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Transparency of Machine Learning Models in Credit Scoring

CRC Conference XVI

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Introduction

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SCALEWORK MAKE SCALE WORK

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Introduction

- Main requirement for Credit Scoring models: provide a risk prediction that is **as accurate as possible**
- In addition, regulators demand these models to be **transparent and auditable**
- Therefore, very **simple predictive models** such as Logistic Regression or Decision Trees are still widely used (Lessmann, Baesens, Seow, and Thomas 2015; Bischl, Kühn, and Szepannek 2014)
- Superior predictive power of modern **Machine Learning algorithms** cannot be fully leveraged
- A lot of **potential is missed**, leading to higher reserves or more credit defaults (Szepannek 2017)

Research Approach

- For an open data set we build a traditional and still state-of-the-art Score Card model
- In addition, we build alternative Machine Learning Black Box models
- We use model-agnostic methods for interpretable Machine Learning to showcase transparency of such models
- For computations we use R and respective packages (Biecek 2018; Molnar, Bischl, and Casalicchio 2018)

The incumbent: Score Cards

Steps for Score Card construction using Logistic Regression (Szepannek 2017)

1. Automatic binning
2. Manual binning
3. WOE/Dummy transformation
4. Variable shortlist selection
5. (Linear) modelling and automatic model selection
6. Manual model selection

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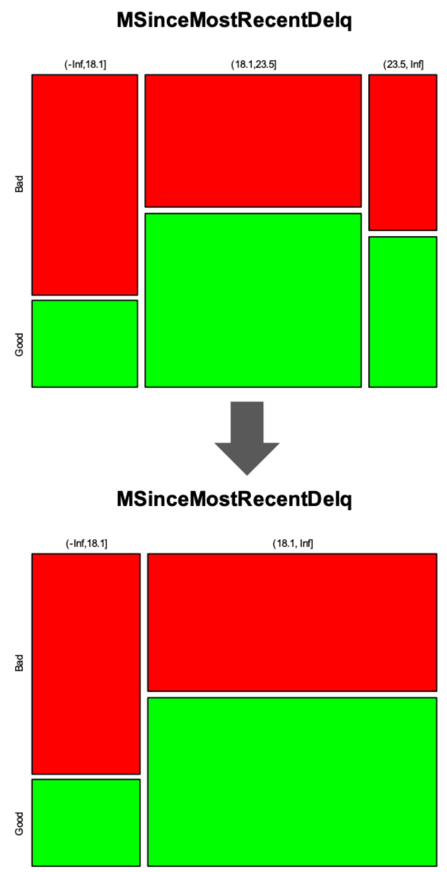


Score Cards: Manual binning

Manual binning allows for

- (univariate) non-linearity
- (univariate) plausibility checks
- integration of expert knowledge for binning of factors

...but: only univariate effects (!)

... and means a lot of manual work

The challenger models

We tested a couple of Machine Learning algorithms ...

- Random Forests (`randomForest`)
- Gradient Boosting (`gbm`)
- XGBoost (`xgboost`)
- Support Vector Machines (`svm`)
- Logistic Regression with spline based transformations (`rms`)

... and also two AutoML frameworks to beat the Score Card

- h2o AutoML (`h2o`)
- mljar.com (`mljar`)

Data set for study: xML Challenge by FICO

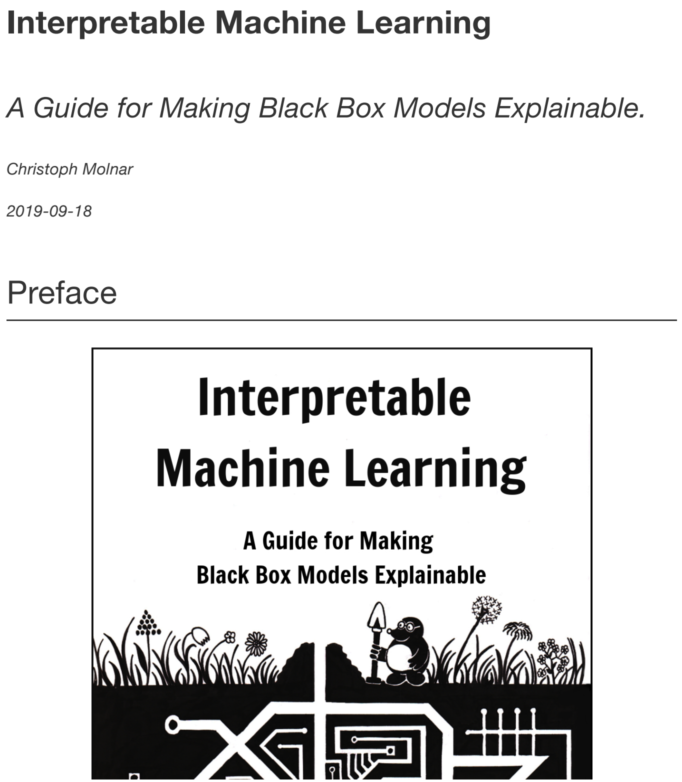
- Explainable Machine Learning Challenge by FICO (2019)
- Focus: Home Equity Line of Credit (HELOC) Dataset
- Customers requested a credit line in the range of $5,000 - $150,000
- Task is to predict whether they will repay their HELOC account within 2 years
- Number of observations: 2,615
- Variables: 23 covariates (mostly numeric) and 1 target variable (risk performance "good" or "bad")

FICO®

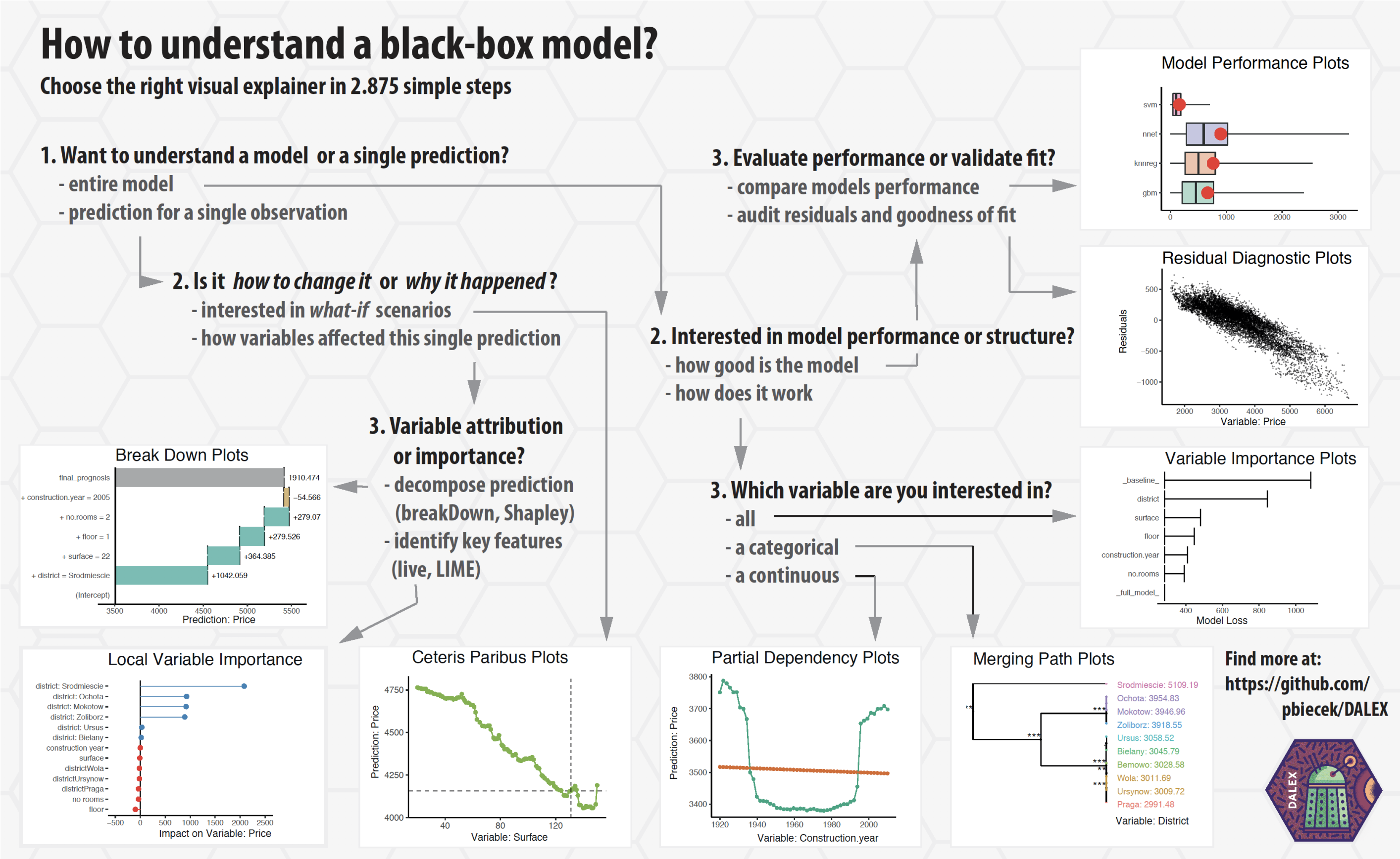
Explainability of Machine Learning models

There are many model-agnostic methods for interpretable ML today; see Molnar (2019) for a good overview.

- Partial Dependence Plots (PDP)
- Individual Conditional Expectation (ICE)
- Accumulated Local Effects (ALE)
- Feature Importance
- Global Surrogate and Local Surrogate (LIME)
- Shapley Values, SHAP
- ...



