CS4248 Assignment 1: Regexs and Language Models

By A0184679H

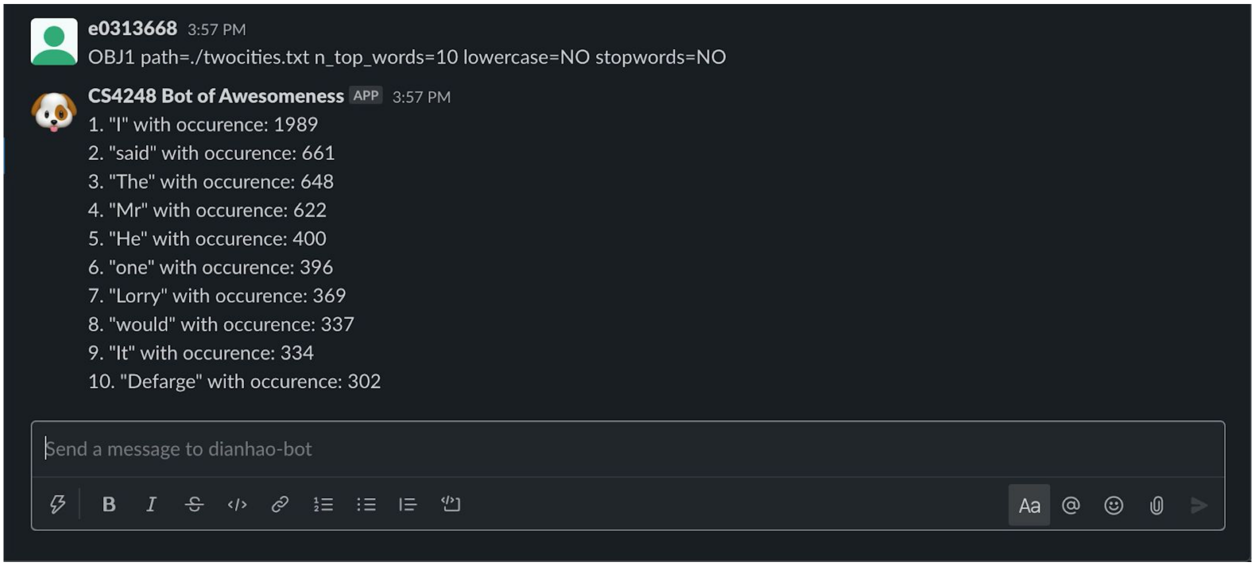
1. **Declaration of Original Work**
   By entering my student ID below, I certify that I completed my assignment independently of all others (except where sanctioned during in-class sessions), obeying the class policy outlined in the introductory lecture. In particular, I am allowed to discuss the problems and solutions in this assignment, but have waited at least 30 minutes by doing other activities unrelated to class before attempting to complete or modify my answers as per that Pokemon Gó rule.

2. **References**
   I give credit where credit is due. I acknowledge that I used the following websites or contracts to complete this assignment.
   - Geeks For Geeks: Removing stop words with NLTK in Python - GeeksforGeeks for learning about the set of stop words
   - Python's Collections documentation: collections — Container datatypes — Python 3.9.1 documentation for learning collections Counter methods
   - Python's Regular Expression documentation: re — Regular expression operations — Python 3.9.1 documentation for learning re methods
   - Matplotlib documentation: matplotlib.pyplot — Matplotlib 3.3.3 documentation for plotting a graph
   - StackOverflow, for debugging purposes
   - Text Generation Using N-Gram Model | by Oleg Borisov | Towards Data Science to learn how to build n-gram model
   - text mining - How to find the perplexity of a corpus - Cross Validated (stackexchange.com) for implementation of perplexity formula in python
   - 3.pdf (stanford.edu) SLP textbook for additional reference
   - CS4248 lecture notes for better understanding of contents

Part 1

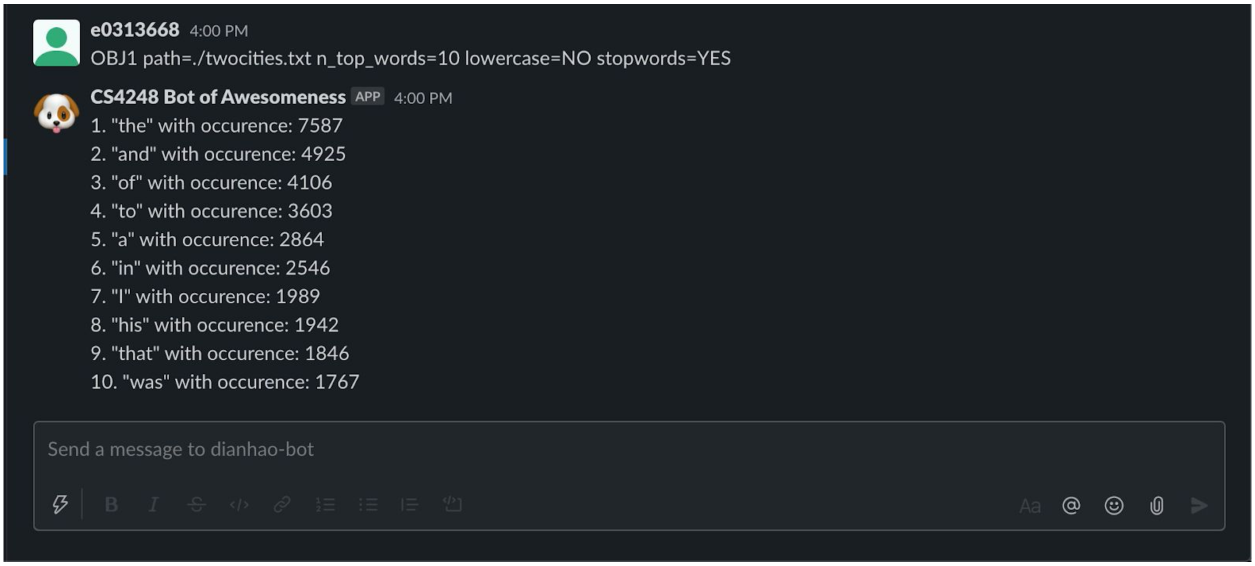
Objective 1 - Tokenization, Zipf’s Law

A. No stopwords, no lowercase:

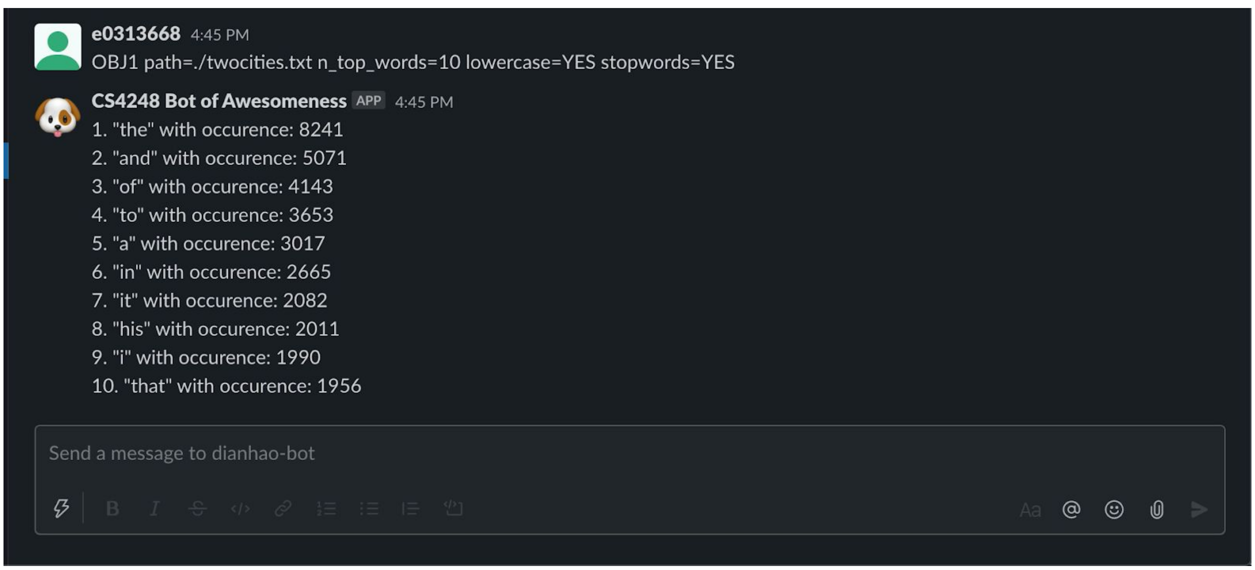


No stopwords, all lowercase:

