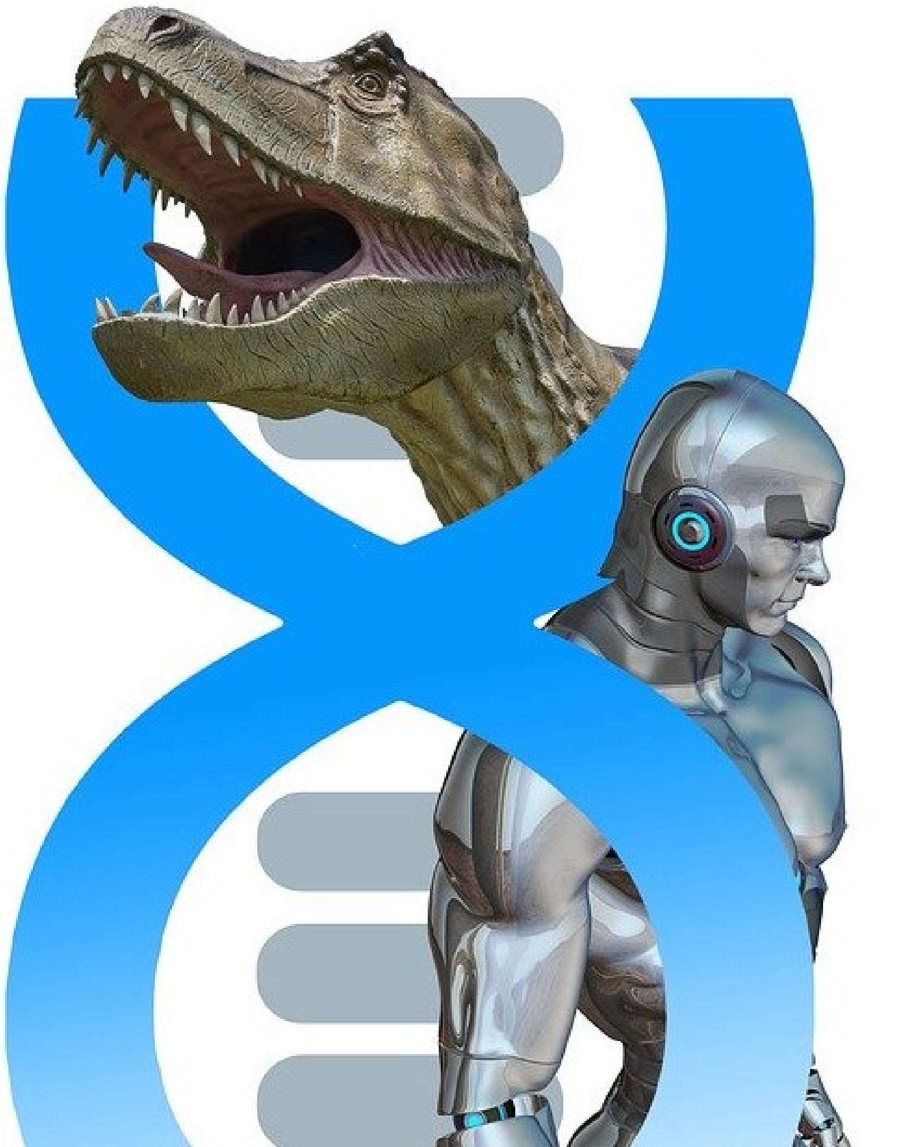
Hes·so // VALAIS WALLIS

School of Engineering



Genetic Algorithms

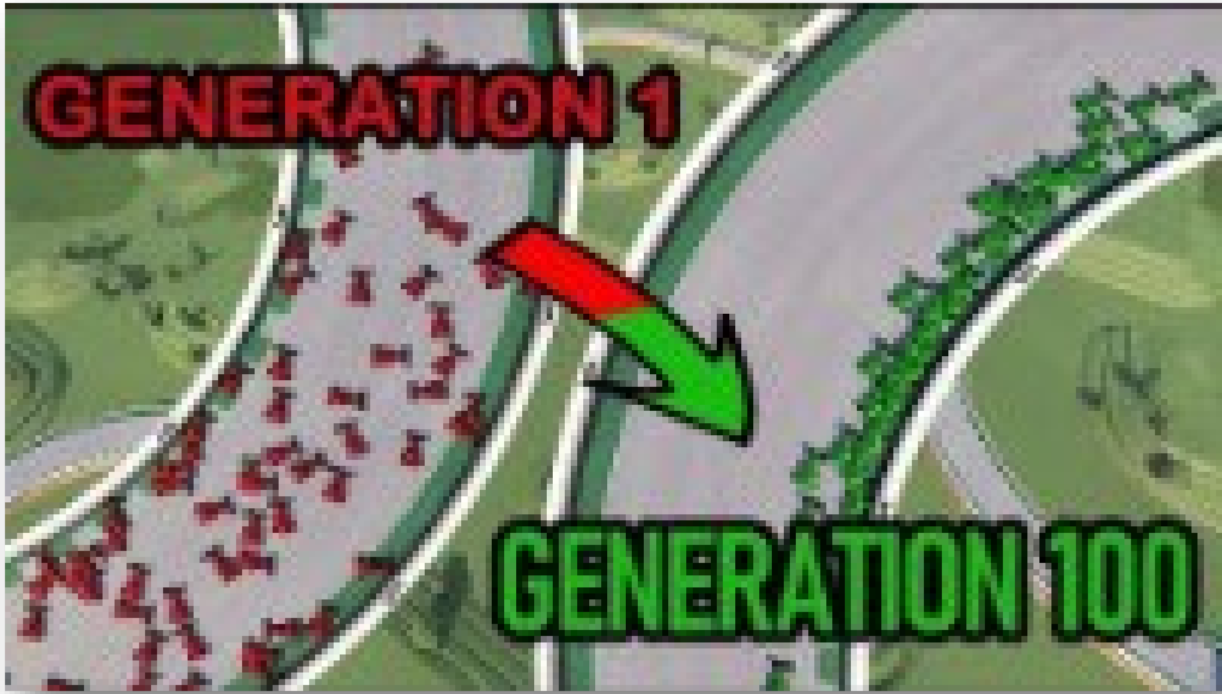
Francesco Carrino

Genetic algorithms

Goal and idea

- **Goal**:
  - To find an approximate solution…
  - …o a complex optimization problem …
  - … within a “reasonable” time frame

- **Principle**: Natural selection



https://youtu.be/a8Bo2DHrrow

Vocabulary: Individual

Definition

- It represents a potential **solution** to the problem.
- It has a set of properties (its "chromosome" or "genes") that can be inherited, mutated, or altered.
- Traditionally, individuals are represented in binary as strings of 0s and 1s (though other encodings are also possible).

