

Author_Identification

September 25, 2022

```
[1]: import pandas as pd
train_data = pd.read_csv("train-authors.csv")
test_data = pd.read_csv("test-authors.csv")
```

```
[2]: import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline
```

```
[3]: train_data.head(5)
```

```
[3]:
```

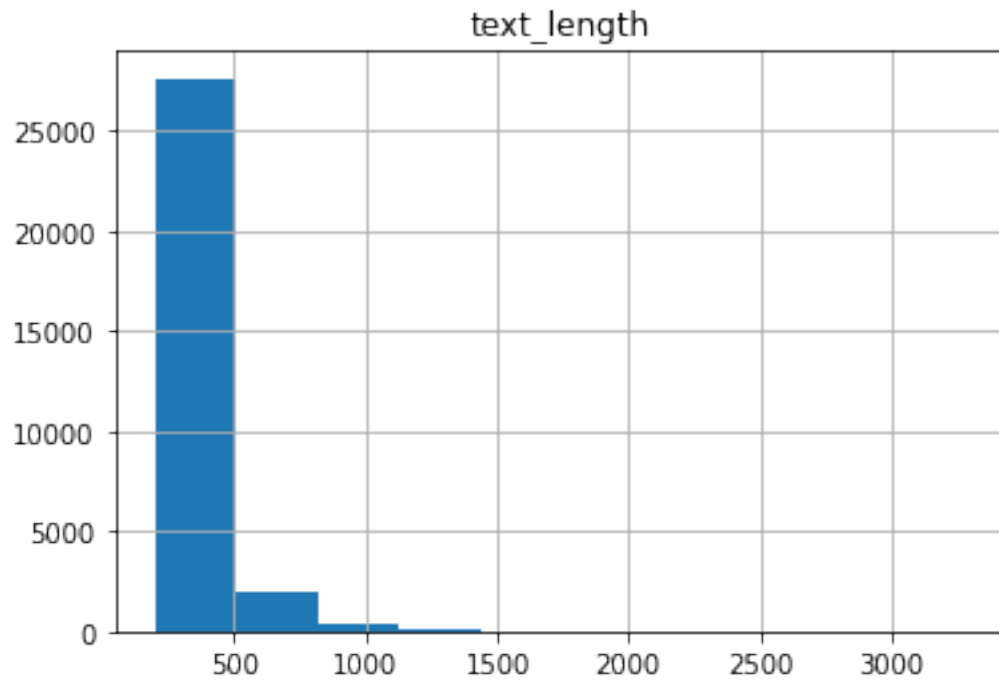
	text	author
0	She wanted clothes to keep her warm, and food...	dickens
1	The question now was, who was the man,\nand w...	doyle
2	I therefore\n smoked a great number of t...	doyle
3	I am partial to the modern\nFrench school. \n...	doyle
4	" She stood smiling, holding up a little slip ...	doyle

```
[4]: train_data['author'].value_counts()
```

```
[4]: defoe      7569
dickens      7493
twain        7478
doyle        7460
Name: author, dtype: int64
```

```
[5]: train_data['text_length'] = train_data['text'].str.len()
```

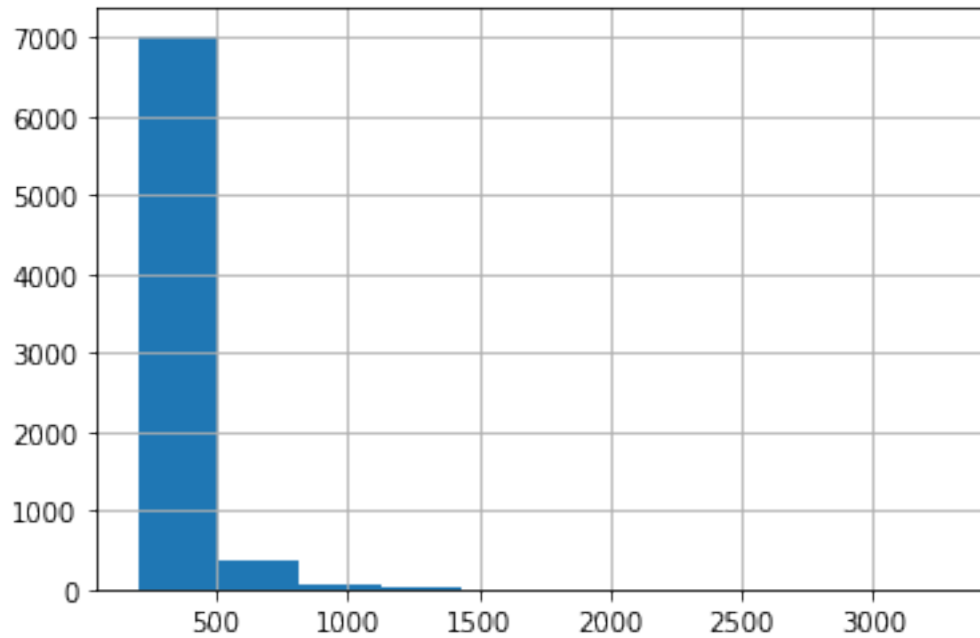
```
[6]: train_data.hist()
plt.show()
```



```
[7]: twain_train = train_data[train_data['author'] == 'twain']['text_length']  
twain_train.describe()
```

```
[7]: count    7478.000000  
mean      309.776678  
std       135.313290  
min       200.000000  
25%      231.000000  
50%      272.000000  
75%      340.000000  
max      3289.000000  
Name: text_length, dtype: float64
```

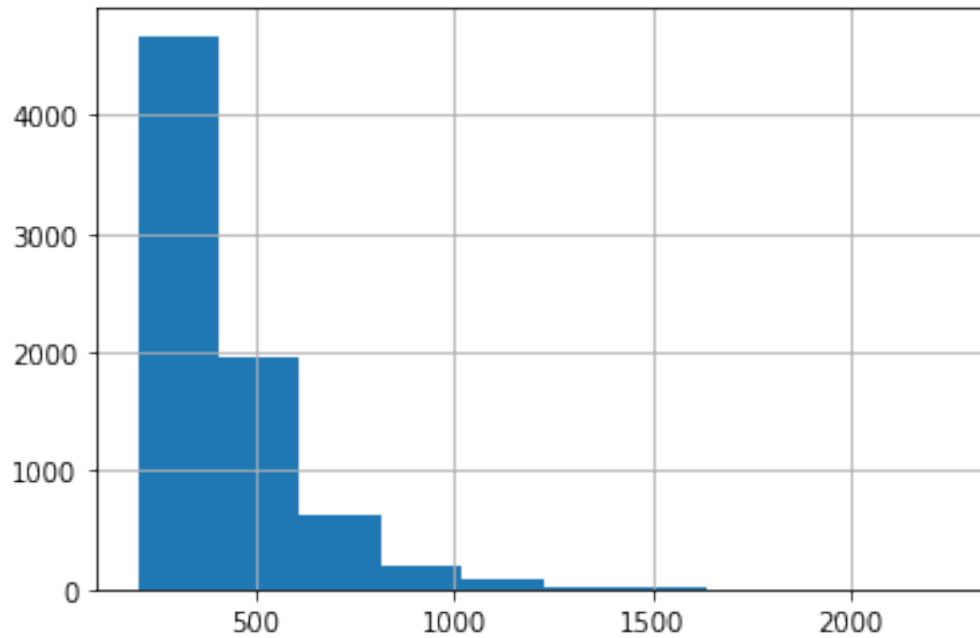
```
[8]: twain_train.hist()  
plt.show()
```



```
[9]: defoe_train = train_data[train_data['author'] == 'defoe']['text_length']  
defoe_train.describe()
```

```
[9]: count      7569.000000  
mean        405.952041  
std         195.312379  
min          200.000000  
25%         267.000000  
50%         353.000000  
75%         483.000000  
max        2249.000000  
Name: text_length, dtype: float64
```

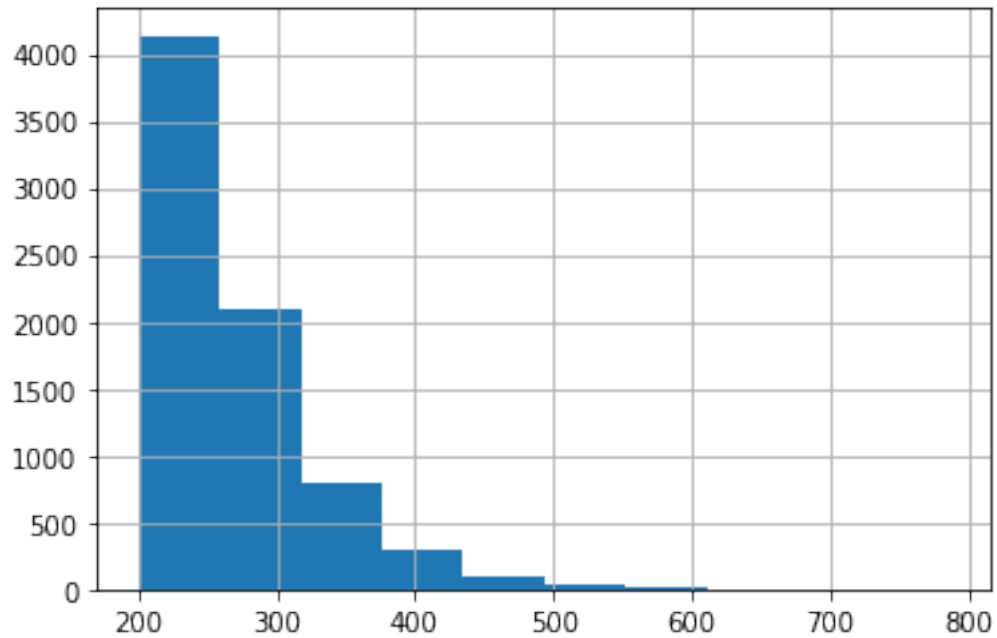
```
[10]: defoe_train.hist()  
plt.show()
```



```
[11]: doyle_train = train_data[train_data['author'] == 'doyle']['text_length']  
doyle_train.describe()
```

```
[11]: count    7460.000000  
mean      266.766622  
std        58.795911  
min        200.000000  
25%        224.000000  
50%        251.000000  
75%        294.000000  
max        787.000000  
Name: text_length, dtype: float64
```

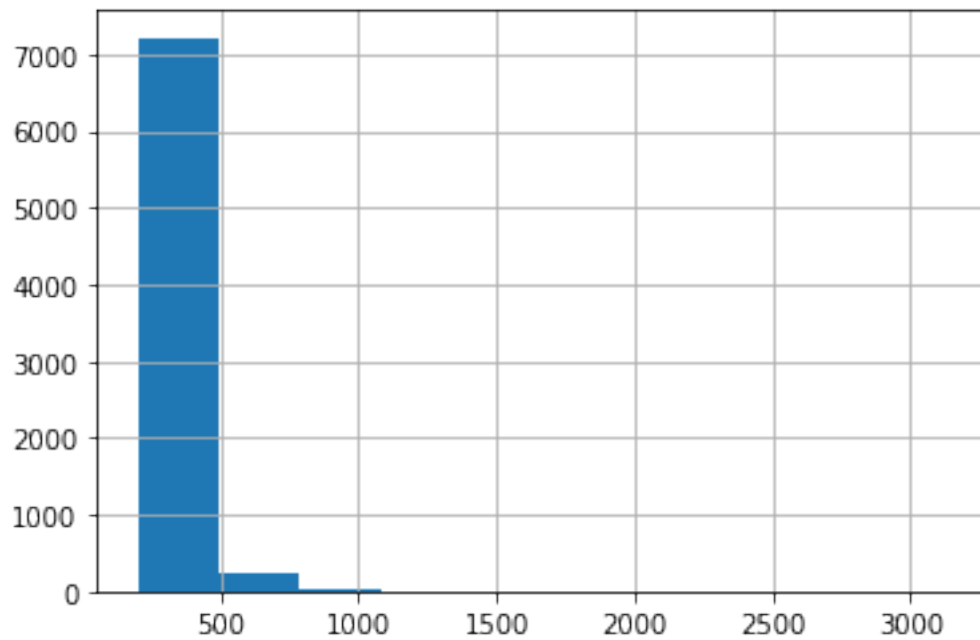
```
[12]: doyle_train.hist()  
plt.show()
```



```
[13]: dickens_train = train_data[train_data['author'] == 'dickens']['text_length']  
      dickens_train.describe()
```

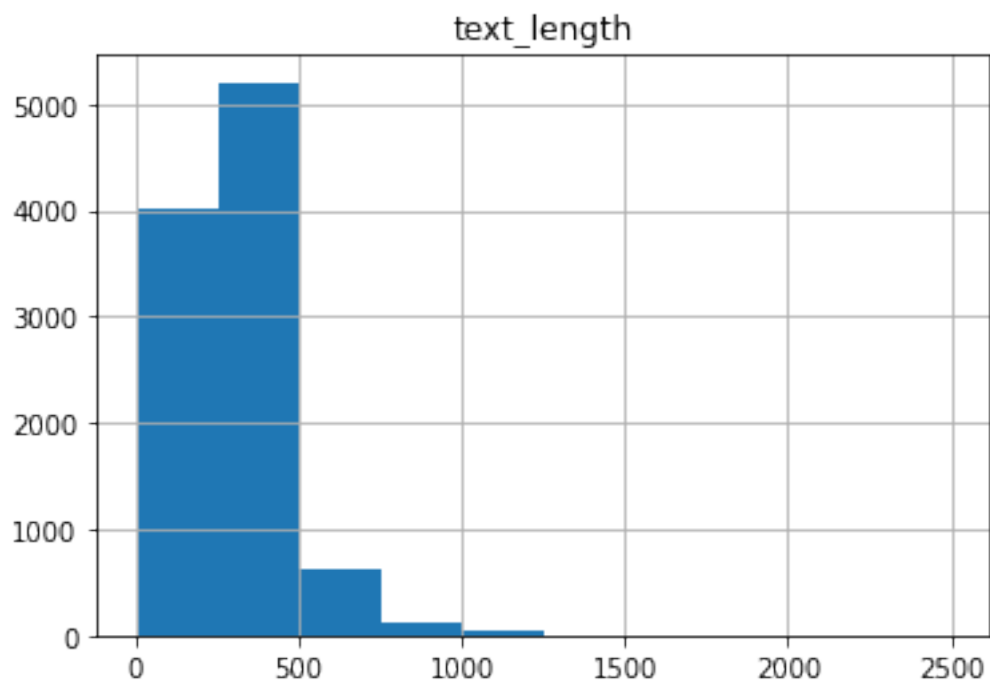
```
[13]: count    7493.000000  
      mean     288.498065  
      std      99.546325  
      min      200.000000  
      25%      225.000000  
      50%      260.000000  
      75%      321.000000  
      max      3141.000000  
      Name: text_length, dtype: float64
```

```
[14]: dickens_train.hist()  
      plt.show()
```



Similarly examine the text length & distribution in test data

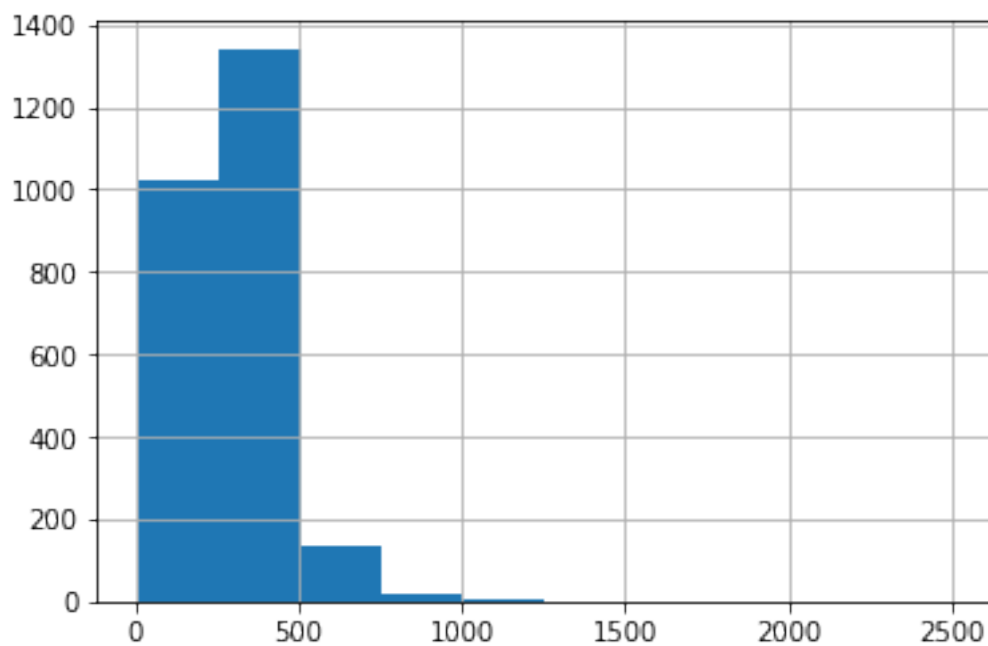
```
[15]: test_data['text_length'] = test_data['text'].str.len()  
test_data.hist()  
plt.show()
```



```
[16]: twain_test = test_data[test_data['author'] == 'twain']['text_length']  
twain_test.describe()
```

```
[16]: count      2522.000000  
mean        307.407613  
std         125.125268  
min           6.000000  
25%        230.250000  
50%        270.000000  
75%        339.000000  
max        2494.000000  
Name: text_length, dtype: float64
```

```
[17]: twain_test.hist()  
plt.show()
```

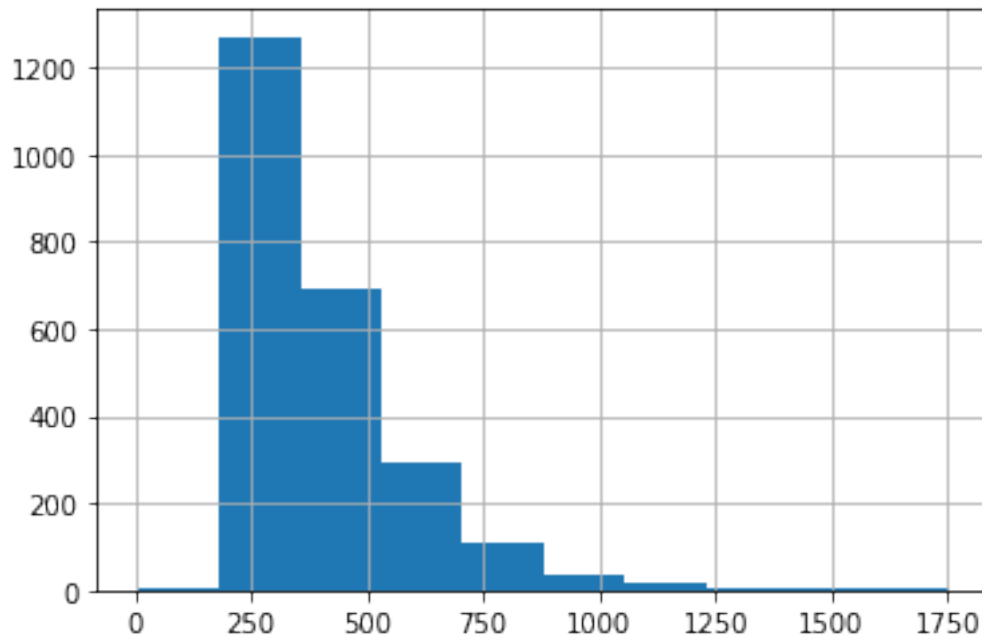


```
[18]: defoe_test = test_data[test_data['author'] == 'defoe']['text_length']  
defoe_test.describe()
```

```
[18]: count      2431.000000  
mean        400.674619  
std         189.809590  
min           6.000000
```

```
25%      262.000000
50%      346.000000
75%      484.500000
max       1755.000000
Name: text_length, dtype: float64
```

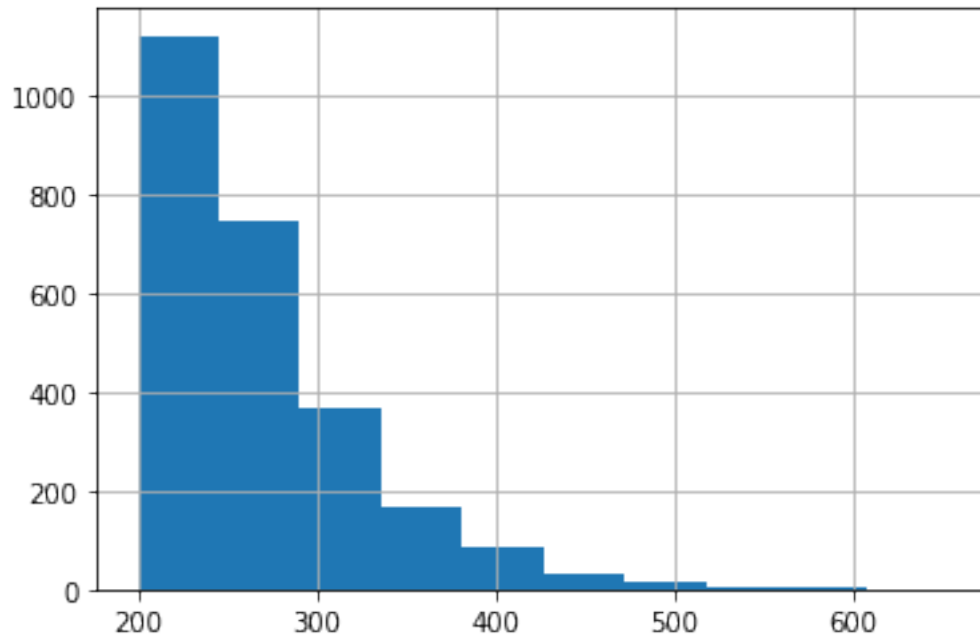
```
[19]: defoe_test.hist()
plt.show()
```



```
[20]: doyle_test = test_data[test_data['author'] == 'doyle']['text_length']
doyle_test.describe()
```

```
[20]: count      2540.000000
mean        268.123622
std          59.771638
min          200.000000
25%          224.000000
50%          254.000000
75%          295.000000
max          654.000000
Name: text_length, dtype: float64
```

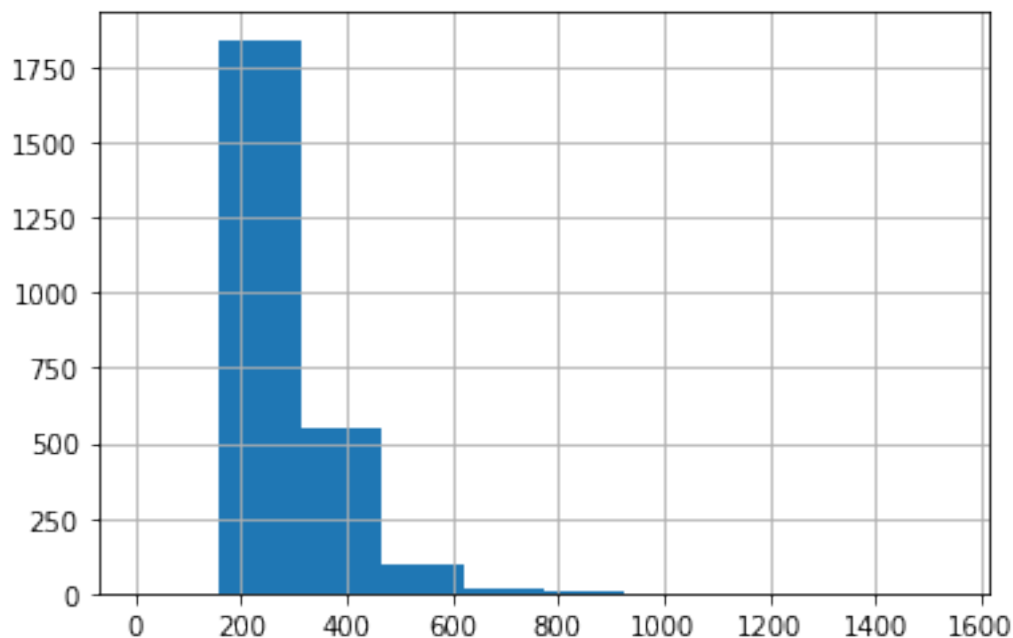
```
[21]: doyle_test.hist()
plt.show()
```

```
[22]: dickens_test = test_data[test_data['author'] == 'dickens']['text_length']  
      dickens_test.describe()
```

```
[22]: count    2507.000000  
      mean     286.886318  
      std      93.134536  
      min       6.000000  
      25%     226.000000  
      50%     260.000000  
      75%     317.000000  
      max    1541.000000  
      Name: text_length, dtype: float64
```

```
[23]: dickens_test.hist()  
      plt.show()
```



Some preprocessing of the target variable to facilitate modelling

```
[24]: # Encoding author label into numbers
train_data['author_num'] = train_data.author.map({'twain':0, 'defoe':1, 'doyle':
↪2, 'dickens':3})
train_data.head()
```

```
[24]:
```

	text	author	text_length	\
0	She wanted clothes to keep her warm, and food...	dickens	251	
1	The question now was, who was the man,\nand w...	doyle	208	
2	I therefore\n smoked a great number of t...	doyle	444	
3	I am partial to the modern\nFrench school. \n...	doyle	292	
4	" She stood smiling, holding up a little slip ...	doyle	227	

	author_num
0	3
1	2
2	2
3	2
4	2

Limiting all text length to 700 characters for both train and test for less outliers in data

```
[25]: train_data = train_data.rename(columns={'text':'original_text'})
train_data['text'] = train_data['original_text'].str[:700]
train_data['text_length'] = train_data['text'].str.len()
```

```
[26]: test_data = test_data.rename(columns={'text': 'original_text'})
test_data['text'] = test_data['original_text'].str[:700]
test_data['text_length'] = test_data['text'].str.len()
```

Define X and y from train data for use in tokenization by Vectorizers

```
[27]: train_data
```

```
[27]:
```

	original_text	author \
0	She wanted clothes to keep her warm, and food...	dickens
1	The question now was, who was the man,\nand w...	doyle
2	I therefore\n smoked a great number of t...	doyle
3	I am partial to the modern\nFrench school. \n...	doyle
4	” She stood smiling, holding up a little slip ...	doyle
...
29995	It ain't anything. There ain't no harm in it...	twain
29996	In my\nyouth the monarchs of England had cea...	twain
29997	Bob Sawyer nodded. \n\n‘So are you, sir,’ sai...	dickens
29998	He was out on the lawn, in through the window...	doyle
29999	“Here he is,” said he, sitting down and flatt...	doyle

	text_length	author_num \
0	251	3
1	208	2
2	444	2
3	292	2
4	227	2
...
29995	429	0
29996	366	0
29997	297	3
29998	361	2
29999	201	2

	text
0	She wanted clothes to keep her warm, and food...
1	The question now was, who was the man,\nand w...
2	I therefore\n smoked a great number of t...
3	I am partial to the modern\nFrench school. \n...
4	” She stood smiling, holding up a little slip ...
...	...
29995	It ain't anything. There ain't no harm in it...
29996	In my\nyouth the monarchs of England had cea...
29997	Bob Sawyer nodded. \n\n‘So are you, sir,’ sai...
29998	He was out on the lawn, in through the window...
29999	“Here he is,” said he, sitting down and flatt...

[30000 rows x 5 columns]

```
[28]: test_data
```

```
[28]:
```

	original_text	author	text_length \
0	Carton," said the man of business. "Good nig...	dickens	214
1	_Is taken, and\nhow_, 154. _Tried, condemned...	defoe	237
2	Through a cousin who\n works with Gelder...	doyle	207
3	\n\nIndeed, nothing was more strange than to s...	defoe	282
4	\n\nOn the rocks above the present city of Alt...	twain	318
...
9995	I was very glad to\nsee her too, and, after a...	dickens	365
9996	"And yet we manage to make ourselves fairly h...	doyle	205
9997	'Why, here they are. '\n\n'No, no; I mean the...	dickens	249
9998	"\n\n'Was Peter Wilks well off?"\n\n'Oh, yes, ...	twain	225
9999	\n\n'Shall I go away, aunt?' I asked, tremblin...	dickens	214

```
text
```

0	Carton," said the man of business. "Good nig...
1	_Is taken, and\nhow_, 154. _Tried, condemned...
2	Through a cousin who\n works with Gelder...
3	\n\nIndeed, nothing was more strange than to s...
4	\n\nOn the rocks above the present city of Alt...
...	...
9995	I was very glad to\nsee her too, and, after a...
9996	"And yet we manage to make ourselves fairly h...
9997	'Why, here they are. '\n\n'No, no; I mean the...
9998	"\n\n'Was Peter Wilks well off?"\n\n'Oh, yes, ...
9999	\n\n'Shall I go away, aunt?' I asked, tremblin...

```
[10000 rows x 4 columns]
```

```
[29]: X = train_data['text']  
y = train_data['author_num']
```

Split train data into a training and a test se

```
[30]: from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,  
↳random_state=123)  
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(24000,) (24000,) (6000,) (6000,)
```

Examine the class distribution in y_train and y_test

```
[31]: print(y_train.value_counts(), '\n', y_test.value_counts())
```

```
1    6087  
3    5996  
2    5962
```

```
0      5955
Name: author_num, dtype: int64
0      1523
2      1498
3      1497
1      1482
Name: author_num, dtype: int64
```

Vectorize the data using Vectorizer

```
[32]: from sklearn.feature_extraction.text import CountVectorizer
      from sklearn.feature_extraction.text import TfidfVectorizer
```

```
[33]: vect = CountVectorizer(lowercase=False, token_pattern=r'(?u)\b\w+\b|\.|\,|\;|\:|\'|\"')
      vect
```

```
[33]: CountVectorizer(lowercase=False, token_pattern='(?u)\\b\\w+\\b|\\b,|\\b.|\\b;|\\b:|\\b_')

```

Learn the vocabulary in the training data, then use it to create a document-term matrix

```
[34]: X_train_dtm = vect.fit_transform(X_train)
```

Examine the document-term matrix created from X_train

```
[35]: print(X_train_dtm)
```

(0, 5237)	3
(0, 36190)	1
(0, 39461)	2
(0, 0)	5
(0, 32712)	1
(0, 36212)	1
(0, 39463)	1
(0, 26868)	1
(0, 32387)	1
(0, 13647)	3
(0, 30931)	1
(0, 28586)	1
(0, 23975)	2
(0, 28869)	1
(0, 1)	4
(0, 11058)	1
(0, 23674)	2
(0, 22834)	1
(0, 27099)	1
(0, 22363)	1
(0, 26331)	1
(0, 24118)	1
(0, 33452)	1
(0, 16422)	1

```

(0, 19762)    1
:
(23999, 36236)    1
(23999, 20944)    1
(23999, 38860)    1
(23999, 21128)    1
(23999, 35895)    1
(23999, 25748)    1
(23999, 36235)    1
(23999, 34918)    1
(23999, 17682)    1
(23999, 29765)    1
(23999, 31392)    1
(23999, 25865)    1
(23999, 38342)    1
(23999, 13408)    1
(23999, 6043) 1
(23999, 21110)    1
(23999, 34251)    1
(23999, 29237)    1
(23999, 32855)    1
(23999, 19964)    1
(23999, 1553) 2
(23999, 29844)    1
(23999, 7130) 1
(23999, 23885)    1
(23999, 8166) 1

```

Transform the test data using the earlier fitted vocabulary, into a document-term matrix

```
[36]: X_test_dtm = vect.transform(X_test)
```

Examine the document-term matrix from X_test

```
[37]: print(X_test_dtm)
```

```

(0, 0)        5
(0, 1)        4
(0, 1835)     1
(0, 3436)     1
(0, 5237)     3
(0, 6883)     2
(0, 6884)     1
(0, 9403)     1
(0, 12598)    1
(0, 13016)    1
(0, 13524)    1
(0, 13528)    1
(0, 13827)    1

```

```

(0, 15964)    1
(0, 17218)    1
(0, 23491)    1
(0, 23674)    2
(0, 23945)    1
(0, 26177)    1
(0, 27099)    1
(0, 27919)    1
(0, 28315)    1
(0, 28860)    1
(0, 32712)    1
(0, 35855)    1
:           :
(5999, 26261) 1
(5999, 26463) 1
(5999, 26636) 1
(5999, 27099) 1
(5999, 27671) 1
(5999, 28390) 1
(5999, 28509) 1
(5999, 29976) 1
(5999, 30330) 1
(5999, 33507) 3
(5999, 33611) 1
(5999, 36075) 1
(5999, 36117) 1
(5999, 36189) 1
(5999, 36204) 1
(5999, 36212) 2
(5999, 36333) 1
(5999, 36360) 1
(5999, 36600) 2
(5999, 38626) 1
(5999, 38860) 1
(5999, 38867) 1
(5999, 39025) 1
(5999, 39445) 1
(5999, 39468) 2

```

Add character counts as a features to the sparse matrix using function `add_feature`

```

[38]: def add_feature(X, feature_to_add):
        from scipy.sparse import csr_matrix, hstack
        return hstack([X, csr_matrix(feature_to_add).T], 'csr')

```

```

[39]: from string import punctuation
        X_train_chars = X_train.str.len()

```

```

X_train_punc = X_train.apply(lambda x: len([c for c in str(x) if c in
↪punctuation]))
X_test_chars = X_test.str.len()
X_test_punc = X_test.apply(lambda x: len([c for c in str(x) if c in
↪punctuation]))
X_train_dtm = add_feature(X_train_dtm, [X_train_chars, X_train_punc])
X_test_dtm = add_feature(X_test_dtm, [X_test_chars, X_test_punc])

```

```
[40]: print(X_train_dtm)
```

```

(0, 0)          5
(0, 1)          4
(0, 4930)       1
(0, 5237)       3
(0, 10684)      1
(0, 11058)      1
(0, 13261)      1
(0, 13465)      1
(0, 13647)      3
(0, 14073)      1
(0, 14220)      1
(0, 16281)      1
(0, 16422)      1
(0, 19762)      1
(0, 21439)      1
(0, 22363)      1
(0, 22834)      1
(0, 23422)      1
(0, 23512)      1
(0, 23674)      2
(0, 23704)      1
(0, 23975)      2
(0, 24118)      1
(0, 26047)      1
(0, 26177)      1
:              :
(23999, 28509)   1
(23999, 28586)   1
(23999, 28758)   1
(23999, 28777)   1
(23999, 29237)   1
(23999, 29765)   1
(23999, 29844)   1
(23999, 31392)   1
(23999, 32855)   1
(23999, 34251)   1
(23999, 34918)   1
(23999, 35895)   1

```


(23999, 36212)	1
(23999, 36228)	3
(23999, 36230)	1
(23999, 36235)	1
(23999, 36236)	1
(23999, 36274)	1
(23999, 36531)	1
(23999, 38342)	1
(23999, 38860)	1
(23999, 38966)	2
(23999, 39461)	1
(23999, 39503)	347
(23999, 39504)	5

```
[41]: print(X_test_dtm)
```

(0, 0)	5
(0, 1)	4
(0, 1835)	1
(0, 3436)	1
(0, 5237)	3
(0, 6883)	2
(0, 6884)	1
(0, 9403)	1
(0, 12598)	1
(0, 13016)	1
(0, 13524)	1
(0, 13528)	1
(0, 13827)	1
(0, 15964)	1
(0, 17218)	1
(0, 23491)	1
(0, 23674)	2
(0, 23945)	1
(0, 26177)	1
(0, 27099)	1
(0, 27919)	1
(0, 28315)	1
(0, 28860)	1
(0, 32712)	1
(0, 35855)	1
:	:
(5999, 26636)	1
(5999, 27099)	1
(5999, 27671)	1
(5999, 28390)	1
(5999, 28509)	1
(5999, 29976)	1

```
(5999, 30330) 1
(5999, 33507) 3
(5999, 33611) 1
(5999, 36075) 1
(5999, 36117) 1
(5999, 36189) 1
(5999, 36204) 1
(5999, 36212) 2
(5999, 36333) 1
(5999, 36360) 1
(5999, 36600) 2
(5999, 38626) 1
(5999, 38860) 1
(5999, 38867) 1
(5999, 39025) 1
(5999, 39445) 1
(5999, 39468) 2
(5999, 39503) 288
(5999, 39504) 7
```

Build and evaluate an author classification model using Multinomial Naive Bayes

```
[42]: from sklearn.naive_bayes import MultinomialNB
      nb = MultinomialNB()
      nb
```

[42]: MultinomialNB()

Tune hyperparameter alpha = [0.01, 0.1, 1, 10, 100]

```
[43]: from sklearn.model_selection import GridSearchCV
      grid_values = {'alpha':[0.01, 0.1, 1.0, 10.0, 100.0]}
      grid_nb = GridSearchCV(nb, param_grid=grid_values, scoring='neg_log_loss')
      grid_nb.fit(X_train_dtm, y_train)
      grid_nb.best_params_
```

[43]: {'alpha': 1.0}

Set with recommended hyperparameters

```
[44]: nb = MultinomialNB(alpha=1.0)
```

Train the model using X_train_dtm & y_train

```
[45]: nb.fit(X_train_dtm, y_train)
```

[45]: MultinomialNB()

Make author predictions for X_test_dtm

```
[46]: y_pred_test = nb.predict(X_test_dtm)
```

Accuracy

```
[47]: from sklearn import metrics
      metrics.accuracy_score(y_test, y_pred_test)
```

```
[47]: 0.9261666666666667
```

F1 score

```
[48]: from sklearn.metrics import classification_report
      report = classification_report(y_test, y_pred_test)
      print(report)
```

	precision	recall	f1-score	support
0	0.93	0.90	0.91	1523
1	0.94	0.97	0.95	1482
2	0.93	0.94	0.94	1498
3	0.92	0.90	0.91	1497
accuracy			0.93	6000
macro avg	0.93	0.93	0.93	6000
weighted avg	0.93	0.93	0.93	6000

Compute the accuracy of training data predictions

```
[49]: y_pred_train = nb.predict(X_train_dtm)
      metrics.accuracy_score(y_train, y_pred_train)
```

```
[49]: 0.9587083333333334
```

Look at the confusion matrix for y_test

```
[50]: metrics.confusion_matrix(y_test, y_pred_test)
```

```
[50]: array([[1371,  46,  50,  56],
        [ 12, 1432,   8,  30],
        [ 31,  15, 1414,  38],
        [ 67,  37,  53, 1340]], dtype=int64)
```

Calculate predicted probabilities for X_test_dtm

```
[51]: y_pred_prob = nb.predict_proba(X_test_dtm)
      y_pred_prob[:10]
```

```
[51]: array([[1.75701289e-12, 5.62686466e-18, 1.15173981e-09, 9.99999999e-01],
        [2.05188323e-09, 5.75150351e-13, 3.08776118e-06, 9.99996910e-01],
        [2.93878431e-01, 1.10697485e-05, 2.79557848e-04, 7.05830941e-01],
```

```
[9.61738619e-01, 4.92103725e-08, 3.82613049e-02, 2.70085307e-08],
[2.34526393e-06, 3.89169584e-08, 3.19793403e-07, 9.99997296e-01],
[9.99328736e-01, 4.16798946e-07, 6.66253151e-04, 4.59382505e-06],
[9.06365827e-08, 1.42241346e-04, 9.99836445e-01, 2.12234778e-05],
[9.63120868e-09, 9.99999577e-01, 1.91982529e-08, 3.94366738e-07],
[2.49280811e-19, 2.40764063e-17, 1.22969696e-08, 9.99999988e-01],
[7.19508098e-09, 1.74787994e-10, 9.96407122e-01, 3.59287109e-03]])
```

Compute the log loss number

```
[52]: metrics.log_loss(y_test, y_pred_prob)
```

```
[52]: 0.32429446190320216
```

```
[53]: test = test_data['text']
# transform the test data using the earlier fitted vocabulary, into a
# document-term matrix
test_dtm = vect.transform(test)
# examine the document-term matrix from X_test
test_dtm
```

```
[53]: <10000x39503 sparse matrix of type '<class 'numpy.int64'>'
      with 463465 stored elements in Compressed Sparse Row format>
```

```
[54]: test_chars = test.str.len()
test_punc = test.str.count(r'\W')
test_dtm = add_feature(test_dtm, [test_chars, test_punc])
test_dtm
```

```
[54]: <10000x39505 sparse matrix of type '<class 'numpy.int64'>'
      with 483465 stored elements in Compressed Sparse Row format>
```

```
[55]: NB_y_pred = nb.predict(test_dtm)
print(NB_y_pred)
```

```
[3 1 0 ... 3 0 3]
```

```
[56]: NB_y_pred_prob = nb.predict_proba(test_dtm)
NB_y_pred_prob[:10]
```

```
[56]: array([[1.14323576e-07, 5.19415896e-14, 2.66765160e-11, 9.99999886e-01],
[1.57537590e-23, 1.00000000e+00, 1.29594645e-27, 1.28732480e-20],
[8.13708962e-01, 1.58019702e-01, 2.51053415e-03, 2.57608013e-02],
[1.06970687e-08, 9.99999779e-01, 2.15308600e-15, 2.10712891e-07],
[9.99999999e-01, 8.71917762e-10, 2.46155020e-11, 3.05540480e-11],
[7.10211074e-09, 9.99999993e-01, 9.44439407e-27, 2.02373928e-10],
[1.35406099e-07, 2.77606748e-07, 9.99551625e-01, 4.47961669e-04],
[4.51392973e-11, 1.01613453e-10, 1.72908678e-12, 1.00000000e+00],
[7.82381656e-13, 9.28101475e-20, 5.12265002e-17, 1.00000000e+00],
```

```
[8.89002582e-01, 1.20911512e-08, 1.95103863e-07, 1.10997211e-01]])
```

```
[57]: result = pd.DataFrame(NB_y_pred_prob,
    ↪columns=['defoe', 'dickens', 'twain', 'doyle'])
result.head()
```

```
[57]:
```

	defoe	dickens	twain	doyle
0	1.143236e-07	5.194159e-14	2.667652e-11	9.999999e-01
1	1.575376e-23	1.000000e+00	1.295946e-27	1.287325e-20
2	8.137090e-01	1.580197e-01	2.510534e-03	2.576080e-02
3	1.069707e-08	9.999998e-01	2.153086e-15	2.107129e-07
4	1.000000e+00	8.719178e-10	2.461550e-11	3.055405e-11

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```