

Turing++ Questions: A Test for the Science of (Human) Intelligence

Tomaso Poggio, Ethan Meyers

■ *There is a widespread interest among scientists in understanding a specific and well defined form of intelligence, that is human intelligence. For this reason we propose a stronger version of the original Turing test. In particular, we describe here an open-ended set of Turing++ questions that we are developing at the Center for Brains, Minds, and Machines at MIT — that is questions about an image. For the Center for Brains, Minds, and Machines the main research goal is the science of intelligence rather than the engineering of intelligence — the hardware and software of the brain rather than just absolute performance in face identification. Our Turing++ questions reflect fully these research priorities.*

It is becoming increasingly clear that there is an infinite number of definitions of intelligence. Machines that are intelligent in different narrow ways have been built since the 50s. We are entering now a golden age for the engineering of intelligence and the development of many different kinds of intelligent machines. At the same time there is a widespread interest among scientists in understanding a specific and well defined form of intelligence, that is human intelligence. For this reason we propose a stronger version of the original Turing test. In particular, we describe here an open-ended set of Turing++ questions that we are developing at the Center for Brains, Minds, and Machines (CBMM) at MIT — that is, questions about an image. Questions may range from what is there to who is there, what is this person doing, what is this girl thinking about this boy, and so on. The plural in questions is to emphasize that there are many different intelligent abilities in humans that have to be characterized, and possibly replicated in a machine, from basic visual recognition of objects, to the identification of faces, to gauge emotions, to social intelligence, to language, and much more. Recent advances in cognitive neuroscience have shown that even in the more limited domain of visual intelligence, answering these questions requires different competences and abilities, often rather independent from each other, often corresponding to separate modules in the brain. The term Turing++ is to emphasize that our goal is understanding human intelligence at all Marr's levels — from the level of the computations to the level of the underlying circuits. Answers to the Turing++ questions should thus be given in terms of models that match human behavior and human physiology — the mind and the brain. These requirements are thus well beyond the original Turing test. A whole scientific field that we call the science of (human) intelligence is

required to make progress in answering our Turing++ questions. It is connected to neuroscience and to the engineering of intelligence but also separate from both of them.

Definitions of Intelligence

We may call a *person* intelligent and even agree among us. But what about a colony of ants and their complex behavior? Is this intelligence? Were the mechanical computers built by Turing to decode the encrypted messages of the German U-boats, actually intelligent? Is Siri intelligent? The truth is that the question of *What is intelligence* is kind of ill-posed as there are many different answers, an infinite numbers of different kinds of intelligence. This is fine for engineers who may be happy to build many different types of intelligent machines. The scientists among us may instead prefer to focus on a question that is well defined and can be posed in a scientific way, on the question of human intelligence. In the rest of the paper we use the term *intelligence* to mean human intelligence.

Understanding Human Intelligence

Consider the problem of visual intelligence. Understanding such a complex system requires understanding it at different levels (in the Marr sense; see Poggio [1981, 2012]), from the computations to the underlying circuits. Thus we need to develop algorithms that provide answers of the type humans do. But we really need to achieve more than just simulate the brain's output, more than what Turing asked. We need to understand what understanding an image by a human brain means. We need to understand the algorithms used by the brain, but we also need to understand the circuits that run these algorithms. This may also be useful if we want to be sure that our model is not just faking the output of a human brain by using a giant lookup table of what people usually do in similar situations, as hinted at the end of the movie *Ex Machina*. Understanding a computer means understanding the level of the software and the level of the hardware. Scientific understanding of human intelligence requires something similar — understanding of the mind as well as of the brain.

Using Behavior and Physiology as a Guide

To constrain our search for intelligent algorithms, we are focusing on creating computational models that match human behavior and neural physiology. There are several reasons why we are taking this approach. The first reason, as hinted above, is to avoid superficial solutions that mimic intelligent behavior under very limited circumstances, but that do not capture the true

essence of the problem. Such superficial solutions have been a prominent approach to the traditional Turing test going back to the ELIZA program written in the 1960's (Weizenbaum 1966). While these approaches might occasionally fool humans, they do not address many of the fundamental issues and thus this approach will fail to match many aspects of human behavior. A second related reason is that algorithms might appear to perform well when tested under limited circumstances, but when compared to the full range of human abilities they might not do nearly as well. For example, deep neural networks work very well on object-recognition tasks, but also fail in simple ways that would never be seen in human behavior (Szegedy et al. 2006). By directly comparing computer systems' results to human behavioral results we should be able to assess whether a system that is displaying intelligent behavior is truly robust (Sinha et al. 2006). A final reason is that studying primate physiology can give us guidance about how to approach the problem. For example, to recognize people based on their faces appears to occur in discrete face patches in the primate brain (see Freiwald and Tsao [2010], and the section below). By understanding the computational roles of these patches we aim to understand the algorithms that are used by primates to solve these tasks (Meyers et al. 2015).

Intelligence Is One Word but Many Problems

Recent advances in cognitive neuroscience have shown that different competencies and abilities are needed to solve visual tasks, and that they seem to correspond to separate modules in the brain. For instance, the apparently similar questions of object and face recognition (what is there versus who is there) involve rather distinct parts of the visual cortex (for example, the lateral occipital cortex versus a section of the fusiform gyrus). The word *intelligence* can be misleading in this context, like the word *life* was during the first half of the last century when popular scientific journals routinely wrote about the problem of life, as if there was a single substratum of life waiting to be discovered to unveil the mystery completely. Of course, speaking today about the problem of life sounds amusing: biology is a science dealing with many different great problems, not just one. Thus we think that *intelligence* is one word but many problems, not one but many Nobel prizes. This is related to Marvin Minsky's view of the problem of thinking, well captured by the slogan Society of Minds. In the same way, a real Turing test is a broad set of questions probing the main aspects of human thinking. Because "intelligence" encompasses a large set of topics, we have chosen visual intelligence in human and nonhuman primates as a primary focus. Our approach at the Center for Brains, Minds, and Machines to visual intelligence includes connections



Figure 1. Street Fair.

Courtesy of Boris Katz, CBMM, from the LableMe database.

to some developmental, spatial, linguistic, and social questions. To further sharpen our focus, we are emphasizing measuring our progress using questions, described in more detail below, that might be viewed as extensions of the Turing test. We have dubbed these Turing++ questions. Computational models we develop will be capable of responding to queries about visual scenes and movies — who, what, why, where, how, with what motives, with what purpose, and with what expectations. Unlike a conventional engineering enterprise that tests only absolute (computational) performance, we will require that our models exhibit consistency with human performance/behavior, with human and primate physiology, and with human development. The term Turing++ refers to these additional levels of understanding that our models and explanations must satisfy.

The Turing++ Questions

Our choice of questions follows in part from our understanding of human intelligence grounded in the neuroscience of the brain. Each question roughly corresponds to a distinct neural module in the brain. We have begun defining an initial set of such problems/questions about visual intelligence, since vision is our entry point into the problem of intelli-

gence. We call such questions Turing++ questions because they are inspired by the classical Turing test but go well beyond it. Traditional Turing tests permit counterfeiting and require matching only a narrowly defined level of human performance. Successfully answering Turing++ questions will require us not only to build systems that emulate human performance, but also to ensure that such systems are consistent with our data on human behavior, brains, neural systems, and development. An open-ended set of Turing++ questions can be effectively used to measure progress in studying the brain-based intelligence needed to understand images and video.

As an example consider the image shown in figure 1. A deep-learning network might locate faces and people. One could not interrogate such a network, however, with a list of Turing++ questions such as What is there? Who is there? What are they doing? How, in detail, are they performing actions? Are they friends or enemies or strangers? Why are they there? What will they do next? Have you seen anything like this before?

