Customer lifetime value modelling for an automotive company

Introduction

Customer lifetime value is the total value that a customer delivers to a company over the course of their relationship with the brand. It includes a customer's whole economic contribution, including purchases, repeat transactions, and prospective referrals, all of which contribute to the company's overall financial effect.

Client is one of the most recognized automobile brands in the world. It is at the echelon of the automobile industry, producing products that are known for a combination of quality, utility, and style, operating in over 150 countries and has production facilities at more than 30 locations worldwide.

The client wants to create a systematic approach for building and measuring the efficacy of a Customer Performance Evaluation based on a variety of factors such as **recency, frequency, monetary value**, and others.

- The technique entails thorough data collecting and analysis, allowing for client segmentation into various groups for in-depth review.
- The technique tries to give a holistic knowledge of each client's contributions to the firm by evaluating criteria such as the frequency of purchases, the frequency of interactions, and the monetary value attributed to each customer.
- The resulting insights not only enable customized engagement methods, but also informed decision-making to maximize client connections and support long-term success.

TransOrg Analytics used various machine learning techniques to analyze customer lifetime value and developed a scoring methodology based on the weights decided by the business for different customer attributes, for the client to execute smart promotions and sales planning.

Solution

TransOrg commenced by consolidating data from multiple data sources for further processing & analysis.

To analyse customer base on different categories and series, TransOrg created an automated script, merged customers having multiple vehicles based on multiple demographic features such as contact information.

Further, different data preparation steps were executed such as cost mapping, customer transaction tagging, name cleaning and data deduplication. RFM segmentation was conducted utilizing a range of attributes, including recency, frequency, monetary value, and average monetary expenditure. These attributes were employed to formulate the data required for constructing the Customer Lifetime Value (CLV) model.

Different filters were used for RFM segmentation which was based on: -

- Customers who share similar age groups, in percentiles according to their recency, frequency, and monetary performance.
- Customers characterized by similar car ownership counts can be grouped, and their positioning in percentiles can be determined based on recency, frequency, and monetary performance.
- The integration of these two factors also enables a dual-tier segmentation strategy for customers.

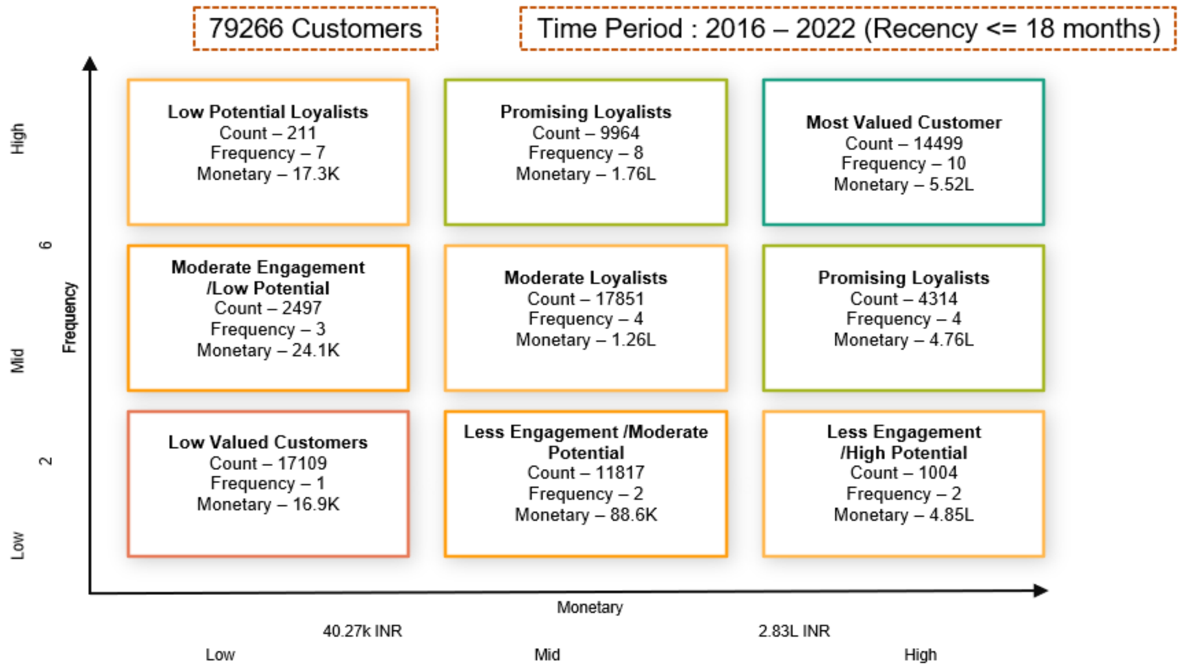

Fig-RFM segmentation of active customers.

