Telecom Customer Churn

April 2, 2025

1 1 Import relevant libraries and Dataset

[1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

# classifier options
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# libraries for evaluating model performance
from sklearn import model_selection
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import f1_score, precision_score, recall_score, fbeta_score
from sklearn.metrics import auc, roc_auc_score, roc_curve
from sklearn import metrics
```

Data source: https://www.kaggle.com/datasets/blastchar/telco-customer-churn

"Predict behavior to retain telecom customers. We can analyze all relevant customer data and develop focused customer retention programs." [IBM Sample Data Sets]

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The data set includes information about:

- Customers who left within the last month
- the column is called Churn.

- Services that each customer has signed up for - phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies.
- Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges Demographic info about customers – gender, age range, and if they have partners and dependents

[2]:
```
df = pd.read_csv('customer_churn.csv')
df
```

[2]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…            …     …              …     …        …     …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
0              No  No phone service             DSL             No  …
1             Yes                No             DSL            Yes  …
2             Yes                No             DSL            Yes  …
3              No  No phone service             DSL            Yes  …
4             Yes                No     Fiber optic             No  …
…             …               …             …            …  …
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0                  No          No          No              No  Month-to-month
1                 Yes          No          No              No        One year
2                  No          No          No              No  Month-to-month
3                 Yes         Yes          No              No        One year
4                  No          No          No              No  Month-to-month
…                 …         …         …             …             …
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year
```

```
     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
0                 Yes           Electronic check          29.85         29.85
1                  No               Mailed check          56.95        1889.5
2                 Yes               Mailed check          53.85        108.15
3                  No  Bank transfer (automatic)          42.30       1840.75
4                 Yes           Electronic check          70.70        151.65
…                …                         …            …            …
7038              Yes               Mailed check          84.80        1990.5
7039              Yes    Credit card (automatic)         103.20        7362.9
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40         306.6
7042              Yes  Bank transfer (automatic)         105.65        6844.5

     Churn
0       No
1       No
2      Yes
3       No
4      Yes
…    …
7038    No
7039    No
7040    No
7041   Yes
7042    No

[7043 rows x 21 columns]
```

- The raw data contains 7043 rows (customers) and 21 columns (features).
- The "Churn" column is the target.
- Dataset displays customers and services subscribed to by those customers. It will be predicted whether customers will churn or not?

2 2 Data Understanding

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
```

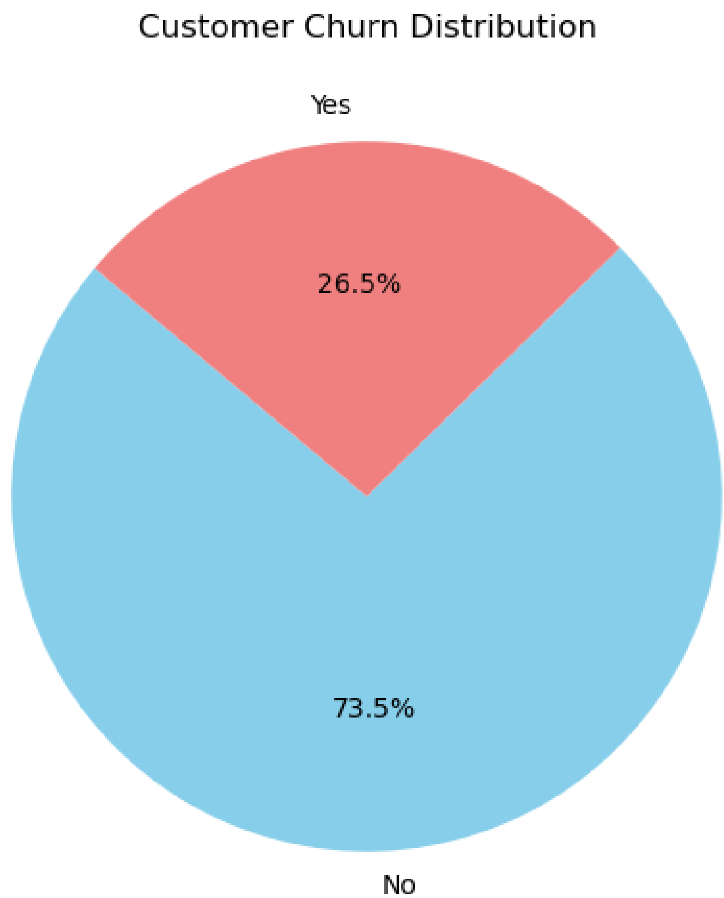
```
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

- NO missing value
- There are still data types that are inappropriate, so they need to be converted

[4]:
```
# Check Target Variable Distribution --> See data on customers whose churn is␣
↪Yes and whose churn is No:
df['Churn'].value_counts()
```

[4]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

[5]:
```
import matplotlib.pyplot as plt

churn_counts = df['Churn'].value_counts()

labels = churn_counts.index.tolist()  # Use the index (Yes/No) as labels
sizes = churn_counts.values.tolist()   # Use the counts as sizes

# Creating the pie chart
plt.figure(figsize=(6, 6))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=140,␣
↪colors=['skyblue', 'lightcoral'])
plt.title('Customer Churn Distribution')  # Set a relevant title

# Show the chart
plt.show()
```

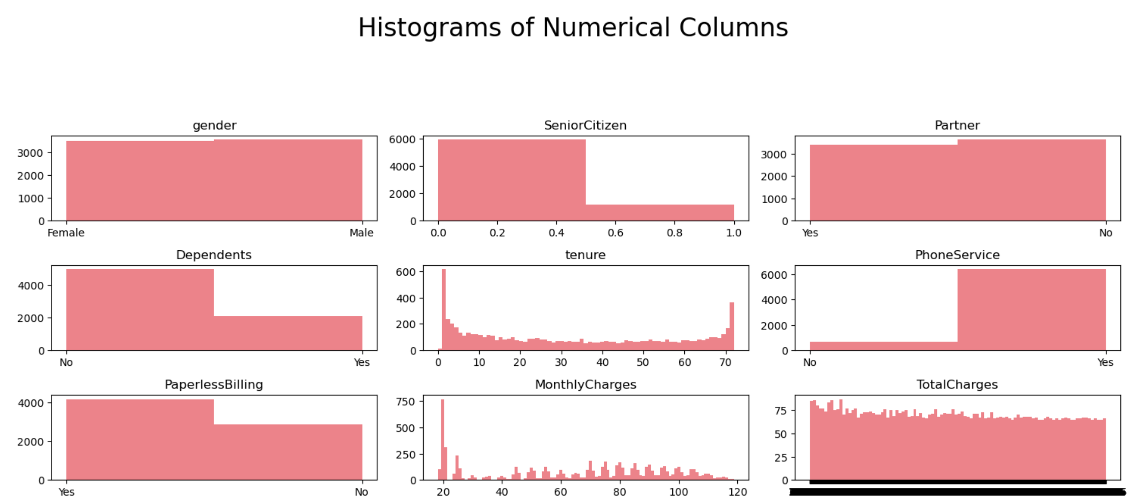


- Number of churns for Yes is 1869 and No is 5174 –> the target data is imbalanced between Yes and No.
- NOTES:
  - In this case, we have class imbalance with few positives. A low churn rate is generally good for a company. Therefore, to reduce churn for the services provided, the company needs to implement marketing strategies.
  - In our business challenges, false negatives are costly. Hence let's keep an eye onto the Precision, Recall & F2 score as well as accuracy, as well as ROC-AUC.

3 3 Exploratory Data Analysis (EDA)

3.1 a. Histogram

[6]:
```
# Plot Histogram of numeric Columns:

df2 = df[['gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'PaperlessBilling',
        'MonthlyCharges', 'TotalCharges']]

#Histogram:

fig = plt.figure(figsize=(15, 12))
plt.suptitle('Histograms of Numerical Columns\n',horizontalalignment="center",fontstyle = "normal", fontsize = 24, fontfamily = "sans-serif")
for i in range(df2.shape[1]):
    plt.subplot(6, 3, i + 1)
    f = plt.gca()
    f.set_title(df2.columns.values[i])

    vals = np.size(df2.iloc[:, i].unique())
    if vals >= 100:
        vals = 100

    plt.hist(df2.iloc[:, i], bins=vals, color = '#ec838a')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```



Key Insights:

These graphs display histograms of numerical columns from a dataset, likely related to customer data (such as telecom customers). Histograms help visualize the distribution of different features. -

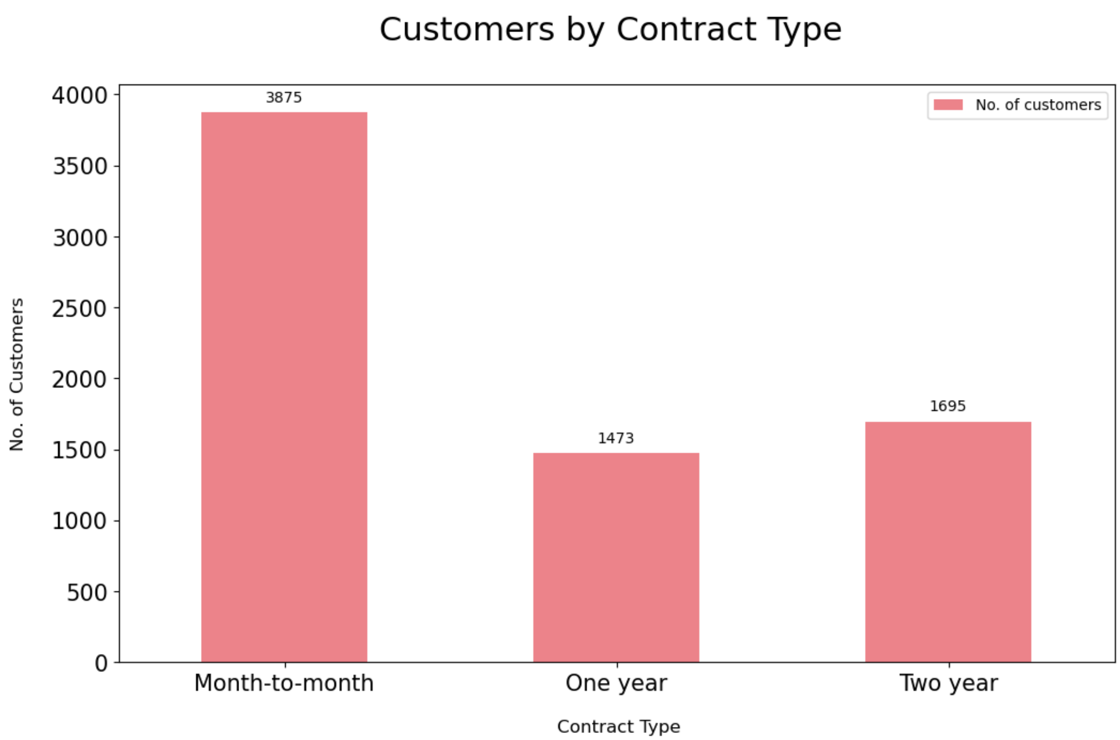
Most customers are not senior citizen (0) and do not have dependant (No) that have phone service (Yes).

- Many customers have a very short tenure (close to 0 months) and have low monthly charges (20-30). A smaller peak exists at the maximum tenure (~70 months), likely representing long-term customers. This distribution suggests a significant portion of customers churn early, while a few stay long-term.
- TotalCharges and MonthlyCharges show many customers pay lower amounts, but some pay much more.
- A higher number of customers use paperless billing (Yes) compared to those who do not.
- Possible data issues: The TotalCharges histogram might need fixing due to missing values or incorrect formatting.

3.2 b. Analyze distribution of Key Categorical Variables

[7]:
```
#(1) Distribution of Contract Type

contract_split = df[[ "customerID", "Contract"]]
sectors = contract_split .groupby ("Contract")
contract_split = pd.DataFrame(sectors["customerID"].count())
contract_split.rename(columns={'customerID':'No. of customers'}, inplace=True)


ax =  contract_split[["No. of customers"]].plot.bar(title = 'Customers by␣
↪Contract Type', legend =True, table = False, grid = False,  subplots =␣
↪False,  figsize =(12, 7), color ='#ec838a', fontsize = 15, stacked=False)

plt.ylabel('No. of Customers\n',horizontalalignment="center",fontstyle =␣
↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.xlabel('\n Contract Type',horizontalalignment="center",fontstyle =␣
↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.title('Customers by Contract Type \n',horizontalalignment="center",␣
↪fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
plt.legend(loc='upper right', fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")

x_labels = np.array(contract_split[["No. of customers"]])

def add_value_labels(ax, spacing=5):
    for rect in ax.patches:
        y_value = rect.get_height()
        x_value = rect.get_x() + rect.get_width() / 2
        space = spacing
        va = 'bottom'
        if y_value < 0:
```

```
            space *= -1
            va = 'top'
        label = "{:.0f}".format(y_value)
        ax.annotate(
            label,
            (x_value, y_value),
            xytext=(0, space),
            textcoords="offset points",
            ha='center',
            va=va)
add_value_labels(ax)
```

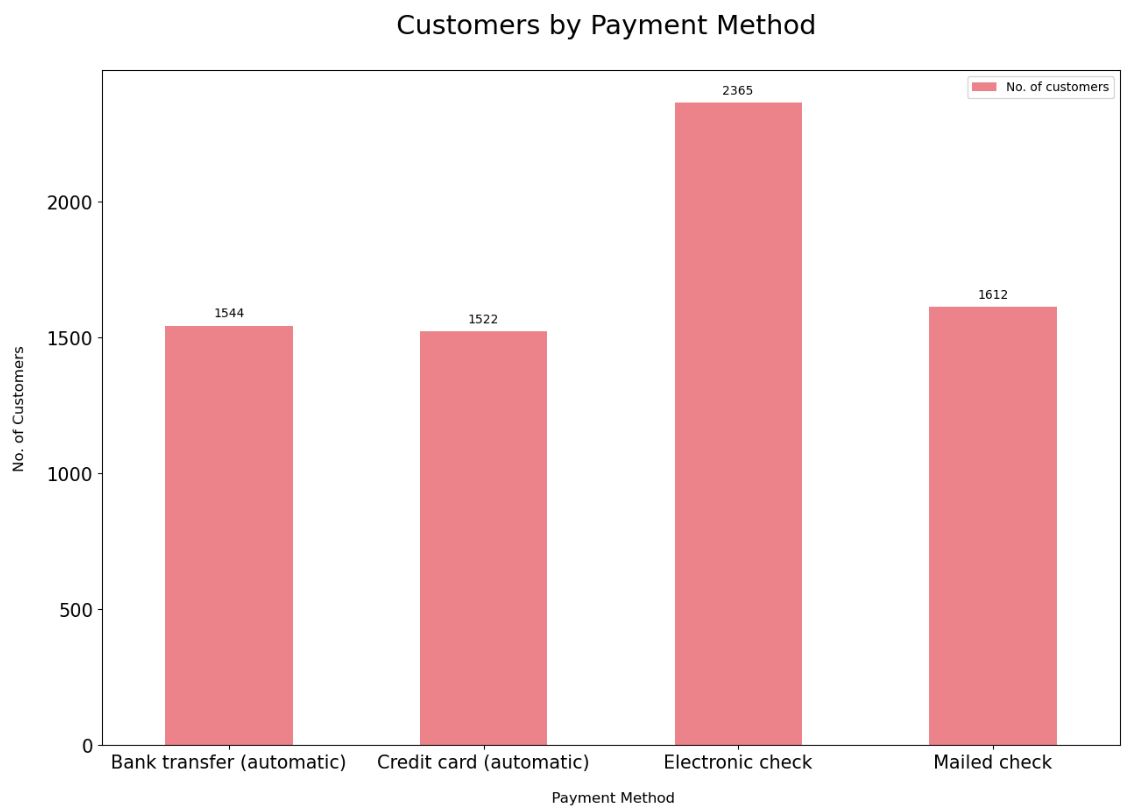


Key Insights: - Most customers (3,875) are on month-to-month contracts.

- Fewer customers have long-term contracts (1,473 for one-year, 1,695 for two-year).
- Short-term contracts may lead to higher churn, as customers can leave more easily.

[8]:
```
#(2) Distribution of Payment Method Type:
payment_method_split = df[[ "customerID", "PaymentMethod"]]
sectors = payment_method_split  .groupby ("PaymentMethod")
payment_method_split  = pd.DataFrame(sectors["customerID"].count())
payment_method_split.rename(columns={'customerID':'No. of customers'},␣
 ↪inplace=True)
```

```python
ax =  payment_method_split [["No. of customers"]].plot.bar(title = 'Customers␣
 ↪by Payment Method', legend =True, table = False, grid = False,  subplots =␣
 ↪False,  figsize =(15, 10), color ='#ec838a', fontsize = 15, stacked=False)

plt.ylabel('No. of Customers\n',horizontalalignment="center",fontstyle =␣
 ↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.xlabel('\n Payment Method',horizontalalignment="center",fontstyle =␣
 ↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.title('Customers by Payment Method \n',horizontalalignment="center",␣
 ↪fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
plt.legend(loc='upper right', fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")

x_labels = np.array(payment_method_split [["No. of customers"]])

def add_value_labels(ax, spacing=5):
    for rect in ax.patches:
        y_value = rect.get_height()
        x_value = rect.get_x() + rect.get_width() / 2
        space = spacing
        va = 'bottom'
        if y_value < 0:
            space *= -1
            va = 'top'
        label = "{:.0f}".format(y_value)
        ax.annotate(
            label,
            (x_value, y_value),
            xytext=(0, space),
            textcoords="offset points",
            ha='center',
            va=va)
add_value_labels(ax)
```



Key Insights:

- Electronic check is the most used payment method (2,365 customers).
- Credit card (automatic) is the least used (1,522 customers).
- Bank transfer (automatic) and mailed check have similar usage (1,544 and 1,612 customers, respectively).

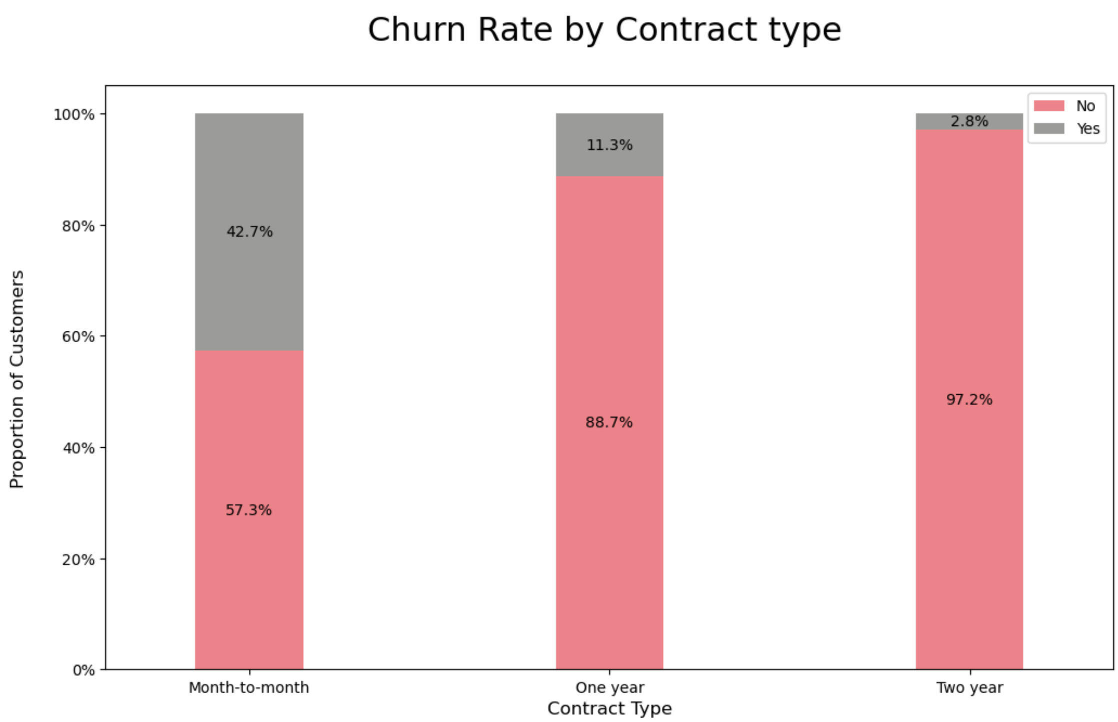
Possible Business Implications: - Since electronic check is the most used, companies should analyze if it is linked to higher churn rates or billing issues.

- Encouraging automatic payments (credit card/bank transfer) may improve retention and reduce late payments.

3.3 c. Analyze the churn type based on contract type

[9]:
```
# Distribution of churn type by contract type

