CUSTOMER CHURN ANALYSIS

A project with the help of Flip Robo to better understand customer churn in the telecom industry with the goal of developing and evaluating various customer churn prediction models.

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Abstract:

Customer churn is a major source of concern in highly competitive service industries, particularly the telecommunications industry.
The study's goal was to develop a predictive churn model that could predict which customers would leave.

Churn analysis can be used to identify the trend of customer attrition.
Customer retention rates have improved as a result of churn analytics efforts.
The appropriate churn analysis insights from the analytics toolbox will help you understand three critical points:
Why do customers leave?
What are the most common sources of consumer dissatisfaction?

Problem Definition:

Sample IBM Dataset and Customer Churn analysis:

Customers leave all telecom companies. Customer churn occurs when customers or subscribers discontinue doing business with a company. Customers in the telecom sector can actively switch between service providers. Because it is relatively expensive to acquire new customers, telecommunications companies that wish to retain their current clientele face a challenge. We were given a churn label indicating whether or not a client had cancelled their membership, as well as cleaned user activity data (features).

Our analysis may reveal how customer churn is related to other factors, identify potential causes, and provide recommendations for improving customer retention rates.

The massive amounts of customer data gathered can be used to develop churn prediction algorithms for this issue. By identifying that group, a company can focus its marketing efforts on the customers who are most likely to leave. Because switching providers is easy, the telecoms industry must focus on preventing customer churn.

In order to create and evaluate multiple customer churn prediction models, we will examine customer data from IBM Sample Data Sets.

Data Analysis:

Data preparation, importing necessary libraries and dataset

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
```

```
##Importing dataset
data = pd.read_csv("https://raw.githubusercontent.com/dsrscientist/DSData/master/Telecom_customer_churn.csv")
```

Overview of dataset

```
data.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	StreamingTV
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	No	No
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	Yes	No
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No	No

5 rows × 21 columns

```
##Shape
data.shape
```

```
(7043, 21)
```

Dataset has 7043 rows and 21 columns

```
##Checking columns
data.columns
```

```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

```
data.info()
```

```
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Observations:

There is one float value among the 21 columns, 18 object types, and two int datatypes. Churn is the only target variable. Each entry in this case uses a distinct value for customerID. Drop this column later. The category variable "SeniorCitizen" has two possible values: 0 and 1. Let's make it an object datatype.

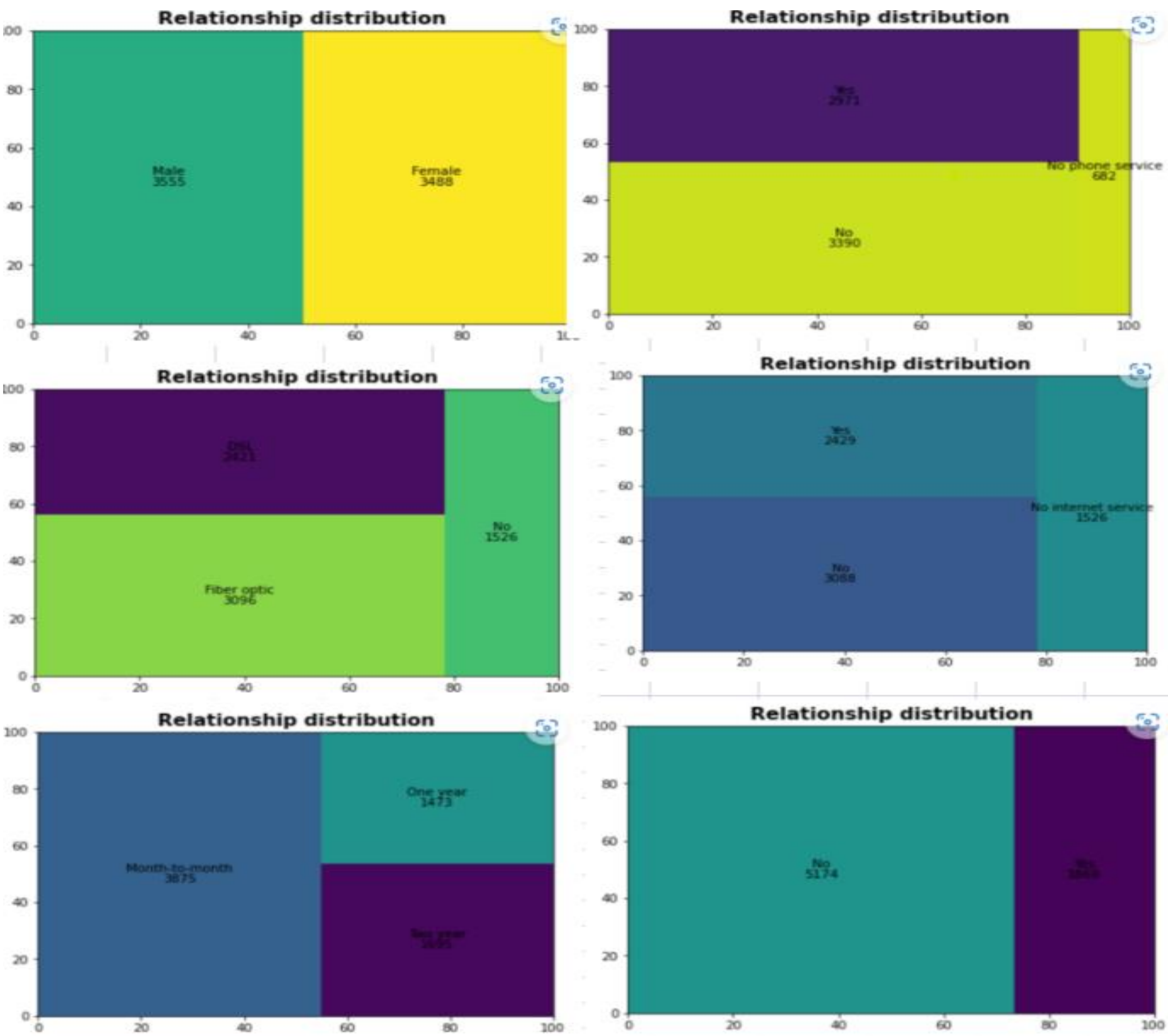
```
# Converting datatype into float

data['TotalCharges']= data['TotalCharges'].astype(float)
```

