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 been 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.

John was a direct intellectual descendant of the cybernetics era, and early on was strongly influenced by the work of von Neumann, Wiener, Ashby, and Turing, all of whom viewed computation as a broad, interdisciplinary enterprise. Thus, John became an early proponent of interdisciplinary approaches to computer science and was 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 CS than within.

John Holland is best known for his invention of *genetic algorithms* (GAs), a family of search and learning methods inspired by biological evolution. Since their invention in the 1960s, GAs, along with related evolutionary computation methods, have become a thriving subfield of computer science, with widespread scientific and commercial applications. While the mechanisms of GAs are well-known to much of the CS community, fewer are aware that GAs were only one offshoot of Holland's much broader motivation—to develop a general theory of adaptation in complex systems. This motivation was the driving force in all of Holland's research.

In this short essay, we sketch four key, recurrent themes in Holland's work on adaptive systems: (1) the evolutionary dynamics of "building blocks"; (2) internal models and perpetual novelty; and (3) the art of scientific modeling; and (4) common properties of complex adaptive systems. We discuss the role these themes have played in computer science, and highlight especially the ideas that we think remain relevant to today's research agendas. [MM says: Are we going to do this?]

2. EVOLUTIONARY DYNAMICS OF "BUILDING BLOCKS"

Holland's goal of developing a general theory of adaptation was spurred both by his early work on computer models of Hebbian learning [?] and his reading of Ronald Fisher's classic work on integrating genetics with Darwinian selection [8]. As Holland further 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 their performance with respect to those environments. Moreover, Holland recognized that for adaptive systems, there is never a state of equilibrium or a final optimum configuration. Due to the environment's perpetual novelty, adaptation is a continual open-ended process. Holland's focus 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 and implicit parallelism:** Adaptation occurs in populations of individuals evolving (or learning) over time, in which statistics can be leveraged to direct population dynamics. Evolution can be thought of as a search for populations that are highly fit with respect to their environment. 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 an implicit, but much larger parallel sample of *traits* making up those individuals. Holland termed this implicit large-scale sampling of traits "implicit parallelism". Importantly, 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.

  To succeed, such a search requires first that useful building blocks be preserved once found, and second that there be an efficient mechanism for combining promising building blocks into higher-order building blocks. Holland proposed using an analog of Darwinian selection for the first and the idea of crossing over in genetics for the second. Holland referred to the building blocks as *schemas.*

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

Several of Holland's early papers (e.g., [**?**, **?**]) and his influential 1975 book *Adaptation in Natural and Artificial Systems* [10] developed a general, formal setting in which these ideas could be expressed mathematically.

[MM SAYS: IF WE WANT TO MAKE THIS SECTION SHORTER, WE COULD CUT EVERYTHING FROM HERE UP TO "[UP TO HERE]" (SEE BELOW)]

Inspired by Bellman [3] and others, Holland explored 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 N trials (pulls) between the arms so as to maximize your total payoff? An example of an extreme *exploitation* strategy would be to alternate between the arms until one of them gives a payoff, and then allocate all future trials to that arm alone. Conversely, an example of an extreme *exploration* strategy would be to randomly allocate the trials, irrespective of the payoff rates you obtain. Obviously, each of these strategies is flawed. What is an optimal strategy? In [**?**, 10] Holland derived an equation for such a strategy and argued that the optimal strategy allocated trials to the observed best arm at a slightly higher rate than exponential. He then extended this result to the *multi-armed bandit* case.

Holland then made an analogy between multi-armed bandits and populations undergoing adaptation: building blocks in a population undergoing adaptation constitute the "arms" of a multi-armed bandit. Each building block can be said to have a probability of "payoff" (i.e., contribution to a given individual's fitness). Thus, in the process of assigning a fitness to each individual in a population, adaptive evolution can be seen as implicitly sampling the many building blocks making up that collection of individuals. The average fitness over many individuals containing a particular building block gives an estimate of that building block's payoff probability.

To show this mathematically, Holland defined an idealization of adaptive evolution: a population-based stochastic process operating on bit strings, involving the "genetic" operators of reproduction, fitness-based selection, crossover, mutation, and inversion.

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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. What made GAs unique among other evolution-inspired algorithms at the time were the mathematical foundations described above, the emphasis on populations and recombination as central mechanisms, and a focus on continual adaptation to non-stationary environments rather than optimization to static environments.

The framework Holland developed in [10] was more general than the genetic algorithm; its aim 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 PERPETUAL NOVELTY

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" in continually changing environments. 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* [12], Holland and his co-authors tackled the question of how cognitive agents can possibly learn 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, say "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 [26]. 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 the model to better reflect reality.

Holland's second key contribution was describing a computational mechanism, the *learning classifier system* [19, 11], 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, control theory, and other fields (e.g., [3, 22]). 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." [25] (p. 182). The if-then rules, when activated, compete to post their results on a shared "message list," modeling the system's short-term memory (again inspired by Hebb's work and AI blackboard systems of the day). Unlike the AI systems, however, new rules were generated automatically using a genetic algorithm.

Successful rules were 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 transferred 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 [22] as a key inspiration for these ideas.

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 [24], control of gas pipeline transmission [9], and modeling the stock market [21]. (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.

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." [13].

4. THE ART OF SCIENTIFIC 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 describing 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.

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].

Holland was interested in models that explored basic principles and mechanisms, even if they did 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.

A given agent-based model encodes a theory about the mechanisms that are relevant for producing the behavior of interest. Agent-based models can facilitate interdisciplinary collaborations because the underlying rules can be easily communicated. The agent-based models championed by Holland were typically idealized versions of complex systems 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].

It should be noted that Holland's view of modeling is by no means typical. For example, in a textbook on computational modeling, the authors offer 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" [23]. This sort of perspective completely rules out the kind of exploratory modeling that Holland was most interested in.

Some researchers dispute that models make any kind of scientific contribution: "Models are metaphors that explain the world we don't understand in terms of worlds we do. They are merely analogies, provide partial insight, stand on someone else's feet. Theories stand on their own feet, and rely on no analogies." [Emanuel Derman, 2012]. [MM SAYS: I COULD NOT FIND REFERENCE FOR THIS QUOTE OUTSIDE SFI VIDEO.] [MM SAYS: Possibly delete this paragraph.]

[NOW WE NEED A STRONG FINISHING SENTENCE TO RESCUE JHH STYLE MODELING.]

5. COMMON 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 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. [add in how many complexity institutes there are worldwide and which others John played a hand in. MM says: Do we really need that?] Holland brought to these discussions his lifelong study of adaptation and a reminder that true 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 complexity: (1) complex systems are composed of many components with nonlinear interactions; (2) such systems are characterized by complex *emergent* behavior, exhibiting higher-order patterns; (3) such systems operate 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) these systems exhibit continual adaptation, adjusting their behavioral rules 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.

To illustrate his ideas about the ubiquity of adaptation, Holland and co-workers developed two exploratory models, the SFI Artificial Stock Market and ECHO.

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, 21] explored a model in which rational traders are replaced by *adaptive* traders—those who learn to forecast stock prices over time. The model allowed testing for the possible 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 was a clear demonstration of the essential role that adaptation plays in complex systems, and illustrated how Holland's theories of continual learning in response to intermittent feedbacks from the environment could be integrated into domain-specific settings.

ECHO [15, 20] was an even more ambitious model that Holland and collaborators developed during the 1990s. ECHO's scope included the evolution of interacting populations of individual agents, which through competition and learning discover symbiotic triads such as the famous ant-fly-caterpillar interaction, the Wiksell triangle of trading relationships in economics, and the immune system's learned ability to distinguish 'self' from 'other.'

ECHO formalized Holland's theories about complex adaptive systems into a runnable computational system where agents evolved external markers (called tags) and internal preferences, and used them to form higher level aggregate structures (trading relationships, symbiotic groups, trophic cascades, interdependent organizations, etc.). ECHO agents sometimes discovered mimicry to deceive competitors, and over time, the model developed increasingly complex structures and behaviors, often reproducing patterns observed in nature. For example, ECHO evolved a diversity of agent types whose rank-frequency distribution closely parallels the well-known Preston curve in ecology, a quantitative statement of the adage that "most species are rare". Many of the insights behind this project are described in Holland's book *Hidden Order* [14]. The broad scope of this project was appealing to immunologists, economists, and evolutionary biologists alike.

Holland's later books, *Emergence* [16], *Signals and Boundaries* [17], and *Complexity: A Very Short Introduction* [18] 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 productively sets a high bar to whch we all should aspire.

6. RELEVANCE TO MODERN CS

[MM says: Do we need this section? Or can we incorporate these points within the previous sections?]

- Evolutionary computation
- Q Learning
- Backprop
- From Turing nomination: "Holland's machine learning system known as the Learning Classifier System (LCS), developed in the early 1980s, incorporated a reinforcement learning algorithm known as the bucket brigade for non-Markovian environments, anticipating by nearly a decade non-Markovian learning algorithms."

- Exploitation versus exploration – relevance to reinforcement learning, other parts of machine learning and optimization.

- Active learning. (Two-armed bandit problem.)

- On-line learning.

7. CONCLUSION

Introduced a few generations of students to computation in natural systems, an idea that today is better accepted. His insights were deeper and more general than what often passes for work in biomimicry, e.g., for robots.

The ideas have had huge impact and should still be a beacon for research in intelligent and complex systems

John's personality and humanity is inextricably tangled up with his intellectual contributions.

8. REFERENCES

[1] W. B. Arthur, J. H. Holland, B. D. LeBaron, R. G. Palmer, and P. Tayler. Asset Pricing Under Endogenous Expectations in an Artificial Stock Market. *SSRN Electronic Journal*, dec 1997.

[2] W. R. Ashby. *An Introduction to Cybernetics*. Chapman & Hall, London, 1956.

[3] R. E. Bellman. *Adaptive Control Processes: A Guided Tour*. Princeton University Press, 1961.

[4] L. B. Booker, D. E. Goldberg, and J. H. Holland. Classifier systems and genetic algorithms. *Artificial Intelligence*, 40(1-3):235–282, sep 1989.

[5] F. B. Christiansen and M. W. Feldman. Algorithms, genetics, and populations: The schemata theorem revisited. *Complexity*, 3(3):57–64, jan 1998.

[6] D. C. Dennett. *Elbow Room: The Varieties of Free Will Worth Wanting*. MIT Press, 1984.

[7] A. Eddington. *The Nature of the Physical World: Gifford Lectures, 1927*. Cambridge University Press, Cambridge, UK, 1927.

[8] R. A. Fisher. *The Genetical Theory of Natural Selection: A Complete Variorum Edition*. OUP Oxford, 1930.

[9] D. E. Goldberg. *Computer-aided gas pipeline operation using genetic algorithms and rule learning*. PhD thesis, University of Michigan, 1983.

[10] J. H. Holland. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. University of Michigan Press, 1975.

[11] J. H. Holland. Escaping brittleness: {T}he possibilities of general purpose learning algorithms applied to parallel rule-based systems. *Machine Learning*, 2:593 – 623, 1986.

[12] J. H. Holland. *Induction: Processes of Inference, Learning, and Discovery*. MIT Press, 1989.

[13] J. H. Holland. Genetic Algorithms. *Scientific American*, 267(1):44–50, 1992.

[14] J. H. Holland. *Hidden Order: How Adaptation Builds Complexity*. Perseus Books, 1995.

[15] J. H. Holland. Echoing emergence: objectives, rough definitions, and speculations for ECHO-class models. In D. Cowan, G. A., Pines, D., and Meltzer, editor, *Complexity: Metaphors, Models, and Reality*, pages 309–342. Perseus Books, nov 1999.

[16] J. H. Holland. *Emergence: From Chaos to Order*. Oxford University Press, 2000.

[17] J. H. Holland. *Signals and Boundaries: Building Blocks for Complex Adaptive Systems*. MIT Press, 2012.

[18] J. H. Holland. *Complexity: A Very Short Introduction*. Oxford University Press, 2014.

[19] J. H. Holland and J. S. Reitman. Cognitive systems based on adaptive algorithms. *ACM SIGART Bulletin*, (63):49, jun 1977.

[20] P. T. Hraber, T. Jones, and S. Forrest. The Ecology of Echo. *Artificial Life*, 3(3):165–190, jan 1997.

[21] R. G. Palmer, W. B. Arthur, J. H. Holland, B. D. LeBaron, and P. Tayler. Artificial economic life: a simple model of a stockmarket. *Physica D: Nonlinear Phenomena*, 75(1-3):264–274, aug 1994.

[22] A. L. Samuel. Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research and Development*, 3(3):210–229, jul 1959.

[23] A. B. Shiflet and G. W. Shiflet. *Introduction to Computational Science: Modeling and Simulation for the Sciences*. Princeton University Press, 2014.

[24] S. F. Smith. *A learning system based on genetic adaptive algorithms*. PhD thesis, University of Pittsburgh, jan 1980.

[25] M. M. Waldrop. *Complexity: The Emerging Science at the Edge of Order and Chaos*, volume 8. Simon and Schuster, 1993.

[26] B. Ziegler. *Theory of Modeling and Simulation*. Wiley Interscience, New York, 1976.