ProgrammingHero

November 14, 2023

[47]:
```
import seaborn as sns
import pandas as pd
import numpy as np
import scipy.stats as stats
file_path = '/content/drive/MyDrive/Dataset/Telco_customer_churn.xlsx'
df = pd.read_excel(file_path, engine='openpyxl')
df_copy = df.copy()
```

[2]:
```
df.head(2)
```

[2]:
```
   CustomerID  Count        Country       State         City  Zip Code  \
0  3668-QPYBK      1  United States  California  Los Angeles     90003
1  9237-HQITU      1  United States  California  Los Angeles     90005

                 Lat Long   Latitude   Longitude  Gender  …        Contract  \
0  33.964131, -118.272783  33.964131 -118.272783    Male  …  Month-to-month
1   34.059281, -118.30742  34.059281 -118.307420  Female  …  Month-to-month

  Paperless Billing    Payment Method  Monthly Charges Total Charges  \
0               Yes      Mailed check            53.85        108.15
1               Yes  Electronic check            70.70        151.65

  Churn Label Churn Value Churn Score  CLTV                   Churn Reason
0         Yes           1          86  3239  Competitor made better offer
1         Yes           1          67  2701                         Moved

[2 rows x 33 columns]
```

#Exploratory Data Analysis(EDA) & Cleaning

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

[3]:
```
(7043, 33)
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
```

```
Data columns (total 33 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         7043 non-null   object
 1   Count              7043 non-null   int64
 2   Country            7043 non-null   object
 3   State              7043 non-null   object
 4   City               7043 non-null   object
 5   Zip Code           7043 non-null   int64
 6   Lat Long           7043 non-null   object
 7   Latitude           7043 non-null   float64
 8   Longitude          7043 non-null   float64
 9   Gender             7043 non-null   object
 10  Senior Citizen     7043 non-null   object
 11  Partner            7043 non-null   object
 12  Dependents         7043 non-null   object
 13  Tenure Months      7043 non-null   int64
 14  Phone Service      7043 non-null   object
 15  Multiple Lines     7043 non-null   object
 16  Internet Service   7043 non-null   object
 17  Online Security    7043 non-null   object
 18  Online Backup      7043 non-null   object
 19  Device Protection  7043 non-null   object
 20  Tech Support       7043 non-null   object
 21  Streaming TV       7043 non-null   object
 22  Streaming Movies   7043 non-null   object
 23  Contract           7043 non-null   object
 24  Paperless Billing  7043 non-null   object
 25  Payment Method     7043 non-null   object
 26  Monthly Charges    7043 non-null   float64
 27  Total Charges      7043 non-null   object
 28  Churn Label        7043 non-null   object
 29  Churn Value        7043 non-null   int64
 30  Churn Score        7043 non-null   int64
 31  CLTV               7043 non-null   int64
 32  Churn Reason       1869 non-null   object
dtypes: float64(3), int64(6), object(24)
memory usage: 1.8+ MB
```

#Total Charges is in Object so we have to convert it into numeric value

[5]:
```
df['Total Charges'] = pd.to_numeric(df['Total Charges'], errors='coerce')
```

0.1 Check missing values

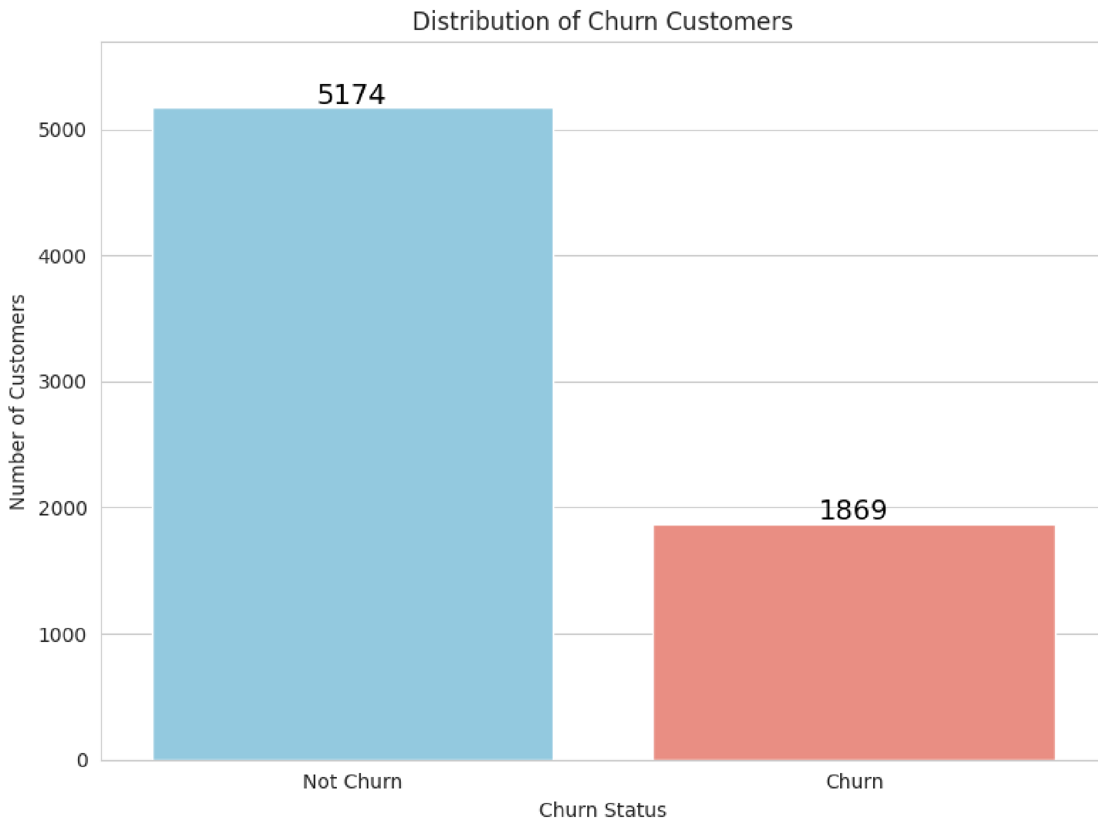
[6]:
```
df.isnull().sum()
```

[6]:
```
CustomerID              0
Count                   0
Country                 0
State                   0
City                    0
Zip Code                0
Lat Long                0
Latitude                0
Longitude               0
Gender                  0
Senior Citizen          0
Partner                 0
Dependents              0
Tenure Months           0
Phone Service           0
Multiple Lines          0
Internet Service        0
Online Security         0
Online Backup           0
Device Protection       0
Tech Support            0
Streaming TV            0
Streaming Movies        0
Contract                0
Paperless Billing       0
Payment Method          0
Monthly Charges         0
Total Charges          11
Churn Label             0
Churn Value             0
Churn Score             0
CLTV                    0
Churn Reason         5174
dtype: int64
```

1 There are 5174 missing values in churn reason. lets gauge the total scenario from the churn value

[7]:
```
import matplotlib.pyplot as plt
import seaborn as sns
exit_counts = df['Churn Value'].value_counts()
exit_percentages = exit_counts
colors = ['skyblue', 'salmon']
sns.set_style('whitegrid')

plt.figure(figsize=(8, 6))
```

```
ax = sns.barplot(x=exit_counts.index, y=exit_counts.values, palette=colors)
ax.set(xlabel='Churn Status', ylabel='Number of Customers', title='Distribution␣
↪of Churn Customers')
plt.xticks([0, 1], ['Not Churn', 'Churn'])
plt.ylim(top=max(exit_counts.values) * 1.1)

for i, v in enumerate(exit_percentages):
    ax.text(i, exit_counts.values[i]+30, f'{v}', fontsize=14, color='black',␣
↪ha='center')
plt.tight_layout()
plt.show()
```



2 There are 11 missing values in the total charges

[8]:
```
df[df['Total Charges'].isna()]
```

[8]:
```
       CustomerID  Count        Country       State            City  Zip Code  \
2234   4472-LVYGI      1  United States  California  San Bernardino     92408
2438   3115-CZMZD      1  United States  California    Independence     93526
```

2568	5709-LVOEQ	1	United States	California	San Mateo	94401
2667	4367-NUYAO	1	United States	California	Cupertino	95014
2856	1371-DWPAZ	1	United States	California	Redcrest	95569
4331	7644-OMVMY	1	United States	California	Los Angeles	90029
4687	3213-VVOLG	1	United States	California	Sun City	92585
5104	2520-SGTTA	1	United States	California	Ben Lomond	95005
5719	2923-ARZLG	1	United States	California	La Verne	91750
6772	4075-WKNIU	1	United States	California	Bell	90201
6840	2775-SEFEE	1	United States	California	Wilmington	90744

	Lat Long	Latitude	Longitude	Gender	…	Contract \
2234	34.084909, -117.258107	34.084909	-117.258107	Female	…	Two year
2438	36.869584, -118.189241	36.869584	-118.189241	Male	…	Two year
2568	37.590421, -122.306467	37.590421	-122.306467	Female	…	Two year
2667	37.306612, -122.080621	37.306612	-122.080621	Male	…	Two year
2856	40.363446, -123.835041	40.363446	-123.835041	Female	…	Two year
4331	34.089953, -118.294824	34.089953	-118.294824	Male	…	Two year
4687	33.739412, -117.173334	33.739412	-117.173334	Male	…	Two year
5104	37.078873, -122.090386	37.078873	-122.090386	Female	…	Two year
5719	34.144703, -117.770299	34.144703	-117.770299	Male	…	One year
6772	33.970343, -118.171368	33.970343	-118.171368	Female	…	Two year
6840	33.782068, -118.262263	33.782068	-118.262263	Male	…	Two year

	Paperless Billing	Payment Method	Monthly Charges \
2234	Yes	Bank transfer (automatic)	52.55
2438	No	Mailed check	20.25
2568	No	Mailed check	80.85
2667	No	Mailed check	25.75
2856	No	Credit card (automatic)	56.05
4331	No	Mailed check	19.85
4687	No	Mailed check	25.35
5104	No	Mailed check	20.00
5719	Yes	Mailed check	19.70
6772	No	Mailed check	73.35
6840	Yes	Bank transfer (automatic)	61.90

	Total Charges	Churn Label	Churn Value	Churn Score	CLTV	Churn Reason
2234	NaN	No	0	36	2578	NaN
2438	NaN	No	0	68	5504	NaN
2568	NaN	No	0	45	2048	NaN
2667	NaN	No	0	48	4950	NaN
2856	NaN	No	0	30	4740	NaN
4331	NaN	No	0	53	2019	NaN
4687	NaN	No	0	49	2299	NaN
5104	NaN	No	0	27	3763	NaN
5719	NaN	No	0	69	4890	NaN
6772	NaN	No	0	44	2342	NaN

```
6840            NaN          No             0           65   5188              NaN

[11 rows x 33 columns]
```

3 Fill in the missing values using monthly charges and tenure months column. if we multiply these two columns value we can fill the missing values of total charges

[9]:
```
df['calc_charges'] = df['Monthly Charges'] * df['Tenure Months']
df['Total Charges'] = np.where(df['Total Charges'].isna() ==␣
 ↪True,df['calc_charges'], df['Total Charges'])
df = df.drop(['calc_charges'], axis=1)
```

[10]:
```
df.isnull().sum()
```

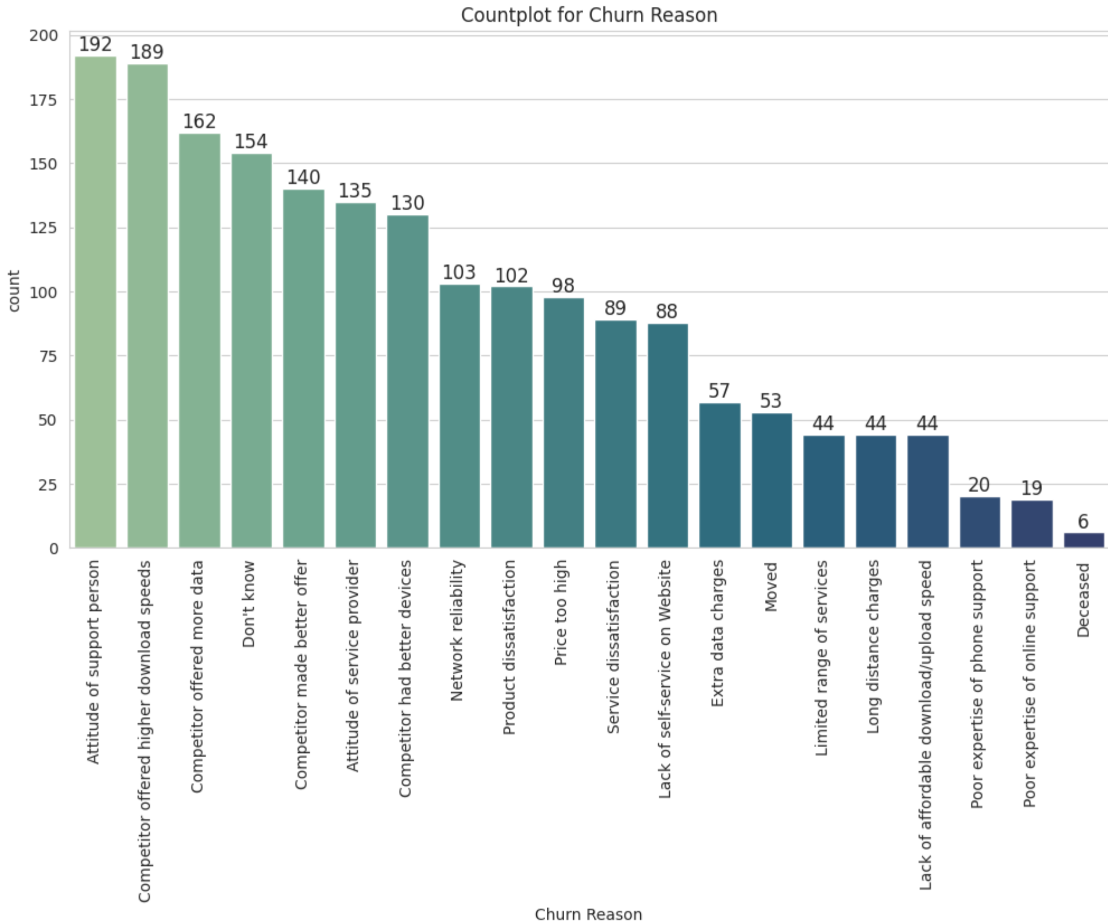
[10]:
```
CustomerID           0
Count                0
Country              0
State                0
City                 0
Zip Code             0
Lat Long             0
Latitude             0
Longitude            0
Gender               0
Senior Citizen       0
Partner              0
Dependents           0
Tenure Months        0
Phone Service        0
Multiple Lines       0
Internet Service     0
Online Security      0
Online Backup        0
Device Protection    0
Tech Support         0
Streaming TV         0
Streaming Movies     0
Contract             0
Paperless Billing    0
Payment Method       0
Monthly Charges      0
Total Charges        0
Churn Label          0
Churn Value          0
```

```
Churn Score              0
CLTV                     0
Churn Reason          5174
dtype: int64
```

[11]:
```
import plotly.express as px
c = ['darkseagreen', 'teal']
px.pie(df.groupby('Churn Label')['CustomerID'].count().reset_index(),
       values='CustomerID',
       names='Churn Label',
       color_discrete_sequence=c,
       title='Pie Chart for Churn Label')
```

26.5% of customers are in churn this means 1869 customers might leave.

[12]:
```
p = 'crest'
fig, ax = plt.subplots(figsize=(12, 6))
sns.set_theme()

ax = sns.countplot(data=df, x='Churn Reason', palette=p, order=df['Churn␣
 ↪Reason'].value_counts().index)
ax.set_title('Countplot for Churn Reason')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)

for container in ax.containers:
    ax.bar_label(container)

plt.show()
```



These are the 20 reasons which lead to customers leave.

[13]:
```
df['Churn Reason'].fillna('Not Applicable', inplace=True)

def categorize_reason(reason):
    if reason=='Not Applicable':
        return np.nan
    elif reason.split(' ')[0]=='Competitor':
        return 'Competition'
    elif reason.split(' ')[-1]=='dissatisfaction':
        return 'Dissatisfaction'
    elif (reason.split(' ')[0]=='Moved') | (reason.split(' ')[0]=='Deceased'):
        return 'Need'
    elif (reason.split(' ')[0]=='Price') | (reason.split(' ')[-1]=='charges'):
        return 'Price'
    elif (reason.split(' ')[0]=='Poor') | (reason.split(' ')[0]=='Attitude'):
        return 'Attitude'
    elif reason=="Don't know":
```

```
        return 'Others'
    else:
        return 'Product'



df['Root Cause'] = df['Churn Reason'].apply(lambda x :␣
 ↪categorize_reason(str(x)))

df['Root Cause'].unique()
```

[13]:
```
array(['Competition', 'Need', 'Price', 'Dissatisfaction', 'Product',
       'Others', 'Attitude', nan], dtype=object)
```

[14]:
```
df1 = df[df['Root Cause'].notnull()]['Root Cause'].value_counts().
 ↪sort_values(ascending=False).reset_index()
df1.rename(columns={'index':'Root Cause', 'Root Cause':'count'}, inplace=True)
df1['cumulative '] = df1['count'].cumsum() / df1['count'].sum() * 100

df1
```

[14]:

	Root Cause	count	cumulative
0	Competition	621	33.226324
1	Attitude	366	52.808989
2	Product	279	67.736758
3	Price	199	78.384163
4	Dissatisfaction	191	88.603531
5	Others	154	96.843232
6	Need	59	100.000000

According to the upper table , the root cause of the Competition should try to be addressed first, followed by the Attitude, Product, Price and so on to minimize the majority of customer churn.

3.1 Geographic Analysis of Churn:

[15]:
```
df.groupby(['Country','State'])['CustomerID'].count()
```

[15]:
```
Country        State
United States  California    7043
Name: CustomerID, dtype: int64
```

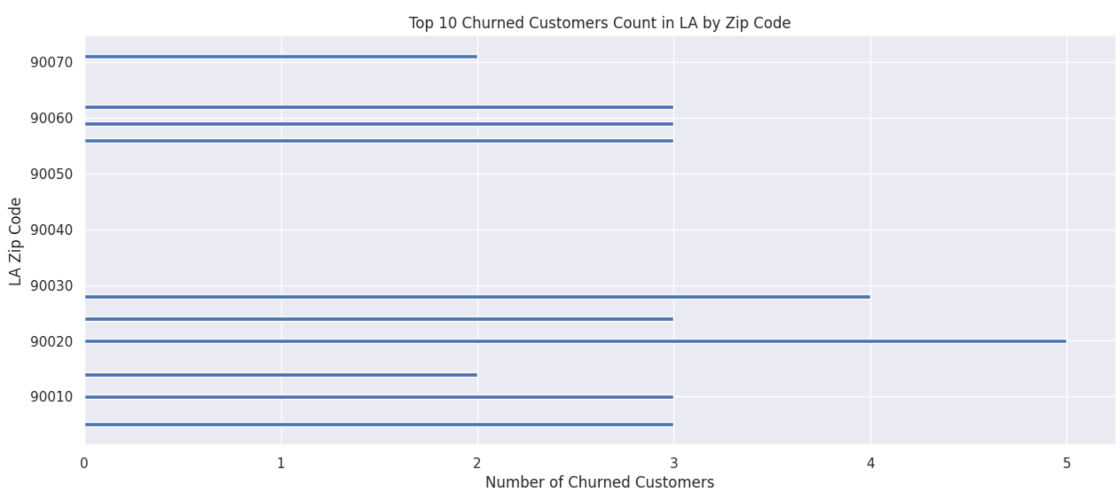
[16]:
```
fig = px.scatter_mapbox(df.groupby(['Latitude','Longitude'])['CustomerID'].
 ↪count().reset_index(), lat="Latitude", lon="Longitude", hover_data=␣
 ↪['CustomerID'], zoom=4, height=300)
fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
```

```
fig.show()
```

[17]:
```
fig = px.bar(df.groupby(['City'])['CustomerID'].count().reset_index().
↪sort_values('CustomerID',
                                                                          ␣
↪    ascending=False).head(50),
             x='City',
             y='CustomerID',
             color = 'CustomerID',
             text = 'CustomerID')
fig.show()
```

We see that the largest number of customers in the Los Angeles, San Diego, San Francisco area.

[18]:
```
churn_yes_states = df.loc[(df['Churn Label'] == 'Yes') & (df['City'] == 'Los␣
↪Angeles'), 'Zip Code']
state_counts = churn_yes_states.value_counts().nlargest(10)

# Get the value counts of each state
LAZipCnt = churn_yes_states.value_counts().nlargest(10)
plt.figure(figsize=(15, 6))

plt.barh(LAZipCnt.index, state_counts.values)

plt.title('Top 10 Churned Customers Count in LA by Zip Code')
plt.xlabel('Number of Churned Customers')
plt.ylabel('LA Zip Code')

plt.show()
```



90020 zip code is the highest followed by 90030 ,90060 and so on

3.2 Geo spatial view of the Lat Long coordinates

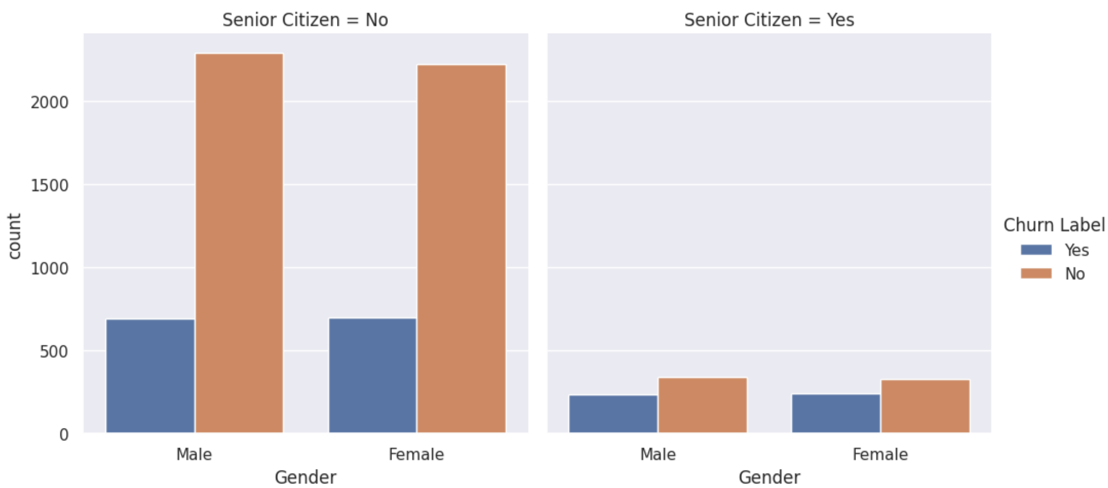
[19]:
```python
import folium

churned_df = df.loc[df['Churn Label'] == 'Yes']
churn_yes_LatLong = churned_df[["Latitude", "Longitude", "City"]]

# Create map object
m = folium.Map(location=[churn_yes_LatLong['Latitude'].mean(),␣
↪churn_yes_LatLong['Longitude'].mean()], zoom_start=8)

# Add markers for each point in the dataset
for index, row in churn_yes_LatLong.iterrows():
    folium.Marker([row['Latitude'], row['Longitude']], popup=row['City']).
↪add_to(m)

m
```

[19]:
```
<folium.folium.Map at 0x7b7014e339a0>
```

4 Demographic Analysis

[20]:
```python
sns.catplot(x='Gender', hue='Churn Label', col='Senior Citizen', kind='count',␣
↪data=df)
```

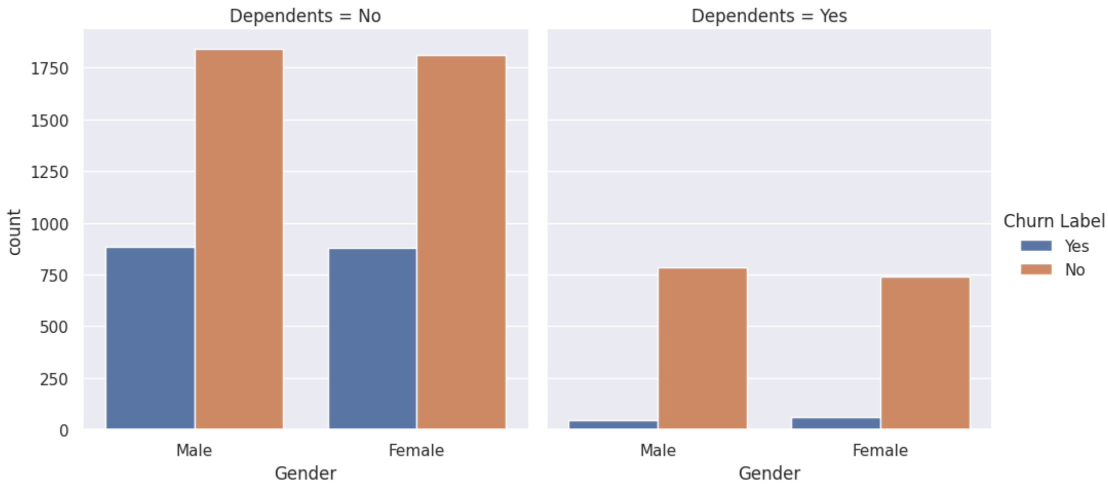
[20]:
```
<seaborn.axisgrid.FacetGrid at 0x7b70170cf4c0>
```



Ratio of Senior Citizen vs. Non Senior Citizen

[21]:
```
sns.catplot(x='Gender', hue='Churn Label', col='Dependents', kind='count',␣
↪data=df)
```

[21]: <seaborn.axisgrid.FacetGrid at 0x7b700fdfee90>



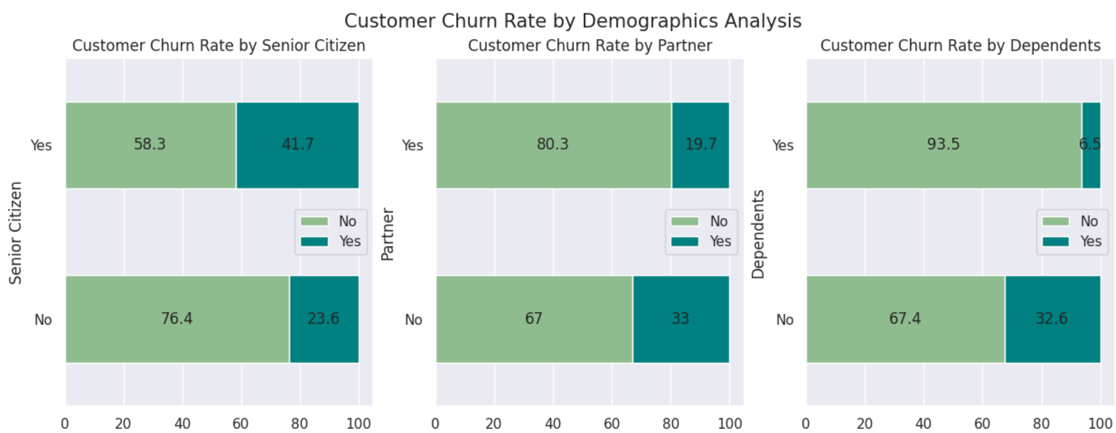
Shows that Males with dependents are churning less than females. However customers without dependents have higher churn values

[22]:
```
sns.catplot(x='Gender', hue='Churn Label', col='Partner', kind='count', data=df)
```

[22]: <seaborn.axisgrid.FacetGrid at 0x7b700fc178b0>

Customers with partners has lower churn chances than the customers without partners

[23]:
```
fig, ax = plt.subplots(1,3,figsize=(15,5))
fig.suptitle('Customer Churn Rate by Demographics Analysis', fontsize=15)

demo = ['Senior Citizen', 'Partner', 'Dependents']

for i, col in enumerate(demo, start=0):
    df1 = df.groupby([col, 'Churn Label']).size().unstack()
    df1.apply(lambda x : round((x/x.sum())*100,1), axis=1).plot(kind='barh',␣
↪stacked=True, color=c, ax=ax[i])
    ax[i].set_title('Customer Churn Rate by {}'.format(col))
    ax[i].legend(loc='best')
    ax[i].grid(axis='y')
    for container in ax[i].containers:
        ax[i].bar_label(container, label_type='center')
```



1. Around (41.7%) of senior citizen customers have left, compared to 23.6% of non senior citizen customers. This suggests that senior citizen customers are more likely to churn.
2. Customers without a partner have a higher chance of churn than customers with a partner, as (33%) of customers without a partner have left.
3. Customers without children, parents or grandparents are prone to churn, as nearly a third (32.6%) of them have left, compared to only 6.5% of customers with dependents.

5 Data Preprocessing(Feature Engineering & Feature Selection)

[24]:
```
from sklearn.base import BaseEstimator, TransformerMixin

class FormatDataFrame(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self
    def transform(self, X, y=None):
```

```
        df = X.copy()

        df['Partner'] = df.Partner.map({'Yes':1,'No':0})
        df['Senior Citizen'] = df["Senior Citizen"].map({'Yes':1,'No':0})
        df['Dependents'] = df.Dependents.map({'Yes':1,'No':0})
        df['Phone Service'] = df["Phone Service"].map({'Yes':1,'No':0})
        df['Multiple Lines'] = df["Multiple Lines"].map({'Yes':1,'No':0,'No␣
↪phone service':0})

        df["IsFiberOptics"] = df["Internet Service"].map({'DSL':0,'Fiber optic':
↪1,'No':0})
        df["IsDSL"] = df["Internet Service"].map({'DSL':1,'Fiber optic':0,'No':
↪0})
        df["Internet Service"] = df["Internet Service"].map({'DSL':1,'Fiber␣
↪optic':1,'No':0})
        df['Online Security'] = df["Online Security"].map({'Yes':1,'No':0,'No␣
↪internet service':0})
        df['Online Backup'] = df["Online Backup"].map({'Yes':1,'No':0,'No␣
↪internet service':0})
        df['Device Protection'] = df["Device Protection"].map({'Yes':1,'No':
↪0,'No internet service':0})
        df['Tech Support'] = df["Tech Support"].map({'Yes':1,'No':0,'No␣
↪internet service':0})
        df['Streaming TV'] = df["Streaming TV"].map({'Yes':1,'No':0,'No␣
↪internet service':0})
        df['Streaming Movies'] = df["Streaming Movies"].map({'Yes':1,'No':0,'No␣
↪internet service':0})
        df["Monthly Contract"] = df["Contract"].map({'Month-to-month':1, 'Two␣
↪year':0, 'One year':0})
        df["Yearly Contract"] = df["Contract"].map({'Month-to-month':0, 'Two␣
↪year':2, 'One year':1})
        df['Paperless Billing'] = df["Paperless Billing"].map({'Yes':1,'No':0})
        df['IsElectricCheck'] = df["Payment Method"].map({'Electronic check':␣
↪1, 'Bank transfer (automatic)': 0,
                                                            'Credit card␣
↪(automatic)': 0, 'Mailed check': 0})

        # remove some column
        df = df.drop(["CustomerID", "Count","City", "Zip Code", "Country",␣
↪"State", "Lat Long", "Churn Score", "CLTV", "Churn Reason",
                      "Contract", "Payment Method", "Churn Label", "Gender"],␣
↪axis=1)

        # First we convert TotalCharges to float and then replace with tenure *␣
↪monthly charges
        # Convert 'Total Charges' column to numeric with errors set to 'coerce'
```

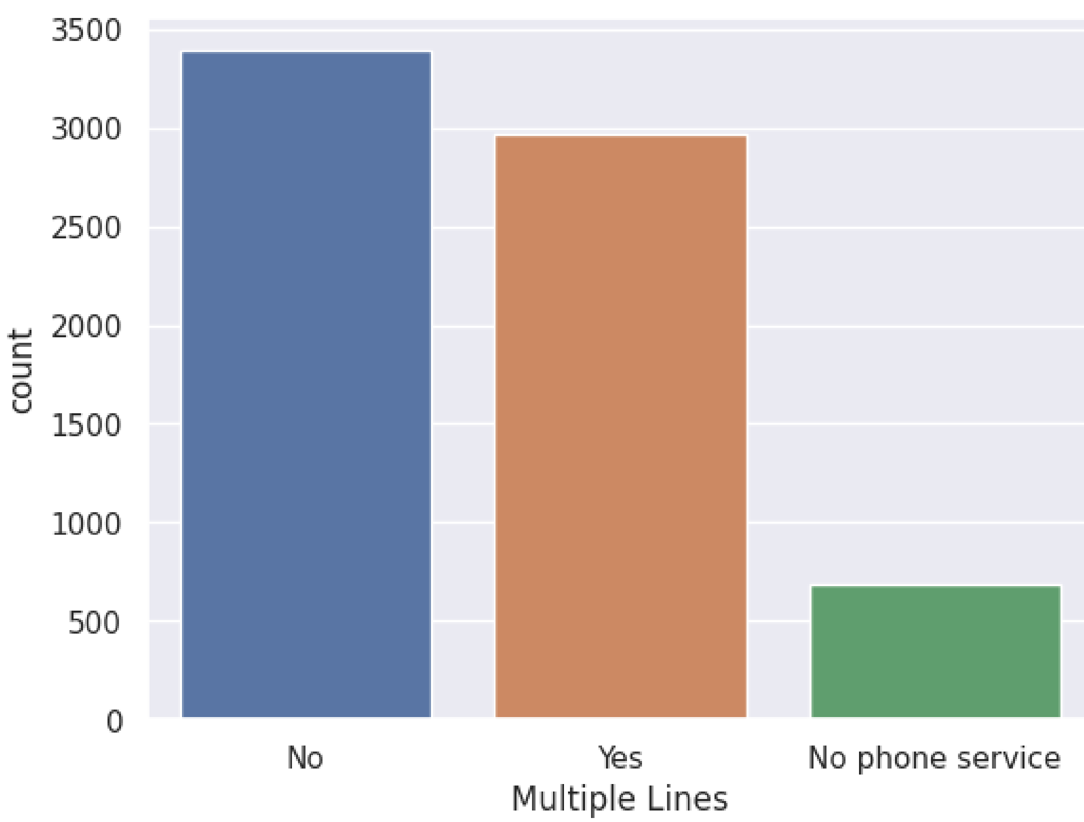
```
        df['Total Charges'] = pd.to_numeric(df['Total Charges'],␣
↪errors='coerce')
        df.loc[df['Total Charges'].isnull()==True,'Total Charges'] =␣
↪df['Monthly Charges'] * df['Tenure Months']

        return df
```

[25]:
```
from sklearn.model_selection import train_test_split

formatDataframe = FormatDataFrame()

# split dataset
train_set, test_set = train_test_split(df_copy, test_size=0.25, random_state=42)
dfse = formatDataframe.fit_transform(train_set)
customer_tr = formatDataframe.fit_transform(train_set)
```

5.1 Service Utilization Analysis:

[26]:
```
sns.countplot(x = 'Multiple Lines',data = df)
```

[26]: <Axes: xlabel='Multiple Lines', ylabel='count'>

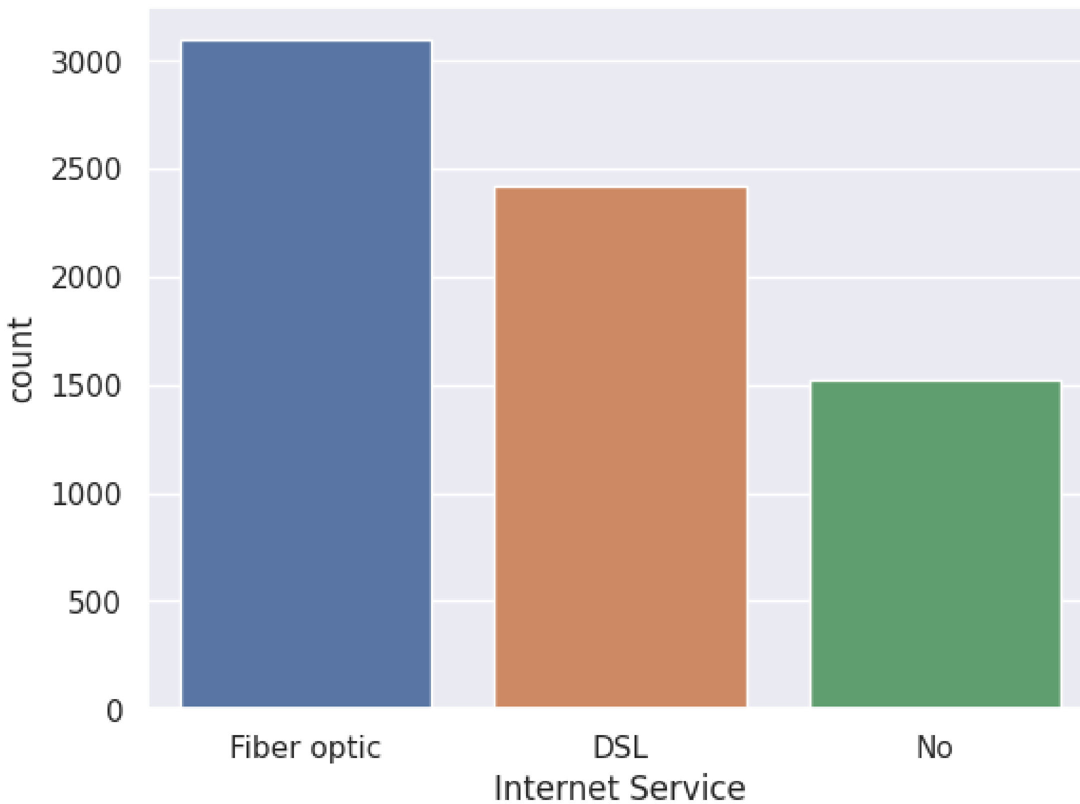


[27]:
```
df[['Multiple Lines', 'Churn Value']].groupby(['Multiple Lines']).mean().
 ↪sort_values('Churn Value',ascending=False)
```

[27]:
```
                  Churn Value
Multiple Lines
Yes                  0.286099
No                   0.250442
No phone service     0.249267
```

[28]:
```
sns.countplot(x = 'Internet Service',data = df,order= df['Internet Service'].
 ↪value_counts().index)
```

[28]: <Axes: xlabel='Internet Service', ylabel='count'>



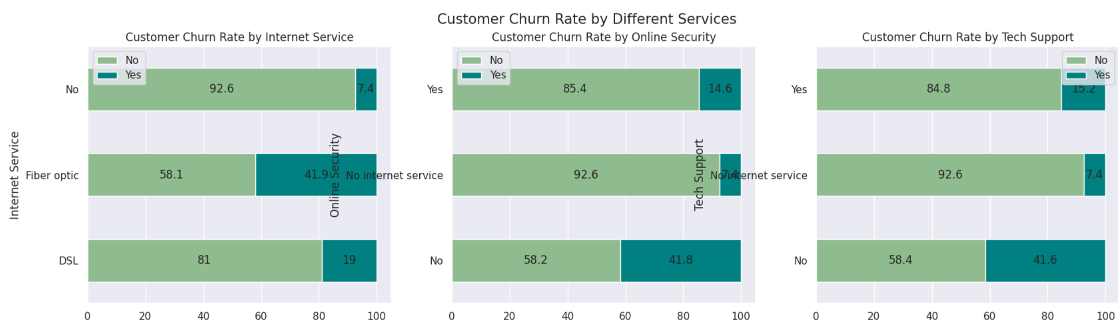
[29]:
```
df[['Internet Service', 'Churn Value']].groupby(['Internet Service']).mean().
 ↪sort_values('Churn Value',ascending=False)
```

[29]:
```
                  Churn Value
Internet Service
```

```
Fiber optic          0.418928
DSL                  0.189591
No                   0.074050
```

Internet service charges lead to dissatisfaction among customers, especially those who have been with the company for a long time.

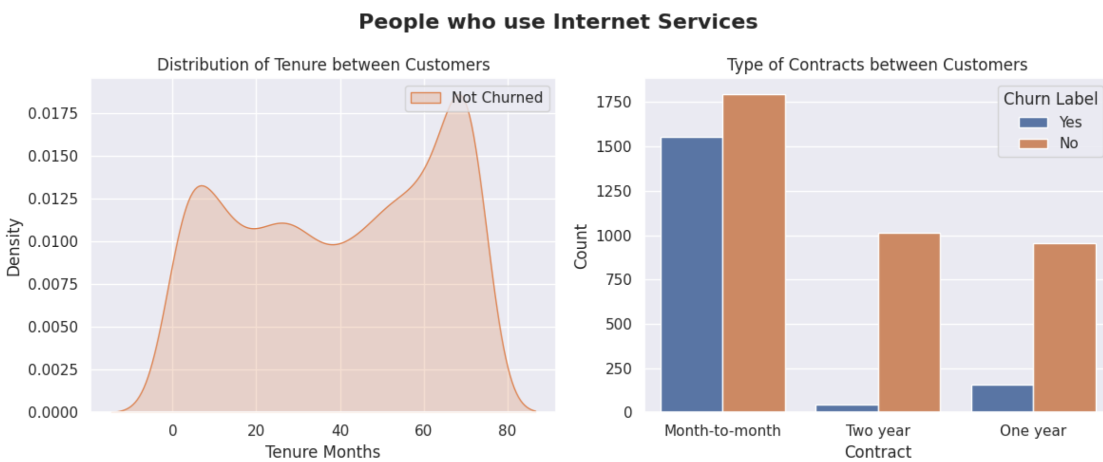
[30]:
```python
fig, ax = plt.subplots(1,3,figsize=(20,5))
fig.suptitle('Customer Churn Rate by Different Services', fontsize=15)

service = ['Internet Service', 'Online Security', 'Tech Support']

for i, col in enumerate(service, start=0):
    df1 = df.groupby([col, 'Churn Label']).size().unstack()
    df1.apply(lambda x : round((x/x.sum())*100,1), axis=1).plot(kind='barh',␣
 ↪stacked=True, color=c, ax=ax[i])
    ax[i].set_title('Customer Churn Rate by {}'.format(col))
    ax[i].legend(loc='best')
    ax[i].grid(axis='y')
    for container in ax[i].containers:
        ax[i].bar_label(container, label_type='center')
```



1. Almost half (41.9%) of customers with fiber-optic internet service have left, which means they are more prone to churn.
2. Customers who do not subscribe to additional online security services tend to churn, as nearly (41.8%) have left, while only 14.6% of customers with additional online security services have left.
3. Almost(41.6%) of customers who don't have a technical support plan have left, compared to just 15.2% of those who have. This means that customers without technical support plan are a greater likelihood to churning.

[32]:
```python
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

churned = df[(df['Internet Service'] == 1) & (customer_tr['Churn Value'] == 1)]
```

```python
not_churned = df[(customer_tr['Internet Service'] == 1) & (df['Churn Value'] ==
    0)]

# 1st subplot: density plot of tenure for churned and non-churned customers who
    use internet service
sns.kdeplot(churned['Tenure Months'], fill=True, label='Churned', ax=axes[0])
sns.kdeplot(not_churned['Tenure Months'], fill=True, label='Not Churned',
    ax=axes[0])
axes[0].set_xlabel('Tenure Months')
axes[0].set_ylabel('Density')
axes[0].set_title('Distribution of Tenure between Customers')
axes[0].legend()

# 2nd subplot: count plot of contracts for customers who use internet service
sns.countplot(data=df[df['Internet Service']!="No"], x='Contract', hue='Churn
    Label', ax=axes[1])
axes[1].set_title('Type of Contracts between Customers')
axes[1].set_xlabel('Contract')
axes[1].set_ylabel('Count')


plt.suptitle('People who use Internet Services', fontsize=16, fontweight='bold')
plt.tight_layout()

plt.show()
```

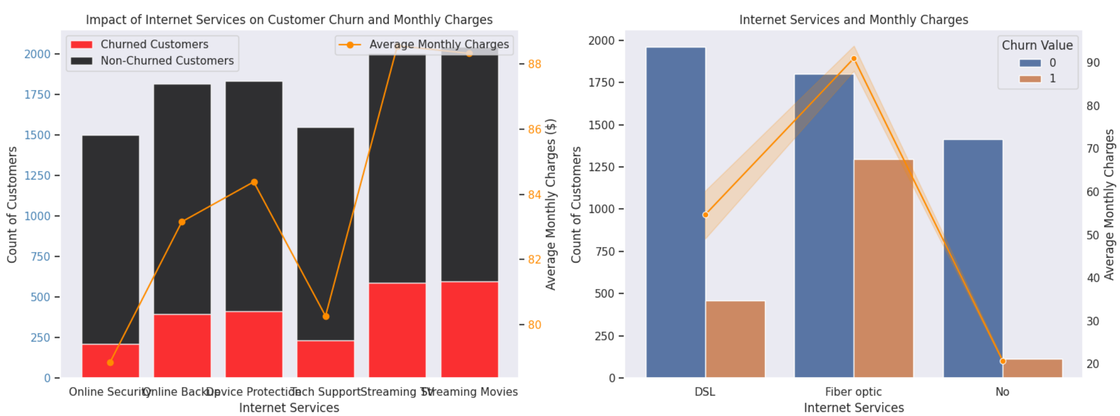


Customers with longer tenure months generally exhibit increased loyalty, showing a propensity to stay with the company. Furthermore, those on a monthly contract are more likely to churn compared to their counterparts on a yearly contract. Additionally, it is noteworthy that customers favor opting for yearly contracts, especially when engaging with certain internet services offered by the company.

[33]:

```python
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

internet_services = ['Online Security', 'Online Backup', 'Device Protection',␣
↪'Tech Support', 'Streaming TV', 'Streaming Movies']
churn_count = [dfse[dfse["Churn Value"]==1][service].sum() for service in␣
↪internet_services]
not_churn_count = [dfse[dfse["Churn Value"]==0][service].sum() for service in␣
↪internet_services]
avg_charges = [dfse[dfse[service]==1]["Monthly Charges"].mean() for service in␣
↪internet_services]

# create a grouped dataframe for counts and average monthly charges
grouped = df.groupby(['Internet Service', 'Churn Value']).agg({'Churn Value':␣
↪'count', 'Monthly Charges': 'mean'})
grouped.columns = ['Count', 'Avg Monthly Charges']
grouped = grouped.reset_index()

# bar chart for counts on left y-axis
axes[0].bar(internet_services, churn_count, color='red', alpha=0.8,␣
↪label='Churned Customers')
axes[0].bar(internet_services, not_churn_count, bottom=churn_count,␣
↪color='black', alpha=0.8, label='Non-Churned Customers')
axes[0].set_ylabel('Count of Customers')
axes[0].tick_params(axis='y', labelcolor='steelblue')

# create twin axes for average charges on right y-axis
ax1 = axes[0].twinx()
ax1.plot(internet_services, avg_charges, marker='o', color='darkorange',␣
↪label='Average Monthly Charges')
ax1.set_ylabel('Average Monthly Charges ($)')
ax1.tick_params(axis='y', labelcolor='darkorange')


axes[0].set_title('Impact of Internet Services on Customer Churn and Monthly␣
↪Charges')
axes[0].set_xlabel('Internet Services')

axes[0].legend(loc='upper left')
ax1.legend(loc='upper right')

axes[0].grid(False)
ax1.grid(False)


sns.barplot(data=grouped, x='Internet Service', y='Count', hue='Churn Value',␣
↪ax=axes[1])
```

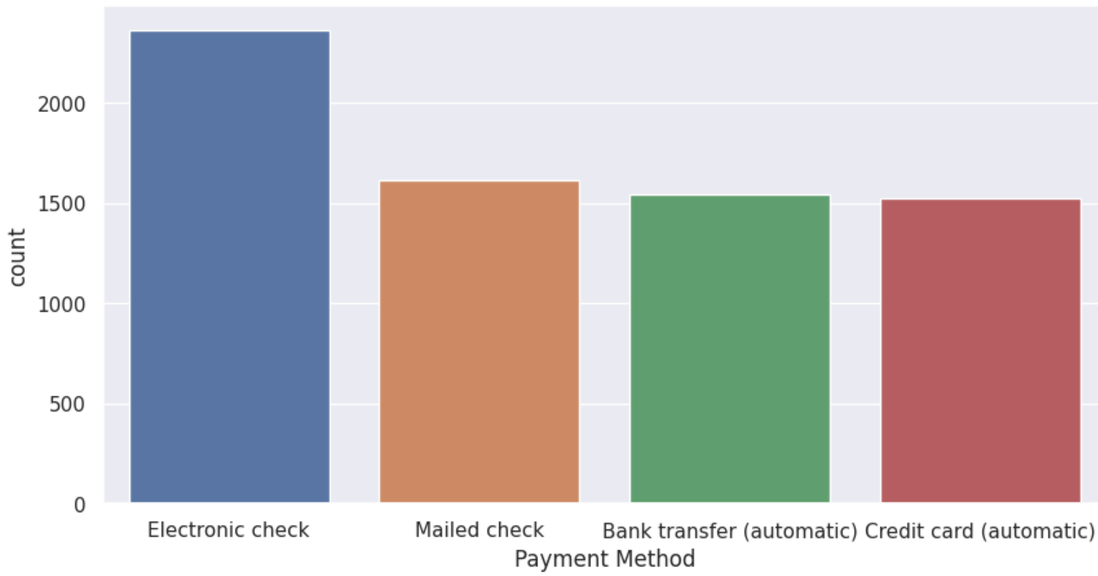
```
axes[1].set_ylabel('Count of Customers')

# create twin axis for average monthly charges
ax2 = axes[1].twinx()
sns.lineplot(data=grouped, x='Internet Service', y='Avg Monthly Charges',␣
↪marker='o', sort=False, ax=ax2, color='darkorange')
ax2.set_ylabel('Average Monthly Charges')

axes[1].set_title('Internet Services and Monthly Charges')
axes[1].set_xlabel('Internet Services')

# remove spines and ticks from right y-axis
ax2.spines['right'].set_visible(False)
ax2.tick_params(axis='y', which='both', length=0)

axes[1].grid(False)
ax2.grid(False)

# adjust layout
plt.tight_layout()

plt.show()
```



1. Online security and tech support are two internet services that customers prefer due to their lower monthly charges compared to other services.
2. Customers tend to choose IsDSL over IsFiberOptics due to its affordability.
3. Similarly the contracts, monthly charges and total charges show the same relationship with the contract. Customers spend mostly on internet services, especially fiber optics, in their monthly charges.

[34]:
```
plt.figure(figsize=(10,5))
sns.countplot(x = 'Payment Method', data = df, order =df['Payment Method'].
↪value_counts().index)
```

[34]: <Axes: xlabel='Payment Method', ylabel='count'>



[35]:
```
df[['Payment Method', 'Churn Value']].groupby(['Payment Method']).mean().
↪sort_values('Churn Value',ascending=False)
```

[35]:
```
                           Churn Value
Payment Method
Electronic check              0.452854
Mailed check                  0.191067
Bank transfer (automatic)     0.167098
Credit card (automatic)       0.152431
```

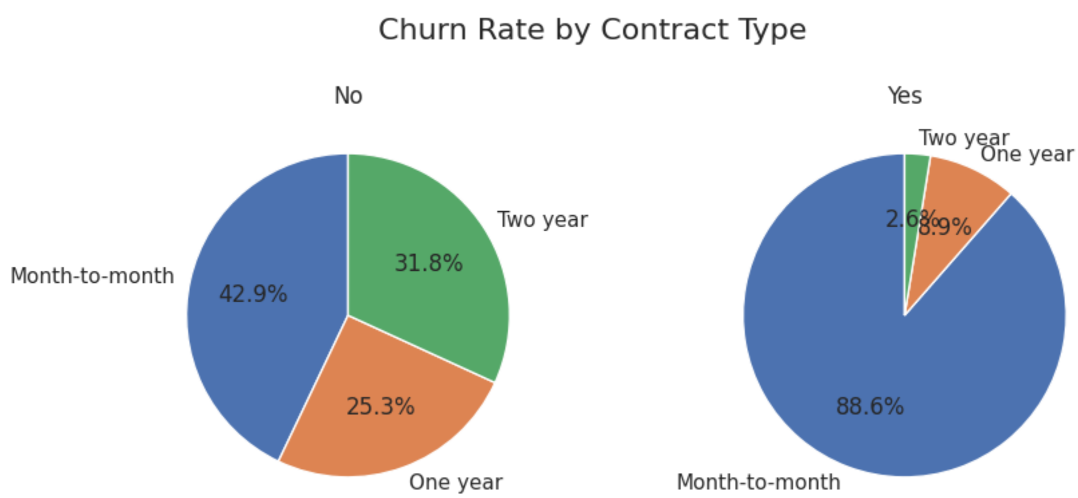
Customers who use electronic checks as a payment method have a higher chance of churning, and the reason for this is not clear.

[36]:
```
df[['Phone Service', 'Churn Value']].groupby(['Phone Service']).mean().
↪sort_values('Churn Value',ascending=False)
```

[36]:
```
               Churn Value
Phone Service
Yes               0.267096
No                0.249267
```

5.2 Contract type

[37]:
```
grouped_data = df.groupby(['Contract', 'Churn Label'])['CustomerID'].count().
↪reset_index()

g = sns.FacetGrid(grouped_data, col='Churn Label', height=4, aspect=1.2)
def draw_pie_chart(*args, **kwargs):
    data = kwargs.pop('data')
    plt.pie(data['CustomerID'], labels=data['Contract'], autopct='%1.1f%%',␣
↪startangle=90)

g.map_dataframe(draw_pie_chart)

g.set_titles(col_template='{col_name}')
g.fig.suptitle('Churn Rate by Contract Type', fontsize=16)
plt.subplots_adjust(top=0.8)

plt.show()
```



Most of the customers (88.6%) who stopped using the service had a Month-to-month contract. This might mean that customers who choose shorter contracts could face fees if they cancel early, or it could be that these are mostly people who wanted to try the service but were not happy with it.

[38]:
```
df.groupby(['Contract','Churn Label'])['Tenure Months'].mean()
```

[38]:
```
Contract        Churn Label
Month-to-month  No             21.033333
                Yes            14.016918
One year        No             41.674063
```

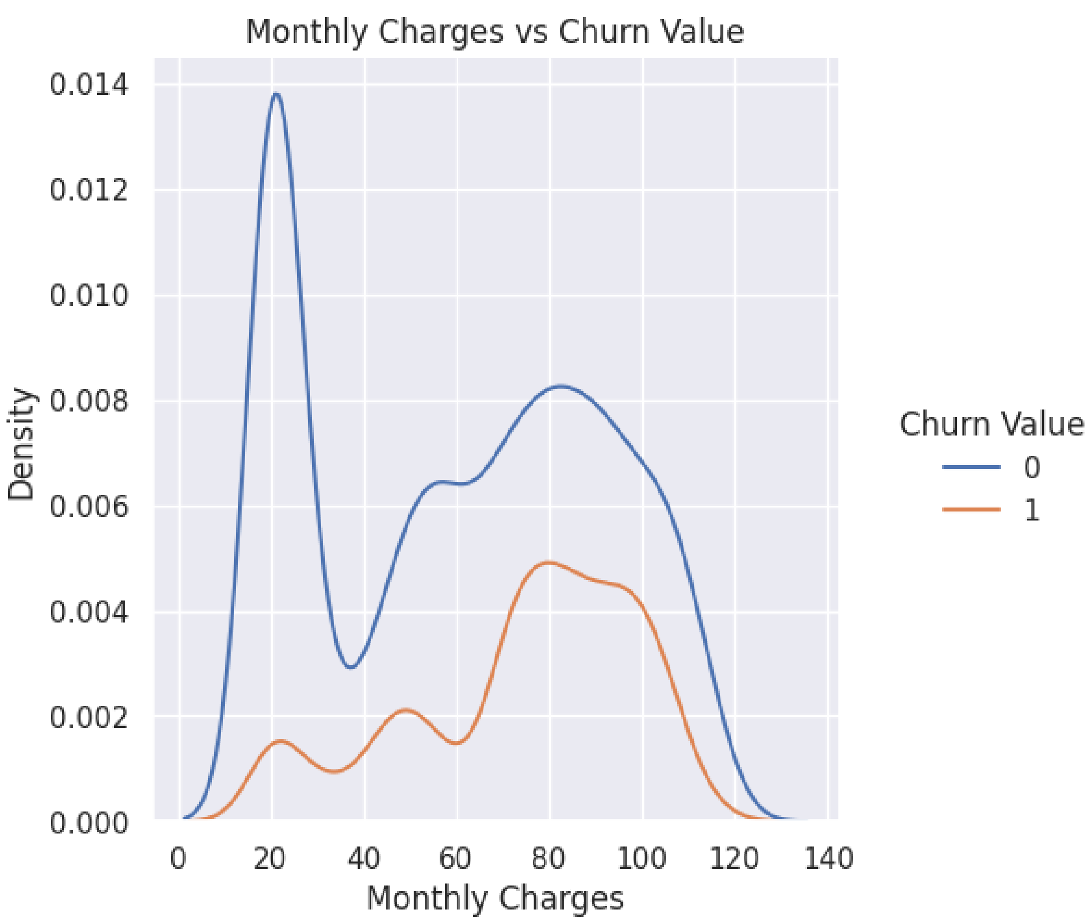
```
                 Yes              44.963855
Two year         No               56.602914
                 Yes              61.270833
Name: Tenure Months, dtype: float64
```

Even for customers who are active in the service, we see the minimum average lifetime in the service for month-to-month contracts. This can be a specific type of contract for certain services, or customers switch to longer types of contracts only after some time of using the service.

5.3 Monthly Charge

[39]:
```
sns.displot(data = df, x= 'Monthly Charges', hue = 'Churn Value', kind = "kde")
plt.title('Monthly Charges vs Churn Value')
```

[39]:
```
Text(0.5, 1.0, 'Monthly Charges vs Churn Value')
```



[40]:
```
df[['Monthly Charges', 'Churn Value', 'Tenure Months']].groupby('Churn Value').
 ↪mean()
```

[40]:

Churn Value	Monthly Charges	Tenure Months
0	61.265124	37.569965
1	74.441332	17.979133

5.4 Remove unimportant columns

[48]:
```
df = df.drop(['Zip Code','Churn Reason','City','Churn Score','Churn␣
 ↪Value','CLTV','CustomerID','Lat Long',
                  'Latitude','Longitude'], axis = 1)
```

[49]:
```
df.to_csv('Teleco-churn-for-training.csv', index=False)
```

Eliminating these columns aids in simplifying the dataset and directing the analysis towards the most crucial features. This can result in more effective and understandable models due to reduced complexity.

[50]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 23 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Count              7043 non-null   int64
 1   Country            7043 non-null   object
 2   State              7043 non-null   object
 3   Gender             7043 non-null   object
 4   Senior Citizen     7043 non-null   object
 5   Partner            7043 non-null   object
 6   Dependents         7043 non-null   object
 7   Tenure Months      7043 non-null   int64
 8   Phone Service      7043 non-null   object
 9   Multiple Lines     7043 non-null   object
 10  Internet Service   7043 non-null   object
 11  Online Security    7043 non-null   object
 12  Online Backup      7043 non-null   object
 13  Device Protection  7043 non-null   object
 14  Tech Support       7043 non-null   object
 15  Streaming TV       7043 non-null   object
 16  Streaming Movies   7043 non-null   object
 17  Contract           7043 non-null   object
 18  Paperless Billing  7043 non-null   object
 19  Payment Method     7043 non-null   object
```

```
 20  Monthly Charges    7043 non-null   float64
 21  Total Charges      7043 non-null   object
 22  Churn Label        7043 non-null   object
dtypes: float64(1), int64(2), object(20)
memory usage: 1.2+ MB
```

[51]:
```
df.shape
```

[51]:
```
(7043, 23)
```

[52]:
```
df.head(5)
```

[52]:
```
   Count        Country       State  Gender Senior Citizen Partner Dependents  \
0      1  United States  California    Male             No      No         No
1      1  United States  California  Female             No      No        Yes
2      1  United States  California  Female             No      No        Yes
3      1  United States  California  Female             No     Yes        Yes
4      1  United States  California    Male             No      No        Yes

   Tenure Months Phone Service Multiple Lines  … Device Protection  \
0              2           Yes             No  …                No
1              2           Yes             No  …                No
2              8           Yes            Yes  …               Yes
3             28           Yes            Yes  …               Yes
4             49           Yes            Yes  …               Yes

  Tech Support Streaming TV Streaming Movies        Contract  \
0           No           No               No  Month-to-month
1           No           No               No  Month-to-month
2           No          Yes              Yes  Month-to-month
3          Yes          Yes              Yes  Month-to-month
4           No          Yes              Yes  Month-to-month

  Paperless Billing             Payment Method Monthly Charges Total Charges  \
0               Yes               Mailed check           53.85        108.15
1               Yes           Electronic check           70.70        151.65
2               Yes           Electronic check           99.65         820.5
3               Yes           Electronic check          104.80       3046.05
4               Yes  Bank transfer (automatic)          103.70        5036.3

  Churn Label
0         Yes
1         Yes
2         Yes
3         Yes
4         Yes
```

[5 rows x 23 columns]

5.5 Convert categorical values into numeric

[53]:
```
df['Churn Label'].replace(to_replace='Yes', value=1, inplace=True)
df['Churn Label'].replace(to_replace='No',  value=0, inplace=True)
```

[54]:
```
from sklearn.preprocessing import LabelEncoder

def encode_data(dataframe_series):
    if dataframe_series.dtype == 'object':
        return LabelEncoder().fit_transform(dataframe_series.astype(str))
    elif dataframe_series.dtype in ['float64', 'int64']:
        return dataframe_series
    else:
        raise ValueError(f"Unsupported data type: {dataframe_series.dtype}")

df = df.apply(encode_data)
df.head(5)
```

[54]:
```
   Count  Country  State  Gender  Senior Citizen  Partner  Dependents  \
0      1        0      0       1               0        0           0
1      1        0      0       0               0        0           1
2      1        0      0       0               0        0           1
3      1        0      0       0               0        1           1
4      1        0      0       1               0        0           1

   Tenure Months  Phone Service  Multiple Lines  …  Device Protection  \
0              2              1               0  …                  0
1              2              1               0  …                  0
2              8              1               2  …                  2
3             28              1               2  …                  2
4             49              1               2  …                  2

   Tech Support  Streaming TV  Streaming Movies  Contract  Paperless Billing  \
0             0             0                 0         0                  1
1             0             0                 0         0                  1
2             0             2                 2         0                  1
3             2             2                 2         0                  1
4             0             2                 2         0                  1

   Payment Method  Monthly Charges  Total Charges  Churn Label
0               3            53.85            157            1
1               2            70.70            925            1
2               2            99.65           6104            1
3               2           104.80           2646            1
4               0           103.70           4265            1
```

```
[5 rows x 23 columns]
```

This is crucial because many machine learning algorithms require numeric input data. By converting categorical data into numeric form, we make the dataset suitable for training and evaluating machine learning models.

SMOTE is a technique used in machine learning and data mining to address the class imbalance problem, particularly in classification tasks.

[55]:
```
from imblearn.over_sampling import SMOTE
over = SMOTE(sampling_strategy = 1)

x = df.drop("Churn Label", axis = 1).values
y = df['Churn Label'].values
```

5.6 Model Building and Validation:

Through our comprehensive exploratory analysis, we have meticulously explored a wide range of machine learning models, categorizing them into two clear groups: classification and regression.

[56]:
```
x,y = over.fit_resample(x,y)
```

[57]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state =2,␣
↪test_size = 0.2)
```

5.7 Classification models

[58]:
```
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_squared_error, confusion_matrix,␣
↪roc_auc_score, accuracy_score, classification_report
import seaborn as sns
import numpy as np

def model(method, x_train, y_train, x_test, y_test):
    # Train the model
    method.fit(x_train, y_train)

    # Make predictions on test data and calculate confusion matrix
    predictions = method.predict(x_test)
    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    c_matrix = confusion_matrix(y_test, predictions)

    # Calculate label percentages and create label strings with counts and␣
↪percentages
```

```
    percentages = (c_matrix / np.sum(c_matrix, axis=1)[:, np.newaxis]).round(2)␣
↪* 100
    labels = [[f"{c_matrix[i, j]} ({percentages[i, j]:.2f}%)" for j in␣
↪range(c_matrix.shape[1])] for i in range(c_matrix.shape[0])]
    labels = np.asarray(labels)

    # Plot confusion matrix with labeled counts and percentages
    sns.heatmap(c_matrix, annot=labels, fmt='', cmap='Blues')

    # Evaluate model performance and print results
    print("RMSE:", rmse)
    print("ROC AUC: ", '{:.2%}'.format(roc_auc_score(y_test, predictions)))
    print("Model accuracy: ", '{:.2%}'.format(accuracy_score(y_test,␣
↪predictions)))
    print(classification_report(y_test, predictions))
```

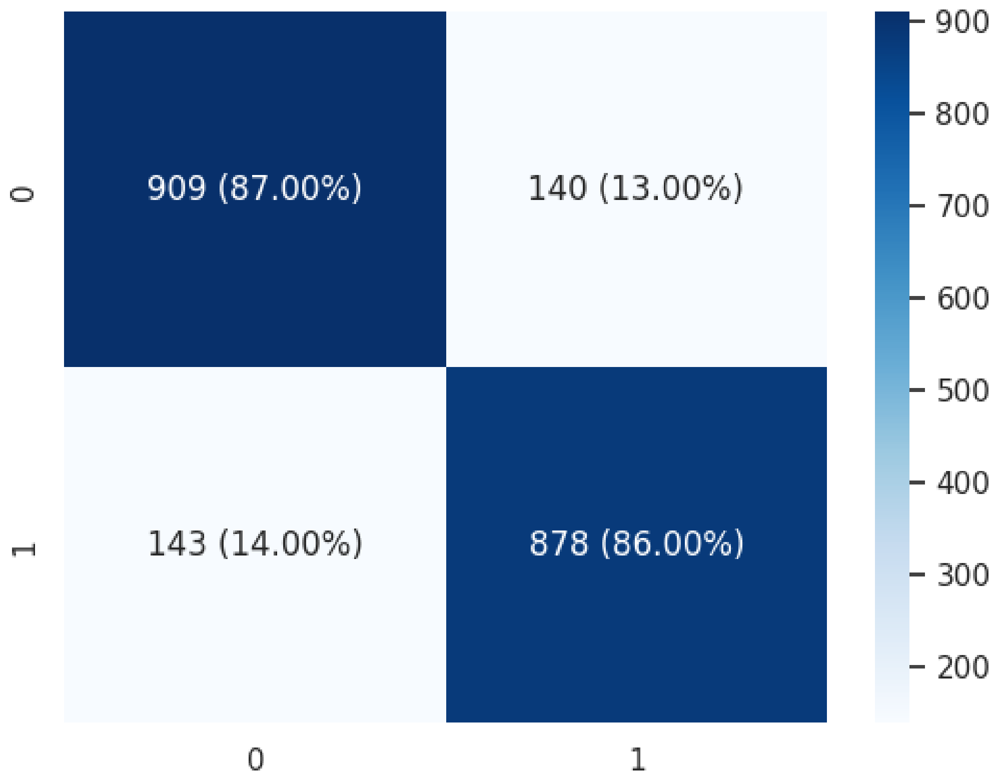
[59]:
```
xgb = XGBClassifier(learning_rate= 0.01,max_depth = 6,n_estimators = 1000)
rf = RandomForestClassifier()
dt = DecisionTreeClassifier(max_depth=15)
```

5.8 Model Evaluation:

5.9 XGBClassifier Classification

[60]:
```
model(xgb,x_train,y_train,x_test,y_test)
```

```
RMSE: 0.3697498828200093
ROC AUC:  86.32%
Model accuracy:  86.33%
              precision    recall  f1-score   support

           0       0.86      0.87      0.87      1049
           1       0.86      0.86      0.86      1021

    accuracy                           0.86      2070
   macro avg       0.86      0.86      0.86      2070
weighted avg       0.86      0.86      0.86      2070
```



The confusion matrix shows that the XGB model performed very well, with an accuracy of 87%. This means that 87% of the examples were correctly classified.

provided metrics describe the performance of a XGBclassification model. Here's a breakdown of each metric:

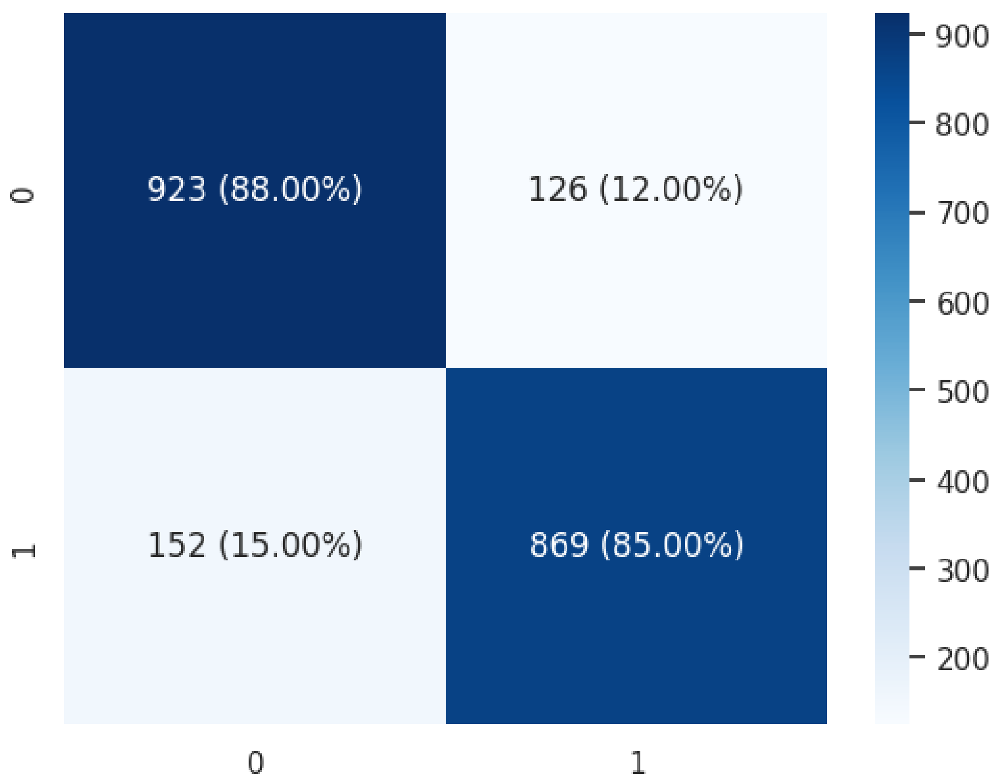
```
RMSE (Root Mean Squared Error): RMSE is a measure of the difference between the predicted valu

ROC AUC (Receiver Operating Characteristic Area Under the Curve): ROC AUC is a measure of the a

Model accuracy: Model accuracy is the proportion of correct predictions made by the model. In t

Precision: Precision is the proportion of positive predictions that are actually correct. In th

Recall: Recall is the proportion of actual positives that are correctly identified as such. In

F1-score: The F1-score is a harmonic mean of precision and recall. It is a measure of the overa
```

Overall, the provided metrics indicate that the model is performing well on this classification task. It has high accuracy, precision, recall, and AUC, and a relatively low RMSE.

6 Random Forest Classifier

[65]:
```
model(rf,x_train,y_train,x_test,y_test)
```

```
RMSE: 0.3664689849198873
ROC AUC:  86.55%
Model accuracy:  86.57%
              precision    recall  f1-score   support

           0       0.86      0.88      0.87      1049
           1       0.87      0.85      0.86      1021

    accuracy                           0.87      2070
   macro avg       0.87      0.87      0.87      2070
weighted avg       0.87      0.87      0.87      2070
```

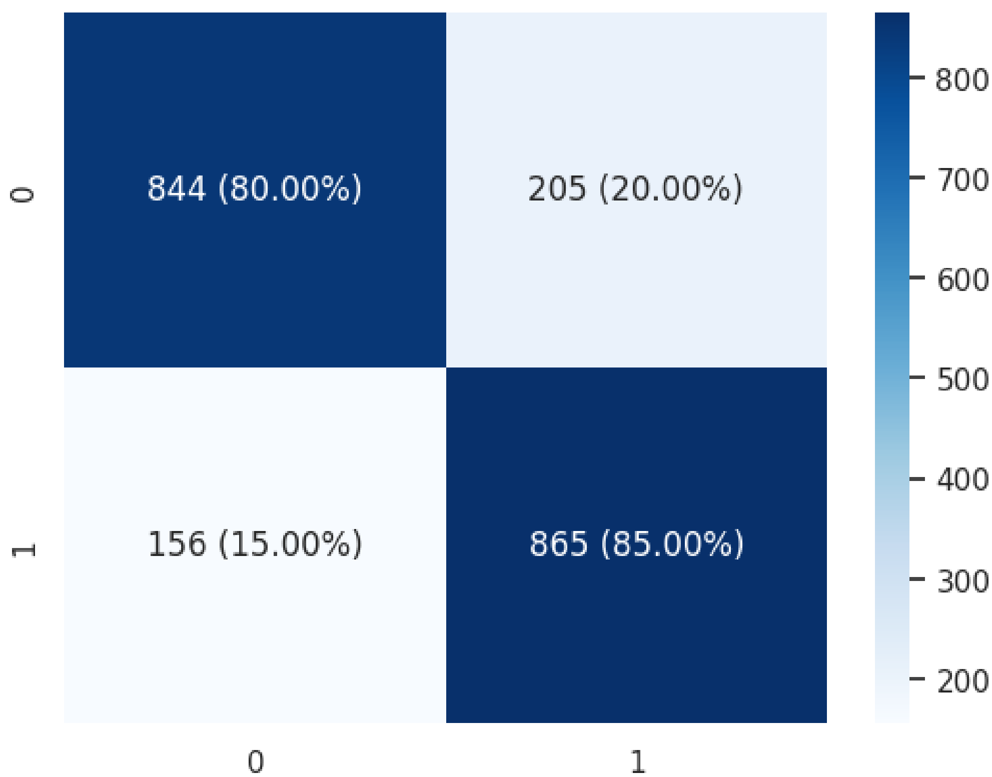


This model shows that the random forest classifier performed well, with an accuracy of 86.43%. This means that 86.43% of the examples were correctly classified. The model was particularly good at classifying the positive class, with an accuracy of 88%. However, the model made more mistakes on the negative class, with an accuracy of 85%.

6.1 Decision Tree Classifier

[66]:
```
model(dt,x_train,y_train,x_test,y_test)
```

```
RMSE: 0.41760763315066507
ROC AUC:  82.59%
Model accuracy:  82.56%
              precision    recall  f1-score   support

           0       0.84      0.80      0.82      1049
           1       0.81      0.85      0.83      1021

    accuracy                           0.83      2070
   macro avg       0.83      0.83      0.83      2070
weighted avg       0.83      0.83      0.83      2070
```



Overall, the provided metrics indicate that the model is performing fairly well on this classification task. It has acceptable accuracy, precision, recall, and AUC, and a moderate RMSE. However, when compared to the previous results, there is a slight decrease in most of the metrics, indicating that there is some room for improvement.

6.2 Regression models

[63]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, mean_absolute_error, mean_squared_error

lr = LogisticRegression(solver='liblinear', max_iter=1000)
lr.fit(x_train, y_train)
lr_predictions = lr.predict(x_test)

# Calculate metrics for the Logistic Regression model
lr_mae = mean_absolute_error(y_test, lr_predictions)
lr_rmse = np.sqrt(mean_squared_error(y_test, lr_predictions))
print("Logistic Regression:")
print(f'Mean Absolute Error (MAE): {lr_mae}')
print(f'Root Mean Squared Error (RMSE): {lr_rmse}')

# Create and fit a Gradient Boosting Regression model
gbm = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,␣
 ↪max_depth=3, random_state=42)
gbm.fit(x_train, y_train)
gbm_predictions = gbm.predict(x_test)

# Calculate metrics for the Gradient Boosting Regression model
gbm_mae = mean_absolute_error(y_test, gbm_predictions)
gbm_rmse = np.sqrt(mean_squared_error(y_test, gbm_predictions))
print("\nGradient Boosting Regression:")
print(f'Mean Absolute Error (MAE): {gbm_mae}')
print(f'Root Mean Squared Error (RMSE): {gbm_rmse}')
```

```
Logistic Regression:
Mean Absolute Error (MAE): 0.2222222222222222
Root Mean Squared Error (RMSE): 0.4714045207910317

Gradient Boosting Regression:
Mean Absolute Error (MAE): 0.22130740382870626
Root Mean Squared Error (RMSE): 0.3108165883603176
```

In the provided context, the lower the MAE and RMSE values, the better the model is at predicting the actual values. Based on the provided values, the Gradient Boosting Regression model performs slightly better than the Logistic Regression model, as it has lower MAE and RMSE values.

6.3 Generate Pdf File

[77]:
```python
!pip install -q nbconvert
```

[74]:
```
!pwd
```

```
/content/drive/MyDrive/Colab Notebooks
```

[ ]:
```

```

[80]:
```
!jupyter nbconvert --to pdf ProgrammingHero.ipynb
```

```
[NbConvertApp] Converting notebook ProgrammingHero.ipynb to pdf
/usr/local/lib/python3.10/dist-packages/nbconvert/filters/datatypefilter.py:41:
UserWarning: Your element with mimetype(s) dict_keys(['text/html']) is not able
to be represented.
  warn(
/usr/local/lib/python3.10/dist-packages/nbconvert/filters/datatypefilter.py:41:
UserWarning: Your element with mimetype(s) dict_keys(['text/html']) is not able
to be represented.
  warn(
[NbConvertApp] Support files will be in ProgrammingHero_files/
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
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[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Making directory ./ProgrammingHero_files
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[NbConvertApp] Making directory ./ProgrammingHero_files
[NbConvertApp] Writing 329536 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 848799 bytes to ProgrammingHero.pdf
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[ ]:
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