

# Adversarial attacks and defenses in explainable artificial intelligence: A survey

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## Abstract

Explainable artificial intelligence (XAI) methods are portrayed as a remedy for debugging and trusting statistical and deep learning models, as well as interpreting their predictions. However, recent advances in adversarial machine learning (AdvML) highlight the limitations and vulnerabilities of state-of-the-art explanation methods, putting their security and trustworthiness into question. The possibility of manipulating, fooling or fairwashing evidence of the model’s reasoning has detrimental consequences when applied in high-stakes decision-making and knowledge discovery. This survey provides a comprehensive overview of research concerning adversarial attacks on explanations of machine learning models, as well as fairness metrics. We introduce a unified notation and taxonomy of methods facilitating a common ground for researchers and practitioners from the intersecting research fields of AdvML and XAI. We discuss how to defend against attacks and design robust interpretation methods. We contribute a list of existing insecurities in XAI and outline the emerging research directions in adversarial XAI (AdvXAI). Future work should address improving explanation methods and evaluation protocols to take into account the reported safety issues.

**Keywords:** explainability, interpretability, adversarial machine learning, safety, security, robustness, review

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## 1. Introduction

Explainable artificial intelligence (XAI) methods (for a brief overview see [1], and for a comprehensive survey refer to [2]), e.g. post-hoc explanations like PDP [3], SG [4], LIME [5], IG [6], SHAP [7], TCAV [8], Grad-CAM [9] to name a few, provide various mechanisms to interpret predictions of machine learning models. A popular critique of XAI, in favour of inherently interpretable models, is its inability to faithfully explain the black-box predictive function [10]. Nevertheless, explanations find success in applications like autonomous driving [11] or drug discovery [12], and can be used to better understand the reasoning of large models like AlphaZero [13].

Recently, adversarial machine learning [AdvML, 14–16] became more prevalent in research on XAI, whereas vulnerabilities of explanations raise concerns about their trustworthiness and security [17]. To assess the scope of these threats, we contribute a systemization of the current state of knowledge concerning *adversarial attacks on model explanations* (Section 3) and *defense mechanisms against these attacks* (Section 4). We summarize the described *failure modes* of XAI in Figure 1. Figure 2 presents one of such attack mechanisms, referred to as *adversarial example* [18–20], i.e. a slight perturbation of an input image drastically changes the explanation of the unchanged class predicted by a model. We can also observe that an aggregation of explanations obtained with different methods shows to be less susceptible to such manipulation [21]. While the most related surveys summarize attacks on model predictions [16, 22], explanation robustness [23], and the application of XAI in AdvML [24], this survey highlights the rapidly emerging cross-domain research in what we call adversarial explainable AI (AdvXAI). We moreover confront it with the closely related work concerning *attacks on machine learning fairness metrics* (Section 5). A thorough overview of over 50 papers allows us to specify the opportunities, challenges and future research directions in AdvXAI (Section 6).

This review serves as an approachable outlook to recognize the potential research gaps and define future directions. We first included visible papers published in major machine learning conferences (ICML, ICLR, NeurIPS, AAAI) and journals (AIj, NMI) since Ghorbani et al. [25]. We then extensively searched their citation networks for papers

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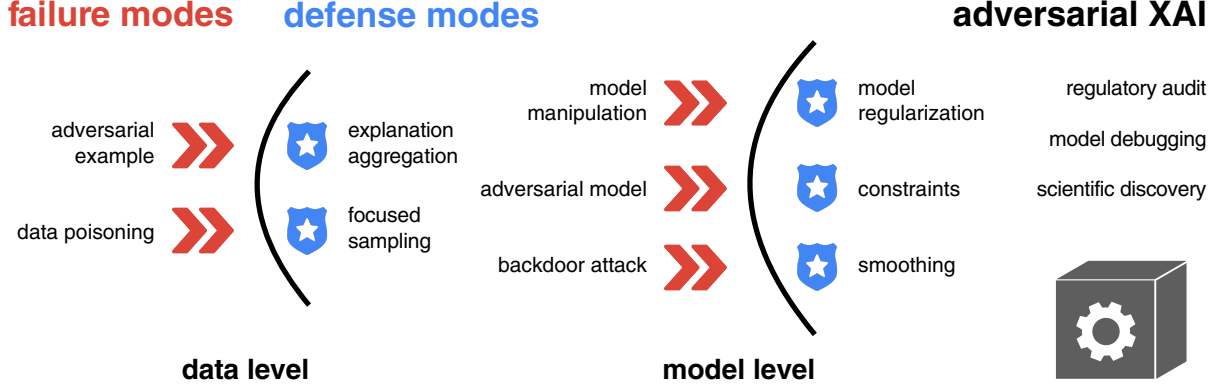


Figure 1: Summary of the possible explainable AI failure modes on data and model levels. Adversarial examples, data poisoning, model manipulation, and backdoor attacks are key safety issues of current machine learning explanations. Defense mechanisms like explanation aggregation and model regularization improve the robustness of XAI applications.

related to AdvXAI published in other venues. We purposely exclude a large number of papers focusing primarily on explanation evaluation without relating to the adversarial scenario [refer to 26].

## 2. Background

Here, we provide a brief introduction to the methodology in adversarial machine learning (Section 2.2) and explainable artificial intelligence (Section 2.3). Readers familiar with basic concepts of these can skip to Section 3.

### 2.1. Notation

Throughout this paper, we mainly consider a supervised machine learning task where model  $f_\theta : \mathcal{X} \mapsto \mathcal{Y}$  is trained to predict an output feature  $\mathbf{Y} \in \mathcal{Y} \subseteq \mathbb{R}$  using input features  $\mathbf{X} \in \mathcal{X} \subseteq \mathbb{R}^d$ . Here,  $\theta$  represents the model’s parameters, e.g. weights of a neural network. We will write it simply as  $f$  when no confusion can arise. Let  $\mathbf{x} \in \mathcal{X}$  be an input vector for which the prediction  $f(\mathbf{x})$  we want to explain. Further, let  $g(\cdot, \cdot)$  denote an explanation function, for which both model and data are the input, where the output domain varies between different explanation methods. For example,  $g(f_\theta, \cdot) : \mathcal{X} \mapsto \mathbb{R}^d$  maps each input feature to its importance or attribution to the model’s prediction. In principle,  $g(f, \mathbf{x})$  denotes a *local explanation* corresponding to a particular prediction, e.g. gradient  $g(f, \mathbf{x}) = \nabla_{\mathbf{x}} f(\mathbf{x})$ , while  $g(f, \mathbf{X})$  denotes a *global explanation*, e.g. feature importance for tabular data. Our goal is to introduce a simple unified notation facilitating a common ground for researchers and practitioners from the intersecting research fields of AdvML and XAI. In what follows, the symbol  $\rightarrow$  denotes an adversarial change in a given object, e.g. a small perturbation of input becomes  $\mathbf{x} \rightarrow \mathbf{x}'$ . We will use the symbol  $\approx$  to denote similarity between two values, e.g. similar predictions  $f(\mathbf{x}) \approx f(\mathbf{x}')$ , and contrary  $\neq$  to denote dissimilarity, e.g. visibly different explanations  $g(f, \mathbf{x}) \neq g(f, \mathbf{x}')$ .

### 2.2. Adversarial machine learning

Since 2004, there has been an enormous development of adversarial methods in (deep) machine learning [27]. In general, these are algorithms that aim to attack the model’s behaviour, which relates to the security, safety, and robustness of AI systems. The most explored class of attacks in machine learning is an *adversarial example* [18, 19, 28], especially in computer vision tasks, where one aims to minimally modify input data so that it fools a model into misclassification.<sup>1</sup> We use the introduced notation to describe this attack strategy in the following way:

$$\mathbf{x} \rightarrow \mathbf{x}' \implies f(\mathbf{x}) \neq f(\mathbf{x}'). \quad (1)$$

<sup>1</sup>Adversarial examples are closely related to counterfactual explanations where the latter aim to interpret the model instead of deceiving it [29].

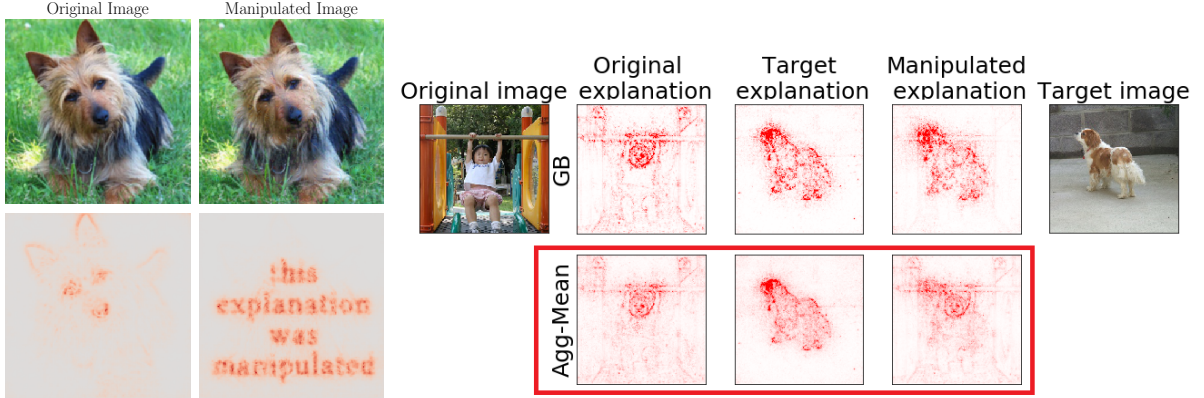


Figure 2: Adversarial example attack on an explanation of the image classifier’s prediction [left: adapted from 20] and an aggregating defense mechanism against this attack [right: adapted from 21].

Adversarial examples are an orthogonal concept to fooling examples – random inputs, e.g. images unrecognizable by humans, for which models predict with very high confidence [30]. Brown et al. [31] propose a method to create adversarial patches that trigger a misclassification when added to an input. Consecutively, Athalye et al. [32] demonstrate the existence of 3D adversarial objects in the physical world, which are misclassified when photographed from multiple viewpoints. In their seminal paper, Su et al. [33] show that it is possible to fool a model into misclassification by perturbing only a single pixel in an image. While imaging data may be the most illustrative, adversarial examples were originally studied for machine learning models predicting on tabular and text data [18, 34]. Adversarial perturbations of text inputs include misspellings, punctuation errors, and swapping words or characters [35].

The threat of manipulating model predictions with adversarial inputs increases the risk of deploying and applying AI systems in the real world. Algorithms that aim to counter attacks become defenses, which include data augmentation [16], model regularization [36], and distillation [37]. Their ultimate goal is to make it harder for an attacker to fool the model’s behaviour, i.e. minimize the potential risk. Often, detecting the attack is a preliminary (and sufficient) step in a successful defense [38].

Another widely studied failure mode of machine learning models is a *backdoor attack* [39, 40], in which (generally) one assumes that the adversary has access to the model, e.g. in a scenario of outsourced training. Its goal is to make the model predict wrong for new inputs with a specific trigger pattern known to an adversary. The most common approach to creating a backdoor is to *poison data* used for training in a way so that the adversarial model remains indistinguishable from the desired one:

$$\left. \begin{array}{l} \mathbf{X} \rightarrow \mathbf{X}' \Rightarrow f_{\theta} \rightarrow f_{\theta'} \\ \mathbf{x} \rightarrow \mathbf{x}' \end{array} \right\} \implies f_{\theta}(\mathbf{x}) \approx f_{\theta'}(\mathbf{x}) \neq f_{\theta'}(\mathbf{x}'). \quad (2)$$

More broadly, various poisoning attacks on machine learning models have been proposed targeting different adversarial goals [41], e.g. decreasing classification accuracy [42]. Refer to [22], for a comprehensive systematization of poisoning attacks (and defenses) related to model predictions.

### 2.3. Explainable artificial intelligence

In parallel with research on AdvML, there has been an increasing interest in methods that allow us to understand and interpret machine learning models [43, 44]. XAI (or explanation) methods become useful in various applications like regulatory audit [45], model debugging [46], or scientific discovery [12]. The origins of explainability relate to AI systems that should provide reasoning for their decisions [47, 48], often comprehensible by humans. Currently, there is an open discussion on whether the developed XAI methodology is sufficient to attain trustworthy AI systems [49, 50].

For example, consider a simple gradient of the (differentiable) model’s output with respect to input as an intuitive explanation of feature influence [4, 51]:

$$g(f, \mathbf{x}) = \nabla_{\mathbf{x}} f(\mathbf{x}). \quad (3)$$

The most explored class of explanations in machine learning are local post-hoc *feature attributions* [5–7, 52], which indicate how much each input feature contributed to the model’s outcome prediction:

$$f(\mathbf{x}) = \sum_{i=1}^d g(f, \mathbf{x})_i. \quad (4)$$

A state-of-the-art approach to obtaining vector  $g(f, \mathbf{x})$  are algorithms estimating Shapley values [7, 52, 53], a solution originating in game theory. Nowadays, there is an abundance of variations considering different data modalities, model algorithms, explanation quality metrics, or the desired computational efficiency [54]. Specifically for tabular data, perturbation-based explanation methods [5, 7] allow to explain individual predictions in a model-agnostic manner. Contrary, gradient-based [6, 55] and propagation-based [56] local post-hoc explanations are more specific to deep neural networks, which are state-of-the-art predictive models trained on unstructured data, e.g. image and text.

Complementary to local explanations are global explanations that summarise patterns in model predictions consistent across a data distribution. *Feature importance* [57–59] measures quantify the model’s reliance on a particular feature. For example, an aggregation of feature attributions for a subset of inputs becomes a natural importance metric [60]:

$$G(f, \mathbf{X}, g) = \sum_{\mathbf{x} \in \mathbf{X}} |g(f, \mathbf{x})|. \quad (5)$$

*Feature effect* [3, 59, 61] explanations, e.g. partial dependence plots [3], visualise a global relationship between the expected model’s prediction and values of a particular feature. Global explanations specific to deep neural networks include concept-based explanations [8], which relate human-understandable concepts to the predicted classes, e.g. how sensitive a prediction of “zebra” is to the presence of stripes in an image.

Closely related to AdvXAI is research on evaluating the robustness of explanations [23] and applying explanation methods in adversarial scenarios [24].

### 3. Adversarial attacks on model explanations

To the best of our knowledge, Ghorbani et al. [25] is the first contribution to mention<sup>2</sup> and propose an *adversarial attack against explanation methods*, specifically gradient-based feature attributions [4, 6] of (convolutional) neural networks. Previous related work discussed the worst-case (adversarial) notion of explanation robustness [62, page 7] and the notion of explanation sensitivity [63, 64]. Crucially, Adebayo et al. [65] introduced randomization tests showing that a visual inspection of explanations alone can favor methods compelling to humans. It raised to attention the need for evaluating the explanations’ quality, especially for deep models, with possible implications in adversarial settings.

Table 1 lists attacks on explanation methods, with the corresponding strategy of changing data, e.g. an adversarial example manipulates the explanation without impacting the prediction [20, 25, 64, 66–68]:

$$\mathbf{x} \rightarrow \mathbf{x}' \implies \begin{cases} g(f, \mathbf{x}) \neq g(f, \mathbf{x}') \\ f(\mathbf{x}) \approx f(\mathbf{x}') \end{cases}, \quad (6)$$

changing the model, e.g. fine-tuning or regularizing weights manipulates explanations without impacting the predictive performance [69, 70]:

$$f_\theta \rightarrow f_{\theta'} \implies \begin{cases} \forall \mathbf{x} \in \mathbf{X} \ g(f_\theta, \mathbf{x}) \neq g(f_{\theta'}, \mathbf{x}) \\ \forall \mathbf{x} \in \mathbf{X} \ f_\theta(\mathbf{x}) \approx f_{\theta'}(\mathbf{x}) \end{cases}, \quad (7)$$

or changing both data and the model, e.g. in the case when an attacker poisons the training dataset [71]:

$$\begin{matrix} \mathbf{X} \rightarrow \mathbf{X}' \Rightarrow f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{matrix} \implies \begin{cases} g(f, \mathbf{x}) \neq g(f', \mathbf{x}') \\ f'(\mathbf{x}) \approx f'(\mathbf{x}') \end{cases}. \quad (8)$$

<sup>2</sup>Note that we acknowledge papers in order of date published, i.e. presented at a conference, as opposed to the first date appearing online, e.g. as a preprint or final proceedings version.

Table 1: Summary of adversarial attacks on explanations of machine learning models. We abbreviate the following: data (D), model (M), explanation (E), image (I), tabular (T), language (Lg), neural network (N), black-box (B), local (L), global (G). [Appendix A](#) lists other abbreviations.

Attack	Changes strategy	Modality dataset	Model algorithm	Explanation method
Ghorbani et al. [25]	D adversarial example	I ImageNet, CIFAR-10	N SqueezeNet, InceptionNet	L SG, IG, DeepLIFT
Kindermans et al. [64]	D adversarial example	I MNIST, ImageNet	N MLP, CNN, VGG	L SG, GI, IG, LRP, ..
Viering et al. [72]	M & D backdoor attack	I ImageNet	N VGG	L Grad-CAM
Subramanya et al. [66]	D adversarial example	I ImageNet, VOC2012	N VGG, ResNet, DenseNet	L Grad-CAM
Heo et al. [69]	M model manipulation	I ImageNet	N VGG, ResNet, DenseNet	L SG, Grad-CAM, LRP
Dombrowski et al. [20]	D adversarial example	I ImageNet, CIFAR-10	N VGG, ResNet, DenseNet, ..	L SG, GI, IG, LRP, ..
Dimanov et al. [70]	M model manipulation	T Credit, COMPAS, Adult, ..	N MLP	L SG, GI, IG, SHAP, ..
Slack et al. [74]	M adversarial model	T Credit, COMPAS, Crime	B rule set	L SHAP, LIME
Lakkaraju and Bastani [75]	E trust manipulation	T Bail	B rule set	G MUSE
Anders et al. [76]	M model manipulation	T credit, I MNIST, CIFAR10, ..	N LR, CNN, VGG	L SG, GI, IG, LRP
Kuppa and Le-Khac [67]	D adversarial example	T PDF, Android, UGR16	N MLP, GAN	L SG, GI, IG, LRP, ..
Zhang et al. [68]	D adversarial example	I ImageNet	N ResNet, DenseNet	L SG, CAM, RTS, ..
Merrer and Trédan [77]	M adversarial model	T Credit	B DT, MLP	L custom
Shokri et al. [78]	– membership inference	T Adult, Hospital, .. I CIFAR-10, ..	B MLP, CNN	L IG, LRP, LIME, ..
Sinha et al. [79]	D adversarial example	Lg IMDB, SST, AG News	B DistilBERT, RoBERTa	L IG, LIME
Zhang et al. [71]	M & D data poisoning	T Fracture, I Dogs	N MLP, ResNet	L SG, CAM
Slack et al. [80]	M model manipulation	T Credit, Crime	N MLP	L counterfactual
Baniecki and Biecek [81]	D data poisoning	T Heart, Apartments	B XGBoost	G SHAP, L SHAP
Brown and Kvinge [82]	D data poisoning	I ImageNet, CUB	N InceptionNet, ResNet, ViT, ..	G TCAV, FFV
Baniecki et al. [83]	D data poisoning	T Heart, Friedman	B MLP, RF, GBDT, SVM, ..	G PDP
Pawelczyk et al. [84]	– membership inference	T Adult, Hospital	B LR, NN	L counterfactual
Laberge et al. [85]	D data poisoning	T COMPAS, Adult, Bank, Crime	B MLP, RF, XGBoost	G SHAP
Noppel et al. [73]	M & D backdoor attack	I CIFAR-10, GTSRB	N ResNet	L SG, Relevance-CAM, ..
Huang et al. [86]	D adversarial example	I MNIST, CIFAR-10, CelebA	B CNN, ResNet, MobileNet	L GI, IG, LRP, LIME, ..

Viering et al. [72] manipulate Grad-CAM explanations of a convolutional neural network by changing its weights, but also proposes to leave a backdoor in the network (triggered by specific input patterns), which allows retrieving original explanations. Noppel et al. [73] extend fooling explanations through fine-tuning and backdoor to consider a red-herring attack that manipulates the explanation to cover an adversarial change in the model’s prediction, e.g. a misclassification:

$$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow \begin{matrix} f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{matrix} \Rightarrow \begin{cases} g(f, \mathbf{x}) \neq g(f', \mathbf{x}') \\ f'(\mathbf{x}) \neq f'(\mathbf{x}') \end{cases}, \quad (9)$$

and a fully disguising attack that aims to show the original explanation for a changed prediction:

$$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow \begin{matrix} f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{matrix} \Rightarrow \begin{cases} g(f, \mathbf{x}) \approx g(f', \mathbf{x}') \\ f'(\mathbf{x}) \neq f'(\mathbf{x}') \end{cases}. \quad (10)$$

For each of the attacks in Table 1, we record the mentioned data modalities with the corresponding datasets used in experiments, as well as model algorithms.

In a black-box setting, Slack et al. [74] manipulate LIME and SHAP explanations for tabular data by exploiting their reliance on perturbing input data for estimation (see Figure 3). The proposed attack substitutes a biased black-box with a model surrogate to effectively hide bias, e.g. from auditors. In detail, an out-of-distribution detector is trained to divide input data such that the black-box’s predictions in-distribution remain biased, but its behavior on the perturbed data is controlled, which makes the explanations look fair:

$$f \rightarrow f' \Rightarrow \begin{cases} \exists \mathbf{x} \in \mathbf{X} \ g(f, \mathbf{x}) \neq g(f', \mathbf{x}) \\ \forall \mathbf{x} \in \mathbf{X} \ f(\mathbf{x}) \approx f'(\mathbf{x}) \end{cases}. \quad (11)$$

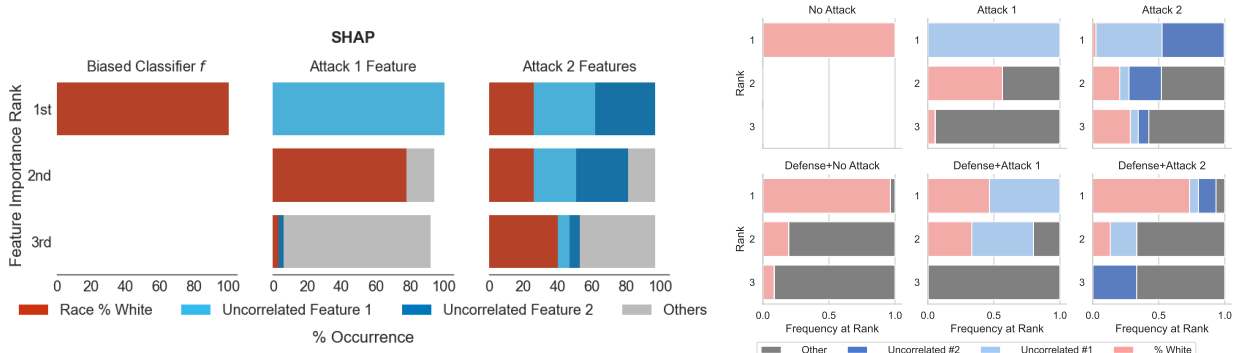


Figure 3: Adversarial model attack on explanations of an unfair classifier predicting credit score [left: adapted from 74] and the defense against this attack that imposes constraints on the data distribution used to estimate explanations [right: adapted from 87].

Merrer and Trédan [77] consider a similar adversarial scenario and show that providing explanations cannot prevent a remote service from hiding the true reasons that lead to its predictions. It concludes that an impractically large number of user queries is required to detect explanation manipulation.

While the majority of adversarial attacks are on local methods for interpreting individual predictions; other attacks specifically target global methods explaining the overall model’s reasoning [75, 81–83, 85]. Instead of changing model or data, Lakkaraju and Bastani [75] introduce misleading rule-based explanations that approximate a model based on the MUSE framework [88]. Results of a user study show that various high-fidelity explanations faithful to the black-box considerably affect human judgement:

$$g \rightarrow g' \implies \begin{cases} g(f, \mathbf{X}) \neq g'(f, \mathbf{X}) \\ \forall \mathbf{x} \in \mathbf{X} \ g'(\mathbf{x}) \approx f(\mathbf{x}) \end{cases} \quad (12)$$

Baniecki and Biecek [81] and Baniecki et al. [83] introduce genetic-based algorithms to manipulate SHAP and PDP explanations respectively. The proposed poisoning attack iteratively changes data used in the process of estimating global explanations, and thus can be exploited by an adversary to provide false evidence of feature importance and effects:

$$\mathbf{X} \rightarrow \mathbf{X}' \implies g(f, \mathbf{X}) \neq g(f, \mathbf{X}'). \quad (13)$$

Laberge et al. [85] consider a similar adversarial scenario and attack global SHAP with biased sampling of the data points used to approximate explanations [an algorithm introduced in 89]. It is done stealthily aiming to minimize the difference in data distributions. Experiments show an improvement in manipulating SHAP over previous work of Baniecki and Biecek [81], which further underlines SHAP’ vulnerability [74]. Huang et al. [86] use a genetic-based algorithm as a black-box attack to craft adversarial examples for local post-hoc explanations of image classification.

Table 2 summarizes the notation used to describe 10 possible attacks on explanations of machine learning models.

We further acknowledge that explanations might be exploited to breach privacy in machine learning applications. Shokri et al. [78] introduce membership inference attacks that use information from feature attributions to determine whether a data point was present in the training dataset. Pawelczyk et al. [84] propose membership inference attacks using counterfactual explanations instead. While many contributions consider the detectability of the attack [66–68], and some propose ways of mitigating the attacks’ effects via robustifying mechanisms [20, 68, 76], we systemize contributions that mostly focus on defending in Section 4.

*Observations.* The majority of proposed attacks assume prior knowledge that the explained model is a neural network, e.g. to utilize gradient descent in constructing adversarial examples or changing model parameters, as opposed to black-box approaches that could work with various model algorithms. Attacking local explanations may impact the model’s behaviour globally [69, 70, 73, 76], and vice versa, fooling global explanations may manipulate local explanations in the process [75, 81, 85]. Both of these interactions could improve detectability in practice. To this date, there are relatively sparse studies concerning adversarial attacks on concept-based explanations, e.g. Brown and Kvinge



Table 2: A summary of 10 possible attacks on explanations of machine learning models.

Attack	Notation	References
adversarial example	$\mathbf{x} \rightarrow \mathbf{x}' \Rightarrow \begin{cases} g(f, \mathbf{x}) \neq g(f, \mathbf{x}') \\ f(\mathbf{x}) \approx f(\mathbf{x}') \end{cases}$	[20, 25, 64, 66–68, 79, 86, 90]
data poisoning (biased sampling)	$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow g(f, \mathbf{X}) \neq g(f, \mathbf{X}')$	[81–83, 85, 89]
data poisoning (in training)	$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow f_\theta \rightarrow f_{\theta'} \Rightarrow g(f_\theta, \mathbf{X}) \neq g(f_{\theta'}, \mathbf{X})$	[91–93]
backdoor attack (fooling)	$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow \begin{cases} f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{cases} \Rightarrow \begin{cases} g(f, \mathbf{x}) \neq g(f', \mathbf{x}') \\ f'(\mathbf{x}) \approx f'(\mathbf{x}') \end{cases}$	[71–73]
backdoor attack (red-herring)	$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow \begin{cases} f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{cases} \Rightarrow \begin{cases} g(f, \mathbf{x}) \neq g(f', \mathbf{x}') \\ f'(\mathbf{x}) \neq f'(\mathbf{x}') \end{cases}$	[73]
backdoor attack (full-disguise)	$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow \begin{cases} f \rightarrow f' \\ \mathbf{x} \rightarrow \mathbf{x}' \end{cases} \Rightarrow \begin{cases} g(f, \mathbf{x}) \approx g(f', \mathbf{x}') \\ f'(\mathbf{x}) \neq f'(\mathbf{x}') \end{cases}$	[73]
model manipulation (e.g. fine-tuning)	$f_\theta \rightarrow f_{\theta'} \Rightarrow \begin{cases} \forall \mathbf{x} \in \mathbf{X} \ g(f_\theta, \mathbf{x}) \neq g(f_{\theta'}, \mathbf{x}) \\ \forall \mathbf{x} \in \mathbf{X} \ f_\theta(\mathbf{x}) \approx f_{\theta'}(\mathbf{x}) \end{cases}$	[69, 70, 76, 80]
adversarial model (vs. local explanation)	$f \rightarrow f' \Rightarrow \begin{cases} \exists \mathbf{x} \in \mathbf{X} \ g(f, \mathbf{x}) \neq g(f', \mathbf{x}) \\ \forall \mathbf{x} \in \mathbf{X} \ f(\mathbf{x}) \approx f'(\mathbf{x}) \end{cases}$	[74, 77]
adversarial model (vs. fairness metric)	$f \rightarrow f' \Rightarrow \begin{cases} g(f, \mathbf{X}) \neq g(f', \mathbf{X}) \\ \forall \mathbf{x} \in \mathbf{X} \ f(\mathbf{x}) \approx f'(\mathbf{x}) \end{cases}$	[94, 95]
trust manipulation	$g \rightarrow g' \Rightarrow \begin{cases} g(f, \mathbf{X}) \neq g'(f, \mathbf{X}) \\ \forall \mathbf{x} \in \mathbf{X} \ g'(\mathbf{x}) \approx f(\mathbf{x}) \end{cases}$	[75]

[82] attack TCAV [8] and FFV [96], counterfactual explanations, e.g. Slack et al. [80] attack counterfactuals for neural networks [97], and overall explanations for language models, e.g. Sinha et al. [79] attack IG and LIME. Research on attacking explanations for image classification relies on a few popular datasets, e.g. ImageNet [98] reoccurs in 8 out of 11 studies. In parallel, a larger variety of tabular scenarios is tested.

#### 4. Defense against the attacks on explanations

Whenever a new attack algorithm is introduced in adversarial machine learning, various ways to address the explanation’s limitations and fix its insecurities are proposed. Chen et al. [100] is one of the first attempts to defend from adversarial examples introduced by Ghorbani et al. [25] via regularizing a neural network. The proposed robust attribution regularization forces IG explanations to remain unchanged under perturbation attacks. Rieger and Hansen [21] propose an alternative defense strategy against such adversarial examples [20, 25], i.e. aggregating multiple explanations created with various algorithms. As the attack targets only a single explanation method, their aggregated mean remains close to the original explanation (shown in Figure 2).

Table 3 lists defenses against the attacks on explanations, where for each, we record the datasets, models and explanation algorithms mentioned in experiments. Excluded from it are works that improve explanation robustness without directly relating to the potential adversarial attack scenario [e.g. see 117–121, and references given there]. We link each defense with an attack, but omit to list all attacks potentially addressed by the defense for brevity. The three missing links are worth clarifying here. Woods et al. [99] is an early work that introduces adversarial explanations, which have improved robustness against adversarial examples targeting model predictions. Similarly, La Malfa et al. [104] proposes to improve explanations of language models against adversarial perturbations. Unlike most of the contributions that focus on algorithms, Schneider et al. [107] conduct a user study with artificially manipulated

Table 3: Summary of defenses against the attacks on explanations of machine learning models. Each work on explanations’ robustness is connected with *up to two* attacks that are mentioned to be potentially addressed by it. We abbreviate the following: data (D), model (M), image (I), tabular (T), language (Lg), neural network (N), black-box (B), local (L), and global (G). [Appendix A](#) lists other abbreviations.

Defense	Attack(s)	Modality dataset	Model algorithm	Explanation method
Woods et al. [99]	–	I ImageNet, COCO, ..	N ResNet	L Grad-CAM
Chen et al. [100]	Ghorbani et al. [25]	I FashionMNIST, Flower, ..	N CNN, ResNet	L IG
Rieger and Hansen [21]	Ghorbani et al. [25] Dombrowski et al. [20]	I ImageNet	N VGG	L SG, IG, LRP, GBP
Boopathy et al. [101]	Ghorbani et al. [25] Dombrowski et al. [20]	I MNIST, CIFAR-10, ..	N CNN, ResNet	L IG, CAM, Grad-CAM
Lakkaraju et al. [102]	Ghorbani et al. [25] Lakkaraju and Bastani [75]	T Bail, Academic, Health	B MLP, RF, GBDT, ..	G MUSE, LIME, SHAP
Wang et al. [103]	Ghorbani et al. [25] Dombrowski et al. [20]	I CIFAR-10, ImageNet, Flower	N ResNet	L SG, IG, SmoothGrad
La Malfa et al. [104]	–	Lg IMDB, SST, Twitter	N MLP, CNN	L Anchors
Ghalebikesabi et al. [105]	Slack et al. [74]	T COMPAS, Adult, Bike, .. I MNIST	B XGBoost, CNN	L SHAP, GradSHAP
Dombrowski et al. [106]	Dombrowski et al. [20]	I CIFAR-10, ImageNet	N CNN, VGG, ResNet	L SG, GI, IG, LRP, ..
Schneider et al. [107]	–	Lg IMDB, WoS	B CNN	L Grad-CAM
Tang et al. [108]	Ghorbani et al. [25] Dombrowski et al. [20]	I MNIST, FashionMNIST	N CNN	L SG
Shrotri et al. [109]	Slack et al. [74]	T Credit, COMPAS, Crime, ..	B RF	L LIME
Gan et al. [110]	Dombrowski et al. [20] Zhang et al. [68]	I ImageNet, CityScapes Lg IMDB, Toxic	NN ResNet, LSTM, ..	L CAM, LRP, LIME, GS, ..
Vreš and Robnik-Šikonja [111]	Slack et al. [74]	T Credit, COMPAS, Crime	B MLP, RF, SVM, ..	L LIME, SHAP, IME
Liu et al. [112]	Ghorbani et al. [25]	I VOC2007	N VGG	L SG
Carmichael and Scheirer [87]	Slack et al. [74]	T Credit, COMPAS, Crime	B rule set	L SHAP, LIME
Joo et al. [113]	Ghorbani et al. [25] Dombrowski et al. [20]	I CIFAR-10, ImageNet	N ResNet, LeNet	L SG, GI, LRP, GBP
Virgolin and Fracaros [114]	Slack et al. [80]	T Credit, COMPAS, Adult, ..	B MLP, RF	L counterfactual
Wicker et al. [115]	Heo et al. [69] Dombrowski et al. [20]	T Credit, Adult, I MNIST, MedMNIST	N MLP, CNN	L GI, DeepLIFT, SHAP
Pawelczyk et al. [116]	Slack et al. [80]	T Credit, COMPAS, Adult	N LR, MLP	L counterfactual

explanations to evaluate if humans can discover the potential attack in practice [related to 75, 122]. Pawelczyk et al. [116] and Virgolin and Fracaros [114] introduce mechanisms to improve the robustness of counterfactual explanations against adversarial perturbations (we link the latter with an otherwise unreferenced attack of Slack et al. [80]).

Boopathy et al. [101] extend the regularization training method of Chen et al. [100] to use an  $l_1$ -norm 2-class interpretation discrepancy measure. Experiments show an improvement in effectiveness and computation cost when defending explanations over previous work [including 100]. Moreover, achieving robust explanations alone improves prediction robustness when explanations are compared with the proposed measure. Wang et al. [103] introduce a smooth surface regularization procedure to force robust attributions by minimizing the difference between explanations for nearby points. Experiments show a trade-off between regularization performance and computation cost [also with



respect to [100]. Notably, models with smoothed geometry become less susceptible to transfer attacks, i.e. where an adversary targeting one explanation method fools other gradient-based explanations as well. Dombrowski et al. [106] and Tang et al. [108] further compare and extend the in-training techniques to regularize neural networks towards improving explanation robustness [also mentioned in 20]. Dombrowski et al. [106] use the approximated norm of the Hessian as a regularization term during training to bound the  $l_2$ -distance between the gradients of the original and perturbed samples, which benefits gradient-based explanations. Joo et al. [113] improve this approach by introducing a cosine robust criterion to measure the *cosine*-distance instead. As shown in experiments comparing the two distance measures, it effectively solves issues with normalizing gradient-based attribution values that are used when interpreting predictions in practice.

Gan et al. [110] employ hypothesis testing to quantify the uncertainty of feature attributions and increase their stability in adversarial scenarios. The proposed MeTFA framework can be applied on top of various explanation methods, relating closely to SmoothGrad [123]. Experiments across image and text classification tasks show the superiority of MeTFA over SmoothGrad, as well as its utility in defending from adversarial examples [68]. Most recent work in this line of research introduces certifiably robust explanations of neural networks [112, 115], which reassure that no adversarial explanation exists for a given set of input or model weights.

In parallel to defending adversarial attacks on gradient-based explanations of neural networks, several works address the possibility of fooling model-agnostic LIME and SHAP [74]. Ghalebikesabi et al. [105] modifies SHAP estimator by sampling data from a local neighbourhood distribution instead of the marginal or conditional global reference distribution. Experiments show that such constructed on-manifold explainability improves explanations’ robustness, i.e. SHAP defends from the attack. Shrotri et al. [109] modifies LIME estimator to take into account user-specified constraints on the input space that restrict the allowed data perturbations. Alike, experiments show that constrained explanations are less susceptible to out-of-distribution attacks. Moreover, analysing differences between the original and constrained explanations allows for detecting an adversarially discriminative classifier. In contrast, Vreš and Robnik-Šikonja [111] introduce focused sampling with various data generators to improve the adversarial robustness of both LIME and SHAP. Instead of directly improving perturbation-based explanation methods, Carmichael and Scheirer [87] propose to “unfool” explanations with conditional anomaly detection. An algorithm based on k-nearest neighbours scores the abnormality of input samples conditioned on their classification labels. Comparing the empirical distribution function of scores between the original and potentially adversarially perturbed samples given a user-defined threshold proves to be effective for attack detection. Removing abnormal samples from the perturbed input set defends an explanation against fooling.

*Observations.* Comparing Tables 1 & 3 highlights existing insecurities in XAI methods; namely, not clearly addressed are backdoor attacks [72, 73], data poisoning attacks [71, 83], attacks specific to language [79] and concept-based explainability [82]. To this date, there are sparse studies concerning defenses against attacks on global explanations, e.g. Lakkaraju et al. [102] robustify model-agnostic global explanations against a general class of distribution shifts related to adversarial perturbations [25].

## 5. Adversarial attacks on fairness metrics

Closely related to adversarial attacks on explanations are attacks on machine learning fairness metrics, e.g. predictive equality [124] and (statistical) demographic parity [refer to 125, for an introduction to machine learning fairness]. Intuitively, algorithms targeting model predictions and accuracy can be applied to manipulate other functions of the model output as well. Table 4 lists a representative set of adversarial attacks on group fairness metrics, with the corresponding strategy of changing data [89], the model [94, 95], or jointly changing data and the model [91–93].

Aivodji et al. [94, 95] introduce fairwashing attacks changing the model, i.e. an adversary approximates an unfair black-box model with a faithful adversarial model appearing as fair:

$$f \rightarrow f' \implies \begin{cases} g(f, \mathbf{X}) \neq g(f', \mathbf{X}) \\ \forall_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x}) \approx f'(\mathbf{x}) \end{cases} \quad (14)$$

Experiments analyse the fidelity-unfairness trade-off and the effect of fairwashing on impacting feature effect explanations (see Figure 4).

Table 4: Related work concerning adversarial attacks on fairness metrics of machine learning models. We abbreviate the following: data (D), model (M), image (I), tabular (T), graph (Gr), neural network (N), black-box (B), and group (G). [Appendix A](#) lists other abbreviations.

Attack	Changes strategy	Modality dataset	Model algorithm	Fairness metric
Aivodji et al. [94]	M adversarial model	T COMPAS, Adult	B RF	G SP
Fukuchi et al. [89]	D data poisoning	T COMPAS, Adult	B RF, LR	G SP
Solans et al. [91]	D & M data poisoning	T COMPAS	B LR, RF, SVM, DT, naïve Bayes	G SP, EOdds
Mehrabi et al. [92]	D & M data poisoning	T Credit, COMPAS, Drug	B MLP	G SP, EOdds
Nanda et al. [90]	D, M adversarial example	I Adience, UTKFace, ..	N VGG, ResNet, DenseNet, ..	G robustness bias
Aivodji et al. [95]	M adversarial model	T Credit, COMPAS, Adult, ..	B MLP, RF, AdaBoost, XGBoost	G SP, PE, EOdds, EOpp
Hussain et al. [93]	D & M data poisoning	Gr Pokec, DBLP	N GCN	G SP, EOdds, EOpp
Ferry et al. [126]	– data reconstruction	T ACSIncome, ACSPublicCoverage	B DT+fairlearn	G SP, PE, EOdds, EOpp

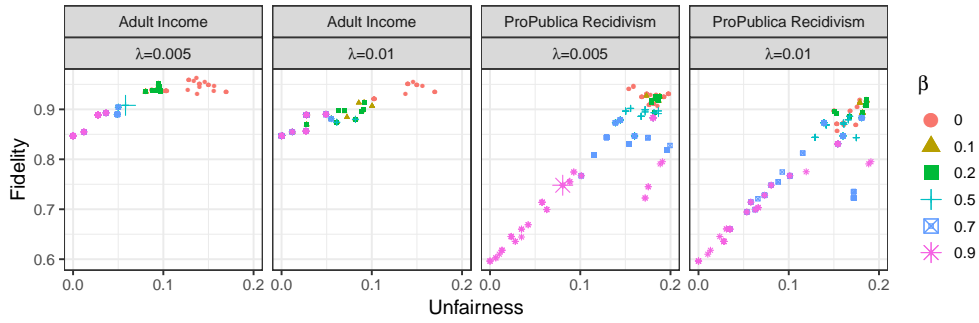


Figure 4: Adversarial model attack on fairness measurements of machine learning models predicting income and recidivism [adapted from 94]. Multiple surrogate rule list models (points) are fitted to faithfully approximate the unfair black-box predictive function. Parameter  $\lambda$  controls the penalty for rule length (complexity) and  $\beta$  controls a trade-off between fidelity and unfairness measured with statistical parity.

Fukuchi et al. [89] introduce a stealthily biased sampling procedure to adversarially craft an unbiased dataset used to estimate fairness metrics. It is formally defined as a Wasserstein distance minimization problem and solved with an efficient algorithm for a minimum-cost flow problem in practice. Experiments focus on quantifying the trade-off between lowering the perceived model bias and detecting adversarial sampling.

Contrary, Solans et al. [91] introduce a data poisoning attack to increase bias as measured with fairness metrics via adding data points to the training dataset so that the model discriminates against a certain group of individuals:

$$\mathbf{X} \rightarrow \mathbf{X}' \Rightarrow f_{\theta} \rightarrow f_{\theta'} \Rightarrow g(f_{\theta}, \mathbf{X}) \neq g(f_{\theta'}, \mathbf{X}). \quad (15)$$

Although the approach relies on the differentiation of neural networks for optimization, experiments show the transferability of data poisoning to other algorithms in a black-box setting. Mehrabi et al. [92] propose alternative data poisoning attacks, also in both black-box and white-box settings relying on gradient computation to optimize a loss function for data sampling. Experiments show an improvement in manipulating fairness over previous work of Solans et al. [91]. Hussain et al. [93] extend data poisoning attacks on fairness to the task of node classification with graph convolutional networks.

Further related is work concerning attacking fairness in imaging, where Nanda et al. [90] introduce the notion of robustness bias, which requires all groups to be equally susceptible to adversarial attacks. Ferry et al. [126] consider a different adversarial scenario where the goal of an attacker is to retrieve a piece of information about a sensitive attribute based on fairness criteria (dataset extraction attack). Related are membership inference attacks on privacy using explanations [78, 84].

*Observation.* Research on attacking fairness metrics focuses on the notion of group fairness, i.e. treating different groups of inputs equally, and omits subgroup or individual fairness, i.e. predicting similarly for similar individuals [see the distinction in 125, table 1].

## 6. AdvXAI: Opportunities, challenges and future research directions

As their popularity grew, XAI methods left the lab and found their way into potentially hostile habitats. In order to defend their position as guardians of the security of AI systems, XAI methods must also demonstrate their resilience to adversarial action. Below, we propose possible short-term and long-term research directions in the AdvXAI field.

*Attacks.* Currently most exploited by the attacks are the first-introduced and most popular XAI methods, e.g. SHAP and Grad-CAM. Future work on adversarial attacks may consider targeting the more recent enhancements that aim to overcome their limitations, e.g. SHAPR that takes into account feature dependence in tabular data [53] or Shap-CAM for improved explanations of convolutional neural networks [127]. Alike model-specific explanations of neural networks, worth assessing is the vulnerability of explanation methods specific to tree-based models, e.g. TreeSHAP [128], but also white-box attacks on explanations assuming prior knowledge that the model is an ensemble of decision trees. Beyond post-hoc explainability, adversarial attacks could target vulnerabilities of the interpretable by-design deep learning models like ProtoPNet [129] and its extensions [e.g. see 130, and its related work]. Finally, there are adversarial attacks on model predictions that actively aim to bypass through a particular defense mechanism [e.g. see 16, table 4] and such a threat of circumventing the defense in XAI is currently unexplored.

*Defenses.* One goal of this survey is to reiterate the apparent insecurities in XAI, i.e. the unaddressed attacks on explanation methods [71–73, 82, 83, 85]. Beyond defense, improving the robustness and stability of algorithms for estimating explanations becomes crucial, e.g. gradient-based [117] and perturbation-based [118–120] methods. Meyer et al. [121] provide theoretical and empirical characterizations of the factors influencing explanation stability under data shifts. We also underline that the possibility of manipulating fairness metrics has detrimental consequences when applied in audit and law enforcement, and therefore developing metrics robust against the attacks is desirable. Note that although a particular XAI method is attacked or defended, in fact, the evidence of model predictions is in question here.

*AdvXAI beyond classical models towards transformers.* Nowadays, the transformer architecture is at the frontier of machine learning research and applications of deep learning in practice [131]. Thus, the adversarial robustness of explanations of large models for various modalities like ViT [132] and TabPFN [133] deserves special attention. For example, Ali et al. [134] extend LRP explanations to transformers, which might propagate the explanations’ vulnerability to adversarial attacks as shown in previous work [69, 76]. We acknowledge that the recently proposed transformer-based foundation models, e.g. SAM [135], more and more frequently include benchmarks specific to evaluating responsibility, e.g. whether segmenting people from images is unbiased with respect to their perceived gender presentation, age group or skin tone [136]. The possibility of attacking such fairness measurements by biased sampling becomes a trust issue [89].

*AdvXAI beyond the image and tabular data modalities.* A majority of contributions surveyed here, so as XAI, concern machine learning predictive models trained on imaging and tabular datasets. Further work is required to evaluate which and how severe are adversarial attacks concerning other data modalities like language [104, 107], graphs [93], time series, multimodal systems, and explanations of reinforcement learning agents [137, 138]. Huai et al. [139] are the first to introduce a model poisoning attack against the explanations of deep reinforcement learning agents, with currently no consecutive directly related work.

*Software, datasets and benchmarks.* To facilitate sustainable research in AdvXAI, one could develop open-source software implementing the reviewed attacks and defenses, which promotes reproducibility and a unified comparison between methods going forward. To this end, software contributions concerning responsible and secure machine learning [140–143] lack the implementation of adversarial attacks on explanations and fairness metrics. Moreover, contributing new real-world datasets and benchmarks specifically aiming at evaluating attacks and defenses in XAI would be valuable [alike 136, 144]. An implementation of such a security benchmark could resemble the Safety Gym framework for testing safe exploration in reinforcement learning [145]. Alongside, competitions have proven to accelerate research in particular domains of machine learning, e.g. the FICO competition for XAI [146].

*Good practices.* Historically, machine learning models were evaluated in train and test settings of data distribution. Adversarial methods broadened the scope of evaluation into adversarial settings, e.g. out-of-distribution data [121]. While there is a need for discussion on whether explanations should be evaluated on train or test data, new adversarial settings described in this survey need to be also taken into account. Another good practice would be to catalogue the collective history of harms or near harms realized in the real world by the deployment of XAI methods, similar to the AI Incident Database [147]. A step further, various certifications of AI systems appear in the context of their deployment in real-world applications [148], which could be applicable to XAI, apart from algorithmic constraints-driven certificates for explanation methods [11, 112, 115].

*Human stakeholders in the context of AdvXAI.* Poursabzi-Sangdeh et al. [122] highlight the pivotal issue that human stakeholders are susceptible to “information overload” in the context of interpretability, i.e. not always presenting more explanations is better [149]. Exploiting this particular failure mode of XAI methods creates new possibilities for attacking their end users [88, 107]. In practice, whether a particular attack or defense is successful will differ between application domains, e.g. explaining financial decisions for regulatory audit [87, 109], or selecting bio-markers for scientific discovery [12]. There are emerging works considering the interactivity of XAI process [e.g. see 149, 150, and references given there], in which case attacks and defenses could exploit the conversational framework of human-model interaction.

*Ethics, impact on society, and law concerning AdvXAI.* Finally, we need to take into account the broader impact adversarial research has on society. How does AdvXAI fit into regulations like AI Act [151], the four-fifths rule of fairness [152], or the right to explanation [45]? For example, commercial stakeholders can perform “XAI-washing”, i.e. imply that a product or service uses XAI to pass some legal requirements when in fact explanations are not authentic, e.g. maliciously crafted with adversarial methods. These questions are yet to be answered. For a more philosophical consideration on explanation robustness, we refer the reader to the argument by Hancox-Li [153] concerning epistemic and ethical reasons for seeking objective explanations.

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## Appendix A. List of abbreviations and proper names (with references)

- Anchors: high-precision model-agnostic explanations [154]
- CAM: class activation mapping [155]
- CNN: convolutional neural network [156]
- DT: decision tree [157]
- EOdds: equalized odds [158]
- EOpp: equal opportunity [158]
- fairlearn software [143]
- FFV: faceted feature visualization [96]
- GBDT: gradient boosting decision tree [3]
- GBP: guided backpropagation [159]
- GCN: graph convolutional network [160]
- GI: gradient input [161]
- Grad-CAM: gradient-weighted class activation mapping [9]
- GS: grid saliency [162]
- IG: integrated gradients [6]
- IME: interactions-based method for explanation [163]
- KNN: k-nearest neighbors [see 164, section 13.3]
- LIME: local interpretable model-agnostic explanations [5]
- LR: logistic regression [see 164, section 4.4]
- LRP: layer-wise relevance propagation [56]
- MLP: multi-layer perceptron [see 164, chapter 11]
- MUSE: model understanding subspace explanations [88]
- PDP: partial dependence plot [introduced in 3, section 8.2]
- PE: predictive equality [124]
- Relevance-CAM: relevance-weighted class activation mapping [165]
- RF: random forest [57]
- RTS: real time saliency [166]
- SG: simple gradient [4]
- SHAP: Shapley additive explanations [7]
- SP: statistical (demographic) parity [see 125, section 4.1]
- SVM: support vector machine [167]
- TCAV: testing with concept activation vectors [8]
- ViT: vision transformer [132]
- XGBoost: extreme gradient boosting [168]

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