Final Report

for

Customer Churn Analysis

Version 1.0

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1. Problem Overview

Customers are the foundation of any business's success. That is why every company tries to do anything to make their customers satisfied. Customer churn is the loss of customers from the business, and it is not good for the endurance of the company on the competitive business ground. Organizations must devise several solutions to address churn issues based on the services they provide. Chatter Box is a Telco company, which means Telecommunication or communication service providing company.

Customer churn management is critical in the competitive and continuously evolving telecom industry. Customers are rapidly changing their telco service providers due to issues with the services, service charges, and other benefits and rewards given by other companies. Even customers are churned new customers are quickly joined. But the major problem is also acquiring new customers. Because acquiring a new customer is more costly than retaining an existing one. So, acquiring, and immediate churning is a very unpleasant situation for telco companies. So, telco companies should find a way to hold their customers.

In our case Chatter Box also has this problem. To solve this problem, we must use descriptive analytics, diagnostic analytics, and predictive analytics. Using those analytics techniques Chatter Box company hopes to reduce the customer attrition rate and get the real advantages of acquiring new customers. Using these approaches Telco company hopes to get a view of the problem and predict the customer churn or not.

To identify the problem and the solution Chatter Box company hopes to use Data Science and Machine Learning approach through visualization of analytics and prediction model to estimate the possibilities to churn on the web-based application. The purpose of building this kind of analytics and predictive application is to make easy decision-making to improve customer retention.

2. Dataset Description

Dataset Name	Customer churn train and test datasets.
Dataset Size	311KB
No.of variables	Train dataset – 19, Test dataset - 18
No.of Data entries	Train dataset – 2321, Test dataset - 1500

Variable Name	Description	Data type
customer_id	Customer identification number	Categorical - Nominal
account_length	Number of months the customer has been with the current telco provider	Metric - Discrete
location_code	Customer location code	Categorical – Nominal
international_plan	If the customer has an international plan or not	Categorical - Nominal
voice_mail_plan	If the customer has a voice mail plan or not	Categorical - Nominal
number_vm_messages	Number of voice-mail messages	Metric - Discrete
total_day_min	Total minutes of day calls	Metric – Continues
total_day_calls	Total number of day calls	Metric - Discrete
total_day_charge	The total charge of day calls	Metric - Continues
total_eve_min	Total minutes of evening calls	Metric - Continues
total_eve_calls	Total number of evening calls	Metric - Discrete
total_eve_charge	The total charge for evening calls	Metric - Continues
total_night_minutes	Total minutes of night calls	Metric - Continues
total_night_calls	Total number of night calls	Metric - Discrete
total_night_charge	The total charge of night calls	Metric - Continues
total_intl_minutes	Total minutes of international calls	Metric - Continues
total_intl_calls	Total number of international calls	Metric - Discrete
total_intl_charge	The total charge of international calls	Metric - Continues
customer_service_calls	Number of calls to customer service	Metric - Discrete
Churn	If the customer left or not (target variable)	Categorical - Nominal

3. Data Pre-processing

The dataset has a customer id, but it is not a variable that affects the target variable. So, we don't consider it as a feature for our dataset.

3.1 Data cleaning

Remove Unwanted Columns

- Datasets show some columns such as 'Unnamed: 20', 'Unnamed: 19', which are not in the data description. These are kinds of errors when creating datasets. So, we can consider them the unwanted columns and remove them.

Remove duplicates

- The training dataset has some duplicate entries. If we train our model with duplicates, then the model will overfit. So, we must remove those duplicates.

Handle Missing values, Outliers, Invalid data

- Both train and test datasets have missing values. It is hard to train a model with missing values because a lot of models which are used in this project (machine learning models in sklearn) are not supported to deal with missing values. So, we must handle missing values. But at this moment it is hard to handle the missing values because missing values techniques are dependent on outliers and missing data.
- These datasets have outliers and invalid data.
  - According to the dataset description, any of these data cannot be negative. But there are some negative values. So, we can mark these negative values as the missing values (NaN s).
  - There are some clearly visible outliers in these datasets. To remove outliers, we normally use quantile bounds. But here we cannot use quantile bounds because quantile bounds cut possible bounds also. So, I created a suggested boundary for every numerical variable going through the test and train datasets comparing box plots of features in both datasets. Now, these boundaries are removing the invalid and outliers from the dataset without removing possible cases.
  - Using suggested boundary set values as NaNs which values go over the boundary.
- Now mark all outliers and invalids as missing values. So, we can replace missing values by using some methods.
- Correlation matrix before the filling missing values shows high correlations sets So, we can use the Regression Model to impute those sets.
- Other missing values of numerical variables are imputed by the median. And, there are a few missing values in categorical variables we can impute them by mode.

