The Logic Traps in Evaluating Post-hoc Interpretations

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Abstract

Post-hoc interpretation aims to explain a trained model and reveal how the model arrives at a decision. Though research on post-hoc interpretations has developed rapidly, one growing pain in this field is the difficulty in evaluating interpretations. There are some crucial logic traps behind existing evaluation methods, which are ignored by most works. In this opinion piece, we summarize four kinds evaluation methods and point out the corresponding logic traps behind them. We argue that we should be clear about these traps rather than ignore them and draw conclusions assertively.

1 Introduction

The inscrutability of deep models has grown in tandem with their power (Doshi-Velez and Kim, 2017), which has motivated efforts to interpret how these black-box models work (Sundararajan et al., 2017; Belinkov and Glass, 2019). Post-hoc interpretation aims to explain a trained model and reveal how the model arrives at a decision. This interpretability is achieved by interpreting a trained model in post-hoc ways (Molnar, 2020).

In recent years, various post-hoc interpretation methods have been proposed. Erasure-based method asserts contributions of features by measuring the change of output after these features removed (Li et al., 2016; Feng et al., 2018; Chen et al., 2020). Gradient-based method uses gradients to study the impact of different features on model output (Sundararajan et al., 2017; Wallace et al., 2019; Hao et al., 2020). Attention-based method uses the magnitude of the attention weights as feature importance scores (Serrano and Smith, 2019; Vashishth et al., 2019; Hao et al., 2020). At the same time, these interpretation methods have received much scrutiny, arguing that the interpretations are fragile or unreliable (Alvarez-Melis and

Jaakkola, 2018; Pruthi et al., 2019; Wang et al., 2020; Slack et al., 2020).

Though the research on post-hoc interpretations has developed rapidly, one growing pain in this field is the difficulty in evaluating. This difficulty comes from the inherent properties of post-hoc interpretation: The reason humans need post-hoc interpretations is that human-readable reasoning process of deep models is inaccessible. However, this reasoning process is the ground truth in evaluating interpretations. This contradiction led that post-hoc interpretations can only be evaluated indirectly. Papers provide diverse and sometimes nonoverlapping evaluation methods to demonstrate their argument. However, there are some logic traps behind these evaluation methods, which are often ignored in most existing works. The lack of a clear statement on these traps has damaged the community in the following aspects:

First, different evaluation methods may give rise to contradictory conclusions, which has caused many debates, such as the argument in using the magnitudes of attention weights as interpretations for transformer-based models (Wiegreffe and Pinter, 2019; Jain and Wallace, 2019; Pruthi et al., 2019; Bastings and Filippova, 2020) and the rebuttal of gradient-based methods (Alvarez-Melis and Jaakkola, 2018; Ghorbani et al., 2019; Wang et al., 2020; Slack et al., 2020). Debates can play a positive role in the development of the community. However, many evaluation methods in these debates fall into crucial logic traps and draw conclusions recklessly. Without a unified understanding of logic traps in existing evaluation methods, these debates seem endless and will never get conclusions.

Second, since some evaluation metrics are widely used, newly proposed work may be required to compare with other works using these metrics. However, the logic traps in these evaluation metrics may make the comparison unfair and not suitable

for assessing the value of new work. Using evaluation metrics to make comparisons without considering the influence of the logic traps has caused unfair comparisons and unnecessary obstacles to new work.

Last, the over-belief in evaluation gives rise to efforts to propose more "accurate" interpretation methods. However, due to the logic traps in existing evaluation methods, the performance improvement is under an unreliable evaluation system. We believe we should pay more attention to other aspects in this research field, such as reducing the impact of indirect evaluation, proposing new interpretation forms, and using interpretations to improve model performance.

In this opinion piece, we summarize four kinds existing evaluation methods and point out the logic traps behind them. We believe a clear statement on these logic traps is important and helpful for the community.

2 Evalution Methods and Corresponding Logic Traps

2.1 Using Human Explanation As the Ground Truth

In this evaluation, interpretations are compared with explanations given by humans.

2.1.1 Related works

Works often demonstrates the effectiveness of interpretations by giving examples consistent with human problem-solving process. For example, Murdoch et al. (2018) shows heat maps generated by different interpretation methods and argues their proposed method is better than others because only it can capture 'favorite' is positive, which is consistent with human understandings. Furthermore, works also use human-annotated labels to evaluate interpretations quantitatively. For example, besides sentence-level annotations for sentence classification, Stanford Sentiment Tree bank binary classification corpus (SST-2) Socher et al. (2013) provides word-level sentiment annotations. Lei et al. (2016); Li et al. (2016); Tsang et al. (2020); Kim et al. (2020) evaluate interpretations by evaluating the consistency between interpretations and word-level sentiment annotations in SST-2.

2.1.2 Logic trap

The decision-making process of neural networks is not equal to the decision-making process of humans.

Jacovi and Goldberg (2020) has discussed this issue and clarified the difference between faithfulness and plausibility, summarized as: *The evaluation criterion should be how accurately the interpretation reflects the actual reasoning process* (faithfulness), not how convincing the interpretation is to humans (plausibility). Jacovi and Goldberg (2020) suggests the evaluation should not involve any human-judgment and human-provided labels.

Different from Jacovi and Goldberg (2020), we suggest that if an interpretation method does not use any human annotations, it can hardly generate plausible results to humans from chaotic. In this circumstance, the plausibility of interpretations can be seen as coming from the reasoning process of deep models, and it can reflect the faithfulness of interpretations. However, plausibility can not be used as a quantitative evaluation criterion. Because neural networks often rely on unreasonable correlations, even when producing correct decisions. Interpretations preposterous to humans may be consistent with the actual reasoning process of deep models.

2.2 Evaluating by Perturbing Features and Calculating Output Change

Since human annotations are not suitable for quantitative evaluation, researchers design diverse evaluation metrics for quantitatively evaluating interpretations. One of the most widely used is perturbing features and calculating output change.

For example, evaluation metrics based on the area over the perturbation curve (AOPC) (Samek et al., 2016) first define an ordered $set_O = \{feature1, feature2, \ldots\}$ according to interpretations, in which features at the front attribute more to the model outputs. Then perturb the top k% features and calculate the average change in the model outputs as AOPC(k). Higher AOPC(k) is better, which means that the features selected by interpretations are essential. The perturbing strategy and functions used to calculate output change diverse among different works.

2.2.1 Related works

Many works (Samek et al., 2016; Shrikumar et al., 2017; Chen et al., 2018; Nguyen, 2018,?; DeYoung et al., 2019; Chen et al., 2020; Kim et al., 2020; Chen and Ji, 2020) use this kind of method to perform evaluation and comparison. For example, Chen et al. (2020) chooses masking tokens

as perturbation and use subtraction and log-odds as calculation functions; Shrikumar et al. (2017) chooses erasing pixels as perturbation and uses log-odds as calculation function.

2.2.2 Logic trap

This evaluation is using interpretations to evaluating interpretations.

Assigning importance for features by calculating output change after perturbing is an interpretation method too. For example, when using erasing one token per time as the perturbing strategy, AOPC(k) degenerates into interpretation method: **leave-one-out** (Li et al., 2016). This evaluation measures how similar two interpretations are, and the one used as the ground truth is determined by the perturbing strategy.

For example, Chen et al. (2020) uses AOPC(k) as evaluation metric, choosing k = 20 and erasing tokens as perturbation. Not surprisingly, erasurebased methods perform well in their evaluation, and even the most simple leave-one-out method generates competitive results. Kim et al. (2020) proposes the out-of-distribution (ODD) problem of erasure-based interpretation methods. Since their proposed interpretation method can be seen as a remedy to the ODD problem caused by erasing tokens, the commonly used perturbing strategy: erases tokens directly, is not suitable for evaluating their proposed method. Kim et al. (2020) also mention it in their paper. Unfortunately, they did not discuss this in-depth but chose to use a perturbing strategy more similar to their proposed method, causing unfair comparison in their favor.

The widespread use of such evaluation metrics has negatively impacted the research field, and the logic trap behind them has not been proposed. We should not use any such metrics to perform the comparison. If we have a method that can get feature importance as the ground truth, why do we need other interpretation methods to get feature importance?

2.3 Evaluating the Consistency after Perturbing Inputs

In this evaluation, works evaluate interpretations by inspecting the consistency of interpretations after perturbing the inputs. The argument is that if the interpretation method is reliable, similar inputs giving rise to the same predictions should have similar interpretations.

2.3.1 Related works

This evaluation is often used to disprove the effectiveness of interpretation methods. Alvarez-Melis and Jaakkola (2018) argues that a crucial property that interpretations should satisfy is robustness to local perturbations of the input. They assert that current popular interpretation methods are not robust. Kindermans et al. (2019) finds that by adding a constant shift to the input data, a transformation with no effect on the model prediction can significantly affect interpretation methods. They assert these interpretations are unreliable. Ghorbani et al. (2019) argues that interpretations of neural networks are fragile by showing that systematic perturbations can lead to dramatically different interpretations without changing the label. Ding and Koehn (2021) evaluates interpretations' faithfulness through model consistency test. They perform substitutions in the input and measure the consistency of feature importance.

2.3.2 Logic trap

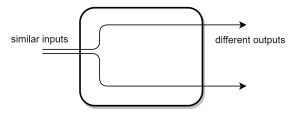
The success of attacking interpretations may be a result of attacking deep models.

First, similar inputs in human eyes are not equal to similar inputs for deep models. It is well known that deep models are susceptible to adversarial attacks (Goodfellow et al., 2014; Papernot et al., 2016; Moosavi-Dezfooli et al., 2016). The adversarial attacks deliberately add some subtle interference that people cannot detect to the input sample, causing the model to give a wrong output with high confidence. The success in adversarial attacks on deep models demonstrates a indistinguishable change in human eyes can cause a very different reasoning process in deep models.

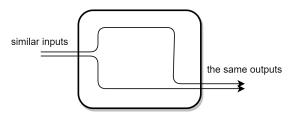
Second, since deep models' prediction has compressed the complicated calculation process into limited categories, giving the same prediction is a very weak constraint to constrict the reasoning process of deep models. For example, there is always half probability of giving the same prediction for a binary classification task even with a random reasoning process.

Thus, it is no surprise that adversarial attacks can find similar input, which causes the same prediction but a different reasoning process. The risk underlying this evaluation is the success of attacking interpretations may be a result of attacking the deep models, as shown in Figure 1, in which we use the path from input to output to represent the reasoning process of deep models visually. Unfor-

tunately, existing works ignore this risk and use adversarial methods to attack interpretations. Not surprisingly, all of them get similar conclusions that existing interpretation methods are fragile or unreliable.



(a) different reasoning processes with different outputs



(b) different reasoning processes with the same outputs

Figure 1: Adversarial attacks on deep models can cause similar inputs with different reasoning processes. Circumstance in (b) may be regarded as a successful attack on interpretations, which falls into the logic trap.

2.4 Manipulating Interpretations

In this evaluation, works prove the unreliability of interpretations by manipulating them and letting the manipulated interpretations focusing on some special features or ignoring some crucial features.

2.4.1 Related works

Jain and Wallace (2019) randomly permutes the attention distributions and searches for maximally different attention distributions that still produce a similar prediction. They claim that attention distributions can not be interpretable because they are not exclusive. Wang et al. (2020) trains an extra model with uniform predictions but large gradients for some particular words. They add this extra model to the original model. Since the extra model generates uniform predictions, predictions of the merged model are dominated by the original model. However, the gradients are influenced by the extra mode. Slack et al. (2020) trains a classifier to distinguish if the inputs are perturbed instances and uses a different sub-model to process perturbed instances. This way, they can control the interpretations of perturbation-based methods such as LIME and SHAP and assert they are not reliable.

2.4.2 Logic trap

The goal of interpretation methods is confused.

We suggest the goal of interpretation methods is confused in their works. Traditional models such as the linear regression model and the decision trees are regarded as interpretable models because their calculation process is easy to analyze. The interpretations of them is based on manual analysis of their calculation process. The deep model is regarded as a black-box model because its calculation process is too complicated to understand and analyze directly, not because its calculation process is inaccessible. Thus, requiring interpretation methods for deep models to give interpretations without access to the calculation process and manual analysis is unfair. The goal of interpretation methods is to help humans understand and analyze a trained deep model, not automatically generate interpretations for any system containing deep models. The manual added pipeline structures in Wang et al. (2020) and Slack et al. (2020) can be easily understand by humans and there is no need to use interpretation methods to interpret these structures. The manipulation of interpretations in their works will easily fail when manual analysis involved.

Jain and Wallace (2019) confuses the interpretation goal because the deep model is damaged in their work. The neural network works as a whole and its parameters are interdependent. Assigning the attention weights generated by parts of the model makes the rest of the model meaningless. The interpretation target in their work can not even be regarded as a trained model, which makes their manipulation meaningless.

2.5 Conclusions

The intrinsic properties of post-hoc interpretations make it cannot be directly evaluated, and there are some crucial logic traps in existing evaluation methods. These logic traps have been ignored for a long time and have brought negative effects to the community. We suggest a clear statement about these traps is important and helpful. Since the logic traps in existing evaluation methods can cause inaccurate evaluation and unfair comparison, we should not focus on improving the performance under an unreliable evaluation system. Other aspects of this field should give rise to more attention, such as the applications of post-hoc interpretations, alleviating the influences of indirect evaluation, and proposing new interpretation forms.

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