Feature Attributions and Counterfactual Explanations Can Be Manipulated

Dylan Slack\textsuperscript{1} Sophie Hilgard\textsuperscript{2} Sameer Singh\textsuperscript{1} Himabindu Lakkaraju\textsuperscript{2}†

Abstract
As machine learning models are increasingly used in critical decision-making settings (e.g., healthcare, finance), there has been a growing emphasis on developing methods to explain model predictions. Such explanations are used to understand and establish trust in models and are vital components in machine learning pipelines. Though explanations are a critical piece in these systems, there is little understanding about how they are vulnerable to manipulation by adversaries. In this paper, we discuss how two broad classes of explanations are vulnerable to manipulation. We demonstrate how adversaries can design biased models that manipulate model agnostic feature attribution methods (e.g., LIME & SHAP) and counterfactual explanations that hill-climb during the counterfactual search (e.g., Wachter’s Algorithm & DiCE) into concealing the model’s biases. These vulnerabilities allow an adversary to deploy a biased model, yet explanations will not reveal this bias, thereby deceiving stakeholders into trusting the model. We evaluate the manipulations on real world data sets, including COMPAS and Communities & Crime, and find explanations can be manipulated in practice.

1. Introduction
Recently, there has been considerable interest in leveraging machine learning (ML) models in critical applications. Consequently, it becomes crucial to ensure that the predictions made by these models are understood and trusted by domain experts (e.g., doctors) and other relevant stakeholders. However, both the proprietary nature and complexity of ML models make it challenging for domain experts to understand them. This behavior motivates the need for tools that can explain models in a faithful and interpretable manner. To this end, several classes of post hoc explanation methods—e.g., local (Ribeiro et al., 2016a; Lundberg & Lee, 2017; Smilkov et al., 2017; Sundararajan et al., 2017), global (Lakkaraju et al., 2016; Letham et al., 2015), prototype/exemplar-based (Chen et al., 2019), and counterfactual explanation (Wachter et al., 2018; Van Looveren & Klaise, 2019) methods—have been proposed.

Such post hoc explanations are used in critical settings to detect discriminatory biases in black box models and decide if such models are trustworthy (Bhatt et al., 2020). Thus, it is crucial to ensure that post hoc explanations are reliable, capture the overall behavior and other critical properties (e.g., fairness) of the underlying models accurately. An initial step towards this goal is to rigorously analyze the behavior of state-of-the-art post hoc explanation methods and identify their vulnerabilities. Recent research has focused on identifying such shortcomings. For example, Adebayo et al. (2018) demonstrated that the explanations output by gradient-based methods are not faithful to the underlying model. Furthermore, Alvarez-Melis & Jaakkola (2018) demonstrated that the explanations output by popular techniques such as LIME and SHAP are unstable, i.e., infinitesimally small changes to instances can cause their post hoc explanations to change drastically.

While prior work has demonstrated some of the vulnerabilities of existing post hoc explanation methods, there is little understanding as to whether adversaries can manipulate explanations and mislead domain experts into trusting clearly untrustworthy models. Understanding this question is crucial because it both underscores the risks of reliance on post hoc explanations and encourages practitioners to exert caution in what they infer from these methods. In this work, we demonstrate how feature attribution methods and counterfactual explanations are vulnerable to manipulation. Specifically, we show that it is possible for adversaries to design models where feature attribution methods return any desired explanation, allowing clearly biased models to look unbiased in explanations. We also demonstrate that it is possible to design models where counterfactual explanations appear unbiased but return much easier to obtain counterfactuals under a slight perturbation, allowing an adversary to selectively perturb instances to generate low cost recourse, thereby introducing hidden biases. We experiment on real world data sets using attribution methods, such as LIME (Ribeiro et al., 2016a), and counterfactual explanation methods, including Wachter’s algorithm (Wachter et al., 2018).
and DiCE (Mothilal et al., 2020) to show the efficacy of the manipulations.

2. Preliminaries

In this section, we introduce notation and provide background on the explanation methods we consider.

2.1. Notation

We use a dataset $\mathcal{D}$ containing $N$ data points, where each instance is a tuple of $x \in \mathbb{R}^d$ and label $y \in \{0, 1\}$, i.e. $\mathcal{D} = \{(x_n, y_n)\}_{n=1}^N$ (similarly for the test set). For convenience, we refer to the set of all data points $x$ in dataset $\mathcal{D}$ as $\mathcal{X}$. Further, we have a model that predicts the probability of the positive class using a datapoint $f : x \rightarrow [0, 1]$. We assume the positive class is the desired outcome (e.g., receiving a loan) henceforth. Last, we also assume we have access to whether each instance in the dataset belongs to a protected group of interest or not, to be able to define fairness requirements for the model. We use $\mathcal{D}_{\text{pr}}$ to indicate the protected subset of the dataset $\mathcal{D}$, and use $\mathcal{D}_{\text{np}}$ for the “not-protected” group. Further, we denote protected group with the positive (i.e. more desired) outcome as $\mathcal{D}_{\text{pos}}$ and with negative (i.e. less desired) outcome as $\mathcal{D}_{\text{neg}}$ (and similarly for the non-protected group).

2.2. Model Agnostic Feature Attribution Explanations

We will focus on the class of model agnostic feature attribution explanations that fit an interpretable local linear model around a prediction in order to explain a complex black box. LIME (Ribeiro et al., 2016b) is one such popular model-agnostic, feature attribution approach. This method explains individual predictions by learning a linear model, $g$, locally around each prediction. Specifically, LIME estimates feature attributions on individual instances, which capture the contribution of each feature on the black box prediction. LIME samples a set of perturbations in the neighborhood of a point and fits a weighted regression, where weighting is determined by distance to the point.

2.3. Counterfactual Explanations

Counterfactual explanations return a data point that is close to $x$ but is predicted to be positive by the model $f$. We denote the counterfactual returned by a particular algorithm $A$ for instance $x$ as $A(x)$. We define the cost of recourse as the effort required to achieve the counterfactual (Venkatasubramanian & Alfano, 2020). In general, counterfactual explanation techniques optimize objectives of the form,

$$G(x, x_{cf}) = \lambda \cdot (f(x_{cf}) - 1)^2 + d(x, x_{cf}) \tag{1}$$

$$A(x) = \arg\min_{x_{cf}} G(x, x_{cf}) \tag{2}$$

Figure 1. PCA applied to the COMPAS dataset (blue) as well as its LIME style perturbations (red). Even in this low-dimensional space, we can see that data points generated via perturbations are distributed very differently from instances in the COMPAS data.

$\lambda x_{cf}$ denotes candidate counterfactual at a particular point during optimization. The first term $\lambda \cdot (f(x_{cf}) - 1)$ encourages the counterfactual to have the desired outcome probability by the model. The distance function $d(x, x_{cf})$ enforces that the counterfactual is close to the original instance and easier to “achieve” (lower cost recourse) and varies by the counterfactual explanation, so as to achieve different desired behaviors. $\lambda$ balances the two terms. We refer to the class of counterfactual explanations that optimize the counterfactual objective through gradient descent or black-box optimization as those that hill-climb the counterfactual objective (e.g., Wachter’s algorithm (Wachter et al., 2018) or DiCE (Mothilal et al., 2020)).

3. Manipulating Explanations Overview

We consider a general problem setting in which explanations may be manipulated by adversaries. We assume an adversarial model owner wishes to train a biased model according to some notion of model bias (e.g., demographic parity (Feldman et al., 2015), recourse fairness (Karimi et al., 2020)) and deploy this model in production. However, a model auditor will use explanations (e.g., LIME, counterfactual explanations) to audit the model for bias. Thus, the adversarial model owner is incentivized to construct a model that is biased but explanations will indicate the model is unbiased, thereby deceiving the auditor.

4. Manipulating Feature Attributions

In this section, we describe how model agnostic feature attribution explanations are vulnerable to manipulation.

4.1. Notion of Bias

We assume that the adversary wishes to deploy a model that predicts the protected group as the negative outcome and non-protected group as the positive outcome. The model
We build the unbiased classifier $\psi$ where we want to devise a model that is biased in predictions but feature attributions do not highly rank sensitive attributes.

4.2. Manipulation

Intuition  As discussed in the previous section, LIME explains individual predictions of a given black box model by constructing local interpretable approximations (e.g., linear models) using perturbations in the vicinity of a given point. However, many instances generated by such perturbations are out of distribution because LIME & SHAP rely on heuristically chosen perturbation functions. We can see this running PCA on a combined dataset of instances and perturbations for LIME in Figure 1.

This intuition underlies our proposed approach. By being able to differentiate between data points coming from the input distribution and instances generated via perturbation, an adversary can create an adversarial classifier (scaffolding) that behaves like the original classifier (perhaps be extremely discriminatory) on the input data points, but behaves arbitrarily differently (looks unbiased and fair) on the perturbed instances, thus effectively fooling LIME or SHAP into generating innocuous explanations.

Training Objective  Assuming $\psi$ is a unbiased classifier (e.g., makes predictions based on innocuous features that are uncorrelated with sensitive attributes), the adversarial classifier $e$ takes the following form:

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

where $\mathcal{X}_{\text{dist}}$ refers to the distribution of real world data. We train a separate classifier to determine if $x \in \mathcal{X}_{\text{dist}}$, simply by training a random forest to discriminate the perturbations generated from LIME and data from the training set.

4.3. Experiments

Setup  We run experiments on the COMPAS (Angwin et al., 2016) dataset. We construct $f$ to be a perfectly discriminatory classifier that uses a sensitive feature i.e., $f$ makes predictions purely based on race (if race = African American, then predict 1, otherwise set predict 0).

We build the unbiased classifier $\psi$ by constructing synthetic uncorrelated features that have zero correlation with sensitive attributes (e.g., race or gender). We experiment with one or two uncorrelated features. When we only have one uncorrelated feature in a particular experiment, $\psi$ solely uses that to make predictions (if uncorrelated feature = 1, then predict 1, else predict 0). On the other hand, when we have two uncorrelated features in an experiment, we base the predictions on the xor of those two features.

Results  To evaluate how successful our attacks are on LIME, we compute the percentage of data points for which race and uncorrelated features show up in top 3 when features are ranked based on feature attributions output by LIME. From these results in figure 2, we can see that the attack is able to fool LIME and shift the feature importance to the uncorrelated feature 100% of the time in both the one feature and two feature cases. Last, the adversarial models make the same predictions as the biased model without the manipulation, indicating the model is still biased. These results demonstrate the attack is effective.

5. Manipulating Counterfactual Explanations

In this section, we show how counterfactual explanations that hill-climb are vulnerable to manipulation.

5.1. Notion of Bias

As the notion of model bias, we assume that the adversarial model owner want to deploy a model that is recourse biased (Karimi et al., 2020; Gupta et al., 2019). Meaning, the recourse costs (as determined by the distance function $d$) is much lower for the non-protected group than the protected group, i.e., $\mathbb{E}_{x \sim \mathcal{P}_P} [d(x, A(x))] \gg \mathbb{E}_{x \sim \mathcal{P}_N} [d(x, A(x))]$. Thus, the adversary is incentivized to create a model that exhibits equal recourse costs between groups on the data distribution but can produce much lower recourse for the non-protected group.

5.2. Manipulation

Intuition  Because counterfactual explanations that hill-climb use gradient descent, it is possible to design a model where the counterfactual explanations converge to drastically different counterfactuals when a small perturbation $\delta$ (a vector of the same dimensions as $x$) is added to instances. We introduce an adversarial objective that leverages this insight. This objective encourages the model to return equal cost recourse between groups, indicating fairness in the
counterfactuals to the auditor. However, counterfactual explanations return much lower cost counterfactuals when the perturbation $\delta$ is added. In this way, the adversary can simply add the perturbation $\delta$ to generate low cost recourse.

We show such an adversarial model in Fig 3 trained on a toy data set. The counterfactual found for the perturbed instance $x + \delta$ is closer to the original instance $x$. This result indicates that the counterfactual found for the perturbed instance $x + \delta$ is easier to achieve than the counterfactual for $x$ found by Wachter’s algorithm! Intuitively, counterfactual explanations that hill-climb the gradient are susceptible to this issue because optimizing for the counterfactual at $x$ versus $x + \delta$ can converge to different local minima.

**Figure 3. Adversarial Model loss surface:** the recourse found for $x$ is higher cost than $x + \delta$ because the local minimum initialized at $x$ is farther than the minimum starting at $x + \delta$, demonstrating the problematic behavior of counterfactual explanations.

**Training Objective for Adversarial Model** We define our objective using the combination of the following terms:

- **Fairness:** The counterfactual algorithm $A$ is unbiased for model $f$.
- **Unfairness:** A perturbation vector $\delta \in \mathbb{R}^d$ leads to lower cost recourse when added to non-protected data, leading to unfairness.
- **Small perturbation:** Perturbation $\delta$ should be small, i.e. we need to minimize $\mathbb{E}_{x \sim D_{\text{train}}} d(x, x + \delta)$.
- **Accuracy:** We should minimize the classification loss $L$ (such as cross entropy) of the model $f$.

This combined training objective is defined over both the parameters of the model $\theta$ and the perturbation vector $\delta$. This objective is complicated by the fact that it involves $A$, a black-box counterfactual explanation approach. Because optimizing the objective involves solving a bi-level optimization problem, we can compute the gradients for $A$ through implicit differentiation (Gould et al., 2016).

**Table 1. Recourse Costs of Manipulated Models:** Counterfactual algorithms find similar cost recourses for both subgroups, however, give much lower cost recourse if $\delta$ is added.

| Communities and Crime | Protected | S-Wach. | Proto. | DiCE |
|-----------------------|-----------|---------|-------|------|
|                       |           |         |       |      |
| Non-Protected         | 35.68     | 54.16   | 22.35 | 49.62|
| Disparity             | 35.31     | 52.05   | 22.65 | 42.63|
| Non-Protected+\delta  | 1.76      | 22.59   | 8.50  | 9.57 |
| Cost reduction        | 20.1×     | 2.3×    | 2.6×  | 4.5× |

5.3. Results

We consider four different counterfactual explanation algorithms as the choices for $A$ that hill-climb the counterfactual objective. We use Wachter’s Algorithm (Wachter et al., 2018), Wachter’s with elastic net sparsity regularization (Sparse Wachter; variant of Dhurandhar et al. (2018)), DiCE (Mothilal et al., 2020), and Counterfactual’s Guided by Prototypes (Van Looveren & Klaise, 2019). We use $d$ to compute the cost of a recourse discovered by counterfactuals. We use the Communities & Crime data set to train the adversarial models. We use a feedforward neural network as the adversarial model.

We evaluate the effectiveness of the manipulated models across counterfactual explanations using both the disparity of the average recourse cost for protected and non-protected groups (i.e., the model seems fair to auditors) and the ratio between the non-protected group and the non-protected group perturbed by $\delta$ (i.e., model can generate low cost recourse for the non-protected group), which we denote as the cost reduction. If the manipulation is successful, we expect the cost reduction to be high.

We provide the results for both datasets in Table 1. All the models trained have within 1% accuracy of baseline neural networks trained on the data without the manipulation (not in table), indicating they are still accurate. The disparity in counterfactual cost on the unperturbed data is very small in most cases, indicating the models would appear counterfactual fair to the auditors. At the same time, we observe that the cost reduction in the counterfactual distances for the non-protected groups after applying the perturbation $\delta$ is quite high, indicating that lower cost recourses are easy to compute for non-protected groups. These results show the adversarial models are successful.

6. Conclusion

In this work, we demonstrate how two broad classes of post hoc explanations are vulnerable to manipulation. These results raise serious concerns around the usefulness of explanations as a tool to endow trust in machine learning models.
Particularly in high stakes settings, these methods can easily be gamed by bad-actors to hide undesirable aspects of models. Further, these results highlight the need to develop machine learning methods that are robust to manipulation in the future, if we are to trust explanation methods.

7. Acknowledgments

We would like to thank the anonymous reviewers for their insightful feedback. This work was supported in part by the NSF awards #IIS-2008461 and #IIS-2008956, Google, Amazon, and the Hasso-Plattner Institut. The views expressed are those of the authors and do not reflect the official policy or position of the funding agencies.

References

Adebayo, J., Gilmer, J., Muelly, M., Goodfellow, I., Hardt, M., and Kim, B. Sanity checks for saliency maps. In *Advances in Neural Information Processing Systems*, pp. 9505–9515, 2018.

Alvarez-Melis, D. and Jaakkola, T. S. On the robustness of interpretability methods. *ICML Workshop on Human Interpretability in Machine Learning*, 2018.

Angwin, J., Larson, J., Mattu, S., and Kirchner, L. Machine bias. *ProPublica*, 2016.

Bhatt, U., Xiang, A., Sharma, S., Weller, A., Taly, A., Jia, Y., Ghosh, J., Puri, R., Moura, J. M. F., and Eckersley, P. Explainable machine learning in deployment. In *Proceedings of the 20th Conference on Fairness, Accountability, and Transparency*, FAT* ’20, pp. 648–657, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450369367. doi: 10.1145/3351095.3375624. URL https://doi.org/10.1145/3351095.3375624.

Chen, C., Li, O., Tao, D., Barnett, A., Rudin, C., and Su, J. K. This looks like that: Deep learning for interpretable image recognition. In Wallach, H., Larochelle, H., Beygelzimer, A., d’Alché-Buc, F., Fox, E., and Garnett, R. (eds.), *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019. URL https://proceedings.neurips.cc/paper/2019/file/adf7ee2dcf14b0e11888e72b43fcb75-Paper.pdf.

Dhurandhar, A., Chen, P.-Y., Luss, R., Tu, C.-C., Ting, P., Shanmugam, K., and Das, P. Explanations based on the missing: Towards contrastive explanations with pertinent negatives. In Bengio, S., Wallach, H., Larochelle, H., Grauman, K., Cesa-Bianchi, N., and Garnett, R. (eds.), *Advances in Neural Information Processing Systems*, volume 31, pp. 592–603. Curran Associates, Inc., 2018. URL https://proceedings.neurips.cc/paper/2018/file/c5ff2543b53f4cc0ad3819a36752467b-Paper.pdf.

Feldman, M., Friedler, S. A., Moeller, J., Scheidegger, C., and Venkatasubramanian, S. Certifying and removing disparate impact. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD ’15, pp. 259–268, New York, NY, USA, 2015. Association for Computing Machinery. ISBN 9781450336642. doi: 10.1145/2783258.2783311. URL https://doi.org/10.1145/2783258.2783311.

Gould, S., Fernando, B., Cherian, A., Anderson, P., Santa Cruz, R., and Guo, E. On Differentiating Parameterized Argmin and Argmax Problems with Application to Bi-level Optimization. *arXiv e-prints*, art. arXiv:1607.05447, July 2016.

Gupta, V., Nokhiz, P., Dutta Roy, C., and Venkatasubramanian, S. Equalizing recourse across groups. 09 2019.

Karimi, A.-H., Barthe, G., Schölkopf, B., and Valera, I. A survey of algorithmic recourse: definitions, formulations, solutions, and prospects. *arXiv e-prints*, art. arXiv:2010.04050, October 2020.

Lakkaraju, H., Bach, S. H., and Leskovec, J. Interpretable decision sets: A joint framework for description and prediction. In *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, pp. 1675–1684, 2016.

Letham, B., Rudin, C., McCormick, T. H., and Madigan, D. Interpretable classifiers using rules and bayesian analysis: Building a better stroke prediction model. *Annals of Applied Statistics*, 2015.

Lundberg, S. M. and Lee, S.-I. A unified approach to interpretable model predictions. In Guyon, I., Luxburg, U. V., Bengio, S., Wallach, H., Fergus, R., Vishwanathan, S., and Garnett, R. (eds.), *Advances in Neural Information Processing Systems 30*, pp. 4765–4774. Curran Associates, Inc., 2017.

Mothilal, R. K., Sharma, A., and Tan, C. Explaining machine learning classifiers through diverse counterfactual explanations. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pp. 607–617, 2020.

Ribeiro, M. T., Singh, S., and Guestrin, C. "why should I trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International
Feature Attributions and Counterfactual Explanations can be Manipulated

Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016, pp. 1135–1144, 2016a.

Ribeiro, M. T., Singh, S., and Guestrin, C. "why should i trust you?": Explaining the predictions of any classifier. In Knowledge Discovery and Data Mining (KDD), 2016b.

Smilkov, D., Thorat, N., Kim, B., Viégas, F. B., and Wattenberg, M. SmoothGrad: removing noise by adding noise. In ICML Workshop on Visualization for Deep Learning, 2017.

Sundararajan, M., Taly, A., and Yan, Q. Axiomatic attribution for deep networks. In International Conference on Machine Learning (ICML), 2017.

Van Looveren, A. and Klaise, J. Interpretable Counterfactual Explanations Guided by Prototypes. arXiv, art. arXiv:1907.02584, July 2019.

Venkatasubramanian, S. and Alfano, M. The philosophical basis of algorithmic recourse. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, FAT* '20, pp. 284–293, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450369367. doi: 10.1145/3351095.3372876. URL https://doi.org/10.1145/3351095.3372876.

Wachter, S., Mittelstadt, B., and Russell, C. Counterfactual explanations without opening the black box: Automated decisions and the gdpr. Harvard journal of law & technology, 31:841–887, 04 2018. doi: 10.2139/ssrn.3063289.