Evolving Intelligence

Lecture 13        I400/I590
Artificial Life as an approach to Artificial Intelligence

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Evolution is a Tautology

- That which survives, persists.
- That which reproduces, increases its numbers.
- Things change.

- Any little niche...
- “The cheapest, least intensively designed system will be ‘discovered’ first by Mother Nature, and myopically selected.” — Dennett (Kinds of Minds)
Evolutionary Algorithms

- Genetic Algorithms are powerful optimizers
  - Good for common engineering tasks, ranging from airfoil design to plant layout
  - Good for management tasks, such as timetables, resource scheduling, and packet routing
  - Even good for evolving learning algorithms and simulated organisms and behaviors
Evolutionary Algorithms

• Making them open-ended is a challenge
  • Many niches and niche creation
    - GAs are good at exploring multiple, simultaneous solutions
  • Self-interpreting digital DNA, artificial chemistries
  • Development processes, responsive to environment
  • Neutral mutations
Evolutionary Constraints

- Evolution is often constrained by its previous successes
  - Can’t afford to lose fitness, even in order to gain it
  - Unable to start from scratch and compete with existing successes
  - Disrupting any existing function may reduce fitness
  - Disrupting metabolic pathways may be fatal
Nervous Systems

• Evolution found and stuck with nervous systems for controlling behavior at all levels of complexity
  • Networks of neurons and synaptic connections
  • Provide all behaviors—including anything that might be considered intelligence—in all organisms more complex than plants, *c. elegans* to *homo sapiens*
  • Some behaviors are innate, so the wiring diagram must matter
  • Some behaviors are learned, so learning—phenotypic plasticity—must also matter
Plasticity in Function

Orientation maps:

Mriganka Sur, et al
Plasticity in Wiring

Patterns of long-range horizontal connections in V1, normal A1, and rewired A1:

Wiring Diagram Matters

- Relative consistency of brain maps across large populations
- Infants predisposed to focus on two dark spots separated by a lighter space between them (face priming)
- Lesion/aphasia studies illustrate specific, limited effects
  - Injury to hippocampus can cause a loss of ability to store new memories
  - Lesions of prefrontal cortex can eliminate ability to plan for the future, make rational decisions, and process emotion
  - Moderate stroke damage to occipital lobe can induce rare Charcot-Wilbrand syndrome (loss of dreams)
- Scarcity of tissue in localized portion of visual system is method of action for gene disorder, Williams Syndrome (lack of depth perception, inability to assemble parts into wholes)
Wiring Diagram + Learning = Brain Maps
Motor Cortex Map
Real & Artificial Brain Maps

Distribution of orientation-selective cells in visual cortex

Monkey Cortex, Blasdel and Salama

Simulated Cortex, Ralph Linsker
Neuronal Cooperation

John Pearson, Gerald Edelman
Neuronal Competition

John Pearson, Gerald Edelman
The Brain Story So Far...

- Brain maps are good
- Brain maps are derived from
  - General purpose learning mechanism
  - Suitable wiring diagram
- Artificial neural networks capture key features of biological neural networks using
  - Hebbian learning
  - Suitable wiring diagram
How to Proceed?

• Design a suitable neural architecture
  • Simple architectures are easy, but are limited to simple (but robust) behaviors
    - W. Grey Walter’s Turtles
    - First few Valentino Braitenberg Vehicles (#1-5, of 14)
  • Complex architectures are much more difficult
    - We know a lot about neural anatomy
    - There’s a lot more we don’t know
    - It is being tried – Steve Grand’s Lucy
How to Proceed?

- Evolve a suitable neural architecture
  - It ought to work
    - Valentino Braitenberg’s Vehicles (#6 and higher)
  - We know it works
    - Genetic Algorithms (computational realm)
    - Natural Selection (biological realm)
Is There Really Any Hope?

• Danny Hillis (“Intelligence as an Emergent Behavior”, *Daedalus* 1988) observes
  
  “It would be convenient if intelligence were an emergent behavior of randomly connected neurons in the same sense that snowflakes and whirlpools are emergent behaviors of water molecules.”

• From Cog Sci/Psychology experiments he estimates that a model brain would need $10^9$ bits and $10^{11}$ bits/sec memory access to support human-level thought (“plus or minus two orders of magnitude”)
Progress with Limited Understanding

- Hillis points to successes with emergent systems developed with limited knowledge (either deliberately or unavoidably):
  - **Cellular automata models of fluid flow**
    - Unit mass, unit speed particles on a hexagonal lattice, behaving as billiard balls, produce laminar, vortical, and turbulent flows “indistinguishable from the behavior of real fluids”
  - **Computational models of evolutionary biology**
    - Evolved sorting algorithms that compete with the best human-designed algorithms to show how “Even a little understanding could go a long way toward the construction of an emergent system.”
Measuring Progress

Spectrum of Life and Intelligence
Graduated Intelligence

• Darwin wrote (The Descent of Man, and Selection in Relation to Sex 1871, 1927, 1936)

“If no organic being excepting man had possessed any mental power, or if his powers had been of a wholly different nature from those of the lower animals, then we should never have been able to convince ourselves that our high faculties had been gradually developed. But it can be shewn that there is no fundamental difference of this kind. We must also admit that there is a much wider interval in mental power between one of the lowest fishes, as a lamprey or lancelet, and one of the higher apes, than between an ape and a man; yet this interval is filled up by numberless gradations.”
Graduated Intelligence

• “A conservative hypothesis: ‘Sentience’ comes in every imaginable grade or intensity, from the simplest and most ‘robotic’, to the most exquisitely sensitive, hyper-reactive ‘human’.” — Dennett (Kinds of Minds)

• Tononi (BMC Neuroscience 2004) discussing a quantitative theory of consciousness based on his information-theoretic Phi:
  - “It also follows that consciousness is not an all-or-none property, but it is graded: to varying degrees, it should exist in most natural (and artificial) systems.”
“The existence of quantitative measures of relevant complexity, however preliminary they may be, raises the important issue of identifying the ranges of values that would be consistent with consciousness. ... it may then become possible to define a measurement scale for a proposed measure of relevant complexity by establishing a value for a known conscious system (for example, an awake human) and a value for a known nonconscious system (for example, the same human during dreamless sleep).”
Spectrum of Intelligence

- Laboratory evidence exists for self-awareness in humans, chimpanzees, orangutans, and elephants.
- Koko the gorilla, Washoe the chimp, and Kanzi the bonobo ape all demonstrate language skills comprehensible to humans.
- Alex the parrot demonstrates language skills comprehensible to humans.
- Betty the crow demonstrates tool creation.
- Various simians and birds in the wild demonstrate tool use and creation.
- Scrub-jays project their own behaviors onto that of conspecifics (exhibit a “theory of mind”) and demonstrate planning for the future.
Spectrum of Intelligence

- Honeybees, with 1M neurons, interpolate visual information, exhibit associative recall, categorize visual information, learn contextual information, and demonstrate the ability to learn the abstract concepts same and different
- Fruit flies, with 250K neurons, learn by association, have short-term, medium-term, and long-term memories, with a short-term working memory of about 5 seconds (comparable to pigeons and other bird species), respond to anesthesia at comparable doses and with progressive loss of brain function like humans, and exhibit a salience mechanism with much in common with the human attention mechanism
- Even with only about 10K neurons, Aplysia californica demonstrates sensitization, habituation, classical, and operant conditioning
Not affiliated with...
What Polyworld Is

• An electronic primordial soup experiment
  • Why do we get science, instead of ratatouille?
    - Right ingredients in the right pot under the right conditions
• An attempt to approach artificial intelligence the way natural intelligence emerged:
  • Through the evolution of nervous systems in an ecology
• An opportunity to work our way up through the intelligence spectrum
• Tool for evolutionary biology, behavioral ecology, cognitive science
What Polyworld Is Not

- Fully open ended
  - Even natural evolution is limited by physics (and previous successes)
- Accurate model of microbiology
- Accurate model of any particular ecology
  - Though it is possible to model specific ecologies
- Accurate model of any particular organism’s brain
  - Though many neural models are possible
- A strong model of ontogeny
Polyworld Overview

• Computational ecology
• Organisms have genetic structure and evolve over time
• Organisms have simulated physiologies and metabolisms
• Organisms have neural network “brains”
  • Control all behaviors
  • Arbitrary, evolved neural architectures
  • Hebbian learning at synapses
• Organisms perceive their environment through vision
• Fitness is determined by Natural Selection alone
  • Bootstrap “online GA” if required
Genetics: Physiology Genes

- Size
- Strength
- Maximum speed
- Mutation rate
- Number of crossover points
- Lifespan
- Fraction of energy to offspring
- ID (mapped to body’s green color component)
Genetics: Neurophysiology Genes

- # of neurons for red component of vision
- # of neurons for green component of vision
- # of neurons for blue component of vision
- # of internal neuronal groups
- # of excitatory neurons per group
- # of inhibitory neurons per group
- Initial bias of neurons per group
- Bias learning rate per group
- Connection density per pair of groups & types
- Topological distortion per pair of groups & types
- Learning rate per pair of groups & types
Neural Architectures for Controlling Behavior using Vision

Input Units

Processing Units

Energy

Random

Move

Turn

Eat

Mate

Fight

Light

Focus
Neural Development

• Generative statistical model may be thought of as capturing the end result of a development process
• Same genetic code may produce multiple distinct phenotypes
• Synaptic weights initialized randomly
• 25 time steps of random noise provided as input to vision system to allow some self-organization (before being placed into the world)
Physiology and Metabolism

- Energy is expended by behavior & neural activity
- Size and strength affect behavioral energy costs (and energy costs to opponent when attacking)
- Neural complexity affects mental energy costs
- Size affects maximum energy capacity
- Energy is replenished by eating food (or other organisms)
- Health energy is distinct from Food-Value energy
- Body is scaled by size and maximum speed
Perception: Neural System Inputs

- Vision
- Internal energy store
- Random noise
Behavior: Neural System Outputs

- Primitive behaviors controlled by single neuron
  - “Volition” is level of activation of relevant neuron
- Move
- Turn
- Eat
- Mate (mapped to body’s blue color component)
- Fight (mapped to body’s red color component)
- Light
- Focus
Behavior Sample: Eating
Behavior Sample: Mating
Behavior Sample: Lighting
Neural System: Internal Units

- No prescribed function
  - Neurons
  - Synaptic connections
Evolving Neural Architectures
Neural System: Learning and Dynamics

- Firing-rate / summing-and-squashing neuron model
  
  \[ x_i = \sum_j a_j^t s_{ij}^t \]
  
  \[ a_i^{t+1} = \frac{1}{1 + e^{-x_i}} \]

- Hebbian learning
  
  \[ s_{ij}^{t+1} = s_{ij}^t + \eta_{kl}^c (a_i^{t+1} - 0.5)(a_j^t - 0.5) \]

  \( s_{ij}^t \) = synaptic efficacy from neuron \( j \) to neuron \( i \) at time \( t \)

  \( a_i^t \) = neuronal activation of neuron \( i \) at time \( t \)

  \( \eta_{kl}^c \) = learning rate for connection of type \( c \) (e-e, e-i, i-e, or i-i) from cluster \( l \) to cluster \( k \)
Neural Dynamics
Emergent Species: “Joggers”
Emergent Species: "Indolent Cannibals"
Emergent Species: “Edge-runners”
Emergent Species: “Dervishes”
Emergent Behavior: Visual Response
Emergent Behavior: Fleeing Attack
Emergent Behaviors:
Foraging, Grazing, Swarming
Ideal Free Distribution in agents with evolved neural architectures.
Ideal Free Distribution in agents with evolved neural architectures
Is It Alive? Ask Farmer & Belin...

- “Life is a pattern in spacetime, rather than a specific material object.”
- “Self-reproduction.”
- “Information storage of a self-representation.”
- “A metabolism.”
- “Functional interactions with the environment.”
- “Interdependence of parts.”
- “Stability under perturbations.”
- “The ability to evolve.”
Information Is What Matters

• "Life is a pattern in spacetime, rather than a specific material object." - Farmer & Belin (ALife II, 1990)
• Schrödinger speaks of life being characterized by and feeding on “negative entropy” (What Is Life? 1944)
• Von Neumann describes brain activity in terms of information flow (The Computer and the Brain, Silliman Lectures, 1958)
• Physicist Edwin T. Jaynes identifies a direct connection between Shannon entropy and physical entropy in 1957
• James Avery's Information Theory and Evolution (2003): Information storage transiently and locally defeats 2nd law of thermodynamics, and is typical of life
• Informational functionalism
  • It's the process, not the substrate
  • What can information theory tell us about living, intelligent processes...
Energy -> Information -> Life

- In 1957 physicist Edwin T. Jaynes pointed out the direct connection between Shannon entropy and physical entropy.

- Ludwig Boltzmann’s grave is embossed with his equation:
  \[ S = k \log W \]
  Entropy = Boltzmann’s-constant
  * \( \log( \text{function of \# of possible micro-states} ) \)

- Claude E. Shannon’s famous measure of information (or uncertainty or entropy) can be written:
  \[ I = K \log \Omega \]
  Entropy = constant (usually dropped)
  * \( \log( \text{function of \# of possible micro-states} ) \)
Energy -> Information -> Life

• John Avery (Information Theory and Evolution) related physical entropy to informational entropy as
  
  \[ 1 \text{ electron volt} / \text{kelvin} = 16,743 \text{ bits} \]

• So converting one electron-volt of energy into heat, at room temperature will produce an entropy change of
  
  \[ 1 \text{ electron volt} / 298.15 \text{ kelvin} = 56.157 \text{ bits} \]

• Thus energy, such as that which washes over the Earth from the Sun, can be seen as providing a constant flow of
  not just “free energy”, but free information

• Living systems take advantage of, and encode this information, temporarily and locally reducing the conversion of energy into entropy
Information and Complexity

• Chris Langton’s “lambda” parameter (ALife II)
  • Complexity = length of transients
  • $\lambda = \#\text{ rules leading to nonquiescent state} / \#\text{ rules}$

Wolfram's CA classes:
- I = Fixed
- II = Periodic
- III = Chaotic
- IV = Complex

• Crutchfield: Similar results measuring complexity of finite state machines needed to recognize binary strings
• Tononi, Sporns, Edelman: Similar results measuring complexity of dynamics in artificial neural networks
“What clashes here of wills gen wonts, oyster gods gaggin fishy gods! Brékke Kékké Kékké! Kóax Kóax Kóax! Ualu Ualu Ualu! Quáouauh!”

“Happy families are all alike; every unhappy family is unhappy in its own way.”

“All work and no play makes Jack a dull boy. All work and no play makes Jack a dull boy. All work and no play makes Jack a dull boy.”

“Randomness, no structure at any level. Non-repeating structure at multiple levels. Identical structure at all levels.”

Reference:

Reference:
Integration

Integration measures the statistical dependence among all elements \( \{x_i\} \) of a system \( X \).

\[
I(X) = \sum_{i=1}^{n} H\{x_i\} - H(X)
\]

\( H\{x_i\} \) is the entropy of the \( i^{th} \) individual element \( x_i \)

\( H(X) \) is the joint entropy of the entire system \( X \)

Note, \( I(X) \geq 0 \).
Note, \( I(X) = 0 \) if all elements are statistically independent

Any amount of structure (i.e. connections) within the system will reduce the joint entropy \( H(X) \) and thus yield positive integration.

\[MI(x_1, x_2) = H(x_1) + H(x_2) - H(x_1x_2)\]

Tononi, Sporns, Edelman, PNAS (1994)
Information and Complexity

- **Complexity**, as expressed in terms of the ensemble average of integration (structure) at all levels:

\[
C_N(X) = \sum_{k=1}^{n} \left[ \frac{k}{n} I(X) - \langle I(X_k) \rangle \right] = \sum_{k=1}^{n/2} \langle MI(X_k; X-X_k) \rangle
\]

- **Functional Segregation**

- **Functional Integration**

**Graphical representation:**

- I(X) – total integration

- Subset size (level) k

- Functional Segregation

- Functional Integration

*Tononi, Sporns, Edelman, PNAS (1994)*
Simpler Complexity

\[ C_n(X) = \sum_{k=1}^{n} \left[ \frac{k}{n} I(X) - \langle I(X_k) \rangle \right] \]

\[ C(X) = H(X) - \sum_i H(x_i | X-x_i) = \sum_i MI(x_i, X-x_i) - I(X) = (n-1)I(X) - n \langle I(X-x_i) \rangle \]
Quantifying Life and Intelligence

• Measure state and compute complexity

• What complexity?
  • Mutual Information
  • Sporns’s functional complexity
  • Tononi’s Phi
  • Adami’s “physical” complexity
  • Gell-Mann & Lloyd’s “effective” complexity

• What state?
  • Chemical composition
  • Electrical charge
  • Aspects of behavior or structure
  • Neuronal states

• Other issues
  • Scale, normalization, sparse data
Information Metrics: Entropy
Information Metrics: Mutual Information

C, D, E: Plots showing mutual information over time steps.
Information Metrics: Integration & Complexity
Is there an evolutionary “arrow of complexity”?


- No - Williams, Lewontin, Levins, Slobodkin, Gould, McShea

Carroll (2001)  
Gould (1994)
Natural and Artificial Trends in Complexity

- Bedau (et al. 1997, Rechsteiner and Bedau 1999) provides evidence of an increasing and accelerating “evolutionary activity” in biological systems not yet demonstrated in artificial life models.

- Turney (1999) uses a simple evolutionary model to suggest that evolvability is central to progress in evolution, and predicts an accelerating increase in biological systems.

- Adami (2000, 2002) defines complexity as the information that an organism’s genome encodes about its environment and demonstrates that asexual agents in a fixed, single niche evolve towards greater complexity.
Sources of Complexity Growth

- Rensch (1960a,b; Bonner 1988) argued that more parts will allow a greater division of labor among parts.

- Waddington (1969; Arthur 1994; Knoll and Bombach 2000) suggested that due to increasing diversity niches become more complex, and are then filled with more complex organisms.

- Saunders and Ho (1976; Katz 1987) claim component additions are more likely than deletions, because additions are less likely to disrupt normal function.

What Kind of Complexity?

- McShea (1996) observes that loose and shifting definitions of complexity allow sloppy reasoning and highly suspect conclusions about evolutionary trends.
- Identifies four distinct categories of complexity:
  - Number of different parts (genes, cells, organs)
  - Number of different interactions between parts
  - Number of hierarchical levels
  - Number of parts or interactions at a given scale
- Suggests there may be upper limits to complexity.
- Discusses (limited) evidence for increases in number of cell types, arthropod limb types, and vertebrae sizes.
- Acknowledges complexity of human brain, but otherwise ignores nervous systems.
- Distinguishes driven vs. passive trends, using changes in minimum values and ancestor-descendent differences.
Driven or Passive?

• Original experiments did not address the distinction between driven and passive sources of complexity
  • Established ability to compute neural complexity of Polyworld agents
  • Demonstrated increase in complexity as evolution proceeds
• Current experiments directly assess driven vs. passive contributions to complexity resulting from natural selection
Natural Selection vs. Random Drift

• By default Polyworld agents are subject to natural selection
  • Genes are passed on as a direct result of success at survival and reproduction
• Goal: Produce a random drift of agent genes in Polyworld in a simulation that is directly comparable to a standard, natural selection run
  • Same initial conditions
  • Same population statistics
    - Same statistics for genetic mutations and crossover operations
Eliminating Natural Selection

- Run standard simulation, logging all births and deaths
- Run random-drift simulation, with following conditions:
  - Use identical initial conditions
  - Eliminate behaviorally generated births and deaths
  - At each time step, for every birth in the standard run, select two parents at random and produce their offspring
    - Deposit the offspring at a random location
  - At each time step, for every death in the standard run, select one agent at random and kill it
- Produces identical statistics for population genetics and comparable visual inputs (“life experiences”) to agents in the two simulations
- Natural selection no longer affects gene histories
Driven vs. Passive Mean Complexity
Driven vs. Passive Max Complexity
Genetic Similarity

Genetic consistency over time

Admix Complexity (bits)

Timestep
Complexity Histogram Over Time - Passive
Complexity Histogram Over Time - Driven
Conclusions

• Evolution selects FOR a complexity increase when it enhances the ability to survive and reproduce.
• Evolution selects mildly AGAINST a complexity increase when existing characteristics are “good enough”
  • Though not shown by these experiments, evolution is known to select AGAINST unneeded but costly complexity.
• At the level of species, evolution of complexity is almost always driven
  • Just not in a single direction.
• Integrating these opposing tendencies over the history of life, may appear passive
  • But ever-increasing “ecospace” may provide an overarching drive towards complexity as well.
• Conflicting evidence for complexity growth in the biological record is to be expected.
• Seemingly conflicting intuitions about a clear evolution of complexity in the paleontological record vs., for example, the longevity of the cockroach and its extreme suitability to its ecological niche are not actually in conflict.
Speculation

• Though current experiments effectively explore complexity dynamics only in a single niche, for hardly more than a single species...

  • Multiple niches, niche creation, and potential arms races associated with competition within a niche are all likely to confer an evolutionary advantage on at least some complexity increases

  • Inherently more complex niches will require greater biological complexity
    - All niches are not created equal

• Increasing the complexity of Polyworld’s ecology—the range of organism-environment interactions and available niches—will allow a measurable selection towards greater neural complexity
Future Directions

• Explore use of complexity measure as fitness function

• More environmental interaction
  • Pick up and put down
    - Pieces of food
    - Pieces of barrier
    - Other agents

• More complex environment
  • More control over more organic food growth patterns
  • Multiple food types

• Additional senses (definitely touch, perhaps smell)
• More complex, spiking neural models
• Assess progress by routinely measuring complexity
Future Directions

• Behavioral Ecology benchmarks
  • Optimal foraging (profitability vs. predation risk)
  • Patch selection/depletion (Ideal Free Distribution)
  • Vancouver whale populations
• Evolutionary Biology problems
  • Speciation = f (population isolation)
  • Altruism = f (genetic similarity)
• Classical conditioning, intelligence assessment experiments
Future Directions

• Source code is available for Mac/Windows/Linux (on Qt) at http://sourceforge.net/projects/polyworld/

• Papers and other materials at http://beanblossom.in.us/larryy/Polyworld.html