Faculties of Human Intelligence

- Visual processing
- Speech, language processing
- Planning, problem solving
- Learning
- Communication, social interaction
- Dexterity, physical skill
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- Why aren’t other animals able to do (all) the same?
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- We are born with human bodies and brains!
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What enables humans to do all these things?
Why aren’t other animals able to do (all) the same?
We are born with human bodies and brains!
And how did we get those?
Theory of Biological Evolution

Charles Darwin (1809–1882) [1]

Natural Selection

[1]

Natural Selection


Coevolution

Angraecum sesquipedale [1]

Coevolution

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Long “spur” [2]

Coevolution

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Xanthopan morganii praedicta [3]

Artificial Selection

1. https://commons.wikimedia.org/wiki/File:Dog_morphological_variation.png. CC image courtesy of Mary Bloom, American Kennel Club on WikiMedia Commons licensed under CC-BY-SA-4.0.
Artificial Selection

Evolutionary Algorithms in Computing

- Inspired by **efficiency of selection paradigm** in natural world.

- Usually **much less complex** in terms of representation, scale, parallelisation.

- Validated by several **empirical successes**, although theory not very strong.

- Means for black box optimisation or **policy search**.

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Evolution and Learning

Evolutionary Function Approximation for Reinforcement Learning.
Evolution and Learning

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- NEAT
- NEAT+Q
- Experiments
- Discussion
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NeuroEvolution of Augmenting Topologies

Additional Details

- **Mutation** by adding nodes and links.

Figure 1: Examples of NEAT’s mutation operators for adding structure to networks. In (a), a hidden node is added by splitting a link in two. In (b), a link, shown with a thicker black line, is added to connect two nodes.

- **Crossover** based on a system to track the evolution of individual genes.

- **Speciation** based on explicit fitness sharing to preserve diversity in population.
Does Learning Help Evolution?

Jean-Baptiste de Lamarck (1744–1829) [1]
Charles Darwin (1809–1882) [2]
James Mark Baldwin (1861–1934) [3]

Does Learning Help Evolution?

- In Lamarckian evolution, weight changes during an agent’s lifetime get passed on to offspring.

- In Darwinian evolution, weight changes during an agent’s lifetime do not get passed on to offspring.

We now know that nature primarily implements Darwinian evolution: information flows through genes.

Is the Darwinian model preferable for the synthetic field of evolutionary computation, too?

The Baldwin effect, which examines learning in the Darwinian context, suggests that populations that learn evolve more quickly (since the starting weights only need to be approximately right, learning can “adjust” appropriately).

Over time, the starting weights themselves become more favourable (will enjoy higher fitness).
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Evolution and Learning

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On-line Evolutionary Computation

- By default, evolutionary computation operates in the off-line or pure exploration mode.
- To some extent the randomness in creating a population results in some exploration, and fitness-based selection amounts to exploitation.
- Yet evaluating a fixed population usually gives each member the same number of episodes.

What if the rewards are counted on-line: that is, each fitness evaluation adds to the overall reward?

Under $\epsilon$-greedy selection, we pick the current best (highest empirical average of fitness) individual w.p. $1 - \epsilon$; w.p. $\epsilon$ we pick an individual uniformly at random.

Under Softmax selection, we pick individual with fitness $f$ w.p. proportional to $e^{f}/\tau$, where $\tau$ is the "temperature".
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Shivaram Kalyanakrishnan (2022)
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Task 1: Mountain Car

Task 2: Server Job Scheduling

Figure 3: The four utility functions used in our experiments.

NEAT+Q vs. NEAT


Figure 4: A comparison of the performance of manual and evolutionary function approximators in the mountain car and server job scheduling domains.
Topologies Evolved by NEAT+Q

Figure 5: Typical examples of the topologies of the best networks evolved by NEAT+Q in both the mountain car and scheduling domains. Input nodes are on the bottom, hidden nodes in the middle, and output nodes on top. In addition to the links shown, each input node is directly connected to each output node. Note that two output nodes can be directly connected, in which case the activation of one node serves not only as an output of the network, but as an input to the other node.

On-line NEAT+Q

Figure 7: The performance of combining evolutionary function approximation with on-line evolutionary computation compared to using each individually in the mountain car and server job scheduling domains.

Darwinian vs. Lamarckian Variants

Figure 10: A comparison of Darwinian and Lamarckian NEAT+Q in the mountain car and server job scheduling domains.

Evolution and Learning

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Conclusion

- Evolution plays a primary role in animal intelligence.
- Modern ML has mostly focused on within-lifetime learning, with evolutionary computation treated as an approach for policy search.
- This week’s article considers evolution as an outer loop and learning within an inner loop.
- Evolutionary computation highly parallelisable, even if it usually takes a much higher aggregate number of samples.
- Synthetic approaches need not be faithful to nature, yet there are many factors in biological evolution to be understood better and incorporated:
  - Cooperation and competition among individuals, species;
  - Implicit and explicit communication;
  - Steady-state populations.
Key References