import matplotlib.ticker as mtick

contract_churn = df.groupby(['Contract','Churn']).size().unstack()

contract_churn.rename(columns={0:'No', 1:'Yes'}, inplace=True)
```

```python
colors  = ['#ec838a','#9b9c9a']

ax = (contract_churn.T*100.0 / contract_churn.T.sum()).T.plot(kind='bar',
                                                                width = 0.3,
                                                                stacked = True,
                                                                rot = 0,
                                                                figsize = (12,7),
                                                                color = colors)





plt.ylabel('Proportion of Customers\n',horizontalalignment="center",fontstyle = "normal", fontsize = "large", fontfamily = "sans-serif")
plt.xlabel('Contract Type\n',horizontalalignment="center",fontstyle = "normal", fontsize = "large", fontfamily = "sans-serif")
plt.title('Churn Rate by Contract type \n',horizontalalignment="center", fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
plt.legend(loc='upper right', fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.text(x+width/2,
            y+height/2,
            '{:.1f}%'.format(height),
            horizontalalignment='center',
            verticalalignment='center')
ax.autoscale(enable=False, axis='both', tight=False)
```



Key Insights: - The longer the contract duration, the lower the churn rate.

- Customers on month-to-month contracts have the highest churn rate, likely because they have more flexibility to switch services.
- Customers with one-year or two-year contracts are more loyal, possibly due to incentives or penalties for early termination.

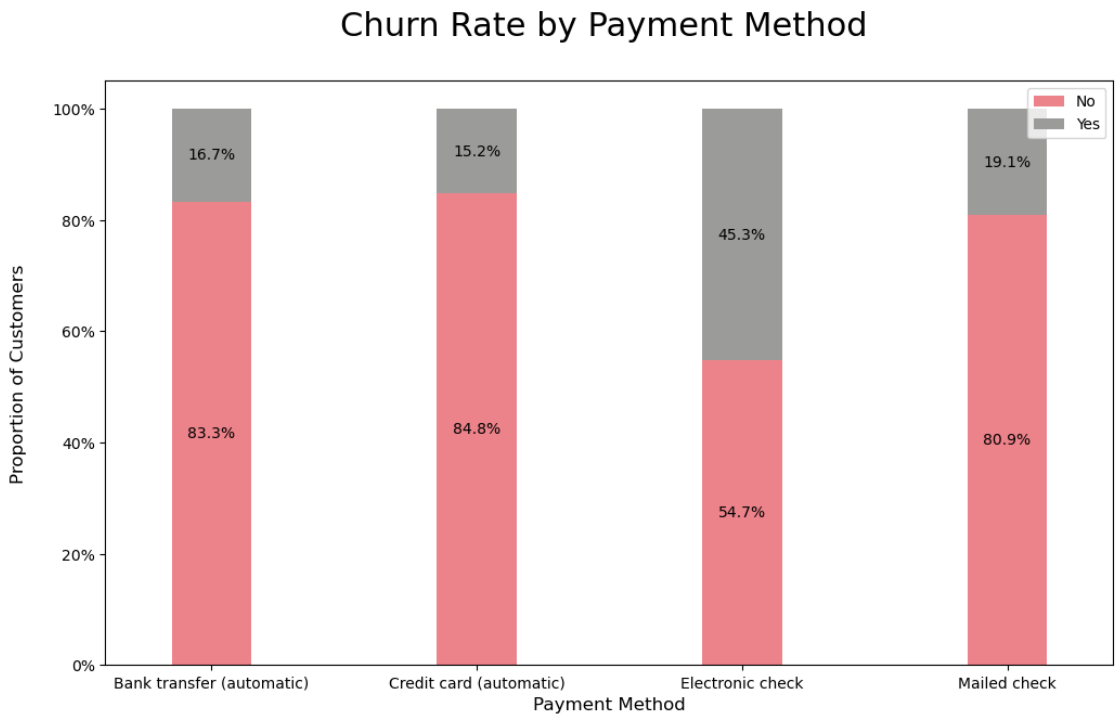
Business Implications: - The company should focus on retaining month-to-month customers by offering incentives (discounts, bundles. etc) to switch to long-term contracts.

- Long-term contracts help with customer retention, so promotions or discounts for annual plans could reduce churn.
- Implement targeted retention strategies for month-to-month customers.
- Analyze competitor strategies to identify market gaps and opportunities.

3.4 d. Analyze churn rate based on payment method

[10]:
```
# Distribution of churn rate by payment method

import matplotlib.ticker as mtick

contract_churn = df.groupby(['PaymentMethod', 'Churn']).size().unstack()

contract_churn.rename(columns={0:'No', 1:'Yes'}, inplace=True)
```

```
colors  = ['#ec838a','#9b9c9a', '#f3babc' , '#4d4f4c']

ax = (contract_churn.T*100.0 / contract_churn.T.sum()).T.plot(kind='bar',
                                                                width = 0.3,
                                                                stacked = True,
                                                                rot = 0,
                                                                figsize =␣
 ↪(12,7),
                                                                color = colors)





plt.ylabel('Proportion of Customers\n',horizontalalignment="center",fontstyle =␣
 ↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.xlabel('Payment Method\n',horizontalalignment="center",fontstyle =␣
 ↪"normal", fontsize = "large", fontfamily = "sans-serif")
plt.title('Churn Rate by Payment Method \n',horizontalalignment="center",␣
 ↪fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
plt.legend(loc='upper right', fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.text(x+width/2,
            y+height/2,
            '{:.1f}%'.format(height),
            horizontalalignment='center',
            verticalalignment='center')
ax.autoscale(enable=False, axis='both', tight=False)
```



Customers who are likely to churn are those who subscribe monthly with manual payments (electronic checks)

Key Insights: - Customers using electronic checks churn the most (45.3%), meaning they leave the service more often.

- Customers with automatic payments (bank transfer & credit card) churn the least (15-16%), meaning they stay longer.
- Mailed check users have moderate churn (19.1%), but still lower than electronic check users.

Business Implications: - Encourage Automatic Payments, such as offering discounts or easy setup for bank transfers & credit cards.

- Reduce Electronic Check Churn such as send reminders, offer better payment options, or give incentives to switch.
- Improve target high-churn customers experience with promotions & flexible payment options.
- Focus on Loyal Customers, for example, providing reward automatic payment users to keep them engaged.

4 4 Data Cleaning and Preprocessing

4.1 a. Data Cleaning

[11]:
```
df.info()
```

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

- No missing value
- However, data type for TotalCharge is not appropriate –> need to be changed.

[12]:
```
# Check the unique value of TotalCharge (categorical data):
df['TotalCharges'].unique()
```

[12]:
```
array(['29.85', '1889.5', '108.15', …, '346.45', '306.6', '6844.5'],
      dtype=object)
```

[13]:
```
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'],errors='coerce') #␣
↪'force' convert from string to numeric, if an error occurs during␣
↪conversion, it will be replaced with NaN
```

[14]:
```python
# Check the result:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

- Data type for TotalCharges has been converted from object to numeric.
- However, there are 11 missing values (11 customers)

[15]:
```python
# Check the columns that have missing values
df[df['TotalCharges'].isnull()]
```

[15]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
488   4472-LVYGI  Female              0     Yes        Yes       0
753   3115-CZMZD    Male              0      No        Yes       0
936   5709-LVOEQ  Female              0     Yes        Yes       0
1082  4367-NUYAO    Male              0     Yes        Yes       0
1340  1371-DWPAZ  Female              0     Yes        Yes       0
3331  7644-OMVMY    Male              0     Yes        Yes       0
3826  3213-VVOLG    Male              0     Yes        Yes       0
4380  2520-SGTTA  Female              0     Yes        Yes       0
```

```
5218  2923-ARZLG    Male              0     Yes        Yes       0
6670  4075-WKNIU  Female              0     Yes        Yes       0
6754  2775-SEFEE    Male              0      No        Yes       0

     PhoneService     MultipleLines InternetService       OnlineSecurity  …  \
488            No  No phone service             DSL                  Yes  …
753           Yes                No              No  No internet service  …
936           Yes                No             DSL                  Yes  …
1082          Yes               Yes              No  No internet service  …
1340           No  No phone service             DSL                  Yes  …
3331          Yes                No              No  No internet service  …
3826          Yes               Yes              No  No internet service  …
4380          Yes                No              No  No internet service  …
5218          Yes                No              No  No internet service  …
6670          Yes               Yes             DSL                   No  …
6754          Yes               Yes             DSL                  Yes  …

         DeviceProtection          TechSupport          StreamingTV  \
488                   Yes                  Yes                  Yes
753   No internet service  No internet service  No internet service
936                   Yes                   No                  Yes
1082  No internet service  No internet service  No internet service
1340                  Yes                  Yes                  Yes
3331  No internet service  No internet service  No internet service
3826  No internet service  No internet service  No internet service
4380  No internet service  No internet service  No internet service
5218  No internet service  No internet service  No internet service
6670                  Yes                  Yes                  Yes
6754                   No                  Yes                   No

          StreamingMovies  Contract PaperlessBilling  \
488                    No  Two year              Yes
753   No internet service  Two year               No
936                   Yes  Two year               No
1082  No internet service  Two year               No
1340                   No  Two year               No
3331  No internet service  Two year               No
3826  No internet service  Two year               No
4380  No internet service  Two year               No
5218  No internet service  One year              Yes
6670                   No  Two year               No
6754                   No  Two year              Yes

                  PaymentMethod MonthlyCharges  TotalCharges  Churn
488   Bank transfer (automatic)          52.55           NaN     No
753                Mailed check          20.25           NaN     No
936                Mailed check          80.85           NaN     No
```

```
1082                Mailed check           25.75            NaN     No
1340     Credit card (automatic)           56.05            NaN     No
3331                Mailed check           19.85            NaN     No
3826                Mailed check           25.35            NaN     No
4380                Mailed check           20.00            NaN     No
5218                Mailed check           19.70            NaN     No
6670                Mailed check           73.35            NaN     No
6754   Bank transfer (automatic)           61.90            NaN     No

[11 rows x 21 columns]
```

[16]:
```python
# Imputation (filling null values) of the TotalCharges column with the value 0
df['TotalCharges'] = df['TotalCharges'].fillna(0)
```

[17]:
```python
# Check the result:
df.info()
```

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

- All data is complete, there are no missing values

- However, there are still many columns with categorical data types, so they need to be label-encoded, but only for columns that have two possible values.

4.2 b. Label Encoding Binary data

[18]:
```
# Copy the dataframe
df_tmp = df.copy()
```

[19]:
```
# Check all columns:
df_tmp.columns
```

[19]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

[20]:
```
encoders = {}         # create encoder object storage for encoded columns

# Label Encoding will be used for columns with 2 or less unique values
le_count = 0
for col in df_tmp.columns[1:]:
    if df_tmp[col].dtype == 'object':
        if len(list(df_tmp[col].unique())) <= 2:
            print(col)
            le = LabelEncoder()
            le.fit(df_tmp[col])
            df_tmp[col] = le.transform(df_tmp[col])   # update the column with␣
 ↪the results of the transformation
            encoders[col] = le
            le_count += 1

print('{} columns were label encoded.'.format(le_count))
```

```
gender
Partner
Dependents
PhoneService
PaperlessBilling
Churn
6 columns were label encoded.
```

Compare the result of label encoding

[21]:
```
# The original data:
df
```

[21]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…          …     …            …     …      …     …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
0              No  No phone service             DSL             No  …
1             Yes                No             DSL            Yes  …
2             Yes                No             DSL            Yes  …
3              No  No phone service             DSL            Yes  …
4             Yes                No     Fiber optic             No  …
…            …                …             …             …  …
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0                  No          No          No              No  Month-to-month
1                 Yes          No          No              No        One year
2                  No          No          No              No  Month-to-month
3                 Yes         Yes          No              No        One year
4                  No          No          No              No  Month-to-month
…                 …         …         …             …             …
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
0                 Yes           Electronic check          29.85         29.85
1                  No               Mailed check          56.95       1889.50
2                 Yes               Mailed check          53.85        108.15
3                  No  Bank transfer (automatic)          42.30       1840.75
4                 Yes           Electronic check          70.70        151.65
…                 …                        …            …           …
7038              Yes               Mailed check          84.80       1990.50
```

```
7039              Yes    Credit card (automatic)        103.20       7362.90
7040              Yes           Electronic check         29.60        346.45
7041              Yes               Mailed check         74.40        306.60
7042              Yes  Bank transfer (automatic)        105.65       6844.50

      Churn
0        No
1        No
2       Yes
3        No
4       Yes
…     …
7038     No
7039     No
7040     No
7041    Yes
7042     No

[7043 rows x 21 columns]
```

[22]:
```
# Data after doing label encoding:
df_tmp
```

[22]:
```
      customerID  gender  SeniorCitizen  Partner  Dependents  tenure  \
0     7590-VHVEG       0              0        1           0       1
1     5575-GNVDE       1              0        0           0      34
2     3668-QPYBK       1              0        0           0       2
3     7795-CFOCW       1              0        0           0      45
4     9237-HQITU       0              0        0           0       2
…            …      …              …        …           …       …
7038  6840-RESVB       1              0        1           1      24
7039  2234-XADUH       0              0        1           1      72
7040  4801-JZAZL       0              0        1           1      11
7041  8361-LTMKD       1              1        1           0       4
7042  3186-AJIEK       1              0        0           0      66

      PhoneService     MultipleLines InternetService OnlineSecurity  …  \
0                0  No phone service             DSL             No  …
1                1                No             DSL            Yes  …
2                1                No             DSL            Yes  …
3                0  No phone service             DSL            Yes  …
4                1                No     Fiber optic             No  …
…              …                …             …              …  …
7038             1               Yes             DSL            Yes  …
7039             1               Yes     Fiber optic             No  …
7040             0  No phone service             DSL            Yes  …
7041             1               Yes     Fiber optic             No  …
```

```
7042              1                No     Fiber optic           Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0                  No          No          No              No  Month-to-month
1                 Yes          No          No              No        One year
2                  No          No          No              No  Month-to-month
3                 Yes         Yes          No              No        One year
4                  No          No          No              No  Month-to-month
…                 …         …         …             …             …
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     PaperlessBilling             PaymentMethod MonthlyCharges  TotalCharges  \
0                   1          Electronic check          29.85         29.85
1                   0              Mailed check          56.95       1889.50
2                   1              Mailed check          53.85        108.15
3                   0 Bank transfer (automatic)          42.30       1840.75
4                   1          Electronic check          70.70        151.65
…                 …                         …            …           …
7038                1              Mailed check          84.80       1990.50
7039                1   Credit card (automatic)         103.20       7362.90
7040                1          Electronic check          29.60        346.45
7041                1              Mailed check          74.40        306.60
7042                1 Bank transfer (automatic)         105.65       6844.50

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

[7043 rows x 21 columns]
```

- Each unique category in a column is assigned a numerical value. For example, in ‘gender’ column with values [“Male”, “Female”], label encoding could convert them to [0, 1]
- It is commonly used when a categorical feature has only two unique values (binary categories).

4.3 c. One-Hot Encoding for the Remaining Categorical Variables

[23]:
```
# Remove the customerID column as it is not significant in the prediction:
identity = df_tmp["customerID"]

df_tmp = df_tmp.drop(columns="customerID")
```

[24]:
```
# One-Hot Encoding for remaining categorical variables:
df_tmp= pd.get_dummies(df_tmp)
df_tmp
```

[24]:
```
      gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0          0              0        1           0       1             0
1          1              0        0           0      34             1
2          1              0        0           0       2             1
3          1              0        0           0      45             0
4          0              0        0           0       2             1
…       …           …       …          …       …          …
7038       1              0        1           1      24             1
7039       0              0        1           1      72             1
7040       0              0        1           1      11             0
7041       1              1        1           0       4             1
7042       1              0        0           0      66             1

      PaperlessBilling  MonthlyCharges  TotalCharges  Churn  …  \
0                    1           29.85         29.85      0  …
1                    0           56.95       1889.50      0  …
2                    1           53.85        108.15      1  …
3                    0           42.30       1840.75      0  …
4                    1           70.70        151.65      1  …
…                 …              …             …     …   …
7038                 1           84.80       1990.50      0  …
7039                 1          103.20       7362.90      0  …
7040                 1           29.60        346.45      0  …
7041                 1           74.40        306.60      1  …
7042                 1          105.65       6844.50      0  …

      StreamingMovies_No  StreamingMovies_No internet service  \
0                   True                                False
1                   True                                False
2                   True                                False
3                   True                                False
4                   True                                False
…                    …                                 …
7038               False                                False
7039               False                                False
7040                True                                False
```

```
7041                True                                   False
7042               False                                   False

      StreamingMovies_Yes  Contract_Month-to-month  Contract_One year  \
0                   False                     True              False
1                   False                    False               True
2                   False                     True              False
3                   False                    False               True
4                   False                     True              False
…                       …                        …                  …
7038                 True                    False               True
7039                 True                    False               True
7040                False                     True              False
7041                False                     True              False
7042                 True                    False              False

      Contract_Two year  PaymentMethod_Bank transfer (automatic)  \
0                 False                                    False
1                 False                                    False
2                 False                                    False
3                 False                                     True
4                 False                                    False
…                     …                                        …
7038              False                                    False
7039              False                                    False
7040              False                                    False
7041              False                                    False
7042               True                                     True

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                     False                            True
1                                     False                           False
2                                     False                           False
3                                     False                           False
4                                     False                            True
…                                         …                               …
7038                                  False                           False
7039                                   True                           False
7040                                  False                            True
7041                                  False                           False
7042                                  False                           False

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

```
4                          False
…                          …
7038                        True
7039                       False
7040                       False
7041                        True
7042                       False

[7043 rows x 41 columns]
```

[25]:
```python
# Original data:
df
```

[25]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…            …     …             …      …          …     …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
0              No  No phone service             DSL             No  …
1             Yes                No             DSL            Yes  …
2             Yes                No             DSL            Yes  …
3              No  No phone service             DSL            Yes  …
4             Yes                No     Fiber optic             No  …
…             …                …               …            …  …
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0                  No          No          No              No  Month-to-month
1                 Yes          No          No              No        One year
2                  No          No          No              No  Month-to-month
3                 Yes         Yes          No              No        One year
4                  No          No          No              No  Month-to-month
…                 …         …         …             …             …
7038              Yes         Yes         Yes             Yes        One year
```

```
7039              Yes          No          Yes              Yes        One year
7040               No          No           No               No  Month-to-month
7041               No          No           No               No  Month-to-month
7042              Yes         Yes          Yes              Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
0                 Yes           Electronic check          29.85         29.85
1                  No               Mailed check          56.95       1889.50
2                 Yes               Mailed check          53.85        108.15
3                  No  Bank transfer (automatic)          42.30       1840.75
4                 Yes           Electronic check          70.70        151.65
…                 …                        …            …             …
7038              Yes               Mailed check          84.80       1990.50
7039              Yes    Credit card (automatic)         103.20       7362.90
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40        306.60
7042              Yes  Bank transfer (automatic)         105.65       6844.50

      Churn
0        No
1        No
2       Yes
3        No
4       Yes
…       …
7038     No
7039     No
7040     No
7041    Yes
7042     No

[7043 rows x 21 columns]
```

Features such as "StreamingMovies," "Contract," or "PaymentMethod" have already been one-hot encoded, where different categories are represented as separated columns. For example, "Contract" column with values: Month-to-month, One year, and Two year has been converted into three separate columns: Contract_Month-to-month, Contract_One year, Contract_Two year

[26]:
```
# Add the CustomerID column:
df_tmp = pd.concat([df_tmp, identity], axis = 1)
```

[27]:
```
# Save the one-hot encoding result for later use
one_hot_columns = df_tmp.columns
```

4.4 d. Split Dataset into Dependent (Targets) and Independent Variables (Features/Predictors)

[28]:
```
# Identify target variable:
target = df_tmp["Churn"]
df_tmp = df_tmp.drop(columns="Churn")
```

4.5 e. Generate training and test datasets

[29]:
```
X_train, X_test, y_train, y_test = train_test_split(df_tmp, target,
                                                     stratify=target, # to␣
 ↪balance the ratio of values in the training and test data
                                                     test_size = 0.2,
                                                     random_state = 0)
```

[30]:
```
print("Dimensi X_train dataset: ", X_train.shape)
print("Dimensi y_train dataset: ", y_train.shape)
print("Dimensi X_test dataset: ", X_test.shape)
print("Dimensi y_test dataset: ", y_test.shape)
```

```
Dimensi X_train dataset:  (5634, 41)
Dimensi y_train dataset:  (5634,)
Dimensi X_test dataset:  (1409, 41)
Dimensi y_test dataset:  (1409,)
```

4.6 f. Removing Identifiers column

[31]:
```
# Removing Identifiers:
train_identity = X_train['customerID']
X_train = X_train.drop(columns = ['customerID'])

test_identity = X_test['customerID']
X_test = X_test.drop(columns = ['customerID'])
```

4.7 g. Feature Scaling

[32]:
```
# Original X train:
X_train
```

[32]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
2499	1	0	0	1	41	1	
5807	1	0	0	0	57	1	
5118	0	0	1	0	42	1	
275	1	0	1	0	5	1	
1350	0	0	1	0	67	1	
…	…	…	…	…	…	…	
1712	0	0	0	0	29	1	

```
1954       1              0         0           0      1             1
525        1              0         0           0     52             1
5748       0              0         0           0     21             1
6513       1              0         1           1     15             1

      PaperlessBilling  MonthlyCharges  TotalCharges  MultipleLines_No  …  \
2499                 0           70.20       2894.55              True  …
5807                 0           18.80       1094.35              True  …
5118                 1           85.90       3729.75             False  …
275                  1           85.40        401.10             False  …
1350                 0           65.65       4322.85             False  …
…                  …             …           …                 …   …
1712                 1           55.25       1620.20             False  …
1954                 1           75.45         75.45             False  …
525                  0           91.25       4738.30              True  …
5748                 1           99.85       1992.55             False  …
6513                 1           59.65        867.10             False  …

      StreamingMovies_No  StreamingMovies_No internet service  \
2499                True                                False
5807               False                                 True
5118                True                                False
275                 True                                False
1350                True                                False
…                  …                                 …
1712                True                                False
1954                True                                False
525                 True                                False
5748               False                                False
6513                True                                False

      StreamingMovies_Yes  Contract_Month-to-month  Contract_One year  \
2499                False                    False               True
5807                False                    False              False
5118                False                     True              False
275                 False                     True              False
1350                False                    False              False
…                    …                       …                 …
1712                False                    False               True
1954                False                     True              False
525                 False                    False               True
5748                 True                     True              False
6513                False                     True              False

      Contract_Two year  PaymentMethod_Bank transfer (automatic)  \
2499              False                                    False
5807               True                                    False
```

```
5118              False                                       False
275               False                                       False
1350               True                                       False
…                 …                                          …
1712              False                                       False
1954              False                                       False
525               False                                       False
5748              False                                       False
6513              False                                        True

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
2499                                  False                           False
5807                                   True                           False
5118                                   True                           False
275                                   False                            True
1350                                  False                           False
…                                     …                              …
1712                                  False                            True
1954                                  False                            True
525                                   False                            True
5748                                   True                           False
6513                                  False                           False

      PaymentMethod_Mailed check
2499                        True
5807                       False
5118                       False
275                        False
1350                        True
…                          …
1712                       False
1954                       False
525                        False
5748                       False
6513                       False

[5634 rows x 40 columns]
```

[33]:

```python
# Feature Scaling:
sc_X = StandardScaler()
X_train2 = pd.DataFrame(sc_X.fit_transform(X_train))
X_train2.columns = X_train.columns.values
X_train2.index = X_train.index.values
X_train = X_train2

X_test2 = pd.DataFrame(sc_X.transform(X_test))
X_test2.columns = X_test.columns.values
```

```
X_test2.index = X_test.index.values
X_test = X_test2
```

[34]:
```
# X train after scaling:
X_train
```

[34]:
```
        gender  SeniorCitizen   Partner  Dependents    tenure  PhoneService  \
2499  0.996103      -0.444067 -0.961343    1.545268  0.363266      0.327252
5807  0.996103      -0.444067 -0.961343   -0.647137  1.016103      0.327252
5118 -1.003913      -0.444067  1.040211   -0.647137  0.404069      0.327252
275   0.996103      -0.444067  1.040211   -0.647137 -1.105616      0.327252
1350 -1.003913      -0.444067  1.040211   -0.647137  1.424126      0.327252
…          …            …         …         …         …          …
1712 -1.003913      -0.444067 -0.961343   -0.647137 -0.126361      0.327252
1954  0.996103      -0.444067 -0.961343   -0.647137 -1.268825      0.327252
525   0.996103      -0.444067 -0.961343   -0.647137  0.812091      0.327252
5748 -1.003913      -0.444067 -0.961343   -0.647137 -0.452779      0.327252
6513  0.996103      -0.444067  1.040211    1.545268 -0.697593      0.327252

      PaperlessBilling  MonthlyCharges  TotalCharges  MultipleLines_No  …  \
2499         -1.203537        0.193982      0.285152          1.030277  …
5807         -1.203537       -1.515002     -0.512822          1.030277  …
5118          0.830884        0.715987      0.655370         -0.970613  …
275           0.830884        0.699362     -0.820119         -0.970613  …
1350         -1.203537        0.042700      0.918274         -0.970613  …
…                  …              …             …               …  …
1712          0.830884       -0.303086     -0.279729         -0.970613  …
1954          0.830884        0.368538     -0.964469         -0.970613  …
525          -1.203537        0.893867      1.102430          1.030277  …
5748          0.830884        1.179806     -0.114677         -0.970613  …
6513          0.830884       -0.156792     -0.613555         -0.970613  …

      StreamingMovies_No  StreamingMovies_No internet service  \
2499            1.237335                            -0.529854
5807           -0.808189                             1.887311
5118            1.237335                            -0.529854
275             1.237335                            -0.529854
1350            1.237335                            -0.529854
…                    …                                  …
1712            1.237335                            -0.529854
1954            1.237335                            -0.529854
525             1.237335                            -0.529854
5748           -0.808189                            -0.529854
6513            1.237335                            -0.529854

      StreamingMovies_Yes  Contract_Month-to-month  Contract_One year  \
2499            -0.792372                -1.116428           1.958584
```

5807	-0.792372	-1.116428	-0.510573
5118	-0.792372	0.895714	-0.510573
275	-0.792372	0.895714	-0.510573
1350	-0.792372	-1.116428	-0.510573
…	…	…	…
1712	-0.792372	-1.116428	1.958584
1954	-0.792372	0.895714	-0.510573
525	-0.792372	-1.116428	1.958584
5748	1.262034	0.895714	-0.510573
6513	-0.792372	0.895714	-0.510573

	Contract_Two year	PaymentMethod_Bank transfer (automatic) \
2499	-0.559447	-0.525181
5807	1.787480	-0.525181
5118	-0.559447	-0.525181
275	-0.559447	-0.525181
1350	1.787480	-0.525181
…	…	…
1712	-0.559447	-0.525181
1954	-0.559447	-0.525181
525	-0.559447	-0.525181
5748	-0.559447	-0.525181
6513	-0.559447	1.904105

	PaymentMethod_Credit card (automatic)	PaymentMethod_Electronic check \
2499	-0.530678	-0.707107
5807	1.884380	-0.707107
5118	1.884380	-0.707107
275	-0.530678	1.414214
1350	-0.530678	-0.707107
…	…	…
1712	-0.530678	1.414214
1954	-0.530678	1.414214
525	-0.530678	1.414214
5748	1.884380	-0.707107
6513	-0.530678	-0.707107

	PaymentMethod_Mailed check
2499	1.825882
5807	-0.547680
5118	-0.547680
275	-0.547680
1350	1.825882
…	…
1712	-0.547680
1954	-0.547680
525	-0.547680

```
5748                     -0.547680
6513                     -0.547680

[5634 rows x 40 columns]
```

5 4 Modeling

5.1 a. Model Selection

[35]:
```
models = []

models.append(('Logistic Regression', LogisticRegression(solver='liblinear',␣
 ↪random_state = 0,
                                                                         ␣
 ↪class_weight='balanced')))

models.append(('Decision Tree Classifier',
               DecisionTreeClassifier(criterion = 'entropy', random_state = 0)))

models.append(('Random Forest', RandomForestClassifier(
    n_estimators=100, criterion = 'entropy', random_state = 0)))
```

5.1.1 Model Evaluation with Cross-Validation

[36]:
```
# Evaluating Model Results: compared 3 models with 10 times cross validation

acc_results = []
auc_results = []
names = []
# set table to table to populate with performance results
col = ['Algorithm', 'ROC AUC Mean', 'ROC AUC STD',
       'Accuracy Mean', 'Accuracy STD']

model_results = pd.DataFrame(columns=col)
i = 0
# evaluate each model using k-fold cross-validation
for name, model in models:
    kfold = model_selection.KFold(n_splits=10)  # 10-fold cross-validation

    cv_acc_results = model_selection.cross_val_score(  # accuracy scoring   #␣
 ↪evaluation matrix: accuracy, roc_a
        model, X_train, y_train, cv=kfold, scoring='accuracy')

    cv_auc_results = model_selection.cross_val_score(  # roc_auc scoring
        model, X_train, y_train, cv=kfold, scoring='roc_auc')
```

```
    acc_results.append(cv_acc_results)
    auc_results.append(cv_auc_results)
    names.append(name)
    model_results.loc[i] = [name,
                         round(cv_auc_results.mean()*100, 2),   # calculate the
 ↪average
                         round(cv_auc_results.std()*100, 2),
                         round(cv_acc_results.mean()*100, 2),
                         round(cv_acc_results.std()*100, 2)
                         ]
    i += 1

model_results.sort_values(by=['ROC AUC Mean'], ascending=False)
```

[36]:

```
                  Algorithm  ROC AUC Mean  ROC AUC STD  Accuracy Mean  \
0       Logistic Regression         84.35         1.64          74.44
2             Random Forest         82.41         2.08          79.07
1  Decision Tree Classifier         66.30         1.96          73.45

   Accuracy STD
0          1.20
2          1.20
1          1.59
```

- An initial evaluation of multiple algorithms is performed using 10-fold cross-validation to avoid overfitting, since cross-validation trains and evaluates the model on different subsets of the training data.
- The mean and standard deviation of ROC AUC and accuracy are calculated for each model where the Models with a high Mean ROC AUC (Logistic regression and random forest) are prioritized for further testing.

5.1.2 Evaluating Selected Models on Test Set

[37]:

```
# Evaluating selected models on test set - Second Iteration:

# Logistic Regression-----------------

# Fitting Logistic Regression to the Training set
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

#Evaluate results

acc = accuracy_score(y_test, y_pred )
```

```
prec = precision_score(y_test, y_pred )
rec = recall_score(y_test, y_pred )
f1 = f1_score(y_test, y_pred )
f2 = fbeta_score(y_test, y_pred, beta=2.0)
roc_auc = roc_auc_score(y_test, y_pred)

results = pd.DataFrame([['Logistic Regression', acc, prec, rec, f1, f2,␣
↪roc_auc]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1␣
↪Score', 'F2 Score', 'ROC-AUC'])



# Random Forest-----------------------

# Fitting Random Forest to the Training set:

classifier = RandomForestClassifier(n_estimators = 72, criterion = 'entropy',␣
↪random_state = 0)
classifier.fit(X_train, y_train)


# Predicting the Test set results
y_pred = classifier.predict(X_test)

#Evaluate results

from sklearn.metrics import confusion_matrix, accuracy_score, f1_score,␣
↪precision_score, recall_score
acc = accuracy_score(y_test, y_pred )
prec = precision_score(y_test, y_pred )
rec = recall_score(y_test, y_pred )
f1 = f1_score(y_test, y_pred )
f2 = fbeta_score(y_test, y_pred, beta=2.0)
roc_auc = roc_auc_score(y_test, y_pred)

model_results = pd.DataFrame([['Random Forest', acc, prec, rec, f1, f2,␣
↪roc_auc]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1␣
↪Score', 'F2 Score', 'ROC-AUC'])

results = pd.concat([results,model_results], ignore_index = True)
```

[38]:
```
# show the results:
results = results.sort_values(["Precision", "Recall", "F2 Score"], ascending =␣
↪False)
```

```python
print (results)
```

```
                 Model  Accuracy  Precision    Recall  F1 Score  F2 Score  \
0  Logistic Regression  0.800568   0.645768  0.550802  0.594517  0.567493
1        Random Forest  0.787083   0.635036  0.465241  0.537037  0.491525

    ROC-AUC
0  0.720812
1  0.684311
```

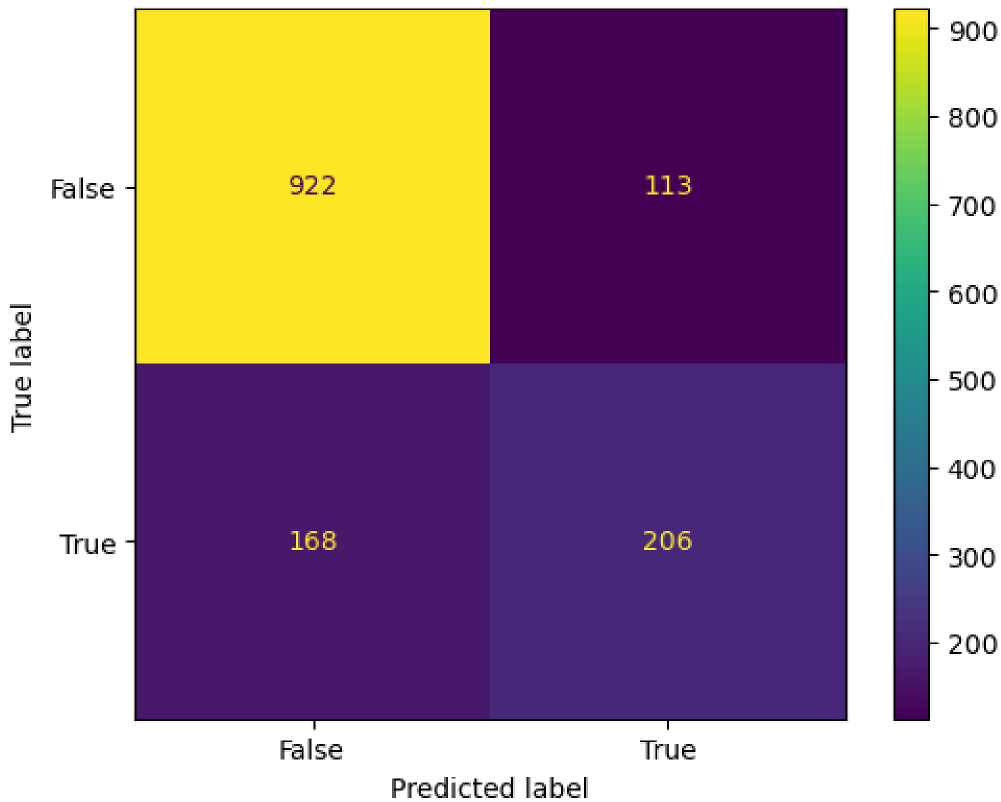
- Accuracy measures the overall correctness of the model. Logistic Regression performs slightly better, correctly predicting 80.06% of cases compared to 78.71% for Random Forest.
- Precision is the proportion of true positives out of all predicted positives. Higher precision means fewer false positives. Logistic Regression has a slightly higher precision, meaning it is better at avoiding false positives than Random Forest.
- Recall measures how many actual positive cases were correctly identified by the model. Higher recall means fewer false negatives. Logistic Regression performs better in recall, meaning it is better at capturing actual positive cases than Random Forest.
- F1 Score is a balance between Precision and Recall. A higher F1 Score indicates a better trade-off between precision and recall. Logistic Regression has a higher F1 score, meaning it performs better at balancing precision and recall.
- F2 Score is similar to F1 Score but places more emphasis on Recall. Logistic Regression is better at capturing positive cases (i.e., it prioritizes minimizing false negatives more effectively than Random Forest).
- ROC-AUC measures the model's ability to distinguish between positive and negative classes. Logistic Regression performs better at distinguishing between classes, meaning it has a stronger ability to separate positive and negative outcomes.
- Logistic Regression is the better model overall for this problem based on the evaluation metrics.

5.2 b. Train & Evaluate the Chosen Model

[39]:
```python
# Fit Logistic Regression on the Training dataset:

classifier = LogisticRegression(random_state = 0, penalty = 'l2')
classifier.fit(X_train, y_train)



# Predict the Test set results
y_pred = classifier.predict(X_test)
```

[40]:
```
# Evaluation of the selected model using a confusion matrix:
cm = confusion_matrix(y_test, y_pred)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = cm,␣
    ↪display_labels = [False, True])
cm_display.plot()
```

[40]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7d87062c4d90>
```



Key Insights This confusion matrix shows how well the churn prediction model performs in classifying customers who will leave (churn) or stay. - True Negatives (TN) = 922 → Customers correctly predicted as not churning. No action needed.

- True Positives (TP) = 206 → Customers correctly predicted as churning. Can be offered promotions to stay.
- False Negatives (FN) = 168 → Customers who churned but were predicted to stay. (Big problem – lost revenue)
- False Positives (FP) = 113 → Customers predicted to churn but actually stayed. (Wastes retention efforts & discounts)

**Business Implication*:

1. Customer Loss (False Negatives – 168 customers left undetected)

- It is hoped that the value will be as small as possible because it could be a big problem for the company (leading to lost revenue)
- Impact: High customer acquisition costs since replacing lost customers is expensive.
- Solution: Improve recall to identify more churners and prevent losses.

2. Unnecessary Retention Efforts (False Positives = 113)

- The company wasted resources offering discounts to customers who would not have left.
- Impact: Reduced profit margins due to unnecessary incentives.
- Solution: Improve precision to target only real churners and reduce wasted retention costs.

[41]:
```
# Evaluate the Selected Model on Test Set:

acc = accuracy_score(y_test, y_pred )
prec = precision_score(y_test, y_pred )
rec = recall_score(y_test, y_pred )
f1 = f1_score(y_test, y_pred )
f2 = fbeta_score(y_test, y_pred, beta=2.0)
roc_auc = roc_auc_score(y_test, y_pred)

results = pd.DataFrame([['Logistic Regression', acc, prec, rec, f1, f2,␣
 ↪roc_auc]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1␣
 ↪Score', 'F2 Score', 'ROC AUC '])

print (results)
```

```
                 Model  Accuracy  Precision    Recall  F1 Score  F2 Score  \
0  Logistic Regression  0.800568   0.645768  0.550802  0.594517  0.567493

   ROC AUC
0  0.720812
```

Strengths: - 80.1% accuracy means most predictions are correct.

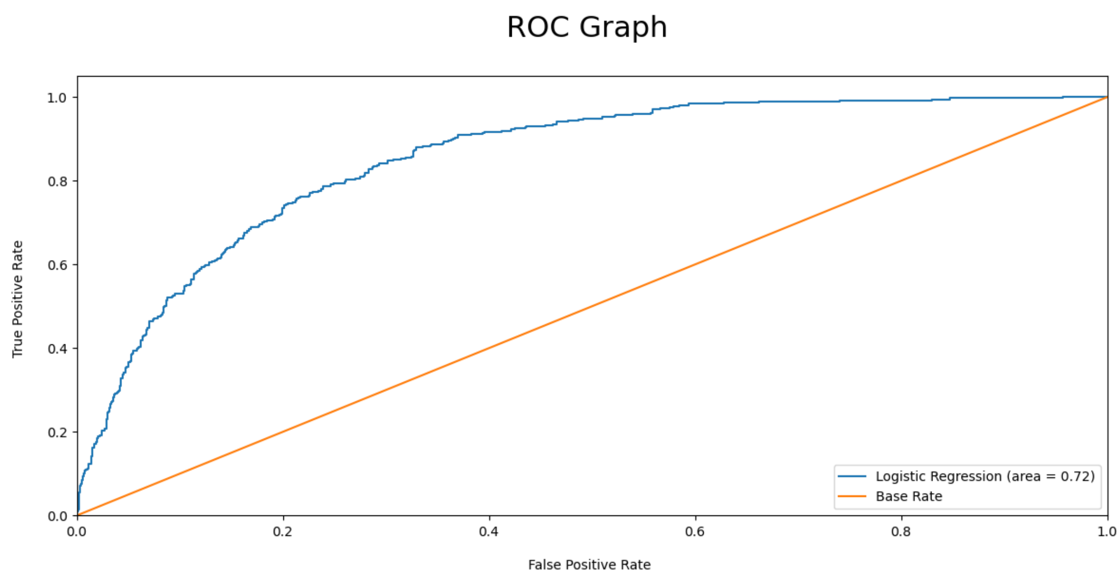
- Decent ROC AUC (72.2%) suggests a good ability to distinguish churners.

Weaknesses & Risks: - Recall (55.3%) is low, meaning many churners are not detected → risk of lost customers and revenue.

- Moderate precision (64.7%) means retention efforts may be wasted on customers who were not actually going to churn.

[42]:
```
# Evaluate the model using ROC Graph

classifier.fit(X_train, y_train)
```

```python
probs = classifier.predict_proba(X_test)
probs = probs[:, 1]
classifier_roc_auc = roc_auc_score(y_test, y_pred )


rf_fpr, rf_tpr, rf_thresholds = roc_curve(y_test, classifier.predict_proba(X_test)[:,1])
plt.figure(figsize=(14, 6))

# Plot Logistic Regression ROC
plt.plot(rf_fpr, rf_tpr, label='Logistic Regression (area = %0.2f)' % classifier_roc_auc)
# Plot Base Rate ROC
plt.plot([0,1], [0,1],label='Base Rate')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])



plt.ylabel('True Positive Rate \n',horizontalalignment="center",fontstyle = "normal", fontsize = "medium", fontfamily = "sans-serif")
plt.xlabel('\nFalse Positive Rate \n',horizontalalignment="center",fontstyle = "normal", fontsize = "medium", fontfamily = "sans-serif")
plt.title('ROC Graph \n',horizontalalignment="center", fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
plt.legend(loc="lower right", fontsize = "medium")
plt.xticks(rotation=0, horizontalalignment="center")
plt.yticks(rotation=0, horizontalalignment="right")



plt.show()
```



6 5 Predicting New Data with Logistic Regression Model

With the Logistic Regression model we obtained above, provide an example of applying the model to predict **a single row** of new customer data. Given values for each of the original variables, use the model to predict whether the customer will churn or not.

6.1 a. Given new data

[43]:
```
new_data = {'customerID': ['7370-BOUSA'],
            'gender': ['Female'],
            'SeniorCitizen': [1],
            'Partner': ['Yes'],
            'Dependents': ['Yes'],
            'tenure': [15],
            'PhoneService': ['No'],
            'MultipleLines': ['No phone service'],
            'InternetService': ['DSL'],
            'OnlineSecurity': ['No'],
            'OnlineBackup': ['Yes'],
            'DeviceProtection': ['No'],
            'TechSupport': ['Yes'],
            'StreamingTV': ['Yes'],
            'StreamingMovies': ['Yes'],
            'Contract': ['Month-to-month'],
            'PaperlessBilling': ['Yes'],
            'PaymentMethod': ['Bank transfer (automatic)'],
            'MonthlyCharges': [40.75],
```

```
            'TotalCharges': [611.25]
            }
```

6.2 b. Train the selected model

[44]:
```
# The model selected according to the modeling results is:

model = LogisticRegression(random_state=0)
model.fit(X_train, y_train)
```

[44]:
```
LogisticRegression(random_state=0)
```

6.3 c. Understanding new data

[45]:
```
# New data to be predicted is created in the form of a dataframe first:
df_new_data = pd.DataFrame(new_data)
df_new_data
```

[45]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7370-BOUSA  Female              1     Yes        Yes      15           No

      MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  No phone service             DSL             No          Yes

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No         Yes         Yes             Yes  Month-to-month

  PaperlessBilling              PaymentMethod  MonthlyCharges  TotalCharges
0              Yes  Bank transfer (automatic)           40.75        611.25
```

[46]:
```
#check the number of columns and their data types:
df_new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        1 non-null      object
 1   gender            1 non-null      object
 2   SeniorCitizen     1 non-null      int64
 3   Partner           1 non-null      object
 4   Dependents        1 non-null      object
 5   tenure            1 non-null      int64
 6   PhoneService      1 non-null      object
 7   MultipleLines     1 non-null      object
 8   InternetService   1 non-null      object
```

```
 9   OnlineSecurity    1 non-null      object
 10  OnlineBackup      1 non-null      object
 11  DeviceProtection  1 non-null      object
 12  TechSupport       1 non-null      object
 13  StreamingTV       1 non-null      object
 14  StreamingMovies   1 non-null      object
 15  Contract          1 non-null      object
 16  PaperlessBilling  1 non-null      object
 17  PaymentMethod     1 non-null      object
 18  MonthlyCharges    1 non-null      float64
 19  TotalCharges      1 non-null      float64
dtypes: float64(2), int64(2), object(16)
memory usage: 292.0+ bytes
```

6.4 d. Label Encoding

[47]:
```python
# Copy the new data first:
df_pred = df_new_data.copy()
```

[48]:
```python
# Label encoding for the categorical columns on new data:

encoders = {}  # create encoder object storage for encoded columns


# List of columns to label encode
columns_to_encode = ['gender', 'Partner', 'Dependents', 'PhoneService',␣
 ↪'PaperlessBilling']

le_count = 0
for col in columns_to_encode:
    if df_pred[col].dtype == 'object':
        if len(list(df_pred[col].unique())) <= 2:
            print(col)
            le = LabelEncoder()
            le.fit(df_pred[col])
            df_pred[col] = le.transform(df_pred[col])  # Update column with␣
 ↪transformed values
            encoders[col] = le
            le_count += 1

print('{} columns were label encoded.'.format(le_count))
```

```
gender
Partner
Dependents
PhoneService
PaperlessBilling
```

```
5 columns were label encoded.
```

[49]:
```python
# Check whether the columns have changed their data type:
df_pred.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        1 non-null      object
 1   gender            1 non-null      int64
 2   SeniorCitizen     1 non-null      int64
 3   Partner           1 non-null      int64
 4   Dependents        1 non-null      int64
 5   tenure            1 non-null      int64
 6   PhoneService      1 non-null      int64
 7   MultipleLines     1 non-null      object
 8   InternetService   1 non-null      object
 9   OnlineSecurity    1 non-null      object
 10  OnlineBackup      1 non-null      object
 11  DeviceProtection  1 non-null      object
 12  TechSupport       1 non-null      object
 13  StreamingTV       1 non-null      object
 14  StreamingMovies   1 non-null      object
 15  Contract          1 non-null      object
 16  PaperlessBilling  1 non-null      int64
 17  PaymentMethod     1 non-null      object
 18  MonthlyCharges    1 non-null      float64
 19  TotalCharges      1 non-null      float64
dtypes: float64(2), int64(7), object(11)
memory usage: 292.0+ bytes
```

6.5 e. One-Hot Encoding

[50]:
```python
# Remove customerID column as it is not significant in prediction (before␣
↪one-hot encoding):
identity = df_pred["customerID"]

df_pred = df_pred.drop(columns="customerID")
```

