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Title:

From Artificial Life to Semiotic Agent Models

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From Artificial Life to Semiotic Agent Models

Review and Research Directions

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1. AGENTS

The term agent is used today to mean anything between a mere subroutine to a conscious entity. There are "helper" agents for web retrieval and computer maintenance, robotic agents to venture into inhospitable environments, agents in an economy, etc. Intuitively, for an object to be referred to as an agent it must possess some degree of autonomy, that is, it must be in some sense distinguishable from its environment by some kind of spatial, temporal, or functional boundary. It must possess some kind of identity to be identifiable in its environment. To make the definition of agent useful, we often further require that agents must have some autonomy of action, that they can engage in tasks in an environment without direct external control. This leads us to an important definition of an agent from the XIII century, due to Thomas Aquinas: an entity capable of election, or choice.

This is a very important definition indeed; for an entity to be referred to as an agent, it must be able to step out of the dynamics of an environment, and make a decision about what action to take next – a decision that may even go against the natural course of its environment. Since choice is a term loaded with many connotations from theology, philosophy, cognitive science, and so forth, I prefer to discuss instead the ability of some agents to step out of the dynamics of its interaction with an environment and explore different behavior alternatives. In physics we refer to such a process as *dynamical incoherence* [Pattee, 1993]. In computer science, Von Neumann, based on the work of Turing on universal computing devices, referred to these systems as *memory-based systems*. That is, systems capable of engaging with their environments beyond concurrent state-determined interaction by using memory to store descriptions and representations of their environments. Such agents are dynamically incoherent in the sense that their next state or action is not solely dependent on the previous state, but also on some (random-access) stable memory that keeps the same value until it is accessed and does not change with the dynamics of the environment-agent interaction. In contrast, state-determined systems are dynamically coherent (or coupled) to their environments because they function by reaction to present input and state using some iterative mapping in a state space.

Let us then refer to the view of agency as a dynamically incoherent system-environment engagement or coupling as the *strong sense of agency*, and to the view of agency as some degree of identity and autonomy in dynamically coherent system-environment coupling as the *weak sense of agency*. The strong sense of agency is more precise because of its explicit requirement for memory and ability to effectively explore and select alternatives. Indeed, the weak sense of agency is much more subjective since the definition of autonomy, a boundary, or identity (in a loop) are largely arbitrary in dynamically coherent couplings. Since we are interested in simulations of decision-making agents, we need to look in more detail to agent based models with increasing levels of dynamical incoherency with their environments.

To summarize:

1. ***Dynamically Coherent Agents***
    a. Rely on subjective (spacial, functional, temporal) definition of autonomy. Function by reaction and are dynamically coupled to environments.
    b. Example: situated robots (wall-following machines), state-determined automata.
2. ***Dynamically Incoherent Agents***
    a. Possess models, syntax, language, decision-making ability. In addition to a level of dynamical coherence with their environments (material coupling), they possess an element of dynamical incoherence implemented by stable memory banks.
    b. Example: anything with symbolic memories and codes.

2. AGENTS: HOLLAND'S COMPLEX ADAPTIVE SYSTEMS

John Holland [1995] defines agents as rule-based input-output elements whose rules can adapt to an environment. These rules define the behavior strategy utilized by agents to cope with a changing environment. He also defines 7 basics or characteristics of agents and multi-agent sysems which further specify the rule-based adaptive behavior of agents:

1. **Aggregation** (Property) has 2 senses
    a. Categorization (agent level): Agents cope with their environments by grouping things with shared characteristics and ignoring the differences.
    b. Emergence of large-scale behavior (multi0agent level): From the aggregation of the behavior of individual agents (e.g. Ants in an ant colony) we observe behavioral patterns of organization at the collective level. This leads to hierarchical organization.
2. **Tagging** (Mechanism). Agents need to be individualized. They possess some identity. This in turn facilitates selection, specialization of tasks, and cooperation as different specific roles and strategies may be defined.
3. **Nonlinearity** (Property). The integration or aggregation of agents in multi-agent systems is most often non-linear, in the sense that the resulting behavior cannot be linearly decomposed into the behavior of individual agents. This also implies that multi-agent systems lead to network causality, as effect and cause of agent behavior follow circular loops that cannot be linearly decomposed into traditional cause and effect chains.
4. **Flows** (Property). Multi-agent systems rely on many connections between agents that instantiate the flow and transfer of interactions, information, materials, etc. Typically, the network of flows is represented with graphs.
5. **Diversity** (Property). Typically, multi-agent systems are heterogeneous, as there exist different agent roles and behaviors. This makes the tagging mechanisms important so that these different roles and behaviors may be identified.
6. **Internal Models** (Mechanism) organize the rules that produce agent behavior and can be used to let agents anticipate expected inputs from the environment. We can divide models in 2 types.

a. *Implicit*: Prescribes a current action under implicit prediction. This is associated with hard-wired rules of behavior (e.g. by natural selection) and implemented by state-determined automata. This kind of model instantiates agents which are dynamically coupled to their environments, e.g. reactive, situated robots.

b. *Explicit*: Use Representations stored in stable (or random access) memory to look ahead by exploring possible alternatives. This type of model produces agents with a level of dynamical incoherence with their environments, since they act not only based on current state and input but also by integrating information stored in memory. This integration can be pursued with more or less complicated reasoning procedures. Since agents with explicit models possess behavior alternatives, we can use them to study decision processes.

7. **Building blocks** (Mechanism). Agents are built with less complicated components. This allows for the instantiation of coded construction, which is essential for the recombination of components to produce new agent with different behavior and models. Natural selection, for instance, acts on the ability to randomly vary descriptions of agents, which are cast on a language coding for building blocks leading to the production of new agents.

Holland’s 7 basics lend themselves to our notions of dynamical incoherence, and therefore we can well use them to describe agents and (complex adaptive) multi-agent systems.

3. REVIEW OF AGENT MODELS: FROM STRATEGIES TO EXPLICIT MODELS AND BELIEFS

3.1 Encounters and Strategies

The agents in the models described in this section are based on game-theoretic strategies, using simple memory architectures. The environments in these models are defined exclusively by other agents, therefore there is really no level of dynamical coupling between agent and environment. Rather, these models aim to study only decision strategies and the evolution of strategies in an environment of other changing strategies. However, the strategies pursued by these agents rely on present state and a memory of only a small number of previous states and encounters. In addition, typically, the agent-rule updating is synchronous (all agents updated at the same time) and there is a determined behavior outcome. This results in dynamically coherent multi-agent systems, since agents cannot choose when and whether to participate, and their rules are determined by a short list of previous states.

3.1.1 Iterated Prisoner's Dilemma: Evolutionary Strategy Dynamics

Idealized model for real-world phenomena such as *arm-races* (Axelrod, 1984) and *Evolutionary Biology* (Maynard-Smith, 1982), iut of Game Theory as defined by Von Neumann, Economics, and Political Science. The dilemma is defined as follows: 2 individuals are arrested for committing a crime together are held in separate cells; no communication is allowed; both are offered the same deal to testify against the other (both know this); if one testifies (defects) gets a suspended sentence (S) and the other gets the total sentence (T); if both testify (defect), the testimony is discredited: both receive a heavy sentence (H); if neither one confesses (cooperate) both are convicted to a lesser sentence (L). These values must obey the following 2 conditions: (1) S>L>H>T and (2) 2L>S+T.

! EVOLUTIONARY PHENOMENA IN SIMPLE DYNAMICS, Kristian Lindgren [1991]. Finite memory strategies for the iterated prisoner's dilemma (IPD) were encoded in a genetic algorithm (GA). Each agent contains a strategy h_m, which specifies how the agent should play each iteration of the prisoner's dilemma game, based on a memory of size m. a_0 denotes what the opponent did in the last encounter, a_1 denotes what the agent did in the last encounter, a_2, what the opponent did in the one but the last encounter, and so forth. The *tit for tat*[1] (TFT) strategy is a strategy of memory m=0, as it only requires memory of what the opponent did last.

  " Details of the GA:

    - Encoding (see figure 1). After ordering the binary possibilities of the rule, only the right side of the rules is encoded as a genetic description. For TFT, the binary possibilities are: 0 or 1 (opponent defected or cooperated)

[1] Defect if opponent defected last, cooperate if opponent cooperated last. Start by cooperating.

and the rule specifies 0 or 1 respectively as a strategy. This wat, TFT is oencode as [01]. See figure 1 for an example of an extension of TFT for m=1.

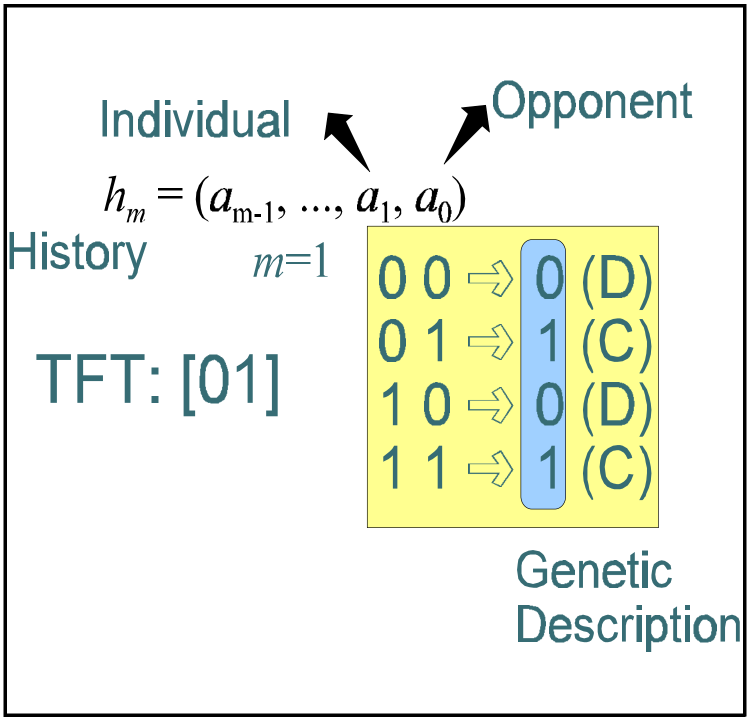

Figure 1: Encoding of IPD strategies in Lindgren's GA.
C denotes cooperate, and D defect.

- The initial population of the GA possesses equal fractions of 4 strategies m=0: [00], [01], [10], and [11]
- Random operators. Point mutations, which flip a bit on the strategy: [01] o [00] (2×10^{-5}); gene duplications which increase the memory size by 1 (do not change actual strategy): [01] o [0101] (10^{-5}); and split mutations, which decrease the memory size by 1 producing two possibly distinct strategies: [1001] o [10] or [01] (10^{-5}).
- Probability of mistake ***p***. Probability that rule will produce opposite outcome.

" Lindgren's experiments show stasis, punctuated equilibria, varying speeds of evolution, mass extinctions, symbiosis, and complexity increase. Unlike Axelrod's and Rappoport's results previously, these experiments show that TFT is not evolutionarily stable as there are strategies which play as well with TFT but better against other strategies.

" Experiments:
- Evolution of strategies of memory 1. See figure 2.

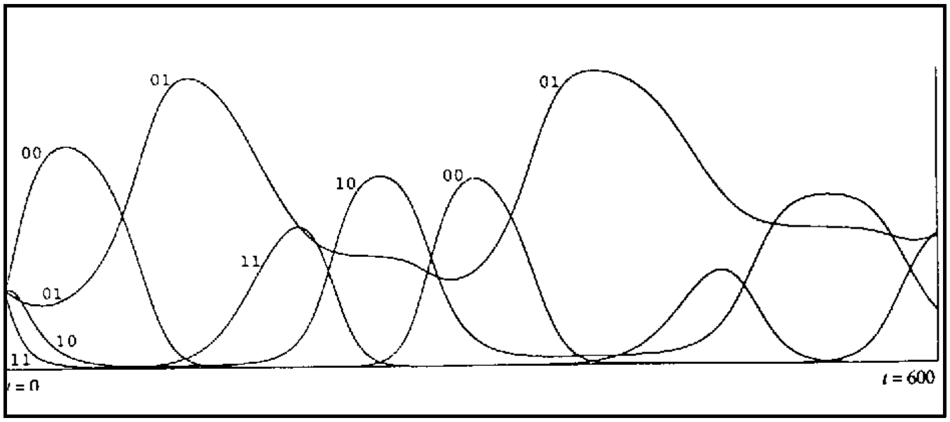

Figure 2: TFT [01] takes over “snakes” [00], the “suckers” [11] grow, and are exploited by Anti- TFT [10] and “snakes”, but TFT eventually takes over again, etc. 600 generations.

- Evolution of strategies of memory 2 and 3. See figure 3.

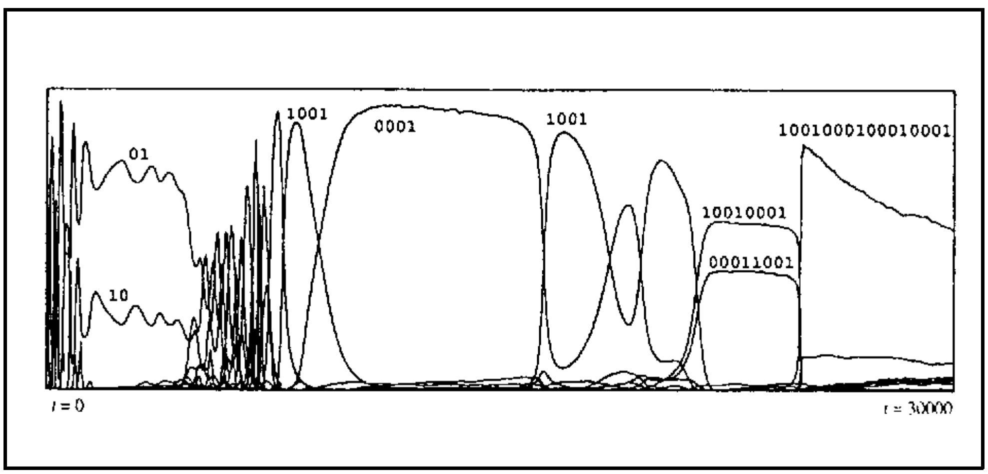

Figure 3: After a long period of strong oscillations we get to a long period of stasis with [0001], followed by oscillations with the arrival of memory 3 strategies in symbiosis (the success of [10010001] depends on the success of [00011001] and vice-versa). 30000 generations.

- Evolution of strategies of memory 4 and beyond. See figure 4.