Exploratory Data Analysis

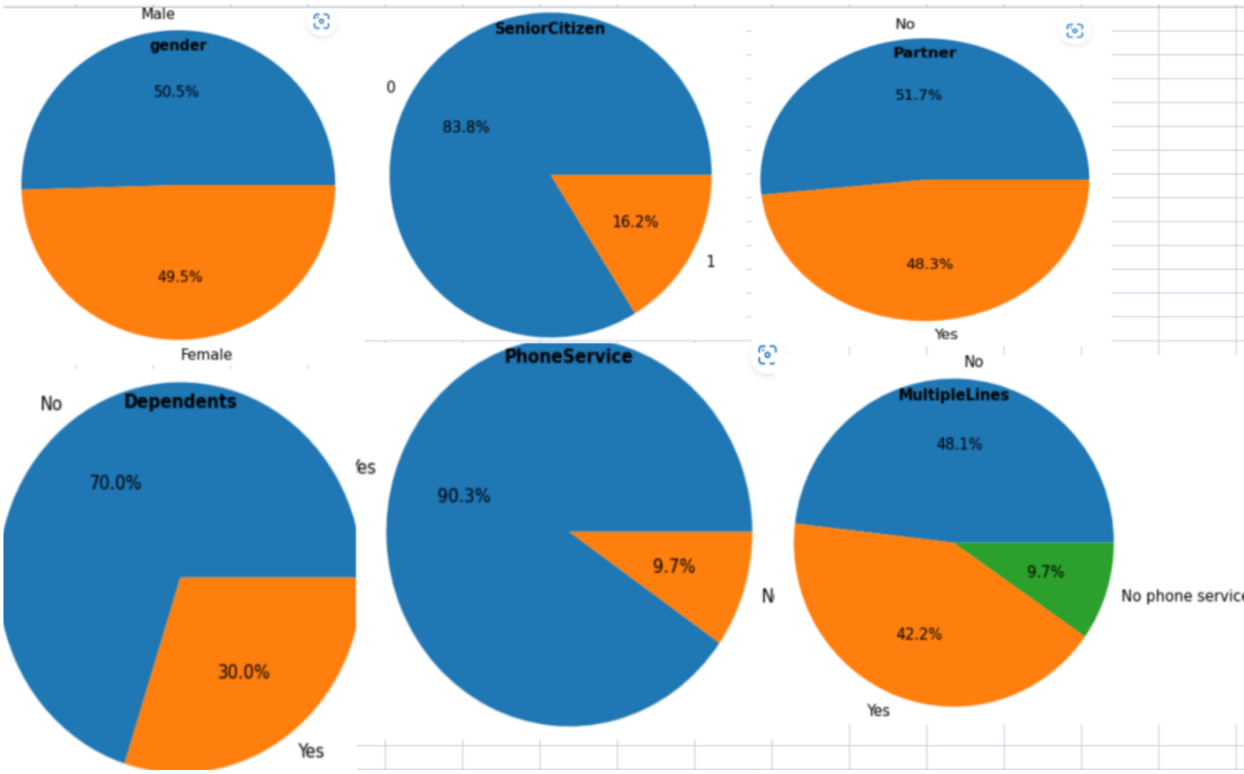
In statistics, exploratory data analysis is a method of examining data sets to highlight their key features, which frequently involves the use of statistical graphics and other data visualization techniques.

EDA is a procedure or method that uses a variety of procedures or methods to format our dataset so that we can achieve our actual goal. In this EDA, we use a variety of tools and Python modules to analyze the entire dataset.

