Part 1.a:

I downloaded the "Charles Dickens Processed.txt" from the Moodle.

Part 1.b:

I am using nltk version 3.7 and it takes around 10 minutes to tokenize the txt file. Because of this my code saves the tokens in a .txt files (one token each row) and reads from it on the subsequent rounds which takes 1 seconds.

Part 1.c:

The pos_tag function takes around 6 minutes to run because of this my code saves the tokens with their pos_tags in a .txt file and reads from it on the subsequent rounds which takes 2 seconds.

Part 1.d:

I updated the "custom lemmatizer.py" function to also lemmatize the verbs and adverbs. I use this function to iterate over the tokens with their pos tags to lemmatize them.

Part 1.e:

I used 2 different for loops to create the bigrams with different window sizes. It is important note that the bigrams also have the pos_tag of the words at this point but they will be removed in the next step.

Part 1.f:

I deleted the bigrams from the list of bigrams form the previous part. The deleted bigrams which are deleted do not satisfy the one of the first 3 conditions for colocation candidates. Then I removed the pos_tags from the bigrams, and contend their frequencies and made a frequency dictionary for the bigrams and eliminated bigrams which accrued less then 10 times. I also created a frequency dictionary for the monograms which will be used in the next part.

Part 2.a:

I wrote functions to calculate the student's t-test, chi- square test, likelihood ratio test. These functions will be further discussed in part 3. One thing which is important to note is for the likelihood ratio test once each binomial probability is calculated I replace it with "math.ulp(0.0)" (around $5 \cdot 10^{-325}$) which is the smallest positive number in python. Then I take the log of each binomial probability and make the next computation with them only turning it back to normal at the end (10^{prob}) .

I iterated over the colocation candidates for the two bigram dictionaries and compute the student's t-test, chi- square test, likelihood ratio test results and saved the result in a dictionary. Then I ordered the dictionaries and printed the first 20 elements of each test for each window size with the, bigram counts and individual word counts.

Part 3.a:

students t-test:

For the students t-test we use a null hypothesis of the two word in a bigram being independent from each other. The formula for students t-test is:

$$t = \frac{\bar{X} - \mu}{\sqrt{\frac{S^2}{N}}}$$

Where \bar{X} is the mean of the test result, S^2 is the variance of the test result, μ is the mean of the null hypothesis and N is the total number of bigrams. \bar{X} is Pr(bigram) = #w1w2 / N. S^2 is variance of a binomial number so it is equal to $Pr(bigram) \cdot (1 - Pr(bigram))$ but because Pr(bigram) is very small we simply use Pr(bigram). μ comes from the assumption of the bigram words being independent so it is simply equal to $Pr(w1) \cdot Pr(w2) = \#w1 \cdot \#w2/N^2$. Finally N = #tokens -1 and because there are 1898607 tokens it is estimated as #tokens.

Pearson's Chi-Square Test:

For the Pearson's Chi-Square test we use a null hypothesis of the two word in a bigram being independent from each other. The formula for Pearson's Chi-Square test is:

$$X^2 = \sum_{i,j} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}}$$

where O_{ij} and E_{ij} are the observed vs expected counts of events i, j. However, there is a short cut for the 2-by-2 case. I used that and because of that I only needed to find O_{ij} values and not E_{ij} values. The formula for the short cut is:

$$X^{2} = \sum_{i,j} \frac{\left(O_{ij} - E_{ij}\right)^{2}}{E_{ij}} = \frac{N(O_{11}O_{22} - O_{12}O_{21})^{2}}{(O_{11} + O_{12})(O_{11} + O_{21})(O_{12} + O_{22})(O_{21} + O_{22})}$$

The $O_{11}=\#w1w2$, $O_{12}=\#w2-\#w1w2$, $O_{21}=\#w1-\#w1w2$, and $O_{22}=N-\#w1-\#w2+\#w2w1$ are found by the given formulas and they can be represented with the table given bellow.

	w2	¬w2
w1	O_{11}	O_{12}
¬w1	O_{21}	022

Likelihood Ratios Test:

