Evolution Strategies for Neural Policy Search

Mid-thesis commitee

Author: Paul Templier[1]

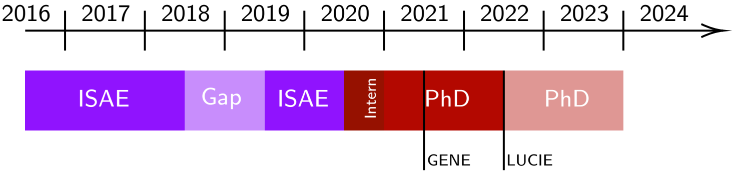
Advisors: Emmanuel Rachelson[1], Dennis G. Wilson[1]

[paul.templier@isae-supaero.fr]

June 29, 2022

[1] University of Toulouse, ISAE-SUPAERO

[Context] Mid-thesis report



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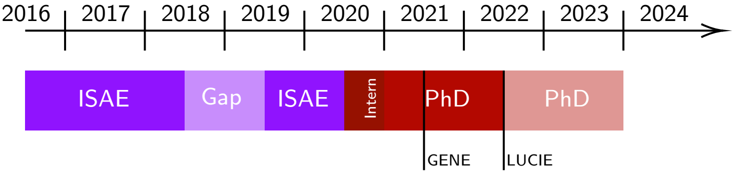

Initial topic

Bio-inspired methods for artificial neural networks

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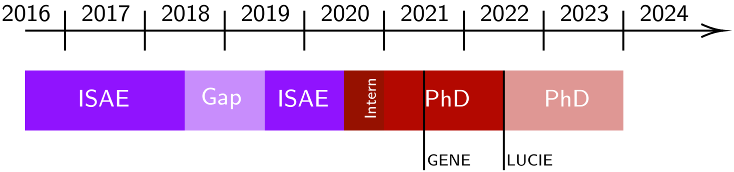

Initial topic

Bio-inspired methods for artificial neural networks

Goal of this report

Organize past and present work, and highlight future research directions.

Content

1. [Context] Context of this PhD

Content

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2. [Policy search] Evolution Strategies for Policy Search
3. [GENE] Representing policies and changing the search space

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6. [Directions] Future work and timeline

[Policy search] Policy search

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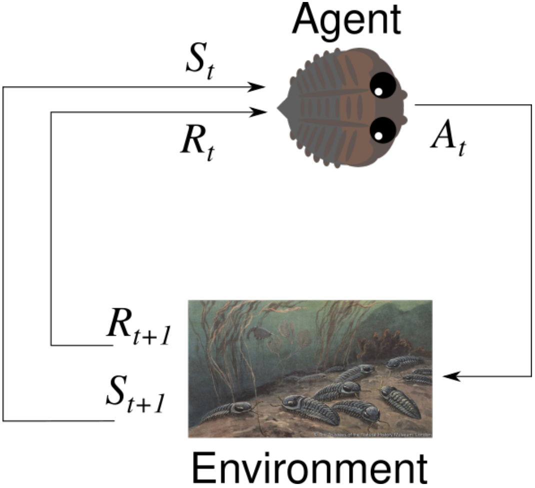
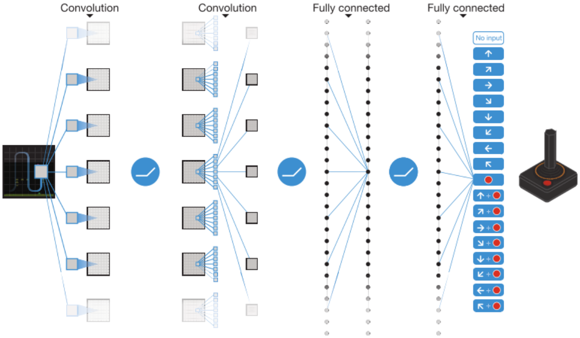


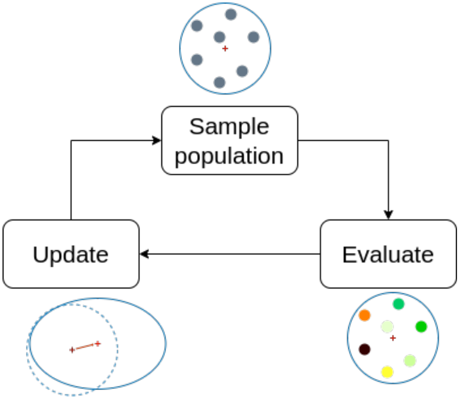
https://github.com/d9w/evolution/blob/master/imgs/erl.png

