In [ ]:
```
import os
#os.getcwd()
import warnings
warnings.filterwarnings('ignore')

import sys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
import sklearn
import scipy.integrate as integrate
import scipy

import statsmodels.api as sm
from statsmodels.formula.api  import ols
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import RFE
from sklearn.feature_selection import RFECV

# importing algorithm, evaluation, and model libraries
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import RidgeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score
from sklearn.model_selection import cross_val_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [ ]:
```
churn_data = pd.read_csv('churn.csv')
```

In [ ]:
```
churn_data.head()
```

Out[ ]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	CallService	MultipleConn
0	2907-ILJBN	Female	0.0	Yes	Yes	11.0	Yes	
1	3896-RCYYE	Female	0.0	No	No	67.0	No	No phone
2	9764-REAFF	Female	0.0	Yes	No	59.0	Yes	
3	6651-RLGGM	Male	0.0	Yes	Yes	67.0	Yes	
4	5879-SESNB	Female	0.0	No	No	11.0	Yes	

5 rows × 21 columns

In [ ]:
```
churn_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12335 entries, 0 to 12334
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   customerID                12335 non-null  object 
 1   gender                    12335 non-null  object 
 2   SeniorCitizen             12335 non-null  float64
 3   Partner                   12335 non-null  object 
 4   Dependents                12335 non-null  object 
 5   tenure                    12335 non-null  float64
 6   CallService               12335 non-null  object 
 7   MultipleConnections       12335 non-null  object 
 8   InternetConnection        12335 non-null  object 
 9   OnlineSecurity            12335 non-null  object 
 10  OnlineBackup              12335 non-null  object 
 11  DeviceProtectionService   12335 non-null  object 
 12  TechnicalHelp             12335 non-null  object 
 13  OnlineTV                  12335 non-null  object 
 14  OnlineMovies              12335 non-null  object 
 15  Agreement                 12335 non-null  object 
 16  BillingMethod             12335 non-null  object 
 17  PaymentMethod             12335 non-null  object 
 18  MonthlyServiceCharges     12335 non-null  float64
 19  TotalAmount               12335 non-null  float64
 20  Churn                     12335 non-null  object 
dtypes: float64(4), object(17)
memory usage: 2.0+ MB
```

In [ ]:
```
churn_data = churn_data.drop_duplicates()
churn_data.shape
```

Out[ ]:
```
(9328, 21)
```

data has no null values

In [ ]:
```
churn_data.isnull().sum()
```

Out[ ]:
```
customerID                0
gender                    0
SeniorCitizen             0
Partner                   0
Dependents                0
tenure                    0
CallService               0
MultipleConnections       0
InternetConnection        0
OnlineSecurity            0
OnlineBackup              0
DeviceProtectionService   0
TechnicalHelp             0
OnlineTV                  0
OnlineMovies              0
Agreement                 0
BillingMethod             0
PaymentMethod             0
MonthlyServiceCharges     0
TotalAmount               0
Churn                     0
dtype: int64
```

dropping customerID

In [ ]:
```
churn_data = churn_data.drop(['customerID'],axis=1)
churn_data.isnull().sum()
```

Out[ ]:
```
gender                    0
SeniorCitizen             0
Partner                   0
Dependents                0
tenure                    0
CallService               0
MultipleConnections       0
InternetConnection        0
OnlineSecurity            0
OnlineBackup              0
DeviceProtectionService   0
TechnicalHelp             0
OnlineTV                  0
OnlineMovies              0
Agreement                 0
BillingMethod             0
PaymentMethod             0
MonthlyServiceCharges     0
TotalAmount               0
Churn                     0
dtype: int64
```

In [ ]:
```
y=churn_data[['Churn']]
x=churn_data.drop(['Churn'],axis=1)
y.shape
```

Out[ ]:
```
(9328, 1)
```

finding the % of churn-Yes Or the mean of Y = Yes

In [ ]:
```
y['Churn'].value_counts()
```

Out[ ]:
```
Yes    5607
No     3721
Name: Churn, dtype: int64
```

In [ ]:
```
# finding genders distribution with churners
churn_percent = (y['Churn'].value_counts() / len(y) * 100)
print(churn_percent)
y_temp = pd.DataFrame(y)
y_temp = np.where(y_temp['Churn']=='No',0,1)
print('churn_percent ',y_temp.mean())
```

```
Yes    60.109348
No     39.890652
Name: Churn, dtype: float64
churn_percent  0.6010934819897084
```

spitting the features categroical & numeric separtely

In [ ]:
```
x_num=x.select_dtypes(include="number")
x_cat=x.select_dtypes(include="object")
```

numeric fields

In [ ]:
```
x_num.columns
```

Out[ ]:
```
Index(['SeniorCitizen', 'tenure', 'MonthlyServiceCharges', 'TotalAmount'], dtyp
e='object')
```

In [ ]:
```
x_num.describe()
```

Out[ ]:

	SeniorCitizen	tenure	MonthlyServiceCharges	TotalAmount
count	9328.000000	9328.000000	9328.000000	9328.000000
mean	0.163885	26.642965	61.341895	1839.159069
std	0.351640	22.491378	27.661949	2008.858997
min	0.000000	1.000000	18.250000	18.800000
25%	0.000000	6.700780	35.392830	288.599227
50%	0.000000	20.325530	64.220312	1052.258266
75%	0.000000	44.345050	84.070699	2777.241953
max	1.000000	72.000000	118.750000	8684.800000

In [ ]:

```
x_num['SeniorCitizen'].value_counts()
```

Out[ ]:

```
0.000000    7420
1.000000    1155
0.660002       1
0.208768       1
0.437521       1
            ...
0.087772       1
0.353116       1
0.387478       1
0.031710       1
0.433856       1
Name: SeniorCitizen, Length: 755, dtype: int64
```

Senior citizen should be Yes or No (1 or 0). But we have some float values here.Incorrect records are about 753 rows. Close to 6% of the data. So replacing them with mode, which is 0.

In [ ]:

```
x_num['SeniorCitizen'] = np.where((x_num['SeniorCitizen'] > 0) & (x_num['SeniorC
x['SeniorCitizen'].value_counts()
```

Out[ ]:

```
0.000000    7420
1.000000    1155
0.660002       1
0.208768       1
0.437521       1
            ...
0.087772       1
0.353116       1
0.387478       1
0.031710       1
0.433856       1
Name: SeniorCitizen, Length: 755, dtype: int64
```

In [ ]:

```
x_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   gender                   9328 non-null   object
 1   Partner                  9328 non-null   object
 2   Dependents               9328 non-null   object
 3   CallService              9328 non-null   object
 4   MultipleConnections      9328 non-null   object
 5   InternetConnection       9328 non-null   object
 6   OnlineSecurity           9328 non-null   object
 7   OnlineBackup             9328 non-null   object
 8   DeviceProtectionService  9328 non-null   object
 9   TechnicalHelp            9328 non-null   object
 10  OnlineTV                 9328 non-null   object
 11  OnlineMovies             9328 non-null   object
 12  Agreement                9328 non-null   object
 13  BillingMethod            9328 non-null   object
 14  PaymentMethod            9328 non-null   object
dtypes: object(15)
memory usage: 1.1+ MB
```

In [ ]:
```
x_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 4 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   SeniorCitizen          9328 non-null   float64
 1   tenure                 9328 non-null   float64
 2   MonthlyServiceCharges  9328 non-null   float64
 3   TotalAmount            9328 non-null   float64
dtypes: float64(4)
memory usage: 364.4 KB
```

treating outliers for numeric columns tenure, MonthlySericeCharges, TotalAmount

In [ ]:
```
upper_limit = x_num['MonthlyServiceCharges'].quantile(0.99)
lower_limit = x_num['MonthlyServiceCharges'].quantile(0.01)
x_num['MonthlyServiceCharges'] = np.where(x_num['MonthlyServiceCharges'] >= uppe
```

In [ ]:
```
upper_limit = x_num['tenure'].quantile(0.99)
lower_limit = x_num['tenure'].quantile(0.01)
x_num['tenure'] = np.where(x_num['tenure'] >= upper_limit, upper_limit, np.where
```

In [ ]:
```
upper_limit = x_num['TotalAmount'].quantile(0.99)
lower_limit = x_num['TotalAmount'].quantile(0.01)
x_num['TotalAmount'] = np.where(x_num['TotalAmount'] >= upper_limit, upper_limit
```

In [ ]:
```
# checking after outlier treatment
x_num.describe()
```

Out[ ]:

	SeniorCitizen	tenure	MonthlyServiceCharges	TotalAmount
count	9328.000000	9328.000000	9328.000000	9328.000000
mean	0.123821	26.642965	61.317044	1835.677311
std	0.329395	22.491378	27.607443	1998.063713
min	0.000000	1.000000	19.300000	20.200000
25%	0.000000	6.700780	35.392830	288.599227
50%	0.000000	20.325530	64.220312	1052.258266
75%	0.000000	44.345050	84.070699	2777.241953
max	1.000000	72.000000	112.236500	7780.474000

discretizing tenure column

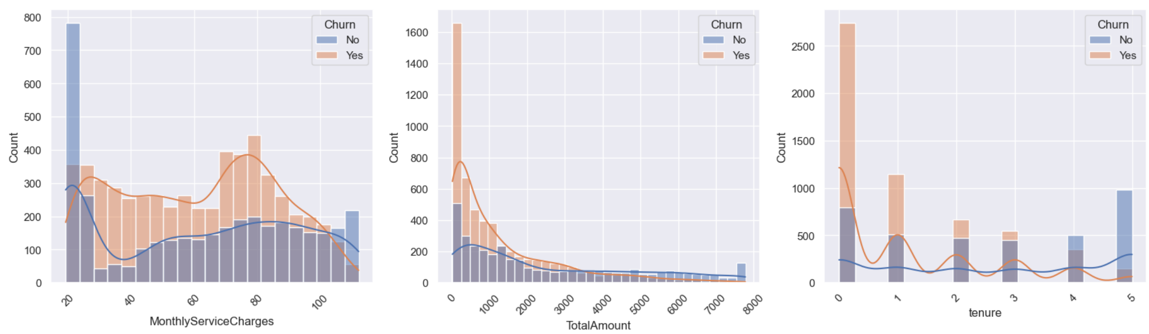
In [ ]:
```
x_tenure_binned = x_num['tenure']
x_tenure_binned = x_tenure_binned.values.reshape(-1, 1)
est = KBinsDiscretizer(n_bins=6, encode='ordinal', strategy='uniform')
Xt = est.fit_transform(x_tenure_binned)
```

In [ ]:
```
x_num['tenure'] = Xt
x_num['tenure'].shape
```

Out[ ]: (9328,)

data visualization of numeric to numeric and selecting all the 3 numeric features as slope is good

In [ ]:
```
plt.figure(figsize = (20,5))
num_cols = ['MonthlyServiceCharges', 'TotalAmount','tenure']
for col in enumerate(num_cols):
    plt.subplot(1,3,col[0]+1)
    sns.histplot(data = x_num, x = col[1], kde = True, hue = y['Churn'])
    plt.xticks(rotation =45)
```



scaling the numeric fields

In [ ]:
```
#x_num_scaled = x_num[['MonthlyServiceCharges','TotalAmount']]
scaler = MinMaxScaler()
#x_num = x_num.values.reshape(1,-1)
x_num[["MonthlyServiceCharges"]] = scaler.fit_transform(x_num[["MonthlyServiceCh
x_num[["TotalAmount"]] = scaler.fit_transform(x_num[["TotalAmount"]])
x_num.head()
```

Out[ ]:

	SeniorCitizen	tenure	MonthlyServiceCharges	TotalAmount
0	0.0	0.0	0.013988	0.027538
1	0.0	5.0	0.366917	0.458611
2	0.0	4.0	0.000000	0.133713
3	0.0	5.0	0.075320	0.215031
4	0.0	0.0	0.602024	0.111910

data visulation of categorical features

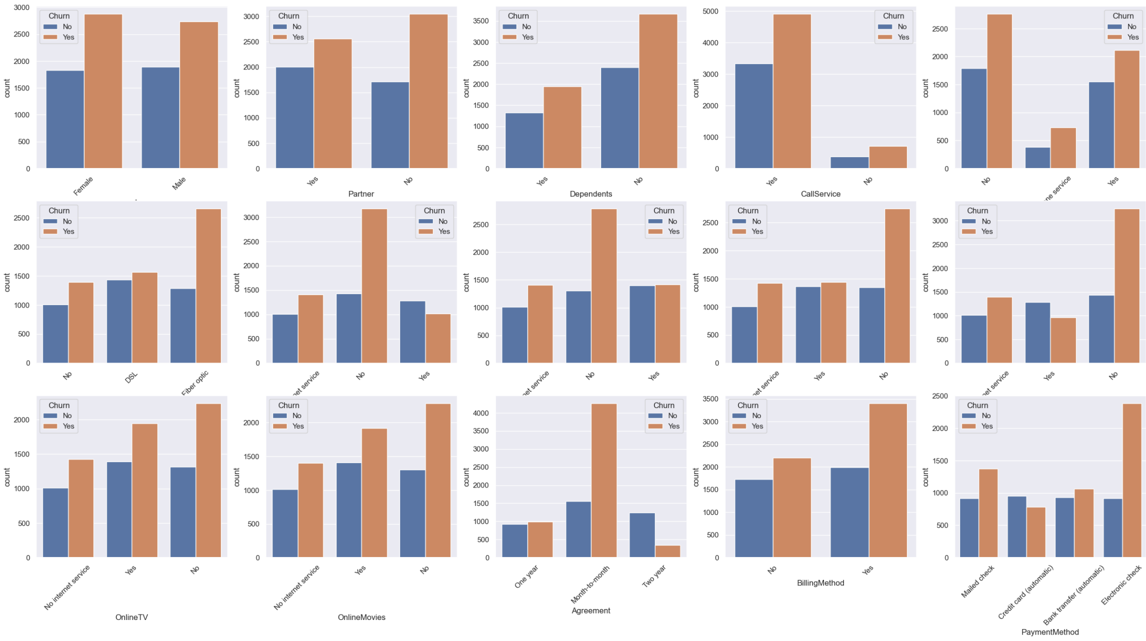
In [ ]:
```
x_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   gender                   9328 non-null   object
 1   Partner                  9328 non-null   object
 2   Dependents               9328 non-null   object
 3   CallService              9328 non-null   object
 4   MultipleConnections      9328 non-null   object
 5   InternetConnection       9328 non-null   object
 6   OnlineSecurity           9328 non-null   object
 7   OnlineBackup             9328 non-null   object
 8   DeviceProtectionService  9328 non-null   object
 9   TechnicalHelp            9328 non-null   object
 10  OnlineTV                 9328 non-null   object
 11  OnlineMovies             9328 non-null   object
 12  Agreement                9328 non-null   object
 13  BillingMethod            9328 non-null   object
 14  PaymentMethod            9328 non-null   object
dtypes: object(15)
memory usage: 1.1+ MB
```

In [ ]:
```
cat_cols = x_cat.columns
list(enumerate(cat_cols))
```

Out[ ]:
```
[(0, 'gender'),
 (1, 'Partner'),
 (2, 'Dependents'),
 (3, 'CallService'),
 (4, 'MultipleConnections'),
 (5, 'InternetConnection'),
 (6, 'OnlineSecurity'),
 (7, 'OnlineBackup'),
 (8, 'DeviceProtectionService'),
 (9, 'TechnicalHelp'),
 (10, 'OnlineTV'),
 (11, 'OnlineMovies'),
 (12, 'Agreement'),
 (13, 'BillingMethod'),
 (14, 'PaymentMethod')]
```

In [ ]:
```python
plt.figure(figsize = (30,15))
for col in enumerate(cat_cols):
    plt.subplot(3,5,col[0]+1)
    sns.countplot(x=col[1], hue=y['Churn'], data=x_cat)
    plt.xticks(rotation =45)
```



dropping gender, partner as there is any big variance

In [ ]:
```python
x_cat = x_cat.drop(['gender','Partner'],axis=1)
x_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   Dependents               9328 non-null   object
 1   CallService              9328 non-null   object
 2   MultipleConnections      9328 non-null   object
 3   InternetConnection       9328 non-null   object
 4   OnlineSecurity           9328 non-null   object
 5   OnlineBackup             9328 non-null   object
 6   DeviceProtectionService  9328 non-null   object
 7   TechnicalHelp            9328 non-null   object
 8   OnlineTV                 9328 non-null   object
 9   OnlineMovies             9328 non-null   object
 10  Agreement                9328 non-null   object
 11  BillingMethod            9328 non-null   object
 12  PaymentMethod            9328 non-null   object
dtypes: object(13)
memory usage: 1020.2+ KB
```

encoding categorical - using label encoding

In [ ]:

```
x_cat_enc = pd.get_dummies(x_cat,drop_first=True)
x_cat_enc.head()
```

Out[ ]:

	Dependents_Yes	CallService_Yes	MultipleConnections_No phone service	MultipleConnections_Yes	Internet(
0	1	1	0	0	
1	0	0	1	0	
2	0	1	0	0	
3	1	1	0	1	
4	0	1	0	1	

5 rows × 24 columns

selecting k-best features

In [ ]:

```
# Select K Best for Categorical Features

selector = SelectKBest(chi2, k=24)
selector.fit_transform(x_cat_enc, y)
# Get columns to keep and create new dataframe with those only
cols = selector.get_support(indices=True)
select_features_df_char = x_cat_enc.iloc[:,cols]
select_features_df_char
```

Out[ ]:

	Dependents_Yes	CallService_Yes	MultipleConnections_No phone service	MultipleConnections_Yes	Inte
0	1	1	0	0	
1	0	0	1	0	
2	0	1	0	0	
3	1	1	0	1	
4	0	1	0	1	
...	...	...	...	...	
12330	1	1	0	0	
12331	0	0	1	0	
12332	1	0	1	0	
12333	1	1	0	0	
12334	0	1	0	0	

9328 rows × 24 columns

In [ ]:
```
select_features_df_char.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 24 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Dependents_Yes                          9328 non-null   uint8
 1   CallService_Yes                         9328 non-null   uint8
 2   MultipleConnections_No phone service    9328 non-null   uint8
 3   MultipleConnections_Yes                 9328 non-null   uint8
 4   InternetConnection_Fiber optic          9328 non-null   uint8
 5   InternetConnection_No                   9328 non-null   uint8
 6   OnlineSecurity_No internet service      9328 non-null   uint8
 7   OnlineSecurity_Yes                      9328 non-null   uint8
 8   OnlineBackup_No internet service        9328 non-null   uint8
 9   OnlineBackup_Yes                        9328 non-null   uint8
 10  DeviceProtectionService_No internet service 9328 non-null   uint8
 11  DeviceProtectionService_Yes             9328 non-null   uint8
 12  TechnicalHelp_No internet service       9328 non-null   uint8
 13  TechnicalHelp_Yes                       9328 non-null   uint8
 14  OnlineTV_No internet service            9328 non-null   uint8
 15  OnlineTV_Yes                            9328 non-null   uint8
 16  OnlineMovies_No internet service        9328 non-null   uint8
 17  OnlineMovies_Yes                        9328 non-null   uint8
 18  Agreement_One year                      9328 non-null   uint8
 19  Agreement_Two year                      9328 non-null   uint8
 20  BillingMethod_Yes                       9328 non-null   uint8
 21  PaymentMethod_Credit card (automatic)   9328 non-null   uint8
 22  PaymentMethod_Electronic check          9328 non-null   uint8
 23  PaymentMethod_Mailed check              9328 non-null   uint8
dtypes: uint8(24)
memory usage: 291.5 KB
```

final features

In [ ]:
```
x_cols_final = pd.concat([x_num,select_features_df_char],axis=1, join="inner")
x_cols_final.columns
```

Out[ ]:
```
Index(['SeniorCitizen', 'tenure', 'MonthlyServiceCharges', 'TotalAmount',
       'Dependents_Yes', 'CallService_Yes',
       'MultipleConnections_No phone service', 'MultipleConnections_Yes',
       'InternetConnection_Fiber optic', 'InternetConnection_No',
       'OnlineSecurity_No internet service', 'OnlineSecurity_Yes',
       'OnlineBackup_No internet service', 'OnlineBackup_Yes',
       'DeviceProtectionService_No internet service',
       'DeviceProtectionService_Yes', 'TechnicalHelp_No internet service',
       'TechnicalHelp_Yes', 'OnlineTV_No internet service', 'OnlineTV_Yes',
       'OnlineMovies_No internet service', 'OnlineMovies_Yes',
       'Agreement_One year', 'Agreement_Two year', 'BillingMethod_Yes',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check'],
      dtype='object')
```

In [ ]:
```
x_cols_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9328 entries, 0 to 12334
Data columns (total 28 columns):
 #   Column                                       Non-Null Count  Dtype  
---  ------                                       --------------  -----  
 0   SeniorCitizen                                9328 non-null   float64
 1   tenure                                       9328 non-null   float64
 2   MonthlyServiceCharges                        9328 non-null   float64
 3   TotalAmount                                  9328 non-null   float64
 4   Dependents_Yes                               9328 non-null   uint8  
 5   CallService_Yes                              9328 non-null   uint8  
 6   MultipleConnections_No phone service         9328 non-null   uint8  
 7   MultipleConnections_Yes                      9328 non-null   uint8  
 8   InternetConnection_Fiber optic               9328 non-null   uint8  
 9   InternetConnection_No                        9328 non-null   uint8  
 10  OnlineSecurity_No internet service           9328 non-null   uint8  
 11  OnlineSecurity_Yes                           9328 non-null   uint8  
 12  OnlineBackup_No internet service             9328 non-null   uint8  
 13  OnlineBackup_Yes                             9328 non-null   uint8  
 14  DeviceProtectionService_No internet service  9328 non-null   uint8  
 15  DeviceProtectionService_Yes                  9328 non-null   uint8  
 16  TechnicalHelp_No internet service            9328 non-null   uint8  
 17  TechnicalHelp_Yes                            9328 non-null   uint8  
 18  OnlineTV_No internet service                 9328 non-null   uint8  
 19  OnlineTV_Yes                                 9328 non-null   uint8  
 20  OnlineMovies_No internet service             9328 non-null   uint8  
 21  OnlineMovies_Yes                             9328 non-null   uint8  
 22  Agreement_One year                           9328 non-null   uint8  
 23  Agreement_Two year                           9328 non-null   uint8  
 24  BillingMethod_Yes                            9328 non-null   uint8  
 25  PaymentMethod_Credit card (automatic)        9328 non-null   uint8  
 26  PaymentMethod_Electronic check               9328 non-null   uint8  
 27  PaymentMethod_Mailed check                   9328 non-null   uint8  
dtypes: float64(4), uint8(24)
memory usage: 841.0 KB
```

In [ ]:
```
x_cols_final.nunique()
```

Out[ ]:
```
SeniorCitizen                                  2
tenure                                         6
MonthlyServiceCharges                       5153
TotalAmount                                 8831
Dependents_Yes                                 2
CallService_Yes                                2
MultipleConnections_No phone service           2
MultipleConnections_Yes                        2
InternetConnection_Fiber optic                 2
InternetConnection_No                          2
OnlineSecurity_No internet service             2
OnlineSecurity_Yes                             2
OnlineBackup_No internet service               2
OnlineBackup_Yes                               2
DeviceProtectionService_No internet service    2
DeviceProtectionService_Yes                    2
TechnicalHelp_No internet service              2
TechnicalHelp_Yes                              2
OnlineTV_No internet service                   2
OnlineTV_Yes                                   2
OnlineMovies_No internet service               2
OnlineMovies_Yes                               2
Agreement_One year                             2
Agreement_Two year                             2
BillingMethod_Yes                              2
PaymentMethod_Credit card (automatic)          2
PaymentMethod_Electronic check                 2
PaymentMethod_Mailed check                     2
dtype: int64
```

In [ ]:
```
y['Churn'] = np.where(y['Churn']=='No',0,1)
y['Churn'].head()
```

Out[ ]:
```
0    0
1    0
2    0
3    0
4    0
Name: Churn, dtype: int32
```

variance influence factor for x_cols_final. we obeserve that there exists very high correlation betweeen tenure, MonthlyServiceCharges, TotalAmount, CallService_Yes features having very high correlation. Also not eliminating any feature here

In [ ]:
```
vif_features = pd.DataFrame()
vif_features['feature_names'] = x_cols_final.columns
```

```
vif_features['vif_values'] = [variance_inflation_factor(x_cols_final, i) for i i
print(vif_features)
```

```
                                feature_names  vif_values
0                               SeniorCitizen    1.283691
1                                      tenure   11.164181
2                       MonthlyServiceCharges   17.803474
3                                 TotalAmount   15.518206
4                              Dependents_Yes    1.621904
5                             CallService_Yes   11.620357
6          MultipleConnections_No phone service    1.589235
7                     MultipleConnections_Yes    2.196782
8                InternetConnection_Fiber optic    4.006358
9                       InternetConnection_No    3.949974
10          OnlineSecurity_No internet service    3.369774
11                         OnlineSecurity_Yes    1.781707
12            OnlineBackup_No internet service    3.389887
13                           OnlineBackup_Yes    1.965955
14  DeviceProtectionService_No internet service    3.458866
15                DeviceProtectionService_Yes    2.039356
16           TechnicalHelp_No internet service    3.284803
17                          TechnicalHelp_Yes    1.855395
18               OnlineTV_No internet service    3.566204
19                               OnlineTV_Yes    2.504054
20           OnlineMovies_No internet service    3.535424
21                           OnlineMovies_Yes    2.458684
22                         Agreement_One year    1.599268
23                         Agreement_Two year    2.228679
24                          BillingMethod_Yes    2.514791
25       PaymentMethod_Credit card (automatic)    1.772461
26             PaymentMethod_Electronic check    2.628250
27                 PaymentMethod_Mailed check    2.104484
```

spliting train and test

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(x_cols_final, y, test_size=0
model_accuracy = {}
#model_accuracy = {'LogisticRegression':[0], 'RandomForestClassifier':[0], 'Grid
```

In [ ]:

```
print("Shape of Training Data",X_train.shape)
print("Shape of Testing Data",X_test.shape)
print("Response Rate in Training Data",y_train.mean())
print("Response Rate in Testing Data",y_test.mean())

# observe that the mean of training and test of y_train and y_test are more or l
```

```
Shape of Training Data (6529, 28)
Shape of Testing Data (2799, 28)
Response Rate in Training Data Churn    0.604074
dtype: float64
Response Rate in Testing Data Churn    0.594141
dtype: float64
```

model execution and summary with coefficients & p-values

In [ ]:
```
import statsmodels.api as sm
#y_train = list(y_train)
model_result = sm.Logit(y_train,X_train).fit()
print(model_result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.538566
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 6529
Model:                          Logit   Df Residuals:                     6501
Method:                           MLE   Df Model:                           27
Date:                Sun, 26 Mar 2023   Pseudo R-squ.:                  0.1978
Time:                        13:34:48   Log-Likelihood:                -3516.3
converged:                       True   LL-Null:                       -4383.1
Covariance Type:            nonrobust   LLR p-value:                     0.000
===============================================================================
================================
                                                 coef    std err          z
P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
--------------------------------
SenseniorCitizen                                -0.2541      0.095     -2.681
0.007      -0.440      -0.068
tenure                                        -0.3301      0.040     -8.289
0.000      -0.408      -0.252
MonthlyServiceCharges                          1.4090      0.234      6.010
0.000       0.950       1.868
TotalAmount                                   -1.0628      0.345     -3.084
0.002      -1.738      -0.387
Dependents_Yes                                 0.3082      0.063      4.864
0.000       0.184       0.432
CallService_Yes                                0.0511      0.103      0.498
0.619      -0.150       0.252
MultipleConnections_No phone service           0.9166      0.108      8.500
0.000       0.705       1.128
MultipleConnections_Yes                        0.2303      0.070      3.281
0.001       0.093       0.368
InternetConnection_Fiber optic                 0.5991      0.088      6.770
0.000       0.426       0.773
InternetConnection_No                          0.3432      0.111      3.090
0.002       0.125       0.561
OnlineSecurity_No internet service             0.0224      0.103      0.217
0.828      -0.180       0.225
OnlineSecurity_Yes                            -0.3181      0.076     -4.213
0.000      -0.466      -0.170
OnlineBackup_No internet service               0.0753      0.103      0.731
0.465      -0.127       0.277
OnlineBackup_Yes                              -0.0783      0.074     -1.058
0.290      -0.223       0.067
DeviceProtectionService_No internet service    0.0806      0.104      0.771
0.440      -0.124       0.285
DeviceProtectionService_Yes                    0.0478      0.076      0.629
0.529      -0.101       0.197
TechnicalHelp_No internet service             -0.0530      0.102     -0.520
0.603      -0.253       0.147
TechnicalHelp_Yes                             -0.3501      0.079     -4.457
0.000      -0.504      -0.196
OnlineTV_No internet service                   0.1919      0.105      1.836
0.066      -0.013       0.397
OnlineTV_Yes                                   0.1198      0.078      1.532
0.126      -0.033       0.273
OnlineMovies_No internet service               0.1157      0.106      1.094
0.274      -0.092       0.323
```

```
OnlineMovies_Yes                                  0.1107      0.077      1.430
0.153      -0.041       0.263
Agreement_One year                               -0.2188      0.076     -2.881
0.004      -0.368      -0.070
Agreement_Two year                               -1.1217      0.104    -10.834
0.000      -1.325      -0.919
BillingMethod_Yes                                 0.1704      0.060      2.832
0.005       0.052       0.288
PaymentMethod_Credit card (automatic)            -0.0805      0.088     -0.914
0.361      -0.253       0.092
PaymentMethod_Electronic check                    0.3306      0.079      4.202
0.000       0.176       0.485
PaymentMethod_Mailed check                       -0.0581      0.083     -0.704
0.481      -0.220       0.104
==============================================================================
================================
```

creating the model

In [ ]:
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

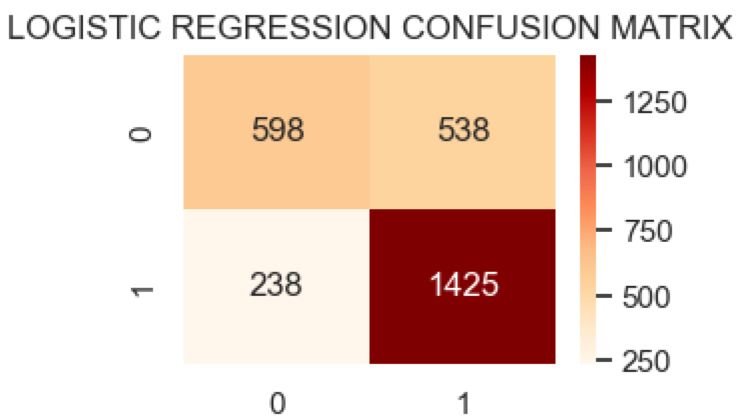
Out[ ]:
```
▾ LogisticRegression
LogisticRegression()
```

predicting the test set results and calculating the accuracy

In [ ]:
```
y_pred_test = logreg.predict(X_test)
score = logreg.score(X_test, y_test)
print('Accuracy score:', score)
model_accuracy['LogisticRegression'] = score
```

```
Accuracy score: 0.7227581279028225
```

In [ ]:
```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_test)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("LOGISTIC REGRESSION CONFUSION MATRIX");
```



classification report

In [ ]:
```
print("classification_report")
print(metrics.classification_report(y_test, y_pred_test))
```

```
classification_report
              precision    recall  f1-score   support

           0       0.72      0.53      0.61      1136
           1       0.73      0.86      0.79      1663

    accuracy                           0.72      2799
   macro avg       0.72      0.69      0.70      2799
weighted avg       0.72      0.72      0.71      2799
```

Training Accuracy vs Test Accuracy, both seemed to be more or less same in accuracy

In [ ]:
```
y_pred_train = logreg.predict(X_train)
print("Training Accuracy", metrics.accuracy_score(y_train, y_pred_train))
print("****************"*5)
print("Test Accuracy", metrics.accuracy_score(y_test, y_pred_test))
```

```
Training Accuracy 0.739163731046102
*******************************************************************************
*
Test Accuracy 0.7227581279028225
```

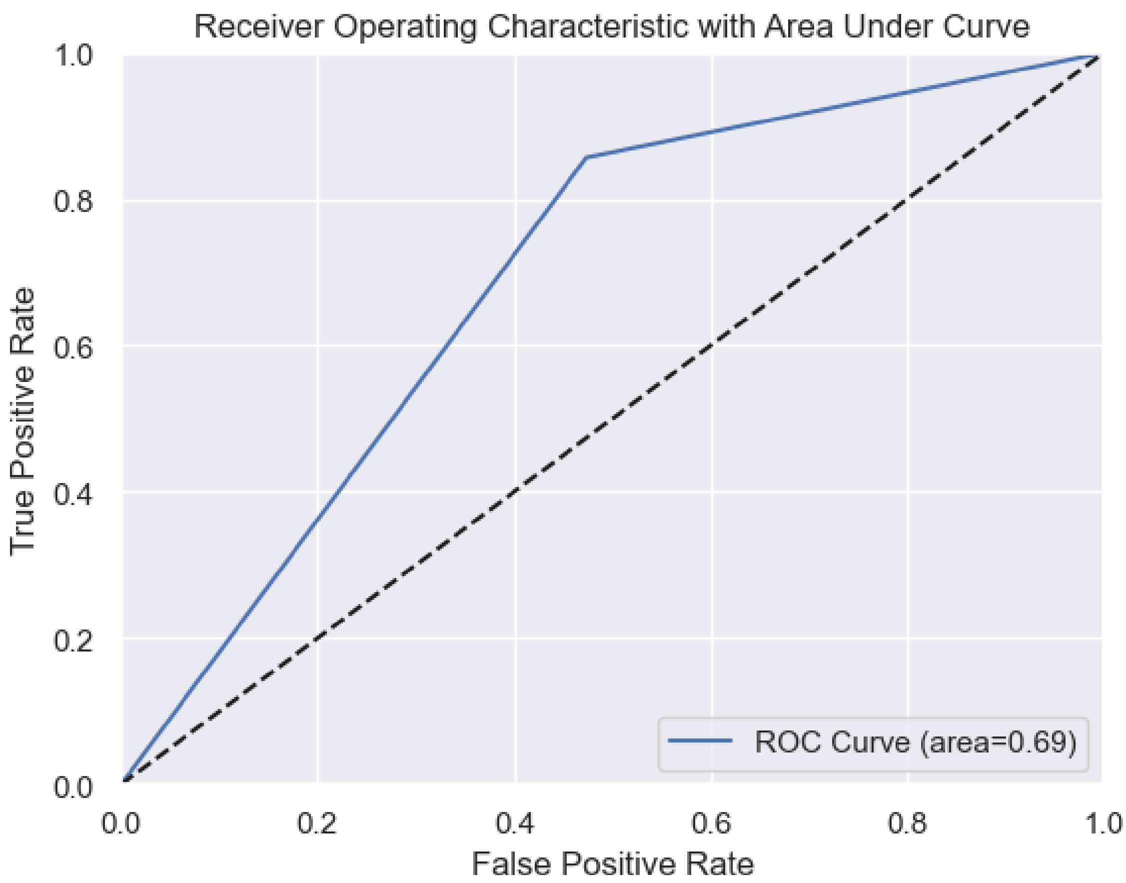
ROC - AUC

In [ ]:
```
logistic_roc_auc = metrics.roc_auc_score(y_test, y_pred_test)
logistic_roc_auc
```

Out[ ]:
```
0.6916467990141693
```

In [ ]:
```
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_test)
```

In [ ]:
```
plt.figure()
plt.plot(fpr, tpr, label = "ROC Curve (area=%0.2f)" %logistic_roc_auc)
plt.plot([0,1],[0,1],'k--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.0])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristic with Area Under Curve")
plt.legend(loc='lower right')
plt.show()
```



performing cross validation and observed that accuracy max is 80% and min 68%

In [ ]:
```python
# cross validation score - K_FOLD method
from sklearn.model_selection import cross_val_score
accuracy = cross_val_score(logreg, X_test, y_test, cv =20)
print(accuracy)
print('accuracy mean ', accuracy.mean())
```

```
[0.72142857 0.72857143 0.72857143 0.75714286 0.74285714 0.75714286
 0.72142857 0.69285714 0.77857143 0.66428571 0.76428571 0.77142857
 0.78571429 0.7        0.69285714 0.73571429 0.73571429 0.72857143
 0.73571429 0.6618705 ]
accuracy mean  0.7302363823227133
```

using Random forest and found that accuracy improved to 78%

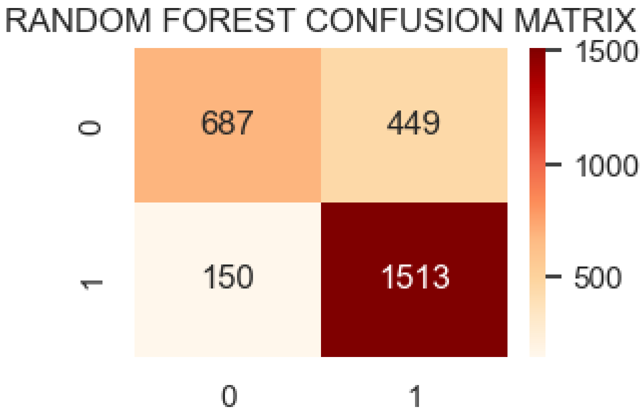
In [ ]:
```python
rclassifier = RandomForestClassifier(n_estimators=25, criterion='gini', random_s
rclassifier.fit(X_train, y_train)
```

Out[ ]:
```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=5, n_estimators=25, random_state=1)
```

In [ ]:
```
y_pred_test_rfc = rclassifier.predict(X_test)
score_rfc = metrics.accuracy_score(y_test, y_pred_test_rfc)
model_accuracy['RandomForestClassifier'] = score_rfc
```

In [ ]:
```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_test_rfc)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("RANDOM FOREST CONFUSION MATRIX")
```

Out[ ]:
```
Text(0.5, 1.0, 'RANDOM FOREST CONFUSION MATRIX')
```



print classification report

In [ ]:
```
print("classification_report")
print(metrics.classification_report(y_test, y_pred_test_rfc))
```

```
classification_report
              precision    recall  f1-score   support

           0       0.82      0.60      0.70      1136
           1       0.77      0.91      0.83      1663

    accuracy                           0.79      2799
   macro avg       0.80      0.76      0.77      2799
weighted avg       0.79      0.79      0.78      2799
```

RandomForestClasifier cross validation

In [ ]:
```
accuracy = cross_val_score(rclassifier, X_test, y_test, cv =20)
print(accuracy)
print('accuracy mean ', accuracy.mean())
```

```
[0.80714286 0.81428571 0.74285714 0.76428571 0.77142857 0.78571429
 0.79285714 0.76428571 0.83571429 0.72142857 0.77857143 0.83571429
 0.78571429 0.77857143 0.77857143 0.8        0.76428571 0.79285714
 0.79285714 0.79856115]
accuracy mean  0.7852852004110996
```

Random forest feature importance

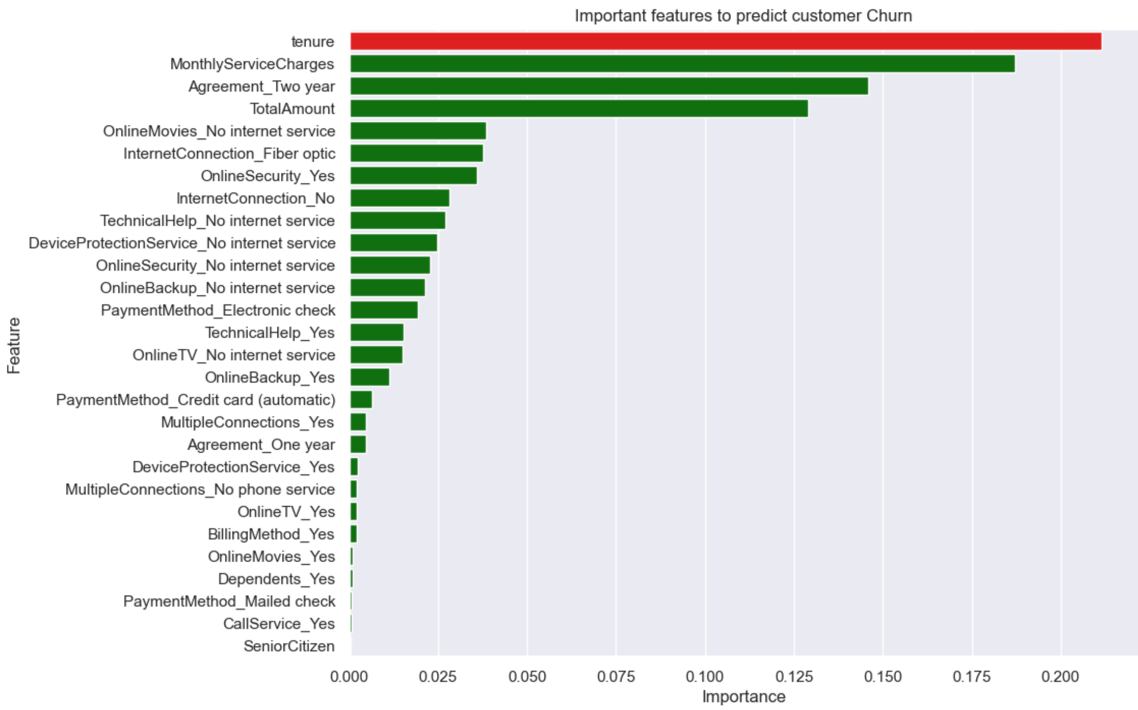
In [ ]:
```
features_imp_dict= {}
for col, val in sorted(zip(x_cols_final.columns, rclassifier.feature_importances
  features_imp_dict[col]=val
features_df_rf = pd.DataFrame({'Feature':features_imp_dict.keys(),'Importance':f
features_df_rf
```

Out[ ]:

	Feature	Importance
0	tenure	0.211375
1	MonthlyServiceCharges	0.187146
2	Agreement_Two year	0.145862
3	TotalAmount	0.128925
4	OnlineMovies_No internet service	0.038637
5	InternetConnection_Fiber optic	0.037694
6	OnlineSecurity_Yes	0.035808
7	InternetConnection_No	0.028067
8	TechnicalHelp_No internet service	0.027064
9	DeviceProtectionService_No internet service	0.024846
10	OnlineSecurity_No internet service	0.022896
11	OnlineBackup_No internet service	0.021353
12	PaymentMethod_Electronic check	0.019439
13	TechnicalHelp_Yes	0.015250
14	OnlineTV_No internet service	0.015148
15	OnlineBackup_Yes	0.011226
16	PaymentMethod_Credit card (automatic)	0.006525
17	MultipleConnections_Yes	0.004846
18	Agreement_One year	0.004833
19	DeviceProtectionService_Yes	0.002495
20	MultipleConnections_No phone service	0.002212
21	OnlineTV_Yes	0.002154
22	BillingMethod_Yes	0.002125
23	OnlineMovies_Yes	0.001145
24	Dependents_Yes	0.000873
25	PaymentMethod_Mailed check	0.000835
26	CallService_Yes	0.000758
27	SeniorCitizen	0.000464

In [ ]:
```
values = features_df_rf.Importance
idx = features_df_rf.Feature
plt.figure(figsize=(10,8))
clrs = ['green' if (x < max(values)) else 'red' for x in values ]
```

```
sns.barplot(y=idx,x=values,palette=clrs).set(title='Important features to predic
plt.show()
```



using GridSearchCV and Random Forest

In [ ]:

```
# selected model up on accuracy score in RandomForestClassifier with Tunned Hype
params = {'n_estimators' : [30],
          'min_samples_split' : [8, 10, 12],
          'criterion' :['gini', 'entropy']
         }

rfc_gscv = GridSearchCV(RandomForestClassifier(),param_grid= params, scoring='ro
rfc_gscv.fit(X_train, y_train)
y_predicted = rfc_gscv.predict(X_test)

rfc_gscv_model = rfc_gscv.best_estimator_
print (rfc_gscv.best_score_, rfc_gscv.best_params_)
```

```
0.9113187256349988 {'criterion': 'gini', 'min_samples_split': 10, 'n_estimator
s': 30}
```

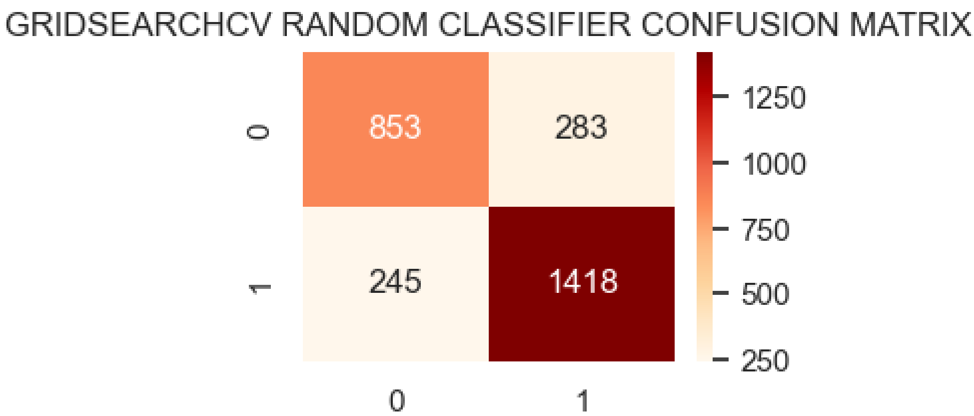
In [ ]:

```
y_pred_gscv = rfc_gscv.predict(X_test)
score_gscv = accuracy_score(y_test, y_pred_gscv)

model_accuracy['GridSearchCV_RFC'] = score_gscv

print("Grid Search CV", score_gscv)
print("classification_report")
print(metrics.classification_report(y_test, y_pred_gscv))
```

```
Grid Search CV 0.8113612004287245
classification_report
              precision    recall  f1-score   support

           0       0.78      0.75      0.76      1136
           1       0.83      0.85      0.84      1663

    accuracy                           0.81      2799
   macro avg       0.81      0.80      0.80      2799
weighted avg       0.81      0.81      0.81      2799
```

In [ ]:
```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_gscv)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("GRIDSEARCHCV RANDOM CLASSIFIER CONFUSION MATRIX")
```

Out[ ]:
```
Text(0.5, 1.0, 'GRIDSEARCHCV RANDOM CLASSIFIER CONFUSION MATRIX')
```



using gradiant boosting classifier (reducing the errors) and further improvement on accuracy to 82%

In [ ]:
```
gbc_classifier = GradientBoostingClassifier(random_state=0,max_depth=5,min_sampl
gbc_classifier.fit(X_train, y_train)
y_pred_gbcl = gbc_classifier.predict(X_test)

score_gbcl = accuracy_score(y_test, y_pred_gbcl)
model_accuracy['GradientBoostingClassifier'] = score_gbcl

print("Gradient Boosting Classifier", accuracy_score(y_test, y_pred_gbcl))
```

```
Gradient Boosting Classifier 0.8177920685959271
```

In [ ]:
```
y_pred_gbcl = gbc_classifier.predict(X_test)
print("Gradient Boosting Classifier", accuracy_score(y_test, y_pred_gbcl))
print("classification_report")
print(metrics.classification_report(y_test, y_pred_gbcl))
```

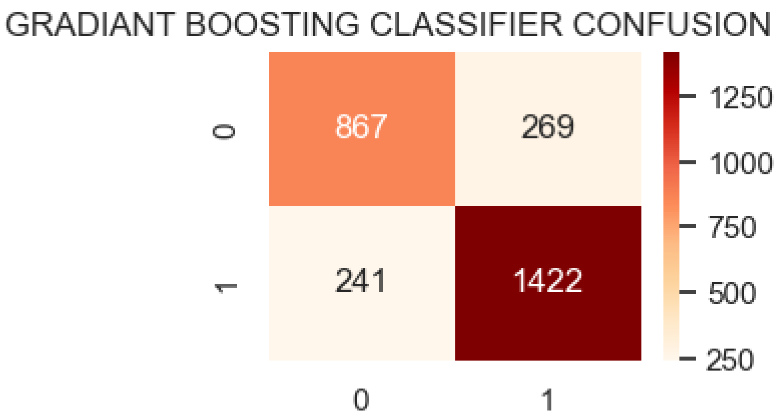
```
Gradient Boosting Classifier 0.8177920685959271
classification_report
              precision    recall  f1-score   support

           0       0.78      0.76      0.77      1136
           1       0.84      0.86      0.85      1663

    accuracy                           0.82      2799
   macro avg       0.81      0.81      0.81      2799
weighted avg       0.82      0.82      0.82      2799
```

In [ ]:

```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_gbcl)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("GRADIANT BOOSTING CLASSIFIER CONFUSION MATRIX")
```

Out[ ]:

```
Text(0.5, 1.0, 'GRADIANT BOOSTING CLASSIFIER CONFUSION MATRIX')
```



understanding the feature importance using gbc

In [ ]:

```
# let's create a dictionary of features and their importance values
features_imp_dict= {}
for col, val in sorted(zip(x_cols_final.columns, gbc_classifier.feature_importar
  features_imp_dict[col]=val
features_df = pd.DataFrame({'Feature':features_imp_dict.keys(),'Importance':feat
features_df
```

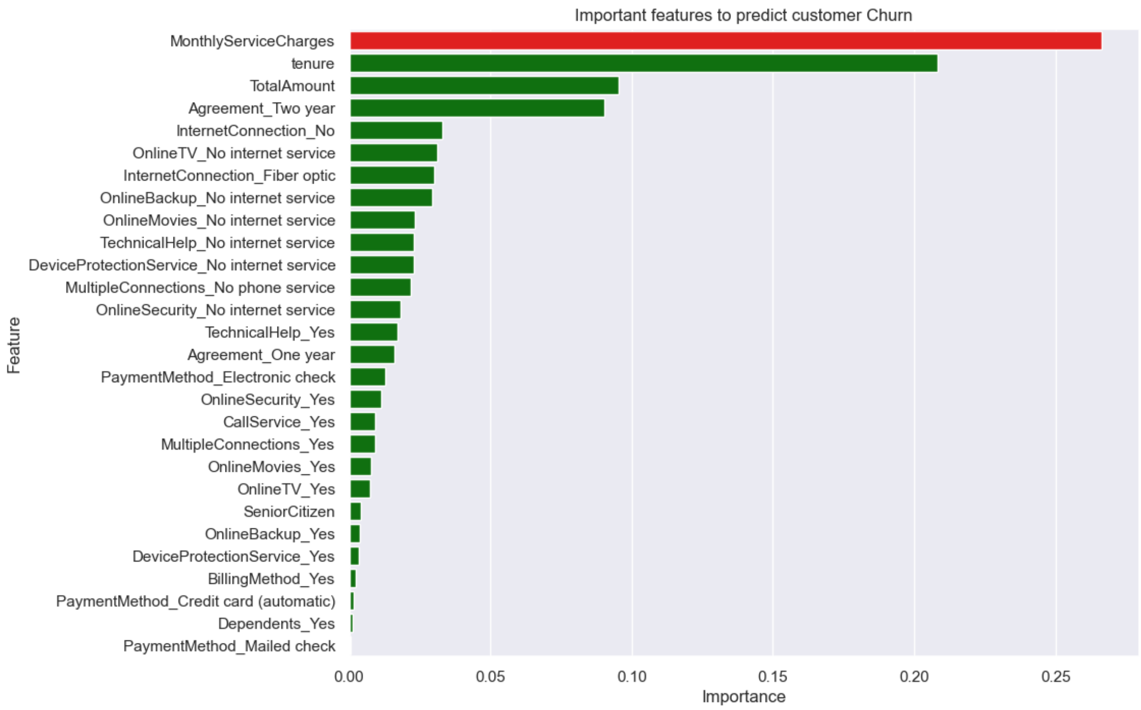
Out[ ]:

	Feature	Importance
0	MonthlyServiceCharges	0.266159
1	tenure	0.208398
2	TotalAmount	0.095333
3	Agreement_Two year	0.090201
4	InternetConnection_No	0.032979
5	OnlineTV_No internet service	0.031074
6	InternetConnection_Fiber optic	0.030000
7	OnlineBackup_No internet service	0.029369
8	OnlineMovies_No internet service	0.023188
9	TechnicalHelp_No internet service	0.022890
10	DeviceProtectionService_No internet service	0.022751
11	MultipleConnections_No phone service	0.021824
12	OnlineSecurity_No internet service	0.018124
13	TechnicalHelp_Yes	0.017099
14	Agreement_One year	0.016186
15	PaymentMethod_Electronic check	0.012911
16	OnlineSecurity_Yes	0.011377
17	CallService_Yes	0.009090
18	MultipleConnections_Yes	0.009051
19	OnlineMovies_Yes	0.007741
20	OnlineTV_Yes	0.007339
21	SeniorCitizen	0.004076
22	OnlineBackup_Yes	0.003640
23	DeviceProtectionService_Yes	0.003506
24	BillingMethod_Yes	0.002522
25	PaymentMethod_Credit card (automatic)	0.001586
26	Dependents_Yes	0.001127
27	PaymentMethod_Mailed check	0.000457

visualizing the important features, gbc

In [ ]:

```
values = features_df.Importance
idx = features_df.Feature
plt.figure(figsize=(10,8))
clrs = ['green' if (x < max(values)) else 'red' for x in values ]
sns.barplot(y=idx,x=values,palette=clrs).set(title='Important features to predic
plt.show()
```



using RidgeClassifier to observe the model

In [ ]:
```
rgclassifier = RidgeClassifier()
rgclassifier.fit(X_train, y_train)
```

Out[ ]:
```
▾ RidgeClassifier
RidgeClassifier()
```

In [ ]:
```
rgclassifier.fit(X_train, y_train)
y_pred_train_rdg = rgclassifier.predict(X_train)
score_train_rdg = accuracy_score(y_train, y_pred_train_rdg)
print('RidgeClassifier training accuracy', score_train_rdg)

y_pred_test_rdg = rgclassifier.predict(X_test)
score_test_rdg = accuracy_score(y_test, y_pred_test_rdg)
model_accuracy['RidgeClassifier'] = score_test_rdg
print('RidgeClassifier testing accuracy', score_test_rdg)
```

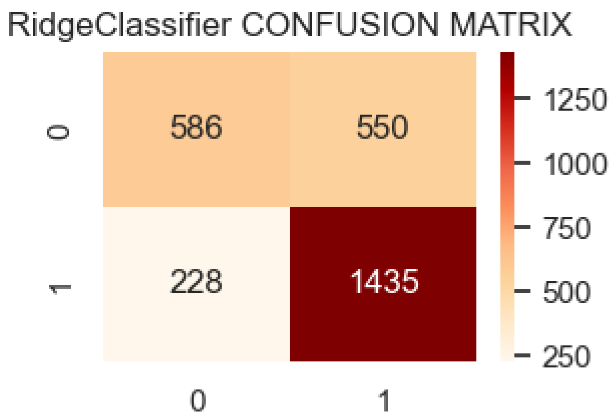
```
RidgeClassifier training accuracy 0.7377852657374789
RidgeClassifier testing accuracy 0.7220435869953555
```

In [ ]:
```
print("classification_report")
print(metrics.classification_report(y_test, y_pred_test_rdg))
```

```
classification_report
              precision    recall  f1-score   support

           0       0.72      0.52      0.60      1136
           1       0.72      0.86      0.79      1663

    accuracy                           0.72      2799
   macro avg       0.72      0.69      0.69      2799
weighted avg       0.72      0.72      0.71      2799
```

In [ ]:
```python
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_test_rdg)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("RidgeClassifier CONFUSION MATRIX")
```

Out[ ]:
```
Text(0.5, 1.0, 'RidgeClassifier CONFUSION MATRIX')
```



using SVC

In [ ]:
```python
svc = SVC()
svc.fit(X_train, y_train)
score = svc.score(X_train, y_train)
print("SVC training dataset: ", score)

cv_scores = cross_val_score(svc, X_test, y_test, cv=10)
print("CV average score: %.2f" % cv_scores.mean())

y_pred_svc = svc.predict(X_test)
score_test_svc = accuracy_score(y_test, y_pred_svc)
model_accuracy['SVC'] = score_test_svc
print('SVC testing accuracy', score_test_svc)

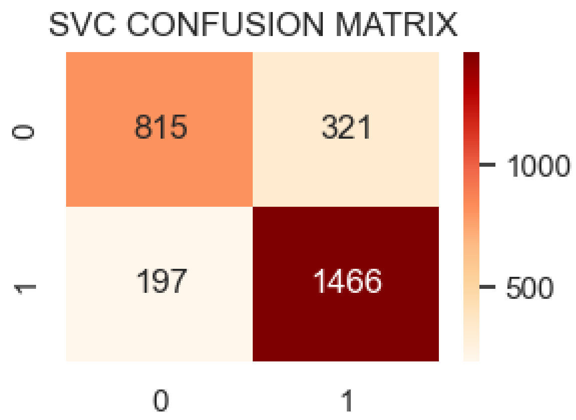
confusion_matrix = metrics.confusion_matrix(y_test, y_pred_svc)
plt.figure(figsize = (3,2))
sns.heatmap(confusion_matrix , annot=True,fmt = "d", cmap='OrRd')
plt.title("SVC CONFUSION MATRIX")

print("SVC classification_report")
print(metrics.classification_report(y_test, y_pred_svc))
```

```
SVC training dataset:  0.8286108132945321
CV average score: 0.80
SVC testing accuracy 0.8149339049660593
SVC classification_report
              precision    recall  f1-score   support

           0       0.81      0.72      0.76      1136
           1       0.82      0.88      0.85      1663

    accuracy                           0.81      2799
   macro avg       0.81      0.80      0.80      2799
weighted avg       0.81      0.81      0.81      2799
```



GridSearchCV(RandomForest), GradiantBoostingClassifier, SVC has better accuracy

In [ ]:
```
model_accuracy
```

Out[ ]:
```
{'LogisticRegression': 0.7227581279028225,
 'RandomForestClassifier': 0.7859949982136477,
 'GridSearchCV_RFC': 0.8113612004287245,
 'GradientBoostingClassifier': 0.8177920685959271,
 'RidgeClassifier': 0.7220435869953555,
 'SVC': 0.8149339049660593}
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