7. Genetic Algorithms

7.1 Introduction

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Outline

- Evolutionary Computing (EC)
- Biological Background
- Landscape Example
- Natural Genetics
- What is a Genetic Algorithm?
- Simple Genetic Algorithm (SGA)
- References

Evolutionary Computing (EC)

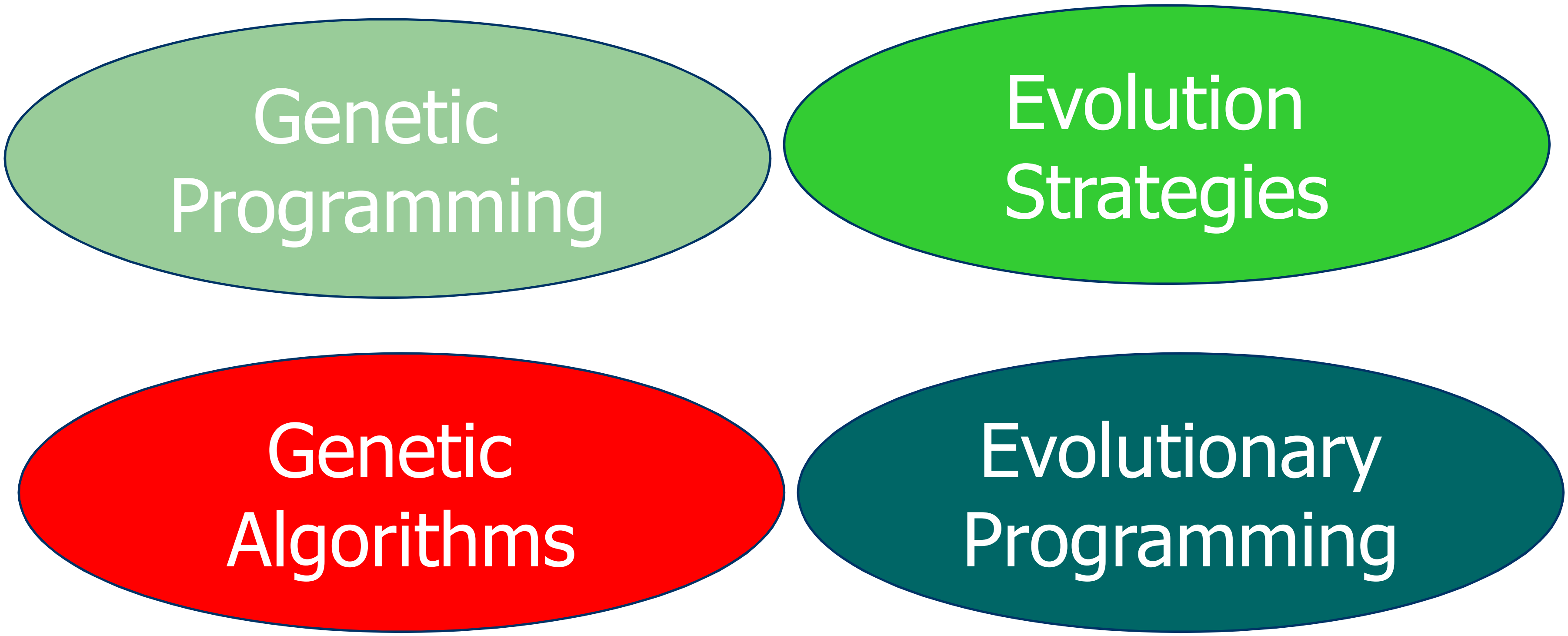
Evolutionary Computing (EC)

- EC is part of computer science
- EC is not part of life sciences/biology
- It draws inspiration from the process of natural evolution
- EC can be applied in biological research

The Main EC Metaphor

EC ⟷	Nature
Optimization problem	Environment
Feasible solutions	Individuals living in that environment
Solutions quality	Fitness (Individual's degree of adaptation to its surrounding environment)

Evolutionary Computing Areas



Brief History

- 1964, Rechenberg introduces evolution strategies
- 1965, L. Fogel, Owens and Walsh introduce evolutionary programming
- 1975, Holland introduces genetic algorithms
- 1992, Koza introduces genetic programming

Motivations for EC

- Nature has always served as a **source** of inspiration for engineers and scientists
- The best problem solver known in nature is:
  - **the (human) brain** that created “the wheel, New York, wars and so on”
  - **the evolution mechanism** that created the human brain

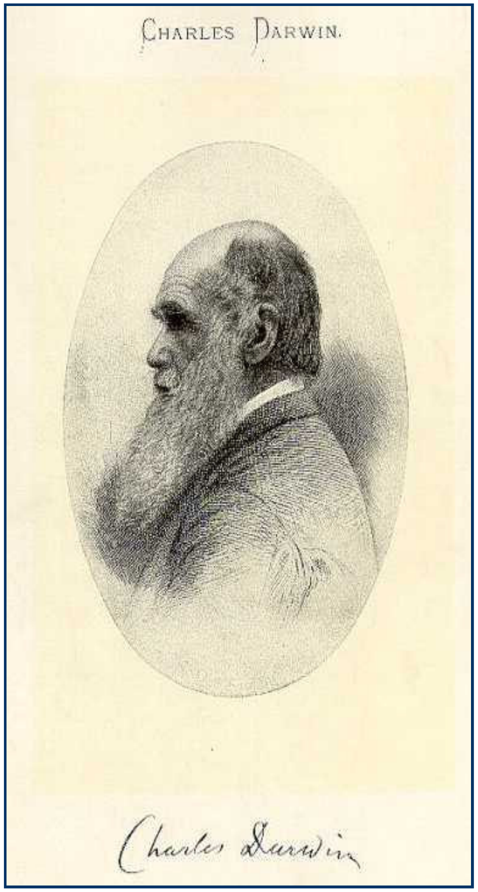
Motivations for EC

- Developing, analyzing, applying problem **solving methods** (**algorithms**) is a central theme in mathematics and computer science
- **Complexity** of problems to be solved **increases**
- Consequence: **Robust problem solving** technology needed
  - Which do not need much tailoring for specific problems, and
  - Deliver good (not necessarily optimal) solutions within acceptable time
- EC do all this

