Roadmap for Human-Centered, Low-Risk Machine Learning

Project Name: MLI-2

H2O.ai Machine Learning Interpretability Team

H_2O.ai

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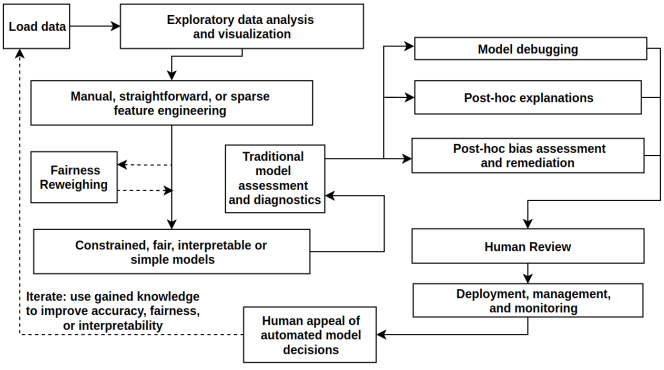
Blueprint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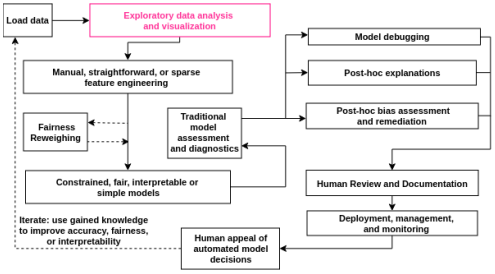
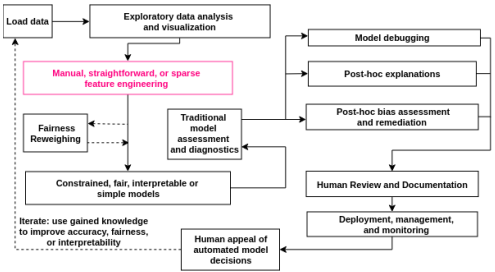
EDA and Data Visualization



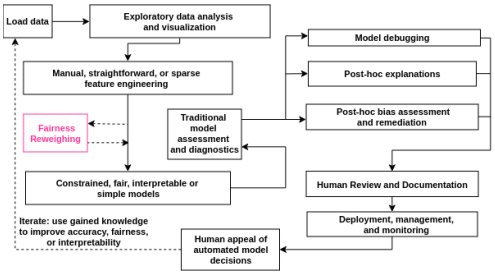
- Implemented in Driverless AI as AutoViz
- OSS: ggplot, seaborn, etc.
- Reference: *The Grammar of Graphics*, Wilkinson, 2006

Manual, Straightforward, or Sparse Feature Engineering



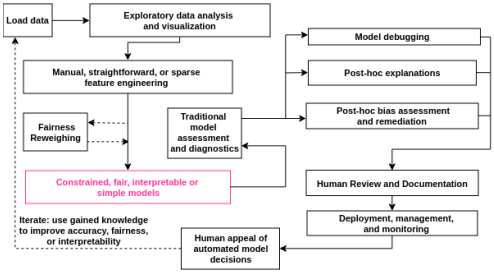
- Implemented in Driverless AI as high-interpretability transformers: frequency, interactions, (monotonic) weight-of-evidence, lags, basics and some Easter eggs in H2O-3
- Decades of custom coding in Hadoop, Python, R, SAS, Spark, SQL, etc.
- Open benchmark of common tools

Fairness Reweighing



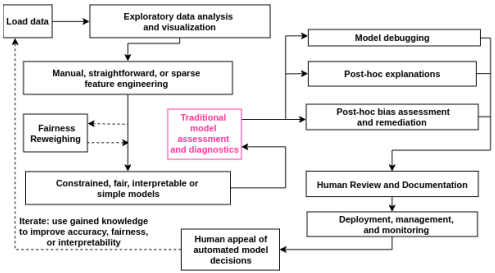
- Newer techniques for reweighing data prior to training to remove disparate impact analysis.
- OSS: IBM AI360
- References: Calders and Verwer, 2010, Kamiran and Calders, 2012,Feldman et al., 2015, Calmon et al., 2017
- Roamap items for MLI-2

Constrained, Fair, Interpretable or Simple Models



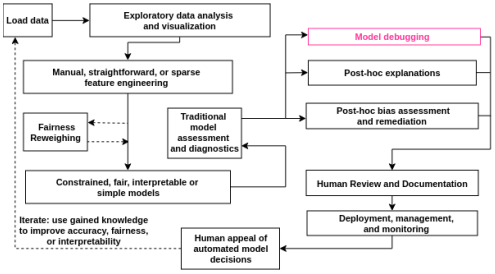
- For best transparency use constrained, simple, or directly interpretable models from the beginning
- Implemented in Driverless AI as GLM, RuleFit, Monotonic GBM, in H2O-3 as GLM, monotonic GBM
- Decision tree, scalable Bayesian rulelist, XNN are roadmap items for MLI-2

Traditional Model Assessment and Diagnostics



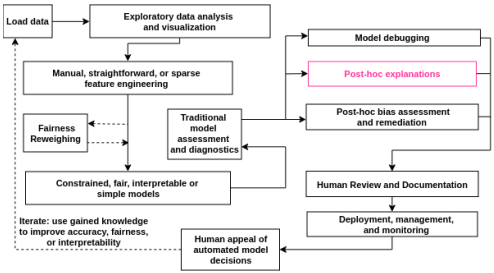
- Confirms model is accurate and meets assumption criteria
- Implemented as model diagnostics in Driverless AI
- Residual analysis is roadmap item for model diagnostics in Driverless AI

Model Debugging



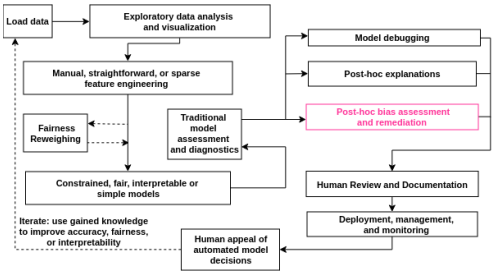
- Newer techniques concerned with understanding and eliminating errors in model predictions; also model testing: "what-if" analysis, random attacks; focus on enhancing *trust*
- "what-if" analysis, explanation of residuals, measures of epistemic uncertainty are roadmap items for MLI-2

Post-hoc Explanations



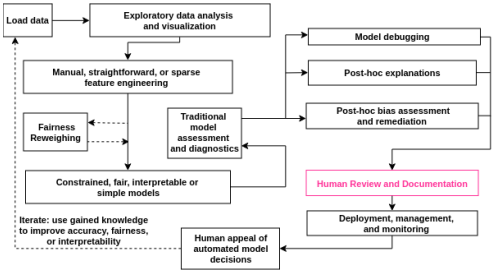
- Explanations enhance *understanding*
- Global feature importance, surrogate decision tree, LIME, LOCO, treeinterpreter and Shapley local feature importance, partial dependence and ICE implemented in current MLI, Friedman's H-statistic implemented in MLI-2
- Shapley is roadmap item for H2O-3; Basic term weights, ALE plots, decision boundary plots are roadmap items for MLI-2

Post-hoc Disparate Impact Assessment and Remediation



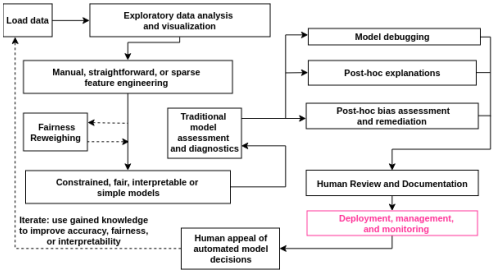
- Disparate Impact Analysis available through code APIs in Driverless AI and H2O-3
- Newer techniques can remove certain types of disparate impact
- Disparate impact remediation is a roadmap item for MLI-2

Human Review and Documentation



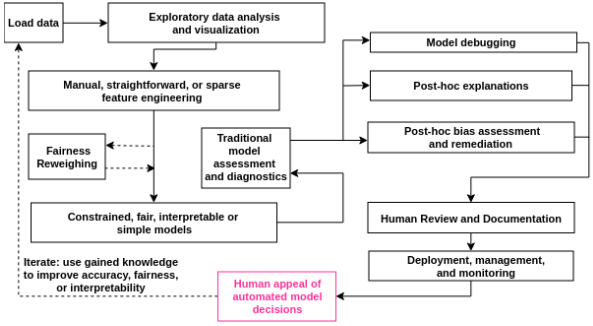
- Implemented as AutoDoc in Driverless AI
- Results from various roadmap items to be added to AutoDoc as appropriate

Deployment, Management, and Monitoring



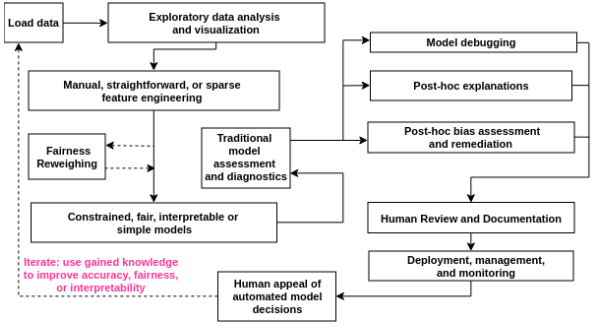
- Monitor models for accuracy and fairness in real-time
- Broader roadmap item for H2O as a company

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



Very important, but probably requires custom implementation for each deployment

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



Improvements, KPIs should not be restricted to accuracy alone

Open Questions

- What is the role for automation?
- How to implement human appeals, is it productizable?

References

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