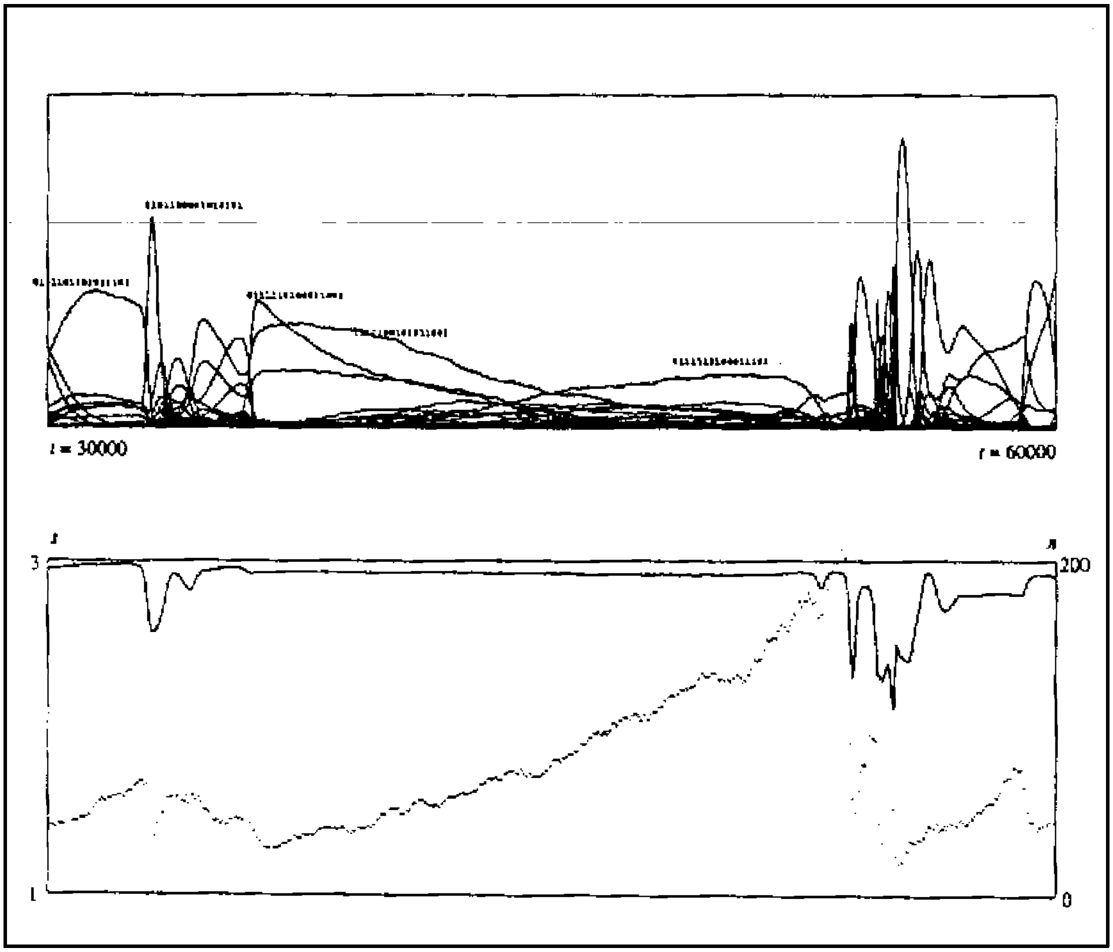

Figure 4: Memory 4 strategies appear establishing a class of 512 strategies that can lead [1xx10xxx0xxxx001]: Cooperative, but if one player accidently defects both players defect twice before returning to cooperative behavior. At this stage we also observe the phenomena of mass extinction. Bottom figure shows the average fitness (full) and number of different strategies (faint). Notice how we can expect periods of large diversity followed by radical mass extinctions. 600000 generations.

! OTHER RELATED WORK.

- Karl Sigmund [1993] offers a very interesting overview of the original work by Axelrod and Rappoport on the IPD.
- Melanie Mitchell [1996] and Klaus Emmeche [1994] offer an overview of Lindgren’s experiments.
- There is no evolutionary stable strategy in IPD [Boyd and Loberbaun,1987; Farrell and Ware, 1989]

3.1.2 Extending the Prisoner's Dilemma

- Including CHOICE AND REFUSAL OF GAME PLAYERS increases the emergence of cooperation and results in more interesting modeling of negotiation strategies as discovered by Stanley, Ashlock and Testfatsion, [1994]. This addition to the IPD tough not a tremendous computational extension, offers a qualitatively different way of modeling choice in the framework of the IPD. In this implementation, agents can refuse to play with other agents given a past history of encounters. This addition can be seen to increase the degree of dynamical incoherency between agents and their environment comprised of other agents as agents can opt to decouple themselves from the on-going strategy dynamics. Not surprisingly, this extension results in higher cooperation as agents can choose to play only with other cooperating agents, thus obtaining higher payoffs.
- Violating the second rule of the PD payoff scheme yields (as expected) strategies that take turns exploiting one another [Angeline, 1994]
- Cooperation also emerges in non-iterated PD in spatially arranged environments [Oliphant, 1994]. In this implementation, agents play the game with other agents in their neighborhood. This allows us to study the emergence of spatially distributed families of strategies.

3.2 Learning and Evolution

The agents in the models described in this section possess more interesting environments with changing or non-trivial demands. The objective of these models is to study how learning and knowledge can interact with evolution.

The Baldwin Effect (organic selection): If learning helps the survival of organisms (more plastic behavior) then this trait should be selected. If the environment is fixed, so that the best things to learn remain fixed, the learned knowledge may be eventually genetically encoded via natural selection. Example: animals capable of learning to avoid a new predator or other environmental danger, will survive long enough to allow genetic variation to eventually discover that avoiding the danger is useful trait to possess at a instinctual, genetically determined level. Waddington [1942] referred to this process as genetic assimilation.

- HINTON AND NOWLAN [1987] EXPERIMENTS: Agents were modeled by a very simple neural network and evolution was modeled by a Genetic Algorithm:
  - 1000 encoded neural nets with 20 potential connections. A connection can be present (1 $\pm$ 25%), absent (0 $\pm$ 25%), and learnable (? $\pm$ 50%).
  - Crossover, no mutation.
  - Fitness: only one layout of 0's and 1's can solve the environment's problem (all others have 0 fitness) 2^{20} possibilities.

- If an agent has incorrect 1 or 0 it will never solve the problem, but those with ?'s have the capacity to learn the correct pattern in 1000 learning trials
- fitness function: $(1 + 19n/1000)$. tradeoff between efficiency and plasticity.

" "Learning" algorithm: Random guessing (network guesses at each trial the value of its connections). It is not a proper algorithm but it allows the modeling of the plastic nature of knowledge.

" Without learning the fitness landscape would be a single spike, with the plasticity of learning it becomes a smoother curve (figure 5).

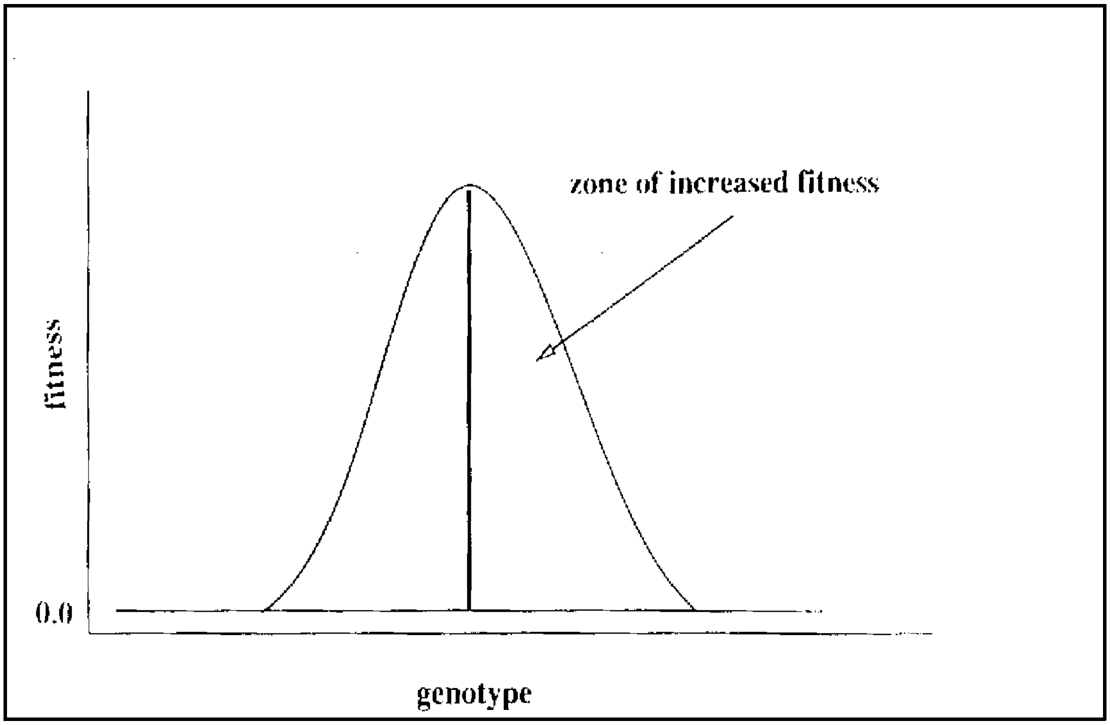

Figure 5: With the possibility of learning, the fitness landscape for the search problem is smoother, with a zone of increased fitness containing individuals able to learn the correct connection settings.

