The Evolution of Understanding:

A Genetic Algorithm Model of the Evolution of Communication

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Keywords: evolution of communication, genetic algorithm, self-organization

Abstract

Much animal communication takes place via symbolic codes, where each symbol's meaning is fixed by convention only and not by intrinsic meaning. It is unclear how understanding can arise among individuals utilizing such arbitrary codes, and specifically, whether evolution unaided by individual learning is sufficient to produce such understanding. Using a genetic algorithm implemented on a computer, I demonstrate that a significant though imperfect level of understanding can be achieved by organisms through evolution alone. The population as a whole settles on one particular scheme of coding/decoding information (there are no separate dialects). Several features of such evolving systems are explored and it is shown that the system as a whole is stable against perturbation along many different kinds of ecological parameters.

Introduction

An act of communication on the part of one system can be defined as one which changes the probability pattern of behavior of another; it is the functional relationship between signal and response (Wilson, 1975). Communication in animals is a very important part of their ecological profile (e.g., Wilson, 1971 and 1975, Halliday and Slater, 1983, Alcock, 1989). Whether social or solitary, animals often encounter members of their own or another species and exchange information. Ethologists analyze such communication along three aspects: (1) the physical channel for the information transfer (such as emitters and detectors of light, sound, or chemicals), (2) the present-day function of the message (such as alarms, advertising or requesting resources, individual or class recognition, and assembly or recruitment), and (3) the evolutionary or cultural derivation of the communication (plausible models of how the behavior evolved from other simpler behaviors and became established within the population).

Dawkins (1982) expounds one popular and very fruitful view of communication: that sending signals is a way of manipulating one's environment to one's advantage (via the actions of other living things). This suggests that selection should favor those signals which maximally increases the likelihood of a particular behavior by another animal, relative to the amount of effort it takes to signal[1]. This also illustrates another general property of communication (pointed out by J. B. S. Haldane): that it often involves great energetic amplification, because the relatively small amount of energy expended in producing a signal is magnified (at the expense of the perceiver) into potentially great consequences.

Thus, one approach is to study the evolution and ecology of signal emitters - to discover how such signals arise and how they benefit the animal and increase its

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[1] Redundancy, conspicuousness, small signal repertoires, memorability, and alerting features are commonly used to achieve this (Wiley and Richards, 1983; Guilford and Dawkins, 1991).

fitness (Dawkins and Krebs, 1978). The complementary approach focuses on the receiver, and asks what discriminatory faculties enable another organism to perceive signals and act upon them in such a way as to maximize its fitness, and to minimize being detrimentally manipulated by others. This involves issues of classification and thresholds, optimal allocation of resources (such as time and energy) for processing various signals, etc.

A third, and somewhat orthogonal approach, involves the theory of games, and allows analysis of general behavioral strategies with respect to conflicts (Rapaport and Chammah, 1965; Axelrod, 1984). The paradigms of arms races, the Prisoner's Dilemma, ESS's (evolutionarily stable strategies), and other such models can be used to shed light on why certain animals behave as they do.

Communication usually takes the form of energy or chemical emissions, or body postures and displays, and as with any information exchange, is supervenient upon a coding system. A symbolic or arbitrary code is one in which the symbols have only a contingent relationship to what they represent. Thus, in English (an arbitrary-coded language), the symbol "dog" (whether written or vocalized) has nothing dog-like about it. It is a symbol the meaning of which is fixed by convention only; it could just as easily have been assigned another meaning. This is in contrast to codes like pictographs and hieroglyphics, where the symbol for dog would actually resemble a little dog, and would of necessity carry that meaning. These kinds of codes are said to be self-grounded, because they carry their meaning (or some part thereof) within the symbols themselves.

Much animal communication takes place via a symbolic code, since things like "wagging the tail" or elaborate dancing rituals do not in and of themselves mean anything; their meaning (if any) is fixed by mutual understanding. A dog's wagging its tail could just as easily mean "I am happy" as "I am very angry" (in contrast to behavior such as displaying sharp teeth or claws, inflating or expanding to seem larger, or spraying with a physiologically noxious chemical, all of which of necessity mean "go away or suffer the consequences" because of their obvious and unambiguous physical meanings).

When human beings design communications systems (like computer networks, telegraphs, etc.), the engineers can agree (using a meta-language) on meanings for the various symbols of the language, so that everyone can understand each other. Clearly, most animals have no opportunity for such a means of fixing referents to symbols (although Wilson, 1975, pp. 191-193, discusses several interesting examples of primate meta-communication, such as contextualization and play). Thus, the problem arises: how are the meanings for completely arbitrary symbolic gestures fixed in a large population, when no one has the opportunity to discuss their meanings with anyone else (no meta-language is available for discussion, and meanings must be assigned *de novo*)? This is also one feature of the problems which would arise on a successful SETI (Search for Extra-Terrestrial Intelligence).

Clearly, most codes used in nature have some self-grounded components (for example, a lengthy and physically-strenuous display may directly indicate the stamina and agility of a prospective mate). Information-bearing behaviors exist on a continuum between purely arbitrary-coded ones and purely self-grounded ones, and it is often difficult for observers to know where a given behavior might lie on such a scale. Ethologists are often concerned with issues of semanticization and ritualization of behaviors as they evolve into formal communication. Thus, it is interesting to ask how much understanding can be achieved within a population of organisms which is subject to evolution only (no individual learning), and which utilizes only arbitrary codes. Unlike the general field of the biology of animal communication (Sebeok, 1977; Guilford and Dawkins, 1991, etc.), very little work currently exists on this issue (see Seyfarth and Cheney, 1980, for one example).

In order to investigate in a controlled context the idea that meanings are fixed by interaction with others (as opposed to denotational theories of meaning), MacLennan (1991) showed that communication can arise when cooperation is rewarded. Werner and Dyer (1991) likewise investigated the evolution of communication in a population of artificial neural networks. Both of these approaches focused on simulating real-world interactions (i.e., simulating pursuit of mates, etc.), and thus provided some level of ecological detail.

In this study, I abstract from such detail (in the spirit of Kanevsky *et al.*, 1991, Kaneko and Suzuki, 1994, and Balescu, 1975), and simulate a system where agents evolve under a selection which rewards mutual understanding, to study how the members of an initially non-communicating population can all converge on particular (and identical) meanings for arbitrary symbols. Once defined, this kind of system can be studied under a variety of perturbations to yield information applicable to all classes of evolving communicators. The experiments described below were designed to answer questions such as: what are the dynamics of such a population? Is there any increase of understanding over time? If so, does the population converge on a single "dialect" or do groups form which can understand each other but not members of other groups? How much mutual understanding can be achieved by these means?

Implementation

In functionalist terms, this problem concerns a population of agents, where each agent has a set of internal states (hunger, anger, closeness to its nest or territory, strength, etc.) and a set of external observables (position of tail, posture of body, display of teeth, manipulation of external objects such as food, etc.). Only these external observables are directly perceived by other creatures. The internal states, while not observable, are what determines the future behavior of the creature.

If chaos is not to ensue (it is here assumed that a population of creatures which all understand each other does better than one where misunderstandings are the norm), each agent is driven (in an evolutionary sense) to attempt to guess or derive the internal states of whatever other agent it interacts with, by observing its external features. There is also usually pressure for each agent to make the mapping of internal states to observables as simple and direct as possible, so that other agents will be able to understand it more easily (though there are cases, such as birds acting as if they were injured to lead predators away from the nest, which exemplify misrepresentation of one’s internal states). The fitness of an agent is defined as the average level of understanding of an agent’s internal states by other members of the population.

The mapping of a given agent’s internal states to observable states, as well as a reverse mapping which the agent uses to guess others’ internal states from their observables, is defined by the agent’s genome. In this model I neglect individual learning and socialization (i.e., an agent’s behavior is assumed to be hardwired from birth), as well as "necessary" codings (the codes are assumed to be truly arbitrary - that all possible mappings between internal states and observables are in themselves indistinguishable with respect to fitness; all that matters in determining fitness is to be understood by other agents).

In interaction, each agent performs a coding on a string of internal state values (the "input" string). The exact nature of the coding is governed by one piece of the agent’s genotype, and represents the physiologically-defined mapping between a creature’s internal states and what it portrays by behavior and body signals. The other agents directly observe this coded string as observables, and decode it (using the complementary piece of their genotype, representing the neural mechanisms by which creatures estimate others’ intent from observed data). Thus, each organism’s genome consists of two "genes," one governing how it maps its internal states for display to others, and the other which governs how it in turn interprets its observations of others. This scheme is illustrated in Figure 1.

The fitness of an organism is highest when others' decodings most closely match the original string (the internal states of the agent). Specifically, the internal states and observables of each individual are represented by vectors of integers; the genomes consist of matrices bearing weights (coefficients) for polynomials which map one vector into another. Thus, for a given vector I representing some set of internal states of agent X (for example, a hungry animal which is moderately strong, and not close to its home territory), the observables vector O is obtained by $O = I \cdot C$, where C is a matrix whose elements are contained in the genome of agent X. In an interaction, another agent observes the vector O, applies its own matrix D, and arrives at its guess as to what agent X's internal states might be ($I' = O \cdot D$). The fitness of individual X is given as the average understanding of its internal states by others:

$$fitness(x) = \frac{\sum_{i=1,\, x \neq R}^{g \cdot \, popsize} U(x,R)}{popsize \cdot g}$$

where R is a randomly-chosen individual, *popsize* is the size of the population, and g is a number between 0.0 and 1.0 which indicates gregariousness (i.e., how many of the other members of the population each individual interacts with, in determining its fitness). This is important because the level of sociality varies very widely among species. Values of g close to 1.0 make this algorithm very computationally intensive because of the combinatorial nature of the fitness function (each member has to interact with every other member). For larger population sizes, this will be impractical (on a single-processor machine).

U(a,b) determines how well agent A is understood by agent B. It is defined as the average error individuals make in attempting to guess one another's internal states by applying their decoding function to the encoded vector:

$$U(a,b) = \sum_{i=1}^{interactions} distance(M, G(F(M)))$$

In this expression, *interactions* determines how many interactions with each individual a given agent has (i.e., how many messages they exchange when computing how well they understand each other). This is important because in "dove-like" (non-violent) species, fitness is determined over a large number of interactions (i.e., no one or few interactions determine fitness because none leads to catastrophic results). In very violent species, a single misunderstanding may lead to death, so fitness needs to be determined over a smaller number of messages. *M* is a random message over the space of valid internal state sets, and *G(F(M))* is agent B’s decoding of agent A’s coding of that message. The maximum understanding occurs when the distance between them is minimal (i.e., the decoding is maximally similar to an inverse of the coding). The distance (simple Pythagorean hypervolume distance) between two vectors is computed as follows:

$$distance(M_1, M_2) = \sqrt{\sum_{i=1}^{length\, M_1} (M_1[i] - M_2[i])^2}$$

A genetic algorithm (GA, pseudocode is given in Figure 2) is used to simulate evolution of this system, with fitness being determined through some number of interactions (on randomly-chosen sets of internal states) with some number of other (randomly-chosen) members of the population. The numbers used in the algorithm are parameters which may be changed to study various properties of this evolving system.

The vector/matrix representation was chosen for this model instead of other possibilities like finite state automata and neural networks because they provided a computationally non-intensive algorithm for coding and decoding (important because of the combinatorial nature of the fitness measure), covered a large area of possible mappings (because every output element can be a function of every input element), supported mutation and crossover operators which were closed with respect to the space of legal genotypes, and provided an obvious (but not unique) optimal solution (the identity matrix $I_{n,m}$ which corresponds to the simplest mapping between inputs and outputs).

Note that there is a fundamental difference between this GA and usual GA applications. In the normal genetic search, each candidate solution has a fitness; this fitness is a measure of how well that solution fits a given problem, and is thus independent of any other solutions which may exist at the time. In this GA simulation however, all fitnesses are relative, since the fitness of an individual is defined by how well others understand it. This has been termed "competitive fitness" (Axelrod 1984, Axelrod, 1987), and has several important consequences: (1) there can be no true elitist selection, since the "best" individuals can easily become poor when others are mutated, and (2) there will be very complex dynamics as the population evolves. Of course, this is much closer to true biological evolution since most characteristics' fitness values are very much dependent on the other members of the ecology. Thus, this is the logical extension of Hillis (1991) which showed that coevolving two separate populations can be beneficial, since in this case, every single individual potentially deforms the others' landscapes.

