Beyond Reason Codes

A Blueprint for Human-Centered, Low-Risk AutoML

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H_2O.ai

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Contents

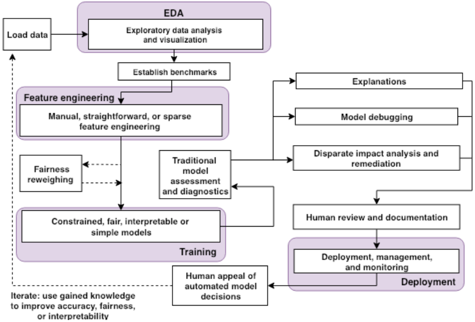
Blueprint

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 interpretable models, fairness, and post-hoc explanations to create a low-risk, human-centered machine learning framework.

Look for *compliance* mode in Driverless AI soon.

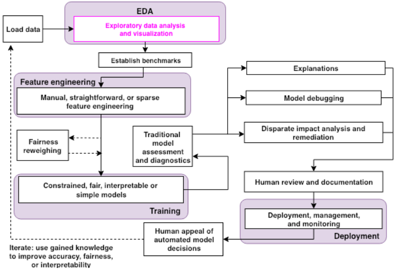
Guidance from leading researchers and practitioners.

Blueprint



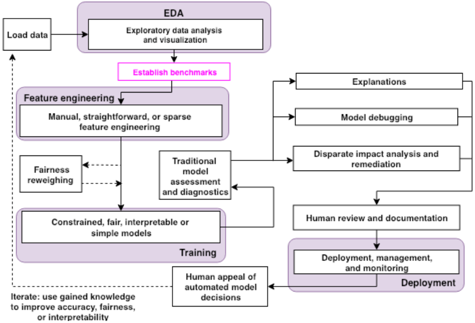
EDA
Load data
Exploratory data analysis and visualization
Establish benchmarks
Feature engineering
Manual, straightforward, or sparse feature engineering
Fairness reweighing
Traditional model assessment and diagnostics
Explanations
Model debugging
Disparate impact analysis and remediation
Human review and documentation
Constrained, fair, interpretable or simple models
Training
Deployment, management, and monitoring
Deployment
Human appeal of automated model decisions
Iterate: use gained knowledge to improve accuracy, fairness, or interpretability

EDA and Data Visualization



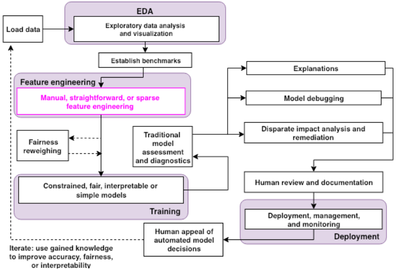
- Know thy data.
- **Automation** implemented in Driverless AI as AutoViz.
- OSS: H2O-3 Aggregator
- References: Visualizing Big Data Outliers through Distributed Aggregation; The Grammar of Graphics

Establish Benchmarks



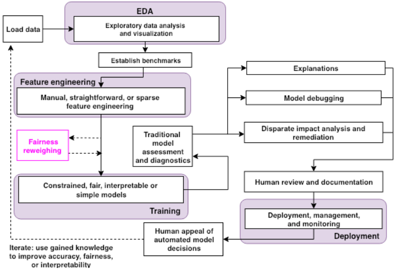
Establishing a benchmark from which to gauge improvements in accuracy, fairness, or interpretability is crucial for good ("data") science and compliance.

Manual, Straightforward, or Sparse 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

Fairness Reweighing



- OSS: IBM AI360
- References: Three Naïve Bayes Approaches for Discrimination-free Classification; Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention
- **Roadmap items for MLI-2**.

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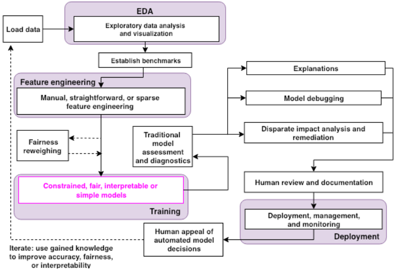
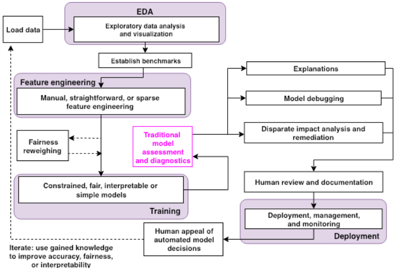
Constrained, Fair, Interpretable or Simple Models



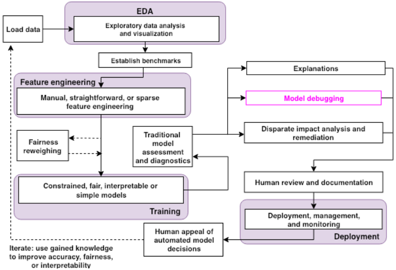
- **Automation** implemented in Driverless AI as GLM, RuleFit, Monotonic GBM.
- References: Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Bayesian Rule Lists (SBRL)
- **LIME-SUP, SBRL, XNN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

Traditional Model Assessment and Diagnostics



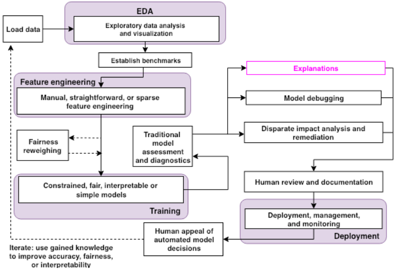
- Residual analysis, Q-Q plots, AUC and lift curves confirm model is accurate and meets assumption criteria.
- Implemented as model diagnostics in Driverless AI.
- **Residual analysis is roadmap item for model diagnostics in Driverless AI.**

Model Debugging



- Understanding and eliminating errors in model predictions by model testing: adversarial examples, "what-if" analysis, random attacks, explanation of residuals.
- OSS: cleverhans, pdpbox, what-if tool
- **Adversarial examples, "what-if" analysis, explanation of residuals, measures of epistemic uncertainty are implemented and roadmap items in MLI-2.**

Post-hoc Explanations

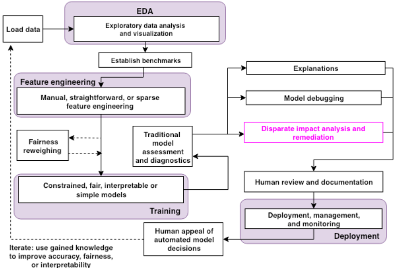


- LIME and Tree SHAP implemented in Driverless AI.
- OSS: lime, shap
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)
- Tree SHAP is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

Interlude: The Time–Tested Shapley Value

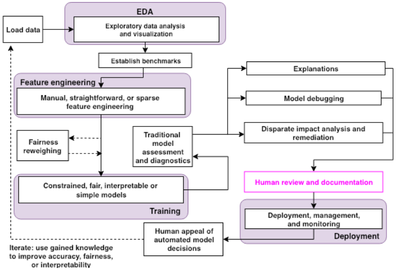
1. **In the beginning**: A Value for N-Person Games, 1953
2. **Nobel-worthy contributions**: The Shapley Value: Essays in Honor of Lloyd S. Shapley, 1988
3. **Shapley regression**: Analysis of Regression in Game Theory Approach, 2001
4. **First reference in ML?** Fair Attribution of Functional Contribution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

Post-hoc Disparate Impact Assessment and Remediation



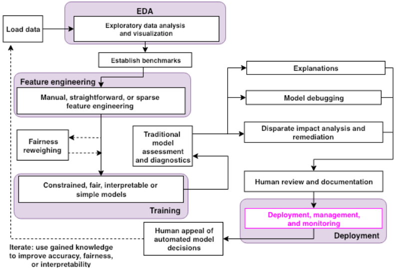
- Disparate impact analysis can be performed manually using Driverless AI or H2O-3.
- OSS: aequitas, IBM AI360, themis
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact
- **Disparate impact analysis and remediation are roadmap items for MLI-2.**

Human Review and Documentation



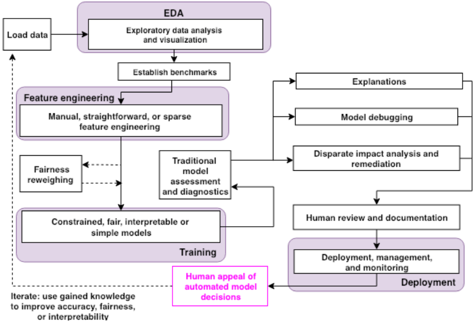
- Implemented as AutoDoc in Driverless AI.
- **Various interpretability and fairness roadmap items to be added to AutoDoc.**

Deployment, Management, and Monitoring



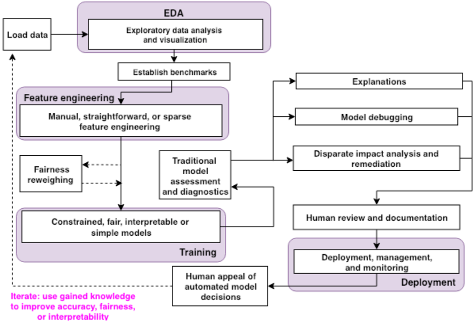
- Monitor models for accuracy and fairness in real-time, track model and data lineage.
- OSS: mlflow, modeldb, awesome-machine-learning-ops metalist
- Reference: Model DB: A System for Machine Learning Model Management
- **Broader roadmap item for H2O.ai.**

Human Appeal



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

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



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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