Classifying Books By Writing Style Using Machine Learning Techniques*

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0 Introduction

In this project we use different machine learning techniques learnt in the course to recognize which book, from a set of books, a given page is from. In particular we were interested in doing this with the seven Harry Potter books in order to see if there is any distinguishable change in writing style as the series progressed.

We used the following techniques:

- Naïve Bayes
- k-Means clustering
- Neural Networks

We used these techniques on both the Harry Potter series of books and on a general benchmark set of 7 books from different genres. We used the general benchmark test to asses our algorithms and see if the results we obtained from the Harry Potter set were due to J.K Rowling's change in writing over time or if it was due to our algorithms being problematic and not suiting this particular problem well. The benchmark set of books included:

- Book1 - The Old Testament (Religion)
- Book2 - A Natural History of Ducks (History)
- Book3 - Lord of the Rings - all 3 books merged into 1 (Fantasy)
- Book4 - Fifty Shades of Grey (Romance)

*This project was done within the frame of the machine learning course (COMS3007) held at the University of the Witwatersrand in 2018

- Book5 - 1922 (Horror)
- Book6 - Macbeth (Shakespearian Novel)
- Book7 - The Adventures of Sherlock Holmes (Crime/Detective)

The process and results are specified below.

1 Naïve Bayes

1.1 Background

The Naïve Bayes Algorithm uses a list of probabilities and Bayes Rule to classify data into groups. The idea of this project was to classify sets of pages from the Harry Potter books into the books in which they belong.

1.2 Methods

1.2.1 Data Pre-Processing

We start off by splitting all the books into page sets (We will explain later how we optimized the 'pageSetSize' which is the number of pages in a set). We then took around 20% of these from each book and set them aside for validation data which we used for training our hyper-parameters, we set a further 20% aside for testing and the remaining 60% we used for training data.

We removed all punctuation from the data, except for question marks and exclamation marks which were separated into their own words as we felt this may give more insight as J.K. Rowling may have asked more questions or written more exclamations in some books than others.

We then took our training data and we calculated the probability for each word appearing in any one page set from each book. We did this by counting the number of page sets a word appears in in each book and dividing it by the total number of page sets in that book. This gave us our probability tables, each of which contain probabilities for around 20 000 words. Each of the tables contains a different number of words because of how the data is split up and which data the trainer sees and which is used for testing (see folder probTables where we have stored each of our tables).

In order to narrow down our dictionary (to improve both speed and accuracy) we decided to remove common words that don't differentiate well between books. We did this by comparing the probabilities for each word of it appearing in each book and if at least one of these seven probabilities where greater than 'upperThreshold' and at least 'requiredNum' probabilities are less than 'lowerThreshold' we then kept the word. By doing this we only keep words that appear often in one or more books and barely appear in multiple other books.

Using the validation data we optimized the hyperparameters: 'pageSetSize', 'upperThreshold', 'lowerThreshold' and 'requiredNum'. We did this using the following algorithm:

Algorithm 1 Naïve Bayes - Keeping Relevant Words

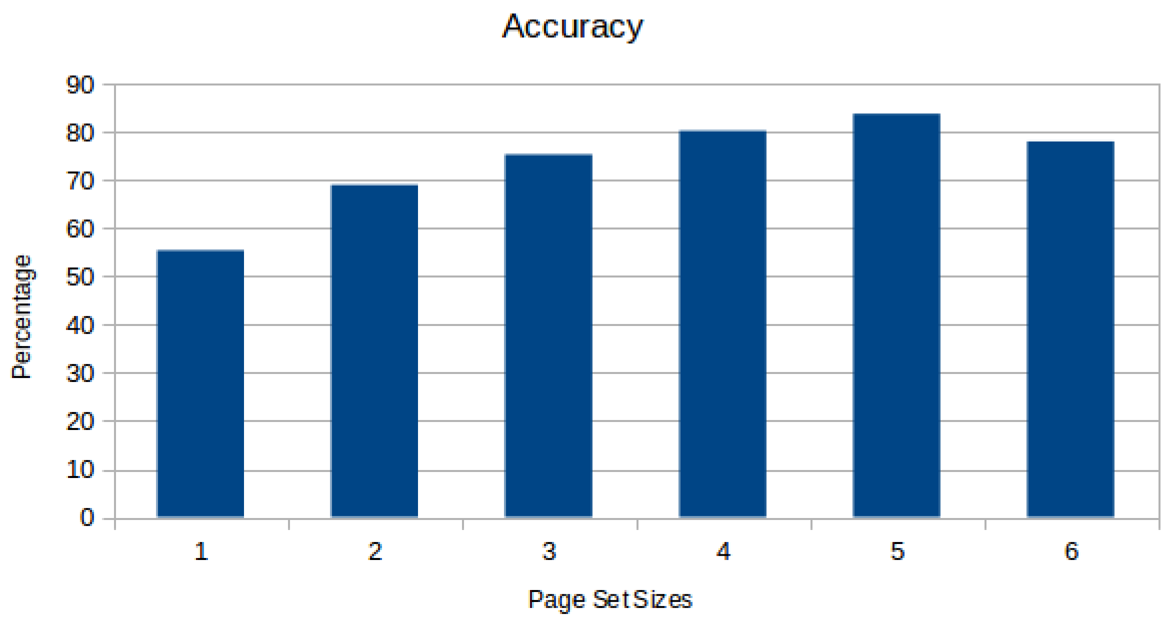
```
for each set of pages do
        create probability table based off size of page set using trainingData
end for
for each requiredNum in range 1 - 5 do

        currTable = probailityTable with words removed based off
                                upperThreshold, lowerThreshold and requiredNum
        while accuracy on validation data is improving do

                while accuracy on validation data is improving do

                        Decrease lowerThreshold by alpha
                        currTable = probailityTable with words removed based off
                                                new upperThreshold, lowerThreshold and require
                        Retest on validation data
                end while

                while accuracy on validation data is improving do
                        Increase upperThreshold by alpha
                        currTable = probailityTable with words removed based off
                                                new upperThreshold, lowerThreshold and require
                        Retest on validation data
                end while

                Change alpha by a factor of a half
                If alpha is less than a threshold exit the loop
        end while
end for
take the pageSetSize, upperThreshold, lowerThreshold and requiredNum
that yield the best accuracy

test on testing data
```

1.2.2 Naïve Bayes Procedure

1.2.3 Hyper-Perameter Tuning

1.3 Results

The following graph shows the accuracy given for the different pageSetSizes on our test data, it should be noted that since there are 7 options a random guess will be correct 14.29% of the time.



