Increasing Trust and Understanding in Machine Learning with Model Debugging

©Patrick Hall*

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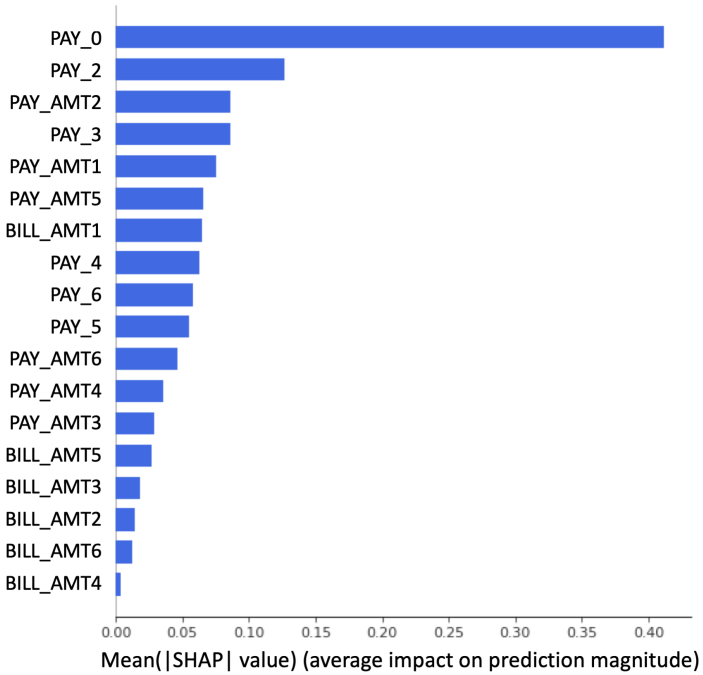
What is Model Debugging?

- Model debugging is an emergent discipline focused on discovering and remediating errors in the internal mechanisms and outputs of machine learning models.†
- Model debugging attempts to test machine learning models like code (because the models are code).
- Model debugging promotes trust directly and enhances interpretability as a side-effect.

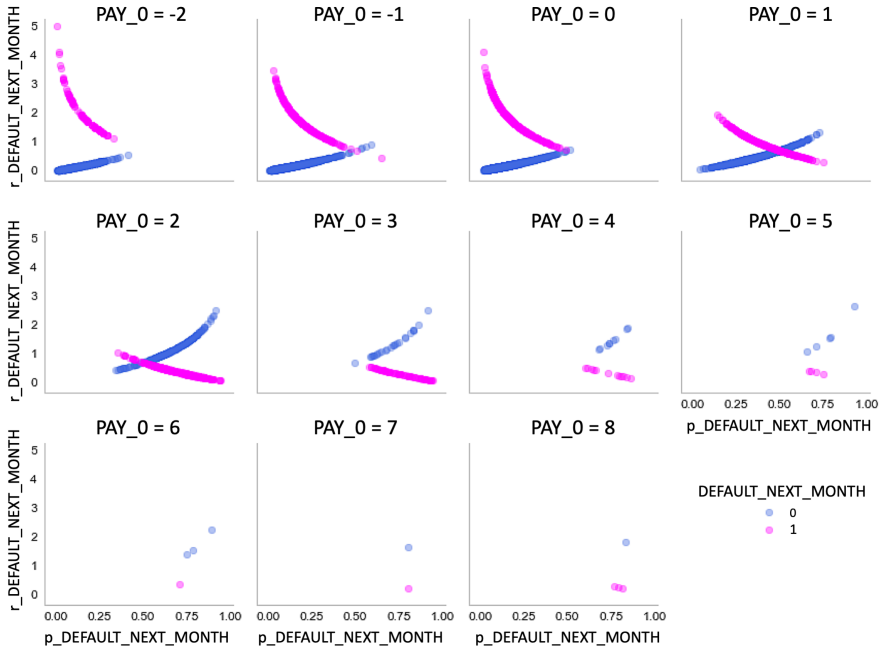
† See https://debug-ml-iclr2019.github.io/ for numerous model debugging approaches.

Why Debug?

Machine learning models can be **inaccurate**.



This probability of default classifier, g_{mono}, over-emphasizes the most important feature, a customer's most recent repayment status, PAY_0.



g_{mono} also struggles to predict default for favorable statuses, $-2 \leq$ PAY_0 < 2, and often cannot predict on-time payment when recent payments are late, PAY_0 ≥ 2.

Why Debug?

