



Beyond Reason Codes

A Blueprint for Human-Centered, Low-Risk AutoML

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H₂O.ai

February 28, 2019

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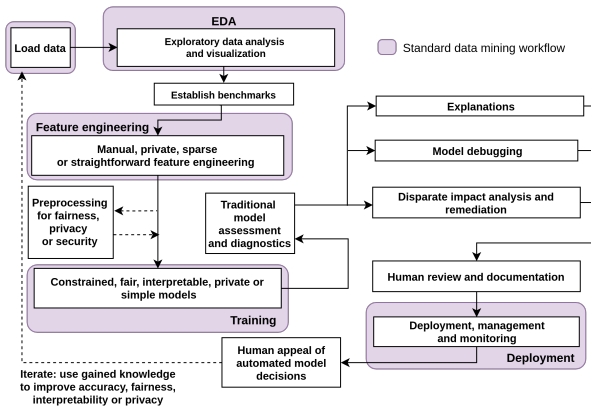
Blueprint

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 and privacy to create a low-risk, human-centered machine learning framework.

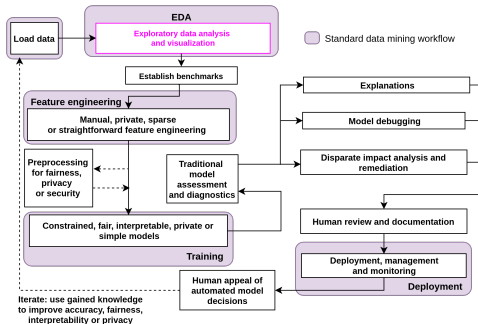
Look for *compliance* mode in Driverless AI soon.

Guidance from leading researchers and practitioners.

Blueprint

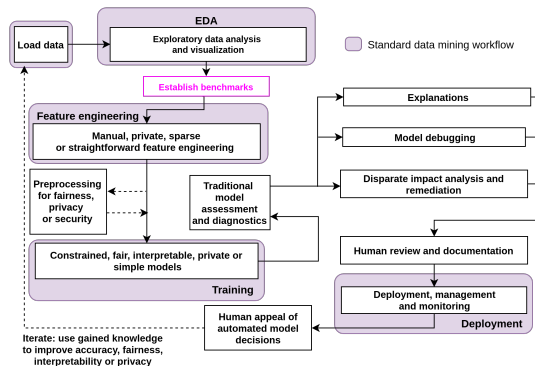


EDA and Data Visualization



- 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

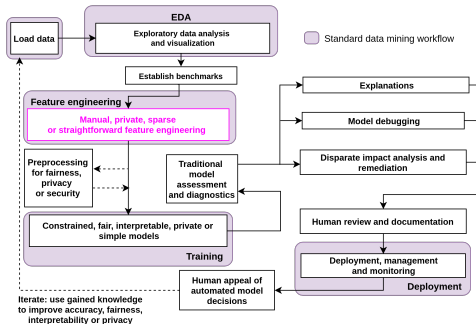
Establish Benchmarks



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

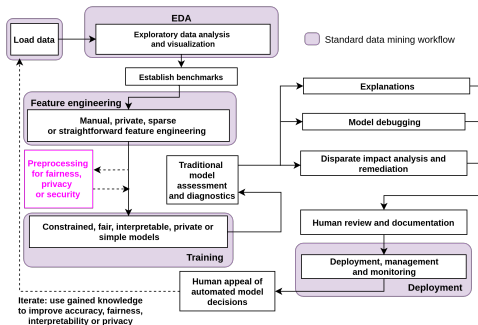


Manual, Private, Sparse or Straightforward Feature Engineering



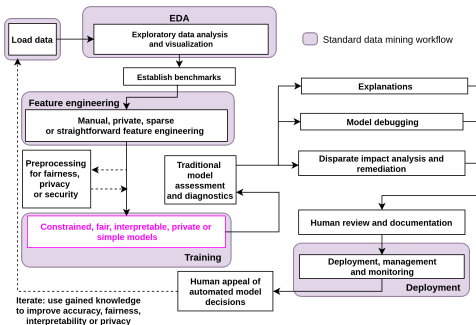
- **Automation** implemented in Driverless AI as high-interpretability transformers.
- OSS: **Pandas Profiler**, **Feature Tools**
- References: Deep Feature Synthesis: Towards Automating Data Science Endeavors; Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering

Preprocessing for Fairness, Privacy or Security



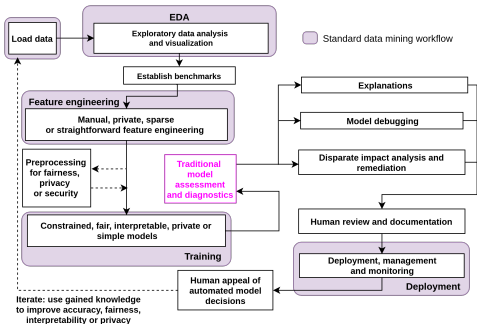
- OSS: IBM [AI360](#)
- References: Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention; Privacy-Preserving Data Mining
- Roadmap items for MLI-2.

Constrained, Fair, Interpretable, Private or Simple Models



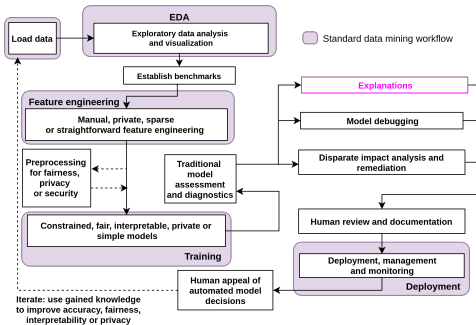
- **Automation** implemented in Driverless AI as GLM, RuleFit, Monotonic GBM.
- References: Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Bayesian Rule Lists (SBRL)
- LIME-SUP, SBRL, XNN are roadmap items for MLI-2.

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

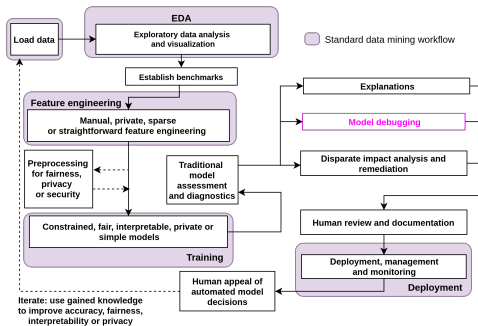


- LIME, Tree SHAP implemented in Driverless AI.
- OSS: [lime](#), [shap](#)
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)
- Tree SHAP is roadmap for H2O-3; Explanations for unstructured data are roadmap for MLI-2.

Interlude: The Time-Tested Shapley Value

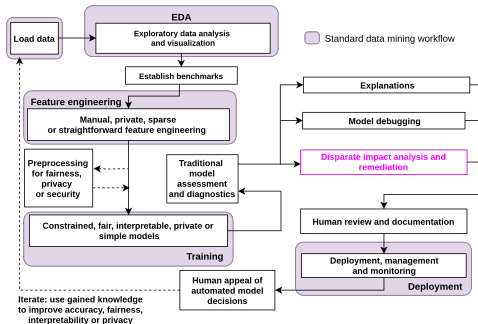
1. **In the beginning:** A Value for N-Person Games, 1953
2. **Nobel-worthy contributions:** The Shapley Value: Essays in Honor of Lloyd S. Shapley, 1988
3. **Shapley regression:** Analysis of Regression in Game Theory Approach, 2001
4. **First reference in ML?** Fair Attribution of Functional Contribution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



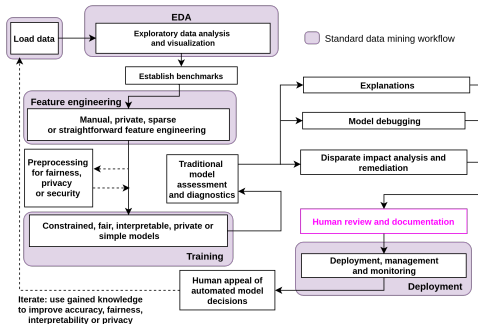
- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and “what-if” analysis.
- OSS: [cleverhans](#), [pdpbox](#), [what-if tool](#)
- Reference: Modeltracker: Redesigning Performance Analysis Tools for Machine Learning
- **Adversarial examples, explanation of residuals, measures of epistemic uncertainty, “what-if” analysis are roadmap items in MLI-2.**

Post-hoc Disparate Impact Assessment and Remediation



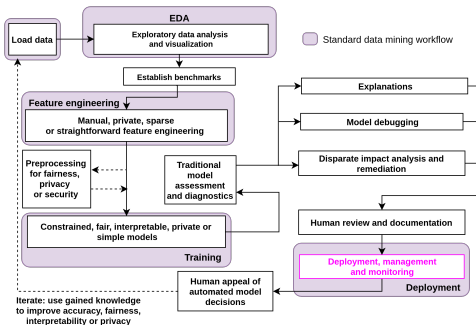
- Disparate impact analysis can be performed manually using Driverless AI or H2O-3.
- OSS: [aequitas](#), IBM [AI360](#), [themis](#)
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact
- **Disparate impact analysis and remediation are roadmap items for MLI-2.**

Human Review and Documentation



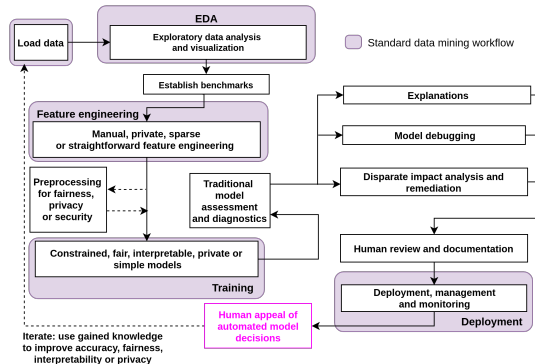
- **Automation** implemented as AutoDoc in Driverless AI.
- **Various fairness, interpretability and model debugging roadmap items to be added to AutoDoc.**

Deployment, Management and Monitoring



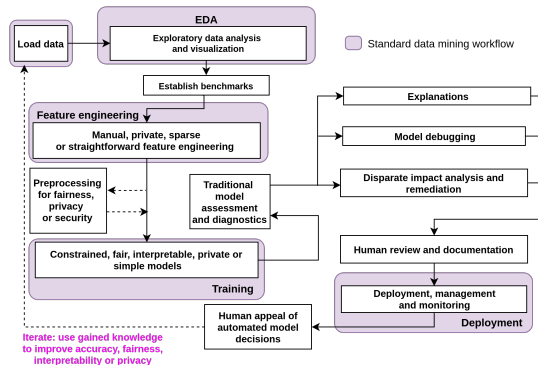
- Monitor models for accuracy, fairness, or privacy in real-time, track model and data lineage.
- OSS: [mlflow](#), [modeldb](#), [awesome-machine-learning-ops](#), [metalist](#)
- Reference: Model DB: A System for Machine Learning Model Management
- **Broader roadmap item for H2O.ai.**

Human Appeal



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

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



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/jphall663/h2oworld_sf_2019/blob/master/main.pdf

Driverless AI API Interpretability Technique Examples:

<https://github.com/h2oai/driverlessai-tutorials>

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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