Customer Churn Prediction Model

July 25, 2025

1 Customer Churn Prediction and Retention Strategy

[87]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.ticker as mtick
import matplotlib.pyplot as plt
%matplotlib inline
```

Load and Explore the Dataset

[88]:
```
dataset = pd.read_csv("Telco-Customer-Churn.csv")
```

[89]:
```
dataset.head()
```

[89]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	…	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	Female	0	Yes	No	1	No	…	No	No	No	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	5575-GNVDE	Male	0	No	No	34	Yes	…	Yes	No	No	No	One year	No				
2	3668-QPYBK	Male	0	No	No	2	Yes	…	No	No	No	No	Month-to-month	Yes				
3	7795-CFOCW	Male	0	No	No	45	No	…	Yes	Yes	No	No	One year	No				
4	9237-HQITU	Female	0	No	No	2	Yes	…	No	No	No	No	Month-to-month	Yes				

```
1              Mailed check          56.95        1889.5    No
2              Mailed check          53.85         108.15   Yes
3  Bank transfer (automatic)         42.30        1840.75    No
4           Electronic check         70.70         151.65   Yes

[5 rows x 21 columns]
```

[90]:
```
dataset.shape
```

[90]:
```
(7043, 21)
```

[91]:
```
dataset.columns.values
```

[91]:
```
array(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn'], dtype=object)
```

[92]:
```
dataset.dtypes
```

[92]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

[93]:
```
dataset.describe()
```

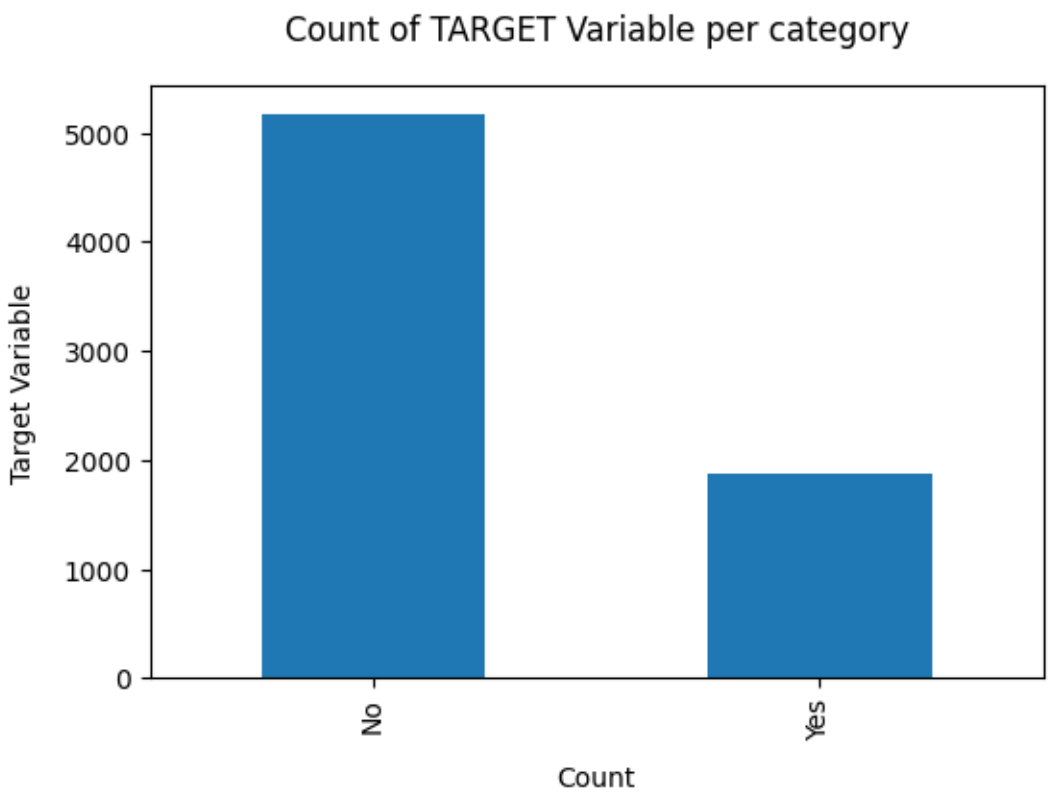
[93]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

[94]:
```
dataset["Churn"].value_counts()
```

[94]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

[95]:
```
dataset["Churn"].value_counts().plot(kind="bar", figsize=(6,4))
plt.xlabel("Count",labelpad=10)
plt.ylabel("Target Variable", labelpad=10)
plt.title("Count of TARGET Variable per category", y=1.05);
plt.show()
```



[96]:
```
100*dataset["Churn"].value_counts()/len(dataset["Churn"])
```

[96]:
```
Churn
No     73.463013
Yes    26.536987
Name: count, dtype: float64
```

1.0.1 Data is highly imbalanced, ratio = 73:27

So we analyse the data with other features while taking the target values separately to get some insights.

[97]:
```
dataset.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
```

[ ]:
```

```

Churn: Target variable (Yes/No)

tenure, MonthlyCharges, TotalCharges: Numeric

Others: Categorical like Contract, PaymentMethod, etc.

1.1 Data Cleaning

Remove customerID as it's not useful

[98]:
```
dataset.drop("customerID", axis=1, inplace=True)
```

[99]:
```
dataset.head(3)
```

[99]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	No	No	One year	No	Mailed check	56.95	1889.5	No
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	53.85	108.15	Yes

[ ]:
```
```

Total Charges should be numeric amount. Let's convert it to numerical data type

[100]:
```
dataset['TotalCharges'] = pd.to_numeric(dataset['TotalCharges'],␣
↪errors='coerce')
```

[101]:
```
# Check for nulls
dataset.isnull().sum()
```

[101]:
```
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
```

```
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

It fills missing values (NaN) in the 'TotalCharges' column with the mean (average) of that column.

[102]:
```
dataset['TotalCharges'].fillna(dataset['TotalCharges'].mean(), inplace=True)
```

```
C:\Users\A8894\AppData\Local\Temp\ipykernel_10748\4072990652.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  dataset['TotalCharges'].fillna(dataset['TotalCharges'].mean(), inplace=True)
```

[103]:
```
# Check for nulls
dataset.isnull().sum()
```

[103]:
```
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
```

```
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

[ ]:

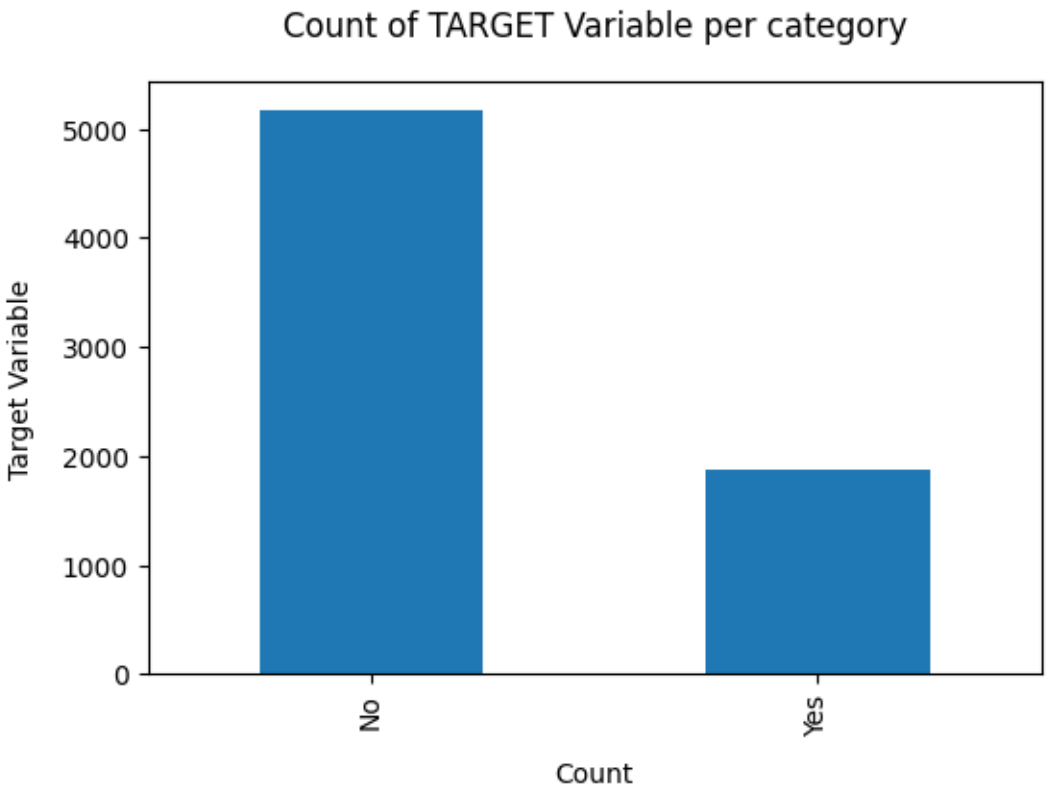
1.2 Exploratory Data Analysis (EDA)

