ASSIGNMENT 2 Write Up

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Project Overview

For this project, we focused on analyzing ten different books written by four different genre authors using the Gutenberg Project. We did four techniques: 20 most common and 20 most uniquely common words in each text excluding stopwords with the goal to compare the differences. We then used natural language toolkit technique for each text to determine the overall tone of the book. Finally, we did clustering to compare two texts and test our hypothesis we created using the NLTK process.

Implementation

The 10 texts we chose were: Sense and Sensibility, Emma, Pride and Prejudice, and Mansfield Park all by Jane Austen, Little Women and Little Men both by Louisa May Alcott, Poirot Investigates and The Man in the Brown Suit both by Agatha Christie, and The Raven and The Cask of the Amontillado by Edgar Allen Poe. The first step we took was to clean each text by removing the header and footer "Start of Project ..." and "End of Project..." details that did not pertain to the actual text.

Our four questions we answered in this project:

- 1. Excluding stopwords, what are the 20 most common words used in each text?
- 2. Excluding stopwords, what are the 20 most common words unique to each text?
- 3. What is the overall tone of each text?
- 4. Using text clustering and text similarities, given all texts but one, which text is this closest to? Then display it on a chart using text clustering.

For the first and second question, our implementation idea was to first create dictionaries of solely the words for each text in order to streamline the project and coding. The similar coding for question one was also used for question two as the questions were similar, however, since question two targeted unique words - we needed to create another dictionary as a first step before implementing question two's main function. This second dictionary would be for 9 out of the 10 texts, in order to compare the 10th text to this dictionary to find words that are unique to the text. There might be a method that uses less steps to answer this question, but this was the easiest conceptually for us to answer the question.

A design decision that we made was with question 3. In order to attack this question, we first considered using NLTK to analyze each sentence that had an exclamation point. Then, we would average the result for each sentence in each text to get the overall tone. This would eventually retrieve the overall tone of the text - the answer, but it would be much too complicated and might end up not giving a fully accurate answer by our implementation technique. Instead, with Professor Zhi's help, we were able to gather the overall tone by a simple code from NLTK that analyzes the entire text in one line and gives the overall tone results. In the beginning, we had this function return the score[compound] but after realizing that this normalized the score and most of the answers we received were 1.0, it wasn't helpful or enough information to analyze, so we changed the function to give the entire score breakdown.

For text clustering, we first had to calculate the text similarity scores. We used this link(https://dev.to/coderasha/compare-documents-similarity-using-python-nlp-4odp) to initially help us create the code. However, the code we created did not utilize all the texts in it's list and rather, by our conceptual understanding, broke down a text by each sentence. With Professor Zhi's help and code, we were able to fix this issue and test it on *The Man in the Brown Suit* by Agatha Christie. As we continued this thought process and worked on our function for text clustering, we realized that for the array part of function, we need the similarity list for each book so we created multiple variables to get the similarity for each text, not just the Agatha Christie novel. Our hope was that when the array printed we could then compare to see where the book was closer to. However, the implementation of that final function did not work out.

Results

Our results for question 1 gathered some interesting insight. A lot of the most frequent 20 words in each text showcased a lot of names and titles such as "mr" or "miss" or "mrs". The text with the highest word count for the most frequent word was *Little Women*, with the most said word being "Jo" for 1250 times. Jo is the main character in the book and this makes sense for it to be the most frequently used. The results also gave insight to the shortest novels, both written by Edgar Allen Poe as both his books didn't break 50 times for the most frequent word. In Poe's *Cask of Amontillado*, the most frequent word "said" occurred 24 times. In fact, the word "said" is found as one of the most common words in 9 out of the 10 texts, the only book it is not most common in, is *The Raven*, another Edgar Allen Poe novel. Another important result we noticed in *Poirot Investigates* and in *The Cask of Amontillado*, both written by different authors, is that the code picked up on multiple spaces in certain spots and counted it as a word which came on the most frequent list. If we were to continue to work on this project and make changes, this would definitely be an issue we would address and fix.

