INTRODUCTION TO CREDIT SCORING & DATA PREPARATION

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INTRODUCTION TO SCORECARDS

What is a Scorecard?

- Common way of displaying the patterns found in a binary response model.
- Typically, people use logistic regression models.
- The main benefit is that a scorecard provides a clear and intuitive way of presenting the regression coefficients.

Scorecard Usage

- Credit Scoring
  - Equifax (http://www.equifax.com/home/en_us)
  - Experian (http://www.experian.com)
  - Transunion (http://www.transunion.com)
- Medicine / Healthcare
  - Trauma and Injury Severity Score (http://www.trauma.org/archive/scores/iss.html)
  - Coronary Heart Disease Risk Calculator (http://www.medcalc.com/heartrisk.html)
- Retail, IT and most cases where binary models can be applied.

CREDIT SCORING

Credit Scoring and Scorecards

- “One of the oldest applications of data mining, because it is one of the earliest uses of data to predict consumer behavior.”
- David Edelman – Credit Director of Royal Bank of Scotland

Credit Scoring and Scorecards

- **Credit scoring** is a statistical model that assigns a risk value to prospective or existing credit accounts.
- A **credit scorecard** is a statistical risk model that was put into a special format designed for ease of interpretation.
- Scorecards are used to make strategic decisions such as accepting/rejecting applicants and deciding when to raise a credit line, as well as other decisions.

Credit Scoring and Scorecards

- The credit scorecard format is very popular and successful in the consumer credit world for a number of reasons:
    1. People at all levels within an organization generally find it easy to understand and use.
    2. Regulatory agencies are accustomed to credit risk models presented in this fashion.
    3. Credit scorecards are straightforward to implement and monitor over time.

Example 1 Scorecard

- Cut-off = 500
- New customer:
  - Months Since Last Miss Payment: 32
  - Home: OWN
  - Salary: $30,000

Variable	Level	Scorecard Points
MISS	$x < 24$	100
MISS	$24 \leq x < 36$	120
MISS	$36 \leq x < 48$	185
MISS	$x \geq 48$	200
HOME	OWN	225
HOME	RENT	110
INCOME	$x < 10{,}000$	120
INCOME	$10{,}000 \leq x < 25{,}000$	140
INCOME	$25{,}000 \leq x < 35{,}000$	180
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$$120 + 225 + 180 = 525$$

- **ACCEPT FOR CREDIT**

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Example 2 Scorecard

- Cut-off = 500
- New customer:
  - Months Since Last Miss Payment: 22
  - Home: OWN
  - Salary: $8,000

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Discrete vs. Continuous Time

- Credit scoring typically tries to understand the probability of default on a customer (or business).
- However, default is also dependent on **time**.
- When will someone default? → **JUST AS IMPORTANT!**

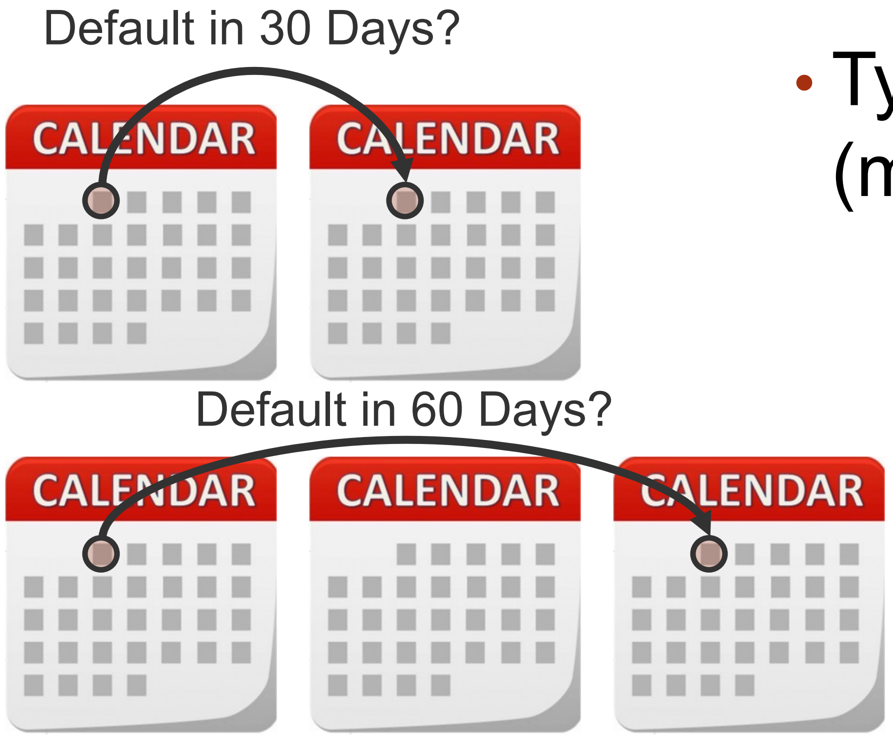
- **Discrete** – Evaluating binary decisions on predetermined intervals of time.
- **Continuous** – Evaluating probability of default as it changes over continuous points in time (survival analysis).

Discrete Time

Discrete Time

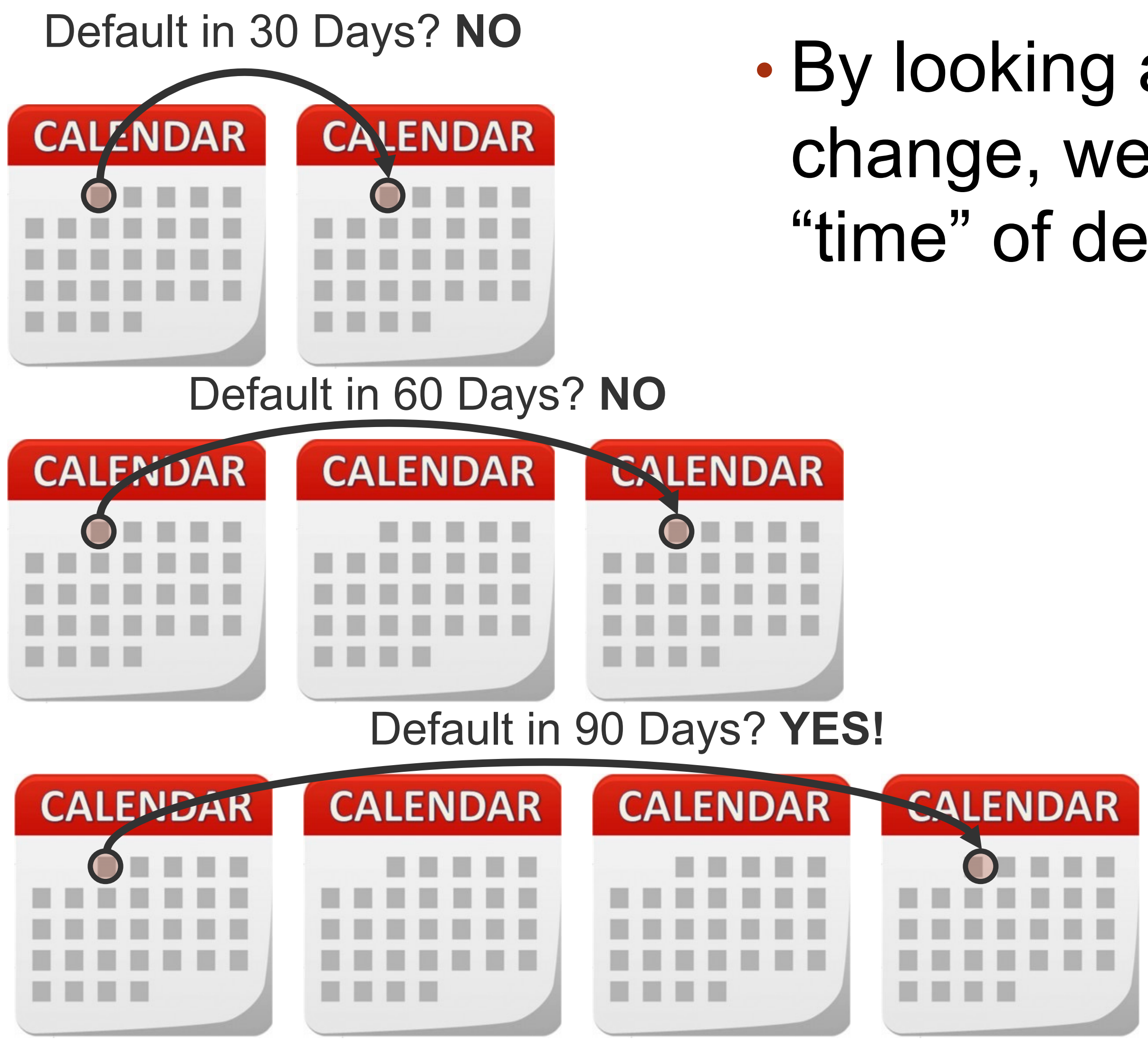
- Discrete time models evaluate the probability of default within a window of time.

Discrete Time



- Typically pick multiple windows (models) to evaluate across.

Discrete Time



- By looking at where decisions change, we can evaluate a “time” of default.

Continuous Time

Default in 42 Days

- Continuous time models provide a probability of default for **every** day.
- From this more exact times of default are possible.

Process Flow

Data Collection
- Variable Selection
- Sample Size
- Sample / Performance Window

Data Cleaning
- Eliminate Duplicates
- Examine / Remove Outliers

Variable Grouping and Selection
- Weights of Evidence (WOE)
- Information Value (IV)
- Gini Criterion

Initial Scorecard Creation
- Logistic Regression
- Accuracy
- Threshold
- Assessment

Reject Inference
- Remove bias resulting from exclusion of rejects

Final Scorecard Creation
- Final Model Assessment

DATA DESCRIPTION

ACCEPTS Data Set

- Type of Product: Auto Loans
- Information available on customers with performing or non-performing loans.
- 5,837 cases of individuals who applied for and were granted an automobile loan.
- 22 variables in all.

Data Dictionary

Variable Name	Description
Age_oldest_tr	Age of oldest trade
App_id	Application ID
Bad	Good/Bad Loan
Bankruptcy	Bankruptcy or Not
Bureau_score	Bureau Score
Down_pyt	Amount of down payment on vehicle
Loan_amt	Amount of Loan
Loan_term	How many months vehicle was financed
Ltv	Loan to Value
MSRP	Manufacturer suggested retail price
Purch_price	Purchase price of vehicle

Variable Name	Description
Purpose	Lease or own
Rev_util	Revolving utilization (balance/credit limit)
Tot_derog	Total number of derogatory trades (go DPD)
Tot_income	Applicant's income
Tot_open_tr	Number of open trades
Tot_rev_debt	Total revolving debt
Tot_rev_line	Total revolving line
Tot_rev_tr	Total revolving trades
Tot_tr	Total number of trades
Used_ind	Used car indicator
Weight	Weight variable

REJECTS Data Set

- Type of Product: Auto Loans
- 4,233 cases of individuals who applied for and were **NOT** granted an automobile loan.
- 21 variables in all – BAD variable not part of data set and should be inferred.
- Used for **reject inference** later in the analysis.

Reject Inference

- **Reject inference** is the process of inferring the status of the rejected applicants based on the accepted applicants model in an attempt to use their information to build a scorecard that is representative of the entire applicant population.
- Reject inference is about solving sample bias so that the development sample is similar to the population to which the scorecard will be applied.

Rejected Inference

- Can we develop a scorecard without rejected applications?

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- Can we develop a scorecard without rejected applications? **YES!**
- Is it **legally permissible** to develop a scorecard without rejected applications?

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Rejected Inference

- Can we develop a scorecard without rejected applications? **YES!**
- Is it **legally permissible** to develop a scorecard without rejected applications? **YES!**
- If yes, then how **biased** would the scorecard model be? **DEPENDS!**

- *"My suggestion is to develop the scorecard using what data you have, but start saving rejected applications ASAP."*
  Raymond Anderson, Head of Scoring at Standard Bank Africa, South Africa

DATA COLLECTION AND CLEANING

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Defining Our Target

- When does someone actually default?
  - Is it when the loan is charged-off?
  - Probably signs of stopped paying before then

- Need to define target variable
  - 90 days past due (DPD) for everything (old approach)
  - 90-180 DPD based on types of loans, business sector, country regulations, etc. (current approach)
    - For example: US mortgages – 180 DPD

Variable Selection

- Criteria for explanatory variables:
  - Expected predictability power
  - Business interpretation
  - Reliability
  - Legal issues
  - Ease in collection
  - Future availability

Feature Engineering

- Variable creation based on business reasoning:
  - Loan to value ratio
  - Number of delinquent accounts
  - Expense to income ratio
  - Credit line utilization
- Omit variables that are highly dependent:
  - Variable clustering!
- Review / remove outlier and abnormal values

Sample Size

- *“There are no hard and fast rules, but the sample selected normally includes at least 1,000 good, 1,000 bad, and about 750 rejected applicants.”* FDIC, Credit Card Activities Manual (https://www.fdic.gov/regulations/examinations/credit_card/index.html)
- No exact answer on the correct sample size.
- Sample size depends on the overall size of the portfolio, the number of explanatory variables you are planning to use, and the number of defaults or claims filled.

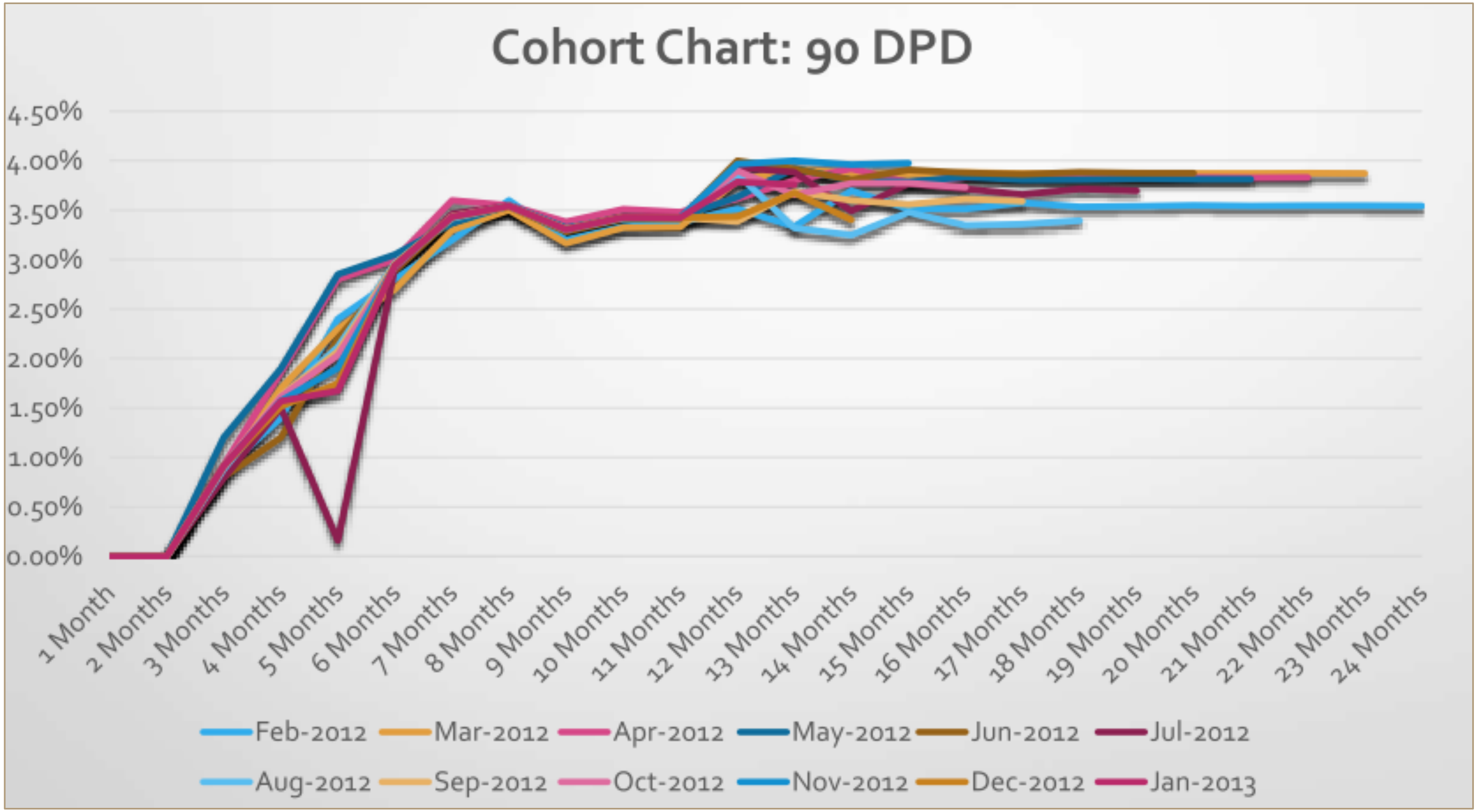
Sample and Performance Window

- The sample must be characteristic of the population to which the scorecard will be applied.
- Example:
  - If the scorecard is to be applied in the subprime lending program, then use a sample that captures the characteristics of the subprime population targeted.

Sample and Performance Window

- Objective:
  - Gather data for accounts opened during a specific time frame.
  - Monitor their performance for another specific length of time to determine if they were good or bad.
- Problems:
  - Accounts opened recently are more similar to accounts that will be opened in the near future.
  - Want to minimize the chances of misclassifying performance – accounts must be monitored long enough to not underestimate expected bad rates.

Sample and Performance Window



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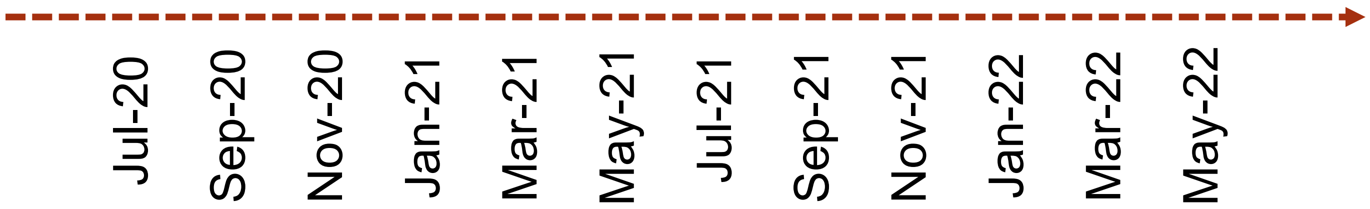
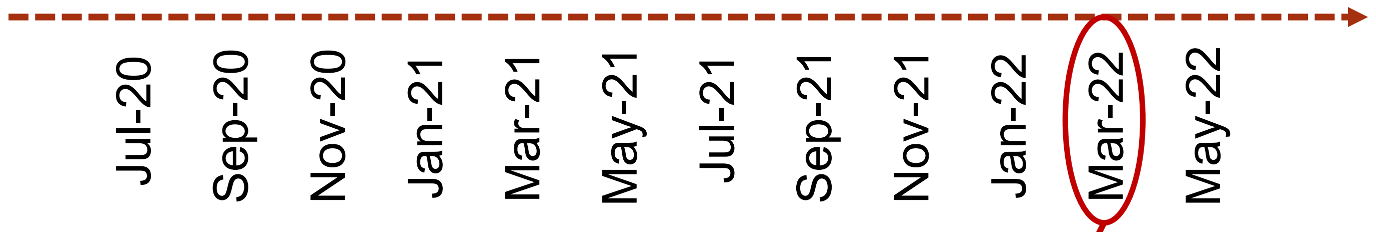


- Based on cohort graph: “Bads” level off about 14 months after loan origination.
- If the analysis is to be performed on March 2022, we select our **sample** from 12-16 months back; this will give an average of 14 months **performance window**.

Sample and Performance Window



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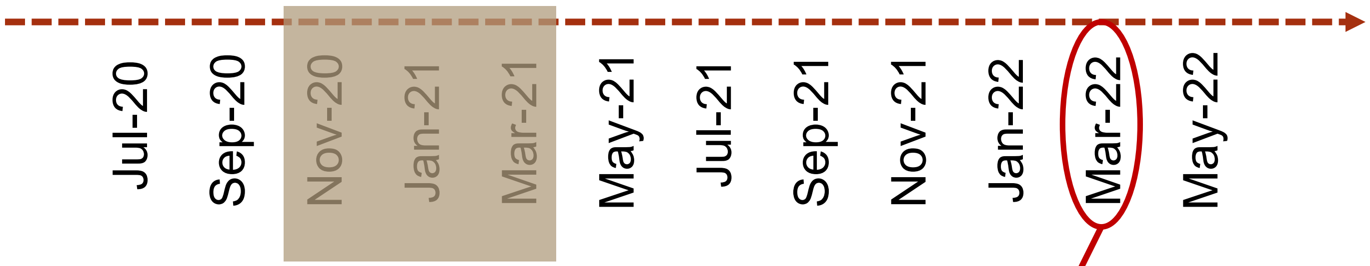

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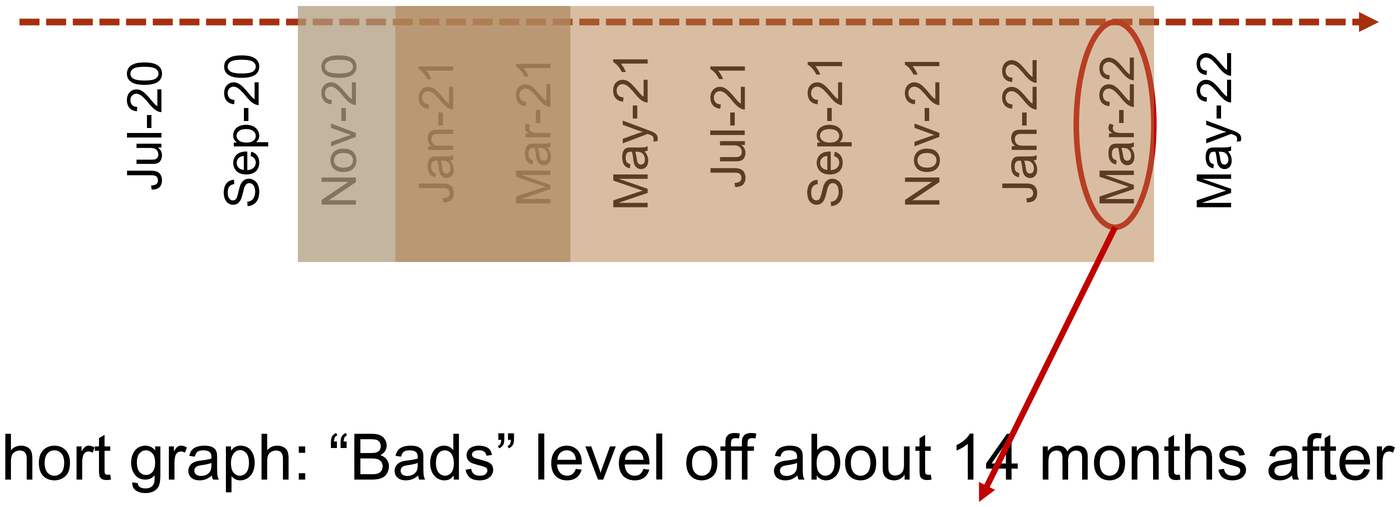

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Sample and Performance Window

- The exact length of the performance window depends on the product.
  - Credit Cards: Typically 1 – 2 years
  - Mortgages: Typically 3 – 5 years
- Sample window length can vary based on data availability as well.