In [1]:
```
!pip install pandas numpy matplotlib seaborn scikit-learn
```

```
Requirement already satisfied: pandas in /home/sargam/.conda/envs/myenv/li
b/python3.11/site-packages (2.2.3)
Requirement already satisfied: numpy in /home/sargam/.conda/envs/myenv/li
b/python3.11/site-packages (2.0.1)
Requirement already satisfied: matplotlib in /home/sargam/.conda/envs/myen
v/lib/python3.11/site-packages (3.10.1)
Requirement already satisfied: seaborn in /home/sargam/.conda/envs/myenv/l
ib/python3.11/site-packages (0.13.2)
Requirement already satisfied: scikit-learn in /home/sargam/.conda/envs/my
env/lib/python3.11/site-packages (1.6.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /home/sargam/.con
da/envs/myenv/lib/python3.11/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /home/sargam/.conda/envs/my
env/lib/python3.11/site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /home/sargam/.conda/envs/
myenv/lib/python3.11/site-packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /home/sargam/.conda/env
s/myenv/lib/python3.11/site-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /home/sargam/.conda/envs/my
env/lib/python3.11/site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /home/sargam/.conda/en
vs/myenv/lib/python3.11/site-packages (from matplotlib) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /home/sargam/.conda/en
vs/myenv/lib/python3.11/site-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /home/sargam/.conda/env
s/myenv/lib/python3.11/site-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /home/sargam/.conda/envs/myen
v/lib/python3.11/site-packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /home/sargam/.conda/env
s/myenv/lib/python3.11/site-packages (from matplotlib) (3.2.3)
Requirement already satisfied: scipy>=1.6.0 in /home/sargam/.conda/envs/my
env/lib/python3.11/site-packages (from scikit-learn) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in /home/sargam/.conda/envs/m
yenv/lib/python3.11/site-packages (from scikit-learn) (1.5.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in /home/sargam/.cond
a/envs/myenv/lib/python3.11/site-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: six>=1.5 in /home/sargam/.conda/envs/myenv/
lib/python3.11/site-packages (from python-dateutil>=2.8.2->pandas) (1.17.
0)
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import precision_score, confusion_matrix, accuracy_s
```

In [3]:
```
# Step 1: Load the dataset
df = pd.read_csv("/home/sargam/Downloads/Social_Network_Ads.csv")
print(df.head())
```

```
    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
3  15603246  Female   27            57000          0
4  15804002    Male   19            76000          0
```

In [4]:
```python
print(df.isnull().sum())
```

```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [6]:
```python
# Step 2: Data Preprocessing
# 2.1: One-hot encode 'Gender' column
df = pd.get_dummies(df, columns=['Gender'], drop_first=True)
```

In [8]:
```python
# 2.2: Drop 'User ID' column as it's not relevant
df = df.drop(['User ID'], axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Age              400 non-null    int64
 1   EstimatedSalary  400 non-null    int64
 2   Purchased        400 non-null    int64
 3   Gender_Male      400 non-null    bool
dtypes: bool(1), int64(3)
memory usage: 9.9 KB
```

In [9]:
```python
# Step 2.3: Remove outliers using the Quantile (IQR) method for numeric c
numeric_cols = df.select_dtypes(include=[np.number]).columns  # Only sele

Q1 = df[numeric_cols].quantile(0.25)
Q3 = df[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
```

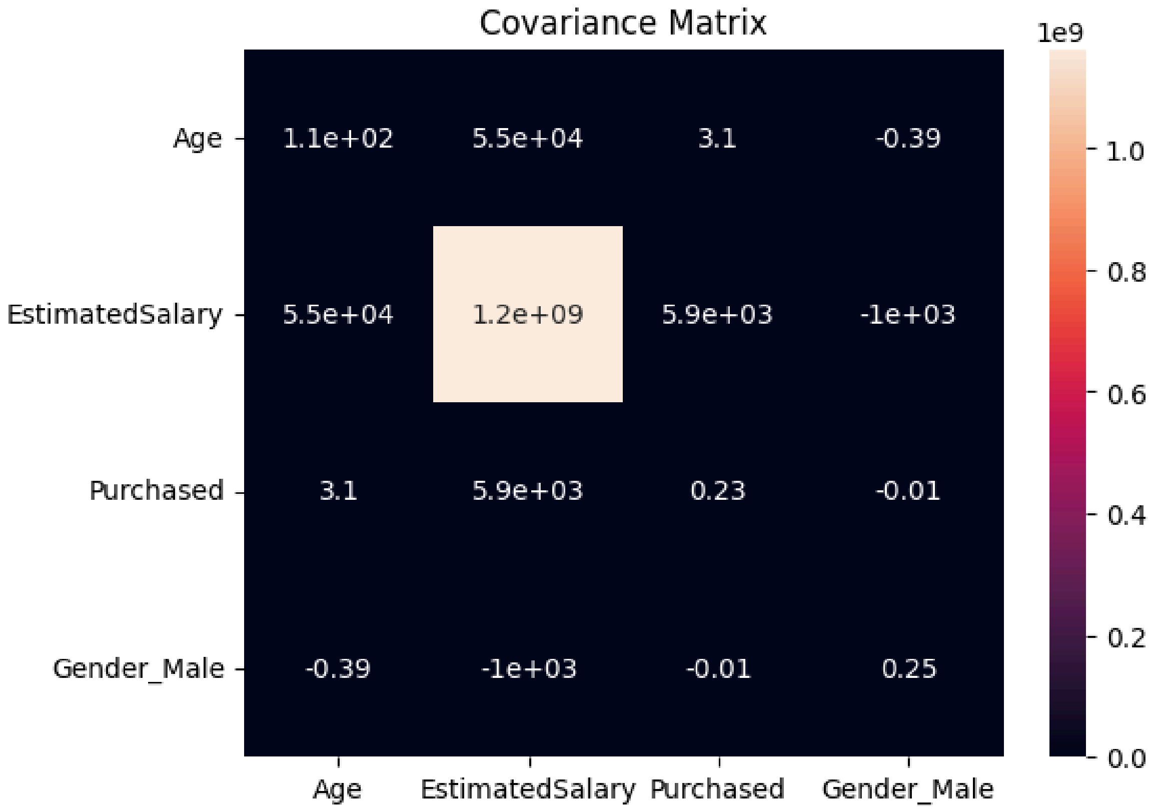
In [10]:
```python
# Define bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

In [11]:
```python
# Remove outliers
df_no_outliers = df[~((df[numeric_cols] < lower_bound) | (df[numeric_cols
```

In [12]:
```python
print("\nNull Values:")
print(df_no_outliers.isnull().sum())
```

```
Null Values:
Age                0
EstimatedSalary    0
Purchased          0
Gender_Male        0
dtype: int64
```

In [13]:
```python
# Step 2.4: Covariance Matrix to select promising features
cov_matrix = df_no_outliers.cov()
sns.heatmap(cov_matrix, annot=True)
plt.title('Covariance Matrix')
plt.show()
```



In [14]:
```python
# Step 3: Prepare the dataset
X = df_no_outliers.drop('Purchased', axis=1)  # Features excluding 'Purch
y = df_no_outliers['Purchased']  # Target variable
```

In [15]:
```python
# Step 4: Split the dataset into training and testing datasets (80% train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

In [16]:
```python
# Step 5: Scale the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [17]:
```python
# Step 6: Train the Logistic Regression Model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[17]:
```
▾ LogisticRegression
LogisticRegression()
```

In [18]:
```python
# Step 7: Predict the test dataset
y_pred = logreg.predict(X_test)
```

In [19]:
```python
# Step 8: Confusion Matrix Evaluation
cm = confusion_matrix(y_test, y_pred)
```

```
print("\nConfusion Matrix:")
print(cm)
```

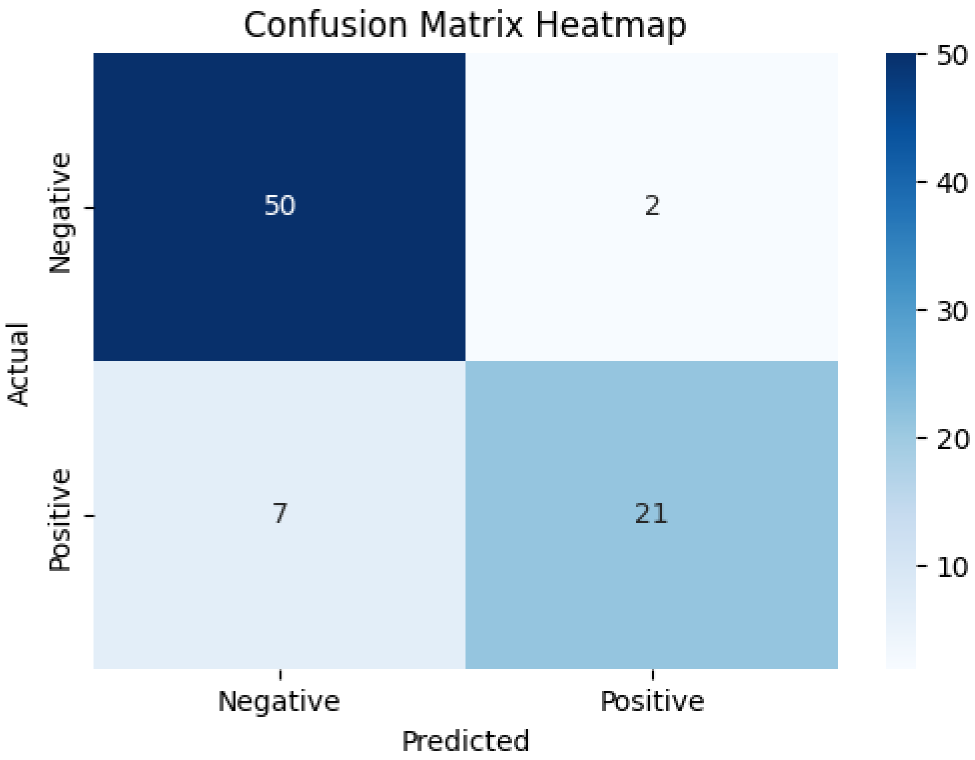
```
Confusion Matrix:
[[50  2]
 [ 7 21]]
```

In [21]:
```
accuracy_percent = accuracy_score(y_test, y_pred) * 100
error_rate = 100 - accuracy_percent
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print(f"\nAccuracy: {accuracy_percent}%")
print(f"Error Rate: {error_rate}%")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
```

```
Accuracy: 88.75%
Error Rate: 11.25%
Precision: 0.9130434782608695
Recall: 0.75
```

In [22]:
```
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Negative
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



In [23]:
```
# Step 9: Comparison between Actual and Predicted
comparison_df = pd.DataFrame({
    'Actual': y_test,
    'Predicted': y_pred
})
```

In [24]:
```
errors = (comparison_df['Actual'] != comparison_df['Predicted']).sum()
```

```python
print(f'Number of misclassified instances: {errors}')
```

```
Number of misclassified instances: 9
```

In [25]:
```python
# Step 10: False Positives and False Negatives
FP = ((comparison_df['Actual'] == 0) & (comparison_df['Predicted'] == 1))
FN = ((comparison_df['Actual'] == 1) & (comparison_df['Predicted'] == 0))
```

In [26]:
```python
print(f'False Positives (FP): {FP}')
print(f'False Negatives (FN): {FN}')
```

```
False Positives (FP): 2
False Negatives (FN): 7
```

In [27]:
```python
# Step 12: Accuracy Calculation
accuracy = accuracy_score(y_test, y_pred)
accuracy_percentage = accuracy * 100
print(f'Accuracy: {accuracy_percentage:.2f}%')
```

```
Accuracy: 88.75%
```

In [28]:
```python
# Step 13: Mean Squared Error for Training and Testing Set
y_train_pred = logreg.predict(X_train)
train_mse = mean_squared_error(y_train, y_train_pred)
print(f'Training Mean Squared Error (MSE): {train_mse:.4f}')
```

```
Training Mean Squared Error (MSE): 0.1844
```

In [29]:
```python
test_mse = mean_squared_error(y_test, y_pred)
print(f'Testing Mean Squared Error (MSE): {test_mse:.4f}')
```

```
Testing Mean Squared Error (MSE): 0.1125
```

In [ ]:
```python

```

In [ ]:
```python

```