With stopwords, no lowercase:



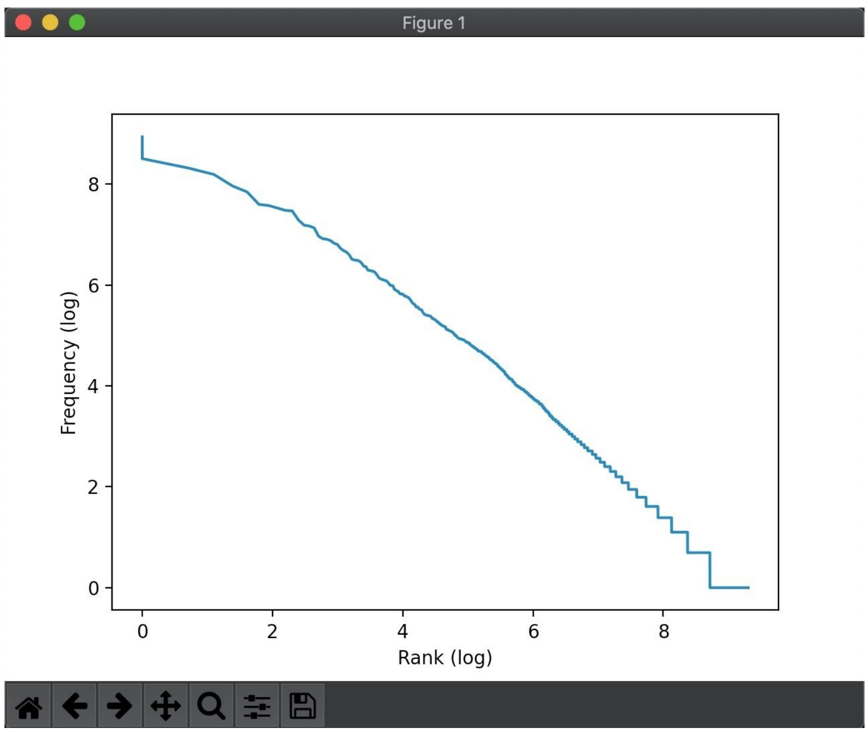
With stopwords, all lowercase:



The corpus I utilised is “A Tale of Two Cities” by Charles Dickens, with a file size of 791 KB. I analysed the result with 4 different conditions as shown above. According to the screenshots, when stopwords are not counted, the word with the most frequency is only 661 for “said” when all characters are lowercase while it is 1989 for “I” when the lowercase condition is false. This is expected because the word “i” a stopword.

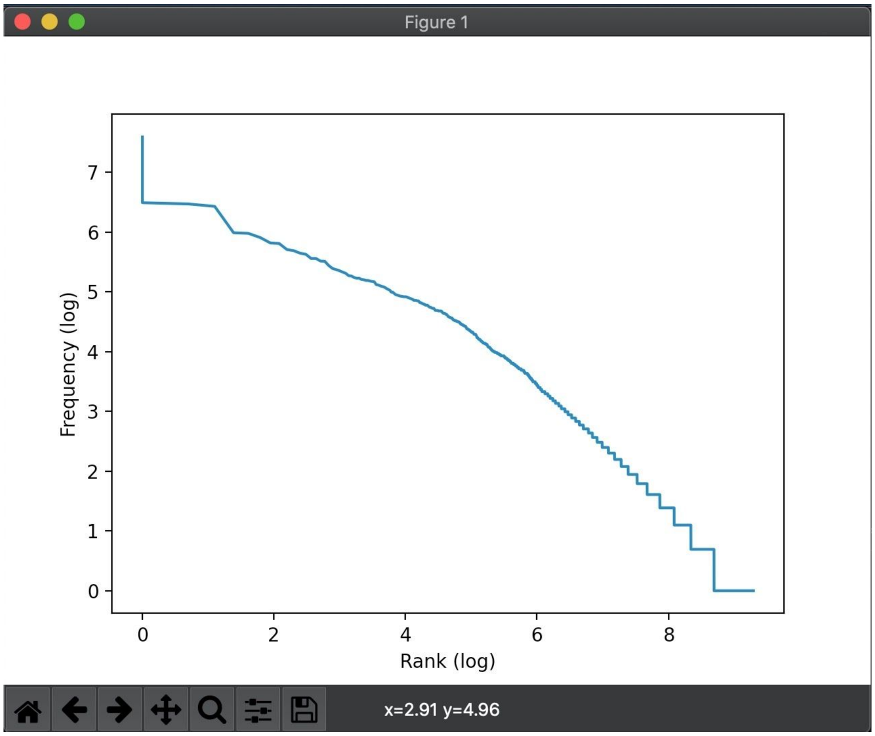
When stopwords are counted, the word with the most frequency is “the” with 7587 occurrences for all lowercase, and also “the” with 8241 occurrences when the lowercase condition is not enforced. The results for both are almost the same, as the words in these results tend to start the beginning of a sentence, and are often stopwords, such as “I”, “that”. One observation is that the word “was” appeared as one of the most frequent words when lowercase, and it is expected because “was” is used to start a sentence, in particular, a question. The result is accepted.

B. With stopwords



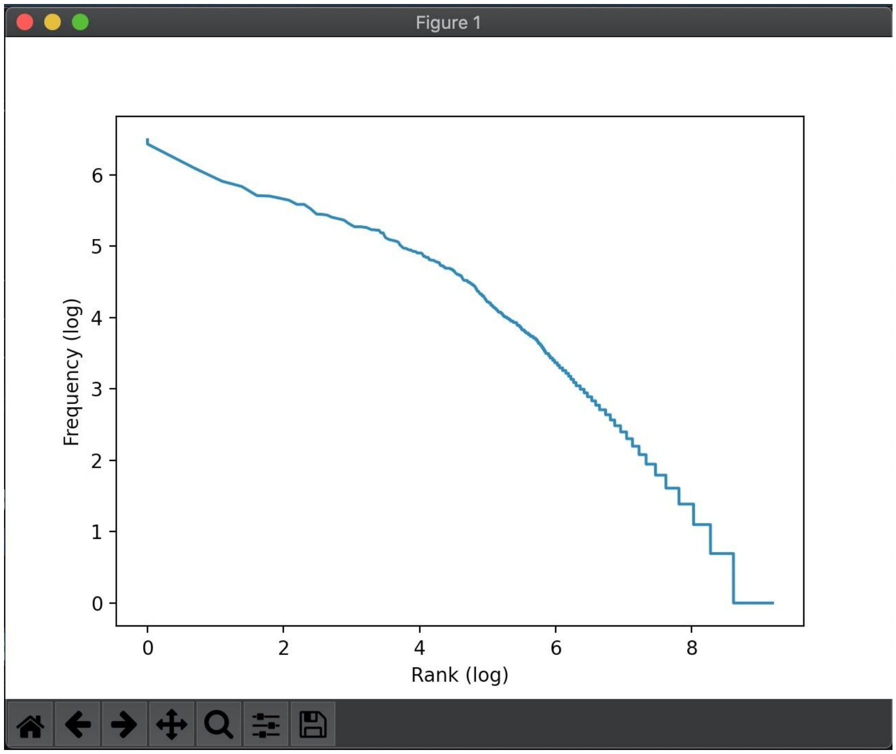
When stopwords are included, the graph of frequency vs rank (in logs) follows Zipf’s Law.

C. Without stopwords



When stopwords are removed, the wordcounts are lower compared to the previous graph, but it is still consistent with Zipf's Law.

D. Without stopwords, lowercase



When stopwords are excluded and the corpus is converted to lowercase, Zipf's Law still holds, albeit the frequency of the words are further decreased due to stop words like "I" are not counted.

Objective 2 - How's the Weather?

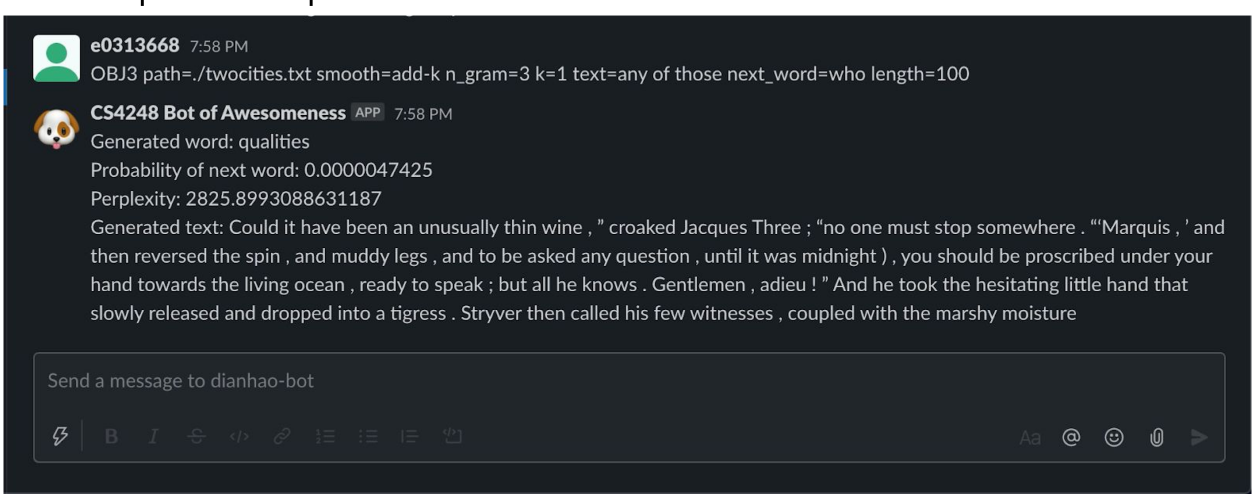
The strategy of distinguishing between a valid query and an invalid input lies in the users' intentions. A valid query can be categorized into two kinds: a question, and a sentence.

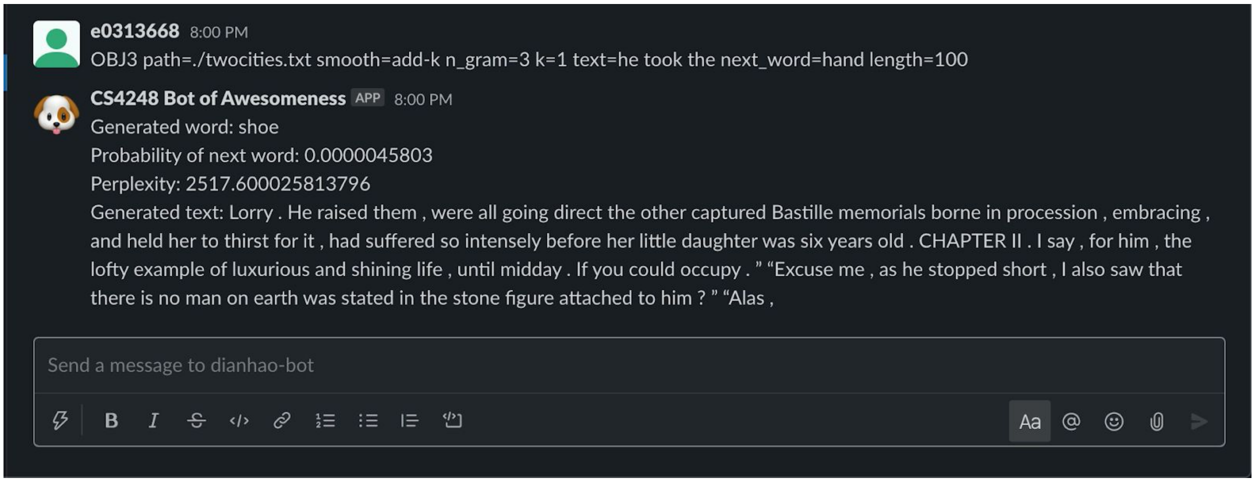
- Question:
  - Observation 1: Certain asking words must exist in a question, such as "what, how, do you know". I prepared a list of these valid words to handle most kinds of asking words.
  - Observation 2: Certain words concerning weather must exist in the query, such as "weather, temperature, foggy, raining". However, these words may have suffix, so I used normalization to reduce the words to its simplest form, and drop alphabets if necessary, such as "freez" to handle "freezing" and "freezy".
  - Observation 3: A location must exist in the question, and either be Singapore, Cairo or London. I used Python's inbuilt regex function to ignore uppercasings (as majority users do not

concern uppercase in text messages), and used regex capturing groups to determine the location that the user is querying.
  - Observation 5: The sentence must end with a question mark.
  - Observation 4: It is also valid for the question to be juxtaposed, such as “can you tell me weather in Singapore?” and “can you tell me Singapore’s weather”? My approach is to generate all regexes combinations of the above observations, and check if any of them is a match.
- Sentence:
  - Observation 1: For a valid query, it must have some kind of instructional word, eg “tell me” or “ask”.
  - Observation 2: It also requires a word that describes the weather context such as “humid” or “weather”.
  - Observation 3: The location is required.
  - Observation 4: The sentence can be inversed too, such as “tell me the weather in singapore”, and “tell me singapore’s weather”.
  - Observation 5: To handle non valid queries, a sentence must include an action word and a weather word to form a valid response. For ambiguous queries like “Singapore weather”, the bot will choose not to answer the query, but “Singapore weather?” is a valid response in this case.

Objective 3:

Some captured outputs:





- Optional implementation: backoff
  - If backoff is enabled, when an unknown context of n-gram is introduced, the (n - 1) gram will be used, and the backoff is carried out until the (n - xth) gram is found or the unigram is used.

Part 2

1. Subtraction Regular Expressions

(?=([a]+) - ([a]+) = ([a]+))\2\3 - \2 = \3

2. Language Models

a. True. Let the length of the text corpus be a, therefore the perplexity of the language model is calculated by

$$PP(\text{test corpus}) = \sqrt[a]{\prod_{i=1}^{a} \frac{1}{q(x_i \mid x_{i-1})}}$$

and because each word in the test is seen at least once in training and for all sentences $p(x_1 \ldots x_n) > 0$, 0 will not appear as a denominator, and the fraction 1 / 0 will not happen. Therefore the perplexity will always be less than $< \infty$.

b. False.

PP (test corpus)

$$= \sqrt[a]{\prod_{i=1}^{a} \frac{1}{q(x_i \mid x_{i-1})}}$$

$$= \sqrt[a]{\prod_{i=1}^{a} \frac{1}{\frac{c^*(x_{i-1}, x_i)}{c(x_{i-1})}}}$$

For the PP to be largest,

$$\prod_{i=1}^{a} \frac{1}{\frac{c^*(x_{i-1}, x_i)}{c(x_{i-1})}}$$

should approach $\prod_{i=1}^{a} N$ such that the PP can have a value of N;

therefore the fraction $\frac{c(x_{i-1}, x_i)}{c(x_{i-1})}$ should have a value of $\frac{1}{N}$.

However, the discount $c^*(x_{i-1}, x_i) = c(x_{i-1}, x_i) - 0.5$ caused the fraction $\frac{1}{\frac{c(x_{i-1}, x_i) - 0.5}{c(x_{i-1})}}$ to yield a greater value than $\frac{1}{\frac{c(x_{i-1}, x_i)}{c(x_{i-1})}}$ as shown below:

$$\frac{1}{\frac{c(x_{i-1}, x_i) - 0.5}{c(x_{i-1})}} = \frac{c(x_{i-1})}{c(x_{i-1}, x_i) - 0.5} > \frac{c(x_{i-1})}{c(x_{i-1}, x_i)},$$

therefore the perplexity

$$\sqrt[a]{\prod_{i=1}^{a} \frac{1}{q(x_i \mid x_{i-1})}} > N + 1.$$

c. True.

$$\sqrt[a]{\prod_{i=1}^{a} \frac{1}{q(x_i|x_{i-1})}}$$

$$= \sqrt[a]{\prod_{i=1}^{a} \frac{1}{\frac{1}{N+1}}}$$

$$= \sqrt[a]{(N+1)^a}$$

$$= N+1$$