20_newsgroups

January 4, 2019

0.1 # Unsupervised NLP

For this NLP project, I decided to use the 20 Newsgroups dataset.

The dataset can be found here: http://qwone.com/~jason/20Newsgroups/

The 20 Newsgroups data set is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups. The data is organized into 20 different newsgroups, each corresponding to a different topic. Some of the newsgroups are very closely related to each other, while others are highly unrelated.

I chose 10 of the most closely related topics and I am going to try and build a classification model to predict which newsgroup a datapoint belongs to.

```
In [1]: import numpy as np
        import pandas as pd
        import glob
        import sklearn
        import os
        import nltk
        import re
        import scipy
        import spacy
        import scipy.stats as stats
        from sklearn.cluster import KMeans
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import GridSearchCV
        from sklearn.pipeline import make_pipeline
        from sklearn.cluster import SpectralClustering
        stats.chisqprob = lambda chisq, df: stats.chi2.sf(chisq, df)
        from sklearn import ensemble
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import train_test_split
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn import metrics
        from nltk.stem import WordNetLemmatizer
        from nltk.tokenize import word_tokenize
        from nltk.corpus import gutenberg, stopwords
```

```
from collections import Counter
%matplotlib inline
```

In [2]:
```
english_stops = stopwords.words('english')
nlp = spacy.load('en')
```

0.1.1 Training Set

In [3]:
```
path = "./data/20news-bydate/20news-bydate-train/"
df_news = pd.DataFrame(columns=['text', 'category'])

allGraphicsFiles = glob.glob(path + 'graphics' + "/*")
allWindowsMiscFiles = glob.glob(path + 'windows_misc' + "/*")
allPcHardwareFiles = glob.glob(path + 'pc_hardware' + "/*")
allMacHardwareFiles = glob.glob(path + 'mac_hardware' + "/*")
allWindowsXFiles = glob.glob(path + 'windows_x' + "/*")
allCryptFiles = glob.glob(path + 'crypt' + "/*")
allElectronicsFiles = glob.glob(path + 'electronics' + "/*")
allMedFiles = glob.glob(path + 'med' + "/*")
allSpaceFiles = glob.glob(path + 'space' + "/*")
allPoliticsFiles = glob.glob(path + 'politics' + "/*")

allFiles = (allGraphicsFiles +
            allWindowsMiscFiles +
            allPcHardwareFiles +
            allMacHardwareFiles +
            allWindowsXFiles +
            allCryptFiles +
            allElectronicsFiles +
            allMedFiles +
            allSpaceFiles +
            allPoliticsFiles)

# for file_ in allFiles:
for idx, file_ in enumerate(allFiles):
    with open(file_, 'r', encoding='utf-8', errors='ignore') as myfile:
        data = myfile.read()

        # Grab label from the directory name
        labelFromDir = re.split(r'\/', allFiles[idx])[-2]

        df_news = df_news.append({'text': data, 'category': labelFromDir}, ignore_inde
```

0.1.2 Test set

In [4]:
```
path = "./data/20news-bydate/20news-bydate-test/"
df_news_test = pd.DataFrame(columns=['text', 'category'])
```

```
allGraphicsFiles = glob.glob(path + 'graphics' + "/*")
allWindowsMiscFiles = glob.glob(path + 'windows_misc' + "/*")
allPcHardwareFiles = glob.glob(path + 'pc_hardware' + "/*")
allMacHardwareFiles = glob.glob(path + 'mac_hardware' + "/*")
allWindowsXFiles = glob.glob(path + 'windows_x' + "/*")
allCryptFiles = glob.glob(path + 'crypt' + "/*")
allElectronicsFiles = glob.glob(path + 'electronics' + "/*")
allMedFiles = glob.glob(path + 'med' + "/*")
allSpaceFiles = glob.glob(path + 'space' + "/*")
allPoliticsFiles = glob.glob(path + 'politics' + "/*")

allTestFiles = (
            allGraphicsFiles +
            allWindowsMiscFiles +
            allPcHardwareFiles +
            allMacHardwareFiles +
            allWindowsXFiles +
            allCryptFiles +
            allElectronicsFiles +
            allMedFiles +
            allSpaceFiles +
            allPoliticsFiles)

# for file_ in allFiles:
for idx, file_ in enumerate(allTestFiles):
    with open(file_, 'r', encoding='utf-8', errors='ignore') as myfile:
        data = myfile.read()

        # Grab label from the directory name
        labelFromDir = re.split(r'\/', allTestFiles[idx])[-2]

        df_news_test = df_news_test.append({'text': data, 'category': labelFromDir}, i
```

In [5]:
```
# Train set
print(f'df_news.shape: {df_news.shape}')
df_news.head()
```

```
df_news.shape: (5774, 2)
```

Out[5]:

	text	category
0	From: cavalier@blkbox.COM (Bill Egan)\nSubject...	graphics
1	From: ch381@cleveland.Freenet.Edu (James K. Bl...	graphics
2	From: rytg7@fel.tno.nl (Q. van Rijt)\nSubject:...	graphics
3	From: uk02183@nx10.mik.uky.edu (bryan k willia...	graphics
4	From: rschmitt@shearson.com (Robert Schmitt)\n...	graphics

In [6]:
```
df_news['category'].value_counts()
```

```
Out[6]: crypt           595
        med             594
        space           593
        windows_x       593
        electronics     591
        windows_misc    591
        pc_hardware     590
        graphics        584
        mac_hardware    578
        politics        465
        Name: category, dtype: int64
```

```
In [7]: # Test set
        print(f'df_news_test.shape: {df_news_test.shape}')
        df_news_test.head()
```

```
df_news_test.shape: (3844, 2)
```

Out[7]:

	text	category
0	From: Scott_Rindfleisch@vos.stratus.com\nSubje...	graphics
1	From: SITUNAYA@IBM3090.BHAM.AC.UK\nSubject: Be...	graphics
2	From: z_nixsp@ccsvax.sfasu.edu\nSubject: Re: T...	graphics
3	From: vax839@tid.es (Juan Carlos Cuesta Cuesta...	graphics
4	From: dts@buoy.cis.ufl.edu (Dave Small)\nSubje...	graphics

```
In [8]: df_news_test['category'].value_counts()
```

```
Out[8]: crypt           396
        med             396
        windows_x       395
        space           394
        windows_misc    394
        electronics     393
        pc_hardware     392
        graphics        389
        mac_hardware    385
        politics        310
        Name: category, dtype: int64
```

0.2 Preprocessing

```
In [9]: def texter(text):
            # Remove special chars
            document = re.sub(r'\W', ' ', text)

            # remove all single characters
            document = re.sub(r'\s+[a-zA-Z]\s+', ' ', document)
```

```
        # Remove single characters from the start
        document = re.sub(r'\^[a-zA-Z]\s+', ' ', document)

        # Substituting multiple spaces with single space
        document = re.sub(r'\s+', ' ', document, flags=re.I)

        tokens = [w for w in word_tokenize(document.lower())
                      if w.isalpha()]

        no_stops = [t for t in tokens
                        if t not in english_stops]

        lemmatized = [WordNetLemmatizer().lemmatize(t) for t in no_stops]

        document = ' '.join(lemmatized)

        return document
```

```
In [10]: # Before Preprocessing
         df_news['text'][0]
```

```
Out[10]: "From: cavalier@blkbox.COM (Bill Egan)\nSubject: Re: Weitek P9000 ?\nNntp-Posting-Hos
```

```
In [11]: df_news['text'] = df_news['text'].apply(texter)
         df_news_test['text'] = df_news_test['text'].apply(texter)
```

```
In [12]: # After Preprocessing
         df_news['text'][0]
```

```
Out[12]: 'cavalier blkbox com bill egan subject weitek nntp posting host houston pub ip psi ne
```

```
In [13]: def mutlt_labels(row):
             if (row == 'crypt'):
                 return 1
             elif (row == 'med'):
                 return 2
             elif (row == 'windows_x'):
                 return 3
             elif (row == 'space'):
                 return 4
             elif (row == 'electronics'):
                 return 5
             elif (row == 'windows_misc'):
                 return 6
             elif (row == 'pc_hardware'):
                 return 7
             elif (row == 'graphics'):
                 return 8
             elif (row == 'mac_hardware'):
```

```
            return 9
        elif (row == 'politics'):
            return 10
        else:
            return row
```

In [14]:
```
df_news['category'] = df_news['category'].apply(mutlt_labels)
df_news_test['category'] = df_news_test['category'].apply(mutlt_labels)
```

In [15]:
```
df_news['category'].value_counts()
```

Out[15]:
```
1     595
2     594
3     593
4     593
6     591
5     591
7     590
8     584
9     578
10    465
Name: category, dtype: int64
```

0.3 BoW

In [52]:
```
# Initialize a CountVectorizer, min appearance of 5 docs
count_vectorizer = CountVectorizer(stop_words="english", min_df=5)

# Transform the training data
counts = count_vectorizer.fit_transform(df_news['text'].values)

# Print the first 10 features
print(count_vectorizer.get_feature_names()[0:10])
```

```
['aa', 'aaron', 'aau', 'ab', 'abad', 'abandon', 'abandoned', 'abbey', 'abbreviation', 'abc']
```

0.4 TF-IDF

In [53]:
```
# Initialize a TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(stop_words="english", min_df=5)

# Transform the training data
tfidfs = tfidf_vectorizer.fit_transform(df_news['text'].values)
```

In [54]:
```
tfidfs.A
```

Out[54]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
```

```
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

0.5 Clustering

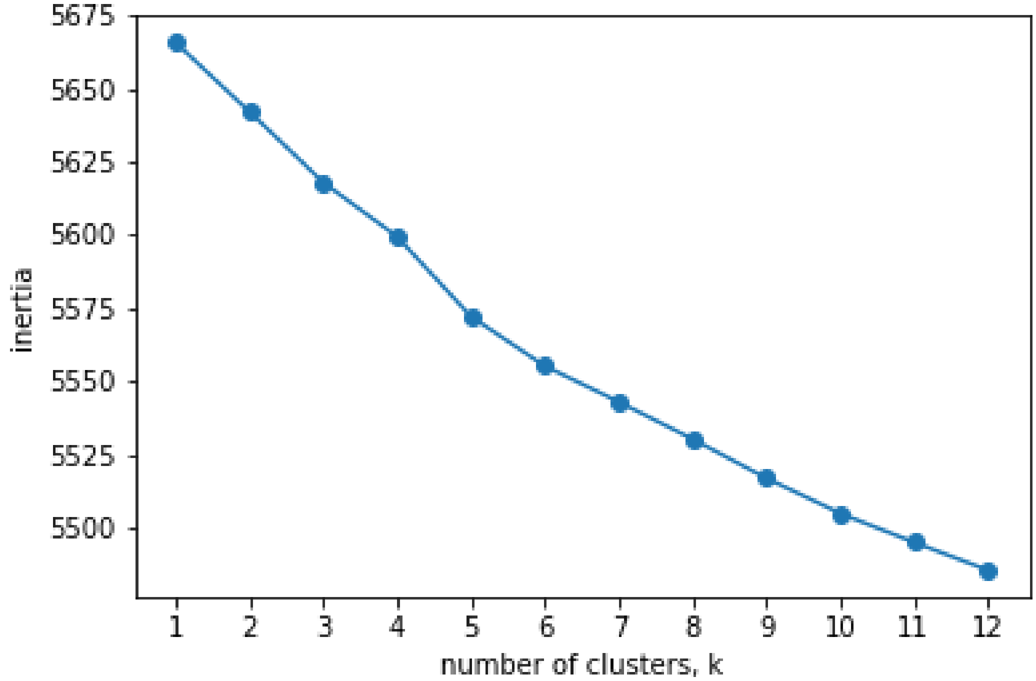
```
In [55]: # Intertias
         ks = range(1, 13)
         inertias = []

         for k in ks:
             # Create a KMeans instance with k clusters: model
             model = KMeans(n_clusters=k)

             # Fit model to samples
             model.fit(tfidfs)

             # Append the inertia to the list of inertias
             inertias.append(model.inertia_)

         # Plot ks vs inertias
         plt.plot(ks, inertias, '-o')
         plt.xlabel('number of clusters, k')
         plt.ylabel('inertia')
         plt.xticks(ks)
         plt.show()
```



It looks like the plot slightly elbows at around 6, so let's try 6 clusters.

```
In [59]: km = KMeans(n_clusters=6)

         # Fit model to samples
         km.fit(tfidfs)

Out[59]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=6, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=None, tol=0.0001, verbose=0)

In [60]: km_6_pred = km.predict(tfidfs)
         metrics.adjusted_rand_score(df_news['category'].values, km_6_pred)

Out[60]: 0.14700480080691355
```

0.6 SpectralClustering

```
In [112]: n_clusters=10

          # Declare and fit the model.
          sc = SpectralClustering(n_clusters=n_clusters)
          sc.fit(tfidfs)

          # Predicted clusters
          predict_sc = sc.fit_predict(tfidfs)
```

In [113]: pd.crosstab(df_news['category'].values, predict_sc)

Out[113]:
```
col_0       0   1    2   3   4   5    6    7    8   9
category
1           9  16  214  17   0   0    1    2  187   0
2          24   0  357   0  58   0    2    4    0   0
3          50   0  228   0   0   0  158    5    4   0
4          13   0  220   0   0   0    0  212    0   0
5         141   0  282   0   0   0    3   17    0   0
6         131   0   90   0   0   0  221    1    0   0
7         287   0  101   0   0  36   16    0    2   0
8         142   0  237   0   0   0   52    7    0   0
9         324   0   97   0   0   8    2    3    0   0
10         23   0  290   0   0   0    0    2    0  34
```

In [114]: metrics.adjusted_rand_score(y_train, predict_sc)

Out[114]: 0.09408574389739935

Performed much worse than Kmeans

0.7 Let's try some cleaning: will clustering improve?

In [102]:
```
tfidf_df = pd.DataFrame(tfidfs.A, columns=tfidf_vectorizer.get_feature_names())
tfidf_df.head()
```

Out[102]:
```
    aa  aaron  aau   ab  abad  abandon  abandoned  abbey  abbreviation  abc  \
0  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
1  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
2  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
3  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
4  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0

  ...  zrepachol   zt  zterm   zu  zurich   zv   zw   zy  zyeh   zz
0 ...        0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
1 ...        0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
2 ...        0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
3 ...        0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
4 ...        0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0

[5 rows x 12425 columns]
```

In [137]:
```
convert_cat = []
to_drop = []

categorical = tfidf_df.columns

for index, feature in enumerate(categorical):
```

```
        cont = pd.crosstab(tfidf_df[feature], df_news['category'], colnames=[None])
        chi2_res = scipy.stats.chi2_contingency(cont)

        # Keep all features with a significant P-value and drop the others
        if chi2_res[1] <= 0.05:
            convert_cat.append(feature)
        else:
            to_drop.append(feature)
```

```
/Users/rook/anaconda3/lib/python3.6/site-packages/pandas/core/reshape/pivot.py:135: FutureWarni
Defaulting to column but this will raise an ambiguity error in a future version
  grouped = data.groupby(keys)
```

In [138]:
```
print(f'convert_cat len: {len(convert_cat)}')
print(f'to_drop len: {len(to_drop)}')
```

```
convert_cat len: 230
to_drop len: 12195
```

In [139]:
```
# Drop cols
tfidf_df_chi2 = tfidf_df.loc[:, ~tfidf_df.columns.isin(to_drop)]
```

In [141]:
```
tfidf_df_chi2.shape
```

Out[141]:
```
(5774, 230)
```

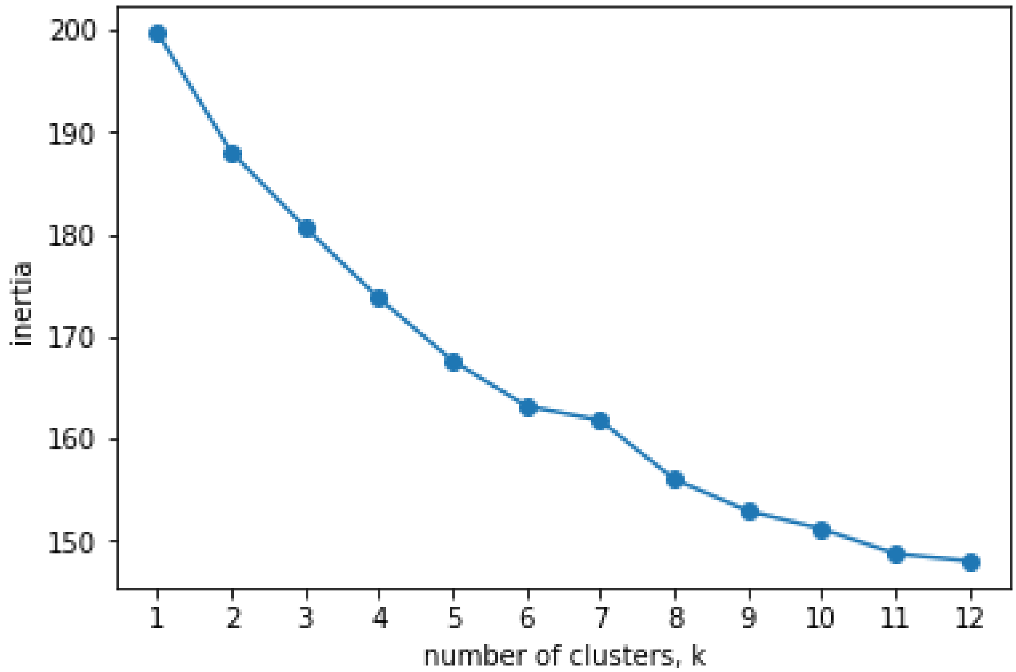
In [142]:
```
# Intertias
ks = range(1, 13)
inertias = []

for k in ks:
    # Create a KMeans instance with k clusters: model
    model = KMeans(n_clusters=k)

    # Fit model to samples
    model.fit(tfidf_df_chi2)

    # Append the inertia to the list of inertias
    inertias.append(model.inertia_)

# Plot ks vs inertias
plt.plot(ks, inertias, '-o')
plt.xlabel('number of clusters, k')
plt.ylabel('inertia')
plt.xticks(ks)
plt.show()
```




```
In [143]: km_7 = KMeans(n_clusters=7)

          # Fit model to samples
          km_7.fit(tfidf_df_chi2)

Out[143]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
              n_clusters=7, n_init=10, n_jobs=1, precompute_distances='auto',
              random_state=None, tol=0.0001, verbose=0)

In [144]: km_7_pred = km_7.predict(tfidf_df_chi2)
          metrics.adjusted_rand_score(df_news['category'].values, km_7_pred)

Out[144]: 0.004232437241477186
```

This perforned much worse than before.

0.8 Add cluster feature

```
In [102]: tfidf_df = pd.DataFrame(tfidfs.A, columns=tfidf_vectorizer.get_feature_names())
          tfidf_df.head()
```

Out[102]:

	aa	aaron	aau	ab	abad	abandon	abandoned	abbey	abbreviation	abc	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

```
3  0.0    0.0  0.0  0.0    0.0      0.0        0.0    0.0           0.0  0.0
4  0.0    0.0  0.0  0.0    0.0      0.0        0.0    0.0           0.0  0.0

   ...    zrepachol   zt  zterm   zu  zurich   zv   zw   zy  zyeh   zz
0 ...           0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
1 ...           0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
2 ...           0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
3 ...           0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
4 ...           0.0  0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0

[5 rows x 12425 columns]
```

In [105]:
```python
tfidf_df['cluster_number'] = km.labels_
tfidf_df.head()
```

Out[105]:
```
    aa  aaron  aau   ab  abad  abandon  abandoned  abbey  abbreviation  abc  \
0  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
1  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
2  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
3  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0
4  0.0    0.0  0.0  0.0   0.0      0.0        0.0    0.0           0.0  0.0

         ...          zt  zterm   zu  zurich   zv   zw   zy  zyeh   zz  \
0        ...         0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
1        ...         0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
2        ...         0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
3        ...         0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0
4        ...         0.0    0.0  0.0     0.0  0.0  0.0  0.0   0.0  0.0

   cluster_number
0               1
1               1
2               1
3               1
4               1

[5 rows x 12426 columns]
```

0.9 Train / Test splits

In [120]:
```python
y = df_news['category']

# Create training and test sets
X_tfidf_train, X_tfidf_val, y_tfidf_train, y_tfidf_val = train_test_split(tfidf_df, y
X_bow_train, X_bow_val, y_bow_train, y_bow_val = train_test_split(counts, y, test_siz

# The Test data was seperate from the rest
# Test set
```

```
X_test = df_news_test['text']
y_test = df_news_test['category']

# Transform the test data
count_test = count_vectorizer.transform(X_test.values)
tfidf_test = tfidf_vectorizer.transform(X_test.values)
```

0.10 Logistic Regression

In [110]:
```
# Instantiate
lr = LogisticRegression()

# Fit the classifier to the training data
lr.fit(X_tfidf_train, y_tfidf_train)

# Create the predicted tags: pred
pred = lr.predict(X_tfidf_val)

print('Training set score:', lr.score(X_tfidf_train, y_tfidf_train))

# Calculate the accuracy score: score
score = metrics.accuracy_score(y_tfidf_val, pred)
print(f'\nTest set score: {score}')

# Calculate the confusion matrix: cm
pd.crosstab(y_tfidf_val, pred)
```

```
Training set score: 0.9540415704387991

Test set score: 0.8601108033240997
```

Out[110]:

col_0	1	2	3	4	5	6	7	8	9	10
category										
1	126	1	6	1	2	0	1	8	0	4
2	0	138	1	2	4	0	1	3	0	0
3	2	0	118	4	2	10	3	9	0	0
4	0	3	2	131	3	0	1	6	2	0
5	0	0	0	2	135	0	4	4	3	0
6	0	0	8	0	2	126	5	7	0	0
7	0	0	3	0	6	13	109	5	12	0
8	0	0	7	0	3	1	3	131	1	0
9	0	0	0	0	6	2	7	5	122	2
10	0	0	1	0	5	1	0	1	2	106

86% accuracy with a basic model is a good sign.

0.11 Logistic Regression: GridSearch

```
In [114]: param_grid = {'C': [0.01, 0.1, 1, 10]}
          grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
          grid.fit(X_tfidf_train, y_tfidf_train)
          print("Best cross-validation score: {:.2f}".format(grid.best_score_))
          print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.88
Best parameters:  {'C': 10}
```

0.12 Remove clustering feature

```
In [116]: X_tfidf_train = X_tfidf_train.loc[:, ~X_tfidf_train.columns.isin(['cluster_number'])]
          X_tfidf_val = X_tfidf_val.loc[:, ~X_tfidf_val.columns.isin(['cluster_number'])]
```

```
In [118]: param_grid = {'C': [0.01, 0.1, 1, 10]}
          grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
          grid.fit(X_tfidf_train, y_tfidf_train)
          print("Best cross-validation score: {:.2f}".format(grid.best_score_))
          print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.89
Best parameters:  {'C': 10}
```

The models actually perform better without the clustering feature. This is not surprising though, considering the low ARI.

0.13 Logistic Regression: BoW

```
In [128]: param_grid = {'C': [0.01, 0.1, 1, 10]}
          grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
          grid.fit(X_bow_train, y_bow_train)
          print("Best cross-validation score: {:.2f}".format(grid.best_score_))
          print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.87
Best parameters:  {'C': 0.1}
```

Did not perform as well as the tf-idf features.

0.14 Logistic Regression: ngrams

```
In [77]: pipe = make_pipeline(TfidfVectorizer(min_df=5), LogisticRegression()) # running the g
         # relatively large grid and the inclusion of trigrams

         param_grid = {"logisticregression__C": [0.001, 0.01, 0.1, 1, 10],
```

```
                      "tfidfvectorizer__ngram_range": [(1, 1), (1, 2)]}

        grid = GridSearchCV(pipe, param_grid, cv=5)
        grid.fit(X_train, y_train)

        print("Best cross-validation score: {:.2f}".format(grid.best_score_))
        print("Best parameters:\n{}".format(grid.best_params_))
```

```
Best cross-validation score: 0.89
Best parameters:
{'logisticregression__C': 10, 'tfidfvectorizer__ngram_range': (1, 2)}
```

No improvement in accuracy over the best td-idf model so far.

0.15 Random Forest

```
In [94]: rfc = ensemble.RandomForestClassifier(n_estimators=100, n_jobs=-1)
         rfc.fit(X_tfidf_train, y_tfidf_train)
```

```
Out[94]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=-1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False)
```

```
In [95]: # Create the predicted tags: pred
         pred = rfc.predict(X_tfidf_val)

         print('Training set score:', rfc.score(X_tfidf_train, y_tfidf_train))

         # Calculate the accuracy score: score
         score = metrics.accuracy_score(y_tfidf_val, pred)
         print(f'\nTest set score: {score}')
```

```
Training set score: 1.0

Test set score: 0.824792243767313
```

0.16 Random Forest: GridSearch

```
In [96]: parameters = {'n_estimators':[100,300,500],
                       'max_features':['sqrt', 'log2'],
                       'min_samples_split':[2,8,20]
                      }
```

```
# Instantiating and fitting Grid Search, then printing best score and best parameters
grid_rfc = GridSearchCV(ensemble.RandomForestClassifier(), param_grid=parameters, cv=5
grid_rfc.fit(X_tfidf_train, y_tfidf_train)
```

```
Out[96]: GridSearchCV(cv=5, error_score='raise',
                estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion=
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False),
                fit_params=None, iid=True, n_jobs=2,
                param_grid={'n_estimators': [100, 300, 500], 'max_features': ['sqrt', 'log2'],
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring=None, verbose=0)
```

```
In [97]: print("Best cross-validation score: {:.2f}".format(grid_rfc.best_score_))
         print("Best parameters:\n{}".format(grid_rfc.best_params_))
```

```
Best cross-validation score: 0.88
Best parameters:
{'max_features': 'log2', 'min_samples_split': 2, 'n_estimators': 500}
```

Logistic regression had the highest accuracy.

0.17 Test Set

```
In [129]: # Instantiate
          lr_final = LogisticRegression(C=10, multi_class='ovr')

          # Fit the classifier to the training data
          lr_final.fit(X_tfidf_train, y_tfidf_train)

          pred_test = lr_final.predict(tfidf_test)

          # Calculate the accuracy score: score
          score_test = metrics.accuracy_score(y_test, pred_test)
          print(f'\nTest set score: {score_test}')
```

```
Test set score: 0.8223204994797086
```

```
In [130]: # Confusion matrix
          pd.crosstab(y_test, pred_test)
```

```
Out[130]: col_0       1    2    3    4    5    6    7    8    9   10
          category
          1         361    0    3    2    7    3    2    6    5    7
          2           1  344    6    3   12    4    5    8    3   10
          3           0    1  301    3    4   29    6   47    4    0
          4           0    8    2  361    5    1    0   10    2    5
          5           8    7    0    4  316   10   28    9   11    0
          6           3    3   24    3    3  280   30   24   17    7
          7           0    2    9    3   23   27  285   10   33    0
          8           4    5   18    7   16   14   10  306    8    1
          9           1    1    2    1   15    9   21    6  328    1
          10          4    9    1    8    2    1    2    1    3  279
```

0.18 Clustering Test Set

```
In [131]: km_6_test = KMeans(n_clusters=6)

          # Fit model to samples
          km_6_test.fit(tfidf_test)
```

```
Out[131]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
              n_clusters=6, n_init=10, n_jobs=1, precompute_distances='auto',
              random_state=None, tol=0.0001, verbose=0)
```

```
In [132]: km_6_pred_test = km_6_test.predict(tfidf_test)
          pd.crosstab(y_test, km_6_pred_test)
```

```
Out[132]: col_0       0    1    2    3    4   5    6   8    9
          category
          1           0  134   22    1    1   1   84   0  153
          2           3  244   11    1    1   0  136   0    0
          3           1    7   58   84    9   3  230   0    3
          4           2  142   13    0  154   0   82   1    0
          5           0   36   21    0    9   5  313   6    3
          6           7   20   33  174    1  41  104  13    1
          7           9   11   15    5    3  72  204  73    0
          8           4   13  120    2    5  18  227   0    0
          9           7    6    6    1    3  35  284  43    0
          10         12  269    5    0    4   0   19   0    1
```

```
In [134]: metrics.adjusted_rand_score(y_test, km_10_pred_test)
```

```
Out[134]: 0.11710507071345574
```

Not great. Similar results to the clustering of the training set.

0.19 # Conclusion

0.20 Explain how clustering and modeling compare for classifying your texts. What are the advantages of each? Why would you want to use one over the other?

Clustering suggests groupings based on patterns in the data. These groupings are typically formed on the basis of similarity. For example, books written by the same author would be clustered together. Clustering can uncover patterns in the data that can be used for inference or for feature engineering purposes. The biggest difference between clustering and classification if that clustering can work without labels.

With a classification problem, you typically have a set of predefined classes and you want to know which class a new object belongs to. With NLP problems, you're typically dealing with a wide dataset given the corpus of words from the documents. This can make clustering a computationally expensive process.

It boils down to what you're trying to accomplish. If you simply want a model to accurately predict what type of genre a book falls under and you have a labeled dataset to train on, then I would go with a classification model. If you're intent is to provide book recommendation, then clustering could potentially be beneficial because it would allow you to see what books are similar to others. The two do not have to be mutually exclusive.

For this use case and with this dataset, I had a difficult time getting a clustering algorithm to perform well but I was able to achieve a test accuracy of 82% using logistic regression.