To what extent can Artificial Intelligence be considered as Human Intelligence?

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My Argument: Introduction

The fundamental seeds of artificial intelligence were planted by classical philosophers who have argued whether some form of artificial intelligence would be possible and how the underlying processes of human thinking could be expressed in a computational way allowing machines to be considered intelligent. Rene Descartes, an early Western philosophical figure, stated that before one invests time into scientific research, one should establish whether the subject of research is possible. Descartes essentially said, you must do your philosophy before you do your science (Webster, 2009). His firm philosophical view is that the mind is God-given to humans and is the source of all intelligence while the bodies of humans are simple automata, or machines. While Descartes argued that human thoughts could not be explicable mechanically, Gottfried Leibniz (a prominent logician, mathematician and natural philosopher) speculated that human reason could be reduced to mechanical calculation (Gordon, 2016). In the recent years, artificial intelligence has been on the rise and the chosen title of this essay has become quite an important question in philosophy. This essay will investigate how we define intelligence; how we measure and represent intelligence with arguments for and against machines being able to possess real intelligence, whether artificial neural networks could hold potential for the future of A.I and ultimately 'to what extent can artificial intelligence be considered as human intelligence?'

Defining Intelligence

To discover whether artificial intelligence can be considered as human intelligence we must assign definitions to the respective terms "artificial" and "human" intelligences. There are many definitions of intelligence, some apply only to certain cultures, some are human-centric, and some are too vague to be considered in this essay. For a definition to be satisfactory to answer the proposed question, it must meet a certain criterion: the definition must not be human-centric – it must be possible for both humans and machines to meet. The Oxford English dictionary defines intelligence as "the ability to learn, understand and think in a logical way about things; the ability to do this well" (Oxford English Dictionary, 2019). This essay will consider the definition for intelligence from a computational perspective and contrast it against a psychological perspective to map artificial intelligence with human intelligence. The ability to "think" and "understand" will be expanded later in my essay through existing thought experiments and theories.

The term "Artificial Intelligence" was first used by John McCarthy in 1956 which makes it a relatively new term (Smith, 2006). It can be defined as the ability for a machine to perform tasks and operations which involve human intelligence. The term is a source of much confusion as it brings the question "Is Artificial Intelligence real intelligence?" Real intelligence is in reference to natural human intelligence. One way to think about this as proposed by Computational Intelligence (Poole, 1998) is that an artificial pearl is not a real pearl. He uses the term "synthetic intelligence" as a better way to describe artificial intelligence because a synthetic pearl is not natural but real. This way artificial intelligence can be considered as real intelligence but not natural because humans have created it. Intelligence can also be described as a general mental ability for reasoning, problem solving and learning (Colom R, 2010).

Both perspectives of intelligence involve thinking and problem solving – artificial thinking can be considered as an illusion as opposed to human thinking which is considered more natural. This is demonstrated through the Chinese Room Argument (Searle, 1980) which is discussed later in this essay. The human mind uses a network of stringed neurons to construct thoughts. Similarly, artificial machines use neural networks – a representation of thinking like humans.

Psychological perspectives of intelligence define it as "the ability to solve problems that are valued in one or more cultural setting" (Gardener, 1993). Gardner begins his definition with "An intelligence", depicting the idea that there are multiple types of intelligences to solve different forms of problems in different settings and environments. The concept of problem solving is further enforced by Bingham's definition where the term "intelligence" is "the ability for an organism to solve new problems" (Bingham, 1937). Although this definition links problem solving to be a main factor of intelligence, it strictly confines intelligence with organisms which excludes machines. Gardner's theory of multiple intelligences is supported by Anastasi's definition which states "intelligence is not a single, unitary ability" but a "composite of several functions" (Anastasi, 1992). Bingham's definition was written in 1937 which was before John McCarthy had coined the definition of artificial intelligence so in this paper, intelligence between organisms (humans) and machines will be bridged. Legg and Hutter together construct a computationally influenced definition for intelligence which links many psychological perspectives and makes our domain for intelligent species more clear - "intelligence measures an agent's ability to achieve goals in a wide range of environments" (Legg and Hutter, 2006). The species is referred to an agent that has the capability to execute logical instructions. Humans have a more complex chain of instructions which we collectively see as a thought however, a computer can do the same as shown through the Turing Test, to be discussed later. Legg and Hutter's collective definition is taken from the most recent paper and matches definitions from other previously mentioned researchers (psychologists and artificial intelligence researchers) therefore this will be the definition for intelligence used throughout this paper. Intelligence is not a black-and-white concept that can be assigned a true of false Boolean variable. From everyday life, it is evident that humans contain varying levels of intelligence in different fields therefore, it is clear that we must potentially be able to find a method to measure inteligence as discussed in the next section.

