

# Neuroevolution

- These are selected (by Yoonsuck Choe) slides from Risto Miikkulainen's tutorial at the GECCO 2005 conference

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# Evolving Neural Networks

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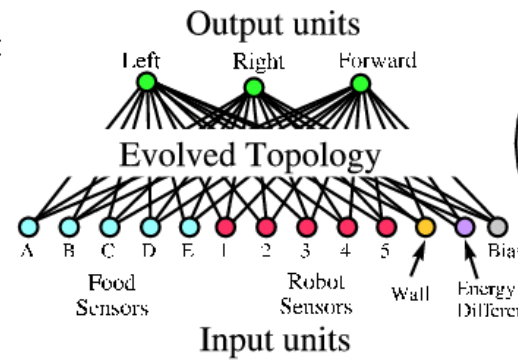
The University of Texas at Austin

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## Neuroevolution Decision Strategies

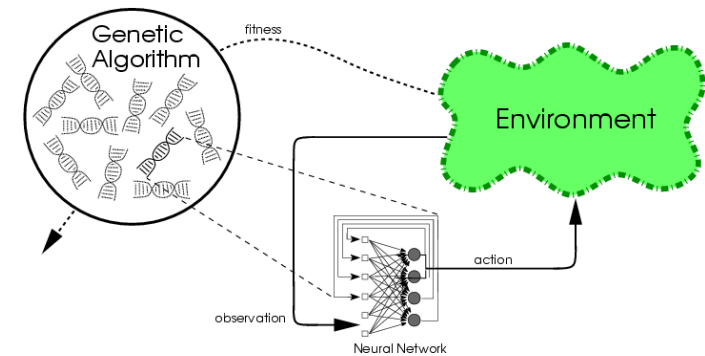
- Input variables describe the state
- Output variables describe actions
- Network between input and output
  - Hidden nodes
  - Weighted connections



- Execution:
  - Numerical activation of input
  - Nonlinear weighted sums
- Performs a nonlinear mapping
  - Memory in recurrent connections
- Connection weights and structure evolved

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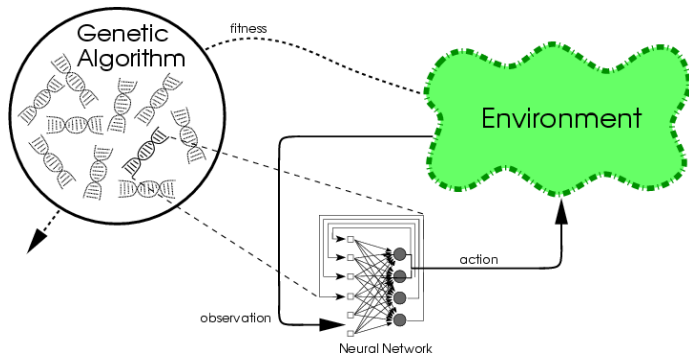
## Conventional Neuroevolution (CNE)



- Evolving connection weights in a population of networks <sup>19,38,39</sup>
- Chromosomes are strings of weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

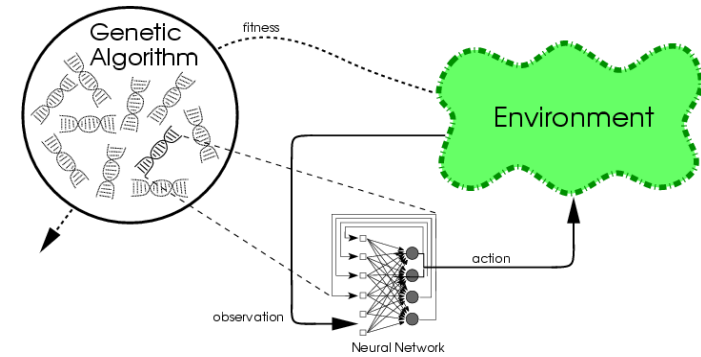
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## Conventional Neuroevolution (2)



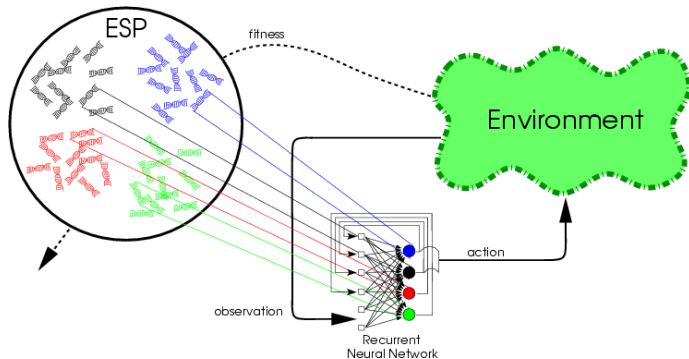
- Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
  - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match!<sub>5</sub>

## Problems with CNE



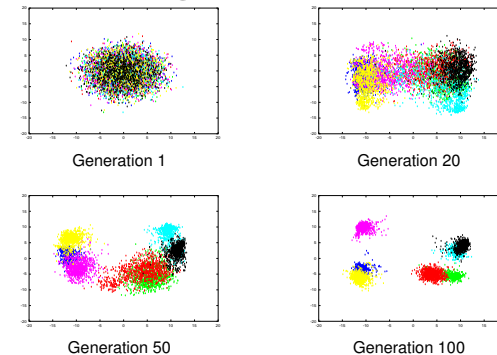
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values<sub>5</sub> at once

## Advanced NE 1: Evolving Neurons



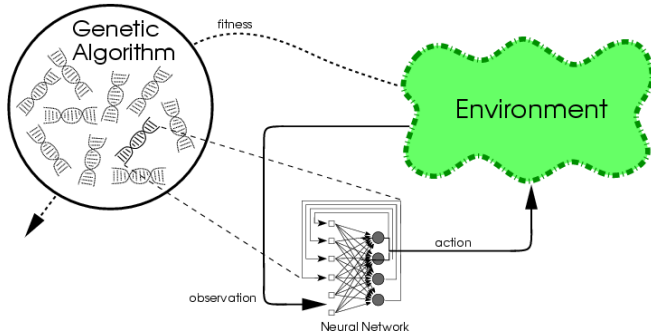
- Evolving individual neurons to cooperate in networks<sup>1,22,24</sup> (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP<sup>2</sup>)
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

## Evolving Neurons with ESP



- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

# Advanced NE 2: Evolutionary Strategies

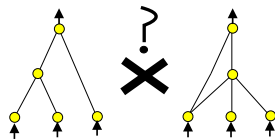


- Evolving complete networks with ES (CMA-ES<sup>15</sup>)
- Small populations, no crossover
- Instead, intelligent mutations
  - Adapt covariance matrix of mutation distribution
  - Take into account correlations between weights
- Smaller space, less convergence, fewer conventions

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## How Can Crossover be Implemented?

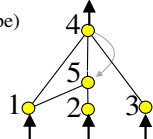
- Problem: Structures do not match



- Solution: Utilize historical markings

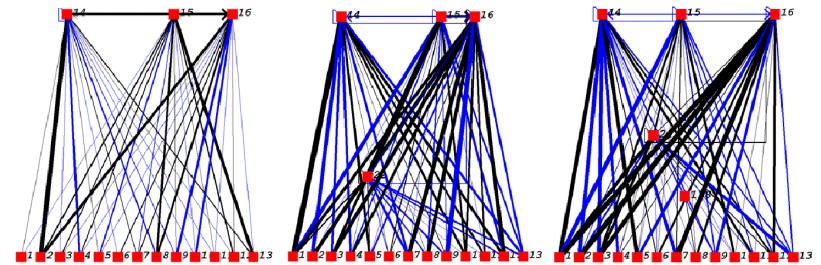
Genome (Genotype)						
Node	Node 1	Node 2	Node 3	Node 4	Node 5	
Genes	Sensor	Sensor	Sensor	Output	Hidden	
Connect	In 1	In 2	In 3	In 2	In 5	In 1
Genes	Out 4	Out 4	Out 4	Out 5	Out 4	Out 5
	Weight 0.7	Weight -0.5	Weight 0.5	Weight 0.2	Weight 0.4	Weight 0.6
	Enabled	DISABLED	Enabled	Enabled	Enabled	Enabled
	Innov 1	Innov 2	Innov 3	Innov 4	Innov 5	Innov 6
						Innov 11

