Student Details

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Course: CS 5402
Assignment: Semester project for date mining
Date: 2021-7-30

Concept Description:

It is not entirely clear who wrote the book "Frankenstein". Though it is commonly accepted to be written by Mary Shelley there has been some debate. According to our assignment "The story of the origin of Frankenstein is almost as fanciful as the story itself. It was written as a writing challenge between Lord Byron, John Polidori, Marry Wollstonecraft Shelly, and Percy Bysshe Shelley while the four shared a lake house in Geneva, Switzerland. I reference the following History.com article as a source on the origin of the Frankenstein novel. [https://www.history.com/news/frankenstein-true-story-mary-shelley (https://www.history.com/news/frankenstein-true-story-mary-shelley)](https://www.history.com/news/frankenstein-true-story-mary-shelley) (Links to an external site.)

There is apparently some controversy on who the actual author of Frankenstein was. I reluctantly reference the following self promotional article that declares the authorship of Frankenstein to be Percy Shelly, and not Mary."

It is my goal to use data mining tools to help determing who the author may have been.

In [34]:
```
from collections import Counter
import nltk
from collections import OrderedDict
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn import metrics
import seaborn
import string

#Only have to run the bottom two lines here once. After the packages a
re installed no need to run again.
#nltk.download('punkt')
#nltk.download('averaged_perceptron_tagger')
```

Data Gathering and Wrangling

> In order to gather my data. I picked the most popular book, excluding Frankenstein for each of the authors from gutenberg.org. I then handcopied and pasted plain text into text files, removed things like forwards written bu other authors. Then I had it all read in using the software below. Since I am going to used instance based approches to train my models, I broke their books down into 1000 work increments, removed punctuation, and used nltk to convert those 1000 works into part of speech values. I divided these values into the total of the pos tags so that all of my instances would be made up of a consistend ratio out of one.

CC coordinating conjunction
CD cardinal digit
DT determiner
EX existential there
FW foreign word
IN preposition/subordinating conjunction
JJ This NLTK POS Tag is an adjective (large)
JJR adjective, comparative (larger)
JJS adjective, superlative (largest)
LS list market
MD modal (could, will)

NN noun, singular (cat, tree)
NNS noun plural (desks)
NNP proper noun, singular (sarah)
NNPS proper noun, plural (indians or americans)
PDT predeterminer (all, both, half)
POS possessive ending (parent\ 's)
PRP personal pronoun (hers, herself, him,himself)
PRP$ possessive pronoun (her, his, mine, my, our)
RB adverb (occasionally, swiftly)
RBR adverb, comparative (greater)
RBS adverb, superlative (biggest)
RP particle (about)
TO infinite marker (to)
UH interjection (goodbye)
VB verb (ask)
VBG verb gerund (judging)
VBD verb past tense (pleaded)
VBN verb past participle (reunified)
VBP verb, present tense not 3rd person singular(wrap)
VBZ verb, present tense with 3rd person singular (bases)
WDT wh-determiner (that, what)
WP wh- pronoun (who)
WRB wh- adverb (how)

> These are the avaliable tags. I chose to go with an approach of having the ratio of each of the tags recorded and each 1000 words would be an instance that I can use to train the model. I chose to use 1000 words becuase of the papers you provided us to read.
> My biggest issue was finding books that were about the same size. This could not be done. I could only find about 10000 words of text written by Jon Polodori. This is another reason I decided to go with a ratio approach.
> Another issue is that not every block of 1000 words had everytag that nltk can produce. So that had to be accounted for. To keep in in order I had to grab all of the values returned in the dictionary with get methods, in a certain order, and return a default of 0 if it did not have that value. This cleared up my issue with missing value and order all at the same time. As I divided each authors book, I also tagged their instances with their respective initials.
>
> After all of this was done, it was written to a csv file to be imported.

In [5]:
```
count = 0
newString = ""
writeable = ""
```

```
orderedKeyList = ['CC', 'CD', 'DT', 'EX', 'FW',
                  'IN', 'JJ', 'JJR', 'JJS', 'MD',
                  'NN', 'NNP', 'NNS', 'PDT', 'PRP',
                  'PRP$', 'RB', 'RBR', 'RBS', 'RP',
                  'TO', 'VB', 'VBD', 'VBG', 'VBN',
                  'VBP', 'VBZ', 'WDT', 'WP', 'WP$', 'WRB']

f = open("testfile.csv", "w")

for x in orderedKeyList:
    f.write(x)
    f.write(",")
f.write("Author")
f.write("\n")

with open('ps.txt','r') as file:

    # reading each line
    for line in file:

        # reading each word
        for word in line.split():

            newString = newString + word
            newString = newString + " "
            count+=1

            if(count == 1000):
                op_string = newString.translate(str.maketrans('', '',
string.punctuation))
                lower_case = op_string.lower()
                tokens = nltk.word_tokenize(lower_case)
                tags = nltk.pos_tag(tokens)
                counts = Counter( tag for word,  tag in tags)
                val= sum(counts.values())

                counts = OrderedDict(sorted(counts.items()))
                for x in orderedKeyList:
                    writeable = counts.get(x,'0')
                    f.write(str(int(writeable)/val))
                    f.write(",")
                f.write("ps")
                f.write("\n")
                newString = ""
                count = 0

count = 0
newString = ""

with open('ms.txt','r') as file:
```

```
    # reading each line
    for line in file:

        # reading each word
        for word in line.split():

            newString = newString + word
            newString = newString + " "
            count+=1

            if(count == 1000):
                op_string = newString.translate(str.maketrans('', '',
string.punctuation))
                lower_case = op_string.lower()
                tokens = nltk.word_tokenize(lower_case)
                tags = nltk.pos_tag(tokens)
                counts = Counter( tag for word,  tag in tags)
                val= sum(counts.values())

                counts = OrderedDict(sorted(counts.items()))
                for x in orderedKeyList:
                    writeable = counts.get(x,'0')
                    f.write(str(int(writeable)/val))
                    f.write(",")
                f.write("ms")
                f.write("\n")
                newString = ""
                count = 0

count = 0
newString = ""

with open('jp.txt','r') as file:

    # reading each line
    for line in file:

        # reading each word
        for word in line.split():

            newString = newString + word
            newString = newString + " "
            count+=1

            if(count == 1000):
                op_string = newString.translate(str.maketrans('', '',
string.punctuation))
                lower_case = op_string.lower()
                tokens = nltk.word_tokenize(lower_case)
```

```
                tags = nltk.pos_tag(tokens)
                counts = Counter( tag for word,  tag in tags)
                val= sum(counts.values())

                counts = OrderedDict(sorted(counts.items()))
                for x in orderedKeyList:
                    writeable = counts.get(x,'0')
                    f.write(str(int(writeable)/val))
                    f.write(",")
                f.write("jp")
                f.write("\n")
                newString = ""
                count = 0

count = 0
newString = ""

with open('lb.txt','r') as file:

    # reading each line
    for line in file:

        # reading each word
        for word in line.split():

            newString = newString + word
            newString = newString + " "
            count+=1

            if(count == 1000):
                op_string = newString.translate(str.maketrans('', '',
string.punctuation))
                lower_case = op_string.lower()
                tokens = nltk.word_tokenize(lower_case)
                tags = nltk.pos_tag(tokens)
                counts = Counter( tag for word,  tag in tags)
                val= sum(counts.values())

                counts = OrderedDict(sorted(counts.items()))
                for x in orderedKeyList:
                    writeable = counts.get(x,'0')
                    f.write(str(int(writeable)/val))
                    f.write(",")
                f.write("lb")
                f.write("\n")
                newString = ""
                count = 0

count = 0
newString = ""
```

```
f.close()
```

Data Import and Display

In [3]:
```
df = pd.read_csv("authatt.csv")
df
```

Out[3]:

	CC	CD	DT	EX	FW	IN	JJ	JJR	JJS
0	0.058000	0.007000	0.118000	0.004000	0.000000	0.159000	0.064000	0.005000	0.003000
1	0.064000	0.004000	0.112000	0.002000	0.001000	0.131000	0.068000	0.001000	0.000000
2	0.051896	0.008982	0.125749	0.000000	0.000000	0.140719	0.077844	0.000998	0.001996
3	0.066866	0.003992	0.127745	0.001996	0.000000	0.143713	0.080838	0.002994	0.000998
4	0.043000	0.003000	0.126000	0.003000	0.000000	0.146000	0.070000	0.001000	0.002000
...	...	...	...	...	...	...	...	...	...
282	0.032934	0.003992	0.101796	0.008982	0.000998	0.120758	0.095808	0.007984	0.004990
283	0.057000	0.001000	0.109000	0.000000	0.000000	0.127000	0.104000	0.004000	0.002000
284	0.068000	0.006000	0.106000	0.006000	0.000000	0.124000	0.099000	0.007000	0.005000
285	0.060000	0.007000	0.083000	0.002000	0.000000	0.122000	0.096000	0.003000	0.004000
286	0.048048	0.007007	0.115115	0.001001	0.000000	0.125125	0.102102	0.006006	0.003003

287 rows × 32 columns

Checking for null values

In [4]:
```
df.isnull().sum()
null_data = df[df.isnull().any(axis=1)]
mylist = null_data.index.values.tolist()
null_data
```

Out[4]:

