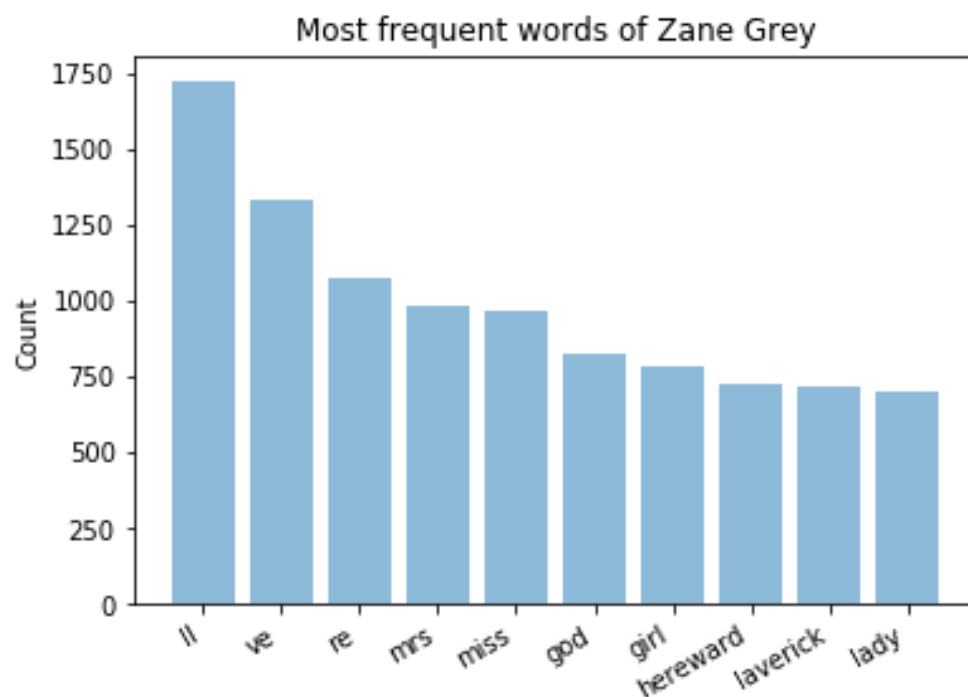
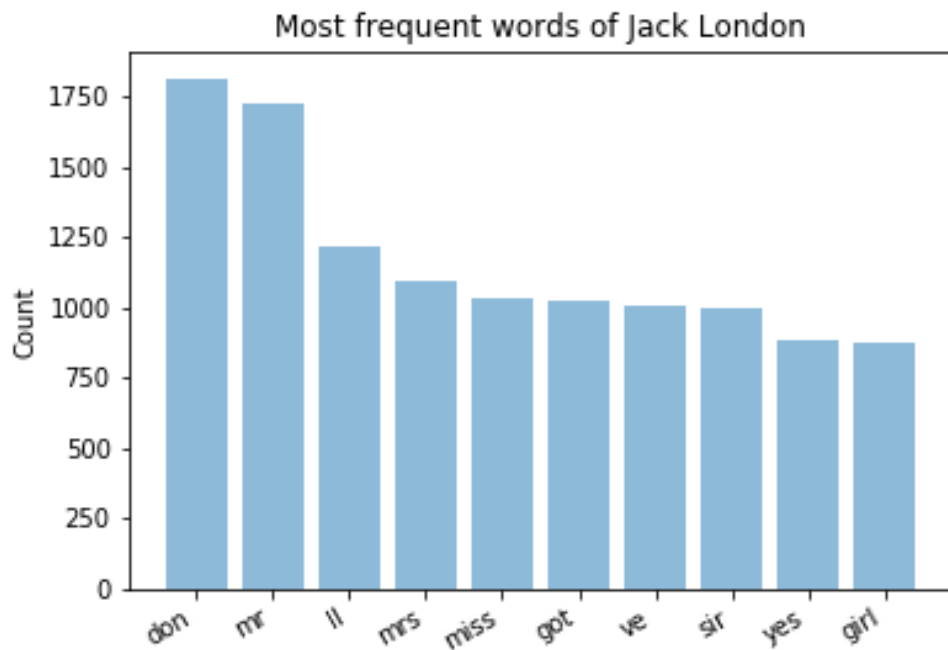


Homework 2: Support Vector Machines & Clustering

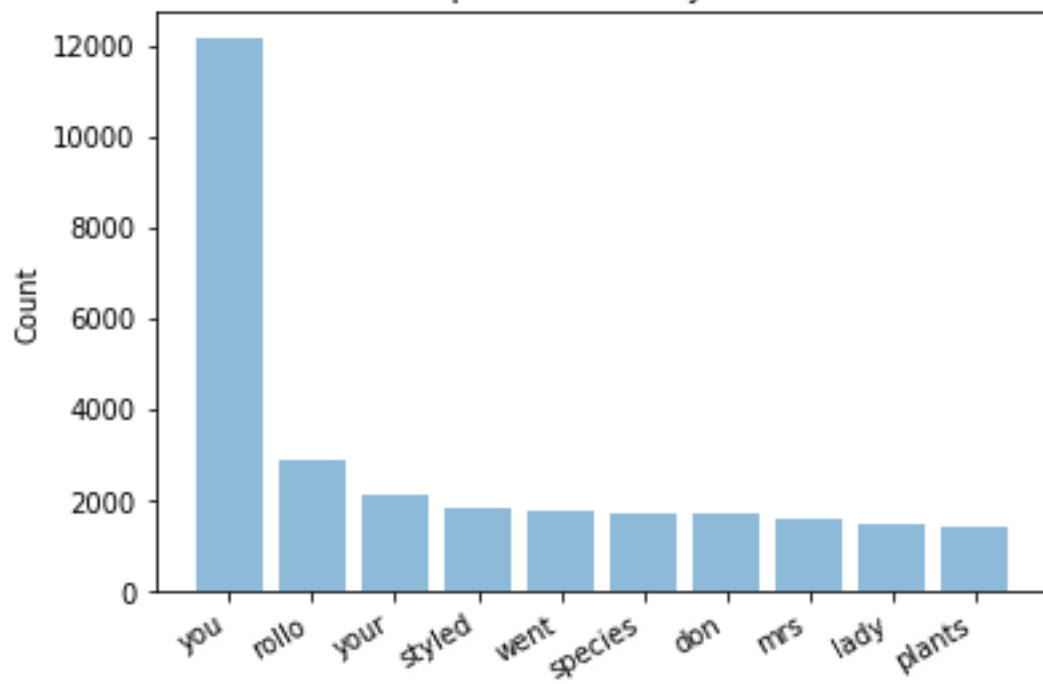
Dumitrescu Gabriel Horia

I) Data Visualization

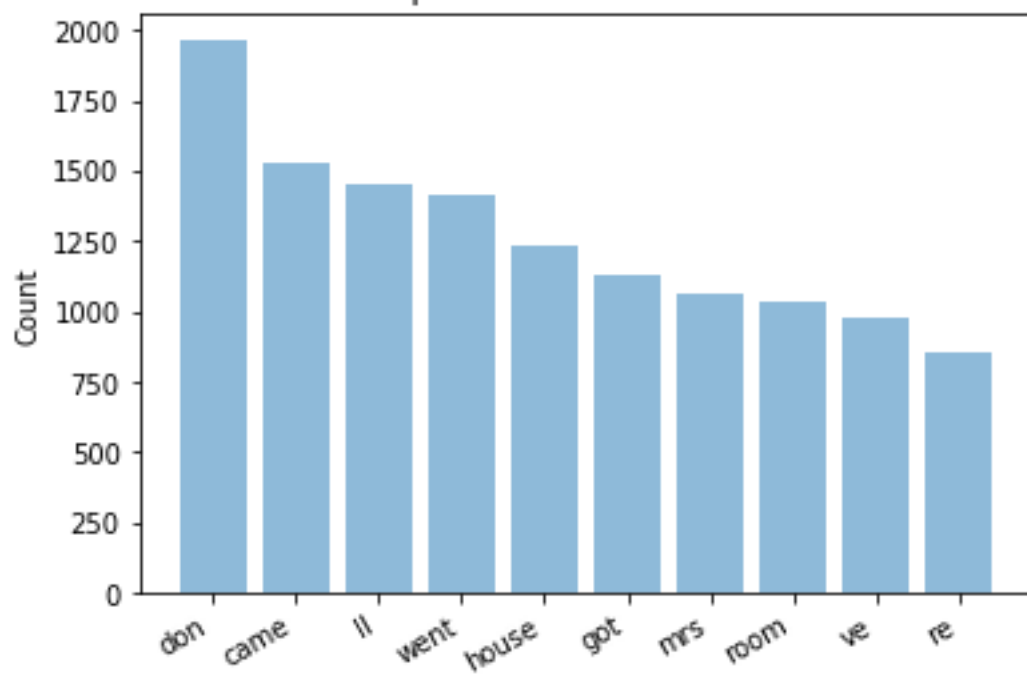
a) Common author words



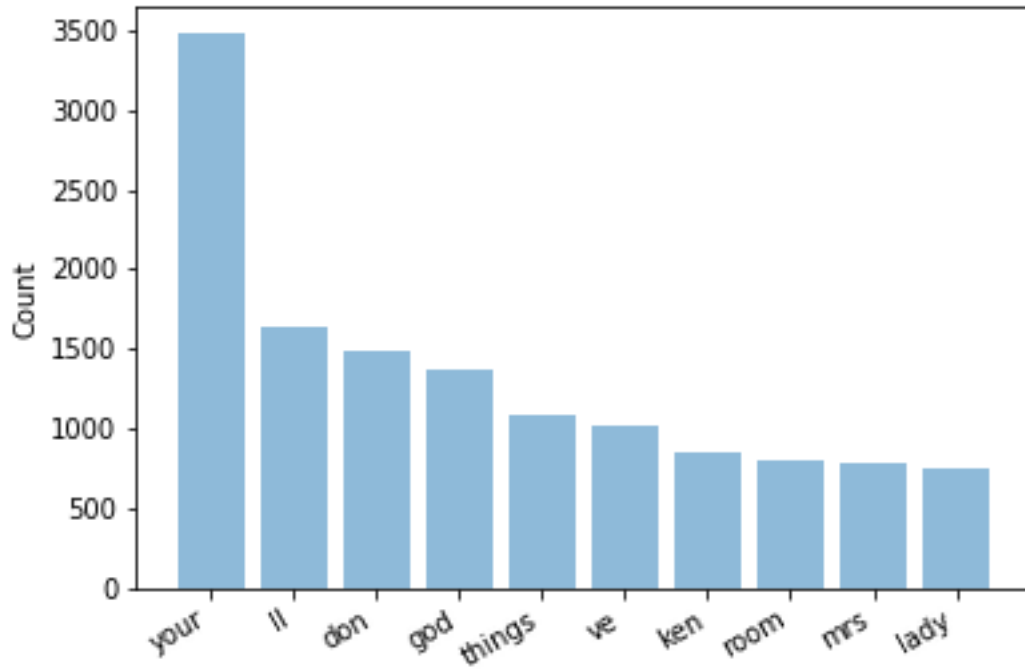
Most frequent words of Jacob Abbott



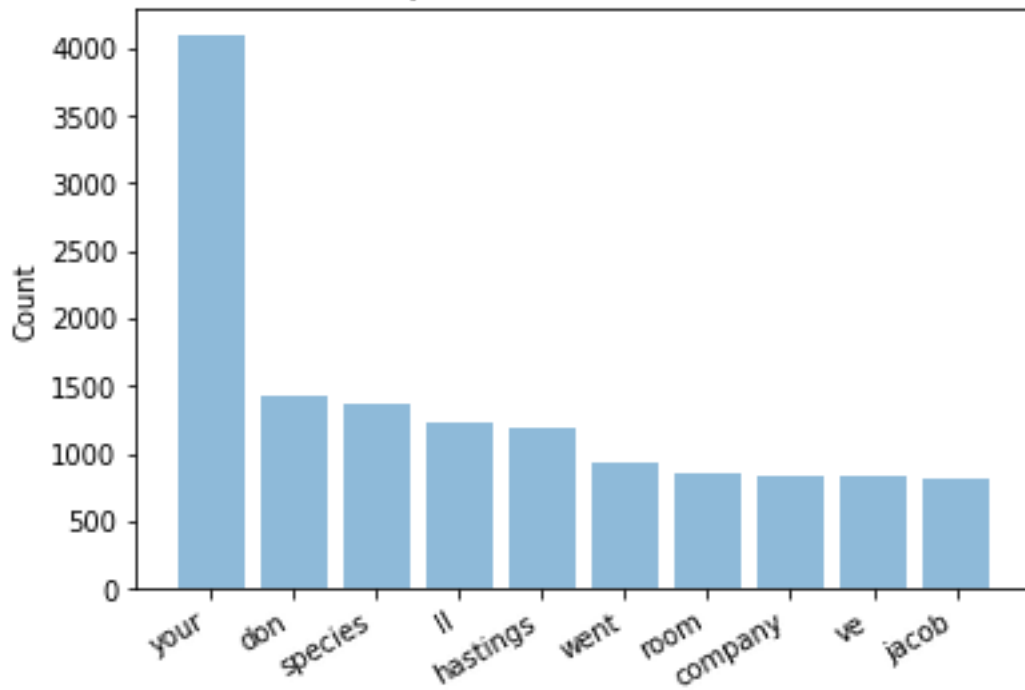
Most frequent words of P G Wodehouse



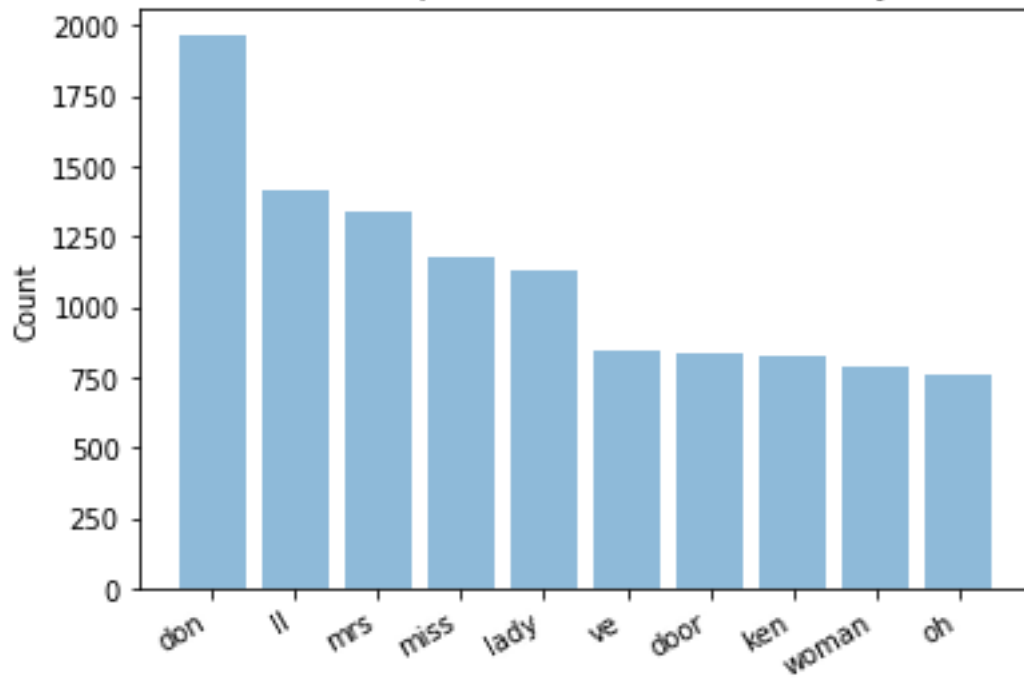
Most frequent words of R M Ballantyne



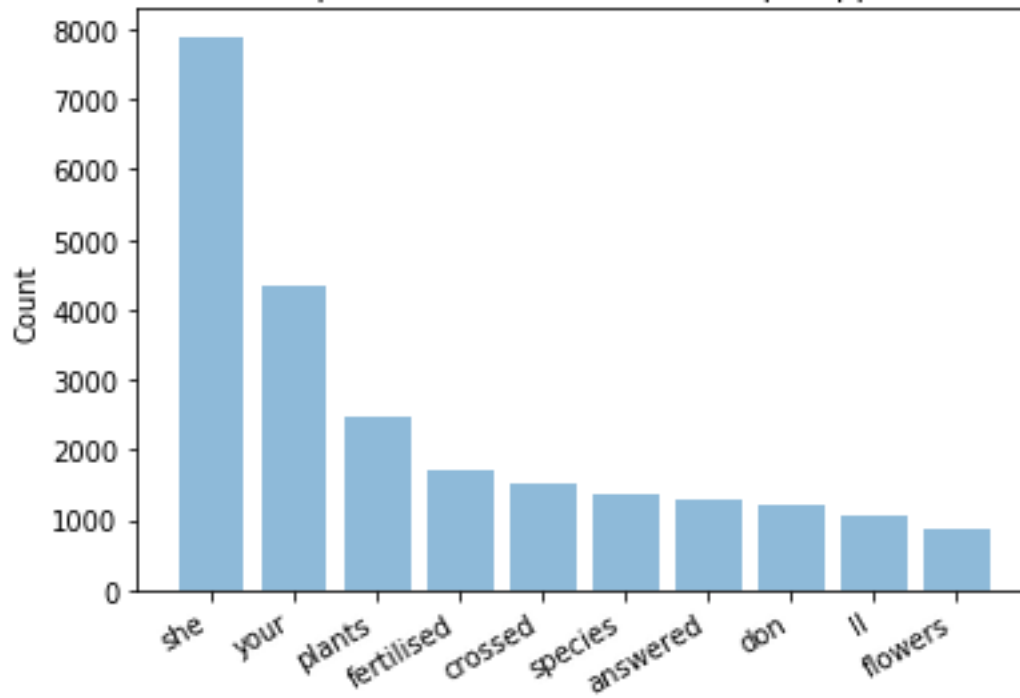
Most frequent words of Harold Bindloss



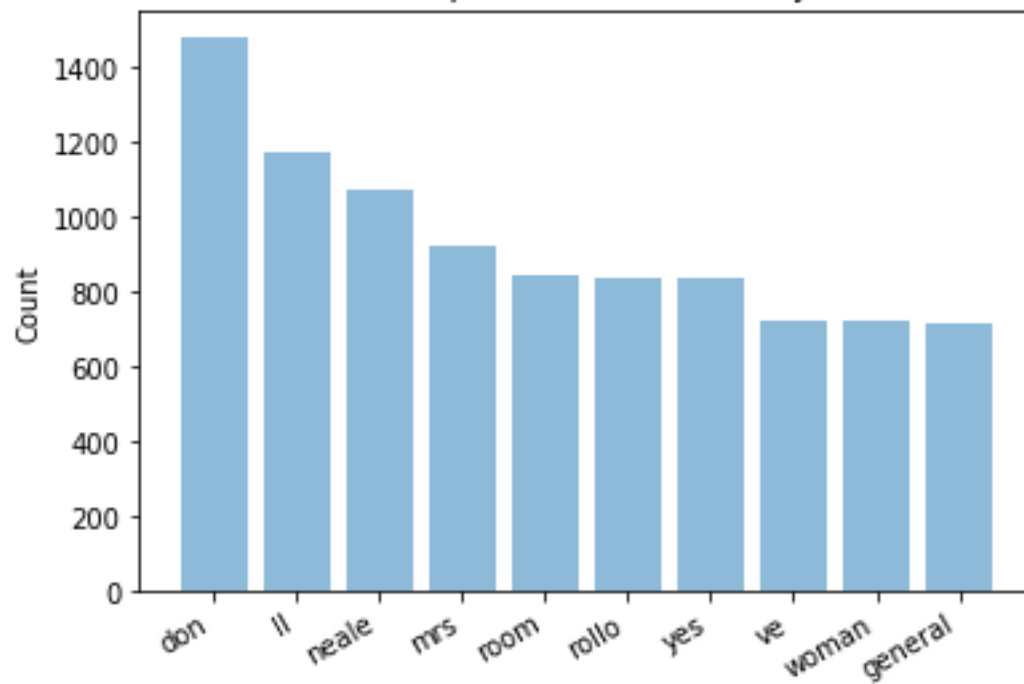
Most frequent words of Thomas Hardy



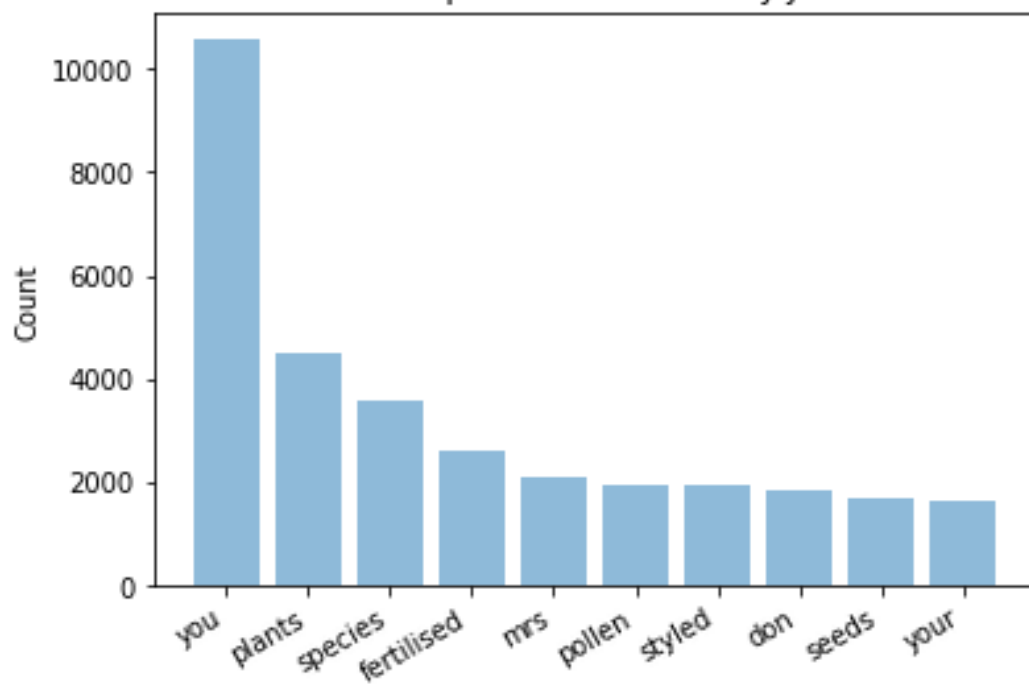
Most frequent words of Edward Phillips Oppenheim



