

On Explainable Machine Learning Misconceptions & Human-Centered Machine Learning

Patrick Hall*[†]
Washington, DC
`patrick.hall@h2o.ai`

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Introduction

Due to obvious community and commercial demand, explainable machine learning (ML) methods have already been implemented in popular open source software and in commercial software.^{1,2} Yet, as someone who has been involved in the implementation of explainable ML software for the past three years, I find a lot of what I read about the topic confusing and detached from my personal, hands-on experiences. This short text presents arguments, proposals, and references to address some observed explainable ML misconceptions. Please note that this text is not an attack on any party, and disagreements with any previous credible opinion pieces are mostly minor and technical.³ This text is instead a call for pragmatism from the trenches. It seeks to promote nuanced debate, responsible use, and continued development of explainable ML, and not dismissal or derision of the discipline. Moreover, this text builds the seemingly natural case for a holistic approach to ML that includes interpretable (i.e. “white-box”) models along with explanatory, debugging, and disparate impact analysis techniques.

To avoid ambiguity, several internal definitions and accompanying examples are put forward before discussing misconceptions. Here *explainable ML* means mostly post-hoc techniques used to understand trained model mechanisms or predictions. Examples of common explainable ML techniques include:

- Local and global feature importance methods, in particular Shapley values [26], [17], [27], [22].
- Local and global model-agnostic surrogate models, such as surrogate decision trees and Local Interpretable Model-agnostic Explanations (LIME) [6], [4], [16], [24].
- Local and global visualizations of model predictions such as accumulated local effect (ALE), 1- and 2-dimensional partial dependence, and individual conditional expectation (ICE) plots [3], [9], [11].

In this text *model debugging* refers to testing ML models to increase trust in model mechanisms and predictions. Examples of model debugging techniques include variants of sensitivity (i.e. “what-if?”), residual analysis, assertions, and units test used to verify the accuracy or security of ML models.⁴ Model debugging should also include remediating any discovered errors or vulnerabilities. Herein *fairness* techniques refer to disparate impact analysis, model selection by minimization of disparate impact, and remediation techniques

*H2O.ai and George Washington University

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¹Like H2O-3, XGBoost, and various other Python and R packages. See: <https://github.com/jphall663/awesome-machine-learning-interpretability> for a longer, curated list of relevant open source software packages.

²For instance Datarobot, H2O Driverless AI, SAS Visual Data Mining and Machine Learning, Zest AutoML, and likely several others.

³For instance, say “Please Stop Explaining Black Box Models for High Stakes Decisions” [25].

⁴And other similar techniques, say those mentioned here: <https://debug-ml-iclr2019.github.io/>.

such as disparate impact removal preprocessing or equalized odds post-processing [8], [15].⁵ In this text *interpretable* or *white-box* models will include linear models, decision trees, constrained or Bayesian variants of traditional black-box ML models, or novel types of models designed to be directly interpretable. (Additional examples of interpretable modeling techniques include explainable neural networks (XNNs), monotonically constrained gradient boosting machines (GBMs)⁶, scalable Bayesian rule lists, or super-sparse linear integer models (SLIMs) [29], [32], [28].⁷) Herein unconstrained, traditional black-box ML models, such as multilayer perceptron (MLP) neural networks and GBMs, are said to be directly uninterpretable, potentially unsafe for use on humans, but not necessarily completely unexplainable.

1 Misconception: Explanations are Necessary and Sufficient to Establish Trust in ML

Explanations are likely necessary for trust in many cases, but certainly not sufficient for trust in all cases. Explanation, as a general concept, is related more directly to understanding and transparency than to trust.⁸ 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 data [18].⁹ 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 ($\text{PAY}_0 > 1$), causing large negative residuals. g_{GBM} is also often unable to predict default if recent payments are made on-time ($\text{PAY}_0 \leq 1$), 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 [12]. When these models performed well, they were trusted.¹⁰ 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 Section 6 and illustrated in Figure 3, 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.

2 Misconception: Transparency in ML is Unnecessary

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 [16], [29].¹¹ 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.¹² If machine learning is used for such decisions it must be explained in terms of adverse action notices.¹³ Shapley values, and other local feature importance approaches, provide

⁵And other similar techniques, say those mentioned here: <http://www.fatml.org/resources/relevant-scholarship>.

⁶As implemented in XGBoost (<https://xgboost.readthedocs.io/en/latest/tutorials/monotonic.html>) or H2O-3 (https://github.com/h2oai/h2o-3/blob/master/h2o-py/demos/H2O_tutorial_gbm_monotonicity.ipynb).

⁷And other similar techniques, say those mentioned here: <https://users.cs.duke.edu/~cynthia/papers.html>.

⁸The Merriam-Webster definition of *explain*, accessed April 21st 2019, does not mention *trust*.

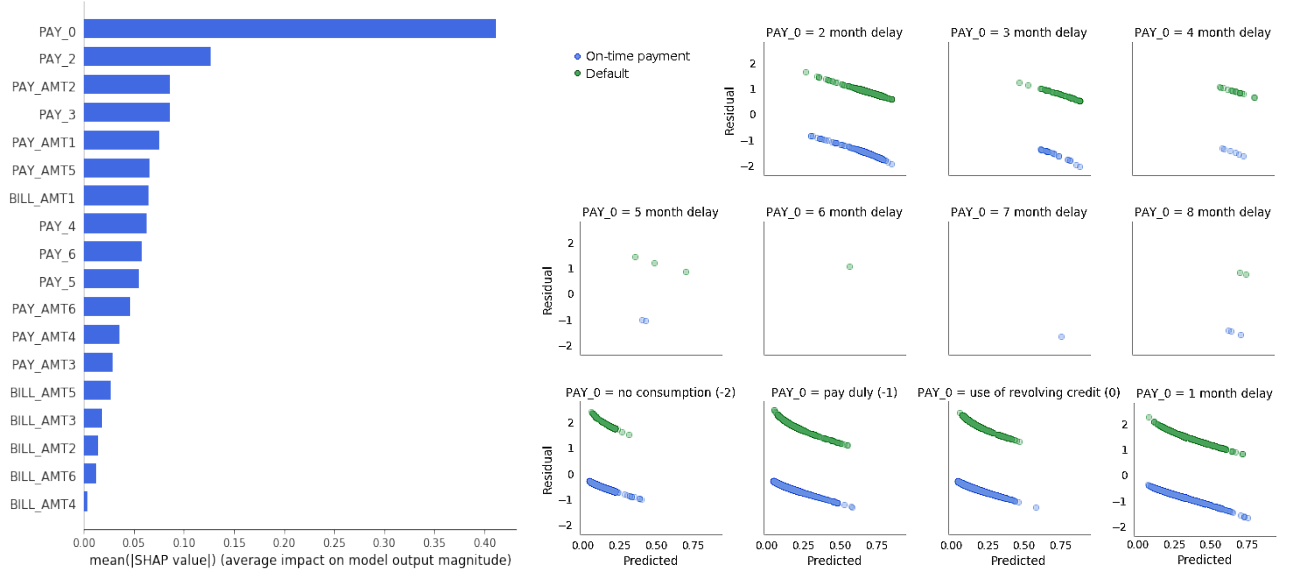
⁹Code to replicate Figure 1 is available here: https://github.com/jphall663/xai_misconceptions.

¹⁰For example: https://www.sas.com/en_ph/customers/hsbc.html, <https://www.kdnuggets.com/2011/03/sas-patent-fraud-detection.html>.

¹¹Working paper: <https://www.linkedin.com/feed/update/urn:li:activity:6526203034966507520>.

¹²See: <https://consumercomplianceoutlook.org/2013/second-quarter/adverse-action-notice-requirements-under-ecoa-fcra/>.

¹³This is apparently already happening: <https://www.prnewswire.com/news-releases/new-patent-pending-technology-from-equifax-enables-configurable-ai-models-300701153.html>.



(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} , 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 ($PAY_0 \leq 1$) and large negative residuals when PAY_0 indicates late payments ($PAY_0 > 1$).

a convenient methodology to rank the direct contribution of input features to final model decisions and potentially generate customer-specific adverse action notices. In a number of other application domains, broader interpretability is also legal necessity. Explanation, along with white-box models, model debugging, disparate impact analysis, and the documentation they enable, can also 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 Fair Housing Act, Federal Reserve SR 11-7, the European Union (EU) Greater Data Privacy Regulation (GDPR) Article 22, and other regulatory statutes [31].

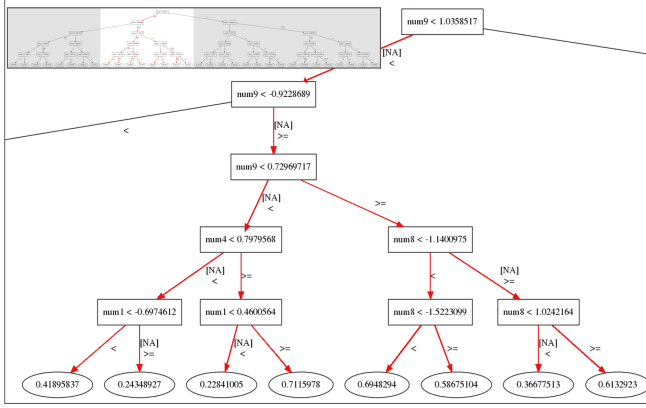
Aside from regulatory mandates, explanation enables logical appeal processes for automated decisions made by ML models. Consider being negatively impacted by an erroneous black-box model decision, say for instance being mistakenly denied a loan or parole. How would you argue your case for appeal without knowing how model decisions were made? According the New York Times, a man named Glenn Rodríguez found himself in this unfortunate position in Upstate New York in 2016.¹⁴

3 Misconception: All the Key Terms in Explainable ML are Undefined

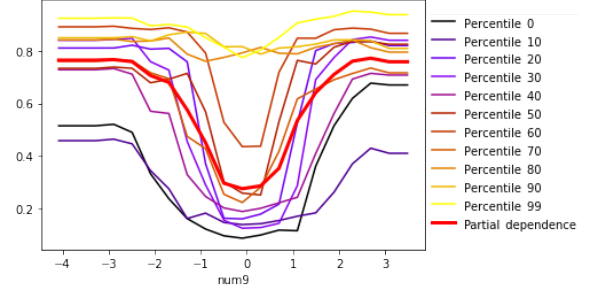
Helpful definitions that apply to explainable ML have been put forward, including:

- **Interpretable:** “The ability to explain or to present in understandable terms to a human” – in “Towards a Rigorous Science of Interpretable Machine Learning” by Doshi-Velez and Kim (2017) [7].
- **A Good Explanation:** “When you can no longer keep asking why” – in “Explaining Explanations:

¹⁴This too is happening today: <https://www.nytimes.com/2017/06/13/opinion/how-computers-are-harming-criminal-justice.html>.



(a) Naïve h_{tree} is an approximate overall flowchart for g_{GBM} .



(b) Partial dependence and ICE curves generated directly for g_{GBM} .

Figure 2: h_{tree} displays known interactions between X_{num9} and X_{num8} (along with potential noise interactions) for $\sim -0.923 < X_{\text{num9}} < \sim 1.04$. Modeling of the known interaction between X_{num9} and X_{num8} in f by g_{GBM} is confirmed by the divergence of partial dependence and ICE curves for $\sim -1 < X_{\text{num9}} < \sim 1$.

An Approach to Evaluating Interpretability of Machine Learning” by Gilpin et al. (2018) [10]. (Gilpin et al. also provide several clear constructs for describing more specific types of explanations.)

While the explainable ML field is far from embracing a clear and accepted taxonomy of concepts or an exhaustive and precise vocabulary, these two thoughtful definitions appear to link explanations to some ML process being interpretable. Moreover, many authors have made significant attempts to grapple with a variety of general concepts related to interpretability and explanations, including “A Survey Of Methods For Explaining Black Box Models” by Guidotti et al. (2018), Zachary Lipton’s “The Mythos of Model Interpretability” (2016), Christoph Molnar’s *Interpretable Machine Learning* (2018), and Adrian Weller’s “Challenges for Transparency” (2017) [13], [20], [23], [30].

4 Misconception: Explainable ML is Just Models of Models

Models of models, or surrogate models, can be helpful explanatory tools, but they are usually approximate, low-fidelity explainers. Aside from 1.) a global 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], [4], [16], [29], [5], **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 contributions which are consistent globally and accurate locally using the trained model itself [27], [22]. An extension of this idea, called tree SHAP, has already been implemented for popular tree ensemble methods [21].

There are many other explainable ML methods that operate on trained models directly such as partial dependence, ALE, and ICE plots [9], [3], [11]. 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 [14]. In Figure 2 an unconstrained GBM, g_{GBM} , models a known signal generating function f :

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

where e signifies the injection of random noise in the form of label switching for roughly 15% of the training

Table 1

h_{GLM} Coefficient	Value
PAY_0 == 4	
PAY_2 == 3	
PAY_5 == 2	
PAY_6 == 2	
BILL_AMT1	
PAY_AMT1	
PAY_AMT3	

and validation observations.¹⁵ g_{GBM} is then trained such that $g_{\text{GBM}} \approx f$. 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 relationship displayed between $X_{\text{num}9}$ and $X_{\text{num}8}$ for $\sim -0.923 < X_{\text{num}9} < \sim 1.04$ in 2a and the divergence of ICE and partial dependence curves in 2b for $\sim -1 < X_{\text{num}9} < \sim 1$ help confirm and understand how g_{GBM} learned the interaction between $X_{\text{num}8}$ and $X_{\text{num}9}$ in f . Like in Figure 1, combining different approaches provided additional, beneficial information about a complex ML model.

Misconception Corollary: Explainable ML is just LIME. LIME, in its most popular implementation, uses local linear surrogate models [24]. LIME is important, and imperfect, but just one of many explainable ML tools. And again, LIME can sometimes be combined with model-specific methods to yield deeper insights. Consider that tree SHAP can provide locally accurate and consistent point estimates for local feature importance whereas LIME can provide approximate information about modeled local linear trends around the same point. Figure ?? shows locally accurate Shapley contributions for a risky customer in a validation set sampled from the UCI credit card dataset. The Shapley values provide accurate point estimates for each feature’s contribution to the prediction of a single, interpretable decision tree model, $g_{\text{tree}}(\mathbf{x})$. The LIME, h_{GLM} coefficients show linear trends for the same features for all risky customers in the validation data.

5 Misconception: Explainable ML Methods Simply Provide Cover to Use Black-Box ML for Nefarious Purposes

If used disingenuously, explainable ML methods probably do provide such cover [1]. But explainable ML methods were designed specifically to crack open those same nefarious and complex black-boxes. See Angwin et al. (2016) for evidence that hacking or stealing of commercial black-box models for oversight purposes is possible [2]. Such investigations would likely only be improved by advances in explanatory and fairness tools. Additionally, many important computer-based technological advances present similar double-edged sword dilemmas, e.g. social media or strong encryption. Rarely does the ability of a tool to be misused for malicious purposes disqualify it from being used as designed.

6 Misconception: Explainable ML Methods and White-box Models are Somehow Mutually Exclusive

A few well-known publications have focused either on white-box modeling techniques (e.g. [28], [32]) or on post-hoc explanations (e.g. [24], [22]), but the two can be used together in the context of a broader and more human-centered machine learning workflow as illustrated in Figure 3.

Consider the seemingly useful example case of augmenting globally interpretable models with local post-hoc explanations: A practitioner could train a single pruned decision tree as a globally interpretable model

¹⁵Code to replicate Figure 2 is available here: https://github.com/h2oai/mli-resources/tree/master/lime_shap_treeint_compare.

Table 2: Basic group parity 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

then use local explanations in the form of Shapley feature importance. This would enable 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 [19], [21], [22]. Isn't an augmented global and local understanding of the model more desirable than the white-box model or the post-hoc explanations alone?

Corollary Misconception: Explainable ML Methods and Fairness Methods are Somehow Mutually Exclusive: Like white-box models, fairness methods (e.g. [15], [8]) are often presented in different articles than post-hoc explanatory methods. However, in banks, using post-hoc explanatory tools such as partial dependence plots to comply with model documentation guidance often goes hand-in-hand with using disparate impact analysis to comply with fair lending regulations.^{16,17,18}

Table 2 displays basic group parity metrics for a monotonically constrained GBM model, g_{mono} , trained on the UCI credit card data.¹⁹ 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 marital status of **other** (for which there is very little training data).

Conclusion

Machine learning systems are used today to make life-altering decisions about employment, bail, parole, and lending.²⁰ The scope of decisions delegated to machine learning 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 addressing some common explainable ML misconceptions, this short text also gives examples of combining innovations from several sub-disciplines of machine learning research to train explainable, fair, and trustable predictive modeling systems. As proposed in Figure 3, using these techniques together can create a new and truly human-centered type of machine learning suitable for use in business- and life-critical decision support.

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¹⁶Working paper: <https://www.linkedin.com/feed/update/urn:li:activity:6526203034966507520>.

¹⁷White paper: <https://www.aba.com/Compliance/Documents/FairLendingWhitePaper2017Apr.pdf>

¹⁸Policy Statement on Discrimination in Lending: <https://www.govinfo.gov/content/pkg/FR-1994-04-15/html/94-9214.htm>

¹⁹Code to replicate Table 2 is available here: https://github.com/jphall663/xai_misconceptions.

²⁰ICLR 2019 model debugging workshop CFP: <https://debug-ml-iclr2019.github.io/>

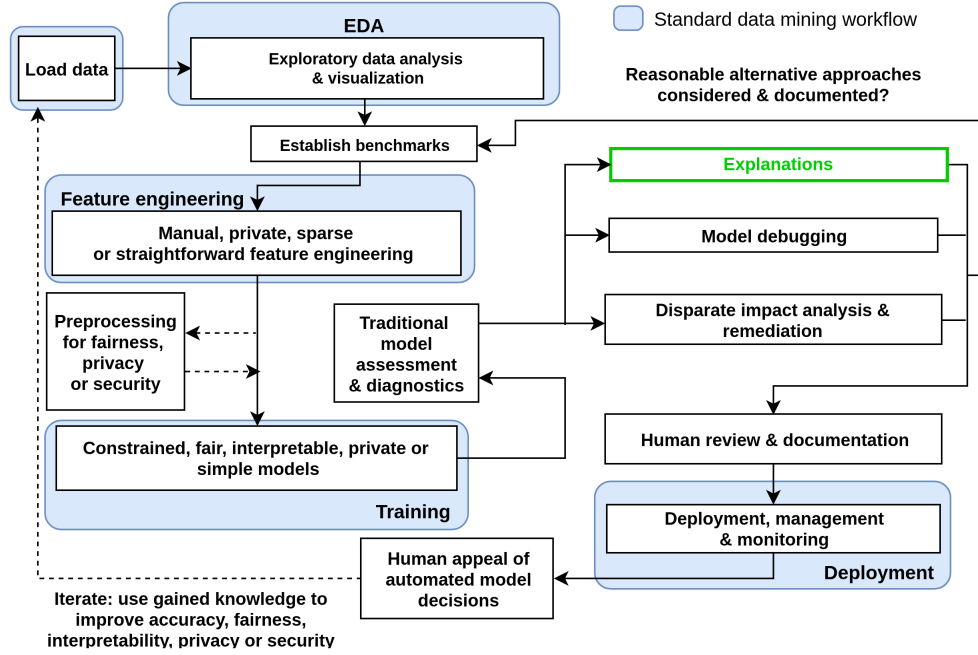


Figure 3: A diagram of a proposed human-centered machine learning workflow in which explanations (highlighted in green) are used along with interpretable models, disparate impact analysis and remediation techniques, and other review and appeal mechanisms to create a fair, accountable, and transparent ML system.

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