1. Introduction

Computers programmed using machine learning (ML) are increasingly capable of solving complex problems in artificial intelligence (AI). Unfortunately, many of these computers are opaque: it is difficult to metaphorically “look inside” so as to understand why these systems do what they do, or how they work.

The opacity of ML-programmed computers gives rise to the black box problem in AI—a problem with significant practical, legal, and theoretical consequences. Practically, end-users are less likely to trust and cede control to machines whose workings they do not understand (Burrell, 2016; Ribeiro, Singh, & Guestrin, 2016), and software engineers are often unable to intervene on such machines so as to quickly and systematically improve their performance (Hohman, Kahng, Pienta, & Chau, 2018). Legally, opacity prevents regulatory bodies from determining whether a particular system processes data fairly and securely (Rieder & Simon, 2017), and hinders end-users from exercising their rights under the European Union’s General Data Protection Regulation (European Commission, 2016). Theoretically, the black box problem makes it difficult to evaluate the potential similarity between artificial neural networks and biological brains (Buckner, 2018), as well as to evaluate the extent to which the computers being developed in AI might actually be considered intelligent (Zednik, 2018).

In order to ward off these consequences, investigators working within the nascent explainable AI (XAI) research program have begun to develop analytic techniques that can be used to render opaque computing systems transparent. Although this research program has commanded significant attention within the AI research community (recent reviews include: Doran, Schulz, & Besold, 2017; Lipton, 2016; Ras, van Gerven, & Haselager, 2018), and within society in a wider sense (see, e.g., Burrell, 2016; Goodman & Flaxman, 2016; Zerilli, Knott, Maclaurin, & Gavaghan, 2018), important methodological questions remain unanswered. Most fundamentally, it remains unclear how explainable AI should actually explain: what is required to render an opaque computing system transparent? Moreover, it remains unclear how explanation in this context relates to other epistemic achievements such as description, prediction.

1 There are two distinct “streams” within the explainable AI research program. The present discussion focuses on efforts to solve the black box problem by analyzing computing systems so as to render them transparent post hoc, i.e., after these systems have been developed and possibly deployed. In contrast, the discussion will not consider efforts to avoid the black box problem altogether, by modifying the relevant ML methods so that the computers being programmed do not become opaque in the first place (for discussion see, e.g., Doran, Schulz, & Besold, 2017).
intervention, and interpretation. Finally, it remains unclear what the prospects are of actually explaining the behavior of ML-programmed computers as they become increasingly powerful, sophisticated, and widespread.

The present discussion answers these methodological questions by articulating a general-purpose recipe for explainable AI—a step-by-step procedure for rendering computing systems transparent. Although the recipe is most clearly illustrated by recent efforts to visualize the activity of deep neural networks in the domain of machine vision, it applies broadly, to systems irrespective of implementation or problem domain. Notably, inspiration will be sought in cognitive science. Indeed, insofar as the problem of explaining the behavior of humans and other biological cognizers, the explainable AI research program can profit from co-opting some of the norms and practices of cognitive science.

The discussion proceeds as follows. Section 2 builds on previous philosophical work by Paul Humphreys (2009) to analyze the oft-used but nevertheless ill-understood notions of ‘opacity’ and ‘transparency’. Section 3 then invokes Tomsett et al.’s (2018) notion of an ‘ML ecosystem’ to distinguish between the different kinds of agents that require explain a computing system’s behavior. It also invokes David Marr’s (1982) levels of analysis framework to better understand these agents’ distinct explanatory requirements. Indeed, different agents within the ML ecosystem can be aligned with different questions in Marr’s explanatory framework—questions about what, why, how, and where a computer program is carried out. Sections 4 and 5 then introduce and evaluate the explanatory contributions of several promising analytic techniques from explainable AI: layer-wise relevance propagation (Montavon, Samek, & Müller, 2018), local interpretable model-agnostic explanation (Ribeiro et al., 2016), feature-detector identification (Bau et al., 2018), and diagnostic classification (Hupkes, Veldhoen, & Zuidema, 2018). Indeed, these sections will show that different XAI techniques answer distinct questions within Marr’s explanatory framework, and thus, satisfy the explanatory demands of different agents within the ML ecosystem. Overall, therefore, the present discussion provides a better understanding of the black box problem, and evaluates the extent to which recent techniques in explainable AI can already be considered to provide a solution.

2. The Black Box Problem in Artificial Intelligence

2.1 From machine learning to the black box problem

The black box problem is commonly said to arise when the computers being developed in AI are opaque. This manner of speaking is grounded in the intuition that a system’s behavior can be explained by “looking inside” so as to understand why it does what it does or how it works. Although many computing systems in AI are constructed from well-understood hardware components that afford no literal obstacle to “looking inside”, they might nevertheless be considered opaque in the metaphorical sense that it is difficult to know exactly how they are programmed.
ML methods are uniquely predisposed for delivering computing systems that are opaque in this metaphorical sense. In order to understand the reasons for this predisposition, it is important to recognize that machine learning is just one approach among many for programming computers to solve complex problems in AI. In order to program a computer to play chess, for example, traditional approaches will typically rely on a software engineer’s ability to formally encode expert knowledge about a particular problem domain (e.g., by representing a grandmaster’s knowledge of chess openings as a series of production rules), and on a computer’s ability to quickly and reliably deploy that knowledge in the service of finding a solution (e.g., by efficiently executing the rules to determine the likelihood that a particular move eventually leads to checkmate).

The ML approach is strikingly different. Rather than rely on a software engineer’s ability to formally encode human knowledge, the ML approach invokes a computer’s number-crunching abilities to discover and encode the relevant knowledge on its own. To this end, software engineers design a learning algorithm and deploy it in a suitable learning environment. In the broad family of supervised learning methods, for example, a learning environment that consists of a historical database of expert-level chess games might be processed by a learning algorithm capable of associating individual moves (“Bishop to B4”, given a particular board position) with eventual outcomes (wins or losses). In another broad family of methods called reinforcement learning, the same kinds of associations might be identified by a learning algorithm that uses extensive trial-and-error within an environment that consists of a series of (real or simulated) games against a human or computer opponent.

The difference between traditional AI and machine learning manifests itself in the number and kinds of programs that that are likely to be developed. Traditional approaches are constrained by human limitations with respect to the knowledge possessed about the problem domain, as well as by a software engineer’s ability to encode that knowledge given limited resources and expertise. As a result, the programs that are actually developed within these approaches are relatively few in number and likely to be low in diversity. In contrast, ML approaches are far less constrained by human limitations. Although humans are of course involved in designing the learning algorithm and in selecting the learning environment, most ML methods are able to identify subtle and unintuitive solutions that would not typically be considered within a more traditional approach. For this reason, whereas computers programmed using traditional AI methods may masterfully and powerfully deploy current chess theory, computers programmed using machine learning may be capable of extending that theory in unexpected ways (see, e.g., Silver et al., 2017).

Given their ability to transcend human limitations in this way, ML methods have become remarkably successful in a wide variety of domains.2 Unfortunately, this success comes at a cost. Unlike the computers being programmed using traditional AI methods, the computers being

---

2 These domains especially include game-playing, autonomous driving and flying, question-answering, natural language processing, machine vision, behavior-prediction, and product-recommendation. That said, the successes within these domains should not, of course, be taken to imply that machine learning methods are all-conquering. Indeed, many AI problems remain unsolved, and in many cases, it is unclear whether, and if so how, ML methods could be used to solve them. Indeed, in many problem domains, traditional AI methods remain far more effective than the methods developed in machine learning (for discussion see, e.g., Lake, Ullman, Tenenbaum, & Gershman, 2017; Marcus, 2018).
programmed using machine learning are characteristically opaque.

