What will it take to generate fairness-preserving explanations?

Jessica Dai [1] **Sohini Upadhyay** [2] **Stephen H. Bach** [1] **Himabindu Lakkaraju** [2]

Abstract

In situations where explanations of black-box models may be useful, the fairness of the black-box is also often a relevant concern. However, the link between the fairness of the black-box model and the behavior of explanations for the black-box is unclear. We focus on explanations applied to tabular datasets, suggesting that explanations do not necessarily preserve the fairness properties of the black-box algorithm. In other words, explanation algorithms can ignore or obscure critical relevant properties, creating incorrect or misleading explanations. More broadly, we propose future research directions for evaluating and generating explanations such that they are informative and relevant from a fairness perspective.

1. Introduction & Motivation

While fairness and explainability are both generally considered core components of "responsible" machine learning, surprisingly little work has explored the two principles in tandem. However, especially in light of common goals of generating explanations for a black-box models, it is critical that the explanation itself can be reliably trusted to illustrate important fairness properties of the black-box. For example, Suresh et al. (2021)'s framework for characterizing stakeholders in explainable machine learning provides *objectives* such as debugging or improving the model, ensuring regulatory compliance, informing downstream actions, justifying actions based on algorithm output, and contesting a decision; and specific *tasks* like assessing the reliability of a prediction; detecting mistaken or discriminatory behavior; and understanding the influence of different inputs. Prior work in this area has outlined similar goals for explanations (Bhatt et al., 2020a). For obvious reasons, if fairness is a concern related to the model more broadly, it is also a critical

consideration for these tasks and objectives in the context of explanations. Furthermore, while of course calculating particular fairness desiderata for the underlying black-box directly might surface unfairness, the stakeholders who are using an explainable ML algorithm may not have access to the information needed for such an analysis; as a result, we might hope that *explanations themselves* contain sufficient and accurate information for any stakeholder to confidently make claims and downstream decisions based on the explanation. This is especially important given that end-users of explanations may be vulnerable to overtrusting or being manipulated by explanations (Lakkaraju & Bastani, 2020).

However, current methods for evaluating explanations are designed to be almost entirely application-agnostic, and therefore do not consider any criteria related to fairness. While terminology varies across the literature, commonly used evaluation metrics for explanations include *fidelity*, the extent to which a surrogate model generated by an explanation algorithm produces predictions similar to the black-box, and *stability*, the extent to which explanations generated for similar (but non-identical) inputs are similar to one another (Bhatt et al., 2020b; Yeh et al.).

A growing portion of the literature points to dangers in focusing solely on these targets when designing explanation algorithms. Slack et al. (2020b) and Zhang et al. (2019), for instance, highlight the high degree of inconsistency of explanations generated by perturbation-based methods under certain parameter settings—in other words, multiple explanations generated for the same input may result in wildly different explanations. Kumar et al. (2020) and Hancox-Li & Kumar (2021), meanwhile, investigate SHAP (Lundberg & Lee, 2017), and find problems from both technical and philosophical perspectives. Under the framework of fairness specifically, Slack et al. (2020a) and Aïvodji et al. (2019) illustrate specific ways in which either a black-box algorithm or an explanation, respectively, may be adversarially constructed such that the explanation, while having high fidelity (or achieving other desirable metrics), misleadingly suggests that the black-box model is fair when in reality it is not. However, adversarial construction may not be necessary for misleading explanations to occur.

For some baseline intuition as to how fairness and explanations may interact, consider the following. Explanations are

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often intended to provide a digestible approximation of the black-box algorithm's decision boundary, whether locally (in the neighborhood of a particular input) or globally (for all possible inputs). Additionally, fairness concerns arise when there is a meaningful difference in how two or more demographic groups are distributed or labelled in the training data, which leads to a meaningful disparity in how the black-box machine learning algorithm performs on the two groups by whatever metric one may choose (Corbett-Davies & Goel, 2018). The demographic information may or may not be used by the black-box. In the case that it is not used, the explanation will not *explicitly* encode information about the sensitive attribute, and an end-user relying on the explanation alone will have little information about the fairness of the black-box. In the case that it is used, such as when fairness-constrained learning algorithms or postprocessing methods are applied, then the black-box may learn a decision boundary such that the boundaries are different when conditioned on group membership. However, explanation methods are not designed to approximate such boundaries. Furthermore, the explanation itself will include information about the sensitive attribute, such as in the form of a feature importance score; it is not immediately clear what the proper interpretation of that score should be. Finally, in either case, the known issue of isolating feature attributions when features may be correlated with one another (Kumar et al., 2020) is especially relevant when considering fairness applications.

1.1. A simple example

Consider the following scenario where the black-box takes in three features: `group`, `x0`, and `x1`, where `group` $\in \{0, 1\}$, `x0` and `x1` are continuous, and `x0` is correlated with group membership. For some reason or another (perhaps by applying a fairness intervention in the training process), the black-box's learned decision boundaries are different when conditioned on group membership: specifically, the black-box predicts **1** for group **0** when `x1` > 6, and for group **1** when `x1` > 5. Figure 1a illustrates this black-box decision boundary.

In the case that both groups constitute 50% of the population, an explanation method that optimizes for fidelity as measured by performance on sampled neighbors will approximate the decision boundary at around `x1` > 5.5—an explanation that is simply incorrect for both groups based on what we know about the black-box. If one group is a minority of the population, however, the explanation's approximated decision boundary will be closer to the majority group's decision boundary, meaning overall better explanations for the majority group and overall worse explanations for the minority group. This is illustrated in Figure 1b, which visualizes the decision boundary learned by LIME: note that the learned boundary is much closer to `x1` > 5, the
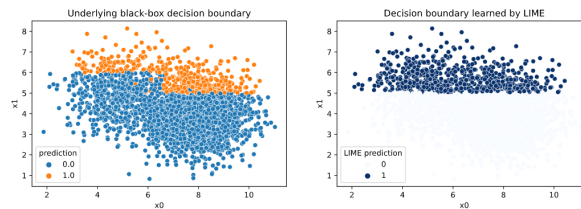
(a) Decision boundary of the black-box
(b) Decision boundary learned by LIME

Figure 1. The true decision boundaries of the black-box vs the decision boundary learned by LIME. The left cluster is the minority group, comprising 27% of the total population.

majority group's boundary, over *all* data points, not just the points corresponding to the majority group. Notably, this is a problem that seems to arise *whenever* group-conditional decision boundaries are meaningfully distinct. The explanations generated here, therefore, may be both misleading and incorrect.

2. Our Framework

We propose a two-part framework for further work in this area: first, determining what constitutes a mismatch in fairness properties; and second, generating fairness-preserving explanations.

2.1. Diagnosing Fairness Mismatch

First, we provide an initial attempt at outlining what metrics or diagnostic tests may be useful in detecting a mismatch in fairness; these also serve, therefore, as potential criteria or definitions for what a fairness-preserving vs fairness-obscuring explanation may look like. These metrics are broadly motivated by the principle that if the model is fair, the explanations should not raise false alarms; similarly, if the model is unfair, the explanations should not suggest that it is innocuous. In this section we attempt to pinpoint what exactly it means for an explanation to "raise a false alarm" or suggest that the model "is innocuous."

Group fairness. There are a variety of metrics through which models can be audited or monitored for group fairness: demographic parity focuses primarily on group-wise outcomes, while other metrics such as equalized odds, equal opportunity, or predictive parity, reflect some combination of the group-conditional confusion matrices (Verma & Rubin, 2018).

Let $\mathcal{M}$ represent a metric of group fairness which takes in the predictions of some model (and potentially information about the true labels); f represent the black-box; E_f be the surrogate model from an explanation for f; and $E_f(\vec{x})$ represent evaluating the surrogate model on some input $\vec{x}$.

Then, group fairness is preserved when:

$$|\mathcal{M}(f(\vec{x})) - \mathcal{M}(E_f(\vec{x}))| \leq \epsilon$$

In other words, when, if substituting the black-box model with the explanation's surrogate model, the predictions generated result in similar values of the fairness metric $\mathcal{M}$.

Two obvious issues arise with this initial proposition. First, while this is straightforward for global explanation methods, many of the most popular explanation methods like LIME (Ribeiro et al., 2016) or SHAP (Lundberg & Lee, 2017) are *local* explanation methods, designed to explain specific points: that is, there is no notion of a *global* surrogate model from which group fairness metrics can easily be calculated. Second, only the demographic parity metric does not require information about the ground-truth labelling of data points; all other metrics require this information. The question then becomes how to determine the set of points x on which $\mathcal{M}$ will be calculated for local explanations. One potential approach is to use the sampled points in the local neighborhood generated by the explanation method, and calculate $\mathcal{M}$ on the neighborhood for each of the points in the dataset. Of course, this approach means that no ground-truth labelling is available for this set of sampled points, and thus the only metric that can be verified to match or mismatch in this way is demographic parity.

Counterfactual fairness. In classification, counterfactual fairness and individual fairness have similar motivations: identifying how the prediction for a particular input x would change if only the group membership of x was changed (Dwork et al., 2012). Though there is debate about the extent to which counterfactual or individual fairness is distinct (if not orthogonal) from group fairness (Lahoti et al., 2019; Binns, 2020), a "fairness-preserving" explanation should nevertheless capture the counterfactual behavior of the black-box model. To that end, let x' represent the input x with a changed value for group membership, and $E_{f(x)}$ illustrate explanations *generated for* input x. Then, counterfactual fairness is preserved when:

$$E_{f(x)} - E_{f(x')} \approx f(x) - f(x')$$

In other words, when the difference between the explanation generated for x and the explanation generated for x' follows the difference between the model's behavior on x and x'. This abstraction also raises open questions about how exactly the similarity should be determined.

Sensitive attribute. The treatment of the sensitive attribute in cases where it is included in the inputs to the black-box model is also worth additional attention. In this case, unlike group and counterfactual fairness, we do not propose a particular normative value of how the sensitive attribute ought to be treated by the explanation algorithm in relation to the black-box. For example, the feature importance for

the sensitive attribute being 0 does not necessarily imply that the black-box is not discriminatory: the influence of the sensitive attribute may have been attributed to another, correlated feature. Moreover, many algorithms for fair machine learning explicitly use the sensitive attribute in order to achieve some measure of fairness, such as the method proposed in Hardt et al. (2016). In this sense, a feature importance of 0 might even be alarming rather than reassuring. As a result, future work in this area may include methods which give more meaningful ways to interpret the influence of the sensitive attribute.

Additional considerations. Finally, of note here is the distinction between *evaluating an explanation algorithm itself* for how well it preserves fairness properties in general, and *evaluating a given, specific explanation* for whether it is preserving relevant fairness properties once the explanation for a particular input or model has been generated. These are different tasks—the first, for example, may be useful for a model developer or engineer in the process of choosing an explanation method, while the second may be more relevant to auditing processes once a black-box model (and a corresponding explanation algorithm) has been deployed. Additional work distinguishing what approaches or metrics might be comparatively useful in either situation is warranted; in particular, all of these proposed metrics require a comparatively high amount of information and access to the black-box, and may be better-suited towards the first task (evaluating algorithms in general) rather than the second (auditing individual explanations).

2.2. Generating Fairness-Preserving Explanations

As discussed above, algorithms for finding explanations typically focus on optimizing for metrics such as fidelity and sensitivity. One approach for generating a fairness-preserving explanation can be similar to early approaches to fair machine learning algorithms: adding a penalty term in the objective function for the extent to which the explanation is fairness-preserving (Kamishima et al., 2012; Zafar et al., 2017). For example, the original LIME objective function (Ribeiro et al., 2016) is as follows:

$$\xi(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

where $\xi(x)$ is the optimal explanation for input x to model f, G is the class of sparse linear models, $\mathcal{L}$ is a measure of fidelity, π_x is a local region around x, and Ω is a measure of complexity. A modified objective function including a term such as $\psi(f, g)$ measuring the preservation of fairness properties described in Section 2.1, fits naturally:

$$\xi_{fair}(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) + \lambda_1 \Omega(g) + \lambda_2 \psi(f, g)$$

