Evaluation of Local Model-Agnostic Explanations Using Ground Truth

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Abstract

Explanation techniques are commonly evaluated using human-grounded methods, limiting the possibilities for large-scale evaluations and rapid progress in the development of new techniques. We propose a functionally-grounded evaluation procedure for local model-agnostic explanation techniques. In our approach, we generate ground truth for explanations when the black-box model is Logistic Regression and Gaussian Naive Bayes and compare how similar each explanation is to the extracted ground truth. In our empirical study, explanations of Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), and Local Permutation Importance (LPI) are compared in terms of how similar they are to the extracted ground truth. In the case of Logistic Regression, we find that the performance of the explanation techniques is highly dependent on the normalization of the data. In contrast, Local Permutation Importance outperforms the other techniques on Naive Bayes, irrespective of normalization. We hope that this work lays the foundation for further research into functionally-grounded evaluation methods for explanation techniques.

1 Introduction

Local model-agnostic explanation techniques estimate the importance of features for the prediction made by a black-box model given a single input instance. Explanation techniques are usually evaluated using two different types of methods. Human-grounded evaluation methods use the judgment of human subjects to evaluate the accuracy of explanations. The subjectivity of human judgment, time, and costs make human-ground evaluation often infeasible. These challenges can be mitigated by functionally-grounded evaluation methods in which different proxy measures are used to evaluate explanation techniques systematically (see [Doshi-Velez and Kim 2017] for more details). The major challenge of functionally-grounded evaluations of explanation techniques is the lack of the ground truth feature importance scores (see [Hooker et al. 2018] for a detailed discussion). In this work, we propose a procedure that extracts the ground truth of feature importance scores for the Logistic Regression and the Naive Bayes models. The extracted ground truth is used to compare different explanation techniques in terms of how similar the explanations are to the ground truth.

Local additive model-agnostic explanation techniques are a category of explanations in which the black-box model’s predicted probability of a single instance for a given class is decomposed into an additive sum of importance scores for all features. Local Interpretable Model-agnostic Explanations (LIME) ([Ribeiro et al. 2016]) and SHapley Additive exPlanations (SHAP) ([Lundberg and Lee 2017]) are examples of widely used techniques to obtain additive explanations. Local Permutation Importance (LPI) outperforms the other techniques on Naive Bayes, irrespective of normalization. We hope that this work lays the foundation for further research into functionally-grounded evaluation methods for explanation techniques.
Importance (LPI) defines the importance score to be the decrease in black-box score when a single feature value is randomly shuffled (Casalicchio et al. [2018]).

The need to find ground truth for explanations is an important step toward evaluating different local additive explanation techniques. One major challenge in finding the ground truth for local additive explanations is that the additive decomposition of a predicted value into the sum of feature importance scores is imposed by the explanation techniques while the black-box model is usually more complex. There are two categories of functionally-grounded methods that evaluate the explanations without the need for ground truth: ablation and robustness evaluation techniques. Ablation techniques (Hooker et al. [2018]) measure the sensitivity of the model’s predicted value after the removal of features with the largest importance scores. The rationale behind this evaluation method is that the more substantial the change in the model’s predicted value, the more accurate are the explanations. Another set of evaluation methods analyze the robustness of explanations following the introduction of noise or redundant features into the explained instance (Álvarez-Melis and Jaakkola [2018], Camburu et al. [2019]). The main rationale behind this category of evaluation techniques is that a robust explanation technique should be resilient with respect to noise and assign relatively low importance scores to redundant features. The main limitation of ablation and robustness evaluation techniques is that changing feature values can shift the distribution of data which can lead to highly uncertain predictions by the black-box model. In addition, there is no objective way to conclude that a robust explanation is accurate or to measure the influence of correlated features in ablation techniques.

In our study, we propose an alternative approach to evaluate explanation techniques that directly involve the extraction of ground truth for explanations. Our evaluation procedure extracts the ground truth for a single instance from the log odds ratio of predictions. To this end, we focus on two models, namely Logistic Regression and Naive Bayes. The extracted ground truth is then used to compare different explanation techniques using Spearman’s rank correlation. We study two local additive explanation techniques, i.e. Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), along with a widely used explanation technique, namely Local Permutation Importance (LPI) (Casalicchio et al. [2018]).

In the next section, a summary of related work with a focus on the evaluation of different explanation techniques is presented. In Section 3, our evaluation procedure is presented. The result from the empirical study including the comparison of different techniques is discussed in Section 4. In Section 5, discussions and concluding remarks including future directions for possible extensions of this study are presented.

2 Related Work

Functionally-grounded evaluation methods of explanation techniques fall into two main categories: ablation methods and analysis of robustness. In Hooker et al. [2018], RemOve And Retrain (ROAR) is proposed to evaluate different explanations techniques that output saliency maps for neural network models. In this framework, the black-box model is retrained on an the auxiliary dataset that stripes pixels deemed important by explanations from the input. The accuracy of the explanations are calculated as the difference between the predicted class probabilities of the original and the auxiliary instance. The results show that explanations of VarGrad (Adebayo et al. [2018]) and SmoothGrad-Squared (Smilkov et al. [2017]) outperform other explanation techniques. ROAR is computationally exhaustive as the underlying model needs to be retrained on a large auxiliary dataset. Another limitation of this evaluation methods is that the new auxiliary data and retrained black-box model deviate from the original data and model and can inhibit new structures and properties.

Explanations are evaluated with regards to their robustness following the introduction of Lipschitz noise to the explained instances in Álvarez-Melis and Jaakkola [2018]. The authors empirically show that some explanation techniques including Local Interpretable Model-agnostic Explanations (LIME) are not robust to the Lipschitz noise and therefore have low robustness. In Camburu et al. [2019], the robustness of Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP) and Learn To eXplain (L2X) (Chen et al. [2018]) are studied following the introduction of irrelevant features to the explained instance in a sentiment analysis task. According to the results, L2X explanations outperform other explanation techniques across different measures of robustness that are proposed in the study. One limitation of this category of evaluation techniques is that changes in the feature values of instances can introduce out-of-distribution data. As a result,
predictions by the black-box model can have high uncertainty as discussed in Lakkaraju et al. [2020], Rahnama and Boström [2019].

In contrast to the studies mentioned in this section, we propose a functionally-grounded procedure that directly measures the accuracy of explanations. Our proposed procedure extracts the ground truth systematically and measures the similarity between an explanation and the ground truth.

3 Methodology

We begin by introducing the notation in Section 3.1. In Section 3.2, we describe our proposed approach to extract the ground truth for Logistic Regression and Naive Bayes from the intrinsic additive decomposition in their log odds ratios. The proposed evaluation procedure of explanation techniques is discussed in Section 3.3.

3.1 Notation

In this section, we formally define the notation used throughout this paper. Let $X \in \mathbb{R}^{m \times n}$ be a data matrix of $m$ instances with $n$ corresponding features. Suppose $x \in X$ is an instance where $x \in \mathbb{R}^n$.

In local additive explanations\(^1\), the conditional probability $P$ of model $f$ decomposes the predicted value for a single instance given a specific class into a linear additive combination. Let $x \in \mathbb{R}^n$ and $p_C(x)$ be the predicted probability score of the instance $x$ by model $f$ with respect to class $C$, hence:

$$p_C(x) = \phi_1 + \ldots + \phi_n$$

where explanations can be represented as $\Phi = \{ (\text{feature } j, \phi_i) | j = 1, \ldots, N \}$.

In practice and due to cognitive limitations of humans, a subset of $\Phi$ is often selected including the top-$K$ ranked elements by absolute value of importance scores where $K \ll N$. In addition, the extracted ground truth is denoted a $\Lambda = (\lambda_1, \ldots, \lambda_N) \in \mathbb{R}^n$ where $\lambda_j$ represents the ground truth for feature $j$.

3.2 Ground Truth

As stated earlier, additive explanations decompose class prediction probability scores into an additive sum of feature importance scores. However, the black-box model usually has no intrinsic additive structure in their prediction functions. In this section, we present an alternative solution to this problem by using the log odds ratios of an instance with respect to a specific class instead of class prediction probability. Since the additive structures are present in the log odds predictions of the Logistic Regression and the Naive Bayes model, contributions of each features to the predicted log odds can be extracted and used as the ground truth.

3.2.1 Logistic Regression

Given a Logistic Regression model in form of $y^{(i)} = w_0 + w_1 x_{i,1} + \ldots + w_n x_{i,N}$ and instance $x_i = (x_{i,1}, \ldots, x_{i,n})$,

$$P(y^{(i)} = 1|x_i, W) = \frac{1}{1 + e^{-\sum_{j=0}^{N} w_j x_{i,j}}}$$ (1)

where $W = (w_1, \ldots, w_n)$. Equation 2 show that the prediction probability function of Logistic Regression has no additive structure. However, we can derive a inherently additive decomposition when deriving the log odds ratio for $X$ with respect to class 1:

$$\log \frac{P(y^{(i)} = 1|x_i, W)}{P(y^{(i)} = 0|x_i, W)} = \sum_{j=0}^{i=N} w_j x_{i,j}$$ (2)

In Equation 2 it is clear that the contribution of feature $j$ to the log odds of an instance with respect to class 1 is $w_j x_{i,j}$ and we consider this to be the ground truth importance score $\lambda_j$ of feature $j$.

\(^1\)Throughout this paper and for brevity, the notion of local additive explanation and local additive model-agnostic explanation are used interchangeably.
3.2.2 Gaussian Naive Bayes

Given input $X$ and class $C$, the prediction function of Gaussian Naive Bayes model\(^2\) for class $C$ and feature $j$ where $j = 1, \ldots, N$ and $i = 1, \ldots, M$,

$$P(x_{i,j}|Y = C) = \frac{1}{\sqrt{2\pi\sigma_{j,C}}} e^{-\frac{(x_{i,j} - \mu_{C,j})^2}{2\sigma_{j,C}^2}} \sim \mathcal{N}(x_{i,j}|\mu_{C,j},\sigma_{j,C}^2)$$ (3)

Similar to the case of Logistic Regression, no additive decomposition can be seen in the probability function. The log odds ratios of an instance $x_i$ with respect to class 1 has an intrinsic natural additive decomposition,

$$\log \frac{P(y^{(i)} = 1|x_i)}{P(y^{(i)} = 0|x_i)} = \log \frac{P(y^{(i)} = 1)}{P(y^{(i)} = 0)} + \sum_{j=1}^{N} \log \frac{\mathcal{N}(x_{i,j}|\mu_{1,j},\sigma_{1,j}^2)}{\mathcal{N}(x_{i,j}|\mu_{0,j},\sigma_{0,j}^2)}$$ (4)

In Equation (4), the contribution of feature $j$ to the log odds ratio of instance $x_i$ with respect to class 1, $\log \frac{\mathcal{N}(x_{i,j}|\mu_{1,j},\sigma_{1,j}^2)}{\mathcal{N}(x_{i,j}|\mu_{0,j},\sigma_{0,j}^2)}$ is used as the ground truth $\lambda_j$ for that feature. Figure 1 shows an example of the ground truth explanation obtained for a single instance from Pima Indians dataset for Logistic Regression and Naive Bayes respectively.

3.3 Evaluation procedure

The outline of our proposed evaluation procedure that measures the similarity between ground truth and explanations is as follows (see Algorithm 1). Given an input $x$, and a black-box model $f$ (Logistic Regression and Naive Bayes\(^3\)), we extract the ground truth $\Lambda$ from the log odds ratio of $x$ with respect to class $C$. In the next step, explanation technique $g$ is selected and the feature importance $\Phi$ of the log odds ratios of $x$ with respect to class $C$ is obtained\(^4\). Given a similarity function $k$, the algorithm calculates the similarity of explanations and ground truth and returns the score $r_{x,f,g}$.

The choice of similarity function is essential in our evaluation procedure. Several studies have used measures such as cosine similarity or Euclidean distance (see Montavon et al. [2018], Yang and Kim [2019]) for measuring similarity between explanations. In our approach, we use Spearman’s Rank correlation (Zar [2005]) as the selected measure of similarity. The rationale behind our choice is that we are interested in measuring the monotonic relationship between the ground truth and explanations. In simpler terms, small changes in the importance score of a single feature which do not result in changes of the relative rank of that feature with respect to all other features should not be taken into account by our choice of similarity function. In addition, Spearman’s rank correlation is interpretable\(^5\).

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\(^2\)The notion of Gaussian Naive Bayes and Naive Bayes are used interchangeably throughout the paper for brevity.

\(^3\)We use the term black-box for Logistic Regression and Naive Bayes to be consistent with the terminology used in the explainability literature.