The results for question two were quite interesting. A lot of the most frequent words that we saw when we compared to the results from question one, were more of names and variation to names, such as "amy's." Another point noticed is that the number of frequencies decreased to less than 100 compared to when we had done question one, suggesting that there were a lot of common words between the texts. In the novel, *Emma*, we noticed that for question 2, the word "surprized" was considered unique, perhaps due to its unique spelling of the word. In addition, Jo, the main character in *Little Women*, is also the main character in *Little Men*, so her name does not show up as most uniquely common for either books when doing question 2.

Emma Results 1:

The most common words are:

1154 mr 787 emma mrs 701 602 miss will 573 must 571 much 486 said 484 one 448 every 435 harriet 415 403 well 398 thing weston 389 think 384 little 361 good 359 never 358 knightley 356

337

know

Emma 2:

The most common unique words are:

787 emma weston 389 knightley 356 elton 320 woodhouse 278 fairfax 210 churchill 193 hartfield 159 highbury 125 harriet's 91 randalls 90 emma's 79 perry 74 elton's 67 isabella 56 weston's 51 donwell 49 dixon 39 woodhouse's 37 surprize 3

Little Men 1:

The most common words are:

said 625 little 611 534 one mrs 382 like 373 dan 363 bhaer 341 will 336 332 nat boys 328 mr 286 282 jο good 280 demi 280 much 275 270 see 239 now 226 nan well 211 daisy 210

Little Men 2:

The most common unique words are:

dan 363 nat 332 silas 50 dan's 35 brook 25	
nat's 23	
nan's 21	
charlie	21
tommy's	20
toby 20	
robby 20	
nursey 17	
goldilocks	14
owl 13	
crane 13	
melons 11	
beans 10	
stuffy's	9
kites 9	
rewards	8

Little Women 1:

Little women 2:

The most common words are:

The most common unique words are:

said 827 beth's 52 little 727 fred 51 one 711 sallie 42 meg 635 haf 31 like 591 moffat 28 amy 572 kate 28 laurie 549 march's 21 will 502 flo 18 good 462 davis 17 beth 415 pickwick 16 now 399 carrol 16 go 394 tina 15 old 378 esther 13 never 375 esther 13 well 368 traveling 12 see 357 roderigo 12 mother 328 gif 12	jo 1250	amy's 80	
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Our results from question 3 yielded that the highest negative component was for *The Cask of Amontillado*, followed by *The Man in the Brown Suit*, followed by *The Raven*. The least negative was *Emma*. The most positive on the other hand was *Little Women*, followed by *Little Men*, followed by *Emma*. The least positive was *Poirot Investigates*. The most neutral was also *Poirot Investigates*, by *The Man in the Brown Suit* (the same author), and *The Raven*. This was interesting and it kind of made sense to us. Agatha Christie novels are usually filled with suspense and mysteries while Edgar Allen Poe's books are usually gloomy and about murder. Jane Austen and Louisa May Alcott books are about adventure, coming of age, and love - so really more on the positive side than negative.

The result from the text similarities part for text clustering technique yielded, to our surprise, that *The Man in the Brown Suit* by Agatha Christie was closest to *Little Men* by Louisa May Alcott. This surprised us because Agatha Christie's novel yielded as the second highest neutral toned book as well as only a 0.12 positivity and 0.096 for

negativity compared to *Little Men* at 0.178 for positivity and 0.086 for negativity. With Christie's book more negative than Alcott's and less positive, we realized that this text similarity technique looks further than tone.

Reflection

This project was a lot of fun and it gave us a good opportunity to try to implement a lot that we had learned so far as well as learn new techniques. The way we went about this project was to first come up with the texts we wanted to work with and the questions we wanted to answer. We then divided the work for questions 1 and 2 between the two of us while paired programming for question 3 and 4 as they used techniques we both were not familiar with. It was extremely helpful to have previous examples to refer to as well as to be able to ask Professor questions on problems we ran into. Pseudo coding became extremely useful for working through our thought process and implementation of coding. If we could do anything better or had more time, we'd work on how to show question 1 and 2 side by side for each text in order to compare the results. We would definitely work further on our fourth function, to figure out how to make it run and display the chart. We did write most of the code and have left it as Pseudo-code. If we were to do this project all over again, it would have been helpful to have more reading materials on the new techniques in order to figure out how to fully utilize the new skills and toolkits.