3.2 Feature Engineering

Encoding Categorical data

- To train the machine learning model we need numerical valued things. But there are some variables with not valued as numerical.
- So, we are normally using encoding techniques to convert them into numerical valued things.
- voice_mail_plan, intetiol_plan, and churn were encoded by Label encoding.
- location_code was encoded by one hot encoder.

Create new features

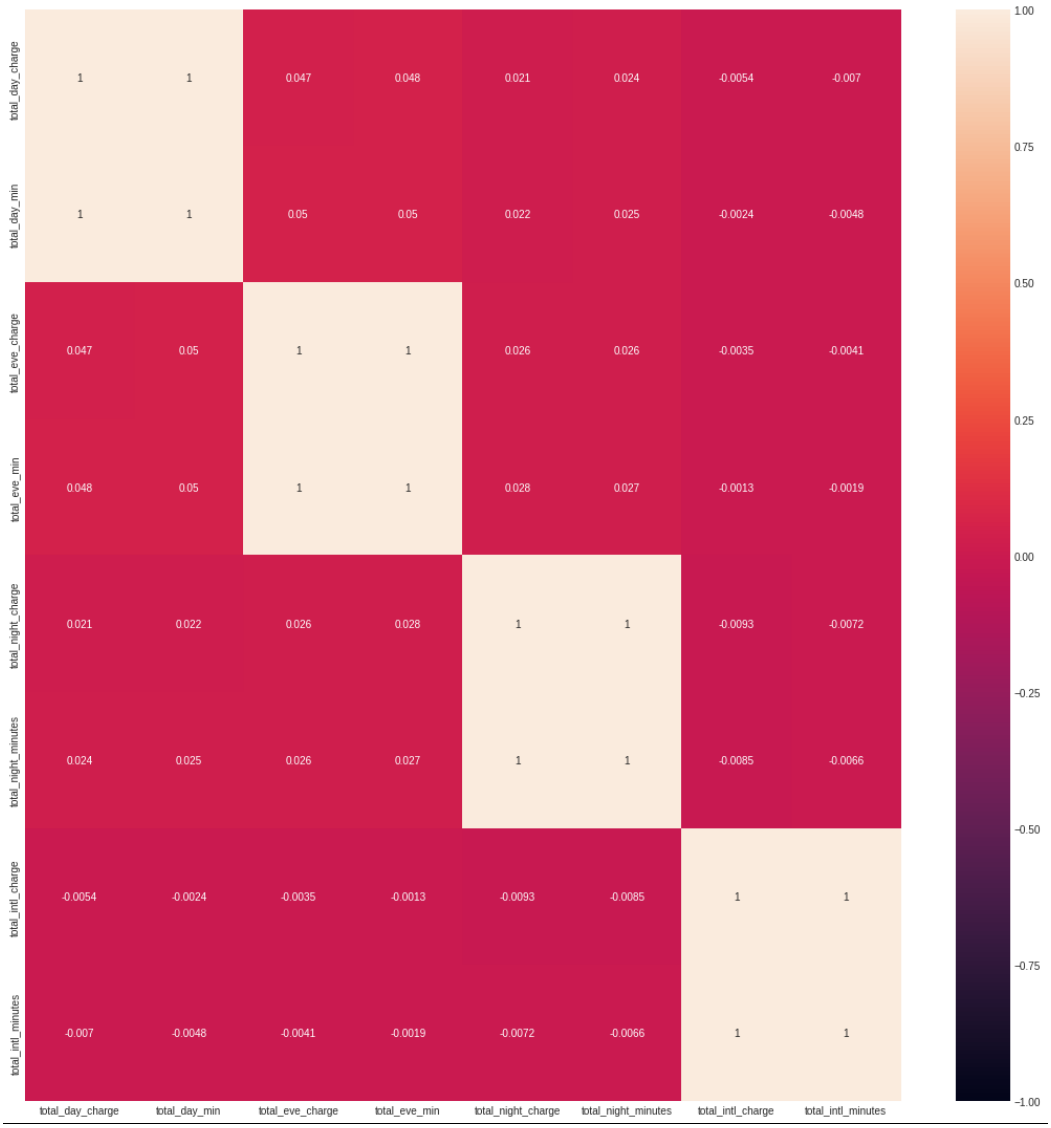
such as,

- no_of_plans = get the number of plans
- total_charge = total_intl_charge + total_night_charge + total_eve_charge + total_day_charge
- total_calls = total_intl_calls + total_night_calls + total_eve_calls + total_day_calls
- total_min = total_intl_minitues + total_night_minutes + total_eve_minitues + total_day_min

