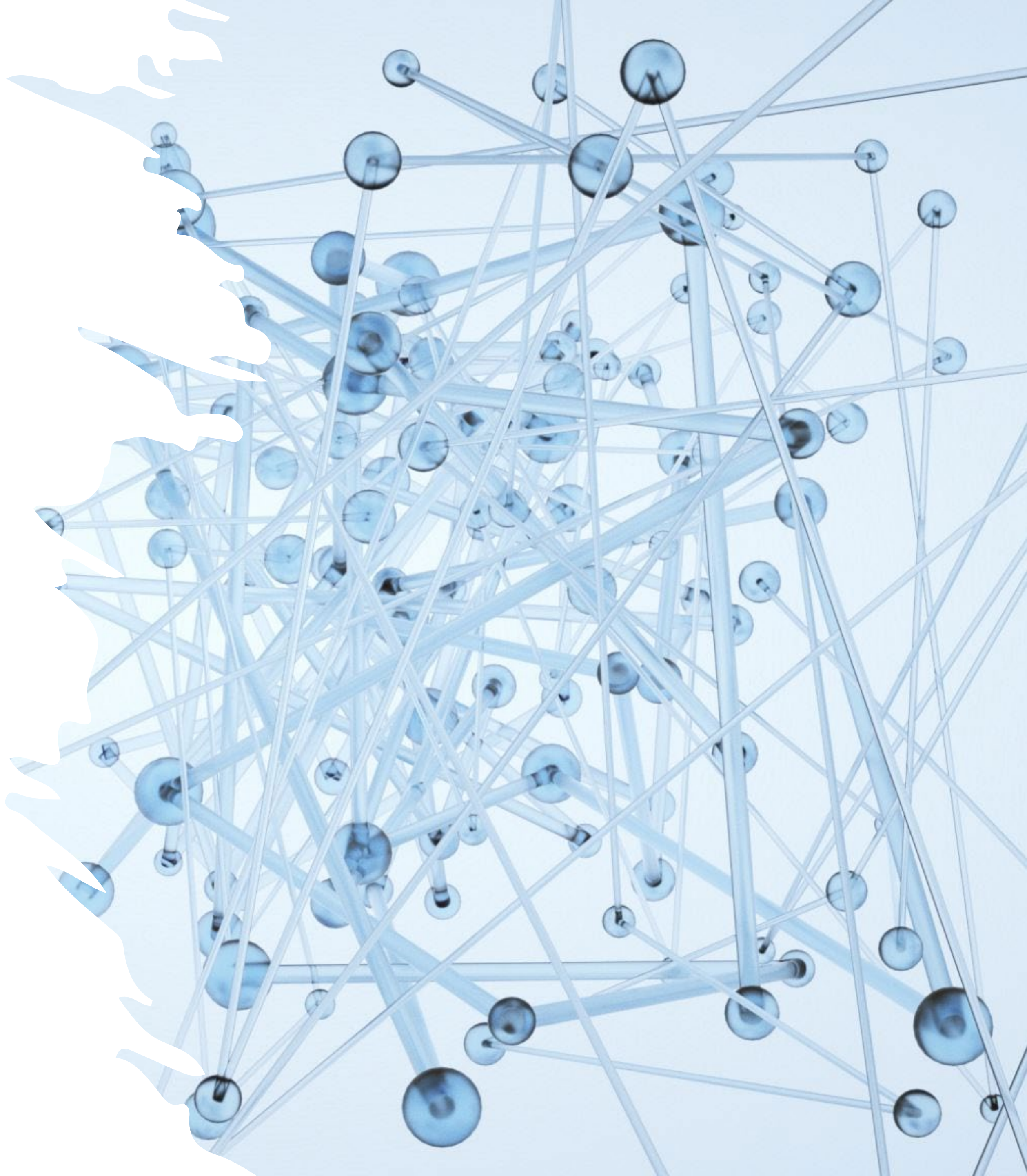
# Concepts of Scoring Training

20th / 21st June 2024

by

APDS Consulting
(Matthew Freeman)

www.apds-analytics.com



# Scorecard Training Agenda

- Introduction
- Credit Analytics and Scoring Concepts
- Decision Areas
  - Origination
  - Behavioural
  - Credit Propensity
- Modelling Steps 1 & 2  (includes a brief discussion on Reject Inference)
  - Sampling
  - Segmentation
  - Characteristic Selection
  - Characteristic Classing
  - Modelling
  - Scorecard Scaling
- Model Diagnostics & Validation
  - Score Level – PSI, Gini, KS & Rank Ordering
  - Characteristic Analysis
- Other Risk Model Issues
  - IRB / IFRS 9 PD, EAD & LGD
- Model Risk Considerations
  - Model Lifecycle
  - Model Management Framework
  - Model Inventory
  - Approval Networks / Committees
- Conclusions

# APDS Consulting - Matthew Freeman Biography

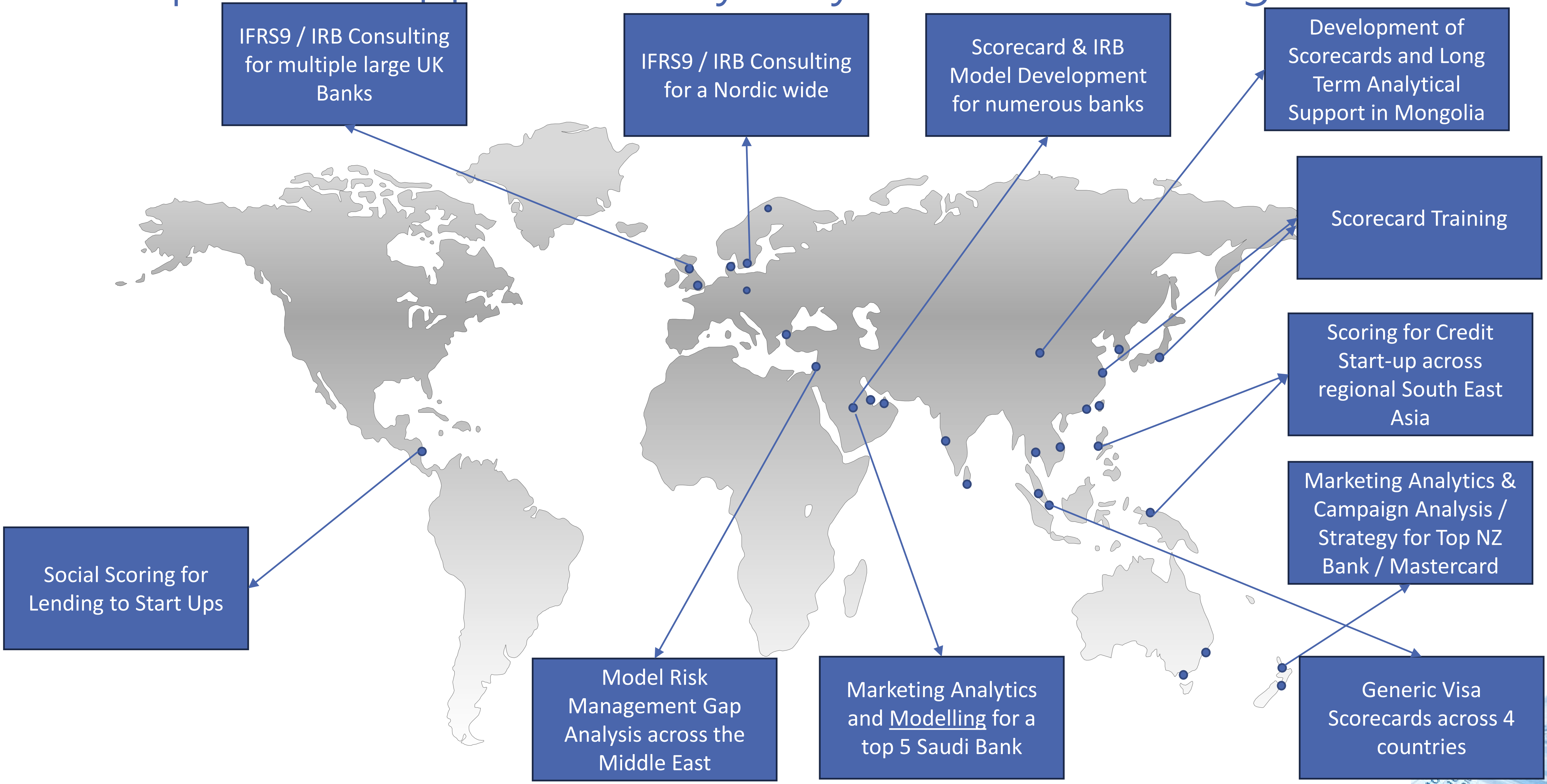
Matthew has twenty plus years retail financial services industry experience, predominantly within the analytical risk management sphere, covering diverse geographies ranging from the United Kingdom and Western Europe, throughout the Middle East and India, China, Asia (North and across the South East) and Australasia (Australia and New Zealand).

Much of this experience has been gained within the big credit risk consulting firms (such as Experian and FICO) and with large banking and finance groups (such as Lloyds, Barclays, United Overseas Bank and GE Capital), developing both operational (supervised segmented application and behavioural scorecards (incorporating statistical and business oriented segmentation), built utilising linear or logistic regression) and regulatory (Basel II & IFRS9 PD, EAD and LGD) models, utilising a wide range of internal and external datasources (which have undergone detailed and specific quality checks to ensure that they are fit for the modelling / analytical purpose for which they are intended). Models and associated strategies have been developed for all the major consumer product groups such as cards, loans and mortgages.

More recently he has started to consider how the new, exciting and developing datasources (reviewing current data scenarios, whilst identifying any data gaps and therefore the need for enhanced data collection that fits with intended business (problem solving) use of the data), thrown up by the Big Data revolution, can be used to help both traditional and new lenders to exploit the opportunities that have been created, including identifying potential high net worth individuals for a wealth management bank, how to source new customers in a risk responsible manner where traditional credit data is thin, but newer innovative sources are abundant or the developing of risk and marketing models for the pre-paid mobile telephone sector in Asia.

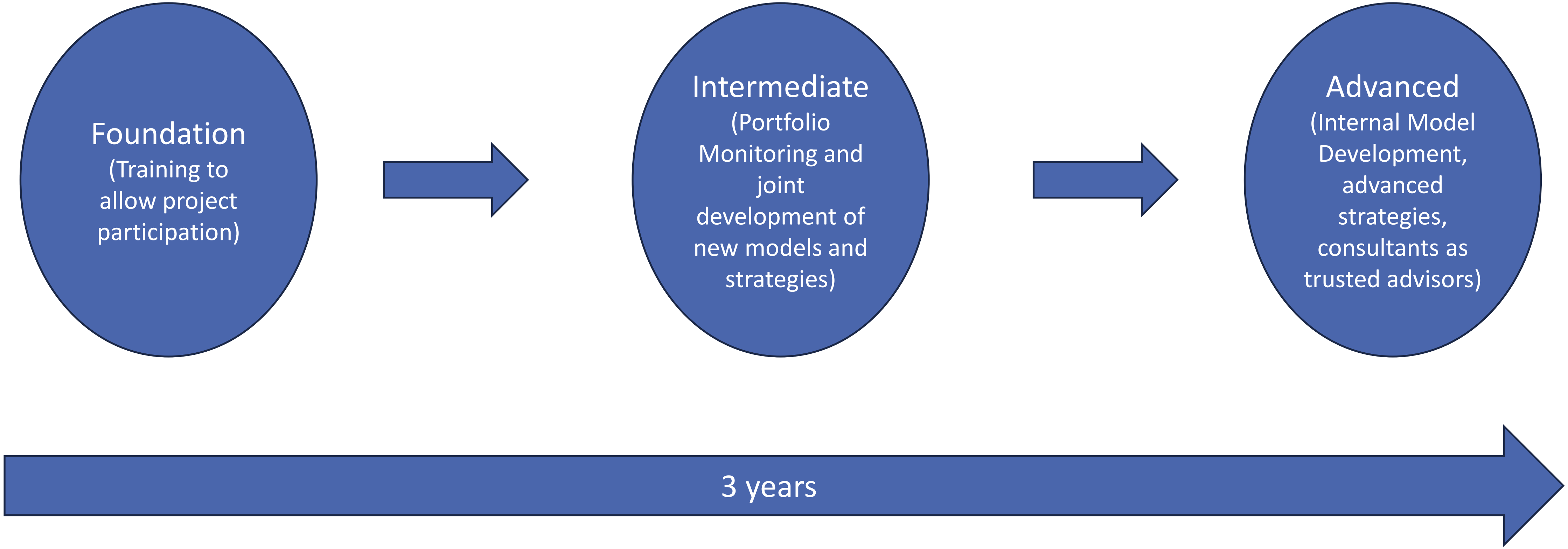
Typically, all data analysis (including quality assurance and data manipulation (merging / creating new advanced combinations of variables) has been carried out utilising the SAS, Python or R software (as well as specialised statistical modelling software (supplied by the likes of Experian, FICO or Paragon Business Solutions).

# Global Experience applied Locally – By APDS Consulting



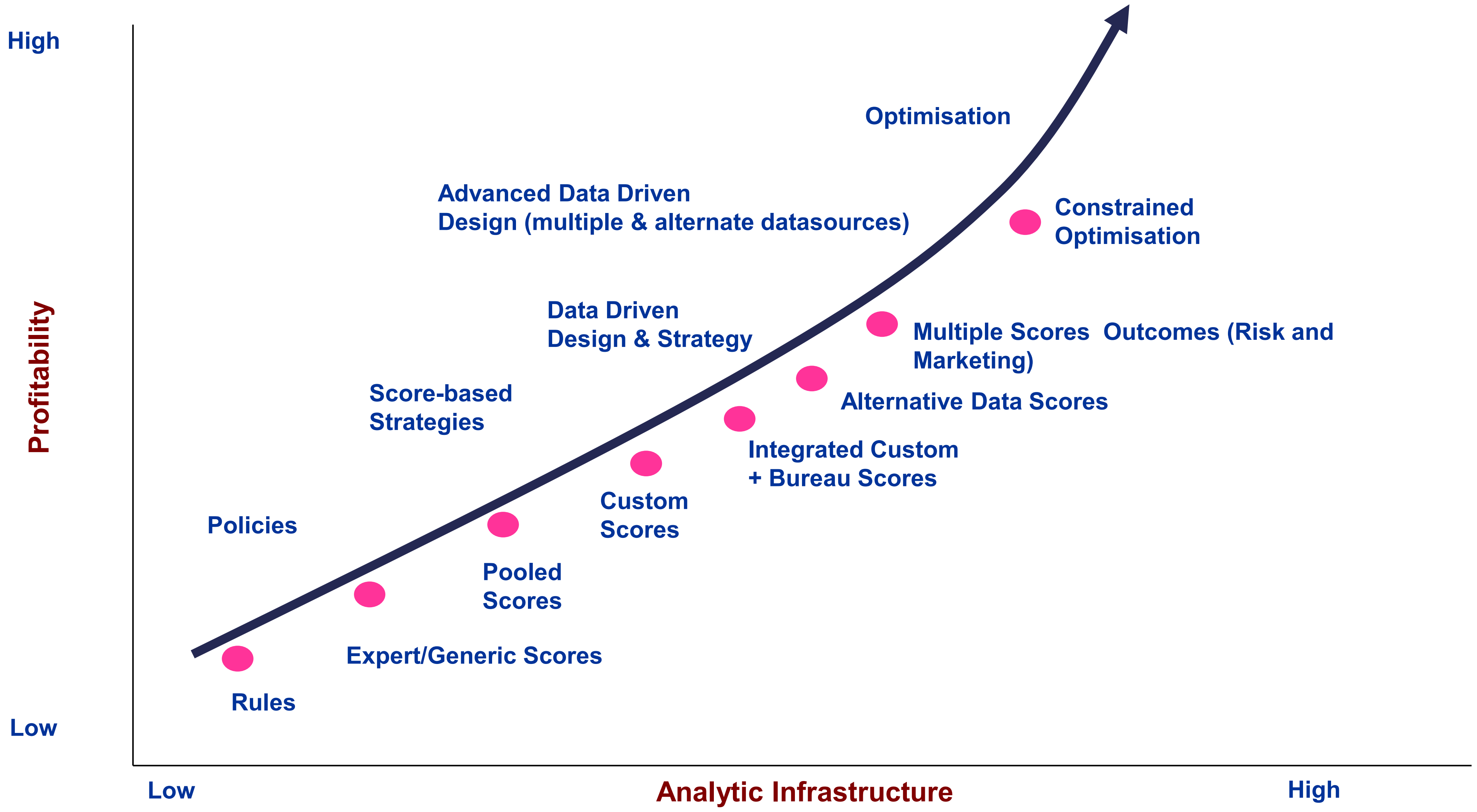
# APDS Clients

# Training and Mentoring – Foundation to Expert Level



# Analytics

# The Analytics Journey



# Credit life cycle Analytics – Decision & Prediction

| Acquisition | Origination | Customer Management | Collections & Recovery |
|---|---|---|---|

## Decisions

| Acquisition | Origination | Customer Management | Collections & Recovery |
|---|---|---|---|
| Whom to target | Approve/Decline | Line Management | Collections priority |
| Product to offer | Line/Loan/Lease amount | Re-pricing/Renewal | Collection action |
| Channel | Price | Authorizations | DCA placements |
| Timing | Up-sell | Cross-sell | Channel placements |
| | | Early Collections | |

## Predictions

| Acquisition | Origination | Customer Management | Collections & Recovery |
|---|---|---|---|
| Response | Risk | Risk | Amount collectible |
| Revenue | Revenue | Revenue | Charge-off |
| Risk | Capacity | Attrition | Bankruptcy |
| | Pre-payment | Capacity | Roll |
| | Fraud | Fraud | |

# Credit life cycle Analytics - Results

### Acquisition

- Increased market share
- Increased share of wallet
- Reduced marketing costs
- Increased revenue

### Origination

- Increased approvals
- Reduced losses
- Increased activation/usage
- Reduced origination costs
- Reduced application fraud

### Customer Management

- Increased revenue
- Reduced losses
- Reduced attrition
- Reduced transaction fraud

### Collections & Recovery

- Reduced losses
- Increased amounts collected
- Reduced customer service and collection costs

**Better Results**

# Questions

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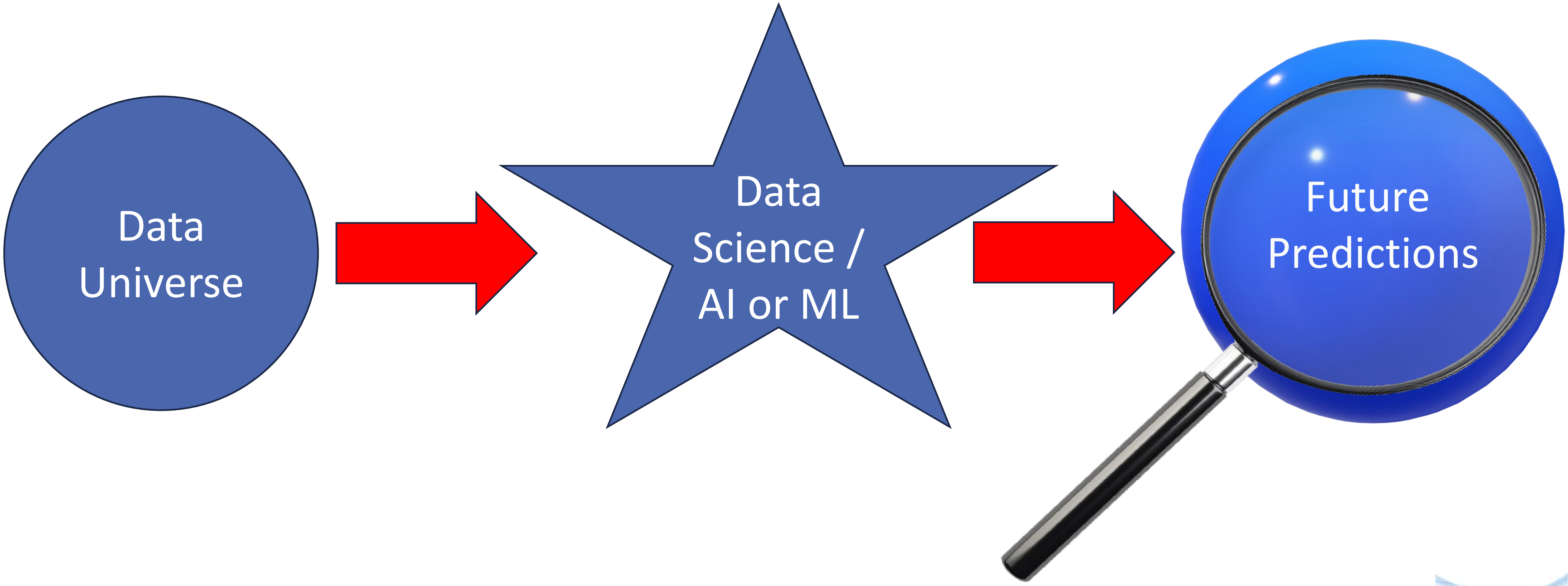
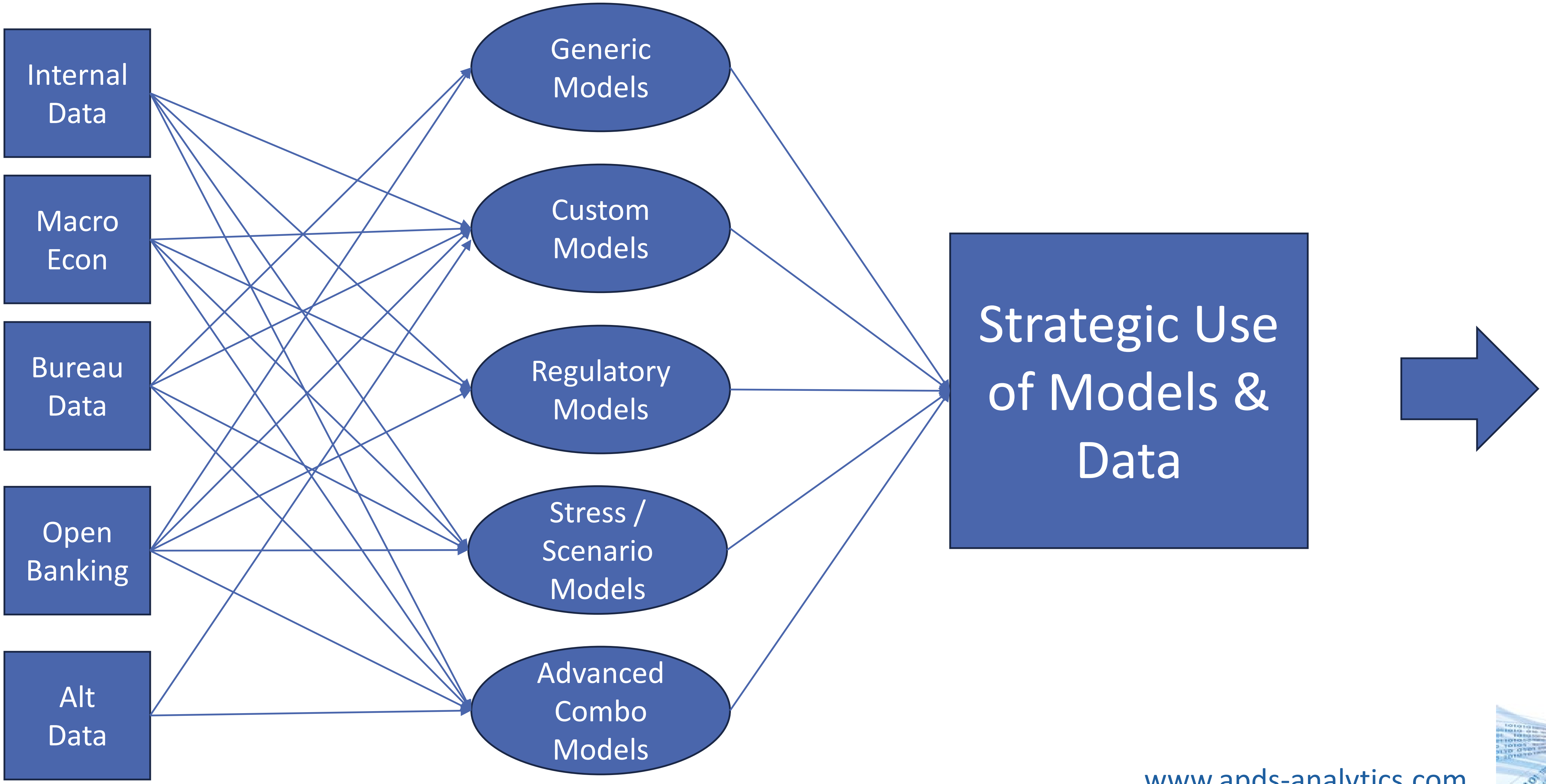
# Scoring Concepts

# Analytics & Scoring - The Concept of Modelling




Using past or historic data to predict future performance

# Credit Risk Analytics – Solving Risk Management Challenges



# Describe Datasources

- Traditional Application Data, obtained from the submitted application form (online or physically) by the applicant (covers demographics, employment, affordability)
- Traditional Bureau Data (collected by an agency from banks / FS Organisations, relating to past and existing credit facilities)
- Transactional Data (date from the use of a credit or debit card)
- Internal (Bank) Performance Data (information about account usage, payments etc)
- Open Banking Data
- Alternate Data, collected from Telcos, Mobile Handsets, Social Media Use, other sources (unconnected to the bank) etc.

**Datasources may differ if the product / applicant is business / commercial

# How Does Scoring Work?

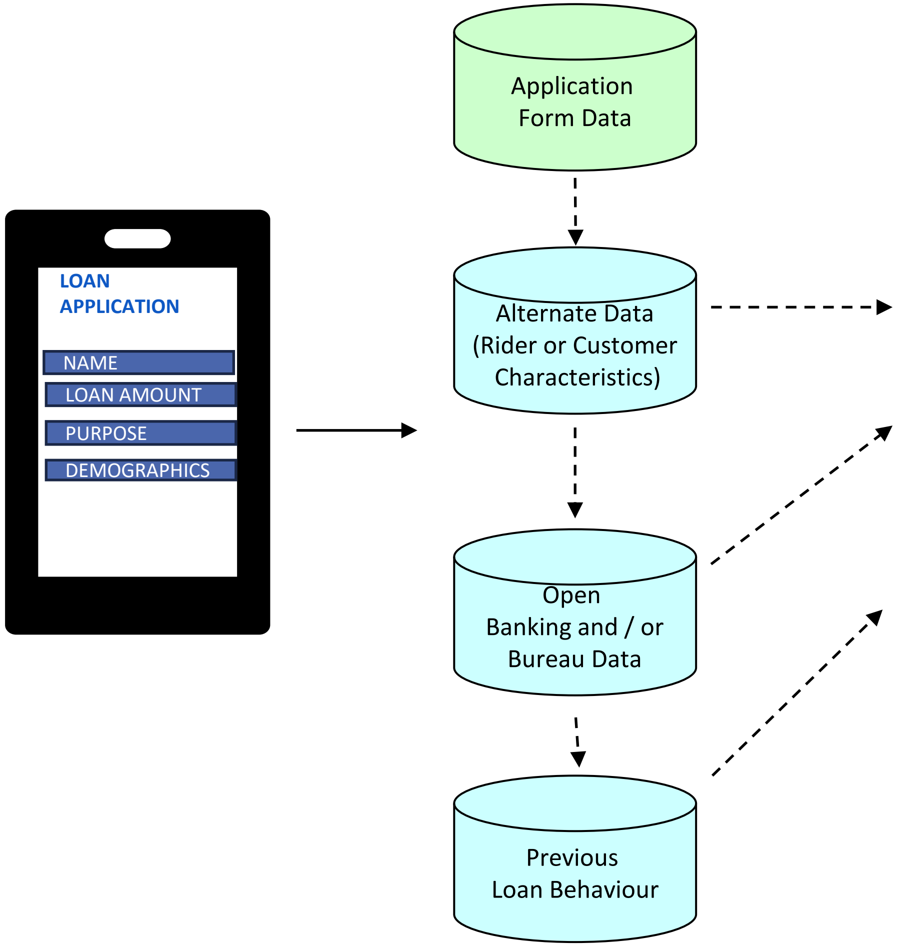
- Scorecards add and subtract points to a baseline constant according to each individual's or account's data
- These scorecards are easy to apply and intuitively simple to understand
- The resulting *score* gives a prediction of future behaviour
- These scores can be used to *rank* a group of individuals to assign the best actions

| EXAMPLE SCORECARD | |
|---|---|
| **Applicant Age in Years** | |
| < 22 | -50 |
| 22 - 25 | -20 |
| 26 – 40 | 0 |
| 41 – 55 | +30 |
| > 55 | 0 |
| **Time as Rider** | |
| <1 | 0 |
| 1 – 2 | -45 |
| 3+ | -100 |
| **Worst Payment Status** | |
| Current | 0 |
| 1 Payment missed | -10 |
| 2 Payments missed | -60 |
| **Etc.** | **Etc.** |
| … | … |

# The Role of Analytics & Scoring

Consider a scorecard built to predict whether a new applicant for a credit product will default on their payments within time X

This scorecard is used when a new customer applies…

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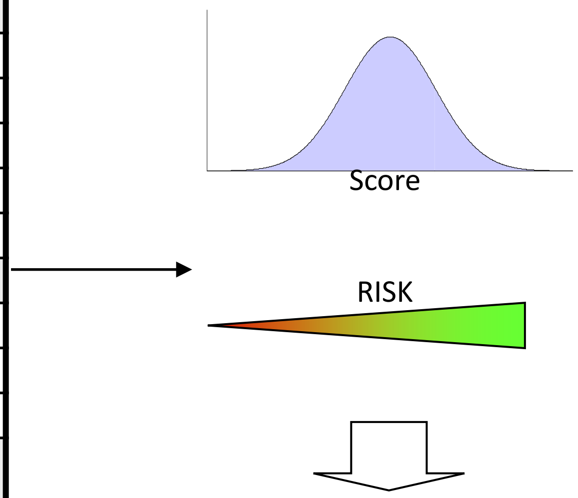
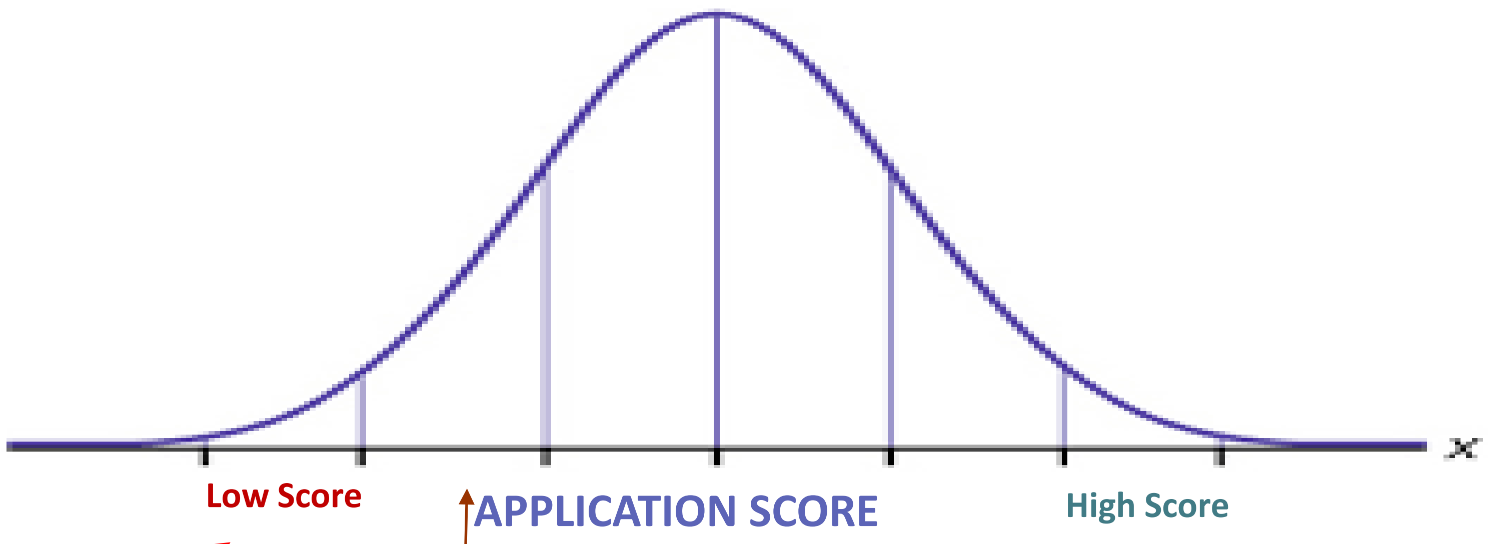



**Take most appropriate action for each individual**

# Using the Scores in Decisions




**Very High Risk**

Worst Applicants. Reject these applicants

**High Risk**

Reject these applicants or give low limits and apply higher pricing.

**Standard Risk**

Good applicants: Accept

**Very Low Risk**

The best applicants. Consider higher limits

# Analytics Across Business Areas

| Business Area | Challenge | Model | Data | Business Outcome |
|---|---|---|---|---|
| Prospecting | • Who is the right customer to target?<br>• How can we cost effective market to the right customer?<br>• Can we pre-screen the risk associated with our targets? | Propensity to Respond<br>Propensity to Take-Up | Alternative Data<br>Demographics<br>Account Management | Improve Customer Loyalty<br>Reduce Marketing Costs<br>Increased Marketing Efficiency<br>Reduced Attrition<br>Increased Revenue / Profits |
| Origination | • Who to accept and reject?<br>• Under what terms and conditions?<br>• Can I X-sell addition products to the applicant? | Application Scores<br>Bureau Scores<br>Application Fraud | Demographics<br>Bureau Data<br>Alternative Data<br>Account Management | Risk Profiles<br>Improved Customer Service<br>Reduced Losses |
| Customer Management | • Which of my existing customers can we x-sell or up-sell additional products and services to?<br>• Which customers can we offer an increase in limit?<br>• How do we determine pre-delinquency treatments? | Behavioural Scores | Demographics<br>Bureau Data<br>Alternative Data<br>Account Management | Risk Profiles<br>Improved Customer Service<br>Increased Market Share<br>Increased Profits<br>Reduced Losses |
| Usage | • How can we identify the customers most likely to use the product more?<br>• How do we identify the profitable customers that are likely to close their facilities? | Revenue Models<br>Utilisation<br>Attrition | Demographics<br>Bureau Data<br>Alternative Data<br>Account Management | Increased Revenue / Profits |
| Collections | • Which delinquent customers to we collect upon?<br>• How do we prioritise collection treatments?<br>• Which accounts do we collect, litigate, sell or write-off? | Collections Scores<br>Payment Projection<br>Loss Forecasts | Demographics<br>Bureau Data<br>Alternative Data<br>Account Management<br>Collections Management | Reduced Losses<br>Increased Recoveries |
| Regulatory Models | • How much capital do we need?<br>• Can we estimate our provisions based upon the lifetime of the facility?<br>• How will the economy affect our capital and provisioning positions in the future? | PD, EAD and LGD models for AIRB<br>PD, EAD and LGD Models for IFRS9<br>Macroeconomic models for stress testing and scenario analysis | Demographics<br>Bureau Data<br>Alternative Data<br>Account Management<br>Collections Management<br>Macroeconomic Data | Capital Planning<br>Expected Loss Calculation for Provisioning<br>Long Term Business Planning |

# Benefits of Credit Scoring

- Automated Decisioning
- High Level of Control
- Reduced Losses
- Increased Revenue
- Increased Portfolio Knowledge
- Optimised Portfolios
- Increased Regulatory Standing
- Engaged Staff
- Maximised Opportunity

# Questions

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# Exercise 1 (1 hour)

- List three areas where the concept of scoring could be applied to your bank / organisation
  - What's the business problem that could be addressed?
  - What data would be used or could be useful?
  - Discuss the business case for doing such a thing?

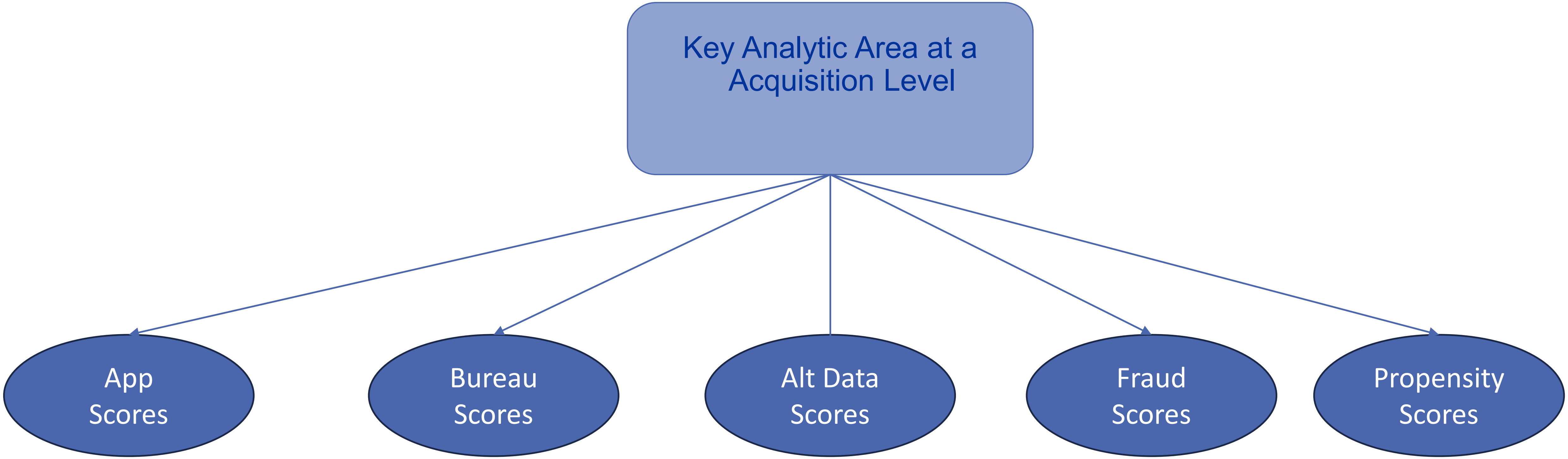
  - Ideation sessions

# Decision Areas

# Acquisition Analytics

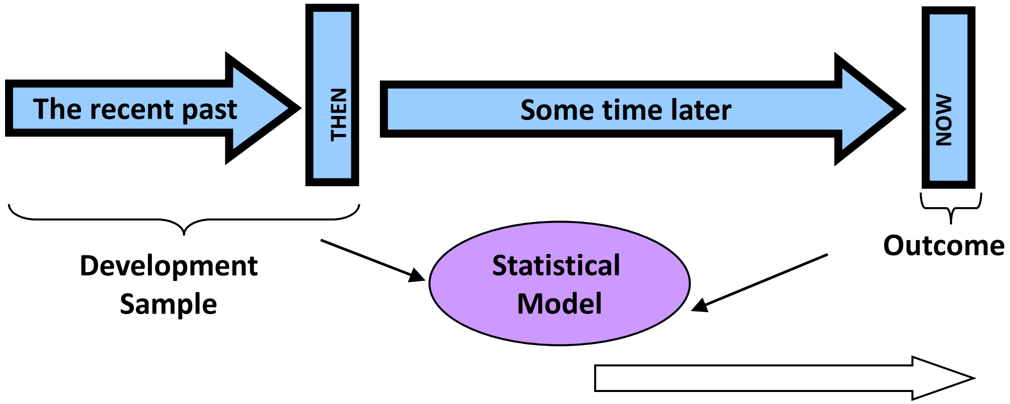
- Is the bank targeting the right customers?
- Is the bank using Alternative Data to target thin file or unbanked customers?
- Is the bank acquiring customers based upon the bank's risk appetite and assigning appropriate terms and conditions based upon the risk profile?
- Does the bank capture and store the right data for the use within scoring and strategy deployment?
- Is the bank maximising the benefits of using date from both internal and external datasources (bureau data / alternative data)?
- Is the bank satisfying the prevailing regulatory compliance criteria?

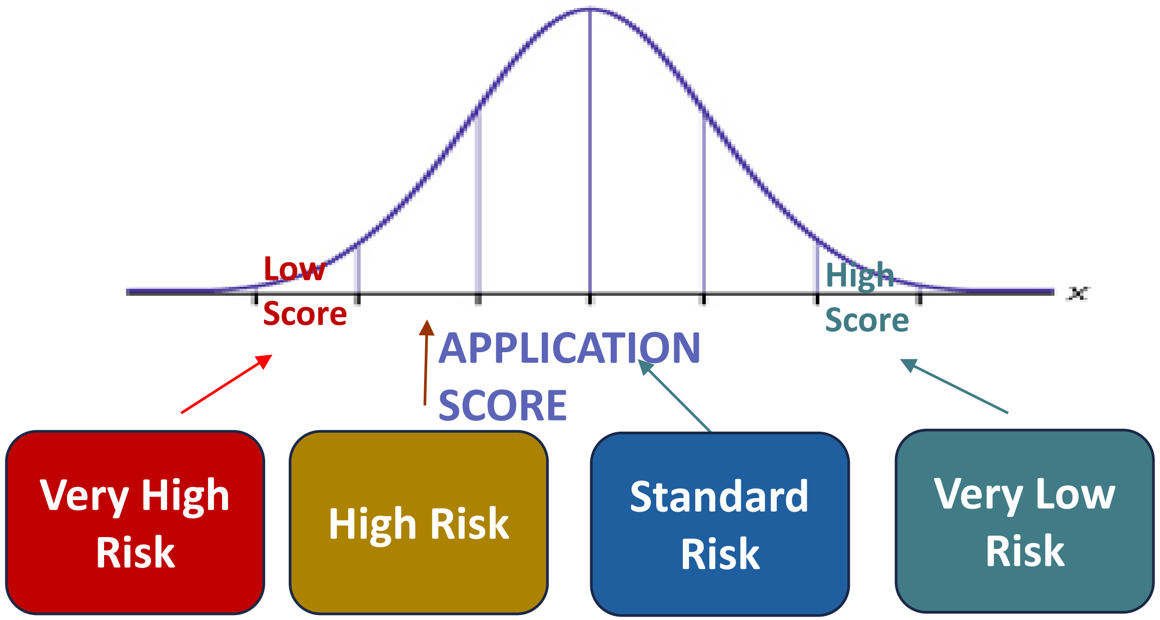
# Acquisition Analytics



# Analytics in the Acquisition Area

## Application Scoring - Overview




**Business Challenge**: Automate the Acquisition decisioning process based on the Risk Profile

**Solution**: Application scorecard build to predict Delinquency Outcome

- Application scorecard using Application Demo data
- Can use Bureau data, and Internal other Product data
- Usually use past Delinquency behaviour to predict outcome i.e. 90+DPD Default definition

**Benefits**:

- Reduction in Bad debts
- Aim of high level of Automation
- Tool for Risk Based Pricing

| | |
|---|---|
| Constant | +800 |
| Age of Applicant | |
| <22 | -50 |
| 22-25 | -10 |
| 26-40 | 0 |
| 41-55 | +30 |
| Worst status Last 6 months | |
| 0 | 0 |
| 1-2 | -45 |
| 3+ | -100 |
| Joint Applicant | |
| Y | +20 |
| N | 0 |

# Acquisition Analytics – Combining Scores

Combining the internal application scores with the bureau scores enables the bank to consider a customer's credit position at other financial institutions and also consider cases that may have been previously rejected if only internal data was considered

**Benefits**

- Increase in predictive power of acquisition decisioning
- Reduction in Bad Debts
- Expansion in the number of applicants that can be offered facilities (e.g. previous high risk internal only applicant can now be referred, instead of rejected)
- Aim for high level of automation

| | | Bureau | | |
|---|---|---|---|---|
| | | Low | Medium | High |
| Application | Very Low | Reject | Reject | Refer |
| | Low | Reject | Refer | Refer |
| | Medium | Reject | Accept | Accept |
| | High | Refer | Accept | Accept |
| | Very High | Accept | Accept | Accept |

# Potential Acquisition & Origination Modelling Datasources

## Models can cover many areas :-

- Origination Models
- Cross-Sell Models
- Income Models
- Affordability Models
- Indebtedness Models
- Fraud Models

**Demographic Data**

- Age
- Residential Status
- Socio-Economic Group
- Occupation
- Location
- Time at Address
- Time in Job
- Etc.

**Product Information**

- Credit Card Limit Requested
- Card Type Requested
- Loan Purpose
- Loan Term
- Property Type
- Borrower Type – Owner Occupier vs Buy-to-Let

**Mobile**

- Pre-Paid Y/N
- Number of device used to pay for goods L3M, L6M
- Time of first daily use
- Average Distance between daytime and nighttime location last week
- Handset Type – Smart vs Analogue

**CRA Data**

- Worst Delq Status (all prod) last 24 months
- Number of Searches Last 3 Months
- Number New Cards Opened Last 6 Months
- Time Since Last Default
- Number of CCJs / Court Judgements Last 6 years

**Open Banking**

- Total Number of Accounts in a Delinquent state
- Total Outstanding Balance
- Our Outstanding as a proportion of Total Outstanding Last Months
- Total Late Fees Paid Last 3 months
- No. Months with delinquency last 3M, L6M, L12m

**Alternate Data**

- Psychometric Data
    - Time Taken to answer moral questions
    - Time taken to answer DoB question
- Tax Records
- Utilities Data

Model Power increases as data availability expands

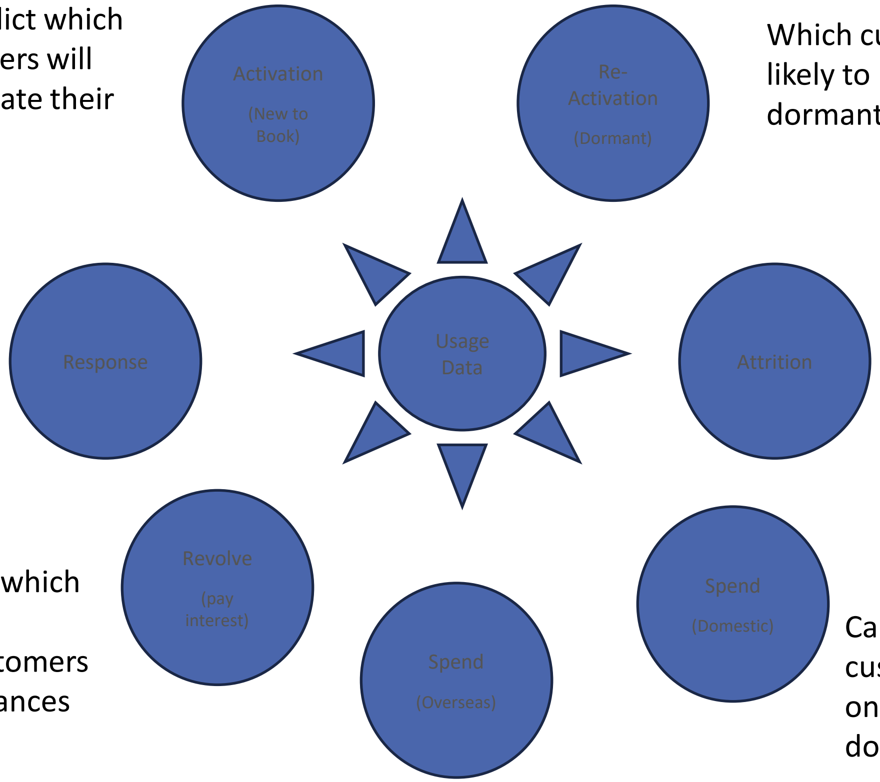
# Modelling Arena

- Collections operations are highly data dependent
- Data used will be generated from account operation, from contacts with the customer within the collections / delinquent environment
- The use of external data, such as open banking and other alternative sources would be encouraged as it provides a much more holistic view

Can we predict which new customers will quickly activate their cards?

Which customers are likely to re-activate a dormant card?

Do we need customer consent?




Which customers are likely to close their accounts?

Can we predict which dormant or transacting customers will revolve balances in the future?

Can we predict which customers will spend on their cards domestically?

Or spend overseas?

# Potential Propensity Modelling Datasources

## Models can cover many areas :-

- Product Propensity –
    - which product, when?
    - Credit Propensity – determining which customers need additional credit
    - Usage – determining which customers will generate the most revenue through greater usage
- Benefits include
    - Strategic Customer Targeting
    - Reduced Marketing Costs
    - Efficient Decisioning Increased Revenue
- Examples
    - Propensity to spend on a Credit Card
    - Propensity to Revolve a balance on a CC
    - Propensity to Attrite / Switch a Mortgage

**Demographic Data**

- Age
- Residential Status
- Socio-Economic Group
- Occupation
- Location
- Time at Address
- Time in Job

**Behavioural Scoring Data**

- Worst Status Last Month / L3M / L6M / L12M
- Min Balance Last Month, L3M, L6M, L12M
- Number of Payments L1M, L3M, L6M, L12M
- Average Payment to Balance Ratio L3M

**Mobile**

- Pre-Paid Y/N
- Number of device used to pay for goods L3M, L6M
- Time of first daily use
- Average Distance between daytime and nighttime location last week

**CRA Data**

- Worst Delq Status (all prod) last 24 months
- Number of Searches Last 3 Months
- Number New Cards Opened Last 6 Months
- Time Since Last Default
- Number of CCJs / Court Judgements Last 6 years

**Transactional Data**

- Number of Purchases Last 3 Months
- Number of Purchases greater than $100 Last Month
- Time since Last Purchase
- Number of Months Revolving Balance Held last 12 months
- Average Value Purchases by MCC last 6 months

**Open Banking**

- Total Number of Accounts in a Delinquent state
- Total Outstanding Balance
- Our Outstanding as a proportion of Total Outstanding Last Months
- Total Late Fees Paid Last 3 months
- No. Months with delinquency last 3M, L6M, L12m

Model Power increases as data availability expands

# Acquisition Analytics – Fraud

- Increasing levels of identity fraud leads to increasing fraud losses at a diverse range of banks
- Data and Models can be used to help the bank identify cases that would require further investigation (searching for anomalies in the data)
    - Application Fraud Models
    - Use of bureau data is permitted
    - Potentially early bads may be classed as fraudulent
- Benefits (taken from a UK example)
    - Referral of 9% of Applications for further investigation
    - Detection of 56% of fraud cases, saving the bank money Example Characteristics include complex interactions, e.g. Age and High Income

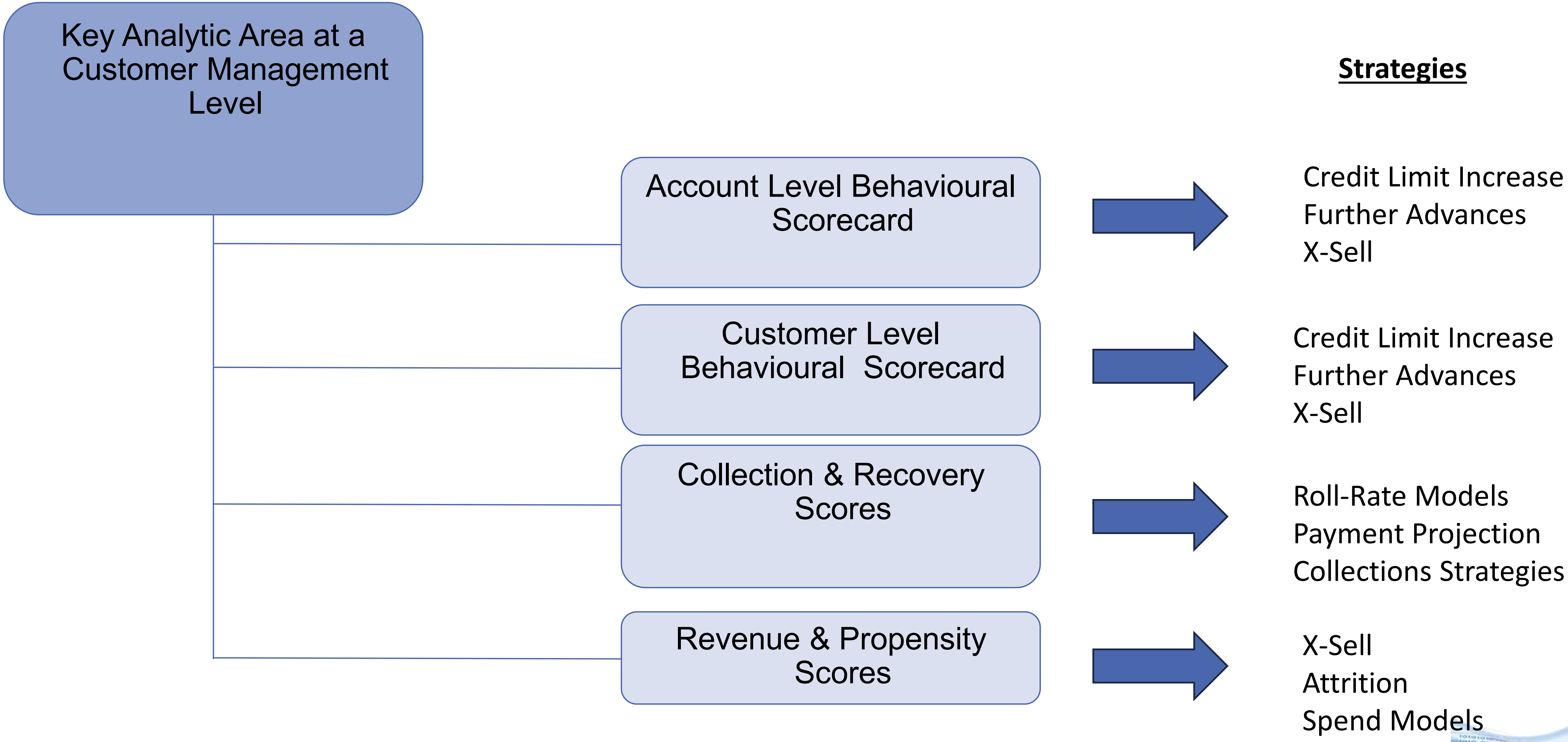
# Analytics and Customer Management

## Maximising the use of the bank’s data that can be mined from existing customers

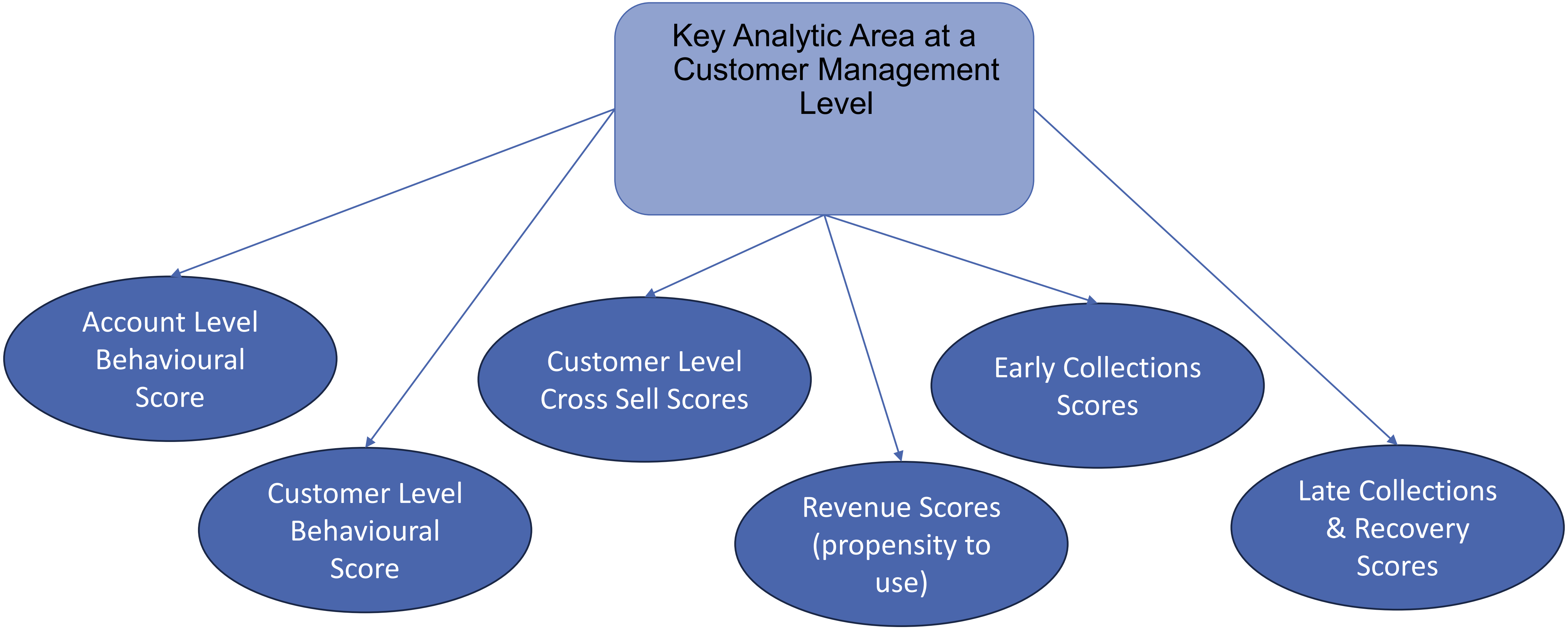
Is the bank pro-actively managing it’s existing customer base to drive revenue and reduce costs?

- Behavioural Scoring in Customer Management
- Is the bank managing relationships at an account level?
- Is the bank managing relationships at a customer level?
- Pro-actively managing the customer base?
- Identifying high value customers for potential upsell / x-sell?
    - Increase Revenue from X-Sell Opportunities and grow the portfolios X-Sell
    - Identify customers that are starting to look vulnerable? (triage)
    - Prioritising the flow into collections and determining appropriate actions
    - Increased (Early) Collection Process Efficiency & Reducing Roll-Rates

# Customer Management Analytics



# Customer Management Analytics



# Looking at Behavioural Scoring and how to use

Portfolio Data

**Behavioural Scoring Chars**
(Examples)

- Max Delq last 6 months
- Numbers times 30+ last 12 months
- Number of Overlimit last 3 months
- Number of Payments greater than minimum payment last 6 months
- Max Utilisation last 9 months
- Number of Collection Calls last 24 months

Segmentation

Modelling

$$\Pr(x) = \frac{e^{\alpha + \sum \beta x}}{1 + e^{\alpha + \sum \beta x}}$$

Clean

Dirty

Delinquent

Default / Late Collections

Strategy

Exposure Management

Cross-Sell

Triage

Exposure Management

Collections Priorisation

Roll-Rate Management

Payment Projection

Recoveries Management

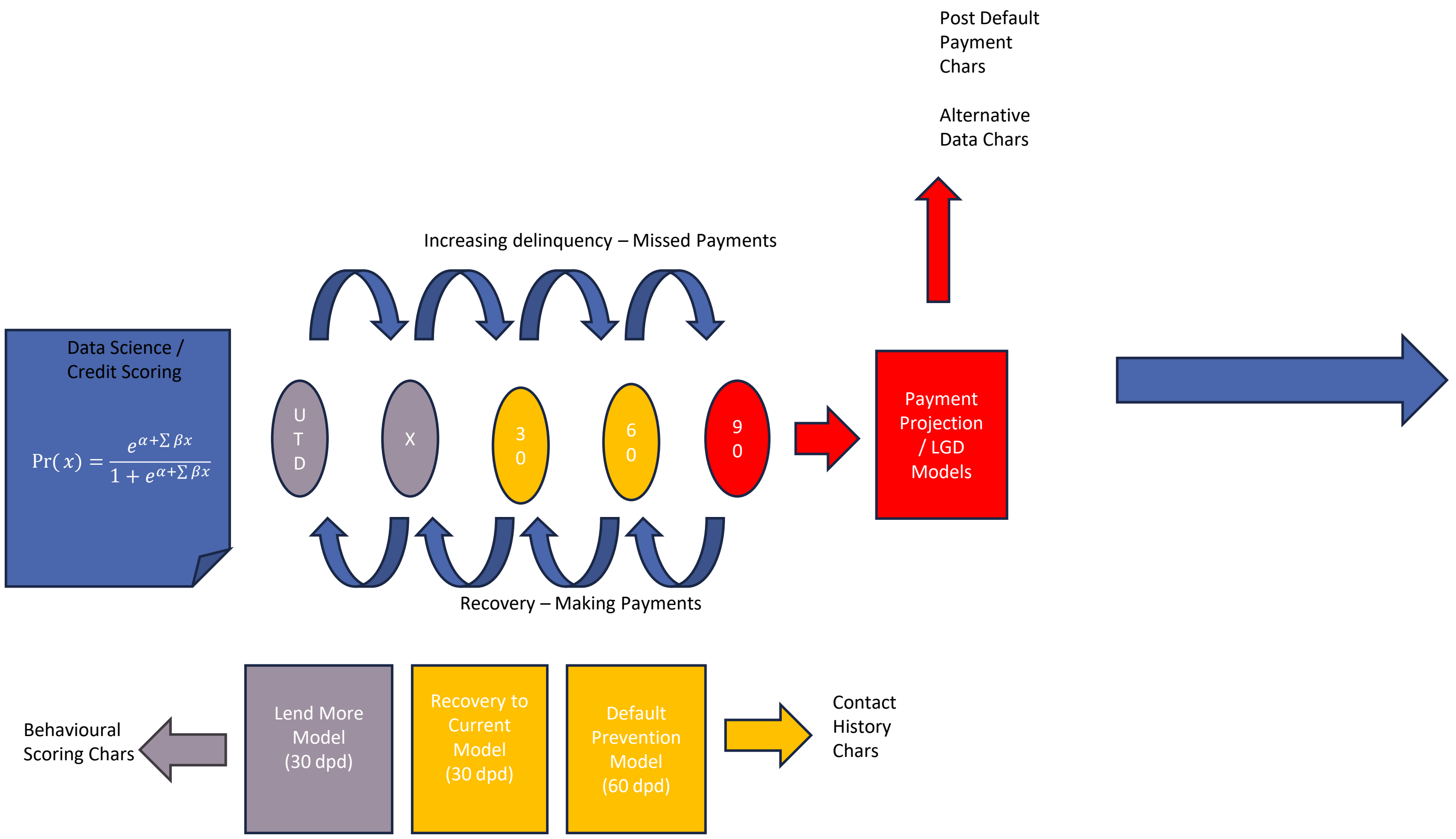
# Customer Management Analytics – Collections Management

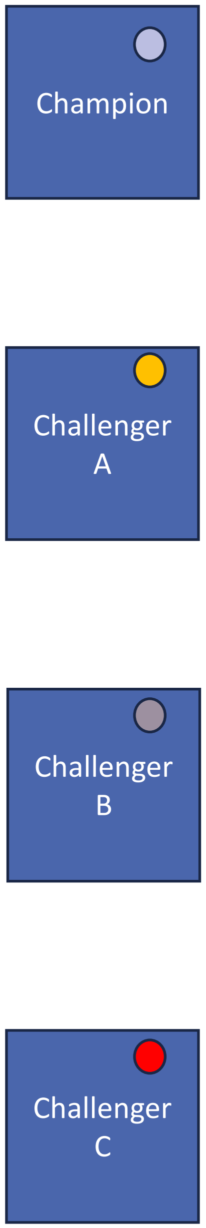
**Account Status**

| | Up To Date | 1-29 Days Past Due | 30 - 90 Days Past Due | 90+ Days Past Due |
|---|---|---|---|---|
| | Behavioural Scoring | | Roll-Rate Model | Payment Projection |
| **Description** | Manage Customers Relationships through<br>• Pro-active limit management<br>• Competitive Pricing<br>• Pre-emptive Triage<br>• X-Sell Programmes | Initiate Customer Contact for<br>• Debt Control<br>• Triage<br>• Limit Management | Continued Customer Contact for<br>• Prioritised Debt Control<br>• Arrears Management<br>• Save the Relationship? | Decision made to end the customer relationship, therefore switch to<br>• Recovery Strategies<br>• Debt Sale<br>• Litigation |
| **Objective** | To maximise profitability by balancing expected revenue with associated levels of risk and exposure | To maximise profitability by balancing expected revenue with associated levels of risk and exposure, whilst catching early delinquency | To minimise roll-rates to non-performing bucket whilst determining whether to save the relationship or minimise loss | To maximise recovery cash-flows and minimise losses to the bank |

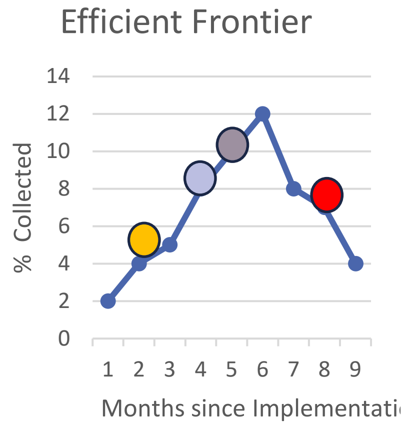
# Champion-Challenger Philosophy

## Modelling



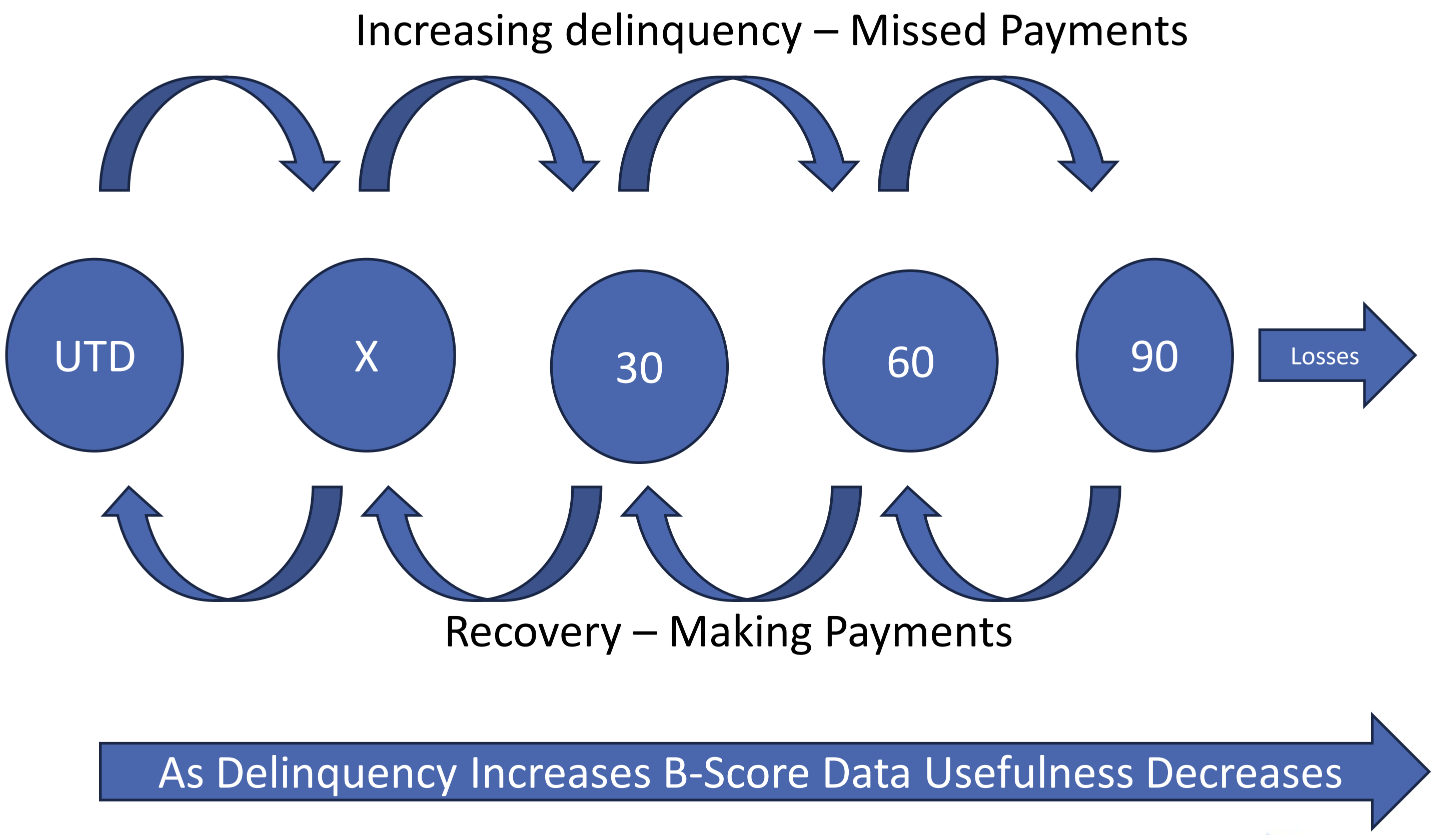

## Monitoring



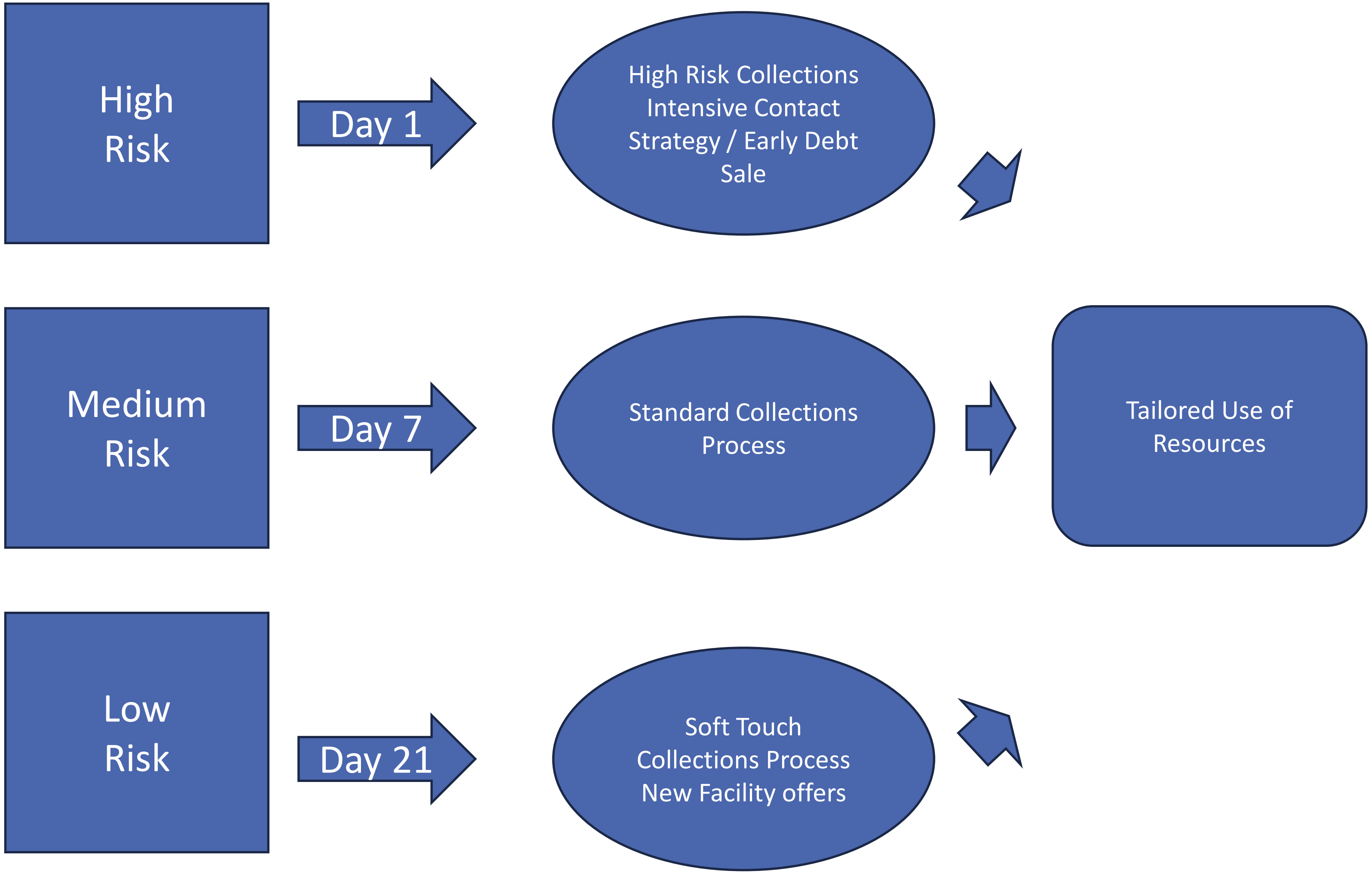

Challenger C too extreme, A not radical enough, B improves over the Champion and becomes incumbent

# Collections & Payment Projection Models

- Credit Customers are obliged to make regular (usually) monthly payments to repay their lending facilities
- Customers are categorised as sitting in a range of buckets, representing the number of missed payments
- If a payment is missed or not made customers will 'roll' to the next delinquency bucket
- If a payment is made the customer will 'roll back' the number of buckets the payments represents
- At 90 days past due the customer is deemed to have 'defaulted', and a loss may be incurred
- NPLs occur at 90 days past due, Banks will aim to avoid a 90-day status
- The predictive power of the behavioural scoring deteriorates the longer the customer is in a delinquent state
- Typically, the bank will look to use contact information collected during the collections process, e.g. Number of Right Party Contacts Last Month or Number of PTP's Kept Last Three Months
- As we move post-default (usually 90 dpd) the data and the model structure changes again, towards recovery payments data and payment projection models (the bank may wish to utilise it's LGD models in this phase or have separate operational without the cost and discounting elements)



# Collection Scores – Basic Strategy




### What is it?

- Behavioural & Collections Scoring is used to predict which accounts or customers will go into the late stages of delinquency (often 3 cycles plus, although more complex performance definition can be used on a product-by-product basis)
- Often the score is grouped into risk grades and appropriate actions taken by grade

### Why

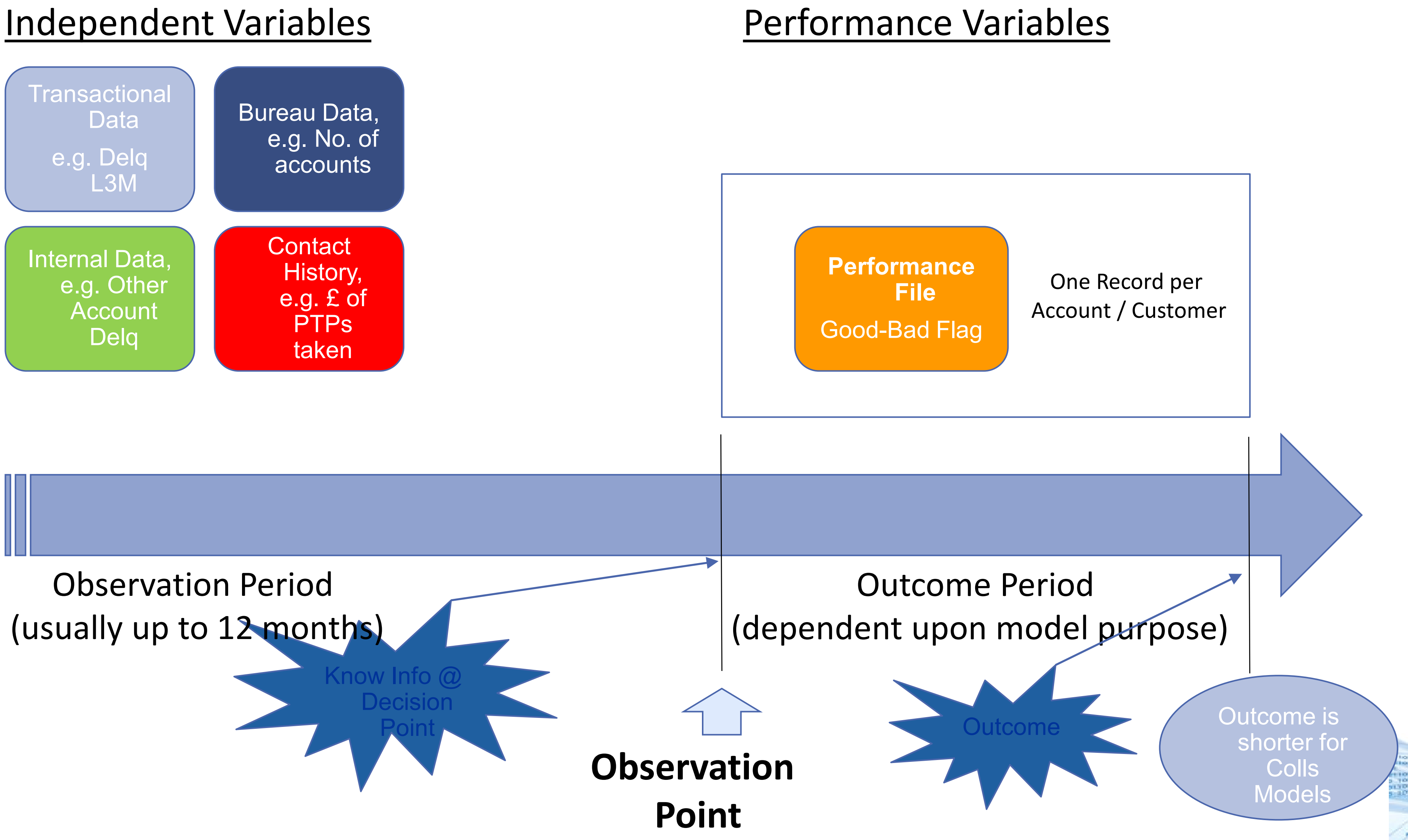
- Identify Future Delinquents, reducing losses
- Identifying cases that will self-cure will allow resources to be concentrated where they are needed
- Identifying x-sell potential will increase revenue

### How?

- A behavioural score is often an integral part of the bank's customer management infrastructure and can be used to determine x-sell opportunities (from a revenue perspective)
- The score is also key to identifying customers that are deteriorating so that preventative measures can be taken to pre-cure before delinquency
- The score would also be used in the early stages of delinquency to prioritise strategies

# Customer Management Analytics - Sampling

Data Elements can be at account or customer level OR be external bureau type chars



# Potential Behavioural & Collections Modelling Datasources

- Collections operations are highly data dependent
- Data used will be generated from account operation, from contacts with the customer within the collections / delinquent environment
- The use of external data, such as open banking and other alternative sources would be encouraged as it provides a much more holistic view

Examples of Data that could be used when Collections Scoring

**Behavioural Scoring Data**

- Worst Status Last Month / L3M / L6M / L12M
- Min Balance Last Month, L3M, L6M, L12M
- Number of Payments L1M, L3M, L6M, L12M
- Average Payment to Balance Ratio L3M

**Mobile**

- Pre-Paid Y/N
- Number of device used to pay for goods L3M, L6M
- Time of first daily use
- Average Distance between daytime and nighttime location last week

**Collections Contact Data**

- Number of right party contact last month
- Number of Promises to Pay Taken L1m, L3M, L6M
- Number of Partial Payments Made L3M, L6M
- Ratio of Payment to Outstanding L3m

**Open Banking**

- Total Number of Accounts in a Delinquent state
- Total Outstanding Balance
- Our Outstanding as a proportion of Total Outstanding Last Months
- Total Late Fees Paid Last 3 months
- No. Months with delinquency last 3M, L6M, L12m

Model Power increases as data availability expands

# Questions

www.apds-analytics.com

# Exercise 2

- Earlier we listed out areas where your bank may apply scoring concepts, now please list or revisit the data you would need to build upon the identified uses

# Discussion Area – Exercise 2

Let’s Talk Data for ABC Bank Scoring Concepts

# Modelling Steps

# Scorecard Development Steps

Design and Data Requirements → Initial Analysis → Variable Reduction (PCA, Correlation, VoI) → Modelling incl Reject Inference → Model Diagnostics → Strategy Develop

Low predictive chars will be business logic check to determine whether they are considered for modelling

**Design**
- Design Workshop
- Business Objective / Problem
- Data Availability
- Portfolio Nuances
- Design Document

Essential that the design is correct and aligned to business requirements

**Initial Analysis**
- Data Read In
- Data Manipulation
- Performance Definitions
- Segmentation
- Sampling
- Initial Analysis Workshop & Report

Design is confirmed through data analysis e.g. the performance definition, the development sample etc

**Modelling**
- Characteristic Classing
- Modelling – Linear vs Logistic Regression
- Model Assessment & Re-model
- Finalisation Workshop & Report

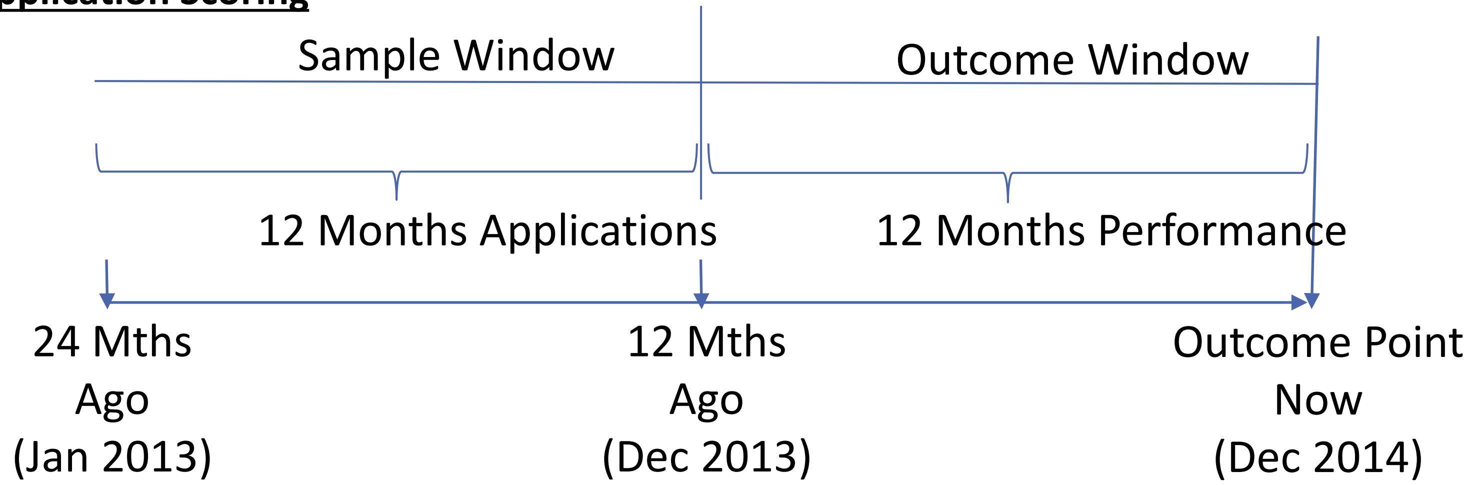
# Data Sample Construction

**Design**
(Business Problem, What Data is Available, High-level Solutionising)

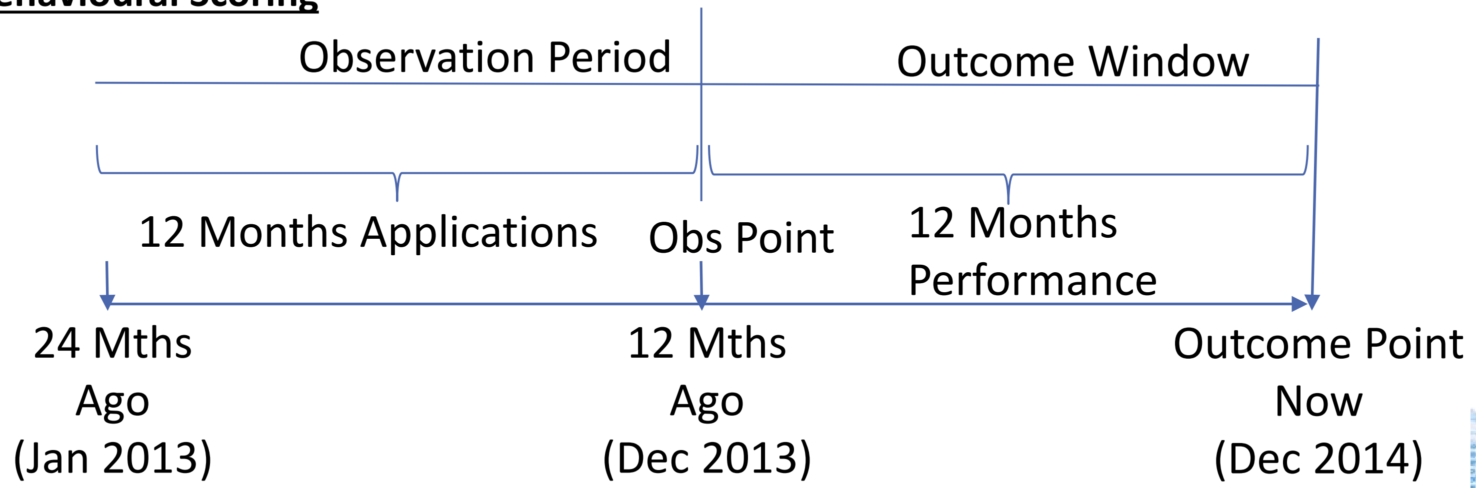
**Data Sourcing**
(extract, merge, quality checks etc.)

**Data Manipulation**
(char derivation, segmentation investigation, performance definitions, exclusions etc.)

**Application Scoring**




**Behavioural Scoring**




*could have multiple sample windows

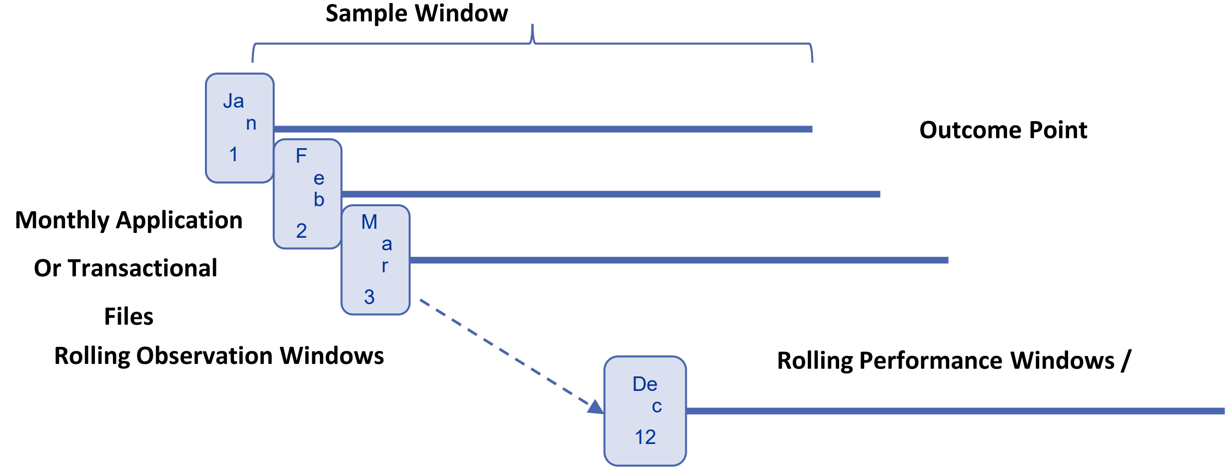
# Data Sample Construction

**Design**
(Business Problem, What Data is Available, High-level Solutionising)

**Data Sourcing**
(extract, merge, quality checks etc.)

**Data Manipulation**
(char derivation, segmentation investigation, performance definitions, exclusions etc.)

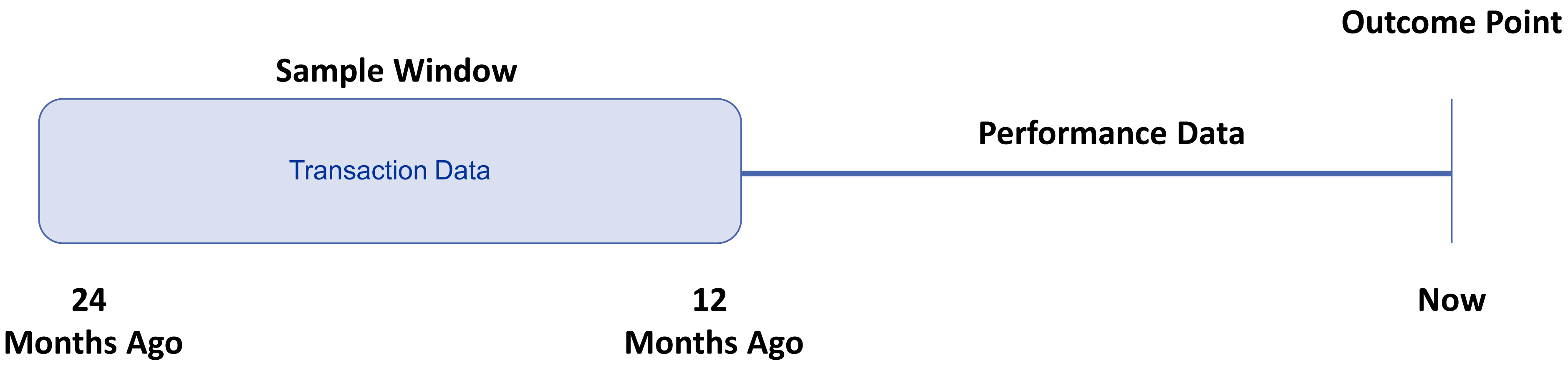
**Modelling Data**




*Typically used when the number of bads is not low, and mature relatively quickly or when the portfolio requires a fixed outcome period (i.e. all bads have the same time to exhibit poor performance)

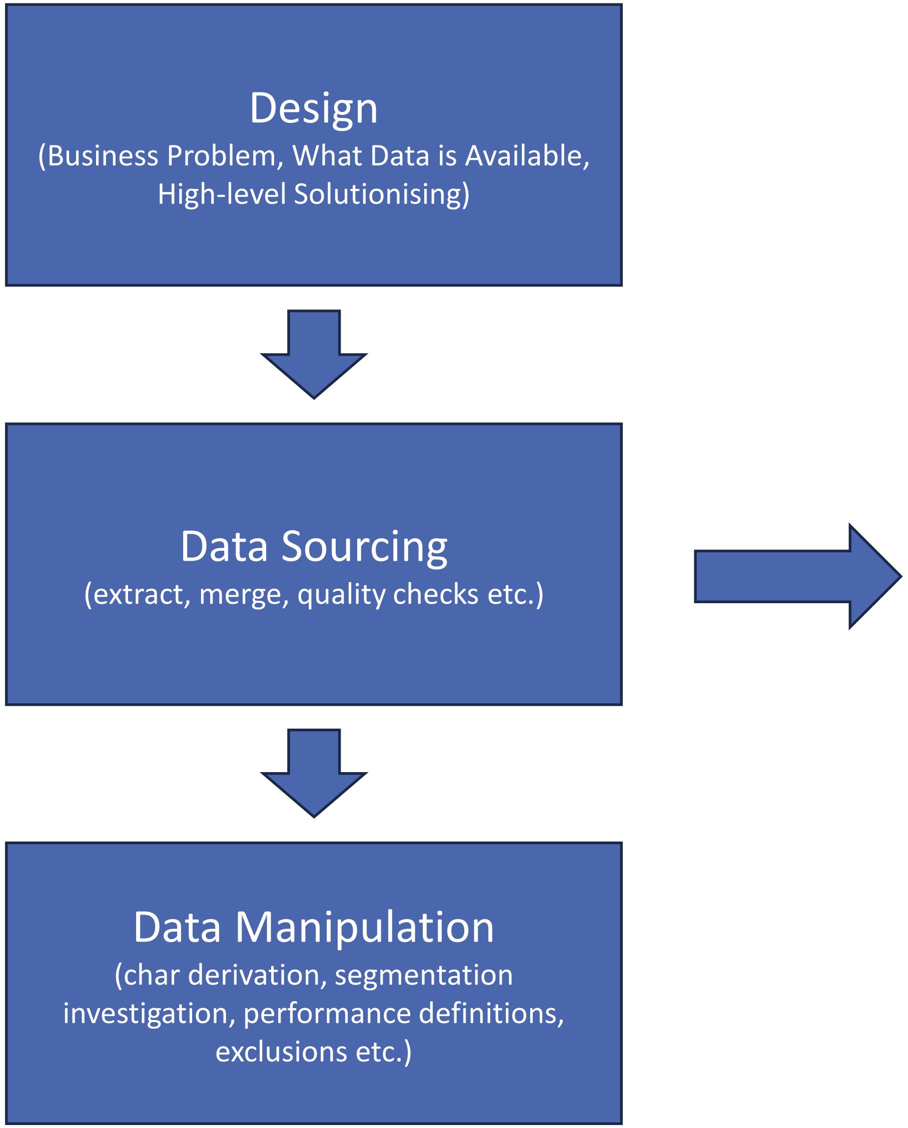
# Development Team Data Sample Construction
# Fixed Window

## Modelling Data



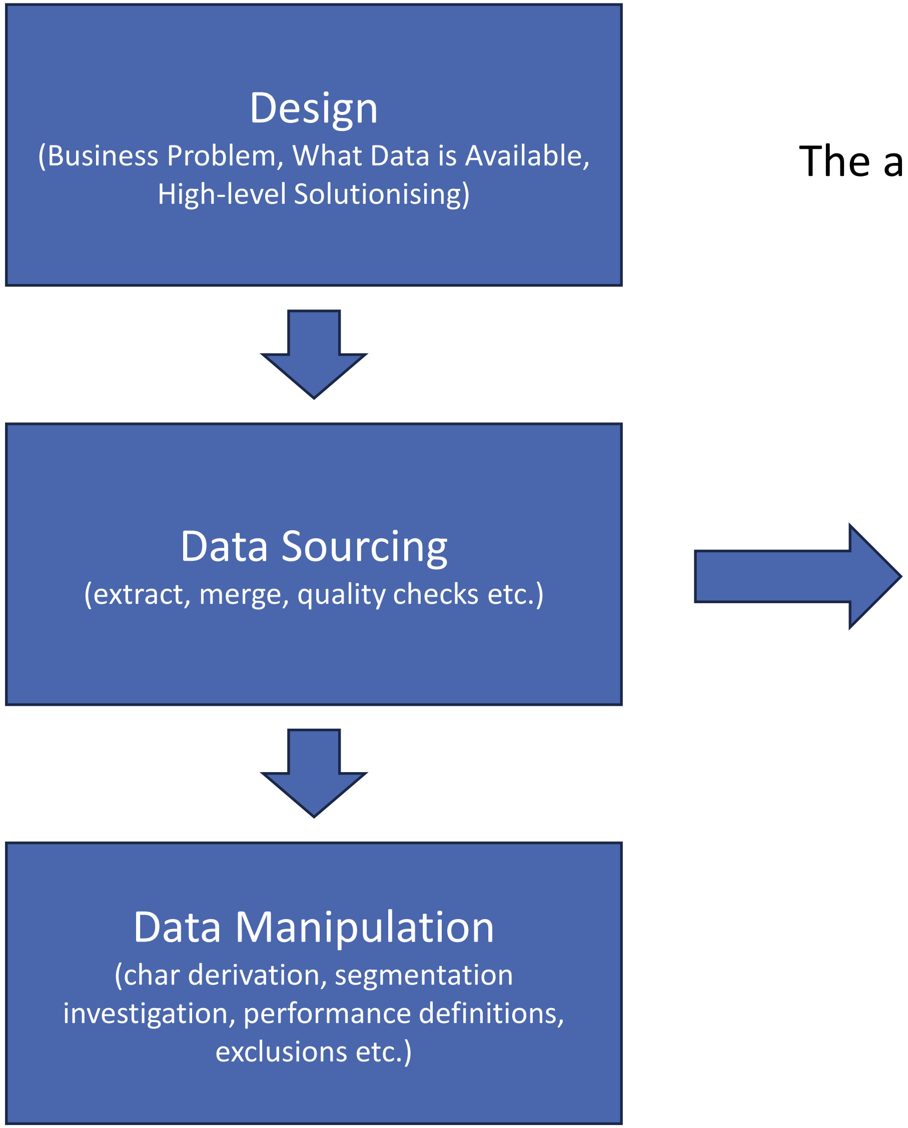

*Typically used when the number of bads is low, the earliest bads are given longer (up to 24 months in this case) to mature

# Example Performance Definition - Complex




| GB Flag | Good-Bad Definition | Classification |
|---|---|---|
| | | |
| 1 | Voluntary Cancel / Close / Deceased / Never Active | Exclusion |
| 2 | Bankruptcy | Bad / Default |
| 3 | Write-Off | Bad / Default |
| 4 | Re-Age / Re-Structured | Bad / Default |
| 5 | Ever 90+ Days Past Due >= $100 in the last 12 months | Bad / Default |
| 6 | Ever 60+ Days Past Due in the last 12 months | Indeterminate / Non-Default |
| 7 | Ever 30+ Days Past Due in the last 12 months | Indeterminate / Non-Default |
| 8 | Ever x-Days Past Due in the last 12 months | Good / Non-Default |
| 9 | Up-to Date in the last 12 months | Good / Non-Default |

# Example Performance Definition - Simple




The aim is to the scorecard development as simple as possible

| GB Flag | Good-Bad Definition | Classification |
|---|---|---|
| 1 | Ever 90+ Days Past | Bad / Default |
| 2 | Ever 30 – 90 Days Past Due in the last 12 months | Indeterminate / Non-Default |
| 3 | Ever 30+ Days Past Due in the last 12 months | Indeterminate / Non-Default |
| 4 | Worst Status  x-Days Past Due in the last 12 months (includes current) | Good / Non-Default |

# Defining Exclusions (Application)

Customers have certain characteristics which the bank views as favourable, therefore the applicant will be accepted regardless of score, e.g.

