A Unified Approach to Evolving Plasticity and Neural Geometry

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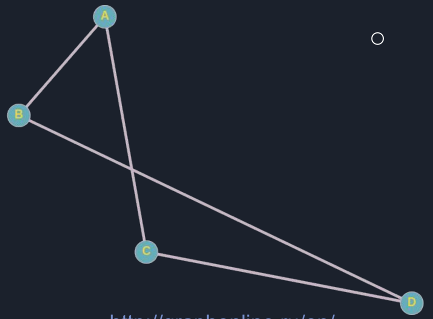
The Brain & Neuroevolution

Creating Artificial Neural Networks

- Hard to replicate brain as artificial neural networks (ANNs)
- Very dynamic, module, and regular
- Neuroevolution = autonomously generating ANNs
    - Evolutionary algorithms
    - Still can't compare to real brain
    - neural topology != neural topography
        - Important for spatial organization



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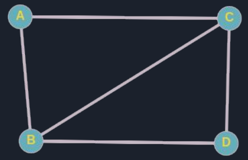
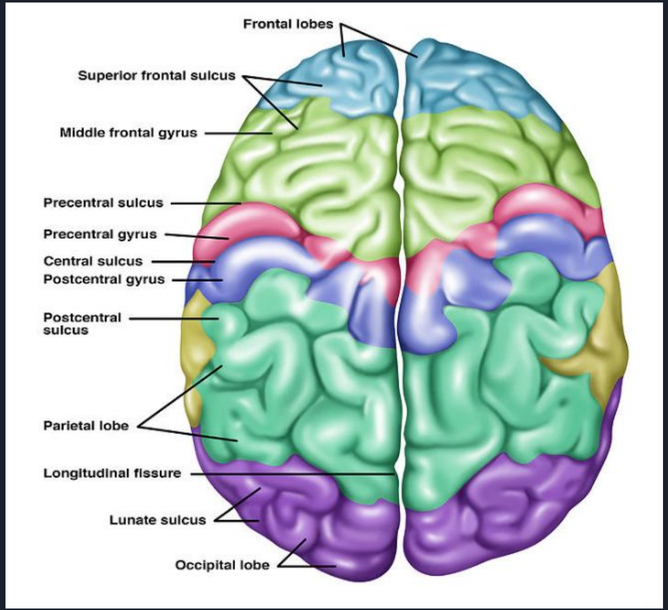




https://fineartamerica.com/featured/2-top-view-of-normal-brain-illustration-gwen-shockey.html

NEAT

NeuroEvolution of Augmenting Topologies

- Evolves increasingly large ANNs
- Takes simple network → adds nodes/connections via mutations
- Searches networks
  - More complex network takes more time
- Direct encoding
  - Each part of solution (gene) gets its own mapping (BAD)
    - similar genes → different encoding → more searching
- Does not scale well

HyperNEAT

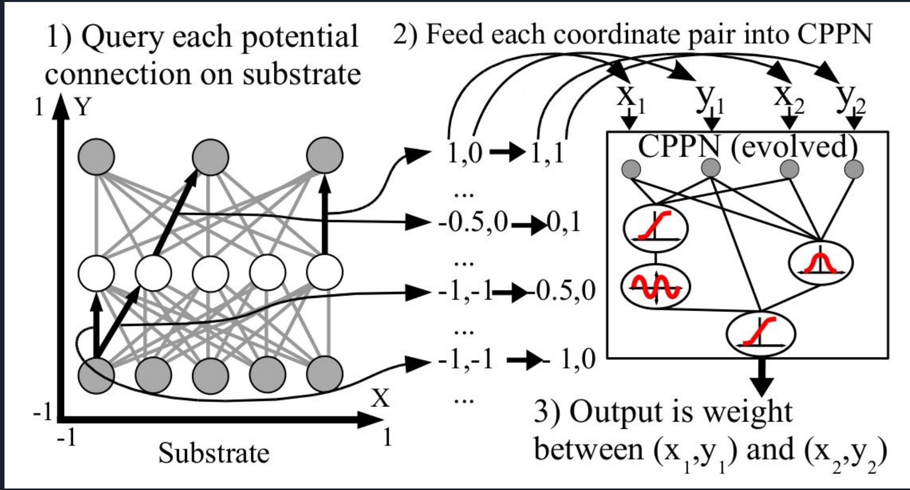
Hypercube-based NEAT

- Indirect encoding
  - Encode solution as function of geometry
    - patterns/regularities (symmetry, repetition)
  - Can compress and reuse these patterns
  - CPPNs
- Nodes/connections need to be placed in certain geometric locations
  - Exploit topography
  - Beneficial for neuroevolution
  - More like real brain

CPPNs

Compositional Pattern Producing Networks

- Abstracted version of DNA
  - Compactly encodes patterns of weights across network's geometry
- Function input = node locations and role
- Function output = weights of connections
- Function return = topographic pattern (substrate)
- Composition of functions/regularities
  - Gaussian (symmetry) and periodic (repetition)
- Can be evolved by NEAT



HyperNEAT: Potential connections → CPPN → Weight of connections

Still Not Good Enough

:(

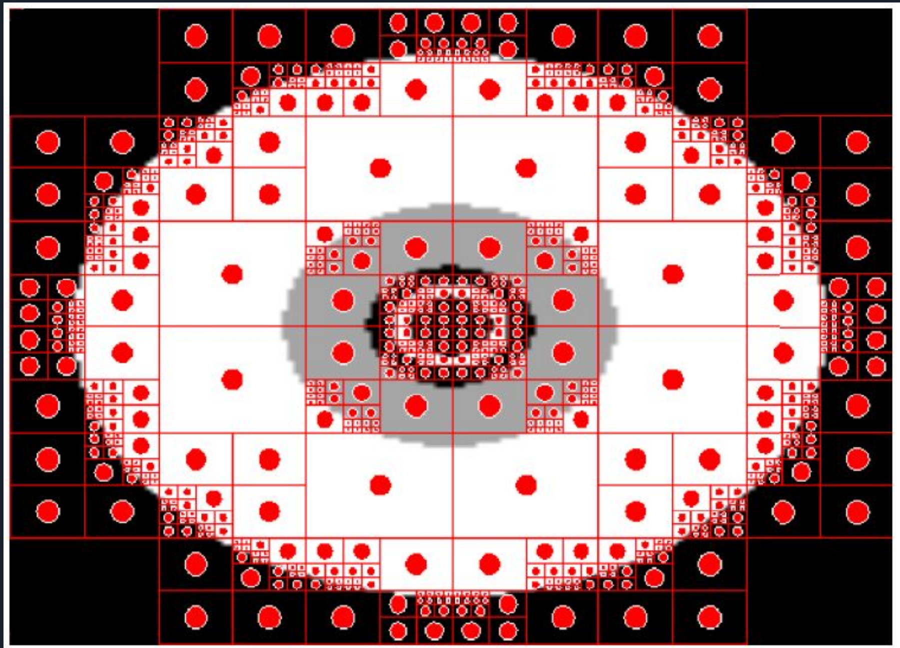
- Static implementations
- No online adaptation
- Needs learning rules
- Needs to be more biologically plausible
- Needs to know locations and roles
- Evolvable-substrate and adaptive HyperNEAT can help

Evolvable Substrate HyperNEAT

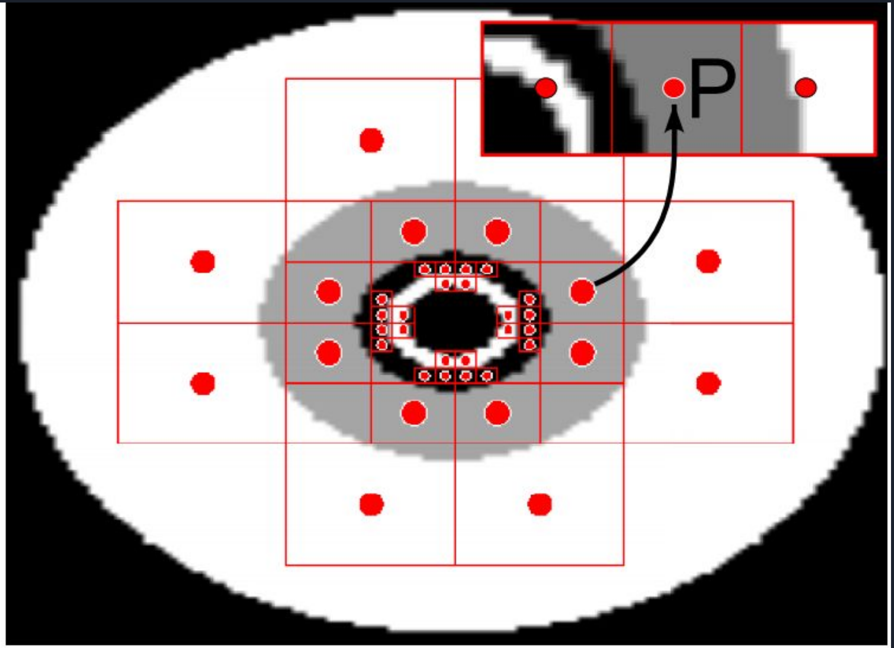
-Locations of hidden nodes determined by CPPN

-The CPPN paints a picture of activations

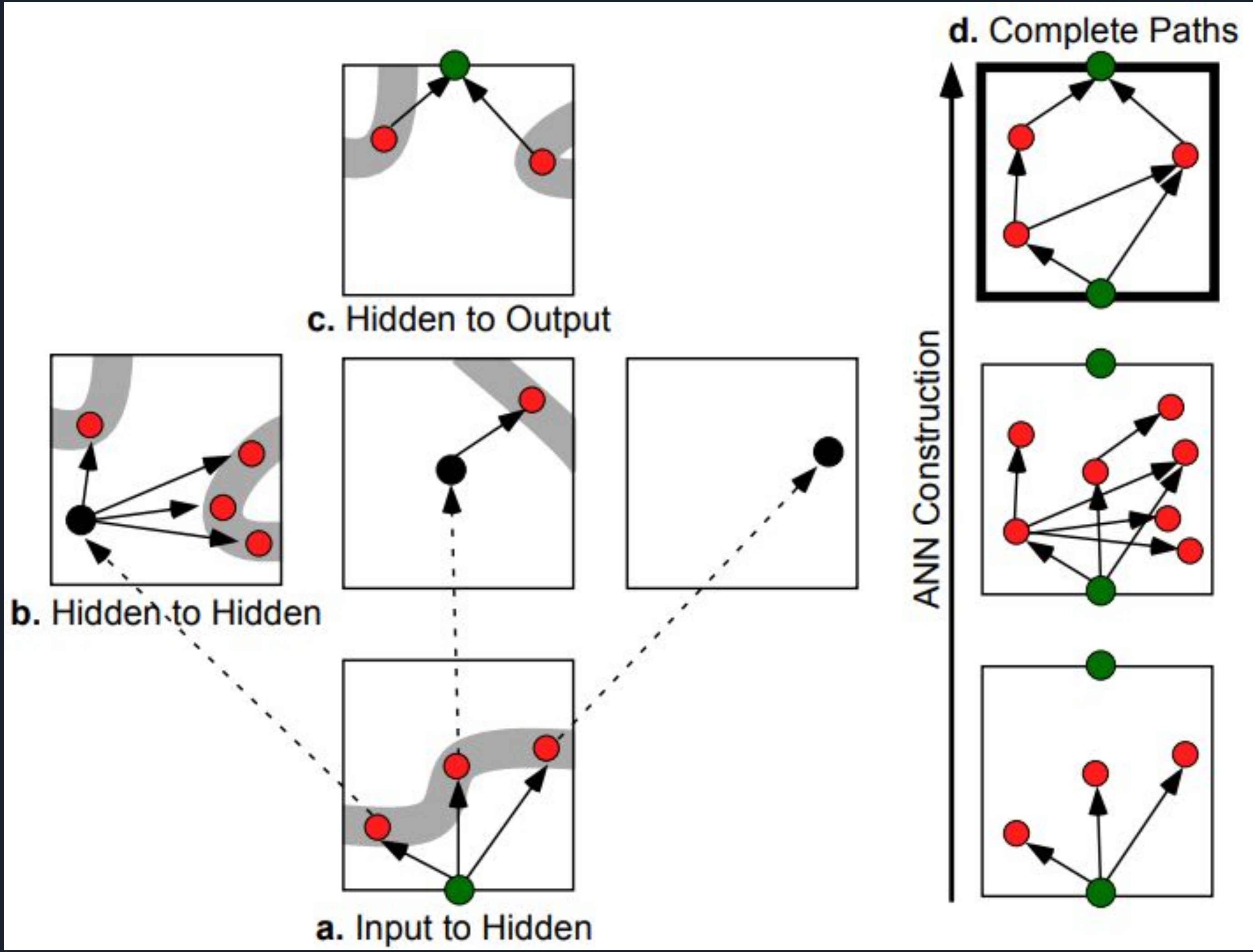
-Chose nodes which give the most information using quadtree algorithm



Quadtree algorithm



Quadtree + band pruning

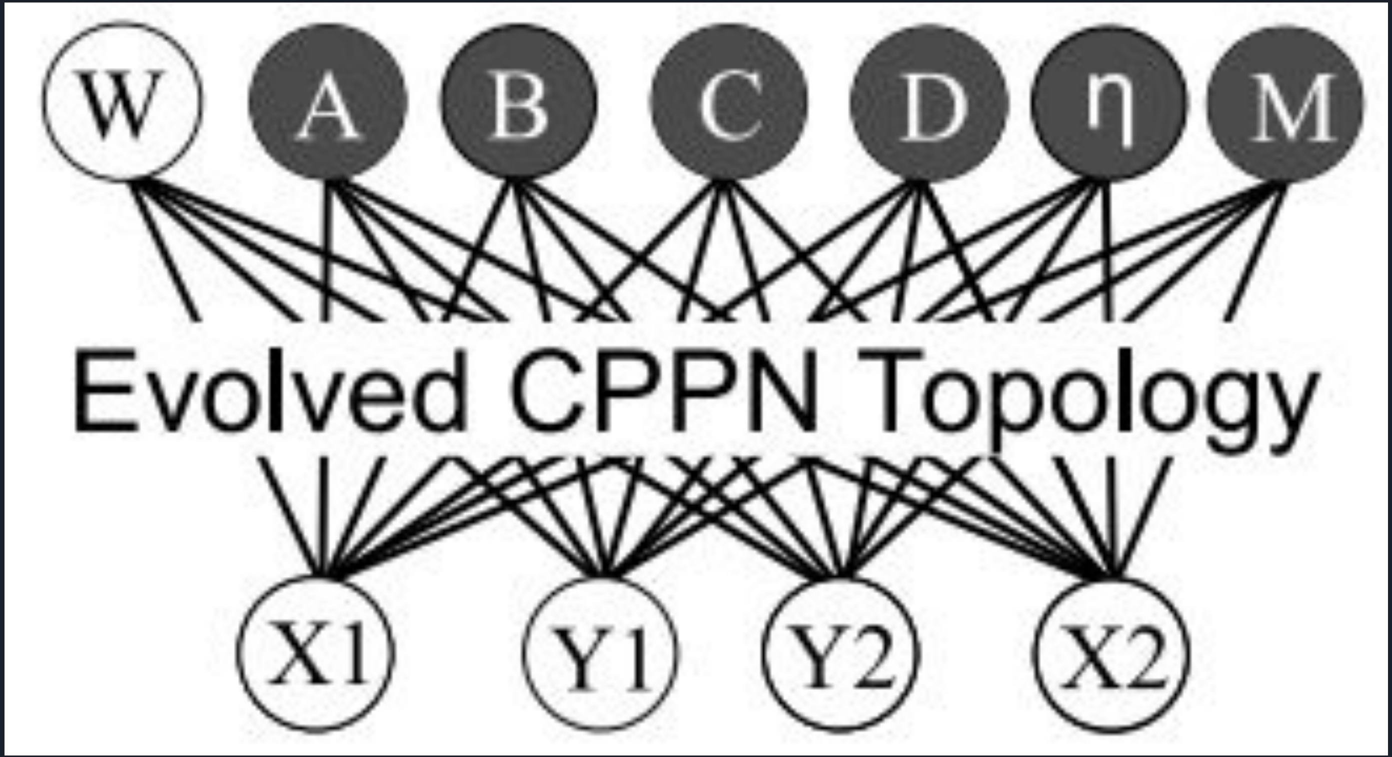

d. Complete Paths
c. Hidden to Output
ANN Construction
b. Hidden to Hidden
a. Input to Hidden

Adaptive HyperNEAT

-Want network which adapts to observations?

-CPPN produces parameters for Hebbian Learning

$$\Delta w_{ji} = \eta \cdot [A o_j o_i + B o_j + C o_i + D]$$


W
A
B
C
D
η
M
Evolved CPPN Topology
X1
Y1
Y2
X2

Adaptive ES-HyperNEAT

- Simultaneously evolves geometry, density, and plasticity, using a combination of the previously developed versions of NEAT.

- CPPN generates 6 additional outputs: Learning rate (n) , Correlation term (A), presynaptic term (B), postsynaptic term (C), constant (D), and modulation (M). Used to simulate Hebbian learning!

$$\Delta w_{ji} = \eta \cdot [A o_j o_i + B o_j + C o_i + D]$$

$$m_i = \sum_{w_{ji} \in Mod} w_{ji} \cdot o_j.$$

Adaptive ES-HyperNEAT

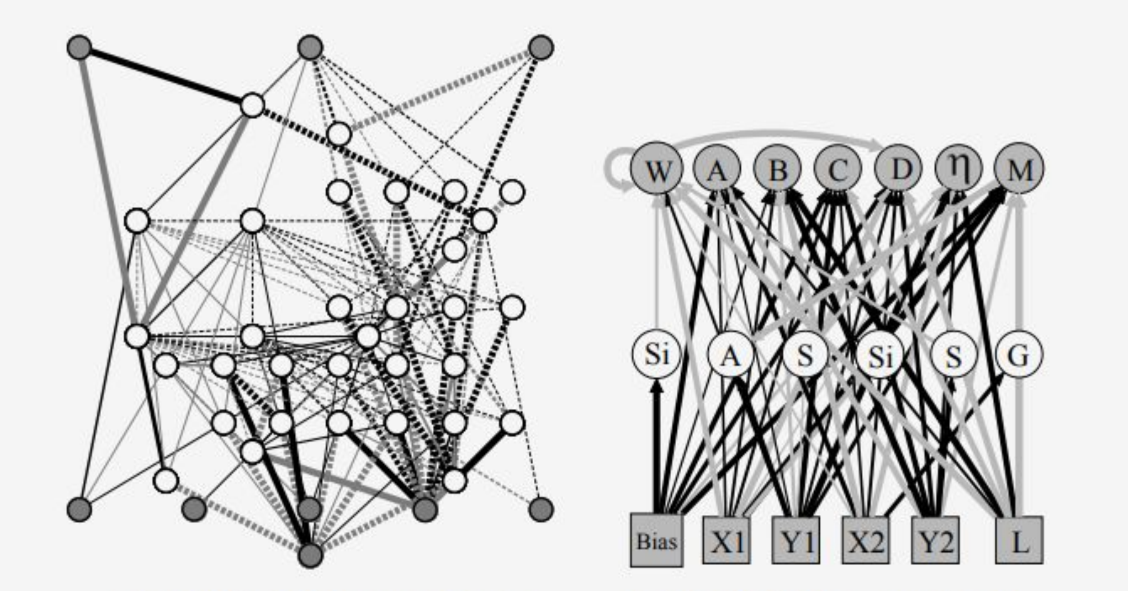
- Each Neuron computes its own modulatory activation (m), which we use to adjust weights of connections between neurons

$$m_i = \sum_{w_{ji} \in Mod} w_{ji} \cdot o_j.$$

$$\Delta w_{ji} = tanh(m_i/2) \cdot \eta \cdot [Ao_j o_i + Bo_j + Co_i + D].$$

- Determines the placement and density of nodes from implicit information gained from the weight output and the modulatory output from the CPPN

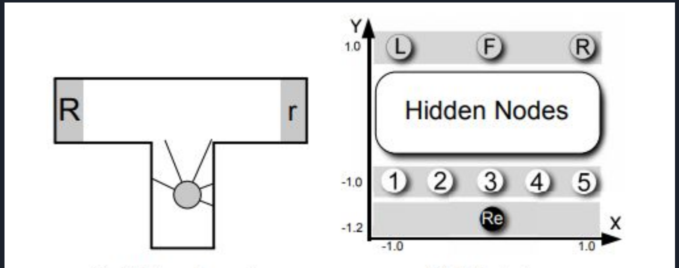
Adaptive ES-HyperNEAT



(a) ANN (1,043 parameters) (b) CPPN (54 parameters)

An example of an ANN generated by it's respective CPPN

Continuous T-Maze Experiment



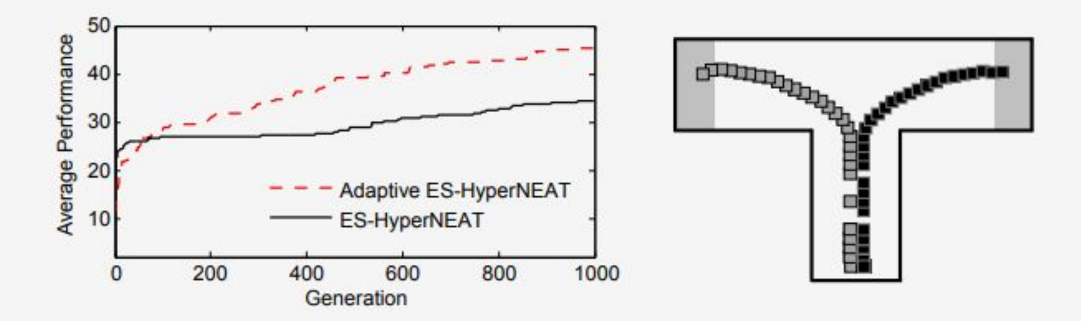
(a) T-Maze Learning (b) Substrate

- Standard test of operant conditioning in animals
- Augmented T-Maze; Higher valued reward is achieved in sequence
- No sensor pre-processing needed, direct input into Adaptive ES-HyperNeat, sensors are correlated geometrically
- Fitness function is maximized when the same reward is consistently collected.
- Ran with:

  1000 generations, 300 individuals, 10% elitism

  Crossover offspring with no mutation (~50%) / direct offspring with mutation (~94%)

Results



(a) T-Maze Training (b) Neuron Activation

- ES-HyperNEAT solving T-Maze at 1 out of 30 runs on average
- Adaptive ES-HyperNEAT found a solution in 19 out of 30 runs on average.
- Augmenting ES-HyperNEAT to adapt is important for adaptation tasks.
- No special sensors, only raw sensor input.
- Neural dynamics start to represent dynamics in nature.
- A single compact CPPN can encode a full adaptive network with full plasticity.