On the Objective Evaluation of Post Hoc Explainers

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Abstract

Many applications of data-driven models demand transparency of decisions, especially in health care, criminal justice, and other high-stakes environments. Modern trends in machine learning research have led to algorithms that are increasingly intricate to the degree that they are considered to be black boxes. In an effort to reduce the opacity of decisions, methods have been proposed to construe the inner workings of such models in a human-comprehensible manner. These post hoc techniques are described as being universal explainers – capable of faithfully augmenting decisions with algorithmic insight. Unfortunately, there is little agreement about what constitutes a “good” explanation. Moreover, current methods of explanation evaluation are derived from either subjective or proxy means. In this work, we propose a framework for the evaluation of post hoc explainers on ground truth that is directly derived from the additive structure of a model. We demonstrate the efficacy of the framework in understanding explainers by evaluating popular explainers on thousands of synthetic and several real-world tasks. The framework unveils that explanations may be accurate but misattribute the importance of individual features.

1 Introduction

The black box nature of many AI systems obscures decision-making processes. This can conceal biases, dubious correlations, and other deficiencies, which come to light especially in the cases of dataset shift [46] and adversarial examples [53, 27]. Furthermore, this disparity in transparency has led to unexpected prejudices in real-world applications, including health care and criminal justice [43, 9]. If this is not motivation enough for reconciliation, current and forthcoming regulation will require transparency and a right to explanation, such as the EU General Data Protection Regulation [20], the US draft “Guidance for Regulation of [AI] Applications” [57], and a United Nations prospective publication [29].

In endeavors to instill trust in these systems, an abundance of explainable AI (XAI) techniques have been introduced. However, these proposed techniques not only approach similar but distinct facets of interpretability – they also associate notions of interpretability (and explanation) with different meanings. Several prevalent taxonomies have aimed to disentangle some of the perplexity of the language and concepts [11, 19, 38]. Nonetheless, there is little consensus as to what interpretability is and, consequentially, how it may be evaluated. Existing efforts to assess the caliber of an XAI method rely on subjective or proxy means, which demonstrably mislead or emphasize plausibility over fidelity [8, 19, 28]. Understanding the fidelity of XAI methods is especially important as they are applied to various high stakes domains within both research and industry, such as medical diagnosis, credit risk analysis, and epidemiological modeling [7, 12, 18].

In this study, we address the absence of truly objective evaluation by constructing a test bed for post hoc explanation methods; whereas ante hoc explainers have an intrinsic notion of interpretability, post hoc methods serve as a surrogate explainer for a black box. We accomplish this by proposing an algorithm that directly maps a broad class of models to post hoc explanations. Crucially, our
evaluation methodology distinguishes between plausible and faithful explanations without subjective or proxy means. We establish our framework as a powerful tool for the comprehensive analysis of explainers through experiments on thousands of synthetic and several real-world problems.

2 Background

Related Work There are several classes of post hoc explanation methods, including salience maps, local surrogate models, and global interpretation techniques. A comprehensive overview can be found in [23][41]. However, here we strictly focus on model agnostic local approximation, which is one of the most prevalent explanation strategies. Specifically, we will consider the LIME [48], SHAP [39], and MAPLE [45] explainers. Previously, LIME has been shown to produce unstable explanations for similar inputs [51][12], and an analysis indicated that it can produce inaccurate explanations [16]. In an adversarial context, LIME and SHAP have been shown to be deceivable by employing an out-of-distribution detector to mask prejudiced decisions [52].

General metrics for the evaluation of explainers have also been proposed. Some works gauge effectiveness by human evaluation and proxy tasks, including subjective ratings and the improvement of human performance [13][54]. Several classes of hand-crafted metrics have been put forward. Those based on erasure attempt to evaluate feature importance by removing parts of an input based on the explanation, e.g., under the assumption that higher-weighted features should affect accuracy more [10][6]. “Fidelity” metrics compare surrogate accuracy relative to the model being explained [35][22]. Another assumption made is that explanations should be robust, where better explanations are considered to be those that do not fluctuate between like instances [4]. Further, some metrics reward monotonic behavior between feature importance and the model response [42]. A more extensive survey of evaluation methods is presented in [60]. The assumptions that these metrics make prevent them from being entirely objective; accurate explainers are not necessarily faithful, plausible explanations may only be convincing, and unexpected explanations may be due to the model rather than the explainer. On the contrary, our work makes no such assumptions about the model nor explainer.

