Toward a New Science of Common Sense*

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Abstract
Common sense has always been of interest in AI, but has rarely taken center stage. Despite its mention in one of John McCarthy’s earliest papers and years of work by dedicated researchers, arguably no AI system with a serious amount of general common sense has ever emerged. Why is that? What’s missing? Examples of AI systems’ failures of common sense abound, and they point to AI’s frequent focus on expertise as the cause. Those attempting to break the resulting brittleness barrier, even in the context of modern deep learning, have tended to invest their energy in large numbers of small bits of commonsense knowledge. While important, all the commonsense knowledge fragments in the world don’t add up to a system that actually demonstrates common sense in a human-like way. We advocate examining common sense from a broader perspective than in the past. Common sense should be considered in the context of a full cognitive system with history, goals, desires, and drives, not just in isolated circumscribed examples. A fresh look is needed: common sense is worthy of its own dedicated scientific exploration.

The Common Sense Gap
The modern-era data-intensive machine learning juggernaut continues to roll on, with a wide array of extraordinary results and significant commercial impact. But an increasing number of articles and books (for instance Pavlov 2020, Marcus and Davis 2019) point out that even the best of current AI falls short of the robust, general intelligence envisioned by the field’s founders. Blunders made by generally powerful systems have been recounted, such as shocking misidentifications of objects by otherwise accurate image recognition programs (Szegedy et al. 2014, Mitchell 2019). Surprising gaffes of seemingly remarkable systems like GPT (Vincent 2020) have been revealed as both humorous and disturbing (Marcus and Davis 2020). Self-driving cars make terrifying unexplainable mistakes (Hogan 2021). Several authors (see, for example Levesque 2017, Marcus and Davis 2014, Mitchell 2019, Toews 2020) have made the case that AI is still missing something critical to avoiding these mistakes, and they identify the missing ingredient as what we would normally call common sense. But recent calls for a new generation of post-modern AI systems with common sense give no real prescription for getting there or a clear idea of what it would really mean for an AI system to have it. Our intention in this paper is to stimulate the field into closing this critical gap.

Expertise and the Brittleness Challenge
Despite the name of the field, Artificial Intelligence’s biggest accomplishments have generally come from expertise rather than any more general kind of intelligence. Our greatest successes have been on tasks in narrow domains or circumscribed challenge problems, such as Go, facial recognition, infectious disease diagnosis, and the like. The most obvious limit of this is what some have called “brittleness”—the failure to produce reasonable outcomes (or, in many cases, any outcomes at all) in the face of challenges just beyond the boundaries of the expertise. This was a well-known shortcoming of the 1980s wave of expert systems, but as recent work has shown, it applies equally well to systems trained with extensive amounts of data (Szegedy et al. 2014, Marcus and Davis 2020, Page Street Labs 2020). AI systems are often fragile and show a noticeable lack of common sense. This may not be a critical problem for a system that only plays chess and whose entire world is limited to a chessboard and chess pieces. But AI’s longer-term vision aspires to embed fully integrated systems in the real world, where artificial agents will need to be able to cope with a wide range of unanticipated events.

The emerging universe of self-driving cars provides a good example. We expect such cars to operate on regular real-world streets with natural phenomena occurring all around them—other drivers, signs and signals, pedestrians and dogs, unpredictable weather and road conditions, etc. But we see that, at least for now, brittleness is still rampant and current systems fail in ways that make it clear they have no common sense to fall back on when their expertise meets its limits (Hogan 2021). They make mistakes that seem counterintuitive or just plain silly. They cannot offer drivers reasons for their behavior and we cannot correct them by offering advice. We end up with fragile, inscrutable, incorrigible systems that can have serious and even fatal consequences when operating in the real world—largely because they have no common sense.

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**What Is Common Sense?**

If we want to develop a plan for building common sense into AI systems, then the natural question to ask is, *what exactly is it?* The point of this paper is that that question has not been sufficiently answered; if common sense were fully defined and its technical challenges clearly articulated, there would be no need for a new call to action. Unfortunately much of the recent writing on common sense in AI is not about what it is and how it can be realized, but about its absence in current systems. There are some thoughtful treatises on how much is missing (see, for example [Davis and Marcus 2015]), and there have been a number of technical efforts focused on isolated fragments of commonsense knowledge (see below), but there is currently no real clarity on how to build an AI system that consistently demonstrates common sense.

In our opinion, here is what common sense is about:

*Common sense is the ability to make effective use of ordinary, everyday, experiential knowledge in achieving ordinary, practical goals.*

There is a lot to unpack in this characterization—words like “ability,” “effective,” “experiential,” and “practical” are easy to gloss over but each is intended quite specifically and is meaningful—but it is not our intention to tackle that here. (We take this up in considerable detail in [Brachman and Levesque 2022].) Rather, we want to show how the idea of making effective use of knowledge leads to a set of scientific questions that we believe are important for the field to consider in a systematic and unified way. Progress on this front would have a very significant impact on the ability of autonomous AI systems to operate in open-ended real life.

**A Focus on Commonsense Knowledge**

Of course the consideration of common sense as an aspect of intelligence is not a new phenomenon in AI. Even John McCarthy’s earliest seminal paper in the field, “Programs with Common Sense” [McCarthy 1958], mentioned it right in the title. And a number of projects since then, including AI’s longest continuously running project—Cyc—have been said to have focused on it [Lenat and Guha 1989; Matuszek et al. 2005; Metz 2016]. But no robust AI system generally and regularly exhibiting common sense has ever emerged from this line of research. Something critical is still lacking.

In our view, the problem is that almost all the attention on common sense in AI to date has focused on the commonsense knowledge that would be required, to the relative exclusion of several elements that are key to the success of natural systems with common sense. Researchers like Doug Lenat and others concentrated on the realm of missing, tacit facts (like “if someone dies, they stay dead” or “you can’t pick something up unless you’re near it”) that most people would know but that were never captured in formal knowledge bases built through knowledge acquisition from experts. Lenat published an interesting article that exemplified this, focusing on a number of complex inferences about the play, *Romeo and Juliet* [Lenat 2019]. Missing “obvious” facts were one reason that expert systems were stymied on edge cases, and their pursuit was a well-justified avenue for addressing the brittleness issue. But it concentrated on only one part of a bigger problem, which we will get to in a moment. (In fairness, the Cyc project has also developed a vast library of inference procedures that allow it to draw conclusions from its knowledge—as of 2019 more than 1100 of these “heuristic reasoning modules” were in place. But while these help join together Cyc’s millions of bits of knowledge to produce novel conclusions, the system overall still appears to be missing the bigger picture that we address below.)

Along similar lines, researchers like Pat Hayes, Jerry Hobbs, Ernie Davis, Ray Reiter and others developed formal theories of various aspects of the commonsense world [Hayes 1985; Hobbs and Moore 1985; Davis 1990; Reiter 2001]. The spectrum of areas of concern of this work was broad: naive physics, time, plans, the minds of agents, even society and ethics. The outputs of these efforts were generally foundational axioms and rules; additional consequences of the specified axioms were logically entailed. To compute these consequences, standard inference mechanisms from logic (monotonic or non-monotonic) were used. Much of this work was sophisticated and insightful, but was generally presented in the form of lists of axioms and proofs. Some of it was implemented in systems that could draw interesting conclusions about the world, but like Cyc, it generally did not result in integrated AI systems situated in the world trying to achieve goals. Examples were mainly offered piecemeal and in isolation.

A different view of commonsense knowledge was embodied in the now decades-old memory-based efforts of Marvin Minsky and Roger Schank and colleagues [Minsky 1985; Schank and Abelson 1977; Schank 1982]. The emphasis was more on the memories of past experiences than on general truths about the world. The focus was less on deriving conclusions from multiple facts and rules, and more on recognizing patterns and drawing analogies between current circumstances and these remembered experiences as a way of solving new problems. Minsky’s ideas about frames and Schank’s work on scripts, plans, and other memory structures were often set in contrast with the more logical work noted above, but in the end, this line of work also spent most of its energy on knowledge and its organization. It should also be noted that even what we have called postmodern efforts in this space, like COMET [Bosselut et al. 2019], which look to build hybrid systems on top of deep learning engines, are still focused on expanding knowledge bases.

**A Broader Perspective**

As mentioned, no system that can generally wield common sense in the frequent and effective way humans do has ever emerged from these lines of work. It has become increasingly clear that no matter the scale of commonsense factual tidbits stored in a knowledge base, this is not enough to get over the fundamental hump of generally robust behavior outside the boundaries of expertise.

The crux of the issue is that *knowing even a vast number of commonsense facts is simply not the same as having and exercising common sense in the real world.* When a person
says to another, “use a little common sense here,” they are not asking only to recall some isolated bits of knowledge. Having common sense is not the same as being able to win some sort of obvious-fact trivia game (“Alex, what weighs more, a wheelbarrow or a grizzly bear?”). When we expect a person to use common sense, what we are insisting on is the use of background knowledge to influence what action to take or how to interpret an unexpected experience. Having common sense is substantially more than having commonsense knowledge. At the very least it is the appropriate and timely application of this knowledge that is critical.

One gets the sense from many presentations of commonsense knowledge in action in AI papers that we are creating the equivalent of locally-scoped “fact calculators,” which can be fed a number of piecemeal facts and (if all goes well) will spit out inferences. This is clearest in the case of systems based directly on logic (à la McCarthy/Cyc): you give the inference engine some axioms, push the “INFER” button, and it can come to some conclusions, perhaps even interesting or unexpected ones. But it’s working in isolation of any contextual situation, goals, and prior history; those are all in the head of the user pressing the buttons. The conclusions are not of any interest or utility to the calculator it-

• Commonsense knowledge: Y ears of work on large commonsense rule bases like Cyc will not be wasted, although in our view, much more focus needs to be placed on the experimental basis of common sense. How are experiences remembered, generalized, and organized so that they can be called to mind when needed? Thought should be given to mechanisms for representing baseline ontological information, general rules of thumb, exceptions, and a host of other items that distinguish commonsense knowledge from other forms of knowledge. Many agree that there are some key domains that need to be accounted for, like knowledge of the physical world, understanding of other agents, time, causality and some others. The Minsky/Schank lines of thinking should be reexami-

• Commonsense reasoning: This needs a careful analysis, definition, and prescription for implementation. For any chain of commonsense inference, we need to be clear on just what the inputs and the expected outputs are going to be. Are all logical consequences to be computed?
If so, what is the plan to ensure this can be done quickly enough? If not, what exactly is going to be left out? Rapid, plausibly sound inference seems to characterize common sense but has been underdeveloped in AI. Analogy and similarity seem central to common sense and their study should be reinvigorated. Both commonsense reasoning in the small—for example, mechanisms for drawing plausible conclusions from inexact statements or dealing with exceptions—as well as broader commonsensical thinking mechanisms—like rough planning and quick-and-dirty decision-making—have important roles.

- **Cognitive architecture**: Critical to the overall phenomenon of common sense is when and how it is invoked and how it fits with the rest of cognition, perception, and action, and how metareasoning comes into play. How it interrelates with goals and drives and overall priorities will be important. Key questions related to focus of attention will need to be addressed, including how attention is focused on relevant items of background knowledge, and how it moves away from one thing to a more promising one. We’ll also need to sort out mechanisms that smoothly allow the agent to give up on commonsense reasoning and move to a more analytical, heavier-workload reasoning effort as needed.

- **Learning**: It is generally agreed that the bulk of the basis for common sense in humans is learned from experience. Machine learning is the dominant technical thread in AI right now, but it has focused heavily on classifiers and predictive technologies like transformers. What would a learning machine look like if it were targeted to learning general knowledge of the sort one sees in Cyc? How would a machine go about learning how to use any knowledge it may have already learned? Can some of the architectural considerations mentioned above be learned or must they be innate in the underlying framework of an AI system? Finally, can common sense itself be taught after the fact? There are some self-help books out there that seem to imply that it can; if so, what are the implications for AI systems?

- **Explanation and advice-taking**: We believe that no system that purports to be autonomous should be deployed without common sense—how common sense relates to autonomy, explanation, and advice-taking will need to be part of this new endeavor. Autonomous systems need to be responsible for their actions and need to be open to taking advice as necessary from others.

These are the key areas that come to mind immediately. There are no doubt other major areas of investigation that the field will prioritize when it starts to grapple with common sense as a whole.

**Building on Prior Work**

A wide variety of great work that has been done in the past will surely need to be incorporated into our new undertaking. There is no doubt that the commonsense knowledge crafted over many years in projects like Cyc and the others mentioned above will be of value. Minsky’s frame ideas tantalizingly hinted at how the knowledge structures should be used, for things like “differential diagnosis” and reconceptualizing. Schank’s work on scripts and reminding will play an important role. And there are other sources of insight from many corners of AI that can be drawn upon, only a sample of which we have mentioned here.

While the psychology literature is surprisingly short on analyses of common sense in adult humans, the work of Sternberg and colleagues on what they call “Practical Intelligence” is clearly relevant (Sternberg et al. 2000). (Sternberg cites four modes of intelligence, and equates one of these—practical intelligence—exactly with common sense.) From an AI perspective there are limitations in this work’s perspective, but it is worth integrating into the big picture of synthetic common sense. Along a different dimension, psychologists have posited a “cognitive continuum,” in which it is postulated that common sense fits in its own position between “intuition” and “analysis” (see Hammond et al. [1987]; Hammond calls common sense “quasi-rationality”). This kind of account may inspire how to build an integrated AI system that allows common sense to be used at the right time and to show its value in frequent avoidance of heavy cognitive burdens. Along related lines, the psychologist Daniel Kahneman postulates a distinction between rapid intuitive processing in what he calls “System 1” and more thoughtful, methodical reasoning in what he calls “System 2” (Kahneman 2011). It is not clear at this stage how well Kahneman’s classification aligns with the common sense/expertise distinction we believe is central to AI. At the very least, it appears that common sense as we see it does not fall neatly within System 1 or within System 2; it instead shares some characteristics with each, and has some critical features not accounted for in either.

Given its focus on simple reasoning using models rather than general rules and abstractions, the work of psychologist Philip Johnson-Laird is worth taking into account (Johnson-Laird 1983). We would also need to account for the difference between common sense and the broader notion of rationality, and explore and build on relationships to bounded and minimal rationality (Simon 1990; Cherniak 1986). The work of Gary Klein on intuitive decision-making is also of potential use (Klein 2007). And prior psychology work on prototypes and exemplars is worthy of incorporation (Rosch and Lloyd 1978; Smith and Medin 1981). From an AI perspective, a number of prior efforts on cognitive architecture (Kotseruba and Tsotsos 2020) will be relevant as well. Classical AI efforts on qualitative reasoning and naive physics will also play a role in the expanded research endeavor we envision.

If all goes well, an ongoing government-sponsored program expressly aimed at common sense should uncover insights and mechanisms to be folded into our larger picture: over the last several years, DARPA has run a program on “Machine Common Sense” (Defense Advanced Research Projects Agency 2021). One part of the program looks to construct a knowledge repository capable of answering queries about commonsense phenomena, a thrust that seems to be of a kind with the work focused on commonsense knowledge mentioned above. This effort should produce some valuable resources for the com-
munity, but will likely manifest the same kind of context-independent behavior about which we expressed concern. However, another thrust of the program focuses on learning from experience, and will investigate early human development in search of inspiration for the development of a foundation for machine common sense. Within this program, a major project by cognitive scientist Joshua Tenenbaum and others has revealed some important insights and technology approaches by attempting to reverse-engineer the core of human common sense (Lake et al. 2017; Tenenbaum 2021). Tenenbaum points out that humans have “more content than we thought” in their starting state and “more [learning] mechanisms than we thought, some of them very smart.” These insights and the project’s outlining of a “commonsense core” will no doubt play an important role in a new science with common sense as its focus.

Recent work on Project Mosaic at the Allen Institute for Artificial Intelligence is also worth consulting (Allen Institute for AI 2022). Among the items of interest in this project is its consideration of benchmarks for measuring progress in machine common sense. Evaluation frameworks and methods are important in any science, and one that focuses on common sense is no different.

Core Research Questions

Taking common sense seriously as its own integrated subject matter leads to a number of important research questions. The key questions of the field will need to be articulated. Here are some candidates:

- What exactly is common sense? What technical definition best suits the needs of AI?
- What are appropriate tests for the presence of common sense? How can we tell if we are getting closer to building it into our AI systems?
- How is experiential knowledge represented, accessed, and brought to bear on current situations? What is the role of analogy? How does the ability to recognize something or see something as another thing (or even as an instance of an abstract concept) develop and get used?
- How is commonsense knowledge learned as new experiences happen? How is the update different when knowledge is acquired through language?
- What ontological frameworks are critical to build into an AI system? Are there special properties of the knowledge of the physical world that need to be handled in a way that is different from its non-physical counterparts?
- What is the relationship between common sense and the broader notion of rationality (including bounded rationality, minimal rationality, etc.)?
- What overall architecture is best suited for the multiple roles of common sense? What mechanism(s) should be used to invoke common sense out of routine, rote processing, and then to sometimes go beyond it to more specialized forms of expertise?
- What role, if any, does metareasoning play?

Refocusing on Common Sense as a Phenomenon

Since the beginning of AI, McCarthy and a limited cohort of researchers have set their sights on giving computers common sense. Unfortunately, while the last sixty-five years has provided us impressive technology that works on narrow problems, it has failed to deliver the ability to deal with the unpredictable open world: we do not have AI systems that can use common sense to solve life’s rampant mundane problems and respond reasonably and practically to unforeseen events. It is frequently said of AI that it can rival the most expert of human experts in many fields but cannot do the everyday things that a six-year-old can. Our belief is that the field’s thinking about common sense has been limited and has unwittingly cornered itself into a focus on common-sense knowledge and isolated islands of inference, and has never looked into what common sense as a whole may be. We need to move from systems with large amounts of independent knowledge fragments to systems that show that they can use common sense in their everyday interactions with the world. The way to do this is to step back and consider common sense in all its glory, including not just the knowledge equivalent of sound bites, but how it is based in experience and how and when it is applied. To get to true AI—systems that can be deployed and operate autonomously in the real world—we need to tackle common sense head on, as a first-class subject of study.

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