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.

Evolving Neural Networks

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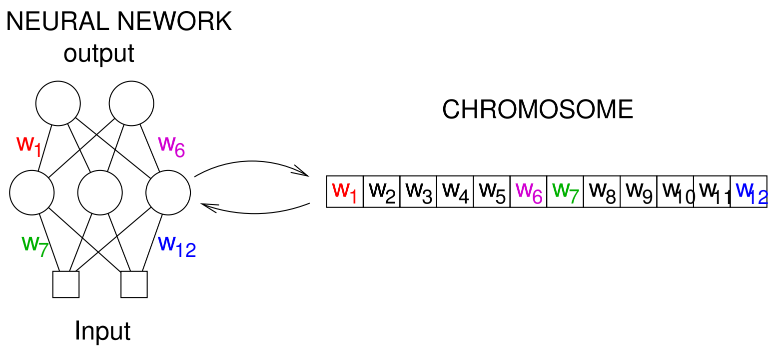
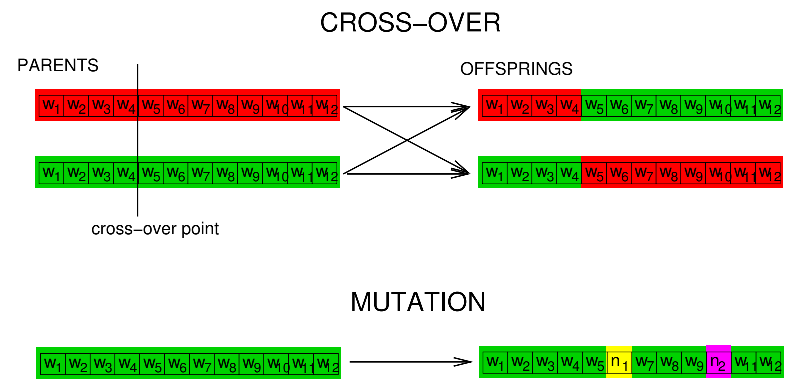
Neuroevolution Basics



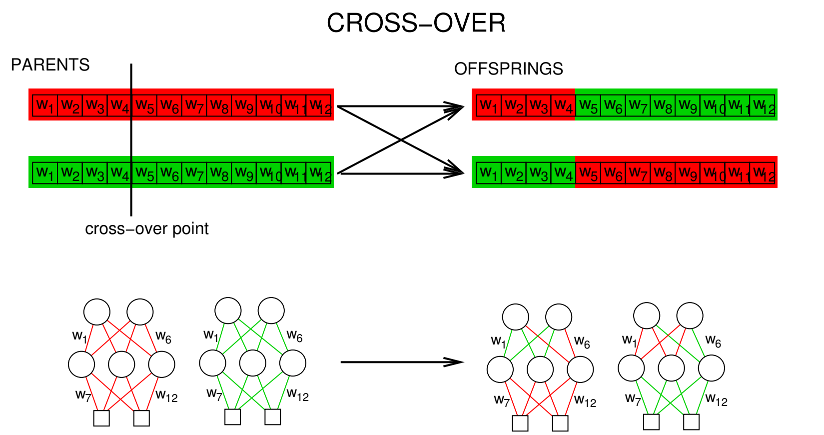
- A single chromosome encodes a full neural network.
- Each gene, a single bit (or a real number), maps to a connection weight in the neural network.

Neuroevolution Basics: Operations



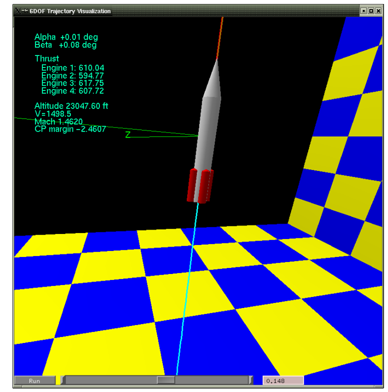
- Cross-over.
- Mutation.

Neuroevolution Basics: Cross-Over in Detail



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

Why Neuroevolution?

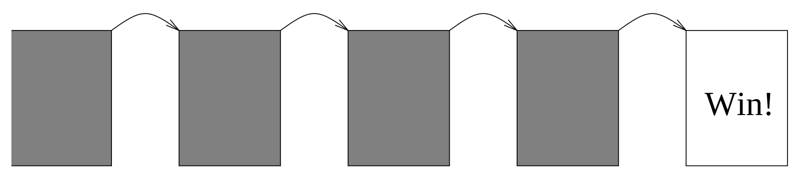


- Neural nets powerful in many statistical domains
  - E.g. control, pattern recognition, prediction, decision making
  - No good theory of the domain exists
- Good supervised training algorithms exist
  - Learn a nonlinear function that matches the examples
- What if correct outputs are not known?