Network (Phenotype)



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# Advanced NE 3: Evolving Topologies

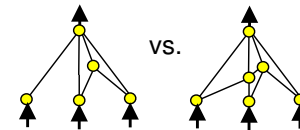


- Optimizing connection weights and network topology<sup>11,40</sup>
- E.g. Neuroevolution of Augmenting Topologies (NEAT<sup>27,29</sup>)
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

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## How can Innovation Survive?

- Problem: Innovations have initially low fitness

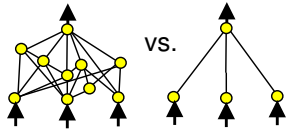


- Solution: Speciate the population
  - Innovations have time to optimize
  - Mitigates competing conventions
  - Promotes diversity

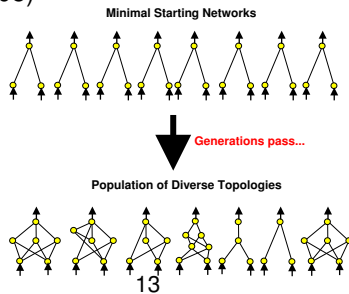
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# How Can We Search in Large Spaces?

- Need to optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify
  - Hidden nodes, connections, input features<sup>37</sup>(Whiteson GECCO'05)



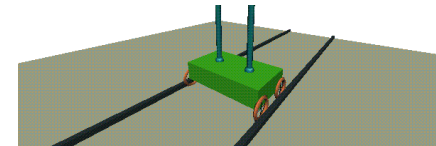
## Extending NE to Applications

- Evolving composite decision makers<sup>36</sup>
- Evolving teams of agents<sup>3,28,41</sup>
- Utilizing coevolution<sup>30</sup>
- Real-time neuroevolution<sup>28</sup>
- Combining human knowledge with evolution<sup>8</sup>

## Further NE Techniques

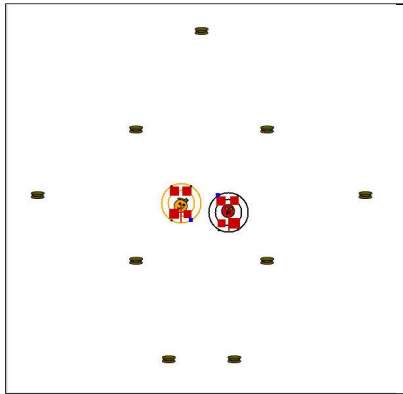
- Incremental evolution<sup>13,33,39</sup>
- Utilizing population culture<sup>2,18</sup>
- Evolving ensembles of NNs<sup>16,23,36</sup>  
(Pardoe GECCO'05)
- Evolving neural modules<sup>25</sup>
- Evolving transfer functions and learning rules<sup>4,26?</sup>
- Combining learning and evolution

## Applications to Control



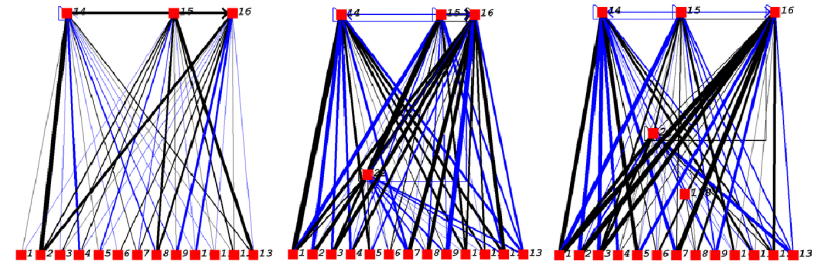
- Pole-balancing benchmark
  - Originates from the 1960s
  - Original 1-pole version too easy
  - Several extensions: acrobat, jointed, 2-pole, particle chasing<sup>23</sup>
- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control<sup>34</sup>

# Competitive Coevolution



- Evolution requires an opponent to beat
- Such opponents are not always available
- Co-evolve two populations to outdo each other
- How to maintain an arms race?

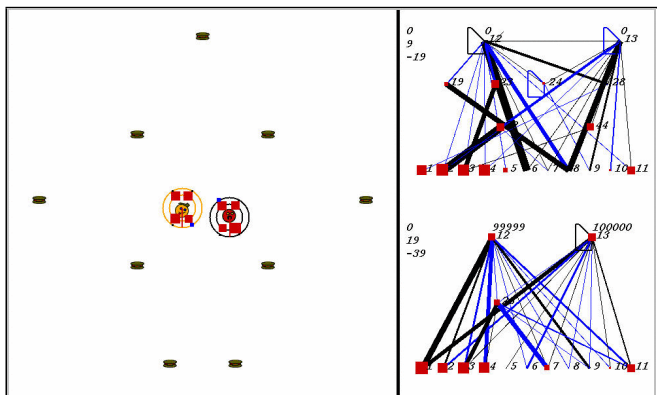
# Competitive Coevolution with NEAT



- Complexification elaborates instead of alters
  - Adding more complexity to existing behaviors
- Can establish a coevolutionary arms race
  - Two populations continually outdo each other
  - Absolute progress, not just tricks

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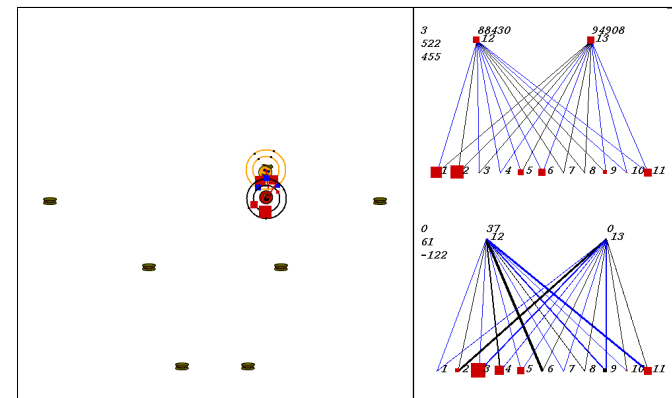
# Robot Duel Domain



- Two Khepera-like robots forage, pursue, evade<sup>30</sup>
  - Collect food to gain energy
  - Win by crashing to a weaker robot

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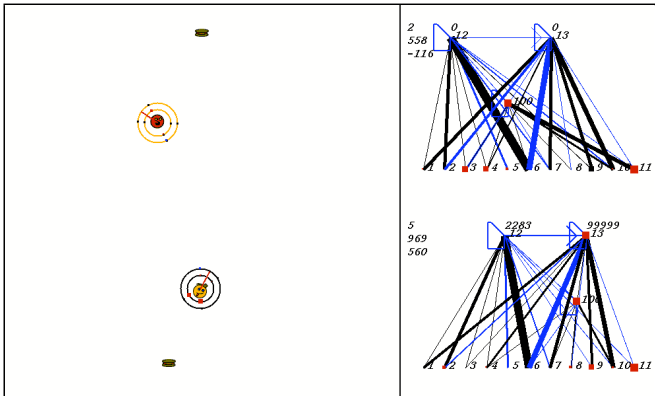
# Early Strategies



- Crash when higher energy
- Collect food by accident
- DEMO

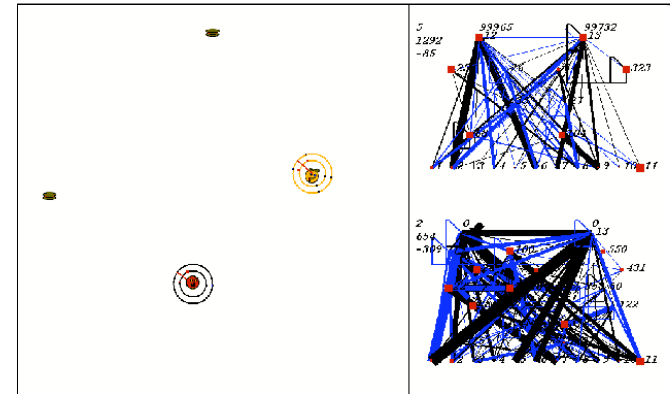
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## Mature Strategies



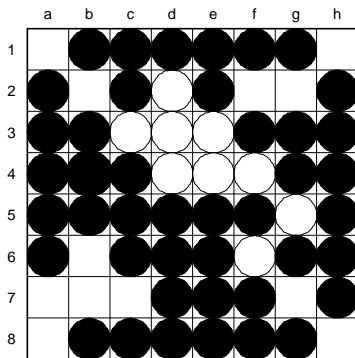
- Collect food to gain energy
- Avoid moving to lose energy
- Standoff: Difficult to predict outcome
- DEMO 21

## Sophisticated Strategy



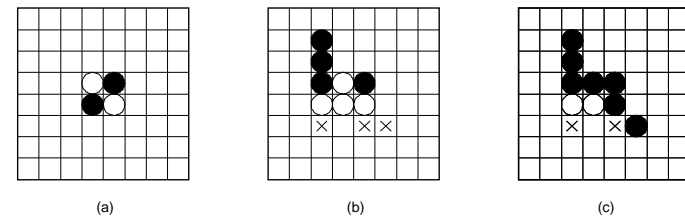
- “Fake” a move up, force away from last piece
- Win by making a dash to last piece
- Complexification → arms race
- DEMO 22

## Applications to Games



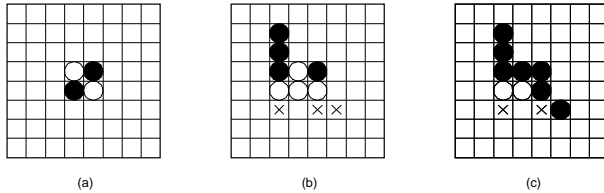
- Good research platform
  - Controlled domains, clear performance, safe
  - Economically important; training games possible
- Board games: beyond limits of search
  - Evaluation functions in checkers, chess<sup>5,9,10</sup>
  - Filtering information in go, othello<sup>20,31</sup>

## Discovering Novel Strategies in Othello



- Players take turns placing pieces
- Each move must flank opponent's piece
- Surrounded pieces are flipped
- Player with most pieces wins

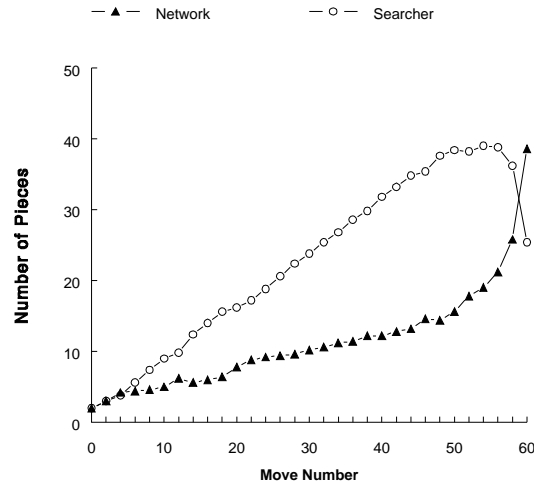
# Strategies in Othello



- Positional
  - Number of pieces and their positions
  - Typical novice strategy
- Mobility
  - Number of available moves: force a bad move
  - Much more powerful, but counterintuitive
  - Discovered in 1970's in Japan