" Fitness never increases in runs without learning, but there is convergence to the solution when learning is introduced (figure 6, from [Belew, 1990]).

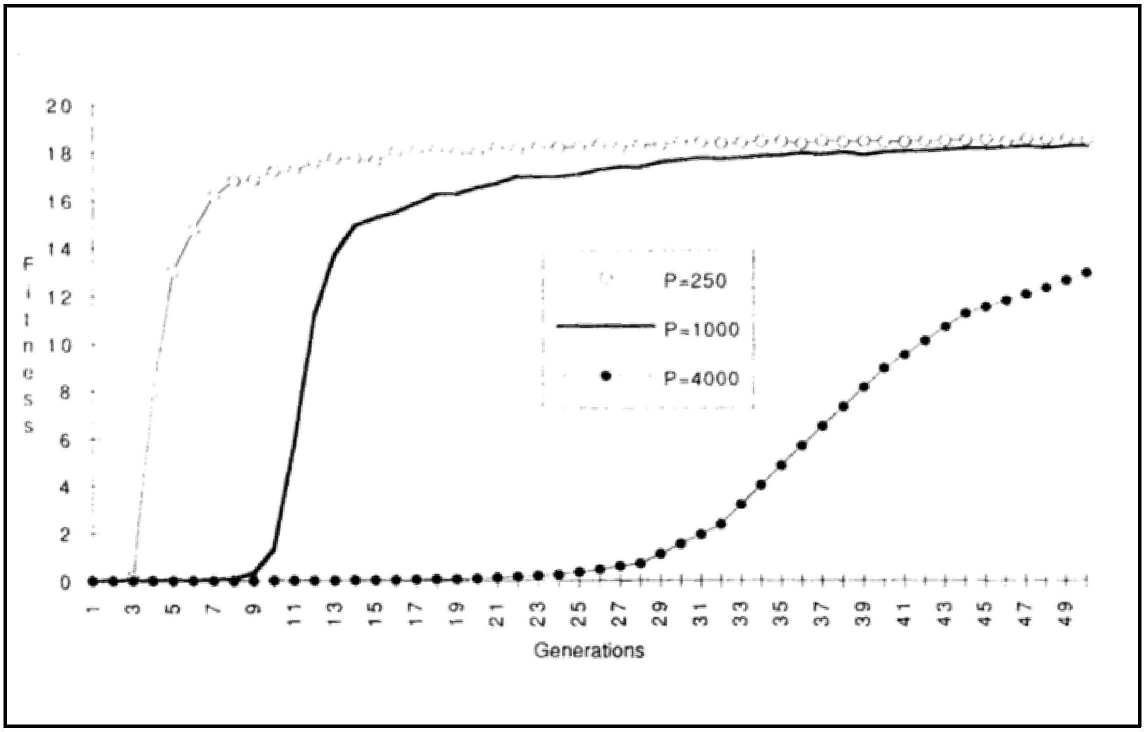

Figure 6: Fitness plot for three runs with 250, 1000, and 4000 agents in population.

- Learning can be a way for genetically coded partial solutions to get partial credit, allowing evolving agents to survive long enough for natural selection to discover the genetic solutions. Belew [1990] showed that after long runs, the number of unfixed positions (?) in the agents' networks decreases, as individuals with genetically encoded correct 1's and 0's eventually appear.
- These experiments show that even such trivial learning processes as random guessing in simple neural networks, will yield advantages to evolving agents in very harsh environments. Leaning provides ontogenetic plasticity to practically impossible phylogenetic solutions.

- EVOLUTIONARY REINFORCEMENT LEARNING, [Ackley and Littman, 1991]. This model is a much more complicated exploration of the interactions between learning and evolution. It relies on an environment with no explicit evolutionary fitness function. Furthermore, unlike a genetic algorithm, agents in a population do not reproduce on every single generation, but only when certain necessary conditions are met. Agents are in this sense asynchronous. This imbues the model with a certain degree of dynamical incoherency between agents rules and environment laws which is both more realistic and important to model decision processes. Another very important aspect of the agent architecture in this model, is the distinction between innate, unchangeable, evaluation rules which denote the agents' "dispositions" or "beliefs" about their situation in the environment and the actual rules of behavior that can change in the lifetime if the agents. A similar architecture seems to be most appropriate to model decision processes for the agent models we envision for this project – even without an evolutionary component.

" The model:
  - Agents in a 2-D environment with food, predators, hiding places, etc.
" Agent architecture with 2 feedforward neural networks:
  - *Evaluation net*: gets agent state as input, produces judgement of how good state is. Fixed from birth (innate dispositions, goals and desires).
  - *Action net*: gets agent state as input, produces a move command (which can have many outcomes). Weights changed during lifetime with backpropagation/reinforcement learning algorithm. Implements the behavior of agents.
  - Fixed Architecture: only weights change for agents.

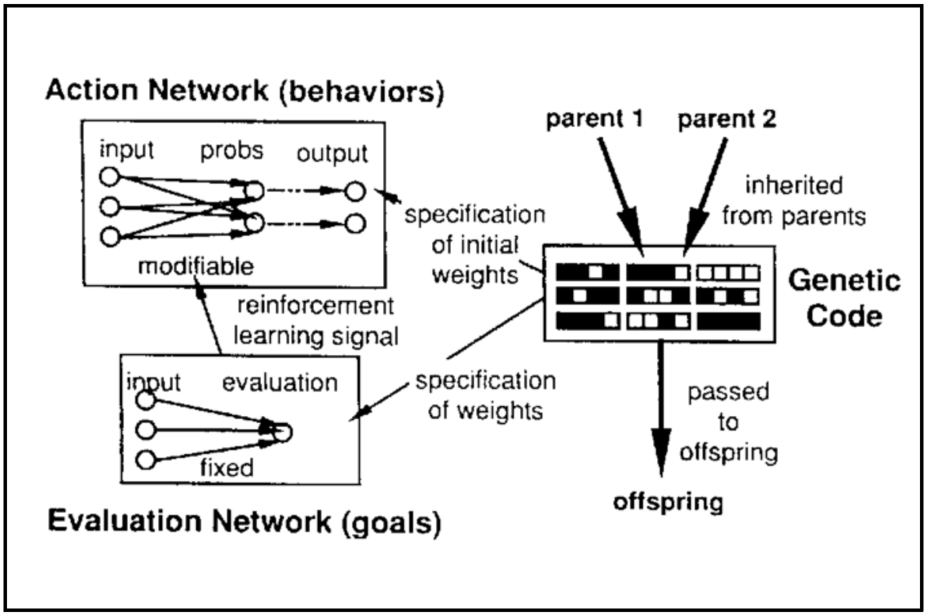

Figure 7: Agent architecture: action and evaluation networks. Architecture is encoded in the agents' genetic descriptions which are used, recombined, and mutated to produce new offspring.

" The evolutionary algorithm uses genetic descriptions for each agent. These descriptions encode (84) weights (of 4 bits) for networks (336 bits).
  - Agents have an energy gauge and die for low values. They must find food to keep energy at viable levels. Agents can only reproduce with enough energy.
  - Agents can reproduce asexually with mutation only and sexually when neighbor exists, with crossover and mutation.

  - Fitness emerges from environment and not from a pre- specified function (artificial life model).
- At each step of the computation the difference between current and previous evaluation is the reinforcement signal to modify weights of the action net. This way, agents learn to act in ways that lead to states “deemed” better by the agent’s own innate evaluation net.
- Agents then move based on the adjusted weights of action net.
- Performance: time to extinction of a population.
- ***Results***: Evolution alone (E) was not much better than random motion (B). Learning plus evolution (ERL) was not much better than learning alone (L). The authors propose that it is easier to generate randomly a good evaluation function than a good action function, since the latter network is simpler. This way, in runs without learning, the evolutionary algorithm cannot find a good behavior network. This is similar to the previous model: the environment is too harsh for evolution. On L runs, conversely, a good evaluation net is usually generated at random initially, and learning is then able to produce a good action bet, while evolution alone can not produce a good action net.

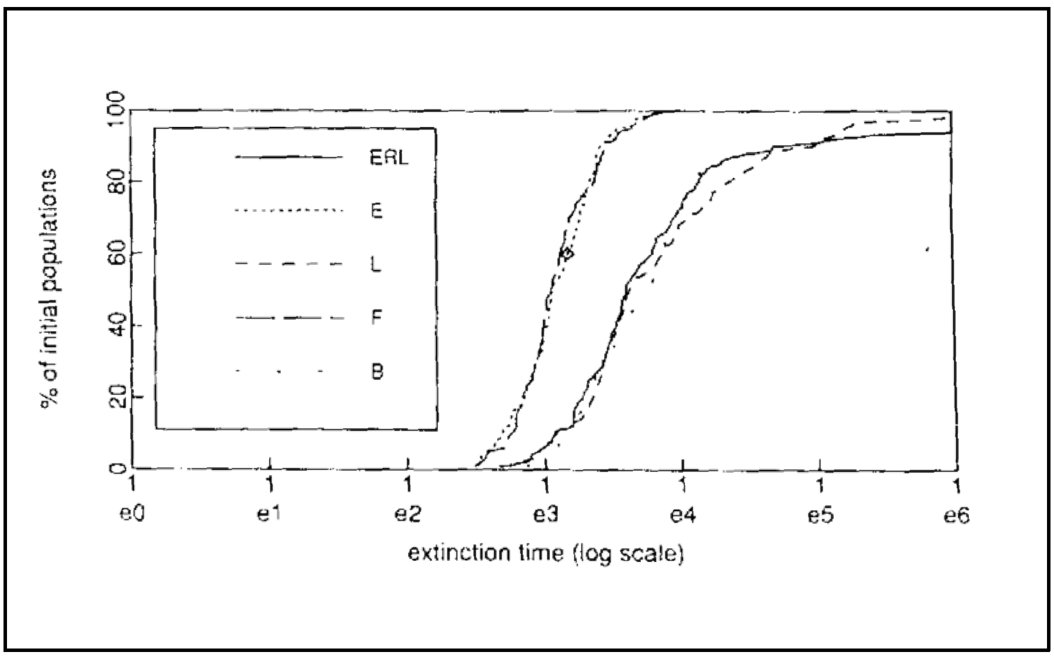

Figure 8: Performance of runs with random motion (B), fixed random action networks (F), learning alone (L), evolution alone (E), and the complete evolutionary reinforcement learning algorithm (ERL).

- Interactions between learning and evolution. The authors used functional constraints analysis, a traditional technique of evolutionary biology which studies the rate of change of different parts of the genome, to gain deeper knowledge about this model. This analysis centers on the notion that the more fixed parts of the genome are assumed to be important for survival during a given period. They observed genes associated with actions concerning food, evaluations concerning food, and genes coding for nothing (inserted for this sake):

- Naturally, non-coding genes have the highest rate of mutation.
- Evaluation genes mutate more, which implies that action genes are more functionally constrained. However, during the first stages of the simulation, evaluation genes are much more stable. Action genes become constrained later. This leads us to conclude that learning is essential in the first stages of the modeling experiment, but genetically encoded behavior for actions in the environment becomes more functionally constrained in latter stages: evidence for the *Baldwin effect*.

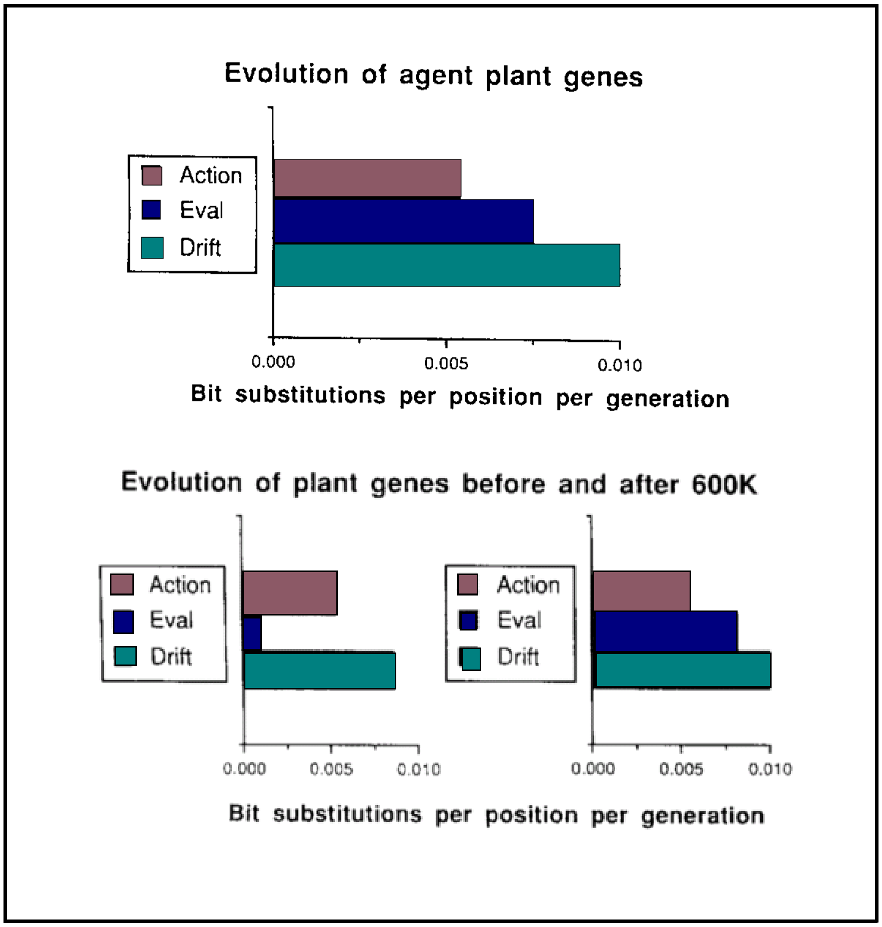

Figure 9: The top graph shows the average number of mutations (bit substitutions) per position per generation for an entire run and for plant agents. Action genes were the most functionally constrained. The bottom graphs separate the mutations before and after 600 generations. This shows that at first, evaluation genes were the most functionally constrained.

3.3 Evolution of Communication

Another class of models with interest to our problem area deals with the emergence and evolution of communication among agents with no explicitly programmed ability to communicate.

- EMERGENT PARTICLE COMPUTATION. Crutchfield and Mitchell [1995]. In this model, "agents" are simple boolean automata organized in a spatial one-dimensional lattice, or 1-D cellular automata (CA). The CA needs to solve a non-trivial task such as the density task: When the initial state of the whole lattice contains a majority of automata/agents with state=1 (0), then the whole lattice should converge to an all-1 (0) state. This is a non-trivial task because each agent has access solely to local information, namely the states of its neighbors, yet the lattice as a whole is expected to perform a global task. Clearly, the task can only be solved with some amount of information integration across the lattice. The experiments were set up in the following way:
  - Lattices of 149 (599, 999) boolean agent automata with boolean rules of radius 3 (7 cells in neighborhood).
  - A Genetic Algorithm (GA) was used to evolve rules to solve this task/environment.
  - A typical result from running the GA is the block-expansion rule (figure 10).

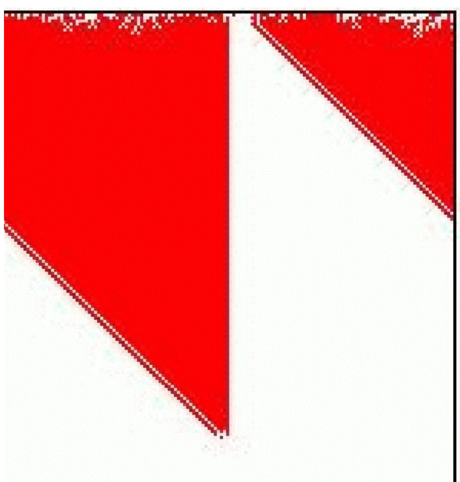

Figure 10:The block-expansion rule simply expands local neighborhoods with a large number of automata in the same state.

  - But occasionally a rule emerges that can solve this task with much better results. These rules create an intricate system of lattice communication. Groups of adjacent automata propagate certain patterns across the lattice, which as they interact with other such patterns "decide" on the appropriate solutions for the lattice as a whole. An intricate system of signaling patterns and its communication syntax has been identified, and can be said to establish the emergence of embedded-particle computation in evolved CA's [Crutchfield and Mitchell, 1995, Hordijk et al, 1996]. The emergent signals (or embedded particles) refer to the borders of the different patterns that develop in the space-time diagrams. If the areas inside these patterns are removed, their boundaries can be identified as a system of signals with a definite syntax, or emergent logic grammar. This syntax is based on a small number of signals, ", $, *, (, 0, and :, and a small number or rules such as: " + * 6 :, meaning that when signals " and * collide, the : signal results. See Figure 11.

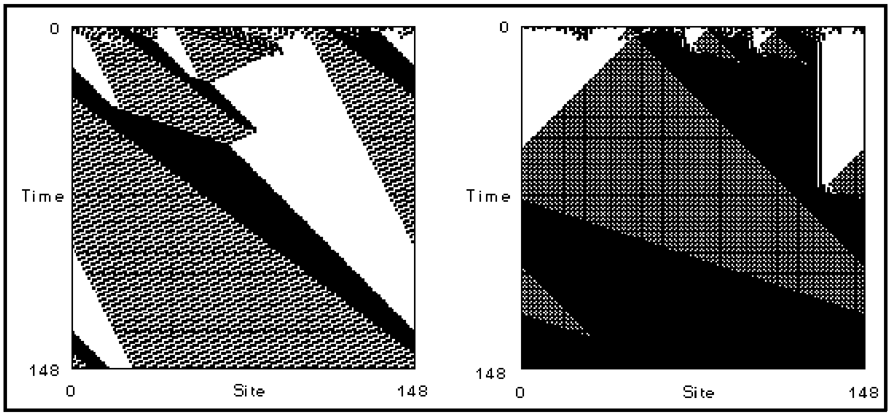

Figure 11: 2 examples of a particle computation rule applied to the density task on a lattice of 149 automata. The figure on the left depicts the case where the rule does not solve the initial configuration (it should converge to all white), while the figure on the right solves the task correctly for the particular initial configuration. The particles refer to the boundaries between the different patterns.

" The system of particle computation uses signals that are capable of integrating distant global information to solve the task. These CA rules rely on a system of signals used to communicate across the lattice and compute the answer to the task: an autonomous sign system that grants great selective advantage to the rules capable of developing it. The particle computation system truly introduces a qualitatively different way of solving the task: through the emergence of autonomous syntax, which allows certain rules to gain access to global lattice information [Rocha, 1998].

" Rocha[1998] has expanded these rules to solve more complicated tasks such as logical operations.

- EVOLUTION OF COMMUNICATION.
  - Werner and Dyer [1991], developed a agent-based computer experiment in the same line of thought as that of Ackley and Littman detailed above, to study the evolution of communication. The environment of these agents was set up so that blind male agents need to wander a 2-D environment in search of female agents with sight and the capacity to emit “sounds”. Each agent has a distinct genome which is interpreted to produce a neural network that defines the agent’s action behavior. This model also does not possess an explicit fitness function for the evolutionary algorithm. Rather, agents are given a certain amount of time to find a mate a reproduce. This produces the desirable asynchrony as agents do not reproduce all in the same time step. This results in overlapping generations with the possibility of inter-generational communication – important for the evolution and transmission of communication and knowledge. These experiments produced a number of very interesting “species” of male-female agents tuned to their own communication protocol or semantic closure. This model will undoubtedly also provide good design principles for our intended simulations.
  - *Evolution of Learning in the Cultural Process*. Hutchins and Hazlehurst [1991] produced an agent-based computer experiment to study how communication can and should emerge from the regularities of a given environment. The show that the evolution of communication is based adaptation of agents’ internal structures to the structure of the environment, that is, coordination between internal and external structure. They embed their experiments in a framework which posits that culture is a *process* that permits the learning of previous generations to have direct effects on the learning of subsequent generations. Their experiments are also fundamentally semiotic, as they posit that the signals that enable communication of culture must be themselves somehow “physically” implemented in a environment. In other words, communication must itself be based on some structure that exists between agents and the environment in addition to agent internal structure and environmental structure. This third kind of structure is of an artifactual nature. This way, the agents of a cultural world have their internal structure shaped by (in coordination with) two kinds of structure in the environment: natural and artifactual. Their experiment is set up to produce agents that may learn a language (using a “physical code) able to mediate between environment regularities and artifactual descriptions of them. Their model sets up a simple environment (loosely based on ethnographic records of California Indians) where there is a relations between moon phase and tide state, which is relevant for agents feeding on shellfish. They use a cultural selection algorithm on agents that possess different neural networks for behavior and knowledge. They show that with the availability of artifactual structure, the learning of the relationship between moon phase and tide state is much more easily discovered and propagated in the population of agents. This model will undoubtedly also provide good design principles for our intended simulations.

- Similar experiments based on culture and language were also performed by MacLennan [1991].

3.4 Agents with Shared Knowledge Structures

The last models of section 3.3 in their dealing with the evolution of communication, rely on the evolution of common structures among agents used to enable communication, e.g. artifactual structures. In this section we deal with models whose goal is to explicitly study the nature and consequences of such shared structure among agents. Being more explicit, these models emanate more from artificial intelligence, social science, and game theory, than from artificial life as the previous models did.

- THE COLLECTIVE CHOICE MODEL of Richards, McKay, and Richards [1998]. This model aims at the investigation of a fundamental problem of social choice models, particularly those used to model collective choice of political alternatives. Previously, it has been showed [e.g. Arrow, 1963, McKelvey, 1979] that the aggregation of elements into a collective choice when many agents and possible choices are involved typically leads to unstable, cyclic outcomes – for instance when we implement majority vote rules on automata. This is clearly at odds with reality where societies are capable of reaching stable political outcomes even in political systems with many available choices. The authors claim that such cyclic behavior exists because the previous system used to study collective choice do not make use of appropriate common structure among agents (this claim is in

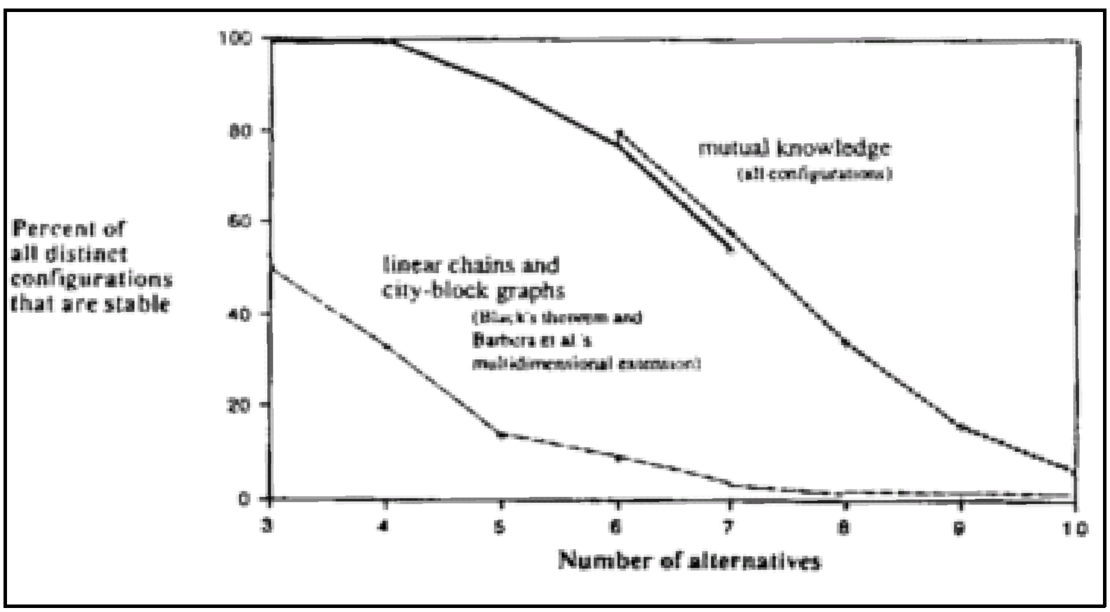

Figure 12:Percent of configurations that are stable under shared knowledge compared with linear constraints (with no constraints the number is zero according to Arrow's theorem).