Vocabulary: individual

Example

- **Racing Car Example**: An individual’s genes might represent the likelihood of performing specific actions when detecting a wall at a certain angle. These actions could include accelerating, braking, turning left, or turning right.

Individual (chromosome)

Accelerating			*Braking*			*Turning left*		*Turning right*	
0	1	1	0	1	0	1	1	0	1

Gene

Vocabulary: Population

Definition and example

- **Definition:** a group of individuals (i.e., *possible solutions* to our problem)

Accelerating			*Braking*			*Turning left*		*Turning right*	
0	1	1	0	1	0	1	1	0	1
1	1	1	0	1	1	1	1	0	1
0	1	1	0	1	1	1	1	0	1
0	1	1	0	1	0	1	1	0	1
0	1	0	0	0	0	1	0	0	1
1	1	1	1	0	1	1	0	1	0
...									
0	1	1	0	1	0	1	1	0	1

Population

Individual

Gene

Vocabulary: Population

Definition

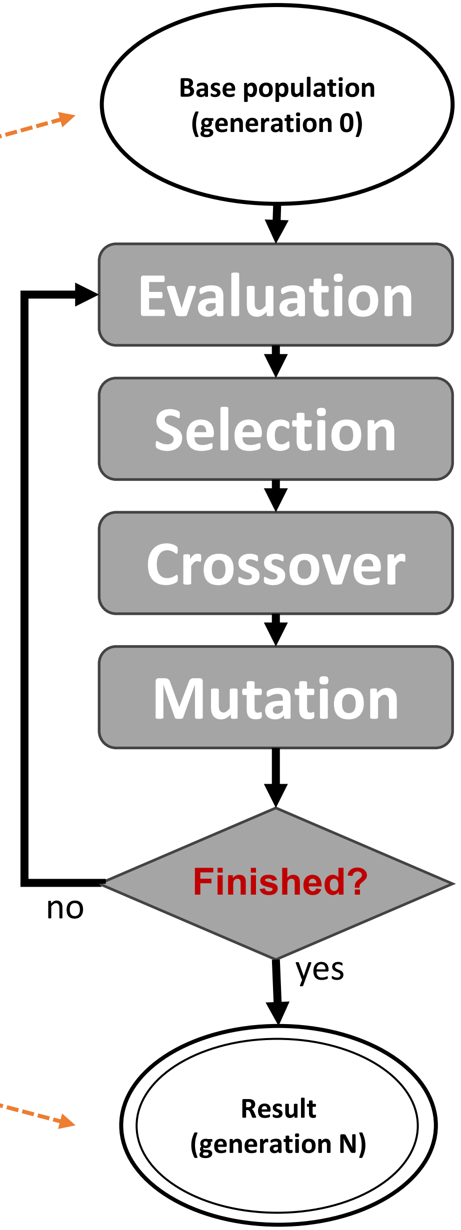
- **Definition:** a group of individuals (i.e., *possible solutions* to our problem)
  - **Generation 1:** typically, randomly generated set of individuals

  - **Generation N**: set of individuals evolved, generation after generation towards (hopefully) the optimum

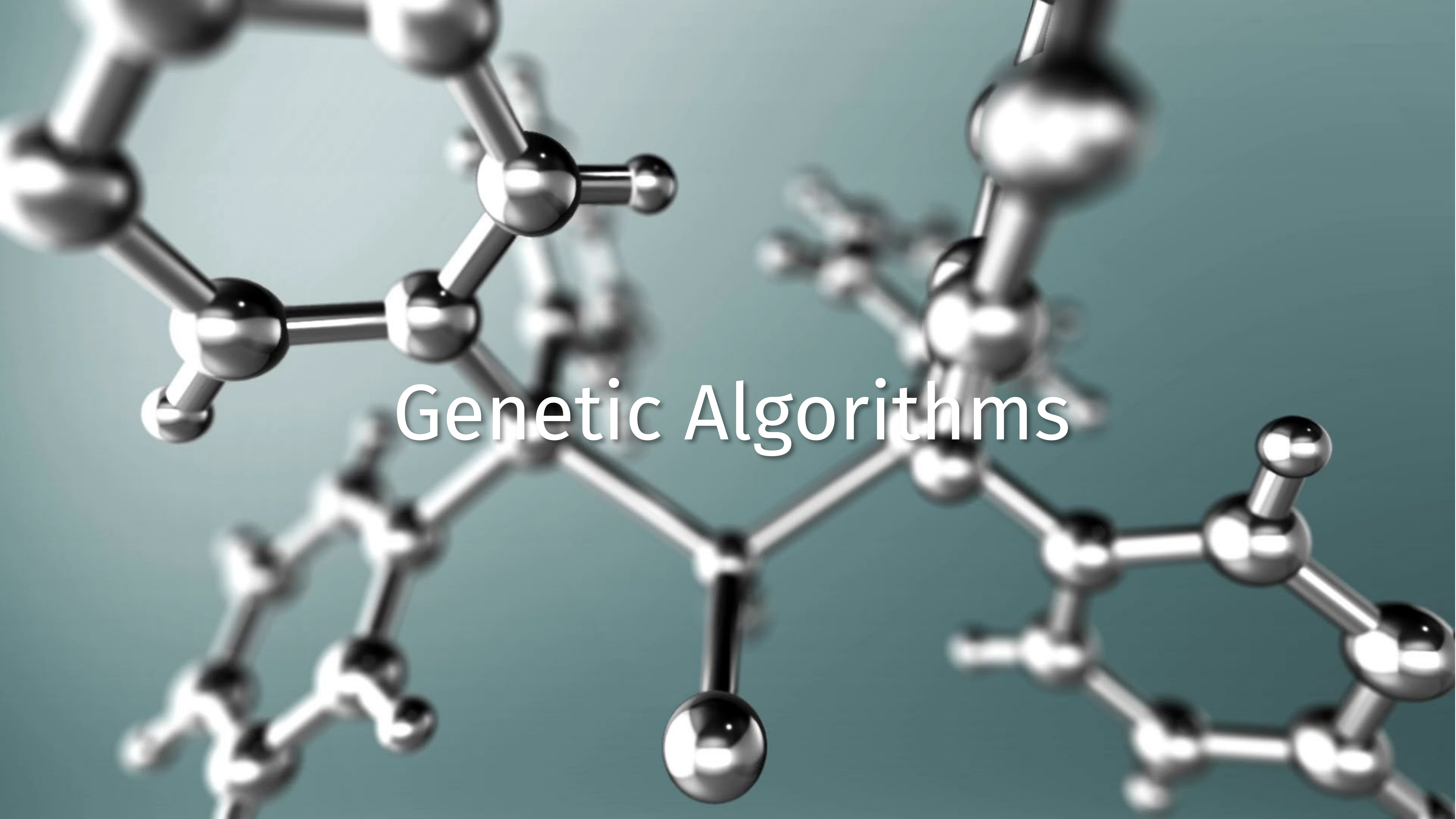
Genetic Algorithms

The algorithm

- Generation 1



- Generation N



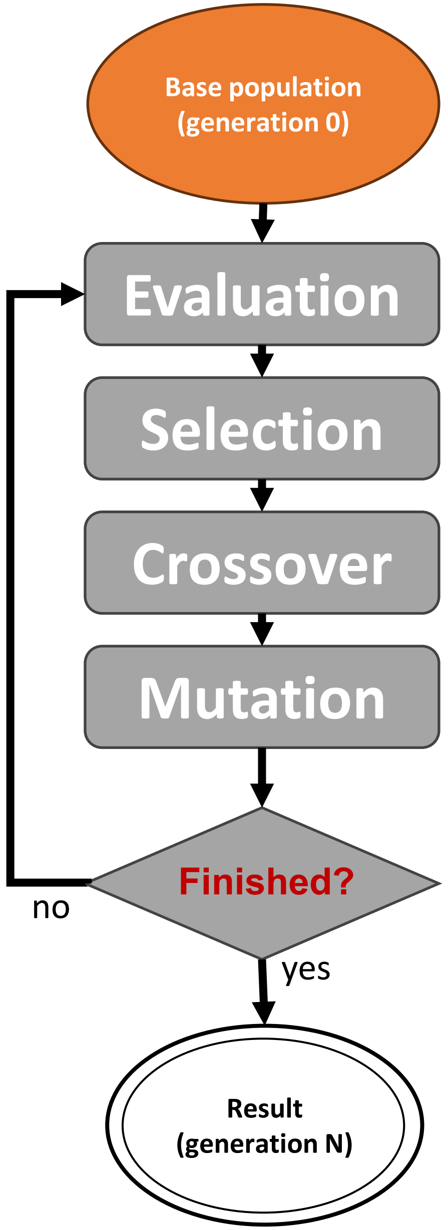
Genetic Algorithms

Initialization

We define our generation 1

- The initial population is (typically) generated randomly
- The population size depends on the nature of the problem…
- …and the computation resource at our disposal

- Typically contains hundreds… or thousands of individuals!

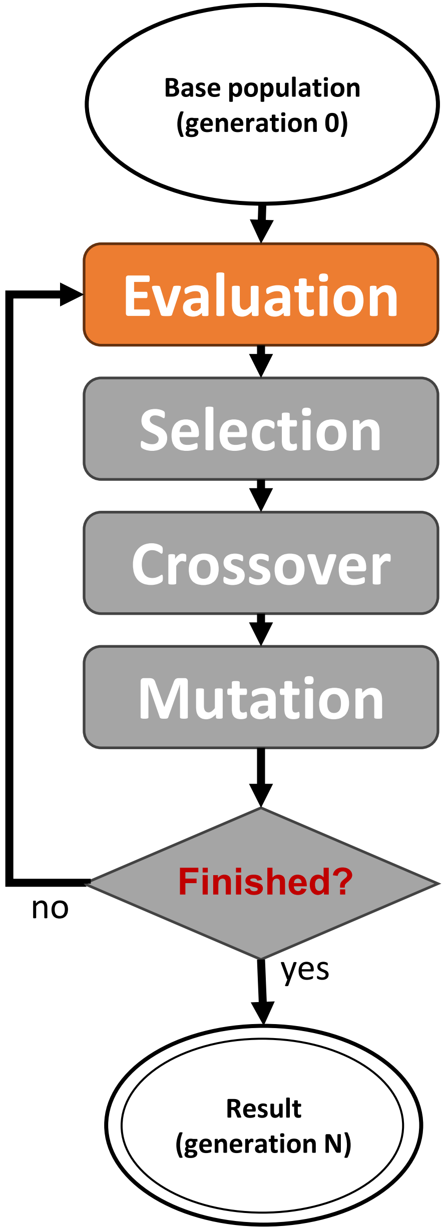


Evaluation

Or “fitness function”

- Must express the **value** to be **maximized** (or minimized) by the algorithm

- Must be able to separate (rank) good solutions from bad solutions

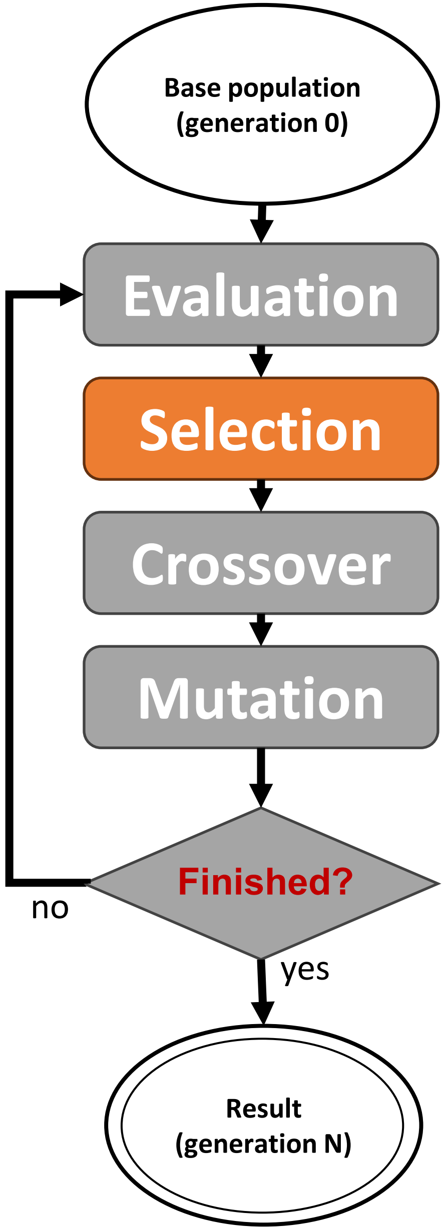


Selection

Survival of the fittest

- **Goal:** Selection of the most "*fit*" individuals who can pass on their genetic information to the next generation.

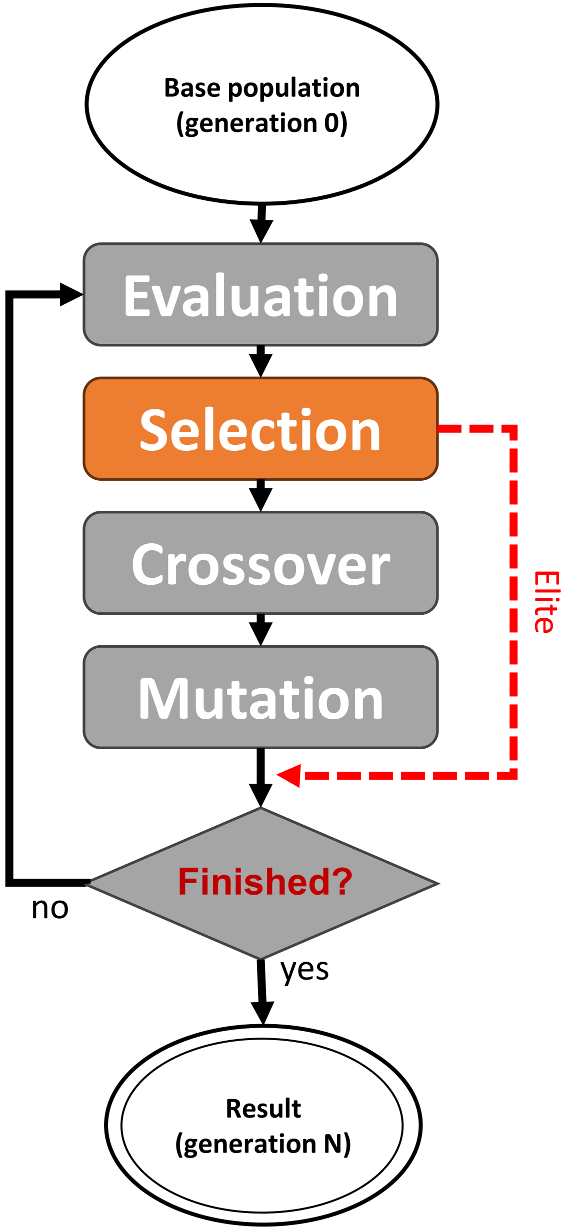
- ***Selection by rank***
  - Individuals with the best fitness score are *always* selected
- ***Proportional selection***
  - The probability of being selected is *proportional* to its fitness score
- ***Tournament selection*** 
  - *Proportional* selection of pairs of individuals. From each pair, the individual with the better fitness score is chosen



Selection

Elitism

- **[Optional approach]** The best individual(s) from the current generation carry over to the next, *unaltered*

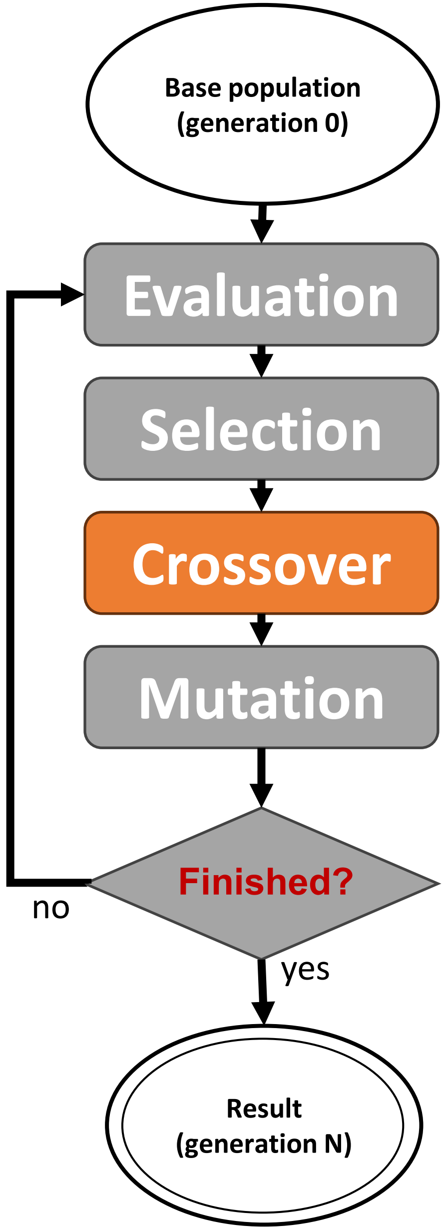


Crossover

Time for love

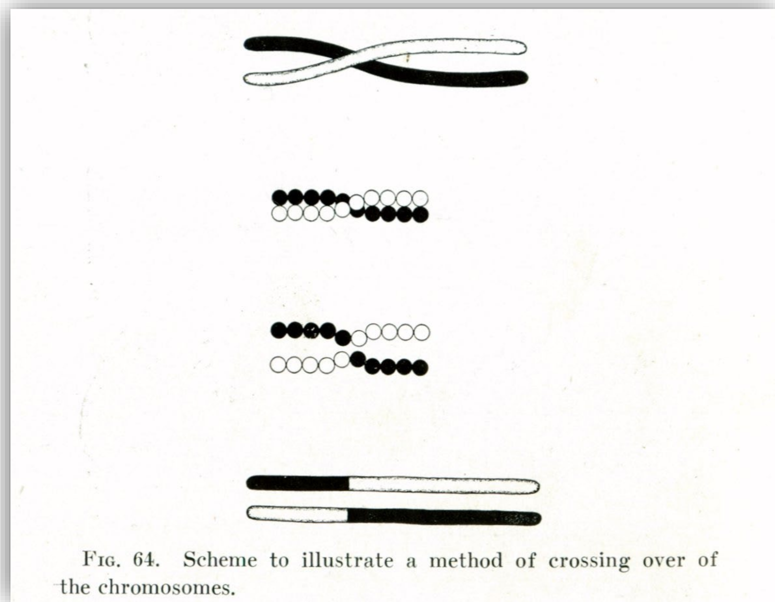
- The “genes” of the individuals selected in the previous step are recombined.
  - Typically, each pair of parents gives rise to a pair of new "child" individuals
  - The aim is to maintain stable the population generation after generation

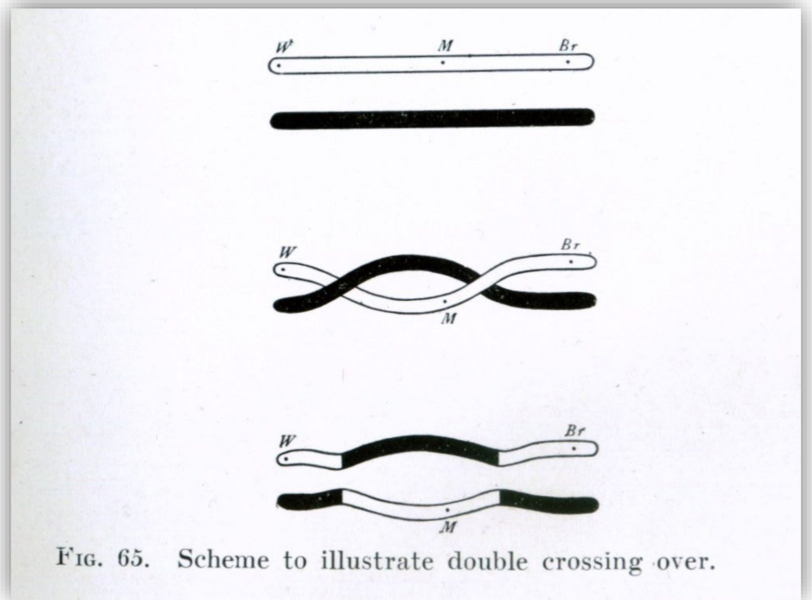
- Several crossing methods exist
  - They depend on the problem and its formulation
  - Typically, genes (properties) from parents are randomly mixed



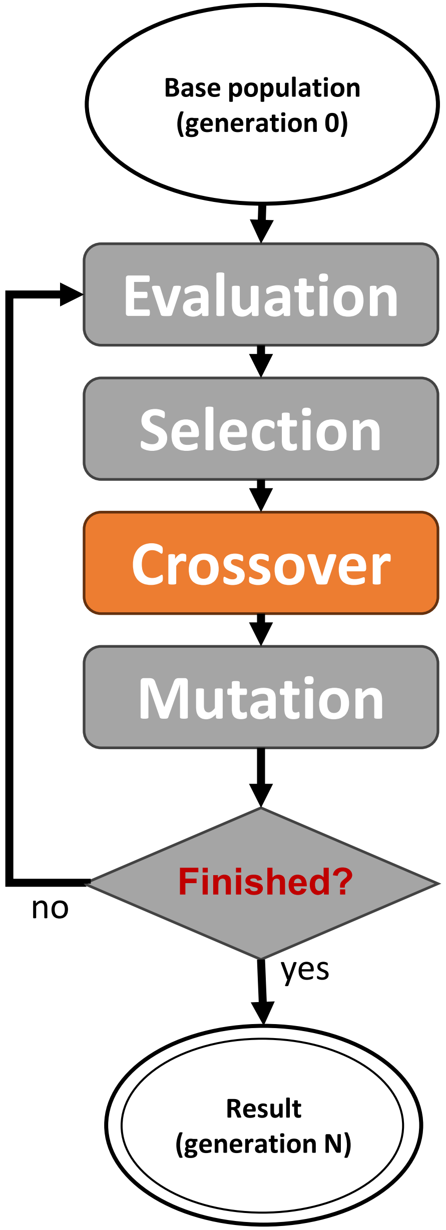
Crossover

Time for love ;-)



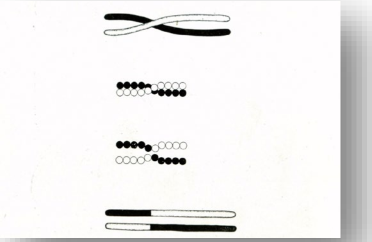


Source: *An early of the genetic phenomenon of crossing over, from Thomas Hunt Morgan's 1916 ''A Critique of the Theory of Evolution'', page 132.*



Crossover

Time for love



Parent 1

Accelerating			Braking			Turning left		Turning right	
0	1	1	0	1	1	1	1	0	1

Parent 2

Accelerating			Braking			Turning left		Turning right	
0	0	0	0	0	0	1	0	0	1

Random “split”

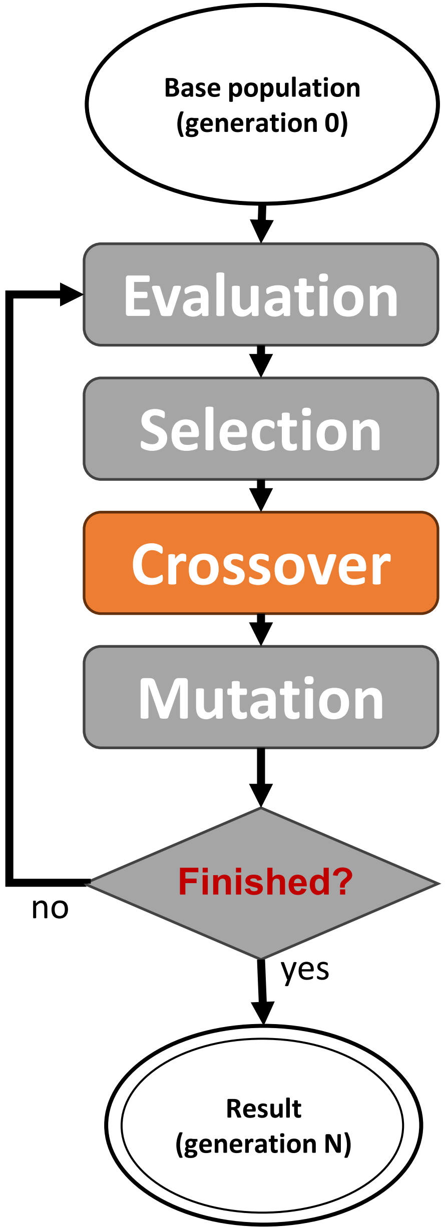
Child 1

Accelerating			Braking			Turning left		Turning right	
0	1	1	0	0	0	1	0	0	1

Child 2

Accelerating			Braking			Turning left		Turning right	
0	0	0	0	1	1	1	1	0	1

Note: Often, whether crossover is performed for a given couple is determined by a probability (e.g., 0.5). This means that sometimes (e.g., 50% of the time), parents proceed directly to the next generation without crossover.



Mutation

- **Randomly**, zero, one or more of the "children's" properties (genes) are changed
- The goal is to explore new solutions that were not considered in the previous generation

Child

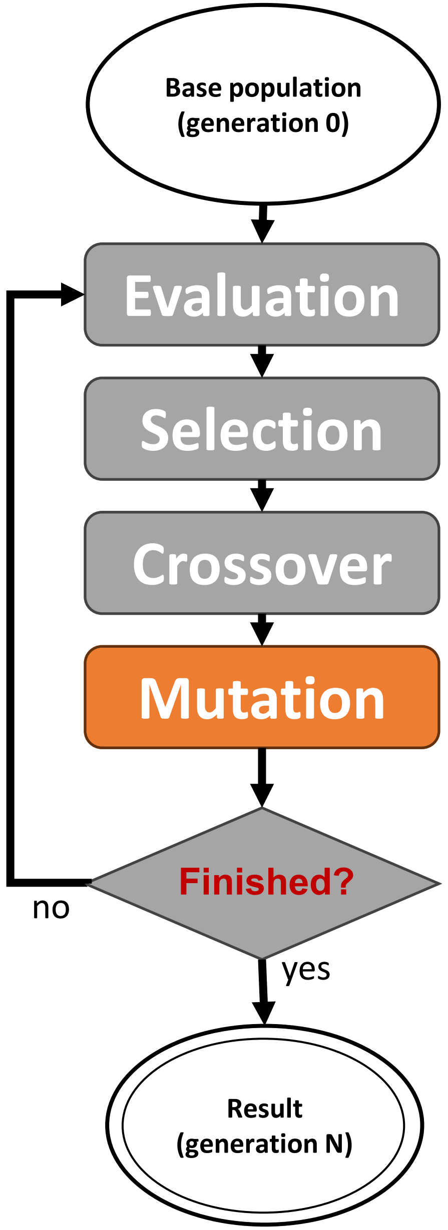
Accelerating			*Braking*			*Turning left*		*Turning right*	
0	0	0	0	1	1	1	1	0	1

Gene selected for mutation

Child (mutated)

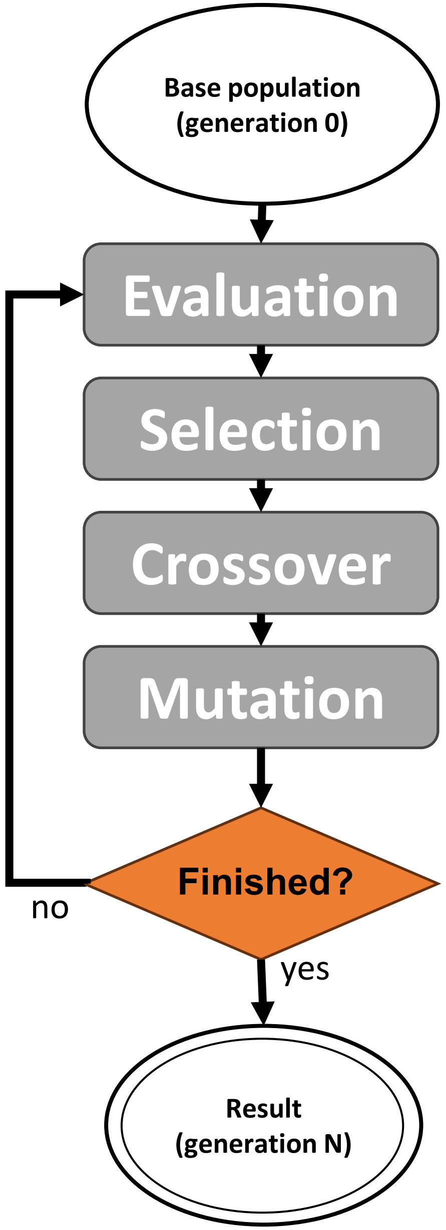
Accelerating			*Braking*			*Turning left*		*Turning right*	
0	0	0	0	1	1	1	1	1	1

Mutated gene



Repeat!

- The whole process is repeated for **N generations**
- The adopted, final solution is represented by the **best individual** of the last generation

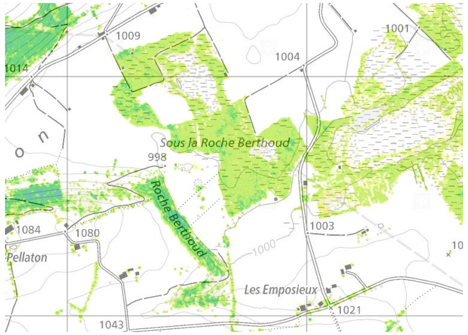


Use cases

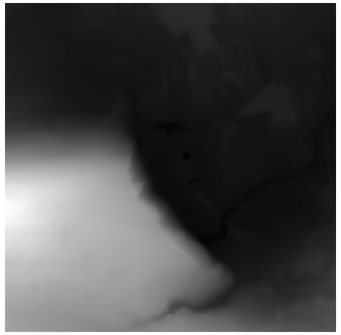
Optimization of Sensor Placement for Birds Acoustic Detection in Complex Fields

Location

Georeferenced Data:



Vegetation map



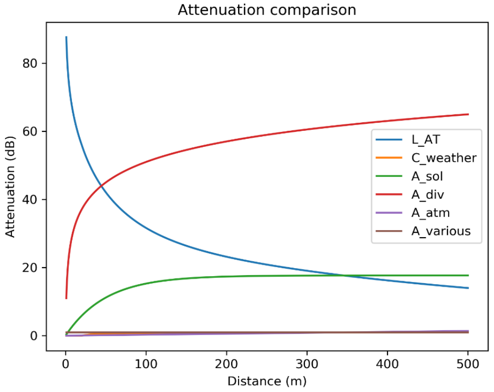
Elevation map

Tabular Data:

	Temp (C°)	Rel humidity (%)	Pressure (hPa)
JAN	-3.06	88.24	896.08
FEB	-2.94	84.30	895.00
MAR	1.44	80.72	894.48
APR	5.08	75.92	895.94
MAY	8.76	79.96	896.68
JUN	13.86	78.84	899.10
JUL	15.40	75.68	899.94
AUG	14.50	78.84	900.88
SEP	9.92	81.82	900.38
OCT	6.40	83.74	899.06
NOV	1.64	87.14	895.00
DEC	-1.08	86.16	901.00

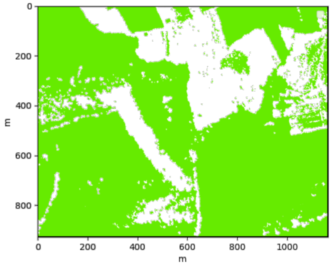
Mean meteorological conditions

Sound propagation model

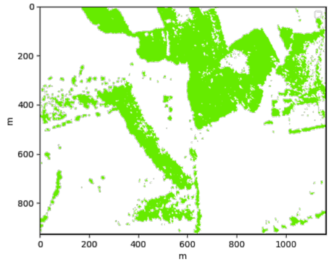


Corncrake

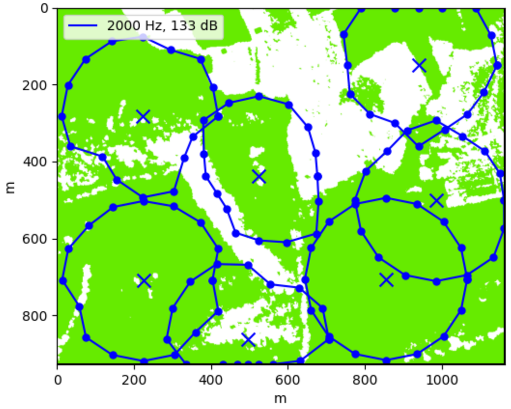
Eurasian Pygmy-owl



Bird who sings in fields



Bird who sings in forests

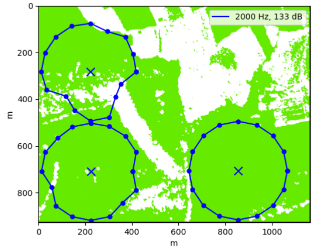


7 sensors
Coverage: 83.9%

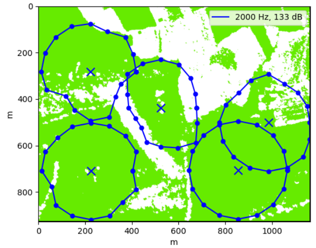
Use cases

Optimization of Sensor Placement for Birds Acoustic Detection in Complex Fields

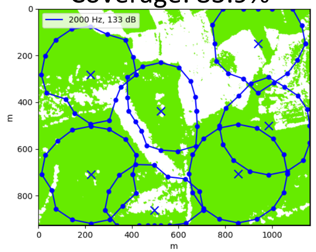
3 sensors
Coverage: 52.2%

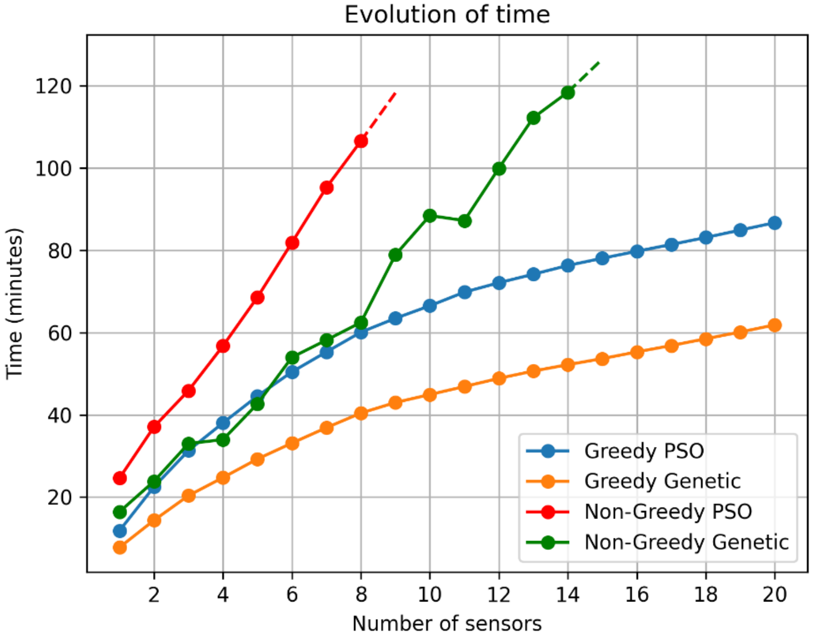


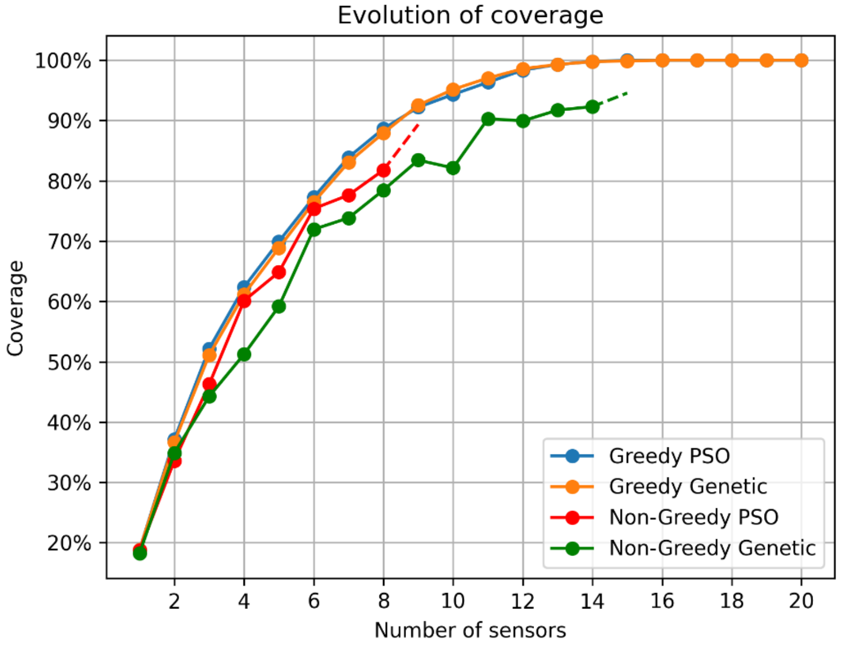
5 sensors
Coverage: 69.9%



7 sensors
Coverage: 83.9%







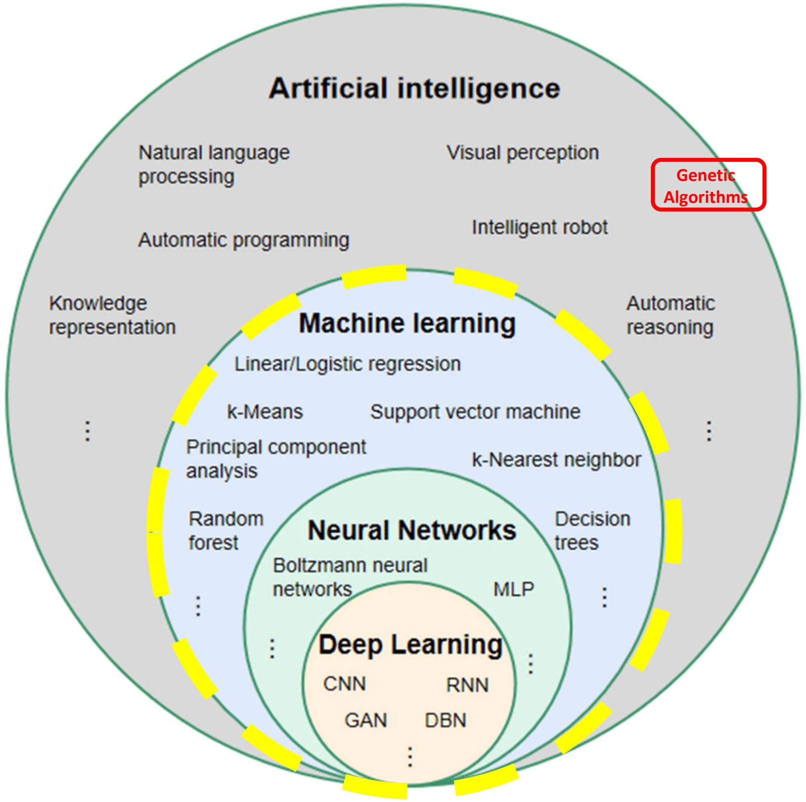
An important note

Genetic algorithms VS Machine learning

- The car example is a mixed use case: they use GA to improve a ML model.

- Typically, at the end of a GA algorithm, we:
  - do ***not*** have a model that learned how to solve a task
  - **have solutions** for a given, specific problem

- This means, if we change the problem (or any of its constraints), we need to run the GA algorithm. Again. From scratch.



Your competences after this course

You should be able to…

- … **explain** the main steps of a genetic algorithm and related terms (evaluation, selection, crossover, mutation, fitness function, etc.)
- … **define** a good fitness function for your problem
- … **improve** your genetic algorithm by identifying and fine-tuning the hyperparameters your algorithm (in the lab)


ANY
QUESTIONS
?