Toward Human-Centered Machine Learning

Patrick Hall

H_2O.ai

June 1, 2019

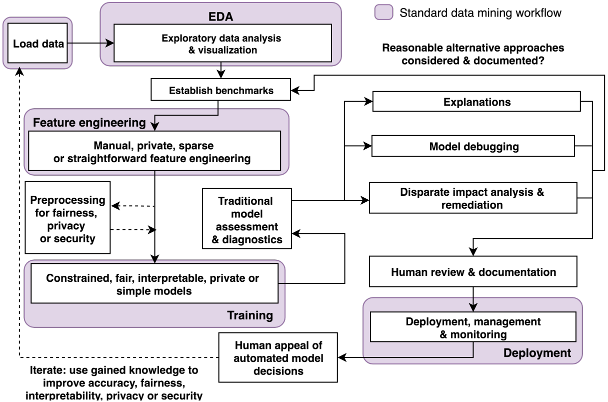
Contents

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.

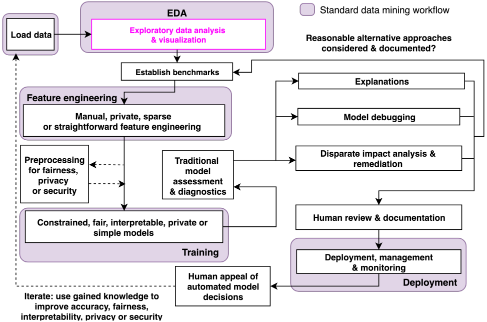
Based on guidance from leading researchers and practitioners.

Blueprint*



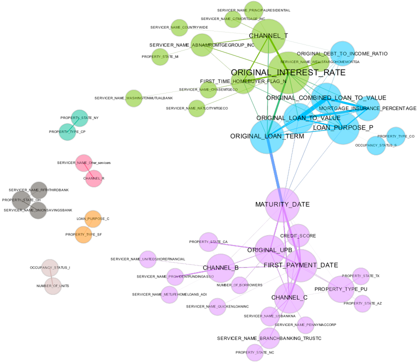
*This blueprint does not address ETL workflows.

EDA and Data Visualization

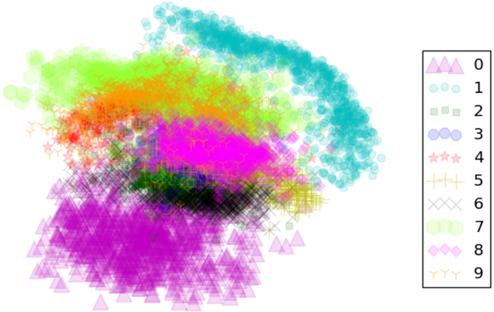


- Know thy data.
- OSS: H2O-3 Aggregator
- References: Visualizing Big Data Outliers through Distributed Aggregation; The Grammar of Graphics

Interlude: My Favorite Visualizations



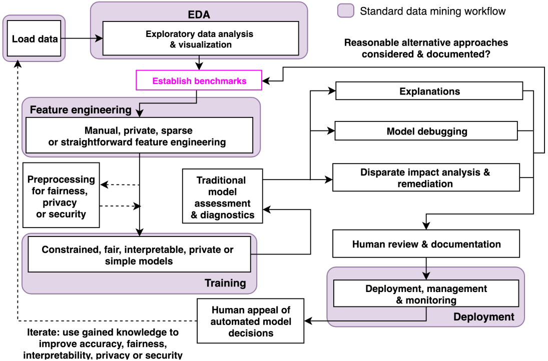
A network graph capturing the Pearson correlation relationships between many *columns* in a lending dataset.



An autoencoder projection the MNIST data. Projections capture sparsity, clusters, hierarchy, and outliers in *rows* of a dataset.

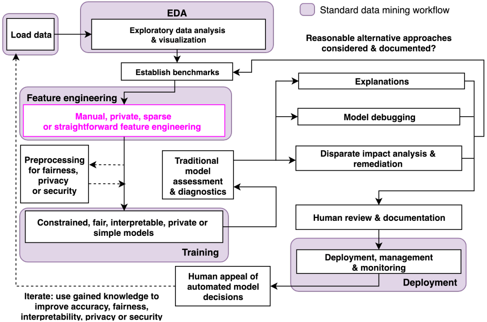
Both of these images capture high-dimensional datasets in just two dimensions.

Establish Benchmarks



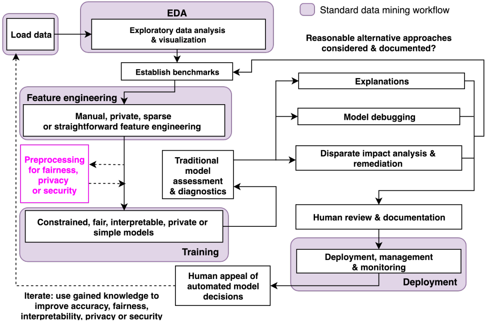
Establishing a benchmark from which to gauge improvements in accuracy, fairness, interpretability or privacy is crucial for good ("data") science and for compliance.

Manual, Private, Sparse or Straightforward Feature Engineering



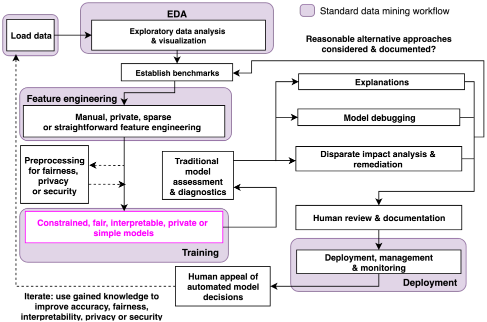
- OSS: Pandas Profiler, Feature Tools
- References: Deep Feature Synthesis: Towards Automating Data Science Endeavors; Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering; t-Closeness: Privacy Beyond *k*-Anonymity and *l*-diversity

Preprocessing for Fairness, Privacy or Security



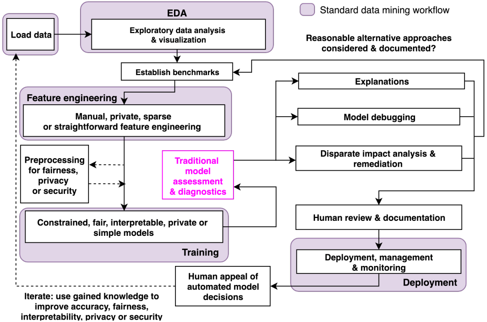
- OSS: IBM AI360
- References: Data Preprocessing Techniques for Classification Without Discrimination; Certifying and Removing Disparate Impact; Optimized Pre-processing for Discrimination Prevention; Privacy-Preserving Data Mining; Differential Privacy and Machine Learning: A Survey and Review

Constrained, Fair, Interpretable, Private or Simple Models



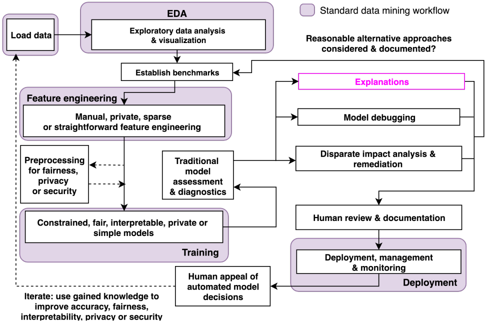
- OSS: Monotonic gradient boosting machines in H2O-3 or XGBoost
- References: Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP); Explainable Neural Networks Based on Additive Index Models (XNN); Scalable Private Learning with PATE; Scalable Bayesian Rule Lists (SBRL); Learning Fair Representations (LFR)

Traditional Model Assessment and Diagnostics



Residual analysis, Q-Q plots, AUC and lift curves etc. confirm model is accurate and meets assumption criteria.

Post-hoc Explanations

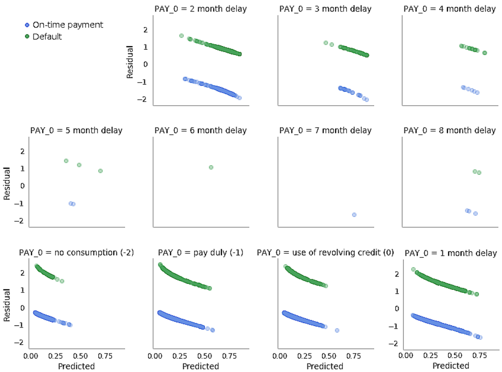


- Explanations enable *understanding* and *appeal* … *not trust*.
- OSS: lime, shap
- References: Why Should I Trust You?: Explaining the Predictions of Any Classifier; A Unified Approach to Interpreting Model Predictions; Please Stop Explaining Black Box Models for High Stakes Decisions (criticism)

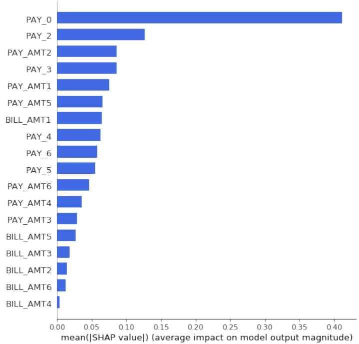
Interlude: The Time–Tested Shapley Value

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

Interlude: Explaining Why Not to Trust



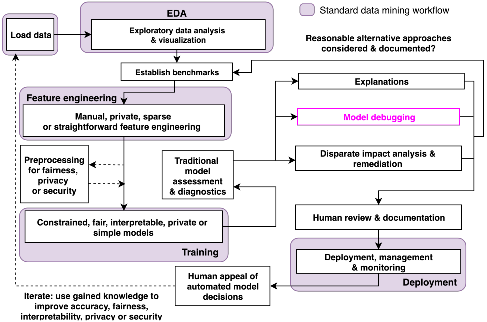
These residuals show a problematic pattern in predictions related to the most important feature, `PAY_0`.



This model over-emphasizes the most important feature, `PAY_0`.

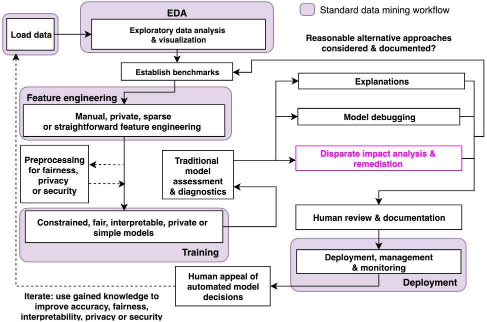
While this model is *explainable*, it's probably not *trustworthy*.

Model Debugging for Accuracy, Privacy or Security



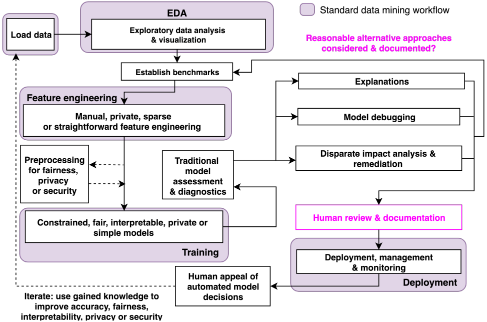
- Eliminating errors in model predictions by testing: adversarial examples, explanation of residuals, random attacks and "what-if" analysis.
- OSS: cleverhans, pdpbox, what-if tool
- References: Modeltracker: Redesigning Performance Analysis Tools for Machine Learning; A Marauder's Map of Security and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

Post-hoc Disparate Impact Assessment and Remediation



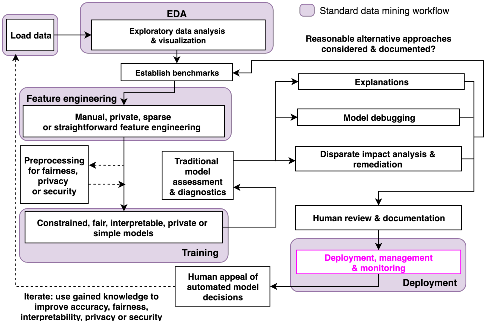
- Disparate impact analysis can be performed manually using nearly any model or library.
- OSS: aequitas, IBM AI360, themis
- References: Equality of Opportunity in Supervised Learning; Certifying and Removing Disparate Impact

Human Review and Documentation



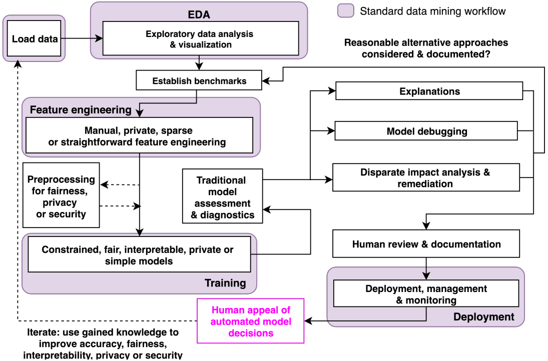
- Reference: Model Cards for Model Reporting
- Documentation of considered alternative approaches typically necessary for compliance.

Deployment, Management and Monitoring



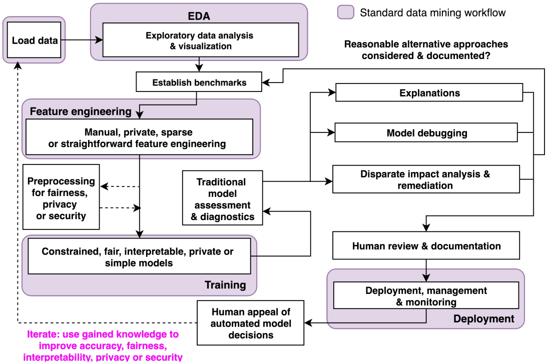
- Monitor models for accuracy, disparate impact, privacy violations or security vulnerabilities in real-time; track model and data lineage.
- OSS: mlflow, modeldb, awesome-machine-learning-ops metalist
- Reference: Model DB: A System for Machine Learning Model Management

Human Appeal



Very important, may require custom implementation for each deployment environment? Related problems exist *today*.

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

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

References

Agrawal, Rakesh and Ramakrishnan Srikant (2000). "Privacy-Preserving Data Mining." In: *ACM Sigmod Record*. Vol. 29. 2. URL: http://alme1.almaden.ibm.com/cs/projects/iis/hdb/Publications/papers/sigmod00_privacy.pdf. ACM, pp. 439–450.

Amershi, Saleema et al. (2015). "Modeltracker: Redesigning Performance Analysis Tools for Machine Learning." In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. URL: https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/amershi.CHI2015.ModelTracker.pdf. ACM, pp. 337–346.

Barreno, Marco et al. (2010). "The Security of Machine Learning." In: *Machine Learning* 81.2. URL: https://people.eecs.berkeley.edu/~adj/publications/paper-files/SecML-MLJ2010.pdf, pp. 121–148.

Calmon, Flavio et al. (2017). "Optimized Pre-processing for Discrimination Prevention." In: *Advances in Neural Information Processing Systems*. URL: http://papers.nips.cc/paper/6988-optimized-pre-processing-for-discrimination-prevention.pdf, pp. 3992–4001.

Feldman, Michael et al. (2015). "Certifying and Removing Disparate Impact." In: *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. URL: https://arxiv.org/pdf/1412.3756.pdf. ACM, pp. 259–268.

References

Hardt, Moritz, Eric Price, Nati Srebro, et al. (2016). "Equality of Opportunity in Supervised Learning." In: *Advances in neural information processing systems*. URL: http://papers.nips.cc/paper/6374-equality-of-opportunity-in-supervised-learning.pdf, pp. 3315–3323.

Hu, Linwei et al. (2018). "Locally Interpretable Models and Effects Based on Supervised Partitioning (LIME-SUP)." In: *arXiv preprint arXiv:1806.00663*. URL: https://arxiv.org/ftp/arxiv/papers/1806/1806.00663.pdf.

Ji, Zhanglong, Zachary C. Lipton, and Charles Elkan (2014). "Differential Privacy and Machine Learning: A Survey and Review." In: *arXiv preprint arXiv:1412.7584*. URL: https://arxiv.org/pdf/1412.7584.pdf.

Kamiran, Faisal and Toon Calders (2012). "Data Preprocessing Techniques for Classification Without Discrimination." In: *Knowledge and Information Systems* 33.1. URL: https://link.springer.com/content/pdf/10.1007/s10115-011-0463-8.pdf, pp. 1–33.

Kanter, James Max, Owen Gillespie, and Kalyan Veeramachaneni (2016). "Label, Segment, Featurize: A Cross Domain Framework for Prediction Engineering." In: *Data Science and Advanced Analytics (DSAA), 2016 IEEE International Conference on*. URL: http://www.jmaxkanter.com/static/papers/DSAA_LSF_2016.pdf. IEEE, pp. 430–439.

References

Kanter, James Max and Kalyan Veeramachaneni (2015). "Deep Feature Synthesis: Towards Automating Data Science Endeavors." In: *Data Science and Advanced Analytics (DSAA), 2015. 36678 2015. IEEE International Conference on*. URL: https://groups.csail.mit.edu/EVO-DesignOpt/groupWebSite/uploads/Site/DSAA_DSM_2015.pdf. IEEE, pp. 1–10.

Keinan, Alon et al. (2004). "Fair Attribution of Functional Contribution in Artificial and Biological Networks." In: *Neural Computation* 16.9. URL: https://www.researchgate.net/profile/Isaac_Meilijson/publication/2474580_Fair_Attribution_of_Functional_Contribution_in_Artificial_and_Biological_Networks/links/09e415146df8289373000000/Fair-Attribution-of-Functional-Contribution-in-Artificial-and-Biological-Networks.pdf, pp. 1887–1915.

Kononenko, Igor et al. (2010). "An Efficient Explanation of Individual Classifications Using Game Theory." In: *Journal of Machine Learning Research* 11.Jan. URL: http://www.jmlr.org/papers/volume11/strumbelj10a/strumbelj10a.pdf, pp. 1–18.

Lipovetsky, Stan and Michael Conklin (2001). "Analysis of Regression in Game Theory Approach." In: *Applied Stochastic Models in Business and Industry* 17.4, pp. 319–330.

References

Lundberg, Scott M., Gabriel G. Erion, and Su-In Lee (2017). "Consistent Individualized Feature Attribution for Tree Ensembles." In: *Proceedings of the 2017 ICML Workshop on Human Interpretability in Machine Learning (WHI 2017)*. Ed. by Been Kim et al. URL: https://openreview.net/pdf?id=ByTKSo-m-. ICML WHI 2017, pp. 15–21.

Lundberg, Scott M and Su-In Lee (2017). "A Unified Approach to Interpreting Model Predictions." In: *Advances in Neural Information Processing Systems 30*. Ed. by I. Guyon et al. URL: http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf. Curran Associates, Inc., pp. 4765–4774.

Mitchell, Margaret et al. (2019). "Model Cards for Model Reporting." In: *Proceedings of the Conference on Fairness, Accountability, and Transparency*. URL: https://arxiv.org/pdf/1810.03993.pdf. ACM, pp. 220–229.

Papernot, Nicolas (2018). "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." In: *Proceedings of the 11th ACM Workshop on Artificial Intelligence and Security*. URL: https://arxiv.org/pdf/1811.01134.pdf. ACM.

Papernot, Nicolas et al. (2018). "Scalable Private Learning with PATE." In: *arXiv preprint arXiv:1802.08908*. URL: https://arxiv.org/pdf/1802.08908.pdf.

References

Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin (2016). "Why Should I Trust You?: Explaining the Predictions of Any Classifier." In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. URL: http://www.kdd.org/kdd2016/papers/files/rfp0573-ribeiroA.pdf. ACM, pp. 1135–1144.

Rudin, Cynthia (2018). "Please Stop Explaining Black Box Models for High Stakes Decisions." In: *arXiv preprint arXiv:1811.10154*. URL: https://arxiv.org/pdf/1811.10154.pdf.

Shapley, Lloyd S (1953). "A Value for N-Person Games." In: *Contributions to the Theory of Games* 2.28. URL: http://www.library.fa.ru/files/Roth2.pdf#page=39, pp. 307–317.

Shapley, Lloyd S, Alvin E Roth, et al. (1988). *The Shapley Value: Essays in Honor of Lloyd S. Shapley*. URL: http://www.library.fa.ru/files/Roth2.pdf. Cambridge University Press.

"t-Closeness: Privacy Beyond *k*-Anonymity and *l*-diversity" (2007). In: *2007 IEEE 23rd International Conference on Data Engineering*. URL:http://www.utdallas.edu/~mxk055100/courses/privacy08f_files/tcloseness.pdf. IEEE, pp. 106–115.

Vartak, Manasi et al. (2016). "Model DB: A System for Machine Learning Model Management." In: *Proceedings of the Workshop on Human-In-the-Loop Data Analytics*. URL: https://www-cs.stanford.edu/~matei/papers/2016/hilda_modeldb.pdf. ACM, p. 14.

References

Vaughan, Joel et al. (2018). "Explainable Neural Networks Based on Additive Index Models." In: *arXiv preprint arXiv:1806.01933*. URL: https://arxiv.org/pdf/1806.01933.pdf.

Wilkinson, Leland (2006). *The Grammar of Graphics*.

— (2018). "Visualizing Big Data Outliers through Distributed Aggregation." In: *IEEE Transactions on Visualization & Computer Graphics*. URL: https://www.cs.uic.edu/~wilkinson/Publications/outliers.pdf.

Yang, Hongyu, Cynthia Rudin, and Margo Seltzer (2017). "Scalable Bayesian Rule Lists." In: *Proceedings of the 34th International Conference on Machine Learning (ICML)*. URL: https://arxiv.org/pdf/1602.08610.pdf.

Zemel, Rich et al. (2013). "Learning Fair Representations." In: *International Conference on Machine Learning*. URL: http://proceedings.mlr.press/v28/zemel13.pdf, pp. 325–333.