Evolving Neural Networks

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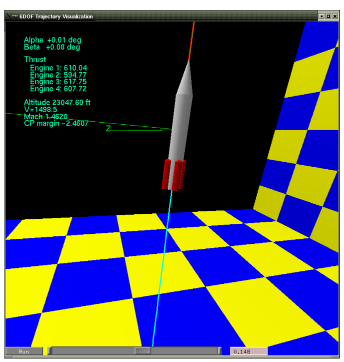
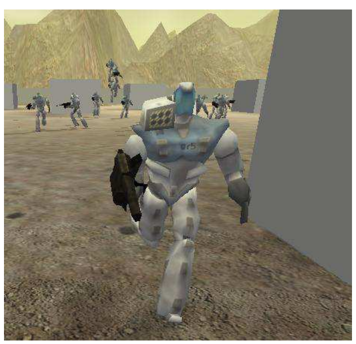
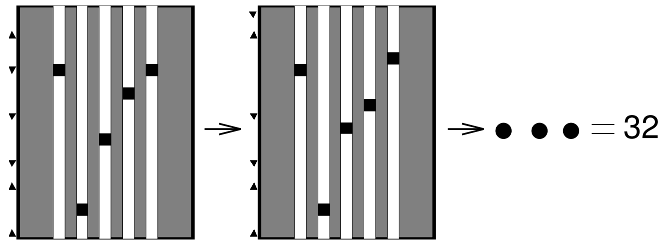
Why Neuroevolution?





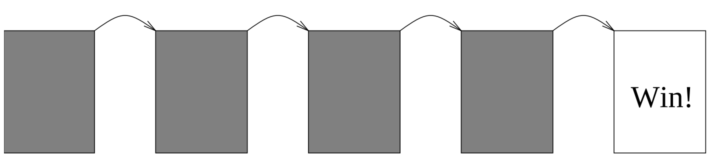
- Neural nets powerful in many statistical domains
  - E.g. control, pattern recognition, prediction, decision making
  - Where no good theory of the domain exists
- Good supervised training algorithms exist
  - Learn a nonlinear function that matches the examples
- What if correct outputs are not known?

Sequential Decision Tasks



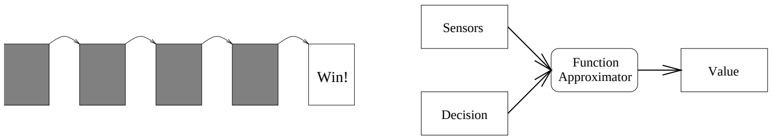
- POMDP: Sequence of decisions creates a sequence of states
- No targets: Performance evaluated after several decisions
- Many important real-world domains:
  - Robot/vehicle/traffic control
  - Computer/manufacturing/process optimization
  - Game playing

Forming Decision Strategies



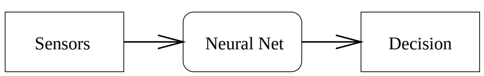
- Traditionally designed by hand
  - Too complex: Hard to anticipate all scenarios
  - Too inflexible: Cannot adapt on-line
- Need to discover through exploration
  - Based on sparse reinforcement
  - Associate actions with outcomes

Standard Reinforcement Learning



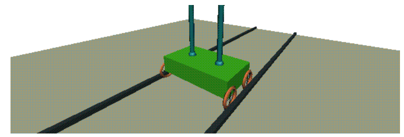
- AHC, Q-learning, Temporal Differences
  - Generate targets through prediction errors
  - Learn when successive predictions differ
- Predictions represented as a value function
  - Values of alternatives at each state
- Difficult with large/continuous state and action spaces
- Difficult with hidden 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[71]

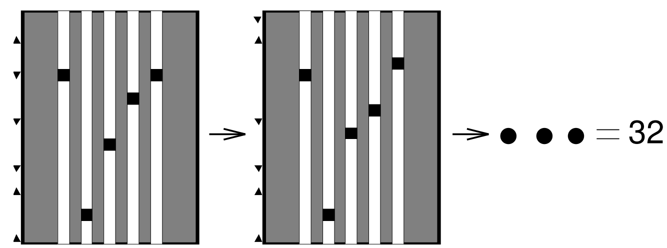
How well does it work?



Poles	Method	Evals	Succ.
One	VAPS	(500,000)	0%
	SARSA	13,562	59%
	Q-MLP	11,331	
	NE	127	
Two	NE	3,416	

- Difficult RL benchmark: Non-Markov Pole Balancing
- NE 3 orders of magnitude faster than standard RL[26]
- NE can solve harder problems

Role of Neuroevolution



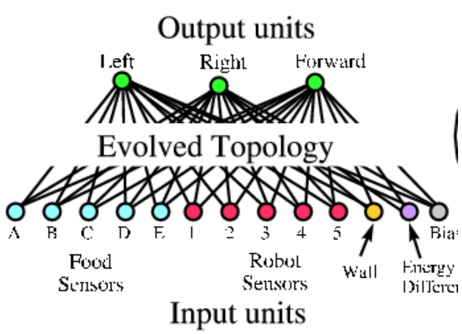
- Powerful method for sequential decision tasks[26;48;83]
  - Optimizing existing tasks
  - Discovering novel solutions
  - Making new applications possible
- Also may be useful in supervised tasks[44;53]
  - Especially when network topology important
- Unique model of biological adaptation and development[49;58;77]

Outline

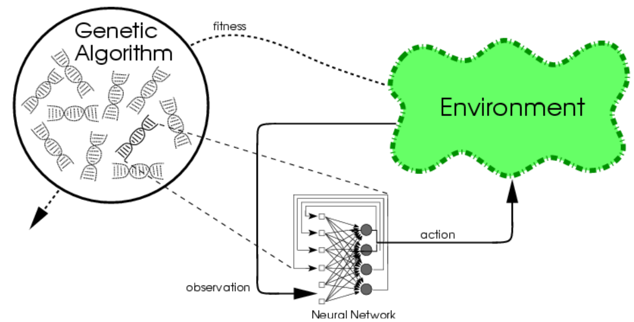
- Basic neuroevolution techniques
- Advanced techniques
  - E.g. combining learning and evolution
- Extensions to applications
- Application examples
  - Control, Robotics, Artificial Life, Games