For likelihood ratio test, our Hypothesis 1 is the two words in the collation is independent so:

$$Pr(w2 | w1) = Pr(w2 | \neg w1) = p$$

And our Hypothesis 2 the two words in the bigram is dependent so:

$$Pr(w2 | w1) = p1 \neq Pr(w2 | \neg w1) = p2$$

Let
$$c_{12} = \#w1w2$$
, $c_1 = \#w1$, $c_2 = \#w2$

So for Hypothesis 1:

$$p = c_2/N$$

$$L(H1) = binom(c_{12}; c_{1}, p) \cdot binom(c_{2} - c_{12}; N - c_{1}, p)$$

So for Hypothesis 2:

$$p_1 = c_{12}/c_1$$

$$p_2 = \frac{c_2 - c_{12}}{N - c_1}$$

$$L(H2) = binom(c_{12}; c_{1}, p_{1}) \cdot binom(c_{2} - c_{12}; N - c_{1}, p_{2})$$

Then the likelihood ratio score which is asymptotically $\chi 2$ distributed is:

$$-2 \cdot \ln \left(\frac{L(H1)}{L(H2)} \right)$$

Part 3.b:

In the Student's t-test threshold because there are too many dimensions of freedom we use the infinite dimension row.

In Pearson's Chi-Square Test threshold, we use a 2-by-2 matrix so our dimensions of freedom is (2-1)(2-1) = 1 and we use that row.

Likelihood Ratios Test threshold the scores are asymptotically $\chi 2$ distributed and because the difference of dimension of freedom between the two hypothesis is 1 we use the df=1 row of the table for Chi-Square.

Appendix:

```
print('The nltk version is {}.'.format(nltk. version ))
f2 = open("Charles Dickens Processed.txt", 'r')
for line in f2.readlines():
f2.close()
       tokens.append(token[:-1])
```

```
f3.close()
        f4.write("\n")
    f4.close()
start time = time.time()
    lemmaized tokens.append((cm.lemmatize(t), t[1]))
start time = time.time()
```

```
bigrams 1 = []
bigrams 2 = []
for i in range(len(lemmaized tokens) - 3):
    bigrams 2.append((lemmaized tokens[i], lemmaized tokens[i + 1]))
    bigrams 2.append((lemmaized tokens[i], lemmaized tokens[i + 3]))
bigrams 2.append((lemmaized tokens[-3], lemmaized tokens[-2]))
bigrams_2.append((lemmaized_tokens[-3], lemmaized_tokens[-1]))
bigrams 2.append((lemmaized tokens[-2], lemmaized tokens[-1]))
print("--- %s seconds bigram creation time ---" % (time.time() - start time))
def CountFrequency(my list):
           freq[item] += 1
start time = time.time()
        bigrams to keep 1.append(bigrams 1[i])
bigrams 1 = bigrams to keep 1
```

```
stopwords = ["i", "me", "my", "myself", "we", "our", "ours", "ourselves",
"you", "yours, "yours", "yourself", "yourselves", "he", "him", "his",
"himself", "she", "her", "hers", "herself", "it", "its", "itself", "they",
"them", "their", "theirs", "themselves", "what", "which", "who", "whom",
"this", "that", "these", "those", "am", "is", "are", "was", "were", "be",
"boot", "boot", "boot", "boot", "boot", "del", "delegate "delegate", "delegate "delegate "delegate "delegate", "delegate "delegat
 "this", "that", "these", "those", "am", "is", "are", "was", "were", "be",
"been", "being", "have", "has", "had", "having", "do", "does", "did", "doing",
"a", "an", "the", "and", "but", "if", "or", "because", "as", "until", "while",
"of", "at", "by", "for", "with", "about", "against", "between", "into",
"through", "during", "before", "after", "above", "below", "to", "from", "up",
"down", "in", "out", "on", "off", "over", "under", "again", "further", "then",
"once", "here", "there", "when", "where", "why", "how", "all", "any", "both",
"each", "few", "more", "most", "other", "some", "such", "no", "nor", "not",
"only", "own", "same", "so", "than", "too", "very", "s", "t", "can", "will",
                                                                    bigrams to keep 1.append(bigrams 1[i])
 bigrams 1 = bigrams to keep 1
 bigram dictionary to keep = {}
  part e bigram dictionary 1 = bigram dictionary 1
 bigram dictionary 1 = bigram dictionary to keep
```

```
bigrams to keep 2.append(bigrams 2[i])
bigrams 2 = bigrams to keep 2
bigrams 2 = bigrams to keep 2
stopwords = ["i", "me", "my", "myself", "we", "our", "ours", "ourselves",
"you", "yours", "yourself", "yourselves", "he", "him", "his",
"himself", "she", "her", "hers", "herself", "it", "its", "itself", "they",
"them", "their", "theirs", "themselves", "what", "which", "who", "whom",
"this", "that", "these", "those", "am", "is", "are", "was", "were", "be",
"been", "being", "have", "has", "had", "having", "do", "does", "did", "doing",
"a", "an", "the", "and", "but", "if", "or", "because", "as", "until", "while",
"af", "at", "but", "for", "with", "against", "between", "inte"
 "a", "an", "the", "and", "but", "if", "or", "because", "as", "until", "while"
"of", "at", "by", "for", "with", "about", "against", "between", "into",
"through", "during", "before", "after", "above", "below", "to", "from", "up",
"down", "in", "out", "on", "off", "over", "under", "again", "further", "then"
"once", "here", "there", "when", "where", "why", "how", "all", "any", "both",
"each", "few", "more", "most", "other", "some", "such", "no", "nor", "not",
"only", "own", "same", "so", "than", "too", "very", "s", "t", "can", "will",
bigrams 2 = bigrams to keep 2
  temp dictinory = CountFrequency(bigrams 2)
bigram dictionary 2 = {k: v for k, v in sorted(temp dictinory.items(),
bigram dictionary to keep = {}
```

```
part e bigram dictionary 2 = bigram dictionary 2
bigram dictionary 2 = bigram dictionary to keep
monogram dictionary = CountFrequency(clean lemmaized tokens)
token count = len(lemmaized tokens)
print("\npart 1.d:")
print(f"that = {monogram dictionary['that']}")
print(f"negligent = {monogram_dictionary['negligent']}")
print(f"london = {monogram_dictionary['london']}")
print("\npart 1.e:")
```

```
H0 = monogram dictionary[key[0]] * monogram dictionary[key[1]] /
rank = 1
bigram dictionary 2[key], monogram dictionary[key[0]],
monogram dictionary[key[1]]]
print("\n\nStudent's t test for window size 1")
```

```
0 12 = monogram dictionary[key[0]] - 0 11
Pearson Chi Square test dictionary1 = {k: v for k, v in
table content = []
rank = 1
   name = key[0] + " " + key[1]
    result row = [rank, name, Pearson Chi Square test dictionary1[key],
bigram dictionary 2[key], monogram dictionary[key[0]],
monogram dictionary[key[1]]]
    c 1 = monogram dictionary[key[0]]
```

```
log L H1 = math.log(H1 term 1) + math.log(H1 term 2)
    temp dictinory[key] = likelihood ratio score
bigram dictionary 2[key], monogram dictionary[key[0]],
monogram dictionary[key[1]]]
    table content.append(result row)
```

```
print("\n\n Likelihood Ratio Test for window size 1")
print(tabulate(table content, headers=['Rank', 'Bigram', "Likelihood Ratio",
print("\n")
    H0 = monogram dictionary[key[0]] * monogram dictionary[key[1]] /
rank = 1
   name = key[0] + " " + key[1]
    result row = [rank, name, t test dictionary[key],
bigram dictionary 2[key], monogram dictionary[key[0]],
monogram dictionary[key[1]]]
```

```
print("\n\nStudent's t test for window size 3")
   0 12 = monogram dictionary[key[0]] - 0 11
   0 21 = monogram dictionary[key[1]] - 0 11
Pearson Chi Square test dictionary = {k: v for k, v in
rank = 1
    name = key[0] + " " + key[1]
bigram dictionary 2[key], monogram dictionary[key[0]],
monogram dictionary[key[1]]]
    table content.append(result row)
```

```
print("\n\nPearson's Chi-Square test for window size 3")
    log L H1 = math.log(H1 term 1) + math.log(H1 term 2)
    log L H2 = math.log(H2 term 1) + math.log(H2 term 2)
    temp dictinory[key] = likelihood ratio score
sorted(temp dictinory.items(), key=lambda item: item[1], reverse=True)}
```

```
monogram dictionary[key[1]]]
print(tabulate(table content, headers=['Rank', 'Bigram', "Likelihood Ratio",
print("\n\npart 3.a:\n")
bigram = ("cursitor", "street")
table_content=[["t-Test", t_test_dictionary1[bigram]],
Pearson_Chi_Square_test_dictionary1[bigram]],
likelihood ratio test dictionary1[bigram]]]
bigram = ("good", "one")
Pearson Chi Square test dictionary1[bigram]],
likelihood ratio test dictionary1[bigram]]]
print("Result table for ('good','one') with window size 1")
print(tabulate(table content, headers=['Test', 'Score']))
```

```
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
```