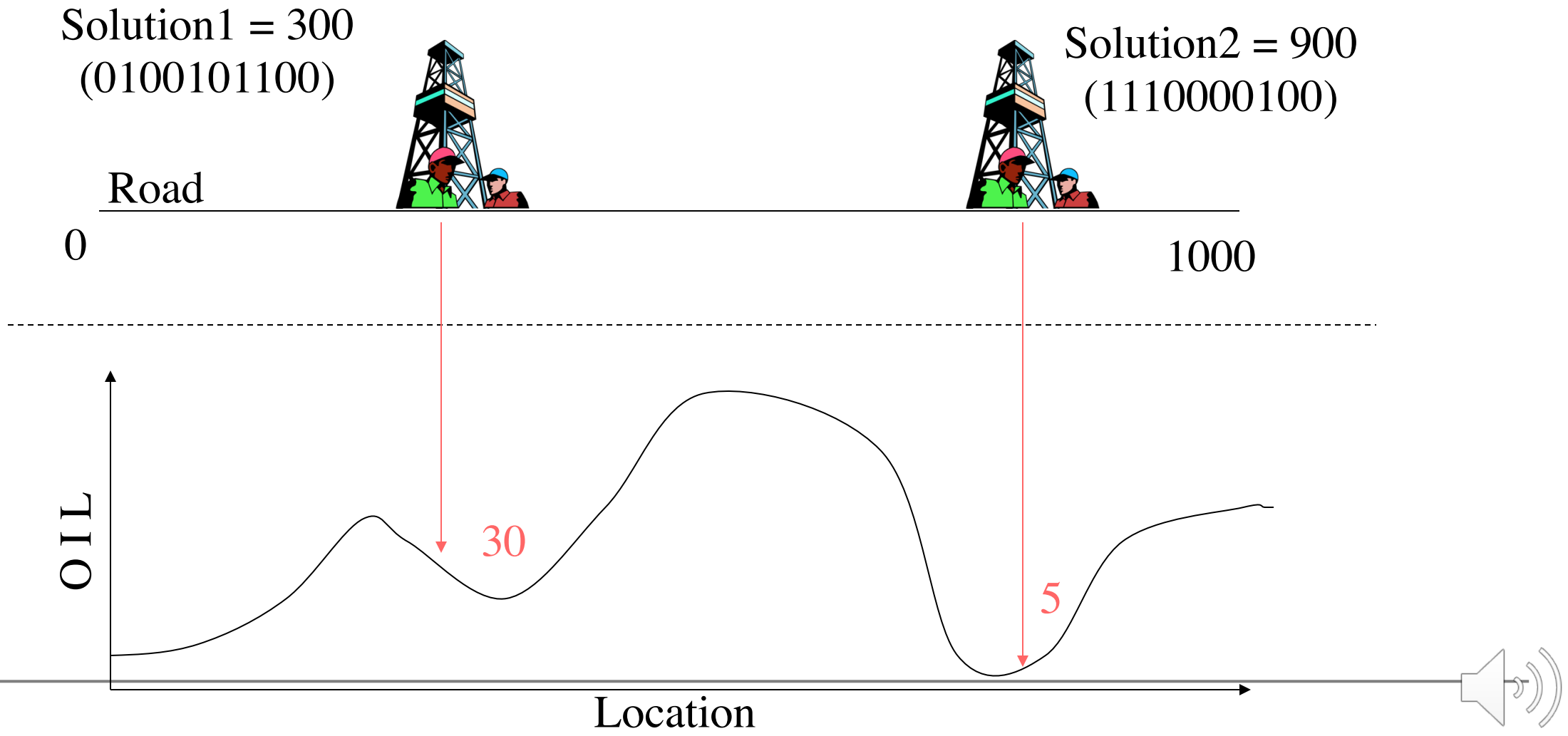
Convert to binary string

	512	256	128	64	32	16	8	4	2	1
900	**1**	**1**	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**0**
300	**0**	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**0**	**0**
1023	1	1	1	1	1	1	1	1	1	1

In GA's these encoded strings are sometimes called "*genotypes*" or "*chromosomes*" *and the individual bits are sometimes called "genes"*



Drilling for Oil

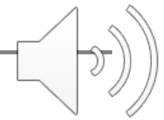


Summary

Our example is really optimisation over a function f(x) where we adapt the parameter x

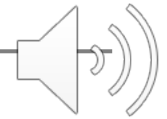
We have seen how to:

- represent possible solutions as a number and encode them in binary strings
- generate a score for each number given a *function* of "how good" each solution is - this is often called a *fitness function*

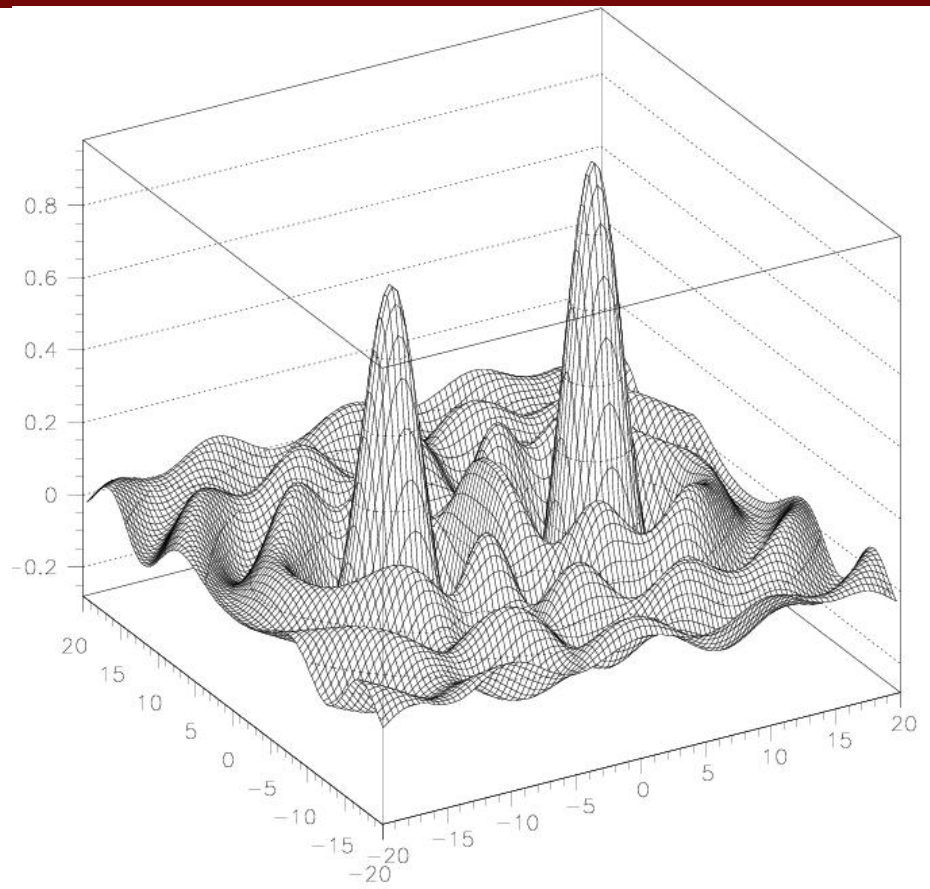


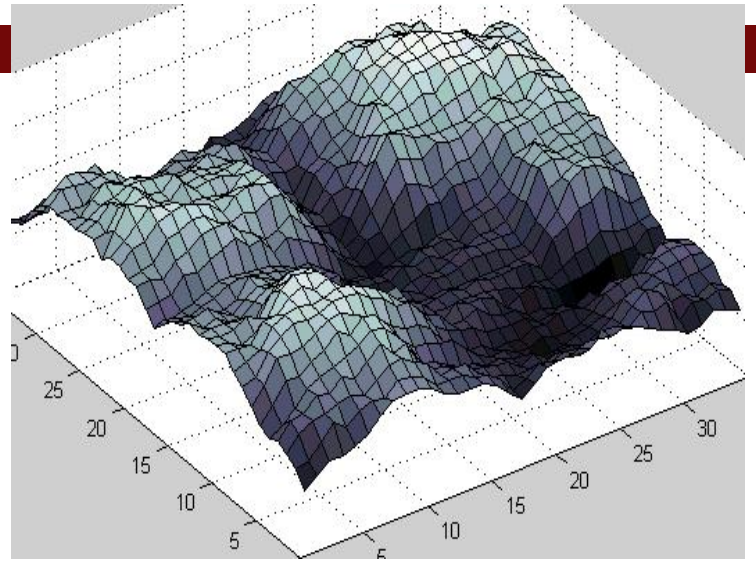
Search Space

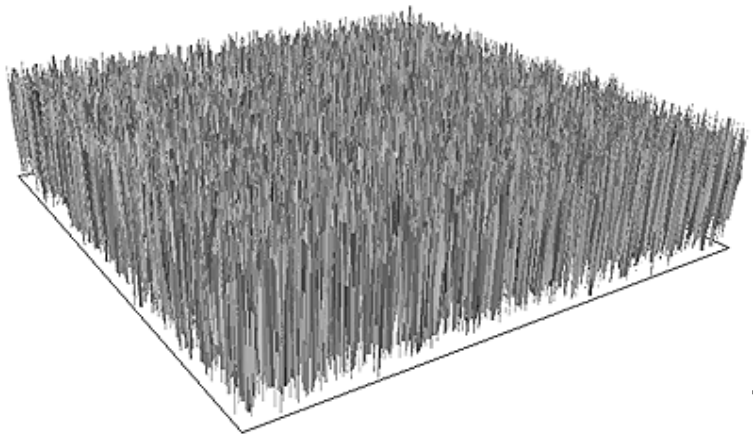
- For a simple function f(x) the search space is one dimensional.
- But by encoding several values into the chromosome many dimensions can be searched e.g. two dimensions f(x,y)
- Search space can be visualised as a surface or *fitness landscape* in which fitness dictates height
- Each possible genotype is a point in the space
- A GA tries to move the points to better places (higher fitness) in the space



Fitness landscapes

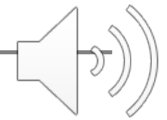






Search Space

- Obviously, the nature of the search space dictates how a GA will perform
- A completely random space would be bad for a GA
- Also GA's can get stuck in local maxima if search spaces contain lots of these
- Generally, spaces in which small improvements get closer to the global optimum are good



Back to the (GA) Algorithm

Generate a *set* of random solutions

Repeat

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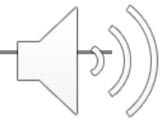
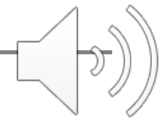
make small changes to some of them

Until best solution is good enough



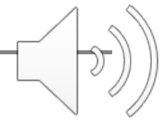
Adding Sex - Crossover

- Although it may work for simple search spaces our algorithm is still very simple
- It relies on random mutation to find a good solution
- It has been found that by introducing "sex" into the algorithm better results are obtained
- This is done by selecting two parents during reproduction and combining their genes to produce offspring



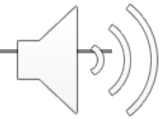
Adding Sex - Crossover

- Two high scoring "parent" bit strings (*chromosomes)* are selected and with some probability (crossover rate) combined
- Producing two new *offspring* (bit strings)
- Each offspring may then be changed randomly (*mutation*)



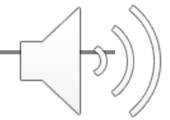
Selecting Parents

- Many schemes are possible as long as better scoring chromosomes more likely selected
- Chromosomes with highest *fitness* should have higher probability to be selected
- "Roulette Wheel" selection can be used:
  - Add up the fitness's of all chromosomes
  - Generate a random number R in that range
  - Select the first chromosome in the population that - when all previous fitness's are added - gives you at least the value R

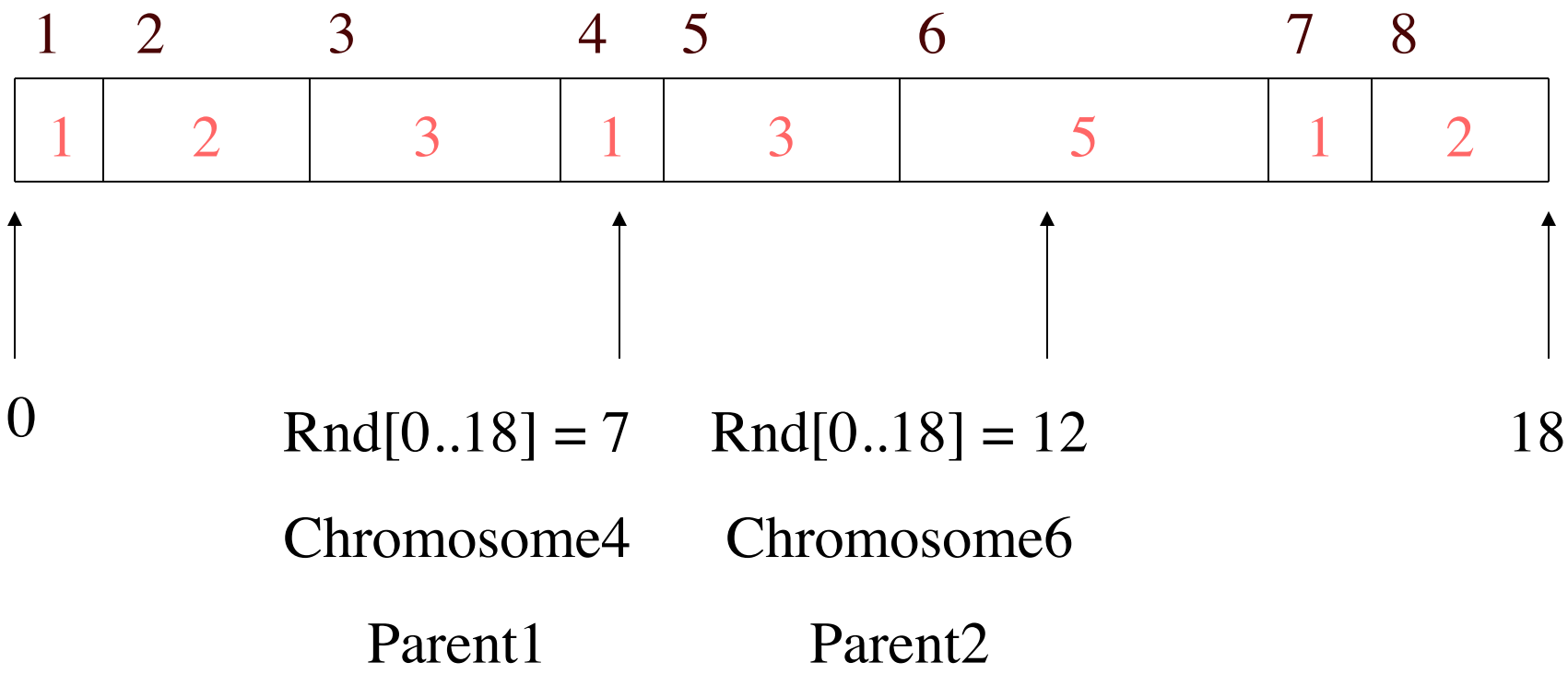


Example population

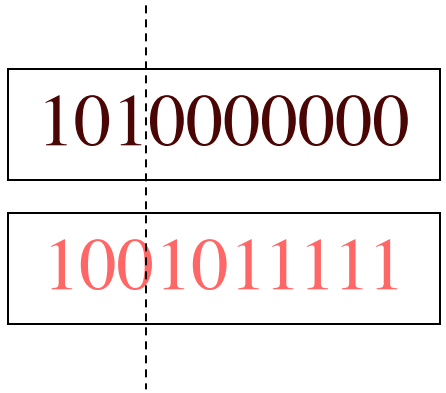
No.	Chromosome	Fitness
1	1010011010	1
2	1111100001	2
3	1011001100	3
4	1010000000	1
5	0000010000	3
6	1001011111	5
7	0101010101	1
8	1011100111	2



