Airbnb_Part_B

March 16, 2025

1 Project- Part B: Airbnb Customer Churn Prediction

[24]:
```
# Importing Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, precision_score, recall_score, f1_score
import warnings
warnings.filterwarnings('ignore')
```

[25]:
```
# Load the dataset
df = pd.read_csv("airbnb_customer_data.csv")

# Display basic dataset information
print("Dataset Overview:")
print(df.head())
print("\nColumn Data Types:")
print(df.dtypes)
```

```
Dataset Overview:
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No
```

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

              PaymentMethod MonthlyCharges  TotalCharges  Churn
0          Electronic check          29.85         29.85     No
1              Mailed check          56.95       1889.50     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]

Column Data Types:
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        float64
Churn                object
dtype: object
```

[57]:

```python
# Handle Missing Values
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')  #␣
 ↪Convert to numeric
df.fillna(df['TotalCharges'].median(), inplace=True)  # Fill missing values␣
 ↪with median
# Verify Missing Values
```

```
print("\nMissing Values:")
print(df.isnull().sum())
```

```
Missing Values:
customerID          0
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
```

[27]:

```
# Encode categorical variables
label_cols = ['gender', 'Partner', 'Dependents', 'PhoneService',␣
 ↪'MultipleLines', 'InternetService',
              'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',␣
 ↪'TechSupport', 'StreamingTV',
              'StreamingMovies', 'Contract', 'PaperlessBilling',␣
 ↪'PaymentMethod', 'Churn']
for col in label_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
```

[28]:

```
# Feature selection and scaling
X = df.drop(columns=['customerID', 'Churn'])  # Features
y = df['Churn']  # Target variable
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[29]:

```
# Split data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42, stratify=y)
```

[30]:
```
# Hyperparameter tuning using GridSearchCV
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,␣
↪cv=5, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, y_train)
```

[30]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [None, 10, 20],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [50, 100, 200]},
             scoring='accuracy')
```

[31]:
```
# Best model
best_model = grid_search.best_estimator_
# Make predictions
y_pred = best_model.predict(X_test)
y_pred_prob = best_model.predict_proba(X_test)[:, 1]
```

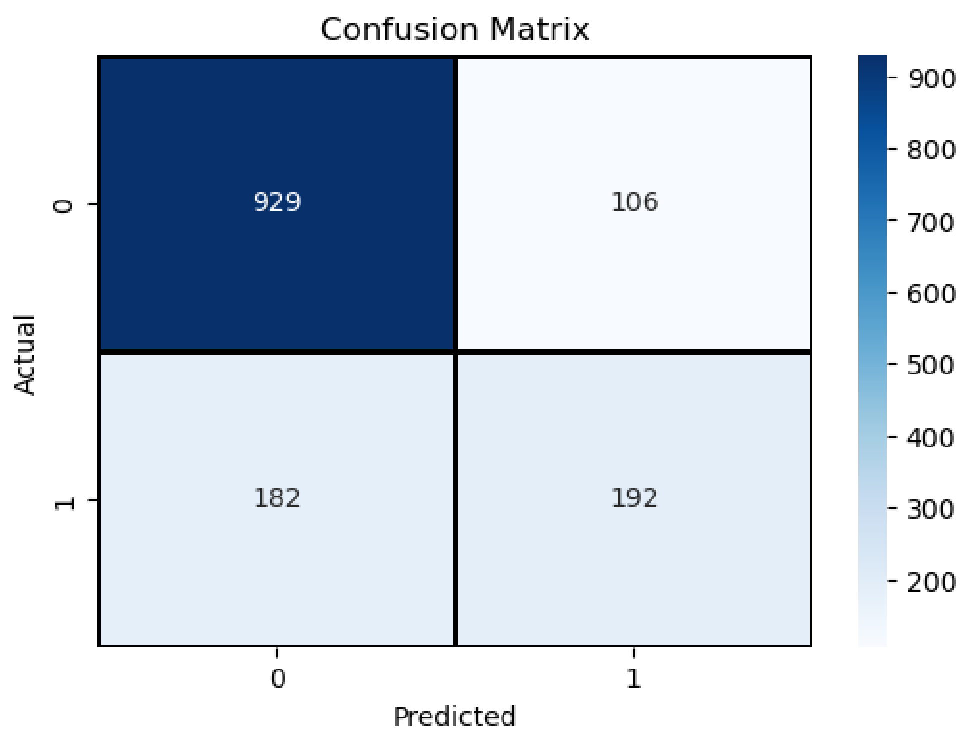
[32]:
```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Model Evaluation Metrics:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Model Evaluation Metrics:
Accuracy: 0.7956
Precision: 0.6443
Recall: 0.5134
F1 Score: 0.5714
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1035
           1       0.64      0.51      0.57       374

