“Why should you trust my interpretation?”
Understanding uncertainty in LIME predictions

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Abstract

Methods for interpreting machine learning black-box models increase the outcomes’ transparency and in turn generates insight into the reliability and fairness of the algorithms. However, the interpretations themselves could contain significant uncertainty that undermines the trust in the outcomes and raises concern about the model’s reliability. Focusing on the method “Local Interpretable Model-agnostic Explanations” (LIME), we demonstrate the presence of two sources of uncertainty, namely the randomness in its sampling procedure and the variation of interpretation quality across different input data points. Such uncertainty is present even in models with high training and test accuracy. We apply LIME to synthetic data and two public data sets, text classification in 20 Newsgroup and recidivism risk-scoring in COMPAS, to support our argument.

1. Introduction

In the past few decades, machine learning algorithms have become increasingly significant for human decision-making in many areas such as automatic diagnosis (Sajda, 2006) and opinion mining (Pak & Paroubek, 2010) etc. However, many machine learning algorithms are “black-box” in that the process of deriving their predictions is hard for humans to understand qualitatively (Lipton, 2016; Doshi-Velez & Kim, 2017). An accessible interpretation of a prediction is crucial for users to establish trust in the outcome, as it helps users understand the importance of each feature in producing black-box outcomes, serves as a key ingredient of a robust validation procedure (Ribeiro et al., 2016), and, more importantly, generates insight into the fairness of the algorithms that facilitates informed corrections to reduce social bias (Madnani et al., 2017).

Indeed, interpretation methods help users assess and establish trust in black-box models and their predictions. However, whether the interpretations themselves are trustworthy is not obvious. Uncertainty in interpretations not only casts doubt on the way of understanding a certain prediction, but also raises concern about the reliability of the black-box model in its entirety. If we are not sure about the true importance of each feature, there is no way to establish confidence in how an outcome is generated and whether the model would handle future data without bias.

In this paper, we address the question: When can we be sure about trusting an interpretation? In particular, we focus on the approach “Local Interpretable Model-agnostic Explanations” (LIME) (Ribeiro et al., 2016), which learns a sparse linear model near the target point by sampling points around it and the coefficients of which are considered representative of feature responsible for the decision.
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However, training this surrogate model involves a sampling procedure that introduces randomness into the interpretation.

2. Problem Setup and Methodology

2.1. Uncertainty in LIME

Given a black box model $f$, and a target point $x$ to be interpreted, LIME chooses a model $g$ from some interpretable functional space $G$ by solving

$$\text{argmin}_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g)$$  \hspace{1cm} (1)

where $\pi_x$ is some proximity measure for closeness to $x$ and $\Omega(g)$ is some penalty for model complexity.

In the implementation, we use K-LASSO as the interpretable model where we could take $\Omega = \infty$ if $\|w_g\|_0 > K$ with $w$ as the coefficient for linear model, and choose to draw sampling with probability proportional to $\pi_x$ to get the data points to train K-LASSO. It is noticing that this procedure involves two sources of uncertainty:

- instability of interpretation trials on a single datapoint
- variation in interpretation quality across different data

2.2. Methodology

To probe the presence of the two aforementioned sources of uncertainty, we run LIME repeatedly on multiple data points. For each data point, we record the cumulative selection frequency of the top few salient features selected by K-LASSO in Lime. We observe the consistency of selected features over different trials to assess LIME’s instability in interpreting this single data point. We then compare LIME interpretations on different data points, where we assess the interpretation quality by observing whether the selected features are informative in the real context.

2.3. Data

2.3.1. Synthetic Data Generation

Given the number of features $N$, we generate training and test data from local sparse linear models on uniformly distributed input in $[0, 1]^N$. To illustrate LIME’s local behavior at different data points, we partition them with a known decision tree. Within each partition, we assign labels on each data point $x$ based on a linear classifier with known coefficients $\beta$ as shown in Equation 2.

$$y(x) = \begin{cases} 
1 & x^T \beta \geq 0 \\
0 & x^T \beta < 0. 
\end{cases} \hspace{1cm} (2)$$

We consider two cases where the number of features is 4 and 8 respectively. Figure 1 presents a way of splitting the data into six leaves for $N = 8$. Coefficients for six leaves in Figure 1 are listed in Table 1, where three out of eight features have nonzero coefficients in each leaf. The data splitting and coefficients for $N = 4$ are presented in Figure 4 and Table 4 in Appendix A.

2.3.2. Real Data Application

We apply LIME to two real-world datasets. We first demonstrate LIME’s variability in text classification with examples from the 20 Newsgroup dataset. Then we analyze the COMPAS Recidivism Risk Score dataset to probe the existence of demographic bias in the recorded decisions.

Text Classification: The 20 Newsgroup dataset is a collection of about 20,000 news documents across twenty newsgroups. As was already noted in (Ribeiro et al., 2016), even for text classification models with low training and test errors as shown in Table 2 in Appendix A, some feature words that LIME selects are quite arbitrary and uninformative. We study this phenomenon further using two examples of classifying documents by content (“Atheism vs. Christianity” and “electronics vs. crypt”) using a Multinomial Naive Bayes classifier.

Table 1. True coefficients for six leaves in generating eight-feature synthetic data.

| Leaf | Coefficients |
|------|--------------|
| 0    | \{1, 1, 1, 0, 0, 0, 0\} |
| 1    | \{0, 1, 1, 1, 0, 0, 0\} |
| 2    | \{0, 0, 1, 1, 0, 0, 0\} |
| 3    | \{0, 0, 0, 1, 1, 0, 0\} |
| 4    | \{0, 0, 0, 0, 1, 1, 0\} |
| 5    | \{0, 0, 0, 0, 0, 1, 1\} |

Figure 1. Decision tree partition of eight-feature synthetic data.
COMPAS Recidivism Risk Score Dataset: The “Correctional Offender Management Profiling for Alternative Sanctions” (COMPAS) is a risk-scoring algorithm developed by Northpointe to assess a criminal defendant’s likelihood to recidivate. The risk is classified as “High”, “Medium” and “Low” based on crime history and category, jail time, age, demographics, etc. We study a subset of the COMPAS dataset collected and processed by ProPublica (Larson et al., 2016), with the goal of examining the presence of demographic bias in risk-scoring. We train a random forest classifier as a “mimic model” (Tan et al., 2018), using selected features and risk assessment text labels from COMPAS model. We examine salient features selected by LIME explanations on multiple COMPAS records.

3. Numerical Results

Synthetic Data: We present results for the case where we apply LIME to interpret black-box models (random forest and gradient boosting tree) trained with eight-feature synthetic data. We run LIME on one data point in each of the six leaves. We first notice that different trials potentially select different features due to sampling variation. Figure 2 shows the cumulative selection frequency of three most salient features in each trial when LIME interprets a random forest model; the case with gradient boosting is shown in Figure 5 in Appendix A. Although the splitting rule might introduce signal into the first three features, none of the other five features is selected over 40 times in the 100 trials. Thus, the interpretation of LIME cannot be considered stable around each single data point. The results for running the same procedure on four-feature synthetic data are presented in Figure 6 and 7 in Appendix A.

Text Classification: As shown in Table 2 in Appendix A, the Naive Bayes classifiers for both “Electronics vs. Crypt” and “Christianity vs. Atheism” have low training and test error. It seems that the model not only fits the training data but also generalizes to the test data well. But as pointed out in (Ribeiro et al., 2016), to establish trust in the model, we need to know which feature words are responsible for the decision. As shown in Figure 3, the selected feature words for the first document (“crypto”, “sternlight” and “netcom”) display no variation for different trials and are relevant in content, which makes the model seem very credible. However, the selected feature words for the second document are not informative at all. Thus, the quality of interpretation varies across different input data. We also include results for “Christianity vs. Atheism” in Table 2 and Figure 8 in Appendix A, which also display a difference in interpretation quality.

Black-box model | Training accuracy | Test accuracy
--- | --- | ---
Random forest | 0.9982 | 0.9445
Gradient boosting | 0.9219 | 0.9128

Table 3. Training and test accuracy of random forest and gradient boosting for eight-feature synthetic data.

| Text example | Training accuracy | Test accuracy |
| --- | --- | --- |
| Atheism & Christianity | 1.0 | 0.9066 |
| Electronic & Crypt | 1.0 | 0.9214 |

Table 2. Training and test accuracy of Naive Bayes Classifier for text classification of 20 Newsgroup data.

COMPAS Recidivism Risk Score Data: We test and analyze LIME interpretation of the random forest classifier with both numerical and categorical features. Unlike the uncertainty we observe in previous experiments on synthetic and 20 Newsgroup data, we see consistent explanation results on different test data points. LIME is applied to two data points that are classified as “high risk” by COMPAS. The results are shown in Figure 9 in Appendix A. We consider these interpretations to be trustworthy due to the following two observations: 1) there is little variation in the selection of important features in different trials on the same data point, and 2) interpretation is consistent for different data points, since the same features are selected for the two different data points, including race and age. Further analysis using LIME suggests that the mimic model is using demographic properties as important features in predicting a risk score. This in turn shows that it is probable that the COMPAS model makes use of demographic features for recidivism risk assessment, so further investigation would be meaningful to gauge the fairness of the algorithm.

4. Conclusion

Interpretation methods for black-box models may themselves contain uncertainty that calls into question the reliability of the black-box predictions and the models themselves. We demonstrate the presence of two sources of uncertainty in the interpretation method “Local Interpretable Model-agnostic Explanations” (LIME), namely the randomness in its sampling procedure and the variation of interpretation quality across different input data points. The uncertainty in LIME is illustrated by numerical experiments on synthetic data, text classification examples in 20 Newsgroup data and recidivism risk-scoring in COMPAS data.
Figure 2. Cumulative selection frequency for eight-feature synthetic data with random forest. We pick one sample in each leaf, repeat LIME 100 times to explain the prediction of the random forest model we trained, and record the three features used by the decision rule in each explanation. Features with true coefficients 1 are marked red in each leaf.

Figure 3. Cumulative selection frequency of top three feature words selected in each of 100 LIME trials for text classification of “electronics vs. crypt”. Words that are informative are marked red.
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A. More Simulation Setting

A.1. Setting for Four Leaves

For sample points with four features, we use the first two dimensions of features as their x and y coordinates. We assign each quadrant to different leaf, and we ignore the sample points on the x or y axis. For each leaf, we assign different coefficients for their features. Specifically, the coefficients are listed in Table 4. We fit and explained both random forest and gradient boosting classifier with the four leaves setting, and the simulation results are presented in the appendix.

| Leaf | Coefficients |
|------|--------------|
| 0    | \{1, 1, 0, 0\} |
| 1    | \{0, 1, 1, 0\} |
| 2    | \{0, 0, 1, 1\} |
| 3    | \{1, 0, 0, 1\} |

Table 4. True coefficients for four leaves in generating four-feature synthetic data.

A.2. More Numerical Results

Text Classification: We select two classes from 20 newsgroup dataset, then apply term frequency-inverse document freque (tf-idf) vectorizer with default settings. Stop words are not removed from resulting tokens as we would like to see if the model is using irrelevant features to predict the results. The model classification accuracy is listed in Table 2. For the the classification between “Electronics” and “Crypt”, we analyze the explanation over two different test data points. We could see from the results that the explanation of test data document one contains several indicative words, such as “crypto”, “netcom” and “Sternlight” in this case. However, the explanation results for test data point two contains only one indicative word “information”. We

| Black-box model | Training accuracy | Test accuracy |
|-----------------|-------------------|---------------|
| Random forest   | 0.9988            | 0.9680        |
| Gradient boosting| 0.9902            | 0.972         |

Table 5. Training and test accuracy of random forest and gradient boosting for four-feature synthetic data.

COMPAS Recidivism Risk Score Data: The COMPAS dataset from ProPublica contains a lot irrelevant columns, as well as null values. We selected twelve relevant columns of the dataset, then drop the rows that contain null value. Specifically, we exclude the decile score columns as it is directly related to the text label. We then encode the categorical features, such as “sex” and “race”, using one-hot encoder, and encode the label text using label encoder. After the simple data pre-process, we trained a random forest classifier on the processed dataset to mimic the COMPAS black-box model, which we do not have access to.
Figure 5. Cumulative selection frequency for eight-feature synthetic data with gradient boosting tree. We pick one sample in each leaf, repeat LIME 100 times to explain the prediction of the gradient boosting tree model we trained, and record the three features used by the decision rule in each explanation. Features with true coefficients 1 are marked red in each leaf.

Figure 6. Cumulative selection frequency for four-feature synthetic data. We pick one sample in each leaf, repeat LIME 100 times to explain the prediction of the random forest model we trained, and record the two most important features in each explanation. Features with true coefficients 1 are marked red in each leaf.
Figure 7. The frequency v.s. most important feature index bar plots for 100 iterations of explanation for the gradient boosting classifier of 4 features synthetic data. We kept the two most important feature during each iteration.

Figure 8. Cumulative selection frequency of top six feature words selected in each of 100 LIME trials for text classification of “Christianity vs. Atheism”. Words that are informative are marked red.
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Figure 9. Cumulative selection frequency of salient feature words for COMPAS mimic model in 50 iterations.

(a) Sample data 1

(b) Sample data 2