Evolving Neural Networks

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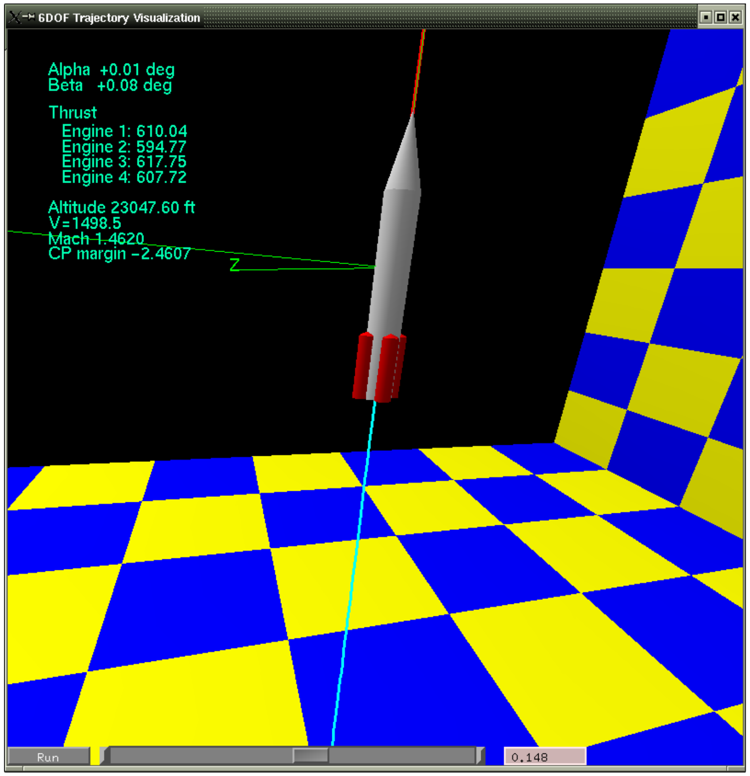
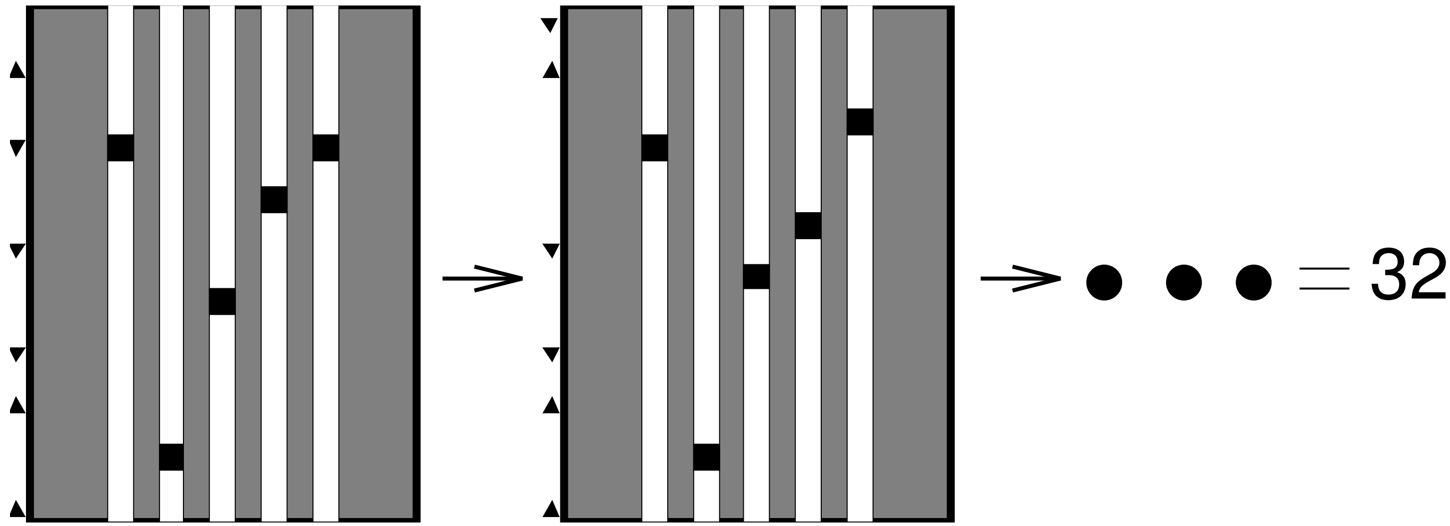
Why Neuroevolution?



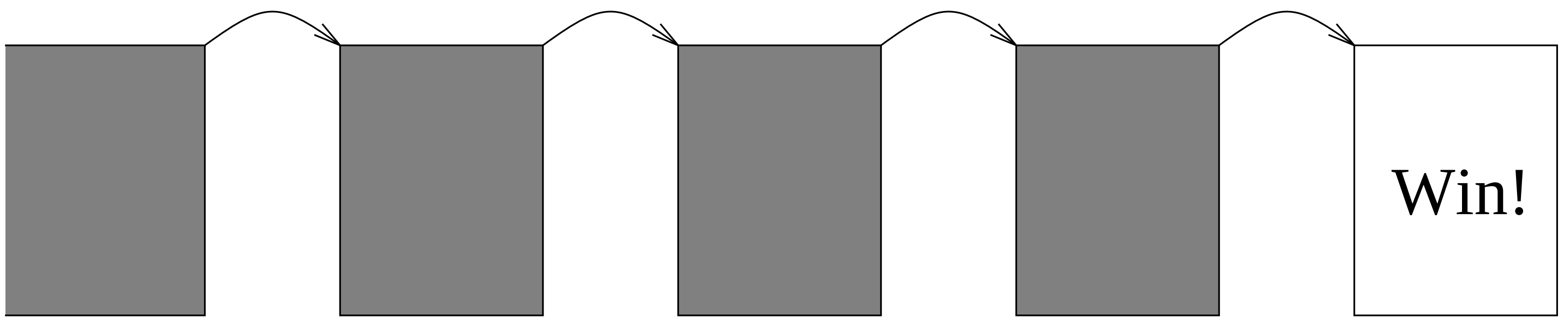
- Neural nets powerful in many statistical domains
  - E.g. control, pattern recognition, prediction, decision making
  - Where no good theory of the domain exists
- Good supervised training algorithms exist
  - Learn a nonlinear function that matches the examples
- What if correct outputs are not known?

Sequential Decision Tasks



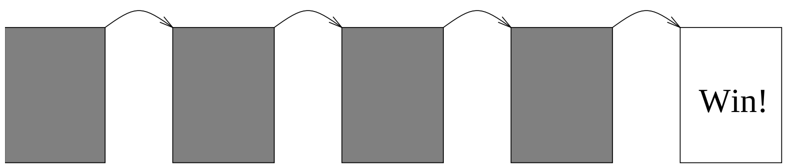
- POMDP: Sequence of decisions creates a sequence of states
- No targets: Performance evaluated after several decisions
- Many important real-world domains:
  - Robot/vehicle/traffic control
  - Computer/manufacturing/process optimization
  - Game playing

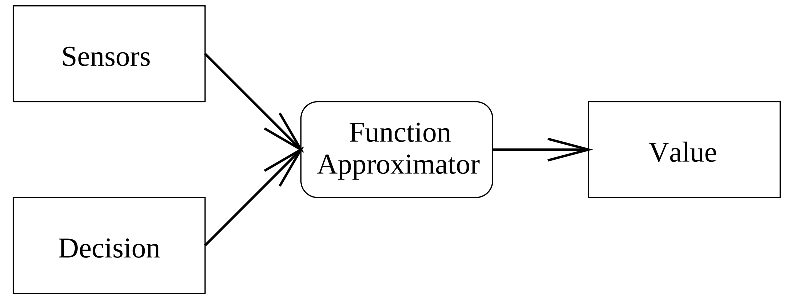
Forming Decision Strategies



- 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

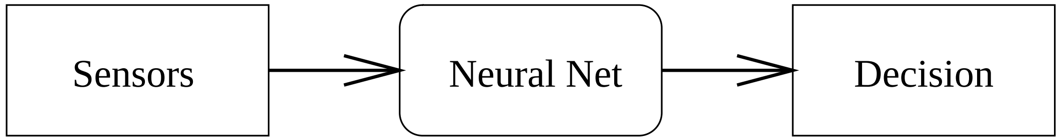
Standard Reinforcement Learning





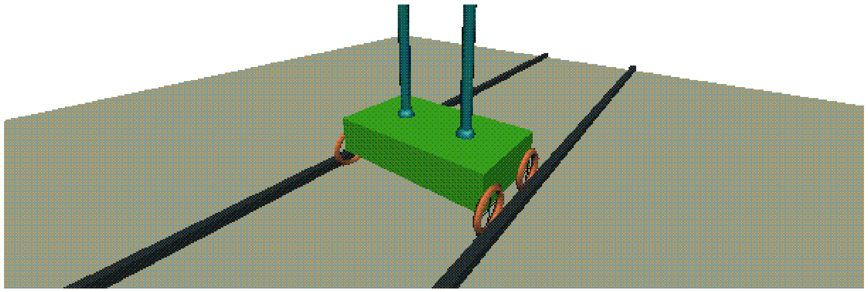
- AHC, Q-learning, Temporal Differences
  - Generate targets through prediction errors
  - Learn when successive predictions differ
- Predictions represented as a value function
  - Values of alternatives at each state
- Difficult with large/continuous state and action spaces
- Difficult with hidden 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[88]

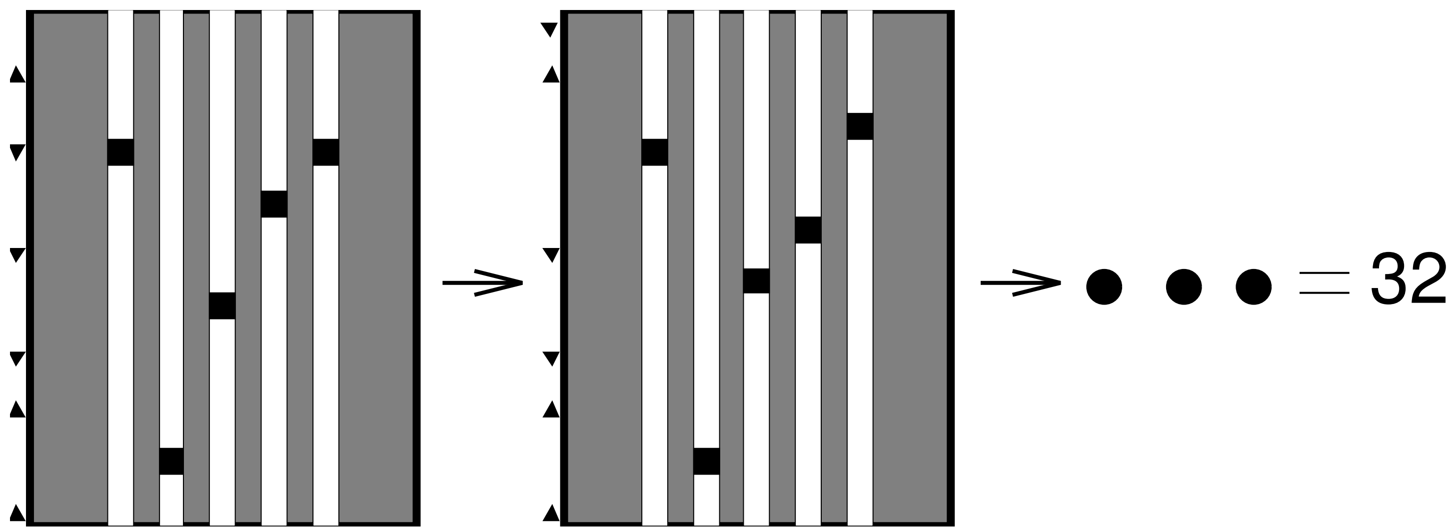
How well does it work?



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[28]
- NE can solve harder problems

Role of Neuroevolution



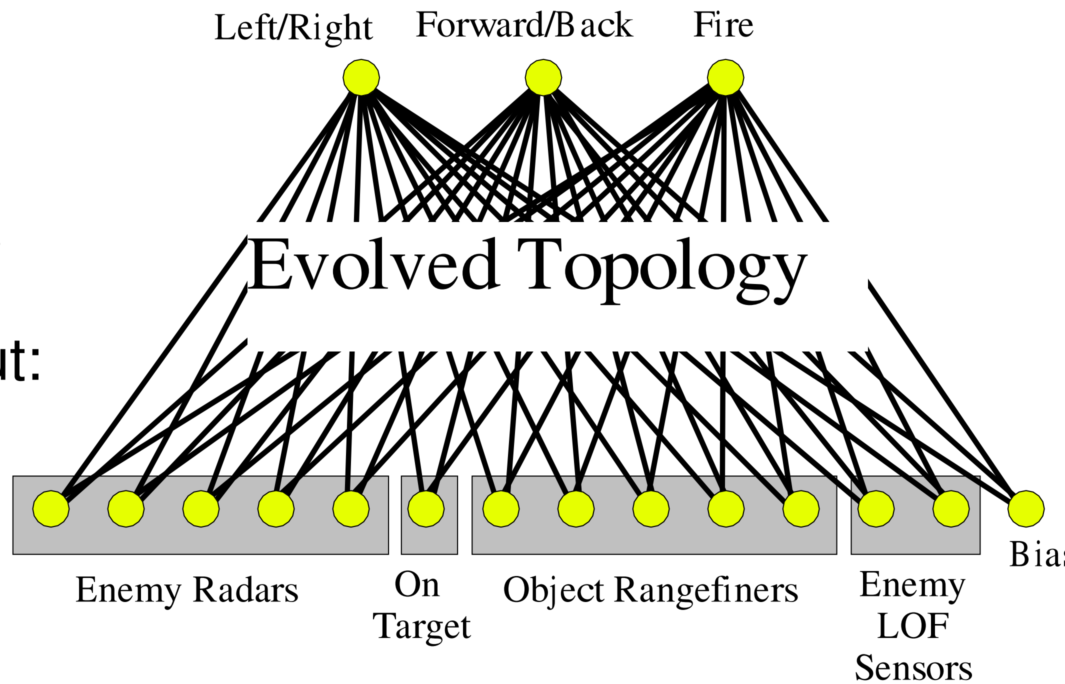
- Powerful method for sequential decision tasks[16;28;54;104]
  - Optimizing existing tasks
  - Discovering novel solutions
  - Making new applications possible
- Also may be useful in supervised tasks[50;61]
  - Especially when network topology important
- A unique model of biological adaptation/development[56;69;99]

Outline

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

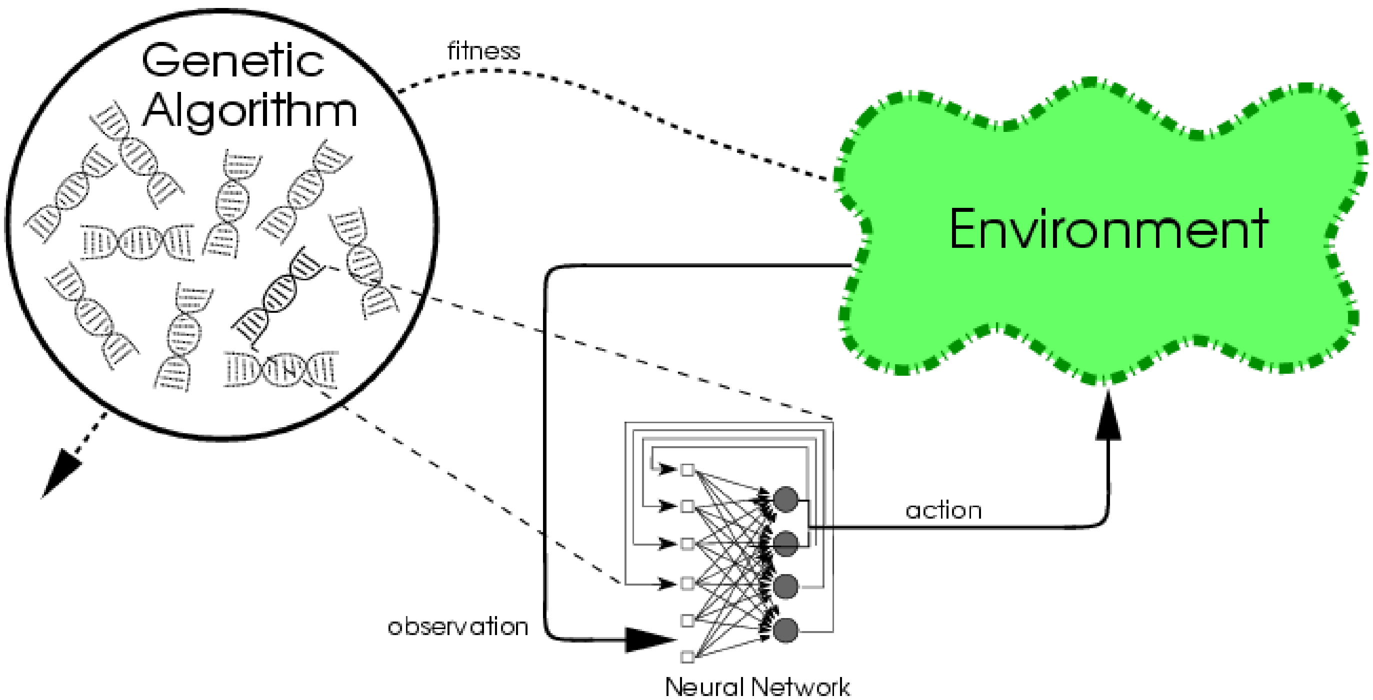
Neuroevolution Decision Strategies

- Input variables describe the state
- Output variables describe actions
- Network between input and output:
  - Nonlinear hidden nodes
  - Weighted connections



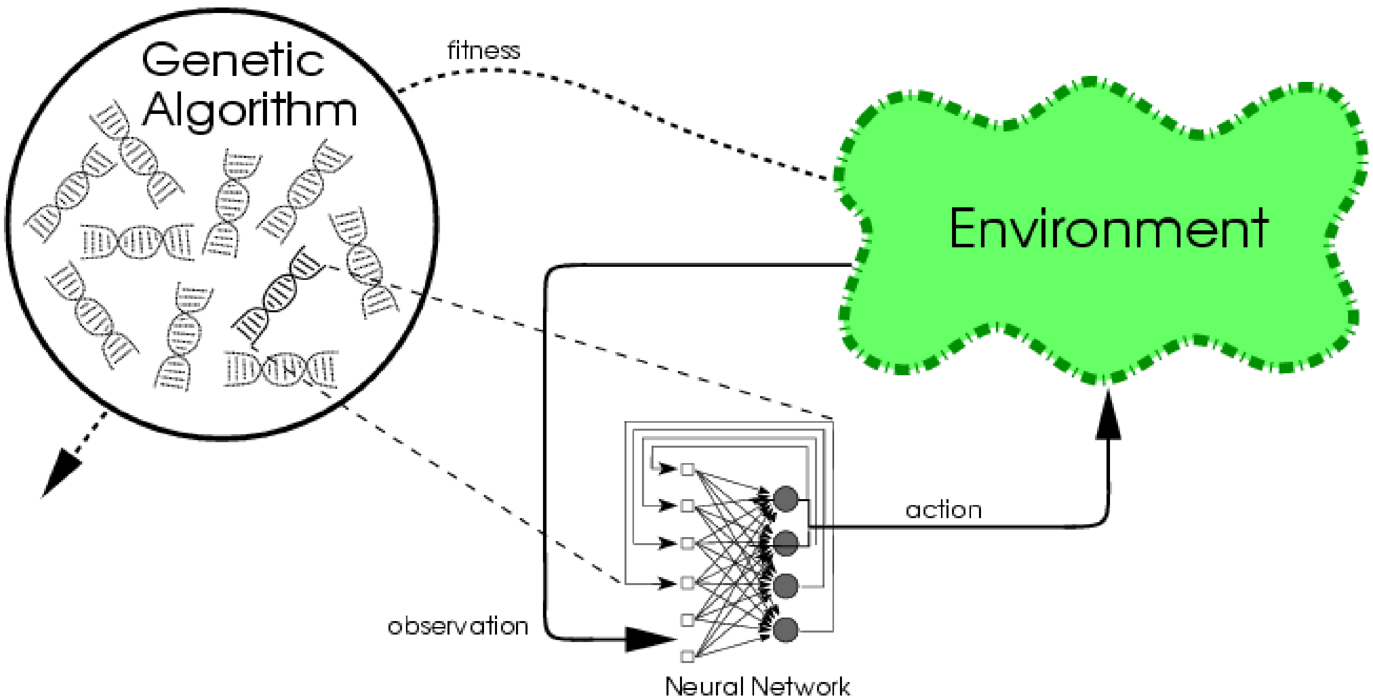
- Execution:
  - Numerical activation of input
  - Performs a nonlinear mapping
  - Memory in recurrent connections

Conventional Neuroevolution (CNE)



- Evolving connection weights in a population of networks [50;70;104;105]
- Chromosomes are strings of connection weights (bits or real)
  - E.g. 10010110101100101111001
  - Usually fully connected, fixed topology
  - Initially random

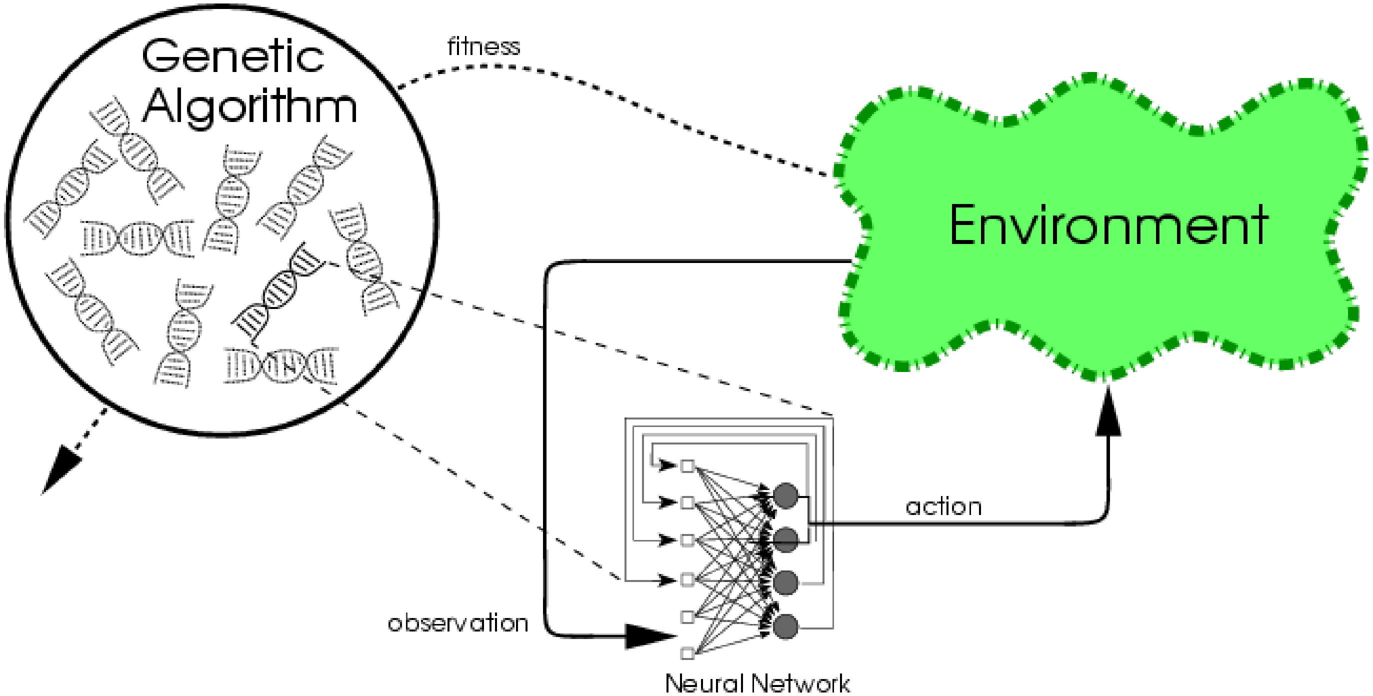
Conventional Neuroevolution (2)



- Parallel search for a solution network
  - Each NN evaluated in the task
  - Good NN reproduce through crossover, mutation
  - Bad thrown away

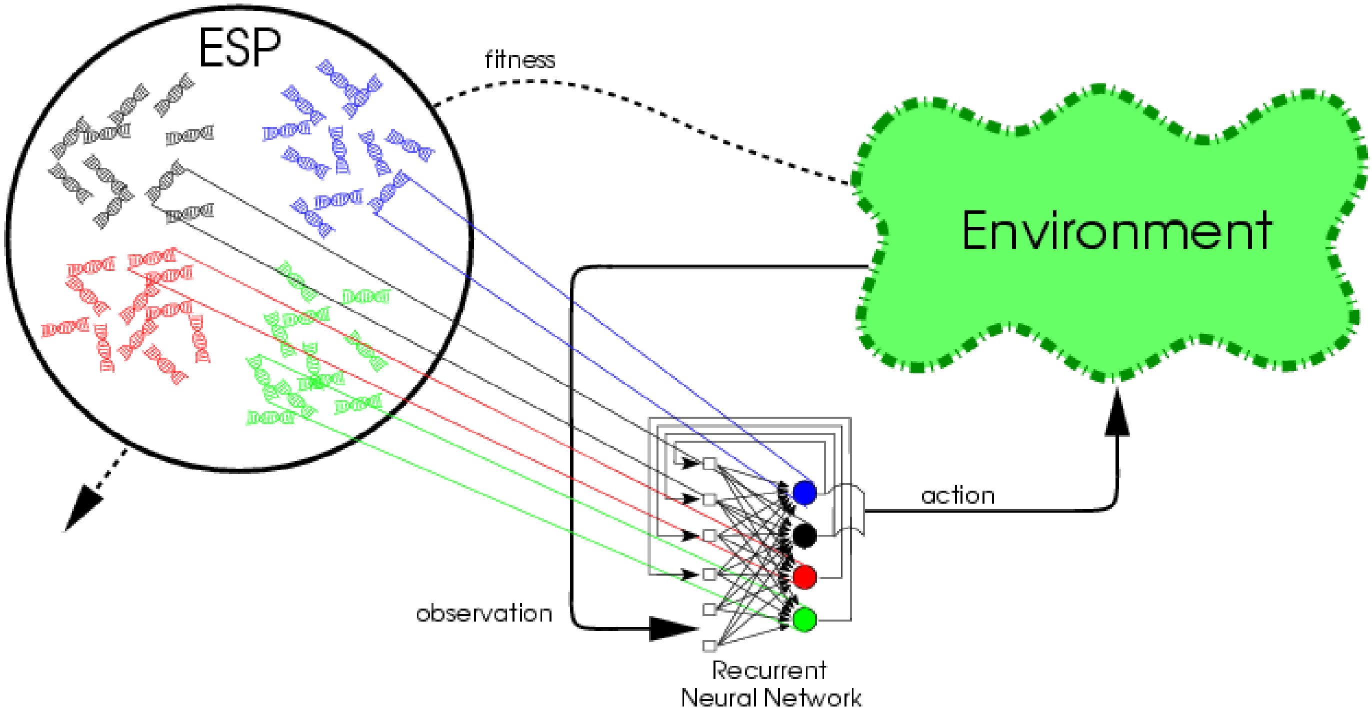
- Natural mapping between genotype and phenotype
  - GA and NN are a good match!

Problems with CNE



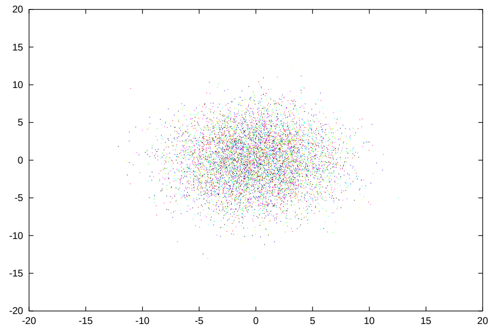
- Evolution converges the population (as usual with EAs)
  - Diversity is lost; progress stagnates
- Competing conventions
  - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
  - Thousands of weight values at once

Advanced NE 1: Evolving Partial Networks

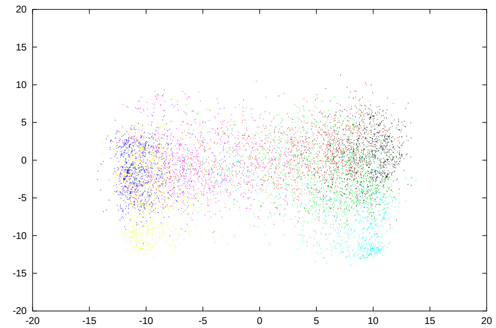


- Evolving individual neurons to cooperate in networks [1;53;61]
- E.g. Enforced Sub-Populations (ESP [23])
  - Each (hidden) neuron in a separate subpopulation
  - Fully connected; weights of each neuron evolved
  - Populations learn compatible subtasks

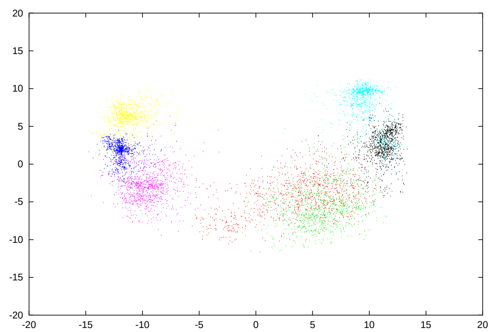
Evolving Neurons with ESP



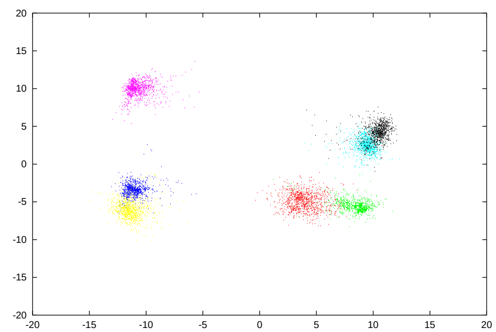
Generation 1



Generation 20



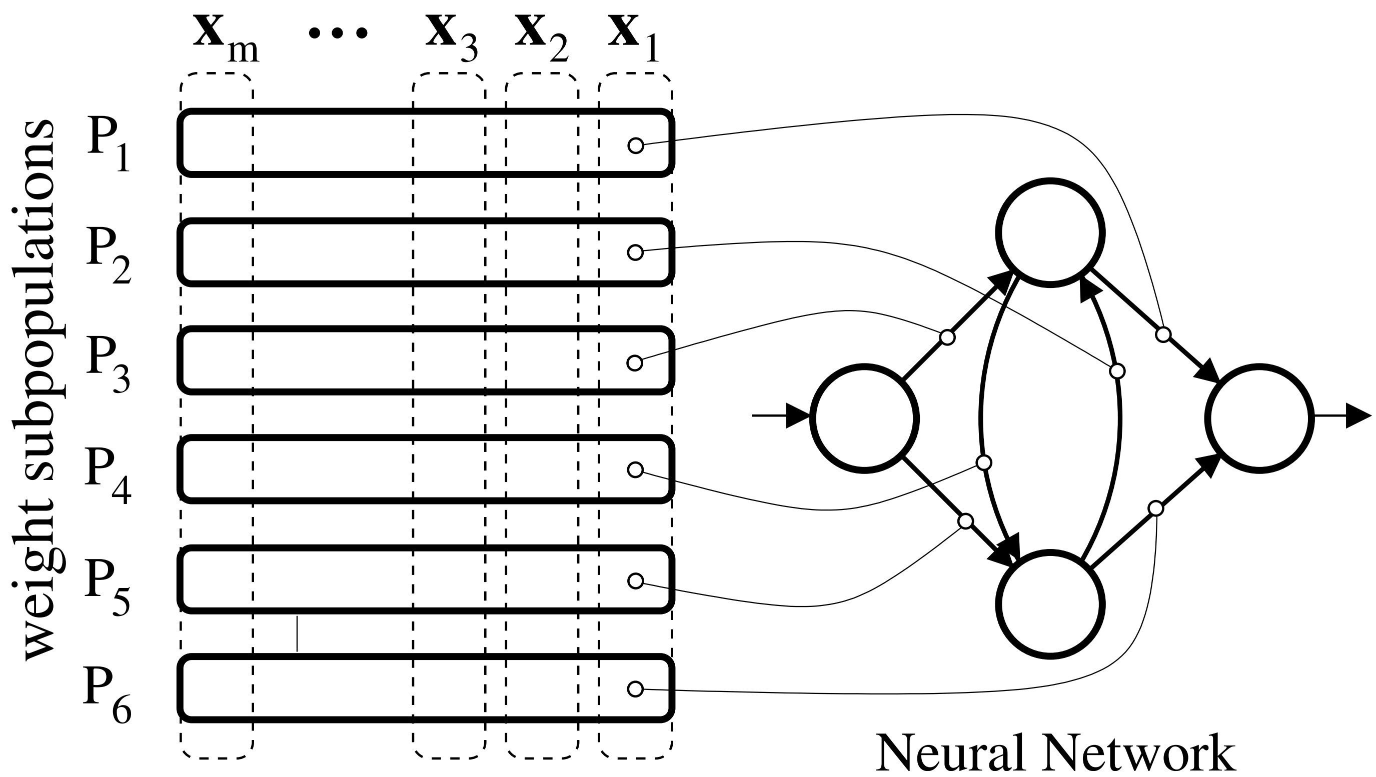
Generation 50



Generation 100

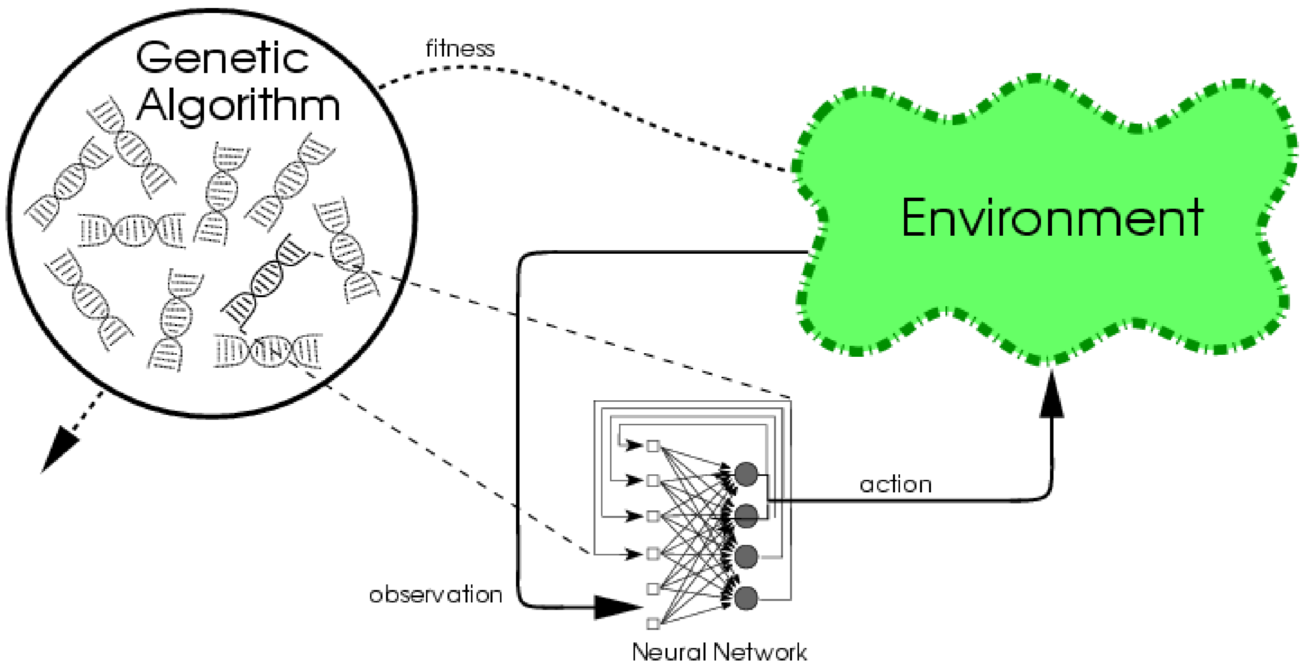
- Evolution encourages diversity automatically
  - Good networks require different kinds of neurons
- Evolution discourages competing conventions
  - Neurons optimized for compatible roles
- Large search space divided into subtasks
  - Optimize compatible neurons

Evolving Partial Networks (2)



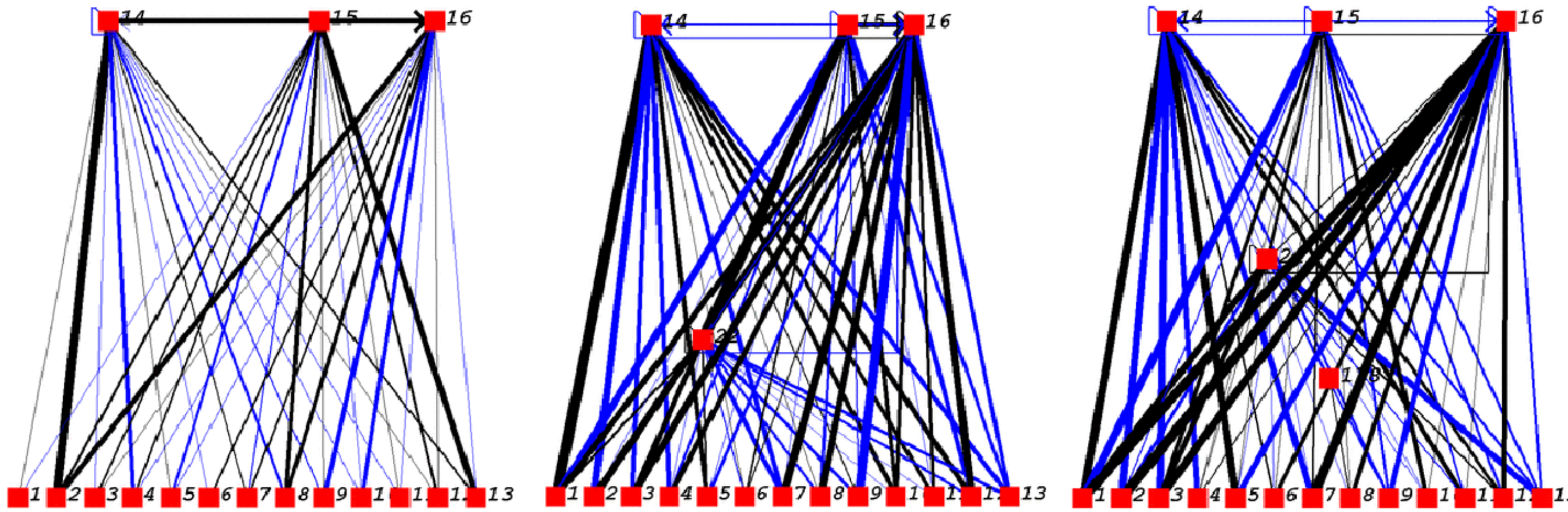
- Extend the idea to evolving connection weights
- E.g. Cooperative Synapse NeuroEvolution (CoSyNE[28])
  - Connection weights in separate subpopulations
  - Networks formed by combining neurons with the same index
  - Networks mutated and recombined; indices permutated
- Sustains diversity, results in efficient search

Advanced NE 2: Evolutionary Strategies



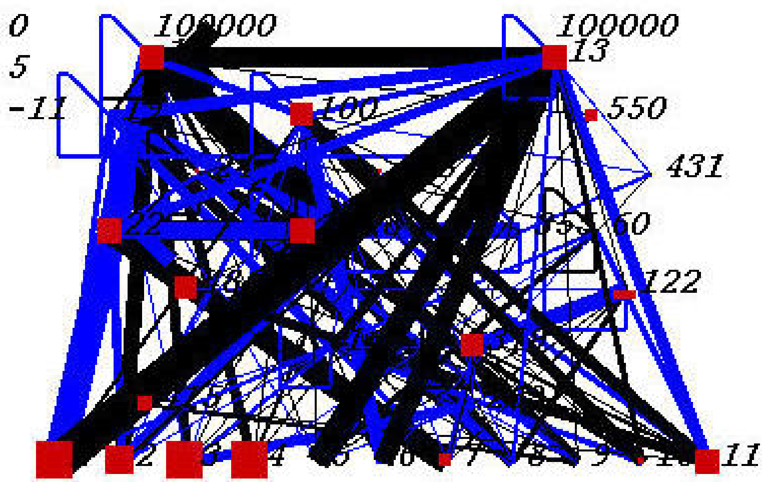
- Evolving complete networks with ES (CMA-ES[35])
- Small populations, no crossover
- Instead, intelligent mutations
  - Adapt covariance matrix of mutation distribution
  - Take into account correlations between weights
- Smaller space, less convergence, fewer conventions

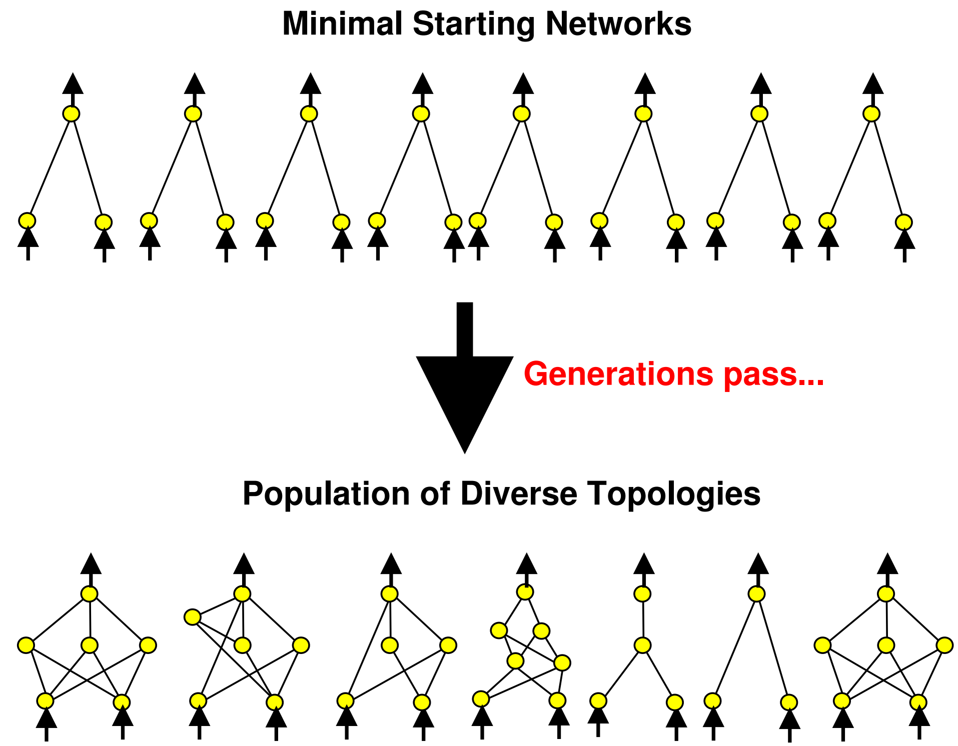
Advanced NE 3: Evolving Topologies



- Optimizing connection weights and network topology [3;16;21;106]
- E.g. Neuroevolution of Augmenting Topologies (NEAT [79;82])
- Based on *Complexification*
- Of networks:
  - Mutations to add nodes and connections
- Of behavior:
  - Elaborates on earlier behaviors

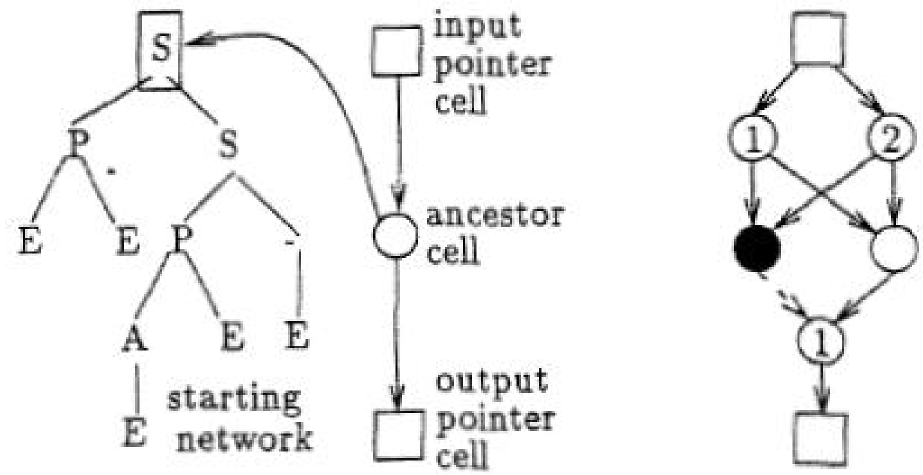
Why Complexification?





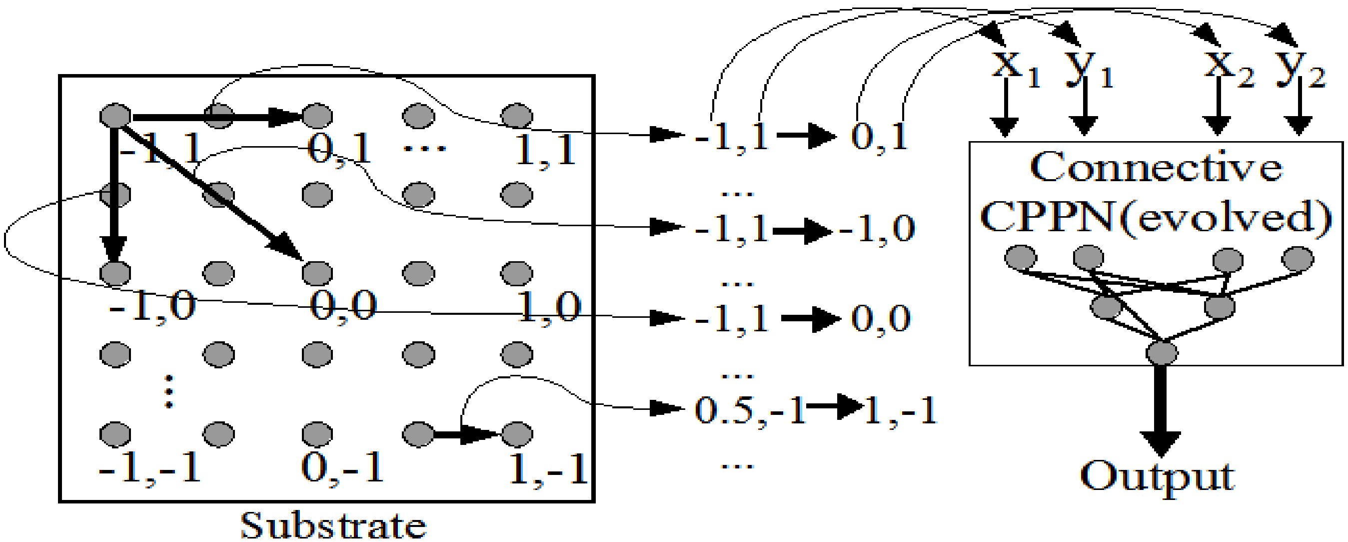
- Problem with NE: Search space is too large
- Complexification keeps the search tractable
  - Start simple, add more sophistication
- Incremental construction of intelligent agents

Advanced NE 4: Indirect Encodings



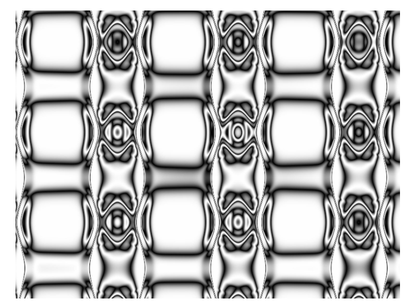
- Instructions for constructing the network evolved
  - Instead of specifying each unit and connection [3;16;49;76;106]
- E.g. Cellular Encoding (CE [30])
- Grammar tree describes construction
  - Sequential and parallel cell division
  - Changing thresholds, weights
  - A "developmental" process that results in a network

Indirect Encodings (2)

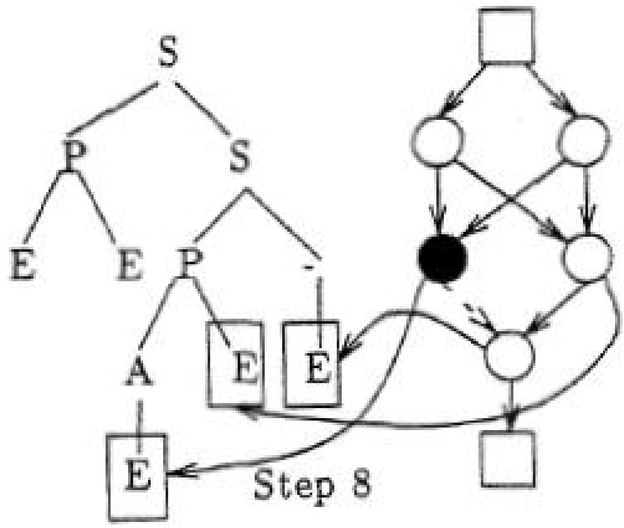


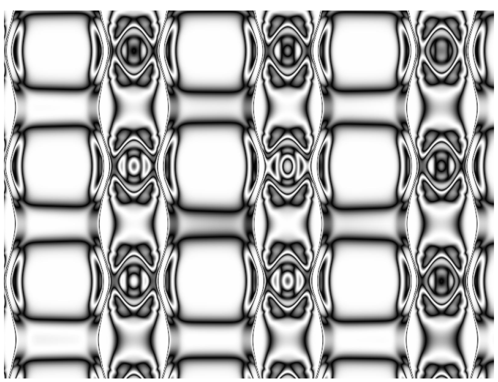
- Encode the networks as spatial patterns

- E.g. Hypercube-based NEAT (HyperNEAT[12])
- 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

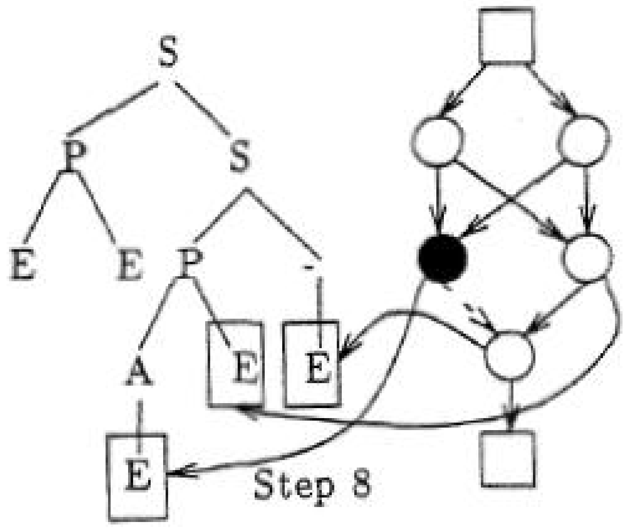


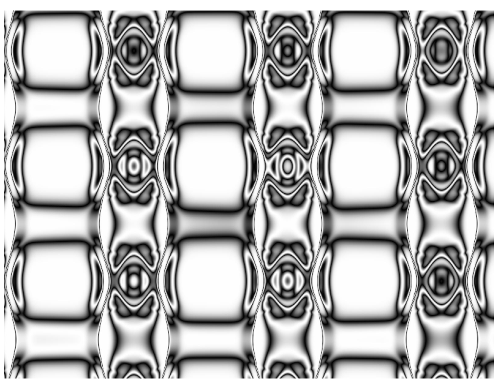


- Smaller search space
- Avoids competing conventions

- 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

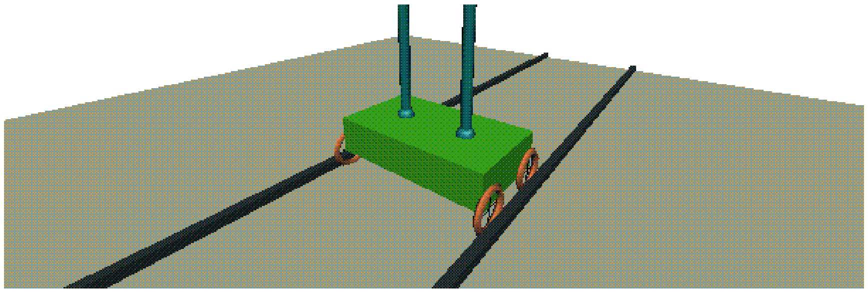
Properties of Indirect Encodings





- Not fully explored (yet)
  - See e.g. GDS track at GECCO
- Promising current work
  - More general L-systems; developmental codings; embryogeny [83]
  - Scaling up spatial coding [13;22]
  - Genetic Regulatory Networks [65]
  - Evolution of symmetries [93]

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

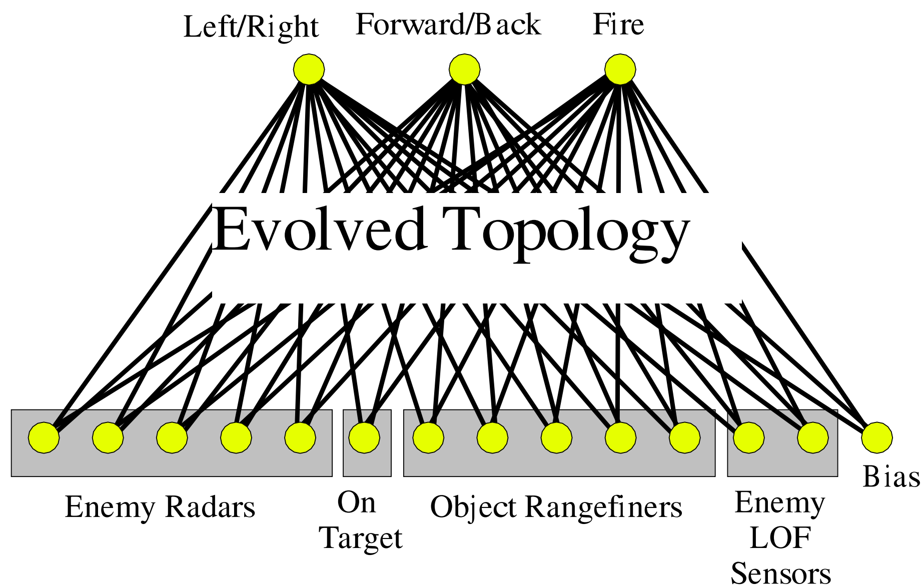
Two poles, no velocities, damping fitness [28]

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

Further NE Techniques

- Incremental and multiobjective evolution [25;72;91;105]
- Utilizing population culture [5;47;87]
- Utilizing evaluation history [44]
- Evolving NN ensembles and modules [36;43;60;66;101]
- Evolving transfer functions and learning rules [8;68;86]
- Combining learning and evolution
- Evolving for novelty

Combining Learning and Evolution

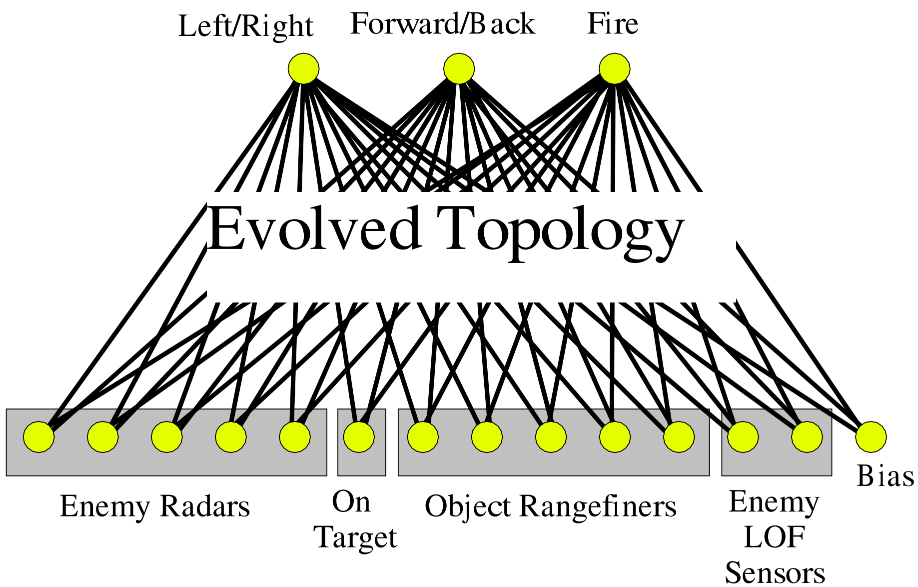


- Good learning algorithms exist for NN
  - Why not use them as well?

- Evolution provides structure and initial weights

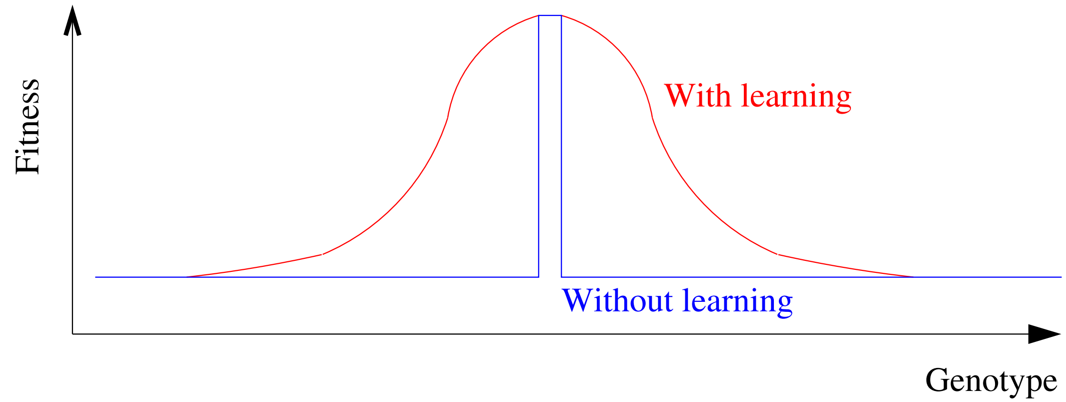
- Fine tune the weights by learning

Lamarckian Evolution



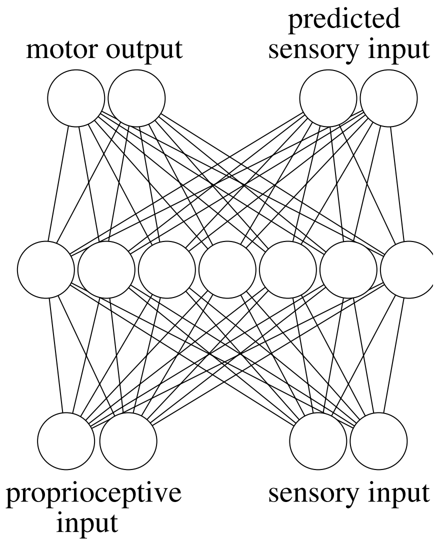
- Lamarckian evolution is possible [7;30]
  - Coding weight changes back to chromosome
- Difficult to make it work
  - Diversity reduced; progress stagnates

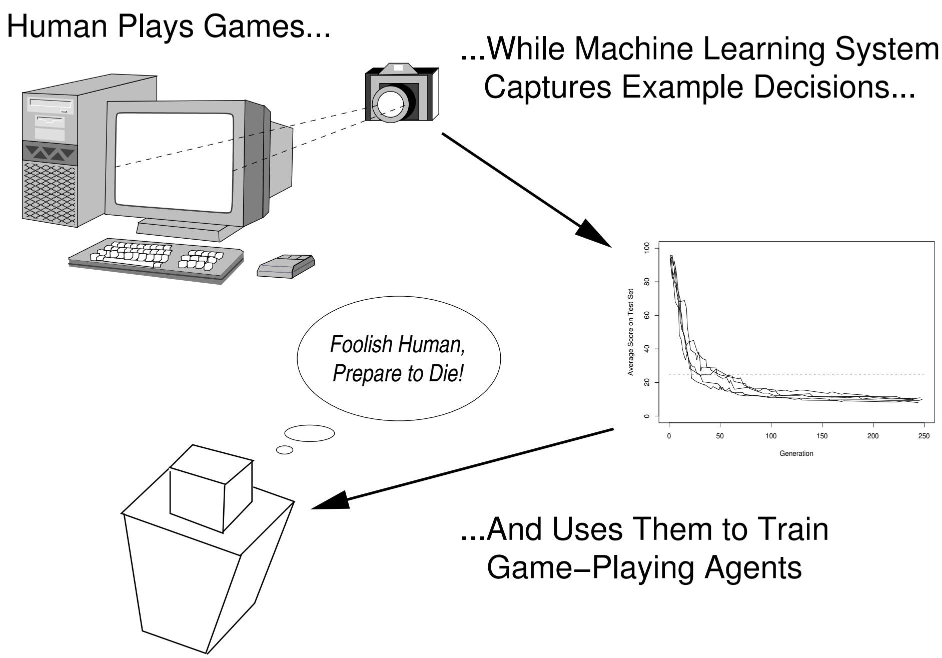
Baldwin Effect



- Learning can guide Darwinian evolution as well [4;30;32]
  - 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

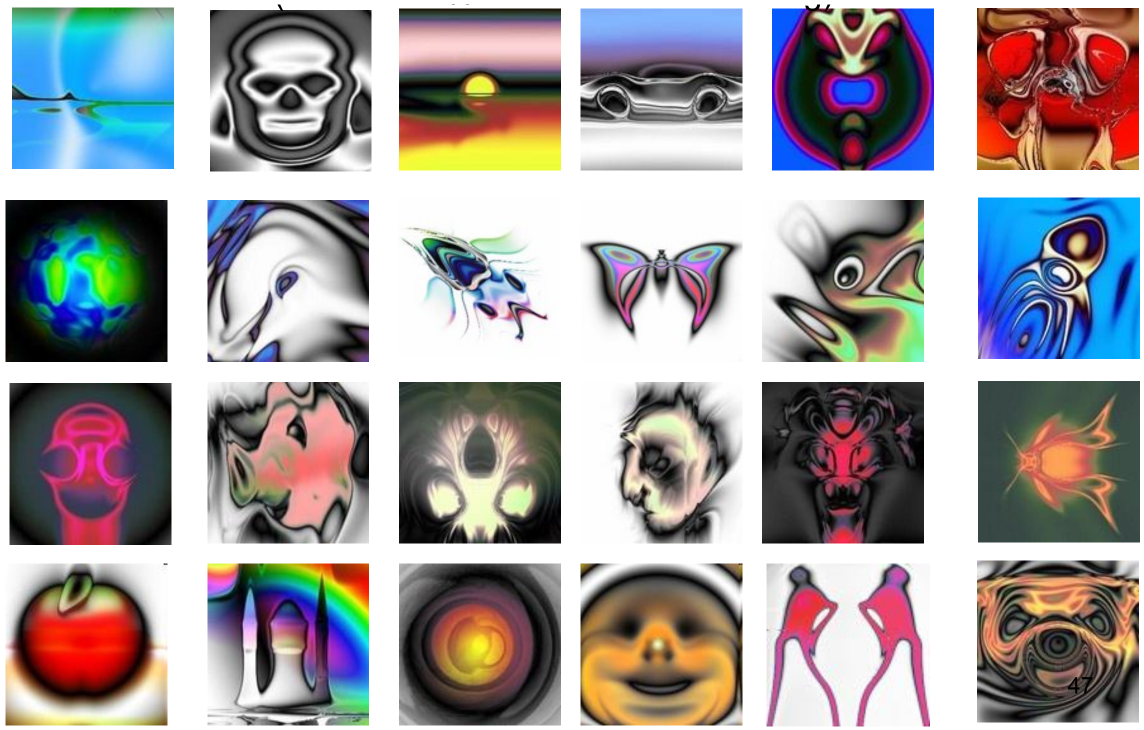
Where to Get Learning Targets?





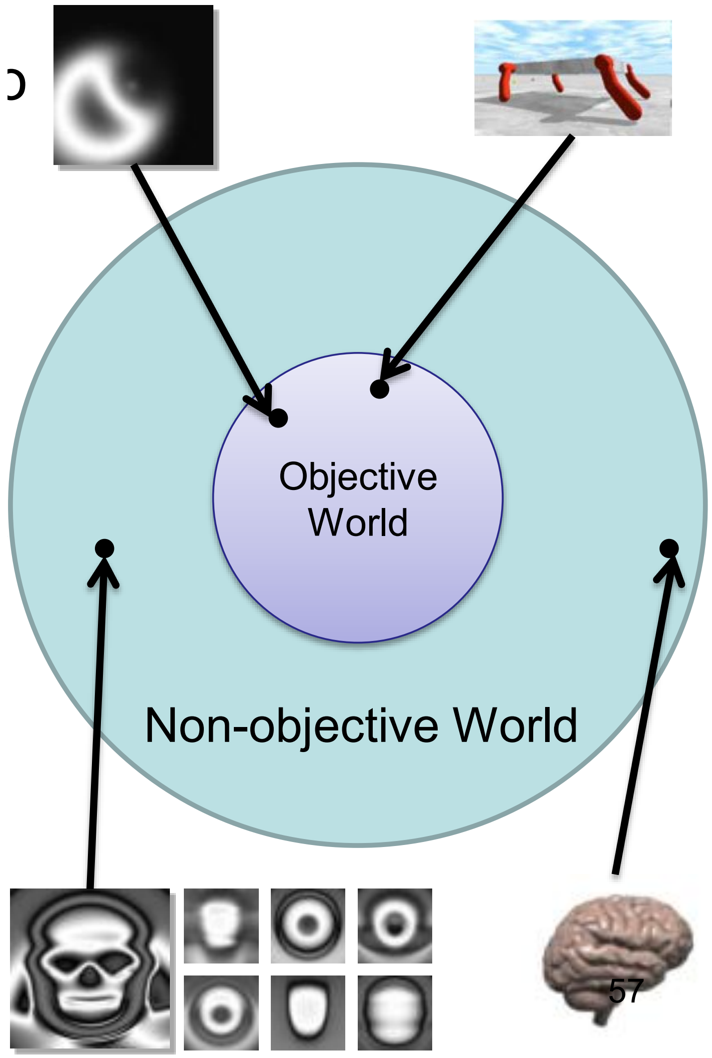
- From a related task [56]
  - Useful internal representations
- Evolve the targets [59]
  - Useful training situations
- From Q-learning equations [102]
  - When evolving a value function
- Utilize Hebbian learning [18;80;95]
  - Correlations of activity
- From the population [47;87]
  - Social learning
- From humans [7]
  - E.g. expert players, drivers

Evolving Novelty



- Motivated by humans as fitness functions
- E.g. picbreeder.com, endlessforms.com[73]
  - 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 [55]
  - Or, even as the only objective [40;41]
- To be different, need to capture structure
  - Problem solving as a side effect
- DEMO (at eplex.cs.ucf.edu/noveltysearch)
- Potential for innovation
- Needs to be understood better

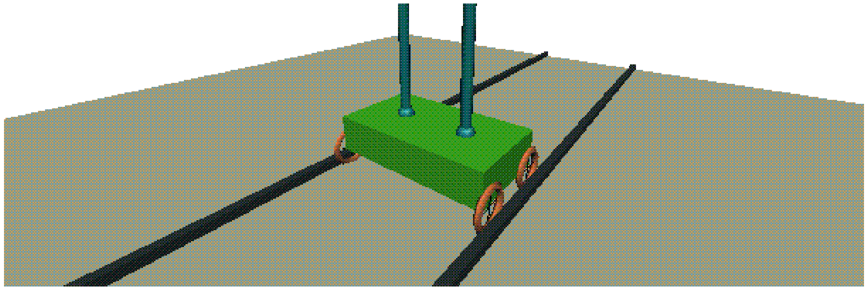
Extending NE to Applications

- Control
- Robotics
- Artificial life
- Gaming

Issues:

- Facilitating robust transfer from simulation [27;92]
- Utilizing problem symmetry and hierarchy [38;93;96]
- Utilizing coevolution [67;84]
- Evolving multimodal behavior [71;72;101]
- Evolving teams of agents [6;81;107]
- Making evolution run in real-time [81]

Applications to Control



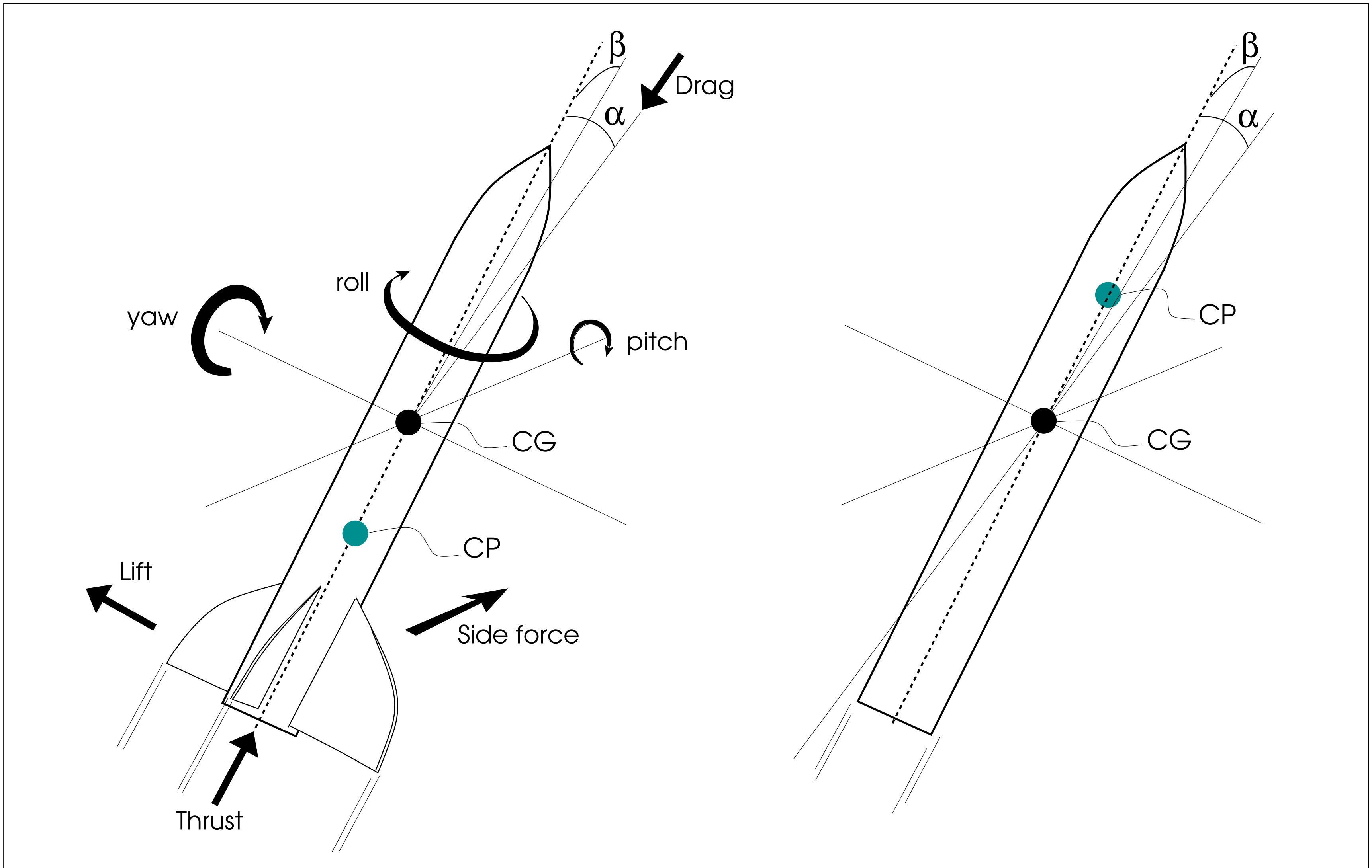
- Pole-balancing benchmark
  - Originates from the 1960s
  - Original 1-pole version too easy
  - Several extensions: acrobat, jointed, 2-pole, particle chasing[60]
- Good surrogate for other control tasks
  - Vehicles and other physical devices
  - Process control[97]

Controlling a Finless Rocket

Task: Stabilize a finless version of the Interorbital Systems RSX-2 sounding rocket[26]

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

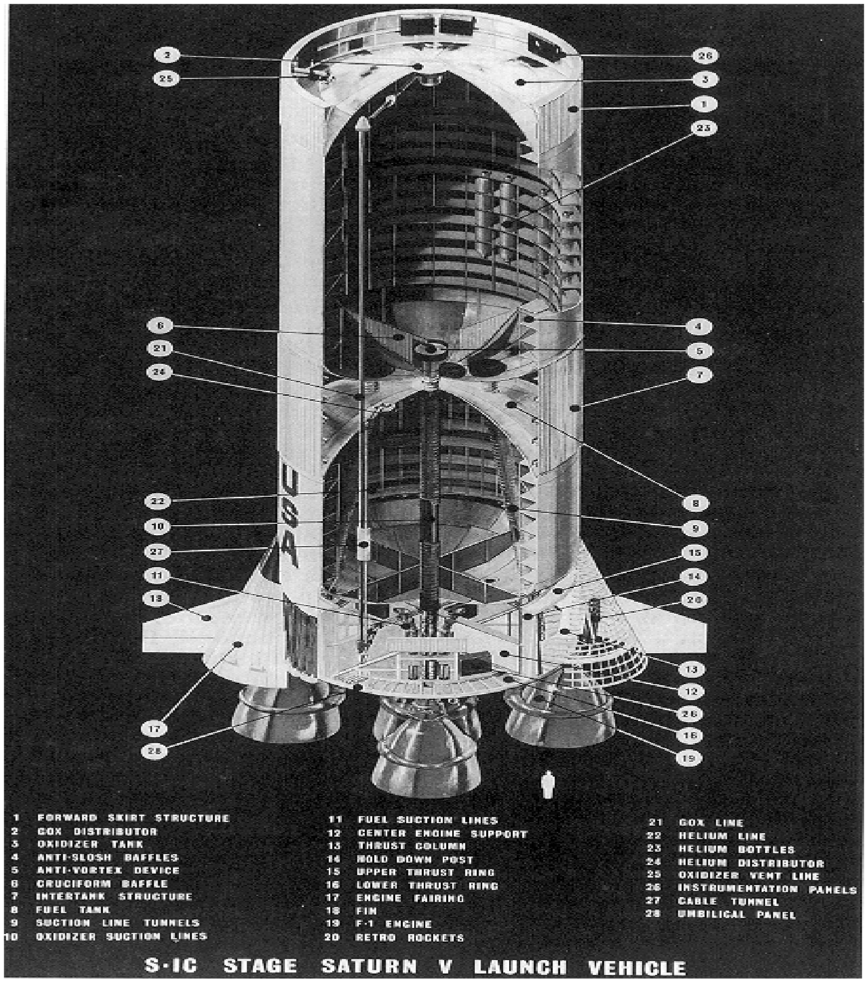
Rocket Stability



(a) Fins: stable

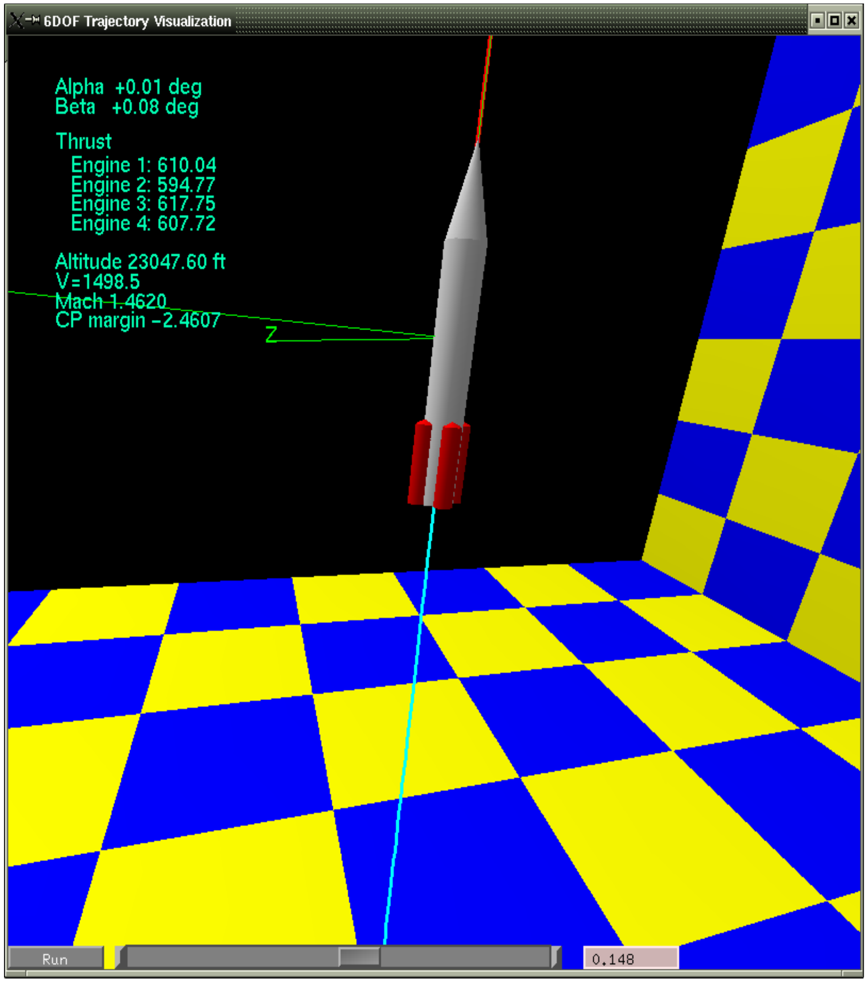
(b) Finless: unstable

Active Rocket Guidance



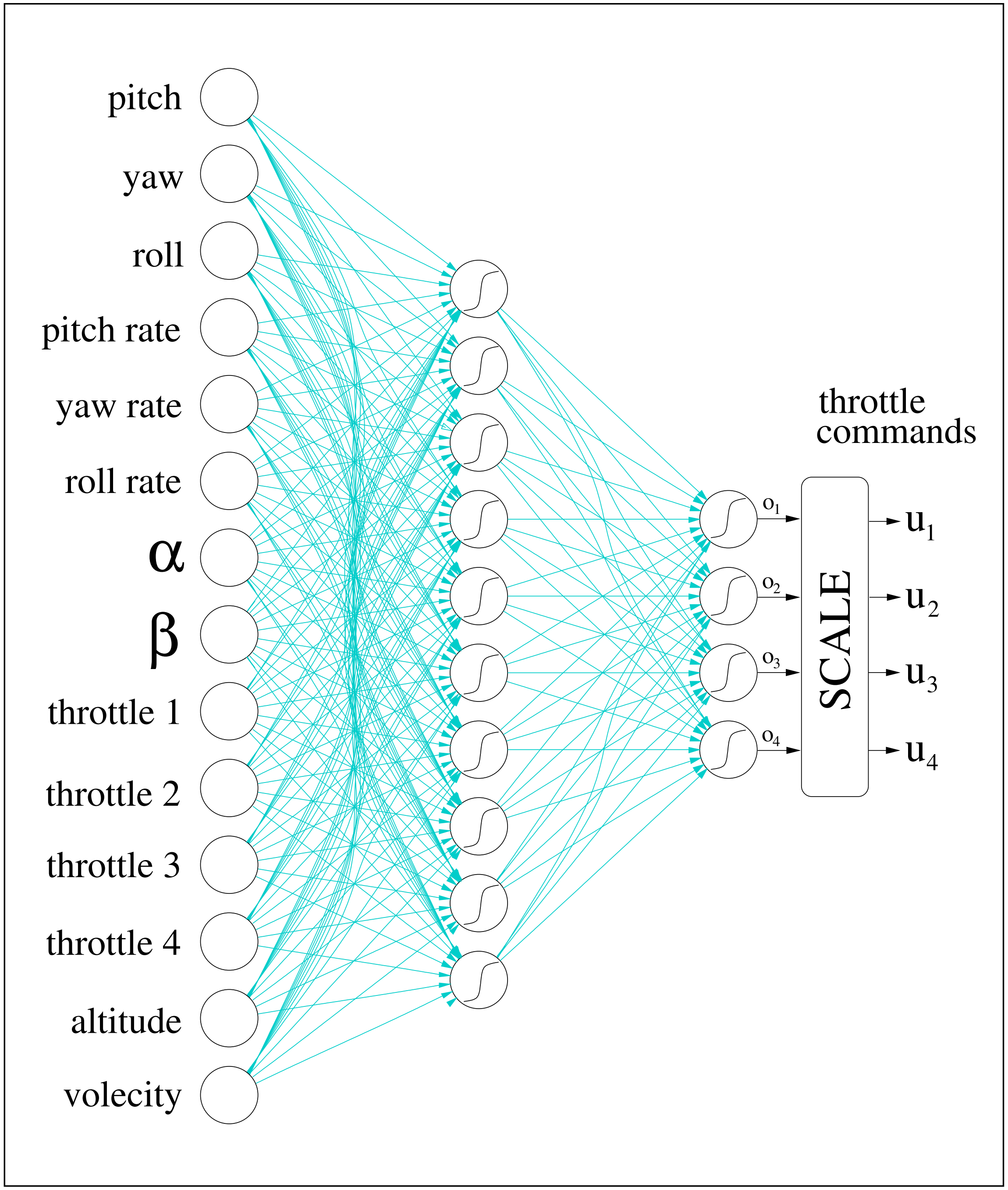
- Used on large scale launch vehicles (Saturn, Titan)
- Typically based on classical linear feedback control
- High level of domain knowledge required
- Expensive, heavy

Simulation Environment: JSBSim

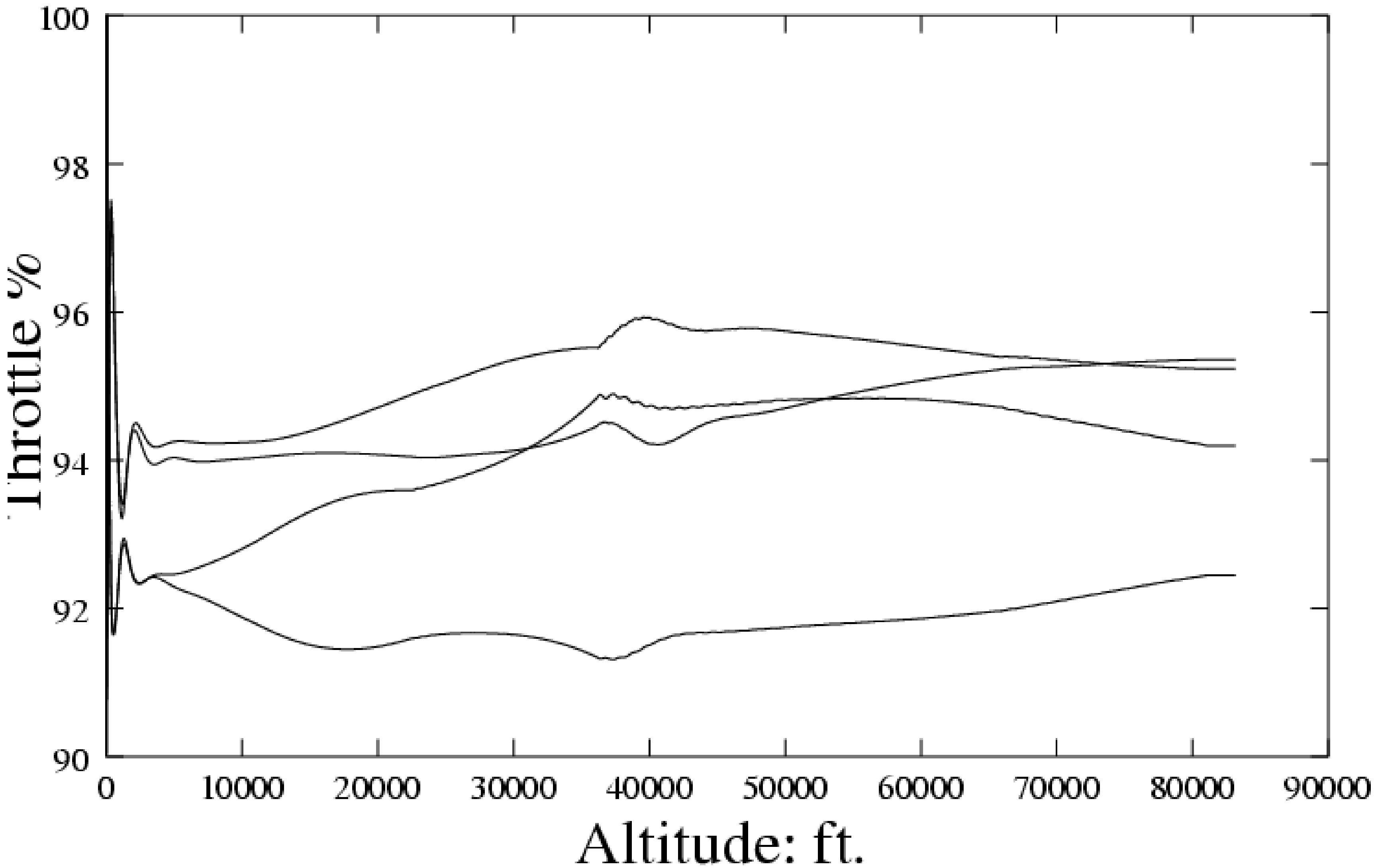


- General rocket simulator
- Models complex interaction between airframe, propulsion, aerodynamics, and atmosphere
- Used by IOS in testing their rocket designs
- Accurate geometric model of the RSX-2

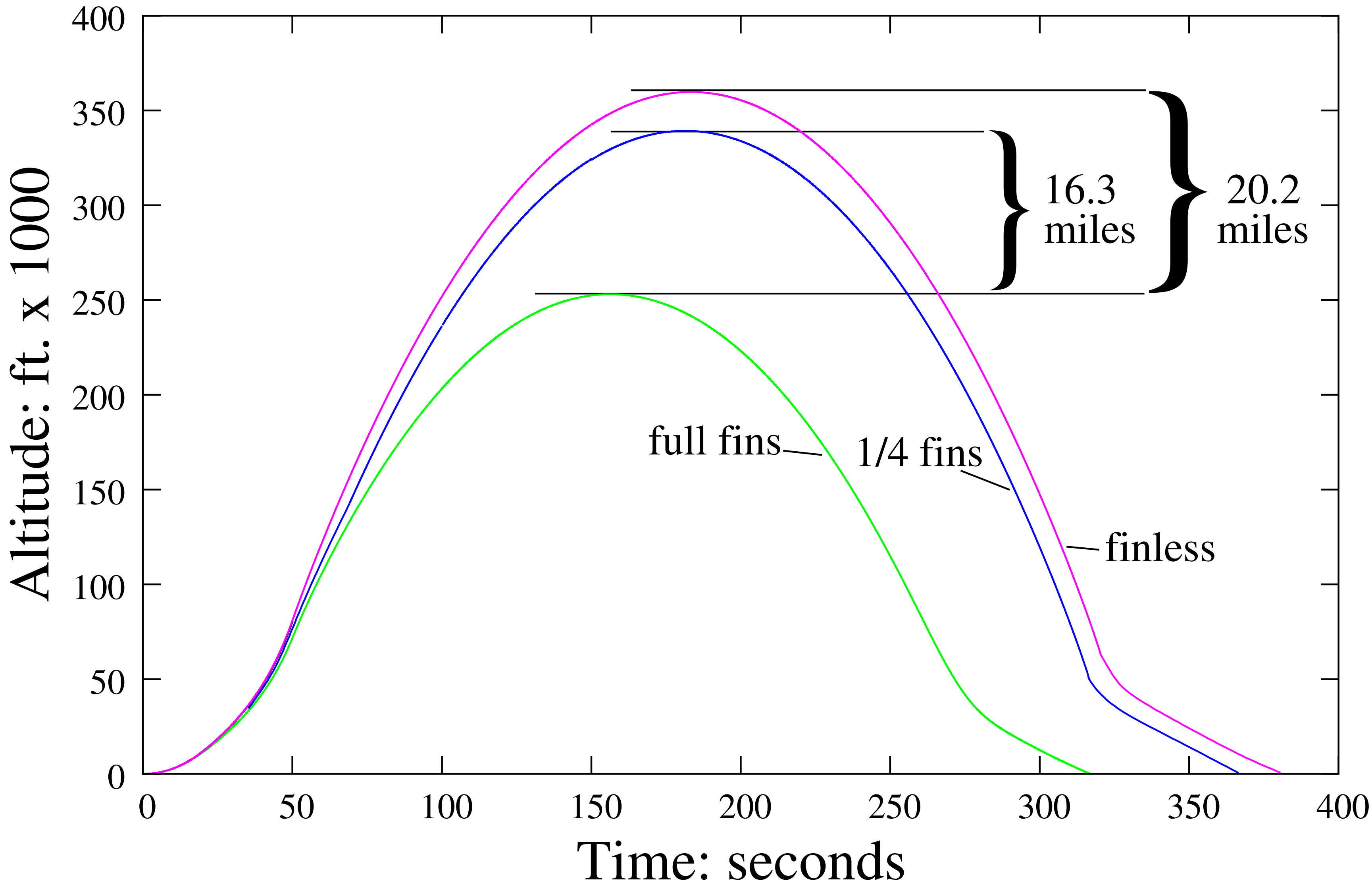
Rocket Guidance Network



Results: Control Policy



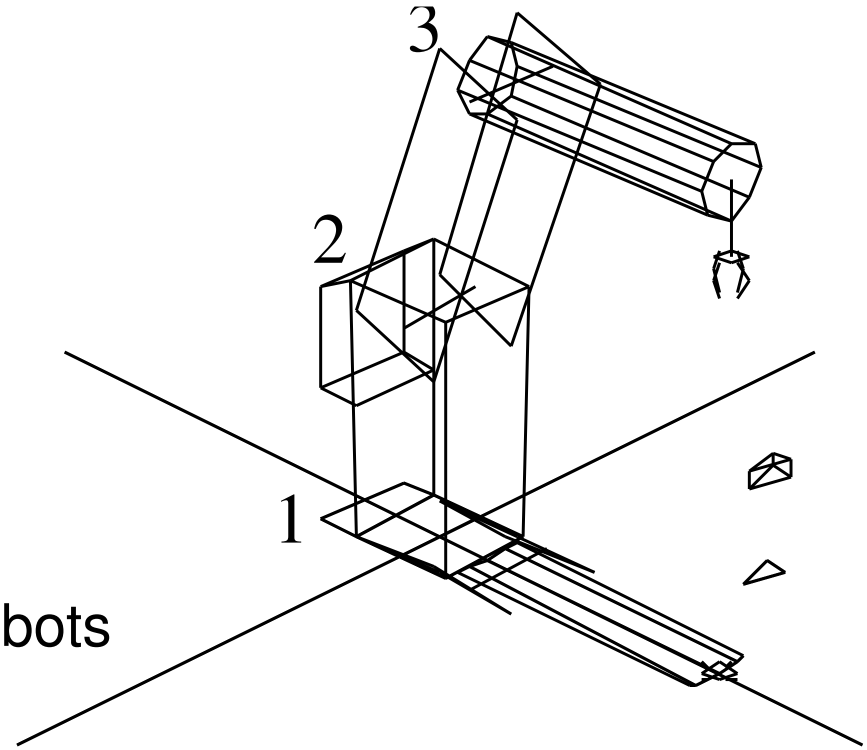
Results: Apogee



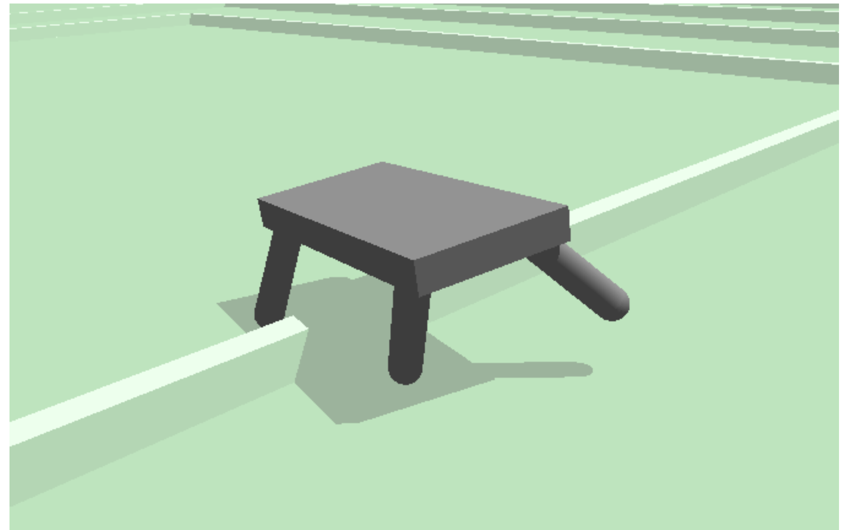
- DEMO (available at nn.cs.utexas.edu)

Applications to Robotics

- Controlling a robot arm [52]
  - Compensates for an inop motor
- Robot walking [34;75;96]
  - Various physical platforms
- Mobile robots [11;17;57;78]
  - Transfers from simulation to physical robots
  - Evolution possible on physical robots

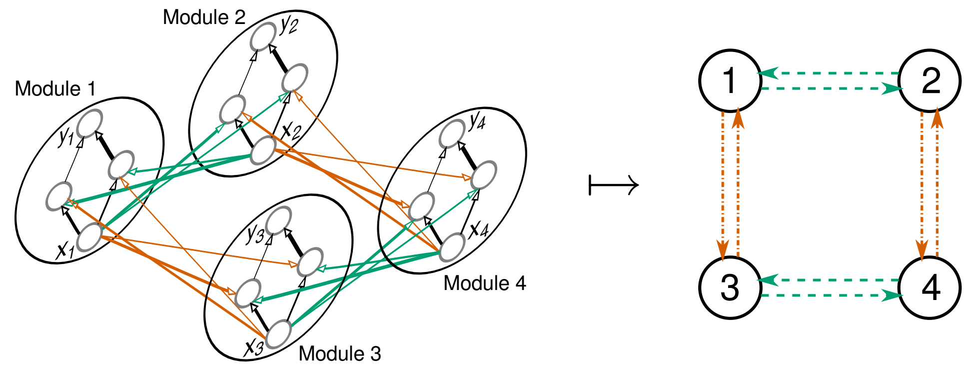


Multilegged Walking



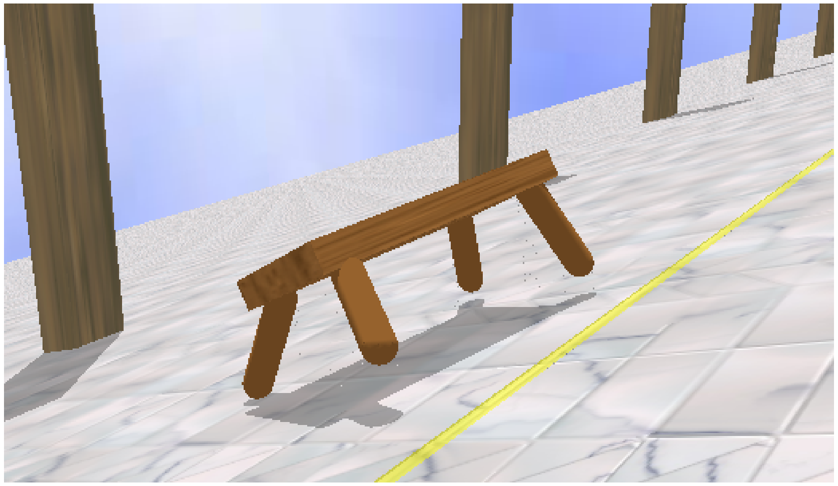
- Navigate rugged terrain better than wheeled robots
- Controller design is more challenging
  - Leg coordination, robustness, stability, fault-tolerance, ...
- Hand-design is generally difficult and brittle
- Large design space often makes evolution ineffective

ENSO: Symmetry Evolution Approach



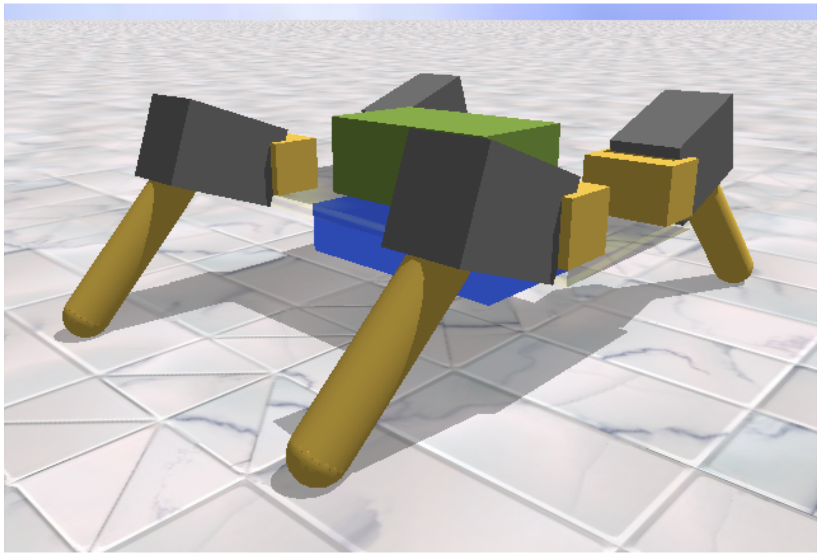
- Symmetry evolution approach [93;94;96]
  - A neural network controls each leg
  - Connections between controllers evolved through symmetry breaking
  - Connections within individual controllers evolved through neuroevolution

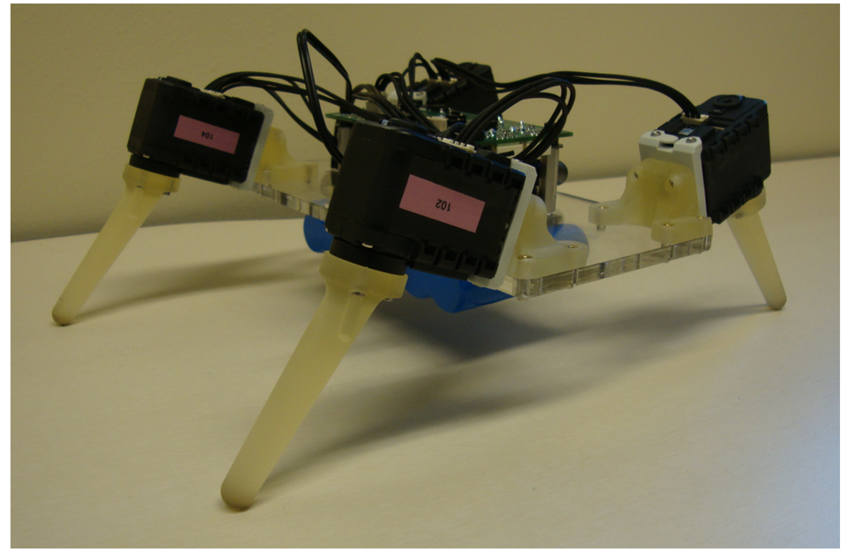
Robust, Effective Solutions



- Different gaits on flat ground
  - Pronk, pace, bound, trot
  - Changes gait to get over obstacles
- Asymmetric gait on inclines
  - One leg pushes up, others forward
  - Hard to design by hand
- DEMO (available at nn.cs.utexas.edu)

Transfer to a Physical Robot



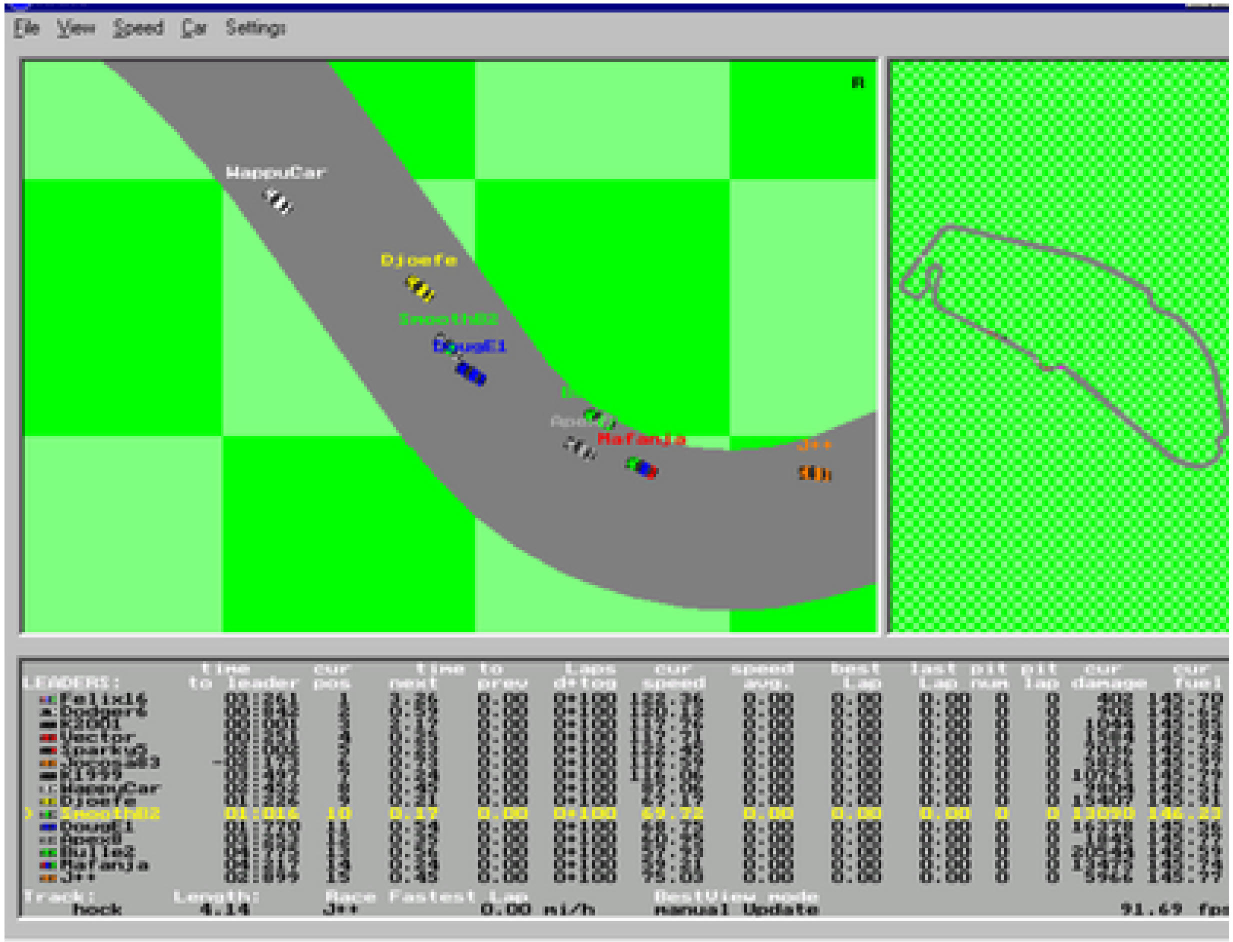


- Built at Hod Lipson's lab (Cornell U.)
  - Standard motors, battery, controller board
  - Custom 3D-printed legs, attachments
  - Simulation modified to match
- General, robust transfer[92]
  - Noise to actuators during simulation
  - Generalizes to different surfaces, motor speeds
  - Evolved a solution for 3-legged walking!
- DEMO (available at nn.cs.utexas.edu)

Driving and Collision Warning

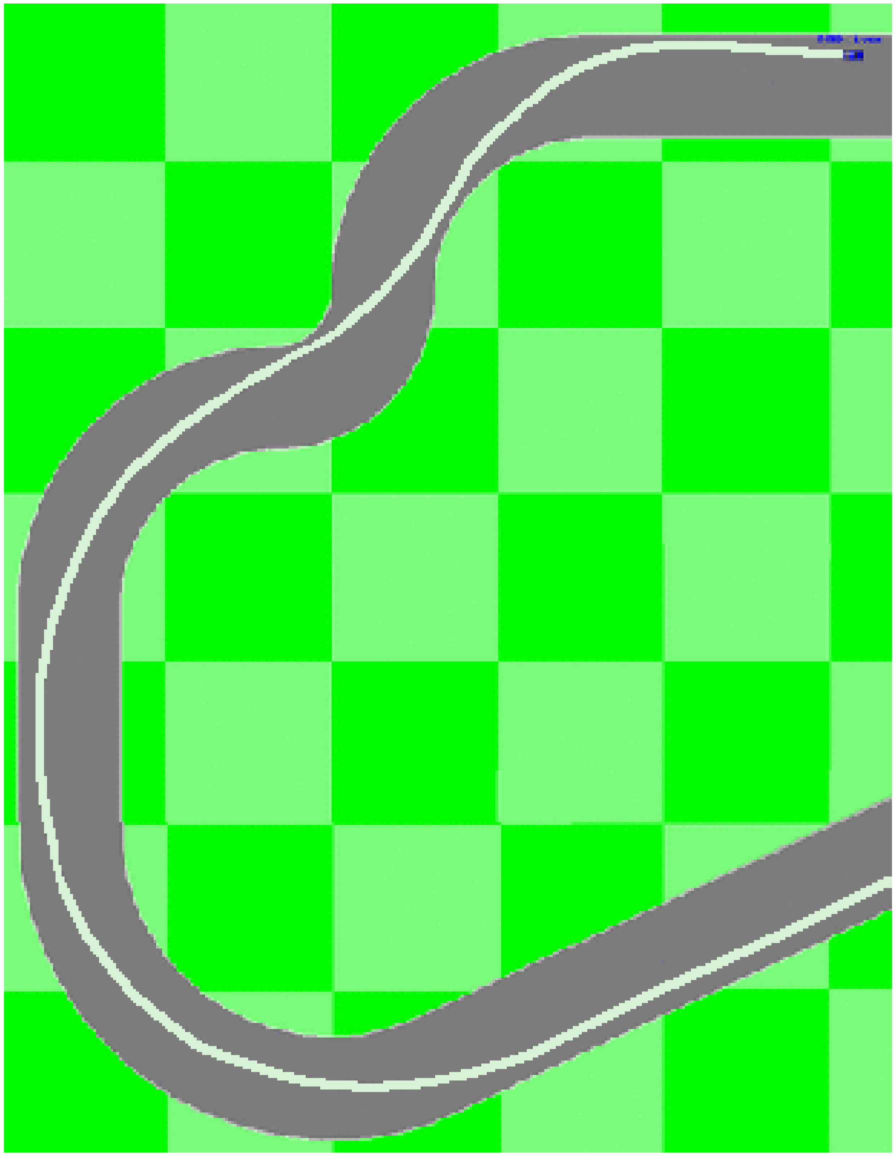
- Goal: evolve a collision warning system
  - Looking over the driver's shoulder
  - Adapting to drivers and conditions
  - Collaboration with Toyota[39]

The RARS Domain



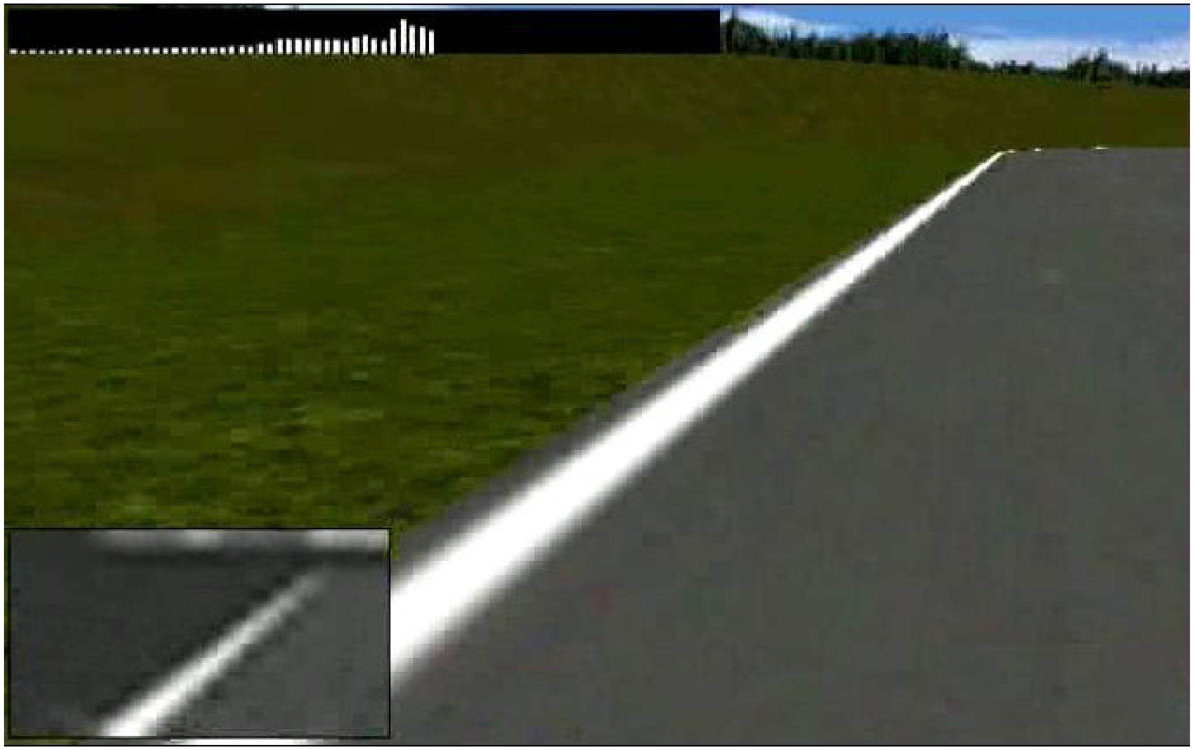
- RARS: Robot Auto Racing Simulator
  - Internet racing community
  - Hand-designed cars and drivers
  - First step towards real traffic

Evolving Good Drivers



- Evolving to drive fast without crashing (off road, obstacles)
- An interesting challenge of its own[89]
- Discovers optimal driving strategies (e.g. how to take curves)
- Works from range-finder & radar inputs
- Works from raw visual inputs (20×14 grayscale)

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 (available at nn.cs.utexas.edu)

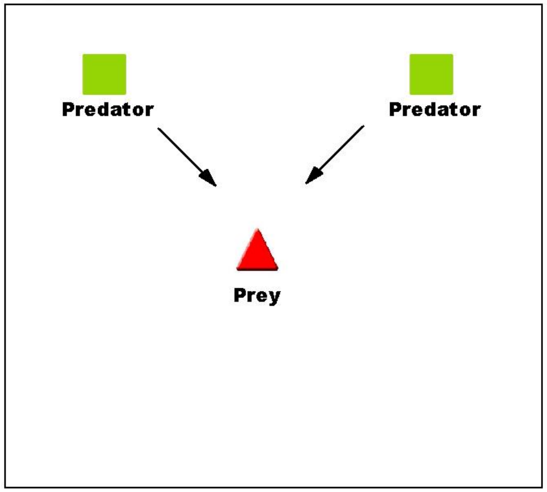
Transferring to the Physical World?

- Applied AI Gaia moving in an office environment
  - Sick laserfinder; Bumblebee digital camera
  - Driven by hand to collect data
- Learns collision warning in both cases
- Transfer to real cars?
- DEMO (available at nn.cs.utexas.edu)

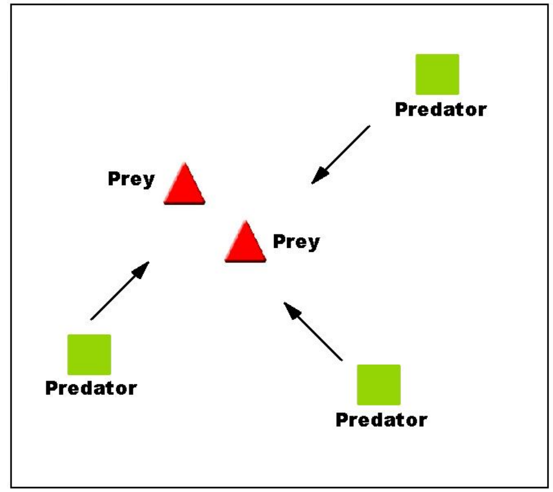
Applications to Artificial Life

- Gaining insight into neural structure
  - E.g. evolving a command neuron [2;37;69]
- Coevolution of structure and function
  - E.g. creature morphology and control [42;77]
- Emergence of behaviors
  - Signaling, herding, hunting... [62;100;107]
- Future challenges
  - Emergence of language [58;63;90;99]
  - Emergence of community behavior

Emergence of Cooperation and Competition



Predator cooperation



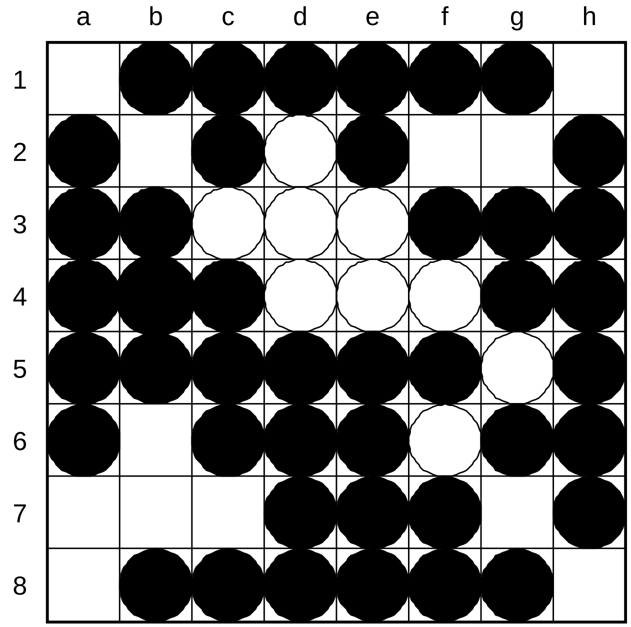
Predator, prey cooperation

- Predator-prey simulations[62;64]
  - Predator species, prey species
  - Prior work single pred/prey, team of pred/prey
- Simultaneous competitive and cooperative coevolution
- Understanding e.g. hyenas and zebras
  - Collaboration with biologists (Kay Holekamp, MSU)
- DEMO (available at nn.cs.utexas.edu)

Open Questions

- Role of communication
  - Stigmergy vs. direct communication in hunting
  - 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

Applications to Games



- Good research platform [48]
  - Controlled domains, clear performance, safe
  - Economically important; training games possible
- Board games: beyond limits of search
  - Evaluation functions in checkers, chess [9;19;20]
  - Filtering information in go, othello [51;85]
  - Opponent modeling in poker [45]

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 (2)

- 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

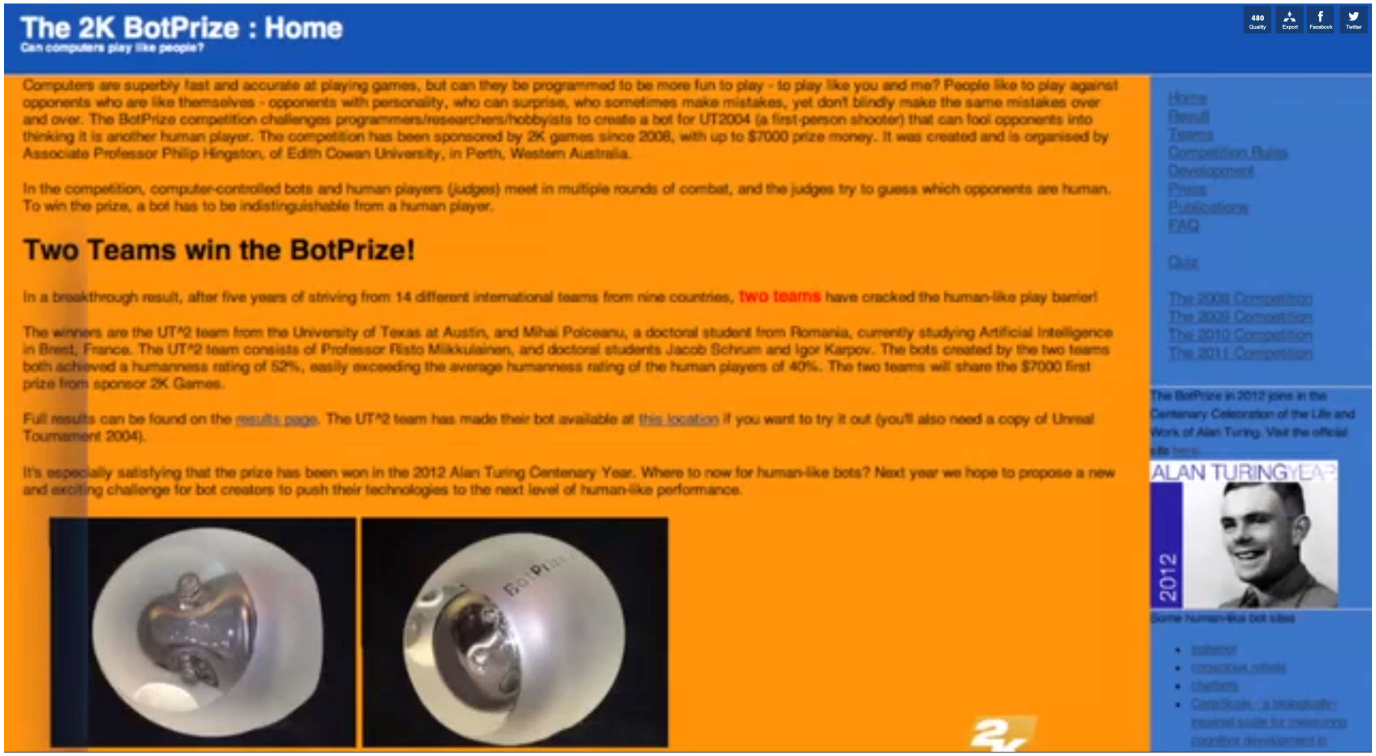
BotPrize Competition

- Turing Test for game bots: $10,000 prize (2007-12)
- Three players in Unreal Tournament 2004:
  - Human confederate: tries to win
  - Software bot: pretends to be human
  - Human judge: tries to tell them apart!
- DEMO (available at nn.cs.utexas.edu)

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!!



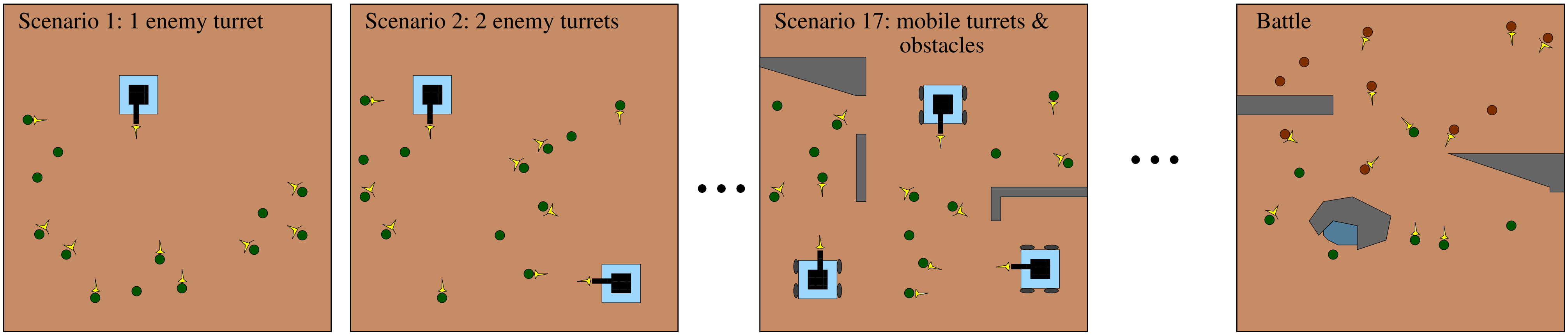
- In 2012, two teams reach the 50% mark!
- Fascinating challenges remain:
  - Judges can still differentiate in seconds
  - Judges lay cognitive, high-level traps
  - Team competition: collaboration as well

A New Genre: Machine Learning Games

NERO
NEURO EVOLVING ROBOTIC OPERATIVES

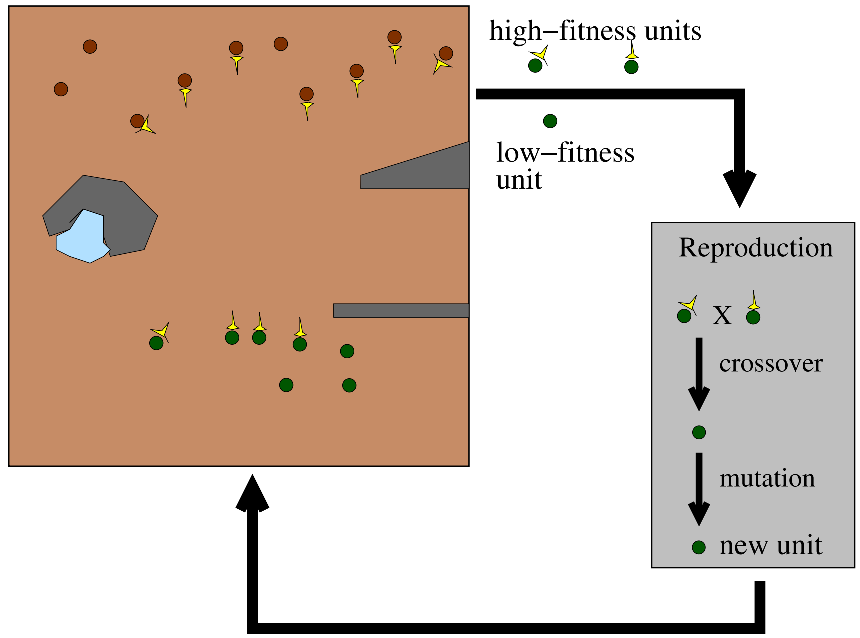
- E.g. NERO
  - Goal: to show that machine learning games are viable
  - Professionally produced by *Digital Media Collaboratory*, UT Austin
  - Developed mostly by volunteer undergraduates

NERO Gameplay



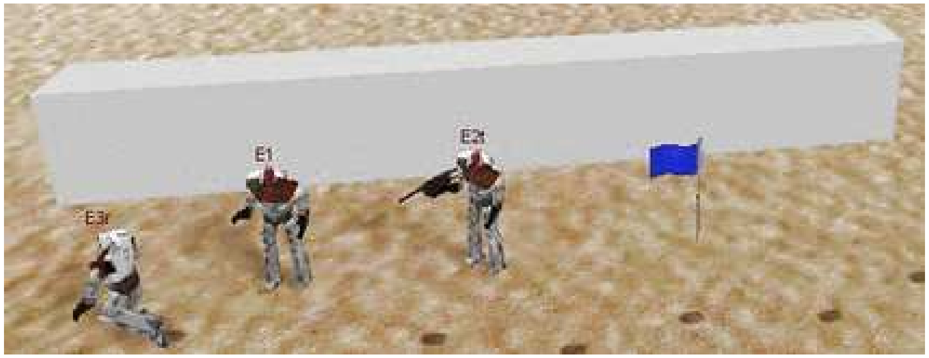
- Teams of agents trained to battle each other
  - Player trains agents through excercises
  - Agents evolve in real time
  - Agents and player collaborate in battle
- New genre: Learning *is* the game[31;81]
  - Challenging platform for reinforcement learning
  - Real time, open ended, requires discovery
- Try it out:
  - Available for download at `http://nerogame.org`
  - Open source research platform version at `opennero.googlecode.com`

Real-time NEAT



- A parallel, continuous version of NEAT[81]
- 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

- DEMO (available at nn.cs.utexas.edu)

Numerous Other Applications

- Creating art, music, dance... [10;15;33;74]
- Theorem proving [14]
- Time-series prediction [46]
- Computer system optimization [24]
- Manufacturing optimization [29]
- Process control optimization [97;98]
- Measuring top quark mass [103]
- 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

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