What Can Neuroevolution Tell Us About Biological Evolution?

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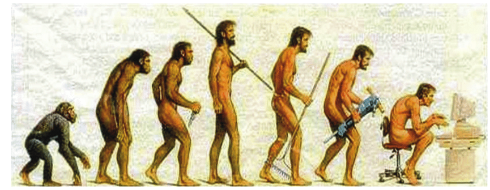
Understanding Biology

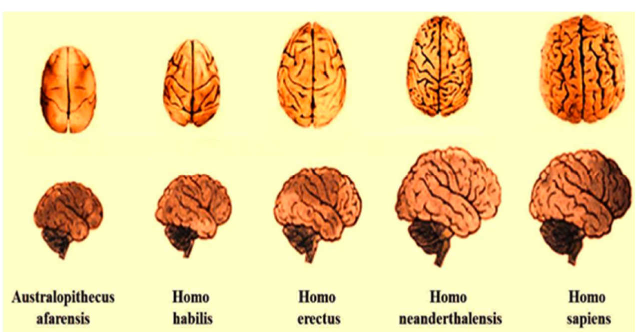
- "Nothing in biology makes sense except in the light of evolution" (Dobzhansky, 1973)
- Difficult to understand structure and function without considering how evolution could have discovered it.
  - E.g. speech arising from mastication (chewing).
- Not all structures are optimal; some are evolutionary remnants.
  - Example: Human tailbone & appendix as vestigial structures.



https://www.uv.es/jgpausas/he.htm

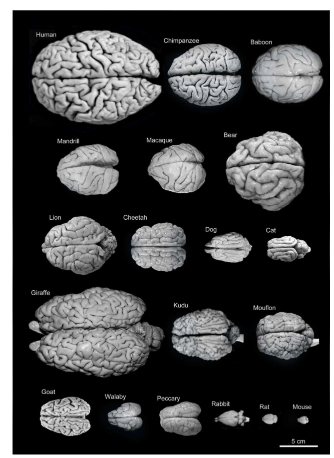
Neuroevolution in Biology

- Goal of neuroscience: Identify how brain structures produce behavior.
- Neuroevolution can help understand the evolution of biological intelligence.
- Key questions:
  - Why do specific neural structures exist?
  - How do genetic and environmental factors combine in development?
  - What evolutionary steps lead to complex behavior?



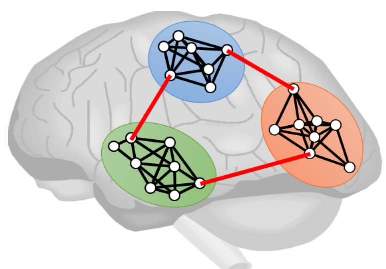
Variation in Brain Organization

- High-level brain organization is consistent across individuals and species.
- Evolution provides successful variations to adapt to niches.
- Artificial agents can simulate environments to understand brain evolution.



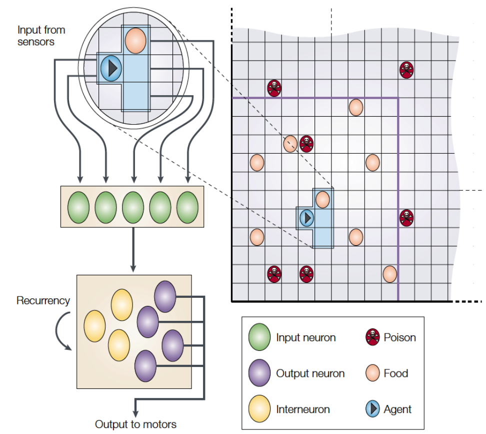
Undertanding Network Structures

- Can go beyond single-cell analysis because have access to full networks.
- Methods:
  - Lesion studies.
  - Shapley value for contribution analysis.
  - Pruning networks to remove non-significant elements.
  - Adaptation of methods for neuroscience (e.g., simulated EEG, fMRI, TMS).
- Examples: Neuron analysis; delays; pattern generators; network motifs; modularity; neuromodulation.



