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

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.
Outline

• Basic neuroevolution techniques
• Advanced techniques
  – E.g. combining learning and evolution
• Extensions to applications
  – 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

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.

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

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\(^1\,\^2\,\^24\) (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

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

Advanced NE 3: Evolving Topologies

- Optimizing connection weights and network topology\(^1\,\^4\,\^0\)
- E.g. Neuroevolution of Augmenting Topologies (NEAT\(^2\,\^7\,\^29\))
- Based on Complexification
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

How Can We Complexify?

- Can optimize not just weights but also topologies
- Solution: Start with minimal structure and complexify\(^3\,\^7\)
- Can search a very large space of configurations!
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

Further Neuroevolution Techniques

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

Neuroevolution Applications

- Evolving composite decision makers\textsuperscript{36}
- Evolving teams of agents\textsuperscript{3,28,41}
- Utilizing coevolution\textsuperscript{30}
- Real-time neuroevolution\textsuperscript{28}
- Combining human knowledge with evolution\textsuperscript{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

- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control

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
  - 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

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

Evolving Against a Random Player

- Network sees the board, suggests moves by ranking
- 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

**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

**Numerous Other Applications**

- Creating art, music
- Theorem proving
- Time-series prediction
- Computer system optimization
- Manufacturing optimization
- Process control optimization
- Etc.
**Conclusion**

- Neuroevolution, mimicking 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.

**References**


