

AI Course

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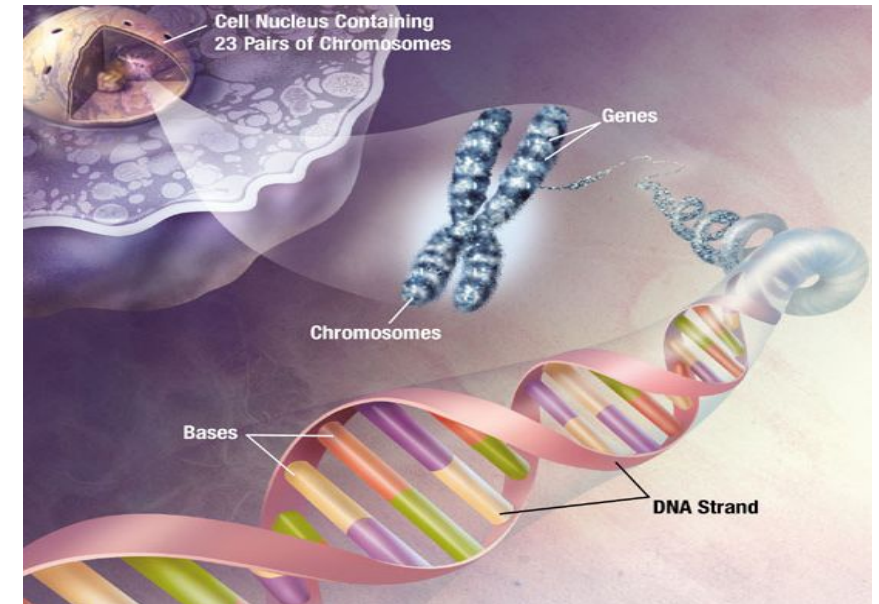
Genetic Algorithm

Genetic Algorithm - *Introduction*

- Genetic algorithm (GA) is a **search heuristic** algorithm, inspired by nature and Darwin's theory of **natural evolution**

- A brief history:

- 1957 – Alex Fraser (geneticist) – Simulation of artificial selection of organisms
- 1970 – Fraser & Burnell, 1973-Crosby (biologist) – Computer simulation of evolution
- 1975 – John Holland – (computer scientist) – Adaptation in Natural and Artificial Systems



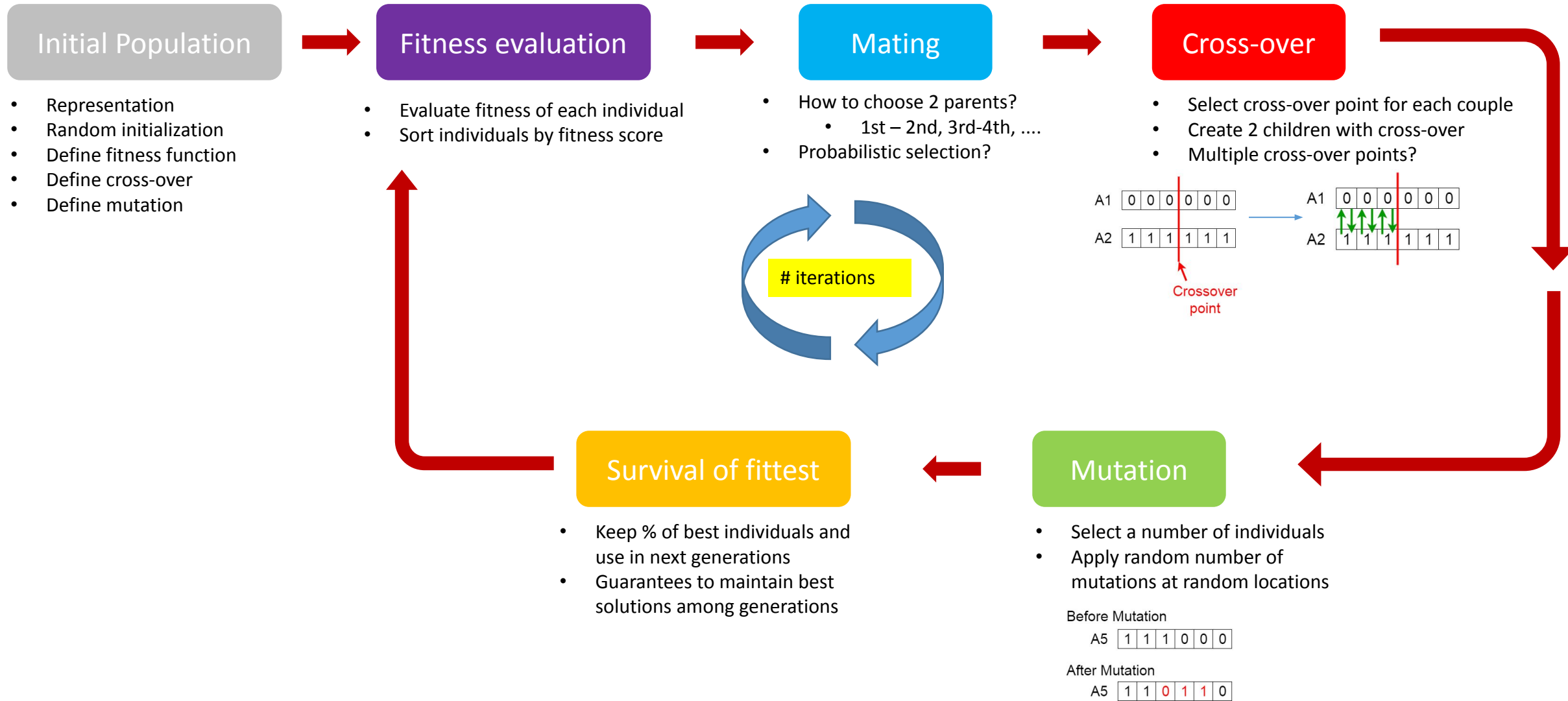
Genetic Algorithm - *Introduction*

- In GA, proposed solutions are represented by **individuals**, individuals form a **population** or **generation**
- Representation of the solution is encoded in the **chromosomes** of each individual
- Genetic operations of cross-over, mutation, survival of the fittest, etc. are used to generate better and better generations (i.e. Better solutions)
- At each iteration, individuals (solutions) are evaluated using a

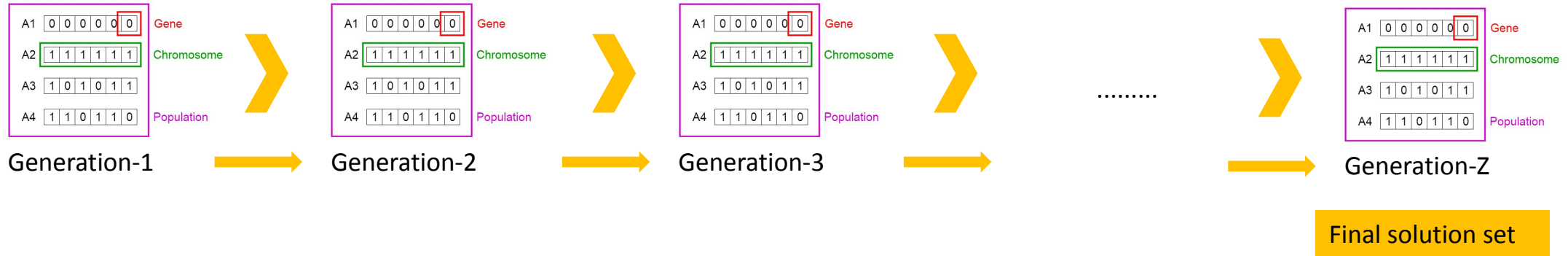
Genetic Algorithm - *Questions*

- What do we aim with GA?
- Can it limit search space?
- Is it able to optimize solution?
- Does it converge (minimize error)?
- Is it brute-force?
- Any limitations?

Genetic Algorithm – *Overview of flow*



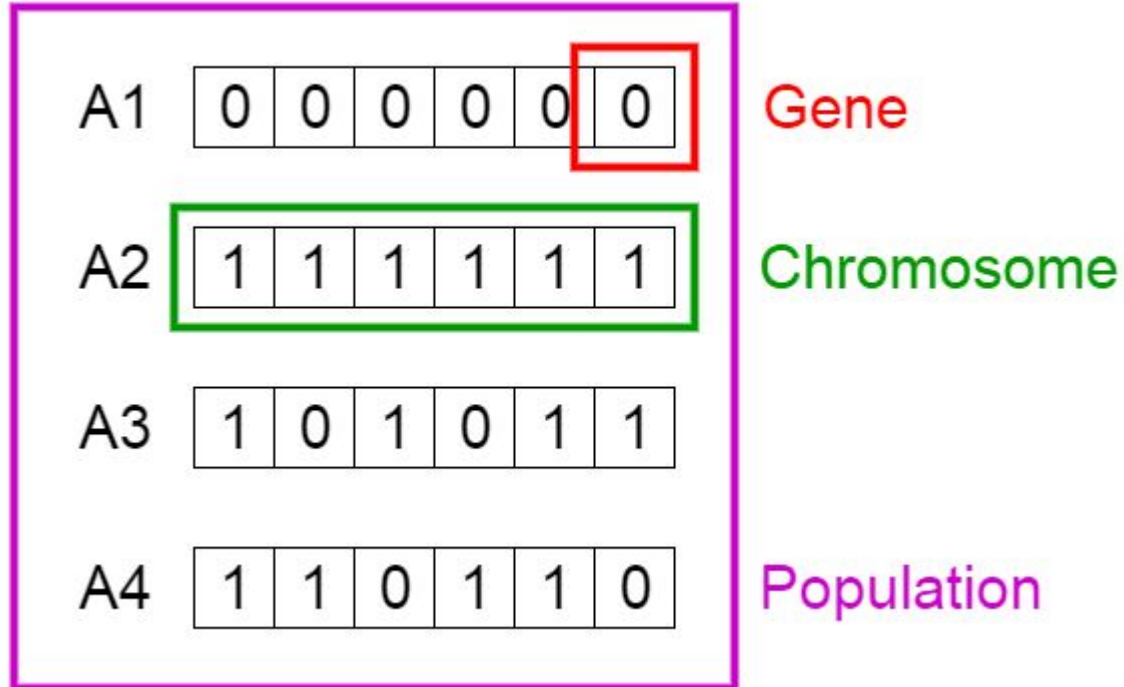
Genetic Algorithm – *Generations*



Generations:

- Like people populations, we start with initial population (Generation-1) and reproduce new individuals (children) for next generation
- **Two parents** in *Generation(t)* will have **two children** in *Generation(t+1)*
- Assumption: Each generation will have new individuals, no individual will live to next generation (*exception: survival of the fittest*)
- For reproduction, we use genetic operations like **cross-over**, **mutation**, **survival of the fittest**
- We need to evaluate (*score*) each individual according to our solution criteria (*fitness function*)

Genetic Algorithm – *Initial population*

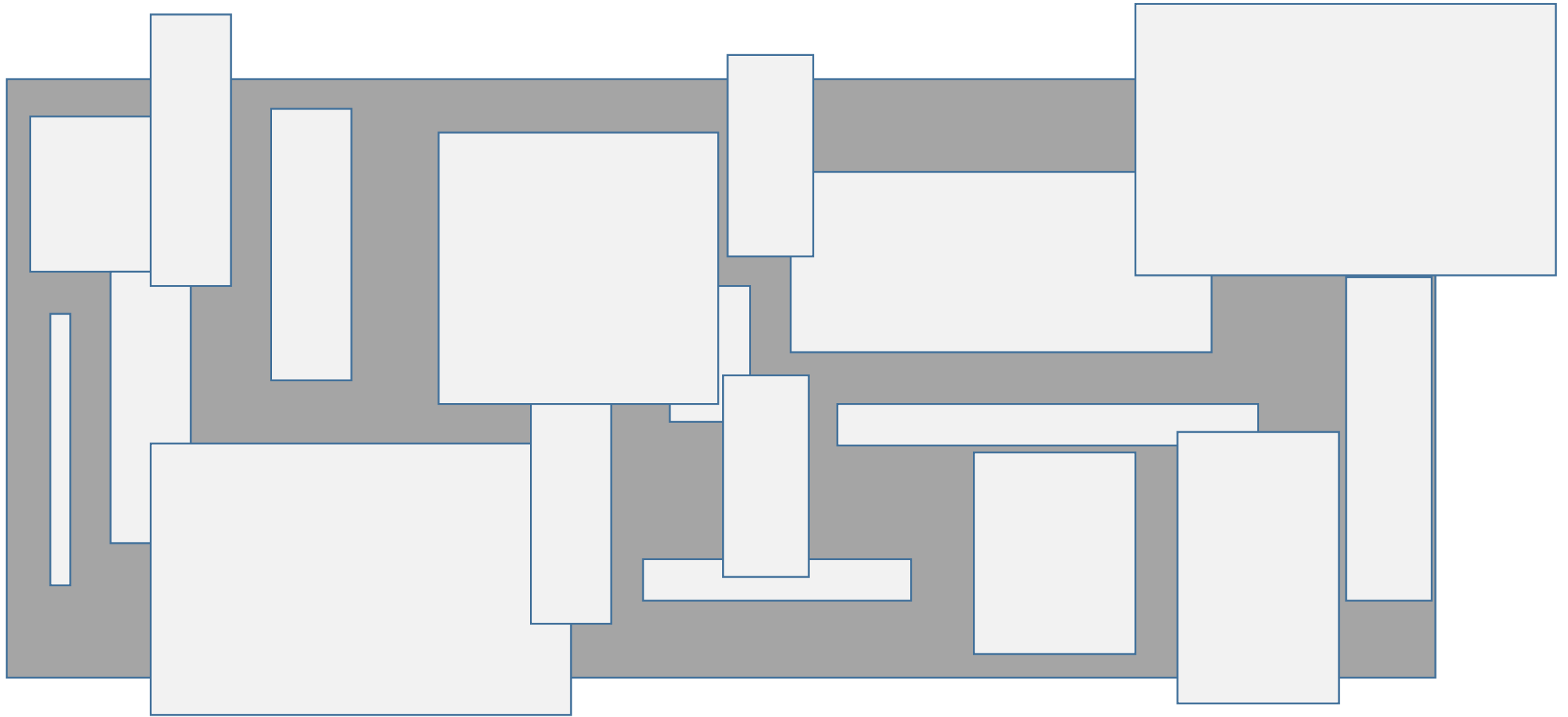


Representation:

- We need to find a suitable way to represent a **candidate solution**
- Solutions are encoded in **chromosomes** of individuals
- **i.e.**, in a layout problem, chromosomes can represent **X,Y coordinates** of each object location
- We will have **N** number of individuals who form the **population**

We can use random initialization!

Genetic Algorithm – *Initial population*



Rectangle Layout Problem – Initialization: *Randomly put on board*

Genetic Algorithm – *Initial population*

Representation:

- Representation is one the **most** critical parts of GA
- Each individual should hold a **candidate solution** of the problem
- Cross-over should not cause **loss of information** of the solution
- Representation should be suitable for genetic operations (*cross-over, mutation, etc.*)

1	100
2	203
3	403
4	2
5	4
6	167
7	800
8	34
9	55
10	38
11	232
12	19
13	432
14	21
15	1
16	0
17	22
18	82
19	88
20	418
21	87
22	2
23	43
24	11
25	24
26	5
27	39
28	50
29	8
30	12

Chromosome

gene

1	189234
2	439853
3	534985
4	539833
5	98530
6	493870
7	543989
8	543593
9	88649
10	102322
11	942802
12	1101942
13	988502
14	932824
15	113492
16	2104589
17	242092
18	842920
19	248298
20	429842
21	221294
22	698720
23	4239853
24	492382
25	839289
26	423989
27	128524
28	429801
29	111342
30	242982

X-coord.	Y-coord.	Color	Cost
120	0	14	1000

Population consists of a certain number of individuals (Chromosomes)

Genetic Algorithm – *Initial population*

Chromosomes could be:

- Bit strings (0101 ... 1100)
- Real numbers (43.2 -33.1 ... 0.0 89.2)
- Permutations of element (E11 E3 E7 ... E1 E15)
- Lists of rules (R1 R2 R3 ... R22 R23)
- Program elements (genetic programming)
- ... any data structure ...

Parent 1

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

Parent 2

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

Child 1

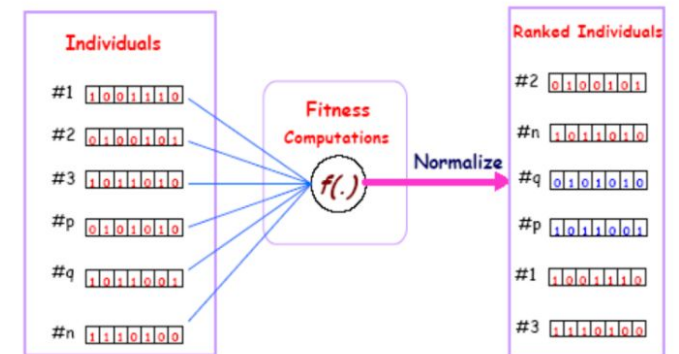
0	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

Child 2

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

Genetic Algorithm – *Fitness Function*

- Fitness function evaluates the **fitness** of each individual **solution candidate**
- Fitness function will produce a single **numeric** score \square **fitness score**
- Fitness scores quantifies, **how desirable**, **how good** the individual is against the **constraints** or **criteria** of solution
- In biology, we can define a fitness function that can tell **how healthy** an individual is



Genetic Algorithm – *Fitness Function*

- We should write the fitness function to optimize our constraints
 - List the **constraints**
 - Try to formulize **evaluation** of constraints
 - Combine all subscores to a **single numeric** score
- Fitness functions are **custom** for each GA, it should be defined for our need
- Fitness scores should be calculated for each individual
- Individuals should be **sorted** according to fitness scores

1	203	1	100	1	100	1	3	1	5
2	100	2	203	2	203	2	203	2	203
3	403	3	403	3	403	3	403	3	403
4	2	4	2	4	4	4	2	4	2
5	4	5	4	5	2	5	4	5	4
6	167	6	167	6	167	6	167	6	800
7	800	7	800	7	800	7	800	7	167
8	34	8	34	8	34	8	34	8	34
9	55	9	55	9	55	9	55	9	55
10	38	10	38	10	38	10	38	10	38
11	232	11	232	11	232	11	232	11	232
12	19	12	19	12	21	12	19	12	19
13	432	13	432	13	432	13	432	13	432
14	21	14	21	14	19	14	21	14	21
15	1	15	1	15	1	15	22	15	1
16	0	16	0	16	0	16	0	16	0
17	22	17	22	17	22	17	22	17	22
18	82	18	82	18	82	18	88	18	82
19	88	19	88	19	88	19	82	19	88
20	418	20	418	20	418	20	418	20	418
21	87	21	87	21	87	21	87	21	87
22	2	22	2	22	2	22	2	22	2
23	43	23	43	23	43	23	43	23	43
24	11	24	11	24	11	24	11	24	11
25	5	25	24	25	24	25	24	25	24
26	24	26	5	26	5	26	5	26	5
27	39	27	39	27	39	27	39	27	39
28	50	28	50	28	50	28	50	28	50
29	8	29	8	29	8	29	8	29	8
30	12	30	12	30	12	30	12	30	12

Sort them all!

103

98

97

88

70

60

58

Genetic Algorithm – *Selection & Mating*

- How to choose 2 parents to create 2 children?

- Random selection
- Select according to fitness from top-to-bottom (1st – 2nd, 3rd – 4th, ...)
- Select with probability of fitness function

$$p_s(\mathbf{m}_i) = \frac{F(\mathbf{m}_i)}{\sum_{j=1}^n F(\mathbf{m}_j)}$$

Fitness	Initial Population		
22	101010100111110101		
9	110011010101011100	Selection	Selected parent string one 110011010101011100
8	111110101111010101		
70	111001111100001001		
19	110011010101011100		
48	101110101111001001		
23	110011010101011100	Selection	Selected parent string two 111001111100001001
38	111001111100001001		

Random selection

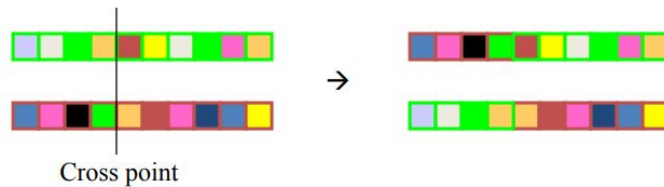
Fitness	Initial Population		
22	101010100111110101		
9	110011010101011100		
8	111110101111010101		
70	111001111100001001	Selection	Selected parent string one 111001111100001001
19	110011010101011100		
48	101110101111001001	Selection	Selected parent string two 101110101111001001
23	110011010101011100		
38	111001111100001001		

Selection by fitness score

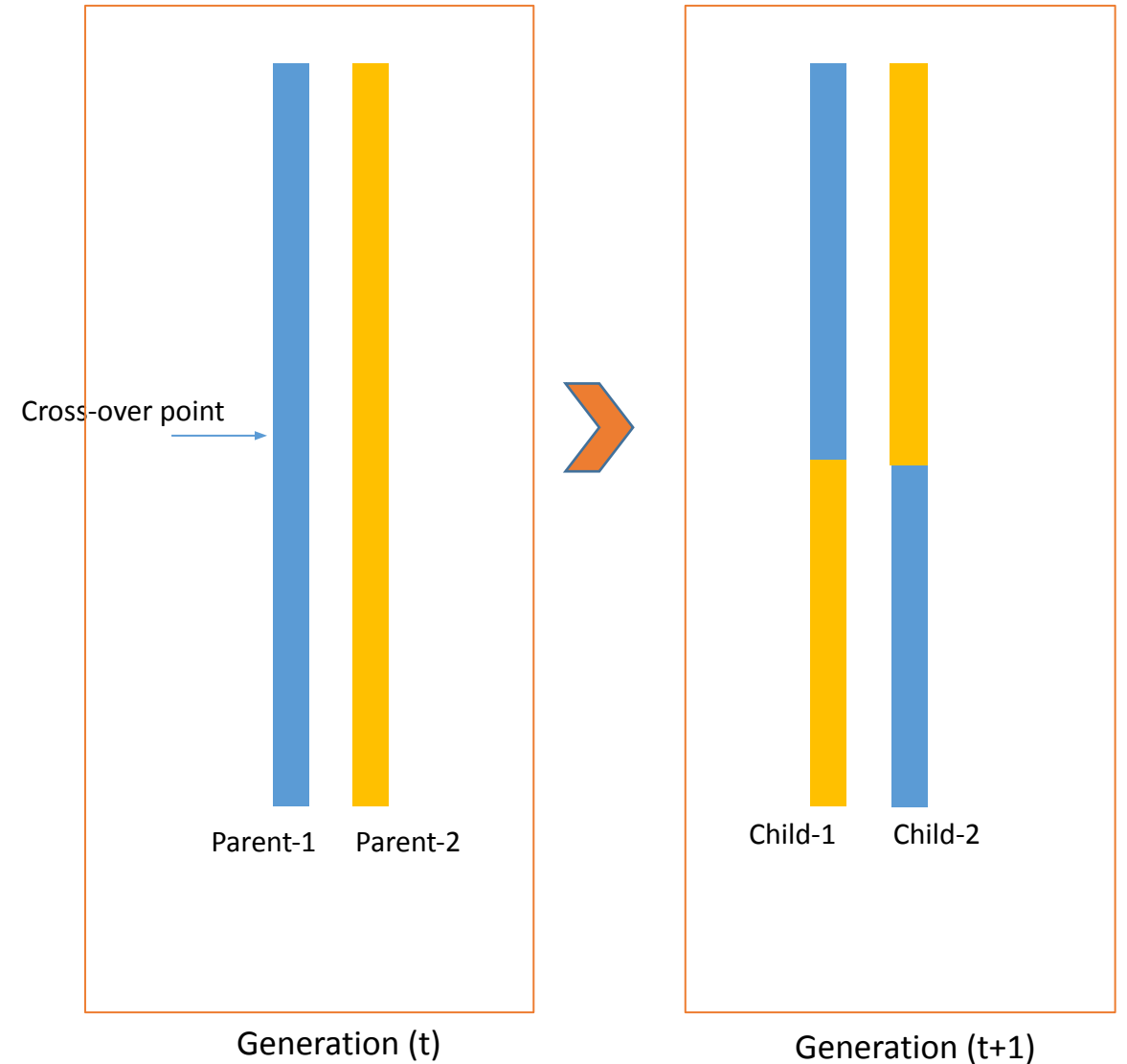
Genetic Algorithm – *Cross-over*

- Select one or more cross-over point
- Exchange genes between chromosomes (individuals)
- Create 2 new individuals for next generation
- All the chromosomes in the population **must re-produce** (create 2 new children)

- Single point crossover



- Two point crossover (Multi point crossover)



Genetic Algorithm – *Cross-over*

- Many variants of cross-over possible
- Example: Uniform cross-over
 - A random subset is chosen
 - The subset is taken from parent 1 and the other bits from parent 2

Subset: BAABBAABBB (Randomly generated)

Parents: 1010001110 0011010010

Offspring: 0011001010 1010010110

Genetic Algorithm - *Mutation*

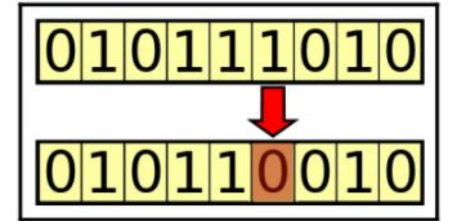
- Randomly change a **bit** of information in chromosomes
- Can create new information, **new solutions!** Creativity?
- It can be applied to only a group of chromosomes
 - Select a percentage of **chromosomes** randomly
 - Select a number of **genes** and change them randomly
- Harmful mutations may kill!
 - Like biological life, mutation may lead to unintended consequences ☐ **Death!**
- Mutation can also lead **better** solutions which did not exist before!



Genetic Algorithm - *Mutation*

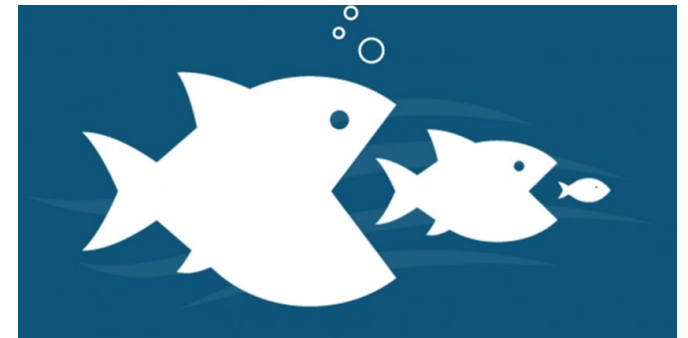
- Mutation can be applied to **multiple** locations within a chromosome
- Mutation can be bitwise changes

1	203	1	203
2	100	2	100
3	403	3	403
4	2	4	2
5	4	5	4
6	167	6	167
7	800	7	800
8	34	8	34
9	55	9	55
10	38	10	38
11	232	11	300
12	19	12	19
13	432	13	432
14	21	14	21
15	1	15	1
16	0	16	0
17	22	17	22
18	82	18	82
19	88	19	88
20	418	20	418
21	87	21	12
22	2	22	2
23	43	23	43
24	11	24	11
25	5	25	5
26	24	26	24
27	39	27	39
28	50	28	50
29	8	29	8
30	12	30	12



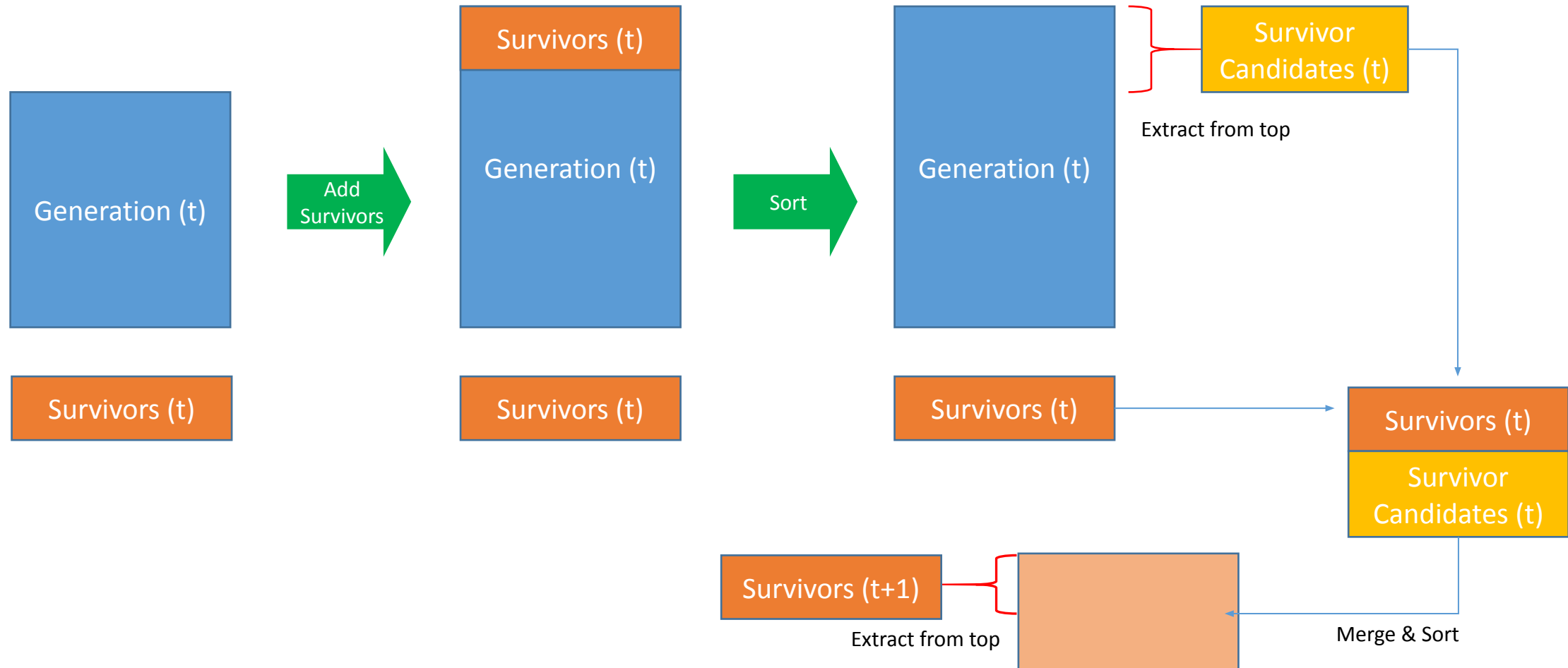
Genetic Algorithm – *Survival of the fittest*

- Individuals are not allowed to move to next generations □ Only **children** will go to next generation. Parents die.
- However this may lead to lose better intermediate solutions between generations
- A possible solution:
 - Keep a list of **best** solutions aside (i.e. Chromosomes with top %10 best fitness score)
 - In each generation, these list of solutions (chromosomes) will **join** population (merged population will be sorted by fitness score)
 - Keep the list **up-to-date** with each generation
- This will ensure that all the good solutions will be used throughout the generations
- Convergence of the algorithm improves!



Genetic Algorithm – *Survival of the fittest*

- Keep a separate list of solutions (chromosomes)



Genetic Algorithm – *Use cases*

- Scheduling problems
- Layout design (box, cargo ship, circuit design)
- Feature engineering
- Model hyper-parameter tuning
- Optimization
- Constraint satisfaction
- Self-updating programs/codes
- Music composing

Genetic Algorithm – *Advantages*

- Parallelism
- A larger set of solution space
- Requires less information
- Provides multiple optimal solutions
- Probabilistic in nature, can **avoid** local min/max
- Genetic representations using chromosomes
- Easy solutions for hard problems, easy to understand concept
- Creativity can be achieved
- Support multi-objective optimization
- Flexible building blocks
- Can work on noisy environments

Genetic Algorithm – *Disadvantages*

- The need for special definitions
- Hyper-parameter tuning
- Computational complexity, can be time-consuming
- Fitness function may be hard to define
- Correct representation can be hard to define
- Convergence not guaranteed