Sequential Decision Tasks

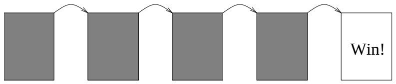
- POMDP: Sequence of decisions creates a sequence of states
- No targets: Performance evaluated after several decisions
- Many important real-world domains:
  - Robot/vehicle/traffic control
  - Computer/manufacturing/process optimization
  - Game playing

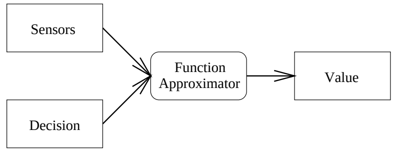
Forming Decision Strategies



- 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

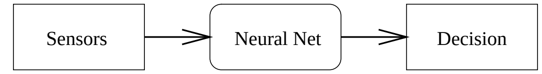
Standard Reinforcement Learning





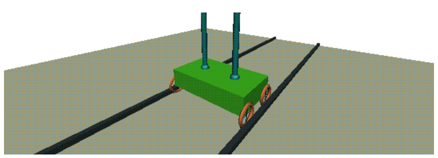
- AHC, Q-learning, Temporal Differences
  - Generate targets through prediction errors
  - Learn when successive predictions differ
- Predictions represented as a value function
  - Values of alternatives at each state
- Difficult with large/continuous state and action spaces
- Difficult with hidden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

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

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

Role of Neuroevolution

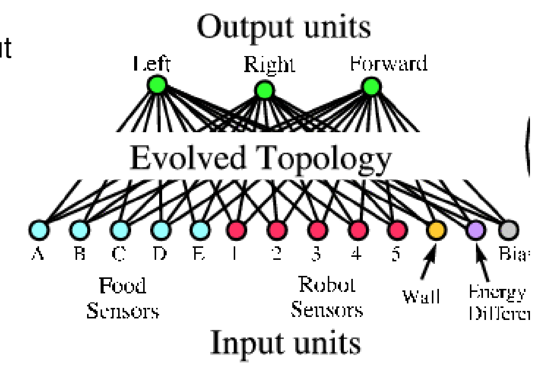
- Powerful method for sequential decision tasks [38? ?]
  - Optimizing existing tasks
  - Discovering novel solutions
  - Making new applications possible
- Also may be useful in supervised tasks [19,24]
  - Especially when network topology important
- Unique model of biological adaptation and development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

Outline

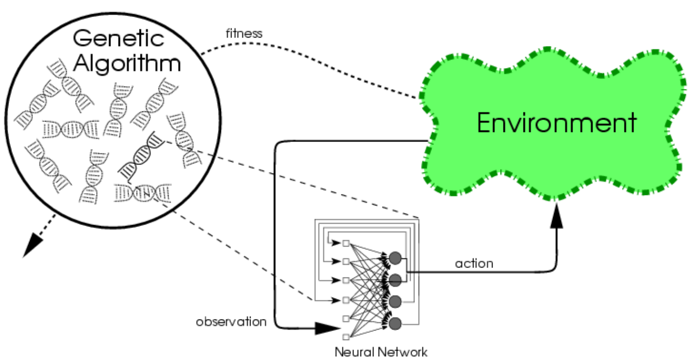
- Basic neuroevolution techniques
- Advanced techniques
  - E.g. combining learning and evolution
- Extensions to applications
- Application examples
  - Control, Robotics, Artificial Life, Games

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

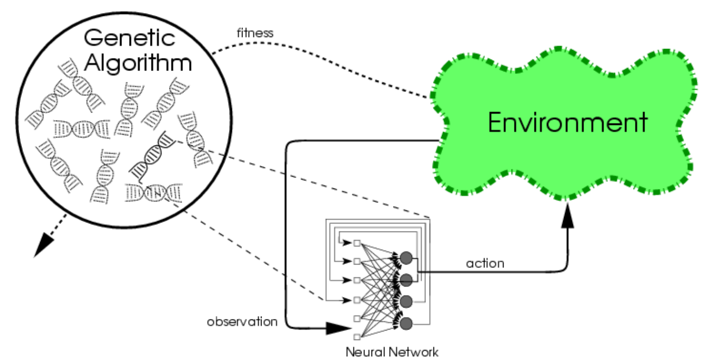


Conventional Neuroevolution (CNE)



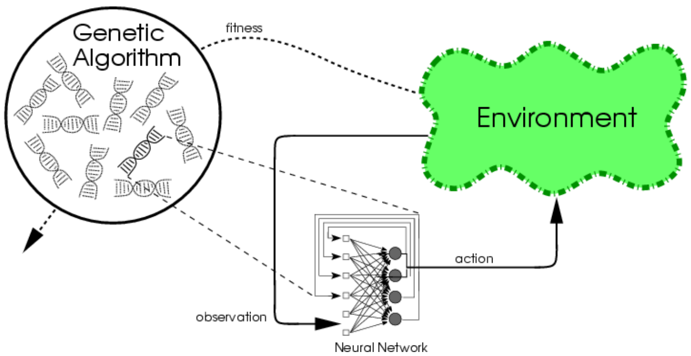
- Evolving connection weights in a population of networks [19,38,39]
- Chromosomes are strings of weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

Conventional Neuroevolution (2)



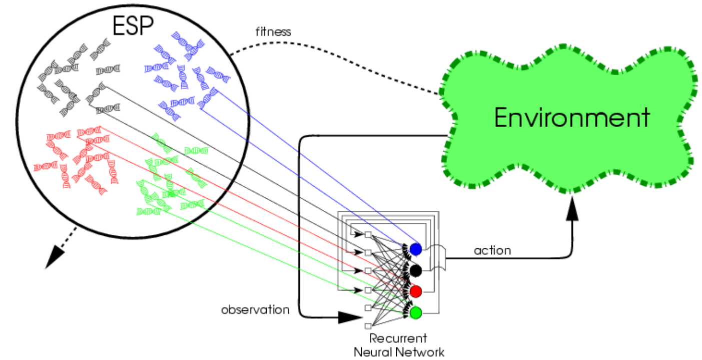
- Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
  - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match!

Problems with CNE



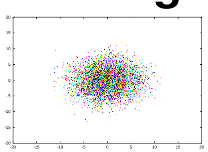
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values at once

Advanced NE 1: Evolving Neurons

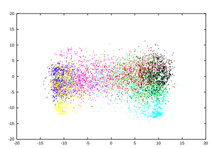


- Evolving individual neurons to cooperate in networks [1,22,24] (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP [?])
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

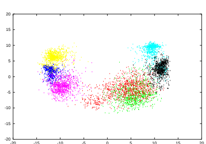
Evolving Neurons with ESP



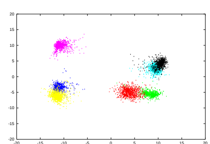
Generation 1



Generation 20



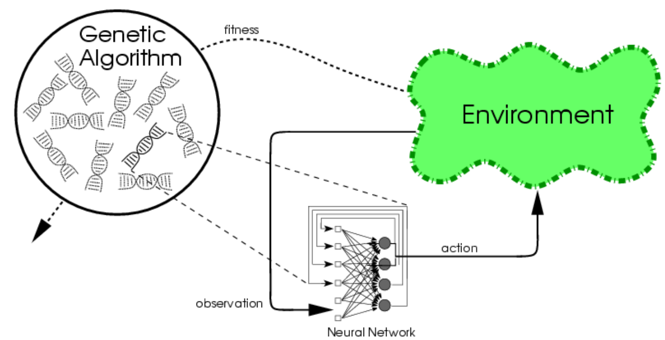
Generation 50



Generation 100

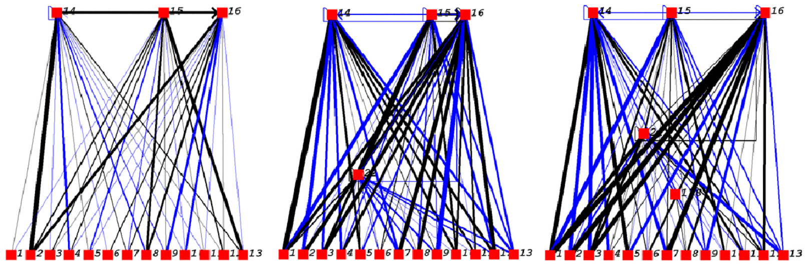
- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

Advanced NE 2: Evolutionary Strategies



- Evolving complete networks with ES (CMA-ES [15])
- 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

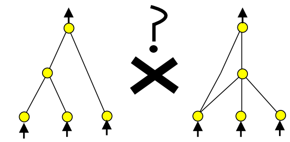
Advanced NE 3: Evolving Topologies



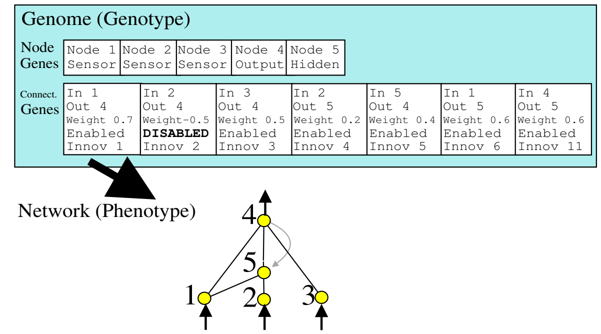
- Optimizing connection weights and network topology[11,40]
- E.g. Neuroevolution of Augmenting Topologies (NEAT[27,29])
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

How Can Crossover be Implemented?

- Problem: Structures do not match

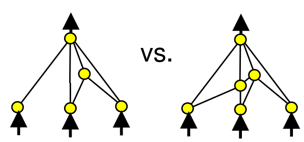


- Solution: Utilize historical markings



How can Innovation Survive?

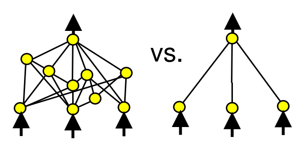
- Problem: Innovations have initially low fitness



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

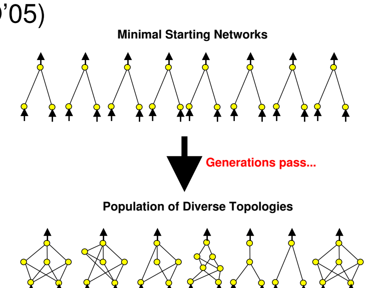
How Can We Search in Large Spaces?

- Need to optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify
  - Hidden nodes, connections, input features[37]

(Whiteson GECCO'05)



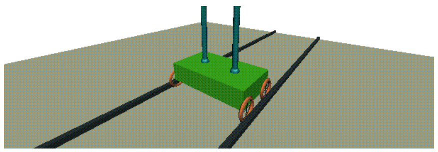
Further NE Techniques

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

Extending NE to Applications

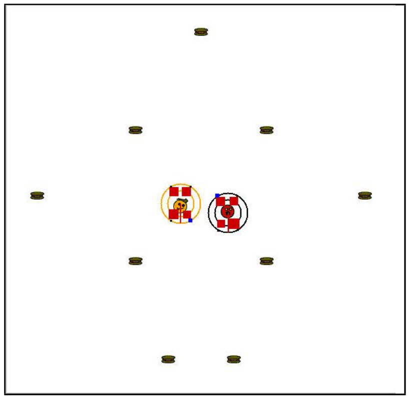
- Evolving composite decision makers[36]
- Evolving teams of agents[3,28,41]
- Utilizing coevolution[30]
- Real-time neuroevolution[28]
- Combining human knowledge with evolution[8]

Applications to Control



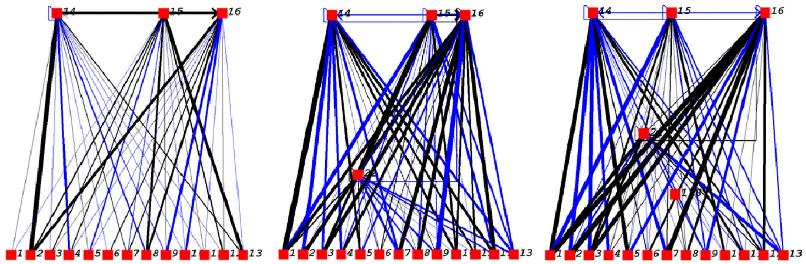
- Pole-balancing benchmark
  - Originates from the 1960s
  - Original 1-pole version too easy
  - Several extensions: acrobat, jointed, 2-pole, particle chasing[23]
- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control[34]

Competitive Coevolution



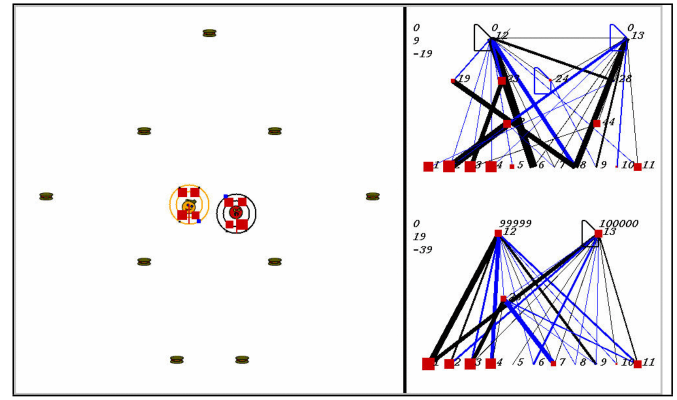
- Evolution requires an opponent to beat
- Such opponents are not always available
- Co-evolve two populations to outdo each other
- How to maintain an arms race?

Competitive Coevolution with NEAT



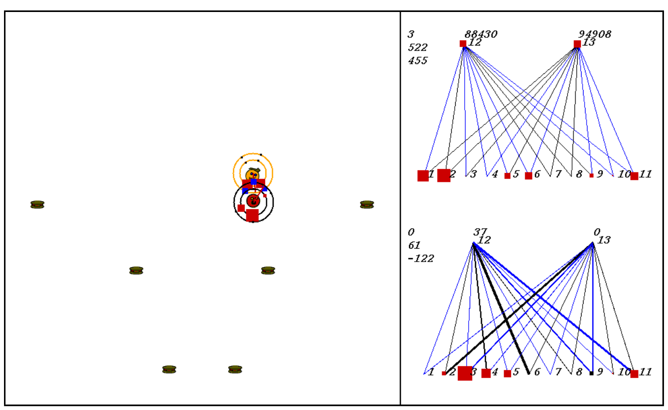
- Complexification elaborates instead of alters
  - Adding more complexity to existing behaviors
- Can establish a coevolutionary arms race
  - Two populations continually outdo each other
  - Absolute progress, not just tricks

Robot Duel Domain



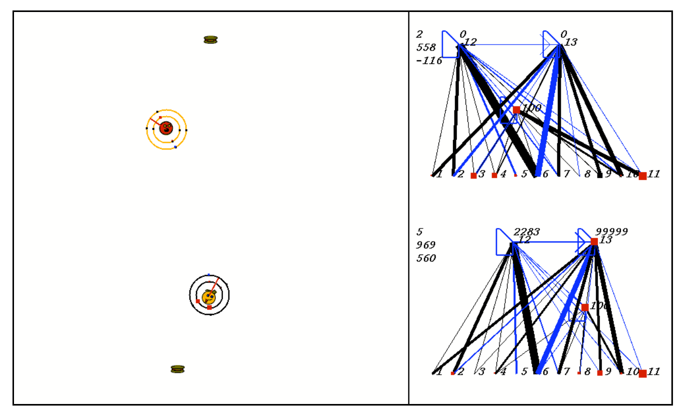
- Two Khepera-like robots forage, pursue, evade[30]
  - Collect food to gain energy
  - Win by crashing to a weaker robot

Early Strategies



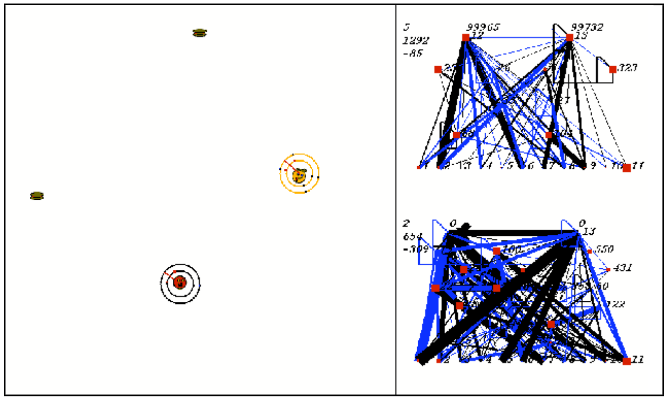
- Crash when higher energy
- Collect food by accident
- DEMO

Mature Strategies



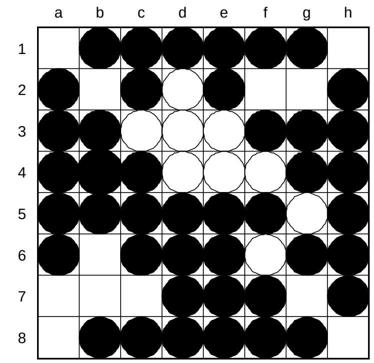
- Collect food to gain energy
- Avoid moving to lose energy
- Standoff: Difficult to predict outcome
- DEMO