- a Premium Banking Customer
- a Brand Ambassador
- a VIP

The bank would like to treat these customers differently from the normal thru the door population when they for credit

- Example Exclusion Rules VIP
    - Staff
    - Students
    - Pre-Approved Customers

# Defining Policy Rules (Application)

- The applicant will automatically be rejected when hit any of the bank's Policy Rules (which define the bank's lending or regulatory criteria)

- Policy Decline Rules are a set of criteria which each applicant must pass regardless of their application score

- Example Policy Rules
  - Age Between 18 and 70
  - Derogatory Records (Bankrupt, Legal Action, Charged Off)
  - Excessive Credit Exposure
  - High Debt to Income Ratios

- Where the bank allows policy exemptions, we may analyse the effectiveness of the policy rules by looking into default rates by exception rule

# Defining Exclusion Rules (Behavioural)

- For the behavioural model the customer is already on book therefore the exclusion rules are slightly different
- There two levels of exclusion rules for existing customer, Observation & Outcome
- Example Observation Exclusion Rules
    - Bad at Observation
    - Inactive in the 12 months prior to Observation Point (no predictive data)
    - Fraud / Lost or Stolen / Dispute
- Example Outcome Exclusion Rules
    - Deceased in the performance window
    - Inactive for the entire performance window
    - Fraud / Lost or Stolen / Dispute

- Basel and IFRS9 Models may have separate exclusion rules, therefore these must be known as the operational scorecards are often the keystone within those model structures

# Exercise 3 – Performance Definitions and Outcomes

- Please define your performance definition for your risk or propensity model
  - What are your key assumptions and the rationale behind your thinking?
  - Please relate your definition back to a business prompt?

# Exercise 3 – Discussion

- Please define your performance definition for your risk or propensity model
- Discussion

# Day 1 - Reflections

- Any Questions?
- Anything you’d like to go over again?

# Defining Data

**Data Sourcing**
(extract, merge, quality checks etc.)

**Data Manipulation**
(char derivation, segmentation investigation, performance definitions, exclusions etc.)

**Data Extract**
(application data, associated performance, sufficient time periods)

**Who?**
Dev Team
Business Reps
IT

1. Spec the data (Dev Team, Business Reps)
2. Extract Data (IT Team)
3. Initial Data Analysis to assess data (Dev Team) quality
    - Depth
    - History
    - Comparisons between segments, e.g. Accepts & Rejects
    - Population Rates
    - Expected Values

- Future Data Availability (Dev Team, IT Team)
- Data Audit Report (Dev Team, Business Reps, IT)

# Data Prep

For data assessment and specification two main areas are investigated. The first step is to look at the **'Quantity'** of data available and whether the information is sufficient (and covers all the necessary fields) to construct appropriate scorecards. The second step is to determine whether the available data is of adequate **'Quality'** and is a more analytic exercise.

Step 1 – Quantity
- Data Quantity assessment of the key data fields for in scope portfolios
- Starting point is always best practice variable lists
- Recommendations of required fields
- Recommendations of going forward fields

Step 2 – Quality
- Review of data elements within each field by assessing population rates, data accuracy through detailed analysis of documentation, data items etc
- Data Quality Assessment should include descriptive statistics, accuracy tests, documentation review and recommendations

| Ref No. | Data Item | Portflio | Best Practice Recommendation | Bank Available |
|---|---|---|---|---|
| 1 | Balance | CC | Y | Y |
| 2 | DPD | CC | Y | Y |
| 3 | Open Date | CC | Y | N |
| 4 | Limit | CC | Y | Y |
| 5 | Payment | CC | Y | Y |

# Data Check & Audit

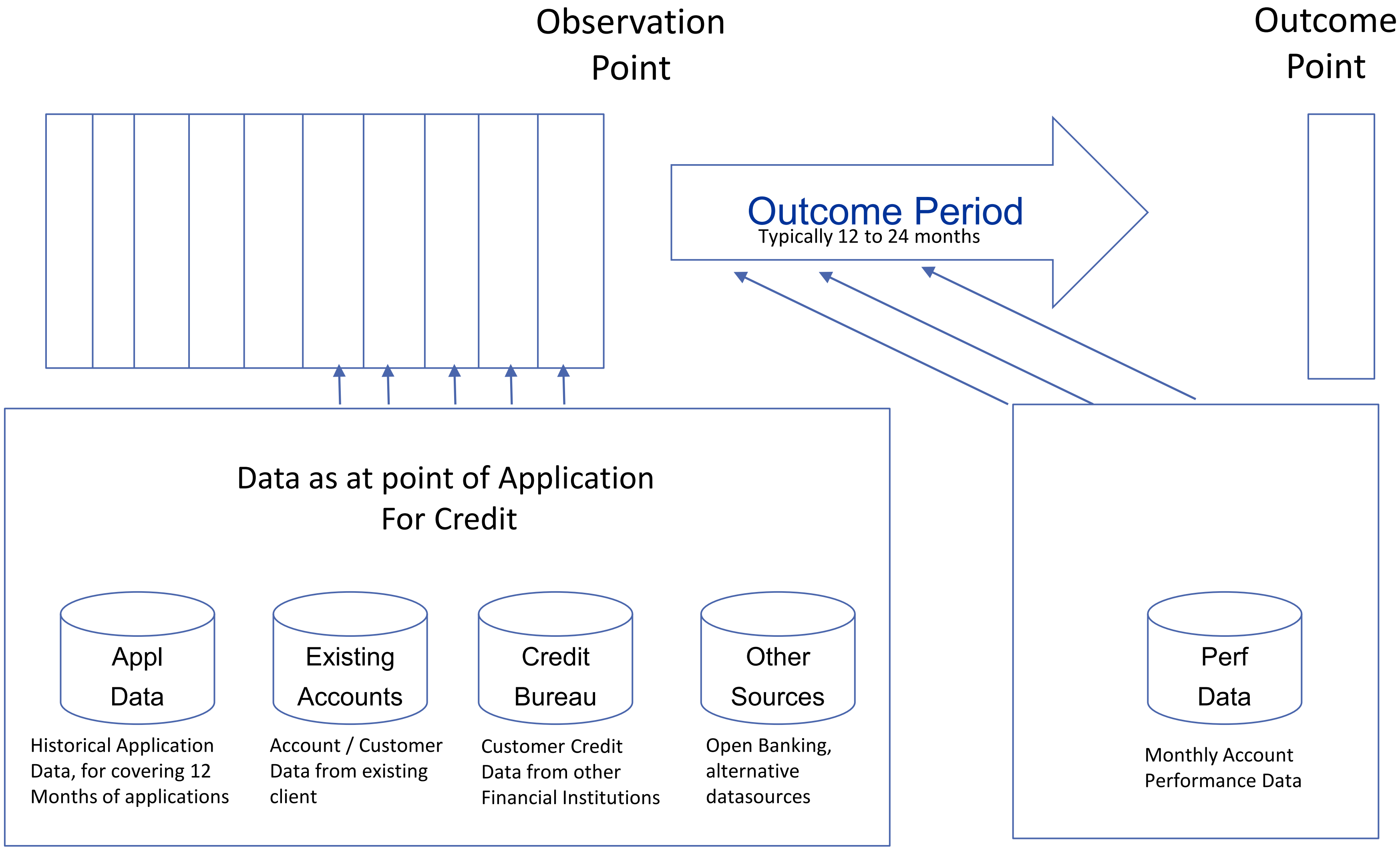
- To determine scorecard development feasibility the following analysis will be undertaken, to determine
  - Depth of Data
  - Breadth of Data
- For Numerical Characteristics, frequencies will be produced investigating the descriptive statistics of mean, min, max to highlight any data anomalies
- For Categorical Characteristics the frequency tables will investigate that the appropriate codes are populated correctly
- For Example
  - Balances are within the expected ranges, i.e. all positive and no abnormally high values
  - Charge-Off is expected to values of A to E but a value of X is observed
  - No. of Written Off accounts is expected to be 2% but 20% of cases have that status#
- Additionally
  - Data Availability to code exclusion rules, good-bad definitions (including the default definition) exist and are well populated
  - The supplied data is logical and no irregular trends are observed, examples include
    - movement through delinquency buckets follows expected trends, i.e. Jan 2013 DPD is 0, but 90 dpd in February
    - Valid Open Dates exist
    - DPD registers a zero value but the account is charged off
    - Number of records the expected number of records

# Data Manipulation

Matching Data (outcome & performance)

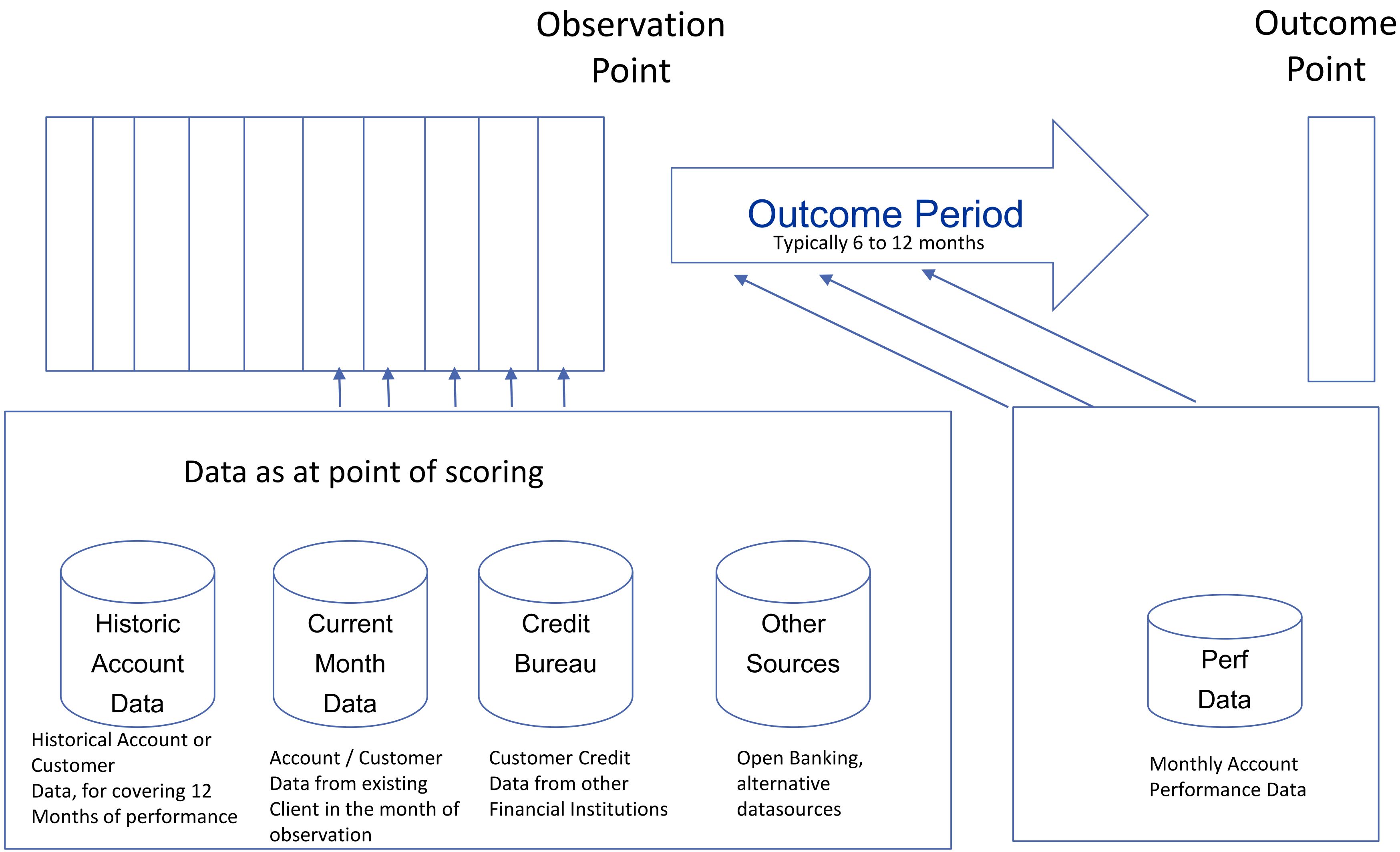
- Valid Match Keys
- Sorted Match Keys on both files (application and performance)
- Explain any duplication (or remove)
- Check the range of the match keys
- Sense check match rates
- Verify that the merged file contains the relevant and correct data
- Investigate any unmatched records

# Data Needed for Application Scorecards




Monthly account performance information for each month in the outcome, used to determine the GB Flag

# Data Needed for Behavioural Scorecards




Monthly account performance information for each month in the outcome, used to determine the GB Flag

# Data Preparation & Initial Analysis

Data Derivation

Raw Data

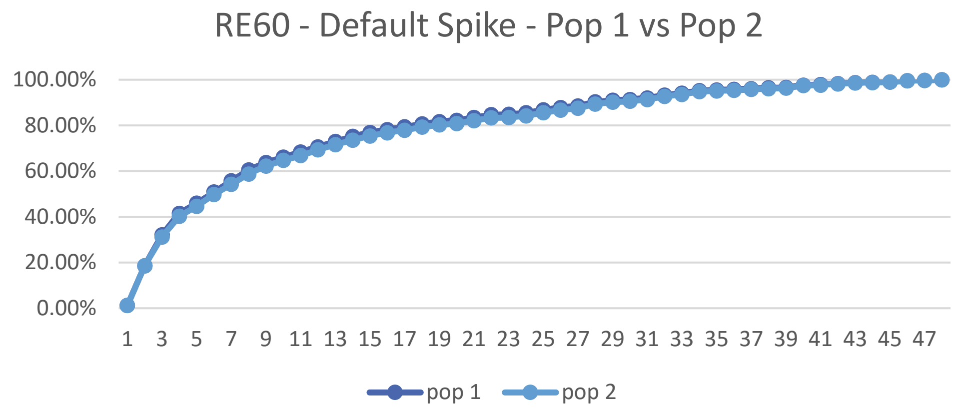
e.g. Max Delq Last 3m
Min Balance last 6m
etc

***'Turning the (raw) data into information'***

Performance Definition

Bad – ever 90 dpd inside X months

Sampling



# Example of Raw to Derived – Turning Data into Information

Raw Data

Derived Data

| Column ID | Column Description | Comment |
|---|---|---|
| CIF_ID | Customer ID | |
| FORACID | Loan Account ID | |
| OPEN_DATE | Loan Open Date | |
| MATURE_DATE | Loan Mature Date | |
| DISBURSED_AMOUNT | Loan Disbursed Amount | |
| SCHM_CODE | Loan Product Code | |
| DR_INTEREST_RATE | Interest rate | |
| BALANCE | Balance as of reporting date | |
| OVERDUE_PRINCIPAL | Overdue in principal | |
| OVERDUE_PDAY | Overdue days in principal | |
| OVERDUE_INTEREST | Overdue in interest | |
| OVERDUE_IDAY | Overdue days in interest | |
| TOTAL_AMT | total overdue amount | overdue principal + interest |
| REPORTDATE | report date | |

| | **Derivations:-** |
|---|---|
| | **Loan / Account Level** |
| 1 | Time to Maturity |
| 2 | Time on Book |
| 3 | Worst Delq status last 3 months (at account level) |
| 4 | Worst Delq status last 6 months (at account level) |
| 5 | Worst Delq status last 12 months (at account level) |
| 6 | Worst Delq status last 24 months (at account level) |
| 7 | Number of Times current-days (no delq) in the last 3 months |
| 8 | Number of Times Current (no delq) in the last 6 months |
| 9 | Number of TimesCurrent (no delq) in the last 12 months |
| 10 | Number of Times current (no delq) in the last 24 months |
| 11 | Number of Times X-days (1-30 dpd) in the last 3 months |
| 12 | Number of Times X-days (1-30 dpd) in the last 6 months |
| 13 | Number of Times X-days (1-30 dpd) in the last 12 months |
| 14 | Number of Times X-days (1-30 dpd) in the last 24 months |
| 15 | Number of Times 30-days (1-30 dpd) in the last 3 months |
| 16 | Number of Times 30-days (1-30 dpd) in the last 6 months |
| 17 | Number of Times 30-days (1-30 dpd) in the last 12 months |
| 18 | Number of Times 30-days (1-30 dpd) in the last 24 months |
| 19 | Number of Times 60-days (1-60 dpd) in the last 3 months |
| 20 | Number of Times 60-days (1-60 dpd) in the last 6 months |
| 21 | Number of Times 60-days (1-60 dpd) in the last 12 months |
| 22 | Number of Times 60-days (1-60 dpd) in the last 24 months |
| 23 | Number of Times 90-days (1-90 dpd) in the last 3 months |
| 24 | Number of Times 90-days (1-90 dpd) in the last 6 months |
| 25 | Number of Times 90-days (1-90 dpd) in the last 12 months |
| 26 | Number of Times 90-days (1-90 dpd) in the last 24 months |
| 27 | Percentage Current last 3 Months |
| 28 | percentage x-days (or greater) last 3 months |
| 29 | Percentage 30 days (or greater) last 3 months |
| 30 | Percentage 60 days (or greater) last 3 months |
| 31 | Percentage 90 days (or greater) last 3 months |
| 32 | Percentage Current last 6 Months |

| | **Customer Level Variables** |
|---|---|
| 1 | Number of Active Loans |
| 2 | Number of Micro Loans (open) |
| 3 | Number of Salary Loans (open) |
| 4 | Number of Salary loans opened last 3 / 6 12 months |
| 5 | Number of Micro loans opened last 3 / 6 12 months |
| 6 | Number of Micro Loans Paid off Last 3 / 6 ./ 12 months |
| 7 | Number of Salary Loans Paid off Last 3 / 6 ./ 12 months |
| 8 | Additional loan opened last month |
| 9 | Number of loans opened in the last 6 months |
| 10 | Number of loans opened in the last 3 months |
| 11 | Ratio of number of loans to new / recent loans (last 3 months) |
| 12 | Ratio of number of loans to new / recent loans (last 6 months) |
| 13 | Time to shortest Maturity |
| 14 | Number of Loans Maturing in the next 3 months |
| 15 | Number of Loans Maturing in the next 6 months |
| 16 | Number of Loans Maturing in the next 12 months |
| 17 | Proportion of Loans maturing in the next 3 / 6 / 12 months |
| 18 | Total Payment Amt (in Month) |
| 19 | Worst Delq status last 3 months (all MCS loans) |
| 20 | Worst Delq status last 6 months (all MCS loans) |
| 21 | Worst Delq status last 12 months (all MCS loans) |
| 22 | Worst Delq status last 24 months (all MCS loans) |
| 23 | Number of Times current-days (no delq) in the last 3 months |
| 24 | Number of Times Current (no delq) in the last 6 months |
| 25 | Number of TimesCurrent (no delq) in the last 12 months |
| 26 | Number of Times current (no delq) in the last 24 months |
| 27 | Number of Times X-days (1-30 dpd) in the last 3 months |
| 28 | Number of Times X-days (1-30 dpd) in the last 6 months |
| 29 | Number of Times X-days (1-30 dpd) in the last 12 months |
| 30 | Number of Times X-days (1-30 dpd) in the last 24 months |

# Data Exercise – 15 Minutes

## Raw Data

‘ min_repordate',
'max_reportdate’,
'CYCLE_COUNT',
'CYCLE_NUM',
'CYCLE_POINT',
'loan_product’,
'CIF_ID',
'FORACID’,
'OPEN_DATE',
'MATURE_DATE',
'DISBURSED_AMOUNT’,
'BALANCE’,
'OVERDUE_DAY',
'TOTAL_AMT',
'REPORTDATE’,
‘Delq Cycle’

]

## Derived Data

Please design 5 derived characteristics
based upon the raw data

And what information are you engineering into the model

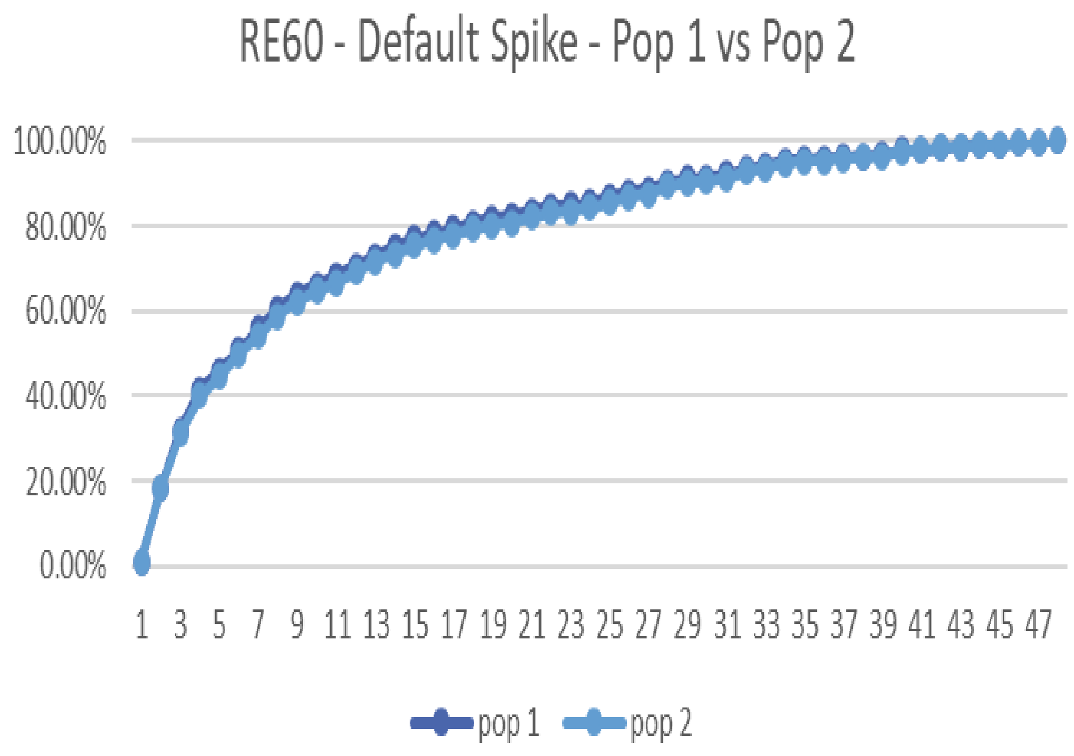
# Sample Window Selection

Considerations for the Sample Window chosen

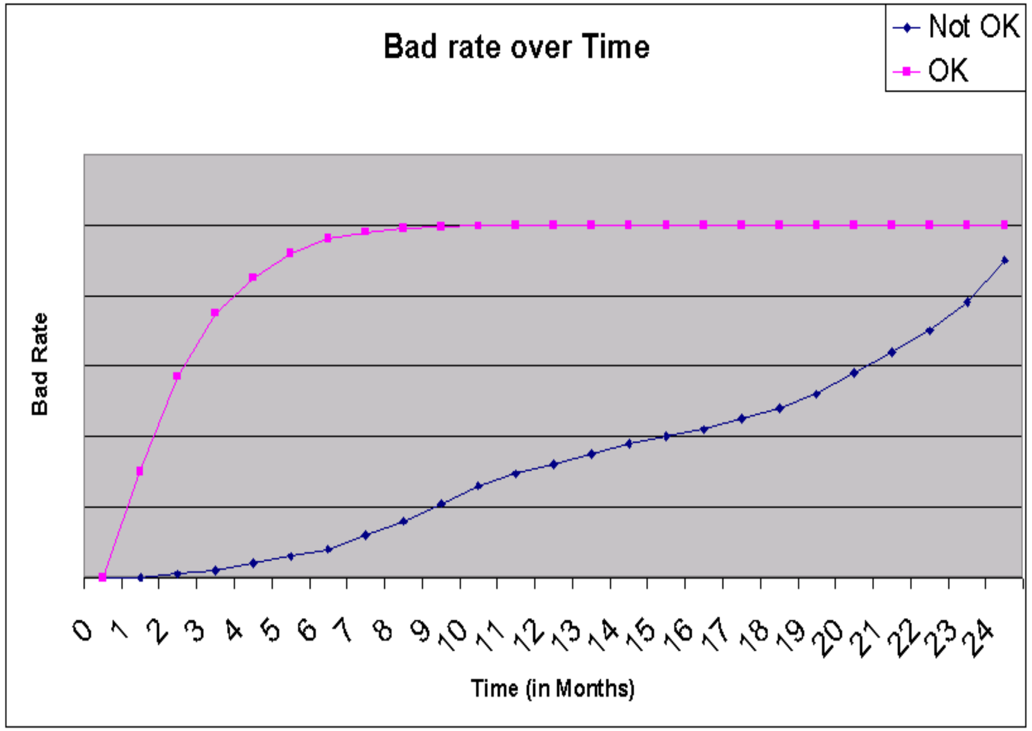
- Volumes
  - Is there enough volume within the good-bad categories? Typically, scorecards require at least 750 of each
  - Do sufficient volumes exist for the suggested or desired scorecard segments?
- Is the Sample Window representative of the ‘Going Forward’ World?
  - Long Outcome Windows may be less relevant
  - Have there been or expected to be changes in the portfolio?
  - Are the products offered today the same as in the past? How do they differ?
  - Have there been any specific marketing events that need considering?
- Data Availability
  - Are all the characteristics available for the entire observation period?
  - Is retrospective bureau data available for the observation period?
- Seasonality
  - Do special events in the year affect the flow of the portfolio, e.g. Christmas?
  - Selecting 12-month observation window help to smooth out spikes in demand or delinquency?

# Vintage Analysis – Length of the window

**Time to Bad Analysis:**




**Vintage Report:**




**Choose period when bad rate is stable / flattens**

**Examination of the Bad Rate over time will identify the exposure required for the outcome period**

# Roll-Rate Analysis – Confirming Good-Bad Definition

## Maintaining Stability

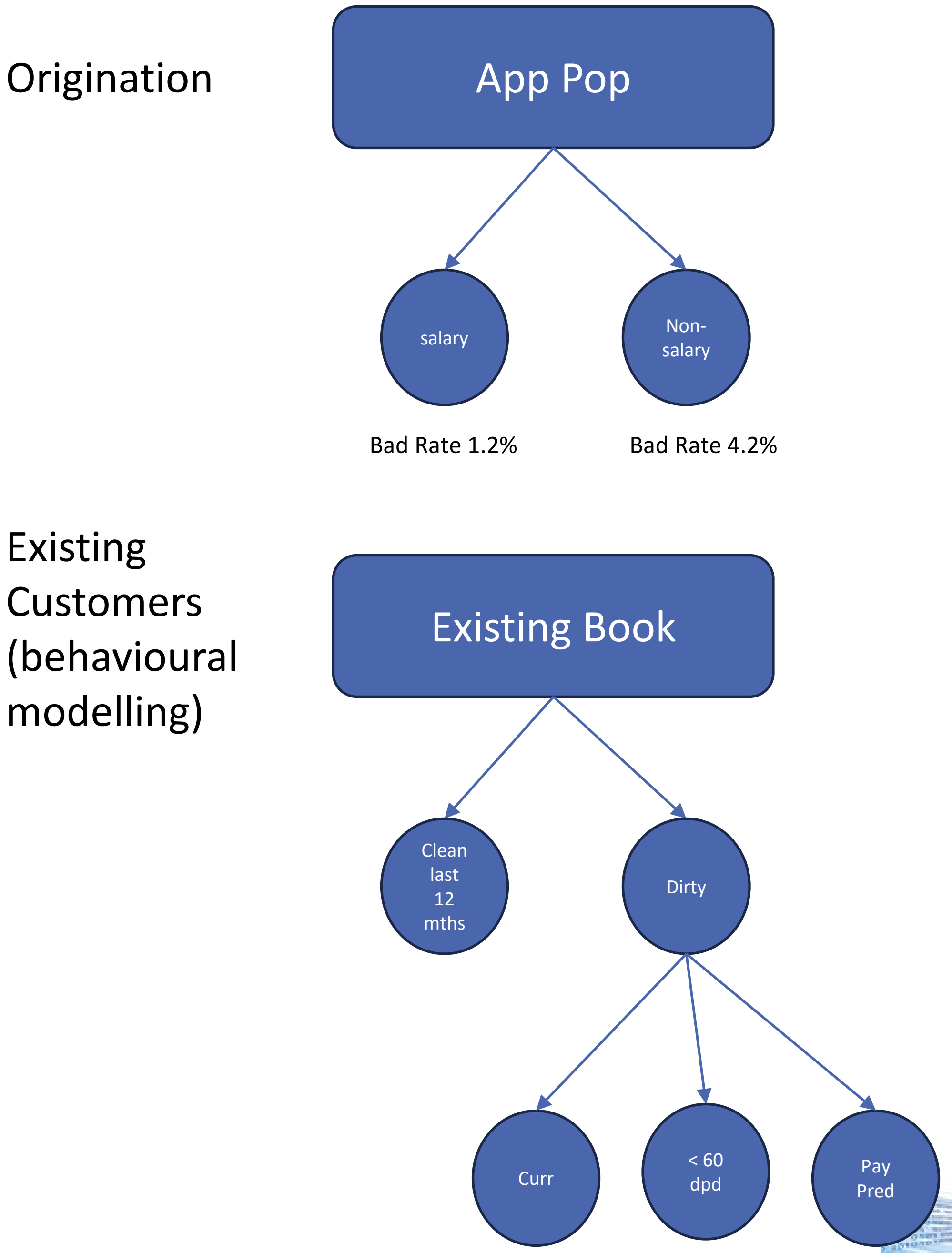
### Example Roll-Rate Analysis:

| | | GB_ind_Dec06 | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | B | B | B | B | B | B | B | B | B | B | B | B | B | B/I | I | I | I | I | I/G | I/G | G | G | G |
| GB_ind_Jun06 | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
| B | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| B | 2 | | 768 | | | | | | | | | | | | | | | | | | | | | |
| B | 3 | | | 1 | | | | | | | | | | | | | | | | | | | | |
| B | 4 | | 1306 | | 356 | 65 | 30 | 10 | 31 | 7 | 106 | 8 | | | 4 | 1 | 7 | | 6 | 6 | | 8 | 14 | 11 |
| B | 5 | | 458 | | 390 | 136 | 58 | 34 | 34 | 18 | 111 | 15 | 2 | 2 | 5 | 16 | 32 | | 19 | 7 | | 12 | 10 | 7 |
| B | 6 | | 21 | | 32 | 17 | 4 | 2 | | | 1 | 3 | | 3 | | | 3 | | 5 | 4 | | 2 | 1 | 2 |
| B | 7 | | 27 | | 73 | 36 | 4 | 2 | 4 | 6 | 2 | 2 | | 6 | 4 | 5 | 3 | | 5 | | | 2 | 2 | |
| B | 8 | | 15 | | 14 | 7 | 1 | 2 | 2 | 1 | 1 | 2 | | 1 | 3 | 1 | | | 5 | 5 | | 6 | 2 | 5 |
| B | 9 | | 9 | | 23 | 9 | 4 | 3 | 1 | 4 | 5 | 17 | | 5 | 5 | | 3 | | 24 | 9 | | 45 | 3 | 11 |
| B | 10 | | | | 18 | 4 | | | 2 | 1 | | 3 | 1 | | | | | | 5 | 4 | 1 | 13 | 168 | 9 |
| B | 11 | | 156 | | 184 | 41 | 8 | 8 | 6 | 7 | 12 | 47 | 3 | 20 | 18 | 2 | 25 | | 76 | 16 | 1 | 18 | 2 | 3 |
| B | 12 | | 165 | | 206 | 57 | 29 | 19 | 5 | 17 | 39 | 19 | 4 | 16 | 13 | 8 | 80 | | 53 | 62 | 1 | 86 | 34 | 6 |
| B | 13 | | 3 | | 32 | 23 | 1 | 2 | 1 | 4 | 1 | 30 | 10 | 9 | 11 | | 4 | | 19 | 15 | | 27 | 14 | 4 |
| B/I | 14 | | 19 | | 129 | 22 | 5 | 2 | 3 | 2 | 4 | 26 | 8 | 7 | 11 | 2 | 7 | | 46 | 19 | 2 | 68 | 9 | 16 |
| I | 15 | | | | 1 | 2 | | | | | | | | | | | | | | 1 | | 3 | 62 | 11 |
| I | 16 | | | | 9 | 4 | | | | | | 5 | 3 | | 2 | | 4 | | 4 | 11 | | 21 | 231 | 24 |
| I | 17 | | | | 3 | 1 | 1 | | | | | | | | | | | | 1 | | | | | 1 |
| I | 18 | | 2 | | 28 | 15 | | 2 | | 2 | 2 | 32 | 31 | 6 | 7 | | 5 | | 16 | 16 | 8 | 71 | 458 | 144 |
| I/G | 19 | | 66 | | 269 | 108 | 2 | 13 | 6 | 13 | 32 | 80 | 59 | 19 | 114 | 8 | 19 | | 196 | 195 | 9 | 674 | 144 | 240 |
| I/G | 20 | | 89 | | 117 | 61 | 6 | 11 | 6 | 13 | 18 | 45 | 71 | 14 | 39 | 6 | 28 | | 106 | 63 | 12 | 296 | 74 | 271 |
| G | 21 | | 2 | | 163 | 79 | 5 | 5 | 2 | 7 | 10 | 26 | 203 | 7 | 21 | 2 | 18 | | 127 | 316 | 91 | 997 | 2268 | 946 |
| G | 22 | | | | | 1 | | | | | | | | | | | | | | 2 | 1 | 4 | 3718 | 14 |
| G | 23 | | 4 | | 533 | 338 | 8 | 11 | 2 | 15 | 38 | 143 | 209 | 34 | 79 | 7 | 81 | | 323 | 410 | 299 | 2109 | 1758 | 9726 |
| | | 0 | 3110 | 1 | 2580 | 1026 | 166 | 126 | 105 | 117 | 382 | 503 | 604 | 149 | 336 | 58 | 319 | 0 | 1036 | 1161 | 425 | 4462 | 8972 | 11451 |

| | | | GB Ind 1-14 | GB Ind 15-20 | GB Ind 21-23 | Flow fr | Flow fr | Flow fr |
|---|---|---|---|---|---|---|---|---|
| GB_ind_Jun06 | | All | Bad | Indet. | Good | Bad | Indet. | Good |
| B | 1 | 0 | 0 | 0 | 0 | N/A | N/A | N/A |
| B | 2 | 768 | 768 | 0 | 0 | 100.00% | 0.00% | 0.00% |
| B | 3 | 1 | 1 | 0 | 0 | 100.00% | 0.00% | 0.00% |
| B | 4 | 1976 | 1919 | 24 | 33 | 97.12% | 1.21% | 1.67% |
| B | 5 | 1366 | 1258 | 79 | 29 | 92.09% | 5.78% | 2.12% |
| B | 6 | 100 | 83 | 12 | 5 | 83.00% | 12.00% | 5.00% |
| B | 7 | 183 | 162 | 17 | 4 | 88.52% | 9.29% | 2.19% |
| B | 8 | 73 | 46 | 14 | 13 | 63.01% | 19.18% | 17.81% |
| B | 9 | 180 | 80 | 41 | 59 | 44.44% | 22.78% | 32.78% |
| B | 10 | 229 | 29 | 10 | 190 | 12.66% | 4.37% | 82.97% |
| B | 11 | 653 | 492 | 138 | 23 | 75.34% | 21.13% | 3.52% |
| B | 12 | 919 | 576 | 217 | 126 | 62.68% | 23.61% | 13.71% |
| B | 13 | 210 | 116 | 49 | 45 | 55.24% | 23.33% | 21.43% |
| B/I | 14 | 407 | 227 | 87 | 93 | 55.77% | 21.38% | 22.85% |
| I | 15 | 80 | 3 | 1 | 76 | 3.75% | 1.25% | 95.00% |
| I | 16 | 318 | 21 | 21 | 276 | 6.60% | 6.60% | 86.79% |
| I | 17 | 7 | 5 | 1 | 1 | 71.43% | 14.29% | 14.29% |
| I | 18 | 845 | 120 | 52 | 673 | 14.20% | 6.15% | 79.64% |
| I/G | 19 | 2266 | 667 | 541 | 1058 | 29.44% | 23.87% | 46.69% |
| I/G | 20 | 1346 | 451 | 254 | 641 | 33.51% | 18.87% | 47.62% |
| G | 21 | 5295 | 509 | 575 | 4211 | 9.61% | 10.86% | 79.53% |
| G | 22 | 3740 | 1 | 3 | 3736 | 0.03% | 0.08% | 99.89% |
| G | 23 | 16127 | 1335 | 1199 | 13593 | 8.28% | 7.43% | 84.29% |
| | | 37089 | 8869 | 3335 | 24885 | 23.91% | 8.99% | 67.10% |

# Why Segment?

- Diverse Customer Profiles
- Improved Accuracy
    - Segmentation enhances the accuracy of risk assessment by accounting for nuances within each customer segment, reducing the likelihood of misclassification.
- Key Reasons for Segmentation
    - **Risk Differentiation –** there are differences within the risk profiles associated with differing segments
    - **Customized Strategies –** segmentation gives the ability to tailor risk management strategies to each segment, optimizing resource allocation and improving overall risk outcomes
    - **Adaptive Modelling -** segmentation allows for adaptive modelling, ensuring that risk assessments remain relevant and effective in dynamic retail environments
    - Implementation Challenges – segmentation allows for differing data by segment to be assessed
- Increased Model Complexity – segmentation may add model risk into the process, increases model management overhead (monitoring, validation, management committees / approvals)



# Confirming Segmentation – Differing Performance

| Current | | | | |
|---|---|---|---|---|
| Interval | Known Woe | Known GB Odds | Totals | Totals % |
| 0 | 3.66 | 40.72 | 453279 | 58.50% |
| 1-10 | 3.24 | 125.86 | 77675 | 10.03% |
| 11-25 | 2 | 39.84 | 65666 | 8.48% |
| 26-40 | 1.32 | 13.37 | 63213 | 8.16% |
| 41-50 | 0.34 | 8.18 | 54362 | 7.02% |
| 51-65 | -1.3 | 5.77 | 23421 | 3.02% |
| 66-80 | -1.8 | 4.5 | 16542 | 2.13% |
| 81-100 | -2.1 | 2.77 | 12652 | 1.63% |
| 101+ | -2.5 | 2.25 | 5643 | 0.73% |
| Others | 0.12 | 10.1 | 2352 | 0.30% |
| total | | 17.17 | 774805 | 100.00% |

**1. Is the Population large enough?**

**2. Are the GB Odds different?**

**3. Is the Risk Profile different?**

**4. Is the Population % distribution different?**

| Delq | | | | |
|---|---|---|---|---|
| Interval | Known Woe | Known GB Odds | Totals | Totals % |
| 0 | 2.1 | 9.52 | 34500 | 32.20% |
| 1-10 | 1.75 | 17.47 | 19876 | 18.55% |
| 11-25 | 1.55 | 8.96 | 18249 | 17.03% |
| 26-40 | 1.5 | 5.06 | 15986 | 14.92% |
| 41-50 | 0.1 | 3.26 | 4500 | 4.20% |
| 51-65 | -0.6 | 2.33 | 4032 | 3.76% |
| 66-80 | -2.3 | 1.58 | 3333 | 3.11% |
| 81-100 | -3.2 | 0.9 | 3121 | 2.91% |
| 101+ | -4.65 | 0.49 | 2321 | 2.17% |
| Others | -1.2 | 6.66 | 1234 | 1.15% |
| total | | 2.46 | 107152 | 100.00% |

Also compare Segment Characteristic Analysis Reports to the total population Characteristic Analysis to assess total differences

# Model Development

Model Prep

Model Construct

Model Check

**Univariate Analysis**

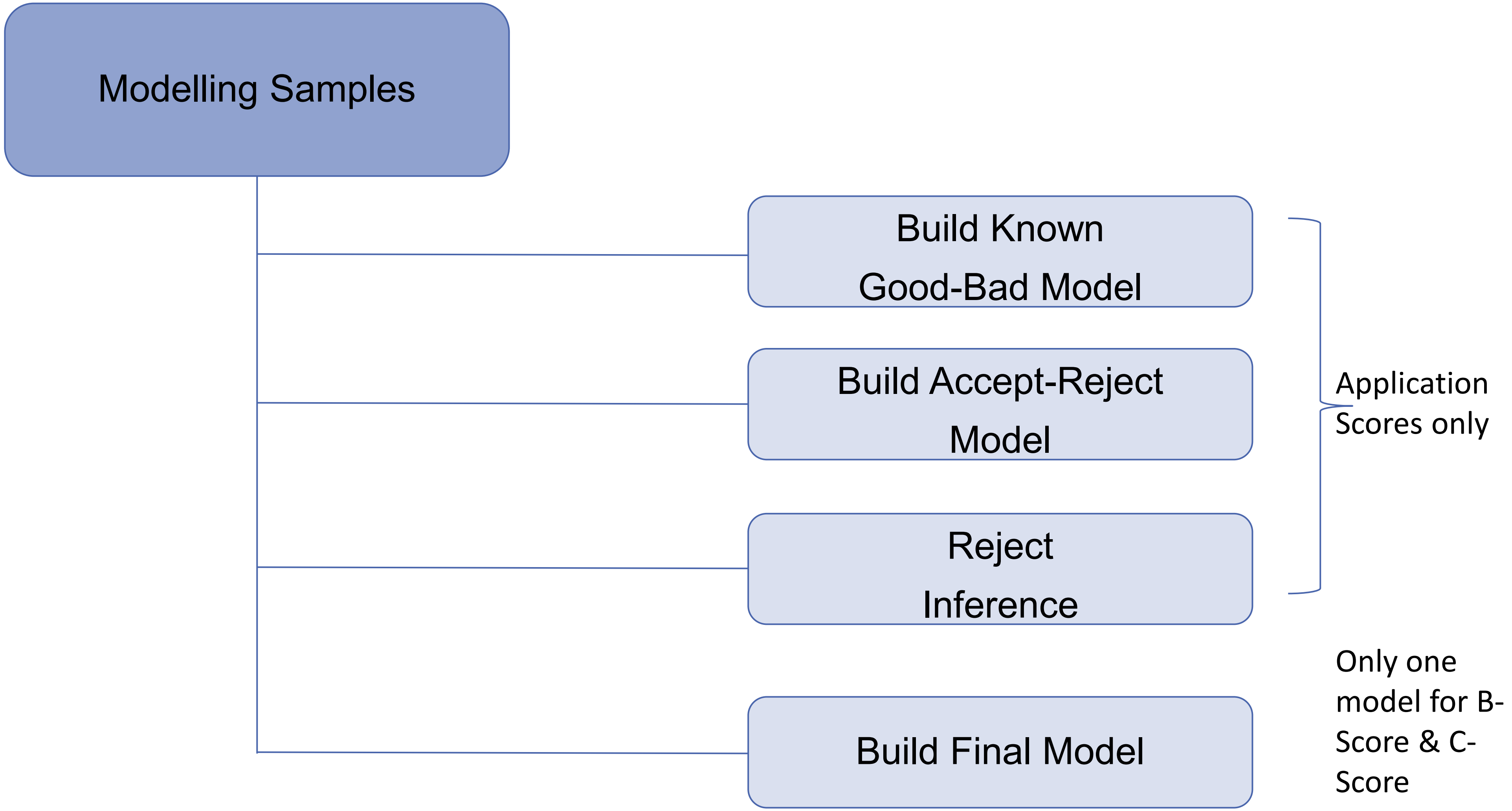
- Variable Reduction
- Population Stability
- Correlation Analysis
- Business Rationale
- Characteristic Analysis

**Modelling**

- Dummy vs Weight of Evidence Models
- Linear Regression
- Logistic Regression
- Decision Trees
- Random Forests

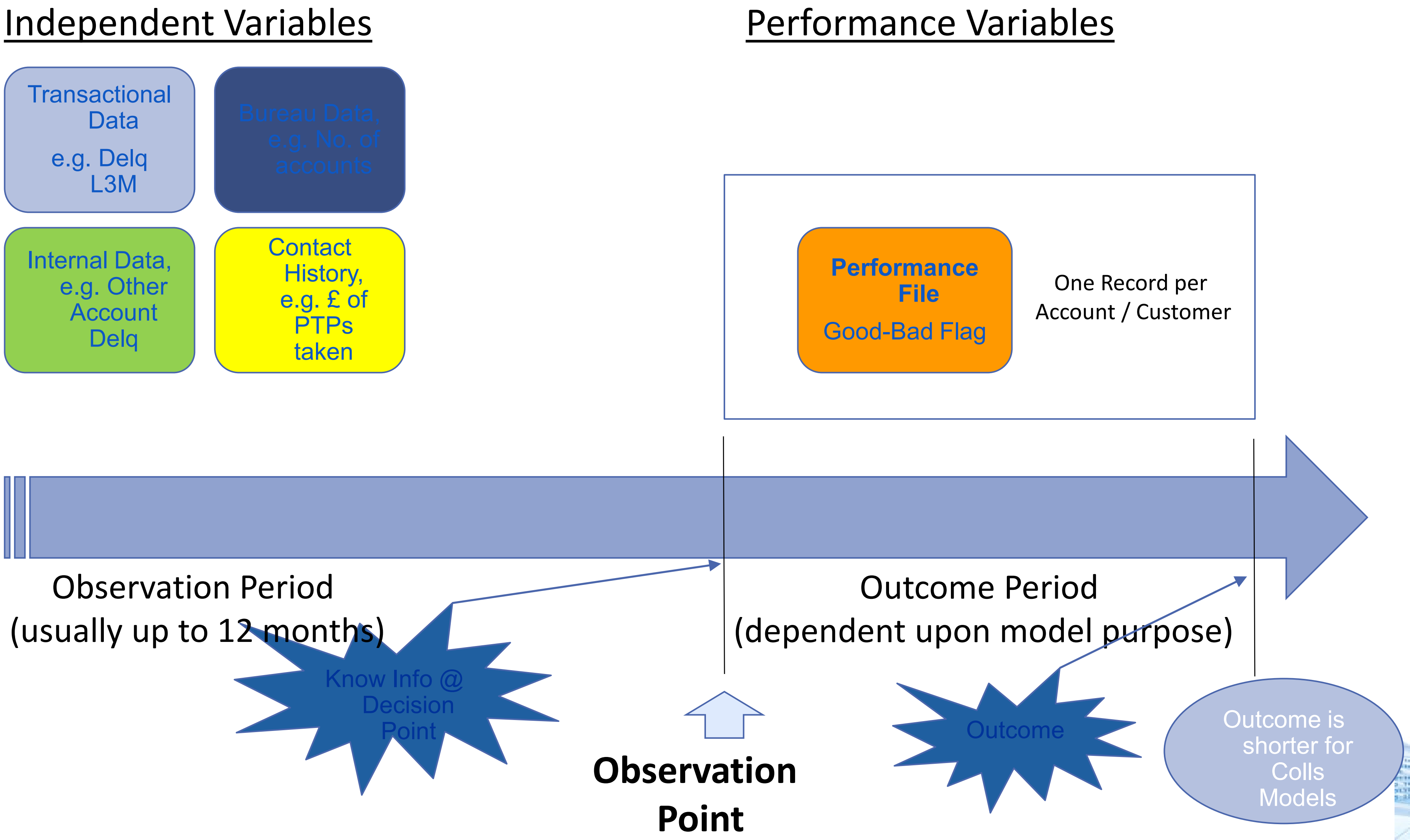
Diagnostics (Score Dist, Gini, KSI etc)

# Modelling Process Flow – Application Scores



# Customer Management Analytics - Sampling

Data Elements can be at account or customer level OR be external bureau type chars



# Introduction to Paragon Modeller
(www.credit-scoring.co.uk)

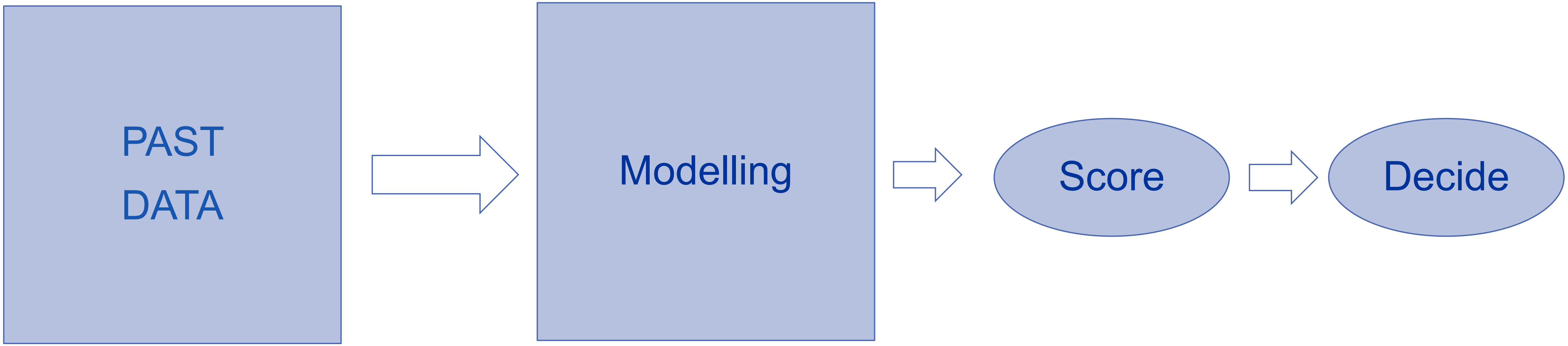
- Reading Modelling Data – Read the given dataset
- Basic Manipulation
- Assigning Good Bad definitions / Generating Characteristics

# Exercise Discussion

- What have we learnt?
- Modeller Questions

# Modelling Steps 2

# Model Process – Univariate Analysis




**<u>Characteristic Reduction</u>**

- PSI
- Characteristic Analysis
- Fine to Coarse Classing
- Correlation Analysis
- Business Rationale

**<u>Statistical Modelling</u>**

- Linear Regression
- Logistic Regression
- Decision Tress
- Random Forests

# Characteristic Reduction

- In Feature Engineering we may generate hundreds / thousands of characteristics
- Importance of Reducing Variables within the Model Selection Process:
- Simplicity and Interpretability (for model / product stakeholders, model validators / approvers & regulators)
- More efficient to build, less opportunity for the developers to engineer in Model Risk
- Reduced likelihood of generalised model over-fitting (tailored specifically to the development data)
- Easier to implement and maintain
- Efficiency in model development, it is impossible to analyse 1000s of characteristics
- Simpler (lower characteristic models) tend to be more robust and less prone (to deterioration) to small changes in the operational environment, therefore are more reliable & robust for longer
- Simpler models have less monitoring, on-going modelling overhead, may introduce less Model Risk

# Correlation Considerations

- Correlation is a measure of how similar or how the information given by the characteristic is the same as the other variable
- Highly correlated variables may interact with each other and cause the models to be over fitted
- Where multicollinearity exists the true relationship between variables may be hidden
- Where correlation exists the opinions of model or portfolio experts may be blunted
- Within the scorecard arena we typically utilise Pearson or Spearman Correlations metrics

**Pearson's Correlation Co-Efficient**: -

$$r = \frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_i - \overline{X})^2 \sum(Y_i - \overline{Y})^2}}$$

Where Xi and Yi are the individual data points, and $\overline{X}$ and $\overline{Y}$ are the means of X and Y, respectively

**Spearman Rank Correlation Coefficient**:-

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

Where $d_i$ is the difference the ranks of the corresponding data points X and Y and n is the number of data

# Selection Statistics
# Weight of Evidence / Value of Information

- Weight of Evidence is a relationship between the proportion of goods and bads with a particular attribute of a cell
- The Value of Information or Information Value is a measure of predictive power across the variable

| Range | Pred. Power | Action |
|---|---|---|
| <= 0.02 | Very Weak | Exclude / Drop |
| 0.02 – <= 0.1 | Weak | Exclude / Drop / Review |
| 0.1 - <= 0.3 | Medium | Include / Keep / Review |
| 0.3 - <= 0.5 | Strong | Include / Keep |
| >= 0.5 | Very Strong | Include / Keep / Review |

**Weight of Evidence**

$$WoE = \ln\left(\frac{\%\,goods}{\%\,bads}\right)$$

**Value of Information**

$$\text{IV} = \sum(\%\,goods - \%\,bads) \times WoE$$

# Exercise – Modeller Field Reduction

- Let’s play with the Field Reducer in Modeller
- Discuss key fields / reduction parameters
- Review the results
  - What’s in the key list?
  - Anything worthwhile or business worthy in the delete list?

# Characteristic Analysis

- At a characteristic level the developer wishes to compare the distribution of goods and bads across the attributes in order to ensure that predictive trends are consistent and intuitive will perceive business logic
- The predictive trends across the attributes should be broadly linear in an increasing or decreasing manner (dependent upon the characteristic)
- Characteristics with counter-intuitive (unexpected) trends will be excluded from further analysis unless the trend can be explained due to business process and procedures, e.g. for product A, older customers are higher risk.
- Additionally, we try to keep greater than 50 goods and 50 bads in each characteristic group
- Records should not be overly concentrated in one attributed band
- We try to reduce the number of attribute groups to 6 or 7 (for low volume scorecards there are likely to be less groups, perhaps 4 or 5)
- Groups are combined into classes of similar risk (risk can be measured by GB Odds, Bad Rate or Weight of Evidence (WoE))
- Categorical fields should be grouped into like meaning categories, e.g. owned and mortgaged property

# Measures of Characteristic Performance

- The developer wishes to ensure that the characteristics used within the model exhibit a degree of stability over time (ensuring that a robust model is constructed)
- The Population Stability Index (PSI) is the standard best practice measure used to determine stability across samples drawn from different time period
- The measure illustrates the discrepancy between two populations (development versus validation), when used with individual characteristics it will show that whether the information being given has changed
- PSI <= 0.1 means that the two populations are sufficient stable for the characteristic to be considered for model entry

| | | | | | PSI | | |
|---|---|---|---|---|---|---|---|
| **Attribute** | **2012** | **2012 Percentage (A)** | **2014** | **2014 Percentage (B)** | **C= A -B** | **D=Ln(a /B)** | **E=C*D** |
| Current | 229,195 | 0.56 | 233923 | 0.57 | -0.01 | -0.0117 | 0.0001 |
| X-dpd | 107,295 | 0.26 | 117,042 | 0.29 | -0.02 | -0.0782 | 0.0017 |
| 30 dpd | 26567 | 0.07 | 16158 | 0.04 | 0.03 | 0.5060 | 0.0132 |
| 60 dpd | 17824 | 0.04 | 15284 | 0.04 | 0.01 | 0.1625 | 0.0011 |
| 90 dpd | 9967 | 0.02 | 7503 | 0.02 | 0.01 | 0.2927 | 0.0018 |
| 120+ dpd | 14847 | 0.04 | 19339 | 0.05 | -0.01 | -0.2556 | 0.0027 |
| | 405,695 | 1.00 | 409249 | 1.00 | | | 0.0205 |

# Measures of Characteristic Performance

- The developer wishes to ensure that the characteristics used within the model are predictive, and utilises the Information Value (IV), also referred to as the Value of Information (VOI) as a measure of relative power
- Measures the discrepancy between goods and bads, taken from the same time based sample
- A Low value of VOI indicates that the good and bad populations are similar and is therefore not predictive, i.e. will not help to separate good and bad accounts or customers

| | | | | | **VOI** | | |
|---|---|---|---|---|---|---|---|
| **Attribute** | **Good** | **Good Percentage (A)** | **Bad** | **Bad Percentage** | **C= A -B** | **D=Ln(a /B)** | **E=C*D** |
| Current | 226,900 | 0.56 | 1,195 | 0.00 | 0.56 | 5.2551 | 2.9238 |
| X-dpd | 105,800 | 0.26 | 897 | 0.00 | 0.26 | 4.7790 | 1.2358 |
| 30 dpd | 25,692 | 0.06 | 674 | 0.00 | 0.06 | 3.6494 | 0.2251 |
| 60 dpd | 16,889 | 0.04 | 886 | 0.00 | 0.04 | 2.9564 | 0.1167 |
| 90 dpd | 8,056 | 0.02 | 1,910 | 0.00 | 0.02 | 1.4480 | 0.0220 |
| 120+ dpd | 9,653 | 0.02 | 5,211 | 0.01 | 0.01 | 0.6252 | 0.0069 |
| | 392,990 | 0.97 | 10,773 | 0.03 | | | 4.5303 |

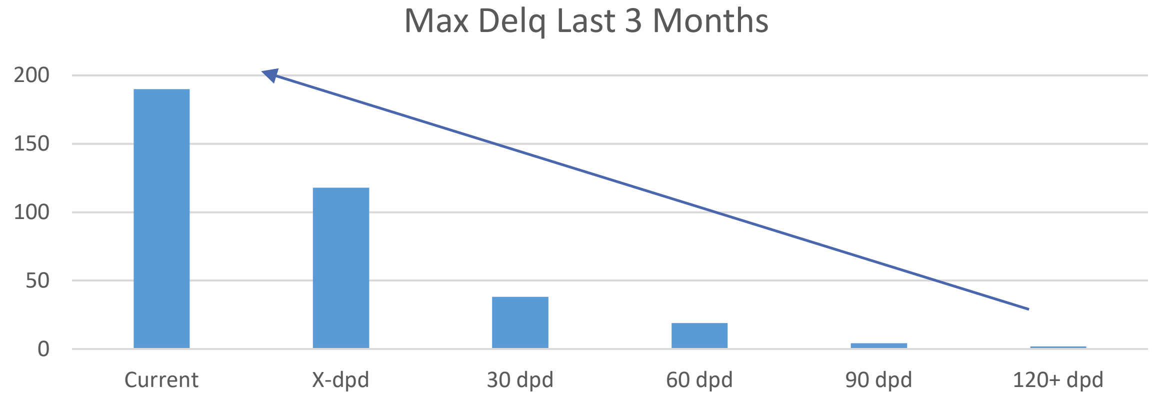
# Measures of Characteristic Performance

- The developer wishes to ensure that the characteristics used within the model are not overly correlated, i.e. telling the same piece of information
- Correlation causes characteristics to come into the model with conflicting predictive trends that may be counter-intuitive and out of line with earlier project analysis (characteristic analysis trends)
- Characteristics with the highest VOI should be selected for regression consideration, assuming they have a correlation co-efficient greater than 0.3 (the threshold can be changed)

| Characterictic | VOI |
|---|---|
| Worst Delq in the last month | 2.61 |
| Worst Delq in the last 3 months | 2.73 |
| Worst Delq in the last 6 months | 2.68 |
| Worst Delq in the last 12 months | 2.71 |

# Characteristic Analysis

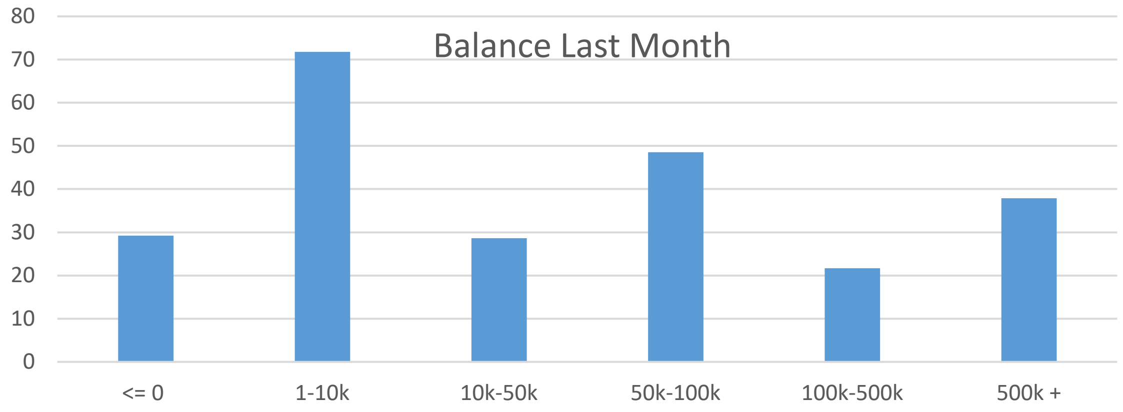
| Attribute | Good | Good % | Bad | Bad % | GB Odds | WoE | Total | Total % |
|---|---|---|---|---|---|---|---|---|
| Current | 226,900 | 0.56 | 1,195 | 0.0029 | 189.8745 | 5.255085 | 228,095 | 56.49% |
| X-dpd | 105,800 | 0.26 | 897 | 0.0022 | 117.9487 | 4.778972 | 106,697 | 26.43% |
| 30 dpd | 25,692 | 0.06 | 674 | 0.0016 | 38.11869 | 3.649427 | 26,366 | 6.53% |
| 60 dpd | 16,889 | 0.04 | 886 | 0.0022 | 19.06208 | 2.956423 | 17,775 | 4.40% |
| 90 dpd | 8,056 | 0.02 | 1,910 | 0.0047 | 4.217801 | 1.448036 | 9,966 | 2.47% |
| 120+ dpd | 9,653 | 0.02 | 5,211 | 0.0127 | 1.852428 | 0.625219 | 14,864 | 3.68% |
| | 392,990 | 0.97 | 10,773 | 0.03 | 36.47916 | | 403,763 | 100.00% |




**Predictive Trend Observed**

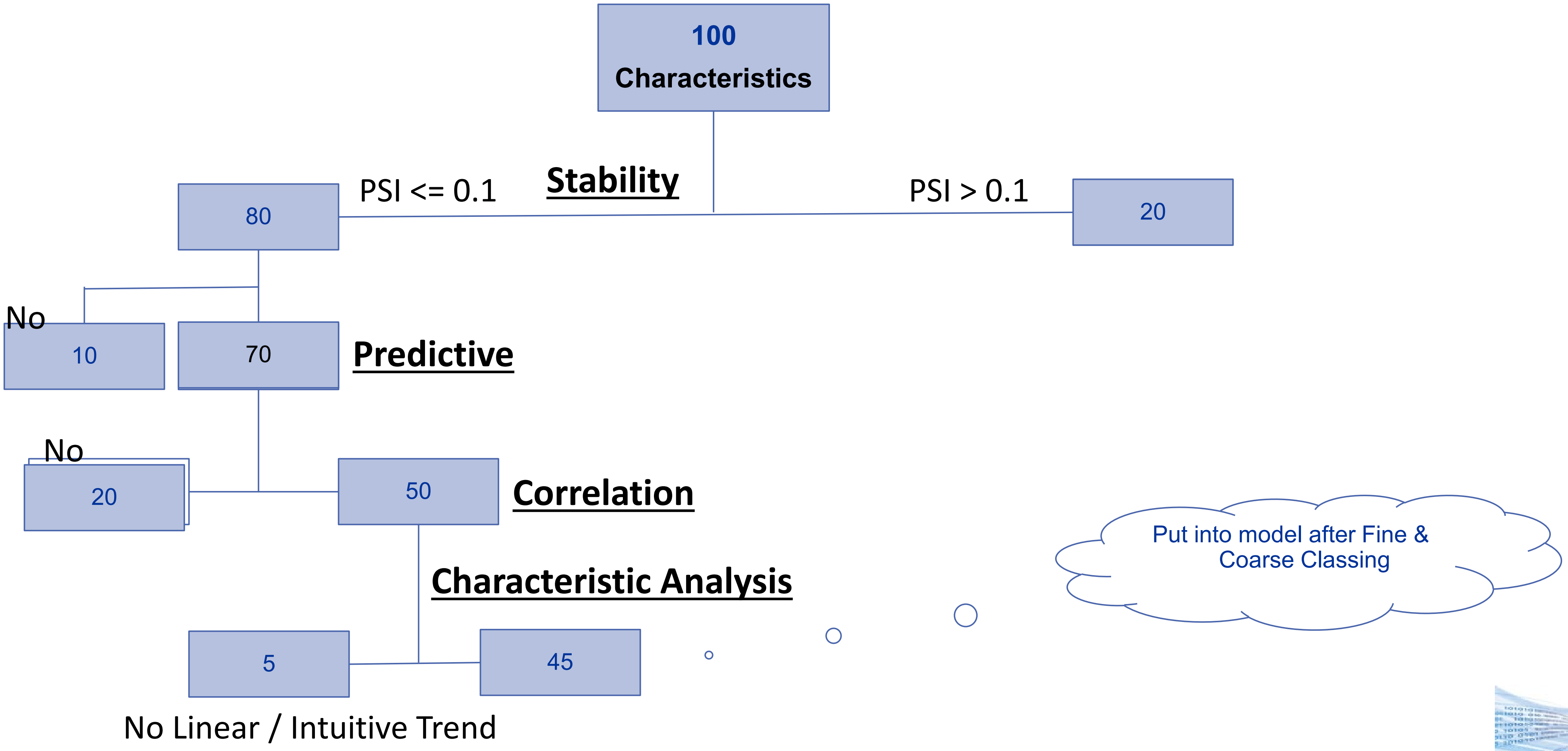
# Characteristic Analysis

| Attribute | Good | Good % | Bad | Bad % | GB Odds | WoE | Total | Total % |
|---|---|---|---|---|---|---|---|---|
| <= 0 | 106,811.00 | 27.19% | 3,655.00 | 34.03% | 29.22326 | 0.799194 | 110,466.00 | 27.37% |
| 1-10k | 98,625.00 | 25.11% | 1,374.00 | 12.79% | 71.77948 | 1.963016 | 99,999.00 | 24.78% |
| 10k-50k | 36,911.00 | 9.40% | 1,289.00 | 12.00% | 28.63538 | 0.783117 | 38,200.00 | 9.47% |
| 50k-100k | 79,624.00 | 20.27% | 1,641.00 | 15.28% | 48.52163 | 1.326964 | 81,265.00 | 20.14% |
| 100k-500k | 46,243.00 | 11.77% | 2,134.00 | 19.87% | 21.66963 | 0.592619 | 48,377.00 | 11.99% |
| 500k + | 24,577.00 | 6.26% | 649.00 | 6.04% | 37.86903 | 1.035638 | 25,226.00 | 6.25% |
| | 392,791.00 | 100.00% | 10,742.00 | 100.00% | 36.56591 | | 403,533.00 | 100.00% |




**None-Predictive Trend Observed**

# Characteristic Reduction for Modelling



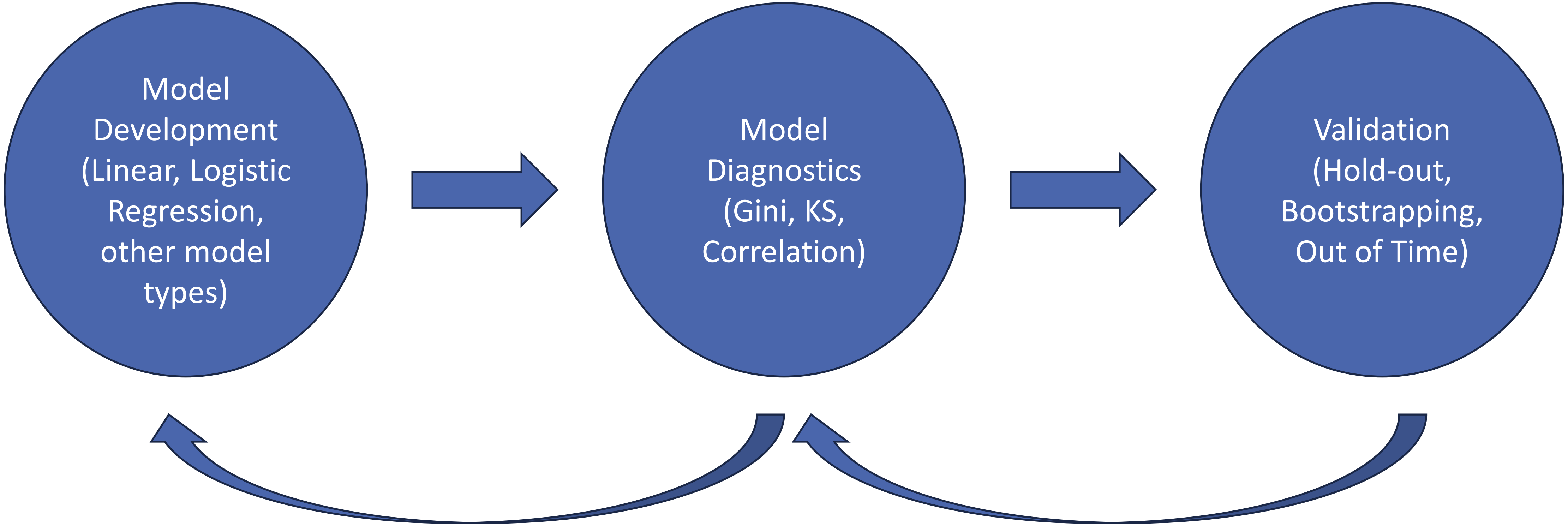
# Characteristic Classing

- For numerical characteristics the first step of the process is to produce a set of fine classed characteristics (it is usual to break the characteristics into 20 fine classes, using a statistic ranking mechanism)
- The process converts the continuous nature of the variable into a categorical characteristic
- Group manually to reduce the number of attributes by ensuring that fine classes with similar GB Odds or Weights or Evidence are coarse classed together
- The Weight of Evidence of each Coarse class can be used within the regression analysis (alternatively Dummies can be modelled)
- Coarse Classes should be created on the following principles:-
  - Increasing / decreasing trends (WoE or GB Odds)
  - Less than 8 coarse classes (for low data models this may be reduced to 4)
  - There should be greater than 2% of the population in each class
  - No. of bads in each coarse class should be greater than 50 or 1% of all bads
  - Unknown classes should be assigned to neutral classes, where WoE is close to zero

# Exercise – Grouping / Classing / Binning

- Scorecard Building Starts now
- Auto-grouping
- Grouping

# Model Development



# Comparing Linear Vs Logistic Regression

Linear Regression

**Advantages**

- Interpretability
- Widely Applicable
- Simplicity
- Can be used with continuous outcomes

**Disadvantages**

- Assumes linearity
- Sensitive to Outliers
- Limited in that it is not well suited to binary outcomes

Logistic Regression

**Advantages**

- Requires Binary Outcomes
- Produces probability based estimates
- Less sensitive to outliers

**Disadvantages**

- Complex Interpretation
- Limited to linear division boundaries

# Linear Regression Vs Logistic Regression (Equations)

General form of Linear Regression

$$\hat{Y}_j = \alpha + \sum_j \beta_j x_j$$

**Where:**
**Y: dependent variable**
**$\alpha$ : general intercept**
**$\beta$: co-efficient applied to the explanatory variable**
**x: explanatory variable**

General form of Logistic Regression

$$\Pr(x) = \frac{e^{\alpha + \sum \beta x}}{1 + e^{\alpha + \sum \beta x}}$$

Linear Regression

The output of the regression model is a probability from 0 to 1

**In Scoring:**
**Y: total score**
**$\alpha$ : constant**
**$\beta$: co-efficient applied to the characteristics**
**x: explanatory variable (e.g. age, income, sex)**

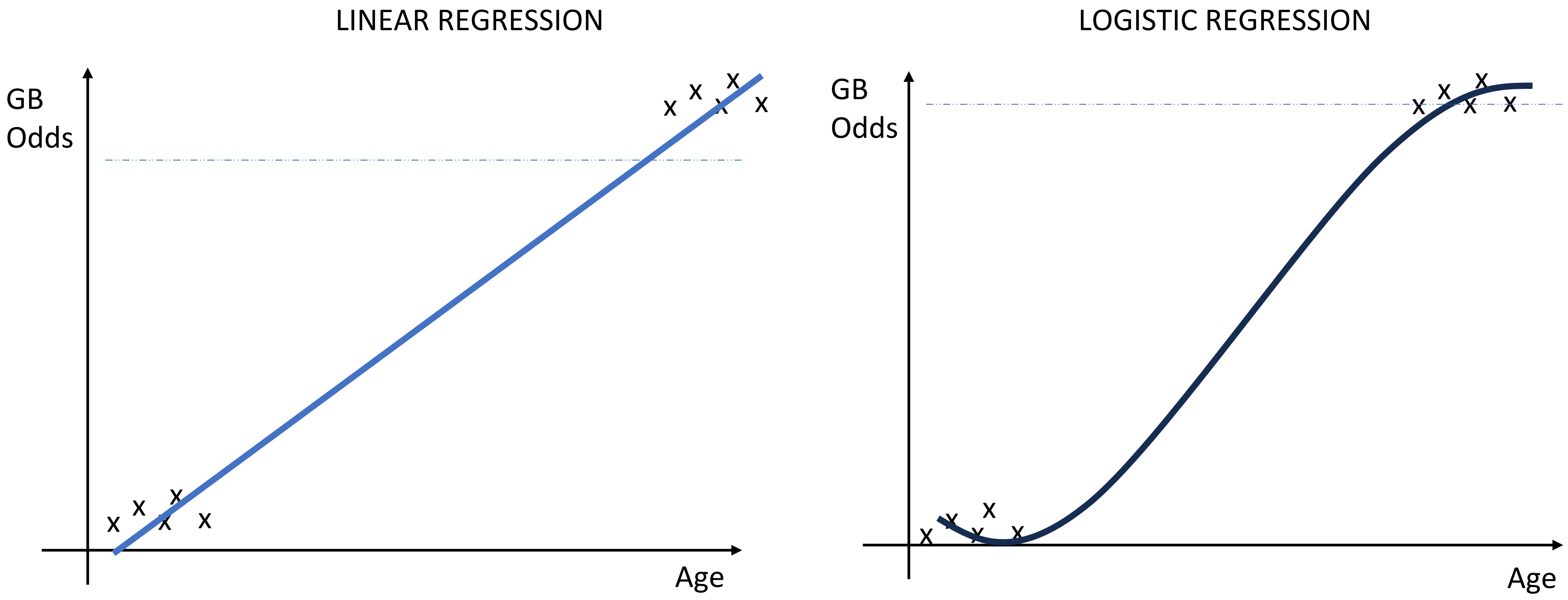
**350 [Y] = 200 [$\alpha$ ] + 50 x $Age_{30-40}$ + 40 x $Income_{50k+}$ + 60 x $Sex_{Female}$**

Other Form of Logistic Regression

$$g(x) = \ln\left[\frac{\Pr(x)}{1 - \Pr(x)}\right] = \alpha + \sum \beta x$$

# Comparing Linear Vs Logistic Regression Graphically

Comparing Graphical Patterns: Logistic Regression Vs Linear Regression




Logistic Regression tends to fit to more of the datapoints, for example predicting score by age & GB Odds

# Dummy Models Versus Weight of Evidence

Dummy Models

**<u>Advantages :-</u>**

- Characteristic Attributes split into dummy variable
- Missing values easily handled
- Encodes monotonically
- Effective in binary classification

**<u>Disadvantages:-</u>**

- Curse of dimensionally when there is are large number of attributes
- Not used in continuous outcome models
- Assumes a linear relationship between variables and target

WoE Models

**<u>Advantages:-</u>**

- Characteristic Attributes assigned their respective weight of evidence
- Applicable to all model types
- Easy to interpret as each attributes becomes a variable
- Variable contribution is easily observed

**<u>Disadvantages:-</u>**

- Increased effort to prepare modelling sample (coding inefficiency)
- Non-monotonic relationships may not be desirable
- Tends to model the extremes
- Does not handle missing variables well

# Score Creation and Scaling (PDO)

Score creation

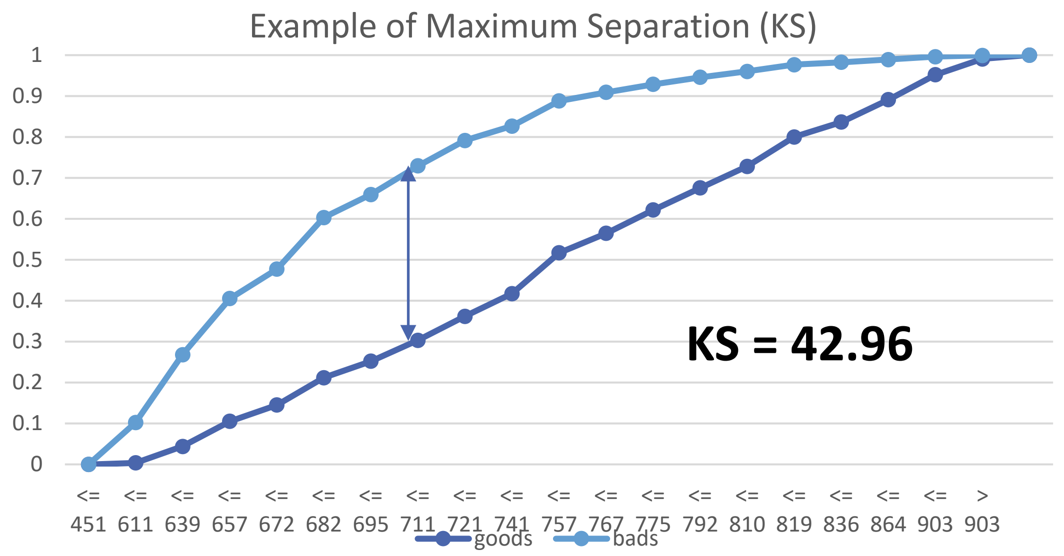
- To create the score for Dummy Models
  - Multiple the Parameter Estimate by a user determined factor
  - Sum across all characteristics, including the intercept
- To create score for WoE Models
  - Multiple the Parameter by the calculated attribute level WoE
  - Sum across all model characterisrics, including the intercept

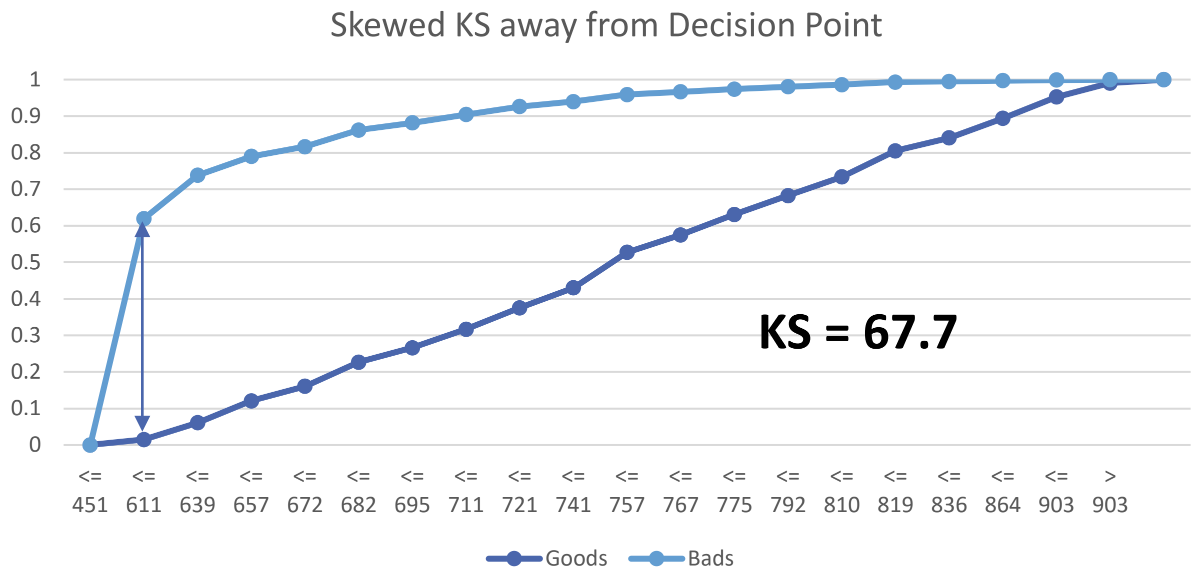
Points to Double the Odds

$$\text{Score} = \sum_{i=1}^{n} \left( -\left( woe_i * \beta + \frac{a}{n} \right) * factor + \frac{offset}{n} \right)$$

- Points to Odds (pdo), often 20 or 50
- Factor = pdo/ln(2)
- Offset = Score – (Factor * ln(odds))
- Scale the scorecards for comparison across the different models
- Comparison is only meaningful if the same performance definition is used

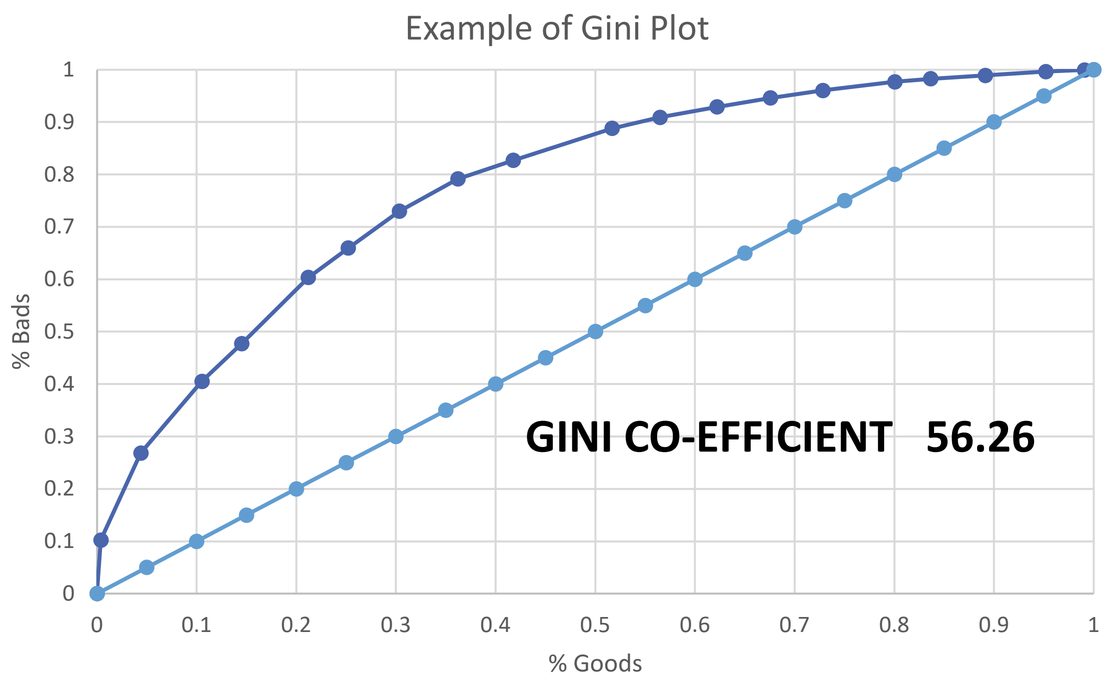
# Model Diagnostics - Kolmogorov–Smirnov (KS)

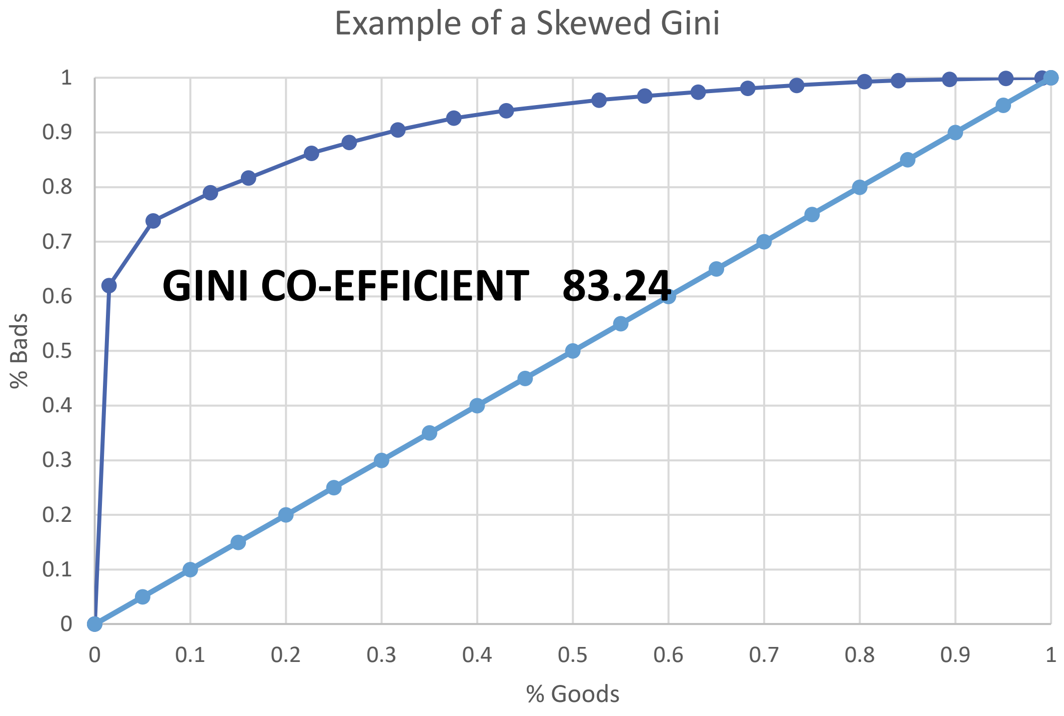



- Maximum difference between cumulative % goods and cumulative % bads
- Advantages: -
  - Standard scale 0.0 - 1.0 comparable across models
  - Identifies area where Scorecard works best (i.e. max separation)
- Disadvantages: -
  - Point of maximum difference may not fall at the decision point

# Model Diagnostics – Gini Co-Efficient / Lorenz Curve / RoC Curve

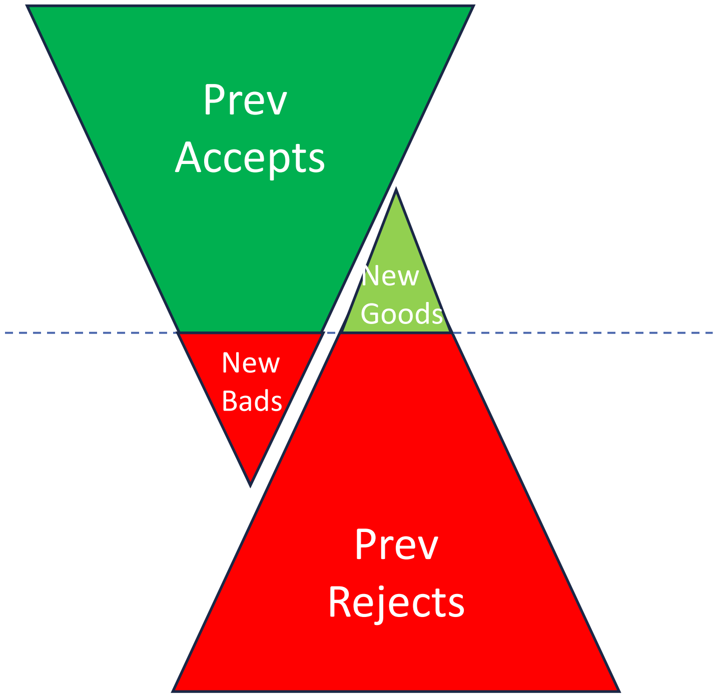


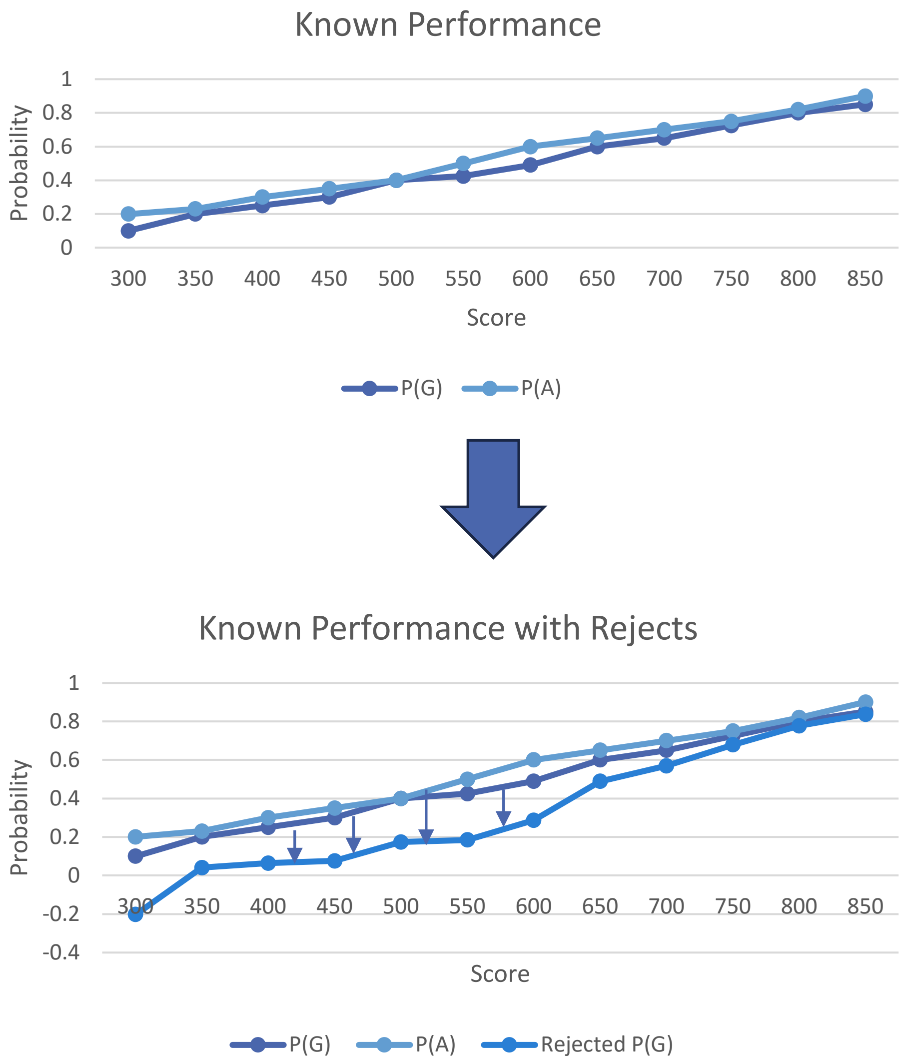




- Measures the difference between the cumulative of goods and bads by score
- Advantages: -
  - Standard scale 0% - 100% comparable across models
- Disadvantages: -
  - Separation may be skewed to high or low scores only

# Reject Inference

By building a new model with reject inference we wish to maximise the number of ‘new goods’ from the old Reject population and minimise the number of ‘new bads’ from the previous Accepted population



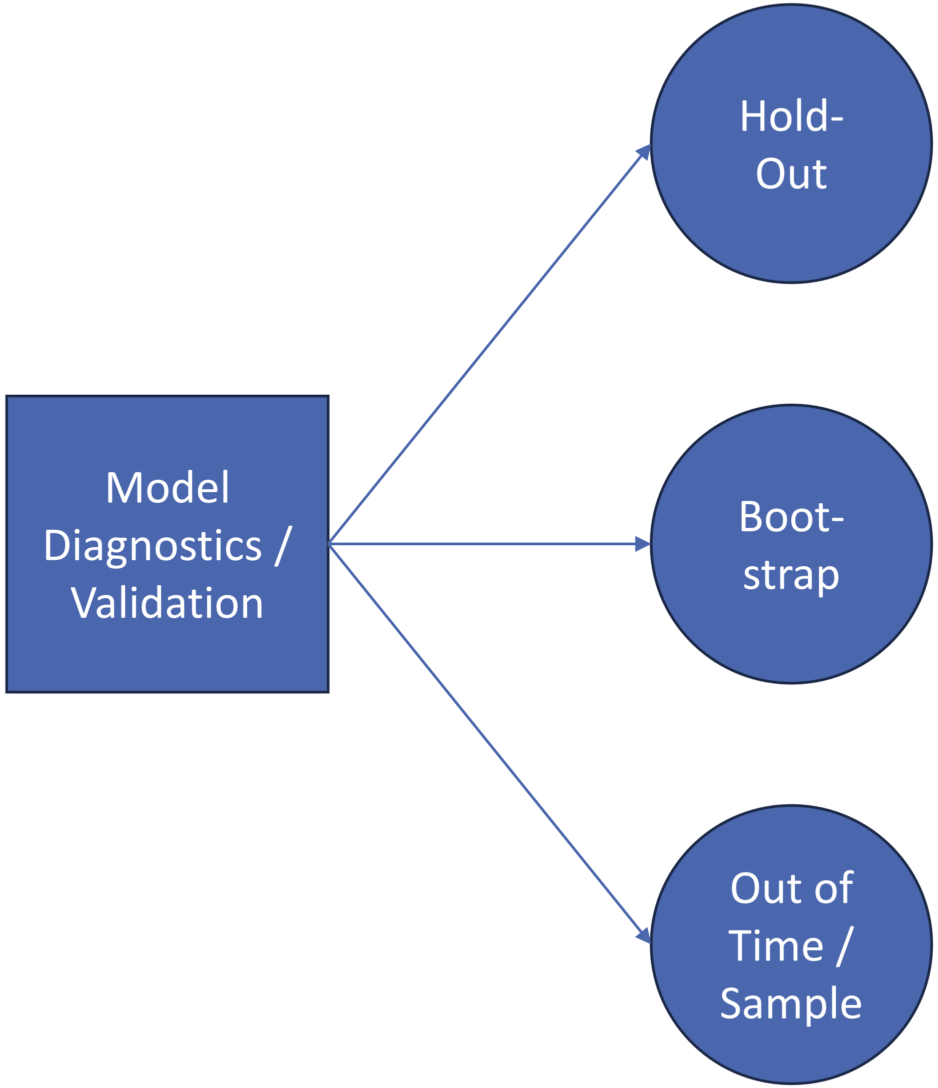




Drag the Rejects P(G) down as we assume rejects would perform worse than known population

# Reject Inference – Alternative Data (Bureau / Open Banking)

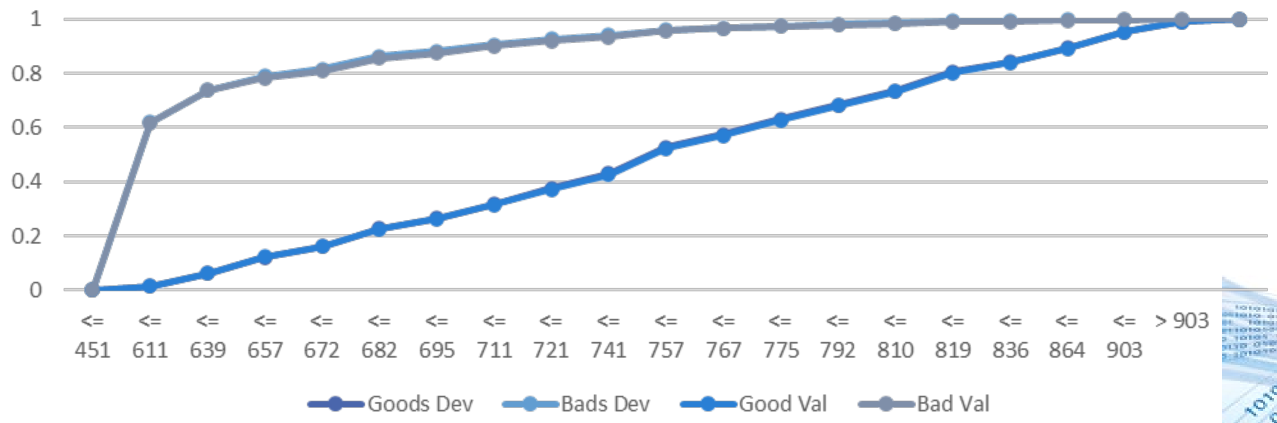
- Bureau Data / Open Banking Data
  - Search for similar loan types applied / approved shortly after reject at other lenders (does the bank have access to the data)
  - Check performance of loans that were written, is this indicative of how the loan would have performed had we accepted it
  - Compare the populations of rejects with the performance of known performance
- Historic Loans (at bank)
- Other Lending Products

# Model Validation




- Model Validation should be carried out
  - as part of the development process
  - as an independent verification of model quality prior to model implementation or use
  - periodically to confirm modelling assumption made at point of development hold and that the model continues to work as designed
- Validation often uses
  - a hold-out sample (develop model on 80% of sample, test on 20%)
  - Boot-strapped validation (random samples pulled from the development sample to test the model)
  - Out of time data sample

Skewed KS away from Decision Point with Validation



# Exercise – Modelling

- Let's build models
- Model Assessment
- Refinement

# Other Models to Consider – IRB / IFRS9

- IRB Models look to utilise multiple models to predict the capital requirements of the bank (by modelling the Probability of Default (PD), Exposure at Default (EAD) and Loss Given Default (LGD)
- IRB Models should be adjusted for cyclicality across the economic cycle
- Model weaknesses need to be address with Margin of Conservatism adjustment
- IFRS9 models typically utilise similar modelling constructs but consider Lifetime PD, EAD and LGD
- Revolving products may have complicated EAD models that aim to predict the amount of the limit that will be consumed by the time of default
- LGD for mortgage products can also be complicated by the recovery processes within the bank and the legal structure / environment in which they operate
- Monitoring and Validation of models is also important (covered in a separate session)

# Why is Model Risk Important?

- What is Model Risk?
  - Financial impact associated with utilising models to make key decisions within a bank or financial institution
  - Reputational risk from making poor decisions
  - Arises from model error and prediction inefficiency
  - Propagated by lack of appropriate controls

- Why is Model Risk important?
  - Models are increasingly used in an ever-expanding range of operational and regulatory decisions
  - If not understood and managed the risk can aggregate to a level that is outside the bank's risk appetite
  - As with all risks, if not managed a financial loss could occur

- Where does Model Risk arise from?
  - From each and every aspect of the model lifecycle
  - We'll focus on model development here

# Regulatory Landscape

- Model Risk Regulations or Guidelines have been published by a number of Regulators, including
  - Federal Reserve (SR11-7 – Guidance on Model Risk - April 2011)
  - Bank of England (SS1/23 – Model Risk Management Principles for Banks – May 2023 )
  - CBUAE (Model Management Standards (MMS) & Guidelines (MMG) – December 2022)
  - ECB (Guide to Internal Models – Oct 2019)
- The Guidance can be
  - Principles based – allows a great deal of freedom in terms of how the models are managed as long as management of the models follows a general path
  - Prescriptive – sets in stone how models should be developed and managed
- More developed markets with sophisticated banking groups tend to have gone down the principles-based approach, whereas developing markets are more prescriptive
- Many global regulators are yet to release guidance, firms in those regions may want to get ahead of the curve

# Thank You

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