La Estadística y Mercados Financieros

Sesión II

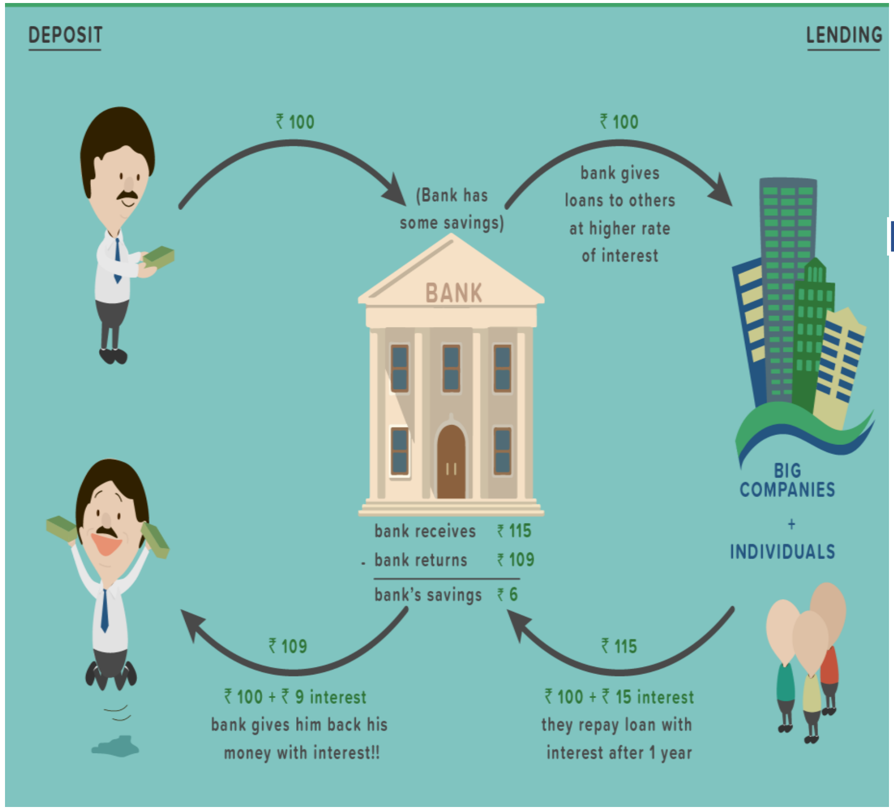
Modelos de Riesgo en los ciclos crediticios

Objetivo:

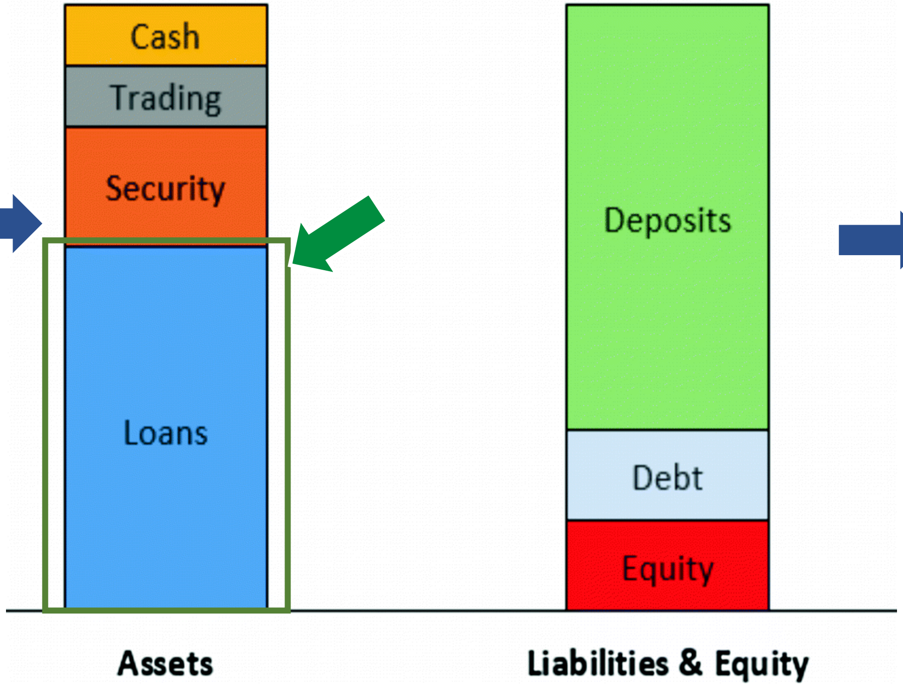
Conocer “*algunos*” modelos de Riesgo Crédito

Recall… Financial Statements for Banks…

How the does a bank work?



Balance Sheet



Income Statement

Non-interest Revenue
Interest Revenue
Total Revenue

Credit loss provisions
Net gain on trading assets/liabilities
EBIT
Interest Expense
Income Before Tax (EBT)
Taxes
Net Income

https://corporatefinanceinstitute.com/resources/knowledge/accounting/financial-statements-for-banks/

II.0 Common Loans Types in Banks

Retail / Minorista (Consumo y Vivienda)	Non Retail (Comercial)
• Residential Mortgages • Home Equity Loans and Lines • Personal Loans • Automobile — Direct and Indirect • Credit Cards	• Commercial Real Estate • Commercial and Industrial • Small Business • Agricultural

Secured = Con Garantía
Unsecured = Sin Garantía

Loans

II.1 Credit Lifecycle

0

Credit application / Origination /Acquisition

Scoring
PD Calculation
Fraud Detection

2

Collection

Recovery Models

1

Monitoring / Behaviour

Behaviour model, PD model, transition matrix, LGD, EAD, Collateral re assessment, reporting

II.2 Credit Lifecycle- Delinquency

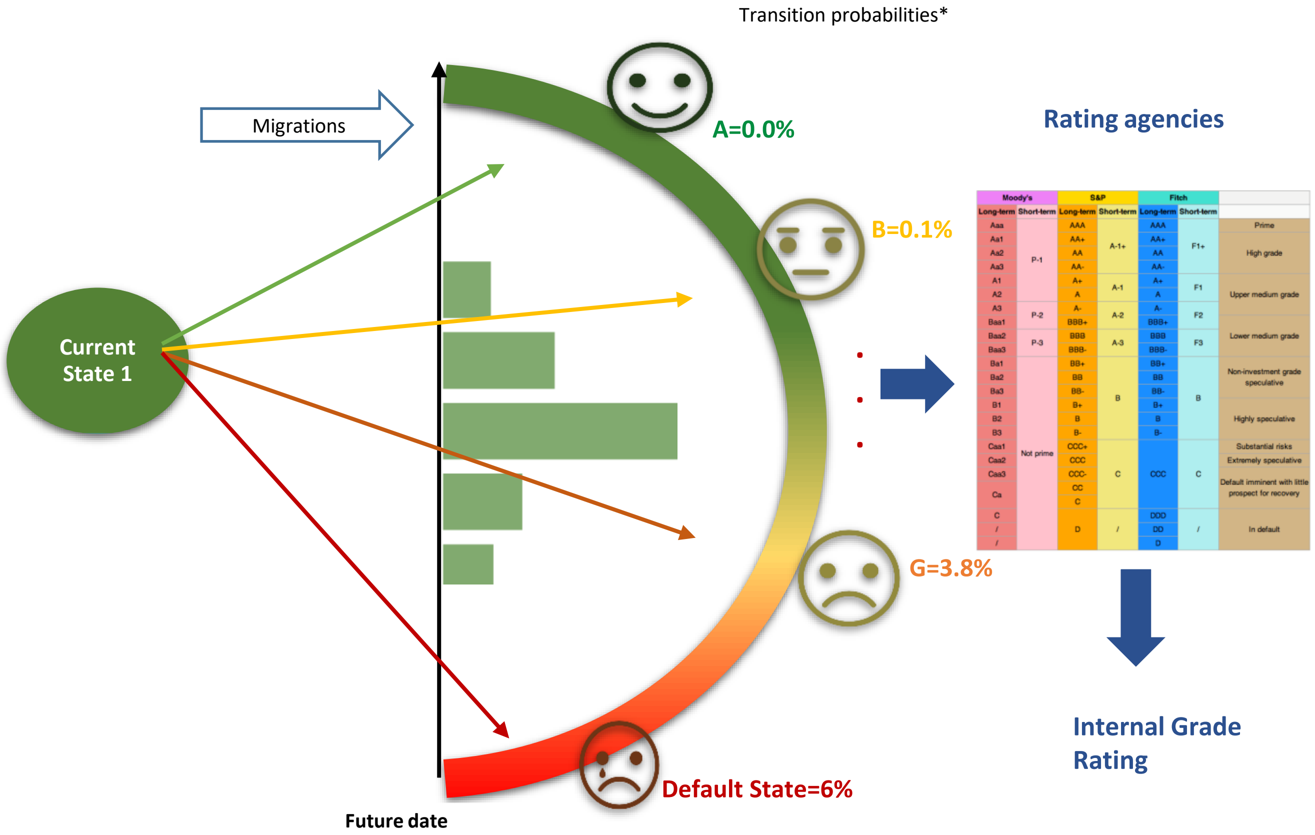
Delinquent describes something or someone who fails to accomplish that which is required by law, duty, or contractual agreement. **Delinquency** occurs as soon as a borrower misses a payment on a loan. In contrast, default occurs when a borrower fails to repay the loan as specified in the original contract.

Retail Banking and Small Business

Status Account	Cycle Past Delinquency (in days)	Classification
Current	0 dpd	Current
1	1-29 dpd	Delinquent
2	30-59 dpd	Delinquent
3	60-89 dpd	Delinquent
4	90+ dpd	Default

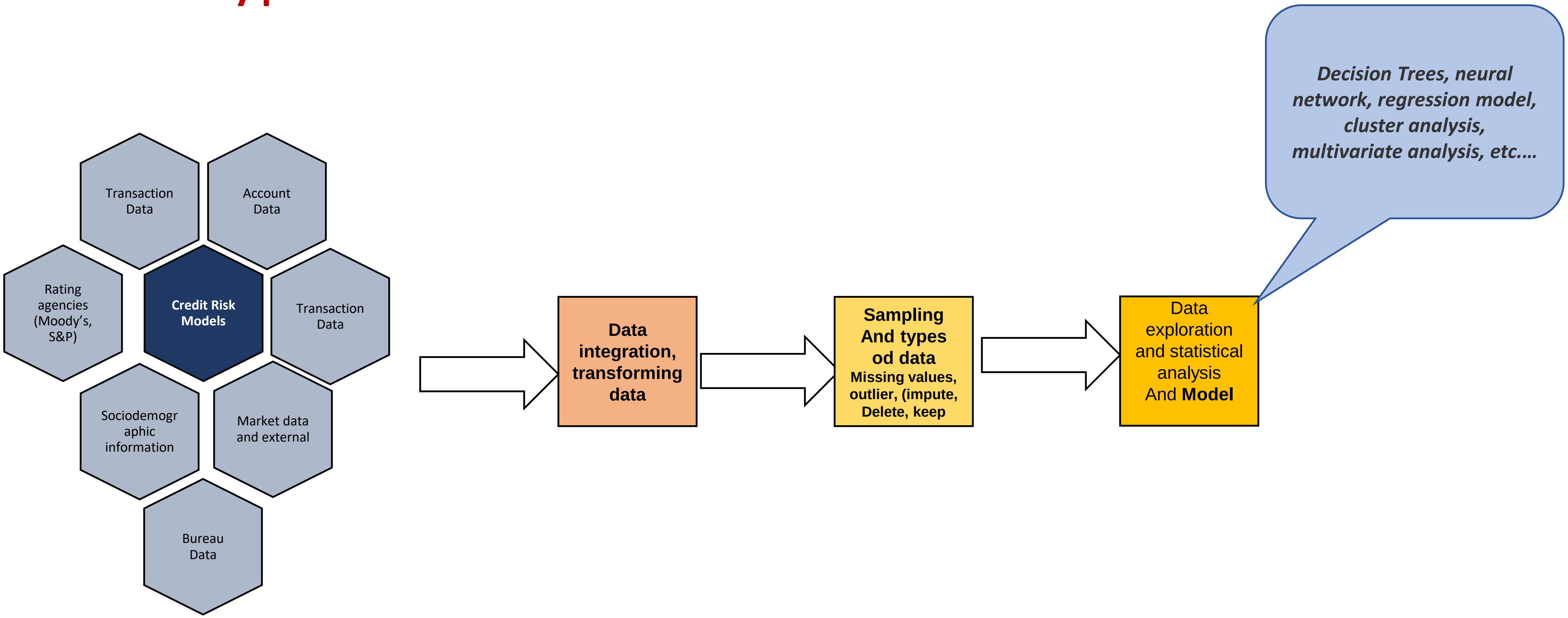
Vendors Vs Internal models

Commercial Loans



*Migration Probabilities to Standardized Distances to Default

II.3 Types of data sources



II.4 Key Characteristics of successful Models

Statistical Accuracy

Interpretability

Operational efficiency

Economical cost

Regulatory Compliance

II.5 Target Variable or Bad definition

*Determination the target variable is the crucial point in the whole development process of credit scoring models, which are an essential part of risk management. Usually some Good/Bad definition is applied.**

Example:

- *An account that is **n**+ days past due within 6 months after observation point is defined as bad (default);*
    - *An account that is 0-30 days past due within 6 months after observation point is defined as good (non-default);*
    - *An account that is 31-60 days past due within 6 months after observation point is defined as indeterminate. The indeterminate accounts are excluded from development process*
- Write-Off or ***k*** or more cycles delinquent at any time during the performance period

