In [1]:
```
import pandas as pd
```

Project 2: Predicting Authorship of the Disputed Federalist Papers

The Federalist Papers are a collection of 85 essays written by James Madison, Alexander Hamilton, and John Jay under the collective pseudonym "Publius" to promote the ratification of the United States Constitution.

Authorship of most of the papers were revealed some years later by Hamilton, though his claim to authorshipt of 12 papers were disputed for nearly 200 years.

Author	Papers
Jay	2, 3, 4, 5, 64
Madison	10, 14, 37-48
Hamilton	1, 6, 7, 8, 9, 11, 12, 13, 15, 16, 17, 21-36, 59, 60, 61, 65-85
Hamilton and Madison	18, 19, 20
Disputed	49-58, 62, 63

The goal of this project is to use NLP and Naive Bayes to predict the author of the disputed papers.

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1. Getting and processing the data

Retrieve an electronic version of the Federalist Papers from the [Gutenberg project (http://www.gutenberg.org/)](http://www.gutenberg.org/). Use the search facility to search for the Federalist Papers. Several versions are available. We'll use the plain text version [1408-8.txt (http://www.gutenberg.org/cache/epub/1404/pg1404.txt)](http://www.gutenberg.org/cache/epub/1404/pg1404.txt)

First, we'll build a dictionary that identifies the author of each Federalist paper. We'll use the phrase To the People of the state of New York to identify the beginning of a paper, and the word PUBLIUS to identify the end of a paper (The word PUBLIUS marks the end of all papers except 37; we'll need to insert PUBLIUS at the end of Paper 37 manually).

In [2]:
```
from re import match
```

In [3]:
```
path = 'Data/papers.txt'
Fed_dict = {}
opening = 'To the People of the State of New York'
closing = 'PUBLIUS'

counter = 0
paper = ''

# build a dictionary with the Federalist papers
with open(path) as f:
    for string in f: #  iterate over the lines of the txt file
        if match(opening, string):
            paper = '' # initialize Federalist Paper as an empty string
            counter += 1 # increase counter
        paper = paper+' '+string.replace('\n','') # remove end of line simbol
 \n; append new line;
        if match(closing, string):
            Fed_dict[counter]=paper # done
```

In [4]:
```
len(Fed_dict)
```

Out[4]: 85

In [5]:
```
# put the Federalist Papers into a DataFrame
papers = pd.DataFrame.from_dict(Fed_dict, orient='index',columns=['paper'])
papers.head(5)
```

Out[5]:

	paper
1	To the People of the State of New York: AFTE...
2	To the People of the State of New York: WHEN...
3	To the People of the State of New York: IT I...
4	To the People of the State of New York: MY L...
5	To the People of the State of New York: QUEE...

In [6]:
```
# authorship function
def author(paper_num):
    'it returns the author of a Federalist Paper'
    # papers authored by Jay:
    Jay_list = [2,3,4,5,64]
    # papers authored by Madison:
    Madison_list = [10,14]+list(range(37,49))
    # papers authored by Hamilton
    Hamilton_list = [1,6,7,8,9,11,12,13,15,16,17]+list(range(21,37))+[59,60,61
]+list(range(65,86))
    # papers authored by Hamilton+Madison
    Hamilton_Madison_list = [18,19,20]
    # disputed papers
    disputed_list = list(range(49,59))+[62,63]
    if paper_num in Jay_list:
        return 'Jay'
    elif paper_num in Hamilton_list:
        return 'Hamilton'
    elif paper_num in Madison_list:
        return 'Madison'
    elif paper_num in Hamilton_Madison_list:
        return 'Hamilton+Madison'
    elif paper_num in disputed_list:
        return 'Disputed'
```

In [7]:
```
# add column author to DataFrame
papers['author'] = papers.index.map(author)
papers.head(5)
```

Out[7]:

	paper	author
1	To the People of the State of New York: AFTE...	Hamilton
2	To the People of the State of New York: WHEN...	Jay
3	To the People of the State of New York: IT I...	Jay
4	To the People of the State of New York: MY L...	Jay
5	To the People of the State of New York: QUEE...	Jay

In [8]:
```
papers.author.value_counts()
```

Out[8]:
```
Hamilton            51
Madison             14
Disputed            12
Jay                  5
Hamilton+Madison     3
Name: author, dtype: int64
```

Step 1: train/test split

In [9]:
```
papers_train = papers[papers.author.isin(['Hamilton','Madison','Jay'])]
papers_test = papers[papers.author=='Disputed']
```

