

# Manipulating Model Explanations: Why you shouldn't trust me

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## ABSTRACT

This paper reviews state-of-the-art approaches to model explanations with a focus on those techniques that try to fool these methods. Based on the findings in the reviewed studies, we conclude that knowledge of the defectiveness of neural networks and their highly sought explanations should be taken with caution. Therefore, the main purpose of this review is to raise awareness that explanations, while helpful, can be fundamentally flawed.

We don't only want the model to be good. We want it to be safe and interpretable. As machine learning models enter critical areas in human lives such as the criminal justice system, medicine or financial systems, the inability for humans to understand these models is dangerous and problematic. Advances in the rising research area of explainable AI seems to be a remedy. However, there is not yet a consensus about the validity and robustness of explanations methods themselves. The main suggestion of this paper is to be cautious about results of explanation methods. Explanations can be fooled just as the underlying machine learning models. So, in the end the question must be posed whether inexplicable models should be used at all if we need other models to explain these models but are not valid themselves ..

## KEYWORDS

Interpretability, Neural networks, adversarial training

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## 1 INTRODUCTION

In recent years, deep learning models have demonstrated superior performance on a variety of tasks [3, 15, 17]. While performance is still increasing and more tasks are being handled, their performance comes at the cost of complexity: models often use millions to billions of parameters to achieve universal function approximation. This complexity means that they remain black boxes that cannot be interpreted even by experts.

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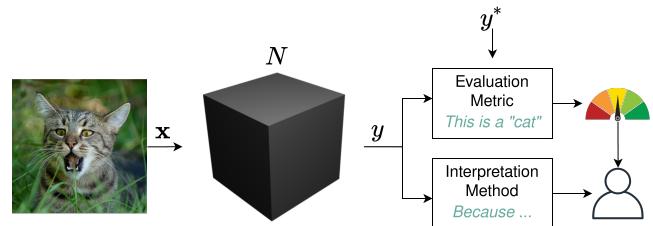
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**Figure 1: Prediction pipeline using a machine learning model, depicted as black box.** Typically, evaluation metrics require the prediction  $y$  and the ground truth label  $y^*$  allowing for the assessment of the model's accuracy. Additionally answering the question *why*, i.e. making the model interpretable for a human, requires additional methods.

Such a black box is able to predict well for unseen yet similar data, answering the question of *what* is the most likely label for an input sample. However, most models will provide no answer to *why* the model chose this label for the instance and which features of the instance were crucial for making this prediction.

For instance, with object recognition one would likely assume that the presence (or absence) of an object in the image causes a model to decide for a specific object category, closely akin to how humans base their decision process. As seen in Figure 1, the presence of the cat in the input image  $x$  should be causing the model to predict the label 'cat'.

Automated algorithms are already in use in critical areas, such as medicine TODOcite, the criminal justice system [4] and the financial sector TODOcite or the piloting of self-driving cars. Thus, as machine learning models are moving out of the lab into the real-world, the inability of humans to understand these models seems even more problematic.

Thus, automated interpretation methods are required to make sense of the reasoning process and robustness of such deep learning based models and to ensure that a model makes decisions without unfair or hidden biases. The research field approaching the explanation or validation of machine learning models is called explainable artificial intelligence (XAI).

Not knowing about the biases of a network the vastly advancing technology of machine learning to be used in high-stakes and safety critical applications and prevent real-life deployment of such systems. Furthermore, the rise in machine learning model deployments also caused the development of adversarial attacks. These attacks attempt to fool a machine learning model by providing deceptive input. Fooling refers to the resulting malfunction of the model.

In particular, it is unclear how the variety of proposed model interpretation methods are related and what common concepts can be used to evaluate and compare them. Many works are dedicated

to establish a formal definition of what it means to be interpretable, and how to select, evaluate and compare methods for generating explanations of machine learning models. [11, 13].

Not knowing about attacks and data arranged to exploit specific vulnerabilities has contributed to a relatively new research field of XAI comprising topics of (1) *model explanations*, (2) *adversarial attacks*, or manipulation methods and (3) the field of *adversarial manipulations of model explanations*. All of this is also known by the name of robust machine learning or even explainable artificial intelligence, as all subfields have the common goal to make models more robust and safe for deployment. (1) refers to the development of techniques that can be used to understand and explain the decision making process of a machine learning model or even the development of models that are inherently interpretable. (2) is the field of detecting vulnerabilities in models that cause models to be deceived by altered input. (3) is the main topic of this paper, i.e. how to fool explanation models in order to detect vulnerabilities and malfunctions in explanation methods.

Detecting such vulnerabilities in models is most crucial

Fragility limits how much we can trust and learn from the interpretations

Most research on explainability focuses on the application of computer vision tasks.

Most works in the field of XAI focus on image classification tasks, mostly because visualizations of a neural networks prediction can be easily verified by a human. The general purpose of image classification is to detect what objects are in an image. If a model works can be checked rather easily (if an image contains a cat, the prediction of a neural network should be cat and not some other object category). However, how it works (*interpretability*), i.e. based on which features in the image the decision is made or which parameters in the model influence the prediction most, is an entirely different matter (*explainability*).

More importantly, while a big motivation for the development of robust and explainable systems is to overcome biases in models, datasets with direct implication of biases are seldomly used and by far not treated as benchmarking scenarios for explainability analyses.

The overview presented in this article examines the existing literature and contributions in the field of XAI focusing on methods to manipulate explanation methods. The critical literature analysis might serve as a motivation and step towards the biggest problems in XAI: How to make sure that interpretations of models are truly valid. This paper is structured as follows...

## 2 INTERPRETATION METHODS

There exists a variety of definitions in the vastly expanding research field of XAI, and the concept of *interpretability* still has no formal commonly used technical meaning [11]. To build on the common ground of existing research, this paper follows the terminology of [2]. The authors make a distinction between the related but different concepts of *interpretability* and *explainability*.

**Interpretability** refers to the extent to which cause and effect can be observed in a model, which can be translated to uncovering *why* a model made prediction  $y$  to an input  $\mathbf{x}$ . Consider the example of image classification from Figure 1. Here, interpretability would

mean that if a cat is present in the image (the cause), the model classifies it to the category 'cat' (the effect). Now imagine we find that the model takes the green meadow in the image as evidence to predict 'cat', and not the cat itself, there is a lack of interpretability, as other features are learned as important than the features that are truly important. This toy example is in fact a common problem in image classification: the over-reliance of models on image background, rather than on objects in the foreground, has been observed for the task of image classification [23].

**Explainability** on the other hand spans methods to uncover *how* a model makes predictions, meaning to observe the inner workings of a model and to literally explain what is happening.

While both concepts seem to be important for the general objective of explainable artificial intelligence, this paper focuses on interpretability. High interpretability is desired as it can help to uncover biases in the model. Suppose a machine learning model is to be deployed for the task of income prediction based on features such as age, race, gender, education and hours of work per week. The performance of the system would mainly be evaluated in terms of the predictive accuracy and the fairness of the system. The former can be evaluated with metrics, such as accuracy on a held-out test set. For the latter, interpretability methods might be applied to observe which input features are used by the model to predict the income. If the model uses sensitive features, such as sex and race as important features, it is systematically biased and thus unfair.

This section offers a taxonomy for machine learning interpretation methods.

There are essentially two ways to achieve interpretability: (1) to use inherently interpretable models or (2) to post-process a model in a fashion that allows to yield insights. The former is known as the development of *surrogate* models and more generally described as *model-agnostic* methods. Option (2) is known as *model-transparent* methods.

A further categorization can be made based on the scope of interpretations: *Local* methods aim at interpretations that are true for a single data points and its neighbors. *Global* methods aim at gaining interpretations that are valid for most data points in a class [10, 14, 24]. The interpretation methods discussed within this paper mostly fall into the class of local explanation methods [12, 16].

Explanation methods aim at making complex and inherently uninterpretable black box models interpretable by creating human readable visualizations. A frequently used type of explanation methods are feature attributions mapping each input feature to a numeric score. This score should quantify the importance of the feature relative to the model output. The resulting attribution map is then visualized as a heatmap projected onto the input sample to interpret the input attributes regarding which ones are the most helpful for forming the final prediction.

### Definition 1: Interpretation Method

We consider a neural network  $N : \mathbb{R}^d \rightarrow \mathbb{R}^k$ . For the task of image classification,  $N$  classifies an input image  $\mathbf{x} \in \mathbb{R}$  in  $k$  categories where the prediction  $f_N(\mathbf{x}) = y \in \{1, \dots, K\}$  is given by  $y = \text{argmax}_i f_N(\mathbf{x})_i$ .

Given the neural network  $N$ , its input vector  $\mathbf{x} \in \mathbb{R}^d$  and the neural networks prediction for input  $\mathbf{x}$ ,  $f_N(\mathbf{x}) = y$ , an interpretation method  $\mathcal{I}$  determines why label  $y$  has been chosen by  $N$  for input

x. The interpretation is given by an output vector  $\mathbf{x} \in \mathbb{R}^d$  where each entry  $h_i$  is mostly a numeric value describing the relevance of an input dimension  $x_i$  of  $\mathbf{x}$  for  $f_N(\mathbf{x})$ . As  $\mathbf{x}$  has the same dimensions as the input  $\mathbf{x}$  it can be mapped to the input, overlaying  $\mathbf{x}$  as a heatmap, where the color value represents the importance of feature  $x_i$  towards the prediction  $f_N(\mathbf{x})$ .

An example is given in TODO. Higher values, implying a stronger relative importance for making the prediction  $f_N(\mathbf{x})$ , is depicted in TODD color.

While all explanation methods try to obtain importance measures for the network prediction, they differ with respect to how these measures are obtained. [21] propose two major categories for explanation strategies, namely *black-box* explanation methods and *white-box* explanation methods. While black-box interpretations assume no knowledge about the underlying model, white-box methods only work by using the model parameters.

This terminology of discriminating between bb and wb models may not be confused with the nature of the underlying models: Models still remain of black-box nature even though a white-box method may contribute to making the decision making process of such a model more insightful.

The following section details the two categories and will give examples of the state-of-the-art interpretation methods within each group.

## 2.1 Model-agnostic methods.

Model-agnostic interpretations assume no knowledge about the model thus treating it as a black box. The underlying model is approximated by learning its behavior with an interpretable model, e.g. a linear model. The interpretable model is also dubbed the 'surrogate' model. The common approach for learning the surrogate is to approximate the relationship between the input samples and the corresponding prediction by the model. As the model itself does not need to be known, these approaches can be used in scenarios where the model itself is not directly accessible. Model-agnostic interpretations are fairly popular and are used in a wide range of applications, ranging from finance and law to medicine and chemistry [7, 22].

A black-box interpretation offers the great advantage of being applicable to any model and offers simplicity because the interpretation is embedded in the model. However, this option of gaining interpretability might be costly for users that already have a high performing model. For this reason, growing need for methods exists that can be applied without retraining or modifying the underlying model.

**LIME.** Local Interpretable Model-agnostic Explanations (LIME) [16] perturbs the input and observes how the predictions change. In image classification, LIME creates a set of perturbed instances by dividing the input image into interpretable components (contiguous superpixels), and runs each perturbed instance through the model<sup>26</sup> to get a probability.

Figure 2 shows an example of LIME applied to an image and the neural network model Inception-v3 [20].

**SHAP.** SHAP [12], short for SHapley Additive exPlanations, calculates an additive feature importance score for each prediction with

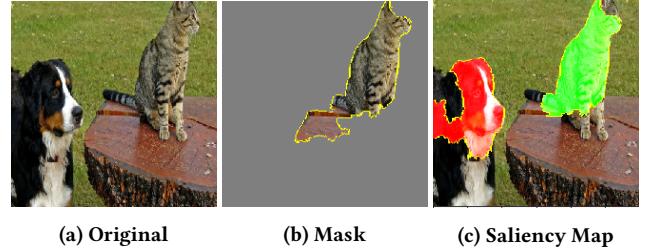


Figure 2: Visualization of LIME.

a set of desirable properties, such as local accuracy or consistency that its antecedents lacked.

## 2.2 Model-transparent methods.

On the other side are model-transparent, or white box, methods where the underlying model is known with all its parameters. Thus, the interpretation can be directly computed by using the model instead of relying on an approximation of  $f_N$  as within the black-box methods. These methods typically rely on the relationship between an input sample, the underlying model's prediction and the associated activations of the models hidden layers. Most methods in this area aim to highlight the features of the input that are important for the prediction. An example for model-transparent methods are gradient based and saliency map based methods.

**Notations.** A model-transparent interpretation method, in the following named interpreter  $\mathcal{I}$ , generates a heatmap

$$h_c^{\mathcal{I}}(\omega) = \mathcal{I}(\mathbf{x}, c; \omega)$$

for a neural network with parameters  $\omega$  and class  $c$ . The heatmap is a vector  $h_c^{\mathcal{I}}(\omega) \in \mathbb{R}^d$ , where the  $j$ -th value  $h_{c,j}^{\mathcal{I}}(\omega)$  represents the importance score of the  $j$ -th input feature  $x_j$  for the final score of class  $c$ .

**Layer-wise Relevance Propagation (LRP)** relies on a Taylor series close to the prediction point rather than partial derivatives at the prediction point itself

**Gradient-weighted Class Activation Mapping (Grad-CAM)** [18] To further improve the quality of the visualization, attribution methods such as heatmaps, saliency maps or class activation methods (GradCAM[292]) are used. Grad-CAM uses the gradients of any target concept, flowing into the final convolutional layer to produce a coarse localization map, highlighting the important regions in the image for predicting the concept

**SimpleGrad (SimpleG)**

**Smooth Grad**

## 3 MANIPULATION METHODS

As outlined in section 2, there are a variety of explanation methods readily available as frameworks and open source implementations. However, there is still little analysis on the robustness and reliability of such methods. While it is already common practice to test machine learning models against adversarial attacks, the same is not

yet the standard for interpretation methods. We argue that these techniques should not be used in critical applications without basic testing of interpretation techniques against adversarial settings.

### 3.1 Adversarial Setting

The focus of most works is on adversarial attacks against the prediction of a machine learning model. Contrary, the focus of this paper is on the attacks on the interpretation without changing the prediction.

A manipulation method refers to a method influencing an interpretation method  $\mathcal{I}$  to yield a wrong interpretation. This influence on the interpretation method is also called *fooling* or an *attack*.

The goal is to apply efficient and for humans imperceptible perturbations to change the interpretability of the input sample while leaving the prediction unchanged.

Formally, the problem can be defined as: **Definition 2: Interpretation Manipulation Method**

A manipulation method  $\mathcal{F}$  is defined as a method for altering the output of an explanation method while leaving the model performance of the neural network  $N$  roughly unchanged. This must be the case, as the attack is targeted to fool the explanation method, and is essentially not targeted to fool the model itself. Fooling the model would only disclose the vulnerability of the model but would not allow to gain insight into the stability of the fooling method. Hence, the main criteria for an explanation manipulation method must be fulfilled:

1. The models prediction stays approximately the same, i.e.  $f_N(x_{adv}) \approx f_N(x)$  or  $f_{N_{adv}}(x) \approx f_N(x)$
2. The explanation map  $h(x_{adv})$  is significantly different to the explanation map resulting from non adversarial models or inputs  $h(x)$ , i.e.  $h(x_{adv})$  or

$$\arg \max_{\delta} = \mathcal{D}(\mathcal{I}(x_i, \omega), \mathcal{I}(x_i + \delta, \omega))$$

3. In case the attack is in the input domain of the model, the perturbation of input samples must be imperceptible by humans. According to [5], the norm of the added perturbation  $\delta$  to an input sample  $x$  thus must be small, i.e.  $\|\delta x\| = \|x_{adv} - x\|_{inf} \leq \epsilon$

Other criteria to a manipulation method are the following:

**Effectiveness.** The manipulation scheme is inexpensive to conduct. Input manipulations are by definition inexpensive, as the perturbation can be applied to single input samples. Model manipulations are more expensive as they require the model parameters to be adapted. However, an adversarial model can be obtained by fine-tuning the model with an adapted objective function. This fine-tuning also has the advantage that the model is adapted to include a systematic bias and can thus be applied to fool explanation methods without further adapting the model or input samples.

**Transferability.** The manipulation does not only fool one type of explanation method, but it's effect transfers to other types.

Most of the explanation methods outlined in sec. section 2 have been shown to be vulnerable to adversarial perturbations. Manipulation methods often show that there exist small feature changes resulting in a change of the explanation methods output while the output of the model itself does not change. Most approaches aim at

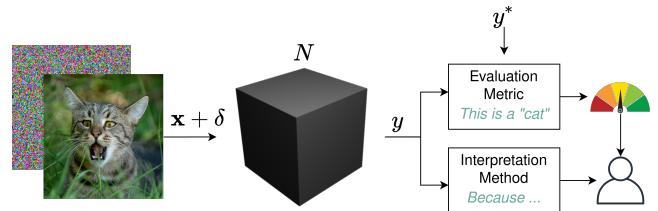


Figure 3: Depiction of an adversarial input manipulation. The model is fine-tuned with altered input samples.

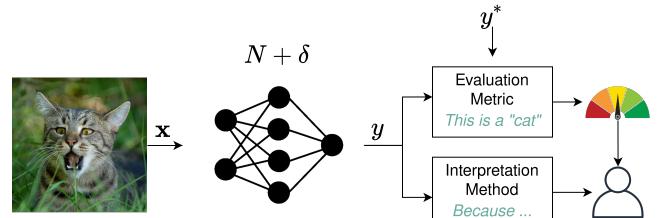


Figure 4: Depiction of an adversarial model manipulation. The model is fine-tuned with the same distribution of input data and a fooling loss.

providing a relevance measure of the input features.

### 3.2 Manipulation Levels

**Adversarial Input Manipulation.** The general approach is to perturb input data while observing the effect of this perturbation on the model prediction. As found in TODO, visually-imperceptible perturbations of an input image can make explanations worse for the same model and interpreter.

**Adversarial Model Manipulation.** Contrary to input manipulations, model manipulations do not operate on the input space but rather on the model parameter space itself. As first introduced by Heo et al. [9] in 2017, this line of research is comparably new. Adversarial model manipulations are obtained by fine-tuning the model on the same data but with an adapted objective function. [9] propose the adapted loss function of

$$\mathcal{L} = \mathcal{L}_{CE}(\mathcal{D}; \omega) + \lambda \cdot \mathcal{L}(\mathcal{D}; \omega; \omega_0)$$

where  $\mathcal{L}_{CE}$  would be the standard cross-entropy classification loss.

The authors find that perturbed model parameters can also make explanations worse for the same input images and interpreters.

Creation of a fooled model by fine-tuning the model with a fooling loss.

**3.2.1 Transferability of Manipulations.** [9] find that fooling one explanation method with a fooling scheme transfers to other methods.

### 3.3 Manipulation Targets

In addition to the categorization of manipulation methods based on the manipulation level, the methods can further be categorized based on the target of their perturbation. The first possibility is

untargeted perturbation. The second is targeted perturbation. Both these styles can be applied on either model and input level.

**Untargeted Manipulations.** The majority of manipulations are untargeted, meaning that the applied perturbations are mostly random and not designed to change the prediction for a specific portion of an input sample.

**Targeted Manipulations.** On the contrary, targeted manipulations are designed to specifically alter the explanation of distinct features of an input instance. Such a specific feature might be an object in the input image in the context of image classification. For instance [9] introduce a fooling scheme in which the interpretations of the classes elephant and school bus are swapped. Manipulations on the level of the model are mostly targeted, as the explanation methods are being fooled by adapting the model parameters.

### 3.4 Evaluation Criteria

As outlined in section section 3, there exists a plethora of interpretations methods differing in the assumption about the model character and also in style how interpretations are obtained. Thus, reliable evaluation methods are required allowing for a choice of an appropriate and robust explanation method. Evaluations of the quality of an explanation method can be separated into qualitative and quantitative evaluations.

**Quantitative Evaluations.** As the goal of interpreter manipulations is to fool an interpreter, thus altering the output of an interpreter, it is straightforward to compare interpretations before and after perturbation [8]. Common metrics for quantitatively measuring this similarity between interpretations are the following:

- **Spearman's rank order correlation.** As interpretation methods rank the features based on their importance, the rank correlation [19] is a natural measure for comparing interpretations.
- **Intersection of the top- $k$  features.** For some tasks, only the top- $k$  features are relevant, such that a comparison between these top- $k$  features is insightful.
- **Fooling Success Rate (FSR).** Heo et al. [9] introduce the concept of the Fooling Success Rate (FSR) with the aim to create a measure for systematically measuring the robustness of an interpretation method to adversarial model manipulations. The FSR measures on how many samples from a dataset an interpretation method  $\mathcal{I}$  is fooled by a model manipulation. The higher the FSR, the more often an interpretation method is fooled.

**Qualitative Evaluations.** As interpretations are attributed to input features, the resulting relevance values  $l$  can be easily mapped to the input vector  $x$ . Looking at these evaluations for specific samples is informative albeit not usable to obtain a general statistic about the explanation methods quality.

## 4 TRANSFERABILITY OF PERTURBATIONS

sec:transferability)

input perturbations do not propagate to the whole validation set. On the contrary, model manipulations are non-local perturbations,

meaning that they do not merely perturb an input sample but rather effect all samples in the way that the model itself is changed.

## 5 EXPLAINING MANIPULATIONS

There is an abundance of examples and scenarios where model explanations fail. However, there are few paper specifically targeting why these manipulations work in the first place.

## 6 UNCOVERING MANIPULATIONS

### 7 SANITY CHECKS FOR INTERPRETERS

Checking the robustness, scope and hence the quality of model interpreters has become an indispensable step in explainable machine learning.

[1] propose a number of randomization tests for saliency-map based interpreters. The authors find that most methods fail their tests, and warn of the danger of visual assessment.

Additionally, in order to account for adversarial model manipulations, Heo et al. [9] propose to expand the criteria for checking the robustness of interpreters further.

## 8 BENCHMARKING INTERPRETATIONS

Evaluating explanation and interpretation methods is difficult as ground truth is mostly lacking. In most applications, it is not known which input features are most important.

## 9 EXPERIMENTS

In this section, several experiments are evaluated that were conducted to replicate findings of other studies. Furthermore these approaches are extended to other domains and datasets.

### 9.1 Explanation Methods

### 9.2 Manipulation Methods

### 9.3 Models

### 9.4 Datasets

**ImageNet German Loan Dataset**

**Recidivism Dataset**

**Adult Income Dataset** The adult income dataset [6] contains .. samples.

## 10 DISCUSSION

This paper summarizes the current approaches to manipulating model interpretation methods. On the one hand, the findings suggest that our models are not fully aligned with how human information processing works. If machine learning models would decide by the criteria we humans employ for tasks such as image classification, there would be no fooling of interpretation models by input or model manipulations. On the other hand, it was shown that advances in machine learning models has led to models that rely too much on the data they are trained on, thus showing a high susceptibility to ood properties or properties that are highly correlated with labels in the dataset but are not distinctive in the real world (such as image backgrounds). Models and interpreters can still be misled in a large and systematic manner.

However, we hope that the vastly expanding and progressing field of XAI will help to move towards more robust, reliable and human-aligned machine learning models.

While there exists a number of review papers on XAI and its various subfields, this report is to the best of our knowledge the first one to comprehensively review manipulation methods for interpreters.

We believe that identifying risks and adversaries helps to open up research on more robust interpretation methods.

Interpretation methods can be categorized based on if they maintain local consistency among explanations (i.e. finding an explanation that is true for single data samples and their neighbors) or based on if they try to find global explanations, being true for all samples of a class. As there exist model manipulations methods, that structurally alter the models by adapting the loss function, this line of global model fooling though being approached is still in its infancy.

## 10.1 Conclusion

Finally, it must be noted that the suitability of a method depends on its application domain.

Much critique has been applied to methods aiming at interpreting complex and potentially non-interpretable models. Some researchers argue it is not worthwhile to study non interpretable systems while dismissing that using inherently interpretable models in the first place might be the better approach.

Adversarial attacks show that machine learning systems are still fundamentally fragile: They may be successful in a number of tasks, but fail to adapt to ood scenarios, i.e. when being applied to unfamiliar territory.

The findings about manipulating interpretations do not suggest that interpretations are completely meaningless, just as adversarial attacks on predictions models do not imply that machine learning models are useless. However, they suggest that there still are fundamental flaws in the way neural networks operate and that much caution and supervision could be applied if they are to be deployed in the real world.

do not suggest that interpretations are meaningless, just as adversarial attacks on predictions do not imply that neural networks are useless.

This paper follows the footsteps of [11], trying to caution against blindly putting faith into post-hoc explanation methods. Moreover, we propose that checking the robustness of interpretation methods not only with respect to adversarial input manipulations but also with respect to adversarial model manipulation should be an proof of concept.

## 10.2 Future Work

We see several possible future directions of future work. Firstly, for approaching the discrepancy of in-lab and real-life applications of, more focus might be laid in the development better performance metrics for both measuring the performance of machine learning models as well as their interpreters. More specifically, it might be fruitful to further investigate the correlation between ood samples and the performance of an interpretation method.

There is also no work proposing a benchmarking for ...

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