Biological Background

Darwin's principles

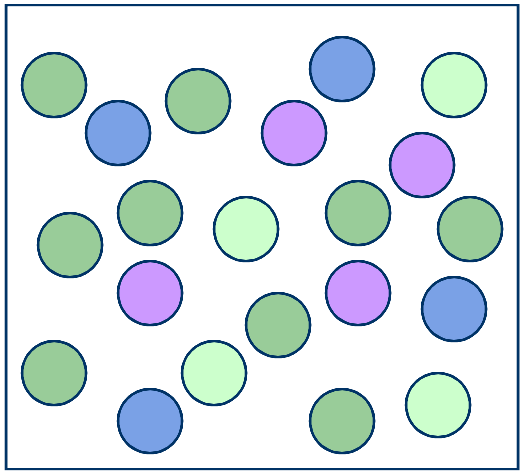
- **Variety** of species individuals within the population
- **Overproduction** of offspring generation
  - Individuals have basic instinct towards reproduction
- **Competition** for limited resources
  - Environment only support a limited number of individuals
- **Survival of the fittest**
  - Those individuals, that are adopted or fit to the environmental condition best, have increased chance of reproduction

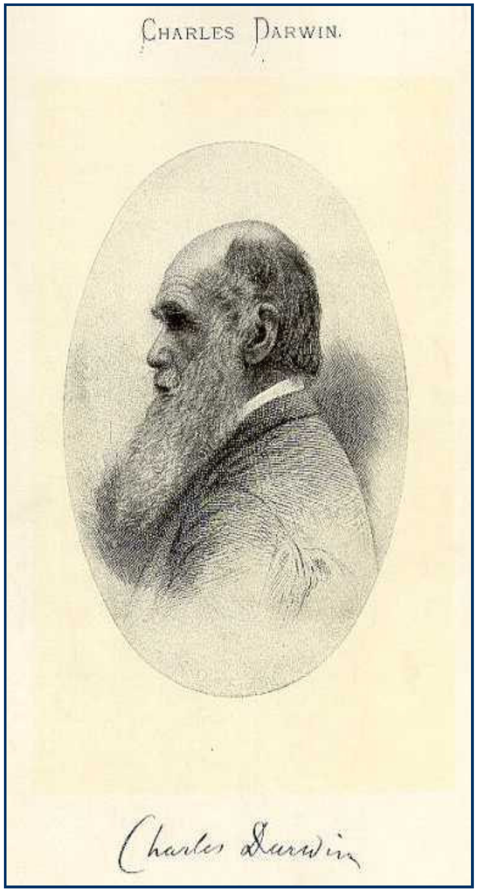


Evolution

How does it work?

- Initial population
  - Variety of shapes, colors, behaviors
  - Each individual fits differently to the environment

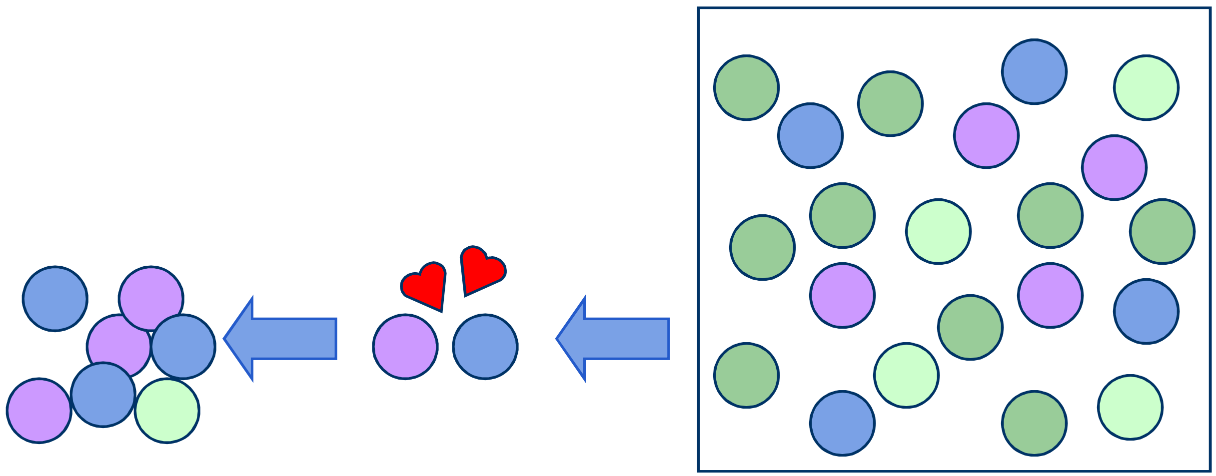


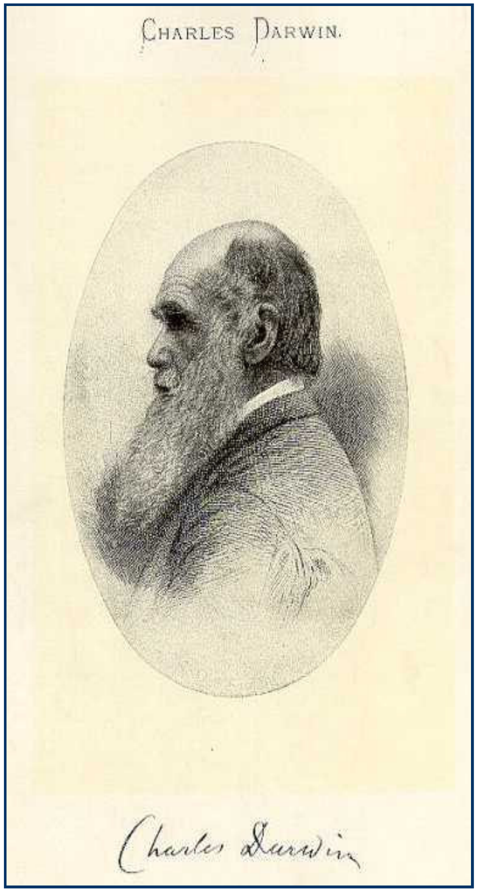


Evolution

How does it work?

- Initial population
- Reproduction
  - Offspring combines both parents properties
  - Siblings may differ in properties
  - Mutations may occur

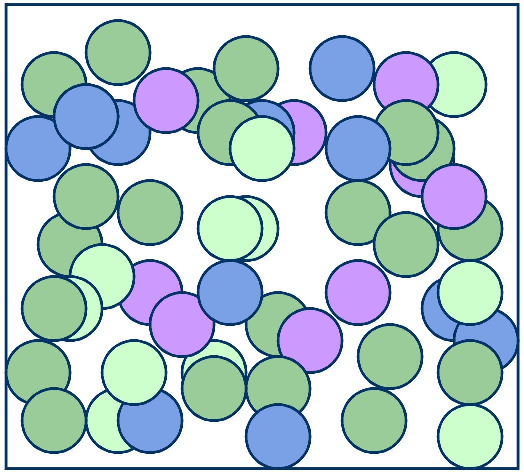


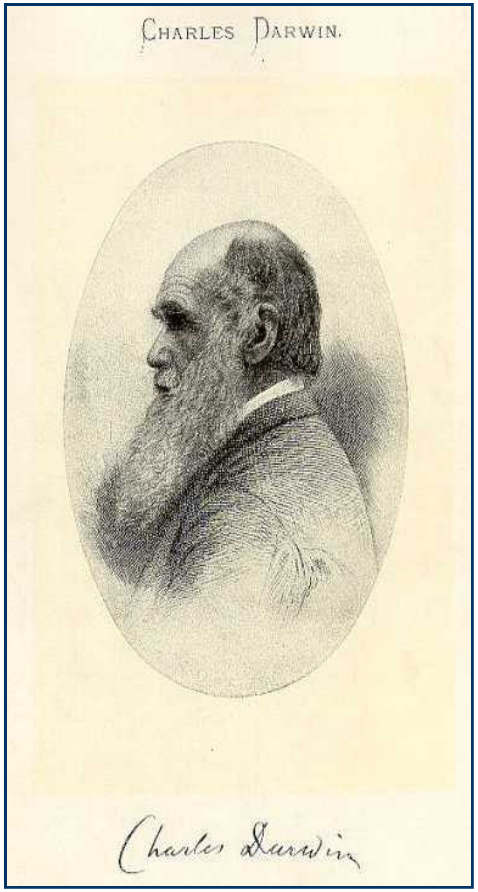


Evolution

How does it work?

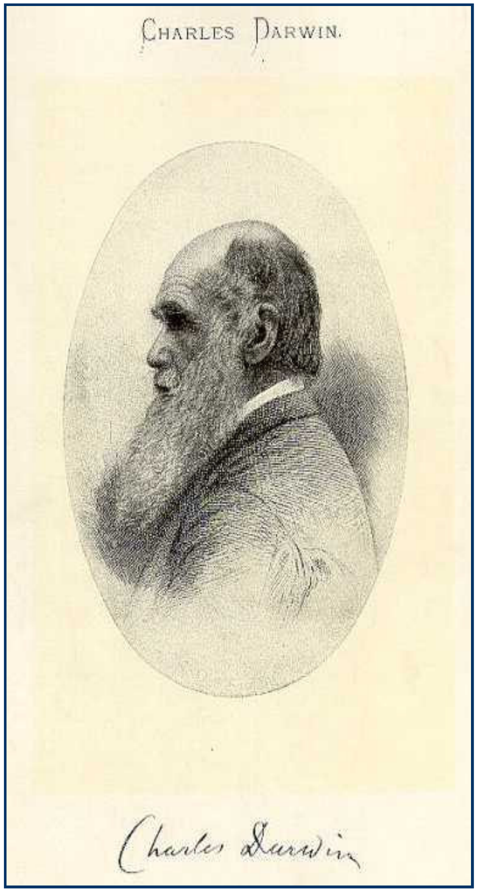
- Initial population
- Reproduction
- Limited environmental resources
  - Only a portion of the individuals survive
  - Survival chances – according to fitness measure





Evolution

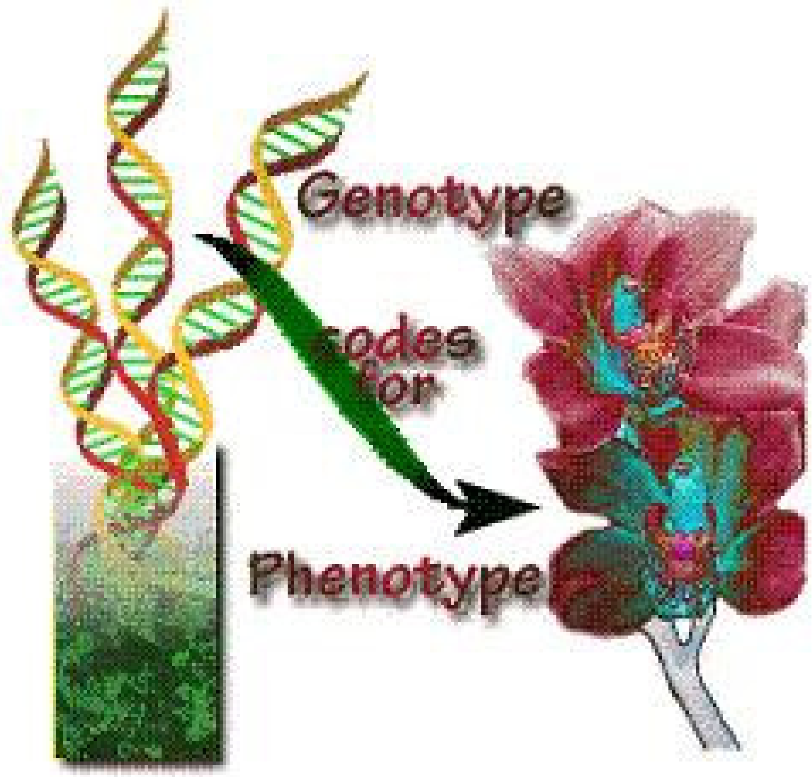
- **Phenotypic traits**:
  - Behaviour / physical differences that affect **response to environment**
  - Partly determined by **inheritance**, partly by factors **during development**
  - Unique to each individual, partly as a result of **random changes**
- If phenotypic traits lead to higher chances of reproduction, then
  - Can be inherited
  - They will tend to increase in subsequent generations
  - Leading to new combinations of traits …



Natural Genetics

Natural Genetics

- The information required to build a living organism is coded in the DNA of that organism
- Genotype (DNA inside) determines Phenotype



Natural Genetics

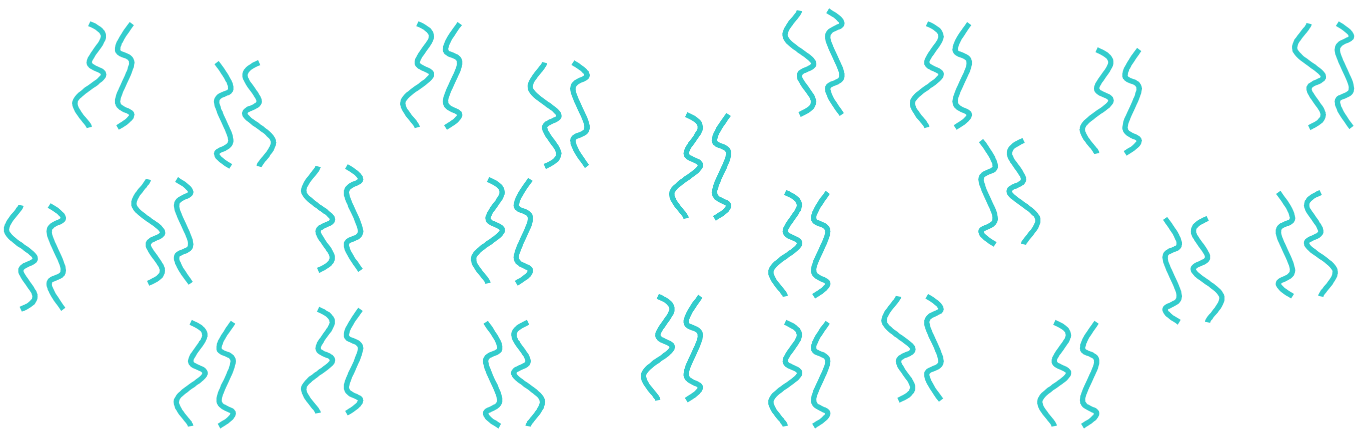
- **Genes** are encoding phenotypic characteristics
  - One gene may affect many traits
  - Many genes may affect one trait
- Small changes in the genotype lead to small changes in the organism (e.g., height, hair colour)
- The posibilities of the **genes** for one property is called **Allele**
- Genotypic variations are consequences of:
  - **Recombination** of genes by sexual reproduction
  - **Mutation** of genes

Genes and the Genome

- The complete genetic information in an individual's genotype is called the **Genome**
- Genes are encoded in strings of DNA called **Chromosomes**
- In most **cells**, there are two copies of each chromosome, called **Diploid**
- Within a species, most of the genetic material is the same

Example

- **Human body cells** contains **23 pairs** of chromosomes which together define the attributes of the individual:

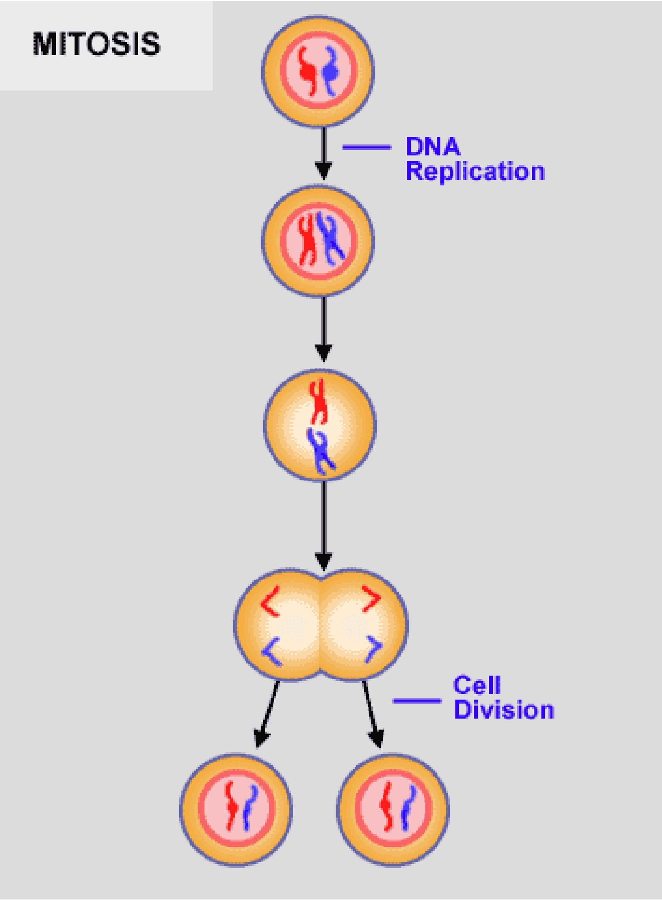


Reproductive Cells

- **Gametes** (i.e, **sperm** and **egg cells**) contain 23 **individual chromosomes rather than** 23 pairs
- Cells (gametes) with only one copy of each chromosome are called **Haploid**
- The haploid **sperm cell merges** with the haploid **egg cell** and forms a diploid cell, called **Zygote**
- The new organism develops from this zygote by the process named **Ontogenesis**
- All body cells contain the **same** genetic information as the zygote it original form

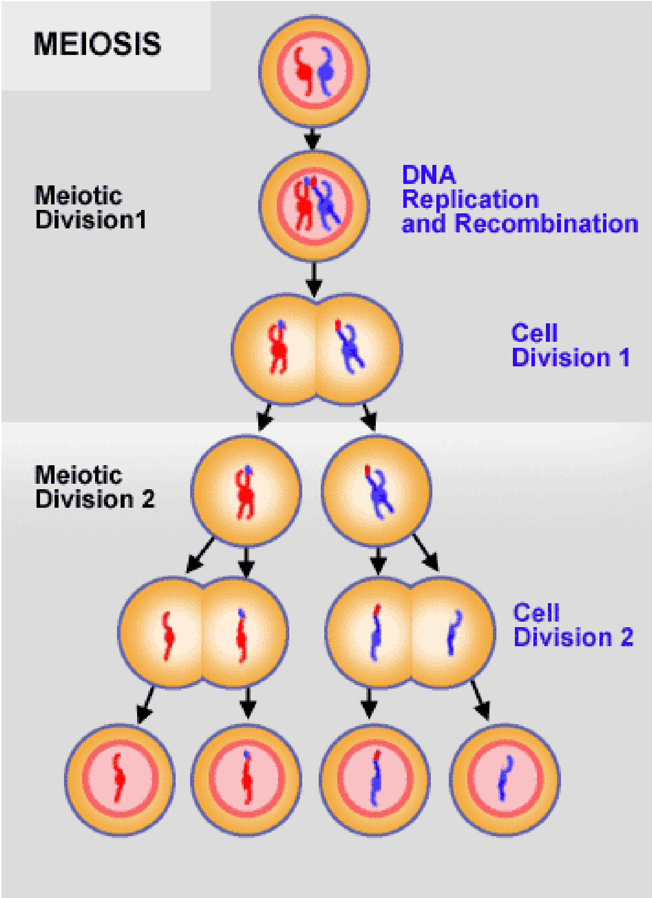
Mitosis

- **Mitosis** is copying the same genetic information to new offspring
- Mitosis is the normal way of growing of multicell structures



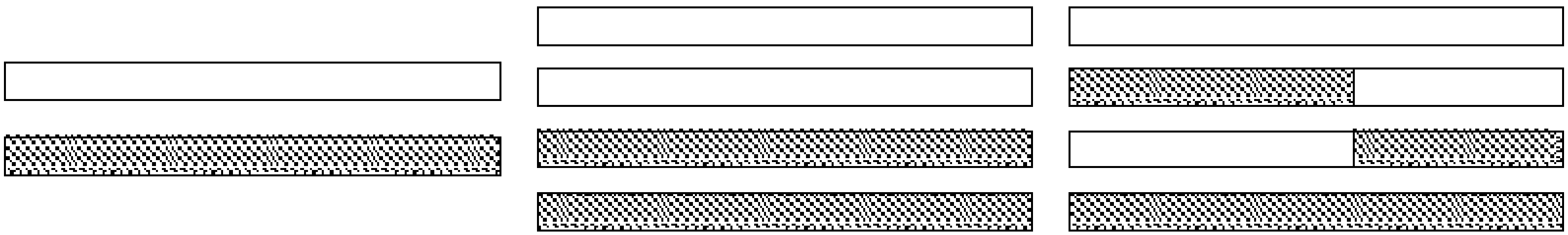
Meiosis

- **Meiosis** is the basis of sexual reproduction
- After meiotic division, gametes appear in the process
- Hence genetic information is shared between the parents in order to create new offspring
- During meiosis the pairs of chromosome undergo an operation called **Crossing over**



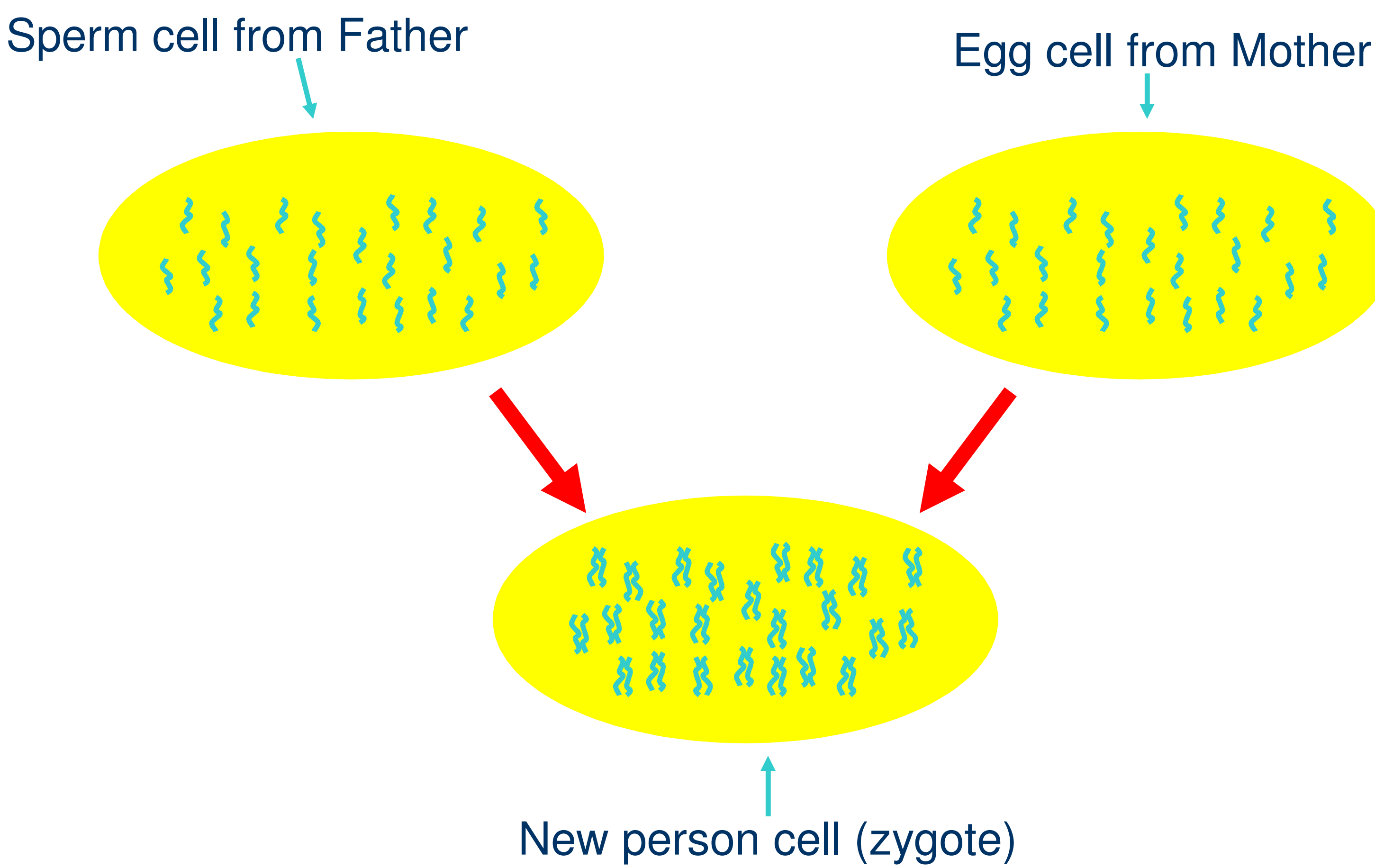
Crossing-over during meiosis

- Chromosome pairs align and duplicate
- Inner pairs link exchange parts of themselves



- Outcome is one copy of **maternal/paternal** chromosome plus two entirely new combinations
- After crossing over one of each pair goes into each gamete

Fertilisation



After fertilisation

- **New zygote** rapidly divides and creating many cells all with the same genetic contents
- Although all cells contain the same genes, depending on, for example where they are in the organism, they will behave differently
- This process of differential behaviour during development is called **ontogenesis**
- All of this uses, and is controlled by, the same mechanism for decoding the genes in DNA

Transcription, translation

A central claim in molecular genetics: only one way flow

Genotype $\longrightarrow$ Phenotype

Genotype $\not\longleftarrow$ Phenotype

Lamarckism (saying that acquired features can be inherited) is thus wrong!

Mutation

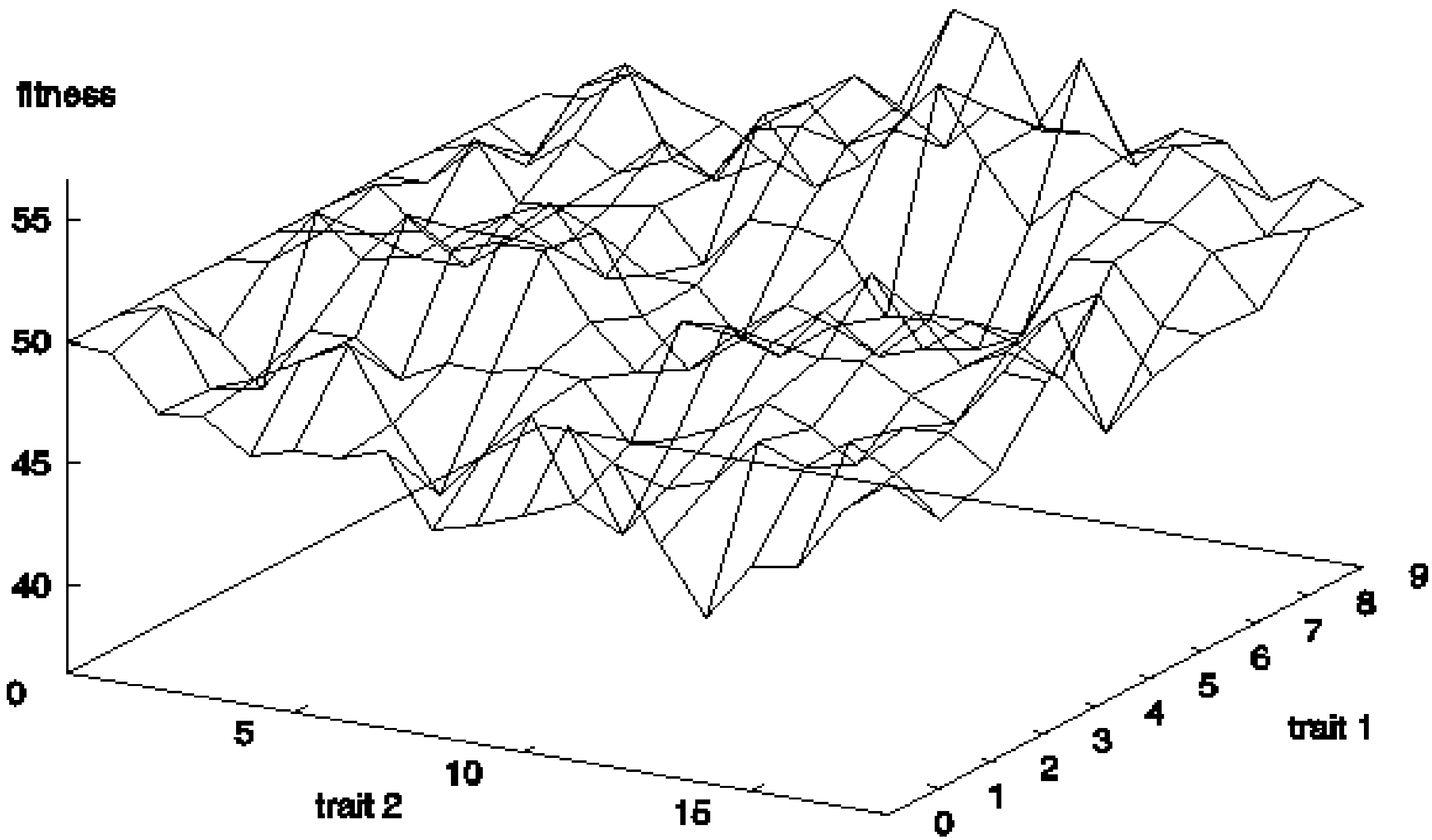
- Occasionally some of the genetic material changes very slightly during this process
- This means that the child might have genetic material information **not inherited** from either parent
- This can be
  - **Disastrous**: offspring in not viable (most likely)
  - **Neutral**: new feature not influences fitness
  - **Advantageous**: strong new feature occurs

Landscape Example

Landscape metaphor

- The **height dimension** belongs to fitness
- The other two (or more) dimensions correspond to **biological traits**
- The x-y-plane holds all possible trait combinations
- Therefore, each different individual (**phenotype**) represents a single point on the landscape
- Population is therefore a “cloud” of points, moving on the landscape over time as it evolves - adaptation

Example with two traits



Landscape metaphor

- Selection “pushes” population up the landscape
- There are a number of points that are better than all their neighbouring solutions, we call each of these points a **local optimum**
- The highest of these points is called **global optimum**
- Random variations in feature distribution (+ or -) arising from sampling error can cause the population down hills, thus crossing valleys and leaving local optima

What is a Genetic Algorithm?

Definition

- A population of individuals exists in an environment with limited resources
- **Competition** for those resources causes selection of those **fitter individuals** that are better adapted to the environment
- These individuals act as seeds for the generation of new individuals through recombination and mutation
- The new individuals have their fitness evaluated and compete for survival.
- Over time **natural selection** causes a rise in the fitness of the population

Definition

- **Genetic Algorithms** are
  - **Bio-Inspired artificial intelligence class,**
  - **stochastic**,
  - **population-based** algorithms

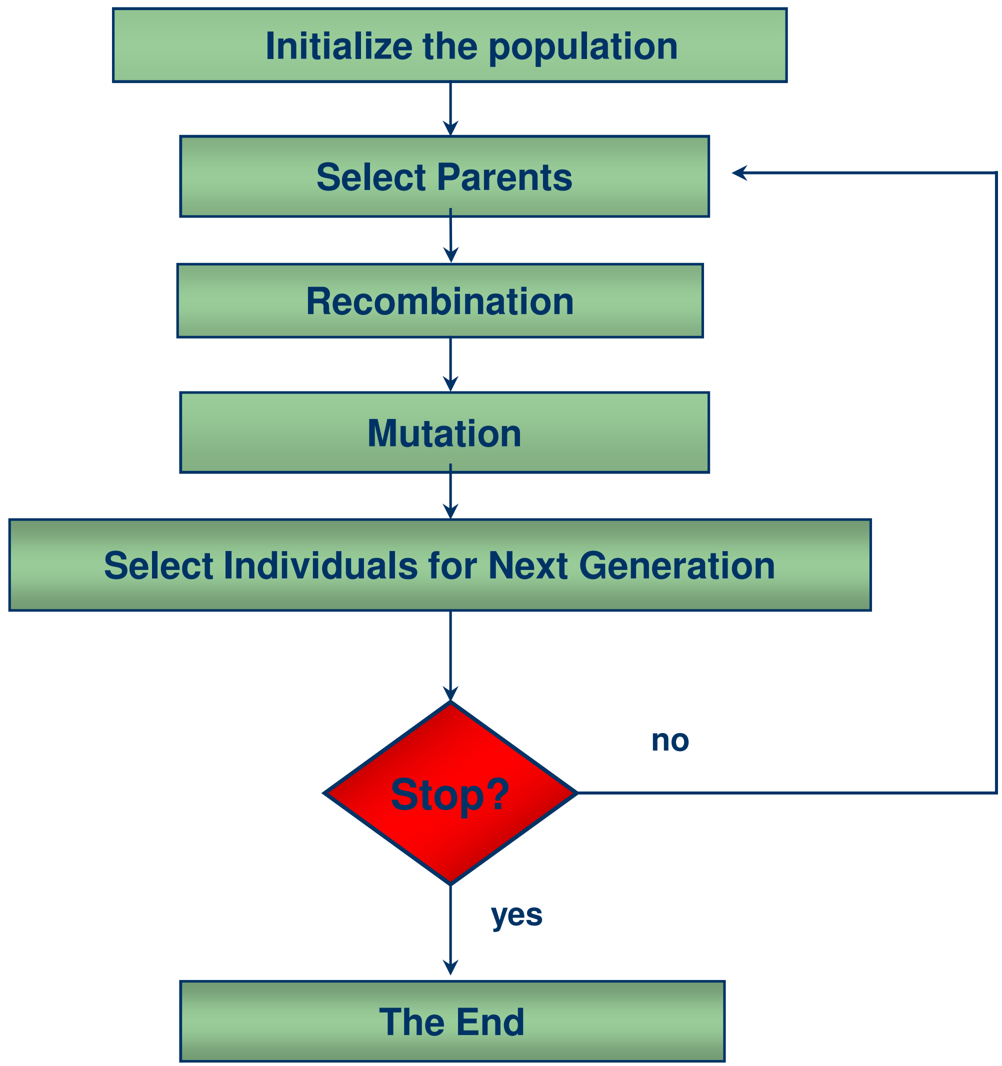
- Typically applied to:
  - hard problems with a large search space
  - discrete optimization

- Developed by **John Holland**, USA in the 1970's

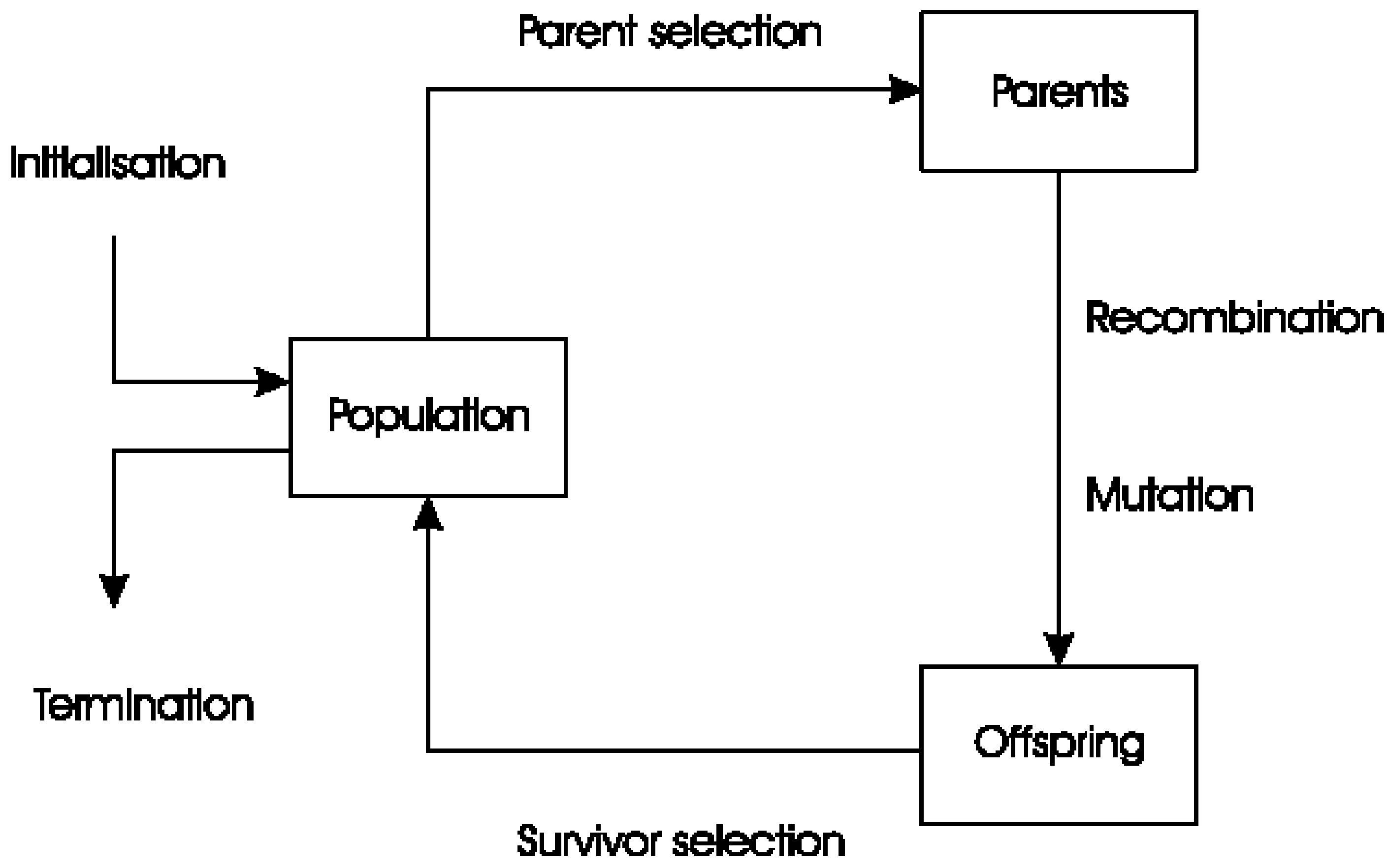
Pseudo-code for typical GA

```
BEGIN
  INITIALISE population with random candidate solutions;
  EVALUATE each candidate;
  REPEAT UNTIL ( TERMINATION CONDITION is satisfied ) DO
    1 SELECT parents;
    2 RECOMBINE pairs of parents;
    3 MUTATE the resulting offspring;
    4 EVALUATE new candidates;
    5 SELECT individuals for the next generation;
  OD
END
```

GA Algorithmic Phases



General Scheme of GA



Simple Genetic Algorithm (SGA)

Simple Genetic Algorithm (SGA)

- Holland's original GA is now known as the **simple genetic algorithm** (SGA)

- Other GAs use different:
  - Representations
  - Mutations
  - Crossovers
  - Selection mechanisms

SGA summary

Representation	Binary strings
Recombination	1-point crossover
Mutation	bit-flipping with fixed probability
Parent selection	Fitness-Proportionate
Survivor selection	All children replace parents
Speciality	Emphasis on crossover

Simple example – $f(x) = x^2$

- **Finding the maximum of a function:**
  - **$f(x) = x^2$**
  - Range [0, 31] → Goal: find max ($31^2 = 961$)
  - Binary representation: string length 5 = 32 numbers (0-31)

genotype	0 0 1 0 1	
mapping	2^4 2^3 2^2 2^1 2^0 16 8 4 2 1	
phenotype	0*16+0*8+1*4+0*2+1*1 = 5	
fitness	25	$= f(x)$

x^2 example

- **x^2 example:**
  - Representation: Binary code
  - Population size: 4
  - Recombination: 1-point crossover
  - Mutation: Bit-flipping with fixed probability
  - Parent selection: Fitness-Proportionate
  - Initialization: Random
- We show one generational cycle done by hand

x^2 example: 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

X^2 example: 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

X^2 example: mutation

String no.	Offspring after xover	Offspring after mutation	x Value	Fitness $f(x) = x^2$
1	0 1 1 0 0	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 1 0 0	18	324
Sum				2354
Average				588.5
Max				729

The simple GA

- SGA Shows many **shortcomings**:
  - Representation is too restrictive
  - Mutation & crossovers only applicable for bit-string & integer representations
  - Selection mechanism sensitive for converging populations with close fitness values
  - Generational population model (step 5 in SGA) can be improved with explicit survivor selection

References

References

- Eiben and Smith. **Introduction to Evolutionary Computing**, Springer-Verlag, New York, 2003.
- J. Dreo A. Petrowski, P. Siarry E. Taillard, **Metaheuristics for Hard Optimization**, Springer-Verlag, 2006.

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