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Big Data Analytics for Customer Lifetime Value Prediction

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Abstract

Predicting all the values that a business can derive from its long-standing relationship with its customers is Customer Lifetime Value. As it helps to create a sustainable relationship with selected customers, the importance of CLV is growing at a brisk pace, generating higher revenue that in turn enhances business growth. With increasing competition, retaining existing customers is more profitable than acquiring new customers. To manage and allocate resources efficiently for each and every customer, big data analytics comes into play. Taking this into account, a large amount of data should be taken into consideration, such as client's attrition, objectives, diverse products and services that they use, client's characteristics viz demographic, psychographic, geographic etc. First step to this is data cleaning, pre-processing and data manipulation to achieve a meaningful outcome or information from the raw data, followed by data analysis and visualization. Techniques that can be recommended for the data analysis and visualization of CLV model can be Stepwise regression, Classification and regression trees (CART), Generalized linear models (GLM). To determine the dynamic view of customer behavior, future marketing strategies and to foster brand loyalty, prediction of a proper CLV model is much needed.

Keywords: CLV, Predictive Models, Pareto/NBD Model, Gamma-Gamma Model, Retail Industry CLV, Purchase Count, Lifetime Value, Monetary Value

1. Introduction

The enhancement of faster processing through Pentium processors introduced back in the early 1990s marked the beginning of the era of information economy. It improved the processing speed of the computers, the ability to run state-of-the-art software devices and store huge amount of data (Kudyba, 2002). Big Data is one of the most hyped terms in today's market and there is no consensus as how to define it. It is not a specific application type but can be rather considered as a collection of trends observed from multiple application types. Big data can include data from web server logs, internet clickstream data, social media content, social media activity reports, customer emails, surveys, CDRs, data from sensors connected to Internet of Things.

Data growth can be classified according to - amount of input data (volume of data), data input type (variety of data), faster ingest of data (velocity of data), data quality or trustworthiness (veracity of data). Through big data analytics it is easier to find unknown patterns and market trends, correlations, association, customer preference and other actionable insights. The analytical observations can lead to better decision making, finding out more effective marketing strategies, new revenue opportunities, improve operational efficiency. It gives competitive advantage over its competitors and provide with business benefits. Big data is used with related concepts of Business Intelligence (BI) and data mining. But the hyped term is different from the other two when data complexity, data volume and the huge data sources are taken into consideration. Data warehouses may not be capable of handling the high processing demands faced due to huge volume of data sets which needs to be frequently updated or even in real-time. With the purpose of collecting, processing and analyzing of big data, a set of new technologies including Hadoop and tools such as YARN, Spark, Hive are budding. These technologies support the processing of vast and diverse data across clustered systems.

With the increase in customer transaction data it has been quite an interest to estimate the value of customers or assessment of customers. This is an important trend in the disciplines such as - accounting, finance and especially marketing catering to various sectors (Petrison, Blattberg & Wang, 1993).

2. Probability Models

2.1 Pareto/NBD Model

Pareto/NBD Model is one of the most widely used methods for calculating Customer Lifetime Value (Schmittlein, Morrison and Colombo, 1987). It is used to predict the future activities of the customer. The order history is considered to be the primary input and takes into order the frequency and recency of the orders. The basic model stimulates two events - coin and dice. The coin is used to determine the churn rate of the customers and dice to determine how many items a customer will order. Pareto distribution is used to model the coin whereas negative binomial distribution is used to model the dice.

The prediction done by this model rests on the following assumptions (Charu, Trisha, Jarred & Edward, 2013):

- Consider the customer to be alive even after they become permanently inactive.
- While alive, the customer's purchasing behavior follows a Poisson process with a transaction rate to be considered.
- There is heterogeneity in transaction rates and drop-out rates across customers that follow a gamma distribution.

This model focuses only on the time length for which a customer is observed, time of the customer's last transaction and how many transactions the customer has made. The demographic or the earlier transaction details are not considered.

2.2 Gamma-Gamma Model: Extension to the Pareto/NBD Model

Pareto/NBD focuses only on the number of transactions/ purchase count throughout lifetime but does not focus on the monetary value component whereas; Gamma-Gamma model focuses on the monetary value also.

Gamma-Gamma model is based on three general assumptions:

- The monetary value of a transaction randomly varies around their average transaction value at customer level.
- The average transaction value is independent of time for an individual but it varies across customers.
- The distribution of average transaction does not dependent of the transaction process across customers. Hence, monetary value i.e. Gamma-Gamma model can be formed separately from the lifetime components and purchase count of the model i.e. the Pareto model.

3. Two Models Together: Estimation of CLV at Customer Level

- The expected number of purchases done by the customer in a forecasted period is computed by Pareto/ NBD model.
- The monetary value to each of these future purchases is assigned by Gamma-Gamma model.
- To forecast CLV for each customer became simplified tying these two models. Comparing CLVs became easier considering the monetary value of lifetime purchases.

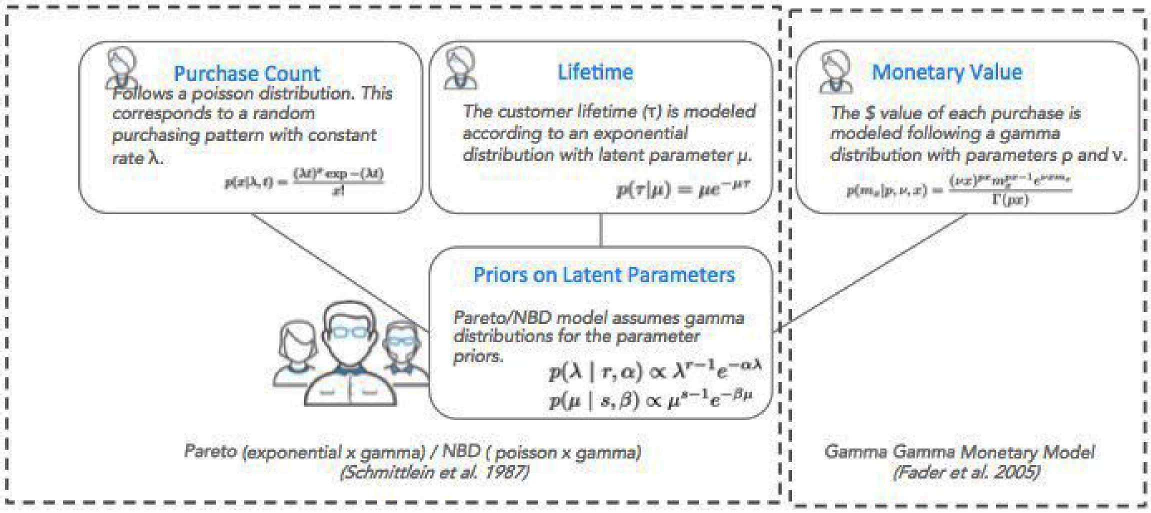

Fig. 1: Two Models: Pareto/NBD and Gamma-Gamma

4. Use Case for Retail Industry

A non-contractual relationship exists between businesses and customers in e-Commerce or retail business. In the non-contractual world, churning of customers happens silently. So, it is more complex to model customer lifetime value for non-contractual businesses and we need prediction for this.

- *Data to Analyze*
  - Customer's last transactions.
  - Is the customer "dead", or is the customer alive but dormant?
  - What is the frequency of repeat purchases made by the customer?
  - The age of the customer or the duration between a customer's first purchase and the end of the period (under consideration).
  - Recency or the age of the customer when they made their most recent purchases (Thus if only 1 purchase is made, the Recency is 0.).
- *RFM (Recency, Frequency, Monetary) Analysis:* RFM analysis is used to quantitatively determine the recency of purchase done by the customer, purchasing frequency of a customer and the expense done by the customer (monetary) from this, probability of customers who are surely alive, can be predicted. Customers having very high frequency and very high recency are likely to be the best customers in future.
- *Prediction of CLV Using Probabilistic Models:* These models (Pareto/NBD model) work on a method which predicts a customer's expected purchases in the next period going by their transactional history. Data should be predicted by the model and tested and cross-validated by machine learning practices to achieve higher model accuracy for predicting CLV. According to that trained model, the historical probability of customer being alive is predicted, given a customer's transaction history. For predicting monetary value, Gamma-Gamma model is ideal, since this model considers the economic component of each transaction and then estimates customer's probability to remain "alive" indicating proper customer's CLV prediction in retail businesses.

5. Value Addition of Pareto and Gamma-Gamma Model for Predictive CLV Calculation

Historical customer lifetime value is the simplest approach for calculating CLV. The historical methods do not account for time. It is solely based on the past transactions but doesn't help in predicting the future activities of the customer. This approach is valid if the customers have same behavioral pattern and over a same time span. Among customers, there can be a good amount of heterogeneity. Historical approach of CLV estimation will apply recency of the last purchase, thereby filtering out the criteria of segregation between the non-active and the active users.

The aim of a predictive model is identifying the purchasing behavior of customers in order to predict the future activities of a customer. In the non-contractual business context, Pareto model is a frequently applied probabilistic model. It focuses on three latent behaviors, the time period for which the customer is in relationship with the company or defining customer lifetime behavior and the number of purchases made by the customer over a given period or the purchase rate. The lifetime distribution follows an exponential distribution with slope μ and the purchase count follows a Poisson distribution with rate λ. The Pareto model is trained to find out the parameters over a particular training period within a minimum time span that corresponds to thrice of the typical inter-purchase time of the customers. Pareto model takes the historic or transaction data as primary input to predict for the future, thereby helping in business contexts.

6. Conclusion

Pareto/NBD model mainly focuses only on modelling purchase count and lifetime but Gamma Gamma model provides monetary aspect of the future purchases also. Hence, Gamma Gamma model is basically the monetary value extension to the Pareto/NBD model. The expenditure of a client is assumed to be independent of the transaction behavior in case of Gamma-Gamma model. Models like Pareto/NBD only predict the transaction behavior, independent of the monetary value and this limitation is being nullified by Gamma-Gamma model.

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