line with the models of the previous section). Indeed, agents in previous models are assumed to make their own choices autonomously. The authors show mathematically and computationally that by establishing a shared knowledge structure, the probability of such cyclic behavior is reduced dramatically (figure 12).

- The shared knowledge structure is implemented as a graph structure among alternatives. Such a graph implements the regularities of a particular choice landscape or environment. It is very reasonable to assume that alternatives are not all equally related (or un-related), but possess some structure. For instance, when deciding what kind of movie we want to watch, we all share some common knowledge: we know that a horror movie is more related to a violent action movie than to a romantic comedy. Likewise, we know that a Christian-democrat party is more related to a social democrat than to a communist party.
- The shared knowledge structure implemented as a graph effectively establishes constraints on the choices which implement the regularities of a given choice system.

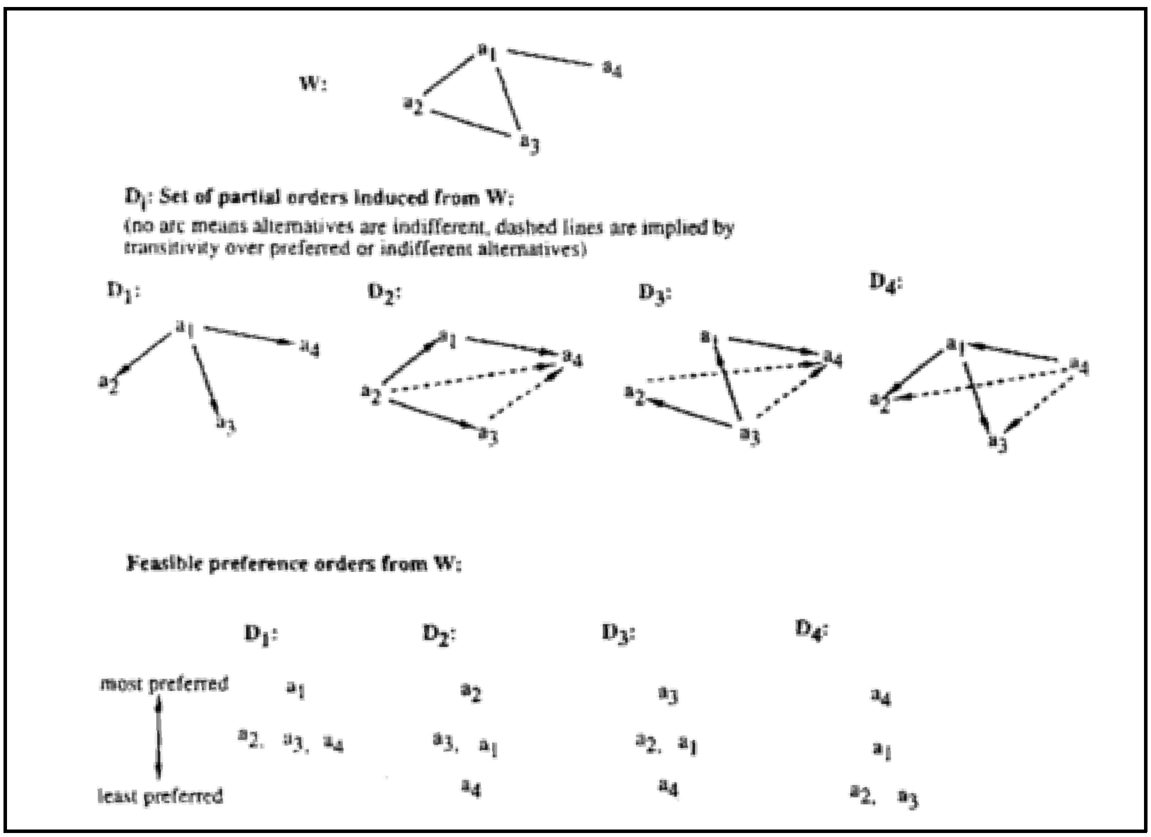

Figure 13: Example of a knowledge structure with 4 choices (above), and respective set of possible partial orders (below).

- From the shared knowledge structure, different partial orders can be established to represent agents with different dispositions towards the shared knowledge structure. For instance, agents who prefer romantic comedies to horror movies, etc. See figure 13.

4. DEVELOPING SEMIOTIC AGENTS

4.1 Design Requirements

4.1.1 Environments: The Selected Self-Organization Principle

In agent-based simulation agents interact in an artificial environment. However, it is often the case that the distinction between agents and environments is not clear. In contrast, in natural environments, the self-organization of living organisms is bound and is itself a result of inexorable laws of physics. Living organisms can generate an open-ended array of morphologies and modalities, but they can never change these laws. It is from these constant laws (and their initial conditions) that all levels of organization we wish to model, from life to cognition and social structure, emerge. These levels of emergence typically produce their own principles of organization, which we can refer to as rules, but all of these cannot control or escape physical law and are “neither invariant nor universal like laws” [Pattee, 1995b, page 27].

The question of what kinds of rules can emerge from deterministic or statistical laws is at the core of the field of Artificial Life [Langton, 1989]. It is also very much the question of generating and studying emergent semantics and decision processes in artificial environments – which we are interested in. However, “without principled restrictions this question will not inform philosophy or physics, and will only lead to disputes over nothing more than matters of taste in computational architectures and science fiction.” [Pattee, 1995b, page 29] For agent-based simulations to be relevant for science in general, the same categories of laws/initial conditions and rules that we recognize in the natural world, need to be explicitly included in an artificial form. For more arguments for the need to explicitly distinguish laws and rules in artificial environments please refer to [Rocha and Joslyn, 1998].

Therefore, the setup of environments for multi-agent simulations needs to:

i ***Specify the dynamics of self-organization***: specify laws and their initial conditions, which are responsible for the characteristics of the artificial environment (including agents) and the emergence of context-specific rules.
   - Example: In Lindgren’s [1991] experiments described in section 3.1.1, the laws of the system are the conditions specified in the iterated prisoner’s dilemma and the genetic algorithm – these are inexorable in this simulation. The context-specific rules are the several strategies that emerge whose success depends on the other strategies which co-exist in the environment and therefore also specify its demands together with the laws. However, the same laws can lead to different transitory rules, and thus, different agent environments.

ii ***Observe emergent or specify constructed semantics***: identify emergent or pre-programmed, but changeable, rules that generate agent behavior in tandem with environmental laws. In particular, we are interested in the behavior of agents that can simulate semantics and decision processes.

- ! Example: The experiments of Hutchins and Hazlehurst described in section 3.3 clearly separate between the laws of the agents' environment (the regularity of tide and moon states) and the artifacts used by the agents to communicate the semantics of these regularities among themselves. The semantics of the artifacts emerges in these simulations.

iii ***Provide a pragmatic selection criteria***: create or identify a mechanism of selection so that the semantics identified in *ii* is grounded in a given environment. This selection criteria is based on constraints imposed both by the inexorable laws of the environment and the emergent rules. When based only on the first, we model an unchanging set of environmental demands (explicit selection), while when we include the second, we model a changing set of environmental demands instead (implicit selection).

- ! Example. Typically the selection criteria is implemented by an evolutionary (genetic or cultural) algorithm with implicit or explicit evaluation function. The explicit function is seen in Hinton and Nowlan experiments, while the implicit function is seen in Ackley and Littman's experiments, both in section 3.2.

A good example of experiments that use the three requirements above are the emergent computation experiments on Cellular Automata (CA) [Mitchell and Crutchfield, 1995] with Genetic Algorithms (GA's), described in section 3.3. Agents (each modeled by an automaton) are constrained to an one-dimensional lattice (the CA) and to a fixed automata production rule , which defines the lower-level virtual laws that lead to emergent behavior in such an environment. The emergent behavior produces different higher level structures to deal with environmental demands, sometimes producing an emergent semantics with a primordial syntax (e.g. particle computation): these are the higher-level, changing rules. Finally, there is an environment which requires a non-trivial task to be performed. The selection mechanism implemented by the GA is an explicit selection function, which directs the self-organization of rules from laws that cope well with the fixed environment.

These three requirements establish a *selected self-organization principle* [Rocha, 1996, 1998, 199?] observed in natural evolutionary systems. This principle is also essential to model the emergence of semantics and decision processes in agent-based simulations which can inform us about natural world phenomena. Essential because without an explicit treatment or understanding of these components in a simulation, it is impossible to observe which simulations results pertain to unchangeable constraints (laws), changeable, emergent, constraints (rules), and selective demands. It is often the case in Artificial Life computational experiments that one does not know how to interpret the results – is it life-as-it-could-be or physics-as-it-could-be? If we are to move these experiments to a modeling and simulation framework, then we need to establish an appropriate modeling relation with natural agent systems which are also organized according to laws, rules, and selection processes.

4.1.2 Agents

The design of semiotic agent models that we are interested in, build up some of the architectures presented in the review above. Semiotic agents, as we see them, need to be based on a few fundamental requirements:

i ***Asynchronous behavior***. In our models, agents do not simultaneously perform actions at constant time-steps, like CA's or boolean networks. Rather, their actions follow discrete-event cues or a sequential schedule of interactions. The discrete-event setup allows for inter-generational transmission of information, or more generally, the cohabitation of agents with different environmental experience. The sequential schedule setup, formalized by Sequential Dynamical Systems (SDS) [Barrett et al, 1999], allows the study of different influence patterns among agents, very important to study decision processes in social networks. The latter are ideal for mathematical treatment as different schedules can be studied in the SDS framework, while the former require statistical experimentation as the collective behavior of discrete-event agents in an environment with stochastic laws and rules cannot be easily studied mathematically.

- ! The discrete-event agent designs we are interested in build on the agents of Ackley and Littman [1991] and the models of the evolution of communication of Werner and Dyer [1991] and Hutchins and Huzlehurst [1991] of 3.2 and 3.3.
- ! The sequential schedule agent designs uses the SDS framework supplemented with the additional points below.

ii ***Situated Communication***. We require that communication among agents be based on the existence of environmental tokens and regularity which must follow the laws of the environment and agent rules. Communication must use resources available in the environment which follows laws and rules, and not rely on unconstrained, oracle-type, universal channels.

- ! This is very much in line with the artifactual nature of communication in Hutchins and Hazlhurst [1991] experiments, or the CA's of Crutchfield and Mitchell [1995] in section 3.3.

iii ***Shared and cultural nature of language and knowledge***. We require that agents share a certain amount of knowledge. This way, agents are not completely autonomous entities with their own understanding of their environments. We are interested in studying social systems which strongly rely on shared knowledge expressed in public languages. Often, in agent-based models, agents reach decisions resting solely on personal rules and knowledge-bases. This autonomous view of agency is unrealistic when it comes to modeling cognitive and social behavior, as ample evidence for the situated nature of cognition and culture [Clark, 1998; Richards et al, 1998; Beer, 1995; Rocha, 1999].

- ! Therefore, our agents build on the graph structures used by Richards et al [1998] to model shared knowledge as described in section 3.4. In particular we expand this framework with the asynchrony (i) and situated communication (ii) agent design requirements. In a sense, combining the models of Richards et al, Hutchins and Hazlehurst [1991] and Werner and Dyer [1991]. We also study emergent shared knowledge structures.

iv **_Capacity to evaluate current status_**. Since a goal of agent-based simulations of social systems is to study decision processes, our agents need to include a means to describe their own preferences and beliefs. This way, agents need to have separate behavior components for action and evaluation. The evaluation component is used by the agent to judge its current status in the environment and then influence the action component. These components can be created and/or evolved independently. This way, we can model agents with different, independent beliefs about their present state and desirable goals.

- ! This capacity is present in the agents of Ackley and Littman (which are similar to those of Werner and Dyer and Hutchins and Hazlhurst). However, our evaluation components are further constrained by shared knowledge structures and situated communication.

v **_Stable, decoupled memory_**. To model more realistically decision processes, and achieve greater dynamical incoherence between agents and environments, we need to move from state-determined behavior components and endow agents with larger, random-access, memory capacity. This implies the storage of a set agents' interactions in memory to aid its evaluation and action behavior. These memory banks persist and can be accessed at any time by the agent, and do not depend on its current state or the state of the environment.

4.1.3 Knowledge: Dynamical Incoherence of Semiotic Agents

Given the environment and agent requirements of 4.1.1 and 4.1.2, we can now discuss the extent of the dynamical incoherency of semiotic agents as described in section 1. Clearly, the multi-agent systems with the requirements above possess elements of dynamical coherency and dynamical incoherency. The dynamic laws of the environment spawn rules of agent behavior which are this way dynamically coupled to the environment. The dynamical incoherence occurs with the following knowledge requirements:

A. Shared knowledge structures which persist in the environment through at least for long intervals of dynamic production;
B. Semantic tokens/artifacts required by situated communication, which persist in the environment, at least for long intervals of dynamic production, until they are picked up by agents;
C. The stable memory banks used by agents to store knowledge are decoupled from the dynamics of the environment.

Note that the asynchrony requirement does not necessarily imply dynamical incoherence. Discrete-event or schedule-driven agents may or may not respond to their cue events or schedules in a dynamical coherent or incoherent manner. If their action and evaluation components are state determined, as the agents of Ackley and Littman or the SDS framework, then they are still dynamically coupled to their environment and its cues. It is only the knowledge requirements which can create a degree of dynamical incoherency, as memory gets decoupled from state-determined interaction.

4.2 Research Problems

1. The asynchrony and situated communication agent requirements establish localized constraints on communication and event-driven actions among agents. We wish to investigate the nature of these constraints. We expect these constraints to be similar to the shared knowledge constraints of the model of Richards et al [1998]. Notice that this model is based on synchronous updating. We postulate that asynchrony and situated communication will result in the ***emergence of a shared knowledge structure*** with the same characteristics of Richards' et al model. Situated communication and asynchrony will implement the realistic situation of having agents' choice be dependent on the choice their neighbors have pursued earlier as well as on the events in their neighborhood. This would be an important theoretical result for the study of choice models.
2. We wish to investigate the relative effect of the 5 agent design requirements on ***networks of influence in multi-agent social models***. Particularly, different discrete-event and scheduling schemes will lead to different influence patterns. But, all other environment and agent requirements will play a role in these patterns.
3. ***Partial shared knowledge structures***. What is the effect of agents possessing only a subset of the overall shared knowledge structure in a given multi-agent system.
4. We also wish to study ***possible disruption to communication and influence networks***. For example, how dependent on situated communication tokens is the stability of a social structure?
5. How does the ***size of the stable memory of agents*** affects the behavior and stability of the multi-agent system?
6. ***How important is the evaluation component*** in a given multi-agent setup? How can it be influenced by other agents?

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