Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods

Jamal Ahmed Bhatti
Alireza Bayat Makou

Winter semester 2021/2022

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5 Best Classifier

6 Hyperparameter sensitivity of LIME and SHAPE parameters

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⇝ These techniques are not fool-proof

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⇝ These techniques are not fool-proof
  - Both rely on input perturbations
  - By guessing the input perturbations a classifier can hide the model biases and send the perturb input to the innocuous model [6]

Applications

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- One can not act without trusting the model if the application is like a medical diagnosis or terrorism detection

Applications

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- Two major problems:
  - Trusting a model
  - Trusting an individual prediction

Claims of the author

- "A novel scaffolding technique that effectively hides the biases of any given classifier by allowing an adversarial entity to craft an arbitrary desired explanation"

Problem Statement I

- Let $\mathcal{D}$ denote the input *dataset* for N points$(x_1, y_1) \dots (x_N, y_N)$. where x_i(vector) denotes the feature value at the dataset point i and y_i is the corresponding class label

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- Let $\pi_x(x')$ denote the *proximity measure/local kernel* between inputs x and x'

Problem Statement II

$$\underset{g \in G}{\arg\min}\, \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

$$\mathcal{L}(f, g, \pi_x) = \sum_{x' \in X'} [f(x') - g(x')]^2 \pi_x(x')$$

Problem Statement II

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- The objective function approximates f in the vicinity of x

Major differences between LIME and SHAP

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The difference lies in the choice of $\Omega(g)$ and $\pi_x(x')$

- $\Omega(g)$ is the number of non-zero weights in the linear model
- $\pi_x(x')$ is defined using L_2 or cosine similarity

- (Kernel) SHAP grounds on game theoretic principles so that it satisfies certain properties

Main ideas

- Adversary wants to fool the post hoc explanation techniues and hide the underlying biases of f
- Adversary provides only f
- The f is trained X_{dist} which neither adversary nor the framework has access
- The X_{dist} is biased but LIME and SHAP will not reveal
- The idea is to train OOD(Out-of-distribution) classifier which can identify if the instance is asked from the perturbed space or from the dataset

Methodology

- Let's asssume ψ is an unbiased classifier and e is the adversarial classifier

$$e(x) = \begin{cases} f(x), & \text{if } x \in X_{dist} \\ \psi(x), & \text{otherwise} \end{cases}$$

- Two kinds of datasets are created X and X_p where X_p is the perturbed dataset with labels if OOD is true or not
- Classifier is trained on $X \bigcup X_p$ with their labels

Datasets

- COMPAS [3]
- Communities and Crime (CC) [5]
- German credit [4]
- Boston Housing [1]
- Student Prediction [2]

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Experimental Setup I

- Random split (90-10)
- Biased Classifier f :
  - Sensitive Feature
  - For instance for COMPAS decision purely based on race
- OOD-Classifier
  - For LIME X was added to $\mathcal{N}(0, 1)$
  - For SHAP, a random subset of features for $x_i \in X$ and replace them by the background distribution
    - Background distribution for SHAP: cluster centers from kmeans with 10 clusters.
  - Classifier: Random forest with 100 tree depth

Experimental Setup II

- Unbiased Classifier ψ:
  - Based on uncorrelated feature with sensitive feature
    - Two Co-related feature: Based on XOR for two features
- Generating Explanation:
  - LIME tabular implementation (default)
  - Kernel SHAP implementation with *kmeans* with 10 clusters as the background distribution (default)

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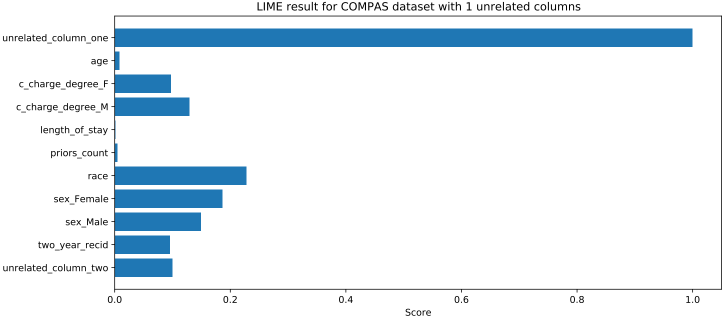
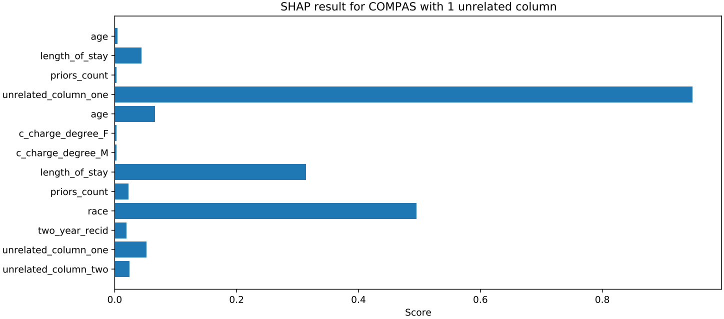
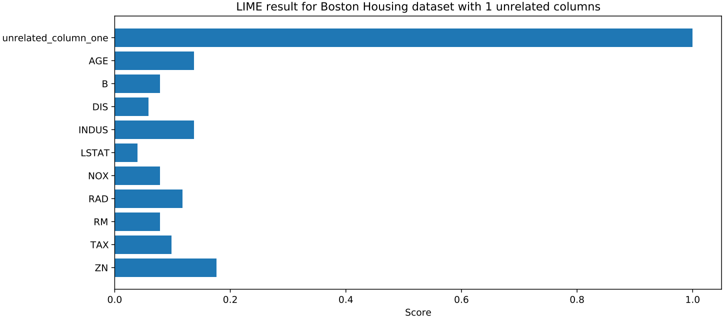
LIME results for COMPAS



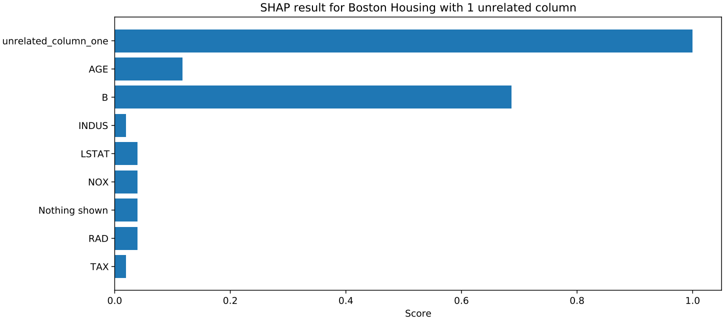
SHAP results for COMPAS



LIME results for Boston Housing



SHAP results for Boston Housing



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- LIME model Boston Housing

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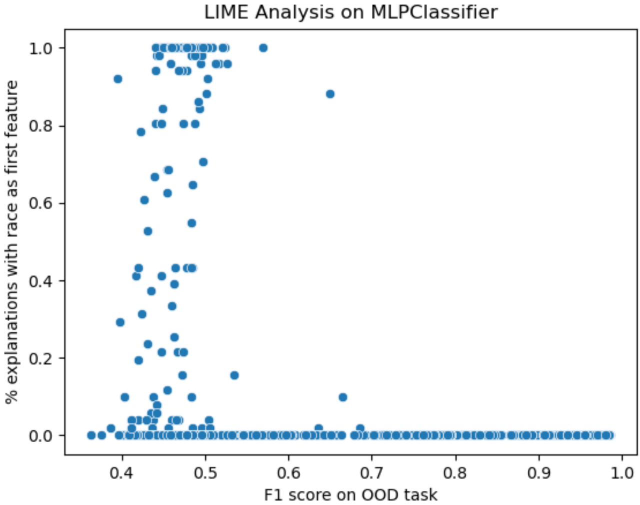
  - Total hyperparameters: 125
  - GridSearch
  - With available computation power only could do for LIME for SHAP it would take months!
- Best Classifier:
  - DecisionTreeClassifier($max_depth = 10, random_state =$ 123454321) (not same as the paper)

Best Classifier II



Best Classifier III

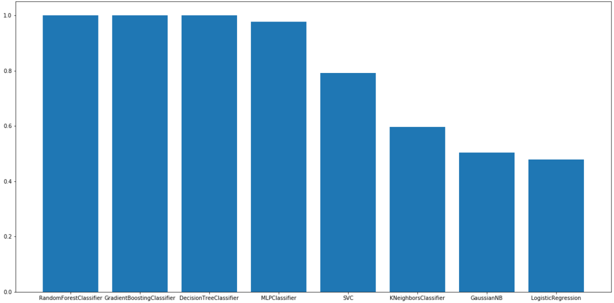


Figure: Best Classifer results, y-axis is the $F-1$ score

Hyperparameter sensitivity of LIME and SHAPE parameters

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References I

- Ali Al Bataineh and Devinder Kaur. "A comparative study of different curve fitting algorithms in artificial neural network using housing dataset". In: *NAECON 2018-IEEE National Aerospace and Electronics Conference*. IEEE. 2018, pp. 174–178.
- Huda Al-Shehri et al. "Student performance prediction using support vector machine and k-nearest neighbor". In: *2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE)*. IEEE. 2017, pp. 1–4.
- Julia Angwin et al. "Machine bias". In: *ProPublica, May 23.2016* (2016), pp. 139–159.
- C Blake, E Koegh, and CJ Mertz. "Repository of Machine Learning". In: *University of California at Irvine* (1999), p. 75.

References II

Michael Redmond and Alok Baveja. "A data-driven software tool for enabling cooperative information sharing among police departments". In: *European Journal of Operational Research* 141.3 (2002), pp. 660–678.

Dylan Slack et al. "Fooling lime and shap: Adversarial attacks on post hoc explanation methods". In: *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. 2020, pp. 180–186.