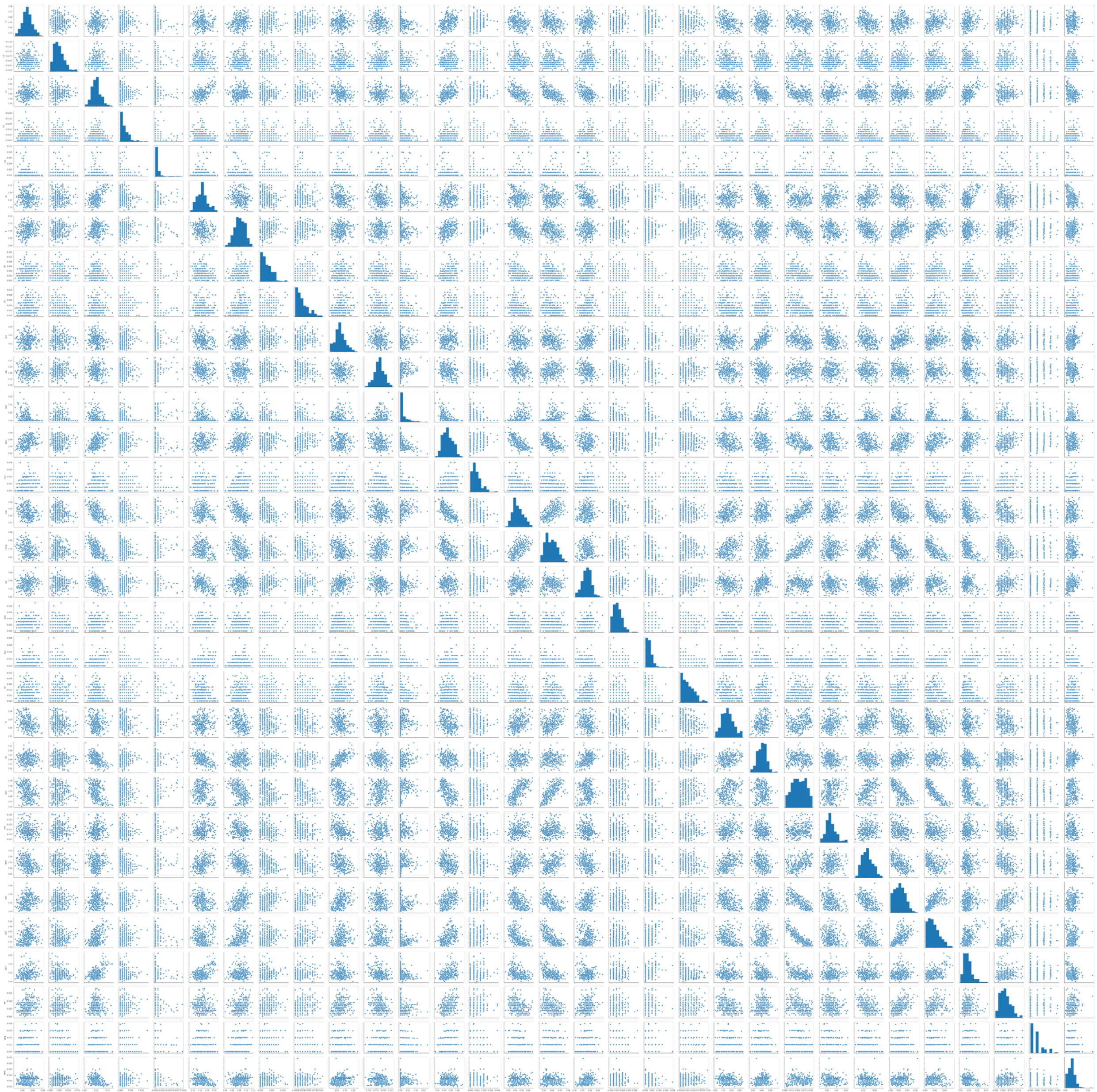
CC	CD	DT	EX	FW	IN	JJ	JJR	JJS	MD	...	VBD	VBG	VBN	VBP	VBZ	WDT	WP

0 rows × 32 columns

Displaying some graphs

In [5]:
```
seaborn.pairplot(df)
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x7fc75bece0d0>

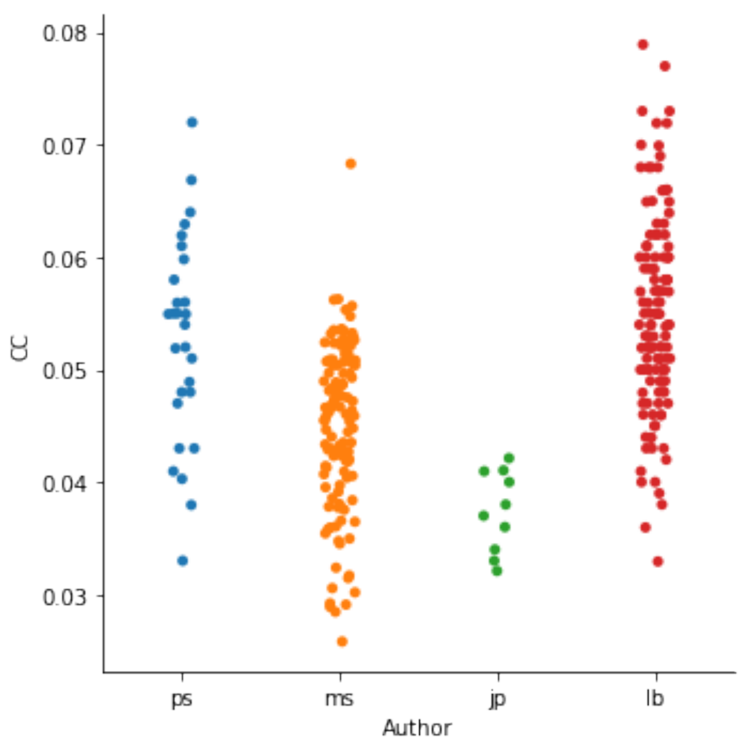


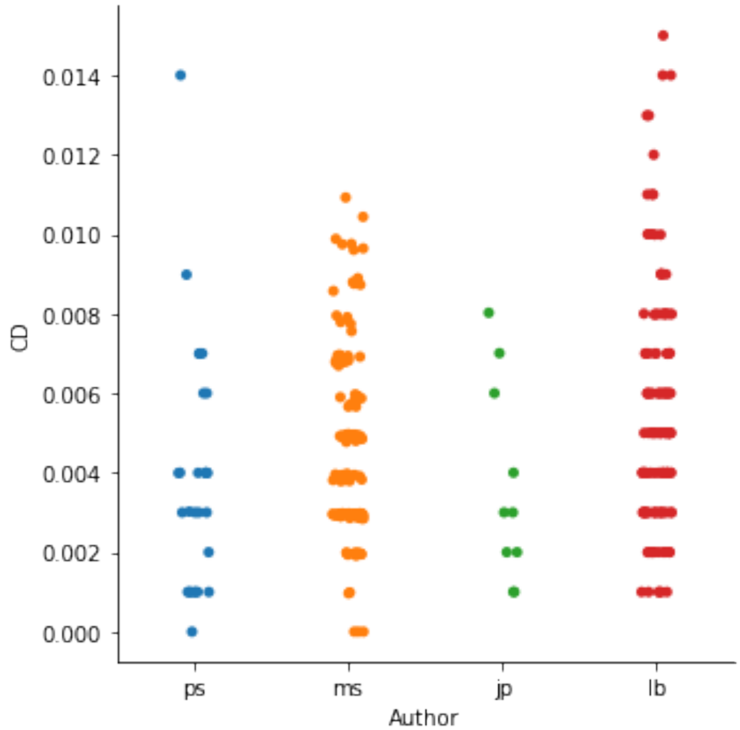
Displaying some more specific data

> The values of NN and IN were the two values with the highest counts, so I am going display them. In doing so, it becomes very clear that some authors can easily be identified with some attributes. For example Mary Shelley is pretty much the only author to have FW ratios above 0.004 also when considerdering NNP Mary Shelley is the only author above 0.005 in which they have numerous above that amount. Given this I believe this data will be able to accurately predict authorship.

In [6]:
```
for x in orderedKeyList:
    data = data = df[[x, "Author"]]
    seaborn.catplot(x="Author", y=x, data = data)
```

```
/Users/brentmoran/opt/anaconda3/lib/python3.7/site-packages/seaborn/
axisgrid.py:311: RuntimeWarning: More than 20 figures have been open
ed. Figures created through the pyplot interface (`matplotlib.pyplot
.figure`) are retained until explicitly closed and may consume too m
uch memory. (To control this warning, see the rcParam `figure.max_op
en_warning`).
  fig, axes = plt.subplots(nrow, ncol, **kwargs)
```




0.014
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0.010
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0.002
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CD
ps
ms
jp
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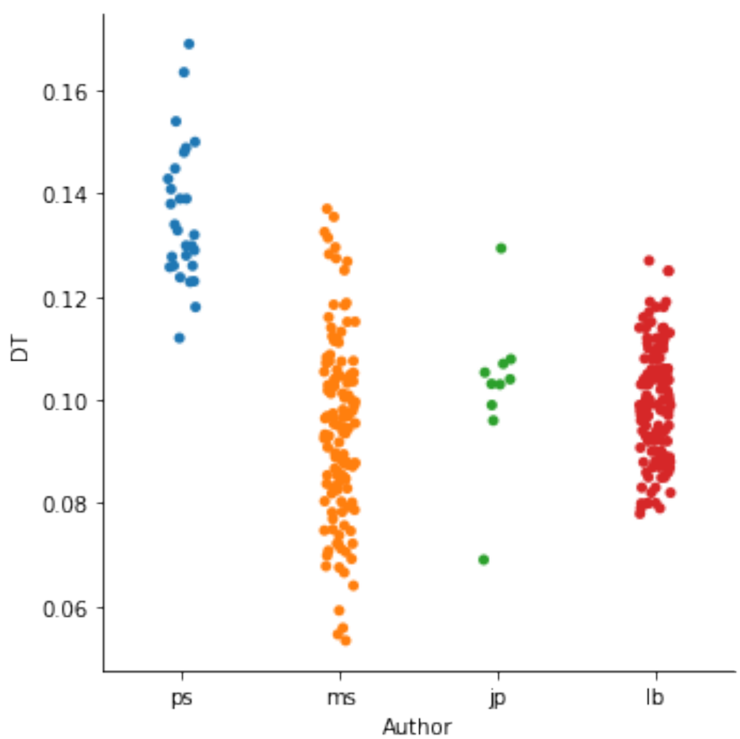
Author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DT
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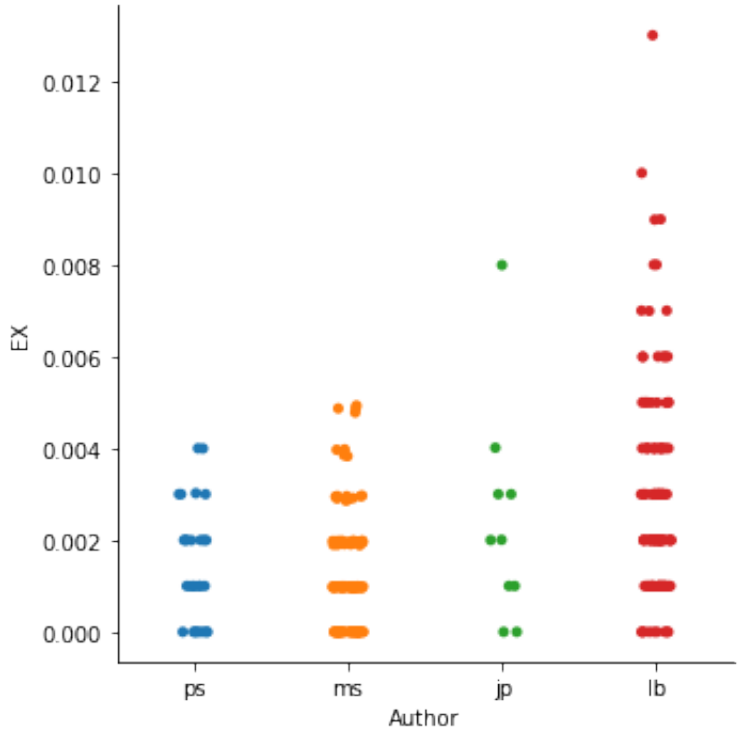
Author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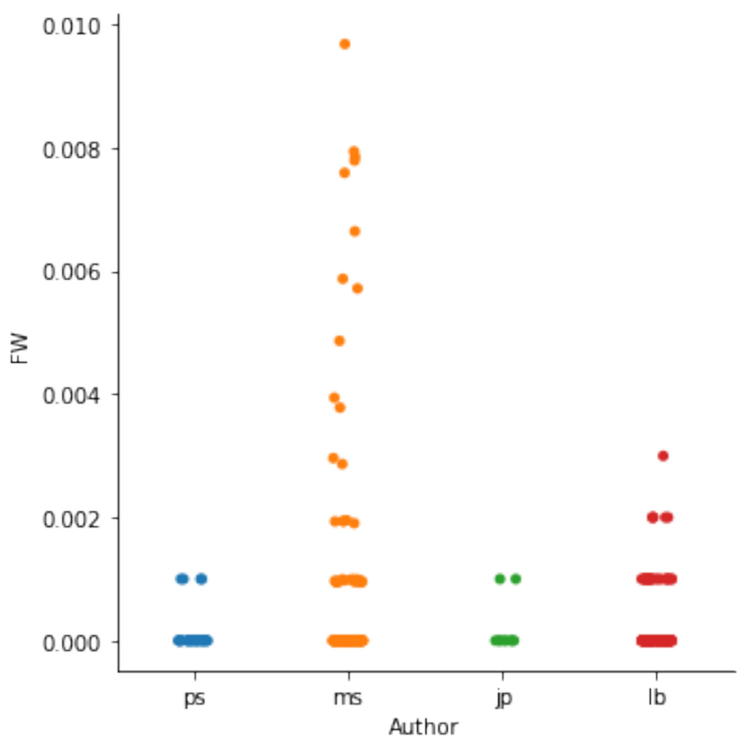
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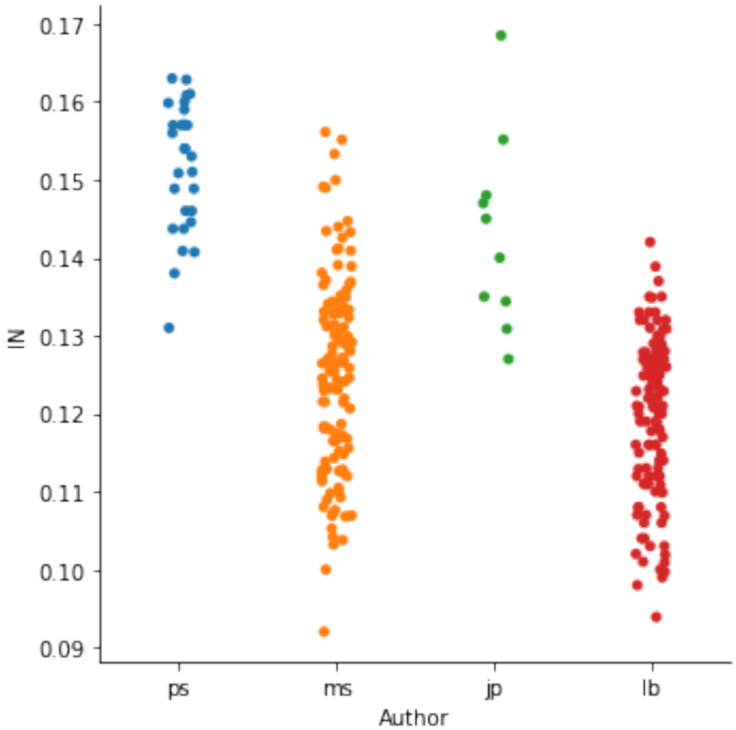
Author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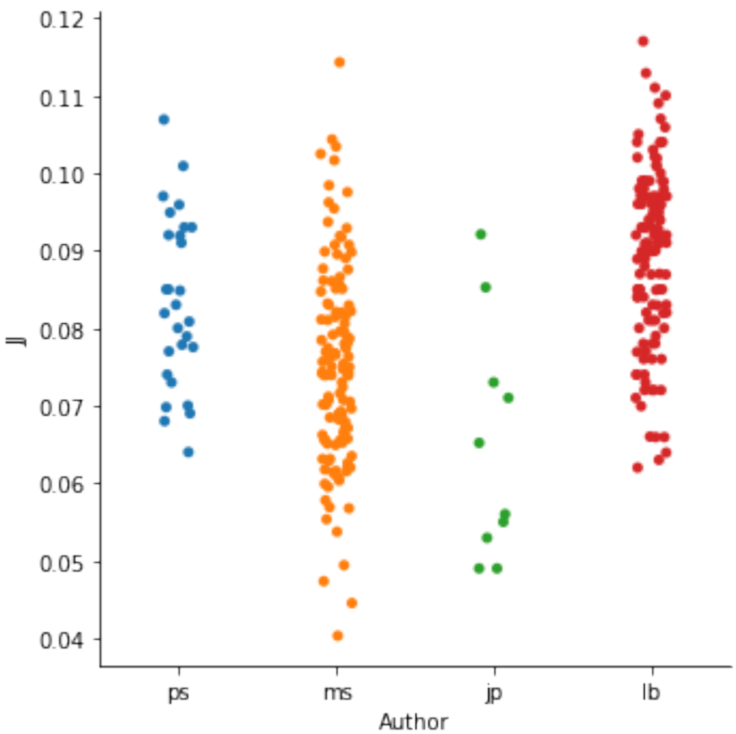
Author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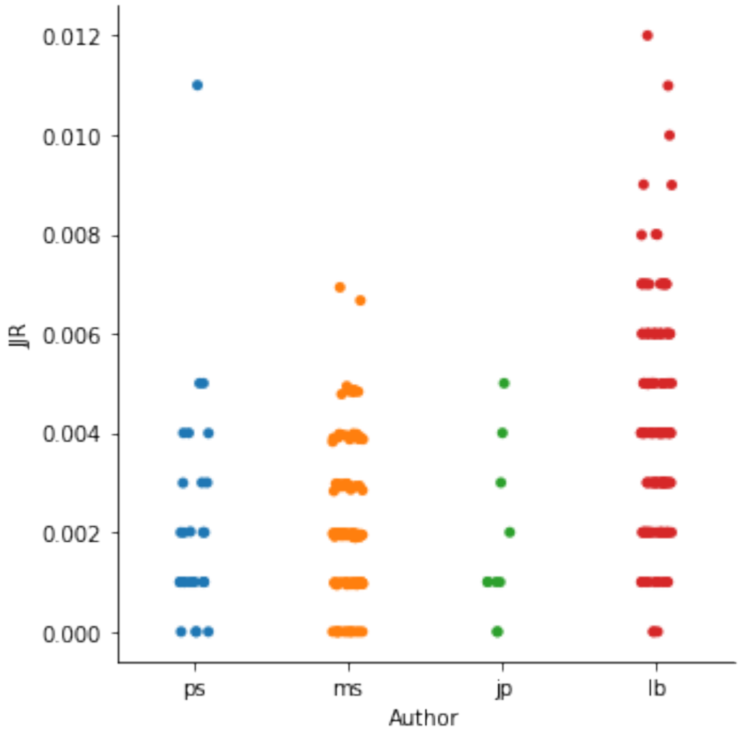
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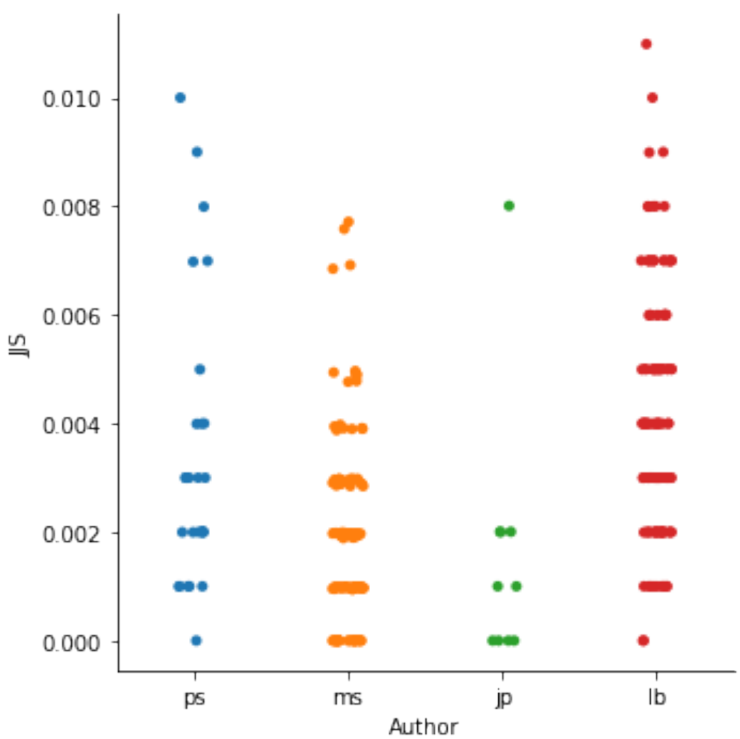
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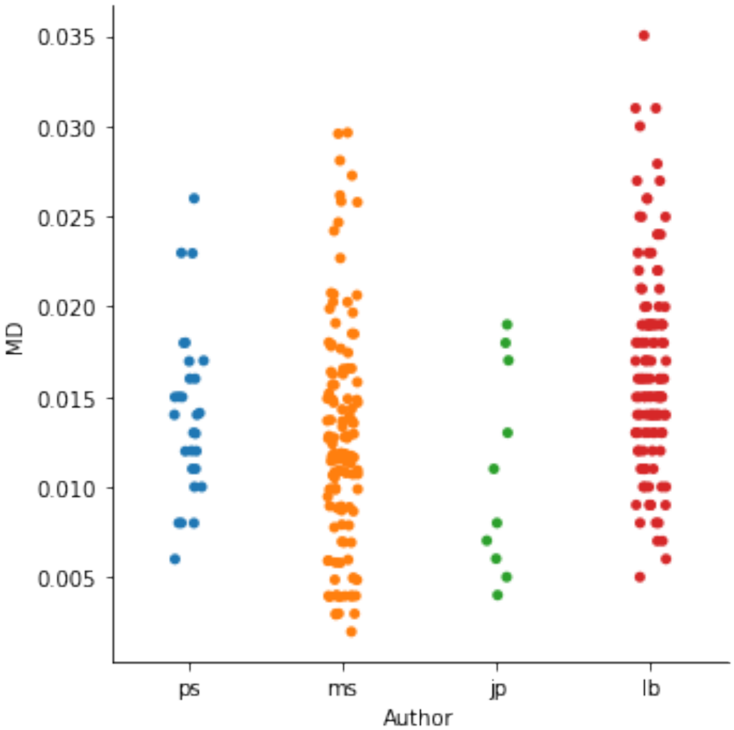
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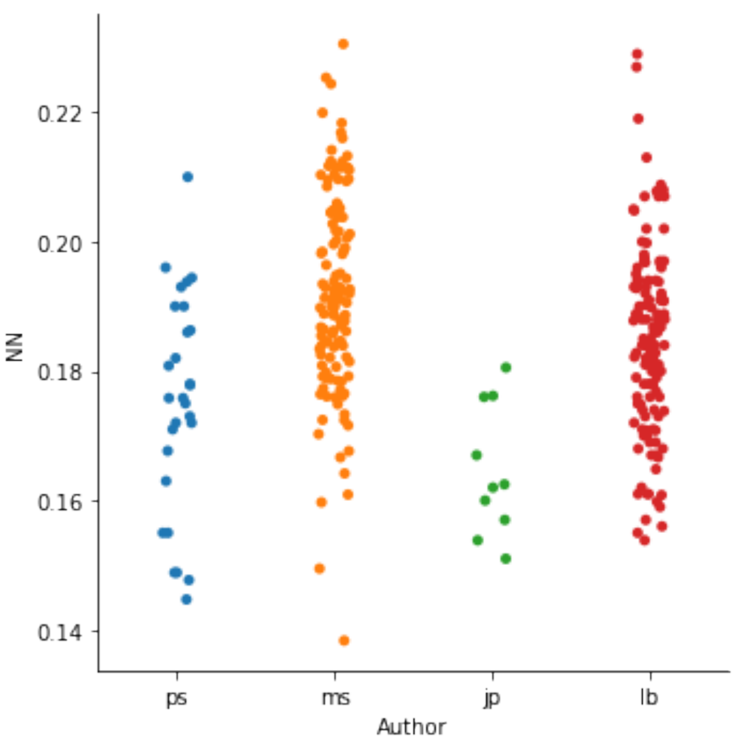
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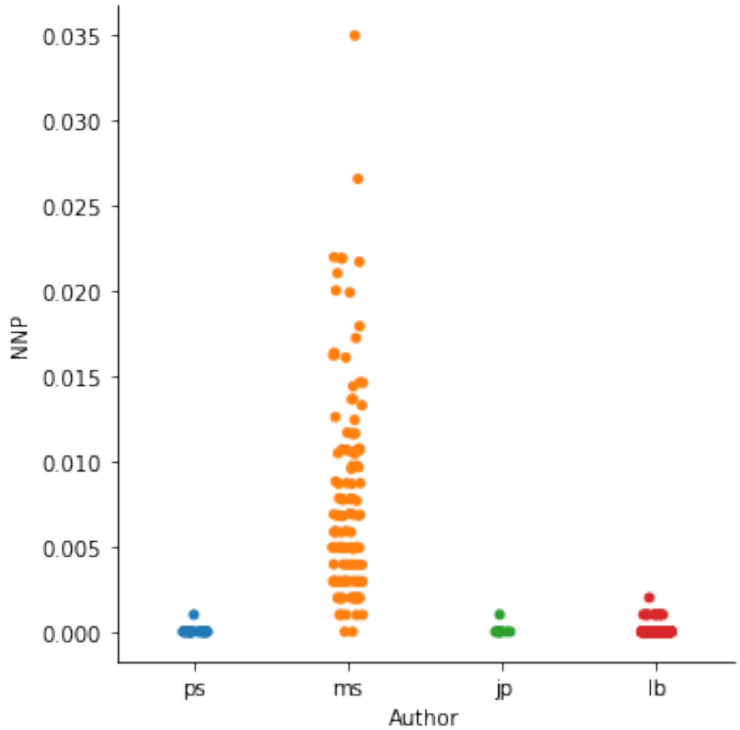
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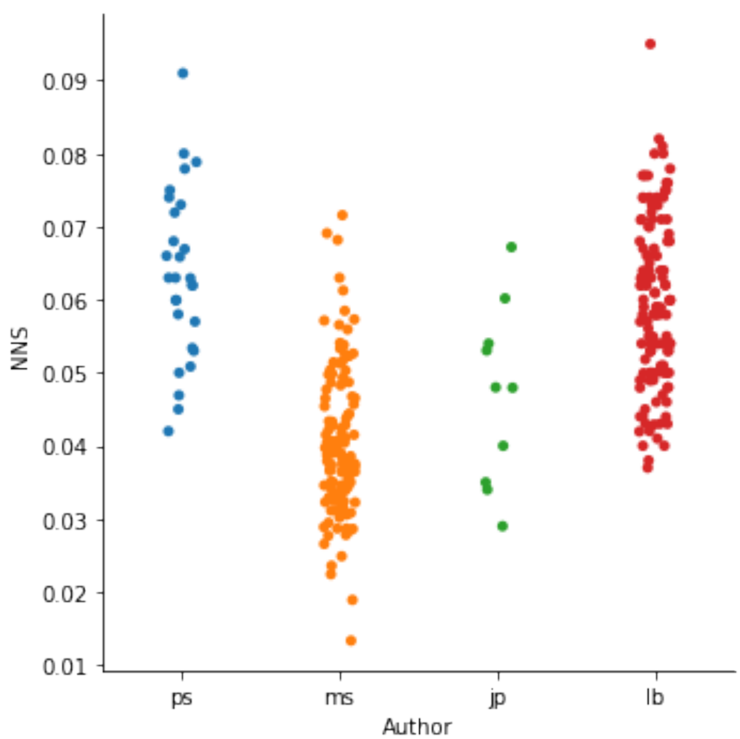
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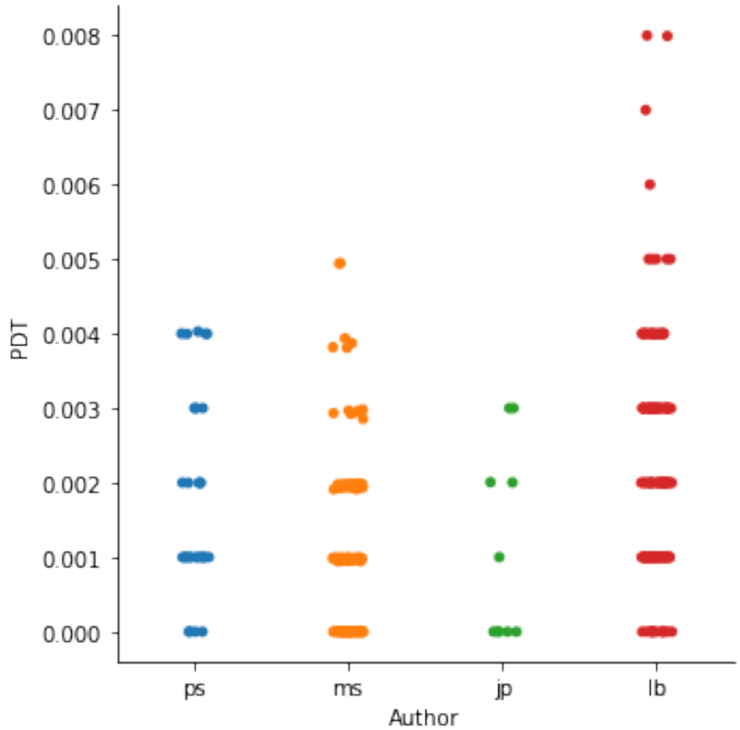
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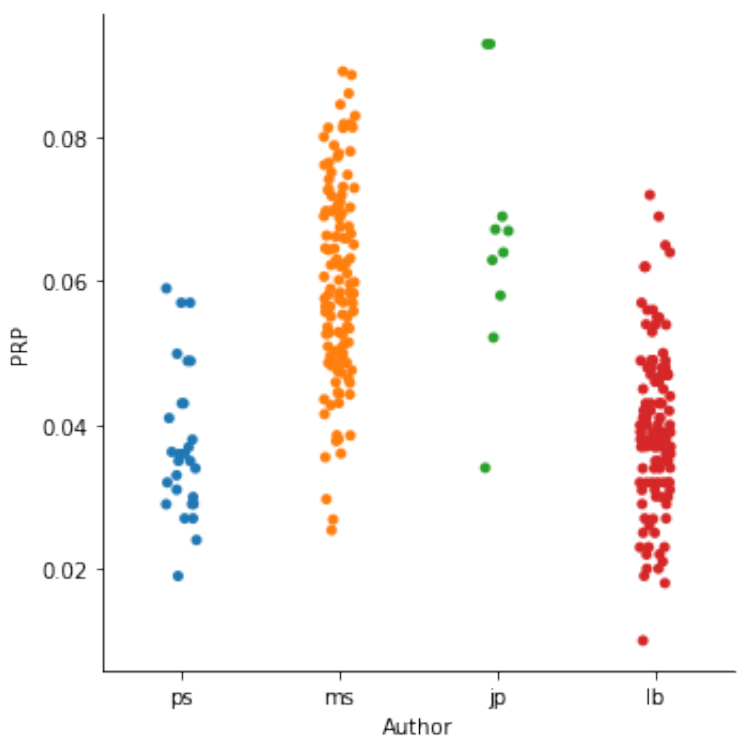
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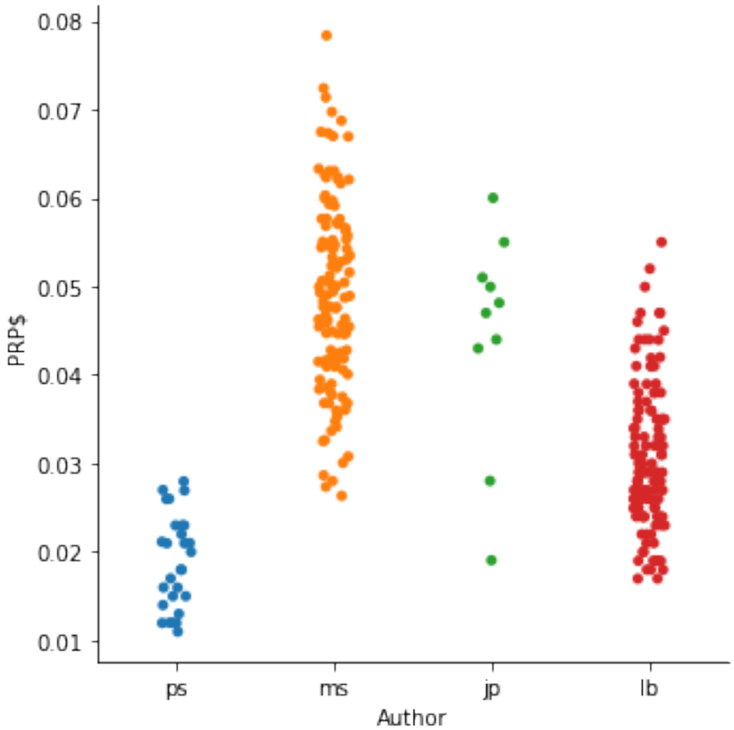
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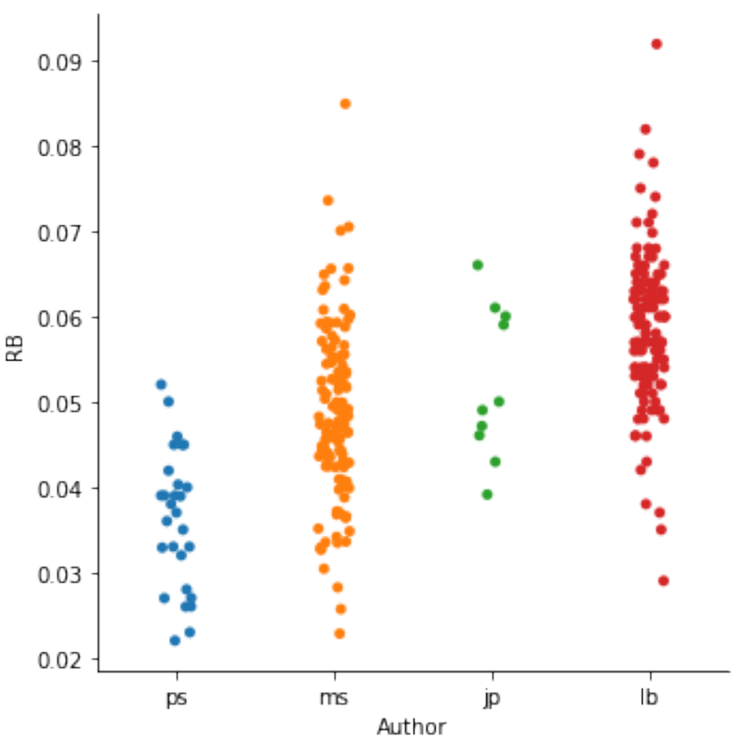
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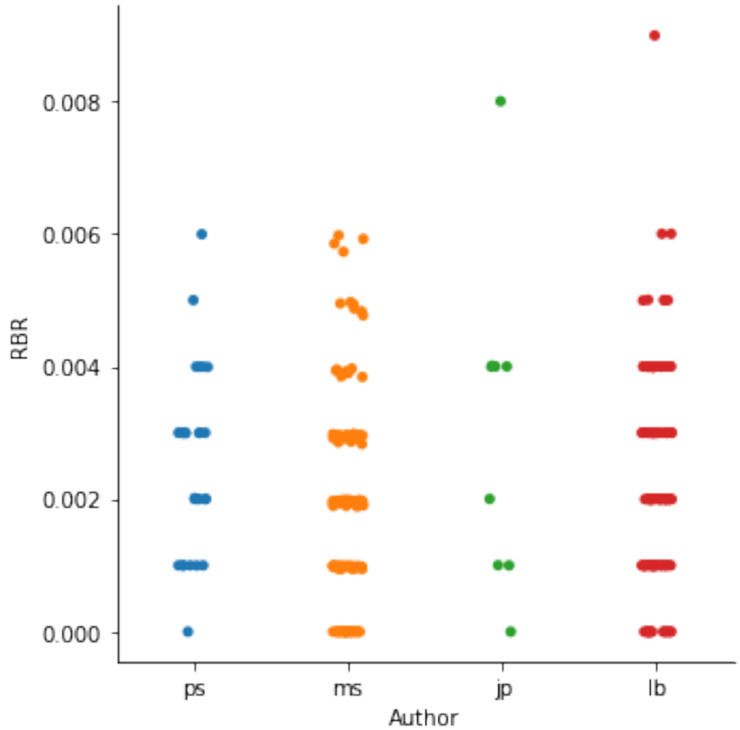

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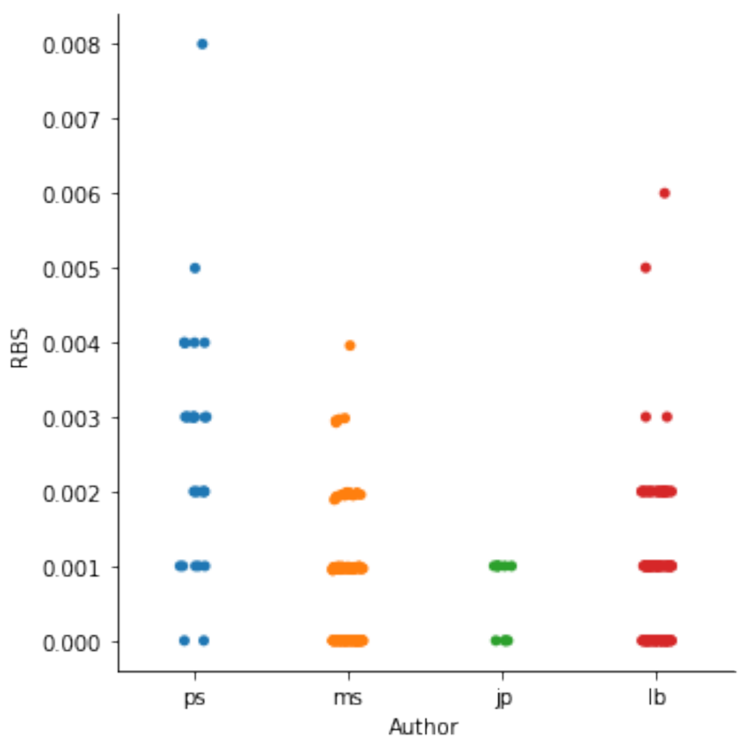

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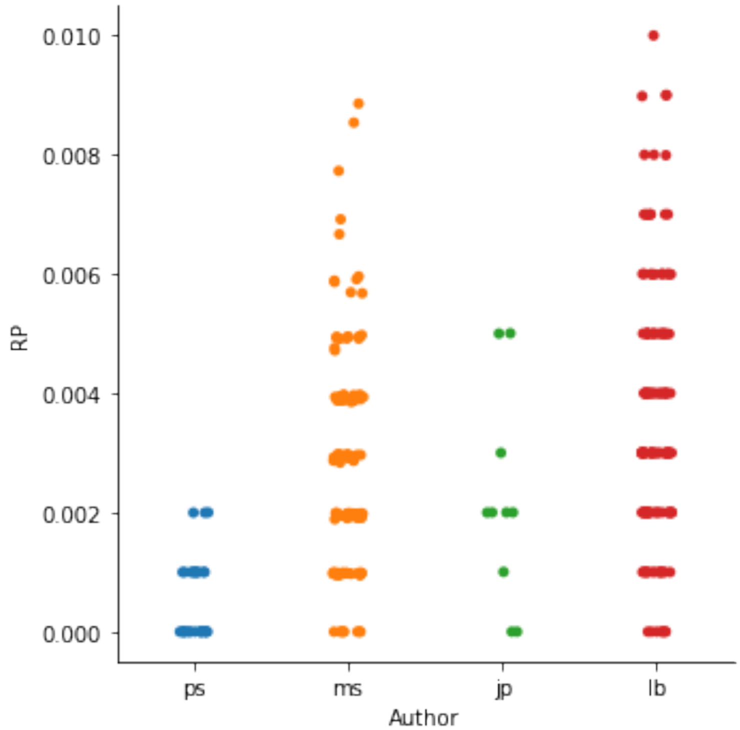

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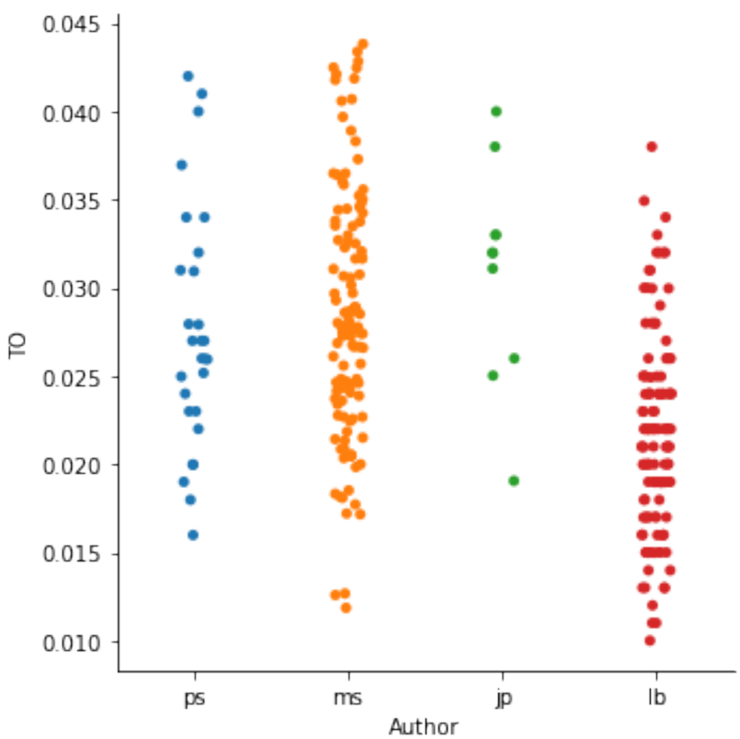

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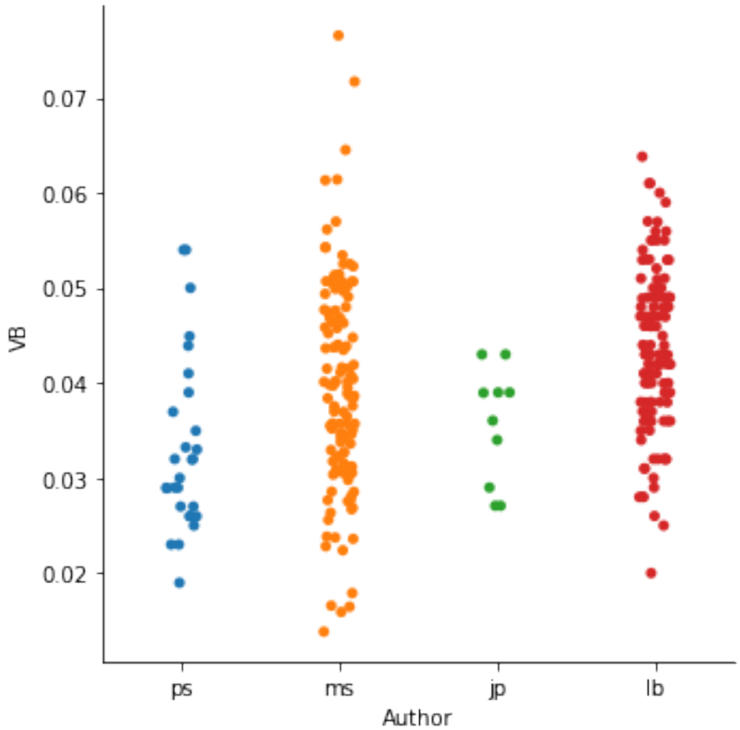
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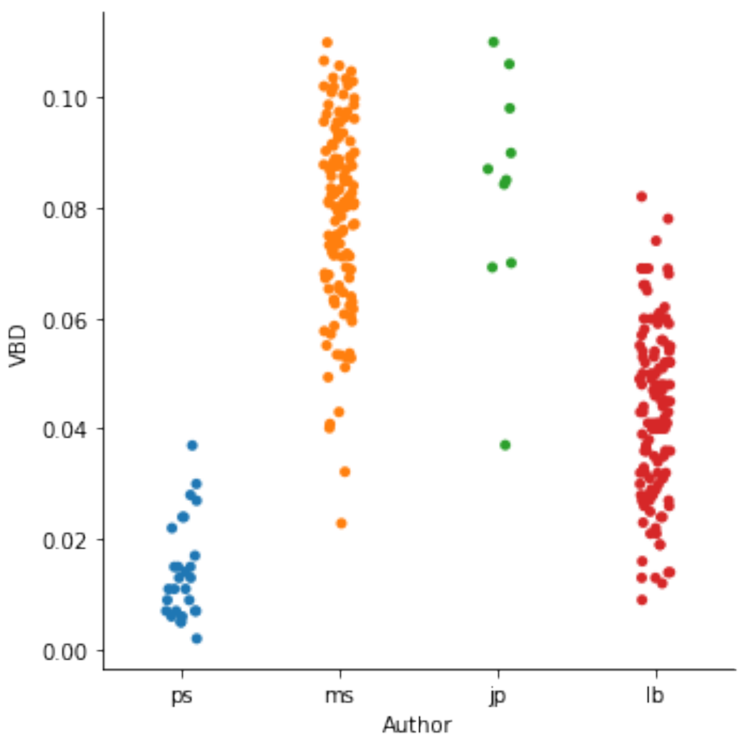
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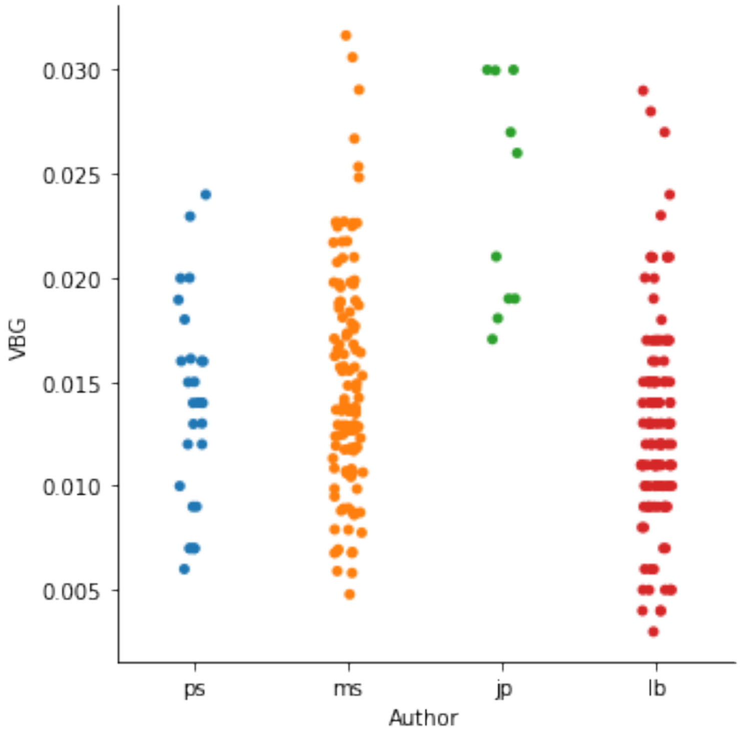

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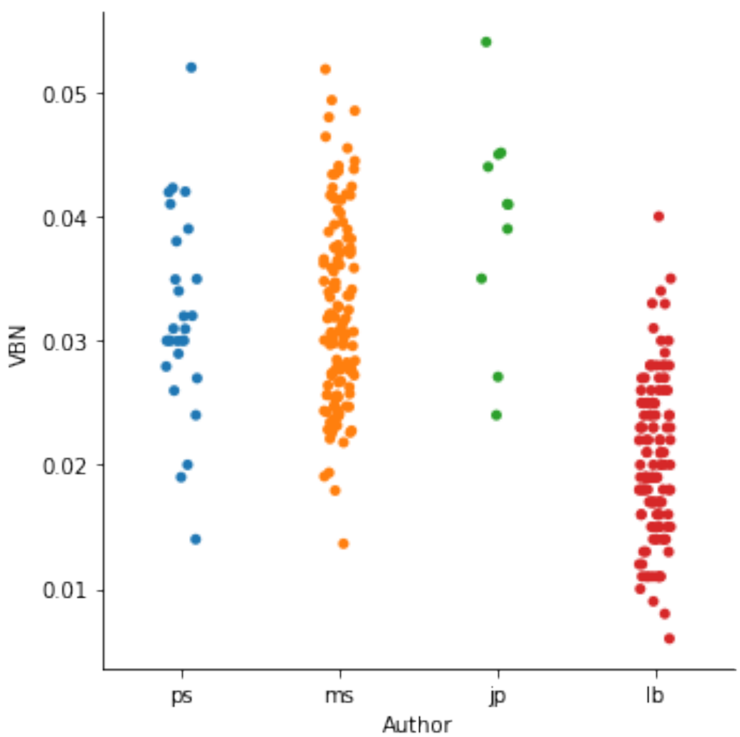

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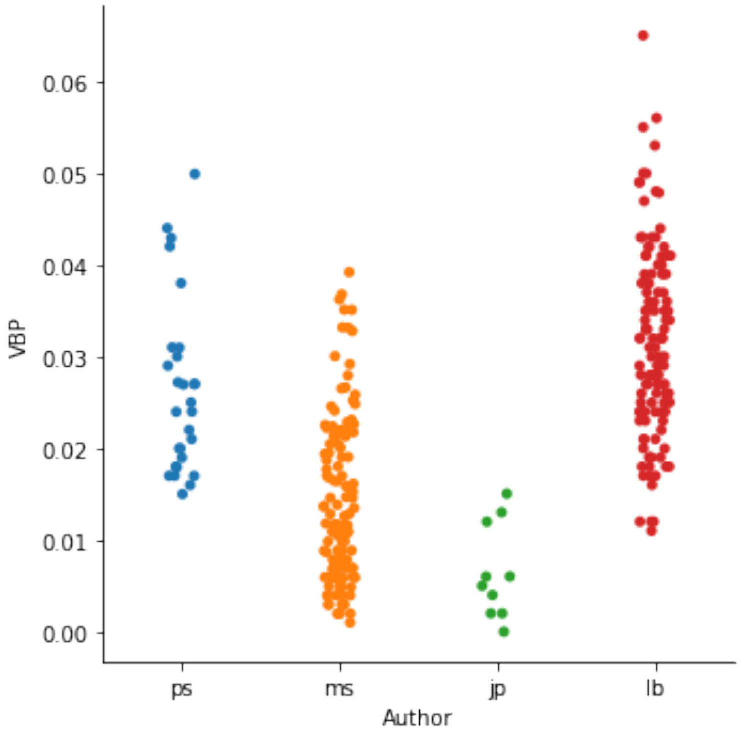
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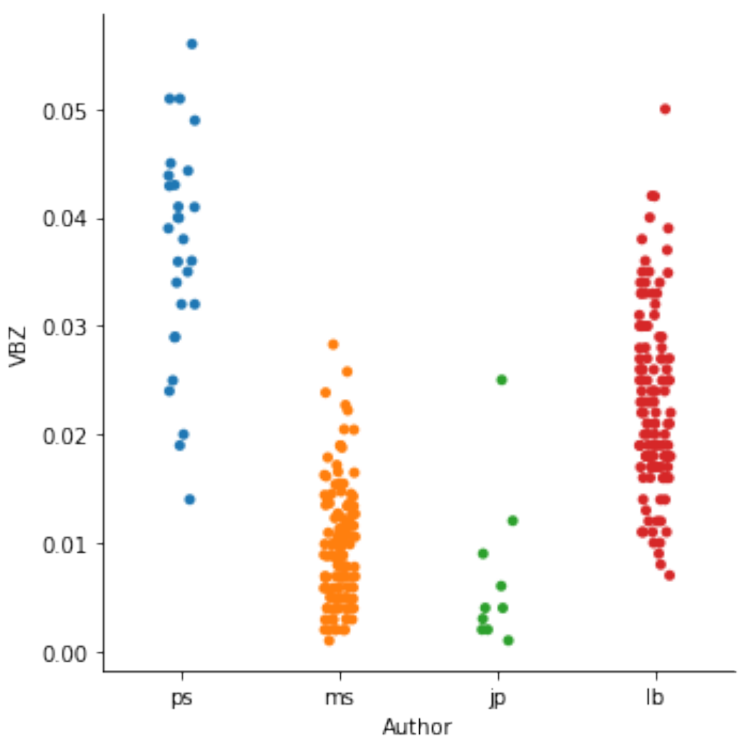
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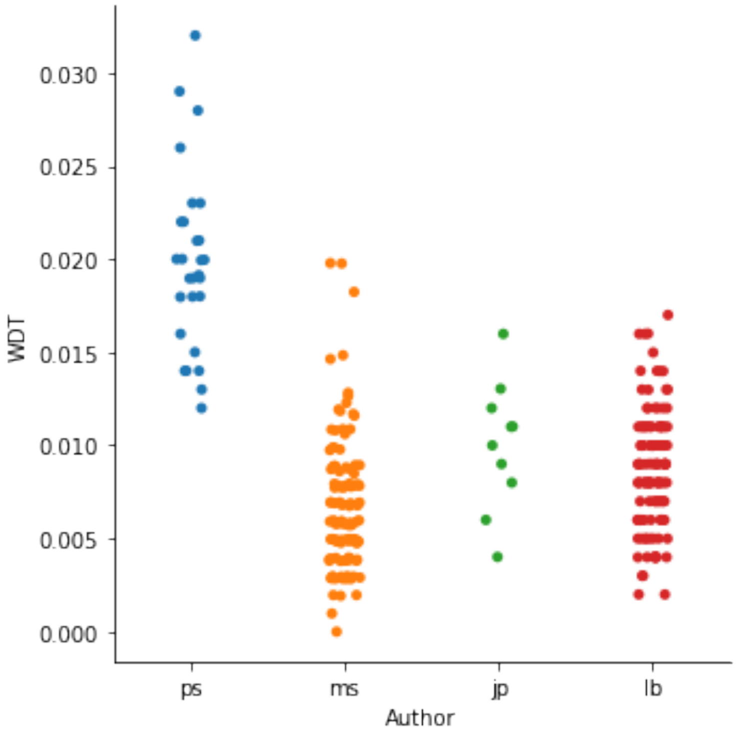
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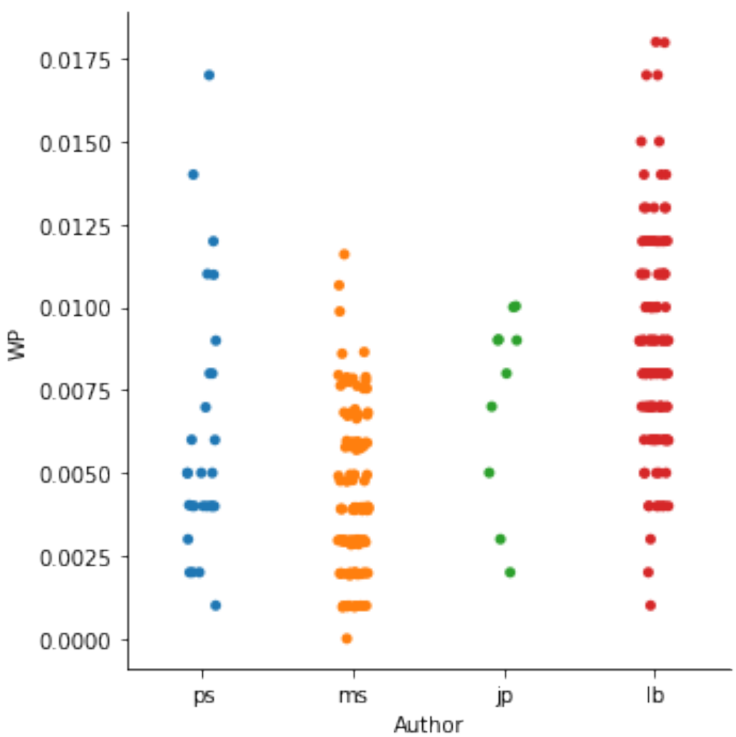
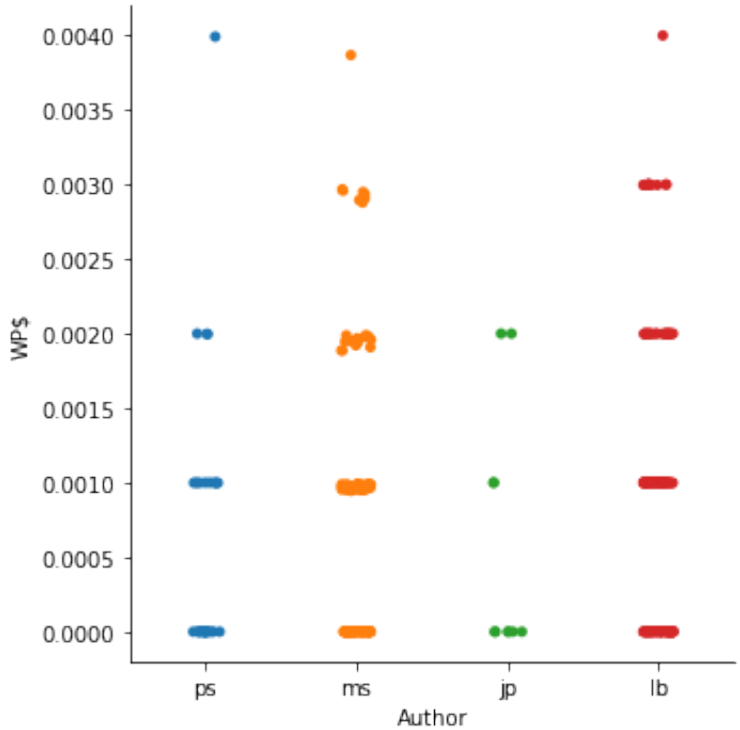
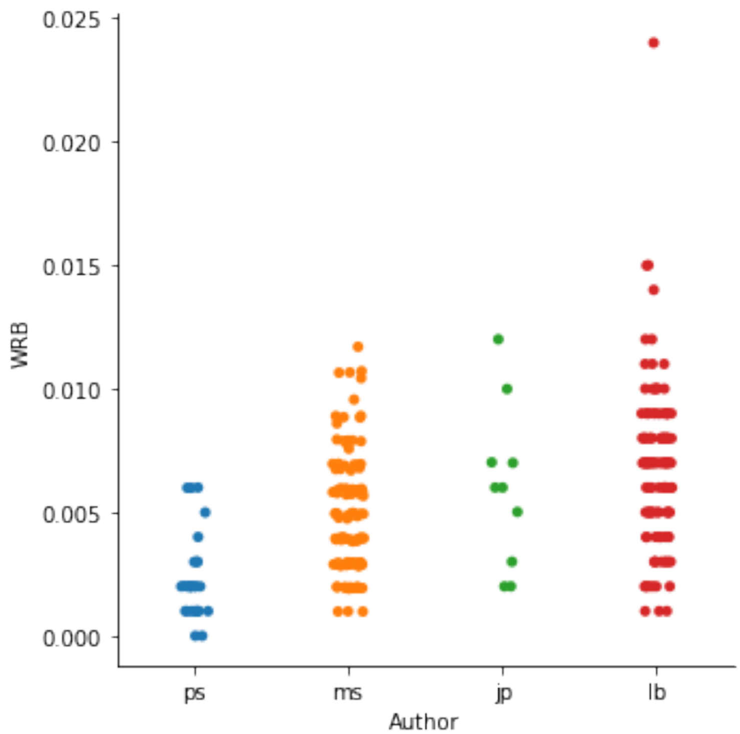
0.015
0.010
0.005
0.000
WDT
ps
ms
jp
lb
Author


0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
WP
ps
ms
jp
lb
Author





Technique one K-Nearest Neighbors

Traning and Analysis - Split test and Training Data

In [8]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, 31].values


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
20)
```

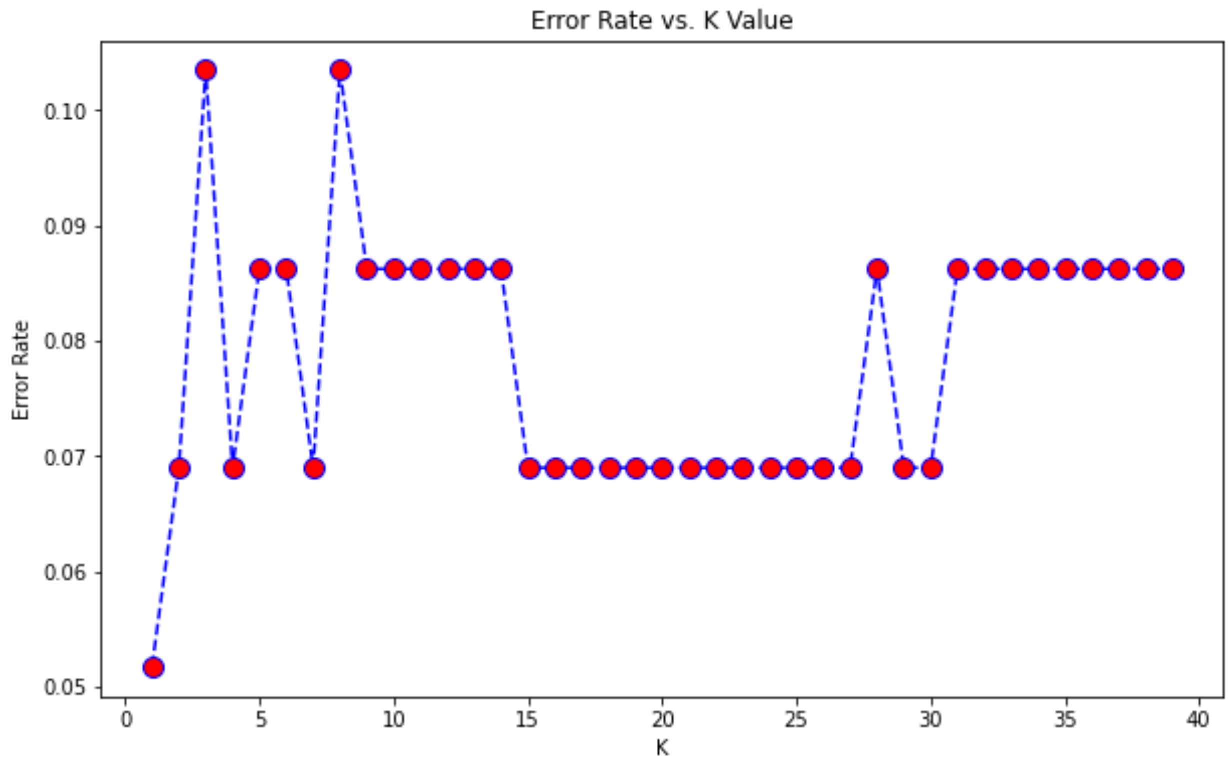
Normalization of Data

In [9]:
```
scaler = StandardScaler()
scaler.fit(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

KNN with results

In [25]:
```
error_rate = []
for i in range(1,40):
    classifier = KNeighborsClassifier(n_neighbors=i)
    classifier.fit(X_train, y_train)
    y_pred = classifier.predict(X_test)
    error_rate.append(np.mean(y_pred != y_test))

plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed', mark
er='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[25]: Text(0, 0.5, 'Error Rate')



In [33]:
```
minIndex = error_rate.index(min(error_rate))
print("Accuracy: " + str(1-error_rate[minIndex])+ " with a k value of: "+str(minIndex+1))
```

```
Accuracy: 0.9482758620689655 with a k value of: 1
```

Technique two - Naive Bayes

Traning and Analysis - Split test and Training Data

In [26]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, 31].values


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

Naive Bayes with results

In [29]:
```
#Create a Gaussian Classifier
gnb = GaussianNB()

#Train the model using the training sets
gnb.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = gnb.predict(X_test)


# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.9655172413793104
```

Technique three - Support Vector Machine

SVM training and results

In [35]:
```
clf = svm.SVC(kernel='linear')
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.3620689655172414
```

Reading in Frankenstein

> Below I read in Frankenstein, turned it into a ratio list as done above. I then manually added the values it printed out into the twodfranks list. I had to add it to a 2d array so it would work with the functions. Then I had it print out the predictions of author. Which it did predict ms or Mary Shelley.

In [44]:
```
franks = []
with open('fs.txt','r') as file:

    # reading each line
    for line in file:

        # reading each word
        for word in line.split():

            newString = newString + word
            newString = newString + " "



op_string = newString.translate(str.maketrans('', '', string.punctuati
on))
lower_case = op_string.lower()
tokens = nltk.word_tokenize(lower_case)
tags = nltk.pos_tag(tokens)
counts = Counter( tag for word,  tag in tags)
val= sum(counts.values())

counts = OrderedDict(sorted(counts.items()))
for x in orderedKeyList:
    writeable = counts.get(x,'0')
    franks.append(int(writeable)/val)

twodfranks = [[0.05160329, 0.00418558, 0.09588536, 0.00076617, 0.00043
984, 0.12515607,
 0.07192111, 0.00194381, 0.00200057, 0.01610386, 0.18558456, 0.0041430
2,
 0.04554484, 0.00107832, 0.05136209, 0.04344495, 0.05045403, 0.0018870
6,
 0.00096481, 0.00183031, 0.02724177, 0.04299092, 0.07385074, 0.0122304
2,
 0.03522985, 0.0203462,  0.00892452, 0.01000284, 0.00509364, 0.0006242
9,
 0.00712259]]
print(franks)
print("\n")
print("Author prediction using Naive Bayes: " + str(gnb.predict(twodfr
anks)))
```

```
[0.051603291713961406, 0.004185584562996595, 0.09588535754824064, 0.
0007661748013620886, 0.00043984108967082 86, 0.1251560726447219, 0.07
19211123723042, 0.0019438138479001136, 0.002000567536889898, 0.01610
3859250851307, 0.1855845629965948, 0.004143019296254257, 0.045544835
41430193, 0.0010783200908059023, 0.05136208853575482, 0.043444948921
67991, 0.050454029511918276, 0.0018870601589103292, 0.00096481271282
63337, 0.0018303064699205448, 0.02724177071509648, 0.042990919409761
64, 0.07385073779795687, 0.012230419977298524, 0.035229852440408625,
0.020346197502837685, 0.008924517593643587, 0.010002837684449489, 0.
005093643586833144, 0.0006242905788876277, 0.007122587968217934]
```

```
Author prediction using Naive Bayes: ['ms']
```

Conclusions

It is clear that SVM is not good at all at predicting the author in these circumstances. KNN did really well with and accuracy of 94.8 percent using a k value of 1. However, it was still beat out by naive bayes which I honestly expected. Naive Bayes acheived and accuracy of 96.5 percent. This is the model that I would use out of the three that I attempted.

In the cell above we ran the Frankenstein book through our Naive Bayes based model. It was able to correctly "according to common belief" attribute the authorship of Frankenstein to Mary Shelley.

Sources

https://www.guru99.com/pos-tagging-chunking-nltk.html (https://www.guru99.com/pos-tagging-chunking-nltk.html)
https://www.nltk.org/book/ch05.html (https://www.nltk.org/book/ch05.html)
https://stackoverflow.com/questions/52933862/sklearn-or-pandas-impute-missing-values-with-simple-linear-regression (https://stackoverflow.com/questions/52933862/sklearn-or-pandas-impute-missing-values-with-simple-linear-regression)
https://stackabuse.com/k-nearest-neighbors-algorithm-in-python-and-scikit-learn (https://stackabuse.com/k-nearest-neighbors-algorithm-in-python-and-scikit-learn)
https://www.geeksforgeeks.org/python-seaborn-pairplot-method/ (https://www.geeksforgeeks.org/python-seaborn-pairplot-method/)
https://towardsdatascience.com/data-science-titanic-challenge-solution-dd9437683dcf (https://towardsdatascience.com/data-science-titanic-challenge-solution-dd9437683dcf)
https://tryolabs.com/blog/2017/03/16/pandas-seaborn-a-guide-to-handle-visualize-data-elegantly/ (https://tryolabs.com/blog/2017/03/16/pandas-seaborn-a-guide-to-handle-visualize-data-elegantly/)
https://datascienceplus.com/k-nearest-neighbors-knn-with-python/ (https://datascienceplus.com/k-nearest-neighbors-knn-with-python/)
https://www.datacamp.com/community/tutorials/svm-classification-scikit-learn-python (https://www.datacamp.com/community/tutorials/svm-classification-scikit-learn-python)