Abstract

Recent engineering developments in specialised computational hardware, data-acquisition and storage technology have seen the emergence of Machine Learning (ML) as a powerful form of data analysis with widespread applicability beyond its historical roots in the design of autonomous agents. However—possibly because of its origins in the development of agents capable of self-discovery—relatively little attention has been paid to the interaction between people and ML systems, although recent developments on Explainable ML are expected to address this, by providing visual and textual feedback on how the ML system arrived at a conclusion. In this paper we are concerned with the use of ML in automated or semi-automated tools that assist one or more human decision makers. We argue that requirements on both human and machine in this context are significantly different to the use of ML either as part of autonomous agents for self-discovery or as part statistical data analysis. Our principal position is that the design of such human-machine systems should be driven by repeated, two-way intelligibility of information rather than one-way explainability of the ML-system’s recommendations. Iterated rounds of intelligible information exchange, we think, will characterise the kinds of collaboration that will be needed to understand complex phenomena for which neither man or machine have complete answers. To reassure the reader that this is not simply wordplay, we propose operational principles—we call them Intelligibility Axioms—to guide the design of a first-step in constructing a collaborative decision-support system. Specifically, for one iteration in the collaboration (human-to-machine-to-human), the principles are intended to encode sufficient criteria for the
following: (a) what it means for information provided by the human to be intelligible to the ML system; and (b) what it means for an explanation provided by an ML system to be intelligible to a human. Using examples from the literature on the use of ML for drug-design and in medicine, we demonstrate cases where the conditions of the axioms are met. Intelligibility of communication is necessary, but not sufficient to extend a single iteration of the collaborative loop to multiple iterations. We describe some additional requirements needed for the design of a truly collaborative decision-support system.

1 Introduction

In the second half of his seminal 1950 paper [35], Alan Turing describes an autonomous agent that has the capacity to alter its programming based on experiments and mistakes, rather than relying on human programmers. Since then, developments in mathematics and computing have been making steady progress in providing the groundwork for Machine Learning, or ML. But it is only recently that we have witnessed a sea-change in the use of ML methods. Driving this change is a combination of the use of special-purpose hardware, large amounts of data from commodity devices and a significant decrease in the cost of storing such data. This has meant that ML can now be part of almost any kind of activity for which data can be collected and analysed. In many such cases, the use of ML is simply to predict accurately. Recently, one form of ML – deep neural networks – have been able to achieve startlingly good performance when provided with sufficient data and sufficiently high computational resources. Progress is also being made to replicate such success when the data are insufficient [36] and computational power is limited [18]. A difficulty has arisen, however, when attempting to exploit the predictive performance of modern ML techniques when the models they construct have to be examined by humans who are not neural network specialists. For example, a modern-day deep neural network may be able to predict, with very high accuracy, the occurrence of malignancies from X-ray images. If what is required is not just what the prediction is, but also an explanation of how that prediction was arrived at, then we hit an “intelligibility bottleneck”, in making the explanation accessible to the clinicians. Some of this arises from a mismatch between what certain ML practitioners view as suitable explanations, and what subject matter experts, or intended end-users, require [3]. More generally, one could view this as a requirement for humans and ML systems to maximise their mutual knowledge, developed over sequences of communicative interactions [6]. Unfortunately some experts regard current techniques for explanation in ML as unfit for purpose, instead relegating ML systems to the status of drugs for which no definitive biological mechanism is understood, but which nonetheless may be effective in clinical practice, subject to the successful outcome of randomised controlled trials [13]. Whilst this may allow ML to be applied by clinicians in areas such as radiology, it falls short of “human-level” performance, at least as
Far as explainability goes

But what does it mean for an explanation from an ML-system to be understandable to the clinician, or, more broadly, to a person who is a specialist, but not in ML, interacting with a ML-based system? At least some shared understanding of the concepts and terminology in a domain appears to be needed for communication between human and machine, just as between humans. Sadly, serious consequences may follow when this is lacking, for example, in the misinterpretation (wilfully or otherwise) of scientific knowledge in legal proceedings [16, 31]. Perhaps we should aim for the kind of explanations that underlie interactions between humans with expertise in a specific area? After all, much of scientific and medical progress has been the result of interaction between groups of such people. However, exactly how such specialists understand each other rarely discussed. Peter Medawar provides some clues:

Here then are some of the criteria used by scientists when judging their colleagues’ discoveries and the interpretations put upon them. Foremost is their explanatory value – their rank in the grand hierarchy of explanations and their power to establish new pedigrees of research and reasoning. A second is their clarifying power, the degree to which they resolve what has hitherto been perplexing; a third, the feat of originality involved in the research, the surprising-ness of the solution to which it led, and so on. Scientists give weight (though much less weight than mathematicians do) to the elegance of a solution. (pg 52, Pluto’s Republic)

It is unclear to what extent the design of ML systems intended for interaction with people explicitly take such criteria into account. Even if they do so implicitly, certainly very little is done to report them explicitly by way of explanation. At any rate, such intricate considerations may not be needed when designing systems in which the role of ML is as part of a tool for decision-support. In this case, the ML-engine is not expected to establish new pedigrees of research, or resolve stubborn perplexities, and is also not the primary decision-maker.

In this substantially more restricted setting, it seems entirely reasonable that the decision-maker provides all relevant information at their disposal to the tool, in a manner intelligible to the tool. If nothing else, this may avoid wasted effort on the part of the decision-support system of re-discovering what is already known. It would also seem to be pointless for the decision-support

\[\text{We recognise that there are clinical settings where explanations may not be required. ARDA, for example, is a highly accurate ML-based tool for diagnosis of diabetic retinopathy (see: https://health.google/caregivers/arda/). Based on the work reported in [14], it has been trained using labelled data provided by over 100 clinicians, and has been tested in a clinical trial. It is a device for triage-assistance in settings where a clinician examines 1000s of patients a day, and the tool is considered adequately field-tested. In this paper we are concerned instead with what needs to be done if explanations are needed.}\]

\[\text{Automated assistants for human specialists are increasingly becoming necessary as the production and complexity of data rapidly outpaces even the abilities of specialists to assimilate and process them. The distinction of ML-as-agent and ML-as-tool in decision-making has been explored extensively in [4].}\]
tool to provide assistance in a manner unintelligible to the person being assisted. These observations lead us directly to a pair of operational criteria for checking for two-way intelligibility between a human specialist and an ML-based tool for decision support.

Before presenting the axioms, we show in Fig. 1 an abstract picture of the ML system envisaged. For simplicity, we will refer to the ML system alone as “the machine”, even though there will be several other components in a complete decision-support system. The machine assists one or more human decision-maker(s), or domain-specialist(s), who may in turn use their domain-knowledge to alter any or all of \( D, U, \pi \) or \( \theta \) for the machine. Again, for simplicity, we will refer to the decision-maker(s), or domain-specialist(s), as “the human”.

We propose intelligibility axioms in the following categories:

**Human-to-Machine.** This concerns intelligibility of the information provided by the human to the machine. For the present, we restrict the information to domain-knowledge and propose an axiom based on machine-performance:

- If the machine uses human domain-knowledge to improve its performance then the domain-knowledge is intelligible to the machine.

**Machine-to-Human Intelligibility.** This concerns the intelligibility to humans of information provided by the machine to account for a prediction. For the present, we will restrict this information to explanations, and propose an axiom on human refutability:

- If the human refutes the machine’s explanation then the machine’s explanation is intelligible to the human.

We will shortly provide examples from the literature where the premises of these axioms are satisfied. Later in the paper, we will also extend the axioms in each category in order to characterise more fully the notions of human- and machine-intelligibility.

At this point, the reader may be concerned about an apparent circularity. For example, in order for the machine to use the domain-knowledge, doesn’t it have to be intelligible in the first place? Similarly, what does it mean to refute an unintelligible explanation? In fact, as conditional statements the axioms identify human- or machine-intelligibility as necessary conditions for some actions by machine or human (using, refuting), but the actions themselves are only sufficient to infer intelligibility. Thus, it is possible, for example, that the human may not refute an explanation, and yet the explanation may be intelligible to the human.

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3With reference to Fig. 1 it is unlikely that a human decision-maker with little or no knowledge of the inner workings of the ML system would nevertheless be able to provide knowledge to alter aspects like \( \pi \) or \( \theta \). In practice, therefore, we would expect that domain-knowledge would be used mainly to alter \( D \) or \( U \). For the rest, the ML-system may have to resort to some internal mechanism for optimised selection from a set of pre-defined alternatives. This set need not be finite, of course.
Figure 1: A generic ML system $\mathcal{M}$ for use in a decision-support system. The human decision-maker provides, at least: data $D$ and $U$, a utility function to be maximised. $\pi$ and $\theta$ are specifications of model-structures and parameters to be optimised: these may be specified by the decision-maker, or drawn by $\mathcal{M}$ from some pre-defined set. The performance of the machine will be obtained using $U$. The decision-maker’s domain-knowledge can affect any of $D$, $U$, $\pi$ or $\theta$. Additionally, the decision-maker may also ask questions $Q_h$ of the machine (for example, “what is the class-label of instance $x$?”), or provide answers $A_h$ to questions $Q_m$ from the ML system which it can pose to the decision-maker (for example, a machine-generated question could be about the reason for a decision-maker’s class-label for a data instance). The ML system provides answers $A_m$ to questions it receives. In this paper, explanations are taken to be a special kind of answer, provided by either human or machine.
Figure 2: A classification problem: (a) Without information about the domain; and (b) With information about the points being on a world-map (from [25]). The ⊕ points are all port cities, which can be easily inferred given knowledge of the land boundaries in (b).

Informally, we will say “human intelligibility holds” to mean the premise of the computer-performance axiom in the human-to-machine category holds. Similarly, by “machine intelligibility holds”, we will mean that the premise of the human-refutability axiom is true.

We note that, in each category, intelligibility can be seen as a ternary relation involving: the information-provider, the information provided, and the information-recipient. In the literature on Explainable ML, this has re-emerged as important requirement for the acceptability of ML (see [23] for a recent example citing earlier work [15], and [21] for an early identification of this).

The remainder of the paper is organised as follows. In Sections 2.1 and 2.2 we clarify each axiom in turn. In Section 3 we explore some consequences of taking the axioms into account when designing an ML-based decision-support tool. Section 4 concludes the paper.

2 Two-way Intelligibility

2.1 Human-to-Machine Intelligibility

We motivate the intelligibility to a machine of human domain-knowledge using an example from [25], reproduced in Fig. 2. Consider first the points in Fig. 2(a). Suppose a machine was given the task of predicting accurately whether a new data point was a ⊕ or a ⊖ from this data. The problem is difficult, and can be made increasingly harder, to the point of apparent randomness, with more data. Now the machine is told – let us say by a geographer – what else is known (Fig. 2(b)). All at once, predictive performance jumps from random-guessing to 100% accuracy simply from the machine inferring that the ⊕ points are port cities. By the Human-to-Machine Intelligibility Axiom, the information provided by the geographer is said to be intelligible to the machine.

Predictive accuracy is used here purely as an example of a utility function.
that the human decision-maker (here, our geographer) wants the machine to maximize. At this point, it is useful to clarify that an increase in predictive performance is only postulated as being sufficient for claiming intelligibility. Nothing is said on about intelligibility if predictive performance does not increase. For example, the machine may already have an encoding of the information provided by the map.

Despite this example, it is still reasonable to ask why it is necessary at all for the human decision-maker to provide domain-knowledge to the ML system. In principle, given sufficient data and computational resources, an ML engine—like a deep neural network—may be able to reconstruct the domain-knowledge for itself. In practice, the difficulty lies in the qualification of “sufficient data and computational resources”. Neither may be available, and the ML engine can under-perform. Now the human decision-maker either does or does not know that this limitation exists. If the limitation is known, then it seems perverse for the decision-maker to withhold information that would help the machine do better, or by providing it in a manner that the machine cannot use. Alternatively, if the limitation is not known, then the only reasonable course for the decision-maker would appear to be to provide what information they have in a manner the machine can use (and possibly ignore if it is redundant). In either case it would appear best to provide the information that is known in some machine-readable form.

Examples from Drug-Design

The design of new drugs is well-known to be time-consuming and expensive process, requiring the involvement of significant amounts of human chemical expertise. It is also one where data can now be generated and tested automatically on a very large scale. One phase in the pipeline of drug-design is that of early stage discovery of “leads”. These are small molecules that could potentially form the basis of a new drug. ML-based models have been used to assist in this by constructing models relating chemical structure to molecular activity (like binding affinity, toxicity, solubility and so on), and even in the generation of entire new small molecules. Reports, both new and old, in the literature have shown that provision of domain-knowledge can make a significant difference to the performance of the ML engine involved.

We show first recent results reported in [10, 11]. The experiments reported consider the inclusion of human-selected domain-knowledge for two kinds of deep neural networks (a multi-layer perceptron, or MLP, and a graph neural network, or GNN). The domain-knowledge consists of the definitions of approximately 100 relations encoding functional groups and ring-structures. Fig. 3 tabulates the number of datasets on which performance improvements are observed, with the inclusion of human domain-knowledge. For each deep network type, for problems in the “Better” column, the machine uses the information provided to improve performance. In each such instance, the Human Intelligibility axiom will infer that the domain-knowledge is intelligible to the machine, but say nothing about the remainder.
Figure 3: The use of domain-knowledge by two kinds of deep neural networks (DNNs): multi-layer perceptrons (MLPs) and graph-neural networks (GNNs). Estimates of performance are obtained on 73 different datasets. Here, “Better” (respectively, “Same” and “Worse”) means the use of domain-knowledge results in an improvement in performance (respectively, no change, and worse performance).

| DNN Type | Comparative Performance (with domain-knowledge) |
|----------|-----------------------------------------------|
| MLP      | Better | Same | Worse |
| GNN      | 71     | 0    | 2     |
|          | 63     | 9    | 1     |

Figure 4: Comparison of the performance of 2 ML systems with subsets of domain-knowledge (based on results reported in [33]). Each subset contains the definitions from the previous subset (that is, $B_1 \subset B_2 \subset B_3 \subset B_4$). The initial change in predictive performance is measured against the baseline performance obtained without any domain-knowledge. Subsequent changes are measured against the performance obtained with the set just earlier in the sequence. Increase and decrease of performance are statistical assessments of improvements in predictive accuracy (that is, the increase in predictive accuracy has to be statistically significant).

| Domain Knowledge | Predictive Performance |
|------------------|------------------------|
|                  | System A | System B |
| B1                | Increases | Increases |
| B2                | Increases | Decreases |
| B3                | No change | Increases |
| B4                | Increases | No change |

Simply providing domain-knowledge does not guarantee intelligibility, as is apparent from Fig. 3. A separate but useful point to note is that intelligibility depends on the recipient of the information. That is, whether or not the domain-knowledge provided is intelligible can depend on the ML system used. This is evident in results reported in an early work reported in [33]. There the same domain-knowledge is provided in the same representation to two symbolic ML systems (say $A$ and $B$). The study examines the progressive increase in domain-knowledge for a well-studied toxicology problem. There a progressive increase in domain-knowledge does not affect the performance of systems $A$ and $B$ in the same way (Fig. 4).

Thus, with some subset of domain-knowledge ($B_2$, for example) our axiom could conclude it was intelligible to system $A$, but remain silent about system $B$, or vice versa ($B_3$, for example)\(^4\).

\(^4\)Actually, most ML systems have several parameters. As ML practitioners are well-aware,
2.2 Machine-to-Human Intelligibility

The principal motivation for the intelligibility of a machine’s explanation is provided by a description by Michie [22] on the need or otherwise for explainability of machine-constructed answers, in the context of human decision-making. We reproduce here some parts of the article that are relevant. The description begins with the construction of a black box for a chess endgame (the interjections in brackets are ours):

At the meeting in Toronto in 1977 of the International Federation for Information Processing, Kenneth Thompson of Bell Telephone Laboratories presented a computer program for playing the chess end-game of King and Queen against King and Rook. He had done this by the ultimate in ‘hammer and tongs’ methods: in the absence of a complete set of rules for playing the end-game, he had previously programmed the machine to work out what to do in every single possible position . . . All these moves were then loaded into a gigantic ‘look-up’ table in the machine’s memory . . . Thompson invited [International Masters] to demonstrate winning play for the Queen’s side against the machine. To their embarrassment they found they could not win, even after many attempts . . . The machine repeatedly conducted the defence in ways which to them were so bizarre and counter-intuitive [like separating King and Rook] that they [the Chess Masters] were left grasping air . . . Naturally [they] found the experience upsetting. They wanted to ask the program to explain its strategy, but this of course neither it nor its author could do. The answer in every case was, ‘It’s in the table.’ (“The strange case of Thompson’s table”, pg. 64, The Creative Computer)

Michie describes how this situation is not very different to the case of machine-learning programs that are unable to explain their decision-making. He sees this as not being especially problematic in some circumstances. However in some other cases, involving decision-making in critical areas, the lack of meaningful feedback from the machine can become a serious issue:

But what if the system were doing something of social importance, such as managing a complex control function in factory automation, transport or defence? Two supervisors, let us imagine, are responsible for intervening manually in the event of malfunction. The system now does the equivalent in industrial or military terms of ‘separating its King and Rook’. ‘Is this a system malfunction?’ the supervisors ask each other. They turn to the system for enlightenment. But it simply returns the same answer over and over again . . .

\footnote{Changing values of parameters can greatly change the performance of the system. Thus, intelligibility can vary even for a single ML system.} \footnote{Surprisingly, he includes the possibility that scientific discovery may even benefit from highly predictive but opaque machine-constructed models, since it would force scientists to develop new explanations for unexpected predictions.}
The problem becomes of global importance when the system being operated is in air traffic control, air defence or nuclear power. As control devices and their programs proliferate, their computations may more and more resemble magical mystery tours . . . Any socially responsible design for a system must make sure that its decisions are not only scrutable but refutable . . . (“The lunatic black box”, pg. 68, *The Creative Computer*)

In this paper, we require that that a machine’s decision is always accompanied by an explanation. Thus, refutation of the decision as described by Michie is taken to be tantamount to refution of the explanation that goes with it. But here we arrive at a difficulty: what exactly is meant by a refutation of an explanation? The term has a well-understood meaning in the natural and mathematical sciences. In the former, explanations are hypotheses about natural phenomena and refutations follow from the result of experiments devised to test assumptions and predictions. In the latter, explanations are proofs, which can be refuted by demonstrating inconsistencies. In our case, we will treat models constructed by an ML system as a hypothesis about the data, and an explanation will refer to descriptions justifying the answer to a question posed to the machine. We will minimally require that the refutation of an explanation will result in the explanation being categorised by the decision-maker as being incomplete (insufficient) or incorrect. As before, refutability of explanations will only constitute a sufficient criterion for intelligibility of the machine’s explanation to the human decision-maker.

**Examples from Medical Informatics**

We illustrate the Machine Intelligibility Axiom using results obtained in medical informatics. This area is chosen here for two reasons. First, clinicians increasingly have access to data of many different kinds collected for individual patients, ranging from traditional test-reports to genomic information in the form of patient-specific single-nucleotide polymorphisms (SNPs). Also available, with some additional effort, are results of treatments and outcomes from across the world, and evidence and data from population studies. If clinical decision-making is to deal effectively with the data, then some form of automated assistance seems inevitable. Secondly, despite increased automation, decision-making is still expected to rest firmly with the clinician, in all but routine monitoring systems. So, what we can expect to see is an increased usage of automated decision-support tools.

First, we look at a recent research study on identification of Covid-19 patients, based on X-ray images. The automated tool described in [17] uses a hierarchical design in which clinically relevant features are extracted from X-ray images using state-of-the-art deep neural networks. Deep neural networks are used to extract features like ground-glass opacity from the X-rays; and the system also includes a network for a deep network for prediction of possible disease (like pneumonia). The output from the deep networks are used by a symbolic
decision-tree learner to arrive at a prediction about Covid-19. Explanations are textual descriptions obtained from the path followed by the decision-tree. Results reported in [17] describe how this neural-symbolic approach compares to an end-to-end monolithic neural approach (the predictive results of the two are comparable). However, our interest here is on the clinical assessment of the explanations produced by the symbolic model by radiologists: Fig. 5 shows an example of a machine’s explanation and a clinician’s assessment of that explanation. A tabulation of assessment on several “test” images is also shown. From the tabulation we can see: (a) The radiologist does not always think the model is correct (this is despite a supposed predictive accuracy of over 99% claimed for the model); (b) The radiologist is more likely to refute the explanation when he thinks the model is wrong; (c) Overall, the radiologist refutes the explanations in a substantial proportion of instances ($13/30 \approx 43\%$ of the instances). For us, it is (c) that is most relevant. With the Machine Intelligibility Axiom, the machine’s explanation is concluded as being intelligible for the 13 instances for which are refuted; and no inference is made on the 17 instances where the radiologist has rated the explanation as sufficient.

To the best of our knowledge, the most direct example of refutations in medical informatics is from an early decision-support tool in chemical pathology. PEIRS [12] was an extremely successful decision-support tool for a pathologist that constantly revised a tree-structured model consisting of rules and exceptions. PEIRS relied entirely on the ability of the pathologist to read, understand and refute the model’s explanation. The refutation in turn triggers a revision to the machine’s model. But is a 30-year old tool even relevant, given today’s ML? We think the answer is “yes”: decision-support tools using the PEIRS approach have continued to be deployed and used with great success [7]. Much of this is based directly on the approach pioneered by PEIRS. In turn, they inherit some of the ML-limitations of PEIRS: we will return to these later in the paper.

In both applications we have described there are instances where the human does not refute the machine’s explanation. Again, that this does not imply unintelligibility. But it does suggest there is room to expand the concept of machine-intelligibility to include some (but not all) instances when explanations are not refuted. We will propose such a modification later in the paper. Finally, as with the previous axiom, intelligibility continues to be recipient dependent — a repeat experiment with a second radiologist found that the explanations refuted were different. Those results are not shown here.

### 2.3 Two Additional Axioms

There is a deficiency in the characterisation of intelligibility we have presented so far. The axioms have nothing to say about when a human gains anything from the machine’s explanation. Also, there is nothing in the axioms about when a human’s explanation being intelligible to a machine. In a truly useful human-machine collaboration, we would expect both to be relevant. We therefore extend the list of axioms to be more balanced:
Not Covid because:
Air-space opacification probability is low, and
Cardiomegaly probability is high; and
Emphysema probability is low
Pneumothorax probability is low
Fibrosis probability is low

The explanation does not mention the right upper lobe air space opacification consistent with Covid

Machine’s explanation

Radiologist’s feedback

| Radiologist’s Opinion about the Model’s Explanation | Prediction |
|---------------------------------------------------|------------|
| Sufficient                                        | Correct: 17 | Wrong: 0  | Unsure: 0 |
| Incomplete                                        | Correct: 1  | Wrong: 3  | Unsure: 1 |
| Incorrect                                         | Correct: 3  | Wrong: 2  | Unsure: 3 |

Figure 5: Top: A chest X-ray (the original image is of low quality); Middle: The machine’s explanation and a senior radiologist’s feedback; and Bottom: A tabulation of the radiologist’s assessment of explanations from the ML-based system on a set of test images.
Human-to-Machine (contd.) We propose a “machine-refutability” axiom:

- If a machine refutes a human’s explanation then the human’s explanation is intelligible to the machine

Machine-to-Human (contd.) We propose a “human-performance” axiom:

- If the human uses the machine’s explanation to improve performance then the machine’s explanation is intelligible to the human.

Although the human-performance axiom mirrors the computer-performance axiom presented earlier, more care will be needed in practice with an “open system” like a human to ensure that improved performance is indeed connected to the use of the machine’s explanation and not due to some other factor (see [1] for an experimental design that attempts to identify conditions under which machine-generated explanations can be directly attributable to improvements in performance).

3 Designing for Two-Way Intelligibility

Thus far we have argued that to enable useful collaboration between human and machine information from one must be intelligible to the other; and we have identified actions by the human and machine that allow us to infer intelligibility. But several aspects remain unspecified. What constitutes an explanation? How does a human or a machine refute an explanation? Can refutations be themselves be refuted? And so on. These are questions that arise in the design of a decision-support system with “built-in” intelligibility. We are as yet in too early a stage in the design of such systems to provide normative definitions for these concepts. Instead, we attempt to understand them better by focusing on the restricted task of learning to classify observations.

3.1 Collaborative Classification

First we examine some entities and relations that characterise the interaction on the \( i \text{th} \) iteration of the collaboration (\( i = 0 \) denotes the initial condition, before any exchange of information between human and machine):

1. \( X \), a set of instances to be classified and \( L \) a set of labels;

2. \( T \), a function that classifies correctly all instances in \( X \). \( T \) will be called the oracle. \( T \) is not known to the human or to the machine;

3. \( B_h(i) \), the domain-knowledge of the human decision-maker, and \( B_m(i) \), the domain-knowledge of the machine, on the \( i \text{th} \) iteration;

\[^{6}\text{We note that this axiom will hold with the use of what Michie calls “Ultra-Strong” ML}\]
4. $H^{(i)}_{B_h}$ is the human decision-maker’s approximation to $T$, and $M^{(i)}_{B_m}$ is the machine’s approximation to $T$. $H^{(i)}_{B_h}$ and $M^{(i)}_{B_m}$ will be called “hypotheses”. We will assume $B^{(i)}_h$ is contained in $H^{(i)}_{B_h}$ and denote the latter by $H_i$. Similarly for $M_i$. In any iteration $i$, none of the $M$’s up to $i$ may be known completely to the human and none of the $H$’s up to $i$ may be known to the machine.

5. The annotation of an instance $x_{H_i}$ using the hypothesis $H_i$ is the pair $(x, H_i(x))$. Similarly for $x_{M_i}$;

6. $Send(X, \mu, Y)$ is a relation denoting that $X$ sends a message $\mu$ to $Y$. Here $X$ and $Y$ can be the human ($h$), machine ($m$) or oracle ($o$). $X$ and $Y$ are assumed to be distinct;

7. $Receive(X, \mu, Y)$ denotes that $X$ receives a message $\mu$ from $Y$. As with $Send$, $X$ and $Y$ are distinct, and can be one of $h$, $m$, or $o$; and

8. $P_{H_i}$ denotes some estimate of the performance of the human, and $P_{M_i}$ the corresponding performance of the machine.

3.1.1 Messages

All collaboration is achieved through messages, which amounts to a kind of conversation between human, machine and, to some extent, with the oracle. Let us assume for the moment that communication between human and machine is instantaneous, noise-free, and free. But none of these are true of communicating to the oracle, which may take time, and is expensive. For the present also we will assume that only the human communicates with the oracle, but will make available to the machine information received from the oracle. Of particular interest to us are messages of the following kind:

Questions. Questions are often, though not always, expected to be about the annotation of an instance. We will distinguish messages with questions by the use of a “?” . For example, $Send(h, (x, L)?, m)$ denotes a question posed by the human to the machine about the machine’s class-label for instance $x$. Here $L$ for variable whose value is to be returned by the machine. Once the message is received by the machine, $Receive(m, (x, L)?, h)$ would be true. Questions to the oracle from the human are similarly denoted by $Send(h, (x, L)?, o)$.

Explanations. Explanations are a class of answers to questions. Messages in this class are of the form $A$ because $R$, where $A$ denotes and answer and $R$ denotes the reason for the answer. Answers to questions about the annotation of an instance, for example, may be explanations of the form $(x, l)$ because $Proof$ where $Proof$ denotes some demonstration of the
reasoning why an instance $x$ has the label $l$. We will use ■ to denote a special kind of reason for an answer $A$, which is to be read as “$A$ is true”. Explanations from the oracle will always be of the form $A$ because ■.

**Refutations.** Refutations are messages that rebut explanations. We restrict refutations to explanations for which the reason isn’t ■ (the oracle’s explanation is therefore irrefutable). For an explanation $E$ of the kind $(x, l)$ because $p$, we distinguish two kinds of refutations based on (apparent) errors in the proof $p$:

- The proof $p$ is overly-specific. A possible refutation is then (overspecific($E$) because $(x', l)$) where $x' \neq x$. That is, the refutation contains a counter-example of an instance $x'$ that has the same label $l$ as $x$ but $(x', l)$ is not derivable by $p$.
- The proof $p$ is overly-general. A possible refutation is then (overgeneral($E$) because $(x', l')$), where $x'$ is possibly different to $x$, and $l' \neq l$. That is, the refutation contains a counter-example of an instance $x'$ with a label $l'$ that is distinct from $l$, but $(x', l)$ is incorrectly derivable by $p$.

### 3.1.2 Practicalities

Constructing a workable collaborative system requires more than just the bare-bones formalisation we have described. Let us look again at Fig. 5. There the radiologist does indeed provide a refutation of the machine’s explanation. But in what we are now proposing, the radiologist must also indicate the area of the right lobe containing the opacification. This will constitute the counter-example in the message sent to the machine. Identifying counter-examples are also not the end of the story. The machine, on receiving a counter-example, has to do something with it: either convince the human that their refutation is invalid, or update its hypothesis. Nothing is more guaranteed to lose the human’s patience with the machine than if it makes the same kind of mistakes on the same kind of data: unfortunately, this is exactly what would result with once-off model construction such as the approach used in [17]. However, we know from PEIRS that revision of tree-structured models is feasible and desirable, as it allowed the machine not to repeat its previous mistakes. Thus, it was not simply the use of refutations, but the resulting corrections that were responsible for developing a sustained collaboration between the human and machine (PEIRS was in routine clinical use for about 4 years and had accumulated about 2000 rules, each resulting from feedback from a pathologist).

There are some important differences between PEIRS and what is being proposed here. First, PEIRS did not have any independent automated ability for hypothesis construction. Instead, the decision-maker was involved in both

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7A proof for an annotated instance $(x, l)$ in a logical sense is specified easily enough as a function $\text{Proof}((x, l))$ that returns a sequence of inference steps $(S_1, S_2, \ldots, S_k)$. However, we do not commit to this form of proof-specification here.
identifying refutations and guiding updates to the machine’s hypothesis. The role of the machine was primarily to focus the decision-maker’s attention to potentially problematic aspects in the data (in itself no mean feat, since the data could often be over 50 separate time-series trajectories, many with gaps, and spanning time-periods of a few hours to several days). Thus, in principle, the machine’s hypothesis could not infer anything different to the human decision-maker, removing the possibility of suggesting anything new on data for which the human decision-maker was uncertain. Thus, it is not possible for the human-performance axiom to hold in principle (in practice, the machine can help maintain human performance by helping manage fatigue). A second difference to what is proposed here is that the domain-knowledge provided by the decision maker was restricted in PEIRS to a one-off identification of a vocabulary of relevant features and functions. Some subsequent construction of new features is possible, but only using functions and features defined over the original vocabulary. This does restrict the expressive power of hypotheses that can be constructed by the machine. The human-refutability axiom will not apply, for example, if instances with different labels become indistinguishable because of the restricted vocabulary. Since the human will not be able to construct a new rule, no corresponding revision of the machine’s hypothesis will occur and the machine-performance axiom will also not hold. In contrast, what we are suggesting allows updates of the domain-knowledge provided by the decision-maker to the machine. This includes the vocabulary. Additionally, modern-day ML systems like deep neural networks that routinely construct internal representations that extend the initial vocabulary: a significant challenge arises in communicating these new concepts in an intelligible way to the human.

What will probably survive from the PEIRS approach though is basic principle of repeated iterations of conjectures and refutations. Even there, a re-examination of the principle will be needed, since it assumes a human is always capable of correctly refuting a machine’s conjecture. There is experimental evidence of how human plus machine performance may be impacted, for example, due to “automation bias” where human specialists can fail to correctly override machine errors [19], or due to a lack of intelligibility of the machine’s explanations [1].

At this point, the reader may be wondering whether the collaborative process we envisage terminates at all, and if it does, in what kind of state? The question is really one of convergence in a mathematical sense. We think this can be addressed mathematically in at least one of two ways: computational learning theory, in the sense of arriving at an acceptable approximation to the oracle after some (bounded number of) queries; or the theory of co-operative games in which some players have primacy over others (for example, the oracle over the human, and the human over the machine). But there is no immediate urgency regarding the definition of convergence. For the present, we can assume that after some exchange of messages the human or machine or both will end up updating their

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8By this we mean an explanation that is at least refutable in principle. One direction is that of proxy explanations using symbolic models that are consistent with the neural models, at least to some limited local extent [28]. The other area of interest is that of self-explaining deep networks, in which each internal construct has a clear meaning [2].
domain-knowledge and corresponding hypothesis. We can therefore imagine the collaboration to be described by sequence of hypotheses \((H_0, H_1, \ldots, H_k, \ldots)\) for human and \((M_0, M_1, \ldots, M_k, \ldots)\) for machine; such that, for each point \(i > 0\), either \(M_i \neq M_{i-1}\) or \(H_i \neq H_{i-1}\). More usefully, if we can ensure on each iteration \(i > 0\), either one of the following occurs:

**Machine-revision.** There is a transfer of domain-knowledge from the human—including refutations—which results in subsequent improvement in machine-performance; or

**Human-revision.** There is a transfer of recommendations from the machine, at least one of whose explanations is not refuted, and which results in subsequent improvement in human-performance.

then we are assured that at least one of the intelligibility axioms holds on each iteration.

How much of what we have described so far be achieved now? At least within the world of symbolic ML, there is a long history of work that is explicitly concerned with human-machine interaction. This includes a very early recognition of the role of domain-knowledge in hypothesis construction [26], Michie’s characterisation of ultra-strong machine learning [21], down to recent studies with human-subjects on identifying a “cognitive window” relating symbolic descriptions constructed by ML to human performance [1]. Implementations have similarly included mechanisms for generating examples and questions for a human [29], refutation-driven revision of hypotheses [12, 24] down to updates allowing a re-shaping of the hypothesis space, based on using and extending the domain-knowledge provided [8].

Despite this substantial body of work—now spanning over 4 decades—on aspects of human-to-machine and machine-to-human information sharing, there is in fact surprisingly little that has emerged in the form of a deployed tool that conducts a sustained human-machine collaboration (PEIRS being a notable exception, albeit with strict limitations on expressivity and ML capabilities). The actual use of symbolic ML has thus not exploited its ability to enable intelligible human-machine collaboration. But part-successes suggest that, with symbolic ML at least, such a collaboration is feasible with current technology. No doubt this will also extend to the use of newer forms of ML that combine neural-and symbolic-representations, which can draw on the work done in the purely symbolic realm (evidence of this already emerging in the design of explanation-driven collaborative decision-making systems for medical images [30]). The extent to which purely neural approaches to ML can be developed for intelligible collaboration with humans remains an open question.

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9It is unsurprising, given this apparent suitability of symbolic ML and our own involvement in the area, that the basic formalisation we provided earlier has strong logical overtones, based on an existing implementation of incremental learning designed for collaborative ML [32]. A recent example of collaborative use of an extended version of this tool is in [27].
4 Conclusion

In this paper we have sought to look beyond the current practice in Explainable Machine Learning. To adopt a popular ML adjective, most of the current focus is on “one-shot explainability”. That is, the machine produces an explanation, without much regard to whom the explanation is for, and even less concern about what it should do if the explanation is thought to have a problem. The situation is somewhat akin to a car that shows you are travelling at 212,085 furlongs per fortnight, and then does nothing if you apply the brakes. Confidence in the car will naturally be dented.

It is our contention that designers of ML-based decision-support tools cannot afford this kind of solipsism. Instead, by design the tools must be concerned with mutual intelligibility. Properties that will assist 2-way intelligibility are:

- We would want the machine to have access to all information the human decision-maker thinks is relevant in a form that the machine can use; and
- We would want human and machine to provide explanations in a form that the other can inspect and evaluate critically, and for each to respond meaningfully to that evaluation.

Both properties are easier to state than to achieve. Let us consider each in turn. For the first, the human decision-maker may not have a clear idea of knowledge that is relevant for the machine. In practice, we have to live with what could be potentially relevant, but then we have another problem: how is this information to be communicated to the machine? McCarthy [20] envisaged this would be done as statements in a formal language that would be directly manipulated by the machine. But this does not have to be necessarily the case. Instead, all that may be needed is for domain-knowledge to be translatable into a form that transforms some or all of the inputs of the ML system, for example: the data, utility function, structure or parameters in Fig. 1. However, in the short- to medium-term, we believe this will require the human decision-maker to have a working knowledge of the ML system, or to employ someone who does. In the longer term, neither of these options are practical, and decision-support tools will need mechanisms to receive information in natural language, and perform any manipulations to its inputs internally. Some progress is being made on processing information in a natural language (see for example, [34]), but we are still far from being able to do this well. Assuming we have the human-supplied information in some machine-usable form, the machine may still need to ask the decision-maker questions to clarify any ambiguities or inconsistencies. To resolve these would undoubtedly need the machine to be able to generate its own data, and ask questions about them. How should it communicate these questions and receive answers? Again, in the long-run, natural human-computer interaction techniques [9] seem inevitable.

In order for the human to evaluate critically the machine’s advice, the advice will have to employ concepts that the decision-maker can recognise. In
the near-term, the machine can achieve this in one of two ways. First, the machine can elect to employ only those concepts that are already known to the decision-maker. The identification of Covid patients in the previous section is an example: the features extracted from chest X-rays were restricted to those identified by a radiologist. A second way is for the machine to show instantiations through some textual or visual means. For example, ML systems that attempted to discover chess concepts showed board positions exemplifying the concept. The chess-expert may then be able to map the machine-identified concept to some part of their chess vocabulary (such as “this is really about Kings in opposition”). In the long-term, as the problems, data and ML systems get more complex, it will not be possible to engineer an adequate set of features beforehand, and mapping to known concepts would not be immediate. We expect this will entail a kind of dialectical exchange of questions and answers between the human and the machine, as the human decision-maker attempts to understand the why the machine is proposing what it does. So intelligibility of the machine’s explanation would be reached, but not without effort. Intelligibility of human explanations could prove even more difficult, especially if those explanations are in a natural language. This will may well require the machine to contain language models for approximating idealised forms of logical reasoning and contradiction detection, which can then form the basis of the machine’s refutation.

But while the issues are challenging, the problem is not insoluble. We have shown examples from the literature where attempts at intelligibility have yielded significant benefits. As decisions and data get more complex, it is evident that if an ML-based decision-support tool is to be of on-going value to the decision-maker, then we must design for both machine and human to learn from each other’s recommendations. Our 3Rs for embarking on the design of 2-way intelligible decision-support with ML are therefore: Refute, Revise, Repeat.

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