Computational Genetics, Physiology, Metabolism, Neural Systems, Learning, Vision, and Behavior

or

PolyWorld: Life in a New Context

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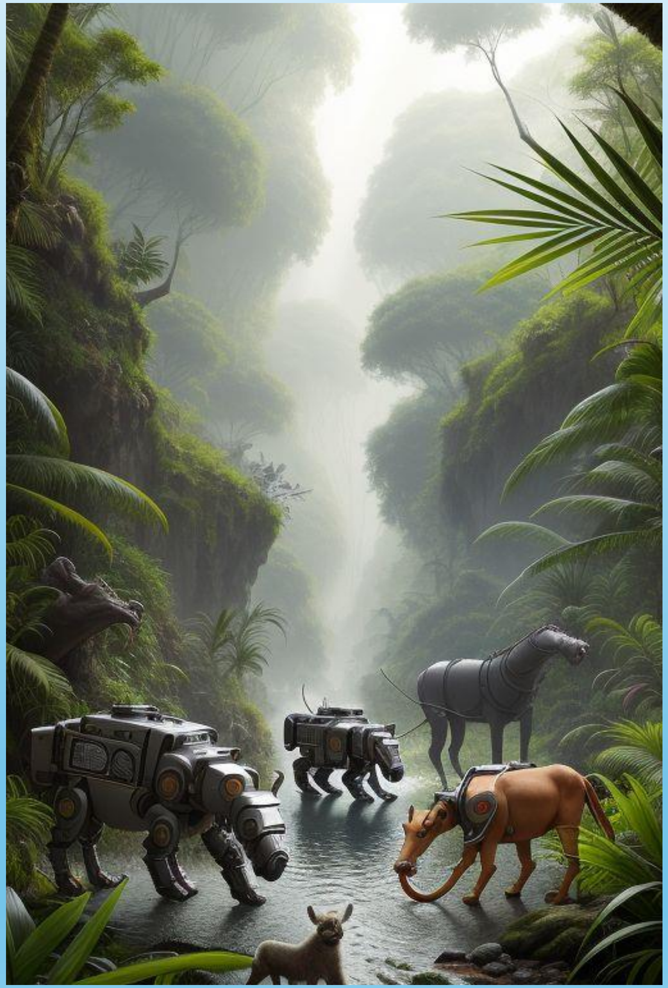


Introduction (1/2)

- Usually, the study of life takes place in the real biological world.
  - Recently, a new field of “artificial life” has emerged, the study of lifelike systems simulated in computers and robots

- This paper discusses a computer model of living organisms and their ecology, called *PolyWorld (PW)*. It is an attempt to bring together all the principle components of real living systems into one single computer system. These include:
  - Genetics
  - Simple Physiologies and Metabolisms
  - Hebbian learning in arbitrary neural network architectures
  - Visual perception
  - A suite of primitive behaviors grounded in the ecology, just complex enough for speciation and inter-species competition
  - Predation, mimicry, sexual reproduction, and social communication are all supported

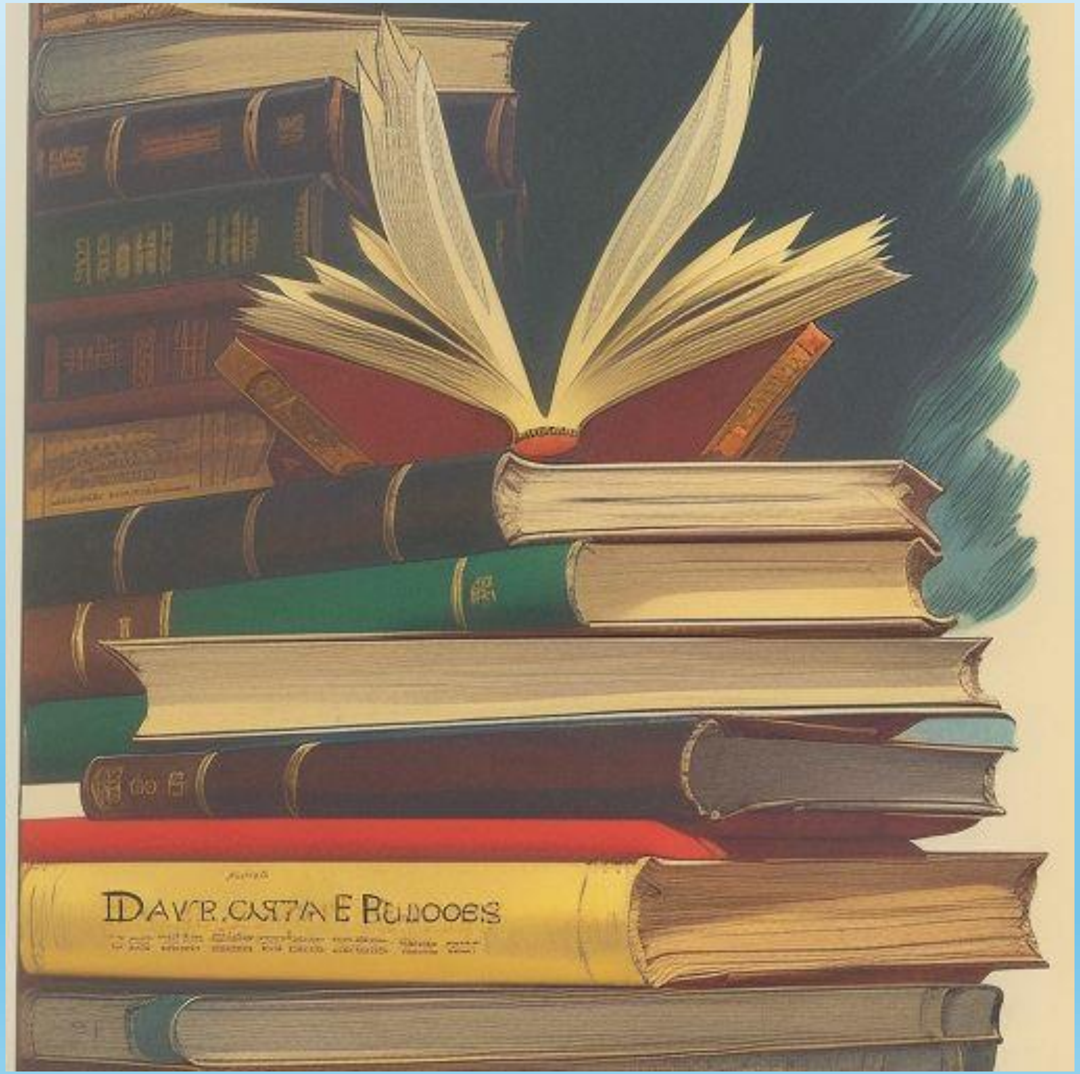
- The resulting survival strategies of the artificial animals, and species, are emergent, due to natural selection and the evolution of neural networks.

Introduction (2/2)

- This is like a “primordial soup” experiment, just starting at a higher level of organization: software-coded genetics and artificial neuron cells.
  - The experiment is to place these features in a competitive ecology, subject them to consistent physics and natural selection, then to observe what happens

- *PolyWorld* can serve as a tool for investigating issues related to evolutionary biology, behaviorial ecology, ethology, and neurophysiology. However, the original motivations were:
  1. To determine if it is possible to evoke complex ethological-level survival strategies and behaviors, without explicitly programming them
  2. To create artificial life that is as close as possible to real life, by combining as many critical components of real life as possible in an artificial system
  3. To begin exploring Artificial Life as a path towards Artificial Intelligence, utilizing the same key elements that led to natural intelligence: *the evolution of nervous systems inside an ecology*

Background



Background (1/5)

This work is inspired by the following works

- W. Grey Walter’s electronic “turtle” nervous system
- Valentino Braitenberg’s bottom-up synthesis-before-analysis approach to systems engineering, including evolutionary algorithm
- Richard Dawkin’s communications of the effectiveness of evolutionary dynamics, including the importance of speciation and reduced viability of divergent species interbreeding, both of which are important elements of *PolyWorld*
- Donald Hebb’s local learning rule for neural networks
- Ralph Linsker’s demonstration of using Hebb’s rule to develop self-organizing neural systems for vision. The results match the early visual systems of real organisms.
- John Pearson & Gerald Edelman using a variant of Hebbian learning and demonstrating important principles of neural/synaptic organization (cooperation and competition for representation) that correspond to phenomena in real organisms

PolyWorld uses the unsupervised Hebbian learning technique in arbitrary evolving neural architectures, then confronts the simulated neural network with survival tasks in a simulated ecology

Background (2/5)

- Conrad and Packer have built systems to explore evolutionary dynamics
- Jefferson et al and Collins have constructed systems dealing tih evolutionary mechanisms, behavorial goals, and learning architectures (Finite State Automata vs. neural networks)
- Taylor et al developed a system to investigate the relationship between individual behavior and population dynamics
- Ackley & Littman built a simulator to demonstrate how evolution can guide a learning mechanism
- Todd and Miller have explored evolutionary selection for different learning algorithms in organisms with simple vision systems and "smell" systems
- Hillis used simple computational ecologies to evolve "ramps" and sorting algorithms
- *Core Wars* is a non-evolving ecology of code fragments. Rasmussen's *VENUS* is an evolving system based on *Core Wars*
- Thomas Ray developed a computational ecology, *Tierra*, based on evolving code fragments
- John Koza developed a system for evolving LISP programs coined "Genetic Programming"

PolyWorld was initially meant to target evolution of neural networks for complex behavioral tasks. However, when considering the behaviors and reproduction strategies that emerged, it can also function as a study in behavioral ecology and evolutionary biology. It is distinguished from the previous ecological simulators by its fidelity to natural biological systems and unique use of a naturalistic visual perception system in the organisms

Background (3/5)

- John Holland's *ECHO* explicitly models predation, with "offense" and "defense" genes that determine the outcome of violent encounters. Holland noted this predation system was essential to the evolution of complex genomes.
  - Similarly, predation is an important aspect of *PolyWorld*; the genes influence violent encounters indirectly, via strength and size, which are used in real-time battles. There is also a behavioral component in *PW,* since the animats are not forced to fight but rather have volition over their violent behaviors, since they control the activation of the "fight" motor neuron.
- Belew et al review work in evolving neural networks, e.g., Harp et al who permit some ontogenetic development, more specifically evolving the synaptic projection radii between neuronal "areas".
  - Similarly, *PW* evolves connection densities and topological distortions of connections between neuronal groups, rather than connections themselves. This makes the neural representation more "developmental" and compact (i.e., indirect encoding) rather than storing every connection explicitly (direct encoding)
- David Chalmers has experimented with evolving supervised neural network learning algorithms, evolving the classic "delta rule" for linear, single layer perceptron. He also varies the diversity of learning tasks, demonstrates a correlation between task diversity and the generality of the evolved learning algorithm, similar to the correlation observed between size of training dataset and generalization in supervised "back-prop" neural networks
  - The author has a special interest in the evolution of unsupervised learning algorithms, though in *PW* a classic Hebb rule is hardcoded (with some of its coefficients evolved). The neural architectures are allowed to evolve. Since the organisms have free movement in a dynamic simulated environment, they will encounter nearly unlimited amount of diverse input for their neural mechanisms to process.

Background (4/5)

- Nolfi et al and Parisi et al have explored evolving connection weights in fixed-architecture feed-forward neural networks controlling simple movements. They are provided angle and distance to food items, and are alone in their environment. They also introduced a “self-supervised” learning technique using backpropagation; they demonstrated an improvement in *evolved* efficiency associated with a *learned* ability to predict sensory consequences of motor activity.
  - *PW* uses an unsupervised learning algorithm and arbitrary neural architectures. It has a more naturalistic vision mechanism and the organisms live together in a competitive ecology
- Renault et al have used visual systems to control computer-generated characters for computer graphics animation. The “vision” uniquely identifies objects and distances to them; the control programs are rule-based and entirely hand-crafted.
  - In contrast, *PW* uses only pixel colors for vision, providing them as input to the non-rule-based neural systems of evolving organisms, without specifying the meaning or use of the information
- Dave Cliff has implemented a neural visual system for a simulated fly. The fly is attached to an unmoving rotating test stand.
  - Organisms in *PW* use vision, but are free to explore their environment, and must use vision to guide their behaviors to survive and reproduce

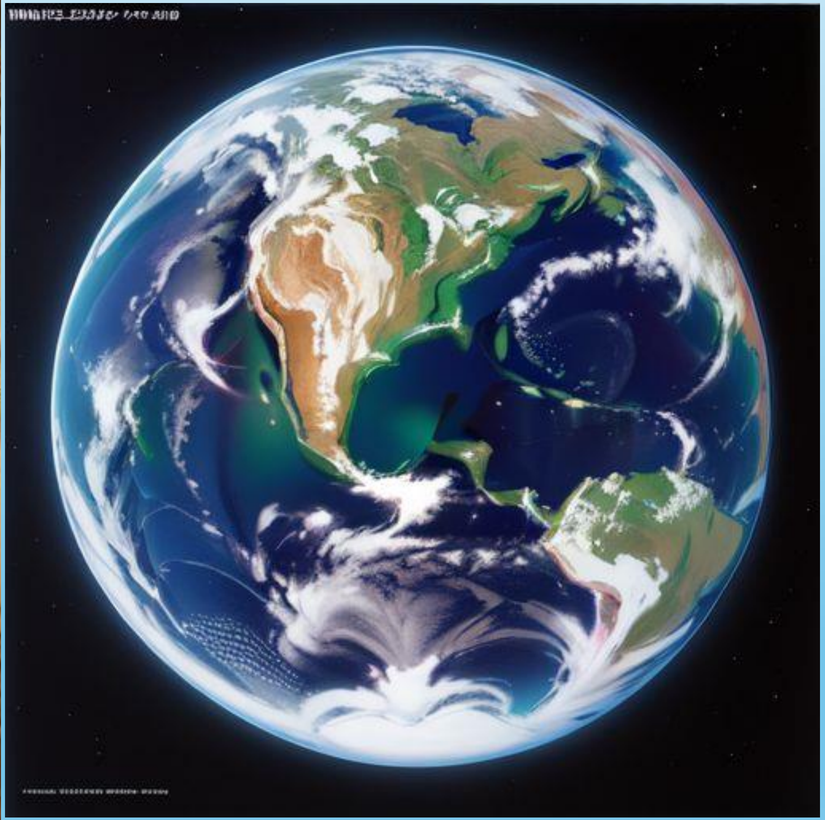
Background (5/5)

- When designing an artificial life experiment, you must first make a decision about the **scale:**
  - what level of detail is desirable (or necessary) for the parameters of the underlying simulation models?
  - At what level does one wish to observe the behaviors?

- In real life, the study of living systems spans from the molecular level, of biochemical processes occurring in nanoseconds, through to the cellular level, such as neural processes in milliseconds, all the way up to global evolutionary processes in geological time scales

- Our current level of computing power does not permit us to start with the simulation of atomic physics, as we might desire. The models of *PW* were meant to allow observing ethological (i.e., animal) behavior, thus the decision was made to model at the **neural level**.

Overview



Overview (1/2)

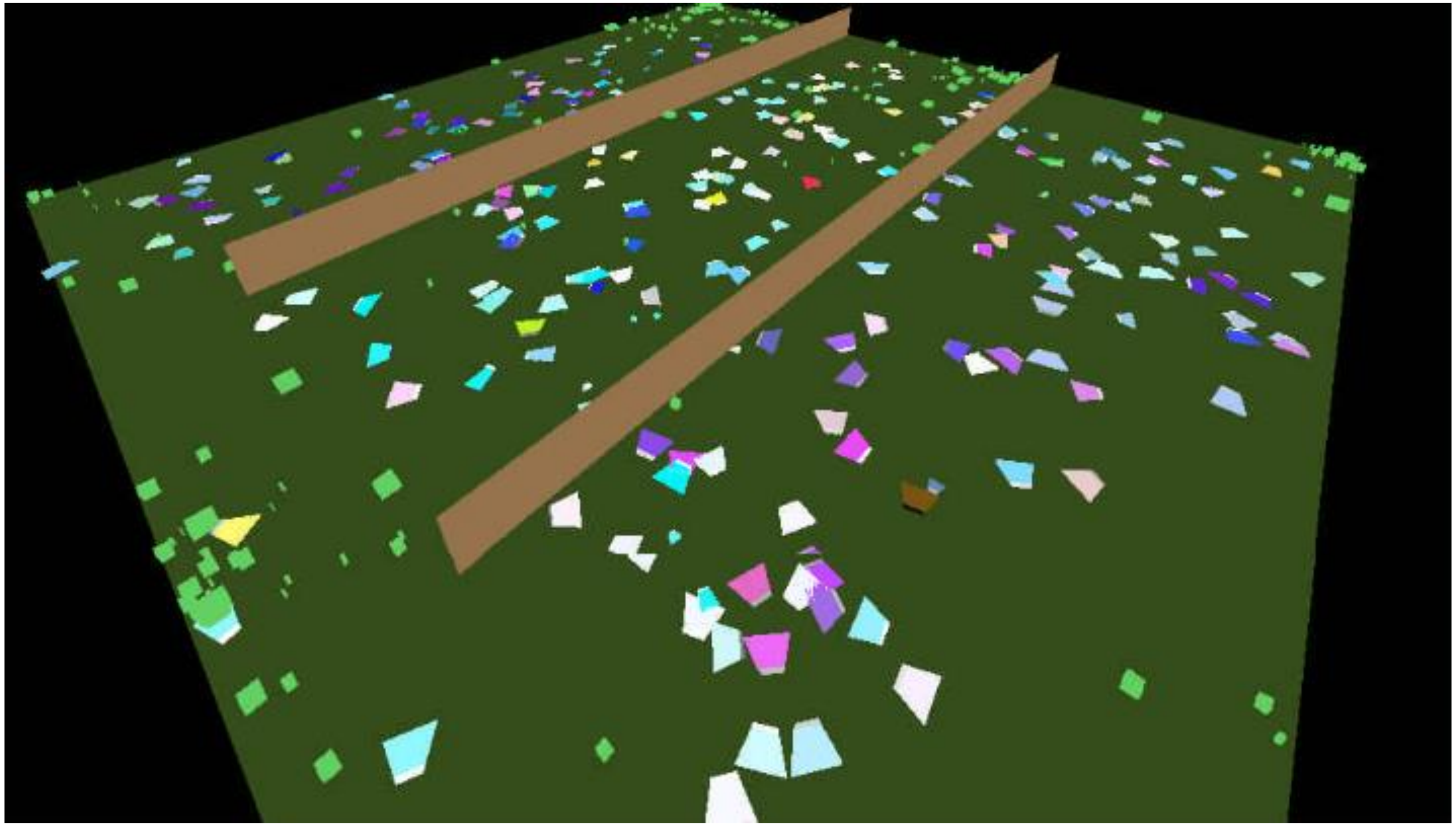
- *PolyWorld* is an ecological simulator of a simple flat world
  - It contains some **barriers** and growing **food**
  - The organisms in the world use **RGB vision** as sensory input. Their neural networks use **Hebbian Learning**. The outputs drive behavior.
  - The organisms are represented by **simple polygon shapes**

- While the **sensory neurons can evolve**, the number of motor neurons are predetermined. There are 7 motor actions (forward, eat, mate, etc.).
  - Organisms expend “energy” with each motor action, and neural activity. They must replenish energy by eating food.
  - There is a *fighting* action, which allows organisms to damage/kill each other. A dead organism’s carcass turns to food, which replenishes energy. So, predation is naturally modeled.

- An organism’s physiology, metabolism, and neural network are determined from its genes. When 2 organisms spatially overlap, they can sexually reproduce if **both** organisms express the *mating* action.

