EXPLAINING THE PREDICTIONS OF ANY IMAGE CLASSIFIER VIA DECISION TREES

Sheng Shi†  Xinfeng Zhang⋆  Wei Fan†

† AI Laboratory, Lenovo Research, Beijing 100094, China
⋆ University of Chinese Academy of Sciences, Beijing 100049, China

ABSTRACT

Despite outstanding contribution to the significant progress of Artificial Intelligence (AI), deep learning models remain mostly black boxes, which are extremely weak in explainability of the reasoning process and prediction results. Explainability is not only a gateway between AI and society but also a powerful tool to detect flaws in the model and biases in the data. Local Interpretable Model-agnostic Explanation (LIME) is a recent approach that uses an interpretable model to form a local explanation for the individual prediction result. The current implementation of LIME adopts the linear regression as its interpretable function. However, being so restricted and usually over-simplifying the relationships, linear models fail in situations where nonlinear associations and interactions exist among features and prediction results. This paper implements a decision Tree-based LIME approach, which uses a decision tree model to form an interpretable representation that is locally faithful to the original model. Tree-LIME approach can capture nonlinear interactions among features in the data and creates plausible explanations. Various experiments show that the Tree-LIME explanation of multiple black-box models can achieve more reliable performance in terms of understandability, fidelity, and efficiency.

Index Terms— Explainable AI, Interpretable Model, Decision Tree, LIME, Local Fidelity

1. INTRODUCTION

In recent years, the fast-growing computing power, enormous consumer and commercial data, and emerging advanced machine learning algorithms jointly stimulate the prosperous of AI [1] [2], which has gone from a science-fiction dream to a critical part of our daily life. Compared to traditional machine learning methods, deep learning has achieved superior performance in perception tasks such as object detection and classification. However, because of the nested non-linear structure, deep learning models usually remain black boxes that are particularly weak in the explainability of the reasoning process and prediction results. In many real-world mission-critical applications, transparency of deep learning models and explainability of the model outputs are essential and necessary in their real deployment process.

Explainable AI is not only a gateway between AI and society but also a powerful tool to detect flaws in the model and biases in the data. The development of techniques on explainability and transparency of deep learning models has recently received much attention in the research community [3] [4] [5] [6]. The relevant research roughly falls into two categories: global explainability and local explainability. Global explainability aims at making the reasoning process wholly transparent and comprehensive [7], [8], while local explainability focuses on extracting input regions that are highly sensitive to the network output to provide explanations for each decision [9] [10] [11] [12].

An effective way to achieve explainability is to use a light-weight function family to create interpretable models. Local interpretable model-agnostic explanations (LIME) identify an interpretable model over the human-interpretable representation that is locally faithful to the original model [9]. The current implementation of LIME in [9] adopts the linear regression as its interpretable function, which represents the prediction as a linear combination of a few selected features to make the prediction process transparent (Linear-LIME). However, being so restricted and usually over-simplifying the relationships, linear regression models fail in some situations where non-linear associations and interactions exist among features and prediction results.

The LIME framework in [9] supports the exploration of a variety of explanation families, such as linear regression and decision trees. In this paper, we implement a Decision Tree-based Local Interpretable Model-agnostic Explanation (Tree-LIME). The decision tree structure creates good explanations as the data ends up in distinct groups that are often easy to understand. Moreover, the tree structure can capture interactions between features in the data. We perform various experiments on explaining two black-box models, the random-forest classifier and Google’s pre-trained Inception neural network [13]. The results show that Tree-LIME explanations achieve more reliable performance than Linear-LIME in terms of understandability, fidelity, and efficiency.

2. INTERPRETABLE MODELS

Using a subset of algorithms from a light-weight function family to create interpretable models is an effective way to
achieve interpretability. In this section, we analyze two representative interpretable models - the linear regression model and the decision tree model. Table 1 shows the properties of two interpretable models. The linear regression displays the prediction as a linear combination of features, while the decision tree represents the reasoning process in a hierarchical structure, which is suitable for capturing the nonlinear association between features and predictions. The monotonicity constraint shown in both models is necessary to ensure the consistency between a feature and the target outcome. Moreover, the decision tree model can automatically capture the diverse interactions between features to predict the target outcome, applicable to both classification and regression tasks.

Depending on the different criteria, various algorithms are capable of constructing a decision tree. The CART [14] is the most popular algorithm which can handle both classification and regression tasks. In this paper, we mainly construct regression decision trees to explain the prediction probability of the image classifier. Figure 1 illustrates a simple regression tree to explain image classification prediction made by Google’s Inception neural network. The predicted top 1 class label is African chameleon ($p = 0.9935$). The highlighted superpixels give intuition as to why the model would choose that class. The decision tree shows that if feature 28, 22, and 30 exist, then the prediction probability is 0.991, which is the mean value of the instances $y$ in this node. Moreover, the importance of the three features is 0.7164, 0.0709, and 0.0259, showing the contribution of the three features in improving the variance.

3. THE TREE-LIME APPROACH

In this section, we first present the interpretable image representations and the decision tree-based LIME approach. Then we discuss the characteristics of Tree-LIME.

3.1. Explanation System of Tree-LIME

Considering the poor interpretability and high computational complexity of the pixel-based image representation, we adopt a superpixel-based explanation system. Each superpixel, as the basic processing unit, is a group of connected pixels with similar colors or gray levels. Figure 2 shows the pixel-based image, superpixel image, and superpixel-based explanation. The interpretable representation of an image $x \in \mathbb{R}^d$ consisting of $d$ pixels and $d'$ superpixels is a binary vector $x' \in \{0, 1\}^{d'}$ where 1 indicates the presence of original superpixel and 0 indicates absence of original superpixel.

We denote the original image classification model being explained as $f$, the interpretable decision tree model as $g$, and the locality fidelity loss as $L(f, g, \pi_x)$, which is calculated by the locally weighted square loss:

$$L(f, g, \pi_x) = \sum_{z, z' \in \mathcal{Z}} e^{(-D(x, z)^2/\sigma^2)} (f(z) - g(z'))^2.$$  \hspace{1cm} (1)

The database $\mathcal{Z}$ is composed of perturbed samples $z' \in \{0, 1\}^{d'}$ which are sampled around $x'$ by drawing nonzero elements at random. Given a perturbed sample $z'$, we recover the sample in the original representation $z \in \mathbb{R}^d$ and get $f(z)$. Moreover, $\pi_x(z) = \exp(-D(x, z)^2/\sigma^2)$ where distance function $D$ is the $L_2$ distance of image $x$ and $z$ is used to capture locality.

We denote the decision tree explanation produced by

| Models       | Linearity | Monotonicity | Feature Interaction | Task                |
|--------------|-----------|--------------|---------------------|--------------------|
| Line regression | Yes       | Yes          | No                  | Classification, Regression |
| Decision tree  | No        | Some         | Yes                 | Classification, Regression |

Fig. 1. A simple regression decision tree explains the image classification results given by Google’s Inception neural network. The top 1 output class label is African chameleon with the prediction probability ($p = 0.9935$).

Fig. 2. Pixel-based image and superpixel image
Tree-LIME as below:

\[ \xi(x) = \arg\min L(f, g, \pi_x) + \text{dep}(g). \]  

(2)

The depth of decision tree \text{dep}(g) is a measure of model complexity. A smaller depth indicates a stronger understandability of model \( g \). In order to ensure both local fidelity and understandability, formula (2) minimizes locality-fidelity loss \( L(f, g, \pi_x) \) while holding \text{dep}(g) low enough. Algorithm 1 shows a simplified workflow diagram of Tree-LIME. Firstly, Tree-LIME gets the superpixel image by using a standard segmentation method. Then the database \( Z \) is constructed by running multiple iterations of the perturbed sampling operation. Finally, within the allowable range of prediction error, Tree-LIME gets the minimum depth decision tree by using the CART method.

**Algorithm 1** Decision Tree based Local interpretable model-agnostic explanation (Tree-LIME)

**Require:** Classifier \( f \), Number of samples \( N \), Instance \( x \), Max depth of tree \( d \)

**Ensure:** time and prediction error of Tree-LIME

1: get superpixel image \( x' \) by segment method 
2: initial \( Z = \{ \} \)
3: for \( i = 1; i < N; i + + \) do 
4: get \( z' \) by sampling around \( x' \)
5: get \( f(x') \) by classifier \( f \)
6: get \( z \) by recovering \( z' \)
7: \( Z \leftarrow Z \cup \{\pi}', f(z), \pi_x(z_i)\})
8: end for 
9: for \( j = 1; j < d \) and \text{error} < \delta; j + + \) do 
10: get decision tree \( g = \text{CART}(Z, \text{maxdepth} = j) \)
11: \text{error} = \|f(x) - g(x')\|
12: end for 
13: output decision tree \( g \), time and prediction error

### 3.2. Characteristics of Tree-LIME

Despite the fact that the amount of research in explainable AI is growing actively, there is no universal consensus on the exact definition of interpretability and its measurement criterion [15]. Ruping first noted that interpretability is composed of three goals - accuracy, understandability, and efficiency [16]. We argue that fidelity is a better description than accuracy since accuracy is easily confused with the performance evaluation criteria of the original black box model. These three goals are inextricably intertwined and competing with each other, as shown in Figure 3. An explainable model with good interpretability should be faithful to the data and the original model, understandable to the observer and graspable in a short time so that the end-users can make wise decisions.

Tree-LIME has many appealing characteristics, such as interpretable, local fidelity, and model-agnostic. It provides a qualitative understanding of features and predictions. It is challenging, if not impossible, to be utterly faithful to the black box model on a global scale. Tree-LIME takes a feasible approach by approximating it in the vicinity of an instance being predicted. Besides, Tree-LIME, as a model-agnostic interpretation, shows excellent flexibility and capability of explaining any underlying machine learning model.

### 4. EXPERIMENTAL RESULTS

In this section, Tree-LIME and Linear-LIME [9] explain the predictions of RandomForeset Classifier and Google’s pre-trained Inception neural network. We compare the experimental results of the two algorithms in terms of understandability, fidelity, and efficiency.

#### 4.1. RandomForeset Classifier on MNIST database

The MNIST database is one of the most common databases used for image classification. It consists of \( 7 \times 10^3 \) small \( 28 \times 28 \) grayscale images of handwritten digits. In this experiment, the image data is split into 70% as the training set and 30% as the test set. Table 2 shows the performance of the random forest classifier. For instance \( x \), the predicted top 1 class is **Seven** \((p=1.0)\). Figure 6 shows the decision tree explanations by Tree-LIME.

| weighted avg | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0.95         | 0.95      | 0.95   | 21000    |

Comparing with Linear-LIME, which can only provide a one-shot explanation, the decision tree structure by Tree-LIME provides a more intuitive explanation. Figure 6 shows that if feature 0 and feature 3 exist, then the prediction probability is 1.0. Moreover, the tree structure can capture the interaction between features in the data. The importance of feature 0 and 3 is 0.9416 and 0.0402, respectively, which tells us the feature 0 makes a significant contribution to predicting the outcome. The prediction error is calculated to measure local
Table 3. The prediction probability and prediction errors of Linear-LIME and Tree-LIME on Google’s Inception neural network.

| Feature     | Inception prob | Pre prob 0 | Pre prob 1 | Pre prob 2 | Pre prob 3 |
|-------------|----------------|------------|------------|------------|------------|
| Lamp        | p(lamp) = 0.4785 | 0.6264     | 0.4309     | 0.1479     | 0.0476     |
| Couch       | p(couch) = 0.4203 | 0.6814     | 0.4682     | 0.2611     | 0.0479     |
| Pillow      | p(pillow) = 0.0227 | 0.0168     | 0.0191     | 0.0059     | 0.0036     |

fidelity. The prediction error of Tree-LIME is 0.0, showing better fidelity than Linear-LIME with an error of 0.0529.

Efficiency is highly related to the time necessary for a user to grasp the explanation. The runtime of CART in Tree-LIME is 0.0020s, which is faster than that of K-LASSO in Linear-LIME [9] - 0.0080s.

4.2. Google’s Inception neural network on Image-net database

We explain the prediction of Google’s pre-trained Inception neural network on the image shown in Figure 5(a). Figures 5(b), 5(c) and 5(d) show the superpixels explanations for the top 3 predicted classes: table lamp (p = 0.4785), studio couch (p = 0.4203) and pillow (p = 0.0227) respectively. Due to space constraints, Figure 6 shows the the explanations of table lamp and studio couch by Tree-LIME. The prediction provides reasonable insight into what the neural network picks upon for each of the classes. This kind of explanation enhances trust in the classifier. Moreover, Table 4 lists the prediction errors of Tree-LIME and Linear-LIME. The prediction error shows that Tree-LIME has a better fidelity than Linear-LIME. Table 4 lists the runtime of CART in Tree-LIME and runtime of K-LASSO in Linear-LIME.

We can conclude from the above results that under less time, Tree-LIME not only has a better understandability but also has a higher fidelity than Linear-LIME.

5. CONCLUSION

The LIME framework in [9] supports the exploration of a variety of explanation families. The current implementation of LIME adopts the linear regression as its interpretable function (Linear-LIME). In this paper, we implement a decision tree-based local interpretable model-agnostic explanation (Tree-LIME). The goal of Tree-LIME is to construct an interpretable decision tree model over the interpretable representation that is locally faithful to the original classifier. We compare Tree-LIME and Linear-LIME in explaining the predictions of RandomForest Classifier and Google’s pre-trained Inception neural network. Experimental results have shown that Tree-LIME exhibits a better understandability and higher fidelity than Linear-LIME using less process time, which covers the ingredients of an ideal explainable AI model - understandability, fidelity, and efficiency.
6. REFERENCES

[1] R. Girshick, “Fast r-cnn,” in 2015 IEEE International Conference on Computer Vision (ICCV), Dec 2015, pp. 1440–1448.

[2] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, June 2017.

[3] Himabindu Lakkaraju, Ece Kamar, Rich Caruana, and Eric Horvitz, “Identifying unknown unknowns in the open world: Representations and policies for guided exploration,” in Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA., 2017, pp. 2124–2132.

[4] Zhiting Hu, Xuezhe Ma, Zhengzhong Liu, Eduard H. Hovy, and Eric P. Xing, “Harnessing deep neural networks with logic rules,” in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers, 2016.

[5] Quanshi Zhang, Ying Nian Wu, and Song-Chun Zhu, “Interpretable convolutional neural networks,” in 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pp. 8827–8836.

[6] Quanshi Zhang, Ruiming Cao, Feng Shi, Ying Nian Wu, and Song-Chun Zhu, “Interpreting CNN knowledge via an explanatory graph,” in Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018, pp. 4454–4463.

[7] Yao Lu, “Unsupervised learning on neural network outputs: With application in zero-shot learning,” in Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI 2016, New York, NY, USA, 9-15 July 2016, 2016, pp. 3432–3438.

[8] Mathieu Aubry and Bryan C. Russell, “Understanding deep features with computer-generated imagery,” in 2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015, pp. 2875–2883.

[9] Marco Túlio Ribeiro, Sameer Singh, and Carlos Guestrin, “Why should I trust you?: Explaining the predictions of any classifier,” in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016, 2016, pp. 1135–1144.

[10] Marco Túlio Ribeiro, Sameer Singh, and Carlos Guestrin, “Model-agnostic interpretability of machine learning,” CoRR, vol. abs/1606.05386, 2016.

[11] Ruth C. Fong and Andrea Vedaldi, “Interpretable explanations of black boxes by meaningful perturbation,” in IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pp. 3449–3457.

[12] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra, “Grad-cam: Visual explanations from deep networks via gradient-based localization,” in IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pp. 618–626.

[13] C. Szegedy, Wei Liu, Yangqing Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2015, pp. 1–9.

[14] Trevor Hastie Jerome Friedman and Robert Tibshirani, “The elements of statistical learning: Data mining, inference and prediction,” in https://web.stanford.edu/~hastie/ElemStatLearn/, 2009.

[15] Christoph Molnar, “Interpretable machine learning: A guide for making black box models explainable,” in Lulu, 1st edition, March 24, 2019; eBook, 2019.

[16] S. Ruping, “Learning interpretable models (phd thesis),” in Technical University of Dortmund, 2006.