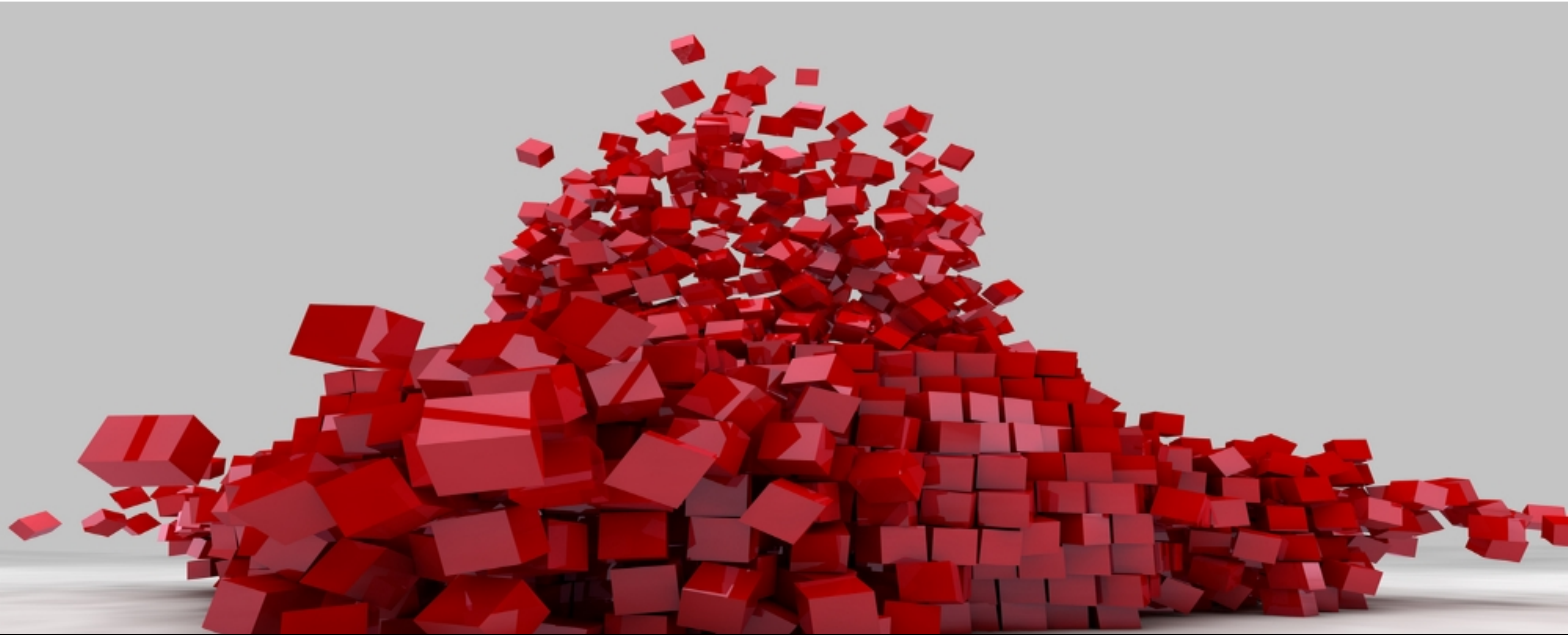


Open Banking current account information has the power to transform credit scoring and lending decisions

A Case Study

Agenda

- What is Open Banking?
- Overview of the case example and available data
- Summary of the challenges
- Our approach to developing an Open Banking credit score
- Summary of the results
- Implications for the industry

What is Open Banking?

Open Banking is the secure way to give providers access to your financial information *

- **The EU Revised Payment Services Directive (PSD2)** and national regulations such as the UK's Open Banking are designed to drive greater transparency, security, innovation and market competition
- It enables bank customers to use third-party service providers to carry out various activities based on their financial data, with their explicit consent
- This requires banks to provide access to customer account data and/or initiate payments to these providers.

Consumer lending is one of the main use cases for Open Banking, where customers can gain better access to credit when sharing their data.

** Source: UK Open Banking Implementation entity*

Open Banking provide a major opportunity to enhance credit scoring significantly

Our project has shown that credit scorecards using using Open Banking data alone have Ginis above 70%

Access to banking transaction data now puts all lenders on a similar level: all lenders now know as much about the customer as his/her own bank does

Based on our findings, we argue that most lending organisations operating in an Open Banking environment have a tremendous opportunity to enhance their credit decisioning capabilities significantly

The project background and result

The challenge

- To develop a predictive behavioural credit scoring model, by using only data which will be realistically available through Open Banking banking API
- To take into account current level of uncertainty related to Open Banking implementation in specific markets

The outcome

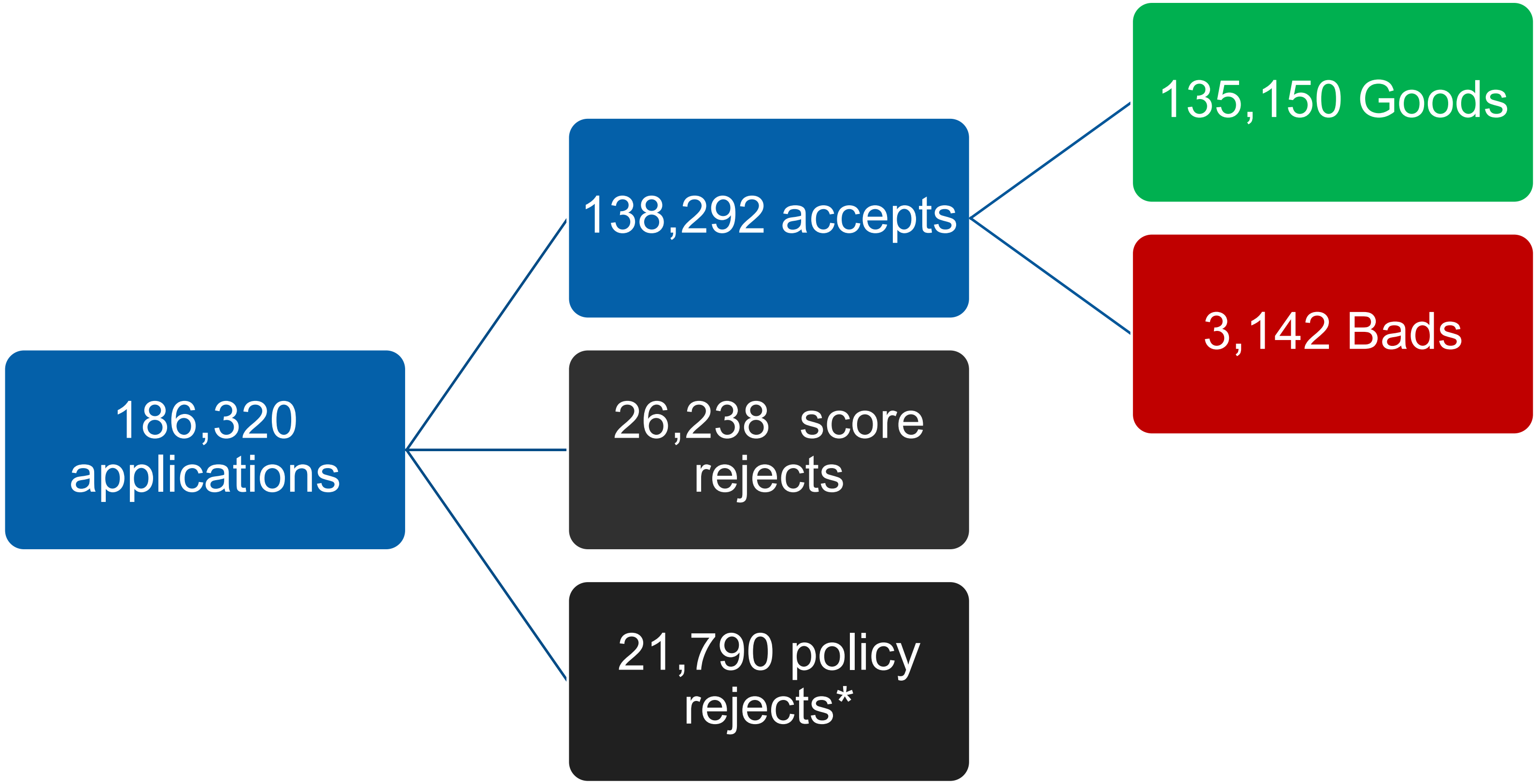
- Developed behavioral credit scoring model with accuracy of Gini of more than 70%
- Multiple models developed for most realistic Open Banking scenarios in the specific market, with good results in all the cases

The scoring model is based on 6 months of C/A transactions

	Data source	Description
Conservative scenario	• **Current account transactions**	• 6 months history prior to application for cash loan, amounts and balance only
	• Default (yes/no)	• Info if the customer defaulted during the observation time window, according to the definition used by the bank
	• Application data (for reject inference)	• Data on all the applicants: info on policy vs. scoring reject rationale; PD calculated by the legacy scoring model
Realistic / Optimistic Scenarios*	A combination of the following*:	
	• Demographic data	• Age
	• Approved overdraft	• Amount of approved overdraft at the day of applying for the cash loan
	• Length of banking relationship	• Year of opening of the current account

** This data was used only in for testing purposes. The deployed model is using data from the Conservative scenario*

Our data set was large enough to allow detailed feature analyses



* *Policy rejects were excluded from scorecard development*

To develop the model, our research combined best practice data science analytics and credit scoring analytics

Created over 3,000 features, ie composite variables created from the raw transaction data

20 different scenarios were evaluated in details

For each scenario, we trained 40 models with different test/train splits to determine stability of error (bootstrapping)

Developed several hundreds of codes, routines and visualisations in Tableau, Python and R

6 different machine learning techniques used, including logistic, linear regression, gradient boosting and neural networks

We created 3000+ of „features” (composite variables) from the transactions dataset

Challenge

- The data differs substantially from the ones used in traditional credit scoring
- Data contains only low-level features, such as individual transactions
- This is comparable to the challenge that machine learning algorithms are now successfully addressing when trained to recognize the content of an image: their input consists of low-level features – in this case, values of pixels of an image

Approach

Created 3000+ aggregate features

- **Simple variables**: minimal, maximal, average transaction,...
- **Aggregate variables**: e.g. max number of days without income, etc.
- **Statistical measures**: median, average, standard deviation of transactions of a certain type
- **Complex variables**, generated by specialized packages (e.g. Fourier transforms of the time series)

The most important variables in the model are often related to variance / deviation of the observed behaviour

The most important variables for one of the best performing models (Example)

- **6months_Current_balance_std_min** - Minimum of monthly standard deviations of current balance in last 6 months prior to application
- **6months_Current_balance_min_max** - Maximum of monthly minimums of current balance in last 6 months prior to application
- **6months_I_mean_min** - Minimum of monthly average outgoing payment in last 6 months prior to application
- **4week_size_of_transactions2week** – Number of transactions in 2 weeks prior to application
- **6months_avg_CTO_minus_DTO_ratio** - Difference between sum of all incoming and outgoing transactions by month: avg of last 3 months / avg of 3 months before
- **pilot_below_11_net_mean** - Average of transactions below xx Eur in the last 6 months prior to application
- **I_max3** – Maximum of outgoing payments in last 3 months prior to application

To deal with the lack of standards, we modelled a number of different scenarios

Challenge

- At the time of modelling, no agreed standard accross EU on data to be shared, as well as in multiple markets
- For e.g. Berlin Group standards, a large variability of possible interpretations
- The credit scoring models built for any specific market need to be flexible enough to cope with multiple future scenarios

Base and Composite scenarios

Variables used	1	2	3	4	5	6	7	8	9	10
Base	●	●	●	●	●	●	●	●	●	●
Tsfresh*						●	●	●	●	●
Age		●					●	●	●	●
City			●							
Overdraft*				●					●	●
Gdays*					●		●		●	

To deal with the noise and correlations, we compared multiple machine learning techniques and chose the best

Challenge

- Irregularity in current account transactions over time
- It is thus difficult to identify specific information such as salary
- In addition, information extracted from current account transactions in the form of specific features or variables is extremely correlated

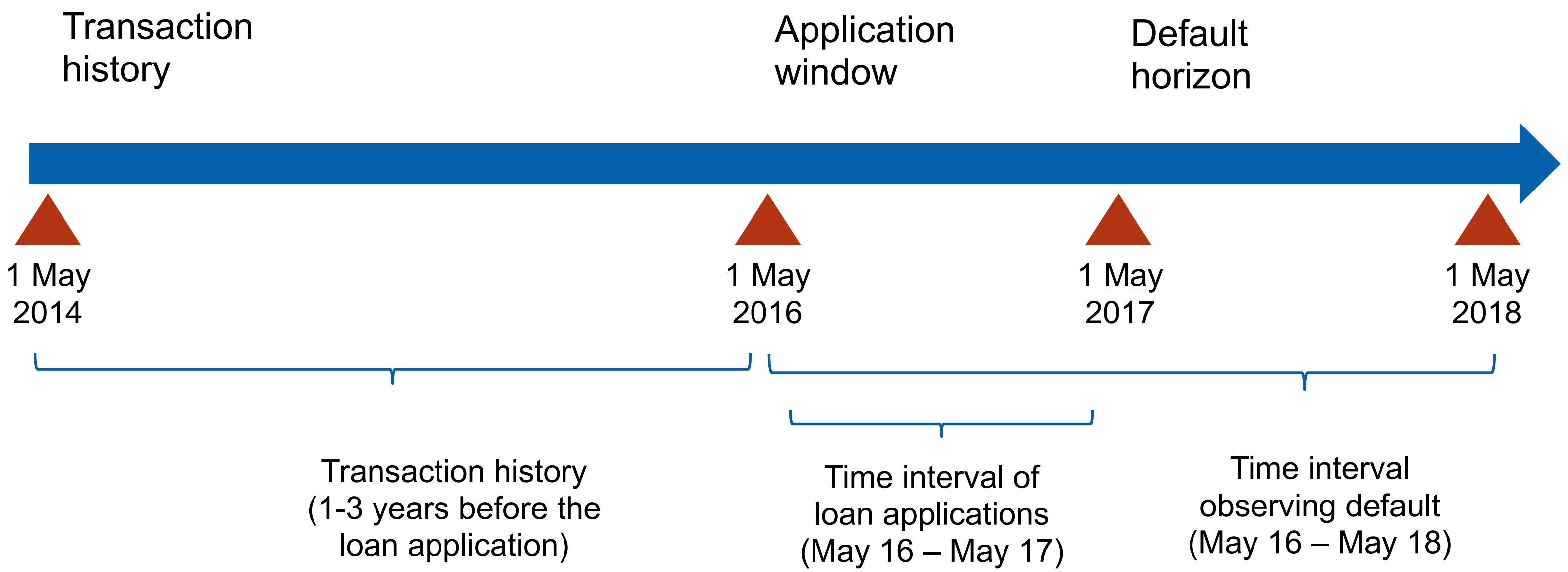
Compared machine learning models

- Logistic regression
- Random forests
- Support-vector machine
- Extreme gradient boosting (XGB)
- Neural networks

The best performing on the test set, deals well with correlated variables

We implemented the approach in line with the practices of the bank

Considered time windows



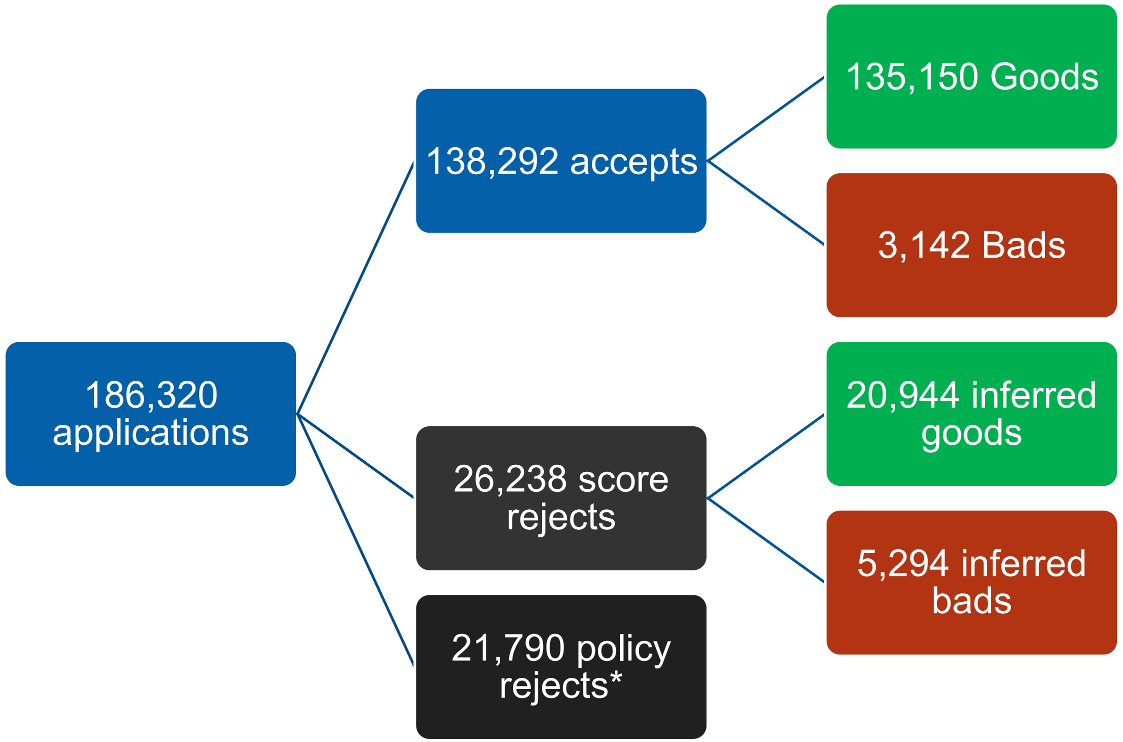
Definition of "bad"

- At lest Euro 250 of overdue payment for more than 90 consecutive days

Summary of the approach – reject inference

We carried out reject inference using a combination of:

- Previous score (PD) used for decisioning
- Accepts performance by score range
- Behaviour on rejects who had another credit product



** Policy rejects were excluded from scorecard development*

For regulatory purposes, we developed models to estimate monthly salary and debt ratio

The requirement

For regulatory purposes,

- Estimate algorithmically monthly salary
- Estimate algorithmically debt ratio
- Establish accuracy of these estimates / predictions

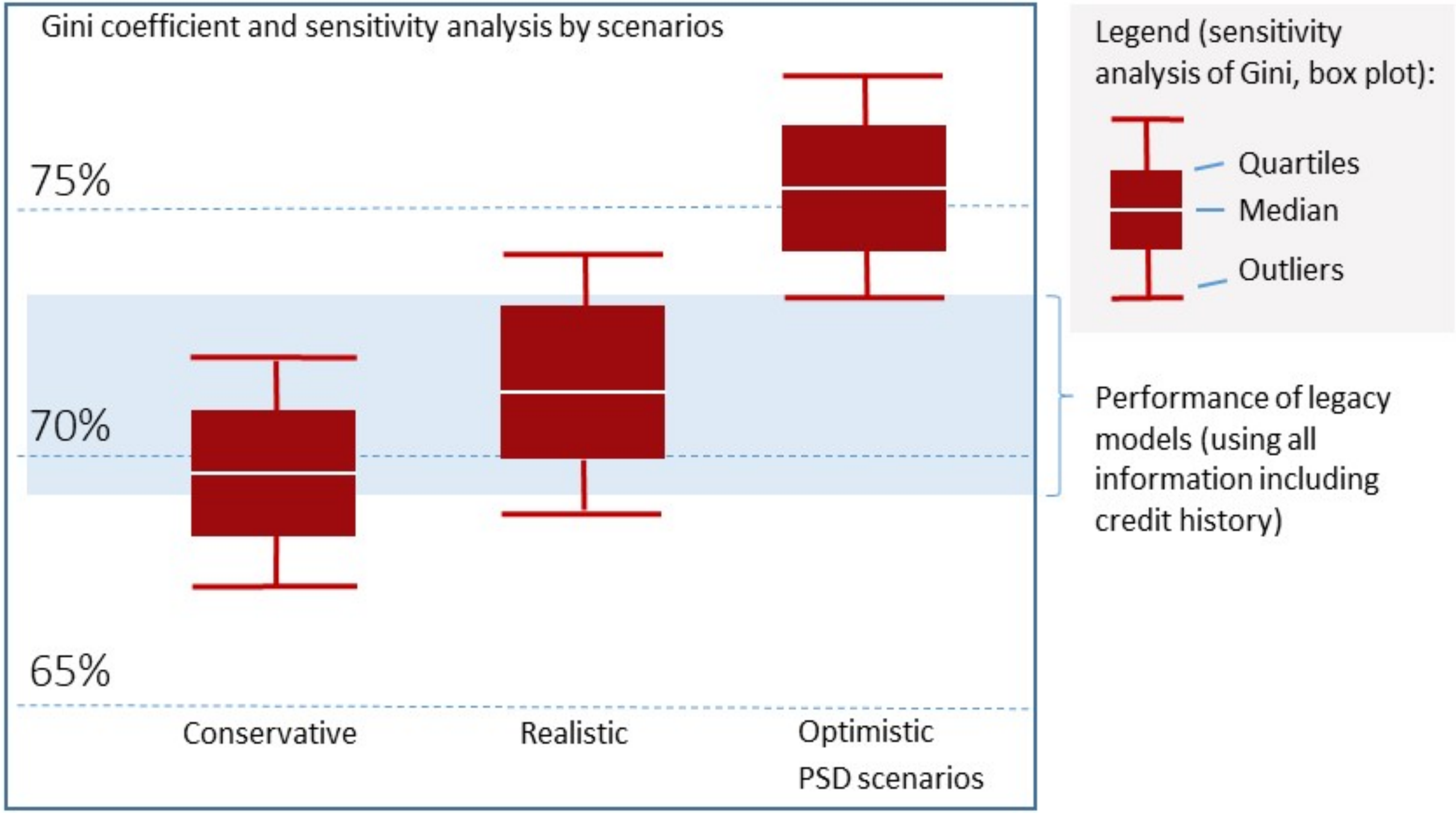
Approach

Developed separate predictive models:

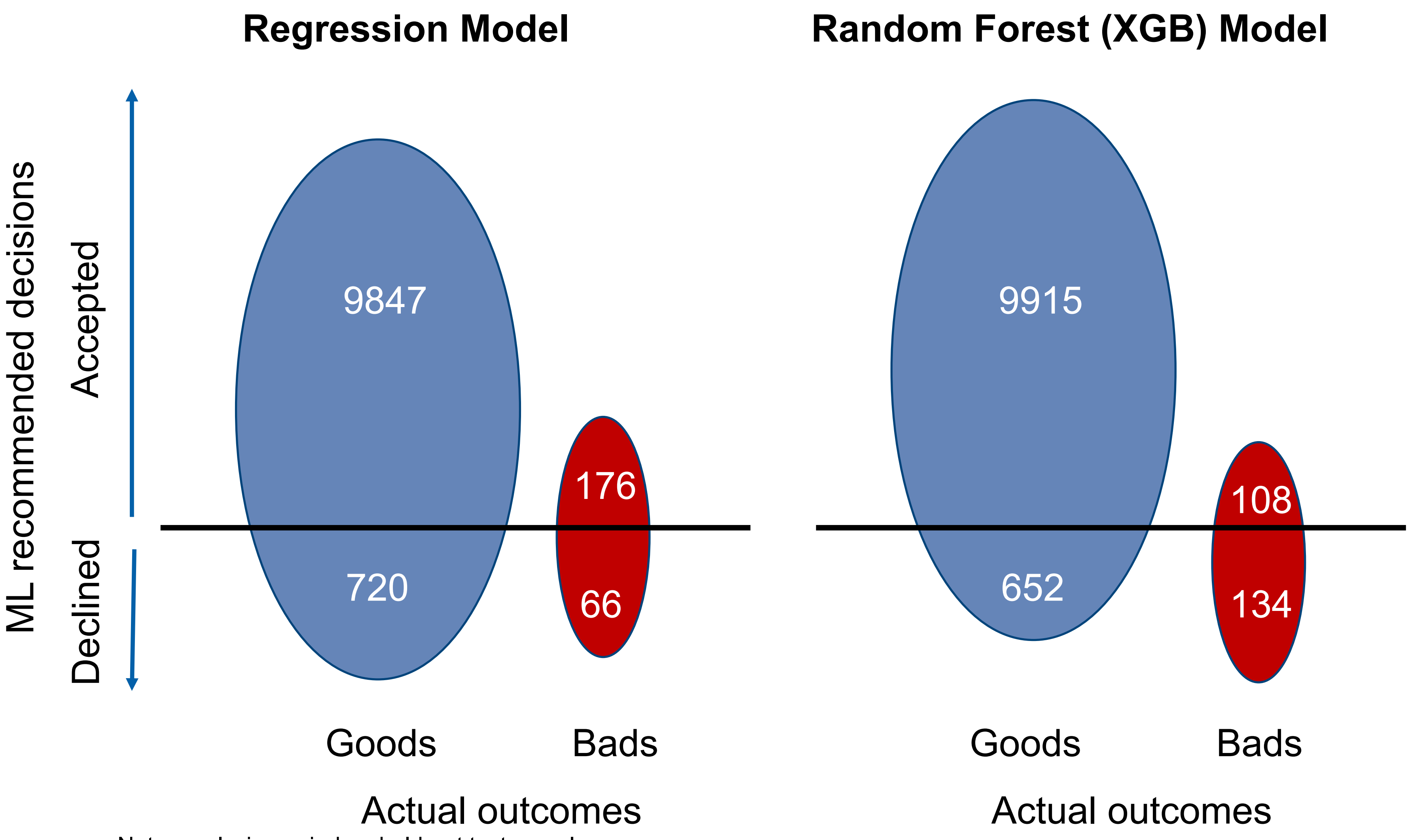
- To predict average monthly salary from the transactional data
- To predict average monthly loan payments from the transactional data
- Established statistical accuracy of these models, satisfactory for regulatory purposes

Outputs of these models as variables **did not significantly** improve predictivity of the credit scoring model

The performance of developed models, measured in Gini, is comparable or better than the legacy models.



The Extreme Gradient Boosting model is performing significantly better than the regression model



The Extreme Gradient Boosting (XGB) model is performing significantly better:
the difference in decisions represents **39% less bad customers**, and close to **1% more good customers** accepted

Note: analysis carried on hold-out test sample

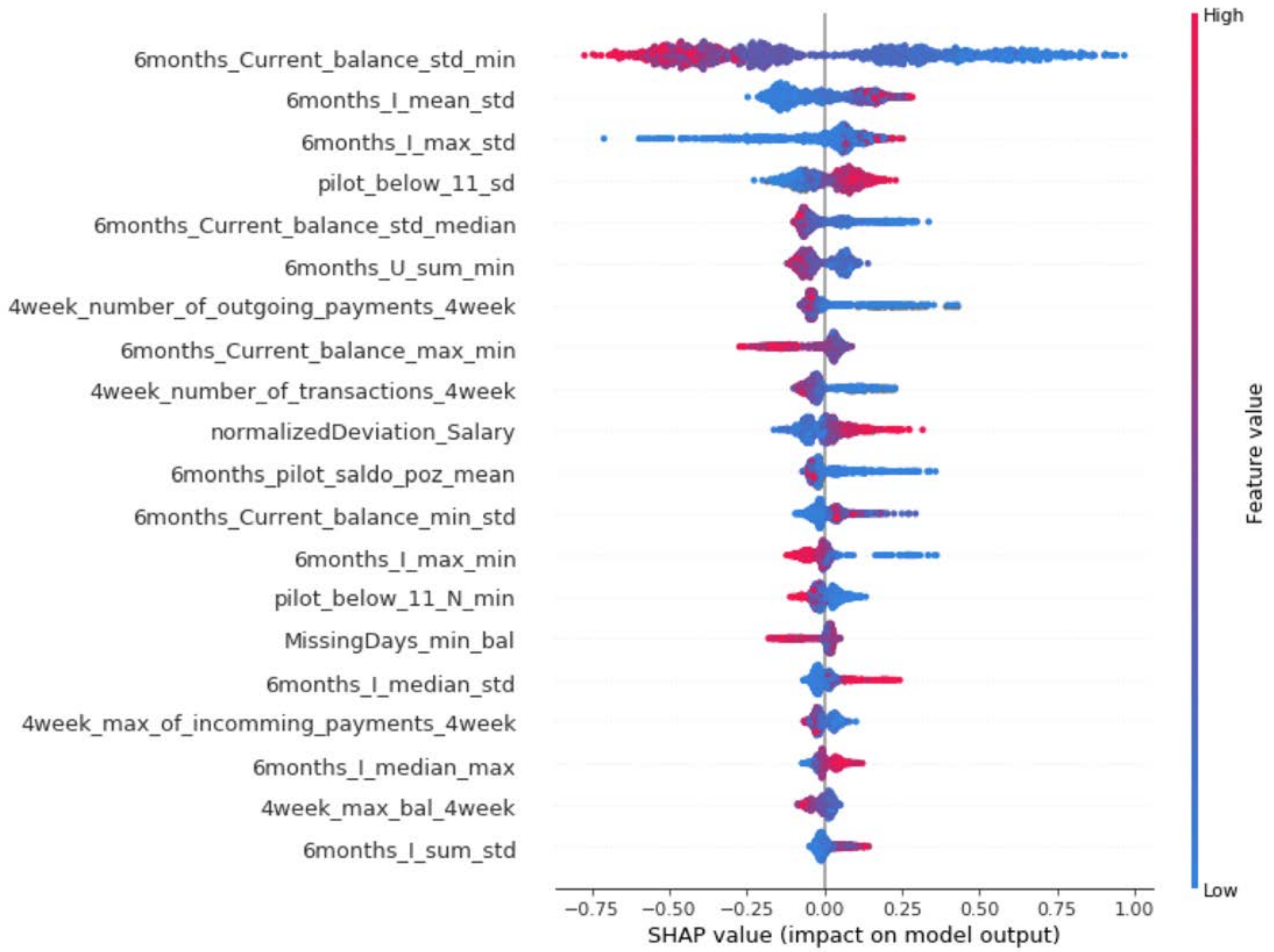
The better performance of XGB models can be understood by much more precise capturing of „feature interactions”

XGB model, score 0.09, classified as bad, actually became bad

Regression model, score 0.05, classified as good, actually became bad

- Regression underpeforms, as two features typically correlated with good clients in this case drive the score up independently of the other variables
- XGB model is able to „dampen” typically good features, depending on other features, thus resulting with a more accurate score

To interpret and monitor the model, we are using the „SHAP" technique



Implications for the industry

Open Banking enables lenders to have access to a new wealth of information that is extremely predictive of credit risk:

This information is granular, recent, and provides a unique perspective on credit applicants financial behavior

Combined with traditional credit history, lenders now have a comprehensive picture to take automated credit decisions

This means:

- Better assessment of credit risk
- Better assessment of affordability
- Faster decisions
- More relevant and adequate credit offers
- Level playing field competition

And this benefits:

- Consumers
- Lenders
- Regulators:
  - ✓ Competition
  - ✓ Conduct
  - ✓ Prudential

cantab predictive intelligence

TRENT Advisory Services

Thank you!

Sinisa Slijepcevic: sinisa@cantbpi.com
Marc Gaudart: mg@trentadvisoryservices.com

cantab predictive intelligence

TRENT Advisory Services