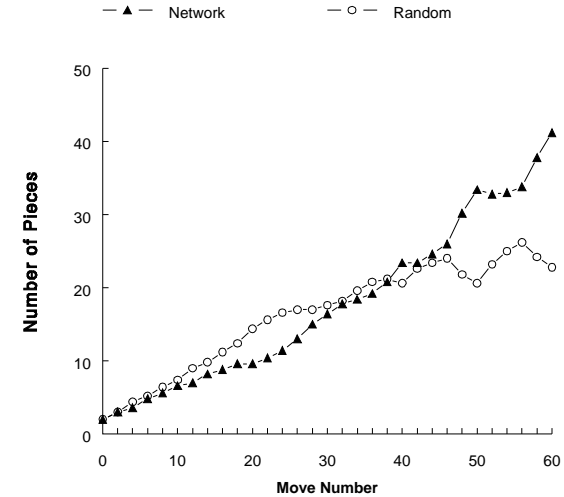
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# Evolving Against an $\alpha\beta$ Program



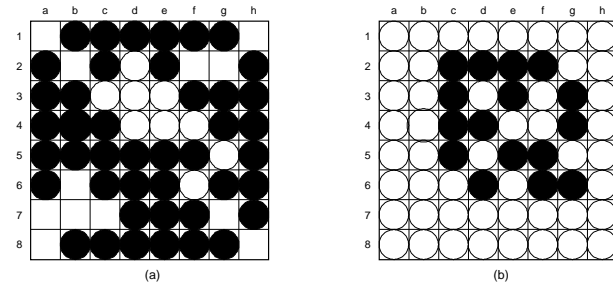
- Iago's positional strategy destroyed networks at first
- Evolution turned low piece count into an advantage
- Mobility strategy emerged!
- Achieved 70% winning percentage

# Evolving Against a Random Player



- Network sees the board, suggests moves by ranking<sup>21</sup>
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

# Example game

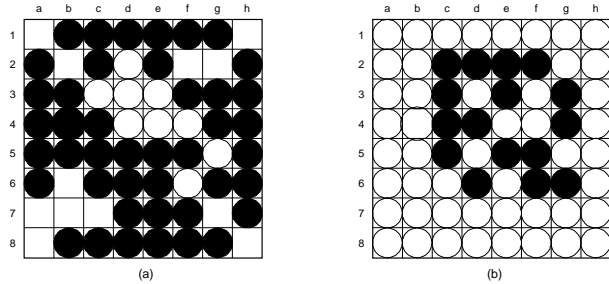


- Black's positions strong, but mobility weak
- White (the network) moves to f2
- Black's available moves b2, g2, and g7 each will surrender a corner
- The network wins by forcing a bad move

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## Discovering Novel Strategies



- Neuroevolution discovered a strategy novel to us
- “Evolution works by tinkering”
  - So does neuroevolution
  - Initial disadvantage turns into novel advantage

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## Numerous Other Applications

- Creating art, music<sup>6</sup>
- Theorem proving<sup>7</sup>
- Time-series prediction<sup>17</sup>
- Computer system optimization<sup>12</sup>
- Manufacturing optimization<sup>14</sup>
- Process control optimization<sup>34,35</sup>
- Etc.

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## Future Challenge: Utilizing Knowledge



- Given a problem, NE discovers a solution by exploring
  - Sometimes you already know (roughly) what works
  - Sometimes random initial behavior is not acceptable
- How can domain knowledge be utilized?
  - By incorporating rules (Yong GECCO'05)
  - By learning from examples

## Conclusion

- NE is a powerful technology for sequential decision tasks
  - Evolutionary computation and neural nets are a good match
  - Lends itself to many extensions
  - Powerful in applications
- Easy to adapt to applications
  - Control, robotics, optimization
  - Artificial life, biology
  - Gaming: entertainment, training
- Lots of future work opportunities
  - Theory not well developed
  - Indirect encodings
  - Learning and evolution
  - Knowledge and interaction

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