



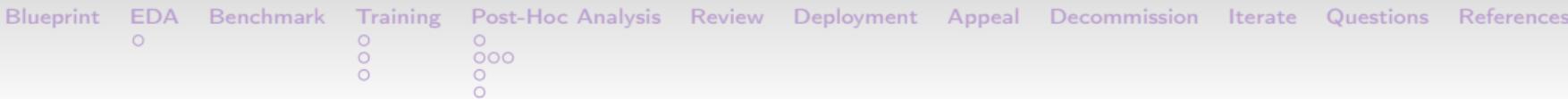
Toward Human-Centered Machine Learning

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Blueprint

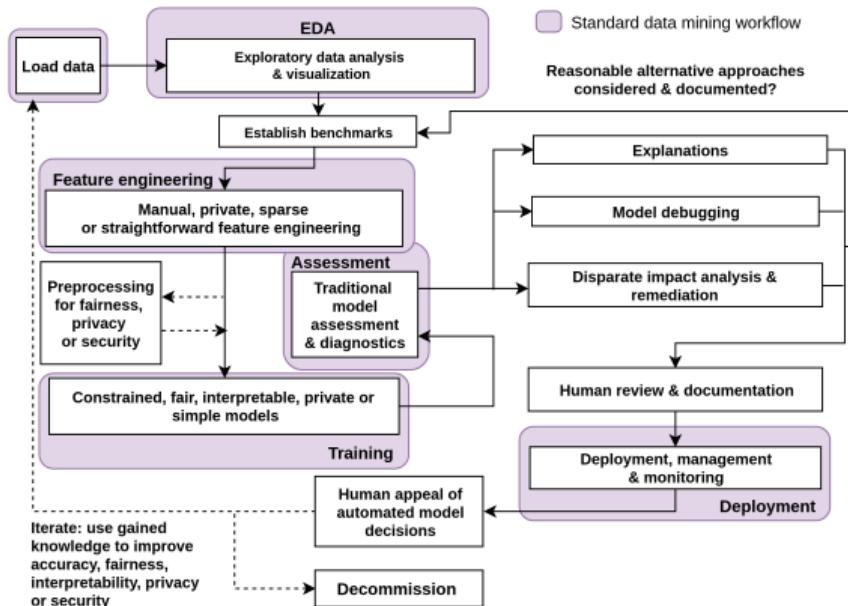
This mid-level technical document provides a basic blueprint for combining the best of AutoML, regulation-compliant predictive modeling, and machine learning research in the sub-disciplines of fairness, interpretable models, post-hoc explanations, privacy and security to create a low-risk, human-centered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

Based on guidance from leading researchers and practitioners.

This document does not seek to redefine *human-centered machine learning* which has a notable presence in the human computer interaction (HCI) literature and is often associated with interactive software for enabling greater human control and understanding of ML processes (Gillies et al., 2016). This document simply seeks to draw attention to mostly newer, but certainly some pre-existing or established, ML techniques that may further the goals of human-centered ML.



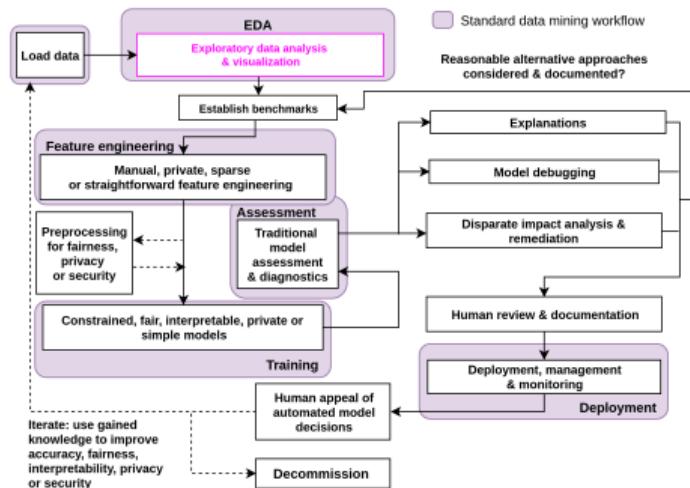
Blueprint[†]



[†]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

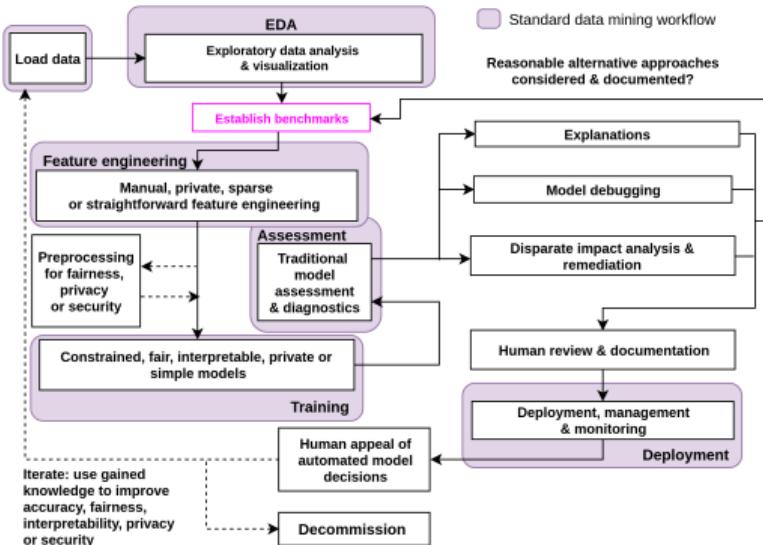


A network graph capturing the Pearson correlation relationships between many *columns* in a lending dataset.

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



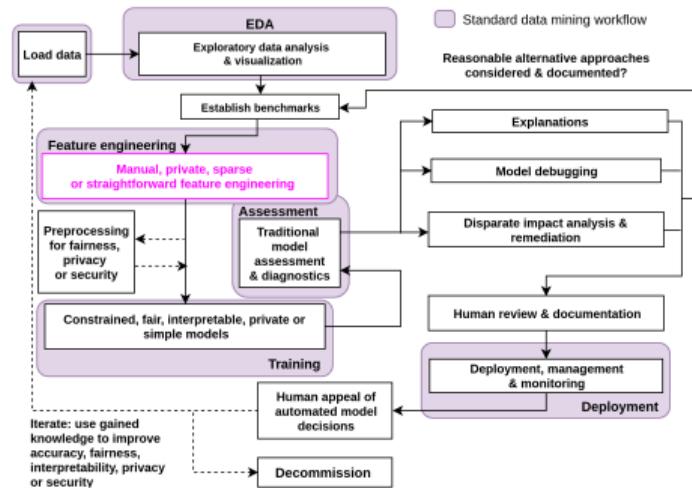
Establish Benchmarks



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



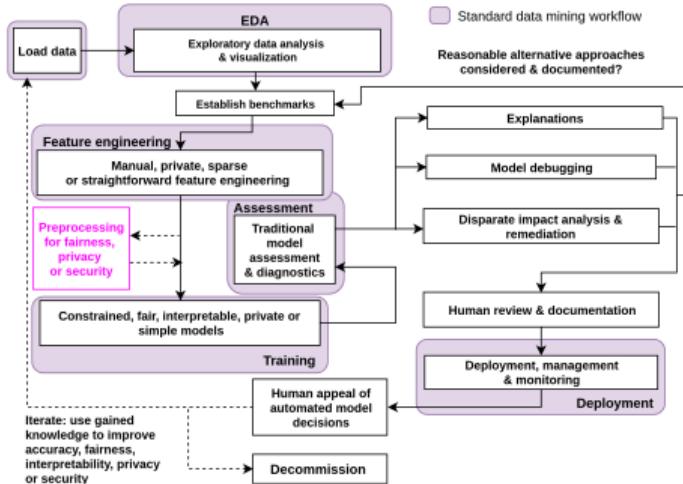
Manual, Private, Sparse or Straightforward Feature Engineering



- 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



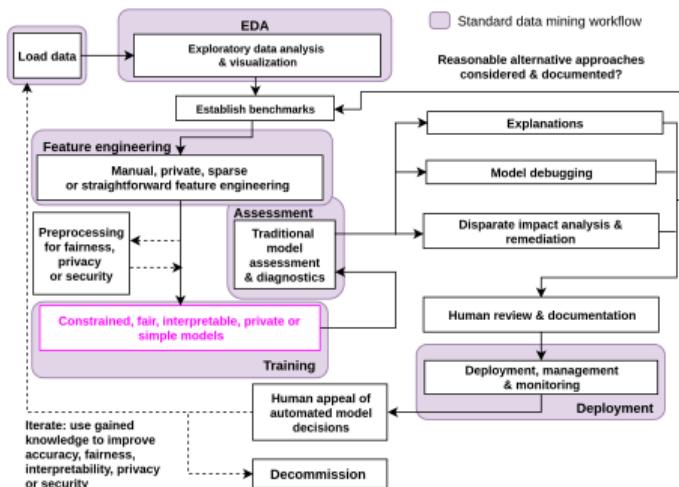
Preprocessing for Fairness, Privacy or Security



- 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



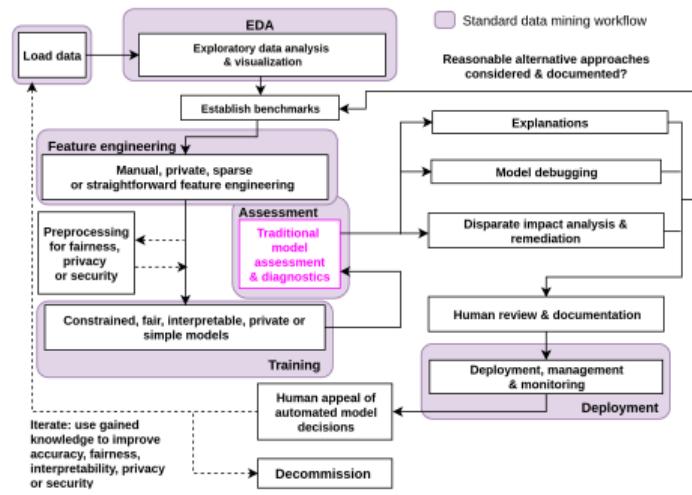
Constrained, Fair, Interpretable, Private or Simple Models



- OSS: Monotonic gradient boosting machines in [H2O-3](#) or [XGBoost](#)
- References: Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Private Learning with PATE; Scalable Bayesian Rule Lists (SBRL); Learning Fair Representations (LFR)



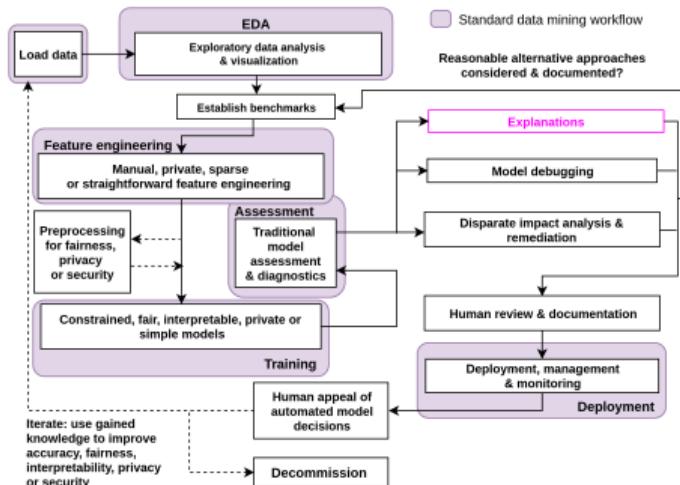
Traditional Model Assessment and Diagnostics



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



Post-hoc Explanations



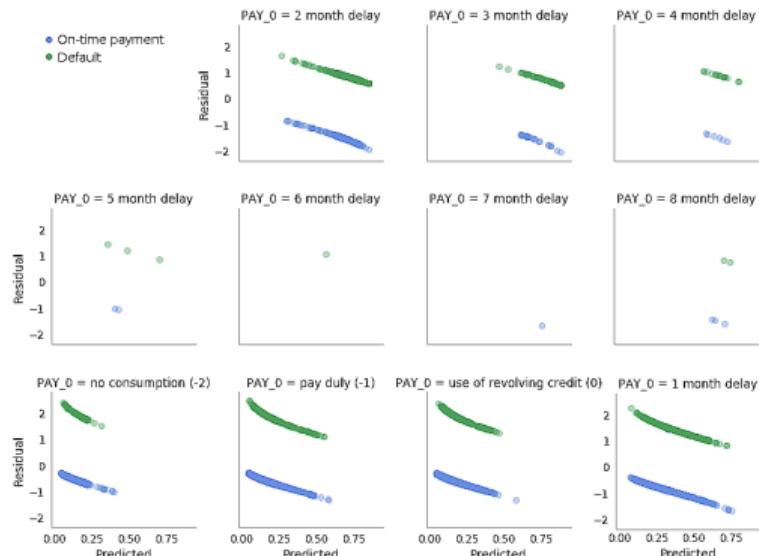
- Explanations enable *understanding* and *appeal* ... *not trust*.
- OSS: [lime](#), [shap](#)
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions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



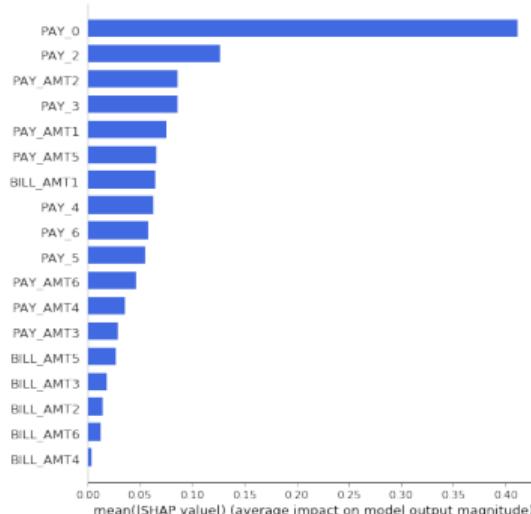
Interlude: The Time-Tested Shapley Value

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.

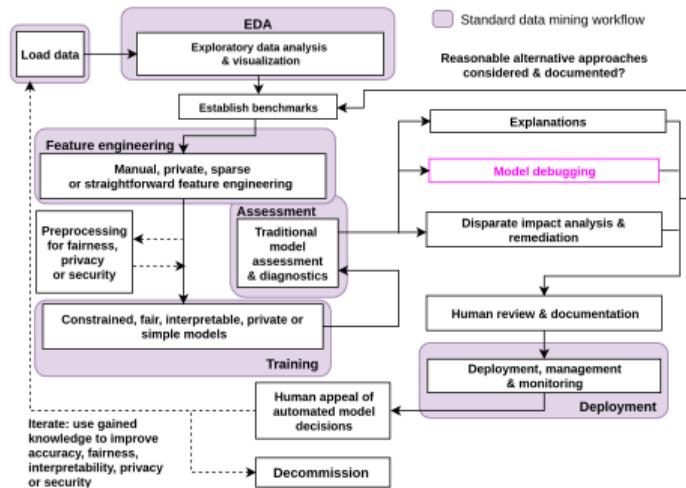


This model over-emphasizes the most important feature, PAY_0.

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



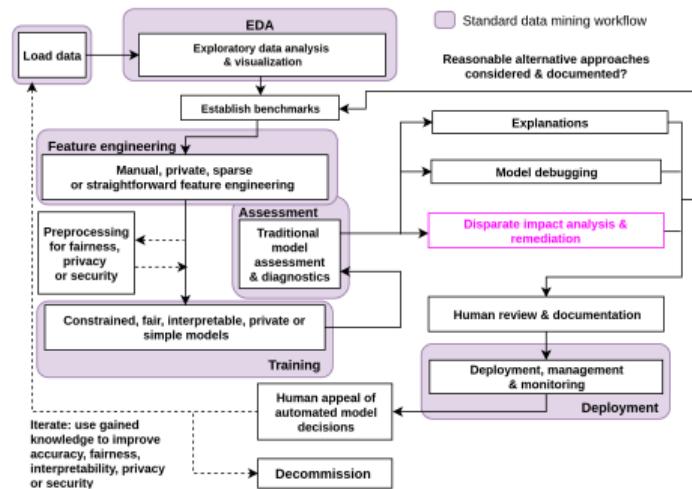
Model Debugging for Accuracy, Privacy or Security



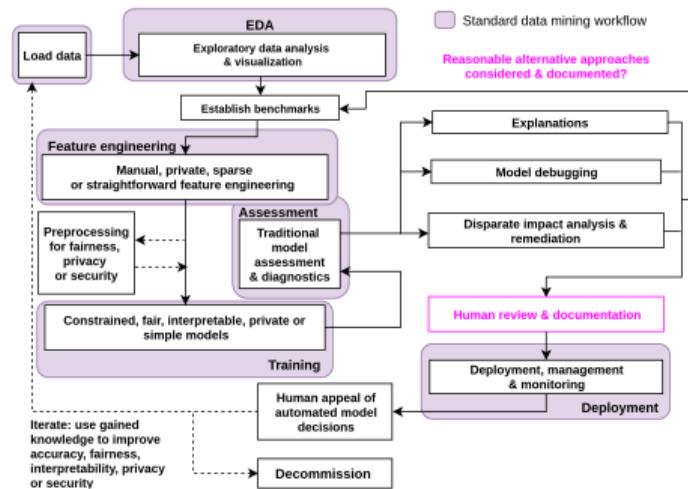
- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and “what-if” analysis.
- OSS: [cleverhans](#), [pdbbox](#), [what-if tool](#)
- References: [Modeltracker: Redesigning Performance Analysis Tools for Machine Learning](#); [A Marauder’s 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](#)



Post-hoc Disparate Impact Assessment and Remediation

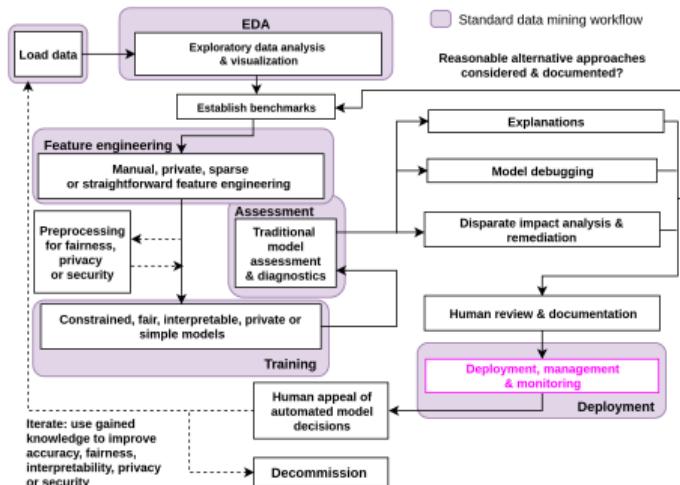


- Disparate impact analysis can be performed manually using nearly any model or library.
- OSS: [aequitas](#), IBM [AIF360](#), [themis](#)
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact



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

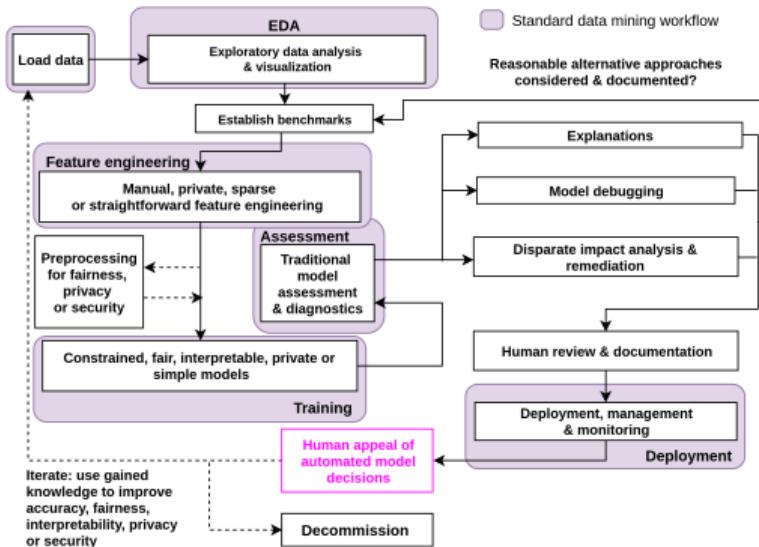
Deployment, Management and Monitoring



- 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



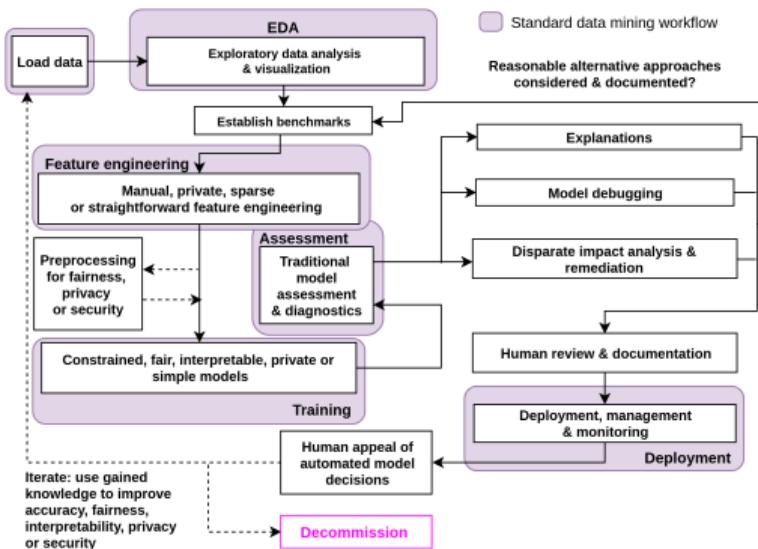
Human Appeal



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



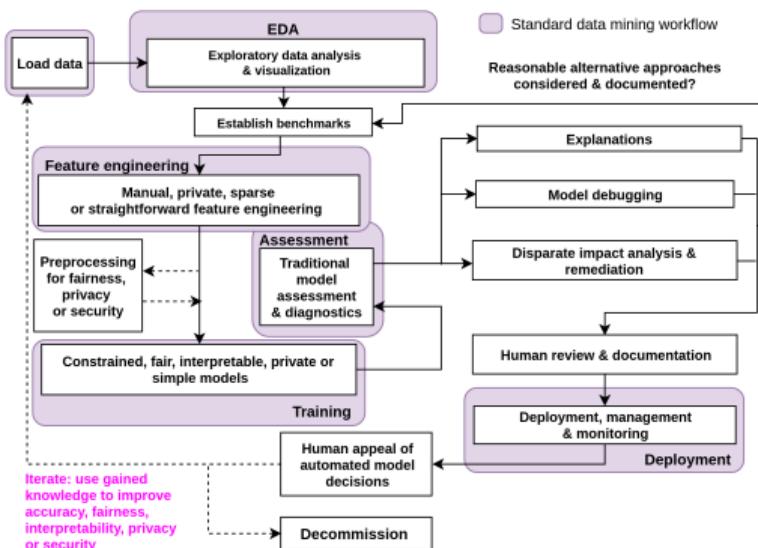
Decommission Model



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.



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



Improvements, KPIs should not be restricted to accuracy alone.



Open Conceptual Questions

- How much automation is appropriate, 100%?
- How to automate learning by iteration, reinforcement learning?
- How to implement human appeals, is it productizable?



References

In-Depth Open Source Interpretability Technique Examples:

https://github.com/jphall1663/interpretable_machine_learning_with_python

"Awesome" Machine Learning Interpretability Resource List:

<https://github.com/jphall1663/awesome-machine-learning-interpretability>



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