It is quite clear a pageSetSize of 5 gives the highest accuracy. Since the pageSetSize of 5 gives the highest accuracy, we use this pageSetSize in our analysis.

Page Set Size	Size Of Training Data	Size Of Validation Data	Size Of Testing Data	Size of Dataset
1	2822	942	943	4707
2	1411	472	472	2355
3	939	315	317	1571
4	705	236	239	1180
5	563	188	192	943
6	470	157	160	787
7	403	135	137	675
8	353	118	122	593
9	313	105	107	525
10	280	95	97	472
11	257	86	89	432
12	233	79	83	395
13	217	73	76	366

Thus the best classifier that we found was trained using the following parameters:

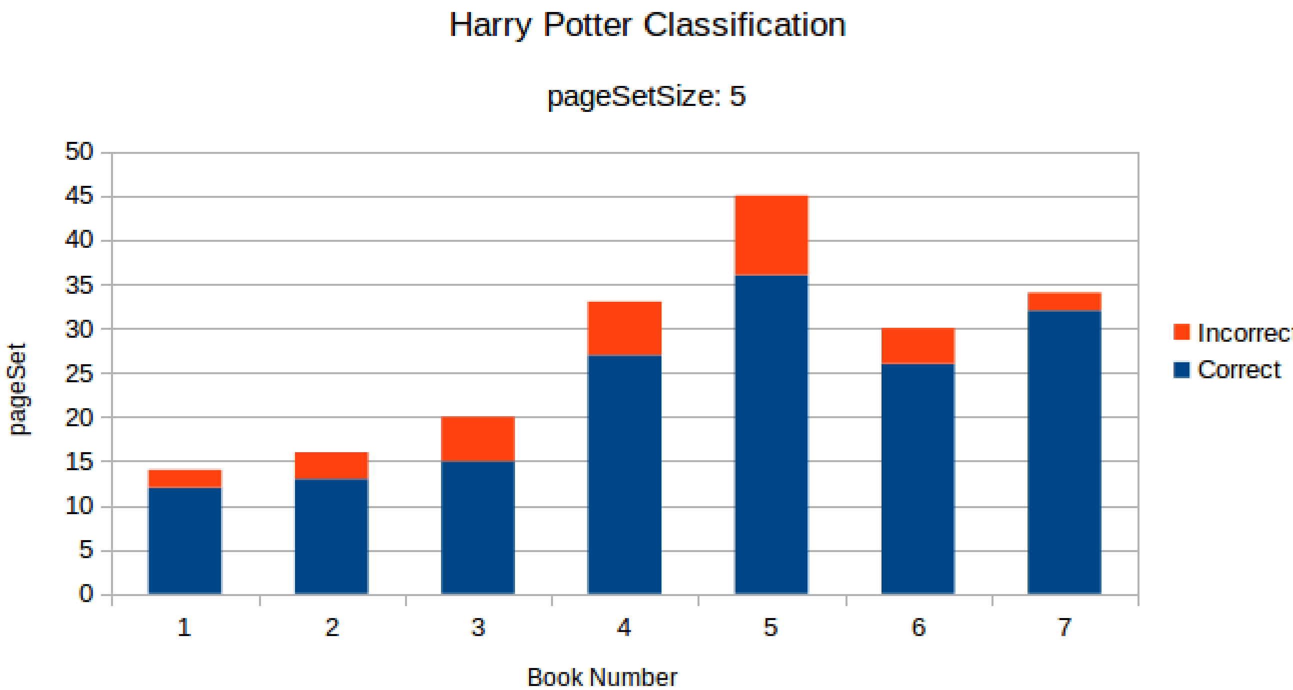
- pageSetSize = 5
- Training pageSets = 563
- Testing pageSets = 192
- Validation pageSets = 188
- Words Used for Classifying = 1594
- requiredNum = 1
- upperThreshold = 0.051875
- lowerThreshold = 0.03125

1.3.1 Confusion Matrix

The following is the confusion matrix we got after testing this classifier on 317 test cases

	1	2	3	4	5	6	7
1	12	2	1	0	2	0	0
2	1	13	1	0	0	0	0
3	1	0	15	2	2	0	0
4	0	0	0	27	1	0	1
5	0	1	2	3	36	1	0
6	0	0	1	1	2	26	1
7	0	0	0	0	2	3	32

This confusion matrix has an accuracy of 83.85%. There a quite a few interesting observations that can be made about the harry potter books from this matrix. The first thing that jumps out as obvious in this matrix (and is reflected in all the others) is an obvious bias to book 5 and book 7.



This could indicate multiple things. The bias towards book 5 could be because book 5 is the largest book out of all seven Harry Potter books. There are could be many references and similarities to the earlier books. Similarly, the bias towards book 7 can be explained in this way. Book 7 is the last book of the entire series which could try summarize the entire plot.