Overview

- A screenshot of *PolyWorld*



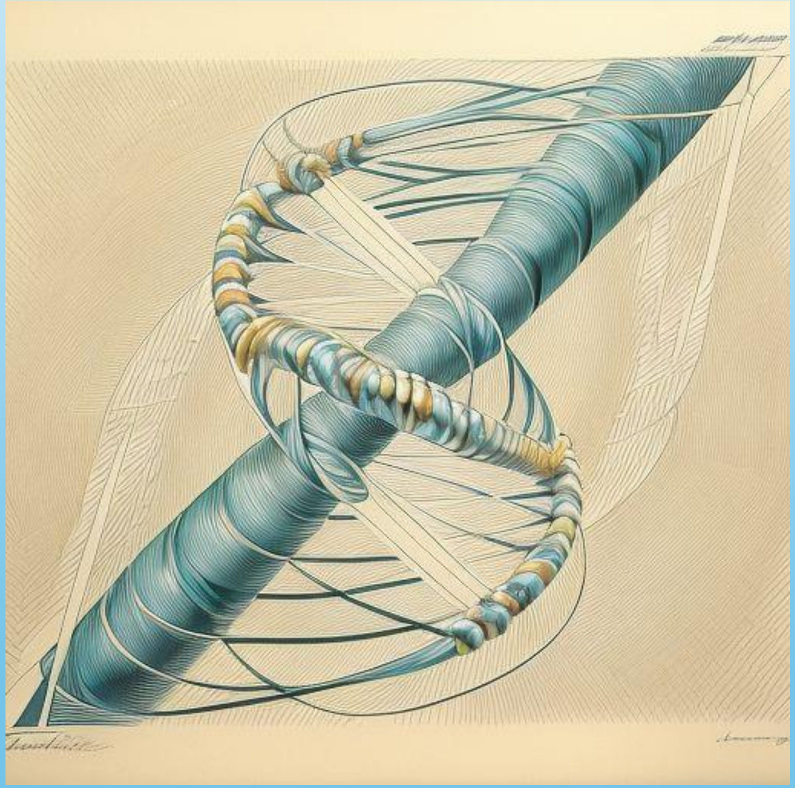
Overview (2/2)

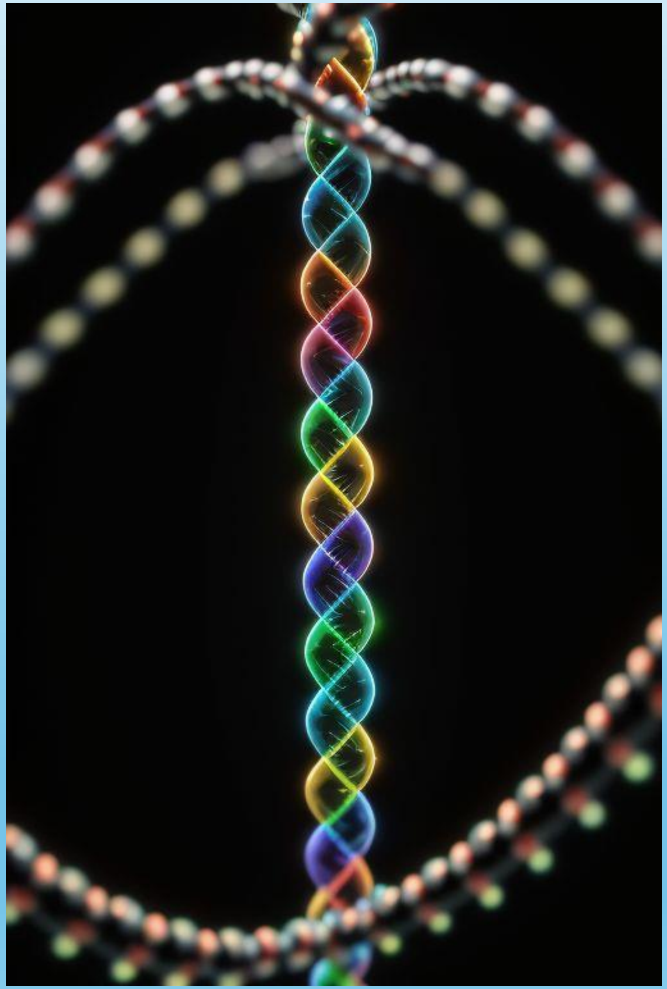
- One way to look at the artificial world is as an **energy balancing problem**.
  - The fittest organism is the one that is best able to replenish its energy by eating food and passing on its genes by mating.
  - The particular activities that the successful organism engages in will be optimal for some particular fitness landscape. The fitness landscape depends on the behavior of the other inhabitants of the world, so it is **dynamic/changing**.
  - Due to the variation of food placement and organism behavior in the world, **the fitness landscape is fundamentally stochastic**. In this way, each world has the potential to be different from other worlds.

- The initial population of organisms is random, so they will not survive/reproduce very well. Until the population evolves to become self-sustaining via reproduction, PW runs an "**on-line genetic algorithm**" to ensure a **minimum number of organisms inhabit the world at any given point**.
  - The fittest organisms are kept in a data structure, and reproduced to "create" new organisms. Random new organisms can also be "created"
  - When population of organisms behave so as to replenish their numbers via "births", they are said to have evolved a "**Successful Behavior Strategy**" (**SBS**), or simply to be "successful". After this point, no new "created" organisms are required, unless the SBS becomes somehow suddenly extincted.

- PW can run at most **300 organisms** with **200 neurons** each. It requires **13 seconds per time step**. An organism had a lifespan on average of about 500 time steps, and took about 100 time steps to produce its first offspring. This allows approx. 500 generations of organisms per week.
  - With only 100 organisms, it only requires about 4 seconds per timestep. With even less organisms, the world can be run in "real-time", at a few frames per second, which is a much more interactive experience for the human user

Genetics





Genetics (1/4)

- An organism's genes encode its physiology (first 8 genes) and neural architecture(the rest). The genes are:

  - size
  - strength
  - maximum speed
  - ID (green coloration)
  - mutation rate
  - number of crossover points
  - life span
  - fraction of energy to offspring
  - number of neurons devoted to red component of vision
  - number of neurons devoted to green component of vision
  - number of neurons devoted to blue component of vision
  - number of internal neuronal groups
  - number of excitatory neurons in each internal neuronal group
  - number of inhibitory neurons in each internal neuronal group
  - initial bias of neurons in each non-input neuronal group
  - bias learning rate for each non-input neuronal group
  - connection density between all pairs of neuronal groups and neuron types
  - topological distortion between all pairs of neuronal groups and neuron types
  - learning rate between all pairs of neuronal groups and neuron types

Table 1. List of genes in organisms of PolyWorld.

- All genes are 8 bits in length. They provide 8 bits of precision between a minimum and maximum value. Extrema values are in the config file. For example, to determine organism size:

  size = minSize + valSizeGene * (maxSize – minSize)

Genetics (2/4)

Physiology genes:

- Size and strength affect the rate at which the organism spends energy and the outcome of fights with other organisms. The sizeis related directly to the maximum energy that can be stored internally. Maximum speed affects metabolic rate.
- The ID gene provides a green color to the organism. Theoretically organisms can see each other, and this may help them differentiate between species (though such complex behavior was not observed)
- Mutation rate determined # of crossover points during reproduction. This, plus maximum lifespan, were meant to permit a meta-level genetics, since these are evolved in natural systems. They are still constrained within reasonable limits (with 1% to 10% mutation rate)
- The final physiology gene controls the fraction of an organism's remaining energy that it will donate to its offspring upon birth. The offspring gets energy from both parents.

Genetics (3/4)

<u>Neural architecture genes:</u>

- The motivations for this encoding was the minimize the number of genes necessary to specify a neural system. Older models used a matrix encoding which was highly inefficient. (for the specifics see the paper)
  - The old method, for N (200) neurons, required N^2 (40,000) genes
  - The new method, for 185 neurons, only required 2,146 genes
  - Since the neural genes greatly outnumber physiology, one crossover point was forced to occur in the physiology genes, otherwise they would be neglected
- A neural genome looks like this:

An organism's genome is allocated and interpreted such that space is available for the maximum possible number of neuronal groups. That is, one of the parameters specified per pair of groups in a network with 3 groups out of a maximum of 5 groups would be accessed as:

1,1 1,2 1,3 -- -- 2,1 2,2 2,3 -- -- 3,1 3,2 3,3 -- --

where the entries marked "--" serve simply as place holders. This is as opposed to an access scheme looking like:

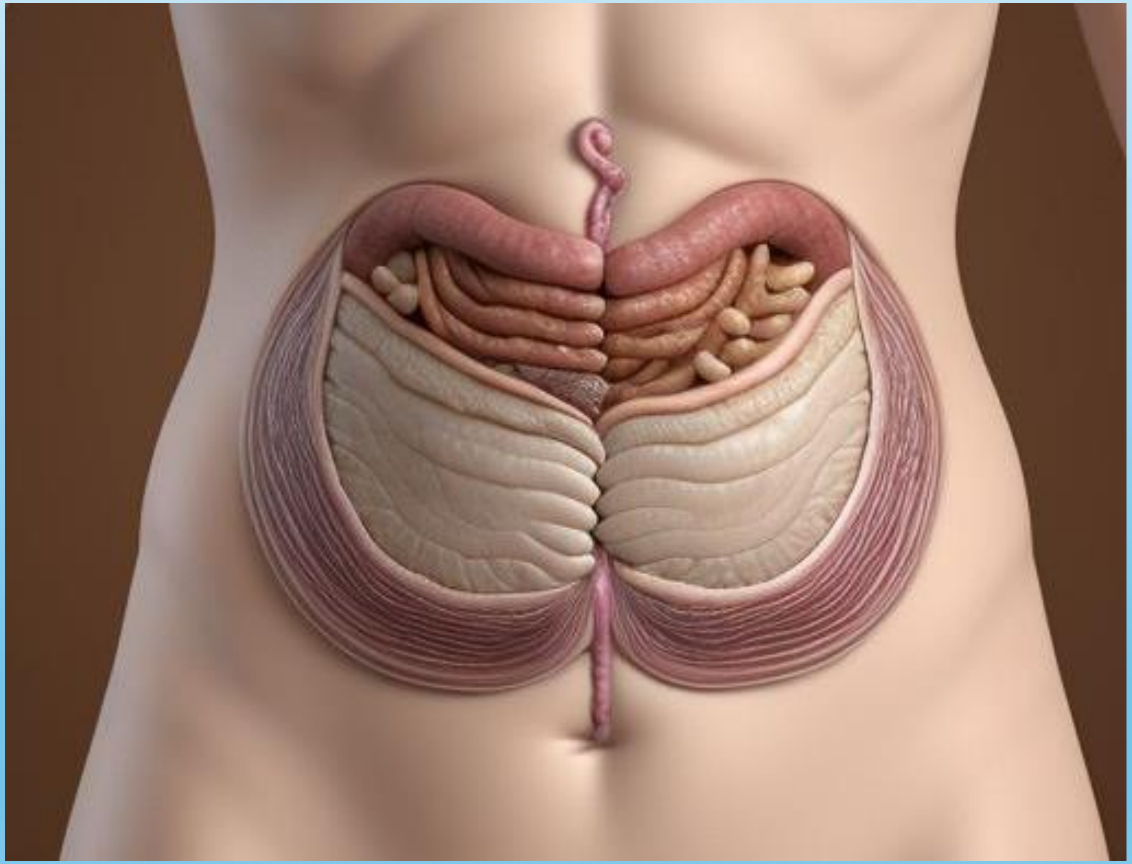
1,1 1,2 1,3 2,1 2,2 2,3 3,1 3,2 3,3

where the entries are contiguous. The reason for this is to permit a smoother evolution of these neural architectures. The addition of a fourth group would leave the old connections intact in the first representation, but not in the second. It is even possible for a useful sub-component of the architecture to ride along dormant in the genes to be expressed at a later time.

Genetics (4/4)

- When an organism is created from scratch, the bits in its genes are zeroed, then turned on with certain bit probability.
  - Unlike most GA's, the probability is not 0.5. The probability is randomly selected from a range (e.g., [0.0,1.0]) for a given organism.
  - The probability of a bit being on within a member of the population is the mean of this range (e.g., 0.5). "This permits a wider variance in local, organism-specific bit probability in early populations, rather than depending entirely on mutation and cross-over to shuffle the bits".
  - It was felt that neural architectures resulting form lower bit densities would be more fit/useful. This mechanism helped explore a range of possibilities.
- There is an optional "miscegenation function" that probabilistically changes the chances for genetically dissimilar organisms to successfully reproduce. (i.e., higher dissimilarity leads to lower chance for viable offspring).
  - In practice, the author does not turn on this function until evolution has progressed significantly, so as to allow as many gene combinations as possible to achieve SBS.

Physiology and Metabolism



Physiology and Metabolism (1/2)

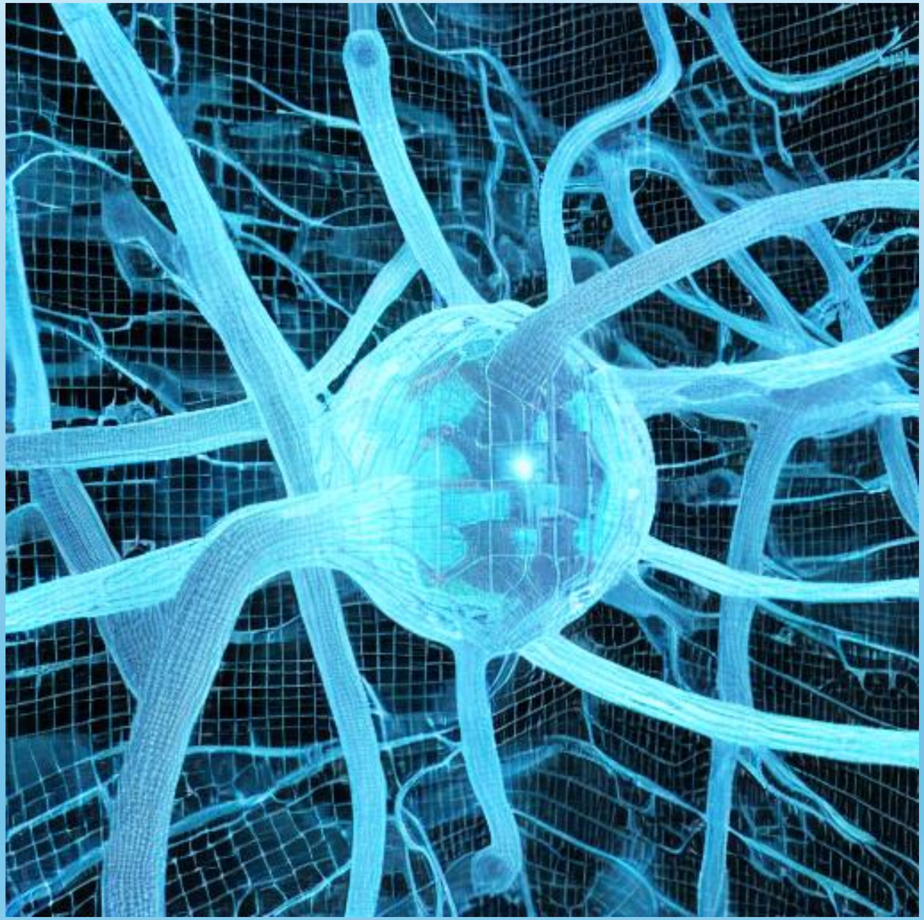
- An organism's *size* determines the maximum amount of energy it can store, and the amount of energy it expends during forward/turning movement. If it can range between minSize and maxSize, and energy capacity ranges from minECap to maxECap, the actual energy capacity is:

  ECap = minECap + (size – minSize) * (maxECap-minECap)/(maxSize-minSize)
  (i.e., if an organism is x% through the size range, it will also be x% through the energy capacity range)
- An organism's *strength* affects its energy expenditure and advantage in a fight. Strength ranges from approx. [0.5,2.0], and directly scales the total energy used in a time step. It also scales the victim's energy loss during a fight.
- Energy expended by an organism's brain is determined linearly by the number of neurons and synapses. They are computed relative to the maximum limit of neurons/synapses allowed in a brain. There are 2 conversion factors (neuron-to-energy and synapse-to-energy) which multiply these counts to determine energy expended per time step.
- Similarly, there are behavior-to-energy conversion factors for each primitive behavior. The total energy expended in a timestep by it is equal to the activation value(in [0,1]) of the behavior/motor neuron.
- Overall, the total energy expenditure is:
  - the sum of behavior energy, plus the neural energy, plus a configurable constant energy drain, all scaled by strength.

Physiology and Metabolism (2/2)

- This setup enabled energy conservation benefits for being small and weak, and predatory advantages to being large and strong. A larger size also allows a larger energy capacity, which makes that energy available for other behavioral activity, including reproduction.
  - The interplay between opposing advantages was intended to produce niches in the fitness landscape, which can change over time.
  - Similarly, there are opposing pressures between energy expenditure and number of neurons.
- There are **two** types of energy storage in an organism: health-energy and food-value-energy.
  - Both are replenished by eating food
  - Both are depleted by neural activity and behaviors
  - Only health-energy is impacted when an organism is attacked
- When an organism's health-energy reaches zero, it dies.
  - Upon death, it is converted into a piece of food containing energy equal to the organism's remaining food-value-energy.
  - By separating health and food energy, the predator-prey interactions become more natural, since an organism can be killed (zero health-energy) while providing lots of nutrition for the attacker (high food-value-energy)
- For aesthetic purposes, an organism's length and width are scaled by its maximum speed (length is multiplied, width is divided), so that faster organisms appear long and sleek, while slower organisms are short and bulky.
  - Theoretically, since visual acuity can evolve, organisms might come to identify another organism's shape and use that to infer its speed.

Neural systems and Learning



Neural systems and Learning (1/3)

- The brain has 3 inputs:
  - RGB vision
  - Internal health-energy store
  - A random value

- The brain has 7 outputs, corresponding to the 7 primitive behaviors
  - Eating
  - Mating
  - Fighting
  - Moving
  - Turning
  - Focusing
  - Lighting

- The hidden neurons have hidden meaning as determined by evolution

- The brain is characterized by parameters specified in the genes. For example, the number of neurons for each color component of RGB vision is separately specified, so that evolution can change the spatial resolution of each color (between1-16 allowed).

Neural systems and Learning (2/3)

- Parameters specify the number of internal neural **groups** (usually 1-5 groups). These are in addition to the 5 input groups and 7 output groups.

- Each neural **group** has excitatory (e-) and inhibitory (i-) neurons. The number of each are specified per-group, between 1-16 neurons of each type.
  - Synaptic connections from e-neurons are always excitatory, from [0,max_weight], whereas connections from i-neurons are always inhibitory, from [-max_weight, -1e-10].

- The bias on each non-sensory neuron changes by a Hebbian learning rule (as though it were a connection coming from an always fully-activated [1.0] neuron).
  - The initial values of bias (between [-1,1]) and bias learning rates (between [0,0.2]) were specified per-group.
  - Unlike other connections in the network, bias is allowed to change sign

- The remaining parameters are specified for each pair of neural groups *and* neuron types. The parameters are connection density (CD), topological distortion (TD), and learning rate (LR).
  - For each pair of groups, separate values for each parameter are specified for each neuron type pairing: e-e, e-i, i-e, and i-i.

Neural systems and Learning (3/5)

- The neural parameters:
  - Connection Density (CD) (ranging [0,1]) determines the extent of connectivity between neural groups. The number of (e.g., e-i) connections from group A to group A is given by:

$$round(CD_{e-i} * N_e(A) * N_i(B))$$

  Where $N_e(G)$ is the number of e neurons in group G (same with i).
  - Topological Distortion (TD) (ranging [0,1]) determines the degree of disorder in mapping connections from one group to another.
    - For TD of 0, synapses are mapped perfectly to contiguous stretches of neurons in the adjacent group/layer.
    - For a TD of 1, synapses are mapped completely randomly from one group to another.
    - This allows the enforcement (or not) of topological maps, such as retinatopic maps that are observed in natural animals.
  - Learning rate (usually ranging [0,0.2]) affects the Hebbian learning equation between each pair of neural groups.

Neural systems and Learning (4/5)

- The idea is to allow somewhat arbitrary neural architectures, to allow nearly any type of neural organization. It allows the establishment of inhibitory and excitatory connections, such as seen in real neural systems.
    - There was no way to model organization based on spatial layout though. It was not deemed necessary due to the small amount of neurons that could be supported by current hardware.
    - Spatial-dependent organization could be supported by having different parameter values depending on the spatial dimension
- Synaptic weights are randomly initialized between min/max values; they were not stored in the genome. Then, the brain is exposed to random noise as visual inputs for a specified number of cycles.
    - This was inspired by Linsker's simulations of visual cortex. This process, with Hebbian learning, resulted in on-center-off-surround visual cells, and orientation-selective cells, such as those observed in human visual cortex.
- Neural network activity could be visualized in *PolyWorld* for any living organism.

Neural systems and Learning (5/5)

- At each time step, the input neurons are set to their values according to the organism's visual field, its health-energy level, and a random number. The neuron is a "sum-and-squash" type. The activation function is a standard sigmoid, in range (0,1), with an adjustable slope.

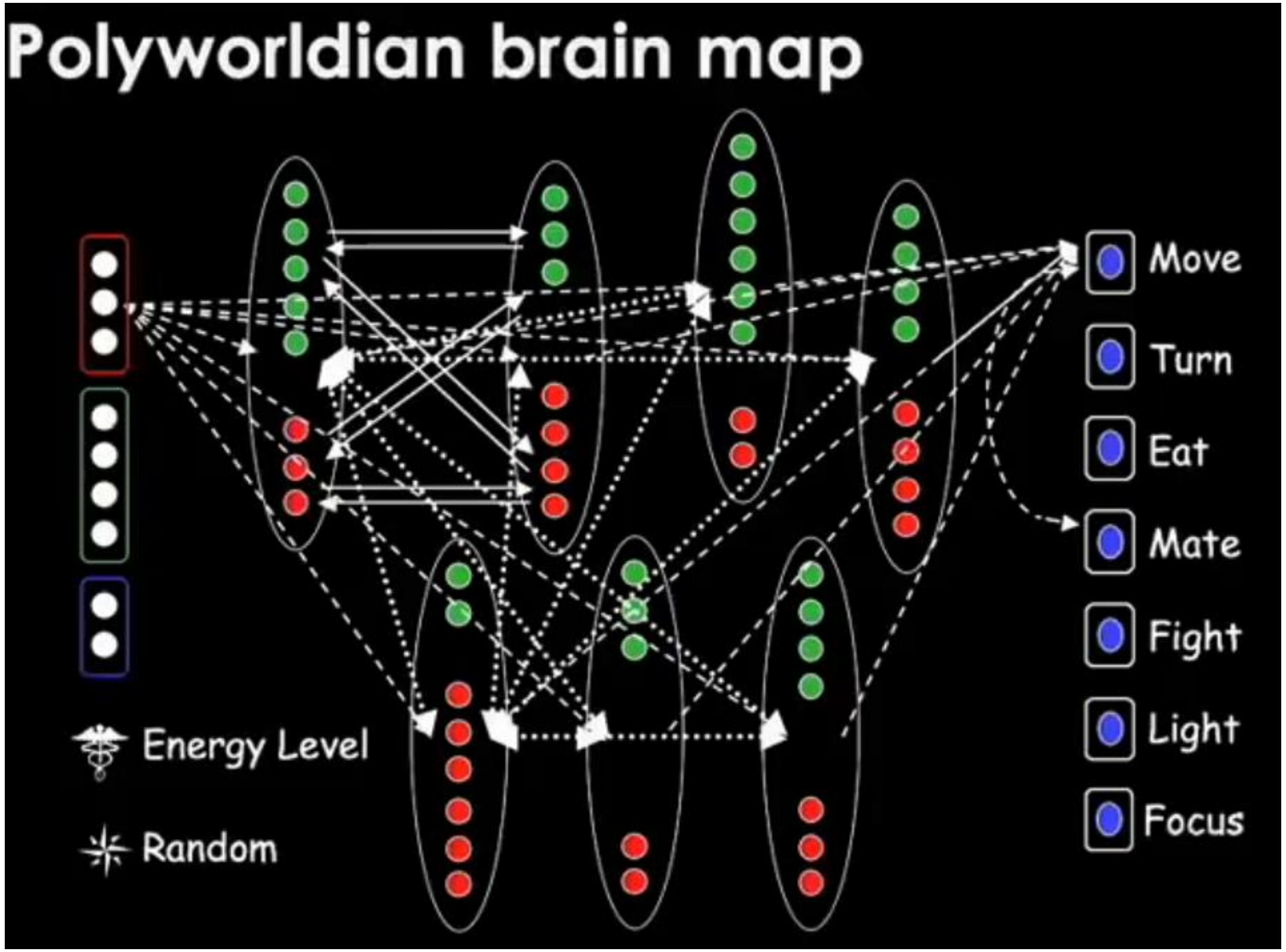
$$x_i = \Sigma a_j^t s_{ij}^t$$

$$a_i^{t+1} = 1 / (1 + e^{-\alpha x_i})$$

- The synaptic efficiencies are updated using a Hebb rule:

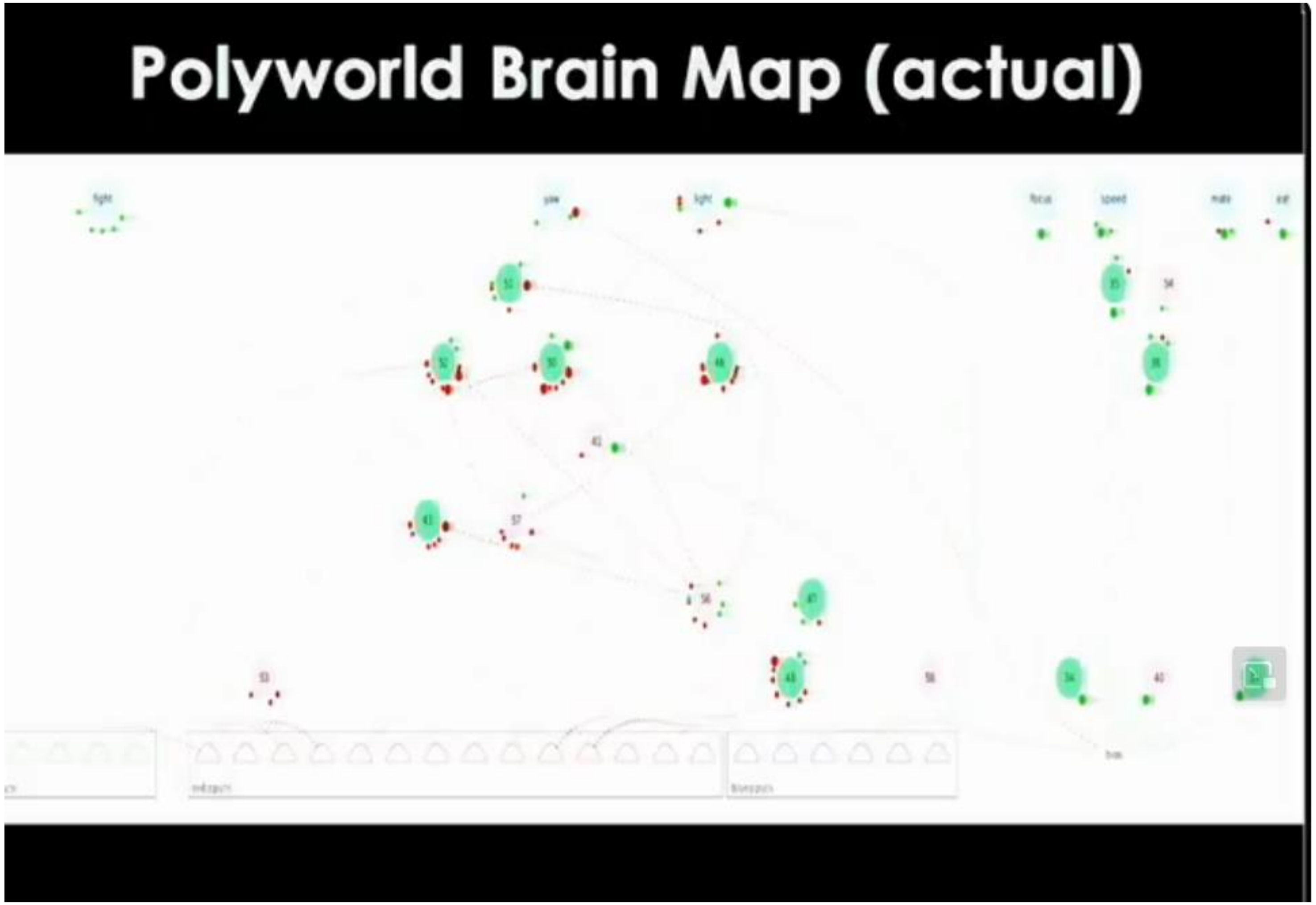
$$s_{ij}^{t+1} = s_{ij}^t + \eta^c{}_{kl} (a_i^{t+1} - 0.5)(a_j^t - 0.5)$$

Neural systems and Learning



https://www.youtube.com/watch?v=_m97_kL4ox0

Neural systems and Learning



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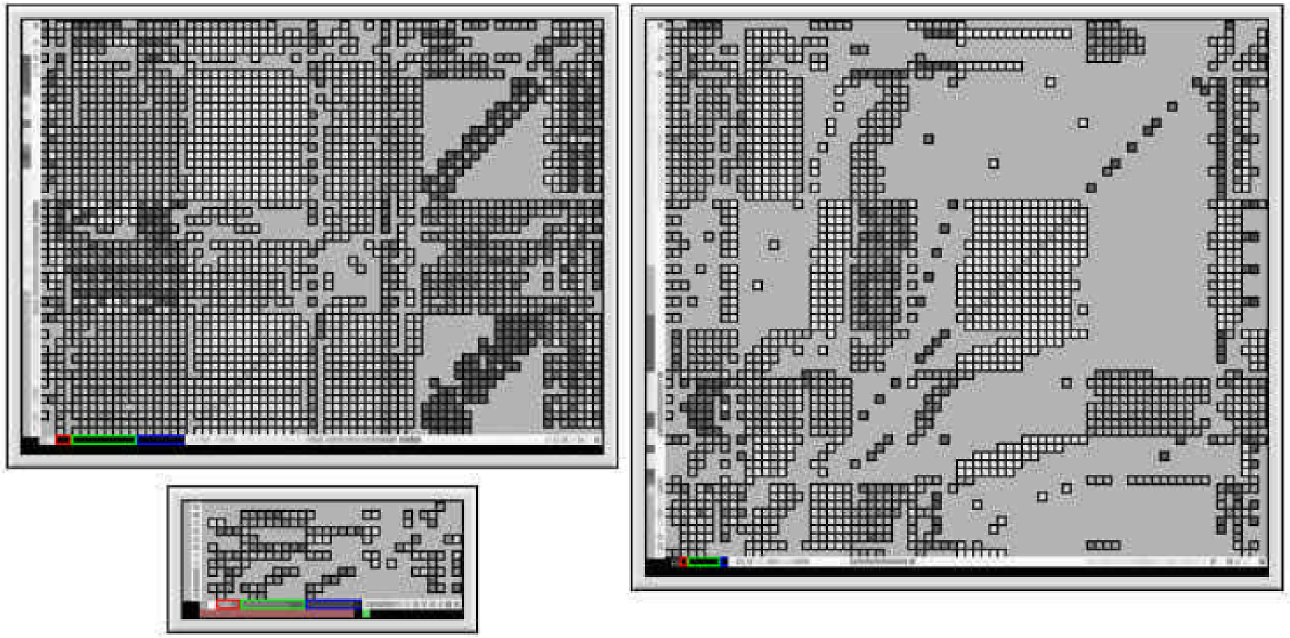
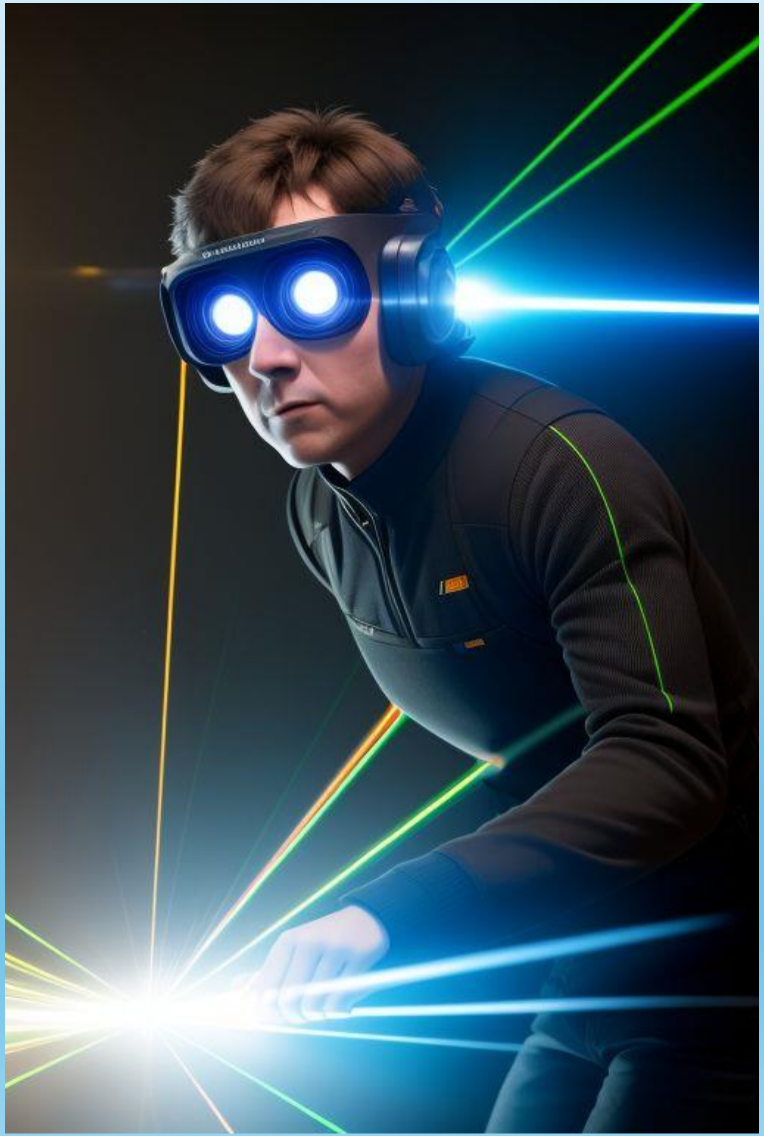


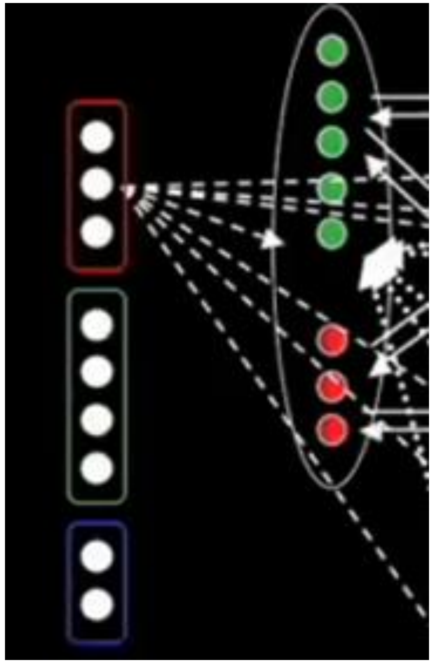
Figure 2. Three sample neural architectures evolved in PolyWorld. Gray-scale is used to denote neural activation (between 0.0 and 1.0) and synaptic efficacy (between -maxEfficacy and +maxEfficacy). At the very bottom of the grid is the color vision buffer. The neural activations at the beginning of this time step are shown in a horizontal row just above the color vision, along with the red, green, and blue input neuron activation levels, and the energy and random input neuron activation levels. White frames are drawn around each neuronal group, except for the vision neurons which are framed in their corresponding color. Black frames are drawn around each synapse, hence the unframed areas are regions of null connectivity. Synapses that appear brighter than the neutral gray background are excitatory; those that appear darker than the background are inhibitory. The leftmost vertical bar shows neuronal biases. The non-input neural activations at the end of this time step are shown in the adjacent vertical bar; again, neuronal groups are framed in white. Hence the diagram may be read as an incomplete crossbar connecting the neuronal states at the beginning of the time step (horizontally) to those at the end of the time step (vertically), through the various synaptic connections.

Vision



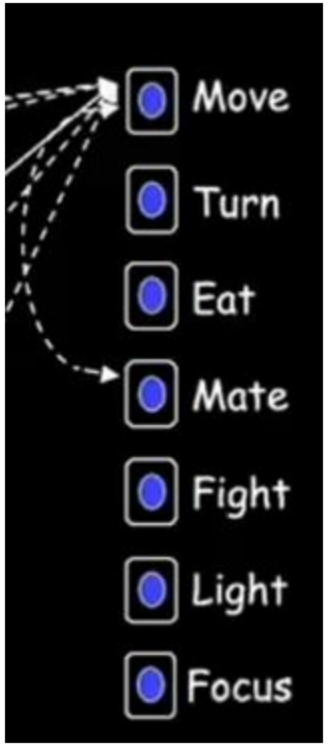
Vision (1/1)

- For each organism, the world is rendered with 22x22 pixel resolution (RGB vision). The row of pixels just above the center is anti-aliased into the resolution of the organism's input neurons.
  - Note that although PolyWorld is 3D, the visual input is just a 1D strip of pixels. This was acceptable because organisms were restricted to movement on the 2D (ground) plane, so they dont need to see up or down.
  - The number of neurons for each RGB color component are evolved. The genes are nearby in the genome, so they tend to crossover together.
- Organisms' visual fields are rendered for the user to see.
- Though the organisms can only see 10 degrees vertically, their horizontal field of view is under neural control.
  - The activation of the "focusing" neuron is mapped between 20 degrees and 120 degrees for the horizontal FOV.
- The sense of visual perception, and embodiment in the environment, provides the organisms' with "grounding" for their cognition



Behavior

Behavior (1/3)



- A set of 7 primitive behaviors are available to all organisms:
    1. Eating
    2. Mating
    3. Fighting
    4. Moving
    5. Turning
    6. Focusing
    7. Lighting
- Each behavior is expressed by the activation of predetermined motor neurons in the brain.
    - The reason for this simple mapping of one neuron to one behavior was due to computational constraints
- The first 3 behaviors require a certain threshold to be exceeded. The magnitude of expression of the other behaviors scales directly with the neuron activation value.
- Energy is expended by each behavior, including eating. The rates of energy expenditure are controlled by scaling factors, configurable and specified in the "worldfile" (world settings)

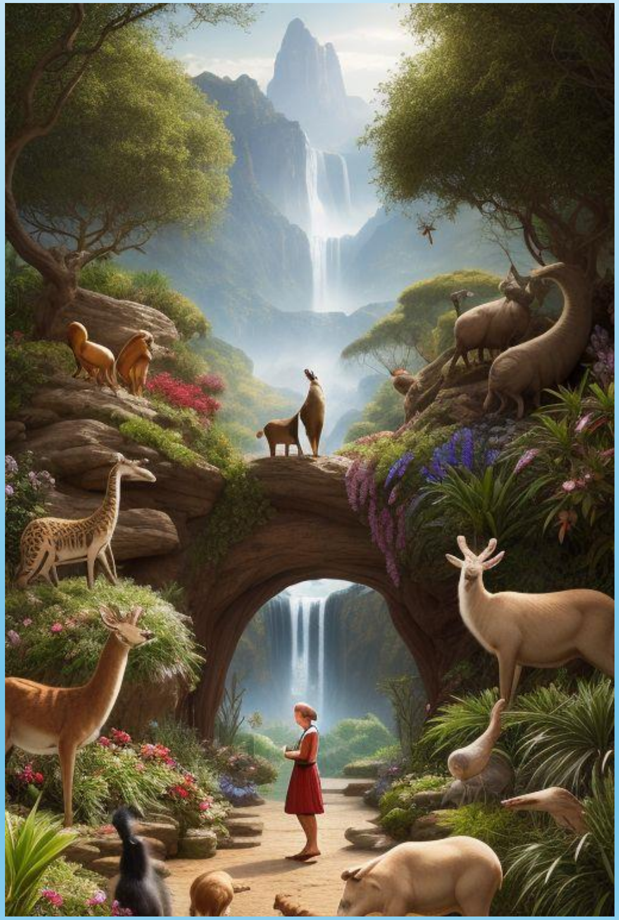
Behavior (2/3)

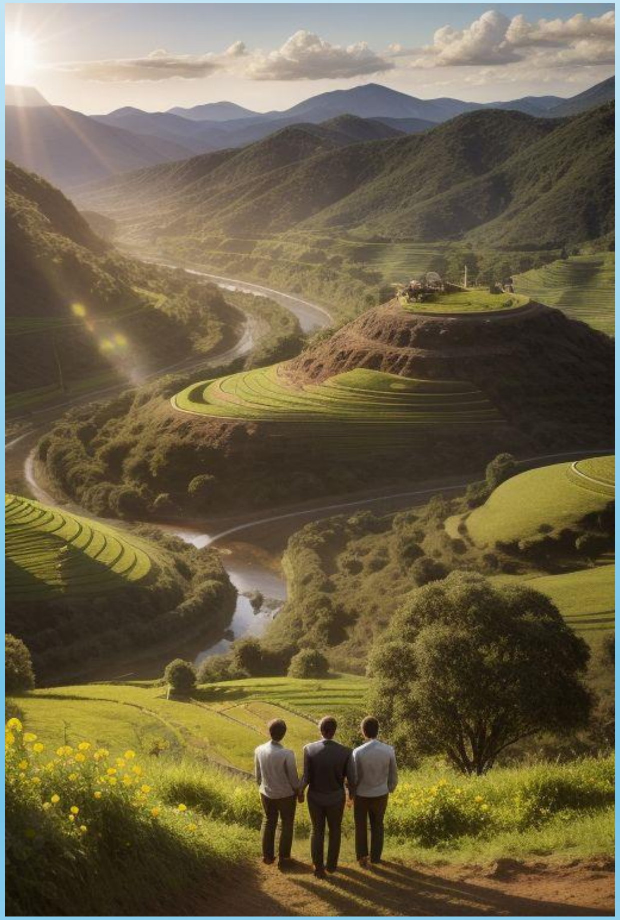
- ***Eating***: the organism can eat food to replenish its energy.
  - The behavior is performed when an organism's body overlaps a piece of food, and the eating neuron is activated. The amount of energy consumed from the food is proportional to the activation of the eating neuron; the activation must exceed a certain threshold.
- ***Mating***: the organism can reproduce, to perpetuate evolution.
  - The behavior is performed when the bodies of 2 organisms overlap, and both organisms express their mating neuron, as defined by a threshold. The outcome of reproduction attempt may be optionally affected by miscegenation (speciation).
- ***Fighting***: the organism can attack other organisms, and defend itself from attacks.
  - The behavior is performed when the bodies of 2 organisms overlap. Only one organism needs to express its fighting neuron (the attacker/predator). The energy depleted from the defender/prey is a function of the neuron's activation, the attacker's current health-energy level, the attacker's strength, and the attacker's size. Their product is scaled by a global attack-to-energy conversion factor.
  - If both organisms express their fighting behavior, each is affected by the other one.
  - Due to the AI's volitional control of these behaviors, the full spectrum of behavior is available from complete pacifism to constant fighting (as observed in the "dervish" species).
  - An organism's desire to fight (fighting activation) is mapped to the red RGB component of the organism's body. This allows humans and other organisms to identify fighting behavior.

Behavior (3/3)

- ***Moving:*** The organism can move around the environment.
  - The organism moves forward by a distance proportional to the activation of the neuron.
- ***Turning:*** The organism can rotate, to look and move around.
  - The organism’s yaw rotates by an amount proportional to the activation of the neuron.
- ***Focusing:*** The organism can narrow its visual field of view (FOV).
  - The organism’s horizontal FOV changes depending on the activation of the neuron.
- ***Lighting:*** The organism can light up its body to signal to other organisms.
  - The organism’s body changes color to bright white depending on the activation of the neuron.
  - In principle, this permits simple communication between organisms (though this has yet to be observed).

The New Context





The New Context (1/2)

- The world is a flat ground plane inhabited by the organisms.
  - Sometimes there are impassable barriers, such as placed by the user. These can isolate populations of organisms
  - Pieces of food are grown in random positions.
  - The world's edges are configurable to be either barriers, or wrap around, or kill organisms who "fall off the edge"

- The number of organisms in the simulation is controlled by
  - 1.) an upper limit, due to computational constraints
  - 2.) a lower limit, to prevent global extinction

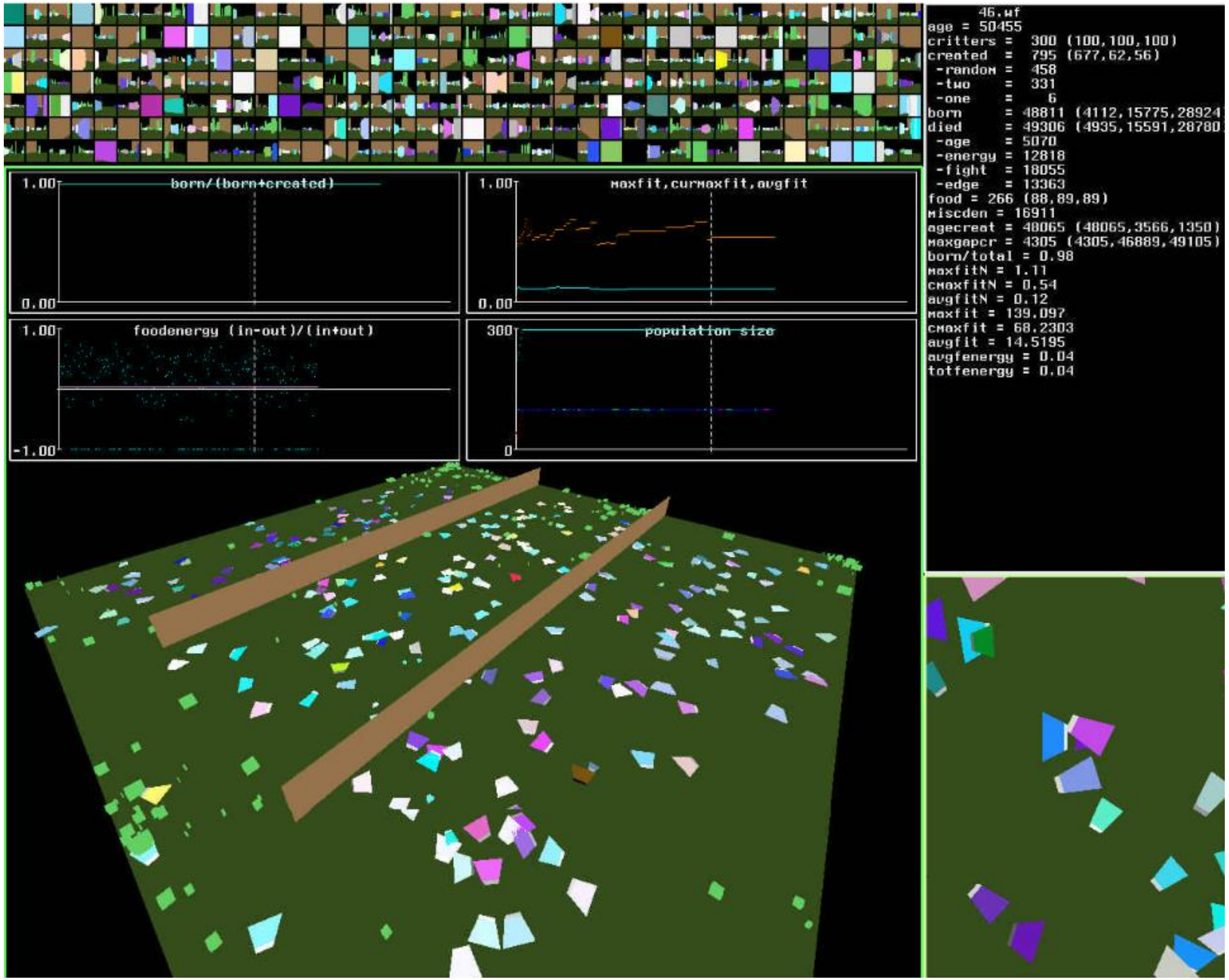
- Food is grown at a configurable rate, up to a maximum of grown food items.
  - The number of food items is guaranteed between a minimum count (by growing) and maximum count (in the case of too many organism deaths).
  - The energy in randomly grown food is randomly determined. The energy in an organism carcass food is the organism's food-energy value at death (or a configurable minimum).

The New Context (2/2)

- There are various monitoring and graphing tools, which allow the user to follow the progress of the simulation. This may help with developing understanding of the evolutionary and neural dynamics, though the graphs are more for creating intuitions than detailed quantitative analysis
  - A window is available to view the brains of the 5 fittest organisms
  - An overhead camera can be used to track an organism, and zoomed in/out
  - There are various graph displaying quantities of interest, such as
    - population size
    - the min/max/average score of fitness function
    - Ratio of organisms “born” to “created”. This will start at zero and asymptote to 1.0 for successful simulations (SBS). Unsuccessful simulations usually peak early.
    - Ratio of difference between simulation food-energy in and food-energy out, to their sum. This ranges from –1 to 1, and asymptotes to 0.0 when energy is conserved. Also shows various quantities to monitor total simulation food-energy.
- A tool can show an analysis of genetic variability in the population using the Hamming distance between organisms in gene space.
  - For display, the normalized instances are divided into as many histogram bins are possible for the vertical size of the graph. Pixel brightness indicates the number of organisms in each bin.
  - In this way, a column of pixels shows the distribution of “genetic separation” for an entire population. Every time there is a birth or death, a new column of pixels is appended. In this way, the graph shows the history of genetic variability.
    - This is a good method because it succinctly shows the history of population genetic variability
    - But it is also weak in that it reduces all genetic differences to a single number, so we cannot tell how much genes differ, not which genes differ.
- *PolyWorld* is open source and written in 15,000 lines of C++.

The New Context

- A screenshot of *PolyWorld*
    - Metrics and graphs
    - Organism information
    - Organism visual fields



Results: Speciation and Complex Emergent Behaviors

Results: Speciation and Complex Emergent Behaviors (1/3)

- In the simulations run so far, the author has observed recurring species (behavior strategies) arise in many of them.
  - No quantification of the species has been attempted yet, due to restrictions on the author's time
  - Quantity analysis may require in-depth graphical and mathematical tools. For now, (qualitative) behavioral analysis is sufficient for developing some understanding of the evolutionary dynamics.

- The following reports only refer to "successful" simulations (i.e., simulations where populations became self-sustaining)

Results: Speciation and Complex Emergent Behaviors (2/3)

<u>List of discovered species</u>:

- ***"Frenetic Joggers"*** [*Wrapped borders*] **–** They run straight ahead at full speed, always expressing mating and eating behaviors. The world wrapped around, and was benign/plentiful enough that the joggers would always manage to intersect with food and each other in their straight path.
- ***"Indolent Cannibals"*** [*Walled borders*] **–** They stand mostly still, near their parents and offspring. They constantly mate with each other, fight/kill each other, and eat each other's corpses.
  - Their perceptual world is "zero-dimensional"
  - Mostly this occurred in simulations before the update forcing parents to transfer energy to offspring, since offspring were a free energy source.
  - By configuring the simulation with balanced energy transfers, they appeared less frequently, usually congregating near the corners of the world. In this case, the organisms usually had limited motor skills, and primarily benefited from the ease of reproduction in groups, rather than the ease of energy sources. This was determined by setting the amount of food gained from consuming carcasses to zero, yet the species still emerged.
- ***"Edge Runners"*** [*Walled borders*] **–** They continuously run along the edges/barriers of the world
  - Their perceptual world is approximately "one-dimensional".
  - This strategy works because other edge runners also exist on the edge. Therefore, the organisms can easily find each other to mate. And, when one dies, its food carcass sits on the edge, which supplied food for the living edge runners.
  - Runners have been observed to speed up, slow down, turn around to run in the opposite direction, and stop running.
- ***"Dervishes"*** [*Deadly borders*] **-** They rapidly turn to keep away from the deadly edges of the world, yet explore well enough to find food and mates.
  - It has been observed persisting for hundreds of generations.
  - Their evolution follows a cyclic exploration of predation/violence vs. cooperation/peace, like the prisoner's dilemma. Various subpopulations evolved these strategies on the continuum. Often entire whole population/subpopulations would follow the same strategy, and gradually transition to another.

Results: Speciation and Complex Emergent Behaviors (3/3)

- The most interesting organisms are hard to classify in a species, especially due to their varied behaviors. In some worlds, there are many different individuals with unique behavior, with no overly dominating species/behavior.
- Complex behaviors have emerged like:
  - Responding to visual stimuli by speeding up
    - Importance: it shows evolution selecting for use of the vision system
  - Responding to an attack by running away/faster
    - Importance: it is a reasonable response to avoid harm.
  - Responding to an attack by fighting back
    - Importance: it is a reasonable response to stop the cause of harm.
  - Grazing, by slowing down near food
    - Importance: It is an efficient feeding strategy. Standing still, rather than moving, allows the organism to extract more energy, in less time, and also spend less energy.
  - Visually seeking food, especially circling it and eating it
    - Importance: similar to grazing.
  - Following other organisms
    - Importance: use of vision with motor control, allows seeking prey and mates. Flocking, chasing, and swarming were observed.

Discussion

Discussion (1/5)

- The study of Artificial Evolution is providing insights into problems of optimization and dynamics of natural selection.
  - This type of Artificial Life is a combination of Artificial Intelligence and Genetic Algorithms
- The *PolyWorld* simulation has been considered a success, since complex emergent behaviors like those of natural living systems (flocking, defending, grazing, following) have already evolved from the simple primitive behaviors plus natural selection on neural systems.
  - The simpler survival strategies can be considered "null hypotheses" about animal behavior. They do not require any complex behavior.
- We can perhaps more easily and fully understand these simulated organisms than natural organisms, because we know the exact method of computation/simulation behind them.
- As more intricate simulations of living systems are developed, we may eventually come to ask if they are "really alive". To answer this, we must answer the question "what is life?". How to differentiate a nonliving digital system from a living one?
  - [*Farmer & Belin*] offer a possible answer to this question, using a set of criteria

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Discussion (3/5)

- “*Life is a pattern in spacetime, rather than a specific material object*”
  - **Yes.** PW organisms are a pattern in a computer. Their cognitive activations change throughout time. They extract nutrients from the environment, keeping a varying level of energy.
- *“Self-Reproduction”*
  - **Probably.** PW organisms find each other and reproduce. Their body does not perform “self-reproduction” in the technical “physical automata” sense. However, with current computational constraints, we are forced to make various abstractions, and the abstraction of DNA copying may not matter.
- “*Information storage of a self-representation*”
  - **Yes, but limited.** The genome represents the self. The representation is not, however, evolvable, and it is not energy. It was predesigned.
- “*A metabolism*”
  - **Yes.** An organism’s metabolism converts food from the environment into energy for internal processes and external behavior. There is only 1 type of nutrient, food, which both sustains life and allows reproduction. Sufficient quantities of the nutrient must be available for reproduction.
  - John Holland’s ECHO accumulates reservoirs of components, which must be sufficiently filled with all the required constituent components to reproduce. Though PW’s metabolism system is simpler, one question to ask, do the details matter as long as the basic functionality is the same?

Discussion (4/5)

- *“Functional interactions with the environment”*
  - **Yes.** They interact with the food in the environment, they expend energy to explore, they interact with other organisms. The more sophisticated organisms should respond behaviorally to changes in the environment.
- “*Interdependence of parts*”
  - **Yes.** All of the parts of the organism are necessary and depend on each other. An organism cannot be separated from their internal energy store. A brain cannot be split into 2 and work the same. The body does nothing without the brain.
- “*Stability under perturbations*”
  - **Yes, but limited.** PW organisms can survive small changes to their environment.
- “*The ability to evolve*”
  - **Yes, but limited.** PW have an evolving genome, but there are limits to the evolution such as no ability to smell, hear, etc. However, all organisms have limited evolution; for example, humans cannot evolve a metal arm. So a question is, how much does the underlying physics matter?

So, organisms in *PolyWorld* mostly fit or entirely fit these criteria to be considered “life”.

Discussion (5/5)

- The open question of “what is life” will continue into the future and influence artificial life.
  - Chris Langton might argue that all of Farmer and Belin’s criteria should result from a self-organizing system, e.g., a cellular automaton.
  - On the other hand, one could argue none of these criteria are necessary. A disembodied AI system, which you can converse and interact with, would seem likelife, despite fitting none of the criteria. Yet perhaps this is not even possible, and the specific design of complex intelligent systems can only be achieved through an evolutionary process.
  - Tom Ray suggested that artificial life only models certain aspects of “real life”, and each effort/perspective is based on the interests and bias of the researcher involved.
  - Langton’s self-reproducing loops met his criteria for life. Ray’s *Tierra* organisms met his criteria (reproduction and evolution).

- The organisms of *PolyWorld* meet the author (Yaeger’s) criteria for life: reproduction, evolution, and ethological-level (i.e., animal-level) behaviors.
  - The work should be improved by future researchers to create organisms which are more obviously intelligent and “alive”. Langton’s *Swarm*, a multi-plane cellular automaton, is one example.

- The question of life may be difficult to conclude, requiring a consensus, as with the Turing test for AI.
  - In time, there may be invented an information-theoretic approach for measuring life. As Von Neumann and Schrodinger suggest “information processing” as the defining aspect of life.

Future Directions

Future Directions (1/3)

- The species and behaviors observed suggest the *PolyWorld* approach is promising for further studies. Especially quantitative studies and benchmarking.

- The neural architectures should be analyzed and we should attempt to understand them.
  - It would be straightforward to try a range of different learning algorithms than the just the Hebbian one attempted here. Also different neural networks, for example, spiking neurons rather than continuous.
  - Biologically motivated ontogenetic and developmental processes, for developing the neural network, are potentially one of the most valuable future directions. Also for their physiologies. PW is a good way to test these.

- More interactions should be supported in the environment, such as to pick up and move food and barriers around.

- The simple metabolism uses one type of nutrient, food. It could be made more complex by adding multiple nutrient/food types, which also makes for a richer environment.
  - There could be an artificial biochemistry occurring “internal” to the organism, which could have certain results.
  - Food growth could be made orderly, rather than randomly spawned

Future Directions (2/3)

- The impact of energy transference was observed to be crucial to the evolutionary process.
  - It would be interesting to analyze energy in the system.
- The impact of isolating populations for speciation has been explored in PW and could be further explored. This direction has been limited due to computational constraints.
- Thousands of interesting experiments could be performed in PW.
  - Monitor brain size (or other characteristics)
  - Monitor fighting between organisms
  - Monitor amount of energy given to offspring
  - Hand-create/engineer neural networks and place the seed organisms in the world
- It is hoped that one day the evolved organisms could be tested in classical psychology experiments, such as classical conditioning. Hebbian learning has shown promise in this direction.

Future Directions (3/3)

- Scale, scale, scale. In the future, with better computers, one could simulate more organisms, with larger brains, and longer simulation.
  - Even the experiments in this paper were not run using parallelization. Modern parallel hardware would allow for massive scaling.

- If there is a question about the validity and usefulness of these research direction, one only needs to point out the benefits that would be derived in many fields: evolution, computer science, ecology, biology, etc.
  - The author mentions a few times, he thinks “it may also be the only ‘right’ way to approach machine intelligence”

- One way to view intelligence is as an evolved adaptive response to a variable environment. Due to our (human/animal) history, this happens to be based on neural cells.
  - *PolyWorld* is an attempt to reproduce intelligence seen in natural animals using natural selection on neural assemblies, just as in the natural world.
  - Although one of the grand goal of AI science is to develop a computer system that is at the human level, it would also be a major achievement to develop a computer system that is at the animal level and fully knowable/understandable.
  - By evolving simple organisms to become more intelligent over time, up through the slug, rat, monkey level, we could confidently know we are on a definitive path towards human-level intelligence.

YouTube video (Google TechTalks) [2007]

Virgil Griffith (CalTech) presents a *PolyWorld* talk:

https://www.youtube.com/watch?v=_m97_kL4ox0