In [10]:
```
len(papers_train), len(papers_test)
```
Out[10]:
```
(70, 12)
```

Step 2: extract feature matrix and target vector

In [11]:
```
X_train = papers_train.paper
y_train = papers_train.author
```

In [12]:
```
X_test = papers_test.paper
```

Step 3: CountVectorizer

In [13]:
```
from sklearn.feature_extraction.text import CountVectorizer
vect = CountVectorizer(stop_words='english')
```

In [14]:
```
# learn training data vocabulary
vect.fit(X_train)
# create document-term matrix
X_train_dtm = vect.transform(X_train)
X_test_dtm = vect.transform(X_test)
```

2. Logistic Regression

In [15]:
```
from sklearn.linear_model import LogisticRegression
log_clf = LogisticRegression(max_iter=2000)

log_clf.fit(X_train_dtm,y_train)
```
Out[15]:
```
LogisticRegression(max_iter=2000)
```

Model evaluation

Problem: we don't have labels for the test set

Option 1 (not recommended): train and test on the same set

In [16]:
```
y_train_pred = log_clf.predict(X_train_dtm)
```

In [17]:
```
from sklearn import metrics
metrics.confusion_matrix(y_train,y_train_pred)
```

Out[17]:
```
array([[51,  0,  0],
       [ 0,  5,  0],
       [ 0,  0, 14]], dtype=int64)
```

In [18]:
```
metrics.accuracy_score(y_train,y_train_pred)
```

Out[18]:
```
1.0
```

The prediction function has an accuracy rate of 1.

Option 2 (recommended): use [cross validation (https://scikit-learn.org/stable/modules/cross_validation.html#cross-validation)](https://scikit-learn.org/stable/modules/cross_validation.html#cross-validation)

In [19]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(log_clf,X_train_dtm,y_train,cv=4,scoring='accuracy')
# we'll use a small number of folds (cv)
scores
```

Out[19]:
```
array([0.72222222, 0.88888889, 0.88235294, 0.58823529])
```

3. Naive Bayes Classification

In [20]:
```
from sklearn.naive_bayes import MultinomialNB
nb_clf = MultinomialNB()

nb_clf.fit(X_train_dtm,y_train)
```

Out[20]:
```
MultinomialNB()
```

Model evaluation

In [21]:
```
y_train_pred = nb_clf.predict(X_train_dtm)
```

In [22]:
```
# option 1
from sklearn import metrics
metrics.confusion_matrix(y_train,y_train_pred)
```

Out[22]:
```
array([[51,  0,  0],
       [ 0,  5,  0],
       [ 0,  0, 14]], dtype=int64)
```

In [23]:
```
metrics.accuracy_score(y_train,y_train_pred)
```

Out[23]:
```
1.0
```

In [24]:
```
# option 2
scores = cross_val_score(nb_clf,X_train_dtm,y_train,cv=4,scoring='accuracy') # we'll use a small number of folds (cv)
scores
```

Out[24]:
```
array([0.72222222, 0.77777778, 0.76470588, 0.76470588])
```

In [25]:
```
scores.mean()
```

Out[25]:
```
0.7573529411764706
```

4. Disputed Federalist Papers

In [26]:
```
# logistic regression prediction
y_test_pred = log_clf.predict(X_test_dtm)
y_test_pred
```

Out[26]:
```
array(['Hamilton', 'Hamilton', 'Madison', 'Hamilton', 'Hamilton',
       'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton',
       'Madison', 'Madison'], dtype=object)
```

In [27]:
```
# naive Bayes prediction
y_test_pred = nb_clf.predict(X_test_dtm)
y_test_pred
```

Out[27]:
```
array(['Hamilton', 'Madison', 'Madison', 'Hamilton', 'Hamilton',
       'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton',
       'Hamilton', 'Hamilton'], dtype='<U8')
```

5. How does Naive Bayes choose between Hamilton and Madison

In [28]:
```
# store the vocabulary of X_train
X_train_words = vect.get_feature_names()
```

In [29]:
```
len(X_train_words)
```

Out[29]:
```
7732
```

In [30]:
```
# examine the first 50 words
print(X_train_words[:50])
```

```
['000', '10', '11', '1685', '1688', '1706', '1774', '1783', '1784', '1786',
'1787', '1808', '195', '1st', '2d', '30', '3d', '4th', '5th', 'abandon', 'aba
ndoned', 'abandoning', 'abate', 'abetted', 'abilities', 'ability', 'able', 'a
blest', 'abolish', 'abolished', 'abolishing', 'abolition', 'abortive', 'aboun
ding', 'abounds', 'abridge', 'abridged', 'abridgements', 'abridging', 'abridg
ment', 'abroad', 'abrogate', 'abrogating', 'absence', 'absolute', 'absolutel
y', 'absolves', 'absorb', 'absorbed', 'abstain']
```

In [31]:
```
# examine the last 50 words
print(X_train_words[-50:])
```

```
['witnesses', 'witty', 'wolsey', 'woman', 'womb', 'won', 'wonder', 'wondere
d', 'wonderful', 'wood', 'word', 'words', 'work', 'workings', 'works', 'worl
d', 'worn', 'worse', 'worst', 'worthy', 'wound', 'wounded', 'wreaked', 'wrec
k', 'wretched', 'writ', 'write', 'writer', 'writers', 'writing', 'writings',
'written', 'wrong', 'wrought', 'wyoming', 'xiv', 'yards', 'year', 'years', 'y
eomanry', 'yes', 'yield', 'yielding', 'yoke', 'yokes', 'york', 'young', 'zale
ucus', 'zeal', 'zealous']
```

In [32]:
```
# Naive Bayes counts the number of times each word appears in each class
nb_clf.feature_count_
```

Out[32]:
```
array([[ 2.,  1.,  1., ...,  0., 12.,  6.],
       [ 0.,  0.,  0., ...,  0.,  1.,  0.],
       [ 0.,  0.,  0., ...,  1.,  9.,  2.]])
```

In [33]:
```
# rows represent classes (Hamilton, Madison, Jay), columns represent words
nb_clf.feature_count_.shape
```

Out[33]:
```
(3, 7732)
```

In [34]:
```
nb_clf.classes_
```

Out[34]:
```
array(['Hamilton', 'Jay', 'Madison'], dtype='<U8')
```

In [35]:
```
# number of times each word appears across all Hamilton's papers
Hamilton_word_count = nb_clf.feature_count_[0,:]
# number of times each word appears across all Madison's papers
Madison_word_count = nb_clf.feature_count_[2,:]
```

In [36]:
```
# create a DataFrame of words with their separate Hamilton and Madison counts
words = pd.DataFrame({'word' : X_train_words, 'Hamilton' : Hamilton_word_count
, 'Madison' : Madison_word_count}).set_index('word')
words.head()
```

Out[36]:

word	Hamilton	Madison
000	2.0	0.0
10	1.0	0.0
11	1.0	0.0
1685	0.0	0.0
1688	2.0	0.0

In [37]:
```
# examine 5 random DataFrame rows
words.sample(5)
```

Out[37]:

	Hamilton	Madison
word		
parliament	9.0	1.0
deriving	1.0	2.0
civilized	1.0	1.0
distinguishing	2.0	0.0
jointly	1.0	0.0

In [38]:
```
# add 1 to Hamilton and Madison counts to avoid dividing by 0
words.Hamilton = words.Hamilton+1
words.Madison = words.Madison+1
```

In [39]:
```
# convert the Hamilton and Madison counts into frequencies
words.Hamilton = words.Hamilton/words.Hamilton.sum()
words.Madison = words.Madison/words.Madison.sum()
```

In [40]:
```
words.sample(5)
```

Out[40]:

	Hamilton	Madison
word		
campaigns	0.000038	0.000043
opposes	0.000019	0.000043
malcontents	0.000038	0.000043
scotland	0.000038	0.000043
application	0.000192	0.000171

In [41]:
```
# calculate the ration of Hamilton-to-Madison and Madison-to-Hamilton for each
word
words['Hamilton_ratio'] = words.Hamilton/words.Madison
words['Madison_ratio'] = words.Madison/words.Hamilton
```

In [42]:
```
words.sample(5)
```

Out[42]:

word	Hamilton	Madison	Hamilton_ratio	Madison_ratio
vicinity	0.000077	0.000043	1.801147	0.555202
condemnation	0.000058	0.000085	0.675430	1.480538
poorest	0.000038	0.000043	0.900574	1.110403
imitated	0.000058	0.000043	1.350860	0.740269
dead	0.000038	0.000085	0.450287	2.220807

In [43]:
```
# top 10 Hamiltonian words
words.sort_values(by='Hamilton_ratio', ascending=False).head(10)
```

Out[43]:

word	Hamilton	Madison	Hamilton_ratio	Madison_ratio
kind	0.001482	0.000085	17.336041	0.057683
intended	0.000693	0.000043	16.210324	0.061689
readily	0.000481	0.000043	11.257169	0.088832
community	0.001347	0.000128	10.506691	0.095177
commonly	0.000443	0.000043	10.356596	0.096557
nomination	0.000443	0.000043	10.356596	0.096557
thirds	0.000423	0.000043	9.906309	0.100946
matters	0.000404	0.000043	9.456022	0.105753
information	0.000385	0.000043	9.005735	0.111040
formation	0.000385	0.000043	9.005735	0.111040

In [44]:
```
# top 10 Madisonian words
words.sort_values(by='Madison_ratio', ascending=False).head(10)
```

Out[44]:

word	Hamilton	Madison	Hamilton_ratio	Madison_ratio
democracy	0.000019	0.000470	0.040935	24.428877
justices	0.000019	0.000427	0.045029	22.208070
reform	0.000019	0.000342	0.056286	17.766456
assumed	0.000019	0.000342	0.056286	17.766456
indirectly	0.000019	0.000299	0.064327	15.545649
whilst	0.000038	0.000556	0.069275	14.435245
thirty	0.000019	0.000256	0.075048	13.324842
unanimous	0.000019	0.000256	0.075048	13.324842
enlarge	0.000019	0.000256	0.075048	13.324842
patient	0.000019	0.000256	0.075048	13.324842

6. Parameter tuning using grid search

In [45]:
```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfTransformer # term-frequency
 transformer
from sklearn.model_selection import GridSearchCV
```

In [46]:
```
pipe = Pipeline(steps=
               [('vect', CountVectorizer()),
                #('tfidf', TfidfTransformer()),
                ('naive_bayes', MultinomialNB())])
pipe
```

Out[46]:
```
Pipeline(steps=[('vect', CountVectorizer()), ('naive_bayes', MultinomialNB
())])
```

In [47]:
```
# parameter dictionary
param_dict = {'vect__ngram_range': [(1, 1), (1, 2)], # (1,1) : use 1-grams (wo
rds); (1,2) : use 1 and 2 grams
              'vect__stop_words' : ['english',None],
              #'tfidf__use_idf': (True, False),
              'naive_bayes__alpha' : [0.0001, 0.001, 0.01,0.1, 1]}
```

In [48]:
```
# grid search
grid = GridSearchCV(pipe, param_dict, cv=4, scoring='accuracy')
```

In [49]:
```
grid.fit(X_train,y_train)
```

Out[49]:
```
GridSearchCV(cv=4,
             estimator=Pipeline(steps=[('vect', CountVectorizer()),
                                       ('naive_bayes', MultinomialNB())]),
             param_grid={'naive_bayes__alpha': [0.0001, 0.001, 0.01, 0.1, 1],
                         'vect__ngram_range': [(1, 1), (1, 2)],
                         'vect__stop_words': ['english', None]},
             scoring='accuracy')
```

In [50]:
```
grid.best_score_
```

Out[50]:
```
0.8284313725490196
```

In [51]:
```
grid.best_params_
```

Out[51]:
```
{'naive_bayes__alpha': 0.1,
 'vect__ngram_range': (1, 1),
 'vect__stop_words': None}
```

In [52]:
```
best_predictor = grid.estimator
best_predictor
```

Out[52]:
```
Pipeline(steps=[('vect', CountVectorizer()), ('naive_bayes', MultinomialNB
())])
```

In [53]:
```
best_predictor.fit(X_train,y_train)
y_test_pred = best_predictor.predict(X_test)
y_test_pred
```

Out[53]:
```
array(['Hamilton', 'Madison', 'Madison', 'Hamilton', 'Hamilton',
       'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton', 'Hamilton',
       'Hamilton', 'Hamilton'], dtype='<U8')
```

7. Data Visualization

In [54]:
```
X_train_dtm.shape
```

Out[54]:
```
(70, 7732)
```

We'll use a Linear Algebra technique called Principal Component Analysis (PCA) to reduce the dimension down to 2 and 3.

In [55]:
```
from sklearn.decomposition import PCA
```

2d visualization

PCA identifies the plane that lies closest to the data, and then it projects the data onto it.

In [56]:
```
pca = PCA(n_components=2)
```

In [57]:
```
pca.fit(X_train_dtm.toarray())
X_train_dtm_reduced = pca.transform(X_train_dtm.toarray())
```

In [58]:
```
X_train_dtm_reduced.shape
```

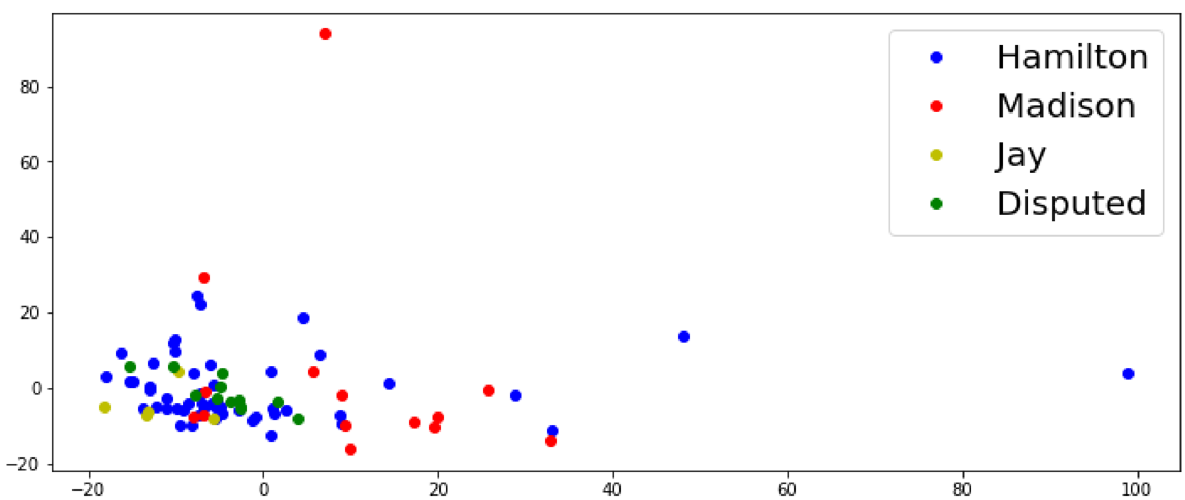
Out[58]:
```
(70, 2)
```

In [59]:
```
X_test_dtm_reduced = pca.transform(X_test_dtm.toarray())
```

In [60]:
```
import matplotlib.pyplot as plt
```

In [61]:
```
plt.figure(figsize=(12,5))
plt.plot(X_train_dtm_reduced[y_train=='Hamilton',0],X_train_dtm_reduced[y_train=='Hamilton',1],'bo', label='Hamilton')
plt.plot(X_train_dtm_reduced[y_train=='Madison',0],X_train_dtm_reduced[y_train=='Madison',1],'ro', label='Madison')
plt.plot(X_train_dtm_reduced[y_train=='Jay',0],X_train_dtm_reduced[y_train=='Jay',1],'yo', label='Jay')
plt.plot(X_test_dtm_reduced[:,0],X_test_dtm_reduced[:,1],'go', label='Disputed')
plt.legend(fontsize=20)
```

Out[61]:
```
<matplotlib.legend.Legend at 0x1dfd41fb848>
```



3d visualization

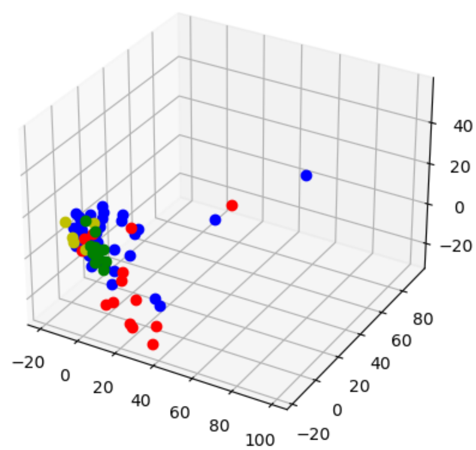
In [62]:
```
pca = PCA(n_components=3)
```

In [63]:
```
pca.fit(X_train_dtm.toarray())
X_train_dtm_reduced = pca.transform(X_train_dtm.toarray())
```

In [64]:
```
X_train_dtm_reduced.shape
```
Out[64]:
```
(70, 3)
```

In [65]:
```
X_test_dtm_reduced = pca.transform(X_test_dtm.toarray())
```

In [66]:
```
# 3d plot
%matplotlib notebook
plt.figure(figsize=(10,5))
plt.axes(projection='3d')
plt.plot(X_train_dtm_reduced[y_train=='Hamilton',0],X_train_dtm_reduced[y_trai
n=='Hamilton',1],X_train_dtm_reduced[y_train=='Hamilton',2],'bo')
plt.plot(X_train_dtm_reduced[y_train=='Madison',0],X_train_dtm_reduced[y_train
=='Madison',1],X_train_dtm_reduced[y_train=='Madison',2],'ro')
plt.plot(X_train_dtm_reduced[y_train=='Jay',0],X_train_dtm_reduced[y_train=='J
ay',1],X_train_dtm_reduced[y_train=='Jay',2],'yo')
plt.plot(X_test_dtm_reduced[:,0],X_test_dtm_reduced[:,1],X_test_dtm_reduced[:,
2],'go')
```



Out[66]:
```
[<mpl_toolkits.mplot3d.art3d.Line3D at 0x1dfd42c6948>]
```

In [ ]: