# Machine Explanations and Human Understanding

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Explanations are hypothesized to improve human understanding of machine learning models and achieve a variety of desirable outcomes, ranging from model debugging to enhancing human decision making. However, empirical studies have found mixed and even negative results. An open question, therefore, is under what conditions explanations can improve human understanding and in what way. Using adapted causal diagrams, we provide a formal characterization of the interplay between machine explanations and human understanding, and show how human intuitions play a central role in enabling human understanding. Specifically, we identify three *core* concepts of interest that cover all existing quantitative measures of understanding in the context of human-AI decision making: *task decision boundary, model decision boundary*, and *model error*. Our key result is that without assumptions about *task-specific intuitions*, explanations may potentially improve human understanding of model decision boundary, but they *cannot* improve human understanding of task decision boundary or model error. To achieve complementary human-AI performance, we articulate possible ways on how explanations need to work with human intuitions. For instance, human intuitions about the relevance of features (e.g., education is more important than age in predicting a person's income) can be critical in detecting model error. We validate the importance of human intuitions in shaping the outcome of machine explanations with empirical human-subject studies. Overall, our work provides a general framework along with actionable implications for future algorithmic development and empirical experiments of machine explanations.

CCS Concepts: • Computing methodologies → Philosophical/theoretical foundations of artificial intelligence; Cognitive science; Theory of mind; • Human-centered computing → HCI theory, concepts and models.

Additional Key Words and Phrases: machine learning, explanations, explainability, interpretability, human intuitions

## 1 INTRODUCTION

Although recent advances in deep learning have led to machine learning (ML) models with impressive performance [26, 42, 53], there are growing concerns about the black-box nature of these models. Explanations are hypothesized to improve human understanding of these models and achieve a variety of desirable outcomes, ranging from helping model developers debug [27], mitigating unfairness by surfacing undesirable model behavior [17, 55], to improving human decision making in critical societal domains [22, 23, 33, 34, 50, 61].

However, empirical experiments with human subjects show mixed results about the utility of machine explanations. As a positive result, the original LIME paper shows that feature importance allows developers to identify spurious features in *topic classification* and improve the model by removing these features [51]. In contrast, Lai and Tan [34] show that feature importance improves human performance slightly in *deceptive review detection*, but human-AI teams fail to outperform AI alone. In fact, this is just one example of many papers that fail to improve the performance of human-AI teams in a wide range of tasks, including recidivism prediction, deceptive review detection, and hypoxemia prediction [6, 12, 22, 23, 28, 33, 41, 50, 58, 59, 61]. An intriguing puzzle is thus what factors drive such mixed results and how we can derive generalizable insights from empirical evaluations of explanations.

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To resolve this puzzle, we need to reason about the interplay between machine explanations and human understanding. We argue that two key questions need to be addressed: 1) what human understanding do explanations strive to improve and how do they connect with the aforementioned desirable outcomes? 2) what role can explanations play in shaping human understanding? Answers to these questions will allow researchers to articulate the conditions under which explanations can improve human understanding and provide a basis for scientific discussions on whether findings can generalize across experiments. In comparison, aiming for an end-to-end hypothesis that directly connects explanations to a desirable outcome, such as "explanations can improve the performance of human-AI teams", does not articulate the mechanism of why explanations help. As a result, it becomes impossible to know whether a positive result can be generalized to a different setting or what is lacking in the current explanations in the case of a negative observation.

In this paper, therefore, we provide a formal understanding of the relationship between machine explanations and human understanding and describe how it can lead to actionable insights for researchers. We start by tackling the question of what human understanding we would like to achieve in the context of human-AI decision making.<sup>1</sup> We identify three core concepts of interest from existing literature: 1) *task decision boundary* (deriving the true label in the prediction problem, the key target for decision making both for humans and models [5, 7, 9, 10, 12, 18, 19, 21, 24, 29, 33, 34, 38, 46, 50, 59, 61]), 2) *model decision boundary* (simulating the model predicted label, evidence of strong human understanding of the model [2, 9, 14, 15, 18, 20, 25, 35, 37–39, 45, 46, 50, 52, 58]), and 3) *model error* (recognizing whether a predicted label is wrong, a useful intermediate variable in decision making and a central subject in trust [4, 5, 7, 9–12, 19, 21, 29, 33, 34, 38, 46, 50, 58, 59, 61]). These measures do not always correlate with one another. For example, with an easily simulatable model (e.g., two-level decision tree), we would observe high accuracy in simulating model predictions, but users may still not be able to detect model error if the task is challenging to users. To further demonstrate the central role of these core concepts, we discuss their relevance for different stakeholders, i.e., decision makers, decision subjects, model developers, and auditors.

To enable a rigorous discussion of how machine explanations can shape human understanding, we develop a theoretical framework with adapted causal diagrams. Causal diagrams help us reason formally about the core concepts as statistical variables and their approximations that people develop for human understanding. Focusing on local human understanding of core variables, we define a base diagram where there are no clear relations between human understanding of core variables. Depending upon what is shown to the person (e.g., the model's prediction on an instance), different causal relationships emerge among the core variables and their human approximations. To formalize this intuition, we introduce a graph operator, *show*, that articulates how assumptions/interventions (henceforth conditions) shape human understanding. We consider two conditions: 1) whether a person has the perfect knowledge of the task and 2) whether machine predicted labels are revealed. Going through these conditions yields a decision tree that describes different scenarios for human-AI decision-making [32].

We then incorporate machine explanations in the framework to vet the utility of explanations in improving human understanding. Our causal diagrams reveal the critical role of task-specific human intuitions in effectively making sense of explanations, providing some light on the mixed findings of behavioral research for different human-AI tasks. We first point out that existing explanations are all derived from model decision boundary. Although explanations can potentially improve human understanding of model decision boundary, they cannot improve human understanding of task decision boundary or model error without assumptions about task-specific intuitions. In other words, *complementary performance* (i.e., human+AI > human & human+AI > AI) is impossible without assumptions about task-specific human intuitions.

<sup>&</sup>lt;sup>1</sup>By the context of human-AI decision making, we refer to all tasks around decision problems, including model debugging and auditing, but exclude other types of human-AI collaboration such as creative writing.

To achieve complementary performance, we articulate possible ways that human intuitions can work together with explanations. For instance, human intuitions about the relevance of features (e.g., education is more important than age in predicting a person's income) can be critical in detecting model error (e.g., age is highlighted as the important feature instead of education).

Finally, we apply our framework to empirically validate the importance of human intuitions through human-subject studies. To allow for full control of human intuitions, we use a Wizard-of-Oz setup [16]. Our experimental results show:

1) when we remove human intuitions by anonymizing all features, humans are more likely to agree with predicted labels compared to the regular condition without anonymizing features; 2) in the regular condition, participants are more likely to agree with the predicted label when the explanation is consistent with human intuitions.

Our work contributes to the goal of developing a rigorous science of explanations [18]. While Doshi-Velez and Kim [18] proposes a taxonomy of evaluations, our goal is to develop a formal theoretical framework on *how* explanations can improve human understanding of these concepts, clarify the limitations of existing explanations, and identify future directions for algorithmic work and experimental studies on explanations. In summary, our main contributions are:

- We propose the first theoretical causal framework to enable a rigorous discussion of human understanding in the context of human-AI decision making;
- We point out the importance of human intuitions in developing and leveraging machine explanations, and identify
  actionable future directions for generating machine explanations;
- We provide the first empirical validation of how task-specific human intuitions affect human-AI decision making through human-subject experiments.

# 2 THREE CORE CONCEPTS FOR MEASURING HUMAN UNDERSTANDING

In this section, we identify three key concepts of interest in human-AI decision making: task decision boundary, model decision boundary, and model error. We present high-level definitions of these concepts and formalize them in §3.<sup>2</sup>

We use a two-dimensional binary classification problem to illustrate the three concepts of interest (Fig. 1). *Task decision boundary*, as represented by the dashed line, defines the mapping from inputs to ground-truth labels: inputs on the left are positive and the ones on the right are negative. *Model decision boundary*, as represented by the solid line, determines model predictions. Consequently, the area between the two boundaries is where the model makes mistakes. This yellow highlighted background captures *model error*, i.e., where the model prediction is incorrect. With a perfect model, the model decision boundary would be an exact match of the task decision boundary, and model error never happens. <sup>3</sup>

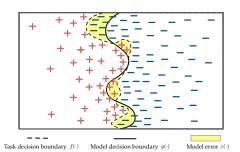


Fig. 1. Illustration of the three fundamental concepts using a binary classification problem. Task decision boundary (dashed line) defines the ground-truth mapping from inputs to labels. Model decision boundary (solid line) defines the model predictions. Model error (highlighted) represents where the model's predictions are incorrect.