Results

In order to study the properties of an evolving system of agents seeking to understand each other, several experiments were performed in which various key parameters of the simulation were changed. In all of these experiments, the top fitness (defined as the scaled $\log_{10}$ of the fitness of the most-fit individual) and the population convergence (defined as the scaled average difference of each individual's matrix from the population's matrix average) were plotted as a function of generation number.

In the first series, the natural (unperturbed) variability of the system was explored, in order to make meaningful analyses of its behavior under alterations of its parameters. Fifty sample runs were performed with the parameters set to the values in column 1 of Table 1. In all of the experiments which follow, all parameters except the one being investigated are set to these values. The results for the 50 preliminary runs are summarized in the schematic of Figure 3. This will be referred to as the "base population."

In general, an evolution of this system consists of three phases, labeled with Roman numerals I through III in Figure 3. A sample plot of one actual run appears in Figure 4.

All repetitions of this experiment gave approximately the same result. The best individual of a randomly-chosen population has a fitness value of about 0.3 ± 0.01. The top fitness rises sharply to a value of about 0.5 until about generation 300 (phase I), then slowly reaches a maximum of 0.6 ± 0.05 by generation 1000 (phase II), and then meanders about that value from then on (phase III). This phase is stable, and no further major increases occur; the population continues to cycle about the value of 0.6 (equivalent to a two orders of magnitude reduction of error in guessing another agent's internal state vector). The population converges quickly (at around generation 100). Thus, it is seen that a population of such agents is able to arrive at a significant though imperfect level of understanding by virtue of evolution alone. Interestingly, the understanding level is not perfect, and never becomes so, even if the evolution is carried out to 10^6 generations. It was also found (data not shown) that the population converges upon one coding, not sub-populations which each utilize a different "language." In all of the experiments described below, the results given represent the average of 5 runs with the same parameters (this represents a balance between getting statistics which are truly representative of the system and having a computationally-feasible set of experiments).

The next series of experiments was designed to study the effect that population size has upon the population dynamics as it evolves understanding. It is difficult to make a hypothesis as to what size is optimal, because while larger populations in GAs tend to locate solutions quicker than small ones, it may well be that it is more difficult for a large population to achieve mutual understanding (due to the larger range of individual codings available). For this experiment, the parameters were those in column 2 of Table 1. For population sizes of 100 or more (up to 5000, data not shown), the results were all like those of the base trials summarized in Figure 3 (data not shown). For a population of size 30, the improvement in fitness from 0.3 to 0.6 occurred in 1500 generations, in an almost linear fashion (Figure 5). For a population of size 10 there was no net improvement whatsoever in 2000 generations (Figure 6). Thus, there is a critical population size (somewhere between 10 and 30) such that smaller populations are unable to achieve effective communication. There is also a critical population size (between 30 and 100) at which the manner in which the population converges on the maximum attainable level of understanding changes.

The next experiments were designed to test the effects of various survival rates upon the rate of the evolution of understanding. For all runs, the parameters were set as in column III of table I. The percentage of top individuals which were allowed to survive between generations varied from 5% to 95%. It was found (data not shown) that survival rates of 5% to 60% are all equivalent in terms of the behavior of the population, and are very similar to that of the base population described in Figure 3. For survival rates of more than 60%, the initial rise in top fitness was slow, and on average the population only reached a fitness of 0.5 in 3000 generations. This implies that the evolution of understanding in animal populations is not very sensitive to the fraction of individuals which survive to breed at each generation, as long as that fraction is small enough to allow effective selection to take place. This transition appears to lie at around 60%.

The next variable to be tested was mutation rate (all other parameters were set to the values in column IV of Table 1). The mutation rate is defined as the number of times a given individual is mutated (values less than 1.0 indicate a probability of being mutated). For mutation rates of 0.1 to 32, the population's behavior is not significantly different from the base population. For rates above 32 the initial rise is slow and the population requires 1500 generations to reach a fitness value of 0.6.

It was also interesting to determine the effect that crossover (rather than pure mutation) had on the population's behavior. When all other parameters are set as in column V of Table 1, crossover was seen to achieve the maximum at around generation 100, and the maximum fitness achieved was somewhat higher (0.65). This is as expected, since crossover tends to lead to more rapid convergence, which here (unlike in most GA applications) is a benefit.

The next series of experiments studied the population behavior under various numbers of internal states and observables. In all experiments the number of internal states and external observables (referred to as N) was equal, and the other variables were set to the values in column VI of Table 1. It was seen that as expected, for smaller values of N understanding was achieved more easily than for large values. For N=3, the population was able to achieve top fitness values of 0.7, whereas when N=5 there was a very slow rise to a fitness value of 0.6. For N=6, the rise was also very slow and achieved a fitness of only about 0.53 (shown in Figure 7).

The next series of experiments studied the importance of the values for gregariousness (i.e., what percent of the population each individual gets to interact with in determining its fitness), and interaction duration (i.e., how many messages are exchanged in an interaction). It was found that when all other parameters are held as in columns VII and VIII respectively, gregariousness levels of 0.05-0.9, and interaction levels of 1-10 all result in the same behavior as the base population. There seems to be an optimal level of gregariousness around 0.4 which gives a maximal fitness of 0.7.

The final series of experiments was designed to explore the stability of an optimal genotype (the $I_{m,n}$ matrix which corresponds to a null coding transformation) under an influx of randomly-coding individuals, and the effect of an in-migration of $I_{m,n}$ individuals on a normally-evolving population. The values for all parameters were set as in column I of Table 1. In the first experiment, a population was allowed to evolve normally, and then various numbers (percentages of the population size from 0 to 90) of individuals bearing the $I_{m,n}$ genotype were artificially inserted into the population. It was seen that injection of 2% or more of $I_{m,n}$ individuals causes the entire population to achieve a fitness level of 0.7 within 50 generations of when the insertion was performed. The state of the population at the time does not matter. Likewise, a population of $I_{m,n}$ individuals is stable against an influx of 99% or fewer random individuals.

Discussion

The major finding of this series of experiments is that a significant level of understanding among units utilizing purely symbolic codes can be achieved through evolution alone. The evolution profile consists of three stages, and is very consistent between runs, suggesting that it is a real feature of such systems. Furthermore, the fitness profile of such a population as a function of time is very stable against perturbations of various parameters. Surprisingly, gregariousness level and interaction duration do not seem to have a large effect on the evolution of understanding. The same is true for a fairly wide range of selection stringencies, and population size. Use of the crossover operator is seen to accelerate convergence on understanding.

The major factors influencing the rate of evolution are the number of internal states and external observables involved in the communication. The results suggest that misunderstandings should be more common in species which utilize larger numbers of signals to represent larger numbers of internal states. It is also seen that once achieved, a good genotype is very stable and as few as 2% of such individuals are able to catalyze optimal understanding among the whole population within 50 generations.

Future Directions

This paper presented only preliminary data on this complex system. Work is currently in progress to investigate several important features of such a model. Firstly, it is important to determine what can be said about the characteristics of the codes upon which such populations converge (such as their complexity and other measures from information theory). It would also be interesting to determine the effects of the following modifications on the rate of convergence: (1) making some portion of the code non-arbitrary (i.e., some mappings of inputs to outputs are physiologically constrained), (2) rewarding simplicity of genome (parsimony) along with understanding, (3) providing loci on the chromosome (meta-GA) which control GA parameters (such as locations of mutation hotspots, whether an individual uses cross-over or mutation, the value for gregariousness, etc.), and (4) keeping a constant ratio of observables to internal states.

Likewise, it is possible to determine whether the system's self-organizing behavior is robust enough to be able to handle additional uncontrollable or very noisy outputs (which simulate external environmental factors unrelated to the internal state of an agent). Finally, a more complex form of this model is also planned which will utilize steady state GAs, as opposed to discrete generational

GAs, and include non-genetic (cultural) information storage, as well as the ability to misrepresent one’s internal state in certain circumstances (lying, as in Dawkins and Krebs, 1978; Dawkins, 1982), and other complexities such as eavesdropping and withholding information.

Acknowledgments

I would like to thank Ginger Levin for many helpful ideas and discussions.

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Figure Legend

1) "Functional diagram of a single agent"
2) "Flow-chart of the algorithm used for the simulation"
3) "Schematic of evolution of base population runs"
4) "Course of evolution of a base population run"
5) "Course of evolution of a population of size 30"
6) "Course of evolution of a population of size 10"
7) "Course of evolution of agents with 6 internal states and 6 observables"

Table Legend

1) "Parameter values for evolution runs in figures 1-7"

Figure 1:

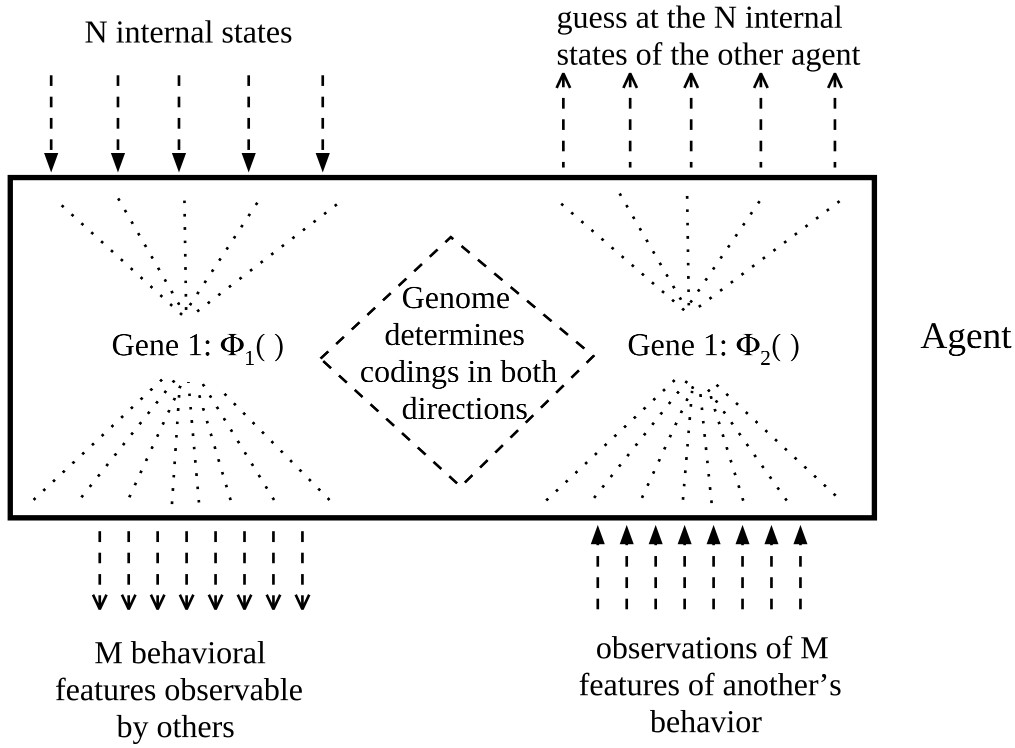
N internal states
guess at the N internal states of the other agent
Gene 1: Φ_1( )
Genome determines codings in both directions
Gene 1: Φ_2( )
Agent
M behavioral features observable by others
observations of M features of another's behavior

Figure 2:

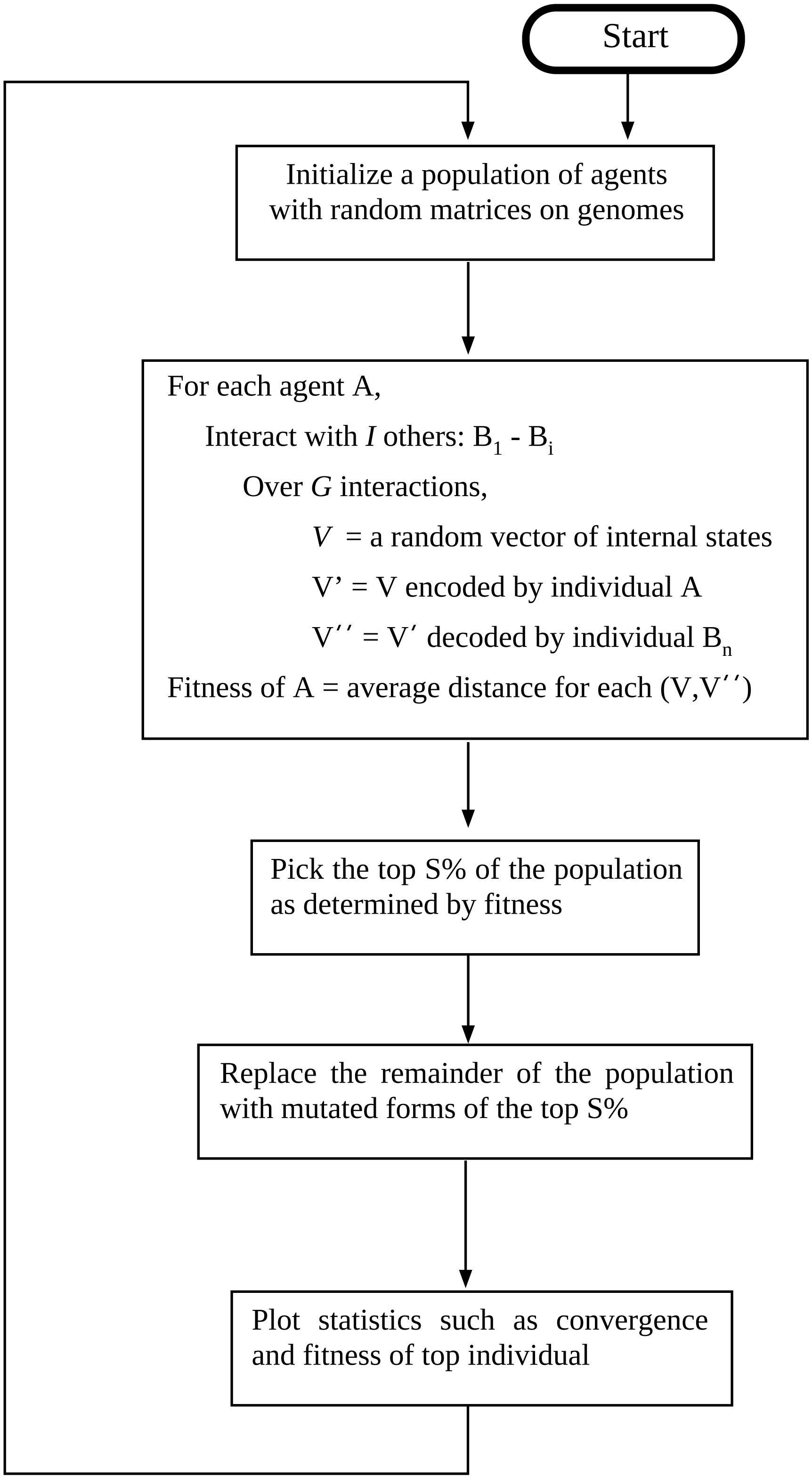
Start
Initialize a population of agents with random matrices on genomes
For each agent A,
Interact with *I* others: B_1 - B_i
Over *G* interactions,
V = a random vector of internal states
V’ = V encoded by individual A
V′′ = V′ decoded by individual B_n
Fitness of A = average distance for each (V,V′′)
Pick the top S% of the population as determined by fitness
Replace the remainder of the population with mutated forms of the top S%
Plot statistics such as convergence and fitness of top individual

Figure 3:

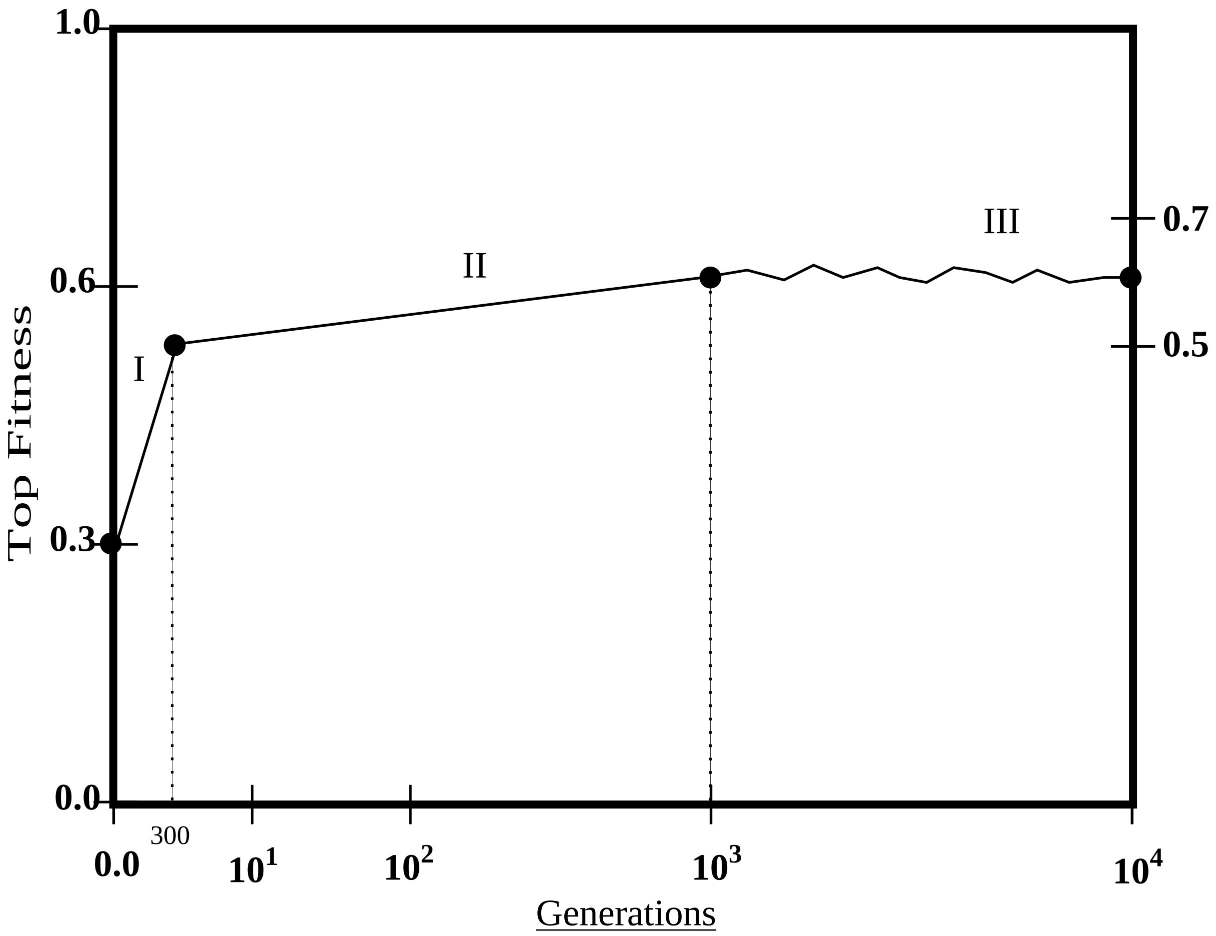
1.0
0.6
0.3
0.0
Top Fitness
0.7
0.5
I
II
III
0.0
300
10^1
10^2
10^3
10^4
Generations

Figure 4:

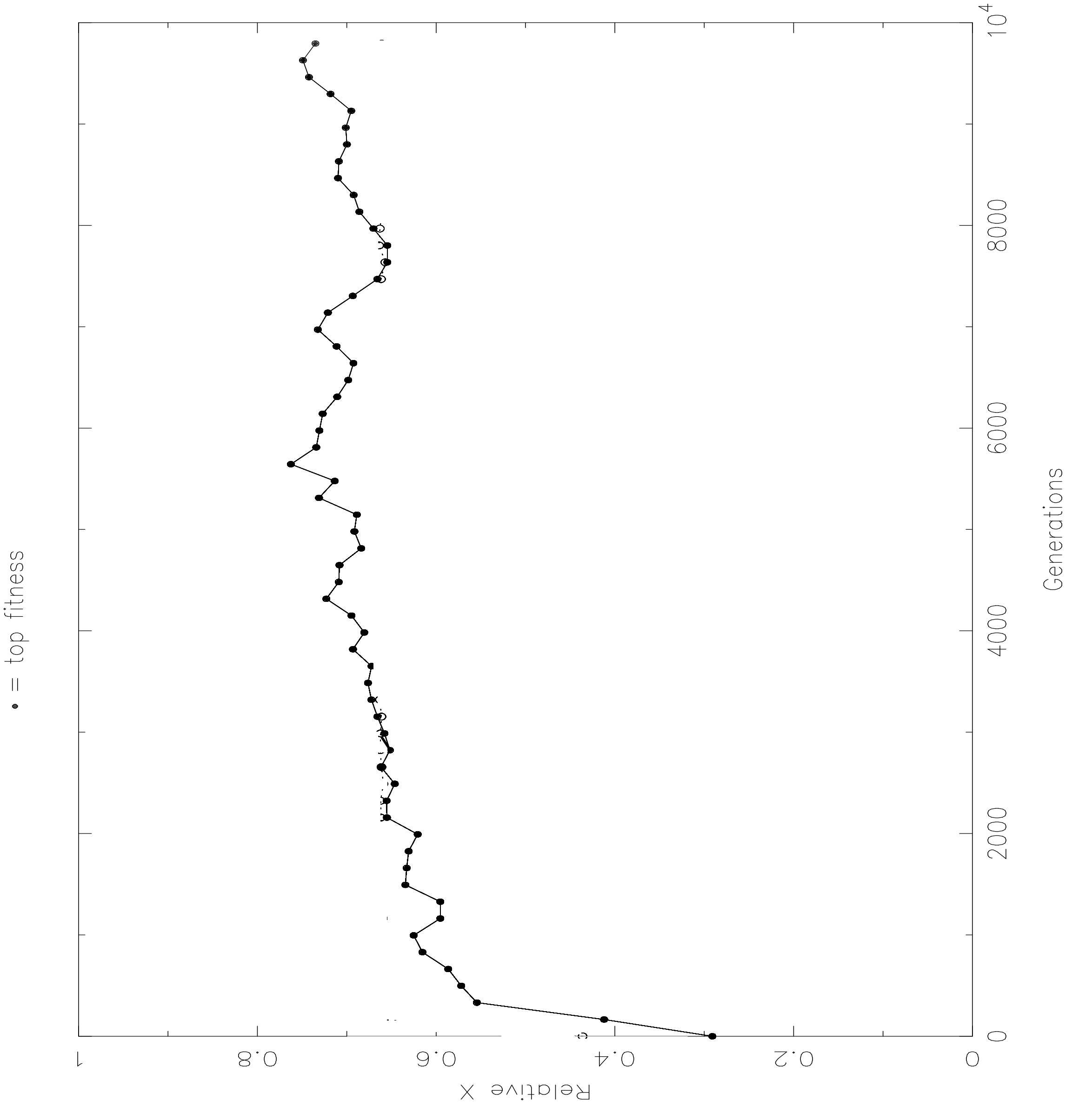
• = top fitness
Relative X
0
0.2
0.4
0.6
0.8
1
Generations
0
2000
4000
6000
8000
10^4

Figure 5:

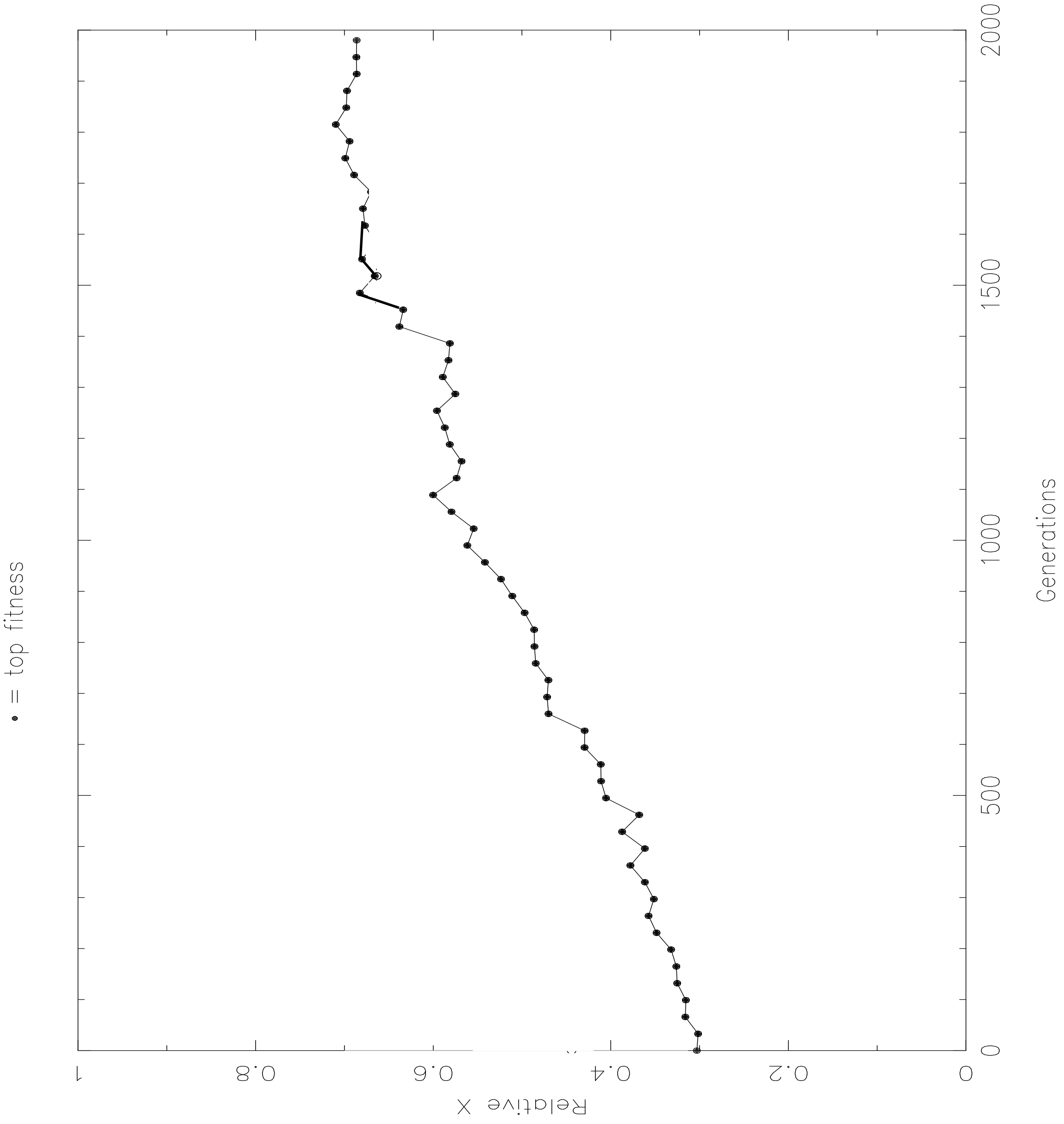
• = top fitness
Relative X
0
0.2
0.4
0.6
0.8
1
Generations
0
500
1000
1500
2000

Figure 6:

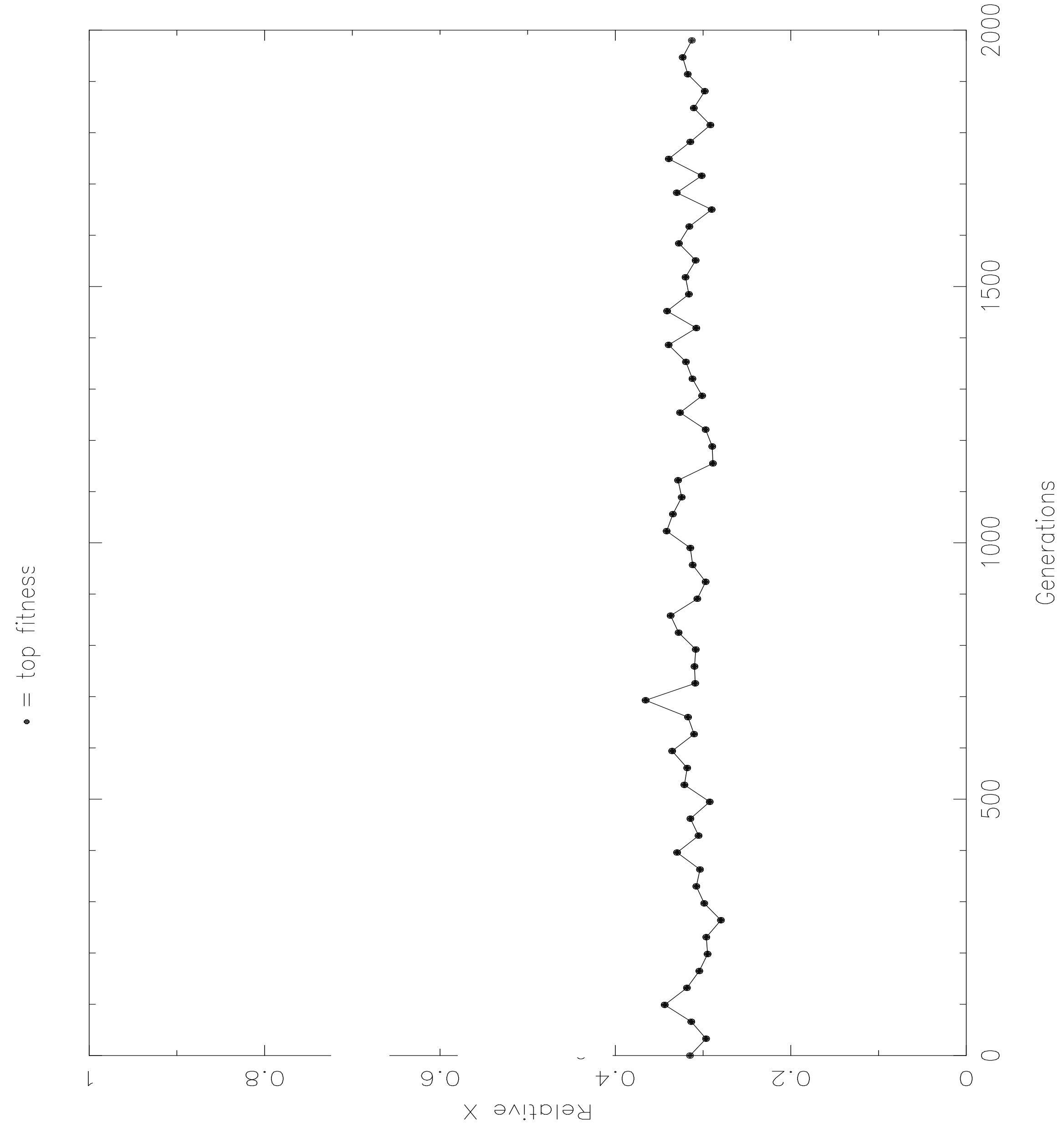
• = top fitness
Relative X
0
0.2
0.4
0.6
0.8
1
Generations
0
500
1000
1500
2000

Figure 7:

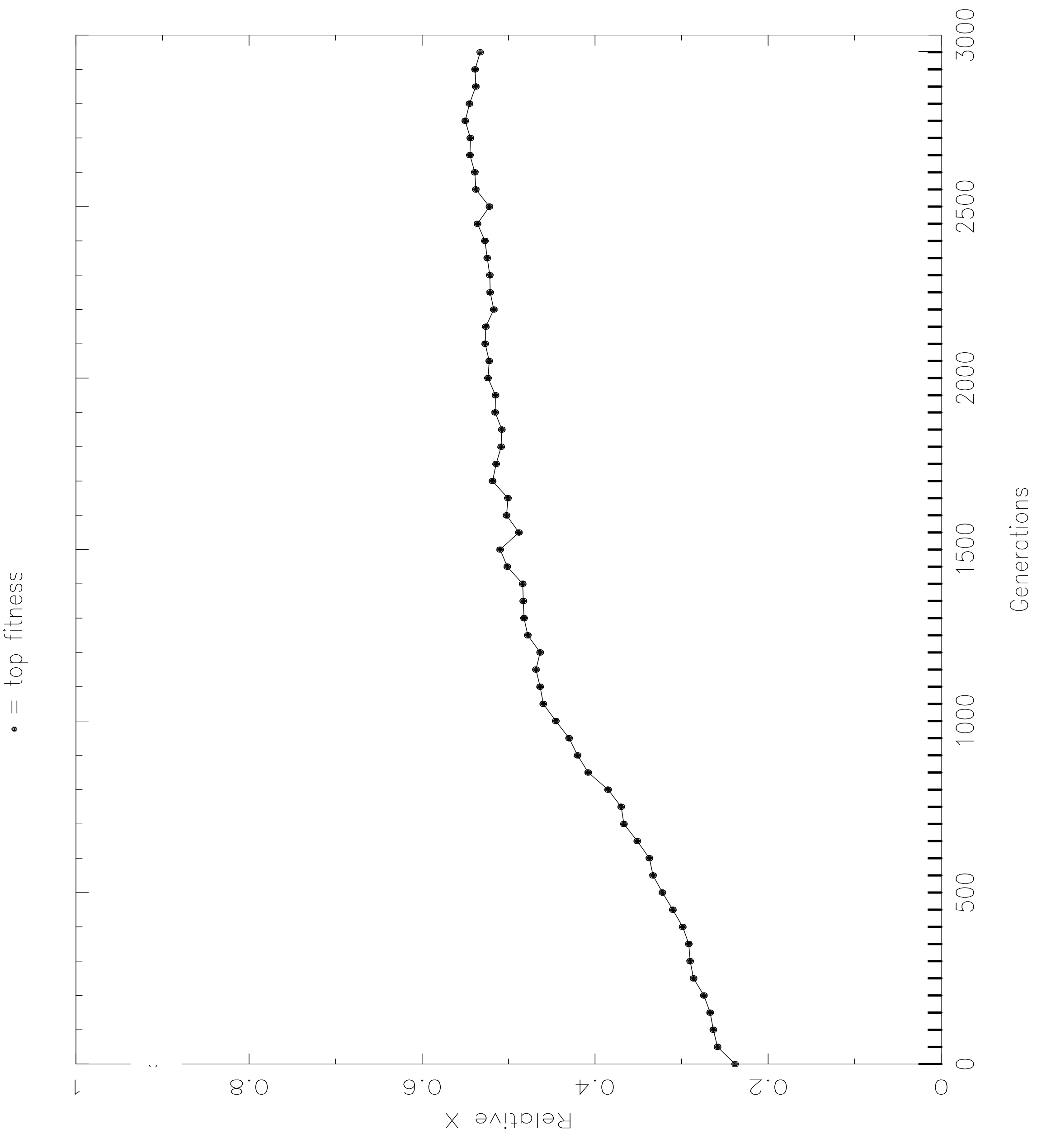
• = top fitness
Relative X
0
0.2
0.4
0.6
0.8
1
Generations
0
500
1000
1500
2000
2500
3000

Table 1:

	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Internal states:	4	4	4	4	4	varied	4	4
Observables:	4	4	4	4	4	varied	4	4
Population size	300	varied	300	300	300	300	300	300
% survivors at each generation	33%	33%	varied	33%	33%	33%	33%	33%
crossover?	no	no	no	no	yes	no	no	no
Mutation rate	5	5	5	varied	5	5	5	5
Gregariousness	10%	10%	10%	10%	10%	10%	varied	10%
Interactions	2	2	2	2	2	2	2	2