Adaptative Computation: An Essay in Memory of John H. Holland

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1. INTRODUCTION

Professor John H. Holland passed away recently in Ann Arbor, MI, where he had served on the University of Michigan faculty for over 50 years. John, as he was known universally to his colleagues and students, leaves behind a long legacy of intellectual achievements.

As a descendant of the cybernetics era, Holland was strongly influenced by the work of von Neumann, Wiener, Ashby, and Turing, all of whom viewed computation as a broad, interdisciplinary enterprise. Thus, Holland became an early proponent of interdisciplinary approaches to computer science and an active evangelist of what is now called *computational thinking*, reaching out enthusiastically to psychologists, economists, physicists, linguists, philosophers, and pretty much anyone he came in contact with. As a result, even though he received what was arguably the world's first computer science Ph.D. in 1959, his contributions are sometimes better known outside of computer science than within.

Holland is best known for his invention of *genetic algorithms* (GAs), a family of search and optimization methods inspired by biological evolution. Since their invention in the 1960s, GAs have inspired many related methods and led to the thriving subfield of *evolutionary computation*, with widespread scientific and commercial applications. While the mechanisms of GAs are well-known, they were only one offshoot of Holland's broader motivation—to develop a general theory of adaptation in complex systems.

In this short essay, we consider this larger framework, sketching the recurring themes that were central to Holland's theory of adaptive systems: (1) discovery and dynamics in adaptive search; (2) internal models and prediction; (3) exploratory modeling; and (4) universal properties of complex adaptive systems.

2. DISCOVERY AND DYNAMICS IN ADAPTIVE SEARCH

Holland's goal of developing a general theory of adaptation began with his early work on computer models of Hebbian learning [24] and his reading of Ronald Fisher's classic book that integrated genetics with Darwinian selection [8]. As Holland read extensively in evolutionary biology, economics, game theory, and control theory, he came to recognize that adaptation was the most central concept in all these fields. That is, these fields all concern populations of agents that must continually obtain information from uncertain changing environments and use it in order to improve performance and enhance the chance of survival.

Moreover, Holland recognized that adaptation must be a continual open-ended process due to perpetually uncertain and changing environments. Thus, adaptive systems never achieve a state of equilibrium or a final optimum configuration. This emphasis on open-ended, non-equilibrium dynamics was in stark contrast with the mainstream approach (at the time) in all these fields—the belief that solving for stable equilibrium dynamics was the scientific goal. Holland's contrary view was that a system in stable equilibrium is essentially *dead*.

Underlying Holland's theory of adaptation are the following core ideas.

- **Populations, sampling, and implicit parallelism:** Evolution can be framed as a search that leverages statistics to direct population dynamics. A population can be thought of as a parallel sampling of many individuals (from the space of possible individuals). Moreover, that same population can be thought of as implicitly sampling a much larger space of *traits* that comprise those individuals. Holland termed this implicit large-scale sampling of traits "implicit parallelism." Evolutionary dynamics biases these samples over time towards high-fitness regions of the search space.

- **Building blocks and recombination:** In a population undergoing adaptation, individuals can be decomposed into *building blocks*—sets of traits that are the evolutionary "atoms" of an individual's fitness or performance. (As an example from biology, Holland gives the *Krebs cycle*, a core cellular metabolic pathway.) Successful individuals are discovered in stages, first by finding useful building blocks through random sampling, and over time recombining such building blocks to create higher-fitness individuals.

- **Exploitation Versus Exploration:** Successful adaptation requires maintaining a balance between *exploitation*, in which successful building blocks propagate in a population, and *exploration*, in which existing building blocks are recombined or mutated in new ways.

Inspired by Bellman [3] and others, Holland formalized the exploitation-versus-exploration tradeoff via an idealized "two-armed bandit" problem. Given a slot machine with two arms, each of which has an unknown payoff probability, how should you allocate trials (pulls) between the arms so as to maximize your total payoff? In [11, 12] Holland argued that the optimal strategy allocates trials to the observed best arm at a slightly higher rate than an exponential function of the trials allocated to the observed worse arm.

Next, Holland showed that in populations undergoing adaptation, building blocks are analogous to arms on a multi-armed bandit. Evaluating an individual in an environment is analogous to pulling selected arms on a multi-armed bandit, where the arms correspond to each of the building blocks making up that individual.

The question of how to balance exploitation and exploration—how to optimally allocate trials to different arms based on their observed payoff—now becomes the question of how to optimally sample in the vast space of possible building blocks, based on their estimated contribution to fitness. Of course, evolution deals in populations of individuals, not building blocks. There is no *e*xplicit mechanism for keeping statistics on how building blocks contribute to fitness. Holland's central idea here is that an approximation to optimal building-block sampling does implicitly occur, as an emergent property of evolutionary population dynamics.

Several of Holland's early papers (e.g., [10, 11]) and his influential 1975 book *Adaptation in Natural and Artificial Systems* [12] developed a general, formal setting in which these ideas could be expressed mathematically. It was this formalization that led to the invention of genetic algorithms, which featured stochastic population-based search, as well as crossover between individuals as a critical operation that allowed successful building blocks to be recombined and tested in new contexts. Holland's aim, however, was more general than a new class of algorithms—his goal was an interdisciplinary theory of adaptation, one that would inform biology, say, as much as computer science [5]. The later, successful application of genetic algorithms to real-world optimization and learning tasks was, for Holland, just icing on the cake.

3. INTERNAL MODELS AND PREDICTION

Internal models are central to Holland's theory of adaptive systems. He posits that all adaptive systems create and use internal models to prosper in the face of "perpetual novelty." Models can be tacit and learned through evolutionary time, as in the case of bacteria swimming up a chemical gradient, or explicit and learned over a single lifespan, as in the case of cognitive systems that incorporate experience into internal representations through learning. In Holland's view, the key activity of an adaptive agent involves building and refining these data-driven models of the environment.

In his second book, *Induction* [14], Holland and his co-authors proposed inductive methods by which cognitive agents can construct—and profit from—internal models by combining environmental inputs and rewards with stored knowledge. In their framework, a model defines a set of equivalence relations over environmental states, together with a set of transition rules which are learned over time based on environmental rewards (or punishments). Models that form valid homomorphisms with the environment allow the system to make accurate predictions. In Holland's conception, the equivalence classes are initially very general, for example, "moving object" and "stationary object." Through experience and learning, these can be specialized into more useful and precise subclasses, say "insect" and "nest." Over time, the adaptive system builds up a default hierarchy of rules covering general cases and refinements for specific classes.

Although the idea of default hierarchies was prevalent in knowledge representation systems of the era, Holland made two key contributions. The first was his emphasis on homomorphisms as a formal way to evaluate model validity, an idea that dates back to Ross Ashby's *An Introduction to Cybernetics* [2]. Holland's student Bernard Ziegler developed this idea into a formal theory of computer modeling and simulation [29]. Even today, these early homomorphic theories of modeling stand as the most elegant approach we know of to characterize when a model is consistent with the environment and how an intelligent agent, human or artificial, can update a model to better reflect reality.

Holland's second key contribution was describing a computational mechanism, the *learning classifier system* [13, 21], to illustrate how a cognitive system could iteratively build up a detailed and hierarchical model of its environment to enhance survival. The key learning elements of this method, the bucket-brigade algorithm combined with a genetic algorithm, presaged many of the ideas in modern reinforcement learning.

Holland's inspiration for classifier systems came from several different disciplines, including Hebbian learning, artificial intelligence, evolutionary biology, economics, psychology, and control theory. Knowledge representation in the form of a population of "if-then" rules seemed like a good choice, not only because of its popularity in AI at the time but also from Holland's early work on modeling Hebbian cell assemblies: "In Hebb's view, a cell assembly makes a simple statement: If such and such an event occurs, then I will fire for a while at a high rate" [28]. The if-then rules, when activated, compete to post their results on a shared "message list," serving as the system's short-term memory (again inspired by Hebb's work and AI blackboard systems of the day). Unlike blackboard systems, however, new rules are generated automatically in a trial-and-error fashion.

Successful rules are strengthened over time if their predictions led to positive rewards from the environment (and weakened otherwise) through a credit-assignment method called the *bucket-brigade* algorithm, in which rules gaining rewards from the environment or from other rules transfer some of their gains to those earlier-firing "stage-setting" rules that set up the conditions for the eventual reward. Holland credited Arthur Samuel's pioneering work on machine learning applied to checkers [25] as a key inspiration for these ideas.