[Policy search] Neural networks



Neural Network used in Deep Q Networks [3]

[Policy search] Evolution Strategies



Evolution Strategy steps

[Policy search] Variants of Evolution Strategies

Evolution Strategies

- (μ, λ) ES
- SNES
- Canonical ES
- OpenAI ES
- CMA-ES
- XNES
- Cross-Entropy Method
- Augmented Random Search

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Neuroevolution for policy search

- large dimensions ($1.6\ .10^6$ parameters)
- expensive evaluation

[Policy search] BERL

Reproduction settings

Reproducing Canonical ES [1] and OpenAI ES [4] on the Arcade Learning Environment.

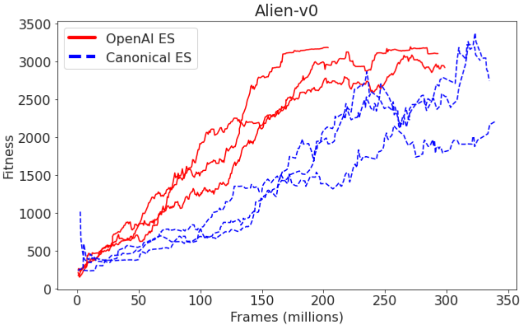

Figure: Evolution of Canonical ES and OpenAI ES on Alien with 800 CPUh compute budget

[GENE] A Geometric Encoding for Neural Network Evolution

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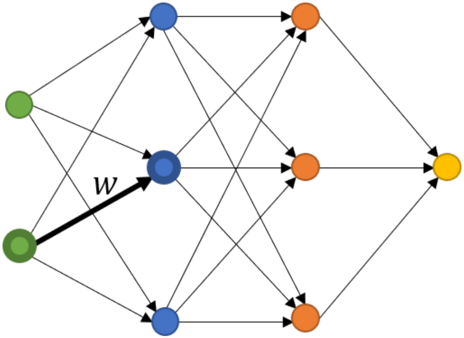

Fully connected
neural network

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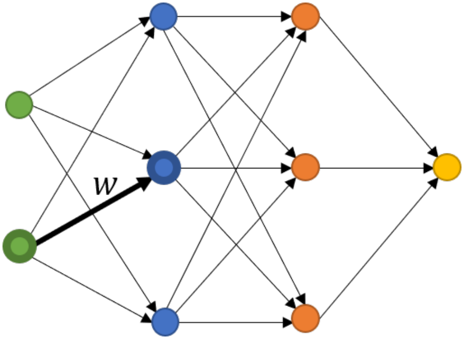

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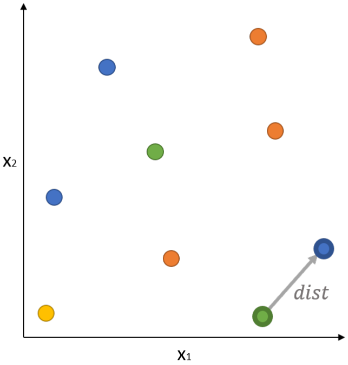