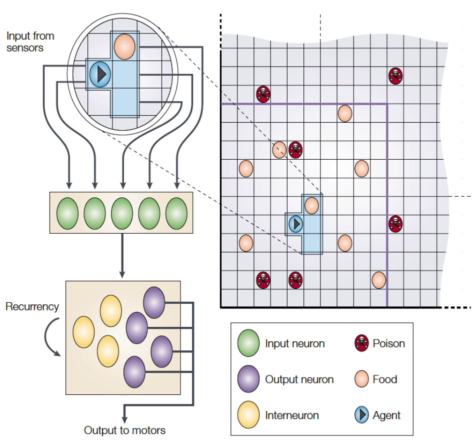
Example 1: Single-Cell Interpretation

- Simulated task: Agent navigates to food while avoiding poison.
- Neural network with 5 sensory, 4 motor, and 6-41 hidden neurons.
- Analyzed in simulated neuroscience experiments.



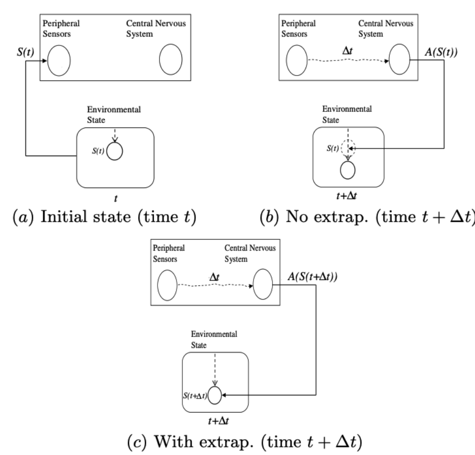
Emergence of Command Neurons

- Command neurons switch behaviors (e.g., navigation to foraging).
- Result in higher fitness for agents.
- Similar command neurons found in aplysia, crayfish, and lobsters.



Example 2: Facilitating Synapses

- Facilitating synapses play roles in temporal sequence processing.
- Activation depends on input and the rate of change in activation: $A(T) = X(t) + r(X(t) - A(t-1))$
- Can compensate for delays in biological neural networks.



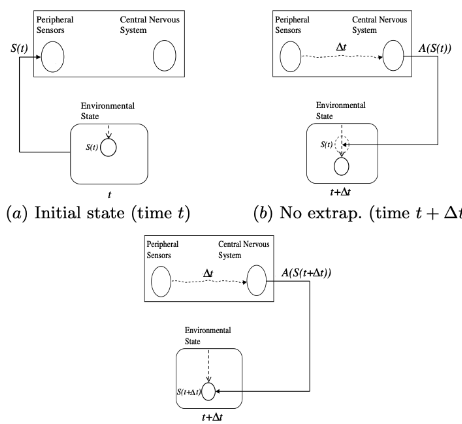
(a) Initial state (time t)

(b) No extrap. (time $t + \Delta t$)

(c) With extrap. (time $t + \Delta t$)

Implications for Predictive Mechanisms

- Delays compensated by synaptic facilitation suggest prediction.
- Predictive mechanisms may be fundamental for cognition.
- Supports theories on predictive coding in the brain.

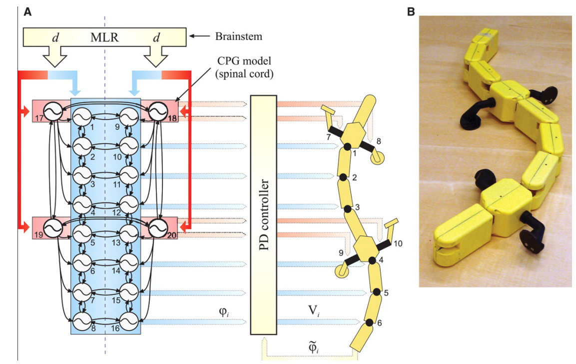


(a) Initial state (time t) (b) No extrap. (time $t + \Delta t$)

(c) With extrap. (time $t + \Delta t$)

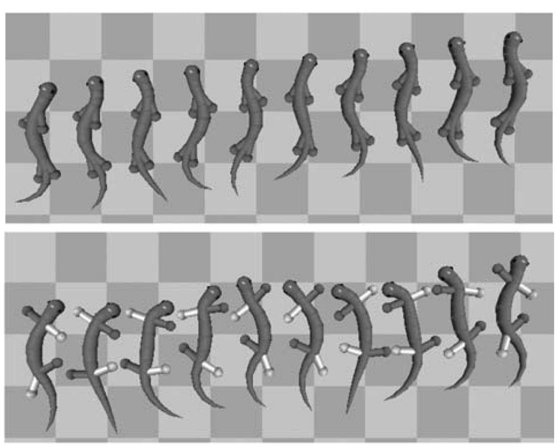
Example 3: Central Pattern Generators (CPGs)

- CPGs control rhythmic activities like walking and swimming.
- Hard to get the design right to reproduce behavior.
- Evolved controllers often outperform hand-designed models.
- Robust enough to put on hardware.



From Swimming to Walking

- The oscillation patterns and connectivity structures closer to biology.
- Same circuit can control both swimming and walking.
- Demonstrating a crucial phase in vertebrate evolution?



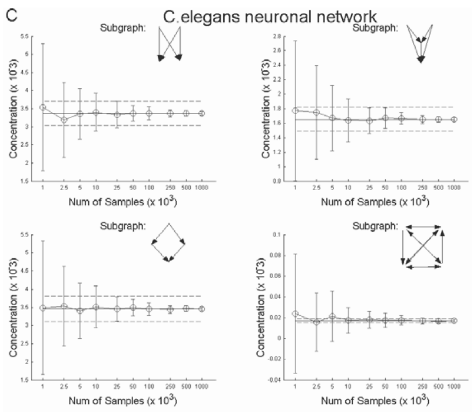
https://youtu.be/YVU8M_xcZec?si=THlSClwkFqnLYI72

Example 4: Network Building Blocks

- If a network is evolved to solve a task (e.g. single pattern recognition) little systematicity.
- However, if multiple tasks solved at once (e.g. multiple patterns), network motifs arise.
- Many tasks have common subgoals expressed as motifs.
- Feedforward loop filters information; single-input generates time variance.

Multifunctionality in the Brain

- Similar motifs found in biological networks
- In general, many areas serve multiple functions.
- E.g. visual areas utilized for language.
- Neuroevolution demonstrates how multifunctionality arises from complexity.



Example 5: Evolutionary Origins of Modularity

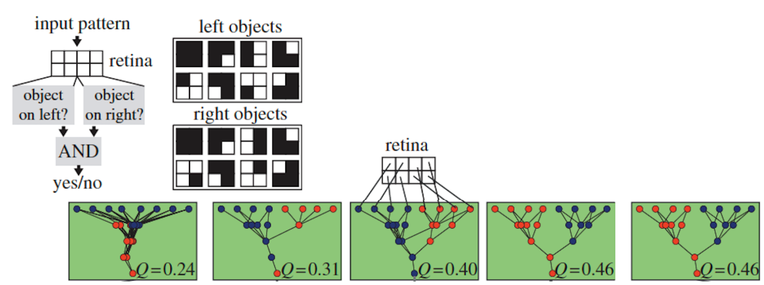
- The brain's structure is influenced by physical requirements as well as computational needs.
- Efficient metabolism and space constraints contribute to its organization.
- Gray matter and white matter distribution is an example of space optimization.

Importance of Minimizing Wiring Length

- Minimizing wiring length is a key principle influencing brain structure.
- Supports the hypothesis that modularity in the brain may have evolutionary origins.
- Modularity simplifies construction, maintenance, and adaptability.

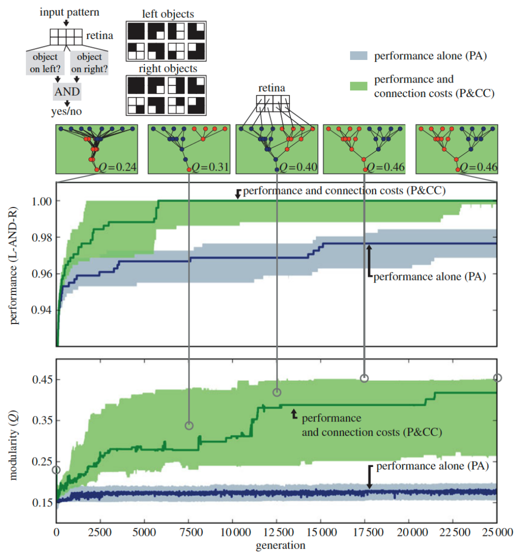
Computational Demonstration of Modularity

- Neuroevolution with two objectives: Performance and wiring length.
- An eight-pixel retina detecting objects on left, right, or both sides.
- Feedforward networks with three hidden layers were evolved.
- Modularity measured by comparing connection density within and across modules.



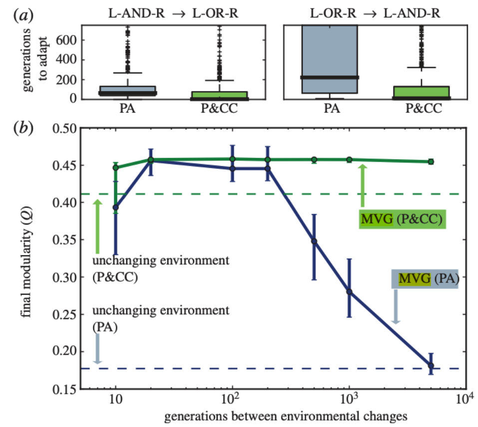
Results of Modularity in Evolution

- Evolution with wiring constraints produced more modular networks.
- Modular networks often corresponded to left/right decision-making.
- Modular networks outperformed nonmodular ones.



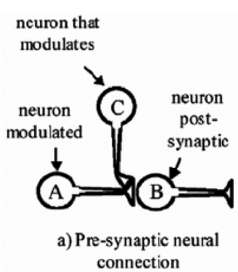
Evolvability of Modular Networks

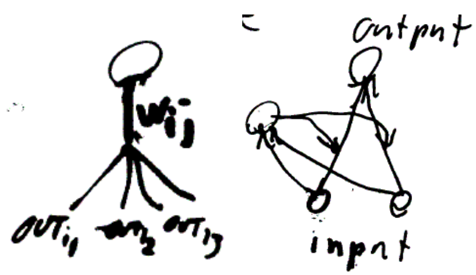
- Modular networks adapt faster to new tasks.
  - Modularly varying goals (MVG), i.e. composed of known subtasks.
- With changing tasks, higher levels of modularity result.
- Suggests that while wiring length drives modularity, adaptation strengthens it.



Example 6: Neuromodulation

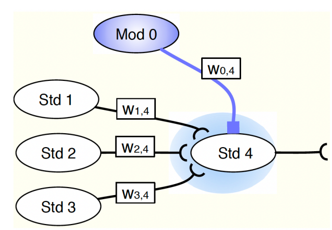
- Neurons affecting input sum or Hebbian weight change multiplicatively.
- Sigma-pi units: networks using both summation and multiplication: $y_j = F_j(\Sigma_i w_{ij} \Pi_i y_i$
- XOR function represented with fewer neurons (e.g., AND, OR, and a selector).
- Applicable to complex tasks like grammar recognition.





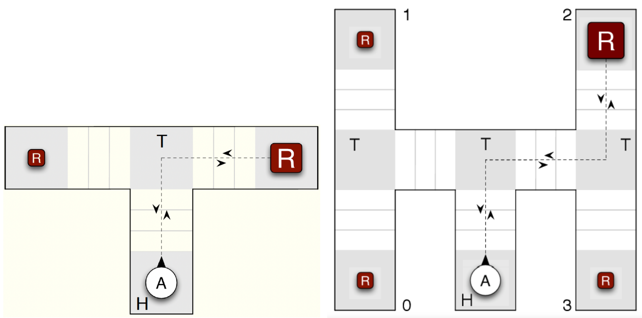
Experiment on Neuromodulation in Evolution

- Neuromodulation integrated with Hebbian plasticity: $w_{ji} = \eta \tanh(o_m)(Ao_jo_i + Bo_j + Co_i + D)$.
- Modulatory neuron influences weight changes and learning rates.



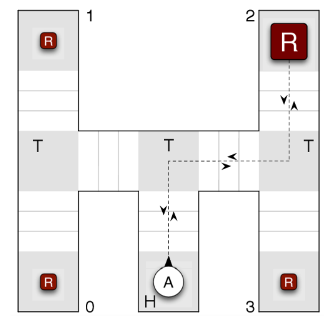
T-Maze Navigation Task

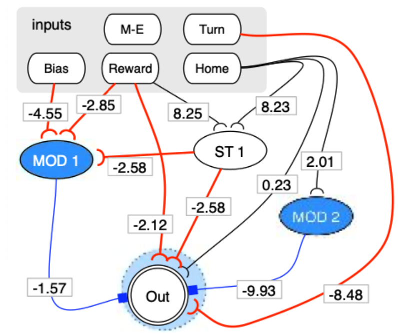
- Navigate a T-maze to reach a reward, adapting to changing reward locations.
- Network topology and Hebbian learning parameters evolved.
- Networks with and without neuromodulation were tested.



Role of Neuromodulation in Performance

- Modulatory networks adapted more reliably than non-modulatory networks.
- When modulation turned off, still performed well locally but not globally.
- Not an add-on, but integrated into the dynamics of behavior.
- Evolution favors solutions that leverage all mechanisms available.



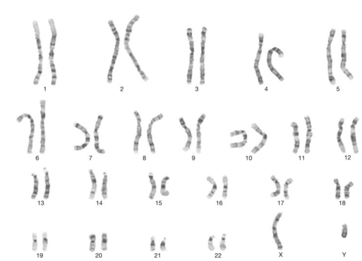


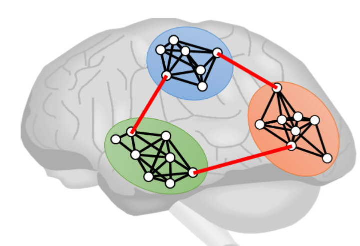
Neurovelution Insight into Developmental Processes

- Key question in cognitive science: How much behavior is innate vs. learned?
- Both nature and nurture contribute to intelligent behavior.
- Initial development and long-term stability often driven by genetically directed learning.

Synergy of Evolution and Development

- With only about 24k human genes; much of brain complexity must be learned.
- Genes provide initial structure, biases, and learning mechanisms.
- Evolution takes advantage of the ability to learn.
- Example: Language as an innate capacity needing environmental input.



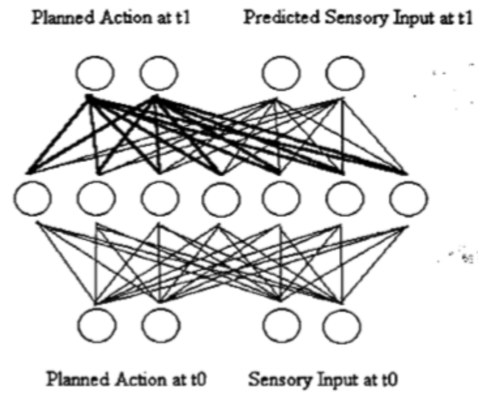


Critical Periods

- Humans have extended development periods compared to other animals.
- Critical periods for acquiring skills such as walking, talking, and social behavior.
- Missing these periods can result in incomplete development.
- Example: Can learn to communicate late, but not grammatically.
- Learning is programmed into development.

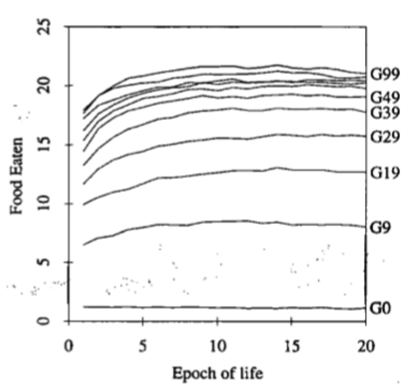
Example 1: Synergy of Evolution and Learning

- Experiment: Simulated creatures in a 2D grid world for foraging.
- Input: Angle and distance to nearest food item, previous action.
- Output: Predicted sensory input and next action.



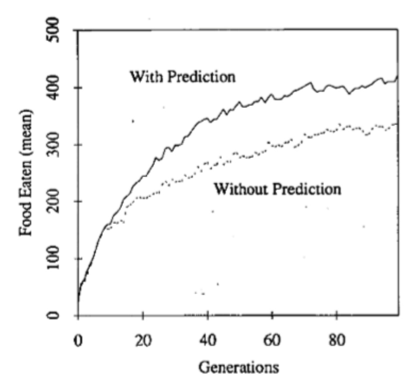
Learning and Evolution in the Model

- Networks trained via gradient descent to predict action outcomes.
- Developmental process enhances evolution by allowing adaptation within a lifetime.
- Prediction ability improves over generations but is not directly genetic.



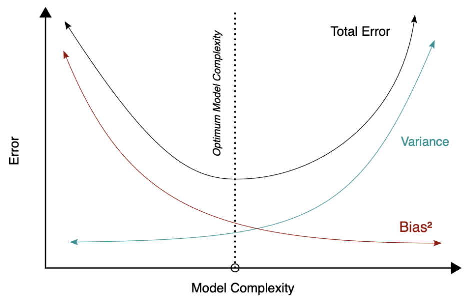
Benefits of Synergetic Development

- Synergetic development facilitates the discovery of better solutions.
- Combines genetic structure with adaptable learning mechanisms.
- Demonstrates evolution's use of learning to enhance adaptability.



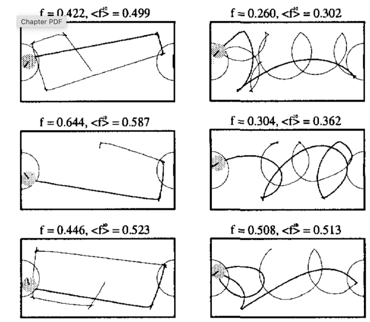
Balancing Bias and Variance

- Evolution and learning: Bias vs. variance balance.
- Evolution: High bias, low variance → general principles.
- Learning: High variance, low bias → specific situations.
- Developmental systems balance these aspects for robust learning.



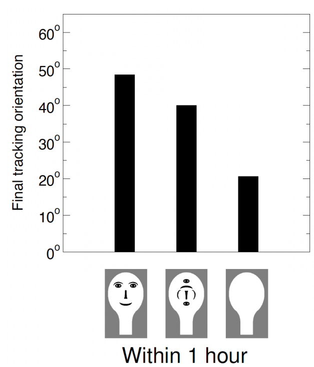
Example 2: Evolving Learning Systems

- Learning parameters can be evolved to enhance task performance.
- Example: Hebbian learning parameters evolved in robot navigation tasks.
- Evolution finds optimal parameters, balancing bias and variance.



Example 3: Establishing Useful Biases

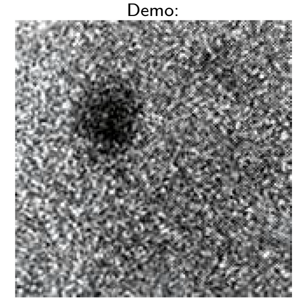
- Visual systems combine genetic predispositions and learning.
- Retinotopy and orientation sensitivity partially innate, refined through early life learning.
- Innate preferences (e.g., face-like patterns) observed in human newborns.



Mechanism of Internal Pattern Generation

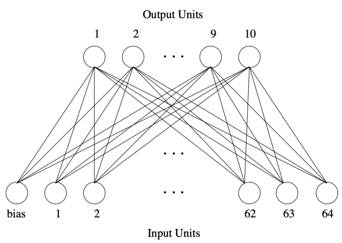
- Evolution uses internal pattern generation for learning bias.
- Examples: Retinal activity waves for orientation detectors, patterns in the ponto-geniculate-occipital loop for face preference.
- Less need for fully specified starting points, evolution provides pattern generation processes.

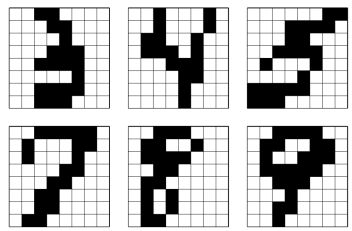
Demo:



Experiment: Pattern Recognition with Neural Networks

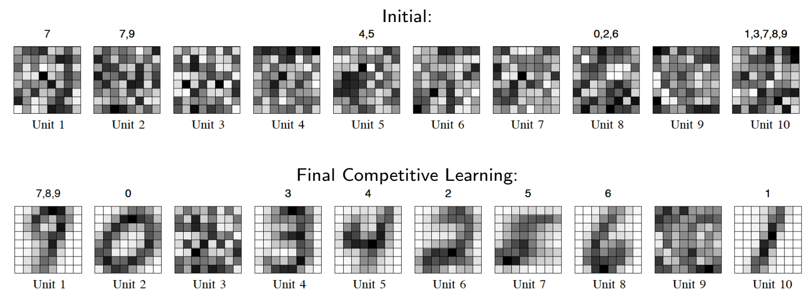
- Task: Recognize handwritten digits (NIST dataset).
- Three approaches: learning, evolution, evolved pattern generation + learning.
- Learning is based on simple Competitive learning model:
  - An array of neurons with input weight vectors w_i
  - Neuron with the closest w_i to input x_i wins
  - Winner's w_i adapted towards the input: $w_i(t+1) = w_i(t) + \eta(x_i - w_i(t))$
  - Learns a categorization of the input vectors





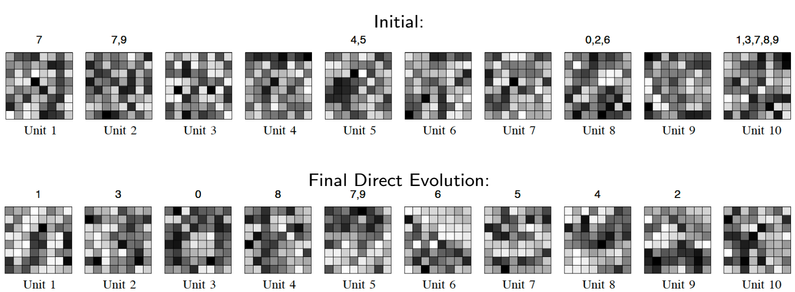
Learning Weight Vectors

- Initial weights are random.
- Competitive learning develops weight vectors resembling digit patterns.
- But struggles with 1/7, 3/8/9, often missing some of these categories.



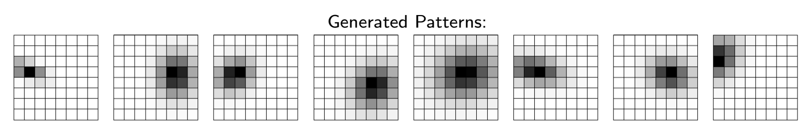
Learning Weight Vectors

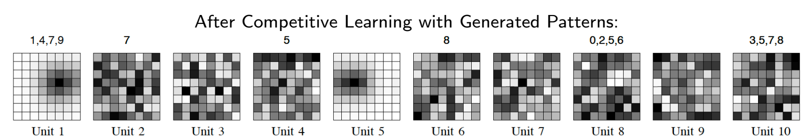
- Evolution does not care about representing digits.
- Evolved weight vectors emphasize key differences for classification.
- Still struggles with 1/7, 3/8/9.



Evolved Patterns

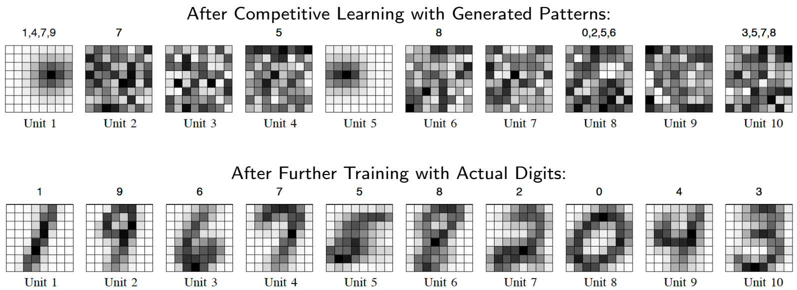
- Evolved pattern generators emphasize horizontal midline locations.
- Hard to learn from actual digits
- Provide initial separation for the difficult categories 1/3/7/8/9.
- Discovered as a useful learning bias by evolution.





Synergy of Evolution and Learning

- Result: Competitive learning with actual digits separates all categories.
- Adaptive systems balance innate structure and postnatal learning.
- Synergy of the two mechanisms.



Example 4: Stability in Continual Learning (hypothesis)

- Pattern generators may stabilize learning over an animal's lifetime.
- Prevents overfitting and catastrophic forgetting.
- Insight for building adaptive, stable artificial systems.