Holland was primarily interested in how the two learning mechanisms (discovery of new rules and apportioning credit to existing rules) could work together to create useful default hierarchies of rules. He emphasized that the competition inherent in the learning and action mechanisms would allow the system to adapt to a continually changing environment without losing what it had learned in the past. Holland put it this way: "Competition among rules provides the system with a graceful way of handling perpetual novelty. When a system has strong rules that respond to a particular situation, that is the equivalent of saying that it has certain well-validated hypotheses.... New rules do not interfere with the system's action in well-practiced situations but wait gracefully in the wings as hypotheses about what to do under novel circumstances." [15].

Although Holland proposed classifier systems as an executable theory of inductive processes in cognition, other researchers took it further, applying it to areas as diverse as poker-playing [27], control of gas pipeline transmission [9], and modeling the stock market [23]. (See Ref. [4] for more details about practical applications of classifier systems.) Today, other reinforcement learning methods are more popular for real-world decision and control problems, but classifier systems can perhaps be thought of as an essential stage-setting method that enabled the development of later approaches.

4. EXPLORATORY MODELING

Given that Holland believed that the ability to learn and manipulate internal models was essential for any adaptive system, it is no surprise that he viewed modeling as essential for scientific inquiry.

Today, we use computational models both for *prediction*—by analyzing data via statistical models—and for *understanding* how systems work—by probing the effects of hypothesized underlying mechanisms. This latter use of models was dear to Holland's heart. In his view, the key to science was understanding the mechanisms that cause a system to behave in a certain way, an aspiration that goes well beyond data fitting methods, which typically focus only on the aggregate behavior of a system.

For example, a purely statistical model that describes the boom and bust pattern of the stock market does not address the underlying mechanisms that lead to these cycles, through the collective actions of myriad individual buy/sell decisions. In contrast, the genetic algorithms for which Holland is so famous are exploratory models of *mechanism*: they provide a simple computational framework in which to explore the dynamics of Darwinian evolution and whether the basic mechanisms of variation, differential reproduction, and heredity are sufficient to account for the richness of our natural world.

Holland's work focused on *e*xploratory models—those that explore basic principles and mechanisms, even if they do not make specific or detailed predictions. Such models can show generically how certain behaviors could be produced. Holland pioneered a style of modeling that has come to be known as "individual-based" or "agent-based," in which every component of a system is represented explicitly—e.g., every trader in a stock market system or every cell in an immune system model—and has a dynamic internal state. In such models, each agent has its own behavior rules, which it can modify over time through learning. In order to capture the behavior of systems under spatial constraints, these models are often defined over spatial structures, such as networks or simple grids.

The exploratory models championed by Holland were idealized and not intended to provide detailed, domain-specific predictions. Instead they were meant to explore possible general mechanisms of complex systems and thus provide insights that might lead to more specific, detailed models. Such idealized models are akin to what Dennett has called "intuition pumps" [6].

The emphasis on exploratory models to build intuitions was an important theme of Holland's work, and he often quoted Eddington's remark on the occasion of the first experimental test of Einstein's theory of relativity: "The contemplation in natural science of a wider domain than the actual leads to a far better understanding of the actual" [7].

It should be noted that Holland's view of modeling is by no means typical. For example, a textbook on computational modeling offers the following definition: "Modeling is the application of methods to analyze complex, real-world problems in order to make predictions about what might happen with various actions" [26]. This perspective rules out the kind of exploratory modeling that Holland was most interested in.

5. UNIVERSAL PROPERTIES OF COMPLEX ADAPTIVE SYSTEMS

Holland was interested in a broad array of adaptive systems—immune systems, ecologies, financial markets, cities, and the brain—systems that are *complex*. In the early 1980s, he teamed up with a small group of scientists, primarily physicists with a sprinkling of economists and biologists, to discuss what properties this wide swath of systems have in common. The discussions helped define the intellectual mission of the Santa Fe Institute (SFI), the first institution dedicated to developing a science of complexity, and the many others that followed. Holland brought to these discussions his lifelong study of adaptation and a reminder that serious theories about complexity would need to look deeper than phenomenological descriptions but also account for the 'how' and 'why' of these systems.

As the discussions matured, a consensus developed about the basic elements of complex systems, which are: (1) composed of many components with nonlinear interactions; (2) characterized by complex *emergent* behavior, exhibiting higher-order patterns; (3) operating at multiple (and often nested) spatial and temporal scales, with some behavior being conserved across all scales and other behaviors changing at different scales, and (4) adaptive, with behavioral rules continually adjusting through evolution and learning. Although this is far from a formal definition of complex systems, most people working in the field today are interested in systems that have these properties.

In the early 1990s, Holland teamed up with other Santa Fe Institute researchers, including several economists, to tackle the mismatch between predictions of rational expectations theory (the then dominant theory in economics) and empirically observed stock market behaviors. In brief, most economic theory of the day assumed that all participants in an economy or financial market are 100% rational and act to maximize their individual gain. In real life, however, actors in economies and markets are rarely wholly rational, and financial markets often deviate from rationality, for example with speculative bubbles and crashes.

The SFI Artificial Stock Market project [1, 23] developed an exploratory model in which rational traders were replaced by *adaptive* traders—those who learn to forecast stock prices over time. The model tested for the emergence of different trading strategies, including *fundamental*, *technical*, or *uninformed* strategies. The simulated market with adaptive trading agents was run many times, and the dynamics of price and trading volumes were compared to observed patterns in real markets. Holland and his collaborators found that the model's dynamics replicated several features of real-life markets.

Although the SFI Stock Market model was highly simplified, it was very influential and led to many follow-on projects. It demonstrated clearly the essential role that adaptation plays in complex systems, and it illustrated how Holland's theories of continual learning in response to intermittent feedbacks from the environment could be integrated into domain-specific settings.

ECHO [17, 22] was an even more ambitious exploratory model that Holland and collaborators developed next. ECHO formalized Holland's idealization of complex adaptive systems into a runnable computational system where agents evolved external markers (called tags) and internal preferences, and then used them to acquire resources, form higher level aggregate structures (such as trading relationships, symbiotic groups, trophic cascades, interdependent organizations, etc.). ECHO agents sometimes discovered mimicry and used it to deceive competitors. In many runs, the model developed increasingly complex structures and behaviors up to a point. When these runs stabilized, the resulting population of agents was found to reproduce several well-known patterns observed in nature, most famously the rank-frequency distribution of species diversity known as the Preston curve in ecology. In layman's terms, ECHO evolved populations where "most species are rare." The broad scope of the model, together with its ability to produce easily identifiable and well-known patterns from nature, was appealing to immunologists, economists, and evolutionary biologists alike. Many of the insights behind this project are described in Holland's third book *Hidden Order* [16].

Holland's later books, *Emergence* [18], *Signals and Boundaries* [19], and *Complexity: A Very Short Introduction* [20] show how the theories of adaptation that Holland developed during the earlier part of his career fit into the larger landscape of complex systems research. Holland's focus on understanding the mechanisms by which complex patterns emerge and change, rather than simply characterizing the patterns themselves (e.g., describing chaotic attractors or power laws), reflected his determination to get to the heart of complex adaptive systems. This determination represents the best of science. Holland's willingness to tackle the hardest questions, develop his own formalisms, and use mathematics to provide insight sets a high bar scientists in all disciplines.

6. CONCLUSION

John Holland was unusual in his ability to absorb the essence of other disciplines, articulate grand overarching principles, and them back them up with computational mechanisms and mathematics. Unlike most researchers he moved seamlessly among these three modes of thinking, developing models that were years ahead of their time. A close reading of his work reveals the antecedents of many ideas prevalent in machine learning today, e.g., reinforcement, learning in non-Markovian environments and active learning. His seminal genetic algorithm spawned the field of evolutionary computation, and his insights and wisdom helped define what are now referred to as the *sciences of complexity.*

Holland's many books and articles have influenced scientists around the work and across many disciplines. Closer to home, he introduced several generations of students at the University of Michigan to computation in natural systems, an idea that even today remains somewhat controversial, despite successes in genetic algorithms for engineering design, biomimicry for robotics, abstractions of phermone trails in ant colonies for optimization methods, and the use of mechanisms from immunology to improve computer security.

Behind the ideas, of course, is the man himself. Everyone who knew John personally will remember the gleam in his eye when he encountered a new idea; his willingness to talk to anyone, no matter how famous or how unfamous; and his incredible generosity and patience. Holland's personality and humanity were somehow inextricably tangled up with his intellectual contributions. Since his death, many of Holland's former students and colleagues have movingly described their desire to emulate his personal qualities as much as his scientific excellence. John Holland's ideas, intellectual passion, and personal approach will serve as beacons for research in intelligent and complex systems for many years to come.

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