[104]:
```
dataset["Churn"].value_counts()
```

[104]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

Target variable distribution

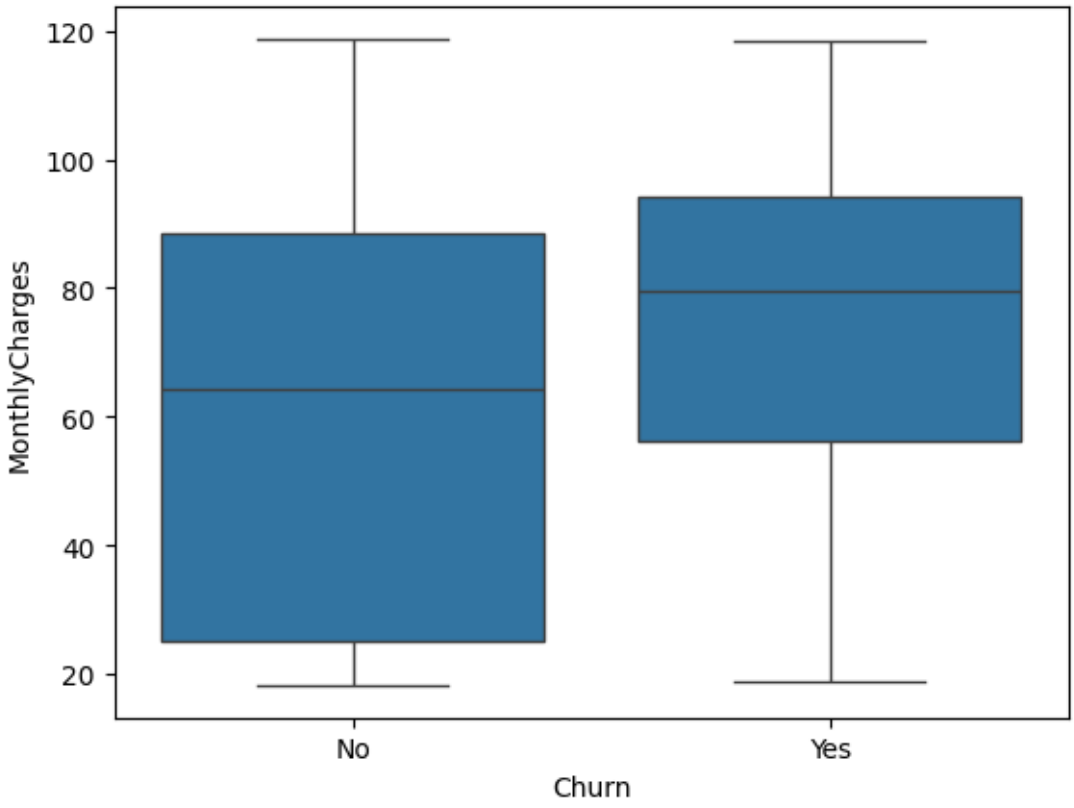
[105]:
```
dataset["Churn"].value_counts().plot(kind="bar", figsize=(6,4))
plt.xlabel("Count",labelpad=10)
plt.ylabel("Target Variable", labelpad=10)
plt.title("Count of TARGET Variable per category", y=1.05);
plt.show()
```



[ ]:

Monthly Charges vs Churn

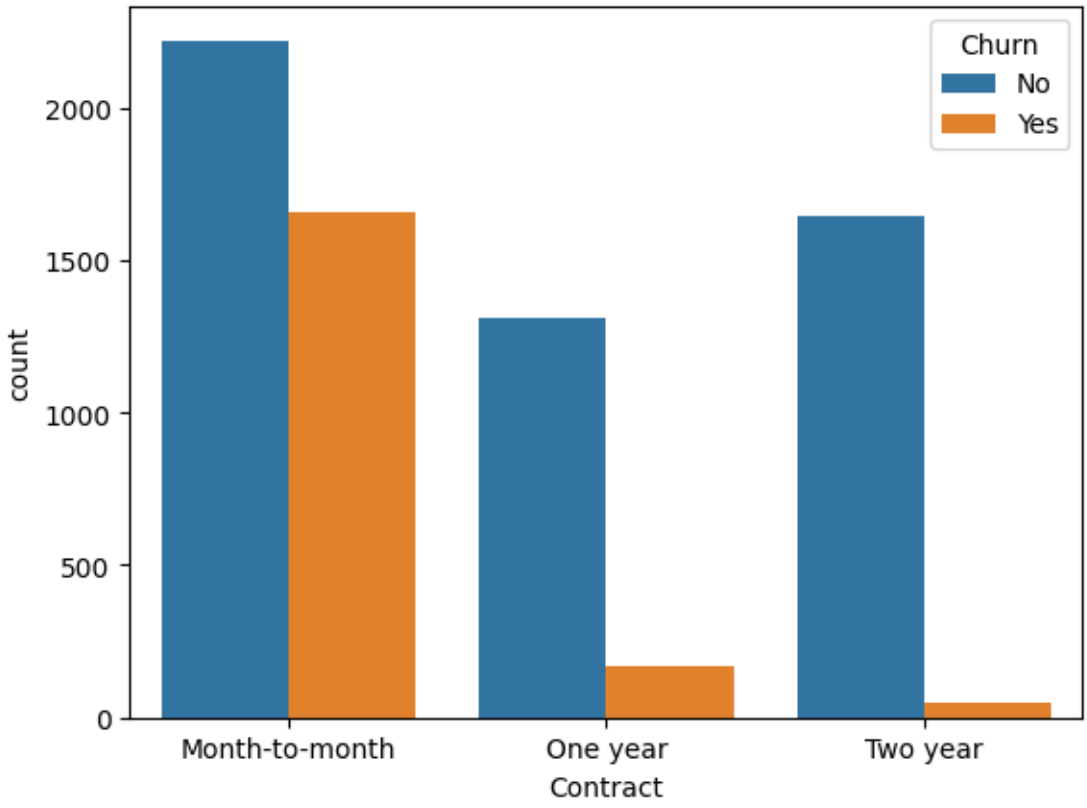
[106]:
```
sns.boxplot(x='Churn', y='MonthlyCharges', data=dataset)
plt.show()
```



[ ]:

Contract type vs Churn

[107]:
```
sns.countplot(x='Contract', hue='Churn', data=dataset)
plt.show()
```



[ ]:

1.3 Encode Categorical Variables

Convert 'Yes'/'No' to 1/0 for Churn

[108]:
```
dataset['Churn'] = dataset['Churn'].map({'Yes': 1, 'No': 0})
```

[109]:
```
dataset.sample(7)
```

[109]:
```
      gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
6246    Male              0      No         No      54          Yes
1495  Female              0     Yes        Yes      52          Yes
147     Male              0      No         No       1          Yes
6057    Male              0      No         No      19          Yes
5057    Male              0      No         No       9          Yes
5646    Male              0      No        Yes       1          Yes
3414  Female              0      No         No      47           No