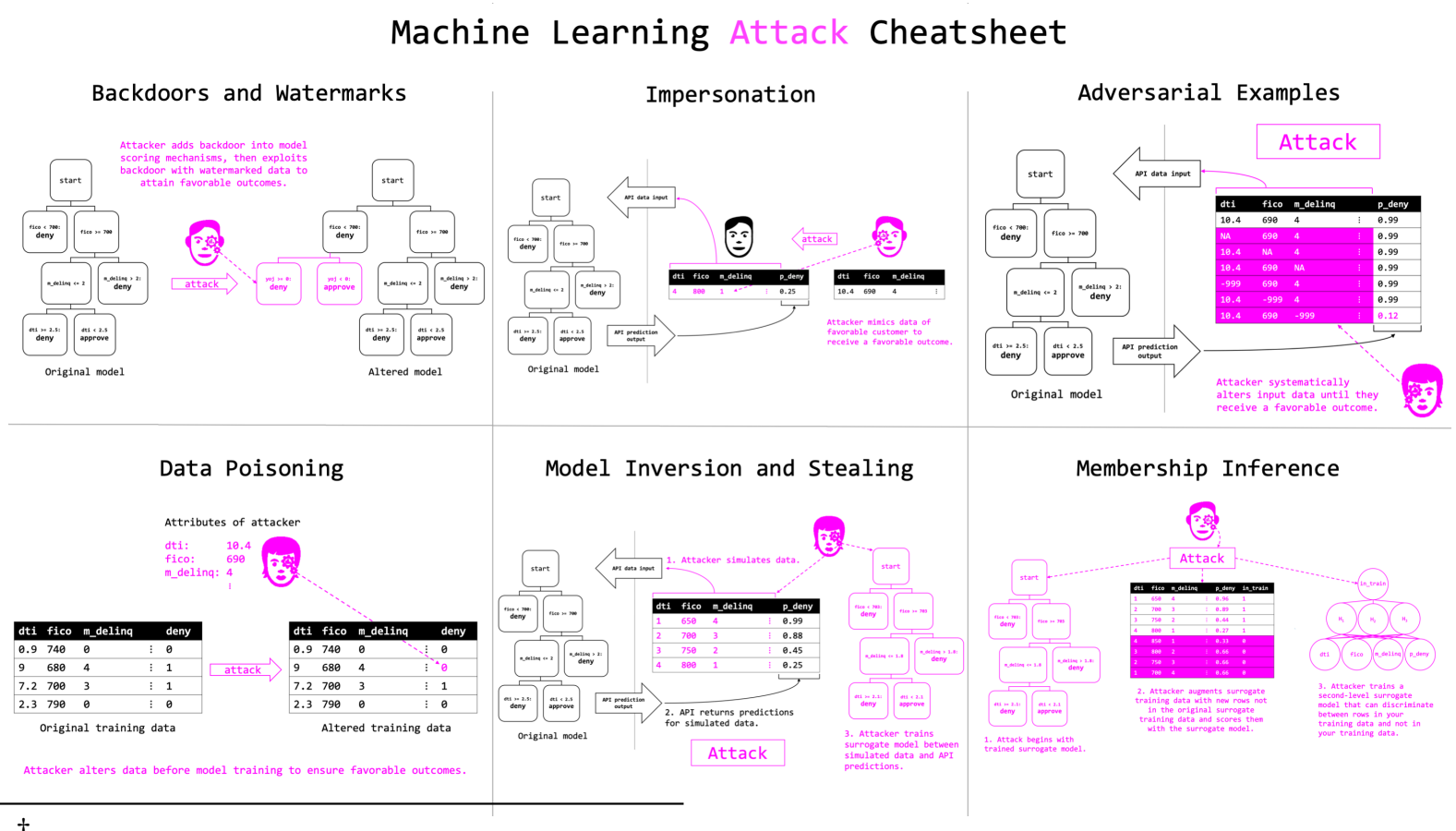
Machine learning models can perpetuate **sociological biases** [1].

	Adverse Impact Disparity	Accuracy Disparity	True Positive Rate Disparity	Precision Disparity	Specificity Disparity
single	0.885	1.029	0.988	1.008	1.025
divorced	1.014	0.932	0.809	0.806	0.958
other	0.262	1.123	0.62	1.854	1.169

Group disparity metrics are out-of-range for g_{mono} across different marital statuses.

Why Debug?

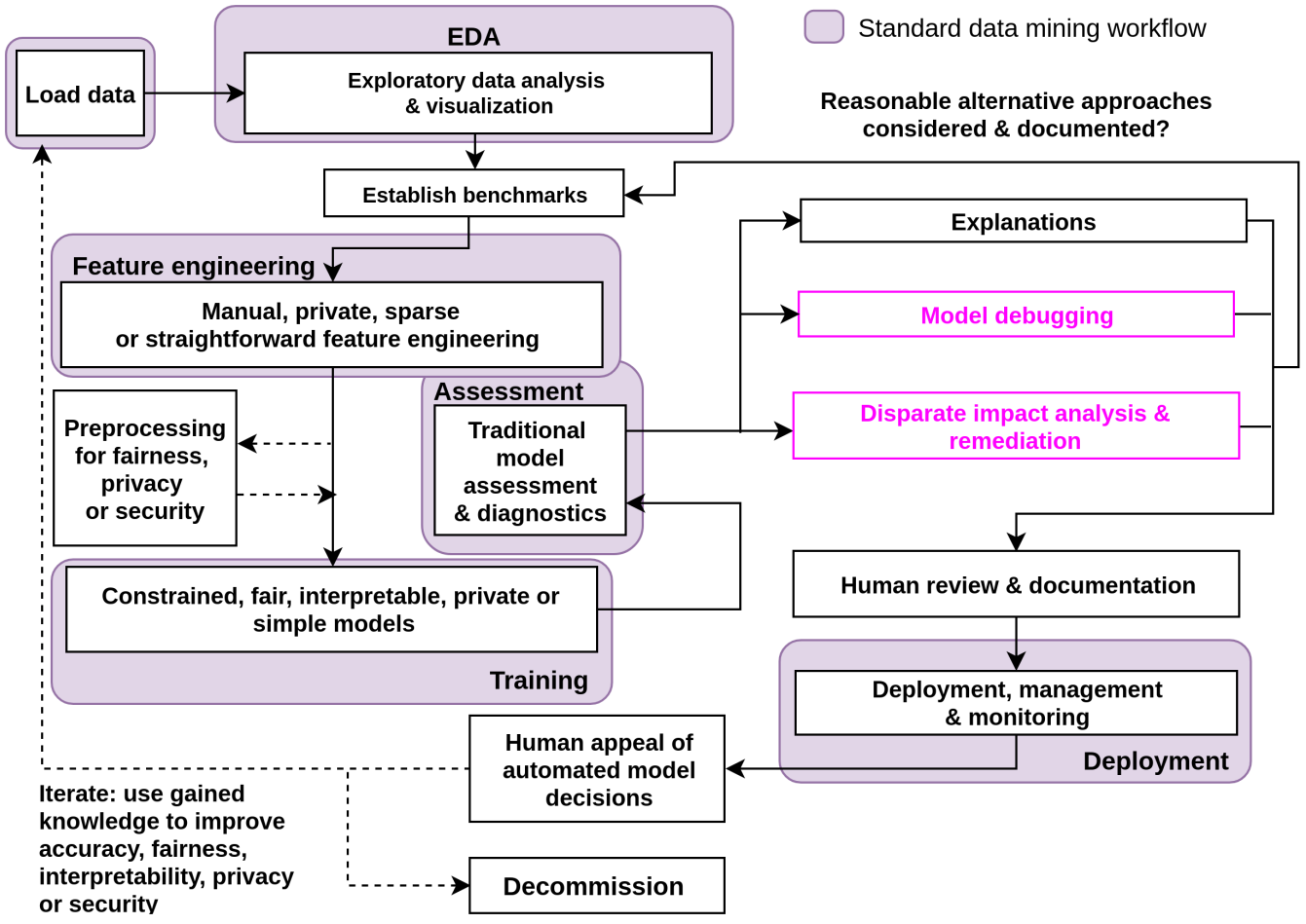
Machine learning models can have **security vulnerabilities** [2], [3], [4].‡



‡See https://github.com/jphall663/secure_ML_ideas for full size image and more information.

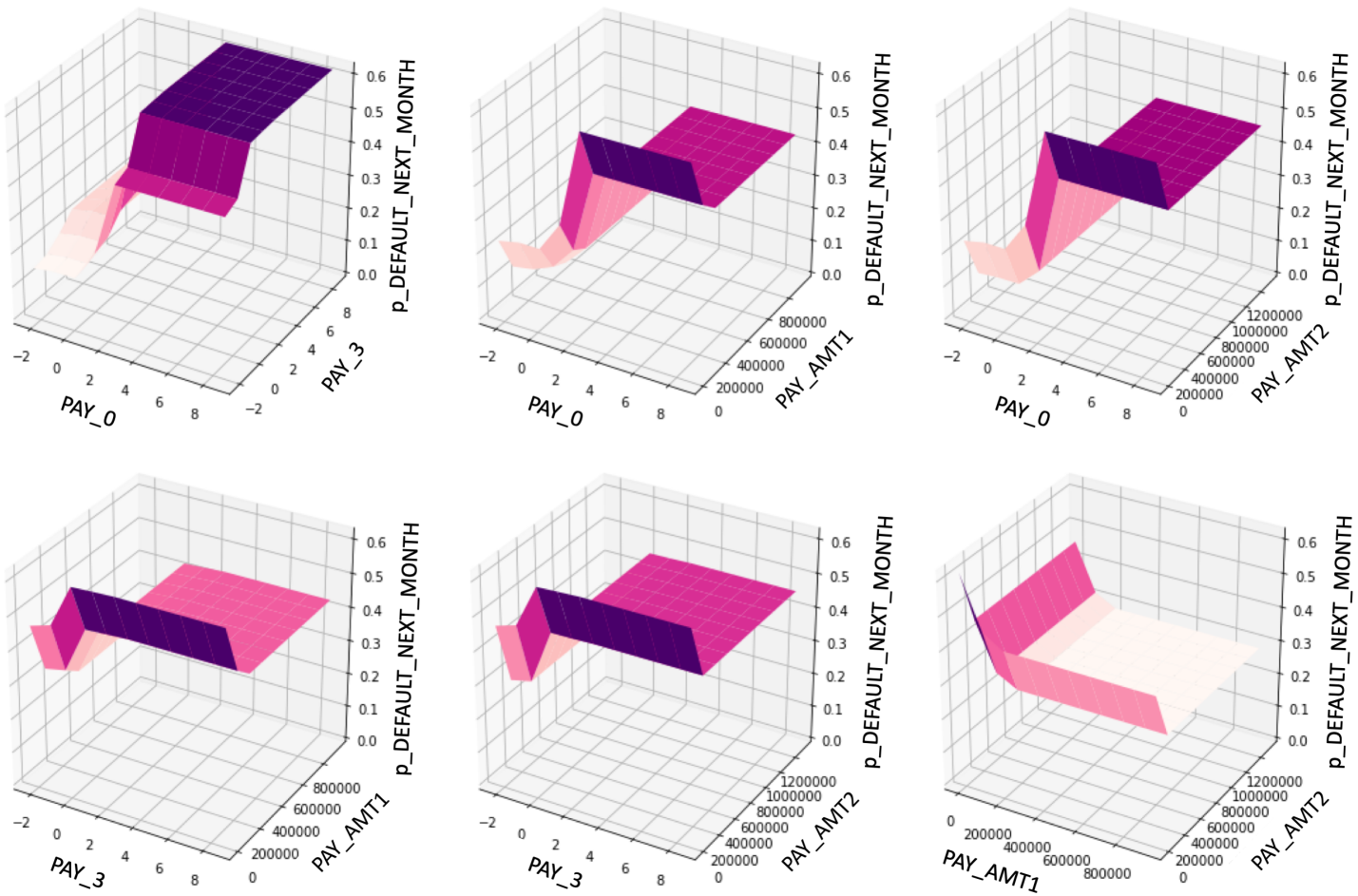
How to Debug Models?

As part of a holistic, low-risk approach to machine learning.[§]

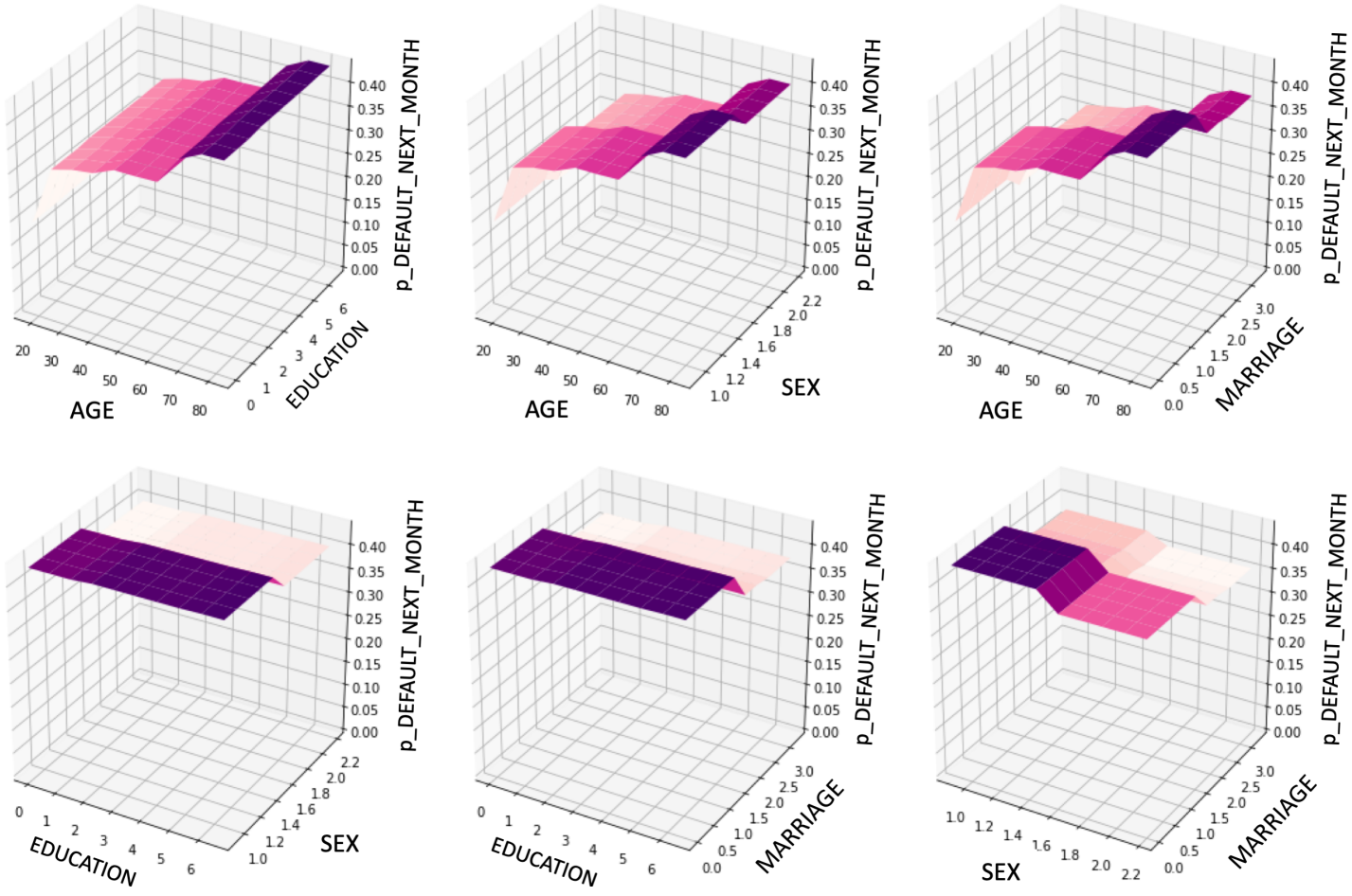


[§] See https://github.com/jphall663/hc_ml for more information.

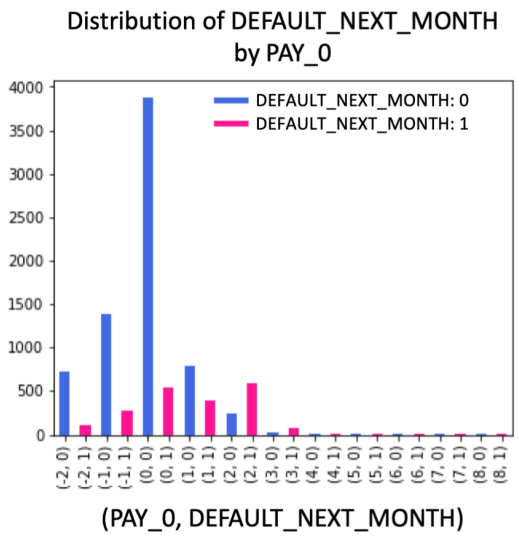
Sensitivity Analysis: Search for Adversarial Examples

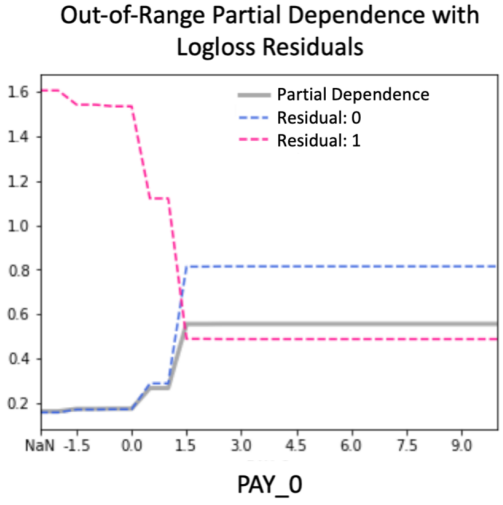


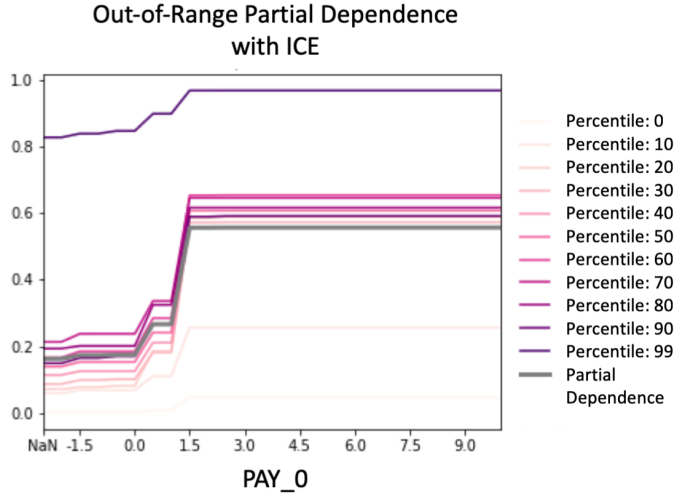
Sensitivity Analysis: Search for Adversarial Examples



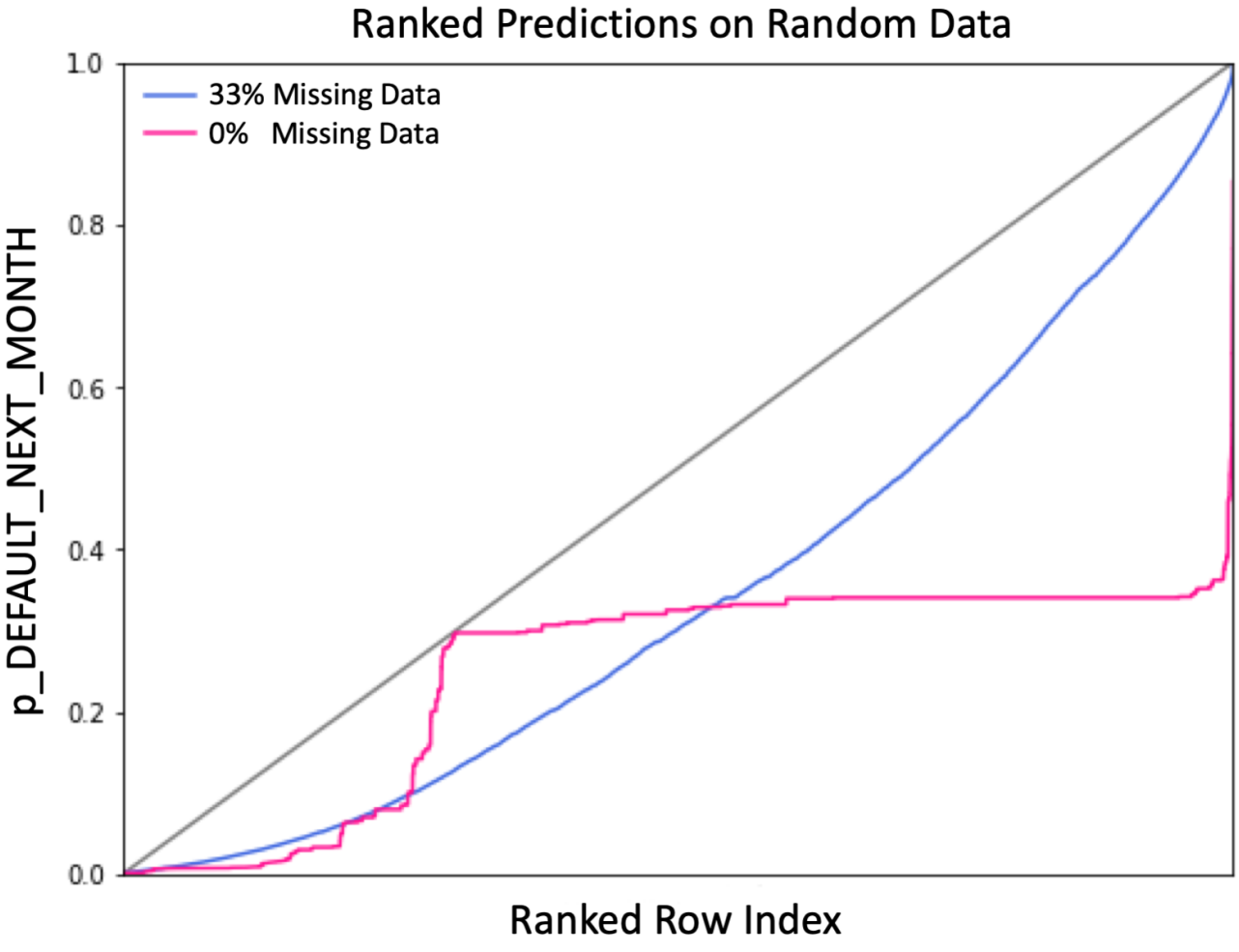
Sensitivity Analysis: Partial Dependence and ICE







Sensitivity Analysis: Random Attacks



Residual Analysis: Disparate Errors

PAY_0	Prevalence	Accuracy	True Positive Rate	Precision	Specificity	Negative Predicted Value	False Positive Rate	False Discovery Rate	False Negative Rate	False Omissions Rate
-2	0.049	0.857	0.3	0.119	0.885	0.961	0.115	0.881	0.7	0.039
-1	0.117	0.805	0.383	0.267	0.861	0.913	0.139	0.733	0.617	0.087
0	0.05	0.864	0.345	0.143	0.891	0.963	0.109	0.857	0.655	0.037
1	0.822	0.457	0.368	0.93	0.871	0.229	0.129	0.07	0.632	0.771
2	1	0.709	0.709	1	0.5	0	0.5	0	0.291	1
3	1	0.748	0.748	1	0.5	0	0.5	0	0.252	1
4	1	0.571	0.571	1	0.5	0	0.5	0	0.429	1
5	1	0.444	0.444	1	0.5	0	0.5	0	0.556	1
6	1	0.25	0.25	1	0.5	0	0.5	0	0.75	1
7	1	0.5	0.5	1	0.5	0	0.5	0	0.5	1
8	1	0.75	0.75	1	0.5	0	0.5	0	0.25	1

SEX	Prevalence	Accuracy	True Positive Rate	Precision	Specificity	Negative Predicted Value	False Positive Rate	False Discovery Rate	False Negative Rate	False Omissions Rate
Male	0.3	0.773	0.513	0.655	0.884	0.809	0.116	0.345	0.487	0.191
Female	0.242	0.788	0.495	0.573	0.882	0.845	0.118	0.427	0.505	0.155

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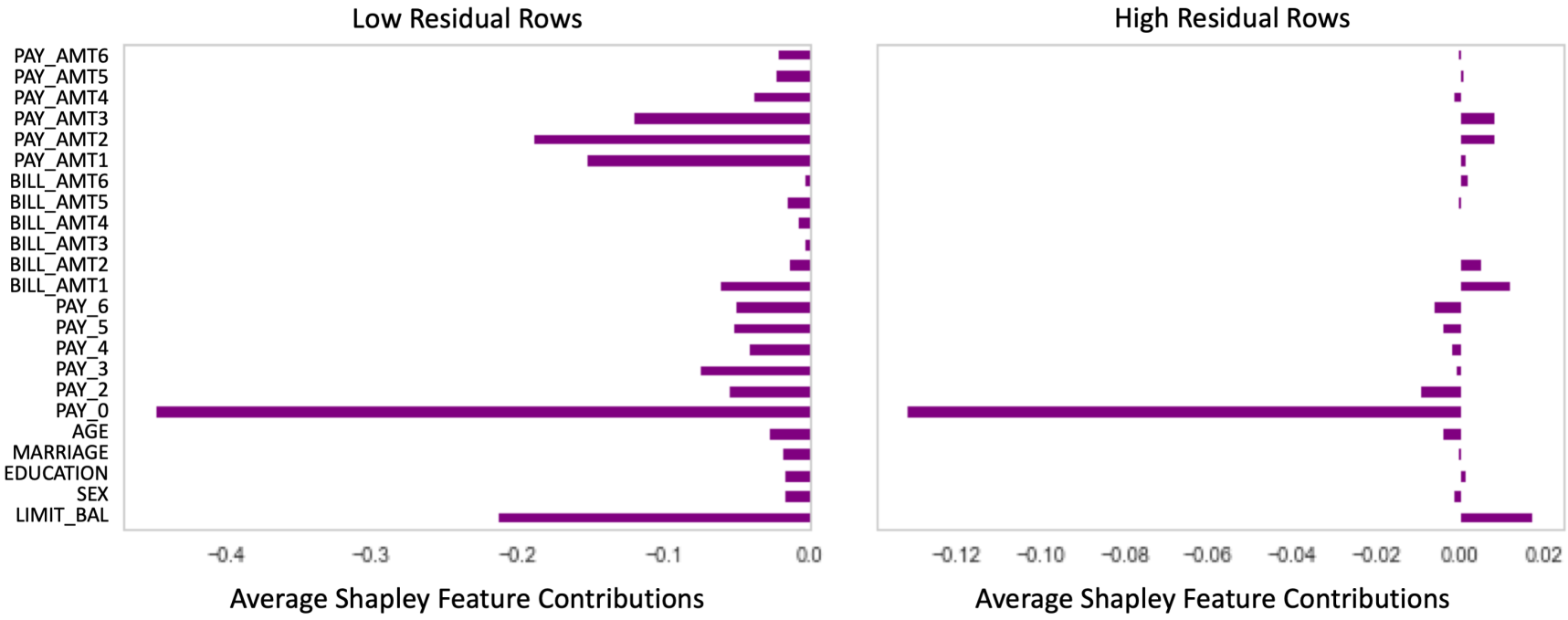
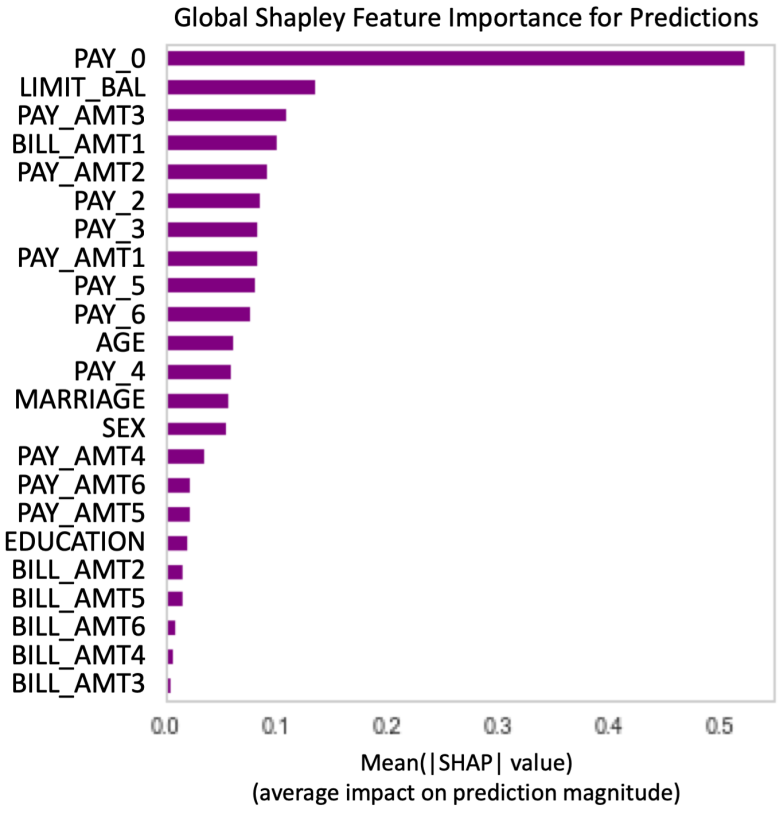
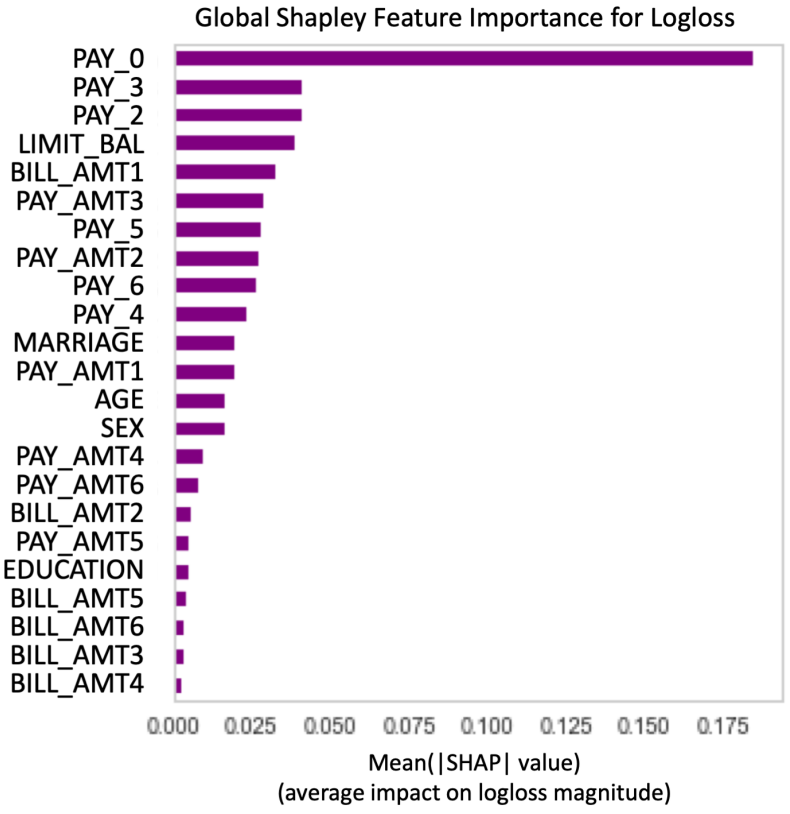
Residual Analysis: Mean Local Feature Contributions

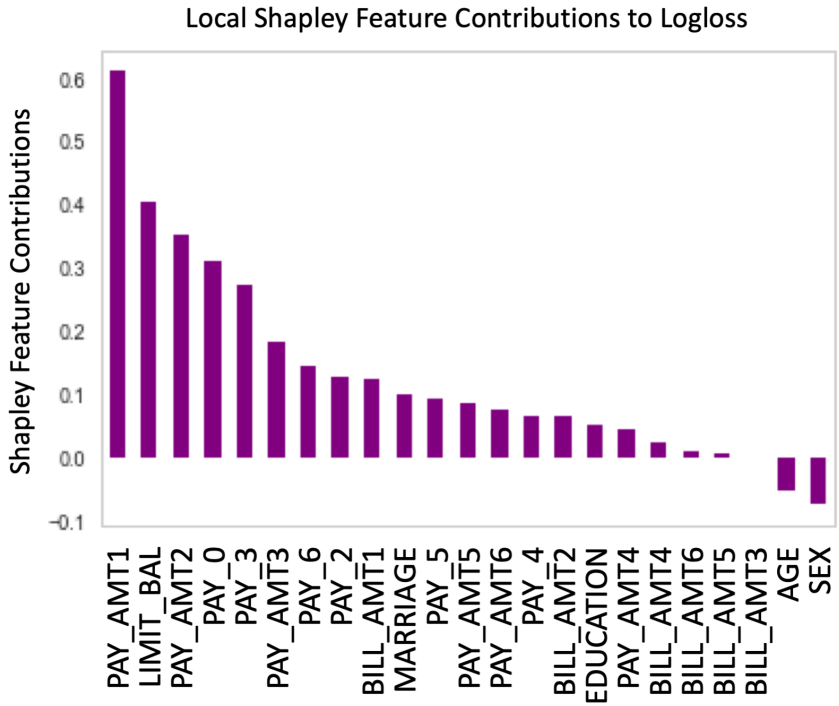


Residual Analysis: Importance for Predictions and Logloss

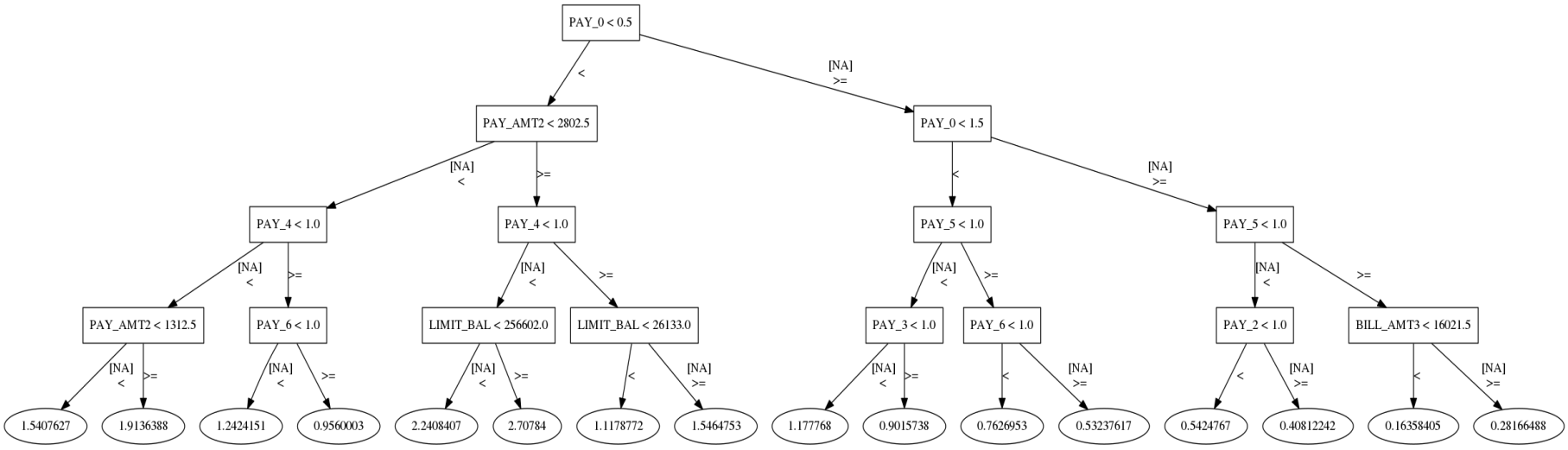




Residual Analysis: Local Contributions to Logloss

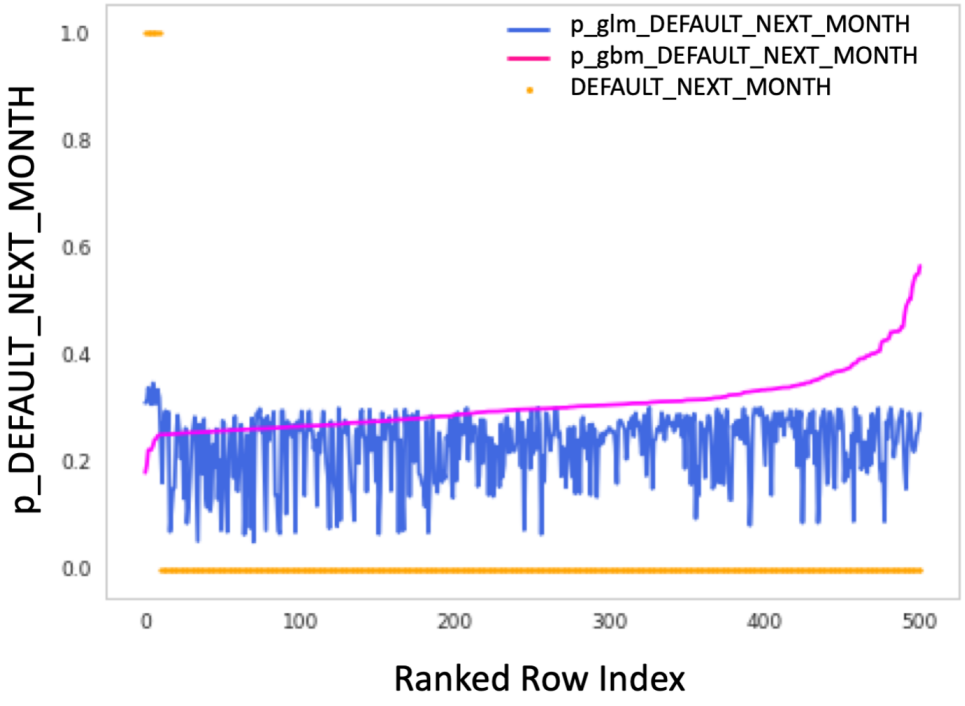


Residual Analysis: Modeling Residuals



Decision tree model of g_{mono} DEFAULT_NEXT_MONTH = 1 logloss residuals with 3-fold CV MSE = 0.0070 and $R^2 = 0.8871$.

Benchmark Models: Compare to Linear Models



References

This presentation:

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[1] Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. URL: http://www.fairmlbook.org. fairmlbook.org, 2018.

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

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