Relationship Distribution among given data



Categorical Data Analysis



Most used electronic check

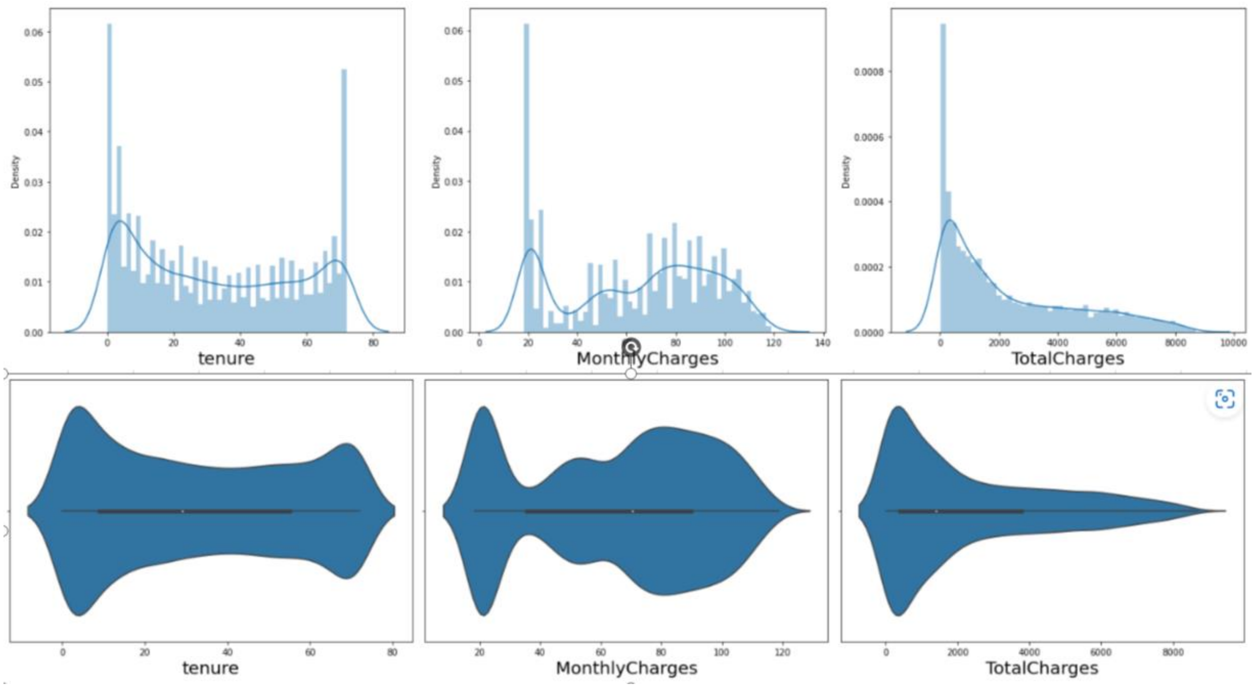
55% customer prefer month to month contract compare to other.

50% customer are having partners

30% customer have dependents on them

16% customer are Senior citizen

Numerical Data Analysis



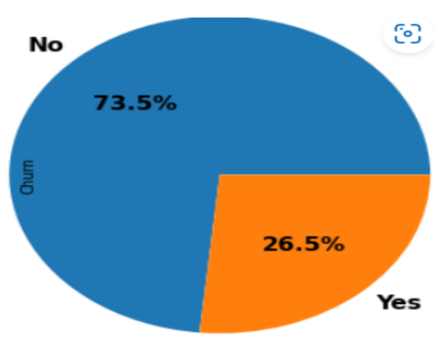
All the data have right skewness

Avg range of age is 0-70

Monthly charges range is 20-120

0 value is present in TotalCharges column

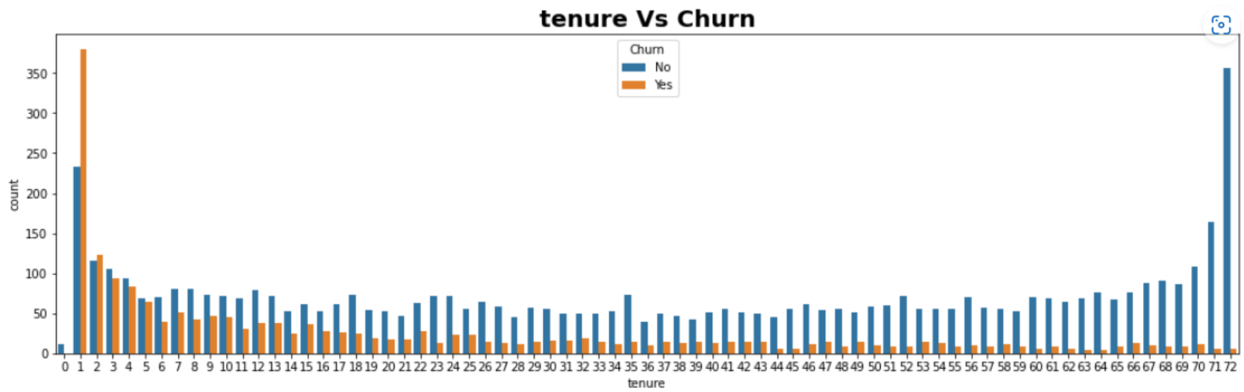
Analysis of Target variable



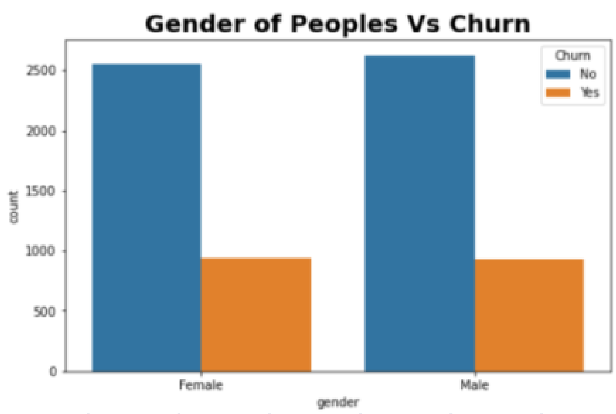
26.5 % customers Churn in last month.

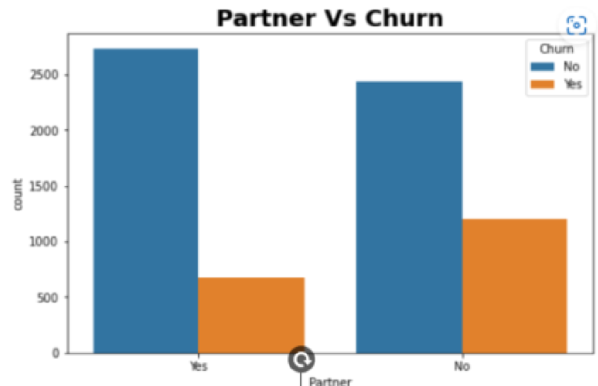
73.5 % customers choose to continue the service in last month.

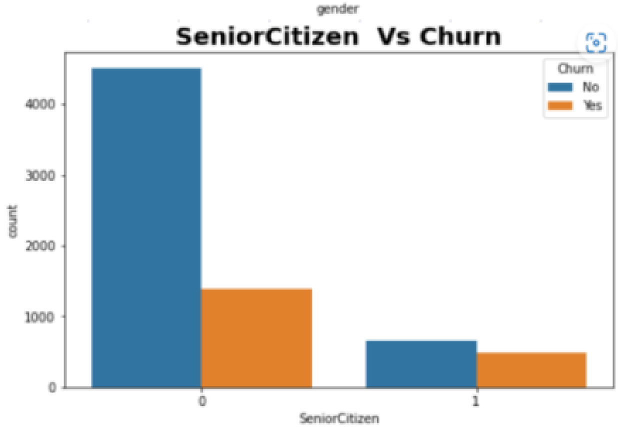
Features on target variable

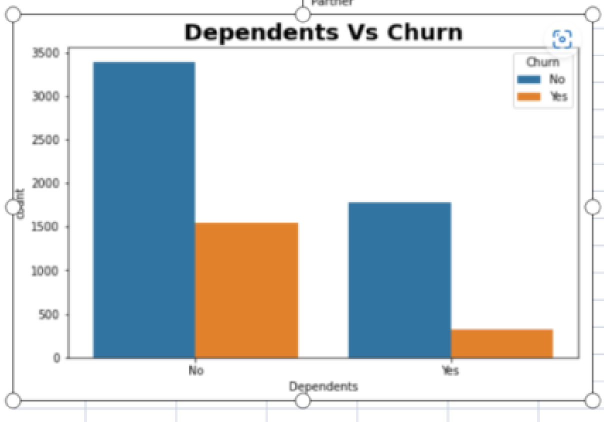


No clear relationship between tenure



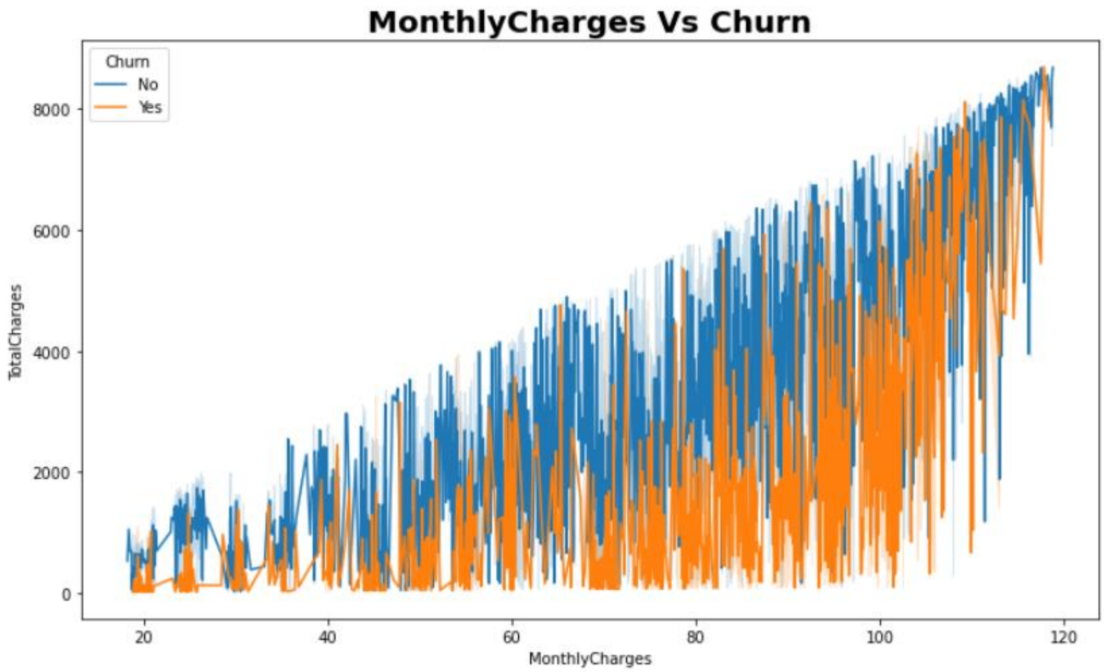






Customers who do not have dependents have a 30% churn rate. Around 85% of all dependent customers are more likely to churn.

Customers who have a partner have a lower churn rate. Customers who do not have a partner are more likely to churn than customers who do have a partner.



If the MonthlyCharges are high, customers are more likely to churn than the rest. If TotalCharges is high, customers are more likely to choose churn than the rest.

Pre-Processing Pipeline:

The feature engineering stage is critical for developing a machine learning model. Machine learning initiatives may succeed or fail. What distinguishes them? Without a doubt, the most important factor is the features that are used.

The pipeline ensures that the preprocessing steps are only performed on training data (or training folds in cross-validation). 3. It ensures that your data is always preprocessed in the same way. This is important, for example, if a categorical feature in the test set belongs to a category that does not exist in the training set.

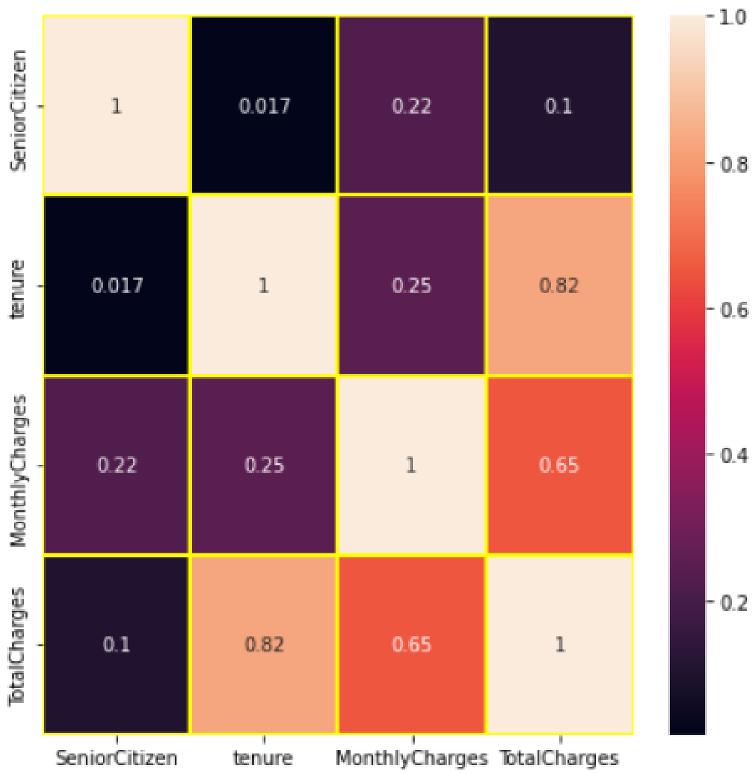
Correlation:

Correlation is high between total charges and tenure. But as we have only 3 numerical features at this time, let's encode the categorical features.

```
data.corr().T
```

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
SeniorCitizen	1.000000	0.016567	0.220173	0.102395
tenure	0.016567	1.000000	0.247900	0.824757
MonthlyCharges	0.220173	0.247900	1.000000	0.650468
TotalCharges	0.102395	0.824757	0.650468	1.000000

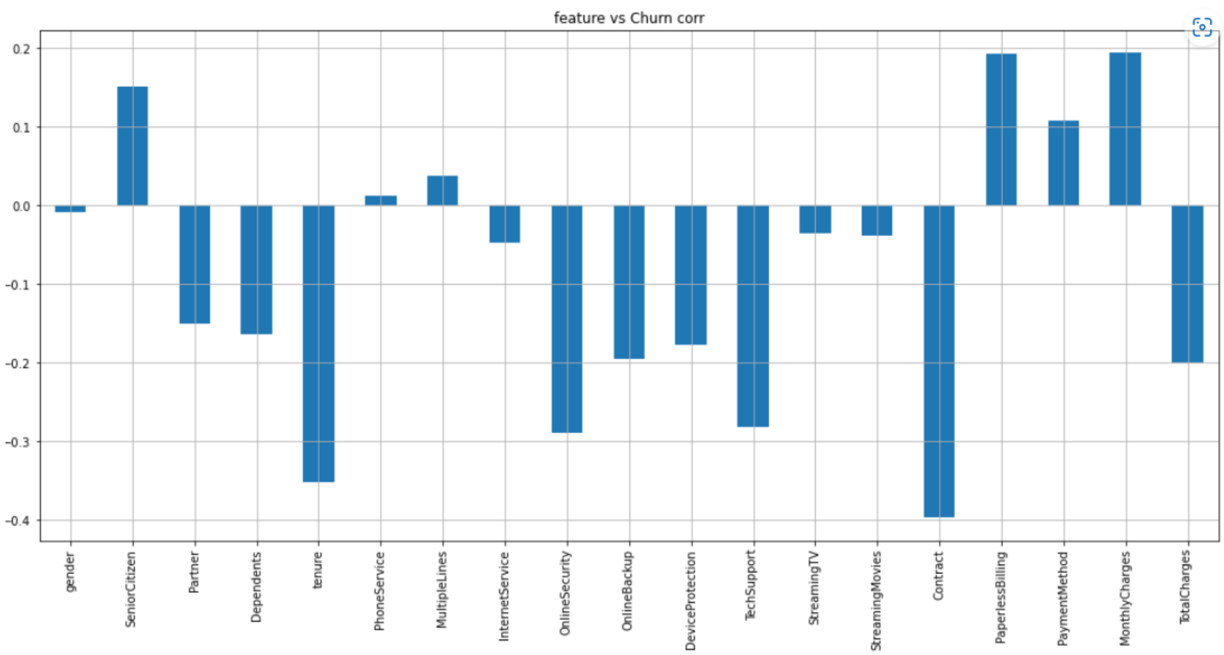
```
plt.subplots(figsize=(7,7))
sns.heatmap(data.corr(), annot= True, linecolor= "yellow",  linewidths= 2)
plt.show()
```



Categorical features Encoding

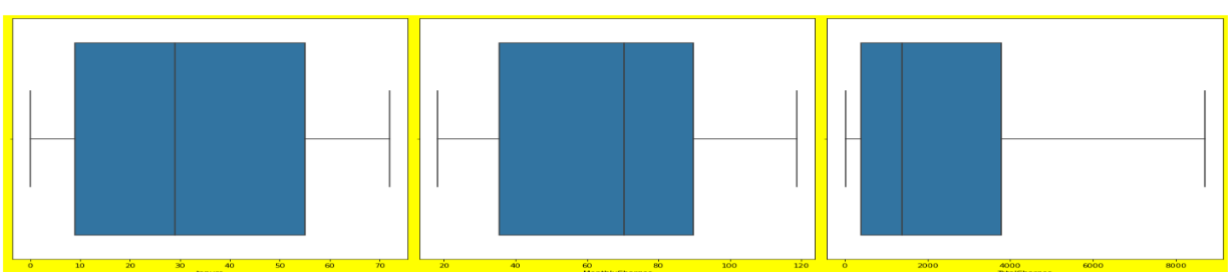
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in cat_features:
    data[i] = le.fit_transform(data[i])
data.head()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV
0	0	0	1	0	1	0	1	0	0	2	0	0	0
1	1	0	0	0	34	1	0	0	2	0	2	0	0
2	1	0	0	0	2	1	0	0	2	2	0	0	0
3	1	0	0	0	45	0	1	0	2	0	2	2	0
4	0	0	0	0	2	1	0	1	0	0	0	0	0



Contract has a very negative relationship with Churn. Paperless billing and monthly charges, on the other hand, are positively related to churn. All of the characteristics are related to one another.

Outliers



Skewness:

```
data[['tenure', 'MonthlyCharges', 'TotalCharges']].skew().sort_values()
```

```
MonthlyCharges   -0.220524
TotalCharges     -0.144899
tenure            0.239540
dtype: float64
```

Data Balancing:

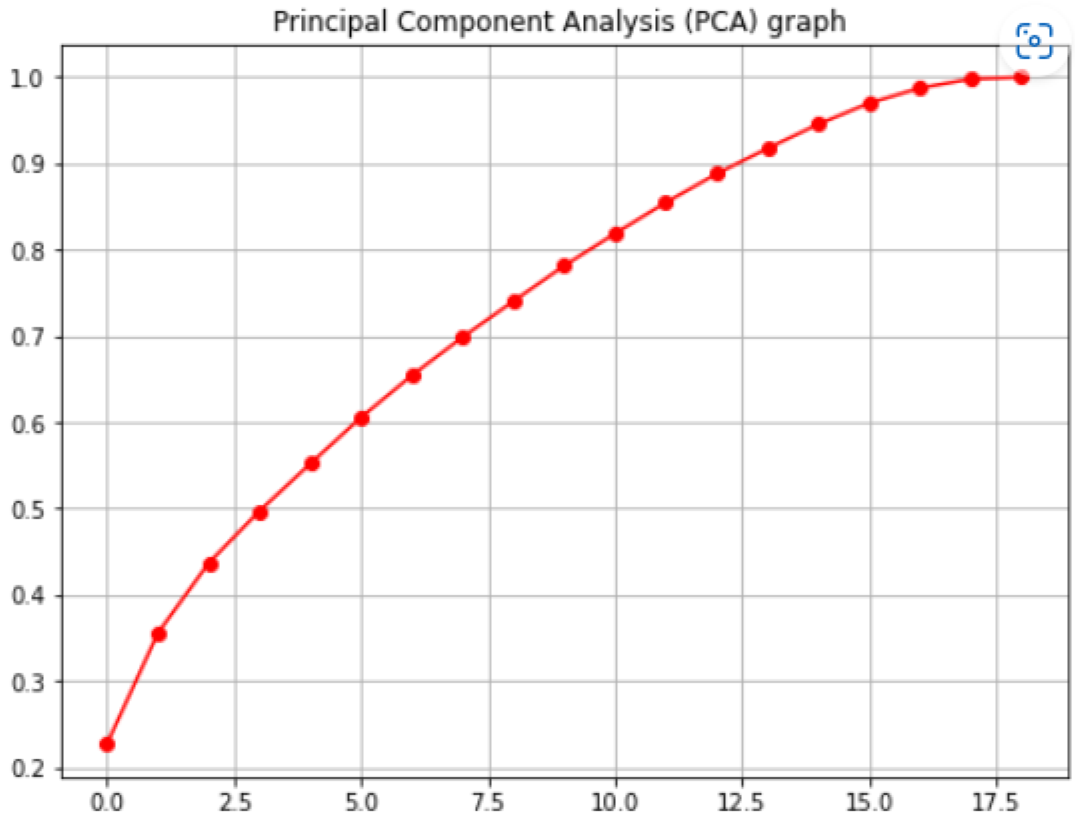
```
from imblearn import under_sampling
from imblearn import over_sampling
from imblearn.over_sampling import SMOTE
```

```
from imblearn.over_sampling import SMOTE
ovrs = SMOTE()

# Splitting data in target and features
x = data.drop(['Churn'], axis =1)
y = data['Churn']
```

Multicollinearity:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif= pd.DataFrame()
vif["VIF"]= [variance_inflation_factor(data.values,i)for i in range(data.shape[1])]
vif["Features"] = data.columns
vif
```

	VIF	Features
0	1.992203	gender
1	1.372640	SeniorCitizen
2	2.821218	Partner
3	1.961200	Dependents
4	13.497891	tenure
5	16.014903	PhoneService
6	2.756853	MultipleLines
7	4.478147	InternetService
8	2.287594	OnlineSecurity
9	2.445350	OnlineBackup
10	2.627903	DeviceProtection
11	2.412647	TechSupport
12	3.235594	StreamingTV
13	3.256673	StreamingMovies
14	4.209950	Contract
15	2.924748	PaperlessBilling
16	3.516126	PaymentMethod
17	18.118004	MonthlyCharges
18	4.806274	TotalCharges
19	1.937378	Churn



95% variance gives the first 14 component.

Building Machine Learning Models:

A machine learning model is a mathematical representation of the results of the training process. Machine learning is the study of various algorithms that can automatically develop a model through practice and historical data. A machine learning model is similar to computer software that can recognize patterns or behaviors based on prior experience or data. The learning algorithm generates a machine learning (ML) model that captures the patterns found in the training data after analyzing the training data for patterns.

Using different Classification ML Models

```
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report,f1_score

from sklearn.linear_model import LogisticRegression

acc_max=0
random_max=0
for i in range(400, 1500):
    x_train,x_test,y_train,y_test = train_test_split(x_scale_new,y,test_size = 0.25, random_state=i)
    log= LogisticRegression()
    log.fit(x_train,y_train)
    y_pred=log.predict(x_test)
    acc= accuracy_score(y_test,y_pred)
    if acc>acc_max:
        acc_max=acc
        random_max=i

print('Best accuracy is', acc_max ,'on Random_state', random_max)
```

```
Best accuracy is 0.8074990336296869 on Random_state 1168
```

The best accuracy on Random_state=1168

Logistic Regression

```
accu score :  0.8001546192500967
cof_mat:
  [[ 997  295]
 [ 222 1073]]
classification report:
               precision    recall  f1-score   support

           0       0.82      0.77      0.79      1292
           1       0.78      0.83      0.81      1295

    accuracy                           0.80      2587
   macro avg       0.80      0.80      0.80      2587
weighted avg       0.80      0.80      0.80      2587

-----------
-----------
training score :  0.778636773611648
testing score :  0.8001546192500967
```

After Hyper Parameter Tuning

```
training score :  0.7795387192372117
testing score :  0.7974487823734054
```

R2 score not improved after using gridsearchCV

DecisionTreeClassifier

```
classification report:

              precision    recall  f1-score   support

           0       0.78      0.74      0.76      1292
           1       0.75      0.79      0.77      1295

    accuracy                           0.77      2587
   macro avg       0.77      0.77      0.77      2587
weighted avg       0.77      0.77      0.77      2587

-----------
-----------
training score :  0.9985826568741142
testing score :  0.7669114804793197
```

After Hyper Parameter Tuning

```
training score :  0.8062105398788816
testing score :  0.7816003092385002
```

The gap between training and testing scores is also narrowing. The accuracy score improves slightly after using GridSearchCV with DecisionTreeClassifier.

GradientBoostingClassifier

```
classification report:

              precision    recall  f1-score   support

           0       0.84      0.78      0.81      1292
           1       0.79      0.85      0.82      1295

    accuracy                           0.81      2587
   macro avg       0.82      0.81      0.81      2587
weighted avg       0.82      0.81      0.81      2587

-----------
-----------
training score :  0.8218013142636258
testing score :  0.8148434480092771
```

After Hyper Parameter Tuning

```
training score :  0.8218013142636258
testing score :  0.8140703517587939
```

No improvement in Accuracy score, training score, testing score after using GridSearchCV with GradientBoostingClassifier

RandomForestClassifier

```
classification report:               precision    recall  f1-score   support

           0       0.82      0.82      0.82      1292
           1       0.82      0.82      0.82      1295

    accuracy                           0.82      2587
   macro avg       0.82      0.82      0.82      2587
weighted avg       0.82      0.82      0.82      2587

-----------
-----------
training score :  0.9985826568741142
testing score :  0.8233475067645922
```

After Hyper Parameter Tuning

```
training score :  0.960185543100116
testing score :  0.8237340548898338
```

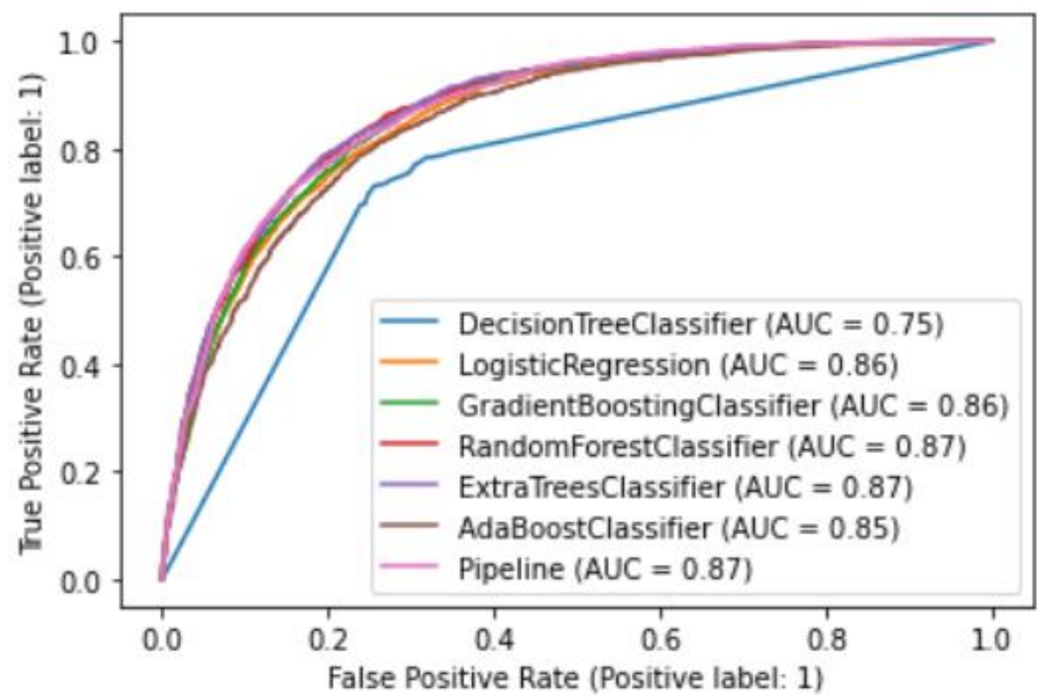
Accuracy score is improved after using GridSearchCV with RandomForestClassifier

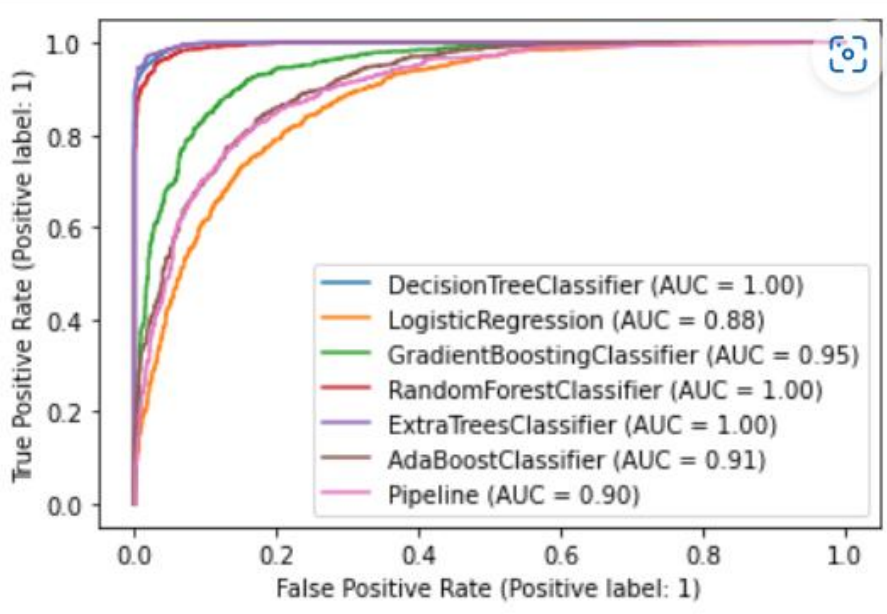
<u>Random Forest Classifier gives the best score.</u>

Cross Validation

```
from sklearn.model_selection import cross_val_score
svm_best = Pipeline([('PCA', PCA()),
                ('SVM', SVC(C=7, gamma=0.01, kernel = "rbf"))])

all_models = [log, grid_clf_best, grid_gbdt_best, grid_rf_best, grid_etc_best, grid_ada_best, svm_best ]

for i in all_models:
    cvscore = cross_val_score(i, x_scale,y, cv =7)
    print('Cross Validation Score of :',i)
    print("\n Cross Validation Score : " ,cvscore)
    print("\nMean CV Score :",cvscore.mean())
    print("\nStd deviation :",cvscore.std())
    print("\n-----------")
    print("-----------")
```

ROC AUC Curve

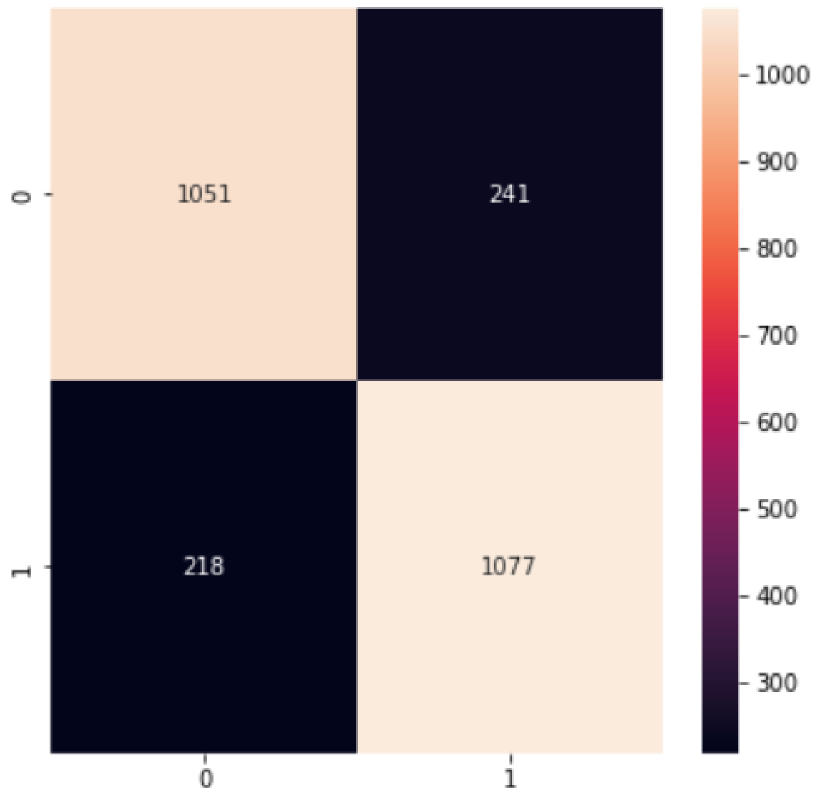




Randomforest is the final model for this dataset

Confusion Matrix:

```
conf = confusion_matrix (y_test, y_pred)

fig , ax = plt.subplots(figsize=(6,6))
sns.heatmap(conf, annot = True, fmt = ".0f")
plt.show()
```



We will save the final model using the Pickle library.

```
import pickle
pickle.dump(grid_etc_best, open("Customer_Churn_Classification_model", "wb"))
load_Customer_Churn_Classification_model= pickle.load(open("Customer_Churn_Classification_model", "rb"))
```

Concluding Remarks:

The telecommunications industry has been harmed by high churn rates and significant churning loss. To avoid problems in the telecommunications industry, effective procedures must be developed and existing ones improved. In this post, we looked at a variety of prediction models and compared their quality indicators. We discovered that SVM Classifier accuracy is significantly higher than logistic regression accuracy, demonstrating the effectiveness of decision trees as a method.

- The vast majority of customers who are likely to leave have no online security.
- Customers are more likely to churn if the plan is monthly.
- The data is subjected to various feature engineering approaches, such as data balance, outlier removal, label encoding, feature selection, and PCA.
- Random Forest is the best model for this dataset.