Preface to the 1992 Edition

When this book was originally published I was *very* optimistic, envisioning extensive reviews and a kind of "best seller" in the realm of monographs. Alas! That did not happen. After five years I did regain some optimism because the book did not "die," as is usual with monographs, but kept on selling at 100–200 copies a year. Still, research in the area was confined almost entirely to my students and their colleagues, and it did not fit into anyone's categories. "It is certainly *not* a part of artificial intelligence" and "Why would somebody study learning by imitating a process that takes billions of years?" are typical of comments made by those less inclined to look at the work.

Five more years saw the beginnings of a rapid increase in interest. Partly, this interest resulted from a change of focus in artificial intelligence. Learning, after several decades at the periphery of artificial intelligence, was again regarded as pivotal in the study of intelligence. A more important factor, I think, was an increasing recognition that genetic algorithms provide a tool in areas that do not yield readily to standard approaches. Comparative studies began to appear, pointing up the usefulness of genetic algorithms in areas ranging from the design of integrated circuits and communication networks to the design of stock market portfolios and aircraft turbines. Finally, and quite important for future studies, genetic algorithms began to be seen as a theoretical tool for investigating the phenomena generated by *complex adaptive systems*—a collective designation for nonlinear systems defined by the interaction of large numbers of adaptive agents (economies, political systems, ecologies, immune systems, developing embryos, brains, and the like).

The last five years have seen the number of researchers studying genetic algorithms increase from dozens to hundreds. There are two recent innovations that will strongly affect these studies. The first is the increasing availability of massively parallel machines. Genetic algorithms work with populations, so they are intrinsically suited to execution on computers with large numbers of processors, using a processor for each individual in the population. The second innovation is a unique interdisciplinary consortium, the Santa Fe Institute, dedicated to the study of complex adaptive systems. The Santa Fe Institute, by providing a focus for intensive interactions among its collection of Nobel Laureates, MacArthur Fellows, Old and Young Turks, and bright young postdocs, has already made a substantial impact in the field of economics. Current work emanating from the Institute promises similar effects in fields ranging from studies of the immune system to studies of new approaches to cognitive science. The future for studies of adaptive systems looks bright indeed.

Fifteen years should provide perspective and a certain detachment. Despite that, or because of it, I still find the 1975 preface surprisingly relevant. About the only change I would make would be to put more emphasis on improvement and less on optimization. Work on the more complex adaptive systems—ecologies, for example—has convinced me that their behavior is not well described by the trajectories around global optima. Even when a relevant global optimum can be defined, the system is typically so "far away" from that optimum that basins of attraction, fixed points, and the other apparatus used in studying optima tell little about the system's behavior. Instead, competition between components of the system, aimed at "getting an edge" over neighboring competitors, determines the aggregate behavior. In all other respects, I would hold to the points made in the earlier preface.

There are changes in emphasis reflected by two changes in terminology since 1975. Soon after the book was published, doctoral students in Ann Arbor began using the term *genetic algorithm* in place of *genetic plan*, emphasizing the centrality of computation in defining and implementing the plans. More recently, I've advocated *implicit parallelism* over *intrinsic parallelism* to distinguish the "implicit" workings of the algorithm, via schemata, from the parallel processing of the populations used by the algorithm.

As a way of detailing some more recent ideas and research, I've added a new chapter, chapter 10, to this edition. In part, this chapter concerns itself with further work on the advanced questions posed in section 9.3 of the previous edition. Questions concerning the design of systems that build experience-based, hierarchical models of their environments are addressed in section 10.1 of the new chapter. Questions concerning speciation and the evolution of ecologies are addressed in terms of the *Echo* models in section 10.3. The Echo models, besides being concerned with computer-based gedanken experiments on these questions, have a broader purpose. They are designed to facilitate investigation of mechanisms, such as competition and trading, found in a wide range of complex adaptive systems. In addition to these discussions, the new chapter also includes, in section 10.2, some corrections to the original edition. Section 10.4 concludes the chapter with a new set of advanced questions and some new speculations.

There is more recent work, still in its earliest stages, that is not discussed in chapter 10. Freddy Christiannsen, Marc Feldman, and I, working through the Santa Fe Institute, have begun to introduce the effects of schemata into much-generalized versions of Fisher's equations. This work is, in part, a follow-up of work of a decade ago, by Bob Axelrod and Bill Hamilton, that began to study the relation of recombination to the prevalence of sex in spite of the two-fold genetic load it incurs. In another direction, some preliminary theoretical investigations, stimulated by the Echo models, suggest that there is a schema theorem that is relevant to any adaptive system that can be described in terms of resource flow—such a system may involve neither reproduction nor defined fitness functions. Also in the wings is a characterization of a broad class of problems or "landscapes" that are relatively easy for genetic algorithms but difficult for both traditional optimization techniques and new weight-changing techniques such as artificial nerve nets and simulated annealing.

At a metalevel, the problem landscapes we've been studying may describe an essential aspect of all problems encountered by complex adaptive systems: Easy (linear, hill-climbing) problems have a short-lived influence on complex adaptive systems because they are quickly exploited and absorbed into the system's structure. Extremely difficult problems ("spikes") almost never influence the behavior because they are almost never solved. This leaves as a major continuing influence the presence of certain kinds of "bottlenecks." These bottlenecks are regions in the problem space that offer improvement but are surrounded by "valleys" of lowered performance. The time it takes to traverse these valleys determines the trajectory, and rate of improvement, of the adaptive system. It seems likely that this rate will be determined, to a great degree, by recombination applied to "building blocks" (schemata) supplied by solutions attached to other regions of high performance.

It is an exciting time to study adaptation in natural and artificial systems; perhaps these studies will yield another edition sometime in the next millenium.

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