The reasons for this characteristic opacity are twofold. First, the computers being programmed using machine learning are *high-dimensional* and *complex*. In particular, *deep neural networks* consist of thousands or even millions of “neural” units and “synaptic” connections, each of which is governed by parameters such as unit biases and connection weights (see, e.g., Schmidhuber, 2014). Learning algorithms (often, but not always, a kind of supervised learning called *backpropagation*) are tasked with setting these parameters from a typically continuous range of values. Notably, the values to which these parameters are set is not determined by the learning algorithm alone, but by the learning algorithm’s interaction with the learning environment. This environment may itself consist of innumerable data points (e.g., within a large database of chess moves and eventual outcomes), every one of which can influence one or all of the system’s parameters. Finally, once the system’s parameters have been set, they typically participate in a cascade of nonlinear interactions that determines the precise way in which novel inputs to the system are transformed into outputs.

The second, and arguably more fundamental, reason for these systems’ characteristic opacity is the limited influence software engineers have on the setting of individual parameter values. Once again, software engineers are of course responsible for designing and selecting the learning algorithm and learning environment that jointly determine the system’s parameters. Nevertheless, they are mostly ignorant of the precise way in which these parameters are eventually set: which parameters are set, when they are set, to which values they are set, and why. Importantly, this ignorance is a feature rather than a bug: it promotes the development of systems that are relatively unconstrained by human preconceptions about what it actually takes to solve a particular AI problem. Put differently, it is *because* software engineers have such a limited influence on the setting of parameter values that the computers being programmed using machine learning are likely to behave in such surprisingly effective ways.

2.2. *What is the black box problem?*

That the computers being programmed using machine learning are characteristically opaque has become a much-discussed fact both within the AI research community and within society in a broader sense. Perhaps surprisingly, however, the notion of ‘opacity’ itself remains relatively ill-understood. On the one hand, many discussions of the black box problem never go beyond the metaphorical idea of “looking inside” so as to understand why a computing system does what it does or how it works. On the other hand, even those discussions that do go beyond the metaphor typically center on software engineers’ aforementioned lack of influence on, and thus, lack of knowledge of, the system’s parameter values. That said, it is important to recognize that knowledge of parameter values is neither necessary nor (in most cases) sufficient for rendering a computing system transparent in an appropriate sense.

Consider again deep neural networks. Given their high dimensional complexity, even complete knowledge of individual connection weights and unit activations does not typically allow
Moreover, deep neural networks are often found to learn high-level representations that capture abstract properties of the learning environment (see, e.g., Bau et al., 2018; Buckner, 2018). In such cases, knowledge of the relevant representations is often more useful than knowledge of individual parameter values for the purposes of explaining the system’s behavior. That said, it remains unclear how to systematically distinguish between these different kinds of knowledge, and thus, what makes one kind of knowledge more useful than another for the purposes of rendering a computing system transparent. What is required, in other words, is a better understanding of the dual notions of ‘opacity’ and ‘transparency’, and thus, a better understanding of the black box problem itself.

Investigating the use of computer simulations in scientific disciplines such as high-energy physics and molecular biology, Paul Humphreys (2009) has provided an analysis of ‘opacity’ that makes a useful starting point for discussions of the black box problem in AI. On Humphreys’ analysis, computing systems are

“opaque relative to a cognitive agent X at time t just in case X does not know at t all of the epistemically relevant elements of the [system]” (Humphreys, 2009, p. 618).

Two features of this analysis are worth emphasizing. First, opacity is agent-relative. That is, a computing system is never opaque in and of itself, but opaque only with respect to some particular agent. Second, opacity is an epistemic property: it concerns the agent’s (lack of) knowledge. According to Humphreys, this knowledge concerns the system’s epistemically relevant elements (EREs). Although Humphreys does not further analyze this notion, it can be fleshed out in a way that is appropriate for current purposes. Thus, an element can be understood as, for example, a step in the process of transforming inputs to outputs, or as a momentary state-transition within the system’s overall evolution over time. An epistemically relevant element is one which is not only known to the agent, but which can be cited by him or her to explain the occurrence of some other element, or of the system’s overall output.

The term ‘explain’ is intentionally ambiguous. Indeed, a computing system’s epistemically relevant elements may take the form of physical structures, mathematical states-of-affairs, or even reasons—among many other things. Accordingly, the presence or absence of any element might be explained causally (“the eight-ball moves because it was impacted by the queue-ball”), mathematically (“the motion vector of the eight-ball is a function of the motion vector of the queue-ball”), or rationally (“the eight-ball was pocketed because Johnny desired to win the game and believed that that sinking the eight-ball was the way to do so”). In general, the kind of explanation being provided depends on the kinds of EREs being invoked, and different kinds of EREs are likely to be suitable for different agents and systems.

This ambiguity in the term ‘explain’ shows why discussions of parameter values are of

---

3 Indeed, software engineers involved in the development of such networks typically already have access to its underlying parameters. Nevertheless, these engineers are often the first to call for more illuminating explanations so as to, for example, demonstrate that the network does in fact do what it is supposed to do (see Section 4), or to improve the network’s behavior when it does not (see Section 5).
limited help when understanding the nature of the black box problem in AI. Although some agents may in fact attempt to explain a computing system’s behavior by citing individual parameter values, many other agents—in particular, agents with more limited cognitive resources, or agents with a more limited understanding of computer programming—will require rather different explanations. Notably, the differences between the relevant explanations center on the differences between epistemically relevant elements. Whereas some agents may be satisfied by explanations that cite a system’s parameter values, others are likely to prefer explanations that cite higher-order representations. Moreover, some agents may require explanations that invoke the physical properties of hardware components, whereas others may instead invoke explanations that cite features such as objects, colors, persons, or intentions in the system’s environment.

The discussion so far shows that the sense in which computing systems are opaque—and thus, the sense in which they should be rendered transparent—differs between agents. Nevertheless, the outline of a general solution to the black box problem is already beginning to take shape: In order to render an opaque computing system transparent, a particular agent must seek knowledge of an appropriate set of epistemically relevant elements with which to explain that system’s behavior. Two questions must be answered before this outline can be fleshed out into a step-by-step “recipe” for explainable AI. Which agents are actually interested in explaining the behavior of computers programmed using machine learning? What are, for these agents, the appropriate epistemically relevant elements? By answering these two questions, it will eventually be possible to evaluate the distinct explanatory contributions of different analytic techniques from explainable AI.

### 3. From Machine Learning to Marr

#### 3.1. Agents in the ML ecosystem

Tomsett et al. (2018) provide a helpful taxonomy of agents within the ML ecosystem—that is, a taxonomy of agents who regularly interact with a computing system developed using machine learning. In particular, six kinds of agents are distinguished according to their unique roles within the ML ecosystem (Figure 1), and Tomsett et al. illustrate these agents’ roles by invoking the example of a loan risk assessment system. Indeed, the risk assessment system is a typical ML application: A supervised learning algorithm can be used to correlate previous applicants’ personal data such as income, age, and home address with their eventual ability to repay loans in a timely manner. On the basis of such correlations, the automated loan risk assessment system can take a new individual’s personal data as input, and generate an output to estimate the financial risk a bank would incur by accepting that individual’s loan application.
Bank employees are the operators and/or executors in the risk assessor’s ecosystem. Operators are agents who “provide the system with inputs, and directly receive the system’s outputs” (Tomsett et al., 2018, p. 10). These are likely to include bank tellers tasked with entering a particular applicant’s personal data into the system, and with receiving the system’s output. In contrast, executors are “agents who make decisions that are informed by the machine learning system” (Tomsett et al., 2018, p. 10). These are likely to include back-office employees who rely on the system’s output to make data-driven decisions about whether or not to accept a particular application.

Another important agent in the ML ecosystem is the decision-subject. In the present example, the decision-subject is the loan applicant: the individual whose data are being processed for the purposes of assessing risk, and who is subject to the executor’s final decision. Decision-subjects are distinguished from data-subjects, individuals whose personal data are contained in the learning environment. In the loan-application example, data-subjects include previous applicants whose personal data and loan-repayment behavior ground the risk assessor’s learned correlations.

Creators are the developers of the computing system. These include software engineers responsible for designing the learning algorithm and for selecting the learning environment. They are also likely to include system administrators responsible for maintaining and possibly fine-tuning the system after it is deployed. Of course, creators might also include hardware engineers tasked with building and maintaining the hardware in which the risk assessor is implemented. That said, many current ML applications are driven by standard-issue hardware components whose workings require no ML-specific knowledge. Perhaps for this reason, Tomsett et al. (2018) do not explicitly consider creators of this kind.

Finally, examiners are “agents tasked with compliance/safety-testing, auditing, or

---

Figure 1: The ML ecosystem. Reproduced from Tomsett et al. (2018).

---

4 Applications that depend on ML-specific hardware components are considered in Section 5.
forensically investigating a system” (Tomsett et al., 2018, p. 13). Thus, examiners are likely to include regulatory bodies charged with determining that the risk assessment system conforms to, for example, data privacy regulations, anti-discrimination laws, and policies designed to prevent financial fraud. Given legislative innovations such as the EU General Data Protection Regulation (GDPR), examiners are likely to play increasingly prominent roles in future ML ecosystems.

3.2. What are the epistemically relevant elements?

Opacity prevents every one of these agents from fulfilling their designated roles within the ML ecosystem. Consider again the loan risk assessment system. If a bank teller does not know that an applicant’s date of birth must be entered YYYYMMDD rather than DDMMYYYY, he or she will be unable to correctly operate the system so as to generate meaningful outputs. If a back-office executor does not know that an output value of 0.794 designates a relatively high level of financial risk, he or she will be unable to make an appropriate decision with respect to a particular loan application. If current applicants (i.e., decision-subjects) are unable to acquire knowledge of the factors that contribute to particular decisions, they cannot exercise their GDPR right to explanation (Goodman & Flaxman, 2016). Similarly, if previous applicants (i.e., data-subjects) are unable to acquire knowledge of the personal data that is stored in the learning environment, they will not be in a position to exercise their GDPR right to information. If examiners such as lawyers or regulatory bodies cannot discern whether the loan risk assessment system has learned to correlate a foreign place of birth with high level of financial risk, they will be unable to identify, and if necessary sanction, possible discrimination. Finally, software engineers who do not know the variables that mediate causally between a system’s inputs and outputs—be they individual system parameters or high-level representations—will be unable to efficiently modify the system’s performance so as to bring it in line with the lawyer’s legal recommendations.

Where opacity is a problem, transparency is the solution. But what exactly is required to render computing systems transparent in a way that will be appropriate to the agents distinguished above? Recall that rendering a computing system transparent involves acquiring knowledge of the system’s epistemically relevant elements. Given their distinct roles within the ML ecosystem—as well as, presumably, their distinct background knowledge and expertise—it seems likely that different agents must acquire different kinds of knowledge.

Indeed, different agents require knowledge of different EREs. Bank tellers tasked with entering inputs and receiving outputs can only operate the system if they know, for example, something about the INCOME, D.O.B. and HOME_ADDRESS variables (in particular, their type), and that the most important output is the value of the RISK variable. Software engineers charged with developing, maintaining and improving the risk assessor’s behavior must be able to identify, characterize, and intervene on the variables—system parameters and/or high-level representations—that mediate the transformation of inputs to outputs. Perhaps surprisingly, several other agents

---

5 Some commentators deny that opacity is a significant obstacle (see, e.g., Zerilli, Knott, Maclaurin, & Gavaghan, 2018). However, these commentators fail to recognize the diversity of agents within the ML ecosystem, and thus, the different senses in which computing systems may be opaque, as well as the different reasons for rendering these systems transparent.
are less likely to be concerned with the system’s variables than with the environmental features that are represented by those variables. In particular, in order to render the loan risk assessment system transparent for their purposes, executors, examiners, data- and decision-subjects are less likely to invoke variables such as INCOME, D.O.B., HOME_ADDRESS, and RISK than to invoke the (learned correlations between) environmental features such as an applicant’s income, date of birth, home address, and financial risk.

These differences in different agents’ explanatory requirements—in particular, their appeals to different kinds of EREs—may be apparent enough in the context of the loan-application example. In order to extend the discussion to other examples, however—that is, in order to understand in a more general sense what is required to render computing systems transparent—it will be necessary to attain a deeper understanding of the different kinds of knowledge that will be required by different agents in order to fulfill their specific roles within the ML ecosystem.

3.3. Toward a Marrian framework for explainable AI

One way of attaining such a deeper understanding is to adopt a more general explanatory framework. Consider David Marr’s (1982) levels of analysis framework, which is thought by many to specify the norms that should be satisfied in order to explain the behavior of cognitive systems as diverse as the human visual system and the sensorimotor system of the house fly. Notably, although it was articulated almost forty years ago, Marr’s framework remains influential in cognitive science today. Moreover, there are reasons to believe that this framework may become equally influential in explainable AI in the future. For one, like many biological cognizers, the computing systems being developed in artificial intelligence can be viewed as information-processing systems in which inputs are systematically transformed into outputs. For another, like the computers being programmed using machine learning, biological cognizers are opaque in the sense that we still do not know exactly why they do what they do or how they work (Zerilli et al., 2018).

Most importantly, however, Marr’s explanatory framework is sufficiently nuanced to illuminate the subtle differences between the knowledge that is required by different agents within the ML ecosystem. Indeed, Marr’s framework centers on the answering of questions at three distinct levels of analysis (McClamrock, 1991; Shagrir, 2010; Zednik, 2017). Insofar as different agents can be thought to ask different kinds of questions, the characteristic answers described by Marr can be used to better understand the different kinds of EREs these agents are likely to invoke in order to render computing systems transparent. Indeed, by adopting Marr’s explanatory framework to evaluate the explanatory contributions of analytic techniques from

---

6 Notably, in order to illustrate and motivate his framework, Marr himself did not only invoke biological cognizers, but also invoked engineered computing systems such as the supermarket cash register. Indeed, the agents who regularly interact with the cash register are closely analogous to the agents in the ML ecosystem: the supermarket employees who operate the register are like operators and/or executors; customers are like decision subjects; the software or hardware engineers charged with constructing and maintaining the cash register are like creators; financial regulatory bodies such as tax auditors are examiners. Although there exist important disanalogies (e.g. the supermarket cash register has no data-subjects), the fact that Marr’s framework is in part motivated by its applicability to engineered systems can be viewed as a reason to believe that may not only inform the study of biological cognizers, but that it may also be deployed in explainable AI.
explainable AI, it will be possible to determine exactly which questions these techniques are suitable for answering, and thus, for which agents and to what extent the analyzed systems can be rendered transparent.

4. Description and Interpretation: The Computational Level

4.1. Questions about what and why

Marr’s computational level of analysis centers on questions about what a system is doing, and on questions about why it does what it does. These questions are intimately related, but importantly different. Questions about what a particular system is doing call for a description of that system’s overall behavior in terms of, for example, a transition function $f$ in which ‘input’ states are mapped onto corresponding ‘output’ states (Figure 2). In the context of the loan risk assessment system, therefore, what-questions are answered by specifying the value of the RISK variable that is generated for any particular combination of input variables such as INCOME, D.O.B., and HOME_ADDRESS.

In contrast, questions about why a system does what it does are questions about that behavior’s “appropriateness” within some particular environment (Marr, 1982, p. 24f). That is, these questions call for interpreting the system’s behavior in terms of recognizable features of the environment—be this the learning environment that (together with the learning algorithm) determines the system’s behavior, or the behavioral environment in which the system is eventually deployed. Insofar as what-questions are answered by specifying a transition function $f$ that maps ‘input’ states onto corresponding ‘output’ states, why-questions concern the environmental regularity or correlation $f’$ that obtains between the inputs and outputs themselves. Specifically, answering a why-question involves showing that there exists a correspondence between $f$ and $f’$ (Shagrir, 2010. See also Figure 2). Thus for example, in the loan-application scenario, why-questions are not answered by describing the values of variables such as INCOME, D.O.B., HOME_ADDRESS, and RISK, but rather by interpreting these values in terms of features such as a particular applicant’s income, date of birth, home address, and level of financial risk.
It can help to view the correspondence between systems and their environments semantically, that is, in representational terms. The system’s ‘input’ and ‘output’ states may be thought to represent the input received from the environment and the output that is generated in response. Likewise, the state-transition $f$ might be thought to track the regularity or correlation $f'$ that obtains between those inputs and outputs. Although more can and should be said about the correspondence that obtains between a computing system and its environment (for discussion see, e.g., Shagrir, 2010), for current purposes it suffices to say that whereas what-questions concern local properties of the computing system itself—often, its representational vehicles—why questions concern features of the surrounding environment—the corresponding representational contents.

4.2. Operators, executors, examiners, data- and decision-subjects

This brief presentation of the computational level can already be used to align different agents within the ML ecosystem with distinct questions within Marr’s explanatory framework. For this reason, it can be used to better understand the kinds of EREs these agents are likely to invoke in order to render computing systems transparent.

Insofar as they are tasked with entering inputs and receiving outputs, operators are most likely to seek answers to questions about what a computing system is doing. That is, their explanatory demands are satisfied—the system is rendered suitably transparent—by describing the inputs that must be entered and the outputs that are generated. In contrast, executors and examiners are far more likely to be concerned with why-questions in which a system’s behavior must be interpreted. To wit, although a back-office executor in the loan-application scenario must know that the risk assessment system computes a value of 0.794, his or her most important task is

---

**Figure 2.** $S_{in}$ and $S_{out}$ are the ‘input’ and ‘output’ states of the computing system, respectively; input and output are the corresponding features of the environment. The solid arrow at the bottom designates the overall behavior of the system, presumably realized in some causal process. The dotted arrow designates a representation (or other kind of correspondence) relationship between the system and its environment. What-questions concern the transition function $f$ from $s_{in}$ to $s_{out}$. Why-questions, in contrast, concern the relationship $f'$ between input and output. Adapted from Shagrir (2010).
to interpret that value as an indicator of significant financial risk. Similarly, it is an examiner’s duty to determine whether a particular assessment has been generated legitimately, or because the system discriminates by associating a foreign place of birth with a high level of financial risk.

Data- and decision-subjects are similarly concerned with questions about why rather than with questions about what. Indeed, since coming into force in May 2018, the GDPR empowers data- and decision-subjects to seek answers to why-questions, but does not similarly extend to what-questions. In particular, the GDPR right to information allows data-subjects to know which personal information is represented, but not how that information is entered, represented, and manipulated. Similarly, the GDPR right to explanation allows decision-subjects to know which factors contributed to a particular outcome (e.g., a low income may lead to a denied application), but not to the way in which those factors are represented, or how the outcomes are actually calculated. Notably, the rationale for focusing on questions about why rather than on questions about what (or on questions about how, see Section 5) is compelling: whereas my personal data belong to me, the data-structures and processes that are actually used to represent and manipulate those data are the property of the AI service provider.

In summary, the distinction between what-questions and why-questions at the computational level captures an important distinction between two different ways of rendering a computing system transparent, each of which is appropriate for different agents within the ML ecosystem. Whereas operators typically seek to render a system transparent by asking what it does and describing its ‘input’ and ‘output’ states, many other agents do so by asking why it does what it does and interpreting those states in terms of environmental features and regularities. Curiously, this means that for several agents in the ML ecosystem, rendering a computing system transparent does not involve “looking inside” the system at all, but rather looking at the environment in which that system’s behavior is learned and performed.

4.3. Input heatmapping

Several XAI techniques can be used to answer questions about what and why. One such technique is input heatmapping, which highlights the features of a system’s input that are particularly relevant to, or predictive of, its output. Some of the most compelling examples of this technique come from the domain of machine vision, in which deep neural networks are used to classify pixelated input images according to the people, objects, properties, or situations they depict. There, input heatmapping typically involves the generation of visualizations—i.e., heatmaps—that emphasize the particular pixels or pixel regions that are most responsible for a particular classification (Figure 3).

Although machine vision may be the domain in which input heatmaps are most intuitive, they may also be used in other domains. For example, input heatmaps may be constructed for audio inputs, highlighting the moments within an audio recording that are most responsible for classifying that recording by musical genre. Moreover, although LRP is specifically designed to work with artificial neural networks, other methods can be used to generate input heatmaps for other kinds of systems.
One concrete approach for developing heatmaps for artificial neural networks is layer-wise relevance propagation (LRP, Montavon et al., 2018). This method deploys a subroutine of the popular backpropagation learning algorithm, in which individual unit activations and connection weights are used to calculate the responsibility that the individual units of an “upstream” layer $l_i$ bear for producing particular levels of activity in the subsequent “downstream” layer $l_{i+1}$. Given a particular classification at the network’s output layer, this subroutine can be deployed in a layer-wise fashion until responsibility-values are calculated for every unit in the network’s input layer. Insofar as these units correspond to, for example, pixels of a particular input image, these responsibility-values can be used to generate a heatmap that highlights the pixels or pixel regions that bear the greatest responsibility for the final classification.

Input heatmaps provide particularly fine-grained answers to questions about what a computing system is doing. Recall that questions of this sort are answered by specifying the transition function $f$ that obtains between a system’s ‘input’ and ‘output’ states. Input heatmaps can help specify $f$, not in terms of the ‘input’ state as a whole (e.g., a whole pixelated image), but in terms of a limited number of elements within that state (e.g., individual pixels). Such fine-grained answers to what-questions are particularly useful for operators. In particular, they greatly enhance an operator’s ability to identify the most likely sources of error. If an error is detected in the ‘output’ state (e.g., the RISK value is inappropriately high), it is more likely to result from high-responsibility elements of the ‘input’ state (e.g., a wrongly-formatted D.O.B. value) than from low-responsibility elements (e.g., a misspelled surname). That said, such fine-grained answers to what-questions can also be exploited by malicious operators such as hackers. Indeed, input heatmaps can be used to design adversarial inputs that appear typical to human observers, but that nevertheless produce radically divergent (and thus, potentially exploitable) outputs due to minor changes to some high-responsibility elements (Szegedy et al., 2013).

Notably, input heatmaps can also be used by creators. Creators are regularly tasked with improving or otherwise changing a system’s overall behavior, and thus, with changing the system’s...
transition function $f$. An input heatmap’s fine-grained answers to what-questions can be used by creators to identify the necessary changes. Thus for example, in order to maximize a system’s processing efficiency and minimize its memory load, an input heatmap might be used to determine whether certain aspects of the input (e.g., pixels at the edge of an image) can be ignored, or whether the memory required to store individual inputs can be reduced by, for example, zeroing the values of low-responsibility elements. Similarly, creators seeking to minimize a system’s susceptibility to adversarial inputs could deploy input heatmaps to, for example, determine that the responsibility for final classifications should be distributed more evenly across all ‘input’ elements. Of course, although creators may invoke input heatmaps to determine the particular changes that must be made, they will normally have to use other techniques—in particular, techniques capable of answering how-questions—in order to know how those changes can actually be achieved.

While input heatmapping can be used by operators (and creators) to better understand what a system is doing, this technique can also be used by agents interested in knowing why the system does what it does. Recall that why-questions are answered by specifying a regularity or correlation $f'$ that obtains between features of the environment, and by showing that this correlation is tracked by the system’s transition function $f$. Input heatmaps can be used to answer why-questions if the environmental features that participate in $f'$ can be discerned by inspecting the map—that is, if the highlighted elements of the ‘input’ state together “look like” some recognizable feature of the environment. Consider again the input heatmaps in Figure 3. The highlighted pixels visually resemble handwritten digits. In particular, the highlighted pixels in the upper-left heatmap visually resemble a handwritten 2 rather than, for example, a handwritten 7. This fact answers a question about why the upper-left input image outputs ‘2’ rather than ‘7’: the output is ‘2’ because the image depicts a 2. Stated more generally, the input heatmaps in Figure 3 show that the system does what it is in fact supposed to do, namely, detect and classify handwritten digits.

In order to better appreciate the importance of answering why-questions in this way, it is worth contrasting the above example with one in which the computing system does not in fact do what it is supposed to do. Consider a well-known historical (albeit probably apocryphal) example in which a neural network learns to visually distinguish enemy tanks from friendly ones. Although the network quickly learns to categorize images of tanks, it does so by tracking an accidental correlation between tank allegiances and weather patterns: whereas the images of friendly tanks were all taken on a sunny day, the enemy tanks were photographed under cloud cover. For this reason, although the system correctly classifies images (what), its reasons for doing so (why) have nothing at all to do with tanks!

Heatmapping techniques such as LRP would be likely to produce visualizations in which the highlighted pixels together resemble clouds in the background, rather than tanks in the foreground. Several different agents could benefit from the availability of such visualizations:

---

8 Gwern Branwen maintains a helpful resource on this particular example, listing different versions and assessing their veracity: [https://www.gwern.net/Tanks](https://www.gwern.net/Tanks) (retrieved January 25th, 2019).
executors at military HQ who must ultimately decide whether or not to shoot at a particular tank, but also examiners at the International Criminal Court tasked with determining whether the resultant action should be considered a war crime. Moreover, tank crews who make up the decision-subjects of the tank-classification system could rest easy in their knowledge that the system can be trusted, and that they are for this reason less likely to perish in a data-driven barrage of friendly fire.

Before moving on to other kinds of questions, it is important to mention an important limitation of the heatmapping technique. Input heatmaps can be used to answer why-questions when the highlighted elements together “look like” some recognizable feature of the environment. That said, machine learning methods are renowned for their ability to identify and track subtle as well as complex features and correlations in the learning environment, many of which are not easily recognized or labeled by human observers. In such cases, the utility of input heatmapping may be limited, and other XAI techniques may have to be invoked instead. One such technique may be local interpretable model-agnostic explanation (LIME, Ribeiro et al., 2016). This technique can be used to simplify the transition function \( f \), which is often nonlinear and therefore difficult to interpret, with a linear approximation that is more readily interpretable by human observers. Although this approximation captures the system’s behavior only for a limited range of inputs, it may nevertheless be useful for answering what- and why- questions when input heatmapping fails.

5. Intervention: The Algorithmic and Implementational Levels

5.1 Questions about how and where

In Marr’s explanatory framework, the levels “below” the computational level of analysis are the algorithmic and implementational levels. The algorithmic level centers on questions about how a system does what it does. Insofar as the system’s behavior is described using a transition function \( f \) from an ‘input’ state to an ‘output’ state, the algorithmic level aims to uncover the mediating states \( s_1, s_2, ..., s_n \) and state-transitions \( s_i \rightarrow s_j \) that appropriately connect ‘input’ and ‘output’ (Figure 4). Put differently, the algorithmic level is concerned with uncovering the program that executes the overall transition \( f \), and to thereby compute or approximate \( f' \) (Shagrir, 2010).^9

---

^9 The algorithm that mediates between ‘input’ and ‘output’—the program being executed—is not to be confused with the learning algorithm that is used to develop (i.e., to program) the system in the first place.
In contrast, the *implementational level of analysis* centers on questions about *where* the program described at the algorithmic level is realized. Where-questions concern the physical components $p_1, p_2, ..., p_m$ in which states are realized and state-transitions are performed (Figure 4). Thus, the implementational level is concerned with the hardware components that are involved in executing the program for $f$.

How- and where-questions are particularly important for the purposes of *intervening* on a system’s behavior. Knowledge of a state $s_i$ or a transition $s_i \rightarrow s_j$ that mediates the overall transition between ‘input’ and ‘output’ can be used to influence that overall transition by changing either one of $s_i$ or $s_i \rightarrow s_j$. Likewise, knowledge of the fact that either $s_i$ or $s_i \rightarrow s_j$ is physically realized in some physical structure $p_i$ can be used to achieve the same goal by, for example, replacing $p_i$ with some other physical structure $p_l$, or by removing $p_i$ altogether.\(^{10}\)

In order to better understand the way in which creators should go about answering how- and where-questions in the context of machine learning, it is instructive to first consider the way these questions are answered in cognitive science. There, answers to how-questions are typically delivered by developing *cognitive models* which describe the processes that govern a particular

\(^{10}\) Although there is a clear sense in which interventions can also be achieved by modifying a system’s inputs—a different $s_{in}$ will typically lead to a different $s_{out}$—interventions on the mediating states, transitions, or realizers are likely to be far more wide-ranging and systematic.
system’s behavior. Notably, the relevant processes are only rarely described in terms of “brute causal” interactions between neuronal structures. More commonly, they are described in terms of the numeric calculation of values, or the step-wise transition between states (Busemeyer & Diederich, 2010). The most important advantage of such descriptions is that they are able to capture a system’s abstract mathematical properties. However, in some cases they also afford relatively straightforward semantic interpretations (Fodor, 1987). That is, certain variables or states of a cognitive model might be said to represent specific features of the environment, so that changes in those variables or transitions between those states capture changes in the things being represented. That said, representational interpretations may not always be forthcoming—for example, because it is unclear which features of the environment are actually being represented (Ramsey, 1997)—nor useful—in particular, when the non-representational description is deemed sufficiently useful for the purposes of interpreting, predicting, and intervening on the system’s behavior (Chemero, 2000).

In turn, where-questions in cognitive science are typically answered by localizing the elements of a cognitive model—i.e., its individual states, state-transitions, variables, or calculations—in specific physical structures such as neurons, neural populations, or brain regions (Piccinini & Craver, 2011; Zednik, 2017). Although cognitive scientists had long denigrated the explanatory relevance of where-questions (Pylyshyn, 1984), it is now widely acknowledged that a proper understanding of the brain is critically important for the purposes of explaining the mind (Shallice & Cooper, 2011). That said, it would be a mistake to think that localization in cognitive science is typically “direct” in the sense of affording simple one-to-one mappings between the individual steps of a process and the parts of an underlying physical structure (Bechtel & Richardson, 1993). Indeed, the functional boundaries between the elements of cognitive models frequently cut across the physical boundaries between physical structures in the brain (Stinson, 2016). Although this should not be taken to indicate that the answering of where-questions is impossible or unimportant, it does show that close attention should be paid to the sense in which, for example, the states and state-transitions of a particular process—and thus, possibly, the corresponding representations and representation-manipulations—might be distributed (Clark, 1993).

5.2. Creators

How might this brief foray into the explanatory norms and practices of cognitive science be relevant to machine learning? Like scientists working to explain the behavior of biological cognizers, the creators of an ML-programmed computer are frequently preoccupied with questions about how and where. On the one hand, software engineers and system administrators tasked with developing, maintaining, fixing, and generally improving a computing system’s behavior need to know not only what that system does, but also how it does it. On the other hand, hardware engineers charged with building and maintaining the hardware in which the system is implemented must know where certain processes could be, or are actually, localized. Notably, much about the way in which how- and where-questions are answered in cognitive science can be used to better understand the way these questions can and should be answered in explainable AI.

Consider how-questions first. Just as in cognitive science it is only rarely useful to look for
“brute-causal” interactions between neuronal structures, in the machine learning context it is only rarely useful to cite individual parameter values such as a neural network’s unit activations or connection weights. Indeed, their high-dimensional complexity makes many ML-programmed computers unpredictable even with complete knowledge of the underlying parameter values. Moreover, there is often no way of knowing in advance whether an intervention on a single parameter will change the relevant system’s behavior entirely, or else affect it in a way that is mostly imperceptible.

Like in cognitive science, therefore, suitable answers to how-questions in explainable AI will in most cases describe abstract mathematical properties of the system whose behavior is being explained. To better understand the kinds of properties that might be sought, consider once again the loan risk assessment system from before. In order to track statistical correlations between previous applicants’ personal data and their ability to repay loans, the risk assessment system is unlikely to categorize new applicants on the basis of simple linear combinations of inputs such as age and income. Rather, the system is more likely to deploy a taxonomy of abstract categories in which the inputs are combined nonlinearly (see also Buckner, 2018). For illustrative purposes, it can help to assume that these categories approximately correspond to folk-psychological character traits such as honest, unscrupulous, high self-control, persevering, or foolhardy. Although an applicant who once was the victim of a ponzi scheme may appear inconspicuous to a bank employee, the automated risk assessment system might, through a nonlinear combination of data points, nevertheless classify that applicant as being foolhardy, and for this reason, risky. In order to properly understand how this system does what it does—and thus, in order to potentially intervene on the system’s behavior—creators would profit from identifying the system’s learned categories, and from characterizing the role these categories play in the generation of particular outputs.

Now, consider where-questions. Recall that questions of this kind were long denigrated in cognitive science. Because many ML applications are driven by standard-issue hardware components, it may be tempting to dismiss where-questions as being similarly irrelevant to explainable AI. But it is important to resist this temptation. Indeed, a growing number of ML applications are driven by ML-specific hardware components. For example, the artificial neural networks used for visual processing in self-driving cars are increasingly implemented on neuromorphic hardware devices that have considerable advantages with respect to speed and power consumption (Pfeiffer & Pfeil, 2018). In this sense, where-questions are hugely important at least for creators tasked with choosing the hardware in which to implement a particular computing system. But where-questions can also be important for creators tasked with maintaining, repairing, or improving a computing system once it has been built and deployed. Knowing the physical location in which certain kinds of data are stored and processed can allow creators to selectively replace hardware components so as to improve the speed or efficiency of the system as a whole. Moreover, in certain scenarios, it may even be important to know where data are processed after the system has stopped working. For example, in the aftermath of a fatal accident involving a self-driving car, it may be necessary to extract the data that was processed in the moments before the
accident, even if the system is no longer operational. In such scenarios, a creator’s ability to answer questions about where certain operations were performed may be instrumental for answering further questions about what the system was doing, as well as why and how.

Surprisingly perhaps, where-questions may sometimes even be important to agents other than creators. Although many computing systems are colloquially said to be realized “in the cloud”, what this actually means is that they are implemented in a device (or a cluster of devices) that is physically far-removed from the agents within the relevant ecosystem. Given the differences in the ways different countries regulate the storage of information, data- and decision-subjects alike may want to know the particular jurisdiction under which their data is being stored and processed. In a related way, examiners may be tasked with developing and enforcing legislation that limits the extent to which data can be exported. Thus, whereas where-questions are typically within the purview of creators, there are some situations in which these questions may also be important to other agents within the ML ecosystem.

5.3. Feature-detectors

One technique for answering how- and possibly even where-questions involves the identification of feature-detectors. Just as what- and why-questions can be answered by highlighting features of the input that bear a high responsibility for the production of certain outputs, how-questions can sometimes be answered by highlighting those features of the input that are most responsible for activity in certain mediating variables. Insofar as the relevant variables are sensitive to a particular feature (i.e., respond reliably when the feature is present), relatively unique (i.e., no other mediating variables are similarly sensitive), and causally efficacious (i.e., they significantly influence the system’s overall output), those variables can be viewed as feature-detectors.

Identifying a system’s feature-detectors—assuming there are any—and exploring their influence on the system’s overall behavior serves well for the purposes of answering questions about how that system works, and sometimes, even about where the relevant feature-detecting operations are carried out.

Consider a recent study due to Bau et al (2018). This study considers generative adversarial networks (GANs) that are capable of producing photorealistic images of scenes depicting, for example, christian churches (Figure 5a). The aim of the study is to identify feature-detectors and explore the systematic effects of surgical interventions. To this end, Bau et al. “dissect” the relevant networks to identify the units or unit clusters that are sensitive and unique with respect to recognizable features such as trees (Figure 5b). Subsequently, they determine the causal efficacy of these (clusters of) units by performing a series of interventions such as activating or ablating (i.e., de-activating) the relevant units. Indeed, through such interventions the authors discover that they can systematically control the presence or absence of features in the generated images, without compromising the overall image quality (Figures 5c and 5d).

11 Curiously, in such scenarios a computing system’s hardware components become analogous to the ‘black box’ voice-recorders used on commercial airliners.

12 Strictly speaking, because the aim of the GANs in this study is not detection but generation, the relevant units may more appropriately be called feature-generators.
Bau et al.’s study exhibits many of the hallmarks of successfully answered how-questions. For one, it shows that interventions on feature-detectors can be used to repair or otherwise improve the relevant system’s performance—a typical task for creators. For example, by identifying and subsequently ablating the feature-detectors for unwanted visual artifacts such as textured patterns where there should be none, they are able to successfully remove those artifacts from the generated images and therefore improve the system’s overall performance. For another, most of the features being detected by the networks in the study are robust with respect to nuisance variations in color, texture and spatial orientation. Thus, the GANs appear to learn just the kinds of high-level representations one would expect to find in high-dimensional complex systems developed using machine learning. Indeed, the authors even speculate that the networks’ representations resemble the conceptual representations that are used by human brains (see also: Buckner, 2018).
As this example shows, the identification of feature-detectors is an effective technique for answering how-questions in the ML ecosystem. That said, it is worth considering the extent to which this technique might be used to answer where-questions as well. Indeed, insofar as a network’s feature-detectors are concentrated in a relatively small number of units and those units are implemented in neuromorphic hardware components, the identification of feature detectors will simultaneously answer questions about how and questions about where. Indeed, in such cases, modifications to the networks’ overall behavior could equally be achieved by, for example, removing or replacing the hardware components that implement specific detectors.

5.4. Diagnostic classification

Feature-detectors can be invoked to answer questions about how and even where, but only when the responsibility for generating particular outputs is concentrated in a relatively small number of system variables (e.g., a small number of network units). In contrast, they cannot normally be invoked when the responsibility is distributed over a large number of variables (e.g., a layer or network as a whole). Indeed, decades-long discussions of connectionist modeling methods in cognitive science suggest that neural networks and similarly high-dimensional systems are likely to exhibit this kind of distributed responsibility (Smolensky, 1988), and thus, are likely to deploy distributed representations (Clark, 1993). For this reason, investigators in explainable AI have good reason to develop alternative techniques that can be used to answer how-questions even when no feature-detectors can be found.

Consider a recent study from computational linguistics, in which Hupkes et al. (2018) explore the capacity of different networks to evaluate expressions with a nested grammatical structure. It has long been known that simple recurrent networks (SRNs, Elman, 1990), like other networks with recurrent feedback connections, perform well when confronted with tasks of this nature. What remains unclear, however, is exactly how these networks do what they do, and in particular, how they store and deploy information over extended periods of time. To wit, assuming that a nested arithmetic expression such as “(5-((2-3)+7))” is processed from left to right, some symbols encountered early (e.g., the ‘5’ and the leading ‘-’) will have to be evaluated only after symbols that are encountered later.

Hupkes et al.’s challenge is to determine whether networks capable of evaluating such nested expressions do so by following either one of two strategies: a recursive strategy in which parenthetical clauses are evaluated only after they are closed (2-3=-1; -1+7=6; 5-6=-1), or a cumulative strategy, in which parentheses are removed from left to right while appropriately “flipping” the operators between ‘+’ and ‘-’ (5-2=3; 3+3=6; 6-7=-1). In order to answer this question about how the relevant networks do what they do, Hupkes et al. deploy diagnostic classifiers: secondary networks that take as inputs the primary network’s hidden-unit activations while a particular symbol is being processed, and that generate as output a value that can be compared to a prior hypothesis about the information that should be represented at that moment. In the present example, the diagnostic classifiers’ outputs are compared to the information that should be represented if the recurrent network were to follow either one of the relevant strategies. For example, after processing the ‘3’ in the arithmetic expression “(5-((2-3)+7))”, a
recurrent network that adheres to the recursive strategy should represent an intermediate sum of -1, whereas one that follows the cumulative strategy should represent a 6. Indeed, Hupkes et al. find that the diagnostic classifiers generate outputs more in line with the cumulative strategy than with the recursive strategy (Figure 6).

![Figure 6. Diagnostic classifier outputs (y-axis) for the cumulative (top) and recursive (bottom) strategies over the course of two distinct expressions (x-axis). The classifiers’ outputs (solid line) are compared to the prior hypotheses (dashed line), revealing an over-all closer fit to the cumulative than to the recursive strategy. Reproduced from Hupkes et al. (2018).](image)

Like feature-detectors, diagnostic classifiers can be used to answer questions about how a particular system does what it does. More precisely, they can be used to determine which information is represented by a system when it receives a particular input, and thus, how that network processes information as the inputs change over time. In a sense, therefore, diagnostic classifiers can be used to trace the particular program—in this case understood as a series of transitions between information-bearing states—that is executed by networks that are capable of performing particular tasks.

Diagnostic classification has at least one important advantage over techniques that center on feature-detectors, but also some significant disadvantages. On the one hand, diagnostic classifiers do not require that the representations in the relevant system be contained in a small number of variables. For this reason, they appear well-suited for answering how-questions even when—as is often likely to be the case—networks solve AI problems by manipulating distributed representations. On the other hand, diagnostic classifiers may be thought to be of comparatively limited explanatory value insofar as they do not afford the ability to intervene on these systems’ behavior. Whereas feature-detectors can be ablated or activated, and the resultant effects can be recorded, it is not clear how a diagnostic classifier’s outputs can be used to systematically modify a system’s behavior. Moreover, whereas in certain cases feature-detectors may be cited to answer where-questions in addition to answering how-questions, diagnostic classifiers are unlikely to address the former other than by indicating that certain representations are realized somewhere
within the system as a whole.

5.5 Overcoming the limits of explainable AI?

This brief review of XAI techniques shows that it is increasingly possible to not only answer questions about what a computing system does and why, but to also answer questions about how it does what it does, and in certain circumstances, where. Thus, explainable AI seems well-equipped to answer the questions that are likely to be asked by different agents within the ML ecosystem. That said, it is important to recognize that the analytic techniques that have been developed thus far have certain characteristic limitations, and to consider how these limitations might eventually be overcome.

As was the case for input heatmapping, the techniques of diagnostic classification and feature-detector-identification work relatively well when a system’s variables can be interpreted semantically—that is, when they can be thought to represent recognizable features of the environment (Clark, 1993). Indeed, feature-detectors are only as informative as the features being detected can be recognized by human observers, and diagnostic classifiers require investigators to already possess a detailed understanding of the programs that might be executed by the system whose behavior is being explained. As has already been observed in the context of LIME, however, there are reasons to believe that the environmental features being detected and the correlations being learned through the use of machine learning are often subtle and difficult to interpret. For this reason, although promising, the XAI techniques reviewed above are limited in scope and utility.

It may once again be worth seeking guidance in cognitive science. There, a major trend is the gradual recognition that semantic interpretation is not always necessary to explain the behavior of humans and other biological cognizers. Indeed, it is now far less frequently assumed than before that the neuronal processes described by cognitive models should—or even can—be described in semantic terms (Chemero, 2000; Ramsey, 1997). For this reason, many cognitive models today instead deploy sophisticated mathematical concepts and analytic techniques that can be used to idealize, approximate, or reduce the dimensionality of the systems being investigated, even if they do not render them semantically interpretable. Although the use of these concepts and techniques may render folk psychological categories inapplicable, they can nevertheless be used to satisfy important explanatory norms such as description, prediction, and intervention.

It seems fair to wonder whether explainable AI might eventually move away from semantic interpretability, and toward idealization, approximation, and dimension-reduction, in a similar way. On the one hand, artificial intelligence is in part an engineering discipline tasked with developing technologies that better the lives of regular individuals. For this reason, it is subject to constraints that pure natural sciences are not. Whereas it may not be important for laypeople to understand the processes that underlie visual perception, it is important that they know why their loan applications are getting rejected. On the other hand, just as society trusts scientists to possess expert knowledge that remains inaccessible to laypeople, it may accept that certain ML
applications can only be explained by mastering the most sophisticated XAI techniques. In this case, it may be necessary to rely on societal mechanisms—for example, the testimony of an expert witness in a court of law—to ensure that an individual’s rights are protected even when that individual cannot him or herself come to know the relevant facts. Thus, although semantic interpretability may often be beneficial, it may not always be essential.

6. Conclusion: A Recipe for Explainable AI

The discussion thus far can be distilled into a relatively straightforward “recipe” for explainable artificial intelligence. This “recipe” consists of a series of steps that should be taken in order to render an opaque computing system transparent, and thus, to solve the black box problem in AI. Of course, although this “recipe” may often succeed, it is important to remember that it is neither likely to be perfect nor unlimited in scope.

The first step in the “recipe” is to identify the agent(s) for which the system is to be rendered transparent. Section 2 above showed that ‘opacity’ is an agent-relative notion, in the sense that different agents are likely to require different kinds of knowledge in order to render a system transparent. Section 3 then introduced the notion of an ‘ML ecosystem’ in order to distinguish between creators, data-subjects, decision-subjects, operators, executors, and examiners. In addition to performing distinct roles within the ML ecosystem, these agents are likely to possess different background knowledge and expertise.

The second step is to identify the questions the relevant agents are likely to ask. To this end, inspiration was sought in cognitive science, and in particular, in Marr’s levels of analysis framework. Whereas operators are most likely to ask questions about what the relevant system is doing, executors, decision-subjects, data-subjects, and examiners are more likely to be concerned with questions about why the system does what it does. In contrast, creators tasked with developing, maintaining, fixing, and improving an ML-programmed computer will mostly be concerned with questions about how the system works, but will in some cases also require answers to questions about where (i.e., in which physical hardware) information is stored and processed.

The third step in the “recipe” is to identify the kinds of epistemically relevant elements that need to be cited in order to answer the questions that are asked. Marr’s levels of analysis framework shows that whereas what-questions are answered by describing the system’s ‘input’ and ‘output’ states, why-questions are answered by interpreting those states in terms of features of the system's environment. Moreover, it shows that how-questions are answered by identifying the states and state-transitions that mediate between the system’s ‘input’ and ‘output’ states, and that where-questions are answered by identifying the physical structures in which those states and state-transitions are realized. Notably, the latter kinds of questions must typically be answered in order to intervene on the system being investigated.

The fourth and final step in the “recipe” for explainable AI is to choose and deploy an
analytic technique capable of answering the relevant kinds of questions by identifying the right kinds of epistemically relevant units. Although new techniques are being developed almost every day, Sections 4 and 5 reviewed some techniques that are particularly promising or that have become particularly influential. In particular, input heatmapping and LIME were revealed to be useful for answering questions about what and why, and thus, for satisfying the explanatory demands of operators, executors, examiners, data- and decision-subjects. In contrast, feature-detector identification and diagnostic classification were revealed to be well-suited for answering questions about how, and to a limited extent, even questions about where. For this reason, these techniques are most likely to be used by creators.

References

Bau, D., Zhu, J.-Y., Strobelt, H., Zhou, B., Tenenbaum, J. B., Freeman, W. T., & Torralba, A. (2018). GAN Dissection: Visualizing and Understanding Generative Adversarial Networks. arXiv, 1811.10597.

Bechtel, W., & Richardson, R. C. (1993). Discovering Complexity: Decomposition and Localization as Strategies in Scientific Research (MIT Press ed.). Cambridge, Mass: MIT Press.

Buckner, C. (2018). Empiricism without magic: transformational abstraction in deep convolutional neural networks. Synthese, 195(12), 5339–5372. https://doi.org/10.1007/s11229-018-01949-1

Burrell, J. (2016). How the machine “thinks”: Understanding opacity in machine learning algorithms. Big Data & Society, 3(1), 205395171562251.

Busemeyer, J. R., & Diederich, A. (2010). Cognitive modeling. Sage.

Chemero, A. (2000). Anti-Representationalism and the Dynamical Stance. Philosophy of Science.

Clark, A. (1993). Associative engines: Connectionism, concepts, and representational change. MIT Press.

Doran, D., Schulz, S., & Besold, T. R. (2017). What Does Explainable AI Really Mean? A New Conceptualization of Perspectives. arXiv, 1710.00794.

Elman, J. L. (1990). Finding Structure in Time. Cognitive Science, 14, 179–211.

European Commission. Regulation (EU) 2016/679 of the European Parliament and of the Council
of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) (2016).

Fodor, J. A. (1987). *Psychosemantics*. Cambrdige, MA: MIT Press.

Goodman, B., & Flaxman, S. (2016). European Union regulations on algorithmic decision-making and a “right to explanation.” *arXiv*, 1606.08813.

Hohman, F. M., Kahng, M., Pienta, R., & Chau, D. H. (2018). Visual Analytics in Deep Learning: An Interrogative Survey for the Next Frontiers. *IEEE Transactions on Visualization and Computer Graphics*.

Humphreys, P. (2009). The philosophical novelty of computer simulation methods. *Synthese*, 169(3), 615–626.

Hupkes, D., Veldhoen, S., & Zuidema, W. (2018). Visualisation and’diagnostic classifiers’ reveal how recurrent and recursive neural networks process hierarchical structure. *Journal of Artificial Intelligence Research*, 61, 907–926.

Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2017). Building machines that learn and think like people. *Behavioral and Brain Sciences*.

Lipton, Z. C. (2016). The mythos of model interpretability. *arXiv*, 1606.03490.

Marcus, G. (2018). Deep learning: A critical appraisal. *arXiv*, 1801.00631.

Marr, D. (1982). *Vision: a computational investigation into the human representation and processing of visual information*. Cambridge, MA: MIT Press.

McClamrock, R. (1991). Marr’s three levels: A re-evaluation. *Minds and Machines*, 1(2), 185–196.

Montavon, G., Samek, W., & Müller, K.-R. (2018). Methods for interpreting and understanding deep neural networks. *Digital Signal Processing*, 73, 1–15. https://doi.org/10.1016/j.dsp.2017.10.011

Pfeiffer, M., & Pfeil, T. (2018). Deep Learning With Spiking Neurons: Opportunities and Challenges. *Frontiers in Neuroscience*, 12. https://doi.org/10.3389/fnins.2018.00774

Piccinini, G., & Craver, C. F. (2011). Integrating psychology and neuroscience: functional analyses as mechanism sketches. *Synthese*, 183(3), 283–311. https://doi.org/10.1007/s11229-011-9898-4
Pylyshyn, Z. W. (1984). *Computation and Cognition*. Cambridge, MA: MIT Press.

Ramsey, W. (1997). Do connectionist representations earn their explanatory keep? *Mind & Language, 12*(1), 34–66.

Ras, G., van Gerven, M., & Haselager, P. (2018). Explanation methods in deep learning: Users, values, concerns and challenges. In *Explainable and Interpretable Models in Computer Vision and Machine Learning* (pp. 19–36). Springer.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). “Why Should I Trust You?”: Explaining the Predictions of Any Classifier. *arXiv, 1602.04938v3*.

Rieder, G., & Simon, J. (2017). Big Data: A New Empiricism and its Epistemic and Socio-Political Consequences. In *Berechenbarkeit der Welt? Philosophie und Wissenschaft im Zeitalter von Big Data* (pp. 85–105). Wiesbaden: Springer VS.

Schmidhuber, J. (2014). Deep Learning in Neural Networks: An Overview. *arXiv, 1404.7828*.

Shagrir, O. (2010). Marr on computational-level theories. *Philosophy of Science, 77*(4), 477–500.

Shallice, T., & Cooper, R. P. (2011). *The Organisation of Mind*. Oxford: Oxford University Press.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., … Hassabis, D. (2017). Mastering the game of Go without human knowledge. *Nature, 550*(7676), 354–359. https://doi.org/10.1038/nature24270

Smolensky, P. (1988). On the proper treatment of connectionism. *Behavioral and Brain Sciences, 11*(1), 1–23.

Stinson, C. (2016). Mechanisms in psychology: ripping nature at its seams. *Synthese, 193*(5), 1585–1614. https://doi.org/10.1007/s11229-015-0871-5

Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I., & Fergus, R. (2013). Intriguing properties of neural networks. *arXiv, 1312.6199*.

Tomsett, R., Braines, D., Harborne, D., Preece, A., & Chakraborty, S. (2018). Interpretable to Whom? A Role-based Model for Analyzing Interpretable Machine Learning Systems. *arXiv, 1806.07552*.

Zednik, C. (2017). Mechanisms in Cognitive Science. In S. Glennan & P. Illari (Eds.), *The Routledge Handbook of Mechanisms and Mechanical Philosophy* (pp. 389–400). London: Routledge.
Zednik, C. (2018). Will Machine Learning Yield Machine Intelligence? In *Philosophy and Theory of Artificial Intelligence 2017*.

Zerilli, J., Knott, A., Maclaurin, J., & Gavaghan, C. (2018). Transparency in Algorithmic and Human Decision-Making: Is There a Double Standard? *Philosophy & Technology*. https://doi.org/10.1007/s13347-018-0330-6