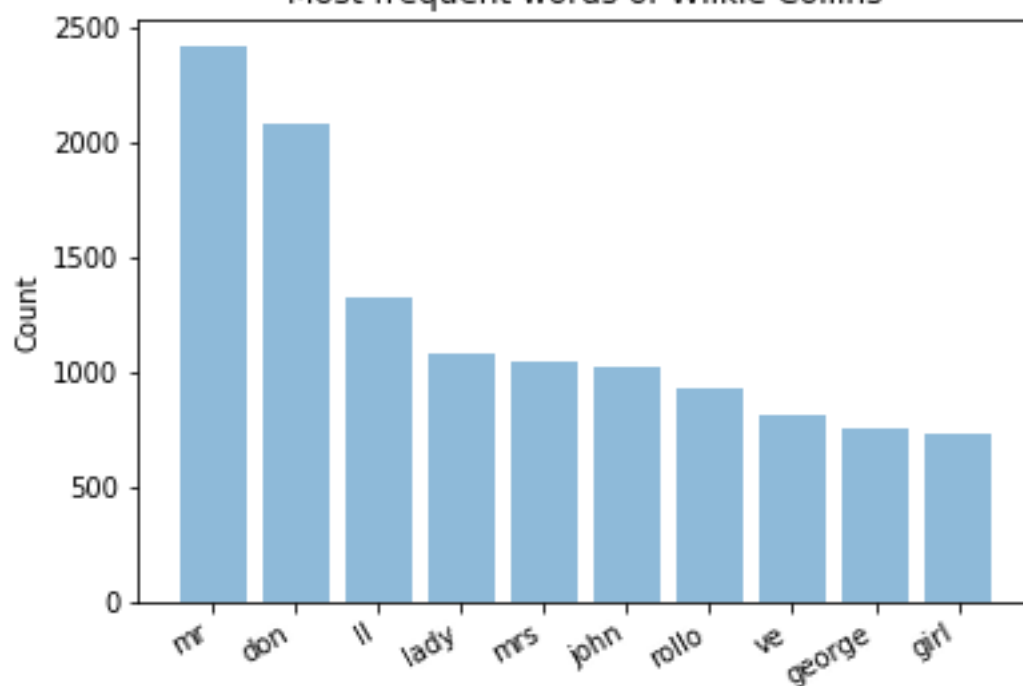
Most frequent words of Lord Byron



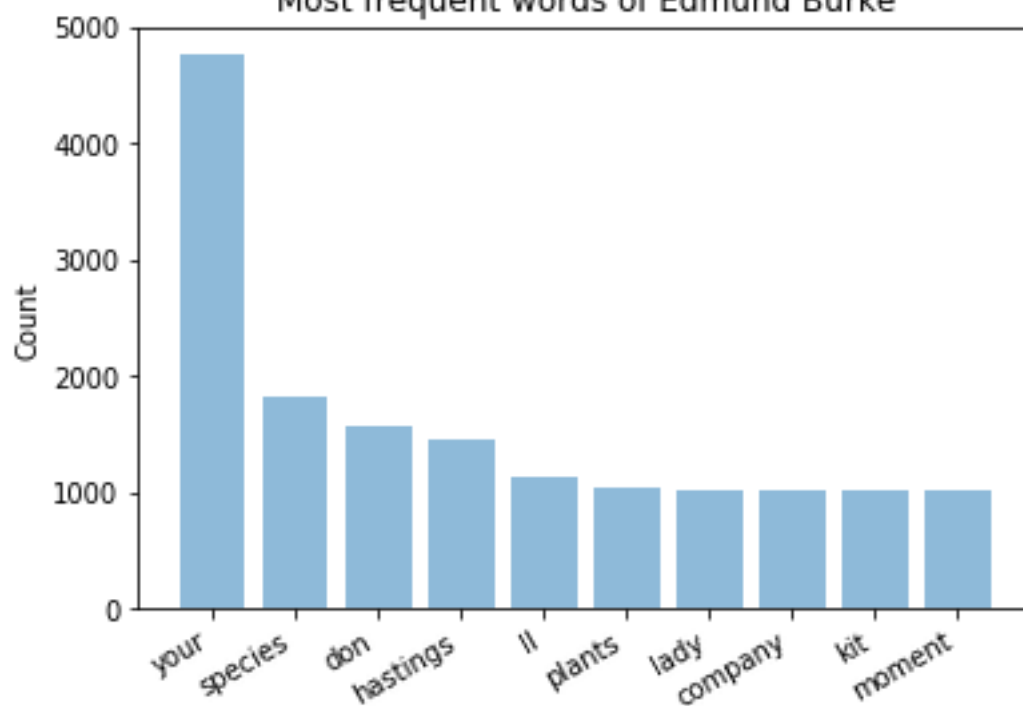
Most frequent words of Henry James

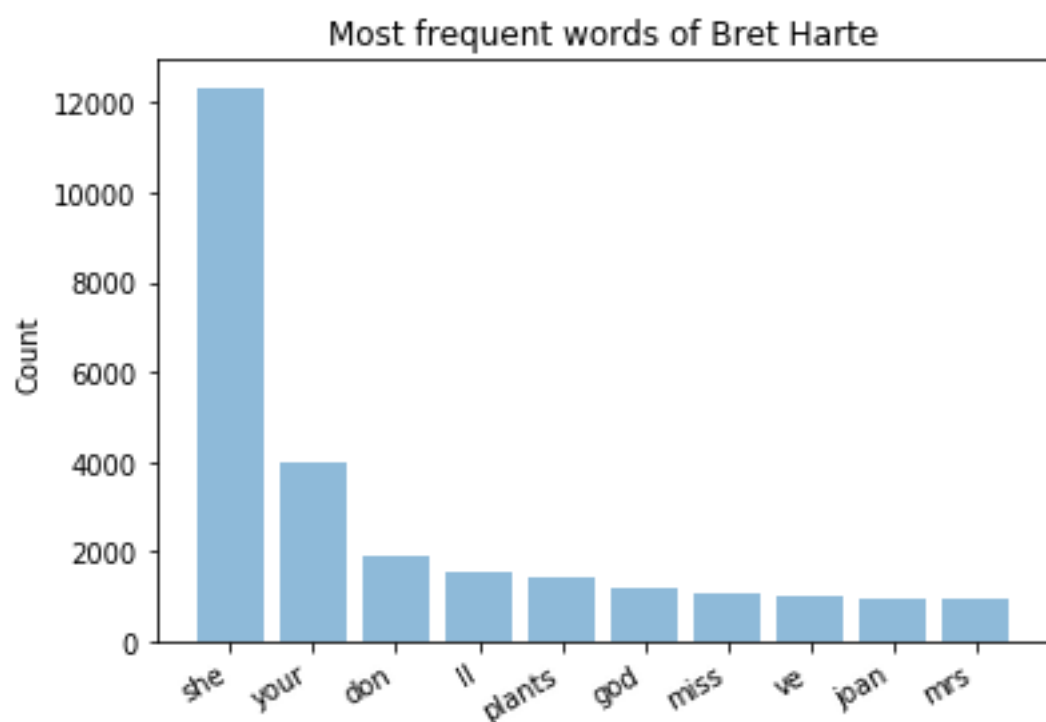
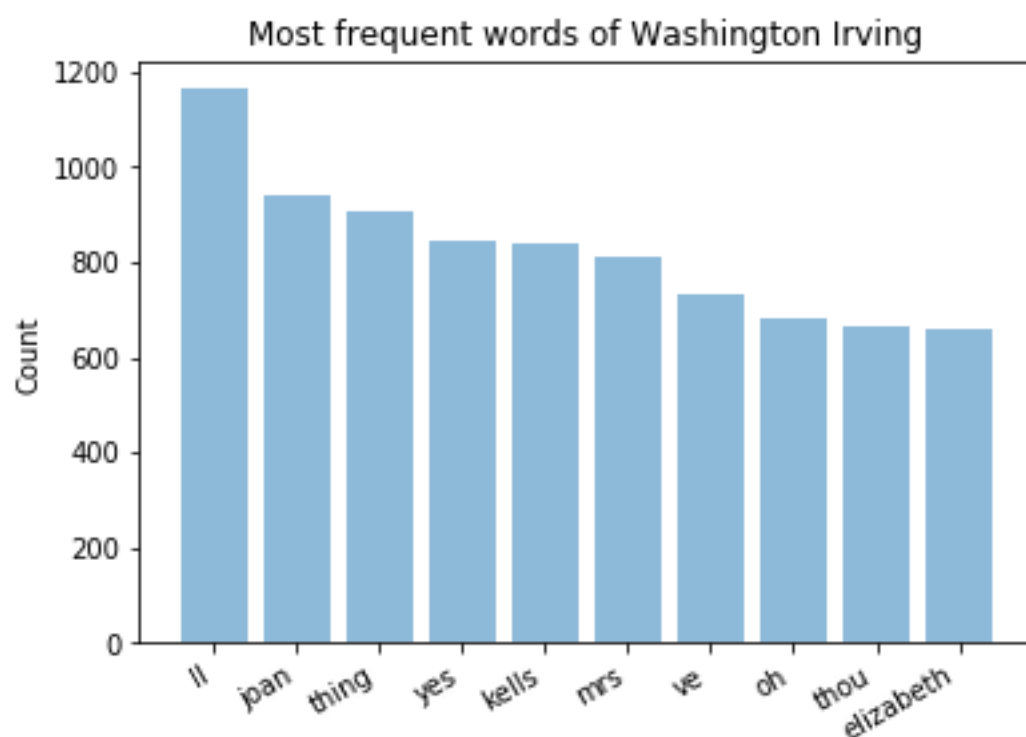


