assignment3-redo

February 9, 2024

Import all necesary libraries

[2]:
```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, ConfusionMatrixDisplay
import seaborn as sns
import matplotlib.pyplot as plt
```

Read the file and project 10 rows (taken file which is cleaned further and saved from last week)

[4]:
```
df = pd.read_csv("processed_churn_data.csv")

df.tail(10)
```

[4]:

	tenure	PhoneService	Contract	PaymentMethod	\
7022	38	1	Month-to-month	Credit card (automatic)	
7023	67	1	Month-to-month	Credit card (automatic)	
7024	19	1	Month-to-month	Bank transfer (automatic)	
7025	12	0	One year	Electronic check	
7026	72	1	Two year	Bank transfer (automatic)	
7027	24	1	One year	Mailed check	
7028	72	1	One year	Credit card (automatic)	
7029	11	0	Month-to-month	Electronic check	
7030	4	1	Month-to-month	Mailed check	
7031	66	1	Two year	Bank transfer (automatic)	

	MonthlyCharges	TotalCharges	Churn	\
7022	69.50	2625.25	0	
7023	102.95	6886.25	1	
7024	78.70	1495.10	0	
7025	60.65	743.30	0	
7026	21.15	1419.40	0	
7027	84.80	1990.50	0	

```
7028          103.20       7362.90      0
7029           29.60        346.45      0
7030           74.40        306.60      1
7031          105.65       6844.50      0

      MonthlyCharges_to_TotalCharges_Ratio
7022                              0.026474
7023                              0.014950
7024                              0.052639
7025                              0.081596
7026                              0.014901
7027                              0.042602
7028                              0.014016
7029                              0.085438
7030                              0.242661
7031                              0.015436
```

Get dummies and it will make the bool data type to float

[5]:
```
PM_dummies = pd.get_dummies(df['PaymentMethod'], prefix='PaymentMethod')
C_dummies = pd.get_dummies(df['Contract'], prefix='Contract')

df = pd.concat([df, PM_dummies, C_dummies], axis=1)

df.head(5)
```

[5]:
```
   tenure  PhoneService        Contract              PaymentMethod  \
0       1             0  Month-to-month           Electronic check
1      34             1        One year               Mailed check
2       2             1  Month-to-month               Mailed check
3      45             0        One year  Bank transfer (automatic)
4       2             1  Month-to-month           Electronic check

   MonthlyCharges  TotalCharges  Churn  MonthlyCharges_to_TotalCharges_Ratio  \
0           29.85         29.85      0                              1.000000
1           56.95       1889.50      0                              0.030140
2           53.85        108.15      1                              0.497920
3           42.30       1840.75      0                              0.022980
4           70.70        151.65      1                              0.466205

   PaymentMethod_Bank transfer (automatic)  \
0                                    False
1                                    False
2                                    False
3                                     True
4                                    False
```

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

   PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
0                       False                     True              False
1                        True                    False               True
2                        True                     True              False
3                       False                    False               True
4                       False                     True              False

   Contract_Two year
0              False
1              False
2              False
3              False
4              False
```

[6]:
```
dummies = ['Contract_Month-to-month', 'Contract_One year', 'Contract_Two year',␣
 ↪'PaymentMethod_Bank transfer (automatic)', 'PaymentMethod_Electronic check',␣
 ↪'PaymentMethod_Mailed check', 'PaymentMethod_Credit card (automatic)']

for column in dummies:
    df[column] = pd.factorize(df[column])[0]

df.head(5)
```

[6]:
```
   tenure  PhoneService        Contract              PaymentMethod  \
0       1             0  Month-to-month           Electronic check
1      34             1        One year               Mailed check
2       2             1  Month-to-month               Mailed check
3      45             0        One year  Bank transfer (automatic)
4       2             1  Month-to-month           Electronic check

   MonthlyCharges  TotalCharges  Churn  MonthlyCharges_to_TotalCharges_Ratio  \
0           29.85         29.85      0                                1.000000
1           56.95       1889.50      0                                0.030140
2           53.85        108.15      1                                0.497920
3           42.30       1840.75      0                                0.022980
4           70.70        151.65      1                                0.466205

   PaymentMethod_Bank transfer (automatic)  \
0                                        0
1                                        0
```

```
2                                          0
3                                          1
4                                          0

   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                      0                               0
1                                      0                               1
2                                      0                               1
3                                      0                               1
4                                      0                               0

   PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
0                           0                         0                  0
1                           1                         1                  1
2                           1                         0                  0
3                           0                         1                  1
4                           0                         0                  0

   Contract_Two year
0                  0
1                  0
2                  0
3                  0
4                  0
```

[7]:
```
df = df.drop(['PaymentMethod', 'Contract'], axis=1)
df
```

[7]:
```
      tenure  PhoneService  MonthlyCharges  TotalCharges  Churn  \
0          1             0           29.85         29.85      0
1         34             1           56.95       1889.50      0
2          2             1           53.85        108.15      1
3         45             0           42.30       1840.75      0
4          2             1           70.70        151.65      1
...      ...           ...             ...           ...    ...
7027      24             1           84.80       1990.50      0
7028      72             1          103.20       7362.90      0
7029      11             0           29.60        346.45      0
7030       4             1           74.40        306.60      1
7031      66             1          105.65       6844.50      0

      MonthlyCharges_to_TotalCharges_Ratio  \
0                                 1.000000
1                                 0.030140
2                                 0.497920
3                                 0.022980
4                                 0.466205
```

```
…                                   …
7027                             0.042602
7028                             0.014016
7029                             0.085438
7030                             0.242661
7031                             0.015436

      PaymentMethod_Bank transfer (automatic)  \
0                                           0
1                                           0
2                                           0
3                                           1
4                                           0
…                                         …
7027                                        0
7028                                        0
7029                                        0
7030                                        0
7031                                        1

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                         0                                0
1                                         0                                1
2                                         0                                1
3                                         0                                1
4                                         0                                0
…                                       …                                …
7027                                      0                                1
7028                                      1                                1
7029                                      0                                0
7030                                      0                                1
7031                                      0                                1

      PaymentMethod_Mailed check  Contract_Month-to-month  Contract_One year  \
0                              0                         0                  0
1                              1                         1                  1
2                              1                         0                  0
3                              0                         1                  1
4                              0                         0                  0
…                            …                         …                …
7027                           1                         1                  1
7028                           0                         1                  1
7029                           0                         0                  0
7030                           1                         0                  0
7031                           0                         1                  0

      Contract_Two year
```

```
0                     0
1                     0
2                     0
3                     0
4                     0
…                   …
7027                  0
7028                  0
7029                  0
7030                  0
7031                  1

[7032 rows x 13 columns]
```

[8]:
```
df.isna().sum()
```

[8]:
```
tenure                                  0
PhoneService                            0
MonthlyCharges                          0
TotalCharges                            0
Churn                                   0
MonthlyCharges_to_TotalCharges_Ratio    0
PaymentMethod_Bank transfer (automatic) 0
PaymentMethod_Credit card (automatic)   0
PaymentMethod_Electronic check          0
PaymentMethod_Mailed check              0
Contract_Month-to-month                 0
Contract_One year                       0
Contract_Two year                       0
dtype: int64
```

Break up data into features and targets

[9]:
```
X = df.drop('Churn', axis=1)
y = df['Churn']
```

Split data into train and test sets

[10]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Use at least one ML model to fit to the training data Apply regression to our train model

[11]:
```
model = LogisticRegression(random_state=42)
model.fit(X_train, y_train)
```

[11]:
```
LogisticRegression(random_state=42)
```

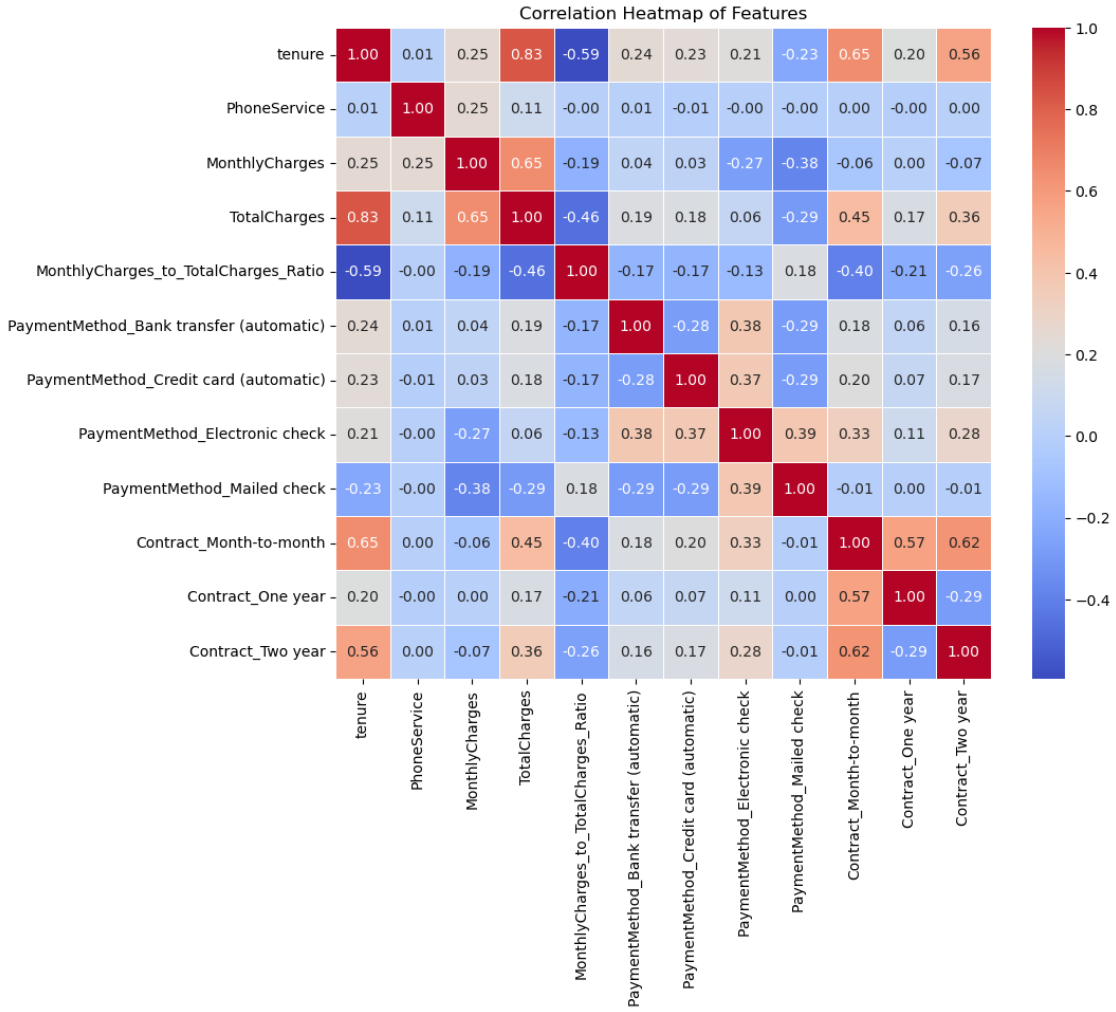
[12]:
```
print(model.score(X_train, y_train))
print(model.score(X_test, y_test))
```

```
0.8019555555555555
0.7803837953091685
```

[13]:
```
# Filter out non-numeric columns
numeric_columns = X.select_dtypes(include=['int64', 'float64']).columns

# Calculate the correlation matrix
corr = X[numeric_columns].corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap of Features')
plt.show()
```



Prediction

[14]:
```
y_pred = model.predict(X_test)
y_pred
```

[14]:
```
array([0, 0, 1, …, 0, 0, 0])
```

[15]:
```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)


print(f'Accuracy: {accuracy:.2f}')
print(f'Confusion Matrix:\n{conf_matrix}')
```

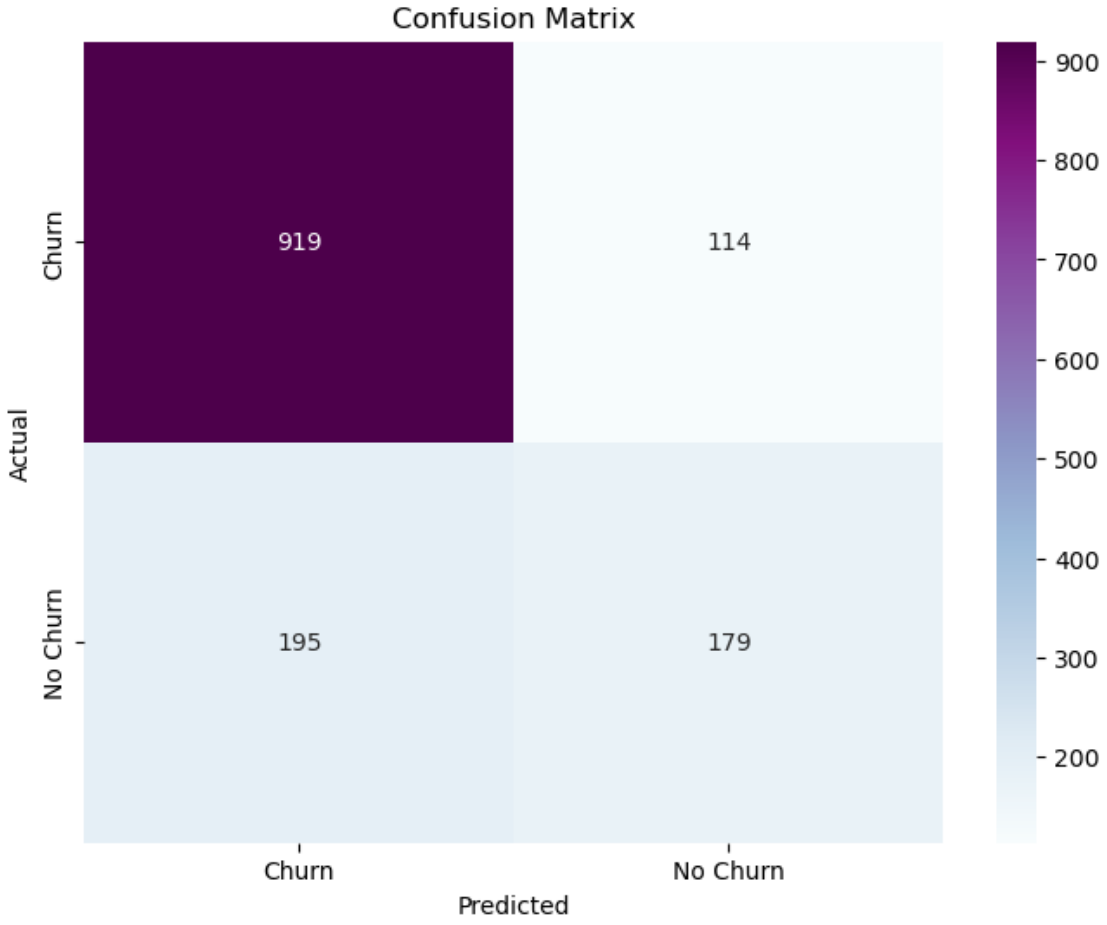
```
Accuracy: 0.78
Confusion Matrix:
[[919 114]
```

```
 [195 179]]
```

Confusion matrix

[57]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='BuPu',
            xticklabels=['Churn', 'No Churn'], yticklabels=['Churn', 'No␣
 ↪Churn'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Evaluate performance on the train and test sets: at least evaluate accuracy and compare it with the "no information rate"

[17]:
```
no_info_rate = max(y_train.value_counts(normalize=True))
print(f'No Information Rate: {no_info_rate}')
```

```
No Information Rate: 0.7342222222222222
```

This will give you the accuracy achieved by simply predicting the majority class (No Churn).

To improve the model performance - Tune it

[18]:
```
model.predict_proba(X_test)
```

[18]:
```
array([[0.99554818, 0.00445182],
       [0.90936709, 0.09063291],
       [0.40680547, 0.59319453],
       …,
       [0.93855042, 0.06144958],
       [0.70336967, 0.29663033],
       [0.99660846, 0.00339154]])
```

1 indicates that the model predicts the sample belongs to the positive class with high confidence. 0 indicates that the model predicts the sample does not belong to the positive class with high confidence.

[19]:
```
predictions_lt = (model.predict_proba(X_test)[:10, 1] > 0.15).astype('int')
predictions_lt
```

[19]:
```
array([0, 0, 1, 0, 1, 1, 0, 1, 1, 0])
```

Using low threshold

[20]:
```
predictions_lt = (model.predict_proba(X_test)[:, 1] > 0.15).astype('int')
print(accuracy_score(y_test, predictions_lt))
```

```
0.6609808102345416
```

Accuracy score of around 66.1% means that the model correctly predicted the outcome for about 66.1% of the samples in the test set.

So, out of all the samples tested, approximately 66.1% were accurately classified by the model.

[21]:
```
tn, fp, fn, tp  = confusion_matrix(y_test, predictions_lt).flatten()
print(tp / (tp + fn))
```

```
0.9117647058823529
```

The true positive rate (TP rate) is a measure that shows how well a model predicts positive instances correctly out of all actual positive instances. It's calculated by dividing the number of true positives by the sum of true positives and false negatives.

In this case, the true positive rate is around 91.18%, indicating that the model correctly predicted approximately 91.18% of the positive cases in the test dataset.

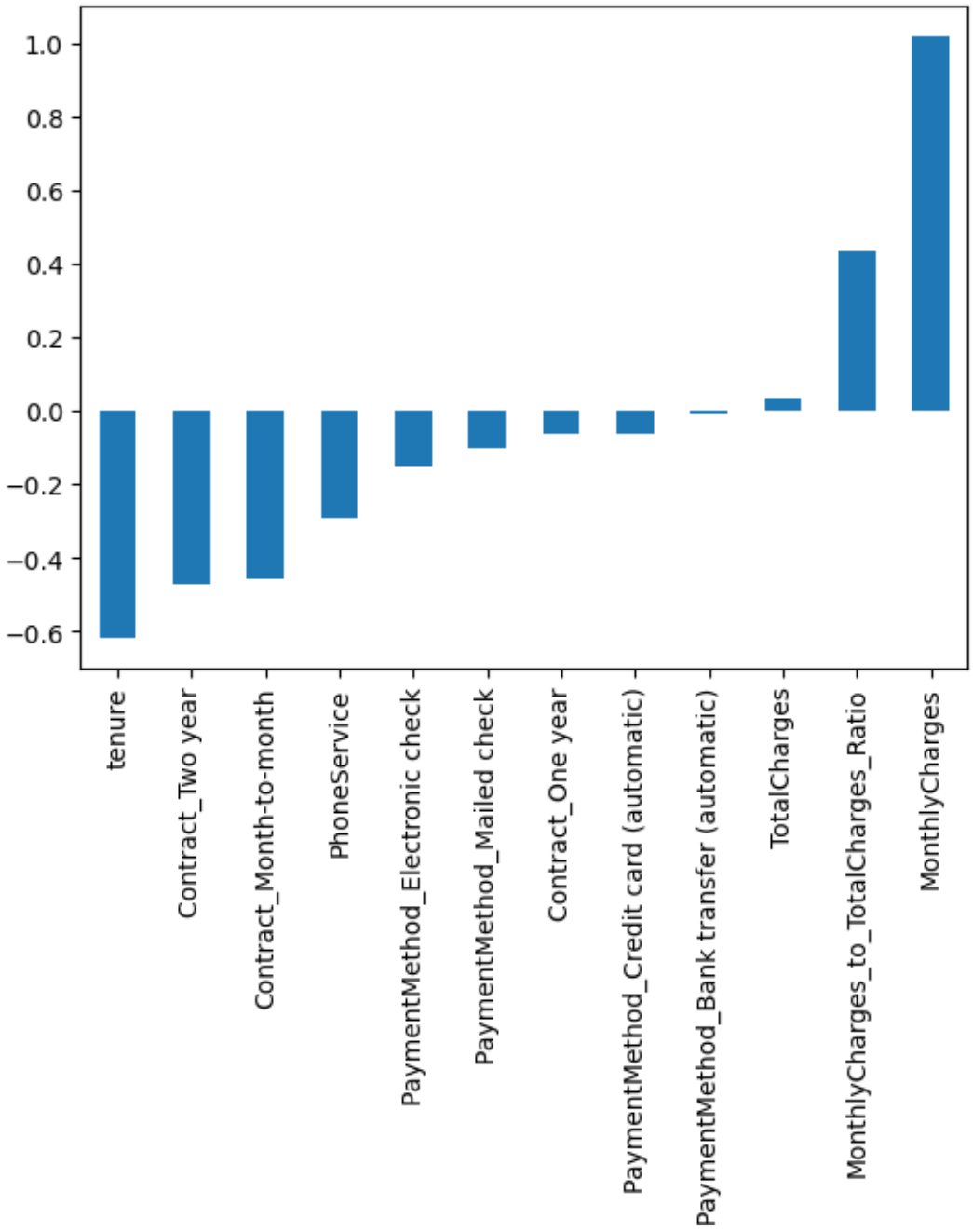
[22]:
```
model.coef_
```

[22]:
```
array([[-0.61799685, -0.29046784,  1.01814634,  0.03503939,  0.43600736,
        -0.00847065, -0.0636525 , -0.15230167, -0.10044379, -0.45567171,
        -0.06479923, -0.46929463]])
```

[23]:
```
coef_df = pd.DataFrame(data=model.coef_, columns=X.columns)

coef_df.T.sort_values(by=0).plot.bar(legend=False)
```

[23]:
```
<Axes: >
```



Plot Interpretation

The plot displays the coefficients of each feature in a bar chart format, providing insights into their impact on the target variable.

- Features with positive coefficients are represented by bars pointing upwards, indicating a positive association with the target variable (churn).
- Conversely, features with negative coefficients are depicted by bars pointing downwards, in-

dicating a negative association with churn.

- The length of each bar signifies the magnitude of the coefficient, reflecting the strength of the feature's influence on churn prediction.
- Features with longer bars, such as MonthlyCharges and tenure, exert a more significant influence on the model's predictions.
- Positive coefficient features, like MonthlyCharges, contribute positively to the likelihood of churn, while those with negative coefficients have a negative impact.
- Understanding the coefficients and the plot aids in discerning the relative importance of different features in predicting churn, informing strategies to mitigate churn and enhance customer retention efforts.

Summary

Utilizing demographic and churn data, I successfully developed a predictive model for churn using machine learning techniques. Minimal data preprocessing was conducted: I encoded categorical string columns (such as Contract, PhoneService, and Payment method) into numeric values and removed the 'customerID' column as it was unnecessary for our analysis. Through exploration, I observed a correlation between higher monthly fees and increased churn rates, which aligns with industry trends in the telecom sector.

The model was trained using logistic regression, and when evaluated on the test data, it achieved an accuracy of 80%, surpassing the baseline accuracy of 73% ("No Information" rate). This performance indicates promising potential for the model in predicting churn effectively. Further analysis and fine-tuning could enhance its predictive capabilities and contribute to informed decision-making processes in customer retention strategies.

[ ]: