

# Beyond Reason Codes

## A Blueprint for Human-Centered, Low-Risk AutoML

H2O.ai Machine Learning Interpretability Team

H<sub>2</sub>O.ai

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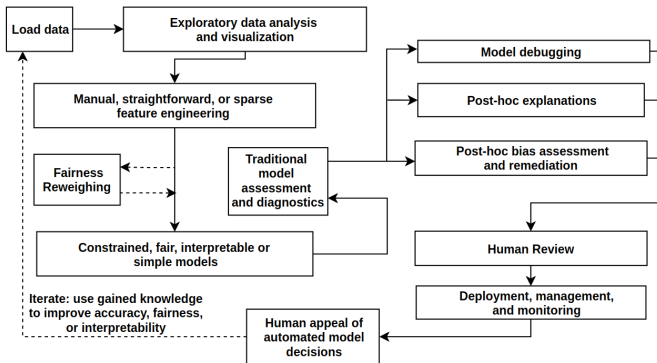
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## Blueprint

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

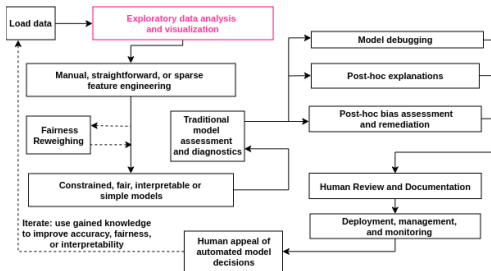
Look for *compliance* mode in Driverless AI soon.

# Blueprint



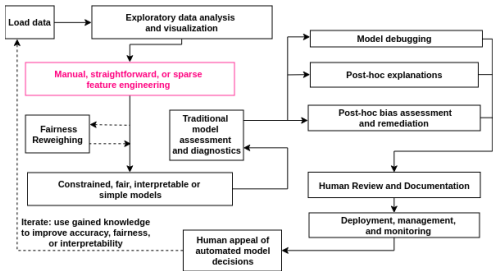


# EDA and Data Visualization



- 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

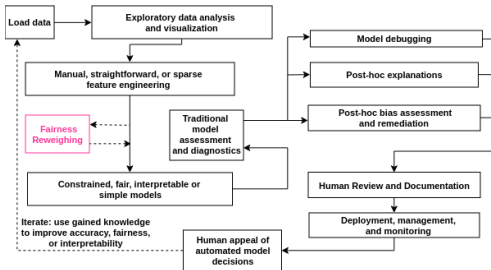
# Manual, Straightforward, or Sparse Feature Engineering



- **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

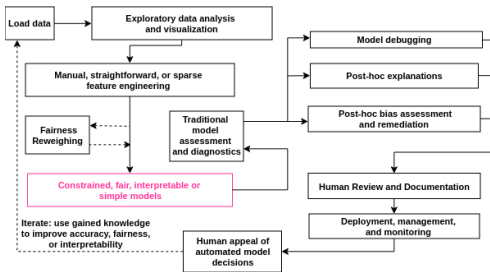


## Fairness Reweighing



- 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.

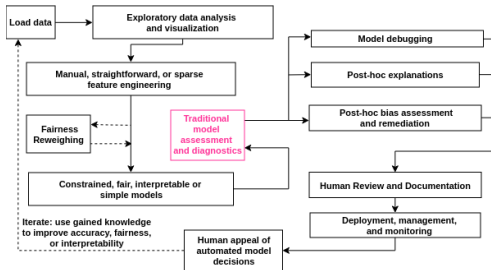
# Constrained, Fair, Interpretable or Simple Models



- **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.

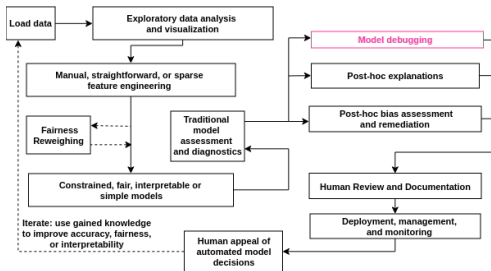


## Traditional Model Assessment and Diagnostics



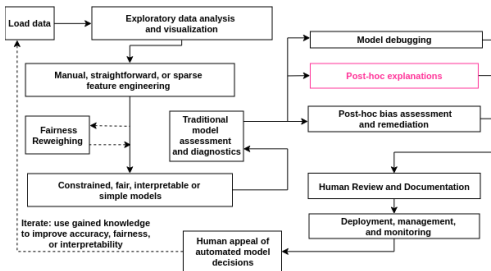
- Residual analysis, Q-Q plots, AUC and lift curves confirm model is accurate and meets assumption criteria.
- Implemented as model diagnostics in Driverless AI.
- Residual analysis is roadmap item for model diagnostics in Driverless AI.

# 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



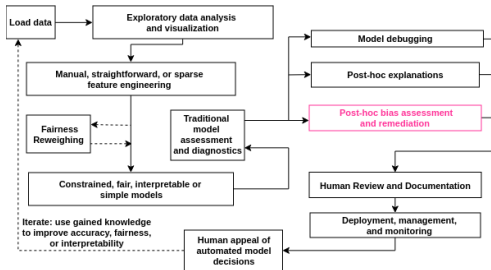
- LIME and Tree SHAP implemented in Driverless AI.
- OSS: [lime](#), [shap](#)
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)
- Tree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



## Interlude: The Time-Tested Shapley Value

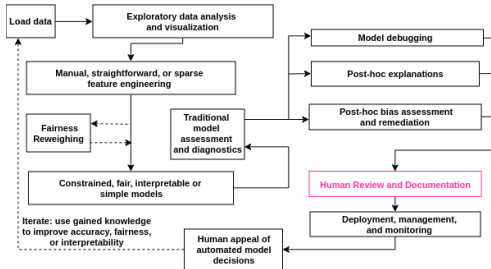
1. **In the beginning:** A Value for N-Person Games, 1953
2. **Nobel-worthy contributions:** The Shapley Value: Essays in Honor of Lloyd S. Shapley, 1988
3. **Shapley regression:** Analysis of Regression in Game Theory Approach, 2001
4. **First reference in ML?** Fair Attribution of Functional Contribution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



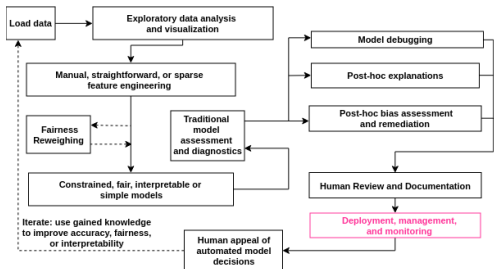
- Disparate impact analysis can be performed manually using Driverless AI or H2O-3.
- OSS: [aequitas](#), IBM [AI360](#), [themis](#)
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact
- **Disparate impact analysis and remediation** are roadmap items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

## Human Review and Documentation



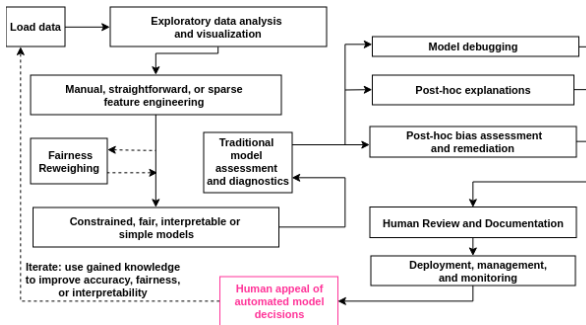
- Implemented as AutoDoc in Driverless AI.
- **Various interpretability and fairness roadmap items to be added to AutoDoc.**

## Deployment, Management, and Monitoring



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

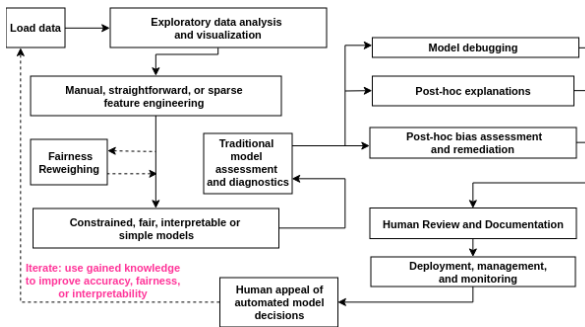
## Human Appeal



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](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](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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