Artificial Life
Summer 2015

Evolutionary Algorithms 3

Master Computer Science [MA-INF 4201]
Mon 8:30 – 10:00, LBH, Lecture Hall III.03a

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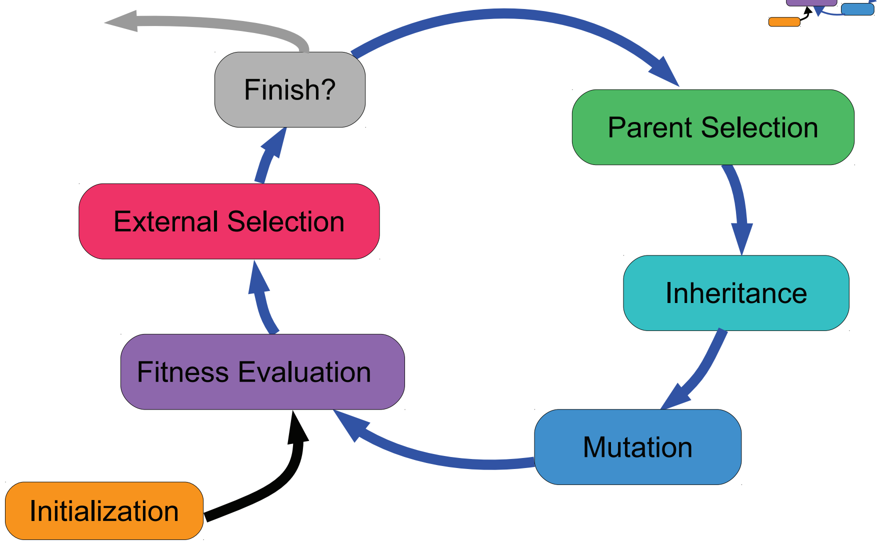
Department of Computer Science, University of Bonn

Overview

- Genome structure
- Example: 8 queens
- Super-individuals
- External-selection and parent-selection combined
- Probabilistic parent-selection
  - Wheel of fortune
  - Tournament selection
- Genetic programming
- Co-evolution

EA cycle of operation



EA: Genome Structure

Naive structuring of the genome:
Pro: easy to implement, only few knowledge necessary.
Con: large search space, a lot of local maxima possible, may be hard or impossible to find a good solution.

"Normal" structuring of the genome:
Pro: still easy to implement, some knowledge necessary, wide variety to implement inheritance and mutation.
Con: still a lot of bad or illegal genomes possible.

Sophisticated structuring of the genome:
Pro: only legal, or good genomes are to be investigated.
Con: profound knowledge about the process and of the kind of possible solutions is required, can become computational expensive to implement inheritance and mutation.

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EA: Example:

Implementing a task using an Evolutionary Algorithm, a series of structuring decision will be necessary.

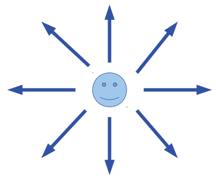
The sequence below is not common theory, but just my personal choice of doing it.

Objective:	specify the objective
Genome:	structure the genome
Fitness Function:	define an appropriate fitness function
Inheritance:	layout the inheritance process
Mutation:	layout the mutation process
Selection Strategy:	specify the selection strategy

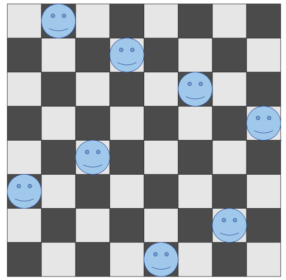
EA: Example: 8 Queens

The 8 queens puzzle with an evolutionary algorithm:

The task of the 8 queens puzzle is to place 8 queens on a chess board (8x8) so that they can not reach each other.



allowed moves for a queen



One of the **92** solutions

chess board with 8x8 = 64 positions

EA: Example: 8 Queens

Very naive implementation of the genome:

a 64 bit binary vector; queen is 1, no queen is 0; more than 8 queens are possible.

This very naive implementation is generating an extremely large search space with 2^64 possible genomes. This is beyond any computing power to be investigated in total.

Semi naive implementation of the genome:

a 64 bit binary vector; queen is 1, no queen is 0; exactly 8 queens == 8 bits set are possible.

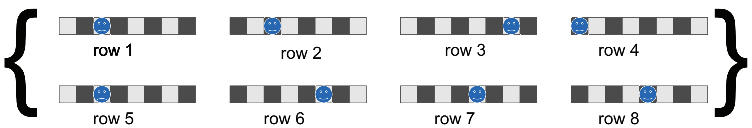
Still the resulting search space is very large.

EA: Example: 8 Queens

Normal/Sophisticated implementation of the genome:

8 rows of 8 bit binary vectors; queen is 1, no queen is 0; each row contains exactly one queen.

This is reducing the search space to $8^8 = 16777216$ possibilities, (which can be managed by brute-force).

Genome =


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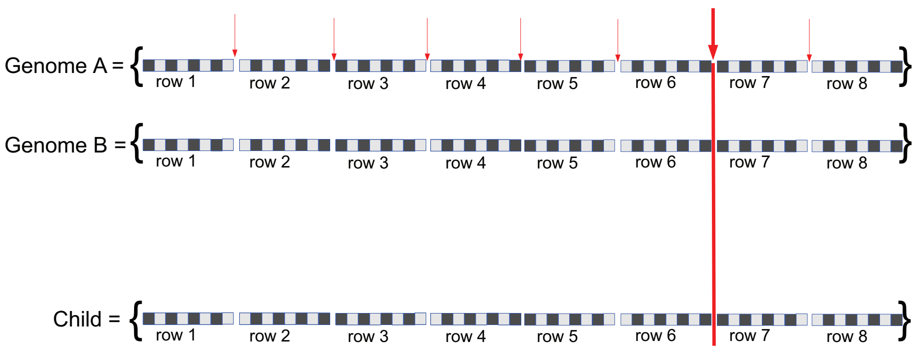
EA: Example: 8 Queens

Inheritance, recombination, 1 point cross over
cross-over points only between the rows



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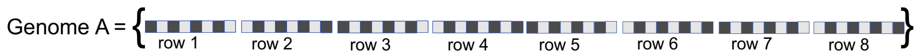
EA: Example: 8 Queens

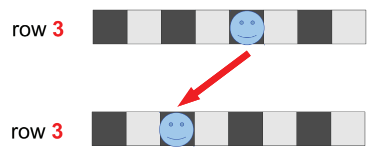
Mutation only the position of the queen within the row is altered



Chose a random row **r** (1, …, 8):
and pick a new random position (1, …, 8) for the queen

before mutation

after mutation



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EA: Example: 8 Queens

A more sophisticated implementation of the genome:

If you have an even more sophisticated idea for structuring the genome, don't forget to shape the inheritance and mutation operators and the fitness function accordingly.