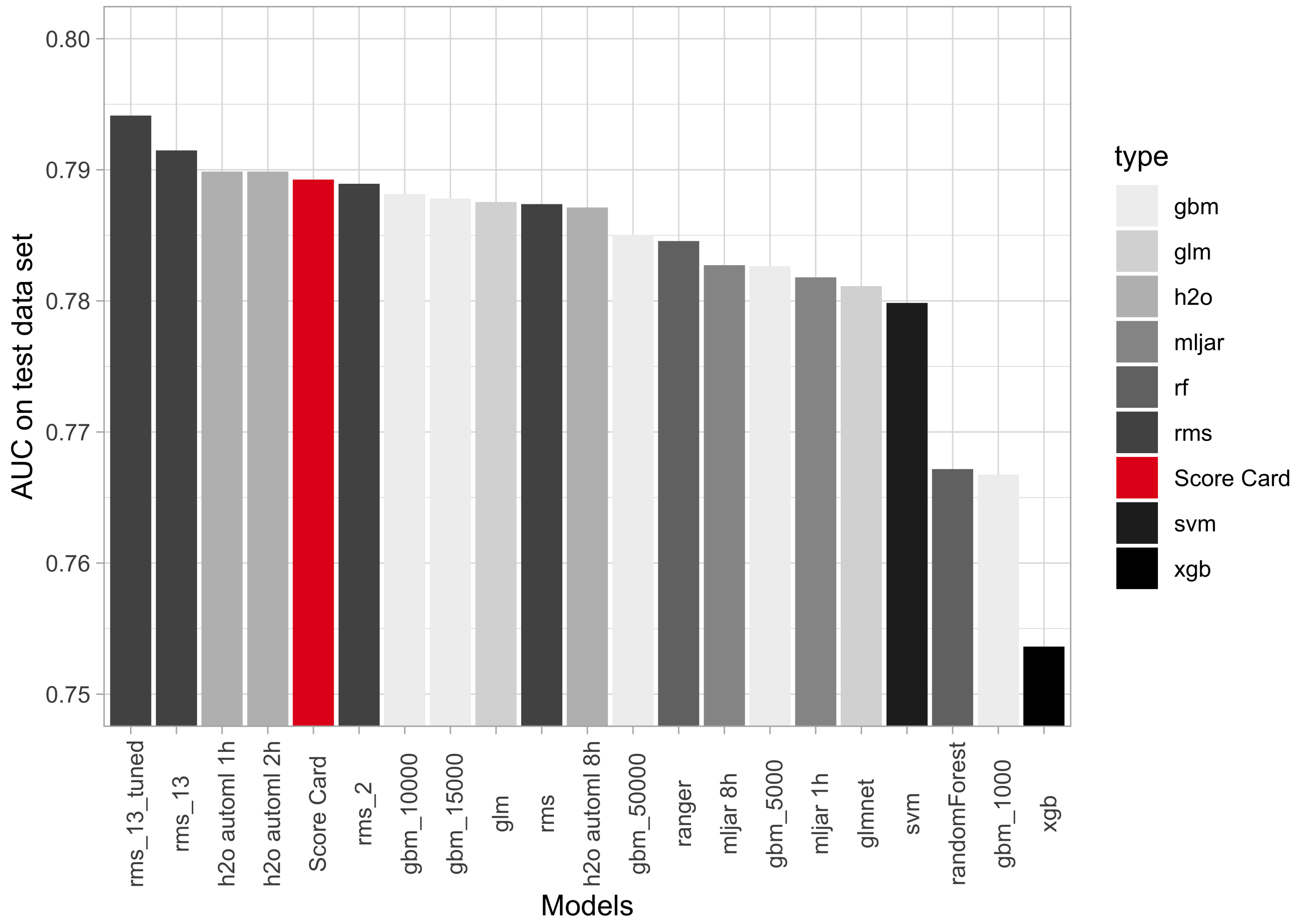
Implementation in R: DALEX



- Descriptive mAchine Learning EXplanations
- DALEX is a set of tools that help to understand how complex models are working

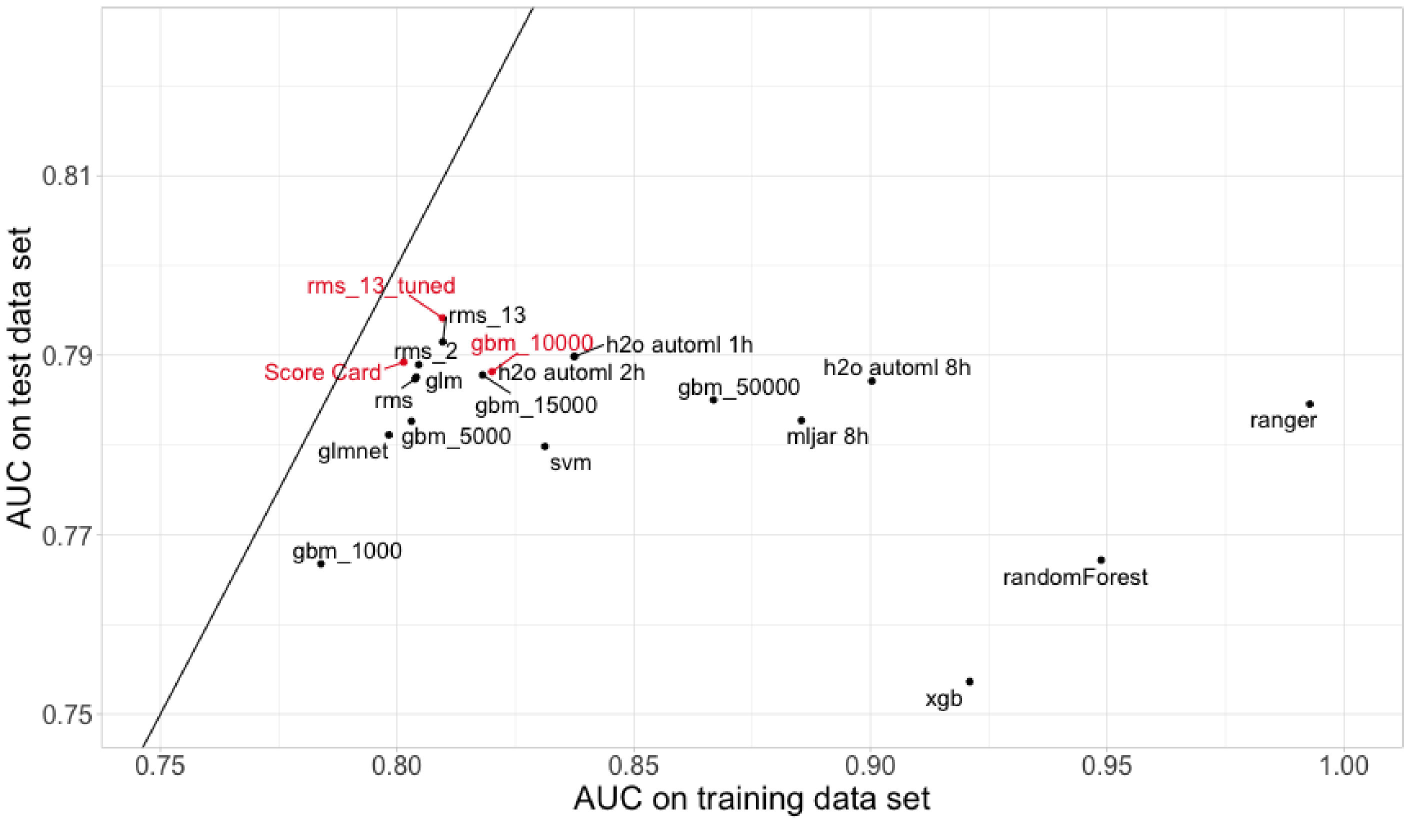
Results: Model performance

Results: Comparison of model performance



- Predictive power of the traditional Score Card model surprisingly good
- Logistic Regression with spline based transformations best, using `rms` by Harrell Jr (2019)

Results: Comparison of model performance

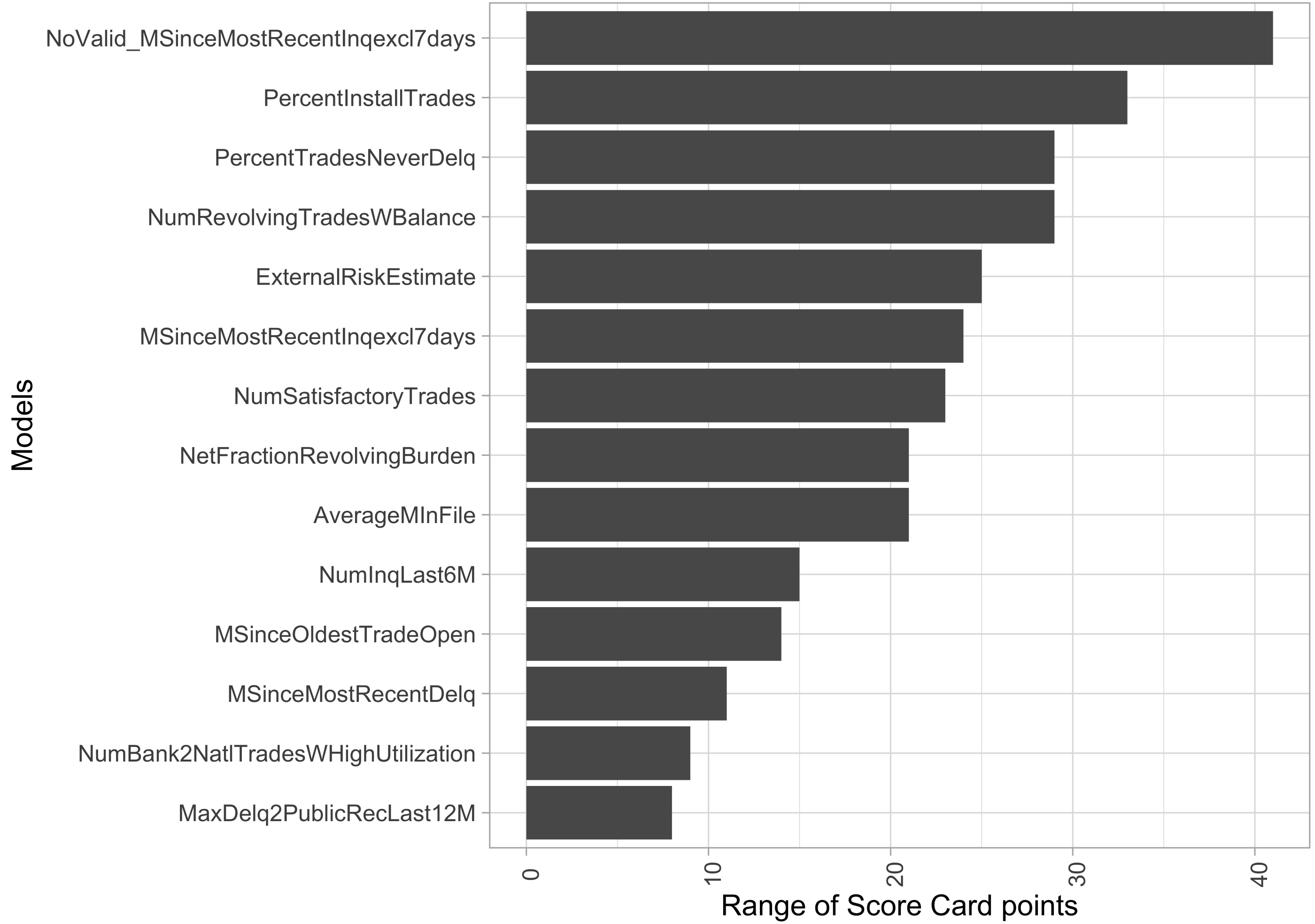


For comparison of explainability, we choose

- the Score Card,
- a Gradient Boosting model with 10,000 trees,
- a tuned Logistic Regression with splines using 13 variables

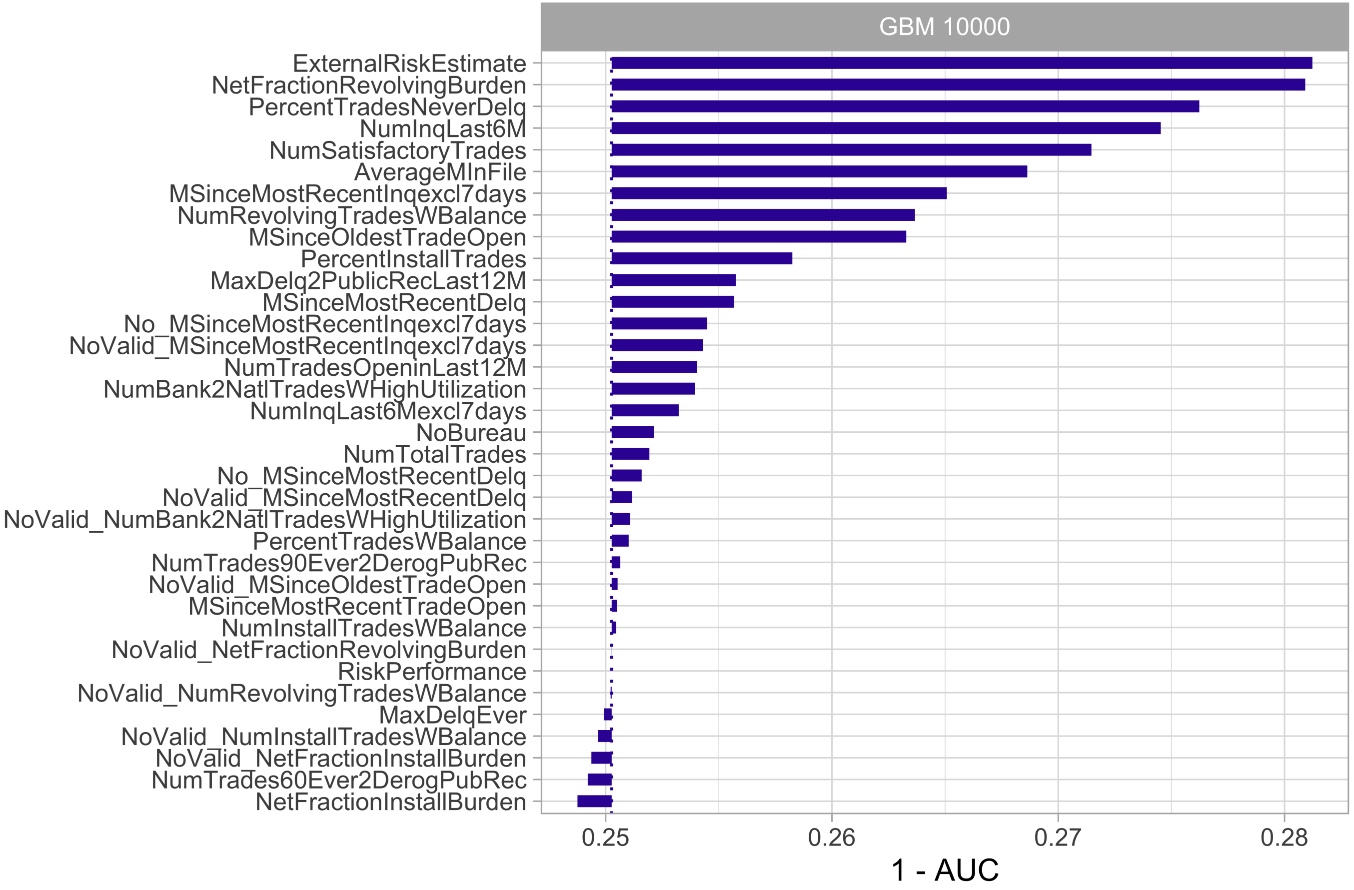
Results: Global explanations

Score Card: Variable importance as range of points



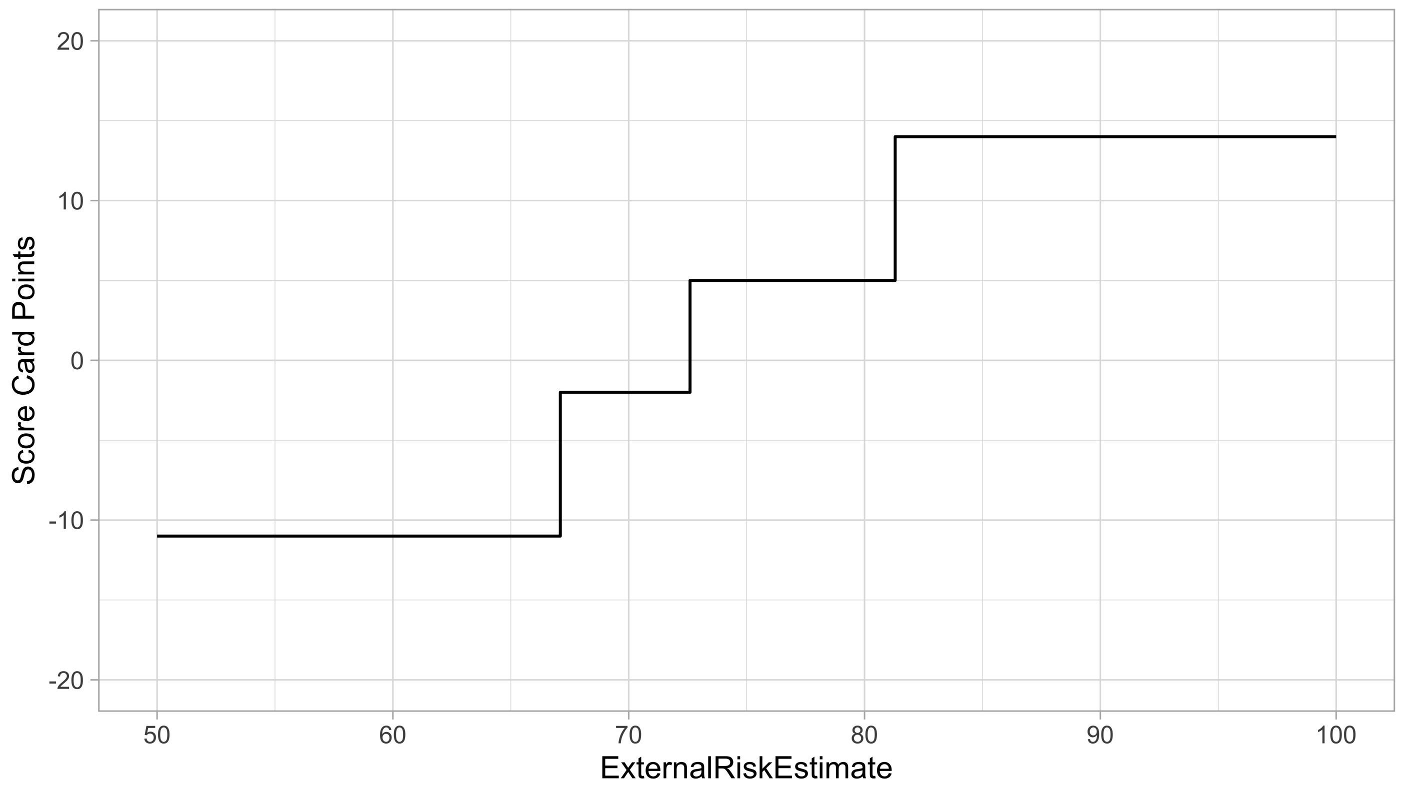
- Range of Score Card point as an indicator of relevance for predictions
- Alternative: variance of Score Card points across applications

Model agnostic: Importance through drop-out loss



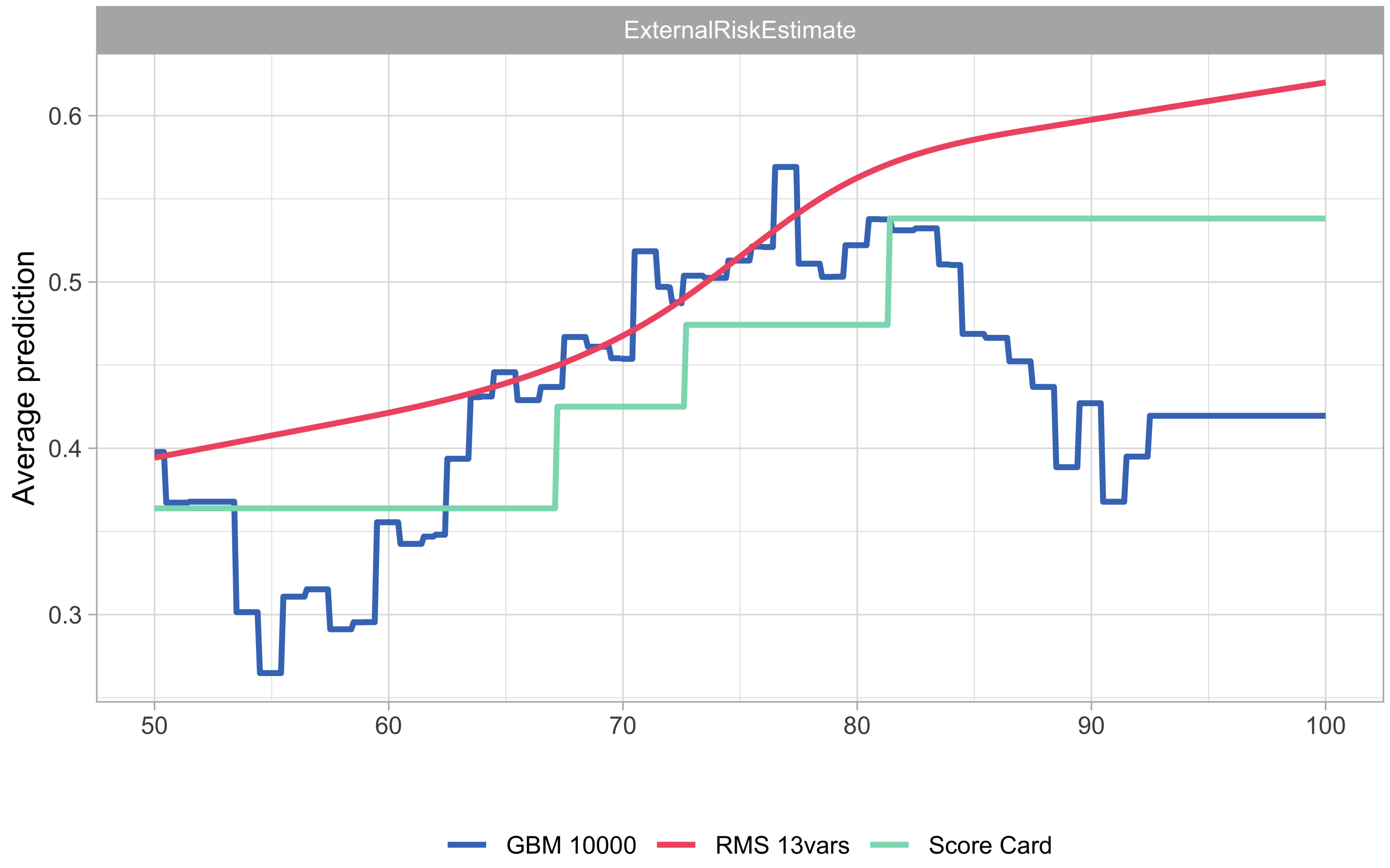
- The drop in model performance (here AUC) is measured after permutation of a single variable
- The more siginficant the drop in performance, the more important the variable

Score Card: Variable explanation based on points



- Score Card points for values of covariate show effect of single feature
- Directly computed from coefficient estimates of the Logistic Regression

Model agnostic: Partial dependence plots



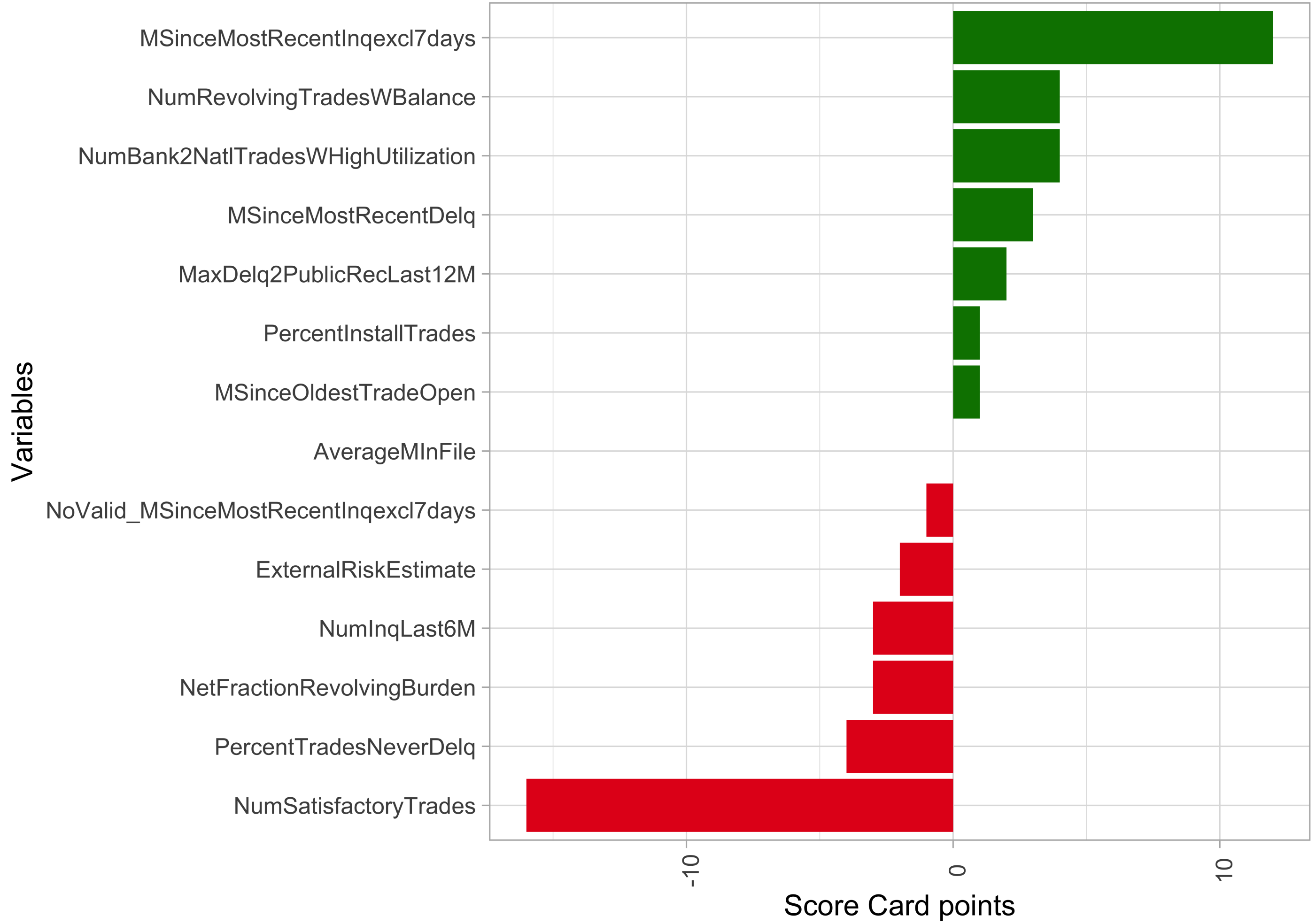
- Partial dependence plots created with (Biecek 2018)
- Interpretation very similar to marginal Score Card points