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

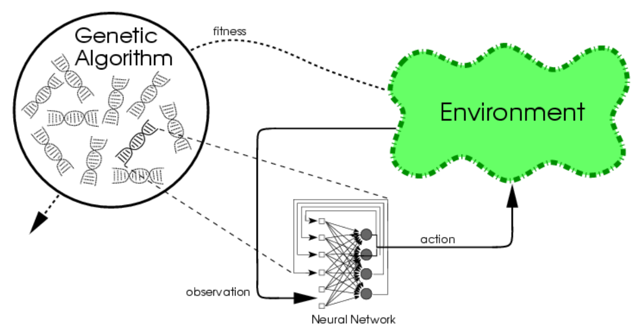


Conventional Neuroevolution (CNE)



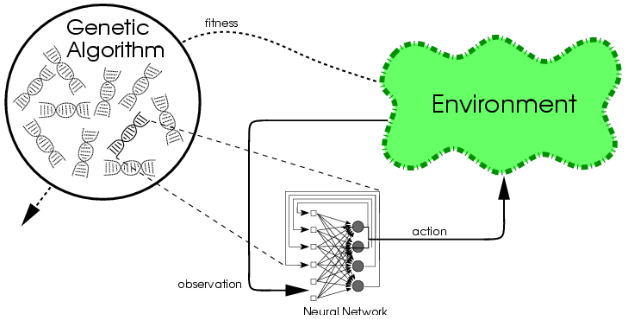
- Evolving connection weights in a population of networks [44;59;83;84]
- Chromosomes are strings of weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

Conventional Neuroevolution (2)



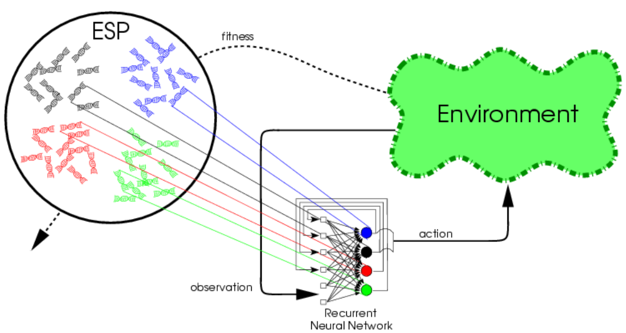
- Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
  - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match!

Problems with CNE



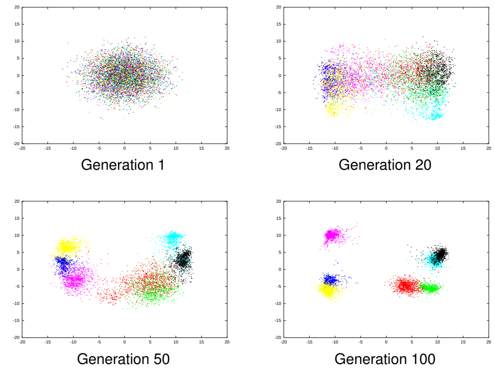
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values at once

Advanced NE 1: Evolving Partial Networks



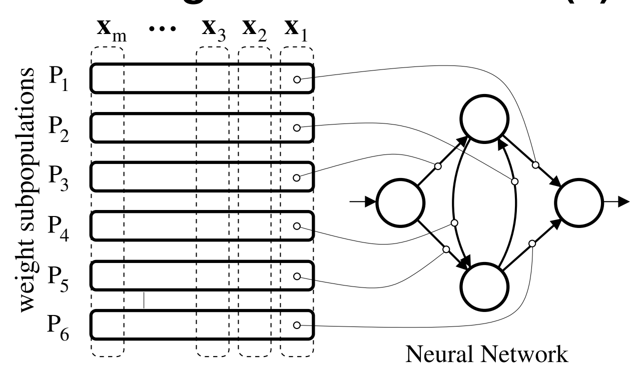
- Evolving individual neurons to cooperate in networks [1;47;53]
- E.g. Enforced Sub-Populations (ESP [22])
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

Evolving Neurons with ESP



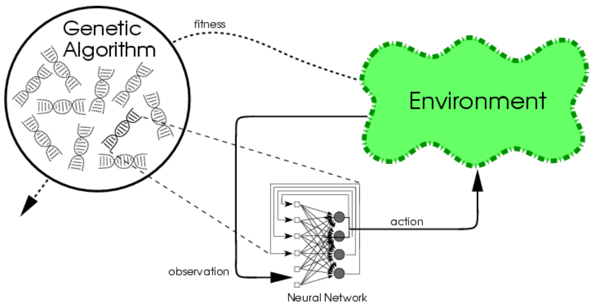
- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

Evolving Partial Networks (2)



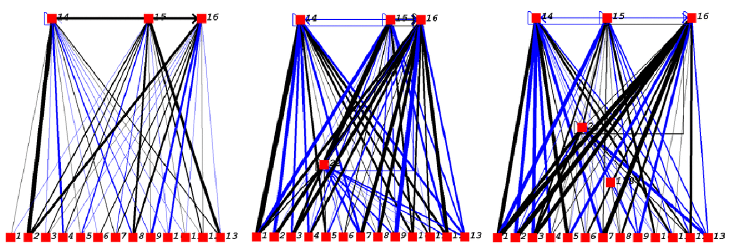
- Extend the idea to evolving connection weights
- E.g. Cooperative Synapse NeuroEvolution (CoSyNE [26])
  - Connection weights in separate subpopulations
  - Networks formed by combining neurons with the same index
  - Networks mutated and recombined; indices permutated
- Sustains diversity, results in efficient search

Advanced NE 2: Evolutionary Strategies



- Evolving complete networks with ES (CMA-ES[32])
- 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

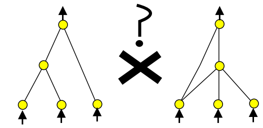
Advanced NE 3: Evolving Topologies



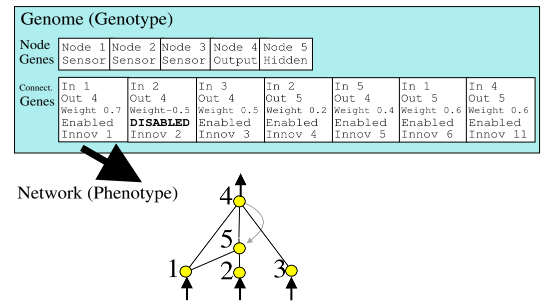
- Optimizing connection weights and network topology[3;20;85]
- E.g. Neuroevolution of Augmenting Topologies (NEAT[64;66])
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

How Can Crossover be Implemented?

- Problem: Structures do not match

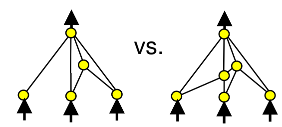


- Solution: Utilize historical markings



How can Innovation Survive?

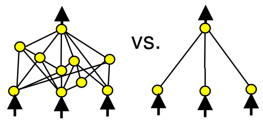
- Problem: Innovations have initially low fitness



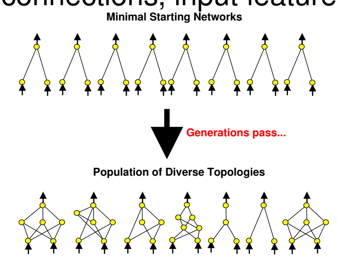
- Solution: Speciate the population
  - Innovations have time to optimize
  - Mitigates competing conventions
  - Promotes diversity

How Can We Search in Large Spaces?

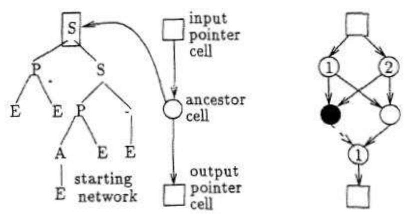
- Need to optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify
  - Hidden nodes, connections, input features[81]

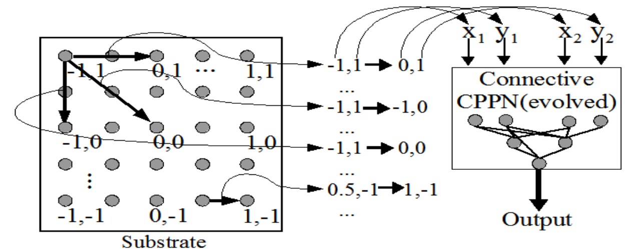


Advanced NE 4: Indirect Encodings

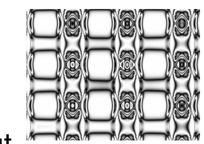


- Instructions for constructing the network evolved
  - Instead of specifying each unit and connection[3;42;62;85]
- E.g. Cellular Encoding (CE[28])
- Grammar tree describes construction
  - Sequential and parallel cell division
  - Changing thresholds, weights
  - A “developmental” process that results in a network

Indirect Encodings (2)

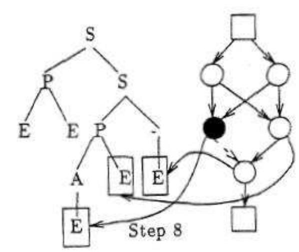


- Encode the networks as spatial patterns
- E.g. Hypercube-based NEAT (HyperNEAT[13])
- Evolve a neural network (CPPN) to generate spatial patterns

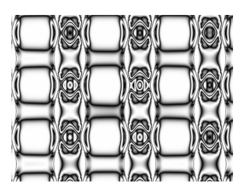


  - 2D CPPN: (x, y) input $\longrightarrow$ grayscale output
  - 4D CPPN: (x_1, y_1, x_2, y_2) input $\longrightarrow$ w output
  - Connectivity and weights can be evolved indirectly
  - Works with very large networks (millions of connections)

Properties of Indirect Encodings

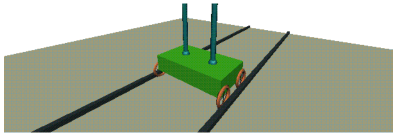


- Smaller search space
- Avoids competing conventions
- Describes classes of networks efficiently
- Modularity, reuse of structures
  - Recurrency symbol in CE: XOR $\longrightarrow$ parity
  - Repetition with variation in CPPNs
  - Useful for evolving morphology



- Not fully explored (yet)
- Promising current work
  - More general L-systems; developmental codings; embryogeny[67]
  - Scaling up spatial coding[14;21] (D’Ambrosio GECCO’08)
  - Genetic Regulatory Networks[54]

How Do the NE Methods Compare?



Poles	Method	Evals
Two	CE	(840,000)
	CNE	87,623
	ESP	26,342
	NEAT	6,929
	CMA-ES	6,061
	CoSyNE	3,416

Two poles, no velocities, damping fitness[26]

- Advanced methods better than CNE
- Advanced methods are still improving
- Indirect encodings future work
- DEMO

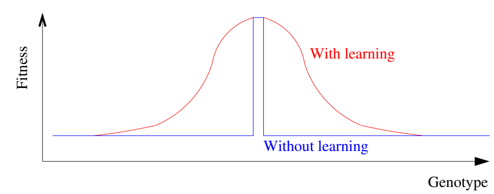
Further NE Techniques

- Incremental evolution[24;73;84]
- Utilizing population culture[5;40]
- Evolving ensembles of NNs[36;52;79]
- Evolving neural modules[55]
- Evolving transfer functions and learning rules[8;57;70]
- Evolving value functions[80]
- Combining learning and evolution

Combining Learning and Evolution

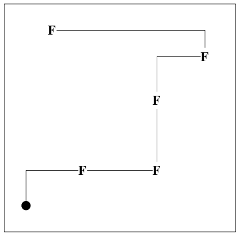
- Good learning algorithms exist for NN
  - Why not use them as well?
- Evolution provides structure and initial weights
- Fine tune the weights by learning
- Lamarckian evolution is possible
  - Coding weight changes back to chromosome
- Difficult to make it work
  - Diversity reduced; progress stagnates

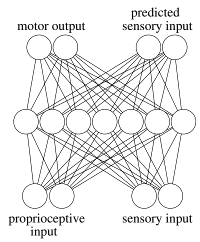
Baldwin Effect



- Learning can guide Darwinian evolution[4;29]
  - Makes fitness evaluations more accurate
- With learning, more likely to find the optimum if close
- Can select between good and bad individuals better
  - Lamarckian not necessary
- How can we implement it?
  - How to obtain training targets?

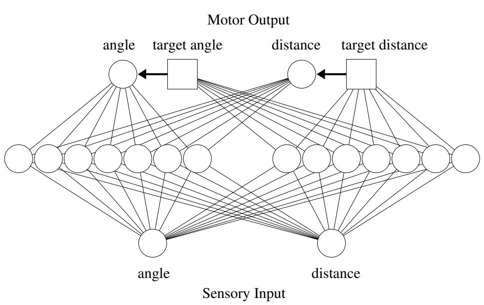
Targets from a Related Task





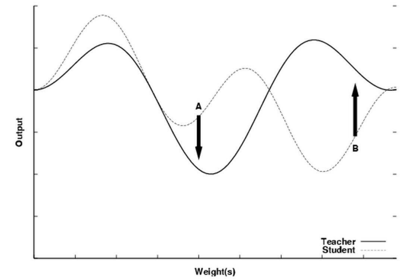
- Learning in a related task is sufficient
- E.g. foraging for food in a microworld[49]
  - Network sees the state, outputs motor commands
  - Trained with backprop to predict the next input
  - Training emphasizes useful hidden-layer representations
  - Allows more accurate evaluations

Evolving the Targets



- Evolve extra outputs to provide targets
- E.g. in the foraging task[51]
  - Motor outputs and targets with separate hidden layers
  - Motor weights trained with backprop, targets evolved
  - Targets do not correspond to optimal performance: Direct system towards useful learning experiences

Targets from the Population



- Train new offspring to imitate parents/champion[40]
  - Trained in population “culture”
- Local search around good individuals
  - Limited training: 8-20 backprop iterations
- Becomes part of the evaluation
  - Individuals evolve to anticipate training
  - Perform poorly at birth, well after training
- Evolution discovers optimal starting points for learning!

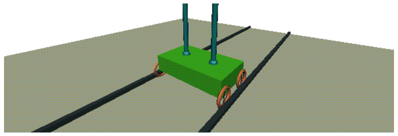
Extending NE to Applications

- Control
- Robotics
- Artificial life
- Gaming

Issues:

- Evolving composite decision makers[79]
- Evolving teams of agents[6;65;86]
- Utilizing coevolution[56;68]
- Real-time neuroevolution[65]
- Combining human knowledge with evolution[7;16;88]

Applications to Control



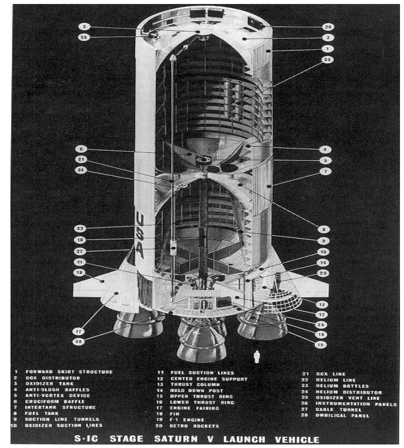
- Pole-balancing benchmark
  - Originates from the 1960s
  - Original 1-pole version too easy
  - Several extensions: acrobat, jointed, 2-pole, particle chasing[52]
- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control[75]

Controlling a Finless Rocket

Task: Stabilize a finless version of the Interorbital Systems RSX-2 sounding rocket[25]

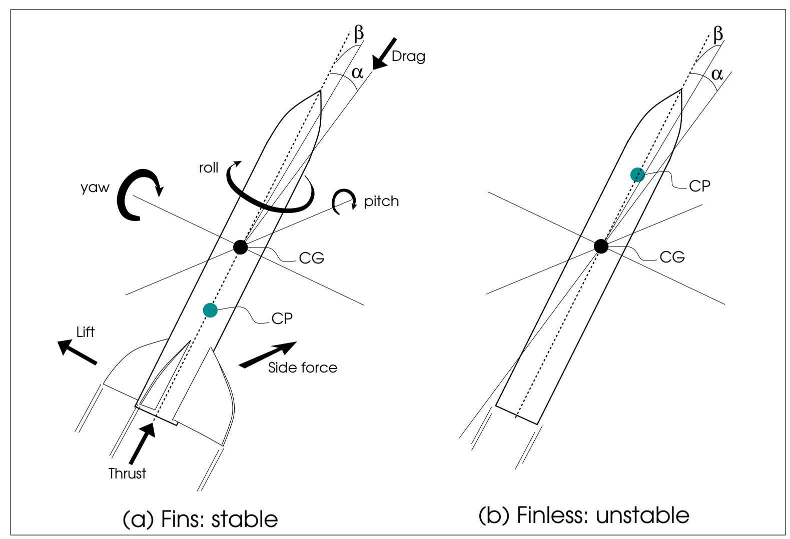
- Scientific measurements in the upper atmosphere
- 4 liquid-fueled engines with variable thrust
- Without fins will fly much higher for same amount of fuel

Active Rocket Guidance



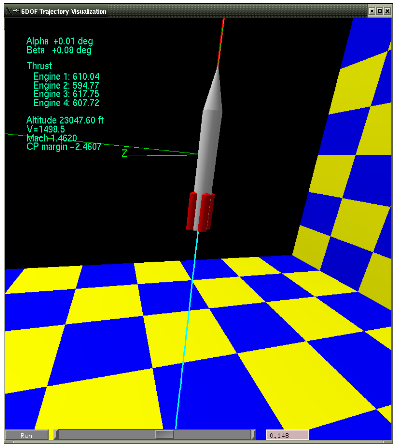
- Used on large scale launch vehicles (Saturn, Titan)
- Typically based on classical linear feedback control
- High level of domain knowledge required
- Expensive, heavy

