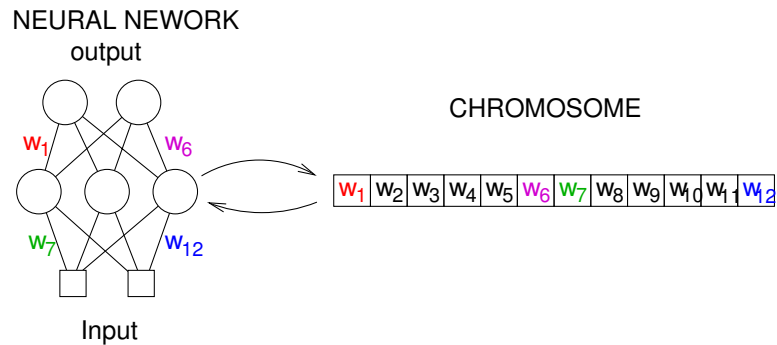


Advanced Topic: Neuroevolution

- CSCE 625 Fall 2013
- These slides from Risto Miikkulainen's tutorial at the GECCO 2005 conference, with slight editing.
- Slides 3 – 5 were added by Yoonsuck Choe.
- To get you started on your term project.

1

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.

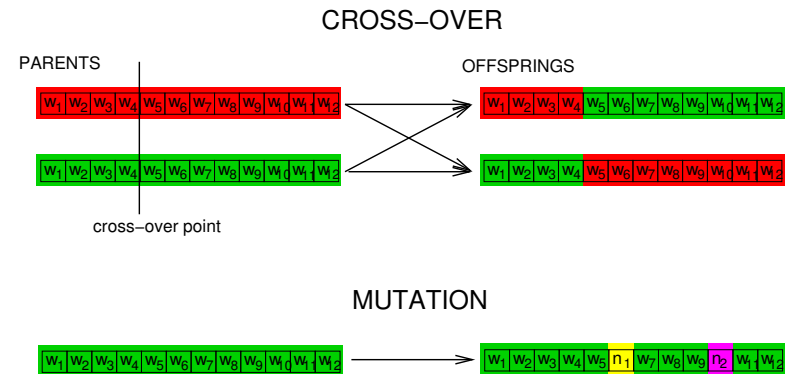
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Evolving Neural Networks

Risto Miikkulainen
Department of Computer Sciences
The University of Texas at Austin
<http://www.cs.utexas.edu/users/risto>

2

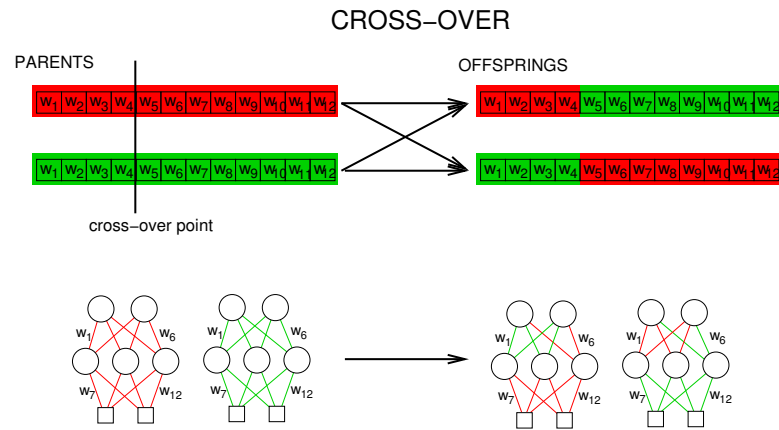
Neuroevolution Basics: Operations



- Cross-over.
- Mutation.

4

Neuroevolution Basics: Cross-Over in Detail



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

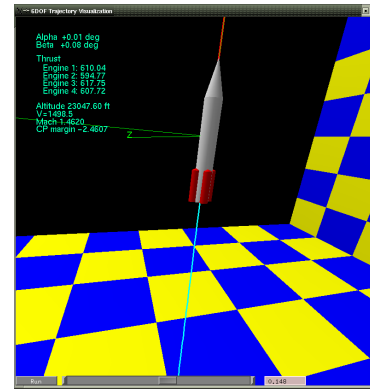
5

Sequential Decision Tasks

- POMDP: Sequence of decisions creates a sequence of states
- No targets: Performance evaluated after several decisions
- Many important real-world domains:
 - Robot/vehicle/traffic control
 - Computer/manufacturing/process optimization
 - Game playing

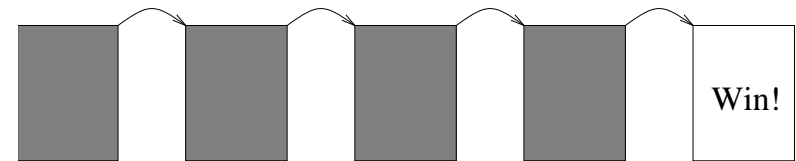
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Why Neuroevolution?



- Neural nets powerful in many statistical domains
 - E.g. control, pattern recognition, prediction, decision making
 - No good theory of the domain exists
- Good supervised training algorithms exist
 - Learn a nonlinear function that matches the examples
- What if correct outputs are not known?

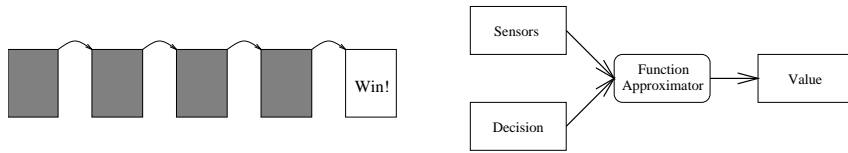
Forming Decision Strategies



- Traditionally designed by hand
 - Too complex: Hard to anticipate all scenarios
 - Too inflexible: Cannot adapt on-line
- Need to discover through exploration
 - Based on sparse reinforcement
 - Associate actions with outcomes

8

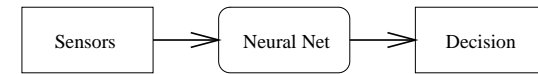
Standard Reinforcement Learning



- AHC, Q-learning, Temporal Differences
 - Generate targets through prediction errors
 - Learn when successive predictions differ
- Predictions represented as a value function
 - Values of alternatives at each state
- Difficult with large/continuous state and action spaces
- Difficult with hidden states

9

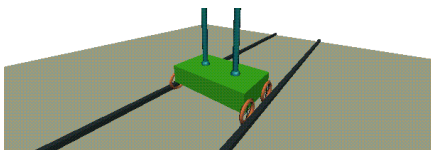
Neuroevolution (NE) Reinforcement Learning



- NE = constructing neural networks with evolutionary algorithms
- Direct nonlinear mapping from sensors to actions
- Large/continuous states and actions easy
 - Generalization in neural networks
- Hidden states disambiguated through memory
 - Recurrency in neural networks

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How well does it work?



Poles	Method	Evals	Succ.
One	VAPS	500,000	0%
	SARSA	13,562	59%
	Q-MLP	11,331	
	NE	589	
Two	NE	24,543	

- Difficult RL benchmark: Non-Markov Pole Balancing
- NE 2 orders of magnitude faster than standard RL
- NE can solve harder problems

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Role of Neuroevolution

- Powerful method for sequential decision tasks^{38? ?}
 - Optimizing existing tasks
 - Discovering novel solutions
 - Making new applications possible
- Also may be useful in supervised tasks^{19,24}
 - Especially when network topology important
- Unique model of biological adaptation and development^{???}

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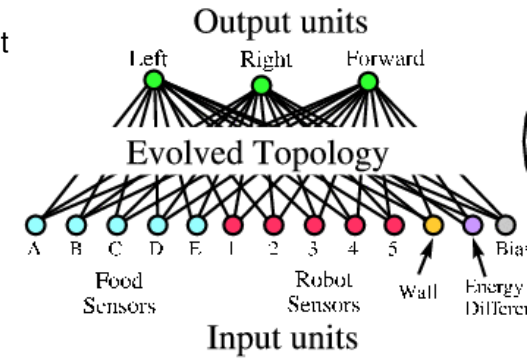
Outline

- 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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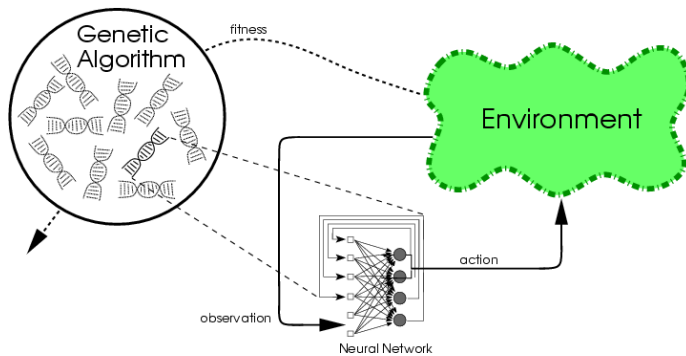
Neuroevolution Decision Strategies

- Input variables describe the state
 - 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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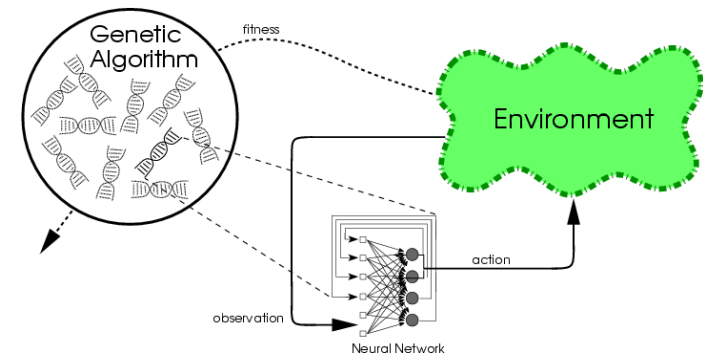
Conventional Neuroevolution (CNE)



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

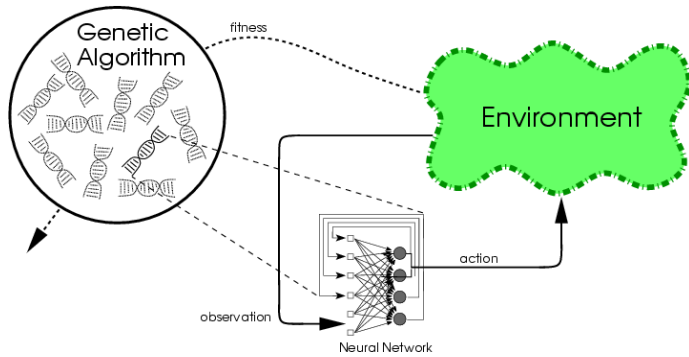
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Conventional Neuroevolution (2)



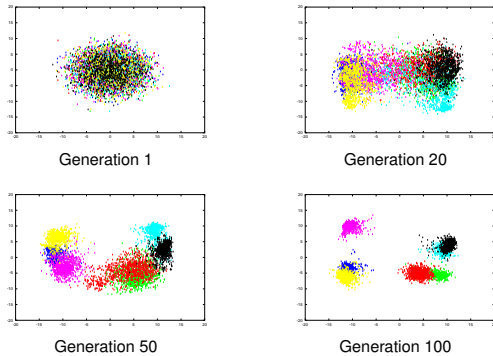
- Each NN evaluated in the task
 - Good NN reproduce through crossover, mutation
 - Bad thrown away
 - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match₆

Problems with CNE



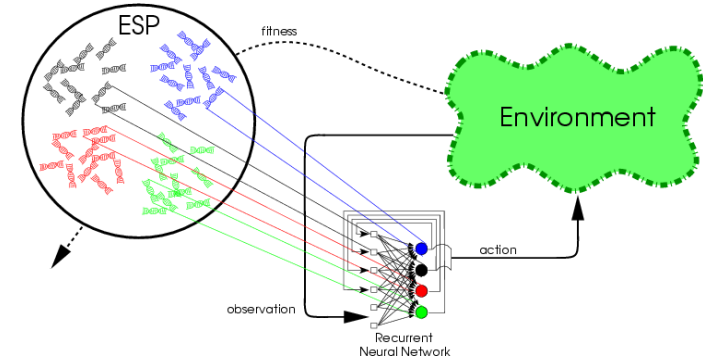
- Evolution converges the population (as usual with EAs)
 - Diversity is lost; progress stagnates
- Competing conventions
 - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
 - Thousands of weight values at once

Evolving Neurons with ESP



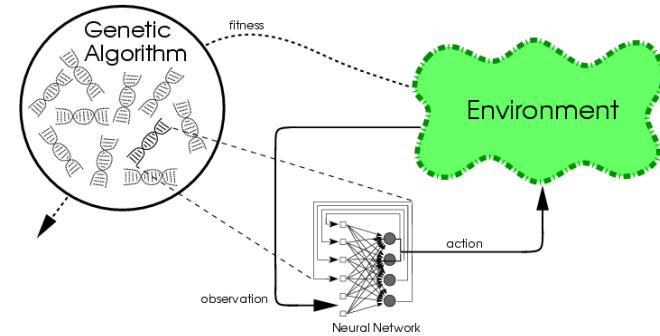
- Evolution encourages diversity automatically
 - Good networks require different kinds of neurons
- Evolution discourages competing conventions
 - Neurons optimized for compatible roles
- Large search space divided into subtasks
 - Optimize compatible neurons

Advanced NE 1: Evolving Neurons



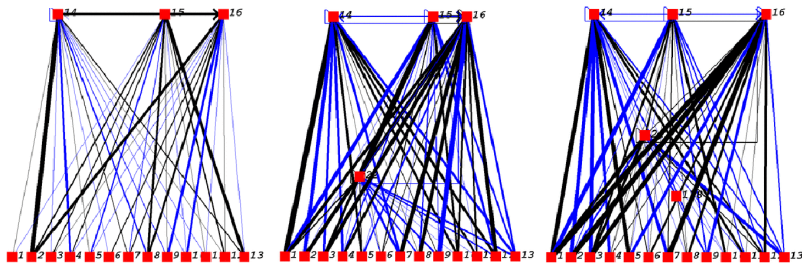
- Evolving individual neurons to cooperate in networks^{1,22,24} (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP²)
 - Each (hidden) neuron in a separate subpopulation
 - Fully connected; weights of each neuron evolved
 - Populations learn compatible subtasks

Advanced NE 2: Evolutionary Strategies



- Evolving complete networks with ES (CMA-ES¹⁵)
- 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

Advanced NE 3: Evolving Topologies

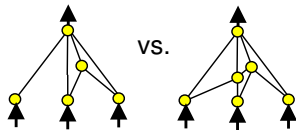


- Optimizing connection weights and network topology^{11,40}
- E.g. Neuroevolution of Augmenting Topologies (NEAT^{27,29})
- Based on *Complexification*
- Of networks:
 - Mutations to add nodes and connections
- Of behavior:
 - Elaborates on earlier behaviors

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How can Innovation Survive?

- Problem: Innovations have initially low fitness

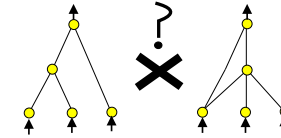


- Solution: Speciate the population
 - Innovations have time to optimize
 - Mitigates competing conventions
 - Promotes diversity

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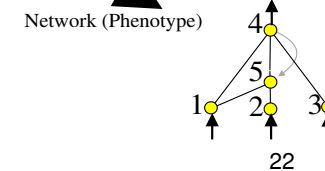
How Can Crossover be Implemented?

- Problem: Structures do not match



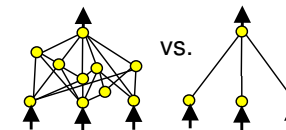
- Solution: Utilize historical markings

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
Genes	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

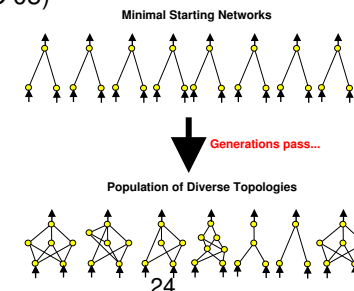


How Can We Search in Large Spaces?

- Need to optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify
 - Hidden nodes, connections, input features³⁷
 - (Whiteson GECCO'05)



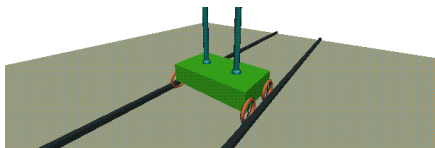
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Further NE Techniques

- 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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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

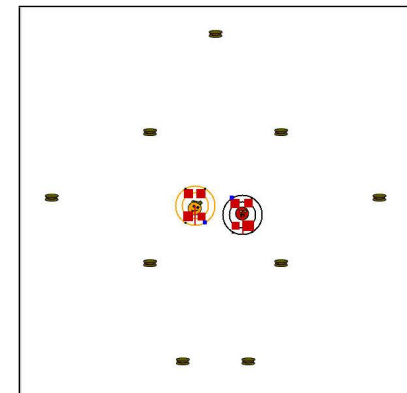
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Extending NE to Applications

- 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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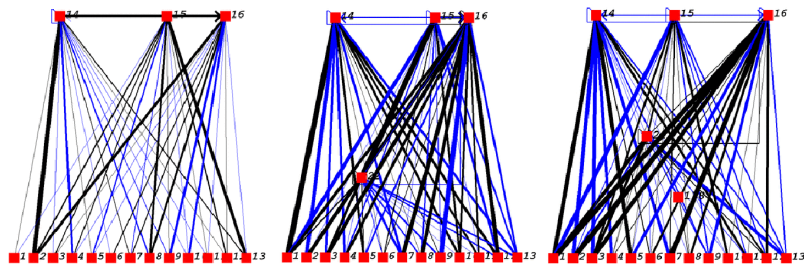
Competitive Coevolution



- 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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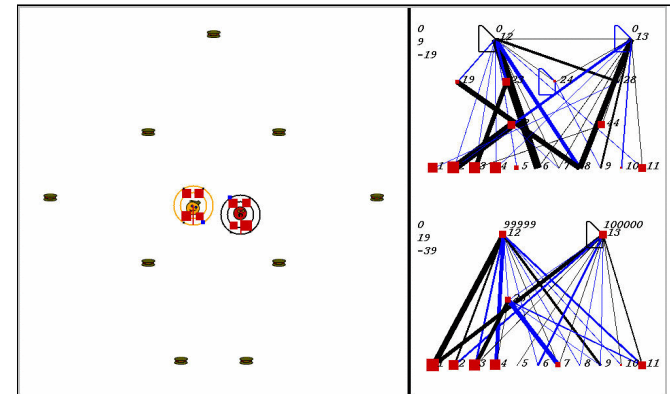
Competitive Coevolution with NEAT



- 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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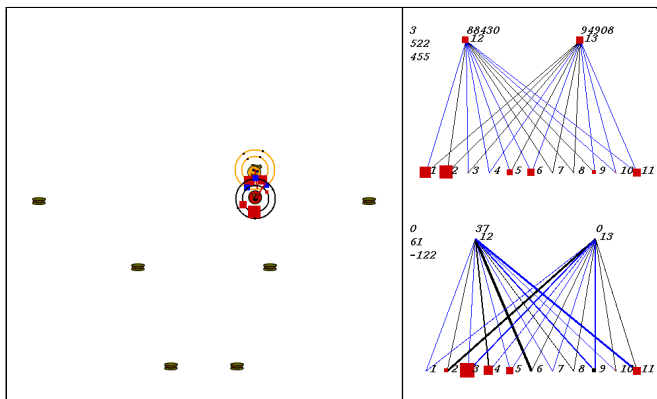
Robot Duel Domain



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

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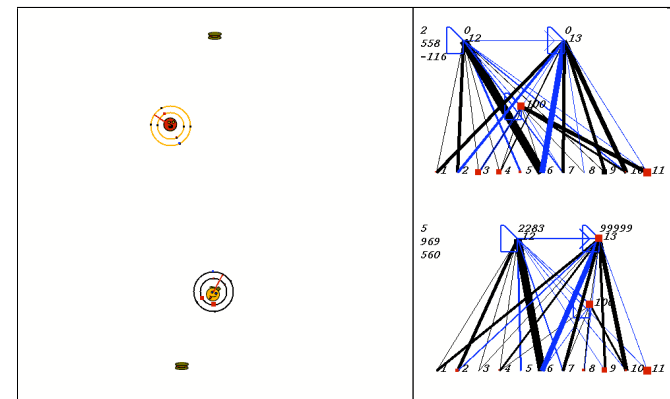
Early Strategies



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

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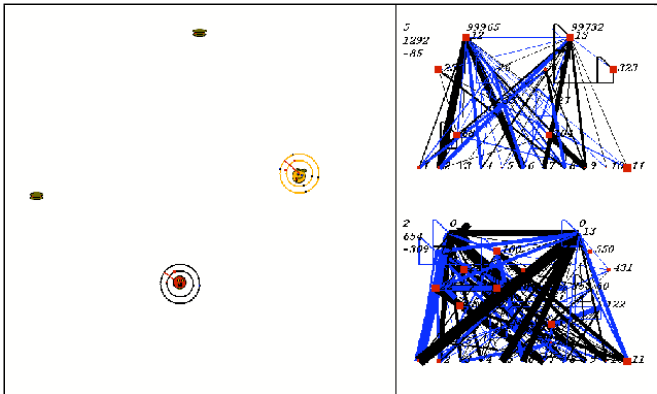
Mature Strategies



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

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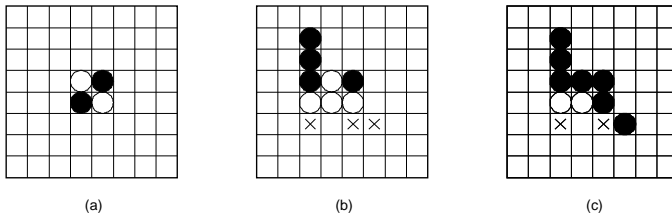
Sophisticated Strategy



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

33

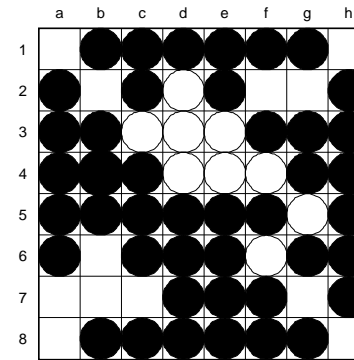
Discovering Novel Strategies in Othello



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

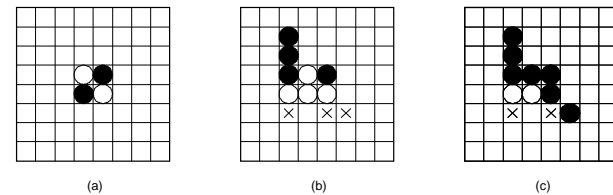
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Applications to Games



- 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}

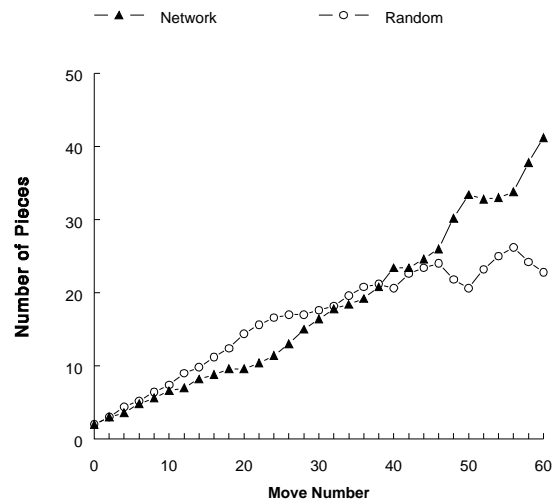
Strategies in Othello



- 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

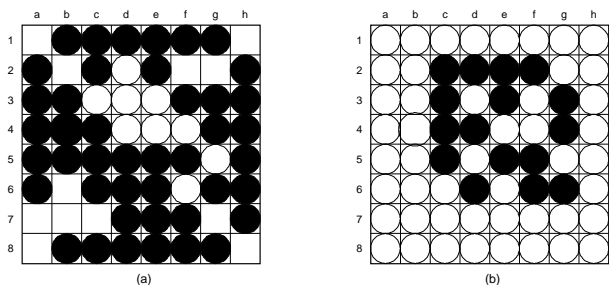
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Evolving Against a Random Player



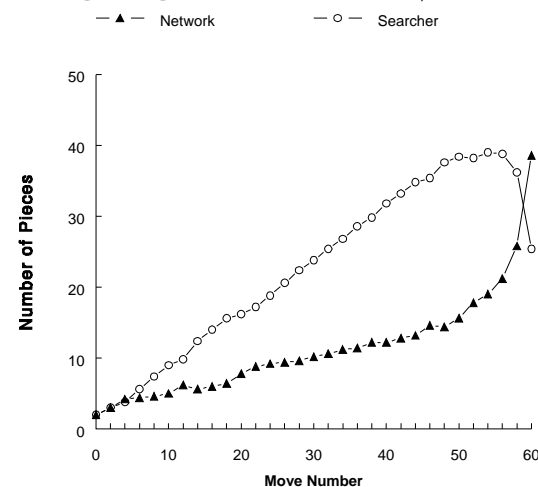
- Network sees the board, suggests moves by ranking²¹
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

Example game



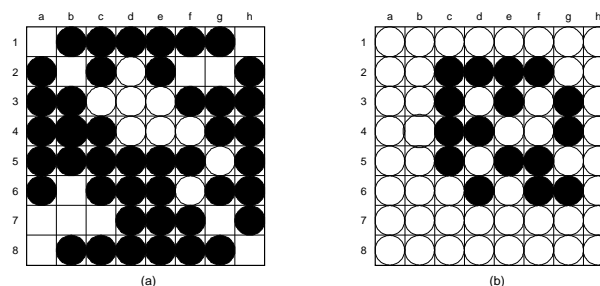
- Black's positions strong, but mobility weak
- White (the network) moves to f2
- Black's available moves b2, g2, and g7 each will surrender a corner
- The network wins by forcing a bad move

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

Discovering Novel Strategies



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

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

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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