Results: Local explanations

Instance-level explanations

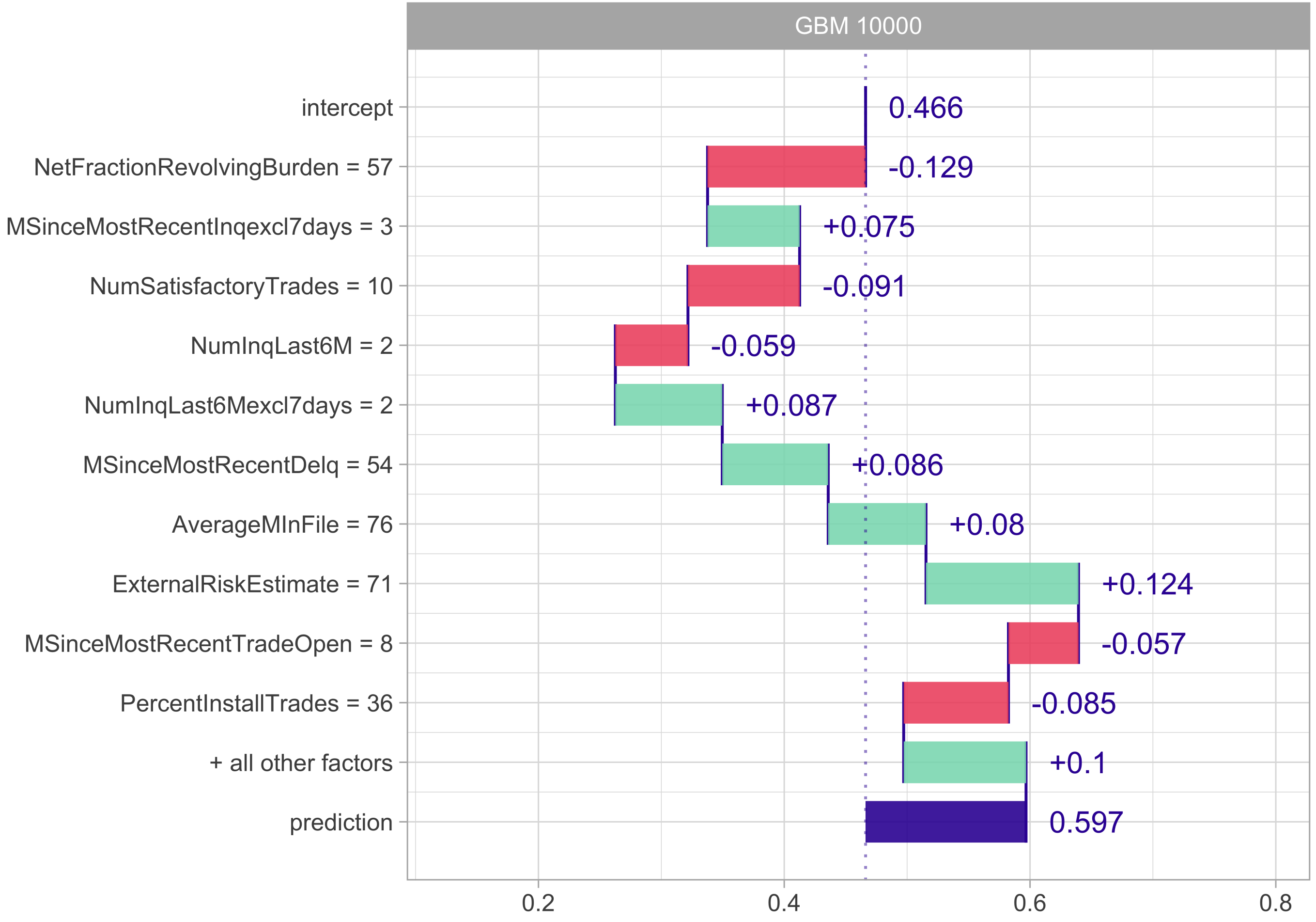
- Instance-level exploration helps to understand how a model yields a prediction for a single observation
- Model-agnostic approaches are
  - additive Breakdowns
  - Shapley Values, SHAP
  - LIME
- In Credit Scoring, this explanation makes each credit decision transparent

Score Card: Local explanations



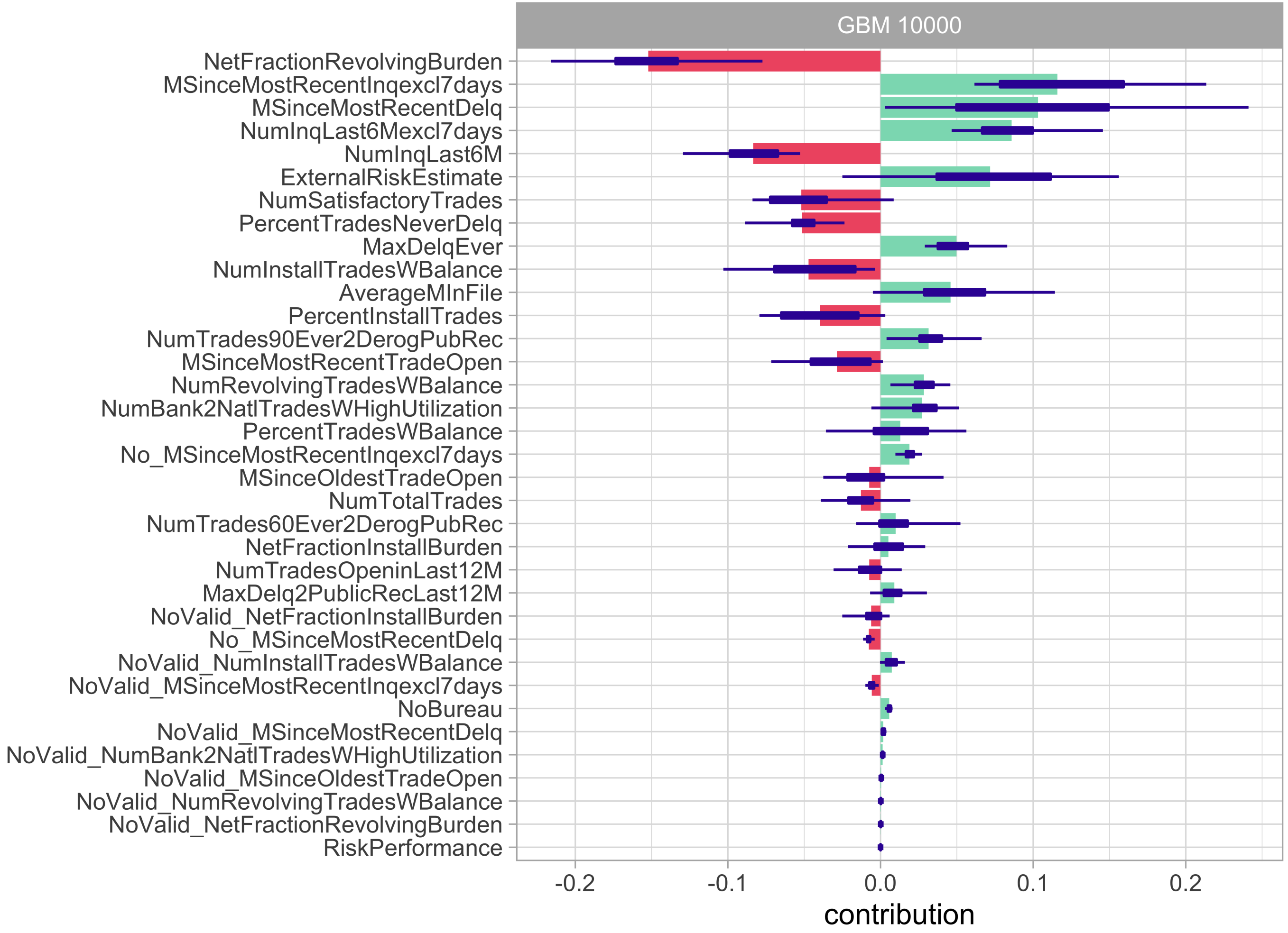
- Instance-level exploration for Score Cards can simply use individual Score Card points
- This yields a breakdown of the scoring result by variable

Model agnostic: Variable contribution break down



- Such instance-level explorations can also be performed in a model-agnostic way
- Unfortunately, for non-additive models, variable contributions depend on the ordering of variables

Model agnostic: SHAP



- Shapley attributions are averages across all (or at least large number) of different orderings
- Violet boxplots show distributions for attributions for a selected variable, while length of the bar stands for an average attribution

Conclusion

Modeldown: HTML summaries for predictive Models

Rf. Biecek, Tatarynowicz, Romaszko, and Urbański (2019)

modelDown

Explore your model!

Basic data information

- 2615 observations
- 35 columns

Explainers

- RMS 13vars (download) (explainers/RMS 13vars.rda)
- GBM 10000 (download) (explainers/GBM 10000.rda)
- Score Card (download) (explainers/Score Card.rda)

Summaries for numerical variables

	vars	n	mean	sd	median	trimmed	mad	min	max	range

Scan me

Conclusion

- We have built models for Credit Scoring using Score Cards and Machine Learning
- Predictive power of Machine Learning models was superior (in our example only slightly, other studies show clearer overperformance)
- Model agnostic methods for interpretable Machine Learning are able to meet the degree of explainability of Score Cards and may even exceed it

References (1/3)

Biecek, P. (2018). "DALEX: explainers for complex predictive models". In: *Journal of Machine Learning Research* 19.84, pp. 1-5.

Biecek, P, M. Tatarynowicz, K. Romaszko, and M. Urbański (2019). *modelDown: Make Static HTML Website for Predictive Models*. R package version 1.0.1. URL: https://CRAN.R-project.org/package=modelDown.

Bischl, B., T. Kühn, and G. Szepannek (2014). "On Class Imbalance Correction for Classification Algorithms in Credit Scoring". In: *Operations Research Proceedings*. Ed. by M. Löbbecke, A. Koster, L. P., M. R., P. B. and G. Walther. , pp. 37-43.

FICO (2019). *xML Challenge*. Online. URL: https://community.fico.com/s/explainable-machine-learning-challenge.

References (2/3)

Harrell Jr, F. E. (2019). *rms: Regression Modeling Strategies*. R package version 5.1-3.1. URL: https://CRAN.R-project.org/package=rms.

Lessmann, S, B. Baesens, H. Seow, and L. Thomas (2015). "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research". In: *European Journal of Operational Research* 247.1, pp. 124-136.

Molnar, C. (2019). *Interpretable Machine Learning. A Guide for Making Black Box Models Explainable*. URL: https://christophm.github.io/interpretable-ml-book/.

Molnar, C, B. Bischl, and G. Casalicchio (2018). "iml: An R package for Interpretable Machine Learning". In: *Journal Of Statistical Software* 3.26, p. 786. URL: http://joss.theoj.org/papers/10.21105/joss.00786.

References (3/3)

Szepannek, G. (2017b). *A Framework for Scorecard Modelling using R*. CSCC 2017.

Szepannek, G. (2017a). "On the Practical Relevance of Modern Machine Learning Algorithms for Credit Scoring Applications". In: *WIAS Report Series* 29, pp. 88-96.

Thank you!

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