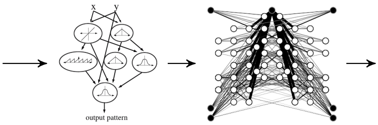
NeuroEvolution

Direct & Indirect Encodings

Evolutionary Computing
Session 5 - 17/09/2024

Kevin Godin-Dubois

Genotype



Behavior

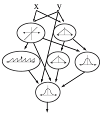
NeuroEvolution

Direct & Indirect Encodings

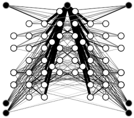
Evolutionary Computing
Session 5 – 17/09/2024

Kevin Godin-Dubois

Genotype →



→



→ Behavior

Contents

- Introduction
- NeuroEvolution of Augmenting Topologies
- HyperNEAT
- Evolvable Substrate HyperNEAT
- Applications

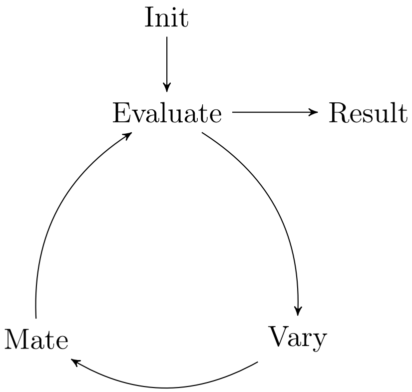
Introduction

Introduction

What is NeuroEvolution?

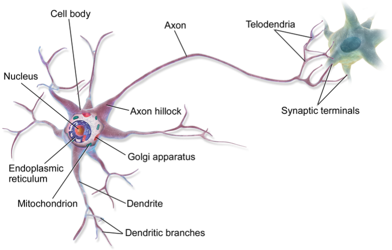
Evolution

In a nutshell

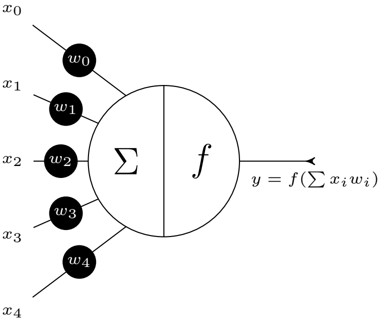


Artificial Neural Networks

Core concepts



Biological neuron



Artificial neuron

[1] W. S. McCulloch et al. "A Logical Calculus of the Ideas Immanent in Nervous Activity". In: **The Bulletin of Mathematical Biophysics** 5.4 (Dec. 1943), pp. 115–133.

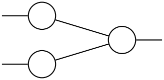
Artificial Neural Networks

Core concepts

Single neuron

Artificial Neural Networks

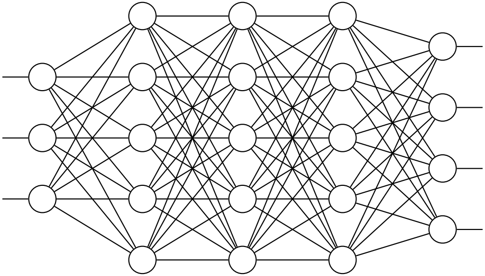
Core concepts



Perceptron

Artificial Neural Networks

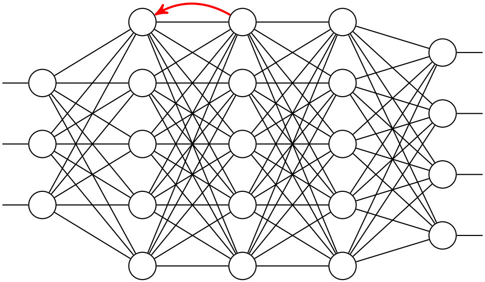
Core concepts



Multi-layer preceptron / Artificial Neural Network

Artificial Neural Networks

Core concepts



Recurrent Neural Network

Artificial Neural Networks

Core concepts

- (Very) high-level abstraction of biological brain
- Non exhaustive list (spiking neurons, CTRNN, CNN, ...)

Artificial Neural Networks

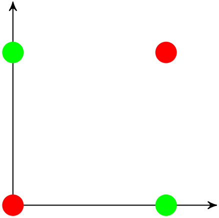
Some highlights

Video generation:
`https://openai.com/index/sora/`

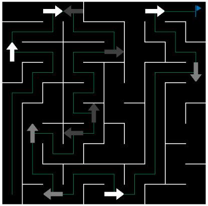
Video-game generation:
`https://gamengen.github.io/`

NeuroEvolution: Why?

- Sparse information



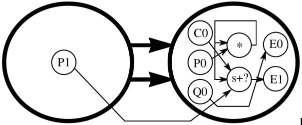
XOR



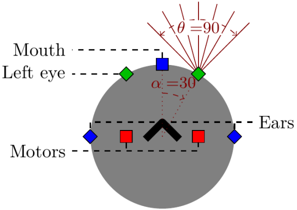
Maze

NeuroEvolution: Why?

- Sparse information
- Body-brain co-evolution



[2]



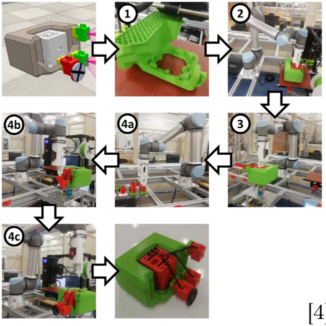
[3]

[2] K. Sims. "Evolving 3D Morphology and Behavior by Competition". In: **Artificial Life** 1.4 (1994), pp. 353–372.

[3] **K. Godin-Dubois** et al. "Specialization or Generalization: Investigating NeuroEvolutionary Choices via Virtual fMRI". In: **ALIFE 2024: Proceedings of the 2024 Artificial Life Conference**. MIT Press, July 2024.

NeuroEvolution: Why?

- Sparse information
- Body-brain co-evolution
- Automated design

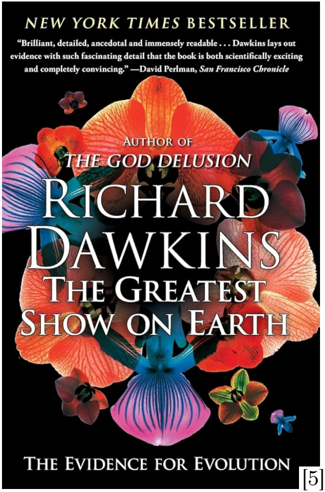


[4]

[4] M. Angus et al. "Practical Hardware for Evolvable Robots". In: **Frontiers in Robotics and AI** 10 (Aug. 2023).

NeuroEvolution: Why?

- Sparse information
- Body-brain co-evolution
- Automated design
- Biomimetism



[5]

[5] R. Dawkins. *The Greatest Show on Earth: The Evidence for Evolution*. London: Bantam press, 2009.

NeuroEvolution: Why?

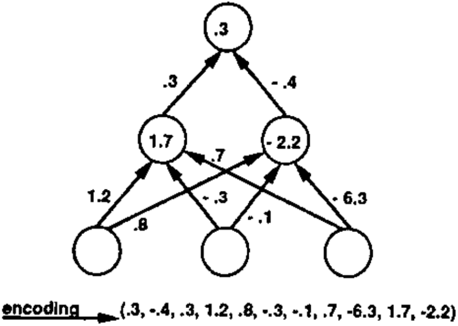
- Sparse information
- Body-brain co-evolution
- Automated design
- Biomimetism
- ...

NeuroEvolution: What?

Evolving *any* component of an Artificial Neural Network

NeuroEvolution: What?

Evolving *any* component of an Artificial Neural Network



[6] D. J. Montana et al. "Training Feedforward Neural Networks Using Genetic Algorithms". In: **Proceedings of the 11th International Joint Conference on Artificial intelligence - Volume 1** 89 (1989), pp. 762–767.

NeuroEvolution: What?

Evolving *any* component of an Artificial Neural Network

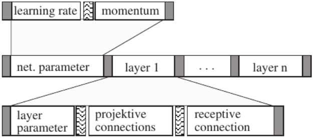


Figure 2: network representation

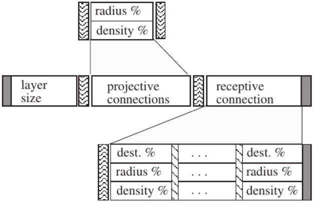
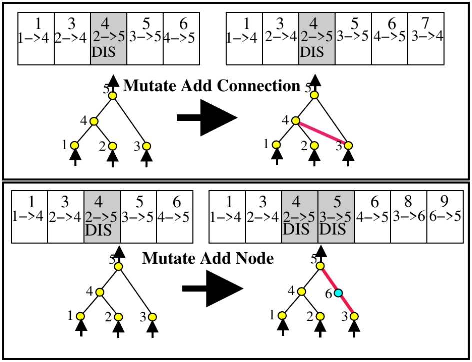


Figure 3: layer representation

[7] M. Mandischer. "Representation and Evolution of Neural Networks". In: **Artificial Neural Nets and Genetic Algorithms**. Vienna: Springer Vienna, 1993, pp. 643–649.

NeuroEvolution: What?

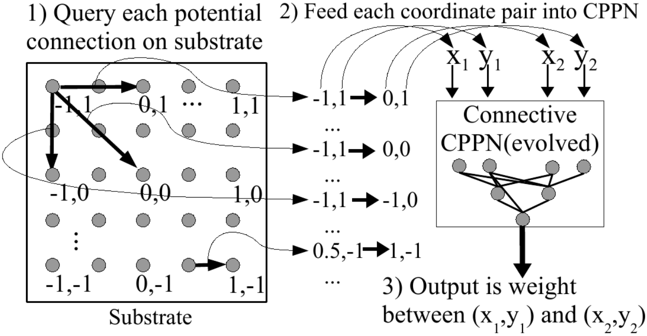
Evolving *any* component of an Artificial Neural Network



[8] K. O. Stanley et al. "Efficient Evolution of Neural Network Topologies". In: **Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No.02TH8600)** 2.figure 1 (2002), pp. 1757–1762.

NeuroEvolution: What?

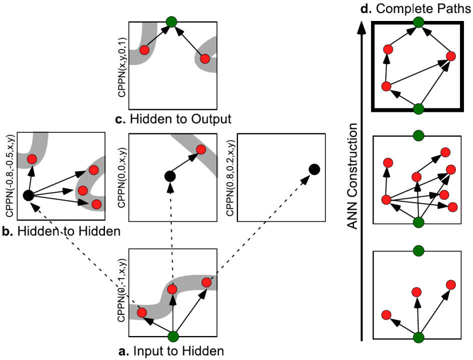
Evolving *any* component of an Artificial Neural Network



[9] K. O. Stanley et al. "A Hypercube-Based Encoding for Evolving Large-Scale Neural Networks". In: **Artificial Life** 15.2 (Apr. 2009), pp. 185–212.

NeuroEvolution: What?

Evolving *any* component of an Artificial Neural Network



[10] S. Risi et al. “An Enhanced Hypercube-Based Encoding for Evolving the Placement, Density, and Connectivity of Neurons”. In: **Artificial Life** 18.4 (2012), pp. 331–363.

NeuroEvolution of Augmenting Topologies

NEAT

NeuroEvolution of Augmenting Topologies

Introduced by Stanley et al.[11]
Reference in NeuroEvolution
60+ derivatives since 2002[12]

Three key elements:

- Historical markings
- Innovation protection
- Incremental growth

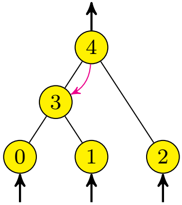
[11] K. O. Stanley et al. "Evolving Neural Networks through Augmenting Topologies". In: **Evolutionary Computation** 10.2 (2002), pp. 99–127.

[12] E. Papavasileiou et al. "A Systematic Literature Review of the Successors of "NeuroEvolution of Augmenting Topologies"". In: **Evolutionary Computation** 29.1 (Mar. 2021), pp. 1–73.

Encoding

In: 0	In: 1	In: 1	In: 2	In: 3	In: 4
Out: 3	Out: 3	Out: 4	Out: 4	Out: 4	Out: 3
Weight: 0.7	Weight: 0.5	Weight: 0.5	Weight: 0.2	Weight: 0.4	Weight: 0.6
Enabled	Enabled	Disabled	Enabled	Enabled	Enabled
Innov: 0	Innov: 2	Innov: 3	Innov: 4	Innov: 5	Innov: 9

Genome
(Genotype)

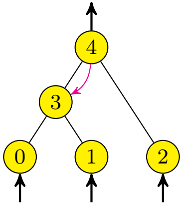


Network
(Phenotype)

Encoding

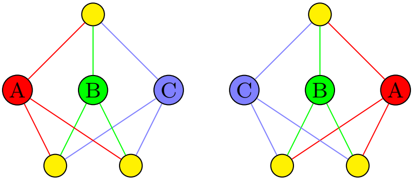
In: 0	In: 1	In: 1	In: 2	In: 3	In: 4
Out: 3	Out: 3	Out: 4	Out: 4	Out: 4	Out: 3
Weight: 0.7	Weight: 0.5	Weight: 0.5	Weight: 0.2	Weight: 0.4	Weight: 0.6
Enabled	Enabled	Disabled	Enabled	Enabled	Enabled
Innov: 0	Innov: 2	Innov: 3	Innov: 4	Innov: 5	Innov: 9

Genome
(Genotype)



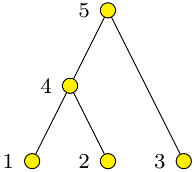
Network
(Phenotype)

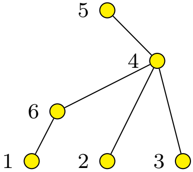
Competing conventions



$[A, B, C] \times [C, B, A]$ (single point) $\rightarrow [C, B, C]$ or $[A, B, A]$
Missing information!

Alignment crossover



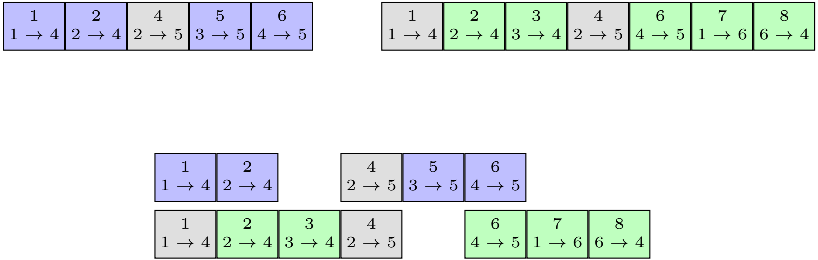


1	2	4	5	6
$1 \to 4$	$2 \to 4$	$2 \to 5$	$3 \to 5$	$4 \to 5$

1	2	3	4	6	7	8
$1 \to 4$	$2 \to 4$	$3 \to 4$	$2 \to 5$	$4 \to 5$	$1 \to 6$	$6 \to 4$

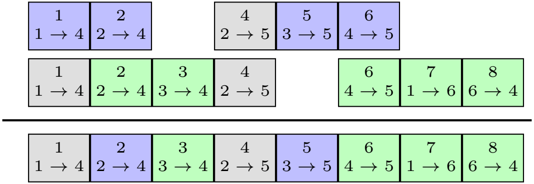
Crossing different topologies?

Alignment crossover



Aligning through historical markers

Alignment crossover

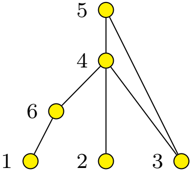


Offspring creation:

- Coin toss for matching genes (1, 2, 4,6)
- Disjoint (3, 5) and excess (7, 8) taken from fitter parent

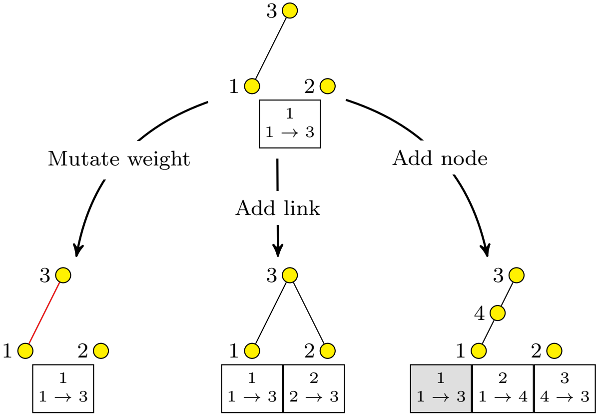
Alignment crossover

1	2	3	4	5	6	7	8
$1 \to 4$	$2 \to 4$	$3 \to 4$	$2 \to 5$	$3 \to 5$	$4 \to 5$	$1 \to 6$	$6 \to 4$



Resulting phenotype

Mutation


3
1
2
1
1 → 3
Mutate weight
Add link
Add node
3
1
2
1
1 → 3
3
1
2
1
1 → 3
2
2 → 3
3
4
1
2
1
1 → 3
2
1 → 4
3
4 → 3

Mutation

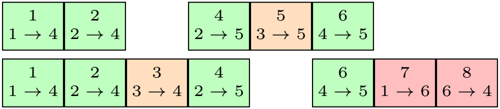
- Also enable/disable
- Missing anything?

Speciation

- Protecting innovation → partitioning into "species"
- Uses genetic distance

Speciation

Genetic distance



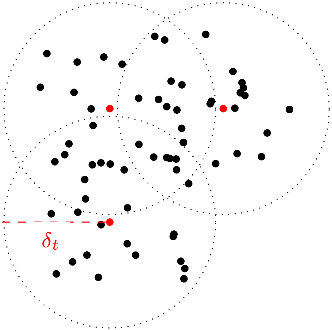
$$\delta = \frac{c_1 E}{N} + \frac{c_2 D}{N} + c_3 \bar{W}$$

Genetic distance using matching, disjoint and excess genes.

c_1, c_2, c_3 controls the relative importance

Speciation

Fitness sharing



Species:

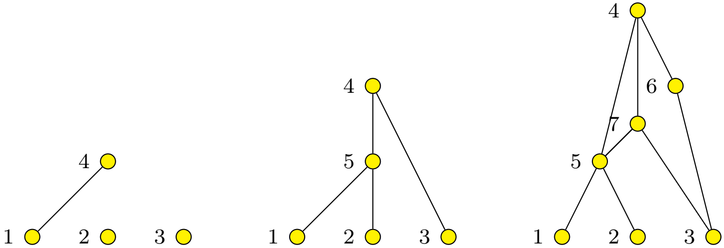
- Representative
- + distance threshold δ_t

Shared fitness:

$$f_i' = \frac{f_i}{|\text{species}(i)|}$$

Protects innovation **and** promotes diversity

Starting minimally



- Justified (fitness) additions
- Minimized dimensionality

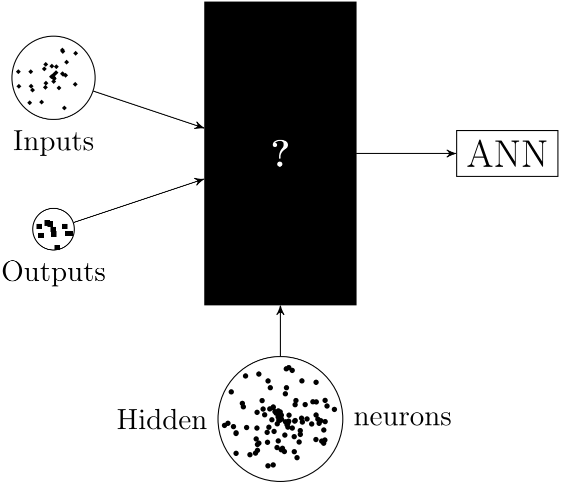
NEAT: Summary

- Start minimally
- Topological mutation
- Historical markings & crossover
- Speciation & shared fitness

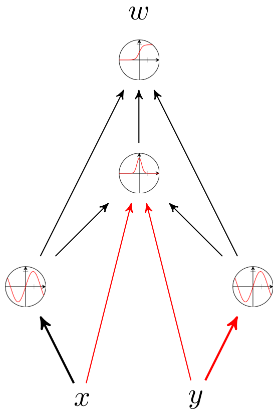
HyperNEAT

HyperNEAT

Building an ANN



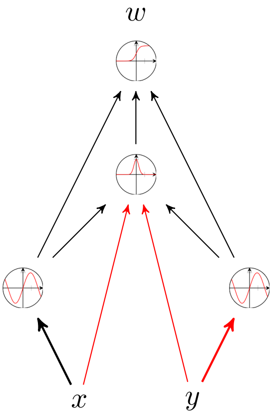
Composite Pattern-Producing Network



Introduced by Stanley (2007)
Evolvable mathematical function
$\mathbb{R}^n \rightarrow \mathbb{R}^m$

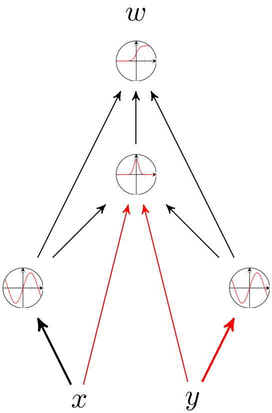
[13] K. O. Stanley. "Compositional Pattern Producing Networks: A Novel Abstraction of Development". In: **Genetic Programming and Evolvable Machines** 8.2 (June 2007), pp. 131–162.

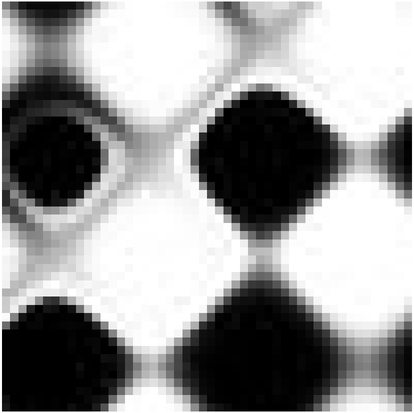
Composite Pattern-Producing Network



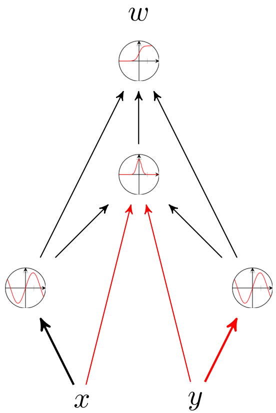
$$s_0 = sin(x)$$
$$s_1 = sin(-y)$$
$$g = e^{-(s_0 - x - y + s_1)^2}$$
$$w = \frac{1}{1 + e^{(s_0 + g + s_1)}}$$

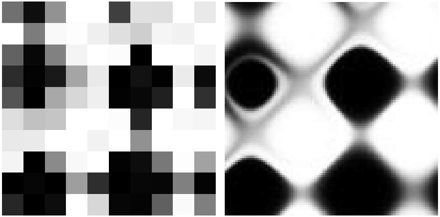
Composite Pattern-Producing Network





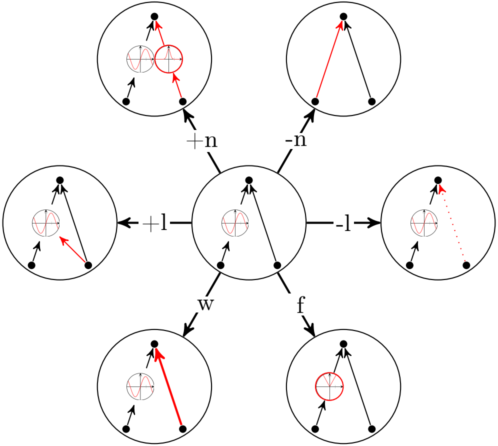
Composite Pattern-Producing Network



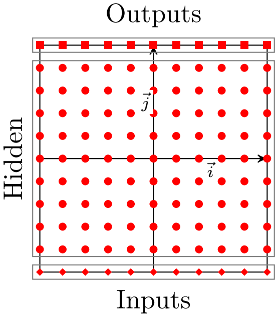


Composite Pattern-Producing Network

Evolution

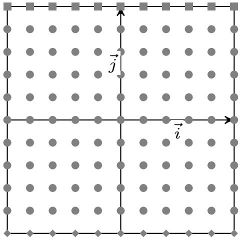


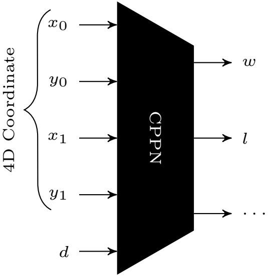
Cartesian substrate and 4D CPPN



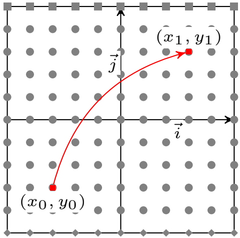
Introduced in Stanley et al. (2009)

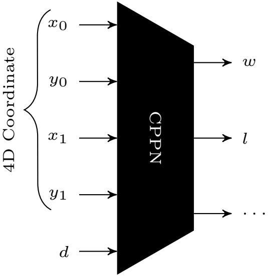
Cartesian substrate and 4D CPPN





Cartesian substrate and 4D CPPN





Advantages

- Efficacy

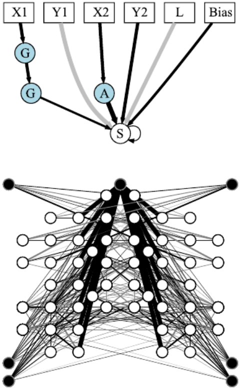


Image from Risi et al. (2012)

Advantages

- Efficacy
- Geometry

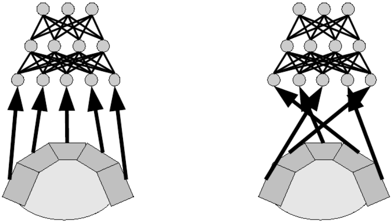
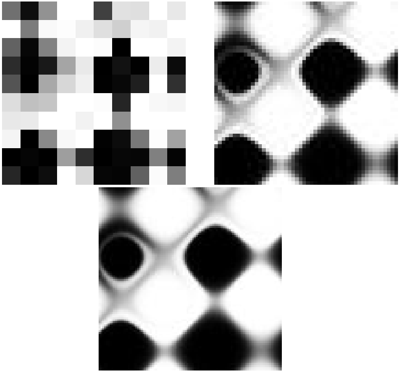


Image from Stanley et al. (2009)

Advantages

- Efficacy
- Geometry
- Scalability



HyperNEAT: Summary

- *Indirect* encoding

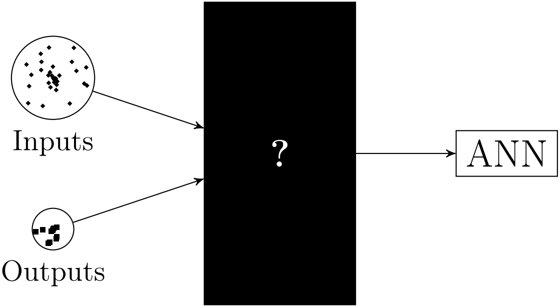
  Genotype CPPN

  Phenotype ANN

- Scalable, geometry-aware

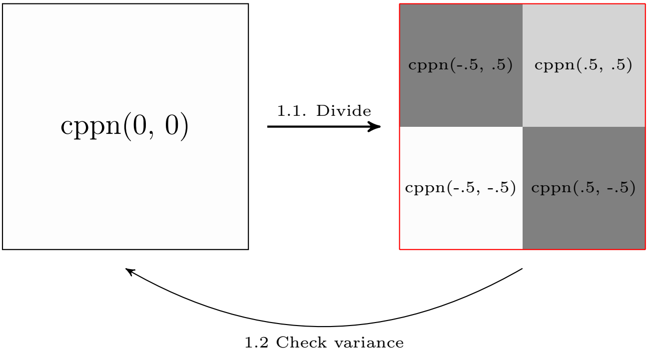
Evolvable Substrate HyperNEAT

Discovering hidden neurons



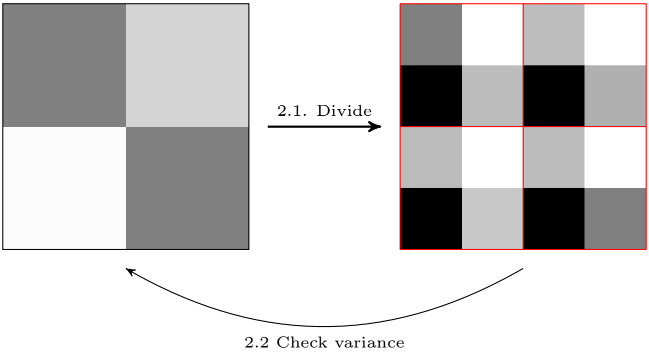
Objective: emergent hidden neurons (position, topology, ...)

Discovering hidden neurons

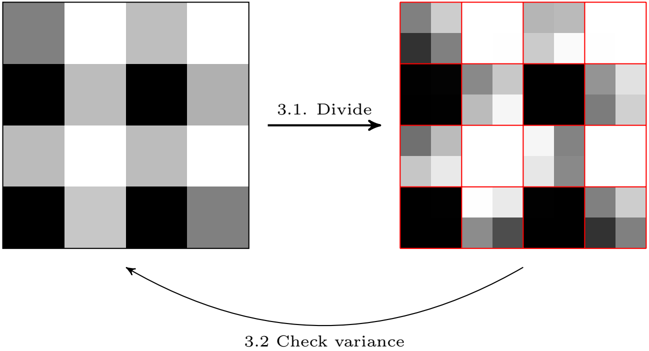


Where $cppn(x, y) \Leftrightarrow cppn(a, b, x, y)$ for a given, fixed input neuron at (a, b)

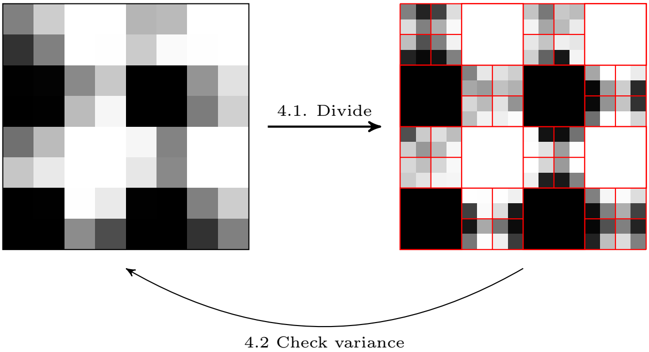
Discovering hidden neurons



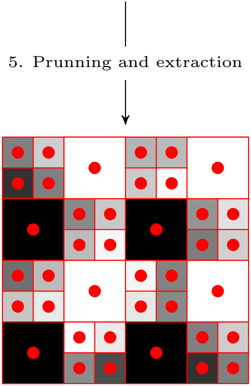
Discovering hidden neurons



Discovering hidden neurons

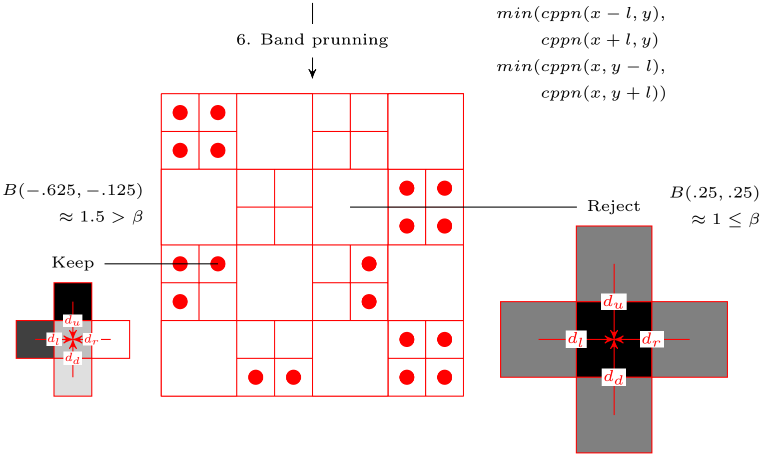


Discovering hidden neurons



Discovering hidden neurons

$$B(x,y,l) = max(min(cppn(x-l,y), cppn(x+l,y)), min(cppn(x,y-l), cppn(x,y+l)))$$



Discovering hidden neurons

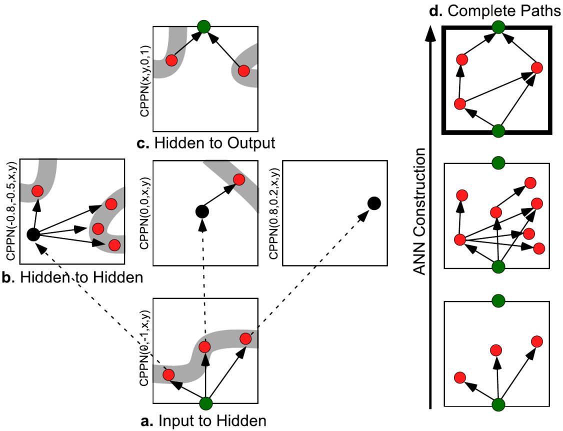


Image from Risi et al. (2012)

And more

- LEO[14]
- Bias
- Hebbian Learning[15]
- ...

[14] P. Verbancsics et al. "Constraining Connectivity to Encourage Modularity in HyperNEAT". In: **Genetic and Evolutionary Computation Conference, GECCO'11** (2011), pp. 1483–1490.

[15] S. Risi et al. "A Unified Approach to Evolving Plasticity and Neural Geometry". In: **The 2012 International Joint Conference on Neural Networks (IJCNN)**. IEEE, June 2012, pp. 1–8.

ES-HyperNEAT: Summary

- Builds upon HyperNEAT
- Automatic discovery of hidden neurons
- Fully emergent topologies

Applications

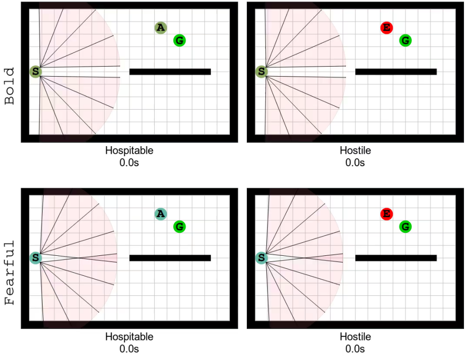
Applications

- Evolutionary Robotics
- Video game agents control
- Evolutionary Biology
- (Deep) Reinforcement Learning
- ...

Source: K. O. Stanley et al. "Designing Neural Networks through Neuroevolution". In: **Nature Machine Intelligence** 1.1 (2019), pp. 24–35

Applications

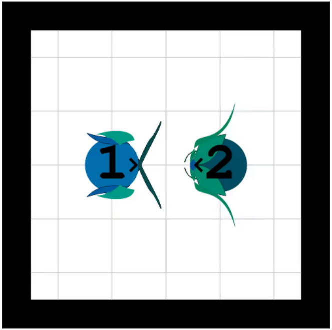
Foraging and avoidance

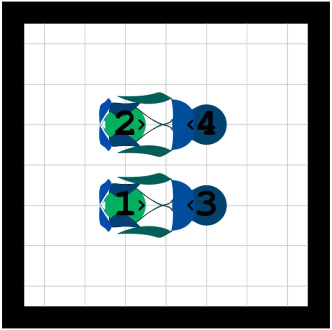


Reach (G), avoid (E), (A) is neutral

Applications

Competition & Co-evolution

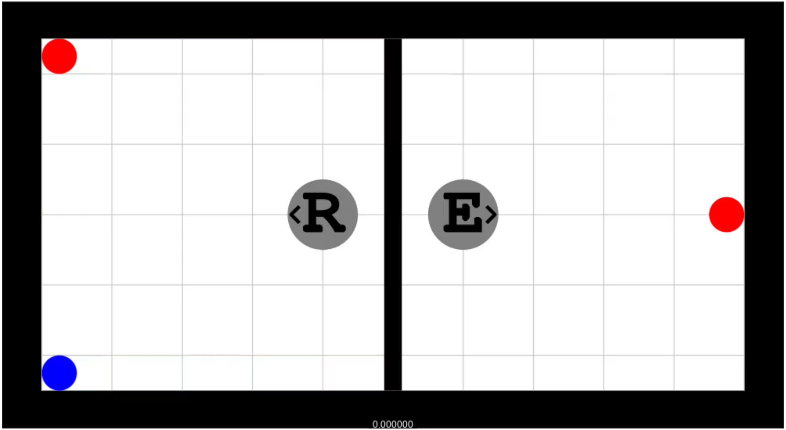




Physical confrontation

Applications

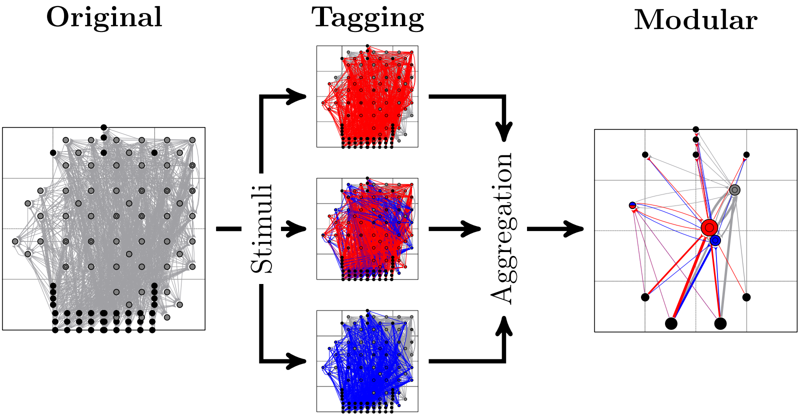
Information sharing



(E) informs (R) of the object's color

Applications

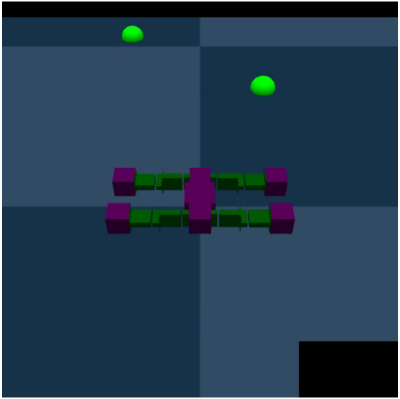
Virtual fMRI



Extracting functional modules from an emergent, dense topology

Applications

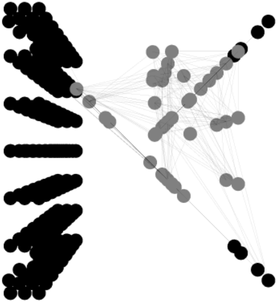
3D modular robots



Collect green, avoid red

Applications

Reinforcement learning



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Summary

Summary

- Evolution of an ANN's parameters
- Always applicable (with drawbacks)
- Indirect encoding: more powerful but more complex
- CPPN: mathematical function

Further reading:

- E. Papavasileiou et al. "A Systematic Literature Review of the Successors of "NeuroEvolution of Augmenting Topologies"". In: **Evolutionary Computation** 29.1 (Mar. 2021), pp. 1–73
- K. O. Stanley et al. "Designing Neural Networks through Neuroevolution". In: **Nature Machine Intelligence** 1.1 (2019), pp. 24–35
- Xin Yao. "Evolving Artificial Neural Networks". In: **Proceedings of the IEEE** 87.9 (1999), pp. 1423–1447
- J. Branke. "Evolutionary Algorithms for Neural Network Design and Training". In: **Workshop on Genetic Algorithms and its Applications** (1995), pp. 1–21

Annexes

- References

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[9] K. O. Stanley, D. B. D’Ambrosio, and J. Gauci. “A Hypercube-Based Encoding for Evolving Large-Scale Neural Networks”. In: **Artificial Life** 15.2 (Apr. 2009), pp. 185–212.

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[11] K. O. Stanley and R. Miikkulainen. "Evolving Neural Networks through Augmenting Topologies". In: **Evolutionary Computation** 10.2 (2002), pp. 99–127.

[12] E. Papavasileiou, J. Cornelis, and B. Jansen. "A Systematic Literature Review of the Successors of "NeuroEvolution of Augmenting Topologies"". In: **Evolutionary Computation** 29.1 (Mar. 2021), pp. 1–73.

[13] K. O. Stanley. "Compositional Pattern Producing Networks: A Novel Abstraction of Development". In: **Genetic Programming and Evolvable Machines** 8.2 (June 2007), pp. 131–162.

[14] P. Verbancsics and K. O. Stanley. "Constraining Connectivity to Encourage Modularity in HyperNEAT". In: **Genetic and Evolutionary Computation Conference, GECCO'11** (2011), pp. 1483–1490.

[15] S. Risi and K. O. Stanley. "A Unified Approach to Evolving Plasticity and Neural Geometry". In: **The 2012 International Joint Conference on Neural Networks (IJCNN)**. IEEE, June 2012, pp. 1–8.

[16] K. O. Stanley et al. "Designing Neural Networks through Neuroevolution". In: **Nature Machine Intelligence** 1.1 (2019), pp. 24–35.

[17] Xin Yao. "Evolving Artificial Neural Networks". In: **Proceedings of the IEEE** 87.9 (1999), pp. 1423–1447.

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[18] J. Branke. “Evolutionary Algorithms for Neural Network Design and Training”. In: **Workshop on Genetic Algorithms and its Applications** (1995), pp. 1–21.