         MultipleLines InternetService       OnlineSecurity  \
6246                No             DSL                  Yes
1495               Yes     Fiber optic                  Yes
```

```
147                 No             DSL                   No
6057                No             DSL                   No
5057               Yes     Fiber optic                   No
5646                No              No  No internet service
3414  No phone service             DSL                  Yes

            OnlineBackup     DeviceProtection          TechSupport  \
6246                 Yes                   No                   No
1495                 Yes                  Yes                   No
147                   No                   No                   No
6057                  No                   No                  Yes
5057                  No                   No                   No
5646  No internet service  No internet service  No internet service
3414                  No                  Yes                  Yes

             StreamingTV      StreamingMovies        Contract  \
6246                 Yes                   No        Two year
1495                  No                  Yes  Month-to-month
147                   No                   No  Month-to-month
6057                 Yes                   No  Month-to-month
5057                  No                   No  Month-to-month
5646  No internet service  No internet service  Month-to-month
3414                  No                   No        Two year

     PaperlessBilling              PaymentMethod  MonthlyCharges  \
6246              Yes  Bank transfer (automatic)           65.30
1495               No  Bank transfer (automatic)           98.15
147               Yes           Electronic check           45.65
6057              Yes    Credit card (automatic)           61.55
5057              Yes           Electronic check           75.85
5646               No               Mailed check           19.25
3414               No               Mailed check           41.90

      TotalCharges  Churn
6246       3512.90      0
1495       4993.40      0
147          45.65      1
6057       1093.20      0
5057        724.65      0
5646         19.25      1
3414       1875.25      0
```

[ ]:

One-hot encode other categorical columns

[110]:
```
dataset = pd.get_dummies(dataset, drop_first=True)
```

[111]:
```
dataset.head(8)
```

[111]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	Churn	gender_Male	\
0	0	1	29.85	29.85	0	False	
1	0	34	56.95	1889.50	0	True	
2	0	2	53.85	108.15	1	True	
3	0	45	42.30	1840.75	0	True	
4	0	2	70.70	151.65	1	False	
5	0	8	99.65	820.50	1	False	
6	0	22	89.10	1949.40	0	True	
7	0	10	29.75	301.90	0	False	

	Partner_Yes	Dependents_Yes	PhoneService_Yes	\
0	True	False	False	
1	False	False	True	
2	False	False	True	
3	False	False	False	
4	False	False	True	
5	False	False	True	
6	False	True	True	
7	False	False	False	

	MultipleLines_No phone service	…	StreamingTV_No internet service	\
0	True	…	False	
1	False	…	False	
2	False	…	False	
3	True	…	False	
4	False	…	False	
5	False	…	False	
6	False	…	False	
7	True	…	False	

	StreamingTV_Yes	StreamingMovies_No internet service	StreamingMovies_Yes	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
5	True	False	True	
6	True	False	False	
7	False	False	False	

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

```
4              False              False                   True
5              False              False                   True
6              False              False                   True
7              False              False                  False

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

   PaymentMethod_Mailed check
0                       False
1                        True
2                        True
3                       False
4                       False
5                       False
6                       False
7                        True

[8 rows x 31 columns]
```

[ ]:

1.4 Feature Scaling

[113]:
```
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

[116]:
```
scaler = StandardScaler()
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
dataset[num_cols] = scaler.fit_transform(dataset[num_cols])
```

[118]:
```
dataset.head(7)
```

[118]:
```
   SeniorCitizen    tenure  MonthlyCharges  TotalCharges  Churn  gender_Male  \
0              0 -1.277445       -1.160323     -0.994971      0        False
1              0  0.066327       -0.259629     -0.173876      0         True
2              0 -1.236724       -0.362660     -0.960399      1         True
3              0  0.514251       -0.746535     -0.195400      0         True
4              0 -1.236724        0.197365     -0.941193      1        False
5              0 -0.992402        1.159546     -0.645874      1        False
6              0 -0.422317        0.808907     -0.147428      0         True
```

```
   Partner_Yes  Dependents_Yes  PhoneService_Yes  \
0         True           False             False
1        False           False              True
2        False           False              True
3        False           False             False
4        False           False              True
5        False           False              True
6        False            True              True

   MultipleLines_No phone service  …  StreamingTV_No internet service  \
0                            True  …                            False
1                           False  …                            False
2                           False  …                            False
3                            True  …                            False
4                           False  …                            False
5                           False  …                            False
6                           False  …                            False

   StreamingTV_Yes  StreamingMovies_No internet service  StreamingMovies_Yes  \
0            False                                False                False
1            False                                False                False
2            False                                False                False
3            False                                False                False
4            False                                False                False
5             True                                False                 True
6             True                                False                False

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

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

   PaymentMethod_Mailed check
```

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

[7 rows x 31 columns]
```

[ ]:

[ ]:

1.5 Train-Test Split

[121]:
```
from sklearn.model_selection import train_test_split
```

[123]:
```
X = data.drop('Churn', axis=1) #This removes the 'Churn' column from data and␣
 ↪assigns the rest to X.
                               #So, X now contains all input features (like␣
 ↪gender, tenure, internet service, etc.)
y = data['Churn']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[ ]:

1.6 Build and Train Models

1. Logistic Regression (Baseline)

[126]:
```
from sklearn.linear_model import LogisticRegression
```

[133]:
```
logmodel = LogisticRegression()
logmodel.fit(X_train, y_train)
```

[133]:
```
LogisticRegression()
```

[134]:
```
predictions = logmodel.predict(X_test)
```

[135]:
```
predictions
```

[135]:
```
array([1, 0, 0, …, 0, 0, 0], shape=(1409,))
```

[136]:
```
np.array(y_test)
```

[136]:
```
array([1, 0, 0, …, 0, 0, 1], shape=(1409,))
```

[ ]:

[ ]:

Let's move on to evaluate our model!

[141]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score
```

[145]:
```
print("Logistic Regression Accuracy:", accuracy_score(y_test, predictions))
print(classification_report(y_test, predictions))
```

```
Logistic Regression Accuracy: 0.8211497515968772
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      1036
           1       0.69      0.60      0.64       373

    accuracy                           0.82      1409
   macro avg       0.77      0.75      0.76      1409
weighted avg       0.82      0.82      0.82      1409
```

[ ]:

[ ]:

2. Random Forest (Improved)

[144]:
```
from sklearn.ensemble import RandomForestClassifier
```

[159]:
```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

[159]:
```
RandomForestClassifier(random_state=42)
```

[160]:
```
y_pred_rf = rf_model.predict(X_test)
```

[161]:
```
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.7927608232789212
              precision    recall  f1-score   support

           0       0.83      0.91      0.87      1036
           1       0.65      0.47      0.54       373

    accuracy                           0.79      1409
   macro avg       0.74      0.69      0.70      1409
```

```
weighted avg       0.78      0.79      0.78      1409
```

[ ]:

[ ]:

[147]:
```
cm = confusion_matrix(y_test, y_pred_rf)
```

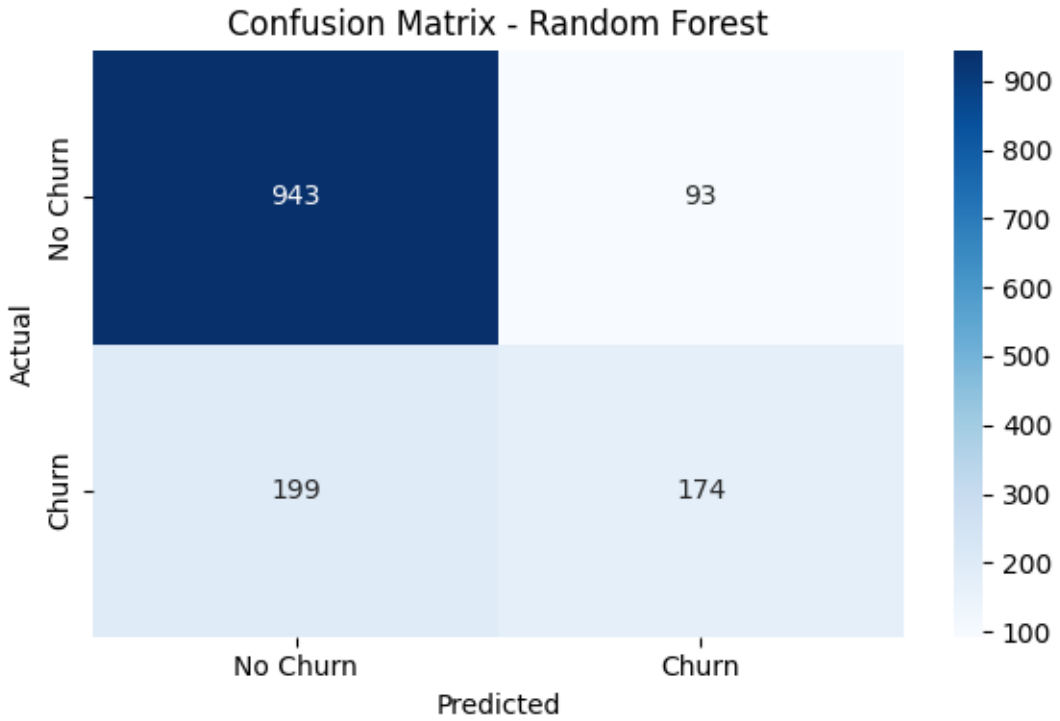
[147]:
```
array([[943,  93],
       [199, 174]])
```

[ ]:

[155]:
```
# Create a heatmap

plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn',␣
 ↪'Churn'], yticklabels=['No Churn', 'Churn'])

plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Random Forest')
plt.tight_layout()
plt.show()
```



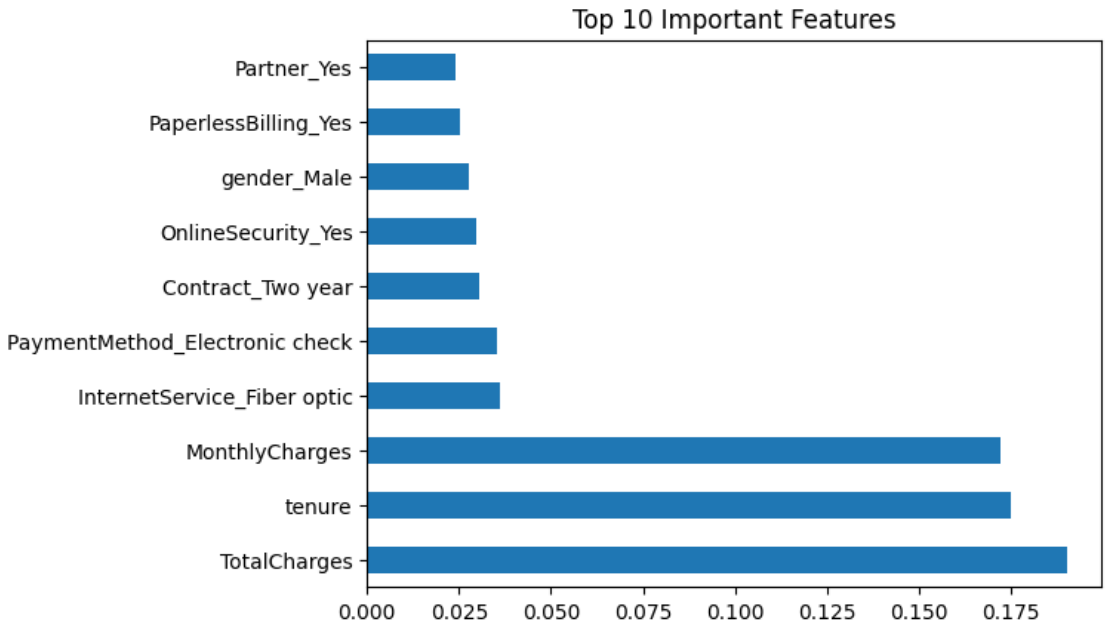
[ ]:

[ ]:

1.7 Importance Feature

[156]:
```
importances = pd.Series(rf_model.feature_importances_, index=X.columns)
importances.nlargest(10).plot(kind='barh')
plt.title("Top 10 Important Features")
```

[156]:
```
Text(0.5, 1.0, 'Top 10 Important Features')
```



[ ]: