

# Advanced AI for Games: Neuroevolution

- CSCE 315
- These slides are from Risto Miikkulainen's tutorial at the GECCO 2005 conference, with slight editing.
- Slides 7 – 9 were added by Yoonsuck Choe.

1

## Evolving Neural Networks

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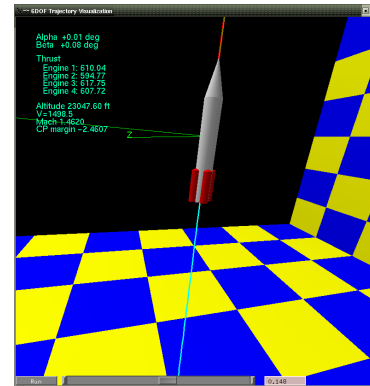
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# Today's Main Topic

- 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

2

## 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.

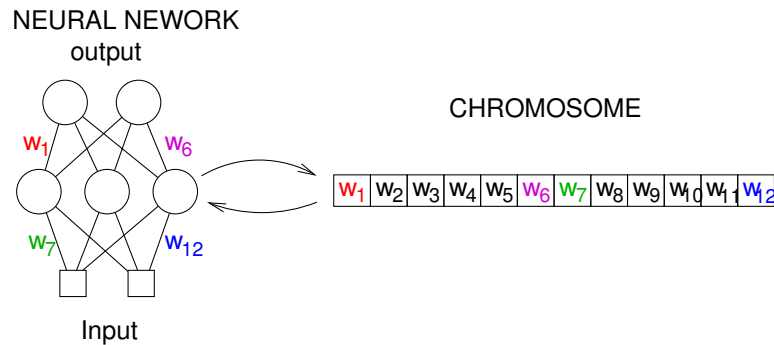
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# Outline

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

5

## Neuroevolution Basics

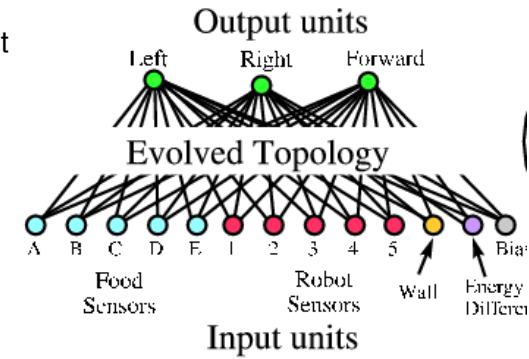


- A single chromosome encodes a full neural network.
- Each gene, a single bit (or a real number), maps to a connection weight in the neural network.

7

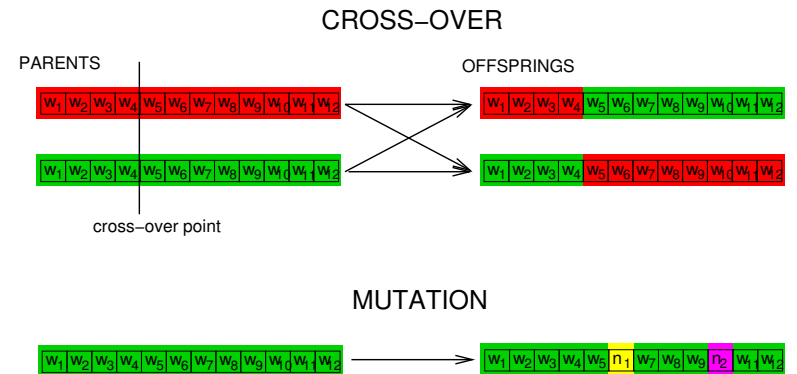
# Neuroevolution Decision Strategies

- 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



6

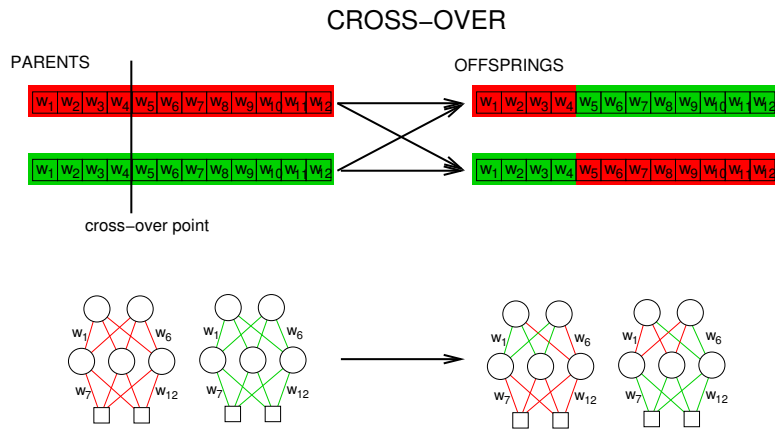
## Neuroevolution Basics: Operations



- Cross-over.
- Mutation.

8

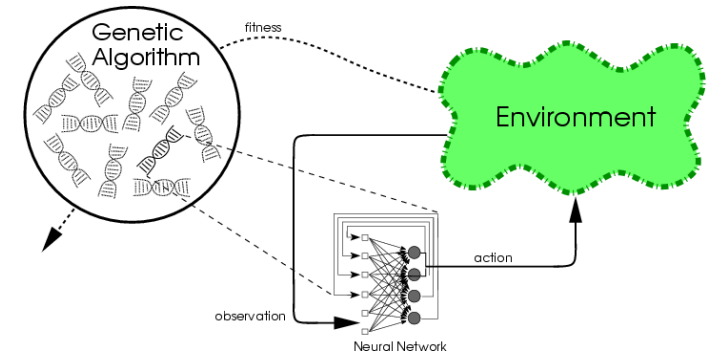
# Neuroevolution Basics: Cross-Over in Detail



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

9

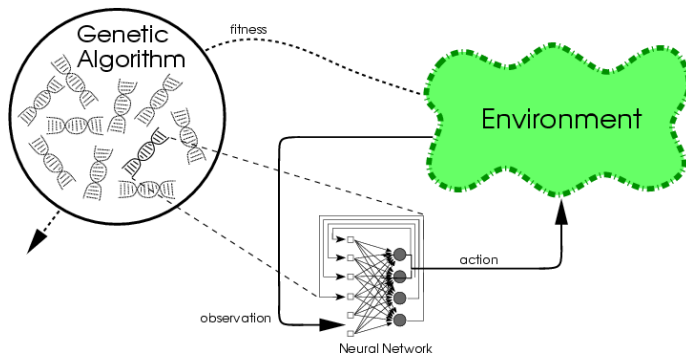
# Conventional Neuroevolution (CNE)



- 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

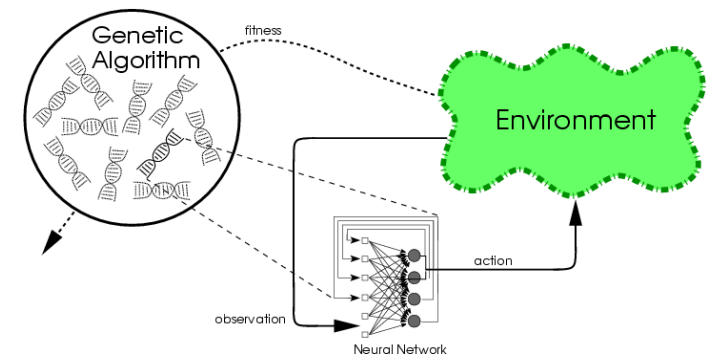
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# Conventional Neuroevolution (2)



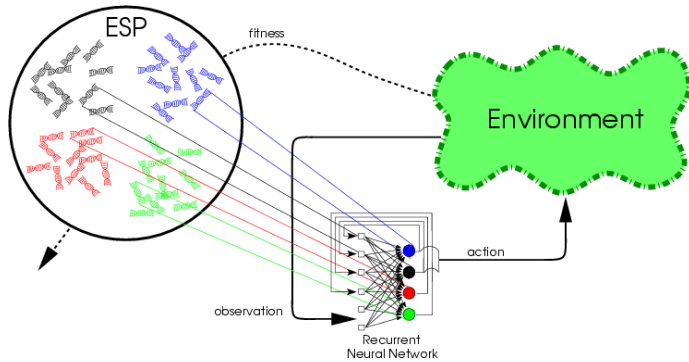
- Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
  - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match<sub>1,1</sub>

# 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>1,2</sub> at once

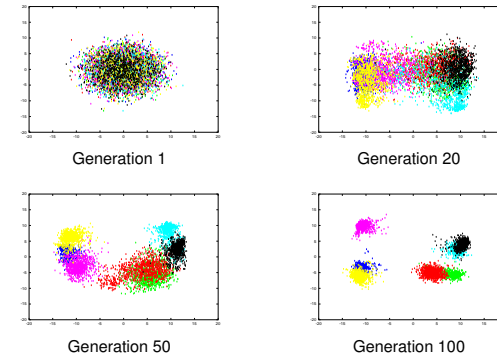
# Advanced NE 1: Evolving Neurons



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

13

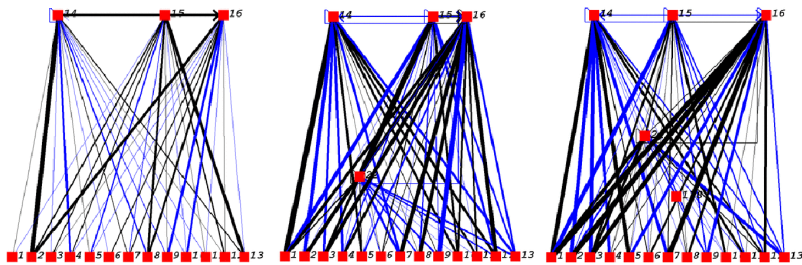
# Advanced NE 2: Evol. Subpopulations



- 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

14

# Advanced NE 3: Evolving Topologies

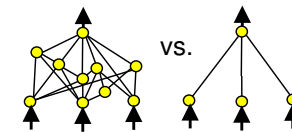


- Optimizing connection weights and network topology <sup>11,40</sup>
- E.g. Neuroevolution of Augmenting Topologies (NEAT <sup>27,29</sup>)
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

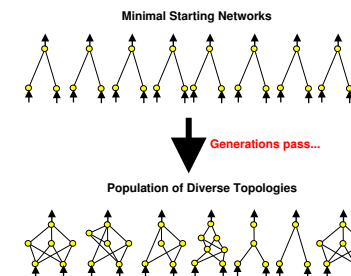
15

# How Can We Complexify?

- Can optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify <sup>37</sup>

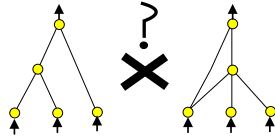


- Can search a very large space of configurations!

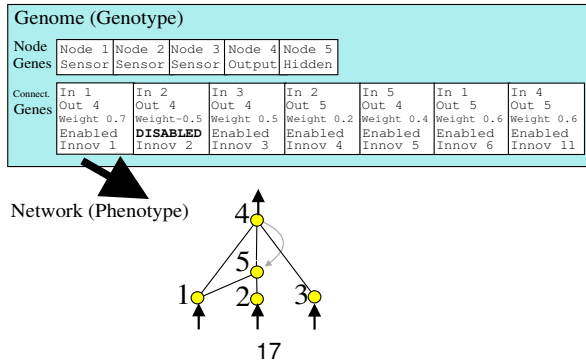
16

# How Can Crossover be Implemented?

- Problem: Structures do not match

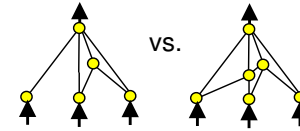


- Solution: Utilize historical markings



# How can Innovation Survive?

- Problem: Innovations have initially low fitness



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

18

# Further Neuroevolution 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

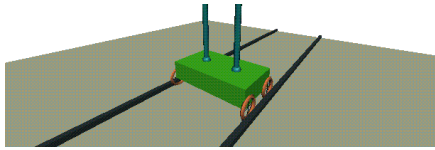
19

# Neuroevolution 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>

20

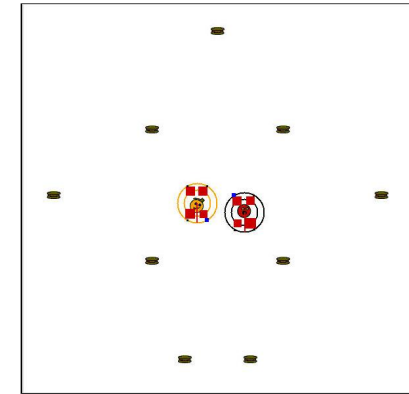
# Applications to Control



- 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>

21

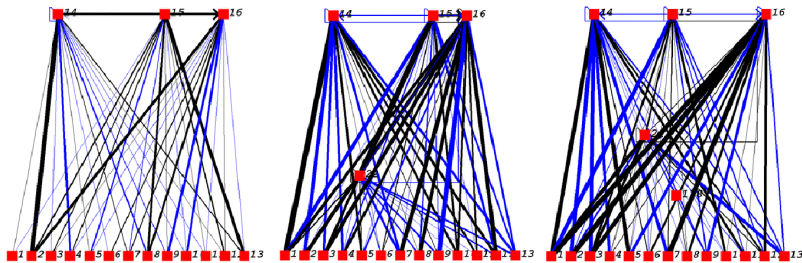
# Competitive Coevolution



- 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?

22

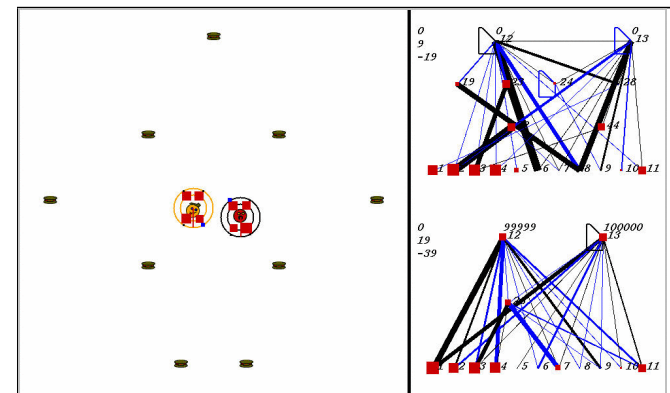
# Competitive Coevolution with NEAT



- 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

23

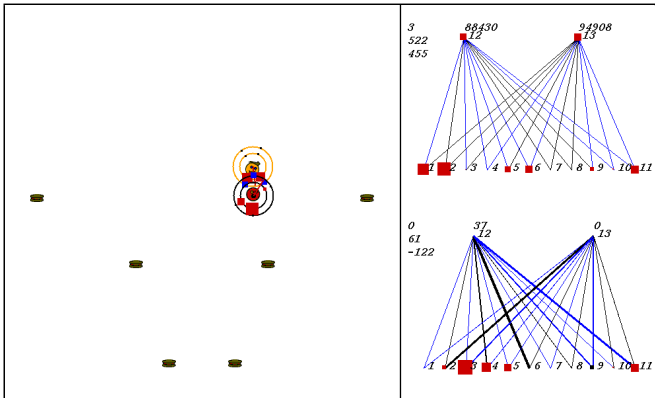
# Robot Duel Domain



- 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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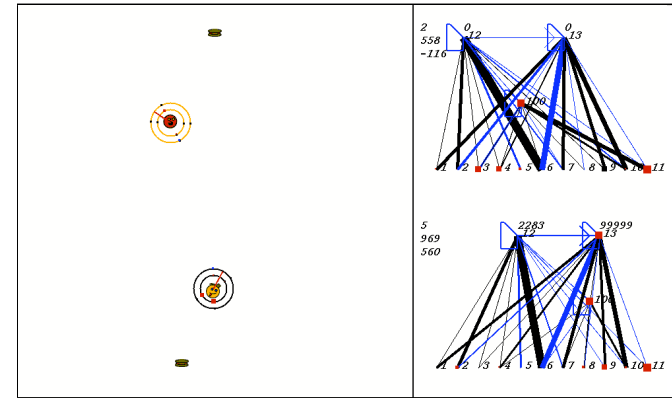
## Early Strategies



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

25

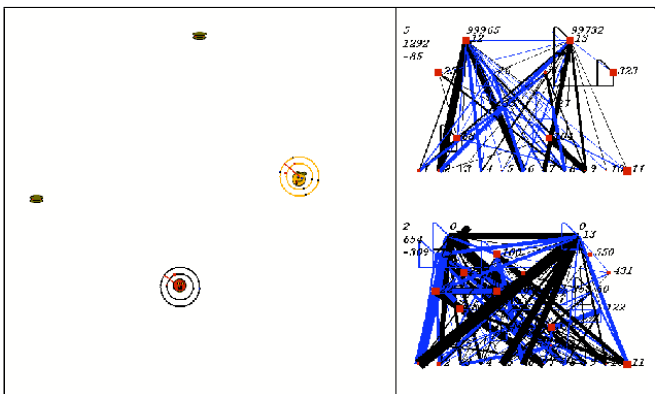
## Mature Strategies



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

26

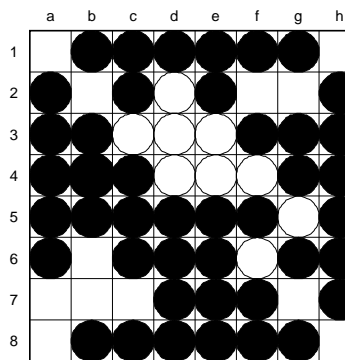
## Sophisticated Strategy



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

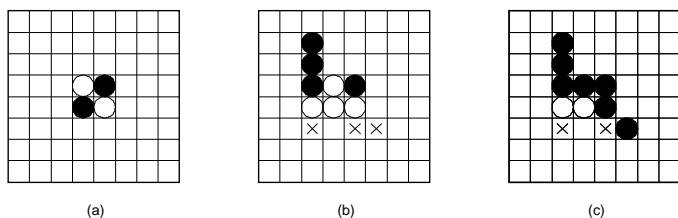
27

## 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>

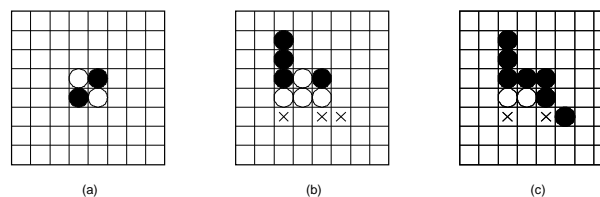
# Discovering Novel Strategies in Othello



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

29

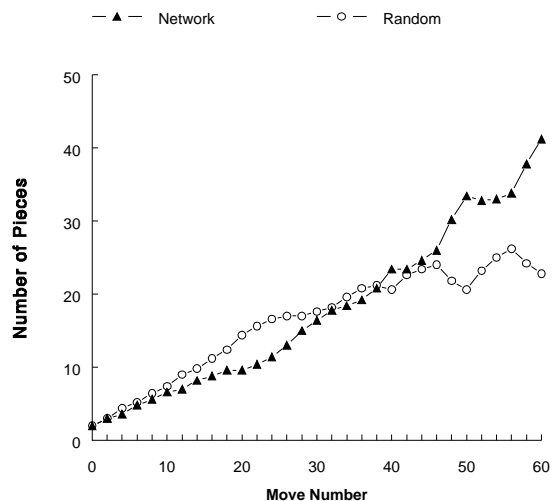
# Strategies in Othello



- 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

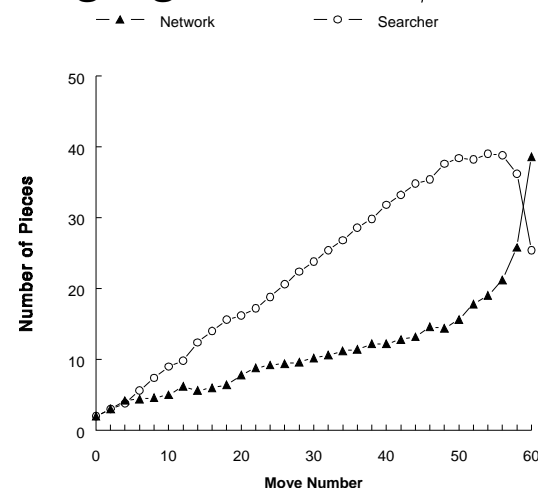
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# Evolving Against a Random Player



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

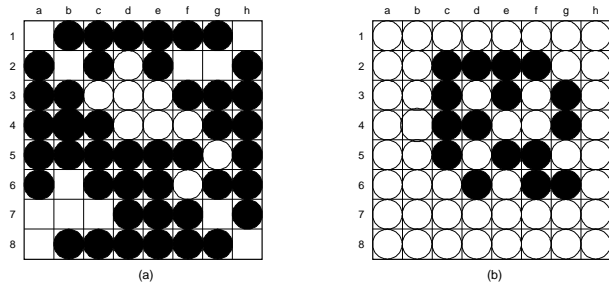
# Evolving Against an $\alpha$ - $\beta$ Program



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



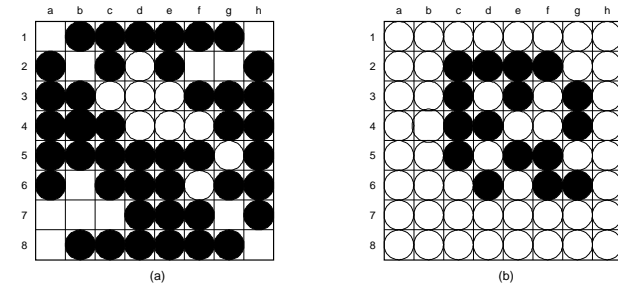
## Example game



- 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

33

## Discovering Novel Strategies



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

34

## 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<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.

36

# 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.

37

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37-2

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37-4

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37-5