We effortlessly recognize objects, agents, and events in this scene. We, but not a computer program, could recognize that this is a street market; several people are shopping; three people are conversing around a stroller; a woman is shopping for a shirt;

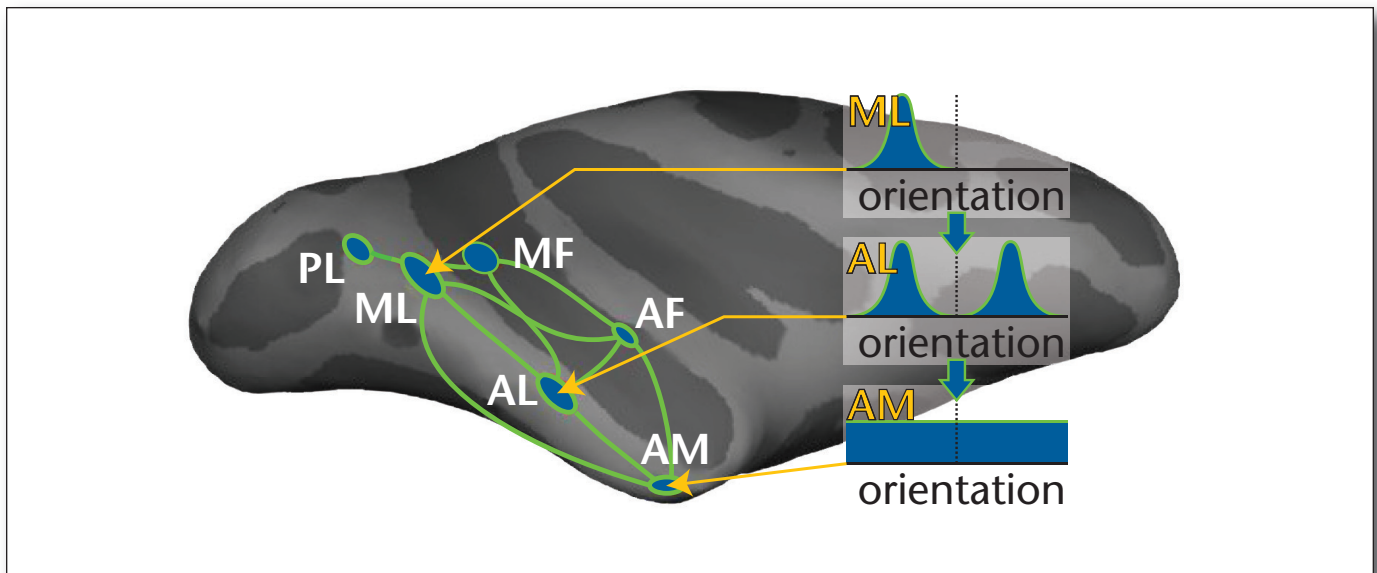


Figure 2. Macaque Visual Cortex Patches Involved in Face Perception.

Courtesy of Winrich Freiwald, CBMM. Modified from Tsao, D. Y.; Moeller, S.; Freiwald, W. A. Comparing Face Patch Systems in Macaques and Humans. In *Proceedings of the National Academy of Sciences of the United States of America*. 2008;105(49): 19514–9.

although the market takes place on a street, clearly no cars are permitted to drive down it; we can distinguish between the pants that are for sale and the pants that people are wearing. We, but not a computer program, could generate a narrative about the scene. It's a fairly warm, sunny day at a weekend market. The people surrounding the stroller are a mother and her parents. They are deciding where they would like to eat lunch.

We would assess the performance of a model built to answer questions like these by evaluating (1) how similarly to humans our neural models of the brain answer the questions, and (2) how well their implied physiology correlates with human and primate data obtained by using the same stimuli.

Our Turing++ questions require more than a good imitation of human behavior; our computer models should also be humanlike at the level of the implied physiology and development. Thus the CBMM test of models uses Turing-like questions to check for humanlike performance/behavior, humanlike physiology, and humanlike development.

Because we aim to understand the brain and the mind and to replicate human intelligence, the challenge intrinsic to the testing is not to achieve best absolute performance, but performance that correlates strongly with human intelligence measured in terms of behavior and physiology. We will compare models and theories with fMRI and MEG recordings, and will use data from the latter to inform our models. Physiological recordings in human patients and monkeys will allow us to probe neural circuitry during some of the tests at the level of individual neurons. We will carry out some of the tests in

babies to study the development of intelligence.

The series of tests is open ended. The initial ones, such as face identification, are tasks that computers are beginning to do and where we can begin to develop models and theories of how the brain performs the task. The later ones, such as generating stories explaining what may have been going on in the videos and answering questions about previous answers, are goals for the next few years of the center and beyond.

The modeling and algorithm development will be guided by scientific concerns, incorporating constraints and findings from our work in cognitive development, human cognitive neuroscience, and systems neuroscience. These efforts likely would not produce the most effective AI programs today (measuring success against objectively correct performance); the core assumption behind this challenge is that by developing such programs and letting them learn and interact, we will get systems that are ultimately intelligent at the human level.

An Example of a Turing++ Question: Who Is There (Face Identification)

The Turing++ question that is most ripe, in the sense of possibility to answer it at all the required levels, is face identification. We have data about human performance in face identification — from a field that is called psychophysics of face recognition. We know which patches of visual cortex in humans are involved in face perception by using fMRI techniques.

We can identify the homologue areas in the visual

cortex of the macaque where there is a similar network of interconnected patches shown in figure 3. In the monkey it is possible to record from individual neurons in the various patches and characterize their properties. Neurons in patch ML are view- and identity-tuned, neurons in AM are identity-specific but more view-invariant. Neurons in the intermediate patch AL tend to be mirror-symmetric: if they are tuned to a view they are also likely to be tuned to the symmetric one.

We begin to have models that perform face identification well and are consistent with the architecture and the properties of face patches (that is, we can make a correspondence between stages in the algorithm and properties of different face patches). The challenge is to have performance that correlates highly with human performance on the same data sets of face images and that predict the behavior of neurons in the face patches for the same stimuli.

In September of 2015, CBMM organized the first Turing++ questions workshop, focused on face identification. The title of the workshop is A Turing++ Question: Who Is There? The workshop introduced databases and reviewed the states of existing models to answer the question who is there at the levels of performance and neural circuits.

The Science of Intelligence

For the Center for Brains, Minds, and Machines the main research goal is the science of intelligence rather than the engineering of intelligence — the hardware and software of the brain rather than just absolute performance in face identification. Our Turing++ questions reflect fully these research priorities.

The emphasis on answers at the different levels of behaviour and neural circuits reflects the levels-of-understanding paradigm (Marr 2010). The argument is that a complex system — like a computer and like the brain/mind — must be understood at several different levels, such as hardware and algorithms/computations. Though Marr emphasizes that explanations at different levels are largely

independent of each other, it has been argued (Poggio 2012) that it is now important to reemphasize the connections between levels, which was described in the original paper about levels of understanding (Marr and Poggio 1977). In that paper we argued that one ought to study the brain at different levels of organization, from the behavior of a whole organism to the signal flow, that is, the algorithms, to circuits and single cells. In particular, we expressed our belief that (1) insights gained on higher levels help to ask the right questions and to do experiments in the right way on lower levels and (2) it is necessary to study nervous systems at all levels simultaneously. Otherwise there are not enough constraints for a unique solution to the problem of human intelligence.

References

- Freiwald, W. A., and Tsao, D. Y. 2010. Functional Compartmentalization and Viewpoint Generalization Within the Macaque Face-Processing System. *Science* 330: 845–851. [dx.doi.org/10.1126/science.1194908](https://doi.org/10.1126/science.1194908)
- Marr, D. 2010. *Vision*. Cambridge, MA: The MIT Press. [dx.doi.org/10.7551/mitpress/9780262514620.001.0001](https://doi.org/10.7551/mitpress/9780262514620.001.0001)
- Marr, D., and Poggio, T. 1977. From Understanding Computation to Understanding Neural Circuitry. In *Neuronal Mechanisms in Visual Perception*, ed. E. Poppel, R. Held, and J. E. Dowling. *Neurosciences Research Program Bulletin* 15: 470–488.
- Meyers, E.; Borzello, M.; Freiwald, W.; Tsao, D. 2015. Intelligent Information Loss: The Coding of Facial Identity, Head Pose, and Non-Face Information in the Macaque Face Patch System. *Journal of Neuroscience* 35(18): 7069–81. [dx.doi.org/10.1523/JNEUROSCI.3086-14.2015](https://doi.org/10.1523/JNEUROSCI.3086-14.2015)
- Poggio, T. 1981. Marr's Computational Approach to Vision. *Trends in Neurosciences* 10(6): 258–262. [dx.doi.org/10.1016/0166-2236\(81\)90081-3](https://doi.org/10.1016/0166-2236(81)90081-3)
- Poggio, T. 2012. The Levels of Understanding Framework, Revised. *Perception* 41(9): 1017–1023. [dx.doi.org/10.1068/p7299](https://doi.org/10.1068/p7299)
- Reichardt, W., and Poggio, T. 1976. Visual Control of Orientation Behavior in the Fly: A Quantitative Analysis. *Quarterly Review of Biophysics* 9(3): 311–375. [dx.doi.org/10.1017/S0033583500002523](https://doi.org/10.1017/S0033583500002523)
- Sinha, P.; Balas, B.; Ostrovsky, Y.; and Russell, R. 2006. Face Recognition by Humans: 19 Results All Computer Vision Researchers Should Know About. *Proceedings of the IEEE* 94(11): 1948–1962. [dx.doi.org/10.1109/JPROC.2006.884093](https://doi.org/10.1109/JPROC.2006.884093)
- Szegedy, C.; Zaremba, W.; Sutskever, I.; Bruna, J.; Erhan, D.; Goodfellow, I. J.; and Fergus, R. 2013. Intriguing Properties of Neural Networks. CoRR (Computing Research Repository), abs/1312.6199. Association for Computing Machinery.
- Weizenbaum, J. 1966. ELIZA—A Computer Program for the Study of Natural Language Communication Between Man and Machine. *Communications of the ACM* 9(1): 36–45. [dx.doi.org/10.1145/365153.365168](https://doi.org/10.1145/365153.365168)

Tomaso A. Poggio is the Eugene McDermott Professor in the Department of Brain and Cognitive Sciences at the Massachusetts Institute of Technology, and the director of the new National Science Foundation Center for Brains, Minds, and Machines at the Massachusetts Institute of Technology, of which MIT and Harvard are the main member Institutions. He is a member of both the Computer Science and Artificial Intelligence Laboratory and of the McGovern Brain Institute. He is an honorary member of the Neuroscience Research Program, a member of the American Academy of Arts and Sciences, a Founding Fellow of AAAI, and a founding member of the McGovern Institute for Brain Research. Among other honors he received the Laurea Honoris Causa from the University of Pavia for the Volta Bicentennial, the 2003 Gabor Award, the Okawa Prize 2009, the AAAS Fellowship, and the 2014 Swartz Prize for Theoretical and Computational Neuroscience. His research has always been interdisciplinary, between brains and computers. It is now focused on the mathematics of learning theory, the applications of learning techniques to computer vision, and especially on computational neuroscience of the visual cortex.

Ethan Meyers is an assistant professor of statistics at Hampshire College. He received his BA from Oberlin College in computer science, and his Ph.D. in computational neuroscience from MIT. His research examines how information is coded in neural activity, with a particular emphasis on understanding the processing that occurs in high-level visual and cognitive brain regions. To address these questions, he develops computational tools that can analyze high-dimensional neural recordings.