To the best of our knowledge, we are not aware of any existing quantitative behavioral measure of human understanding that does not belong to one of these three concepts of interest.

<sup>&</sup>lt;sup>2</sup>In this work, we omit subjective measures.

<sup>&</sup>lt;sup>3</sup>We present a deterministic example for ease of understanding and one can interpret this work with deterministic functions in mind. In general, one can also think of model decision boundary, task decision boundary, and model error probabilistically.

Building on a recent survey [32], we identify 30 papers that: 1) use machine learning models and explanations with the goal of improving human understanding; and 2) conduct empirical human studies to evaluate human understanding with quantitative metrics. Although human-subject experiments can vary in subtle details, the three concepts allow us to organize existing work into congruent categories. We provide a reinterpretation of existing behavioral measures using the three concepts below; a detailed summary is in Appendix A.

Measuring human understanding of model decision boundary via human simulatability. A straightforward way of model decision boundary evaluation is to measure how well humans can simulate the model predictions, or in other words, the human ability of forward simulation/prediction [18]. Humans are typically asked to simulate model predictions given an input and some explanations [2, 9, 14, 15, 18, 20, 25, 35, 37–39, 45, 46, 50, 52, 58]. For example, given profiles of criminal defendants and machine explanations, participants are asked to guess what the AI model would predict [58].

Measuring human understanding of model decision boundary via counterfactual reasoning. Sometimes researchers measure human understanding of the decision boundary by evaluating participants' counterfactual reasoning abilities [20, 39]. Counterfactual reasoning investigates the ability to answer the 'what if' question. In practice, participants are asked to determine the output of a perturbed input applied to the same ML model [20]. Lucic et al. [39] asked participants to manipulate the input to change the model output.

Measuring human understanding of model decision boundary via feature importance. Additionally, Wang and Yin [58] also tested human understanding of model decision boundary via feature importance, specifically by (1) asking the participants to select among a list of features which one was most/least influential on the model's predictions and (2) specifying a feature's marginal effect on predictions. Ribeiro et al. [51] asked participants to perform feature engineering by identifying features to remove, given the LIME explanations. These can be viewed as a coarse inquiry into properties of the model's model decision boundary.

Measuring human understanding of task decision boundary and model error via human+AI performance. Similar to the application-grounded evaluation defined in Doshi-Velez and Kim [18], one of the most well-adopted evaluation measurement of human understanding is to measure human understanding of the task decision boundary through human+AI performance [5, 7, 9, 10, 12, 18, 19, 21, 24, 29, 33, 34, 38, 46, 50, 59, 61]. In those experiments, participants are shown machine predictions and explanations, then they are asked to give a final decision based on the information, with the goal of achieving complementary performance. For example, human decision-makers are asked to predict whether this defendant would re-offend within two years, given a machine prediction and explanations [58]. Note that for binary classification problems, measuring human understanding of the model error is equivalent to measuring human understanding of the task decision boundary if machine predictions are shown.

Measuring human understanding of model error through human trust. In some other cases, trust or reliance is introduced as a criterion reflecting the human understanding of the model error. Explanations are used to guide people to trust an AI model when it is right and not to trust it when it is wrong. Hence, by analyzing when and how often human follows machine predictions, trust can reflect the human understanding of the model error [10, 58, 61]. In other cases, the measure of human understanding of model error can be used as an intermediate measurement towards measuring task decision boundary [4, 5, 7, 9, 11, 12, 19, 21, 29, 33, 34, 38, 46, 50, 59], where human subjects are asked whether they agree with machine predictions.

#### 3 A THEORETICAL FRAMEWORK OF HUMAN UNDERSTANDING

Based on the three concepts mentioned above, we introduce a theoretical framework of human understanding in the context of human-AI decision making. We do not discuss machine explanations yet; instead, we formalize the relationship between task decision boundary, model decision boundary, and model error, as well as human understanding of them. This framework enables a rigorous discussion on human understanding as well as the underlying assumptions/interventions that shape the relationship between those understanding.

#### 3.1 Defining Core Functions and Human Understanding of them

Formally, the three concepts of interest are functions defined w.r.t. a prediction problem and a machine learning model:

- Task decision boundary is a function f: X → Y that represents the groundtruth mapping from an input X to the
  output Y.
- Model decision boundary is another function  $g : \mathbb{X} \to \mathbb{Y}$  that represents our ML model which outputs a prediction  $\hat{Y}$  given an input. g is usually trained to be an approximation of f. We assume that we are given a model g; the training process of g (and the connection between f and g) is not crucial for this work.
- Model error represents the model's error; it is an indicator of whether the model prediction differs from the groundtruth for an input:  $z(X, f, g) = \mathbb{I}[f(X) \neq g(X)], \forall X \in \mathbb{X}$ . We use z(X) for short when the omitted arguments f and g are clear from context, which maps an input X to whether the model makes an error Z.

We call them *core* functions as they underpin human understanding. We refer to the outputs of core functions for an instance X, Y,  $\hat{Y}$ , and Z as the three core variables. Note that the core functions do not involve any people; they exist even in absence of human understanding.

We use  $f^H$ ,  $g^H$ , and  $z^H$  to denote the human's *subjective* approximations of the core functions, each of them being a function with the same domain and codomain as its objective counterpart. These human approximations can be interpreted as mental models, influenced by the human's knowledge (both on the prediction problem and the ML model), and can change over time as the human-AI interaction progresses.

We can rephrase common cooperative tasks in human-AI decision making in terms of the core functions and human understanding grouped by stakeholders:

- For **decision makers** such as doctors, judges, and loan officers, the main goal is to improve their understanding of task decision boundary  $(f^H)$ .
- For decision subjects such as patients, defendants, and loan applicants, the object of interest can differ even for
  these three examples. Patients care about the task decision boundary more, while defendants and loan applicants
  may care about the model decision boundary and especially model error, and would like to figure out how they can
  appeal model decisions.
- Model developers might be most interested in model error, and the eventual goal is to change the model decision boundary.
- For algorithm auditors, the main goal is to figure out whether the model decision boundary and model error conform to laws/regulations.

The distance between core functions and their human approximations can be used as a measure for human understanding. Since human approximations are theoretical constructs that only exist in the human brain, we need to perform user studies to measure them. For example, we can ask a human to guess what the model would have predicted for a given input X; the human's answer  $\hat{Y}^H$  characterizes their *local* understanding of the model decision boundary. In the

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Variable	Function	Description
X	_	Input instance
Y	$f: \mathbb{X} \to \mathbb{Y}$	Task decision boundary
Ŷ	$g: \mathbb{X} \to \mathbb{Y}$	Model decision boundary
Z	$z:\mathbb{X} \to \mathbb{Z}$	Model error
$Y^H$	$f^H: \mathbb{X} \to \mathbb{Y}$	Human understanding of the task decision boundary
$\hat{Y}^H$	$g^H: \mathbb{X} \to \mathbb{Y}$	Human understanding of the model decision boundary
$Z^H$	$z^H: \mathbb{X} \to \mathbb{Z}$	Human understanding of the model error
Н	_	Task-specific human intuitions
E	_	Machine explanations

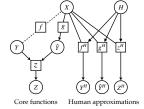


Table 1. A summary of notations.

Fig. 2. Visualizing the relations between core functions, local variables, and human approximations of them.

rest of the paper, one can interpret "human understanding" with this particular measurement of human approximations. Perfect human understanding thus refers to 100% accuracy in such measurement.

In the interest of space, we assume that the approximation functions remain static and examine a human's local understanding with our framework in the main paper; in other words, we assume that the human employs a consistent mental model for all instances and only reason about  $Y^H$ ,  $Z^H$ ,  $\hat{Y}^H$ . We note that improving human global understanding is often the actual goal in many applications, and encourage the reader to see discussions on global understanding in Appendix §D. Table 1 summarizes the notations for core functions and human understandings.