More relevant to our study, several works have proposed the use of ground truth explanations to evaluate explainers. Guidotti developed a framework for the evaluation of post hoc explanations of synthetic models using ground truth [21]. Ground truth is assigned depending on the learning task, e.g., the gradient with respect to each feature for linear classification tasks on tabular data. In [61], a dataset modification procedure is proposed to coerce a model to rely on certain features. These modified features are used as the ground truth with justification that they must be more important to the model, as long as they increase accuracy. While these notions of ground truth are well-defined, they deviate from ours as they are derived by proxy means.

Local Post Hoc Explanation Local post hoc explainers act as a surrogate to a black box model and estimate the feature importance for a single decision. In contrast, global explainers provide explanations of a model for an entire dataset. With the ability to query the model, explainers aim to recover the local model response about an instance while isolating the most important features to produce comprehensible explanations. These methods may additionally use a background dataset to estimate statistics about the data and model. It should be noted that local explanations can also be used in aggregate to gain a global understanding of a model. We consider explainers that provide attribution-based explanations where the attribution of a feature, or group of features, is the estimated contribution to the model decision value.

Partial dependence plots (PDP) [15] estimate the average marginal effect of a subset of features on the output of a model using the Monte Carlo method. When the subset comprises one or two features, the model output is plotted as a function of the feature values. PDPs give a global understanding of a model this way, but can also yield a local explanation for the specific feature values of a data point.

Local interpretable model-agnostic explanations (LIME) [48] explains by learning a linear model from a randomly sampled neighborhood around z-score normalized instances. Feature selection is controlled by hyperparameters that limit the total number of features used in approximation, such as the top-\(k\) largest-magnitude coefficients from a ridge regression model.

Model agnostic supervised local explanations (MAPLE) [45] employs a tree ensemble, e.g., a random forest, to estimate the importance (the net impurity) of each feature. Feature selection is performed
upfront on the background data by iteratively adding important features to a linear model until error is minimized on held out validation data. For local explanations, MAPLE learns a ridge regression model on the background data distribution with samples weighed by the tree leafs relevant to the explained instance.

Shapley additive explanations (SHAP) \[39\] takes a similar but distinct approach from LIME by approximating the Shapley values of the conditional expectation of a model. Feature selection is controlled using a regularization term. Note that when we write SHAP, we are specifically referring to Kernel SHAP, which is distinguished from its other variants for trees, structured data, etc. An extension of SHAP to handle dependent features has also been proposed [1], which we refer to as SHAPR after the associated R package. In effort to improve the accuracy of SHAP explanations, SHAPR estimates the conditional distribution assuming features are statistically dependent. Several approximations of this distribution are proposed, including the multivariate Gaussian and empirical conditional distributions.

3 Framework for Evaluating Post Hoc Explainers

To realize proxy-less explainer evaluation, we construct a framework that has explainers attempt to explain a broad class of white box models. These models have a concise notion of ground truth which has direct equivalence relations to all considered explainers. We also introduce a novel algorithm to enable the maximally fair comparison of ground truth and explanations. Figure 1a shows a high-level overview of the framework.

White Box Formulation  We consider a general form of white box models, similar to, but distinct from, generalized additive models (GAMs). The additive structure leads to concise definitions of feature contributions while still allowing for feature interactions, high dimensionality, and highly nonlinear effects. Note that, here, white box does not imply human-comprehensibility, but rather that precise feature contributions can be extracted. Let $X \in \mathbb{R}^{n \times d}$ be a matrix with $n$ samples and $d$ features, $D = \{i \mid 1 \leq i \leq d\}$ be the set of all feature indices, and $F(\cdot)$ be an additive function comprising $m_F$ effects. Each effect $f_j(\cdot)$ is a non-additive function that takes a subset of features $D_{f_j} \subseteq D$ as input and yields an additive contribution $C_{f_j}$ to the model output, as shown in Equation (1).

$$\begin{align*}
F(X) &= \sum_{j}^{m_F} f_j \left( X_{\cdot, D_{f_j}} \right) = \sum_{j}^{m_F} C_{f_j}
\end{align*}$$

Figure 1b illustrates this formulation.

For explainers, we denote local estimates of the model as $\hat{F}(\cdot)$ which comprise a summation of $m_{\hat{F}}$ effects $\hat{f}_k(\cdot)$. The explainers evaluated in this work have $m_{\hat{F}} \leq d$, however, explainers with $m_{\hat{F}} > d$ are compatible with both the framework formulation and implementation.
Figure 2: Examples of MATCHEFFECTS and MaIoU (Equation 2) in facilitating fair comparison between two sets of explanations. (a) A simple example demonstrating MATCHEFFECTS for a hypothetical medical task. Like colors from each side of the graph can be directly compared. (b) A strict matching between effects severs partially correct effects from comparison and yields a harsh MaIoU. (c) MATCHEFFECTS fairly groups together effects for comparison and gives a more reasonable MaIoU – ideally, the sum of the true contributions is equivalent to the sum of the explained contributions in each group (component). (d) Importantly, MaIoU defines the goodness of a match, in this case indicating that a superficially perfect explanation is uninformative and incorrect.

**Synthetic Models**: We generate synthetic models with controlled degrees of sparsity, order of interaction, nonlinearity, and size. This parameterization allows us to study how different model characteristics affect explanation quality. Here, each $f_j(\cdot)$ is a composition of random non-additive unary and/or binary operators for a random subset of features $D_f$. Expressions are generated based on these parameters and we verify that the domains and ranges are in $\mathbb{R}$. See Appendix D for details of our algorithm used to generate such models, as well as examples of generated expressions.

**Learned Models**: We consider two types of learned models: GAMs and sparse neural networks. The former was introduced as a rich but simple model: capable of modeling nonlinear effects while conducive for understanding feature significance [26]. Each $f_j(\cdot)$ is a smooth nonparametric function that is fit using splines. A link function relates the summation of each $f_j(\cdot)$ to the target response, such as the identity link for regression and the logit link for classification.

The sparse neural networks we consider have the same additive structure, but each $f_j(\cdot)$ is instead a fully-connected neural network (NN). Each NN can have any architecture, operates on $D_f$, and yields a scalar value for regression or a vector for classification. The output is the summation of each NN with a link function similar to the GAM. This structure is related to the neural additive model proposed in [3]. This formulation also holds for convolutional NNs (CNNs), which can have a non-unary $m_F$ as long as the receptive field does not cover the full image. See Appendix B for more details.

**Ground Truth Alignment** With the framework formalism, we now have a model and an explainer, each of which comprises a set of effects. Because there may not be a one-to-one correspondence between the two sets, we cannot directly compare the effects. Consider the case of a model with
an interaction effect, i.e., some $|D_f| \geq 2$; if the explanation has no $D_f = D_j$, then a direct comparison of feature contributions is not possible. To this end, we introduce the MATCHEFFECTS algorithm, which matches subsets of effects between the model and explainer.

To achieve this matching, we consider all $D_f$ and $D_k$ to be the left- and right-hand vertices, respectively, of an undirected bipartite graph. Edges are added between effects with common features; we consider effects to be atomic and respect the non-additive structure where it exists in the model being explained. Thus, contributions may not be given for individual features. We then find the connected components of this graph to identify groups of effects with inter-effect dependencies. If every component contains an exact match, for example, if $\text{match}_F = \{\{2\}, \{2, 3\}\}$ and $\text{match}_E = \{\{2\}, \{2, 3\}\}$, then each contribution by $\{2\}$ and $\{2, 3\}$ will be compared separately. MATCHEFFECTS is formalized in Algorithm 1 and illustrated for a few examples in Figure 2. This process guarantees the most fair and direct comparison of feature contributions, and does not rely on gradients, sensitivity, or other proxy means [21][10][13]. The worst-case time complexity of MATCHEFFECTS is $O(m_F m_E d)$ and the space complexity is $O(m_F m_E)$ (see Appendix B for proofs).

Algorithm 1: MATCHEFFECTS

```
Input: $D_F = \{D_f \mid 1 \leq j \leq m_F\}$, the set of feature subsets operated on by model $F$
Input: $D_E = \{D_k \mid 1 \leq k \leq m_E\}$, the set of feature subsets operated on by explainer $\hat{F}$
Result: Corresponding sets of effects that can be compared

// add edges between effects with mutual features
1 $E \leftarrow$ new array;
2 for $D_f \in D_F$ do
3   for $D_k \in D_E$ do
4     if $|D_f \cap D_k| > 0$ then
5       $E$.append($\{D_f, D_k\}$);
6 $V \leftarrow D_F \cup D_E$; // effects are vertices
7 $G \leftarrow (V, E)$;
8 $CCs \leftarrow$ CONNECTEDCOMPONENTS($G$);
9 matches $\leftarrow$ new array;
// unpack the components
10 for $\{V_c, E_c\} \in CCs$ do
11   // $V_c$ and $E_c$ comprise the vertices and edges of component $c$, respectively
12   $match_F \leftarrow$ new array;
13   $match_E \leftarrow$ new array;
14 for $D_c \in V_c$ do
15   $match_F$.append($D_c$);
16 else
17   $match_E$.append($D_c$);
18 if $match_F = match_E$ then
19   // elements of identical sets are each a perfect match: do not group
20 for $D_c \in match_F$ do
21   $matches$.append($\{D_c, \{D_c\}\}$);
22 else
23   $matches$.append($\{match_F, match_E\}$);
24 return matches
```

One could exploit this algorithm by producing explanations that attribute the entire output of the model to a single effect comprising all $d$ features; comparison of contributions could trivially yield perfect but uninformative scores. Likewise, a model with such interaction effects, like most deep NNs, would render this evaluation inconsequential. To mitigate, we introduce a metric that evaluates the goodness of the matching. Let $E_c$ be the set of edges of a single component found by MATCHEFFECTS. For an edge $\{D_f, D_k\} \in E_c$, the intersection-over-union (IoU), also known as the Jaccard index, is calculated between $D_f$ and $D_k$. The total goodness for a component is the average of the IoU
We then need to scale the coefficients $\Theta$ within a tolerance.

Appendix A for the unary and binary operators, parameters, and operation weights considered in CCs where $x$ vector $\Theta$ Furthermore, LIME and MAPLE provide feature-wise explanations as the coefficients $\Theta$. We use 4 Experimental Results dummy variables are present.

Last, we consider the explanation of an effect to be also details hyperparameters used to train the GAMs and sparse NNs, and the hardware used to run experiments. Last, we consider the explanation of an effect to be $0$ if every estimated contribution is within a tolerance. This is a fairer evaluation and tends to favor the explainers in experiments when dummy variables are present.

Equivalence Relations to Explainers With MATCHEFFECTS and MaloU defined, a direct comparison between true and explained effect contributions is nearly possible. However, some adaptation is still required due to the use of normalization and differing definitions of “contribution” between explainers. Here, we bridge together these definitions. LIME normalizes the data as z-scores, i.e., $z = (x_i - \mu_i)/\sigma_i$, before learning a linear model. We then need to scale the coefficients $\Theta = \{\theta_i \mid 1 \leq i \leq d\}$ of each local linear model using the estimated means $\mu_i$ and standard deviations $\sigma_i$ from the data as follows.

$$\theta'_0 = \theta_0 - \sum_i \frac{\mu_i \theta_i}{\sigma_i} \quad (4) \quad \theta'_i = \frac{\theta_i}{\sigma_i} \quad (5)$$