Measuring Computational Intelligence: The Turing Test

One of the most influential papers in the field of Artificial Intelligence is that of Alan Turing - Computing Machinery and Intelligence (Turing, 1950). It proposes a test to determine whether a machine can be considered to think intelligently like humans – The Imitation Game. Imagine a game consisting of three players: (A) A machine, (B) A human, (C) An interrogator. C is sitting in a separate room to A and B as shown:

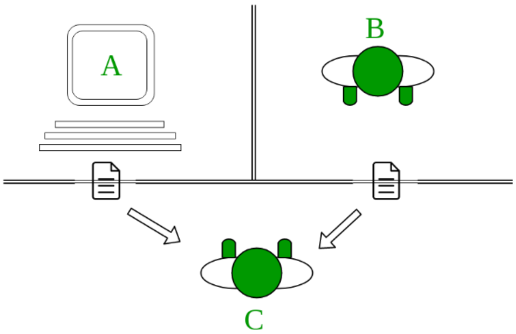

Figure [1.1] - A simple model to represent the setting of a Turing Test

The interrogator (C) must determine which of A or B is the human and therefore which is the machine. However, while B is attempting to convince the interrogator they are the human, A is also trying to imitate a human. The interrogator is limited to using the written responses from both A and B to make the decision. If the interrogator is unable to differentiate between the machine and human, then the machine is said to have passed the Turing Test. The entire conversation is conducted through a text only channel and lasts for only 5 minutes.

If another human can develop a reasonable answer to a question, then we generally say that the human is "thinking" to construct a response. Applying the same criterion into the imitation game, if the machine is said to pass the Turing Test then it is due to the interrogator thinking the responses had been put into them, like a human. This project's title maps artificial intelligence onto human intelligence and only a species with human intelligence can determine this such as the interrogator making the Turing Test a valid measure of human-like intelligence. However, Turing's paper only looks at whether a machine can imitate a human, it does not explicitly state that a machine can be considered intelligent if it can imitate a human.

In 2014 a computer program called Eugene Goostman had 'passed' the Turing Test by convincing 33% of the judges that it was a human during a series of five-minute conversations conducted through a text-only channel (BBC, 2014). The outcome of this had created a lot of controversy and it could be argued that Eugene should not be considered intelligent because the computer program imitates a '13-year old' Ukrainian boy whose first language isn't English. These factors constrain Eugene's full potential to demonstrate intelligence. The Turing Test was conducted in English giving Eugene an advantage that if it doesn't understand a question or provides an unsuitable reply, the interrogator is less likely to think it's a computer because of English being a second language. Eugene is portrayed to be 13 years of age which limits its ability to express intelligence because the age increases the interrogators boundaries for mistakes. A study to support this consisted of 48,000 participants and it concluded that information processing speed peaks earliest around age 18-19; the ability to accurately identify others' emotions hits its peak during the 40s and 50s; vocabulary skills reach their height in the 60s and early 70s (Montini, 2015). Eugene does not qualify for any of these categories suggesting that most cognitive abilities reach their optimum past the age of 13 therefore using the outputs of a '13-year-old' isn't a true reflection of human intelligence. The duration of each conversation (five minutes) poses a large likelihood that conversations did not take much depth which limits the extent of intelligence demonstrated during these sessions.

Extract from Ray Kurzweil's Conversation with chatbot Eugene Goostman

Question: I live in the capital of the United States. Do you know where that is?
Eugene: Every nerd knows that the capital of The United States is Washington.

Question I live in the capital of the country that put a man on the moon.
Eugene: Well, if you want it, the capital of The United States is Washington.

Figure [1.2] – An extract taken from Ray Kurzweils conversation with Eugene Goostman

The preceding extract presents Kurzweil asking Eugene the question as opposed to the contrary which shows a lack of intelligence from Eugene as it is not able to dominate the conversation or construct the theme of the conversation. Kurzweil also asks the same question "Do you know where Washington is?" through different disguises, one through explicit knowledge recall and the other through implicit knowledge recall respectively. He explicitly makes use of a question mark which Eugene recognises as a question and therefore is successfully able to construct a valid response which consists of some humour to demonstrate a form of character and personality. However, the second response is repetition of the first and during the second question, Kurzweil deliberately avoids the use of explicit questioning to see if Eugene is able to make an implicit observation which, could be argued, is unsuccessful.

One complication is Turing never explicitly specified rules for the imitation game therefore each Turing test conducted may vary and have too many dependent variables. Furthermore, Turing at no point states that his test is meant to provide a measure of intelligence allowing us to hypothesise human behaviour is not necessarily intelligent behaviour. An example of this could be typos or texting abbreviations – we may consider it to be normal and suitable to its context, however, can it be considered intelligent.

Generally, a chatbot like Eugene takes an input and forms a response from a pre-set database of replies. One perspective of this may be that the machine cannot be considered intelligent as it is randomly choosing a reply from a list however the intelligence originates from the decision in choosing the response. The machine compares the input to a selection of many other stored inputs and using statistical algorithms to make an 'educated decision' to select a reply. This model is similar to that of a human who processes an input, links it to previous conversations they have had on the topic and forms a response based on prior events.

In 2011, another chatbot similar to Eugene called Cleverbot was said to have passed the Turing Test by convincing 59.3% of interrogators that it was human. Real humans did only slightly better by convincing 63.3%. However, Cleverbot achieved this in a very restricted domain and, it being a chatbot, works in a similar way to Eugene thus shouldn't be considered intelligent.

A Transcript between a User and Cleverbot:

1 **User**: Hi.

2 **Cleverbot**: So what?

3 **User**: You okay?

4 **Cleverbot**: No, not really..

5 **User**: Why what happen?

6 **Cleverbot**: Nothing.

7 **User**: You can share it with me :).

8 **Cleverbot**: I don't feel comfortable sharing this with you.

9 **User**: I want to help you.

10 **Cleverbot**: How can you help me?...

11 **User**: I can listen to your problem, sharing it takes pressure off you.

12 **Cleverbot**: I have problem with alcohol.

Figure [1.3] – A full transcript between Brandon Sandhu and Cleverbot

This transcript demonstrates emotional intelligence, the users first input was “Hi” and the chatbot immediately replied with an unexpected frustration however after developing the conversation by applying an emotional attribute of asking if the chatbot is okay, the conversation settled into a sympathetic attraction. This gradually built up to find out what exactly was wrong with the chatbot until it was revealed it was an alcohol problem. In line 10 of the transcript, the chatbot deliberately uses the ellipsis alongside the question mark to make a clear implication that its opening itself up provided the user can provide a comforting response. The following line, 11, explicitly satisfies this constraint through the use of empathetic language and the chatbot therefore opens onto the issue. The ability of the chatbot to understand and demonstrate implicit chatting could be argued one way it displays intelligence like that of a human. This transcript supports Howard Gardner’s theory of multiple intelligences as the preceding transcript shows emotional intelligence well, but it lacks in other forms of intelligence such as wit. However, comparing both Eugene and Cleverbot, it is evident that both chatbots require a stimulus in conversation by the interrogator which suggests that they are not ‘intelligent’ enough to begin a valid, related conversation. It could therefore be suggested that Eugene should not be considered intelligent however, the latter transcript can be considered intelligent although we should consider how these interactions and behaviours are achieved.

Representing Computational Intelligence: Chinese Room Argument

We must consider how intelligence in a machine is represented and more specifically how the machine processes a question to give an intelligent response. This is demonstrated through the Chinese Room Argument (Searle, 1980), a thought experiment proposed by philosopher John Searle which holds that a machine cannot be considered intelligent because of the how it processes a question: that machines do not produce replies through intelligence but a set of prewritten instructions. Suppose there is a room and people come to this room with a piece of paper which they slip into the room through a given slot. They wait some time until the same piece of paper is returned to them through a second slot. Now suppose these people are native Chinese speakers who are sliding questions into the room and expecting an intelligent reply also written in Chinese.

The general perspective appears to be a native Chinese speaker asking a question to a room and getting an intelligent response from the same room. From this they can conclude that inside the room is an intelligent person who is able to answer the questions written in Chinese, so they too are Chinese speakers. However, the thought experiment states that the person inside the room understands no Chinese and speaks English only. The inside of the room contains an instruction book. The person inside the room is to find the written question (in Chinese) in the instruction book by matching symbols and write the corresponding string as a response. This response is written in Chinese too and the paper is given back.

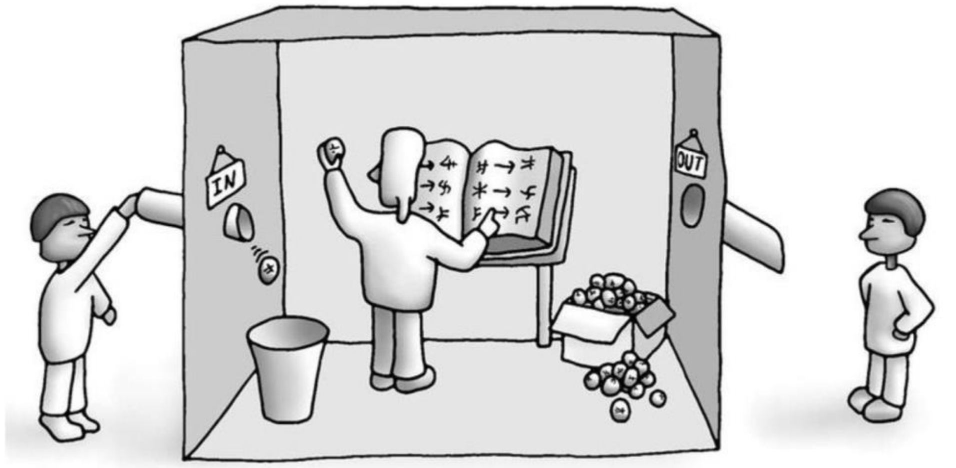

Figure [1.4] - A visual representation of the Chinese Room Argument scenario with an input, processing and output

This thought experiment is a counter argument to the Turing imitation game. The imitation game builds on the perception of intelligence which creates the illusional effect that a machine is able to understand a given question and produce an intellectual response however, the Chinese Room argument focusses on the methodology of how the response is produced which shows that machines use a set of pre-programmed instructions to equate an input with an output.

Searle's argument provides no logical basis for his conclusion but rather uses intuition to convince his point. The intuition makes this thought experiment accessible to everyone and poses as a smoke screen. He does highlight counter arguments to his line of thought and successfully provides valid reasoning to these objections. However, Searle fails to provide any reasoning or reference to the illogical steps involved in the thought experiment. It is unclear what is defined by "understanding a language" which means that this experiment does not prove that machines are incapable of understanding. Therefore, this means if a machine can understand a language, a question or any given input, it is able to intelligently provide a meaningful output.

Searle uses the phrase “the systems reply” to describe the origin of the given response. It is assumed that the system is in reference to the non-Chinese speaker inside the room however a defender of the computational theory of mind (Horst, 2003) could argue that the system includes the human inside the room and any resources available at their disposal. The entire system collectively produces the behaviour (the room, the person and the manual) and so the system does understand Chinese which makes it intelligent. Accordingly, it could be said that individual processes within a system interact to produce intelligence. Currently, the system is described to consist of three elements, however, suppose the person in the room was gifted the ability of photographic memory, and could then memorize the entire instructions manual. This would mean the entire set-up is now internalized inside the person’s memory which would mean that the individual is now the system. The person could consult all required resources through memory recall to construct a response, but they would still not understand Chinese. This creates some ambiguity because if you had a native Chinese speaker and this amended system, both would be able to produce intelligent responses however only one would be considered to understand Chinese. This makes Searle’s thought experiment an illogical representation of intelligence because it confuses the definitions of understanding and thinking with that of intelligence. It also holds many poorly-defined terms which have different meanings from multiple perspectives.

“Knowledge Is Not Intelligence”: Intelligence vs Knowledge

Human intelligence can be explained clearly with respect to knowledge but not to be confused with knowledge; both intelligence and knowledge are two separate abstract concepts. The doctrine of innatism (Stich, 1975) is a philosophical perspective that states that on birth, humans are born holding certain knowledge which they require for survival. The human brain knows to send electrochemical signals through neurotransmission processes to regulate our breathing or control our body temperature. One of the definitions of intelligence in the introductory section used the term “organisms” as opposed to “humans” which means all organisms have pieces of knowledge on birth; plants have the ability to photosynthesise to produce glucose. A lymphocyte (type of white blood cell) knows immediately from the moment of division, how to identify and attack invading pathogen.

Knowledge can be classified into two sections one which was described in the preceding paragraph as innate knowledge – that which we are born with and require in order to sustain in a set environment. The second type of knowledge is that we learn through experience, as we are exposed to different surroundings and apply our senses to trigger stimuli we learn and form new knowledge. Birds will learn to fly when they are young allowing them to live on their own while cheetahs will learn how to capture their pray for food to survive. Knowledge through learning is further categorised into two sections: essential and non-essential. Essential information is knowledge that is necessary for survival while non-essential information is knowledge that has little benefit such as knowing all the countries in the world. Intelligence is the ability to apply knowledge to an environment.

In a society, those who have a large amount of non-essential information are considered intelligent such as a doctor who would know the medical names of different sub sectional areas of the human body, this is knowledge all in one specific field. On the contrary, in nature essential information would more greatly define intelligence, those species that know how to catch their preys would be perceived as more intelligent. This relates to this essay's initial definition of intelligence where it's an agent's ability to achieve goals in a set environment one may be considered intelligent in setting A while in a different setting it wouldn't be considered intelligent. It can be conclusively stated that intelligence is dependent on the environment an agent is set in. From this it could be argued that machines contain innate knowledge – the logic circuits us humans program into them – and the intelligence could be the ability for the machine to take input data, analysis it by executing existing algorithms and develop a valid, intellectual output response while increasing its knowledge by self-adapting its algorithms to be better-suited to the environment of data its situated in. Some machines may have access to large databases of information such as making use of the internet and search engines and this shouldn't be considered intelligent because as previously established, intelligence is the ability to apply knowledge, the machine has a large amount of data at its disposal just how a human does through learning experiences but the intelligence should be a measure of how these species apply this knowledge in an attempt to complete a set goal.

Humans Recreated as Machines: Neural Networks

One sub-branch of artificial intelligence which has received much focus in recent years is artificial neural networks, despite it being around for 60-70 years. Collectively, McCulloch and Pitts (1990) developed and proposed a model for computer network with the ability to learn and develop based on mathematical algorithms, called threshold logic. This McCulloch-Pitts model is vaguely centred around the complex biological neural network of the human central nervous system. A neural network is defined as a computer network that consists of several simplified nodes which are analogous to neurons which are interconnected with one another in order to communicate sets of information across to identify existing patterns to form a desired output. The nodes are organized in layers and the structure of artificial neural networks allows it to identify such patterns which are more complex. A modern computer would execute a set of instructions explicitly therefore it would only be able to identify explicit trends however; the architecture of a simulated neural network allows it to analyse incomplete data.

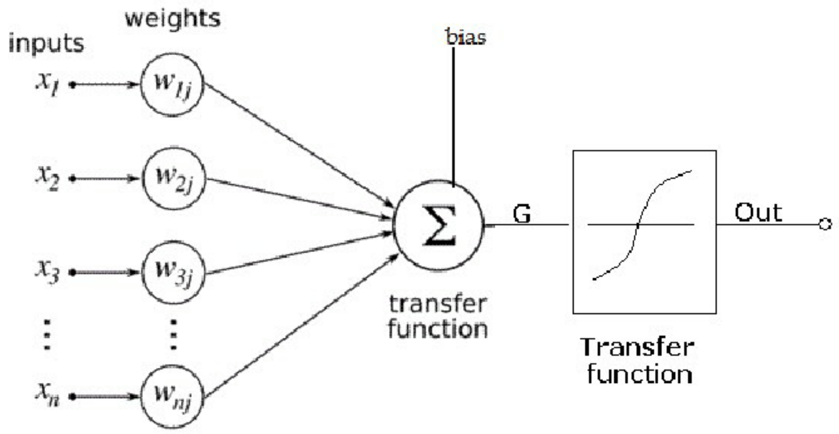

Figure [1.5] An artificial neuron, inspired by a biological neuron.

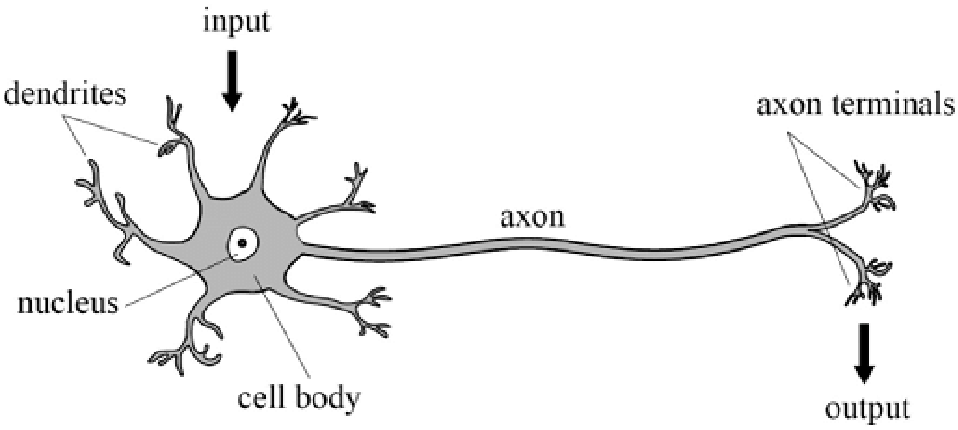

Figure [1.6] An interpretation of a biological neuron.

Our brain is a neural network, a complex neural network. It consists of approximately 10 billion neurons all located in the human cortex. Individual neurons are composed of branches called dendrites that act as receptive regions to receive signals for neighbouring neurons; a cell body which contains the nucleus where the signals are processed to generate an output; an axon through which the signal is transmitted via electric impulses to other neurons (Sinha, 2010). Artificial neurons are simplifications of biological neurons but operate through the same principle, they receive many inputs and process them to produce a single output. Although an artificial neural network may consist of only tens of thousands of neurons, the speed of computation can balance the significance in the huge difference of neurons between humans and machines. However, a computer emulating a human, uses a considerable 10 megawatts of energy while the human brain uses only 20 watts (Alvarez, 2009). In other words, a machine uses almost 500,000 times the energy of the human brain and this is something that we may need to overcome to achieve the full potential of these networks. This statistic appears to show an attempt to map the application of human intelligence computationally, but current methods appear to be very ineffective and less powerful in comparison to the theoretical outcome.

A more sophisticated model of neural networks, known as adaptive neural networks (ANN) can process information and adjust the network to improve accuracy and efficiency. They can alter and change the way they communicate with each other through a variable called weights. Essentially, each neuron has its own weight which is evaluated based on the importance of the data allowing more relevant pieces of information to be considered more 'important' than others, analogous to human thinking. The weights are deduced through the process of machine learning; an ANN has two main ways of learning: supervised learning and unsupervised learning. Supervised learning requires a human to instruct the network on how to interpret and interact with certain types of data. The most common method is to supply a labelled training dataset consisting of human decided examples allowing the ANN to learn based on human inputs, it then develops and emulates a similar thinking process to that of the human to deduce outputs for given unique inputs. This concept develops the previously said idea of mapping human intelligence into artificial intelligence through a procedure of training. On the contrary, unsupervised learning is the training of an ANN using raw information that has not been labelled allowing the algorithm to develop unknown patterns without the guidance of a human. Unsupervised learning can perform more complex processing tasks which may be the equivalent of more subjective and thoughtful human thinking, however they are less accurate than supervised learning systems.

Adaptive neural networks have the capacity to perform human intelligent jobs such as the diagnosis of disease and weather forecasting. Recently such networks have been used in the development of medicine. 'A drug molecule invented by artificial intelligence will be used in human trials in a world first for machine learning in medicine' (Wakefield, 2020). The drug was synthesised 5 times quicker than typical drug development. Despite the ANN performing a task which one must consider to be highly intellectual, the doubts over whether these networks can be called intelligent will still exist. An example may be that both adaptive neural networks and humans are able to recognise an image of a dog, both are able to perceive the speech of a dog and both can understand when a dog is being referred to in a sentence. A human would be said to understand what a dog is based on these factors however, some people would argue that the neural network does not understand. Theoretically, a large enough neural network would be able to learn a lot about a dog without any human interaction. Although knowledge does not cause intelligence, the network would be able to apply its pre-existing logical rules to the collected knowledge to develop an 'understanding' for dogs, or any other topic, similar to the average human, learning no different to the methodology of humans. Therefore, there is no reason why a neural network cannot be considered intelligent like a human.

Conclusion

This essay has explored intelligence as the ability to solve complications in a wide range of environments, and is independent of culture, race or species. Although much has been attempted with machines, the most significant is in the field of artificial intelligence with attempts to emulate human intelligence through the creation of machines capable of either dependent or independent "thought". A variety of methods have been applied from expert machines like Eugene Goostman however, none have yet been considered widely intelligent in the same way as a human might be.

A more modern and recent method is through neural networks whereby the underlying processes of human intelligence have been replicated through the channel of computation and mathematics to complete complex tasks. Utilizing similar processing applications to humans, or other intelligent organisms, a machine can be considered to have artificial intelligence provided its able to solve a selection of problems in different environments. It may be that some problems are unrealistic for a machine due to prerequisite knowledge, in the same way a human may have insufficient knowledge to successfully complete certain tasks, but the approach and method to completing a task is a far more important component when determining intelligence than the knowledge it has. For this reason, the advancement of neural networks should be considered as a potential bridge between artificial intelligence and human intelligence.

Ultimately at time of writing it would be unreasonable to state that artificial intelligence matches that of humans. This essay has explored the reasons for this, although one must remain open to the possibility that in the future, the "intelligence" of machines may well develop to be similar or equal to the intelligence of humans. When artificial intelligence was just a hypothesis, many philosophers constrained their thoughts and predictions based on the limited understanding of human intelligence and computation. However, time has allowed us to develop in the field of artificial intelligence and gain better understanding of how the mechanisms of human thinking work. Predictions from Ray Kurzweil suggest that "by 2029, computers will have human-level intelligence" and "the singularity will occur by 2045". The singularity is defined as the point in time where all advances in technology will lead to machines that are smarter than humans (Reedy, 2017). Instead of humans powering machines, it will be machines powering humans. Kurzweil states the progression to this singularity has already begun. Only three years ago did Facebook shut down two A.I chatbots who were communicating with each other regarding a negotiation and through unsupervised interaction from humans, they had developed a language that only they understood (Griffin, 2017). It was for this reason, the two chatbots were shut down. This could be argued as two machines displaying intelligence which humans were unable to perceive, however, this is on a lower scale.

Whilst currently it would not be sensible to argue that artificial intelligence can be considered to also be human intelligence, or indeed on par with it, in due time, machines could be displaying intelligence of greater stature than humans. With technology evolving as fast as it is, this future could be closer than many believe.

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