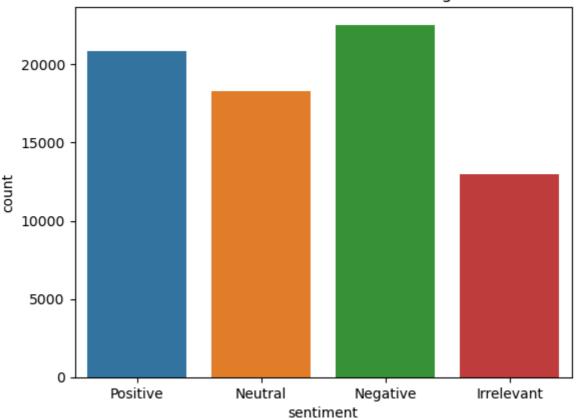
```
In [20]:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.model_selection import train_test_split, RandomizedSearchCV
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
         from sklearn.pipeline import Pipeline
         from sklearn.preprocessing import FunctionTransformer
         import re
         import warnings
         from scipy.stats import uniform
         warnings.filterwarnings('ignore')
In [21]:
         # Load the datasets
         train_data = pd.read_csv('C:/Users/v/Desktop/MAYURA/Data Science Projects/Twitter S
         validation_data = pd.read_csv('C:/Users/v/Desktop/MAYURA/Data Science Projects/Twit
         # Rename columns
         train_data.columns = ['id', 'topic', 'sentiment', 'text']
         validation_data.columns = ['id', 'topic', 'sentiment', 'text']
         # Display the first few rows of the datasets
         print(train_data.head())
         print(validation_data.head())
                        topic sentiment \
              id
         0 2401 Borderlands Positive
         1 2401 Borderlands Positive
         2 2401 Borderlands Positive
         3 2401 Borderlands Positive
         4 2401 Borderlands Positive
         0 im getting on borderlands and i will murder yo...
         1 I am coming to the borders and I will kill you...
         2 im getting on borderlands and i will kill you ...
         3 im coming on borderlands and i will murder you...
         4 im getting on borderlands 2 and i will murder ...
              id
                      topic
                              sentiment \
                  Facebook Irrelevant
         0 3364
         1
           352
                    Amazon
                              Neutral
         2 8312 Microsoft
                            Negative
         3 4371
                            Negative
                     CS-GO
         4 4433
                               Neutral
                    Google
                                                         text
         0 I mentioned on Facebook that I was struggling ...
         1 BBC News - Amazon boss Jeff Bezos rejects clai...
         2 @Microsoft Why do I pay for WORD when it funct...
         3 CSGO matchmaking is so full of closet hacking,...
         4 Now the President is slapping Americans in the...
In [22]: # Check for missing values and data types
         print(train_data.info())
         print(train data.describe())
         print(validation data.info())
         print(validation_data.describe())
         # Distribution of the target variable
```

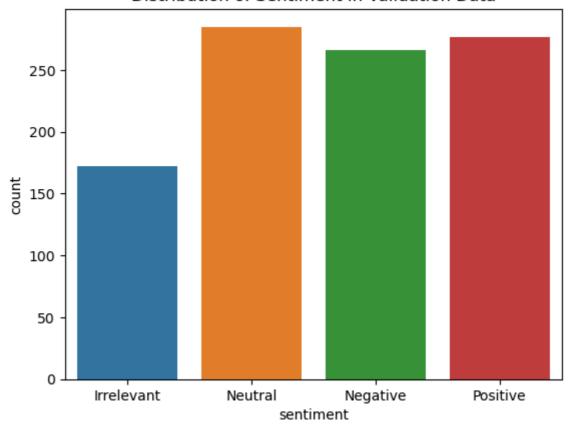
```
print(train_data['sentiment'].value_counts())
        print(validation_data['sentiment'].value_counts())
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 74682 entries, 0 to 74681
        Data columns (total 4 columns):
         # Column Non-Null Count Dtype
        --- -----
                      _____
           id
                      74682 non-null int64
         0
            topic 74682 non-null object
         1
         2
           sentiment 74682 non-null object
         3 text 73996 non-null object
        dtypes: int64(1), object(3)
        memory usage: 2.3+ MB
        None
        count 74682.000000
        mean 6432.586165
        std 3740.427870
        min
                  1.000000
              3195.000000
        25%
              6422.000000
        50%
        75%
              9601.000000
        max 13200.000000
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1000 entries, 0 to 999
        Data columns (total 4 columns):
         # Column Non-Null Count Dtype
                      -----
         0 id
                     1000 non-null int64
            topic 1000 non-null object
             sentiment 1000 non-null object
         2
            text 1000 non-null object
        dtypes: int64(1), object(3)
        memory usage: 31.4+ KB
        None
                        id
        count 1000.000000
        mean
               6432.088000
        std 3728.310569
        min
                6.000000
        25%
              3247.750000
        50%
              6550.000000
        75%
              9661.750000
              13197.000000
        max
        sentiment
        Negative
                     22542
        Positive
                     20832
        Neutral
                    18318
        Irrelevant
                     12990
        Name: count, dtype: int64
        sentiment
        Neutral
                     285
        Positive
                     277
        Negative
                     266
        Irrelevant
                     172
        Name: count, dtype: int64
In [23]: # Visualizing the distribution of the target variable in the training set
        sns.countplot(x='sentiment', data=train_data)
        plt.title('Distribution of Sentiment in Training Data')
        plt.show()
```

## Distribution of Sentiment in Training Data



In [24]: # Visualizing the distribution of the target variable in the validation set
 sns.countplot(x='sentiment', data=validation\_data)
 plt.title('Distribution of Sentiment in Validation Data')
 plt.show()





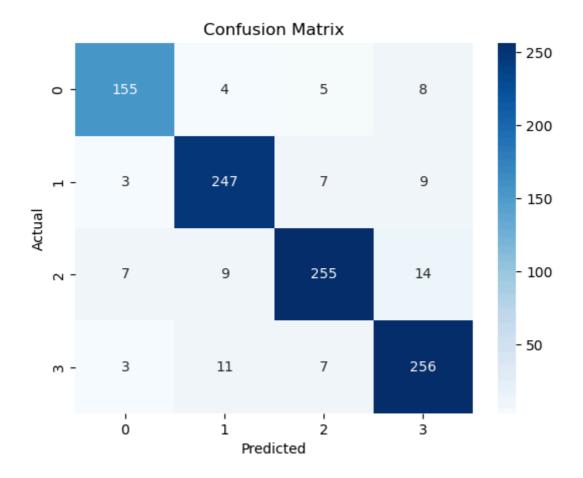
```
# Remove any rows with NaN values in the 'text' or 'sentiment' columns
In [25]:
         train_data.dropna(subset=['text', 'sentiment'], inplace=True)
         validation_data.dropna(subset=['text', 'sentiment'], inplace=True)
         # Check for null values again
         print(train_data.isnull().sum())
         print(validation_data.isnull().sum())
         id
                      a
                      0
         topic
         sentiment
         text
         dtype: int64
         id
         topic
         sentiment
         text
         dtype: int64
In [26]: # Text preprocessing function
         def preprocess_text(text):
             text = text.lower()
             text = re.sub(r'[^a-z\s]', '', text)
             text = re.sub(r'\s+', ' ', text).strip()
             return text
         # Apply text preprocessing
In [27]:
         train_data['text'] = train_data['text'].apply(preprocess_text)
         validation_data['text'] = validation_data['text'].apply(preprocess_text)
In [29]: # Splitting the data into training and validation sets
         X_train, X_test, y_train, y_test = train_test_split(train_data['text'], train_data[
         # Display the shapes of the splits
         print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
         (59196,) (14800,) (59196,) (14800,)
In [30]: # Initializing TF-IDF Vectorizer
         tfidf = TfidfVectorizer(max_features=10000, ngram_range=(1,3))
         # Function for Model Evaluation
         def evaluate_model(model, X_test, y_test):
             y_pred = model.predict(X_test)
             print("Accuracy: ", accuracy_score(y_test, y_pred))
             print("Classification Report:\n", classification_report(y_test, y_pred))
             cm = confusion_matrix(y_test, y_pred)
             sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
             plt.xlabel('Predicted')
             plt.ylabel('Actual')
             plt.title('Confusion Matrix')
             plt.show()
In [31]:
         # Building a pipeline for the model
         pipeline = Pipeline([
             ('tfidf', tfidf),
              ('logreg', LogisticRegression(solver='liblinear'))
         ])
In [32]:
         # Hyperparameter tuning
         param_dist = {
              'logreg__C': uniform(0.01, 10),
```

```
'logreg__penalty': ['12', '11']
         random_search = RandomizedSearchCV(pipeline, param_distributions=param_dist, n_iter
         random_search.fit(X_train, y_train)
         Fitting 5 folds for each of 50 candidates, totalling 250 fits
▶ estimator: Pipeline
            ▶ TfidfVectorizer
          ▶ LogisticRegression
In [33]: # Best parameters
         print("Best parameters found: ", random_search.best_params_)
        Best parameters found: {'logreg_C': 9.498855372533333, 'logreg_penalty': '11'}
         # Best model
In [34]:
         best_model = random_search.best_estimator_
         # Model Evaluation on test set
In [35]:
         evaluate_model(best_model, X_test, y_test)
         # Model Evaluation on validation set
         evaluate_model(best_model, validation_data['text'], validation_data['sentiment'])
        Accuracy: 0.7675675675676
        Classification Report:
                      precision recall f1-score support
                                            0.72
          Irrelevant
                          0.76
                                  0.68
                                                     2696
                                  0.82
                                                     4380
            Negative
                         0.81
                                             0.81
                                   0.74
                                                      3605
             Neutral
                          0.72
                                             0.73
            Positive
                          0.76
                                  0.79
                                             0.78
                                                      4119
                                             0.77
                                                     14800
            accuracy
                       0.77
0.77
                                  0.76
                                            0.76
                                                     14800
           macro avg
                                            0.77
                          0.77
                                  0.77
        weighted avg
                                                     14800
```

## **Confusion Matrix** - 3500 251 297 314 0 -- 3000 - 2500 157 3589 336 298 ႕ -- 2000 - 1500 204 2679 394 328 ۷-- 1000 207 266 388 3258 m -- 500 3 0 1 2 Predicted

Accuracy: 0.913 Classification Report:

CIUSSITICUCION	кероге.			
	precision	recall	f1-score	support
Irrelevant	0.92	0.90	0.91	172
Negative	0.91	0.93	0.92	266
Neutral	0.93	0.89	0.91	285
Positive	0.89	0.92	0.91	277
accuracy			0.91	1000
macro avg	0.91	0.91	0.91	1000
weighted avg	0.91	0.91	0.91	1000



In []: