Genetic Algorithms

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Parallel optimization inspired by biological evolution

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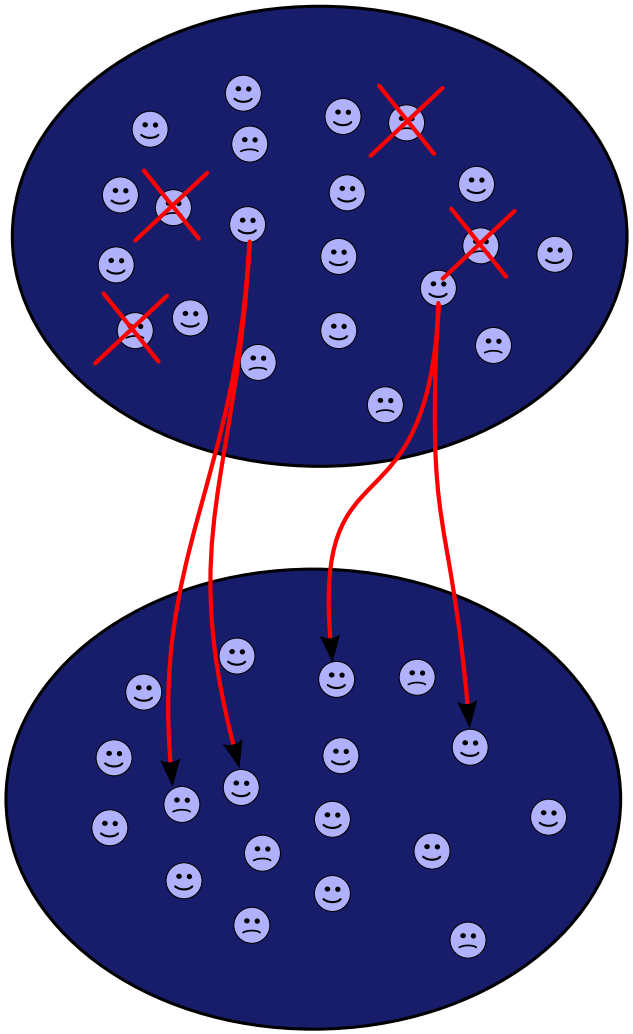
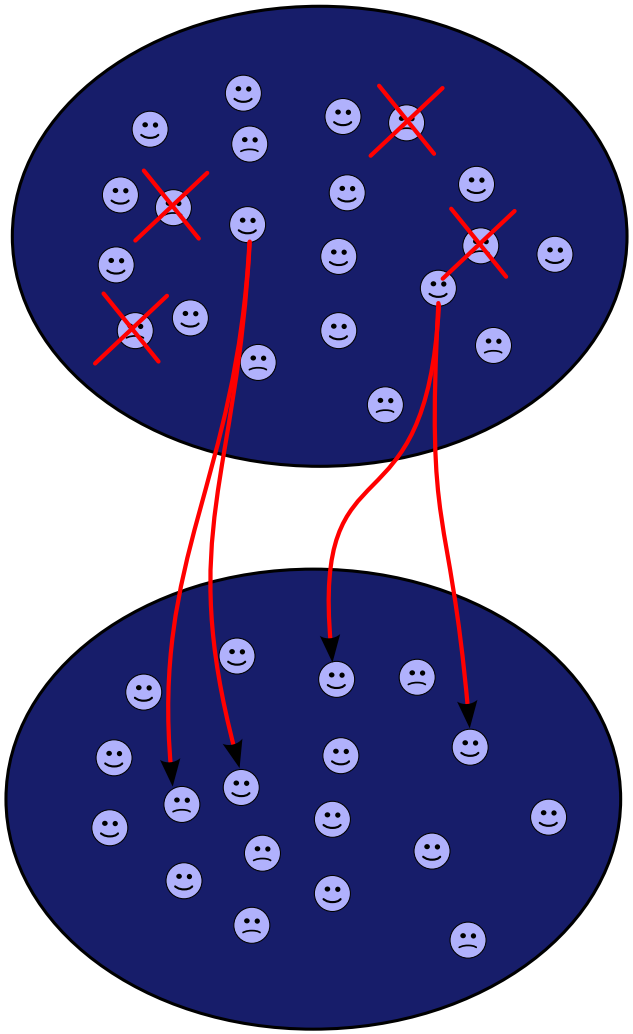
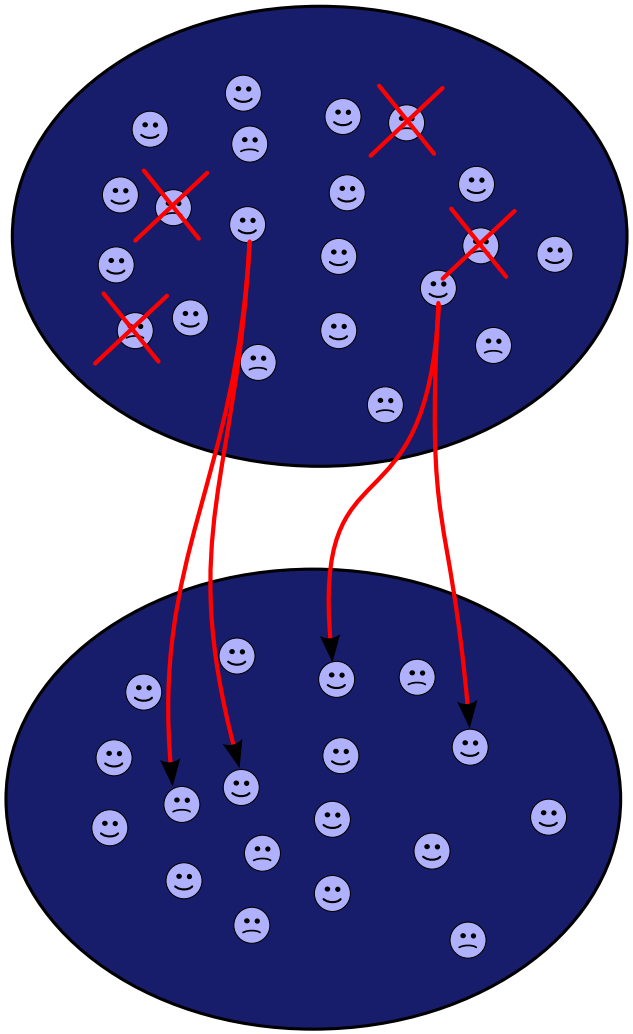
Parallel optimization inspired by biological evolution

- Populations of Hypotheses
- Selection Process
- Local Variation

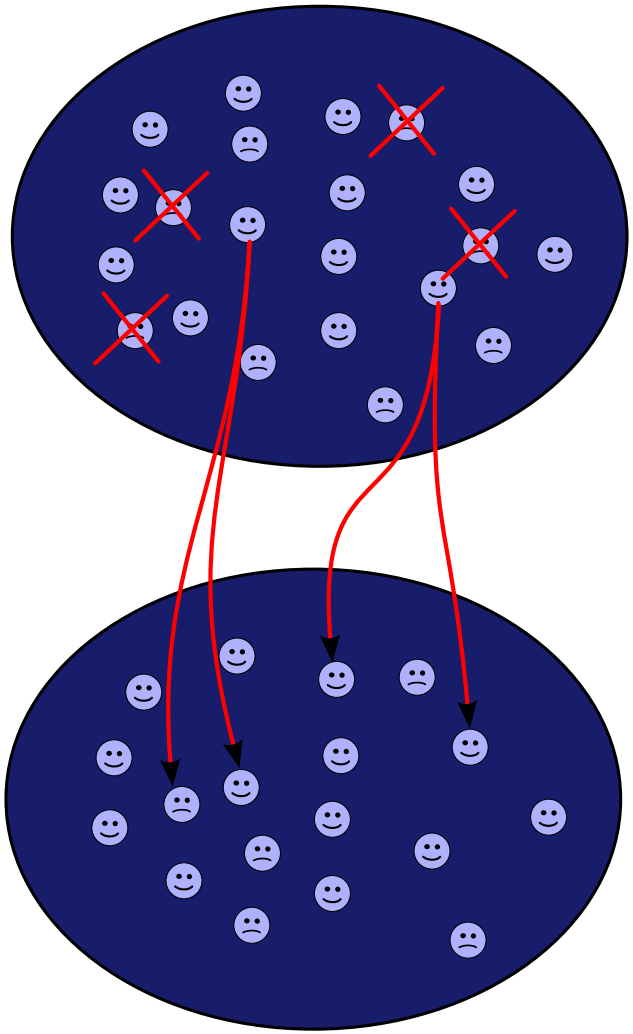




- Population of Individuals



- Population of Individuals
- Selection of the best individuals



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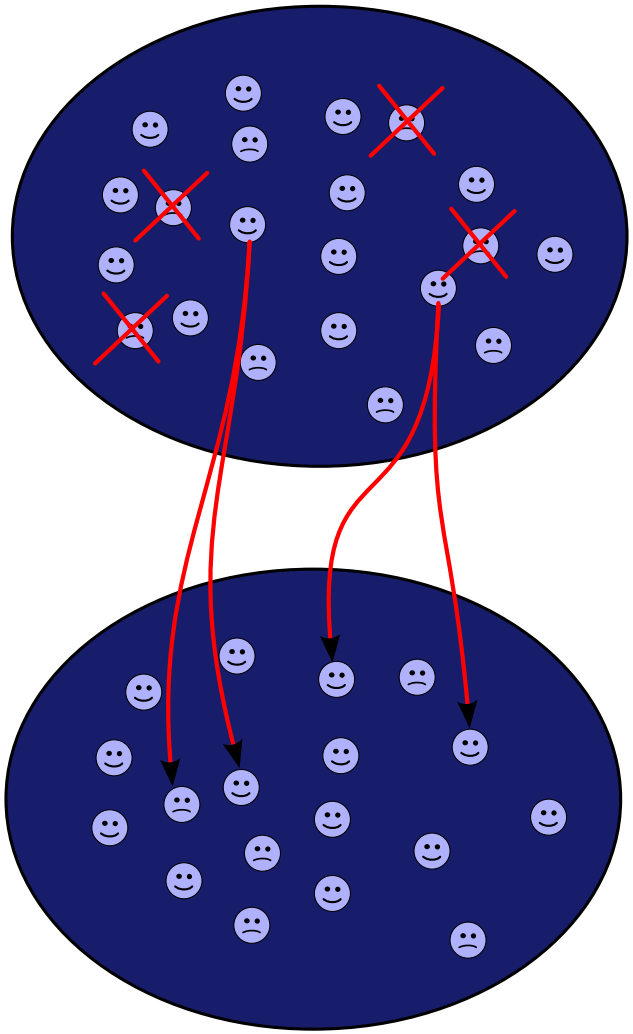
- Variation creates new individuals



- Population of Individuals
- Selection of the best individuals
- Variation creates new individuals
- New Generations created iteratively

How are different hypotheses stored?

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Chromosomes — Binary Strings

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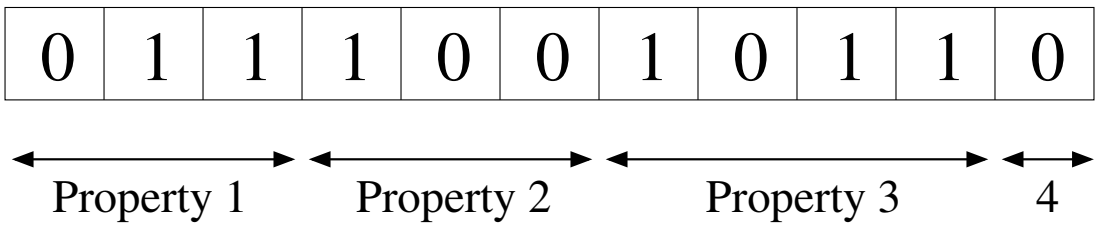

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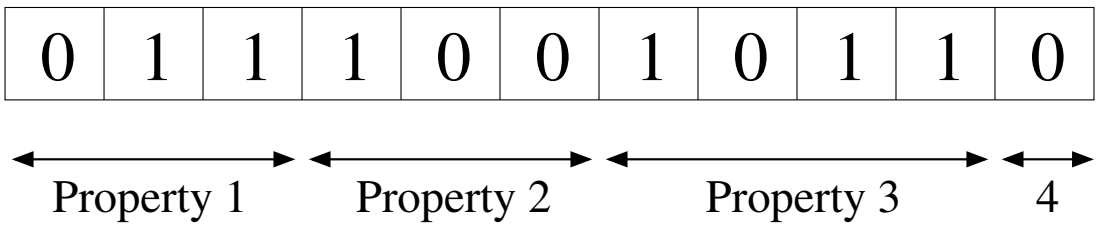

- Genotype
  The actual representation (the chromosome)
- Fenotype
  Properties of the individual (interpretation)

Example: Optimal choice of edges in a graph

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The edges are encoded as a bit string

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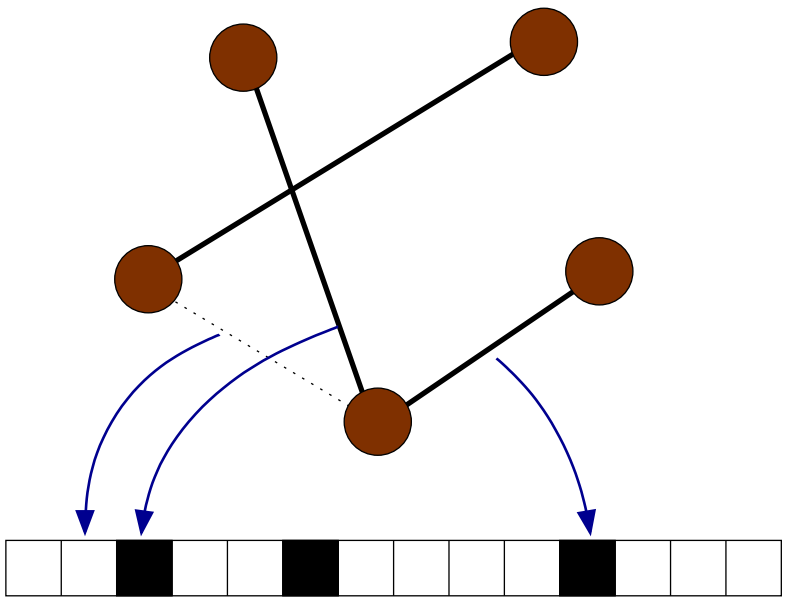

Do we *have* to use bit strings?

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Variants:

- Other integers than only 0/1

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Do we *have* to use bit strings?

Variants:

- Other integers than only 0/1
- Real numbers
- Variable length
- Tree structures

Fitness Function

Measure of how good the hypothesis is

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Evaluating the fitness functions is normally the *most time consuming* part of a genetic algorithm

Selection

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Basic idea: Preserve individuals with a high fitness

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  Probability of survival proportional to f

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Basic idea: Preserve individuals with a high fitness

- Roulette selection
  Probability of survival proportional to f
- Ranking selection
  Selection based on order instead of the actual fitness value
- Tournament selection
  Random pairs are formed and the one with highest fitness survives
- Elitism
  The best individuals in a generation are guaranteed to survive

- Mutations
  Small random modifications
- Crossovers
  Mixing of individuals content

Mutations

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- Make random changes to the contents of the chromosome

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- Make random changes to the contents of the chromosome
- Choice of coding makes a big difference

Crossovers

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- Select two individuals with high fitness
- Exchange parts of the chromosome with each other

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One-point crossover
Multi-point crossover

Application on ordinary optimization problems

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- Mutations
  Redistribution parallel to the x and y axis
- Crossovers
  New points with x from one parent and y from the other

Example: Optimized code generation from a compiler

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ACOVEA — Analysis of Compiler Options via Evolutionary Algorithms

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Software for finding the optimal compiler options for a given C program

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Ordinary programming languages are not suitable

- Tree with operators
- List of instructions

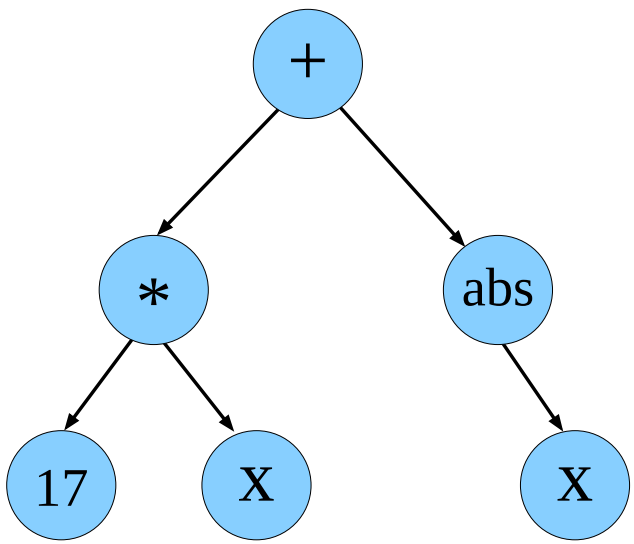
Example

Function Approximation

Example

Function Approximation

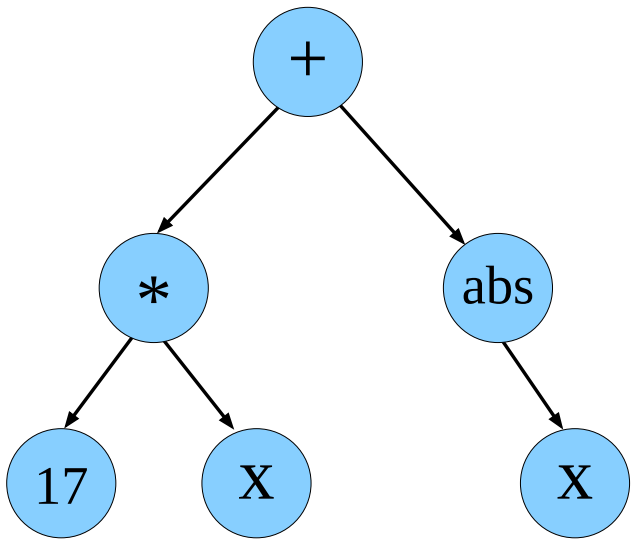
Representation of the program



Example

Function Approximation

Representation of the program



- Mutations

Example

Function Approximation

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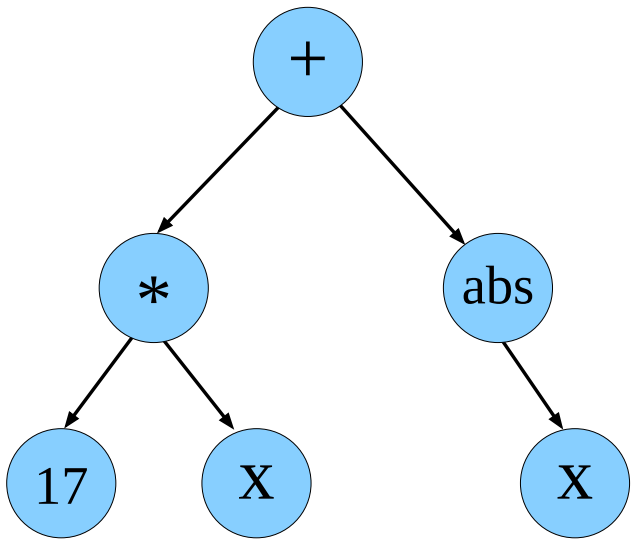
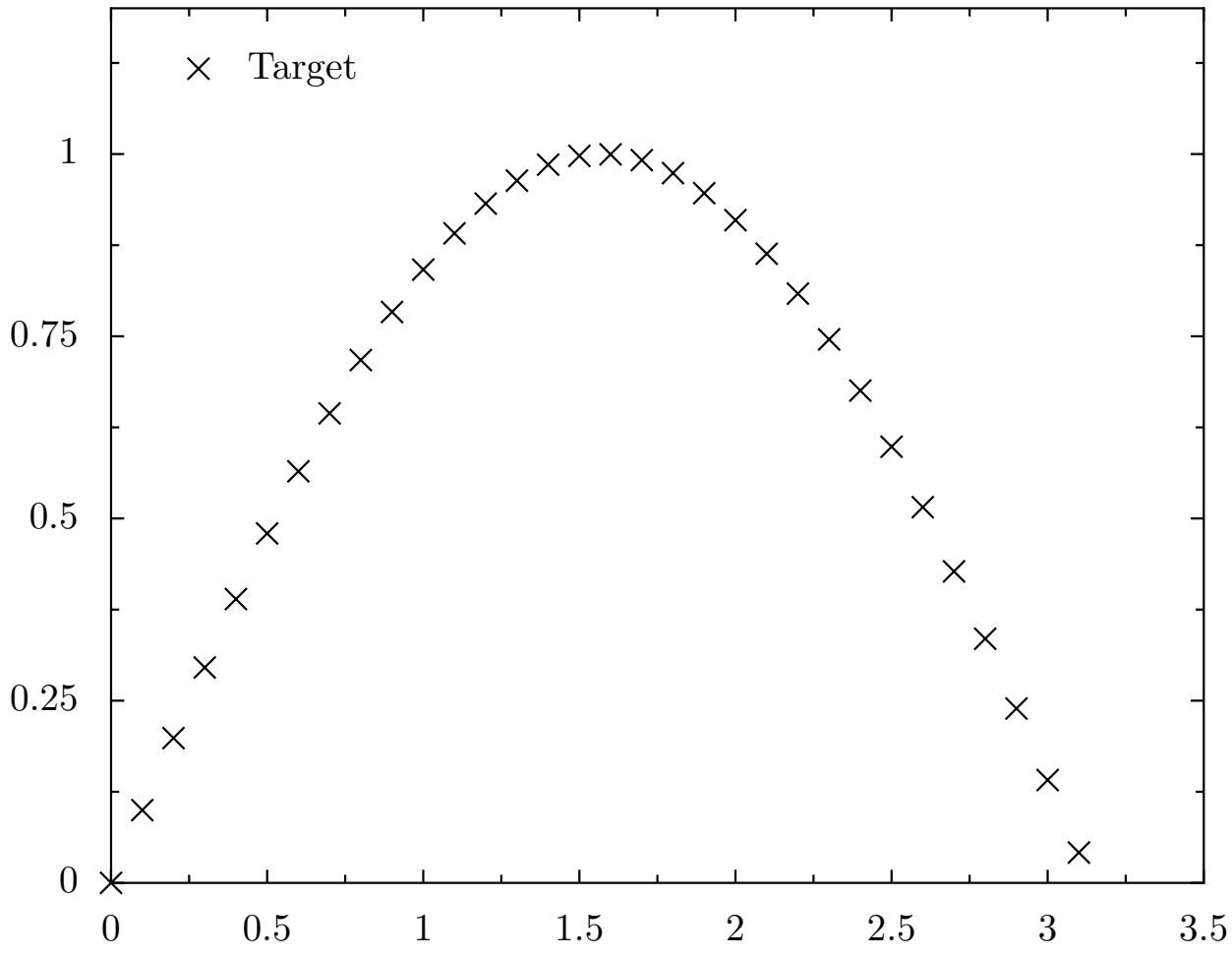
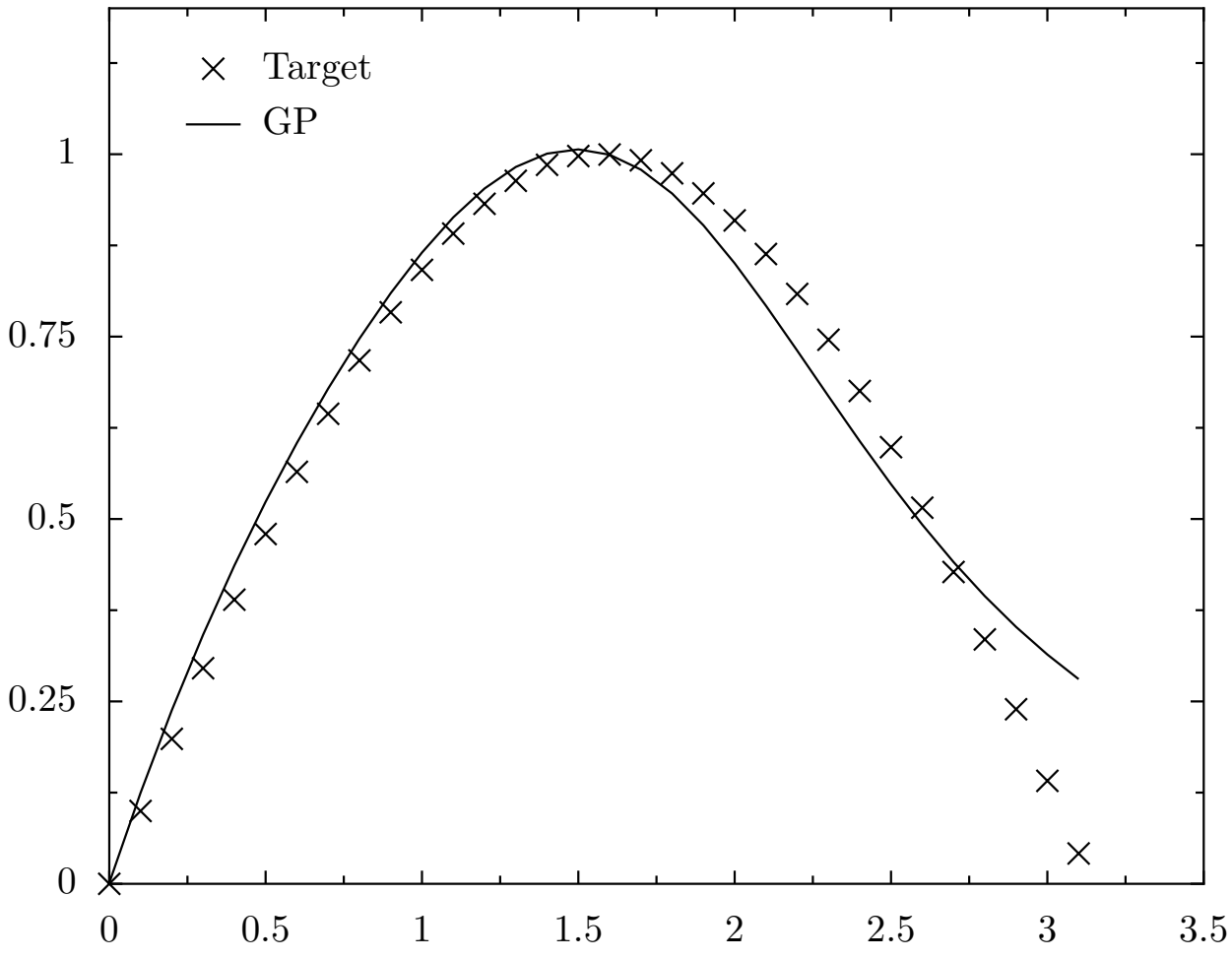


- Mutations
- Crossovers

Goal Function



Solution found by the algorithm



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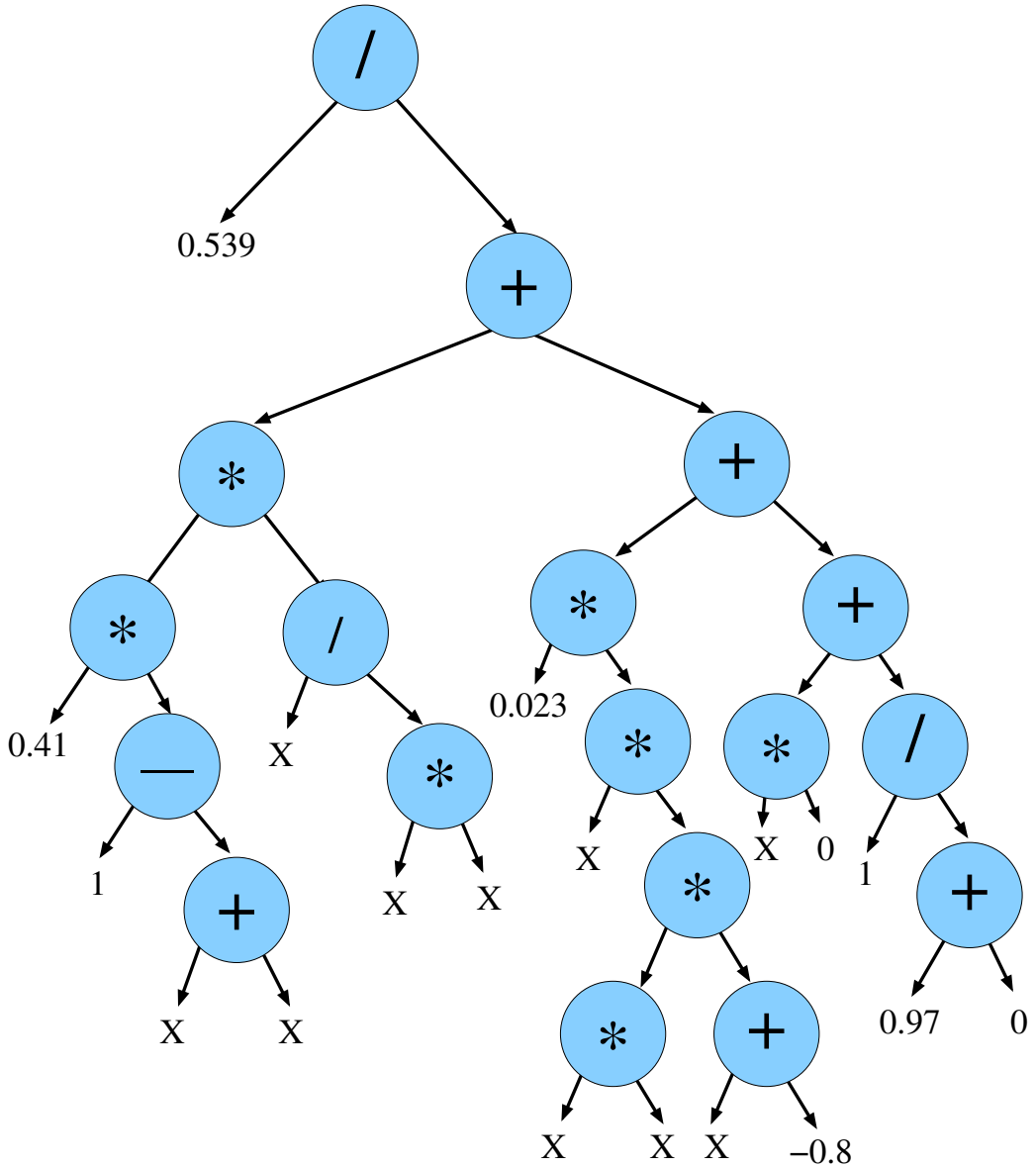

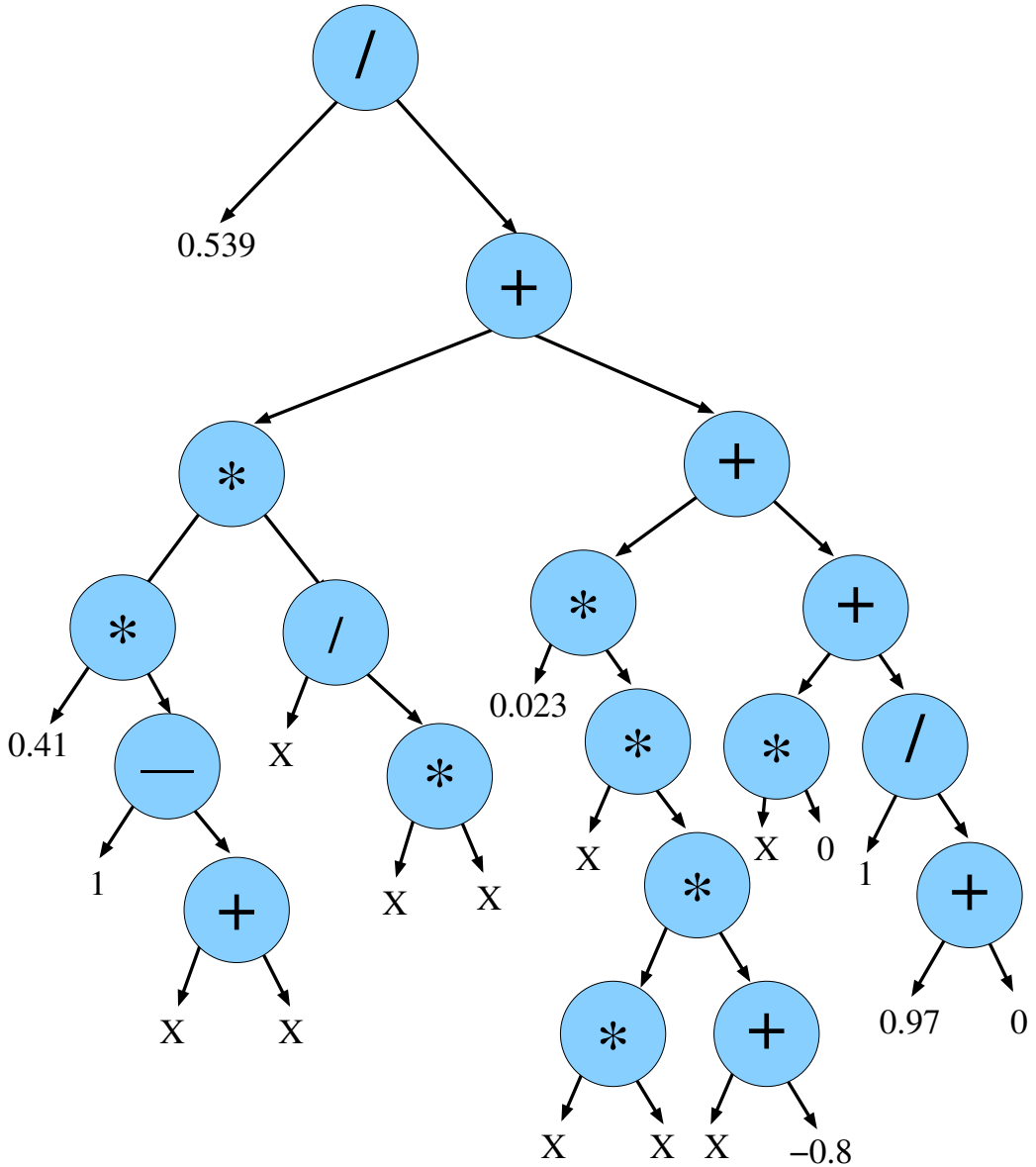

Bloating

Accumulation of unnecessary parts in chromosomes with variable length