In SHAP, the notion of feature importance is the approximation of the mean-centered independent feature contributions for an instance. The expected value $\mathbb{E}[F(X)]$ is estimated from the background data SHAP receives. In order to allow for valid comparison, we add back the expected value of the true contribution $\mathbb{E}[C_{f_j}]$ estimated from the same data. However, since a 1:1 matching is not a guarantee, we must consider all effects grouped by said matching:

$$C_{\text{match},F} = \sum_{k \in \text{match}_F} \hat{f}_k(x_{*,k}) + \sum_{j \in \text{match}_F} \mathbb{E}[C_{f_j}] \quad (6)$$

The same procedure applies to SHAPR. See Appendix B for the derivations of these relations.

Furthermore, LIME and MAPLE provide feature-wise explanations as the coefficients $\Theta$ of a linear regression model. In turn, we must simply compute the product between each coefficient and feature vector $x_{*,i}, \theta_i$ to yield the contribution to the output according to the explainer.

4 Experimental Results

Setup We use SymPy [40] to generate synthetic models and represent expressions symbolically as expression trees. This allows us to automatically discover the additivity of arbitrary expressions. See Appendix A for the unary and binary operators, parameters, and operation weights considered in random model generation. All stochasticity is seeded for reproducibility, and all code is documented and open-sourced. The framework is implemented in Python [55] with the help of SymPy and the additional libraries NumPy [24], SciPy [56], pandas [59], Scikit-learn [44], Joblib [32], mpmath [53], pyGAM [50], PDPbox [31], alibi [36], Matplotlib [3], and seaborn [58]. Furthermore, we build a Python interface to the r [47] package shapr [49] using rpy2 [17]. Appendix A also details hyperparameters used to train the GAMs and sparse NNs, and the hardware used to run experiments. Last, we consider the explanation of an effect to be $0$ if every estimated contribution is within a tolerance. This is a fairer evaluation and tends to favor the explainers in experiments when dummy variables are present.

1The source code for this work is available on GitHub: https://github.com/craymichael/PostHocExplainerEvaluation
2See the documentation of numpy.allclose for details
Figure 3: Average cosine distances (top) and Euclidean distances (bottom) between ground truth and explained effect contributions as a function of $d$. A robust linear regression fit is plotted on top of the scatter plot with a 99% confidence interval estimated with 1,000 bootstrap resamples. The y-axis has an upper limit of the 99% percentile for visualization purposes. Explainers produce worse explanations when the order of feature interactions and the number of features increase.

**Evaluation** We measure the error between the ground truth and explanation using a few metrics. The set of contributions for a data sample can be thought of as a vector collectively, thus we can compute the distance between them. First considered is Euclidean distance to understand the magnitude of the disagreement with the ground truth. To quantify the disagreement in orientation (rotation), we utilize cosine distance (i.e., $1 - \cos$ cosine similarity), which is bounded by the interval $[0, 2]$ with our data – a distance of one indicates orthogonal contributions and a distance of two indicates contributions pointing in opposite directions. We also consider normalized (interquartile) root-mean-square error (NRMSE) for comparing individual effects, as defined by Equation (7)

$$\text{NRMSE}(a, b) = \frac{1}{Q^a_3 - Q^a_1} \sqrt{\frac{\sum_i^n (a_i - b_i)^2}{n}}$$  (7)

where $Q^a_3$ and $Q^a_1$ are the third and first quartiles of $a$, respectively.

**Synthetic Problems** We first demonstrate our framework on 2,000 synthetic models that are generated with a varied number of effects, order of interaction, number of features, degree of nonlinearity, and number of unused (dummy) variables. For each, we discard models with invalid ranges and domains that do not intersect with the interval $[-1, 1]$. The data of each feature $X^*_{i,j}$ is sampled independently from a uniform distribution $U(-1, 1)$. We draw $n$ samples quadratically proportional to the number of features $d$ as $n = 500\sqrt{d}$. The explainers are evaluated on each model with access to the full dataset and black box access to the model.

Of the 2,000 models, 16 were discarded due to the input domain producing non-real numbers. Furthermore, the explainers were not able to explain every model due to invalid perturbations and resource exhaustion. The former occurred with PDP, LIME, and SHAP, typically due to models with narrower feature domains, while the latter occurred with MAPLE and SHAPR due to the inefficient use of background data and intrinsic computational complexity. In total, 82%, 39%, 80%, 91%, and 40% of models were successfully explained by PDP, LIME, MAPLE, SHAP, and SHAPR, respectively. We consider the failure of producing explanations for a valid input a limitation of the explainers and their implementations.

Results demonstrate the efficacy of the proposed framework in understanding explanation quality, as well as factors that influence it when paired with the experimental design. As the dimensionality, the degree of interactions, and the number of interactions increase, the disagreement between ground
truth and explanation grows. Figure 5 illustrates these results for all of the explained synthetic models. Because LIME failed to explain a substantial portion of synthetic models, it appears to improve with an increased $d$ in the leftmost plots; in reality, it only succeeded in explaining simpler models with a larger $d$. SHAP performs the best relative to the other explainers, maintaining both a closer and more correctly-oriented explanation compared to the ground truth. Interestingly, the ranking of LIME and MAPLE swaps when comparing average cosine and Euclidean distances. Whether more similar orientation or magnitude is desired depends upon the application. Appendix C includes additional experiments with synthetic models, including evaluation as a function of the number of number of interactions, number of nonlinearities, and dummy features.

**Real-World Case Studies** Incomprehensible models applied to real-world problems require transparency when the stakes are high. Local explanations on this type of data need to be faithful to the model, otherwise they can propagate spurious relationships. To this end, we evaluate GAMs and sparse NNs on several real-world datasets.

The Boston housing dataset \[25\] contains median home values in Boston, MA, that can be predicted by several covariates, including sensitive attributes, *e.g.*, those related to race. Models that discriminate based off of such features necessitate that their operation be exposed by explanations. We also evaluate explainers on the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) recidivism risk dataset \[5\]. The dataset was collected by ProPublica in 2016 and contains covariates, such as criminal history and demographics, the proprietary COMPAS risk score, and recidivism data for defendants from Broward County, Florida. The FICO Home Equity Line of Credit (HELOC) dataset \[14\], introduced in a 2018 XAI challenge, is also used in this work. It comprises anonymous HELOC applications made by consumers requesting a credit line in the range of $5,000 and $150,000. Given the credit history and characteristics of an applicant, the task is to predict whether they will be able to repay their HELOC account within two years. Last, we evaluate on a down-sampled version of the MNIST dataset \[37\]. With the aim of reducing explainer runtime and improving comprehensibility of effect-wise results, we crop then resize each handwritten digit in the dataset to $12 \times 10$ and only include a subset of the 10 digits. See Appendix A for more details.

Table 1 contains the aggregate results across all real-world datasets for the considered models. Among the considered explainers, SHAP outperforms on all datasets and models. Surprisingly, SHAPR performs worse than SHAP, but still ranks well compared to the other explainers. PDP, LIME, and MAPLE produce poor explanations in general, and all explainers struggled more with the GAMs than the considered NNs. We also visualize a subset of results in Figure 4 as feature shapes. This shows more clearly that several explainers do not faithfully explain some of the feature contributions. For example, SHAPR, MAPLE, and LIME fail to satisfactorily unearth how the proportion of African Americans by town can be predicted by the index of accessibility to radial highways.

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\(^3\)While the Boston housing dataset is widely studied as a baseline regression problem, the data column (“B”) is notably controversial; the original paper \[25\] includes and preprocesses the data as $B = 1000(B' - 0.63)^2$ where $B'$ is the proportion of African Americans by town.
### Table 1: Real-world explainer results on several datasets for GAMs and NNs. Here, explainer error is the cosine distance which is averaged over all samples and classes, if applicable. SHAPR is not implemented for data with categorical variables in this work.

| Dataset | Model | Explainer Error |
|---------|-------|-----------------|
|         |       | PDP | LIME | MAPLE | SHAP | SHAPR |
| Boston  | GAM   | 0.340 | 0.709 | 0.652 | 0.001 | 0.111 |
|         | NN    | 0.278 | 0.182 | 0.431 | 0.001 | 0.209 |
| COMPAS  | GAM   | 0.821 | 0.781 | 0.863 | 0.000 | –     |
|         | NN    | 0.328 | 0.062 | 0.274 | 0.001 | –     |
| FICO    | GAM   | 0.795 | 0.949 | 0.962 | 0.003 | –     |
|         | NN    | 0.761 | 0.193 | 0.270 | 0.001 | –     |
| MNIST   | CNN   | 0.660 | 0.253 | 0.318 | 0.049 | 0.175 |

Americans living in an area (feature B), according to the NN, drive the housing price. This type of failure is incredibly misleading to any user and potentially damaging if the model is deployed. Fortunately, in this instance, SHAP reveals this relationship within reasonable error. However, this is not always the case for SHAP. The COMPAS visualization shows another example of explanations of the “Age” feature of a GAM. Again, several explainers produce misleading and noisy explanations. See Appendix C for all visualizations of feature shapes, the best and worst explanations per dataset by each explainer, heat maps, and more results.

### 5 Discussion

The proposed framework is capable of objectively evaluating explainers and discovering characteristics of models that drive infidelity. Unlike previous work, our evaluation methodology moves beyond considering the plausibility of explanations and alleviates the need for proxy or subjective metrics. Rather, we compare explanations to ground truth that is directly derived from the additive effects of the model being explained. We demonstrate the capability of our framework to expose limitations of explainers; in experiments, several popular explainers produced inadequate accounts of the model decision-making process, especially when the number of features and feature interactions increased.

The shortcomings of these explainers are due to their underlying assumptions which do not hold true for the majority of models, especially the assumptions of independent features and local linearity. These assumptions are further impacted by the explainer hyperparameters, such as the kernel width for LIME or the background summarization method for SHAP. Tuning of these parameters is dependent upon the data and model. In practice, these knobs can be adjusted until the explanations “look right,” which is not realistic when the most faithful hyperparameters need to be derived from the black box itself. This is especially troubling as studies show that data scientists overtrust interpretability techniques [34]. With the results of our study, even those practitioners who do not abuse these explanation tools may still be mislead.

It is important to consider that a caveat of our evaluation methodology is that poor explanation methods can be identified, but it cannot prove that an explainer is faithful for all models. Thus, this framework can be seen as a benchmark and a testing ground for explainer quality. Emphasizing some of the arguments made in [42, 60], our framework can alleviate some of the financial and other resource burdens by filtering out explainers, e.g., before a user study, that do not meet satisfactory marks. Moreover, this filtering of explainers can reduce liabilities and aid in meeting AI regulations.

### Future Work

A natural extension of this work would be to use the framework to evaluate additional explanation methods and guide the improvement of explainer quality. We believe that progress within this class of explainers will emerge by accounting for interdependence between features, better defining locality, and scaling computation for high-dimensional data. Another interesting direction would be to extend the evaluation formulation to other data formats, e.g., rules and text. Furthermore, we intend to evaluate the quality of existing hand-crafted evaluation metrics to understand how faithful they are.
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Supplemental Material

Due to the size of the supplemental material for this work, we have elected to provide a link instead of appending to the main paper. We highly recommend viewing the additional results and visualizations of explanations within our framework. The material is structured as follows:

- Appendix A: Reproducibility
- Appendix B: Proofs and Derivations
- Appendix C: Additional Results and Figures
- Appendix D: Synthetic Model Generation

The material is hosted at the public URL: https://drive.google.com/file/d/1m9jVVT_XsQqjxr2EvUfF5bhh2m4yN7R/view?usp=sharing

Alternatively, if you are reading this paper on arXiv, the material has been uploaded as an ancillary file.