Beyond Reason Codes

A Blueprint for Human-Centered, Low-Risk AutoML

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H_2O.ai

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Contents

Blueprint

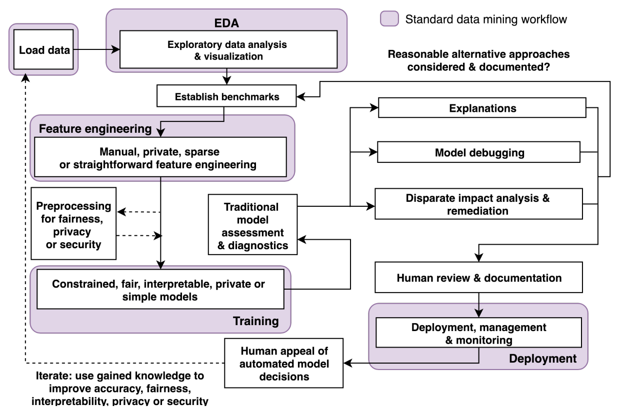
This mid-level technical document provides a basic blueprint for combining the best of AutoML, regulation-compliant predictive modeling, and machine learning research in the sub-disciplines of fairness, interpretable models, post-hoc explanations, privacy and security to create a low-risk, human-centered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

Look for *compliance* mode in Driverless AI soon.*

Guidance from leading researchers and practitioners.

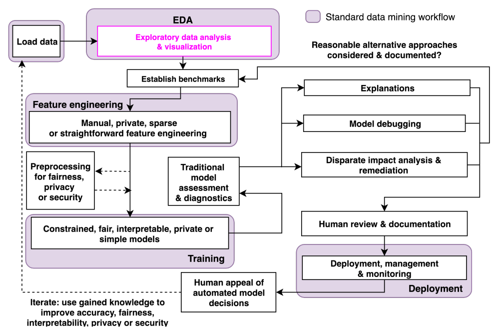
* This presentation or associated materials are not legal compliance advice.

Blueprint[†]



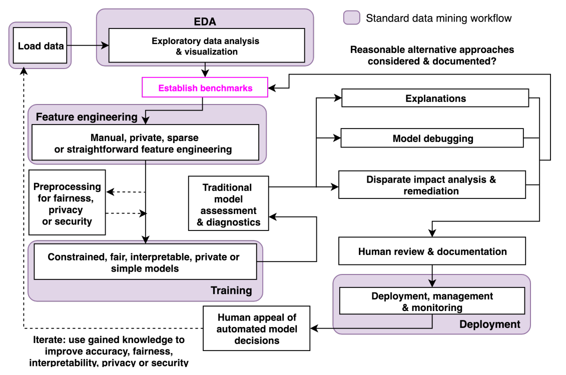
[†] This blueprint does not address ETL workflows.

EDA and Data Visualization



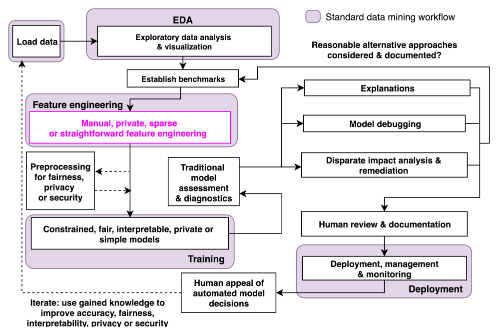
- Know thy data.
- **Automation** implemented in Driverless AI as AutoViz.
- OSS: H2O-3 Aggregator
- References: Visualizing Big Data Outliers through Distributed Aggregation; The Grammar of Graphics

Establish Benchmarks



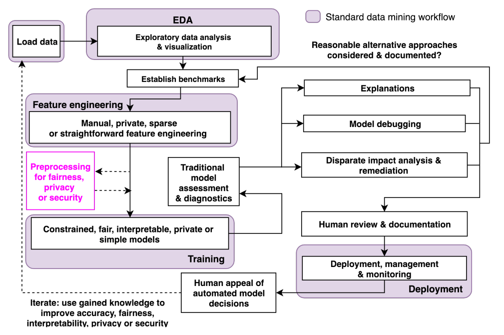
Establishing a benchmark from which to gauge improvements in accuracy, fairness, interpretability or privacy is crucial for good ("data") science and for compliance.

Manual, Private, Sparse or Straightforward Feature Engineering



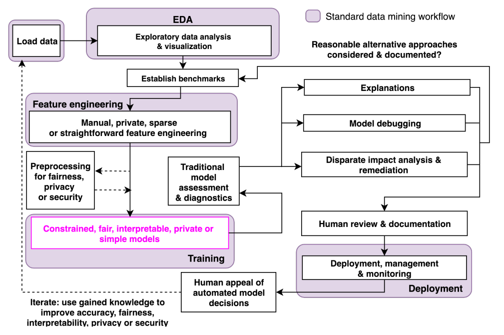
- **Automation** implemented in Driverless AI as high-interpretability transformers.
- OSS: Pandas Profiler, Feature Tools
- References: Deep Feature Synthesis: Towards Automating Data Science Endeavors; Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering

Preprocessing for Fairness, Privacy or Security



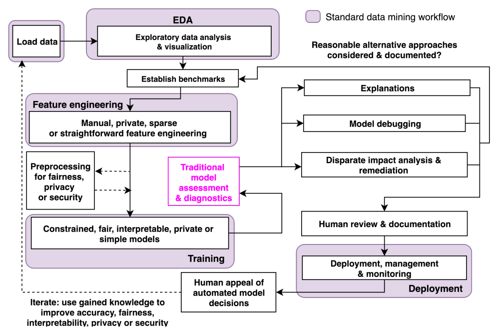
- OSS: IBM AI360
- References: Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention; Privacy-Preserving Data Mining
- **Roadmap items for H2O.ai MLI.**

Constrained, Fair, Interpretable, Private or Simple Models



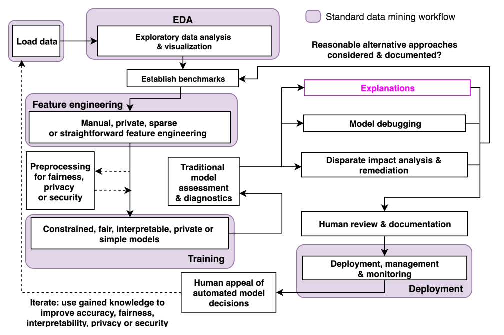
- **Automation** implemented in Driverless AI as GLM, RuleFit, Monotonic GBM.
- References: Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Bayesian Rule Lists (SBRL)
- **LIME-SUP, SBRL, XNN are roadmap items for H2O.ai MLI.**

Traditional Model Assessment and Diagnostics



- Residual analysis, Q-Q plots, AUC and lift curves confirm model is accurate and meets assumption criteria.
- Implemented as model diagnostics in Driverless AI.

Post-hoc Explanations

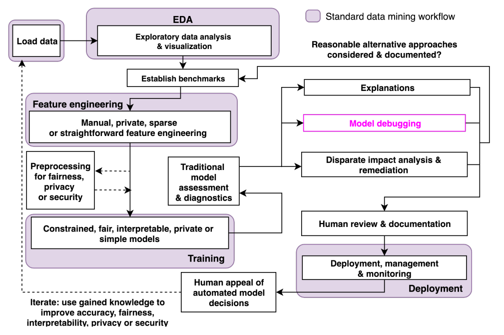


- LIME, Tree SHAP implemented in Driverless AI.
- OSS: lime, shap
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)
- Tree SHAP is roadmap for H2O-3; **Explanations for unstructured data are roadmap for H2O.ai MLI.**

Interlude: The Time–Tested Shapley Value

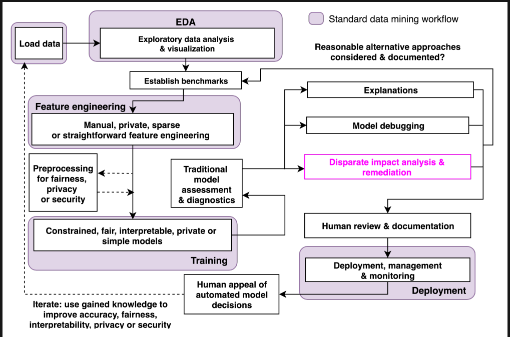
1. **In the beginning**: A Value for N-Person Games, 1953
2. **Nobel-worthy contributions**: The Shapley Value: Essays in Honor of Lloyd S. Shapley, 1988
3. **Shapley regression**: Analysis of Regression in Game Theory Approach, 2001
4. **First reference in ML?** Fair Attribution of Functional Contribution 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

Model Debugging for Accuracy, Privacy or Security



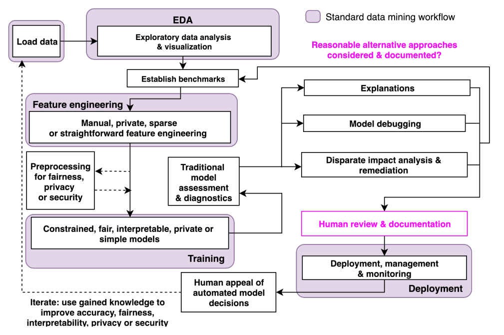
- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and "what-if" analysis.
- OSS: cleverhans, pdpbox, what-if tool
- References: Modeltracker: Redesigning Performance Analysis Tools for Machine Learning; A Marauder's Map of Security and Privacy in Machine Learning: An overview of current and future research directions for making machine learning secure and private
- **Adversarial examples, explanation of residuals, measures of epistemic uncertainty, "what-if" analysis are roadmap items in H2O.ai MLI.**

Post-hoc Disparate Impact Assessment and Remediation



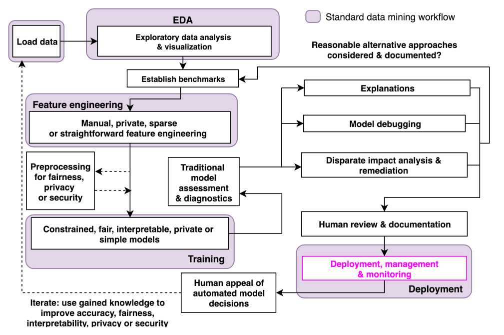
- Disparate impact analysis can be performed manually using Driverless AI or H2O-3.
- OSS: aequitas, IBM AI360, themis
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact
- **Disparate impact analysis and remediation are roadmap items for H2O.ai MLI.**

Human Review and Documentation



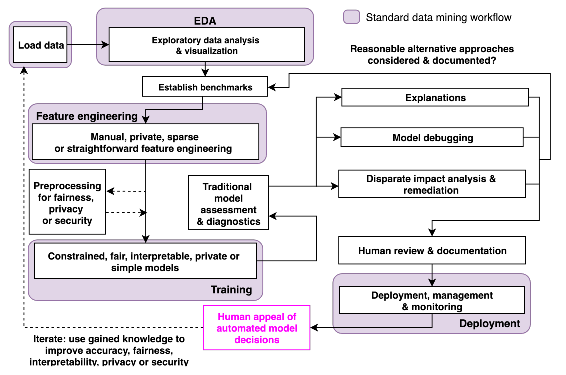
- **Automation** implemented as AutoDoc in Driverless AI.
- **Various fairness, interpretability and model debugging roadmap items to be added to AutoDoc.**
- Documentation of considered alternative approaches typically necessary for compliance.

Deployment, Management and Monitoring



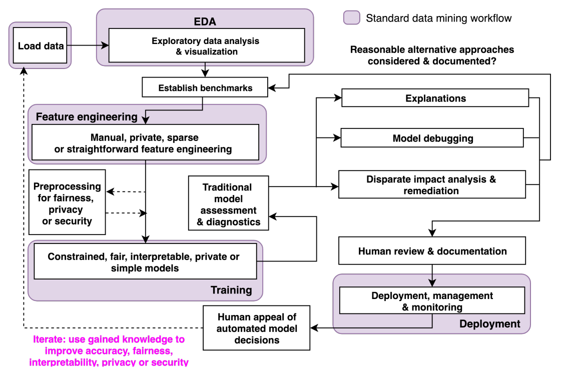
- Monitor models for accuracy, disparate impact, privacy violations or security vulnerabilities in real-time; track model and data lineage.
- OSS: mlflow, modeldb, awesome-machine-learning-ops metalist
- Reference: Model DB: A System for Machine Learning Model Management
- Broader roadmap item for H2O.ai.

Human Appeal



Very important, may require custom implementation for each deployment environment?

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

This presentation:
https://github.com/navdeep-G/gtc-2019/blob/master/main.pdf

Driverless AI API Interpretability Technique Examples:
https://github.com/h2oai/driverlessai-tutorials/tree/master/interpretable_ml

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

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

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