For Customer Lifetime Value (CLV) modelling, there were many methodologies that deal with the portion of CLV associated with direct purchases, but the two most broad classes are generally defined as: -

- Historical CLV
- Predictive CLV

TransOrg used predictive modelling approach where, it segmented the problem statement into two parts. Here CLV was defined as combination of two things which were **purchase visit frequency** and **average order value.**

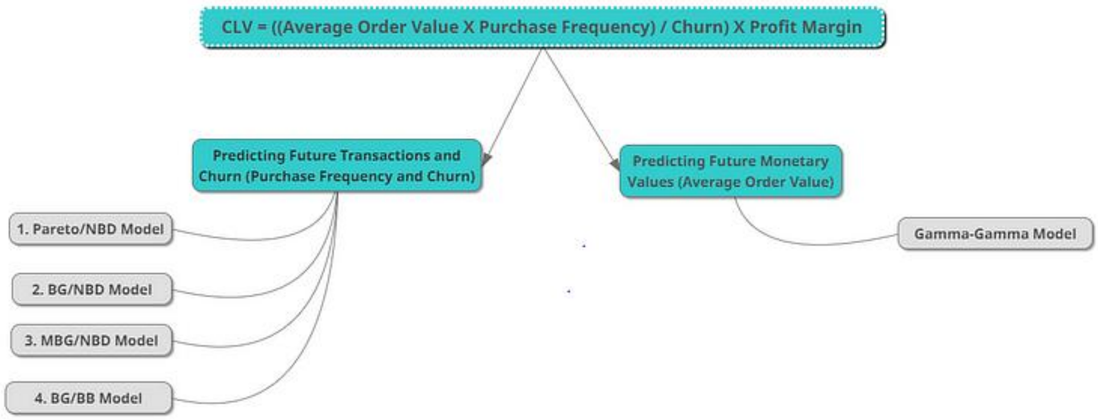

Fig-Segmentation of CLV

Mathematically combined CLV can be represented as

CLV = Expected Number of Transactions * Expected Monetary Value per Transaction

Model for Purchase visit frequency was developed by TransOrg where the basic mechanism that model used was-

1.Buying Pattern:

- The distribution was employed to gauge the likelihood of a customer making a specific number of repeat purchases in a set time period.
- It assumed that customers had a certain purchase frequency (how often they bought) that followed a specific distribution.
- The BG aspect considered that customers might have varied purchase frequencies based on individual characteristics.

2.Dropout Likelihood:

- The Negative Binomial distribution gauged the number of purchases a customer would likely make before becoming inactive.
- It assumed that customers had a certain chance of becoming inactive after each purchase.
- This captured the notion that customers might have lost interest after a certain number of purchases.

To add the monetary aspect of the problem, TransOrg modelled the monetary value using the Gamma-Gamma Model, by utilizing earlier developed model and trained this model, for customers who made repeat purchases with the client i.e., frequency > 0. Because, if the frequency is 0, it means that they were a one-time customer and, considered already dead.

- The Gamma-Gamma model was directed at the monetary aspect of customer transactions, focusing on estimating the variability in transaction amounts.
- By leveraging parameters of the Gamma distribution, this model dealt with the distribution of transaction values for each customer.
- The insights it provided encompassed the average transaction value and the diversity in transaction sizes.

Further, a customer score calculation mechanism was developed by assigning different weighted score based on various attributes provided by the company and total customer score was generated out of 100.

Time Period : 2016 – 2022

Weight	Attributes	Customer 1	Customer 2	Customer 3
10	Recency	3 months => 10	12 months => 3	6 months => 7
5	Frequency	4 Job Cards => 5	2 Job Cards => 3	1 Job Card =>2
30	Historical Monetary	2L => 30	40k =>10	1.5L => 20
10	Future Monetary	3L =>10	1L => 3	2L =>7
5	SF Contract	No Loans => 0	Loan Taken => 5	No Loans => 0
10	Super Customer	3 VINs => 10	2 VINs => 5	1 VIN => 0
10	Car Segment	GKL => 10	KKL => 7	UKL => 0
5	BSI/BRI Customer	BSI & BRI => 5	No Package => 0	BSI => 3
15	(LSM) Future Retail	Booked => 15	No enquiry => 0	TD Provided => 8
100	Max Customer Score	95 Good	36 Poor	47 Average

Fig-Customer Score Calculation using CLV.

- The scores were derived based on the rules defined by the business and the model had certain flaws which has been handled in the predictive model.
- Machine Learning based model was built to understand the customer spending pattern and predict the future spending value.
- Assigning score based on the weights decided by the business for different customer attributes.

Impact

Clear insights for Customer Lifetime Value enabled client for customized engagement method, informed decision making to maximize client connection and support long term success.
There was an increase in model performance developed by TransOrg in comparison to client's inhouse model which they were using earlier.

Contact Us

Follow us: www.transorg.com Email: info@transorg.com