

# Explore, Explain, and Debug

aka Interpretable Machine Learning



Przemysław Biecek

# Use case FIFA 2019





# FIFA 19 complete player dataset

18k+ FIFA 19 players, ~90 attributes extracted from the latest FIFA database



Karan Gadiya · updated a year ago



# FIFA19



Data

Kernels (304)

Discussion (21)

Activity

Metadata

Download (9 MB)

New Notebook



Your Dataset download has started.  
Show your appreciation with an upvote

1640



Usability 10.0

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Tags data visualization, feature engineering, random forest, sports, regression analysis

Description

Context

Football analytics

```
library("gbm")
fifa_gbm <- gbm(ValueNum~,  

                  data = fifa19,  

                  n.trees = 250,  

                  interaction.depth = 3)
```

Source: <https://www.kaggle.com/karangadiya/fifa19/data>



Full name	Ádám Csaba Szalai
Date of birth	9 December 1987
Place of birth	Budapest, Hungary
Playing position	Striker

wikipedia

Prediction from GBM model: 7 344 354 EUR

How? Why? Really?

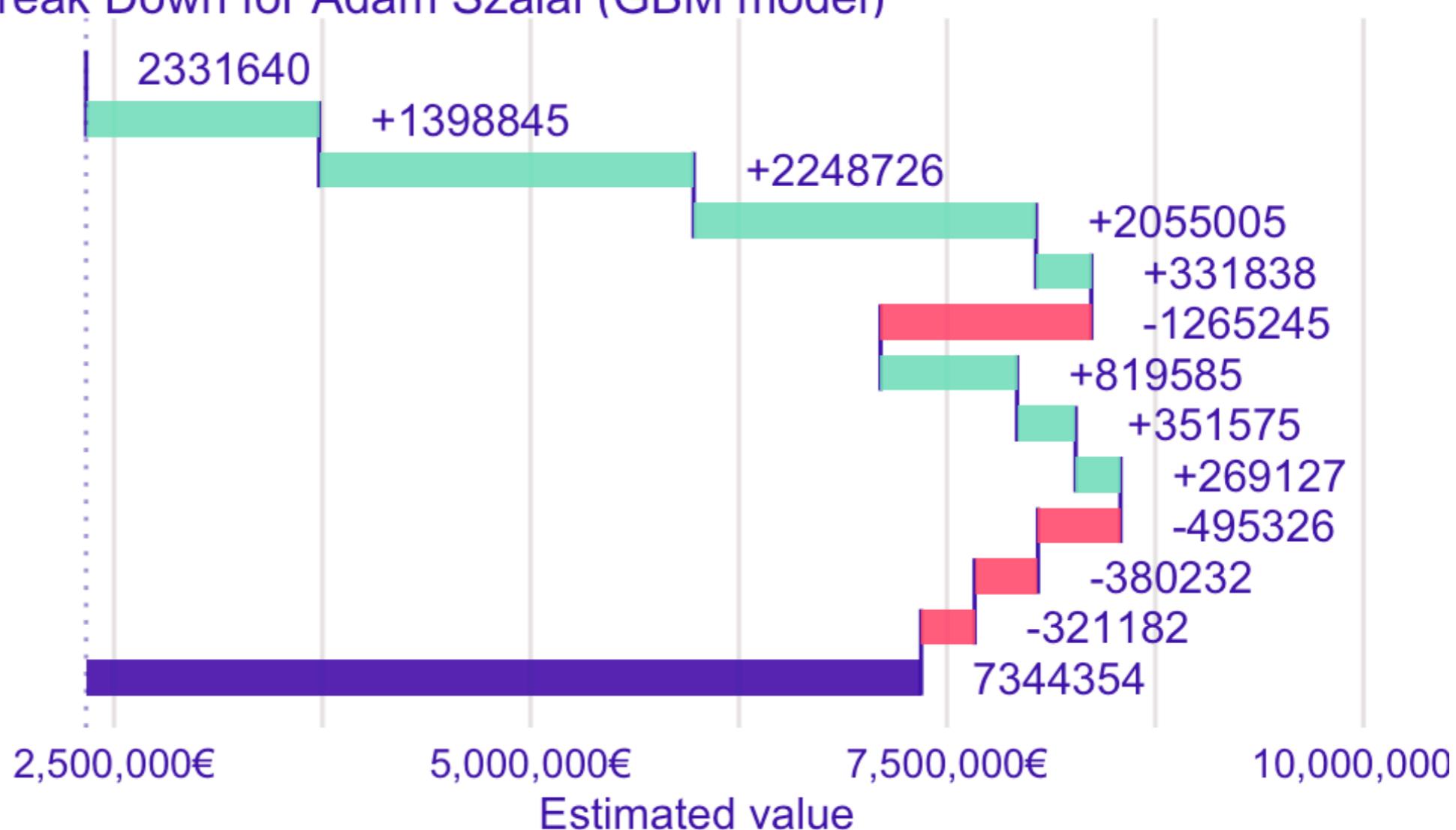


Full name Ádám Csaba Szalai  
Date of birth 9 December 1987  
Place of birth Budapest, Hungary  
Playing position Striker

wikipedia

intercept 2331640  
Finishing = 80 +1398845  
Reactions = 76 +2248726  
HeadingAccuracy = 84 +2055005  
BallControl = 75 +331838  
Age = 30 -1265245  
Strength = 87 +819585  
Positioning = 78 +351575  
ShotPower = 82 +269127  
SprintSpeed = 46 -495326  
Jumping = 64 -380232  
+ all other factors -321182  
prediction 7344354

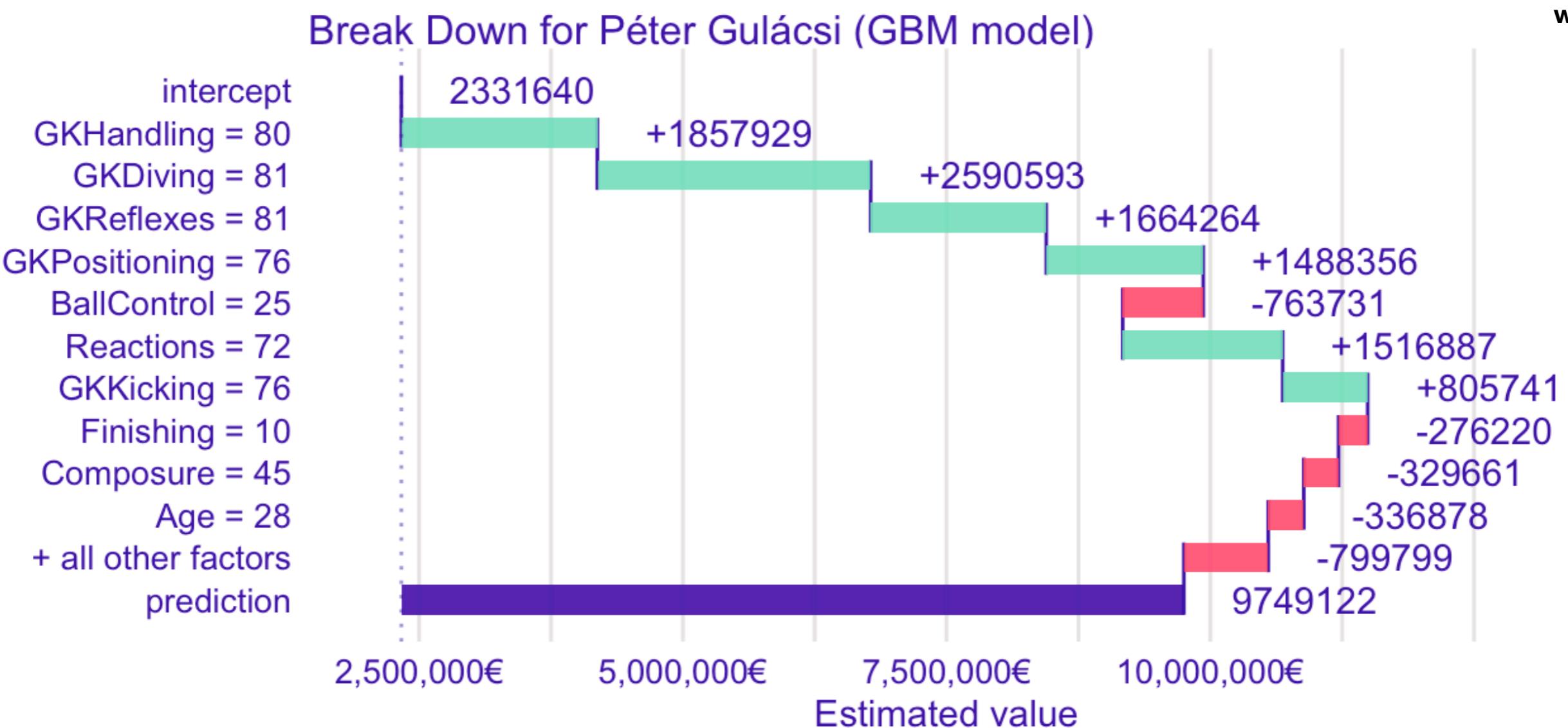
### Break Down for Ádám Szalai (GBM model)



Full name	Péter Gulácsi
Date of birth	6 May 1990
Place of birth	Budapest, Hungary
Playing position	Goalkeeper



wikipedia

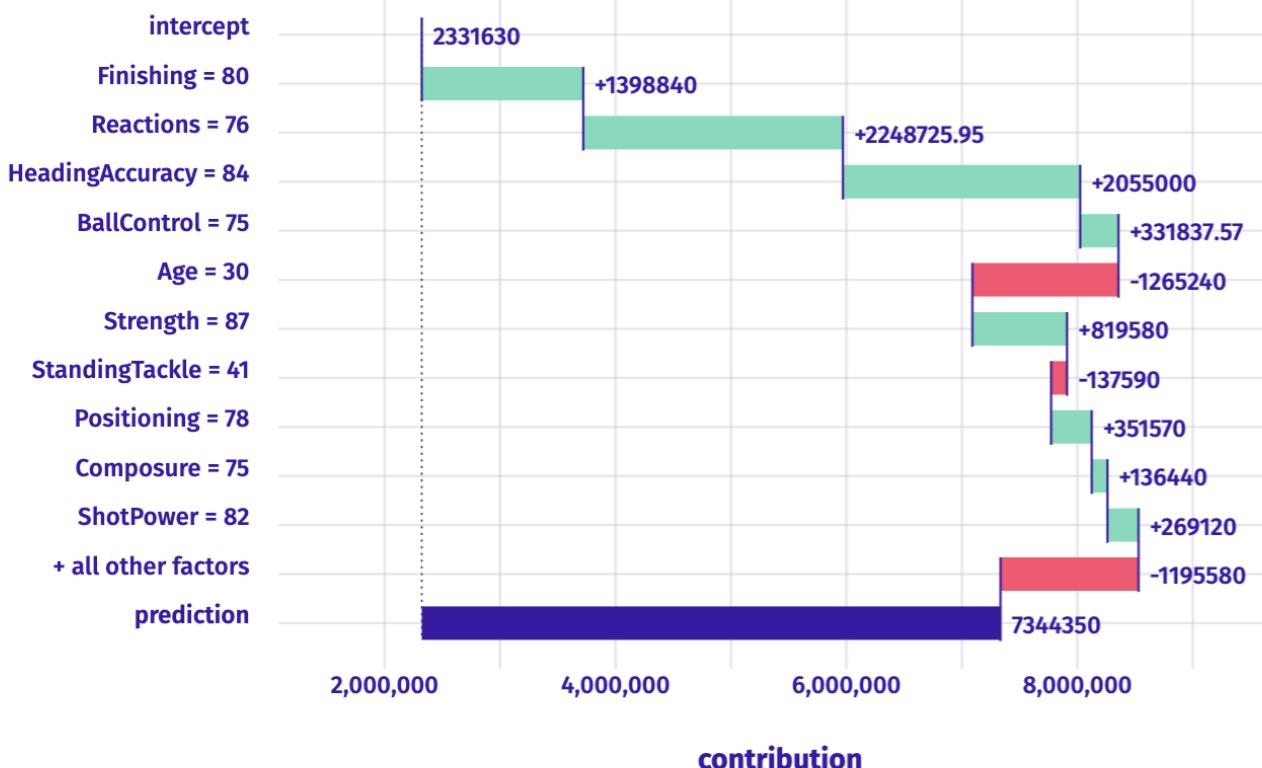


# Interactive Model Studio for FIFA 2019 GBM model

Ádám Szalai

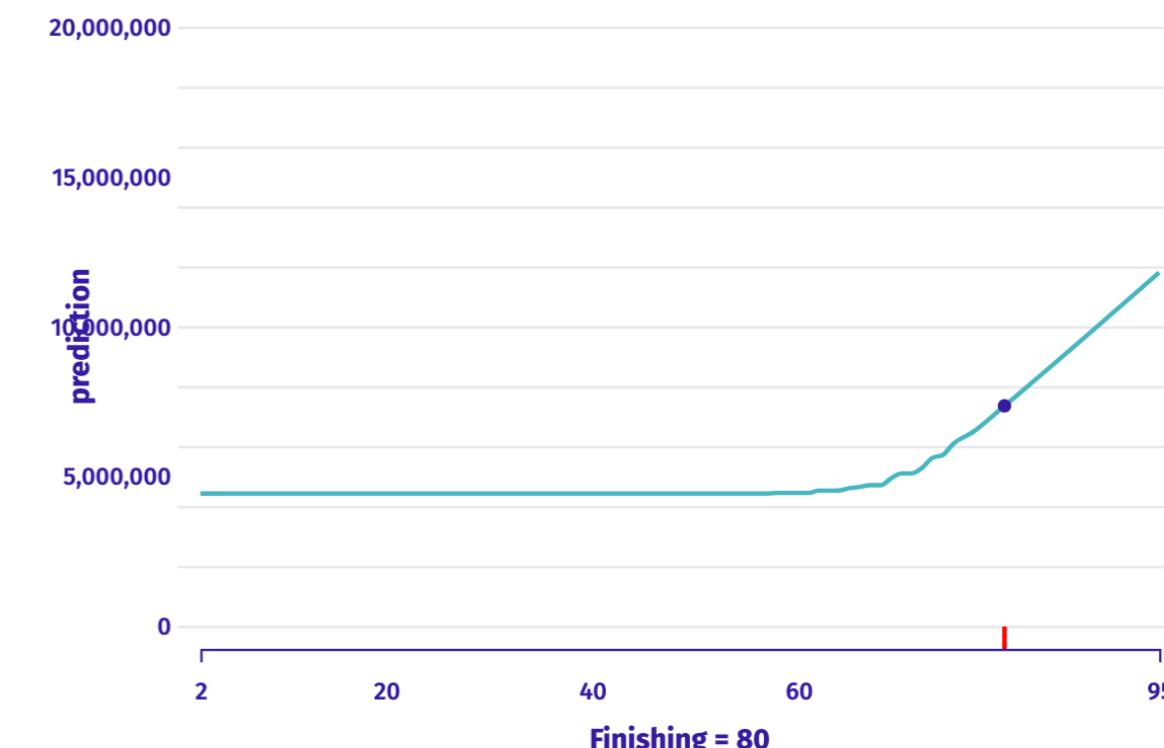


## Break Down



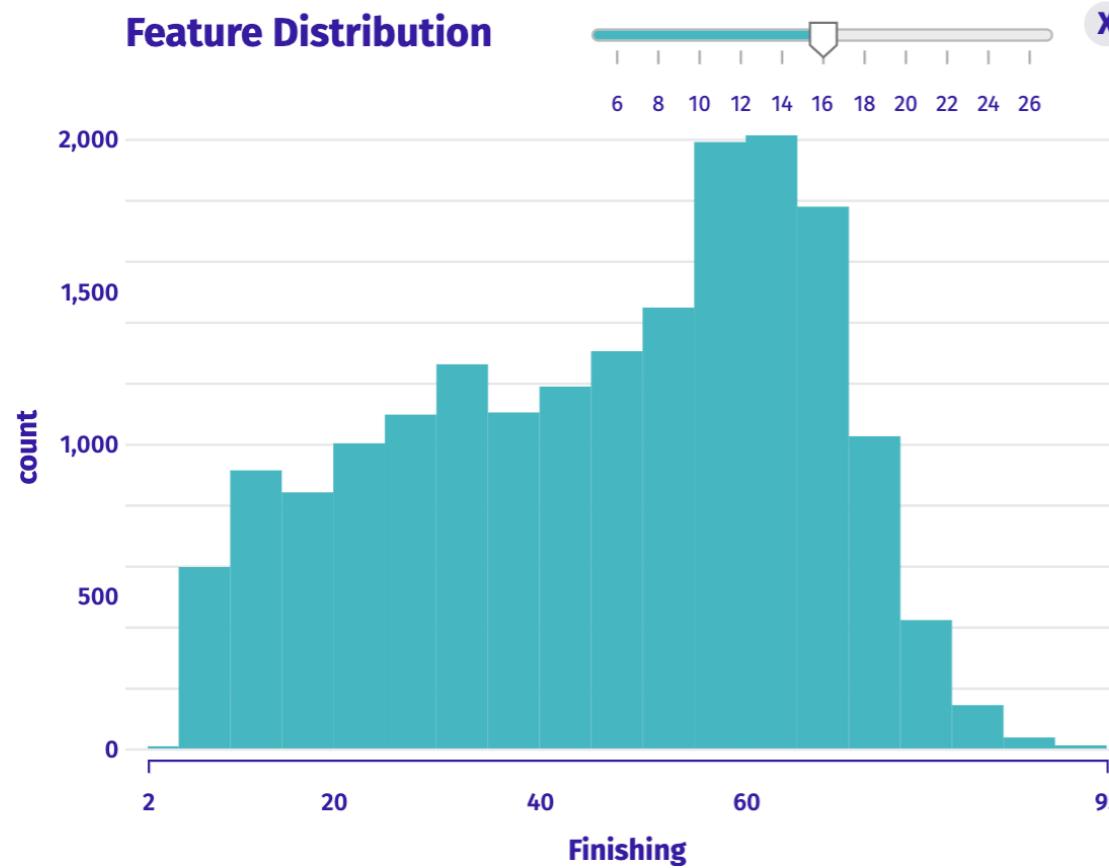
D X

## Ceteris Paribus



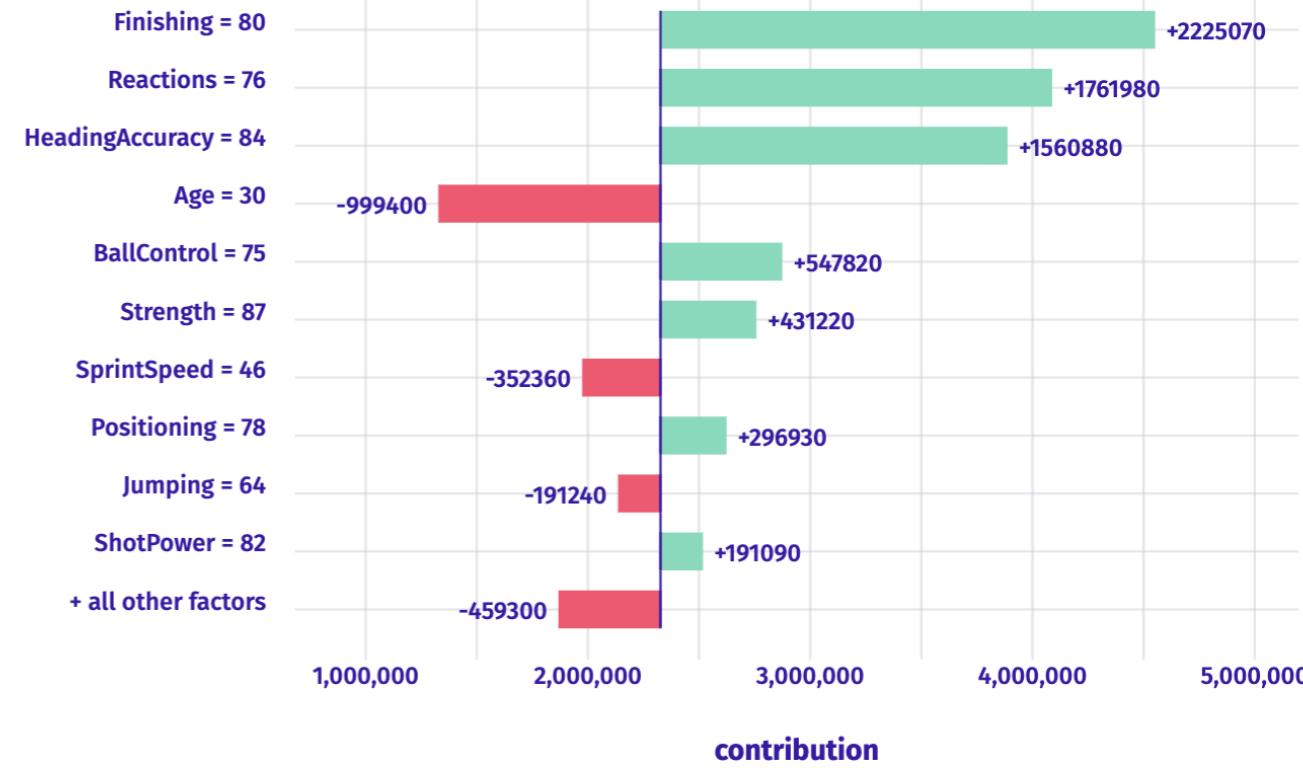
D X

## Feature Distribution



X

## SHAP Values



D X

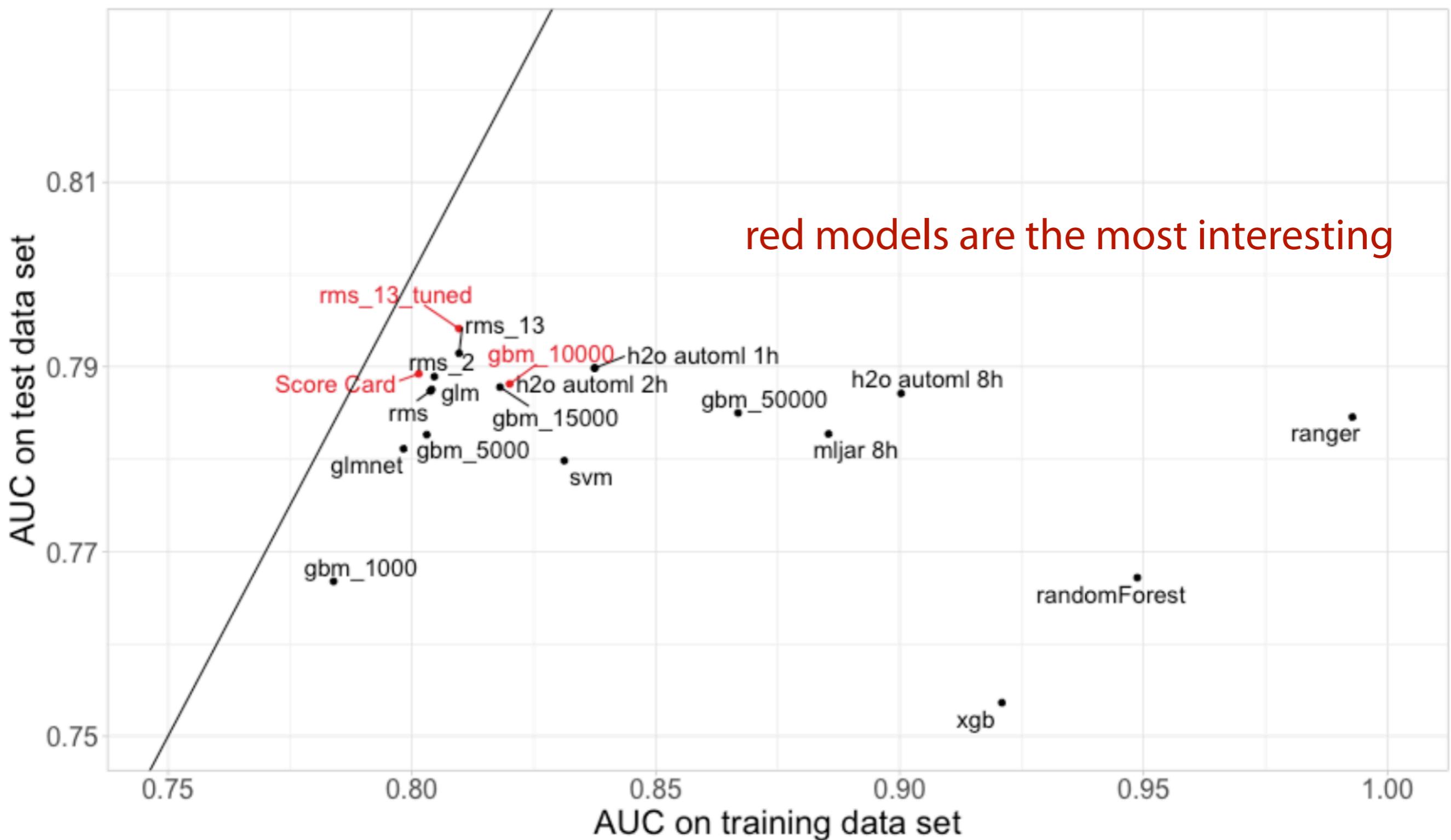
# Use case Credit Scoring

# Data set for study: xML Challenge by FICO

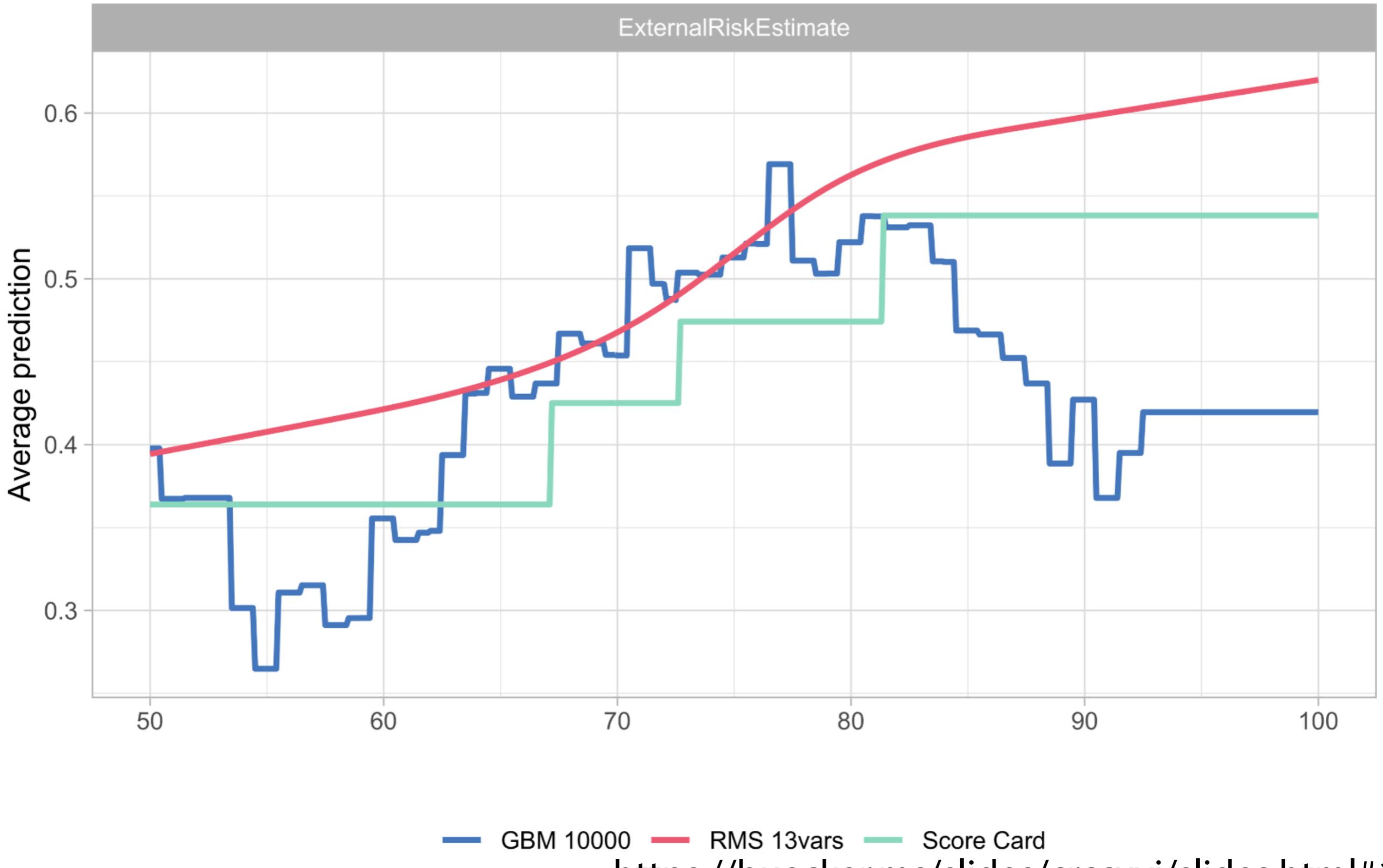
- Explainable Machine Learning Challenge by FICO (2019)
- Focus: Home Equity Line of Credit (HELOC) Dataset
- Customers requested a credit line in the range of \$5,000 - \$150,000
- Task is to predict whether they will repay their HELOC account within 2 years
- Number of observations: 2,615
- Variables: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

<https://buecker.ms/slides/crccxvi/slides.html#1>

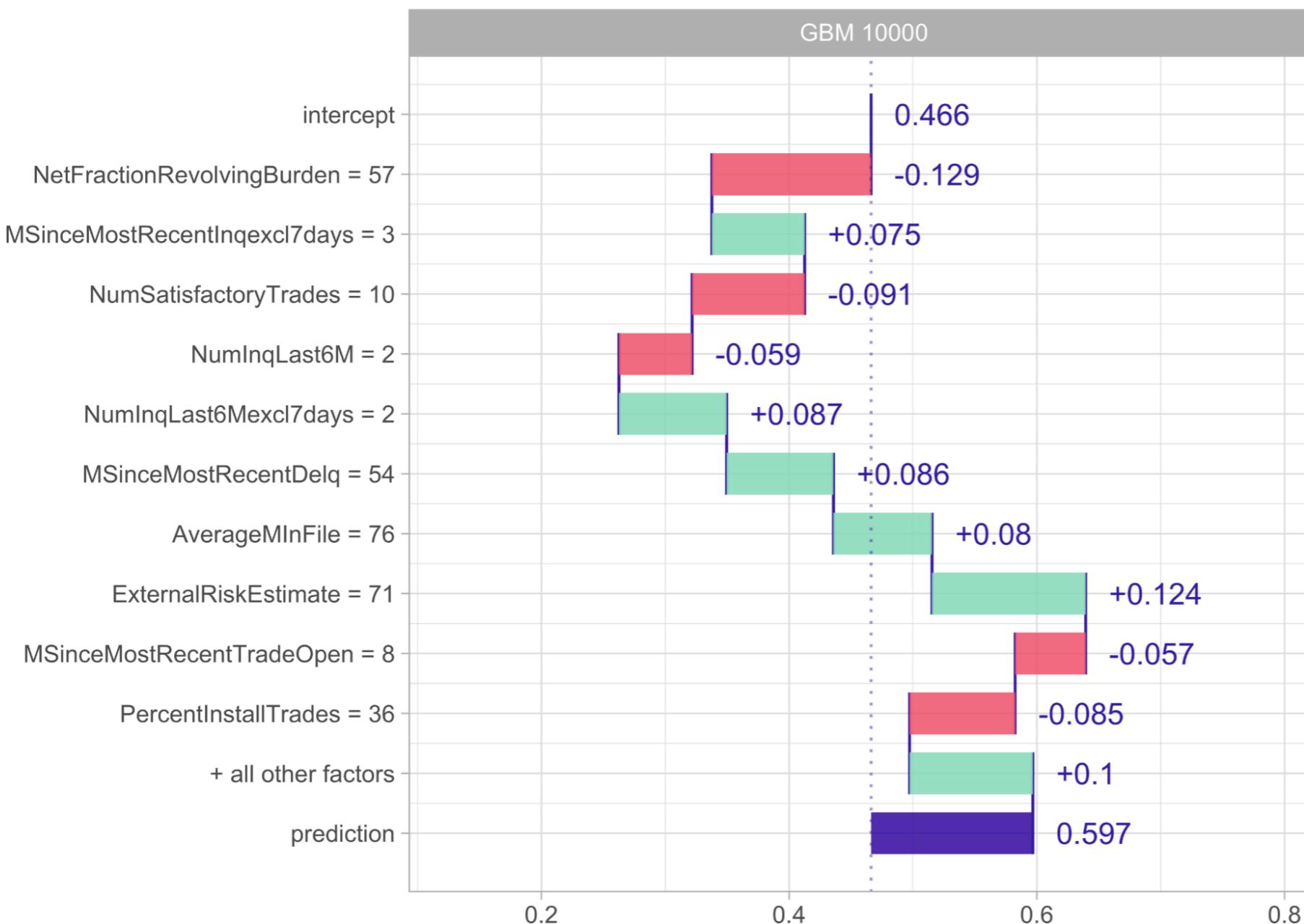
# Performance for selected modeling methods



# Partial Dependency Plot for the most important feature



# Model agnostic: Variable contribution break down



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

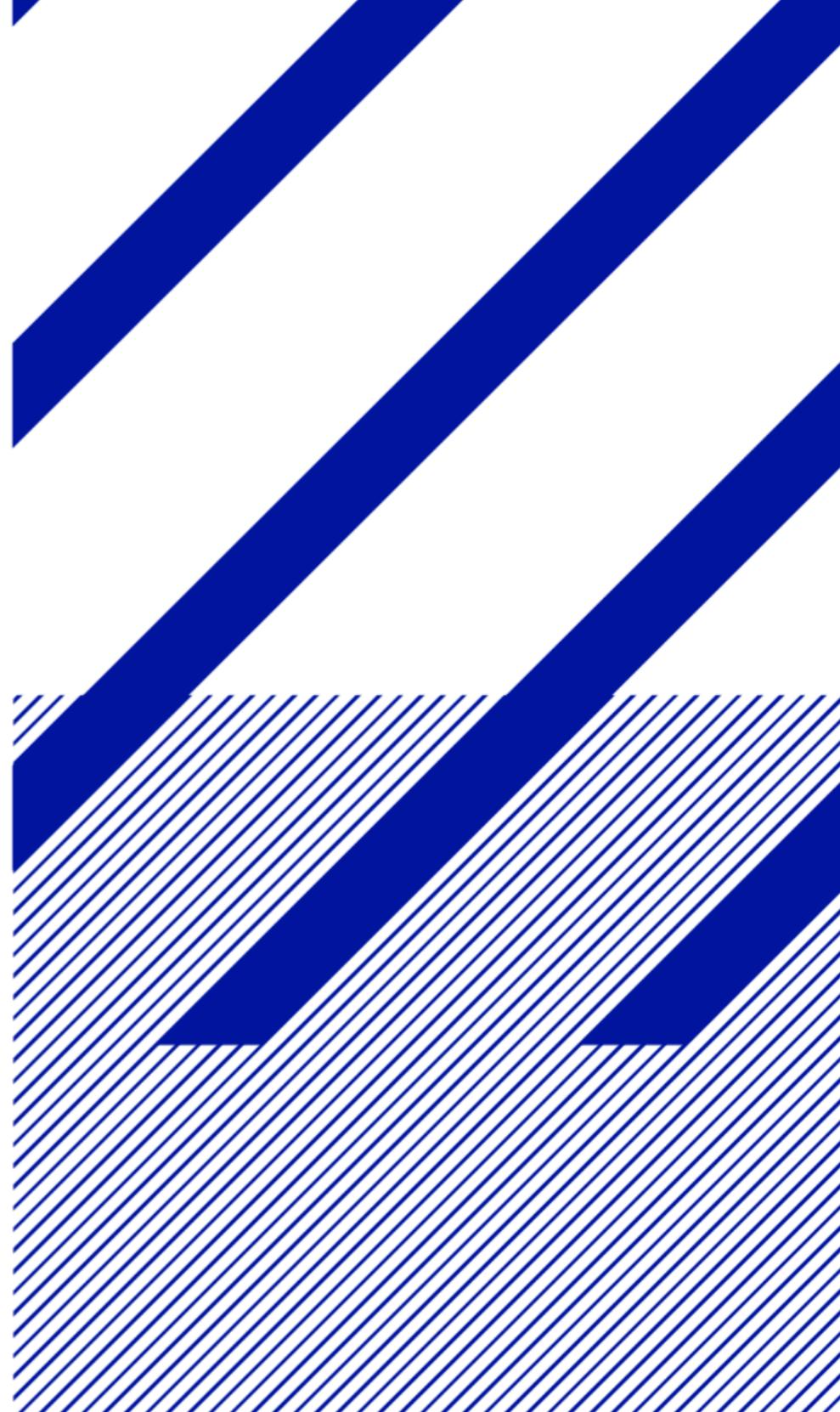
# Transparency of Machine Learning Models in Credit Scoring

CRC Conference XVI

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Michael Bücker, Gero Szepannek, Przemyslaw Biecek,  
Alicja Gosiewska and Mateusz Staniak

28 August 2019



<https://buecker.ms/slides/crccxvi/slides.html#1>

Model specific / agnostic  
explainability

## Model specific

- + Exploits the structure of a model
- + Allow for deep diagnostic
- Explanations cannot be easily compared between models
- You need to create an explainer for every possible model structure

Examples:

- `randomForestExplainer`
- `EIX` - `lightgbm/xgboost` explainer

## Model agnostic

- + Explanations can be compared between different models
- + Can be used to any model (model is a black box)
- Explanations are (in most cases) approximations, they may be inaccurate or wrong
- It is easy to miss some quirks

Examples:

- LIME / SHAP / Break Down / Partial Dependency Profiles / Permutational Feature Importance

Local / global  
explainability

# Local explanations

- + Focused on a single observation
- + Good for dissecting of a single prediction
- + Good for debugging

- Feature effects may be different for different observations
- Tricky for correlated features

# Global explanations

- + Focused on a model
- + Good for global model summaries
- + Good for comparisons

- Local behaviour may be different
- For non-additive models they may be too simplistic

## Examples:

- LIME / SHAP / Break Down
- Ceteris Paribus

## Examples:

- Feature Importance
- Partial Dependency Profiles

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Branch: master ▾

DALEX / README.md

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# Descriptive mAchine Learning EXplanations

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## Overview

The `DALEX` package (Descriptive mAchine Learning EXplanations) helps to understand how complex models are working. The main function `explain()` creates a wrapper around a predictive model. Wrapped models may then be explored and compared with a collection of local and global explainers. Recent developments from the area of Interpretable Machine Learning/eXplainable Artificial Intelligence.

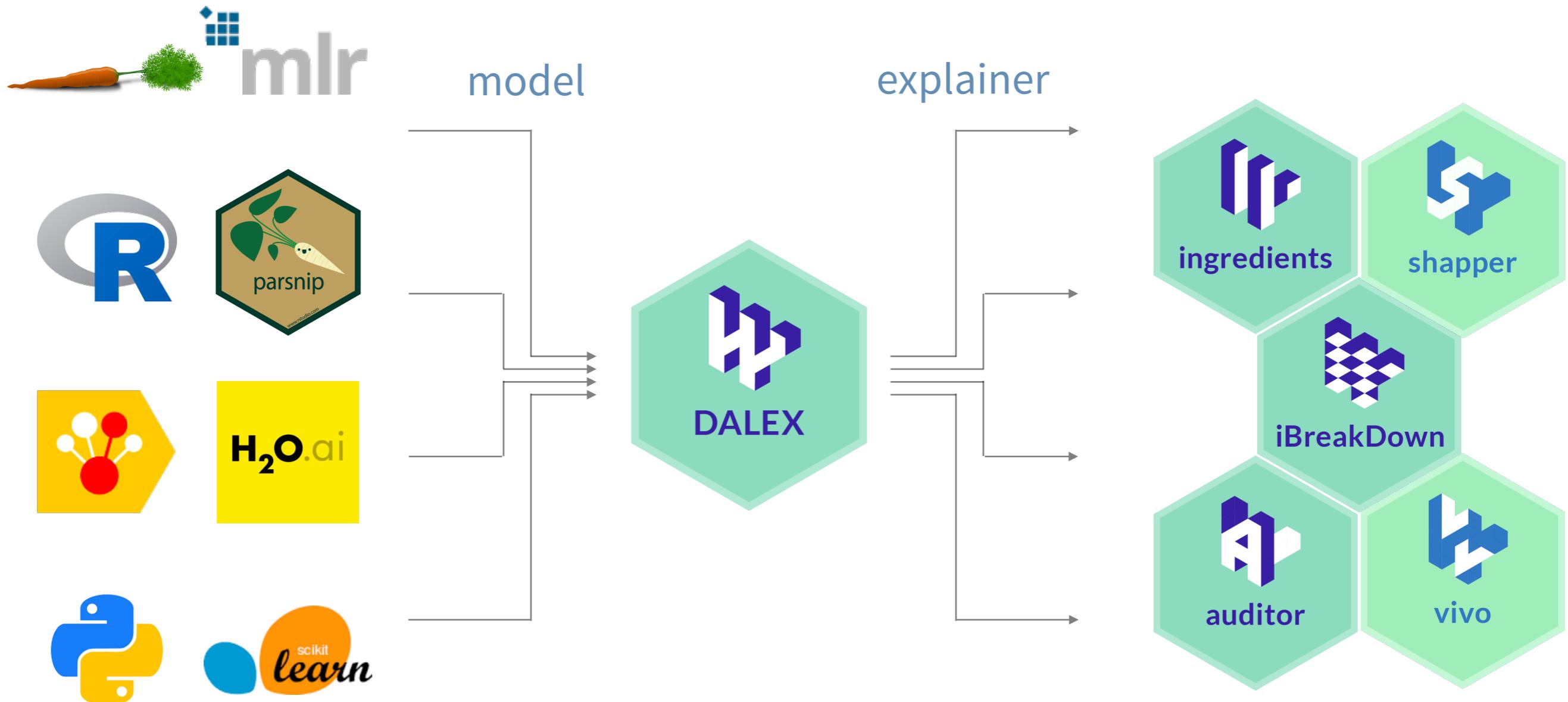
The philosophy behind `DALEX` explanations is described in the [Predictive Models: Explore, Explain, and Debug](#) e-book. The `DALEX` package is a part of [DrWhy.AI](#) universe.

If you work with `scikitlearn`, `keras`, `H2O`, `mljar` or `mlr`, you may be interested in the `DALEXtra` package. It is an extension pack for `DALEX` with easy to use connectors to models created in these libraries.

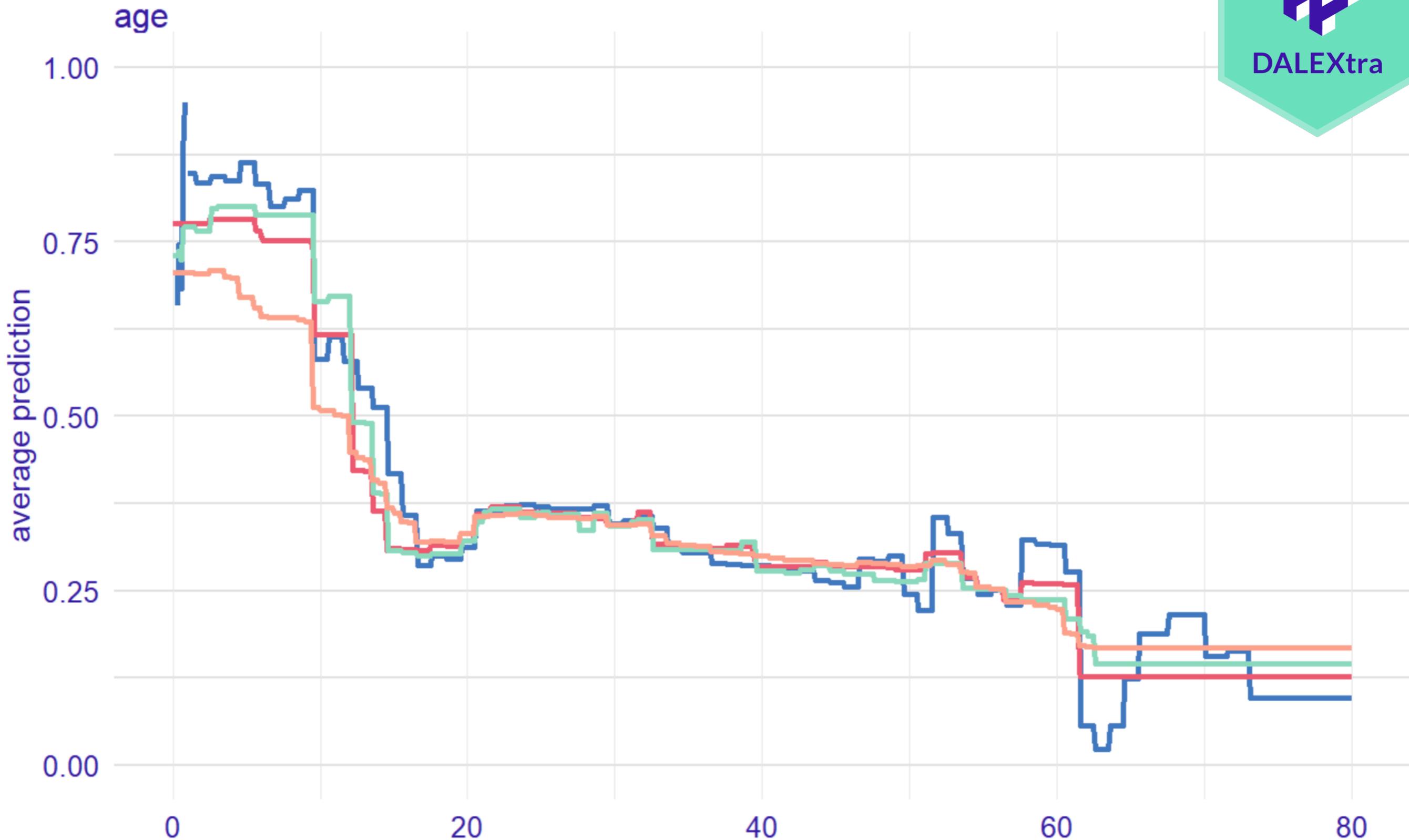
Make models  
not wars

DALEX wraps a model available in R or python or through REST API into a standardised container.

Other tools for XAI may then work on the model despite its internal structure.

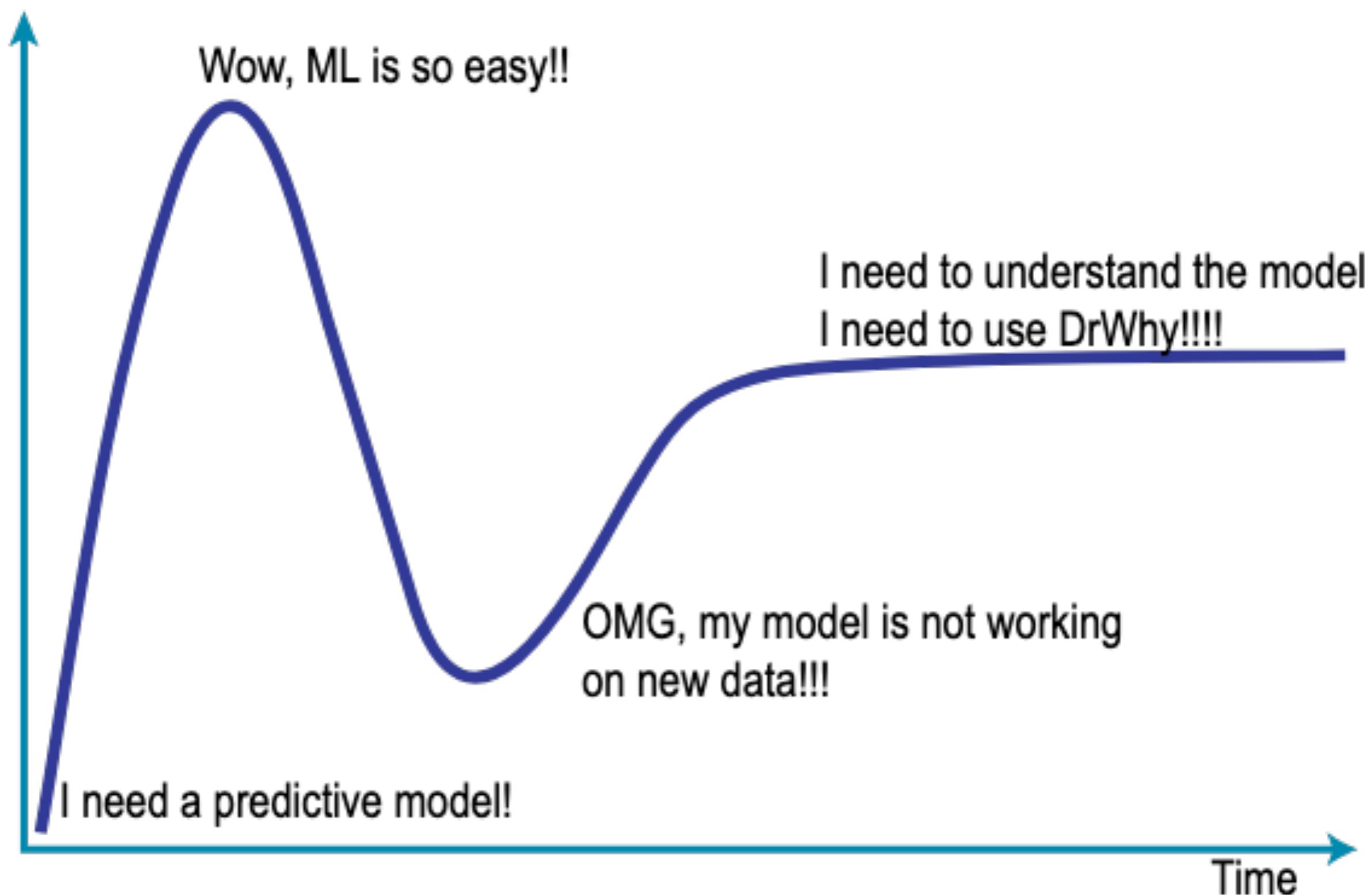


CatBoost (R) gbm (h2o/java) gbm (python/sklearn) gmb (R)



# Why should we care?

# Hype Cycle for Predictive Models



Thank you!