Here, λ_1 and λ_2 are tuning parameters for the complexity Ω and fairness-preservation term ψ, respectively.
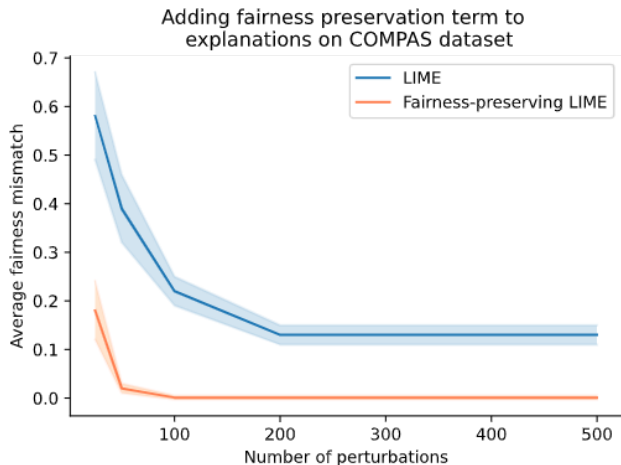
Figure 2. Original vs fairness-preserving LIME algorithms: number of perturbations used for LIME vs average fairness mismatch over explanations for all points in the dataset.

Figure 2 illustrates the results of using this modified, fairness-preserving objective function when finding the explanation ξ. Here, the dataset used was COMPAS; the black-box was a three-layer deep neural net; and ψ is derived from the group fairness equation in Section 2.1. Specifically, $\psi = |DP(f(x)) - DP(E_f(x))|$, where DP is the demographic parity metric: $P(Y = 1|S = 1) - P(Y = 1|S = 0)$. In this experiment, the number of perturbations used to generate the LIME explanation was varied to show the asymptotic fairness mismatch, as a greater number of perturbations generally results in a higher-certainty explanation. The fairness mismatch plotted on the y-axis is calculated exactly in the same way as ψ explained above. Our introduction of this approach is meant more as a provocation to start the conversation rather than a full-fledged proposal or argument that this method is necessarily ideal; however, the results are promising and warrant further investigation in this direction.

3. Discussion & Conclusion

In this work, we have given some intuition and preliminary results as to why it is important to probe the fairness of explanations: not just because of the often high-stakes and consequential goals for which explanations are used, but because existing explanation methods focusing on metrics like fidelity may result in misleading and incorrect explanations *even in the absence of an adversarial actor* constructing explicitly discriminatory black-boxes, or designing explanation methods that explicitly hide discrimination. Furthermore, fairness can also be viewed as a specific lens on performance for the model overall. In fact, the phenomenon illustrated in Figure 1 can be considered to be a performance issue—strictly incorrect decision boundaries,

though the minority group's decision boundary is much more incorrect—that can be detected by testing for fairness mismatch as proposed in Section 2. Of course, the exact behavior in this scenario may be the consequence of LIME's choice to focus on sparse linear models, and choosing a more complex interpretable model class (such as shallow decision trees) may alleviate the issue.

Nevertheless, an action like this is only made possible by the first step of diagnosing the fairness mismatch between the black-box and the explanation's surrogate model. Thinking about explanations in this context, therefore, also raises broader questions about the extent to which explanations are in fact capturing what we want; or, alternatively, ways in which the limitations of particular explanations or explanation methods may be communicated clearly to stakeholders and end-users.

In this work, we suggested a framework for evaluating the fairness-preserving properties of explanations, and proposed one generic approach for producing fairness-preserving explanations. However, this extended abstract is also meant to argue for the consideration of evaluation metrics for explanations more broadly: while fairness was the first angle we considered, there are undoubtedly additional necessary properties of the model—even privacy, for example—that explanations should preserve.

Acknowledgements

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