Clarity in Complexity

Workshops for Vietnam Prosperity Joint-Stock Commercial Bank

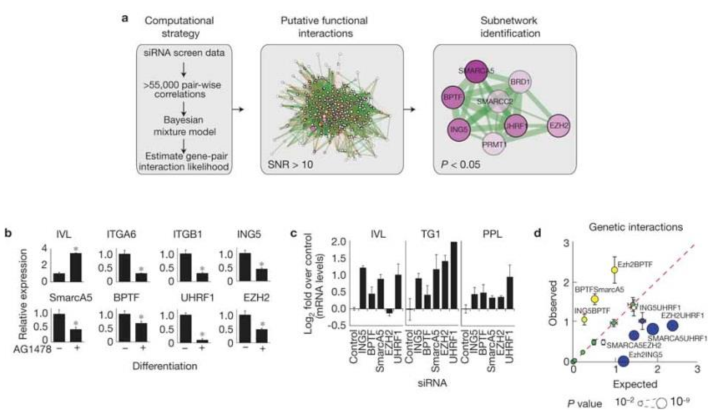
— Scorecards on Retail Portfolio

Agenda

Introduction to Statistical Modeling

What is Statistical Model?

Academically, a statistical model is a formalization of relationships between variables in the form of mathematical equations. It describes how one or more random variables are related to one or more other variables. Generally speaking, a statistical model can be use for certain purpose such as decision making, marketing or operational event detection etc. A modern bank will face wealth while apply statistical model in business operation.



Why Statistical Model?

- Data driven
- Objective
- Reliable
- Robust
- Legal compliance
- ……

Introduction to Credit Scoring

What is Credit Scoring?

- A tool used to evaluate the level of **risk** associated with applicants or customers
- In its simplest form, a scorecard consists of a group of characteristics, statistically determined to be predictive in separating good and bad accounts

Why Credit Scoring?

Objective	Credit scoring model is developed by large scale of data and come up with predictive information, reflect all kinds of consumer credit performance and pattern. In the implementation stage, the scorecard will not be affected by personal feeling, bias, or any change of scenario or emotion by person.
Consistency	Credit scoring model remain unchanged in implementation stage, decision made by whoever or whatever department, the evaluation will be same retain the same model.
Accuracy	Credit scoring model developed based on law of large number and statistical methodology, the predictive factors can be estimated accurately depending on quality of the data, skills, knowledge and experience from developer.
Comprehensiveness	During the development of credit scoring model, usually variable with predictive power can be obtain within the data. The use of statistical method can easily estimate, compare, filter these variables and results of multi-dimension model, which cover various kind of information from consumer.
Effectiveness	Because credit scoring model can be automatically ran by computer, the only thing it need is to enter relevant information artificially and result can be gain in a few second. This is suitable specially for consumer loan and credit card.

Types of Methods Used in Credit Scoring Model

Model with Dependent Variable:

- Logistic Regression
- Linear Regression
- Generalized Linear Model
- Non-linear Modelling
- Decision Trees
- Categorical Modelling
- Discriminant Analysis
- Back Propagation Neural Network
- Probabilistic Neural Network
- Survival Analysis

Model without Dependent Variable:

- Cluster Analysis
- K-Nearest Neighbours
- SOM (Self-Organizing Map, AKA Kohonen Network)

Scorecards Type During Customer Life Cycle

Traditional Scorecards on Credit Life Cycle

Application Scorecard

During the process of recruiting customers, application scoring is used to assess the customers' risk for delinquency in future from a statistical perspective

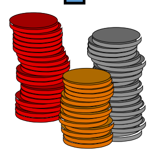
Application Scoring Can Be Applied in

- ✓Credit risk assessment
- ✓Loans limit decisions
- ✓Credit limit approval

Model Developing Technique

✓General approaches: logistic regression, linear programming

✓Data: customers' demography information, information from credit bureau and etc.



Behavior Scorecard

From a statistical perspective, the behavior scoring can be used in quantitative risk assessment for existing customers' according to the their internal data which can also provide customers the periodic scores.

Behavior Scoring Can Be Applied in

- ✓Limit management
- ✓Account management, renewal , assessment
- ✓Risk monitoring

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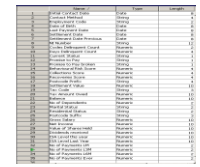
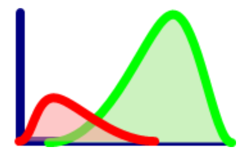




C-score

Collection Scorecard

Collection scoring is used in the classification of different groups' repaying capacity for delinquent customers, and it will separate those customers who need special handling.

Collection Scoring Can Be Applied in

- ✓ risk monitoring
- ✓ Collection strategy formulation

Model Developing Technique

✓General approaches: logistic regression, linear programming

✓Data: Customer's behavior information, delinquent data, collection data

Scorecard Business Application Associate with Risk and Marketing

	Account Acquisition	Account Management	Collection

Risk Management	• Pre-Screen
	• Application
	• Application Fraud
	• Bankruptcy
		• Behavioral
		• Trigger/Event
		    • Cash Usage
		    • CLI
		• Transaction Fraud
			• Early-Stage Collection
			• Late- Stage Collection
			• Recovery

Marketing Efforts	▪ Response • Activation • Purchase Propensity	• Profitability • Usage • Activation/Re-activation • Attrition/Retention • Pre-payment • Cross-Sell	

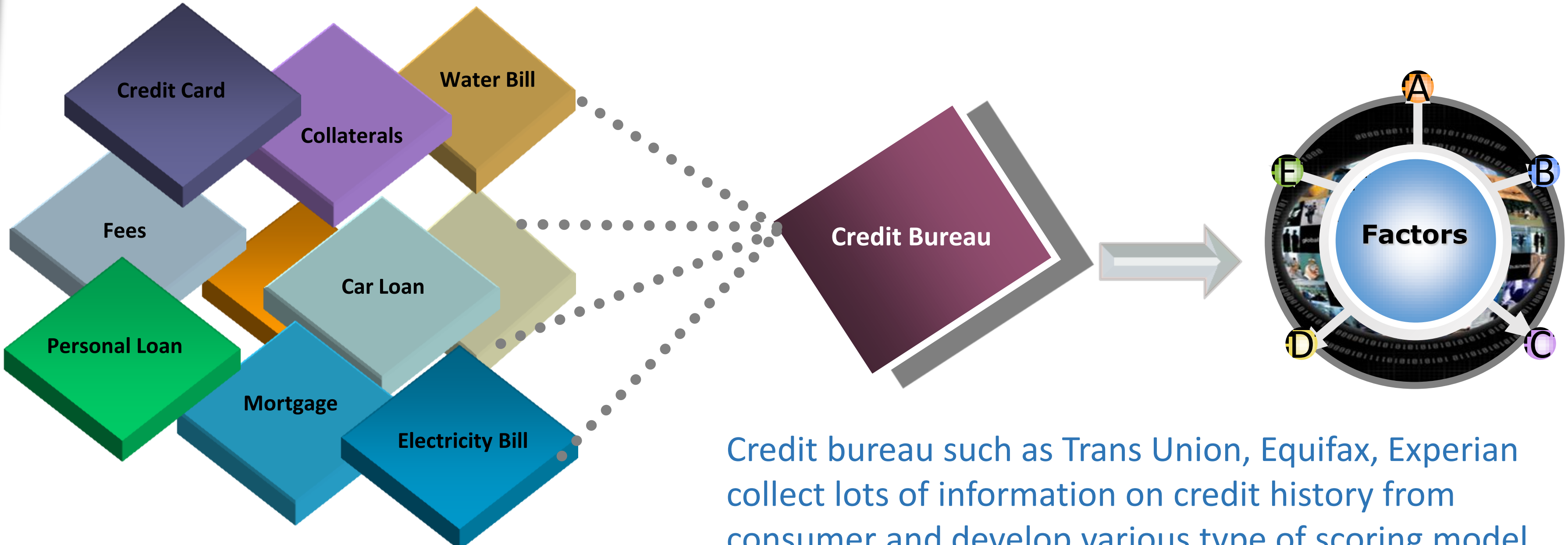
Introduction to Credit Bureau scoring model

What is Credit Bureau?

Credit Bureau is a institution in purpose of collecting, storing and managing individual consumer's information from various sources and provide credit report to consumer for variety of uses.

What is Credit Bureau scoring model?

Credit Bureau scoring model is a model based on information provided by Credit Bureau. Information such as Credit Record , is a collection of individual's borrowing and bill-paying (E.g. Loan) performance. This sorts of information are powerful and can be modeled to predict consumer's future performance.



Credit bureau such as Trans Union, Equifax, Experian collect lots of information on credit history from consumer and develop various type of scoring model.

Agenda

Application of Credit Scoring Model in Banking Industry

- **Strategy design, Strategy Optimization and Basel Compliance**

➢ Strategy

- Approval/Decline
- Line Assignment
- Line Management
- Risk Base Pricing/Re-pricing
- Collection

➢ Optimization

- Segmentation
- Simulation
- Champion/Challenge
- Tracking/Monitoring
- P & L framework

➢ Basel Solutions

- PD Calibration
- Risk Rating System

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Introduction to Application Scorecard

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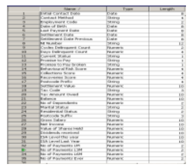
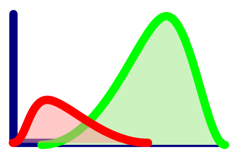
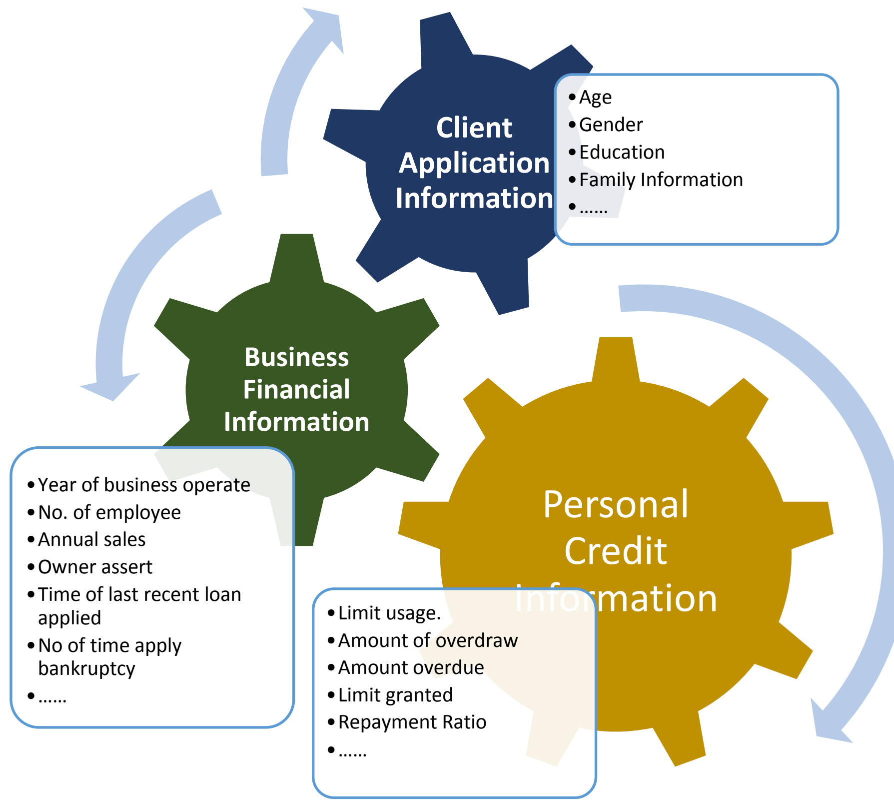




Possible variables assessed in application scorecard



The question arise that whether or not this information are available to bank?

Application Scorecard - Example

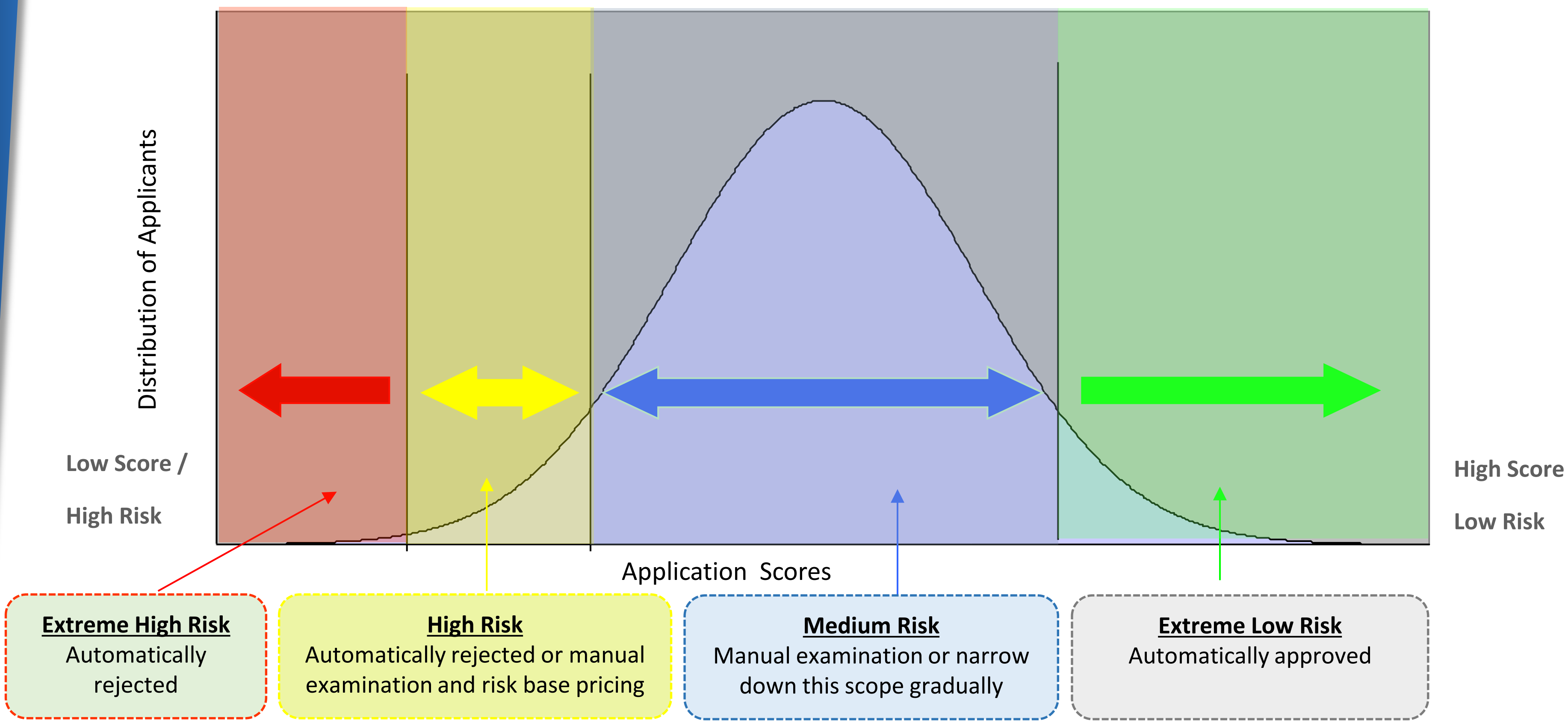
Example Only

	Score
Age	
18 - < 21	6
21 - < 30	10
30 - < 40	28
40 - < 50	35
50 – or more	42
No Information	10
Number of Dependents	
0	14
1	14
2	25
3 or more	10
No Information	14
Martial Status	
Single	14
Married	30
Divorced	5
Others	14
No Information	14
Residential Status	
Own	40
Rent	15
Live with Parents	20
Employer Provided	22
No Information	20

	Score
Time at Address	
< 1 year	18
1 - < 3 years	20
3 - < 6 years	25
6 - < 10 years	30
10 or more years	40
No Information	25
Time at Employer	
< 6 months	16
6 months - < 3 years	20
3 - < 5 years	27
5 or more years	38
No Information	20
Credit Card Reference	
Yes	27
No	10
No Information	18
Credit Bureau Information(negative)	
Yes	-30
No	15
No Investigation	0
No Information	0

How Application Score Can Be Use in Business Process
Cut-off setting

The use of application scores for approval & line assignment can dramatically save monetary cost and time, which will be more benefit on customer quick expand and acquisition stage:



- Increase the automatic approval rate and reduce manual examination scope to improve the approval efficiency.
- When scorecards models are implemented for the first time : It is advisable to take the relatively straightforward approval strategy by maintaining the current approval rate or bad debt rate.
- When equipped with the profitability analysis data and the ability to track and predict the profits-driven factors：set the cut-off value based on your profitability analysis

Introduction To Behavior Scorecard

Behavior Scorecard

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Behavior Scoring Can Be Applied in

- ✓**Limit management**
- ✓**Account management, renewal , assessment**
- ✓**Risk monitoring**

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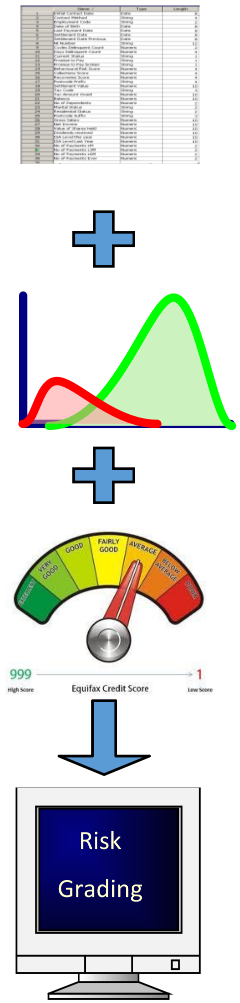
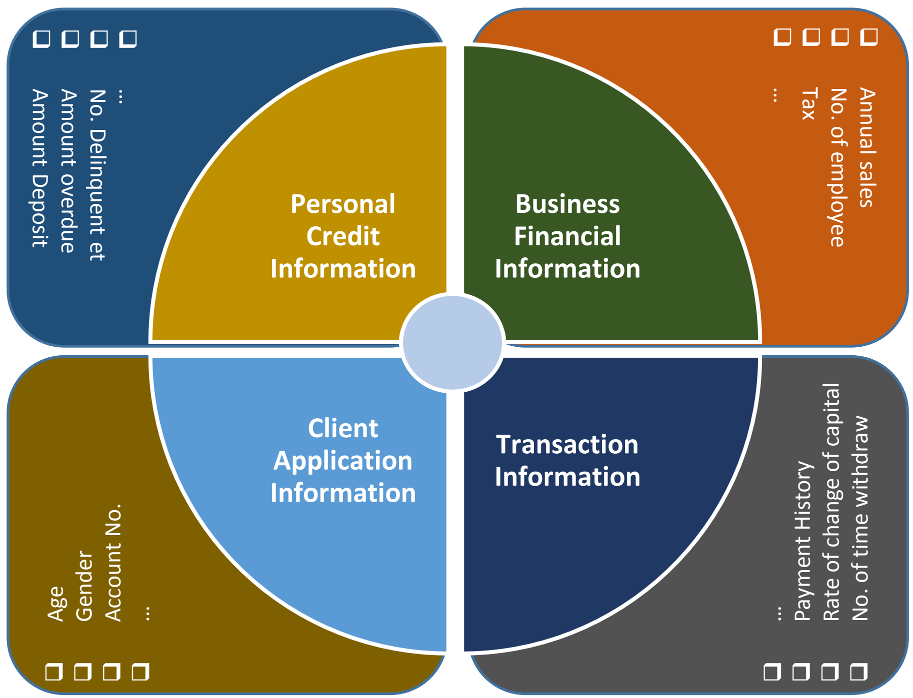
✓General approaches: logistic regression, linear programming

✓Data: Customer’s Behavior information and etc.



Possible variables assessed in behavior scorecard



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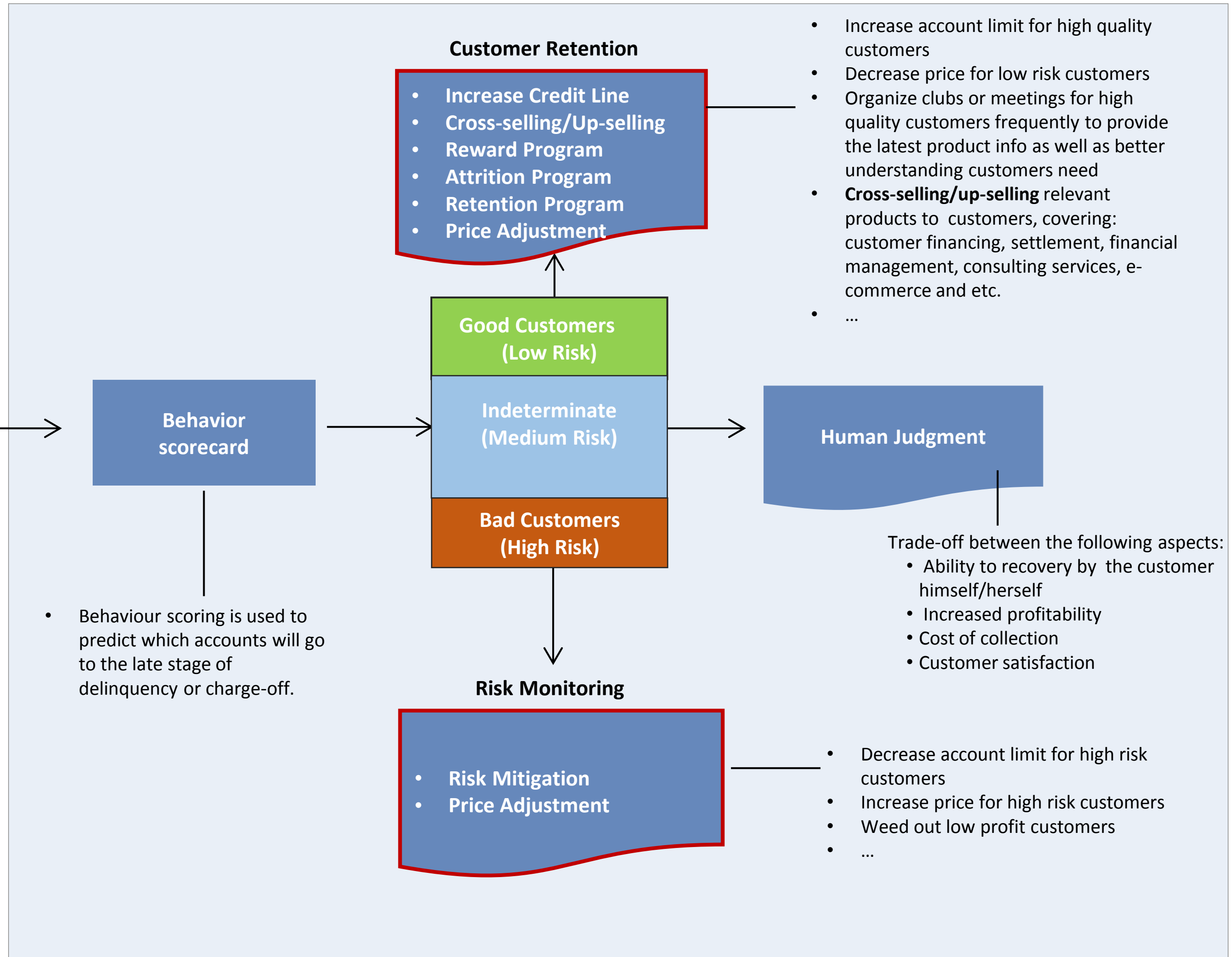
Application of Behavior Scorecard in Account Management Process

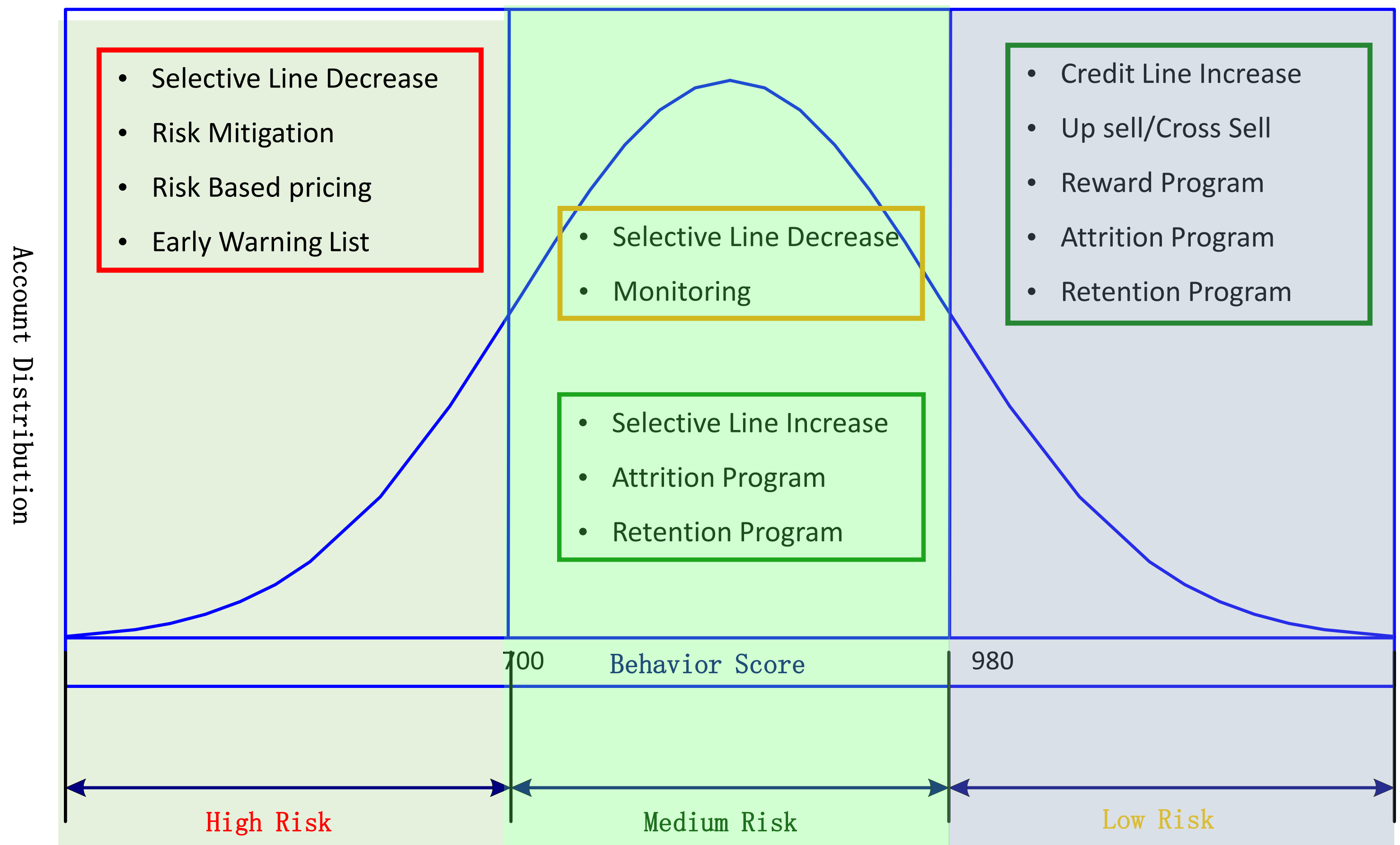
Manage all accounts after lending to achieve profit optimization from the following aspect :

- Marketing Strategy: dig out more from high quality customers
- Risk Monitoring: control & minimize risk loss
- Limit Management

Account Management After Lending



Behavior Scorecard Application Example



Introduction to Collection Scorecard

Collection Scorecard

Collection scoring is used in the classification of different groups' repaying capacity for delinquent customers, and it will separate those customers who need special handling.

Collection Scoring Can Be Applied in

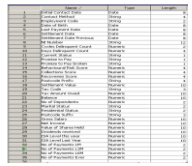
✓ **risk monitoring**

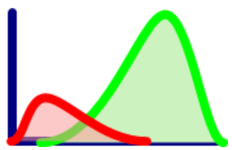
✓ **Collection strategy formulation**

Model Developing Technique

✓General approaches: logistic regression, linear programming

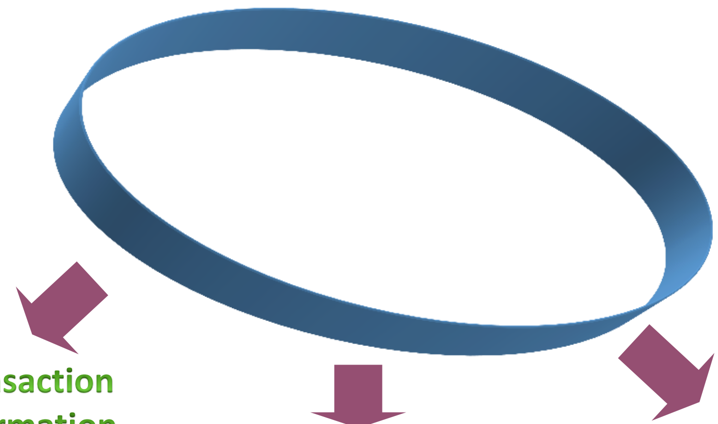
✓Data: Customer's behavior information, delinquent data, collection data





Credit Decision

Possible variables assessed in collection scorecard



Transaction Information

- Highest current level of delinquency-all products
- Total customer level delinquent balances
- Number of delinquent accounts
- …

Financial Information

- Year of business operate
- No. of employee
- Annual sales
- Owner assert
- Time of last recent loan applied
- No of time apply bankruptcy
- ……

Personal Credit Information

- Limit usage.
- Amount of overdraw
- Amount overdue
- Limit granted
- Repayment Ratio
- ……

Application of Collection Scorecard in Delinquent Customer Process

Manage the currently delinquent accounts after lending to achieve profit optimization from the following aspects:

- Marketing Strategy: profits gained by customer delinquent
- Risk Monitoring: control & minimize risk loss

Delinquent Customers → **Collection Scorecard** → **Collection Strategy**

Collection Scorecard

- Predicts probability that a loan late for a given number of days (x) will be late for another given number (y) of days.
- It can be divided into different collection stages: Early-stage, Middle-stage, Late-stage.

Number of days overdue

30 days — *60 days* — *90 days*

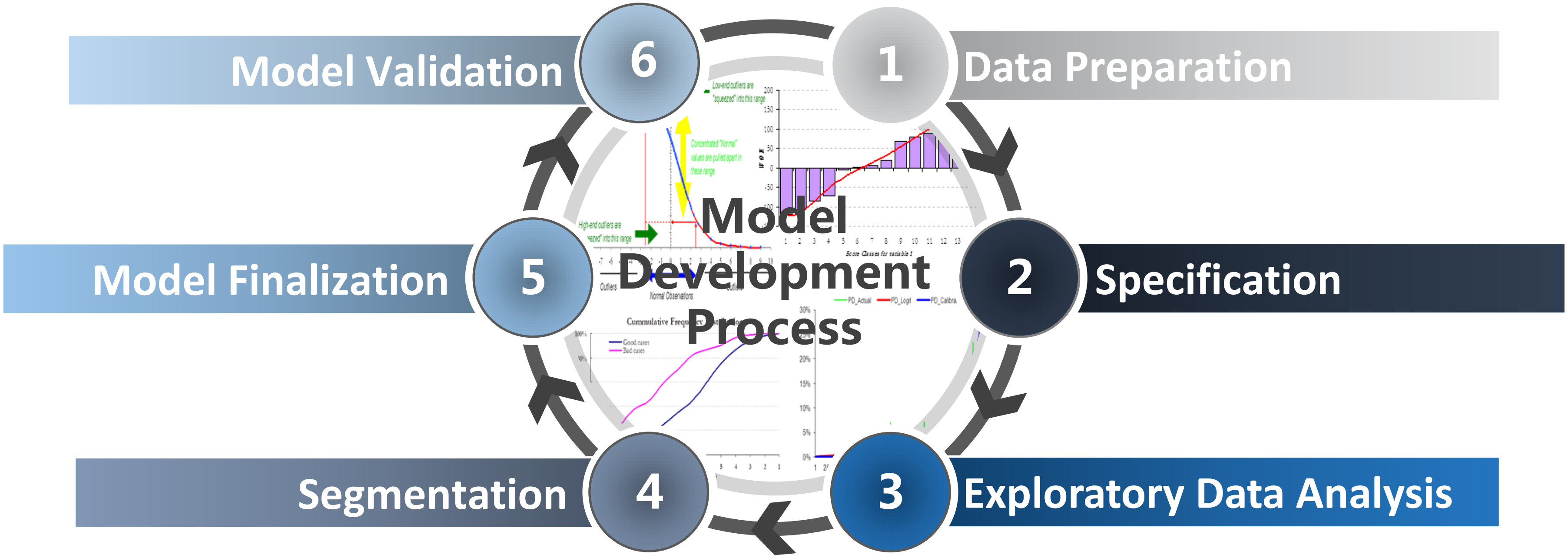
M1: Early-stage score	M2: Early-stage score	M3: Middle-stage score	M3+: Late-stage score
Predict the roll rate from M1 to M3. Accounts in M1 typically have high cure rate, or low roll-rate to M3 while it is the largest portion among all delinquent customers. The objective is to differentiate the customers who have high roll rate to M3 and adopt appropriate collection strategy to this group of customers while ignoring those who are likely self-cure.	Predict the roll rate from M2 to M3. The number of account in this stage is much smaller compared to those in M1. In this stage we could use scorecard to find out if the customer has repayment ability (or partial repayment ability) and help them restructure the debt portfolio in order to lower the losses.	Predict the roll rate into 3+ cycle. Typically, significant amount of the customers in this delinquent group would likely to become charge-off accounts (M3+). However, it is beneficial to have Middle-stage score defined for M3 customers. Trade-off between model implementation/maintenance costs to their benefits.	Predict the expected collection amount. We should choose the proper methods to collect these accounts depending on their risk exposure, repayment ability and previous repayment behavior etc. Efficient collection management allows banks to continue to improve recovery amount per collection costs.

Collection Strategy

- Adopt different collection treatments for different group of customers during varies of delinquent stage.
- Trade-off between: Cost, recover and customer satisfaction

Agenda

EntroFine Credit Scoring Model Development Methodology



1
- Source data selection
- Variables selection criteria
- Data extract & cleansing
- Data integration and attributes aggregation
- ……

2
- Modeling type
- Modeling approach
- Sample window
- G/B/I/E definition
- ….

3
- G/B/I/E flag derivation
- Descriptive statistics
- Characteristic analysis
- Classing
- ……

4
- Assess benefit and need of multiple models
- “Master / niche” modeling
- ……

5
- Reject Inference process (for application scorecard)
- Final scorecard model
- Scorecard alignment
- Modelling documentation
- ……

6
- Sample validation
- Cross-time validation
- Risk grading and cut-off
- Modeling Tracking/Monitoring
- ……

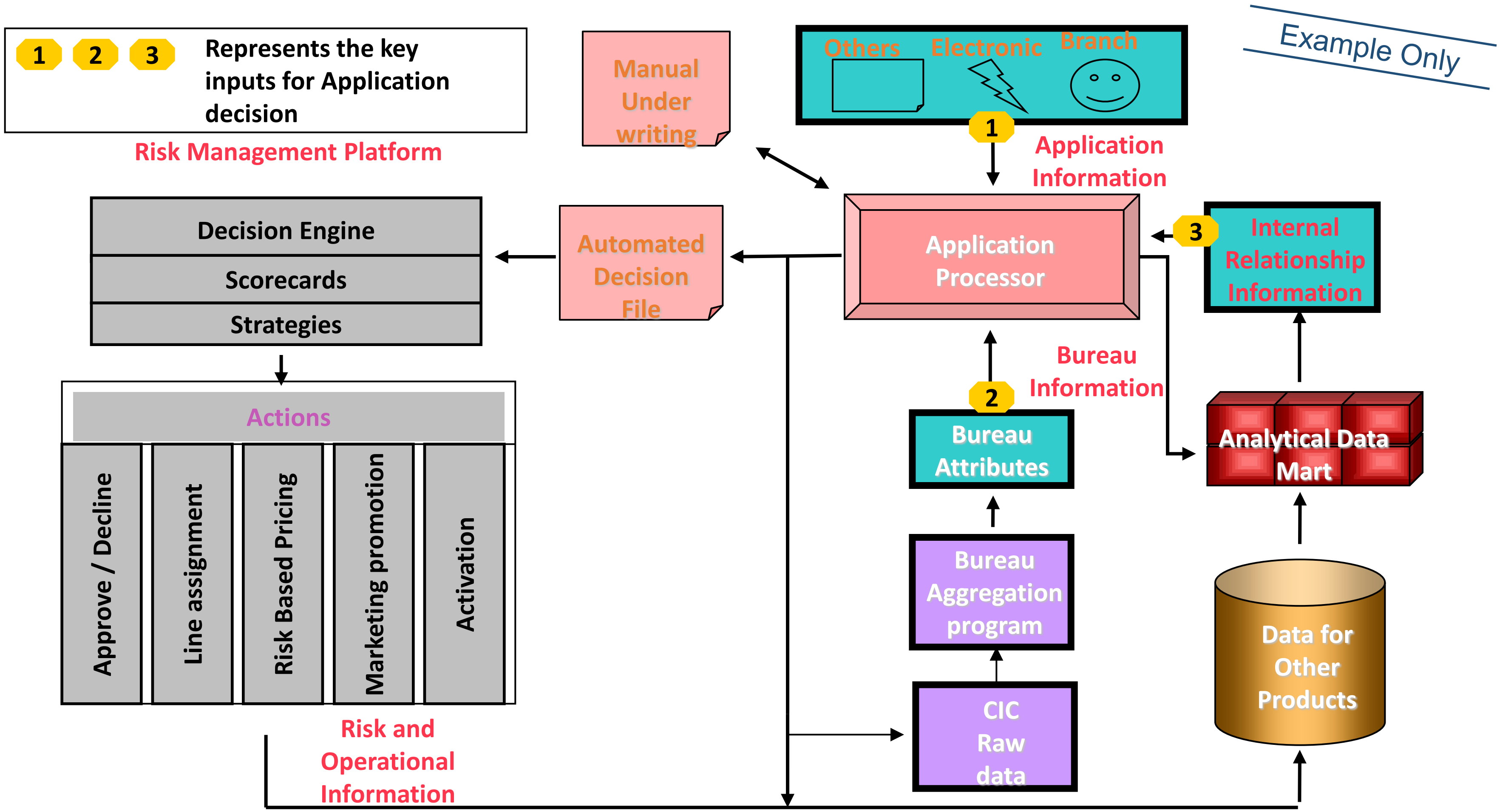
1 Data Preparation Phase
Session Outline

1.1 Data Requirement
1.2 Source of Data
1.3 Data integration and attributes
1.4 Variable selection criteria
1.5 Data Treatment

1.1: Data Requirement

For Statistical modeling approach, the bank should consider how much historical data they have. “Enough” data will ensure successful and more accurate the model will be. If the situation that the data for certain purpose is lacking too much, bank may consider judgmental or hybrid approach for development of scorecard or buy external data to development models.

1.2 Source of Data
Typical Data Sources for Origination/Application Model



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1.3 Data Integration and Attributes

EntroFine Risk Analytics Record (ERAR) provide the bank what types of data should be collected for scorecard refer to EntroFine professionals practices from more than 30 counties

Application Scoring Model

- ❑ Application
- ❑ Demographic
- ❑ Internal Relationship
- ❑ Credit Bureau

Example Only

Behavior Scoring Model

- ❑ Application
- ❑ Demographic
- ❑ Payment History
- ❑ Internal Relationship
- ❑ Credit Bureau

Collection Scoring Model

- ❑ Application
- ❑ Demographic
- ❑ Payment History
- ❑ Internal Relationship
- ❑ Collection
- ❑ Credit Bureau

Application/Demographic attributes
- ❑ Income, age, gender, marital status, residential status, length of residency, education, occupation, Collateral value, LTV, etc.

Bureau attributes
- ❑ Number of bankcard open in last 12 months
- ❑ Total balance for all trades
- ❑ Number of trades 90+ DPD
- ❑ Average bankcard utilization over 6 months
- ❑ Maximum credit limit for bankcard
- ❑ The age of trade

Internal relationship
- ❑ Deposit information
- ❑ Debt income ratio
- ❑ Others

Application/Demographic information
- ❑ Age, Gender, Marital status, Income, Residential, Occupation, Collateral value, LTV etc.