Go ahead,

feel free to do experiments

EA: Example: 8 Queens

The objective, is to find a placement of the 8 queens so that they can't reach each other.

The fitness function for the EA should reflect this:

a large value of **f** if the placement is o.k. **I**
a small value of **f** if the placement is not o.k. **O**

A fitness function that yields a binary value (**O**,**I**) is not a good idea for an evolutionary algorithm.

The resulting fitness surface is flat (**O**), with only a few isolated peeks (**I**).

The value of this kind of fitness function is not reflecting, that a genome can be close to a possible solution.

EA: Example: 8 Queens

The objective, is to find a placement of the 8 queens so that they can't reach each other.

An appropriate fitness function for an EA must be shaped accordingly;

In addition, the fitness function **f** value should implement, that genomes **g,** close to an optimal solution should yield a larger fitness value **f(g)** than those far away.

The optimal would be, to have a fitness function **f(g)** that is proportional to the distance between the genome **g** to an optimal genome **g***.

Unfortunately this is not possible in general.

EA: Example: 8 Queens

The objective, is to find a placement of the 8 queens so that they can't reach each other.

A proposal for a fitness function for the 8 queens problem:

Each possibility that one queen can attack another queen is counted as **-1**
The fitness value **f(g)** is the sum of all attack possibilities.

This yields a graded response as required,
with a maximal value **f(g*) = 0.0** when no attack is possible.

Caution:
This fitness function is only appropriate if the number of queens is fixed to 8 *(0 queens => 0 attack possibilities)*

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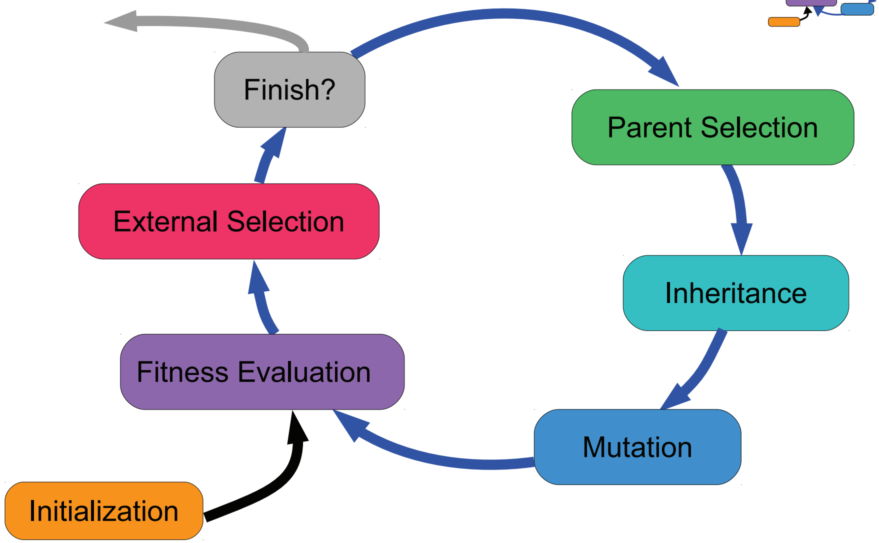
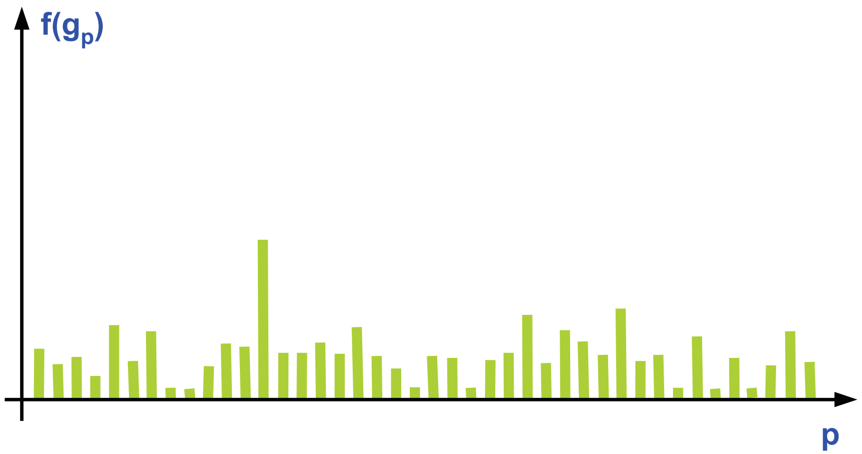
EA cycle of operation



EA: **Super-Individual**

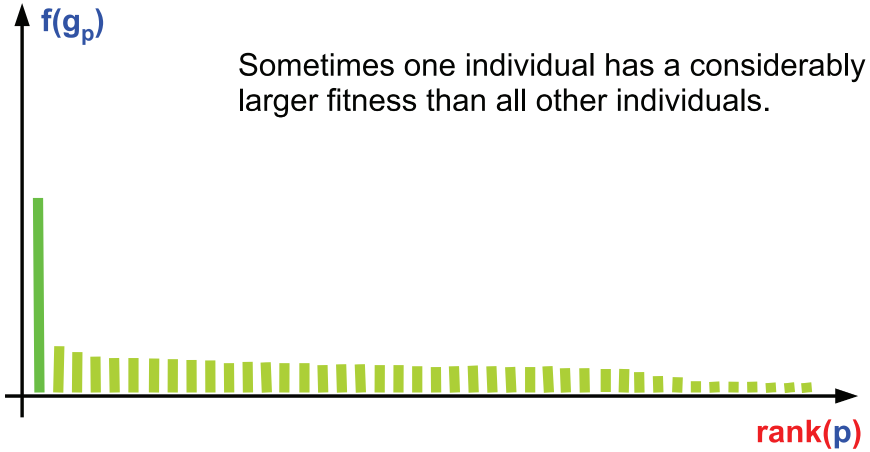
Fitness values will vary within the population.



EA: **Super-Individual**

Sorted fitness values.

Sometimes one individual has a considerably larger fitness than all other individuals.



