Responsible Machine Learning*

Lecture 6: ML Best Practices

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Contents

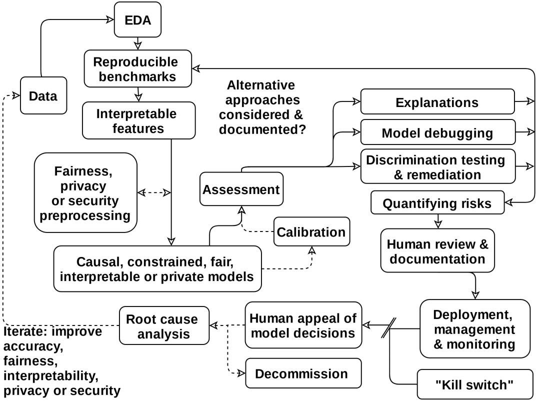
Preface

This mid-level technical document provides a basic blueprint for combining innovations in AutoML, regulation-compliant predictive modeling, and machine learning research in the sub-disciplines of fairness, interpretable models, post-hoc explanations, privacy and security to create a low-risk machine learning framework.

This document presents potential technical solutions to the **intersectional** harms posed by opaqueness, inaccuracy, social bias, or security vulnerabilities in machine learning.

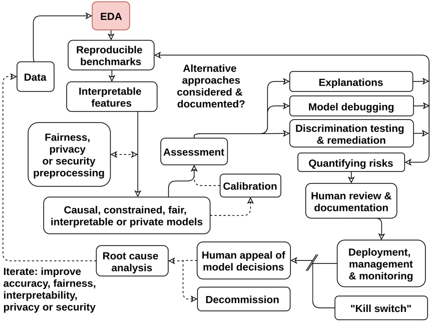
Racism, sexism, cyber-crime and other issues discussed in this document have not been solved, and likely cannot be solved, by technology alone.

Responsible ML Blueprint†



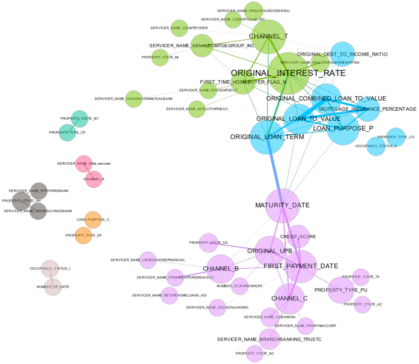
† This blueprint does not address ETL workflows.

EDA and Data Visualization

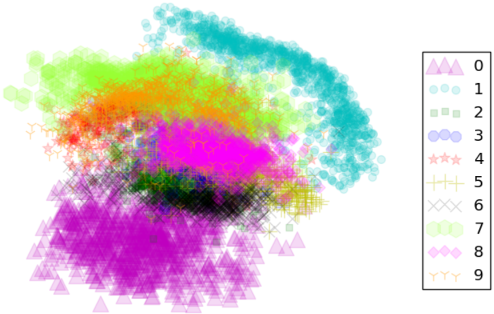


- Know thy data.
- OSS: H2O-3 Aggregator
- References: Visualizing Big Data Outliers through Distributed Aggregation; The Grammar of Graphics

Interlude: My Favorite Visualizations



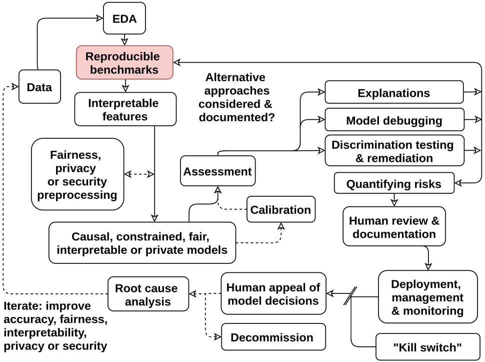
A network graph capturing the Pearson correlation relationships between many *columns* in a lending dataset.



An autoencoder projection of the MNIST data. Projections capture sparsity, clusters, hierarchy, and outliers in *rows* of a dataset.

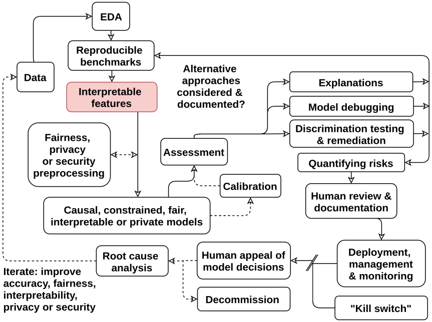
Both of these images capture high-dimensional datasets in just two dimensions.

Establish Benchmarks



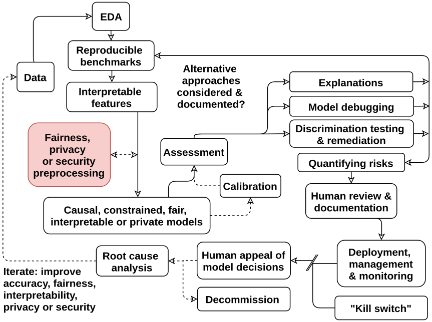
Establishing reproducible benchmarks from which to gauge improvements in accuracy, fairness, interpretability or privacy is crucial for good ("data") science and for compliance.

Manual, Private, Sparse or Straightforward Feature Engineering



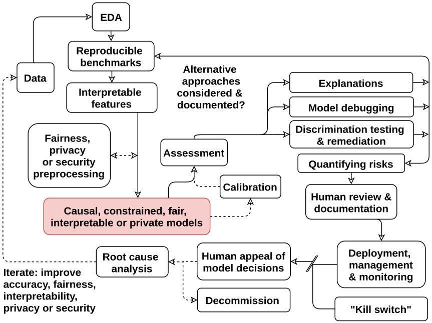
- OSS: elasticnet, Feature Tools
- References: Sparse Principal Component Analysis; Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering; *t*-Closeness: Privacy Beyond *k*-Anonymity and *l*-diversity

Preprocessing for Fairness, Privacy or Security



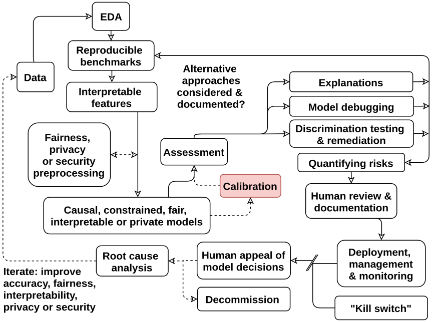
- OSS: IBM AIF360
- References: Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention; Privacy-Preserving Data Mining; Differential Privacy and Machine Learning: A Survey and Review

Constrained, Fair, Interpretable, Private or Simple Models



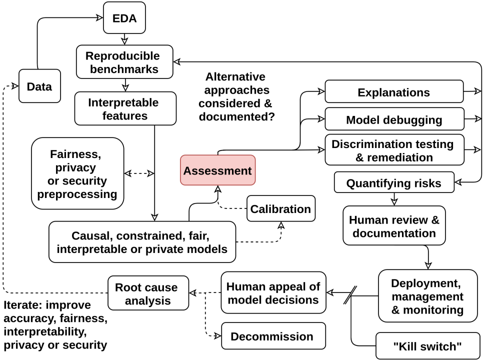
- OSS: Accurate Intelligible Models with Pairwise Interactions (GA2M/EBM); Rudin Group models e.g. Scalable Bayesian Rule Lists (SBRL); Monotonic gradient boosting machines in H2O-3 or XGBoost; pymc3
- References: Scalable Private Learning with PATE; Mitigating Unwanted Biases with Adversarial Learning; Bayesian Networks; Explainable Neural Networks Based on Additive Index Models (XNN)

Prediction Calibration



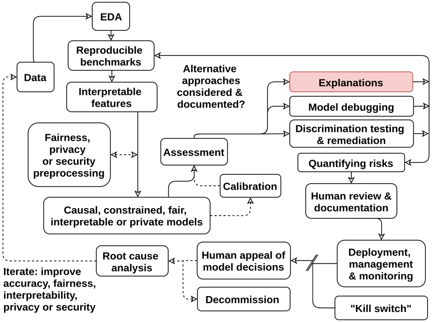
- Just because a number is in $[0, 1]$ does not make it a probability.
- OSS: scikit-learn
- References: Predicting Good Probabilities with Supervised Learning

Traditional Model Assessment and Diagnostics



Residual analysis, Q-Q plots, AUC and lift curves etc. confirm model is accurate and meets assumption criteria.

Post-hoc Explanations

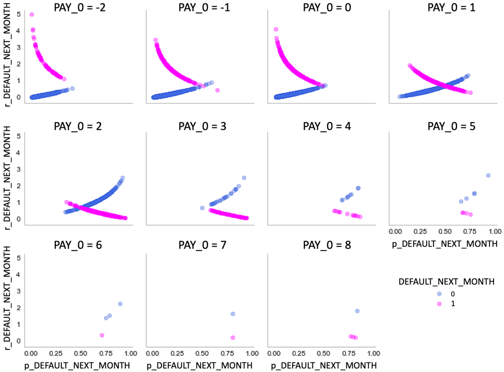


- Explanations enable *understanding* and *appeal* ... *not trust*.
- OSS: alibi, shap
- References: Counterfactual Explanations without Opening the Black Box: Automated Decisions and the GPDR; A Unified Approach to Interpreting Model Predictions; Interpreting Blackbox Models via Model Extraction; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)

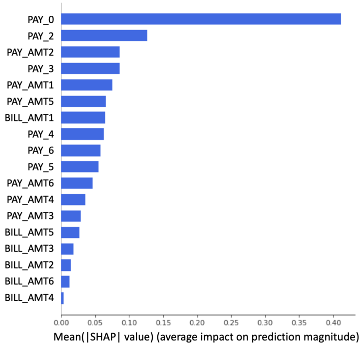
Interlude: The Time–Tested Shapley Value

1. **In the beginning**: A Value for N-Person Games, 1953
2. **Nobel-worthy contributions**: The Shapley Value: Essays in Honor of Lloyd S. Shapley, 1988
3. **Shapley regression**: Analysis of Regression in Game Theory Approach, 2001
4. **First reference in ML?** Fair Attribution of Functional Contribution in Artificial and Biological Networks, 2004
5. **Into the ML research mainstream, i.e. JMLR**: An Efficient Explanation of Individual Classifications Using Game Theory, 2010
6. **Into the real-world data mining workflow ... *finally***: Consistent Individualized Feature Attribution for Tree Ensembles, 2017
7. **Unification**: A Unified Approach to Interpreting Model Predictions, 2017

Interlude: Explaining Why Not to Trust



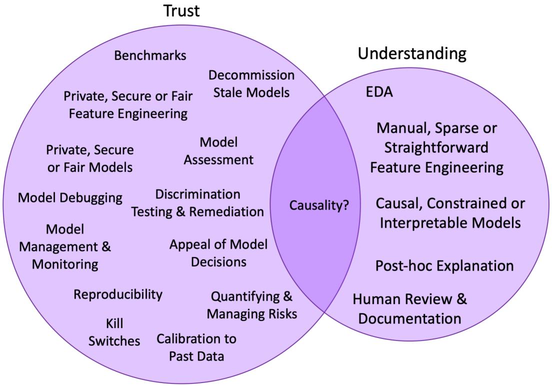
These residuals show a problematic pattern in predictions related to the most important feature, `PAY_0`.



This model over-emphasizes the most important feature, `PAY_0`.

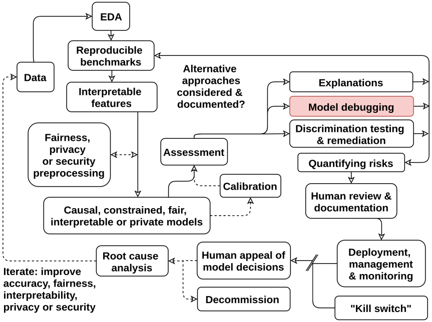
While this model is *explainable*, it's probably not *trustworthy*.

Interlude: Trust and Understanding



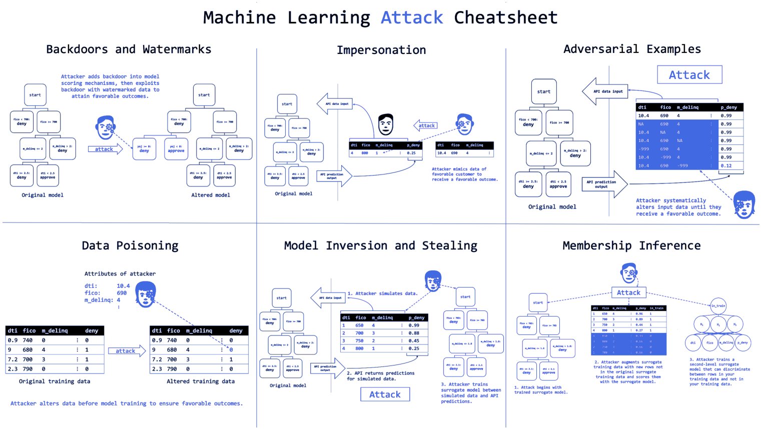
Trust and understanding in machine learning are different but complementary goals, and they are technically feasible *today*.

Model Debugging for Accuracy, Privacy or Security



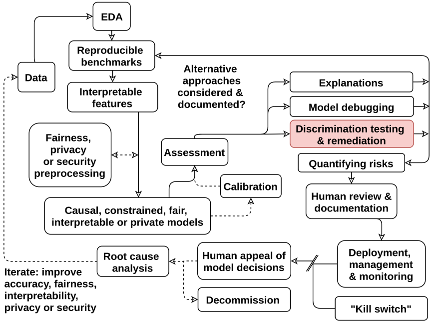
- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and "what-if" analysis.
- OSS: cleverhans, pdpbox, what-if tool
- References: Modeltracker: Redesigning Performance Analysis Tools for Machine Learning; A Marauder's Map of Security and Privacy in Machine Learning: An overview of current and future research directions for making machine learning secure and private; The Security of Machine Learning

Machine Learning Attacks‡



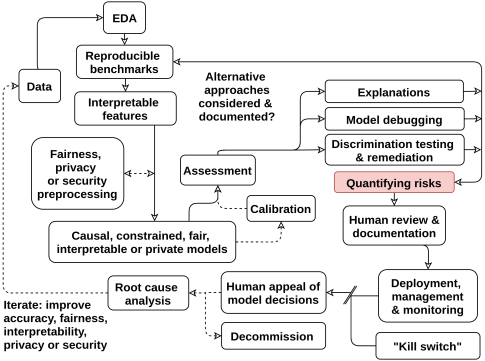
‡See https://github.com/jphall663/secure_ML_ideas for full size image and more information.

Post-hoc Disparate Impact Assessment and Remediation



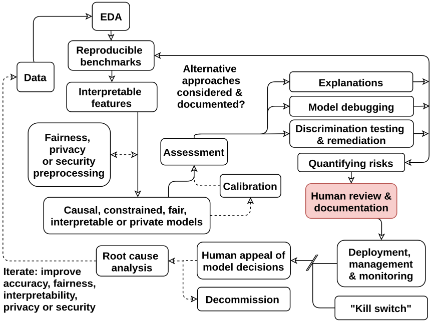
- Social bias testing should include group fairness tests and should attempt to consider individual fairness.
- OSS: aequitas, IBM AIF360, themis
- References: Fairness Through Awareness; Decision Theory for Discrimination-aware Classification; Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact

Quantify and Plan for Risk



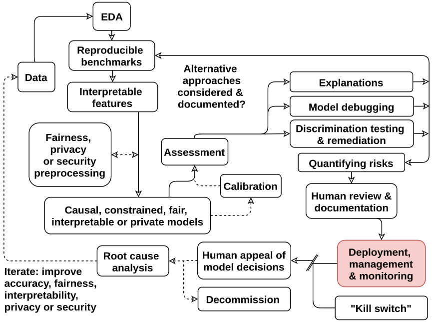
Your model will be wrong. Stake-holders need to understand and be prepared for the human and financial costs of these wrong decisions.

Human Review and Documentation



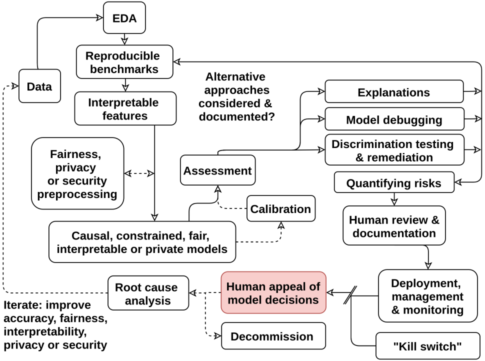
- Reference: Model Cards for Model Reporting
- Documentation of considered alternative approaches typically necessary for compliance.

Deployment, Management and Monitoring



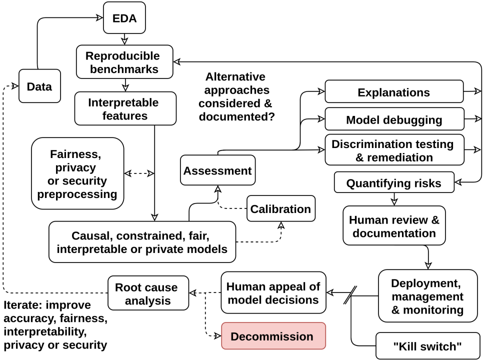
- Monitor models for accuracy, disparate impact, privacy violations or security vulnerabilities in real-time; track model and data lineage.
- OSS: mlflow, modeldb, awesome-machine-learning-ops metalist
- Reference: Model DB: A System for Machine Learning Model Management

Human Appeal



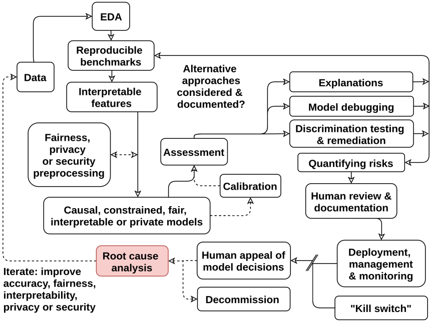
Very important, may require custom implementation for each deployment environment? Related problems exist *today*.

Decommission Model



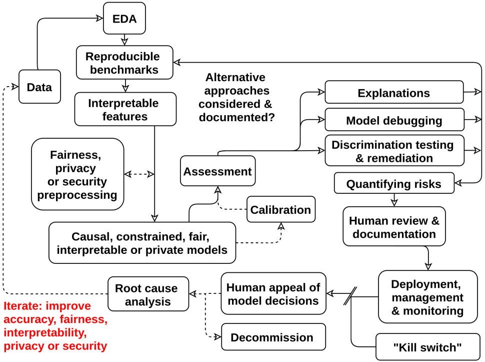
When a model becomes absolutely or relatively inaccurate, unfair, or insecure it must be taken out of service, but saved in an executable and reproducible manner.

Causality



- Root cause analysis: can root causes be identified, verified? Formalized into model architecture?
- OSS: dowhy, pymc3
- References: The Book of Why: the New Science of Cause and Effect; Probabilistic Programming in Python using PyMC3

Iterate: Use Gained Knowledge to Improve Accuracy, Fairness, Interpretability, Privacy or Security



Improvements, KPIs should not be restricted to accuracy alone.

References

These slides:

https://github.com/jphall663/hc_ml

"Awesome" Machine Learning Interpretability Resource List:

https://github.com/jphall663/awesome-machine-learning-interpretability

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