

Turing Test Considered Mostly Harmless

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Abstract Turing's landmark paper on computing machinery and intelligence is multifaceted and has an underemphasized ethical dimension. Turing's notion of "intelligence" and "thinking" was far more encompassing than the common anthropocentric view may suggest. We discuss a number of open and underrated problems that the common interpretation of the Turing test as a test of machine intelligence entails. We suggest that a more meaningful question than "Can machines think?" is whether modern computing machinery can *amplify* human intelligence. We cite examples ranging from traditional silicon-based environments to carbon-based, living organisms in order to illustrate that this kind of intelligence amplification is indeed happening today. We conclude that in its interpretation as a test of machine intelligence, the Turing test may indeed be harmful for artificial intelligence (AI); in its wider interpretation, however, it remains an inspiring source for philosophy and AI alike.

Keywords: Turing Test, Imitation Game, Machine Intelligence, Intelligence Amplification, Creativity.

§1 Introduction

“May not machines carry out something which ought to be described as thinking but which is very different from what a man does?”

– Alan Turing, 1912–1954

It is difficult to find any other example in computer science that has stirred as many heated debates as the Turing test has since its conception more than six decades ago.⁴³⁾ For many years, the test has been extolled and deprecated, attacked and defended, over and over again (e.g.,^{14, 35)}). The Turing test is commonly seen as *the* ultimate benchmark test for demonstrating that a machine “has intelligence.” Whereas the test was initially a driving force for AI, it has lost its impetus over the last two decades. Since the 1990’s, the test has nearly vanished from the research agendas and is now practically confined to the history books, with the exception of the annual *Loebner Prize in Artificial Intelligence* competition.^{*1}

The spectrum of opinions on the Turing test is truly wide. Some consider the Turing test as harmful for AI and that it should therefore be abandoned as a research goal;^{21, 47)} others still consider it a grand challenge for AI.¹³⁾ Recently, tests that are inspired by the Turing test are being proposed in systems biology²⁰⁾ and synthetic biology.¹⁷⁾ In the spirit of the common interpretation of the Turing test, these tests involve computer models of living organisms. If the responses or behaviors of these computer models are indistinguishable from those of their natural analogs, then these models have passed such a test. Likewise, if a synthetically engineered cell is indistinguishable from a natural cell, then that synthetic cell has passed the “imitation test.”

The field of computational creativity is a relatively new scientific area that relates well to the Turing test and AI.^{*2} Like AI in its fledgling stages, computational creativity struggles with the definition of its core concept – what is “creativity?” Like “intelligence” or “thinking,” the concept of “creativity” is difficult to grasp. Turing-style tests are therefore considered to evaluate machine creativity, for example, in the field of artificially created music.¹⁰⁾

Given the resurfacing interest in the Turing test, our goal here is to revisit and analyze Turing’s original⁴³⁾ paper while paying attention to the controversial discussions that have happened over the last 50 years. Although the Turing test is widely regarded as a formal test of machine intelligence, we question whether this interpretation is warranted, given the actual content of Turing’s landmark paper published in 1950 and his remarks in the years after. Our observation is not an entirely new one, though; indeed, alternative readings of⁴³⁾ have been

^{*1} <http://www.loebner.net/Prizef/loebner-prize.html> (accessed: 19 October 2012).

^{*2} Computational creativity is a relatively young discipline that emerged from AI and like AI, hugely benefits from today’s powerful computer hardware and software. The field pursues the question about the ultimate nature of creativity similar to the way AI studies machine intelligence. For example, it is possible to use programmable machines as vehicles to better understand creativity or as devices for the explicit construction of devices demonstrating human-level creativity.

proposed.¹⁶⁾

Still, even if we assume that Turing did not have a formal test in mind, is it a problem to use it as such? Here, we argue that the answer is “yes.” We discuss several underrated problems in order to support our argument. We then use examples from computational science and unconventional computing in order to illustrate that modern computing machines can at least serve intelligence amplification. Whether – and to what extent – modern computing machinery amplifies intelligence, therefore, should be the question of interest, not least because it is meaningful and measurable. This alternative question makes the original question whether a machine can think or not secondary. Of course, our challenge is not meant to entirely eradicate Turing’s question. On the contrary, we acknowledge its fundamental contribution to science and believe that Turing’s landmark paper⁴³⁾ is going to remain an inspirational source for future generations of computer scientists, philosophers, and AI practitioners.*³

§2 The Turing Test, Revisited

A first observation about the Turing test is that, over time, it has diverted into various flavors. Saygin et al.³⁵⁾, for instance, provide an excellent overview about this development. In addition, it is perhaps not widely appreciated that Turing proposed two different experimental designs for his test. The first design, which is commonly known as “the” (classic) Turing test, is derived from the imitation game and described in his landmark paper.⁴³⁾ Two years after its publication, Turing described the second design in a BBC interview. It is necessary, therefore, to mention that here, we will focus only on what has become known as the “classic” Turing test. First, we will briefly revisit the two different tests.

2.1 The Imitation Game and the Turing Test (1950)

The (gender-based) imitation game is a three-party game played by a man, a woman, and a judge (whose gender is irrelevant). In a blinded teletyped conversation, the man tries to fool the judge by pretending to be a woman. The judge then asks in turn questions to find out who is the man and who is the woman. If the man can trick the judge, then the man wins. Figure 1 schematically illustrates this game.

Turing considered his original question “Can machines think?” meaningless because of the difficulty to define unambiguously what is meant by “machine” and “thinking.” He therefore proposed the imitation game as a proxy, that is, as a game where a machine plays the role of the man. If a machine pretended to be a human being, could a judge tell it apart from a real human being (whose gender is irrelevant)? This new game is known as the classic Turing test and is illustrated in Fig. 2.

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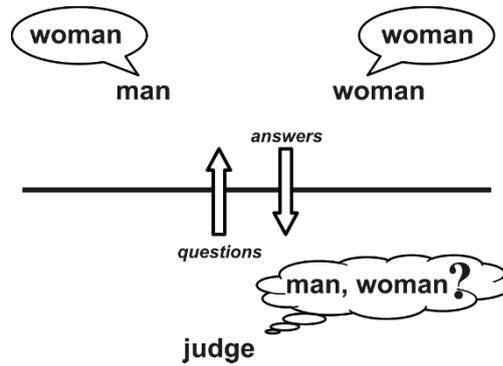


Fig. 1 The Imitation Game⁴³⁾

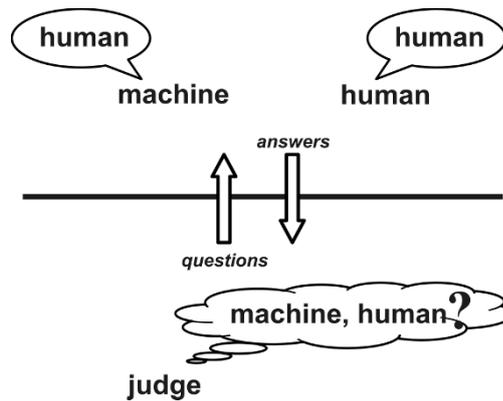


Fig. 2 The Classic Turing Test⁴³⁾

Turing then made the following prediction:

“I believe that in about fifty years’ time it will be possible to programme computers [...] to make them play the imitation game so well that an average interrogator will not have more than 70 per cent chance of making the right identification after five minutes of questioning.”^{43, p.442)}

Thus, Turing believed that at least 3 out of 10 judges would be tricked by the machine after five minutes of questioning. This paragraph is quite remarkable for at least two reasons. First, the stated success criterion is that the machine should fool at least 30% of the judges, not 70%, as it is often misunderstood. Second, and most importantly, note that Turing does not mention the word “test” but “imitation game.” The mentioned criteria – 30% success, average interrogator, five minutes of questioning – seem rather ad-hoc. Furthermore, there is no mentioning of sample size estimation or randomization. Given the words that Turing chose, it is questionable whether he had a formal test in mind.

2.2 The Turing Test (1952)

In a 1952 BBC interview, Turing, Braithwaite, and Jefferson discussed the question “Can Automatic Calculating Machines Be Said To Think.” Turing then described his “test” as follows:

Turing: “I don’t want to give a definition of thinking, but if I had to I should probably be unable to say anything more about it than that it was a sort of buzzing that went on inside my head. But I don’t really see that we need to agree on a definition at all. The important thing is to try to draw a line between the properties of a brain, or of a man, that we want to discuss, and those that we don’t. To take an extreme case, we are not interested in the fact that the brain has the consistency of cold porridge. We don’t want to say ‘This machine’s quite hard, so it isn’t a brain, and so it can’t think.’ I would like to suggest a particular kind of test that one might apply to a machine. You might call it a test to see whether the machine thinks, but it would be better to avoid begging the question, and say that the machines that pass are (let’s say) ‘Grade A’ machines. The idea of the test is that the machine has to try and pretend to be a man, by answering questions put to it, and it will only pass if the pretence is reasonably convincing. A considerable proportion of a jury, who should not be expert about machines, must be taken in by the pretence. They aren’t allowed to see the machine itself - that would make it too easy. So the machine is kept in a far away room and the jury are allowed to ask it questions, which are transmitted through to it: it sends back a typewritten answer.”

Braithwaite: “Would the questions have to be sums, or could I ask it what it had had for breakfast?”

Turing: “Oh yes, anything. And the questions don’t really have to be questions, any more than questions in a law court are really questions. You know the sort of thing. ‘I put it to you that you are only pretending to be a man’ would be quite in order. Likewise the machine would be permitted all sorts of tricks so as to appear more man-like, such as waiting a bit before giving the answer, or making spelling mistakes, but it can’t make smudges on the paper, any more than one can send smudges by telegraph. We [h]ad better suppose that each jury has to judge quite a number of times, and that sometimes they really are dealing with a man and not a machine. That will prevent them saying ‘It must be a machine’ every time without proper consideration. Well, that’s my test. Of course I am not saying at present either that machines really could pass the test, or that they couldn’t. My suggestion is just that this is the question we should discuss. It’s not the same as ‘Do machines think,’ but it seems near enough for our present purpose, and raises much the same difficulties.”^{46, p.3-6)}

It is surprising that this design deviates so much from the initially pro-

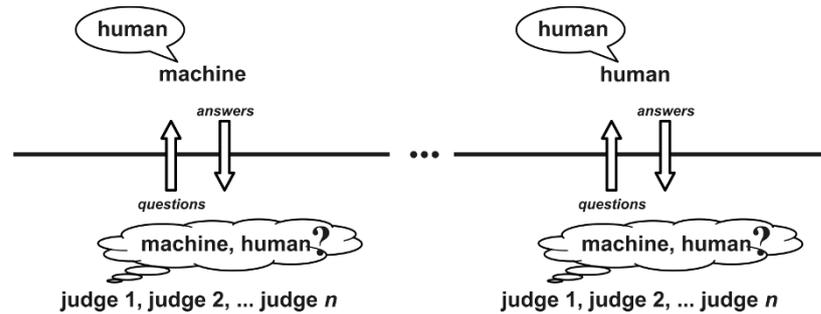


Fig. 3 The Turing test as described during the BBC interview 1952¹⁴⁾

posed one. In contrast to the original imitation game, the questions are now asked by a *jury* comprising several judges, and the game involves *either* a machine *or* a human being. This experiment is then to be repeated “quite a number of times,” as illustrated in Fig. 3. We speculate that Turing used the word “test” rather loosely and in the same meaning as “game.” Thus, our interpretation is different from that by Copeland and Proudfoot,¹⁵⁾ for example, who argue that Turing’s remarks in the BBC interview from 1952 indicate that he, in fact, intended to propose a test.

2.3 The Common Interpretation of the Turing Test

We reviewed the interpretations of some of the most influential writers on the Turing test. French, for example, noted:

“His test, today called the Turing test, was the first operational definition of machine intelligence.”^{19, p.164)}

In a similar vein, Hodges, perhaps Turing’s most well-known biographer, wrote:

“His 1950 paper [...], most famous for the wit of the Turing test of intelligence [...].”^{23, p.163)}

Hayes and Ford noted:

“[Turing] seems to have been suggesting the imitation game as a definite goal for a program of research.”^{21, p.972)}

Searle, inventor of the Chinese room argument, commented:

“[...] if our aim in Artificial Intelligence (AI) is to produce machines that can successfully simulate human intelligence then the Turing Test gives us a criterion for judging our own success and failure.”^{39, p.140)}

Block wrote:

“The computer is intelligent if and only if the judge cannot tell the difference between the computer and the person. Turing’s definition

finessed the difficult problem of specifying nonmentalistically the behavioral dispositions that are characteristic of intelligence by bringing in the discrimination behavior of a human judge. And the definition generalizes. Anything is intelligent if, and only if it can pass the Turing test.” ^{8, p.378)}

Shannon and McCarthy noted:

“One interesting definition has been proposed by A.M. Turing: a machine is termed capable of thinking if it can, under certain prescribed conditions, imitate a human being by answering questions sufficiently well to deceive a human questioner for a reasonable period of time.” ^{40, p.v-vi)}

These are just some of the remarks that are echoed in numerous essays on the Turing test. Still, they paint a rather precise picture of what the commonly held view is: the Turing test is widely regarded as “the” test of machine intelligence, offering an operational definition of “thinking” or “intelligence.”

§3 Revisiting “Computing Machinery and Intelligence”

We analyzed Turing’s paper⁴³⁾ and conclude that its common interpretation is questionable, or at least misses an important dimension.

Figure 4 (with key parts highlighted) provides a schematic overview of this analysis. Interestingly, we counted the word “intelligen*” (highlighted in blue; * means wildcard) only three times, once in the title, once on page 456 (“The experimenter, by the exercise of intelligence, should be able to speed

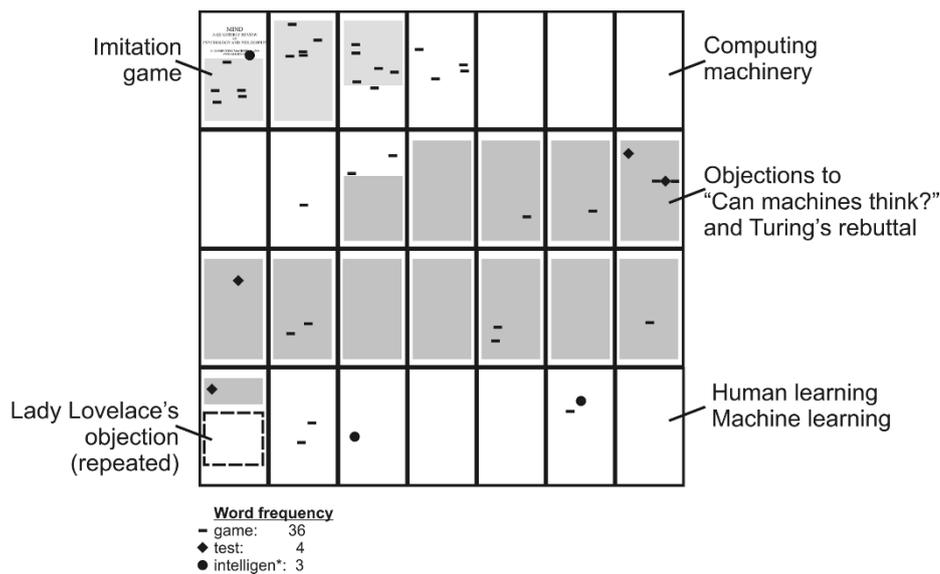


Fig. 4 The 28 pages of Turing’s “Computing Machinery and Intelligence,”⁴³⁾ with key parts highlighted and word frequency count.

it up.”), and once on page 459 (“Intelligent behaviour presumably consists in a departure from the completely disciplined behaviour involved in computation [...]”). Similarly, the word “test” occurs only four times on 28 pages, specifically:

“This argument appears to be a denial of the validity of our test. [...] Probably he would be quite willing to accept the imitation game as a test.” ^{43, p.446)}

The juxtaposition of “test” and “game” might suggest that Turing uses both terms interchangeably, but does it follow from that he had a formal test in mind? He uses the word “game” far more often: 36 times! This imbalance, combined with the fact that the test criteria seem rather ad-hoc, suggests that Turing used the term “test” colloquially rather than formally.

Turing’s paper contains 28 pages in total. When we look at the overall structure, we note that the first two and half pages are devoted to the imitation game. The next seven pages revolve around the computing machinery that Turing considers for the game and contains some technical remarks on the basic operation of such devices. Interestingly, the central part of the paper is entirely focused on nine objections to the question “Can machines think?” Turing discusses and tries to refute these objections by using logical and philosophical reasoning. Among these objections, Turing paid particular attention to Lady Lovelace’s objection, which states that

“The Analytical Engine has no pretensions to *originate* anything. It can do *whatever we know how to order it to perform.*” ^{43, p.450)} (italics by Lady Lovelace)

For Turing, this means that a machine “can never take us by surprise,” ^{43, p.450)} to which he objects – tongue in cheek, perhaps – that machines take him by surprise quite frequently. But Turing took Lovelace’s objection certainly as the most serious one. This might also explain why he came back to it at the beginning of the last section, which talks about how machine learning might be modeled on human learning. Further, Turing did neither propose a definition of “intelligence” nor did he propose a definition of “thinking.” Even the attempt at a definition of “intelligence” or “thinking” is nowhere to be found. Consequently, it is a problem to interpret the Turing test as an operational test of “intelligence” or “thinking.” This aspect has been pointed out before, for example, Whitby observed

“[...] the mistaken view that Turing’s paper contains an adequate operational definition of intelligence.” ^{47, p.53)}

Copeland,¹⁴⁾ too, criticized that Turing’s landmark paper is widely misinterpreted as proposing a test of machine intelligence. Copeland, however, maintains that “Turing did indeed intend his game to be a test,”^{14, p.524)} yet without saying a test for what.

In Turing ⁴³⁾, Turing himself tried to avoid the question what “thinking” actually is:

“The original question, ‘*Can machines think?*’ I believe to be too meaningless to deserve discussion.” ^{43, p.440}

Turing was similarly elusive in the 1952 BBC interview when he was reluctant to define “thinking,” saying that “thinking” is as “a sort of buzzing inside [his] head.” ^{46, p.3}) Later on, in the same interview, Turing remarked that

“From this point of view one might be tempted to define thinking as consisting of ‘those mental processes that we don’t understand.’ If this is right, then to make a thinking machine is to make one which does interesting things without our really understanding quite how it is done.” ^{46, p.19})

This paragraph is related to Lady Lovelace’s objections that machines can never originate something anew. Although Turing’s statement is again rather vague, it is clear that he refers here to creativity, i.e., the act of creating interesting output that we cannot explain. Artificial creativity must have been an important issue for Turing. We will therefore discuss this issue in greater depth in Section 4.2.

Our observations may be summarized by the simple conclusion that we need to dispel the myth that the Turing test is a formal test of machine intelligence. But is there then an alternative way to read Turing⁴³? Let us consider the following pivotal sentence:

“May not machines carry out something which ought to be described as thinking but which is very different from what a man does?” ^{43, p.435})

This is a truly remarkable quotation because Turing’s own words are in stark contrast with the widely held views described in the previous section. This rhetorical question marks a renunciation of the anthropocentric view of “thinking.” Taken a step further, could this question even be interpreted that a machine failing the imitation game may nonetheless be able to think, albeit differently from what a human does? In a similar vein, Cowen and Dawson concluded that

“Turing’s paper is about the possibility of unusual forms of intelligence, our inability to recognize those intelligences, and the limitations of indistinguishability as a standard for defining intelligence.” ^{16, p.2})

We believe that the Turing test provides a framework for a discussion of the fundamental concepts of thinking and intelligence. Specifically, which non-human processes could we describe as “thinking” or “being intelligent?” We believe that Turing wanted to encourage us to abandon our anthropocentric view and to adopt a broader view on these phenomena. It is precisely this hoped-for change in perspective that we see reflected in the following paragraph:

“Nevertheless I believe that at the end of the century the use of words and general educated opinion will have altered so much that one will

be able to speak of machines thinking without expecting to be contradicted.”^{43, p.440})

§4 Problems Resulting from Interpreting the Turing Test as a Test of Machine Intelligence

The question we now want to address is the following. Assuming that Turing did not intend to propose a formal test of machine intelligence, would it be a problem to use it as such, nonetheless? We believe that the answer to this question is “yes.” We will first briefly revisit some of the common objections to the Turing test, and then discuss some arguments that, to our knowledge, have received scant attention so far.

4.1 Common Objections

There certainly is no shortage of criticisms of the Turing test. First, if the test is understood as a test of intelligence, then it is circular: it defines the very notion (“intelligence”) that it claims to be a test for.²¹⁾

Second, the test focuses on only a tiny aspect of intelligence, namely human conversational skills and notably the skills at deceiving. It is obvious that many humans would fail the test, so what is the point of subjecting a machine to it?

Third, the Turing test is not diagnostic: the outcome of the test is a binary decision, “pass” or “fail,” without any indications on how to improve the machine or on what a partial success might look like.^{13,47)} This argument also contradicts Searle’s statement that “[...] the Turing Test gives us a criterion for judging our own success and failure.”^{39, p.140)}

Finally, a number of *gedankenexperiments* tried to attack the Turing test from various angles. The most prominent experiments include the Blockhead argument,⁷⁾ the Chinese Room argument,³⁸⁾ as well as associate priming and rating games.¹⁸⁾ These arguments, however, have been criticized (see ¹⁴⁾, for instance, for an excellent discussion).

4.2 Underrated Objections

[1] Computational creativity

Lady Lovelace’s objection that machines can never take us by surprise is, as we have mentioned above, quite an important argument for Turing. This aspect of surprise or, more generally, creativity, is what Abramson¹⁾ calls the *epistemic-limitation condition on intelligence*. If a machine performs in unpredictable (yet interesting) ways, then it fulfills the condition.

But what is this thing called “creativity,” anyway? There exists a panopticum of sometimes substantially diverse definitions of creativity (e.g., see ^{9,37)} or ²⁶⁾). For example, Kryssanov et al. consider creativity as a “cognitive process that generates solutions to a task, which are novel or unconventional and satisfy certain requirements.”^{26, p.332)} They note two essential cognitive mechanisms of creativity: (i) divergent thinking, which generates orig-

inal, new ideas, and (ii) convergent thinking, which logically evaluates a variety of possible solutions to find the optimal one. *Bisociation* is a term that Koestler coined to denote a creative process involving “the sudden interlocking of two previously unrelated skills, or matrices of thought.”^{25, p.121} Boden⁹) distinguishes between two main types of creativity: (i) improbabilist creativity (i.e., constructing new concepts by combining existing ones); and (ii) impossibilist creativity (i.e., mapping a concept into a new space; for example, Matzinger’s revolutionary insights into the controlling role of T-cells in immune system responses, which were allegedly triggered by her dog chasing sheep). Impossibilist creativity is a deeper type of creativity as it requires the mapping, exploration, and transformation of conceptual spaces.⁹ According to the theory by Mednick,²⁹) creativity can operate through three components: (i) serendipity (i.e., relationships are found by chance), (ii) similarity (i.e., remote associations, for instance through a metaphor model), or (iii) mediation (i.e., cognitive problem-solving).³⁷) According to Mednick, the more remote associated concepts are, the more creative is the resulting idea. However, the creative idea must not be only original but also practically useful.

Quite naturally, creativity and intelligence seem closely entwined. Abramson¹) claims that machines that do not meet the epistemic limitation condition, i.e., that are not creative, cannot be deemed intelligent, and vice versa, creativity is essential for intelligence. The Turing test, however, completely fails at taking creativity into account. Bringsjord et al.¹¹) therefore proposed the alternative Lovelace test, which rests upon a restrictive epistemic relation between an artificial agent A , its output o , and a human H . The agent A , designed by H , passes the Lovelace test if and only if:

1. A outputs o .
2. A ’s outputting o is not the result of a fluke hardware error, but rather the result of processes A can repeat.
3. H (or someone who knows what H knows, and has H ’s resources) cannot explain how A produced o .

This test also has some limitations, though. First, the quality of an idea should be somehow assessed. For instance, according to Mednick, a creative idea should be practically useful. In its normal usage, the word “creative” has a qualitative dimension, implying novelty, usefulness, ingenuity or perhaps even beauty. The Lovelace test, however, says nothing about the nature of the output o , apart from the fact that it cannot be explained by H . Second, let us assume that another human plays the role of the intelligent agent A . The test specifications actually do not allow this mind game, as A was said to be designed by H . Let us further assume that the output o is truly creative. Would A be able to repeat the processes that led to o ? At least if volition is to be involved, it is questionable whether A could repeat the processes. Thus, A would fail the test despite being creative. Finally, although intelligence and creativity are certainly connected, they are not the same thing.

[2] Underrated statistical issues

The first problem in this new context relates to a confounding element: the test fails to disentangle the observer (i.e., the judge) from the phenomenon (i.e., the machine trying to convince the judge that it is a human being). Let us assume that a machine passes the Turing test – does that mean that the machine is genuinely intelligent or does it mean that the judges were just gullible? The role of the judges is crucially important for the outcome of the test. Also, the judges know that they are judges. How much does this knowledge bias their questions and their decisions? Ideally, the judges should be unaware of their role – thus, the test should be blinded to alleviate the observer bias.

Hayes and Ford²¹⁾ mention another critical problem: the confirmation of the null hypothesis. Suppose that we derive a statistical test based on the Turing test. Let the outcome of this test be a p -value, i.e., the probability of obtaining experimental results as extreme as or more extreme than the actually observed ones, given that the null hypothesis, H_0 , is true. Here, the null hypothesis is that no difference exists between the conversational skills of man and machine. If we consider the p -value small enough, then we reject H_0 ; otherwise, we fail to reject it. However, if we fail to reject a null hypothesis, then it does not follow that we accept the hypothesis as being true. Confirming the null hypothesis is nearly impossible because, in the words of Hayes and Ford,

“It is impossible either to completely define the experimental conditions (how hard should one look for the thing that might not be there?) or to come to a firm conclusion (what if one had looked harder, or differently?).” ^{21, p.973)}

Another problem of course is that we need to work with samples from the target population. A p -value is always a statement about populations. But in our context, what are these populations? In fact, we have only one instance of a machine that we compare with one human being. Alternative test designs have been proposed (e.g.,⁴⁾), but these tests, too, have limitations. Thus, coercing the Turing test into a statistical test remains a challenging problem.

[3] Evolving connotations and moving goalposts

A further problem pertains to the definition of terms. Turing was quite clear that terms need to be defined and consequently began his paper as follows:

“I propose to consider the question, ‘Can machines think?’ This should begin with definitions of the meaning of the terms ‘machine’ and ‘think’.” ^{43, p.433)}

All too often, however, no definitions for key terms are given in papers about the Turing test, and the terms therefore often remain elusive. We could live with this state of affairs if these terms were then not used interchangeably, implying that they refer to the same thing. All too often, no distinction seems to be made between “thinking,” “ability to think,” “reasoning,” “reason;” “intelligence,” “consciousness,” “mindfulness,” and “having a mind;” “having a brain”

and “humanness,” as if all these words meant the same thing. In a similar vein, “being mindless” and “lacking intelligence” is sometimes understood to mean the same thing. The juxtaposition of words as in “[...] genuinely intelligent machines and mindless machines.”^{35, p.483}) is another confusing example – is “intelligent” really the opposite of “mindless?” And in what way is a “genuinely intelligent” machine different from a merely “intelligent” one?

We find it even expedient to consider the difference between the noun “intelligence” and the adjective “intelligent.” An agent may have “intelligence” (whatever that is) yet perform an act that is not “intelligent,” and vice versa. So what do we wish to measure – is it an intrinsic ability of the agent or is it something that is linked to an act?

Turing⁴³) believed that the use of words would change over time so that we might indeed speak of machines thinking, at the end of the century. However, the very notion of “intelligence” is also evolving. What we consider “intelligent” today we may not consider “intelligent” tomorrow. Would a machine that had passed the Turing test be labeled “intelligent once and for all,” as Harel argues?^{20, p.496}) That can be questioned. Today, there are countless examples ranging from automated speech recognition to chess computers at grandmaster level that would certainly have surprised Lady Lovelace, to say the least. Likewise, as early as in the 1960’s the famous ELIZA computer program, which was written by the late AI pioneer Joseph Weizenbaum, was able to produce occasional bursts of human-like interaction. So technically, we might argue that they have passed the Turing test. Still, in 2012, where computer systems such as IBM’s Watson, for instance, are supreme champions in popular quiz shows where contestants engage in an answer-and-question style competition, we would arguably not consider these earlier programs intelligent.^{*4} Hence, in our attempt to subject a machine to a test of intelligence, we are moving the goalpost because our own perception of “intelligence” changes over time. Thus, if we describe something as “intelligent,” we imply that it is intelligent only at a given moment in time. In 1946, Alan Turing noted on the game of chess:

“This... raises the question ‘Can a machine play chess?’ It could fairly easily be made to play a rather bad game. It would be bad because chess requires intelligence. We stated...that the machine should be treated as entirely without intelligence. There are indications however that it is possible to make the machine display intelligence at the risk of its making occasional serious mistakes. By following up this aspect the machine could probably be made to play very good chess.”^{22, p.17})

In 1997, Deep Blue, a computer specifically developed to play chess, won a game against the then reigning world chess champion Garry Kasparov who allegedly said that “he sometimes saw deep intelligence and creativity in the machine’s moves”:^{28, p.191})

^{*4} IBM Watson Research Center; <http://www.watson.ibm.com/index.shtml> (accessed 19 October 2012).

“[...] The decisive game of the match was Game 2 [...] we saw something that went beyond out wildest expectations [...] The machine refused to move to a position that had a decisive short-term advantage – showing a very human sense of danger.” ^{28, p.191)}

Would Turing (and most of his contemporaries) have considered Deep Blue intelligent? The answer is probably “yes,” and this shows the dilemma that we are facing: we are constantly moving the goalpost of what might constitute machine intelligence.

[4] Unconventional computing

For the imitation game, Turing only permitted digital computers, but his writing makes it clear that his idea of “machines” must have been much broader, and that he even did not make a clear demarcation between man and machine:

“It is natural that we should wish to permit every kind of engineering technique to be used in our machines [...] Finally, we wish to exclude from the machines men born in the usual manner.” ^{43, p.435)}

Let us now adopt a broader view on machines. One of the fundamental characteristics of complex and evolvable systems is robustness,^{6,36)} which is believed to be characterized by: *(i)* modularity – the system’s components “work together” synergistically; *(ii)* redundancy – some of the components share an identical function; *(iii)* feedback control – the system can detect and react to changes in the environment; *(iv)* spatial compartmentalization – the system has an embodiment with compartments that exchange information with each other; *(v)* distributed processing – collectively, the components give rise to a higher, system-level *gestalt* (e.g., a swarm); and furthermore, for biological systems, *(vi)* extended phenotype – a biosystem could affect its environment to increase its chances of survival. For example, termite mounds might be regarded as the extended phenotype of a termite’s genome. Similarly, albeit contentious, human societies and cultures might also be regarded as the extended phenotypes of the human genome.

Two aspects are particularly interesting here: spatial compartmentalization and distributed processing. An example of a complex system is a biological neural system that has learned an association between patterns and can therefore abstract to similar but new patterns. If we now consider a problem-solving process that involves a machine, then we could argue that that machine is an integral part of a complex system. Thus, if we consider such a process “intelligent,” could we then argue that the machine deserves at least some credit for the intelligent process?

Problem-solving is an important ability of biological systems and essential for survival. Natural problem-solving strategies have inspired the design of highly efficient machine learning algorithms, i.e., algorithms that improve their performance with experience. Many of these algorithms fall into the remit of optimization and were inspired by the intelligent problem-solving strategies ob-

served among insect societies such as, for example, ants and bees. The relatively young field of unconventional computing provides several examples of intelligent problem-solving. In unconventional computing, the computing machines, however, are not necessarily based on silicon only. *Physarum polycephalum* is a true slime mold that has demonstrated astonishing problem-solving capabilities such as maze solving,^{31,42)} remembering and anticipating periodic events,³⁴⁾ as well as primitive decision-making.²⁷⁾ This amoeboid organism is a large aggregate of protoplasm whose network of tubular veins enables it to explore its environment.^{2,32)} In its vegetative state, this organism slowly crawls along surfaces, mainly searching for food and avoiding sunlight. The two main stimuli (food and light) can be used to train the organism to solve computational tasks. Despite lacking a central nervous system, *P. polycephalum* can make decisions bearing resemblance to a primitive form of intelligent behavior.²⁷⁾ *P. polycephalum* might therefore be considered a programmable, massively parallel, and living computer. These physarum machines only follow physical and biological laws, though, and what we see as “intelligent behavior” is merely an expression of their responses to external stimuli.

Apart from applications in robotics and the unconventional computing paradigm, physarum machines have received only scant attention in other computer science-related domains. One reason for the still limited interest is certainly that, as a living computer, it is extremely slow, compared with conventional computers. However, computational time is not always a critical factor (e.g., in tasks such as optimal route planning, time sometimes plays a secondary role). Physarum machines are therefore an interesting novel approach to tackle computational tasks that require slow but “intelligent” decision-making. Indeed, physarum machines were recently used to solve the multi-armed bandit problem,²⁴⁾ which is a classical machine learning task.

Another example for unconventional computing are naturally occurring, self-organizing collectives of simple organisms, such as bacteria, which often exhibit amazing problem-solving capabilities despite their lack of a nervous system.⁶⁾ A key element of a bacterial system is *quorum sensing*, the regulation of gene expression in response to fluctuations in cell-population density.³⁰⁾ Bacteria can use quorum sensing as a means of *communication* with each other, for example, to orchestrate attacks by synchronously releasing toxins. Natural quorum sensing was relatively recently discovered, and artificial quorum sensing is a very young field of research in artificial life.³⁾

What is important here is the fact that seemingly primitive organisms (such as real bacteria or digital creatures) are capable of evolving intricate means of communication that allow them to act in unison and give rise to a higher, system-level phenotype that bears resemblance to primitive forms of intelligence. The previous examples also indicate that “intelligent communication” does not necessarily need to be defined from a strictly anthropocentric point of view, as in the imitation game. When Turing wrote that

“There would be no question of the machines dying, and they would be able to converse with each other to sharpen their wits,”^{44, p.475)}

he was referring to digital machines, not living computers. Today, however, it has become possible to program living organisms with specific functions.⁵⁾ For example, Tamsir et al.⁴¹⁾ implemented all possible two-input gates including the XOR and equal function in a colony of *Escherichia coli* bacteria. Indeed, such machines can die and converse with each other.

§5 Intelligence Amplification

For his imitation game, Turing allowed only digital computers, not engineered carbon-based artifacts. If we consider conventional computers only, can they amplify human intelligence, help us refine or even discover new theories about the natural world, hence “make us think?” In order to shed light on this question, we propose the *dungeon dilemma*, which is mathematically identical to the *Monty Hall problem*, a variant of the *three prisoners problem*. However, the *dungeon dilemma* frames the problem in a different context involving a computer as a critical component.

Here is how it goes. Imagine that Bob is the prisoner in a dungeon. There are three locked doors. The jailor has the keys to these doors and begins to talk to Bob as follows.

Jailor: “Only one of these doors leads to freedom. I know which one. If you can find that door, then you may leave the dungeon; otherwise, you will stay. Which door do you choose?” As Bob has no further information, he thinks that his choice really does not matter – any door can be the good one.

Bob: “I’ll take the door in the middle, then.” With a big smile, the jailor does not open the middle door but the left door.

Jailor: “Good that you haven’t chosen the left door. See? There is a brick wall behind it! So are you sure that you want me to unlock the middle door? Or perhaps would you like to switch to the right door? Remember, only one door leads to freedom; the other one has a brick door behind it, like the door that I have just opened.” Bob hesitates a moment.

Bob (thinking): “Why should I change my mind now? After all, there are two doors left. So my chances are now 50:50, aren’t they? But why does he make this proposal, actually? Perhaps I am right with my choice, and he just wants to trick me? Or maybe I am wrong, and he wants to give me another chance? Or perhaps he would have opened one of the two doors with a brick wall behind, anyway, regardless of whether I was right or wrong with my first hit. I really can’t tell.” Bob’s head starts spinning. But his thoughts about the jailor’s psychology do not get him anywhere. Then Bob has the following idea.

Bob (thinking): “I wonder how many prisoners in the same situation could get out by sticking to their initial choice, and how many prisoners could get out by changing their mind. If the numbers are about the same, then it really does not matter whether I stick to the middle door or switch to the right door. But if the numbers are different, then I know what to do!” Luckily, Bob had his laptop with him. Hastily, he hacks in a few lines of code in R³³⁾ that simulate his situation. Bob assumes that the jailor would open one of the doors with a brick wall behind, regardless of Bob’s initial choice. To his great surprise, Bob obtains the following result: of 100 prisoners in the same situation, 32 would

stay in prison by sticking to their initial choice, whereas 68 would go free by changing their mind. This means that his chances of leaving the dungeon are about twice as high if he changes his mind, that is, if he chooses the right door! Not without hesitation, Bob decides to tell the jailor that he decided to switch to the right door.

Bob: “*I’ll take the right door.*”

Jailor: “*Congratulations! You are free to go!*”

Then the jailor unlocks the right door, and Bob happily leaves the dungeon.

Bob’s hastily hacked R code

```
n <- 100; k <- NULL; s <- NULL
for (i in 1:n){
  x <- sample(c(1,0,0)); y <- sample(c(1,2,3))[1]
  keep <- x[y]; p <- which(x==0); o <- setdiff(p,y)
  if(keep==1){o <- sample(o)[1]}; swap <- x[c(-y,-o)]
  k <- c(k,keep); s <- c(s,swap) }
stay <- sum(k)/n*100; free <- sum(s)/n*100
```

Once escaped from the dungeon, Bob started to study his program. He observed that the estimates for `stay` and `free` become more stable with increasing values of n ; and for very large values, he observed that `stay` $\approx \frac{1}{3}$ and `free` $\approx \frac{2}{3}$.

Bob eventually also found an analytical solution to the problem. Before the jailor had opened the left door, his chances^{*5} of being right were $\frac{1}{3}$. Let $P(\text{door})$ denote the chance that a door leads to freedom. Then $P(\text{middle door}) = \frac{1}{3}$. One of the doors must lead to freedom, so $P(\text{left door}) + P(\text{middle door}) + P(\text{right door}) = 1$. This means that $P(\text{left door}) + P(\text{right door}) = 1 - P(\text{middle door}) = 1 - \frac{1}{3} = \frac{2}{3}$. So, the chance that either the left or the right door leads to freedom is $\frac{2}{3}$. This is what he could have inferred *before* the jailor opened the left door. *After* the jailor had opened the left door, he knows that a brick wall is behind it; thus, $P(\text{left door}) = 0$. It therefore follows that $P(\text{right door}) = \frac{2}{3} - 0 = \frac{2}{3}$. Hence, the chances of leaving the dungeon are *exactly* twice as high if he decides to switch to the right door.

The dungeon dilemma is a variation of the Monty Hall problem, which gained popularity through a game in the TV show “Let’s make a deal.” In the TV show, the quiz master, Monty Hall, offered the candidates to choose among three doors. Behind only one of the doors, there is a prize. After the candidate had announced his choice, Monty Hall opened a non-winning door and offered the candidate to switch. This game sparked heated debates, even among statisticians. Most people found the correct solution counter-intuitive and wrongly believed that the chances are 50:50 after the non-winning door had been opened.

^{*5} We intentionally choose the term “chance” in lieu of “probability” to avoid disgressing on frequentist and Bayesian interpretations of “probability” in this context.

The dungeon dilemma frames the decision-making problem in a deliberately extreme (and actually trivially simple) scenario. But in doing so, it also nicely illustrates a synergistic problem-solving process by a man and a machine. Neither entity alone could have solved the problem alone. Bob knew how to specify and code the problem, while the machine “knew” how to execute it. Neither Bob nor the machine could have known or even guessed the experimental results (i.e., the numeric values of **stay** and **free**).

How would Turing have interpreted these results? We can of course only speculate. But we remember that Turing devoted a lot of attention to Lady Lovelace’s objections that machines can never surprise us or never originate anything. In a 1951 BBC broadcast, Turing remarked the following:

“If we give the machine a programme which results in its doing something interesting which we had not anticipated, I should be inclined to say that the machine had originated something, rather than to claim that its behaviour was implicit in the programme, and therefore that the originality lies entirely with us. I will not attempt to say much about how this process of ‘programming a machine to think’ is to be done.” ^{45, p.6)} (original underlining)

The human brain is certainly incapable of running a Monte Carlo simulation similar to Bob’s computer. In fact, why should it? There was never any Darwinian pressure selecting for that particular trait. But if there ever had been, then we would consequently observe it, and we would not exclude that trait from “thinking.” In “Intelligent machinery, a heretical theory,” Turing wrote:

“‘You cannot make a machine to think for you.’ This is a commonplace that is usually accepted without question. It will be the purpose of this paper to question it.” ^{44, p.256)}

In a sense, we might argue that a machine *did* the thinking for Bob.

§6 Discussion

So, “can machines think?” Let us consider the following questions first:

1. “Is walking with an artificial leg ‘walking’?”
2. “Can humans fly?”

Regarding the first question, some people might point out that under some circumstances, “hobbling” might describe the movement more precisely. Generally, however, most would certainly agree that moving with an artificial leg (or legs) is still a form of walking. In this context, we have no problem to use the same verb to denote the same action, regardless of whether the action is actually performed by an artificial device or a natural limb. In fact, it is doubtful that anyone would question whether penguins or humanoid robots can walk. “Walking” is acceptable to describe the observed action.

What about the second question? “Flying” is of course not an intrinsic ability of human beings, so if we understand the question as referring to an

intrinsic property, then the answer must be “no.” However, we now commonly say that humans can fly, understanding that a machine (aircraft, glider, etc.) is being used (but imagine that this question had been asked in medieval times). The Wikipedia entry for the list of Apollo astronauts, for example, includes the following sentence: “While three astronauts flew to the Moon twice, none of them landed on the Moon more than once.” Although the action of “flying” is not directly performed by a human being, there is no semantic problem with the use of the verb. The context disambiguates the meaning. Analogously, we can find examples of verbs that generally are only used to describe human (and not animal) behavior, such as “love.”

We believe that Turing’s original question won’t be settled any time soon. The question cannot be disentangled from the semantics of language and how we use it. Turing was right that meanings and usages of words change over time, but his prediction that “at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted”^{43, p.440}) was arguably not. We speculate that the general opinion is still uneasy with denoting the processing in computational machines as “thinking” because thinking is something that only humans do. This reflects Chomsky’s remark that “[...] people think, not their brains [...]”^{12, p.106}) But the use of verbs like “walk” and “fly” has evolved, so perhaps the use of “think” might evolve, too?

§7 Conclusions

The Turing test has nearly vanished from research agendas today, and some consider the Turing test even harmful for AI.²¹) Here, we argued that this pessimistic view is warranted only if we interpret it as a test of machine intelligence. This interpretation, however, misses an important dimension of Turing’s landmark paper. We offered an alternative reading, and in the light of Turing’s other musings, it is questionable whether he intended to propose a formal test or definition of machine intelligence. In fact, we believe that Turing intended to encourage us to look at alternative forms of intelligence or thinking that are different from what humans do. From that perspective, Turing’s landmark paper remains relevant as an inspirational source, serving well as a framework for the discussion of key issues in philosophy and AI today.

Specifically, the imitation game is relevant when we study it with an emphasis on the human psychology: how easily can we be fooled by sophisticated computer programs on the Internet and tricked into disclosing sensitive data? How could we design programs able to detect those other programs that are trying to fool us into believing that they are humans?

This paper took a step ahead of the question “Can machines think?” by suggesting a creativity-encouraging feed-back mechanism between human intelligence and the increasing smartness and problem-solving skill demonstrated by many computer-based applications and systems in a variety of conventional as well as unconventional computing environments. The observation that “AI is the business of using computation to make machines act more intelligently, or

to somehow amplify human intelligence,” as noted by Hayes and Ford,^{21, p.977} summarizes this point rather well. And perhaps, Bob in the dungeon dilemma, where a simple computer program could indeed somehow amplify his intelligence, couldn’t agree more.

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