Artificial Intelligence for Advanced Human-Machine Symbiosis

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Abstract. Human capabilities such as memory, attention, sensory bandwidth, comprehension, and visualization are critically important but all have innate limitations. However, these human abilities can benefit from rapidly growing computational capabilities. We can apply computational power to support and augment cognitive skills that will bolster the limited human cognitive resource and provide new capabilities through this symbiosis. We now have the ability to design human-computer interaction capabilities where the computer anticipates, predicts, and augments the performance of the user and where the human supports, aids, and enhances the learning and performance of the computer. Augmented cognition seeks to advance this human-machine symbiosis through both machine understanding of the human (such as physical state sensing, cognitive state sensing, psychophysiology, emotion detection, and intent projection) and human understanding of the machine (such as explainable AI, shared situation awareness, trust enhancement, and advanced UX). The ultimate result being a truly interactive symbiosis where humans and computers are tightly coupled in productive partnerships that merge the best of the human with the best of the machine. As advances in artificial intelligence (AI) accelerate across a myriad of applications, we seek to understand the current state-of-the-art of AI and how it may be best applied for advancing human-machine symbiosis.

Keywords: Artificial intelligence · Human-machine teaming
Augmented Cognition · Human-machine symbiosis · Situation awareness

1 Introduction

Humans have been seeking ways to perform work easier and better since the first instance stone hit flint. All tool use is at its basis an instance of a human and machine (even a simple machine like a wedge or screw) interacting to make a job easier. A hammer can apply more force to a given area than a human could alone but the hammer is useless without the human to wield it. In modern times, our tools have become more and more complex to work with humans to perform ever more difficult jobs (or perform simple jobs more effectively). A modern washing machine works with a human to make the job of washing clothes much easier. The human uses their skills to transport, sort, and load the machine, then the machine uses its skills to sense dirt level, load level, adjust water height and temperature, and repeat repetitive actions

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(something machines are especially good at) to agitate the clothes and then spin the excess water out. This pairing of man and machine makes the entire process easier and faster - a prime example of the benefits of humans and machines working together to improve the system's ability to perform *physical* work. In the cognitive domain, the use of computers and basic software is a further example of machines and humans working together to aid *mental* work. The power of a simple spreadsheet comes from the pairing of a human - who can set up and initialize data sets, with a machine - that can perform rapid accurate calculations and store them in memory indefinitely – to allow the human to easily transform, visualize and share data. Through millions of years of evolution, humans have evolved an innate capacity for intuition, analogy, creativity, and induction to ask complex questions, but we still struggle and require years of schooling to master computation and logic, and require rote repetition to develop large semantic memory stores (what's the capitol of Wyoming?), areas where machines excel to quickly and accurately help answer our questions.

While something like a spreadsheet is a simple example of humans and machines working together, what many imagine now is a next step, where humans and advanced intelligent machines team together seamlessly and symbiotically to perform ever more complex cognitive and physical tasks. To do this, requires the development of machines that think and understand, at least to a level where they can understand and anticipate human actions and intent, and communicate this understanding.

As with human cognition and human teams, a primary aspect for success is context. Successful decisions and actions are not made in a vacuum but require knowledge of the current environment - what has happened in the past as well as future possible actions and outcomes. Ask any experienced team leader to speculate on a decision they may make in the future and they will usually respond "It depends." It depends on their situation awareness of the world they are acting in, on the abilities and state of the people and systems they are interacting with, and on their ability to trust and understand what those people and systems may do. Within the human-computer symbiosis paradigm, these aspects are equally important for success. To aid researchers, designers, developers, and potential users of these systems, we need to understand how humans and machines may team together in the future - how machines can be made to start to understand and adapt to context through advanced artificial intelligence techniques, how they can use this to develop a shared situation awareness with their human teammate, how they can start to learn about their human teammate's emotional and cognitive state, and the importance of developing trust between man and machine in order for these systems to be successful.

2 Artificial Intelligence and Human-Machine Teaming

Since the first imagining of so-called thinking machines or artificial intelligence (AI), there has been much debate as to whether machines would, could, or should supplant humans or enhance humans. In theory, intelligent machines could be designed to do either. These systems have been differentiated as "cognitive prostheses" - designed to replace human capability vs "cognitive orthotics" – designed to enhance and add to human capabilities [1]. While even a prosthetic system requires some level of interaction, orthotic systems are designed from the beginning to be a tool for direct human teaming. As Nirenburg states:

> *"Orthotic systems… are intended to collaborate with humans on carrying out tasks, serving as high-functioning members of a society populated by a mixture of humans and artificial intelligent agents. As the intelligent agents in this society, orthotic systems must both perform tasks and communicate at a human level."*

These orthotic systems are synonymous with our human-machine symbiosis paradigm where humans and machines work seamlessly within the same world model to understand and solve problems.

A qualitative example of the difference between prosthetic and orthotic implementations of a technology is in the use of facial recognition. Facial recognition technology within Facebook acts independently of a human operator to detect and identify faces within images posted online. Even though the output may eventually be used by a human to, say, annotate pictures of relatives, once built, the systems itself no longer requires human interaction for it to perform its task. In fact, except by the programmer, there is no way for a human to interact and change how the system processes faces. It is simply a tool or prosthetic for the human. However, if we incorporate the same facial recognition technology into an augmented reality display, we can track the faces within a crowd and automatically bring up information about an acquaintance we are talking to that could help us interact with them. Here, the system acts as an orthotic display. If we also paired this real-time facial recognition technology with emotion detection algorithms that could detect the friend's emotional state, and combined that with measures of our own emotional state (through physiological or voice stress sensing, and language understanding), the system may actually be able to detect and help diffuse an ensuing argument. In addition, in real time or in review, we could provide feedback to the machine's situational assessment system allowing it to learn subtle nuances of human-human interaction to improve its algorithms – a symbiotic interaction between the machine and user making each better.

The core to these systems lies in the underlying intelligence of the software and design of architectures to support shared situation awareness and a common world model and goals – the world of artificial intelligence.

2.1 1st Wave AI – Handcrafted Systems

To date, artificial intelligence (AI) has developed many useful prosthetic tools and techniques for performing very specific functions. However, as complex as these programs and expert systems can be, they are very brittle and must follow specific rules and logic and be written line by line by human designers. This is the so-called handcrafted AI, now called "1st wave AI" [2]. Even a standard simple computer program can be considered to fall into this category as they are designed and coded to perform a specific purpose. For example, a C program that does a simple bubble sort (Fig. 1) could still be considered a rudimentary form of AI as it is replacing what a human brain would do with a computer algorithm - a first step in emulating human cognition.

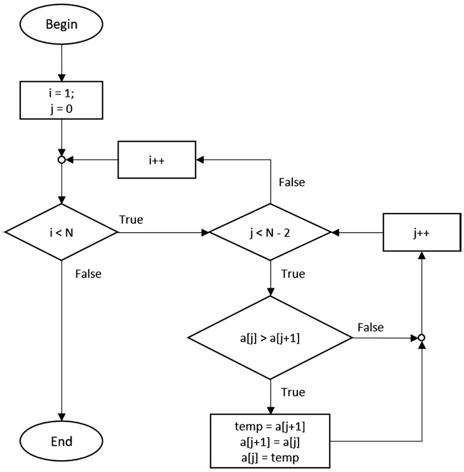

Fig. 1. Flow chart for a simple bubble sort

The key aspect of 1st wave AI is that programmers first figure out how to solve the problem, then they code the solution in a step-by-step manner. This can get very complex, but it is still the encoding of a solved problem. Our feeling that these programs do not count as AI may reflect the so-called "AI Effect" [3] that any problem that has been solved is no longer considered difficult and therefore is no longer in the realm of AI. As Brooks states "Every time we figure out a piece of it, it stops being magical; we say, 'Oh, that's just a computation." [4] But a system that can automatically take a large random data set and organize it is certainly a time saving tool that fits within the paradigm of being a tool for helping and replacing human mental work and is at its base level a form of AI. However, the inherent limits of 1st wave AI and the desire for systems that show more emergent intelligence have led to the next step of AI.

2.2 2nd Wave AI – Statistical Systems

The 2nd wave of AI is currently in its heyday and consists of statistical systems that use powerful new techniques and computing resources to perform statistical object recognition and look for patterns in large batches of data. Originating with neural network algorithms first developed in the 1950s [5], these systems originally sought to mirror human brain organization by mimicking the neural connectivity of neurons and synapses at a very simplistic level. Within neural nets (also called connectionist models), "neurons" have a simple input/output structure and perform one layer of processing between each subsequent "synaptic" connection layer. The analogy with human brain systems is so tenuous however, that most system practitioners now talk more of nodes and layers as opposed to neurons and synapses.

With the development of the latest deep neural net (DNN) algorithms and increased computing power, these systems have become powerful enough to recognize categorical objects ("cat", "car") and faces (Fig. 2) in images, beat human chess masters, and surpass humans at language recognition (however not language understanding).

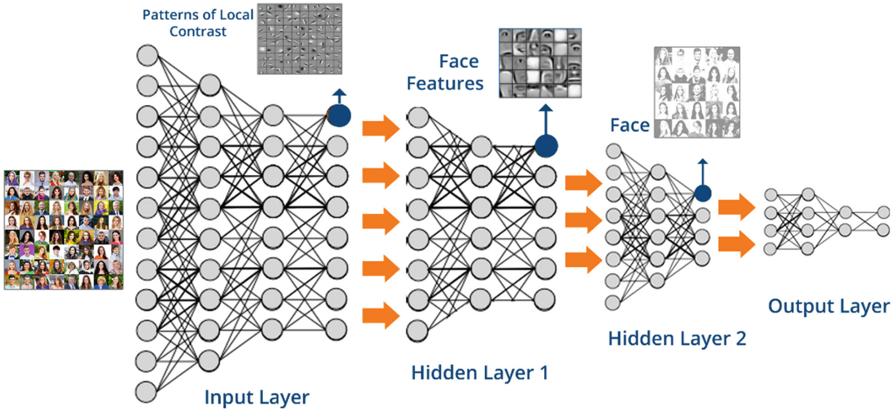

Fig. 2. Structure of a deep neural net (DNN) for facial recognition [6].

While extremely powerful, there are several drawbacks to these statistical systems. First is the requirement of tens of thousands of examples for the system to learn. Second is the limited ability of the system once trained to only perform specific tasks. For example, a system trained to recognize a cat in images can do quite well at recognizing cats but will fail completely if suddenly asked to recognize a maple tree. A chess playing bot that could beat a Grand Master would be unable to perform the first move in Go. These systems have no general or real-time interactive learning ability, they cannot work with dynamic goals and context, nor cope with abstract reasoning or language comprehension. In addition, because of their statistical nature, these systems do not easily lend themselves to explanation. The systems develop a black box solution to their specific problem making it extremely difficult to understand and debug errors, for example. While there are large efforts to try to develop workarounds and solutions to this explain-ability issue, an alternative approach lies in the so called 3rd wave of AI which is designed to supplant the issue altogether and develop machine-based cognitive reasoning systems more analogous to human reasoning and capabilities.

2.3 3rd Wave AI – Cognitive Architectures

The 3rd wave of artificial intelligence designs systems that use contextual adaptation – systems that, like humans, can reason, learn, and adapt to their environments. Third wave AI is founded on the *cognitive systems paradigm* [7] which distances itself from the current mainstream statistical AI and seeks to understand the fundamental processes of how cognitive systems - humans and machines - can reason, learn, and explain.

A main focus on the development of cognitive systems is on the development of cognitive architectures that form a framework for the basic components and connectivity of the various modules. An architecture can be thought of as a fixed set of structures and mechanisms or processes. Complex systems can be decomposed into an architecture and its content which, when combined, results in behaviors. Cognitive behaviors have certain aspects: they are goal-oriented, reflect a rich complex environment, require a large amount of knowledge, require the use of symbols and abstractions, are flexible, and require experience and learning [8].

Cognitive architectures are theories of fixed mechanisms and structures that underlie this cognitive behavior – human or otherwise. These cognitive architectures form the blueprint for the development of software intelligent agents to solve higher level problems. This blueprint consists of "its representational assumptions, the characteristics of its memories, and the processes that operate on those memories" [9].

Laird et al. [10] have recently published a Standard Model of the Mind that seeks to formally unify the components and processing design of all human-like cognitive systems be they based in AI, neuroscience, or robotics (Fig. 3).