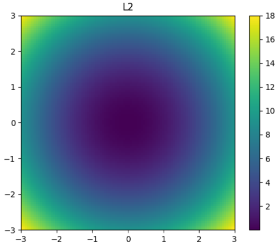
GENE encoding

[GENE] GENE: Distance functions

$$w_{i,j} = dist(n_i, n_j) \tag{1}$$

Euclidean distance

$$\sqrt{\sum_{k=1}^{D} \left(n_1^k - n_2^k\right)^2} \tag{2}$$



[GENE] GENE: Weight distribution

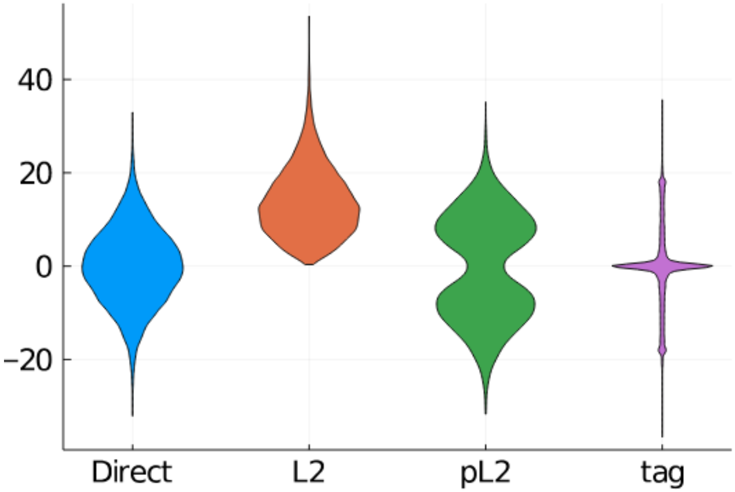


Figure: Distribution of weight values in networks evolved with different encodings.

[GENE] Competitive results - Arcade Learning Environment

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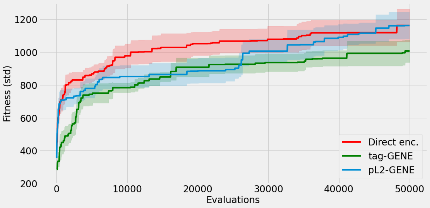

Figure: SNES on SpaceInvaders

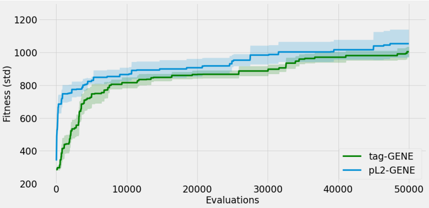

Figure: XNES on SpaceInvaders

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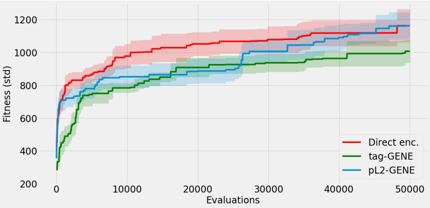

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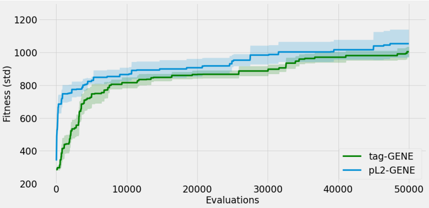

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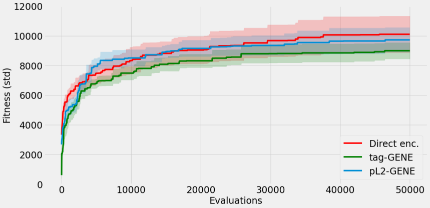
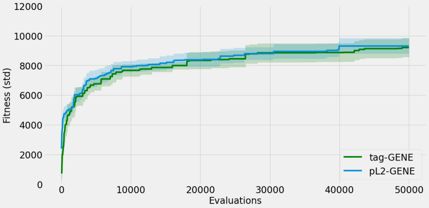


Figure: SNES on Krull



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[GENE] Improving results - Arcade Learning Environment

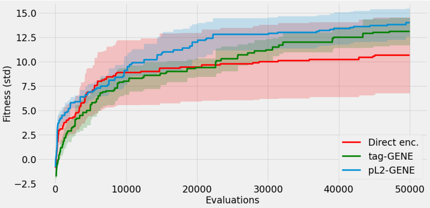
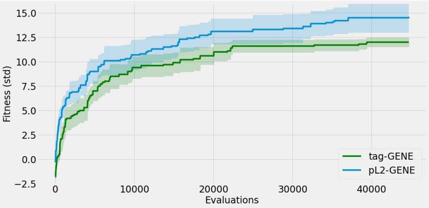


Figure: SNES on IceHockey



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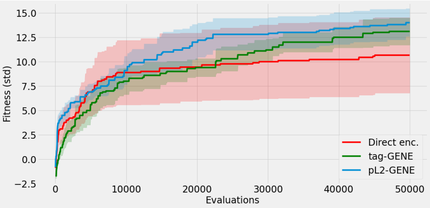

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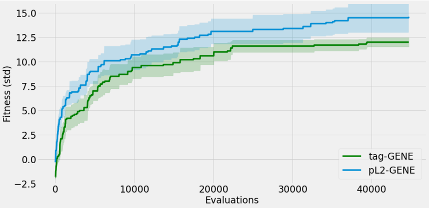

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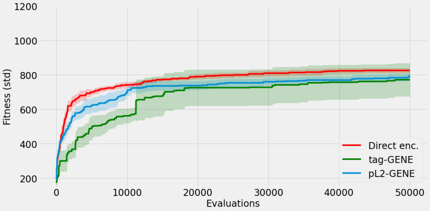

Figure: SNES on Seaquest

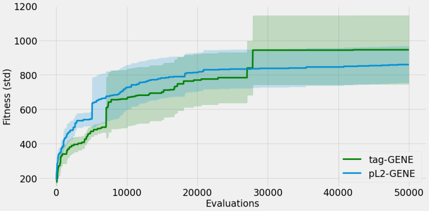

Figure: XNES on Seaquest

[GENE] Computational cost

Evolutionary Strategy update of μ and σ

Encoding	D	Genes		Mean time (s)	Memory (KiB)
pL2-GENE	3	804	SNES	0.000357	630.56
pL2-GENE	10	2211	SNES	0.000678	1372.16
Direct	-	5609	SNES	0.001350	3133.44
pL2-GENE	3	804	XNES	1.475000	1352663.04
pL2-GENE	10	2211	XNES	14.244000	11806965.76
Direct	-	5609	XNES	119.976000	79765176.32

[GENE] Future Work

Distance functions

Design new distance functions, or optimize them through co-evolution.

Hybrid encoding

Switch between indirect and direct encodings during the evolution.

Gradient descent

Use backpropagation and gradient descent to optimize genomes instead of evolution.

Complex networks

Design encodings for convolution layers and recurrent networks.

[Search direction] DQNES

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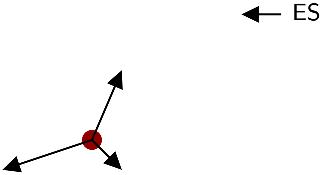

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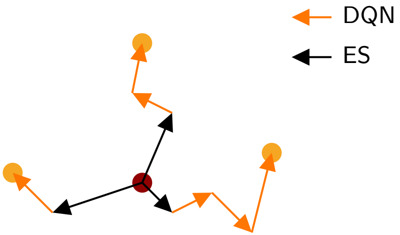

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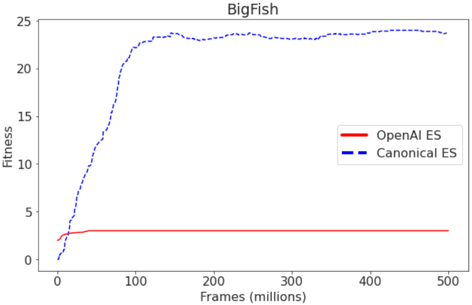

Figure: ES on BigFish, same level

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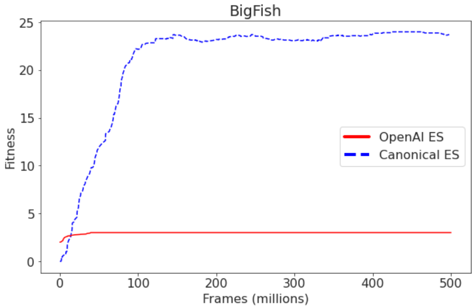

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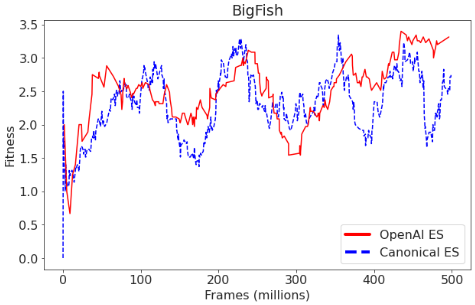

Figure: ES on BigFish, random level

[Noisy fitness] The LUCIE selection procedure

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Objective: identify the **best μ** individuals with as **few evaluations** as possible. [2]

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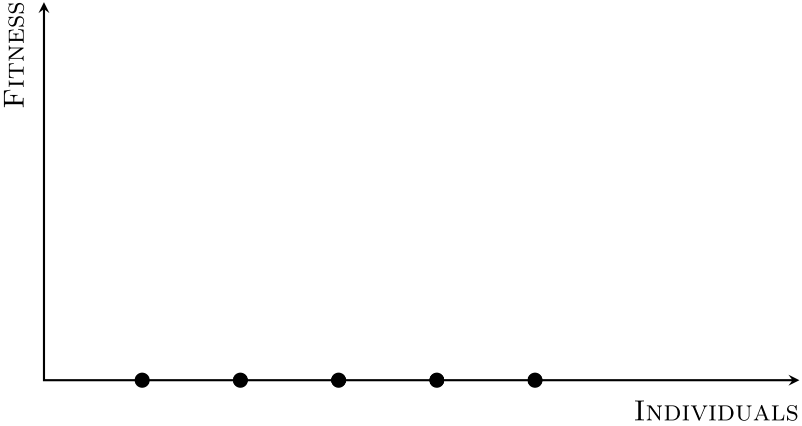

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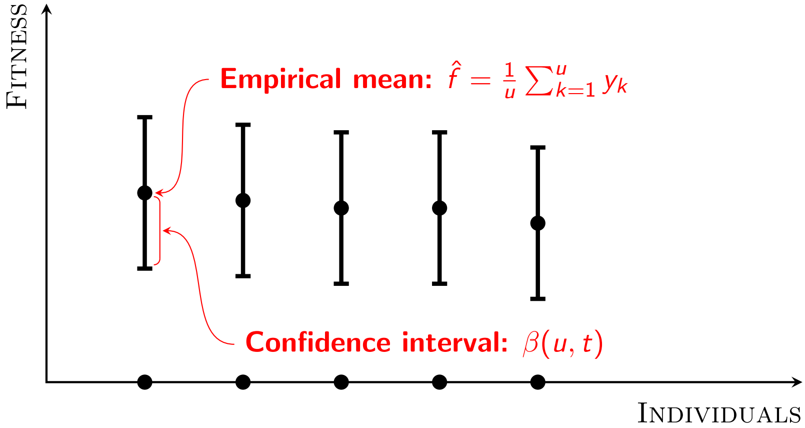

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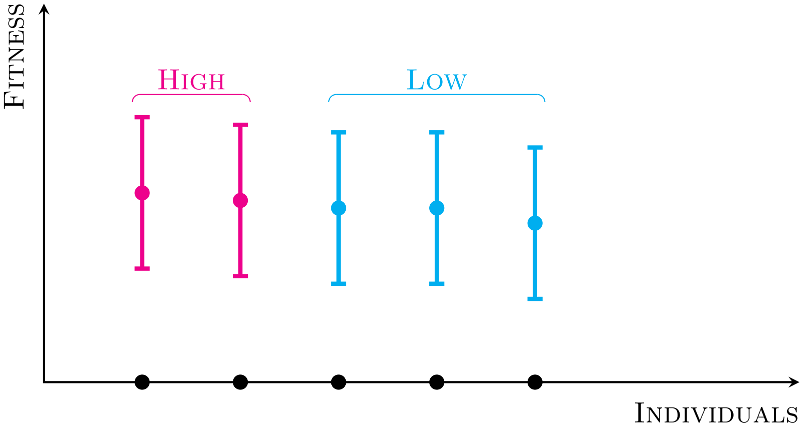

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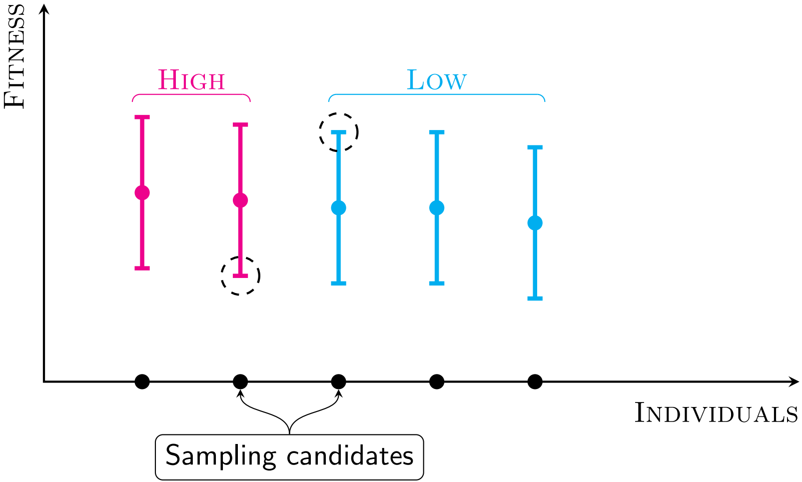

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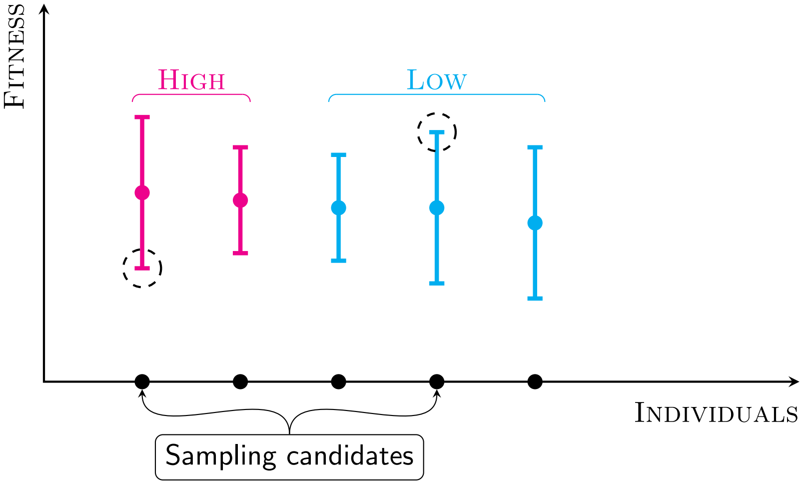

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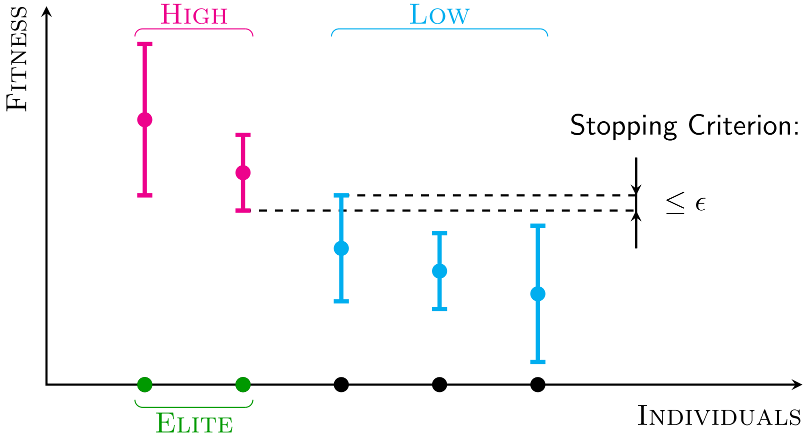

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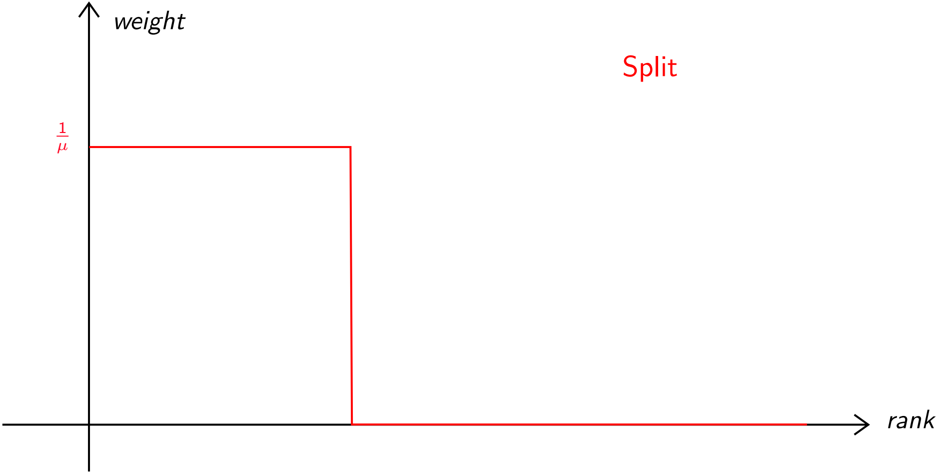

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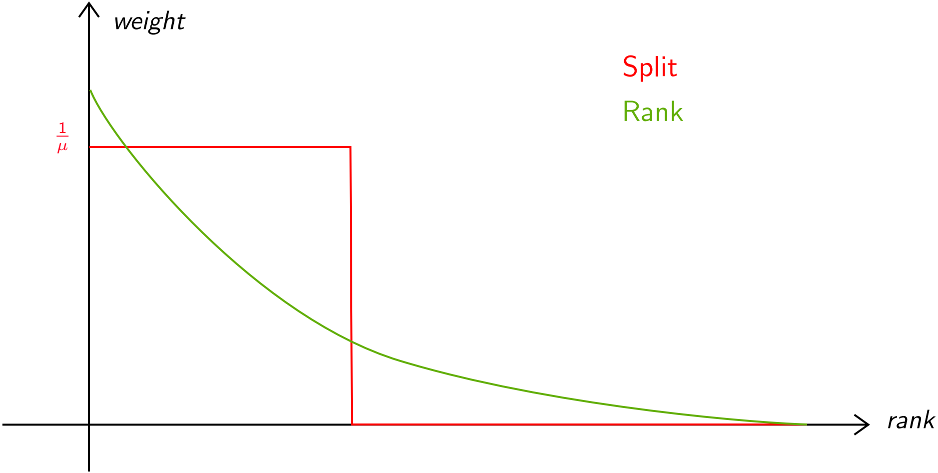

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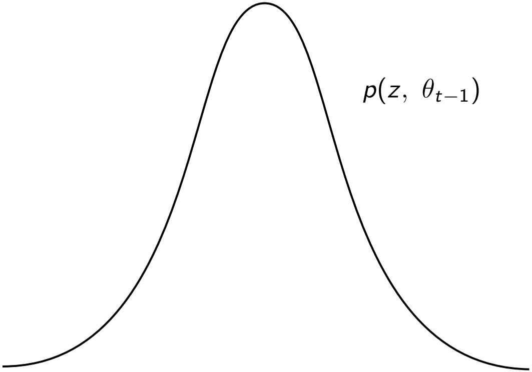

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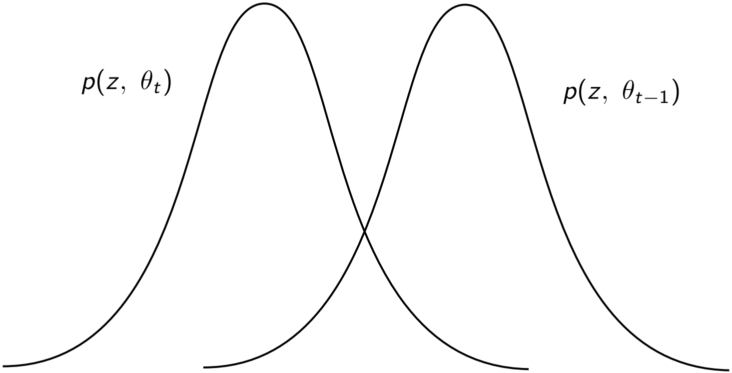

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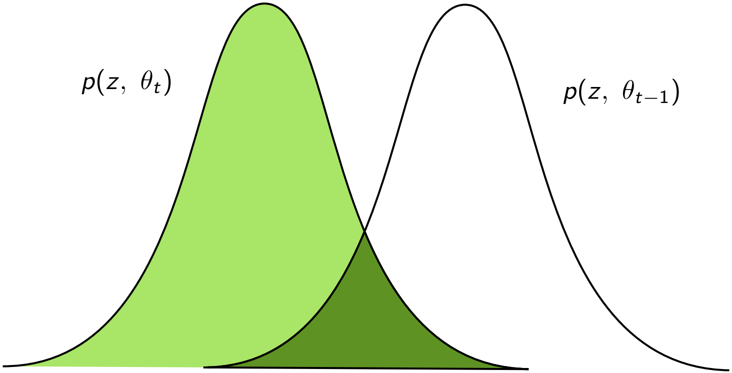

[Search direction] OneMax and LeadingOnes

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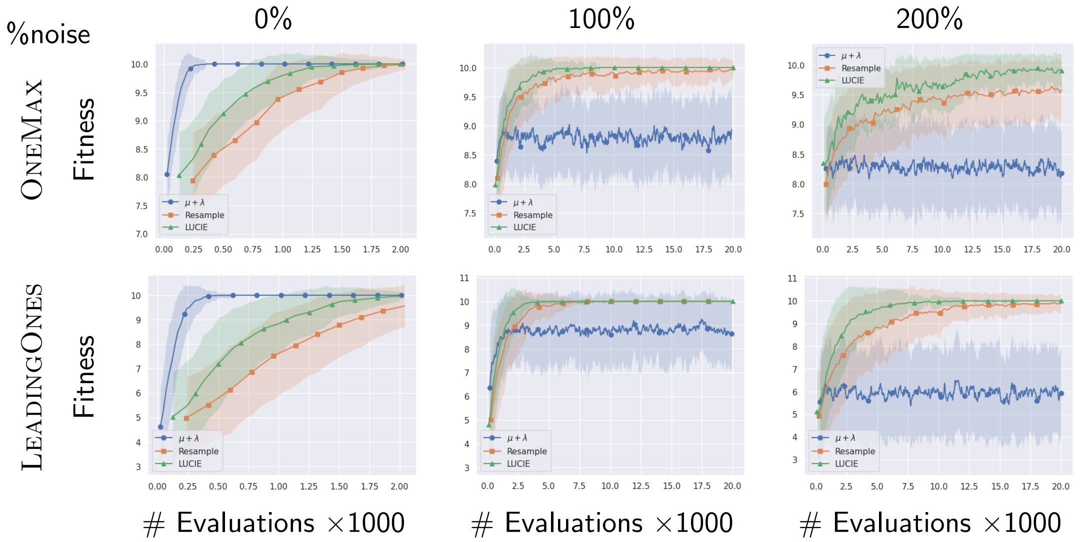

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LUCI ES

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- Ranking in Bandit problems
- Heritage (Importance Mixing, elitism)
- Scalability

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ES for Policy Search

- Neuroevolution constraints and theory
- Ablation study of existing methods

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ES for Policy Search

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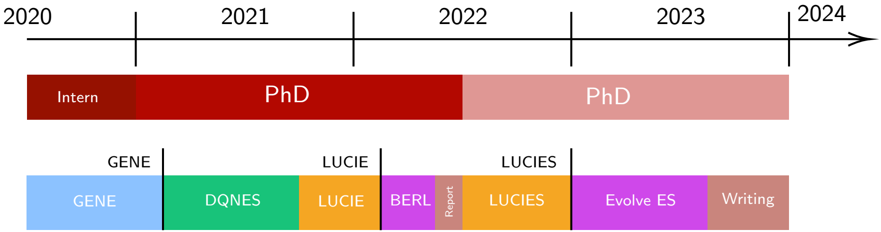
Evolving Evolution Strategies

- Make ES methods emerge from scratch
- Neuromodulation: adapting ES during the evolution

[Directions] Timeline



References I

P. Chrabaszcz, I. Loshchilov, and F. Hutter.
Back to Basics: Benchmarking Canonical Evolution Strategies for Playing Atari.
pages 1419–1426, 2018.

E. Lecarpentier, P. Templier, E. Rachelson, and D. G. Wilson.
LUCIE: An Evaluation and Selection Method for Stochastic Problems.
In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO 2022)*, 2022.

V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al.
Human-level control through deep reinforcement learning.
nature, 518(7540):529–533, 2015.

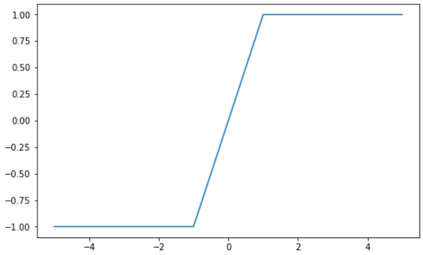
References II

T. Salimans, J. Ho, X. Chen, S. Sidor, and I. Sutskever.
Evolution Strategies as a Scalable Alternative to Reinforcement Learning.
Mar. 2017.

[GENE] Signed distances

Bounded identity function

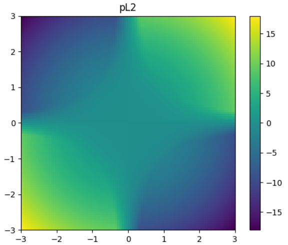
$$\alpha : \begin{cases} \text{if } x \geq 1 : \alpha(x) = 1 \\ \text{if } x \leq -1 : \alpha(x) = -1 \\ \text{else: } \alpha(x) = x \end{cases} \tag{3}$$



[GENE] Distance functions

pL2-GENE

$$\alpha \left(\prod_{k=1}^{D} n_1^k - n_2^k \right) \sqrt{\sum_{j=1}^{D} \left(n_1^j - n_2^j \right)^2} \quad (4)$$



tag-GENE

$$\sum_{j=2}^{D} \alpha (n_1^j - n_2^1) e^{-|n_1^j - n_2^1|} \quad (5)$$