Prediction of Customer Transactional Net Promoter Score (tNPS) Using Machine Learning

A Telecommunication Company Case Study

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Abstract. In many retail organisations, transactional Net Promoter Score (tNPS) is used to quantify customer satisfaction. It is also one of the alternative measures used in customer retention strategies and assessing customer loyalty. Customers who are dissatisfied rarely express their dissatisfaction before leaving. This makes customer retention strategies more difficult for business organisations. Machine learning can be leveraged to predict the tNPS using the past data which would assist in data-driven decision making to identify the unhappy customers. Case study company provided the tNPS report dataset comprises 10715 rows and 30 columns, and the service request report dataset has 28,7729 rows and 41 columns. Five machine learning models were developed by following Cross-Industry Standard Process for Data Mining research method. The best model is selected by the F-Score metric. Multilayer perceptron neural network performed the best compared to Decision Tree, Random Forest, Gradient Boosted Trees, and Logistic Regression with F- Score 0. 876. This finding would be useful to identify the customers service request that will score a high tNPS. The implications and limitations are discussed.

Keywords: Transactional Net Promoter Score (tNPS) · Prediction · Machine learning · Telecommunication company · Case study

1 Introduction

Customers nowadays demand a frictionless and hassle-free experience with their service provider. Customer satisfaction is a vital indicator of success for everyone from frontline service employees to C-suite executives. Customers who are dissatisfied do not return. Furthermore, dissatisfied clients rarely express their discontent before departing. Businesses have increasingly used Net Promoter Score (NPS) as a measure of customer satisfaction and a predictor of sales growth [1]. Customer churn, or the risk that

A. Asmawi (Ed.): ICTIM 2022, AEBMR 228, pp. 166–179, 2022.
https://doi.org/10.2991/978-94-6463-080-0_14

present customers will end their association with a company, is one of the most important problems that any company, regardless of industry, faces. Customer churn is typically caused by mismanagement, which causes client relationships to degrade, or by competitive actions, such as providing ample more tempting products or services. NPS is not only used to assess customer satisfaction, it is also one of the alternate measure used in customer retention strategies [2], determining customer satisfaction [1] and loyalty [3].

The Net Promoter Score (NPS) is a numerical evaluation given by customers after they have purchased a product or service. It ranges from 0 to 10. Customer surveys are the primary source of a company's NPS, which commonly ask for a numeric rating, in response to the question "How likely are you to rate the company's products /services?" [1]. However, about only 15–20% of customers respond to the NPS survey after their interactions with customer support service. Organizations have two major challenges: poor survey response rates and the possible loss of valuable insights from non-respondents [4].

To obtain the remaining NPS scores, a rule-based approach entails numerous lengthy and complex procedures, resulting in a system that is neither scalable nor reusable. As a result, most forward-thinking businesses are attempting to solve this challenge using machine learning approach. There are two types of NPS; transactional and relational. Transactional NPS (tNPS) is obtained immediately after a customer received a service or product which is more related to that particular transaction. Relational NPS is obtained for the overall customer experience with the company. This study attempts to predict tNPS for a telecommunication company.

The purpose of this study is to use a voice customer dataset to predict if a service request would receive a high tNPS score by applying data analytics and machine learning techniques. This study contributes the organisation predict NPS scores for the remaining 80% of customers who don't respond to the survey using a machine learning approach. More strategies may be planned ahead of time and performed faster, if it is possible to forecast which sorts of service requests will earn a higher tNPS score and which will receive a lower tNPS score. This could result in a better outcome than anticipated. Also this study contributes to the literature by leveraging machine learning techniques to assist business organizations to make informed decision based on their data.

2 Research Methodology

This study followed cross-industry standard process for Data Mining (CRISP-DM) methodology to build classification machine learning model [5]. CRISP-DM consists of six phases which are explained below.

2.1 Business Understanding

The project's goal is determined in this first phase, both from a business and data science standpoint. This research aims to help the company by predicting whether or not a customer-requested service will get a high tNPS. The research goal in terms of data science is to develop a binary classification model to predict the tNPS target variable.

Table 1. Variables used in this study

Attributes	Description
SR_Num	Report Number
Segment_Group	Customer Group Segment
Type	Type of Report
Category	Sub Type (Category) of report
Sub_Category	Sub-Category of Report
Res_24Hrs	Report Aging
Source	Source of Complaints
Closed_Code	Reported Close Code
State	Account Location (state)
Score	tNPS Score
Nes category	Score Category
Nes response	Comment From the customer

2.2 Data Understanding

The second phase entails gathering the essential data, assessing its quality, and analysing it using various statistical and visualisation techniques. The case study telecommunication company provided two datasets from their customer interaction database for this study: customer satisfaction report and tNPS report for the month of April 2021. The tNPS report dataset comprises 10715 rows and 30 columns, whereas the service request report dataset has 28,7729 rows and 41 columns.

Service Request report captures every interaction with a customer and assigned a unique number. Later customers will be selected randomly to give their feedback by sending short message service (SMS). Customers can reply to the SMS by visiting the URL link included in the message. All feedback will be recorded in the tNPS report However, not all consumers will answer in the proper format within the allotted period. Both datasets were merged in to one master dataset using their service request id attribute. The first author of this study is the domain expert and applied his knowledge to select the variables from the dataset for further analysis. After removing unwanted and irrelevant and highly correlated variables, the final dataset has 28,7729 rows and 12 columns which are shown in Table 1. Exploratory data analysis was performed at this phase using statistical techniques and visualization tools which are presented in the result section.

2.3 Data Pre-processing

In the third phase, the raw data is converted in to a structured data by cleaning, recoding and computing new variables, in order to apply selected machine learning techniques. The total number of service requests in the data set was 28,7729, however only 7707 (2.6%) received tNPS from customers. As a result, the final dataset had 7707 rows. The tNPS is a numeric variable that can have a value of 0 to 10.

The tNPS is used to categorise customers into three groups: “detractor” clients, “neutral” clients, and “promoters” clients. tNPS values 0 to 6 indicate “detractor” clients, tNPS values 7 or 8 are associated with “neutral” clients, and tNPS values 9 or 10 are connected with “promoters” clients [1, 2]. The tNPS is used to create a categorical variable in this study, with values 9 and 10 indicating high tNPS and the rest of the values indicating low tNPS. The dataset is also standardised using the min-max and z-score normalisation approaches in order to apply the Multilayer perceptron neural network algorithm.

2.4 Modelling

A detailed literature review showed there are many supervised machine learning algorithms are applied for classification problems. Classifiers can be created using a variety of methods, including information-based learning, similarity-based learning, error-based learning, and probability-based learning. The best model for understanding decision logic in this study was information-based learning (a decision tree algorithm family) [6]. Also, the accuracy and interpretability of machine learning models are always a trade-off [7]. Because the focus of this research is on model interpretability, this study primarily uses the decision tree algorithm family as well as the multilayer perceptron neural network technique.

Decision Tree algorithm has been applied in many different context such as predicting customer churn [8], predicting bank failure [9] and to select algorithms to predict electricity consumption [10]. Random Forest and gradient boosted tree algorithms are mostly used along with decision tree as they belong to the same family [2]. Logistic Regression has shown better performance in predicting credit rating changes [11], predicting customer satisfaction through net promotor score prediction [2]. Neural network though it is called as the black box method, it has been applied to predict customer satisfaction in many different contexts. For example, it has been used to predict restaurants service quality [12], predicting customer satisfaction through net promotor score prediction [2] and as predicting customer churn [8]. Therefore, this study leveraged the above mentioned machine learning algorithm to predict tNPS. Each of these machine learning algorithms produce machine learning models and then the hyper parameters will be varied to identify the optimal parameter settings in which each model performance at its best for the given data set.

2.5 Evaluation

Each of these machine learning algorithms generates machine learning models, which are then tweaked to find the best parameter settings for the given data set. The performance evaluation measure F-score is used to choose the best model. The optimal models for each of the machine learning algorithms are the deliverables from the modelling process.

2.6 Deployment

This is the last phase of CRISP-DM in which the best machine learning model identified from the previous phase will be recommended for deployment.

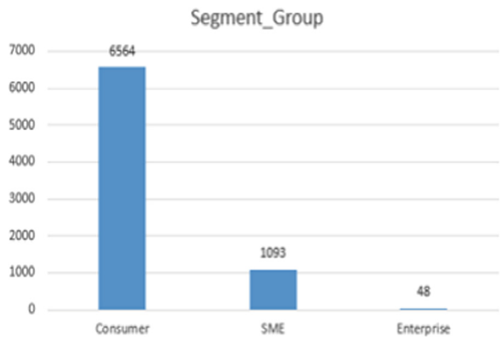

Fig. 1. Customer segment.