EA: **Super-Individual**

Sometimes, the combination of selection and inheritance is producing a so called: **Super-Individual.**

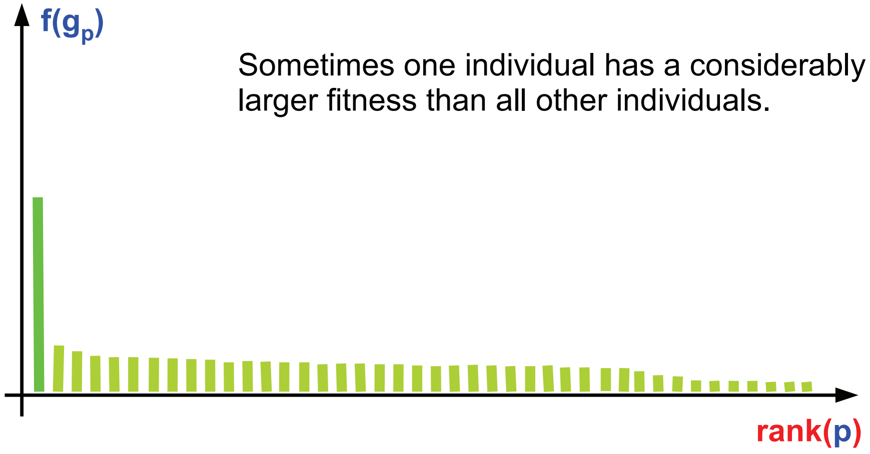
The fitness values throughout the population will typically vary.

In the case, that one individual has a considerably larger fitness than all other individuals, it can happen that this individual is selected more often (e.g. fitness proportional selection, $\mu \ll \lambda$, …).

Thus, it will produce more offspring than other individuals, increasing the number of individuals with a high fitness; which is explicitly intended by the principle of inheritance.

EA: Super-Individual

Sorted fitness values.



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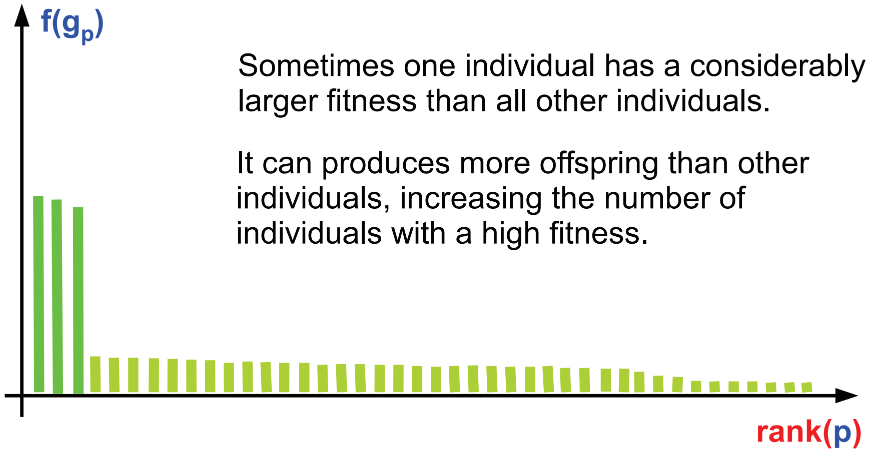
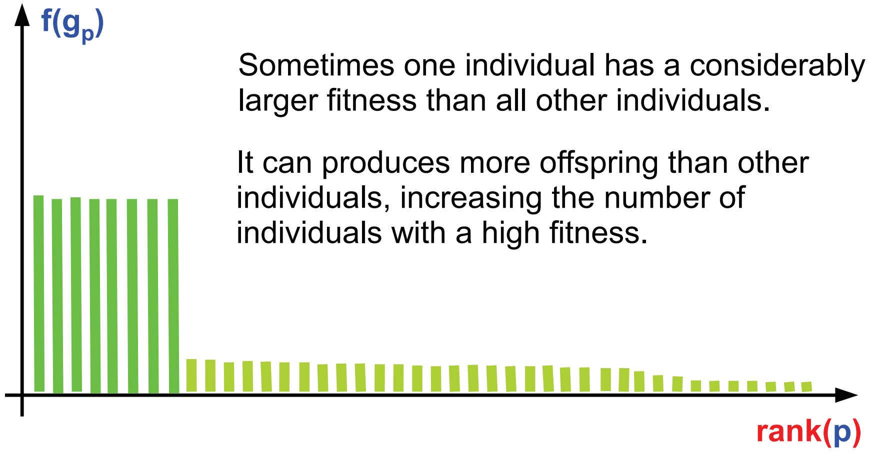


Sometimes one individual has a considerably larger fitness than all other individuals.

It can produces more offspring than other individuals, increasing the number of individuals with a high fitness.

EA: Super-Individual

Sorted fitness values.



Sometimes one individual has a considerably larger fitness than all other individuals.

It can produces more offspring than other individuals, increasing the number of individuals with a high fitness.

EA: Super-Individual

Sometimes, the combination of selection and inheritance is producing a so called: **Super-Individual.**

It can happen, that an individual with a rather high fitness is generating so much offspring, that they **dominate** the entire population.

Which means, that a large percentage of the population has identical (or almost identical) genomes.

On one hand, a **Super-Individual** with a large fitness is good for the overall performance of the population,

on the other hand, if a large percentage of the population has identical genomes the **diversity** throughout the population is lost.

EA: Super-Individual

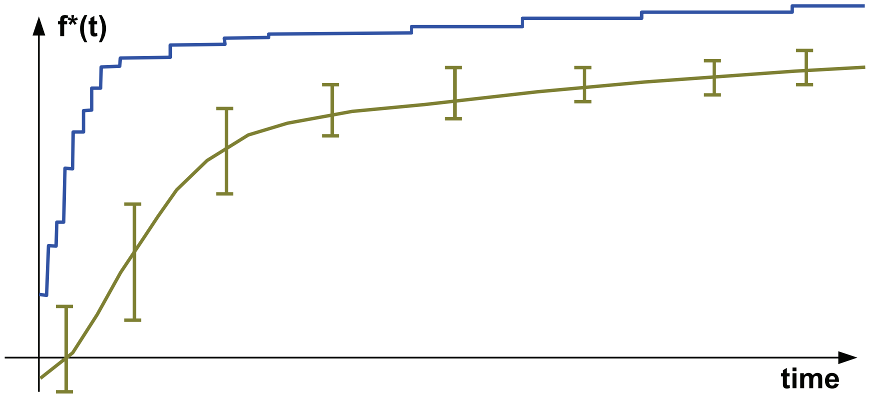
Generally speaking, the occurrence of a super-individual should be **avoided** to maintain the necessary diversity within the population (EAs are multi hypothesis approaches).

The detection of a super-individual can be really hard.
A hint for the occurrence is a shrinking variance of fitness values in the parent population.

A close investigation of the performance graph is helpful.

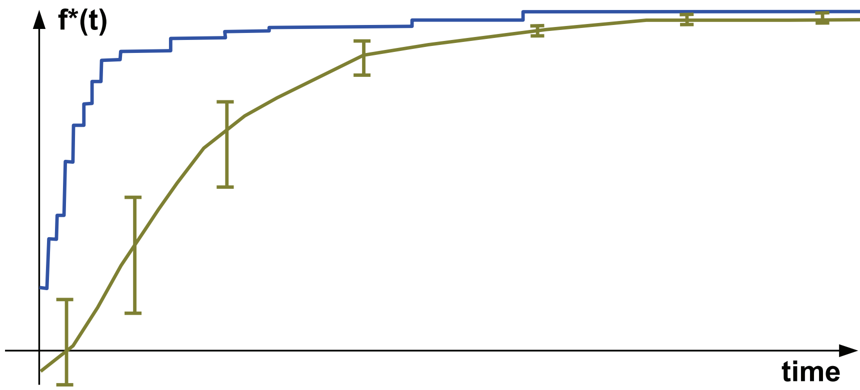
EA: Performance Graph

The performance graph is showing the development of the fitness f*(t) of the best individual and the average fitness in each generation with respect to time.



EA: Performance Graph

The performance graph might me an **indicator** for the occurrence of a super-individual dominating the population.



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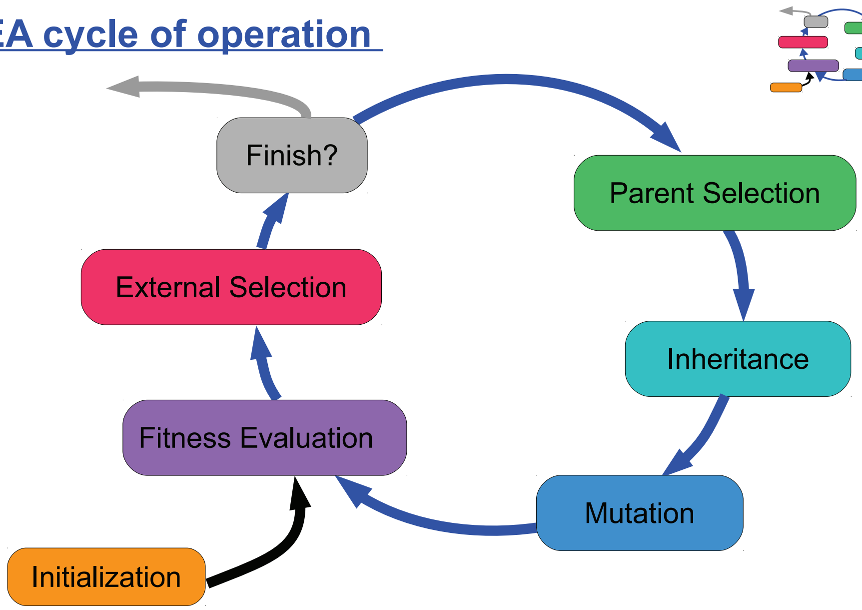
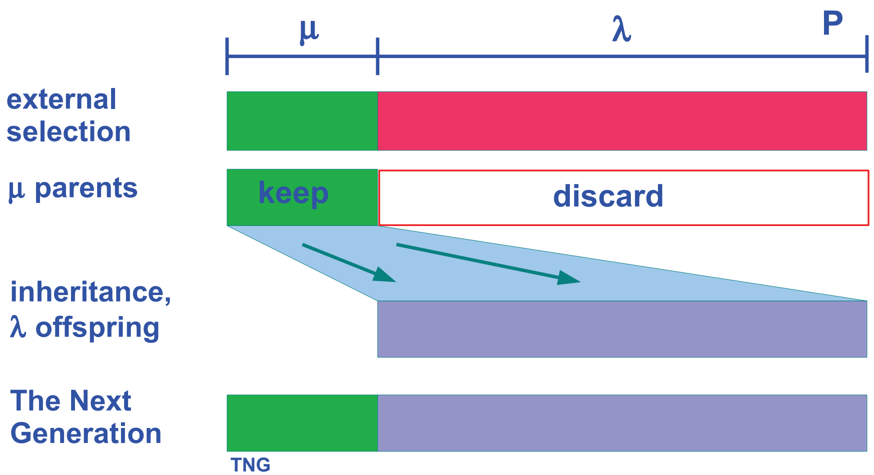
EA cycle of operation



EA: **External Selection** **Parent Selection**

Have **P**, keep μ, generate λ offspring



EA: **External Selection** **Parent Selection**

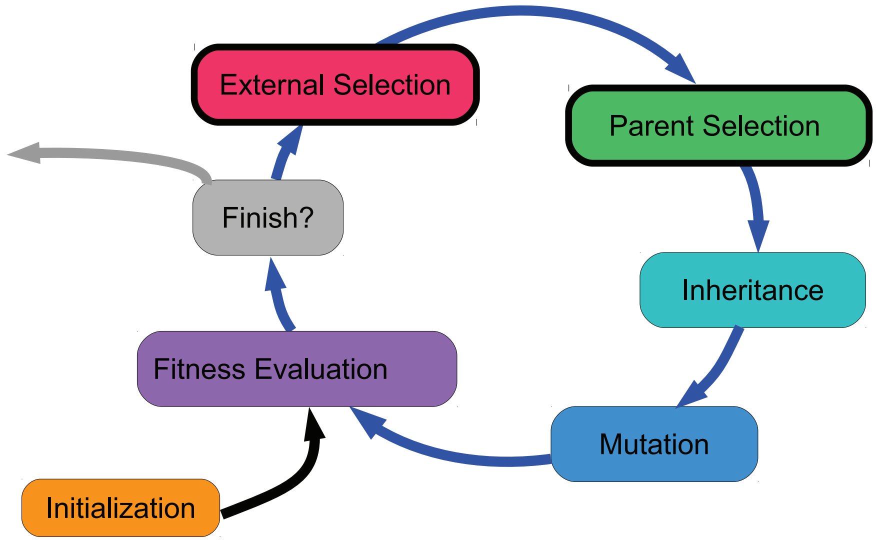
(1 + 1): $\mu=1$ one parent, $\lambda=1$ one child,
inheritance by copying, only mutation
rank based, deterministic external selection

(1 + λ): $\mu=1$ one parent, λ children, offspring,
inheritance by copying, only mutation
rank based, deterministic external selection

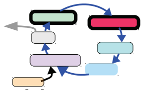
(μ + λ): μ parents, λ offspring, parents survive
recombination, mutation, external selection.

(μ , λ): μ parents, λ offspring,
recombination, mutation, external selection,
parents are discarded.

EA cycle of operation



EA: Parent Selection External Selection



An alternative scheme to operate the evolutionary algorithm is to **separate** parent selection from external selection**.**

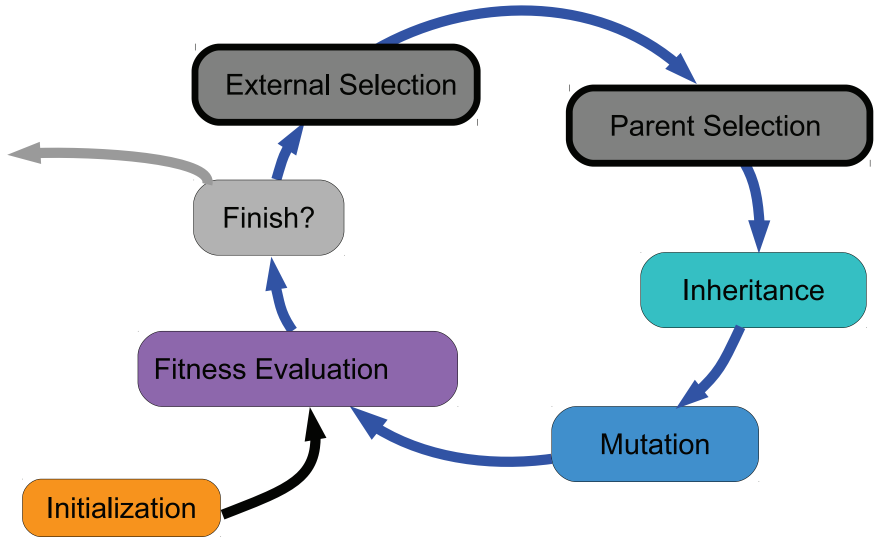
Then, within **external selection**, the μ individuals to survive, are selected from the complete population of P individuals, and λ individuals are discarded .

And, within **parent selection** the parents are selected from the complete population as well, building the pool of parents for subsequent inheritance.

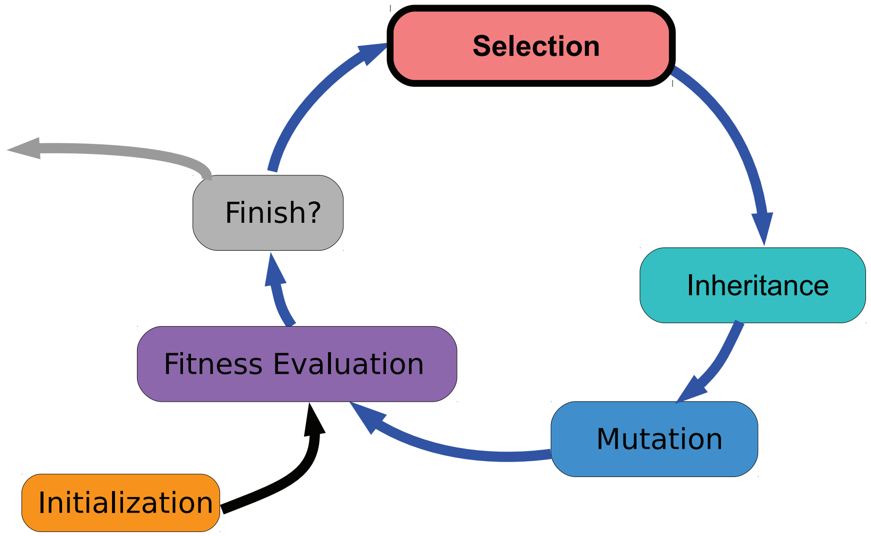
The **inheritance step** generates λ new individuals, from the pool of parents; the pool of parents is erased afterwards.

The Next Generation is build by combining the μ survivors with the λ offspring ($\mu + \lambda = P$).

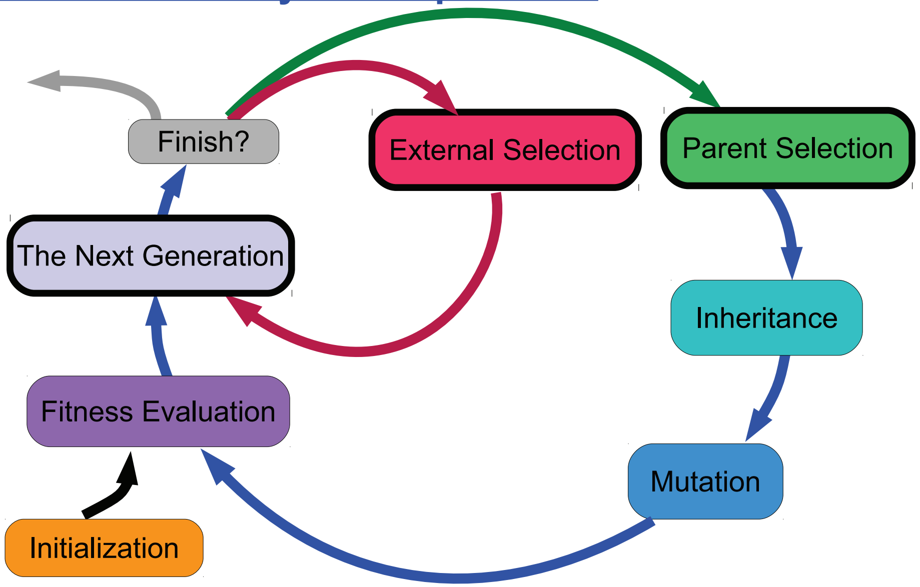
EA cycle of operation



EA cycle of operation

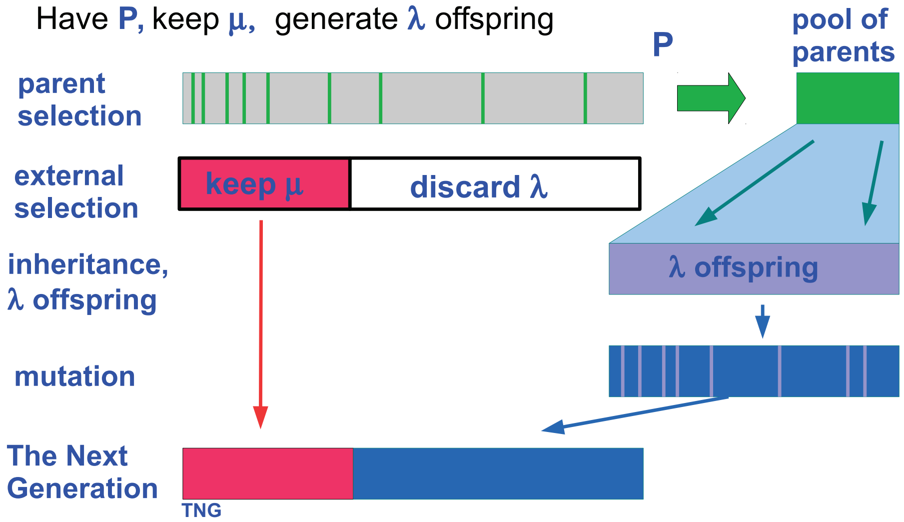


EA alternative cycle of operation

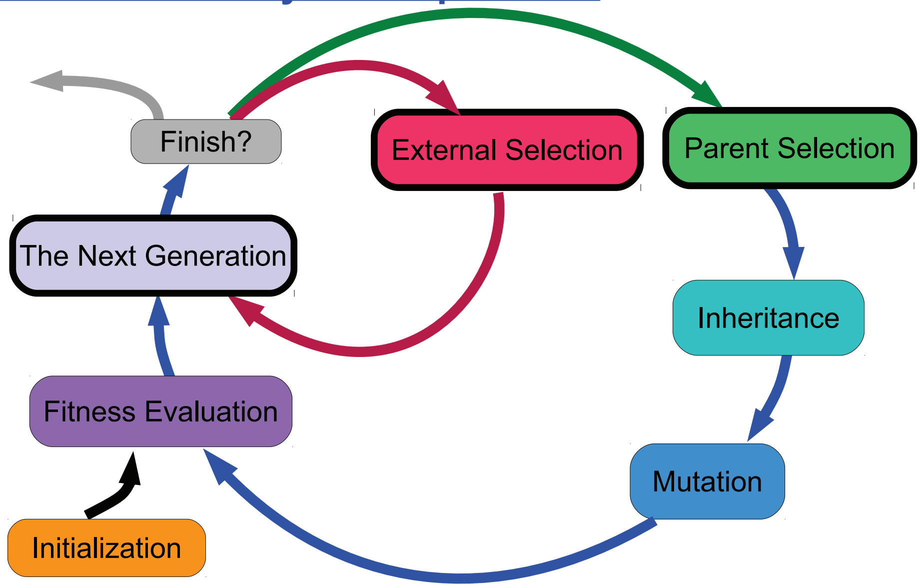


EA: Parent Selection / External Selection

Have **P**, keep μ, generate λ offspring



EA alternative cycle of operation



EA: Selection

Common strategies for the **selection** are:

- random choice
- schedule based, e.g. round robin
- fitness based elitism:
  - fitness proportional choice
  - rank proportional choice
- fitness based stochastic:
  - fitness proportionate, probabilistic choice
  - rank proportionate, probabilistic choice
- combinations of the above

EA: External Selection

Elitism is a way to design the selection, and inheritance steps to shape the next generation following the principle of **Exploitation**.

Using elitism a subset of the population is surviving (excluding mutation), and will be part of the next generation.

Typically the μ best individuals are chosen to survive.

The **(** $\mu + \lambda$ **)** deterministic, rank dependent strategy, with taking the μ best individuals as parents is a common implementation of elitism.

But the pool of parents, and the elite of μ surviving individuals can be different.

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EA: Parent Selection

Within parent selection one has to try to obey the two principles of **Exploration** and **Exploitation** at the same time.

Of course, one is trying to use the acquired knowledge as good as possible, while maintaining the diversity within the population.

Therefore it is a good idea to build up the pool of parents with a lot of the best individuals and explicitly take some individuals with a lower performance.

A common way to implement this is to make the probability of being chosen for the pool of parents depending on the achieved fitness **f(g)**:

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A common way to implement this is to make the probability of being chosen for the pool of parents depending on the achieved fitness **f(g)**:

~~fitness proportional~~ or **rank proportional**

EA: Parent Selection

It showed to be feasible to make up the set of parents with those individuals, that have shown a good fitness **f(g)**, and explicitly include additional individuals that have not performed as good.

A **probabilistic parent selection**, depending on the reached fitness values **f(g)** is a common way to implement this.

Common probabilistic, fitness based parent selection:
- **Wheel of Fortune,** (Roulette-Wheel Selection)
- Tournament selection
- Boltzmann Selection, Softmax-Selection

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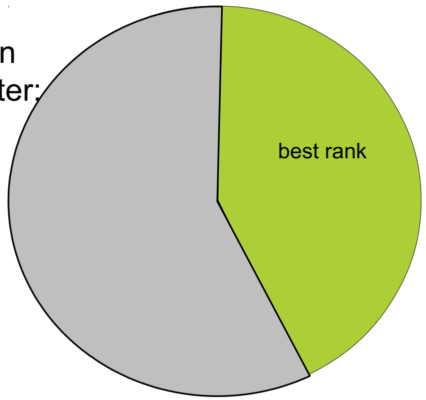
EA: Parent Selection

A widely used way to implement a probabilistic, rank proportionate parent selection is the **wheel of fortune**,

Where the probability ω to be chosen is larger, when the fitness $f(g)$ is better; is larger, when the rank $r(f(g))$ of the individual is smaller.



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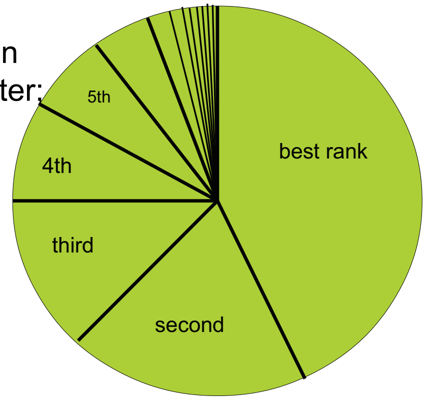
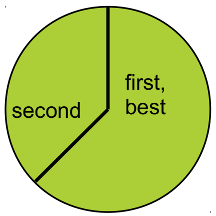
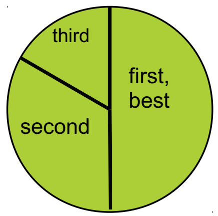


EA: Parent Selection

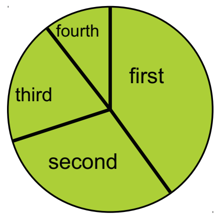
„**Wheel of Fortune**",.
The chance, or the probability ω to be chosen is larger with smaller fitness dependent rank $r(f(g))$ of the individual.



P=2:
2/3 + 1/3 = 1.0



P=3:
3/6 + 2/6 + 1/6 = 1.0



P=4:
4/10 + 3/10 + 2/10 + 1/10 = 1.0

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Common probabilistic, fitness based parent selection:
- Wheel of Fortune, (Roulette-Wheel Selection)
- **Tournament selection**
- Boltzmann Selection, Softmax-Selection

EA: Parent Selection

Another common way to shape the parent selection, is called **tournament selection**.

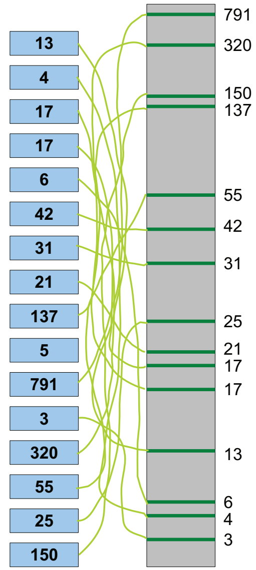
Some individuals are taken randomly from the population, and compared pairwise (randomly chosen) in a form of **tournament**, the winner of each tournament is now eligible for the pool of parents.

To further increase the fitness of the pool of parents, the winning individuals can now undergo further stages of tournaments among each other.

Easy to implement, easy to control the selection pressure.

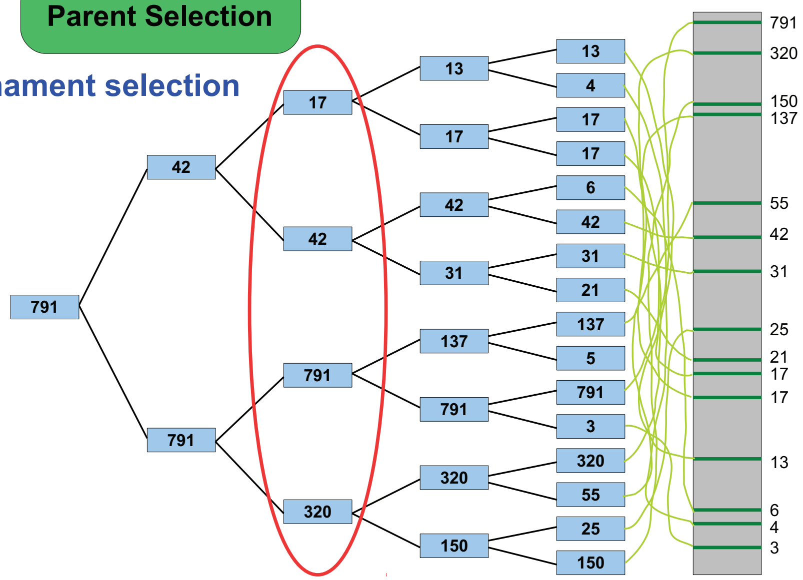
EA: Parent Selection

Tournament selection



EA: Parent Selection

Tournament selection



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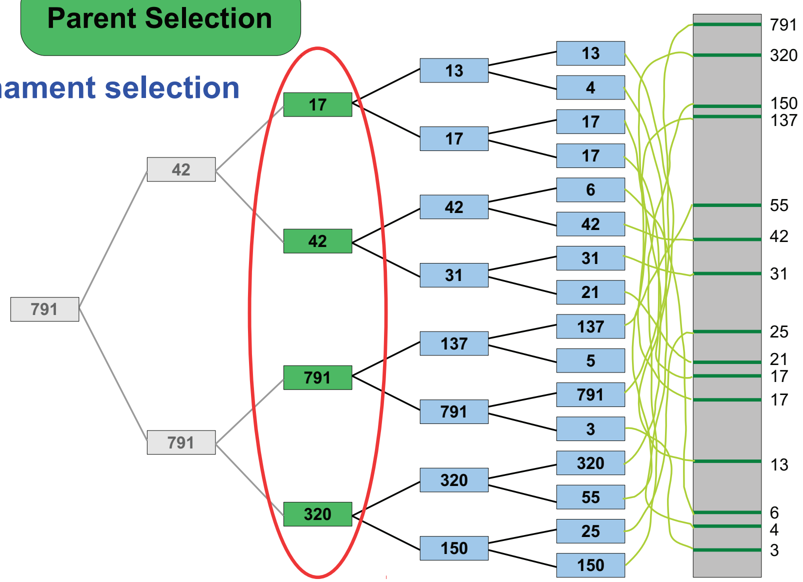

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Historic Remarks, Different Approaches

Evolutionary Computation (EC)

Swarm Behavior / Swarm Intelligence
- Ant Algorithm
- Ant Colony Optimization
- Particle Swarm Optimization

Evolutionary Algorithms (EA)
- Genetic Algorithms (GA)
- **Genetic Programming (GP)**
- Evolutionary Strategies (ES)
- **Evolutionary Programming (EP)**

Historic Remarks, Different Approaches

Evolutionary Computation (EC)

Evolutionary Algorithms (EA)

- Genetic Algorithms (GA)
  John Henry Holland (1975)
- Evolutionary Strategies (ES)
  Ingo Rechenberg (1965), Hans-Paul Schwefel (1970)
- **Evolutionary Programming (EP)**
  Lawrence J. Fogel (1964)
- **Genetic Programming (GP)**
  N.A.Barricelli (1954), R.M.Friedberg (1958)

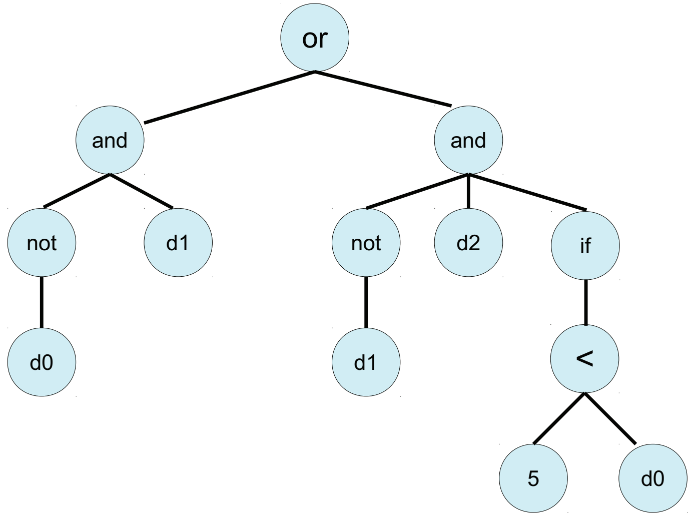
EA: Genetic & Evolutionary Programming

Although proposed as an alternative approach to "normal computer programming", the subject of **Genetic or Evolutionary Programming** refers to EA applications where the genome is regarded as a sequence of commands (a program).

The fitness **f(g)** of the genome **g** is the quality the program achieves within the given application.

The basis for genetic programming is typically not the source code level, but a genome that is representing a formal description of the code (syntax graph, prefix notation of functions, …).

EA: Genetic & Evolutionary Programming



not d0 AND d1 OR not d1 AND d2 AND if(5<d0)

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EA: Co Evolution

Within a normal evolutionary algorithm a fitness function **f(g)** is used to evaluate the performance of all P genomes g_i from the population.

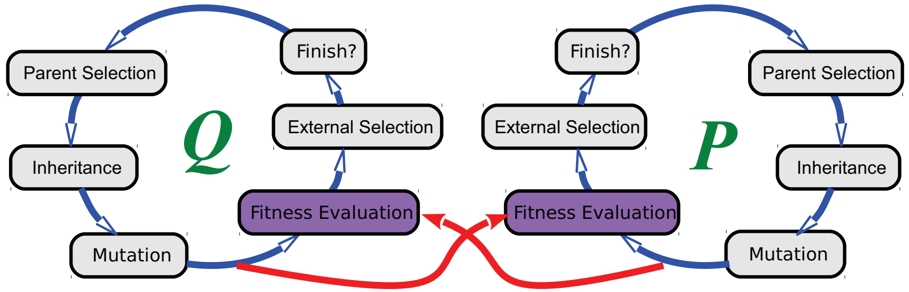
Lets take a second population with **Q** individuals and a second fitness function **h(g).**

Now these two populations are interconnected via their fitness functions **f** and **h** , where one population is creating the fitness for the other population, and vice versa.

The population is not evaluated against a static fitness function, but against a changing other population.
The performance of one population is the fitness for the others population.

EA: Co Evolution

Two populations are interconnected via their fitness functions where one population is creating the fitness for the other population, and vice versa.
The performance of one population is the fitness for the other population.



EA: Co Evolution

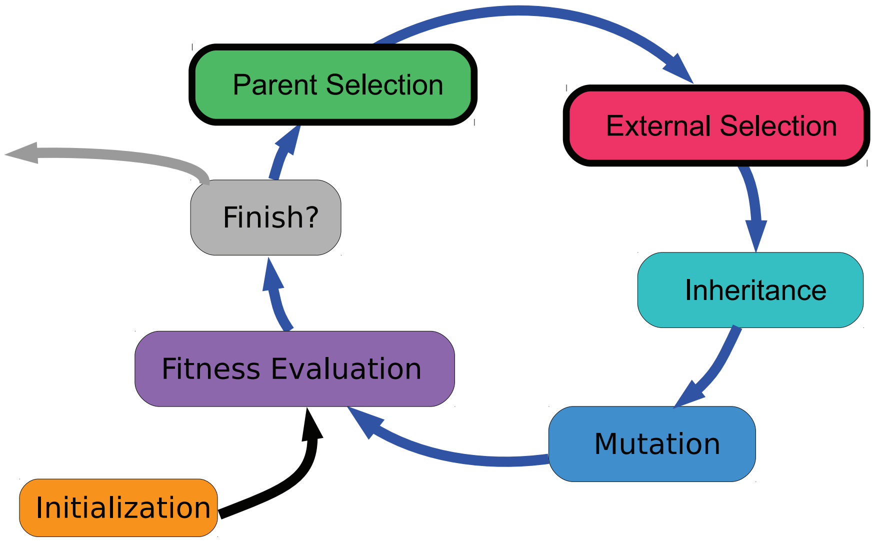
Co evolution can be used to simulate the development of two species interacting:

e.g. a predator-prey system
or two agents, or two players in games, ...

Since both fitness functions, are not static but changing over time, a final objective is sometimes hard to determine.

The achieved results in co evolution for one population is only use-able in interaction with the other population.

EA alternative cycle of operation



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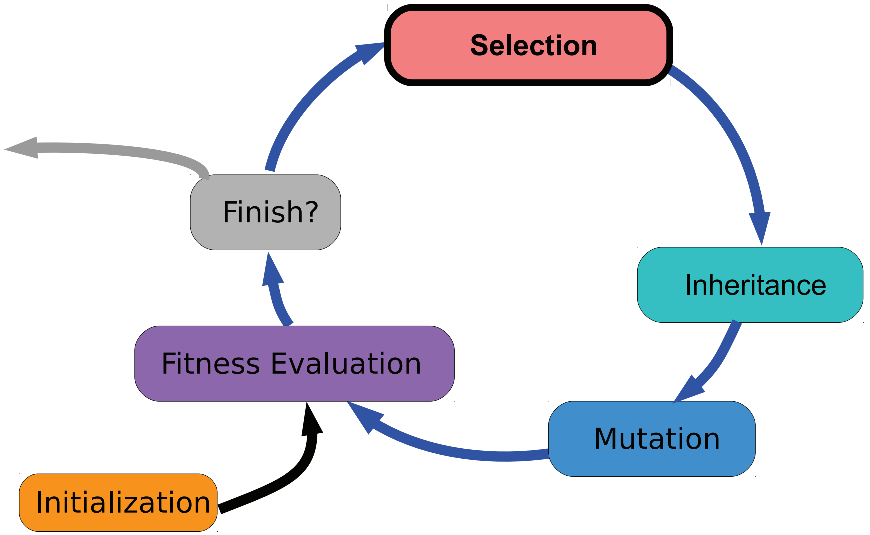
EA alternative cycle of operation



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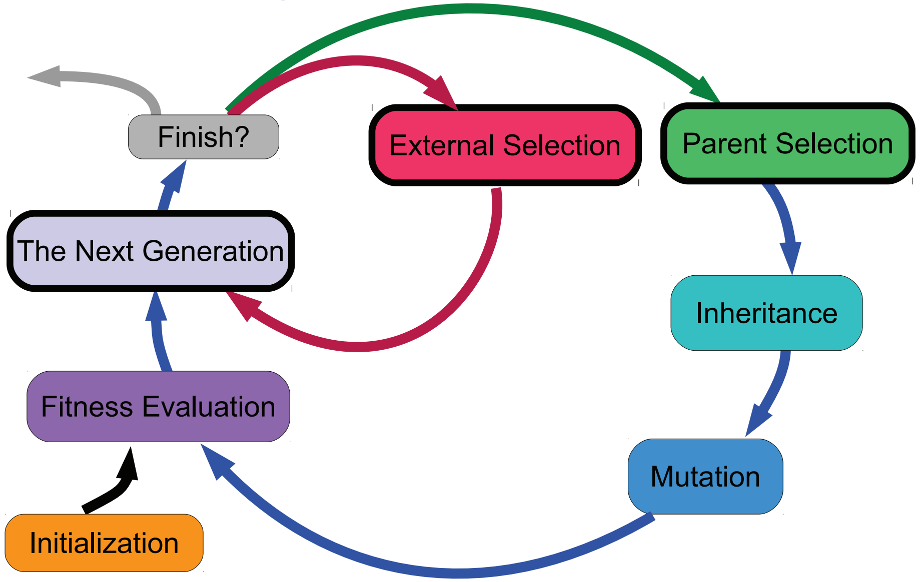
EA alternative cycle of operation



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Artificial Life
Summer 2015

Evolutionary Algorithms 3

Thank you for your patience

Master Computer Science [MA-INF 4201]
Mon 8:30 – 10:00, LBH, Lecture Hall III.03a

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