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Transparency of Machine Learning Models in Credit Scoring

CRC Conference XVI

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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 et al. 2015; Bischl et al. 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 will built a traditional and still state-of-the-art Score Card model
- In addition, we built 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 et al. 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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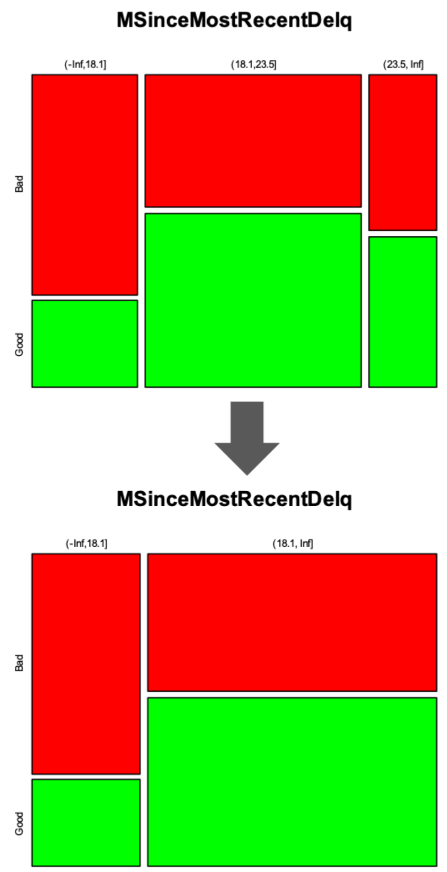
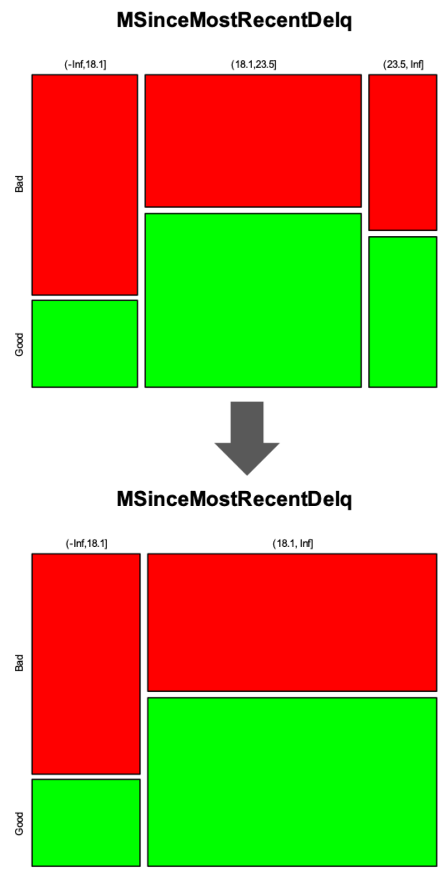


The incumbent: Score Cards

Manual binning allows for

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

...but: only univariate effects (!)



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

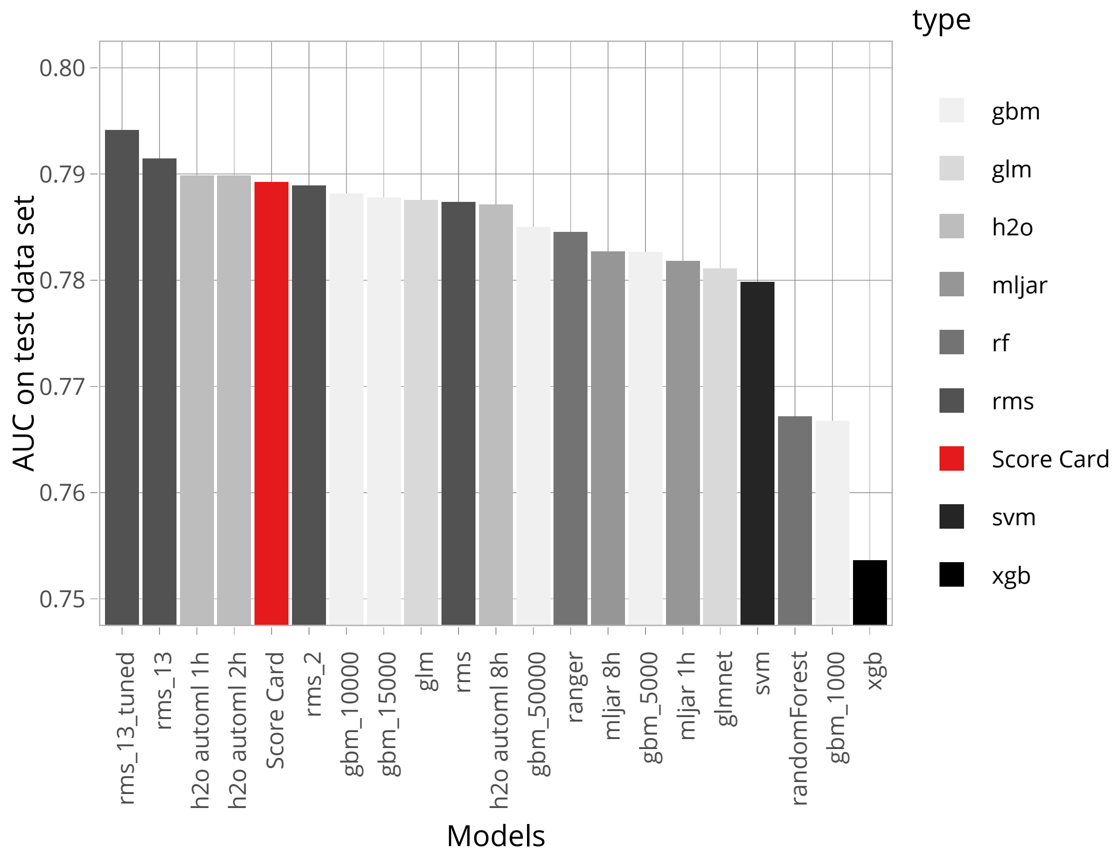
- h2o AutoML (`h2o`)
- mljar.com (`mljar`)

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®

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)

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
- …

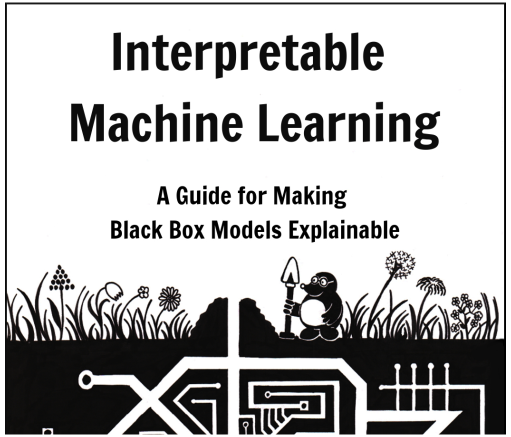
Interpretable Machine Learning

A Guide for Making Black Box Models Explainable.

Christoph Molnar

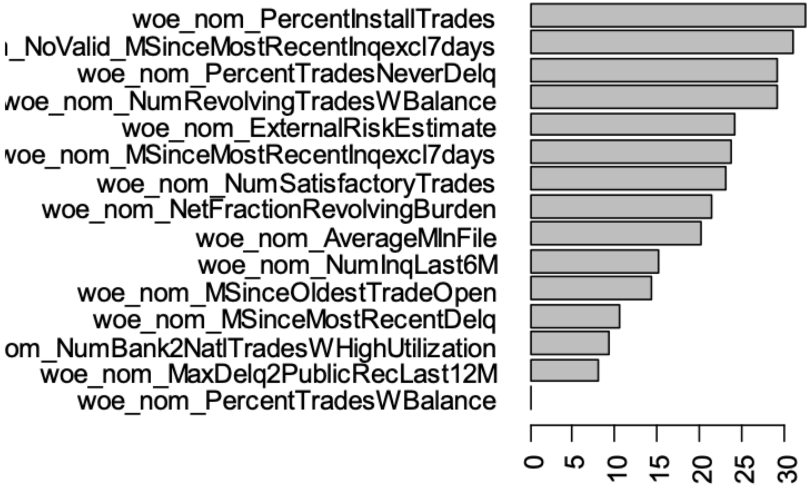
2019-07-16

Preface



Results: Variable importance for global explainability

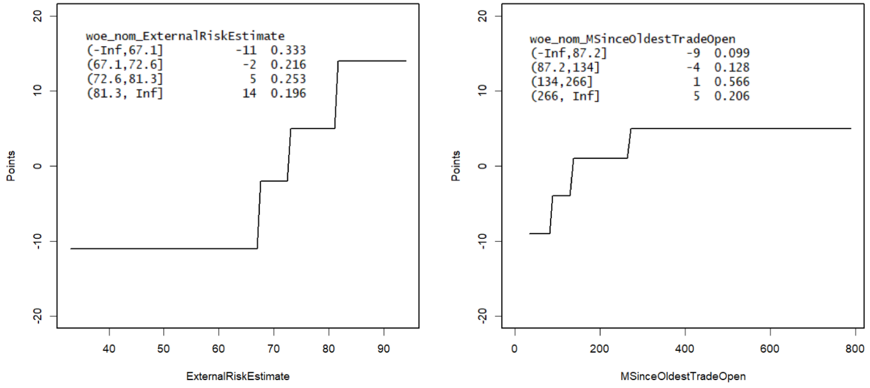
Score Card (Score points)



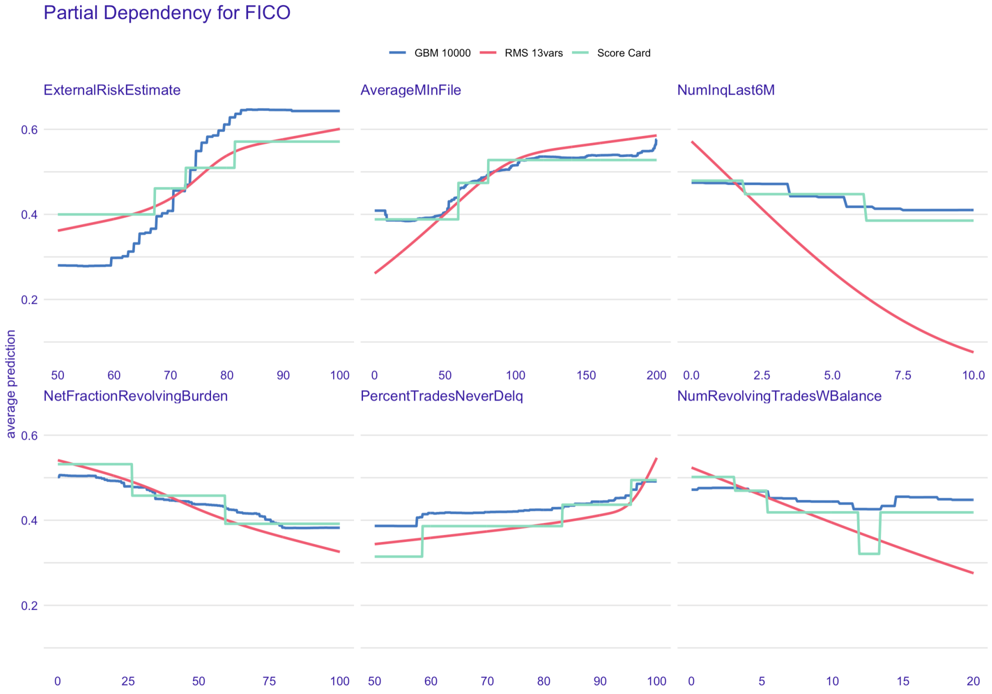
RMS Model (...)

Results: Univariate Effects and Partial Dependence Plots

Score Card (Score points)

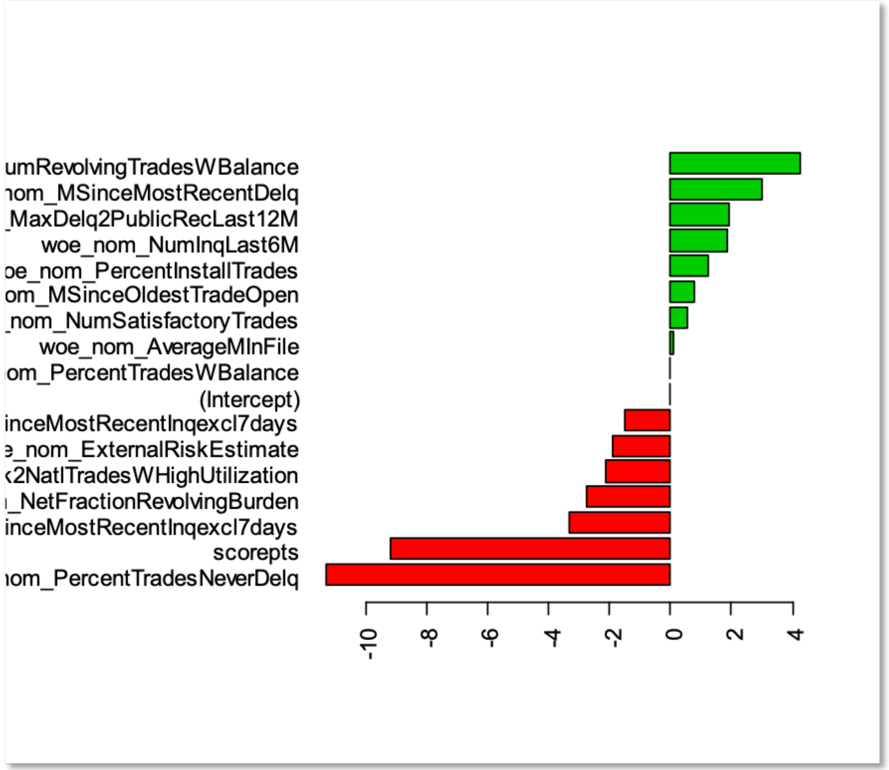


RMS Model (...)



Results: Local explanations and LIME

Score Card (Score points)



Modeldown: HTML summaries for predictive Models

Rf. Biecek et al. (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

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 achieve to make predictions explainable in the same way

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Thank you!

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