# **Executive Summary**

# **Introduction**

## **Background**

## **Model Usage**

The model developed would be leveraged for assessing the credit worthiness of the customers applying for availing credit facilities of different retail products of the bank. The Model will complement the current underwriting process, which is a rule-based decision-making process. In addition to complimenting the current underwriting process, model will be used to estimate the risk score for the customers that reflects their credit worthiness.

## **Key Model Features**

Model is developed based on standard logistic regression where the log odds of the outcome are modelled as a linear combination of the predictor variables, as illustrated in the equation below.

Where,

pi is Probability of an account being ‘bad’ or ‘good’

β0 is Model Intercept

β1, is Model coefficient

Predictor variables were selected based on their predictive ability to discriminate between good and bad customers using binning process. Standard analytic process that involved data exploratory analysis, univariate analysis, regression estimation, analysing model results, scaling, back testing of model was followed as part of model estimation.

## **Assumptions and Limitations**

**Assumptions**

Scorecard developed will be used to assess the creditworthiness of the customers applying for all any of the retail facility – personal loan, credit card, auto loan and home loan. It is assumed that the customers applying any retail credit facility will have mostly similar credit risk characteristics.

**Limitations**

Of the total applications obtained for the model development, about 94% of the applications were received and a decision was taken between Jun-2017 to Dec-2018. Due to this, model results and predictions may largely reflect the business strategies that prevailed at that time.

# **Data for Model Development**

The application scorecard for the bank’s retail portfolio was developed using the internal historical account level data spanning 6 years from Jun-2017 to May-2023. Bank’s retail portfolio consists of four products: Personal Finance, Housing Finance, Credit Cards; and Auto Loan.

## **Data Sources**

Reliable and refined data is needed for scorecard development, with a minimum acceptable number of “Non-Defaults” and “Defaults”. Data on several dimensions of customer profile was considered for scorecard development to encompass comprehensive customer behaviour.

Data required for the application scorecard development is broadly classified into following categories:

1. **Application Data**:

This is the information captured on the credit application at the time customer applies for availing a retail credit facility from the bank. This includes customer demographic data attributes like age, gender, education level, employment status, income, nationality, marital status, number of dependents etc.

Bank’s Retail credit department, with the help of IT team, extracted the details of retail customers who applied and secured a credit facility with the Bank from Jun-2017 to May-2023.

Dataset provided included 19,063 applications that were disbursed with the latest application date being 16-May-2023 and latest disbursal date being 19-May-2023. Table below shows the quarterly applications received by different retail products between Jun-2017 and May-2023:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Application Quarter** | **Personal Loan** | **Credit Cards** | **Housing Loan** | **Auto Loan** |
| Q2-2017 | 412 | 447 | 1 | 7 |
| Q3-2017 | 1,587 | 1247 | 11 | 7 |
| Q4-2017 | 1,038 | 1793 | 16 | 18 |
| Q1-2018 | 721 | 1827 | 28 | 10 |
| Q2-2018 | 182 | 1155 | 26 | 2 |
| Q3-2018 | 205 | 648 | 45 | 4 |
| Q4-2018 | 82 | 387 | 36 | 0 |
| Q1-2019 | 44 | 156 | 17 | 0 |
| Q2-2019 | 30 | 28 | 9 | 0 |
| Q3-2019 | 23 | 32 | 18 | 0 |
| Q4-2019 | 9 | 0 | 2 | 0 |
| Q1-2020 | 5 | 2 | 0 | 0 |
| Q2-2020 | 2 | 0 | 0 | 0 |
| Q3-2020 | 5 | 0 | 0 | 0 |
| Q4-2020 | 13 | 0 | 3 | 0 |
| Q1-2021 | 20 | 18 | 10 | 3 |
| Q2-2021 | 23 | 9 | 17 | 1 |
| Q3-2021 | 20 | 15 | 11 | 0 |
| Q4-2021 | 29 | 8 | 10 | 0 |
| Q1-2022 | 54 | 7 | 8 | 0 |
| Q2-2022 | 47 | 8 | 18 | 2 |
| Q3-2022 | 46 | 5 | 7 | 0 |
| Q4-2022 | 10 | 1 | 1 | 0 |
| **Total Applications** | **4,607** | **7,793** | **294** | **54** |

* Only 294 housing loan and 54 auto loans were disbursed during the above period.
* Number of loans/ cards disbursed after 2018 has reduced significantly.
* Less than 100 loans/ cards disbursed in the year 2020 across all the products.

Dataset provided also contained the following customer/ account specific and demographic information obtained/ collected at the time of application:

|  |  |
| --- | --- |
| 1. Nationality | 1. Savings account balance at application |
| 1. Application date | 1. Last six months average account balance |
| 1. Disbursed date | 1. Number of loan products with CBI |
| 1. AECB Score | 1. Is existing product at bank delinquent |
| 1. Product being applied for | 1. First time mortgage buyer? |
| 1. Marital Status | 1. Loan to Value ratio |
| 1. Residential Status in UAE | 1. Age |
| 1. Number of years in UAE | 1. DSR Ratio |
| 1. Employer Category (A/B/C/ Restricted etc.) | 1. Blacklisted? |
| 1. Total number of years months in job | 1. Purpose of product |
| 1. Total Monthly Salary | 1. Loan Multiples |
| 1. Has account with the bank | 1. Frequency of Top Ups |
| 1. Salary transferred to bank | 1. Number of Dependents in UAE |
| 1. Account opening date with CBI |  |

1. **Performance Data**

Payment behaviour is the metric used to assess the performance of an account whose application was approved, and credit facility is granted. Days past due (DPD) is used to assess the payment behaviour of the account.

Account level monthly DPD data was obtained from the following sources for the model development:

1. **From Mar-2012 to Dec-2019**

Account level monthly data was extracted from the bank’s database. Dataset contained days past due (DPD) information for all the accounts on books as on every month-end from Mar-2012 to Dec-2019. Dataset also contained month end outstanding balance and product identifier for each account.

1. **Data from Jan-2020 to May-2022**

Bank calculates the IFRS9 ECL on monthly basis. Data required for ECL calculation are automatically extracted/ generated from the databases using scheduled BO queries by the bank’s IT team in multiple reports. These reports contain month-end account level information required for ECL calculation. Account level DPD and outstanding exposure are obtained from each month’s loans and advances report.

## **Data Availability and Quality**

Of the total applications obtained for the model development, about 94% of the applications were received and a decision was taken between Jun-2017 to Dec-2018

It was observed that data were missing on many predictor variables. Below is the list of independent variables where data was missing/ blank for significant number of accounts.

**Credit Cards**

* AECB score was missing for about 12% of the credit card accounts
* ‘Employer Category’ was missing for about 61%
* ‘Total Monthly Salary’ was missing for about 32% of the sample
* Last six months average account balance was missing for almost all the accounts
* ‘Number of loans products at bank with CBI’ was blank for about 52% of the accounts
* ‘Number of Dependents in UAE’ was missing for 61% of the accounts

**Personal Loan**

* AECB score was missing for about 23% of the credit card accounts
* About 83% of the accounts belongs to Employer Category ‘A’ and hence this was not used for model development.
* As per the current lending strategy, salary transfer is a must for availing the personal loan from the Bank. About 96% of the sample accounts have done so to obtain the loan. Hence this was also not used for model development.
* ‘Number of Dependents in UAE’ was missing for 44% of the accounts

Additionally, about 99% of all the accounts under both personal loan and credit card products are residents of the UAE. Hence variable ‘Residential Status in UAE’ was not used in model development.

## **Exclusions**

Of the total 19,063 applications, several applications were excluded from further analysis based on the following criteria:

|  |  |  |
| --- | --- | --- |
|  | **# Excluded** | **# Remaining** |
| **Total Applications** |  | **19,063** |
| Duplicate applications | 339 | 18,724 |
| No DPD history available in DPD dataset | 3,653 | 15,071 |
| Accounts that were disbursed after 30-Nov-2022 \* | 88 | 14,983 |
| Accounts with less than 6-month DPD history, post disbursal date \*\* | 1,607 | 13,376 |
| Accounts where difference in DPDs of two successive months is >31 days \*\*\* | 628 | 12,748 |
| Accounts that were originated in year 2017 \*\*\*\* | 6,265 | **6,483** |

\* Since the DPD data was available only till 31-May-2023, only 5 or less months of DPD will be available for accounts that were disbursed after 30-Nov-2022. At least 6-months DPD data is required to assess the payment behaviour of an account and determine it defaulted or not. Hence accounts that were disbursed after 30-Nov-2022 were excluded.

\*\* Like above, an account must have reasonable length of DPD to evaluate the payment behaviour. A minimum of 6-month DPD information has been considered for the model development. Accounts that had less than 6-month DPD history, post disbursal date have been excluded. Justification for choosing a 6-month DPD window has been provided in the following section.

\*\*\* DPD Issue: It was observed that historical DPD of some accounts was more than 31 days between two months. These unexplainable and outlier accounts were excluded from the default rate calculation process if such inconsistencies occur either in observation point or in the performance window that follows it.



\*\*\*\* AECB score was not available for the accounts that were approved/ originated during the year 2017. As this is one of the critical information used in decision making, these accounts were excluded from the model development process.

A total of 6,483 accounts remained for further analysis after applying the above exclusion criteria.

Both data quality and exclusion sections above underline the serious challenges faced with respect to accuracy and completeness of the data obtained for the model development. This resulted incorporating fair amount subjectivity in the variable binning, in assigning scores to the final scorecard, including manually adding/ force fitting some of the predictors that are critical for underwriting process, but no data available for them in the development sample.

# **Definition of Default**

Scorecards are developed using the assumption that “future performance will reflect past performance”. Based on this assumption, the performance of previously opened accounts is analyzed to predict the performance of future accounts. To perform this analysis, historical data collected for accounts opened during a specific timeframe, and their performance is monitored for another specific length of time to determine if they were good or bad. This is usually done by monitoring the payment behavior of the approved account over a period of months, post disbursal. Choice of performance window length and DPD threshold determines the sample size used for the model development.

Performance window is a period after the disbursal date, where the payment behavior of an approved account is monitored using DPD to determine whether they are defaulted or not. An account is considered as ‘default’ if the contractual payment obligations are past due for a given number of days during the performance window.

While the usual length of the performance window is generally 12-months, 91 days past due is the commonly used DPD threshold for defining an account as ‘default’. However, three different DPD thresholds were explored – 31, 61 and 91 days past due – keeping the 12-month performance window.

Default rate under different thresholds was calculated for each portfolio as follows:

* For each approved account, obtained twelve-month DPD information following the disbursal month.
* Monthly payment behavior of these accounts was monitored during the 12-month performance window using the days past due (DPD).
* Accounts whose DPD was greater than the selected DPD threshold (31/ 61/ 91) days during the performance window were classified as defaulted accounts.
* Calculate observed default rate (ODR) for each product as follows:

Table below shows the observed default rates calculated based on different DPD thresholds:

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Product** | **Total Accounts** | **91 DPD & above** | | **61 DPD & above** | | **31 DPD & above** | |
| **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** |
| Auto Loan | 27 | 0 | 0% | 0 | 0% | 1 | 3.70% |
| Housing Loan | 274 | 0 | 0% | 1 | 0.36% | 1 | 0.36% |
| Personal Loan | 1,768 | 46 | 2.60% | 67 | 3.79% | 135 | 7.64% |
| Credit Card | 4,414 | 78 | 1.77% | 93 | 2.11% | 204 | 4.62% |

The sample size is an important feature of any empirical study in which the goal is to make inferences about a population from a sample. Larger sample sizes generally lead to increased precision when estimating unknown parameters. As observed in the above table, both total number of applications and following default rates are too small in case of housing loan and auto loans products.

It can be observed from the above table that default rates increase with the reduced DPD threshold used to identify an account as ‘default’. Using widely used 91 DPD as the threshold resulted in very low default rates. Though conservative 31 DPD threshold resulted in comparatively higher default rates, models developed using this threshold may lead to higher false positives resulting in higher rejection rates. Hence, it was decided to recognize an application as default if it had ever 61 days and above past due in the 12-month performance period that follows the disbursal month.

To summarize, based on discussions with the retail credit team, it was decided that:

* Scorecard development is not a viable option for auto loan and housing Loan products due to low volume and no/ low defaults.
* 61 days past due in the 12-month performance window will be used, which will result in more default accounts and more conservative, compared to 91 DPD criteria.
* Separate models will be developed for credit cards and personal loan products.

# **Model Development**

Following sections illustrate the model development steps.

## **Selection of Independent Variables/ Predictors**

The selection of characteristics to be included in the development sample is a critical part of the development process. This step, where characteristics are carefully selected, reinforces the need for some business thought to be put into every phase of the scorecard development process.

Application-level dataset obtained also contained the following customer/ account specific and demographic information obtained/ collected at the time of application. These customer specific factors are used as independent variables to develop the model.

|  |  |
| --- | --- |
| 1. Nationality | 1. Savings account balance at application |
| 1. Application date | 1. Last six months average account balance |
| 1. Disbursed date | 1. Number of loan products with CBI |
| 1. AECB Score | 1. Is existing product at bank delinquent |
| 1. Product being applied for | 1. First time mortgage buyer? |
| 1. Marital Status | 1. Loan to Value ratio |
| 1. Residential Status in UAE | 1. Age |
| 1. Number of years in UAE | 1. DSR Ratio |
| 1. Employer Category (A/B/C/ Restricted etc.) | 1. Blacklisted? |
| 1. Total number of years months in job | 1. Purpose of product |
| 1. Total Monthly Salary | 1. Loan Multiples |
| 1. Has account with the bank | 1. Frequency of Top Ups |
| 1. Salary transferred to bank | 1. Number of Dependents in UAE |
| 1. Account opening date with CBI |  |

## **Assessing the Predictive Power Independent Variables**

At this stage, the predictor variables were needed to be tested for their predictive ability to discriminate between good and bad accounts. To assess and/ or improve the predictive power, these variables were grouped using the binning process.

In the binning process number of levels of a non-numeric factor are consolidated/ reduced to achieve parsimony while preserving, as much as possible, the predictive power of the factor. Additionally, numeric factors are transformed into non-numeric factors for better discrimination among the underlying patterns. Binning offers following advantages:

* Increases scorecard stability: some factor values can rarely occur and will lead to instability if not grouped together.
* Improves quality: grouping of similar attributes with similar predictive strengths will increase scorecard accuracy.
* Allows to understand logical trends of “Default/ Non-default” deviations for each factor.
* Prevents scorecard impairment otherwise possible due to seldom reversal patterns and extreme values.
* Prevents overfitting (overtraining) possible with numerical variables.

Criteria for binning:

* Values of a non-numeric factor that shows similar default rates have been grouped together.
* In case of numeric variables, binning is performed in such a way that there is monotonicity in the bins and default rates follow either increasing or decreasing trend. For example, accounts in higher salary bin must have lowest default rate compared to accounts in lower salary buckets.

Following constraints have been applied in the binning process:

* A general “minimum 5% in each bin” rule has been applied to enable meaningful analysis.
* There are no groups with 0 counts for default and non-default.
* The default rate and WOE are sufficiently different from one bin to the next (i.e., the grouping has been done in a way to maximize differentiation between defaults and non-defaults).

Binning is an iterative process where it involves combining one or more values of a factor with comparatively similar default rates in each iteration to check whether the grouping resulted in enough number of accounts in the bin and default rate that is different from the other bins.

As discussed earlier, about 94% of the accounts that form the sample for the model development are from before Jan-2019, bins created from this data may not be relevant due to change in lending strategy and practices. Hence, all binning iterations/ solutions were thoroughly discussed with the retail credit department to assess whether the groupings of the values under various factors conform with the current credit evaluation process. Where required, data driven bins were modified to form the new bins, while doing so may lead to grouping of values with different default rates or results in creation of bins with less than 5% of the sample size.

Tables below shows the selected binning solution for each factor for both personal loan and credit card products.

**Personal Loan**

It was observed that all the variables chosen for the model development showed fair degree of predictive power with respect to personal loan product default rate, except for number od dependents in the UAE.



There were no defaults observed for the >750 AECB score bin and that would have resulted in division by zero error in calculating the WOE and information value. Hence a proxy value of 0.1 was used to facilitate the calculations. AECB score was not available for about 23% of the accounts used for the model development.







There were no defaults observed in UAE bin. A proxy value of 0.1 was used to facilitate the calculations of WOE and information value.











**Credit Card**

The tables below illustrate the variable binning and corresponding weight of evidence and information value. It was observed that important variables like monthly salary and DSR ratio, age, months in job and months in UAE have very weak predictive power.





Monthly salary, which is one of the important predictors, was missing for about 31% of the accounts.





Credit card portfolio is heavily concentrated towards Indian nationals, which contributes to around 60% of the development sample, whereas UAE nationals were accounting to only 2% of the sample.









Number of Dependents in UAE’ was missing for 61% of the accounts.



For the model development, WoE approach was used, where actual values of each bin were replaced with the WOE value. In this approach logistic regression will fit a linear regression equation of predictors (or WoE-coded continuous predictors) to predict the logit-transformed binary default/ non-default dependent variable.

## **Model Specification**

Application Scorecards are tools that allow organisations to predict the probability that an applicant will behave in a particular way. In our case, objective is to estimate the probability or likelihood an applicant will default on the payment within next 12-months. Information provided by the applicant at the time of applying for the credit/ loan facility are used to estimate this likelihood of default.

Various statistical techniques are used to link the observed payment behaviour of a sample of previously approved accounts with the information provided at the time of application. Logistic regression analysis is one of widely used statistical technique for developing scorecard models. Logistic regression estimates the probability of an event occurring, such as default and non-default, based on a given dataset of independent factors.

This model assumes that the credit quality of each account is driven by a set of accounts level risk factors, as specified below,

Where,

pi is Probability of an account being ‘bad’ or ‘good’

β0 is Model Intercept

β1, is Model coefficient

In case of both personal loan and credit card models, target variable (also called as dependent variable) is binary variable where each account has been tagged as either 1 (default) or 0 (non-default). This variable was regressed on the previously binned independent factors using logistic regression. Logistic regression produces the coefficients for each significant independent variable included in the analysis. These coefficients are used to estimate the probability of customer defaulting.

Separate models were developed for both personal loan and credit card products. Due to smaller sample size, models were developed on the full dataset and the validation was performed on the actual approve/ reject decisions that were taken during the April-2024 and May-2024 months.

Below sections illustrate the logistic regression output and the validation results for each model.

## **Model Estimation Results**

**Personal Loan Model**

Table below shows the model summary and coefficients estimated by the logistic regression model:

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Dep. Variable: Default flag No. Observations: 1768

Model: Logit Df Residuals: 1760

Method: MLE Df Model: 7

Pseudo R-squ.: 0.2038 Log-Likelihood: -226.93

converged: True LL-Null: -285.00

Covariance Type: nonrobust LLR p-value: 4.877e-22

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|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Predictor Variable** | **Variable Segment** | **WOE** | **Coefficient** | **Standard Error** | **p-Value** |
| Model Intercept |  | **-** | -2.6975 | 0.370 | 0.000 |
| Nationality | UAE | 192.4776 | -0.0082 | 0.002 | 0.0000 |
| India | 58.4166 |
| Egypt, Jordan | 4.7572 |
| All Others | (18.3822) |
| Philippines | (35.1342) |
| Pakistan, Syria | (125.5934) |
| Is Existing Product Delinquent | No | 234.1670 | -0.0074 | 0.003 | 0.007 |
| Yes | (34.1346) |
| AECB Score | >750 | 304.2489 | -0.0067 | 0.002 | 0.006 |
| 650 to <=750 | 24.4761 |
| <650 & No Information | (63.0640) |
| DSR ratio | <=25 | 88.7465 | -0.0074 | 0.003 | 0.026 |
| >25 to <=35 | 41.9621 |
| >35 to <=49 | 6.2752 |
| >49 | (54.2358) |
| Months in Job | >120 | 172.5063 | -0.0047 | 0.003 | 0.084 |
| 60 to 120 | 30.1091 |
| 25 to 60 | (30.5310) |
| <25 | (102.8544) |
| Number of Months in UAE | >120 | 115.0868 | -0.0085 | 0.005 | 0.063 |
| 60 to 120 | 18.4412 |
| 25 to 60 | (43.5591) |
| <25 | (127.9480) |
| Total Monthly Salary | >40k | 184.0895 | -0.0052 | 0.003 | 0.060 |
| >20k to <=40k | 48.1508 |
| >10k to <=20k | 2.5419 |
| <=10k | (52.8382) |

**Assessing the Model Predictive Power:**

Models are developed with the objective of identifying a potential default account with a fair likelihood of default probability. Decile analysis is performed to assess the predictive power of the model. The analysis involves dividing the dataset into ten equal groups such that each group should have the same number of accounts. It ranks accounts in the order from most likely to default to least likely to default. The decile analysis is a helpful tool to understand how the top deciles of our sample are behaving compared to the others.

Following steps are performed in decile analysis:

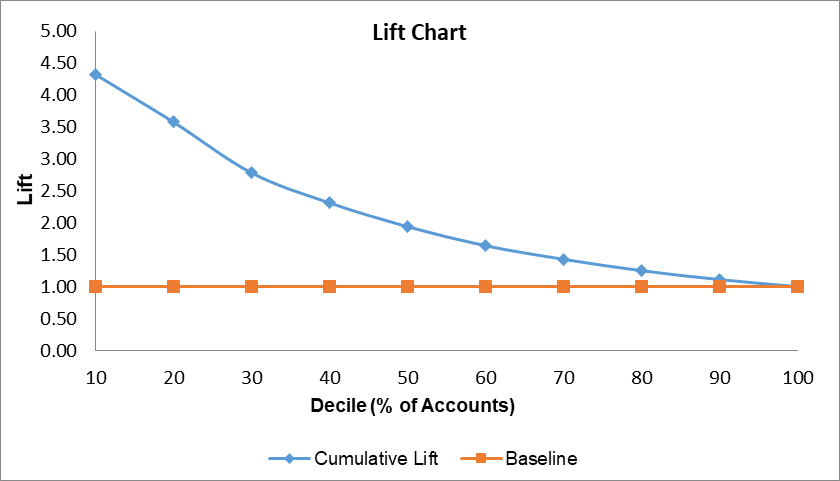
* Calculate the probabilities for each account using the above equation.
* Sort the accounts in descending order of the calculated probabilities.
* Divide the whole dataset into 10 groups such that each group contains approximately equal number of observations.
* Calculate total number of observed defaulted accounts and compute actual default rate in each decile.
* Calculate the average predicted probabilities in each decile.

A good model is one that captures most of the defaulted accounts in top deciles and fewer defaults in lower deciles, in decreasing order. A model that captures at least 60% of the observed default accounts in the top 3 deciles is said to be decent model.

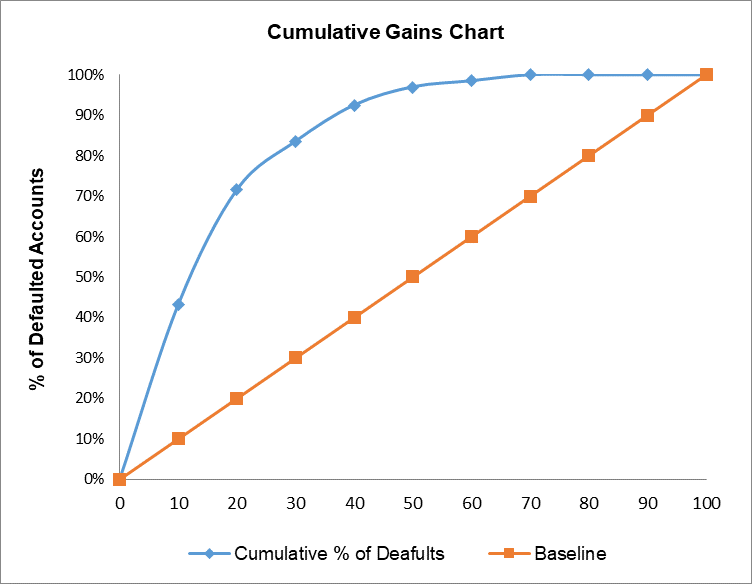
Decile analysis was performed on both development sample and results are given in the table below:

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Decile | Non-Default | Defaults | Total | Default Rate | Avg. Predicted Probability | Lift | Cumulative Gains | Gini Coefficient |
| 1 | 148 | 29 | 177 | 16.38% | 17.43% | 4.33 | 43.28% | 0.72 |
| 2 | 158 | 19 | 177 | 10.73% | 8.80% | 3.58 | 71.64% | 0.43 |
| 3 | 169 | 8 | 177 | 4.52% | 5.40% | 2.78 | 83.58% | 0.20 |
| 4 | 170 | 6 | 176 | 3.41% | 3.01% | 2.31 | 92.54% | 0.13 |
| 5 | 174 | 3 | 177 | 1.69% | 1.68% | 1.94 | 97.01% | 0.06 |
| 6 | 176 | 1 | 177 | 0.56% | 0.90% | 1.64 | 98.51% | 0.02 |
| 7 | 175 | 1 | 176 | 0.57% | 0.46% | 1.43 | 100.00% | 0.01 |
| 8 | 177 | 0 | 177 | 0.00% | 0.17% | 1.25 | 100.00% | 0.00 |
| 9 | 177 | 0 | 177 | 0.00% | 0.06% | 1.11 | 100.00% | 0.00 |
| 10 | 177 | 0 | 177 | 0.00% | 0.01% | 1.00 | 100.00% | 0.00 |
| **Total** | **1,701** | **67** | **1,768** | **3.79%** |  |  |  | **68.7%** |

It is observed that selected model captures around 83% of the observed defaulted accounts in first 3 deciles. While the portfolio default rate is 3.79%, closest calculated probability score falls in the 4th decile. That means accounts that scores more than the portfolio default rates are all falls in the top 4 deciles, and these can be either rejected or examined carefully before being approved.



A lift of one means there is no gain compared with the number of accounts targeted at random. Lift greater than one indicates using the model is better than selecting the accounts at random.



**Credit Card Model**

Logistic regression models were developed for the credit card product also, in line with the model developed for the personal loan product. However, best model that was developed for the product contained only five independent variables.

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Logit Regression Results

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Dep. Variable: Default flag No. Observations: 4414

Model: Logit Df Residuals: 4408

Method: MLE Df Model: 5

Pseudo R-squ.: 0.1368 Log-Likelihood: -389.31

converged: True LL-Null: -450.99

Covariance Type: nonrobust LLR p-value: 6.080e-25

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Coef std err z P>|z| [0.025 0.975]

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Intercept -3.8478 0.132 -29.181 0.000 -4.106 -3.589

Is Existing Product Delinquent -0.0098 0.003 -3.789 0.000 -0.015 -0.005

Nationality -0.0092 0.002 -3.695 0.000 -0.014 -0.004

Months in job -0.0071 0.003 -2.040 0.041 -0.014 -0.000

Age -0.0068 0.003 -2.105 0.035 -0.013 -0.000

AECB score -0.0091 0.001 -6.283 0.000 -0.012 -0.006

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Many variables that are important for the credit decisioning, were not statistically significant in any of the models developed. This was already reflected in the quality of the data obtained for credit card product where values were missing for many important variables, that in turn resulted in very low information value.

## **Model Selection**

Both the models were thoroughly discussed with the retail credit department. After thoughtful discussions, it was decided to use the model developed based on the personal loan data for the entire retail portfolio. this is due to the fact that customers seeking a retail credit facility mostly share the common risk factors.

Additionally, it was also decided to add few more factors to the scorecard that did not come as a significant factor during the logistic regression model development using the personal loan accounts data. These factors were recommended by the retail credit team, considering the current underwriting strategy. These factors include

* Age of the customer
* Length of relationship with the bank (years) and
* Employment Category.

# **Scaling**

Scaling refers to the range and format of scores in a scorecard and the rate of change in odds for increases in score. There are various scales in use in the industry. One of the most common scaling methodologies is the scorecard with discrete scores scaled logarithmically, with the odds doubling at every 20 points.

Since the logistic regression model was developed using the weight of evidence as input, score for each attribute/ bin of a variable was calculated as:

Where:

WOEj = Weight of evidence for each grouped independent variable

*a* = Intercept term from logistic regression

*=* regression co-efficient of independent variable from the logistic regression

*n* = Number of independent variables included in the model

*k* = number of groups/ bins in each independent variable

Factor = PDO / ln (2)

Offset = Base Score – (Factor \* ln (Odds))

Where PDO is *Points to Double the Odds*

The above formula calculates the scores to be assigned to each grouped attribute, for every characteristic in the scorecard developed, and sums all the scores for each attribute to provide the final score.

The following parameters have been used for calculation of scores:

* Number of Predictor Variables = 7 + 3 (Seven statistically significant variables from logistic regression model. Three variables added manually based on discussion with credit team)
* Base Score = 500 at 10:1 odd
* PDO = 20
* Factor = 28.85
* Offset = 433.56

The table below shows the results of scaling of variable categories:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Predictor Variable** | **Variable Segment** | **WOE** | **Regression Coefficient** | **Score** | **Weight** | **Weighted Score** |
| Nationality | UAE | 192.4776 | -0.0082 | 92 | 3.25 | 27 |
| India | 58.4166 | 60 | 3.25 | 18 |
| Egypt, Jordan | 4.7572 | 48 | 3.25 | 14 |
| All Others | (18.3822) | 42 | 3.25 | 12 |
| Philippines | (35.1342) | 38 | 3.25 | 11 |
| Pakistan, Syria | (125.5934) | 17 | 3.25 | 5 |
| Sanctioned |  | 0 | 3.25 | 0 |
| Is Existing Product Delinquent | No | 234.1670 | -0.0074 | 96 | 3.25 | 29 |
| Yes | (34.1346) | 39 | 3.25 | 12 |
| AECB Score | >750 | 304.2489 | -0.0067 | 94 | 19 | 162 |
| 650 to <=750 | 24.4761 | 51 | 19 | 88 |
| <650 & No Information | (63.0640) | 34 | 19 | 59 |
| DSR ratio | <=25 | 88.7465 | -0.0074 | 80 | 14 | 102 |
| >25 to <=35 | 41.9621 | 55 | 14 | 71 |
| >35 to <50 | 6.2752 | 48 | 14 | 61 |
| >=50 | (54.2358) | 35 | 14 | 44 |
| Months in Job | >120 | 172.5063 | -0.0047 | 70 | 6 | 38 |
| 60 to 120 | 30.1091 | 51 | 6 | 28 |
| 25 to 60 | (30.5310) | 42 | 6 | 23 |
| <25 | (102.8544) | 33 | 6 | 18 |
| Number of Months in UAE | >120 | 115.0868 | -0.0085 | 75 | 8.50 | 58 |
| 60 to 120 | 18.4412 | 51 | 8.50 | 39 |
| 25 to 60 | (43.5591) | 36 | 8.50 | 28 |
| <25 | (127.9480) | 15 | 8.50 | 12 |
| Total Monthly Salary | >40k | 184.0895 | -0.0052 | 80 | 14.25 | 104 |
| >20k to <=40k | 48.1508 | 54 | 14.25 | 70 |
| >10k to <=20k | 2.5419 | 47 | 14.25 | 61 |
| <=10k | (52.8382) | 39 | 14.25 | 50 |
| Employer's Sector | Government & GRE |  |  | 80 | 14 | 102 |
| Services, Construction, Oil & Gas |  |  | 70 | 14 | 89 |
| Manufacturing & Healthcare |  |  | 60 | 14 | 76 |
| Retail |  |  | 50 | 14 | 64 |
| Others |  |  | 40 | 14 | 51 |
| Real Estate & Trading |  |  | 30 | 14 | 38 |
| Age in Years | 21 to 30 |  |  | 80 | 8.50 | 62 |
| 31 to 40 |  |  | 70 | 8.50 | 54 |
| 41 to 50 |  |  | 60 | 8.50 | 46 |
| >50 |  |  | 50 | 8.50 | 39 |
| Employment Category | Government |  |  | 80 | 6 | 44 |
| Category A |  |  | 70 | 6 | 38 |
| Category B |  |  | 60 | 6 | 33 |
| Category C |  |  | 50 | 6 | 27 |
| Restricted/ Not Listed |  |  | 25 | 6 | 14 |
| Length of relationship with the bank (years) | >10 |  |  | 80 | 3.25 | 24 |
| 5 to 10 |  |  | 70 | 3.25 | 21 |
| 1 to 5 |  |  | 60 | 3.25 | 18 |
| <1 |  |  | 50 | 3.25 | 15 |

Some demographic variables like AECB score, monthly salary and DSR ratio are more important in deciding whether to approve or reject a credit application compared to other factors. Hence the scores were re-calculated to give higher weightage to parameters that were considered important in decision making. Below is the list of variables, ordered with the highest weightage:

|  |  |
| --- | --- |
| **Parameter** | **Weightage** |
| AECB Score | 19.00 |
| Monthly Salary | 14.25 |
| DSR Ratio (%) | 14.00 |
| Employer's Sector | 14.00 |
| Age (in years) | 8.50 |
| Months in the UAE | 8.50 |
| Employment Category | 6.00 |
| Months in Job | 6.00 |
| Nationality | 3.25 |
| Length of relationship with the bank (years) | 3.25 |
| Is Existing Product with Bank Delinquent? | 3.25 |
| **Total** | **100** |

For each bin, weighted score was calculated as follows:

Where: *n* = number of independent variables included in the model

**Neutral Score**

A neutral score is calculated for each independent variable in the scorecard. Any independent variable for which an applicant scores below the neutral score is then a potential reason for decline.

Where:

is the score of ith bin of an independent variable

is the percentage of accounts under ith bin of an independent variable

**Score Cut Off**

Minimum score is the score an applicant would get if he/ she scores lowest on all the independent variables. Whereas maximum score is the score an applicant would get if he/ she scores highest possible score on all the independent variables. Thus, minimum and maximum scores for an existing customer is 300 and 750, respectively. For a new customer, minimum and maximum score range is 275 to 700.

Cut-off score is the score an applicant must obtain to consider for approving the application. Cut-off score is calculated as the sum of the neutral scores across all the independent variables. Cut-off score for existing customers is set at 425, whereas cut-off score for new customers is set at 375.

Any application whose score is below the cut-off score is rejected. Additionally, if an application’s score is above the cut-off score but the score on three variables is below the neutral score, such applicants are also rejected.

if an application’s score is above the cut-off score but the score on at least four variables is in the mid-range (neither good nor bad), then such applications would be referred for further review by the retail credit team.

# **Model Back Testing**

Retail credit team reviewed the retail application scorecard and conducted tests on 64 cases of personal loans and credit cards, excluding secured products. These are the new accounts that were approved during April-2024 and May-202. Here are the results and observations:

* Out of the 64 cases tested, the scorecard accepted 60 and rejected 4.
* Among the accepted cases, 54 were approved, and 10 were declined.
* More than 50% of the approved cases had deviations.

Above observation from the retail credit team can be summarised in a classification matrix as below:

|  |  |  |  |
| --- | --- | --- | --- |
|  | | Predicted | |
| Rejected | Accepted |
| Actual | Rejected | 4 | 6 |
| Accepted | 0 | 54 |

* True Positives (Acceptance of Goods) 54
* True Negatives (Decline Bad accounts) 04
* False Positives (Acceptance Bads) 06
* False Negatives (Decline of Goods) 00

Based on the above, it can be observed that model has an accuracy rate of 90.63%. However, model has accepted six of the 10 accounts that were rejected by the credit team. This is largely due to gaps in data used for the model development and current underwriting strategies. It should also be noted that more than 50% of the approved cases had deviations.

# **Next Steps**

Finance and Market risk team has created an excel based tool which credit team can use it to calculate the score and get accept/ reject decision based on the specific score cutoff. Scorecard will be deployed compliment the current decision-making process and to get the risk score for each application. Additionally, credit team will score the already approved accounts in the past months. In both the cases, credit team will note down the reasons that resulted the scorecard to misclassify (accepting an account that rejected/ rejecting an account that is accepted based on current strategy) accounts. Scorecard will be augmented to incorporate these observations to improve the accuracy rates.

Additionally, as the scorecard is built on very old data, scorecard will be redeveloped as and when the sufficient data available, which is more recent and reflects the current lending strategies of the retail banking group.

# **Appendix 1: Default Rates**

**Personal Loan: Quarterly observed default rates at different DPD thresholds**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Application Quarter** | **91 DPD & above** | | **61 DPD & above** | | **31 DPD & above** | |
| **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** |
| Q2-2017 | 14 | 3.40% | 22 | 5.34% | 44 | 10.68% |
| Q3-2017 | 59 | 3.72% | 88 | 5.55% | 149 | 9.39% |
| Q4-2017 | 39 | 3.76% | 52 | 5.01% | 80 | 7.71% |
| Q1-2018 | 28 | 3.88% | 33 | 4.58% | 45 | 6.24% |
| Q2-2018 | 5 | 2.75% | 5 | 2.75% | 5 | 2.75% |
| Q3-2018 | 2 | 0.98% | 3 | 1.46% | 5 | 2.44% |
| Q4-2018 | 1 | 1.22% | 1 | 1.22% | 1 | 1.22% |
| Q1-2019 | 0 | 0.00% | 1 | 2.27% | 1 | 2.27% |
| Q2-2019 | 0 | 0.00% | 1 | 3.33% | 1 | 3.33% |
| Q3-2019 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2019 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q2-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q3-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2021 | 1 | 5.00% | 1 | 5.00% | 1 | 5.00% |
| Q2-2021 | 0 | 0.00% | 0 | 0.00% | 1 | 4.35% |
| Q3-2021 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2021 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q2-2022 | 0 | 0.00% | 0 | 0.00% | 2 | 4.26% |
| Q3-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| **Total** | **149** | **3.23%** | **207** | **4.49%** | **335** | **7.27%** |

**Credit Card: Quarterly observed default rates at different DPD thresholds**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Application Quarter** | **91 DPD & above** | | **61 DPD & above** | | **31 DPD & above** | |
| **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** | **# Defaults** | **Default Rate** |
| Q2-2017 | 14 | 3.40% | 22 | 5.34% | 44 | 10.68% |
| Q3-2017 | 59 | 3.72% | 88 | 5.55% | 149 | 9.39% |
| Q4-2017 | 39 | 3.76% | 52 | 5.01% | 80 | 7.71% |
| Q1-2018 | 28 | 3.88% | 33 | 4.58% | 45 | 6.24% |
| Q2-2018 | 5 | 2.75% | 5 | 2.75% | 5 | 2.75% |
| Q3-2018 | 2 | 0.98% | 3 | 1.46% | 5 | 2.44% |
| Q4-2018 | 1 | 1.22% | 1 | 1.22% | 1 | 1.22% |
| Q1-2019 | 0 | 0.00% | 1 | 2.27% | 1 | 2.27% |
| Q2-2019 | 0 | 0.00% | 1 | 3.33% | 1 | 3.33% |
| Q3-2019 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2019 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q2-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q3-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2020 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2021 | 1 | 5.00% | 1 | 5.00% | 1 | 5.00% |
| Q2-2021 | 0 | 0.00% | 0 | 0.00% | 1 | 4.35% |
| Q3-2021 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2021 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q1-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q2-2022 | 0 | 0.00% | 0 | 0.00% | 2 | 4.26% |
| Q3-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| Q4-2022 | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% |
| **Total** | **149** | **3.23%** | **207** | **4.49%** | **335** | **7.27%** |