Most frequent words of Wilkie Collins

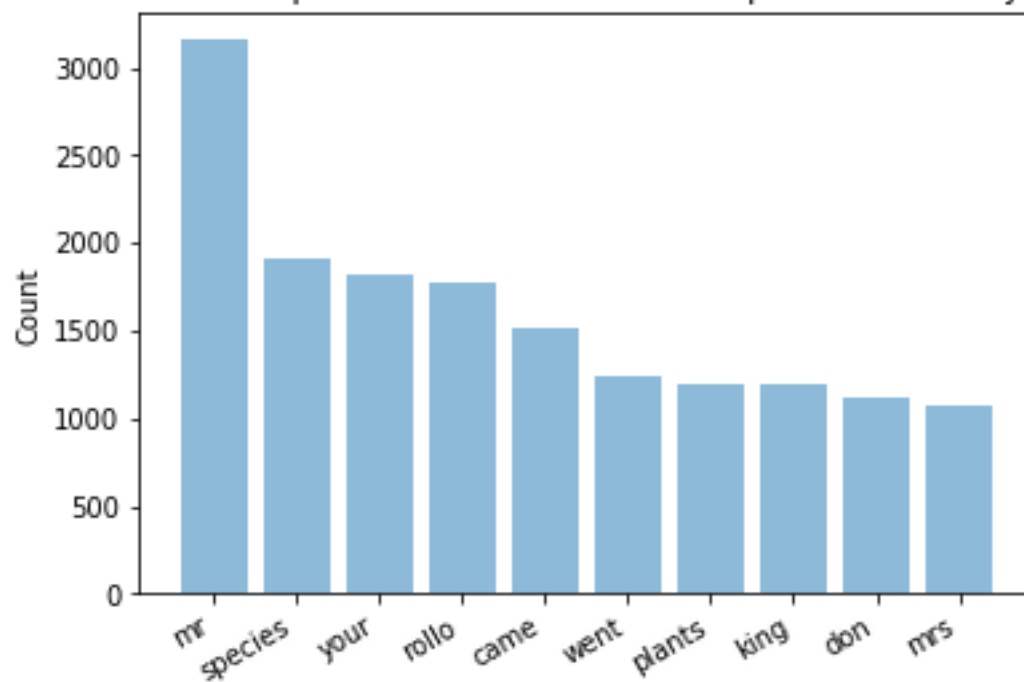


Most frequent words of Edmund Burke

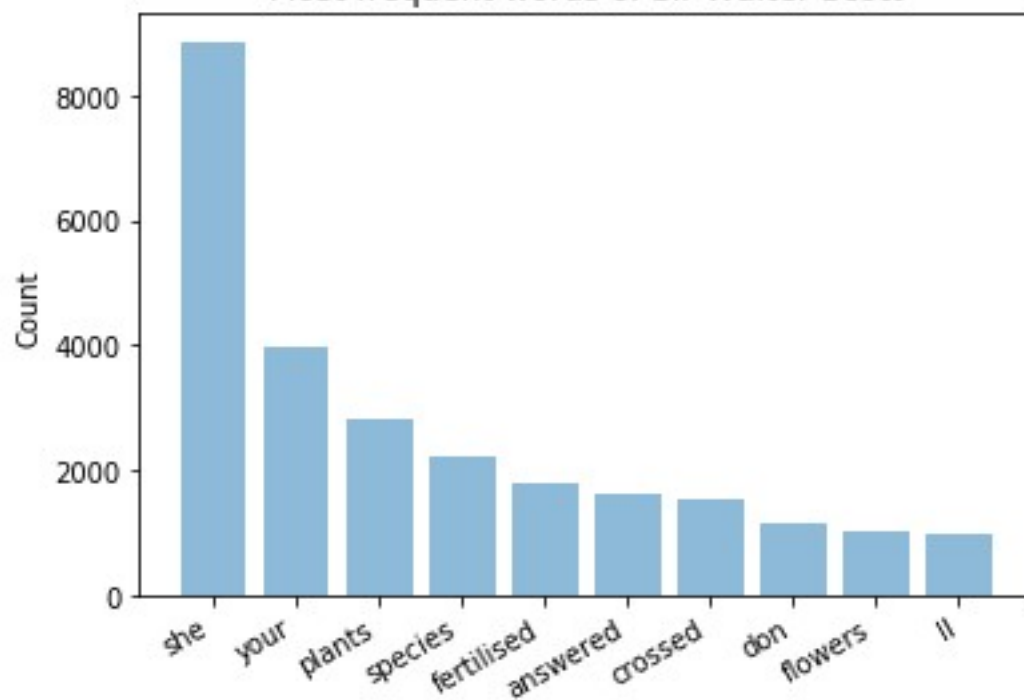


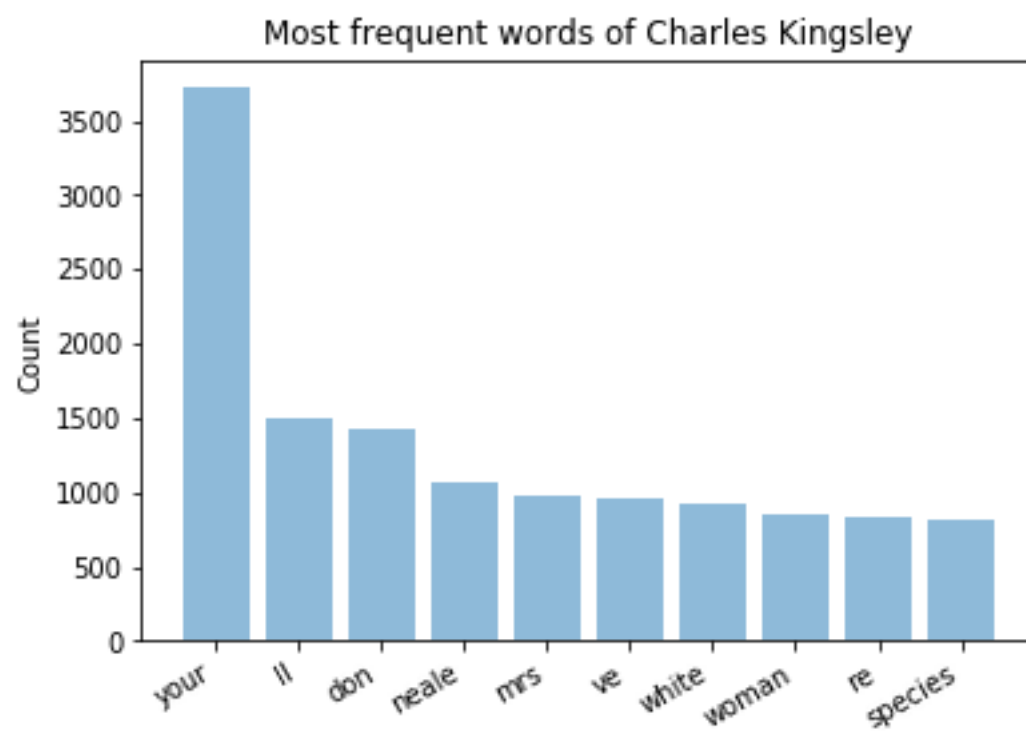
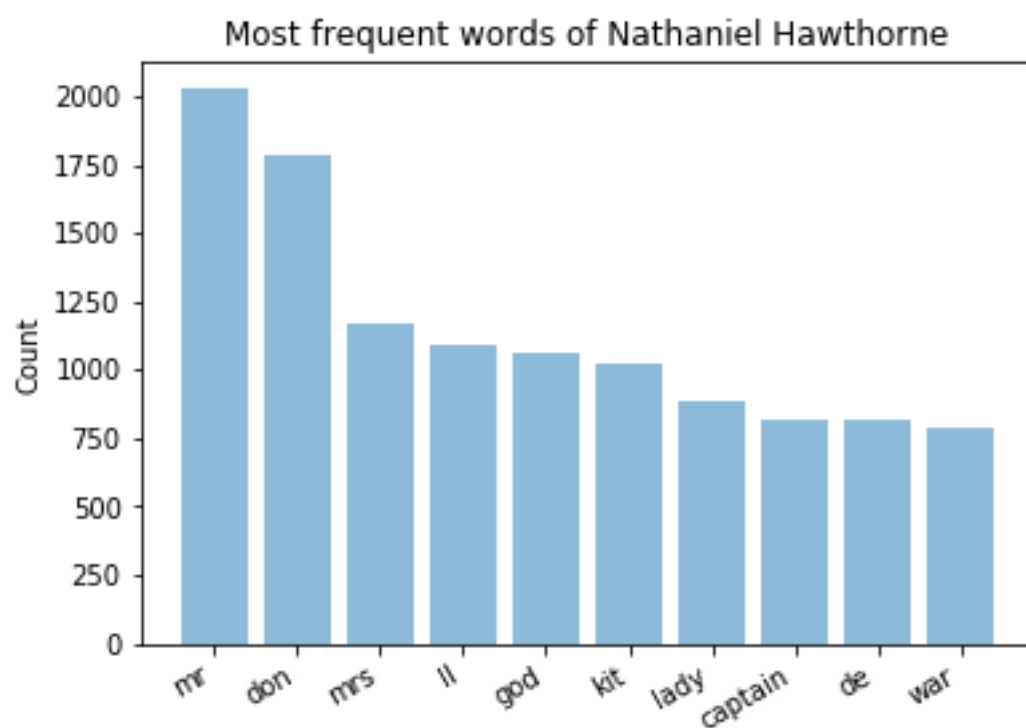


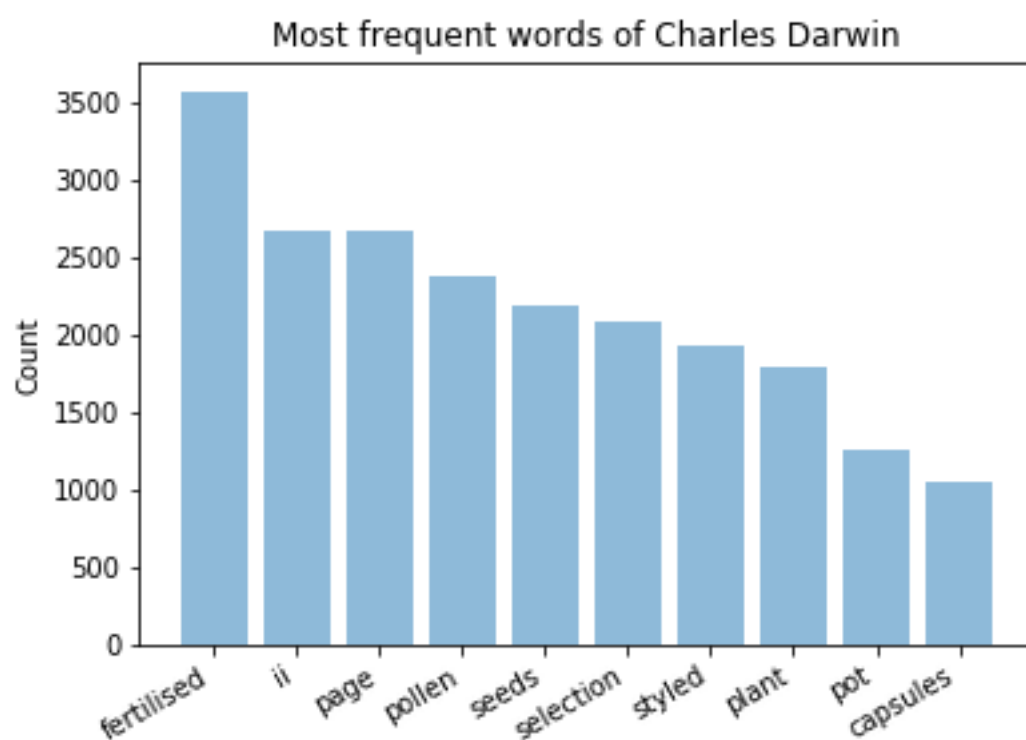
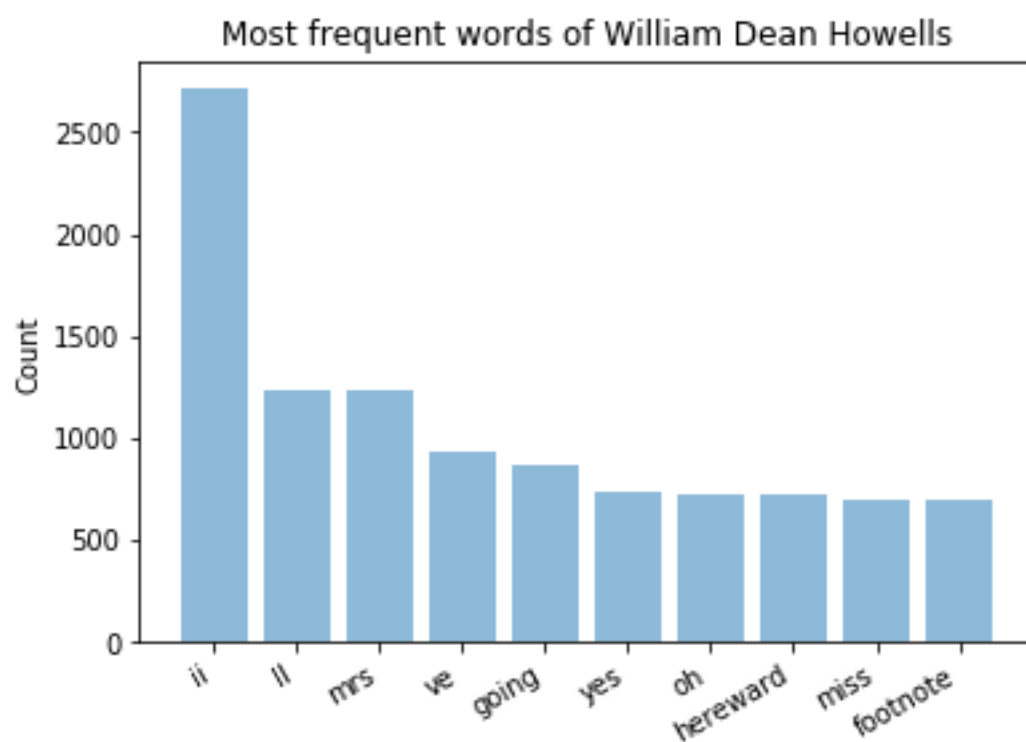
Most frequent words of William Makepeace Thackeray



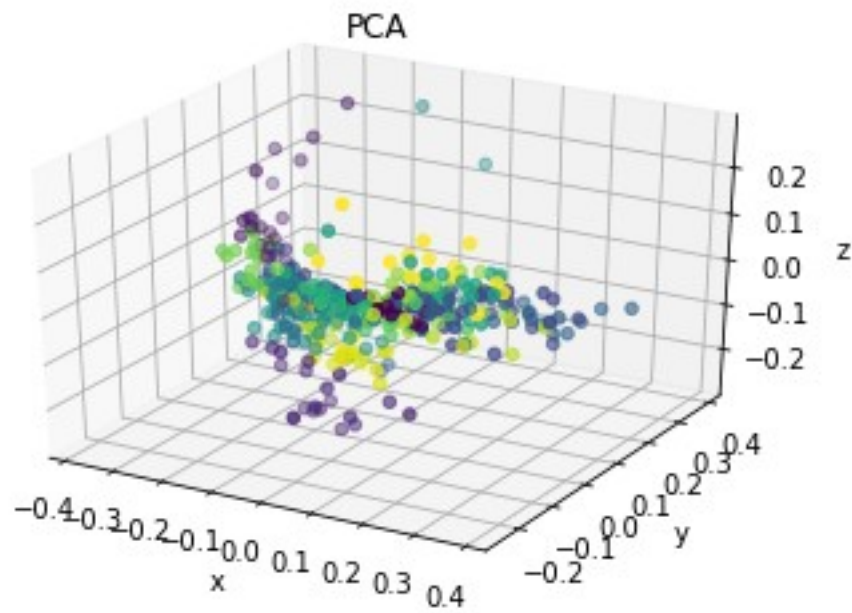
Most frequent words of Sir Walter Scott



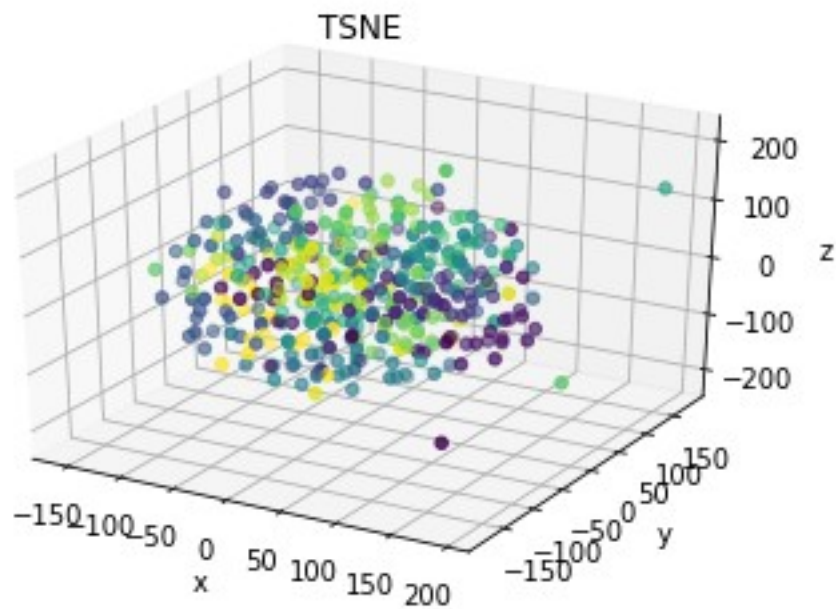




b)PCA Visualization(In jupyter notebook this can be rotated)



c)TSNE Visualization



II) Data preprocessing

a) I dropped the 'Unnamed: 0' column;

b) I created X, an array of 400 books and y, an array of their author names;

c) I encoded y with numeric values;

d) I represented the book texts in 3 ways:

-count vectorizer: it was useful for plotting the count of words ;

-tfidf vectorizer: it was fast and yielded the best results for all of my models;

-word2vec: unfortunately this method was very expensive computationally. No matter how much I played with the parameters and tried to optimize the code, this process takes a lot of time and, most importantly, a lot of RAM. The only way I could get this to not receive a memory error was trimming it down so much, that it was too simple of a notation to represent the books (more on its performance later). In the future, I'll use this for shorter documents, on computers with more ram and with stemming done beforehand. Another good solution is using sentence2vec or doc2vec instead;

e) I reduced the dimensionality of X to 400 (the number of samples), by using PCA. This increased performance, especially training time;

f) For classification, I split the data into : X_train, X_test, y_train, y_test with a ratio of 0.8 for training and 0.2 for testing. I used StratifiedShuffleSplit from sklearn to preserve the percentage of samples for each class;

h) Tfidf and count vectorizers removed accents and performed other character normalizations

I) I stemmed all words. Warning: stemming takes a lot of time the first time.

[illegible]

```

SUPPORT VECTOR MACHINES
Accuracy: 1.0

Macro Precision: 1.0
Micro Precision: 1.0
Weighted Precision: 1.0

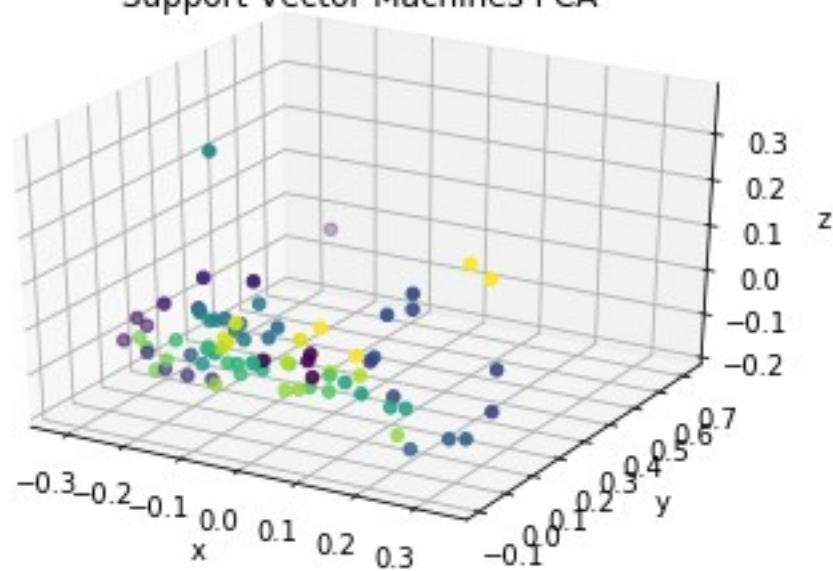
Macro Recall: 1.0
Micro Recall: 1.0
Weighted Recall: 1.0

Macro F1: 1.0
Micro F1: 1.0
Weighted F1: 1.0

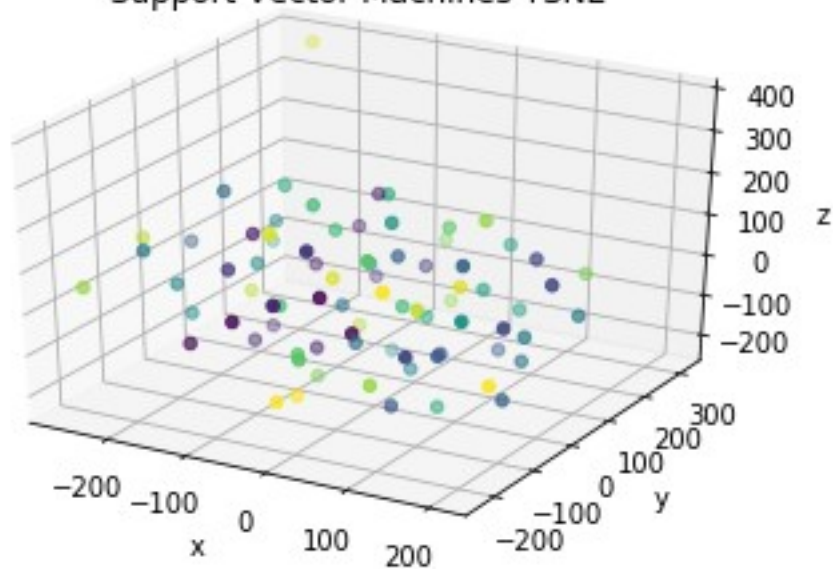
```

	precision	recall	f1-score	support
Jack London	1.00	1.00	1.00	4
Zane Grey	1.00	1.00	1.00	4
P G Wodehouse	1.00	1.00	1.00	4
Harold Bindloss	1.00	1.00	1.00	4
Jacob Abbott	1.00	1.00	1.00	4
R M Ballantyne	1.00	1.00	1.00	4
Thomas Hardy	1.00	1.00	1.00	4
Edward Phillips Oppenheim	1.00	1.00	1.00	4
Lord Byron	1.00	1.00	1.00	4
Henry James	1.00	1.00	1.00	4
Wilkie Collins	1.00	1.00	1.00	4
Edmund Burke	1.00	1.00	1.00	4
Washington Irving	1.00	1.00	1.00	4
Bret Harte	1.00	1.00	1.00	4
William Makepeace Thackeray	1.00	1.00	1.00	4
Sir Walter Scott	1.00	1.00	1.00	4
Nathaniel Hawthorne	1.00	1.00	1.00	4
Charles Kingsley	1.00	1.00	1.00	4
William Dean Howells	1.00	1.00	1.00	4
Charles Darwin	1.00	1.00	1.00	4
avg / total	1.00	1.00	1.00	80

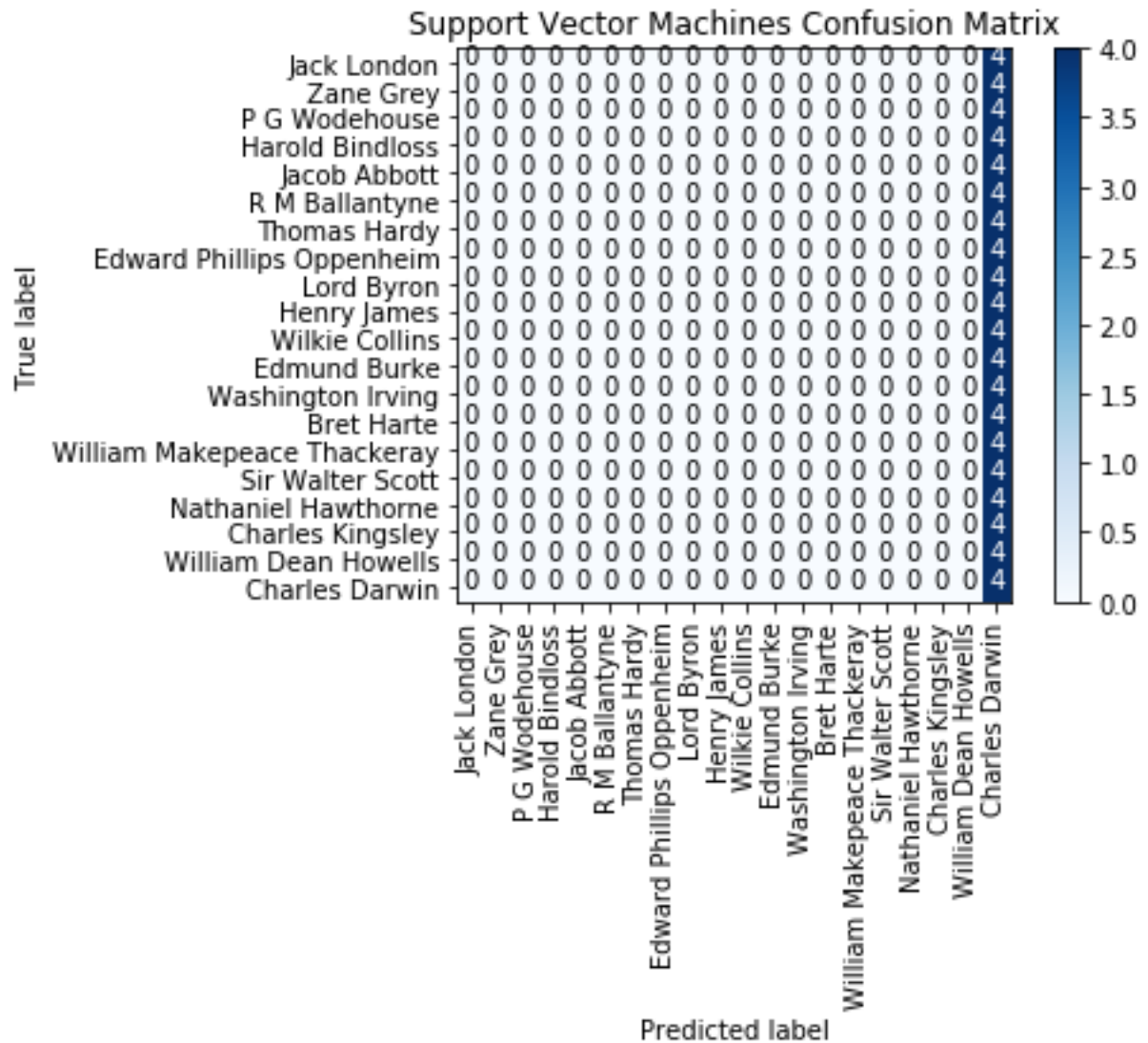
Support Vector Machines PCA



Support Vector Machines TSNE



But, with the input from word2vec, even SVM had terrible performance. It only guessed Charles Darwin.




```

Splitting done
Training done
Vectorization done
400 112015 6
Nddarray conversion done

SUPPORT VECTOR MACHINES
Accuracy: 0.05

Macro Precision: 0.0025
Micro Precision: 0.05
Weighted Precision: 0.0025

Macro Recall: 0.05
Micro Recall: 0.05
Weighted Recall: 0.05

Macro F1: 0.0047619047619047615
Micro F1: 0.050000000000000001
Weighted F1: 0.0047619047619047615

```

	precision	recall	f1-score	support
Jack London	0.00	0.00	0.00	4
Zane Grey	0.00	0.00	0.00	4
P G Wodehouse	0.00	0.00	0.00	4
Harold Bindloss	0.00	0.00	0.00	4
Jacob Abbott	0.00	0.00	0.00	4
R M Ballantyne	0.00	0.00	0.00	4
Thomas Hardy	0.00	0.00	0.00	4
Edward Phillips Oppenheim	0.00	0.00	0.00	4
Lord Byron	0.00	0.00	0.00	4
Henry James	0.00	0.00	0.00	4
Wilkie Collins	0.00	0.00	0.00	4
Edmund Burke	0.00	0.00	0.00	4
Washington Irving	0.00	0.00	0.00	4
Bret Harte	0.00	0.00	0.00	4
William Makepeace Thackeray	0.00	0.00	0.00	4
Sir Walter Scott	0.00	0.00	0.00	4
Nathaniel Hawthorne	0.00	0.00	0.00	4
Charles Kingsley	0.00	0.00	0.00	4
William Dean Howells	0.00	0.00	0.00	4
Charles Darwin	0.05	1.00	0.10	4
avg / total	0.00	0.05	0.00	80

IV) Clustering

a) K-MEANS Clustering

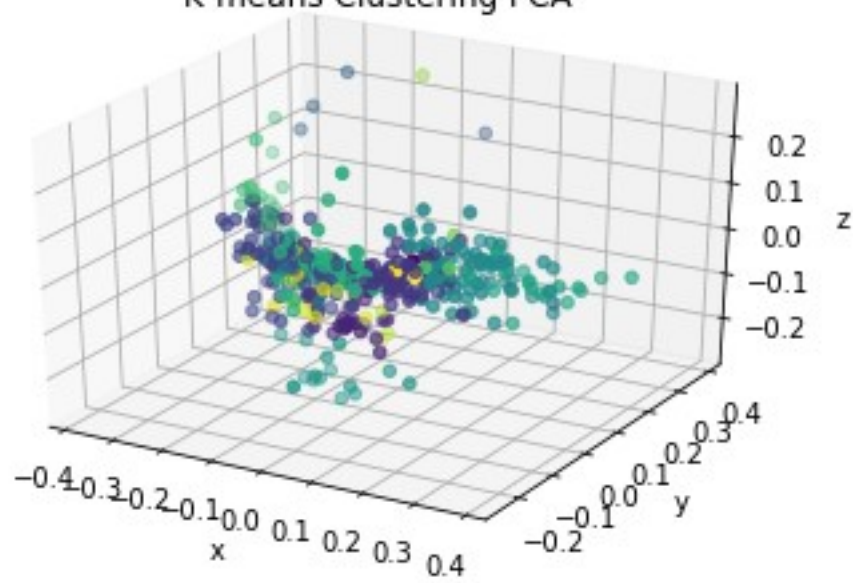
This clustering method was okay. I played around with parameters in search of a better clustering. I searched all of the scores I could find and even invented one myself and calculated the mean of the scores. I experimentally tried grid searching based on that score, but I was unsuccessful. The visualizations look a bit different to the real labels. I plotted a contingency matrix to see what clusters it considers.

```
K-MEANS CLUSTERING
Adjusted random score: 0.3313898857705675
Silhouette score: 0.027653979987670906
Homogeneity score: 0.6017368344966921
Completeness score: 0.7606545580556893
V-measure score: 0.6719271252182586
Fowlkes-Mallows score: 0.4198204822089874
Calinski-Harabaz score: 10.412352898355994
Supervised-like Accuracy: 0.36
Mean Score: 0.4533118379625522
```

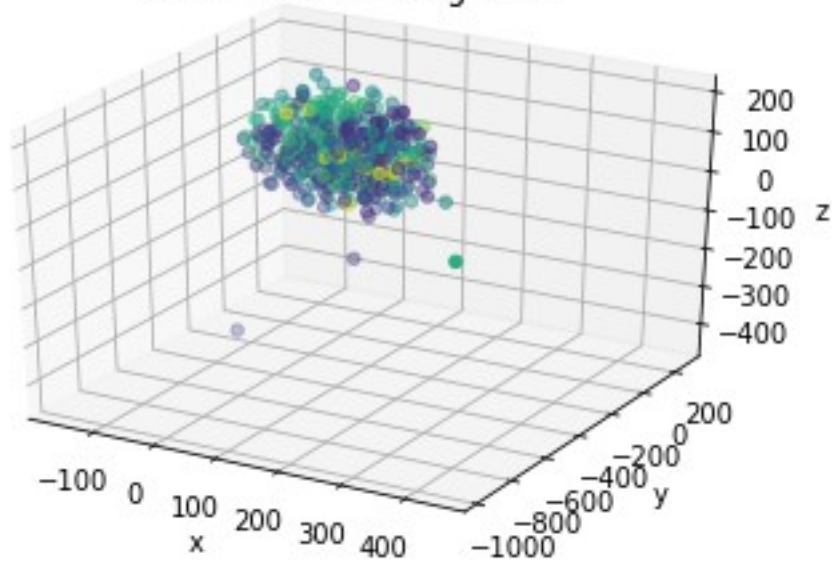
K-means Clustering Contingency Matrix

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Jack London	17	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0
Zane Grey	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P G Wodehouse	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Harold Bindloss	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jacob Abbott	0	0	0	0	10	1	0	0	0	0	0	0	0	0	0	0	0	9	0	0
R M Ballantyne	1	0	0	0	5	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomas Hardy	0	0	2	0	0	0	13	3	0	0	0	0	0	0	0	0	0	0	2	0
Edward Phillips Oppenheim	17	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
Lord Byron	1	0	0	0	0	0	0	12	7	0	0	0	0	0	0	0	0	0	0	0
Henry James	0	0	0	0	0	0	0	1	0	17	0	0	0	0	0	0	1	0	0	1
Wilkie Collins	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0
Edmund Burke	0	0	0	0	19	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Washington Irving	10	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0
Bret Harte	0	0	0	0	0	0	0	16	0	2	0	1	0	1	0	0	0	0	0	0
William Makepeace Thackeray	0	0	0	0	0	1	0	0	0	0	0	19	0	0	0	0	0	0	0	0
Sir Walter Scott	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0
Nathaniel Hawthorne	0	0	0	0	1	0	0	2	0	0	0	17	0	0	0	0	0	0	0	0
Charles Kingsley	5	0	1	0	0	8	0	4	0	0	0	0	0	0	0	0	0	2	0	0
William Dean Howells	10	0	1	0	0	0	0	4	0	0	0	0	0	0	0	5	0	0	0	0
Charles Darwin	7	0	0	0	7	3	0	0	0	0	0	0	1	0	1	0	0	1	0	0

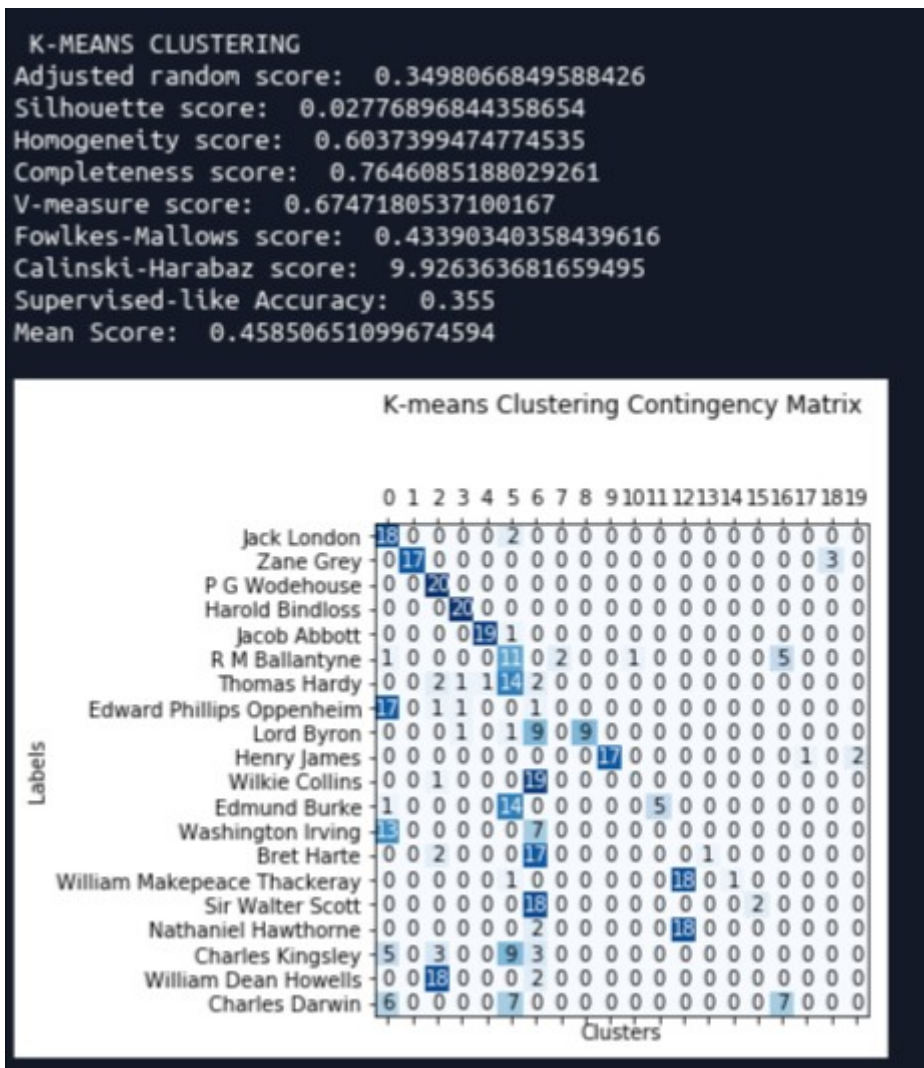
K-means Clustering PCA



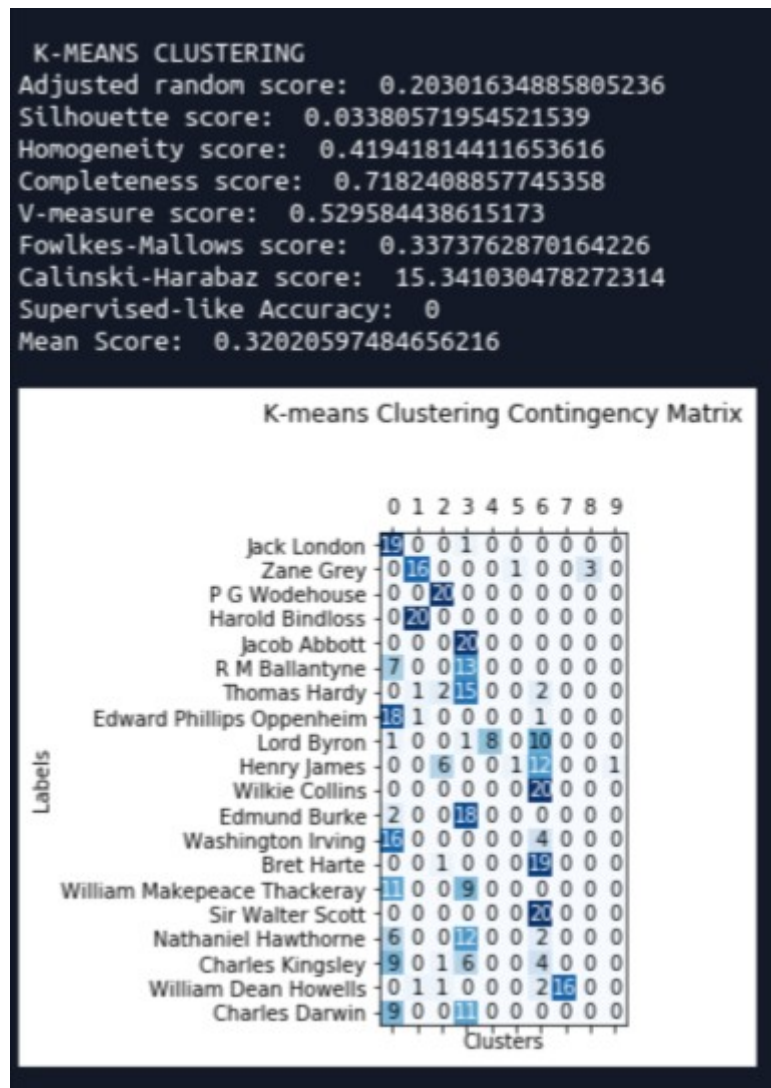
K-means Clustering TSNE



The scores are slightly lower with a 'random' init instead of the default 'kmeans++' and the clusters are a bit more uneven,



Also, these are the clusters it considers for n_components=10:



This clustering was very uneven and had low scores.

b) DBSCAN

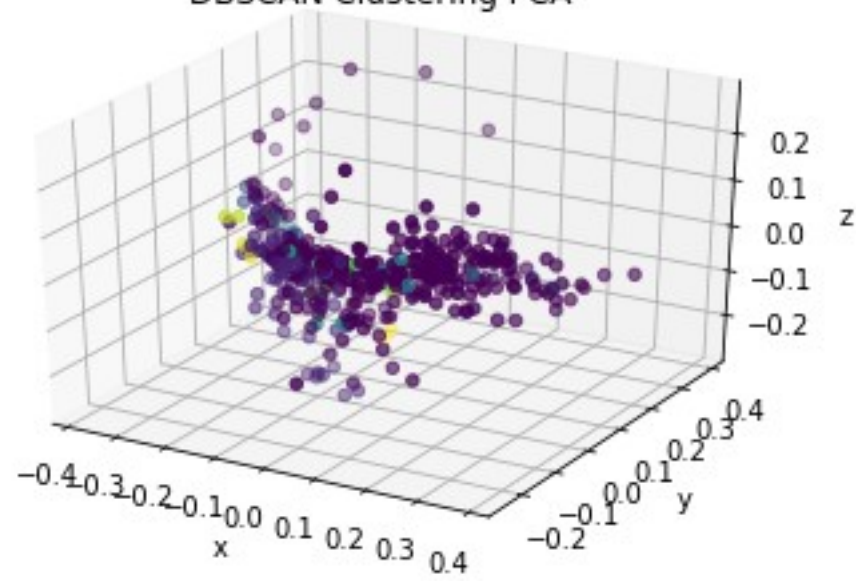
This was my worst clustering. For this task, DBSCAN is not reliable. After an endless parameter search, I've found `eps=0.22` and `min_samples=2` to at least cluster the data into 21 clusters. It's scores are the worst and clusterings are very uneven. It picks a little difference in writing styles (some authors have 2 works making up whole clusters). Visualizations also show data dominated by only one color.

```
DBSCAN CLUSTERING
Adjusted random score: 0.02313504110243203
Silhouette score: -0.16284291145863064
Homogeneity score: 0.18554660977788143
Completeness score: 0.5266080869328964
V-measure score: 0.2744076411018804
Fowlkes-Mallows score: 0.20362923963104584
Calinski-Harabaz score: 2.172199028120283
Supervised-like Accuracy: 0
Mean Score: 0.15006910101250076
```

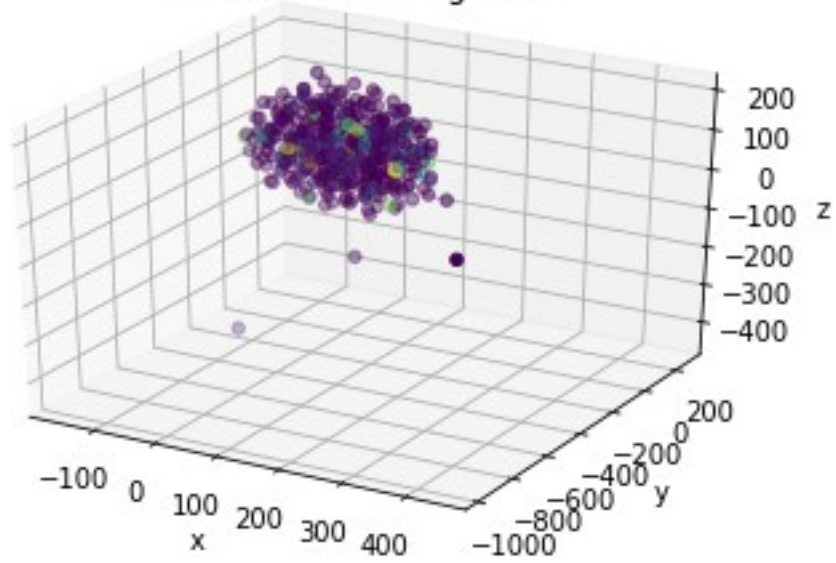
DBSCAN Clustering Contingency Matrix

[illegible]

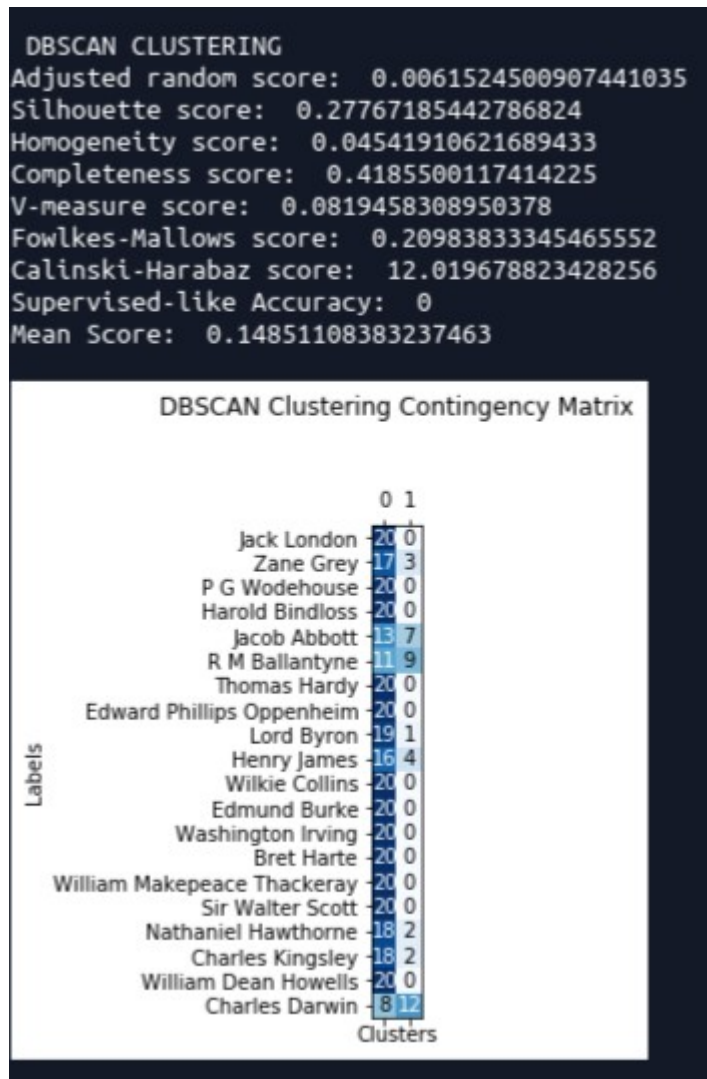
DBSCAN Clustering PCA



DBSCAN Clustering TSNE



This is what the default DBSCAN looks like. Still very bad.



And this is what I imagine grid searching cluster parameters will result in.



This is the best clustering. The scores are the highest, the visualizations are the closest to the labels and the contingency matrix looks almost like a confusion matrix.

```

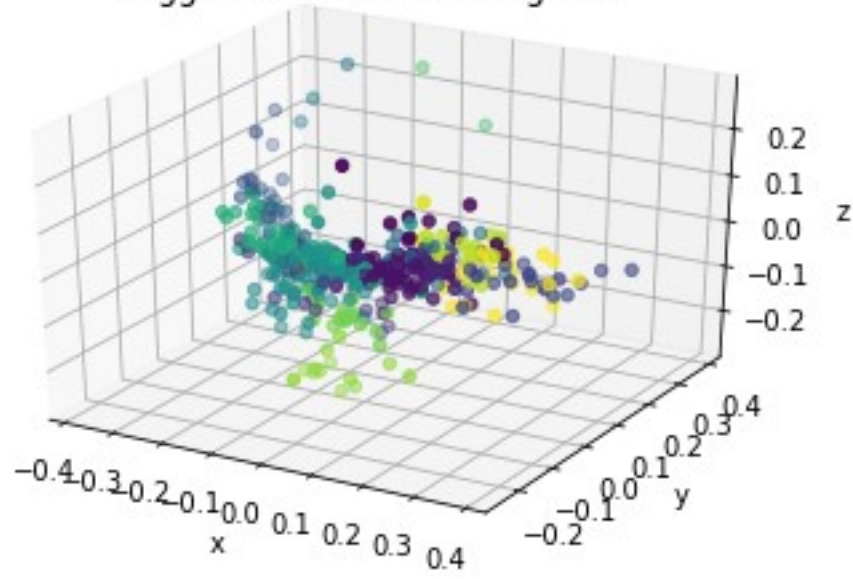
AGGLOMERATIVE CLUSTERING
Adjusted random score: 0.5523978685612789
Silhouette score: 0.03988273512898861
Homogeneity score: 0.7590471562887041
Completeness score: 0.8373313541770564
V-measure score: 0.7962697807477112
Fowlkes-Mallows score: 0.5928063265681183
Calinski-Harabaz score: 11.80960890146283
Supervised-like Accuracy: 0.585
Mean Score: 0.5946764602102653

```

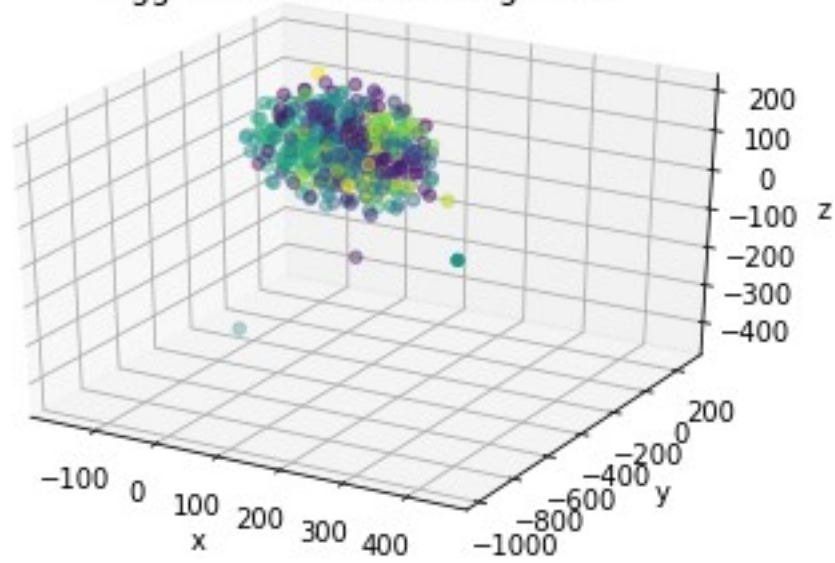
Agglomerative Clustering Contingency Matrix

[illegible]

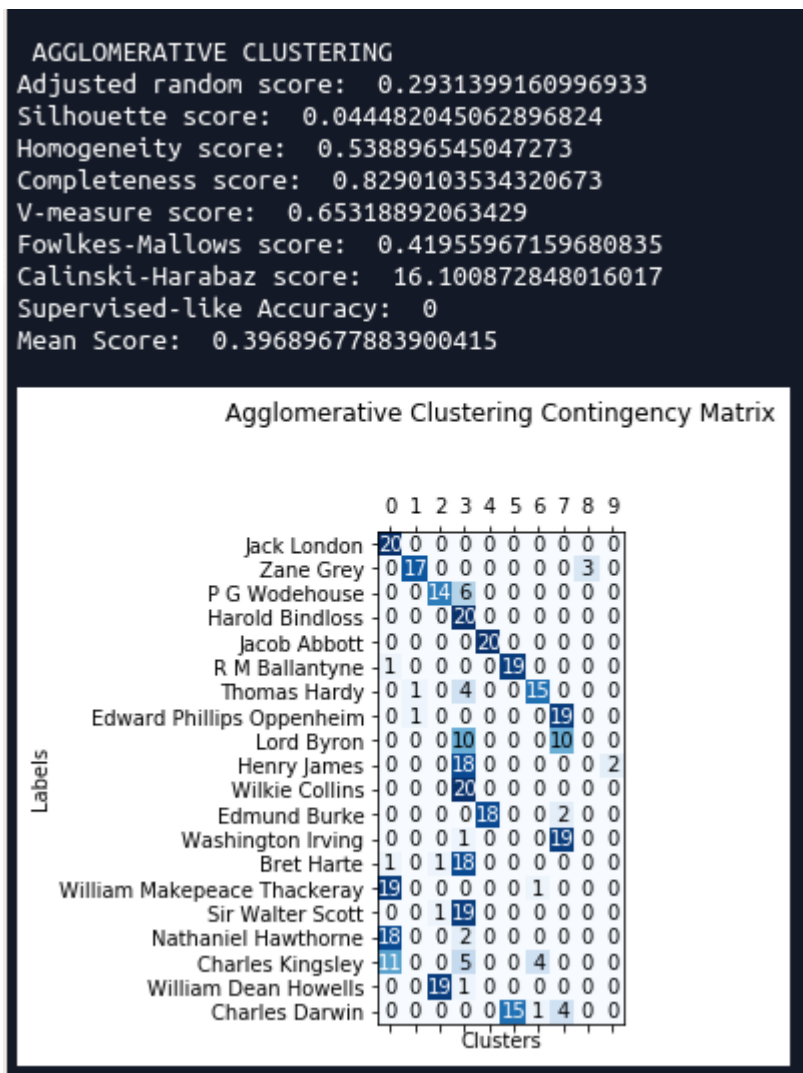
Agglomerative Clustering PCA



Agglomerative Clustering TSNE



This is how it clusters with n_components=10. Only 8 labels are meaningful, the last 2 are very small. Not very good, but still comparable to kmeans.



Needed to run my code:

<https://pypi.org/project/stemming/1.0/>

<https://pypi.org/project/gensim/>