Customer Churn Prediction

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1 Project Description:

The objective of this project is to analyze customer churn in the telecommunications industry using the "Telco Customer Churn" dataset from Kaggle. The dataset contains details of telecom customers, including demographic information, account details, and usage patterns. By leveraging this data, the goal is to build a predictive model to identify factors contributing to customer churn and develop strategies to retain valuable customers.

The data can be found at https://www.kaggle.com/datasets/blastchar/telco-customer-churn

2 Key Objectives:

Data Exploration and Preprocessing: Perform exploratory data analysis (EDA) to understand the dataset's structure and clean it by handling missing values, outliers, and encoding categorical variables. Feature Engineering: Create new features to improve model performance by identifying patterns in the customer behaviors and account details. Model Development: Use machine learning algorithms (such as logistic regression, decision trees, random forests, or XGBoost) to build a churn prediction model. The model will predict whether a customer will churn based on the available features. Model Evaluation: Assess the performance of the model using evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to ensure it is robust and reliable. Insights and Recommendations: Based on model predictions and analysis, generate actionable insights on how to reduce churn, targeting key factors that impact customer retention. Tools and Technologies:

Python (Pandas, NumPy, Scikit-learn) Jupyter Notebooks Data Visualization (Matplotlib, Seaborn) Machine Learning Algorithms (Logistic Regression, Decision Trees, Random Forests, XG-Boost) Expected Outcomes:

A trained predictive model capable of forecasting customer churn. In-depth analysis of key features contributing to churn. Strategic recommendations for improving customer retention in a telecom business.

3 Part 1: Data Pre-processing

I) Importing the dataset and exploring its properties.

[1]:
```
#Importing all the necessary libraries.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
df.sample(5)
```

[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
154	3077-RSNTJ	Female	0	Yes	Yes	6	
3620	9373-WSLOY	Male	1	Yes	No	33	
975	2834-JRTUA	Male	0	No	No	71	
1975	4703-MQYKT	Male	0	No	No	21	
5232	1755-RMCXH	Male	0	Yes	Yes	2	

	PhoneService	MultipleLines	InternetService	OnlineSecurity	…	\
154	Yes	No	No	No internet service	…	
3620	No	No phone service	DSL	No	…	
975	Yes	Yes	Fiber optic	Yes	…	
1975	Yes	No	No	No internet service	…	
5232	Yes	No	No	No internet service	…	

	DeviceProtection	TechSupport	StreamingTV	\
154	No internet service	No internet service	No internet service	
3620	Yes	Yes	Yes	
975	Yes	Yes	Yes	
1975	No internet service	No internet service	No internet service	
5232	No internet service	No internet service	No internet service	

	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	\
154	No internet service	Month-to-month	No	Mailed check	
3620	No	Month-to-month	Yes	Electronic check	
975	Yes	Two year	Yes	Electronic check	
1975	No internet service	Two year	No	Mailed check	
5232	No internet service	Month-to-month	No	Mailed check	

	MonthlyCharges	TotalCharges	Churn
154	19.70	113.5	No
3620	50.00	1750.85	No
975	108.05	7532.15	Yes
1975	19.60	390.4	No
5232	20.30	40.25	No

```
[5 rows x 21 columns]
```

[3]:
```
df.shape
```

[3]:
```
(7043, 21)
```

[4]:
```
df.columns
```

[4]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
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
```

[6]:
```
#Finding the statistical summary of the dataset.
df.describe().transpose()
```

[6]:

	count	mean	std	min	25%	50%	75%	max
SeniorCitizen	7043.0	0.162147	0.368612	0.00	0.0	0.00	0.00	1.00
tenure	7043.0	32.371149	24.559481	0.00	9.0	29.00	55.00	72.00
MonthlyCharges	7043.0	64.761692	30.090047	18.25	35.5	70.35	89.85	118.75

[7]:
```
print(df.dtypes)
```

```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

[8]:
```
#Finding the categorical variables.
df.select_dtypes(include='object').columns
```

[8]:
```
Index(['customerID', 'gender', 'Partner', 'Dependents', 'PhoneService',
       'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'Contract', 'PaperlessBilling', 'PaymentMethod', 'TotalCharges',
       'Churn'],
      dtype='object')
```

[9]:
```
len(df.select_dtypes(include='object').columns)
```

[9]:
```
18
```

[10]:
```
df.select_dtypes(include=['float64','int64']).columns
```

[10]:
```
Index(['SeniorCitizen', 'tenure', 'MonthlyCharges'], dtype='object')
```

[11]:
```
len(df.select_dtypes(include=['float64','int64']).columns)
```

[11]:
```
3
```

II) Dealing with missing values.

