

# Credit Risk Scoring Perspective on East African Banks

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# Credit Risk Scoring Perspective on East African Banks

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# Retail Credit Scoring

# Agenda

1. Introduction
2. Importance of Credit Scoring for Retail Exposures
3. Credit Scoring: Setting and Challenges
4. Implications and Applications
5. Q&A

1

Introduction

# 2

## Importance of Credit Scoring for Retail Exposures

# Why do we care about measuring Credit Risk?

- » **Credit Risk** is associated with a potential event when a counterparty will be unable to meet its financial obligations in full → we need to control arising credit risks
- » Proper Credit Risk Management covers
  - Identification, evaluation and **measurement** of Credit Risk
  - Monitoring, reporting and effective communication
  - Actions and efforts to meet regulatory and underwriting standards
- » Existence of an efficient set of Credit Risk models is a **must** in the current global situation
- » Credit Scoring model is an essential piece of such modelling set



# A Holistic Modelling Approach

Risk modelling to drive the business model of a bank

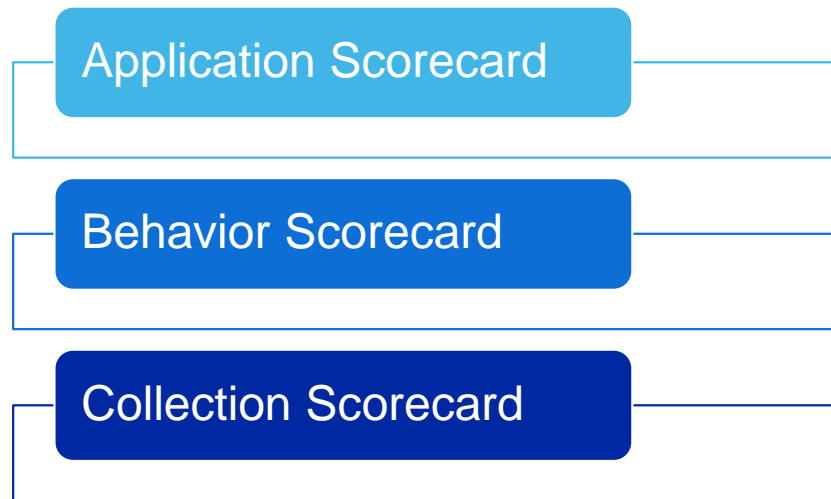


# 3

## Credit Scoring: Setting and Challenges

# Scorecard Introduction

- » Scorecard models are built to rank order borrowers in terms of their default risk.
- » It does not identify “good” or “bad” applications on an individual basis. It provides statistical odds, or probability, that an applicant with any given score will be “good” or “bad”.
- » Scorecards are developed using the assumption that “future performance will reflect past performance.” Based on this, the performance of previously opened accounts is analyzed in order to predict the performance of future accounts.



Characteristic	Class	Coeff	Points
LTV	0-50%	-1.258	45
	50-70%	-0.895	33
	70-90%	0.589	-10
	90%+	1.089	-28
Region	North	0.689	-14
	Center	0.213	-2
	South	-0.325	9
Marital Status	Single	0.8	-30
	Married	-0.8	30
Months on Book	<2 years	-0.986	24
	≥ 2 years	0.589	-16
Constant		-3.258	420

Score = 461

# Scorecard Types

Data is a key but alternatives are present



## Data-based

Approach based on historical (3-5 years) data for Retail exposures.

*Requires: High-quality data on defaulted and performing facilities including customer and loan-level characteristics*



## Hybrid

Approach based both on historical (3-5 years) data and expert surveys

*Requires: Part of data on defaulted and performing facilities; Expert surveys on expected default patterns*



## Judgmental

Approach based exclusively on expert surveys

*Requires: Extensive surveys on expected default patterns*

# Scorecard Model Build Methodology

## Six Steps Approach

**Sample Building.** To ensure that the data used mirrors the Bank's experience and business.

**Binning.** To discretize each variable's information. This ensures simplicity to the tool.

**Model Performance.** To assess the capacity of the model in discriminating good and bad accounts.



**Variable Selection.** To consider the most significant variables as potential predictors.

**Model Build.** To select the most important predictors and assign them the correct weight in predicting the default event.

**Model Validation.** To validate the efficacy of the model on independent samples.

# Scorecard Key Components



## Target Variable

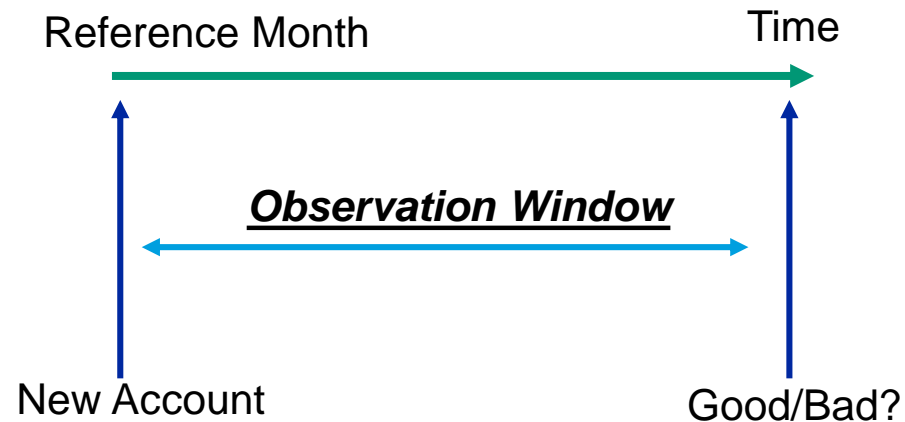
The target variable is the **default flag**. The flag is defined internally in each institution.

- » Days past due
- » Unlikelihood to pay
  - Forbearance
  - Litigation
  - Deceased
  - Bankruptcy



## Observation Window

Gather data for accounts opened during a specific time frame, and monitor their performance for **time window** to determine if they were good or bad.



## Scorecard Characteristics

Relevant **credit and loan characteristics** should be included to be selected as predictors.

### Internal data

- » Performance
- » Product
- » Loan / Customer characteristics
- » Internal scores

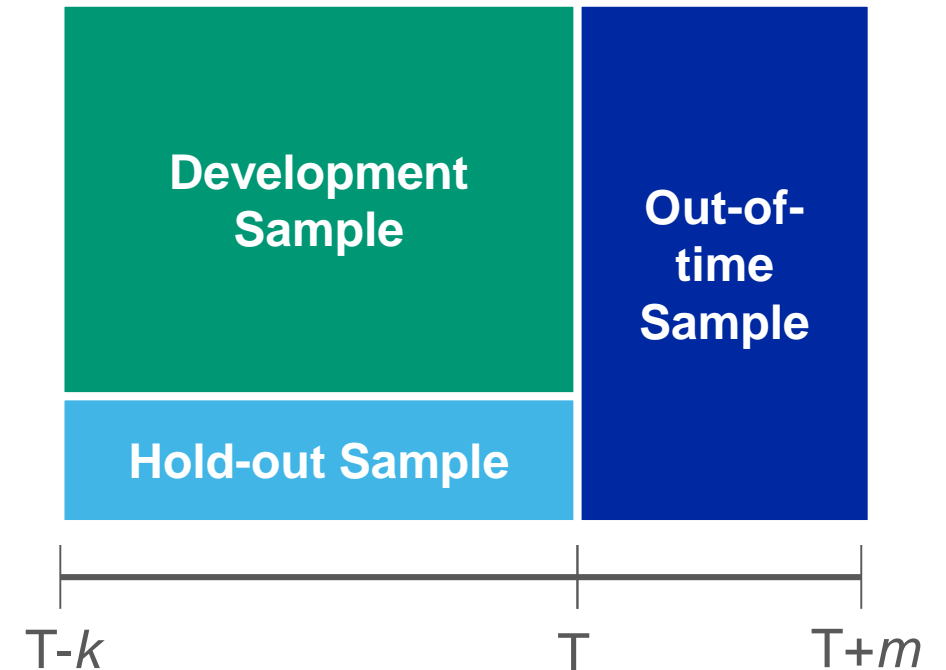
### External data

- » Bureau or partner data
- » Other sources

# Scorecard Sample Building

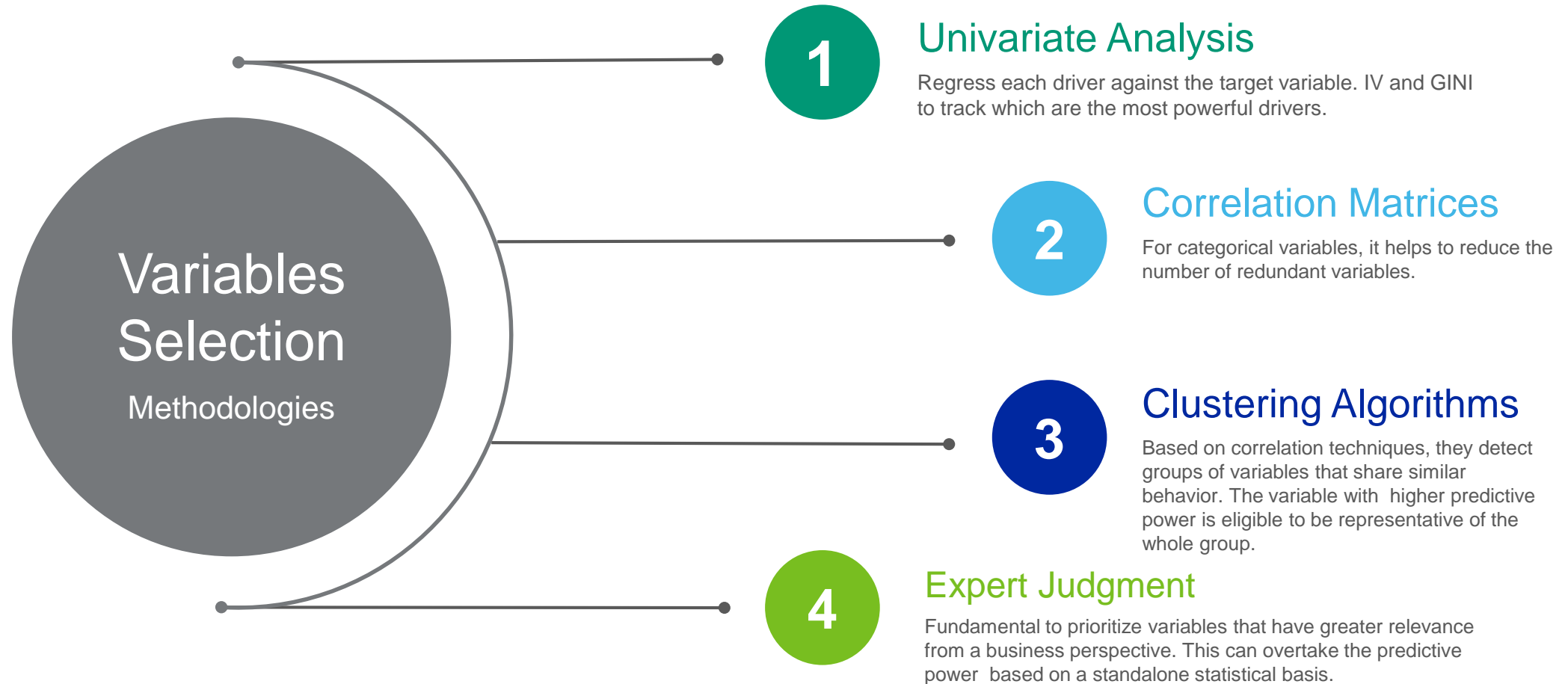
## Step 1

- » Development and holdout samples should cover
  - The longest possible time frame in terms of observation dates
  - The same time-frame
- » Development sample should contain more records than the holdout
- » Typically: 60/40, 70/30, 80/20 split depending on the sample size. It is important that the holdout contain enough goods/ bads
- » Where sample sizes are small, the scorecard can be developed using 100% of the sample and validated using several randomly selected samples of 50% to 80% each
- » Out-of-time sample contains observations completely separated in time from the development/holdout sample; typically 6-12 months
- » Typically about 2,000 each of goods, bads, and rejects are sufficient for scorecard development.
- » Distribution of goods and bads should not be statistically different in development and validation samples (Kolmogorov-Smirnov test can be used for this purpose).



# Variable Selection

## Step 2





# Binning Approaches

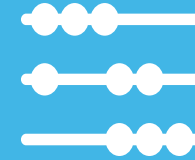
## Step 3



### Experience-Based

Based on experience and industry knowledge

May be subjective and difficult to defend



### Statistically-Based

Using statistical techniques to define unique bins

More objective and rigorous

# Model Building

## Step 4

» The most popular model estimation techniques are:

- **Logistic regression**

- › Straightforward and sufficiently robust.
- › Algorithms to control for tolerance, stepwise entrance of the drivers
- › Results between 0 and 1.

- **Decision Tree algorithms**

- › Finds the best split between variables to maximize discrimination
- › Not easy to control in the split/weight they provide

- **Machine learning algorithms**

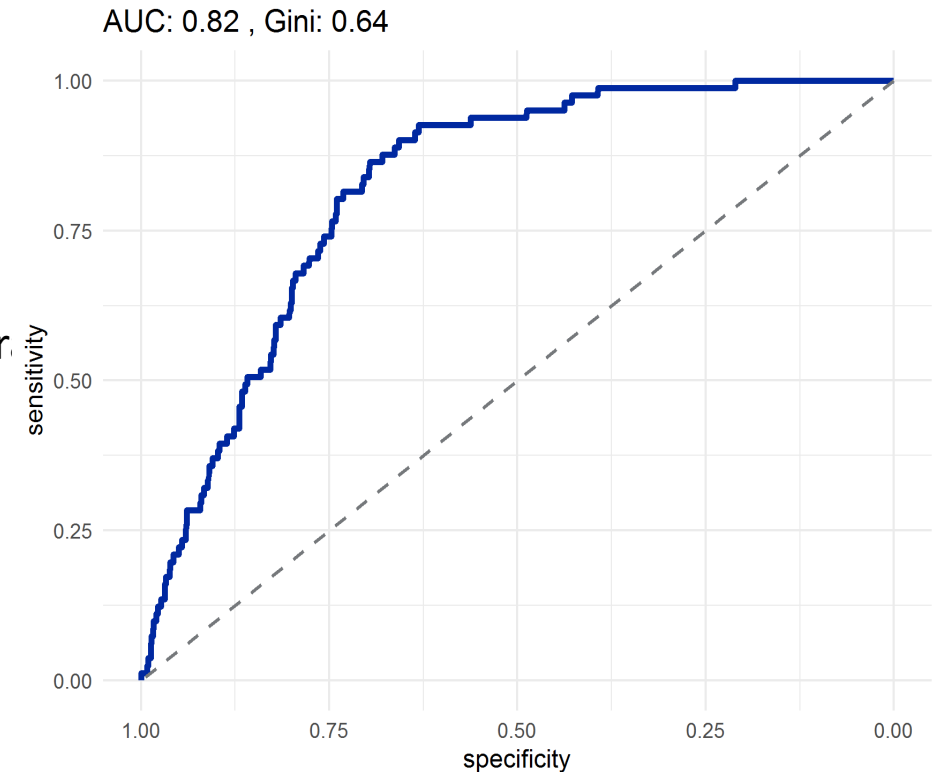
# Model Performance

## Step 5

The effectiveness of the scorecard can be verified under the following risk-metrics:

- » **Gini Coefficient:** ability to measure the rank-order capability (i.e. distinguishing good/bad accounts).  
Benchmark values: 40-60% (Application scorecard), 70-80% (Behaviour Scorecard)
- » **AUROC:** ability to measure accuracy of classification.  
Benchmark values: 50% (Random guess), 100% (perfect correct predictions)

Both these metrics are recommended by the Basel Committee (Working paper n.14- Studies on the Validation of Internal Rating System)



# Model Validation

## Step 6

The model is built on the development sample. It is therefore important to test on independent samples its effectiveness, using the same risk-metrics describes previously.

### **Out-of-Sample validation**

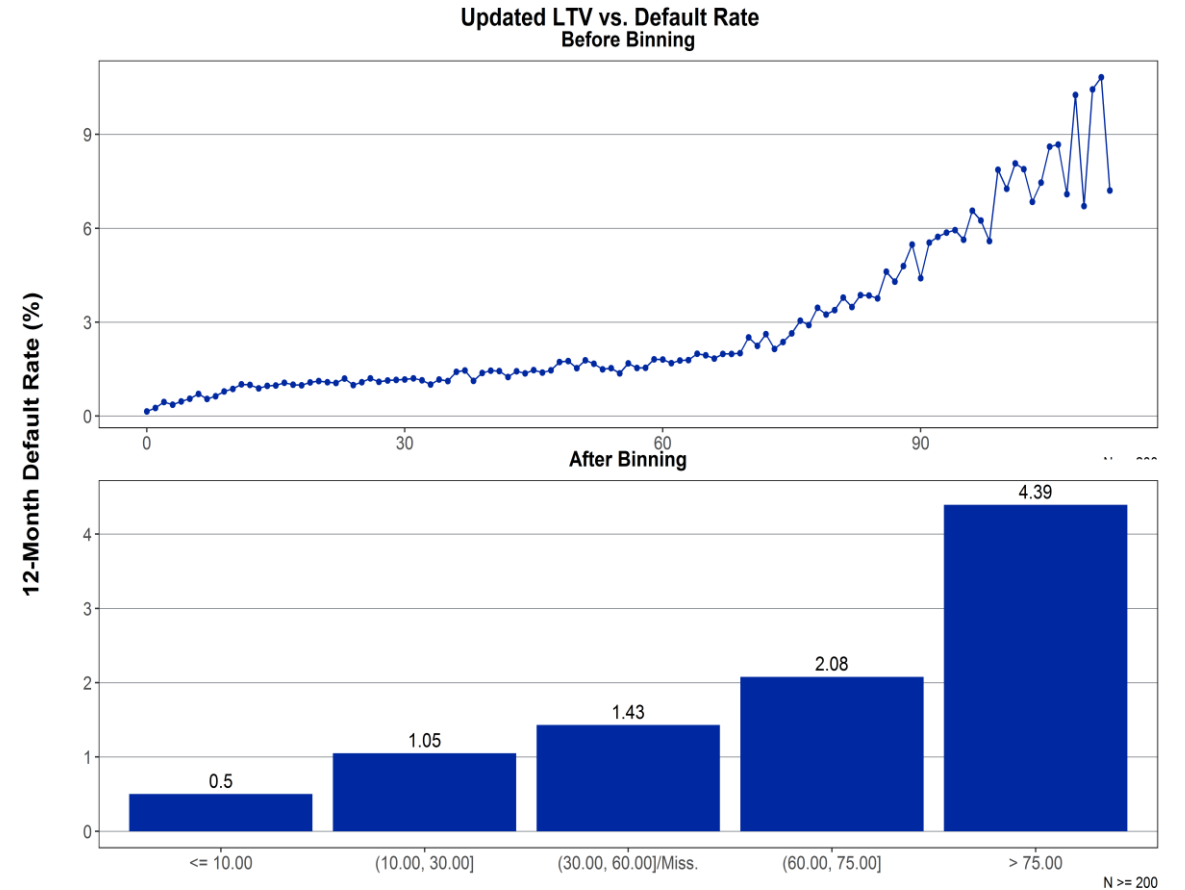
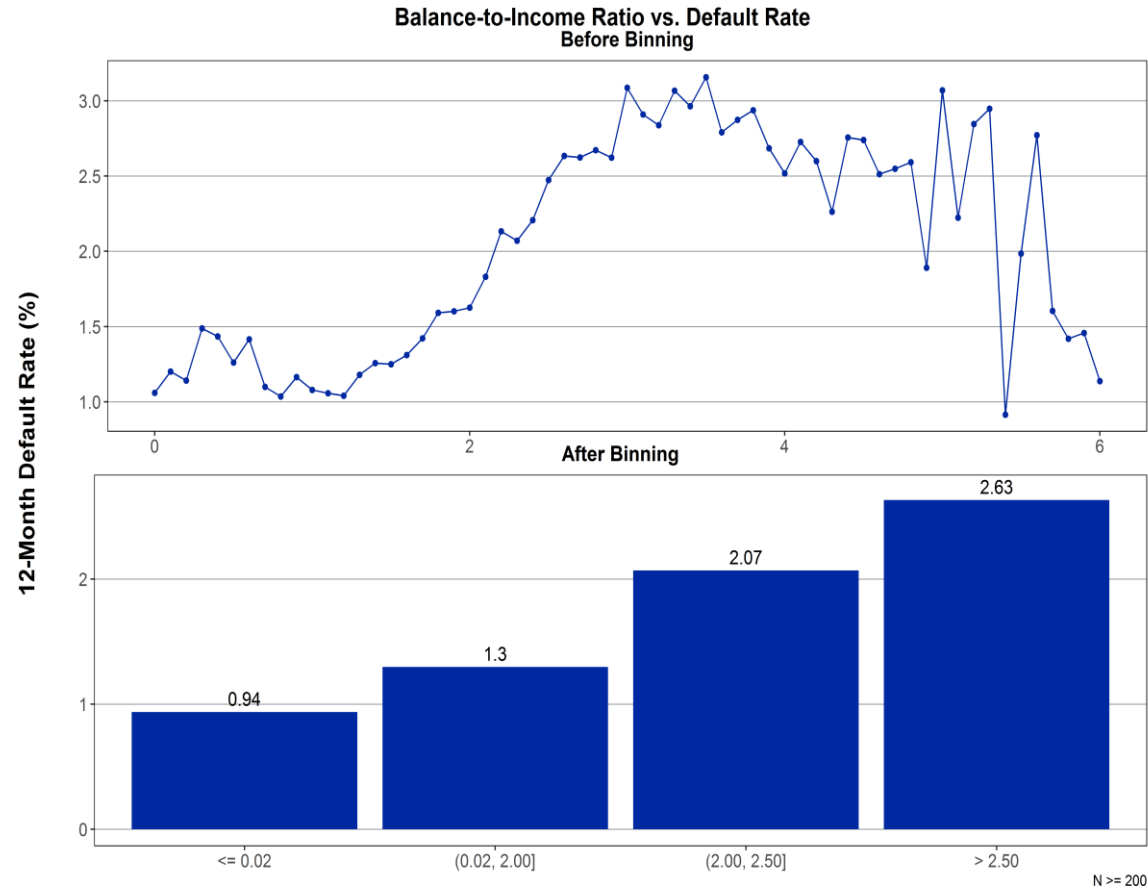
» Testing the model on the holdout sample. Same time-frame but independent observations.

### **Out-of-Time validation**

» Testing the model on the out-of-time sample. This sample is taken from a different time-frame.

# Case Study

## Sample Binning: UK Behavioral Scorecard Model



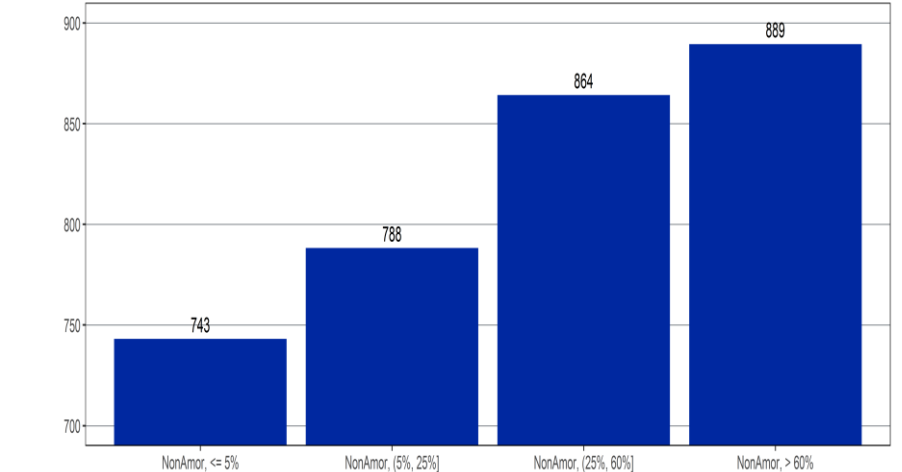
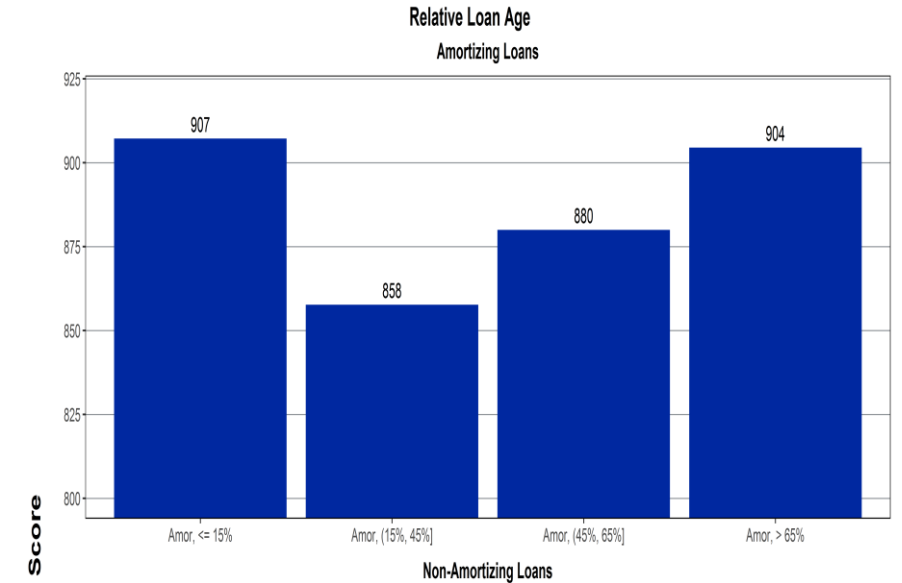
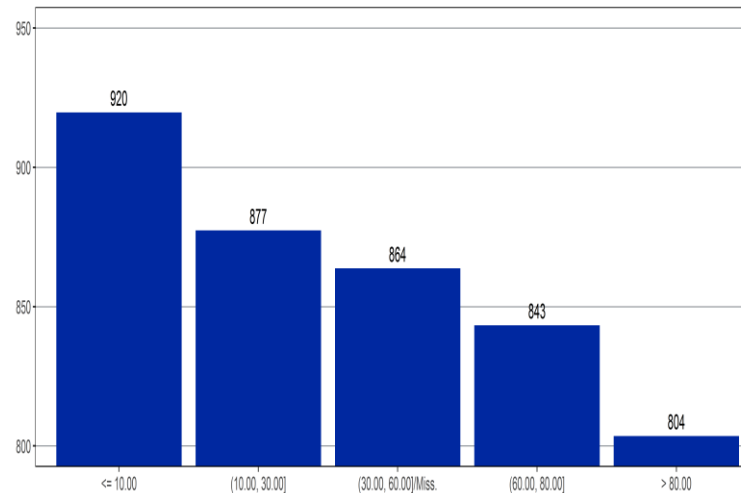
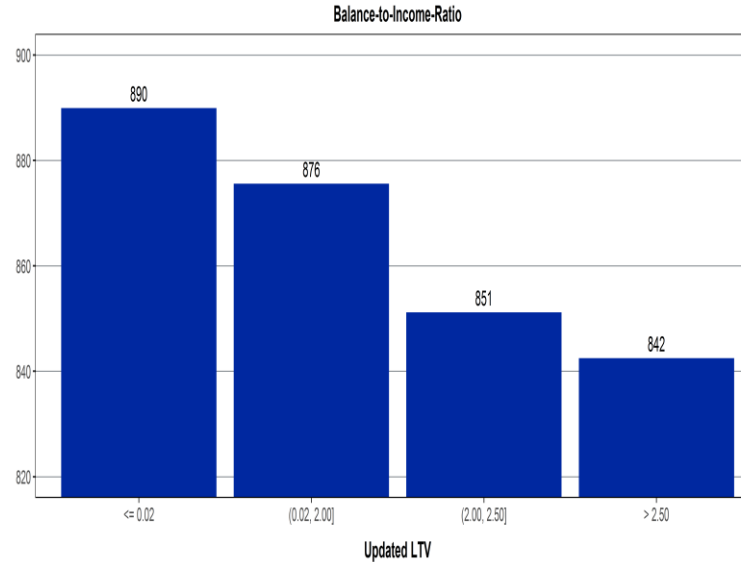
# Case Study: UK Behavioral Scorecard Model

## ACCOUNT-1 - GOOD ACCOUNT

Payment Type	Linear Installments
Balance-to-Income	0.2
CCJ	No
Bureau Credit Score	Excellent
Employment Status	Full Time Employed
Relative Loan Age	70%
Months in Arrears	Current
Occupancy Type	Second Home
Updated LTV	8%
PD	0.15%
Score	970.25

## ACCOUNT-2 - BAD ACCOUNT

Payment Type	Increasing Installments
Balance-to-Income	> 2.5
CCJ	Yes
Bureau Credit Score	Fair
Employment Status	Employed w/ Partial Support
Relative Loan Age	4%
Months in Arrears	Current
Occupancy Type	Owner Occupied
Updated LTV	75%
PD	51.05%
Score	496.96



# Case study: SME Scorecard build based on size

A business with small/medium size and the business with financial data



Very small business with almost no reliable financial or enterprise information



- » **Examples:** mid-size family business, multi-partner small business
- » **Typical Scorecard Characteristics:**
  - firm-level data, including SME's financial reports, enterprise information such as taxation, shareholder change, foreign investment, legal entity data
  - person-level data, including primary owner and his related parties' personal credit history
- » **Modelling Approach:** traditional scorecards building

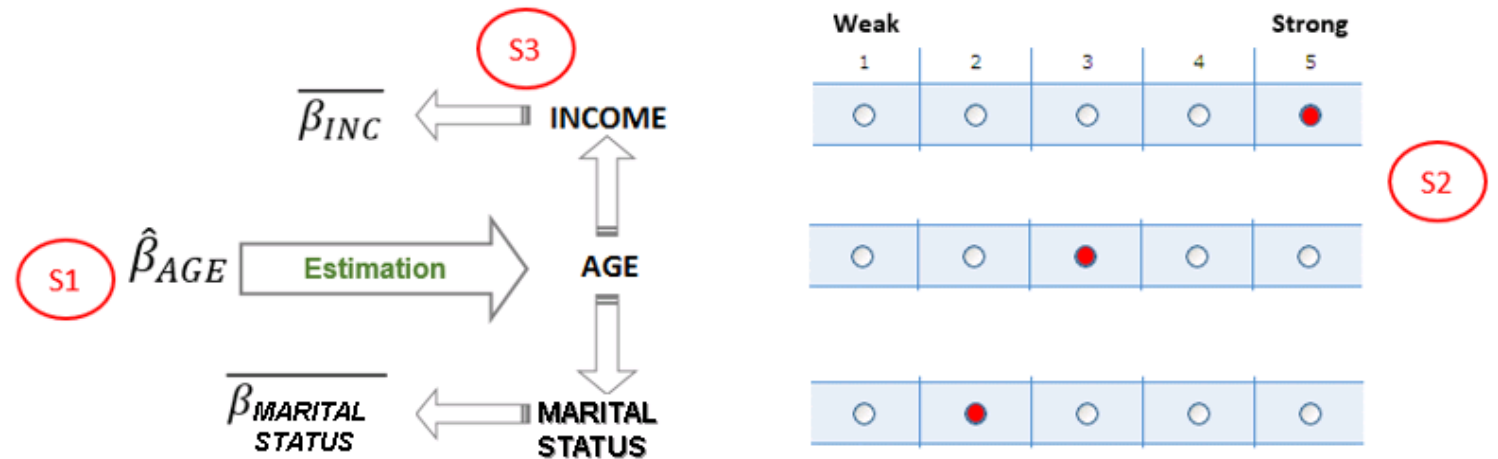


- » **Examples:** one-man business such as a coffee shop, small family workshop
- » **Typical Scorecard Characteristics:**
  - quantitative measures of owner's personal characteristics and any available firm-level data
  - qualitative measures such as business prospects, owner's management skills, market recognition
- » **Modelling Approach:** hybrid model with SME owner's personal scorecards + qualitative expert overlay or traditional scorecards building if enough data available

# Case study: Scorecard Building with limited information

## Hybrid Approach

- » Quite often, full data are not available and the standard modelling approach might provide rather limited information for a proper scorecard.
- » To deal with such cases, the missing information can be supplemented by expert knowledge.
- » We overlap information to integrate qualitative data into the empirical model.



$$PD_{\text{hybrid model}} = \frac{1}{1 + \exp[-(b_0 + \underbrace{b_{11} * x_{11} + \dots + b_{k1} * x_{k1}}_{\text{WOE of variables from quantitative model}} + \underbrace{b_{12} * x_{12} + \dots + b_{k2} * x_{k2}}_{\text{WOE of variables with no data available}})]}$$

**Step 1.** We estimate an empirical model on the limited data available and ask the Bank to provide the ranking and importance of other variables for the modelled risk metrics.

**Step 2.** Based on the rank ordering of the variables, build-back the coefficient estimates for the variables from the expert questionnaire.

**Step 3.** Calibrate the model to coefficients to match the default rate in the data.



4

Implications and Applications

# Challenges and nuances

- » *Implementation* ← should be driven by model, data and environment
  - **Data**: what is collected currently? What will be collected in future?
  - **Environment**: who will be providing data and running model? How frequent? Does it involve Cloud solution?
  - **Purpose**: what is the model use? How results of the run will be used? Will the model be linked to other models in placed? What is post analysis?
  - **Model**: how complicated the model is?
- » *Monitoring* ← should act as regular review of model output and performance
  - Is it accurate? Is it performing well? How stable are the results?

# Implementation

## Graphical User Interface

- » Example of GUI which designed to be located on local Bank's server
- » PD and Score are calculated based on provided inputs
- » Other tabs can present joint portfolio analysis or batch run (scoring whole portfolio at once)

**Application scores for credit cards**

Variables selection & output

Histograms

Results table

**Region**

Where is the customer from?

Alexandria

Canal Area

Delta

Sinai

Upper Egypt

North, South or Middle Cairo

**Adjusted income**

What is customer's income (inflation-adjusted, in Egyptian pounds)?

Less or equal to 2,145

Between 2,145 and 5,643

Higher than 5,643

No information

**Education**

What is customer's education?

No education

Elementary school

High school

Diploma

Bachelor's degree

Master's degree

PhD

Other

No information

**Credit card limit**

What is customer's credit card limit (in Egyptian pounds)?

Less or equal to 2,000

Between 2,000 and 3,000

Higher than 3,000

**Gender**

Female

Male

**Age**

What is customer's age?

0 50 100

0 10 20 30 40 50 60 70 80 90 100

**Customer's name**

John Doe

**Probability of default of this customer:**

0.01260168

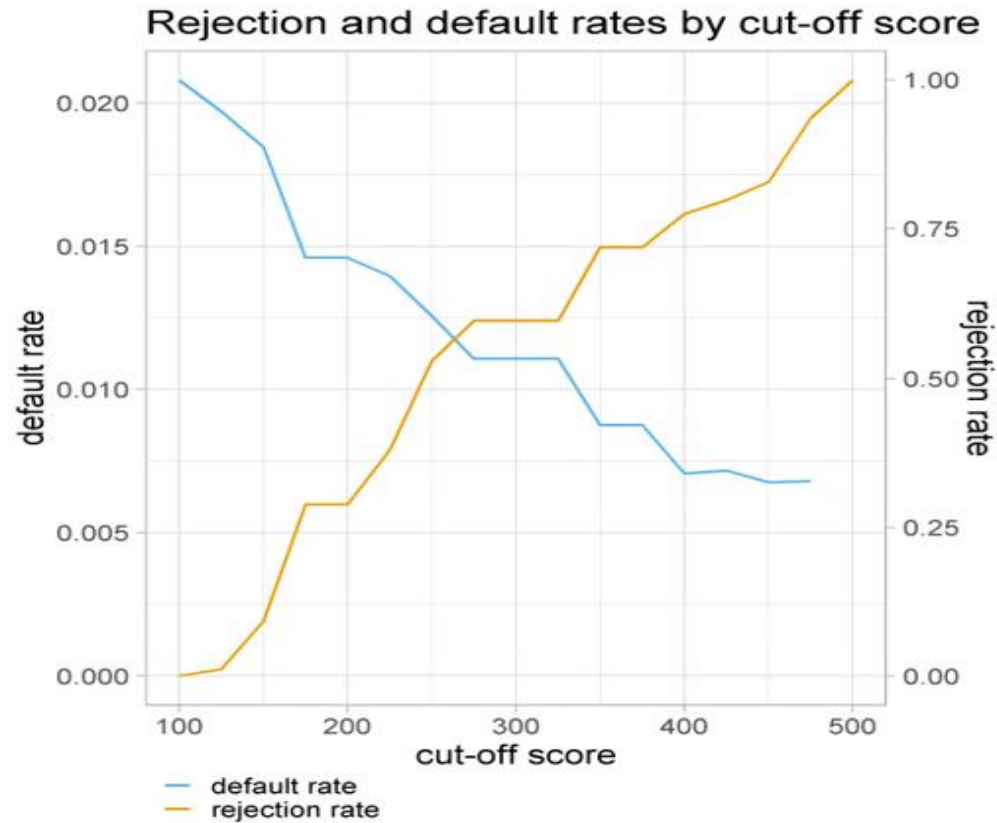
**Application score of this customer:**

277.6876

Update

# Implementation and Use

Model use strategy to support faster decision making and limit setting



		Actual performance	
		Good	Bad/Fraud
Scorecard prediction	Good	1 Correctly passed	2 False negative cases
	Bad/ Fraud	3 False positive cases	4 Correctly suspended

# Monitoring Model Performance

An established approach to monitoring model performance

Discrimination	Accuracy	Stability
<p>Model ability/power to discriminate between events and non-events, e.g., defaults and performers, and the power to rank-order risk. Applicable to choice models with binary outcome (e.g., PD or scorecard models).</p>	<p>Model ability to deliver accurate best estimate/prediction of output. Applicable to virtually all models with quantifiable output and an observable real-world counterpart.</p>	<p>Comparison of distributional aspects of development sample, on the one hand, with those of any other sample, usually production.</p>
<ul style="list-style-type: none"> <li>» Gini/ROC               <ul style="list-style-type: none"> <li>– K-S Statistic</li> </ul> </li> <li>» Brier Score</li> </ul>	<ul style="list-style-type: none"> <li>» Deviation of Actual from Predicted</li> <li>» HL/Chi-square test</li> </ul>	<ul style="list-style-type: none"> <li>» Population Stability</li> <li>» Characteristic Stability</li> </ul>

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