Proposed Guidelines for the Responsible Use of Explainable Machine Learning

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1 Introduction

Explainable machine learning (ML) enables human learning from ML, human appeal of automated model decisions, regulatory compliance, and white-hat hacking and security audits of ML models.[1,2] Explainable ML (i.e. e*x*plainable *a*rtificial *i*ntelligence or XAI) has been implemented in numerous open source and commercial packages and explainable ML is also an important, mandatory, or embedded aspect of commercial predictive modeling in industries like financial services.[3,4,5] However, like many technologies, explainable ML can be misused, particularly as a faulty safeguard for harmful black-boxes, e.g. *fairwashing*, and for other malevolent purposes like stealing models and sensitive training data [1], [35], [37], [40]. To promote best-practice discussions for this already in-flight technology, this short text presents internal definitions and a few examples in Section 2 before covering the details of responsible use guidelines in Sections 3.1 – 3.4. This text concludes in Section 4 with the seemingly natural argument for a holistic approach to ML that includes interpretable (i.e., *white-box*) models along with explanatory, debugging, and disparate impact testing techniques for mission- or life-critical ML systems.

2 Definitions and Examples

While explainable ML practitioners have seemingly not yet adopted a clear taxonomy of concepts or a precise vocabulary, many authors have grappled with a variety of general concepts related to interpretability and explanations. Some of these efforts include: "A Survey Of Methods For Explaining Black Box Models" (Guidotti et al. [18]), "The Mythos of Model Interpretability" (Lipton [27]), *Interpretable Machine Learning* (Molnar [31]), "Interpretable Machine Learning: Definitions, Methods, and Applications" (Murdoch et al. [33]), and "Challenges for Transparency" (Weller [43]). To decrease ambiguity herein, this section addresses the terms and phrases *interpretable*, *explanation*, *explainable ML*, *interpretable, i.e. white-box, models*, *model debugging techniques*, *unwanted sociological bias*, and *fairness techniques*.

[1] In the U.S., interpretable models, explanations, disparate impact testing, and the model documentation they enable may be required under the Civil Rights Acts of 1964 and 1991, the Americans with Disabilities Act, the Genetic Information Nondiscrimination Act, the Health Insurance Portability and Accountability Act, the Equal Credit Opportunity Act (ECOA), the Fair Credit Reporting Act (FCRA), the Fair Housing Act, Federal Reserve SR 11-7, and the European Union (EU) Greater Data Privacy Regulation (GDPR) Article 22 [44].

[2] "Proposals for Model Vulnerability and Security": `https://www.oreilly.com/ideas/proposals-for-model-vulnerability-and-security`.

[3] "Awesome machine learning interpretability": `https://github.com/jphall663/awesome-machine-learning-interpretability`.

[4] E.g., Datarobot, H2O Driverless AI, SAS Visual Data Mining and Machine Learning, Zest AutoML.

[5] "Deep Insights into Explainability and Interpretability of Machine Learning Algorithms and Applications to Risk Management": `https://ww2.amstat.org/meetings/jsm/2019/onlineprogram/AbstractDetails.cfm?abstractid=303053`.

33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada.

2.1 Interpretable and Explanation

Doshi-Velez and Kim [9] define interpretability in machine learning as, "the ability to explain or to present in understandable terms to a human." Professor Sameer Singh of the University of California at Irvine (UCI), co-inventor of the local interpretable model-agnostic explanation (LIME) technique, defines *explanation* as a, "collection of visual and/or interactive artifacts that provide a user with sufficient description of a model's behavior to accurately perform tasks like evaluation, trusting, predicting, or improving a model."[6] And Gilpin et al. [14] posit that a *good explanation* occurs when modelers or consumers "can no longer keep asking why" in regards to some machine learning model behavior. These three thoughtful characterizations link explainability to interpretability, give clarity on explanation, and provide an abstract goal for any explainability task.

2.2 Explainable ML and Interpretable Models

Herein *explainable ML* means mostly post-hoc analysis and techniques used to understand trained model mechanisms or predictions. Examples of common explainable ML techniques include:

- Local and global feature importance, e.g., Shapley and derivative-based variable attribution [3] [24], [29], [36], [39].
- Local and global model-agnostic surrogate models, e.g., surrogate decision trees and LIME [6], [7], [8], [21], [34], [42].
- Local and global visualizations of model predictions, e.g., accumulated local effect (ALE) plots, 1- and 2-dimensional partial dependence plots, and individual conditional expectation (ICE) plots [5], [13], [15].

Although difficult to quantify, credible research efforts into scientific measures of interpretability are underway [12], [32], and the ability to measure degrees of interpretability implies it's not a binary, on-off quantity.[7] Here unconstrained, traditional black-box ML models, such as multilayer perceptron (MLP) neural networks and gradient boosting machines (GBMs), are said to be directly uninterpretable, potentially unsafe for use in life- or mission-critical applications, but not necessarily completely unexplainable. In this text *interpretable models* will include linear models, decision trees, rule-based models, constrained or Bayesian variants of traditional black-box ML models, or novel types of models designed to be directly interpretable. Examples of newer interpretable modeling techniques include explainable neural networks (XNNs), explainable boosting machines (EBMs, GA2Ms), monotonically constrained GBMs, scalable Bayesian rule lists, or super-sparse linear integer models (SLIMs), [28], [41], [42], [45].[8,9,10]

2.3 Model Debugging Techniques

Herein *model debugging techniques* test ML models to increase trust in mechanisms and predictions. Debugging techniques include model assertions, security audits, variants of sensitivity (i.e., *what-if?*) analysis, variants of residual analysis and residual explanation, and unit tests to verify the accuracy or security of ML models [2], [23].[11] Model debugging should also include remediating any discovered errors or vulnerabilities.

2.4 Unwanted Sociological Bias and Fairness Techniques

In this text, *unwanted sociological bias* encompasses several forms of discrimination that may manifest in ML, including overt discrimination, disparate treatment, and disparate impact (DI),

[6] "Proposed Guidelines for Responsible Use of Explainable Machine Learning": `https://github.com/jphall663/kdd_2019`.

[7] "Quantifying Interpretability of Arbitrary Machine Learning Models Through Functional Decomposition," Figure 3 [32].

[8] As implemented in: `https://github.com/microsoft/interpret`.

[9] As implemented in: `https://xgboost.readthedocs.io/en/latest/tutorials/monotonic.html` or `https://github.com/h2oai/h2o-3/blob/master/h2o-py/demos/H2O_tutorial_gbm_monotonicity.ipynb`.

[10] And similar methods, e.g.: `https://users.cs.duke.edu/~cynthia/papers.html`.

[11] And similar methods, e.g., `https://debug-ml-iclr2019.github.io/`.

i.e., unintentional discrimination. DI may be caused by model misspecification, inaccurate or incomplete data, or data that has differing correlations or dependencies among demographic groups of individuals, driving differences in favorable model outcomes. A model is said to be biased if, (1) group membership is not independent of the likelihood of a favorable outcome, or, (2) under certain circumstances, membership in a *subset* of a group is not independent of the likelihood of a favorable outcome (i.e., *local* bias). Underlying discrimination that causes bias may or may not be illegal, depending on how it arises and applicable discrimination laws. Here *fairness techniques* are used to diagnose and remediate unwanted sociological bias in ML models. Diagnosis approaches include DI testing and other tests for bias [10]. Remediation methods tend to involve model selection by minimization of bias, preprocessing training data, e.g., reweighing [22], training unbiased models, e.g., adversarial de-biasing [46], or post-processing model predictions, e.g., by equalized odds [20].[12]