Payment information
- ❑ Month on book
- ❑ Average balance over last 12 months
- ❑ Maximum utilization over last 12 months
- ❑ Maximum delinquency status

Transactional Attributes
- ❑ Average number of transactions within last 12 months
- ❑ Number of cash advance within last 6 months
- ❑ Average transactional amount within last 12 months

Promotional Attributes
- ❑ Total amount of balance transfer during last 12 months
- ❑ Number of CLI last 24 months

Bureau Attributes
- ❑ Similar set as designed for Application score

Communication Information
- ❑ What kind of contact method used, sms, e-mail, mail, phone call, visit, court, etc.
- ❑ Whether have reached this customer
- ❑ Any promise about payment

Historical Payment information
- ❑ Similar set as previous ones

Bureau Attributes
- ❑ Similar set as previous ones

Collection Information
- ❑ Delinquency status
- ❑ Payment
- ❑ ……

1.4 Variable Selection Criteria

- Select variables that is available in the data source
- Select variables with less missing value
- Select variables with less zero or N/A value
- ……

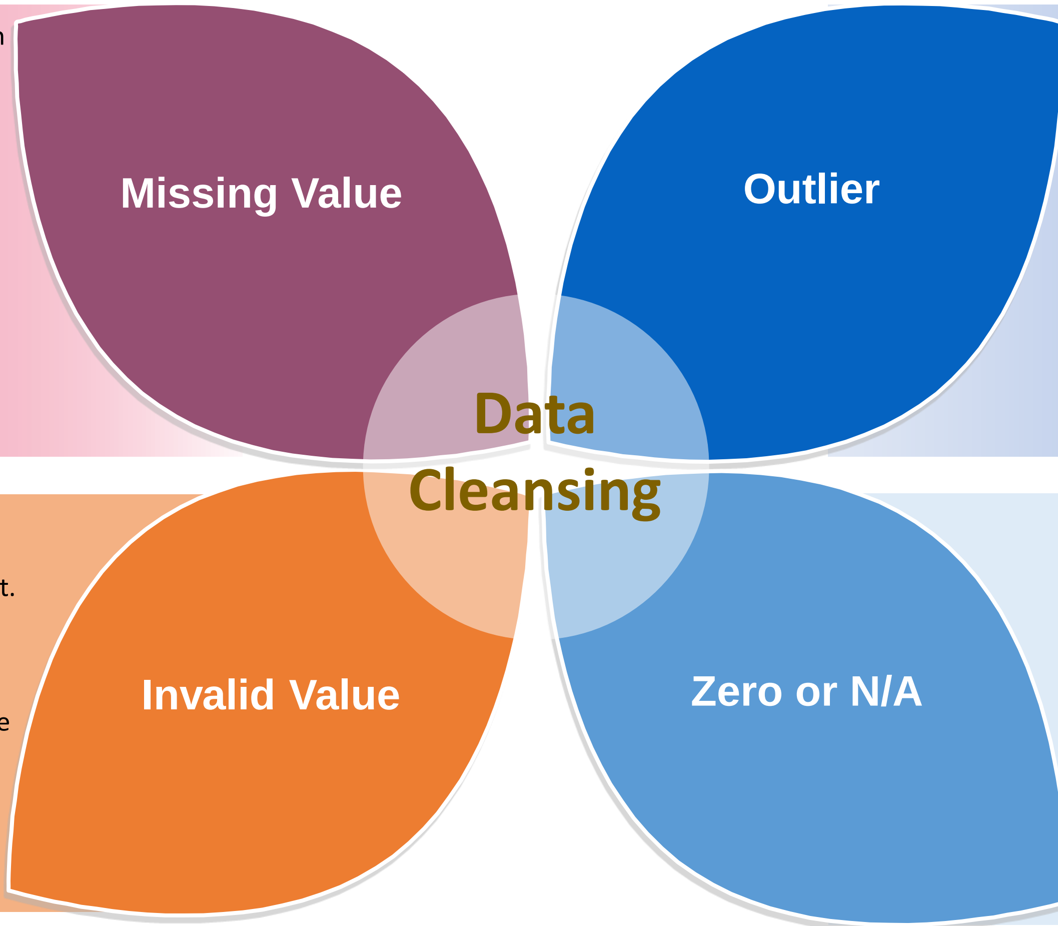
1.4 Data Treatment
Data Cleansing

Sometimes value is missing in some field, the following option are available to deal with missing value

- Artificial re-fill in the field if its available
- If the of missing value is large (e.g >20%), consider dropping this field.
- If the field is important to be included in the model, fill in with medium or mean.

Outlier are those value which is seem as “unusual”. Either too large or too small will significant affect the mean and medium as well as the robustness of the model. Options to deal with outlier are

- Check if its miss filled-in
- Delete or replace 99 or 1 percentile values
- Dixon test and transformation



Invalid Value are those value which filled-in incorrectly or value with no standard format. Example such as value with 0.01 and 1%.To deal with this value, since the result of this value may become outlier, the treatment is similar to deal with outlier in this case.

Zero or N/A value can be the similar case to deal with missing value. However, it would be better to understand the reason whoever filled in these value. In some case, there is a situation where you can replace zero or N/A with other meaningful value after knowing the situation.

1.4 Data Treatment (Cont.')
Data Transformation

Binning and **Log** transformation are the most common data transformation techniques use to deal with data for certain purpose. Normally speaking, transformation is used when the distribution of the data does not meet the modelling requirement. Transformation technique can be applied to make data more closely meet the assumption of the model which is applied.

Common data transformation techniques are:

- Binning
- Log transformation
- Square root
- Box-Cox
- Fisher

2: Specification
Session Outline

2.1 GBIE Definition
2.2 Time Window Specification
2.3 Modeling Approach

2.1 G/B/I/E Definition
Good Bad Definition

Good Bad definition is applied at the outcome point to assess the level of risk associated with each account. To define “good” and “bad” of a account, bank must consider the following:

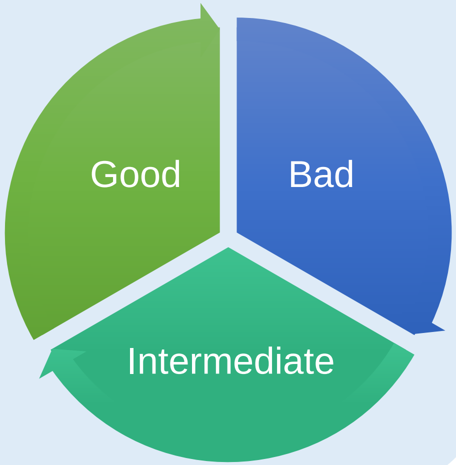
- The definition of “Bad” must match with bank overall policy
- The definition of “Bad” must account the duration of performance period
- The definition of “Bad” must consider account’s performance during performance period or end of the performance period
- The definition of “Bad” must consider the fact that certain situation can be classified as indeterminate
- The definition of “Bad” must be simple, not too complicated

Default Definition by Basel

“A default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place:

1. The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held)
2. The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current.”

❖ Good: Never in 30+ days past due (DPD)
❖ Bad: Ever in 60+ days past due (DPD)
❖ Indeterminate: Ever in 30 to 59 DPD



2.1 G/B/I/E Definition (Cont.’)
Bad Definition Using Roll Rates

- Measures the percentage of accounts or dollars that “roll” from one stage of delinquency to the next
- Individual accounts are not tracked, only the volume for a particular bucket
- Roll rates are averaged across of risk segments for the total portfolio
- The critical use of roll-rate is the “net charge-off” rate as it gives the amount of charge-off at the end of the next month

Example Only

	TOTAL	DAYS PAST DUE (DPD)							
		1 - 29		30 - 59		60 - 89		90 - 119	
	S$ ('000)	S$ ('000)	%	S$ ('000)	%	S$ ('000)	%	S$ ('000)	%
2005									
JAN	292,135	37,109	14.8%	3,393	10.7%	1,279	**32.4%**	996	**62.6%**
FEB	291,908	43,068	17.4%	5,000	13.5%	1,196	**35.3%**	984	**76.9%**
MAR	293,640	32,910	13.7%	4,269	9.9%	1,435	**28.7%**	865	**72.3%**
APR	292,075	37,069	14.7%	3,915	11.9%	1,657	**38.8%**	1,076	**75.0%**
MAY	293,204	35,222	14.3%	4,488	12.1%	1,439	**36.8%**	1,191	**71.9%**
JUN	295,380	35,701	14.3%	3,604	10.2%	1,703	**37.9%**	1,058	**73.5%**
JUL	297,866	36,999	14.7%	3,438	9.6%	1,398	**38.8%**	1,033	**60.7%**
AUG	305,039	32,779	12.9%	3,823	10.3%	1,367	**39.8%**	923	**66.0%**
SEP	311,169	39,886	15.1%	4,031	12.3%	1,283	**33.6%**	964	**70.5%**
OCT	316,937	37,916	14.4%	3,929	9.9%	1,538	**38.2%**	867	**67.6%**
NOV	318,288	41,949	15.5%	4,777	12.6%	1,687	**42.9%**	1,071	**69.6%**
DEC	311,656	33,816	12.6%	4,054	9.7%	1,423	**29.8%**	1,123	**66.5%**
2005 AVG	301,608	37,035	14.5%	4,060	11.1%	1,451	**36.1%**	1,013	**69.4%**
2006									
JAN	309,084	43,723	16.2%	3,618	10.7%	1,558	**38.4%**	947	**66.5%**
FEB	315,311	41,455	16.1%	5,870	13.4%	1,402	**38.7%**	1,122	**72.0%**
MAR	314,092	31,981	12.1%	3,643	8.8%	1,639	**27.9%**	957	**68.3%**
APR	313,603	45,189	16.5%	4,215	13.2%	1,385	**38.0%**	1,099	**67.1%**
MAY	314,248	31,454	12.1%	4,688	10.4%	1,417	**33.6%**	1,000	**72.3%**
JUN	316,415	38,671	14.1%	3,712	11.8%	1,598	**34.1%**	976	**68.9%**
2006 YTD AVG	313,792	38,746	14.5%	4,291	11.4%	1,500	**35.1%**	1,017	**69.2%**
Overall AVG	305,669	37,605	14.5%	4,137	11.2%	1,467	**35.8%**	1,014	**69.3%**

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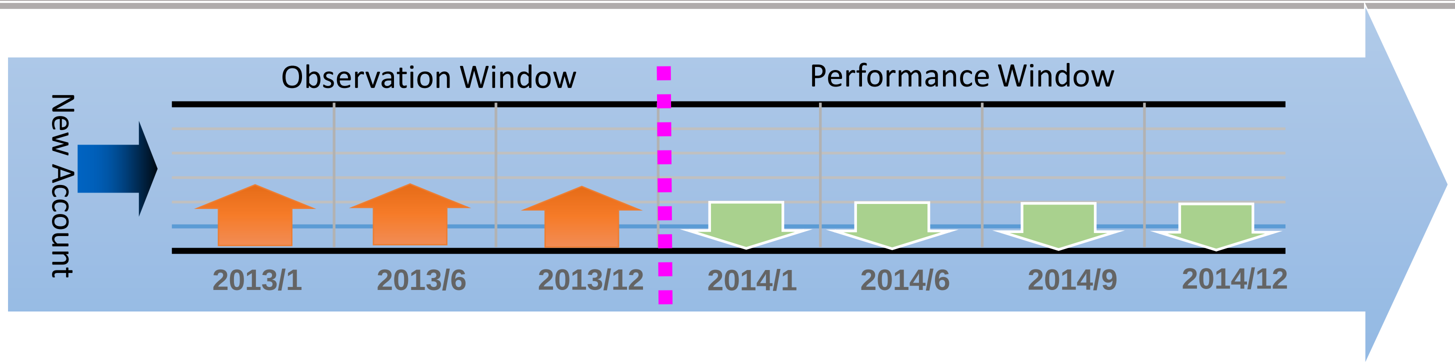
2.1 G/B/I/E Definition (Cont.')
Exclusion/Indeterminate Definition

Accounts are excluded in order to remove bias and uncertainty from the development sample. Examples of exclusions are - do not meet current policy criteria, incomplete information and special handling like:

- VIPs
- Staffs
- Frauds
- Bankrupt accounts
- Inactive accounts
- Cancelled accounts
- Closed accounts

Accounts who are not significant good/bad are defined as Indeterminate, which will not be used to develop models

2.2 Time Window Specification
Introduction to observation & performance window



Observation window: refers to the time frame within which data are extracted and used in selecting a subset of variables for predicting actual account performance. This is the period of time that applications made will be extracted specifically for use within the scorecard development modelling process.

- Generally 12-24 months for account acquisition, 6-12 months for account management
- May be refined by viewing delinquency curves
- Best approach is performance window of equal length for each account, but sample size is also very critical

Performance window: refers to the time frame which data are selected for monitoring actual account performance. This is the period of time between the observation point and the point where the final performance is assessed.

- Recent enough to be representative of current population
- Dated enough to allow accounts to have established payment behavior
- Long enough to meet minimum sample size requirements and to accommodate seasonality concerns

<u>Method 1 - Fixed observation window</u>

- A fixed observation window typically, 12 months, is used to count defaults based on a fixed assessment date. For example all accounts are taken as at 31 Dec 2013 and defaults are counted if they default within 12 months from the date of assessment

<u>Method 2 – Fixed duration window</u>

- The fixed duration method uses the date of each default as the starting point, as opposed to the date of assessment as in Method 1 above. The date of the PD, LGD and EAD assessments for each defaulted customer is taken as the assessment exactly 12 months prior to the default occurring.

3 Exploratory Data Analysis
Session Outline

3.1 Descriptive Statistic
3.2 Variable Selection Criteria
3.3 Characteristic analysis

3.1 Descriptive Statistic Univariate Analysis

Univariate Analysis

Summary of Statistic

- **Objective**
  - Understand the distribution of the population
- **Methods**
- Box plot
- QQ plot
- Histogram

Student Test Statistic

- **Objective**
  - Classify whether a variable can distinct good/bad account
- **Methods**
  - Normally reject hypothesis when p-value less than 0.05

Accurate Ratio Analysis

- **Objective**
  - Calculate Variable's accurate ratio

Preliminary Variable Selection

- **Objective**
  - Select the most significant t-score variable
  - Select the most high AR value variable

Univariate analysis involves checking the distribution of a single variable. Points that access here are **central tendency** measured by ***mean, median and mode***; **dispersion** measured by ***range and quintiles***; **spread** measured by ***variance and standard deviation***; **shape** measure by ***skewness and kurtosis***. Characteristic **distribution** can be depicted in graphical or tabular format such as ***histograms and stem-and-leaf display***.

Once summary statistic is made, a brief insight about data set we interpreted can be our guidance for simple t-statistic to test the dependence of single variable to good/bad. E.g. A significant of mean differences between variables in good/bad accounts.

The objective of this process is to preliminary select the variables enter into multivariate analysis.

3.1 Descriptive Statistic (Cont.’) Multivariate Analysis

Multivariate Analysis

Classing

Correlation Analysis

- **Objective**
  - Check correlation between variables. Determine if variables meet the modelling requirement.

Multivariate Analysis

- **Objective**
  - Variable Decomposition
- **Methods**
  - Principle Component Analysis
  - Factor Analysis
  - Canonical Analysis
  - Ace Clustering
  - Discrimination Analysis
  - ……

Stepwise Discriminate Analysis (or modified stepwise regression technique) is applied to identify the most predictive combination of variables for preliminary development

- The objective of the StepDisc procedure in SAS is to determine the most powerful combination of characteristics out of all possible candidates in the variable pool.
- Partial R-square will be evaluated
- The top characteristics that remain are the most likely candidates for the final model.

3.2 Principles for Variable Selection

Variable selection stage identify which variable should be included in the modelling phase, key consideration are listed below:

Statistical Consideration

- ❑ Predictive Power
- ❑ Stability across time and portfolio
- ❑ Correlation between factors

Judgmental Consideration

- ❑ Comprehensive customer view
- ❑ Parsimonious and intuitive
- ❑ Consistency across portfolios
- ❑ Prior experience from benchmark and expert opinion
- ❑ Implementation Consideration

With initial variable set, which is often includes hundreds of, in order to simplify the model, variables need to be reduced, methods for variable decomposition and model simplified are

- Factor analysis
- Canonical analysis
- Principal component analysis
- Stepwise Discriminate Analysis is applied to identify the most predictive combination of variables for preliminary development

3.2 Characteristic Analysis

The following indicators and analysis were computed to help ascertain the validity and degree of importance of scoring and potential scoring characteristics for the scorecard development:

Frequency and Distribution Analysis

- This analysis helped to detect characteristics that were not meaningful or unusual trends through the frequency distributions tabulated for the attributes for each characteristic.

Coarse / Fine Classing

- The process of grouping individual attributes into appropriate number of attributes for each characteristic was performed based on guiding principles such as similarities in odds, information values or nature etc.

Odds Analysis

- Odds are calculated for each attribute for every relevant characteristic.

$$Odds = \frac{\%Number\ of\ Goods}{\%Number\ of\ Bads}$$

Weight of Evidence (WOE)

- Here the neutral ratio is set at 0. A negative ratio means there are more Bad than Goods and conversely for a positive ratio, there are more Good than Bad.

$$WOE = LogOdds = \log\left(\frac{Number\ of\ Goods}{Number\ of\ Bads}\right)$$

Information Value (IV)

- Information Values are used to assess whether a particular characteristic contributes significantly to the scorecard.

$$IV = (Good\% - Bad\%) \times LogOdds$$

- Usually characteristics with IVs, less than 0.02, are deemed insignificant and hence excluded from the scorecard. However it is also highly dependent on many other factors, such as number of available characteristic candidates and relative IVs among different characteristics.

3.2 Characteristic Analysis (Cont.')

Example Only

Gender	Bad	Good	Total	Bad%	Good%	Total	Odds	WOE	IV
Male	550	20,079	20,629	74.324%	59.819%	60.132%	0.8048436	-0.217107	0.03149
Female	190	13,487	13,677	25.676%	40.181%	39.868%	1.5649263	0.447839	0.06496
Total	740	33,566	34,306	100.000%	100.000%	100.000%			0.09645

Occupation	Bad	Good	Total	Bad%	Good%	Total	Odds	WOE	IV
No Info	0	96	96	0.000%	0.286%	0.280%	0	0	0.00000
I	65	5,165	5,230	8.784%	15.388%	15.245%	1.7518185	0.560654	0.03702
II	191	10,254	10,445	25.811%	30.549%	30.447%	1.1835649	0.168531	0.00798
III	92	3,842	3,934	12.432%	11.446%	11.467%	0.9206651	-0.082659	0.00082
IV	68	1,575	1,643	9.189%	4.692%	4.789%	0.510627	-0.672116	0.03022
V	250	9,496	9,746	33.784%	28.291%	28.409%	0.8373997	-0.177454	0.00975
VI	64	2,882	2,946	8.649%	8.586%	8.587%	0.9927643	-0.007262	0.00000
VII	10	256	266	1.351%	0.763%	0.775%	0.5643806	-0.572026	0.00337
All	740	33,566	34,306	100.000%	100.000%	100.000%			0.08917

Education	Bad	Good	Total	Bad%	Good%	Total	Odds	WOE	IV
Primary/Secondary	213	9,502	9,715	28.784%	28.308%	28.319%	0	0	0.00000
Diploma/Certificate	29	1,975	2,004	3.919%	5.884%	5.842%	1.5014167	0.406409	0.00799
Pre-University	172	13,430	13,602	23.243%	40.011%	39.649%	1.7213917	0.543133	0.09107
Degree & Above	326	8,659	8,985	44.054%	25.797%	26.191%	0.5855747	-0.535162	0.09771
All	740	33,566	34,306	100.000%	100.000%	100.000%			0.19676

4 Segmentation
Session Overview

4.1 Determine Scorecard Segment

4.1 Determine Scorecard Segments Overview

Segmentation is a process of assigning accounts in a particular portfolio to different segments according to their exposures to risk, and homogeneity is used to describe the degree of similarity (in terms of risk) within a segment.

When there are more homogeneous subpopulations within a large enough portfolio, segmentation of the portfolio may be required.

Objective is to identify the optimal population splits upon which a suite of models will **maximize** the predictive power of the overall scoring system. Determine the degree to which multiple models built on individual population segments will **improve** performance of scoring system.

Identify the segmentation scheme that will provide the **greatest lift** in model performance

Scorecards of different segments may have the same variables, but their parameter estimates may be significantly different or may have opposite signs, which may result in very different scores.

Considerations for segmenting scorecards:

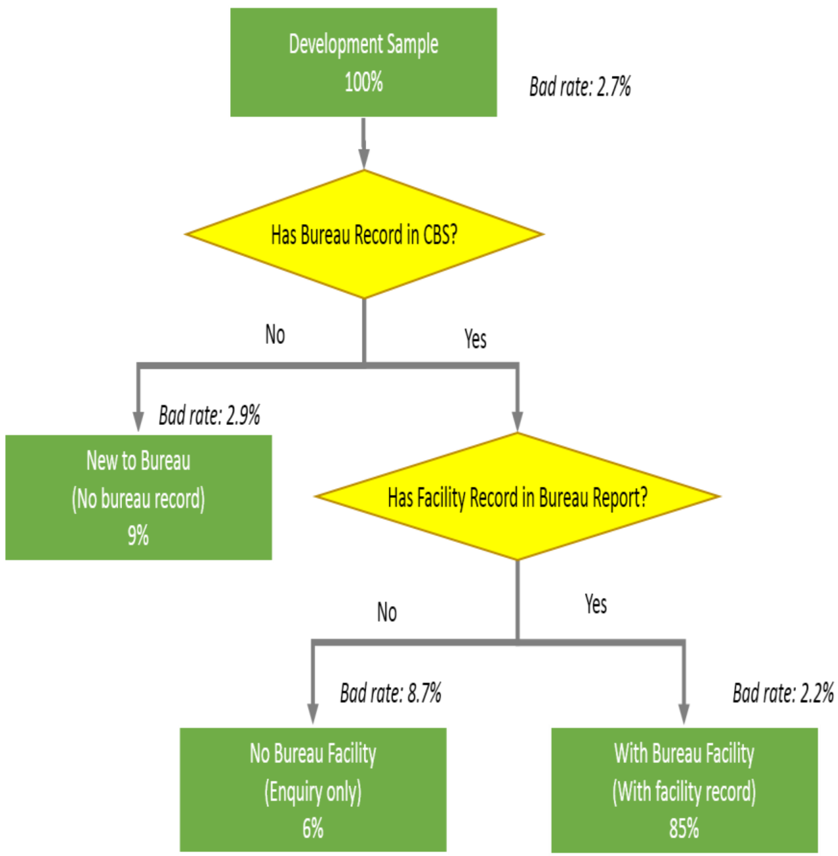
- Population Volume
- Business Logical Sense
- Can be implemented
- Stability of the Characteristic (PSI)
- No. of Bad
- GB Index Different
- Risk Profile Different
- Population Distribution Different

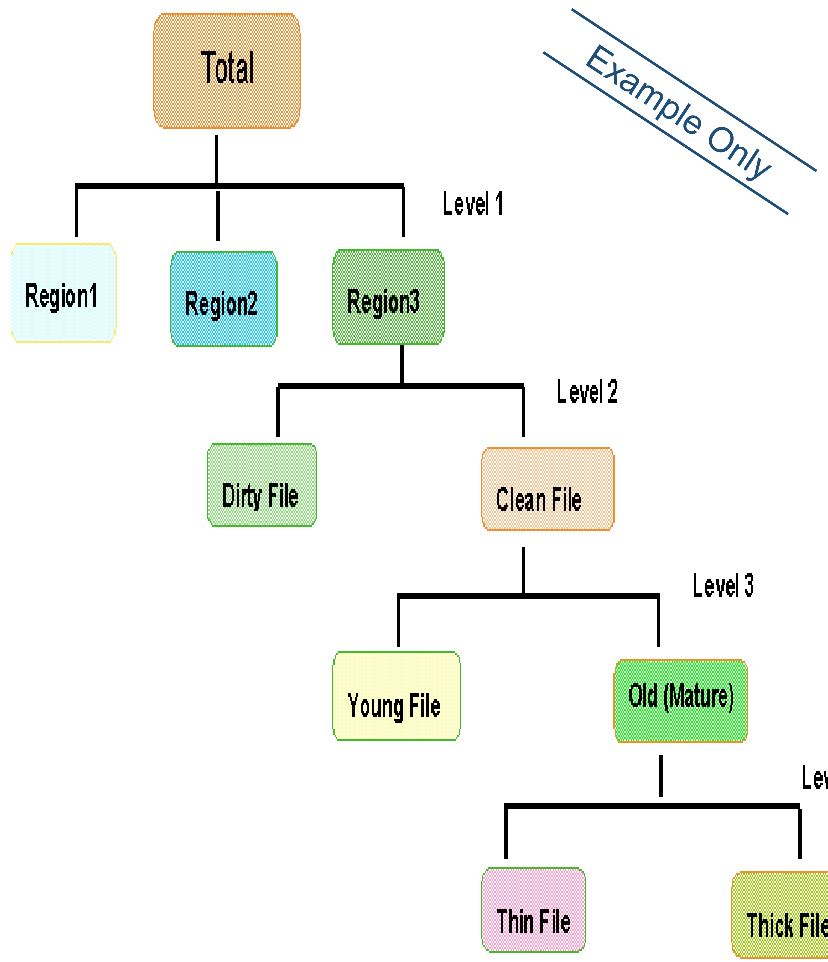
4.1 Determine Scorecard Segments (Cont.')
Procedure for Segmentation Analysis

- Master/niche multi-step modeling approach
  - **Master = Total population**
  - **Niche = Sub-population**

Step 1 –	**Develop a master model on the total population**
Step 2 –	**Evaluate performance of master model on each niche segment**
Step 3 –	**Develop a model on each niche segment**
Step 4 –	**Evaluate performance of niche model on each niche segment**
Step 5 –	**Assess improvement in performance of niche models for each niche over the master model**
Step 6 –	**Provide portfolio statistics** **- Sub-population volume** **- Sample size** **- Bad rate** **- Approval and booking rates**

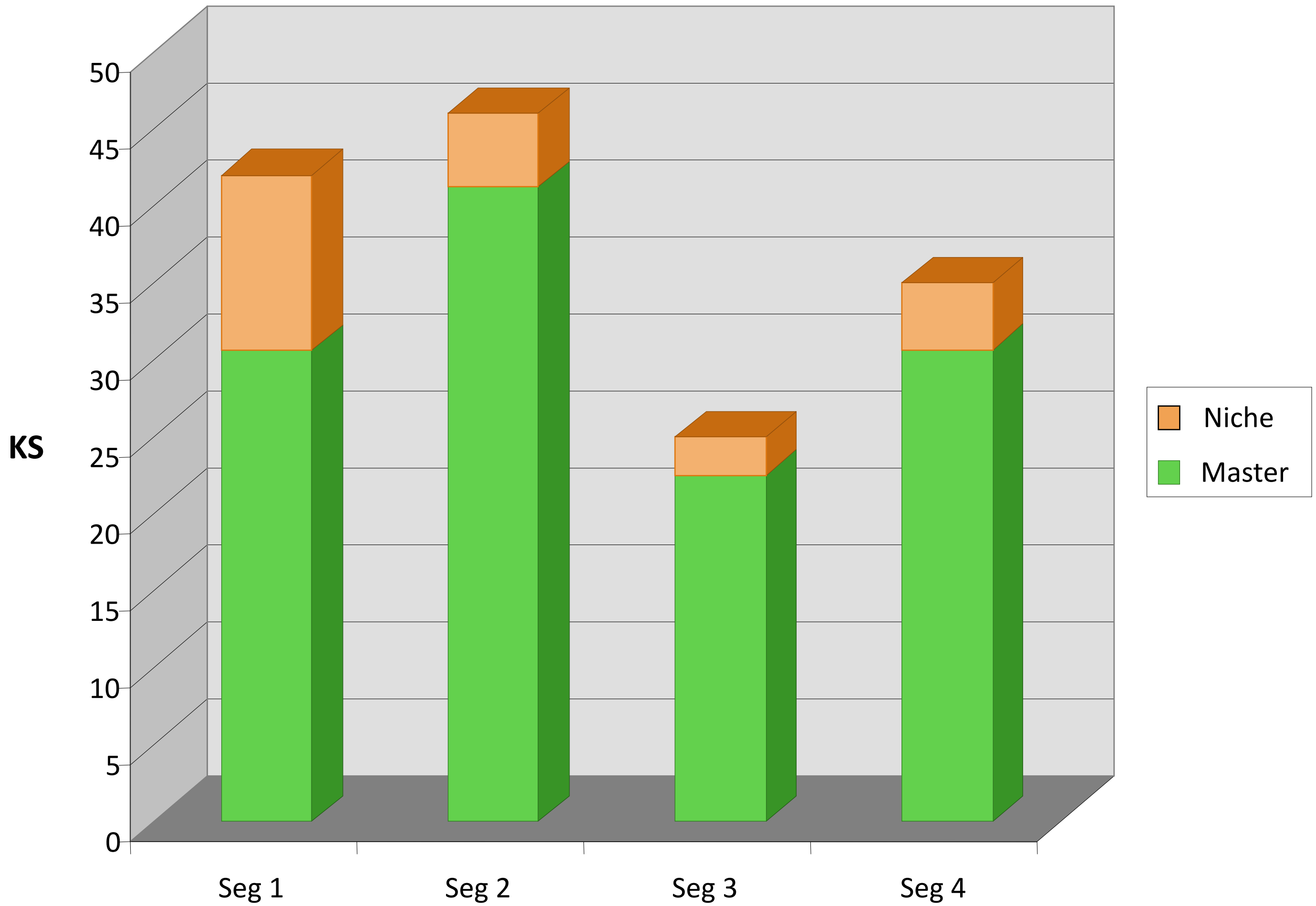
4.1 Determine Scorecard Segments (Cont.')
Example of Scorecard Segmentation





4.1 Determine Scorecard Segments (Cont.')
Segmentation approach – Master / Niche

- **Segment evaluation**



5 Model Finalization

5.1 Reject Inference Process
Overview of Reject Inference

What is reject inference?

The process of theoretically inferring a probability of good onto previously rejected accounts

Why reject inference?

- Counter skewness in Accepted Population
- Mimic "Through the door" population

Is Reject Inference always necessary?

- Reject rate is so low that accepts represent TTD

Best Practice

- Accept / Reject Model
- Good / Bad Model
- Reject Inference Process

What are the challenges

- Infer dependent variable/outcome based on available information
- Independent variables: Bank must retain sufficient information on rejects, both width and length wise.

5.1 Reject Inference Process (Cont.')
Main Steps for Reject Inference Process

1. **Good/Bad Model Development**
2. **Accept/Reject Model Development**
3. **Reject Inference Performed**
4. **Final Scoring Model Development**

1. Good/Bad Model Development

- Discriminate between accepted good and accepted bad accounts
- Assign a Predicted prob. of good to these accounts
- Population:
  - Good
  - Bad

2. Accept/Reject Model Development

- Discriminate between accepted and rejected applications
- Assign a Predicted prob. of accept to all applications
- Population:
  - Good
  - Bad
  - Indeterminate
  - Not Taken Up
  - Rejects

Accepts

5.2 Modeling Finalization

- Scorecards models finalization and make alignment to scores results

Variables(A)	Description(B)	Group(C)	Weight(D)	Score(E)	Transformation
Intercept			2.8354	606	Score (E)=800+50*(D-LN(250))/LN(2)
LTV1	Collateral Rate	<50%	0.7266	52	Score (E)=50*D/LN(2)
LTV2		[50%,60%)	0.277	20	Score (E)=50*D/LN(2)
LTV3		[60%,65%)	0.2504	18	Score (E)=50*D/LN(2)
		>=65%	0	0	Score (E)=50*D/LN(2)
MRTST1	Marital status	Married	0.4695	3[illegible]	Score (E)=50*D/LN(2)
		Others	0	0	Score (E)=50*D/LN(2)
EDUCATION1	Education	Bachelor above	0.5097	37	Score (E)=50*D/LN(2)
		Others	0	0	Score (E)=50*D/LN(2)
ARCHI	Floor space	<=120	0.2589	19	Score (E)=50*D/LN(2)
		>120	0	0	Score (E)=50*D/LN(2)
AGE1	Age	<=25	-0.2019	-15	Score (E)=50*D/LN(2)
AGE2		(25,35]	-0.1557	-11	Score (E)=50*D/LN(2)
		>35	0	0	Score (E)=50*D/LN(2)
TITLE1	Technical title	Middle Above	0.1105	8	Score (E)=50*D/LN(2)
		Others	0	0	Score (E)=50*D/LN(2)
SEXID	Sex	Male	0	0	Score (E)=50*D/LN(2)
		Female	0.1271	9	Score (E)=50*D/LN(2)

5.3 Risk grade and score cut off

Risk grade and score cut off

Risk	Applicants						Total	
Grade	#	%	#	%	G:B	G:B	#	%
	Goods	Goods	Bads	Bads	Odds	Index	Apps	Apps
18	491	1.62	342	12.44	1.44	766B	982	2.31
17	767	2.53	265	9.65	2.89	381B	1276	3.01
16	653	2.16	197	7.18	3.31	333B	1051	2.48
15	976	3.22	203	7.39	4.80	229B	1505	3.55
14	1001	3.31	194	7.07	5.15	214B	1523	3.59
13	1180	3.90	196	7.11	6.03	182B	1763	4.15
12	1226	4.05	163	[illegible]	7.53	146B	1819	4.29
11	1370	4.53	177	6.43	[illegible]	142B	2007	4.73
10	768	2.54	85	3.08	[illegible]	121B	1095	2.58
9	2781	9.19	233	8.48	11.93	[illegible]	3930	9.26
8	1583	5.23	128	4.64	12.40	113G	2257	5.32
7	2005	6.63	154	5.61	13.00	118G	2833	6.68
6	2038	6.73	109	3.97	18.66	170G	2777	6.54
5	1675	5.54	69	2.50	24.33	221G	2302	5.42
4	2153	7.11	81	2.96	26.48	241G	2895	6.82
3	2890	9.55	75	2.71	38.80	353G	3795	8.94
2	2344	7.75	42	1.52	55.97	509G	3073	7.24
1	4356	14.40	37	1.34	118.52	1077G	5551	13.08
TOTAL	30257		2750		11.00	100B	42434	

Score Reject – High Risk

Score Refer Band – Send to underwriter

Accepts – Low Risk

Terms may vary as risk decreases

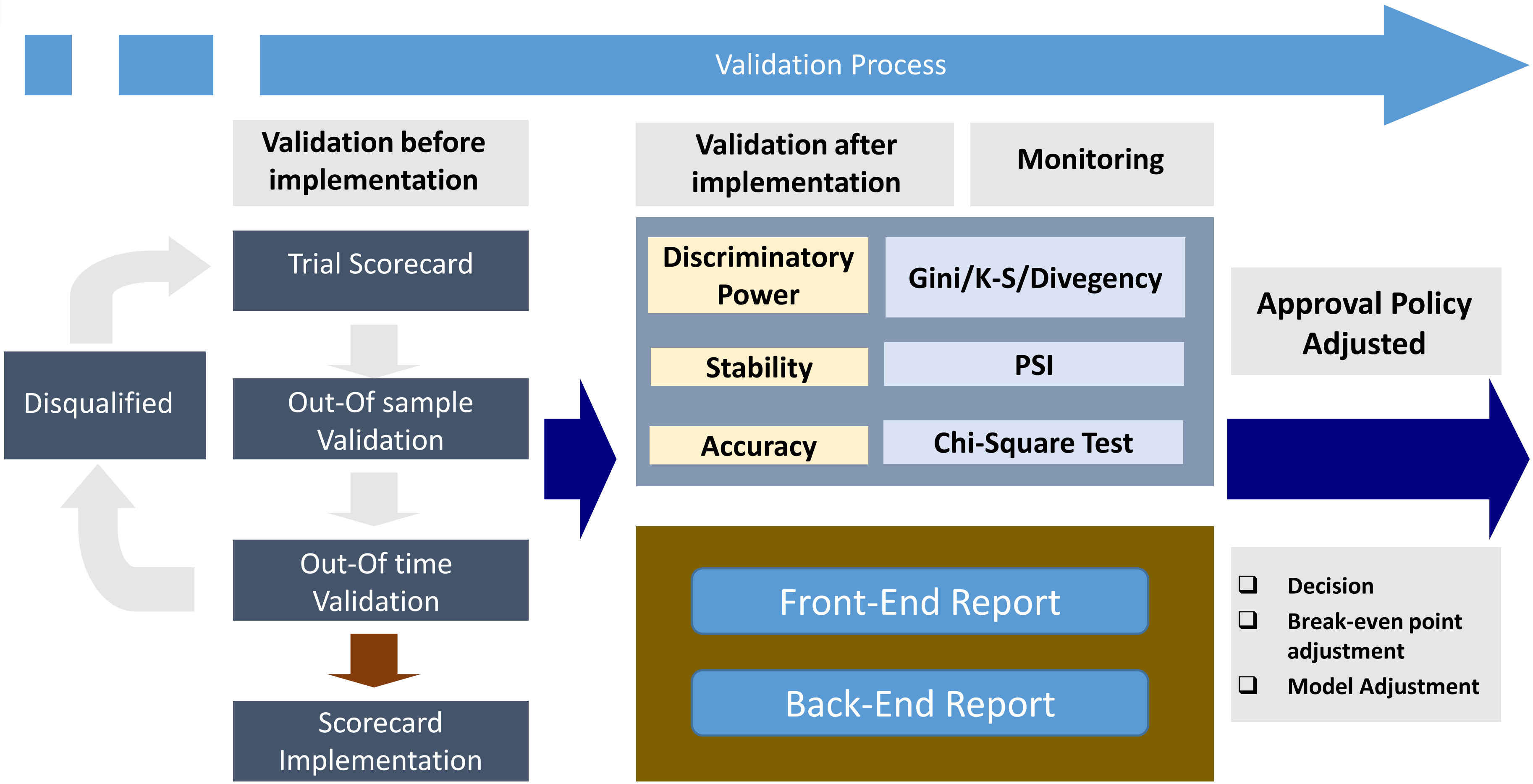
Analysis used to determine the most appropriate cut-offs for the business

EXAMPLE

6 Model Validation & Monitoring Report

6.1 Model validation
6.2 Monitoring report

6. 1 Model Validation
Model Validation Process Overview



6. Model Validation (Cont.')
Introduction to Scorecard Validation

Why Validation?

- Confirm over-modeling has not occurred - robustness
- Identifies the strength of a model on a more recent population
- Compare similarities in similar populations, i.e., development Goods versus Validation Goods

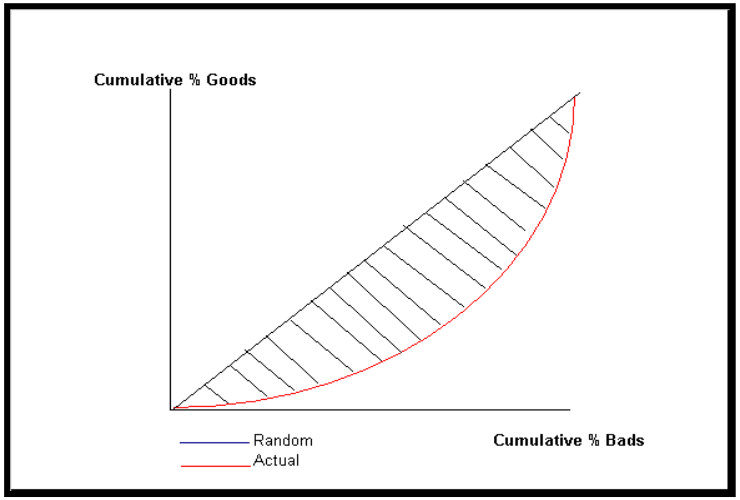
Methods of Validation

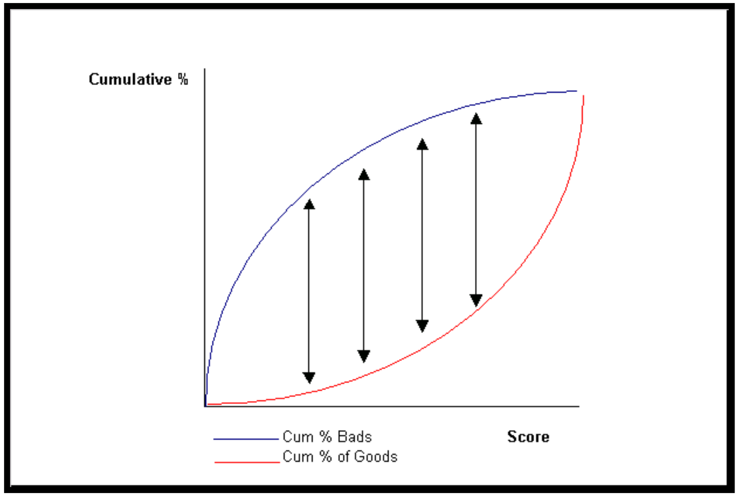
- Hold out sample validation
  - A random portion of development sample is set aside
- Cross validation (CV)
  - Utilize a population from a different time period to test model robustness

6. Model Validation (Cont.')
Access Discriminatory Power

Gini measures the area in between what would be a cumulative random vs. "Good" or "Bad" population

- Higher Gini coefficients mean greater discrimination – 100 means perfect discrimination
- Declining Gini's over time indicate a decrease in the power of the scorecard





The Kolomogorov-Smirnov Test measures how differently the scorecard ranks the Good and Bad populations are within your score distribution.

- ❖ Calculates the maximum difference between the cumulative number of "Good" and the cumulative number of "Bad"
- ❖ The higher the Maximum Difference the more efficient your scorecard is at separating Good and Bad
- ❖ Declining KS over time indicate a decrease in the power of the scorecard

6. Model Validation (Cont.')
Access Stability

Using Score PSI to Measure Population Shift

- **Threshold:**
  - PSI<=0.1: little or no difference between two score distributions
  - 0.1<PSI<0.25: some change has taken place, but it is too small to determine whether it is an isolated incident or a persistent trend
  - PSI>=0.25: signifies a large shift.
- **Population shift does not mean scorecard no longer valid**
  - The width of the distribution means that scorecard is still ranking applicants from high to low risk
  - A population shift alone can be managed by changing score cut-off
- **Rank ordering power should be closely monitored**
  - Degenerating predictability is main concern

Score	Development		YYYYMM		E=D-B	F=LN(D/B)	G=E*F
Range	# (A)	% (B)	# (C)	% (D)			
Low-768	2,329	9.99	3,110	10.00	0.0002	0.0016	0.0000
769-849	2,341	10.04	3,088	9.93	-0.0011	-0.0106	0.0000
850-890	2,367	10.15	3,123	10.04	-0.0010	-0.0104	0.0000
891-923	2,330	9.99	3,104	9.98	-0.0001	-0.0007	0.0000
924-946	2,311	9.91	3,052	9.82	-0.0009	-0.0094	0.0000
947-967	2,297	9.85	3,173	10.20	0.0036	0.0355	0.0001
968-989	2,360	10.12	3,113	10.01	-0.0011	-0.0106	0.0000
990-1012	2,351	10.08	3,059	9.84	-0.0024	-0.0243	0.0001
1013-1045	2,316	9.93	3,148	10.12	0.0019	0.0194	0.0000
1046-High	2,322	9.96	3,125	10.05	0.0009	0.0094	0.0000
PSI							**0.0003**

6.2 Scorecard Monitoring Reports

Introduction

- Are score overrides being kept to a minimum?
- Does the scorecard continue to rank the risk of loans as expected or has performance deteriorated?
- Have the characteristics of loan applicants changed?
- Has the score distribution of booked loans changed?

Types of Reports?

- Front-End Reports
  - May be generated soon after the score has been implemented.
  - Do not report anything dealing with loan performance but are concerned with score distributions and the distribution of score characteristics.

- Back-End Reports
  - Are designed to measure the scorecard's effectiveness

Front-end Reports

Population Stability and Approval Rate Report

Example Only

INDICATORS	BENCHMARKS	PERFORMANCE
Population Stability Analysis (PSI)	< 10%, stable population	7.14%
Characteristic Analysis	≤ ± 4, no significant shift in variables	9.22
Highside Overrides	< 10% of TTD	11.78%
Lowside Overrides	< 10% of TTD	3.23%
Separation Analysis (KS), 30+ dpd	≥ 20%, indicates separation ability	17.43%
Separation Analysis (KS), 60+ dpd	≥ 20%, indicates separation ability	25.75%
Separation Analysis (KS), 90+ dpd	≥ 20%, indicates separation ability	27.77%

Clarity in Complexity

Front-end Reports

Characteristic Analysis Report

Example Only

Months on Book	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Jul-03
<9 Months	5.07%	5.90%	7.02%	8.43%	8.64%	8.83%
9-<24 Months	33.27%	31.49%	30.67%	29.70%	29.22%	27.41%
24-<72 Months	30.14%	30.10%	29.17%	28.54%	28.15%	29.07%
72 Months & Above	31.52%	32.51%	33.15%	33.33%	33.99%	34.69%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Total No. of Times in X+ DPD Last 6 Months	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Jul-03
0	71.13%	69.73%	70.17%	70.33%	70.64%	70.32%
1	14.42%	15.26%	14.69%	14.62%	14.70%	14.71%
2 & Above	14.45%	15.01%	15.14%	15.05%	14.66%	14.97%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

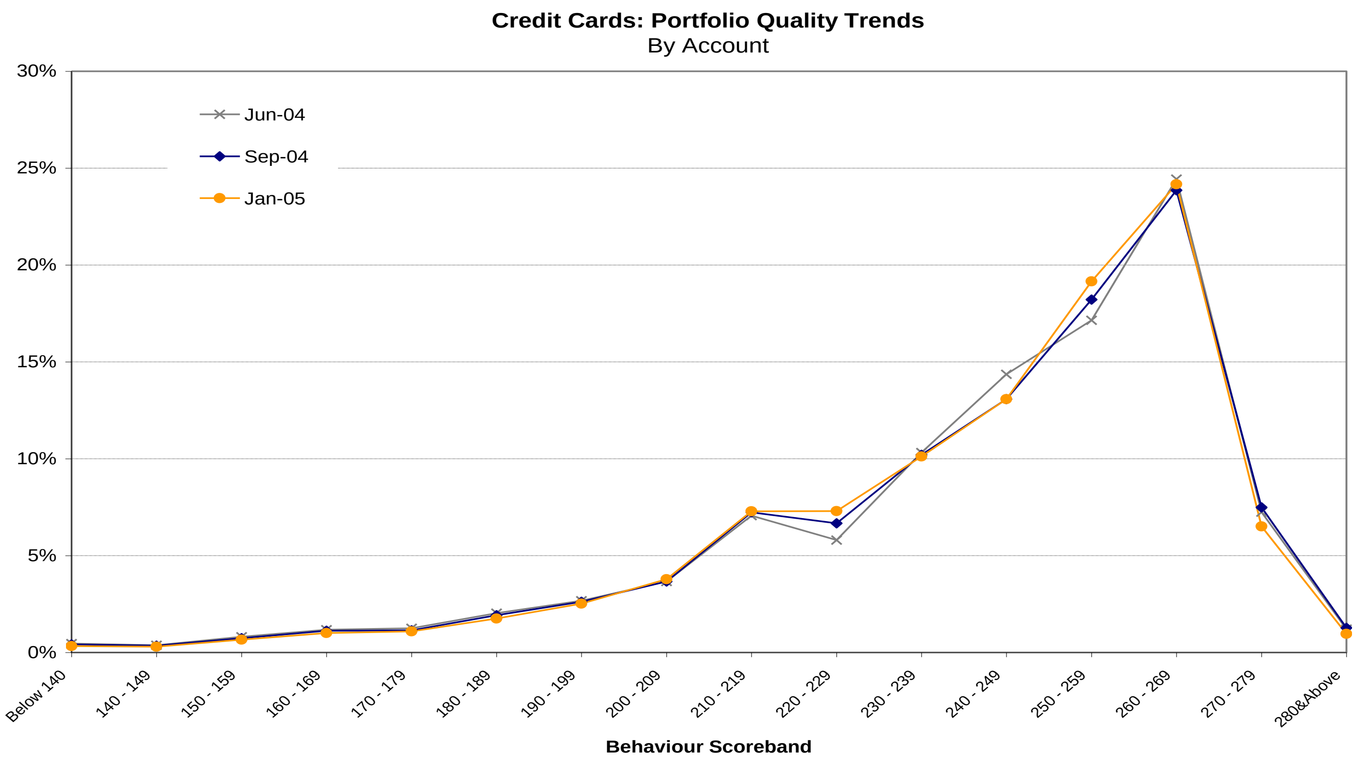
Total No. of Times in 30+ DPD Last 6 Months	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Jul-03
0	95.17%	94.92%	94.54%	94.61%	94.70%	94.82%
1 & Above	4.83%	5.08%	5.46%	5.39%	5.30%	5.18%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Excess Indicator	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Jul-03
Yes	2.10%	2.09%	2.09%	2.13%	2.29%	2.19%
No	29.76%	30.25%	30.11%	29.81%	29.86%	30.18%
Never	68.14%	67.66%	67.80%	68.07%	67.85%	67.64%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Front-end Reports

Portfolio Quality Trend

Example Only

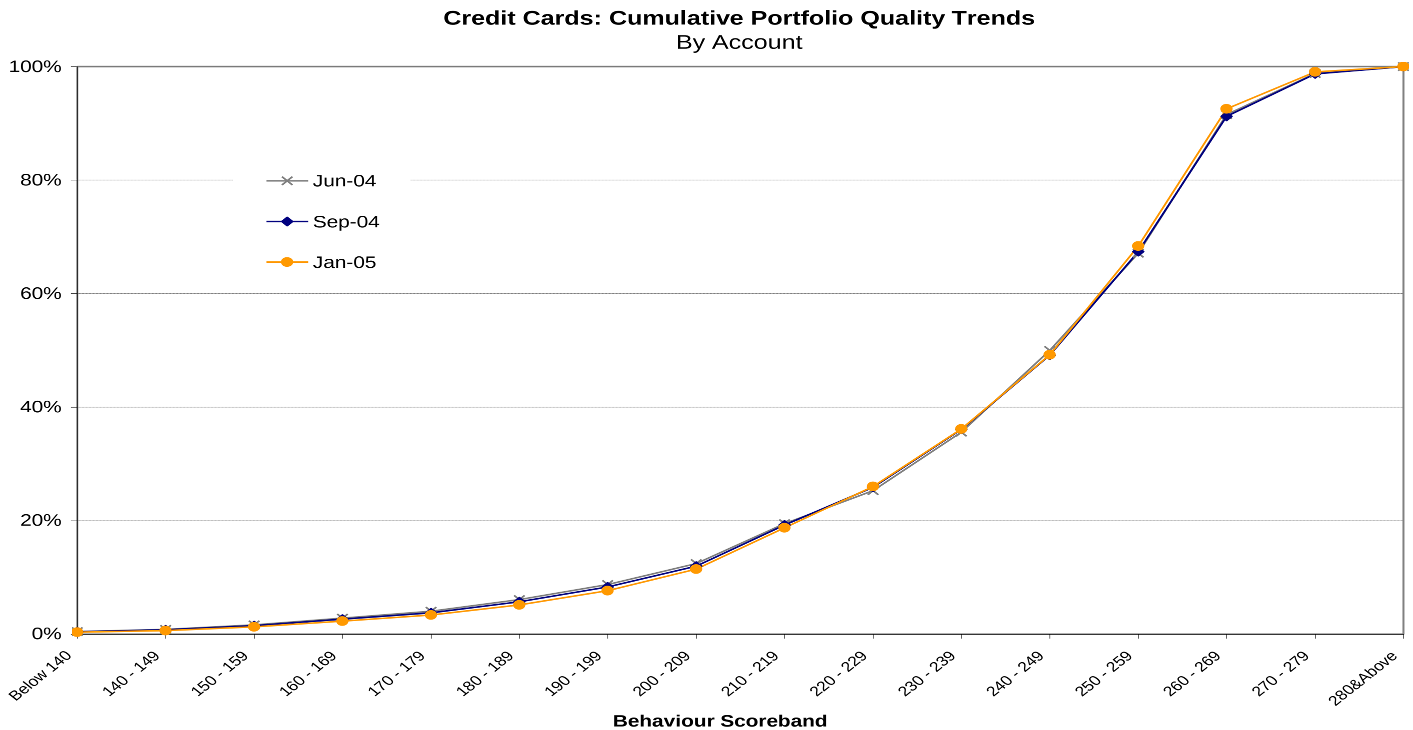


Clarity in Complexity

Front-end Reports

Cumulative Portfolio Quality Trend

Example Only

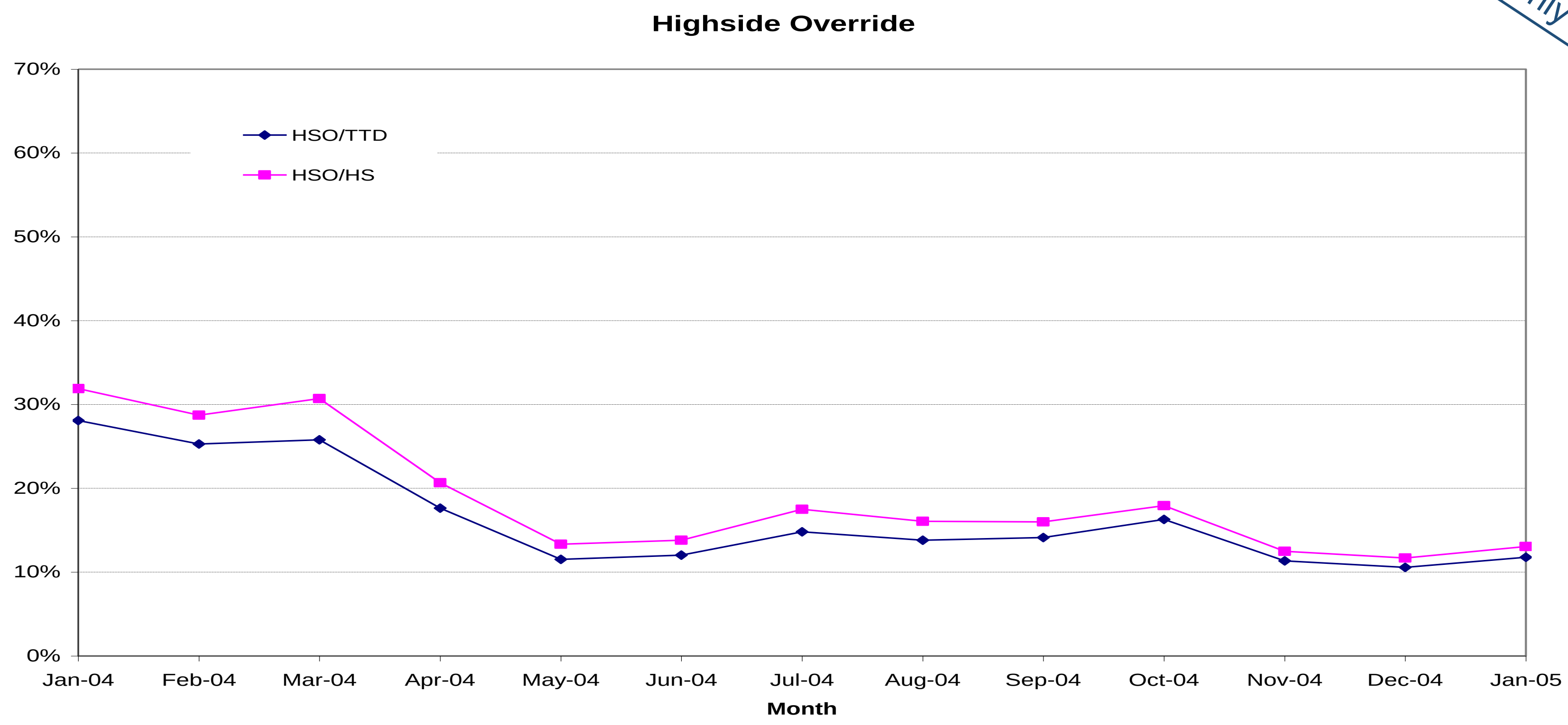


Clarity in Complexity
ENTROFINE

Front-end Reports

Override Rate Report

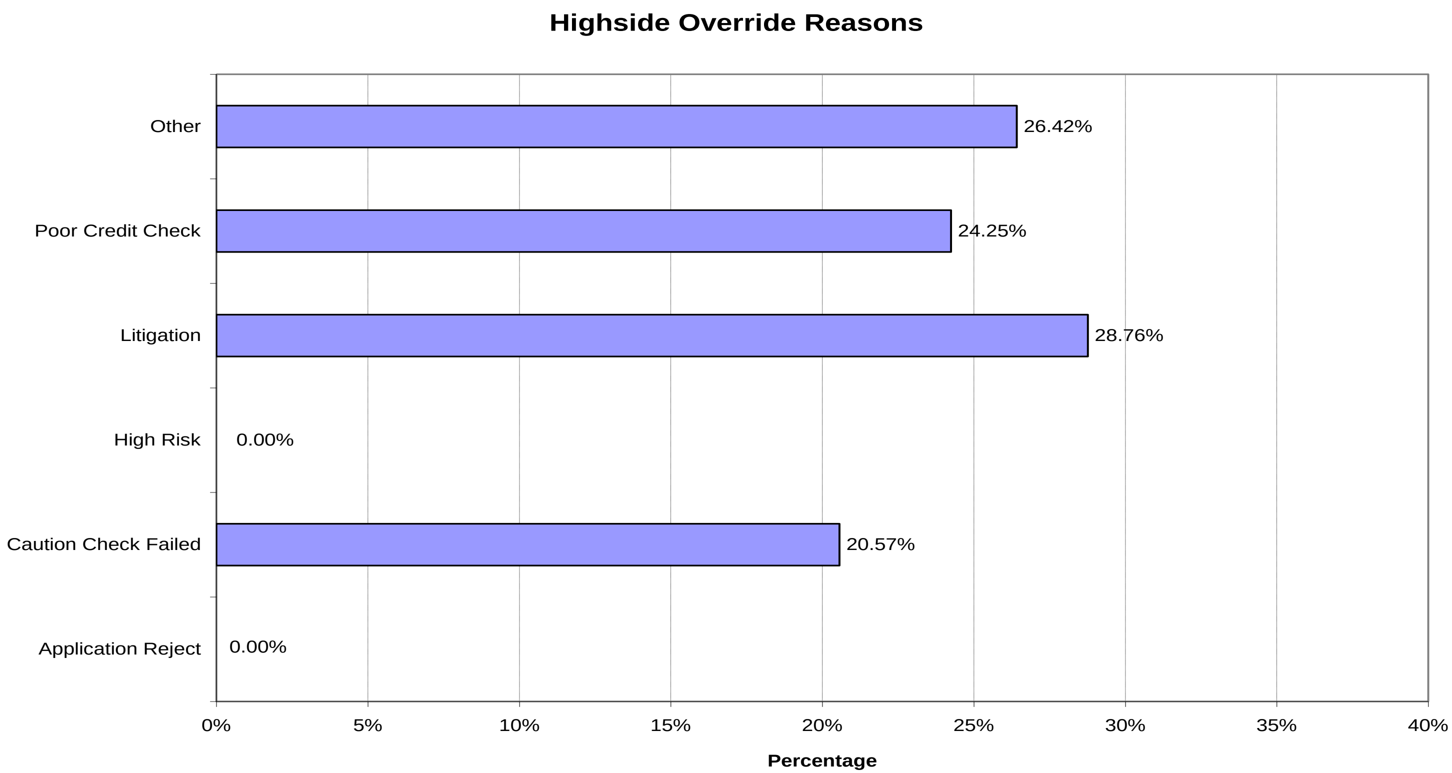
Example Only



Front-end Reports

Override Reason Report

Example Only



Front-end Reports

Override Reason – Working File

Example Only

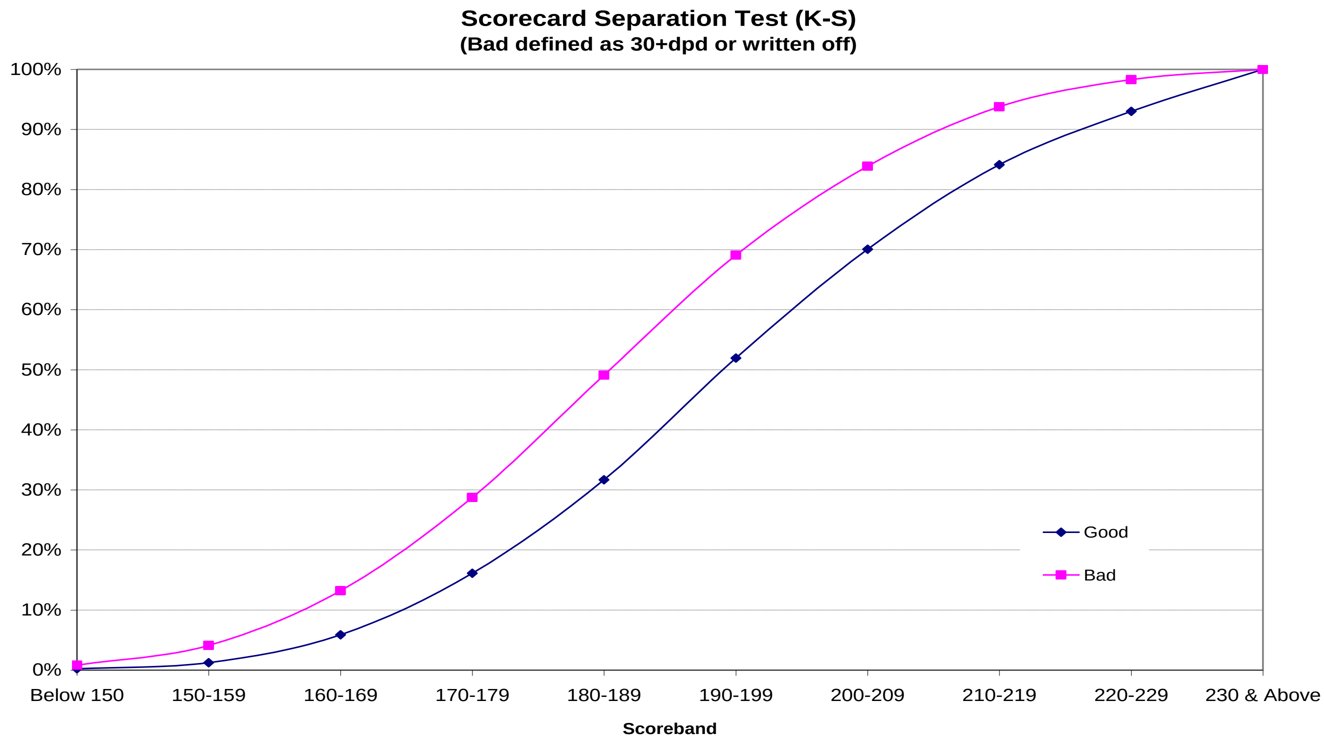
HSO Reasons								
Reasons	175 - 184	185 - 194	195 - 204	205 - 214	215 - 224	225 - 234	>=235	Total
2nd Card/HROs	135	107	71	66	34	17	4	434
Bad Credit Check	245	268	305	236	167	95	50	1366
Legal/Bankrupt/Cancelled/List	176	245	247	203	116	44	29	1060
Fraud/Counterfeit	5	2	2	3	1	0	0	13
Total	561	622	625	508	318	156	83	2873
Total Processed	1480	1541	1441	1161	724	420	265	7032

	ScoreBands							
HSO Reasons	175 - 184	185 - 194	195 - 204	205 - 214	215 - 224	225 - 234	>=235	**Total**
A:2nd Card/HROs	9.12%	6.94%	4.93%	5.68%	4.70%	4.05%	1.51%	6.17%
B:Bad Credit Check	16.55%	17.39%	21.17%	20.33%	23.07%	22.62%	18.87%	19.43%
C:Legal/Bankrupt/Cancelled/List	11.89%	15.90%	17.14%	17.48%	16.02%	10.48%	10.94%	15.07%
D:Fraud/Counterfeit	0.34%	0.13%	0.14%	0.26%	0.14%	0.00%	0.00%	0.18%
Total	37.91%	40.36%	43.37%	43.76%	43.92%	37.14%	31.32%	40.86%

Back-end Reports

Good / Bad Separation Report

Example Only



Back-end Reports

Good / Bad Separation Report

Example Only

K-S Test

Score Band	No. of Good A/Cs	No. of Bad A/Cs	Cum Good A/Cs (%)	Cum Bad A/Cs (%)	Abs. Cum Separation (%)
A	B	C	D	E	F
Below 150	151	20	0.2%	0.8%	0.62%
150-159	732	79	1.2%	4.1%	2.86%
160-169	3,290	220	5.9%	13.2%	7.33%
170-179	7,244	374	16.1%	28.7%	12.60%
180-189	11,006	491	31.7%	49.1%	17.41%
190-199	14,341	482	51.9%	69.1%	17.14%
200-209	12,830	357	70.1%	83.9%	13.81%
210-219	9,952	239	84.1%	93.8%	9.66%
220-229	6,303	109	93.0%	98.3%	5.28%
230 & Above	4,938	41	100.0%	100.0%	0.00%
Total	70,787	2,412		**K-S =**	**17.41%**

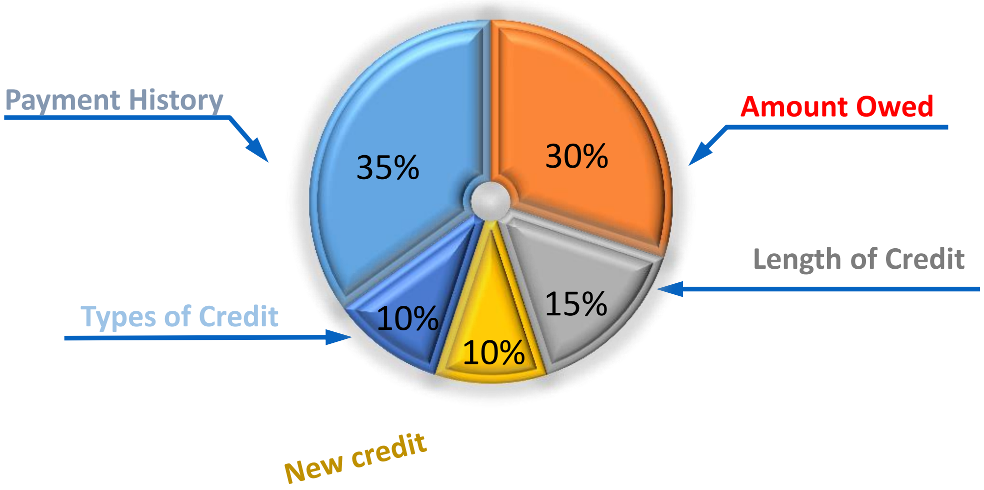
A	Scoreband. Normally 10-scoreband is used by banks..
B	Number of good accounts of OTD portfolio. The age of accounts should be at least 3 months.
C	Number of bad accounts of OTD portfolio. The age of accounts should be at least 3 months.
D	Cumulative good accounts in percentage.
E	Cumulative bad accounts in percentage.
F	Defined as ABS(D - E) by score band.
K- S	K-S value defined as Max(F).
Bad	Defined as ever 30+ days past due or written off.

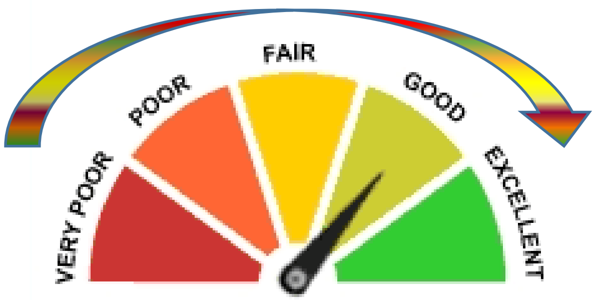
Agenda

Case Study – Application Scorecard (CC)

- A generic scorecard was implemented for Personal Loan in Nov 2000
- Credit Cards adopted credit scoring and used the same scorecard for its application processing in Jan 2001
- As at Jan-2002, a total of 25,315 applications have been scored
- Monthly scorecard performance review since Jul 2001 showed unsatisfactory separation ability: scorecard does rank order risks, but with a weak separation ability (K-S below 15)

The percentages are depending on the importance of the five categories for the general population.

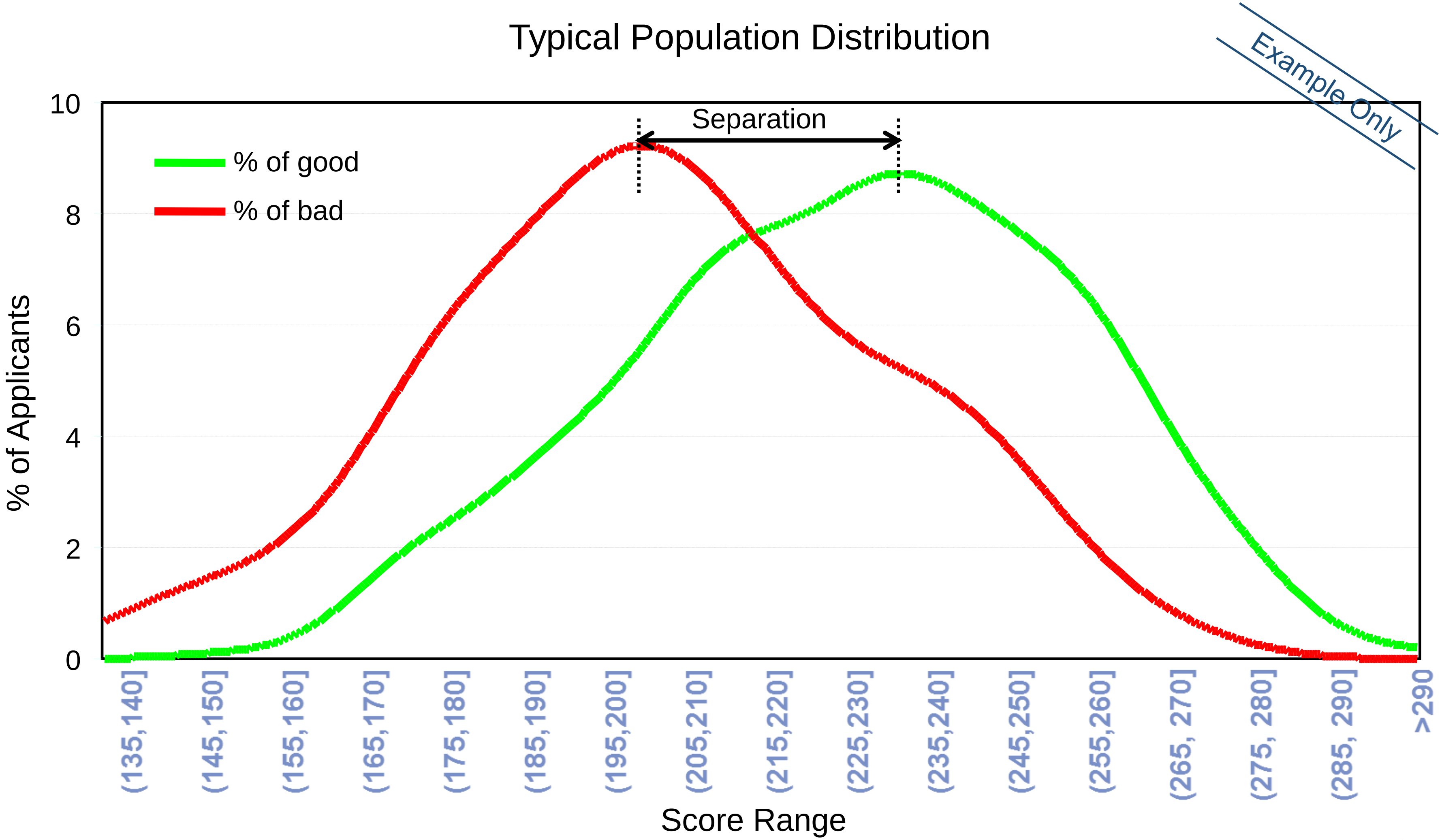




Generic Score range form 300-850. The Higher the score, the lower the risk. But no score says whether a specific individual will be a “Good” or “Bad”
*No clear good/bad definition

Clarity in Complexity

Scorecard Performance



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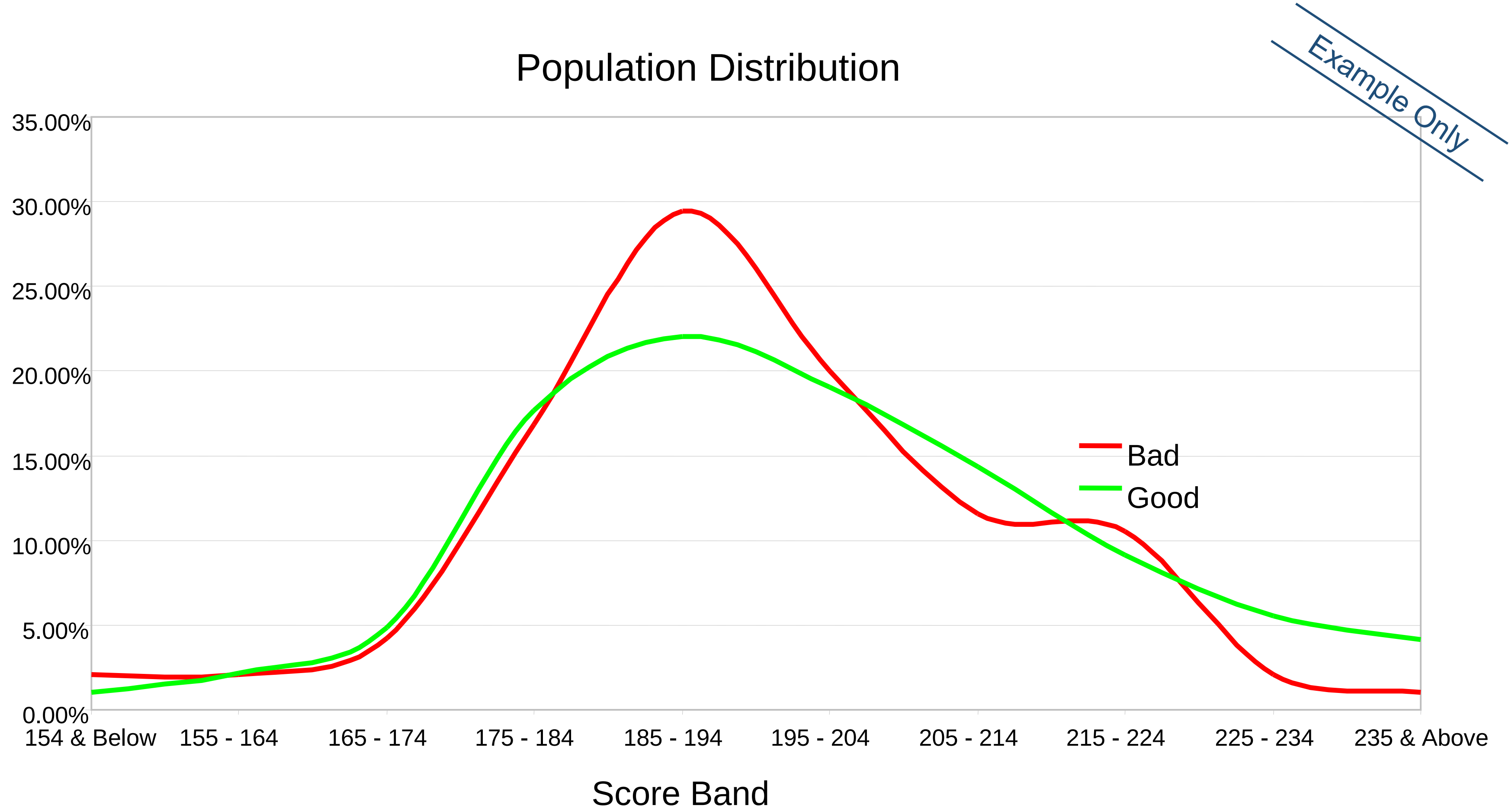
Performance of Existing Scorecard



*Population comprises all scored applications since Jan-01, with at least 5 months on book as at Nov-01

Is the Scorecard Separating Goods & Bads?

A Scorecard's power is measured by its KS Statistic*

- KS of Less than 20 : Not worth using scorecard
- KS of 20 - 40 : Fair
- KS of 41 - 50 : Good
- KS of 51 - 75 : Very Good
- KS of More than 75 : Too good to be true!

* KS - Kolgomorov-Smirnov

- KS Statistic is the maximum difference (separation) between the cumulative percentage of goods and cumulative percentage of bads in a population

Source : Handbook of Credit Scoring, Elizabeth Mays

Background

- Monthly scorecard performance review showed unsatisfactory separation ability
- Scorecard does rank order risks, but with a weak separation ability (K-S below 15)

- Better understanding of and access to data
- Customization is necessary and possible

Scorecard Design & Development

Sample Window

- Application data (Jun 1999 - Oct 2000)
- Performance data (Jun 1999 - Oct 2001)
- Exposure period
  - min: 12 months on book ("MOB")
  - max: 29 MOB

Sample Size of 11,961

- Good: 5,135
- Bad: 997
- Others: 5,829

Scorecard Design & Development

Good / Bad Definition

- Good : never past due*
- Bad : ever in 30+ days past due (dpd) / written off
- Indeterminate/Exclusions : include ever in 1-29 dpd, deceased, closed and inactive accounts

Development Sample vs Holdout Sample

- 80% of the sample was used to develop the scoring model - Development Sample
- Remaining 20% was used to validate the model - Holdout Sample

*measured by number of days past due from the next statement date

Scorecard

Characteristics	Range of score
Gender	X- XX
Education Level	X- XX
Marital Status	X- XX
Age	X - XX
Time with Present Employer	X - XX
Time at Present Address	X - XX
Occupation	X - XX
Application Type (New) (with or w/o supplementary application)	X - XX
Billing Address Type (New)	X - XX

Summary of Changes

Introduced 2 new characteristics

- Application Type (i.e. with / without supplementary application)
- Billing Address Type

Removed 6 existing characteristics

- Nationality
- PR Indicator
- Residential Status
- No. of Dependents
- No. of Non-OCBC Credit Cards
- Availability of Bank Reference

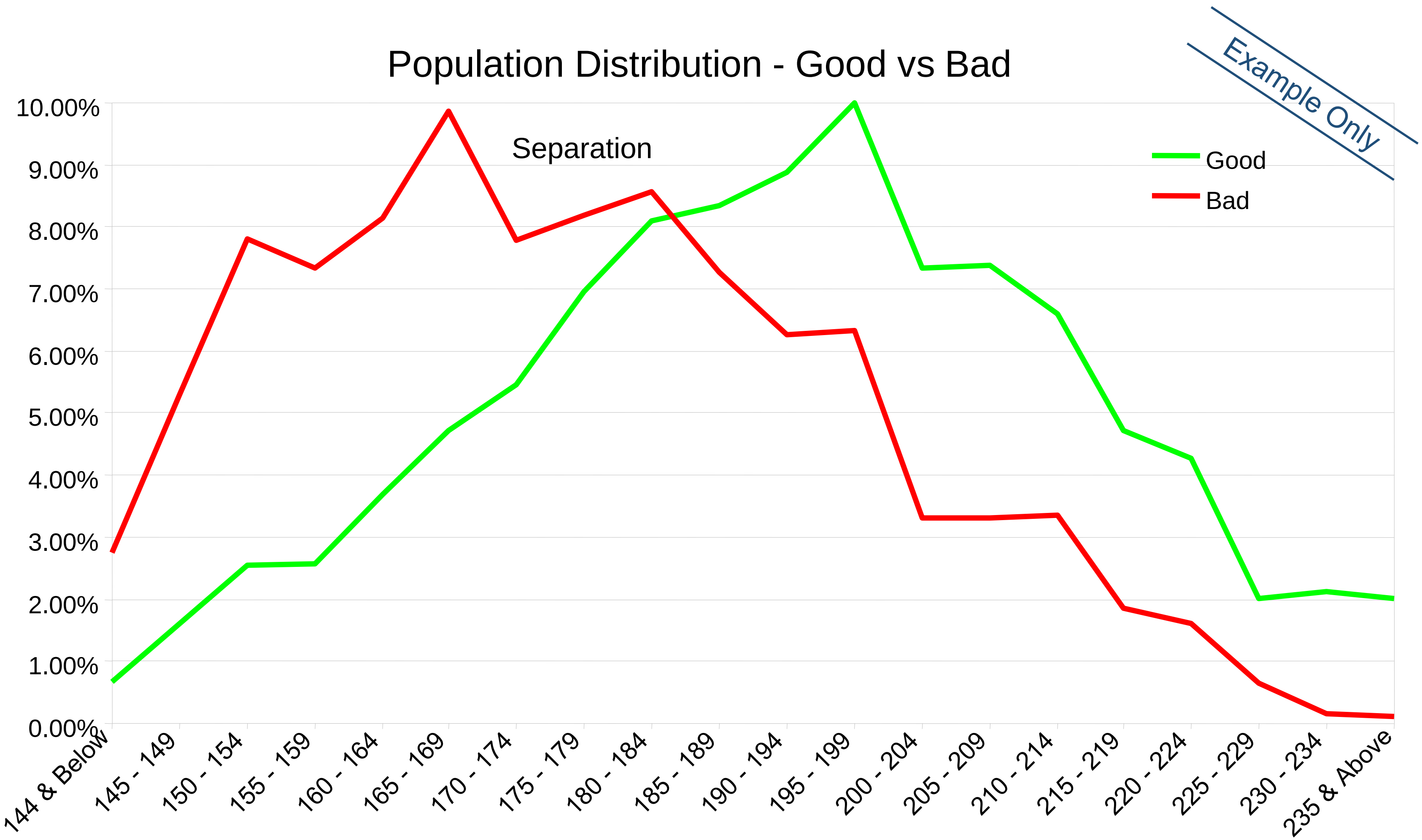
Insignificant during model building

Data inconsistency

Unavailability of data in CARDS system

Revised the weights of remaining 7 characteristics

Scorecard Performance – Distribution



 Strictly confidential

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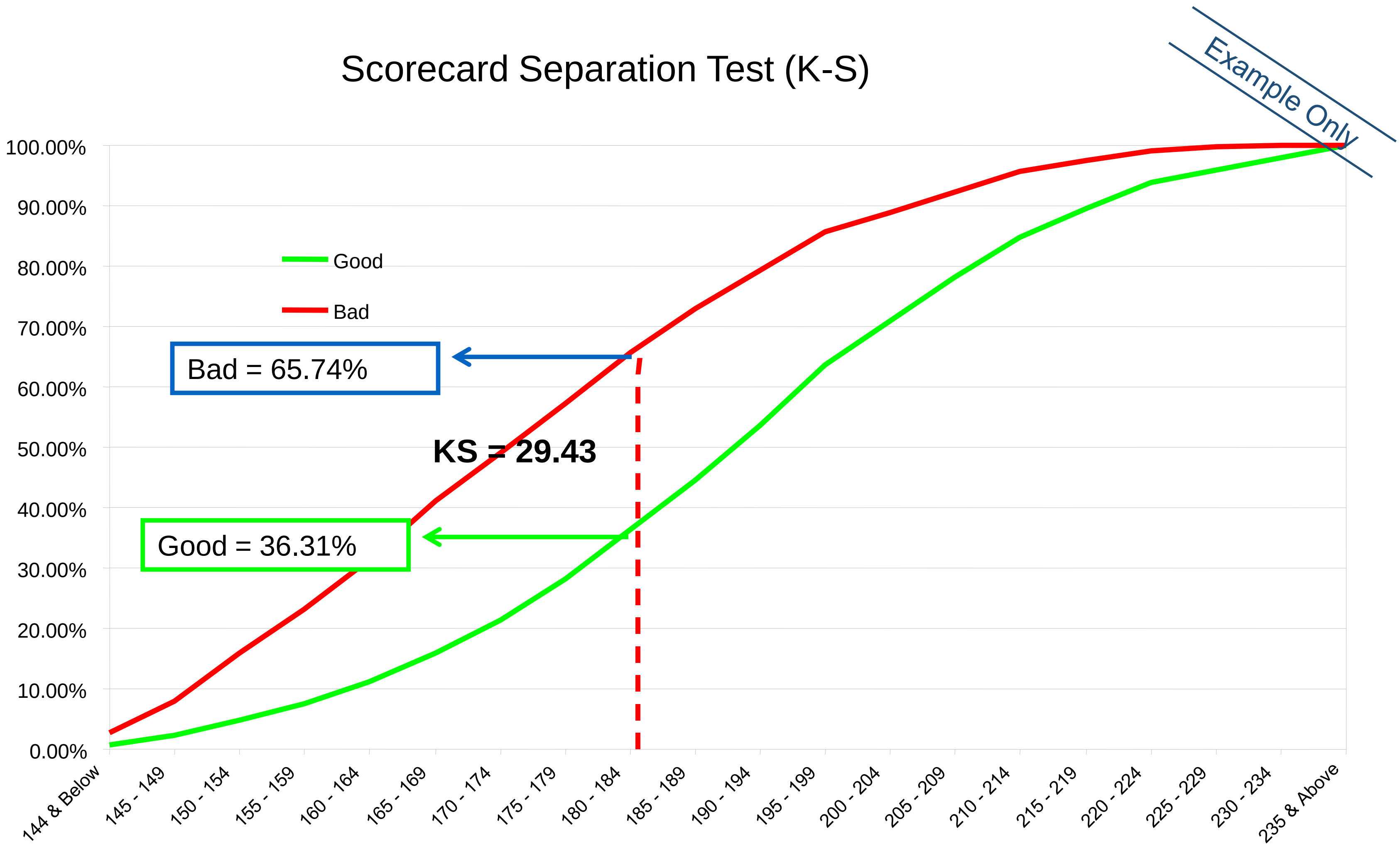
Scorecard Performance – Cumulative Distribution

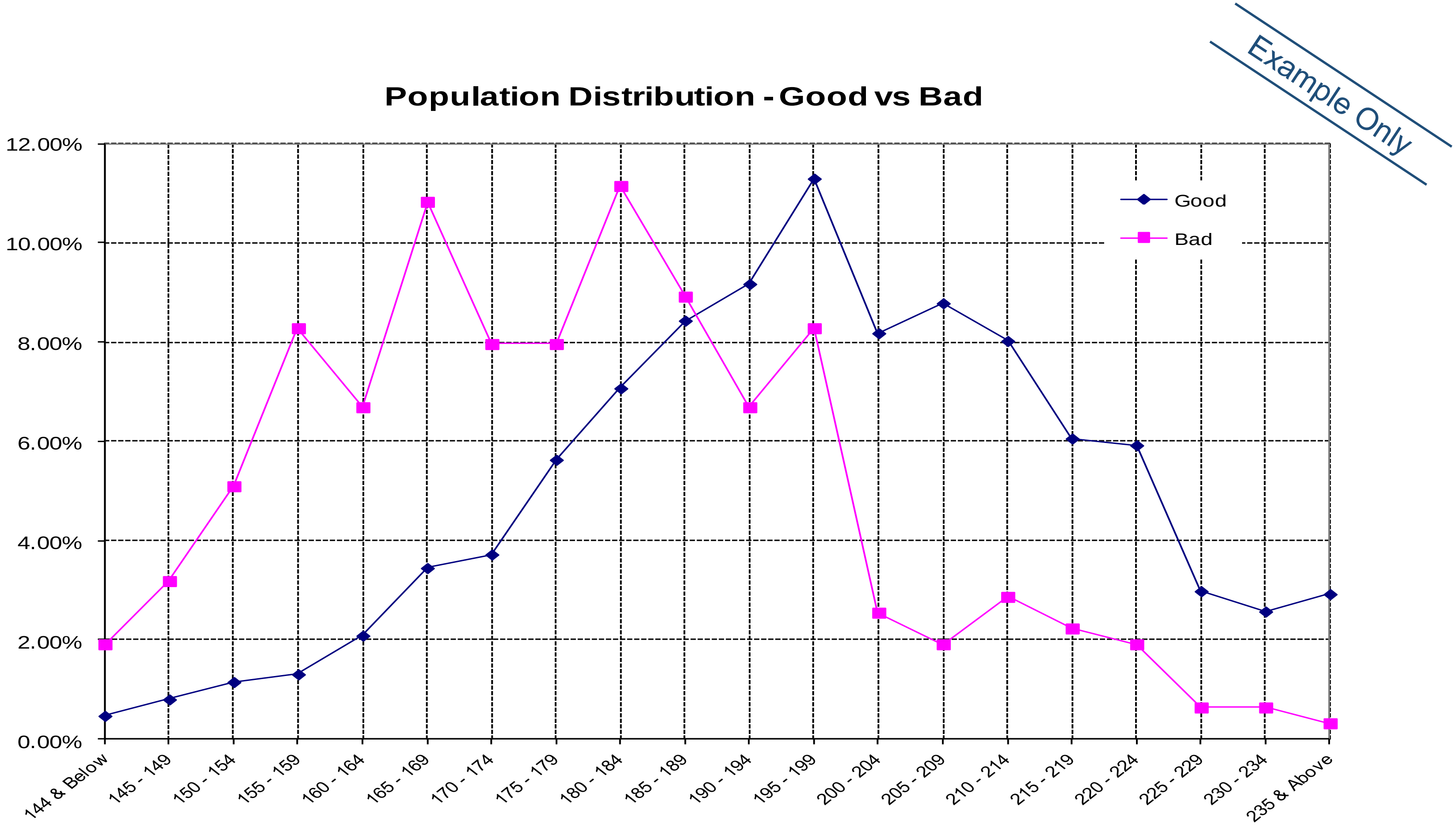


Scorecard Performance - KS Test

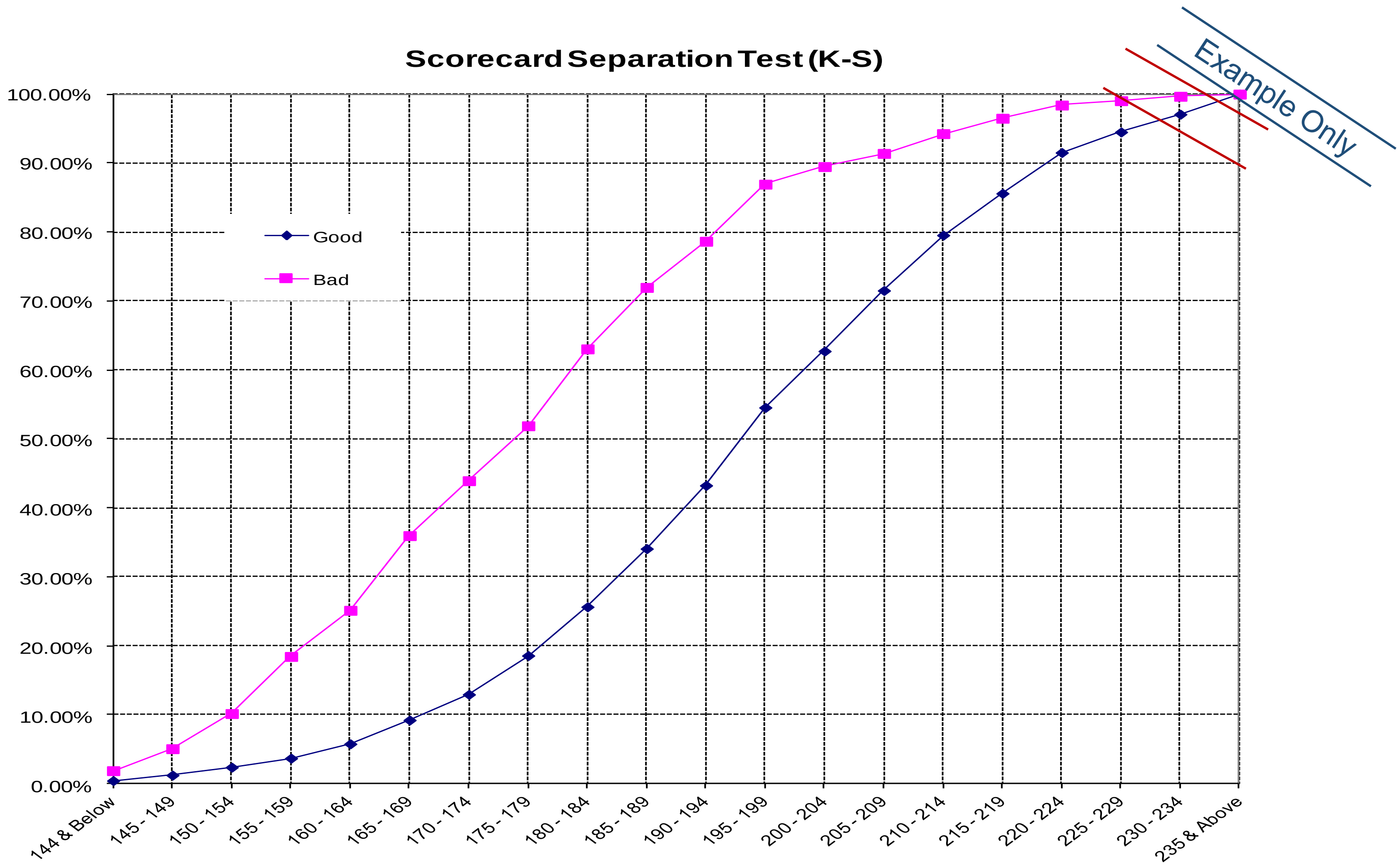
Example Only

Score Band	No. of Good A/Cs	No. of Bad A/Cs	Cum Good A/Cs (%)	Cum Bad A/Cs (%)	Abs. Cum Separation (%)
144 & Below	53	54	0.66%	2.76%	2.10%
145 - 149	129	104	2.27%	8.06%	5.79%
150 - 154	205	153	4.82%	15.86%	11.04%
155 - 159	207	144	7.39%	23.21%	15.81%
160 - 164	296	160	11.08%	31.35%	20.27%
165 - 169	379	194	15.80%	41.21%	25.41%
170 - 174	438	153	21.25%	49.00%	27.74%
175 - 179	559	161	28.21%	57.17%	28.97%
180 - 184	652	168	36.31%	65.74%	29.43%
185 - 189	670	143	44.65%	73.02%	28.37%
190 - 194	715	123	53.54%	79.29%	25.75%
195 - 199	804	124	63.54%	85.63%	22.09%
200 - 204	590	65	70.88%	88.95%	18.07%
205 - 209	593	65	78.26%	92.27%	14.01%
210 - 214	530	66	84.86%	95.62%	10.76%
215 - 219	380	37	89.58%	97.48%	7.90%
220 - 224	344	32	93.87%	99.09%	5.23%
225 - 229	162	13	95.88%	99.74%	3.86%
230 - 234	170	3	98.00%	99.89%	1.89%
235 & Above	161	2	100.00%	100.00%	0.00%
Total	8037	1963			
				K-S =	29.43%

Performance - Known Good & Bad (90+DPD)



Performance - Known Good & Bad (90+DPD)



Performance - Known Good & Bad (90+DPD)

Example Only

Score Band	No. of Good A/Cs	No. of Bad* A/Cs	Cum Good A/Cs (%)	Cum Bad A/Cs (%)	Abs. Cum Separation (%)
144 & Below	24	6	0.47%	1.91%	1.44%
145 - 149	41	10	1.27%	5.10%	3.83%
150 - 154	59	16	2.41%	10.19%	7.78%
155 - 159	67	26	3.72%	18.47%	14.75%
160 - 164	107	21	5.80%	25.16%	19.36%
165 - 169	177	34	9.25%	35.99%	26.74%
170 - 174	191	25	12.97%	43.95%	30.98%
175 - 179	289	25	18.60%	51.91%	33.31%
180 - 184	363	35	25.67%	63.06%	37.39%
185 - 189	433	28	34.10%	71.97%	37.88%
190 - 194	471	21	43.27%	78.66%	35.39%
195 - 199	580	26	54.57%	86.94%	32.38%
200 - 204	420	8	62.75%	89.49%	26.74%
205 - 209	451	6	71.53%	91.40%	19.87%
210 - 214	412	9	79.55%	94.27%	14.72%
215 - 219	311	7	85.61%	96.50%	10.89%
220 - 224	304	6	91.53%	98.41%	6.88%
225 - 229	153	2	94.51%	99.04%	4.54%
230 - 234	132	2	97.08%	99.68%	2.60%
235 & Above	150	1	100.00%	100.00%	0.00%
Total	5135	314			
				K-S =	37.88%

* Defined as ever 90+dpd or written off

Validation - Holdout Samples - PSI

SCORE BANDS	DEV SAMPLE	DEV%	VAL SAMPLE	VAL%	DIFF%	WOE	PSI
144 & Belo	108	1.08%	134	1.34%	0.26%	0.219	0.06%
145 - 149	233	2.33%	182	1.82%	-0.51%	-0.246	0.13%
150 - 154	358	3.58%	284	2.84%	-0.74%	-0.232	0.17%
155 - 159	351	3.51%	389	3.89%	0.37%	0.101	0.04%
160 - 164	456	4.56%	500	5.00%	0.44%	0.093	0.04%
165 - 169	573	5.73%	594	5.94%	0.21%	0.037	0.01%
170 - 174	591	5.91%	612	6.12%	0.21%	0.035	0.01%
175 - 179	719	7.19%	711	7.11%	-0.09%	-0.012	0.00%
180 - 184	820	8.20%	737	7.37%	-0.83%	-0.106	0.09%
185 - 189	813	8.13%	817	8.17%	0.04%	0.005	0.00%
190 - 194	838	8.38%	830	8.30%	-0.08%	-0.009	0.00%
195 - 199	928	9.28%	1002	10.02%	0.74%	0.076	0.06%
200 - 204	655	6.55%	748	7.48%	0.93%	0.133	0.12%
205 - 209	658	6.58%	582	5.82%	-0.76%	-0.123	0.09%
210 - 214	596	5.96%	495	4.95%	-1.01%	-0.186	0.19%
215 - 219	417	4.17%	425	4.25%	0.08%	0.020	0.00%
220 - 224	376	3.76%	464	4.64%	0.88%	0.211	0.19%
225 - 229	174	1.74%	159	1.59%	-0.15%	-0.092	0.01%
230 - 234	173	1.73%	116	1.16%	-0.57%	-0.402	0.23%
235 & Abov	163	1.63%	220	2.20%	0.57%	0.298	0.17%
Total	10000	100.00%	10000	100.00%			**1.60%**

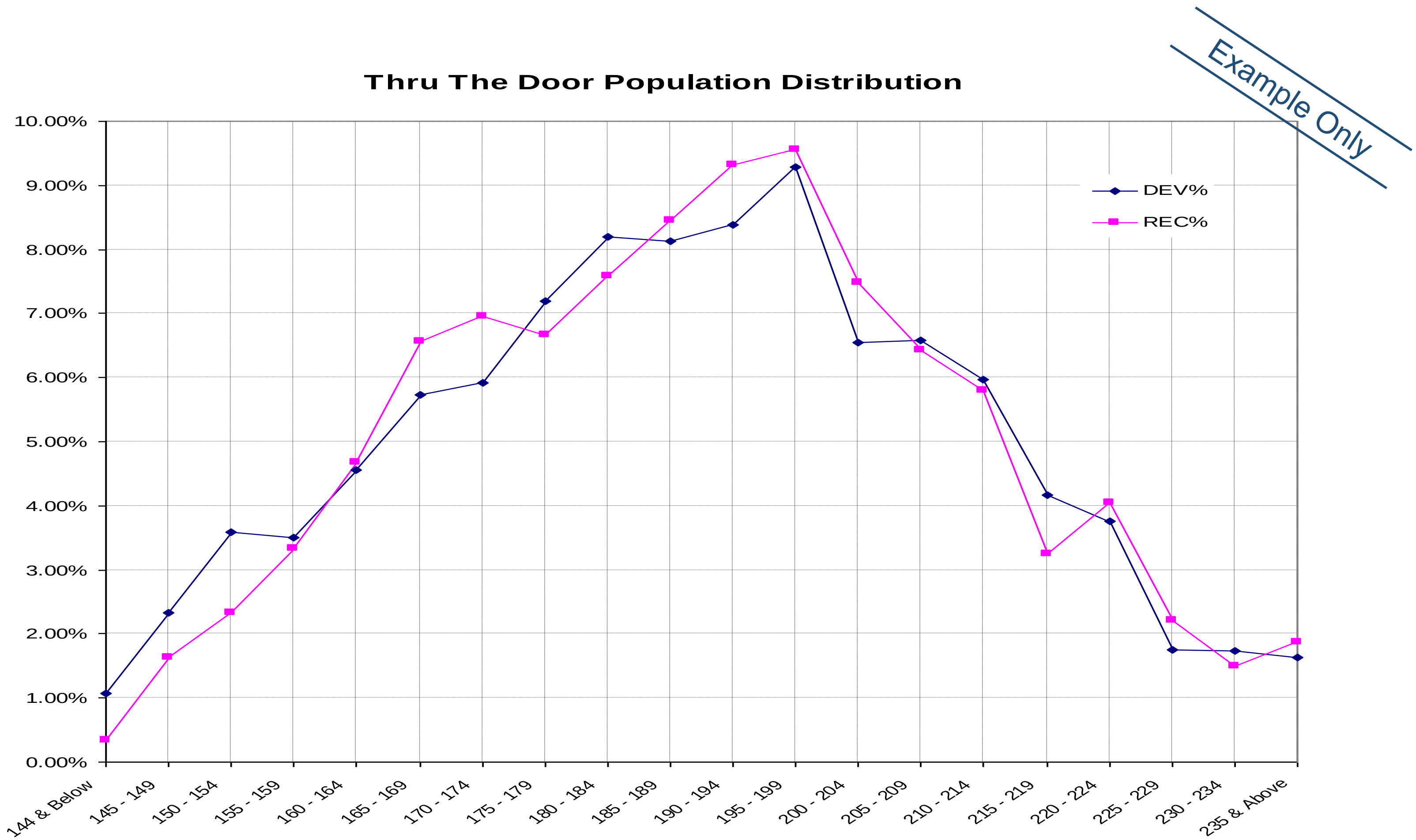
Example Only

Validation - Holdout Samples - KS Test

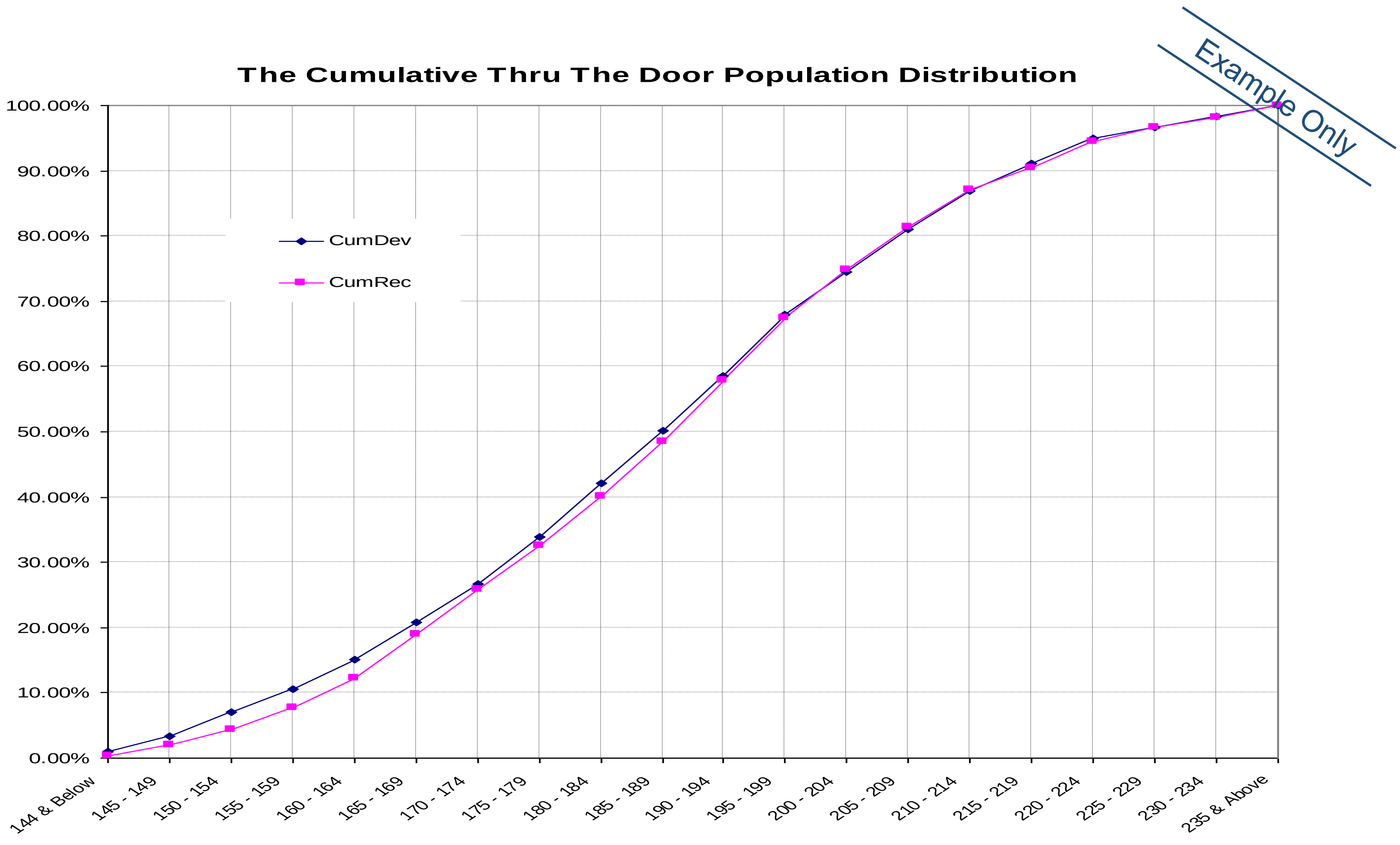
Score Band	No. of Good A/Cs	No. of Bad A/Cs	Cum Good A/Cs (%)	Cum Bad A/Cs (%)	Abs. Cum Separation (%)
144 & Below	85	49	1.06%	2.52%	1.47%
145 - 149	103	79	2.34%	6.61%	4.27%
150 - 154	178	106	4.54%	12.10%	7.56%
155 - 159	206	183	7.09%	21.56%	14.47%
160 - 164	318	182	11.03%	30.99%	19.96%
165 - 169	414	180	16.17%	40.29%	24.12%
170 - 174	450	162	21.74%	48.68%	26.94%
175 - 179	558	153	28.66%	56.58%	27.92%
180 - 184	562	175	35.62%	65.64%	30.02%
185 - 189	683	133	44.10%	72.54%	28.45%
190 - 194	701	129	52.78%	79.24%	26.46%
195 - 199	838	164	63.17%	87.70%	24.53%
200 - 204	658	90	71.33%	92.35%	21.02%
205 - 209	543	39	78.06%	94.38%	16.32%
210 - 214	461	34	83.77%	96.14%	12.37%
215 - 219	385	40	88.55%	98.20%	9.65%
220 - 224	446	18	94.07%	99.14%	5.07%
225 - 229	158	1	96.03%	99.19%	3.16%
230 - 234	106	10	97.35%	99.69%	2.35%
235 & Above	214	6	100.00%	100.00%	0.00%
Total	8066	1934			
				K-S =	30.02%

Example Only

Validation - Population Stability Analysis



Validation - Population Stability Analysis



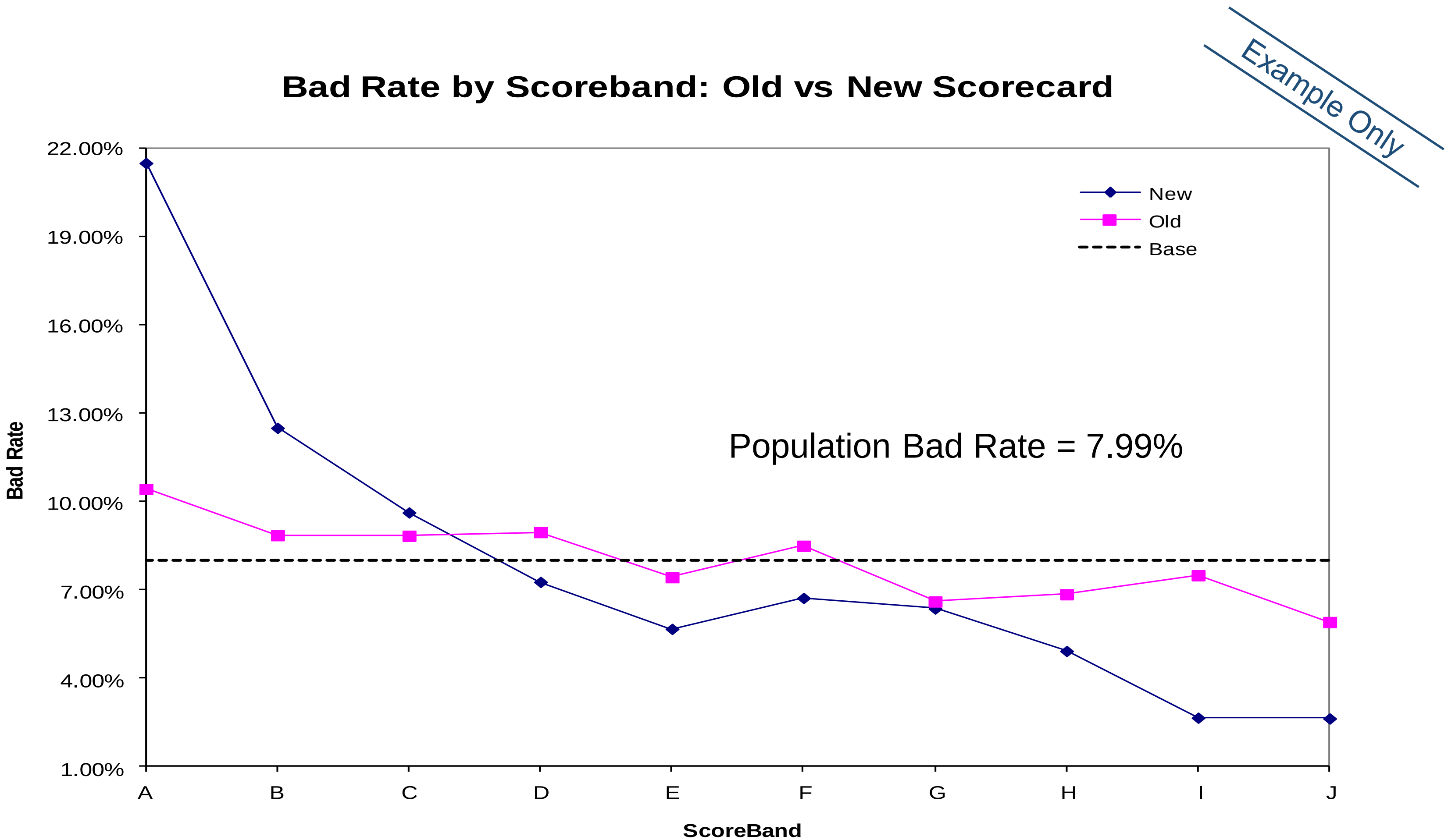
Clarity in Complexity

Validation - Population Stability Analysis

Example Only

SCORE BANDS	DEV SAMPLE	DEV%	RECENT SAMPLE	REC%	DIFF%	WOE	PSI
144 & Below	108	1.08%	13	0.34%	-0.73%	-1.148	0.84%
145 - 149	233	2.33%	62	1.63%	-0.70%	-0.359	0.25%
150 - 154	358	3.58%	89	2.34%	-1.24%	-0.427	0.53%
155 - 159	351	3.51%	127	3.33%	-0.18%	-0.052	0.01%
160 - 164	456	4.56%	178	4.67%	0.11%	0.024	0.00%
165 - 169	573	5.73%	250	6.56%	0.83%	0.136	0.11%
170 - 174	591	5.91%	265	6.96%	1.05%	0.163	0.17%
175 - 179	719	7.19%	254	6.67%	-0.52%	-0.076	0.04%
180 - 184	820	8.20%	289	7.59%	-0.61%	-0.078	0.05%
185 - 189	813	8.13%	322	8.45%	0.33%	0.039	0.01%
190 - 194	838	8.38%	355	9.32%	0.94%	0.107	0.10%
195 - 199	928	9.28%	364	9.56%	0.27%	0.029	0.01%
200 - 204	655	6.55%	285	7.48%	0.93%	0.133	0.12%
205 - 209	658	6.58%	245	6.43%	-0.15%	-0.023	0.00%
210 - 214	596	5.96%	221	5.80%	-0.16%	-0.027	0.00%
215 - 219	417	4.17%	124	3.26%	-0.91%	-0.247	0.22%
220 - 224	376	3.76%	154	4.04%	0.29%	0.073	0.02%
225 - 229	174	1.74%	84	2.21%	0.46%	0.235	0.11%
230 - 234	173	1.73%	57	1.50%	-0.24%	-0.147	0.03%
235 & Above	163	1.63%	71	1.86%	0.23%	0.133	0.03%
Total	10000	100.00%	3809	100.00%			**2.68%**

Comparison Study - Bad Rate (30+DPD)



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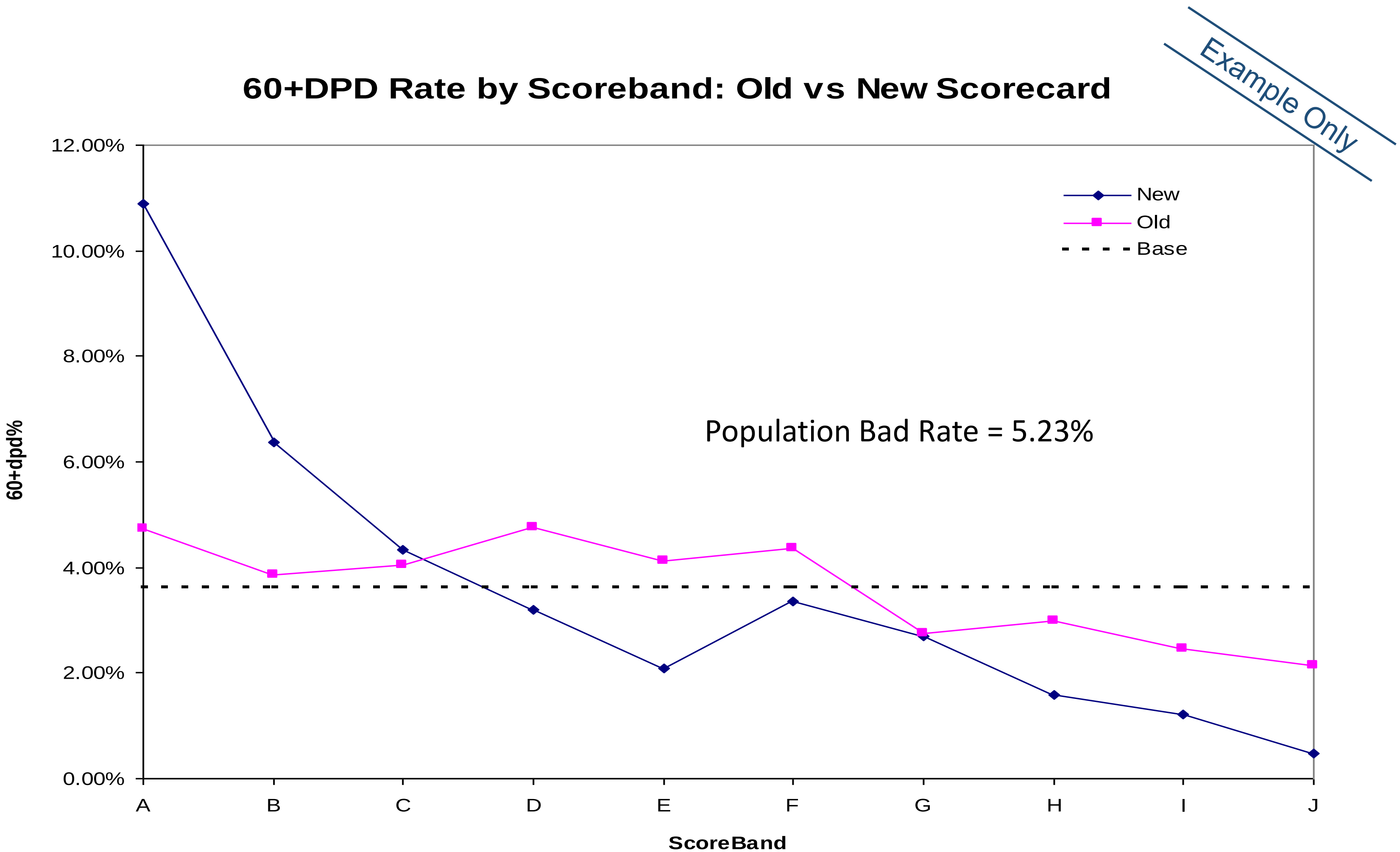
Comparison Study - Bad Rate (60+DPD)



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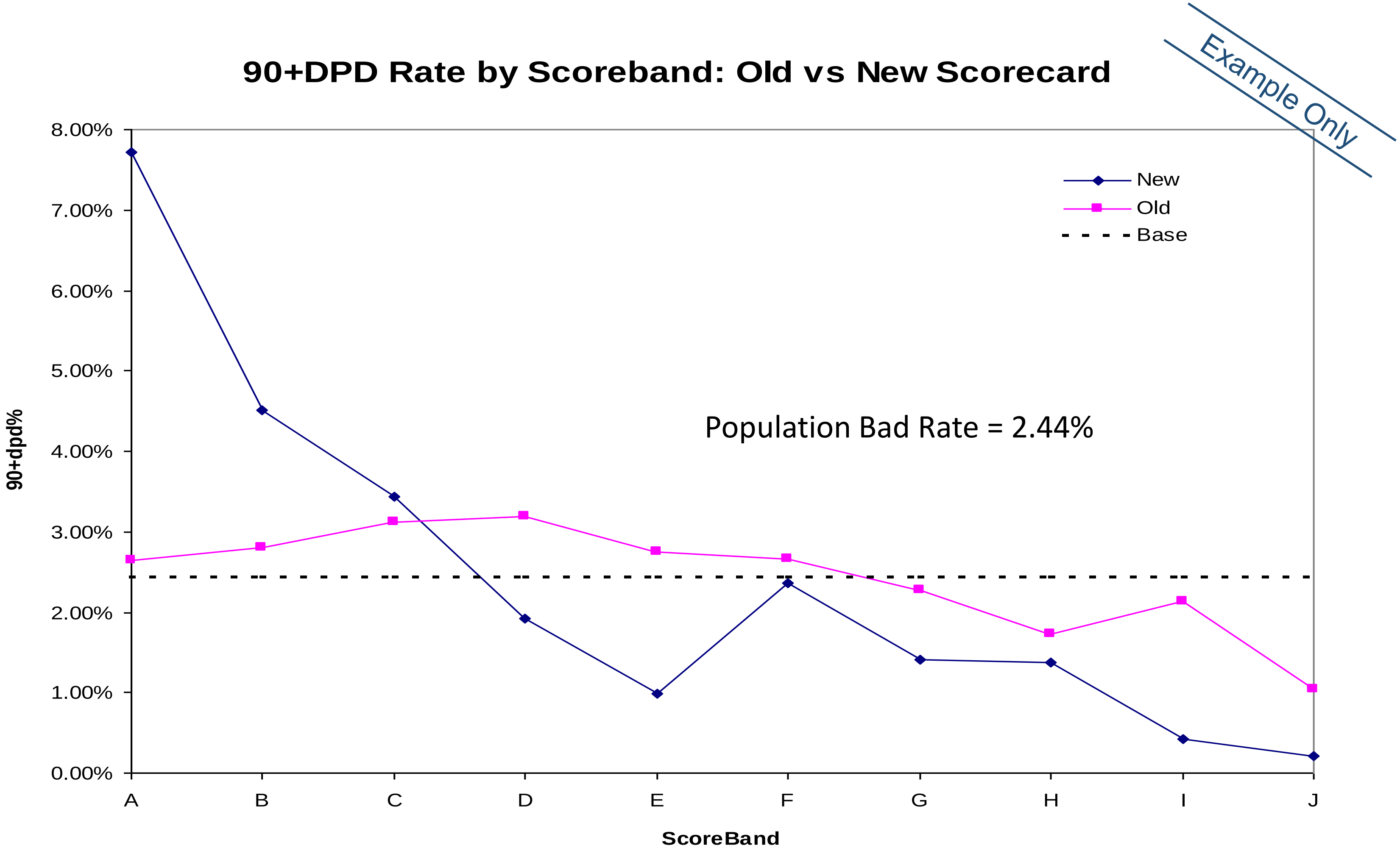
Comparison Study - Bad Rate (90+DPD)



Clarity in Complexity

Comparison Study: K-S Tests for Existing Scorecard

Example Only

Score	Number of Accounts					Cumulative Distribution				Separation Test (K-S)		
Band	Ever 90+	Ever 60+	Ever 30+	Good	Total	Ever 90+	Ever 60+	Ever 30+	Good	Ever 90+	Ever 60+	Ever 30+
A	13	22	49	423	472	10.88%	13.07%	13.05%	9.74%	1.14%	3.34%	3.32%
B	13	18	42	430	472	22.39%	23.72%	24.14%	19.64%	2.75%	4.08%	4.50%
C	15	19	42	430	472	35.20%	34.92%	35.20%	29.55%	5.65%	5.38%	5.66%
D	15	23	42	430	472	48.31%	48.08%	46.42%	39.44%	8.87%	8.64%	6.98%
E	13	19	35	437	472	59.63%	59.46%	55.73%	49.50%	10.13%	9.95%	6.23%
F	13	21	40	432	472	70.53%	71.47%	66.37%	59.45%	**11.08%**	**12.02%**	**6.92%**
G	11	13	31	441	472	79.82%	79.03%	74.64%	69.60%	10.23%	9.43%	5.04%
H	8	14	32	440	472	86.92%	87.29%	83.22%	79.72%	7.20%	7.57%	3.50%
I	10	12	35	437	472	95.70%	94.09%	92.60%	89.77%	5.93%	4.32%	2.83%
J	5	10	28	444	472	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%
Total	115	171	377	4344	4721							

Clarity in Complexity
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Comparison Study : K-S Tests for Proposed Scorecard

Example Only

Score	Number of Accounts					Cumulative Distribution				Separation Test (K-S)		
Band	Ever 90+	Ever 60+	Ever 30+	Good	Total	Ever 90+	Ever 60+	Ever 30+	Good	Ever 90+	Ever 60+	Ever 30+
A	36	51	101	371	472	31.67%	30.07%	26.90%	8.53%	23.14%	21.54%	18.37%
B	21	30	59	413	472	50.23%	47.67%	42.55%	18.04%	32.18%	29.63%	24.51%
C	16	20	45	427	472	64.35%	59.65%	54.60%	27.86%	**36.48%**	**31.78%**	**26.74%**
D	9	15	34	438	472	72.25%	68.47%	63.70%	37.94%	34.30%	30.53%	25.76%
E	5	10	27	445	472	76.29%	74.24%	70.81%	48.19%	28.10%	26.05%	22.62%
F	11	16	32	440	472	85.96%	83.51%	79.23%	58.33%	27.63%	25.18%	20.90%
G	7	13	30	442	472	91.77%	90.96%	87.20%	68.51%	23.26%	22.45%	18.69%
H	6	7	23	449	472	97.39%	95.32%	93.37%	78.84%	18.55%	16.48%	14.53%
I	2	6	13	460	472	99.13%	98.70%	96.70%	89.42%	9.71%	9.28%	7.28%
J	1	2	12	460	472	100.00%	100.00%	100.00%	100.00%	0.00%	0.00%	0.00%
Total	115	171	377	4344	4721							

Clarity in Complexity

Agenda

1. Introduction to Scorecards
2. Business Application of Scorecards
3. Scorecards Development Approach
4. Business Case
5. **Our Solution for Scorecards Development**

About Our Approach

The modeling of scorecards is not so straightforward that we need to thoughtfully consider all the abstract theoretical work on the modeling methodology as well as all the concrete tasks from the initial stage of the data preparation, to the middle stage of model building, to the final stage of model validation and delivery. To handle this complicated process efficiently, EntroFine adopts a step by step approach to split the whole modeling process into six digestible sub-tasks, so that we can confirm no missing of important work, meanwhile produce the high-quality and effective solutions meeting all the essential goals and standards of the scorecard building practice.

1 Data Preparation
- Source data selection
- Variable selection criteria
- Data extract & data cleansing
- Data integration and attributes aggregation (Monthly data profile)

2 Specification
- Modeling type
- Modeling approach
- Sample window
- G/B/I/E definition

3 Exploratory Data Analysis
- G/B/I/E flag derivation
- Descriptive statistics
- Characteristic analysis
- Classing

4 Segmentation
- Assess benefit and need of multiple models
- Segmentation analysis
- "Master/niche" modeling

5 Model Finalization
- Reject inference process
- Final scorecard model
- Scorecard alignment
- Modeling documentation

6 Model Validation
- Sample validation
- Cross-time validation
- Risk grading and cut-off
- Modeling tracking /monitoring