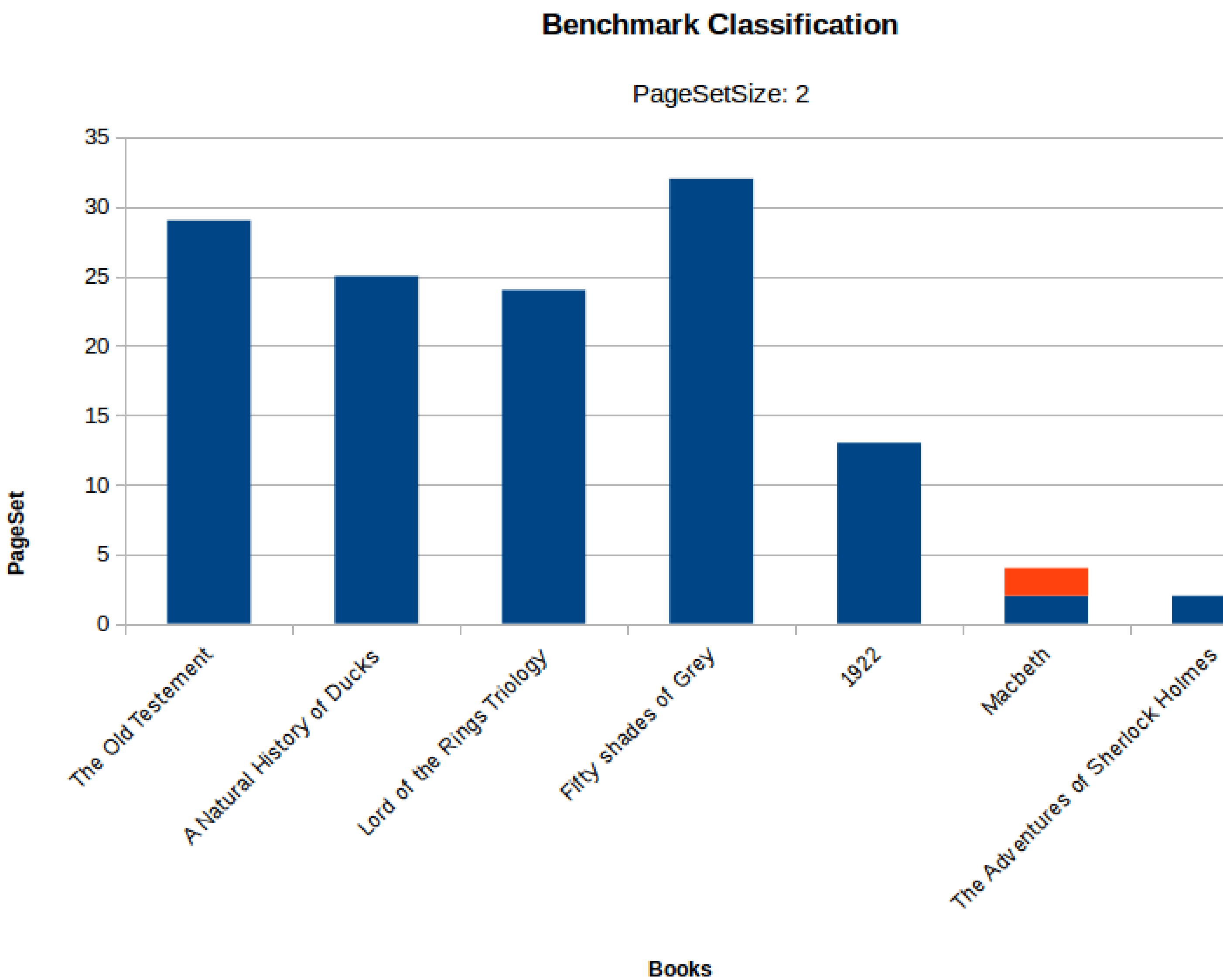
We expect a misclassified page set is more likely to be classified as either the previous book or the following book. According to the confusion matrix, this is mostly the case. However, we note that book 5 has the highest number of misclassifications and they are spread out. We attribute this to the fact that book 5 is the largest book in the series and contains the most words.

Interestingly, book 1 and book 7 have the least number of misclassifications. It makes sense to think of book 1 as the introductory book, hence it is a bit unique. This shows J. K. Rowling's writing style did change from the first book. Book 7 is obviously not referenced throughout the series (as it is the last book) but can reference previous books. We see that book 7 is only misclassified once as book 4 and 6, which interestingly tells us book 7 is very much different to the other books.

1.4 Benchmark dataset results

Using the Benchmark Books with a PageSetSize of 2 we got an accuracy of 98.45% with the following confusion matrix:

	1	2	3	4	5	6	7
1	29	0	0	0	0	0	0
2	0	25	0	0	0	0	0
3	0	0	24	0	0	2	0
4	0	0	0	32	0	0	0
5	0	0	0	0	13	0	0
6	0	0	0	0	0	2	0
7	0	0	0	0	0	0	2



We see that our Naive Bayes algorithm performed really well in classifying different genres. This is expected as different genres have different forms of writing styles and story lines leading to a specific subset of words used in the different books. We note that Macbeth was easily confused with the Lord of the Rings. This could be due to the fact that both books are fairly old and have a more similar language style compared to the other books. We also know that Macbeth does contain some fantastical words and many words pertaining to a royal language, many of which is frequently used in the Lord of the Rings. Since the Lord of the Rings is a larger book with more characters, places and jargon, it is not confused for Macbeth.

1.5 Conclusion

The Naive Bayes algorithm turned out to work well for classifying books. It was able to classify the Harry Potter series fairly well and was able to give us information about the books. We learned that book 5, 6, and 7 are similar to each other which tells us that J.K Rowling's style of writing did not change much during the last three books and that book 1 and book 7 are quite different from any other books which indicates the storyline was introduced and has been changed for those particular books.

In our Benchmark test we found out that our algorithm is classifying accurately as it classified the different genres of books as expected.

2 k-Means Clustering

2.1 Background

k-Means clustering is a form of unsupervised learning that takes unlabeled data and groups (aka clusters) data points together in order to highlight patterns. The amount of groups produced by this algorithm, k, can be changed and thus create different groups and highlight different patterns, and even force data points that appear like they should be in separate groups to mix if a low number of generated groups is chosen. This algorithm is done iteratively by grouping points around a center and then reinitializing the center to be the average of the new points around it. A problem that this algorithm has is the random initialization of the centers of the clusters before the iteration starts may prohibit the algorithm from finding optimal clusters by chance - thus it is important to run this algorithm multiple times in order to see consistent patterns.

We attempt to use the k-Means algorithm to see if there are any interesting patterns between the different Harry Potter books and to try to spot different instances that might have caused changes in the writing style. This is a test case for a more generic problem of analyzing text and finding patterns between different texts.

2.2 Methods

2.2.1 Data Pre-Processing

All the books we use are formatted to simple text files, with all the sentences directly after each other in a single line and pages being split up using new line characters. Each book is read in separately, and a dictionary of the words in the book is compiled, with each word having a value of the amount of times it appeared in the book. We chose to make all of the words lower case, in order to prevent the same word appearing different when it was at the beginning of a sentence or not. We also took out "s"s at the end of words, this is a bit controversial since we elimintae the existance of plural words, but we thought the advantage of grouping words with their plurals was more important as it stressed the meaning of the words. We treated the different punctuation characters as separate words. We then normalize the dictionaries by dividing the value of each word by the total amount of words in the book the dictionary represents (including duplicates of words in the book). This is done in order to not bias the data towards larger books.

After normalizing in all of the books and creating dictionaries we search through the dictionaries and screen out the words that are not unique to any single book. Within those words we also have a threshold of how common the word is (how big its value is after normalization) and only keep words which have values above the threshold. We keep the option to remove words, as well as the threshold of removing words, as hyper-parameters and experiment with both (see section 2.2.3).

We then took the books and merged the books pages together so that multiple pages would appear as a single page. This created books with fewer, longer, pages. The amount of pages we merged together was kept as a hyper-parameter we fine-tuned between different tests (see section 2.2.3). After having our newly formatted books we took each page within each book and gave it a value within a domain consisting of N dimensions, one for each word that was left in our dictionary. The amount of dimensions in the domains, N, relies on the words left after removing words, and as such relies on the threshold for removal of words, but is generally very large. The value of a page was an N-tuple given by the amount of times each word (represented by a dimension) appeared in the page divided by the amount of words in the book.

Note: The normalization we applied to the dictionaries is not applicable to a page per page basis, as a single page doesn't necessarily consist all of the appearance of a single word. Thus we needed to normalize them separately and that is the reason for the division by the amount of words of the book when a page is being given a value.

These final page values were used as points for the k-means algorithm to try to cluster.

2.2.2 k-Means Procedure

The "k" in k-Means represents the amount of clusters we attempted to cluster our data to. This value was kept as a hyper-parameter and was fine-tuned between different tests (see section 2.2.3).

The first thing we needed to do when starting the k-Means procedure was to randomize the centers of the initial clusters. With our first attempts we randomized the centers in the N dimensional domain, where in each dimension it was initialized between the minimum value given to any page on that dimension and the maximum value any page was given on that dimension. This produced a lot of centers that were centered in places where no pages were allocated for them, and there clusters were empty. Though this remained a problem throughout we managed to mitigate it to an extent by initializing the center points more in the center of the data points. This was done by randomizing the location of each center in each dimension within an interval around the average of values of the pages in that dimension. In hindsight we could have used a normal distribution to achieve this, but we ended up hard coding limits for the centers manually.

After initializing the centers we performed the following k-Means algorithm:

We printed out the amount of pages from each book in each cluster and followed that to see if any interesting patterns emerged.

2.2.3 Hyper-Parameter Tuning

The hyper-parameters that we tuned between runs were:

- Amount of pages to be merged when reformatting the books
- k - the amount of clusters to use
- Whether to remove words
- The threshold for removing words

All of our tests were made with a baseline of

- Amount of pages to be merged when reformatting the books= 1

Algorithm 2 k-Means

```
Initialize clusters to be empty
while(clusters have changed in last iteration) do
        for each page do
                Check which cluster center is closest \
                        to page and assign it to that cluster
        end for

        for each cluster center do
                Change cluster center  to the average \
                        of all the points in the cluster.
        end for
end while
```

- k=7
- removal = True
- threshold for removing word = 0.4×10^{-5}

and changed a single variable from this arrangement for each round. We do this with a constant random seed as to produce consistency. This may be problematic if this specific random seed is not particularly good, but we thought it would mitigate the risk for testing (especially since we chose 42 as the random seed).

The baseline gave us the following results after 42 epochs:

```
cluster 0 book_count: [104, 120, 96, 2, 1, 6, 1]
cluster 1 book_count: [88, 52, 6, 0, 0, 0, 1]
cluster 2 book_count: [11, 7, 19, 268, 851, 105, 272]
cluster 3 book_count: [13, 23, 81, 411, 247, 393, 460]
cluster 4 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 5 book_count: [39, 56, 215, 128, 5, 220, 111]
cluster 6 book_count: [92, 119, 69, 0, 0, 4, 4]
```

Pages merged when reformatting It is noticeable that increasing the pages being merged gives better results. This is presumably because if the newly formatted pages are larger then it is more likely that they contain a word from our dictionary, and represents the book it came from better, as such it will be located nearer to other pages from that book. We come to this conclusion from the following results:

While using a merge variable of 10 (merging every 10 pages into a single page) gives us a result after 37 epochs of:

```
cluster 0 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 1 book_count: [5, 1, 0, 0, 0, 0, 0]
cluster 2 book_count: [1, 1, 1, 14, 106, 2, 14]
cluster 3 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 4 book_count: [28, 30, 2, 0, 0, 0, 0]
cluster 5 book_count: [0, 0, 0, 67, 5, 67, 71]
```

```
cluster 6 book_count: [1, 6, 46, 0, 0, 4, 0]
```

We can clearly see that using a merge variable of 10 gives us more meaningful results than the baseline results that used a merge value of 1. Since we have less total pages to assess we lose some of the precision in our results, but certain patterns can be more easily observed.

These patterns include the fact that cluster 2 clearly classifies book 5, even though some similarities with other books occur. Clusters 1 and 4 classify books 1 and 2, which are apparently similar. Cluster 5 classifies books 4,6 and 7 which seem to be similar, and a bit of book 5 gets caught in the middle. Cluster 6 mostly classifies book 3 with a bit of noise from books 1,2 and 6.

k - The amount of clusters to use Using a low value of k limits the amount of information we can get from our clustering, as there is less room for movement between clusters. On the other hand more clusters can make the results seem random or otherwise illogical. This could be caused by a cluster of pages that should clearly be together getting split into multiple clusters because multiple cluster centers were initialized near the points of all of those pages.

That being said, an advantage of more clusters could be that you can end up having more random centers not initially located where they never get any pages in there clusters. This is a problem in our case in particular, as our domain space is very large and a few cluster centers tend to dominate the dataset and "capture" all the pages. More cluster centers will thus avoid dominant clusters from forming. It should be noted that we will also end up with more empty clusters as a result, but those can just be ignored, as well as the fact that it takes longer to compute for more clusters.

Ideally we would use 7 clusters and see the clusters split the books apart exactly, but this was not the case. Also in order to get meaningful information about similarities between the books we would want different books to be clustered together in different formations, and for that we might want to use less than 7 clusters. At the end of the day the correct amount of clusters is a balancing act depending on which type of information we hope to get from our data.

Using k=3 after 22 epochs we obtained:

```
cluster 0 book_count: [93, 114, 330, 273, 26, 404, 258]
cluster 1 book_count: [237, 249, 105, 0, 0, 5, 5]
ster 2 book_count: [17, 14, 51, 536, 1078, 319, 586]
```

Using k=5 after 57 epochs we obtained:

```
cluster 0 book_count: [56, 92, 217, 65, 1, 148, 57]
cluster 1 book_count: [114, 142, 100, 3, 2, 4, 1]
cluster 2 book_count: [11, 9, 25, 313, 916, 138, 336]
cluster 3 book_count: [23, 24, 117, 428, 185, 436, 453]
cluster 4 book_count: [143, 110, 27, 0, 0, 2, 2]
```

Using k=10 after 22 epochs we obtained:

```
cluster 0 book_count: [68, 92, 73, 4, 0, 10, 0]
cluster 1 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 2 book_count: [11, 7, 18, 240, 827, 91, 257]
cluster 3 book_count: [11, 19, 70, 394, 266, 342, 424]
cluster 4 book_count: [0, 0, 0, 0, 0, 0, 0]
```

```
cluster 5 book_count: [56, 65, 139, 19, 2, 36, 11]
cluster 6 book_count: [87, 47, 6, 0, 0, 0, 1]
cluster 7 book_count: [23, 38, 119, 152, 9, 245, 152]
cluster 8 book_count: [91, 109, 61, 0, 0, 4, 4]
cluster 9 book_count: [0, 0, 0, 0, 0, 0, 0]
```

Mild improvements can be seen using k=20, but the computation took very long and was not worth the difference (the results are too large to paste here).

We also hoped to be able to see similarities between books by forcing them to get clustered together when using a small k, but this did not end up happening. For the most part using a small k just made the clusters appear more random, and no clear distinctions could be made.

Removing words - True/False Without removing words we are left with 20455 words, which will make for a very slow clustering process. An argument can be made that if we are looking for difference in writing style, and not just difference in character names, objects, places and other unique words in a book, it is necessary to keep all of the words. On the other hand using non-unique words can create a lot of noise within the data.

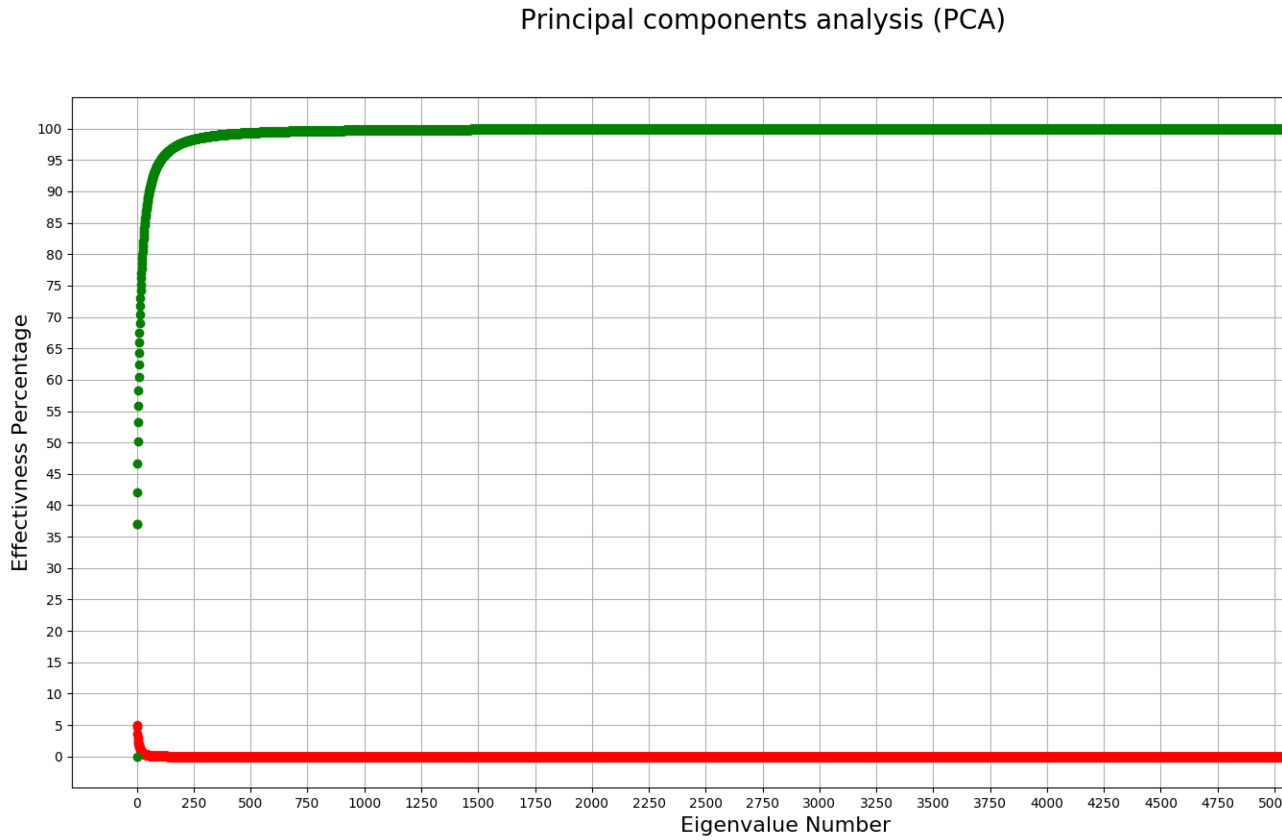
Our final results without removing words after 91 epochs are:

```
cluster 0 book_count: [161, 97, 0, 0, 0, 1, 0]
cluster 1 book_count: [11, 11, 50, 405, 0, 572, 265]
cluster 2 book_count: [37, 57, 344, 1, 3, 5, 4]
cluster 3 book_count: [126, 201, 74, 0, 0, 0, 1]
cluster 4 book_count: [6, 7, 11, 61, 568, 48, 88]
cluster 5 book_count: [3, 2, 0, 0, 0, 0, 0]
cluster 6 book_count: [3, 2, 7, 342, 533, 102, 491]
```

For the remainder of the tests we did remove words because it took very long to run a test without removing words which was not conducive for running multiple tests. However we still obtained meaningful results from tests while removing words.

Removing words threshold After we screen the dictionary, to keep only words that are unique for a single book, we also use a threshold for how common a word is in that book to tell us whether we want to keep the word in the dictionary or remove it. If a word is unique, but its normalized value is less than the threshold we consider it to be irrelevant for our purposes and remove it.

We used a PCA to gather a benchmark of how many features, in our case words, should be kept. The following PCA graph was obtained when running on the dictionary of all unique words after removal of non-unique words (with a threshold of 0):



Since we have 8300 words after removing for unique words it wasn't possible to plot the PCA as a histogram. Even after removing all the eigenvalues that were equal to zero we were left with thousands of words. Instead we plotted only the non-zero eigenvalues as separate points in a scatter plot. The eigenvalue are the red dots, for each x-value there is an eigenvalue, and the scale is according to the percentage of effectiveness of that eigenvalue. The green dots are the cumulative values of the eigenvalues to that point.

We can see that around the 500th eigenvalue we start to have significant stagnation and were around 98% total efficiency, and after the 1500th eigenvalue we barely see any movement at all whilst also being above 99.5% total efficiency. Thus we aimed at testing while setting our threshold variable such that we would be left with 500 words and 1500 words to see what results we would get, initially assuming that any more than 1500 words wouldn't add any meaningful information.

We could have sacrificed a little more efficiency and tried around 150-200 words to get around 97% efficiency, but 500 words produced fast enough testing and realistically it isn't easier to intemperate 150 dimensions than it is 500 dimensions, so we wouldn't have gained anything else from it. Also, as we will see, the results for 500 words seemed to have lost too much information for our liking as it is.

Our results keeping 520 words using threshold of 1.53×10^{-5} after 33 epochs are:

```
cluster 0 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 1 book_count: [125, 113, 90, 51, 11, 105, 46]
```

```
cluster 2 book_count: [129, 122, 62, 2, 0, 9, 1]
cluster 3 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 4 book_count: [63, 102, 189, 228, 129, 294, 221]
cluster 5 book_count: [30, 40, 145, 528, 964, 320, 581]
cluster 6 book_count: [0, 0, 0, 0, 0, 0, 0]
```

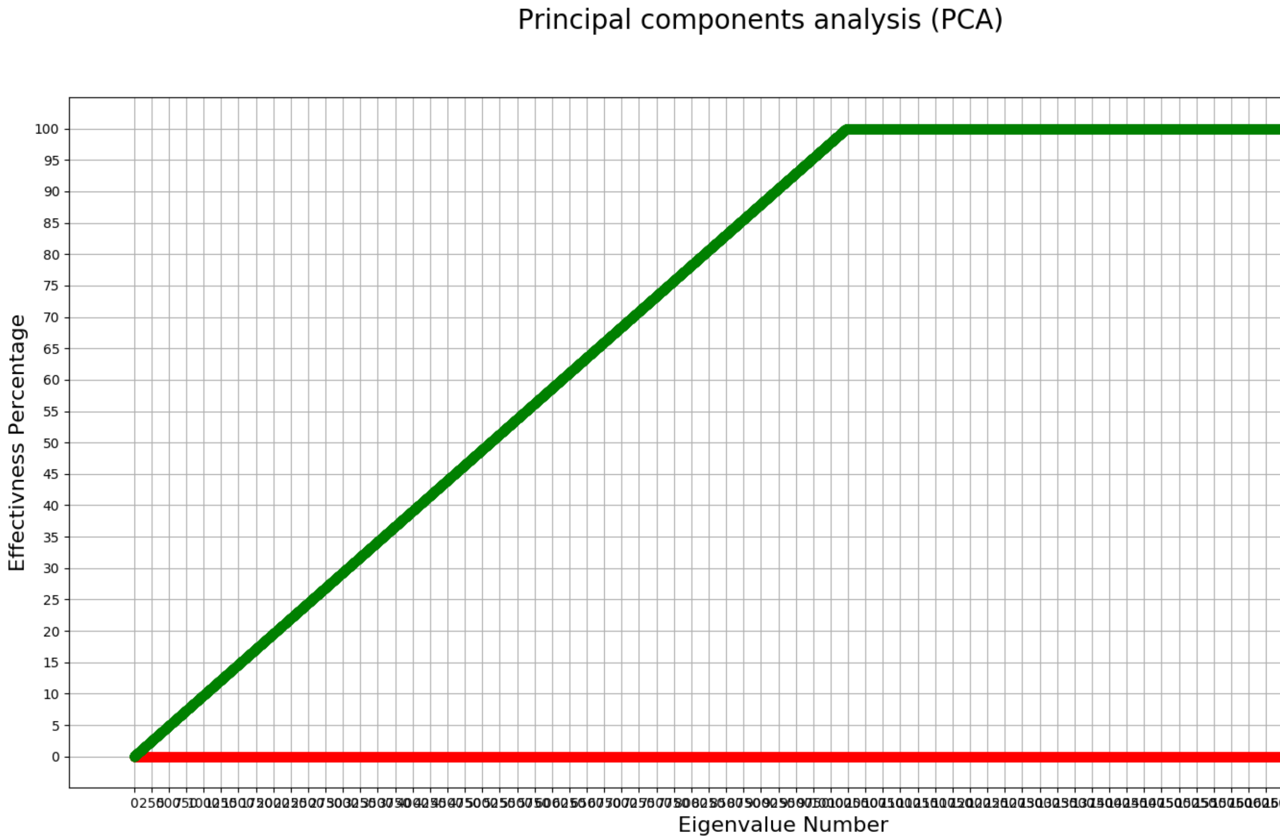
Some general meaning can still be found in these results, such as the distinction of books 1 and 2 from the others but it is alot less clear, it seems this is reducing the dimensions by too much.

Our results keeping 1582 words using threshold of 1.17×10^{-5} after 52 epochs are:

```
cluster 0 book_count: [19, 26, 100, 518, 966, 301, 557]
cluster 1 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 2 book_count: [125, 112, 58, 2, 0, 5, 0]
cluster 3 book_count: [36, 63, 170, 234, 125, 296, 234]
cluster 4 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 5 book_count: [74, 74, 75, 10, 3, 23, 14]
cluster 6 book_count: [93, 102, 83, 45, 10, 103, 44]
```

It should be noted that these results were obtained using a different random seed as with the one use in the baseline test as that one gave us 2 dominant clusters that didn't change. These results are still unclear relative to the ones using 8300 words. There was no clear explanation to why this is according to the PCA we obtained, making us conclude that we are doing something wrong.

We also tried to look at the PCA without removing words and got the following:



We can see that the values of all eigenvalues are roughly the same and all very low, but accumulate because of the large number of them. Around 10200 there is a negative jump in the eigenvalues. This will explain why we got bad results when using 1500 words, as we can see in this PCA thats only around 15% total efficiency.

2.3 Results

The best results we managed to get used the hyper-parameters:

- Amount of pages to be merged when reformatting the books = 10
- k=7
- removal = True
- threshold for removing word = $0.4 \cdot 10^{-5}$

The results we obtained were:

```
cluster 0 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 1 book_count: [5, 1, 0, 0, 0, 0, 0]
```

Algorithm 3 Initial attempt (words to 2D plane)

```
choose a word from dictionary - give it a value of 1.
for curr_word in dictionary do
        previous words values sum = 0
        for each word that already has a value do
                previous words values sum += \
                        word value * amount that word appeared in all books together
        end for
        curr_word = previous words values sum + 1
end for
```

```
cluster 2 book_count: [1, 1, 1, 14, 106, 2, 14]
cluster 3 book_count: [0, 0, 0, 0, 0, 0, 0]
cluster 4 book_count: [28, 30, 2, 0, 0, 0, 0]
cluster 5 book_count: [0, 0, 0, 67, 5, 67, 71]
cluster 6 book_count: [1, 6, 46, 0, 0, 4, 0]
```

We can see a clear distinction between books 1,2,3 and books 4,5,6,7 as only clusters 2 and 6 has both groups represented, and the contrary amount there is nearly negligible. Furthermore we can see that book 5 is relatively distinguishable from books 4,6 and 7, as cluster 2 focuses primarily on book 5 and cluster 5 focuses primarily on books 4,6, and 7. We can also see from clusters 1,4 and 6 that book 3 is mostly distinguishable from books 1 and 2, but that books 1,2 aren't easily separable.

It is interesting to see a clear gap between the first 3 books and the later 4 books. This could have many different reasons, but a quick search brought up that the first Harry Potter movie came out between the time book 3 came out and book 4 came out, with a very unscientific hunch we could assume it might of had an impact.

2.4 Benchmark Dataset Results

2.5 First Attempt

Previous to the current method of k-Means we attempted to process the data in a different way. Initially we wanted to be able to graph our data in a 2D plane in order to have it easily visualized. We devised the following algorithm to process the words from the books left after the removal stage and give them values on a 2D plane:

This algorithm insured us a unique value for each word as well as the fact that it was impossible to sum up different words and get a value of another existing word (i.e. we could never have something like "harry" + "ron" = "hermione"). This is due to the fact that each word in the dictionary is larger than the sum of all instances of all the words before it. Thus given X words the sum of those words is larger than the largest word in the input but smaller than any word with a larger value than that of the largest word in the input.

Another advantage of this was that by merely splitting up the initial dictionary into N sub-dictionaries we could run this algorithm on each sub-dictionary and thus get a representation of our data in any N dimensions we wanted.

After some time of working with this algorithm for processing data we realized that this method either arranges the pages in a completely random way that cannot be clustered in any meaningful way, or we can structure the data in a way that predefines the pages in clusters - and thus any data we get is very biased and gives meaningless results. This is due to the nature of the values we give the words: what ends up happening is that when you give a value to a page for a dimension, this value will be in between the value of the word with the largest value in the page and the value of the word that is the next largest in the sub-dictionary of this dimension (as explained above). Doing this for each dimension of the domain would create "boxes" in the domain that are exclusive to pages from a certain book. If we randomize the order of the words on each axis, these "boxes" would be located randomly on the board which essentially makes the domain look like white noise. If we order the way the words get their values on the axis (i.e. all words from book 1 get a smaller value than all those from book 2, etc.) then we just artificially make the clusters of pages of each book, and using k-means to cluster it will just cluster our artificially made clusters and give meaningless results.

2.6 Conclusion

For the most part the results seem to show that differences between the 7 books in the Harry Potter series can be found, and some books can tend to be grouped together by the words that they use. This shows that the use of the k-Means algorithm can be useful for analyzing trends with time of word-based datasets. The k-Means algorithm is relatively quick to compute and has little moving parts to adjust (i.e. hyper-parameters) and as such provides an easy test bed for testing out different theories via clustering. This being said k-Means can also be very deceiving at times, and it is important to make sure that the data processing is done with care and does not introduce any biases.

If we were to redo this project from scratch the following points could have been improved:

- It would have probably been more efficient to do the PCA first and adjust the threshold for words before adjusting the other hyper parameters. This would have made the rest of our tests much quicker and would have allowed us to try more combinations.
- We should have probably run the tests on the benchmark set of books in order to assess what we should expect to get while we run our tests on the Harry Potter dataset.
- We should have had our base hyper-parameters use a larger page merge variable. This would have made all of our testing faster.
- Using a Gaussian when randomly initializing the centers location.

If all of these points were done then we would have probably been able to run the tests on the full dictionary of words (or at least as much of it as the PCA recommended), with removal of random words instead of non-unique words, which would have given us more meaningful results in terms of writing style as opposed to just different characters, objects, places etc. that appeared in the different books. Generally it would have allowed us to run more tests with different random centers initializers and that could have helped us tune our hyper-parameters better and also get more diverse and informative results.

Another thing we could have tried using was t-SNE, a library that helps scale down dimensions and visualize the dataset.

3 Hard Code

3.1 Background

Hard coding is using the basic tools given in a programming language to logic out an answer to a given problem.

Algorithm 4 Hard Coding

```
total classifications = 0
correct classifications = 0
for each book do
        for each page in the book do
                total classifications += 1
                for each word in our database do
                        if the word is in the book do
                                if the page came from the same book the word came from:
                                        correct classifications += 1
                                        go to testing next page
                                end if
                        end if
                end for
                if the page did not contain any word for the database do
                        randomly choose a book
                end if
        end for
end for
result = correct classifications / total classifications
```

After a while of trying different machine learning techniques we realized that our data processing was manipulating the data in such a way that just using a simple if statement in a couple of loops would probably be able to solve the classification problem.This was due to the fact that we were removing all words that weren't unique to a specific book, thus all we needed to do is identify if one of the words that were left over were in a given page, and knowing which book gave us this word in the database in the first place we could then know which book the page was from.

We also noticed that by choosing to keep unique words we were skewing a bit from our initial goal of discovering writing patterns and ended up just identifying pages via new character names or objects or places from the different books. Looking at it from this aspect makes it seem much more like a simple problem that can be hard coded.

3.2 Methods

3.2.1 Data Pre-Processing

For data processing we did the exact same thing done in the data processing for k-Means (see 2.2.1) up to the point of merging pages. The only thing to note is that we chose a threshold of 0 while removing data (thus keeping all of the words that were unique per a single book).

3.2.2 Hard Coding Procedure

The algorithm used is a follows:

There are improvements that can be made to this algorithm, such as taking semi unique words into account, but we found the results we got were good enough to prove our point and it was unnecessary to continue tinkering.

3.2.3 Hyper-Parameter Tuning

The only hyper-parameter we could tune was:

- The amount of pages to be merged

We chose to keep this at 1 (thus not merging any pages) as this would give us the least probability to find a unique word, and thus is the hardest case. If this would give us a good result then that would be the strongest statement possible.

3.3 Results

Using this method we managed to get 99.63% accuracy (4683/4700 pages correctly classified). In case we just got lucky with our random picks we also tried to run the algorithm without a random pick of a book if no unique words were found in a page, and that gave use 95.59% accuracy (4681/4700 pages correctly classified). These results were also obtained significantly faster than any of our machine learning methods, as the computation time could be counted in a few seconds as apposed to several minutes for the other methods

As mentioned earlier if we were to merge more pages, or take semi-unique words into account we could probably improve upon this result, but we felt that the results were good enough to make our point.

3.4 Conclusions

Machine learning is cool, but can sometimes over-complicate a problem. If you find yourself going down a rabbit hole - Occam's razor can save you a lot of time, energy and frustration. That being said, the different techniques did give us some insight that we could not obtain using the hard coding method, such as which books appear more similar and around which books did J.K Rowling start using more different words.

4 Final Thoughts