Telecom Customer Churn Prediction

P - 191 - Group(3) - Working Team

- Ankita Kiran Sutar
- Lakshmi Priya
- Madasu Manjusha
- Muktagucha Manisha
- Nikita Anil Kesarkar
- Suraj Santosh Temkar
- Triveni Gunwant Chapekar
- Vaishnavi Tandle

INTRODUCTION

Churn prediction is one of the most popular big data set that are used cases in business. It consists of detecting customers who are likely to leave the company. Churn is a problem for telecom companies because it is more expensive to acquire a new customer than to keep your existing one from leaving the company.

Most of the telecom companies suffer from voluntary churn. Churn rate does have a strong impact on the life time value of the customer because it affects the length of service and also the future revenue for the company.

In this situation the company tries to identify in advance about the customers who are going to churn. Then the company especially for those customers will provide with some special offers. But this approach can bring the company a huge loss if it is not predicted accurately.

DATASET DETAILS

The datafile 'Churn.csv' contains a total of 20 features for 5000 customers. Each row corresponds to a client of a telecommunications company for whom it has collected information about the type of plan they have contracted, the minutes they have talked, or the charge they pay every month.
The data set includes the following variables:

- state: Categorical, for the 51 states and the District of Columbia.
- Area.code
- account.length: how long the account has been active.
- voice.plan: yes or no, voicemail plan.
- voice.messages: number of voicemail messages.
- intl.plan: yes or no, international plan.
- intl.mins: minutes customer used service to make international calls.
- intl.calls: total number of international calls.
- intl.charge: total international charge.
- day.mins: minutes customer used service during the day.
- day.calls: total number of calls during the day.
- day.charge: total charge during the day.
- eve.mins: minutes customer used service during the evening.
- eve.calls: total number of calls during the evening.
- eve.charge: total charge during the evening.
- night.mins: minutes customer used service during the night.
- night.calls: total number of calls during the night.
- night.charge: total charge during the night.
- customer.calls: number of calls to customer service.
- churn: Categorical, yes or no. Indicator of whether the customer has left the company (yes or no).

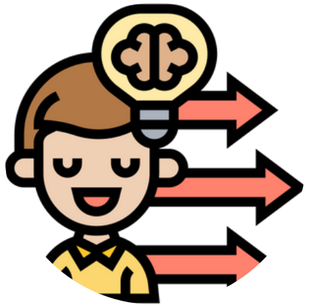
Business Objective

01 Customer churn is a big problem for telecommunications companies. Indeed, their annual churn rates are usually higher than 10%. For that reason, they develop strategies to keep as many clients as possible.

02 This is a classification project since the variable to be predicted is binary (churn or loyal customer). The goal here is to model churn probability, conditioned on the customer features.

Project Architecture

Collection of data



Business understanding

EDA

Deployment

Model Building

EDA

EXPLORATORY DATA ANALYSIS

- **Data collection**
- **Finding all variables & understanding them**
- **Cleaning the dataset**
- **Identify correlated variables**
- **Choosing the right statistical methods**
- **Visualizing & analyzing results**

Processing Data

```
[26] df.head()
```

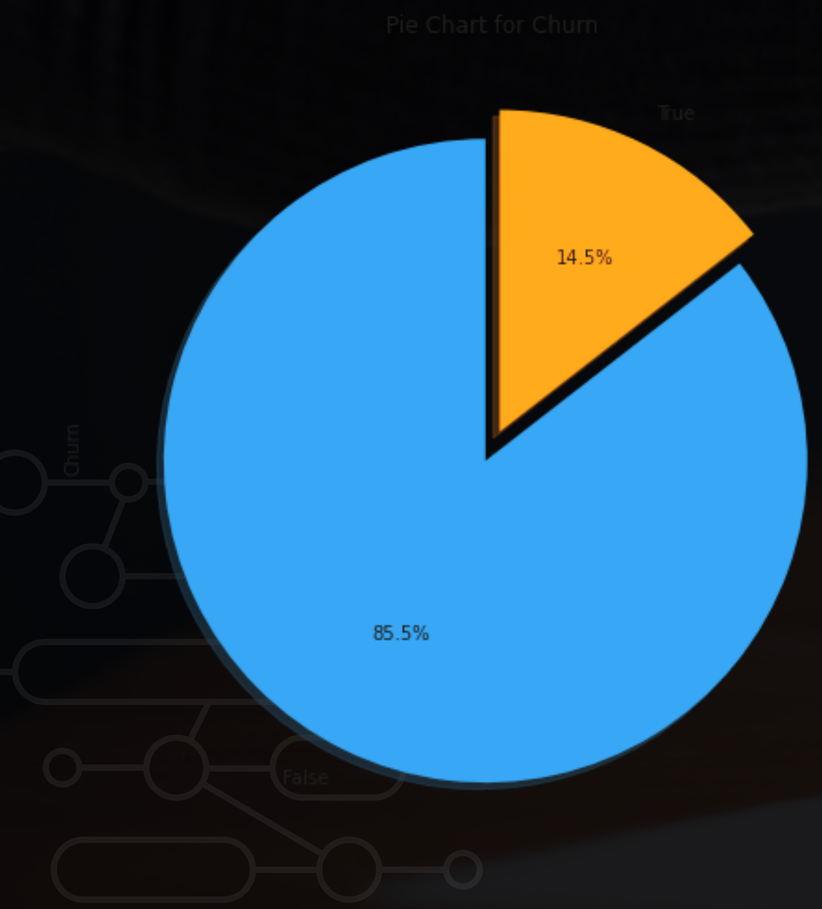
	Unnamed: 0	state	area.code	account.length	voice.plan	voice.messages	intl.plan	intl.mins
0	1	KS	area_code_415	128	yes	25	no	10.0
1	2	OH	area_code_415	107	yes	26	no	13.7
2	3	NJ	area_code_415	137	no	0	no	12.2
3	4	OH	area_code_408	84	no	0	yes	6.6
4	5	OK	area_code_415	75	no	0	yes	10.1

5 rows × 21 columns

- No duplicate values (0)
- Found missing values (31)-removed the values
- Found wrong datatypes('eve.min','day.charge')-changed to float
- Number of numerical variables (15)
- Discrete Variables Count (2)
- Continuous Feature Count (13)
- categorical variables (5)
- Data is correlated

Visualizations

Analyzing Target Variable (Churn)

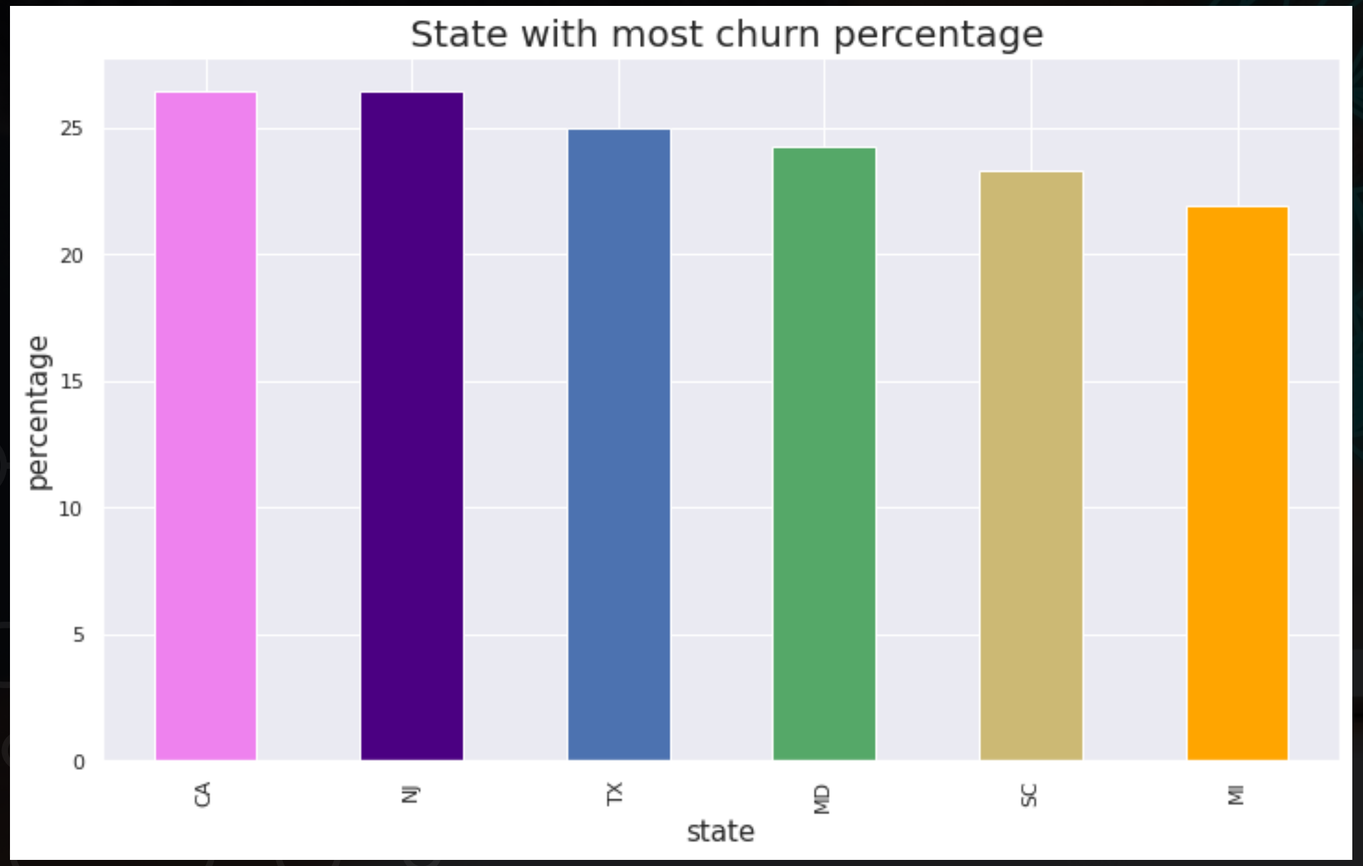


Report :

After analyzing the results we can see only 15% customers are churned. Let’s check the other features and relation between them correlated with churn.