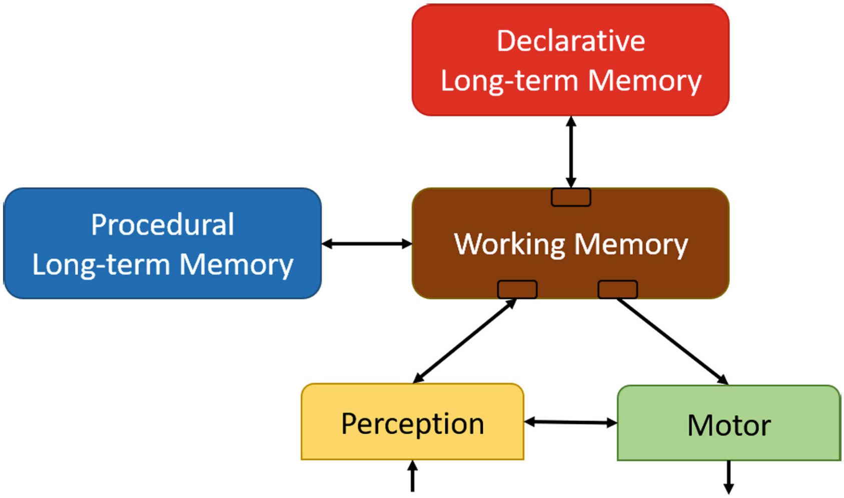

Fig. 3. The standard model of the mind [10].

This standard model integrates components of memory, perception, and action with processes for learning, communication, and representation. The core fundamentals of the Standard Model are:

(1) Processing yields bounded rationality not optimality
(2) There is significant parallel processing (within and across modules)
(3) Complex behavior arises from a sequence of independent cognitive cycles that operate in their local context
(4) Declarative and procedural long-term memories contain symbol structures and associated quantitative metadata
(5) Global communication is provided by short-term memory: rule-like conditions and actions exert control by altering the contents of working memory
(6) Global control is provided by procedural long-term memory
(7) Factual knowledge is provided by declarative long-term memory
(8) Long-term memory content is learnable

(9) Procedural learning involves at least reinforcement learning and procedural composition
(10) Declarative learning involves the acquisition of facts and tuning of metadata
(11) Perception yields symbol structures with associated metadata in specific working memory buffers
(12) Attentional bottleneck constrains information available in working memory
(13) Perception can be influenced by top-down information from working memory
(14) Motor control converts symbol structures to external actions
(15) There can be multiple motor modules

Within this standard framework, however, there is some diversity in the approaches and goals of different cognitive architectures and models. Some approaches, like ACT-R [11], seek to directly model and re-create how the human mind works in order to study and learn from it. However, other cognitive architectures, like Soar [8], seek to re-create and optimize these human abilities and capabilities within the computer without necessarily directly modeling exactly how the human may do it (analogs as opposed to homologs). A deeper dive into the design of the Soar architecture shows the advantages of these systems for developing the requisite contextual adaptation needed for human-machine symbiosis.

Soar is designed to have a basis in cognitive behavior that lends itself to a shared awareness with humans. It is optimized to support knowledge-intensive reasoning, hierarchical reasoning, planning, and reactive execution. Soar is grounded in Newell's *unified theory of cognition* [12] and incorporates decades of experience in cognitive research into an architecture that is reusable across new cognitive models. The Soar architecture assumes cognitive behavior is goal-oriented and that behavior is a reflection of movement through a problem space to make decisions to reach the required goal. It is both a theory of what cognition is and a computational implementation of that theory. Soar has features that mimic human cognition such as perception, working memory, procedural memory, semantic memory, episodic memory, reinforcement learning, and decision making. Soar deals well in complex environments by having an ability to apply algorithms based on the context of the situation and the type and quality of the data. Additionally, Soar's primary advantage is that it is designed for *satisficing* - trying to find an acceptable option based on what it knows. The architecture is built to work even when dealing with incomplete data, when data is out of order, or is unexpected. This ability gives Soar (and cognitive architectures in general) a major advantage over standard math-based or rigid AI approaches for human-machine teaming applications.

However, regardless of the specific cognitive system architecture that may eventually be used for human-machine symbiosis, a main challenge for any interaction (whether human-human or human-machine) is the coordination of intent, expectations, and effects across actors so as to achieve one or more common goals. Characteristics like trust, shared situation awareness, and intent recognition will be key to this endeavor.

3 Situation Awareness

In 2012, the Defense Science Board (DSB) recognized a gap in autonomy research, determining that research was focusing far more on the computer and levels of autonomy than on useful design principles that support the human-system interaction and dynamic function allocation between human and machine [13]. To achieve any level of human-machine symbiosis, the human and the machine must share understanding and situation awareness (SA) and adapt to the needs and capabilities of the other.

Teaming of any sort requires the need to maintain SA of many relevant aspects of task performance and outcomes and to achieve an allocation of roles, functions, behavioral capabilities, and resources which serves the integrated team. This includes:

(1) Staying aware of all important activities and events
(2) Predicting outcomes and activities so as to proactively address them
(3) Making decisions about how to best act or react
(4) Shifting and regaining awareness when multiple activities occur simultaneously
(5) Triaging and offloading tasks when overloaded
(6) Recognizing faults or failures (within the system and within the process)

For human-machine teaming applications, we adopt the standard definition of situation awareness as “the **perception** of the elements in the environment within a volume of time and space, the **comprehension** of their meaning, and the **projection** of their status in the near future.” [14] However, human-machine teaming adds the complexity of requiring both the human’s SA of the world (including knowledge of the state of the autonomous teammate) and also the machine’s SA of the world (including knowledge of the state of the human operator) with the ideal being a state of shared situation awareness between human and machine.

For human-machine symbiosis, the advantage of cognitive systems and cognitive architectures is that they have built in analogs to the standard SA processes of perception (or sensing), comprehension (or reasoning), and projection (or planning). Using these components, the cognitive system can develop its own model for situation awareness in the form of an internal operating picture (IOP) which monitors goals and objectives, tasks, operator and system states, and sensor feeds with the goal of developing a computational “mental” model of an expert’s SA within the autonomous system [15].

While only a first step towards the level of shared SA required for human-machine symbiosis, the IOP that emerges within cognitive systems is based on the in-memory store of separate indexed data structures for things like: objects in the world, tasks, goals and objectives, and other relevant state items. Once developed, the IOP is maintained by a set of processes that are continuously monitoring incoming state messages from the environment and either simply taking them in and storing them (perception), making additional computational inferences on them (comprehension), or planning for future action and events (projection).

The ability for an intelligent machine to maintain an internal operating picture can form the basis for situation awareness for both human users and the machine. Within a decision support application, the system could output its "knowledge" using a smart interaction module (such as a display or natural language communication) to provide alerts or events, allocate tasks, or otherwise inform the user, allowing the human user to take intelligent actions. The IOP also provides a mechanism for the machine to take in information about the human user to start to understand the state of the human operator and allow the system to adapt as necessary to the human's cognitive and emotional state.

4 Human State Sensing

The growth of "affective computing" (devices to discern human emotions) holds promise to revolutionize computing interaction by engaging users at a deeper level. During human-human interaction, much information is passed between people through body language, tone, affect, facial expression, and more, to relay valuable information about the human's state emotional state and ability to cope with a situation. Standard human-machine interaction (like keyboard and mouse or even current speech systems), lack this ability to discern the user's emotional state and glean valuable information about how to interact with the user.

In the early 2000s, DARPA's Augmented Cognition (AugCog) program saw a major push to incorporate human cognitive state sensing within computer interfaces to provide "order of magnitude increases in available, net thinking power resulting from linked human-machine dyads." [16] The ultimate goal of AugCog, and operational neuroscience programs like it, is a complete human-machine symbiosis where the human understands and intuitively reacts to the machine and the machine understands and "intuitively" reacts to the human. In order for this level of interaction to be achieved, systems will need to be developed to recognize human stress responses (e.g., cognitive load) and emotions.

The core of current affective computing systems is the use of speech intonation and facial expressions to discern human emotion. While functional for general use (such as improving tutoring systems), these measures are not robust enough for many applications which need systems that are connected to the operator and sense emotional and physiological responses discreetly and, ideally, before the operator has an outward response. This type of interaction would allow teaming with machines that can sense and react in real-time before emotions cause issues to be avoided or rectified.

Physiological sensing may be able to provide this capability but to date it's use for real time sensing has been problematic. The accurate determination and measurement of psychophysiological constructs requires a thorough understanding of physiological signals and their cognitive correlates. The fundamental challenge for quantitative, sensor-based cognitive and emotional modeling is the complexity of the underlying physiology. Several distinct physiological processes influence the physiological responses and the various external sensing systems may pick up different elements or admixtures of stress, workload, and/or emotional response in varying degrees making it hard to isolate any one construct.

Workload itself has been studied for decades and has shown it can be a valuable measure of human state for computer interaction [17, 18]. The primary goal of workload assessment within human-computer interaction to date has been to use these signals to inform when to mitigate workload effects by either offloading tasks or changing the interaction in some way. However, some users can perform under a high workload with little stress or reaction (or even a positive sense of challenge) while others may start to have adverse emotional reactions even though their workload remains fairly low. For nuanced interaction within a human-machine symbiosis paradigm, the machine should be able to sense not just high workload, but the human's emotional state. Emotion is a primary aspect for conveying and understanding human reactions to events and there is a strong relationship between human emotional episodes and the way humans subsequently think and act.

The key to reliable measures of workload, strain, and other human state sensing may lie in the development of an intelligent AI-based signal classifier and cognitive system-based reasoner based on 3rd wave AI architectures. These system would provide the ability to take in a variety of psychophysiological signals, understand the context and environment that is leading to the generation of those signals, and reason across incomplete complex data sources to understand the user state. This capability would not only allow for better individualized and context-based signal classification, it would form a direct input to the machine's IOP and correlate the human state response to the task criticality and the user's ability to adequately perform the task given an emotional response. This type of classifier would be a valuable construct for aiding machine awareness of user state and allowing it to adapt and respond more intuitively to user actions and needs.

5 Trust in Autonomous Systems

Even with properly designed 3rd wave architectures, IOPs for situation awareness, and machine sensing of human state, decision making between teams of humans and automated systems or agents invokes all of the problems and opportunities of human-automation interaction in general, but adds dimensions of close coordination and behavioral unpredictability. Humans use shared training, culture, natural language (including jargon, affect, "body language", etc.) and the simple fact of sharing human-centric expectations ("common sense") to make this coordination tractable and yet flexible. Even then, humans have developed particular forms, protocols, heuristics, and procedures to enhance coordinated decision making and trust. The challenge for human-machine symbiosis is to achieve at least this degree of trust and shared expectations with minimal communication overhead, while still preserving the computational speed and precision that machines afford. Within the human-machine teaming paradigm, trust can be defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" [19].

The goal is not necessarily to achieve 100% operator trust in an autonomous system, but rather to achieve the right level of trust in the system: trust that is appropriately calibrated to accurately reflect system intent, performance level, and context. Excessive trust in a non-perfect system will lead to over-reliance and error.

Excessive distrust in a system will result in disuse and increased human tasking. Appropriate or "calibrated" trust, will only be achieved reliably when transparency is established between man and machine where transparency is defined as the extent to which the intent, ability, and constraints of the autonomy are accurately perceived. The degree to which we can achieve calibrated human-machine trust is dependent upon aspects of the human, the context, and the system.

The challenge is to identify the antecedents of trust and to develop usable, empirically-derived guidelines for future systems that will help foster human-machine trust calibration through improved autonomous system designs and human-machine team training approaches. These factors are widely varied, with some being attributes of the user (e.g., age, gender, culture, experience, biases), some being attributes of the system (e.g., accuracy, reliability, error types, communication modes/styles), and some being attributes of the human-system task context (e.g., task complexity, risk, workload). Further, these factors are embedded within a construct of human-machine transparency, which is essential to achieving calibrated trust. With his focus on achieving calibrated human-machine trust, Lyons [20] has introduced a model of human-machine transparency that reflects several dimensions of the human-machine teaming relationship, including system intent, system goals and tasks, analytic principles, environment or context, division of labor, and system understanding of the human state. This paradigm may provide the scaffolding for the trust relationship required for human-machine symbiosis in the future.

6 Conclusions

The goal of human-machine symbiosis is to design physical and cognitive devices that enhance and add to human capabilities. For this goal, systems need to be "intelligent" and capable of understanding humans but do not necessarily need to re-create how humans think. While direct human modeling homologs may enhance the machines ability to understand, it is not a necessary condition of human-machine symbiosis where analogs may prove equally valuable. Intelligent machines based on neural networks and other machine learning techniques are powerful tools but just like screwdrivers and automobiles, they are designed to help humans solve very specific goals. Systems for human-machine symbiosis will need much broader capabilities in that they seek to aid humans across a wide swath and variety of dynamic problem solving in a seamless way. For this advanced interaction, a more general artificial intelligence, such as those grounded in cognitive systems, will have to be a core attribute of the machine. That is not to say that these systems should be built only around cognitive architectures. It is easy to imagine that the best systems may be hybrids, utilizing neural networks for aspects of vision and classification, combining them with strict rules-based expert systems for doing rote actions, and placing them under the auspices of higher level cognitive reasoning systems. The ultimate result being a truly interactive symbiosis where humans and computers are tightly coupled in productive partnerships that merge the best of the human with the best of the machine.

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