Collections Scoring

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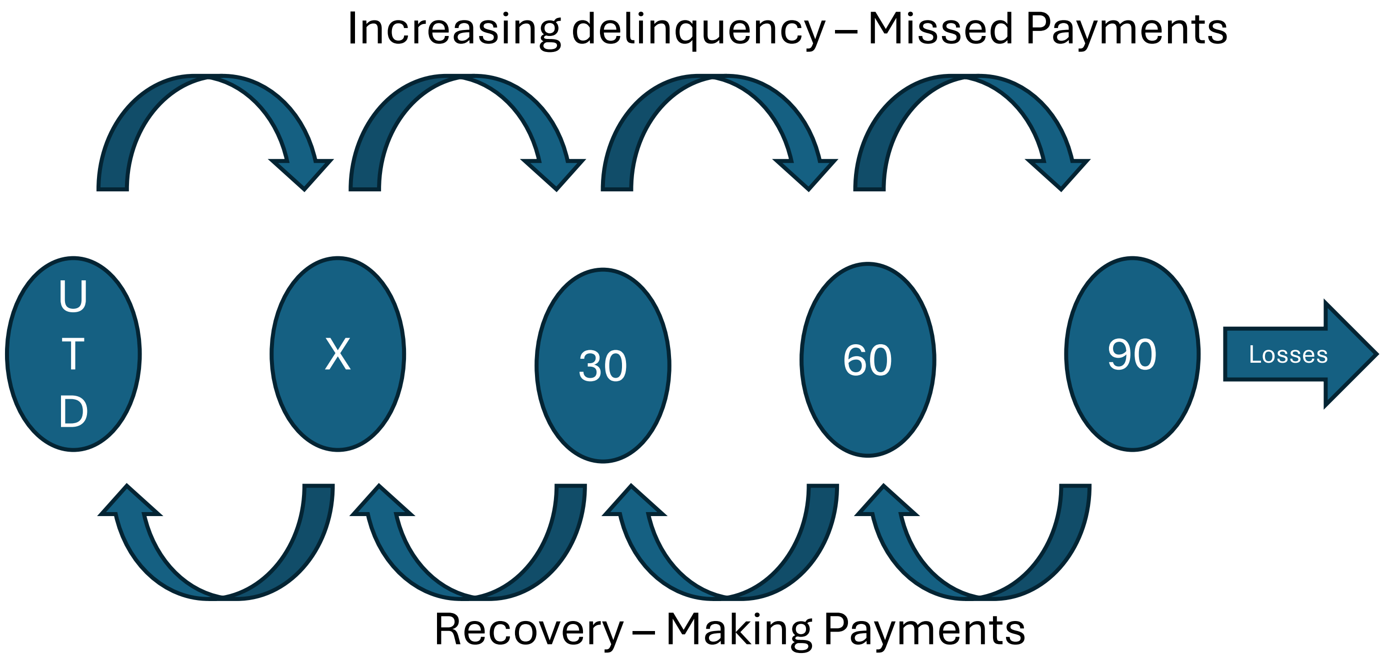
Problem Statement

- 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



What is Collections Scoring?

- Collections Scoring targets accounts that are delinquent with the aim to control the roll rate from bucket to bucket
- Outcomes are used to prioritise the order in which customers are contacted when delinquent
  - Calling Strategies
  - Letter Strategies
- Recovery or Payment Projection Models aim to predict the amount of collected post default
  - Early Debt Sale
  - Recoveries Strategies
  - Input into Loss Given Default (LGD)

Benefits of Collections Scoring

- Focus on Roll Rates to Current
- Resource Prioritisation (best collectors on hardest cases)
- Reduced Default Rates and lower ECLs
- Reduced NPLs
- Increased Revenue
- Collection Case Prioritisation (hard core delq, most attention)
- Advanced Analytically Strategies
- Champion Challenger Strategies (constant evolution)

Lower Losses, Higher Revenue – Improved ECL

How to use Behavioural & Collections Scoring?

Portfolio Data

Behavioural& Collections 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 PTPs Taken Last 3 Months
- Number of PTPs Kept last 12 months
- Proportion of PTPs Kept last 12 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

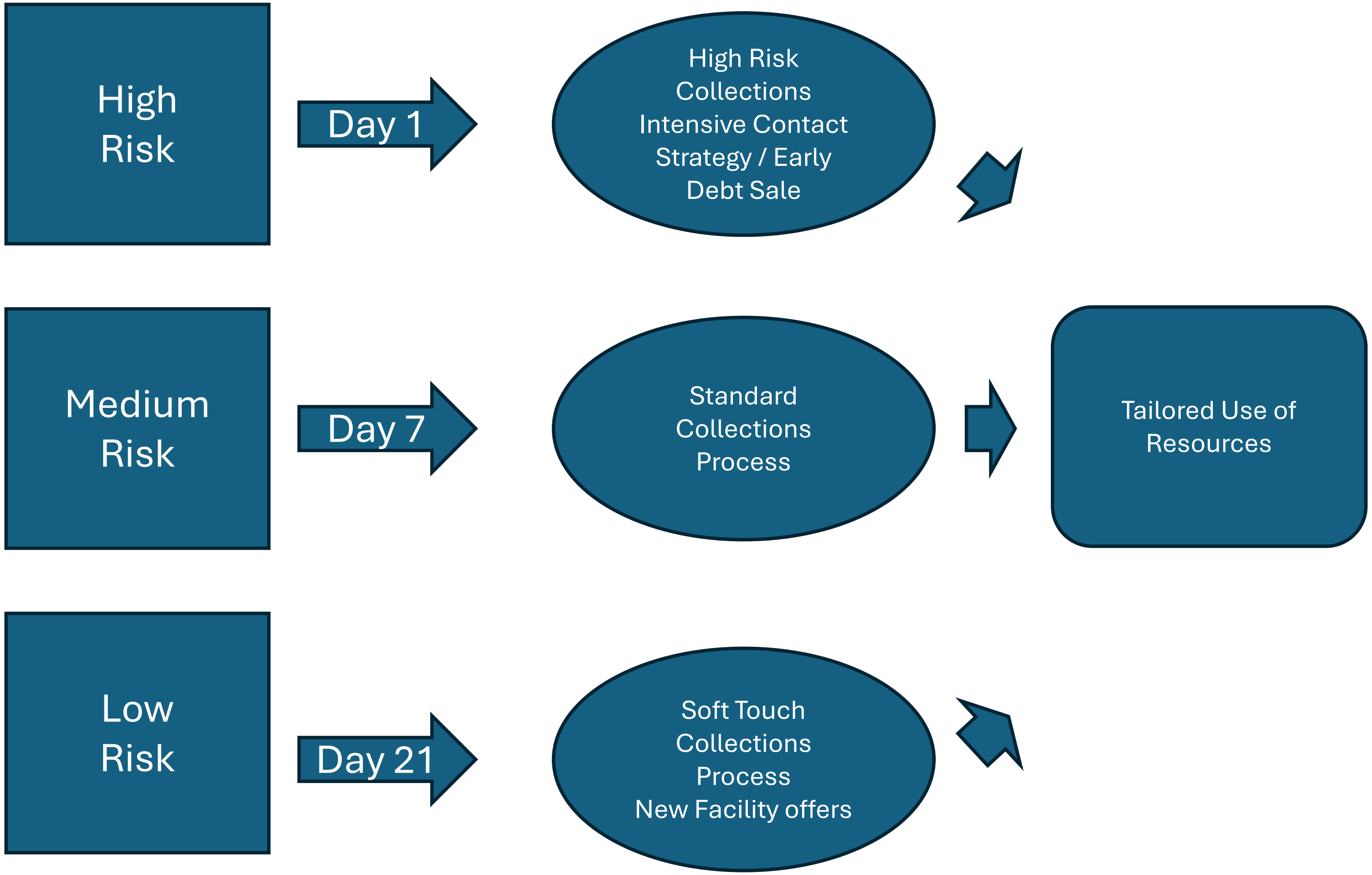
Payment Projection

Recoveries Management

B-Score

C-Score

Customer Analytics



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 in to 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 – Collections Management

Account Status

	Up To Date	1-29 Days Past Due	30 - 90 Days Past Due	90+ Days Past Due
	Behavioural Scoring	Behavioural Scoring	Roll-Rate Model	Payment Projection
Description	Manage Customers Relationships through • Pro-active limit management • Competitive Pricing • Pre-emptive Triage • X-Sell Programmes	Initiate Customer Contact for • Debt Control • Triage • Limit Management	Continued Customer Contact for • Prioritised Debt Control • Arrears Management • Save the Relationship?	Decision made to end the customer relationship, therefore switch to • Recovery Strategies • Debt Sale • 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

Modelling – Model Types

Static Model

Fixed Performance Window
Final Delq Status Performance Definition

Roll Rate Model

Rolling Window
(for data volume)
Performance Definition based on Improved / Worsened Delq

Segmented by Delq Bucket

Rolling or Fixed Performance Window
Final Delq Status Performance Definition

Data Utilised

- Demographics
- Standard Behavioural Score Chars
- Contact History
- Promises to Pay (Keep / Broken)
- Collections Experience
- Payment History / Frequency
- Delinquency Status and Movements

Performance Definitions

Model	Goods	Bads	Indeterminates
Static	Final Delq Status Current	30+ dpd	X-Days
Rolling	Improvement over Start Position	Worse than Start Position	Same as Start Position
Segmented X-Days	Current	30+ dpd	X-days dpd
Segmented 30-Days	Current, X-Days	60+ dpd	30-days dpd
Segmented 60-Days	Current, X-Days	60+ dpd	30-days dpd
Segmented 90+	Payment Projection	Continuous	

Potential Collections Modelling Datasources

Examples of Data that could be used when Collections Scoring

- 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

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 Promises to Pay Kept last month, Last 6m etc.
- Number of Partial Payments Made L3M, L6M
- Ratio of Payment to Outstanding L3m

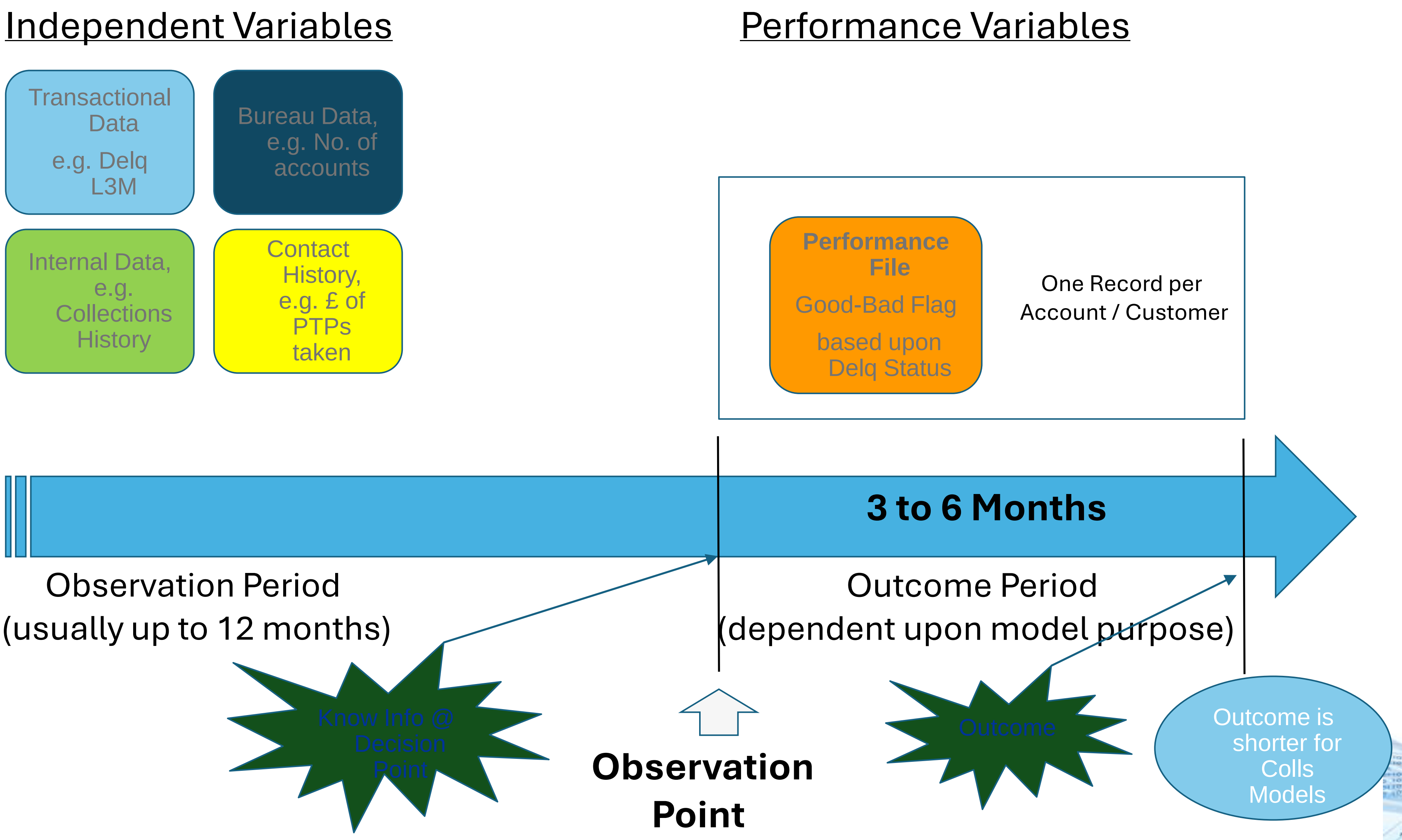
Open Banking

- 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

Customer Management Analytics - Sampling

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



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
α: general intercept
β: 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

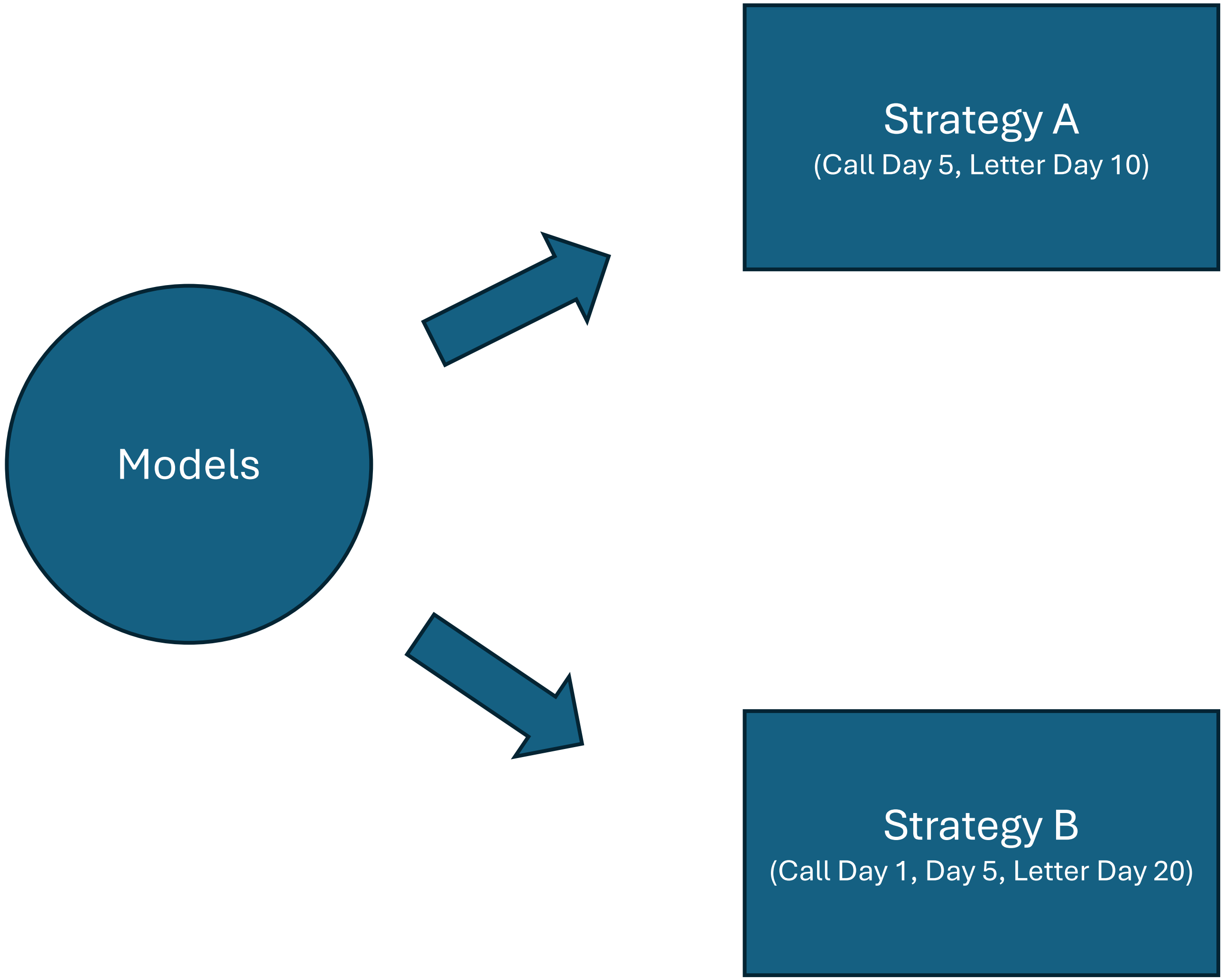
In Scoring:
Y: total score
α: constant
β: co-efficient applied to the characteristics
x: explanatory variable (e.g. age, income, sex)

350 [Y] = 200 [α] + 50 x $\text{Age}_{30\text{-}40}$ + 40 x Income_{50k+} + 60 x Sex_{Female}

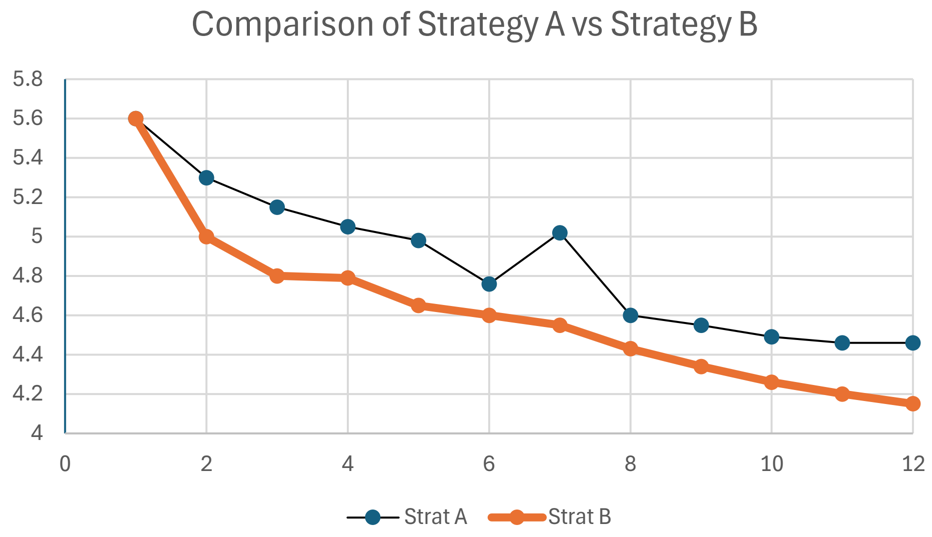
Other Form of Logistic Regression

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

Champion-Challenger Strategies



Default Rates by Strategy across 12 months post implementation



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