# Evolution Strategies for Neural Policy Search

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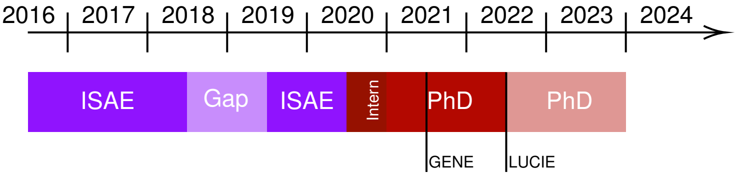
# Plan

# Mid-thesis report



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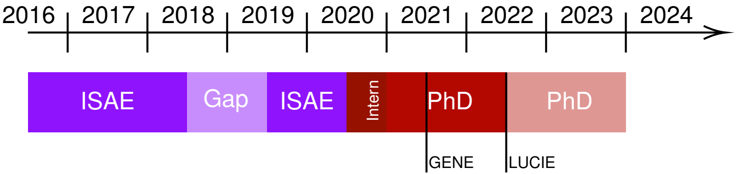


## Initial topic

Bio-inspired methods for artificial neural networks

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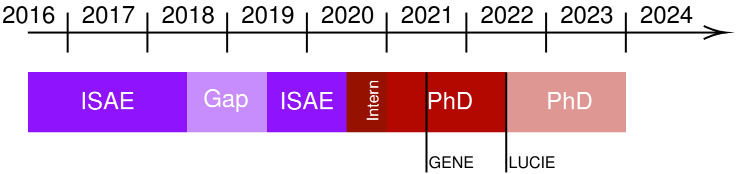


**Initial topic**

Bio-inspired methods for artificial neural networks

**Goal of this report**

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

# Content

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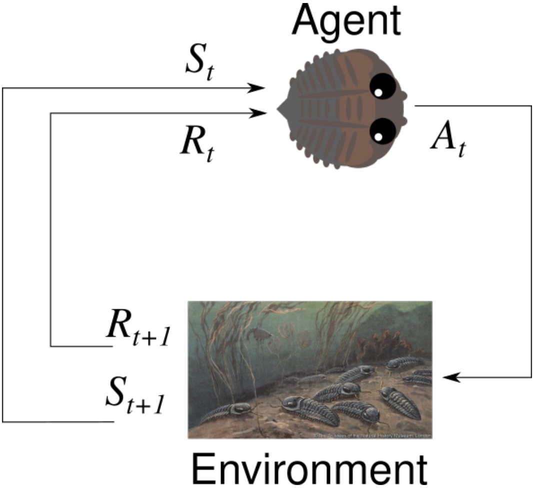
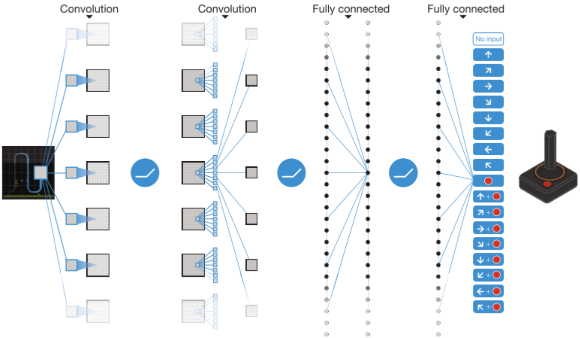
# Policy search

# Policy search

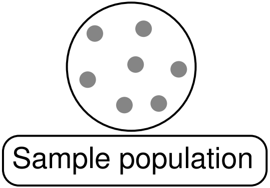


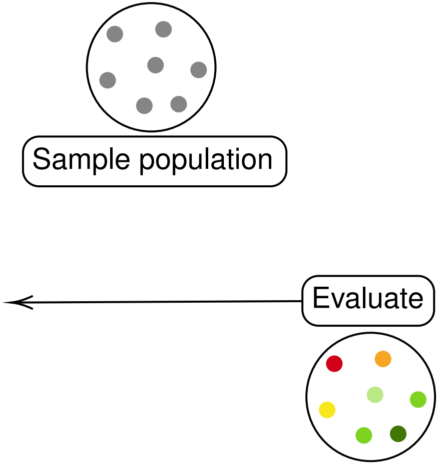

https://github.com/d9w/evolution/blob/master/imgs/erl.png

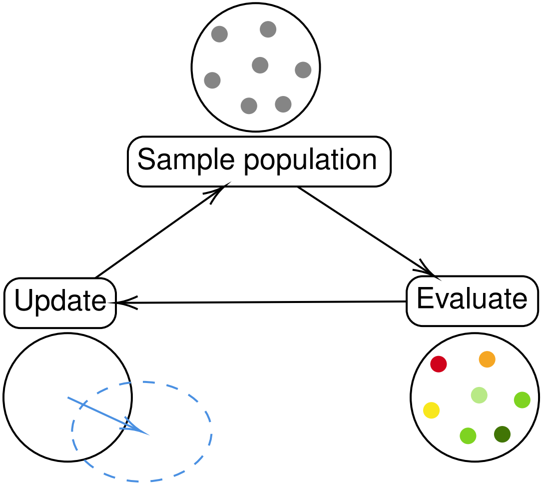
# Neural networks




Neural Network used in Deep Q Networks [?]


Sample population


Sample population
Evaluate


Sample population
Evaluate
Update

# Variants of

## Evolution Strategies

- $(\mu, \lambda)$ 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

## Reproduction settings

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

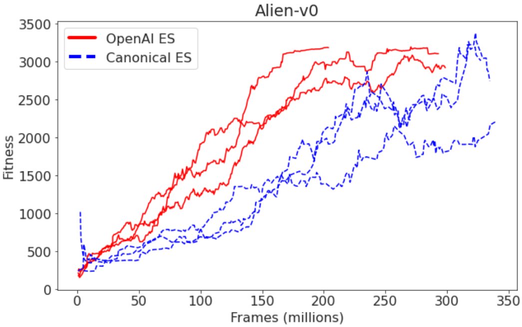


Figure: Evolution of Canonical ES and OpenAI ES on Alien with 800 CPUh compute budget

# A Geometric Encoding for Neural Network Evolution

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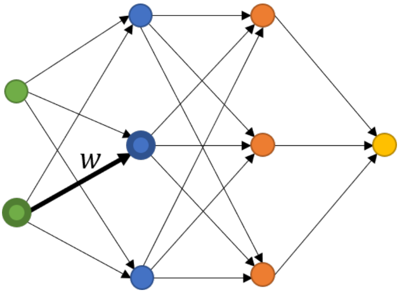


Fully connected
neural network

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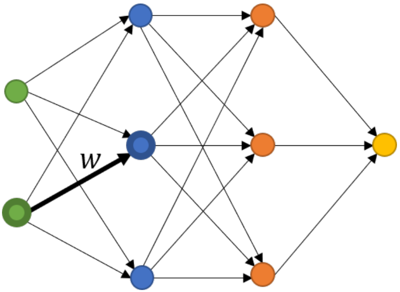


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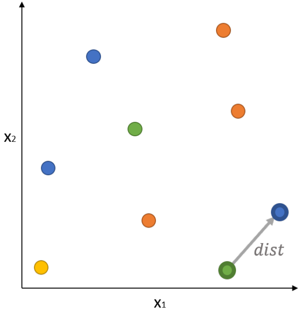


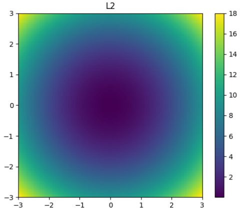

GENE encoding

# : Distance functions

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

## Euclidean distance

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



# : Weight distribution

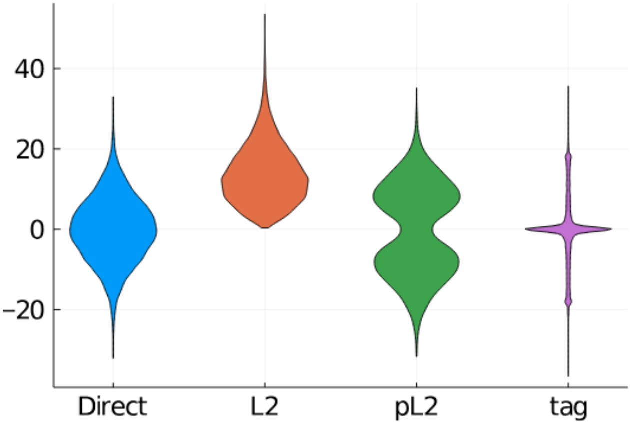



Figure: Distribution of weight values in networks evolved with different encodings.

# Competitive results - Arcade Learning Environment

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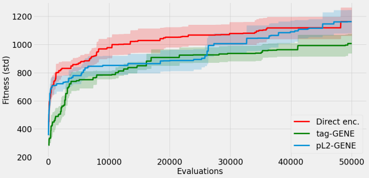


Figure: SNES on SpaceInvaders

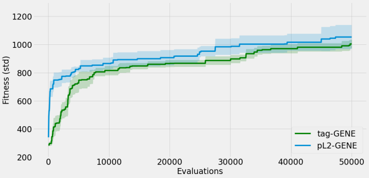


Figure: XNES on SpaceInvaders

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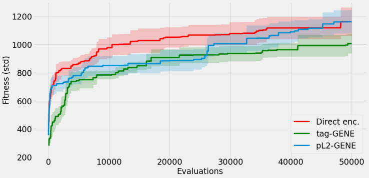


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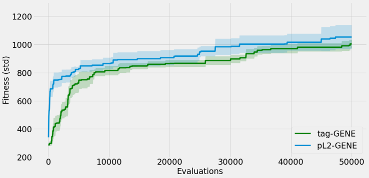


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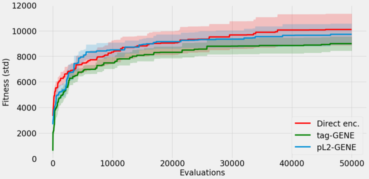


Figure: SNES on Krull

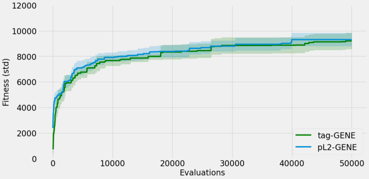


Figure: XNES on Krull

# Improving results - Arcade Learning Environment

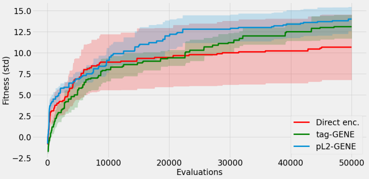


Figure: SNES on IceHockey

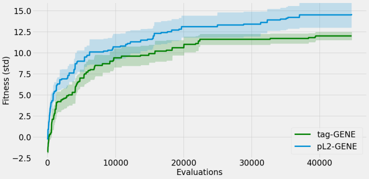


Figure: XNES on IceHockey

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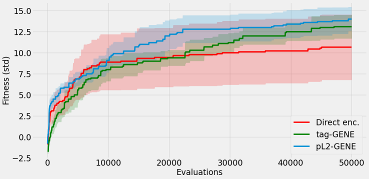


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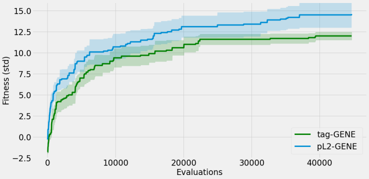


Figure: XNES on IceHockey

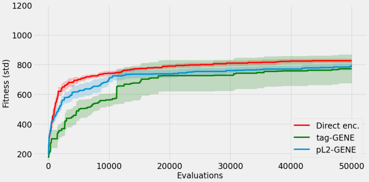


Figure: SNES on Seaquest

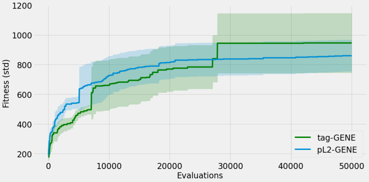


Figure: XNES on Seaquest

# Computational cost

## Evolutionary Strategy update of $\mu$ and $\sigma$

| 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 |

### Distance functions

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

### Gradient descent

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

### Hybrid encoding

Switch between indirect and direct encodings during the evolution.

### Complex networks

Design encodings for convolution layers and recurrent networks.

# ES on noisy environments

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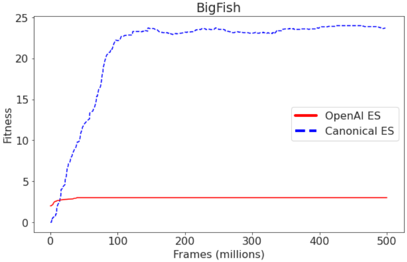


Figure: ES on BigFish, same level

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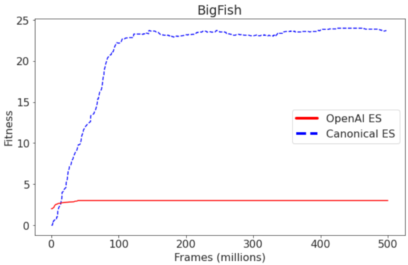


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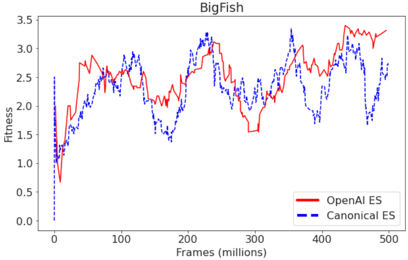


Figure: ES on BigFish, random level

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**Objective:** identify the **best** $\mu$ individuals with as **few evaluations** as possible. [**?**]

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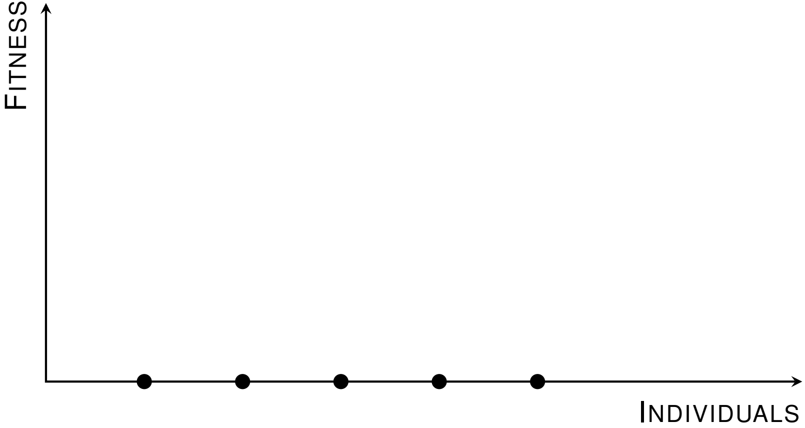

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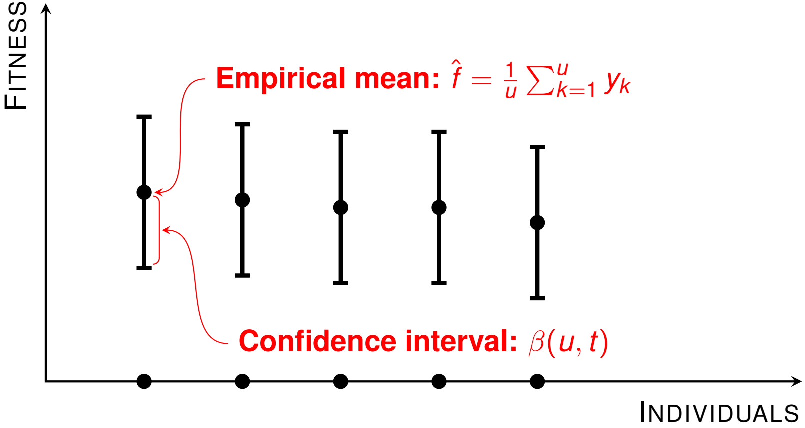

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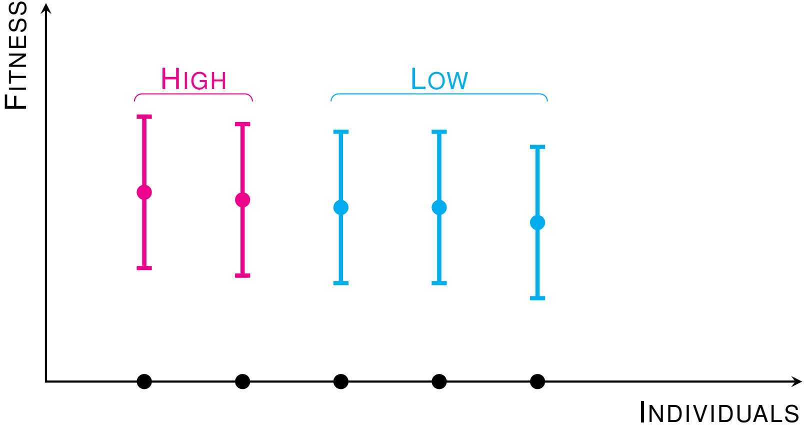

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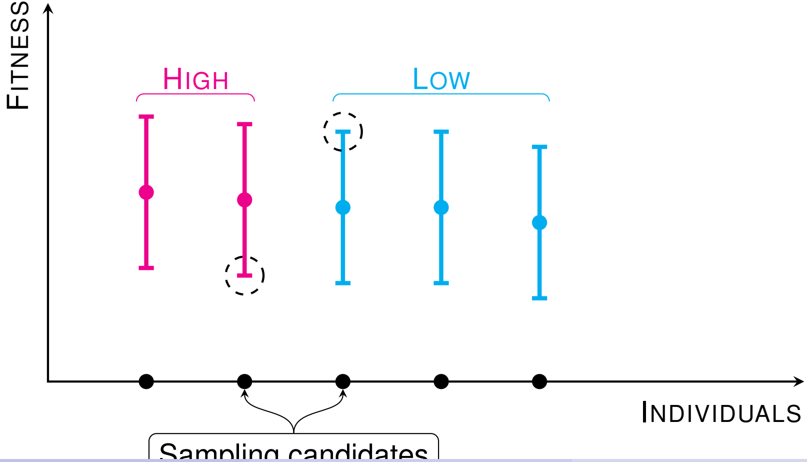

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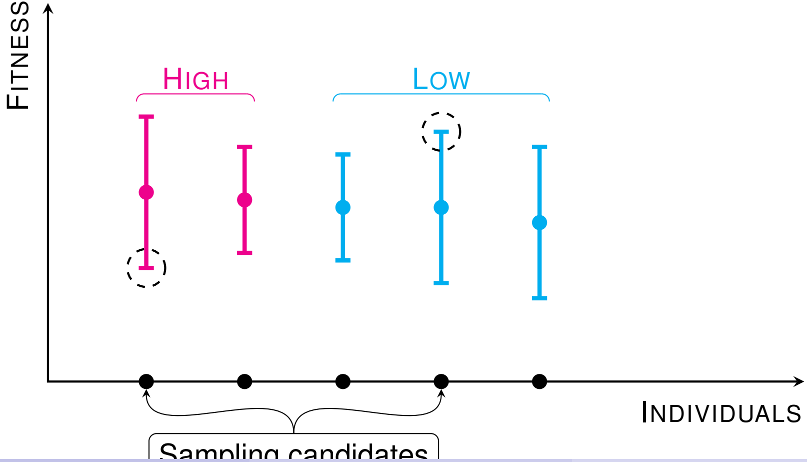

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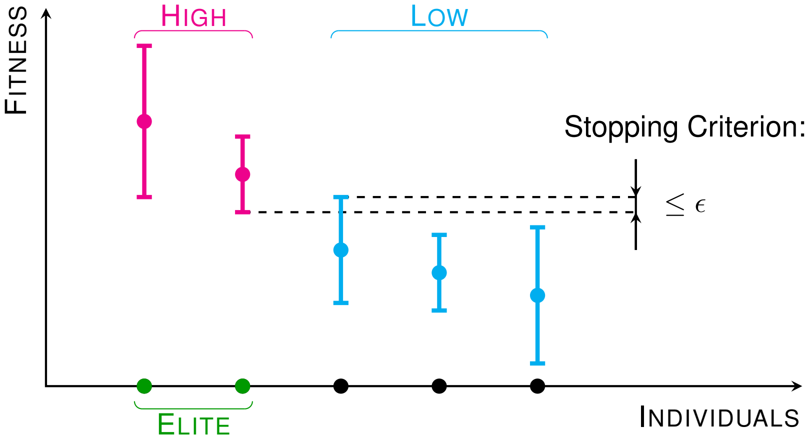

# OneMax and LeadingOnes

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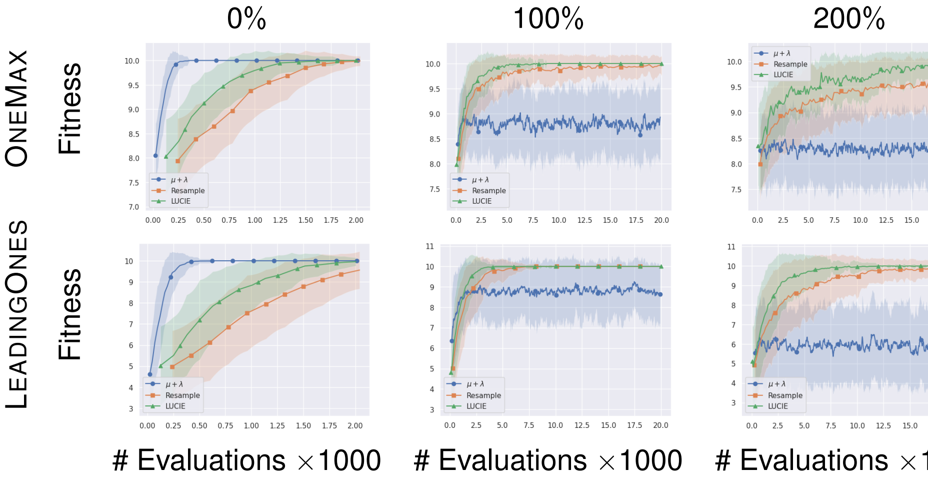
2cm(0cm,0.9cm) %noise



# for Evolution Strategies

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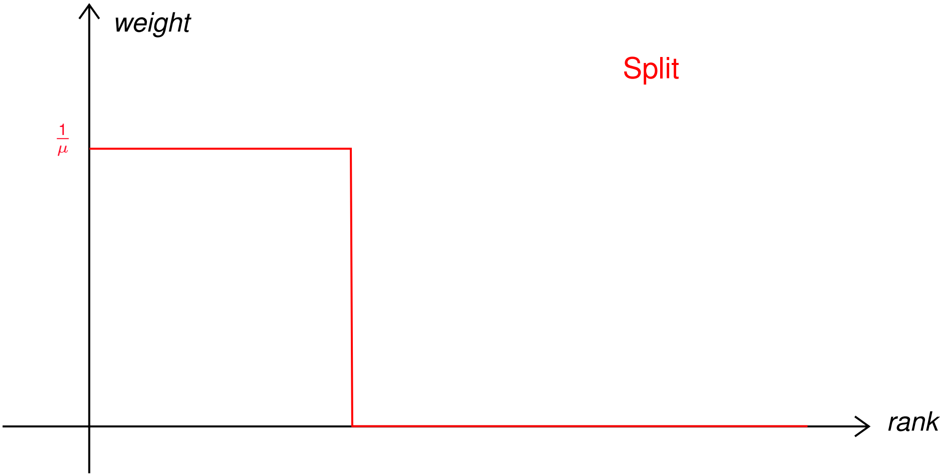
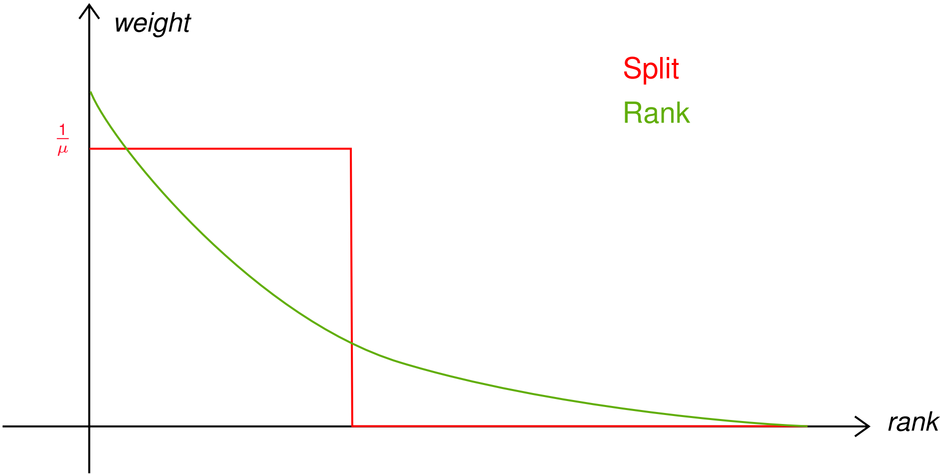

weight
Split
$\frac{1}{\mu}$
rank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# Importance Mixing for LUCI ES

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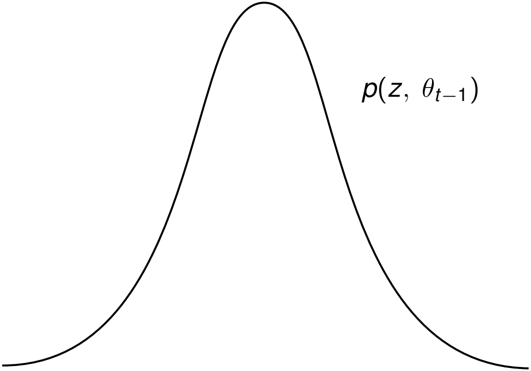

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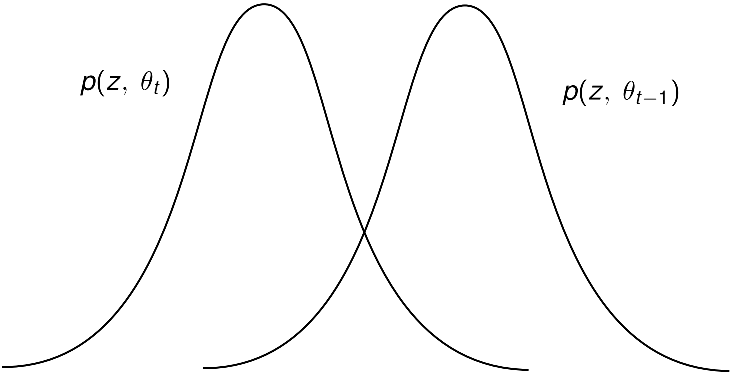

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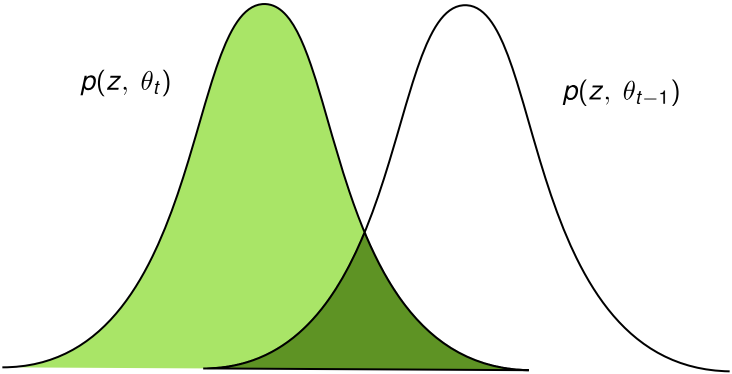
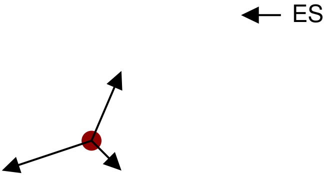
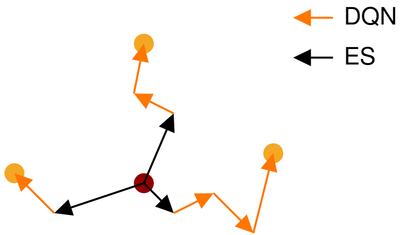



ES


DQN
ES

# Future work

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## LUCI ES

- Explore $(\mu, \lambda)$ ES
- Ranking in Bandit problems
- Heritage (Importance Mixing, elitism)
- Scalability

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- Neuroevolution constraints and theory
- Ablation study of existing methods

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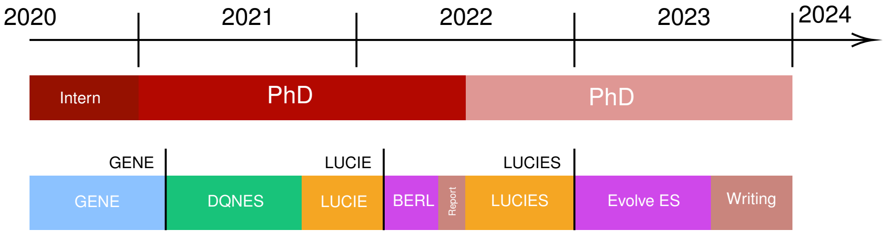
## Evolving Evolution Strategies

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

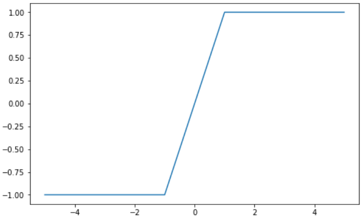
# Timeline


2020
2021
2022
2023
2024
Intern
PhD
PhD
GENE
LUCIE
LUCIES
GENE
DQNES
LUCIE
BERL
Report
LUCIES
Evolve ES
Writing

# Signed distances

## Bounded identity function

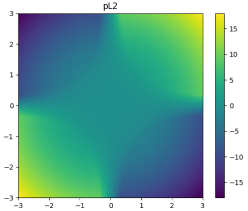
$$\alpha : \begin{cases} \text{if } x \geq 1 : \alpha(x) = 1 \\ \text{if } x \leq -1 : \alpha(x) = -1 \\ \text{else: } \alpha(x) = x \end{cases} \tag{3}$$



# Distance functions

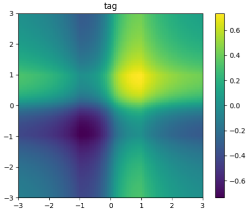
## pL2-GENE

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



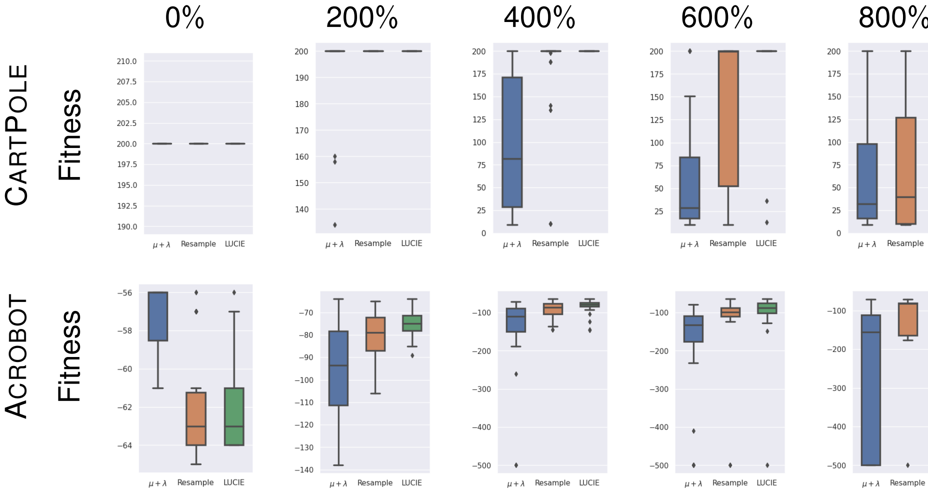

## tag-GENE

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



# Classic Control

2cm(0cm,0.7cm) %noise



# References I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Evolution Strategies as a Scalable Alternative to Reinforcement Learning.
Mar. 2017.