

Evolutionary Algorithms in Deep Learning and Reinforcement Learning

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Should we use EA or classical RL?

Evolution Strategies as a Scalable Alternative to Reinforcement Learning

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Abstract

We explore the use of Evolution Strategies (ES), a class of black box optimization algorithms, as an alternative to popular MDP-based RL techniques such as Q-learning and Policy Gradients. Experiments on MuJoCo and Atari show that ES is a viable solution strategy that scales extremely well with the number of CPUs available: By using a novel communication strategy based on common random numbers, our ES implementation only needs to communicate scalars, making it possible to scale to over a thousand parallel workers. This allows us to solve 3D humanoid walking in 10 minutes and obtain competitive results on most Atari games after one hour of training. In addition, we highlight several advantages of ES as a black box optimization technique: it is invariant to action frequency and delayed rewards, tolerant of extremely long horizons, and does not need temporal discounting or value function approximation.

Advantages of EA

- simple, easy to apply
- black-box
- hillclimbing + diversity
- highly parallelizable
- very flexible framework (e.g. self-adaptation, genetic programming)
- crossover
- populations (!!)

Drawbacks of EA

- no gradients (slow)
- prefer small to medium search spaces
- black-box
- susceptible to representation

Evolving Algorithms

Neural Architecture Evolution in Deep Reinforcement Learning for Continuous Control

Jörg K.H. Franke^{*,1}, Gregor Koehler^{*,2}, Noor Awad¹, Frank Hutter^{1,3}

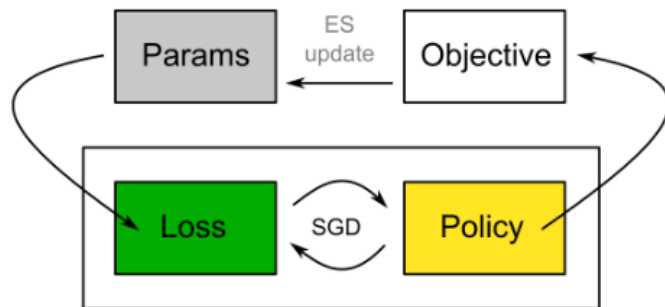
¹University of Freiburg

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³Bosch Center for Artificial Intelligence

Evolved Policy Gradients

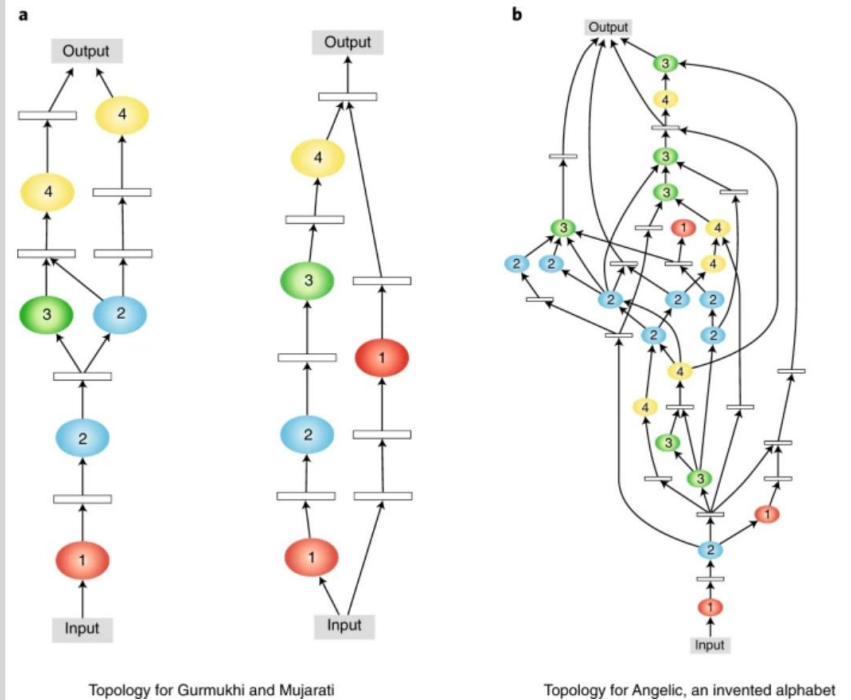
Rein Houthoofd¹ Richard Y. Chen¹ Phillip Isola^{1,2,3} Bradly C. Stadie² Filip Wolski¹
Jonathan Ho^{1,2} Pieter Abbeel^{1,2}



Evolutionary Architecture Search For Deep Multitask Networks

Jason Liang, Elliot Meyerson, and Risto Miikkulainen
Sentient Technologies, Inc. and
The University of Texas at Austin

Fig. 2: Sample evolved topologies of modules for the Omniglot multitask learning benchmark.

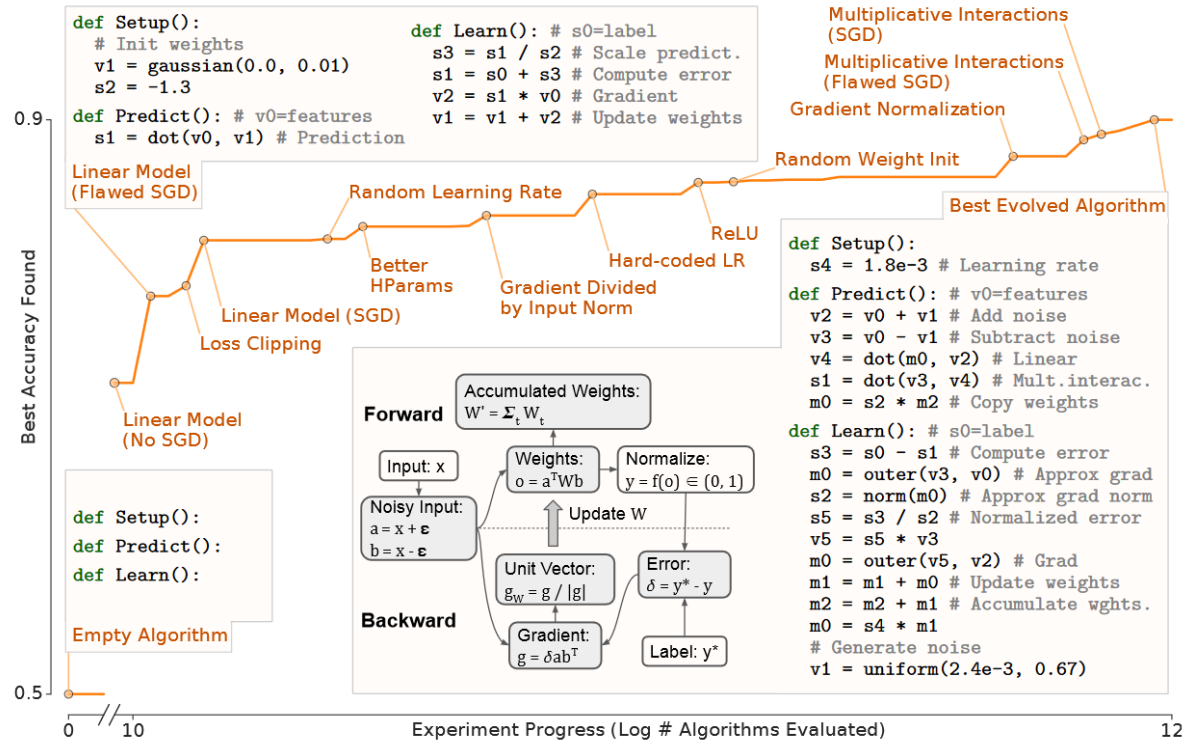


Evolving Algorithms

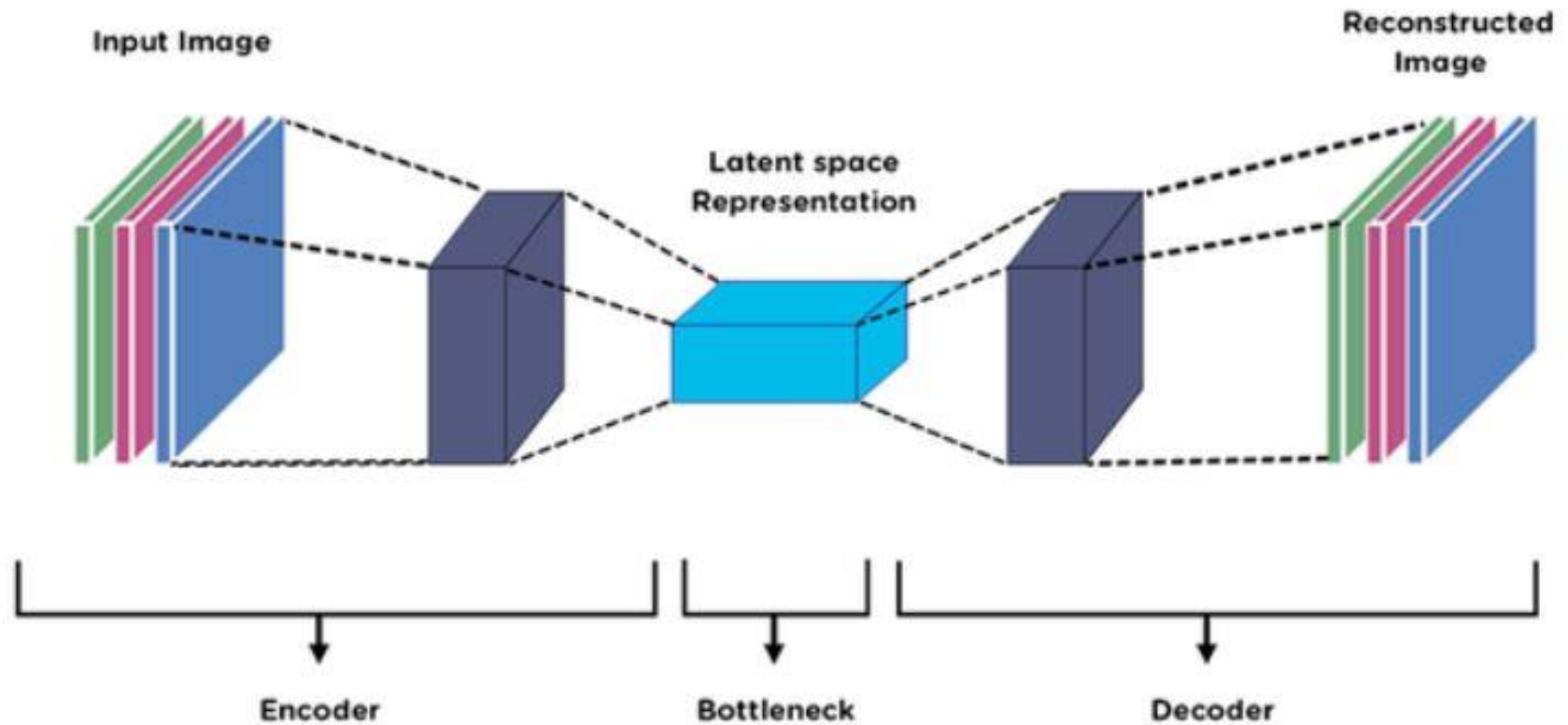
AutoML-Zero: Evolving Machine Learning Algorithms From Scratch

Esteban Real^{*1} Chen Liang^{*1} David R. So¹ Quoc V. Le¹

```
# sX/vX/mX = scalar/vector/matrix at address X.
# "gaussian" produces Gaussian IID random numbers.
def Setup():
    # Initialize variables.
    m1 = gaussian(-1e-10, 9e-09) # 1st layer weights
    s3 = 4.1 # Set learning rate
    v4 = gaussian(-0.033, 0.01) # 2nd layer weights
def Predict(): # v0=features
    v6 = dot(m1, v0) # Apply 1st layer weights
    v7 = maximum(0, v6) # Apply ReLU
    s1 = dot(v7, v4) # Compute prediction
def Learn(): # s0=label
    v3 = heaviside(v6, 1.0) # ReLU gradient
    s1 = s0 - s1 # Compute error
    s2 = s1 * s3 # Scale by learning rate
    v2 = s2 * v3 # Approx. 2nd layer weight delta
    v3 = v2 * v4 # Gradient w.r.t. activations
    m0 = outer(v3, v0) # 1st layer weight delta
    m1 = m1 + m0 # Update 1st layer weights
    v4 = v2 + v4 # Update 2nd layer weights
```



Search in Latent Space



Search in Latent Space

V. Volz, J. Schrum, J. Liu, S. M. Lucas, A. Smith, and S. Risi
GECCO '18, July 15–19, 2018, Kyoto, Japan

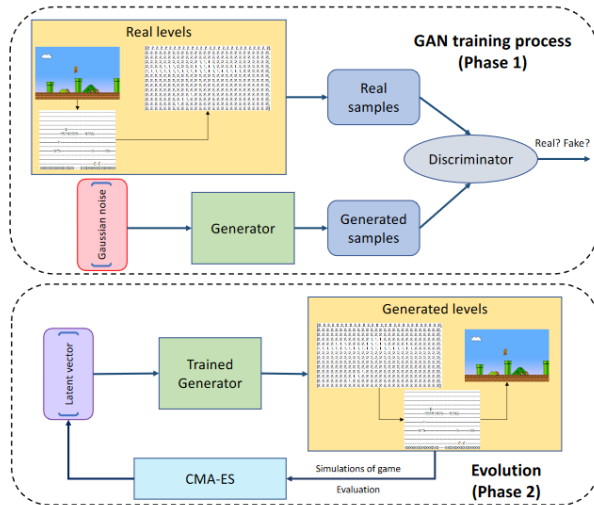
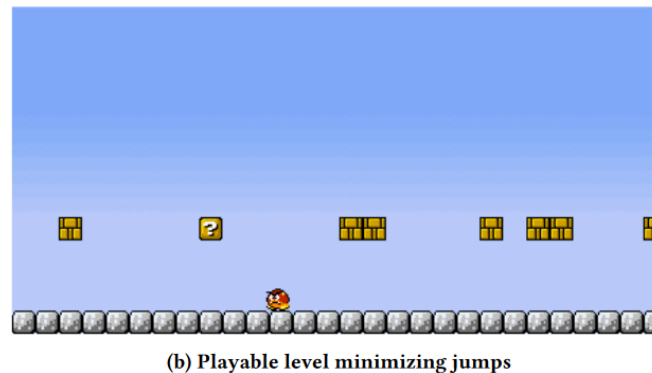
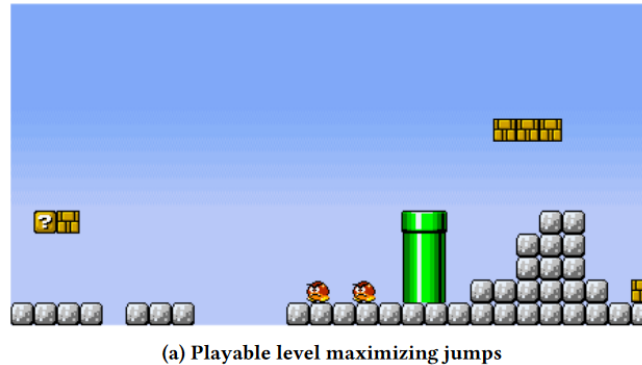
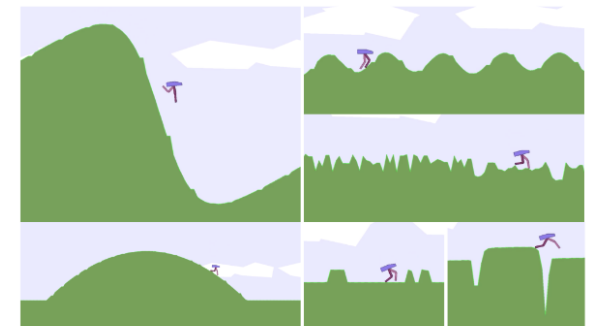


Figure 1: Overview of the GAN training process and the evolution of latent vectors. The approach is divided into two distinct phases. In Phase 1 a GAN is trained in an unsupervised way to generate Mario levels. In the second phase, we search for latent vectors that produce levels with specific properties.



Enhanced POET: Open-Ended Reinforcement Learning through Unbounded Invention of Learning Challenges and their Solutions

Rui Wang¹ Joel Lehman¹ Aditya Rawal¹ Jiale Zhi¹ Yulun Li¹ Jeff Clune^{*2} Kenneth O. Stanley^{*1}



(b) Sample environments from a single run of Enhanced POET.

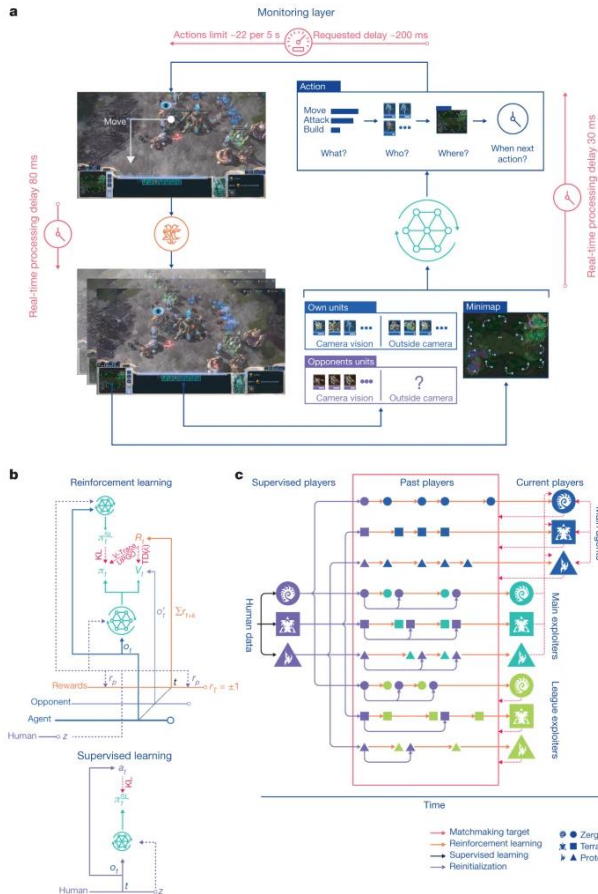
Populations of Agents

Article | Published: 30 October 2019

Grandmaster level in StarCraft II using multi-agent reinforcement learning

Oriol Vinyals , Igor Babuschkin, [...]David Silver 

Nature **575**, 350–354 (2019) | [Cite this article](#)



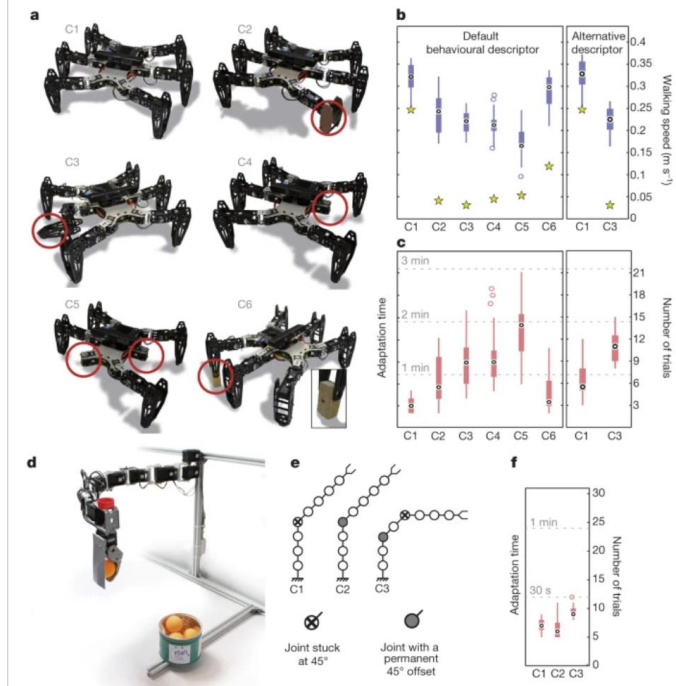
Published: 27 May 2015

Robots that can adapt like animals

Antoine Cully, Jeff Clune, Danesh Tarapore & Jean-Baptiste Mouret 

Nature **521**, 503–507 (2015) | [Cite this article](#)

Figure 3: Main experiments and results.



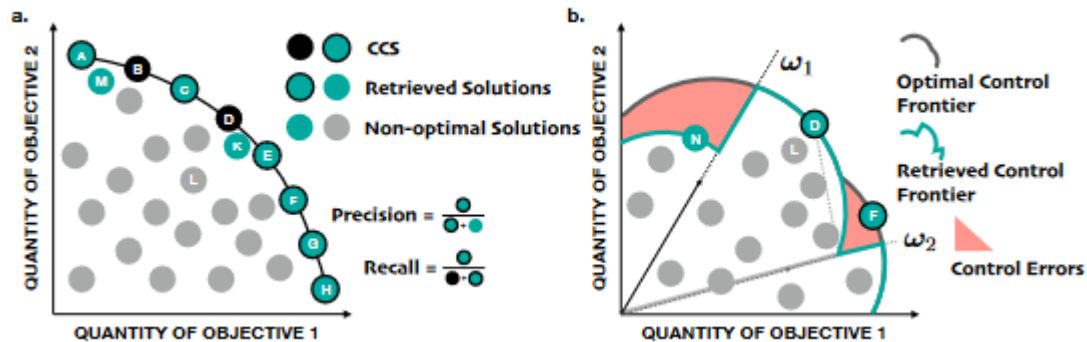
Multiobjective Optimization

A Generalized Algorithm for Multi-Objective Reinforcement Learning and Policy Adaptation

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Review Article | Published: 07 January 2019

Designing neural networks through neuroevolution

Kenneth O. Stanley , Jeff Clune , Joel Lehman  & Risto Miikkulainen 

Nature Machine Intelligence **1**, 24–35 (2019) | [Cite this article](#)

**Thank you
for your attention!**