[51]:
```python
# Check the result:
df_pred.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 19 columns):
 #   Column            Non-Null Count  Dtype
```

```
---  ------            --------------  -----
 0   gender            1 non-null      int64
 1   SeniorCitizen     1 non-null      int64
 2   Partner           1 non-null      int64
 3   Dependents        1 non-null      int64
 4   tenure            1 non-null      int64
 5   PhoneService      1 non-null      int64
 6   MultipleLines     1 non-null      object
 7   InternetService   1 non-null      object
 8   OnlineSecurity    1 non-null      object
 9   OnlineBackup      1 non-null      object
 10  DeviceProtection  1 non-null      object
 11  TechSupport       1 non-null      object
 12  StreamingTV       1 non-null      object
 13  StreamingMovies   1 non-null      object
 14  Contract          1 non-null      object
 15  PaperlessBilling  1 non-null      int64
 16  PaymentMethod     1 non-null      object
 17  MonthlyCharges    1 non-null      float64
 18  TotalCharges      1 non-null      float64
dtypes: float64(2), int64(7), object(10)
memory usage: 284.0+ bytes
```

CustomerID column has been deleted

[52]:
```
# One-hot encoding for remaining categorical variables:
df_pred= pd.get_dummies(df_pred)
df_pred
```

[52]:
```
   gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0       0              1        0           0      15             0

   PaperlessBilling  MonthlyCharges  TotalCharges  \
0                 0           40.75        611.25

   MultipleLines_No phone service  InternetService_DSL  OnlineSecurity_No  \
0                            True                 True               True

   OnlineBackup_Yes  DeviceProtection_No  TechSupport_Yes  StreamingTV_Yes  \
0              True                 True             True             True

   StreamingMovies_Yes  Contract_Month-to-month  \
0                 True                     True

   PaymentMethod_Bank transfer (automatic)
0                                     True
```

[53]:
```python
# Adding missing columns to new data:
for kolom in one_hot_columns:
    if kolom not in df_pred.columns:
        df_pred[kolom] = 0
```

[54]:
```python
# Check whether the data type has changed to numeric or not:
df_pred.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 42 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   gender                                   1 non-null      int64
 1   SeniorCitizen                            1 non-null      int64
 2   Partner                                  1 non-null      int64
 3   Dependents                               1 non-null      int64
 4   tenure                                   1 non-null      int64
 5   PhoneService                             1 non-null      int64
 6   PaperlessBilling                         1 non-null      int64
 7   MonthlyCharges                           1 non-null      float64
 8   TotalCharges                             1 non-null      float64
 9   MultipleLines_No phone service           1 non-null      bool
 10  InternetService_DSL                      1 non-null      bool
 11  OnlineSecurity_No                        1 non-null      bool
 12  OnlineBackup_Yes                         1 non-null      bool
 13  DeviceProtection_No                      1 non-null      bool
 14  TechSupport_Yes                          1 non-null      bool
 15  StreamingTV_Yes                          1 non-null      bool
 16  StreamingMovies_Yes                      1 non-null      bool
 17  Contract_Month-to-month                  1 non-null      bool
 18  PaymentMethod_Bank transfer (automatic)  1 non-null      bool
 19  Churn                                    1 non-null      int64
 20  MultipleLines_No                         1 non-null      int64
 21  MultipleLines_Yes                        1 non-null      int64
 22  InternetService_Fiber optic              1 non-null      int64
 23  InternetService_No                       1 non-null      int64
 24  OnlineSecurity_No internet service       1 non-null      int64
 25  OnlineSecurity_Yes                       1 non-null      int64
 26  OnlineBackup_No                          1 non-null      int64
 27  OnlineBackup_No internet service         1 non-null      int64
 28  DeviceProtection_No internet service     1 non-null      int64
 29  DeviceProtection_Yes                     1 non-null      int64
 30  TechSupport_No                           1 non-null      int64
 31  TechSupport_No internet service          1 non-null      int64
 32  StreamingTV_No                           1 non-null      int64
 33  StreamingTV_No internet service          1 non-null      int64
```

```
 34  StreamingMovies_No                     1 non-null      int64
 35  StreamingMovies_No internet service    1 non-null      int64
 36  Contract_One year                      1 non-null      int64
 37  Contract_Two year                      1 non-null      int64
 38  PaymentMethod_Credit card (automatic)  1 non-null      int64
 39  PaymentMethod_Electronic check         1 non-null      int64
 40  PaymentMethod_Mailed check             1 non-null      int64
 41  customerID                             1 non-null      int64
dtypes: bool(10), float64(2), int64(30)
memory usage: 398.0 bytes
```

6.6 f. Scaling

[55]:
```
# Delete customerID column (before scaling process):
identity = df_pred["customerID"]

df_pred = df_pred.drop(columns="customerID")
```

[56]:
```
# Delete the Churn column to be predicted (churn column is not included in␣
↪scaling):
churn_pred = df_pred["Churn"]

df_pred = df_pred.drop(columns="Churn")
```

[57]:
```
# Check the number of columns to see if it matches the dataframe columns in the␣
↪training process:
df_pred.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 40 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   gender                                 1 non-null      int64
 1   SeniorCitizen                          1 non-null      int64
 2   Partner                                1 non-null      int64
 3   Dependents                             1 non-null      int64
 4   tenure                                 1 non-null      int64
 5   PhoneService                           1 non-null      int64
 6   PaperlessBilling                       1 non-null      int64
 7   MonthlyCharges                         1 non-null      float64
 8   TotalCharges                           1 non-null      float64
 9   MultipleLines_No phone service         1 non-null      bool
 10  InternetService_DSL                    1 non-null      bool
 11  OnlineSecurity_No                      1 non-null      bool
 12  OnlineBackup_Yes                       1 non-null      bool
 13  DeviceProtection_No                    1 non-null      bool
```

```
 14  TechSupport_Yes                          1 non-null      bool
 15  StreamingTV_Yes                          1 non-null      bool
 16  StreamingMovies_Yes                      1 non-null      bool
 17  Contract_Month-to-month                  1 non-null      bool
 18  PaymentMethod_Bank transfer (automatic)  1 non-null      bool
 19  MultipleLines_No                         1 non-null      int64
 20  MultipleLines_Yes                        1 non-null      int64
 21  InternetService_Fiber optic              1 non-null      int64
 22  InternetService_No                       1 non-null      int64
 23  OnlineSecurity_No internet service       1 non-null      int64
 24  OnlineSecurity_Yes                       1 non-null      int64
 25  OnlineBackup_No                          1 non-null      int64
 26  OnlineBackup_No internet service         1 non-null      int64
 27  DeviceProtection_No internet service     1 non-null      int64
 28  DeviceProtection_Yes                     1 non-null      int64
 29  TechSupport_No                           1 non-null      int64
 30  TechSupport_No internet service          1 non-null      int64
 31  StreamingTV_No                           1 non-null      int64
 32  StreamingTV_No internet service          1 non-null      int64
 33  StreamingMovies_No                       1 non-null      int64
 34  StreamingMovies_No internet service      1 non-null      int64
 35  Contract_One year                        1 non-null      int64
 36  Contract_Two year                        1 non-null      int64
 37  PaymentMethod_Credit card (automatic)    1 non-null      int64
 38  PaymentMethod_Electronic check           1 non-null      int64
 39  PaymentMethod_Mailed check               1 non-null      int64
dtypes: bool(10), float64(2), int64(28)
memory usage: 382.0 bytes
```

[58]:
```
# Scaling:

df_pred_sc = sc_X.fit_transform(df_pred.loc[0].values.reshape(1,-1))
```

[59]:
```
df_pred_sc
```

[59]:
```
array([[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0.]])
```

6.7 g. Predict new customer data

[60]:
```
# Predict for customers on new data:
model = LogisticRegression(random_state=0)

y_pred = np.expm1(classifier.predict(df_pred_sc))
print(f"Prediction Result: {y_pred[0]}")
```

```
Prediction Result: 0.0

/opt/conda/envs/anaconda-panel-2023.05-py310/lib/python3.11/site-
packages/sklearn/base.py:464: UserWarning: X does not have valid feature names,
but LogisticRegression was fitted with feature names
  warnings.warn(
```

[61]:
```python
# Re-merge Customer ID column:
df_pred = pd.concat([df_pred, identity], axis = 1)
```

[62]:
```python
# Add predicted churn column:
new_data['Churn'] = [y_pred[0]]
new_data
```

[62]:
```
{'customerID': ['7370-BOUSA'],
 'gender': ['Female'],
 'SeniorCitizen': [1],
 'Partner': ['Yes'],
 'Dependents': ['Yes'],
 'tenure': [15],
 'PhoneService': ['No'],
 'MultipleLines': ['No phone service'],
 'InternetService': ['DSL'],
 'OnlineSecurity': ['No'],
 'OnlineBackup': ['Yes'],
 'DeviceProtection': ['No'],
 'TechSupport': ['Yes'],
 'StreamingTV': ['Yes'],
 'StreamingMovies': ['Yes'],
 'Contract': ['Month-to-month'],
 'PaperlessBilling': ['Yes'],
 'PaymentMethod': ['Bank transfer (automatic)'],
 'MonthlyCharges': [40.75],
 'TotalCharges': [611.25],
 'Churn': [0.0]}
```

[63]:
```python
# Show new customer prediction frame data:

pd.DataFrame(new_data)
```

[63]:
```
    customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7370-BOUSA  Female              1     Yes        Yes      15           No

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0         Yes         Yes             Yes  Month-to-month              Yes
```

```
                PaymentMethod MonthlyCharges  TotalCharges  Churn
0  Bank transfer (automatic)          40.75        611.25    0.0

[1 rows x 21 columns]
```

The Logical Regression model predicts that new customers are in class 0, which means the customer will not churn (continue to use the service)