Retail Collections

Behavioural Scorecard Development

Project Specification

For 123Retail

Version 1.0

CONTENTS

DOCUMENT HISTORY

Date of Issue	Document Version	Sections Affected	Modification Details	Document Author
July 2020	1.0	All	Document Update	Evgeniya Toteva

1. INTRODUCTION

1.1 Purpose of the Document

This document details the scoring model development for the 123Retail Collections Scorecard Project.

The Project Specification is produced as a result of the initial Project Design meeting and defines the work that will be carried out by Experian and the deliverables that will be provided to 123Retail.

1.2 Contents of the Document

The document is divided into the following sections:

- Project Overview
- Description of Data Requirements
- Model Development Summary
- Model Validation
- Scorecard Assessment & Strategy Recommendations
- Sign-off Document

2. PROJECT OVERVIEW

1.1 Collections Scorecard Definition

A collections scorecard is a type of behavioural scorecard – it is a statistical model that assigns a score to an existing customer of the given lender who has already gone behind in his/her credit payment commitments. A high score will imply a high probability of repaying all debt owed, and a low score signifies a low probability of repaying all the debt.

1.2 123Retail Overview

123Retail is a large home shopping company operating over 20 brands and retailers. They offer credit through a variety of channels including internet and telephone applications.

123Retail's existing collections strategy was built in 2006 and is based on a generic bureau index provided by Experian.

It has been assessed that the current solution is no longer suitable to apply onto the present pool of 123Retail customers. Hence, it has been agreed that Experian will build a bespoke collections model for 123Retail – to reflect the most up-to-date data available from 123Retail.

1.3 Project Objectives

The project will be considered a success if:

- A bespoke collections score is built to reflect the most recent behavioural data from 123Retail;
- The newly developed score outperforms the 'generic' bureau index on the development sample;
- A strategy can be built around the new collections score – in order to optimise collections going forward – by increasing debt collected and reducing time and monetary costs associated with the collections process.
  An example strategy analysis is provided later in this project specification.

3. DATA REQUIREMENTS

3.1 Sample Window

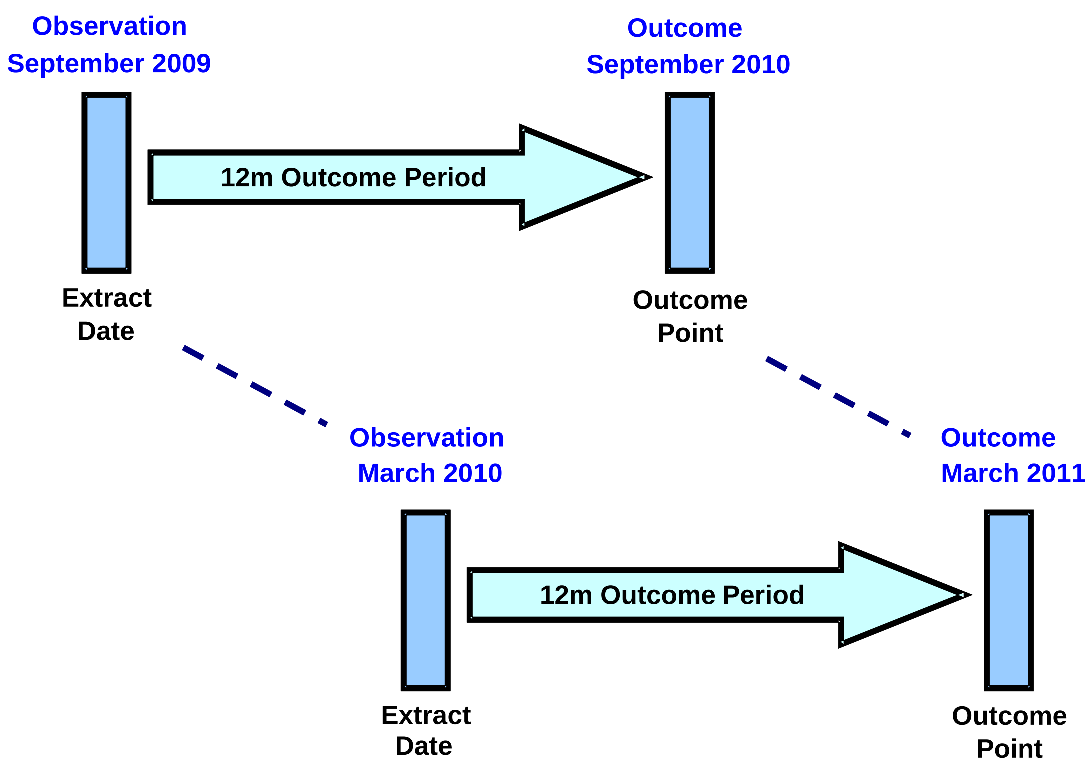
Data has been extracted as at three observation points in time:

- 17th September 2009
- 3rd December 2009
- 18th March 2010

123Retail has extracted the data which is deemed representative of the customer pool on which the newly developed collections score and strategy will be applied going forward.

3.2 Outcome Period

123Retail has applied a rolling 12-month outcome period on the observed accounts – i.e., the Good Bad Flag has been derived based on the performance of the account over a 12-month period after extract date:



3.3 Good Bad Flag

The final Good Bad Flag definition is detailed below:

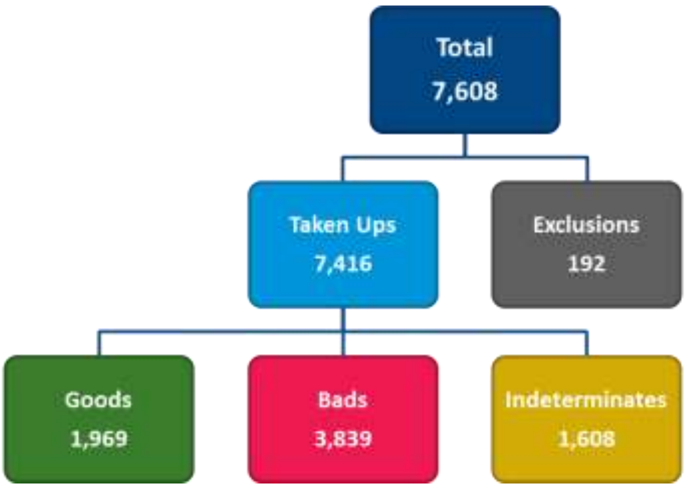
Good Bad Flag	Account performance
Good	• More than 3 payments made since account entered collections AND • Default amount less than or equal to £2,000
Indeterminate	• 2 payments made since account entered collections AND • Default amount less than or equal to £2,000
Bad	• 0 or 1 payment made since account entered collections OR • Default amount more than £2,000

3.4 Weighting

No sampling or weighting have been conducted as part of the data preparation. Therefore, the scorecard will be built on an unweighted development sample.

3.5 Population Flow

The composition of the constructed development sample is detailed in the population flow below:



Bad Rate = 51.77%
Good Bad Odds = 0.51

The high volume of Bad accounts, as well as the Bad rate and Good/Bad odds statistics shown above, confirm the relatively high-risk profile of this derogatory sample. This is as expected given that this is a collections scorecard development project based on accounts that have already fallen into arrears.

4. MODEL DEVELOPMENT

4.1 Model Development Steps

The 'standard' model development steps will be followed during this project – as per Experian's best practice methodology for behavioural scorecard devolvement:

- Prepare the development sample – the data preparation stage has been completed by 123Retail;

- Load the data into Jupyter Notebook (Google Colab):
    - The tool to be used is Python and more specifically ACES Toolbox for all modelling;
    - A new notebook/project path/project structure has to be created in Jupyter Notebook for this scorecard development;
    - The data that should be loaded is the file "**Retail_data.csv**" in the following folder.
    - At this point you should verify the data by checking the number of observations, the number of columns, the type of the variables etc.

- Validate the Good Bad Flag volumes – i.e., ensure the volumes in the population flow above are seen on the data in Jupyter Notebook;

- Apply Data Dictionary to the variables Type_Of_Application and WS_L6M_Accs_Open_More_Than_12M
    - *Hint: Check the meaning of the values of the these variables in the provided Data Dictionary by the client Retail 123. Then write a function and apply it to your data (you can see "data_dictionary.py" from your case study)*

- Perform Data Audit on the data and exclude any variables with %Missing > 90% and with 1 Unique Values.
    - Explore the Data Audit report and decide which variables are not going to be used further for modelling

- Create 80% development and 20% validation subpopulations;
  Hint: You can use the variable Random_Number or train_test_split from sklearn

- Export the development, validation and all samples in pickle format

- Fine-class modelling variables in a new notebook (*do not forget to start your script with the necessary preliminaries – importing necessary libraries/python toolbox functionalities, import your datasets)* ;
  Hint: No need to fine-class Unique ID, Extract Date, Good Bad Flag, Random Number. Be careful about population on which to fine-class, be careful about Other category, special values, interval band values (business sense).
  Run a Characteristic Analysis Report and order your variables in the summary page by VInfo. Discuss and remove any variable with lower VInfo than 0.02 before moving on to Coarse Classing

- Coarse-class modelling variables;
  Hint: At this point, you may wish to remove Exclusions and exclude them from any classings, reports, models, etc. from this point onward!
  The client will never apply this scorecard onto Exclusions.
  Be careful about the relevant subpopulation on which to coarse-class, be careful about business logic, smooth trend, enough Goods & Bads.
  Refer to Day 3 scripts of the SP and apply firstly automatic transformation to your coarse classing, then move on to manual changes if necessary.
  Do not forget to export all your selection sets in json format.

- Produce a CA Report including both your FC and CC, for easier review of the variables add colour coding to your classings and a bar chart.

- Run regression models in Jupyter Notebook (Google Colab) – 123Retail's preference is to use Stepwise Linear Regression;
  Hint: Note that this is a behavioural model – hence, no Reject Inference is performed and no Parcelled model will be built. Your 'final' model will be a Known Good Bad Model.
  Be careful about subpopulations, correlation issues, and illogical trends.
  Hint: During the iteration process you can refer to the day 4 and 5 scripts, you may choose to save the outputs of each model in terms of selection sets and/or models, so that you may have better track of the changes you do along the way. And use them as starting points

- Validate the model – the validation methodology is detailed below;

- Assess the 'final' model:
  - Evaluate the discriminative power on Development, Validation and Total populations;
  - Evaluate the Gini improvement above the previously used Bureau Index;

- Propose a new collections strategy based on the new score – details of the strategy design are provided below.

Hint: During your independent work – you may wish to refer to:

- *The demo videos – for specific details on running reports, classings, models, etc. in Jupiter Notebook;*
- *The scripts from the Bank Case Study – for specific details on running reports, classings, models, etc. in Jupyter Notebook;*
- *The presentations and Project Specification from the Bank Case Study – to see more information regarding processes, formulas and statistics or the general flow of the process;*
- *The data dictionary – for information on the meaning of the characteristics and the values that they can take on.*

<u>All necessary documents mentioned above could be found embedded in the Appendix</u>

5. SCORECARD VALIDATION

In order to comply with the Guide to Credit Scoring 2000, scorecard developers are required to validate the results shown in the development sample on a separate, independent sample of data (hold out or out of sample) and also a recent sample.

In this development project the model validation will be achieved by developing the scorecard on a randomly selected 80% of the population and testing whether the scorecard is equally effective on the remaining 20% of the population ('validation' or 'hold-out' sample).

The method used to test this effectiveness is the Kolmogorov-Smirnov Test (K-S Test). This non-parametric test involves a comparison of the distribution of goods, bads and total population between the development sample and the validation sample.

In addition to the K-S test, the overall discrimination of the model on the 80% development, 20% hold-out and 100% total populations should be compared to ensure that there are no significantly different results – typically around a 2-point Gini difference is considered insignificant.

6. MODEL RESULTS & ASSESSMENT

The final score will be assessed in terms of its:

- Overall discriminative power by itself – as measured by the Gini coefficient;
- Gini uplift beyond the Bureau Index currently implemented by 123Retail;
- Ability to result in a bespoke collections strategy tailored to the needs of 123Retail. See examples below.

The model is to be assessed on the 100% total population (less any Exclusion customers).

Strategy based on score only

One way of applying the bespoke collections score is to split the customer base into different risk groups on which to apply different collections strategies. Bad rate can be used as a measure of risk.

The initial split of the score should be granular, such that optimal bands can be achieved.
'Optimal' bands are groups of:

- Significantly different profile – e.g., refer to the bad rate differences below;
- Reasonable size – not too small and not too large – e.g., between around 5-50%;
- Robust statistical measures – i.e., at least 50 good and 50 bad accounts to render the bad rate a statistically significant metric.

Hint: You may want to create a 2-3% fine-classing of the final score in a selections set and then coarse-class to create the categories with different Risk based on Bad Rate.

Here is an example of score splits based on bad rate:

Measure	High Risk [Low : 100]	Medium Risk [101 : 300]	Med-Low Risk [301 : 800]	Low Risk [801 : High]	Total
# Total	2,896	5,784	37,484	11,596	57,760
% Total	5.01%	10.01%	64.90%	20.08%	100.00%
# Goods	70	529	18,226	7,036	25,861
# Bads	1,873	3,285	7,575	981	13,714
Bad Rate	90.83	76.70	27.17	11.22	31.91

You would normally want the extreme groups to be relatively small – 5-10% of the total population for the high-risk group and 20-40% for the low-risk group. Typically, the neutral or Med-Low risk group is left to be the largest.

Four different collections paths can now be applied – for example:

- SMS for the **Low Risk** ones;
- Letter for the **Med-Low Risk** ones;
- Call for the **Medium Risk** ones;
- Personal visit or direct sell to a debt collection agency for the **High Risk** ones.

Strategy based on a combination of score and another predictor

Another approach to the collections strategy design may be to consider the bespoke collections score in combination with a 'key' variable to segment the customer pool into different risk groups. The 'key' metric can be agreed based on:

- Client preference – e.g., from previous strategies applied or knowledge of the market specifics;
- Experian recommendation – e.g., from similar experience with clients in the same or similar industry;
- Data/statistics driven result from running a segmentation tool.

In this strategy design, 123Retail has specifically required that **Age of Account** be analysed in combination with the newly developed bespoke score.
123Retail is open to reviewing additional splits of Score – if time permits and Experian decides to investigate further options.

Guidelines: To do the above strategy we are going to use a Cross Tabulation Report from the Python Toolbox, that is going to allow us to cross the bins of two different variables and display the relevant statistics (# Total, % Total, # Goods, # Bads, Bad Rate) for each group.

Import of Cross Tabulation Report:

```
from acestbx_pyace.reporting import CrossTabulationReport
```

Initialization:

```
cross_tab_report = CrossTabulationReport(format=True)
```

Calculating a Report:

```
cross_tab_report.fit(selection_set, var1, var2, y, columnset='known')
```

where:

- *selection_set - A selection set including data for the DataFrame's columns that will be included in the Cross Tab report.*
- *var1 - A Pandas Series object with the first variable to cross.*
- *var2 - A Pandas Series object with the second variable to cross.*
- *y - A Pandas Series object with the GB Flag.*

Viewing the Results:

```
cross_tab_report.view(display_only=True)
```

Export the Report in Excel:

```
cross_tab_report.export(dest_path, name='Cross Tab Report')
```

where:

- *dest_path - Existing directory in which the Cross Tab Report file will be saved. Exception is raised if the given dest_path does not exist.*
- *name='Cross Tab Report' - The name of the Cross Tab Report file. Default is 'Cross Tab Report'.*

Hint: An example script was provided to you (Cross Tabulation Example.ipynb)

Here is an example of such matrix strategy analysis:

		High Risk [Low : 100]	Medium Risk [101 : 300]	Med-Low Risk [301 : 800]	Low Risk [801 : High]	Total
Young Accounts [Low : 12]	# Total	2167	3278	9412	24	**14881**
	% Total	3.75%	5.68%	16.30%	0.04%	**25.76%**
	# Goods	52	376	3897	18	**4343**
	# Bads	1471	1998	3107	3	**6579**
	Bad Rate	92.57	79.89	43.22	14.29	**58.22**
Middle Aged Accounts [13 : 36]	# Total	729	1800	12412	566	**15507**
	% Total	1.26%	3.12%	21.49%	0.98%	**26.85%**
	# Goods	18	123	6040	329	**6510**
	# Bads	402	976	2549	78	**4005**
	Bad Rate	84.99	71.55	26.79	16.22	**33.85**
Old Accounts [37: High]	# Total	0	706	15660	11006	**27372**
	% Total	0.00%	1.22%	27.11%	19.05%	**47.39%**
	# Goods	0	30	8289	6689	**15008**
	# Bads	0	311	1919	900	**3130**
	Bad Rate	N/A	74.4	17.16	10.92	**15.77**
Total	# Total	**2896**	**5784**	**37484**	**11596**	**57760**
	% Total	**5.01%**	**10.01%**	**64.90%**	**20.08%**	**100.00%**
	# Goods	**70**	**529**	**18226**	**7036**	**25861**
	# Bads	**1873**	**3285**	**7575**	**981**	**13714**
	Bad Rate	**90.83**	**76.7**	**27.17**	**11.22**	**31.91**

The collections paths to be used in this case could be five – for example:

- SMS for the **dark green** ones;
- First letter for the **light green** ones;
- Second letter for the **yellow** ones;
- Call for the **orange** ones;
- Personal visit or directly sell to a debt collection agency for the **red** ones.

7. PROJECT SPECIFICATION SIGN-OFF DOCUMENT

This form (or a corresponding letter) should be completed and returned to Experian Decision Analytics, to accept that this Project Specification (Version 1.0) is a true and accurate representation of the requirements of 123Retail.

Signed by:

……………………………………………………………………………………………………

(123Retail Representative)

Name: John Doe

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Date:

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Duly authorised
for & on behalf of : 123Retail

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