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ABSTRACT The genetic algorithm (GA) is a computational procedure that 'evolves' solutions to optimization problems by generating populations of possible solutions, and then by treating these solutions metaphorically as individuals that can 'mate' and 'compete' to 'survive' and 'reproduce'. In this paper, I explore how culturally specific notions of evolution, population, reproduction, sex/gender, and kinship inflect the ways GAs are assembled and understood. Combining the results of fieldwork among GA workers with analysis of GA texts, I contend that the picture of 'nature' embedded in GAs is resonant with the values of secularized Judeo-Christian white middle-class US-American and European heterosexual culture. I also maintain that GA formulations are accented by languages inherited from sociobiology. I argue that examining GAs can help us track how dominant meanings of 'nature' are being stabilized and refigured in an age in which exchanges of metaphor between biology and computer science are increasingly common.

Recombination, Rationality, Reductionism and Romantic Reactions:

Culture, Computers, and the Genetic Algorithm

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When Charles Darwin, in *On the Origin of Species*, tried to convince his skeptical readership of the reality and efficacy of natural selection, he appealed to their understanding of animal husbandry and artificial selection to demonstrate how species might, under selective forces operating over long periods of time, come to change. Today, reversing Darwin's reasoning, a small cadre of computer scientists, engineers, and others are invoking the example of natural selection to suggest to their colleagues that the logic of 'evolution' might be used to 'breed' more flexible artificial systems, and to 'generate' superior solutions to optimization and engineering problems. People working in *evolutionary computation* employ formulations from population and chromosomal genetics to develop new approaches to computer problem solving and programming. *Evolutionary programming, evolution strategies, genetic programming* and *genetic algorithms* are among the most popular paradigms in this new terrain.[1] In this paper, I dissect the 'genetic algorithm' (GA), a class of procedure that 'evolves' solutions to problems by generating populations of possible solutions, and

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then by treating these solutions metaphorically as individuals that can 'mate', 'mutate' and 'compete' to 'survive' and 'reproduce'.

My purpose is to examine how GA researchers construct and construe a computing procedure that they take to be modelled after nature. I maintain that culture-specific conceptions of the individual, population, sex, reproduction, gender, kinship, and economy inflect the way this 'genetic algorithm' is fashioned. The picture of nature embedded in most GAs is populated with images of individuals, lineages, families and communities resonant with the values and practices of white middle-class US-American and European heterosexual culture, the culture to which most of its practitioners belong. I will not argue that the cultural ideas constitutive of GAs render them operationally incoherent, and neither will I maintain that researchers should take on board different views of biology to make 'better' programs. My concern is rather to show that GAs are culturally situated, and so do not mirror an unmediated 'nature'.

The analysis I present mixes the results of fieldwork among GA researchers with critical analysis of GA texts, situating both ethnographic and textual data in cultural and historical contexts. My arguments are built on interviews with researchers, attendance at GA workshops, readings of the primary literature, and my own attempts to tame a genetic algorithm. I conducted most of my ethnography at the Santa Fe Institute for the Sciences of Complexity (SFI), a research centre in New Mexico devoted to computer modelling of non-linear dynamics in complex systems. This fieldwork was one limb of a larger anthropological project I undertook among the community of people working in 'Artificial Life', a species of theoretical biology motivated by the idea that life is an abstract process that can be modelled, simulated and even realized in a variety of media, most notably computers.[2] In compiling the material for this paper, I interviewed 25 GA researchers, mostly affiliated with SFI (primarily as postdocs or visiting fellows and faculty, since the roster of people at SFI changes frequently), mostly men, and mostly persons with primary training in computer science.

In addition to arguing that GAs are fed on the staples of specific sociocultural forms of life, I contend that constructions of evolution in GAs find nourishment in the biological language genetic algorithmists inherit from neo-Darwinism and sociobiology. I also hold that their visions of 'nature as a problem-solver' reveal the persistence of a theological view of natural selection as an agent, and that their search for 'fit' individuals is tied to a political, economic and philosophical commitment to methodological individualism, and to a belief that the future brings progress.

I find the field of GAs interesting because I think it can provide an exemplar of dominant visions of the natural world in the late 20th century, indicate how culturally powerful beliefs about nature can be embedded in material objects and procedures, and alert us to how the meaning of nature is being refigured, as some people convince themselves that a computational process can be well described with terms drawn from evolutionary biology. But while GA theory is concerned with transplanting ideas from the natural to the artificial, it is not entirely about blurring the boundary between the two. More often it is about *policing* that boundary. Claiming that GAs work so well because they mimic nature, practitioners disavow the human construction of that nature, holding up the algorithm's effectiveness as a measure of the validity of stories about natural selection. GAs are engineered to emulate nature, to display those rational, progressive features of evolution. In his widely used introductory text on GAs, David Goldberg gives voice to the metaphysical anxiety that supports the radical separation between nature and artifice, but that also makes the hybrid entity called the GA viable: 'because genetic algorithms are rooted in both natural genetics and computer science, the terminology used in the GA literature is an unholy mix of the natural and the artificial'.[3]

The logic of GAs and of evolutionary computation promises to transform the texture of our everyday experience of computers. As 'natural' logic is injected into the computational process, some of us may come to understand computers as 'effective' because they deploy 'natural' principles in their operation. The cultural commitments embedded in these constructions of nature may become increasingly difficult to discern as the black boxes of GA programs and products are sealed shut. It will be important to specify what sorts of social ideas nest in our constructions of nature – not so that we can ferret them out (which would be impossible), but so that we can see that our pictures of nature represent a social accomplishment with which diverse audiences can engage. I view this paper as an intervention into GA work, and thus as similar to anthropologist Diana Forsythe's work on the cultural construction of 'expert knowledge' in AI, in which Forsythe seeks both to contextualize and to contest her informants' notions of knowledge.[4]

A Brief History of Genetic Algorithms

There are many places one could begin a history of GAs. One might start with the mathematician John von Neumann, who speculated about self-reproducing automata that could evolve. One might claim that molecular biology in the 1950s, founded on the metaphor of DNA as a coded program, made inevitable the notion of evolutionary computation. One could write of the 1960s, when a few programmers began tinkering with evolutionary ideas.[5] The conventional tale, though, opens with computer scientist John Holland's *Adaptation in Natural and Artificial Systems*,[6] in which Holland drew parallels between processes in population genetics, macro-economics, game theory and programming, and in which he sketched the canonical GA. From there, the story follows the fortunes of the GA from 'bit player' in a trickle of PhD theses in the 1970s and early 1980s, to 'headliner' in a growing number of late 1980s and early 1990s GA conferences and their spin-offs.

I want to start by situating GAs in the context of debates in computer science and artificial intelligence (AI). From the 1950s until the 1980s, the central problem in AI had been to find the best way formally to represent and manipulate knowledge.[7] It had become axiomatic that intelligence could be characterized as the rational manipulation of symbols that represented aspects of the world. By the mid- and late-1980s, however, the rational and formalistic vision of intelligence came under attack by those in the AI community who felt that it was an unrealistic image of cognition, and an ineffective model for engineering more flexible and 'intelligent' machines. Some, in a hermeneutic turn of thought, suggested that intelligence grew out of a continual reinterpretation and re-encountering of an ever-changing world.[8] Others maintained that if computer scientists wanted to manufacture intelligent behaviour, they needed first to mimic the life processes that support intelligence. In a move that recalled practices of interdisciplinary borrowing in early cybernetics, computer scientists plundered biology for new ideas and analogies. Researchers building neural nets were inspired by the neuronal architecture of the brain. And GAs were elaborated after the grandest natural process of all: evolution. As David Goldberg, a student of John Holland's, phrased it, genetic algorithms were to be 'search algorithms based on the mechanics of natural selection and natural genetics'.[9]

Psychologist Sherry Turkle has termed the turn to natural models in computer science a 'romantic reaction' to formal, mechanistic and rationalistic approaches to crafting intelligence.[10] Many people I interviewed did indeed spotlight what they called the 'holistic', 'decentralized' and 'biological' aspects of GAs, and a few said that the 'aesthetics' of GAs were more in tune than traditional AI with 'the way nature really built intelligent machines like us'. One person told me that the use of the biological metaphor served to make the whole programming paradigm 'more personal, more intuitive'.

While Turkle's notion of the 'romantic reaction' pinpoints a notable trend, I think that she exaggerates the incompatibility of romantic impulses and rationalistic commitments. Genetic algorithmists' image of nature is nothing if not a recombination of rationalism and reductionism – especially when it relies on the assumption that evolution is ultimately an optimizing engineer that busies itself with sorting through and modifying biological blueprints. David Goldberg, in a kind of natural theology manifesto for the digital age titled 'Zen and the Art of Genetic Algorithms', romantically entreats researchers to 'let nature be your guide',[11] but reminds us that, '[d]espite their intuitive appeal... it is crucial that we back [our] fuzzy feelings and speculations about genetic algorithms using cold, mathematical facts'.[12]

From the GA community's official perspective, metaphysical attraction to a romantic and rational nature has not been the chief incentive for developing the GA. One impetus has been the arrival of massively parallel computers capable of running an enormous number of calculations simultaneously, and of churning through thousands of iterations quickly. Goldberg argues that GAs perform better than various other optimization procedures, including calculus-based search, enumerative search and random search. The GA often does better than many other procedures on the 'travelling salesman' problem, graph-colouring problems, scheduling problems and a variety of engineering design problems which require multivariate optimization.

From a small cluster of interest at the University of Michigan in the early 1980s has developed a large 'GA community', numbering in the mid-hundreds. This community, producing an ever-growing constellation of theory and applications, is dispersed at an array of US-American and European universities, private corporations, and US government organizations like the Navy and Air Force. Most genetic algorithmists are computer scientists from academia or industry, and have limited biological training; most have learned biology from college textbooks, informal conversations, and the occasional collaboration with a biologist. Recently, a few population biologists and geneticists have become interested in GAs and Artificial Life. As the community has grown, it has become more international, though most GA research is still done by people in the US and Europe. Well over 90% of researchers are men, though some of the top people in the field are women. The community regularly congregates at international conferences, and many universities now offer courses in GAs. Researchers maintain contact through email, and many subscribe to the 'GA Digest' distributed over the Internet by a group at the US Office of Naval Research.

In spite of the institutional infrastructure the GA community has built, and in spite of the community's vast efforts to convince mainstream computer scientists that GAs 'really work', many still consider the GA to be a fringe technique. In some ways, however, this has only made GAs more attractive to those who identify the GA with the novel, the visionary and the unexpected, in the ever-mutating world of 1990s computer science.

Hacking a Genetic Code: How the Genetic Algorithm Works

GAs follow an analogy with the behaviour of genes in populations of sexually reproducing organisms, and are loosely based on neo-Darwinian notions of natural selection. A GA begins with a randomly generated population of possible solutions to a given problem (the GA is usually used to solve problems for which the answer is a non-obvious choice out of an enormous set of possibilities). Solutions may be predictive procedures, strategies for playing games, or values to be plugged into a complex equation. These solutions are encoded as fixed-length bit strings composed of zeros and ones, and each string is interpreted metaphorically as a 'chromosome' that codes for one 'individual' in the population. In this formulation, individuals are equal to their 'genome' of one unpaired 'chromosome'. The zeros and ones making up the bit strings are thought of as analogous to the discrete alphabet of four nucleotide bases that form DNA.

This randomly generated population of bit strings contains a variety of individuals, some of which are understood to be 'fitter' than others. In the GA, 'fitness' is usually judged by the individual's ability to perform a given task, or to optimize a preprogrammed 'objective function' – where 'objective' means 'goal'. As Stephanie Forrest puts it,

> Each individual is tested empirically in an 'environment' and is assigned a numerical evaluation of its merit by a fitness function *F*. The environment can be almost anything – another computer simulation, interactions with other individuals in the population, actions in the physical world (by a robot, for example), or a human's subjective judgment.[13]

Once the GA ascertains initial fitnesses in a bit string population, 'parent' strings are chosen to 'reproduce', usually in proportion to their observed fitness. Some parents may be simply copied into the next generation, but most are chosen to be in a 'mating pool', and are 'mated at random' and in pairs. Each pair produces two 'child' strings by swapping fixed lengths of their chromosomes. This process, like the biological one that inspires it, is called 'recombination' – though, more often, 'crossover'. The use of the word 'crossover' slips a bit from fidelity to 'biology': in the genetics of heredity in sexually reproducing diploid organisms, crossover refers to the exchange of material between homologous chromosomes during meiosis, the process that produces gametic cells (eggs and sperm). It is a kind of recombination, but is not identical to sexual recombination.[14]

Here is an example of how crossover works: bit strings A(1) and A(2) have been chosen to 'mate'. In the diagram below, the '|' indicates the site following which code will be exchanged. A'(1) and A'(2) are the offspring strings of this mating.

```
parental pair: A (1) = 10101100|0101
               A (2) = 00110110|1111

offspring:     A'(1) = 101011001111
               A'(2) = 001101100101
```

'Mutations' are occasionally introduced into the 'gene pool' by randomly switching some bits from zeros to ones, and vice versa (usually after all crossovers have taken place). The population size remains constant as generations of 'children' replace their 'parents', and in turn become parents themselves. The GA repeats this process until the experimenter is satisfied with the individuals that emerge. This usually takes several hundred generations – adding up, of course, to very little time in the world outside the computer. As the GA iterates, it produces tables of population statistics so that the experimenter can keep abreast of the performance of individuals.

The main program for a simple GA in Pascal looks like this:[15]

```
begin                    {begins main program}
 gen :=0;                {sets things up}
 initialize;
 repeat                  {main iterative loop}
  gen := gen + 1;
  generation;            {creates a new population through se-
                         lect, crossover, and mutation}
  statistics (popsize, max, avg, min, sumfitness, newpop);
  report (gen);          {writes population report}
  oldpop := newpop;      {advances the generation}
 until (gen >= maxgen)
end.                     {ends main program}
```

Other evolutionary computation approaches vary from this general recipe. John Koza's brand of genetic programming uses programs, not bit strings, as the 'genetic material'.[16] In Koza's world, programs written in languages like Lisp and C map on to trees such that two trees (programs) may exchange subtrees (procedures) at randomly designated nodes. Koza summarizes how genetic programming works, and in so doing gives us the standard rhetoric of evolutionary computation:

> [W]e start with a population of hundreds or thousands of randomly generated computer programs of various randomly determined sizes and shapes. We then genetically breed the population of computer programs, using the Darwinian principle of survival and reproduction of the fittest and the genetic operation of sexual recombination (crossover). Both reproduction and recombination are applied to computer programs selected from the population in proportion to their observed fitness in solving the given problem. Over a period of many generations, we breed populations of computer programs that are ever more fit in solving the problem at hand.[17]

A Simple Sample Problem

To make it clear how a simple GA wends its way through a problem, I take the following elementary example from Stephanie Forrest.[18] Suppose we want to find a maximum value for the function

$$f(x, y) = yx^2 - x^4,$$

where x and y can vary between 0 and 7 (this function can be solved analytically, but if it were not it would be a perfect candidate for solution by the GA). Possible values for x and y can be represented in a bit string by making sub-lengths of the string represent each parameter. Since x and y vary between 0 and 7, we only need three bits to represent each number in binary (000 being zero and 111 being seven); this means that we need a string only six bits long to represent any possible solution. A solution where x is 1 and y is 5 would be represented as 001101, where the first three digits code for $x = 1$, and the second for $y = 5$. The fitness of a bit string like this can be ascertained by decoding the bit string into decimal values, and plugging these into the function $f(x, y) = yx^2 - x^4$. In a GA program written in Pascal, the work of determining the fitness might be done in a subroutine looking something like this:

```
function    objfunc (x:real, y:real): real;
{fitness function f(x,y) = y times x squared - x to the fourth}
const
begin
   objfunc := y*power(x,2) -power(x,4);
   {power(a,b) returns a raised to the b}
end;
```

Denaturing the Genetic Algorithm: The Culture in the Computation

Pictures of 'Nature'

The elaboration of the GA is enabled by a fundamental belief that 'nature' and 'culture', natural and artificial, are separate domains, that our understandings of nature can be clean of socially constructed categories, and that, through careful study of natural example, natural process can be mimicked and transposed into artifacts. Introductory chapters in GA textbooks persistently refer the reader to objective nature with sentences that begin, 'In nature...', or 'Like nature...'.[19] In the view of most researchers, nature is a domain to be studied rationally, and is itself understood to be rationally organized according to discoverable, consistent and, perhaps, parsimonious laws. Scientific rationality sees itself reflected in rational nature. Such an image of nature does not preclude a certain romantic (even religious) appreciation of that 'nature' which stands apart from, and can be resourced by, human activity. One prominent GA researcher told me in interview that working with GAs 'just increases your awe at how things in nature could come into existence'.

In 'Zen and the Art of Genetic Algorithms', David Goldberg brings the romantic view of nature into an orientalist New Age when he suggests that 'Western' reductionistic views of nature can be coupled with holistic 'Eastern' views.[20] He writes:

> By combining careful attention to natural precedent with a holism not unlike that of Zen, genetic algorithmists can relinquish their yen for control, thereby letting GAs perform their actual chores as natural genetics and natural selection have performed so well for four billion years of the evolutionary process.[21]

When we follow Goldberg's advice to 'let nature be your guide', we are led back to a nature that speaks unmediated by human voices:

> ...if we are trying to develop non-linear systems that search and learn, we had better (at least) start off by imitating systems that work. To do otherwise is *Homo sapiens* chauvinism, plain and simple.[22]

This appropriation of 'Eastern' thought by 'Western scientists' (where 'Eastern' codes for an experiential, primitive, and unmediated view of the world) parallels a recent incorporation of stereotypically 'feminine' visions of the natural world by a traditionally masculine computer science. The masculinist imperatives of standard AI – rationality, objectivity, disinterestedness and control – which ensured that many of the people practising computer science were people who had been crafted as masculine subjects,[23] are slowly giving way to what are commonly characterized as more intuitive, more 'ecological', more 'natural' – even more 'Gaian' – programming techniques. In a conversation with two heterosexual men about how their gendered subjectivity might be implicated in the ways they did their science, I was told that the GA allowed them to express and work with a side of themselves that was more intuitive, perhaps more stereotypically 'feminine'. It seems to me that this way of putting things shores up the category of gender even as it purports to erode it, keeping 'femininity' stable as a resource that men might mine to 'broaden' their intellectual work. GAs have become popular in computer science in part, I think, because many new generation computer scientists exist in a milieu in which it is fashionable to think 'ecologically', to rekit traditionally 'hard' technoscience as 'kinder and gentler'.[24]

Most genetic algorithmists rely implicitly on a view of nature as an *agent*. John Koza writes that 'nature creates highly complex problem-solving entities via evolution'.[25] Artificial Life researcher Chris Langton said in a recent lecture: 'Nature is our best teacher for engineering; she's had lots of time to work on problems'; and at the Artificial Life IV meeting at MIT in 1994, Langton declared, with a nod to GA researchers, that 'We have to bring about nature in a computer, so that it can be the agent of natural selection'.[26] I might point out, however, following sociologist Howard Kaye, that understanding natural selection as an agent is to read our purposes on to 'nature'; natural selection is not an agent, and cannot in fact even be a process. It is a 'statistical artifact, not a set of operations and actions organized and directed towards some end'.[27]

In 1994, a GA workshop at SFI which I attended highlighted the extent to which algorithmists hope to emulate nature *in silico* exactly by assuming that natural selection is 'a set of operations and actions'. Those invited included a few population geneticists, who were called upon to help researchers understand the 'ecological' and 'population' dynamics 'emerging' in their computational populations. The assumption was that population genetics could be useful in understanding these phenomena precisely because researchers had successfully managed to capture natural mechanisms in an artificial medium. One population geneticist implicitly confirmed this by suggesting impatiently that workers were 'rediscovering' certain well-known results in population genetics.

For many GA researchers, nature can itself be considered as a computational system that finds solutions to physical and biological design problems. And nature is understood on the model of the best sort of computer available nowadays – a computer that does massively parallel processing, searching from a population of points simultaneously. As programmer David Ackley put it bluntly at one workshop I attended: 'Nature is probably a parallel computation of some sort'. Visions of 'nature as computer' are reinforced by researchers' sense that computers are becoming more 'natural'. One researcher told me that computers are not just models of adaptive systems, but might be adaptive systems themselves. Another said:

> As computers become more and more sophisticated, they have more and more properties in common with living things than they do with bridges.... I really do believe that in the next five years people are going to start looking at computer systems as much more biologically oriented... you see this already with computer viruses... and that's just the first step.

More people, she contended, will take seriously 'biology as a metaphor for computation'.

Nature, a living – sometimes nurturing, sometimes hostile – being in 17th-century European cosmology was de-vivified and mechanized in the 18th and 19th centuries, only to be resuscitated as an enormous computer in the 20th century – a computer that occupies itself with shuffling through successive generations of organisms and genes to find solutions to optimization problems. The tradition of attributing 'feminine' traits to nature continues across these different visions.[28] David Goldberg informs us that nature has become a more pragmatic woman in her computational incarnation: 'nature is no spendthrift, nor is she given to whimsy or caprice'.[29]

While nature is a key symbol in GA work, most GA researchers speak more about 'evolution'. GA scientist Melanie Mitchell told me, 'Everyone in the GA world gets interested in GAs because it's a metaphor for evolution. That's why they like it'. And David Goldberg writes: 'New users are drawn to genetic algorithms by the plausible appeal of a methodology based on nature's search procedure of choice'.[30] But the focus on evolution doesn't do away with ideas about natural order and agency; in fact, when nature is replaced by evolution, it metamorphoses into a more scientific agent, populating the world with rational, creative, and competitive organisms made in its own image.

Notions of Evolution

Most of what genetic algorithmists say about evolution centres on how good evolution is at 'designing' complicated things. One person put it to me this way:

> Natural selection is very good at designing complex organisms. GAs are modelled on natural selection so they have at least a chance of doing so too.

And a researcher at SFI opined that:

> There are a lot of problems we want to solve and we don't know how to solve them. On the other hand, we have evolution out there as an example which has solved all of these incredibly hard problems.

For many genetic algorithmists, evolution is an optimizing agent.[31] Artificial Life researcher Tom Ray has asserted: 'Genetic algorithms exploit the power of evolution to find optimal solutions to problems'.[32] Because many people using GAs are concerned with problems in engineering design, such views are not surprising.

While most researchers would probably say that evolution is simply descent with modification, their attention to optimization often leads them to suggest that evolution is a force of progress and improvement, a suggestion reminiscent of Christian views of nature as designed by a benevolent God. As philosopher James G. Lennox has pointed out, 'the application of value concepts to nature is based on the theological assumption that the Creator acted with good intentions'.[33] In his discussion of the GA process, researcher Lawrence Davis writes:

> If all goes well throughout [the] process of simulated evolution, an initial population of unexceptional chromosomes will improve as parents are replaced by better and better children. The best individual in the final population produced can be a highly evolved solution to the problem.[34]

David Goldberg believes that nature uses evolution 'in her expedient pursuit of betterment'.[35] One researcher reported in interview that...

> ... when people say 'I want to use evolution to solve my problem', [they] usually think of some kind of notion of improvement or more efficient use of resources or something like that...

but she cautioned that...

> ... if you looked it up in the dictionary, it probably doesn't mean that. It probably means just change of some kind.

Often enough, researchers point to humans as a shining example of the design power of evolution. One scientist said to me that 'evolution is a system – basically the only system we've ever seen that can create entities of great complexity like us'. And when another person told me of the power of evolution to generate 'amazing' things, he said: 'just look at us'. The idea that humans would be a noteworthy achievement of evolution suggests a secularization of Judeo-Christian rankings of creatures in Creation, or an evolutionary reforging of the Great Chain of Being. One researcher toasted the achievements of evolution when he contended that 'Evolution has brought us to the point of being able to implement evolution in other media', where by 'us' he meant 'humanity', but referred really only to those scientists fortunate to be doing evolution's will in this way.

Pictures of evolution as an optimizing agent are not restricted to genetic algorithms; they are also common in recent evolutionary biology, and most sharply in sociobiology, which understands the biotic world as the result of genes and individuals acting to maximize their fitnesses.[36] I bring up sociobiology here because it has had an important influence on GA theory. This is primarily because it focuses on the 'behaviour' of genes in populations, favours quantitative methods, and is an easily and popularly available evolutionary framework; many of my informants cited evolutionary biologist Richard Dawkins' best-selling work on 'selfish genes' as central to their thinking.[37]

Most researchers take it as axiomatic that evolution is a process that can be abstracted from 'the biological world' and implemented in computers. Most I spoke with maintained that ideas and technologies might be said to evolve, so it was no surprise that computer procedures could do the same thing. In her article in *Science*, Stephanie Forrest captures the notion that makes possible the idea of evolution as an abstract process. It is 'a computational view of evolution in which the mechanisms of natural selection, inheritance, and variation serve primarily to transmit and process information'.[38] In an interview with one prominent GA researcher, I was told that 'what's really going on in evolution is some kind of information processing'. Such a view of genetic evolution as an abstract informational process which can be implemented in different media has a charter in early molecular biology descriptions of DNA as a code or text which can be 'translated' and 'transcribed'. As historian of science Donna Haraway notes:

> It is not an accident that modern genetics is pursued as a linguistic science, with attention to signs, punctuation, syntax, semiotics, machine read-out, directional information flow, codons, transcription and so on.[39]

In the 1970s, evolutionary biologists and philosophers like Richard Dawkins and David Hull, in their efforts to outline an abstract theory of evolution, coined terms like 'replicator', 'vehicle' and 'interactor' – terms that could refer as easily to organisms as to technologies and ideas.[40] Evolution has been untethered from its biological referent to the point where one of my informants was able to show me a GA program he wrote, and to ask me to 'watch evolution happen in the computer'. Another argued that not only are computer systems complex systems in the fullest sense (being non-linear, exhibiting self-organization), but that they can also be described as emerging out of an evolutionary process. Software, hardware, operating systems, compilers, programs, are always changing, and not always in sync with one another. For this person, the whole cultural-economic matrix that produces computers is driven by an evolutionary logic: 'Evolution is just rampant in the software life cycle', she commented. Here a process primarily driven by the imperatives of ever-innovating, flexible capitalist production is seen as displaying a 'natural' logic.

Before proceeding, I should say something about the epistemological assumptions that allow researchers systematically to interpret their algorithms as containing entities that are 'evolving', 'mutating', 'mating' and 'recombining'. What is necessary for these interpretations is a metaphorical armature that can map formal processes to words with both scientific and commonsense meanings.[41] Once this mapping is done, researchers can use still higher-level terms to discuss 'emergent' dynamics. At a talk I heard at a GA workshop, one researcher cautioned that the utility of the structures that evolve in the GA is largely a matter of the judgement and interpretation of the experimenter. All that is 'really' happening, the speaker continued, is that bit strings are recombining, mutating, and reproducing. This commitment to a lower-level ontology grounds the entire idea that genetic algorithms really do capture something of 'the genetic process'. For GA people, a computational world and a rational selection are the setting and logic for the drama of evolution, both as it occurs in the real universe and in the computer. In the GA, the players in this drama are individual bit strings and their related fitnesses.

Organism/Individual/Bit String and Environment

In the GA, populations are made of individuals, described as naked chromosomes made of zeros and ones. The relationship between alleles, genotype, phenotype, individual and population is set out in the following data type declarations for a simple GA in Pascal:[42]

```
const maxpop     = 100;
      maxstring  = 30;
type  allele     = boolean; {Allele = bit position}
      chromosome = array [1..maxstring] of allele; {string of bits}
      individual = record
                    chrom:chromosome; {Genotype = bit string}
                    x:real;           {Phenotype = unsigned integer}
                    fitness:real;     {Objective function value}
                    parent1,parent2,xsite:integer; {parents & cross pt}
                    end;
      population = array [1..maxpop] of individual
```

Proceeding in this declaration from the largest unit to the smallest, we see that type *population* is an array of type *individual*, and ranges from 1 to the maximum population allowed, here 100. Type *individual* is a *record*, and is described by its bit string genotype (chrom), its phenotype (here, the decoded parameter value *x*), its fitness (the objective function), and information about its parents. Type *chromosome* is itself an array of type *allele*, which is just bit position, zero or one.

The GA individual is made simply of genes (bit strings), which are in turn made of alleles (bits). Its genetic description or genotype is 'decoded' in the problem 'environment' specified by its objective function, in order to yield its 'behaviour' or phenotype. In a simple GA then, individuals' characteristics are determined by the text of their genotypes (themselves determined by parental genotypes), as these are read in a particular environment. In spite of the fact that fitness must always be relative to problem environment in the GA, a phenotype is, as David Goldberg has put it, simply a 'decoded structure'.[43]

The idea that genes make the organism is a philosophy known as 'genetic determinism', versions of which thrive in some strains of evolutionary biology – most notably in sociobiology, which grants genes the power completely to shape the organisms in which they reside.[44] The idea that a genome is a representation of an organism is foundational for the

GA's concern with matching possible problem solutions (phenotypes) with their proper 'genetic representation'. Philosopher Susan Oyama locates the idea that genes are a 'blueprint' for an organism in a Western metaphysical tradition of separating form from matter, of assuming that ontogeny is merely the playing out of a developmental 'program', and that 'information . . . exists before the interactions in which it appears'.[45] Biologist Richard Lewontin argues that:

> Isolating the gene as the 'master molecule' is . . . an ideological commitment, one that places brains above brawn, mental work as superior to mere physical work, information as higher than action.[46]

But the view of organisms as containing programs has been well assimilated in evolutionary biology, especially in the wake of cybernetics, in which organisms are seen as control and communication devices, capable of updating, over generational time, the code which constructs them. In 1976, prominent evolutionary biologist Ernst Mayr articulated this idea precisely:

> The young in some species appear to be born with a genetic program containing an almost complete set of ready-made, predictable responses to the stimuli of the environment.[47]

John Koza's recent insight that programs as well as bit strings might be 'evolved' is made possible by an understanding that organisms are already analogous to programs. In an interview with a prominent Artificial Life researcher, I was told that:

> After a while the analogy between self-replicating programs and living organisms becomes so perfect that it becomes perverse to call it merely an analogy. It becomes simpler just to redefine the word 'organism' to apply to both chemical and software creatures. What they have in common is much more important than how they differ.

In the Pascal declaration earlier, individuals are designated as the fundamental building blocks of populations. While this may seem to be a simple and unproblematic relation, it not only continues a general reductionism, but it also refers us to a methodological assumption best described as atomic individualism: 'the assumption that a composite property of a system both can and should be represented by the aggregation of properties inhering in the individual atoms constituting that system . . .'.[48] The individual in this formulation is seen as prior to its environment, prior to its resources, and prior to other individuals. Evolutionary biology, as it has been elaborated in liberal Western society, has often taken methodological individualism as its foundation, and has assumed that a world of autonomous individuals means a world of individuals in competition. In a typical GA, differential survival is the direct result of competition between individuals with encoded and essential properties.

The historical but not logically necessary link between individualism and competition has meant that evolutionary biologists have been hard pressed to explain altruistic behaviour – that is, helping behaviour which potentially lowers an individual's reproductive success. In an effort to hold on to the essentially competitive picture of evolution, some sociobiologists have argued that genes are the real entities which act to increase their representation in successive generations.[49] This focus allows the theorist to explain selfless individuals while not abandoning a commitment to methodological individualism. Genes are now the selfish agents, and they look after their 'extended phenotype' as it is spread across various related individuals. In this view, organisms maximize, not their individual fitness, but their 'inclusive fitness'; they act to propagate their genes, whether these are present in themselves or in relatives whose survival and reproduction they can aid.

In this game to get their genes into the next generation, all individuals are structurally equal, all just bags of genes. And so it is in the GA. Each bit string is just a collection of genes. As historian of science Evelyn Fox Keller writes of the bag-of-genes idea in evolutionary biology:

> Effectively bypassed with this representation were all the problems entailed by sexual difference, by the contingencies of mating and fertilization that result from the finitude of actual populations and simultaneously, all the ambiguities of the term reproduction as applied to organisms that neither make copies of themselves nor reproduce by themselves.[50]

Keller suggests that the normative organism in bean-bag genetics is 'masculine'; it gets its genes into the gene pool, but doesn't then need to look after them in a process that includes pregnancy and possible genetic and other modifications which happen during this sequence. The GA individual is patterned after this bean-bag idea, and encodes the 'masculine' bias of the theory. As in so many other places, male physiology is taken as normative, while female physiology is seen as deficient, or as laden with 'supplementary' features. A male friend of mine who works on GAs commented, when I asked him about the absence of development, embryogenesis and gestation in GAs, that pregnancy was merely 'an implementation problem'.

Because of the importance of genes in the GA, patterns of zeros and ones that recur in individual strings are often of more interest than individual solutions. In *Genetic Programming*, John Koza writes:

> . . . in the genetic algorithm, as in nature, the individuals actually present in the population are of secondary importance to the evolutionary process. In nature, if a particular individual survives to the age of reproduction and actually reproduces sexually, at least some of the chromosomes of that individual are preserved in the chromosomes of its offspring in the next generation of the population. . . . It is the genetic profile of the population as a whole . . . as contained in the chromosomes of the individuals of the population, that is of primary importance.[51]

In *The Selfish Gene*, Richard Dawkins provides the sociobiological precedent and parallel for this view: 'we [humans] are the survival machines – robot vehicles blindly programmed to preserve the selfish molecules known as genes'.[52] Note that Dawkins' phrasing of the issue relies on a computational metaphor, illustrating the self-referential character of GAs, which borrow ideas from a biology already filled with computational analogies.[53] The ways in which this 'robot vehicle' idea gets into the ways in which people talk can be stunning. At a Santa Fe Institute workshop on computation and evolutionary biology, one man remarked: 'Here we are sitting around the table, when all we're about is replicating'.

Fitness and Adaptation

In the GA, the measure of an individual's value is its 'fitness'. Because much GA work is done with engineering applications in mind, this 'fitness' is usually explicitly tied to function maximization or optimization. As Artificial Life researcher Norman Packard summarizes: 'Organisms are replaced by specifications of a device or dynamical rule', and 'the fitness function is typically given by an engineering goal'.[54] John Holland writes: 'Depending on the problem, the measure of fitness could be business profitability, game payoff, error rate, or any number of other criteria'.[55] In most GAs, bit-string 'fitness' is optimized in prestructured and pre-existing environments, and researchers hold that '[e]valuation functions play the same role in genetic algorithms that the environment plays in natural evolution'.[56] Populations of individuals improve as they solve environmentally given problems. As Melanie Mitchell and Stephanie Forrest caution, however: 'Explicit fitness evaluation is the most biologically unrealistic aspect of GAs'.[57]

Richard Lewontin has argued that the radical separation between organism and environment in much evolutionary biology ignores how the two coexist and might co-construct one another; and, in so doing, it reworks 'a theological view of a preformed physical world into which organisms are fitted'.[58] Biologist Brian Goodwin once commented to me that he detected such a theological view in stories of GA strings climbing towards higher fitnesses, stories he saw as iconic of the ways neo-Darwinist biology retells Christian salvation tales.[59]

Seeing evolution as a process of fitness maximization requires the view that most physical and behavioural traits exist because they have been adaptive – that is, because they have been helpful in allowing organisms to survive and 'reproduce'. It also requires the assumption that such characters have been under genetic control – an assumption easily made in the GA, since traits are in fact under such control. Here, again, there are parallels with sociobiology, which has been staunchly adaptationist, explaining all traits as evolved genetic adaptations to the environment. As Stephen Jay Gould notes, however, biological traits are so interdependent that it makes little sense to talk of particular traits or behaviours being optimized.[60] Philosopher John Dupré writes:

> The attempt to identify the optimum state of a particular trait of an organism inevitably involves the assumption that that trait can be considered in isolation from the rest of the organism.... Item by item

> optimization is not something that can be expected from the invisible hand of natural selection.[61]

Many GA workers would, of course, concede that genes can have multiple effects, and that selection on one trait can be linked to the emergence of other, often deleterious traits. At one GA workshop I attended, considerable discussion revolved around lessons researchers might learn from practices of animal breeding. Breeding, it was argued, was not (or should not be) a question of maximization, nor really of optimization, but of prudent compromise to produce improved specimens.[62]

Donna Haraway has noted that the recent focus of evolutionary biology on optimization rather than maximization distances it somewhat from a natural theological view of nature as perfect. These days, nature takes a long view, and finds optimal balances among large numbers of variables: 'The point of systems design is optimization. Optimization does not mean perfection. A system has to be good enough to survive under given conditions'.[63] As John Koza writes:

> Nature creates structure over time by applying natural selection driven by the fitness of the structure in its environment. Some structures are better than others; however, there is not necessarily any single correct answer. Even if there is, it is rare that the mathematically optimal solution to a problem evolves in nature (although near-optimal solutions that balance several competing considerations are common). Nature maintains and nurtures many inconsistent and contradictory approaches to a given problem.[64]

So while the GA certainly has ties to Panglossian pictures of nature, it also incorporates views of nature as a pragmatic accountant, economistically balancing costs and benefits to arrive at 'satisficing' solutions to problems.[65] This view retools the organism as a clattering of compromises thrown together in search of a good-enough solution. The GA mimics a nature that produces solutions just in time, a nature not too different in its improvizational rationality from the new systems of capitalist manufacture which produce products in small batches and in flexible response to an ever-changing market.

The Population

Ever since Darwin, individuals have been understood in biology as members of populations. And populations evolve over time, as patterns of variation among interbreeding individuals change. This evolutionary axiom is basic to GAs. But the idea of the population is one that has a history. When we speak of populations, we trade in ideas about normality, health, 'family planning', boundaries and, often, conceptions of population diversity as a simple resource for the production of élite individuals.

The idea of population came into elaboration in the late 18th and early to mid-19th centuries, when newly founded nation-states began to conduct censuses, and to initiate projects of social improvement aimed at the newly 'discovered' scientific object called 'society'. Populations came to be

FIGURE 1
Goldberg's Population Statistics

Population Report

Generation 6					Generation 7					
#	string	x	fitness		#	parents	xsite	string	x	fitness
1)	111100011010010010101111110001	1.0135E+09	0.5615	|	1)	(8, 6)	7	111111001011000000101111000100	1.0599E+09	0.8779
2)	111111001000100010011111110011	1.0592E+09	0.8726	|	2)	(8, 6)	7	111111001000000010011011101100	1.0591E+09	0.8715
3)	111111001000000010011111110100	1.0591E+09	0.8715	|	3)	(9,24)	9	111111001000000010011010100111	1.0591E+09	0.8715
4)	111110011110000000101111100100	1.0481E+09	0.7849	|	4)	(9,24)	9	111111101000000010000111110111	1.0675E+09	0.9430
5)	111111001101100001101111010110	1.0605E+09	0.8834	|	5)	(6,18)	3	111111011000001110101111100100	1.0633E+09	0.9070
6)	111111001011000000101111101100	1.0599E+09	0.8779	|	6)	(6,18)	3	111110001011000000111111101100	1.0431E+09	0.7484
7)	111111001001100000101111101100	1.0595E+09	0.8747	|	7)	(10,22)	22	101110011100000010011111110111	7.7910E+08	0.0405
8)	111111001000000010011011000100	1.0591E+09	0.8715	|	8)	(10,22)	22	111111001111010000101111100100	1.0610E+09	0.8872
9)	111111101000000010000011100111	1.0675E+09	0.9430	|	9)	(15,15)	30	111110011010000010011111110001	1.0470E+09	0.7772
10)	111111001100000010011111110111	1.0601E+09	0.8801	|	10)	(15,15)	30	111110011010000010011111111001	1.0470E+09	0.7772
11)	111111001000000010011111110111	1.0591E+09	0.8715	|	11)	(12,12)	5	111111111000000000011111010001	1.0716E+09	0.9807
12)	111111101000000010011111110001	1.0675E+09	0.9430	|	12)	(12,12)	5	111111101000000010011111110001	1.0675E+09	0.9430
13)	111011011000000010000011000101	9.9616E+08	0.4724	|	13)	(26,16)	15	111111001010000000101101110111	1.0596E+09	0.8757
14)	111111001001110000101111110000	1.0595E+09	0.8752	|	14)	(26,16)	15	111110010110000010101111100100	1.0460E+09	0.7694
15)	111110011010000010011111110001	1.0470E+09	0.7772	|	15)	(20, 1)	30	111111001000000010010011000101	1.0591E+09	0.8715
16)	111111001010000010101111100100	1.0596E+09	0.8758	|	16)	(20, 1)	30	111100011010010010101111110001	1.0135E+09	0.5615
17)	111110011110000010110011101111	1.0481E+09	0.7850	|	17)	(9,10)	30	111111101000000010011011100111	1.0675E+09	0.9430
18)	111111011000001110101111100100	1.0633E+09	0.9070	|	18)	(9,10)	30	111111001100000010011111110111	1.0601E+09	0.8801
19)	111111001000000010011111110000	1.0591E+09	0.8715	|	19)	(3, 8)	14	111111011000000010011111110100	1.0633E+09	0.9066
20)	111111001000000010010011000101	1.0591E+09	0.8715	|	20)	(3, 8)	14	111111001000000010011011000100	1.0591E+09	0.8715
21)	111110011110000010101111110000	1.0481E+09	0.7850	|	21)	(1,26)	8	111110010110000000001110110001	1.0460E+09	0.7694
22)	101110011110010010101111100100	7.7969E+08	0.0408	|	22)	(1,26)	8	111100011010010010101111111111	1.0135E+09	0.5615
23)	111111101000000010011111110001	1.0675E+09	0.9430	|	23)	(18,20)	30	111011011000001110101111110100	9.9621E+08	0.4726
24)	111111001000000010011111110111	1.0591E+09	0.8715	|	24)	(18,20)	30	111111001000000010010010000101	1.0591E+09	0.8715
25)	111111111000000010011111100100	1.0717E+09	0.9807	|	25)	(14,30)	3	111111001001100000101111100000	1.0595E+09	0.8747
26)	111110010110000000101111110111	1.0460E+09	0.7694	|	26)	(14,30)	3	111111001001110000101111010100	1.0595E+09	0.8752
27)	111111001001110001101111110000	1.0595E+09	0.8752	|	27)	(23, 3)	18	111111001001000010011111110001	1.0593E+09	0.8736
28)	011110011000010010000011000101	5.0968E+08	0.0006	|	28)	(23, 3)	18	111111101100000010011111110100	1.0685E+09	0.9523
29)	111111001100000010011011110001	1.0601E+09	0.8801	|	29)	(24, 2)	30	111111001000010010001111110111	1.0591E+09	0.8720
30)	111111001001100000101111100100	1.0595E+09	0.8747	|	30)	(24, 2)	30	111111001000100010011111110011	1.0592E+09	0.8726

Note: Generation 7 & Accumulated Statistics: max=0.9807, min=0.0405, avg=0.8100, sum=24.2997, nmutation=201, ncross= 71

Source: Goldberg, op. cit. note 3, 75, Figure 3.18, 'SGA run, generation report t = 6–7'. Population statistics from D. Goldberg, *Genetic Algorithms in Search Optimization and Machine Learning*, © 1989 Addison-Wesley Publishing Company Inc. Reproduced by permission of Addison-Wesley Longman Publishing Company, Inc.

characterized by the various statistics which nation-states used to ascertain which categories of people existed. These numbers could be used to shape a social policy, designating ways to rationalize population processes in order to promote the growth of 'desirable' groups.[66] Population was a natural-technical object that could be brought into healthy, optimal states by proper and productive health and sexual practices. Sexual activity became an important link between the individual and the population: sex was to be 'managed, inserted into systems of utility, regulated for the greater good of all, made to function according to an optimum'.[67] Darwin's theory of evolution in populations, arriving some 20–40 years after the great flurry of statistical activity which Ian Hacking has called the 'avalanche of printed numbers' (in the 1820s through 1840s),[68] was possible because of the advent of population thinking; populations naturally contained variations with respect to fertility, health and mortality, and populations could be optimized, improved, their differences categorized and controlled. Though much early statistical work was motivated by an idea that differences could be shown to be the result of different social circumstances – of poverty, for example – by the mid- and late-19th century, there was a tendency to see differences as stemming from innate characters.[69]

John Koza's discussion of what one can do with the population tabulations of a GA brings together the idea of progress through rational procreation and the monitoring of this with bureaucratic apparatus:

> A genealogical audit trail can provide . . . insight into why the genetic algorithm works . . . two parents were selected to be in the mating pool in a probabilistic manner on the basis of their fitness . . . they then came together to participate in crossover. Each of the offspring produced contained chromosomal material from both parents. In this instance, one of the offspring was fitter than either of its two parents.[70]

David Goldberg's GA provides the user with population statistics, so that readers can track the fittest strings and find out who their parents were (see Figure 1).

The individual exists in relation to the population primarily through 'reproduction'; healthy populations are the result of healthy, eugenic reproductive (productive) practices in diverse populations. That the spectre of eugenics haunts most descriptions of the GA is acknowledged by popular journalist Gibbons Burke, in an article about how GAs might model financial markets. After detailing how the GA works, Burke writes:

> If this sounds hauntingly like some Hitlerian eugenics nightmare, don't fret. No blood will be shed because these traders, this entire market, exist only in the memory of a NeXT computer at the Santa Fe Institute in New Mexico.[71]

One article in a business and technology magazine described the GA as 'a kind of silicon version of eugenics'.[72] In a GA, just as in an Enlightenment nation-state, a good population is like a good economy; measuring means and ends and using (sexual) energy prudently to 'make' better babies. The language of evolutionism is saturated with the categories of industrial capitalism: organisms must be good workers, and must produce and reproduce efficiently.[73] Haraway writes:

> Without question, the modern evolutionary concept of a population, as the fundamental natural group, owes much to classical ideas of the body politic, which in turn are inextricably interwoven with the social relationships of production and reproduction.[74]

When people using the GA use the idea of the 'population', they call upon a concept shaped by the complex dynamics Haraway describes.

Sex, Sexuality, Reproduction, Gender and Kinship

The GA evolves populations of solutions through a process modelled largely on the dynamics of evolution in populations of sexually reproducing animals – or, more precisely, sexually reproducing animals with sequestered germ cell lineages.[75] Humans are an example of such an animal, and because of this, many culturally built ideas about family, kinship, gender, sexuality and reproduction find their way into the analogies that structure the GA. Certainly, affairs would be different if asexual plants were the model, or if polyploid sexual organisms like maize were taken as the template for the GA.

The sexually reproducing couple and their children. In the standard GA, strings pair up to produce offspring using the procedure called crossover, thought of as analogous to 'sexual recombination'. As John Holland puts it:

> Biological chromosomes cross over one another when the two gametes meet to form a zygote, and so the process of crossover in genetic algorithms does in fact closely mimic its biological model.[76]

And Lawrence Davis writes:

> In nature, crossover occurs when two parents exchange parts of their corresponding chromosomes. In a genetic algorithm, crossover recombines the genetic material in two parent chromosomes to make two children.[77]

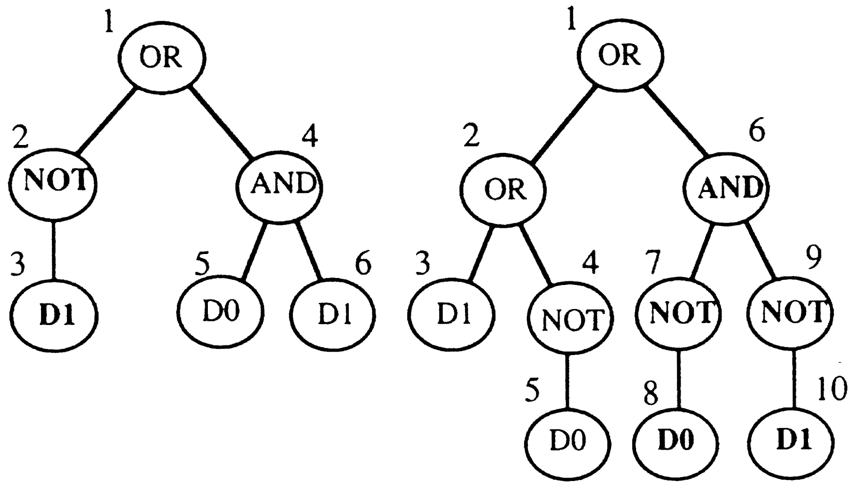
The terms 'parents' and 'children' are routinely used to refer to GA bit strings' 'generational' relation to one another (see Figure 2).[78]

There are a number of ways in which we might understand the exchange of bits between strings, but the metaphor of productive heterosex is gleefully emphasized by most authors. David Goldberg writes:

> With an active pool of strings looking for mates, simple crossover happens in two steps: (1) strings are mated randomly, using coin tosses to pair off the happy couples, and (2) mated string couples cross over, using coin tosses to select the crossing sites.[79]

At a talk at SFI one day, I heard a notable algorithmist say, about 'crossover' in the GA, that he thought intuitively about it by 'thinking

FIGURE 2
Two Parental Computer Programs



Source: Koza, op. cit. note 16, 101, Figure 6.5, 'Two parental computer programs'. From J. Koza, *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, © 1992 MIT Press. Reproduced by permission of MIT Press.

about what it means to recombine my genes and my wife's genes'. In these descriptions, monogamous heterosexual marriage (even if random) is considered a realistic template for natural processes of sexual coupling for reproduction.

In the GA, parents are understood to be eugenically fit, and productive of offspring that are different from (and potentially fitter than) them. As Koza says:

> The crossover operation produces two offspring. The two offspring are usually different from their two parents and different from each other. Each offspring contains some genetic material from each of its parents.[80]

And Holland writes: 'The algorithm favors the fittest strings as parents..., and so above-average strings will have more offspring in the next generation'.[81] The idea that children will be different from (and better off than) their parents is premised on an understanding of kinship as a system which continually generates future possibilities. Anthropologist Marilyn Strathern describes this cultural view of the future:

> Increased variation and differentiation invariably lie ahead, a fragmented future as compared with the communal past. To be new is to be different.[82]

> Kinship delineated a developmental process that guaranteed diversity, the individuality of persons and the generation of future possibilities.[83]

The commonsense of the Euro-American kin system inhabits the GA, which fashions children as 'new individuals' that emerge from parental relations.

Crossover is the key genetic operator in the GA. Many believe that it is this operator that makes the GA work. The 'recombination' of sub-strings allows a population to produce many different kinds of individuals quickly, thereby exploring the solution space more rapidly:

> This mixing allows creatures to evolve much more rapidly than they would if each offspring simply contained a copy of the genes of a single parent, modified occasionally by mutation.[84]

In this model, 'sex' is a source of innovation, and allows species to be adaptively flexible.

As the key operator in the GA, crossover has been subject to intense scrutiny. Some have argued that a persistent problem in the GA is premature convergence to local optima:

> In optimization, when the GA fails to find the global optimum, the problem is often attributed to premature convergence, which means that the sampling process converged on a local rather than the global optimum.[85]

The GA often finds a local optimum quite quickly. Some have proposed that this can be remedied by introducing different sorts of 'mating restrictions' into the algorithm: strings might be prevented from having 'incest', or they might be encouraged not to 'mate' with strings too different from themselves.[86] In discussions around this latter strategy, GA researchers often employ highly racialized imagery; some write about 'miscegenation' in connection with mating restriction.[87]

Directions for sexual determination and differentiation. The standard GA, for all its use of crossover and sex, does not rely explicitly on any sort of 'sexual difference'. But if there is something to the idea that efficient 'reproductive' sex is founded on sexual difference, some genetic algorithmists reason, why not try to make GA models more life-like, and introduce such differentiation into genetic algorithms? Most proposals for introducing differentiation centre on introducing diploid genetics.

Most genetic algorithms work with haploid (single, unpaired) 'chromosomes' which trade 'genes' 'sexually' (even as they are not – and need not be – sexually differentiated). Diploidy (pairing chromosomes) gives organisms chromosome pairs (humans have 23; X and Y are possibilities for pair number 23 and are commonly called the 'sex' chromosomes), and allows for gene effects to be masked or inhibited by dominance. Diploidy can be a useful operator for genetic algorithmists seeking to draw a genotype/phenotype distinction (and has been so used by some researchers), but it does not necessarily imply sexual differentiation, as some seem to imagine. David Goldberg has outlined a diploidic reproductive scheme for the GA which, in the course of reproducing diploid bit strings, activates program procedures named 'gametogenesis' and 'fertilization'.[88] While diploidic bit strings alternate 'fertilizing' one another and there is no structural disparity between them, the very idea that one does something to the other recapitulates the Aristotelian notion that one sex is passive, while the other is active. And the use of the word 'fertilizing' recalls metaphors of males' sperm as 'seed' and females' bodies as 'soil' – images which deny and devalue the creative biological contribution made to offspring during pregnancy.[89]

But more thoroughgoing 'sexual differentiation' for bit strings is already the subject of speculation. David Goldberg muses that genetic algorithms, after all, are based on the 'mating' of possible solutions or optimal programs. Using what he terms 'straightforward reasoning', Goldberg hypothesizes that introducing sexual differentiation among strings might lead to more efficient algorithms because, as he says: 'Clearly, the establishment of sex difference effectively divides a species into two (or more) cooperative groups', and 'allows males and females to specialize somewhat'; 'cooperation and specialization', he holds, are 'implied by natural sex difference'.[90] Goldberg suggests that a population of bit strings can be divided into 'hunters' and 'nurturers', to allow more efficient search. The notion that existing divisions of labour are based on 'natural' sex difference has been the subject of many social and scientific criticisms and challenges in the biological and anthropological literature.[91] But if resting his ideas on unstable assumptions gets Goldberg into questionable territory when the time comes to talk about sexual difference, so does his logic; he takes (his opinion of) the *outcome* of sexual divisions of labour as the reason for their *origin* – a functionalist fallacy, assuming that which is to be proven. While 'hunting' and 'nurturing' are, of course, nothing more than 'wishful mnemonics', as Drew McDermott has called such imaginatively named computer procedures,[92] they profoundly influence how we design and understand what programs do. Goldberg sums up his assumption that his impression of human sexual politics will be adequate for a GA model:

> The details of sex determination are handled differently in different species; however, the human example is sufficiently representative for us to use as a model.[93]

The idea that sex is 'determined' indexes a commitment to the idea that it is essential, likely genetic. Standard cultural and scientific definitions of sex focus on genitals, chromosomes, gonads, hormones and behaviour, but in fact these do not always line up very neatly.[94] And this is just in humans; definitions need to be modified to explain items like sequentially hermaphroditic animals, parthenogenetic lizards and varieties of polymorphously sexual plants.

This attention to trying to bring 'real' sex into GAs reveals a conviction that sexual feeling (conflated with heterosexual feeling) must have evolved to facilitate reproduction. I found this conviction made explicit to me by many of my (overwhelmingly heterosexual) informants. But while there are certainly connections between sex and generation, sexual activity comes in many flavours, not all of which are about reproduction – and not all of which can be connected to a functionalist account of how species get perpetuated. Heterosexuality as an identity or stable practice need not logically exist for evolution in sexual organisms to occur. Perhaps one of the roots of confusion is that we conflate sex as an activity with sex as a biological identity. The idea that one can 'have sex' as well as 'have a sex' is a linguistic trick that guides us into believing that having a sex *in contrast to another's* is a prerequisite for sexual activity (this is likely also to be instrumental in semantic slippage between 'sex' and 'recombination'). As feminist theorist Monique Wittig puts it:

> The category of sex is the political category that founds society as heterosexual. As such it does not concern being but relationships..., although the two aspects are always confused when they are discussed.[95]

And as rhetorician Judith Butler argues, sex is a construct so filled with presumptions about gender that sex is already a gendered concept.[96]

The family. In the hegemonic folk kinship constructs of white middle-class America, the act of heterosexual intercourse which 'produces' children is thought to be the generative knot which produces 'families' and makes people 'related'.[97] Familial relations, in this idiom, imply relations of solidarity and shared destiny. These are the meanings called upon by Lingyan Shu and Jonathan Schaeffer in their article about GAs and classifier systems.[98] Classifier systems are machine-learning systems that make use of the coordinated action of populations of rules. Rules can be coded as bit strings, making possible the evolution of classifier systems, using the GA. Shu and Schaeffer hope to make it easier for structures of interacting rules to emerge in the competitive world of the GA. They write:

> A method is proposed in this paper in which structural ties are used to achieve coherence, impose cooperation and encourage co-adaptation among classifiers. At the lowest level, classifiers (*individuals*) are grouped into *families*. Members of a family cooperate to maximize both the family's strength and the individual member's strength.... Therefore, the fates of the family members are bound together...families that contain good classifiers and classifier structures would survive over those containing improper classifiers.[99]

The metaphor of family is also strong enough to force a sort of exogamy between classifier families: 'The probability of a genetic operation between families is much higher than that between classifiers in a family'.[100]

According to Marilyn Strathern, when Darwin wrote his *On the Origin of Species*, he sketched his picture of evolutionary relatedness after analogies to human kinship:

> Darwin drew on the prevailing ideas of his time concerning genealogy and relatedness between human beings in order to depict degrees of affinity between other species. In the twentieth century Euro-Americans have turned this back on itself, and conceive biological relatedness as primordial and prior to the constructs human beings build upon it.[101]

'Relative' has become, for many of us, a biological term. In *American Kinship*, anthropologist David Schneider tried to summarize what exactly kinship is for US-Americans:

> In American cultural conception, kinship is defined as biogenetic. This definition says that kinship is whatever the biogenetic relationship is. If science discovers new facts about biogenetic relationship, that this is what kinship is and was all along, although it may not have been known at the time.[102]

This is also generalizable to many Europeans.

Many Euro-Americans say that people are related by 'blood'. A few people I interviewed used this term, though they often corrected themselves by saying that what really tethers people together is 'genes' – which of course demonstrates Schneider's point about how kinship terms track biogenetic beliefs, only then to be understood as identical with them. And since genetics is information, information structures that spawn other information structures can be sensibly described as 'parents'. What is preserved in a description like this is the sense that family ties are about lines of descent. One GA researcher told me that he would 'define a family as parents and children, without going laterally'. Another said that being related to someone meant that 'you have common descent', though she insisted that people could be adopted into such relationships, and should then be considered 'related'. What these formulations have in common is a focus on the nuclear family and on the parent–child link, a link that privileges the constant reproduction of future relations and individuals and is of a piece with the ways in which GAs generate futures full of new solution strings.

A Genetic Information Economy

The 'nature' which GAs are modelled after is often figured as an economic system – measuring costs against benefits, speculating on new inventions and innovations, being the 'banker' that keeps track of 'fitness' as a kind of 'profit'. Understanding nature as an economy has a rich heritage in biology, but GAs bring this into the information age.

In GAs designed to perform multi-objective optimization, balancing the various factors involved is done using cost–benefit language – the language of 'trade-offs'. GAs are said to strike 'a balance between exploration and exploitation'.[103] Holland writes: 'Deciding to what degree the present should be mortgaged for the future is a classic problem for all systems that adapt and learn'.[104] We are told that allocating a greater number of trials to strings of high fitness is analogous to extending 'credit' to individuals, based on promise of future success. Goldberg notes that the equations that govern such allocation are similar to compound interest equations.[105] And he writes that mutation is 'like an insurance policy... it helps prevent the irrecoverable loss of potentially important genetic material'.[106]

Perhaps the starkest economisms in GA theory come out in discussions of classifier systems. Goldberg writes about the environment in which system rules evolve:

> The relative value of different rules is one of the key pieces of information that must be learned. To facilitate this type of learning, classifier systems force classifiers to coexist in an information-based service economy. A competition is held among classifiers where the right to answer relevant messages goes to the highest bidder, with the subsequent payment of bids serving as a source of income to previously successful message senders. In this way a chain of middlemen is formed from manufacturer (the detectors) to consumer (environmental action and pay-off).[107]

Rules build up credit, and there is therefore a sort of 'internal currency' in the system. As Goldberg expresses it:

> The exchange and accumulation of an internal currency provides a natural figure of merit for the application of genetic algorithms. Using a classifier's bank balance as a fitness function, classifiers may be reproduced, crossed, and mutated....[108]

These are not fortuitous metaphors: they come from a biology already in dialogue with economics. Donna Haraway notes that...

> ...it is a striking fact that the formal theory of nature embodied in sociobiology is structurally like advanced capitalist theories of investment management, control systems for labour, and insurance practices based on population disciplines.[109]

What makes GA borrowings from economics new is the contention that biology, like economics, is an informational system. In the late 20th century, economic transactions organized around the exchange of information – trading on the currency or derivatives markets – have become increasingly prevalent.[110] For many of the researchers discussed here, some GA ideas come directly from economics: John Holland, for one, is an active participant in the evolutionary economics programme at SFI.

The Fruits of Artificial Evolution: GA Applications

GAs may well be used to design a variety of technologies that we encounter in our everyday lives. Presently, they are being employed in the design of networked manufacturing technologies, pattern recognition protocols, military aircraft, telecommunication networks and database query tools. They are also being used in computer models of the stock market (here 'individuals' encode strategies for trading, and some GA programs have already been used in on-line trading), and in the manufacture of simulation tools for game-theoretic political science. GAs have become indispensable tools in Artificial Life, where they are used as the building blocks of virtual organisms in simulated worlds, and as programs for running real-world robots. GAs are also being made available to consumers (see Figure 3).

FIGURE 3
Artificial Life... Real Solutions

Source: An advertisement for Evolver^{TM}. Trademark and Copyright Axcélis, Inc. Reproduced with Permission.

The funding of GA work is diverse, but prominent sources (in America) are the US Army, NASA, the DoD, the US Navy, the NSF, as well as computer companies like Texas Instruments and Sun Microsystems. Genetic algorithmists have a fair chance of introducing 'naturalistic' machines into the ecology of everyday life, of 'strewing' our landscape with machines, programs and designed processes just as 'natural' as nature itself. They are positioned as powerful techno–bio–political agents, helping to refashion/reinforce our common sense and categories.

Transposing 'Nature' into the Key of Culture

As the 20th century twists to a close, technologies of genetic engineering, *in vitro* fertilization, nanotechnology and naturalistic computation have begun to blur the boundary between what has been considered 'natural' and 'artificial'.[111] One might say that the 'natural' and the 'cultural' are recombining in new ways. One interpretation of this process, and one that many GA scientists might provide, is that 'nature' is being successfully transposed into artifacts. Another, complementary, interpretation is that 'culture' is tinkering with and modifying what counts as 'natural', but is only doing so in accordance with 'nature', since culture is itself a 'natural system'. What these views miss is how 'nature' is always heavy with culturally specific meanings – meanings that are always changing and that, today, are transforming in response to the information and computing technologies that claim to capture and reveal naturalistic logic.

I have argued here that the new informatic stories about nature and evolution nestled in genetic algorithms contain enduring assumptions about, among other things, atomic individualism, Euro-American kinship, heterosexual gender ideology, and free-market economics. I think an awareness of how such assumptions are packaged into artifacts and thereby made invisible – as well as available for incorporation into other technologies – is especially important for tracking the changing meanings of 'nature' in an age in which the organic and technological are increasingly implicated in one another. In spite of its mutating character, 'nature' remains a key symbol for those of us who have been the inhabitants and victims of Western Judeo-Christian culture. It has meant that which is rationally ordered, wise, inevitable, just, moral and fixed. Whether the 'efficacy' of the GA stabilizes existing ideas about what is 'natural', or whether it calls attention to the artifactual, social and contingent character of any account of 'nature', remains to be seen. I would favour the second possibility. I would like the blurring of boundaries between the natural and the social to give us a world in which we are more aware that we make the world we live in – though, to paraphrase Marx, not under conditions of our own choosing. We live in a world where technologies congeal social, material and symbolic meanings – and technologies modelled 'after nature' are no exception.

Genetic algorithms, and other breeds of adaptive computation, might well produce objects and programs that have many of the traits we associate with the living: the capacity to reproduce, survive, surprise, act semi-autonomously, and so on. I emphasize that whatever happens will be a social accomplishment – that if GAs become effective and popular tools in engineering, they will nevertheless encase the cultural logics of the people who fashion them. Diana Forsythe, in a recent paper about knowledge engineers in this journal, argued that:

> Those whose ways of knowing and doing are classified as 'knowledge' and 'expertise' by the builders of expert systems will often find their view of the world reinforced and empowered by this powerful emerging technology.[112]

No less with GAs: those whose understandings of nature are installed in computer programs may well find their view of the world reinforced and empowered by this new, 'evolutionary' technology. But GAs are an instantiation of a culturally specific understanding of 'biology' – and, as such, offer only one way of understanding, implementing, and refashioning the 'natural'.

Notes

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1. For an overview, see *Evolutionary Computation*, Vol. 1, No. 1 (Spring 1993).
2. This research is reported in my dissertation: Stefan Helmreich, *Anthropology Inside and Outside the Looking-Glass Worlds of Artificial Life* (unpublished doctoral dissertation, Department of Anthropology, Stanford University, 1995). The ethnographic aspect of my project draws inspiration from sociologists and cultural anthropologists who have worked as participant-observers in laboratories: see, for example, Bruno Latour and Steve Woolgar, *Laboratory Life* (Beverly Hills, CA: Sage, 1979); Karin Knorr-Cetina, *The Manufacture of Knowledge* (Oxford: Pergamon, 1981); Sharon Traweek, *Beamtimes and Lifetimes* (Cambridge, MA: Harvard University Press, 1988); and Emily Martin, *Flexible Bodies* (Boston, MA: Beacon Books, 1994).
3. David E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning* (Reading, MA: Addison-Wesley, 1989), 21.
4. Diana E. Forsythe, 'Engineering Knowledge: The Construction of Knowledge in Artificial Intelligence', *Social Studies of Science*, Vol. 23, No. 3 (August 1993), 445–77.
5. See John Holland, 'Information Processing in Adaptive Systems', *Information Processing in the Nervous System, Proceedings of the International Union of Physiological Sciences*, Vol. 3 (1962), 330–39; Holland, 'Outline for a Logical Theory of Adaptive Systems', *Journal of the Association for Computing Machinery*, Vol. 3 (1962), 297–314; I. Rechenberg (trans. B.F. Toms), 'Cybernetic Solution Path of an Experimental Problem', Royal Aircraft Establishment Translation No. 1122 (Farnborough, Hants.: Ministry of Aviation, RAE, UK, 1965); Lawrence J. Fogel, Alvin J. Owens and Michael J. Walsh, *Artificial Intelligence through Simulated Evolution* (New York: John Wiley, 1966); J.D. Bagley, *The Behavior of Adaptive Systems Which Employ Genetic and Correlation Algorithms* (unpublished doctoral dissertation, University of Michigan, 1967).
6. John Holland, *Adaptation in Natural and Artificial Systems* (Ann Arbor, MI: The University of Michigan Press, 1975).
7. See Terry Winograd and Fernando Flores, *Understanding Computers and Cognition* (Reading, MA: Addison-Wesley, 1986); Winograd, 'Thinking Machines: Can There

Be? Are We?', in James J. Sheehan and Morton Sosna (eds), *Boundaries of Humanity: Humans, Animals, Machines* (Berkeley, CA: University of California Press, 1991), 198–223.

8. Notably Winograd & Flores, op. cit. note 7, and Rodney Brooks, 'Intelligence without Representation', *Artificial Intelligence*, Vol. 47 (1991), 139–59.
9. Goldberg, op. cit. note 3, 1.
10. Sherry Turkle, 'Romantic Reactions: Paradoxical Responses to the Computer Presence', in Sheehan & Sosna (eds), op. cit. note 7, 224–52.
11. David E. Goldberg, 'Zen and the Art of Genetic Algorithms', in J. David Schaffer (ed.), *Proceedings of the Third International Conference on Genetic Algorithms* (San Mateo, CA: Morgan Kaufmann 1989), 80–85, at 81.
12. Goldberg, op. cit. note 3, 27.
13. Stephanie Forrest, 'Genetic Algorithms: Principles of Natural Selection Applied to Computation', *Science*, Vol. 261 (13 August 1993), 872–78, at 873.
14. This is something Stephanie Forrest notes (ibid.). One could argue, as some have, that because each GA 'parent' is made of one 'chromosome' and is 'haploid', the conceptual difference between crossover and recombination is unimportant.
15. From Goldberg, op. cit. note 3, 69 (comments modified). I refer the reader to Goldberg for the full detail of procedures 'generation' and 'crossover'.
16. John Koza, *Genetic Programming: On the Programming of Computers by Means of Natural Selection* (Cambridge, MA: MIT Press, 1992).
17. Ibid., 4.
18. Forrest, op. cit. note 13.
19. For example: 'nature does it better' (Goldberg, op. cit. note 3, 2); 'In nature, biological structures that are more successful in grappling with their environment survive and reproduce at a higher rate' (Koza, op. cit. note 16, 1); 'Like nature, [Holland's algorithms] knew nothing about the type of problem they were solving' (Lawrence Davis [ed.], *Handbook of Genetic Algorithms* [New York: Van Nostrand Reinhold, 1991], 3).
20. Goldberg, op. cit. note 11, 80–81.
21. Ibid., 80.
22. Ibid., 82.
23. See Paul N. Edwards, 'The Army and the Microworld: Computers and the Politics of Gender Identity', *Signs*, Vol. 16, No. 1 (Autumn 1990), 102–27.
24. See Kevin Kelly, *Out of Control: The Rise of Neo-Biological Civilization* (Redwood City, CA: Addison-Wesley, 1994), a book on 'complexity science' that directly links naturalistic computation and ecological consciousness.
25. Koza, op. cit. note 16, 6.
26. These quotations from Chris Langton are taken from my own notes. Unless otherwise cited, quotations in the text from GA researchers are from my interviews and field notes.
27. Howard L. Kaye, *The Social Meaning of Modern Biology* (New Haven, CT: Yale University Press, 1986), 53.
28. See Carolyn Merchant, *The Death of Nature: Women, Ecology, and the Scientific Revolution* (New York: Harper & Row, 1980).
29. Goldberg, op. cit. note 3, 149. Not everyone working with the GA is as taken with nature as researchers like David Goldberg. One physicist said to me: 'I don't buy into those arguments that because nature does it this way, that's the best way of doing it or whatever . . . I mean, nature is not optimal by a long way and by any reasonable criteria'.
30. Goldberg, op. cit. note 11, 80.
31. But not all: see Kenneth De Jong, 'Genetic Algorithms: A 10 Year Perspective', in John J. Grefenstette (ed.), *Proceedings of the First International Conference on Genetic Algorithms* (Hillsdale, NJ: Lawrence Erlbaum Associates, 1985), 169–77, at 170.

32. Tom Ray, 'Is It Alive or Is It GA?', in Richard K. Belew and Lashon B. Booker (eds), *Proceedings of the Fourth International Conference on Genetic Algorithms* (San Mateo, CA: Morgan Kaufmann, 1991), 527–35, at 527.
33. James G. Lennox, 'Teleology', in Evelyn Fox Keller and Elisabeth A. Lloyd (eds), *Keywords in Evolutionary Biology* (Cambridge, MA: Harvard University Press, 1992), 324–33, at 328.
34. L. Davis, 'What is a Genetic Algorithm?', in Davis (ed.), op. cit. note 19, 1–22, at 5.
35. Goldberg, op. cit. note 3, 309.
36. See Edward O. Wilson, *Sociobiology* (Cambridge, MA: Belknap/Harvard University Press, 1975), 67.
37. Richard Dawkins, *The Selfish Gene* (Oxford: Oxford University Press, 1976).
38. Forrest, op. cit. note 13, 872.
39. Donna Haraway, 'The Biological Enterprise: Sex, Mind, and Profit from Human Engineering to Sociobiology', in her *Simians, Cyborgs, and Women* (New York: Routledge, 1991), 43–68, at 46.
40. See Richard Dawkins, 'Replicator Selection and the Extended Phenotype', in Elliott Sober (ed.), *Conceptual Issues in Evolutionary Biology* (Cambridge, MA: MIT Press, 1984), 125–41.
41. See Evelyn Fox Keller and Elisabeth A. Lloyd, 'Introduction to Keywords in Evolutionary Biology', in Keller & Lloyd (eds), op. cit. note 33, 1–6.
42. Goldberg, op. cit. note 3, 61.
43. Ibid., 22.
44. Haraway, op. cit. note 39.
45. Susan Oyama, *The Ontogeny of Information* (Cambridge: Cambridge University Press, 1985), 27.
46. Richard Lewontin, *Biology as Ideology: The Doctrine of DNA* (New York: Harper Collins, 1991), 48.
47. Ernst Mayr, *Evolution and the Diversity of Life* (Cambridge, MA: Harvard University Press, 1976), 23.
48. Evelyn Fox Keller, 'Language and Ideology in Evolutionary Theory, Part I', in her *Secrets of Life, Secrets of Death: Essays on Language, Gender and Science* (New York: Routledge, 1992), 113–27, at 115.
49. See W.D. Hamilton, 'The Genetical Evolution of Social Behavior', *Journal of Theoretical Biology*, Vol. 7, No. 1 (July 1964), 1–51.
50. Evelyn Fox Keller, 'Language and Ideology in Evolutionary Theory: Reading Cultural Norms into Natural Law', in Sheehan & Sosna (eds), op. cit. note 7, 85–102, at 96.
51. Koza, op. cit. note 16, 37.
52. Dawkins, op. cit. note 37, ix.
53. Dawkins has recently made his equations between DNA and information processing more explicit, and has become a champion of Artificial Life: see Richard Dawkins, *River Out of Eden* (New York: Basic Books, 1995).
54. Norman Packard, 'Intrinsic Adaptation in a Simple Model for Evolution', in Christopher Langton (ed.), *Artificial Life* (Redwood City, CA: Addison-Wesley, 1989), 141–55, at 142.
55. John Holland, 'Genetic Algorithms', *Scientific American* (July 1992), 66–72, at 67.
56. Davis, op. cit. note 34, 2.
57. Melanie Mitchell and Stephanie Forrest, 'Genetic Algorithms and Artificial Life', *Artificial Life*, Vol. 1, No. 3 (Spring 1994), 267–90, at 282.
58. Richard Lewontin, 'Adaptation', in Sober (ed.), op. cit. note 40, 235–51, at 237.
59. And see Kaye, op. cit. note 27.
60. Stephen Jay Gould, *Ever Since Darwin* (New York: W.W. Norton, 1979), esp. Chapter 12, 103–10.
61. John Dupré, 'Global versus Local Perspectives on Sexual Difference', in Deborah Rhode (ed.), *Theoretical Perspectives on Sexual Difference* (Stanford, CA: Stanford University Press, 1990), 47–62, at 53–54.

62. Some genetic algorithmists have proposed looking closely at the science of animal breeding: see Heinz Mühlenbein and Dirk Schlierkamp-Voosen, 'The Science of Breeding and its Application to the Breeder Genetic Algorithm BGA', paper availability announced in the *Evolutionary Programming Digest*, Vol. 1, No. 18 (1993), distributed over the Internet and obtained through anonymous ftp from ftp.gmd.de.
63. Haraway, op. cit. note 39, 64.
64. Koza, op. cit. note 16, 6–7.
65. On the concept of satisficing, see Herbert A. Simon, *The Sciences of the Artificial* (Cambridge, MA: MIT Press, 1969), 35–37.
66. See Daniel J. Kevles, *In the Name of Eugenics* (Berkeley, CA: University of California Press, 1985), 13.
67. Michel Foucault (trans. Robert Hurley), *The History of Sexuality*, Vol. 1 (New York: Vintage Books, 1978), 24.
68. See Ian Hacking, 'Biopower and the Avalanche of Printed Numbers', *Humanities in Society*, Vol. 5, Nos 3/4 (1982), 279–95, at 279.
69. Kevles, op. cit. note 66; the argument I am referring to occupies roughly the first third of the book's text.
70. Koza, op. cit. note 16, 25.
71. Gibbons Burke, 'Good Trading a Matter of Breeding?', *Futures*, Vol. 12, No. 5 (October 1993), 26–29, at 26.
72. Andrew Jenks, 'Datadance with a Double Helix: Studying Complex Problems with Genetic Math', unpaginated article reprint from *Washington Technology*, Vol. 9, No. 2 (1994).
73. Foucault, op. cit. note 67, 141.
74. Donna Haraway, 'Animal Sociology and a Natural Economy of the Body Politic: A Political Physiology of Dominance', in op. cit. note 39, 7–20, at 7.
75. To have a sequestered germ-line means that changes to somatic cells do not affect the germ cells involved in the transmission of genetic material. Analogies between GAs (in which organisms are modelled as equivalent to a haploid chromosome) and populations of animals with sequestered germ-cell lineages are thus rather imperfect at the organism level. In light of this observation, Melanie Mitchell once told me that GAs are actually 'more like bacteria sex than human sex'. If GAs were elaborated with this analogy more frequently in mind, they might look quite different.
76. Holland, op. cit. note 55, 68.
77. Davis, op. cit. note 34, 16.
78. In Lisp, these 'parental programs' would look like this: (OR **(NOT D1)** (AND D0 D1)), and (OR (OR D1 (NOT D0)) **(AND (NOT D0) (NOT D1))**).
79. Goldberg, op. cit. note 3, 16.
80. Koza, op. cit. note 16, 23.
81. Holland, op. cit. note 55, 68.
82. Marilyn Strathern, *After Nature: English Kinship in the Late Twentieth Century* (Cambridge: Cambridge University Press, 1992), 21.
83. Ibid., 39.
84. Holland, op. cit. note 55, 66. One of my informants discussed the utility of sex in abstract terms: 'It's an ergodic mixer allowing unconscious "communication" among widely different trial attempts'.
85. Robert E. Smith, Stephanie Forrest and Alan S. Perelson, 'Searching for Diverse, Cooperative Populations with Genetic Algorithms' (Santa Fe Institute preprint 92-06-027, 1992), 4.
86. See Larry J. Eshelman and J. David Schaffer, 'Preventing Premature Convergence in Genetic Algorithms by Preventing Incest', in Belew & Booker (eds), op. cit. note 32, 115–22, at 115.
87. See Larry Yaeger, 'Polyworld: Life in a New Context', in Christopher Langton (ed.), *Artificial Life III* (Redwood City, CA: Addison-Wesley, 1994), 263–98.
88. Goldberg, op. cit. note 3, 162–65.

89. See Carol Delaney, 'The Meaning of Paternity and the Virgin Birth Debate', *Man*, Vol. 21 (1986), 494–513, and Delaney, *The Seed and the Soil* (Berkeley, CA: University of California Press, 1991).
90. Goldberg, op. cit. note 3, 181–82.
91. See, for example, Ruth Bleier, *Science and Gender* (New York: Pergamon Press, 1984); Bleier, *Feminist Approaches to Science* (New York: Pergamon Press, 1986); Jane Collier and Sylvia Yanagisako (eds), *Toward a Unified Analysis of Gender and Kinship* (Stanford, CA: Stanford University Press, 1987); Anne Fausto-Sterling, *Myths of Gender* (New York: Basic Books, 1985); Ruth Hubbard, *The Politics of Women's Biology* (New Brunswick, NJ: Rutgers University Press, 1990).
92. Drew McDermott, 'Artificial Intelligence Meets Natural Stupidity', in John Haugeland (ed.), *Mind Design* (Cambridge, MA: MIT Press, 1981), 143–60, at 144.
93. Goldberg, op. cit. note 3, 181.
94. See Fausto-Sterling, op. cit. note 91.
95. Monique Wittig, 'The Category of Sex', in her *The Straight Mind* (Boston, MA: Beacon Press, 1992), 1–8, at 5.
96. Judith Butler, *Gender Trouble* (New York: Routledge, 1989).
97. See David Schneider, *American Kinship* (Chicago, IL: The University of Chicago Press, 1968). Note that one need not be white or middle-class to participate in the cultural imaginary normatively leashed to those historical-demographic categories.
98. Lingyan Shu and Jonathan Schaeffer, 'HCS: Adding Hierarchies to Classifier Systems', in Belew & Booker (eds), op. cit. note 32, 339–45.
99. Ibid., 339–40 (emphasis in original).
100. Ibid., 340.
101. Marilyn Strathern, *Reproducing the Future: Anthropology, Kinship, and the New Reproductive Technologies* (New York: Routledge, 1992), 16.
102. Schneider, op. cit. note 97, 23.
103. Holland, op. cit. note 55, 69.
104. Ibid.
105. Goldberg, op. cit. note 3, 30.
106. Ibid., 23.
107. Ibid., 222.
108. Ibid.
109. Haraway, op. cit. note 39, 59.
110. See David Harvey, *The Condition of Postmodernity* (Oxford & Cambridge, MA: Blackwell, 1989), esp. Chapter 9, 'From Fordism to Flexible Accumulation', 141–72.
111. Strathern, op. cit. note 101, esp. her Introduction, 'Artificial Life', 1–12.
112. Forsythe, op. cit. note 4, 470.

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