

A Systematic Review on Model-agnostic XAI Libraries^{*}

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Abstract. During the last few years, the topic of explainable artificial intelligence (XAI) has become a hotspot in the ML research community. Model-agnostic interpretation methods propose separating the explanations from the ML model, making these explanation methods reusable through XAI libraries. In this paper, we have reviewed some selected XAI libraries and provide examples of different model agnostic explanations. The context of the research conducted in this paper is the iSee project¹ that will show how users of Artificial Intelligence (AI) can capture, share and re-use their experiences of AI explanations with other users who have similar explanation needs.

Keywords: XAI, libraries, model agnostic models

1 Introduction

Interpretability and trust have become a requirement for black-box AI models applied to real-world tasks like diagnosis or decision-making processes. At a high level, the literature distinguishes between two main approaches to interpretability: *model-specific* (also called transparent or white box) models and *model-agnostic* (post-hoc) surrogate models to explain black-box models [15, 9, 10]. Transparent models are ones that are inherently interpretable by users. Consequently, the easiest way to achieve interpretability is to use algorithms that create interpretable models, such as decision trees, simple nearest-neighbour models, or linear regression. However, the best-performing models are often not interpretable, or they are partially interpretable [7]. It is a permanent challenge to ensure the high accuracy of a model while maintaining a sufficient level of comprehensibility. Model-agnostic interpretation methods propose separating

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¹ Intelligent Sharing of Explanation Experience by Users for Users
<https://isee4xai.com/>

	LIME	Anchors	SHAP	PDP	ALE	Counterfactuals	CEM
Interpret	✓		✓	✓			
Alibi		✓	✓		✓	✓	✓
Aix360	✓		✓				✓
Dalex	✓		✓	✓	✓		
Dice						✓	

Table 1. Explainers by library.

the explanations from the ML model. The main advantage is flexibility although some authors consider this type of post-hoc explanations as limited *justifications* because they are not linked to the real reasoning process occurring in the black box. The context of the research conducted in this paper is the *iSee project* that aims to provide a unifying platform where personalized explanations are created by reasoning with Explanation Experiences using Case-based reasoning (CBR). This is a very challenging, long-term goal as we want to capture complete user-centered explanation experiences on complex explanation strategies. Our proposal relies on an ontology to help to the knowledge-intensive representation of previous experiences, different types of users and explanation needs, characterization of the data, the black-box model, and the contextual properties of the application domain and task. We aim to be able to recommend what explanation strategy better suits an explanation situation. One of the first tasks in the *iSee project* is to be able to characterize the existing XAI libraries. Explainers of these libraries will be the building blocks of our library of reusable explanation strategies that will be described using the unified terminology defined by the ontology.

In this position paper, we have reviewed some existing XAI libraries: Interpret, Alibi, Aix360, Dalex, and Dice. We have compared different options to explain the same black box prediction model with the same training data and the most relevant explanation methods, namely: Local Interpretable Model-Agnostic Explanations (LIME), Anchors, Shapley Additive Explanations (SHAP), Partial Dependence Plots (PDPs), Accumulated Local Effects (ALE) and counterfactual explanations. Section 2 describes the methodology to compare the libraries and their explainers (see Table 1) and defines the variables used to perform a quantitative analysis of the libraries in Section 3. The XAI methods are analysed through a qualitative evaluation described in Section 4. Finally, Section 5 concludes the paper by discussing and comparing the libraries.

2 Methodology

We propose different variables that allow us to compare the XAI libraries. The resulting quantitative analysis of the libraries is presented in Section 3, whereas a qualitative evaluation focusing on the XAI methods is included in Section 4.

Feature	Mean	Std.	Min	25%	50%	75%	90%	Max
Age	26.82	8.50	13.00	20.00	25.00	32.00	37.00	84.00
Num. of sexual partners	2.51	1.64	1.00	2.00	2.00	3.00	4.00	28.00
First sexual intercourse	16.98	2.80	10.00	15.00	17.00	18.00	20.00	32.00
Num. of pregnancies	2.19	1.43	0.00	1.00	2.00	3.00	4.00	11.00
Smokes (y/n)	0.14	0.35	0.00	0.00	0.00	0.00	1.00	1.00
Smokes (years)	1.20	4.06	0.00	0.00	0.00	0.00	3.00	37.00
Hormonal Contraceptives (y/n)	0.69	0.46	0.00	0.00	1.00	1.00	1.00	1.00
Hormonal Contraceptives (years)	1.97	3.60	0.00	0.00	0.25	2.00	7.00	30.00
Intrauterine device (y/n)	0.10	0.30	0.00	0.00	0.00	0.00	0.00	1.00
Intrauterine device (years)	0.44	1.81	0.00	0.00	0.00	0.00	0.00	19.00
Sexually transmitted disease (y/n)	0.09	0.29	0.00	0.00	0.00	0.00	0.00	1.00
Num. STDs	0.16	0.53	0.00	0.00	0.00	0.00	0.00	4.00
Num. STD diagnoses	0.09	0.30	0.00	0.00	0.00	0.00	0.00	3.00
Biopsy	0.06	0.25	0.00	0.00	0.00	0.00	0.00	1.00

Table 2. Basic statistical description of the data set used to evaluate the libraries.

Documentation and usability. Is the documentation well-structured and self-explanatory? Good documentation should be complemented with usage examples which makes the library easy to use.

Interpretability metrics. Refers to the availability of metrics such as accuracy, recall, ROC/AUC values, mean squared error, etc. These metrics allow users to evaluate the performance of a model.

Available explainers such as LIME[11], SHAP [8], Counterfactuals [13], Anchors[12], PDPs[5], ALE plots [1], CEMs [3] and others.

Analysis and description capabilities of the training data: refers to the availability of tools that allow a better interpretation of data itself such as marginal and scatter plots, data imbalances, etc.

Interactivity, meaning the user is able to dive deeper into the explanation that is outputted by looking into certain features or other aspects more thoroughly.

Personalization. Refers to the capability of providing different explanations according to the user’s requirements.

Dependencies. Development language/environment and requirements (if any). Use of other methods from libraries such as TensorFlow, SKLearn, and others. We also take into consideration the use of wrapper classes and methods of the original author’s implementation of certain explainers.

The use case consists on explaining the prediction of cervical cancer given by two different models: a random forest (RF) classifier and a multi-layer perceptron (MLP), both with a scikit-learn back-end. The dataset used to train both models was extracted from the UCI Machine Learning repository [4]. It contains 858 instances. Table 2 summarizes its statistical descriptors. Note that the data set is quite unbalanced, as only 6% of the individuals had cervical cancer.

The RF model was built with 100 estimators and was configured so it would adjust the weights inversely proportional to class frequencies. In this way, it is possible to mitigate data imbalances moderately. However, this approach cannot be done when building an MLP, which affected the performance of the model considerably. Our MLP was built with two hidden layers, 100 neurons for the first and 50 neurons for the second. The selected optimization algorithm was

	Interpret	Dice	ALIBI	Aix360	Dalex
Documentation and usability	Very good	Good	Very good	Very good	Good
Metrics	ROC/AUC	No	Linearity measure and trust scores	Faithfulness and monotonicity	F1, accu, prec, recall, ROC/AUC, R^2 , MAD
Explainers	3	1	5	3	4
Analysis	Yes	No	No	Yes	No
Interactivity	Yes	No	No	No	No
Personalization	No	No	No	No	No
Dependencies	Python 3.6+	Python 3+	Python 3.6+	Python 3.6+	Python 3.6+

Table 3. Analysis of the XAI libraries

Adam. The random forest had an accuracy of 88.8%, a precision of 10%, and a recall of 6.2%. On the other hand, the MLP model had an accuracy of 87.4%, a precision of 13.3%, and a recall of 12.5%. It is shown that both models have a considerable rate of false negatives which may be something to take into account because of the sensitive nature of this particular problem.

3 Quantitative analysis of the XAI Libraries

This section describes the XAI libraries according to the features described in the previous section (see Table 3).

InterpretML is one of the most popular XAI libraries. It offers state-of-the-art explanations for black-box models both locally and globally. It implements a dashboard that makes the communication process between the end-users and the program more interactive, allowing them to have a better understanding of the explanation. Table 4 contains its analysis.

Dice whose name comes from Diverse Counterfactual Explanations, uniquely focuses on counterfactual generation. Three different approaches can be taken when using dice in order to find counterfactuals: using random sampling, k-d trees, or genetic algorithms. Its simplicity of use makes Dice a great candidate when the only explanation needed is various counterfactuals. Table 5 contains its analysis.

ALIBI provides local and global explanation methods for classification and regression problems for both with and black-box models. It is a broad library with many different explainers. One of the strengths of this library is that some explainers are compatible with Tensorflow models, such as CEM and counterfactuals, thus increasing its versatility. Table 6 contains its analysis.

Aix360 is a multipurpose library that provides some of the most up-to-date explainers available. Besides implementing the widely accepted LIME and

Documentation and usability	The documentation is well-structured and explanatory. Usage examples are provided in a simple fashion so the user is able to begin using the library very quickly. This library is very intuitive and using it should not arise any issues for less-experienced users.
Metrics	ROC/AUC values.
Explainers	3
Analysis	Yes. It provides marginal plots and class histograms.
Interactivity	It has a dashboard feature that allows the end-user to further inquire into different features and compare different explanations of the same instance.
Personalization	Not available
Dependencies	Python 3.6+. For the LIME and SHAP explainers, wrapper classes are used based on the original implementation developed by [11] and [8], respectively.

Table 4. Analysis of InterpretML.

Documentation and usability	The documentation is straightforward and provides various examples. It is very simple as this library uniquely relies on counterfactual generation.
Metrics	Not available.
Explainers	1
Analysis	Not available.
Interactivity	This library does not provide interactivity, but the data is presented in an easy-to-interpret format.
Personalization	Not available.
Dependencies	Python 3+. It does not use other external interpretability libraries. However, depending on the backend of the model, it may rely on Tensorflow and Pytorch.

Table 5. Analysis of Dice.

SHAP methods, algorithms like Protodash [6] and CEM with Monotonic Attribute Functions show some of the latest, local explainers available. Aix360 also provides global explainers such as Generalized Linear Rule Models and model performance metrics. Table 7 contains its analysis.

Dalex is a multipurpose library that focuses on model-agnostic explanations for black-box models. The core methodology behind it is to create a wrapper around the given model that can later be explained through a variety of local and global explainers. This library implements well-known explainers such as LIME, SHAP, and ALE, and also allows measuring the fairness of the model. It provides plenty of different performance metrics according to the given model. Dalex is complemented by the *Arena*² visual dashboard, that allows interactive exploration and personalization of the explanation. Table 8 contains Dalex quantitative analysis.

² <https://arena.drwhy.ai/docs/>

Documentation and usability	The documentation is very extensive and educational. Not only does it explain how to use the methods, but gives a mathematical background for each explainer. However, the examples provided for some explainers only cover the explanation of models with a Tensorflow backend, which may cause difficulties to users who are not experienced in this environment.
Metrics	Linearity measure and trust scores.
Explainers	5
Analysis	Not available.
Interactivity	This library is not interactive. The process is finished once the explanation is outputted. In fact, most explanations are given in a low-level fashion as raw data that the user may need to convert to a more interpretable format.
Personalization	Not available.
Dependencies	Python 3.6+. This library is heavily based on tensorflow. For the SHAP explainer, it uses the original implementation of the author [8].

Table 6. Analysis of ALIBI.

4 Qualitative evaluation of the XAI methods

This section presents a descriptive evaluation of the XAI methods provided by the libraries, focusing on the visualization of the explanations. In order to grasp a general idea of the inner mechanics of the models, using **SHAP** as a global explanation method is typically a good first approach although it has a high computational cost. The results obtained for our use case are shown in Figure 1.

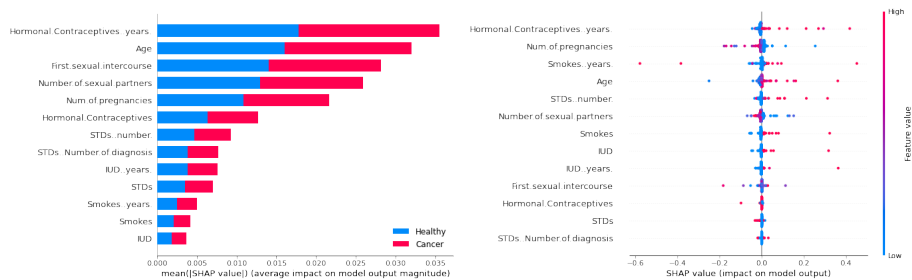


Fig. 1. Average SHAP values RF (left)/MLP (right) models. Plot from Dalex.

The features that impact the prediction the most on average for the random forest model are the number of years using hormonal contraceptives, the age of the individual, and the age of their first sexual intercourse. The years of smoking barely contribute to the predictions of the model on average. On the other hand, the SHAP summary plot for the MLP model, which may be somewhat harder to understand, still gives the major contribution to the hormonal contraceptive

Documentation and usability	The documentation is clear and extensive. It provides many usage examples with different data sets that make the library easy to use. The Aix360 website offers interactive tutorials as complementary guidance for its use.
Metrics	Faithfulness and monotonicity. Faithfulness refers to the correlation between the feature importance assigned by the interpretability algorithm and the effect of features on model accuracy. On the other hand, monotonicity tests whether model accuracy increases as features are added in order of their importance.
Explainers	3
Analysis	Yes. Particularly, the Protodash algorithm is able to find prototypes that help summarizing the data set.
Interactivity	This library does not provide the interactivity feature. Explanations are outputted to the users in the format of graphics or plain data, and there is no further interaction between the user and program.
Personalization	Not available. However, the importance of personalization of the explanations is referenced in the official website throughout the interactive demo. It outlines that different users look for different kinds of explanations (as it is the purpose in the iSee project).
Dependencies	Python 3.6+. The implementation of the original authors is used for the LIME and SHAP explainers [11][8]

Table 7. Analysis of Aix360.

feature, but then comes the number of pregnancies and the years of smoking. Something interesting about this plot is that the years of smoking contribute both negatively and positively in different situations when the instance values are high, which might indicate that the model is not properly calibrated.

The **partial dependence plots** are also useful when globally examining the behavior of a single feature. In Figure 2, the respective plots of the random forest and MLP models are shown for the feature of years using hormonal contraceptives. Although the average impact on the random forest model is higher, the interpretation is the same for both plots; the more years using hormonal contraceptives, the greater the average response on the prediction is. However, this last statement is only true when variables are not correlated. Furthermore, the density indicates that most instances focus on a range between 0 and 1.88 years which makes the resulting graphs less reliable as the value of this feature increases.

An unbiased alternative method that does consider correlations is **ALE**. Although ALE plots are an excellent way to cope with the shortcomings of PDPs regarding correlation, the reliability related to the density of instances is still the same.

When the aim is to explain individual predictions, **LIME** is one of the most used methods. It perturbs the dataset to get predictions for new, proximate samples that allow adjusting the weighting and training of an interpretable, linear

Documentation and usability	The documentation is good and plenty of examples are provided. Other complementary resources such as tutorials are provided as well. However, it may be hard to find the exact usage illustration for a specific explainer in a notebook since they are organized by data sets.
Metrics	There are many different metrics provided depending on the nature of the problem. For classification, F1 score, accuracy, recall, precision, specificity, and ROC/AUC are provided. For regression problems there is mean squared error, R squared, and median absolute deviation.
Explainers	4
Analysis	Not available.
Interactivity	Not included although the Dalex Arena allows the user easily comparing different explanations for the same problem and even different models.
Personalization	Not available.
Dependencies	Python 3.6+. For the LIME and SHAP explainers, wrapper classes are used based on the original implementations [11, 8].

Table 8. Analysis of Dalex.

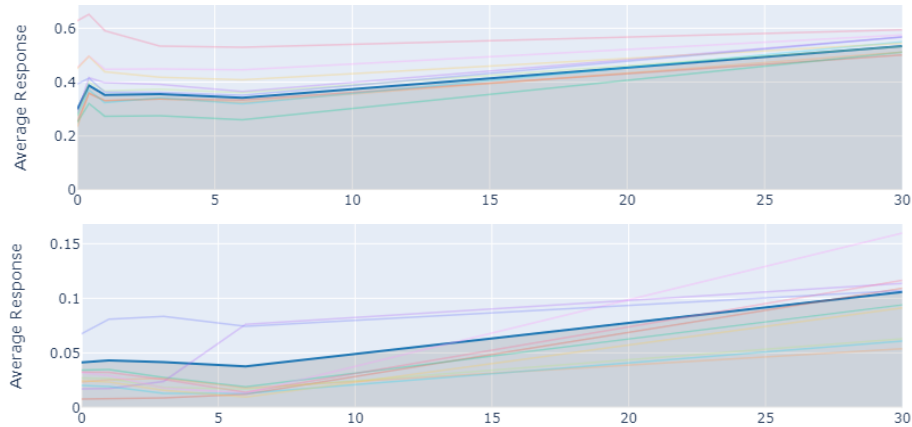


Fig. 2. Partial dependence plot of the years using hormonal contraceptives feature of the RF (top) and MLP (bottom) models. Plot from InterpretML.

model. This interpretable model provides a local explanation because its training is based on the proximity of the generated data points to the original instance. In Figure 3, a specific instance A is explained using LIME on the random forest model. The attributes of instance A, that obtains a positive prediction, are presented in Table 9. The plot shows that the features that affect the prediction the most around the given instance are hormonal contraceptives and STD-related ones. Other features, such as years of smoking and the number of pregnancies are considerably less impacting, even though they have high values in compar-

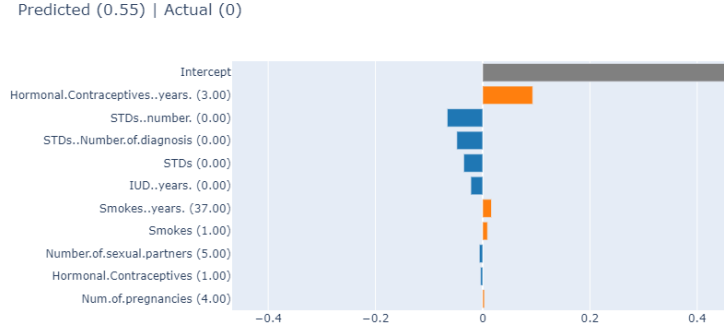


Fig. 3. LIME plot of an positive instance. Plot from InterpretML.

Features	Instance A (+)	Instance B (-)
Age	52	25
Number.of.sexual.partner	5	2
First.sexual.intercourse	16	18
Num.of.pregnancies	4	2
Smokes	1	10
Smokes..years.	37	0
Hormonal.Contraceptives	1	1
Hormonal.Contraceptives..years.	3	0.25
IUD	0	0
IUD..years.	0	0
STDs	0	0
STDs..number.	0	0
STDs..Number.of.diagnosis	0	0

Table 9. Features of two instances predicted as positive (instance A) and negative (instance B) by the for cancer.

ison with the average. This interpretation may represent properly the behavior of the model locally around the given instance. However, it does not necessarily represent the global behavior of the model.

Anchors provide conditions that are locally sufficient to determine a prediction with a certain degree of confidence. Let us look at Instance in Table 9. This instance was predicted as negative for cancer. Using anchors we obtain the following conditional rule:

Anchor: Age <= 31.00 AND
 STDs..number. <= 0.00
 Precision: 0.97
 Coverage: 0.69

The anchor given is that when the age is less or equal to 31 and the individual has not had any STD, the model classifies the individual as healthy with a precision of 97% and the coverage, representing the extent of the area of the perturbation space to which this rule applies, is rather high with 69%. The

Counterfactual	Sexual partners	Pregnancies	Smokes (years)	Contraceptives (years)
1	-	-	5.3	0.7
2	1	-	8.6	-
3	-	1	24.7	-

Table 10. Counterfactuals generated using DICE. The cells containing a hyphen represent no change from the original instance.

simplicity of anchor makes them excellent to obtain local explanations that are easy to interpret. However, the given rule may be too complicated or have low precision and coverage in certain cases.

If the focus is to provide contrastive, concise, and easy-to-interpret individual explanations, **counterfactuals** are one of the best choices. Using again the individual from table 3, we restrict the features to vary to years of smoking, the number of pregnancies, years using hormonal contraceptives, and the number of sexual partners. The counterfactuals generated are shown in Table 5; only the indicated features are included, the rest remains the same. All the counterfactuals generated show a considerable decrease in the years of smoking value, but there are interesting combinations of features. For example, if the individual had had only 1 pregnancy instead of 5, smoked for 24.7 years instead of 37, the classification would have changed.

5 Conclusions

This review of the XAI libraries allowed us to have a better understanding of some of the most popular and up-to-date explainers that machine learning and data scientists use to explain black-box models. Although all the libraries reviewed had their pros and cons, some of them proved to be highly versatile and interactive, making the process of obtaining good explanations considerably easier. To conclude this paper, we provide some subjective opinions of each library regarding its usability, variety, interactivity, and other characteristics. If we had to rank the libraries, InterpretML would probably get first place. Even though it is not the most extensive library, its usability and neat interfaces make it the number one choice for explainability. Interpret is very easy to use as most of its explainers barely require a single function call specific to the explainer used. The explanations generated are shown in the dashboard, which is an interactive interface that allows switching the visualization depending on the attribute that is emphasized, and even shows different explanations for the same model. This makes Interpret a very versatile tool if what we need is to obtain various explanations and compare them in a way we can choose the one that better fits our needs. Additionally, its documentation is well structured and complemented with several examples. It is a library that a person with little experience in machine learning would be able to use properly in a short time. However, this library only provides LIME and SHAP as local explainers, and partial dependence plots, which does not provide the same reliability as ALE

plots. If Interpret widened its explainer repertoire, it would undoubtedly be the best option for machine learning explainability. Curiously, Interpret developers have also developed Dice, which is a separate library that uniquely focuses on counterfactual generation. Although Dice is considerably different from the rest of the libraries reviewed in this paper, it proved to be a solid option to obtain counterfactual explanations. In fact, the algorithm configuration is much more straightforward and intuitive than the one in Alibi. This library also outputs the counterfactuals in an easy-to-understand fashion by using dataframes. Generally speaking, it is easy to use, and the examples provided in the documentation are illustrative and completely model-agnostic, in contrast to Alibi. In most aspects, Dice is considerably better than the approach offered in Alibi as it allows generating counterfactuals easily and outputting them in an interpretable way. Unfortunately, a simple and interactive visualization of explanations is not available in most of the XAI Libraries. Moreover, for counterfactual generation and CEM from Alibi or Aix360, the explanations are given in a low-level format that is hard to read and comprehend. Consequently, the programmer must process this data in order to convert it to a more readable format. This is one of the main issues of both libraries since explainers do not provide a high-level abstraction of the output so end-users can easily understand the explanations. Although Alibi is the most extensive library out of all reviewed ones, the way the explanations are outputted is somewhat of a letdown. Furthermore, many of the usage examples given are heavily oriented to Tensorflow models, which is a disadvantage when the model to be explained has a different backend. Despite the fact that the documentation is very specific and illustrative of the concepts behind each of the explainers available, for users without a deep background in machine learning and interpretability, using this library may prove to be difficult. On the good side, Alibi has a wide variety of explainers and is the only reviewed library that offers explanations through anchors. However, it does not include LIME. On the other hand, Aix360 is not as complete as Alibi regarding basic explainers, but it includes many other innovative model and data explanation methods such as Protodash and Profweight that may be worth diving deeper into. There are also other global explanation methods such as Boolean Decision Rules via Column Generation [2] and Generalized Linear Rule Models [14] that are not available at any other library than Aix360. Moreover, its documentation is well developed and there are many tutorials available on the official website. However, the implementation of basic explainers such as LIME, SHAP, and CEM does not offer any advantages over other libraries that also implement them. Lastly, we have Dalex, which is not so different from the previous libraries described. One of the few reasons to use it over Interpret is that it provides ALE plots, while only PDPs are available in Interpret. It does not have contrastive methods such as counterfactuals and CEM but it does provide tools for data analysis and feature importance methods. The documentation is appropriately organized but some of the methods are outdated, specifically the ones for the SHAP plotting. In conclusion, choosing one of these libraries over the others depends on the spe-

cific needs and preferences of the person who will be using them since there is considerable overlapping between them.

We conclude that one of the greatest downfalls of the XAI libraries currently available is the lack of interactivity and personalization of the explanations. Only InterpretML allows a simple interaction between the user who receives the explanations and the program and none of the libraries reviewed provide any form of personalization.

The idea behind the iSee project is to provide personalized explanations that suit the needs of the person receiving them, by analyzing user interactions using a case-based reasoning system. In this way, it will be possible to merge the already existing explainability methods with a user-oriented approach that aims to improve the machine learning interpretability field.

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