# 3.2 Causal Graph Framework for Core functions

To reason about human understanding, we need to understand how core functions relate to each other, and how interventions may affect human understanding. To do so, we adapt causal directed acyclic graphs (causal DAGs) to formalize a causal model for the core functions of human understanding. We start with a simple diagram (Fig. 2) without assumptions about human intuitions.<sup>4</sup>

Let us first look at core functions on the left in Fig. 2. We use a functional view to represent  $\hat{Y} = g(X)$ : we add a functional node (g in a square) on the edge from X to  $\hat{Y}$  to indicate that g controls the causal link from X to  $\hat{Y}$ . g is treated as a parent of  $\hat{Y}$ . As X is the input of g and does not affect g, there is no arrowhead from X to g. Alternatively, one can use a parametric view and use a node g to capture all variables in g and add g as a parent of g, in addition to g (see Appendix §B). We use the functional view because it simplifies the visualization, but it deviates slightly from the standard causal diagrams. g and g are connected with a dashed line through g since we do not assume the causal direction between them. g is the binary indicator of whether g and g are different. According to d-separation [48], g is independent of g given g and g are collider for g and g and g entails g in binary classification.

Next, in Fig. 2 on the right, we introduce task-specific intuitions, H, that defines human mental models of the core functions. We emphasize task-specific to capture intuitions about the current problem, as opposed to generic intuitions such as that humans can interpret saliency maps or humans can update their understanding over time. Fig. 2(b) shows a base version of how human intuitions relate to human understanding of core variables. For now, we do not make any assumptions about human intuitions, we simply connect human intuition with their understanding through  $f^H$ ,  $g^H$ ,  $z^H$ . As H directly influence  $f^H$ ,  $g^H$ ,  $z^H$ , there is an arrowhead in the links from H to  $f^H$ ,  $g^H$ ,  $z^H$ . Later, we will discuss more realistic instantiations, e.g.,  $Z^H$  when  $\hat{Y}$  is given.

Looking together at Fig. 2, d-separation suggests that human approximation of core variables are independent from core variables given X, without extra assumptions about human intuitions. Therefore, a key goal of our work is to articulate what assumptions we make and how they affect the causal diagrams.

<sup>&</sup>lt;sup>4</sup>Throughout this paper, *X* in the diagrams refer to a test instance that the model has *not* been trained on.

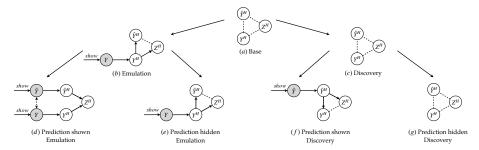


Fig. 3. Causal diagrams visualizing the relationship between a human's local understanding. With the base diagram at the root, we organize its realizations based on different conditions in a two-level decision tree. Undirected dashed lines represent ambiguous causal links. The bidirectional dashed line in subfigure (d) represents the correlation between  $\hat{Y}$  and Y potentially induced by the prediction model. Shaded nodes and their edges represent show operations.

#### 3.3 A New Operator

Next, we analyze human local understanding  $(Y^H, \hat{Y}^H, Z^H)$  on the right of Fig. 2). Without extra assumptions, the causal direction between  $Y^H, \hat{Y}^H, Z^H$  is unclear, because their generation process is controlled by the human brain, a black box. We visualize this ambiguity by connecting nodes with undirected dashed links in Fig. 3(a) as the base diagram.

The base diagram is not useful in its current state; in order to use the diagram to reason about human understanding, we need *realizations* of the base diagram where dashed links are replaced by solid, directional links. No realization is universally correct, and each realization requires certain assumptions or interventions, which we refer to as *conditions*.

Condition 1—emulation vs. discovery. To delineate the feasibility of various base diagram realizations, we introduce two conditions. The first condition is an assumption about human knowledge, i.e., that the human has perfect knowledge about task decision boundary; in other words,  $f^H$  perfectly matches f and  $Y^H = Y$  for all inputs. Problems where human labels are used as ground truth generally satisfy this condition, e.g., topic classification, reading comprehension, and object recognition. We follow Lai et al. [33] and call them emulation task, in the sense that the model is designed to emulate humans; by contrast, discovery problems are the ones humans do not have perfect knowledge of task decision boundary (e.g., deceptive review detection recidivism prediction). It follows that human understanding of task decision boundary is irrelevant in emulation tasks, but achieving complementary performance is a key goal in discovery tasks.

Condition 2—prediction shown vs. hidden. An alternative condition is an intervention that presents the model prediction  $\hat{Y}$  to the human. Given this information, a rational human would gain a perfect understanding of the *local* model decision boundary and always predict  $\hat{Y}^H = \hat{Y}$ .

**The** *show* **operator**. To describe the effect of applying these conditions, we introduce a new syntax for manipulating causal diagrams: the *show* operator. When *show* is applied to a core variable, that information becomes available to the human. For example,  $show(\hat{Y})$  means that the human can see the model prediction for X. This operation draws an equivalence between the core variable and the human approximated counterpart, assuming that the human is rational.

We introduce the new *show* operator as opposed to the standard *do* operator for two reasons. First, *show* operator introduces new variables to the causal diagram instead of setting the value of an existing variable (e.g., Y and  $\hat{Y}$  in Fig. 3 and E in §4). Second, the *show* operator can change the causal diagram as we reason about human understanding, including changing edges and variables. Notation-wise, *show* allows us to specify the condition for human approximations; for example,  $Y^H_{show}(\hat{Y})$  denotes the local understanding of task decision boundary given predicted label  $\hat{Y}$ .

<sup>&</sup>lt;sup>5</sup>Emulation and discovery can be seen as two ends of a continuous spectrum. The emulation vs. discovery categorization determines the set of causal diagrams that applies to the problem; this decision is at the discretion of practitioners that design experiments using our framework.

In Fig. 3, applying *show* operator leads to two changes: it adds a link from a core variable to the corresponding human approximation, and it removes influences from other human approximations. For example, under the emulation condition visualized in Fig. 3b, show(Y) adds a link from Y to  $Y^H$  and removes all other edges going into  $Y^H$ , effectively disambiguating the relation between  $Y^H$  and the two other variables.

## 3.4 Characterizing Relationship between Core Functions & Human Understandings

Fig. 3 visualizes the realizations of the base diagram under the two conditions and organizes them in a two-level decision tree. At the root, we have the base diagram. At the next level, we have two realizations based on whether condition 1 is satisfied: diagram (b) for emulation and diagram (c) for discovery. The branches at the leaf level are determined by condition 2, i.e., whether model prediction  $\hat{Y}$  is shown. Next, we unfold the effect of these two conditions.

**Effect of** show(Y). We observe differences in the diagrams between emulation and discovery tasks. First, human local understanding of task decision boundary  $Y^H$  is collapsed with Y in emulation tasks (Fig. 3b), so no edge goes into  $Y^H$ , and  $Y^H$  affects  $Z^H$  and  $\hat{Y}^H$ . However, in discovery tasks (Fig. 3c), since  $Y^H \not\equiv Y$ , the edge connections remain the same, i.e., we are unable to rule out any connections for now. Hence, human understanding of task decision boundary is usually not of interest in emulation tasks [14, 45]. In comparison, human understanding of both model decision boundary and task decision boundary is explored in discovery tasks [5, 19, 47, 58].

**Effect of**  $show(\hat{Y})$ . We start with emulation tasks, where the relationships are relatively straightforward because the human understanding of task decision boundary is perfect  $(Y^H \equiv Y)$ . When  $\hat{Y}$  is shown (Fig. 3d), human understanding of local predicted label becomes perfect, i.e.,  $\hat{Y}^H \equiv \hat{Y}$ . It follows that  $Z^H = I(Y^H \neq \hat{Y}^H) = I(Y \neq \hat{Y}) = Z$ . This scenario happens in debugging for emulation tasks, where model developers know the true label, the predicted label, and naturally whether the predicted label is incorrect for the given instance. It is clear that the desired understanding is not local, but about global model decision boundary. Refer to Appendix  $\hat{Y}$  for discussions on global understanding.

In comparison, when  $\hat{Y}$  is not shown (e.g., an auditor tries to extrapolate the model prediction), recall  $Y^H \equiv Y$  in emulation tasks, so  $Y^H$  can affect  $\hat{Y}^H$  and  $Z^H$ . As shown in Fig. 3e, the connection between  $\hat{Y}^H$  and  $Z^H$  remains unclear. In discovery tasks, when  $\hat{Y}$  is shown (Fig. 3f),  $\hat{Y}^H \equiv \hat{Y}$ . The relationships between  $Y^H$  and  $Z^H$ , however, remain unclear and can be potentially shaped by further information such as machine explanations. When  $\hat{Y}$  is not shown (Fig. 3g), we do not receive any new information in discovery tasks. Therefore, Fig. 3g is the same as the base diagram where all interactions between local understandings are possible, which highlights the fact that no insights about human understandings can be derived without any assumption or intervention.

**Implications.** Our framework reveals the underlying mechanism of human local understanding with two important conditions: 1) knowing the task decision boundary; and 2) showing machine predictions  $\hat{Y}$ . Such conditions allow us to rule out connections between human understanding of core variables. For example, in emulation with prediction shown, the relationship between all variables is simplified to a deterministic state.

Another implication is that we need to make explicit assumptions in order to make claims such as human performance improves because human understanding of the model error is better (i.e., humans place appropriate trust in model predictions). Because there exist dashed links between variables, for example, in discovery tasks with prediction shown, we can not tell whether it is  $Y^H \to Z^H$  or  $Z^H \to Y^H$ , nor can we tell from observational data without making assumptions. The alternative hypothesis to "appropriate trust  $\to$  improved task performance" is that  $\hat{Y}$  directly improves human understanding of the task decision boundary. In these ambiguous cases, the role of explanations can be seen as shaping which scenario is more likely, and it is critical to make the assumptions explicit to support causal claims.

#### 4 MACHINE EXPLANATIONS AND HUMAN INTUITIONS

Explanations of machine predictions can provide richer information about the model than predicted labels and are hypothesized to improve human understanding of core variables. In this section, we use our framework to discuss the utility and limitations of machine explanations. We first show that without assumptions about human intuitions, explanations can improve human understanding of model decision boundary, but not task decision boundary or model error. As a result, *complementary performance in discovery tasks is impossible*. We then discuss possible ways that human intuitions can allow for effective use of explanations and lay out several directions for improving the effectiveness of explanations. Our analyses highlight the importance of articulating and measuring human intuitions in leveraging machine explanations to improve human understanding.

## 4.1 Limitations of Explanations without Human Intuitions

Existing explanations are generated from g (Fig. 4(a)). We first introduce explanation (E) to our causal diagram. Since the common goal of explanation in the existing literature is to explain the underlying mechanism of the model, E is derived from g and thus we argue that explanation should have only one parent, g, among the core functions. For example, gradient-based methods use gradients from g to generate explanations [3, 54]. Both LIME [51] and SHAP [40] use local surrogate models to compute importance scores, and the local surrogate model is based on g. Counterfactual explanations [43, 57] typically identify examples that lead to a different predicted outcome from g. In all of these explanation algorithms, there is no connection between E and f or g.

In addition, there should be no connection between *E* and task-specific intuitions, *H*. Conceptually, only task-agnostic human intuitions are incorporated by existing algorithms of generating explanations. It is well recognized that humans cannot understand all parameters in a complex model, so promoting sparsity can be seen as incorporating some human intuition. Similarly, the underlying assumption for transparent models is that humans can fully comprehend a certain class of models, e.g., decision sets [35] or generalized linear models [13, 44]. In counterfactual explanations, it is assumed that by contrasting similar examples, people can recognize the differentiating feature and thus derive feature importance [31]. However, none of these assumptions about the human intuitions are about task decision boundary, model error, or human understanding of them.

Now we discuss the effect of explanations on human understanding without assuming any task-specific human intuitions (i.e., without adding new edges around *H*).

Explanations can improve human understanding of model decision boundary, but cannot improve human understanding of task decision boundary or model error. We start with the cases where predicted labels are not shown. Fig. 4(b1) shows the subgraph related to  $\hat{Y}$  and  $\hat{Y}^H$  from Fig. 2. Without explanations,  $\hat{Y}$  and  $\hat{Y}^H$  are independent given X. Fig. 4(b2) demonstrates the utility of machine explanations. Because of the shared parent (g) with  $\hat{Y}$ , the introduction of E can improve human understanding of model decision boundary,  $\hat{Y}^H$ . Note that our discussion on improvement is concerned with the upper bound of understanding assuming that humans can rationally process information if the information is available. This improvement holds regardless of the assumption about  $Y^H$  (i.e., both in emulation and discovery tasks).

When predicted labels are shown, improving human local understanding of model decision boundary is irrelevant, so we focus on task decision boundary and model error. In emulation tasks (show(Y)), and once provided with predicted labels  $(show(\hat{Y}))$ , humans would achieve perfect accuracy at approximating the three core variables. Because this perfect local understanding also holds in emulation tasks without machine explanations, explanations have no practical

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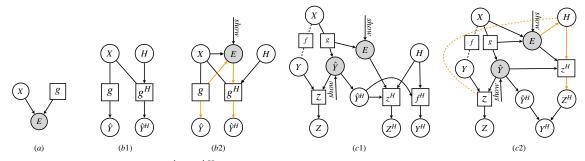


Fig. 4. (a) E is generated from g. (b1)  $\hat{Y}$  and  $\hat{Y}^H$  are independent given X. (b2) The utility of E: E can improve human understanding of model decision boundary. (c1) E cannot improve human understanding of task decision boundary and model error without human intuitions. (c2) Combined with human intuitions, E can improve task decision boundary and model error. We use orange lines to highlight the links that lead to positive utility of E. We omit links from X to  $f^H$  and  $z^H$  for simplicity.

utility in this setting. That is, machine explanations cannot help humans achieve better approximation than showing predicted labels in local understanding. Note that this is only true for local human understanding, explanations can still potentially improve global understanding, which explains the success of model debugging in an emulation task, topic classification in Ribeiro et al. [51].

In comparison, Fig. 4(c1) shows the diagram for the more interesting case, discovery tasks. Explanations are often hypothesized to improve human decision making, i.e., bringing  $Y^H$  closer to Y. However, if we do not make assumptions about human intuitions, although E can affect  $f^H$ , it cannot bring any additional utility over showing  $\hat{Y}$ . The reason is that d-separation indicates that given the prediction g and X, the explanation E is independent of Y and Z. That is, E cannot provide any extra information about Y (task decision boundary) and Z (model error) beyond the model. Moreover, the model cannot provide any better approximation of Y than  $\hat{Y}$ . Alternatively, we can also think of the functional form. If we cannot make any assumption about H,  $g^H_{show(E,\hat{Y})}$  is no different from  $g^H_{show(\hat{Y})}$ . It is plausible for a person to follow machine predictions when they have no intuitions about a task at all. Therefore, complementary performance is impossible without extra assumptions about human intuitions.

As a concrete example, consider the case of deceptive review detection with an alien who does not understand English (i.e., guaranteeing that there is no intuition about this task). Machine explanation such as feature importance cannot provide meaningful information to the decision maker, i.e., the alien. We will design experiments in §5 to simulate a case without human intuitions.

#### 4.2 Explanation + Human Intuitions

Next, we discuss how explanations can be integrated with human intuition to achieve an improved understanding in discovery tasks (recall that  $Z^H$  and  $Y^H$  are entailed in emulation tasks when  $\hat{Y}$  is shown). We have seen that E itself does not reveal more information about Y or Z beyond g. Therefore, an important role of E is in shaping human intuitions. We present two possible ways.

Activating prior knowledge about model error. *E* can activate prior human knowledge that can reveal information about model error (Fig. 4(c2)). We examine two sources of such prior knowledge that is concerned with *what* information should be used and *how*. First, human intuitions can evaluate *relevance*, i.e., whether the model leverages relevant information from the input based on the explanations. For example, human intuitions recognize that "chicago" should not be used for detecting deceptive reviews or that race should not be used for recidivism prediction, so a model prediction

relying on these signals may be more likely wrong. The manifestation of relevance depends on the explanation's form: feature importance directly operates on pre-defined features (e.g., highlighting race for tabular data or a word in a review), example-based explanations or counterfactual explanations narrow the focus of attention to a smaller (relevant) area of the input. Note that the intuition of relevance only applies to the input and does not consider the relation between the input and output.

Second, human intuitions can evaluate *mechanism*, i.e., whether the relationship between the input and the output is valid. Linear relationship is a simple type of such relation: human intuitions can decide that education is negatively correlated with recidivism, and thus that a model making positive predictions based on education is wrong. In general, mechanisms can refer to much more complicated (non-linear) relations between (intermediate) inputs and labels.

Fig. 4(c2) illustrates such activations in causal diagrams. The link from E to H highlights the fact that human intuitions when E is shown are different from H without E because these intuitions about model error would not have been useful without machine explanation. We refer to H in Fig. 4(c2) as  $H_{show(E)}$ . If  $H_{show(E)}$  is correlated with Z (indicated by the dash link), then  $Z^H$  is no longer independent from Z (e.g., education should be negatively correlated with recidivism) and can thus improve  $Y^H$  because Z is a collider for Y and  $\hat{Y}$ , leading to complementary performance. It is important to emphasize that this potential improvement depends on the quality of  $H_{show(E)}$  (e.g., whether education is actually negatively correlated with recidivism). The lack of useful task-specific human intuitions can explain the limited human-AI performance in deceptive review detection [34].

Expanding human intuitions. Another way that explanations can improve human understanding is by expanding human intuitions (see Fig. 10 in the appendix). Consider the example of "Chicago" as an important indicator for deceptive reviews in Lai et al. [33]. "Chicago" is reliably associated with deceptive reviews in this dataset are for two reasons: 1) people are less likely to provide specific details when they write fictional texts (theory I); 2) deceptive reviews in this dataset are written by crowdworkers on mechanical Turk for hotels in Chicago (fact II). Highlighting the word for "Chicago" (relevance) and its connection with deceptive reviews (mechanism) is counterintuitive to most humans because this is not part of common human intuitions. But if machine explanations can expand human intuitions and help humans derive theory I, this can lead to improvement of the human understanding of task decision boundary (i.e., humans develop new knowledge from machine explanations). Formally, the key change in the diagram for this scenario is that E influences human intuitions in the next time step  $H_{t+1}$ .

# 4.3 Towards Effective Explanations for Improving Human Understanding

Machine explanations are only effective if we take into account human intuitions. We encourage the research community to advance our understanding of task-specific human intuitions, which are necessary for effective human-AI decision making. We propose the following recommendations.

Articulating and measuring human intuitions. It is important to think about how machine explanations can be tailored to either leveraging prior human knowledge or expanding human intuitions, or other ways that human intuitions can work together with explanations.

First, we need to make these assumptions about human intuitions explicit so that the research community can collectively study them rather than repeating trial-and-error with the effect of explanations on an end outcome such as task accuracy. We recommend the research community be precise about the type of tasks, the desired understanding, and the required human intuitions to achieve success with machine explanations.

Second, to make progress in experimental studies with machine explanations, we need to develop ways to either control or measure human intuitions. This can be very challenging in practice. To illustrate a simple case study, we will present an experiment where we control and measure human intuitions in human-AI decision making.

**Incorporate** f **and** z **into explanations.** An important premise for explanations working together with human intuitions is that machine explanations capture the mechanism or the relevance underlying the model. Indeed, faithfulness receives significant interest from the ML community for the sake of explaining the mechanisms of a model. However, faithfulness to g alone is insufficient to improve human understanding of task decision boundary and the model error.

In order to effectively improve human understanding of f and z, it would be useful to explicitly incorporate f and z into the generation process of E. For example, a basic way to incorporate z is to report the error rate in a development set. In the case of deceptive review detection, it could be when "Chicago" is used as an important feature, the model is 90% accurate. This allows humans to have access to part of model error and have a more accurate  $Z^H$ .

To summarize, we emphasize the following three takeaways:

- Current machine explanations are mainly about the model and its utility for human understanding of the task decision boundary and the model error is thus limited.
- Human intuitions are a critical component to realize the promise of machine explanations in improving human understanding and achieving complementary performance.
- We need to articulate our assumptions about human intuitions and measure human intuitions, and incorporate
  human intuitions, f, and z into generating machine explanations.

## 5 EXPERIMENTS

To illustrate an application of our proposed framework, our experiments test two hypotheses about the impact of human intuition on their interaction with machine explanations. First, when people do not have sufficient intuition to judge whether the model is correct, they are more likely to agree with the model (H1; see discussion on Fig. 4(c1)). Second, when people do have intuition, they are more likely to agree with the model when model explanations are consistent with their intuitions (H2; see discussion on Fig. 4(c2)).

To simulate real-world decision making, we follow the standard cooperative setting where the participants make predictions with the assistance of both model prediction and feature importance explanation. We use a synthetic model that allows us to create feature importance explanations such that either the participant has no intuition about the highlighted feature or the highlighted feature importance agrees with the participant's intuition.

## 5.1 Experiment Design

We focus on the key considerations in this section and more details about experiments can be found in Appendix §F. **Task: income prediction.** Our hypotheses are about how people's decisions are affected by the the alignment between their intuitions and the information presented about the model. So it's crucial that we can manipulate this alignment and control for confounders. Inspired by the Adult Income dataset [8], we choose the task of predicting a person's annual income based on their profile because people generally have intuitions about what factors determine income but are unlikely to know every person's income (hence a discovery task). We simplify the available features so that we can control for confounders. In our version, each profile contains only two attributes, age and education, and the participant need to make a binary prediction: whether the person's annual income is above or below \$50K.



Fig. 5. Screenshots of the interfaces for the anonymized group (a) and the regular group (b).

**Human intuition in income prediction.** Following §4.2, we consider human intuitions on relevance and mechanism. We define relevance (**R**) as the intuition that education is more important than age, and mechanism (**M**) as the intuition that income positively correlates with both features.

To better understand what these intuitions entail, let's consider Alice who believes **R** and **M**. For a profile with high education and low age, as Alice believes that education is more important than age (**R**), she will rely more on education; as she believes that education positively correlates with income, she will likely predict high income without any AI assistance. In Fig. 6, We use the background color to represent Alice's likely predictions: blue for high income and red for low income. When machine prediction and explanation are shown, these intuitions can be used to evaluate the consistency of explanations.

Alignment with human intuition. Next, we explain how we implement "alignment with intuition", still using participant Alice as the example. Intuitively, alignment with  $\mathbf{R}$  is determined by whether the explanation highlights the right feature. Since  $\mathbf{R}$  specifies that education is more important than age, a feature importance explanation that's aligned with  $\mathbf{R}$  should highlight education. Similarly, alignment with  $\mathbf{M}$  is determined by whether the model prediction is consistent with the highlighted feature: if the highlighted feature has a high value, the model should predict high income. In Fig. 6, we use a cross to visualize the violation of  $\mathbf{R}$  and border for the violation of  $\mathbf{M}$ . Note that even if the explanation violates  $\mathbf{R}$  (i.e., highlighting age instead of education),  $\mathbf{M}$  can be supported if high age  $\rightarrow$  high income or low age  $\rightarrow$  low income.

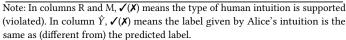
**Measuring human intuitions.** Participants may not necessarily hold these assumed intuitions (i.e., **R** and **M**), we thus measure human intuitions by asking participants about which feature is more important and whether the correlation is positive (see Appendix §F.4).

**Removing human intuition.** To study H1, we need to "remove" human intuitions. To do that, we anonymize the features (education and age) to feature A and feature B. Fig. 5a provides an example profile with removed intuitions. As a result, participants should have limited intuitions about this task, especially on relevance.

**Synthetic data.** To understand human decision making with the information provided from the model, we consider four groups of data in the table in Fig. 6: AB are consistent with both **R** and **M**, CD violates **R**, EF violates **M**, and GH violates **R** and **M**. Fig. 6 also presents a pictorial view. A-H enumerates all possible combinations of logically consistent explanations and predictions in the two off-diagonal quadrants. We focus on these two quadrants because 1) relevance does not matter for profiles that are high education & high age or low education & low age and 2) participants are more likely to ignore information from our models.

Specifically, we construct 'high education low age' samples as masters with age varying from 23 to 26. 'low education high age' samples are middle school with age varying from 46 to 49. To avoid the task being too artificial, we use

R	M	Ŷ	Identifier	Education	Age	Prediction	Explanation
1	/	1	• A • B	High	Low	>50K	Education Education
X	,	Х	● B	Low High	High Low	<50K <50K	Age
^	•	^	× D	Low	High	>50K	Age
	Х	х	• E	High	Low	<50K	Education
•	^	^	o F	Low	High	>50K	Education
×	х	,	⊗ G	High	Low	>50K	Age
^	^	•	<b>8</b> H	Low	High	<50K	Age



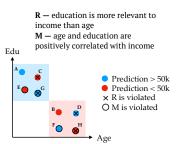


Fig. 6. We present our instances on the left and visualize them on the right. The background color represents Alice's likely predictions: blue (red) means > 50K (< 50K).

different ages for A-H for a participant. To further remove the potential effect due to the differences between ages, we create two groups of data so that the average age is the same for ABCD and EFGH. We randomly assign participants to a data group and ensure that each group is assigned to a similar number of participants.

**Agreement** as the evaluation metric. Since our hypotheses are formed around the agreement between human and model predictions, the focus is on model error. We infer  $Z^H$  by measuring the agreement between  $Y^H$  and  $\hat{Y}$ .

**Summary.** To summarize, there are two groups in our experiment, *regular* and *anonymized*. Each participant sees eight (ABCDEFGH) randomly shuffled examples. Since we evaluate two intuitions, we extend our two main hypotheses into the following four. We use agreement(·) to represent the average agreement on multiple data groups.

- **H1** (Over-reliance without intuition): Without sufficient intuition, people tend to blindly follow model predictions: agreement(anonymized) > agreement(regular).
- **H2a** (Alignment with **R** correlates with agreement): In the regular group, people are more likely to agree with model predictions when **R** is supported: agreement(AB) > agreement(CD).
- **H2b** (Alignment with **M** correlates with agreement): In the regular group, people are more likely to agree with model predictions when **M** is supported: agreement(AB) > agreement(EF).
- **H2c** (Alignment with **R** & **M** increases agreement): In the regular group, people are more likely to agree with model predictions when their intuitions are supported: agreement(AB) > agreement(GH).

For  $\mathbf{H1}$ , we use t-test to compare subjects in different conditions. For  $\mathbf{H2}$ , we have a within-subject design and use paired t-test to compare the agreement rate of the same participants for instances with different identifiers.

Limited validity of H2a, H2b for evaluating explanation consistency. We emphasize that although H2a and H2b are reasonable hypotheses, they cannot support the causal effect of explanation consistency. As shown in Fig. 3(f), the link between  $Y^H$  and  $Z^H$  is unclear in discovery tasks when predicted labels are shown. With our simplified setup, when only  $\mathbf{R}$  or  $\mathbf{M}$  is violated,  $Y^H$  is different from  $\hat{Y}$  without any assistance. Even if explanation does not shape H (Fig. 4(c1)) (i.e., humans ignore machine explanations), H2a and H2b can hold. In contrast, H2c can only hold when explanation works together with human intuition and  $Z^H \to Y^H$  (Fig. 4(c2)). In other words, as predictions are the same in GH as AB, any observed difference should be attributed to the effect of explanations. This discussion showcases the utility of our framework in experiment design.

**Study details.** We use crowdsourcing platform Prolific<sup>6</sup> and recruit 242 participants; 136 in the regular group, 106 in the anonymized group, following our power analysis (participant demographics in the appendix). Among the regular,

<sup>&</sup>lt;sup>6</sup>https://prolific.co

70 hold the assumed intuitions. Participants are first presented with brief information about the study and a consent form. Next, for the regular group, to measure their intuitions, they are asked about which feature is more important and whether the correlation is positive. For anonymized group, they skip this step. Then, participants proceed to complete the main part of the study, in which they answer 8 adult income prediction questions. The order of instances is randomized across participants. As a final step, they complete an exit survey.

## 5.2 Results

**H1 (Over-reliance without intuition).** In order to compare the agreement across two conditions (anonymized vs. regular group), we compute user-level agreement in each condition and run the independent t-test between users in the two conditions. Consistent with H1, our results show that users in anonymized group are more likely to agree with AI compared with users in regular group (t = 7.29, p < 0.001). The average agreement rate for users in no intuition group is as high as 70.64%, compared to 54.32% in regular group. In other words, without any strong intuitions about the underlying task, humans over-rely on AI predictions.

**H2a** (Alignment of R). For the rest of the hypotheses, we use paired t-test only on the users that hold the assumed intuitions in Fig. 6. We first investigate the agreement of **R**. Consistent with H2a, the agreement of AB is 90.71%, much higher than CD (25.00%). The difference is statistically significant (t = 14.25, p < 0.001).

**H2b** (Alignment with M). Similarly, we investigate agreement for alignment with M. Consistent with H2b, the agreement with AB is 90.71%, much higher than that with EF (22.14%). The difference is statistically significant (t = 15.01, p < 0.001).

**H2c** (Alignment with R & M; explanation consistency). H2a and H2b can hold even when participants ignore machine explanations. Our final hypothesis controls for the predicted label and examines the role of explanations. Consistent with the hypothesis, the average agreement rate of AB is 90.71% and GF is 83.57%, and the difference is statistically significant (t = 2.44, p = 0.017). This result is consistent with early work on explanation coherence [56].

In summary, results from our experiment have confirmed all the hypotheses, including H1 and H2c, and demonstrate how task-specific human intuitions shape the outcome of a study on the effect of machine explanations.

## 6 CONCLUSION

In this work, we propose the first theoretical work to formally characterize the interplay between machine explanations and human understanding. We identify core concepts of human understanding and reveal the utility and limitations of machine explanations. By focusing on explaining the model, current machine explanations cannot improve human understanding of task decision boundary and model error in discovery tasks. Our work highlights the important role of human intuition. First, we recommend the research community explicitly articulate human intuitions involved in research hypotheses. Hypotheses such as "explanations improve human decisions" cannot contribute generalizable insights, because they can hold or fail depending on human intuitions. Second, we identify future directions for algorithmic development and experimental design. We need to take into account task-specific human intuitions in algorithms that generate machine explanations and develop methods to measure human intuitions and characterize the changes resulting from machine explanations in experimental design.

**Limitations.** Our theoretical framework is only a first step towards understanding the interplay between machine explanations and human understanding. For instance, we do not consider the effect of showing  $\hat{Y}$  on human intuitions. Our discussions are mostly based on information entailed by causal diagrams without accounting for psychological biases in human intuitions (e.g., issues related to numeracy [34, 49]).

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#### A A SUMMARY OF RECENT EMPIRICAL STUDIES

We surveyed literature of recent empirical studies that include quantifiable metric for evaluating human understanding with machine explanations. In Table 2 we present a summary of recent empirical studies and provide a reinterpretation with the three core concepts: model decision boundary g, model error z, and task decision boundary f, as we defined in the main paper.

## **B PARAMETRIC VIEW**

An alternative parametric view of Fig. 2 using  $\theta$  to represent all the parameters of a ML model g is given in Fig. 7. This view does not highlight that human global understanding of core functions should be functions.

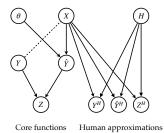


Fig. 7. Parametric view of Fig. 2. We introduce  $\theta$  to represent the parameters of the ML model q and remove all the function notes.

#### C GATE NOTATION FOR THE show OPERATOR

Our *show* operator can be rewritten using gate notation [60]. For example, Fig. 8 shows the diagram under the emulation condition; this diagram is equivalent to Fig. 3(b) which uses our *show* notation. Since the gate is just an intervention written differently, a *show* operation can also be rewritten as a regular intervention. As a corollary, *show* does not represent conditional probability: in  $\mathbb{E}[Y^H = Y|show(\hat{Y})]$  and  $\mathbb{E}[Y^H = Y]$ ,  $Y^H$  is generated by two distinct processes.

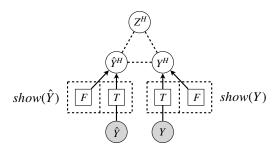


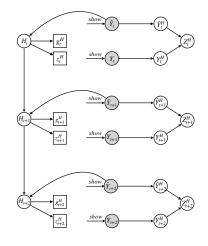
Fig. 8. The partial realization of the base diagram under the emulation condition, visualized using gate notation; the semantics of the diagram is equivalent to Fig. 3.b which uses our *show* operation.

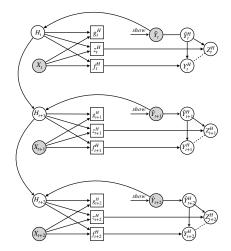
## **D** GLOBAL UNDERSTANDING

Similar to §3.4, we discuss how interventions and assumptions can shape human global understanding. We discuss the two representative settings with concrete examples in (Fig. 9) and the other settings are similar to derive.

	Model		Explanations	<i>g</i>	z	f
[1]	Generalized additive models	Shown	Global feature importance (shape function of GAMs)	1	Х	X
[36]	Decision trees/random forests	Shown	Rule-based explanations (tree-based explanation); Counterfactual explanations (counterfactual examples)	/	Х	X
14]	Convolution Neural Networks	Hidden	Local feature importance (attention, gradient-based)	✓	Х	X
15]	Decision trees/random forests	Shown	Local feature importance (perturbation-based SHAP)	1	X	X
45]	Logistic regression; Shallow (1- to 2-layer) neural networks	Hidden	Local feature importance (gradient-based, perturbation-based (LIME))	/	X	X
10]	Wizard of Oz	Shown	Model uncertainty (classification confidence (or probability))	Х	1	/
50]	Linear regression	Shown	Presentation of simple models (linear regression); Information about training data (input features or information the model considers)	1	/	•
5]	RoBERTa; Generalized additive models (GAMs)	Shown	Model uncertainty (classification confidence (or probability)); Local feature importance (perturbation-based (LIME)); Natural language explanations (expert-generated rationales);	X	/	•
58]	Logistic regression	Shown	Example-based methods (Nearest neighbor or similar training instances); Counterfactual explanations (counterfactual examples); Global feature importance (permutation-based);	/	/	×
61]	Decision trees/random forests	Shown	Model uncertainty (classification confidence (or probability)); Local feature importance (perturbation-based SHAP); Information about training data (input features or information the model considers)	X	/	•
7]	Logistic regression	Shown	Natural language explanations (model-generated rationales)	Х	/	,
38]	Support-vector machines (SVMs)		Local feature importance (coefficients)	1		
39]	Decision trees/random forests	Hidden	Counterfactual explanations (contrastive or sensitive features)	1		
24]	Recurrent Neural Networks	Shown	Model uncertainty (classification confidence (or probability))	Х		
]	Wizard of Oz	Mixed	Example-based methods (Nearest neighbor or similar training instances)			
52]	VQA model (hybrid LSTM and CNN)	Hidden	Rule-based explanations (anchors)	/		
20]	Logistic regression; Decision trees/random forests; Shallow (1- to 2-layer) neural networks		$Counterfactual\ explanations\ (counterfactual\ examples);\ Presentation\ of\ simple\ models\ (decision\ trees,\ logistic\ regression,\ one-layer\ MLP)$	✓	X	X
46]	Other deep learning models	Shown	Local feature importance (video features)	1	1	/
59]	Decision trees/random forests	Hidden	Model uncertainty (classification confidence (or probability)); Local feature importance (perturbation-based SHAP)	X	✓	•
34]	Support-vector machines (SVMs)	Shown	Example-based methods (Nearest neighbor or similar training instances); Model performance (accuracy)	X	/	/
29]	Other deep learning models	Shown	Model uncertainty (classification confidence (or probability)); Local feature importance (gradient-based)	X	/	/
21]	Other deep learning models	Shown	extractive evidence	Х	1	/
19]	Generalized additive models (GAMs)	Shown	Model uncertainty (classification confidence (or probability)); Global example-based explanations (prototypes)	X	/	•
11]	Wizard of Oz	Shown	Model uncertainty (classification confidence (or probability))	Х	1	Х
35]	Bayesian decision lists	Hidden	Rule-based explanations (decision sets)	✓	Х	Х
33]	BERT; Support-vector machines (SVMs)	Shown	Local feature importance (attention); Model performance (accuracy); Global example-based explanations (model tutorial)	X	/	/
2]	Convolution Neural Networks	Hidden	Local feature importance (propagation-based (LRP), perturbation-based (LIME)) $$	1	X	Х
12]	Recurrent Neural Networks	Shown	Local feature importance (attention)	X	1	/
25]	Other deep learning models	Shown	Local feature importance (perturbation-based (LIME)); Rule-based explanations (anchors); Example-based methods (Nearest neighbor or similar training instances); Partial decision boundary (traversing the latent space around a data input)	1	X	X
51]	Support-vector machines (SVMs) and Inception neural network	Shown	Local feature importance (perturbation-based (LIME))	/	X	Х

Table 2. A summary of recent empirical studies measuring human understanding with machine explanations. The papers are sorted by time, starting form the newest. Note: columns g, z, and f mean model decision boundary, model error, and task decision boundary respectively.  $\checkmark$  (or  $\checkmark$ ) means the study measures (or does not measure) the corresponding type of human understanding.





- $(a) \ {\it Emulation: prediction shown (e.g.\ model\ debugging)}$
- (b) Discovery: prediction shown (e.g. AI assisted decision making in recidivism task)

Fig. 9. (a): Emulation task with prediction shown; (b): Discovery task with prediction shown. We use the dotted arrow to represent the temporal updates of human global understanding. In each of the setting, we illustrate 3 time steps from t to t + 2.

**Emulation tasks with machine prediction shown (Fig. 9(a)).** We start with a simple example, emulation tasks with machine prediction shown. Model debugging for developers is one of the examples. In this case, human intuition at time step t derives human global understanding  $g^H$  and  $z^H$  directly. Since it is an emulation task,  $f^H$  is not of interest, we omit it in the graph. For human local understanding, as  $\hat{Y}$  is shown,  $\hat{Y}^H \equiv \hat{Y}$ . Also, given the emulation assumption,  $Y^H \equiv Y$ . We add subscript t to indicate time steps.

This scenario captures the dynamics of debugging. At the human local understanding level, Fig. 9(a) at each time step looks the same as Fig. 3(d). As we have discussed, the relationship between local variables is deterministic. Knowing whether the model is correct for this single case is not particularly useful for debugging, but the key difference from the local version (Fig. 3(d)) is the edge from observations ( $\hat{Y}_t$ ) to human intuition  $H_t$  and the temporal updates of human intuitions (the edge from  $H_t$  to  $H_{t+1}$ ). In other words, model developers can update their belief of the model error  $z^H$  and the decision boundary  $g^H$  and decide the scope of this bug and whether this is a bug that needs to be fixed or can be fixed. The case of debugging highlights that global understandings are often the targets in human-AI interaction and updates in human belief is critical for understanding changes in global understanding.

Explanation (E) can be incorporated in this figure and increase the connection between  $g^H$  and g because g is a parent of E.

**Discovery task with prediction shown (Fig. 9b).** A concrete example of this scenario is AI-assisted decision making in the recidivism task [30], where judges make bailing decisions giving risk estimation ( $\hat{Y}$ ). The update in  $f^H$  indicates the fact that we are interested in improving global human understanding of task decision boundary. Similar to the local case, we do not know the exact relationship between  $Z^H$  and  $Y^H$  for the local variable. Therefore, an alternative path to improve  $Y^H$  is by improving global human understanding of model error ( $z^H$ ), then  $Z^H$ , leading to  $Y^H$  with  $\hat{Y}$  shown.

Similar to our discussion in §4, by showing machine predictions, human global understanding of  $g^H$  can be updated. However, it is impossible to see updates on  $z^H$  and  $f^H$  beyond g since human understanding is bounded by the ML model without assumptions about human intuitions. Combined with human intuitions and machine explanations E,  $z^H$  and  $f^H$  can be potentially updated.

**Implications.** The first takeaway is that improving global understanding is often the actual target of interventions. For instance, in emulation tasks with machine predictions shown, although local understandings have deterministic relations with each other, the key open question lies in how understanding local error relates to updates in the global understanding of model error.

Second, in order to improve global understanding, it is critical to understand the updates in human global understanding. Interventions are ideally designed so that  $f^H \sim f$ ,  $g^H \sim g$ ,  $z^H \sim u$ , depending on the application. Therefore, we observe that showing predicted labels only reveals information about g, and the information related to f and g is constrained by g. This observation highlights the limited utility of showing predicted labels.

Finally, our framework shows that there does not have to be links between  $f^H$ ,  $g^H$ , and  $z^H$ . Although we may often be interested in conclusions such as calibrating trust improves human performance, the causal link may be unidentifiable and this relationship can also change over time. This observation reveals a fundamental limit in understanding the effect of machine explanations on human understanding. That said, it is possible to identify a causal relation between  $Z^H$  and  $Y^H$  by making additional assumptions on the diagrams (e.g., there is no temporal updates in human mental models, in other words, all time steps are independent of each other).

#### **E EXPANDING HUMAN INTUITIONS**

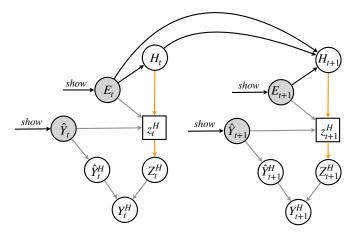


Fig. 10. Explanations E help expanding human intuitions by influencing human intuitions in the next time step.

## **F EXPERIMENT DETAILS**

#### F.1 Data

Table 3 shows the data instances we constructed and used in our experiment.

# F.2 Participants

In the end, we recruited 242 participants via Prolific, 106 in anonymized group, and 136 in regular group. Among the regular participants, 70 hold the assumed intuitions. Participants' age range from 18 to 79 with an average of 38. There are 121 female and 121 male participants. Participation was limited to adults in the US and first language is English. We

Instance ID	Education	Age	Feature A	Feature B	Predicted label (?\$50K)	Explanation	Identifier
1	Masters	25	0.85	0.13	>	Education	• A1
2	Masters	24	0.85	0.10	>	Education	• A2
3	Middle school	46	0.15	0.83	<	Education	<ul><li>B1</li></ul>
4	Middle school	49	0.15	0.93	<	Education	<ul><li>B2</li></ul>
5	Masters	26	0.85	0.17	<	Age	<b>⊗</b> C1
6	Masters	23	0.85	0.07	<	Age	<b>⊗</b> C2
7	Middle school	48	0.15	0.90	>	Age	<b>⊗</b> D1
8	Middle school	47	0.15	0.87	>	Age	<b>∞</b> D2
9	Masters	23	0.85	0.07	<	Education	<b>●</b> E1
10	Masters	26	0.85	0.17	<	Education	<b>●</b> E2
11	Middle school	47	0.15	0.87	>	Education	F1
12	Middle school	48	0.15	0.90	>	Education	<ul><li>F2</li></ul>
13	Masters	24	0.85	0.10	>	Age	<b>⊗</b> G1
14	Masters	25	0.85	0.13	>	Age	<b>⊗</b> G2
15	Middle school	49	0.15	0.93	<	Age	<b>⊗</b> H1
16	Middle school	46	0.15	0.83	<	Age	<b>⊗</b> H2

Table 3. The data instances used in our experiment.

also prescreen participants based on their approval rate (97% to 100%). The median time taken for each participant is 3.32 minutes and they are paid \$0.60, which leads to an hourly payment of \$10.85.

# F.3 Participants' agreement report

In table 4, we report participants' average agreement across different groups and different categories (identifiers) of instances.

In anonymized, we average 106 participants. Each participant did one question from each data instance category (identifier). In regular, we average

Identifier	Agreement (anonymized)	Agreement (regular)
• A	40.75%	85.71%
<ul><li>B</li></ul>	45.26%	95.71%
<b>8</b> C	41.41%	32.86%
<b>×</b> D	39.31%	17.14%
• E	47.25%	28.57%
o F	48.70%	15.71%
<b>⊗</b> G	48.45%	74.29%
<b>⊗</b> H	48.70%	92.86%

Table 4. Participants' agreement by the identifier in anonymized group

# F.4 User interface design

**Task description and attention check.** After participants agree with the online consent form, they will be re-directed to a page including a description of the task and an attention check, as shown in Fig. 11.

**Measuring human intuitions.** For regular group, participants are re-directed to the preliminary questionnaire page after they read the task description and passed the attention check. We calibrate human intuition in terms of relevance (R) and mechanism (M) using the 4 questions as shown in Fig. 12.



In this task, you will go through the **profiles of 8 people**. For each profile, you will **predict whether the person's annual income is above or below \$50K.** 

Each profile contains two facts about a person:

- Education (from middle school to masters). Roughly half of the profiles are above high school (e.g., masters) and half are equal or below (e.g., middle school).
- Age (from 20 to 50 years old). Roughly half of the profiles are above 30 and half are below.

About half of the profiles have an annual income of above \$50k.

An Artificial Intelligence (AI) model will assist you on this task. The AI model uses education, age, and many other factors. For each profile, you will see the AI's prediction and an explanation which points out the key information used to make the prediction. The AI is not perfect, and hopefully the explanation can help you identify its mistakes.

It is important that you complete the exit survey to receive a unique code that is required to be compensated. Please submit the unique code after completing the HIT.

Please answer the questions below carefully. The questions test your understanding of this experiment. You will be **disqualified** from the study if any question is answered incorrectly.

## \*1. What is your task in this study?

- O To find the level of education of a person.
- O To predict whether a person's income is above 50K or not.
- O To find the age of the highest income person.
- O To evaluate an Al's performance on income prediction.
- \*2. I have to answer an exit survey after the study to get a unique code, which should be submitted in order to get the compensation.
  - O Yes. I agree.
  - No. I don't need to submit the code to get compensated.



Fig. 11. Task description and attention check. The user is required to select the correct answers before they are allowed to proceed to the training phase. The correct answers can be inferred from the given text on this page.

**Exit survey.** After participants have done with all the prediction problems, they will proceed to an exit survey page, as shown in Fig. 13.

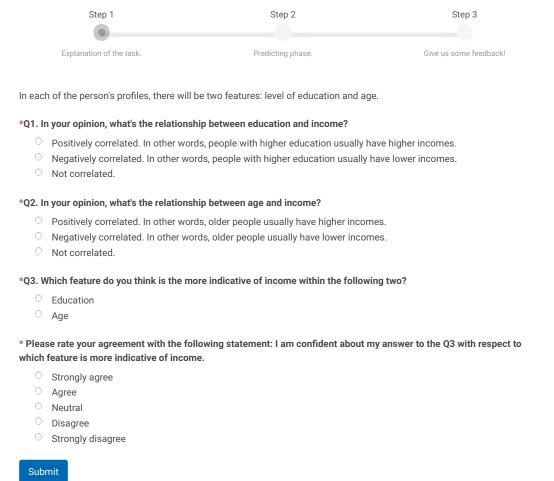


Fig. 12. Preliminary questions to calibrate human intuitions. If a participant agrees that both education and age are positively correlated with income and he/she thinks education is more important, the participant holds intuitions consistent with both R and M.

	Step 1		Step 2	Step 3
				•
	Explanation of th	e task.	Predicting phase.	Give us some feedback!
		Thank you	for participating in this sur	vey.
		Please an	nswer the following questio	ns.
*Which	n feature do you	hink is more important after	the study?	'
0	Education			
0	Age			
* What	is your gender?			
0	Female			
0	Male			
0	I prefer not to a	nswer		
* What	is your age?			
0	18-25			
0	26-40			
0	41-60			
	61 and above			
0	I prefer not to a	nswer		
* What	_	egree or level of school you h	nave completed? If current	ly enrolled, select the highest degree
		ol, no diploma, and below		
		duate, diploma or the equival	lent (for example: GED)	
0			·-··· (·-·· -··)	
0		/vocational training		
0	Bachelor's degre	ee or above		
0	I prefer not to a	nswer		
* Pleas	se explain how yo	u leveraged AI assistance ir	n making predictions.	
* Do yo	ou have any sugg	estions to our experiment de	esign and web interface?	
.,	, , , , , , , , , , , , , , , , , , , ,			
Subr	nit			

Fig. 13. Exit survey.