Visualizations

Analyzing State vs Churn

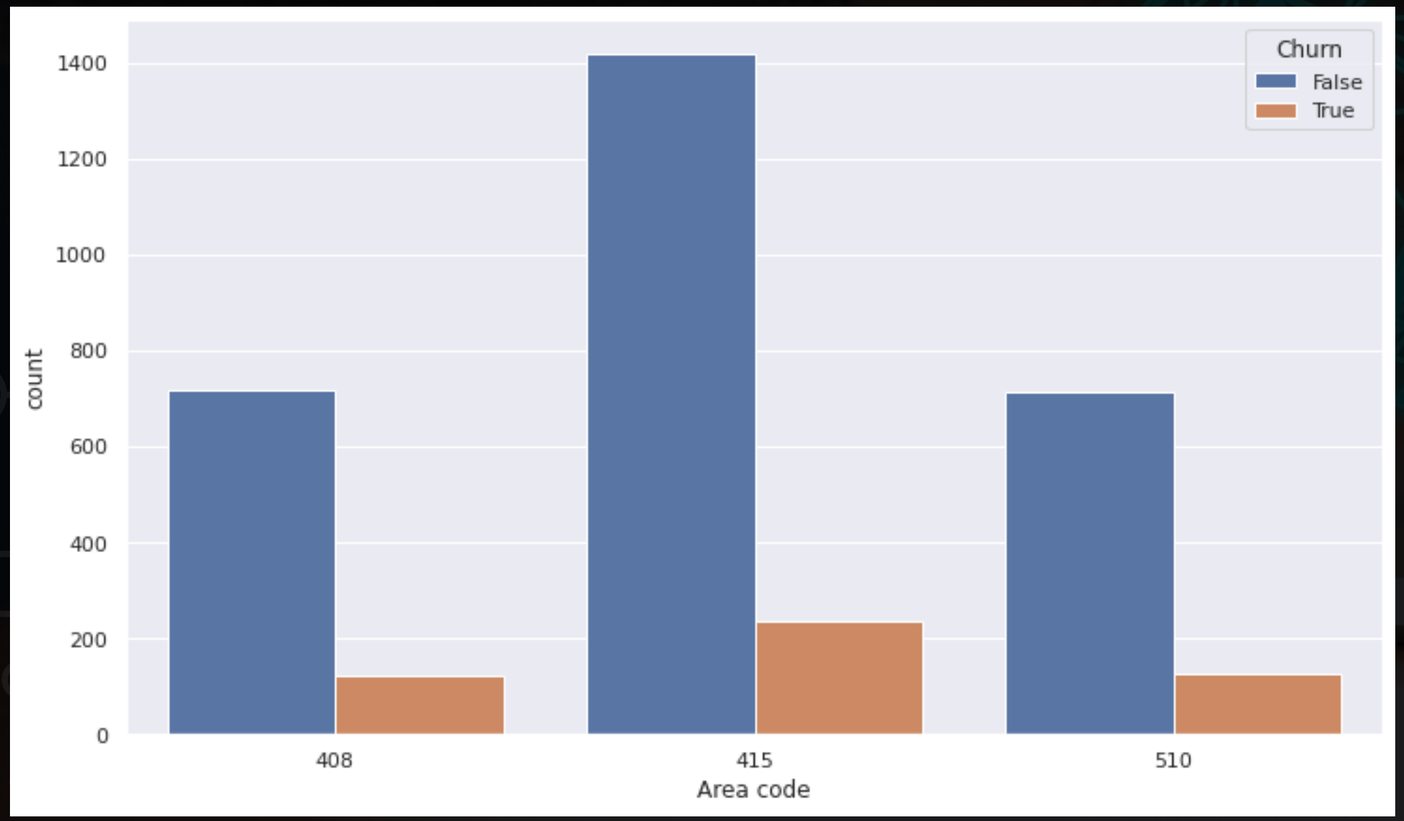


Report :

There are 51 unique states present that have different churn rate.
From the analysis CA, NJ, TX, MD, SC, MI are the ones who have a higher churn rate of more than 21

Visualizations

Analyzing Area.code vs Churn

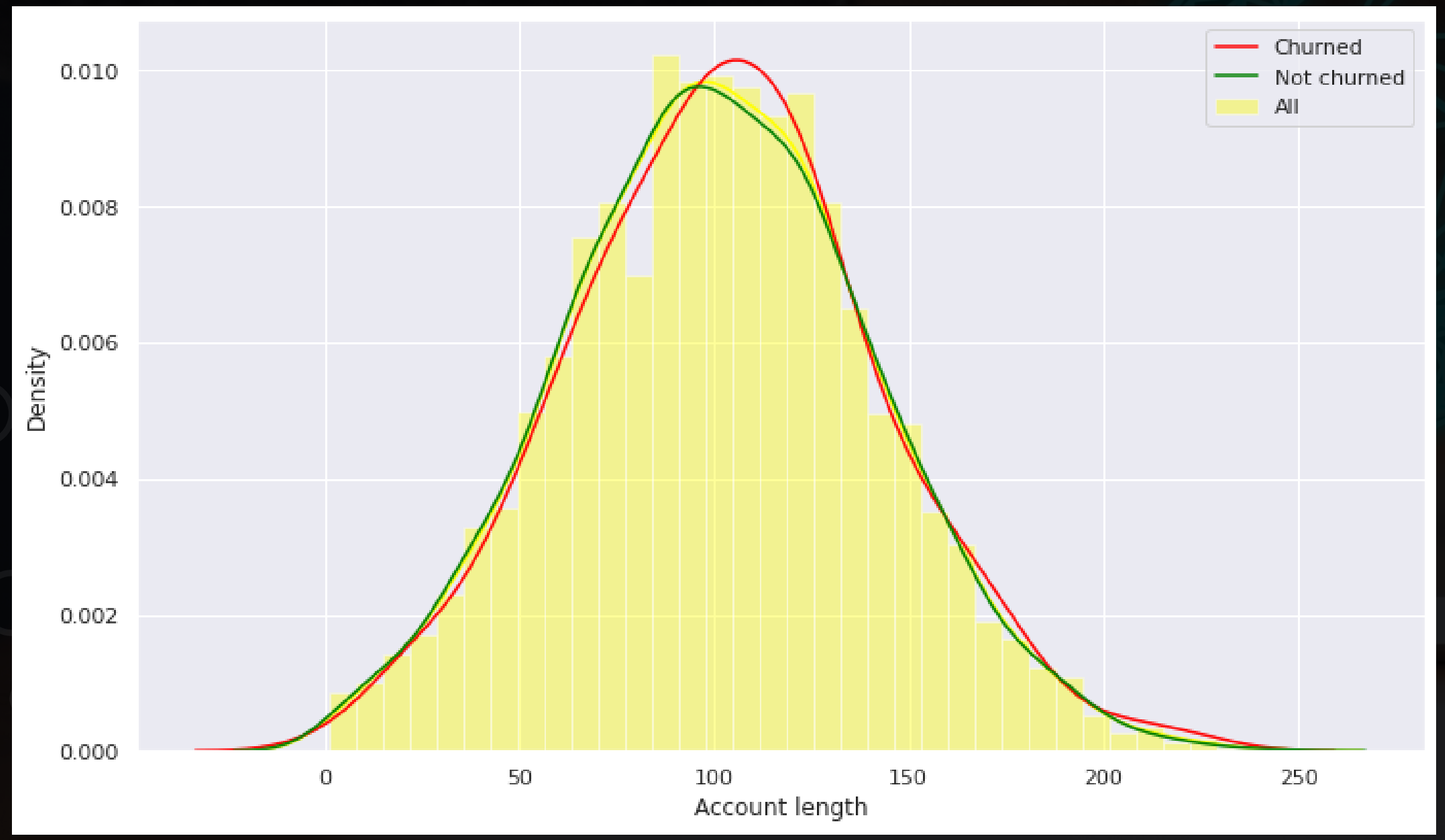


Report :

There are 3 unique values in area.code. 415 has most churn rate compared to other two. The churn rate has no much difference almost same. There is no relationship between area.code and churn due to which the customer leaves the operator.

Visualizations

Analyzing Acc.len vs Churn

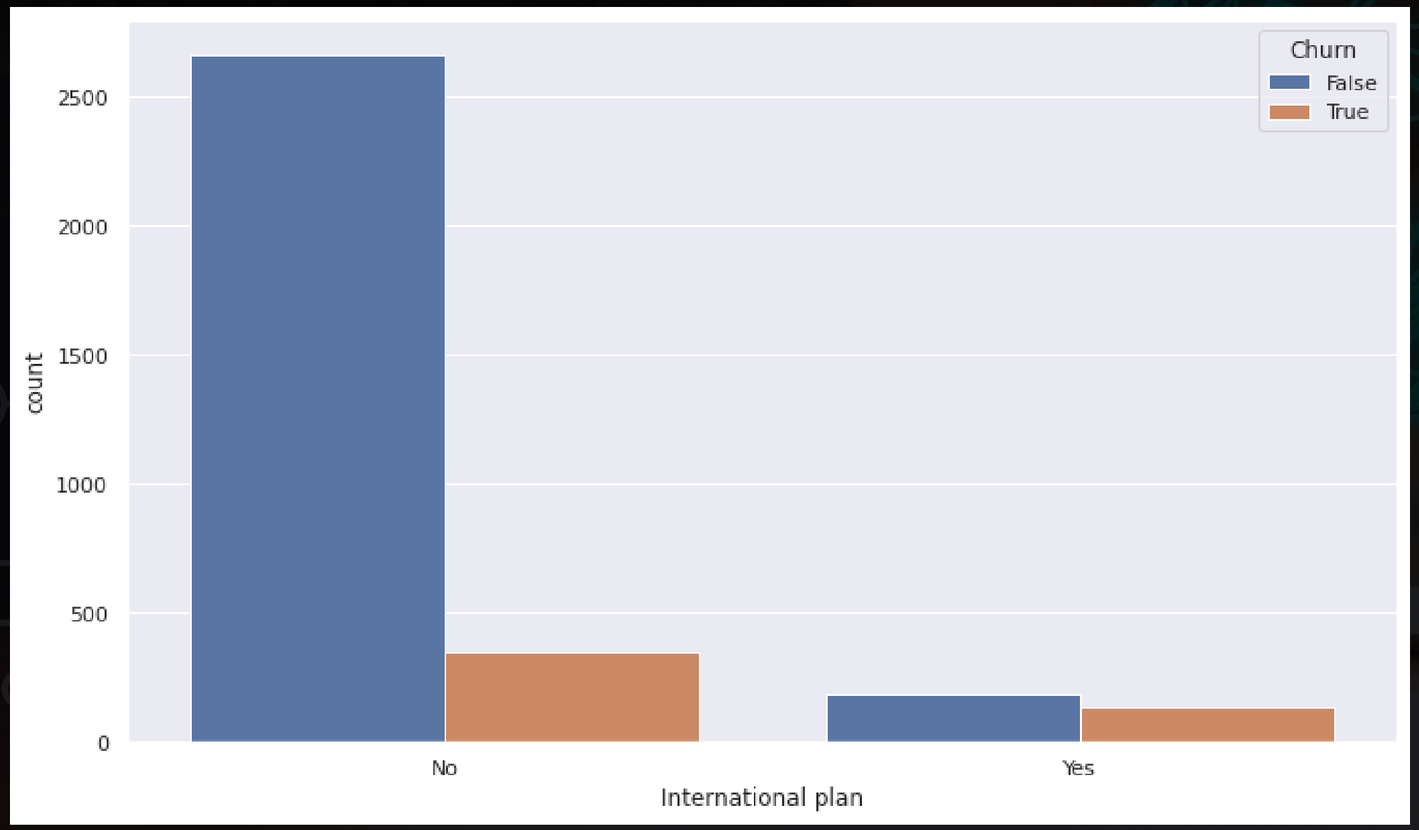


Report :

In this feature also we didn’t find any relation between acc.len and churn as there is no much difference between them.

Visualizations

Analyzing Intl.plan vs Churn

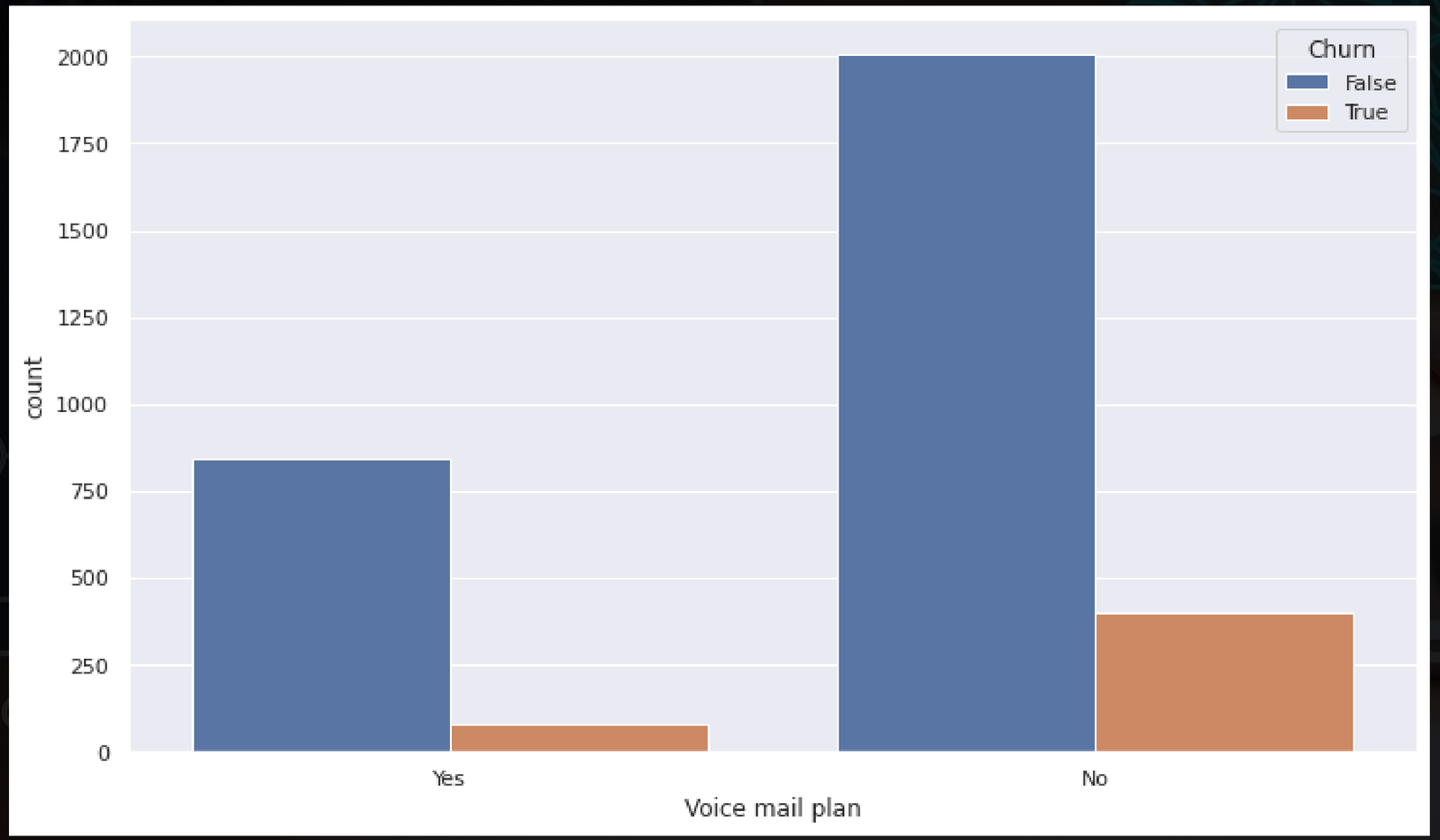


Report :

There are 3010 customers who don't have an international plan.
There are 323 customers who have an international plan.
Among those who have an international plan 42.4 % people churn.
Whereas among those who don't have a international plan only 11.4 % people churn.
So basically the people who bought International plans are churning in big numbers.

Visualizations

Analyzing Voice.plan vs Churn

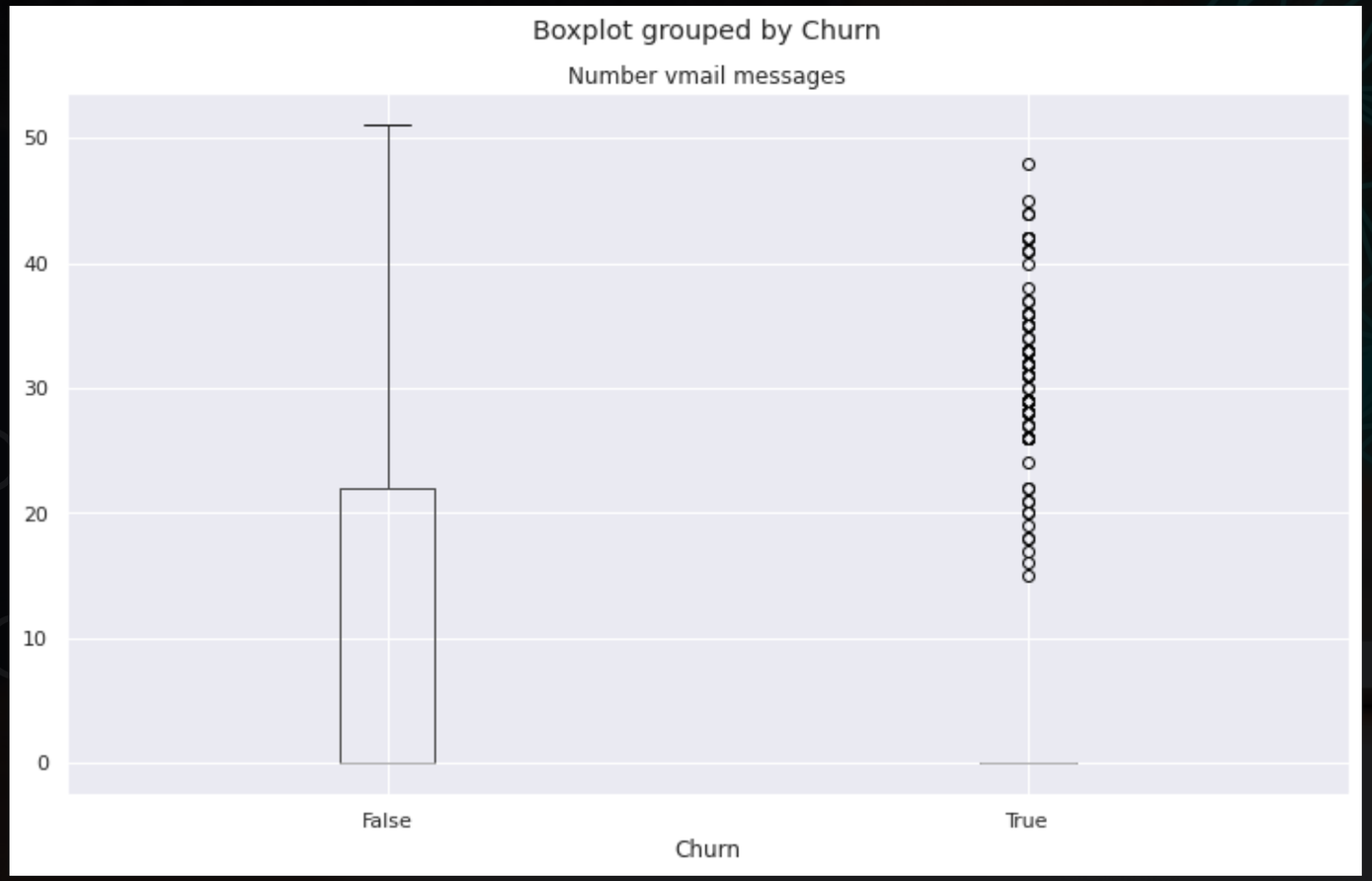


Report :

As we can see there is are no clear relation between voice.plan and churn. There is no much difference.

Visualizations

Analyzing Voice.msgs vs Churn

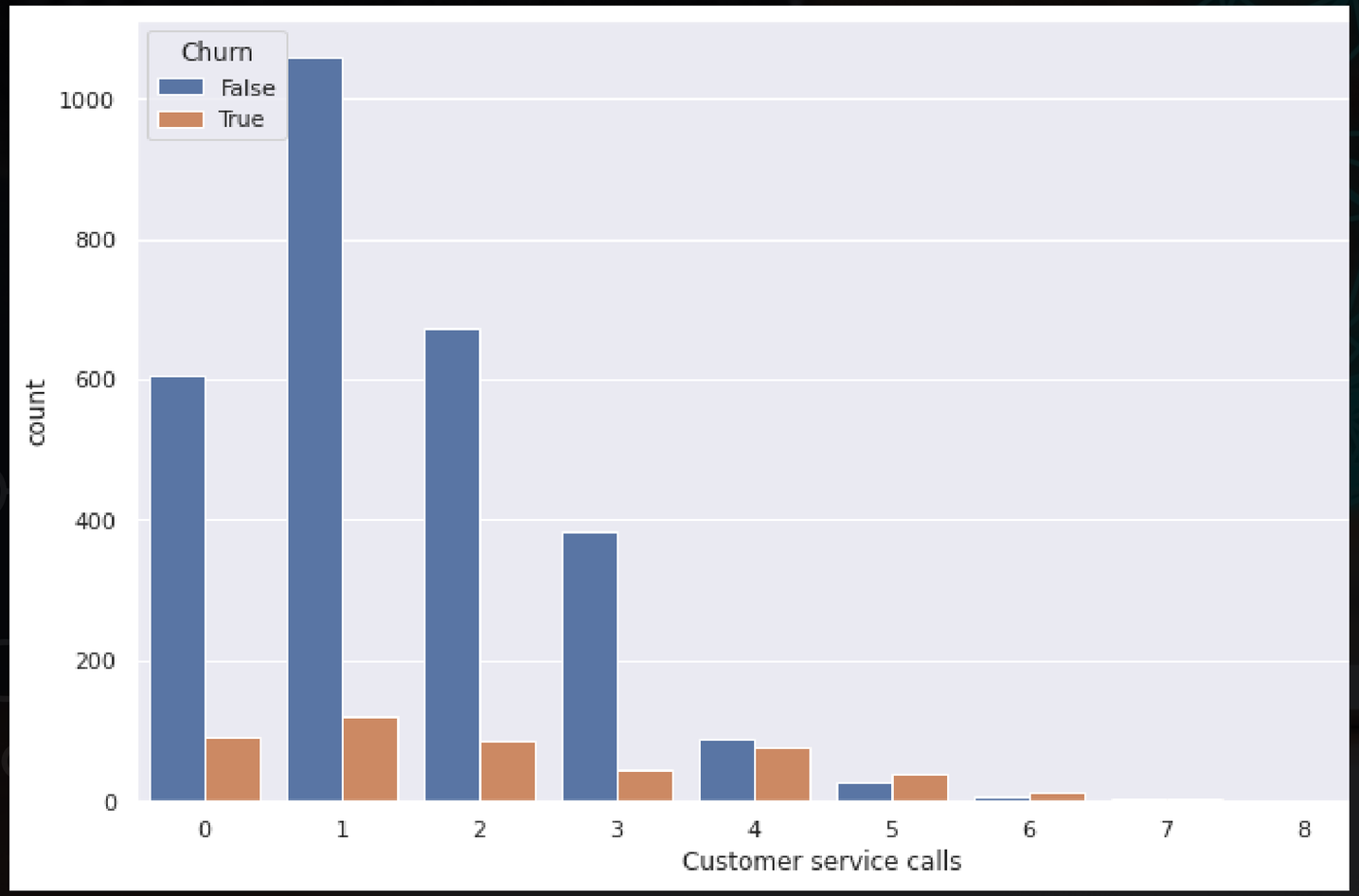


Report :

After analyzing the voice mail feature data we get an insight that when there are more than 20 voice-mail messages then there is a churn.

Visualizations

Analyzing Cust.calls vs Churn

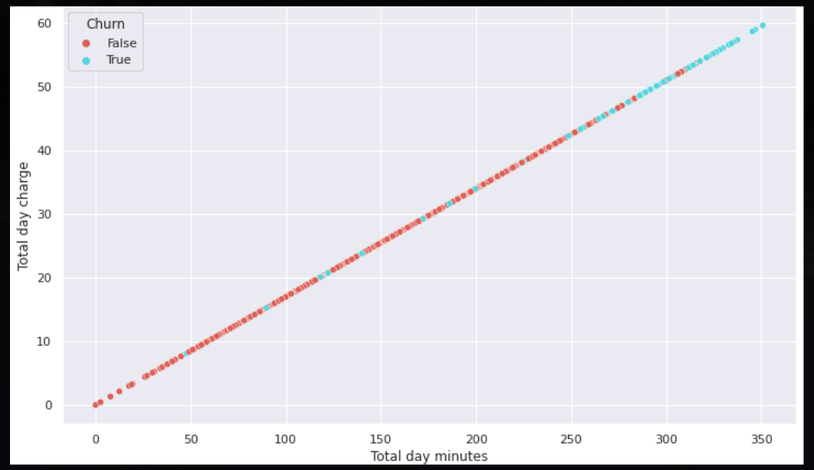


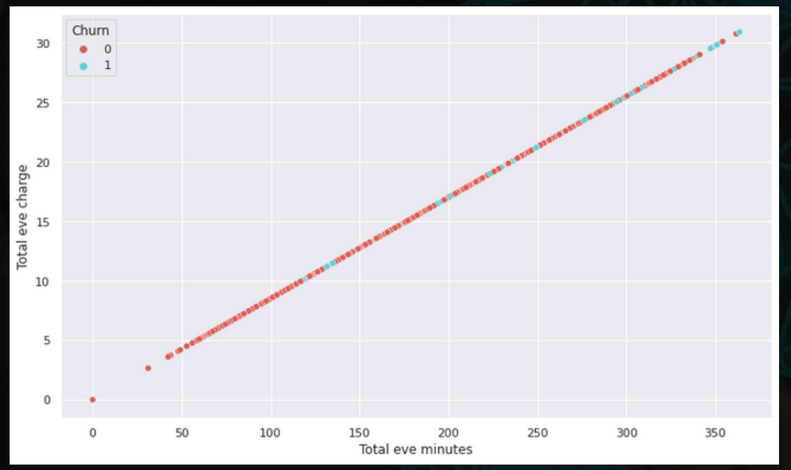
Report :

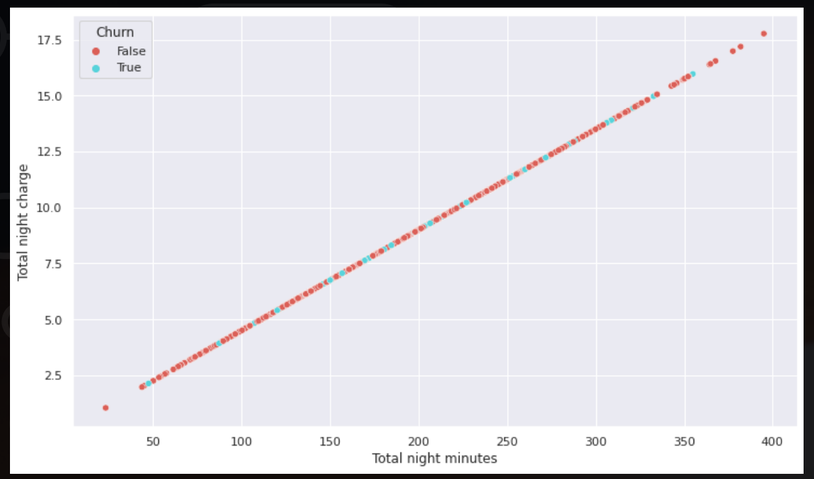
By analysis, mostly because of bad customer service, people tend to leave the operator. The data indicating that those customers who called the service center 5 times or above those customer churn percentage is higher than 60% and customers who have called once also have a high churn rate indicating their issue was not solved in the first attempt.So operator should work to improve the service call.

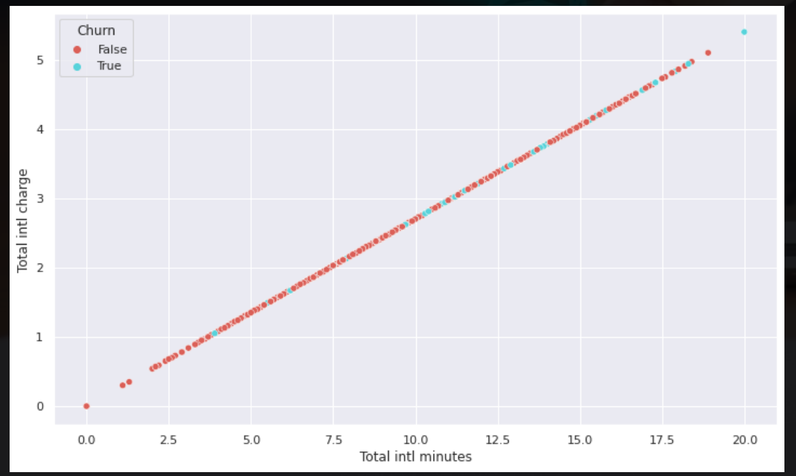
Visualizations

Analyzing all Day.Eve.Night.Intl. (calls,mins,charge) vs Churn







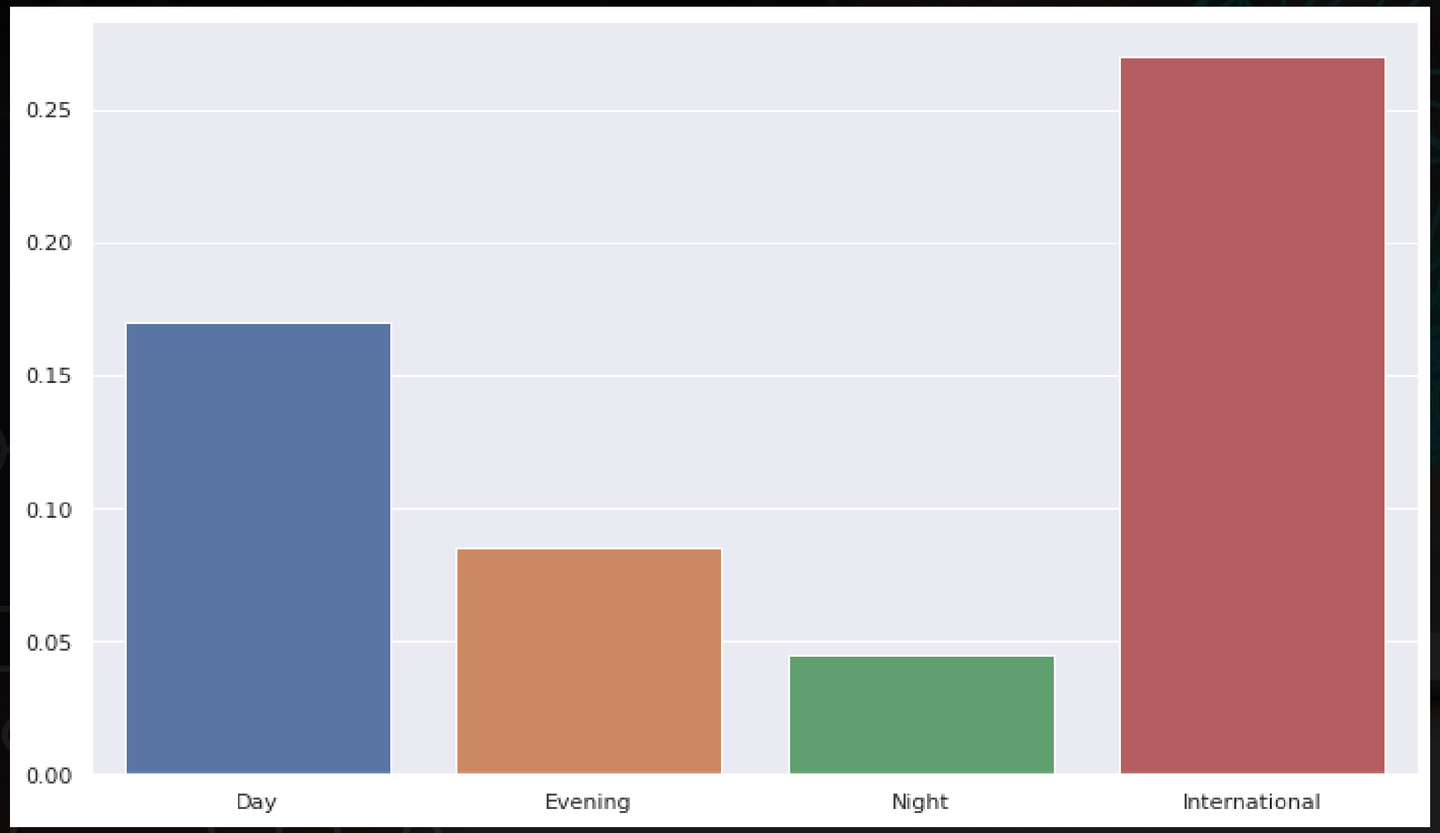


Report :

As these data sets are numerical data type, so for analyzing with the 'churn' which is a categorical data set, we are using mean, median.

Visualizations

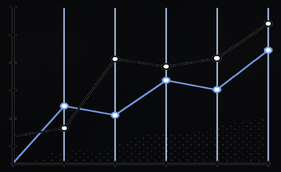
Analyzing relation between overall call charge and overall call minutes



Report :

After analyzing the dataset we have noticed that total day/night/eve .mins/call/charges are not put any kind of cause for churn rate. But international call charges are high as compare to others it's an obvious thing but that may be a cause for international plan customers to churn out.

Visualizations

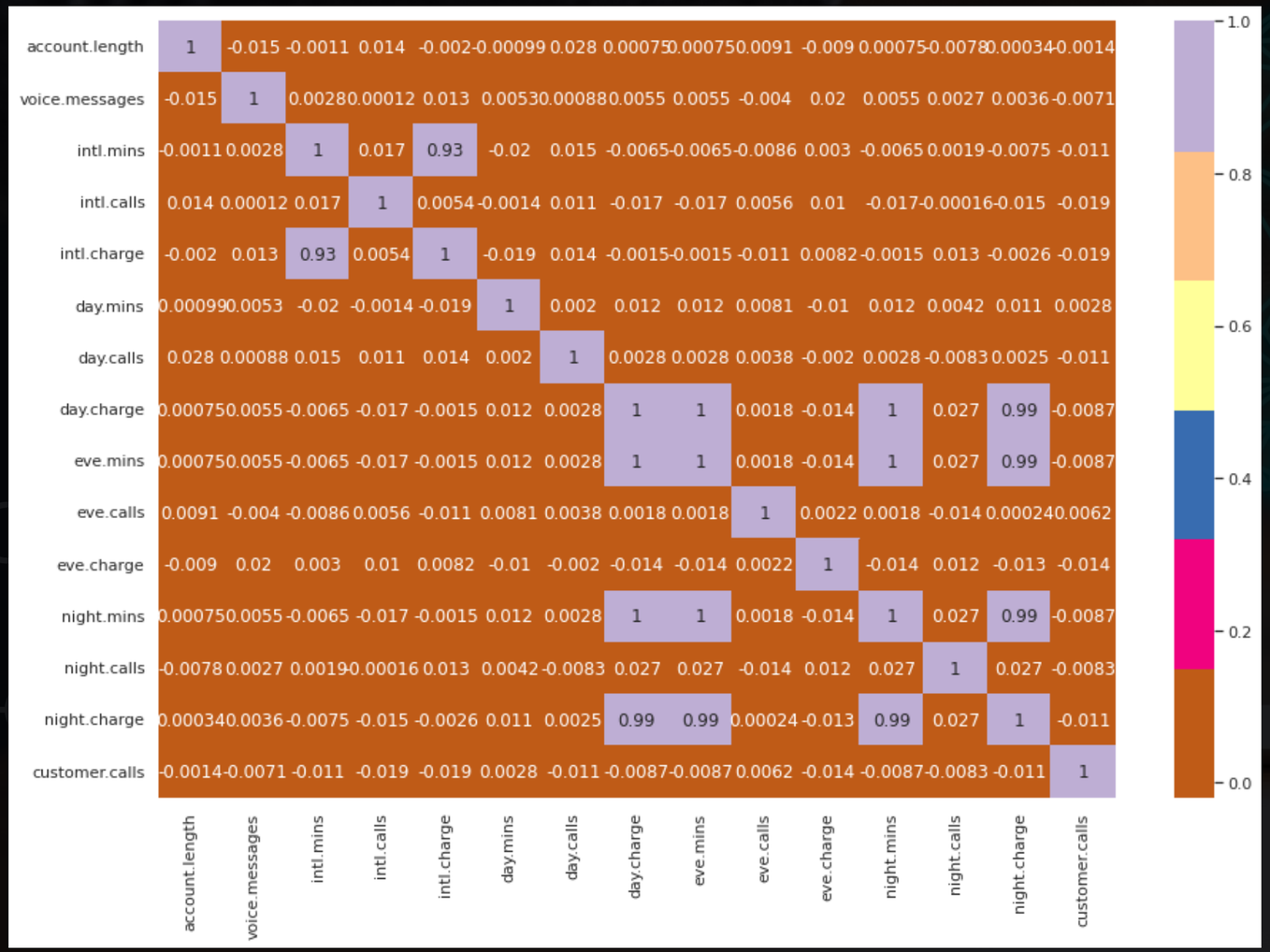


Graphical Analysis

1. Univariate Analysis : we analyze data over a single column from the numerical dataset, for this we use 3 types of plot which are box plot, strip plot, dist plot
2. Bivariate Analysis : We analyze data by taking two columns into consideration from a dataset, here we only take numerical data type column, for this visualization we use Box plot, scatter plot
3. Multivariate Analysis : We analyze data by taking more than two columns into consideration from a dataset, for this we using correlation plot, correlation matrix, correlataion heatmap, pair plot

Visualizations

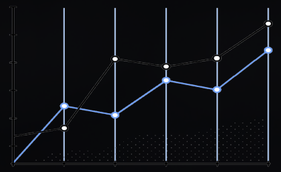
Analyzing Correlated Variables (HeatMap)



Report :

|r| = [>0.8] = Strong Correlation
|r| = [0.5-0.8] = Moderate Correlation
|r| = [<0.5] = Weak Correlation

Visualizations



Analyzing summary from all the visulizations

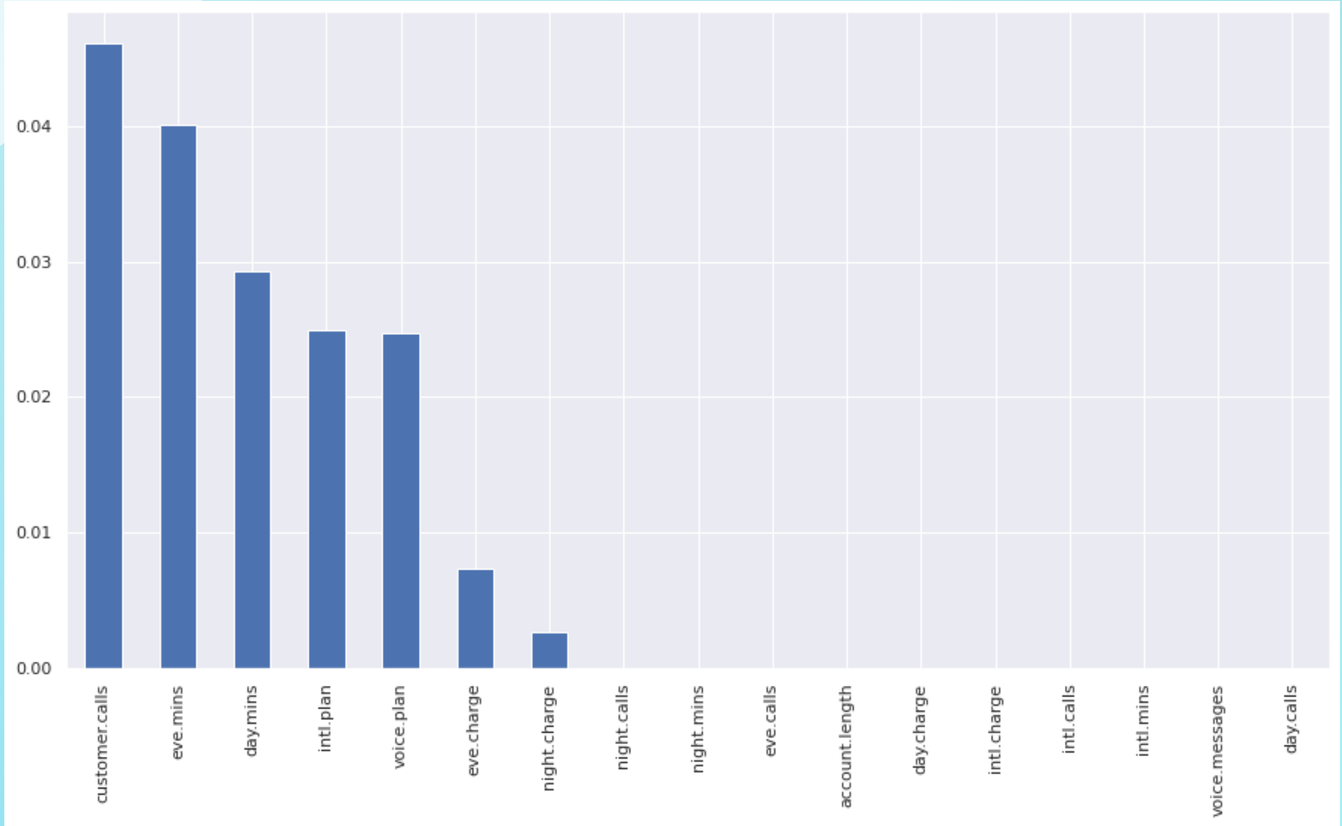
Report :

- Improve network coverage churned state
- In international plan provide some discount plan to the customer
- Improve the voice mail quality or take feedback from the customer
- Improve the service of call center and take frequently feedback from the customer regarding their issue and try to solve it as soon as possible

Feature Selection

1) Performing mutual info regression

```
[ ]  from sklearn.feature_selection import mutual_info_regression
     # determine the mutual information
     mutual_info=mutual_info_regression(x_train,y_train)
     mutual_info
```



Report:

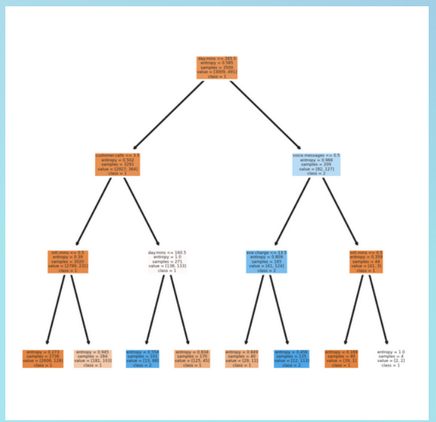
By the plot we can observe "cust.calls,eve.min,day.min,int.plan,voice.plan,nit.pcharge,eve.charge are Important

Feature Selection

2) Performing Decision Tree Classifier Using Entropy Criteria (C5.0)

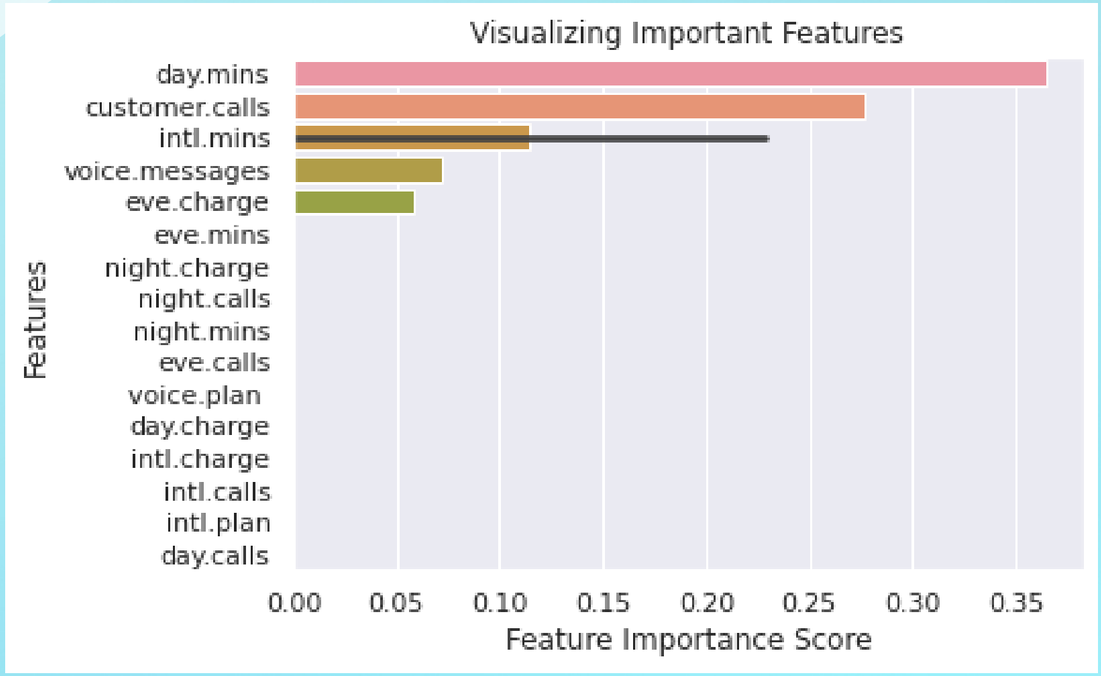
```
[53] from sklearn.tree import  DecisionTreeClassifier
     from sklearn import tree
     from sklearn.metrics import classification_report
     from sklearn import preprocessing

[54] # Pruning the Decision Tree
     model = DecisionTreeClassifier(criterion = 'entropy',max_depth=3)
     model.fit(x_train,y_train)

     DecisionTreeClassifier(criterion='entropy', max_depth=3)

[55] # PLot the decision tree
     from sklearn import tree
     tree.plot_tree(model);
```

Tree



```
# Accuracy
np.mean(preds==y_test)
```

```
0.9046666666666666
```



Report:

By the plot we can observe "cust.calls,intl.min,day.min,voice.msgs,charge,eve.charge are Important

Categorical to Numerical

```
# Encoding categorical columns
df3=pd.get_dummies(df2,columns=['state','area.code'])
df3
```

	account.length	voice.plan	voice.messages	intl.plan	intl.mins	intl.calls	intl.charge	day.mins
0	128	1	25	0	10	3	2	265
1	107	1	26	0	13	3	3	161
2	137	0	0	0	12	5	3	243
3	84	0	0	1	6	7	1	299
4	75	0	0	1	10	3	2	166

Smote for Imbalanced data

Resampling data is one of the most commonly preferred approaches to deal with an imbalanced dataset. There are broadly two types of methods for this i) Under sampling ii) Oversampling. In most cases, oversampling is preferred over under sampling techniques. The reason being, in under sampling we tend to remove instances from data that may be carrying some important information.

```
# Before balancing
y.value_counts()
```

```
churn
0        4264
1         705
dtype: int64
```



```
# After balancing
from imblearn.over_sampling import SMOTE
smote= SMOTE(sampling_strategy ='minority')
X_sm,y_sm=smote.fit_resample(x,y)
y_sm.value_counts()
```

```
churn
0        4264
1        4264
dtype: int64
```

Scaling down the data to keep the values in same range

```
# standardizing the data
# standardizing can help features arrive in more digestible form for these algorithms
scaler=preprocessing.StandardScaler()
a=scaler.fit_transform(x)
a
```

```
array([[ 0.69894149,  1.66712012,  1.27314513, ..., -0.58012157,
         1.002002  , -0.57611859],
       [ 0.16984882,  1.66712012,  1.3469729 , ..., -0.58012157,
         1.002002  , -0.57611859],
       [ 0.92569549, -0.5998368 , -0.57254912, ..., -0.58012157,
         1.002002  , -0.57611859],
       ...,
       [-0.98911606, -0.5998368 , -0.57254912, ..., -0.58012157,
         1.002002  , -0.57611859],
       [ 0.2202386 , -0.5998368 , -0.57254912, ..., -0.58012157,
        -0.998002  ,  1.73575375],
       [-0.35924384,  1.66712012,  1.93759506, ..., -0.58012157,
         1.002002  , -0.57611859]])
```

Model Building

- Gradient Boost Classifier
- Support Vector Machines
- Random Forest Classifier
- K Nearest Neighbor Classifier
- Decision Tree Classifier
- Logistic Regression

Gradient Boost Classifier (GBC)

```
from sklearn.model_selection import StratifiedKFold
from sklearn.base import clone
skfolds=StratifiedKFold(n_splits=10,random_state=42,shuffle=True)

from sklearn.ensemble import GradientBoostingClassifier
gbc=GradientBoostingClassifier(random_state=42)

for train_index, test_index in skfolds.split(x,y):
  clone_clf=clone(gbc)
  x_train_folds=a[train_index]
  y_train_folds=(y[train_index])
  x_test_fold=a[test_index]
  y_test_fold=(y[test_index])
  clone_clf.fit(x_train_folds,y_train_folds)
  y_pred=clone_clf.predict(x_test_fold)
  n_correct=sum(y_pred==y_test_fold)
  print("Results for GB",n_correct/len(y_pred))
```

Results :

```
Results for GB 0.95
Results for GB 0.962
Results for GB 0.956
Results for GB 0.954
Results for GB 0.96
Results for GB 0.946
Results for GB 0.948
Results for GB 0.932
Results for GB 0.948
Results for GB 0.948
```

Support Vector Machine (SVM)

```
from sklearn.svm import SVC
svc_clf=SVC(random_state=42)

for train_index, test_index in skfolds.split(x,y):
  clone_clf=clone(svc_clf)
  x_train_folds=a[train_index]
  y_train_folds=(y[train_index])
  x_test_fold=a[test_index]
  y_test_fold=(y[test_index])
  clone_clf.fit(x_train_folds,y_train_folds)
  y_pred=clone_clf.predict(x_test_fold)
  n_correct=sum(y_pred==y_test_fold)
  print("Results for SVM",n_correct/len(y_pred))
```

Results :

```
Results for SVM 0.868
Results for SVM 0.866
Results for SVM 0.87
Results for SVM 0.868
Results for SVM 0.868
Results for SVM 0.87
Results for SVM 0.872
Results for SVM 0.868
Results for SVM 0.86
Results for SVM 0.864
```

Random Forest Classifier (RF)

```
from sklearn.ensemble import RandomForestClassifier
rf_clf=RandomForestClassifier(random_state=42)

for train_index, test_index in skfolds.split(x,y):
  clone_clf=clone(rf_clf)
  x_train_folds=a[train_index]
  y_train_folds=(y[train_index])
  x_test_fold=a[test_index]
  y_test_fold=(y[test_index])
  clone_clf.fit(x_train_folds,y_train_folds)
  y_pred=clone_clf.predict(x_test_fold)
  n_correct=sum(y_pred==y_test_fold)
  print("Results for RFC",n_correct/len(y_pred))
```

Results :

```
Results for RFC 0.928
Results for RFC 0.946
Results for RFC 0.926
Results for RFC 0.934
Results for RFC 0.946
Results for RFC 0.936
Results for RFC 0.94
Results for RFC 0.916
Results for RFC 0.908
Results for RFC 0.934
```

K Nearest Neighbor Classifier (KNN)

```
from sklearn.neighbors import KNeighborsClassifier
knn_clf=KNeighborsClassifier()

for train_index, test_index in skfolds.split(x,y):
  clone_clf=clone(gbc)
  x_train_folds=a[train_index]
  y_train_folds=(y[train_index])
  x_test_fold=a[test_index]
  y_test_fold=(y[test_index])
  clone_clf.fit(x_train_folds,y_train_folds)
  y_pred=clone_clf.predict(x_test_fold)
  n_correct=sum(y_pred==y_test_fold)
  print("Results for KNN",n_correct/len(y_pred))
```

Results :

```
Results for KNN 0.95
Results for KNN 0.962
Results for KNN 0.956
Results for KNN 0.954
Results for KNN 0.96
Results for KNN 0.946
Results for KNN 0.948
Results for KNN 0.932
Results for KNN 0.948
Results for KNN 0.948
```

Decision Tree Classifier (DT)

```
from sklearn.tree import DecisionTreeClassifier
dt_clf=DecisionTreeClassifier(random_state=42)

for train_index, test_index in skfolds.split(x,y):
    clone_clf=clone(gbc)
    x_train_folds=a[train_index]
    y_train_folds=(y[train_index])
    x_test_fold=a[test_index]
    y_test_fold=(y[test_index])
    clone_clf.fit(x_train_folds,y_train_folds)
    y_pred=clone_clf.predict(x_test_fold)
    n_correct=sum(y_pred==y_test_fold)
    print("Results for DT",n_correct/len(y_pred))
```

Results :

```
Results for DT 0.95
Results for DT 0.962
Results for DT 0.956
Results for DT 0.954
Results for DT 0.96
Results for DT 0.946
Results for DT 0.948
Results for DT 0.932
Results for DT 0.948
Results for DT 0.948
```

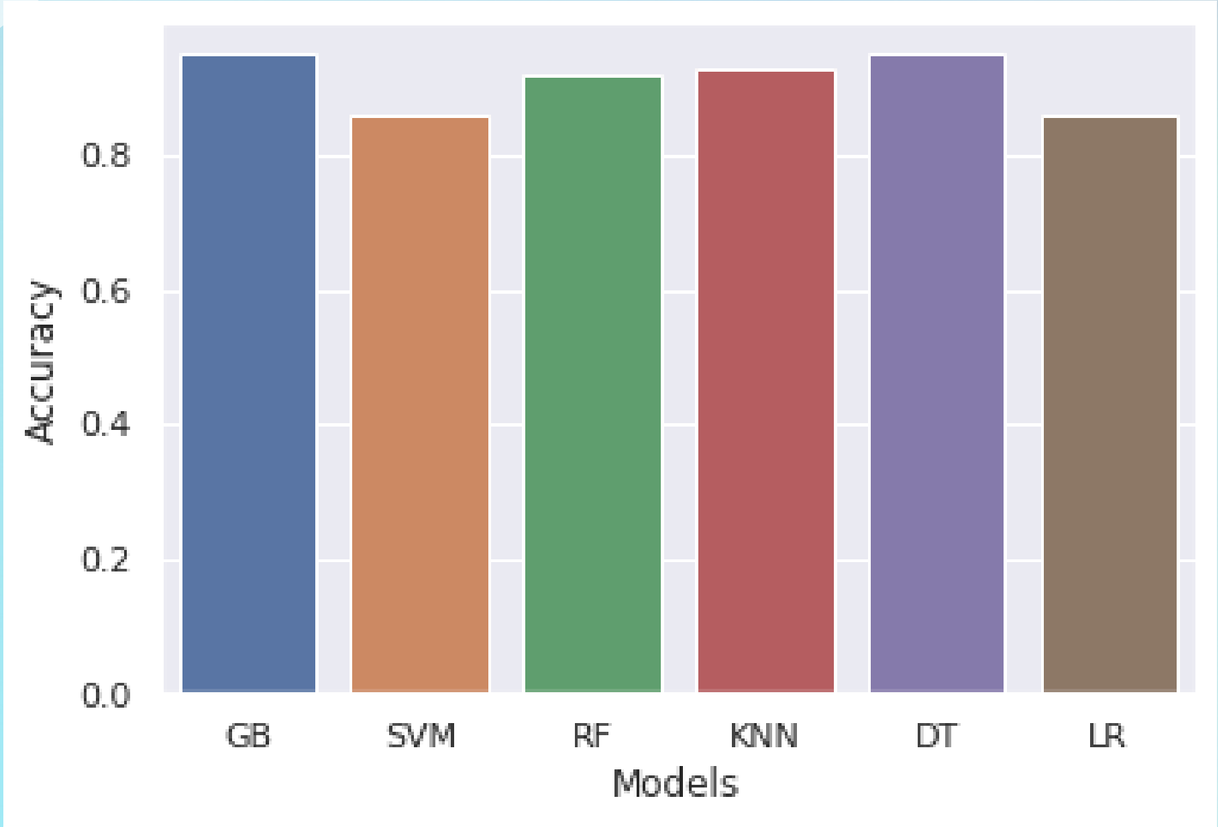
Logistic Regression (LR)

```
from sklearn.linear_model import LogisticRegression
lr_clf=LogisticRegression(random_state=42)

for train_index, test_index in skfolds.split(x,y):
  clone_clf=clone(lr_clf)
  x_train_folds=a[train_index]
  y_train_folds=(y[train_index])
  x_test_fold=a[test_index]
  y_test_fold=(y[test_index])
  clone_clf.fit(x_train_folds,y_train_folds)
  y_pred=clone_clf.predict(x_test_fold)
  n_correct=sum(y_pred==y_test_fold)
  print("Results for LR",n_correct/len(y_pred))
```

Results :

```
Results for LR 0.868
Results for LR 0.872
Results for LR 0.874
Results for LR 0.858
Results for LR 0.858
Results for LR 0.872
Results for LR 0.878
Results for LR 0.856
Results for LR 0.854
Results for LR 0.862
```

Analyzing Best Model



Gradient Boost Classifier (GBC)

Cross Validation

K-Fold :

```
from sklearn.model_selection import KFold
model=GradientBoostingClassifier(random_state=42)
kfold_validation=KFold(10)
import numpy as np
from sklearn.model_selection import cross_val_score
results=cross_val_score(model,x,y,cv=kfold_validation)
print(results)
print(np.mean(results))
```

```
[0.96  0.948 0.958 0.948 0.952 0.932 0.964 0.934 0.948 0.974]
0.9518000000000001
```

K-Folds cross validation is one method that attempts to maximize the use of the available data for training and then testing a model. It is particularly useful for assessing model performance, as it provides a range of accuracy scores across (somewhat) different data sets.

Cross Validation

Stratified K-Fold :

```
from sklearn.model_selection import StratifiedKFold
skfold=StratifiedKFold(n_splits=5)
model=GradientBoostingClassifier(random_state=42)
scores=cross_val_score(model,x,y,cv=skfold)
print(np.mean(scores))
```

```
0.9517999999999999
```

Implementing the concept of stratified sampling in cross-validation ensures the training and test sets have the same proportion of the feature of interest as in the original dataset. Doing this with the target variable ensures that the cross-validation result is a close approximation of generalization error.

Model Deployment

Model deployment is the process of putting machine learning models into production. This makes the model's predictions available to users, developers or systems, so they can make business decisions based on data, interact with their application (like recognize a face in an image) and so on.

- Step 1: Create a new virtual environment using Pickle library.
- Step 2: Install necessary libraries.
- Step 3: Build the best machine learning model and Save it.
- Step 4: Test the loaded model.
- Step 5: Create main.py file.
- Step 6: Open local path in prompt and deploy to predict.

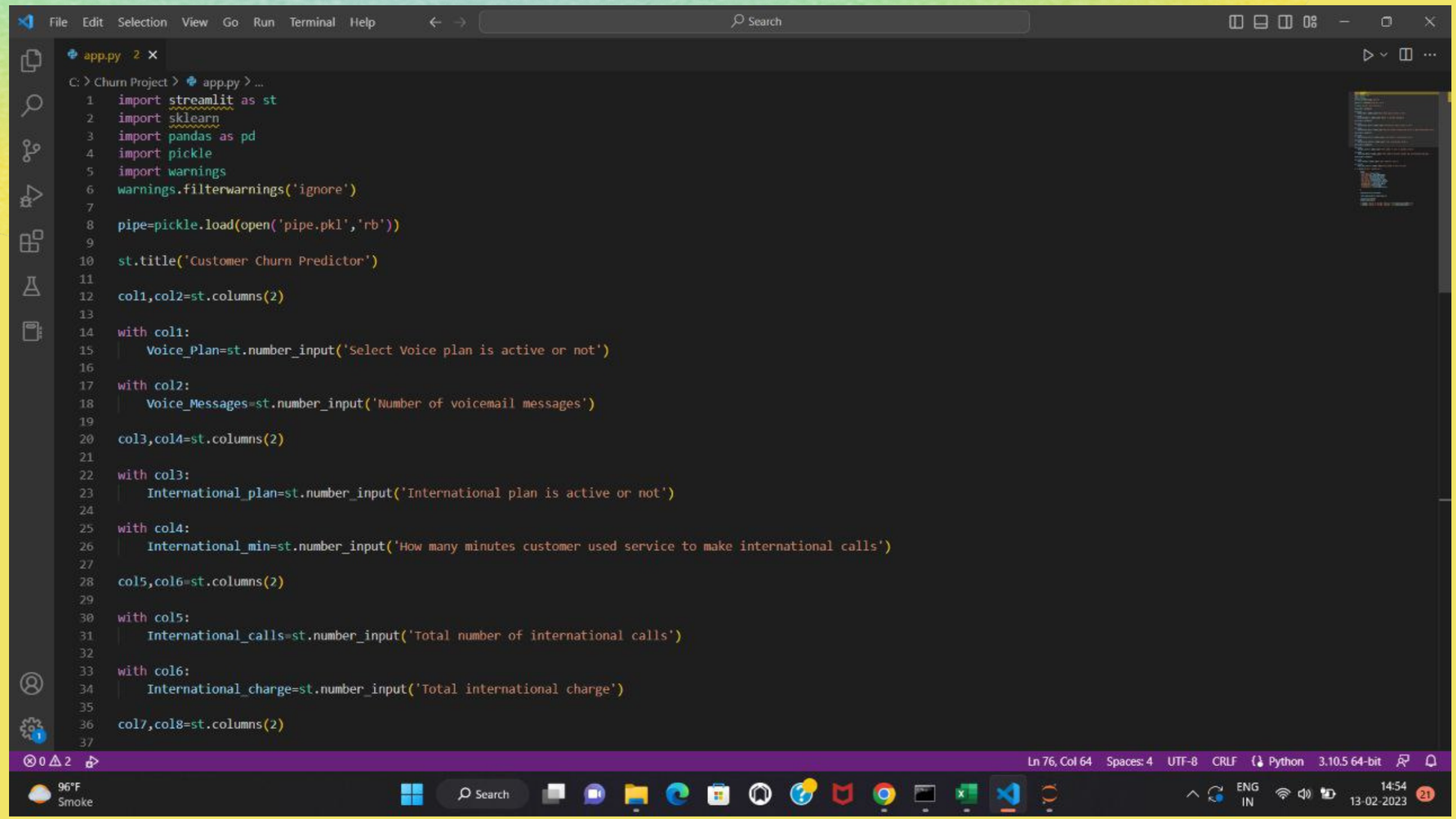
Model Deployment

Saving the final model :

```
In [142]:
pipe=Pipeline(steps=[('step1',GradientBoostingClassifier())])
pipe.fit(x_train,y_train)

Out[142]:
Pipeline(steps=[('step1', GradientBoostingClassifier())])

In [143]:
y_pred=pipe.predict(x_test)

In [144]:
pipe.predict_proba(x_test)[10]

Out[144]:
array([0.96621062, 0.03378938])

In [145]:
pipe1=Pipeline(steps=[('step1',RandomForestClassifier())])
pipe1.fit(x_train,y_train)

Out[145]:
Pipeline(steps=[('step1', RandomForestClassifier())])

In [146]:
pipe1.predict_proba(x_test)[10]

Out[146]:
array([0.88, 0.12])

In [147]:
import pickle
pickle.dump(pipe,open('pipe.pkl','wb'))

In [ ]:
```

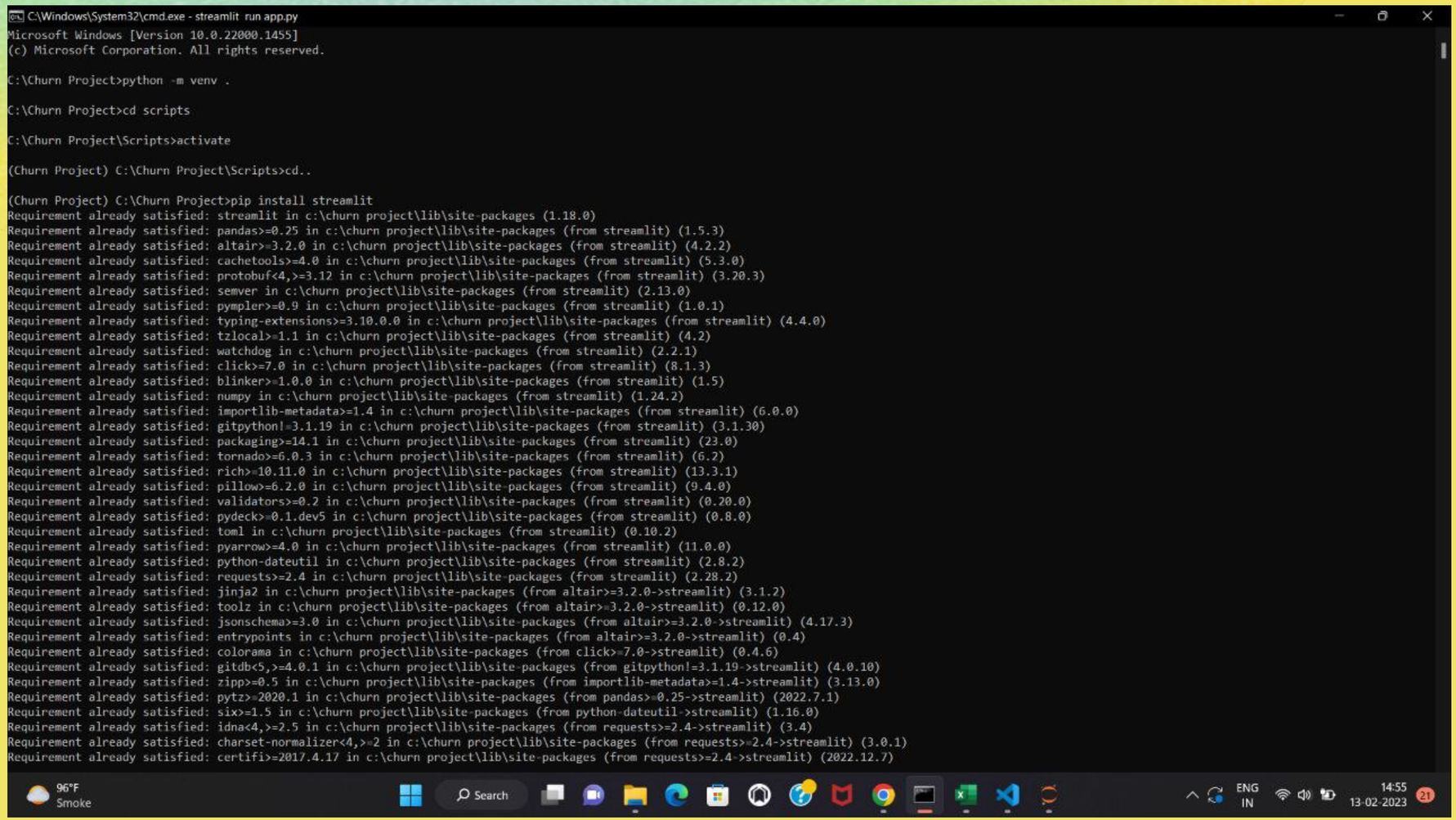
Model Deployment

Creating Main app.py file :



Model Deployment

Cmd prompt :



Model Deployment

Churn Predictor Webpage :