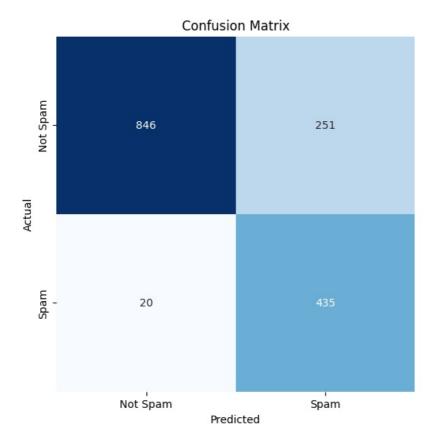
Classify the email using the binary classification method. Email Spam detection has two states: a) Normal State – Not Spam, b)

Abnormal State – Spam. Use K-Nearest Neighbors for classification. Analyze their performance. Dataset link: The emails.csv dataset on the Kaggle https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv

```
In [16]: import pandas as pd
         from sklearn.model selection import train test split
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import confusion_matrix, accuracy_score
         import seaborn as sns
         import matplotlib.pyplot as plt
In [17]: # Load the dataset
         df = pd.read_csv("C:/Users/Atharva/OneDrive/Desktop/LP3 code/emails.csv")
         print(df.head())
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In [18]: # Drop the 'Email No.' column as it's just an identifier
         X = df.drop(columns=['Email No.', 'Prediction']) # Drop 'Email No.' and 'Prediction' columns
         y = df['Prediction']  # 'Prediction' column is the target (spam = 1, not spam = 0)
In [19]: # Split the dataset into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
In [20]: # Normalize the data (standardize the features for better performance with KNN)
         scaler = StandardScaler()
         X train = scaler.fit transform(X train)
         X_test = scaler.transform(X_test)
In [21]: # Initialize and train the KNN model
         knn = KNeighborsClassifier(n neighbors=5) # You can adjust 'n neighbors' as needed
         knn.fit(X train, y train)
Out[21]: v
             KNeighborsClassifier
         KNeighborsClassifier()
In [22]: # Make predictions on the test set
         y_pred = knn.predict(X_test)
In [23]: # Calculate and print performance metrics
         conf_matrix = confusion_matrix(y_test, y_pred)
         accuracy = accuracy_score(y_test, y_pred)
In [24]: # Display results
         print(f"Confusion Matrix:\n{conf matrix}")
         print(f"Accuracy: {accuracy:.2f}")
        Confusion Matrix:
        [[846 251]
        [ 20 435]]
        Accuracy: 0.83
In [25]: # Visualization of the confusion matrix using Seaborn
         plt.figure(figsize=(6, 6))
         sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False,
                     xticklabels=['Not Spam', 'Spam'], yticklabels=['Not Spam', 'Spam'])
         plt.title("Confusion Matrix")
         plt.xlabel('Predicted')
         plt.ylabel('Actual')
         plt.show()
```



In [ ]:

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