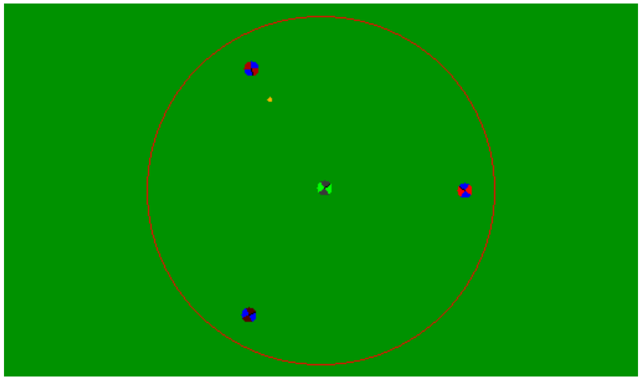
From Low-level Control to High-level Strategy

- Low-level control: Adjusting single behaviors (e.g., moving a leg faster).
- High-level strategy: Coordinating multiple behaviors.
- Example: Keepaway soccer: GetOpen, Intercept, Hold, EvaluatePass, Pass
- Challenge: Switching between behaviors effectively.

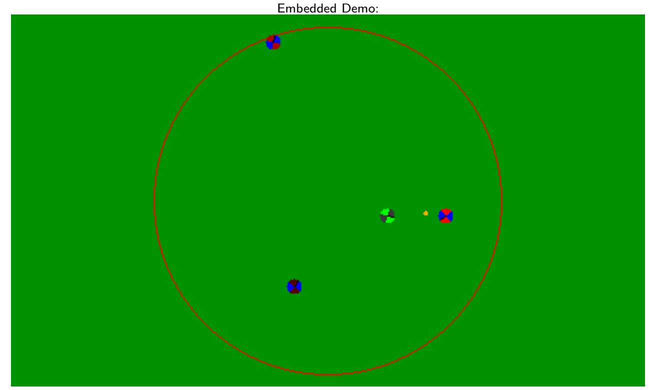


(Whiteson & Kohl 2005)

Direct Evolution

- Mapping sensors directly to actions
- Difficult to separate behaviors
- Ineffective combinations result

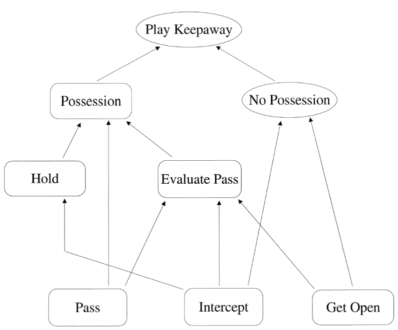
Embedded Demo:



(Whiteson & Kohl 2005)

Coevolution Approach

- Evolve a separate network for each behavior
- A decision tree to decide which network to activate

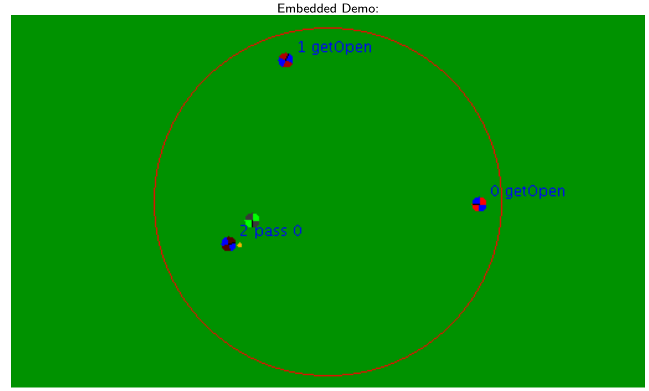


(Whiteson & Kohl 2005)

Flexible Multimodal Behavior

- Discovering flexible multimodal behavior is a key step toward general intelligence.
- Keepaway task:
  - Networks learn individual tasks
  - Learn to anticipate other tasks as well: Lining up for a pass
  - Cooperative coevolution of multimodal behavior

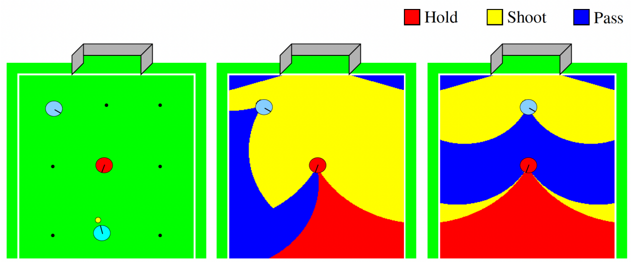
Embedded Demo:



(Whiteson & Kohl 2005)

Challenge 1: Abrupt Switching Between Behaviors

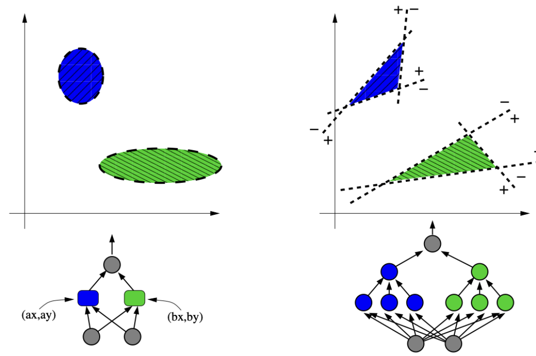
- Some strategies require abrupt behavior changes.
- Example: Small changes in soccer can shift the optimal action from holding to shooting or passing.
- Difficult to capture in a decision tree.
- Can we eolve a network to do it?



(Kohl & Miikkulainen 2008)

Using Radial Basis Activation Functions

- Radial Basis Functions (e.g. elongated Gaussians) activate neurons in local regions.
  - Many sigmoidal nodes are needed for the same effect.
  - Easier to discover fractured regions.

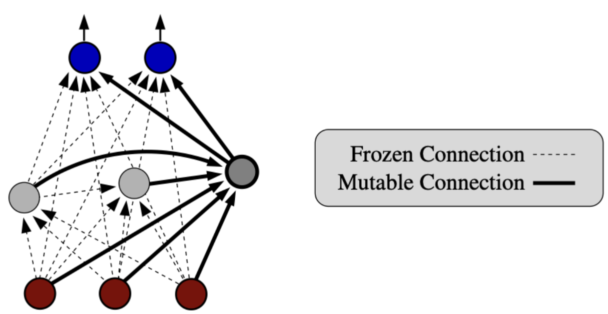


(Kohl 2009)

RBF vs. sigmoid activation functions

Using Cascaded Network Structures

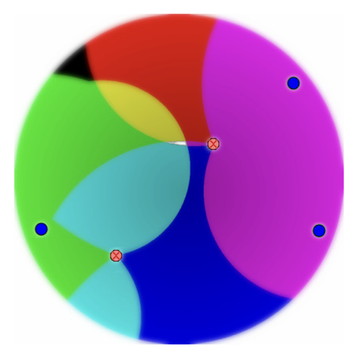
- Cascaded networks: new hidden neurons added on top of earlier ones.
- Earlier connections are frozen.
- Each new neuron refines the boundaries of existing behaviors.



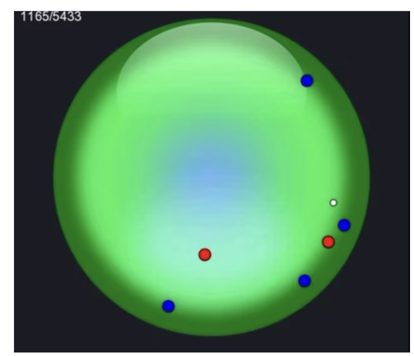
(Kohl & Miikkulainen 2011)

RBF + Cascade Make Abrupt Changes Possible

- Scales to 4v2 Keepaway.


(Kohl & Miikkulainen 2011)

Number of teammates available for a pass

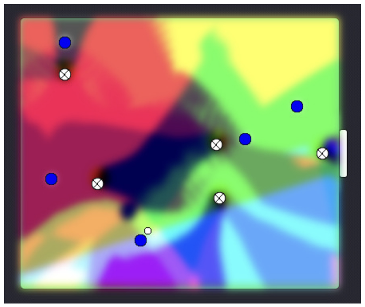


(Kohl 2009)

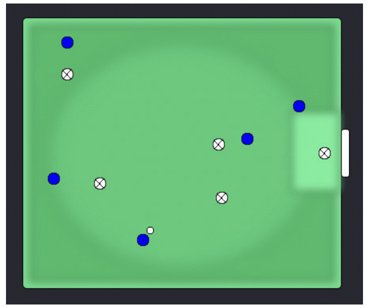
Demo link: `https://vimeo.com/2155250`

RBF + Cascade Make Abrupt Changes Possible

- Scales to 5v5 half-field soccer.



Subsets of actions (of 6) available)

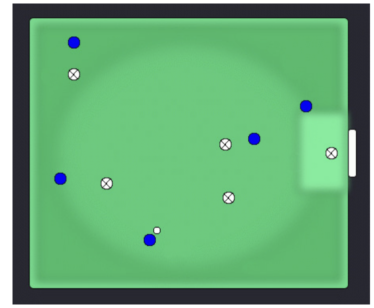


Demo link: `https://vimeo.com/5698040`

(Kohl & Miikkulainen 2011)

Challenge 2: Blending and Interleaving Behaviors

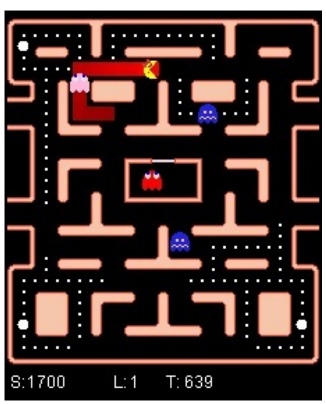
- Intelligent agents often combine several behaviors.
- Example: Switching between offense and defense in soccer.
  - They can be blended or rapidly interleaved.



(Kohl & Miikkulainen 2011)

Example: Ms. Pac-Man

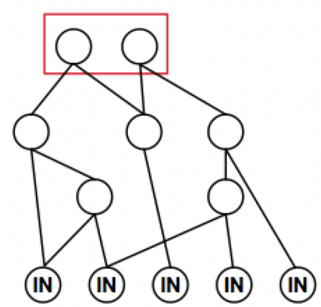
- In Ms. Pac-Man, agents perform several tasks:
  Eat pills, avoid ghosts, eat powerpills, eat ghosts.
- Sometimes interleaved but clearly separate.
- Sometimes blended into multiple tasks at once.
- How can we evolve such complex combinations of behaviors?



(Schrum 2014)

Evolving a Simple Control Network

- Simple networks can be evolved for Ms. Pac-Man, but they struggle with behavior separation.
- Results: Poor performance due to blended behaviors.
- Neuroevolution can learn multiple behaviors, but it needs a more sophisticated approach to switch effectively.

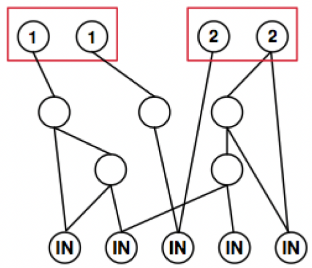


(Schrum 2014)

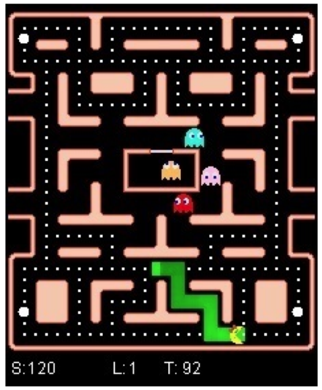
Demo link:
`https://youtu.be/hkcvd8Aitd8`

Multitask Networks for Isolated and Interleaved Tasks

- Multitask networks with separate outputs can be evolved for threatening and edible ghosts.
- Decide on which outputs to use based on a rule.
- These networks work well in isolated or interleaved tasks.
- However, they still struggle in blended situations where multiple behaviors are required simultaneously.



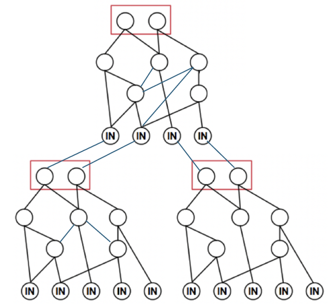
Embedded Demo:

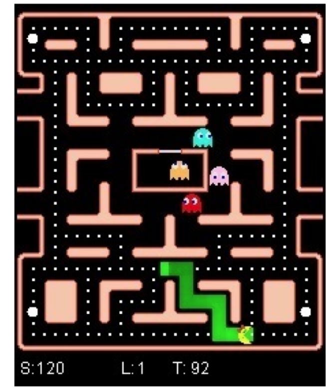


(Schrum 2014)

Expert-designed Subtasks and Combiner Networks

- Evolve separate networks for each behavior, and a combiner network to switch between them.
- Evolve one network for threatening and another for edible ghosts.
- The combiner could be gating or transforming the task-specific outputs.
- Possible to blend, but three coevolving populations difficult to converge.

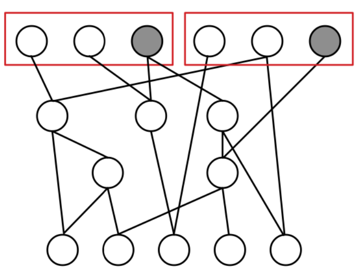


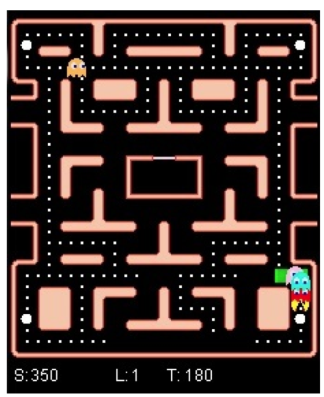


(Schrum 2014)

Preference Neurons: Letting Evolution Discover Task Divisions

- Preference neurons allow evolution to decide when to switch behaviors.
- Each output module is coupled with a preference neuron, indicating when it should be used.
- Evolution can add modules similarly to nodes and connections in NEAT.
- This method enables evolution to discover more flexible and effective task divisions.

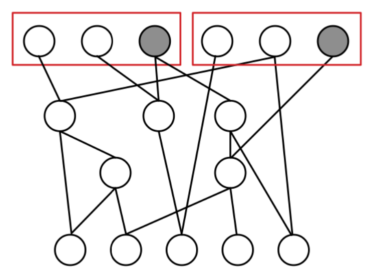




(Schrum and Miikkulainen 2016)

Surprising Strategy Discovery: Luring

- Evolution discovered an unexpected strategy: luring ghosts toward a power pill, then eating them up.
- One module dedicated to this strategy.
- Human designers may not have discovered this behavior.



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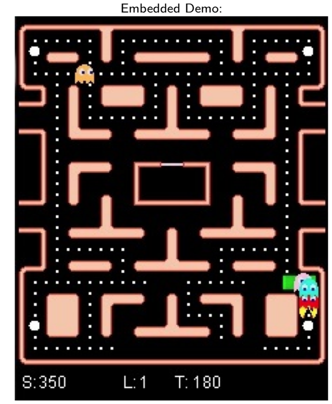
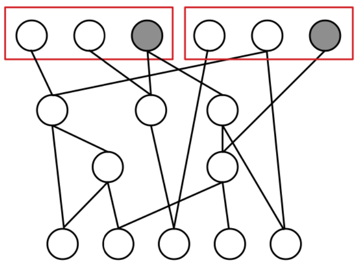
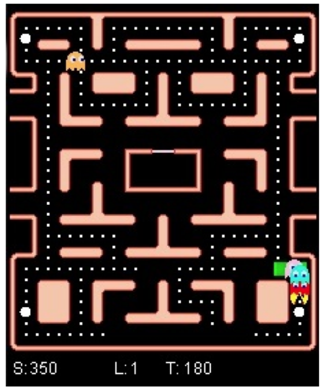


(Schrum and Miikkulainen 2016)

Discovering Effective Task Divisions

- The same luring module was used to escape threatening ghosts in tight spaces!
- A very different task division:
  - Luring and escaping used only 5% of the time, but it counts.
  - Eating pills, avoiding ghosts, chasing ghosts with the other module 95% of the time; variations with a common base.
- With the freedom to explore different strategies, evolution finds surprising and powerful solutions.

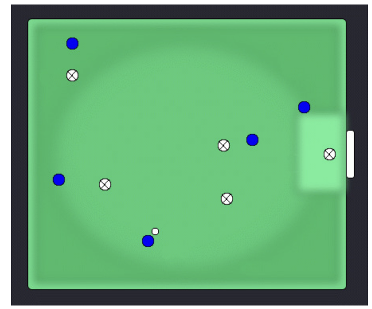




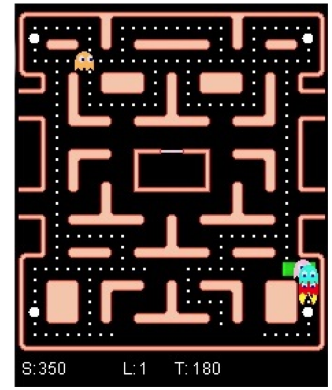
(Schrum and Miikkulainen 2016)

Conclusion on Discovering Flexible Strategies

- High-level strategies require flexible switching and blending of multiple behaviors.
- RBF nodes, Cascaded networks, modular networks with preference neurons allow evolution to discover such strategies.
- Optimal behaviors can be surprising, e.g. blending and luring.



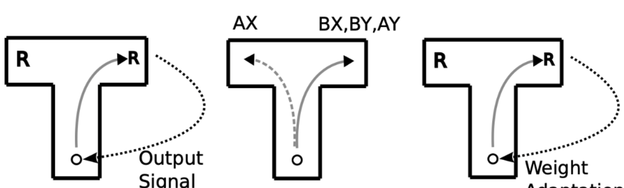
(Kohl & Miikkulainen 2011)



(Schrum & Miikkulainen 2016)

Scaling up to Cognitive Behaviors

- Cognitive behaviors include communication, memory, and learning.
- These behaviors are complex and difficult to evolve.
- The challenge: They require circuitry that doesn't help until it works.
- Need to overcome deception during evolution.

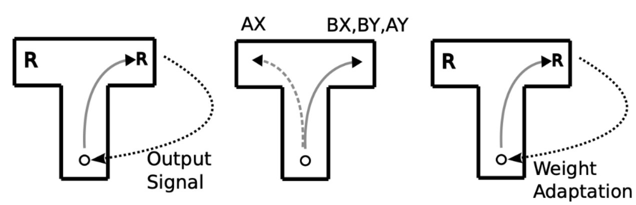


(a) Communication (b) Memory (c) Learning

(Lehman and Miikkulainen 2014)

Example: T-maze Task

- The T-maze task illustrates how communication, memory, and learning can evolve.
- The agent must navigate to the reward at the correct end of the T-maze.
- Evolution struggles when the reward location changes frequently, requiring cognitive strategies.

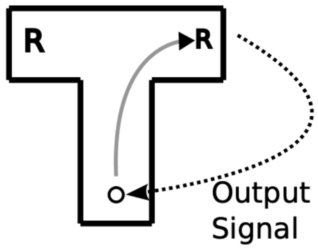


(a) Communication (b) Memory (c) Learning

(Lehman and Miikkulainen 2014)

Deception in Evolving Communication

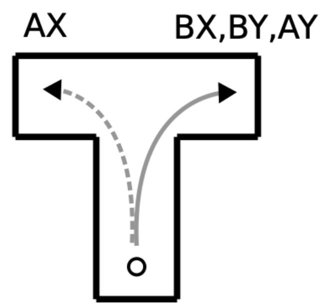
- To evolve communication, agents must develop mechanisms to send, receive, and interpret signals.
- Deception occurs because partial solutions are not helpful unless all components work together.



(Lehman and Miikkulainen 2014)

Deception in Evolving Memory

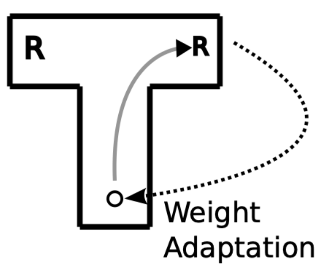
- Receives a signal at start: if AX, go left; if BX, BY, AY, go right.
- To evolve memory, agents must store activations, retrieve them at the right time, and interpret them.
- Similar to communication, but internal to the network.
- Deception occurs because partial solutions are not helpful unless all components work together.



(Lehman and Miikkulainen 2014)

Deception in Evolving Learning

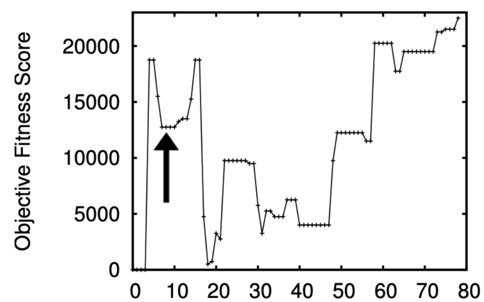
- To evolve learning, agents must develop a learning rule that reinforces good outcomes.
- Deception occurs because adaptation is mostly harmful—until it works.



(Lehman and Miikkulainen 2014)

Discovering Cognitive Behaviors with Novelty Search

- Fitness-based evolution reactive, i.e. always left or always right.
- Novelty search can overcome deception through stepping stones.
- The lineage of solutions shows multiple stepping stones:
  - E.g. going to the opposite corridor with some communication inputs.



(Lehman and Miikkulainen 2014)

Novelty Search and Cognition

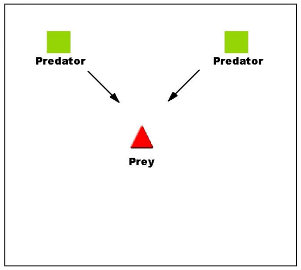
- How did cognition really evolve in biology?
  - No explicit reward for novelty, but there are multiple goals and niches.
  - Stepping stones can be rewarded for entirely other reasons.
  - E.g. evolution of language based on social structure?
- Still a challenge, but its time may have come!

(Londolozi Images 2019)

Scaling up further: Coevolution

- Coevolution: Agents evolve in competition or cooperation with each other.
- It drives agents to develop more sophisticated and adaptable behaviors.
- Discussed at length in next few weeks.

(Souders 2005)



(Rawal et al. 2010)

Conclusion on Evolving Behavior

- **Evolving control, i.e. single behaviors:**
  - Neuroevolution excels at discovering robust control solutions for dynamic, noisy, and nonlinear tasks.
  - Creative behaviors are discovered that compensate for physical imperfections or limitations.
  - Adapting to new conditions outside training is a major challenge.
- **Evolving strategy, i.e. multiple behaviors**
  - Complex strategies, such as switching between behaviors, can be evolved with the right architectures.
  - They can result in surprisingly effective combinations.
  - Evolving cognitive behaviors such as communication, memory, and learning is a major challenge.