PREDICTING EMPLOYEE RETENTION REPORT

1. Data Understanding

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[1] Python

```python
data=pd.read_csv("Employee_data.csv")
data
```

[2] Python

	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performance Rating	Number of Promotions	...	Number of Dependents	Job Level	Company Size	Company Tenure (In Months)
0	8410	31	Male	19	Education	5390	Excellent	Medium	Average	2	...	0	Mid	Medium	89.0
1	64756	59	Female	4	Media	5534	Poor	High	Low	3	...	3	Mid	Medium	21.0
2	30257	24	Female	10	Healthcare	8159	Good	High	Low	0	...	3	Mid	Medium	74.0
3	65791	36	Female	7	Education	3989	Good	High	High	1	...	2	Mid	Small	50.0
4	65026	56	Male	41	Education	4821	Fair	Very High	Average	0	...	0	Senior	Medium	68.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
74605	13450	44	Female	20	Healthcare	7578	Fair	Medium	Low	2	...	3	Mid	Large	52.0
74606	2386	45	Male	26	Technology	8342	Excellent	Very High	Below Average	3	...	4	Mid	Medium	NaN
74607	36968	28	Female	3	Technology	9763	Poor	Low	Average	0	...	3	Senior	Small	67.0
74608	24276	37	Male	3	Education	3644	Fair	High	Average	2	...	4	Entry	Medium	16.0
74609	9839	38	Male	28	Media	6172	Good	High	High	0	...	2	Mid	Medium	84.0

74610 rows × 24 columns

```python
data.info()
```

[3] Python

74609	9839	38	Male	28	Media	6172	Good	High	High	0	...	2	Mid	Medium	84.0

74610 rows × 24 columns

```python
data.info()
```

[3] Python


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74610 entries, 0 to 74609
Data columns (total 24 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Employee ID               74610 non-null  int64
 1   Age                       74610 non-null  int64
 2   Gender                    74610 non-null  object
 3   Years at Company          74610 non-null  int64
 4   Job Role                  74610 non-null  object
 5   Monthly Income            74610 non-null  int64
 6   Work-Life Balance         74610 non-null  object
 7   Job Satisfaction          74610 non-null  object
 8   Performance Rating        74610 non-null  object
 9   Number of Promotions      74610 non-null  int64
 10  Overtime                  74610 non-null  object
 11  Distance from Home        72698 non-null  float64
 12  Education Level           74610 non-null  object
 13  Marital Status            74610 non-null  object
 14  Number of Dependents      74610 non-null  int64
 15  Job Level                 74610 non-null  object
 16  Company Size              74610 non-null  object
 17  Company Tenure (In Months)  72197 non-null  float64
 18  Remote Work               74610 non-null  object
 19  Leadership Opportunities  74610 non-null  object
...
 22  Employee Recognition      74610 non-null  object
 23  Attrition                 74610 non-null  object
dtypes: float64(2), int64(6), object(16)
memory usage: 13.7+ MB
```

2. Data Cleaning

Data Cleansing

```
data.isnull().sum()
```

[4] Python

```
Employee ID                    0
Age                            0
Gender                         0
Years at Company               0
Job Role                       0
Monthly Income                 0
Work-Life Balance              0
Job Satisfaction               0
Performance Rating             0
Number of Promotions           0
Overtime                       0
Distance from Home          1912
Education Level                0
Marital Status                 0
Number of Dependents           0
Job Level                      0
Company Size                   0
Company Tenure (In Months)  2413
Remote Work                    0
Leadership Opportunities       0
Innovation Opportunities       0
Company Reputation             0
Employee Recognition           0
Attrition                      0
dtype: int64
```

```
#clean the null values
data['Distance from Home'].fillna(data['Distance from Home'].median(), inplace=True)
data['Company Tenure (In Months)'].fillna(data['Company Tenure (In Months)'].median(), inplace=True)
```

```
#test the data again
data.isnull().sum()
```

[6] Python

```
Employee ID                 0
Age                         0
Gender                      0
Years at Company            0
Job Role                    0
Monthly Income              0
Work-Life Balance           0
Job Satisfaction            0
Performance Rating          0
Number of Promotions        0
Overtime                    0
Distance from Home          0
Education Level             0
Marital Status              0
Number of Dependents        0
Job Level                   0
Company Size                0
Company Tenure (In Months)  0
Remote Work                 0
Leadership Opportunities    0
Innovation Opportunities    0
Company Reputation          0
Employee Recognition        0
Attrition                   0
dtype: int64
```

```
# Identify and handle redundant values within categorical column
# Step 1: Select categorical columns
cat_cols = data.select_dtypes(include='object').columns

# Step 2: Preview unique values before cleaning
for col in cat_cols:
    print(f"Before cleaning - {col}:\n", data[col].unique())
```

```
...   Before cleaning – Gender:
       ['Male' 'Female']
      Before cleaning – Job Role:
       ['Education' 'Media' 'Healthcare' 'Technology' 'Finance']
      Before cleaning – Work-Life Balance:
       ['Excellent' 'Poor' 'Good' 'Fair']
      Before cleaning – Job Satisfaction:
       ['Medium' 'High' 'Very High' 'Low']
      Before cleaning – Performance Rating:
       ['Average' 'Low' 'High' 'Below Average']
      Before cleaning – Overtime:
       ['No' 'Yes']
      Before cleaning – Education Level:
       ['Associate Degree' 'Masterâ€™s Degree' 'Bachelorâ€™s Degree'
       'High School' 'PhD']
      Before cleaning – Marital Status:
       ['Married' 'Divorced' 'Single']
      Before cleaning – Job Level:
       ['Mid' 'Senior' 'Entry']
      Before cleaning – Company Size:
       ['Medium' 'Small' 'Large']
      Before cleaning – Remote Work:
       ['No' 'Yes']
      Before cleaning – Leadership Opportunities:
       ['No' 'Yes']
      ...
      Before cleaning – Employee Recognition:
       ['Medium' 'Low' 'High' 'Very High']
      Before cleaning – Attrition:
       ['Stayed' 'Left']
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

```python
# we get the education as the flaws is there then to change it

import unidecode

# Step 1: Identify all object-type columns
cat_cols = data.select_dtypes(include='object').columns

# Step 2: Define a cleaning function
```

```python
# we get the education as the flaws is there then to change it

import unidecode

# Step 1: Identify all object-type columns
cat_cols = data.select_dtypes(include='object').columns

# Step 2: Define a cleaning function
def clean_text(val):
    if isinstance(val, str):
        val = val.strip()  # Trim spaces
        val = unidecode.unidecode(val)  # Fix encoding artifacts
        val = val.replace("â€™", "'").replace("â€“", "–")  # Extra fixes
        return val.title()  # Standard capitalization
    return val

# Step 3: Apply cleaning function
for col in cat_cols:
    data[col] = data[col].apply(clean_text)

# Optional: Check cleaned values
for col in cat_cols:
    print(f"{col}:\n", data[col].value_counts(dropna=False), "\n")
```

[8] Python

```
...   Gender:
       Male      40898
      Female    33712
      Name: Gender, dtype: int64

      Job Role:
       Technology    19350
      Healthcare    17107
      Education     15679
      Media         12011
      Finance       10463
      Name: Job Role, dtype: int64

      Work-Life Balance:
       Good         28196
```

```python
data['Education Level'] = data['Education Level'].replace({
    'Bacheloraeur(Tm)S Degree': "Bachelor's Degree",
    'Masteraeur(Tm)S Degree': "Master's Degree"
})
```

[9] Python

```python
for col in cat_cols:
    print(f"Before cleaning - {col}:\n", data[col].unique())
```

[10] Python

```
Before cleaning - Gender:
 ['Male' 'Female']
Before cleaning - Job Role:
 ['Education' 'Media' 'Healthcare' 'Technology' 'Finance']
Before cleaning - Work-Life Balance:
 ['Excellent' 'Poor' 'Good' 'Fair']
Before cleaning - Job Satisfaction:
 ['Medium' 'High' 'Very High' 'Low']
Before cleaning - Performance Rating:
 ['Average' 'Low' 'High' 'Below Average']
Before cleaning - Overtime:
 ['No' 'Yes']
Before cleaning - Education Level:
 ['Associate Degree' "Master's Degree" "Bachelor's Degree" 'High School'
 'Phd']
Before cleaning - Marital Status:
 ['Married' 'Divorced' 'Single']
Before cleaning - Job Level:
 ['Mid' 'Senior' 'Entry']
Before cleaning - Company Size:
 ['Medium' 'Small' 'Large']
Before cleaning - Remote Work:
 ['No' 'Yes']
Before cleaning - Leadership Opportunities:
 ['No' 'Yes']
...
Before cleaning - Employee Recognition:
 ['Medium' 'Low' 'High' 'Very High']
Before cleaning - Attrition:
```


```
Before cleaning - Performance Rating:
 ['Average' 'Low' 'High' 'Below Average']
Before cleaning - Overtime:
 ['No' 'Yes']
Before cleaning - Education Level:
 ['Associate Degree' "Master's Degree" "Bachelor's Degree" 'High School'
 'Phd']
Before cleaning - Marital Status:
 ['Married' 'Divorced' 'Single']
Before cleaning - Job Level:
 ['Mid' 'Senior' 'Entry']
Before cleaning - Company Size:
 ['Medium' 'Small' 'Large']
Before cleaning - Remote Work:
 ['No' 'Yes']
Before cleaning - Leadership Opportunities:
 ['No' 'Yes']
...
Before cleaning - Employee Recognition:
 ['Medium' 'Low' 'High' 'Very High']
Before cleaning - Attrition:
```


```
 ['Stayed' 'Left']
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

+ Code + Markdown

```python
# to check the redudancy
data[['Years at Company', 'Company Tenure (In Months)']].corr()
```

[11] Python

	Years at Company	Company Tenure (In Months)
Years at Company	1.000000	0.435156
Company Tenure (In Months)	0.435156	1.000000

```python
#after checking that we drop the employee id there is no use of it
data.drop(columns=['Employee ID'], inplace=True)
```

3. Train-Validation Split

Train- Validation Split

```python
from sklearn.model_selection import train_test_split

# Define features and target variable
X = data.drop(columns=['Attrition'])  # predictors
y = data['Attrition']  # target (Stayed/Left)

# Encode target if needed (e.g., Yes/No to 1/0)
y = y.map({'Stayed': 0, 'Left': 1})  # Optional: for numeric modeling

# Perform split (70% train, 30% validation)
X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y  # maintain class balance
)
```

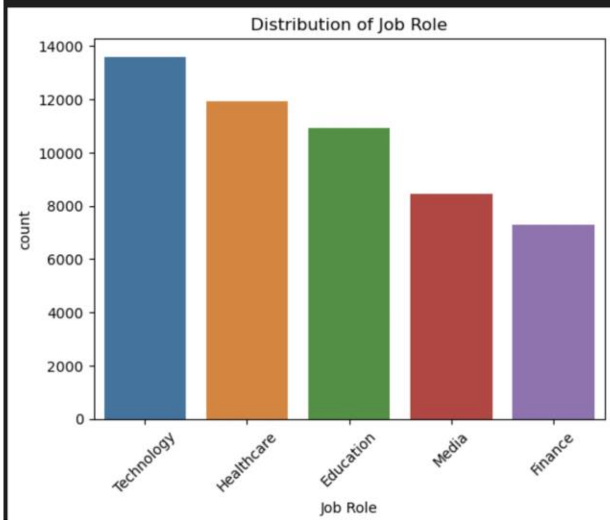
[13] Python

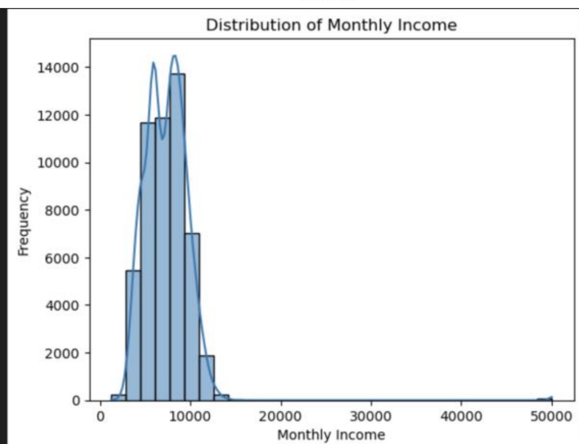
EDA on Training Data

```python
#Goal: Analyze the distribution of individual features.
# Categorical Example: Job Role
sns.countplot(x='Job Role', data=X_train, order=X_train['Job Role'].value_counts().index)
plt.xticks(rotation=45)
plt.title('Distribution of Job Role')
plt.show()

# Numerical Example: Monthly Income
sns.histplot(X_train['Monthly Income'], kde=True, bins=30)
```

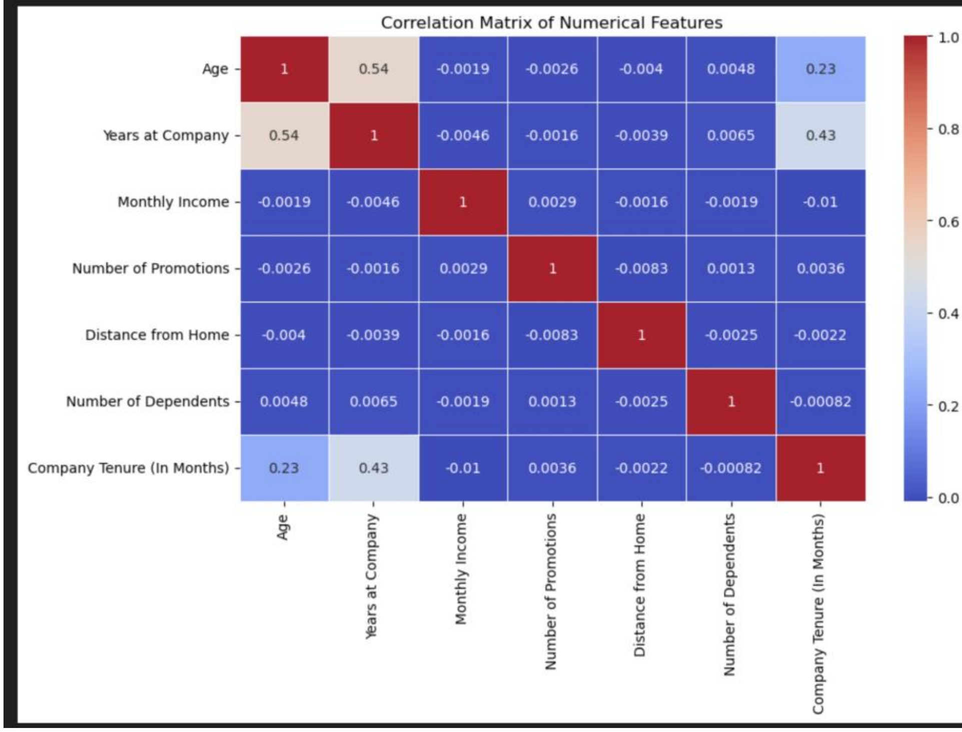
4. EDA on Training Data

```python
sns.countplot(x='Job Role', data=X_train, order=X_train['Job Role'].value_counts().index)
plt.xticks(rotation=45)
plt.title('Distribution of Job Role')
plt.show()

# Numerical Example: Monthly Income
sns.histplot(X_train['Monthly Income'], kde=True, bins=30)
plt.title('Distribution of Monthly Income')
plt.xlabel('Monthly Income')
plt.ylabel('Frequency')
plt.show()
```





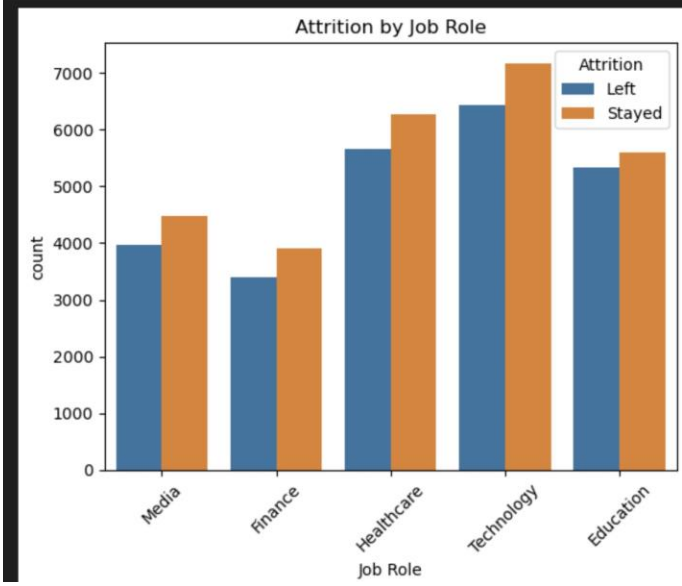

```python
#Goal: Identify linear relationships among numeric variables.
# Correlation Matrix
numeric_cols = X_train.select_dtypes(include=['int64', 'float64']).columns
corr_matrix = X_train[numeric_cols].corr()

plt.figure(figsize=(10,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```

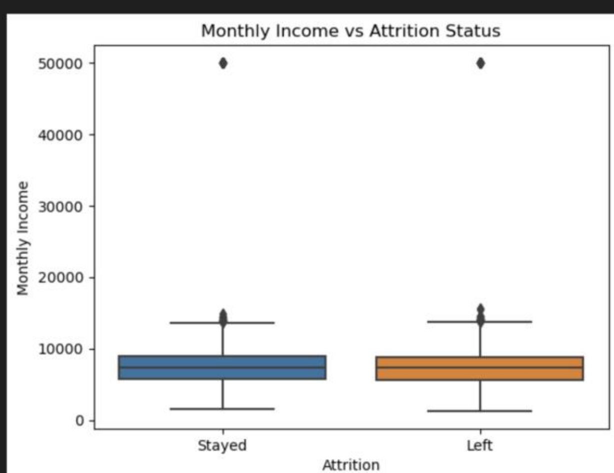



```python
#Check if the attrition target is imbalanced.
# Visualizing class distribution in training set
y_train.value_counts(normalize=True).plot(kind='bar', color=['mediumseagreen', 'tomato'])
plt.title('Attrition Distribution in Training Set')
plt.xticks(ticks=[0,1], labels=['Stayed', 'Left'], rotation=0)
plt.ylabel('Proportion')
plt.show()
```


```python
#Explore how features influence attrition.
# Categorical vs Target: Attrition by Job Role
sns.countplot(x='Job Role', hue=y_train.map({0: 'Stayed', 1: 'Left'}), data=X_train)
plt.xticks(rotation=45)
plt.title('Attrition by Job Role')
```

```python
sns.countplot(x='Job Role', hue=y_train.map({0: 'Stayed', 1: 'Left'}), data=X_train)
plt.xticks(rotation=45)
plt.title('Attrition by Job Role')
plt.show()

# Numerical vs Target: Income vs Attrition
sns.boxplot(x=y_train, y=X_train['Monthly Income'])
plt.xticks([0, 1], ['Stayed', 'Left'])
plt.title('Monthly Income vs Attrition Status')
plt.xlabel('Attrition')
plt.ylabel('Monthly Income')
plt.show()
```





Feature Engineering

```python
# Step 1: Identify categorical columns
cat_cols = X_train.select_dtypes(include='object').columns

# Step 2: Create dummy variables using one-hot encoding
```

5. EDA on Data Validation [OPTIONAL]

6. Feature Engineering

```python
# Step 1: Identify categorical columns
cat_cols = X_train.select_dtypes(include='object').columns

# Step 2: Create dummy variables using one-hot encoding
X_train_encoded = pd.get_dummies(X_train, columns=cat_cols, drop_first=True)
X_val_encoded = pd.get_dummies(X_val, columns=cat_cols, drop_first=True)

# Step 3: Align columns in both sets
X_train_encoded, X_val_encoded = X_train_encoded.align(X_val_encoded, join='left', axis=1, fill_value=0)
```

```python
from sklearn.preprocessing import StandardScaler

# Step 1: Identify numerical columns to scale
num_cols = ['Age', 'Monthly Income', 'Distance from Home', 'Company Tenure (In Months)', 'Number of Promotions', 'Number of Dependents']

# Step 2: Initialize and fit scaler
scaler = StandardScaler()
X_train_encoded[num_cols] = scaler.fit_transform(X_train_encoded[num_cols])
X_val_encoded[num_cols] = scaler.transform(X_val_encoded[num_cols])
```

```python
#print the shape of the scaling
print("X_train_encoded shape:", X_train_encoded.shape)
print("X_val_encoded shape:", X_val_encoded.shape)
```

```
X_train_encoded shape: (52227, 41)
X_val_encoded shape: (22383, 41)
```


```python
# Step 1: Identify numerical columns to scale
num_cols = ['Age', 'Monthly Income', 'Distance from Home', 'Company Tenure (In Months)', 'Number of Promotions', 'Number of Dependents']

# Step 2: Initialize and fit scaler
scaler = StandardScaler()
X_train_encoded[num_cols] = scaler.fit_transform(X_train_encoded[num_cols])
X_val_encoded[num_cols] = scaler.transform(X_val_encoded[num_cols])
```

```python
#print the shape of the scaling
print("X_train_encoded shape:", X_train_encoded.shape)
print("X_val_encoded shape:", X_val_encoded.shape)
```

```
X_train_encoded shape: (52227, 41)
X_val_encoded shape: (22383, 41)
```


```python
#to check that scaling is worked or not
print("Monthly Income - mean:", X_train_encoded['Monthly Income'].mean())
print("Monthly Income - std deviation:", X_train_encoded['Monthly Income'].std())
```

```
Monthly Income - mean: -1.172741758525679e-16
Monthly Income - std deviation: 1.000009573729683
```

Model Building

```python
# Final features available
print("Number of features used:", X_train_encoded.shape[1])
```

7. Model Building

Model Building

```python
# Final features available
print("Number of features used:", X_train_encoded.shape[1])
```

[22] Python

```
Number of features used: 41
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score

# Step 1: Instantiate model
model = LogisticRegression(max_iter=1000, class_weight='balanced', random_state=42)

# Step 2: Fit model
model.fit(X_train_encoded, y_train)

# Step 3: Predict on validation set
y_pred = model.predict(X_val_encoded)

# Step 4: Evaluate
print("Confusion Matrix:\n", confusion_matrix(y_val, y_pred))
print("\nClassification Report:\n", classification_report(y_val, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_val, model.predict_proba(X_val_encoded)[:,1]))
```

[23] Python

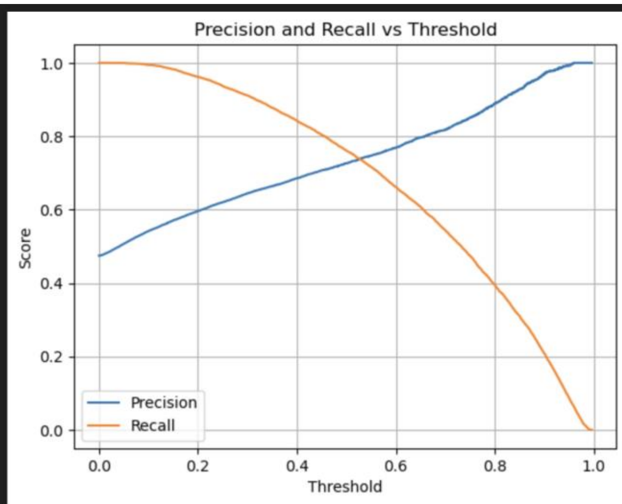
```
Confusion Matrix:
 [[8709 3048]
 [2541 8085]]

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.74      0.76     11757
           1       0.73      0.76      0.74     10626
```


```
Confusion Matrix:
 [[8709 3048]
 [2541 8085]]

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.74      0.76     11757
           1       0.73      0.76      0.74     10626
```


```

    accuracy                           0.75     22383
   macro avg       0.75      0.75      0.75     22383
weighted avg       0.75      0.75      0.75     22383

ROC-AUC Score: 0.8422704505556164
```

```python
from sklearn.metrics import precision_recall_curve
import numpy as np
import matplotlib.pyplot as plt

# Step 1: Get predicted probabilities
y_scores = model.predict_proba(X_val_encoded)[:,1]

# Step 2: Calculate precision and recall for thresholds
precision, recall, thresholds = precision_recall_curve(y_val, y_scores)

# Step 3: Plot Precision-Recall vs Threshold
plt.plot(thresholds, precision[:-1], label='Precision')
plt.plot(thresholds, recall[:-1], label='Recall')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision and Recall vs Threshold')
plt.legend()
plt.grid()
plt.show()

# Step 4: Choose a threshold (e.g., one where precision ≈ recall)
optimal_idx = np.argmax(precision + recall)
optimal_threshold = thresholds[optimal_idx]
print("Optimal Threshold:", optimal_threshold)
```

[24]




```
Optimal Threshold: 0.22637879896280366
```

```python
# Apply new threshold
y_pred_adjusted = (y_scores > optimal_threshold).astype(int)

# Reevaluate
print("Confusion Matrix (Adjusted):\n", confusion_matrix(y_val, y_pred_adjusted))
print("Classification Report (Adjusted):\n", classification_report(y_val, y_pred_adjusted))
```

[25] Python

```
Confusion Matrix (Adjusted):
 [[ 5285  6472]
 [  514 10112]]
```


```python
# Apply new threshold
y_pred_adjusted = (y_scores > optimal_threshold).astype(int)

# Reevaluate
print("Confusion Matrix (Adjusted):\n", confusion_matrix(y_val, y_pred_adjusted))
print("Classification Report (Adjusted):\n", classification_report(y_val, y_pred_adjusted))
```

[25] Python

```
Confusion Matrix (Adjusted):
 [[ 5285  6472]
 [  514 10112]]
```


```
Classification Report (Adjusted):
              precision    recall  f1-score   support

           0       0.91      0.45      0.60     11757
           1       0.61      0.95      0.74     10626

    accuracy                           0.69     22383
   macro avg       0.76      0.70      0.67     22383
weighted avg       0.77      0.69      0.67     22383
```

Prediction and Model Evaluation

+ Code + Markdown

```python
# Predict class labels on validation set using optimal threshold
y_pred_proba = model.predict_proba(X_val_encoded)[:, 1]

# (Optional) Use adjusted threshold if determined
threshold = optimal_threshold  # use your earlier calculated threshold
y_pred = (y_pred_proba > threshold).astype(int)
```

[26] Python

```python
from sklearn.metrics import accuracy_score
```

8. Prediction and Model Evaluation

Prediction and Model Evaluation

```python
# Predict class labels on validation set using optimal threshold
y_pred_proba = model.predict_proba(X_val_encoded)[:, 1]

# (Optional) Use adjusted threshold if determined
threshold = optimal_threshold  # use your earlier calculated threshold
y_pred = (y_pred_proba > threshold).astype(int)
```

[26] Python

```python
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_val, y_pred)
print("Model Accuracy:", round(accuracy, 4))
```

[27] Python

```
Model Accuracy: 0.6879
```

```python
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_val, y_pred)
print("Confusion Matrix:\n", cm)

# Assign values
TN, FP, FN, TP = cm.ravel()

print(f"True Positive (TP): {TP}")
print(f"True Negative (TN): {TN}")
print(f"False Positive (FP): {FP}")
print(f"False Negative (FN): {FN}")
```

```
Confusion Matrix:
 [[ 5285  6472]
 [  514 10112]]
True Positive (TP): 10112
True Negative (TN): 5285
False Positive (FP): 6472
False Negative (FN): 514
```

```python
# Sensitivity (Recall for class 1)
sensitivity = TP / (TP + FN)

# Specificity (Recall for class 0)
specificity = TN / (TN + FP)

print("Sensitivity (Recall for 'Left'):", round(sensitivity, 4))
print("Specificity (Recall for 'Stayed'):", round(specificity, 4))
```

[29] Python

```
Sensitivity (Recall for 'Left'): 0.9516
Specificity (Recall for 'Stayed'): 0.4495
```

```python
from sklearn.metrics import precision_score, recall_score

precision = precision_score(y_val, y_pred)
recall = recall_score(y_val, y_pred)

print("Precision (for 'Left'):", round(precision, 4))
print("Recall (for 'Left'):", round(recall, 4))
```

[30] Python

```
Precision (for 'Left'): 0.6097
Recall (for 'Left'): 0.9516
```