Intelligence Emerging: Introduction

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1 Exploration and Emergence

From the comfort and safety of a soft rubber floor, I have watched my children grapple with climbing walls. Vertical explorers, spider people, they silently struggle upward toward the victory bell, with legs extending, retracting, then extending again, weight shifting and hands clutching for a centimeter or two of ledge. They blend tentative, decisive, reversible and unforgiving movements, making progress that often requires time-lapsed photography to appreciate.

Though some ascents appear methodical, even well-planned, others seem more like vertical random walks, with moves being tossed out there to see what gives; the climber is just winging it, spitting ball, or flying by the seat of his pants. This book claims that the rudiments of cognition work in a similar manner: by myriad microprocesses relying on little more than persistence and dumb luck to find their own footholds, their own stability. And from these many, predominantly localized, acts of random exploration, the phenomenon of intelligence arises.

Emergence, the formation of global patterns from solely local interactions, is a frequent and fascinating theme in popular science books, and for good reason. There is something very intriguing and pure about a collection of simple agents that indirectly team up to produce something complex, without the slightest hint of central control.

The examples are endless. Social insects alone provide dozens, from the building of mounds, hives and nests, to role and task allocation, to the formation of optimal routes to food sources [9]. The expansive, branching, highly-dynamic pathways generated by raiding army ants [6] justify the term super-organism even though the individual organisms are nearly blind and rely on pheromone signals for guidance. These chemicals are typically emitted when ants leave the nest (a.k.a. bivouac) - thus marking the route for return trips - and when raiding ants find prey, and begin carting it back to the bivouac. At the front of a raiding swarm, ants move slowly, tentatively, in search of prey. When ants succeed, their pheromones attract (many) others, and portions of the front converge quickly upon the area of high prey density; and the more ants that succeed in finding prey, the more pheromones that get emitted, and the more reserves that invade to continue the conquest. Conversely, ants that venture a few centimeters ahead of the front without encountering prey nor pheromones quickly rebound back to the front before beginning another scouting expedition. Via the trial-and-error movement of numerous ants supplemented with a pheromone-mediated collective memory, the emerging super-organism efficiently forages large swaths of land.

The formation of capillary networks in the body exhibit similar emergence, albeit via different chemical signals [20]. The low oxygen levels in undernourished tissues induce the expression of a particular gene (VeGF), which stimulates vascularization in the area. Thus, the circulatory pathway branches and grows to efficiently match the spatial pattern of oxygen demand, just as the ant swarm distributes to match prey density.

Not to be outdone by ants nor blood vessels, networks in the brain arise from multiple forms of distributed search. First, neurons migrate along glial pathways to their proper locations using filopodia (slim cytoplasmic spikes) that
repeatedly extend and retract in search of stable attachment sites [20] - much like the limbs of climbing-wall enthusiasts. Next, in attempts to find proper recipients for their electrochemical signals, neurons sprout axons that explore surrounding extracellular spaces in search of compatible chemical markers [16]. Once again, progress stems from repeated extensions and retractions of the axonal growth cone, with the resulting network tailored to the sizes, chemical tags and activity levels of the intertwined neural populations.

The functional differentiation of neural regions also exhibits considerable emergence, based on patterns of perceptual stimulation and the nascent task demands. For example, the mammalian visual cortex is replete with ocular dominance columns: alternating neural neighborhoods that preferentially respond to stimuli from one eye or the other, but (generally) not both. These show up as stripes (the emergent global pattern) in stained regions of cortex. Pre- and post-natal processes combine to form these segregated regions [11], with axonal migration driven by chemical gradients (as described above) producing minor innervation biases: individual neurons may have slightly more incoming axons from one eye than the other. After birth, the asynchronous stimulation of each eye (which, in the real world, is much more common than synchronous stimulation) produces heterogeneous activity patterns in the visual cortex, but with little patchiness. However, one additional local mechanism quickly accentuates the minor biases: young axons that succeed in stimulating a target neuron often sprout extra branches, thus allowing them to connect to and stimulate neighboring neurons. Via parallel runs of this process, millions of times over, the cortex gradually separates into distinct columns dedicated to one eye or the other.

This well-known fact of neuroscience closely resembles other, more classic, examples of emergent grouping and segregation found in the popular literature. For instance, ants use only local cues to both aggregate corpses and sort larvae into groups based on their size [9]. Simulation studies [1] show that segregated city neighborhoods emerge naturally when people have a) a preference of living near similar people, and b) the occasional ability to relocate.

Finally, every fan of emergence is familiar with the synchronous flashing of fireflies, popularized by the book, Synch [19]. Among humans, similar entrainment occurs at concerts, plays, and sporting events, where entire crowds may clap or chant in unison, not because anyone leads the way, but simply due to the strong effect of neighboring stimuli upon one’s own sound-producing rhythm [1]. Once again, these traditional examples have direct parallels in the brain, where the emergent synchrony of neural activation a) stems from the dominating influence of afferent activity, and b) plays a key role in everything from perceptual binding (of diverse but co-occurring stimuli) to sequence learning to task switching (within the same neural group) between memory formation and recall [5].

So the brain and cognition are a potpourri of emergence. However, neither arises from one (or even a few) processes. Hence neither fits neatly into a popular-science chapter on the topic. Intelligence is emergent (and driven by trial-and-error search) across many temporal and spatial scales. This book examines instances of search and emergence from several neurobiological levels in the attempt to deepen our understanding of cognition and improve our ability to automate it.

2 Intelligence

Have you ever tried to define intelligence? Using a dictionary for this chore often leads to a confusing, ultimately circular, pathway among words such as knowledge, thought, understanding, reasoning and rationality. So pick your favorite route through this maze of ill-defined concepts, or simply settle on a working definition that helps frame your own investigations into the matter. My personal favorite has evolved into:

 Doing the right thing at the right time, as judged by an outside human observer.

This is a very behavioristic, black-box, definition: it evaluates intelligence based on the result of a process (such as thought), not the process itself. Of course, since we do not fully (or maybe even vaguely) understand the process, it is
hard to include its details in the definition of intelligence; we are essentially on the outside of this black box, pawing and peering, but coming away with only a few hints as to the grand mechanism.

So this definition may be a convenient cop-out for one hoping to keep the cans of philosophical worms closed up tight. Maybe concepts such as thought and rationality will eventually have well-accepted, formal, and non-circular definitions of their own upon which a definition of intelligence might stand. But maybe not. It could well be that everything just below the surface of an intelligent act is actually quite confusing: there is no logical, deterministic explanation of how the agent’s situation produces its action. The process may be very stochastic - not random, but not fully deterministic either. It may even include hints (or large doses) of chaos.

Intelligence may emerge from all this stochasticity in ways that we will eventually understand but can never fully predict. This might lead to an improvement of the earlier definition:

The activation of neural processes $P_1, P_2, \ldots, P_n$, yielding a cumulative result that evokes an action that, when assessed by an external human observer, appears to be the correct response to the current situation.

So what are $P_1, P_2, \ldots, P_n$? This is the gist of my interaction with neuroscientists: I joke about wanting them to list up the key neural mechanisms that underlie their view of intelligence, and then I will promise to scurry back to my artificial-intelligence lab, never to bother them again.

Unfortunately, I am too old to wait any longer for this list, and have spent several years digging around the neuroscience literature in hopes of assembling it myself. Alas, these have also turned out to be very high hopes - the digging continues - but a few gems have come to my attention. Some are straight from experimental neuroscience, while others involve the fruits of computational neuroscience, and still others stem from artificial intelligence (AI). None give the complete picture, and some may (despite their current status) turn out to be either a) patently false, scientifically, or b) completely useless for the engineering of automated intelligences. But all provide interesting explanations of how various low-level aspects of intelligence arise from processes that bear little resemblance to logic but exhibit high degrees of emergence and trial-and-error search.

In fact, this investigation gives grounds for the claim that the adaptivity that is so crucial to advanced intelligence is the emergent result of many (serial, parallel, subsuming and subsumed) trial-and-error search processes. Since trial-and-error is the antithesis of truly intelligent search, it is easy to conclude that the activities at just a level or two below the intelligent act are comparably unintelligent. They may ooze with interesting biology but have no apparent ties to the psychology of rationality.

Have you ever tried to recall the name of, say, a celebrity? You know that you know it, and you have some vague idea of the beginning letters, or the sound of the name, but you cannot spit it out. Then, an hour later, while doing some completely-unrelated task, out pops the celebrity's name, seemingly from nowhere. Few would dispute memory's pivotal role in intelligence, but equally few could explain this tip-of-the-tongue scenario without invoking something at least bordering on emergence; and in general, many everyday mental pursuits seem to involve it. The study of intelligence from an emergent perspective includes investigations into the neural bases of memory and learning, of which this book includes several.

However, the mystery goes deeper than this. $P_1, P_2, \ldots, P_n$ may not be enough to capture the full emergent character of intelligence. Biologists are fond of saying that no living systems (nor their parts) can be completely understood without considering their evolutionary origins; and in fact, it is often the case that biological designs make no sense whatsoever - they would earn failing grades as engineering-school projects - unless one takes evolution into account.

Darwinian evolution is frequently cast as a search process grounded in variation, inheritance and selection - from which highly fit genotypes emerge. Phenotypes then arise from genotypes through developmental processes that are, quite likely, the most intricate and impressive examples of emergence known to modern science. And the border between
development and post-natal plasticity often blurs, lending increasing scope to the emergence underlying faculties such as learning.

Thus, the story of intelligence emerging encompasses several levels of adaptivity, all of which receive ample attention in this book. The goal is not a complete picture of natural intelligence, nor a new style of AI system that outperforms all others, but rather, a deeper inquiry into a) some of the principles that motivated the newer, biology-based perspective of AI, and b) some others that could prove useful.

3 Adaptivity

One of the key differences between primitive and complex lifeforms is the degree to which they can adapt to changing conditions: more sophisticated and intelligent organisms can handle a wider range of new and unforeseen situations. Starfish adapt to limb loss by growing new ones; chameleons adapt to changing backgrounds by altering their skin color; many mammals adapt to seasonal temperature variation by changing the thickness of their coats; and of course, humans adapt to a gauntlet of daily challenges via a mixture of off-the-shelf and exceptionally-creative solutions.

From a longer time perspective, species adapt to changing environments via evolution; and the nature of today’s animal intelligences surely reflect many of these past worlds that the brains and bodies of the time had to navigate. Characteristics of many of those brains not only linger in the design of our own, but are predominant features, with only a few small (but architecturally-encompassing) tweaks needed to boost general mammalian intelligence to that of primates and humans.

Between the timescales of minute-to-minute daily activity and evolutionary progression lies that of development, a process spanning days, weeks, months, and even years. At this level, nature offers some of the most impressive examples of emergence, as complete organisms self-organize in a gradually-unfolding cellular dance. However, the adaptive nature of development often goes unnoticed, particularly during the early pre-natal stages, since the environment (e.g. womb) has evolved to be a reasonably stable environment. Furthermore, DNA clearly exerts considerable control over development, giving the (false) impression that nature doggedly follows the DNA script to build a being. However, DNA hardly encodes all of the details of the full-blown organism; rather, it serves as a recipe for a multitude of adaptive cellular mechanisms that, together, will produce the fully-formed individual. Furthermore, many of those processes will continue to work in the background during post-natal life, often supplanting repeated minute-to-minute regulatory behavior with longer-term adaptive change, as described in Bateson’s classic work [2] on the economy of flexibility.

These three levels of adaptivity are commonly called phylogenetic (P), ontogenetic (O) and epigenetic (E); and artificial systems that employ elements of each often bear the POE label. In this book, I argue that POE capabilities are critical for the attainment of intelligence by emergent means, whether the system is biological or artificial; and the following section on artificial intelligence (AI) reveals a growing appreciation for the role of emergence in producing thinking machines. Though this newer approach to AI, grounded more in biology than psychology, does take a completely different angle on the intelligence issue, there is no reason to toss out the baby with the bathwater in embracing the emergent perspective.

Though the view of formal logic as fundamental for intelligence is somewhat outdated, the conceptual tools popularized by logic-based and other knowledge-intensive approaches to AI, namely search and representation, deserve careful consideration in alternate AI paradigms. In particular, the P, O and E of POE both embody and arise from search processes, some of which have only recently come to light via empirical discoveries and theoretical advances. Thus, search and the representations that enable it, become fundamental aspects of many approaches to AI, including those grounded in the power of emergence and the perspective of complex systems.
4 The Low Road to Artificial Intelligence

In the late 1950’s, the field of Artificial Intelligence began in a blaze a glory. Within a decade or so of its inception, computers were solving geometry and physics problems at a college freshman level, playing chess like regional champions, diagnosing serious illnesses on par with expert physicians and designing complex VLSI circuits. No problem was too complex, but, as AI researchers discovered in the 1980’s, many were too simple.

Indeed, the capabilities that humans take for granted, our basic sensorimotor skills such as walking, climbing, and grasping for objects, turned out to be orders of magnitude more difficult to program than backgammon, bridge and biochemical analysis. By the mid 1980’s, AI researchers realized that a serious shortcoming in their systems was none other than commonsense. AI systems behaved like idiot savants, producing exceptional results on a wide range of situations, but floundering miserably on cases that demanded basic intuitions about the world, intuitions that most humans have acquired by their second birthday.

Many attempts were made to force-feed this common sense into AI systems, in much the same manner and using similar knowledge-representation formats as had been successfully used to load expert rules-of-thumb into AI systems. In fact, the whole AI subfield of qualitative reasoning (QR) [10] was dedicated to this aim. Although QR produced many useful paradigms whose applications range from intelligent tutoring to plant monitoring to automobile and Mars-rover diagnosis, it did little to fortify AI systems with that broad base of general knowledge needed to transform idiot-savants into well respected (and trusted) gurus.

As AI was facing this disappointing truth in the 1980’s, a related, but diametrically-opposed field began to take root: Artificial Life (ALife) [13]. Although ALife researchers primarily sought to understand the life process at a level far removed from that of neuroscience and psychology, the basic philosophy had immediate implications and inspiration for AI, although only a few AI researchers took note. The essential transferable concepts from ALife to AI were situatedness and embodiment. Although often trivial in their detail, the vast majority of ALife systems consist of simulated organisms that reside in environments (situatedness) and have a body (embodiment) whose survival depends upon a fruitful interaction with those surroundings. This Alife-inspired route to AI bears acronym’s such as SEAI (Situated and Embodied AI) and Bio-AI (Biologically-inspired AI), which this book uses interchangeably.

Classic AI systems, often called GOFAI (Good Old-Fashioned AI) systems, assume away all environmental and bodily factors to focus on cognition in a vacuum. This works well for chess but fails consistently in robotics. As GOFAI researchers found out, general abstract-reasoning systems do not plug-and-play with any set of sensors and motors. General commonsense exists not in a platform-independent piece of software, but in a behavioral repertoire that is finely tuned to the structure and dynamics of both body and environment. And although some aspects of this repertoire are easily explained in everyday terms and rules-of-thumb, many are the unique province of biology and engineering. Logics, so common to GOFAI, are of little utility, but many of ALife’s kernel concepts: emergence, competition, cooperation, etc., form the backbone of this low road to understanding intelligence [8].

For that handful of AI researchers [4, 18] who saw ALife as more than cute, abstract simulations of self-organization, but as a more fundamentally sound approach to cognition, the motivating thesis can be approximated as:

Complex intelligence is better understood and more successfully embodied in artifacts by working up from low-level sensory-motor agents than by working down from abstract cognitive mechanisms of rationality (e.g. logic, means-ends analysis, etc.).

Essentially, Bio-AI researchers believe that GOFAI’s holy grail, common sense, comes only via the learned experiences of a body in a world. There are significant limits to how much knowledge one body (a teacher or an expert-system designer) can transfer to another (a student or an expert system), and with common sense, these limits are very stringent. Whereas ”I think, therefore I am” might have been an appropriate slogan for GOFAI, it’s converse more aptly summarizes Bio-AI. That is, by living, we acquire common sense, which then supports more complex reasoning.
Figure 1: Comparison of advances in animal evolution versus computer capabilities, with each number denoting the approximate number of years that the (natural or artificial) system has possessed a respectable level of the given attribute. Whereas animals arose with sense-and-act abilities that eventually expanded to handle advanced cognition and then formal, explicit, calculation; computers were originally designed for calculation and later enhanced to tackle reasoning and autonomous robotic tasks.

Andy Clark [7] uses the term *cognitive incrementalism* to denote this general bootstrapping of intelligence:

This is the idea that you do indeed get full-blown, human cognition by gradually adding bells and whistles to basic (embodied, embedded) strategies of relating to the present at hand.

The world-renowned roboticist, Hans Moravec [14] draws an interesting parallel between the evolution of living organisms and that of computers. As summarized in Table 1, animals have always had the ability to sense and act but have gradually evolved cognitive and calculation capacities, while the evolution of computers has gone in the opposite direction, from their World-War II roots as industrial-strength calculators, to advanced automated reasoning during the heydays of GOFAI, to the more recent appearance of relatively sophisticated autonomous robots.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Animals (years)</th>
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<tr>
<td>Sense &amp; Act</td>
<td>10,000,000</td>
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<tr>
<td>Reason</td>
<td>100,000</td>
<td>40</td>
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<td>Calculate</td>
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Bio-AI must recognize that sensing-and-acting organisms cannot (in all probability) simply evolve an independent reasoning unit or calculating module in a single generation. The relatively homogeneous nature of the human brain (in terms of the basic electrochemical properties of its neurons) and reasonably tight integration of its regions indicate that any newly-evolved region would both a) have similar neural machinery as that of the pre-existing sense-and-act areas, and b) be required to communicate with those areas. Hence, any evolutionary brain improvements would be both enabled and constrained by previously-evolved sensorimotor mechanisms.

The grand challenge to cognitive incrementalism may come from the work of Lakoff and Nunez [12], who explain mathematical reasoning, both simple and complex, as an extension of our sensorimotor understanding of the world. The neuroscientific grounding of their theory is weak, but the metaphorical ties between embedded and embodied action on the one hand and mathematical concepts on the other are striking. By linking everyday sensing and acting to one of man’s most abstract cognitive endeavors, the author’s implicitly motivate a Turing-type challenge for Bio-AI: build a sense-and-act robot that evolves the ability to do mathematics.

Ignoring the obvious difficulty of this challenge, the general Bio-AI philosophy and its bottom-up approach to knowledge acquisition hold some promise. After all, one can hardly deny the importance of first-hand experience in learning simple facts of life such as that wet things can be slippery, sharp things can cut, and loud sounds can warn of unpleasant immediate futures. However, the cruel realities of engineering raises major obstacles, as all roboticists know.

Whereas GOFAI began with a divergent radiation of impressive applications that displayed many forms of (shallow) intelligence, Bio-AI seems to have converged on a menagerie of wall-following robots, all of which have very deep, functional (albeit implicit) understandings of their own body and domain: a barren floor surrounded by walls. To date, there are no biologically-inspired robots that display transferable common sense. That is, many systems behave intelligently and exhibit minimally cognitive behaviors, such as perceptual classification, attentional focusing, etc. [3], but the common sense is so tightly embedded in reactive routines (or controllers with simple notions of internal state) that it evades reuse for other tasks. So far, sensing and acting have not produced common-sense scaffolding for cognitive activities, such as the planning of motor sequences.
After 20 years of Bio-AI, cognitive scientists probably expect more. GOFAI adherents can arguably write-off Bio-AI as overly-optimistic biological envy in the same way that an AI scruffy might criticize a neat’s logical approaches to intelligence as mere mathematical envy. Still, the fact remains that GOFAI was built on a computational foundation that was rock-solid for building useful engineering tools but flimsy and misleading as a model of intelligence. Bio-AI has yielded a few useful artifacts, such as floor-sweeping and lawn-mowing robots, and a host of insect-like intelligences, but the functional cornerstone (normally neural networks or other systems of distributed processors) maps much more readily to the basis of animal behavior than do GOFAI’s theorem provers, frames and semantic networks. Bio-AI is clearly paying the price for building a proper biologically-rooted foundation, but as GOFAI’s failures in cognitive science indicate, a field’s initial progress is not a clear indicator of its ultimate success.

Regardless of the rather weak state of the art in Bio-AI vis-a-vis its ultimate goals, the bottom-up approach to machine intelligence holds a promise that deserves continued exploration. Of course, it is the path followed by nature, and since natural evolution took hundreds of millions of years to go from simple multicellular organisms to humans, one cannot expect a synthetic progression to happen overnight, no matter how many computers are crunching away on the task. Still, a royal helping of skepticism is in order. After all, many aspects of natural intelligence may only be contingencies of the past 3 billions years of life on earth, not vital principles of cognition. For instance, mass, volume and general structural constraints imposed on the brain and cranium - by the process of childbirth, the energetic demands of signal-processing cells, the conversion of DNA recipes into fully-functioning organisms, and the common need to funnel visual and auditory information through a mere pair of receptors - seem only peripherally related to general issues of artificial intelligence.

The idiosyncrasies of the human brain should therefore be viewed as fascinating mechanisms for achieving intelligence, but certainly not as prerequisites for all forms of sophisticated thought. This book’s conviction in the bottom-up approach stems not from these large-scale aspects of neuroanatomy, but from the general intuition that a neural substrate, or some similar network of relatively simple, interconnected processors, is most effective for the representations and information processing that underlie intelligence. The brains of extant organisms are simply enlightening illustrations of anatomical scaffolding that supports the emergence of mind from the interactions of basic computational units. Obviously, brains provide many insights into intelligence, but many GOFAI researchers have ignored it.

Similarly, over a half century of GOFAI research has shed considerable light upon issues of mind and machine. Bio-AI followers who dismiss these results as merely engineering or as grounded in the weaker sciences of psychology, sociology and economics, are disregarding huge conceptual resources. For example, one of the early battle cries of Bio-AI was reasoning without representation [4], a nice reductionistic idea - and one supported by a host of slick examples in simple domains - but one that has proven exceptionally difficult to realize for complex tasks. Traditional knowledge representation (KR), as formulated by GOFAI workers over the years, may not directly apply to bottom-up approaches to intelligence, but KR concepts still offer considerable leverage. Similarly, search, a fundamental process for most of GOFAI, has extensive and diverse connections to emergent intelligence, though the superficial algorithms often differ between GOFAI and Bio-AI.

5 Evolving Neural Networks

This book champions the use of evolving artificial neural networks (EANNs) as an emergent route to artificial intelligence. Its biological inspiration comes directly from the brain and its evolution, but the conceptual inspiration comes from GOFAI, Bio-AI and fields such as Complex Adaptive Systems (CAS) and Dynamic Systems, where emergence has special significance. The CAS literature abounds with references to intelligence as yet another emergent phenomenon, but details are generally lacking.

In the brain, the same type of signal (an action potential) can represent anything from the feel of leather, the taste of zucchini, the sound of Grandpa’s voice, and the motor movements necessary to swing a baseball bat; to abstract concepts such as baseball’s infield fly rule, center domination in chess, and a Hausdorff space in topology. It all
depends upon which neurons in which regions are exchanging the signal, along with what other signals are currently being sent among other neurons. Thus, simulated neural mechanisms should possess the needed generality to both a) govern sensorimotor as well as high-level cognitive behavior, and b) support an evolutionary emergence of the latter from the former.

In fact, the commitment to a neural mechanism also seems to entail an evolutionary design process. Essentially, the basic structure of brains is beyond the design capabilities of standard engineering. Brains tend to have modules, but these are very tightly interconnected, with tens or hundreds of thousands of projections between one another. This violates most principles of engineering design, particularly software engineering’s, which prefer well-encapsulated modules with a limited number of signaling pathways. Although neuroscientists often characterize biological neural networks as box-and-arrow diagrams, they are well aware of a) the extreme complexity of connections both within and between the boxes, and b) the strong contribution of this spaghetti wiring to intelligence.

Although duplicating the complexity of an entire mammalian brain seems far fetched (at least today), the basic pattern of highly interconnected neural modules is feasible on a smaller scale, in artificial neural networks with 10000 neurons, instead of 100 billion. So Bio-AI can set its sights on large, but not necessarily huge, neural networks and attempt to find useful topologies in this intermediate size class. For such networks, designing useful connection patterns by hand seems ominous. And even if the topology is hand-made, the weights between nodes are nearly impossible to hand code and must either be a) learned from experience using algorithms such as back-propagation, or b) discovered by search techniques, where simulated evolution is one of the most popular for the job.

Evolutionary algorithms (EAs) can function as either a replacement for or another level of adaptation on top of the ANN learning algorithms. They permit the exploration of a wide design space of topologies. In addition, ANNs with recurrent connections (i.e., from downstream neurons back to upstream neurons) are so difficult to train with standard learning techniques that many researchers use EAs instead, to evolve proper weight vectors. Real brains exhibit extremely high recurrency, which many neuroscientists believe to be a critical foundation of cognitive processes such as attention and learning, so this is a topological trait that synthetic brains will need to incorporate.

In short, to find proper topologies and weight vectors for complex neural networks, evolutionary algorithms are extremely useful. Again, this may not be a coincidence, since natural evolution takes much of the honor for the amazing complexity of our own brains.

And so, to appreciate Bio-AI’s prospects of achieving high-level intelligence, familiarity with ANNs and EAs seems prerequisite. Several of this book’s chapters will introduce these concepts and expound upon their contributions to emergent intelligence.

6 Deciphering Knowledge and Gauging Complexity

A huge advantage of logical and other declarative approaches to knowledge representation lies in the ease with which humans can analyze and interpret not only the results of the system, but the knowledge content and inference process as well. The system’s intelligence is easily explained in human-friendly concepts, since these often comprise the set of primitive terms for the representation.

Unfortunately, the secrets of success in neural systems are much less transparent. Though the overt behavior of a neural system - for example, in terms of the motions taken by an ANN-controlled robot - is readily comprehended, the actual reasoning done by the net yields few explicit clues, merely large vectors of activation values and synaptic weights. These activity and strength readings typically arise from simple local behaviors such as signal spreading and Hebbian learning, but the emergent knowledge/competence of the network resides in the global patterns of both firing activity and synaptic influence. Additional tools are required to find and evaluate these non-local structures, which often span both space and time.
Information theory has become a popular framework for detecting global patterns in complex networks of simple, locally-interacting components. It helps pinpoint interactions of a semi-causal (or at least correlational) nature wherein the patterns in one spatiotemporal network region can predict those in another. This basic recognition of relationships between patterns above the local level yields valuable insights into network functionality. It now becomes possible (at least in theory) to prove that the thought of Grandma, though distributed across the activation values of many neurons, has a strong tendency to evoke thoughts of her popular oatmeal cookies.

Summing over the many pattern-based interactions supported by neuron populations, researchers can now formalize the complexity of entire networks. These metrics help inform comparative neuroanatomical studies across both a) species, and b) developmental stages, giving formal, mathematical accounts of, for example, why humans handle symbol processing better than chimps, or why creativity often declines with age. Thus, information theory allows the fruits of emergent POE processes to be recognized, and their complexity appreciated.

Furthermore, just as the action potential serves as a common currency for information exchange between all parts of the brain, whether perceptual, motor or deeply cognitive, the non-physical concept of information applies not only to the entire neural network, but to the body and environment as well. Hence, information theory formalizes the entire scope of a situated and embodied AI system, allowing an evaluation of emergent complexity in the complete super-system.

Thus, this book will attempt to justify at least some claims of the emergent complexity of intelligence with information-theoretic assessments. In addition to quantifying the impressive intricacy of emergent thinking mechanisms, these metrics also indicate the form and effects of knowledge in neural systems.

7 A Network of Inspiration

Today, much of AI involves building sophisticated engineering systems, regardless of their relationship to human intelligence. However, in its infancy, AI was tied very tightly to fields such as cognitive science. In fact, two of the (small group of) early pioneers of both disciplines were the same Carnegie Mellon researchers: Allan Newell and Herbert Simon. Their psychological and computational studies laid the groundwork for both fields. Though they worked extensively with logic-based reasoning systems [15], which were highly regarded models of natural intelligence, Simon also authored one of the most influential books on emergent intelligence, Sciences of the Artificial [17].

A philosophical cornerstone of Newell and Simon’s work was the Physical Symbol System Hypothesis (PSSH), which states that physical symbol systems (e.g. logical theorem provers) provide both necessary and sufficient bases for intelligent behavior. Though the sufficiency half of PSSH seems obvious: many physical symbol systems exhibit intelligent behavior, the claim of necessity raises many eyebrows (though I can remember myself, as a naive young graduate student, wanting to prove exactly this argument).

Anyone who has studied and/or implemented logical (or more generally, symbolic) reasoning systems appreciates their complexity. In fact, they are quite a bit harder to code than many types of neural networks. Yet, Simon views the complexity of human behavior as the work of a complex environment forcing the moves of a simple (but presumably symbolic) controller (i.e. brain), in much the same way that a (relatively dumb) ant traverses an intricate route due to the complexity of the surrounding terrain. Clearly, reconciling the necessity half of the PSSH with the wandering-ant view of intelligence requires a deeper explanation. How can anyone claim that an intelligent system requires symbol processing if it is simply being shoved around by its environment?

Simon rescues the argument by including an agent’s memories as part of the environment; his research into human expertise shows that proficiency at mental tasks primarily depends upon a huge, well-indexed store of experiences, not upon a powerful search procedure. Constructing and efficiently accessing those memories would then be the major
job of the symbol-processing system. In short, trial-and-error is fine as long as the choices of the trial stage are far from random, but rather, based on well-indexed memories of previous problem-solving episodes. In fact, Simon [17] equates problem solving with selective trial and error:

All that we have learned ... points to the same conclusion: that human problem solving, from the most blundering to the most insightful, involves nothing more than varying mixtures of trial and error and selectivity. The selectivity derives from various rules of thumb, or heuristics, that suggest which paths should be tried first and which leads are promising (pg. 195).

This insight extends quite naturally to all three levels of adaptivity, since evolution, development and learning all exhibit strong signs of trial-and-error search molded by overriding selective mechanisms, many of which stem from historical contingencies. Just as a species’ phylogeny strongly biases the viability of evolutionary change - since all new structures must properly interface with the old ones - an organism’s lifetime experiences filter and modify ideas that arise during problem-solving. Furthermore, many aspects of development involve structural search wherein conduits, such as microtubules, axons and capillaries, grow in search of pre-existing targets, whose presence fortifies (and absence extinguishes or redirects) these extensions.

Unlike frictionless planes in physics, blank slates in biology mislead more than enlighten. The context of emergent intelligence normally matters. It tightly constrains all three adaptive processes and thus strongly biases that which emerges from them.

As a simple example of the parallels between search in classic AI and in biology, begin by considering the K-Queens problem, a staple in many AI texts. The goal is to place K queens on a K x K chessboard such that no two queens attack one another. The two main classes of search algorithms for solving this and many other problems are incremental and local, also known as partial-solution and complete-solution methods, respectively.

In incremental search, queens are placed on the board, one by one. Whenever a newly-placed queen attacks another, the placement is modified. If all possible placements for the queen create attacks, then the algorithm backtracks to a previously-placed queen and tries to reposition it. Failure to do so results in further backtracking. This combination of sequential placement of queens intermixed with backtracking and repositioning eventually produces a complete solution: an attack-free placement strategy for all K queens. An animation of this process shows a vine growing from the start state (representing a chess board without queens) at the top of the screen to deeper sites (representing boards with some queens), then retracting to higher points, then plunging again in a different direction. This combination of upward and downward movement of the vine’s tip continues until a state with K non-attacking queens is found, somewhere near the bottom of the screen.

This animation closely resembles real movies of axonal growth cones searching for target neurons. In these fascinating glimpses of neural network formation, immature neurons emit many neurites, which grow in all directions. Each extends, then retracts, then reorients and extends again. In this case, there are many vines. However, only those finding the most promising paths to target neurons extend large distances (i.e. a few millimeters) and eventually form synapses with the targets. Initially, many synapses form, but as the brain matures, many are pruned, leaving only the essential connections. There is no master plan for the network’s structure, just a general ability to explore by growth, retraction and regrowth.

Returning to AI, the second major search paradigm, local search, involves the (rather immediate) generation of complete solution attempts followed by a simple loop among two actions: a) testing the solution(s) for proximity to the goal, and b) tweaking the solution(s), often in random or only mildly-intelligent ways. For instance, a local-search approach to K-Queens begins by randomly placing K queens on the board, often one per row. The number of attacking queens then provides an estimate of the solution’s quality. Tweaking entails moving one or a few queens, normally those involved in attacks. Amazingly enough, for problems such as K-Queens, if tweaking involves either random repositioning or weak heuristics (such as moving a queen to the column in its current row that causes the least number
of attacks), the local-search algorithm can regularly find solutions, even for K in the millions (whereas the incremental method has problems with more than 25 or so queens). Just tossing (solutions out there) and tweaking can go a long way!

The activity of neural networks during recall gives this same local-search impression. Driven by parallel updates of each node, complete patterns of neural activity, often spanning an entire network, repeatedly morph into new forms and gradually transition to states that are most compatible with the constraints imposed by the networks existing synaptic strengths - which are strongly determined by previous experiences. Thus, past knowledge exerts a form of selection upon the evolving activity patterns, sculpting them into a form that matches the constraints. This knowledge supports an otherwise uninteresting search process, akin to the wandering of a dumb ant along a complex terrain, which itself is analogous to the intricate collection of synaptic strengths.

In summary, the relationships between AI and biological intelligence have taken many forms over the years. Early AI systems were inspired by many psychological findings, while popular AI concepts (e.g. rationality, satisficing and heuristics) and tools - the von Neumann computer in general and logical-reasoning systems in particular - significantly impacted theories of human cognition. Today, a newer brand of AI, motivated by neuroscience and evolutionary theory, provides a more plausible model of natural intelligence while also producing a good many sophisticated problem-solving systems that rely heavily upon stochasticity and emergence, in stark contrast to the deterministic, proof-driven techniques of GOFAI.

Surprisingly, two of GOFAI’s cornerstone concepts, search and representation, remain quite useful for understanding the emergent nature of cognition and for cultivating digital intelligences. This book promotes that perspective by examining these two concepts and their relationships to the phylogenetic, ontogenetic and epigenetic forms of adaptivity that underlie emergent intelligence. A full appreciation of these interactions will hopefully bring science just a little bit closer to the list.

8 Traveling Light

So buckle up for a brief journey along the exciting, but bumpy, low-road to intelligence. There is no need to pack a lot of philosophical baggage associated with the definitions of intelligence, knowledge, rationality, etc. This is a vacation from all that. Instead, the focus shifts squarely to neurons, under the assumption that, whatever goes on down at that level plays a crucial role in intelligence. The second assumption is that multi-level adaptivity is the hallmark of intelligence. The main goal of our journey is to illuminate the contributions of neural systems to that adaptivity using a set of conceptual tools from GOFAI and Bio-AI: search, representation, emergence and complexity. These take up little room in a suitcase, but the reader must decide if they are fitting attire for one so noble as the king of human faculties.

References


