Evolving Neural Networks

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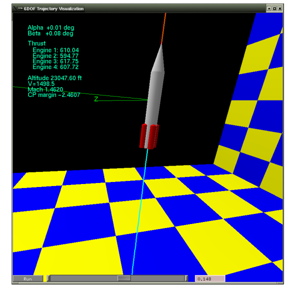
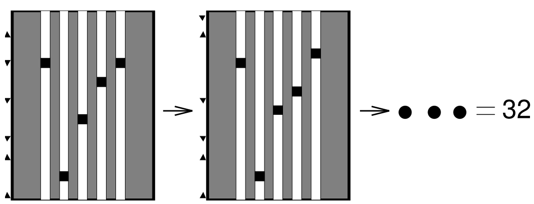
Why Neuroevolution?



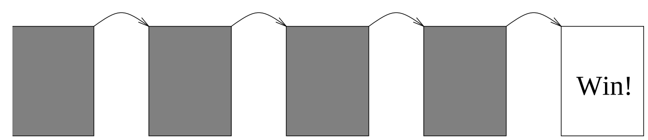
- Neural nets powerful in many statistical domains
  - E.g. control, pattern recognition, prediction, decision making
  - Where no good theory of the domain exists
- Good supervised training algorithms exist
  - Learn a nonlinear function that matches the examples
- What if correct outputs are not known?

Sequential Decision Tasks



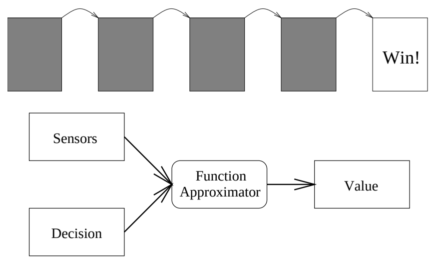
- Sequence of decisions creates a sequence of states
- No targets: Performance evaluated after several decisions
- Many important real-world domains:
  - Robot/vehicle/traffic control
  - Computer/manufacturing/process optimization
  - Game playing

Forming Decision Strategies



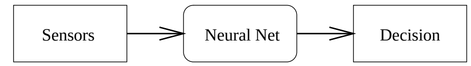
- Traditionally designed by hand
  - Too complex: Hard to anticipate all scenarios
  - Too inflexible: Cannot adapt on-line
- Need to discover through exploration
  - Based on sparse reinforcement
  - Associate actions with outcomes

Standard Reinforcement Learning



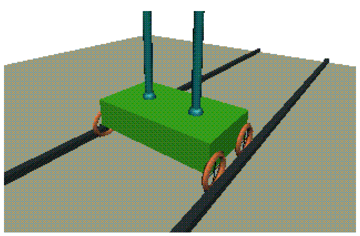
- AHC, Q-learning, Temporal Differences
  - Generate targets through prediction errors
  - Learn when successive predictions differ
- Predictions represented as a value function
  - Values of alternatives at each state
- Difficult with large/continuous state and action spaces
- Difficult with hidden 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[95]
  - Deep Reinforcement Learning[68,77] (Rawal et al. GECCO'16)

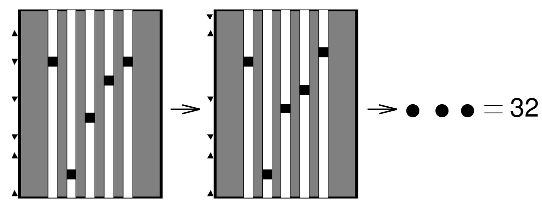
How Well Does It Work?



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 2-3 orders of magnitude faster than standard RL[29]
- NE can solve harder problems

Role of Neuroevolution

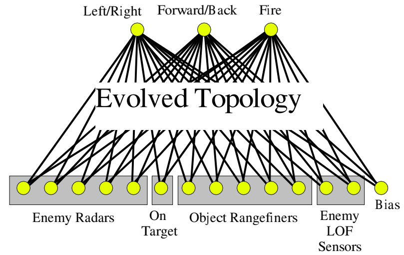


- Powerful method for sequential decision tasks[17,29,59,111]
  - Optimizing existing tasks
  - Discovering novel solutions
  - Making new applications possible
- Also may be useful in supervised tasks[55,66]
  - Especially when network topology important
- A unique model of biological adaptation/development [61,75,106]

Outline

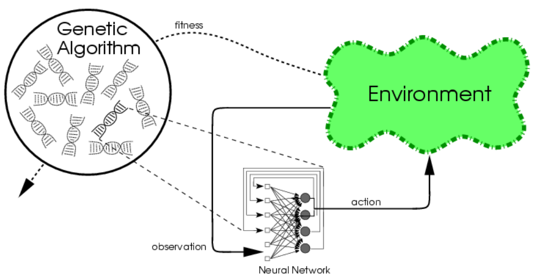
- Basic neuroevolution techniques
- Advanced techniques
  - E.g. combining learning and evolution; novelty search
- Extensions to applications
- Application examples
  - Control, Robotics, Artificial Life, Games

Neuroevolution Decision Strategies



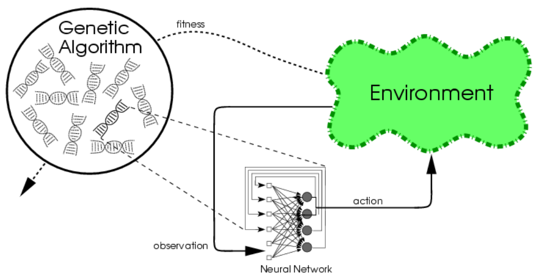
- Input variables describe the state observed through sensors
- Output variables describe actions
- Network between input and output:
  - Nonlinear hidden nodes
  - Weighted connections
- Execution:
  - Numerical activation of input
  - Performs a nonlinear mapping
  - Memory in recurrent connections (POMDP!)

Conventional Neuroevolution (CNE) I



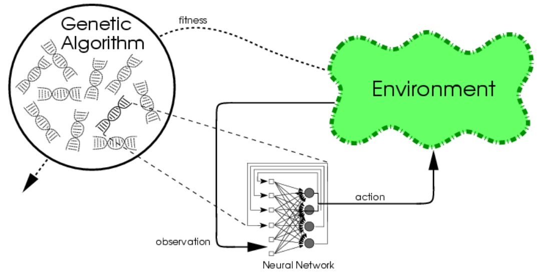
- Evolving connection weights in a population of networks [55,76,111,112]
- Chromosomes are strings of connection weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

Conventional Neuroevolution II



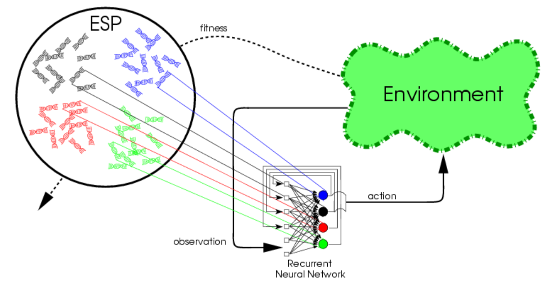
- Parallel search for a solution network
  - Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away
- Natural mapping between genotype and phenotype
  - GA and NN are a good match!

Problems with CNE



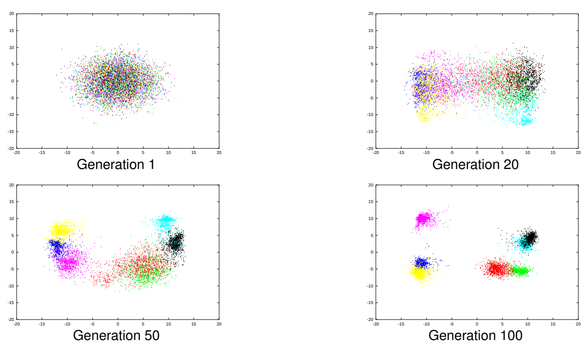
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values at once

Advanced NE 1: Evolving Partial Networks I



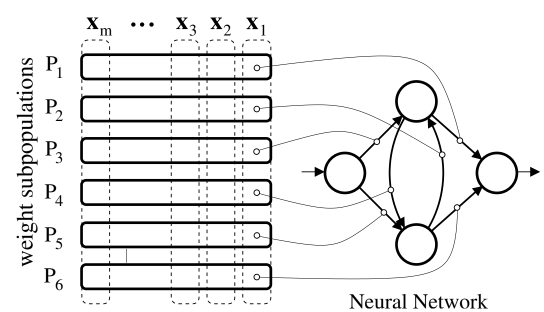
- Evolving individual neurons to cooperate in networks [1,58,66]
- E.g. Enforced Sub-Populations (ESP [24])
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

Evolving Neurons with ESP



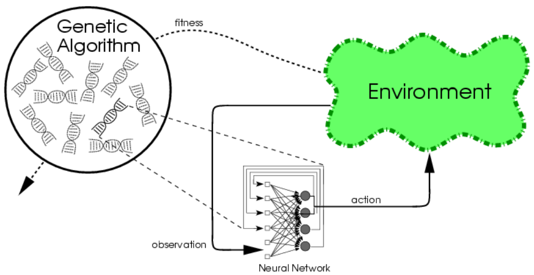
- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

Evolving Partial Networks II



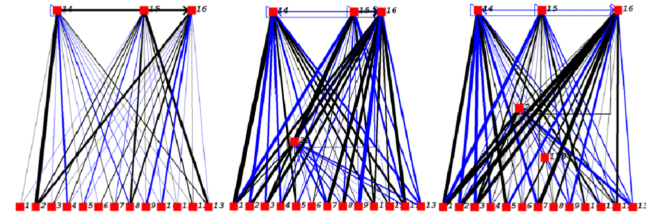
- Extend the idea to evolving connection weights
- E.g. Cooperative Synapse NeuroEvolution (CoSyNE [29])
  - Connection weights in separate subpopulations
  - Networks formed by combining neurons with the same index
  - Networks mutated and recombined; indices permutated
- Sustains diversity, results in efficient search

Advanced NE 2: Evolutionary Strategies



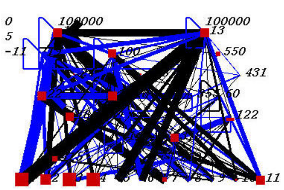
- Evolving complete networks with ES (CMA-ES[36])
- Small populations, no crossover
- Instead, intelligent mutations
  - Adapt covariance matrix of mutation distribution
  - Take into account correlations between weights
- Smaller space, less convergence, fewer conventions

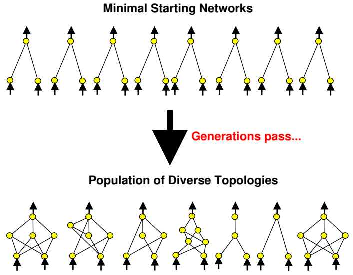
Advanced NE 3: Evolving Network Structure



- Optimizing connection weights and network topology[3,17,22,113]
- E.g. Neuroevolution of Augmenting Topologies (NEAT[86,89])
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

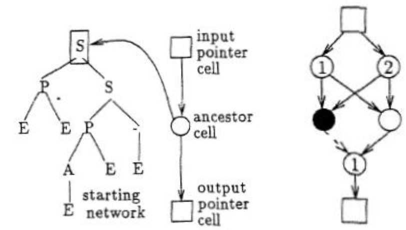
Why Complexification?





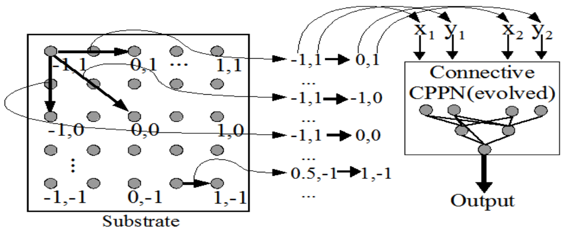
- Challenge with NE: Search space is very large
- Complexification keeps the search tractable
  - Start simple, add more sophistication
- Incremental construction of intelligent agents

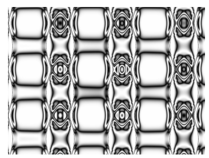
Advanced NE 4: Indirect Encodings I



- Instructions for constructing the network evolved
  - Instead of specifying each unit and connection[3,17,54,83,113]
- E.g. Cellular Encoding (CE[31])
- Grammar tree describes construction
  - Sequential and parallel cell division
  - Changing thresholds, weights
  - A “developmental” process that results in a network

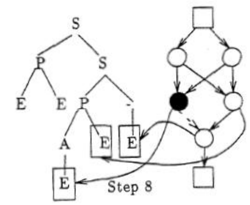
Indirect Encodings II

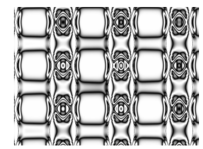




- Encode the networks as spatial patterns
- E.g. Hypercube-based NEAT (HyperNEAT[13])
- Evolve a neural network (CPPN) to generate spatial patterns
  - 2D CPPN: (x, y) input → grayscale output
  - 4D CPPN: (x_1, y_1, x_2, y_2) input → w output
  - Connectivity and weights can be evolved indirectly
  - Works with very large networks (millions of connections)

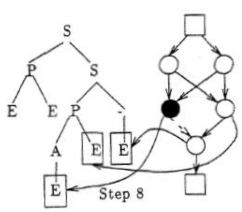
Properties of Indirect Encodings I

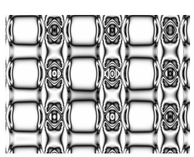




- Smaller search space
- Avoids competing conventions
- Describes classes of networks efficiently
- Modularity, reuse of structures
  - Recurrency symbol in CE: XOR → parity
  - Repetition with variation in CPPNs
  - Useful for evolving morphology

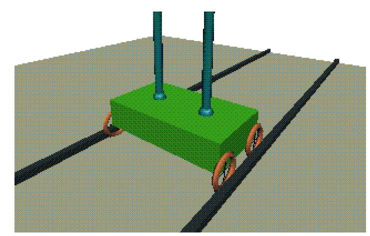
Properties of Indirect Encodings II





- Not fully explored (yet)
  - See e.g. CS track at GECCO
- Promising current work
  - More general L-systems; developmental codings; embryogeny[90]
  - Scaling up spatial coding[14,23]
  - Genetic Regulatory Networks[71]
  - Evolution of symmetries[103]

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[29]

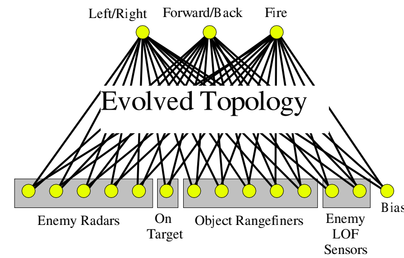
- Advanced methods better than CNE
- Advanced methods still under development
- Indirect encodings future work

Further NE Techniques

- Incremental and multiobjective evolution[26,79,98,112]
- Utilizing population culture[6,51,94]
- Utilizing evaluation history[48]
- Evolving NN ensembles and modules[37,47,65,72,108]
- Evolving transfer functions and learning rules[9,74,93]
- Bilevel optimization of NE[46]

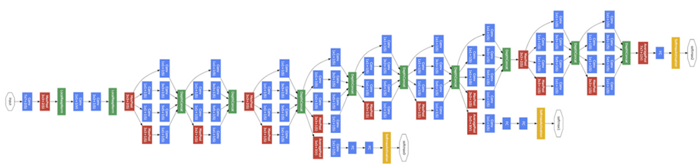
- Combining learning and evolution
- Evolving for novelty

Combining Learning and Evolution



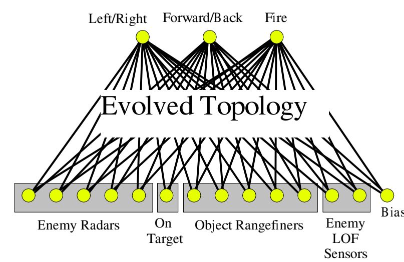
- Good learning algorithms exist for NN
  - Why not use them as well?
- Evolution provides structure and initial weights
- Fine tune the weights by learning

Evolving Deep Learning Architectures



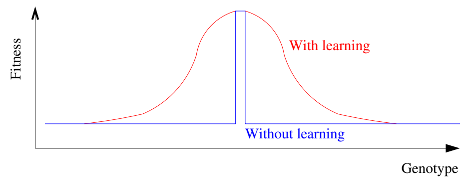
- Different (complex) architectures for different tasks
  - Topology, hyperparameters seem to matter
- Can optimize through evolution
- Exceeds available computation
  - Each DL network trains for 2 days on a GPU
- LSTM architectures more feasible?

Lamarckian Evolution



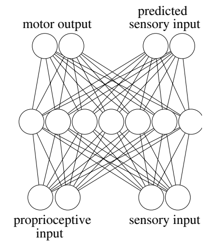
- Lamarckian evolution is possible[8,31]
  - Coding weight changes back to chromosome
- Difficult to make it work
  - Diversity reduced; progress stagnates

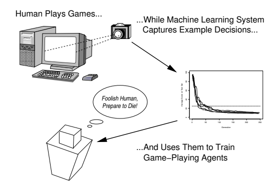
Baldwin Effect



- Learning can guide Darwinian evolution as well[5,31,33]
  - 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

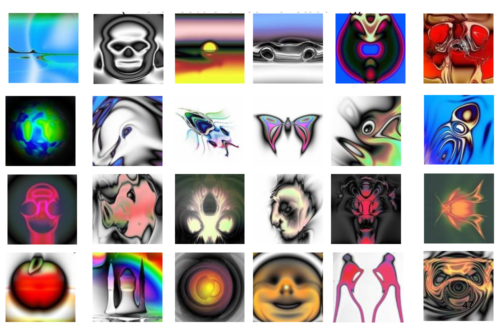
Where to Get Learning Targets?





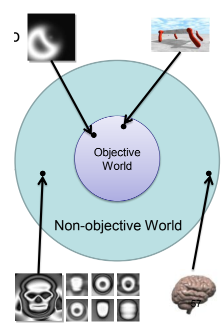
- From a related task[61]
  - Useful internal representations
- Evolve the targets[64]
  - Useful training situations
- From Q-learning equations[109]
  - When evolving a value function
- Utilize Hebbian learning[19,87,101]
  - Correlations of activity
- From the population[51,94]
  - Social learning
- From humans[8]
  - E.g. expert players, drivers

Evolving Novelty



- Motivated by humans as fitness functions
- E.g. picbreeder.com, endlessforms.com[80]
  - CPPNs evolved; Human users select parents
- No specific goal
  - Interesting solutions preferred
  - Similar to biological evolution?

Novelty Search



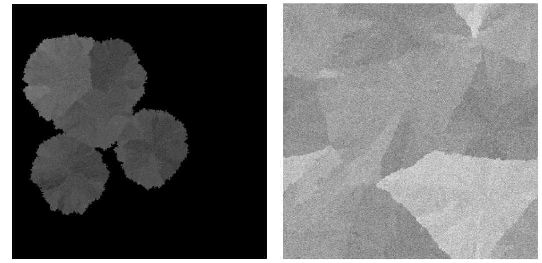
- Reward maximally different solutions
  - Can be a secondary, diversity objective[60]
  - Or, even as the only objective[40,43]
- To be different, need to capture structure
  - Problem solving as a side effect
- Potential for innovation
- Model of biological evolution, niching[42]
- Needs to be understood better

Novelty S. Mechanisms: Deception

gen 12 gen 20 gen 36 gen 49 gen 74

- Deception is not a problem
  - Stepping stones survive if they are novel
- Important e.g. in evolution of cognitive behavior
  - Memory, learning, communication are deceptive[41]
- Difficult to discover with objective-based search

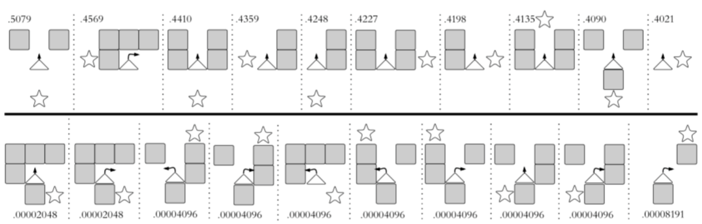
Novelty S. Mechanisms: Evolvability



(c) Extinction Random - 2,000 Gens. (d) Extinction Random - 15,000 Gens.

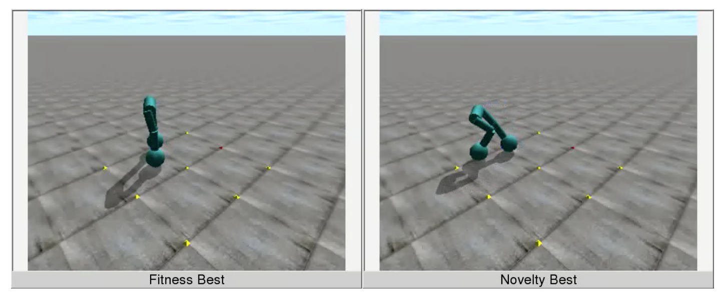
- Extinction events helpful[42]
  - E.g. 90% of population decimated occasionally
  - Remaining lineages radiate through niches
- They select for more evolvable lineages
  - Discover better solutions faster
- Harmful in objective-based search!

Novelty S. Mechanisms: Behavior Characterization



- Novelty of behavior needs to be measured
  - Requires a way to characterize behavior
  - Generic, hand-coded, or...adaptive?
- Collect generic data in one maze: <Behavior,Fitness>
  - Which features predict success/failure best?
  - Use to characterize behavior in other mazes
- Behavior characterizations that matter[52] (Meyerson et al. GECCO'16)

Novelty Search Demo



- Fitness-based evolution is rigid
  - Requires gradual progress
- Novelty-based evolution is more innovative, natural
  - Allows building on deceptive solutions
- DEMO

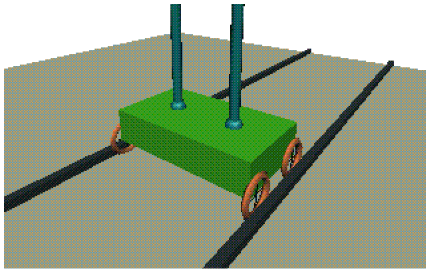
Extending NE to Applications

- Control
- Robotics
- Artificial life
- Gaming

Issues:

- Facilitating robust transfer from simulation[28,99]
- Utilizing problem symmetry and hierarchy[39,102,103]
- Utilizing coevolution[73,91]
- Evolving multimodal behavior[78,79,108]
- Evolving teams of agents[7,88,114]
- Making evolution run in real-time[88]

Applications to Control



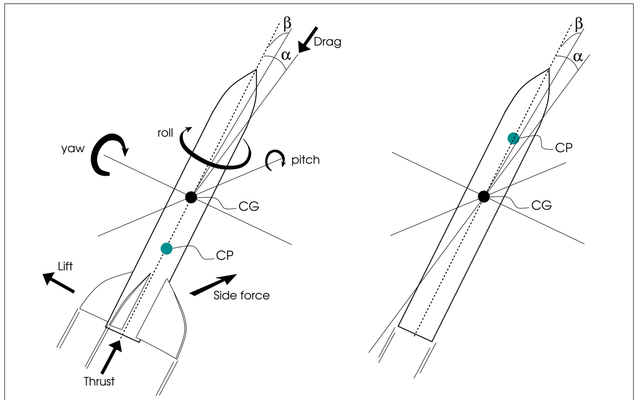
- Pole-balancing benchmark
  - Originates from the 1960s
  - Original 1-pole version too easy
  - Several extensions: acrobat, jointed, 2-pole, particle chasing[65]
  - DEMO
- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control[104]

Controlling a Finless Rocket

Task: Stabilize a finless version of the Interorbital Systems RSX-2 sounding rocket[27]

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

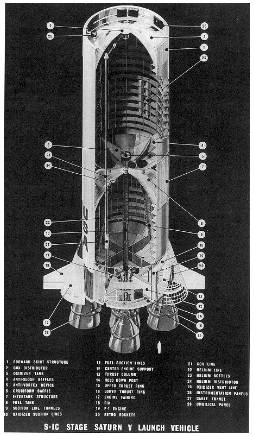
Rocket Stability



(a) Fins: stable

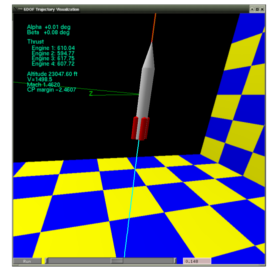
(b) Finless: unstable

Active Rocket Guidance



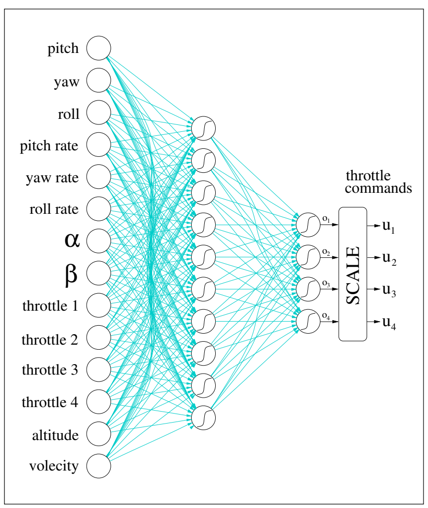
- Used on large scale launch vehicles (Saturn, Titan)
- Typically based on classical linear feedback control
- High level of domain knowledge required
- Expensive, heavy

Simulation Environment: JSBSim

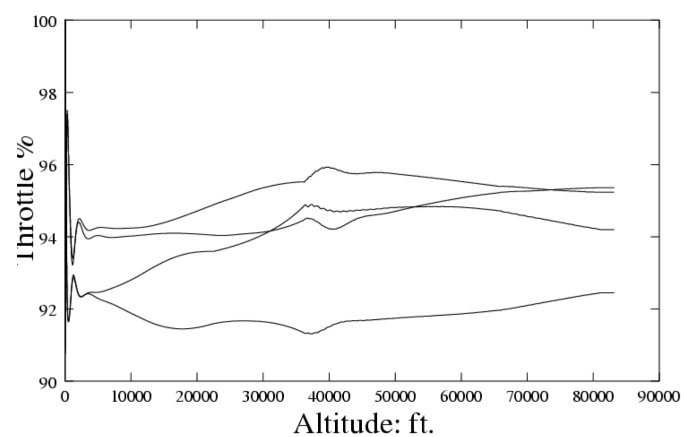


- General rocket simulator
- Models complex interaction between airframe, propulsion, aerodynamics, and atmosphere
- Used by IOS in testing their rocket designs
- Accurate geometric model of the RSX-2

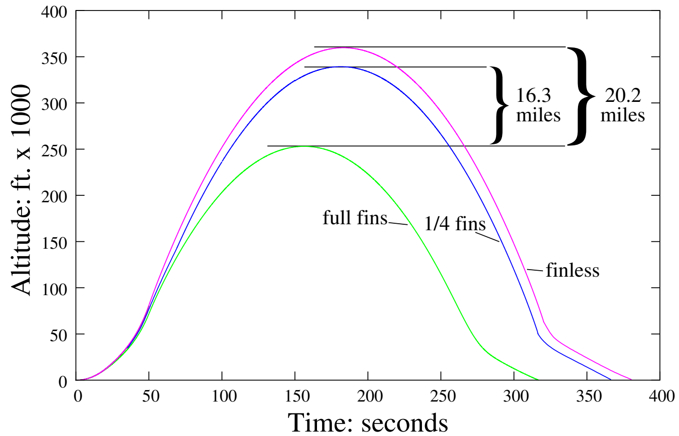
Rocket Guidance Network



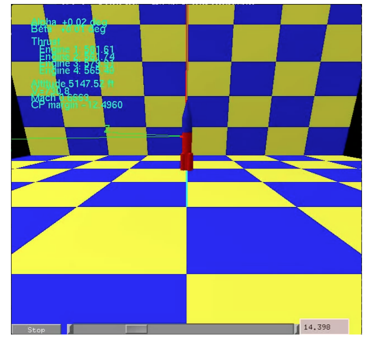
Results: Control Policy

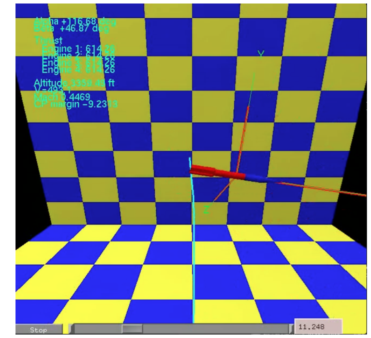


Results: Apogee

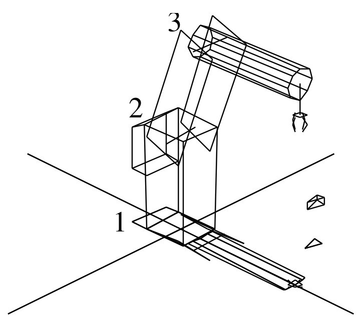


Finless Rocket Control Demo


Evolved active stabilization

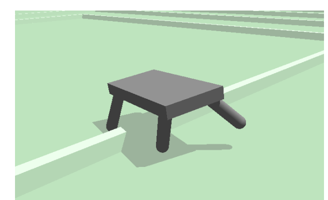

No active stabilization

Applications to Robotics



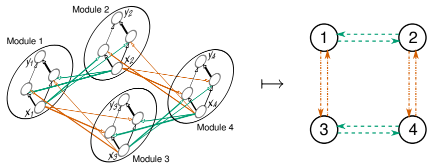
- Controlling a robot arm[57]
  - Compensates for an inop motor
- Robot walking[35,82,102]
  - Various physical platforms
- Mobile robots[12,18,62,85]
  - Transfers from simulation to physical robots
  - Evolution possible on physical robots

Multilegged Walking



- Navigate rugged terrain better than wheeled robots
- Controller design is more challenging
  - Leg coordination, robustness, stability, fault-tolerance, ...
- Hand-design is generally difficult and brittle
- Large design space often makes evolution ineffective

ENSO: Symmetry Evolution Approach



- Symmetry evolution approach[100,102,103]
  - A neural network controls each leg
  - Connections between controllers evolved through symmetry breaking
  - Connections within individual controllers evolved through neuroevolution

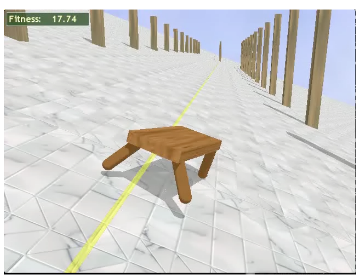
Versatile, Robust Gaits


Different gaits


Obstacle field

- Different gaits on flat ground
  - Pronk, pace, bound, trot
  - Changes gait to get over obstacles
- DEMO

Innovative, Effective Solutions

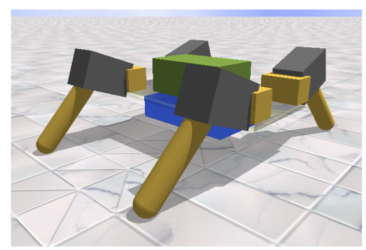


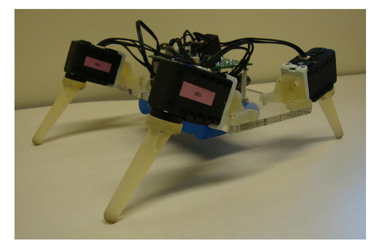
Evolved

Handcoded

- Asymmetric gait on inclines
  - One leg pushes up, others forward
  - Hard to design by hand
- DEMO

Transfer to a Physical Robot I

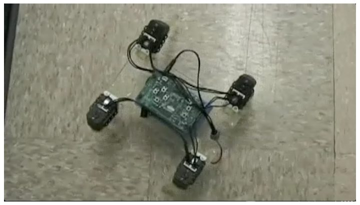

Simulated


Real

- Built at Hod Lipson's lab (Cornell U.)
  - Standard motors, battery, controller board
  - Custom 3D-printed legs, attachments
  - Simulation modified to match
- General, robust transfer[99]
  - Noise to actuators during simulation
  - Generalizes to different surfaces, motor speeds
- DEMO

Transfer to a Physical Robot II


Evolved

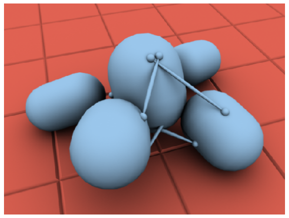

Handcoded

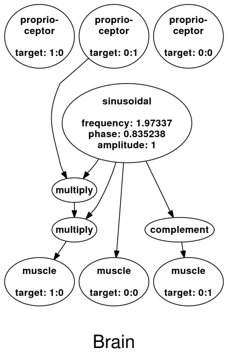
- Evolved a solution for three-legged walking!
- DEMO

Applications to Artificial Life

- Gaining insight into neural structure
  - E.g. evolving a command neuron[2,38,75]
- Understanding animal behaviors
  - Signaling, herding, hunting...[63,67,69,70,97,106,107,114]

Body-Brain Coevolution

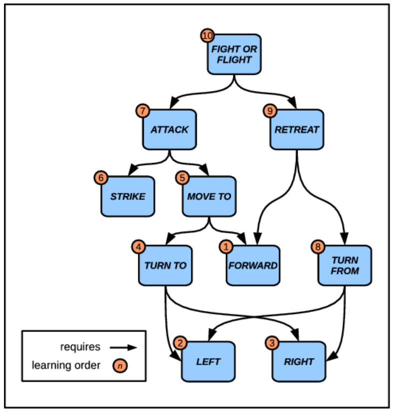

Body



Brain

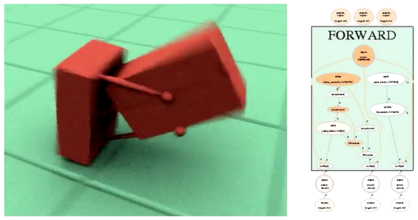
- Evolved Virtual Creatures[44,45,84]
  - Body: Blocks, muscles, joints, sensors
  - Brain: A neural network (with general nodes)
  - Evolved together in a physical simulation
- Syllabus, Encapsulation, Pandemodium

Syllabus



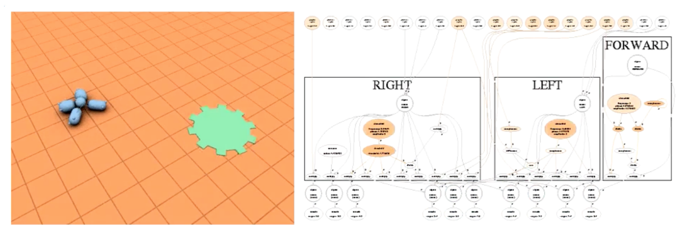
- Constructed by hand; body and brain evolved together

Encapsulation



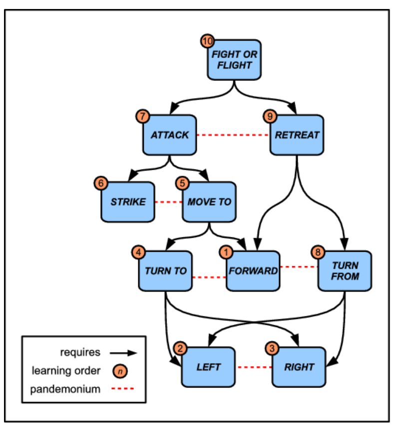
- Once evolved, a trigger node is added
- DEMO

Pandemonium



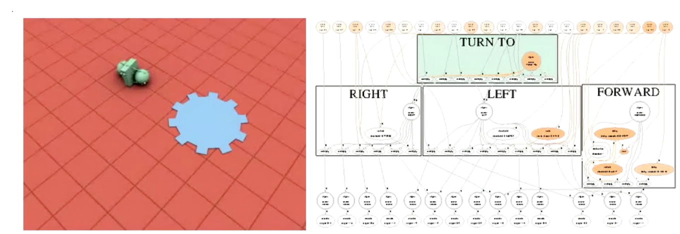
- Conflicting behaviors: Highest trigger wins
- DEMO

Evolving Fight-or-Flight Behavior



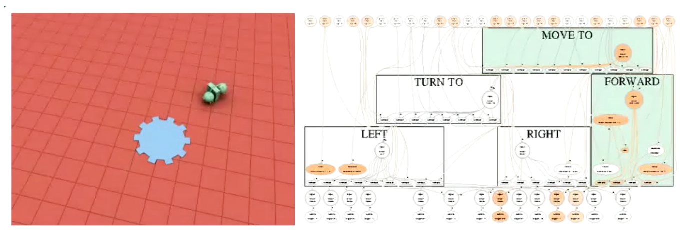
- Step-by-step construction of complex behavior
- Primitives and three levels of complexity
- DEMOS

Turn to Light



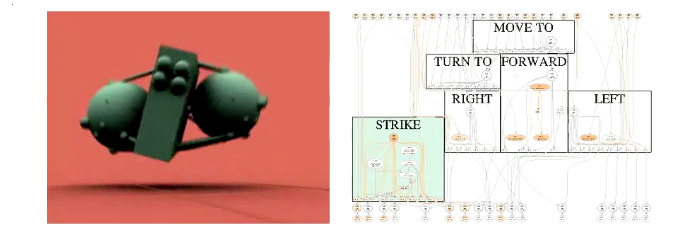
- First level of complexity
- Selecting between alternative primitives

Move to light



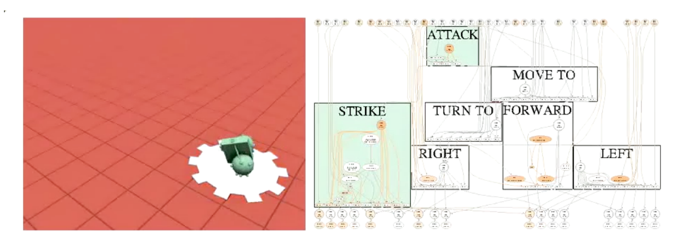
- First level of complexity (Sims 1994)
- Selecting between alternative primitives

Strike



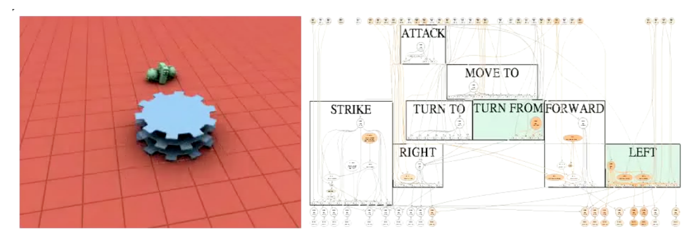
- Alternative behavior primitive

Attack



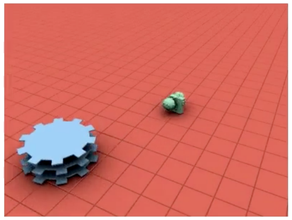
- Second level of complexity (beyond Sims and others)

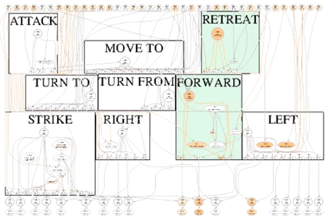
Turn from Light



- Alternative first-level behavior

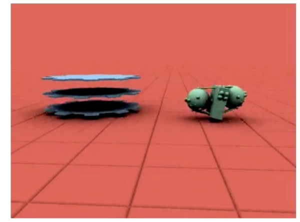
Retreat

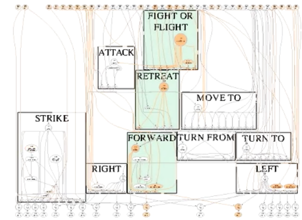




- Alternative second-level behavior

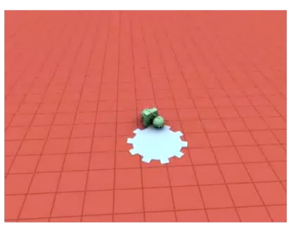
Fight or Flight

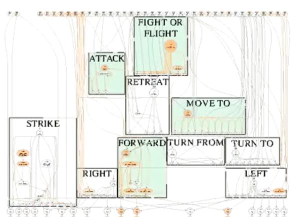




- Third level of complexity

Insight: Body/Brain Coevolution

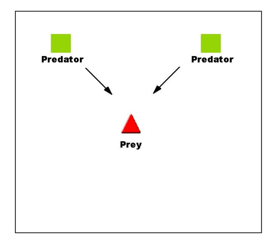




- Evolving body and brain together poses strong constraints
  - Behavior appears believable
  - Worked well also in BotPrize (Turing test for game bots)
- What about constraints from the environment?

Coevolution of Behavior

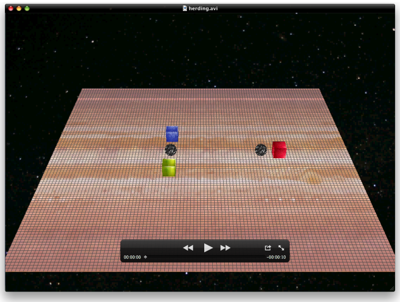
Natural predators and prey



Formalization of behavior

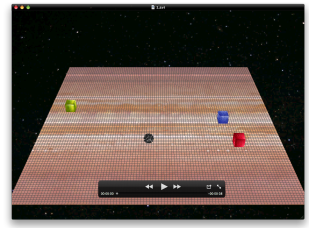
- Complex cooperation observed in pursuit and evasion
  - Motivated by biology, esp. hyenas vs. zebras (Kay Holekamp, MSU)
  - Largely innate, possible to see behaviors and their evolution
- Such behaviors evolve together, in coevolutionary environment
  - Simultaneous competitive and cooperative coevolution[67,70]

Experimental Setup

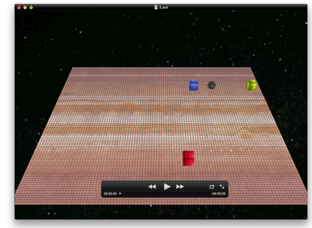


- Toroidal grid world
- Predators, prey move with same speed in 4 directions
- No direct communication between team members
  - Communication still possible through stigmergy
- Does a coevolutionary arms race result?

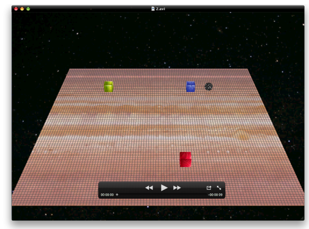
Predator-Prey Arms Race Demo I



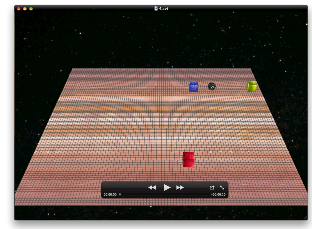
50-75: Single predator catches prey



75-100: Prey evades by circling

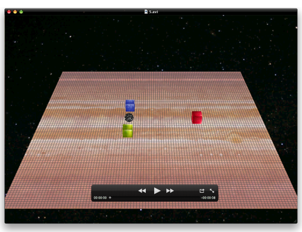


100-150: Two predators cooperate

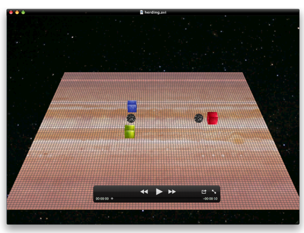


150-180: Prey baits and escapes

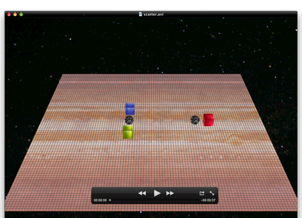
Predator-Prey Arms Race Demo II



180-200: All predators cooperate



200-250: Predators herd two prey

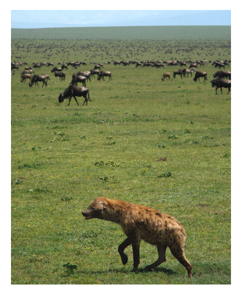


250-300: Prey evade by scattering

Complex behaviors don't evolve in a vacuum

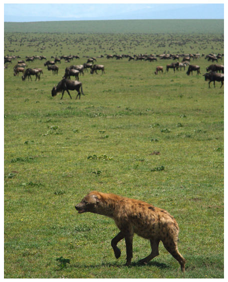
- Result from coevolutionary arms race
- Embedded in a changing environment

Open Questions



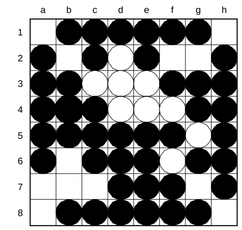
- Role of communication
  - Stigmergy vs. direct communication in hunting[114]
  - Quorum sensing in e.g. confronting lions
- Role of rankings
  - Efficient selection when evaluation is costly?
- Role of individual vs. team rewards
- Can lead to general computational insights

Bigger Questions



- Gaining insight into cognitive architectures
  - Executive, perception, emotion, memory
- Emergence of language, learning, social structures
- May require overcoming deception
  - Through speciation, niching in nature[42]
  - Through novelty search in computation?[41]

Applications to Games



- Good research platform[53]
  - Controlled domains, clear performance, safe
  - Economically important; training games possible
- Board games: beyond limits of search
  - Evaluation functions in checkers, chess[10,20,21]
  - Filtering information in go, othello[56,92]
  - Opponent modeling in poker[49]

Video Games

- Economically and socially important
- GOFAI does not work well
  - Embedded, real-time, noisy, multiagent, changing
  - Adaptation a major component
- Possibly research catalyst for CI
  - Like board games were for GOFAI in the 1980s

Video Games II

- Can be used to build “mods” to existing games
  - Adapting characters, assistants, tools
- Can also be used to build new games
  - New genre: Machine Learning game

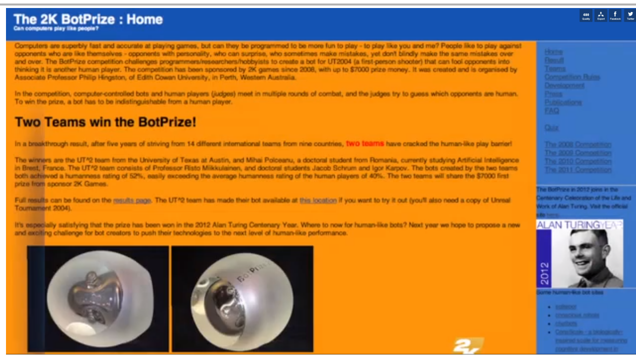
Evolving Humanlike Behavior

- Botprize competition, 2007-2012
  - Turing Test for game bots ($10,000 prize)
- Three players in Unreal Tournament 2004:
  - Human confederate: tries to win
  - Software bot: pretends to be human
  - Human judge: tries to tell them apart!

Evolving an Unreal Bot

- Evolve effective fighting behavior
  - Human-like with resource limitations (speed, accuracy...)
- Also scripts & learning from humans (unstuck, wandering...)
- 2007-2011: bots 25-30% vs. humans 35-80% human
- 6/2012 best bot better than 50% of the humans
- 9/2012...?

Success!!!



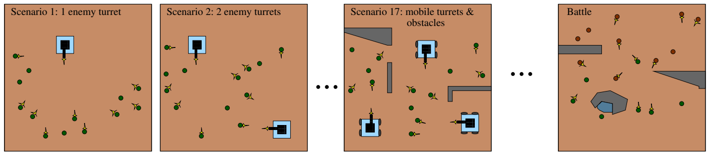
- In 2012, two teams reach the 50% mark!
- Fascinating challenges remain:
  - Judges can still differentiate in seconds
  - Judges lay cognitive, high-level traps
  - Team competition: collaboration as well
- DEMO

A New Genre: Machine Learning Games

NERO
NEURO EVOLVING ROBOTIC OPERATIVES

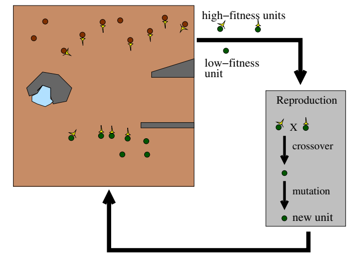
- E.g. NERO
  - Goal: to show that machine learning games are viable
  - Professionally produced by *Digital Media Collaboratory*, UTAustin
  - Developed mostly by volunteer undergraduates

NERO Gameplay



- 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[32,88]
  - Challenging platform for reinforcement learning
  - Real time, open ended, requires discovery
- Try it out:
  - Available for download at `http://nerogame.org`
  - Open source research platform version at `opennero.github.io`

Real-time NEAT



- A parallel, continuous version of NEAT[88]
- Individuals created and replaced every n ticks
- Parents selected probabilistically, weighted by fitness
- Long-term evolution equivalent to generational NEAT

NERO Player Actions

- Player can place items on the field
  e.g. static enemies, turrets, walls, rovers, flags
- Sliders specify relative importance of goals
  e.g. approach/avoid enemy, cluster/disperse, hit target, avoid fire...
- Networks evolved to control the agents

NERO Training Demos

Approach Enemy

Switch to Avoid

Avoid, first-person

Maze Running

NERO Battle Demo

Aggressive vs. Avoidant

Teams of three

Numerous Other Applications

- Creating art, music, dance...[11,16,34,81]
- Theorem proving[15]
- Time-series prediction[50]
- Computer system optimization[25]
- Manufacturing optimization[30]
- Process control optimization[104,105]
- Game strategy optimization[4]
- Measuring top quark mass[110]
- Etc.

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

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 needs to be developed
  - Indirect encodings
  - Learning and evolution
  - Knowledge, interaction, novelty

Further Material

- Slides (including the bibliography) available at www.cs.utexas.edu/users/risto/talks/ne-tutorial
- Demos are at www.cs.utexas.edu/users/risto/talks/ne-tutorial and many more at nn.cs.utexas.edu
- A Scholarpedia article on Neuroevolution is at www.scholarpedia.org/article/Neuroevolution
- A step-by-step neuroevolution exercise (evolving behavior in the NERO game) is at www.cs.utexas.edu/users/risto/talks/ne-tutorial

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