

Today's Main Topic

Neuroevolution

- CSCE 636
- Neuroevolution slides are from Risto Miikkulainen's tutorial at the GECCO 2005 conference, with slight editing.

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- Neuroevolution: Evolve artificial neural networks to control behavior of robots and agents.
- Main idea: Mimic the natural process of evolution that gave rise to the brain, the source of intelligence.
 - Population
 - Competition
 - Selection
 - Reproduction and mutation

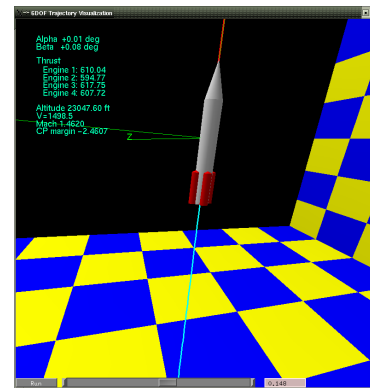
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Evolving Neural Networks

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Why Neuroevolution?



- Neural networks already successful in many domains.
- However, in certain domains, it is hard to fit the existing framework and learning algorithms.
- Hard domains: fin-less rocket control, robotic agent control, etc.

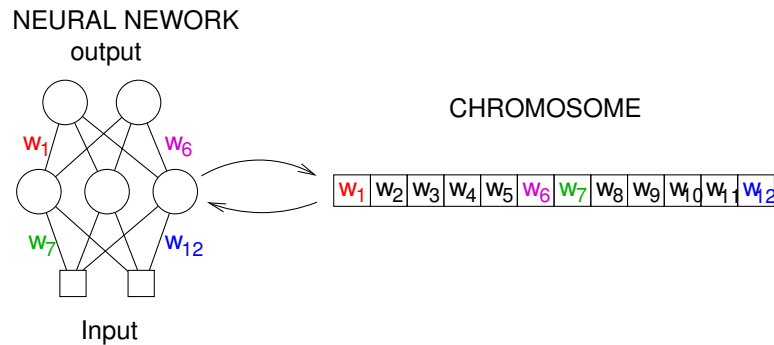
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Outline

- Basic neuroevolution techniques
- Advanced techniques
 - E.g. combining learning and evolution
- Extensions to applications
- Application examples
 - Control, Robotics, Artificial Life, Games

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Neuroevolution Basics

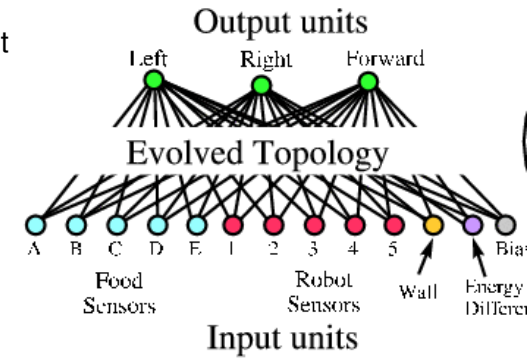


- A single chromosome encodes a full neural network.
- Each gene, a single bit (or a real number), maps to a connection weight in the neural network.

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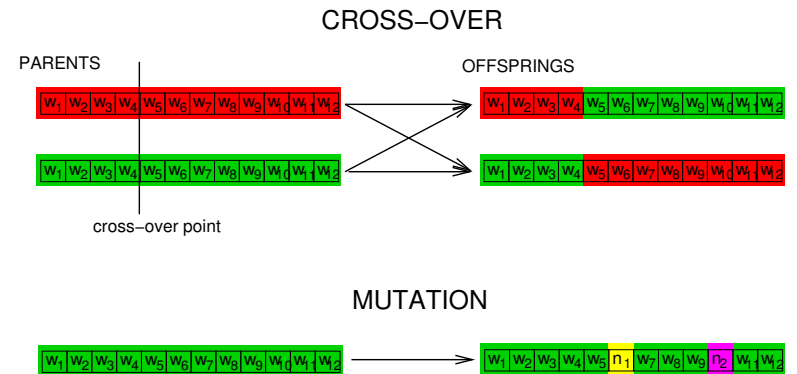
Neuroevolution Decision Strategies

- 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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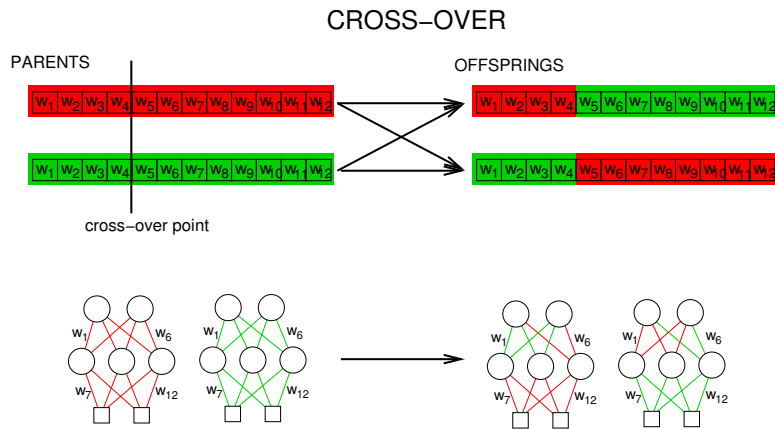
Neuroevolution Basics: Operations



- Cross-over.
- Mutation.

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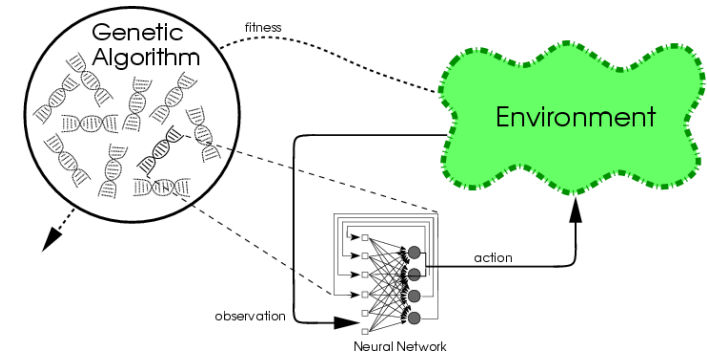
Neuroevolution Basics: Cross-Over in Detail



- Cross-over of two individuals produces two offsprings with a mixed heritage.

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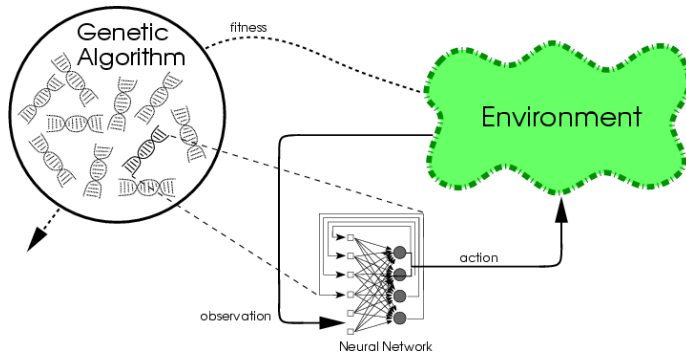
Conventional Neuroevolution (CNE)



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

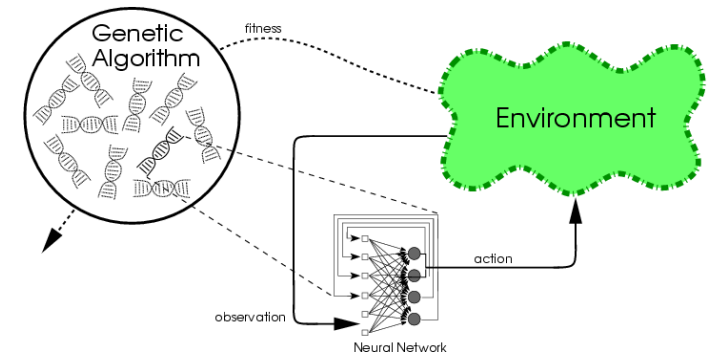
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Conventional Neuroevolution (2)



