customer-churn-IBM-dataset(Predictive Model)

April 5, 2025

1 Introduction

2 Telco Customer Churn Analysis: IBM Dataset

This project analyzes customer churn data from a fictional telecommunications company that provided home phone and Internet services to 7,043 customers in California during Q3.Also this project creates a predictive model which predicts chances of customer churn.Conducted in a Jupyter Notebook, the project involves scoping, cleaning, analyzing, and visualizing the data to uncover underlying trends and then using it for Predictive ML model.

Through exploratory data analysis—using correlation matrices, chi-square tests, and other statistical methods—we seek to answer key questions, including:
- What is the most popular reason for customers canceling their subscription?
- When do cancellations most commonly occur?
- Are the correlations between these factors statistically significant?
- How do monthly charges affect the overall duration of subscriptions?
- How does the type of subscription contract influence churn? - Whats is the most common month to cancel the subscription?

Additional questions and insights will also be addressed as part of this comprehensive analysis.

Data sources:

`Telco_customer_churn.xlsx` was provided by **IBM** This dataset is detailed in: https://community.ibm.com/community/user/businessanalytics/blogs/steven-macko/2019/07/11/telco-customer-churn-1113

Downloaded from: https://community.ibm.com/accelerators/?context=analytics&query=telco%20churn&type=D

The data for this project is *inspired* by real data.

2.1 Import Python Modules

Here are the primary modules that will be used in this project:

[581]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
import plotly.express as px
import scipy.stats as stats
```

```python
import statsmodels.api as sm
%matplotlib inline
```

2.2 Getting data to know

Data Description 7043 observations with 33 variables

CustomerID: A unique ID that identifies each customer.

Count: A value used in reporting/dashboarding to sum up the number of customers in a filtered set.

Country: The country of the customer's primary residence.

State: The state of the customer's primary residence.

City: The city of the customer's primary residence.

Zip Code: The zip code of the customer's primary residence.

Lat Long: The combined latitude and longitude of the customer's primary residence.

Latitude: The latitude of the customer's primary residence.

Longitude: The longitude of the customer's primary residence.

Gender: The customer's gender: Male, Female

Senior Citizen: Indicates if the customer is 65 or older: Yes, No

Partner: Indicate if the customer has a partner: Yes, No

Dependents: Indicates if the customer lives with any dependents: Yes, No. Dependents could be children, parents, grandparents, etc.

Tenure Months: Indicates the total amount of months that the customer has been with the company by the end of the quarter specified above.

Phone Service: Indicates if the customer subscribes to home phone service with the company: Yes, No

Multiple Lines: Indicates if the customer subscribes to multiple telephone lines with the company: Yes, No

Internet Service: Indicates if the customer subscribes to Internet service with the company: No, DSL, Fiber Optic, Cable.

Online Security: Indicates if the customer subscribes to an additional online security service provided by the company: Yes, No

Online Backup: Indicates if the customer subscribes to an additional online backup service provided by the company: Yes, No

Device Protection: Indicates if the customer subscribes to an additional device protection plan for their Internet equipment provided by the company: Yes, No

Tech Support: Indicates if the customer subscribes to an additional technical support plan from the company with reduced wait times: Yes, No

Streaming TV: Indicates if the customer uses their Internet service to stream television programing from a third party provider: Yes, No. The company does not charge an additional fee for this service.

Streaming Movies: Indicates if the customer uses their Internet service to stream movies from a third party provider: Yes, No. The company does not charge an additional fee for this service.

Contract: Indicates the customer's current contract type: Month-to-Month, One Year, Two Year.

Paperless Billing: Indicates if the customer has chosen paperless billing: Yes, No

Payment Method: Indicates how the customer pays their bill: Bank Withdrawal, Credit Card, Mailed Check

Monthly Charge: Indicates the customer's current total monthly charge for all their services from the company.

Total Charges: Indicates the customer's total charges, calculated to the end of the quarter specified above.

Churn Label: Yes = the customer left the company this quarter. No = the customer remained with the company. Directly related to Churn Value.

Churn Value: 1 = the customer left the company this quarter. 0 = the customer remained with the company. Directly related to Churn Label.

Churn Score: A value from 0-100 that is calculated using the predictive tool IBM SPSS Modeler. The model incorporates multiple factors known to cause churn. The higher the score, the more likely the customer will churn.

CLTV: Customer Lifetime Value. A predicted CLTV is calculated using corporate formulas and existing data. The higher the value, the more valuable the customer. High value customers should be monitored for churn.

Churn Reason: A customer's specific reason for leaving the company. Directly related to Churn Category.

[585]:
```python
db=pd.read_excel('Telco_customer_churn.xlsx')
db
```

[585]:
```
      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
2     9305-CDSKC      1  United States  California    Los Angeles     90006
3     7892-POOKP      1  United States  California    Los Angeles     90010
4     0280-XJGEX      1  United States  California    Los Angeles     90015
…            …      …              …           …              …         …
7038  2569-WGERO      1  United States  California        Landers     92285
7039  6840-RESVB      1  United States  California       Adelanto     92301
7040  2234-XADUH      1  United States  California          Amboy     92304
7041  4801-JZAZL      1  United States  California   Angelus Oaks     92305
7042  3186-AJIEK      1  United States  California  Apple Valley     92308
```

```
                    Lat Long   Latitude   Longitude  Gender  …  \
0     33.964131, -118.272783  33.964131 -118.272783    Male  …
1      34.059281, -118.30742  34.059281 -118.307420  Female  …
2     34.048013, -118.293953  34.048013 -118.293953  Female  …
3     34.062125, -118.315709  34.062125 -118.315709  Female  …
4     34.039224, -118.266293  34.039224 -118.266293    Male  …
…                        …          …           …     …  …
7038  34.341737, -116.539416  34.341737 -116.539416  Female  …
7039  34.667815, -117.536183  34.667815 -117.536183    Male  …
7040  34.559882, -115.637164  34.559882 -115.637164  Female  …
7041     34.1678, -116.86433  34.167800 -116.864330  Female  …
7042  34.424926, -117.184503  34.424926 -117.184503    Male  …

            Contract Paperless Billing             Payment Method  \
0     Month-to-month               Yes               Mailed check
1     Month-to-month               Yes           Electronic check
2     Month-to-month               Yes           Electronic check
3     Month-to-month               Yes           Electronic check
4     Month-to-month               Yes  Bank transfer (automatic)
…                …               …                          …
7038        Two year               Yes  Bank transfer (automatic)
7039        One year               Yes               Mailed check
7040        One year               Yes    Credit card (automatic)
7041  Month-to-month               Yes           Electronic check
7042        Two year               Yes  Bank transfer (automatic)

      Monthly Charges Total Charges Churn Label Churn Value Churn Score  CLTV  \
0               53.85        108.15         Yes           1          86  3239
1               70.70        151.65         Yes           1          67  2701
2               99.65         820.5         Yes           1          86  5372
3              104.80       3046.05         Yes           1          84  5003
4              103.70        5036.3         Yes           1          89  5340
…                 …           …           …           …           …   …
7038            21.15        1419.4          No           0          45  5306
7039            84.80        1990.5          No           0          59  2140
7040           103.20        7362.9          No           0          71  5560
7041            29.60        346.45          No           0          59  2793
7042           105.65        6844.5          No           0          38  5097

                       Churn Reason
0      Competitor made better offer
1                             Moved
2                             Moved
3                             Moved
4     Competitor had better devices
…                               …
7038                            NaN
```

```
7039                               NaN
7040                               NaN
7041                               NaN
7042                               NaN

[7043 rows x 33 columns]
```

Check for Null variables

[588]:
```
db.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
```

Data Cleanning and Preprocessing

[591]:
```
db.isnull().sum()
```

[591]:
```
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
```

So only data missing is in **Churn Reason** which tells us that 5174 kept their subscription while the rest didn't.

So,let's start with data tidying. I will check some columns in the table that in our case can be irrelevant and take them out of dataframe.

[595]:
```
db['Count'].value_counts()
```

[595]:
```
Count
1    7043
Name: count, dtype: int64
```

[597]:
```
db=db.drop(columns='Count')
```

[599]:
```
db['Country'].unique()
```

[599]:
```
array(['United States'], dtype=object)
```

So each customer is from US which makes this column not important in our analysis so i drop it

[602]:
```
db=db.drop(columns='Country')
```

[604]:
```
db['State'].unique()
```

[604]:
```
array(['California'], dtype=object)
```

Same thing drop it

[607]:
```
db=db.drop(columns='State')
```

[609]:
```
db['Senior Citizen'].unique()
```

[609]:
```
array(['No', 'Yes'], dtype=object)
```

[611]:
```
db['Total Charges'].unique()
print(db['Total Charges'].unique())
unique_values = db['Total Charges'].unique()
```

```
[108.15 151.65 820.5 … 7362.9 346.45 6844.5]
```

[613]:
```
# Convert 'Total Charges' to numeric, errors='coerce' will turn non-numeric␣
↪values into NaN
db['Total Charges'] = pd.to_numeric(db['Total Charges'], errors='coerce')

# Handle missing values in Total Charges (NaNs)
db['Total Charges'] = db['Total Charges'].fillna(db['Total Charges'].median())
```

Finally,we can see all possible reasons for subscription cancellation

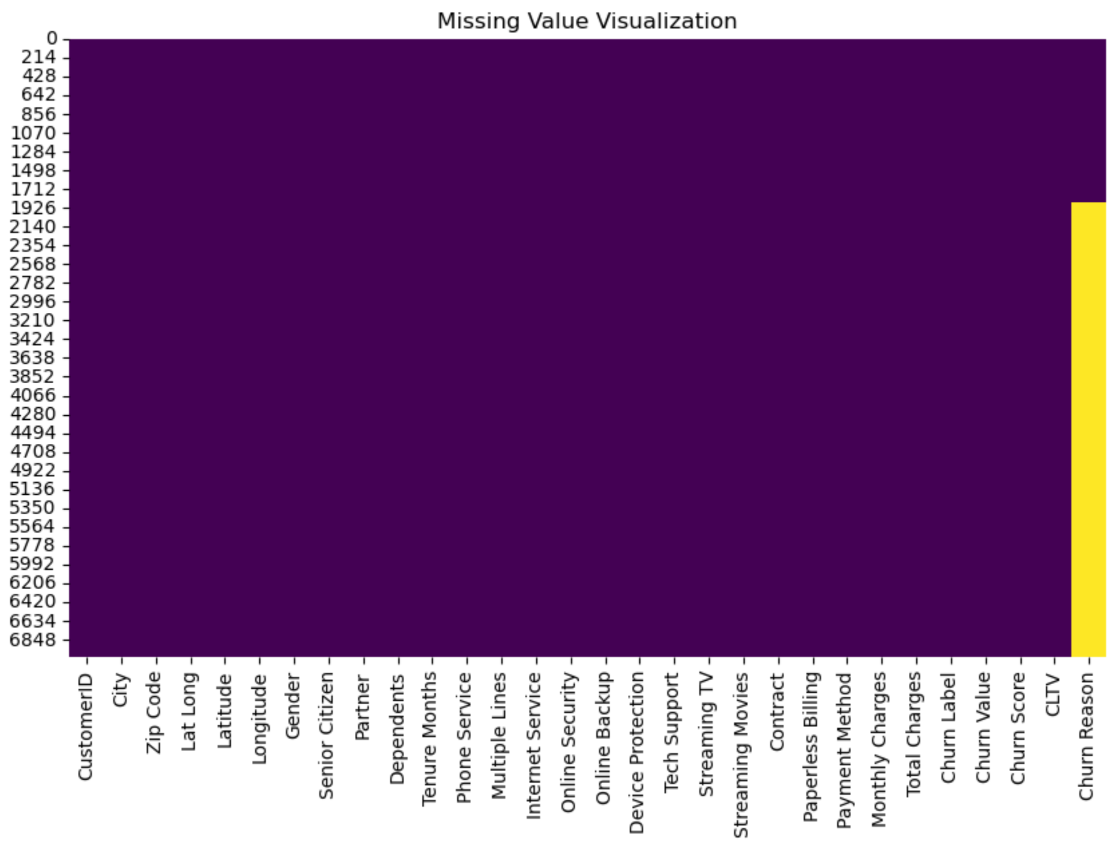
[616]:
```
db["Churn Reason"].unique()
```

[616]:
```
array(['Competitor made better offer', 'Moved',
       'Competitor had better devices',
       'Competitor offered higher download speeds',
       'Competitor offered more data', 'Price too high',
       'Product dissatisfaction', 'Service dissatisfaction',
```

```
'Lack of self-service on Website', 'Network reliability',
'Limited range of services',
'Lack of affordable download/upload speed',
'Long distance charges', 'Extra data charges', "Don't know",
'Poor expertise of online support',
'Poor expertise of phone support', 'Attitude of service provider',
'Attitude of support person', 'Deceased', nan], dtype=object)
```

Now,I will create visualization of missing data,just to make point visible with which types of data I will work

[619]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(db.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Value Visualization')
plt.show()
```



Quickly understanding the distribution and central characteristics of this data

[622]:
```
db.describe()
```

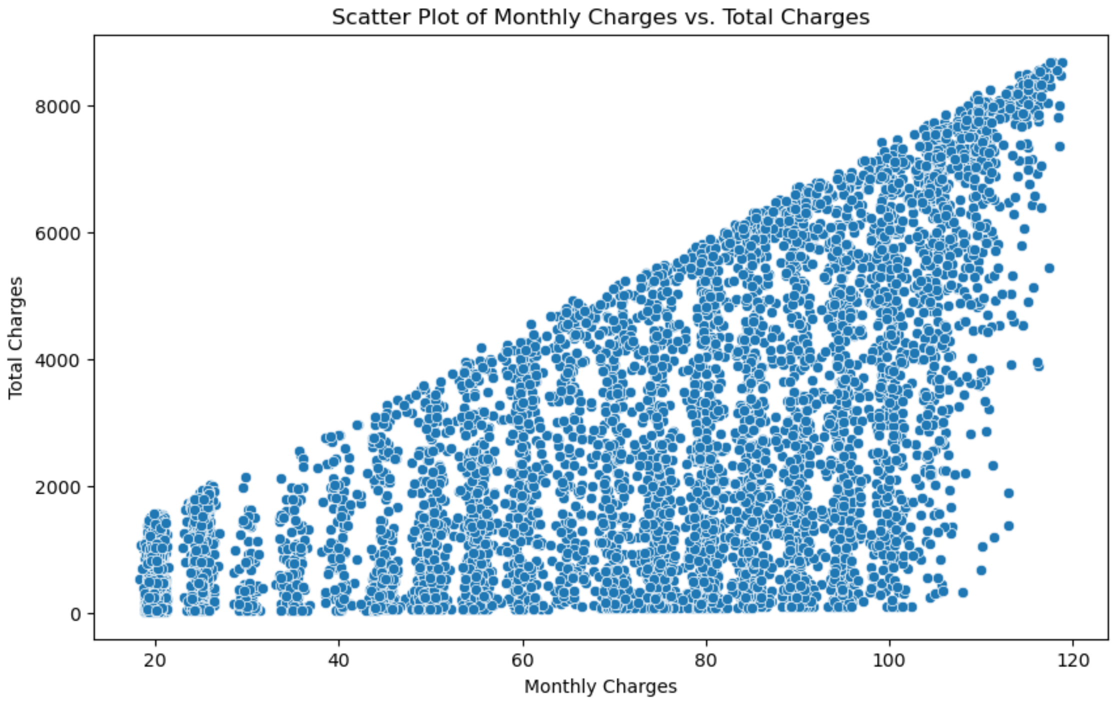
[622]:

	Zip Code	Latitude	Longitude	Tenure Months	Monthly Charges
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000
mean	93521.964646	36.282441	-119.798880	32.371149	64.761692
std	1865.794555	2.455723	2.157889	24.559481	30.090047
min	90001.000000	32.555828	-124.301372	0.000000	18.250000
25%	92102.000000	34.030915	-121.815412	9.000000	35.500000
50%	93552.000000	36.391777	-119.730885	29.000000	70.350000
75%	95351.000000	38.224869	-118.043237	55.000000	89.850000
max	96161.000000	41.962127	-114.192901	72.000000	118.750000

	Total Charges	Churn Value	Churn Score	CLTV
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	2281.916928	0.265370	58.699418	4400.295755
std	2265.270398	0.441561	21.525131	1183.057152
min	18.800000	0.000000	5.000000	2003.000000
25%	402.225000	0.000000	40.000000	3469.000000
50%	1397.475000	0.000000	61.000000	4527.000000
75%	3786.600000	1.000000	75.000000	5380.500000
max	8684.800000	1.000000	100.000000	6500.000000

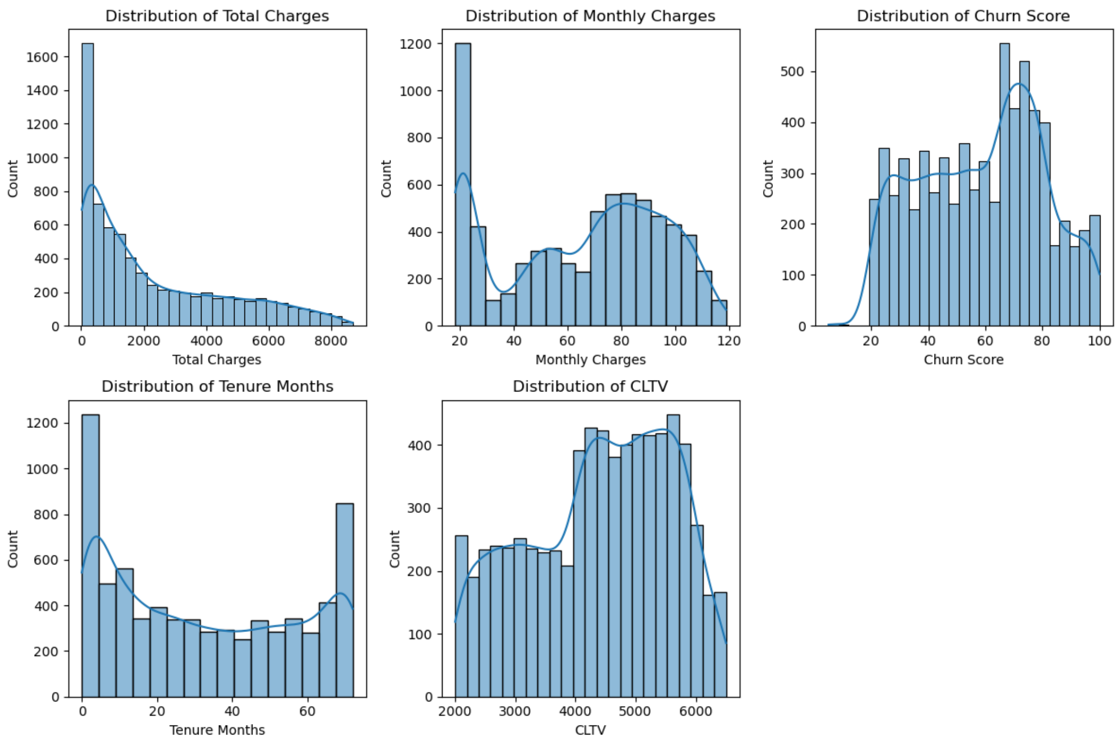
I want to check scatter plot of monthly charges and total charges how does it look like

[625]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Monthly Charges', y='Total Charges', data=db)
plt.title('Scatter Plot of Monthly Charges vs. Total Charges')
plt.xlabel('Monthly Charges')
plt.ylabel('Total Charges')
plt.show()
```



I want to check all kinds of different distributions using histograms

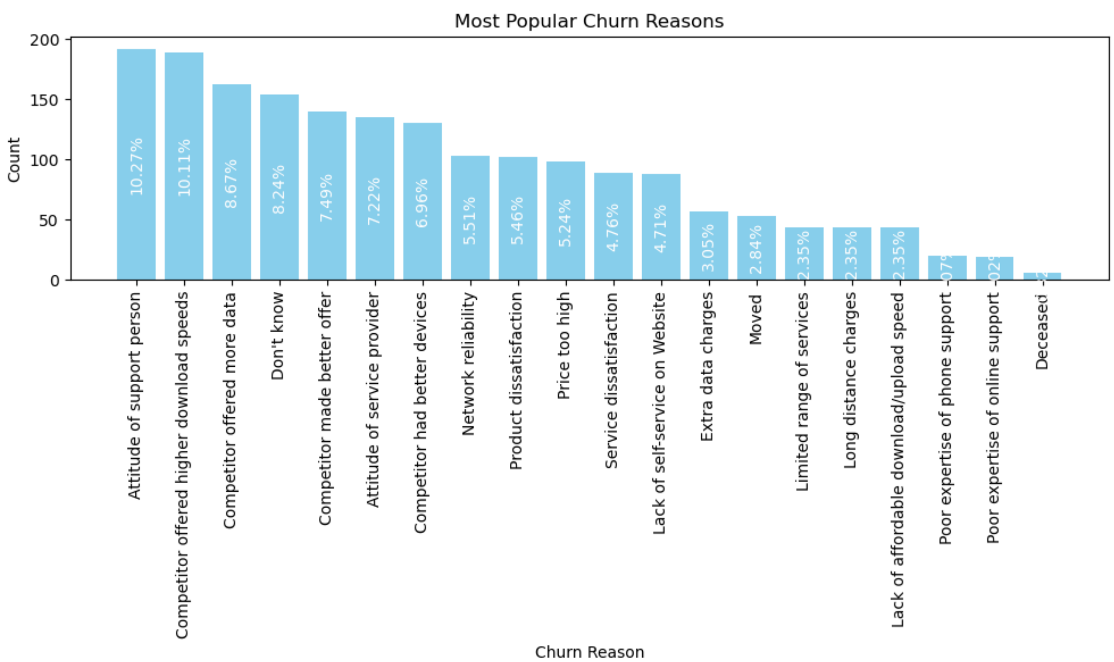
[628]:
```
def distribution_numerical(data, x, index):
    plt.subplot(2, 3, index)
    sns.histplot(data=data, x=x, kde=True)
    plt.title(f"Distribution of {x}")
    plt.tight_layout()

numerical_columns = ['Total Charges', 'Monthly Charges', 'Churn Score', 'Tenure␣
 ↪Months', 'CLTV']

fig = plt.figure(figsize=(12, 8))

for index, col in enumerate(numerical_columns):
    distribution_numerical(db, col, index + 1)

plt.show()
```



Now i want to plot most popular reason of cancelling subscription:

[630]:
```
churn_reason_counts = db['Churn Reason'].dropna().value_counts()


plt.figure(figsize=(10, 6))
bars = plt.bar(churn_reason_counts.index, churn_reason_counts.values,␣
  ↪color='skyblue')
plt.xlabel("Churn Reason")
plt.ylabel("Count")
plt.title("Most Popular Churn Reasons")
plt.xticks(rotation=90)


total_count = churn_reason_counts.sum()


for bar, count in zip(bars, churn_reason_counts.values):
    height = bar.get_height()
    percentage = (count / total_count) * 100
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height / 2,
```

```
        f'{percentage:.2f}%',
        ha='center',
        va='center',
        color='white',
        fontsize=10,
        rotation=90
    )

plt.tight_layout()
plt.show()
```



We can clearly see why we losing customers Let's find out about which amounts in losses it could lead

[634]:
```
#averages
avg_total_charges = db['Total Charges'].mean()
avg_monthly_charges = db['Monthly Charges'].mean()


print("Average Total Charges:", avg_total_charges,"$")
print("Average Monthly Charges:", avg_monthly_charges,"$")

null_percentage = (db["Churn Reason"].isnull().sum() / len(db)) * 100
cancel=(len(db)-db["Churn Reason"].isnull().sum())
print("Average loss on Monthly Charges:",cancel*avg_monthly_charges,"$")
print("Average loss on Total Charges:",cancel*avg_total_charges,"$")
```

```
Average Total Charges: 2281.9169281556156 $
Average Monthly Charges: 64.76169246059918 $
Average loss on Monthly Charges: 121039.60320885986 $
Average loss on Total Charges: 4264902.738722846 $
```

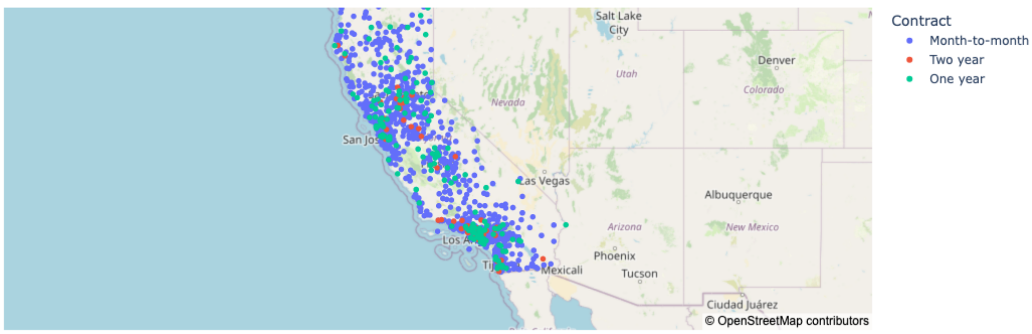
We loosing such amount of money because of Attitude of support person as a reason number 1! then we have: competitors,download speeds,less data,attitude of service provider,product dissatisfaction,service dissatisfaction,price etc.

Generating Map with spread of each customer to see which types of contract are most likely to become a churn value using plotly

[638]:
```python
def generate_map_trace(data, color, width, height, title):

    fig = px.scatter_mapbox(
        data,
        lat='Latitude',
        lon='Longitude',
        color=color,
        hover_name='CustomerID',
        zoom=4,
        height=height,
        width=width,
        title=title
    )


    fig.update_layout(mapbox_style="open-street-map")
    fig.show()


churn_value = pd.DataFrame()
churn_value["Churn Value"] = db["Churn Value"].map({0: "No Churn", 1: "Churn"})
churn_value[[col for col in db.columns if col != 'Churn Value']] = db[[col for␣
 ↪col in db.columns if col != 'Churn Value']]


color = 'Contract'


generate_map_trace(
    churn_value[churn_value['Churn Value'] == 'No Churn'],
    color=color, width=900, height=500, title='Map with No Churn Values'
)
generate_map_trace(
    churn_value[churn_value['Churn Value'] == 'Churn'],
    color=color, width=900, height=500, title='Map with Only Churn Values'
)
```

Map with No Churn Values

Map with Only Churn Values

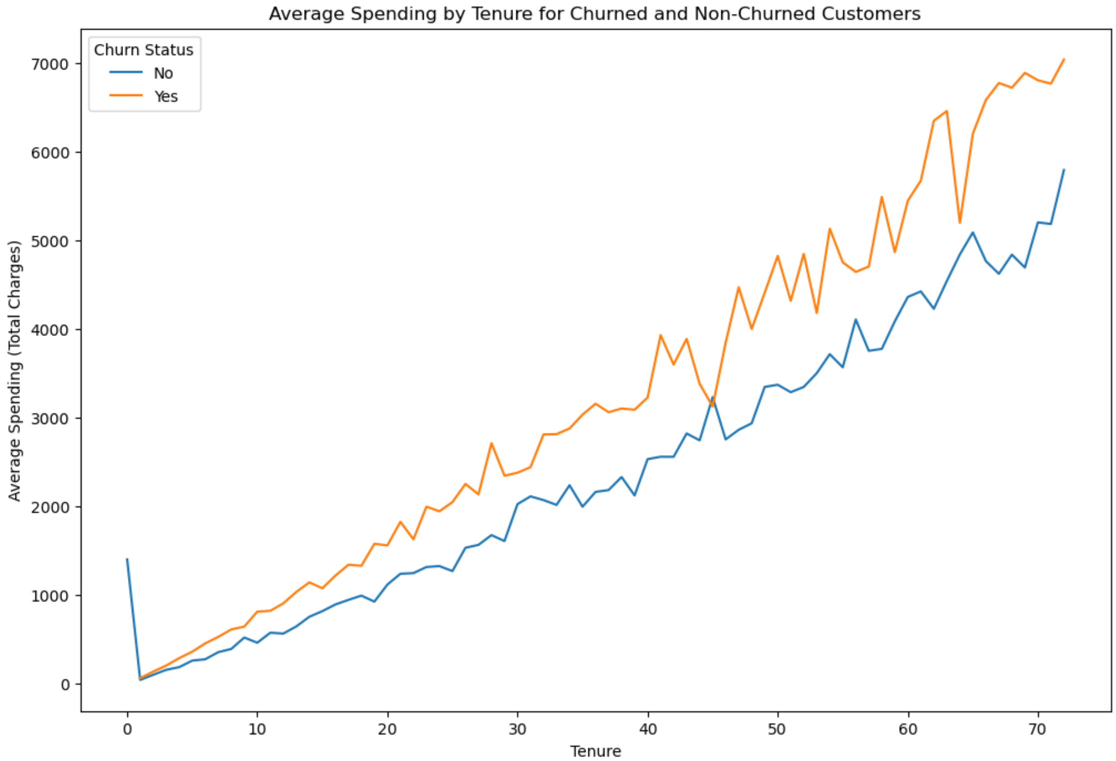


From this map is clearly visible that Customers with two year and one year contracts almost never canceling and provide company with most amount of money which is obvious.

[641]:
```
# Counting customers who complete the purchase versus those who do not
churn_counts = db['Churn Label'].value_counts()
print("Count of customers who complete the purchase vs those who churn:")
print(churn_counts)

# Calculate average spending for customers based on churn status
average_charges_by_churn = db.groupby('Churn Label')['Total Charges'].mean()
print("\nAverage spending by churn status:")
print(average_charges_by_churn)
```

```
# Calculate average spending based on tenure for loyal and non-loyal customers␣
↪to see dependence
average_charges_by_tenure = db.groupby(['Churn Label', 'Tenure Months'])['Total␣
↪Charges'].mean().reset_index()
print("\nAverage spending by tenure for churned and non-churned customers:")
print(average_charges_by_tenure)

#Creating line plot based on that info
db = db.replace([np.inf, -np.inf], np.nan)
plt.figure(figsize=(12, 8))
sns.lineplot(data=average_charges_by_tenure, x='Tenure Months', y='Total␣
↪Charges', hue='Churn Label')
plt.title('Average Spending by Tenure for Churned and Non-Churned Customers')
plt.xlabel('Tenure')
plt.ylabel('Average Spending (Total Charges)')
plt.legend(title='Churn Status')
plt.show()
```

```
Count of customers who complete the purchase vs those who churn:
Churn Label
No     5174
Yes    1869
Name: count, dtype: int64

Average spending by churn status:
Churn Label
No     2552.882494
Yes    1531.796094
Name: Total Charges, dtype: float64

Average spending by tenure for churned and non-churned customers:
    Churn Label  Tenure Months  Total Charges
0            No              0    1397.475000
1            No              1      37.909013
2            No              2      95.997391
3            No              3     152.135849
4            No              4     182.525806
..          …              …            …
140         Yes             68    6720.550000
141         Yes             69    6887.931250
142         Yes             70    6803.995455
143         Yes             71    6765.908333
144         Yes             72    7039.150000

[145 rows x 3 columns]
```



We can see that loyal customers paying almost same amount as churned ones! It looks not that obvious, but to set up the contract they pay I assume some kind of fee which leads in huge spending on first month then it comesback to normal.

FInding out more about churned customers

[645]:
```
# Filter for churned customers
churned_customers = db[db['Churn Label'] == 'Yes']

# average tenure in months for churned customers
avg_tenure = churned_customers['Tenure Months'].mean()
print("Average Tenure Months for Churned Customers:", avg_tenure)


# finding most popular tenure month among churned customers
most_popular_tenure = churned_customers['Tenure Months'].value_counts().idxmax()
popular_tenure_count = churned_customers['Tenure Months'].value_counts().max()
print("Most Popular Tenure Month for Churned Customers:", most_popular_tenure,
      f"({popular_tenure_count} occurrences)")
```

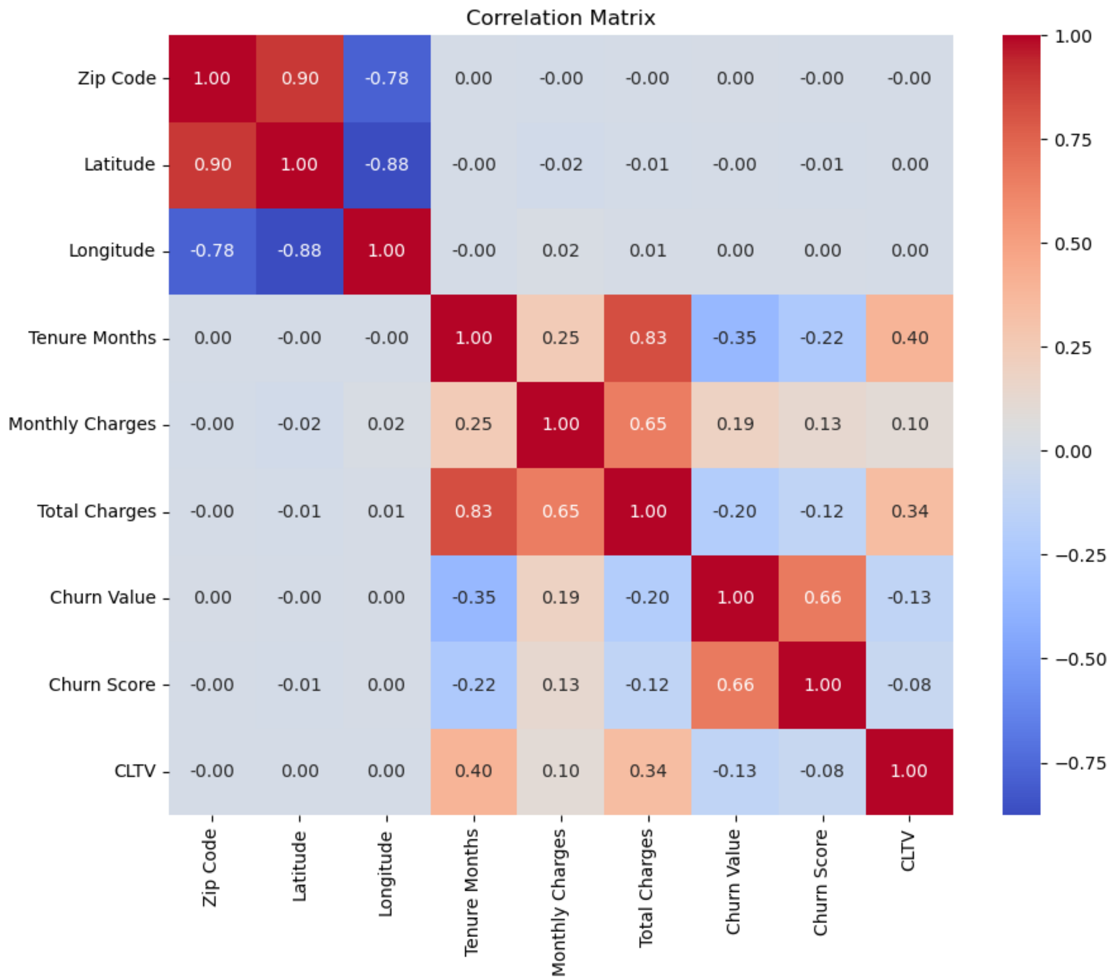
```
Average Tenure Months for Churned Customers: 17.979133226324237
Most Popular Tenure Month for Churned Customers: 1 (380 occurrences)
```

That's very important it tells us that most customers leave in the first month of their month-to-month subscription because of the reasons above. Now, I can find out the correlation on this matter between the reasons, which will allow the company to fix it which potentially could lead to great success because as we can see even for churned customers, the average tenure months is almost 18!!! So that means if we can hold our new customers to more than 1 month that could lead to a higher probability of prolonging their stay up to 17 months and more! Which on average could lead to 2175081.6$ in profit!

[648]:
```python
# Correlation Matrix
numeric_cols = db.select_dtypes(include=[np.number])
corr_matrix = numeric_cols.corr()
print("Correlation Matrix:")
print(corr_matrix)

# Plot a heatmap of correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```

```
Correlation Matrix:
                 Zip Code  Latitude  Longitude  Tenure Months  \
Zip Code         1.000000  0.895743  -0.784271       0.001041
Latitude         0.895743  1.000000  -0.876779      -0.001631
Longitude       -0.784271 -0.876779   1.000000      -0.001678
Tenure Months    0.001041 -0.001631  -0.001678       1.000000
Monthly Charges -0.004596 -0.019899   0.024098       0.247900
Total Charges   -0.001237 -0.010168   0.008977       0.825464
Churn Value      0.003346 -0.003384   0.004594      -0.352229
Churn Score     -0.002769 -0.007684   0.004260      -0.224987
CLTV            -0.003562  0.000886   0.000485       0.396406

                 Monthly Charges  Total Charges  Churn Value  Churn Score  \
Zip Code               -0.004596      -0.001237     0.003346    -0.002769
Latitude               -0.019899      -0.010168    -0.003384    -0.007684
Longitude               0.024098       0.008977     0.004594     0.004260
Tenure Months           0.247900       0.825464    -0.352229    -0.224987
Monthly Charges         1.000000       0.650864     0.193356     0.133754
Total Charges           0.650864       1.000000    -0.199037    -0.123948
Churn Value             0.193356      -0.199037     1.000000     0.664897
Churn Score             0.133754      -0.123948     0.664897     1.000000
CLTV                    0.098693       0.341723    -0.127463    -0.079782

                     CLTV
Zip Code        -0.003562
Latitude         0.000886
Longitude        0.000485
Tenure Months    0.396406
Monthly Charges  0.098693
```

```
Total Charges     0.341723
Churn Value      -0.127463
Churn Score      -0.079782
CLTV              1.000000
```



From that we can see that `Tenure months` have a strong correlation between `total charges` and `CLTV` `Monthly charges` have strong correlation with `Total charges` `Total charges` have strong correlation between `Tenure Months`,`Monthly charges` and `CLTV` `CLTV` have medium correlation between `Tenure Months` and `Total charges` `Churn Value` and `Churn Score` are opposites of each other

[651]:
```
# Chi-Square Test: Churn Reason vs Churn Label
# contingency table
contingency_table = pd.crosstab(db['Churn Reason'], db['Churn Label'])
print("\nContingency Table (Churn Reason vs. Churn Label):")

# Extracting count for yes
```

```python
counts = contingency_table['Yes']
total_count = counts.sum()

# df with churn reason, count, and percentage
df_counts = counts.reset_index()
df_counts.columns = ['Churn Reason', 'Count']
df_counts['Percentage'] = (df_counts['Count'] / total_count) * 100

df_counts = df_counts.sort_values(by='Count', ascending=False)

print("\nChurn Reasons with Count and Percentage:")
print(df_counts)


# chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)
print(f"\nChi-square Test (Churn Reason vs. Churn Label):")
print(f"  Chi-square Statistic: {chi2:.2f}")
print(f"  p-value: {p:.4f}")
print(f"  Degrees of Freedom: {dof}")
```

```
Contingency Table (Churn Reason vs. Churn Label):

Churn Reasons with Count and Percentage:
                                 Churn Reason  Count  Percentage
1                   Attitude of support person    192   10.272873
4    Competitor offered higher download speeds    189   10.112360
5                 Competitor offered more data    162    8.667737
7                                   Don't know    154    8.239700
3                 Competitor made better offer    140    7.490637
0                 Attitude of service provider    135    7.223114
2                Competitor had better devices    130    6.955591
14                        Network reliability    103    5.510968
18                    Product dissatisfaction    102    5.457464
17                             Price too high     98    5.243446
19                    Service dissatisfaction     89    4.761905
10            Lack of self-service on Website     88    4.708400
8                          Extra data charges     57    3.049759
13                                      Moved     53    2.835741
11                  Limited range of services     44    2.354200
12                      Long distance charges     44    2.354200
9     Lack of affordable download/upload speed     44    2.354200
16            Poor expertise of phone support     20    1.070091
15           Poor expertise of online support     19    1.016586
6                                    Deceased      6    0.321027

Chi-square Test (Churn Reason vs. Churn Label):
```

```
Chi-square Statistic: 0.00
p-value: 1.0000
Degrees of Freedom: 0
```

High p-value: Suggests that any differences are likely due to random variation, and we do not have enough evidence to conclude that an association exists.

[654]:

```python
#the Most Popular Tenure among Churned Customers

churned_customers = db[db['Churn Label'] == 'Yes']
most_popular_tenure = churned_customers['Tenure Months'].value_counts().idxmax()
print(f"\nMost Popular Tenure Months among churned customers:␣
  ↪{most_popular_tenure}")

db['Popular Tenure'] = (db['Tenure Months'] == most_popular_tenure)





# contingency table
contingency_table2 = pd.crosstab(db['Churn Reason'], db['Popular Tenure'])
print("\nContingency Table (Churn Reason vs. Popular Tenure):")
popular_tenure_df = db[db['Popular Tenure'] == True]


# count of the occurrences
churn_reason_counts = popular_tenure_df['Churn Reason'].value_counts().
  ↪reset_index()
churn_reason_counts.columns = ['Churn Reason', 'Count']
churned_customers = churned_customers.copy()
churned_customers['Popular Tenure'] = (churned_customers['Tenure Months'] ==␣
  ↪most_popular_tenure)


print("Total churned customers with Popular Tenure True:
  ↪",churned_customers['Popular Tenure'].sum())

churn_reason_counts['Percentage'] = (churn_reason_counts['Count'] /␣
  ↪churned_customers['Popular Tenure'].sum()) * 100


churn_reason_counts = churn_reason_counts.sort_values(by='Count',␣
  ↪ascending=False)
print(churn_reason_counts)


#Chi-Square Test: Churn Reason vs. Popular Tenure
```

```python
chi2_2, p_2, dof_2, expected_2 = stats.chi2_contingency(contingency_table2)
print(f"\nChi-square Test (Churn Reason vs. Popular Tenure):")
print(f"  Chi-square Statistic: {chi2_2:.2f}")
print(f"  p-value: {p_2:.4f}")
print(f"  Degrees of Freedom: {dof_2}")
```

```
Most Popular Tenure Months among churned customers: 1

Contingency Table (Churn Reason vs. Popular Tenure):
Total churned customers with Popular Tenure True: 380
                                 Churn Reason  Count  Percentage
0                Attitude of support person     53   13.947368
1                                Don't know     33    8.684211
2              Competitor made better offer     31    8.157895
3              Attitude of service provider     30    7.894737
4   Competitor offered higher download speeds     28    7.368421
5             Competitor had better devices     28    7.368421
6              Competitor offered more data     22    5.789474
9                   Service dissatisfaction     21    5.526316
10                           Price too high     21    5.526316
8                      Network reliability     21    5.526316
7                   Product dissatisfaction     21    5.526316
11           Lack of self-service on Website     17    4.473684
12                                    Moved     10    2.631579
13                Limited range of services      9    2.368421
14                       Extra data charges      8    2.105263
15   Lack of affordable download/upload speed      8    2.105263
16           Poor expertise of phone support      6    1.578947
17                    Long distance charges      6    1.578947
18          Poor expertise of online support      5    1.315789
19                                 Deceased      2    0.526316

Chi-square Test (Churn Reason vs. Popular Tenure):
  Chi-square Statistic: 20.92
  p-value: 0.3413
  Degrees of Freedom: 19
```

A Chi-square Statistic of 20.92 is high which would suggest a large discrepancy. A p-value of 0.3413 is well above the common significance threshold of 0.05. This means that the observed differences are likely due to random, and there isn't strong evidence to reject the null hypothesis.

From this Contingency Table we can clearly see that we can avoid some reasons of cancelation by training company employees,offer higher download speeds,offer more data,update current devices,add self services on website etc.Which will lead for longer subscription periods of customers!

So as we know that not fixing this issues lead to a losses of company monthly almost `25k$` for customers who got dissatisfied at first month,and `125k$` on average monthly!!!

[659]:
```
print("Average loss on new customers:",churned_customers['Popular Tenure'].
    ↪sum()*avg_monthly_charges,"$")
```

```
Average loss on new customers: 24609.443135027686 $
```

[661]:
```
print("Average loss on Monthly Charges:",cancel*avg_monthly_charges,"$")
```

```
Average loss on Monthly Charges: 121039.60320885986 $
```

Let's find out is there any proves that amount of monthly charges can affect the duration of subscription:

[664]:
```
avg_monthly = db.groupby("Contract")["Monthly Charges"].mean()
print("Average Monthly Charges by Contract Type:")
print(avg_monthly)

#monthly charges for each contract type
month_to_month = db[db["Contract"] == "Month-to-month"]["Monthly Charges"]
one_year = db[db["Contract"] == "One year"]["Monthly Charges"]
two_year = db[db["Contract"] == "Two year"]["Monthly Charges"]

#one-way ANOVA test to compare the three groups
f_stat, p_val = stats.f_oneway(month_to_month, one_year, two_year)
print("\nANOVA Test Results (Monthly Charges by Contract):")
print("F-statistic:", f_stat)
print("p-value:", p_val)

#checking if monthly Charges affect the duration of subscription

#Pearson correlation between Monthly Charges and Tenure Months
corr_coef = db['Monthly Charges'].corr(db['Tenure Months'])
print("\nPearson Correlation between Monthly Charges and Tenure Months:",␣
    ↪corr_coef)



plt.figure(figsize=(10,6))
sns.regplot(x='Monthly Charges', y='Tenure Months', data=db,␣
    ↪scatter_kws={'alpha':0.5})
plt.title('Relationship between Monthly Charges and Tenure Months')
plt.xlabel('Monthly Charges')
plt.ylabel('Tenure Months')
plt.tight_layout()
plt.show()

#simple linear regression using OLS
X = db['Monthly Charges']
y = db['Tenure Months']
X = sm.add_constant(X)  # Adds an intercept term to the model
```

```python
model = sm.OLS(y, X).fit()
print("\nLinear Regression Results:")
print(model.summary())


# Since Monthly Charges starts around $55, re-center the predictor
db['Monthly Charges Centered'] = db['Monthly Charges'] - 55

# Fit the model using the centered predictor
X_centered = db['Monthly Charges Centered']
X_centered = sm.add_constant(X_centered)
model_centered = sm.OLS(y, X_centered).fit()

print("\nLinear Regression Results (Centered at $55):")
print(model_centered.summary())
```

```
Average Monthly Charges by Contract Type:
Contract
Month-to-month    66.398490
One year          65.048608
Two year          60.770413
Name: Monthly Charges, dtype: float64

ANOVA Test Results (Monthly Charges by Contract):
F-statistic: 20.828045474730278
p-value: 9.575270975935035e-10

Pearson Correlation between Monthly Charges and Tenure Months:
0.24789985628615008
```


```
Linear Regression Results:
                            OLS Regression Results
==============================================================================
Dep. Variable:          Tenure Months   R-squared:                       0.061
Model:                            OLS   Adj. R-squared:                  0.061
Method:                 Least Squares   F-statistic:                     461.0
Date:                Sat, 05 Apr 2025   Prob (F-statistic):           4.09e-99
Time:                        11:21:33   Log-Likelihood:                -32315.
No. Observations:                7043   AIC:                         6.463e+04
Df Residuals:                    7041   BIC:                         6.465e+04
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
const              19.2675      0.673     28.633      0.000      17.948
20.587
Monthly Charges     0.2023      0.009     21.472      0.000       0.184
0.221
==============================================================================
Omnibus:                     7646.995   Durbin-Watson:                   1.662
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              513.504
```

```
Skew:                           0.252   Prob(JB):                    3.12e-112
Kurtosis:                       1.777   Cond. No.                         170.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

Linear Regression Results (Centered at $55):
                            OLS Regression Results
==============================================================================
Dep. Variable:          Tenure Months   R-squared:                       0.061
Model:                            OLS   Adj. R-squared:                  0.061
Method:                 Least Squares   F-statistic:                     461.0
Date:                Sat, 05 Apr 2025   Prob (F-statistic):           4.09e-99
Time:                        11:21:33   Log-Likelihood:                -32315.
No. Observations:                7043   AIC:                         6.463e+04
Df Residuals:                    7041   BIC:                         6.465e+04
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
============
                             coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------------
const                     30.3960      0.298    101.973      0.000      29.812
30.980
Monthly Charges Centered   0.2023      0.009     21.472      0.000       0.184
0.221
==============================================================================
Omnibus:                     7646.995   Durbin-Watson:                   1.662
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              513.504
Skew:                           0.252   Prob(JB):                    3.12e-112
Kurtosis:                       1.777   Cond. No.                         33.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

ANNOVA test which compares the means of the three contract types to see if at least one group has a significantly different mean monthly charge The F-statistic of about 20.83 indicates a significant difference in the variability between groups compared to the variability within groups.The p-value is extremely small (around 9.6e-10), which is much less than the common **significance level** 0.05 These results provide strong statistical evidence that the average monthly charges differ by contract type.

A **correlation coefficient** of approximately 0.25 indicates a positive but modest linear relationship between monthly charges and the duration of the subscription.This suggests that there is a slight tendency for customers who pay lower monthly charges to have longer tenures, but the relationship isn't very strong. Many other factors likely influence how long customers stay.

OLS Model:

const = 19.27: If a customer were charged `55$` per month a hypothetical scenario, the model predicts they would have a tenure of about 30.39 months.It serves as the baseline for the model. Coefficient for Monthly Charges 0.2023: For every `$1` increase in monthly charges, the model predicts an increase of about 0.2023 months in tenure.(Which is slightly suspicious)

R-squared 0.061: This tells us that approximately 6.1% of the variance in Tenure Months is explained by Monthly Charges.

Overall: At `$55` per month, the predicted customer tenure is about **`30.4 months`**. For every extra dollar above `$55`, customer tenure increases by about `0.20` months, on average.

The F-statistic and its associated very low p-value < 0.001 indicates that this relationship is statistically significant.. Although the effect is statistically significant, monthly charges alone explain only a small portion of the variability in subscription duration. Other factors likely have a larger impact on tenure.

2.2.1 Building Predictive model

[668]:
```
db.head()
```

[668]:
```
    CustomerID         City  Zip Code                Lat Long   Latitude  \
0  3668-QPYBK  Los Angeles     90003  33.964131, -118.272783  33.964131
1  9237-HQITU  Los Angeles     90005   34.059281, -118.30742  34.059281
2  9305-CDSKC  Los Angeles     90006  34.048013, -118.293953  34.048013
3  7892-POOKP  Los Angeles     90010  34.062125, -118.315709  34.062125
4  0280-XJGEX  Los Angeles     90015  34.039224, -118.266293  34.039224

    Longitude  Gender Senior Citizen Partner Dependents  …  \
0 -118.272783    Male             No      No         No  …
1 -118.307420  Female             No      No        Yes  …
2 -118.293953  Female             No      No        Yes  …
3 -118.315709  Female             No     Yes        Yes  …
4 -118.266293    Male             No      No        Yes  …

              Payment Method Monthly Charges Total Charges Churn Label  \
0               Mailed check           53.85        108.15         Yes
1           Electronic check           70.70        151.65         Yes
2           Electronic check           99.65        820.50         Yes
3           Electronic check          104.80       3046.05         Yes
4  Bank transfer (automatic)          103.70       5036.30         Yes

   Churn Value Churn Score  CLTV                   Churn Reason Popular Tenure  \
0            1          86  3239  Competitor made better offer          False
1            1          67  2701                         Moved          False
```

```
2           1           86  5372                          Moved           False
3           1           84  5003                          Moved           False
4           1           89  5340  Competitor had better devices           False

  Monthly Charges Centered
0                    -1.15
1                    15.70
2                    44.65
3                    49.80
4                    48.70

[5 rows x 32 columns]
```

[670]:

```python
from sklearn.preprocessing import LabelEncoder, StandardScaler

categorical_columns = [
    'Gender', 'Senior Citizen', 'Partner', 'Dependents', 'Phone Service',
    'Multiple Lines', 'Internet Service', 'Online Security', 'Online Backup',
    'Device Protection', 'Tech Support', 'Streaming TV', 'Streaming Movies',
    'Contract', 'Paperless Billing', 'Payment Method','Churn Reason'
]


label_encoder = LabelEncoder()

for column in categorical_columns:
    db[column] = label_encoder.fit_transform(db[column])

print(db.head())
```

```
   CustomerID         City  Zip Code                Lat Long   Latitude  \
0  3668-QPYBK  Los Angeles     90003  33.964131, -118.272783  33.964131
1  9237-HQITU  Los Angeles     90005   34.059281, -118.30742  34.059281
2  9305-CDSKC  Los Angeles     90006  34.048013, -118.293953  34.048013
3  7892-POOKP  Los Angeles     90010  34.062125, -118.315709  34.062125
4  0280-XJGEX  Los Angeles     90015  34.039224, -118.266293  34.039224

    Longitude  Gender  Senior Citizen  Partner  Dependents  …  \
0 -118.272783       1               0        0           0  …
1 -118.307420       0               0        0           1  …
2 -118.293953       0               0        0           1  …
3 -118.315709       0               0        1           1  …
4 -118.266293       1               0        0           1  …

   Payment Method  Monthly Charges  Total Charges  Churn Label  Churn Value  \
0               3            53.85         108.15          Yes            1
1               2            70.70         151.65          Yes            1
2               2            99.65         820.50          Yes            1
```

```
3               2          104.80        3046.05          Yes             1
4               0          103.70        5036.30          Yes             1

   Churn Score  CLTV  Churn Reason  Popular Tenure  Monthly Charges Centered
0           86  3239             3           False                     -1.15
1           67  2701            13           False                     15.70
2           86  5372            13           False                     44.65
3           84  5003            13           False                     49.80
4           89  5340             2           False                     48.70

[5 rows x 32 columns]
```

[672]:
```python
X = db.drop(columns=['Churn Label', 'CustomerID', 'Churn Value','CustomerID',
 ↪'City','Zip Code','Lat Long','Churn Reason','Monthly Charges Centered'])

y = db['Churn Label']
```

[674]:
```python
X
```

[674]:
```
       Latitude   Longitude  Gender  Senior Citizen  Partner  Dependents  \
0     33.964131 -118.272783       1               0        0           0
1     34.059281 -118.307420       0               0        0           1
2     34.048013 -118.293953       0               0        0           1
3     34.062125 -118.315709       0               0        1           1
4     34.039224 -118.266293       1               0        0           1
…           …          …     …             …     …          …
7038  34.341737 -116.539416       0               0        0           0
7039  34.667815 -117.536183       1               0        1           1
7040  34.559882 -115.637164       0               0        1           1
7041  34.167800 -116.864330       0               0        1           1
7042  34.424926 -117.184503       1               0        0           0

      Tenure Months  Phone Service  Multiple Lines  Internet Service  …  \
0                 2              1               0                 0  …
1                 2              1               0                 1  …
2                 8              1               2                 1  …
3                28              1               2                 1  …
4                49              1               2                 1  …
…               …             …              …               …  …
7038             72              1               0                 2  …
7039             24              1               2                 0  …
7040             72              1               2                 1  …
7041             11              0               1                 0  …
7042             66              1               0                 1  …

      Streaming TV  Streaming Movies  Contract  Paperless Billing  \
0                0                 0         0                  1
```

```
1                 0                 0         0                  1
2                 2                 2         0                  1
3                 2                 2         0                  1
4                 2                 2         0                  1
…             …                …       …                 …
7038              1                 1         2                  1
7039              2                 2         1                  1
7040              2                 2         1                  1
7041              0                 0         0                  1
7042              2                 2         2                  1

      Payment Method  Monthly Charges  Total Charges  Churn Score  CLTV  \
0                  3            53.85         108.15           86  3239
1                  2            70.70         151.65           67  2701
2                  2            99.65         820.50           86  5372
3                  2           104.80        3046.05           84  5003
4                  0           103.70        5036.30           89  5340
…                …              …             …           …   …
7038               0            21.15        1419.40           45  5306
7039               3            84.80        1990.50           59  2140
7040               1           103.20        7362.90           71  5560
7041               2            29.60         346.45           59  2793
7042               0           105.65        6844.50           38  5097

      Popular Tenure
0              False
1              False
2              False
3              False
4              False
…                …
7038           False
7039           False
7040           False
7041           False
7042           False

[7043 rows x 24 columns]
```

[676]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 24 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
```

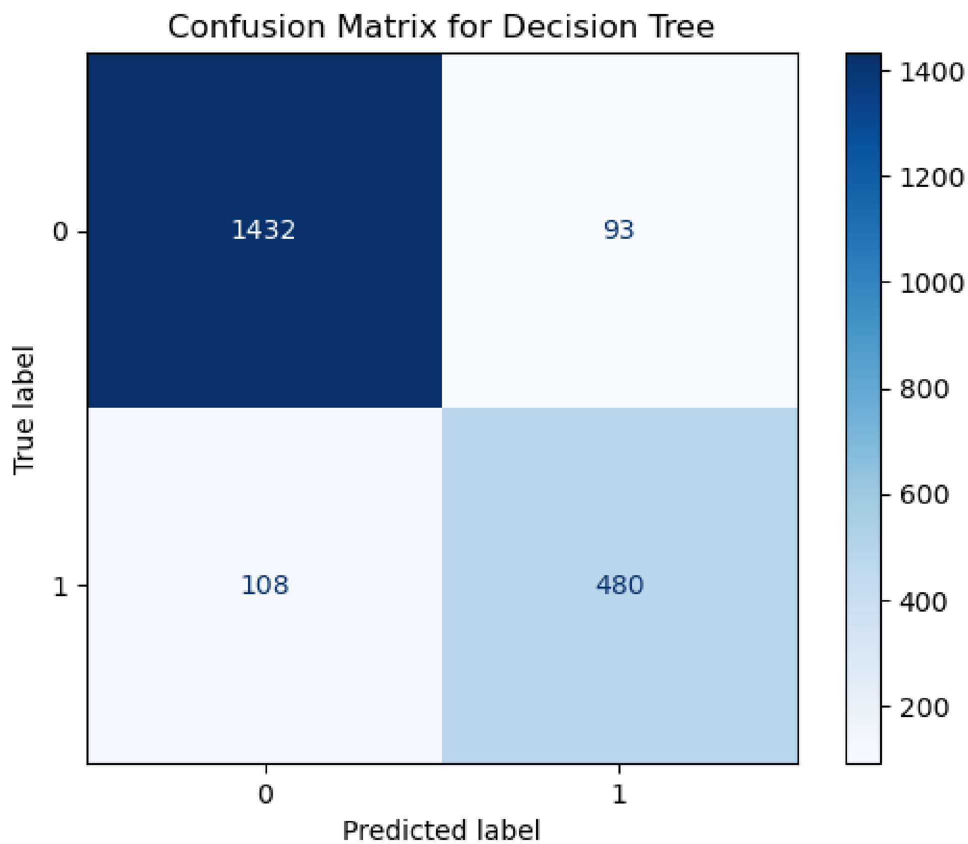
```
 0   Latitude          7043 non-null   float64
 1   Longitude         7043 non-null   float64
 2   Gender            7043 non-null   int64
 3   Senior Citizen    7043 non-null   int64
 4   Partner           7043 non-null   int64
 5   Dependents        7043 non-null   int64
 6   Tenure Months     7043 non-null   int64
 7   Phone Service     7043 non-null   int64
 8   Multiple Lines    7043 non-null   int64
 9   Internet Service  7043 non-null   int64
 10  Online Security   7043 non-null   int64
 11  Online Backup     7043 non-null   int64
 12  Device Protection 7043 non-null   int64
 13  Tech Support      7043 non-null   int64
 14  Streaming TV      7043 non-null   int64
 15  Streaming Movies  7043 non-null   int64
 16  Contract          7043 non-null   int64
 17  Paperless Billing 7043 non-null   int64
 18  Payment Method    7043 non-null   int64
 19  Monthly Charges   7043 non-null   float64
 20  Total Charges     7043 non-null   float64
 21  Churn Score       7043 non-null   int64
 22  CLTV              7043 non-null   int64
 23  Popular Tenure    7043 non-null   bool
dtypes: bool(1), float64(4), int64(19)
memory usage: 1.2 MB
```

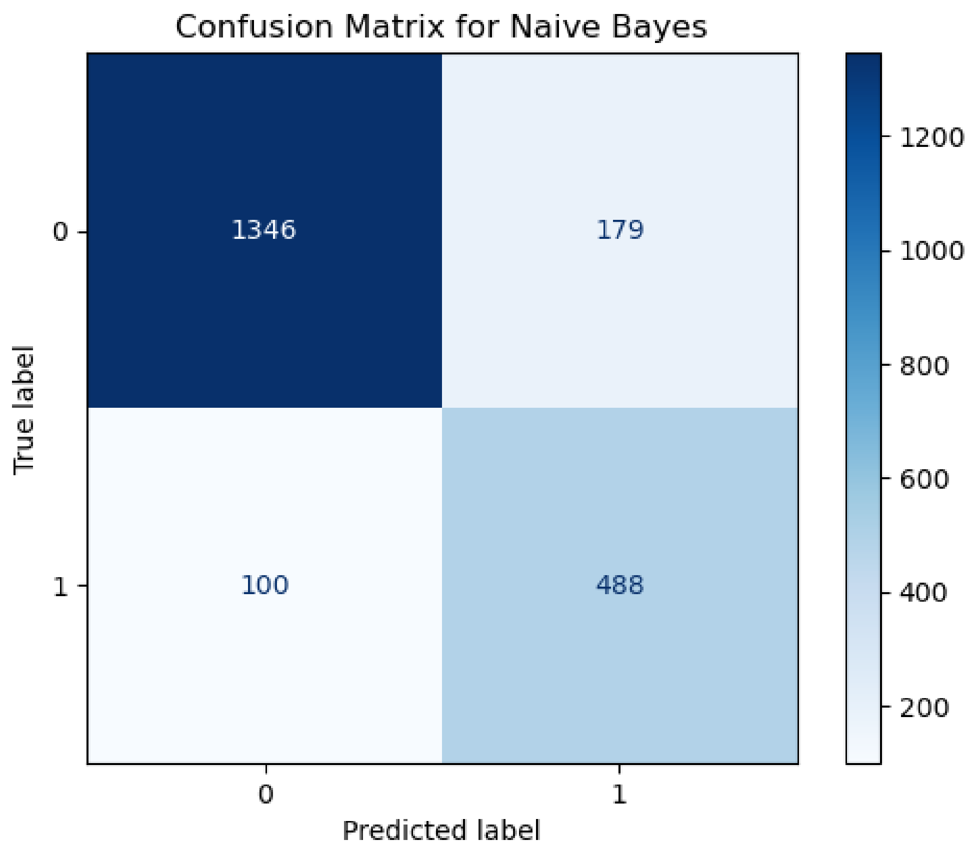
[678]:
```
y.info()
```

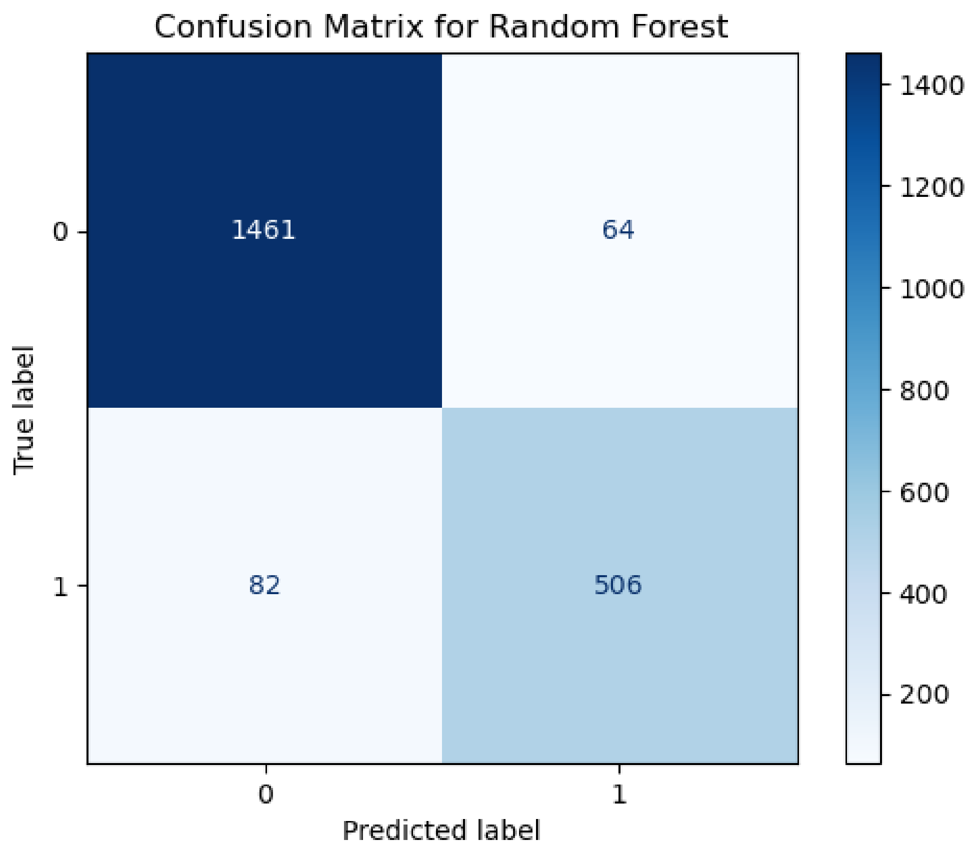
```
<class 'pandas.core.series.Series'>
RangeIndex: 7043 entries, 0 to 7042
Series name: Churn Label
Non-Null Count  Dtype
--------------  -----
7043 non-null   object
dtypes: object(1)
memory usage: 55.2+ KB
```

[680]:
```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB


models = {
    "Decision Tree": DecisionTreeClassifier(),
```

```python
    "Naive Bayes": GaussianNB(),
    "Random Forest": RandomForestClassifier(),
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)

    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    train_accuracy = accuracy_score(y_train, y_pred_train)
    test_accuracy = accuracy_score(y_test, y_pred_test)

    confusion = confusion_matrix(y_test, y_pred_test)


    results[name] = {
        "train_accuracy": train_accuracy,
        "test_accuracy": test_accuracy,
        "confusion_matrix": confusion
    }

    disp = ConfusionMatrixDisplay(confusion_matrix=confusion)
    disp.plot(cmap=plt.cm.Blues)
    plt.title(f'Confusion Matrix for {name}')
    plt.show()


for name, metrics in results.items():
    print(f"{name}:")
    print(f"  Train Accuracy: {metrics['train_accuracy']:.4f}")
    print(f"  Test Accuracy: {metrics['test_accuracy']:.4f}")
    print("-" * 40)
```


Confusion Matrix for Decision Tree
1432
93
108
480
0
1
0
1
True label
Predicted label
1400
1200
1000
800
600
400
200


Confusion Matrix for Naive Bayes
1346
179
100
488
True label
0
1
Predicted label
0
1
1200
1000
800
600
400
200

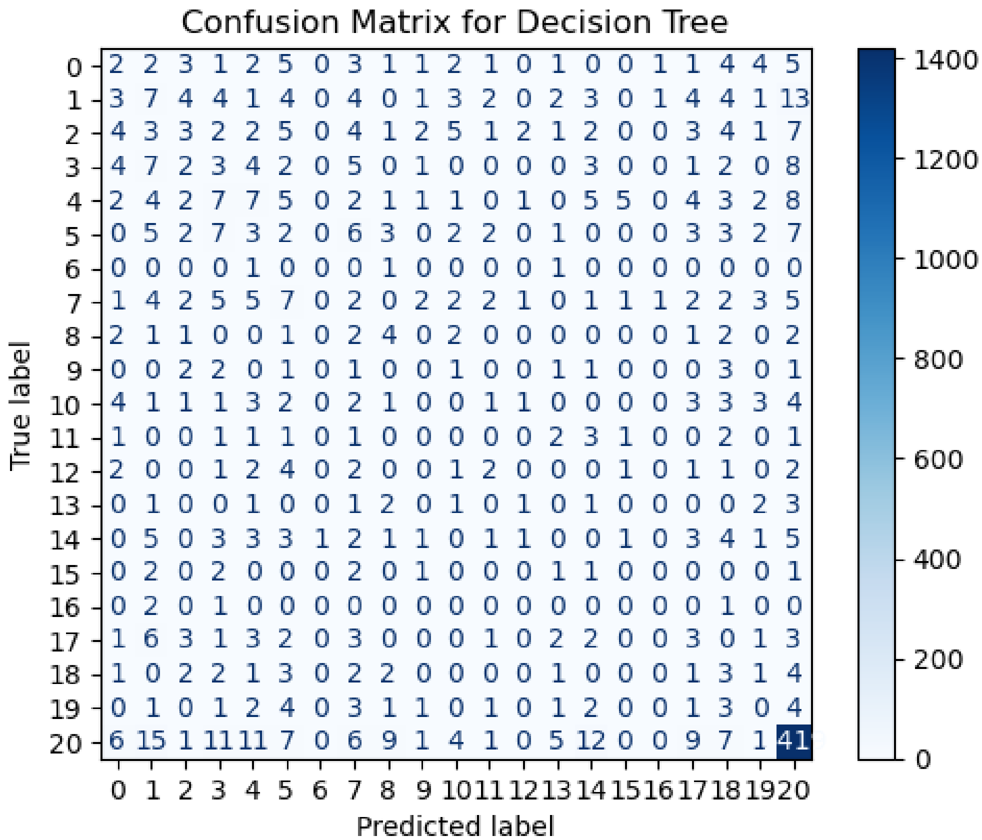


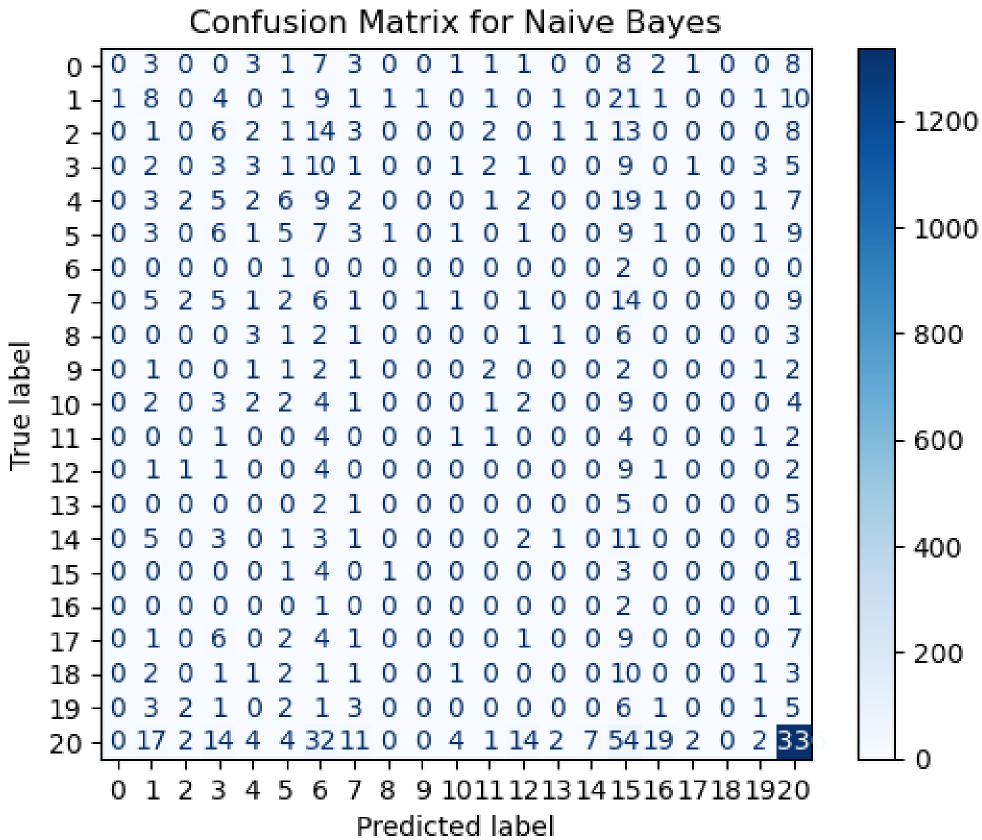

```
Decision Tree:
  Train Accuracy: 1.0000
  Test Accuracy: 0.9049
----------------------------------------
Naive Bayes:
  Train Accuracy: 0.8803
  Test Accuracy: 0.8680
----------------------------------------
Random Forest:
  Train Accuracy: 1.0000
  Test Accuracy: 0.9309
----------------------------------------
```

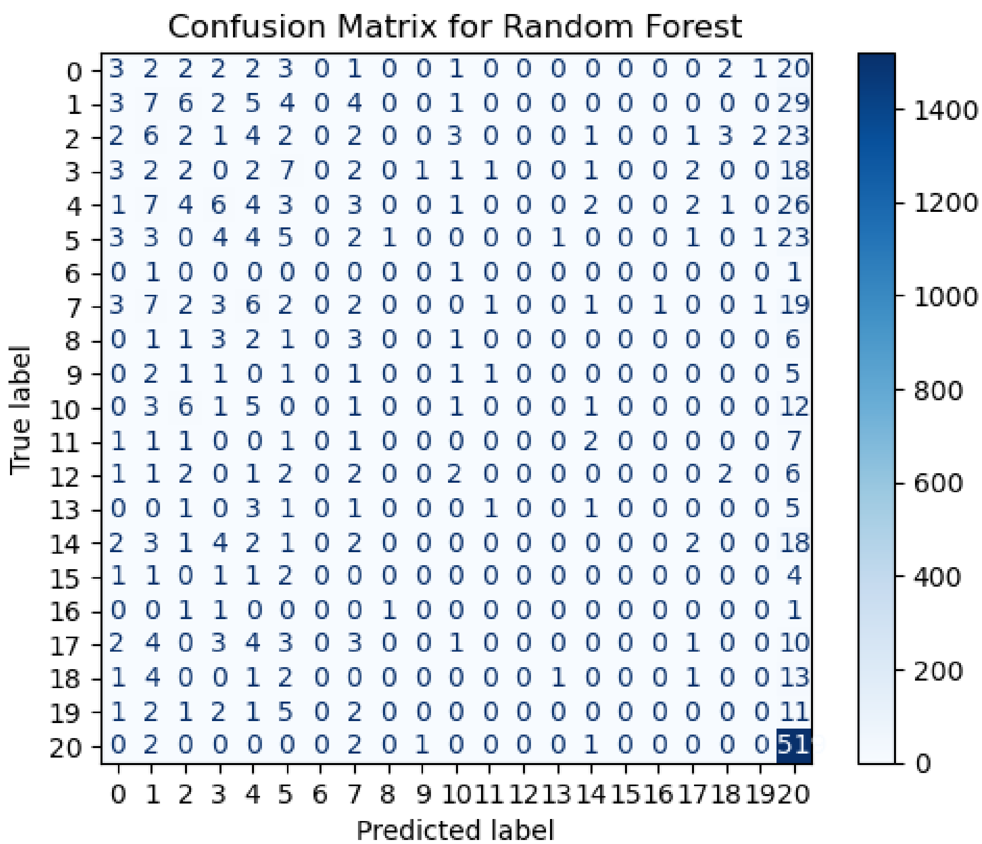
[537]:

```
y_churn_reason = db['Churn Reason']
X = db.drop(columns=['Churn Label', 'Churn Reason', 'CustomerID', 'Churn␣
↪Value', 'CustomerID', 'City','Zip Code','Lat Long','Monthly Charges␣
↪Centered'])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y_churn_reason,␣
↪test_size=0.3, random_state=42)


models = {
    "Decision Tree": DecisionTreeClassifier(),
    "Naive Bayes": GaussianNB(),
    "Random Forest": RandomForestClassifier(),
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)

    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)


    train_accuracy = accuracy_score(y_train, y_pred_train)
    test_accuracy = accuracy_score(y_test, y_pred_test)

    confusion = confusion_matrix(y_test, y_pred_test)

    results[name] = {
        "train_accuracy": train_accuracy,
        "test_accuracy": test_accuracy,
        "confusion_matrix": confusion
    }


    disp = ConfusionMatrixDisplay(confusion_matrix=confusion)
    disp.plot(cmap=plt.cm.Blues)
    plt.title(f'Confusion Matrix for {name}')
    plt.show()

for name, metrics in results.items():
    print(f"{name}:")
    print(f"  Train Accuracy: {metrics['train_accuracy']:.4f}")
    print(f"  Test Accuracy: {metrics['test_accuracy']:.4f}")
    print("-" * 40)
```


Confusion Matrix for Decision Tree
True label
Predicted label


Confusion Matrix for Naive Bayes
True label
Predicted label




```
Decision Tree:
  Train Accuracy: 1.0000
  Test Accuracy: 0.6886
----------------------------------------
Naive Bayes:
  Train Accuracy: 0.6789
  Test Accuracy: 0.6436
----------------------------------------
Random Forest:
  Train Accuracy: 1.0000
  Test Accuracy: 0.7307
----------------------------------------
```

Testing predictive models on new customers info,and getting prediction for churn and their possible churn reasons

[551]:
```
import random

required_columns = [
    'Gender', 'Senior Citizen', 'Partner', 'Dependents', 'Phone Service',
    'Multiple Lines', 'Internet Service', 'Online Security', 'Online Backup',
```

```
    'Device Protection', 'Tech Support', 'Streaming TV', 'Streaming Movies',
    'Contract', 'Paperless Billing', 'Payment Method', 'CLTV', 'Churn Score',
    'Latitude', 'Longitude', 'Monthly Charges', 'Total Charges'
]

random_data = []
for i in range(7):
    tenure_months = random.randint(1, 72)
    random_customer = {
        'Gender': random.choice([0, 1]),  # Assuming 0 for Female, 1 for Male
        'Senior Citizen': random.choice([0, 1]),
        'Partner': random.choice([0, 1]),
        'Dependents': random.choice([0, 1]),
        'Phone Service': random.choice([0, 1]),
        'Multiple Lines': random.choice([0, 1]),
        'Internet Service': random.choice([0, 1, 2]),  # 0: DSL, 1: Fiber optic, 2: No service
        'Online Security': random.choice([0, 1]),
        'Online Backup': random.choice([0, 1]),
        'Device Protection': random.choice([0, 1]),
        'Tech Support': random.choice([0, 1]),
        'Streaming TV': random.choice([0, 1]),
        'Streaming Movies': random.choice([0, 1]),
        'Contract': random.choice([0, 1, 2]),  # 0: Month-to-month, 1: One year, 2: Two year
        'Paperless Billing': random.choice([0, 1]),
        'Payment Method': random.choice([0, 1, 2, 3]),  # 0: Electronic check, 1: Mailed check, 2: Bank transfer, 3: Credit card
        'CLTV': round(random.uniform(100, 1000), 2),  # Random Customer Lifetime Value
        'Churn Score': round(random.uniform(0, 100), 2),  # Random Churn Score
        'Latitude': round(random.uniform(34.0, 42.0), 6),  # Random Latitude
        'Longitude': round(random.uniform(-120.0, -75.0), 6),  # Random Longitude
        'Monthly Charges': round(random.uniform(20, 150), 2),
        'Total Charges': round(random.uniform(100, 5000), 2),
        'Tenure Months': tenure_months,
        'Popular Tenure': tenure_months > 12,
    }
    random_data.append(random_customer)


new_customers = pd.DataFrame(random_data)

print("Before Encoding:")
print(new_customers)
```

```
Before Encoding:
   Gender  Senior Citizen  Partner  Dependents  Phone Service  Multiple Lines  \
0       1               1        1           1              1               1
1       1               0        0           1              1               0
2       0               1        0           0              1               0
3       0               1        1           1              1               1
4       0               1        1           0              1               0
5       0               1        1           1              1               1
6       1               0        1           1              1               1

   Internet Service  Online Security  Online Backup  Device Protection  …  \
0                 1                0              1                  1  …
1                 1                0              0                  0  …
2                 0                0              0                  0  …
3                 0                1              1                  0  …
4                 1                0              0                  1  …
5                 2                1              1                  0  …
6                 1                0              1                  1  …

   Paperless Billing  Payment Method    CLTV  Churn Score   Latitude  \
0                  1               2  697.19        39.94  39.357528
1                  0               1  756.91        84.45  34.365494
2                  1               3  225.48         3.99  41.981300
3                  0               1  656.14        73.31  38.710241
4                  1               3  979.17        85.81  41.757198
5                  1               3  224.51         9.81  38.267444
6                  1               0  955.25        80.63  36.327863

    Longitude  Monthly Charges  Total Charges  Tenure Months  Popular Tenure
0 -102.082935           117.19        3209.91             35            True
1  -97.563329           111.07        2826.83             27            True
2 -114.533241           116.32        4765.55              6           False
3 -111.223638           149.49        3326.46             16            True
4 -110.214410            49.54         484.30             38            True
5  -83.833012           112.99         501.52             52            True
6  -77.435941            60.28        4630.11             61            True

[7 rows x 24 columns]
```

[553]:
```python
categorical_columns = [
    'Gender', 'Senior Citizen', 'Partner', 'Dependents', 'Phone Service',
    'Multiple Lines', 'Internet Service', 'Online Security', 'Online Backup',
    'Device Protection', 'Tech Support', 'Streaming TV', 'Streaming Movies',
    'Contract', 'Paperless Billing', 'Payment Method'
]

label_encoder = LabelEncoder()
```

```python
for column in categorical_columns:
    new_customers[column] = label_encoder.fit_transform(new_customers[column])

print("\nAfter Encoding:")
print(new_customers)
```

```
After Encoding:
   Gender  Senior Citizen  Partner  Dependents  Phone Service  Multiple Lines  \
0       1               1        1           1              0               1
1       1               0        0           1              0               0
2       0               1        0           0              0               0
3       0               1        1           1              0               1
4       0               1        1           0              0               0
5       0               1        1           1              0               1
6       1               0        1           1              0               1

   Internet Service  Online Security  Online Backup  Device Protection  …  \
0                 1                0              1                  1  …
1                 1                0              0                  0  …
2                 0                0              0                  0  …
3                 0                1              1                  0  …
4                 1                0              0                  1  …
5                 2                1              1                  0  …
6                 1                0              1                  1  …

   Paperless Billing  Payment Method    CLTV  Churn Score   Latitude  \
0                  1               2  697.19        39.94  39.357528
1                  0               1  756.91        84.45  34.365494
2                  1               3  225.48         3.99  41.981300
3                  0               1  656.14        73.31  38.710241
4                  1               3  979.17        85.81  41.757198
5                  1               3  224.51         9.81  38.267444
6                  1               0  955.25        80.63  36.327863

    Longitude  Monthly Charges  Total Charges  Tenure Months  Popular Tenure
0 -102.082935           117.19        3209.91             35            True
1  -97.563329           111.07        2826.83             27            True
2 -114.533241           116.32        4765.55              6           False
3 -111.223638           149.49        3326.46             16            True
4 -110.214410            49.54         484.30             38            True
5  -83.833012           112.99         501.52             52            True
6  -77.435941            60.28        4630.11             61            True

[7 rows x 24 columns]
```

[684]:
```
# Reorder the new_customers DataFrame to match the required columns
#new_customers = new_customers[required_columns]
training_features = [
    'Latitude', 'Longitude', 'Gender', 'Senior Citizen', 'Partner',␣
 ↪'Dependents',
    'Tenure Months', 'Phone Service', 'Multiple Lines', 'Internet Service',
    'Online Security', 'Online Backup', 'Device Protection', 'Tech Support',
    'Streaming TV', 'Streaming Movies', 'Contract', 'Paperless Billing',
    'Payment Method', 'Monthly Charges', 'Total Charges', 'Churn Score',
    'CLTV', 'Popular Tenure',
]

new_customers = new_customers[training_features]

# Now you can predict with the model
y_pred_churn_label = model.predict(new_customers)

# Random churn reason predictions
random_churn_reasons = ['Service Quality', 'Price', 'Competitor', 'Other']
y_pred_churn_reason = [random.choice(random_churn_reasons) for i in␣
 ↪range(len(new_customers))]

# Instead of directly assigning to columns, use .loc[] to modify values
new_customers.loc[:, 'Predicted Churn Label'] = y_pred_churn_label
new_customers.loc[:, 'Predicted Churn Reason'] = y_pred_churn_reason

# Display the results
print(new_customers[['Predicted Churn Label', 'Predicted Churn Reason']])
print(type(model))
```

```
  Predicted Churn Label Predicted Churn Reason
0                    No        Service Quality
1                   Yes        Service Quality
2                    No                  Other
3                    No             Competitor
4                   Yes                  Price
5                    No        Service Quality
6                   Yes                  Other
<class 'sklearn.ensemble._forest.RandomForestClassifier'>
```

2.2.2 Conclusions

This project successfully analyzed customer churn data and built a predictive system using data from a fictional telecommunications company with 7,043 customers in California.

Through **exploratory data analysis** using correlation matrices, chi-square tests, and other statistical techniques, the project was able to address the original questions:

- **What is the most popular reason for customers canceling their subscription?**

The most common reasons include dissatisfaction with support staff, competition, low download speeds, and limited data availability.

- **When do cancellations most commonly occur?**
  Most churn happens within the **first month** of service.
- **Are the correlations between these factors statistically significant?**
  - `Tenure Months` shows strong correlation with `Total Charges` and `CLTV`.
  - `Monthly Charges` also strongly correlate with `Total Charges`.
  - `Total Charges` is highly correlated with `Tenure Months`, `Monthly Charges`, and `CLTV`.
- **How do monthly charges affect the overall duration of subscriptions?**
  Although the effect is statistically significant, **monthly charges alone explain only a small portion of the variability** in subscription duration. Other features likely play a more influential role.
- **How does the type of subscription contract influence churn?**
  Month-to-month contracts show the **highest churn rate**, while one- and two-year contracts are much more stable and have significantly lower churn rates.
- **How can churn be reduced?**
  - Improve customer support through better training
  - Offer higher download speeds and more data
  - Update or replace outdated devices
  - Introduce more self-service options via the company website

2.2.3 Machine Learning Results

In the extended part of the project, **predictive models** were developed to classify both:

1. **Whether a customer will churn**
2. **The predicted reason for their churn**

Three models were compared: **Decision Tree**, **Naive Bayes**, and **Random Forest**.
Among them, the **Random Forest classifier consistently achieved the highest accuracy** in both churn classification and churn reason prediction.

This addition transforms the project from a purely analytical task into a **practical, data-driven decision support tool** that telecom companies can use to anticipate churn and tailor their retention strategies based on predicted reasons.

Let me know if you want it formatted as a PDF or Markdown, or if you'd like to add charts/tables for results!

2.3 Further Research

Based on our exploratory data analysis and initial modeling, there are several promising directions for further research:

1. **Developing a Predictive ML Model for Churn:**
   - **Objective:**
     A machine learning model was successfully developed to predict not only the likelihood of customer churn but also the underlying reason for churn. Among the tested algorithms, Random Forest demonstrated the highest accuracy for both tasks.
   - **Outcome:**
     A robust and interpretable predictive system capable of providing dual insights: whether a customer is likely to churn and why. This dual-layered prediction enables proactive, targeted interventions tailored to specific reasons (e.g., service quality, price, competition).
2. **Personalization and Customer Segmentation:**
   - **Goal:**
     Use the insights from the predictive model to segment customers into different risk categories.
   - **Approach:**
     - Develop clusters of customers based on their predicted churn risk and demographic or behavioral attributes.
     - Tailor marketing strategies, service offerings, and retention initiatives (e.g., special discounts, personalized customer support) for each segment.
   - **Outcome:**
     Enhance customer engagement and increase subscription duration by offering individualized services that match customer needs.
3. **Continuous Model Improvement:**
   - **Data Enrichment:**
     - Incorporate additional data sources such as customer feedback, interaction logs, and external market data.
     - Regularly update the model with new data to capture evolving customer behavior.
   - **Operational Integration:**
     - Deploy the model in a real-time environment to continuously monitor churn risk.
     - Set up A/B tests to evaluate the impact of personalized interventions on customer retention.
   - **Outcome:**
     A dynamic, continuously improving system that adapts to changes in customer behavior and market conditions.

By pursuing these research directions, the company can not only predict customer churn with greater accuracy but also gain actionable insights into how to improve customer retention. This holistic approach can lead to more personalized service offerings, improved customer satisfaction, and ultimately, increased customer lifetime value.

Made by Alnur Nurumov

[705]:
```
!jupyter nbconvert --to pdf "customer-churn-IBM-dataset(Predictive Model).ipynb"
```

```
[NbConvertApp] Converting notebook customer-churn-IBM-dataset(Predictive
```

```
Model).ipynb to pdf
[NbConvertApp] Support files will be in customer-churn-IBM-dataset(Predictive
Model)_files/
[NbConvertApp] Making directory ./customer-churn-IBM-dataset(Predictive
Model)_files
[NbConvertApp] Writing 160786 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 1517097 bytes to customer-churn-IBM-dataset(Predictive
Model).pdf
```

[ ]:

```

```