When and How to Fool Explainable Models (and Humans) with Adversarial Examples

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Abstract

Reliable deployment of machine learning models such as neural networks continues to be challenging due to several limitations. Some of the main shortcomings are the lack of interpretability and the lack of robustness against adversarial examples or out-of-distribution inputs. In this paper, we explore the possibilities and limits of adversarial attacks for explainable machine learning models. First, we extend the notion of adversarial examples to fit in explainable machine learning scenarios, in which the inputs, the output classifications and the explanations of the model's decisions are assessed by humans. Next, we propose a comprehensive framework to study whether (and how) adversarial examples can be generated for explainable models under human assessment, introducing novel attack paradigms. In particular, our framework considers a wide range of relevant (yet often ignored) factors such as the type of problem, the user expertise or the objective of the explanations in order to identify the attack strategies that should be adopted in each scenario to successfully deceive the model (and the human). These contributions intend to serve as a basis for a more rigorous and realistic study of adversarial examples in the field of explainable machine learning.

1 Introduction

Deep neural networks still face several weaknesses that hamper the development and deployment of these technologies, despite their outstanding and ever-increasing capacity to solve complex artificial intelligence problems. One of the main shortcoming is their black-box nature, which prevents analyzing and understanding their reasoning process, while such a requirement is increasingly demanded in order to guarantee a reliable and transparent use of artificial intelligence. To overcome this limitation, different strategies have been proposed in the literature [1], ranging from post-hoc explanation methods (which try to identify the parts, elements or concepts in the inputs that most affect the decisions of trained models) [2, 3, 4, 5], to more proactive approaches which pursue a transparent reasoning by training inherently interpretable models [6, 7, 8, 9, 10, 11].

Another issue that threatens the reliability of deep neural networks is their low robustness to adversarial examples [12], which, indeed, can be seen as a direct implication of their lack of human-like

reasoning. Therefore, improving the explainability of the models is as well a promising direction to achieve adversarial robustness, hypothesis which is supported by recent works which show that interpretability and robustness are connected [13, 14, 15, 16]. At the same time, the assumption of explainable classification models introduces new questions regarding the definition of adversarial examples: can adversarial examples be deployed if humans observe not only the input but also the output classification or the corresponding explanation?

In this paper, we shed light on this question by incrementally extending the notion of adversarial examples for explainable machine learning scenarios, in which humans can not only assess the input sample, but also compare it to the output of the model. These extended notions of adversarial examples allow us to exhaustively analyze the possible attacks that can be produced by means of adversarially changing the model's classification and explanations, either jointly or independently (that is, changing the explanation without altering the output class, or vice versa). Our analysis leads to a comprehensive framework that establishes whether (and how) adversarial attacks can be generated for explainable models under human supervision. Moreover, we thoroughly describe the requirements that adversarial examples should satisfy in order to be able to mislead an explainable model (and even a human) depending on multiple scenarios or factors which, despite their relevance, are often overlooked in the literature of adversarial examples for explainable models, such as the expertise of the user or the objective of the explanation. All these contributions are intended to establish a basis for a more rigorous study of the vulnerabilities of explainable machine learning in adversarial scenarios.

2 Related work

2.1 Overview of explanation methods

In this section, we summarize the explanation methods proposed in the literature, in order to present the terminology and taxonomy that will be used in the subsequent sections to develop our analytical framework on adversarial examples in explainable models.

2.1.1 Scope, objective and impact of the explanations

The objective of an explanation is to justify the behavior of a model in a way that is easily understandable to humans. However, different users might be interested in different aspects of the model, and, therefore, the explanations can be generated for different scopes or objectives.

Overall, the **scope** of an explanation can be categorized as local or global [1]. On the one hand, **local** methods aim to characterize or explain the model's prediction for each particular input individually, for example, by identifying the most relevant parts or features of each input. On the other hand, **global** methods attempt to expose the general reasoning process of the model, for instance, summarizing (e.g., using a more simple but interpretable model) when a certain class will be predicted, or describing to what extent a particular input-feature is related to one class. Since in this paper we will address the vulnerability of explainable models to adversarial examples, we we will focus on local methods.

In addition, explanations can be used, even for the same model, for different **functional purposes**. For instance, users querying the model for a credit loan might be interested in explaining the output obtained for their particular cases only, whereas a developer might be interested in discovering why that model misclassifies certain input samples. At the same time, an analyst can be interested in whether that model is biased against a social group for unethical reasons. At a higher level, all these purposes are based on necessities involving ethics, safety or knowledge acquisition, among others [17]. Based on the functional purpose of the explanations and the particular problem, domain or scenario in which they are required, another relevant factor should be taken into consideration: the **impact** of the explanations, which can be defined as the consequence of the decisions made based on the analysis of the explanation. Healthcare domains are clear examples in which the consequences of the decisions can be severe.

Despite the relevance of these factors, they are often overlooked when local explanation methods are designed or evaluated [17, 18]. The same happens for adversarial attacks in explainable models. We argue that the context, the functional purpose and the impact of explanations should be key factors when designing adversarial attacks against explainable models, since a different attack strategy

needs to be adopted in each context to successfully deceive the model (and the human). This will be discussed in detail in Section 3.

2.1.2 Types of explanations

Different types of explanations exist depending on how the explanation is conveyed:

Feature-based explanations: assign an importance score to each feature in the input, based on their relevance for the output classification. Common feature-based explanations (specially in the image domain) are activation or saliency maps, which highlight the most relevant parts of the input. Other approaches are based on perturbation-based methods, which alter an input (for instance, by removing or masking some regions) to assess which parts are the most relevant ones for the prediction. Although feature-based explanations such as saliency maps are the most employed ones in the literature (particularly in the image domain), previous works have identified that such explanations can be unreliable and misleading [4, 8, 19, 20, 21, 22].

Example-based explanations: the explanation is based on comparing the similarity between the input at hand and a set of *prototypical* inputs that are representative of the predicted class. Thus, the classification of a given input sample is justified by the similarity between it and the prototypes of the predicted class. We will refer to these types of explanations as **prototype-based explanations** in the paper, although different forms of example-based explanation exist, such as the strategy proposed in [23], where influence functions are employed to estimate the training images *most responsible* for a prediction. Recent works have integrated prototype-based explanations directly in the learning process of neural networks, so that the classification is based on the similarities between the input and a set of prototypes [6, 7, 8, 9], achieving a more interpretable reasoning. The prototypes can represent an entire input describing one class (e.g., a prototypical handwritten digit "1" in digit classification) [6], or represent image-parts or semantic concepts [7, 9, 8].

Rule-based explanations: these explanation methods aim to expose the reasoning of a model in a simplified or human-understandable set of rules, such as logic-rules or if-then-else rules, which represent a natural form of explanations for humans. Rule-based explanations are particularly well-suited when the input contains features which are easily interpretable. In this paper, special attention will be given to **counterfactual explanations** [24]. Although counterfactual explanations can be considered, in their form, as rule-based explanation, we will consider them separately in some cases due to their conditional or hypothetical reasoning nature, as the aim is suggesting the possible changes that should happen in the input to receive a different (and frequently more positive) output classification (e.g., "a rejected loan request would be accepted if the subject would have a higher income").

Overall, the most suitable type of explanation depends on the domain, the scope and the purpose of the explanation, as well as on the expertise level of the users querying the model. We refer the reader to [1, 17, 25] for a more fine-grained overview of explanation methods.

2.2 Reliability of explanations under adversarial attacks

Some explanation methods in the literature have been proven to be unreliable in adversarial settings. In [26, 27, 28, 29, 30], it is shown that small changes in input samples can produce drastic changes in feature-importance explanations, while maintaining the output classification. In [26], the proposed attacks are also evaluated in the example-based explanations proposed in [23], based on estimating the relevance of each training image for a given prediction by using influence-functions. In [31], adversarial attacks capable of changing the explanations while maintaining the outputs are created for self-explainable (prototype-based) classifiers. In [29, 30], it is shown that adversarial examples can also produce wrong outputs and (feature-importance) explanations at the same time, or change the output while maintaining the explanations [29].

The authors of [32] show that trustworthy explanations can be produced for a biased or an untrust-worthy model, thus manipulating user trust. This approach is, however, not based on adversarial attacks, as they focus on producing a global explanation model that closely approximates the original (black-box) model but which employs trustworthy features instead of sensitive or discriminatory

features (which are actually being used by the original model to predict). Similarly, in [33, 34] *adversarial* models are generated, capable of producing incorrect or misleading explanations whithout harming their predictive performance. In [33], a fine-tuning procedure is proposed to adversarially manipulate models, so that saliency map based explanations drastically change (becoming ineffective in highlighting the relevant regions) whereas the accuracy of the model is maintained.

Some works have also tried to justify the vulnerability of explanation methods to adversarial attacks, or the links between them. In [26, 27], the non-smooth geometry of decision boundaries (of complex models) is blamed, arguing that, due to these properties, small changes in the inputs implies that the direction of the gradients (i.e., normal to the decision boundary) can drastically change. As most explanation methods rely on gradient information, the change in the gradient direction implies a different explanation. In [29, 30], the vulnerability is attributed to a gap between predictions and explanations. It is an open question whether this hypothesis holds for self-explainable models, which have been trained jointly to classify accurately and to provide explanations. Finally, theoretical connections between explanations and adversarial examples are established in [13, 35].

2.3 Further connections between adversarial examples and interpretability

Paradoxically, using explanations to support or justify the prediction of a model can imply security breaches, as they might reveal sensitive information [36]. For instance, an adversary can use explanations of how a black-box model works (e.g., what features are most relevant in a prediction) in order to design more effective attacks. Similarly, in this paper we will show that justifying the classification of the model with an explanation makes it possible to generate types of deception using adversarial examples that, without explanations, it would not be possible to generate (e.g., to convince an expert that a misclassification of the model is correct).

On another note, recent works have shown that robust (e.g., adversarially trained) models are more interpretable [13, 14, 15, 16]. In [13], this is justified by showing that the farther the inputs are with respect to the decision boundaries, the more aligned are the inputs with their saliency maps, thus, being more interpretable.

Finally, the commonalities between interpretation methods and adversarial attacks and defenses are analyzed in [37], showing how adversarial methods can be reinterpreted from an interpretation perspective, and discussing how techniques from one field can bring advances into the other. Our paper, however, addresses a different objective. In contrast to [37], which focuses on highlighting the similarities between particular methods from both (explainable and adversarial machine learning) fields, in this paper we propose a comprehensive framework to study if (and how) adversarial examples can be generated for explainable models under human assessment.

3 Extending adversarial examples for explainable machine learning scenarios

In this section, we extend the notion of adversarial examples to fit in explainable machine learning contexts. For this purpose, we start from a basic definition of adversarial examples, and incrementally discuss more comprehensive scenarios in which the human subjects judge not only the input sample, but also the model's decisions, including the output classification and the corresponding explanations. To the best of our knowledge, no prior work has addressed comprehensively this type of generalization of adversarial examples.

This extended definition allows us to provide a general framework that identifies the way in which an adversary should design an adversarial example to deploy effective attacks even when a human is assessing the prediction process. The introduced framework also identifies the most effective ways of deploying attacks depending on factors such as the type of problem or the way in which the explanation is conveyed. From an adversary perspective, this framework provides a comprehensive road map for the design of malicious attacks in realistic scenarios involving explainable models and a human assessment of the predictions. From a developer or a defender perspective, this road map helps to identify the most critical requirements that their explainable model should satisfy to be reliable.

3.1 Scenarios in which human subjects are aware of the model predictions

Regular adversarial attacks are based on the assumption that an adversary can introduce a perturbation into an input sample, so that:

- 1. The perturbation is not noticeable to humans, and, therefore, the ground-truth class of the perturbed input does not change.
- 2. The class predicted by a machine learning model changes.

Note that, according to this general definition of adversarial examples, the human criterion is only considered regarding the input sample, without any human assessment of the model's output. Maintaining this assumption, then the same definition of adversarial examples can be applied in the context of explainable machine learning. However, this assumption is not realistic, as the point of explainable models is to assess not only their classification but also their reasoning. For these reasons, the following question arises: are regular adversarial examples useful in practice when the user is aware of the output?

To address this question, we start by discussing four different scenarios, based on the agreement of the following factors: f(x), the model's prediction of the input; h(x), the classification performed by a human subject; and y_x , the ground-truth class of an input x (which will be unknown for both the model and the human subject in the prediction phase of the model). For clarification, we assume that a human misclassification $(h(x) \neq y_x)$ can occur in scenarios in which the addressed task is of high complexity (e.g., medical diagnosis) or the label of an input is ambiguous (e.g., sentiment analysis). Although a human misclassification might be uncommon in simple problems such as object recognition, even in such cases ambiguous or challenging inputs can be found. Finally, unless specified, we will assume expert subjects, that is, subjects with knowledge in the task and capable of providing well-founded classifications.

According this framework, the four possible scenarios are as follows:

- 1. Both the model and the human subject agree with the ground-truth class of the input, that is: $f(x) = h(x) = y_x$.
- 2. The model has misclassified the input whereas it is well classified by the human subject: $f(x) \neq h(x) = y_x$. This is, indeed, the case produced when an adversarial example is classified, as will be described below.
- 3. The human observer (incorrectly) disagrees with the model's prediction, which is correct: $h(x) \neq f(x) = y_x$.
- 4. Both the model and the human subject wrongly classify the input: $f(x) \neq y_x \land h(x) \neq y_x$ If h(x) = f(x), the model's prediction will be (wrongly) considered as correct according to the human criterion. Otherwise, the model's output will be considered incorrect, but for wrong reasons.

According to the described casuistry, adversarial attacks aim to produce the second scenario (i.e., $f(x) \neq h(x) = y_x$), by imperceptibly perturbing an input x_0 that satisfies $f(x_0) = h(x_0) = y_{x_0}$ (i.e., the first scenario) so that the model's output is changed, but without altering the human perception of the input (what, therefore, implies $h(x) = y_x = y_{x_0}$). However, assuming that the user is aware of the output, the fulfillment of the attack is subject to whether human subjects can correct the detected misclassification, or have control over the implications of that prediction. For example, an adversarial traffic signal will only produce a dramatic consequence in autonomous cars if the drivers do not take the control with sufficient promptness.

Regarding the remaining cases, they do not fit in the definition of an adversarial attack since either the input is misclassified by the human subject $(h(x) \neq y_x)$ or the model is not fooled $(f(x) = h(x) = y_x)$. Nevertheless, assuming a more general definition, scenarios involving human misclassifications could be potentially interesting for an adversary. Similarly to *regular* adversarial attacks, which force the second scenario departing from the first one, an adversary might be

¹Different degrees of expertise can be considered for a more comprehensive scenario, such as unskilled subjects, or partially skilled subjects capable of providing basic judgments about the input (for instance, a subject might not be able to visually discriminate different species of reptiles, yet be able to visually classify an animal as a reptile and not as another animal class).

interested in forcing the fourth scenario departing from the third one. Let us take as an example a complex computer-aided diagnosis task through medical images, in which an expert subject fails in its diagnosis while the model is correct. In such cases, we can induce a **human error confirmation** attack by forcing the model to confirm the (wrong) medical diagnosis produced by the expert, that is, forcing $f(x) = h(x) \neq y_x$.

Based on the above discussion, we can determine that some types of adversarial attacks can still be effective even when the user is aware of the output. Nonetheless, paradoxically, it is possible to introduce new types of adversarial attacks when the output classification is supported by explanations, as we show in the following section.

3.2 Scenarios in which human subjects are aware of the explanations

The scenarios described in the previous section can be further extended for the case of explainable machine learning models, as the explanations for the predictions come into play. As a consequence, each of the cases defined above can be subdivided into new subcases depending on whether the explanations match the output class or whether humans agree with the model's explanations. To avoid an exhaustive enumeration of all the possible scenarios, we focus only on the ones that we identify as interesting from an adversary perspective. From this standpoint, given an explainable model, adversarial examples can be generated by perturbing a well classified input (for which the corresponding explanation is also correct and coherent) with the aim of changing the output class, the provided explanation or both at the same time.

To formalize these scenarios, let us denote $A_f(x)$ the explanation provided to characterize the decision f(x) of a machine learning model, and $A_h(x)$ the explanation provided by a human-subject according to its knowledge or criteria. The agreement of a human subject with the explanation provided by the model will be denoted as $A_f(x) \approx A_h(x)$ (that is, the model's explanation is coherent for a human), whereas the disagreement will be denoted as $A_f(x) \neq A_h(x)$. Similarly, we will denote $A(x) \sim y_x$ if an explanation A(x) is consistent with the reasons that characterize the ground-truth class of the input (that is, if the explanation correctly characterizes or supports the classification). For simplification, unless specified, we assume that $h(x) = y_x$ and that $A_h(x) \sim y_x$, this is, the human classification of an input into one class is correct and is based on reasons consistent for that class.

The identified scenarios are as follows:

- A.1 $f(x) = y_x \land A_f(x) \neq A_h(x)$. In this case, the model is right but the explanations are incorrect or differ from the ones that would be provided by a human. Adversarial attacks capable of producing such scenarios have been studied in recent works for post-hoc feature-importance explanations [26, 27, 28, 29, 30] and for self-explainable prototype-base classifiers [31], showing that small perturbations can produce a drastic change in the explanations without changing the output.
 - A.1.1 More particularly, we can imagine a scenario in which $A_f(x) \sim y_x$ despite $A_f(x) \neq A_h(x)$, for instance, if the explanations point out to relevant and coherent properties to classify the input as y_x (at least partially), but which do not compose the most relevant or correct explanation (with respect to the given input) according to a human criterion. From an adversary's perspective, changing the explanations without forcing a wrong classification allows to introduce **confusing recommendations**. For illustration, a model can (correctly) reject a loan request but accompanied with a wrong explanation, preventing the applicant from correcting the actually relevant deficiencies of the request. Similarly, a wrong explanation of a medical diagnosis system might lead to a wrong treatment or prescription. In addition, **biased or discriminative explanations** could be produced with this attack scheme, for instance, attributing a loan rejection to sensitive features (e.g., racial or religious). Such an explanation could **make the models look unreliable or untrustworthy for users**. Oppositely, **biases could be hided by producing trustworthy explanations to manipulate user trust** [32].
- A.2 $f(x) \neq y_x \land A_f(x) \neq A_h(x)$. In this case both the classification and the explanation provided by the model are incorrect. Adversarial attacks capable of producing such scenarios

have been investigated in recent works [29, 30]. More particularly, we identify two specific sub-cases as relevant when a human assesses the entire classification process:

- A.2.1 $A_f(x) \sim f(x)$. In this case, the fact that the provided explanation is coherent with the (incorrectly) predicted class can increase the confidence of the human in the prediction, being therefore interesting from an adversary perspective. We identify this case as the most direct extension of adversarial examples for explainable models, as **the model is not only fooled but also supports its own misclassification with the explanation**.
- A.2.2 $A_f(x) \not\sim f(x)$. This case is similar to the previous one (A.2.1), with the important difference that the model's explanation is now coherent with a class y' different to f(x) and y_x (assuming that $A_h(x) \sim y_x$, then $A_f(x) \neq A_h(x) \Rightarrow A_f(x) \not\sim y_x$). Thus, we are in a scenario in which a total mismatch is produced between all the considered factors. Whereas these attacks are an interesting case of study, they are also the most challenging to be deployed in practice without the inconsistencies being noticed.
- A.3 $f(x) \neq y_x \land A_f(x) \approx A_h(x) \land A_f(x) \sim y_x$. In this case, the model's classification is wrong but the provided explanations are coherent from a human perspective with respect to the ground-truth class y_x . The agreement in the explanations can increase the confidence in the model, but, at the same time, the output is not consistent with the explanation. However, the consistency issue might be solved by finding an input for which the explanation not only satisfies $A_f(x) \sim y_x$ but also $A_f(x) \sim f(x)$, for instance, by finding an **ambiguous explanation** that is applicable to both classes.

3.3 Possible attack strategies based on the explanation method employed

Whereas our framework considers models' explanations in their most general form, the way in which an explanation is conveyed determines how humans process and interpret the information. This implies that some attack strategies might be more suitable for some type of explanations than for others. Moreover, the way in which an adversarial example is generated for an explainable machine learning model will also depend on the type of explanation. For these reasons, in this section we briefly discuss in which way an adversarial example should be designed depending on the type of explanation or the particular type of attack to be produced.

- Feature-based explanations: the highlighted parts or features need to be coherent with the classification, and correspond to (I) human-perceivable, (II) semantically meaningful and (III) relevant parts. A common criticism to feature-based explanations such as saliency maps is that they identify the relevant parts of the inputs, but no how the models are processing such parts [20]. Thus, an adversarial attack could take advantage of this limitation. First, a particular region of the input can be highlighted to support a misclassification of the model and to convince the user (assuming that such region contributes to predict an incorrect class), which is interesting particularly for targeted adversarial attacks (that is, when the objective of the attack is to produce a specific incorrect output). An attack could also highlight irrelevant parts to mislead the observer, or generate ambiguous explanations by highlighting multiple regions or providing a uniform map, which are strategies well-suited for untargeted attacks (that is, when the aim is to change the output of the model, without any preference in the incorrect class).
- **Prototype-based explanations:** in this case, for the human to accept the given explanation, the key features of the closest prototypes should (I) be perceptually identifiable in the given input, and, ideally, (II) contain features correlated with the output class. The contrary should happen for the farther prototypes, that is, their key features should not be present in the input nor be correlated with the output class (or, ideally, be opposite). In order to achieve these objectives, the more general the prototypes (e.g., if they represent semantic concepts or parts of inputs rather than completely describing an output class), the higher the chances of producing explanations that could lead to a wrong classification while being coherent with a human perception, such as ambiguous explanations.
- **Rule-based explanations** can be fooled by targeting explanations which are aligned with the model output (e.g., the explanation justifies the prediction or at least mimics the model behavior), but which employ reliable, trustworthy or neutral features [34]. For instance,

- a model for criminal-recidivism prediction could provide a negative assessment based on unethical reasons whereas the explanation is taken as ethical.
- Counterfactual explanations: in this case, the objective of an adversarial attack could be forcing a particular counterfactual explanation, suggesting changes on irrelevant features (thus preventing correcting the actually relevant deficiencies), or forcing a biased or discriminatory explanations in detriment of the model's fairness.

3.4 Desiderata for adversarial attacks in different scenarios involving explainable machine learning models

In Table 1, we describe the main characteristics or desiderata that an adversarial attack should satisfy in different scenarios in order to be successful. We build on the idea that common tasks, problems or applications have common categories, and that explanations or interpretation needs are different in each of them [17]. Thus, adversarial attacks (or, oppositely, the defensive countermeasures) should also be designed differently for each type of explanation, focusing on the more relevant or crucial factor in each case. The scenarios described in Table 1 comprise different degrees of expertise of the human in supervision of the classification process and different functional purposes of the explanation. It is important to note that a particular problem or task could belong to more than one scenario (i.e., scenarios are not mutually-exclusive). Moreover, we emphasize that some of the scenarios involve factors which are difficult to quantify in a formal way (e.g., the expertise of a user). Nevertheless, we believe that it is necessary to consider such detailed scenarios in order to rigorously discuss which type of adversarial examples can be realizable in practice.

The first scenario described in Table 1 (S1) comprises tasks in which the implications of the decisions made by the model cannot be controlled by the user, or cases in which there is no time for a human supervision of the predictions. Despite the relevance of some tasks that fall into this category (e.g., autonomous cars or massive content filtering), humans cannot thoroughly evaluate each possible prediction. For this reason, explanations are not of practical use in such cases, so the main (or only) goal of an adversary is to produce an incorrect output.

Nevertheless, interpretability or explainability can be desirable properties for any model (including those developed for the scenario S1) in order to debug or validate them (S2 scenario). For instance, a model developer might want to explain the decisions of a self-driving car (even if the end-user will not receive explanations when the model is put into practice) to assess why it has provided an incorrect output, to validate its reasoning process or to gain knowledge about what the model has learned. In such cases, an adversary could justify a misclassification of the model (A.2.1, A.3), hide an inappropriate behavior when the model predicts correct but for the wrong reasons (A.1.1), or produce wrong outputs and explanations at the same time (A.2). The same attack strategies are applicable in scenarios in which the models' decisions are taken as more relevant or imperative than the experts' judgment (S3). The main difference with respect to the scenario S1 is that, in this case, explanations can be useful or relevant even when the model is deployed or employed by the end-user, and, therefore, the attack should also take the explanations into consideration instead of considering only the output class.

In addition, we consider four different scenarios depending on the expertise level of the user querying the model, which range from no expertise (**S4**), medium expertise (**S5**) and high expertise (**S6**). The case of no expertise (**S4**) is the simplest one from the perspective of the adversary, as any attack scheme can be produced without arousing suspicions, taking advantage of the user inexperience. For the same reason, models deployed in such scenarios should also be the ones with more security measures against adversarial attacks. If the user's expertise is medium (**S5**), the explanation is expected to clarify the classification to the user. Thus, the explanation should be sufficiently consistent with the main semantic features in the input (e.g., the user might not be able to diagnose a medical image, but can identify the relevant spots depending on what is being diagnosed, such as darker spots in skin-cancer diagnosis), and/or sufficiently consistent with the output class (A.1.1, A.2.1, A.3). Similarly, if the user has a partial expertise (**S7**), which could happen in hierarchical classification tasks, then the adversary needs to ensure that the output and the explanations are coherent only with the factors or features that are familiar for the user.

A user with high expertise (S6), by definition, will realize that a model is producing a wrong output or explanation. Therefore, the only way to mislead the model and convince the human of a wrong prediction is by means of ambiguity (A.1.1, A.3). For instance, in an image classification task, two

objects can appear at the same time, being possible to produce a wrong class with a reasonable explanation (e.g., highlighting the secondary object as the most relevant one). In addition, in problems in which the inputs are inherently ambiguous, such as natural language processing tasks, different but reasonable explanations can be produced for the same input.

Finally, in some cases the explanations might be more interesting, necessary or challenging than the output itself (S8). Some representative tasks are predictive maintenance (e.g., it might be more interesting knowing why certain system will fail than just knowing that it will fail) or medical diagnosis (e.g., discovering why a model has diagnosed a patient as being at high risk for a particular disease might be the main priority to prevent the disease or provide a better treatment). For these reasons, a change in the explanation is critical for such models, being particularly sensitive to the attacks described in A.1 (or those described in A.2.1, if the misclassification of the model is difficult to notice by the user).

4 Conclusions

In this paper, we have introduced a comprehensive framework to rigorously study the possibilities and limitations of adversarial examples in explainable machine learning scenarios, in which the input, the model's predictions and the explanations are assessed by humans. First, we have extended the notion of adversarial examples in order to fit in such scenarios, which have allowed us to examine different adversarial attack paradigms. Furthermore, we thoroughly analyze how adversarial attacks should be designed in order to mislead explainable machine learning models (and humans) depending on a wide range of factors such as the type of task addressed, the expertise of the users querying the model, as well as the type, scope or impact of the explanation methods used to justify the decisions of the models. Overall, the proposed framework provides a comprehensive road map for the design of malicious attacks in realistic scenarios involving explainable models and a human supervision, contributing to a more rigorous study of adversarial examples in the field of explainable machine learning.

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Scenario	Representative Examples	Applicable Attacks
S1: Impossibility of correcting the output or controlling the implications of the decision in time.	Fast-decision making scenarios (e.g., autonomous cars) or automatized processes (e.g., massive online content filtering).	• Any adversarial attack capable of producing a change in the output class.
S2: Model debugging, development, validation, etc.	Applicable to any task.	 A.2.1, A.3 (justify model's misclassifications). A.1.1 (mask inappropriate behaviors, e.g., hiding biases by producing trustworthy outputs or explanations). A.2 (produce wrong outputs and explanations jointly).
S3: Models' decisions are more imperative than experts' judgments.	Risk of criminal recidivism or credit risk management.	
S4: User with no expertise.	Scenarios in which the decision criteria are secret, hidden, or unknown (e.g., banking or financial scenarios, malware classification problems, etc.).	• Any adversarial attack scheme (taking advantage of the user's inexperience).
S5: User with medium expertise (the model is expected to clarify or support its predictions).	Challenging scenarios (e.g., complex medical diagnosis) or unfore- seeable scenarios (e.g., macroeconomic predic- tions, risk of criminal recidivism, etc.).	 A.1.1, A.2.1, A.3. The explanation needs to be consistent with the input patterns and/or consistent with the output class.
S6: User with high expertise.	Tasks in which the inputs can be ambiguous (e.g., NLP tasks such as sentiment analysis or multiple object detection in the image domain).	• A.1.1, A.3 (Attacks involving generating ambiguous explanations).
S7: User with partial or mixed expertise (i.e., expert in some factors but clueless in others).	Hierarchical classification.	• The output and the explanation should be consistent with the known factors (either regarding input features or the output class).
S8: Explanations even more relevant than the classification itself.	Predictive maintenance, medical diagnosis or credit/loan approval (e.g., with a wrong explanation users can not modify or correct the deficiencies).	• A.1, A.2.1 (e.g., maintain the output but produce totally or partially wrong explanations, or produce unethical explanations).

Table 1: Possible scenarios in which explainable machine learning models can be deployed, and a guideline on how adversarial attacks should be designed in each case in order to pose a realistic threat.

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