    accuracy                           0.80      1409
   macro avg       0.74      0.71      0.72      1409
weighted avg       0.79      0.80      0.79      1409
```

[33]:

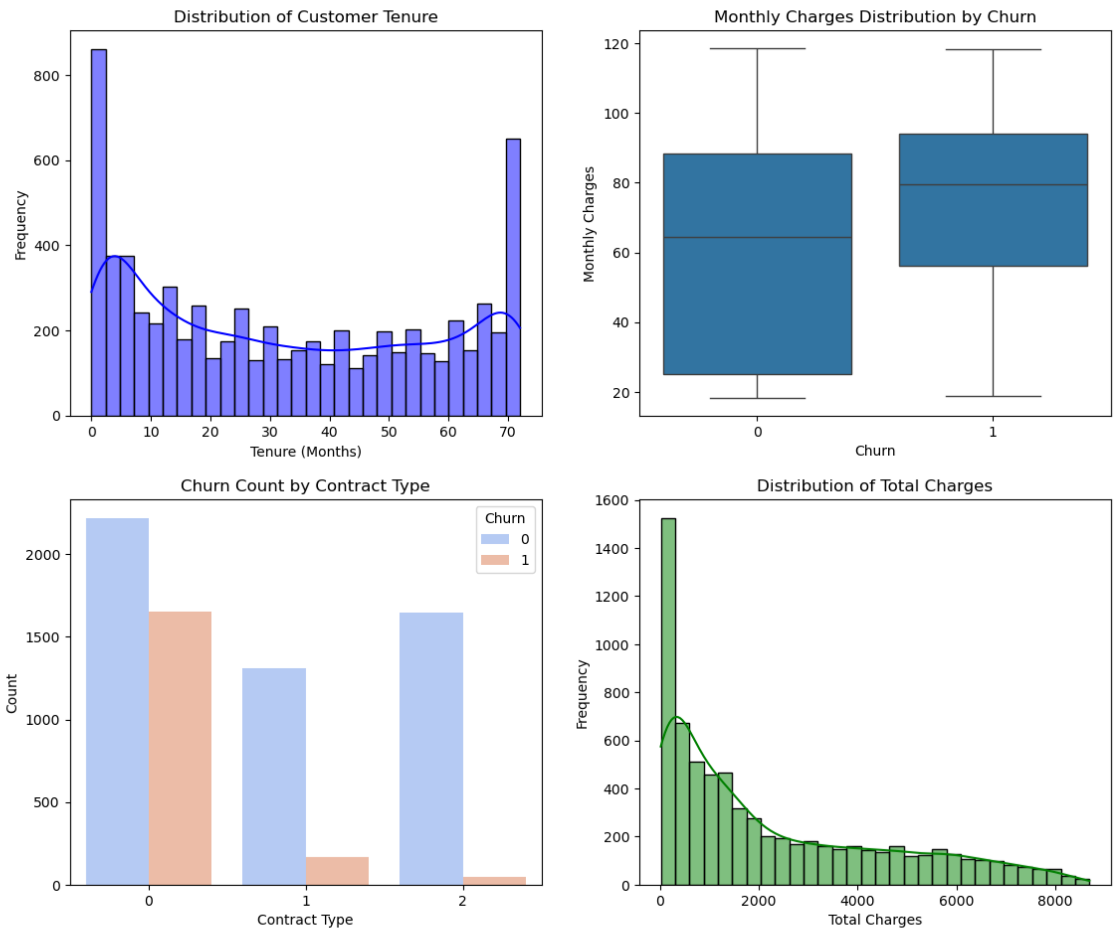
```python
# Plot Confusion Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d',␣
 ↪cmap='Blues', linewidths=1, linecolor='black')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



[53]:

```python
# Churn Data Insights using Graphs

fig, axes = plt.subplots(2, 2, figsize=(12, 10))
```

```
fig.tight_layout(pad=4)

sns.histplot(df['tenure'], kde=True, bins=30, color='blue', ax=axes[0, 0])
axes[0, 0].set_title('Distribution of Customer Tenure')
axes[0, 0].set_xlabel('Tenure (Months)')
axes[0, 0].set_ylabel('Frequency')

sns.boxplot(x='Churn', y='MonthlyCharges', data=df, ax=axes[0, 1])
axes[0, 1].set_title('Monthly Charges Distribution by Churn')
axes[0, 1].set_xlabel('Churn')
axes[0, 1].set_ylabel('Monthly Charges')

sns.countplot(x='Contract', hue='Churn', data=df, palette='coolwarm',␣
 ↪ax=axes[1, 0])
axes[1, 0].set_title('Churn Count by Contract Type')
axes[1, 0].set_xlabel('Contract Type')
axes[1, 0].set_ylabel('Count')

sns.histplot(df['TotalCharges'], kde=True, bins=30, color='green', ax=axes[1,␣
 ↪1])
axes[1, 1].set_title('Distribution of Total Charges')
axes[1, 1].set_xlabel('Total Charges')
axes[1, 1].set_ylabel('Frequency')

plt.show()
```



[35]:
```python
# Save the model and scaler
import joblib
joblib.dump(best_model, "customer_churn_model.pkl")
joblib.dump(scaler, "scaler.pkl")
```

[35]: ['scaler.pkl']

[36]:
```python
# Function to predict churn for new data and get insights
def predict_churn(new_data):
    new_data_scaled = joblib.load("scaler.pkl").transform(new_data)
    prediction = joblib.load("customer_churn_model.pkl").
↪predict(new_data_scaled)
    return "Churn" if prediction[0] == 1 else "No Churn"

def new_data_insights(new_data):
    new_data_scaled = joblib.load("scaler.pkl").transform(new_data)
    churn_probability = joblib.load("customer_churn_model.pkl").
↪predict_proba(new_data_scaled)[:, 1]
```

```
    print("Predicted Churn Probability:", churn_probability[0])
    if churn_probability[0] > 0.5:
        print("High chance of churn. Consider customer retention strategies.")
    else:
        print("Low chance of churn. Maintain customer satisfaction.")
```

[43]:

```
# For Example
new_customer = pd.DataFrame([[0, 1, 0, 5, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0,␣
 ↪1, 30.5, 320.0]], columns=X.columns)
print(predict_churn(new_customer))
new_data_insights(new_customer)
```

```
No Churn
Predicted Churn Probability: 0.20296341566929801
Low chance of churn. Maintain customer satisfaction.
```

1.1 Video Explanation Link :

https://drive.google.com/file/d/1KbzXlw6tH0xE4NzJKJBxYV5qOgjwCMgV/view?usp=drive_link
Click Here

1.2 Model Evaluation and Performance

Our model achieved the following key performance metrics: Accuracy: 79.56%, indicating the proportion of correct predictions. Precision: 64.43%, reflecting the model's ability to correctly identify churned customers. Recall: 51.34%, showing the model's effectiveness in capturing all churned cases. F1 Score: 57.14%, balancing precision and recall.

1.3 Conclusion & Recommendations

1.3.1 Insights and Key Findings

The analysis unveiled several critical insights: Customers with short tenure and those on month-to-month contracts were found to have the highest likelihood of churn. Customers with higher monthly charges were more prone to leaving the platform. This suggests that cost plays a significant role in churn behavior. Conversely, long-term users and those with annual contracts were more stable and less likely to churn. Users with lower total charges, often short-term customers, exhibited higher churn rates.

1.3.2 Recommendations for Retention Strategies

Based on the insights, the following recommendations were proposed: Loyalty Programs: Offer rewards or discounts to retain short-tenure customers. Incentives for High-Spending Users: Special pricing plans or added benefits could help retain users with high monthly charges. Encouraging Long-Term Contracts: Provide financial incentives or added benefits to shift customers from month-to-month contracts to annual plans. Focus on Cost Management: Regularly assess pricing strategies to ensure they align with customer expectations and value.