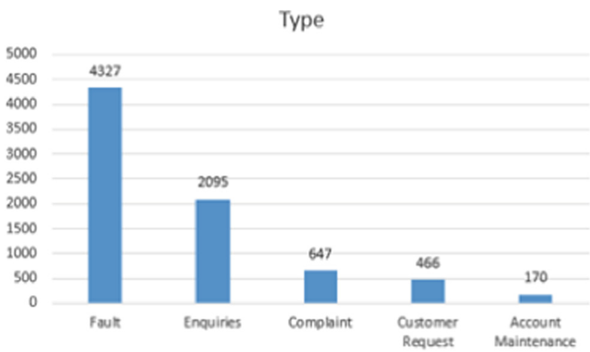

Fig. 2. Types of service request.

3 Results and Discussion

3.1 Descriptive Analytics

Descriptive analytics of the dataset is presented in Fig. 1 through Fig. 6. The dataset consists of 7705 customers with 12 variables which included three types of customer category;85% consumers,14% SMEs and 1% of enterprise. From the total number of service requests, there were 56% (4327 reports) fault reports, 27% (2095 reports) enquiries, 9% (647 reports) complaint, 6% (647 reports) customer request, and 2% (170 reports) account maintenance (See Figs. 2, 3, 4 and 5).

For the category of the reports, there were 37% (2882 reports) service failure, 19% (1445 reports) service quality, 11% (846 reports) billing, 10% (797 reports) fulfilment, 10% (755 reports) product/service, 6% (485 reports) assurance, 4% (315 reports) touch points, 2% (124 reports) customer profile, and 1% others. For the sub-category reports, the top 5 sub-categories were 20% (1560 reports) HSI DOWN, 13% (1020 reports) HSI connection issue, 7% (506 reports) charges, 5% (391 reports) application procedures, and 5% (376 reports) HSI & voice down.

Most reports were resolved within 24 h, with 14% (1066 reports) taking longer than 48 h and 13% (972 reports) taking less than 48 h. Almost all complaints were made over

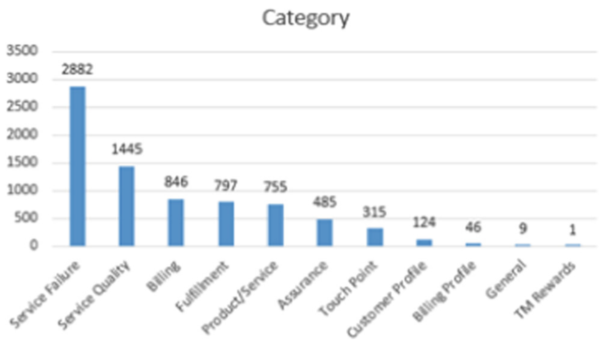

Fig. 3. Service category.

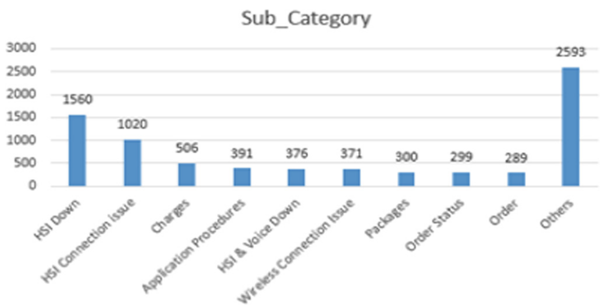

Fig. 4. Service sub-category.

Fig. 5. Service closed code.

the phone, at (7704), and one was posted on social media. For the close code portion, which was the conclusion of the case. Normally this was the remarks by the party who fixed the issue, such as technician, or the contact centre personnel based on the remarks or response from the stakeholders. The top 5 cases were 28% (2179 reports) local loop SMS with the remarks from the technician, 21% (1593 reports) customer enquiry, 11%

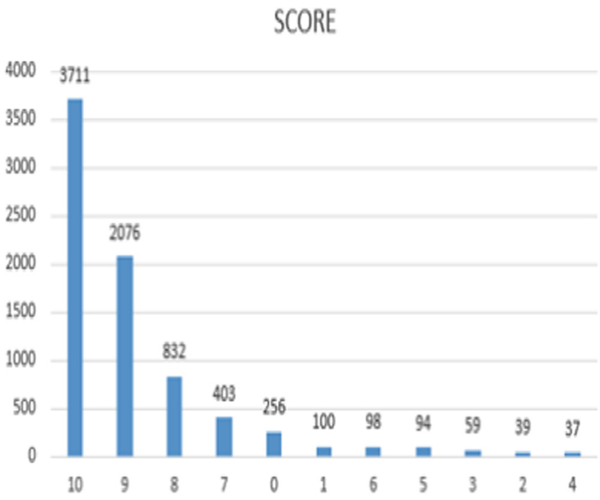

Fig. 6. tNPS score.

(813 reports) "empty/no comment", 10% (794 reports) resolved after troubleshooting, and 9% (661 reports) will call back.

In terms of client location, Selangor had 45% (3463 consumers), Johor had 11% (859 customers), "unavailable/empty" had 6% (481 customers), Kuala Lumpur had 5% (412 customers), and Perak had 5% (385 customers). For the tNPS, 48% (3711 replies) picked 10 and 27% (2976 responses) chose 9. Promoter scores were assigned to both 9 and 10. With 16% (1235 replies), scores 6 and 7 were classified as passive, and scores 0–6 were classified as detractor (683 responses). Most consumers reacted with simply a score and no remarks, with 55% (4268 responses) and 45% (3437 responses) with comments, respectively, from the overall response.

3.2 Supervised Classification Models

To predict tNPS score, five machine learning algorithms; Decision Tree, Random Forest, Gradient Boosted Trees, Logistic Regression and Multilayer perceptron neural network were applied. Hyper-parameters were tuned for each of the models in order to find the best one. Tables 2, 3, 4, 5 and 6 show the different hyper-parameter tuning options for each of the models in order to find the best model. Table 7 compares all five classification models.

Table 2. Hyper- parameter tweaking for Decision Tree

Partitioning	Quality Measure	tNPS	F-measure	Accuracy
50:50	Gini Index	High	0.854	0.754
		Low	0.199	
	Gain Ratio	**High**	**0.856**	**0.756**
		Low	**0.207**	
60:40	Gini Index	High	0.844	0.737
		Low	0.177	
	Gain Ratio	High	0.848	0.743
		Low	0.185	
70:30	Gini Index	High	0.847	0.742
		Low	0.166	
	Gain Ratio	High	0.848	0.744
		Low	0.174	
80:20	Gini Index	High	0.856	0.755
		Low	0.168	
	Gain Ratio	High	0.855	0.754
		Low	0.175	
85:15	Gini Index	High	0.845	0.735
		Low	0.1	
	Gain Ratio	High	0.845	0.735
		Low	0.1	
90:10	Gini Index	High	0.853	0.750
		Low	0.172	
	Gain Ratio	High	0.851	0.747
		Low	0.171	

Table 3. Hyper- parameter tweaking for Random Forest

Partitioning	Quality Measure	tNPS	F-measure	Accuracy
50:50	Gini Index	High	0.859	0.758
		Low	0.145	
	Information Gain Ratio	High	0.859	0.758
		Low	0.143	
60:40	Gini Index	High	0.864	0.766
		Low	0.161	
	Information Gain Ratio	High	0.866	0.769
		Low	0.164	
70:30	Gini Index	High	0.87	0.774
		Low	0.161	
	Information Gain Ratio	**High**	**0.87**	**0.775**
		Low	**0.158**	
80:20	Gini Index	High	0.861	0.761
		Low	0.128	
	Information Gain Ratio	High	0.861	0.76
		Low	0.131	
85:15	Gini Index	High	0.854	0.75
		Low	0.116	
	Information Gain Ratio	High	0.853	0.748
		Low	0.11	
90:10	Gini Index	High	0.869	0.774
		Low	0.171	
	Information Gain Ratio	High	0.869	0.774
		Low	0.171	

Table 4. Hyper- parameter tweaking for Gradient Boosted Tree

Partitioning ratio	tNPS	F-measure	Accuracy
50:50	High	0.858	0.757
	Low	0.146	
60:40	High	0.866	0.769
	Low	0.182	
70:30	High	0.852	0.748
	Low	0.166	
80:20	High	0.863	0.764
	Low	0.166	
85:15	High	0.854	0.752
	Low	0.178	
90:10	**High**	**0.872**	**0.78**
	Low	**0.213**	

Table 5. Hyper- parameter tweaking for Multilayer perceptron neural network model

Normalization	Partitioning	tNPS	F-measure	Accuracy
Min-Max	50:50	High	0.861	0.762
		Low	0.152	
Z-Score		High	0.849	0.744
		Low	0.162	
Min-Max	60:40	High	0.866	0.769
		Low	0.154	
Z-Score		High	0.863	0.763
		Low	0.129	
Min-Max	70:30	High	0.856	0.753
		Low	0.144	
Z-Score		High	0.854	0.752
		Low	0.173	

(*continued*)

Table 5. (*continued*)

Normalization	Partitioning	tNPS	F-measure	Accuracy
Min-Max	80:20	High	0.861	0.762
		Low	0.172	
Z-Score		High	0.857	0.755
		Low	0.168	
Min-Max	85:15	High	0.853	0.747
		Low	0.093	
Z-Score		High	0.854	0.751
		Low	0.143	
Min-Max	**90:10**	High	0.872	0.778
		Low	0.166	
Z-Score		**High**	**0.876**	**0.783**
		Low	**0.126**	

Table 6. Hyper- parameter tweaking for Logistic regression model

Partitioning	Quality Measure	tNPS	F-measure	Accuracy
50:50	Stochastic average gradient	High	0.864	0.762
		Low	0.028	
	Interactively reweighted least squares	High	0.864	0.762
		Low	0.028	
60:40	Stochastic average gradient	High	0.861	0.757
		Low	0.011	
	Interactively reweighted least squares	High	0.861	0.757
		Low	0.011	
70:30	Stochastic average gradient	High	0.858	0.753
		Low	0.047	
	Interactively reweighted least squares	High	0.858	0.753
		Low	0.047	
80:20	Stochastic average gradient	High	0.855	0.748
		Low	0.02	
	Interactively reweighted least squares	High	0.855	0.748

(*continued*)

Table 6. (*continued*)

Partitioning	Quality Measure	tNPS	F-measure	Accuracy
		Low	0.02	
85:15	**Stochastic average gradient**	**High**	**0.869**	**0.769**
		Low	**0.043**	
	Interactively reweighted least squares	**High**	**0.869**	**0.769**
		Low	0.043	
90:10	Stochastic average gradient	High	0.874	0.776
		Low	NA	
	Interactively reweighted least squares	High	0.874	0.776
		Low	NA	

Table 7. Comparison of all FIVE classification models

models	Partitioning	Quality Measure	tNPS	F-measure	Accuracy
Decision Tree	50:50	Gain Ratio	High	0.856	0.756
			Low	0.207	
Random Forest	70:30	Information Gain Ratio	High	0.87	0.775
			Low	0.158	
Gradient Boosted Tree	90:10		High	0.872	0.78
			Low	0.213	
Neural Network (MLP	**90:10**		**High**	**0.876**	**0.783**
			Low	**0.126**	
Logistic Regression	85:15	Stochastic average gradient	High	0.869	0.769
			Low	0.043	
		Interactively reweighted least squares	High	0.869	
			Low	0.043	

The multilayer perceptron neural network obviously outperforms the other models, as shown in the Tables 2, 3, 4, 5, 6 and 7. However, all five machine learning models are able to classify high tNPS service requests with F-score values more than 0.85 and accuracy is higher than 0.756 (75.6%). This is greater than the 54% accuracy reported by Velez et al. (2020) in predicting NPS using neural network and gradient boosting tree approaches [2].

Companies are frequently required to make important decisions about their customers' loyalty and retention based on analytical models designed to estimate both churn likelihood and Net Promoter Score (NPS). Although these models' predictive power is vital, interpretability is also critical because the judgments that must be taken based on their results must be properly justified [2].

4 Conclusion

This study attempted to predict tNPS by applying machine learning algorithms by adopting cross industry standard process for data mining. Five machine learning models were developed and found Multilayer perceptron neural network performed the best compared to Decision Tree, Random Forest, Gradient Boosted Trees, and Logistic Regression. The limitation of this study is the imbalanced dataset which can be addressed by oversampling or underdamping methods. In order to understand the general characteristics of service requests that obtain high or low tNPS, decision tree rules can be generated. Our future study will attempt to address these limitations.

Acknowledgments. The authors would like to thank the telecommunication case study company for providing the data set.

Authors' Contributions. Rathimala Kannan Conceptualization, Writing-original draft preparation. Chee Yoong Yan Data curation. Kannan Ramakrishnan Writing-Review & Editing. Dedy Rahman Wijaya Validation.

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