\(^4\)In Section 4.4 we have performed experiments in which we show the effect of obtaining feature importance $\Phi$ from the prediction probability scores of the black-box model on our evaluation procedure.

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Algorithm 1 Evaluating Explanations

**Input** $x$: instance, $f$: black-box, $g$: explanation method $k$: Spearman’s rank correlation, $\Lambda$: ground truth

**Output** $r_{x,f,g}$: correlation value

1: $\Phi \leftarrow g(f,x)$
2: $\Lambda \leftarrow t(f,x)$
3: $r_{x,f,g} \leftarrow k(\Phi, \Lambda)$

with respect to the existence of a significance threshold for correlation values and the direction of the correlation.

We are interested in comparing different techniques based on their similarity to the ground truth across all datasets. Let $d_i$ be the $i$-th dataset ($i = 1, ..., T$) where $T$ is the total number of datasets. Suppose $R_{f,g}^i = \{r_{x_k,f,g}|k = 1, ..., m\}$ is obtained by applying Algorithm 1 for $m$ test instances in the $i$-th dataset. For dataset $i$, the median value of $R_{f,g}^i$ scores from each explanation technique is calculated, and techniques are then ranked in a descending using this value for model $f$. In simpler terms, the techniques that generate higher median rank correlation values will be ranked lower in the $i$-th dataset when explaining model $f$. The overall ranks for each technique are the average ranks over $T$ datasets and therefore explanation techniques with a lower average ranks outperform the techniques with a higher average ranks for model $f$.

4 Empirical Investigation

4.1 Experimental setup

The proposed evaluated procedure is applied to explanations of Logistic Regression and Naive Bayes models. We compare the explanations extracted with LIME, SHAP, and LPI to the ground truth explanations. More specifically, we are using TabularLIME when obtaining LIME explanations for LOGISTIC and KernelShap for SHAP explanations. We evaluate our procedure on 20 different tabular datasets, all concerning binary classification tasks. The experiments were run on a Ubuntu 18.10 Intel(R) Core(TM) i9-7980XE 2.60GHz CPU with 18 cores and 20GB memory. In the experiments, numerical features are standardized and categorical features are encoded as one-hot vectors. For datasets for which no separate test set has been provided at the source, a hold-out set of 25% was used. The random search was used for tuning the hyper-parameters of the Logistic Regression model. The number of samples generated for LIME and SHAP is 5000. In the case of LPI, it is the size of the training set as suggested in Casalicchio et al. [2018]. This means the sample size of LPI is half the size of LIME and SHAP samples on average.

Table 5 includes the test accuracy of Logistic Regression and Naive Bayes models along with the abbreviated names of each dataset used in the empirical experiments of this study. As stated earlier, since our ground truth are extracted from log odds ratios of instances with respect to a specific class, all examined explanation techniques are adjusted to decompose the log odds ratios of a given instance. LPI explanations are adjusted to rank importance scores for the difference in the log odds prediction following the random permutations of features.

In Section 4.2, we compare the selected explanations techniques against our ground truth. As stated earlier, we compare the log odds ratio of a single instance with respect to a specific class instead of class probability scores. This is necessary as the extracted ground truth is based the log odds ratio (see Equation 2 and 4). In 4.3, we show that the comparison is substantially affected by the choice of pre-processing technique that is applied on the numerical features in each dataset. In section 4.4, we compare all techniques with the ground truth when explanations are obtained from predicted probability scores instead of log odds ratio.

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5 Negative Spearman’s rank correlation indicate the decreasing monotonic relationship of the two vectors
6 All datasets are publicly available and follow the ethics and data protection guidelines. Information about the datasets is provided in the Appendix. Code to replicate the experiments is attached as supplementary material.
7 Hyper parameters were chosen after 100 trials with the hyper-parameter space consisting of L1 and L2 regularization with the regularization parameter selected from a uniform distribution of values between 0 to 4.
8 The table is in the Appendix.
Table 1: Average rank of explanation techniques based on the median rank correlation across all datasets

| Technique | Logistic Regression | Naive Bayes |
|-----------|---------------------|-------------|
|           | LIME | SHAP | LPI | LIME | SHAP | LPI |
| Average Rank (All datasets) | 2.1 | 2.08 | **1.82** | 2 | 2.7 | **1.3** |

4.2 General performance

In this section, we perform experiments that evaluate explanation techniques against the extracted ground truth using rank correlation. To the best of our knowledge, this is the first study that examines the explanations of log odds ratios of explanation techniques.

The box-plot including quartiles of the Spearman rank correlation values for each technique is shown for using logistic regression in Figure 2. The shaded area in the figure represent the significant correlation threshold where \( \text{corr} > 0.7 \). In some cases, the explanation techniques provide explanations that correlate significantly with the ground truth, e.g. SHAP explanations on the Banknote dataset for the Naive Bayes model and LPI explanations on the Haberman dataset for the case of the Logistic Regression model. To our surprise, LIME explanations show median values below or close to zero across many datasets with large standard deviations, e.g. breast cancer, Pima Indians, Banknote, Iris, and Haberman. One important pattern that can be seen in Figure 2 is that the Spearman’s rank correlation values from explanation techniques are more likely to be significant where the black-box model is Logistic Regression compared to Naive Bayes across numerous datasets, e.g. Adult, Heart Disease, Churn and HR.

We present the average performance of the different explanation techniques in Table 1. As stated in Section 3.3, the explanation techniques with lower average ranks over all datasets outperform techniques with higher average ranks. It can be seen that LPI explanations outperform other techniques for both black-box models. In addition, the minimum difference between average ranks of LPI and other techniques is 3.5 times larger in the case of the Naive Bayes model compared to the Logistic Regression model.

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\*The rank of explanation techniques based on median Spearman’s rank correlation for each dataset can be found in Appendix.

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Figure 2: Box-plots of Spearman’s rank correlation of explanation techniques when the underlying model is Logistic Regression (top) and Naive Bayes (bottom). The shaded area visualizes the threshold where \( \text{corr} > 0.7 \).
Figure 3: Box-plots of Spearman’s rank correlation of explanation techniques when the black-box model is Logistic Regression (top) and Naive Bayes (bottom) under min-max transformation. The shaded area visualizes the threshold where $\text{corr} > 0.7$.

Table 2: The average rank of explanation techniques across all datasets for each pre-processing transformation

| Transformation          | Logistic Regression | Naive Bayes |
|-------------------------|---------------------|-------------|
|                         | LIME    | SHAP  | LPI  | LIME    | SHAP  | LPI  |
| Normalization           | 2.1     | 2.075 | 1.825| 2       | 2.7   | 1.3  |
| Min-max Scaling         | 1.525   | 1.925 | 2.55 | 1.925   | 2.65  | 1.425|
| Inter-quartile Normalization | 2.275 | 1.375 | 2.35 | 1.975   | 2.65  | 1.375|

4.3 Pre-processing Effect

As stated earlier, numerical features were normalized and the encoded categorical values are processed as one-hot vectors in the experiments of Section 4.2. In this section, we show that different pre-processing transformations on numerical features have a direct effect on the ranks of explanation techniques over multiple datasets. We have included the results of applying two other pre-processing techniques including min-max scaling and inter-quartile pre-processing in this section.

Figure 4: Box-plots of Spearman’s rank correlation of explanation techniques when the black-box model is Logistic Regression (top) and Naive Bayes (bottom) under inter-quartile transformation. The shaded area visualizes the threshold where $\text{corr} > 0.7$. 

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Table 3: The average rank of explanation techniques with normalization where explanation techniques decompose probability scores

|                        | Logistic Regression | Naive Bayes |
|------------------------|---------------------|-------------|
|                        | LIME    | SHAP | LPI  | LIME | SHAP | LPI  |
| Standardization        | 2.1     | 2.12 | 1.78 | 1.98 | 2.75 | 1.27 |
| Min-max Scaling        | 1.48    | 1.92 | 2.6  | 2    | 2.7  | 1.3  |
| Inter-quartile Normalization | 2.22 | 1.48 | 2.3  | 2.02 | 2.7  | 1.27 |

The box-plots of rank correlations for each explanation techniques are visualized after min-max (Figure 3) and inter-quartile scaling (Figure 4). Table 2 contains the summary of the rank of all explanation techniques for each pre-processing transformation averaged over all datasets. SHAP and LIME explanations marginally outperform the other techniques in the case of min-max and inter-quartile scaling respectively. Examples of this trend for LIME explanations can be seen in datasets such as Attrition, Breast Cancer, Pima Indians and Banknote data sets when explaining Logistic Regression as can be seen in Figure 3. Similarly, SHAP explanations show substantial improvements in explaining Logistic Regression for data sets such as Breast Cancer, Spambase, Seismic and Thera as shown in Figure 4. LPI explanations outperform all explanation techniques across all pre-processing techniques applied when examining the Naive Bayes model.

4.4 Comparison based on prediction probability

In Section 3.3, we derived the feature importance values \( \Phi \) from explanation technique \( g \) based on the log odd ratios of instance \( x \) with respect to class \( C \). In this section, we investigate whether obtaining feature importance \( \Phi \) from explanation techniques based on the prediction probability score instead of the log odd ratios value affects our evaluation of explanation techniques. Table 3 shows the results for average rank of explanation techniques over all datasets. As it can be seen from the table, using prediction probability has insignificant effects on the average ranks of explanations across all datasets and therefore similar conclusions can be made for the most outperforming technique when explaining Naive Bayes and Logistic Regression.

5 Concluding remarks

In this study, we propose an evaluation procedure for comparing local additive explanations to ground truth local explanations. We showed two examples of extracting ground truth from white-box models that have intrinsic additive representations, namely Logistic Regression and Naive Bayes. Our comparison procedure is based on Spearman’s Rank Correlation between the explanation vectors obtained from an explanation technique against our ground truth. Using our method, we were able to conclude what relative performance can be expected of the explanation techniques for the considered model types. The empirical experiments compared explanations obtained from different techniques such as LIME, SHAP and LPI on 20 tabular datasets. Based on our comparison, each explanation technique can outperform other techniques depending on the choice of pre-processing transformation applied to the datasets. In the case of Naive Bayes, the explanations of LPI outperform the other techniques across all pre-processing techniques.

The limitations of our proposed approach are two-fold. Firstly, we have focused on comparing the accuracy of explanation of Logistic Regression and Naive Bayes and the comparison of explanations of other class of black-box models are omitted. In addition, we have focused on the binary classification tasks in our empirical study.

One obvious future direction is identifying procedures in which ground truth can be extracted from other classes of machine learning models. The challenge is to derive the ground truth in the models where intrinsic additive structures are not present such as in decision trees.

On a final note, it should be emphasized that the proposed framework should be seen as complementary to human-grounded evaluations. The functionally-grounded evaluation methods could be seen as means to make the development of new candidate techniques more efficient; they allow for
rejecting some candidates early on, but the finally produced candidates will most likely still need to be qualitatively evaluated in a user-centered context in the end.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
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3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
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   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [N/A]
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   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
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A Appendix

A.1 datasets
The URL to all datasets used throughout this study are presented in Table 4.

A.2 Experiments
The accuracy of the Logistic Regression and Naive Bayes models are shown in Table 5. The rank of each explanation techniques according to median Spearman’s rank correlation in a descending order across different datasets and underlying models are depicted in Table 6.

A.3 Pre-processing Effect
A.3.1 Min-max scaling
In Table 7, we present the rank of explanation techniques based on median Spearman’s correlation for each dataset when min-max scaling is performed in data sets.

A.3.2 Inter-quartile normalization
In Table 7, we present the rank of explanation techniques based on median Spearman’s correlation for each dataset when inter-quartile pre-processing is performed in data sets.
Table 4: List of datasets used in this study

| Dataset          | URL                                                                 |
|------------------|----------------------------------------------------------------------|
| Adult            | https://archive.ics.uci.edu/ml/datasets/adult                      |
| Attrition        | https://www.kaggle.com/philschmidt/employee-attrition-eda          |
| Audit            | https://www.kaggle.com/sid321axn/audit-data                        |
| Banking          | https://www.kaggle.com/rashmiranu/banking-dataset-classification   |
| Banknote         | https://archive.ics.uci.edu/ml/datasets/banknote/authentication     |
| Breast Cancer    | https://archive.ics.uci.edu/ml/datasets/breast+cancer+wisconsin+   |
|                  | (diagnostic)                                                       |
| Churn            | https://www.kaggle.com/surendharanp/personal-loan                  |
| Donors           | https://www.kaggle.com/momohmustapha/donorsprediction              |
| Pima Indians     | https://www.kaggle.com/uciml/pima-indians-diabetes-database        |
| Haberman         | https://archive.ics.uci.edu/ml/datasets/haberman's+survival        |
| Hattrick         | https://www.kaggle.com/juandelacalle/hattrickorg-matches-dataset   |
| Heart Disease    | https://archive.ics.uci.edu/ml/datasets/heart+disease              |
| HR               | https://www.kaggle.com/sid321axn/audit-data                        |
| Insurance        | https://www.kaggle.com/mhdzahier/travel-insurance                  |
| Iris             | https://archive.ics.uci.edu/ml/datasets/iris                      |
| Loan             | https://www.kaggle.com/teertha/personal-loan-modeling              |
| Seismic          | https://archive.ics.uci.edu/ml/datasets/seismic-bumps              |
| Spambase         | https://archive.ics.uci.edu/ml/datasets/spambase                   |
| Thera            | https://www.kaggle.com/surendharanp/personal-loan                  |
| Titanic          | https://www.kaggle.com/c/titanic                                   |

Table 5: Accuracy of Logistic Regression (LR) and Naive Bayes (NB) models with normalization on all datasets

| Dataset          | LR  | NB  | Dataset          | LR  | NB  | Dataset          | LR  | NB  |
|------------------|-----|-----|------------------|-----|-----|------------------|-----|-----|
| Adult            | 0.841 | 0.805 | Donor            | 1   | 0.99 | Iris             | 1   | 1   |
| Attrition        | 0.99 | 0.974 | Pima Indians     | 0.802 | 0.766 | Loan             | 1   | 1   |
| Audit            | 0.962 | 0.649 | Haberman         | 0.962 | 0.649 | Seismic          | 0.946 | 0.837 |
| Banking          | 0.906 | 0.879 | Hattrick         | 0.939 | 0.897 | Spambase         | 0.921 | 0.808 |
| Banknote         | 0.98 | 0.854 | Heart Disease    | 0.829 | 0.829 | Thera            | 1   | 1   |
| Breast Cancer    | 0.965 | 0.916 | HR               | 0.77 | 0.749 | Titanic          | 0.794 | 0.78 |
| Churn            | 0.805 | 0.826 | Insurance        | 0.987 | 0.953 |                  |      |     |
Table 6: Rank of explanation techniques based on median Spearman’s rank correlation within each dataset for Logistic Regression and Naive Bayes models

|                      | Logistic Regression | Naive Bayes |
|----------------------|---------------------|-------------|
|                      | LIME    | SHAP | LPI | LIME | SHAP | LPI |
| Adult                | 1       | 3    | 2   | 1    | 3    | 2   |
| Attrition            | 1       | 3    | 2   | 2    | 3    | 1   |
| Audit                | 2       | 3    | 1   | 2    | 3    | 1   |
| Banking              | 2       | 1    | 3   | 2    | 3    | 1   |
| Banknote             | 3       | 1    | 2   | 3    | 2    | 1   |
| Breast Cancer        | 3       | 1    | 2   | 3    | 2    | 1   |
| Churn                | 1       | 2    | 3   | 1.5  | 3    | 1.5 |
| Donors               | 3       | 2    | 1   | 2    | 3    | 1   |
| HR                   | 2       | 3    | 1   | 1    | 3    | 2   |
| Haberman             | 3       | 1.5  | 1.5 | 3    | 2    | 1   |
| Hattrick             | 3       | 1    | 2   | 1    | 2    | 3   |
| Heart Disease        | 3       | 1    | 2   | 1    | 3    | 2   |
| Insurance            | 1       | 3    | 2   | 1.5  | 3    | 1.5 |
| Iris                 | 3       | 2    | 1   | 3    | 2    | 1   |
| Loan                 | 1       | 2    | 3   | 2    | 3    | 1   |
| Pima Indians         | 3       | 1    | 2   | 3    | 2    | 1   |
| Seismic              | 1       | 3    | 2   | 2    | 3    | 1   |
| Spambase             | 3       | 2    | 1   | 2    | 3    | 1   |
| Thera                | 1       | 3    | 2   | 2    | 3    | 1   |
| Titanic              | 2       | 3    | 1   | 2    | 3    | 1   |
| **Average (All data sets)** | **2.1** | **2.08** | **1.82** | **2** | **2.7** | **1.3** |
| **Standard Deviation (All data sets)** | **0.89** | **0.84** | **0.66** | **0.69** | **0.46** | **0.53** |

Table 7: Rank of explanation techniques based on median Spearman rank correlation when decomposing log odds ratio under the effect of minmax pre-processing

|                      | Logistic Regression | Naive Bayes |
|----------------------|---------------------|-------------|
|                      | LIME    | SHAP | LPI | LIME | SHAP | LPI |
| Adult                | 1       | 3    | 2   | 1    | 3    | 2   |
| Attrition            | 2       | 1    | 3   | 2    | 3    | 1   |
| Audit                | 2       | 3    | 1   | 1    | 3    | 2   |
| Banking              | 2       | 1    | 3   | 2    | 3    | 1   |
| Banknote             | 1       | 2.5  | 2.5 | 3    | 2    | 1   |
| Breast Cancer        | 1       | 2    | 3   | 3    | 2    | 1   |
| Churn                | 1       | 2    | 3   | 1    | 3    | 2   |
| Donors               | 1       | 2    | 3   | 2    | 3    | 1   |
| HR                   | 2       | 3    | 1   | 1    | 3    | 2   |
| Haberman             | 1.5     | 1.5  | 3   | 3    | 2    | 1   |
| Hattrick             | 2       | 1    | 3   | 1    | 2    | 3   |
| Heart Disease        | 1       | 2    | 3   | 1    | 3    | 2   |
| Insurance            | 1       | 3    | 2   | 1.5  | 3    | 1.5 |
| Iris                 | 1       | 2.5  | 2.5 | 3    | 2    | 1   |
| Loan                 | 2       | 1    | 3   | 2    | 3    | 1   |
| Pima Indians         | 1       | 2    | 3   | 3    | 2    | 1   |
| Seismic              | 2       | 1    | 3   | 2    | 3    | 1   |
| Spambase             | 2       | 1    | 3   | 3    | 2    | 1   |
| Thera                | 2       | 1    | 3   | 2    | 3    | 1   |
| Titanic              | 2       | 3    | 1   | 1    | 3    | 2   |
| **Average (All data sets)** | **1.52** | **1.92** | **2.55** | **1.92** | **2.65** | **1.42** |
| **Standard Deviation (All data sets)** | **0.49** | **0.79** | **0.72** | **0.81** | **0.48** | **0.58** |
| Data Set         | Logistic Regression | Naive Bayes |
|------------------|---------------------|-------------|
|                  | LIME | SHAP | LPI | LIME | SHAP | LPI |
| Adult            | 1    | 2    | 3   | 1    | 3    | 2   |
| Attrition        | 1    | 2    | 3   | 2    | 3    | 1   |
| Audit            | 2    | 1    | 3   | 1    | 3    | 2   |
| Banking          | 2    | 1    | 3   | 2    | 3    | 1   |
| Banknote         | 3    | 1    | 2   | 3    | 2    | 1   |
| Breast Cancer    | 3    | 1    | 2   | 3    | 2    | 1   |
| Churn            | 2    | 1    | 3   | 1    | 3    | 2   |
| Donors           | 3    | 2    | 1   | 2    | 3    | 1   |
| HR               | 3    | 2    | 1   | 1    | 3    | 2   |
| Haberman         | 2.5  | 1    | 2.5 | 3    | 2    | 1   |
| Hattrick         | 2    | 1    | 3   | 1    | 2    | 3   |
| Heart Disease    | 3    | 1    | 2   | 1    | 3    | 2   |
| Insurance        | 1    | 3    | 2   | 1.5  | 3    | 1.5 |
| Iris             | 3    | 1.5  | 1.5 | 3    | 2    | 1   |
| Loan             | 2    | 1    | 3   | 2    | 3    | 1   |
| Pima Indians     | 3    | 1    | 2   | 3    | 2    | 1   |
| Seismic          | 2    | 1    | 3   | 2    | 3    | 1   |
| Spambase         | 2    | 1    | 3   | 3    | 2    | 1   |
| Thera            | 2    | 1    | 3   | 2    | 3    | 1   |
| Titanic          | 3    | 2    | 1   | 2    | 3    | 1   |
| Average (All data sets) | 2.28 | 1.38 | 2.35 | 1.98 | 2.65 | 1.38 |
| Standard Deviation (All data sets) | 0.7 | 0.57 | 0.74 | 0.78 | 0.48 | 0.57 |