The Role of Artificial Intelligence Research Methods in Cognitive Science

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Abstract

The gold standard for cognitive science is transdisciplinary cognitive modeling of human behavior evaluated by quantitative comparisons with experiments involving human participants. However, this restrictive standard excludes much work in the history of cognitive science, and we argue sticking to this strict definition would impede future work in the field. In this paper, we examine conceptions of cognitive science and apply them to a breakdown of different kinds of cognitive modeling and AI, demonstrating that many different kinds of AI research have contributions to make to cognitive science. Even when a system cannot be evaluated by direct quantitative comparisons, rigorous methods exist to evaluate even novel qualitative work's contribution.

Keywords: Artificial intelligence; cognitive modeling; cognitive science; empirical evaluation; qualitative methods; AI methodology; philosophy of science.

Introduction

In theory, cognitive science is a broad field, encompassing psychology, artificial intelligence, linguistics and many other disciplines. Yet in practice, we have encountered two significant restrictions on what kind of artificial intelligence (AI) research is considered a legitimate contribution to cognitive science: first, that the only acceptable evaluation of an AI model is statistical comparison with an existing system or with humans; and second, that the only acceptable AI models are those that explicitly model humans or animals.

In this paper we argue that the above restrictions are misconceptions. These misguided standards would not only exclude many kinds of legitimate cognitive science work in the future, but also exclude some important findings from cognitive science's history. As a field, we should have solidarity if not consensus on what are acceptable methods for AI research in cognitive science, and these misconceptions discourage important work yet to be done.

To make this argument, we will categorize the kinds of artificial intelligence research relevant to cognitive science. AI itself is the attempt to build and understand agents that can behave intelligently, but it can be roughly broken into "Engineering AI," which builds agents without modeling natural intelligences, and "Psychological AI," which models processes in natural intelligent agents. Psychological AI is often called "cognitive modeling" when it involves quantitative comparisons with the data collected in psychological experiments.

Engineering AI is, by a wide margin, most of AI research. Because Psychological AI explicitly attempts to model humans and animals, its role in cognitive science research is clear; however, we will argue that Engineering AI also has a role to play by providing important constraints on what kinds of intelligent systems are possible, and what kinds of knowledge or processes are necessary. Similarly, we will argue that Psychological AI has a role to play in cognitive science even when it is not a formal "cognitive model."

Part 1 of this document examines Psychological AI. In it, we argue for the legitimacy of qualitative results in cognitive modeling research. We begin by outlining opposing arguments that qualitative results are inferior to quantitative results, or perhaps only good for hypothesis generation, or are even worthless altogether. While there is nothing wrong with quantitative results, there are many worthwhile projects for which quantitative evaluations are inappropriate or impossible. Further, pioneering cognitive modeling research, which we should encourage researchers to pursue, often *requires* the use of qualitative results.

Part 2 examines Engineering AI. In it, we argue that at least some Engineering AI is legitimate cognitive science research, in spite of it not modeling natural intelligences. To make this case, we examine conceptions of cognitive science on the axes of interdisciplinarity and inclusiveness, and describe a range within these axes where Engineering AI can make meaningful contributions to cognitive science.

We will conclude by summarizing our categorization of artificial intelligence methods, and by highlighting how Engineering and Psychological AI are critical to the progress of cognitive science, both as ways of breaking new ground and as ways of avoiding garden paths.

Part 1: Psychological AI and Cognitive Modeling

The Fable of Car World

In Car World, a group of scholars were creating faster and faster cars. Their students would come up with a new *vehicle, and would show, quantitatively, that it was faster than previous cars. If it wasn't the fastest car on a flat road, it might have better traction on ice, inclines, or sand. Car technology was progressing quite well, car speeds and traction were compared statistically, and nobody doubted the scientific integrity of the field.*

Then a student wanted to create a vehicle that could fly. At her proposal defence, she described how it might work, her reasons for thinking so, and even showed some prototype "gliders" that stayed in the air for quite a while, even if they were not powering themselves.

One of the committee members cut her off. "Hold on. How are you going to evaluate this?"

"Well," she said, "if what I build actually flies, then it worked, and supports the theories I used to create it."

"But what are you going to compare it to? Will it be faster than the cars we have now?"

"No. Rocket cars are faster. But my vehicle will fly—"

"Well, will it have better traction, then?"

"No, it will actually lose traction when it takes off. But speed and traction aren't the point, it's going to fly—"

"So you won't have any quantitative comparisons to demonstrate support for your theory?"

"I can't think of how," she said, getting nervous. "All previous vehicles don't fly, and their...altitude, in any case, was never measured."

The committee member, frustrated, threw up his hands. "If you don't have a quantitative evaluation, I don't see how you can show that you've made any contribution."

Another committee member tried to help. "Maybe if you could use the theories you have to make a car..."

Psychological AI can make several kinds of contribution to cognitive science, which we will now describe and defend. The prototypical contribution is cognitive modeling: using a Psychological AI system to model experimental findings.

1) Empirical Quantitative Cognitive Modeling

This involves creating a cognitive model that outputs numbers. The evaluation of the model is done by comparing this output (often with correlation) to quantitative data collected in a psychology experiment (as we refer to human participants experiments in this paper). As in all AI, the model is an implementation of a theory—in this case a process explanation of the phenomenon investigated in the psychology experiment. The main contribution of the work is the theory and the model. Its evaluation is the statistical testing done to compare its outputs to dependent variables from the psychology experiment.

We assume that nobody will object to research in the style of (1); however, it has drawbacks. It requires modeling of something that *can be studied* with a psychology experiment that produces quantitative output. This severely limits the cognitive phenomena this method can investigate.

It is difficult or impossible to collect quantitative data on many interesting and important cognitive phenomena, such as dreaming, planning, consciousness, reasoning, and interactions between these subsystems (Langley, 2012). Cognitive psychology investigates them with dependent measures such as response times and percentages of correct answers. These measures can legitimately be used broadly, but are not without limitations. Correlations between a psychological experiment and model behavior only establish weak equivalence of the model to human cognition. Strong equivalence requires validating that the details of the implementation match the processes of human cognition, which requires separate experimentation (Pylyshyn 1984).

A more important limitation on cognitive modeling is the source of the psychological data used for comparison. This data can be collected by other researchers or by the modeler.

1.1) The Modeler Runs the Experiment

In this type of research, a cognitive model that outputs numbers is evaluated against quantitative data collected in a psychology experiment run by the modeler.

The benefits of (1.1) are obvious. The contribution becomes the experiment and the model combined. The modeler is not limited to only those problems that other people have decided are important. If there are no existing data, the modeler can collect them in an experiment tailored to tease out the theoretical features of the model.

The drawbacks are somewhat less obvious. Experiments take a great deal of time to do, and not every modeler knows how to do them properly. Getting an experiment right is difficult, and necessarily uses time that could have been spent on model implementation, which itself is not trivial. This usually requires a tradeoff, because the resources of a research group are generally limited.

The resources of a student are more limited, and, running an experiment has an opportunity cost: less time spent refining the model. For computationally-focused students, this is problematic, as computer science hiring committees can see psychological experiments as a waste of time.

1.2) The Modeler Uses Someone Else's Data

Alternatively, modelers may use someone else's data, which saves time for programming the model. However, this *severely* limits what the researcher can study.

First, the researcher is restricted to quantitative data the experimenter thought to *record*. Experimental research is hypothesis-driven, and experimentalists generally don't collect data not relevant to their hypotheses. It's not just that extraneous measures add clutter to what would otherwise be elegant experimental designs; they can even work against the publication of a paper. For one experiment, the first author did not collect certain data because he would have been obliged to report he collected them, to run statistical tests on them, possibly with null results—leaving him unable to defend why he collected them in the first place, at least not to the satisfaction of typical referees. If future modelers need those data, they are out of luck.

Second, even assuming data the modeler would find useful are collected, they are often not *published*. Many researchers only report measures that result in significant differences, even though other measures might be useful to a future modeler. It is important to note that the purpose of the model might well be different from the hypothesis of the experiment it is modeling. Worse, collected data *themselves* are often not published, only descriptive measures of them. If the original experimenter cannot (or will not) get the data to the modeler, the modeler is limited to the summary information the experimenter decided to report. Even online journals do not typically publish pages and pages of numbers. The value of large unrefereed archives of data is dubious, but even if one could be established, it will not be possible to recover data for most papers published in the past. If researchers want to compare the model's results to some aspect of the experiment that wasn't published, they are again out of luck.

Finally, and perhaps most damning, with (1.2) the modeler is essentially following up on someone else's work rather than pioneering his or her own. This is not a recipe for making breakthroughs.

In spite of these extraordinary limitations, (1.1) and (1.2) are generally considered to be the highest standard for cognitive modeling.

2) Psychological AI with Novel Functionality

As an alternative to direct quantitative comparisons to psychological experimental data, a researcher could focus just on creating a computer model of a cognitive ability that humans have, regardless of whether someone has designed a psychology experiment to explore it. This model should generate predictions, either qualitative or quantitative, that could be tested with a psychology experiment, but the modeler need not run this experiment. Ideally, a paper using this methodology explores what such an experiment might look like, and make specific predictions.

If the core of the scientific method is theory generation, hypothesis generation, and hypothesis testing, then (2) focuses just on theory and hypothesis generation. Although frowned upon in psychology, non-experimental science is an important part of many disciplines, including theoretical biology, theoretical geology, theoretical sociology, and especially theoretical physics. Famously, Einstein's (1905) paper on special relativity contained a detailed model, specific predictions…but only a call for experiments to test his hypotheses (Isaacson, 2007). Psychology is unusual among the sciences in that it does not have a large theoretical subdivision within the discipline itself.

Psychological AI can generate hypotheses about human beings. This is tricky, because the researcher is not *evaluating* the hypothesis to either AI's or psychology's highest standards. However, if the AI is interesting enough, and built on solid cognitive principles, it can be of value.

For example, one might build a spatial inference system based on what is known of spatial inference. The model could behave in ways that make predictions that could be tested in the laboratory on people. Robert West (personal communication) calls this "forward engineering."

Rather than judge this kind of modeling on the standards of experimental psychology, think of it as computational philosophy. Philosophers doing theoretical psychology often do not run experiments that could test their theories, yet they can point experimental work in fruitful directions.

In (2), the researcher must demonstrate that the task has not been done before, or that the way the task is solved is different in some way. If the model exhibits novel behavior or uses a different method, then the very fact that the model worked as designed *is an acceptable evaluation all by itself,* even without statistical testing. This is true because the model shows that the theory *can work* in a computational intelligent agent—which is *not* true for all proposed pen-and-paper psychological theories. Like the plane in Car World, the model does something brand new. Showing that a model can work at all is an important step towards showing that cognition works that way in humans.

Still, a system that demonstrates novel functionality might be hard to evaluate: the more novel the functionality, the fewer other works will be appropriate for comparison. We first examine systems that generate meaningful numbers.

2.1) Novel Quantitative Psychological AI

The model the researcher creates could generate quantitative data: the size of the system's output, the number of steps taken, the percentage of correct responses, and so on. This does not mean, however, that there are any *other* data which would be sensible to compare it with using statistical tests. This is the situation we explored with the Carworld fable.

The lack of a suitable comparison does not preclude comparison in the future, either with experimental results or the results of other models. It's just that these comparisons need not happen in the modeling paper itself.

The lack of a suitable comparison also does not mean that the system cannot be evaluated. For example, theoretically significant subcomponents can be ablated (removed) to identify the system's sources of power. The second author's model of contextual spreading activation (Francis 2000) was tested in this fashion by ablating its contextual features. Similar approaches are detailed in many books, papers and symposia (e.g., Cohen, 1995; Walsh, 1998; 2000).

2.2) Novel Qualitative Psychological AI

Not all systems can be measured quantitatively, or when they can, the available measures may not be interesting or meaningful. Of course, to determine that a system has exhibited a behavior, its behavior must be measurable; when that measurement is not numerical, we call it qualitative.

For example, suppose a model generated pictures that looked like Picasso paintings. The images of course can be described with numbers, but those numbers are not explicitly generated by the model. One could run participants to judge how much the images looked like Picasso's, but this would require running an experiment, and the work would be subject to the same trade-off as (1.1). Even if one argued that a graduate student's dissertation should require such an experiment, both the model and the experiment testing the model are distinct contributions, and reporting each one adequately could fill an average conference paper.

There is an analogous problem in computer graphics, which is why we chose the Picasso example. A researcher might, for instance, create a model that generates graphics that appear as a brick wall does when hit with a wrecking ball. How does the researcher evaluate how realistic it is? Or even how realistic it looks? Even though books have been written on the principles of perceptual realism (Thompson, Fleming, Creem-Regehr & Stefanucci 2011) justifying claims about a specific model still would require experimental evaluation. Yet texts on graphics such as Parent's (2008) have no experimental evaluations and refer to psychological research largely in the facial and behavioral animation chapters. Graphics progresses largely without human participant experiments because ultimately the quality of graphics depends on subjective experience. The graphics benefits from the work of excellent modelers, even those who have poor skills at running psychology experiments.

So does cognitive science.

Part 2: Engineering AI

Engineering AI may appear irrelevant to cognitive science. Whether it is depends on one's conception of what cognitive science research is and should be.

For our purposes, there are two aspects to a conception of what cognitive science should be: its proper research methodologies (the tools it uses for investigation) and its proper subject matter (the phenomena it investigates.)

Cognitive Science Methodology

One aspect of cognitive science methodology is its multidisciplinarity: how interdisciplinary does research need to be to qualify as cognitive science? An *inclusive* approach includes any research (on the proper subject matter) in any of cognitive science's component disciplines.

There are varying degrees of the *exclusive* approach, but all require some amount of multidisciplinarity. A *weakly exclusive* approach might merely require comparing findings with problems and theories in another participating discipline. We will call this simply "interdisciplinarity." However, this would exclude from cognitive science many historically interesting findings. For example, this would likely exclude Quillian's (1968) work on semantic memory, even though Collins and Loftus (1975) cite it as the direct inspiration of their seminal cognitive science work on spreading activation—and both are included in *Readings in Cognitive Science* (Collins & Smith, 1988), a required text at the author's alma mater.

A *strictly exclusive* approach might require that each piece of research involve methodologies from more than one discipline. For example, doing a psychology experiment and some cognitive modeling in the same work. We will call this stricter conception "transdisciplinarity." Requiring transdisciplinarity would exclude enormous amounts of research, including much of that published in the *Cognitive Science* journal and conference proceedings, and is thus too restrictive. For example, Schank's (1977) work on scripts and Hayes's (1978) work on naïve physics would be excluded—cutting more out of Collins and Smith (1988).

Another aspect of cognitive science methodology is its "level of analysis:" at what level of granularity do theories need to be to qualify as cognitive science? An essential aspect of cognitive science is that it operates at the cognitive level—it views the mind as an information processor. This is why behaviorist psychology studies are often not considered cognitive science, except in the most inclusive sense of the term. The level of analysis issue is potentially a problem for psychology and philosophy theories, but because all AI happens at an information-processing level, it qualifies as cognitive science with respect to the levels of analysis question, and we will not discuss it further.

Cognitive Science Subject Matter

The part of the *subject matter* question relevant to the current discussion involves what *kind of intelligent systems* are under the purview of cognitive science.

The narrowest view we have encountered is that only projects relating to *symbolic* human cognition are part of cognitive science. A slightly more typical view is that only those projects relating to *human* cognition are acceptable. A slightly broader conception includes all *animal* cognition. The broadest includes non-human intelligences, potentially including intelligent computer systems, alien intelligences (if we ever find any) and distributed cognitive systems (such as companies, anthills, human-machine interfaces, immune systems, etc.)

Is Engineering AI Cognitive Science?

Engineering AI does not model natural minds. Its findings are about intelligence and cognition in the abstract. Both the exclusive methodology and the restrictive subject matter conceptions of cognitive science exclude Engineering AI. For example, many researchers in AI work on planning algorithms. They do not try to make their planners think the way people or animals do, nor do they compare their results with results from other fields. Their focus is developing better planners with respect to planning performance metrics. Under the most restrictive definitions, this work would be excluded from cognitive science.

AI is a component field of cognitive science, and planning is a cognitive process (in humans, other animals, machines, and distributed cognitive systems). An inclusive, broad conception of cognitive science as the study, by whatever means necessary, of *all minds*, and not just natural minds, would include all AI work in cognitive science.

We believe it is a stretch to call all AI work cognitive science, but the most restrictive subject matter conceptions are misguided. Engineering AI can shed light on the nature of cognition itself, informing the wider community about possibilities and limits through implementation. For example, a certain planning method might intuitively not appear to work for a given task, but Engineering AI, just like (2), can provide *existence proofs* showing that a given method is even possible.

Engineering AI research can also establish limits. It is harder to show that a particular kind of process *cannot* accomplish a particular task, but failure provides a weak form of disproof: after many failed attempts, the community is legitimately entitled to some doubt. For example, many but not all AI researchers believe reactive agents cannot solve planning problems (see the discussions in Chapters 2 and 25 of Russell and Norvig, 2003). Theorems provide a stronger form of disproof, constraining all possible cognitive systems. For example, the theory of inductive bias in machine learning rules out pure blank slate learning systems (see section 2.7.3 of Mitchell, 1997), and Minsky and Papert's (1988) work on perceptrons showed that a learning system can only learn what it can represent.

Minsky and Papert's work also provides an example of how Engineering AI can connect to cognitive science: they explicitly made arguments connecting their mathematical discoveries to general intelligent systems. All Engineering AI is acceptable under the inclusive methodology and broad subject matter views of cognitive science, but under more exclusive views, AI work must either relate its findings to other fields (interdisciplinarity) or use methodologies from other disciplines (transdisciplinarity) to be considered a contribution to cognitive science. We believe that transdisciplinarity is too restrictive, but that work must make interdisciplinary arguments to be cognitive science. Although we might give a pass to early work, contemporary cognitive scientists have no excuse not to address other subdisciplines.

Yet, even if one were to argue that an Engineering AI system that focused purely on an engineering problem was not cognitive science, that does not mean that the work has no *contribution* to make to cognitive science. For example, an Engineering AI algorithm could show how a particular problem could be solved, leading to the development of (2) style cognitive science model, or even a (1) style cognitive science model quantitatively compared with data collected from an experiment with human participants. Clearly, the Engineering AI system that made the Psychological AI system possible should be cited in the related work section of any paper describing the cognitive modeling work, and therefore counts as a contribution.

In conclusion, Engineering AI, which we will number (3) in this paper, should always be regarded as a legitimate cognitive science contribution *if* it situates itself within the other cognitive science subdisciplines. But because Engineering AI is not cognitive modeling, it must be evaluated in its own way—and again we begin by examining quantitative comparisons with existing systems.

3.1) Empirical Quantitative Engineering AI

In this approach, the researcher's AI generates quantitative output that can be compared statistically to the output of a previous AI implementation—ideally, showing an improvement. Just like (1), it has the benefit of rigor and suffers the drawback of requiring the researcher to do what's been done before, just a little better. Langley (2011) says that this kind of research "...has encouraged incremental progress on standardized problems."

Just as quantitative comparison of models to psychology experiment findings is the highest standard for cognitive modeling, quantitative comparison of one AI to another is the highest standard for AI modeling, deserving or not.

3.2) Novel Quantitative Engineering AI

A researcher could create an AI that both demonstrates novel functionality *and* generates quantitative output, but this output would not be comparable to the output of any other AI. Like the plane in Carworld, there are no other AIs to which a truly new system can profitably be compared.

However, there still might be some performance metric that is usable, such as computational complexity, real-time performance, percentage of correct answers with respect to a real-world task, and so on. For example, the first computer vision system that recognized faces could not be compared to any existing system, nor was it an attempt to model human performance at the task. It was actually evaluated by showing that the facial recognition features operated at *better* than human level (Bledsoe, 1966).

3.3) Novel Qualitative Engineering AI

A less rigorous, but still acceptable method (in some circles) is to demonstrate a capability of an AI that no other AI has. This has overlap with qualitative cognitive modeling (2), but with less emphasis on what natural intelligences can do.

Minksy (1968) argues AI essentially began with three cybernetic systems that demonstrated novel human-like capabilities: achieving goals (Rosenblueth, Weiner, & Bigelow, 1943), representing concepts (McCulloch & Pitts, 1943), and using analogies (Craik, 1943).

These seminal works of AI, while inspired by human behaviors, were neither what we would consider cognitive models, nor were they comparable to other AI results. Indeed, as they broke new ground, how could they be?

Conclusion

Many of these issues exist on a continuum, and we expect that different readers will respond to them with different intuitions. In spite of this, we hope that our analysis will provide a structured way to think about these issues.

We have sketched out an ontology of cognitive modeling and AI contributions with the potential to contribute to cognitive science research, and outlined how each of these areas can be rigorously evaluated, even when direct comparisons are impossible:

1) Empirical Quantitative Cognitive Modeling
    1.1) The Modeler Runs the Experiment
    1.2) The Modeler Uses Someone Else's Data
2) Novel Psychological AI
    2.1) Novel Quantitative Psychological AI

2.2) Novel Qualitative Psychological AI
3) Engineering AI
3.1) Empirical Quantitative Engineering AI
3.2) Novel Quantitative Engineering AI
3.3) Novel Qualitative Engineering AI

We have also presented conceptions of cognitive science according to subject matter (from a narrow focus on humans to a broad focus on all intelligences) and methodology (from exclusive transdisciplinarity through intermediate interdisciplinary to broadly inclusive approaches). We argued that interdisciplinarity is what should be required of a modern cognitive science contribution. Some older unidisciplinary works are either grandfathered into cognitive science, or acceptable as non-cognitive science that nonetheless influenced cognitive science.

Even though quantitative comparison is thought to be the highest standard in science, legitimate cognitive modeling and AI findings do not require quantitative comparisons, nor even quantitative output.

In terms of subject matter, which AIs count as cognitive contributions depends on where one stands with respect to the relevance insight into artificial minds in their own right. Several examples of Engineering AI of the past have made important contributions. We do not take a strong stance on this particular issue.

Our community's misguided "high" standards for science would exclude the great results of the past, as well as potentially inhibit important discoveries of the future, because pioneering, seminal work often involves novel approaches that are quantitatively incomparable to past projects. As such we encourage a broader conception of the role of computer modeling in cognitive science—one that will lead to more of the groundbreaking work that makes AI a thriving, innovative field.

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