Biologically-inspired algorithms and models

6. Cooperative and competitive coevolution

Maciej Komosinski

Coevolution

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Question: how does this affect the fitness function landscape?

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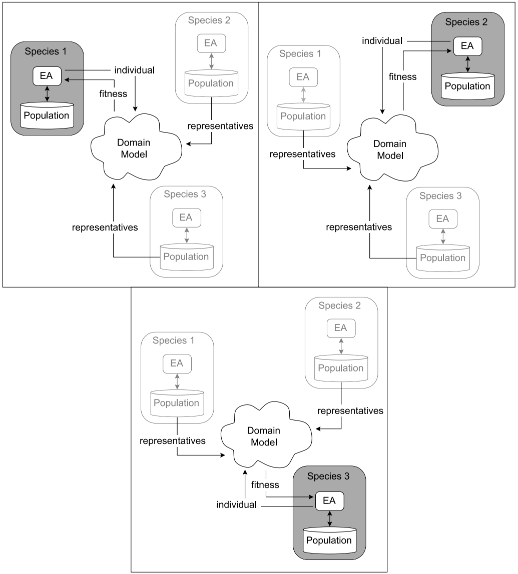
- Suppose we divide the solution into components that go into separate (genetically independent) populations – so the genetic representation and operators in each population may be completely different. How to evaluate the quality of each part?

The architecture explored by Potter and De Jong



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  - Adding a new species, for example initialized randomly: when the system is in stagnation – no increase in the quality of the best individual.
  - Removing an existing species: for example when its contribution to cooperation (the difference between the quality of individuals with and without it) is below a specified threshold.

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T_1:

```
11111111111111111111111111111111################################
################################11111111111111111111111111111111
```

T_2:

```
1111111111111111################################################
################1111111111111111################################
################################1111111111111111################
################################################1111111111111111
```

T_3:

```
11111111########################################################
########11111111################################################
################11111111########################################
########################11111111################################
################################11111111########################
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################################################11111111########
########################################################11111111
```

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1111111111111111################################################
################1111111111111111################################
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```

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11111111########################################################
########11111111################################################
################11111111########################################
########################11111111################################
################################11111111########################
########################################11111111################
################################################11111111########
########################################################11111111
```

Half-length

```
Species 1: 1111111111111111111111111111111110100110001000111111100010110111
Species 2: 0010000001001110110100001000100011111111111111111111111111111111
```

Quarter-length

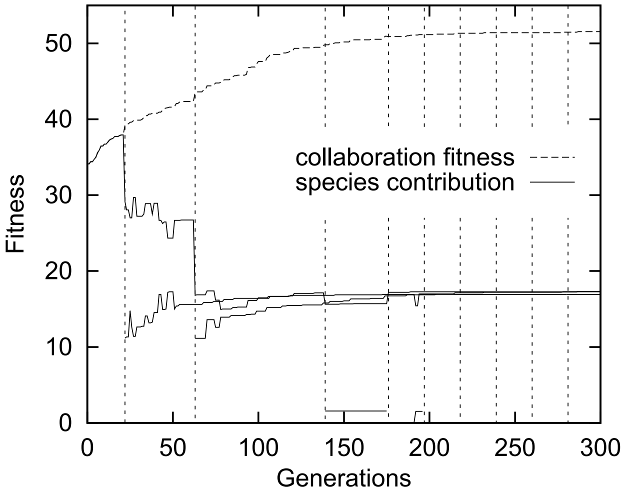
```
Species 1: 1111111111111111000110011001010011111111111111110111111111110111
Species 2: 1111111110111111111110101111111111111111111111111000010100010000
Species 3: 0101010101101101111111011111110100001010001011101111111111111111
Species 4: 1001101110011000111111111111111110110100010100011010101101101111
```

Eighth-length

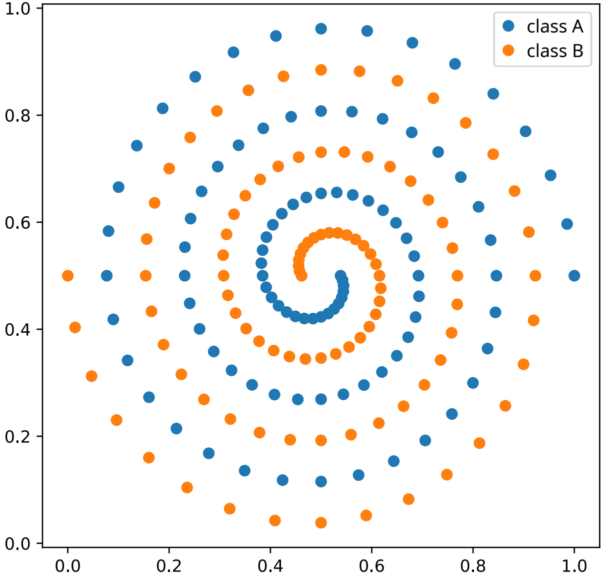
```
Species 1: 1100100011111110001011110100000011001011111111110011010011110010
Species 2: 1011111001010001111111110010101110010000101101111110111011010010
Species 3: 1010111100000111111101111001000011100110011110111101111100000111
Species 4: 0000111011111111101110010111101011111111010001101100010111111101
Species 5: 1101100100100010110000111100101111111111100101011001000111111111
Species 6: 0001011011111011011010001111111100110011111111101111111100110000
Species 7: 1111001011111110100000101011010100100100100010111000111111111111
Species 8: 1111111110001101111000001111111101011010110111101100001111101010
```

[PD00] Experiment 1: binary string covering – coevolutionary run

Automatically determined number of species; vertical lines are the generations when a species was added as a result of detected stagnation (22, 63, 138) or removed due to its small contribution (oscillations starting from 176).

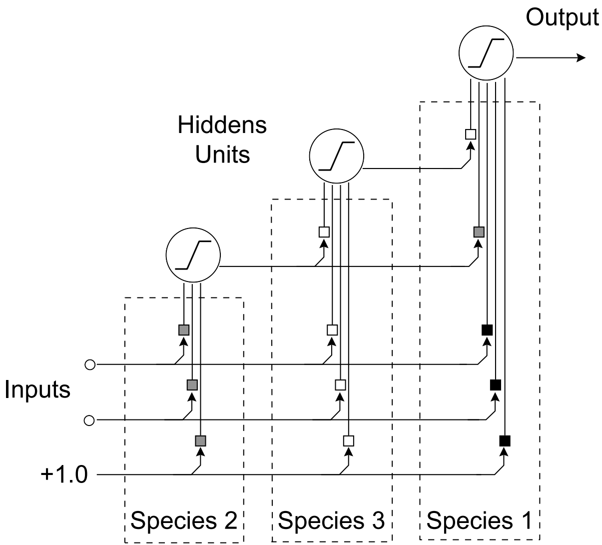


[PD00] Experiment 2: classification of a tricky dataset



[PD00] Experiment 2: classification of a tricky dataset

Cascade-correlation NN (cf. gradient boosting): a simple heuristics as a reference and coevolving species



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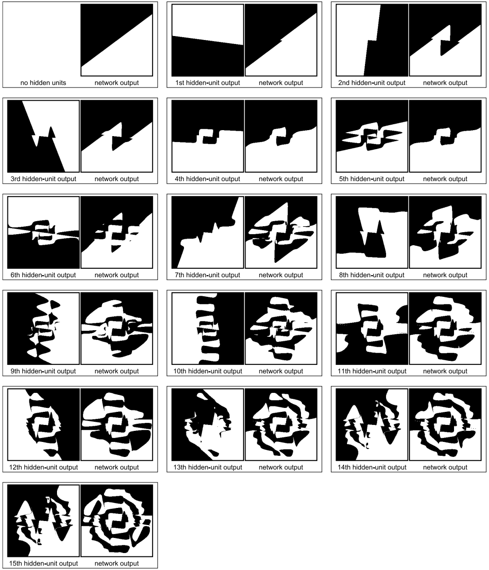
Cascade neural network results: the training heuristics



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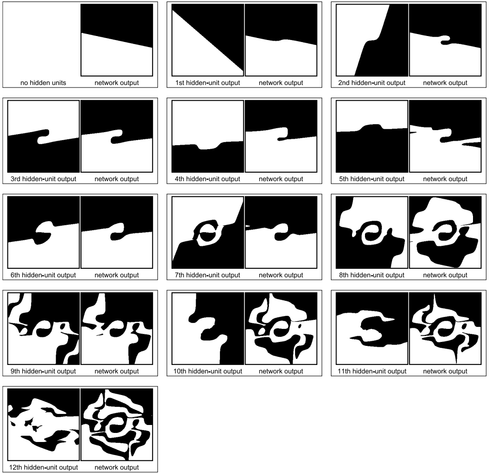
Cascade neural network results: cooperative coevolution



Competitive coevolution – the desired behavior

A typical example: coevolution (optimization) of a strategy [Elf+21]. An individual represents the knowledge reflected by a strategy (e.g., it may be the weights of the criteria used to evaluate the situation on the board in a game). The evaluation of an individual is obtained, for example, by playing many games against the other individuals (each playing according to their own strategy).

Discussion: if we start such a process and wait long enough, do we get the master strategy? If not, why not? (provide reasons – the list of possible problems).

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Difficulties: we want an *arms race* (perpetual competition), but we may end up in an *MSS – Mediocre Stable State* (stagnation – poor, lasting condition). Too strong an opponent will not allow to distinguish between average and bad solution; too weak – between average and good. The evaluation of each solution depends on the others (an external, objective "teacher" solves this problem while eliminating the advantages of coevolution). The evaluation of a strategy may not be transitive.

Competitive coevolution – problems and remedies

- Discussion of sample scenarios: GP (a population of expressions and a population of tests), chess playing strategies, soccer, tennis and the intransitivity of "betterness", rock–paper–scissors, a local fencing school and diversity (cf. *exploiter agents* in AlphaStar), nature.

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- Remedies: *competitive fitness sharing* (increasing the value of those solutions that win against tests (opponents) challenging for other solutions [RB95]), a specific selection of the test set, maintaining *hall of fame* or sets of Pareto-nondominated solutions and tests.

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