Sophisticated Strategy



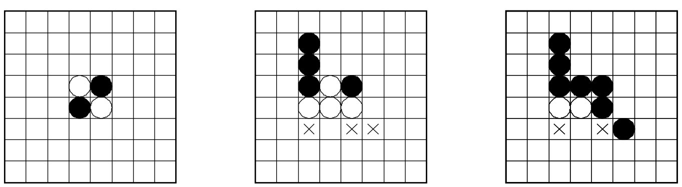
- "Fake" a move up, force away from last piece
- Win by making a dash to last piece
- Complexification $\longrightarrow$ arms race
- DEMO

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]

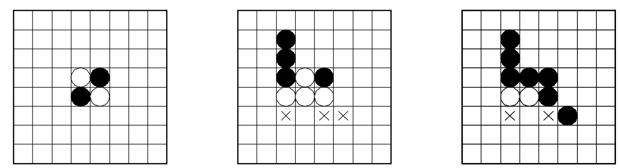
Discovering Novel Strategies in Othello



(a) (b) (c)

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

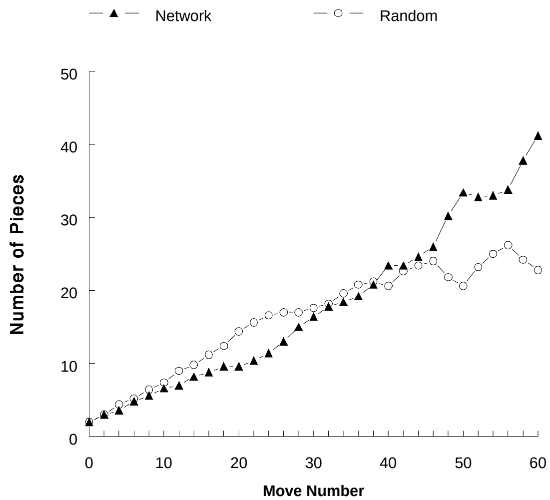
Strategies in Othello



(a) (b) (c)

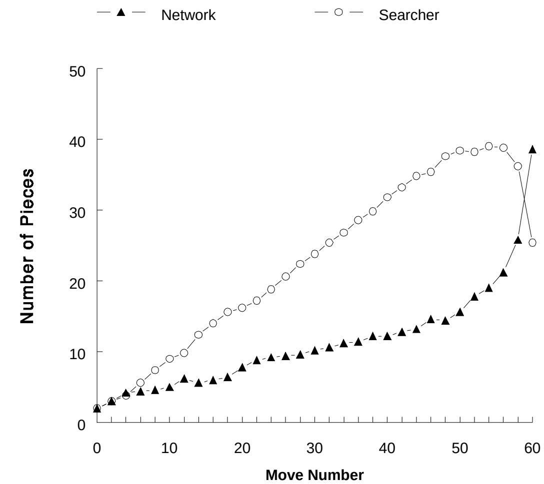
- Positional
  - Number of pieces and their positions
  - Typical novice strategy
- Mobility
  - Number of available moves: force a bad move
  - Much more powerful, but counterintuitive
  - Discovered in 1970's in Japan

Evolving Against a Random Player



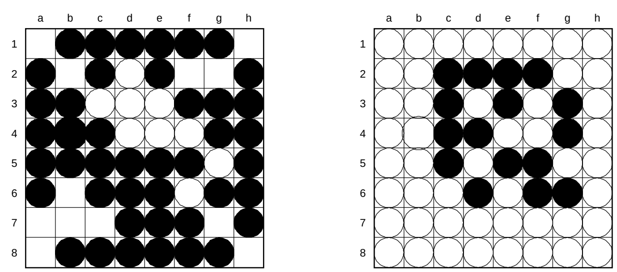
- Network sees the board, suggests moves by ranking[21]
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

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

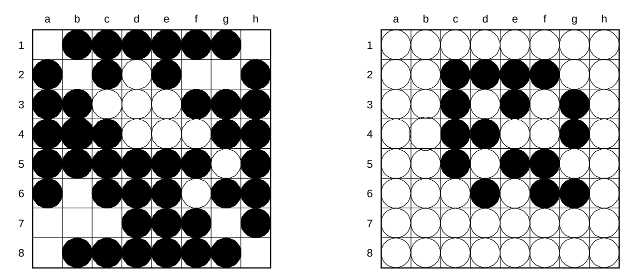
Example game



(a) (b)

- 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

Discovering Novel Strategies



(a) (b)

- 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

Numerous Other Applications

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

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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