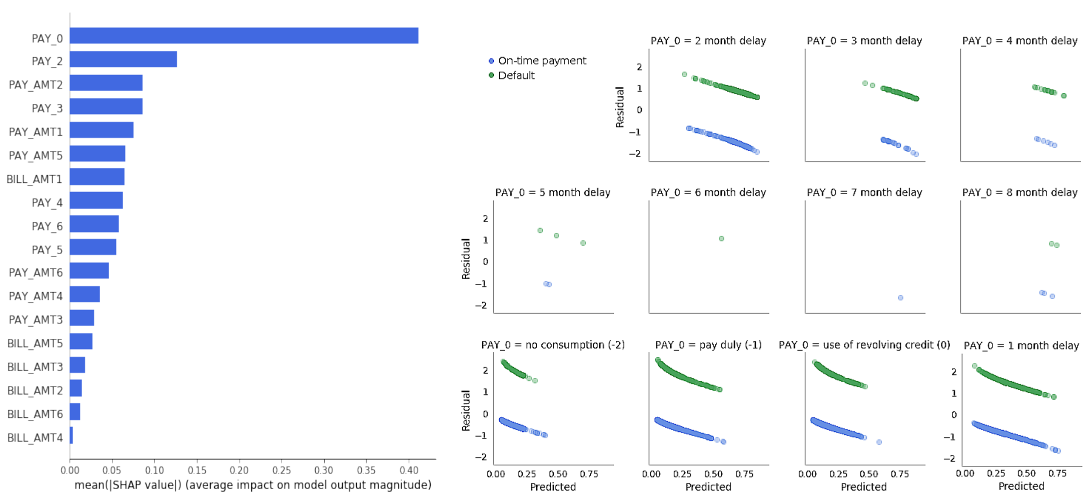
3 Proposed Guidelines for Responsible Use

Four guidelines are proposed and discussed in Sections 3.1 – 3.4 to assist practitioners in avoiding any unintentional misuse or in identifying any intentional abuse of explainable ML techniques. The guidelines are:

1. Use explanations to enable understanding.
2. Learn how explainable ML is used for nefarious purposes.
3. Augment surrogate models with direct explanations.
4. Use fully transparent ML mechanisms for systems that affect humans.

Important corollaries to the guidelines are also highlighted and simple, reproducible software examples accompany the guidelines to avoid hypothetical reasoning whenever possible.

3.1 Guideline: Use Explanations to Enable Understanding.



(a) Consistent global Shapley feature importance values for g_{GBM}.

(b) g_{GBM} deviance residuals and predictions by `PAY_0`.

Figure 1: An unconstrained GBM probability of default model, g_{GBM}, generally over-emphasizes the importance of the input feature `PAY_0`, a customer's most recent repayment status. g_{GBM} produces large positive residuals when `PAY_0` indicates on-time payments (`PAY_0` ≤ 1) and large negative residuals when `PAY_0` indicates late payments (`PAY_0` > 1). Combining explanatory and debugging techniques shows that g_{GBM} is explainable, but probably not trustworthy.

While they are likely necessary for trust in many cases, explanations are certainly not sufficient for trust in all cases. Explanation, as a general concept, is related more directly to understanding and

[12] And similar methods, e.g., `http://www.fatml.org/resources/relevant-scholarship`.

transparency than to trust.[13] Typically, explanations only increase trust in models as a side-effect, when they are acceptable to human users by some criteria. Simply put, one can understand and explain a model without trusting it. One can also trust a model and not be able to understand or explain it. Consider the following example scenarios.

- **Explanation and understanding without trust**: In Figure 1, global Shapley explanations and residual analysis identify a pathology in an unconstrained GBM model, g_{GBM}, trained on the UCI credit card dataset [25].[14] g_{GBM} over emphasizes the input feature `PAY_0`, or a customer's most recent repayment status. Due to over-emphasis of `PAY_0`, g_{GBM} is often unable to predict on-time payment if recent payments are delayed (`PAY_0` > 1), causing large negative residuals. g_{GBM} is also often unable to predict default if recent payments are made on-time (`PAY_0` ≤ 1), causing large positive residuals. In this example scenario, g_{GBM} is explainable, but not trustworthy.
- **Trust without explanation and understanding**: Years before reliable explanation techniques were widely acknowledged and available, black-box predictive models, such as autoencoder and MLP neural networks, were used for fraud detection in the financial services industry [16]. When these models performed well, they were trusted.[15,16] However, they were not explainable or well-understood by contemporary standards.

If trust in models is your goal, then explanations alone are not sufficient. However, as discussed in Sections 3.4 and 4 and illustrated in Figure 4, in an ideal scenario, explanation techniques would be used with a wide variety of other methods to increase accuracy, fairness, interpretability, privacy, security, and trust in ML models.

3.2 Guideline: Learn How Explainable ML is Used for Nefarious Purposes.

When used disingenuously, explainable ML methods can provide cover for misused or intentionally abusive black-boxes [1]. Explainable ML methods can also enable hacking or stealing of models or data through public prediction APIs or other endpoints [37], [40]. Moreover, explainable ML methods are likely to be used for other nefarious purposes in the future and may be used for unknown destructive purposes now. Responsible practitioners need to understand the malevolent side of this technology to better detect and correct misuse and abuse.

3.2.1 Corollary: Use Explainable ML for White-hat Hacking or Red-team Testing.

Use explainable ML techniques to test ML systems for vulnerabilities to model stealing, inversion, and membership inference attacks.

3.2.2 Corollary: Explainable ML Can be Used to Crack Nefarious Black-boxes.

Used as white-hat hacking tools, explainable ML can help draw attention to accuracy or bias problems in proprietary black-boxes. See Angwin et al. [4] for evidence that cracking proprietary black-box models for oversight purposes is possible.[17]

3.2.3 Corollary: Explainable ML is a Privacy Vulnerability.

Recent research shows that providing explanations along with predictions eases attacks that can compromise sensitive training data [38].

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[13] The Merriam-Webster definition of *explain*, accessed Sept. 8th 2019, does not mention *trust*: `https://www.merriam-webster.com/dictionary/explain`.

[14] Code to replicate Figure 1: `https://nbviewer.jupyter.org/github/h2oai/xai_guidelines/blob/master/global_shap_resid.ipynb`.

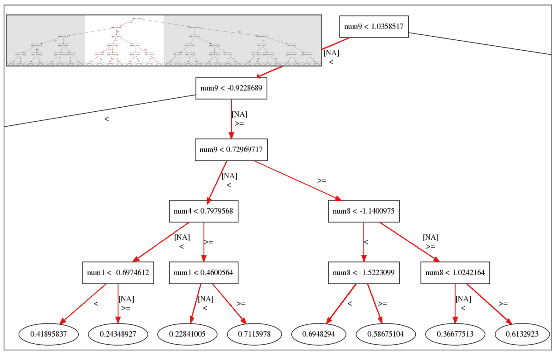
[15] "Reduce Losses from Fraudulent Transactions": `https://www.sas.com/en_ph/customers/hsbc.html`.

[16] "SAS Secures Technology Patent for Better Fraud Detection Performance": `https://www.kdnuggets.com/2011/03/sas-patent-fraud-detection.html`.

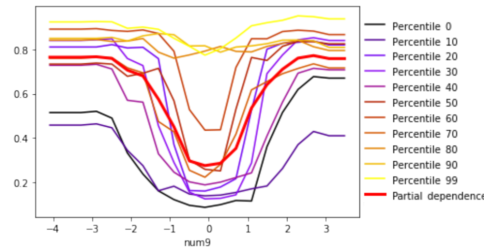
[17] This text makes no claim on the quality of the analysis in Angwin et al. (2016), which has been criticized [11]. This now infamous analysis is presented only as evidence that motivated activists can crack proprietary black-boxes using surrogate models and other explanatory techniques. Moreover, such analyses would likely improve with established best-practices for explainable ML.

3.3 Augment Surrogate Models with Direct Explanations.

Models of models, or surrogate models, can be helpful explanatory tools, but they are usually approximate, low-fidelity explainers. Aside from 1.) a global or local summary of a complex model provided by a surrogate model can be helpful sometimes and 2.) much work in explainable ML has been directed toward improving the fidelity and usefulness of surrogate models [6], [7], [8], [21], [42], *many explainable ML techniques have nothing to do with surrogate models!* One of the most exciting breakthroughs for supervised learning problems in explainable ML is the application of a coalitional game theory concept, Shapley values, to compute feature attributions which are consistent globally and accurate locally using the trained model itself [29], [39]. An extension of this idea, called tree SHAP, has already been implemented for popular tree ensemble methods [30].



(a) Naïve h_{tree}, *a surrogate model*, forms an approximate overall flowchart for the explained model, g_{GBM}.



(b) Partial dependence and ICE curves generated *directly from the explained model*, g_{GBM}.

Figure 2: h_{tree} displays known interactions in $f = X_{\text{num1}} * X_{\text{num4}} + |X_{\text{num8}}| * X_{\text{num9}}^2$ for $\sim -1 < X_{\text{num9}} <\sim 1$. Modeling of the known interactions in f by g_{GBM} is also highlighted by the divergence of partial dependence and ICE curves for $\sim -1 < X_{\text{num9}} <\sim 1$. Explanations from a surrogate model have augmented and confirmed findings from a direct model visualization technique.

There are many other explainable ML methods that operate on trained models directly such as partial dependence, ALE, and ICE plots [5], [13], [15]. Surrogate models and explanatory techniques that operate directly on trained models can also be combined, for instance by using partial dependence, ICE, and surrogate decision trees to investigate and confirm modeled interactions [19]. In Figure 2, an unconstrained GBM, g_{GBM}, models a known signal generating function f:

$$f(\mathbf{X}) = \begin{cases} 1 & \text{if } X_{\text{num1}} * X_{\text{num4}} + |X_{\text{num8}}| * X_{\text{num9}}^2 + e \geq 0.42 \\ 0 & \text{if } X_{\text{num1}} * X_{\text{num4}} + |X_{\text{num8}}| * X_{\text{num9}}^2 + e < 0.42 \end{cases} \tag{1}$$

where e signifies the injection of random noise in the form of label switching for roughly 15% of the training and validation observations.[18] g_{GBM} is then trained such that $g_{\text{GBM}}(\mathbf{X}) \approx f(\mathbf{X})$ in training and validation data. h_{tree}, displayed in Figure 2a, is extracted such that $h_{\text{tree}}(\mathbf{X}) \approx g_{\text{GBM}}(\mathbf{X}) \approx f(\mathbf{X})$ in validation data. Partial dependence and ICE plots are generated directly for g_{GBM} in the same validation data and overlaid in Figure 2b. The parent-child node relationships displayed in h_{tree} for $\sim -1 < X_{\text{num9}} <\sim 1$ in 2a and the divergence of ICE and partial dependence curves in 2b for $\sim -1 < X_{\text{num9}} <\sim 1$ help confirm and explain how g_{GBM} learned the interactions in f. As in Figure 1, combining different approaches provided additional, beneficial information about a ML model.

3.3.1 Corollary: Augment LIME with Direct Explanations.

LIME is important, imperfect (like every other ML technique), and one of many explainable ML tools. LIME, in it's most popular implementation, uses local linear surrogate models to explain regions of complex, machine-learned response functions [34]. Like other surrogate models, LIME can be combined with model-specific methods to yield deeper insights. Consider that tree SHAP can provide

[18]Code to replicate Figure 2: `https://nbviewer.jupyter.org/github/h2oai/xai_guidelines/blob/master/dt_surrogate_pd_ice.ipynb`.

Table 1: Coefficients for a local linear interpretable model, h_{GLM}, with an intercept of 0.77 and an R^2 of 0.73. h_{GLM} is trained on a segment of the UCI credit card dataset containing higher-risk customers with late most recent repayment statuses, $\mathbf{X}_{PAY\_0>1}$, and the predictions of a simple decision tree, $g_{\text{tree}}(\mathbf{X}_{\text{PAY\_0>1}})$.

h_{GLM} Feature	h_{GLM} Coefficient
`PAY_0 == 4`	0.0009
`PAY_2 == 3`	0.0065
`PAY_5 == 2`	−0.0006
`PAY_6 == 2`	0.0036
`BILL_AMT1`	3.4339e−08
`PAY_AMT1`	4.8062e−07
`PAY_AMT3`	−5.867e−07

locally accurate and consistent point estimates for local feature importance as in 3b. LIME can then provide approximate information about modeled local linear trends around the same point. Table 1 contains LIME h_{GLM} coefficients for a local region of a validation set sampled from the UCI credit card data defined by `PAY_0 > 1`, or customers with a fairly high risk of default due to late most recent payments.[19] h_{GLM} models the predictions of a simple interpretable decision tree model, g_{tree}, displayed in 3a. h_{GLM} coefficients show linear trends between features in the sampled set $\mathbf{X}_{\text{PAY\_0>1}}$ and $g_{\text{tree}}(\mathbf{X}_{\text{PAY\_0>1}})$. Because h_{GLM} is relatively well-fit (0.73 R^2) and has a logical intercept (0.77), it can be used along with Shapley values to reason about the modeled average behavior for risky customers and to differentiate the behavior of any one specific risky customer from their peers under the model. This additional information can be useful for model debugging and compliance purposes.

3.4 Use Fully Transparent ML Mechanisms for Systems That Affect Humans.

Explanation, along with white-box models, model debugging, disparate impact analysis, and the documentation they enable, are often required under numerous regulatory statutes in the U.S. and E.U., and explainable ML tools like surrogate models, partial dependence plots, and global feature importance are already used to document, understand, and validate different types of models in the financial services industry [21], [42].[1, 5] Moreover, adverse action notices are mandated under the Equal Credit Opportunity Act (ECOA) and the Fair Credit Reporting Act (FCRA) for many credit lending, employment, and insurance decisions in the United States.[20] If ML is used for such decisions it must be explained in terms of adverse action notices.[21] Shapley values, and other local feature importance approaches, provide a convenient methodology to rank the direct contribution of input features to final model decisions and potentially generate customer-specific adverse action notices. In these application domains, interpretability is simply a legal necessity.

Aside from regulatory mandates, explanation enables logical appeal processes for automated decisions made by ML models. Consider being negatively impacted by an erroneous black-box model decision, say for instance being mistakenly denied a loan or parole. How would you argue your case for appeal without knowing how model decisions were made? According to the New York Times, a man named Glenn Rodríguez found himself in this unfortunate position in a penitentiary in Upstate New York in 2016.[22]

Some may argue that, outside of regulated dealings, for a model with little or no impact on humans and that has been thoroughly and responsibly tested by knowledgeable practitioners, that explanation is *really* unnecessary. While that statement appears technically true, the counter argument in this case centers on human learning from ML models. Explanatory techniques allow practitioners to gain insights from complex models about nonlinear or faint phenomena and complex interactions –

[19] Code to replicate Table 1: .

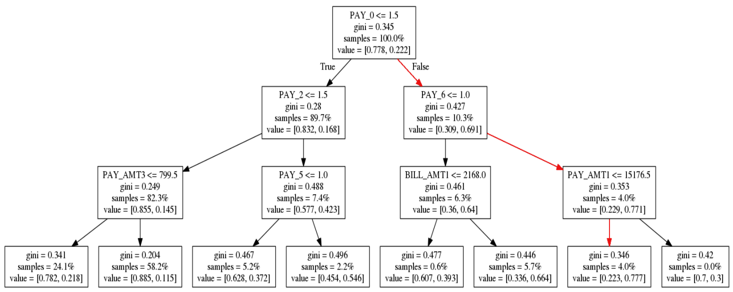
[20] See: `https://consumercomplianceoutlook.org/2013/second-quarter/adverse-action-notice-requirements-under-ecoa-fcra/`.

[21] This is apparently *already* happening: `https://www.prnewswire.com/news-releases/new-patent-pending-technology-from-equifax-enables-configurable-ai-models-300701153.html`.

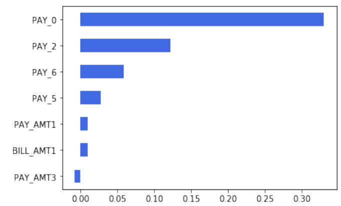
[22] This too is happening *today*: `https://www.nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html`.

information that may sometimes be unlearnable by linear models. Also, why go through the weeks, months, or years of training and deploying a production ML system, and not take a small percentage of that time to learn about the model's findings?

3.4.1 Guideline Corollary: Use Interpretable Models Along with Explanation Techniques.



(a) Simple decision tree, g_{tree}, trained on the UCI credit card data to predict default with validation AUC of 0.74. The decision policy for a high-risk individual is highlighted in red.



(b) Locally-accurate Shapley contributions for the highlighted individual's probability of default.

Figure 3: A simple decision tree, g_{tree}, is trained on the UCI credit card dataset to predict probability of default. g_{tree} has a validation AUC of 0.74. The decision-policy for a high-risk customer is highlighted in 3a and the locally-accurate Shapley contributions for this same individual's predicted probability are displayed in 3b. The Shapley values are helpful because they highlight the local importance of `PAY_2`, the individual's second most recent repayment status, which could be underestimated by examining the decision policy alone.

A few well-known publications have focused either on white-box modeling techniques (e.g. Ustun and Rudin [41], Yang et al. [45]) or on post-hoc explanations (e.g. Lundberg and Lee [29], Ribeiro et al. [34]), but the two can be used together in the context of a broader and more human-centered ML workflow as illustrated in Figure 4. Consider the seemingly useful example case of augmenting globally interpretable models with local post-hoc explanations. A practitioner could train a single decision tree, a globally interpretable model, then apply local explanations in the form of Shapley feature importance as illustrated in Figure 3.[23] This enables the practitioner to see accurate numeric feature contributions for each model prediction in addition to the entire directed graph of the decision tree. Even for interpretable models, such as linear models and decision trees, it has been shown that Shapley values present accuracy and consistency advantages over standard feature attribution methods [26], [30], [29]. Shapley values also enable the ranking of input features for each model decision, which is likely helpful for FCRA and ECOA compliance. Another twist on the idea of combining explainable ML methods and white-box models is described in "Surrogate Assisted Feature Extraction for Machine Learning (SAFE ML)" (Gosiewska et al. [17]). In the SAFE ML approach, features learned by more complex models are extracted and used in an explainable fashion to increase the accuracy of more interpretable models. Aren't either of these augmented processes more desirable than either a white-box model or post-hoc explanations alone?

3.4.2 Corollary: Use Explanations Along with Disparate Impact Testing.

Like white-box models, fairness methods (e.g. Feldman et al. [10], Hardt et al. [20]) are often presented in different articles than post-hoc explanatory methods. However, in banks for example, using post-hoc explanatory tools along with DI analysis is often necessary to comply with model documentation guidance and with fair lending regulations.[24] To clarify, explanatory techniques should *not* replace disparate impact testing for bias detection purposes, but in general, explanations increase transparency and understanding of model mechanisms and predictions while disparate impact auditing and remediation increases trust that model predictions are as fair as possible. As

[23] Code to replicate Figure 3 is available here: `https://github.com/jphall663/responsible_xai`.

[24] See: `https://www.ffiec.gov/pdf/fairlend.pdf`, `https://files.consumerfinance.gov/f/documents/201510_cfpb_ecoa-narrative-and-procedures.pdf`.

in previous sections, trust and understanding are different but complimentary goals achieved by combining multiple approaches.

Table 2: Basic group disparity metrics across different marital statuses for monotonically constrained GBM model, g_{mono}, trained on the UCI credit card dataset.

	Adverse Impact Disparity	Accuracy Disparity	TPR Disparity	TNR Disparity	FPR Disparity	FNR Disparity
`married`	1.00	1.00	1.00	1.00	1.00	1.00
`single`	0.89	1.03	0.99	1.03	0.85	1.01
`divorced`	1.01	0.93	0.81	0.96	1.25	1.22
`other`	0.26	1.12	0.62	1.17	0	1.44

Table 2 displays basic group disparity metrics for a monotonically constrained GBM model, g_{mono}, trained on the UCI credit card data.[25] In this example scenario, g_{mono} displays group parity according to the four-fifths rule with `married` as the reference level for single customers, but exposes potential disparate impact for `divorced` customers and customers with martial status of `other` (for which there is very little training data). Alternative models with less disparate impact or other remediation processes should be considered in such cases to increase trust ML systems.

3.4.3 Corollary: Explanation is Not a Frontline Fairness Tool.

In high-stakes and commercially viable uses of explainable ML in credit lending, insurance, and employment in the U.S. that fall under FCRA, ECOA, or other applicable regulations, demographic attributes cannot be used in predictive models and thus their contribution to models cannot be assessed using accurate, direct explainable ML techniques. Even when demographic attributes can be used in models, it has been shown that explanations may not detect bias [1]. Given these drawbacks, it is recommended that fairness techniques are used to test for and remediate bias, and explanations are used to understand bias when appropriate.

3.4.4 Corollary: Use Bias Testing Along with Constrained Models.

Because unconstrained ML models can treat similar individuals differently due to small differences in their data values, unconstrained models can cause local bias that is not detectable with standard bias testing methods that analyze group fairness [**?**]. To minimize local bias when using ML, and to ensure standard bias or DI testing methods are most effective, pair such testing with constrained models.

4 Conclusion

ML systems are used today to make life-altering decisions about employment, bail, parole, and lending.[26] The scope of decisions delegated to ML systems seems likely only to expand in the future. Many researchers and practitioners are tackling disparate impact, inaccuracy, privacy violations, and security vulnerabilities with a number of brilliant, but perhaps siloed, approaches. By presenting some straightforward explainable ML guidelines, this short text also gives examples of combining innovations from several sub-disciplines of ML research to train explainable, fair, and trustable predictive modeling systems. As proposed in Figure 4, using these techniques together can create a new and more human-centered type of ML potentially better-suited for use in business- and life-critical decision support than conventional methods.

[25] Code to replicate Table 2: `https://nbviewer.jupyter.org/github/h2oai/xai_guidelines/blob/master/dia.ipynb`.

[26] ICLR 2019 model debugging workshop CFP: `https://debug-ml-iclr2019.github.io/`.

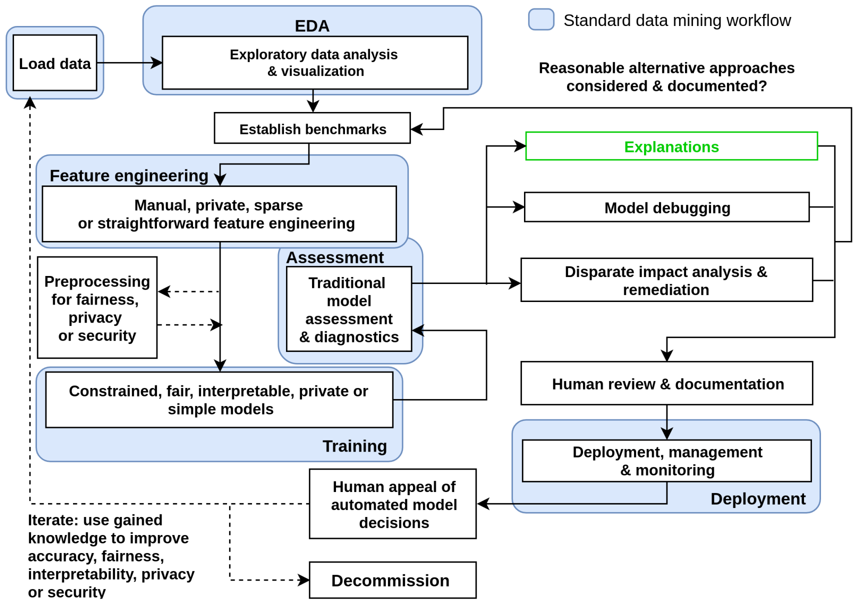


Figure 4: A diagram of a proposed human-centered ML workflow in which explanations (highlighted in green) are used along with interpretable or white-box models, disparate impact analysis and remediation techniques, and other review and appeal mechanisms to create a fair, accountable, and transparent ML system.

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