
A PROPOSED TEST FOR HUMAN-LEVEL INTELLIGENCE IN AI

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Abstract

The need for a meaningful test for intelligence in AI becomes increasingly pressing as AI systems grow more sophisticated. Several approaches have been proposed for intelligence tests, ranging from solving puzzles, understanding natural language, or learning and adapting to new situations. I here propose that instead of assessing intelligence based on conversational text (Turing test) or creativity (Lovelace test), a superior test assesses the capacity to make scientific discovery. However, it is critical to note there are different categories of such discovery. Level 1 discovery is defined here as piecing together scattered facts in the scientific literature, something that approaches impossibility for a human who cannot read the literature in its entirety nor enjoy perfect recall. Level 1 discoveries will be meaningful and important, but there is an important distinction to be drawn: Level 2 discoveries require the building and simulation of new models rather than simply a joining of facts. Einstein's discovery of special relativity or Darwin's proposal of evolution by natural selection are examples that extend beyond simple interpolation and instead require novel frameworks. In summary, scientific discovery can serve as a meaningful test of intelligence – but this requires distinguishing different levels, and in this proposal only Level 2 discoveries will serve to demonstrate human-level intelligence.

Introduction

One of the central, unsolved mysteries in modern neuroscience is how intelligence arises from collections of billions of cells in our brains. Therefore we are yoked with a second mystery: could intelligence arise in alternative complex systems such as artificial brains?

Transformer models (Guerra et al., 2017) have exploded onto the scene with unexpected successes in writing (Chen et al., 2019), visual art (Galanos et al., 2021), coding (Berabi et al., 2021), music

composition (Tan et al., 2020), and more, reviving old questions about intelligence with a new sense of urgency. How do we meaningfully measure intelligence in an artificial system? How do we know whether AI is intelligent, or instead whether it is playing a massive statistical game and humans are simply anthropomorphizing?

It is not always easy to know why sometimes the answer returned from a large language model (LLM) seems impressive, but we may agree that pulling text and

parroting it back – or even probabilistic interpolation – does not represent intelligence. An LLM, presumably, has no idea whether it is generating a poem, a terrorist manifesto, instructions for building a spaceship, or a heartbreaking story about an orphaned child. Nor does it care. Modern computation simply digests words and outputs statistical correlations (Searle, 2009). Google Translate, for example, can take a sentence in Russian and return a translation in Amharic, but it is simply algorithmic: it neither interprets nor understands the words.

This is no criticism of a correlative approach, but as will be explained below, we may not want to confuse that with human-level intelligence. There is also a deeper reason to be suspicious of claims of intelligence: despite the resounding successes of LLMs, their outputs often lack common sense – i.e. expose the lack of a meaningful model of the world (Davis, 2023).

Given these questions about the “intelligence” in AI, what methods would we have to assess this?

Turing test

In 1950, the mathematician and computer scientist Alan Turing asked how one might determine whether a machine exhibits human-like intelligence, and he proposed an experiment he called the imitation game (Chomsky, 2009). An AI, programmed to simulate human speech, is placed in a closed room. In a second closed room is a human. An evaluator communicates with both via a computer terminal, with the job of figuring out which is the machine and which the human. If the evaluator cannot tell, that is the moment when machine intelligence has finally arrived at the level of human intelligence: it

has passed the imitation game – or what we now call the Turing Test.

The development of LLMs has surmounted the bar set by the Turing test. But we are left with uncertainty about whether to equate conversational ability with intelligence. In part this is because of the ease of anthropomorphization: we readily assign human qualities to non-human things around us, such as animals, toys in animated films, or random moving shapes (Heider & Simmel, 1944; Eagleman, 2015).

Therefore, just because a person believes an LLM’s answer was quite clever tells us little about whether it exhibited meaningful intelligence: It only tells us something about the willingness of the observer to assign intention.

Therefore, the imitation game may no longer be the best test for meaningful intelligence. Other ideas have been proposed – because while the Turing Test measures something about AI language processing, it doesn’t necessarily require the AI to demonstrate creative thinking or originality.

Lovelace test

Foretelling such concerns, Bringsford et al proposed the Lovelace Test. This was named after Ada Lovelace, the 19th century mathematician (and often considered the first computer programmer) who said “only when computers originate things should they be believed to have minds” (Bringsjord et al., 2003). The Lovelace test therefore focuses on the creative capabilities of AI systems. To pass the Lovelace Test, a machine must create an original work, such as a piece of art or a novel, that it was not explicitly designed to produce. This test aims to assess whether AI systems can exhibit creativity and autonomy, which are key aspects of human capabilities. The idea

is that true intelligence involves creative and original thinking, not just the ability to follow pre-programmed rules or algorithms.

In 2014 the Lovelace 2.0 test was proposed (Riedl, 2014), which calls upon the human evaluator to specify the constraints that will make the output novel and surprising. The example cited in Reidl's paper is to "create a story in which a boy falls in love with a girl, aliens abduct the boy, and the girl saves the world with the help of a talking cat."

We now know this is trivial for an LLM, which suggests the Lovelace test is totally insufficient and only represents the recent limits of our imagination. After all, it is not difficult to mix inputs in a way that makes the system seem intelligent, when it is really only doing a mash-up.

Other tests of AI intelligence include the Winograd Schema Challenge (Levesque et al., 2012), which tests a machine's ability to understand natural language, and the Allen AI Science Challenge (Schoenick et al., 2017), which tests a machine's ability to answer 8th grade science questions. There has also been a growing interest in developing tests that can measure the intelligence of AI systems in a more comprehensive way. One such test is the Artificial General Intelligence (AGI) Test (Bostrom, 2014), which asks whether a machine can perform any intellectual task that a human can.

Limitations of previous tests merit the proposal of another test that is more direct, testable, and possibly more straightforward to judge.

Scientific discovery

A meaningfully intelligent system should be able to do scientific discovery.

A version of the scientific discovery test was proposed by Shoucheng Zhang (Zhou

et al., 2018; Than, 2018). He asserted that the most important thing humans do is make scientific discoveries, and the day an AI can make real discoveries is the day it becomes as smart or smarter than us.

The current paper springboards from this suggestion to define some important parameters and refinements.

Level 1 scientific discovery

Envision this scenario: you ask an AI a biomedical question about what kind of compound would best bind to a receptor to trigger a cascade that causes a particular gene to get suppressed. And imagine that an LLM tells you an amazingly clever answer that had not previously been known by scientists before.

We might assume the AI has performed some extraordinary scientific reasoning, but this will not necessarily be the case. Instead, the LLM will often pass the test simply because it is more well-read than any human on the planet, by literally millions of times.

To clarify this point, imagine a typical, giant biomedical library. A fact is stored in a paper in a journal on one shelf, another seemingly unrelated fact lives on a shelf seven stacks away, and a third fact is hidden on the bottom shelf on the other side of the library in a book from 1979. It is almost infinitesimally unlikely that any human could hope to have read a one-millionth of the biomedical literature, and even more unlikely that they would be able to hold all three of these critical facts in their mind at the same time. However, this is trivial for a large language model, and has the potential to be incredibly useful for science.

Therefore, we will surely see new science being done by LLMs – but in this case not because of conceptualization or

human-like reasoning, but instead simply because it knows facts that seem to fit together. Thus, with the right sorts of questions, we will find that modern AI sometimes appears to pass the scientific discovery test.

I propose that we categorize such science – in which the facts already exist in the literature – as *Level 1* discovery. LLMs will excel at Level 1 discovery because they have read the entirety of the literature and have a perfect memory. Such breakthroughs will happen commonly, and they're going to be immensely important, as we have so many gems buried in mountains of data.

Level 2 scientific discovery

However, I want to distinguish a second level of scientific discovery. *Level 2* discovery refers to scientific progress that requires conceptualization (and typically re-conceptualization) to arrive at the next level – not just a remixing or connecting of what is already there.

As an example, consider the young Albert Einstein imagining something he had not seen before. He asked himself what it would be like if he could catch up with and ride a beam of light. This led him to derive the special theory of relativity. Importantly, he was not simply piecing facts in the literature together; he was instead reaching into the unknown, asking new sorts of questions, and trying out new models of the world to see if any of them could work.

Similarly, when Charles Darwin considered the animal species he saw around him, he also imagined all the species he did *not* see, but who might have existed. In this way, he was able to build a new world model in which most species did not survive, and we only see those animals whose mutations caused survival or

reproductive advantages over others. These were not facts he collected from papers: He was developing a new model of the world.

Although I use Einstein and Darwin for illustration, this kind of Level 2 science is not restricted to large paradigm shifts. Instead, a great deal of meaningful, daily science is driven by this kind of imagination of new models.

Therefore, I define Level 2 science as the most material test for human-level intelligence. When AI can do science in this way – generating new ideas and frameworks, not just simply connecting extant facts – then AI will have matched (or exceeded) human intelligence.

For clarity I offer a related example. The way a working scientist reads a journal paper is not simply by correlating words (although that may be part of it) – but often by concentrating on what was *not* said. *Why did the authors cut off the x-axis at 30? What if they had extended the graph – would the line have reversed its trend? Why didn't the authors mention the hypothesis of Smith et al?* One of my mentors, Francis Crick, operated under the assumption that he should disbelieve 25% of what he read in the literature.

Whether because of fraud, error, statistical fluctuations, manipulation, or the wastebasket effect, the bottom line is that the literature is rife with errors (Williams et al., 2019). When scientists read papers, they know this, and they therefore read in an entirely different manner than LLMs. A scientist wonders about other possibilities. A scientist chews on what is missing. A scientist envisions the next experiment that could confirm or disconfirm the hypotheses and frameworks in the paper.

For completeness, we also define Level 0 discovery: this defines a situation in which AI “discovers” something the scientist doing

the search had not previously known (but was known by others). This is a trivial event that commonly proves capable of fooling observers into concluding that AI is intelligent. Because anthropomorphization is an easy trap to fall into, Level 0 discovery is considered insignificant for the present purposes.

Conclusions

Human-level intelligence should be defined by the discovery of new science. However, critically, the present proposal works to distinguish things that the searcher did not know (Level 0) from the piecing together of scattered facts (Level 1) from generating new world-models and simulating them for evaluation (Level 2). Only Level 2 is considered a meaningful test of human-level intelligence.

The levels outlined here are likely to end up with blurry boundaries. LLMs will often generate answers and we will find ourselves unable to determine whether it had been previously written somewhere in the literature and we simply did not know it (Level 0), or whether the AI is piecing together disparate pieces in the literature (Level 1), or whether the AI has derived a truly new world-model to simulate and

explain the data (Level 2). Thus, distinguishing the level of discovery will not always be an easy task with bright lines of demarcation. Nonetheless, this distinction hopes to offer some clarification as things move forward.

For clarity, I do not suggest there is something magical about the way humans accomplish Level 2 thinking: Presumably we just run algorithms on the self-reconfiguring wetware of the brain (Eagleman, 2020). As most scientists have seen thousands of experiments in their careers, we know the process of asking questions, generating new frameworks, and understanding how to test those frameworks. That suggests the possibility that our machines may also reach Level 2.

However, as of this writing, it appears that the current incarnations of AI, as impressive as they are, do not reach Level 2 scientific problem solving. When they do, then we will have crossed a line into artificial thinking that is truly intelligent.

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