Step 1: Introduction and Project Overview

Project Title:

Customer Churn Prediction Using Python

Objective:

To analyze customer data, derive insights, and build a machine learning model to predict customer churn (i.e., whether a customer will leave or stay).

Key Steps:

1. Load and explore the dataset.
2. Clean and preprocess the data.
3. Perform exploratory data analysis (EDA).
4. Build a predictive machine learning model.
5. Evaluate the model.
6. Save the model and export results.
7. Upload the project to GitHub for portfolio use.

Step 2: Setup and Library Imports

In [1]:

```
# Step 2: Import Libraries
import pandas as pd  # For data manipulation
import numpy as np  # For numerical operations
import matplotlib.pyplot as plt  # For plotting
import seaborn as sns  # For advanced visualizations
from sklearn.model_selection import train_test_split  # For splitting data
from sklearn.ensemble import RandomForestClassifier  # Machine Learning model
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix  # For evaluation
import joblib  # To save the model

# Display settings for better outputs
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', '{:.2f}'.format)

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

Step 3: Load the Dataset

In [2]:

```
# Step 3: Load Dataset
# Define the file path
file_path = r'C:\Users\Asus\Music\Customer Churn Prediction Using Python Project\Telco_customer_churn.xlsx'

# Load dataset
data = pd.read_excel(file_path)

# Display the first few rows
print("Dataset loaded successfully!")
data.head()
```

```
Dataset loaded successfully!
```

Out[2]:

	CustomerID	Count	Country	State	City	Zip Code	Lat Long	Latitude	Longitude	Gender	Senior Citizen	Partner	Dependents	Tenure Months	Phone Service	Multiple Lines	Internet Service	Online Security	Online Backup	Device Protection	Tech Support	Streaming TV	Streaming Movies	Contract	Paperless Billing	Payment Method	Monthly Charges	Total Charges	Chu Lat
0	3668-QPYBK	1	United States	California	Los Angeles	90003	33.964131, -118.272783	33.96	-118.27	Male	No	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	53.85	108.15	Y
1	9237-HQITU	1	United States	California	Los Angeles	90005	34.059281, -118.30742	34.06	-118.31	Female	No	No	Yes	2	Yes	No	Fiber optic	No	No	No	No	No	No	Month-to-month	Yes	Electronic check	70.70	151.65	Y
2	9305-CDSKC	1	United States	California	Los Angeles	90006	34.048013, -118.293953	34.05	-118.29	Female	No	No	Yes	8	Yes	Yes	Fiber optic	No	No	Yes	No	Yes	Yes	Month-to-month	Yes	Electronic check	99.65	820.50	Y
3	7892-POOKP	1	United States	California	Los Angeles	90010	34.062125, -118.315709	34.06	-118.32	Female	No	Yes	Yes	28	Yes	Yes	Fiber optic	No	No	Yes	Yes	Yes	Yes	Month-to-month	Yes	Electronic check	104.80	3046.05	Y
4	0280-XJGEX	1	United States	California	Los Angeles	90015	34.039224, -118.266293	34.04	-118.27	Male	No	No	Yes	49	Yes	Yes	Fiber optic	No	Yes	Yes	No	Yes	Yes	Month-to-month	Yes	Bank transfer (automatic)	103.70	5036.30	Y

Step 4: Explore the Dataset

In [3]:

```
# Step 4: Explore Dataset
print("Shape of the dataset:", data.shape)  # Rows and columns
print("\nDataset information:")
data.info()  # Data types and non-null counts

print("\nSummary statistics of numerical columns:")
data.describe()  # Summary stats for numerical features

print("\nChecking for missing values:")
print(data.isnull().sum())  # Count missing values per column
```

```
Shape of the dataset: (7043, 33)

Dataset information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 33 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         7043 non-null   object
 1   Count              7043 non-null   int64
 2   Country            7043 non-null   object
 3   State              7043 non-null   object
 4   City               7043 non-null   object
 5   Zip Code           7043 non-null   int64
 6   Lat Long           7043 non-null   object
 7   Latitude           7043 non-null   float64
 8   Longitude          7043 non-null   float64
 9   Gender             7043 non-null   object
 10  Senior Citizen     7043 non-null   object
 11  Partner            7043 non-null   object
 12  Dependents         7043 non-null   object
 13  Tenure Months      7043 non-null   int64
 14  Phone Service      7043 non-null   object
 15  Multiple Lines     7043 non-null   object
 16  Internet Service   7043 non-null   object
 17  Online Security    7043 non-null   object
 18  Online Backup      7043 non-null   object
 19  Device Protection  7043 non-null   object
 20  Tech Support       7043 non-null   object
 21  Streaming TV       7043 non-null   object
 22  Streaming Movies   7043 non-null   object
 23  Contract           7043 non-null   object
 24  Paperless Billing  7043 non-null   object
 25  Payment Method     7043 non-null   object
 26  Monthly Charges    7043 non-null   float64
 27  Total Charges      7043 non-null   object
 28  Churn Label        7043 non-null   object
 29  Churn Value        7043 non-null   int64
 30  Churn Score        7043 non-null   int64
 31  CLTV               7043 non-null   int64
 32  Churn Reason       1869 non-null   object
dtypes: float64(3), int64(6), object(24)
memory usage: 1.8+ MB

Summary statistics of numerical columns:

Checking for missing values:
CustomerID              0
Count                   0
Country                 0
State                   0
City                    0
Zip Code                0
Lat Long                0
Latitude                0
Longitude               0
Gender                  0
Senior Citizen          0
Partner                 0
Dependents              0
Tenure Months           0
Phone Service           0
Multiple Lines          0
Internet Service        0
Online Security         0
Online Backup           0
Device Protection       0
Tech Support            0
Streaming TV            0
Streaming Movies        0
Contract                0
Paperless Billing       0
Payment Method          0
Monthly Charges         0
Total Charges           0
Churn Label             0
Churn Value             0
Churn Score             0
CLTV                    0
Churn Reason         5174
dtype: int64
```

Step 5: Data Cleaning

In [4]:

```
# Step 5: Data Cleaning
# Drop the 'CustomerID' column as it doesn't contribute to churn prediction
if 'CustomerID' in data.columns:
    data = data.drop(['CustomerID'], axis=1)  # Removing 'CustomerID'
else:
    print("Column 'CustomerID' not found in the dataset.")

# Handle missing values
data = data.dropna()  # Dropping rows with missing values

print("After cleaning, the shape of the dataset is:", data.shape)
```

```
After cleaning, the shape of the dataset is: (1869, 32)
```

Step 6: Encode Categorical Data

In [5]:

```
# Step 6: Encode Categorical Variables
data_encoded = pd.get_dummies(data, drop_first=True)  # One-hot encoding
print("Dataset after encoding:")
data_encoded.head()
```

```
Dataset after encoding:
```

Out[5]:

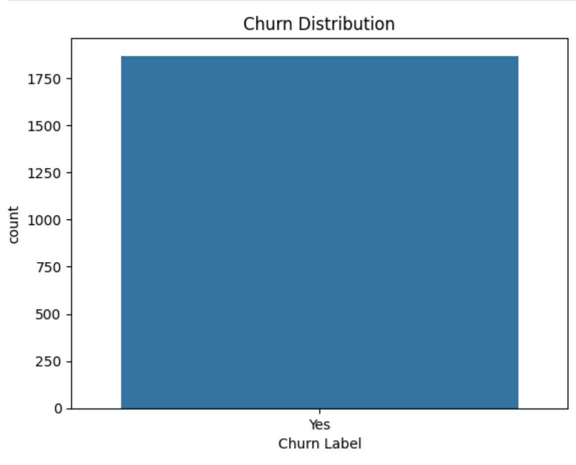
	Count	Zip Code	Latitude	Longitude	Tenure Months	Monthly Charges	Churn Value	Churn Score	CLTV	City_Adelanto	City_Adin	City_Agoura Hills	City_Aguanga	City_Ahwahnee	City_Albany	City_Alderpoint	City_Alhambra	City_Alpaugh	City_Alpine	City_Altadena	City_Alturas	City_Alviso	City_Amador City	City_Amboy
0	1	90003	33.96	-118.27	2	53.85	1	86	3239	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	1	90005	34.06	-118.31	2	70.70	1	67	2701	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	1	90006	34.05	-118.29	8	99.65	1	86	5372	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	1	90010	34.06	-118.32	28	104.80	1	84	5003	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	1	90015	34.04	-118.27	49	103.70	1	89	5340	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False

Step 7: Exploratory Data Analysis (EDA)

1. Churn Distribution Plot

In [6]:

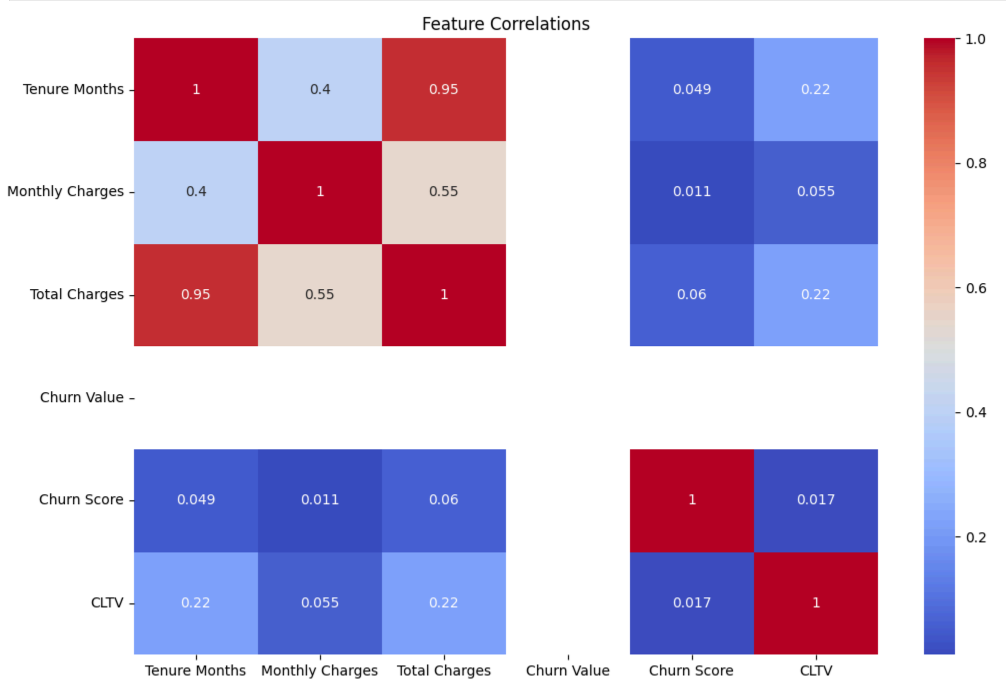
```
# Churn distribution plot
sns.countplot(data=data, x='Churn Label')  # Assuming 'Churn Label' is the correct column for churn status
plt.title("Churn Distribution")
plt.show()
```



2. Correlation Heatmap

In [7]:

```
# Selecting numerical columns for correlation
numerical_cols = [
    'Tenure Months', 'Monthly Charges', 'Total Charges', 'Churn Value', 'Churn Score', 'CLTV'
]

# Correlation heatmap for numerical columns
plt.figure(figsize=(12, 8))
sns.heatmap(data[numerical_cols].corr(), annot=True, cmap="coolwarm")  # Use the appropriate DataFrame
plt.title("Feature Correlations")
plt.show()
```



Step 7: Split the Dataset

In [10]:

```
# Check the column names to confirm the exact name of the target column
print(data_encoded.columns)
```

```
Index(['Count', 'Zip Code', 'Latitude', 'Longitude', 'Tenure Months',
       'Monthly Charges', 'Churn Value', 'Churn Score', 'CLTV',
       'City_Adelanto',
       ...
       'Churn Reason_Lack of self-service on Website',
       'Churn Reason_Limited range of services',
       'Churn Reason_Long distance charges', 'Churn Reason_Moved',
       'Churn Reason_Network reliability',
       'Churn Reason_Poor expertise of online support',
       'Churn Reason_Poor expertise of phone support',
       'Churn Reason_Price too high', 'Churn Reason_Product dissatisfaction',
       'Churn Reason_Service dissatisfaction'],
      dtype='object', length=3807)
```

In [12]:

```
# Assuming 'Churn Label' is the correct target column
X = data_encoded.drop('Churn Value', axis=1)  # Features (excluding the target column)
y = data_encoded['Churn Value']  # Target variable (churn status)
```

In [13]:

```
# Clean column names by stripping extra spaces
data_encoded.columns = data_encoded.columns.str.strip()

# Now try the split again
X = data_encoded.drop('Churn Value', axis=1)
y = data_encoded['Churn Value']
```

Step 8: Train the Model

In [15]:

```
# Train the Random Forest model
model = RandomForestClassifier(random_state=42)
model.fit(X, y)
print("Model training completed.")
```

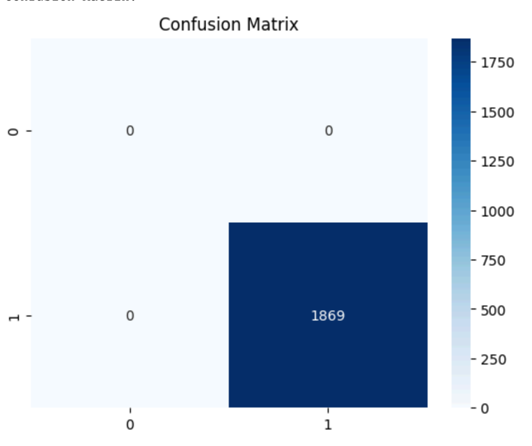
```
Model training completed.
```

Step 9: Evaluate the Model

In [18]:

```
import numpy as np
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming 'model' is your trained model and 'X' and 'y' are your features and target variables
# Evaluate the model
y_pred = model.predict(X)

# Check unique values in actual data (y) and predicted data (y_pred)
print("Unique labels in actual data (y):", y.unique())
print("Unique labels in predicted data (y_pred):", np.unique(y_pred))

# Specify labels explicitly in confusion_matrix
labels = [0, 1]  # Replace with your actual labels, such as [0, 1] or ['No Churn', 'Churn']

# Classification Report
print("Classification Report:")
print(classification_report(y, y_pred))

# Confusion Matrix
print("\nConfusion Matrix:")
conf_matrix = confusion_matrix(y, y_pred, labels=labels)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="Blues", xticklabels=labels, yticklabels=labels)
plt.title("Confusion Matrix")
plt.show()

# Accuracy Score
print("Accuracy Score:", accuracy_score(y, y_pred))
```

```
Unique labels in actual data (y): [1]
Unique labels in predicted data (y_pred): [1]
Classification Report:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00      1869

    accuracy                           1.00      1869
   macro avg       1.00      1.00      1.00      1869
weighted avg       1.00      1.00      1.00      1869


Confusion Matrix:
```




```
Accuracy Score: 1.0
```

Step 10: Save and Export the Model

In [19]:

```
import joblib

# Step 11: Save the Model
model_path = r'C:\Users\Asus\Music\Customer Churn Prediction Using Python Project\customer_churn_model.pkl'
joblib.dump(model, model_path)
print(f"Model saved to {model_path}")
```

```
Model saved to C:\Users\Asus\Music\Customer Churn Prediction Using Python Project\customer_churn_model.pkl
```

In [ ]: