```
In [1]: from sklearn.datasets import fetch 20newsgroups
         from sklearn.model_selection import train_test_split
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.naive_bayes import MultinomialNB
         from sklearn.pipeline import make_pipeline
         from sklearn import metrics
         import matplotlib.pyplot as plt
         import seaborn as sns
In [2]: # Load the dataset
         newsgroups = fetch_20newsgroups(subset='all', shuffle=True, random_state=42)
         newsgroups
Out[2]: {'data': ["From: Mamatha Devineni Ratnam <mr47+@andrew.cmu.edu>\nSubject: Pens fans reactions\nOrganization: Post 0
         ffice, Carnegie Mellon, Pittsburgh, PA\nLines: 12\nNNTP–Posting–Host: po4.andrew.cmu.edu\n\n\n\n\angle
         ers of Pens fans are pretty confused about the lack\nof any kind of posts about the recent Pens massacre of the Dev
         ils. Actually,\nI am bit puzzled too and a bit relieved. However, I am going to put an end\nto non-PIttsburghers'
         relief with a bit of praise for the Pens. Man, they\nare killing those Devils worse than I thought. Jagr just showe
         d you why\nhe is much better than his regular season stats. He is also a lot\nfo fun to watch in the playoffs. Bowm
         an should let JAgr have a lot of\nfun in the next couple of games since the Pens are going to beat the pulp out of
         Jersey anyway. I was very disappointed not to see the Islanders lose the final\nregular season game.
         RULE!!!\n\n",
           'From: mblawson@midway.ecn.uoknor.edu (Matthew B Lawson)\nSubject: Which high-performance VLB video card?\nSummar
         y: Seek recommendations for VLB video card\nNntp-Posting-Host: midway.ecn.uoknor.edu\nOrganization: Engineering Com
         puter Network, University of Oklahoma, Norman, OK, USA\nKeywords: orchid, stealth, vlb\nLines: 21\n\n My brother i s in the market for a high-performance video card that supports\nVESA local bus with 1-2MB RAM. Does anyone have s
         uggestions/ideas on:\n\n - Diamond Stealth Pro Local Bus\n\n - Orchid Farenheit 1280\n\n - ATI Graphics Ultra Pr
         o\n\n - Any other high-performance VLB card\n\nPlease post or email. Thank you!\n\n - Matt\n\n--\n | Matt hew B. Lawson <----- (mblawson@essex.ecn.uoknor.edu) | \n --+- "Now I, Nebuchadnezzar, praise and exal
         t and glorify the King --+-- \n | of heaven, because everything he does is right and all his ways | are just." - Nebuchadnezzar, king of Babylon, 562 B.C. | \n',
           'From: hilmi-er@dsv.su.se (Hilmi Eren)\nSubject: Re: ARMENIA SAYS IT COULD SHOOT DOWN TURKISH PLANES (Henrik)\nLi
In [3]: text_categories = newsgroups.target_names
         text_categories
         # Print the text categories
         print("Text Categories:")
         for i, category in enumerate(text_categories):
             print(f"{i}: {category}")
         print("Number of unique classes: {}".format(len(text_categories)))
         Text Categories:
         0: alt.atheism
         1: comp.graphics
         2: comp.os.ms-windows.misc
        3: comp.sys.ibm.pc.hardware
         4: comp.sys.mac.hardware
         5: comp.windows.x
         6: misc.forsale
         7: rec.autos
         8: rec.motorcycles
        9: rec.sport.baseball
         10: rec.sport.hockey
         11: sci.crypt
         12: sci.electronics
        13: sci.med
         14: sci.space
         15: soc.religion.christian
         16: talk.politics.guns
         17: talk.politics.mideast
         18: talk.politics.misc
         19: talk.religion.misc
         Number of unique classes: 20
In [4]: # Split the dataset
         train_data, test_data, y_train, y_test = train_test_split(newsgroups.data, newsgroups.target, test_size=0.2, random_
In [5]: # Create a pipeline that combines the TfidfVectorizer and the MultinomialNB classifier
         model = make_pipeline(TfidfVectorizer(stop_words='english'), MultinomialNB())
         model
Out[5]:
                Pipeline
          ▶ TfidfVectorizer
            ▶ MultinomialNB
```

```
In [6]: # Train the model
        model.fit(train_data, y_train)
Out[6]:
               Pipeline
          ▶ TfidfVectorizer
           ▶ MultinomialNB
In [7]: # Make predictions
        y_pred = model.predict(test_data)
        y_pred
Out[7]: array([ 9, 12, 14, ..., 0, 0, 14])
In [8]: # Evaluate the model
        accuracy = metrics.accuracy_score(y_test, y_pred)
        print(f'Accuracy: {accuracy * 100:.2f}%')
        Accuracy: 87.85%
In [9]: # Print classification report
        print(metrics.classification_report(y_test, y_pred, target_names=newsgroups.target_names))
                                                 recall f1-score
                                   precision
                                                                     support
                      alt.atheism
                                        0.85
                                                   0.86
                                                             0.86
                                                                        151
                    comp.graphics
                                        0.88
                                                   0.84
                                                             0.86
                                                                         202
                                                                        195
         comp.os.ms-windows.misc
                                        0.87
                                                   0.85
                                                             0.86
        comp.sys.ibm.pc.hardware
                                        0.65
                                                   0.85
                                                             0.74
                                                                        183
           comp.sys.mac.hardware
                                        0.94
                                                   0.87
                                                             0.90
                                                                         205
                   comp.windows.x
                                        0.95
                                                   0.85
                                                             0.90
                                                                         215
                     misc.forsale
                                        0.93
                                                   0.72
                                                             0.81
                                                                        193
                                                   0.94
                                                                        196
                        rec.autos
                                        0.91
                                                             0.92
                  rec.motorcycles
                                        0.89
                                                   0.95
                                                             0.92
                                                                        168
               rec.sport.baseball
                                        0.95
                                                   0.95
                                                             0.95
                                                                        211
                rec.sport.hockey
                                        0.90
                                                   0.99
                                                             0.94
                                                                        198
                                                   0.97
                        sci.crypt
                                        0.91
                                                             0.94
                                                                         201
                  sci.electronics
                                        0.92
                                                   0.82
                                                             0.86
                                                                        202
                          sci.med
                                        0.97
                                                   0.94
                                                             0.96
                                                                        194
                                        0.88
                                                   0.99
                                                             0.93
                                                                        189
                        sci.space
          soc.religion.christian
                                        0.72
                                                   0.99
                                                             0.83
                                                                        202
                                                   0.97
               talk.politics.guns
                                                             0.88
                                                                        188
                                        0.81
           talk.politics.mideast
                                        0.94
                                                   0.99
                                                             0.97
                                                                        182
              talk.politics.misc
                                        0.96
                                                   0.75
                                                             0.84
                                                                        159
              talk.religion.misc
                                        1.00
                                                   0.31
                                                             0.47
                                                                        136
```

0.88

0.87

0.87

3770

3770

3770

accuracy macro avg

weighted avg

0.89

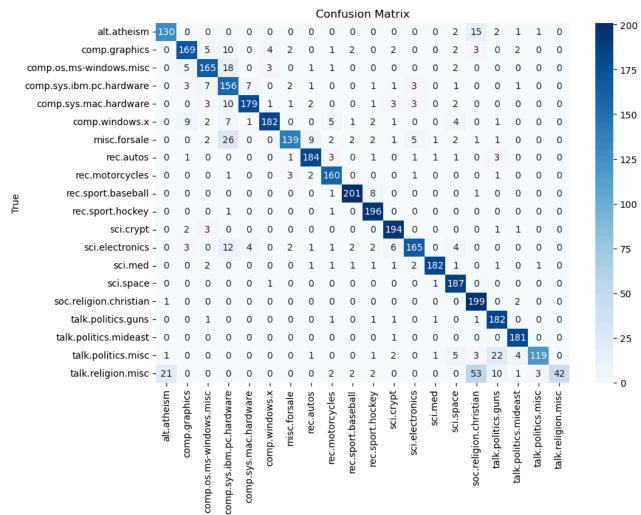
0.89

0.87

0.88

```
In [10]: # Compute confusion matrix
    conf_matrix = metrics.confusion_matrix(y_test, y_pred)

# Plot confusion matrix
    plt.figure(figsize=(10, 7))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=newsgroups.target_names, yticklabels=newsgro
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()
```



Predicted

```
In [11]: # Print train and test data with their respective categories
print("\nTrain Data Categories:")
for i in range(len(train_data)):
    print(f"Document {i}: Category = {text_categories[y_train[i]]}")

print(f"Document {i}: Category = {text_categories[y_test[i]]}")

Document 806: Category = comp.windows.x
Document 807: Category = comp.sys.mac.hardware
Document 808: Category = comp.sys.mac.hardware
Document 809: Category = rec.motorcycles
Document 809: Category = alt.atheism
Document 810: Category = alt.atheism
Document 812: Category = comp.sys.ms=windows.misc
Document 813: Category = comp.sys.ibm.pc.hardware
Document 813: Category = comp.sys.ibm.pc.hardware
Document 814: Category = rec.sport.hockey
Document 815: Category = rec.sport.hockey
Document 817: Category = comp.sys.mac.hardware
Document 818: Category = comp.sys.mac.hardware
Document 819: Category = comp.sys.mac.hardware
Document 820: Category = comp.sys.mac.hardware
Document 821: Category = talk.politics.mideast
Document 822: Category = talk.politics.misc
Document 823: Category = talk.politics.misc
Document 824: Category = talk.politics.misc
Document 825: Category = talk.politics.misc
Document 826: Category = talk.politics.misc
Document 827: Category = talk.politics.misc
Document 828: Category = talk.politics.misc
Document 829: Category = talk.politics.misc
```