An Introduction to Neuroevolution

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Evolutionary, Genetic and Neuroevolution Algorithms

Evolutionary Algorithms

„A generic population-based and meta-heuristically optimized algorithmic solution to an applied problem“

(Source: [16])

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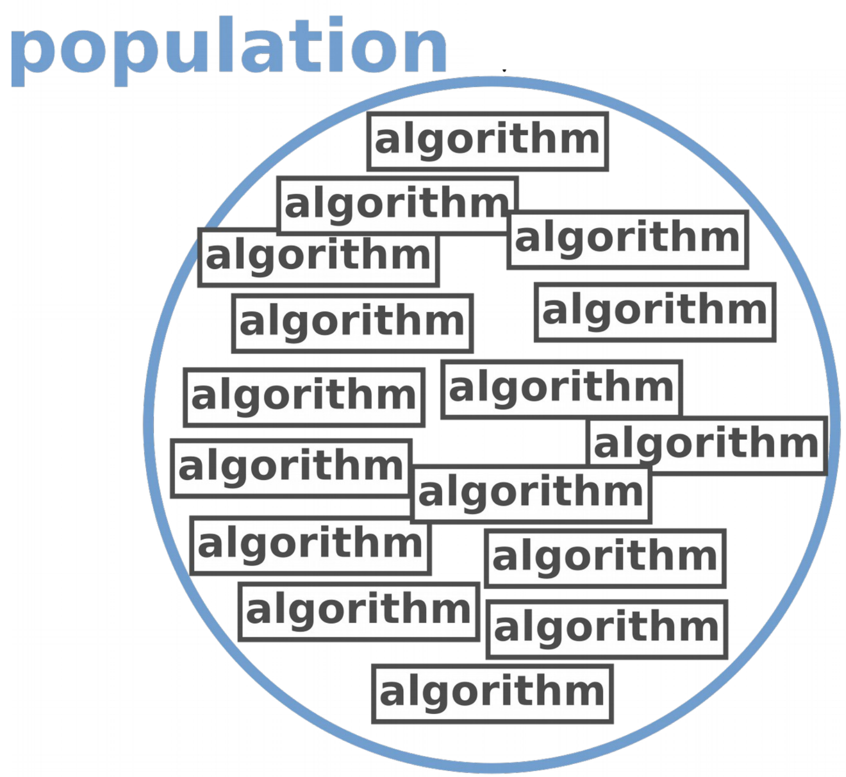

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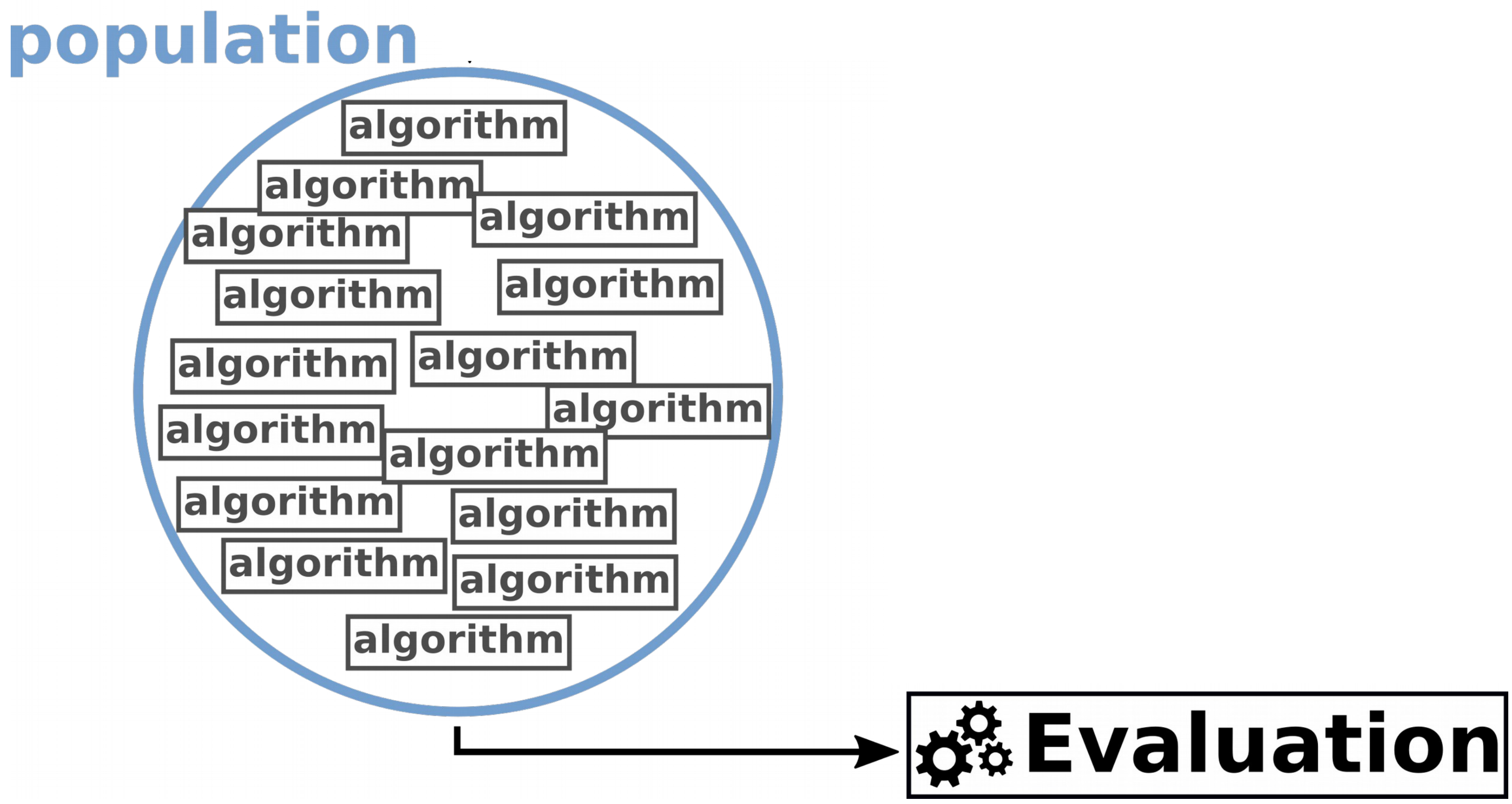

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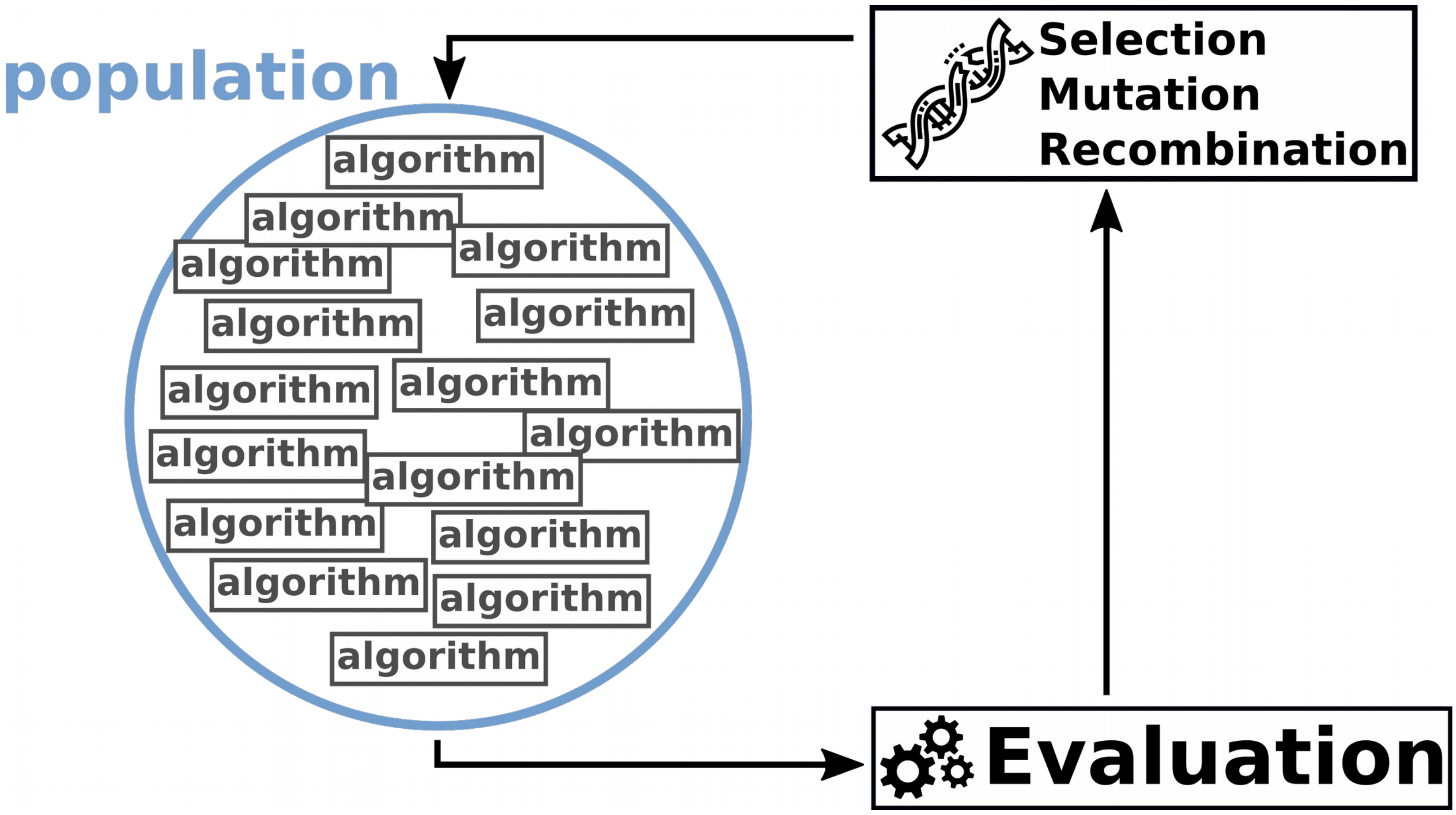


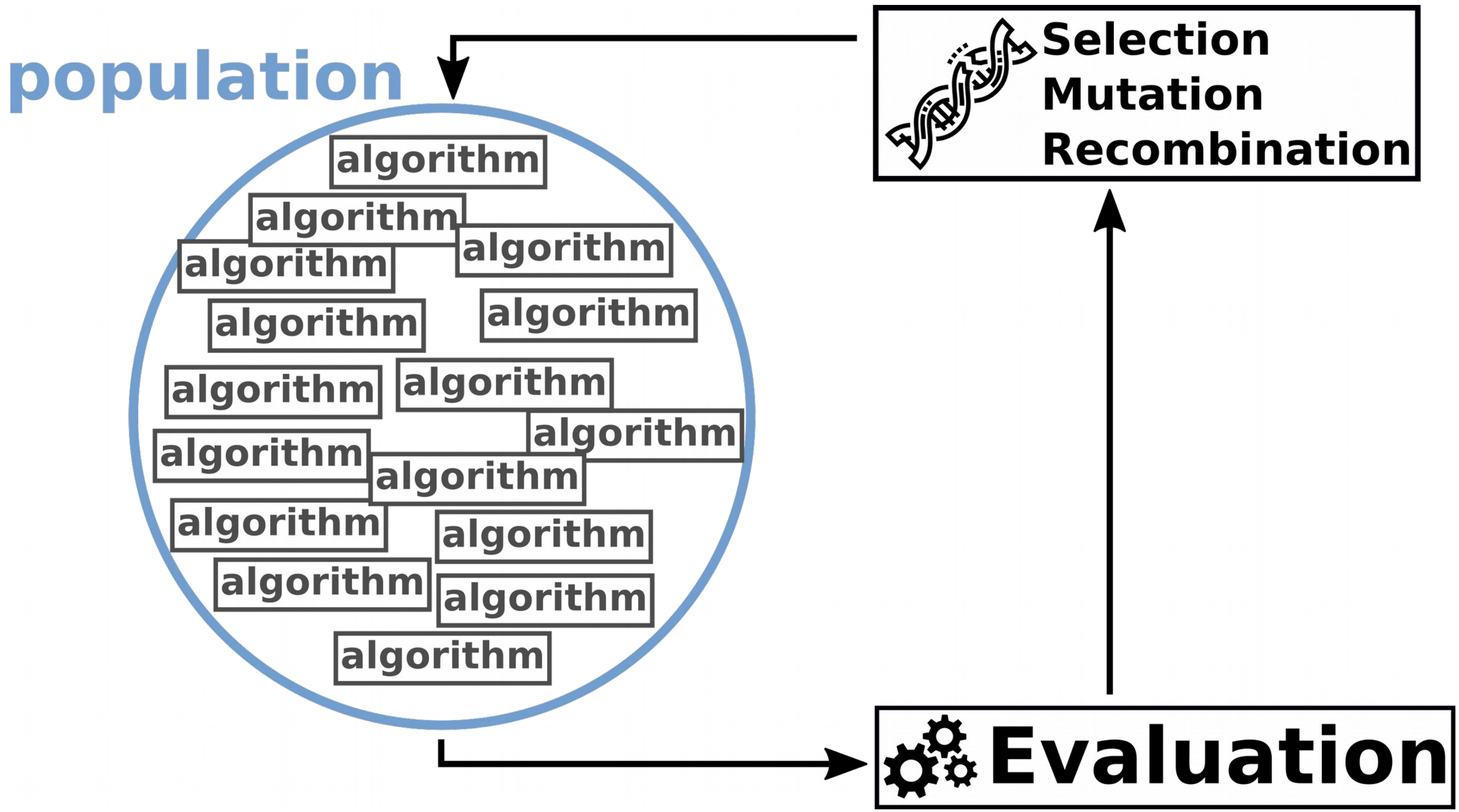
Evolutionary Algorithms – Mutation

```
max_number = 0
for number in list:
    if number > max_number:
        number++

return max_number
```

Evolutionary Algorithms – Mutation

```
max_number = 0
for number in list:
    if number > max_number:
        number++
        max_number = number

return max_number
```

Evolutionary Algorithms



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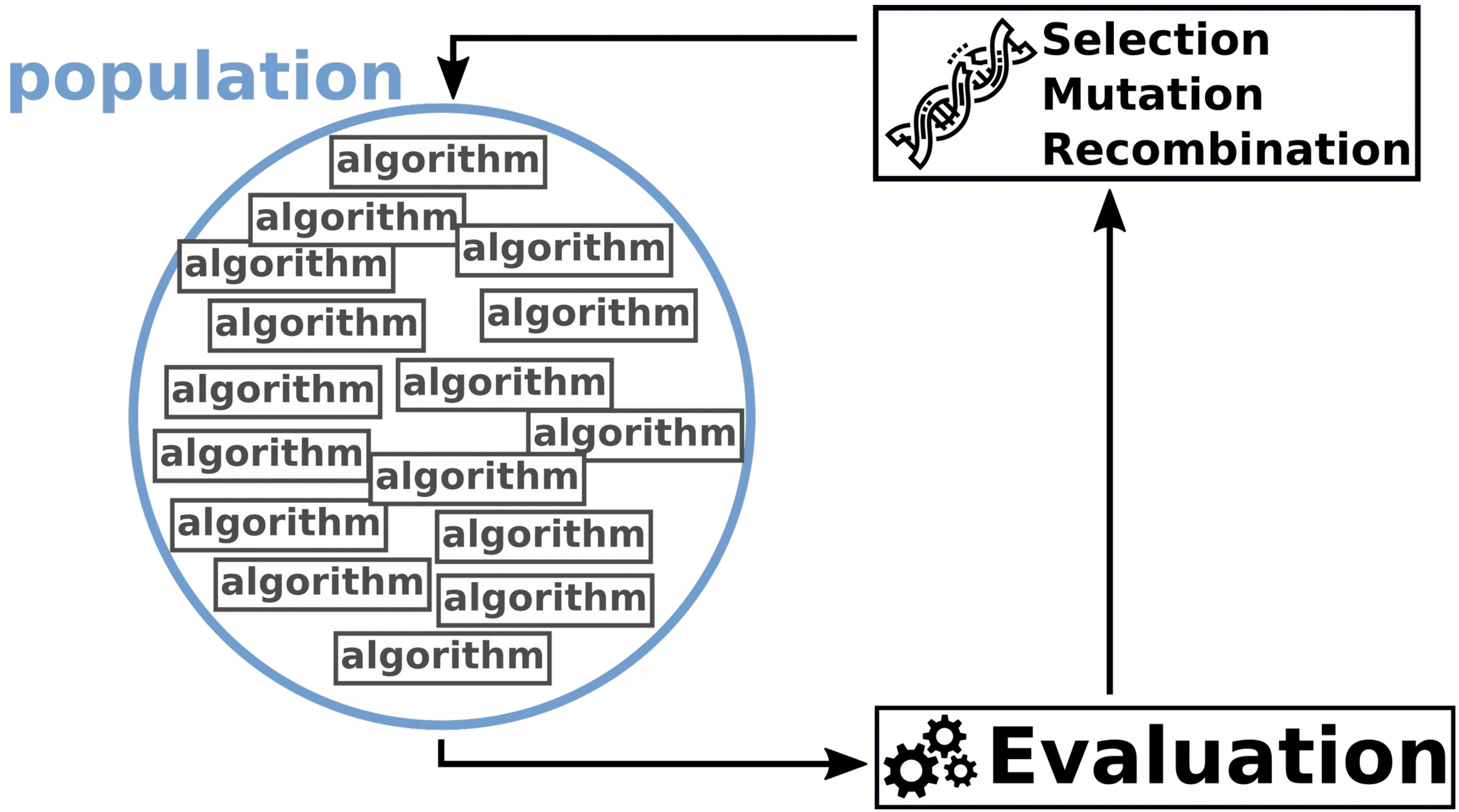


Evolutionary Algorithms

„A generic population-based and meta-heuristically optimized al-gorithmic solution to an applied problem“

(Source: [16])

Genetic Algorithms

```
max_number = 0
for number in list:
    if number > max_number:
        number++

return max_number
```

(a)

```
0010 0000 0100 1010 0011 0111
```

(b)

Genetic Algorithms

```
max_number = 0
for number in list:
   if number > max_number:
        number++

return max_number
```

(a)

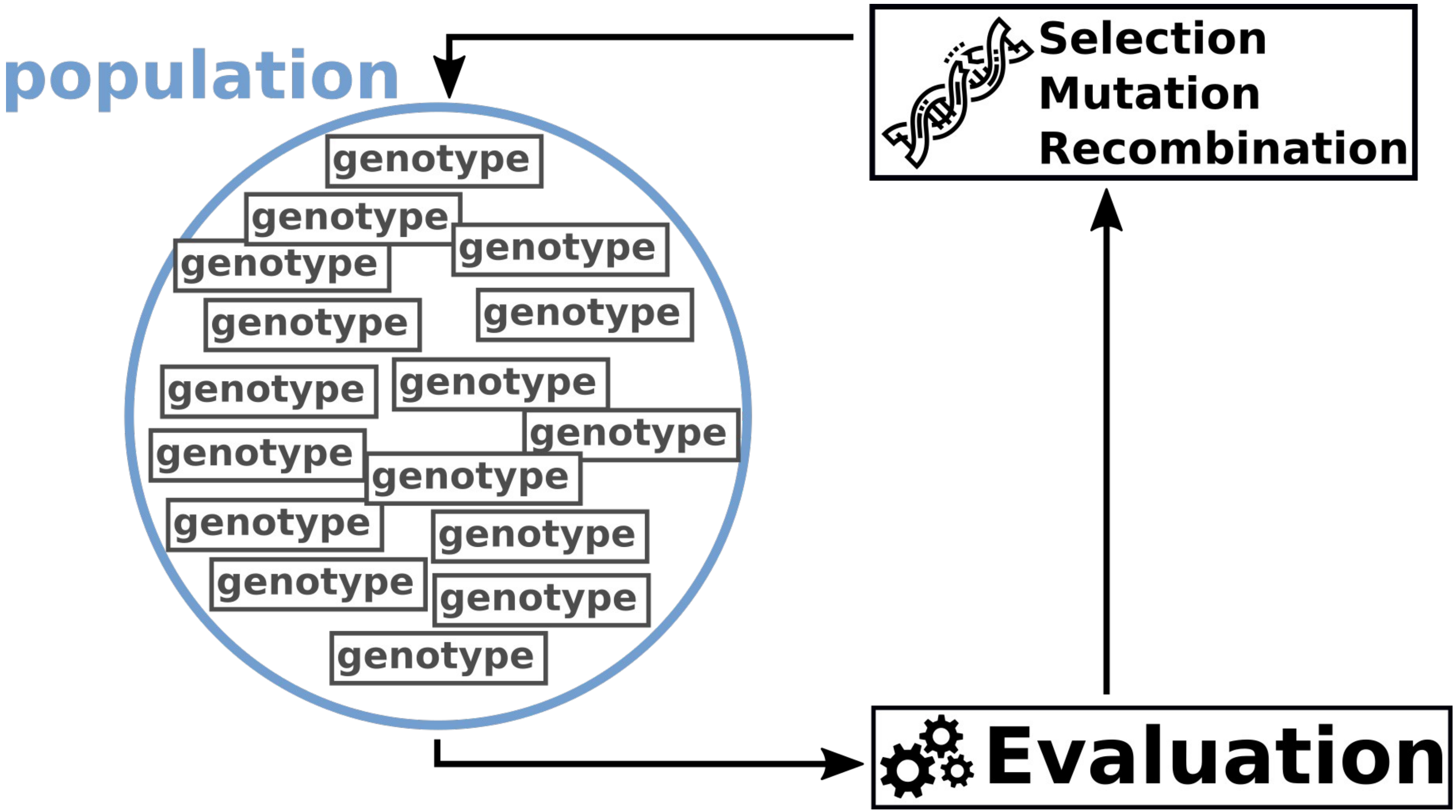
[phenotype]

```
0010 0000 0100 1010 0011 0111
```

(b)

[genotype]

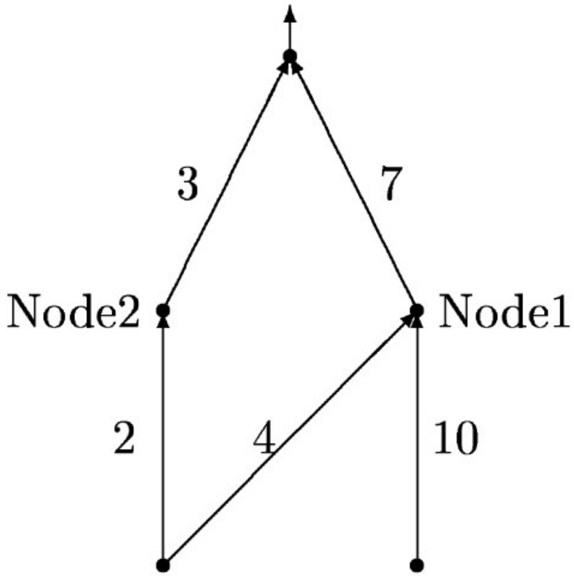
Genetic Algorithms



Neuroevolution

„A *neuroevolution algorithm* is a *genetic algorithm*, whose search-space (genotypes) consists **only** of artificial neural networks. A *genetic algorithm* in turn is an *evolutionary algorithm* that evolves genotypes through **mutation, recombination and selection.**“

Neuroevolution



(a)

[phenotype]

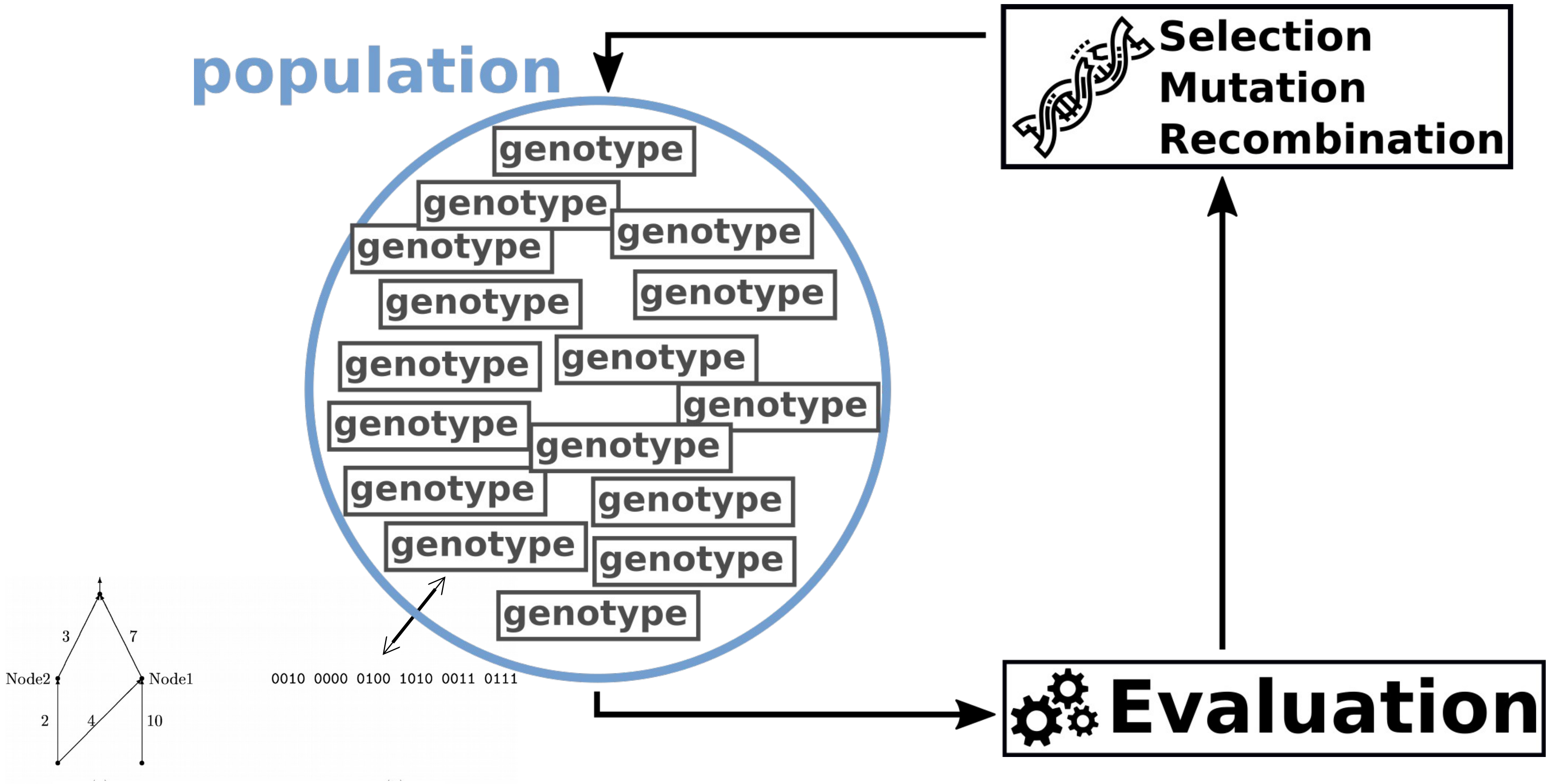
0010 0000 0100 1010 0011 0111

(b)

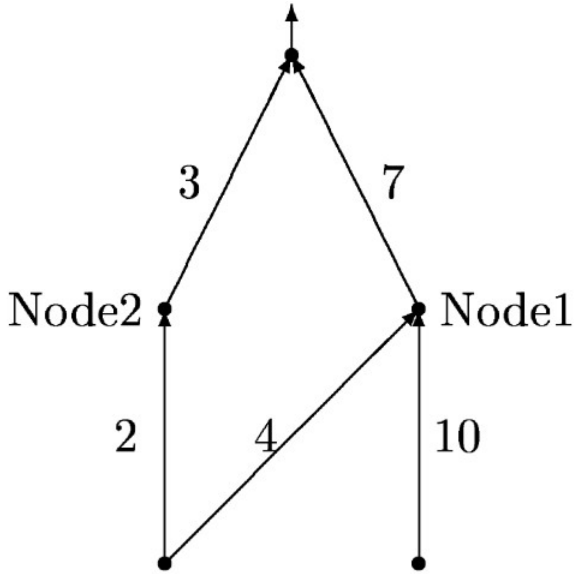
[genotype]

Source: [4]

Neuroevolution



Neuroevolution – Mutation



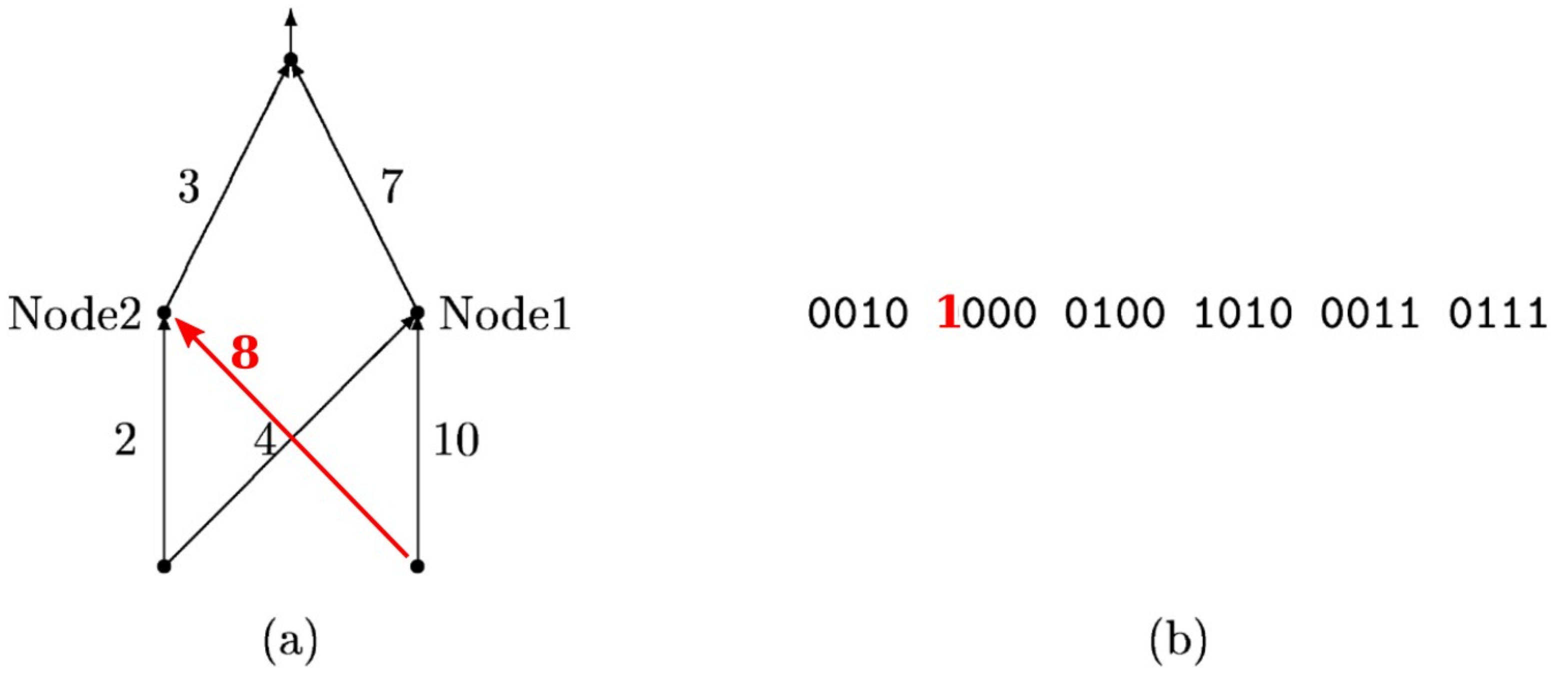
(a)

0010 0000 0100 1010 0011 0111

(b)

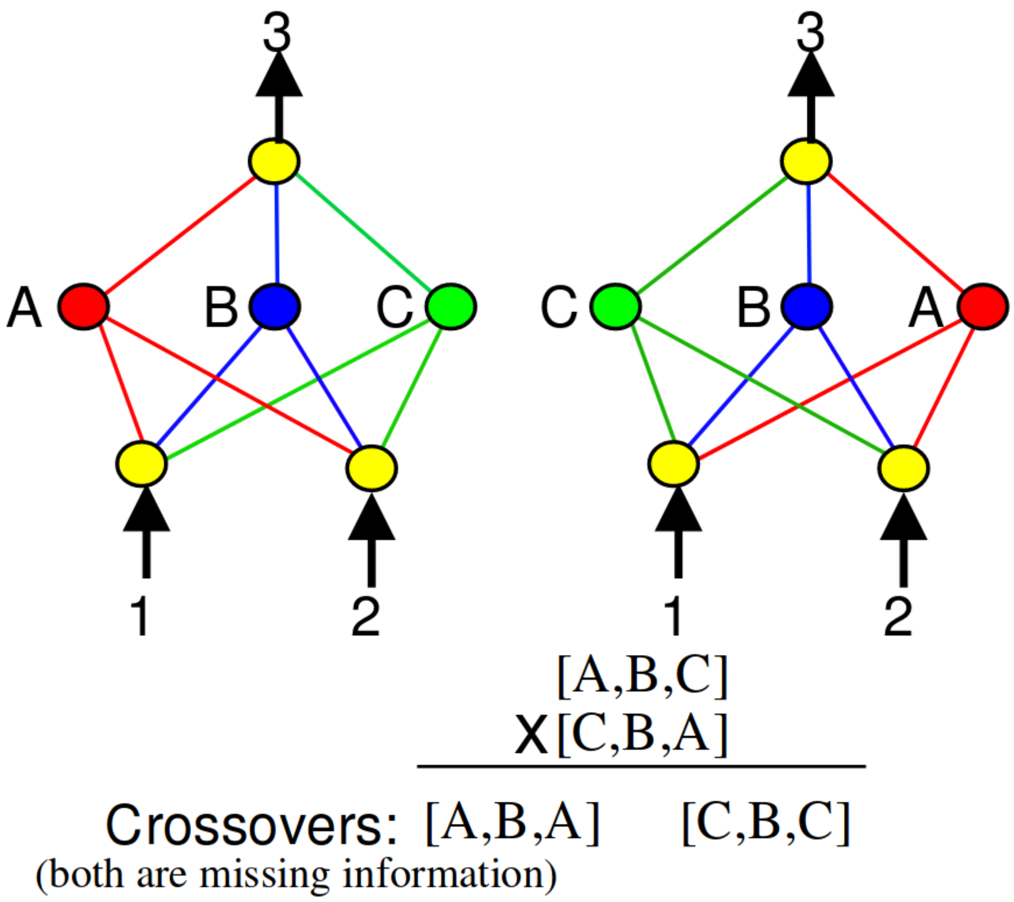
Source: [4]

Neuroevolution – Mutation



Source: [4], modified

Neuroevolution – Recombination



Source: [7]

Neuroevolution – Selection

Periodical **removal** of the **lowest performing algorithms** in the population

Neuroevolution

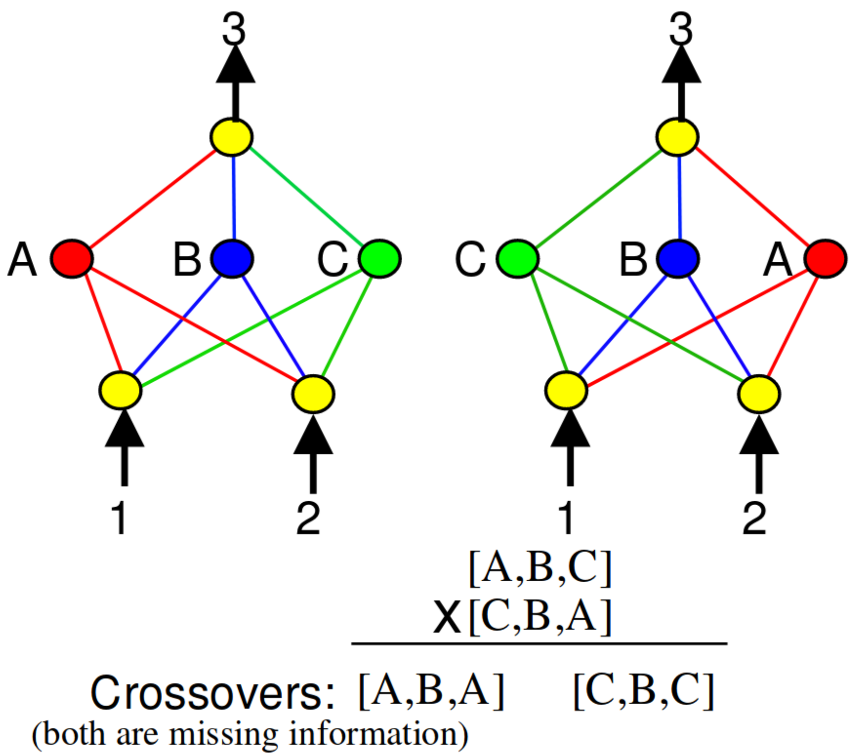
„Neuroevolution is the - possibly boundless - process in which by the means of a genetic algorithm the population of artificial neural networks is increasingly optimized in order to maximize the accuracy or fitness of the best ANN.“

Neuroevolution of Augmenting Topologies (abbr. NEAT)

Neuroevolution of Augmenting Topologies

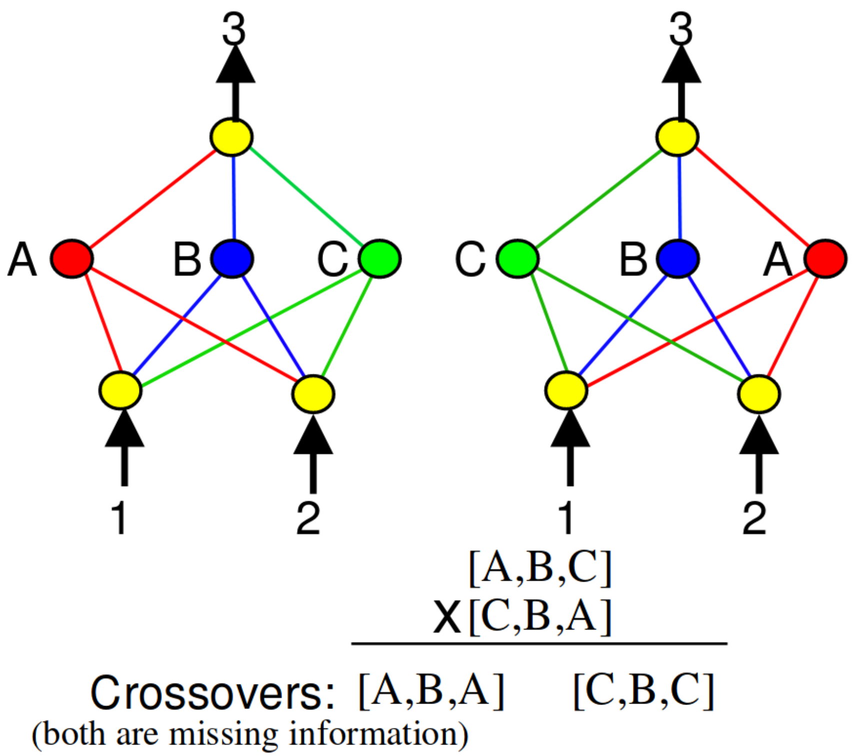
- Published in 2002 by Kenneth O.Stanley and Risto Miikkulainen [6]
- Outperformed all contemporary neuroevolution systems when introduced [8]
- Achieved performance because it solved a fundamental problem in neuroevolution, while still being elegantly simple [8, chap. 3.2]
- Still one of the most prominent neuroevolution systems today and considered a benchmark in the field [22]

NEAT – Principle of Historical Markings



Source: [7]

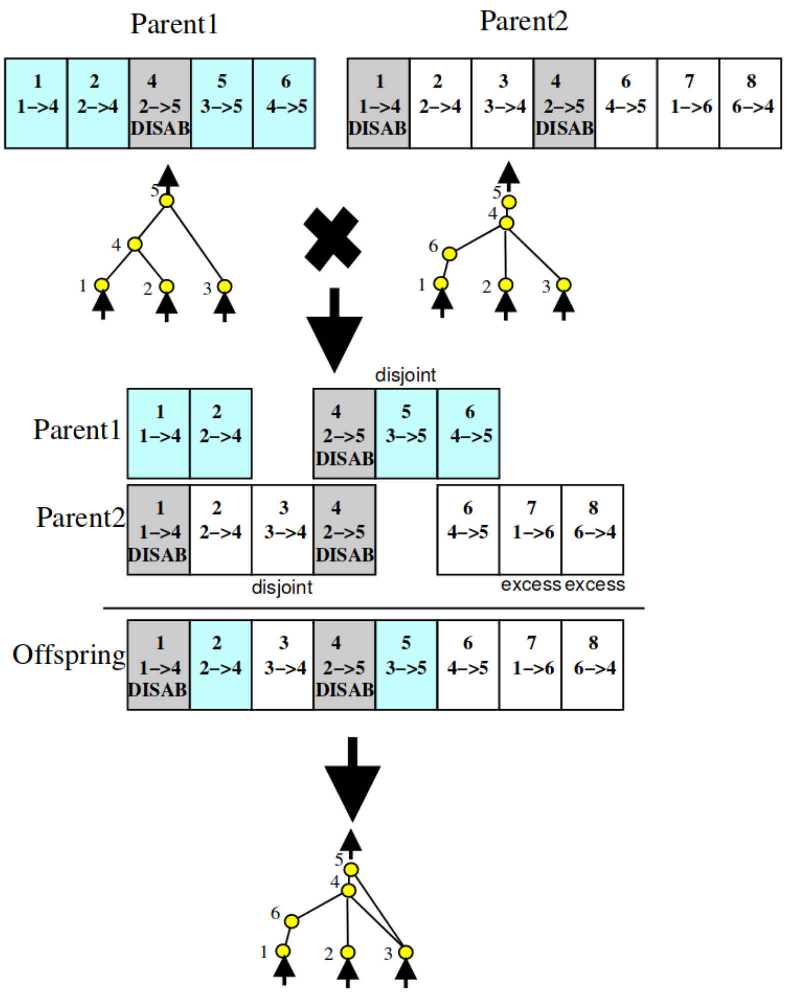
NEAT – Principle of Historical Markings



Source: [7]

Principle: „Enable information-preserving crossovers by keeping track of genes – and their presence in genomes – by introducing ***innovation numbers***"

NEAT – Principle of Historical Markings



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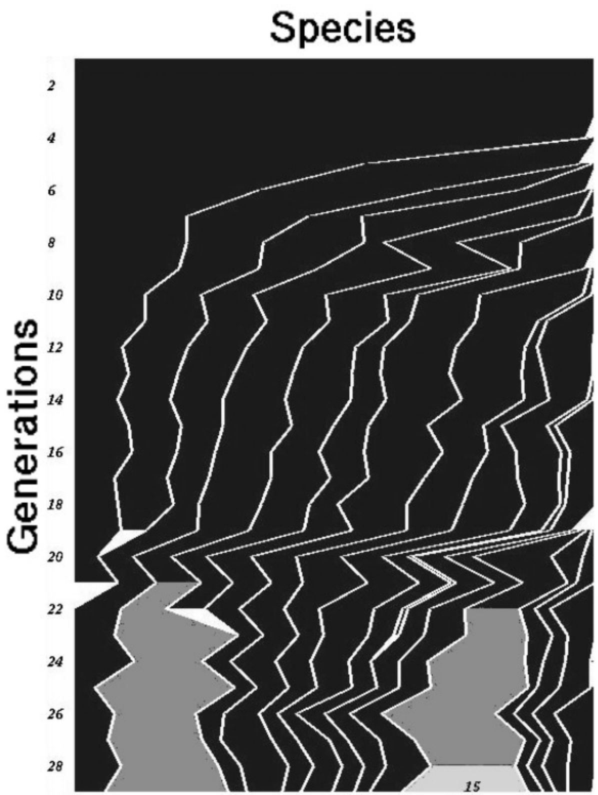
NEAT – Principle of Speciation

Principle: „Protect innovation by **dividing population into niches** according to their distinctiveness and only comparing niches against one another"

NEAT – Principle of Speciation



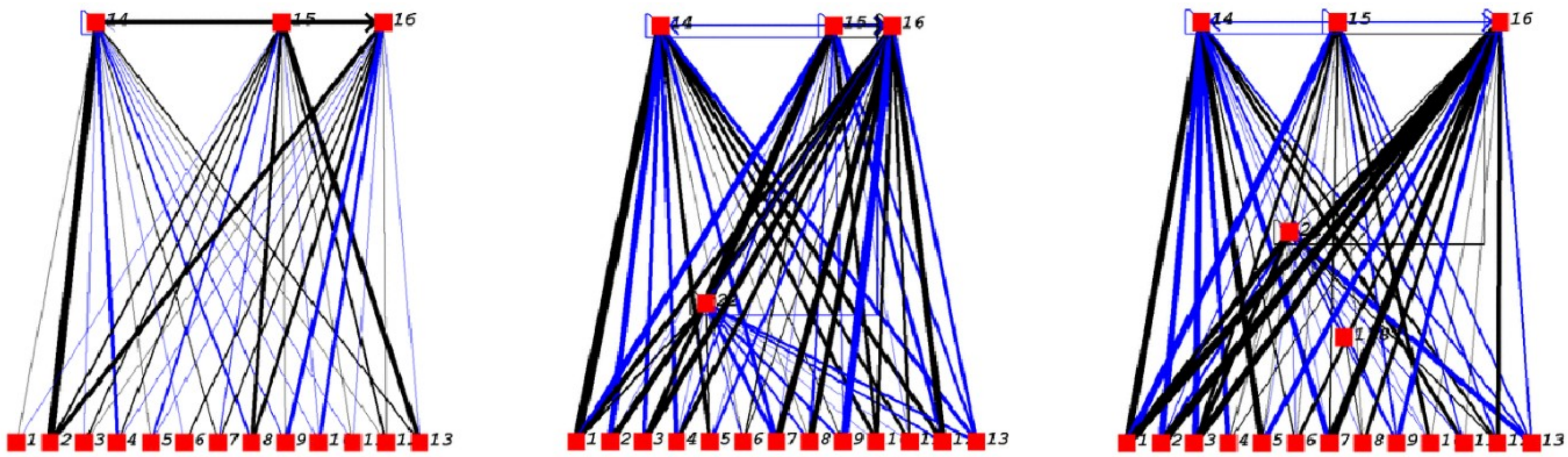
Source: [8]

Principle: „Protect innovation by **dividing population into niches** according to their distinctiveness and only comparing niches against one another"

NEAT – Principle of Complexification

Principle: „Keep topology purposeful by providing a **minimal initial population**, which is **only expanded upon**“

NEAT – Principle of Complexification



(a) Generation 100 (b) Generation 267 (c) Generation 315

Source: [8]

Principle: „Keep topology purposeful by providing a **minimal initial population**, which is **only expanded upon**“

Neuroevolution of Augmenting Topologies

The key aspects of NEAT as a neuroevolution system:

- Facilitates innovation through lossless recombination (*Principle of Historical Markings*)
- Protects innovation through speciation (*Principle of Speciation*)
- Keeps solutions minimal (*Principle of Complexification*)

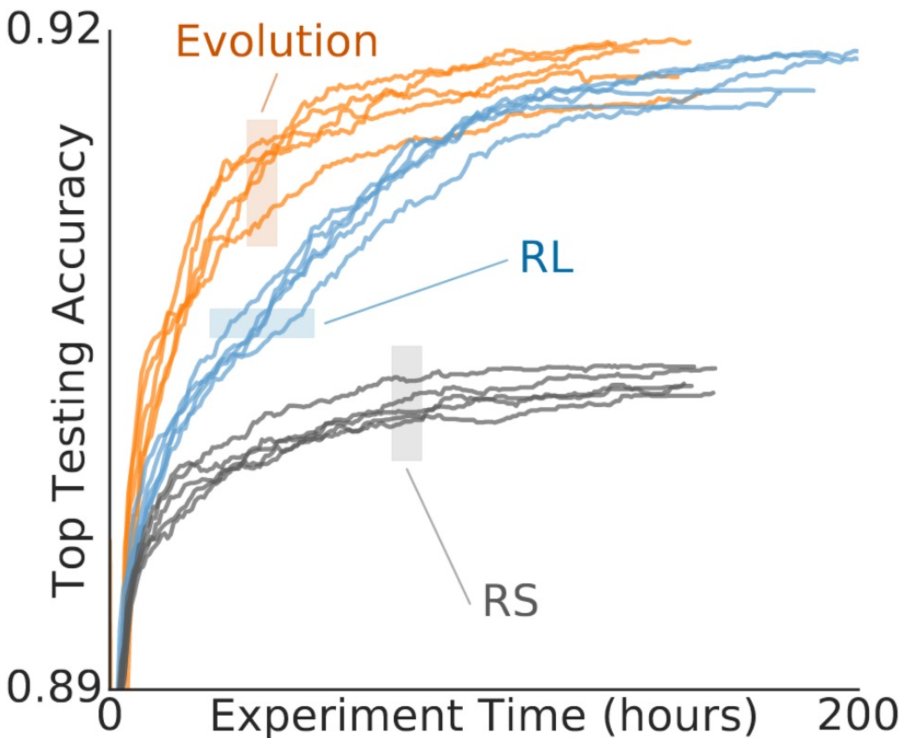
Neuroevolution Performance and Practical Applications

Neuroevolution – Performance

Model	# Parameters	# Multiply-Adds	Top-1 / Top-5 Accuracy (%)
Incep-ResNet V2 [44]	55.8M	13.2B	80.4 / 95.3
ResNeXt-101 [48]	83.6M	31.5B	80.9 / 95.6
PolyNet [51]	92.0M	34.7B	81.3 / 95.8
Dual-Path-Net-131 [7]	79.5M	32.0B	81.5 / 95.8
GeNet-2 [47]*	156M	–	72.1 / 90.4
Block-QNN-B [52]*	–	–	75.7 / 92.6
Hierarchical [30]*	64M	–	79.7 / 94.8
NASNet-A [54]	88.9M	23.8B	82.7 / 96.2
PNASNet-5 [29]	86.1M	25.0B	82.9 / 96.2
AmoebaNet-A (N=6, F=190)*	86.7M	23.1B	82.8 / 96.1
AmoebaNet-A (N=6, F=448)*	469M	104B	83.9 / 96.6

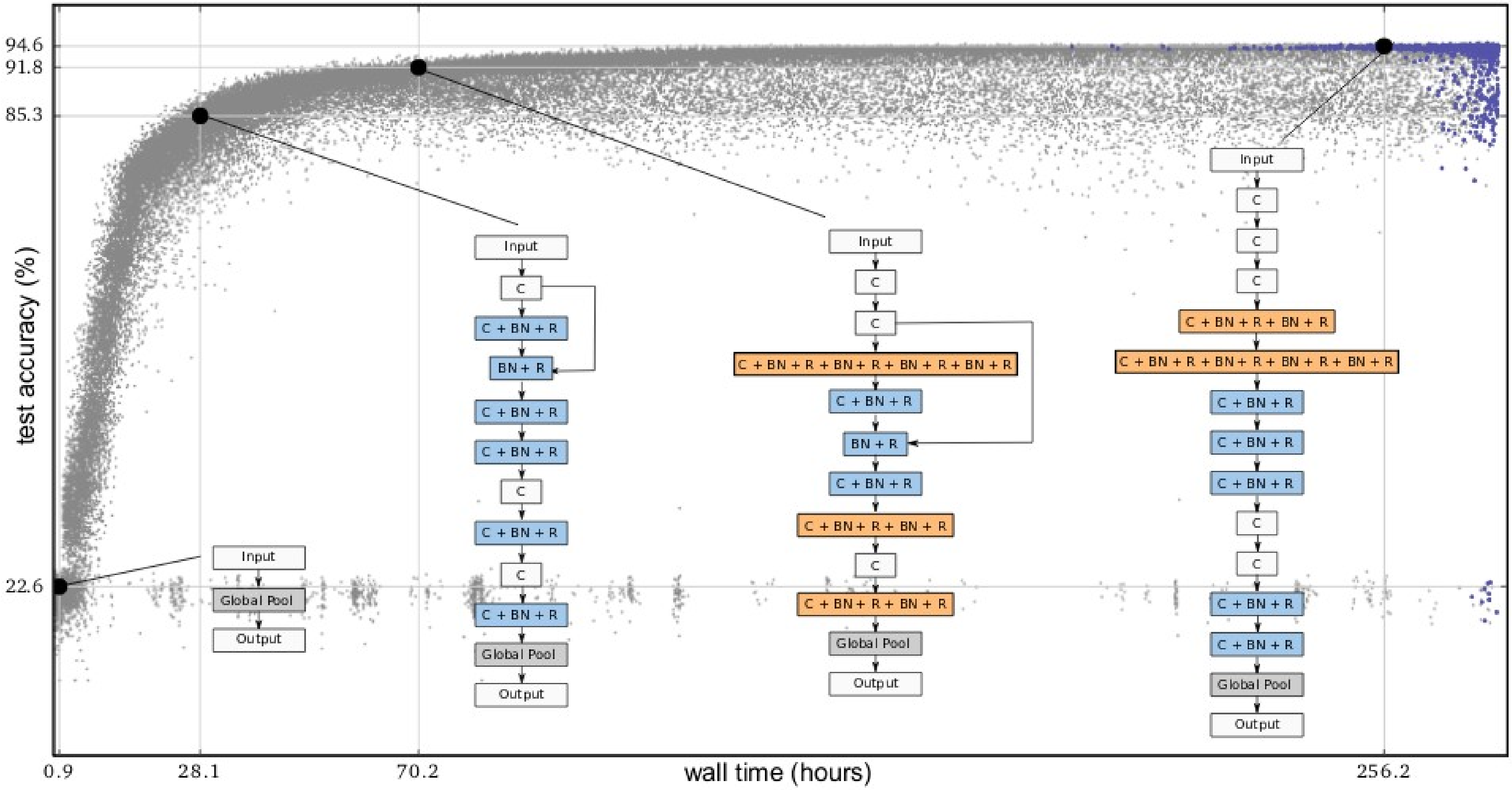
Source: [23]

Neuroevolution – Performance



Source: [23]

Neuroevolution – Performance



Source: [23]

Neuroevolution – Practical Example

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