Rocket Stability



(a) Fins: stable (b) Finless: unstable

Simulation Environment: JSBSim



- General rocket simulator
- Models complex interaction between airframe, propulsion, aerodynamics, and atmosphere
- Used by IOS in testing their rocket designs
- Accurate geometric model of the RSX-2

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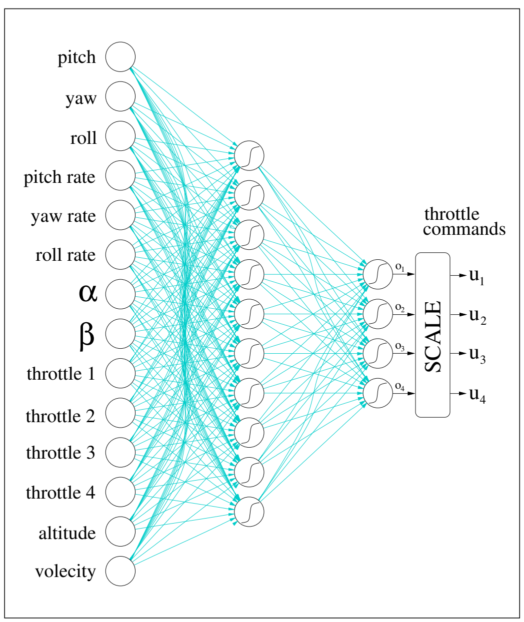
Rocket Guidance Network



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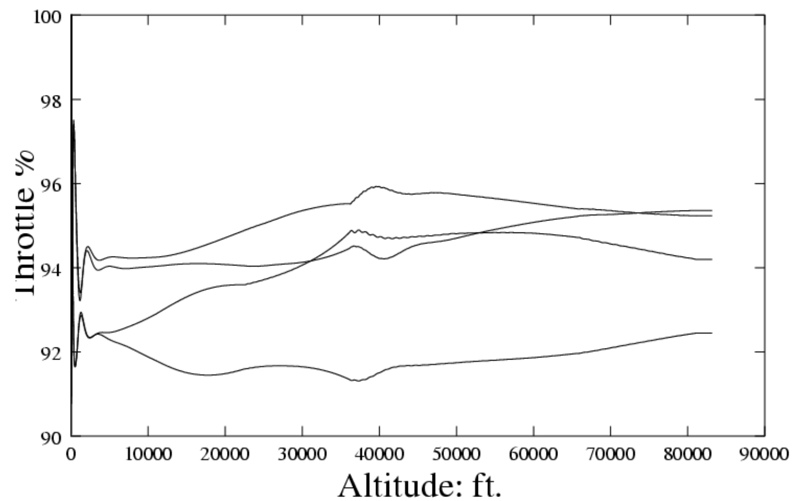
Results: Control Policy



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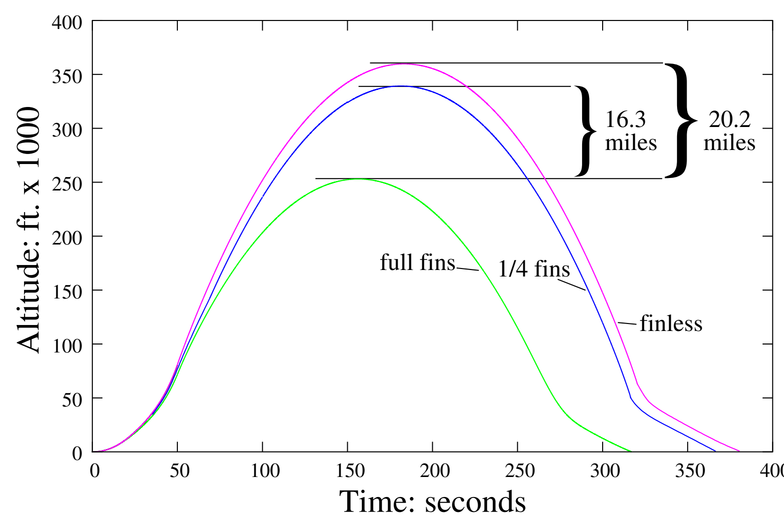
Results: Apogee



- DEMO

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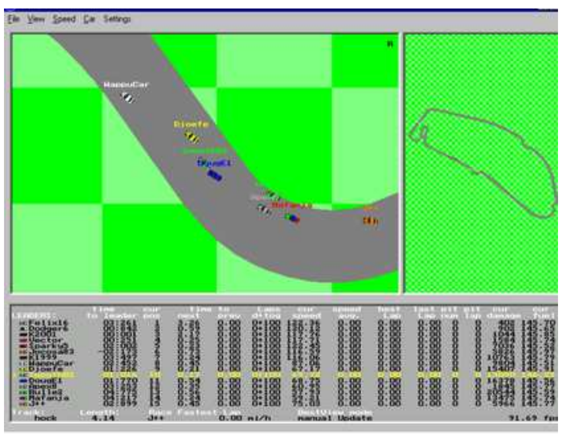
Driving and Collision Warning

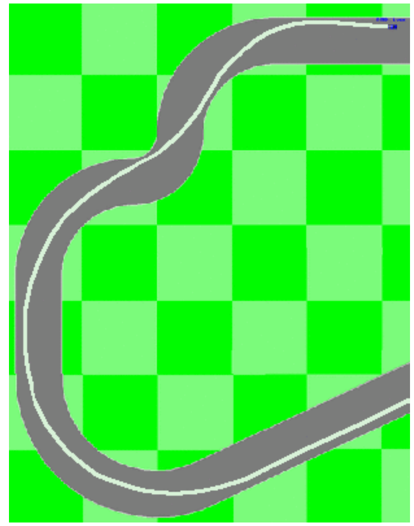
- Goal: evolve a collision warning system
  - Looking over the driver's shoulder
  - Adapting to drivers and conditions
  - Collaboration with Toyota[35]

The RARS Domain



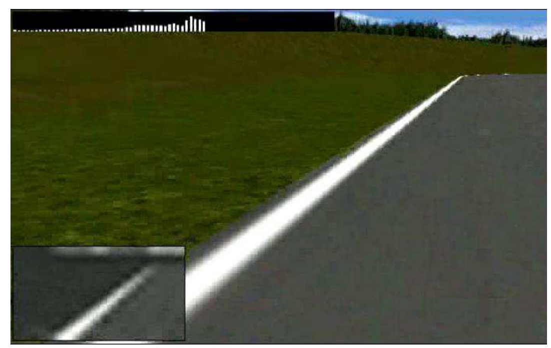
- RARS: Robot Auto Racing Simulator
  - Internet racing community
  - Hand-designed cars and drivers
  - First step towards real traffic

Evolving Good Drivers



- Evolving to drive fast without crashing (off road, obstacles)
- An interesting challenge of its own[72]
- Discovers optimal driving strategies (e.g. how to take curves)
- Works from range-finder & radar inputs
- Works from raw visual inputs
- DEMO

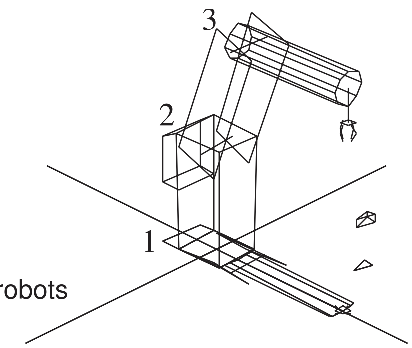
Evolving Warnings



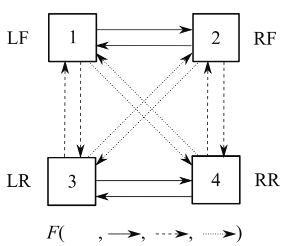
- Evolving to estimate probability of crash
- Predicts based on subtle cues (e.g. skidding off the road)
- Compensates for disabled drivers
- Human drivers learn to drive with it!
- DEMO

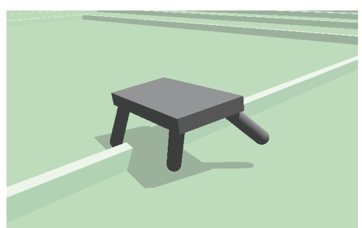
Applications to Robotics

- Controlling a robot arm [46]
  - Compensates for an inop motor
- Robot walking [31;61;74]
  - Various physical platforms
- Mobile robots [11;17;50;63]
  - Transfers from simulation to physical robots
  - Evolution possible on physical robots



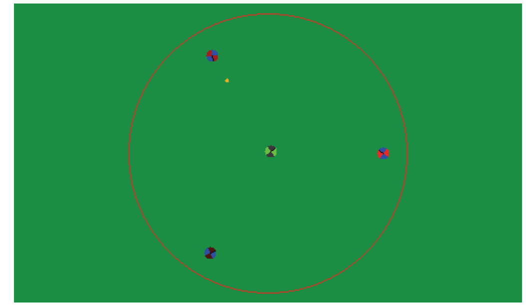
Multilegged Walking





- Modular NE approach [74] (Valsalam GECCO'08)
- Utilize symmetry
  - Evolve one controller module, duplicate for each leg
- Different gaits: pronk, pace, bound, trot...
  - Changes gait to get over obstacles
- DEMO

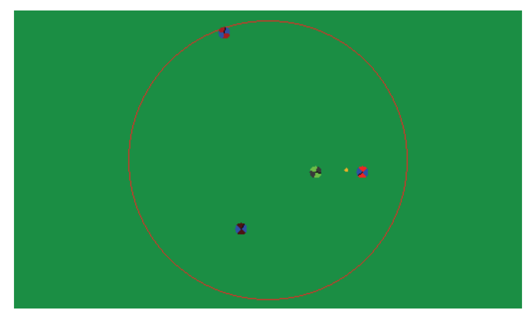
Robotic Soccer



- E.g. robocup soccer "Keepaway" task [79]
- Three keepers, one (algorithmic) taker
- Includes many behaviors:

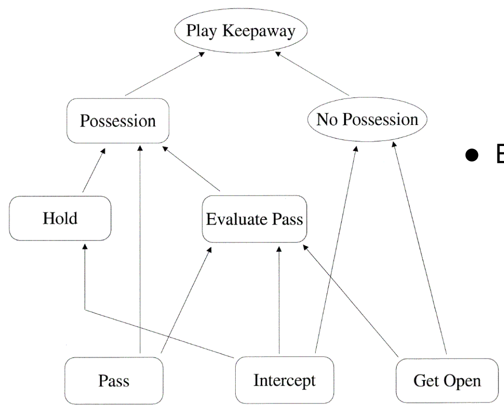
  Get-Open, Intercept, Evaluate-Pass, Pass...

Direct Evolution



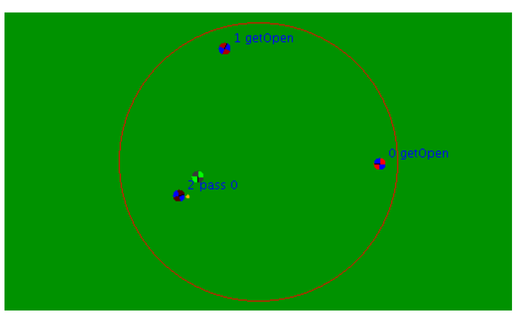
- Mapping sensors directly to actions
  - Difficult to separate behaviors
  - Ineffective combinations evolve
- DEMO

Cooperative Coevolution



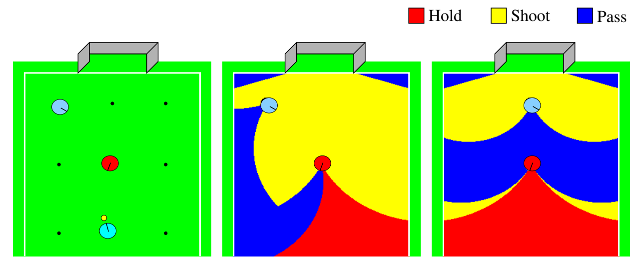
- Evolve multiple actions
  - Each one in a separate network
  - Decision tree to decide on actions

Cooperative Coevolution (2)



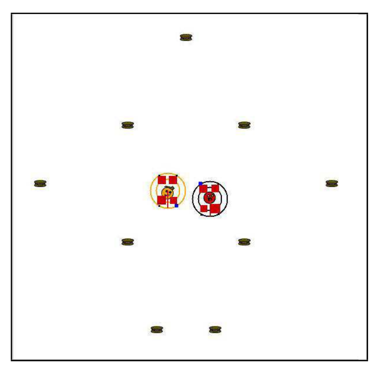
- Networks learn individual tasks
- Learn to anticipate other tasks
  - Lining up for a pass
- Cooperative coevolution of composite behavior
- DEMO

Evolving A High-Level Strategy



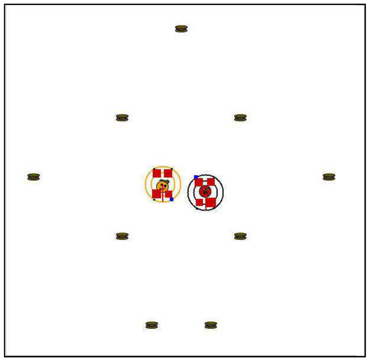
- Evolving the decision making network[34]
- Difficult because the domain is *fractured*
  - Optimal action changes frequently and discontinuosly
- Need to evolve local decisions: RBF-NEAT
  (Kohl GECCO'08)

Applications to Artificial Life



- Gaining insight into neural structure
  - E.g. evolving a command neuron[2;33;58]
- Emergence of behaviors
  - Signaling, herding, hunting...[77;78;87]
- Future challenges
  - Emergence of language
  - Emergence of community behavior

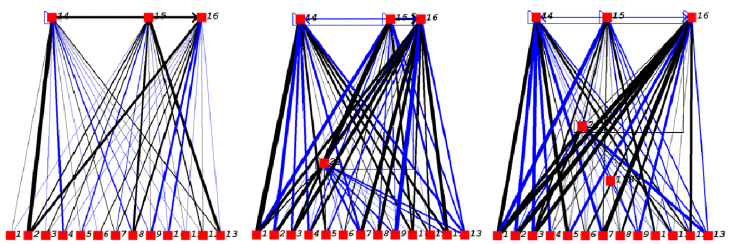
Competitive Coevolution



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

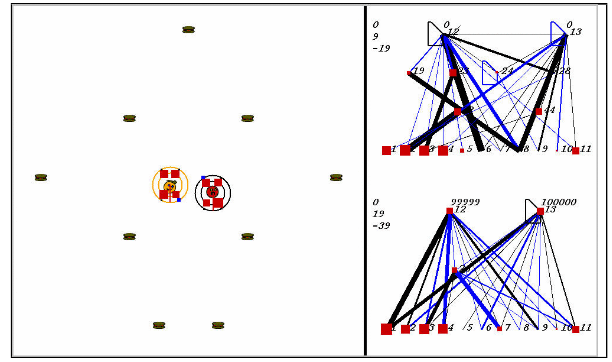
- Co-evolve two populations to outdo each other
- How to maintain an arms race?[43]

Competitive Coevolution with NEAT



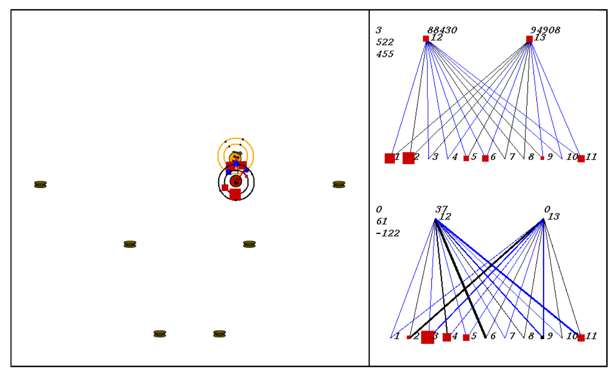
- Complexification elaborates instead of alters
  - Adding more complexity to existing behaviors
- Can establish a coevolutionary arms race
  - Two populations continually outdo each other
  - Absolute progress, not just tricks

Robot Duel Domain



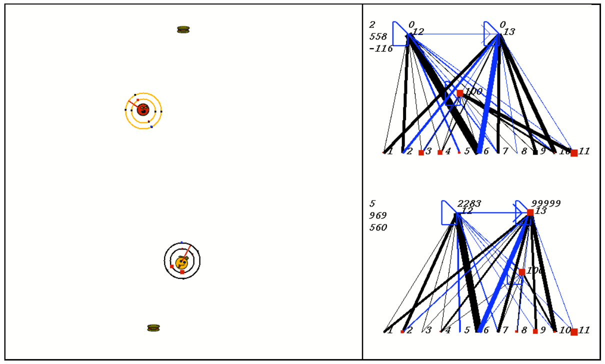
- Two Khepera-like robots forage, pursue, evade[68]
  - Collect food to gain energy
  - Win by crashing to a weaker robot

Early Strategies



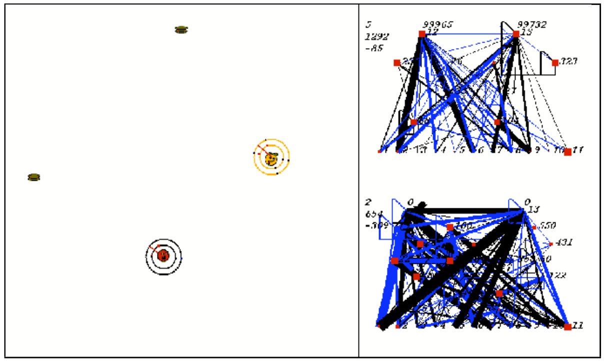
- Crash when higher energy
- Collect food by accident
- DEMO

Mature Strategies



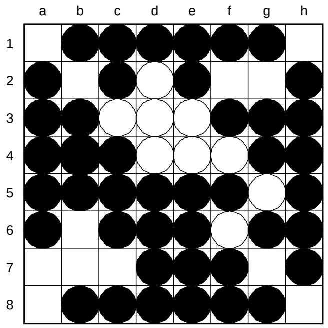
- Collect food to gain energy
- Avoid moving to lose energy
- Standoff: Difficult to predict outcome
- DEMO

A 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

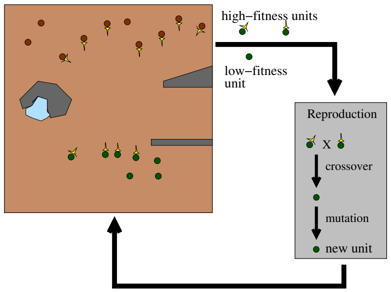


- Good research platform[41]
  - Controlled domains, clear performance, safe
  - Economically important; training games possible
- Board games: beyond limits of search
  - Evaluation functions in checkers, chess[9;18;19]
  - Filtering information in go, othello[45;69]
  - Opponent modeling in poker[37]

Video Games

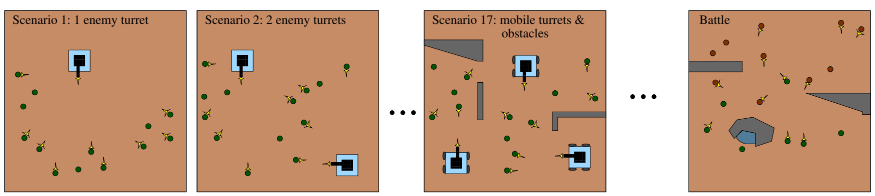
- Economically and socially important
- Adaptation an important future goal
  - More challenging, more fun games
  - Possible to use for training people
- How to make evolution run in real time?

Real-time NEAT



- A parallel, continuous version of NEAT [65]
- Individuals created and replaced every n ticks
- Parents selected probabilistically, weighted by fitness
- Long-term evolution equivalent to generational NEAT

NERO: A Complex Game Platform

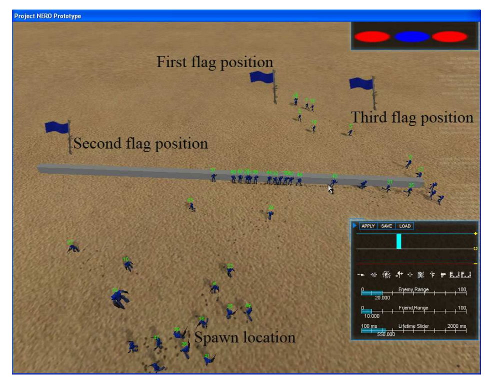


- Teams of agents trained to battle each other
  - Player trains agents through excercises
  - Agents evolve in real time
  - Agents and player collaborate in battle
- New genre: Learning *is* the game
- Challenging platform for reinforcement learning
  - Real time, open ended, requires discovery
- DEMO

Utilizing Human 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 [12;88]
  - By learning from examples [7]

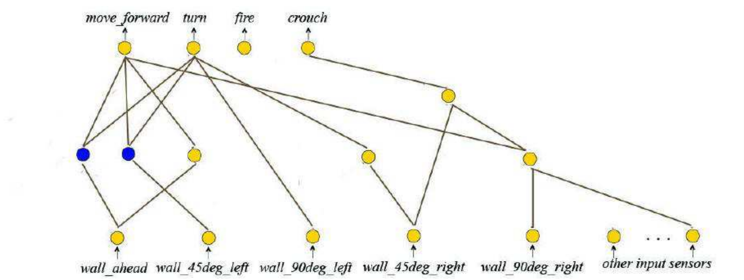
Incorporating Rules into NE



E.g. how to go around a wall in NERO

- Specify as a rule:
  - *wall_ahead: move_forward, turn_right*
  - *wall_45deg_left, move_forward, turn_right_slightly*
- Convert into a network with KBANN [38]

Incorporating Rules into NE (2)



- KBANN network added to NEAT networks
  - Treated as complexification
  - Continues to evolve
  - If advice is useful, it stays
- Initial behaviors, on-line advice
- Injecting human knowledge as rules
- DEMO

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Lessons from NERO

- NEAT is a strong method for real-time adaptation
  - Complex team behaviors can be constructed
  - Novel strategies can be discovered
- Problem solving with human guidance
- NE makes a new genre of games possible!

(NERO details, download: http://nerogame.org:
NERO 2.0 (interactive battle) August 2007;
OpenNERO (research platform) August 2008)

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Numerous Other Applications

- Creating art, music[10;30;60]
- Theorem proving[15]
- Time-series prediction[39]
- Computer system optimization[23]
- Manufacturing optimization[27]
- Process control optimization[75;76]
- Finding the top quark[82]
- Etc.

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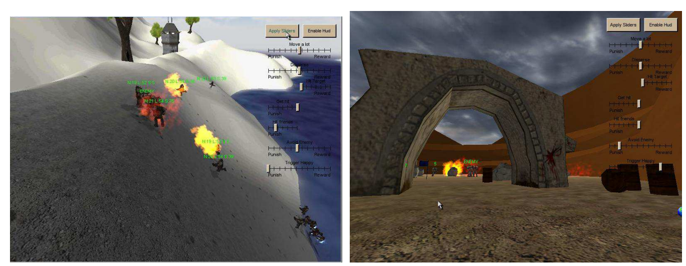
Evaluation of Applications



- Neuroevolution strengths
  - Can work very fast, even in real-time
  - Potential for arms race, discovery
  - Effective in continuous, non-Markov domains
- Requires many evaluations
  - Requires an interactive domain for feedback
  - Best when parallel evaluations possible
  - Works with a simulator & transfer to domain

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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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