

MACHINE LEARNING BASED DYNAMIC CUSTOMER CHURN PREDICTION BY CUSTOMER BEHAVIOUR

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Abstract: *Churn studies have been used for years to achieve profitability and to establish a sustainable customer-company relationship. Machine learning is one of the contemporary methods used in churn analysis due to its ability to process huge amounts of customer data. In current days, the customers are getting more attracted towards the quality of service (QoS) provided by the organizations. However, the current era is evidencing higher competition. Nevertheless, efficient customer relationship management systems can be advantageous for the organization for gaining more customers, maintaining customer relationships and improve customer retention by adding more profit to the organizational business. Furthermore, the machine learning models such as support vector machine algorithms can add more value to the customer retention strategies. The results showed that the deep learning model achieved better classification and prediction success than other compared models.*

Keywords: *Churn prediction, quality of service, machine learning, and Customer churn modelling, Predictive analytics.*

I. INTRODUCTION

In the competitive world of sophisticated retail enterprise, customer footprint is a major concern. In the retail domain, monthly termination of transactions and termination of customers is stated [1]. It translates into a potential lack of benefits for the organization. In addition, it has emerged as an important issue for retaining

consumers. Therefore, it is important to identify users who may leave the organization in the short term. This method has been described as a prediction of manthan. The idea of abandonment is the place of analytical control software about clients from a wide angle. This utility position is a secondary part of

modelling customer behaviour in pattern analysis. From a marketing standpoint, Charan's concept relates to customer loyalty and customer rate standards that can be linked. By looking at the basic variable units of the consumer price, they demonstrate the investment or value associated with the transaction of the relevant behaviour during the lifetime of the buyer. These are the only variables that are important in modelling customer behaviour. Frequency and Money (RFM) has recently become one of the most commonly used variable units in modelling consumer behaviour.

Many studies in recent years have effectively linked the diagnosis of RFM to data mining methods [2]. Some studios start users using RFM diagnostics and then implement log mining methods to develop models for a certain number of key users. In addition, information mining techniques can be considered effective in predicting models, according to research completed in the remaining years. Developing smart-prediction models is an important task involving many tests, ranging from identifying the best predictive variables to selecting an effective prediction method based on those variables. Retail industries gather a great deal of customer information, and using past purchasing records and buyer price opportunities can be estimated

to determine if they can leave or stay. Because of the need to process large amounts of information, deep learning methods are important for buyers' foot modelling in updated device learning techniques.

The overall performance of the rotation prediction model is largely based on variables selected from the data set. Traditional strategies have two major limitations. i) Among the client's many features, extracting a feature is particularly tedious and time-consuming and is often performed by an expert. ii) Circulation forecasting model is often developed for a particular dataset. Because deep-insight techniques can automatically discover useful capabilities, a deeper domain algorithm can be applied to the user's predictions in the retail domain. Especially in studies with various input attributes, it is important to apply the latest ML strategies in conjunction with DL to provide better predictive results. This study developed and applied a deep neural community structure for analysis using supermarket transaction datasets. The gift of experimental results is that deep learning models offer accurate solutions like traditional models without manual interactions to extract features. This test tests a customer's footsteps using a retail insight algorithm and compares its overall

performance with other well-known step modelling strategies [3].

Consumers often play a key role in increasing the profits and sales of each organization. Therefore, to promote customer happiness, the organization's managers need to maintain a green user relationship control system by helping to select the target customers and maintain an effective association with them. In addition, the CRM device can be useful for the company in determining the maximum outstanding customer group and their behaviour. It helps the employer to understand retention strategies better. Also, the higher the buyer's loyalty, the lower the customer's monthly rate. Therefore, device tracking algorithms, including assist vector algorithms, can add value to avoid buyers' frustration. This record will create customer retention awareness using the help vector system, gaining knowledge to increase customer loyalty and increase retention.

II. RELATED WORK

Churning manifests itself either voluntarily because the consumer voluntarily decides to terminate family members with a particular vendor or unintentionally when the employer's action relocates family members to a particular entity. Coercive agitation arises in cases where the user no

longer complies. A set of guidelines set by the trade within a specific basis, and for this situation, it may be due to illegal means such as theft or refusal to pay on time. Consumer satisfaction with an organization's competitive advantage voluntarily motivates the movement. Churning evaluation practice is healthy for any organization dealing with different user types.

There have been churn modelling programs in the retail domain, and we will review the most effective studies that can be done in this area with a focus on RFM and gain a deeper understanding of packages in the context of churn. The research is entirely based on contract-based sales sectors, including telecommunications, banking, hedging, etc. A customer has to sign an agreement to receive service from a provider. Therefore, a user who terminates the contract is classified as a churner by the trading company. In contrast, a user who continues to receive general services is classified as a non-churner. For a non-contractual environment involving the retail area, churn prediction was to determine who was churning. The study of predictions within the retail region has been handled differently in the literature, using unusual forms of functions and models. Table 1 provides retail phase prediction research

using in-depth information from algorithms, logistics regression, and neural networks.

Van den Poel [4] recommended a definition of partial abandonment for non-contractual arrangements. Customers who do not store for 3 consecutive months or make purchases under a pre-determined spending constraint can be considered churners. They used an RFM model with transaction events and demographic variables to predict Churn and used logistical regression, neural networks and random forests to estimate the model.

Migueis et al. [5] developed a model based primarily on RFM to predict customer engagement using a succession of product category purchase records. Purchase records are considered a basket analysis technique and, as simple as that, the purchased product used for the version. Logistic regression techniques are used to review the RFM version.

Migueis et al. [6] developed an RFM model using predictive strategies, Multivariate Adaptive Regression Splines, and logistic regression. These investigations are based primarily on RFM data and lack data on purchases under promotional information.

Dingli et al. [7] retail industry study compared deep learning, convoluted neural networks, and Boltzmann machine

algorithms to predict manthan. Datasets and capabilities were not known, but RFM was declared for use.

Bashir et al. [8] used a version of Feature Learning Deep Learning for large-scale enterprise (B2B) classification. Transactional records (RFM) were used as a data set with 6000 users. Martines et al. [9] proposed customer predictions with a new set of customer-related features updated monthly from previous purchases and used state-of-the-art tools to gain insights from algorithms. They found that promoting the classification tree has become superior to others with excessive accuracy and classification performance.

Alboukaey et al. [10] proposed a daily based churn prediction model and suggested daily behaviors as a multivariate time to predict churn. A statistical model, an RFM model, A Long Short-Term Memory (LSTM) model and a Convolution Neural Network (CNN) model were applied on a mobile telecom dataset. They found that daily based churn prediction was better than the monthly based predictions.

Umayaparvathi and Iyakutti [11] emphasize on feature selection of the churn prediction models. They suggested that deep learning methods were as successful as the traditional methods

without picking or extracting features from datasets like the others.

III. CHURN PREDECTION

Examining the customer attrition rate in an organization implies the process of churn analysis. In the telecommunication industries, the churn can be identified as the number customers who had discontinued their subscription in a certain time period. A typical churn rate measures the number of customers moving in and out within a given time period. Moreover, for the telecommunication industry, the movement of the customers from one company to another is called churn. The current scenario is evidencing a higher number of churn customers as the particular industry is trying hard to retain more profitable customers. The algorithm the train your data set and model is shown in the Figure 2. Moreover, the churn can be classified into two types. In case of non-payment of the bills, fraud activity or any such activity, when the industry itself decides to remove the consumers, it is named as involuntary churn. In contrast to this, when the customer intended to change or leave the organization, the particular activity becomes a voluntary churn. However, In case of the telecom industry, the continuous increase in the number of service providers is becoming the vital reason for creating more churn customer

for the companies. Nevertheless, understanding the customer demand and gaining loyal customer can eliminate the churn in a higher rate.

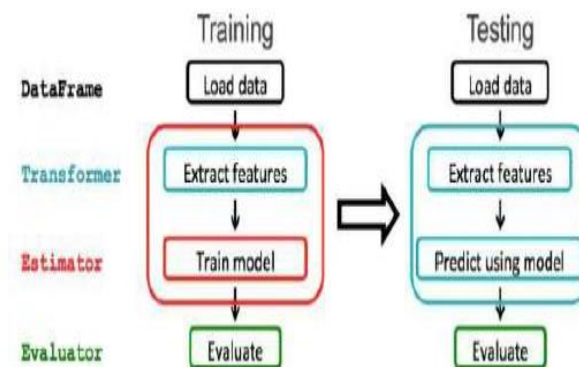


Fig.1 An algorithmic flowchart

IV. PREDICTION OF THE CHURNING USING A MACHINE ALGORITHM

Data analysis is one of the most convenient ways of perceiving instances of customer's deprival in business, for instance, the use of E-commerce conveniently utilizes the databases of consumers in strategizing on the way forward to be adopted by a firm in pursuit of maintaining a smooth flow of commerce in the product market. Pre-processing of data is a hub that puts a producer on the limelight of being familiar with consumer behaviour in association with their premises. For instance, it is considerably better to utilize the machine algorithm in running a regression analysis that will depict the consumer behavior in

correspondence to various organizations and products. It is recommendable to present the results in graphical presentations that will convince the managing team on the way to combat the malpractice by customers. Analytical data analysis tools should fall into play, especially in giving the marketing team a quick capture of the on-going typical market behavior. Categorization plays a critical role in identifying the strongholds and weak points of a company to its trading behavior. Also, in the broader context, the variable distribution tables will give clear evidence of the mean and the mode aspects of the purchasing teams.

Machine learning can be considered as the effective application of the artificial intelligence, which has been widely used by the telecom industries in evaluating and nullifying the customer churn. Support vector machine learning is one vital machine learning algorithm that efficiently performs the data analysis for predicting the churn. Moreover, the support vector machine (SVM) algorithm encompasses with a series of supervised learning methods for separating the data points. The support vector machine works by mapping the data in order to create hyper planes.

The optimal hyper plane in the support vector machine can be described as indicated in Fig. 2.

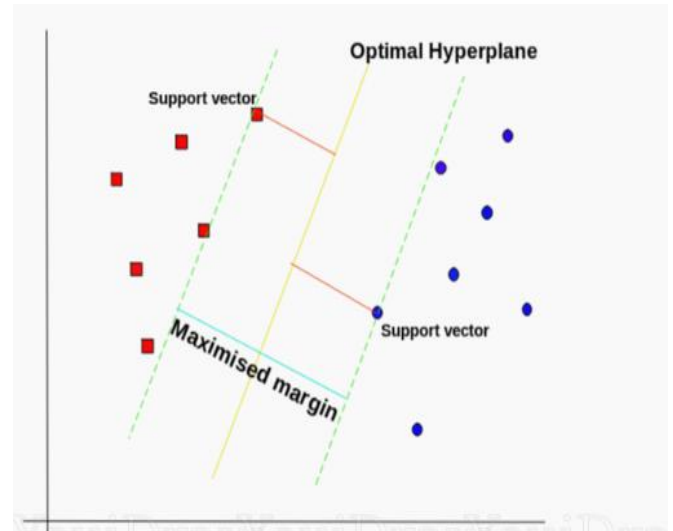


Fig.2 Optimal Hyperplane using the SVM algorithm

The support vector machine algorithm is one of the most effective methods of predicting churn rate. In examining traditional methods of predicting rotation, SVM allows the problem perspective to rely on subsets of information sets, giving comparative computational advantages in perspective. Also, instead of minimizing educational errors, Help Vector focuses on minimizing machine roll set generalization errors. Adopting this approach is becoming a major hurdle for forecasting in the telecommunications industry. The figure below shows four fully SVM based frameworks as a way to wait for the rotation.

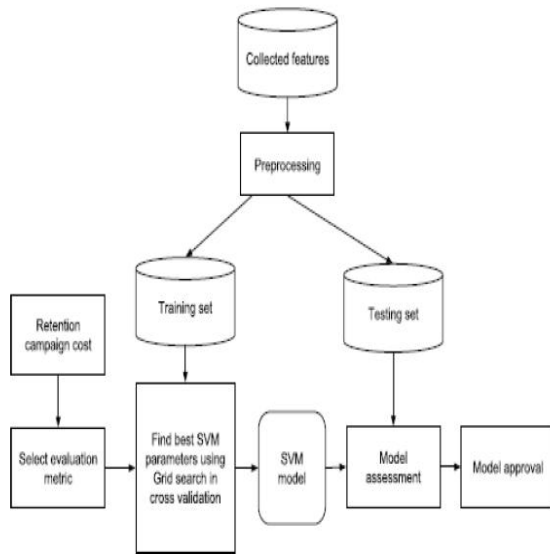


Fig.3 Churn Prediction Framework

V. CONCLUSION

Therefore, from the above conversation, it can be concluded that regardless of the form of the business company, almost every company should submit customer churn. Customer retention is a way to maintain customer loyalty by knowing what the customer needs and is served. The Powerful churn prediction model will help organizational control predict the customer's churn. Depending on the complex statistics of the telecommunications industry, vector devices can be powerful in predicting the churn rate. The previous document focuses on the concept of customer retention and forecasting. In addition, the use of helpful vector gadgets in an attempt to beautify the churn prediction system is discussed here, along with the algorithm.

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