[12]:
```
missing_data = df.isnull()
print(missing_data.head())
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print(" ")
```

```
   customerID  gender  SeniorCitizen  Partner  Dependents  tenure  \
0       False   False          False    False       False   False
1       False   False          False    False       False   False
2       False   False          False    False       False   False
3       False   False          False    False       False   False
4       False   False          False    False       False   False

   PhoneService  MultipleLines  InternetService  OnlineSecurity  …  \
0         False          False            False           False  …
1         False          False            False           False  …
2         False          False            False           False  …
3         False          False            False           False  …
4         False          False            False           False  …

   DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract  \
0             False        False        False            False     False
1             False        False        False            False     False
2             False        False        False            False     False
3             False        False        False            False     False
4             False        False        False            False     False

   PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges  Churn
0             False          False           False         False  False
1             False          False           False         False  False
2             False          False           False         False  False
3             False          False           False         False  False
4             False          False           False         False  False

[5 rows x 21 columns]
customerID
customerID
False    7043
```

```
Name: count, dtype: int64

gender
gender
False    7043
Name: count, dtype: int64

SeniorCitizen
SeniorCitizen
False    7043
Name: count, dtype: int64

Partner
Partner
False    7043
Name: count, dtype: int64

Dependents
Dependents
False    7043
Name: count, dtype: int64

tenure
tenure
False    7043
Name: count, dtype: int64

PhoneService
PhoneService
False    7043
Name: count, dtype: int64

MultipleLines
MultipleLines
False    7043
Name: count, dtype: int64

InternetService
InternetService
False    7043
Name: count, dtype: int64

OnlineSecurity
OnlineSecurity
False    7043
Name: count, dtype: int64

OnlineBackup
```

```
OnlineBackup
False    7043
Name: count, dtype: int64

DeviceProtection
DeviceProtection
False    7043
Name: count, dtype: int64

TechSupport
TechSupport
False    7043
Name: count, dtype: int64

StreamingTV
StreamingTV
False    7043
Name: count, dtype: int64

StreamingMovies
StreamingMovies
False    7043
Name: count, dtype: int64

Contract
Contract
False    7043
Name: count, dtype: int64

PaperlessBilling
PaperlessBilling
False    7043
Name: count, dtype: int64

PaymentMethod
PaymentMethod
False    7043
Name: count, dtype: int64

MonthlyCharges
MonthlyCharges
False    7043
Name: count, dtype: int64

TotalCharges
TotalCharges
False    7043
Name: count, dtype: int64
```

```
Churn
Churn
False    7043
Name: count, dtype: int64
```

[13]:
```
#Converting the Monthly charges column into float.
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
```

[14]:
```
df['TotalCharges'].isnull().sum()
```

[14]:
```
11
```

[15]:
```
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].mean())
```

[16]:
```
#Converting Tenure to int
df['tenure'] = df['tenure'].astype(int)
```

[17]:
```
#dropping the customer id column.
dataset = df.drop(columns=['customerID'])
```

[18]:
```
dataset.head()
```

[18]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Electronic check	29.85	29.85
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	No	No	One year	No	Mailed check	56.95	1889.50
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	53.85	108.15
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes	No	No	One year	No	Bank transfer (automatic)	42.30	1840.75
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	No	No	Month-to-month	Yes	Electronic check	70.70	151.65

```
2              Yes              Mailed check           53.85        108.15
3               No  Bank transfer (automatic)           42.30       1840.75
4              Yes           Electronic check           70.70        151.65

  Churn
0    No
1    No
2   Yes
3    No
4   Yes
```

III) Feature Engineering.

[19]:
```
for column in dataset.select_dtypes(include='object').columns.tolist():
    print(dataset[column].unique())
```

```
['Female' 'Male']
['Yes' 'No']
['No' 'Yes']
['No' 'Yes']
['No phone service' 'No' 'Yes']
['DSL' 'Fiber optic' 'No']
['No' 'Yes' 'No internet service']
['Yes' 'No' 'No internet service']
['No' 'Yes' 'No internet service']
['No' 'Yes' 'No internet service']
['No' 'Yes' 'No internet service']
['No' 'Yes' 'No internet service']
['Month-to-month' 'One year' 'Two year']
['Yes' 'No']
['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
['No' 'Yes']
```

[20]:
```
print(df.select_dtypes(include='object').columns)
```

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

[21]:
```
#One hot encoding
dataset = pd.get_dummies(data=dataset,drop_first=True)
```

[22]:
```
dataset.head()
```

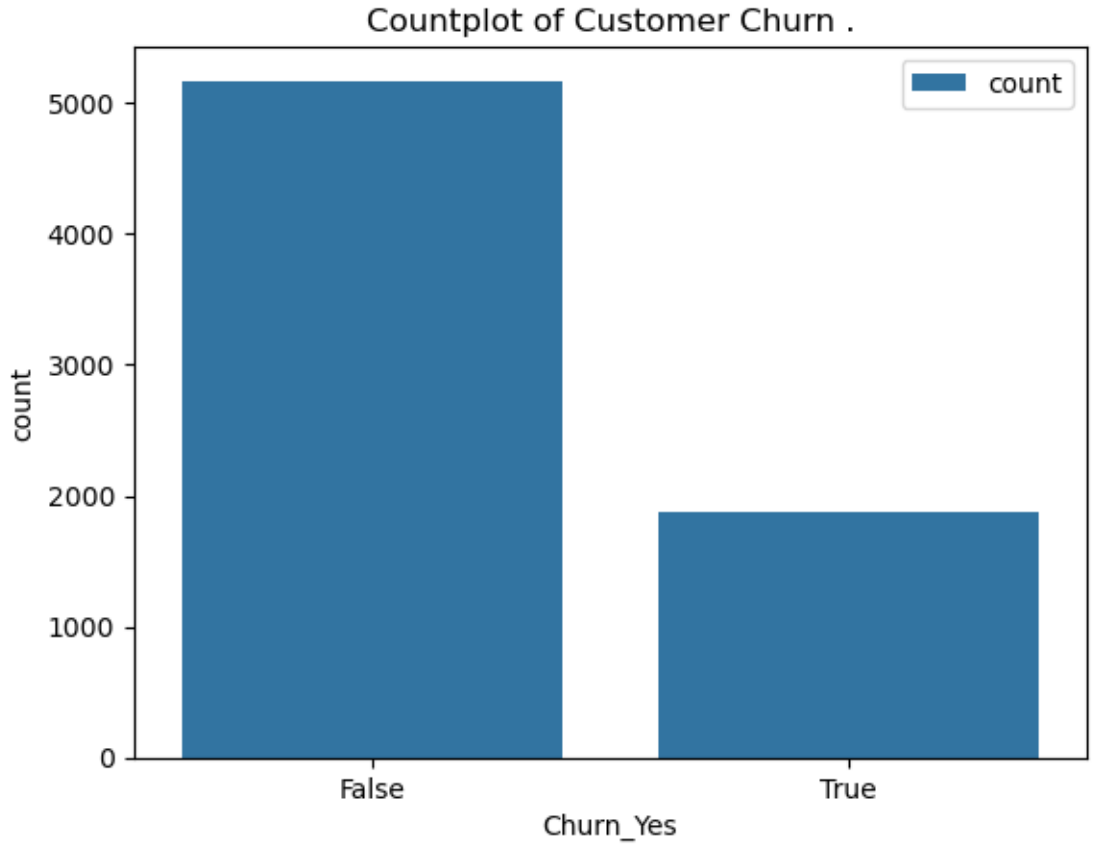
[22]:
```
   SeniorCitizen  tenure  MonthlyCharges  TotalCharges  gender_Male  \
0              0       1           29.85         29.85        False
```

```
1              0      34           56.95       1889.50         True
2              0       2           53.85        108.15         True
3              0      45           42.30       1840.75         True
4              0       2           70.70        151.65        False

   Partner_Yes  Dependents_Yes  PhoneService_Yes  \
0         True           False             False
1        False           False              True
2        False           False              True
3        False           False             False
4        False           False              True

   MultipleLines_No phone service  MultipleLines_Yes  …  StreamingTV_Yes  \
0                            True              False  …            False
1                           False              False  …            False
2                           False              False  …            False
3                            True              False  …            False
4                           False              False  …            False

   StreamingMovies_No internet service  StreamingMovies_Yes  \
0                                False                False
1                                False                False
2                                False                False
3                                False                False
4                                False                False

   Contract_One year  Contract_Two year  PaperlessBilling_Yes  \
0              False              False                  True
1               True              False                 False
2              False              False                  True
3               True              False                 False
4              False              False                  True

   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                  False                           True
1                                  False                          False
2                                  False                          False
3                                  False                          False
4                                  False                           True

   PaymentMethod_Mailed check  Churn_Yes
0                       False      False
1                        True      False
2                        True       True
3                       False      False
4                       False       True
```

```
[5 rows x 31 columns]
```

IV) Visualization.

[23]:
```
sns.countplot(dataset,x='Churn_Yes', label='count')
plt.title('Countplot of Customer Churn .')
plt.show()
```



[24]:
```
#Count of customers who did not churn.
(dataset.Churn_Yes==0).sum()
```

[24]:
```
5174
```

[25]:
```
#Count of customers who churned.
(dataset.Churn_Yes==1).sum()
```

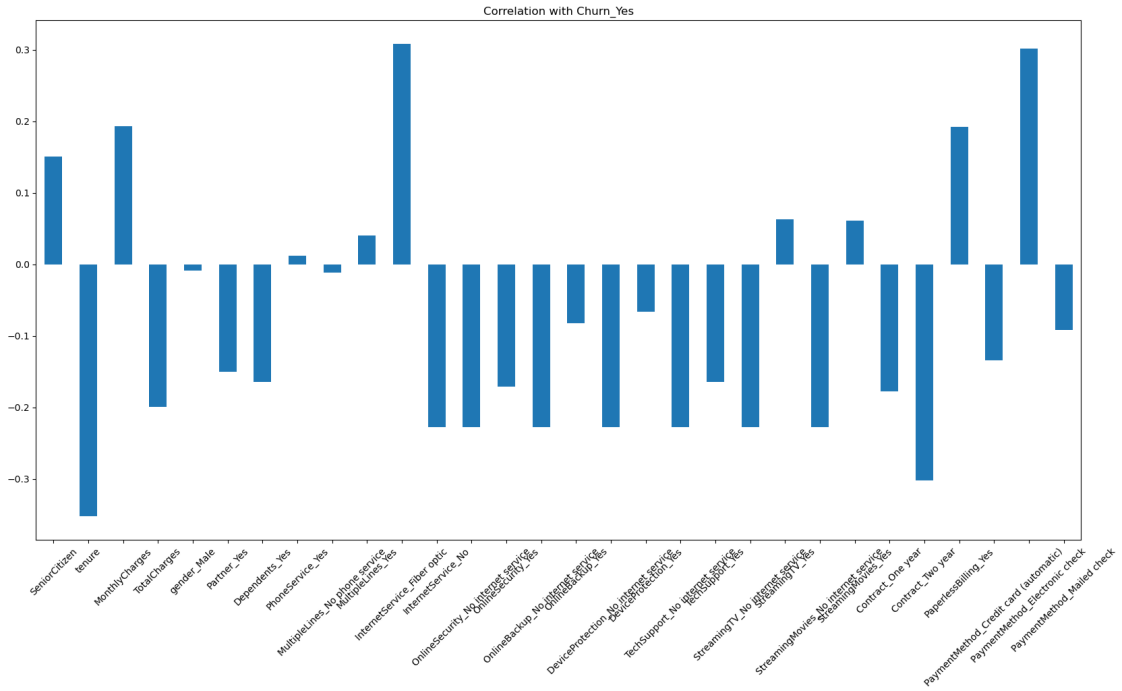
[25]:
```
1869
```

V) Correlation matrix and heatmap.

[26]:
```
dataset_2 = dataset.drop(columns='Churn_Yes')
```

[27]:
```
dataset_2.corrwith(dataset['Churn_Yes']).plot.bar(
    figsize=(20,10),
    title = 'Correlation with Churn_Yes',
    rot = 45)
```

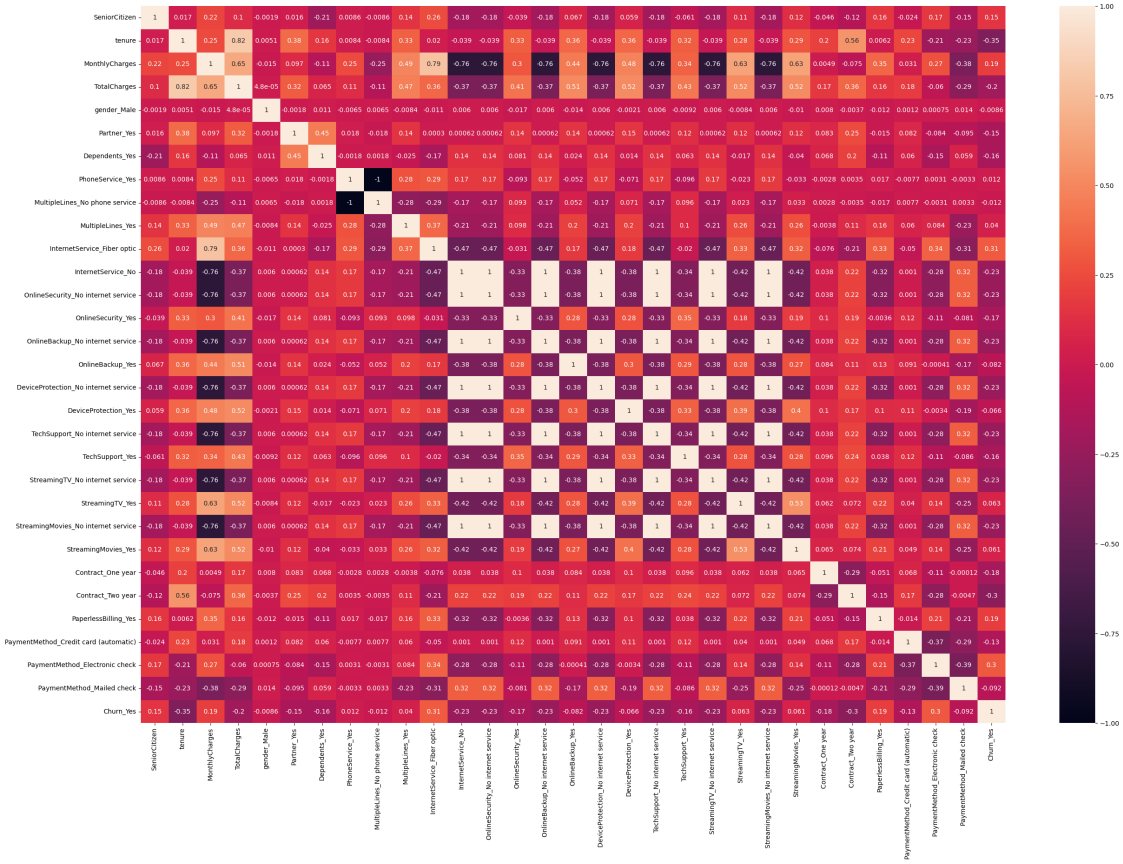
[27]: <Axes: title={'center': 'Correlation with Churn_Yes'}>



[28]:
```
corr = dataset.corr()
```

[29]:
```
plt.figure(figsize=(30,20))
sns.heatmap(corr, annot= True)
```

[29]: <Axes: >



VI) Splitting the dataset into train and test sets.

[30]:
```
#Independent variable.
X = dataset.iloc[:,1:-1].values
```

[31]:
```
X.shape
```

[31]: (7043, 29)

[32]:
```
#Dependent variable.
y = dataset['Churn_Yes']
```

[33]:
```
y.shape
```

[33]: (7043,)

[34]:
```
from sklearn.model_selection import train_test_split
```

[35]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=101)
```

[36]:
```
X_train.shape
```

[36]:
```
(5634, 29)
```

[37]:
```
X_test.shape
```

[37]:
```
(1409, 29)
```

[38]:
```
y_train.shape
```

[38]:
```
(5634,)
```

[39]:
```
y_test.shape
```

[39]:
```
(1409,)
```

VII) Feature Scaling.

[40]:
```
from sklearn.preprocessing import StandardScaler
```

[41]:
```
scaler = StandardScaler()
```

[42]:
```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[43]:
```
X_train
```

[43]:
```
array([[ 1.61582085,  0.72339921,  1.7993843 , …, -0.52077767,
        -0.71389516, -0.54713275],
       [ 1.61582085,  1.69727405,  2.73952482, …, -0.52077767,
        -0.71389516, -0.54713275],
       [ 0.35214874,  0.32150908,  0.32817053, …,  1.9202052 ,
        -0.71389516, -0.54713275],
       …,
       [-1.15610507,  0.45158141, -0.86292471, …, -0.52077767,
         1.4007659 , -0.54713275],
       [ 1.2489483 ,  1.42045346,  2.03077119, …, -0.52077767,
         1.4007659 , -0.54713275],
       [-1.27839592, -1.49283308, -0.99996588, …,  1.9202052 ,
        -0.71389516, -0.54713275]])
```

[44]:
```
X_test
```

[44]:
```
array([[ 1.57505723,  1.18532272,  2.15722142, …, -0.52077767,
         1.4007659 , -0.54713275],
       [-1.27839592, -0.64069259, -0.98866739, …, -0.52077767,
        -0.71389516,  1.82771001],
       [-1.27839592, -1.5128442 , -1.00023121, …, -0.52077767,
        -0.71389516,  1.82771001],
```

```
…,
[ 1.61582085, -1.32440609, -0.21338313, …, -0.52077767,
 -0.71389516, -0.54713275],
[ 0.96360298, -0.1204033 ,  0.47111523, …,  1.9202052 ,
 -0.71389516, -0.54713275],
[ 0.96360298,  1.27704039,  1.53133813, …, -0.52077767,
 -0.71389516, -0.54713275]])
```

4 Part 2: Building the models.

I) Logistic Regression.

[45]:
```
from sklearn.linear_model import LogisticRegression
```

[46]:
```
model_lr = LogisticRegression(random_state=0)
```

[47]:
```
model_lr.fit(X_train, y_train)
```

[47]:
```
LogisticRegression(random_state=0)
```

[48]:
```
y_pred = model_lr.predict(X_test)
```

[49]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score,␣
↪precision_score, recall_score
```

[50]:
```
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
```

[51]:
```
results = pd.DataFrame([['Logistic Regression', acc, f1, prec, rec]],
                       columns= ['Model', 'Accuracy', 'F1 Score', 'Precision',␣
↪'Recall'])
```

[52]:
```
results
```

[52]:

	Model	Accuracy	F1 Score	Precision	Recall
0	Logistic Regression	0.799148	0.583211	0.668919	0.516971

[53]:
```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[928  98]
 [185 198]]
```

Cross Validation.

[54]:
```
from sklearn.model_selection import cross_val_score
```

[55]:
```
accuracies = cross_val_score(estimator=model_lr, X=X_train,y = y_train, cv=10)
print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

```
Accuracy is 80.47%
Standard deviation is 1.71%
```

II) Random Forest Classifier

[56]:
```
from sklearn.ensemble import RandomForestClassifier
```

[57]:
```
classifier_rf = RandomForestClassifier(random_state=0)
classifier_rf.fit(X_train, y_train)
```

[57]:
```
RandomForestClassifier(random_state=0)
```

[58]:
```
y_pred = classifier_rf.predict(X_test)
```

[59]:
```
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
model_results = pd.DataFrame([['Random Forest', acc, f1, prec, rec]],
                       columns= ['Model', 'Accuracy', 'F1 Score', 'Precision',␣
 ↪'Recall'])
```

[60]:
```
model_results
```

[60]:

	Model	Accuracy	F1 Score	Precision	Recall
0	Random Forest	0.775727	0.513846	0.625468	0.436031

[61]:
```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[926 100]
 [216 167]]
```

Cross Validation.

[62]:
```
accuracies = cross_val_score(estimator=classifier_rf, X=X_train,y = y_train,␣
 ↪cv=10)
print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

```
Accuracy is 79.71%
Standard deviation is 1.65%
```

III) XB Boost Classifier

[65]:
```
pip install xgboost
```

```
Collecting xgboost
  Using cached xgboost-2.1.3-py3-none-win_amd64.whl.metadata (2.1 kB)
Requirement already satisfied: numpy in c:\users\omen\anaconda4\lib\site-
packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\omen\anaconda4\lib\site-
packages (from xgboost) (1.13.1)
Using cached xgboost-2.1.3-py3-none-win_amd64.whl (124.9 MB)
Installing collected packages: xgboost
Successfully installed xgboost-2.1.3
Note: you may need to restart the kernel to use updated packages.
```

[66]:
```
from xgboost import XGBClassifier
```

[67]:
```
classifier_xg = XGBClassifier()
```

[68]:
```
classifier_xg.fit(X_train, y_train)
```

[68]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[69]:
```
y_pred = classifier_xg.predict(X_test)
```

[70]:
```
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
model_xg_results = pd.DataFrame([['XGBClassifier', acc, f1, prec, rec]],
                      columns= ['Model', 'Accuracy', 'F1 Score', 'Precision',␣
 ↪'Recall'])
model_xg_results
```

[70]:

	Model	Accuracy	F1 Score	Precision	Recall
0	XGBClassifier	0.77005	0.52907	0.596721	0.475196

[71]:
```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[903 123]
 [201 182]]
```

Cross Validation.

[72]:
```
accuracies = cross_val_score(estimator=classifier_xg, X=X_train,y = y_train,␣
 ↪cv=10)
print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

```
Accuracy is 78.75%
Standard deviation is 1.64%
```

[75]:
```
'''Based on accuracy, Logistic Regression is the best model but I used XGBoost␣
 ↪Classifier.'''
```

[75]:
```
'Based on accuracy, Logistic Regression is the best model but I used XGBoost
Classifier.'
```

5 Part 3: Using Randomized Search to find the best parameters.(XGBoost Classifier)

[76]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[78]:
```
parameters = {
    'learning_rate':[0.05, 0.1, 0.15, 0.20, 0.25, 0.30],
    'max_depth':[3,4,5,6,7,8,10,12,15],
    'min_child_weight':[1,3,5,7],
    'gamma':[0.0,0.1,0.2,0.3,0.4],
    'colsample_bytree':[0.3,0.4,0.5,0.7]}
```

[79]:
```
parameters
```

[79]:
```
{'learning_rate': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3],
 'max_depth': [3, 4, 5, 6, 7, 8, 10, 12, 15],
 'min_child_weight': [1, 3, 5, 7],
 'gamma': [0.0, 0.1, 0.2, 0.3, 0.4],
 'colsample_bytree': [0.3, 0.4, 0.5, 0.7]}
```

[80]:
```
random_search = RandomizedSearchCV(estimator=classifier_xg,␣
 ↪param_distributions= parameters, n_iter=10, scoring='roc_auc',n_jobs=-1,␣
 ↪cv=5, verbose=3)
```

[81]:
```
random_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

[81]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           callbacks=None,
                                           colsample_bylevel=None,
```

```
                                   colsample_bynode=None,
                                   colsample_bytree=None, device=None,
                                   early_stopping_rounds=None,
                                   enable_categorical=False,
                                   eval_metric=None, feature_types=None,
                                   gamma=None, grow_policy=None,
                                   importance_type=None,
                                   interaction_constraints=None,
                                   learning_rate…
                                   monotone_constraints=None,
                                   multi_strategy=None,
                                   n_estimators=None, n_jobs=None,
                                   num_parallel_tree=None,
                                   random_state=None, …),
                   n_jobs=-1,
                   param_distributions={'colsample_bytree': [0.3, 0.4, 0.5,
                                                             0.7],
                                        'gamma': [0.0, 0.1, 0.2, 0.3, 0.4],
                                        'learning_rate': [0.05, 0.1, 0.15, 0.2,
                                                          0.25, 0.3],
                                        'max_depth': [3, 4, 5, 6, 7, 8, 10, 12,
                                                      15],
                                        'min_child_weight': [1, 3, 5, 7]},
                   scoring='roc_auc', verbose=3)
```

[82]:
```
random_search.best_estimator_
```

[82]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.4, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.2, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.05, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=7, max_leaves=None,
              min_child_weight=5, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[83]:
```
random_search.best_params_
```

[83]:
```
{'min_child_weight': 5,
 'max_depth': 7,
 'learning_rate': 0.05,
 'gamma': 0.2,
 'colsample_bytree': 0.4}
```

[84]:
```
random_search.best_score_
```

[84]:
```
0.8478762786241578
```

6 Part 4: Final Model.

[86]:
```
model = XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.4, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.2, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.05, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=7, max_leaves=None,
              min_child_weight=5, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None)
model.fit(X_train, y_train)
```

[86]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.4, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.2, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.05, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=7, max_leaves=None,
              min_child_weight=5, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[89]:
```
y_pred = model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
final_model_results = pd.DataFrame([['Final Model', acc, f1, prec, rec]],
                       columns= ['Model', 'Accuracy', 'F1 Score', 'Precision',␣
 ↪'Recall'])
final_model_results
```

[89]:

	Model	Accuracy	F1 Score	Precision	Recall
0	Final Model	0.792051	0.547141	0.670455	0.462141

Cross Validation.

[88]:
```
accuracies = cross_val_score(estimator=model, X=X_train,y = y_train, cv=10)
print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

```
Accuracy is 80.16%
Standard deviation is 1.68%
```

7 Part 5: Predicting a single observation.

[90]:
```
dataset.head()
```

[90]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_Male	Partner_Yes	Dependents_Yes	PhoneService_Yes	MultipleLines_No phone service	MultipleLines_Yes	…	StreamingTV_Yes	StreamingMovies_No internet service	StreamingMovies_Yes	Contract_One year	Contract_Two year	PaperlessBilling_Yes	PaymentMethod_Credit card (automatic)	PaymentMethod_Electronic check
0	0	1	29.85	29.85	False	True	False	False	True	False	…	False	False	False	False	False	True	False	True
1	0	34	56.95	1889.50	True	False	False	True	False	False	…	False	False	False	True	False	False	False	False
2	0	2	53.85	108.15	True	False	False	True	False	False	…	False	False	False	False	False	True	False	False
3	0	45	42.30	1840.75	True	False	False	False	True	False	…	False	False	False	True	False	False	False	True
4	0	2	70.70	151.65	False	False	False	True	False	False	…	False	False	False	False	False	True	False	False

```
0                                    False                                True
1                                    False                               False
2                                    False                               False
3                                    False                               False
4                                    False                                True

   PaymentMethod_Mailed check  Churn_Yes
0                        False      False
1                         True      False
2                         True       True
3                        False      False
4                        False       True

[5 rows x 31 columns]
```

[101]:
```
dataset.loc[1].values
```

[101]:
```
array([0, 34, 56.95, 1889.5, True, False, False, True, False, False,
       False, False, False, True, False, False, False, True, False, False,
       False, False, False, False, True, False, False, False, False, True,
       False], dtype=object)
```

[104]:
```
single_obsv = [[34, 56.95, 1889.5, True, False, False, True, False, False,
       False, False, False, True, False, False, False, True, False, False,
       False, False, False, False, True, False, False, False, False, True]]
```

[105]:
```
model.predict(scaler.transform(single_obsv))
```

[105]:
```
array([0])
```

[106]:
```
'The customer will not churn.'
```

[106]:
```
'The customer will not churn.'
```

[ ]:
```

```