Neuroevolution

- These are selected slides from Risto Miikkulainen's tutorial plus additional slides for clarification.
- Yoonsuck Choe

Evolving Neural Networks

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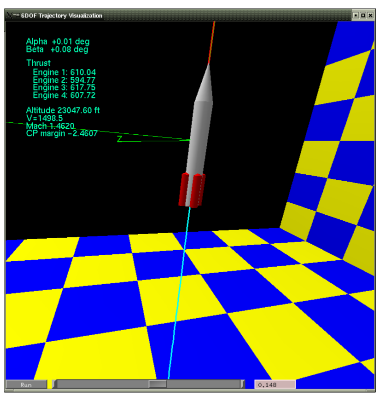
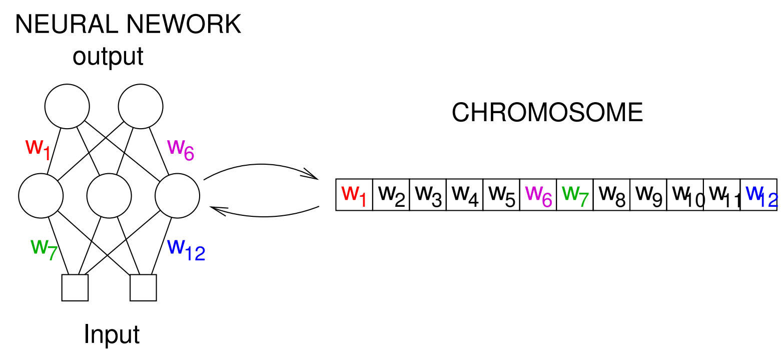
Why Neuroevolution?



- 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?

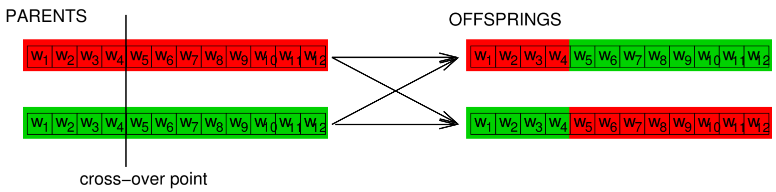
Neuroevolution Basics



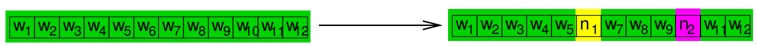
- A single chromosome encodes a full neural network.
  - Inputs hooked up to sensors, and outputs to actuators.
- Each gene, a single bit (or a real number), maps to a connection weight in the neural network.

Neuroevolution Basics: Operators

CROSS–OVER



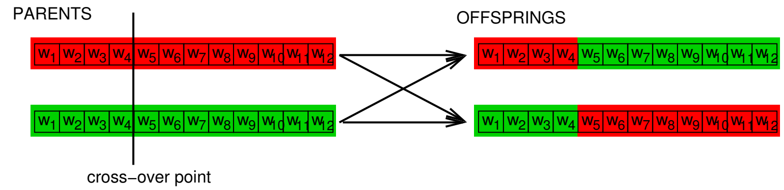
MUTATION

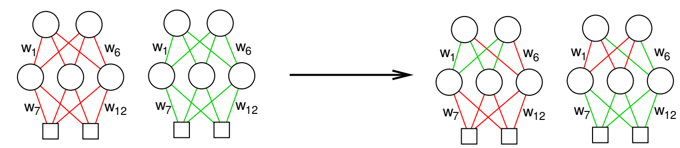


- Cross-over: Combine traits from both parents.
- Mutation: Introduce randomness (innovation).

Neuroevolution Basics: Cross-Over in Detail

CROSS–OVER

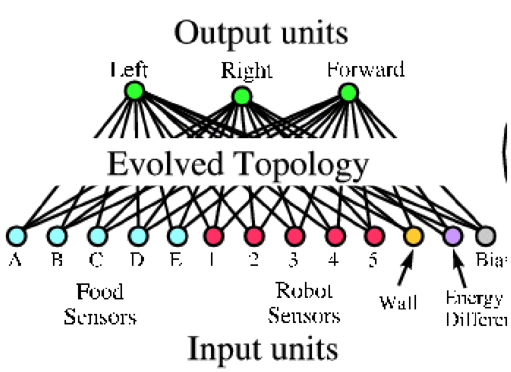




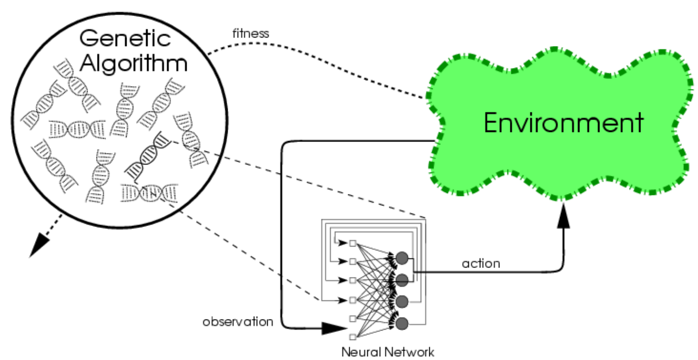
- Cross-over of two individuals produces two offsprings with a mixed heritage.

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

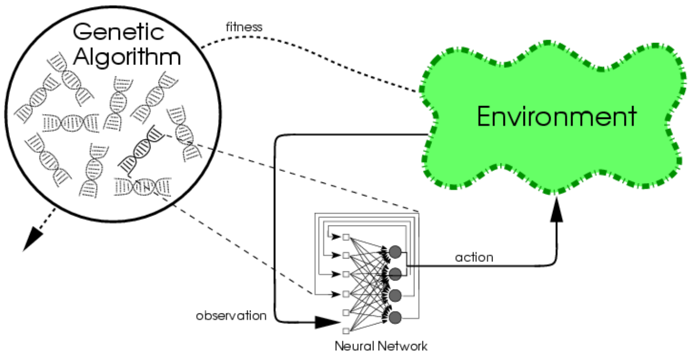


Conventional Neuroevolution (CNE)



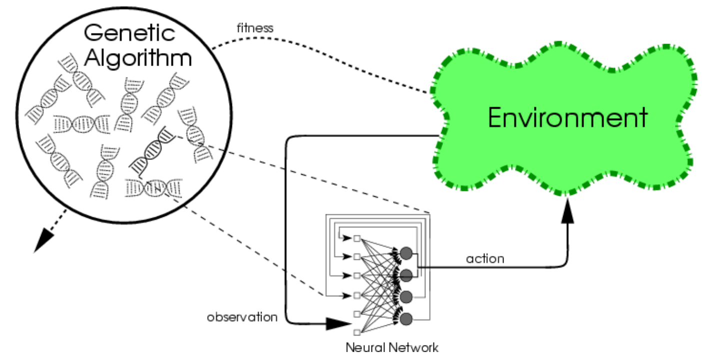
- Evolving connection weights in a population of networks [19, 38, 39]
- Chromosomes are strings of weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

Conventional Neuroevolution (2)



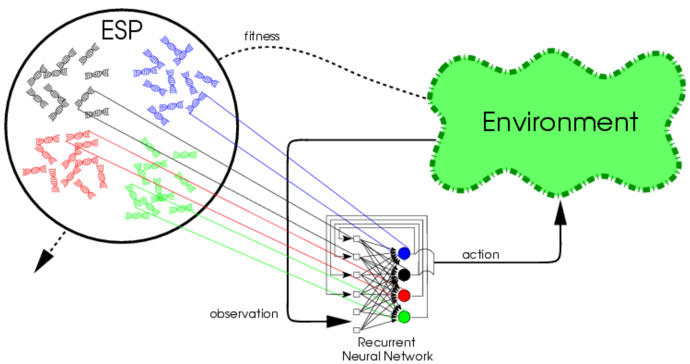
- Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
  - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match!

Problems with CNE



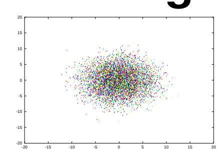
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values at once

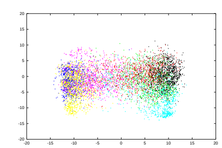
Advanced NE 1: Evolving Neurons

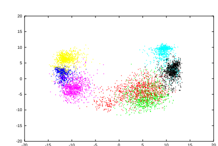


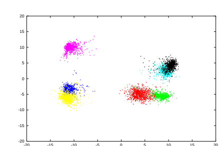
- Evolving individual neurons to cooperate in networks [1, 22, 24] (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP[**?**])
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

Evolving Neurons with ESP


Generation 1

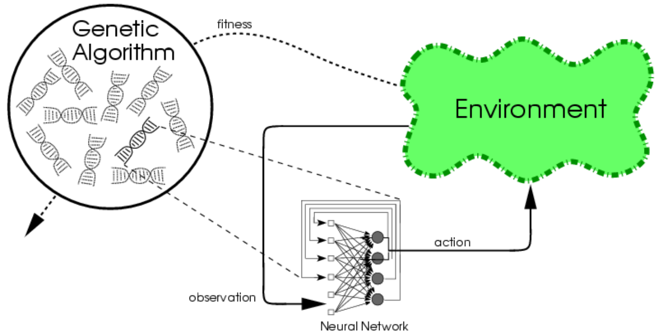

Generation 20


Generation 50


Generation 100

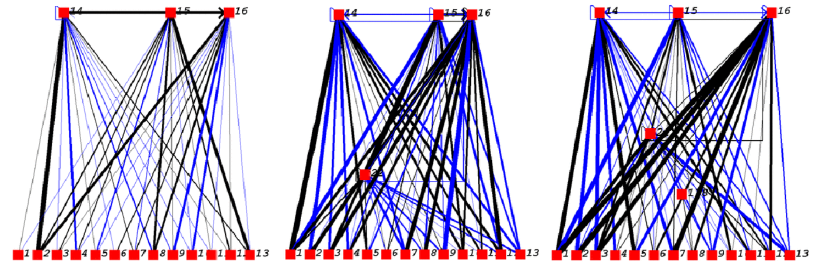
- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

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

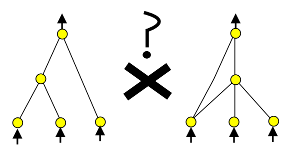
Advanced NE 3: Evolving Topologies



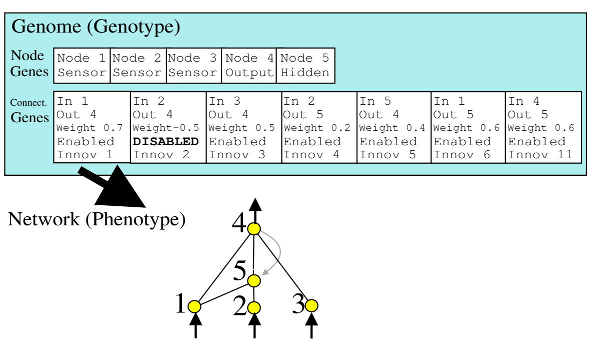
- Optimizing connection weights and network topology [11, 40]
- E.g. Neuroevolution of Augmenting Topologies (NEAT[27, 29])
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

How Can Crossover be Implemented?

- Problem: Structures do not match

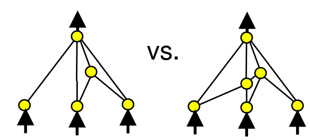


- Solution: Utilize historical markings



How can Innovation Survive?

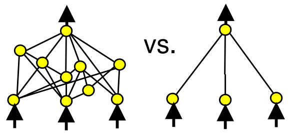
- Problem: Innovations have initially low fitness



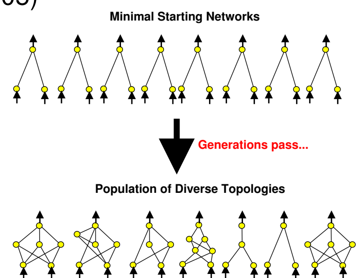
- Solution: Speciate the population
  - Innovations have time to optimize
  - Mitigates competing conventions
  - Promotes diversity

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)



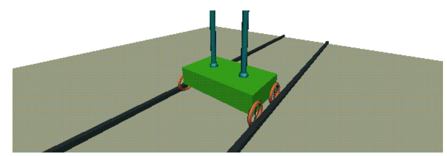
Further NE Techniques

- 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

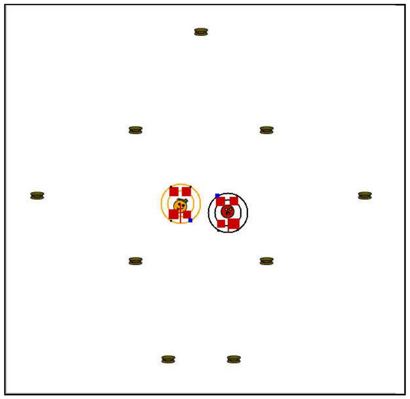
- Evolving composite decision makers [36]
- Evolving teams of agents [3, 28, 41]
- Utilizing coevolution [30]
- Real-time neuroevolution [28]
- Combining human knowledge with evolution [8]

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]

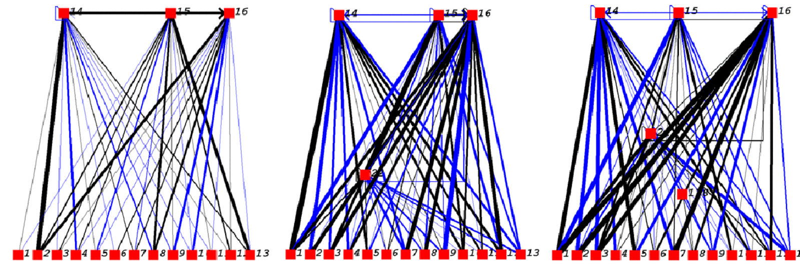
Competitive Coevolution



- Evolution requires an opponent to beat
- Such opponents are not always available

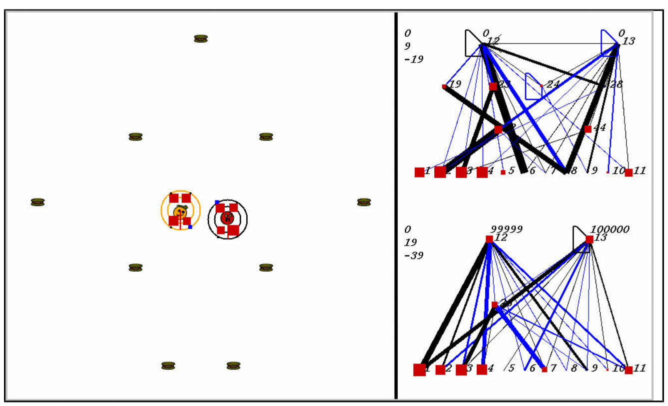
- Co-evolve two populations to outdo each other
- How to maintain an arms race?

Competitive Coevolution with NEAT



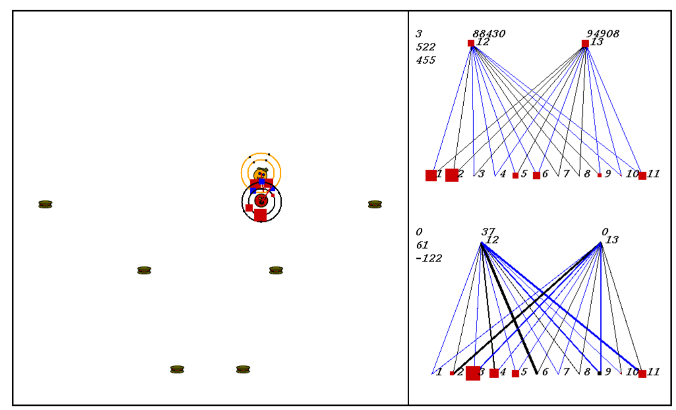
- Complexification elaborates instead of alters
  - Adding more complexity to existing behaviors
- Can establish a coevolutionary arms race
  - Two populations continually outdo each other
  - Absolute progress, not just tricks

Robot Duel Domain



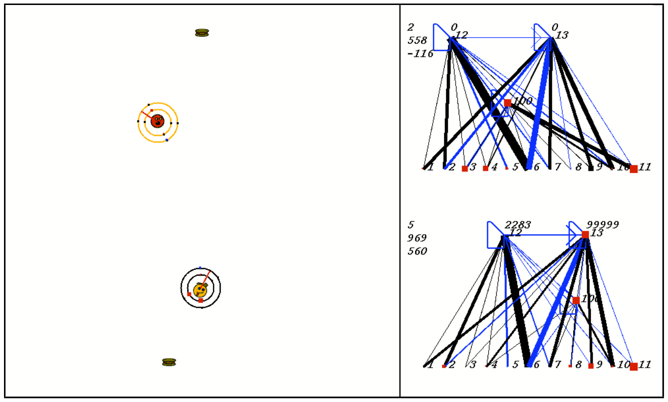
- Two Khepera-like robots forage, pursue, evade[30]
  - Collect food to gain energy
  - Win by crashing to a weaker robot

Early Strategies



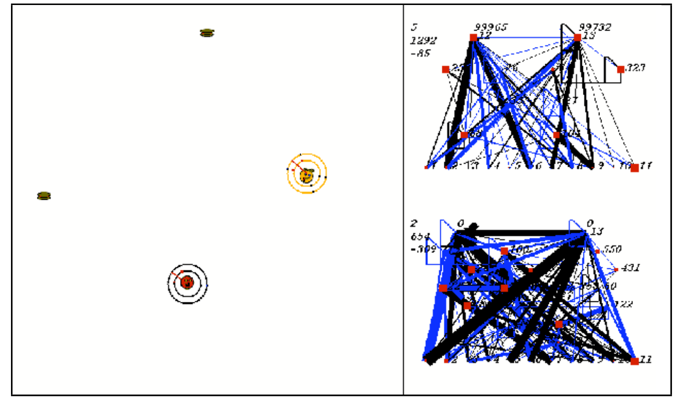
- Crash when higher energy
- Collect food by accident
- DEMO

Mature Strategies



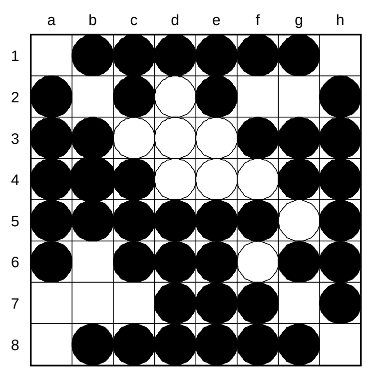
- Collect food to gain energy
- Avoid moving to lose energy
- Standoff: Difficult to predict outcome
- DEMO

Sophisticated Strategy



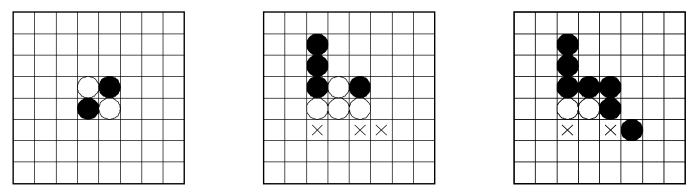
- “Fake” a move up, force away from last piece
- Win by making a dash to last piece
- Complexification → arms race
- DEMO

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]

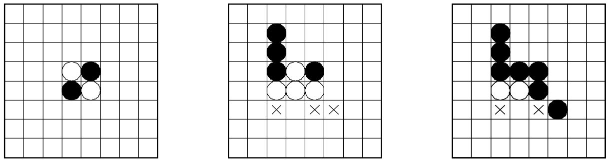
Discovering Novel Strategies in Othello



(a) (b) (c)

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

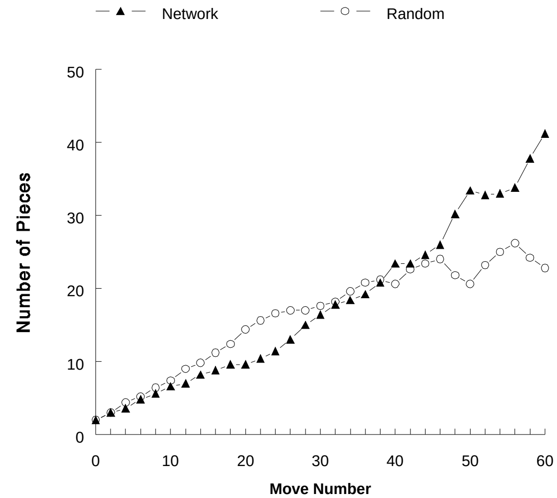
Strategies in Othello



(a) (b) (c)

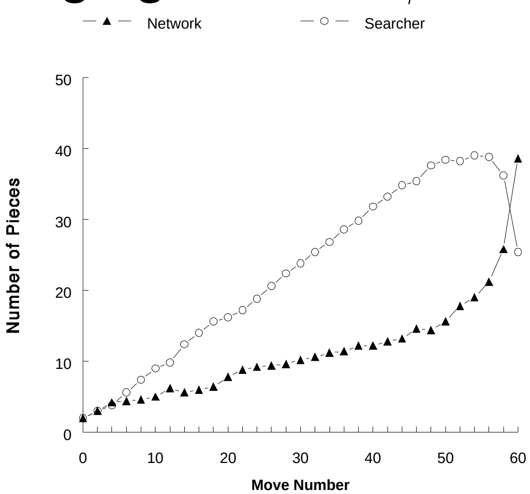
- Positional
  - Number of pieces and their positions
  - Typical novice strategy
- Mobility
  - Number of available moves: force a bad move
  - Much more powerful, but counterintuitive
  - Discovered in 1970's in Japan

Evolving Against a Random Player



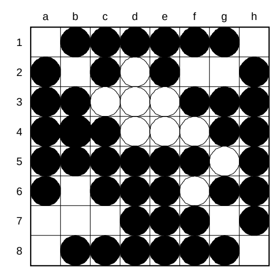
- Network sees the board, suggests moves by ranking [21]
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

Evolving Against an α-β Program

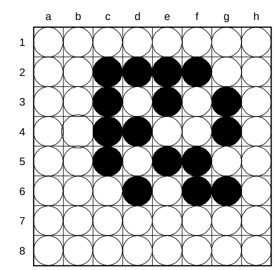


- Iago's positional strategy destroyed networks at first
- Evolution turned low piece count into an advantage
- Mobility strategy emerged!
- Achieved 70% winning percentage

Example game



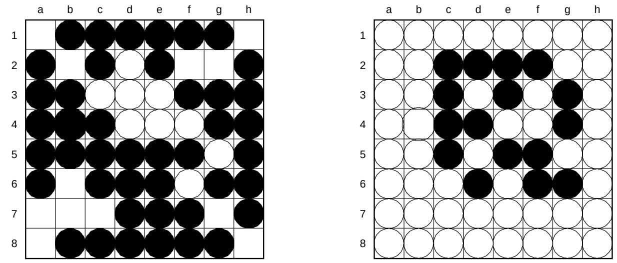
(a)



(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

Other Applications of NEAT

- NERO (NeuroEvolution of Robotic Operatives): Interactive neuroevolution for realtime strategy game-like environment (`http://nerogame.org`)
- Dancing, driving, generation of art, etc.
- See Ken Stanley’s web page.

NERO Details

1. Approach Enemy
2. Hit Target
3. Avoid Fire
4. Approach Flag
5. Stick Together
6. Stand Guard

[NERO Demo]

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

More Exciting Stuff

- Open-ended learning
  - `https://twitter.com/jeffclune/status/1241016690680270849`
  - `https://arxiv.org/abs/2003.08536`
- AutoML-Zero: Evolutionary search discoveres funamental ML algorithms from scratch.
  - `https://twitter.com/quocleix/status/1237528603564204033`
  - `https://arxiv.org/abs/2003.03384`
- and many more!

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