

Artificial Life Summer 2015

Learning from Nature Evolutionary Algorithms Optimization Inspired by Biology

Master Computer Science [MA-INF 4201]

Mon 8:30 – 10:00, LBH, Lecture Hall III.03a

Dr. Nils Goerke, Autonomous Intelligent Systems,
Department of Computer Science, University of Bonn

Some important dates:

Next Thursday 4.6.2015, is , Corpus Christi (Fronleichnam),
University is **closed** (no lectures, building is closed, ...)
shops are **closed**, restaurants are **open**,

Thus, there will be no exercises on Thursday 4.6.2015.
We will discuss the content in the exercises next week,
but of course, you can attend the exercises on Tuesday, 2.6.2015,

Written examination, is scheduled for:

Thursday, **30. July 2015** from **10:00** to 11:40,
LBH Building, Lecture Hall: III.03a

Re-Sit examination, will probably be:

Tuesday, **8. Sept 2015** from **10:00** to 11:40,
LBH Building

Overview:

- Evolutionary Computation
- Historic Remarks
- Different Approaches
- Idea of Evolutionary Algorithms (EA)
- EA Steps
 - Individual, Genome, Fitness, Population
 - Parent selection
 - Inheritance
 - Mutation
 - Fitness evaluation
 - External selection

Evolutionary Computation:

Optimization inspired by Biology

Evolutionary Computation (EC):

What is it?

Where does it come from?

Where can it be found?

Why is it interesting for Computer Science?

Historic Remarks, Different Approaches

The field is at the moment denominated as
Evolutionary Computation (EC).

EC comprises several approaches and ideas

- that have been developed independently (60ies),
- that follow the same basic guideline and
- that have (later) been found to be so closely related to each other,
- that they can be seen as different variants or dialects of the same basic principles.

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)

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Optimization (some basics):

Optimization is typically based on optimizing a criterion of some objective function $f(s)$:

- minimizing some costs
- maximizing some fitness

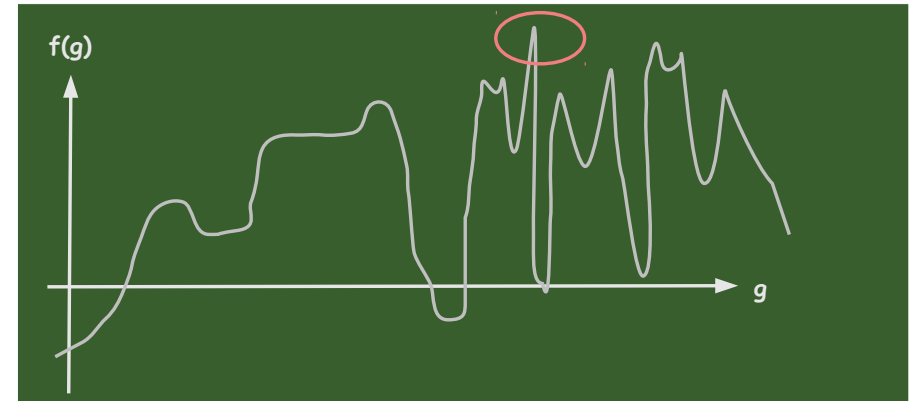
Optimization is the process of finding a position s^* in search space S that optimizes the objective function $f(s) \in \mathbb{R}$,

$$f(s^*) \leq f(s) \quad \forall s \in S \quad (\text{in case of minimization})$$

$$f(s^*) \geq f(s) \quad \forall s \in S \quad (\text{in case of maximization})$$

Optimization:

Draw a **nasty fitness function** on the blackboard:



Global vs. Local Optimization:

Global optimization attempts to find the absolute best (global) optimum for a given problem.

Finding a global optimum (there might be several) is definitively one of the the hardest tasks in optimization.

Beside the global optimum, there can be local optima (typically there are a lot of them).

Local optimization is attempting to find an extremum in the vicinity of a starting point, that is good, or at least sufficient for the given problem.

There is a chance to find a global optimum, even with local optimization methods; **but you never know.**

Overview:

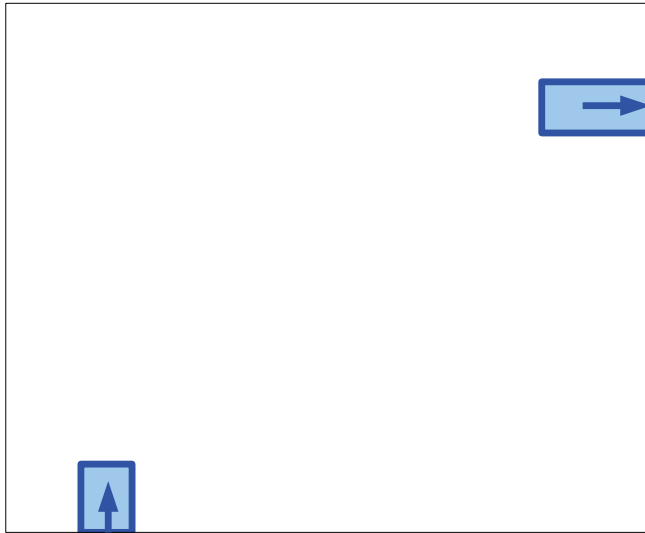
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EA:**Example: Fkt Maximum****I. Rechenbergs tubing problem**

The fuel flows into the tube from the left. The fuel should leave the tube (top right) such that the resistance of the fluid is minimized.

The question is how the two tubes should be connected, i.e. what is the shape of the connecting tube?

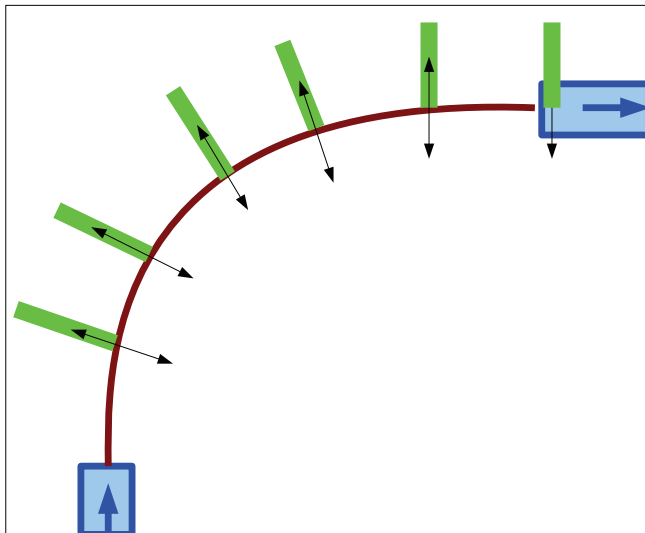
From: AI Lab,
University of Zurich

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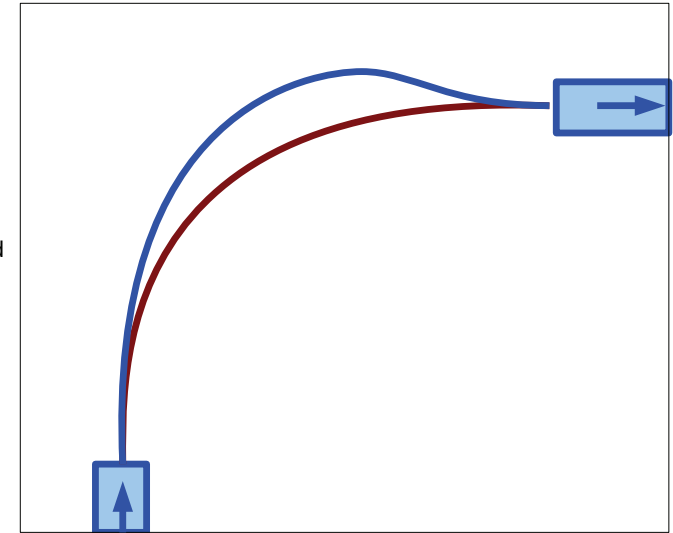
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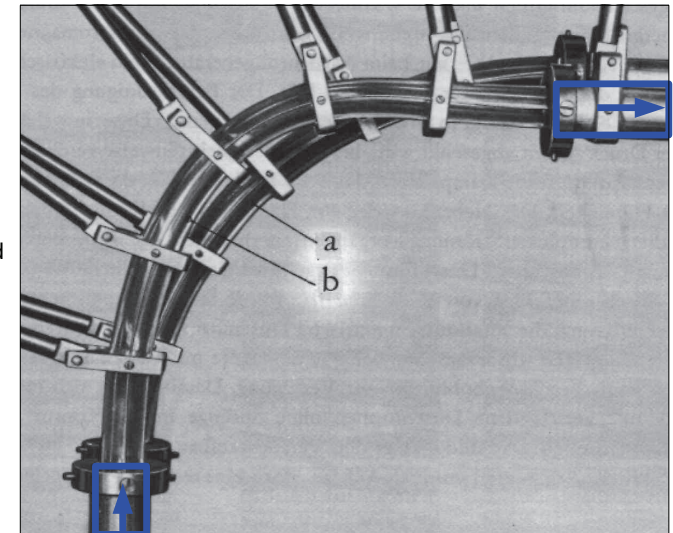
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Idea of Evolutionary Algorithms (EA)

The whole family of algorithms denominated as **Evolutionary Algorithms** was inspired by a series of ideas and principles from living nature.

Especially the principles of **Evolution** (C.Darwin) and **Reproduction** and **Inheritance** (G.Mendel) and the discovery of the **Genome**, and the **DNA** (1953, J.Watson, F.Crick) have inspired the development of EAs in the 50ies and 60ies of the last century.

Thus, major parts of EAs are designed in analogy to the biological role model.

Different Approaches

Evolutionary Computation (EC)

Evolutionary Algorithms (EA)

- Genetic Algorithms (GA)

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Idea of Evolutionary Algorithms (EA)

Several aspects and terms of Evolutionary Algorithms are directly borrowed from biology:

- Population of Individuals
- Survival of the fittest
- Selection
- Inheritance
- Reproduction
- Mating
- Recombination
- Cross-Over
- Mutation
- Genome

Idea of Evolutionary Algorithms (EA)

Evolutionary Algorithms perform a stochastic optimization using a modified **Multi-Start** approach, (**Multi-Hypothesis** approach).

Instead of working with one single hypothesis, several different hypotheses will be regarded at the same time (working „quasi“ in parallel).

Within an Evolutionary Algorithm, each of the multi hypotheses is called an **Individual**.
The collective of all **Individuals** is called the **Population** of the **Evolutionary Algorithm**.

Idea of Evolutionary Algorithms (EA)

Each **Individual** of the **Population** will typically have a different position \mathbf{s}_p in search space \mathbf{S} , and thus, a different fitness $f(\mathbf{s}_p)$.

The position \mathbf{s}_p in search space is defining the individual \mathbf{p} ;
 \mathbf{s}_p is called the **Genome** of \mathbf{p} .

Some of the **Individuals** might represent acceptable solutions, close to a local optimum, or even close to the global one.
Some of them represent mediocre solutions.
Some might represent just rubbish (most will).

Idea of Evolutionary Algorithms (EA)

The entire **Population** carries more information about the objective function than, any of those single **Individuals** alone.

Keep the good ones.
Discard the bad ones.

This is the implementation of the biological principle:

Selection

„Survival of the fittest“

Idea of Evolutionary Algorithms (EA)

The **Selection** (whom to keep, whom to discard) is performed with respect to the result achieved by the objective function $f(\mathbf{s})$.

This is called „**External Selection**“, because the objective function $f(\mathbf{s})$ is provided by the environment from external the EA.

(sometimes called „**Environmental Selection**“)

The result of this **External Selection** is a reduced population, with only the best individuals surviving.

Idea of Evolutionary Algorithms (EA)

The individuals, that survived the **external selection** process, are now entitled to restock the population to its original size. They are called **parents**, and are allowed to generate **offspring**

Re-stocking the population could in principle be done by generating complete new individuals. But it is assumed (and proven) that using some of the already acquired information for the new individuals is preferable.

This is an implementation of the biological principles:

Reproduction and Inheritance

Idea of Evolutionary Algorithms (EA)

To transport some of the information from the previous generation, into the next generation (**inheritance**), the **offspring** are generated out of the **genome** of the **parents**.

The most popular way in Evolutionary Algorithms is to select two parents from the remaining population (**parent selection**), and to generate offspring by mixing, or combining the genome of these parents. This is called:

Mating and Recombination

Idea of Evolutionary Algorithms (EA)

Inheritance with **parent selection**, and **reproduction** of **offspring** via **mating** and **recombination** is used to benefit from the information already acquired (**exploitation** of knowledge).

On the other hand, it is a valuable idea to explore new positions **s** in search space **S**, on a stochastic or random basis.

This way of **exploration** is implemented in EAs using a random alteration of the existing **genomes**. It is called:

Mutation

Idea of Evolutionary Algorithms (EA)

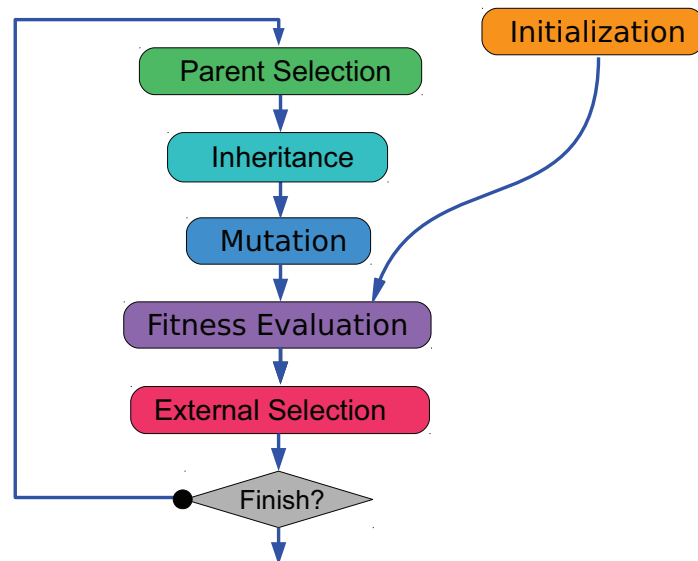
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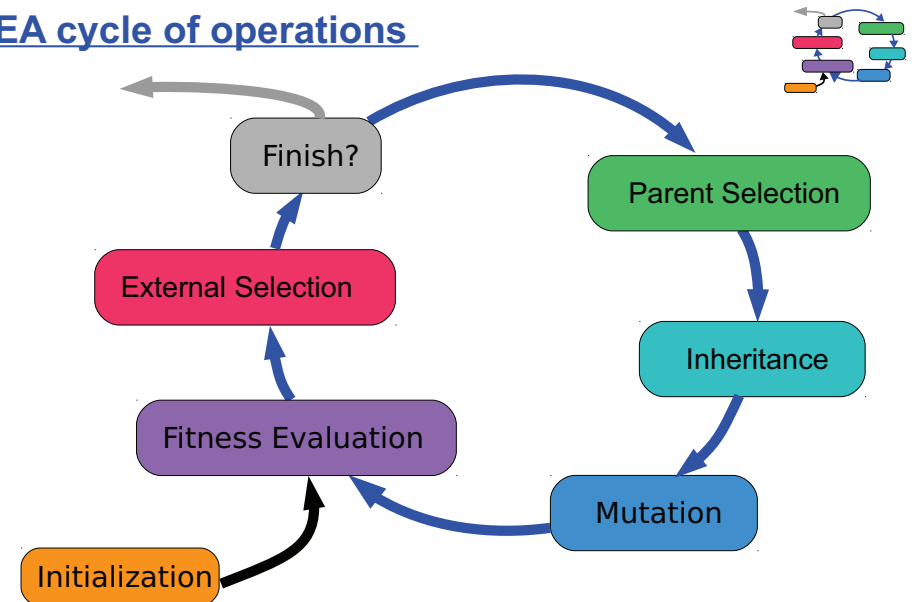
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EA steps

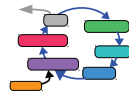


EA cycle of operations



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EA:**Population, Individual, Genome, Fitness**

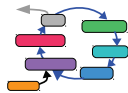
An Evolutionary Algorithm works with a **population** of single **individuals**.

Each **individual** owns a **genome**.

A **genome** is a set of parameters **s** out of a search space **S**.

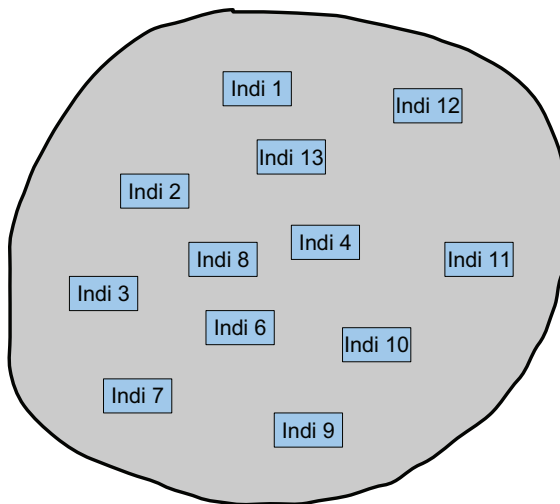
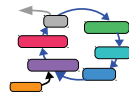
The **genome** s_p of an **individual** **p** is evaluated with respect to a fitness function **f** (objective function).

The result $f(s_p)$ of this evaluation is called f_p **fitness** of the individual **p**.

EA:**Population of Individuals**

A **population** of individuals with individual **genomes**.

Indi 1	O	O	I	I	O	I	O	I	O	I	O	I	O	O	I
Indi 2	O	I	I	O	O	O	I	I	I	O	O	I	I	O	O
Indi 3	I	O	I	I	O	I	I	I	O	I	I	I	I	O	O
Indi 4	O	I	I	O	I	O	I	I	O	O	I	O	I	O	I
Indi 5	O	O	O	I	I	I	O	O	O	I	I	I	O	O	O
Indi 6	O	I	O	I	I	O	O	I	I	O	O	I	O	O	I
Indi 7	O	I	O	I	O	I	O	I	O	O	I	O	I	O	I
Indi 8	O	O	O	I	O	O	O	O	O	I	I	O	O	I	O

EA:**Population of Individuals**

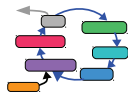
A **population** is a set or group of individuals.

Indi 1 Indi 2 ...

Each **individual** has an individual genome.

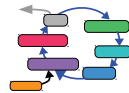
A **genome** is a set of parameters **s** out of a search space **S**.

O O I I O I O I O I I O I I O O I

EA:**Genome**

A **genome** is a set of parameters **s** out of a search space **S**. The genome determines the properties and capabilities of an individual (phenotype).

Indi 1	O	O	I	I	O	I	O	I	O	I	I	O	I	O	O
--------	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

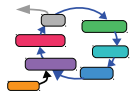
EA:**Genome**

A **genome** is a set of parameters **s** out of a search space **S**. The genome determines the properties and capabilities of an individual (phenotype).

The implementation of a **genome** can be a simple string of bits, can be a vector of integer or real values, or can be a set of items, (or something else).

A **genome** can even be a string of characters, like a computer program, or a complete text.

A **genome** does not even has to have a fixed length.
The length can change during the optimization of the EA.

EA:**Fitnessfunction**

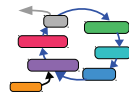
The **fitness function f** calculates the fitness value **f(s)** for each individual **genome s**.

The fitness value is a scalar value.

Larger fitness is indicating a better individual.

The fitness is heavily depending on the application!

The mapping from **genome** to **fitness value** can be directly, e.g. by a mathematical function, or can be a complicated process, e.g. the performance of a soccer playing, walking robot.

EA:**Genome**

A **genome** can be

a simple string of bits:

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

a vector of values:

17	0.38	2.0e-7	42	3.141
----	------	--------	----	-------

a set of items:

{ Car, Banana, Monday, USB-Stick }

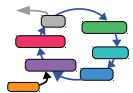
a string of characters:

„Throatwobbler Mangrove“

From: Monty Python's Flying Circus: Episode 22, Cosmetic surgery

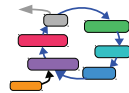
a complete computer program.

```
#include "Evolutionary_Algorithms.h"
int main()
{
    int P = 1000; // size of population
    int L = 20;   // length of genome
}
```

EA:**Fitness value**

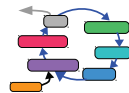
The **fitness function f** calculates the fitness value **f(s)** for each individual **genome**.

Indi 1	0 0 1 1 0 1 0 1 0 1 1 0 0 1	f(1) = 9
Indi 2	0 1 1 0 0 0 1 1 1 0 0 1 1 0 0	f(2) = 9
Indi 3	1 0 1 1 0 1 1 1 0 1 1 1 1 0 0 1	f(3) = 12
Indi 4	0 1 1 0 1 0 1 1 0 0 1 0 1 0 1	f(4) = 9
Indi 5	0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1	f(5) = 8
Indi 6	0 1 0 1 1 0 0 1 1 0 0 1 0 0 0 1	f(6) = 8
Indi 7	0 1 0 1 0 1 0 1 0 1 0 1 0 1 0	f(7) = 8
Indi 8	0 0 0 1 0 0 0 0 0 1 1 0 0 1 0 0	f(8) = 5

EA: Fitness value

The **fitness function f** calculates the fitness value $f(s)$ for each individual **genome**.

Indi 1	0 0 1 1 0 1 0 1 0 1 1 0 1 1 0 0 1	$f'(1) = 2$
Indi 2	0 1 1 0 0 0 1 1 1 1 0 0 1 1 1 0 0	$f'(2) = 4$
Indi 3	1 0 1 1 0 1 1 1 0 1 1 1 1 1 0 0 1	$f'(3) = 5$
Indi 4	0 1 1 0 1 0 1 1 0 0 1 0 1 0 1 0 1	$f'(4) = 2$
Indi 5	0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1	$f'(5) = 3$
Indi 6	0 1 0 1 1 0 0 1 1 0 0 1 0 0 0 1 1	$f'(6) = 2$
Indi 7	0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0	$f'(7) = 1$
Indi 8	0 0 0 1 0 0 0 0 0 1 1 0 0 1 0 0 1	$f'(8) = 2$

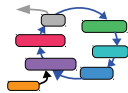
EA: Population

The **EAs**, as multi-hypothesis approach are working with a complete **population** of individuals.

Typically, the number of hypothesis is equal to the number **P** of individuals; **P** is called the size of the population.

In general, it is a good advise, to keep the size of the **population** fixed; but it is possible to change **P**.

Special approaches and extensions of EAs divide the **population** into several **sub-populations**, that may be treated differently.

EA: Population

How large shall the size of the **population** be?

There are several aspects that influence the choice of **P**:

- enough richness, diversity of hypothesis
- costs for evaluating the individuals
- computing costs for the entire algorithm

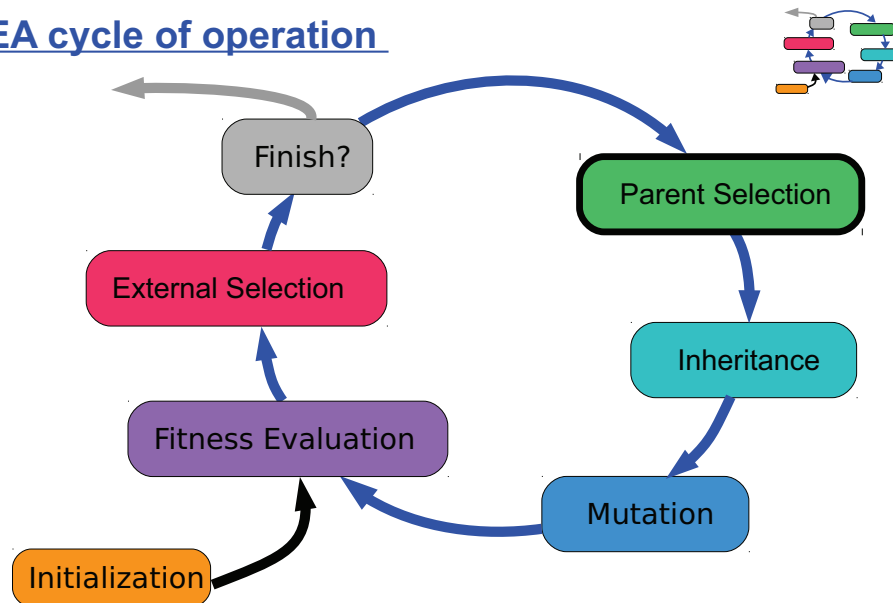
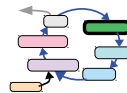
- keep it simple, keep it small

P = 50 ... 1000 (simulations)

P = 5 ... 50 (real world experiments)

Overview:

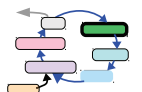
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EA cycle of operationEA: Parent Selection

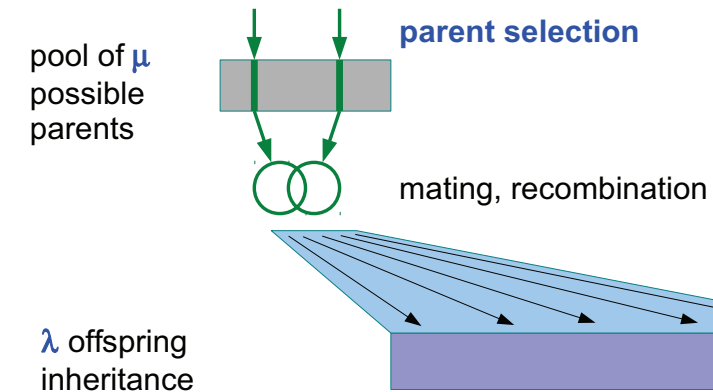
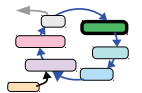
The μ individuals that survived the external selection process, are the pool to select the **parents** from.

Those **parents** selected, will have to generate λ offspring.

For every inheritance process, a number of k individuals (parents) are selected from the pool of possible parents for **mating + recombination**.

EA: Parent Selection

Out of the μ remaining individuals the k -parents are chosen for the inheritance step to generate λ offspring.

EA: Parent Selection

Common strategies for the **parent selection** are:

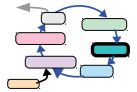
- random choice
- schedule based, e.g. round robin
- fitness based elitism:
 - fitness proportional choice
 - rank proportional choice
- fitness based stochastic:
 - fitness proportionate, probabilistic choice
 - rank proportionate, probabilistic choice
- combinations of the above

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EA:

Inheritance



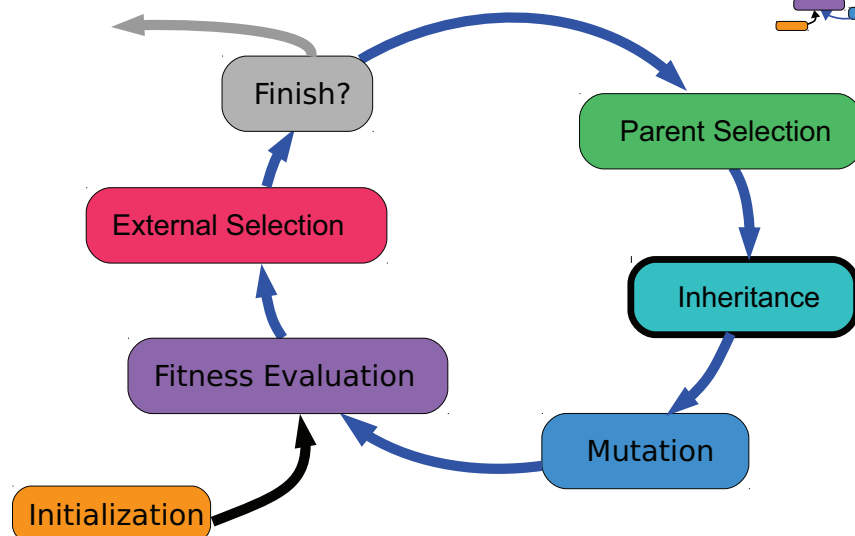
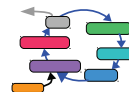
Inheritance is the principle of transporting some of the information from the previous generation (parents), into the next generation, by generating the **offspring** out of the **parents genomes**.

Thus, generating offspring means to create new individuals with new genomes.

Inheritance in the context of Evolutionary Algorithms means to use the genomes of those **parents** that have been selected.

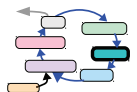
There is a wide variety of possible ways to generate offspring.

EA cycle of operation



EA:

Inheritance



The most popular mechanism to implement the **inheritance** principle is to use $k=2$ parents and to **combine** their genomes (mostly called recombination).

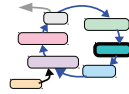
The most popular mechanism to implement **recombination** of 2 genomes is **cross over**:

Inheritance:

- **recombination**
 - by **cross over**
 - (other recombination operators)
- (other inheritance mechanism)
 - (other inheritance operators)
 - ...

EA:

Inheritance



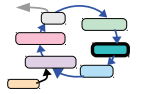
Recombination by 1-point cross over:

Select two parents, **A** and **B** and **recombine** their genomes by taking one part from parent **A** and the other part from parent **B**

Choose a **random point C** where to split the genomes, and recombine the four remaining fractions to build new individuals, containing partial information from both parents.

EA:

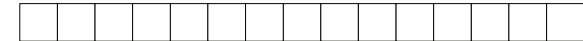
Inheritance



Recombination by 1-point cross over:

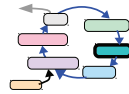
cross over point **C**Parent **A**:Parent **B**:

Child 1:



EA:

Inheritance



Recombination by 1-point cross over:

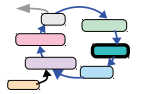
Parent **A**:Parent **B**:

Child 1:



EA:

Inheritance

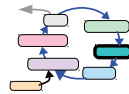


Recombination by 1-point cross over:

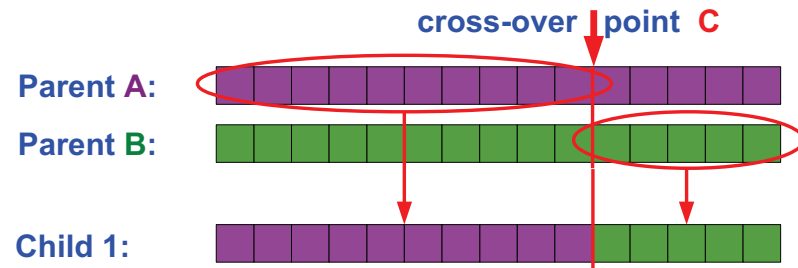
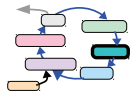
cross over point **C**Parent **A**:Parent **B**:

Child 1:



EA: Inheritance

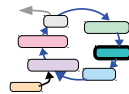
Recombination by 1-point cross-over:

**EA: Inheritance**

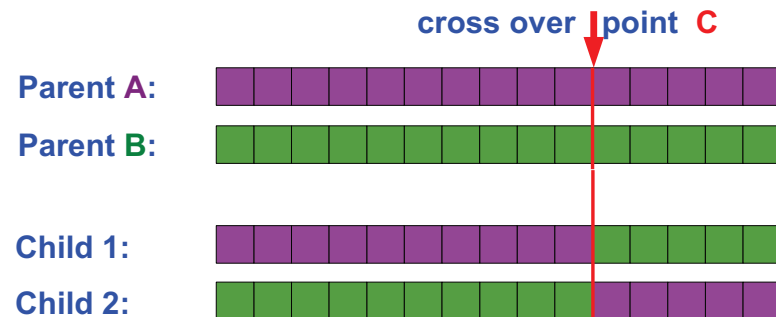
$k=2$ and $k>2$, recombination with k parents

Several ways to **combine** (or **re-combine**) the genomes of the k parents have been proposed. Some of them rely on a special structure of the genome.

- **N-point cross over** (the most popular)
- **mean-values**, one component, all components
- **max, min, sum, difference** of values
- **union, intersection** of **sets** of items
- **concatenate** (strings)
- ...

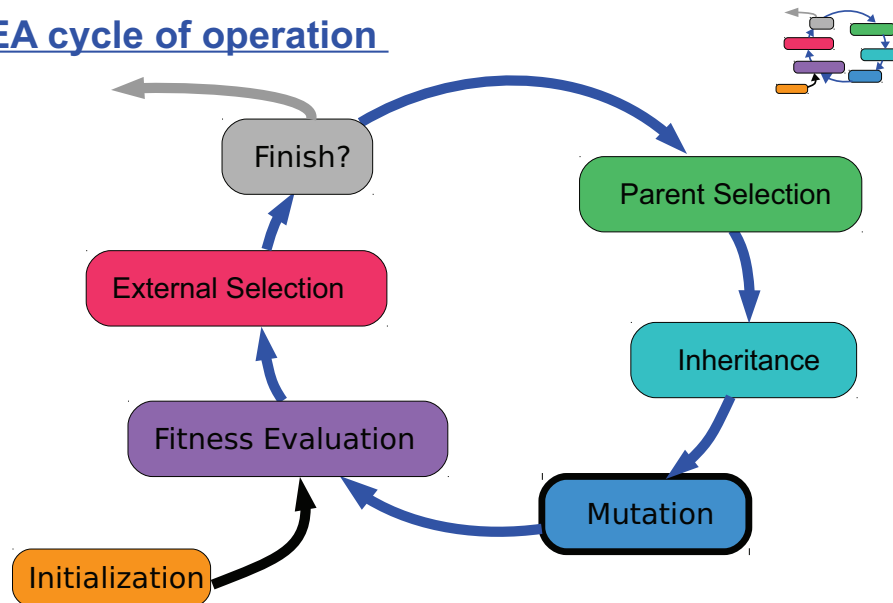
EA: Inheritance

Recombination by 1-point cross over:

**Overview:**

- Evolutionary Computation
- Historic Remarks
- Different Approaches
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 - **Mutation**
 - Fitness evaluation
 - External selection

EA cycle of operation



EA: Mutation

The job of the **mutation** step is to maintain the **diversity** of the genomes within the population:

Different positions in search space sample the fitness function at different points.

Changing the genome by **mutation** is implementing the **exploration** principle of **stochastic optimization**.

EA: Mutation

Depending on the different way the information is coded in the genome, the layout of the **mutation** step is to be designed differently.

Some common mutation operators are:

- **Binary genome**: a bit-flip
- **Vector of parameters**: change of value
- **Set of items**: replace a single item
- **String of characters**: replace a single character
- **Sequence**: change order within sequence
- **Other**: other method

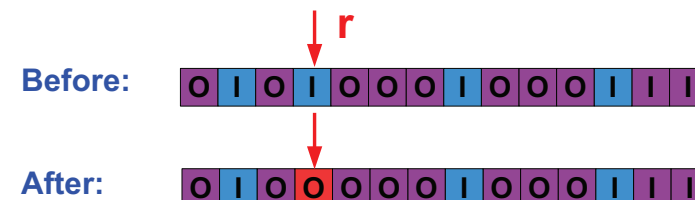
Special codings of the genome will require that the **mutation** is paying respect to this coding.

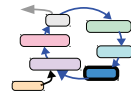
EA: Mutation

The **mutation** for a binary genome is typically implemented as one or more **bit-flips**:

Method 1:

Choose a random position **r** in the genome and **flip** that **bit**. This yields a 100% chance that the genome is changed; the resulting Hamming distance is always exactly 1.



EA: Mutation

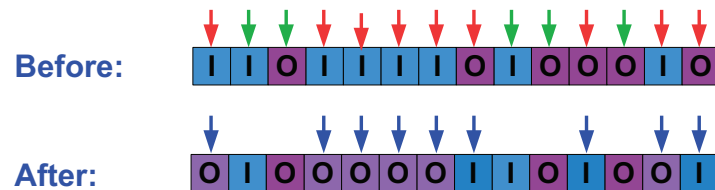
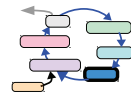
The **mutation** for a binary genome is typically implemented as one or more **bit-flips**:

Method 2:

Go through all positions in the genome, and **flip** each **bit** with a given **bit-flip-probability** ω .

There is a chance, that all bits are flipped, and a chance that none is flipped.

$$0.0 < \omega < 1.0$$

**EA:** Mutation & Inheritance

It is possible, that the **inheritance** and the **mutation** process yield invalid genomes, which represent hypotheses **s** from outside the allowed search space **S**.

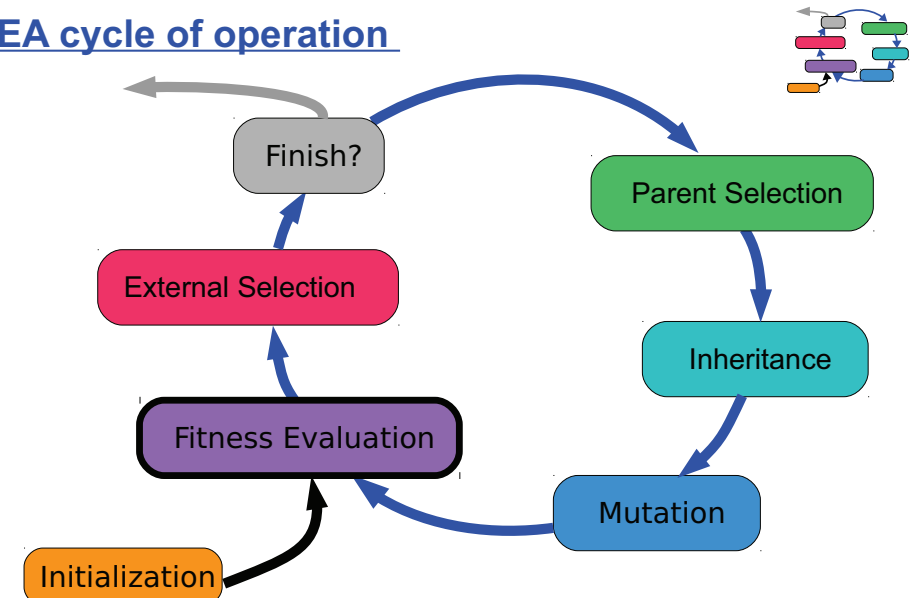
Those illegal genomes would stress the optimization process in an unwanted way.

Therefore, it is a good advise, to take precautions against illegal genomes (if possible, and economic):

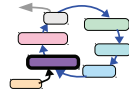
- shape the structure of the genome,
- shape the structure of the inheritance,
- shape the structure of the mutation.

Overview:

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EA cycle of operation

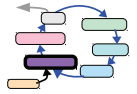
EA: Fitness Evaluation



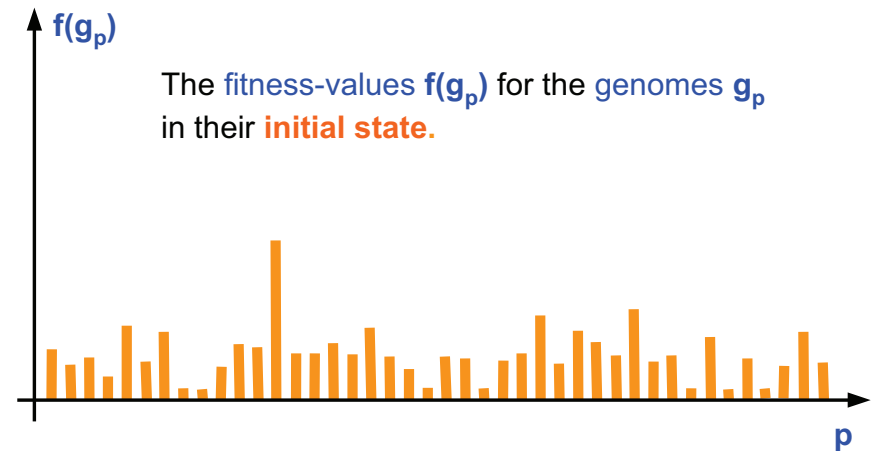
The **fitness** of each individual is evaluated with respect to the **fitness-function** (most case identical to the objective function). For Evolutionary Algorithms, it is usual to have a **fitness** function that is to be maximized.

If the **fitness evaluation** is expensive, it is a good idea to process only the new individuals/genomes from the **inheritance** step, including those individuals/genomes that have changed during **mutation**.

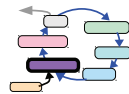
EA: Fitness Evaluation



Distribution of **fitness values** over the population.



EA: Fitness Evaluation



The **fitness $f(g_p)$** of each individual **p** is evaluated with respect to the application using the given **fitness-function $f(g)$** .

Genome g_p

$p=P$

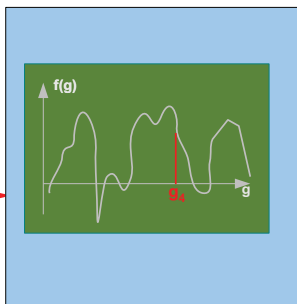
$p=5$

$p=4$

$p=3$

$p=2$

$p=1$



Fitness Value $f(g_p)$

$f(g_p) =$

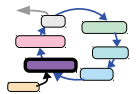
$f(g_4) = ???$

$f(g_3) = 0.228$

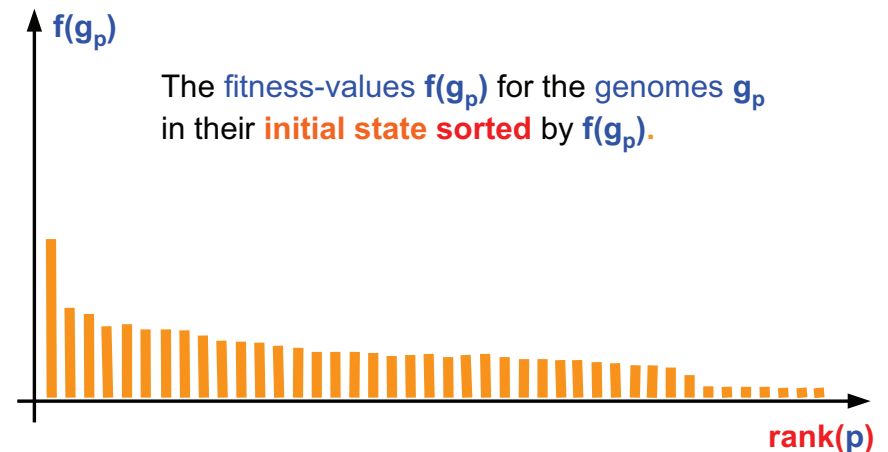
$f(g_2) = -171.0$

$f(g_1) = 0.5$

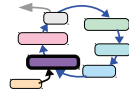
EA: Fitness Evaluation



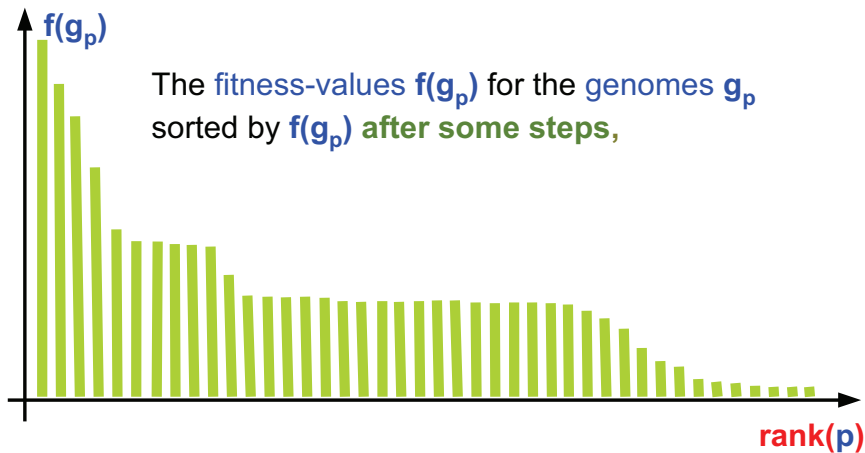
Distribution of **fitness values** over the population.



Fitness Evaluation

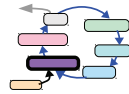


Distribution of **fitness values** over the population.

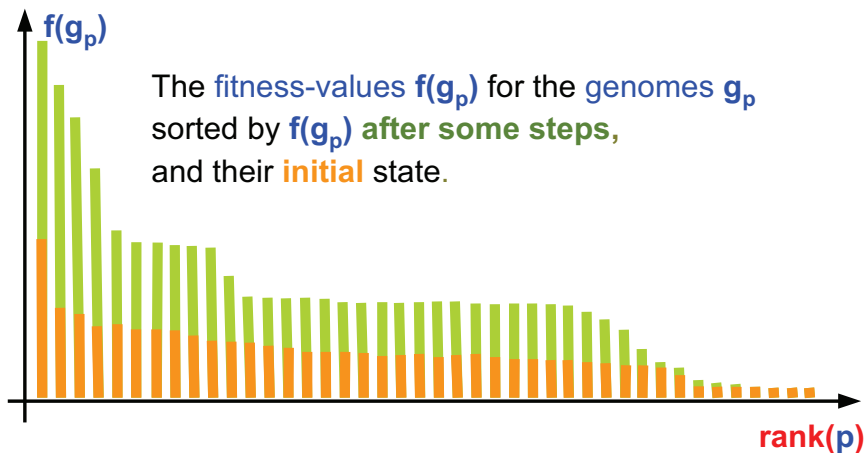


EA:

Fitness Evaluation



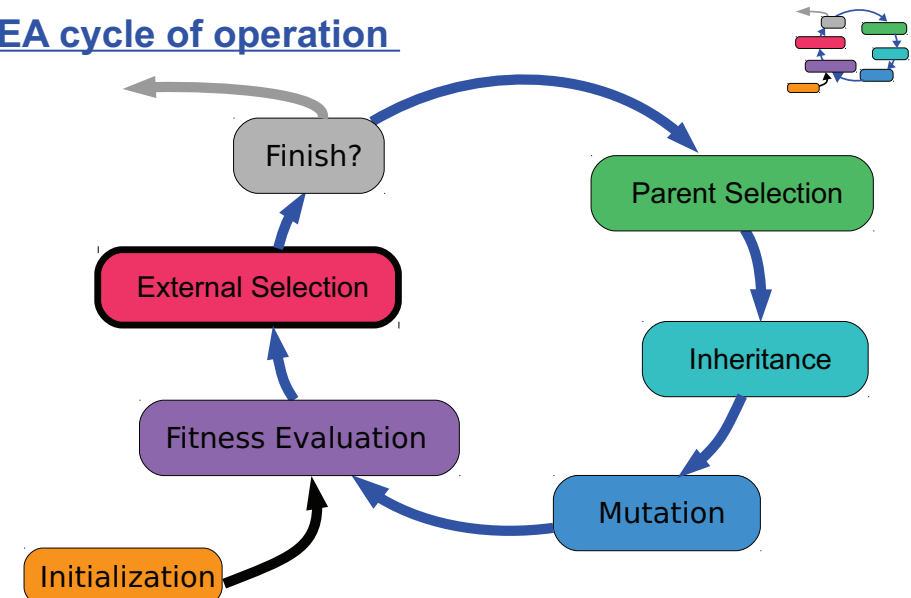
Distribution of **fitness values** over the population.

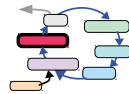


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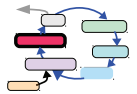
EA cycle of operation



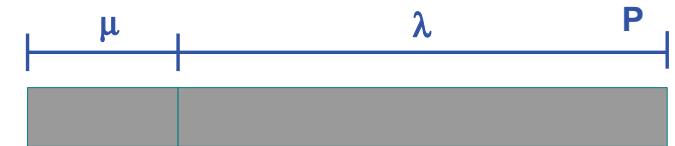
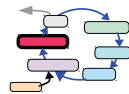
EA: External Selection

The purpose of the **selection process** is to keep the „Best“, and discard the „Losers“.
The **selection** is based on the achieved **fitness**, which is obtained by the **fitness function**, quasi from **external** to the EA.

The μ individuals that survive the **external selection** process, will be the pool for the **parents** of the next generation. Later on, from these μ parents the λ offspring will be generated through the inheritance process.

EA: External Selection

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

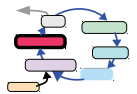
**EA:** External Selection

The two questions for the **external selection** are:

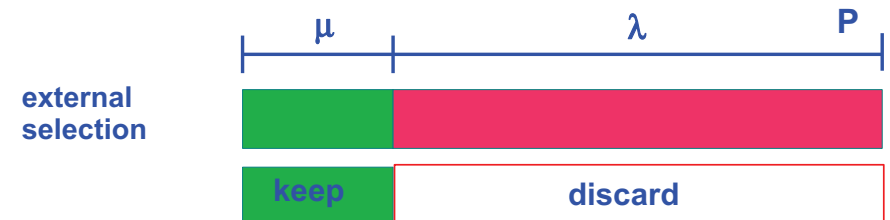
How many (μ) of the individuals shall survive?
and
Which are the ones to keep?

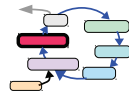
A common way is to keep the population constant to **P** individuals.

discard λ by external selection
and keep μ as pool for the parents,
then generate λ offspring for the next generation.

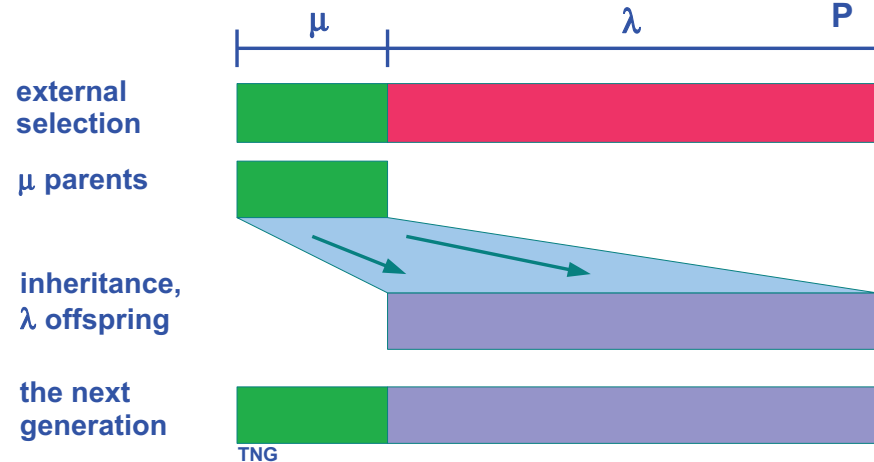
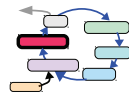
EA: External Selection

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



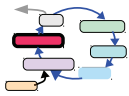
EA: External Selection

Have P , keep μ , generate λ offspring

**EA:** External Selection

Common strategies for the **external 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

There are different ideas and principles behind the selection of the μ possible parents from the population, with special pros and cons.

- **deterministic** or **stochastic** selection
- **fitness dependent** selection
- **fitness proportional** selection
- **rank-based** selection
- **tournament** selection
- **life-time based** selection
- **combinations** of the above + more

Artificial Life Summer 2015

Learning from Nature
Evolutionary Algorithms
Optimization Inspired by Biology

Thank you for your attention

Dr. Nils Goerke, Autonomous Intelligent Systems,
Department of Computer Science, University of Bonn