Responsible Machine Learning

A Blueprint for Human Trust and Understanding in Real-World Machine Learning Systems

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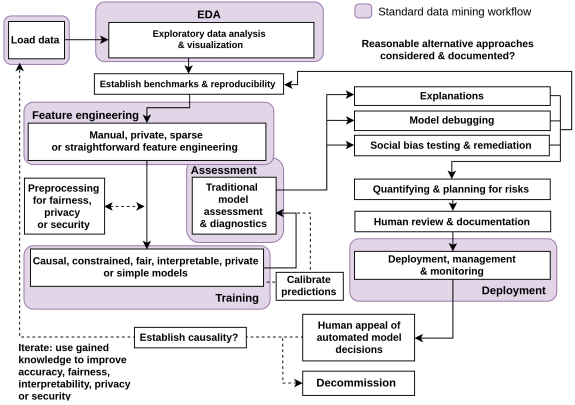
Blueprint

This mid-level technical document provides a basic blueprint for combining the best of 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, human-centered machine learning framework.

Based on guidance from leading researchers and practitioners.

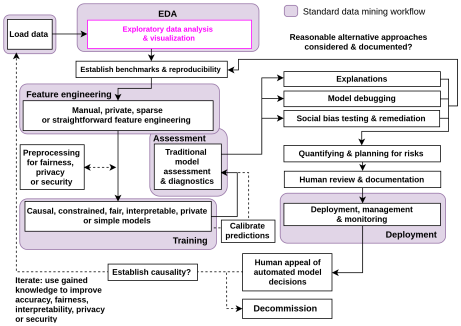
Racism, sexism, cyber-crime and other issues discussed in this document have not been solved, and likely cannot be solved, by technology alone.

Blueprint†



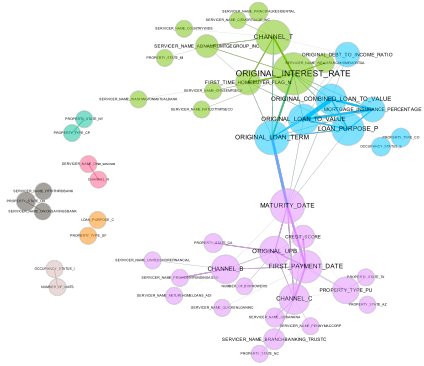
† This blueprint does not address ETL workflows.

EDA and Data Visualization

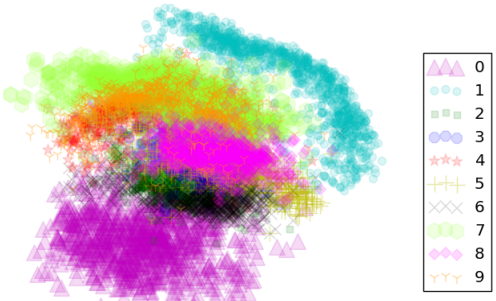


- Know thy data.
- OSS: H2O-3 Aggregator
- References: Visualizing Big Data Outliers through Distributed Aggregation; The Grammar of Graphics

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.

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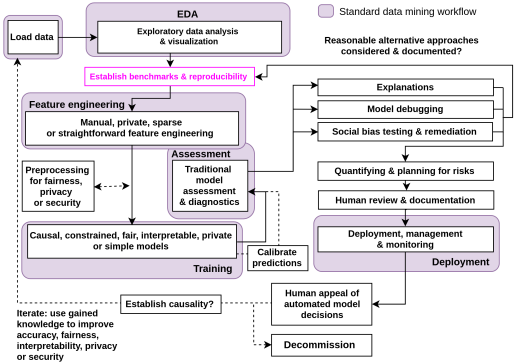
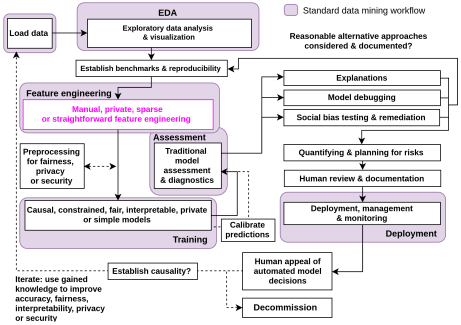
Establish Benchmarks



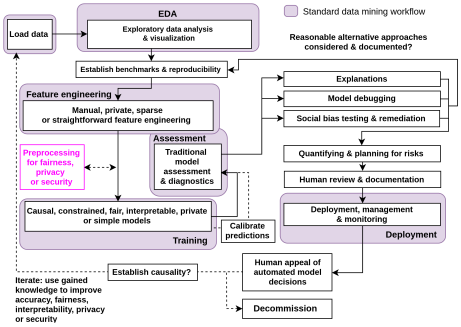
Establishing a benchmark from which to gauge improvements in accuracy, fairness, interpretability or privacy is crucial for good ("data") science and for compliance.

Manual, Private, Sparse or Straightforward Feature Engineering



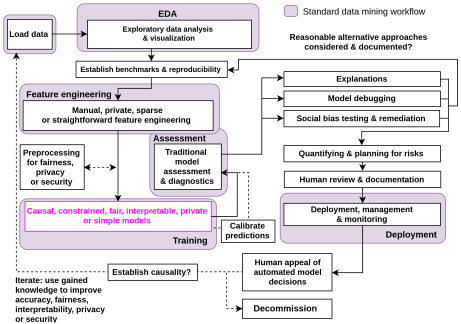
- OSS: Pandas Profiler, Feature Tools
- References: Deep Feature Synthesis: Towards Automating Data Science Endeavors; Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering; t-Closeness: Privacy Beyond k-Anonymity and l-diversity

Preprocessing for Fairness, Privacy or Security



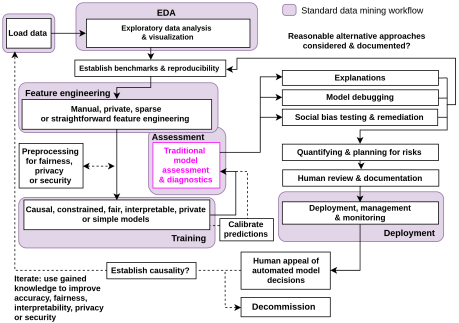
- OSS: IBM AIF360
- References: Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention; Privacy-Preserving Data Mining; Differential Privacy and Machine Learning: A Survey and Review

Constrained, Fair, Interpretable, Private or Simple Models



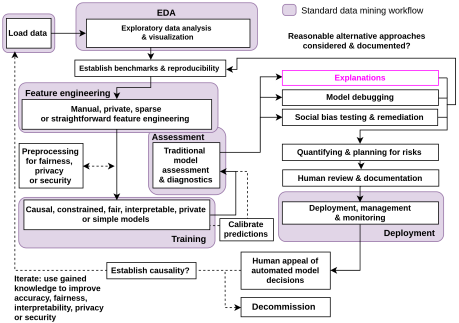
- OSS: Monotonic gradient boosting machines in H2O-3 or XGBoost
- References: Accurate Intelligible Models with Pairwise Interactions (GA2M/EBM); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Private Learning with PATE; Scalable Bayesian Rule Lists (SBRL); Learning Fair Representations (LFR)

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

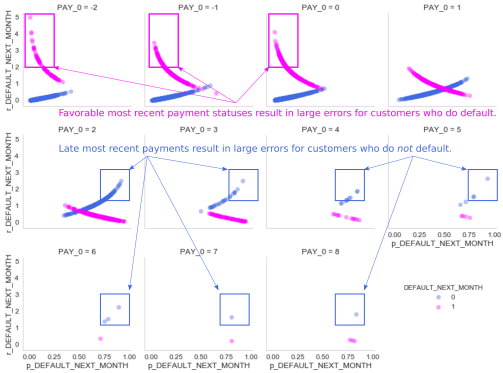


- Explanations enable *understanding* and *appeal* ... *not trust*.
- OSS: lime, shap
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)

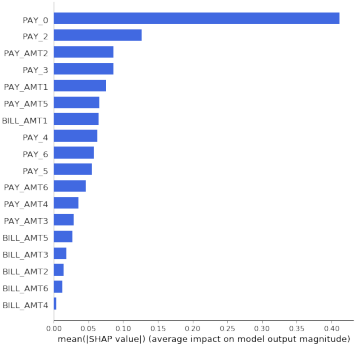
Interlude: The Time–Tested Shapley Value

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*.

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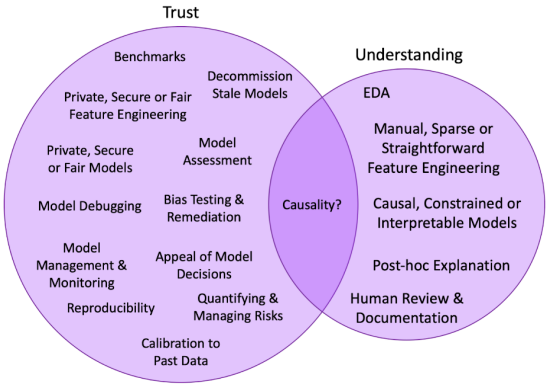
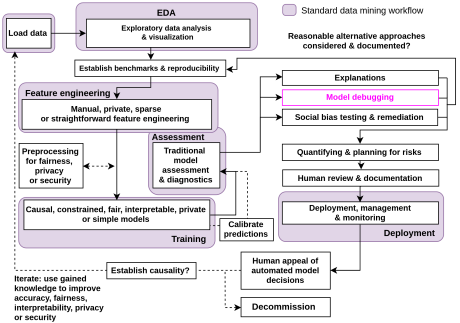
Interlude: Trust and Understanding



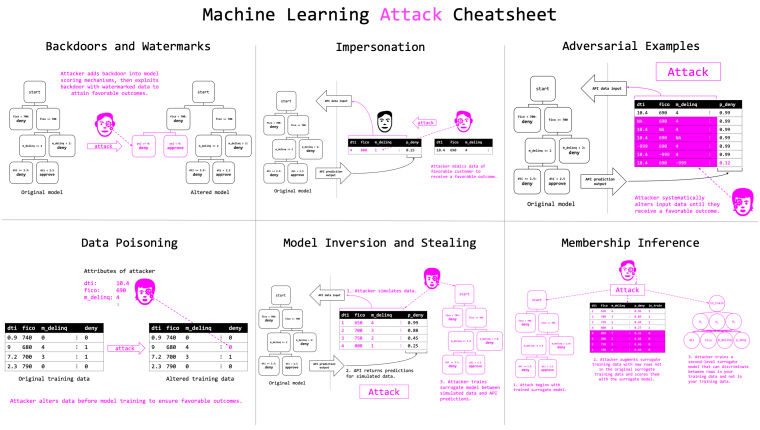
Trust and understanding in machine learning are different but complementary goals, and they are technically feasible *today*.

Model Debugging for Accuracy, Privacy or Security

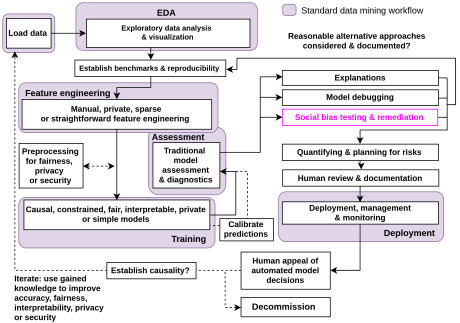


- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and "what-if" analysis.
- OSS: cleverhans, pdpbox, what-if tool
- References: Modeltracker: Redesigning Performance Analysis Tools for Machine Learning; A Marauder's Map of Security and 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



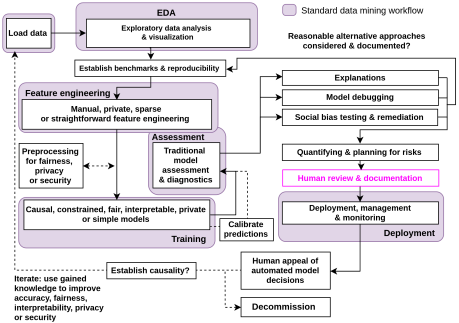
Post-hoc Disparate Impact Assessment and Remediation



- Disparate impact analysis can be performed manually using nearly any model or library.
- OSS: aequitas, IBM AIF360, themis
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact

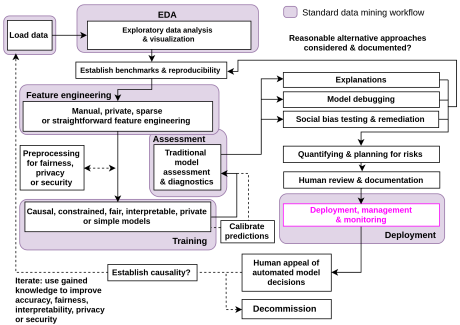
Quantify and Plan for Risk

Human Review and Documentation



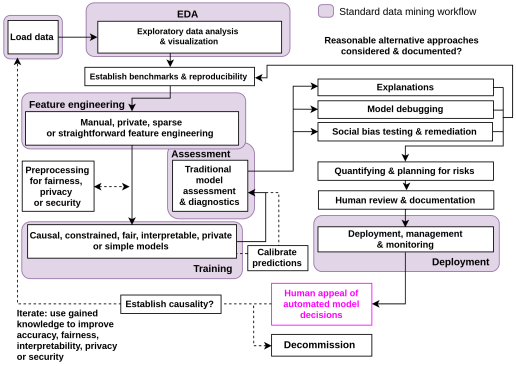
- Reference: Model Cards for Model Reporting
- Documentation of considered alternative approaches typically necessary for compliance.

Deployment, Management and Monitoring



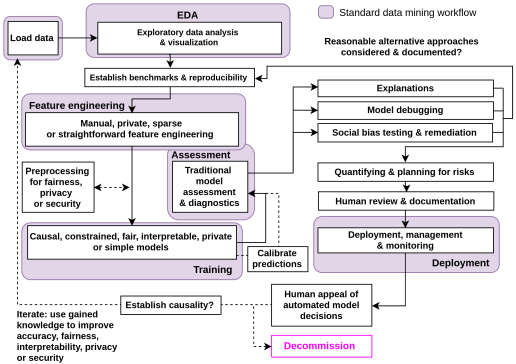
- Monitor models for accuracy, disparate impact, privacy violations or security vulnerabilities in real-time; track model and data lineage.
- OSS: mlflow, modeldb, awesome-machine-learning-ops metalist
- Reference: Model DB: A System for Machine Learning Model Management

Human Appeal



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

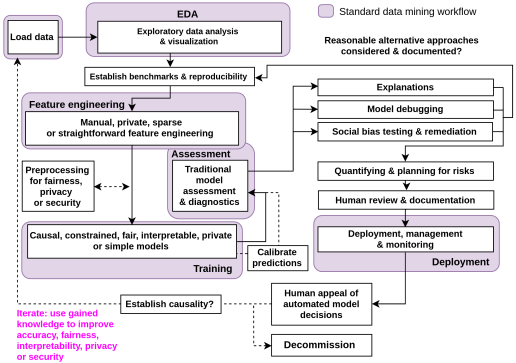
Decommission Model



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.

Root Cause Analysis

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



Improvements, KPIs should not be restricted to accuracy alone.

References

In-Depth Open Source Interpretability Technique Examples:
https://github.com/jphall663/interpretable_machine_learning_with_python

"Awesome" Machine Learning Interpretability Resource List:
https://github.com/jphall663/awesome-machine-learning-interpretability

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