Roulette Wheel Selection



Crossover - Recombination



Parent1

Parent2

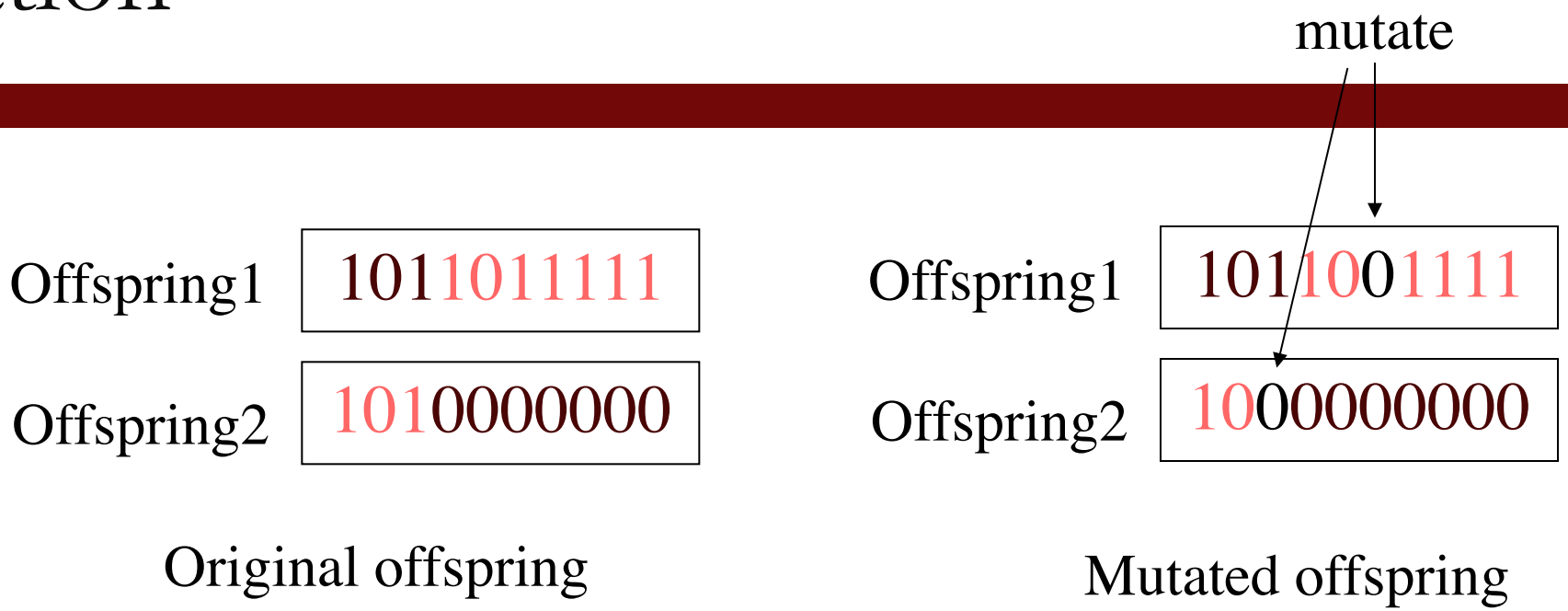
Offspring1 1011011111

Offspring2 1010000000

Crossover single point - random

With some high probability (*crossover rate*) apply crossover to the parents. (*typical values are 0.8 to 0.95*)

Mutation



With some small probability (the *mutation rate*) flip each bit in the offspring (*typical values between 0.1 and 0.001*)

Back to the (GA) Algorithm

Generate a *population* of random chromosomes

Repeat (each generation)

- Calculate fitness of each chromosome
- Repeat
  - Use roulette selection to select pairs of parents
  - Generate offspring with crossover and mutation
- Until a new population has been produced

Until best solution is good enough