Dear Manager,

Thanks for the dataset provided. The below table highlights the summary statistics from the three datasets received before quality assessment and cleaning the data

|  |  |  |  |
| --- | --- | --- | --- |
| Table name | No. of records | customer ids | Date data received |
| Customer demographic | 20,000 | 4,000 | 24-02-2022 |
| Customer address | 3999 | 3999 | 24-02-2022 |
| Transaction data | 20,000 | 20,000 | 24-02-2022 |
|  |  |  |  |

This table here depicts the data set after quality assessment and cleaning the data

|  |  |  |  |
| --- | --- | --- | --- |
| Table name | No. of records | Distinct customer ids | Date data received |
| Customer demographic | 4000 | 4000 | 24-02-2022 |
| Customer address | 3999 | 3999 | 24-02-2022 |
| Transaction data | 20,000 | 3496 | 24-02-2022 |

Notable data quality issues that were encountered and the methods used to mitigate the identified data inconsistencies are as follows. Furthermore, recommendations have been provided to avoid the reoccurrence of data quality issues and improve the accuracy of the underlying data used to drive business decisions.

● Accuracy :

Additional customer id’s in the ‘Transactions table’ and ‘Customer Address table’ but not in ‘Customer Master (Customer Demographic)’

Mitigation:

Please ensure that all tables are from the same period. Only customers in the Customer Master list will be used as a training set for our model. This indicates that the data received may not be in sync with each other which may skew the analysis results if there are missing data records. Please refer to excel file ‘data\_outliers.xlsx’ for the list of outliers between tables.

● Completeness:

Various columns, such as the brand of a purchase, or job title, have empty values in certain records

Mitigation: If only a small number of rows are empty, filter out the record entirely from the training set for prediction. Else, if it is a core field, impute based on distribution in the training dataset. For key datasets, such as transactions, less than 1% of transactions (totalling less than 0.1% of revenue) have missing fields. These records have been removed from the training dataset.

● Consistency:

Inconsistent values for the same attribute (e.g. Victoria being represented as “V”, “Vic” and “Victoria”)

Mitigation: Use regular expression to replaced extended values into abbreviations to ensure consistency across addresses.

Recommendation: Enforce a drop-down list for the user entering the data rather than a free text field. In order to construct meaningful variables for the model, the data has been cleaned to avoid multiple representations of the same value. Additionally, gender records where ‘U’ have been replaced based on the distribution from the training dataset.

● Values up to Date:

Inconsistent data type for the same attribute (e.g. numeric values for some fields and strings for others)

Mitigation: Convert selected records in characters to numeric. Remove non-numeric characters from string.

Recommendation: Ensure that fact tables in the given database have constraints on data types. Having different data types for a given field make it difficult to interpret results at the later stage. Therefore, appropriate data transformations are made to ensure consistent data types for a given field.

Note: The data and information in this document is reflective of a hypothetical situation and client. This document is to be used for KPMG Virtual Internship purposes only. Moving forward, the team will continue with the data cleaning, standardisation and transformation process for the purpose of model analysis. Questions will be raised along the way and assumptions documented.

After we have completed this, it would be great to spend some time with your data SME to ensure that all assumptions are aligned with Sprocket Central’s understanding.

Kind regards,

Ojieh Kingsley.