4. Insights from data analysis

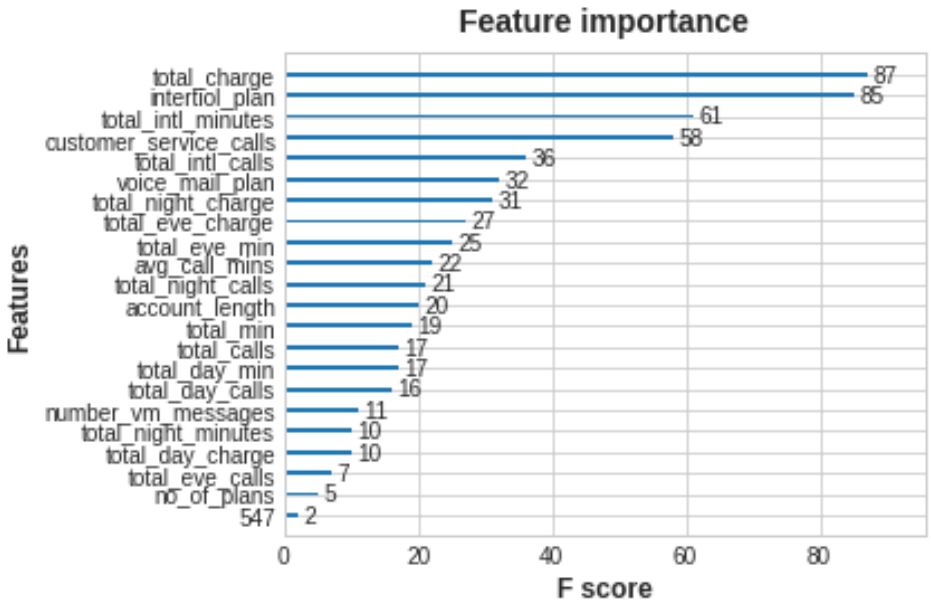
Insight 1

- As the first derived insight, we can show the high correlation between some features.
- This is derived after setting all outliers and invalid data as NaNs.
- So, one-to-one correlation can be used to compute NaN values.

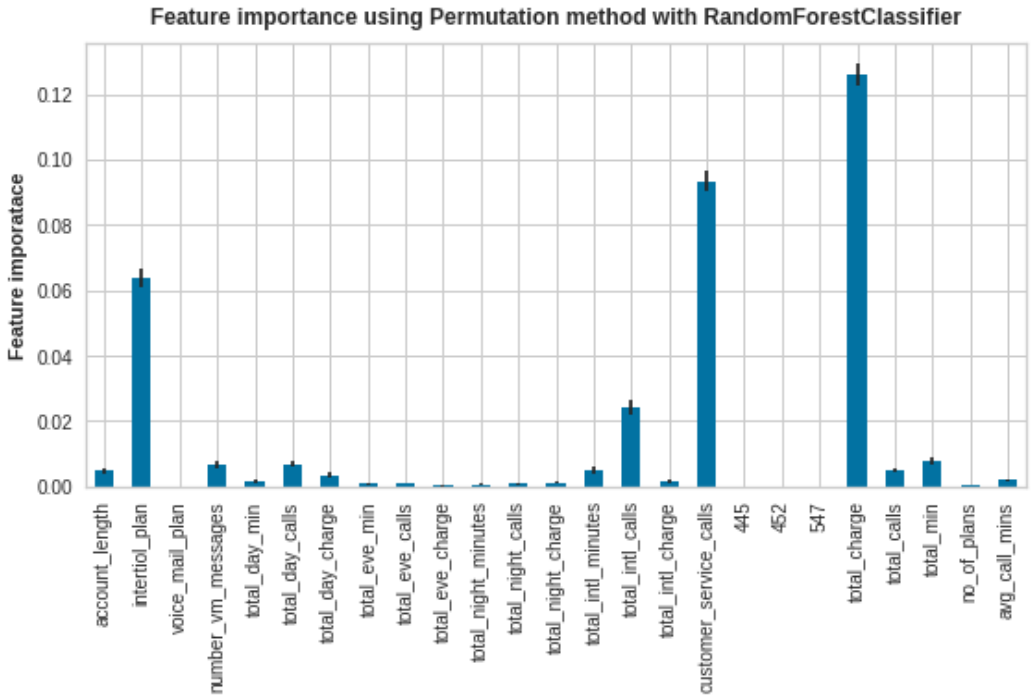


Insight 2

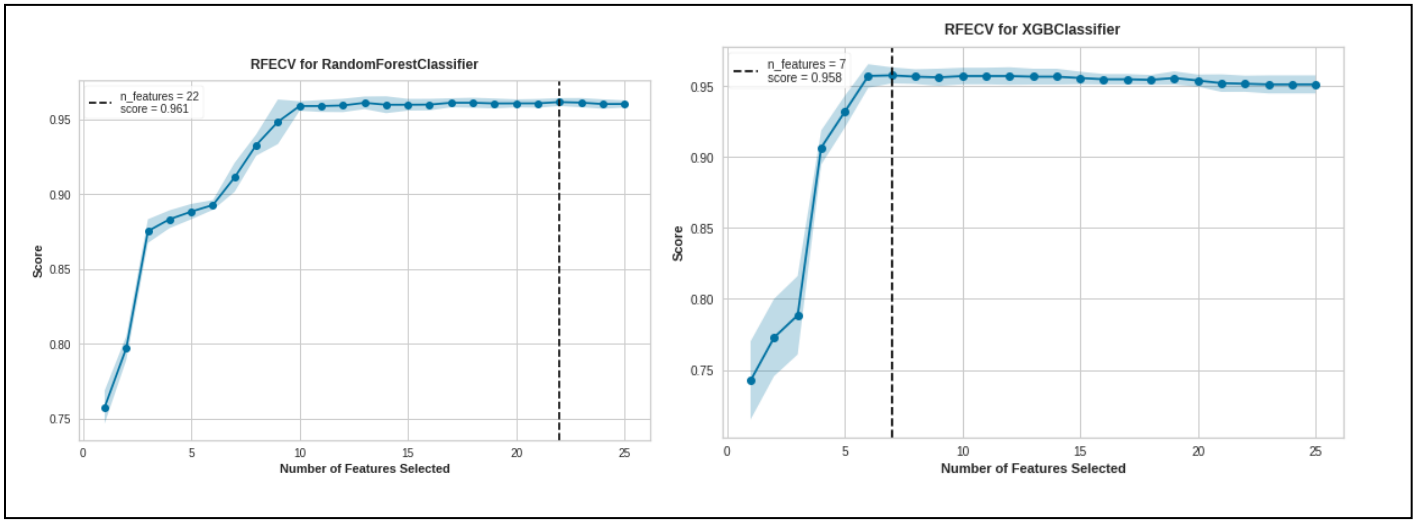
Identify most influential columns that increase Churn



Feature importance using XGBClassifier



- by looking at features importance generated by using XGBClassification and permutation with RandomForestClassifier model we select total_charge, intretiol_plan, total_intl_minitues , customer_service_calls, total_intl_calls five most influential features that increase customer churn.

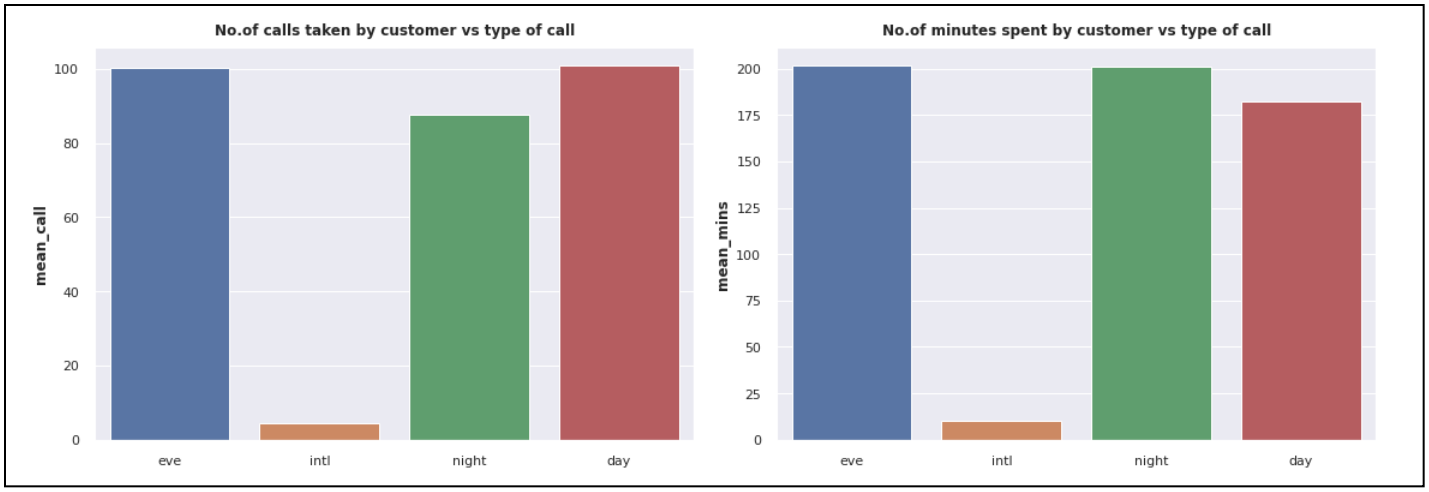


- Using recursive feature importance for RandomForesetClassifier and XGBClassifier can be used to select how many numbers of features to use.

Insight 3

Type of call customers prefers to take.

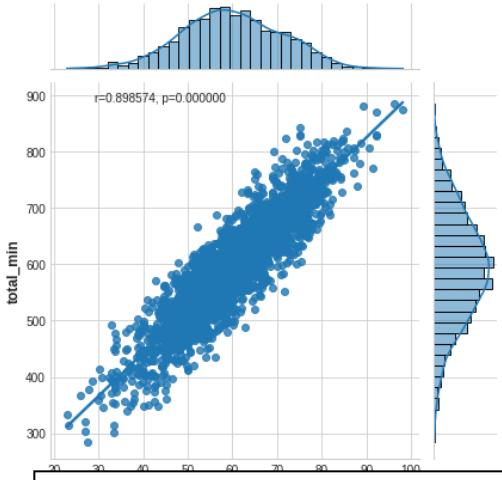
- The dataset has 4 types of calls.
  - Evening calls
  - Night calls
  - Day time calls
  - International calls
- So, which type of calls do customers most prefer to get.



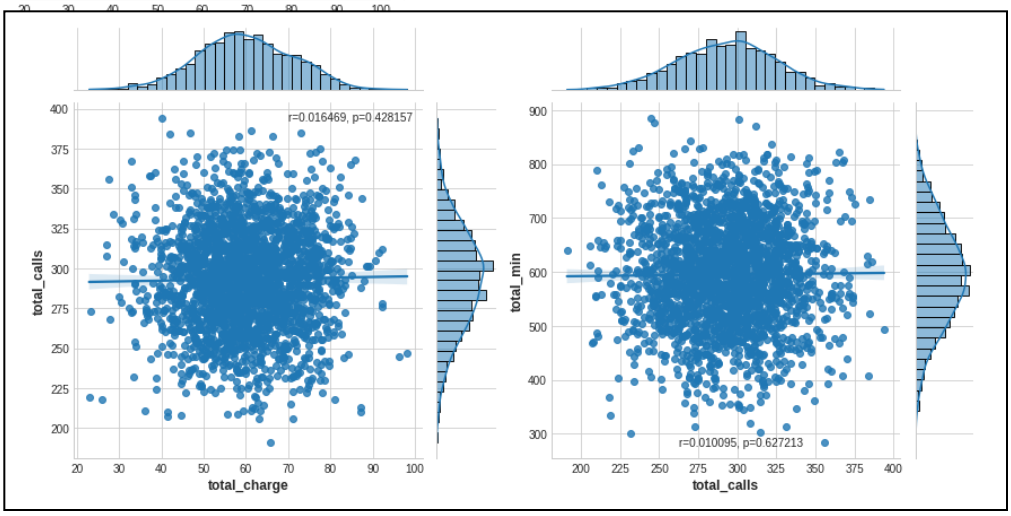
- ❖ by looking at the overall customer graph a smaller number of customers are taking international calls. And most customers prefer to take day and evening calls. And they are spent more time in the evening and night on calls.

Insight 4

Correlations between total_min, total_charge, total_calls only total_min and total_charge got higher Pearson correlation.



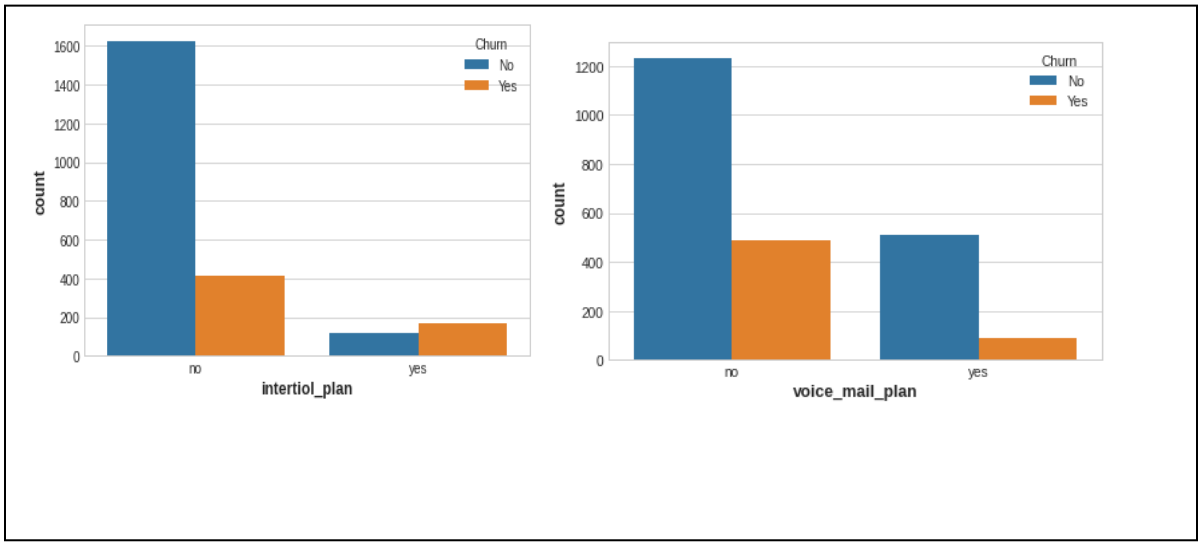
- ❖ According to Pearson correlation, there is a higher correlation between total mins.
- ❖ The Positive Pearson correlation value is 0.8985.
- ❖ So, total_min and total_charge has good linear relation.

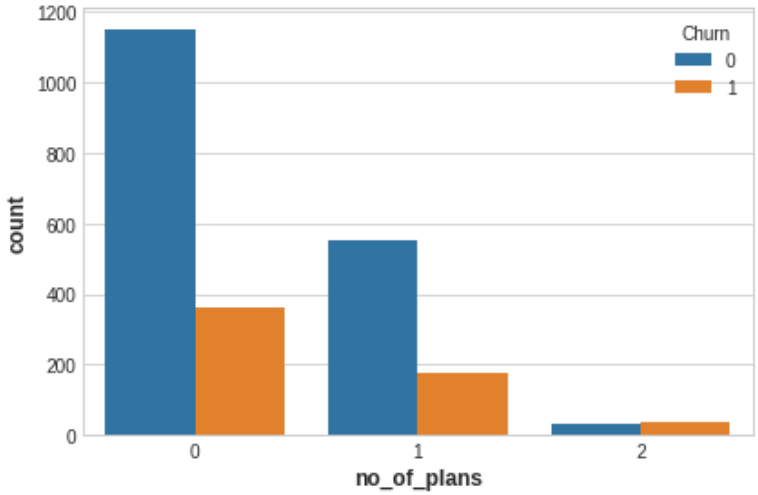


- ❖ Pearson correlation of
  - total_charge vs total_calls :0.01646
  - total_min vs total_calls : 0.01009
    are very low values.
    So, no linear relationships between them.

Insight 5

Most customers who select voice_mail_plan prefer to stay with the service.





- Most customers prefer to without having any plan.
- Customer who has one plan prefer to stay with the service.
- Most customers who have international plans prefer to leave the service.
- Most customers who select a plan, stay with the service because they select voice_mail_plan as their plan.