**R. Anderson, The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation. Oxford University Press, Oxford, 2007. https://pdfs.semanticscholar.org/cf6f/c3ca615000159dff84bf524aeb8bb9918a2d.pdf*

II.6 Logistic Regression Model - example

$$Score = \frac{1}{1 + \exp(-\mathbf{b}'\mathbf{x_i})}$$

$$= \frac{1}{1 + \exp\left(-(c + \beta_1 WoE_{i,1} + \beta_2 WoE_{i,2} + \cdots + \beta_9 WoE_{i,9})\right)}$$

Where
c: Value of the intercept returned by the regression.
β_j: j^{th}-*Characteristic* estimate value.
$WoE_{i,j}$= weight of evidence from the i^{th}-Attribute of the j^{th}-Characteristic.

The logistic regression function for this end is defined as:

$$logit(p_i) = \ln\left(\frac{\rho_1 \pi_o}{\rho_o \pi_1}\right) + \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

$$\boldsymbol{Score} = \sum_{j,i=1}^{k,n} \left(-\left(woe_j * \beta_i + \frac{a}{n}\right) * Factor + \frac{Offset}{n}\right)$$

Where
k = number of variable.
n = number of attributes in each variable.
α = intercept from the logistic regression (adjusted).
β_i = regression parameter for each variable.
$woe_{i,j}$ = weight of evidence of the variable i attribute j.

II.7 Models - Data Sampling

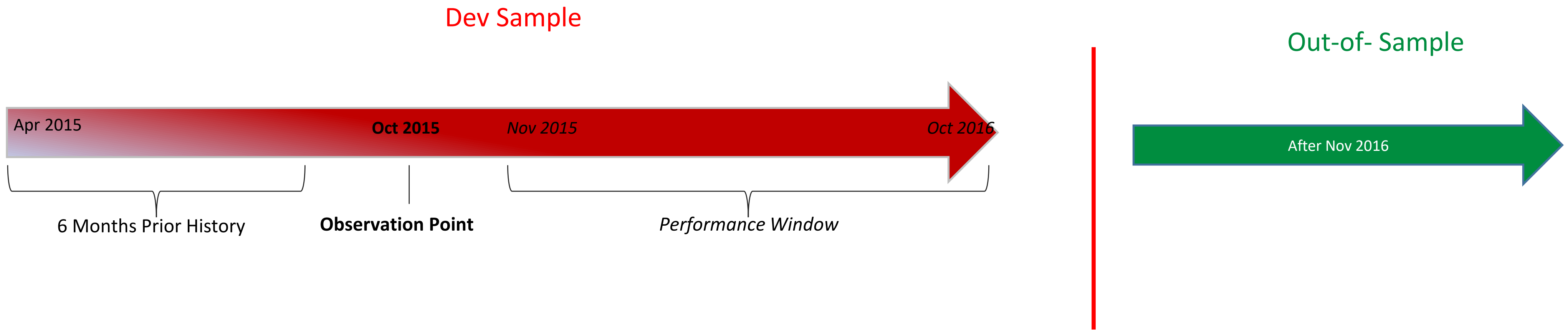
Sample: *Delinquent Accounts* or other delinquent status

Observation Point: The month when a snapshot of account status is obtained

Observation Period: Past period up to observation point, which account and customer data is observed

Target Variable: Write-Off

Performance Window: 12 months after observation point



To minimize the seasonality effect, a separate observation points were considered for modeling

II.8 Modelling Goal

To identify the **top 20%** of delinquent accounts who are going to *write off* … capturing **80% of the write-off balances**

… to decrease current Monthly Average Gross Write-off

II.9 Origination Retail models exposures

Sample: Origination models for new accounts

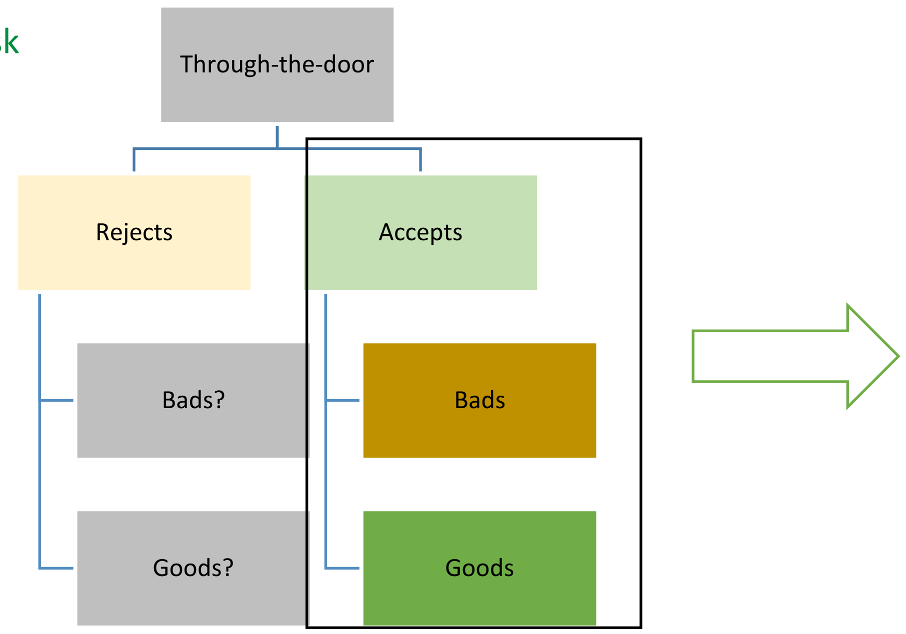
Observation Point: The month when a snapshot of account status is obtained

Observation Period: Past period up to observation point, which account and customer data is observed

Target Variable: Delinquent account

Performance Window: 6,12,18,24, 36 + months after observation point

Reject Inference problem in Credit Risk

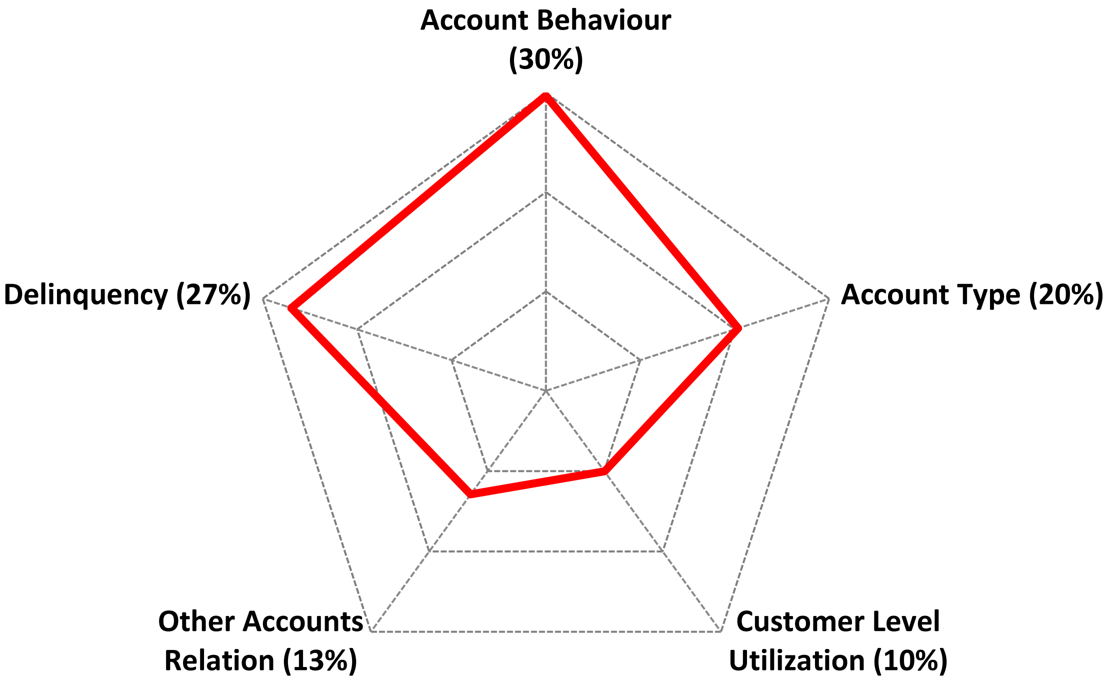


Logistic Regression
For credit Scoring

II.10 example of Behaviour Model

- The model has **8 inputs**
- Using a dual matrix approach the model identifies
  77% of write-off dollars within the top **26% of accounts**

Model Performance	
KS	0.50
AR	0.67



II.11 Strategy Illustration

High Outstanding Balance Low

High Likelihood of default Low

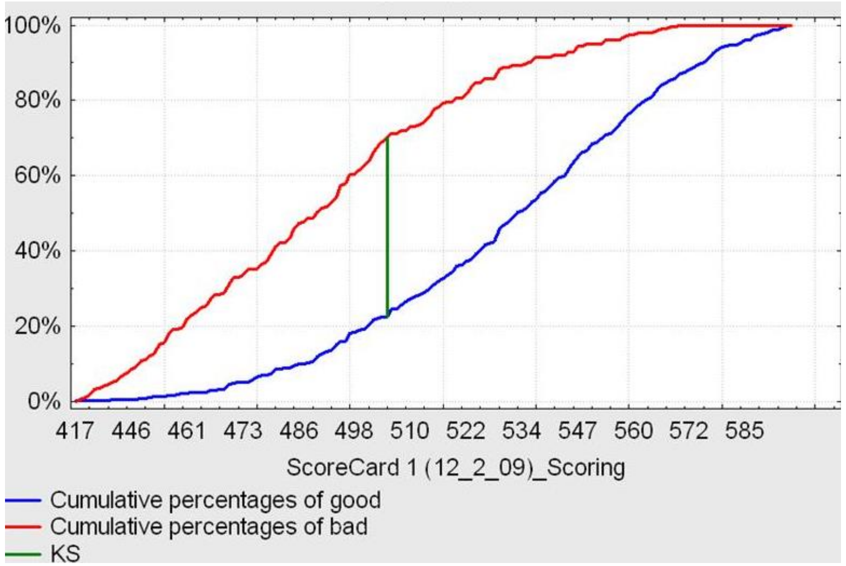
Score Band	Stats	Outstanding Balance				
		$2000+	$1500-2000	$1000-1500	$500-1000	<$500
< 615	% of Accounts	2.3%	1.2%	2.5%	7.3%	1.8%
	% of chgoff amount	17.9%	4.8%	6.4%	11.3%	1.1%
	Avg $ chgoff/Account	$2,619	$1,330	$853	$520	$207
615-629	% of Accounts	1.7%	0.9%	1.8%	5.3%	3.0%
	% of chgoff amount	10.7%	2.6%	2.8%	4.6%	1.2%
	Avg $ chgoff/Account	$2,124	$1,008	$516	$291	$129
630-644	% of Accounts	2.3%	1.3%	2.5%	6.3%	5.8%
	% of chgoff amount	8.8%	1.9%	2.5%	3.5%	1.3%
	Avg $ chgoff/Account	$1,254	$502	$331	$187	$77
645-659	% of Accounts	2.4%	1.2%	2.4%	5.7%	8.0%
	% of chgoff amount	6.1%	1.3%	1.1%	1.8%	0.9%
	Avg $ chgoff/Account	$852	$352	$159	$105	$38
660-674	% of Accounts	2.1%	1.0%	1.9%	4.7%	8.7%
	% of chgoff amount	3.6%	0.4%	0.6%	0.8%	0.5%
	Avg $ chgoff/Account	$570	$123	$98	$54	$18
675+	% of Accounts	1.4%	0.6%	1.3%	3.0%	9.5%
	% of chgoff amount	1.0%	0.0%	0.3%	0.1%	0.2%
	Avg $ chgoff/Account	$234	$22	$70	$9	$8

With this approach the top 26% of delinquent accounts is able to capture 77% of write off dollars*

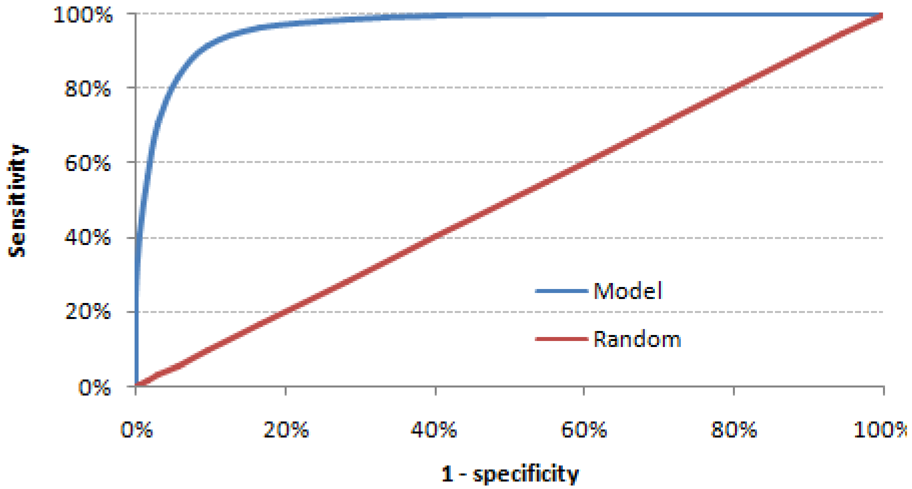
* Results based on Out-of-Time sample

II.13 Model Performance

Kolmogorov-Smirnov Statistic
This measures the maximum vertical separation (deviation) between the cumulative distributions of goods and bads.



Accuracy Ratio
To determine the methodology's the predictive power a ROC is used, the curve is constructed having in one axis the total of credits (cumulative %) and the total of defaulted loans (cumulative %). To this area under the curve (AUROC) the Accuracy Ratio is associated with values ranging from 0.5 to 1.0 (from random to perfect model).



II.14 Variables

Some variables examples

Retail Exposures

Characteristics
Cycles Past Due (1,2,3) at the Observation
Maximum Delinquency in Past 6 Months
Combination of 1 Cycle and 3 cycles Delinquency lifetime
Account Type (secured-Unsecured)
Months Since Last Deposit into the Current Account
Payment in Months 1-6 over Balance in Months 2-7
Tenure in Months of type of account
Combination of Tenure and CA Balance
Maximum Utilization in Last 6 months
of Months Payment is Less than Standard Installment Amount in Past 6 Months
Ratio of Current balance over the average balance of Past 6 Months
The Sum of Arrears Value of all segments Accounts in Current Month
Bureau external data
Months Since Last Cash Advance
Months Since Last Payment
Market data from Facebook, other, etc.

NonRetail Exposures

Characteristics
working capital / total assets
retained earnings / total assets
earnings before interest and tax / total assets
market value of equity / total liabilities
sales / total assets
Financials status

II.15 Limitations

Data !!!!