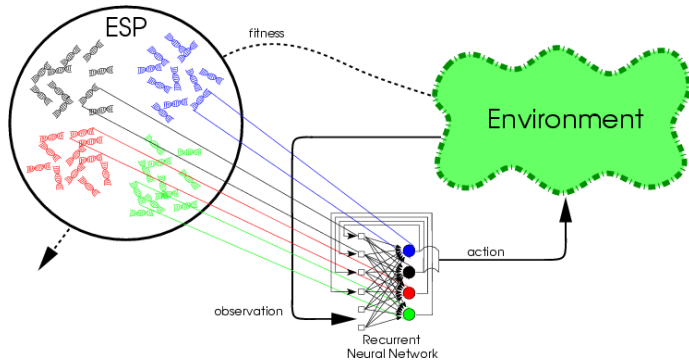
- Each NN evaluated in the task
 - Good NN reproduce through crossover, mutation
 - Bad thrown away
 - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match_{1,1}

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_{1,2} at once

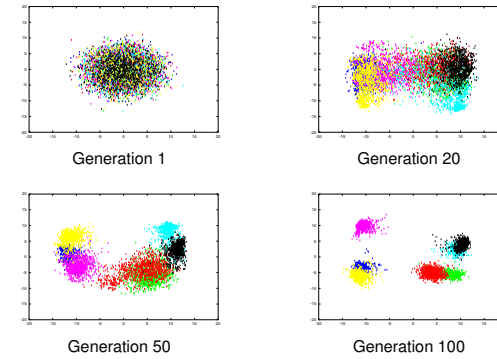
Advanced NE 1: Evolving Neurons



- Evolving individual neurons to cooperate in networks^{1,22,24} (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP²)
 - Each (hidden) neuron in a separate subpopulation
 - Fully connected; weights of each neuron evolved
 - Populations learn compatible subtasks

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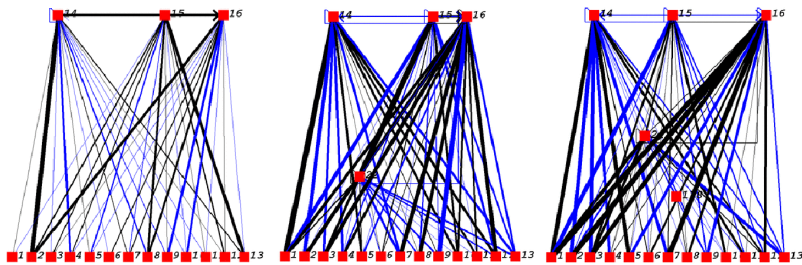
Advanced NE 2: Evol. Subpopulations



- 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

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Advanced NE 3: Evolving Topologies

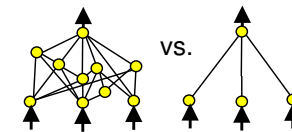


- Optimizing connection weights and network topology^{11,40}
- E.g. Neuroevolution of Augmenting Topologies (NEAT^{27,29})
- Based on *Complexification*
- Of networks:
 - Mutations to add nodes and connections
- Of behavior:
 - Elaborates on earlier behaviors

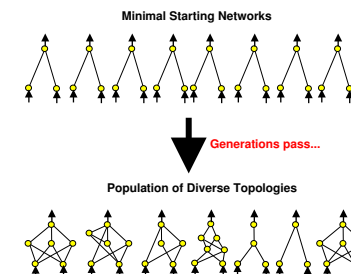
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How Can We Complexify?

- Can optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify³⁷

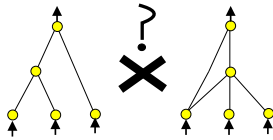


- Can search a very large space of configurations!

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How Can Crossover be Implemented?

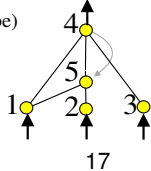
- Problem: Structures do not match



- Solution: Utilize historical markings

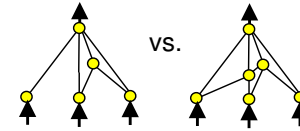
Genome (Genotype)					
Node	Node 1	Node 2	Node 3	Node 4	Node 5
Genes	Sensor	Sensor	Sensor	Output	Hidden
Connect Genes	In 1	In 2	In 3	In 2	In 5
	Out 4	Out 4	Out 4	Out 5	Out 4
	Weight 0.7	Weight-0.5	Weight 0.5	Weight 0.2	Weight 0.4
	Enabled	DISABLED	Enabled	Enabled	Enabled
	Innov 1	Innov 2	Innov 3	Innov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

Network (Phenotype)



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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Further Neuroevolution Techniques

- Incremental evolution^{13,33,39}
- Utilizing population culture^{2,18}
- Evolving ensembles of NNs^{16,23,36}
(Pardoe GECCO'05)
- Evolving neural modules²⁵
- Evolving transfer functions and learning rules^{4,26?}
- Combining learning and evolution

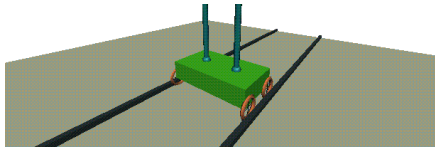
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Neuroevolution Applications

- Evolving composite decision makers³⁶
- Evolving teams of agents^{3,28,41}
- Utilizing coevolution³⁰
- Real-time neuroevolution²⁸
- Combining human knowledge with evolution⁸

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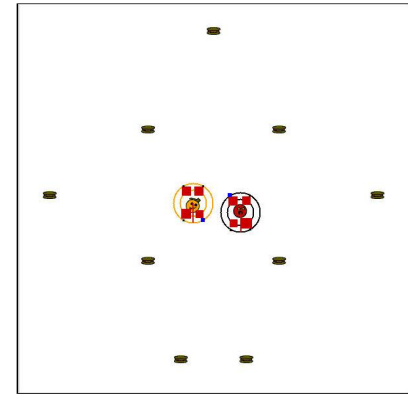
Applications to Control



- Pole-balancing benchmark
 - Originates from the 1960s
 - Original 1-pole version too easy
 - Several extensions: acrobat, jointed, 2-pole, particle chasing²³
- Good surrogate for other control tasks
 - Vehicles and other physical devices
 - Process control³⁴

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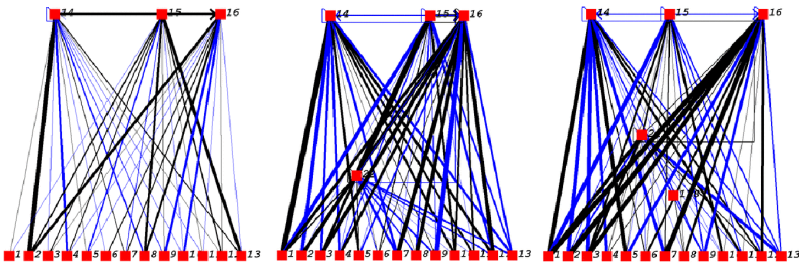
Competitive Coevolution



- 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?

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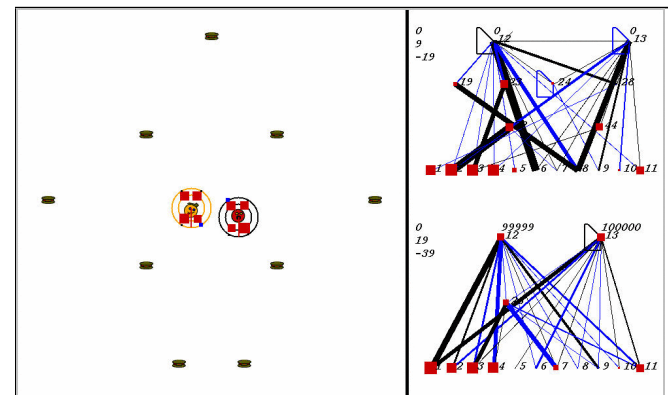
Competitive Coevolution with NEAT



- 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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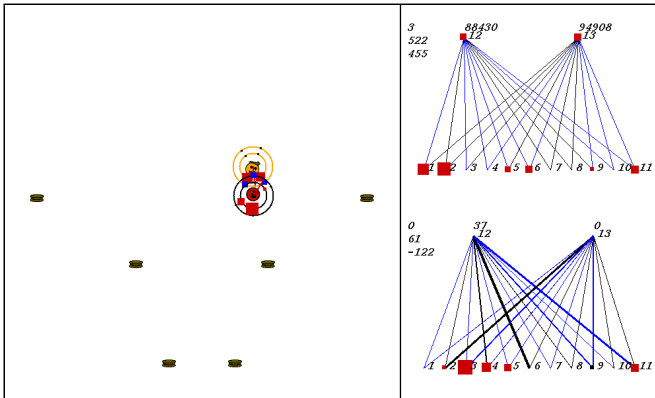
Robot Duel Domain



- Two Khepera-like robots forage, pursue, evade³⁰
 - Collect food to gain energy
 - Win by crashing to a weaker robot

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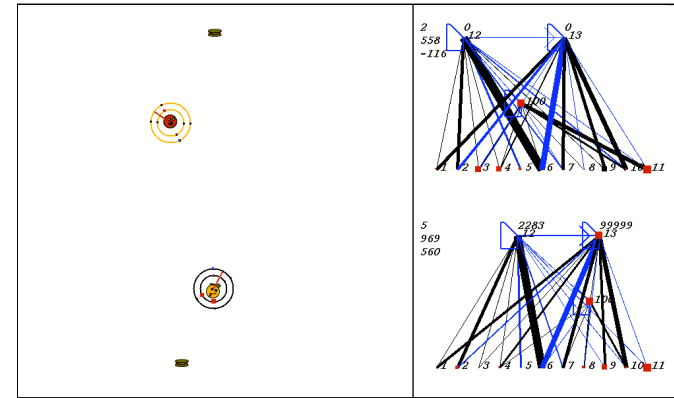
Early Strategies



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

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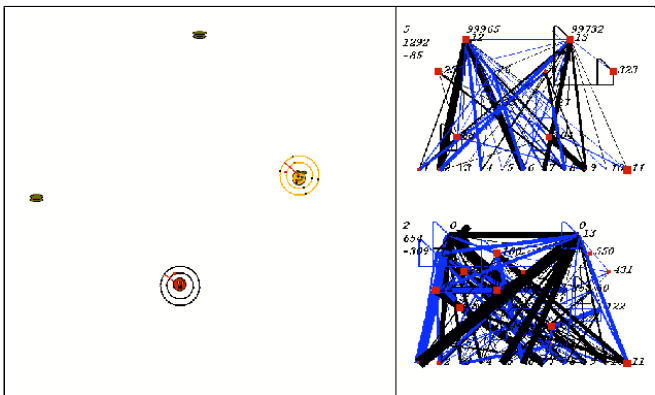
Mature Strategies



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

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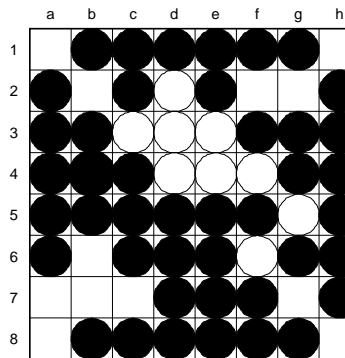
Sophisticated Strategy



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

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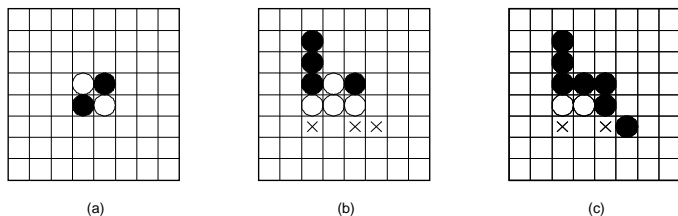
Applications to Games



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

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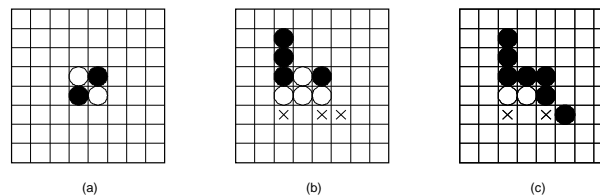
Discovering Novel Strategies in Othello



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

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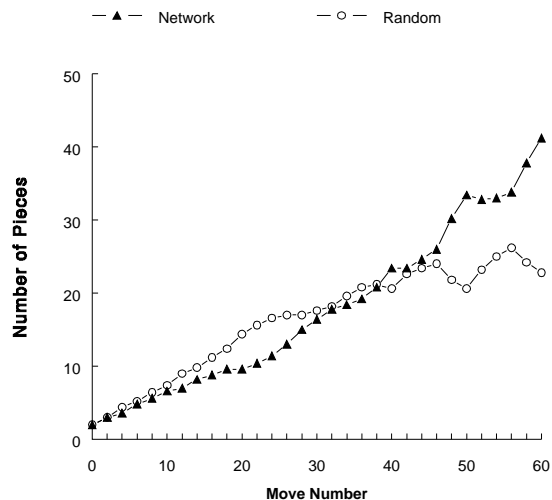
Strategies in Othello



- 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

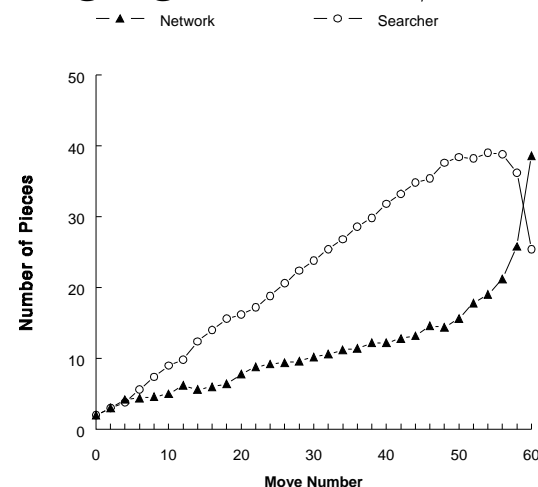
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Evolving Against a Random Player



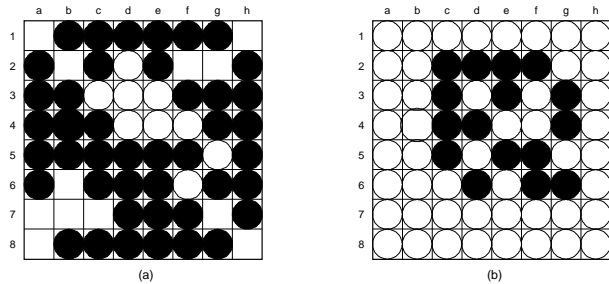
- Network sees the board, suggests moves by ranking²¹
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

Evolving Against an α - β Program



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

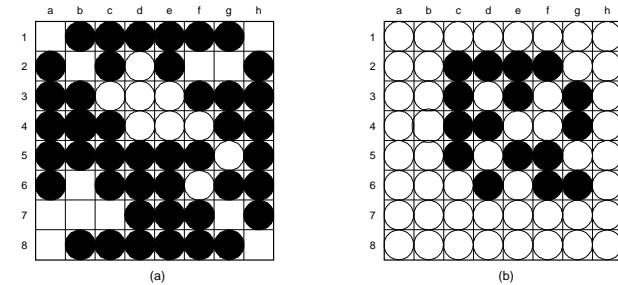
Example game



- 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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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

Numerous Other Applications

- Creating art, music⁶
- Theorem proving⁷
- Time-series prediction¹⁷
- Computer system optimization¹²
- Manufacturing optimization¹⁴
- Process control optimization^{34,35}
- Etc.

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Conclusion

- Neuroevolution, mimicing the natural process of evolution, is an effective strategy for constructing complex and useful behavior.
- Neuroevolution often performs well for reinforcement learning tasks.
- Analyzing the resulting network is a challenge.

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