Problems:

1. Data Collection:

- **Select 1 page at random from your favorite literary book (2 pages if it is very short).**
  - **Count the number of sentences. For each of the sentences, determine how many words each contains. Your sample will consist of datapoints on the number of words in each sentence.**
  - **Count the length of each of the words on the page(s).**
- **Obtain the same information from a news or a magazine article. Try to get information on roughly the same number of words and the same number of sentences that you have collected.**

A page has been randomly selected from Yann Martel's book 'Life of Pi', which consists of 52 sentences and 740 words in total. A similar random sample has been selected from 'SpaceX Falcon Heavy Launch' news article and it contains a total of 42 sentences and 765 words. The number of words in each sentence and the length of each word for the book and the article is determined using the following Python code. The selected information of book and article is imported in Python from respective text files.

```
## Import libraries
import re
from string import punctuation

## Reading the text of book/news article
with open('LifeOfPi.txt', 'r') as myfile: # LifeOfPi, SpaceX
    data=myfile.read().replace('\n', ' ')

## Splitting the text on "., ! and ?" to get sentences
sentences = re.split('(?<=[.!?]) +', data)

## Initializing
sent_length = []  ## Stores number of words in a sentence
word_length = []  ## Stores number of letters in a word

for line in sentences:
    words=line.split()  ## Splitting sentences on space to get words
    sent_length += [len(words)]  ## Gives sentence length & stores in vector
    for w in words:  ## Loop to count letters in each word
        len_word = len(w)  ## Gives word length
        count_pun = 0  ## Initialize punctuation count
        for c in w: ## To count punctuations in w
            if c in punctuation:
                count_pun += 1
        len_word -= count_pun  ## Subtracting puntuation count from words
        word_length += [len_word]  ## Stores length of words in a vector
```

The samples of sentences' word count and words' length from the book and article obtained using the code above are shown in Table 1 and Table 2, respectively. These samples are then imported in R for further analysis.

Table 1 Sample of sentences' word count from book and article

Sample	Datapoints
Book (n = 52)	8, 21, 12, 6, 7, 64, 16, 38, 16, 23, 10, 2, 11, 10, 12, 6, 19, 17, 5, 24, 8, 11, 19, 33, 17, 7, 13, 6, 15, 20, 9, 41, 7, 17, 34, 7, 16, 19, 3, 4, 8, 6, 15, 5, 26, 3, 6, 11, 6, 6, 10, 5
Article (n = 42)	5, 28, 22, 15, 22, 21, 16, 35, 12, 25, 18, 14, 26, 9, 16, 10, 14, 20, 11, 16, 41, 24, 38, 18, 9, 19, 14, 11, 12, 22, 15, 16, 13, 26, 8, 28, 26, 13, 12, 20, 6, 19

Table 2 Sample of words' length from book and article

Sample	Datapoints
Book (n = 740)	1, 7, 2, 10, 3, 3, 5, 4, 1, 3, 3, 3, 1, 4, 2, 5, 2, 1, 4, 2, 3, 2, 1, 6, 2, 5, 2, 5, 4, 7, 4, 7, 11, 3, 2, 8, 7, 2, 1, 6, 8, 7, 6, …………., 3, 4, 2, 3, 5, 2, 3, 7, 2, 2
Article (n = 765)	6, 3, 4, 2, 5, 3, 10, 6, 4, 4, 6, 3, 3, 10, 3, 7, 3, 4, 7, 2, 2, 1, 8, 9, 6, 2, 3, 7, 3, 6, 6, 6, 5, 4, 5, 6, 3, 12, 7, 6, 2, 11, …………., 3, 3, 4, 4, 6, 2, 3, 5, 2, 3

2. Project Objective:

- **Compare the information from the book and from the article. Are there any differences (words in each sentence for book vs article; word length for book vs article)?**
- **Apply appropriate statistical procedures (descriptive statistics, confidence intervals, hypothesis tests, etc.). Include appropriate figures (such as histograms and boxplots) to assess and illustrate any differences you find. When performing confidence intervals / hypothesis tests, make sure your assumptions are met.**

a) Comparing word counts in each sentence for book vs article: (i.e. Table 1 samples)

The files containing samples of sentences' word count are first read in R, and a summary of the center and spread of the data is obtained. The R code and summary statistics of sentences' word count for both the book and the article are shown below.

```
# Importing the samples of sentences' word count for book and article
df1 = as.numeric(read.table("LifeOfPi.csv", nrows=1, skip=0, header = FALSE))
df2 = as.numeric(read.table("SpaceX.csv", nrows=1, skip=0, header = FALSE))
# Sample size
n1 = length(df1) # Book
n2 = length(df2) # Article
# Summary Statistics
summary(df1) # Book
summary(df2) # Article
```

```
> # Summary Statistics
> summary(df1) # Book
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   2.00    6.00   11.00   14.23   17.50   64.00 
> summary(df2) # Article
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   5.00   12.25   16.00   18.21   22.00   41.00 
```

At first glance both these samples appear to be skewed. The spread between the third quartile and the max is greater than the spread between the min and the first quartile for both samples. A boxplot is shown in Figure 1 which shows that the data appears to be skewed with median of sentences' word count in the article being larger than that in the book. Also, both these boxplots show some outliers. Further, histograms in Figure 2 confirms positive skewness of data in both samples.

Finally, a normal Q-Q plot is shown in Figure 3. The plots show that the points do not fall closely on the identity line with greater departure from normal in the tails. Thus, the data of both samples does not appear to be normal. The R implementation is also shown.

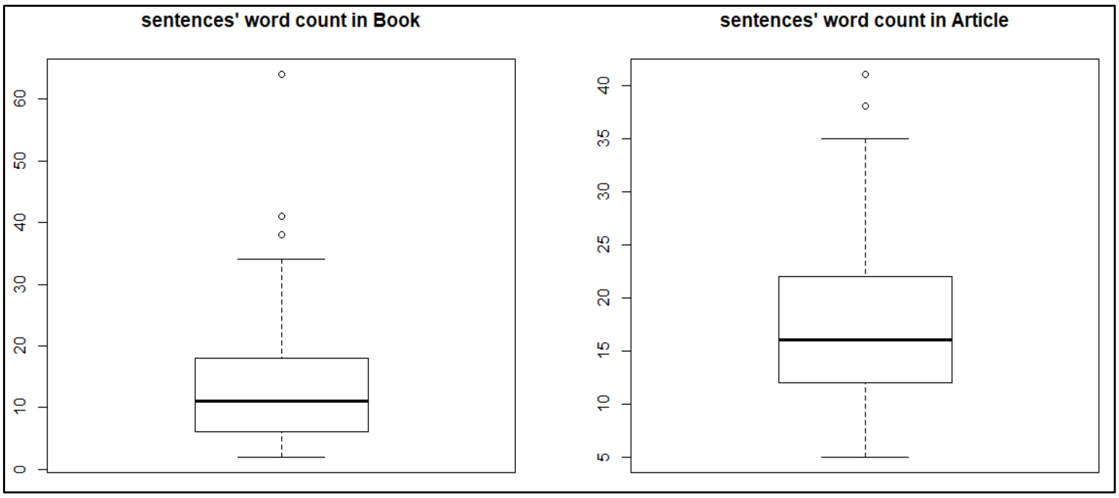

Figure 1 Boxplot of sentences' word count for Book and Article

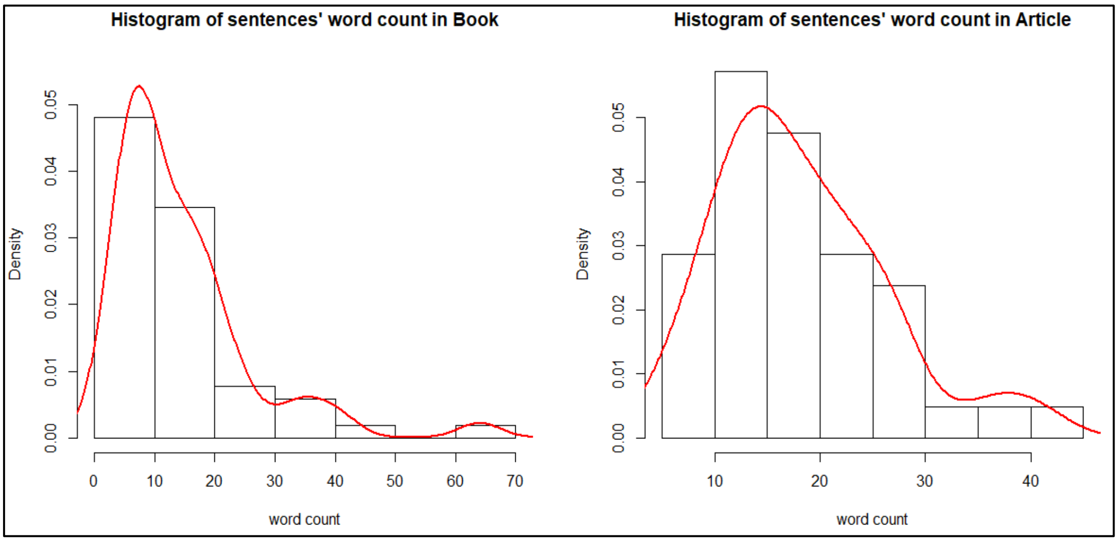

Figure 2 Histogram of sentences' word count for Book and Article

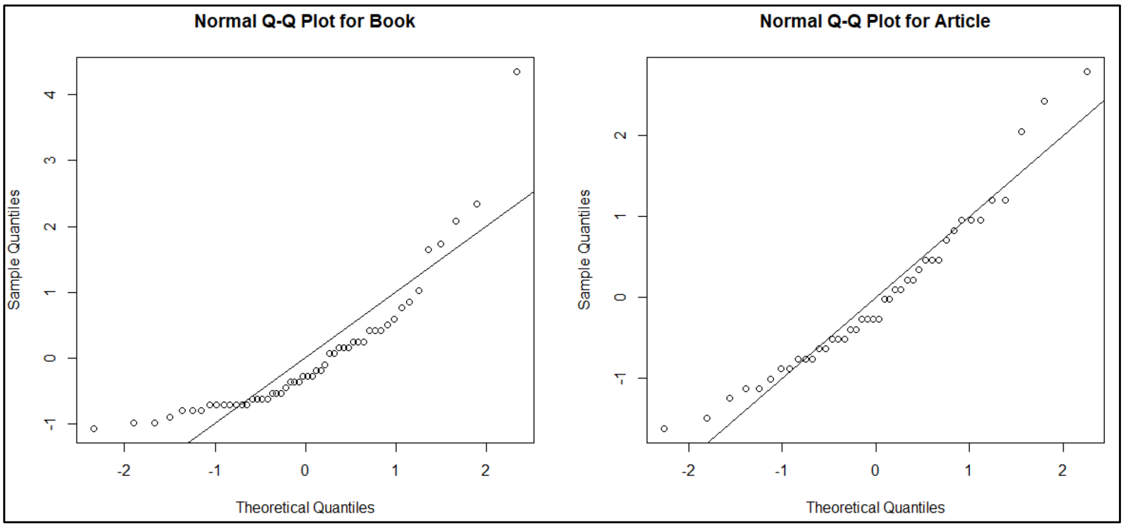

Figure 3 Normal Q-Q Plot of sentences' word count for Book and Article

```
# Creating Boxplots
par(mfrow=c(1,2))
boxplot(df1, main = "sentences' word count in Book")
boxplot(df2, main = "sentences' word count in Article")

# Creating Histograms
par(mfrow=c(1,2))
hist(df1, freq = FALSE, main = "Histogram of sentences' word count in Book",
     xlab = "word count", ylim = c(0,0.055))
lines(density(df1), lwd = 2, col = 'red')
hist(df2, freq = FALSE, main = "Histogram of sentences' word count in Article",
     xlab = "word count")
lines(density(df2), lwd = 2, col = 'red')

# Drawing the QQ-plot (drawn for standardized data)
par(mfrow=c(1,2))
qqnorm((df1-mean(df1))/sd(df1), main = "Normal Q-Q Plot for Book")
abline(0,1) # drawing a 45-degree reference line
qqnorm((df2-mean(df2))/sd(df2), main = "Normal Q-Q Plot for Article")
abline(0,1) # drawing a 45-degree reference line
```

We next see if the data in both samples can be transformed to something that is closer to being normally distributed. We examine the logarithm of the data. First, the boxplots of the log of the data appears to be more evenly distributed as shown in Figure 4. Now there are no outliers seen in both the samples. Also, the histograms appear to be centered and closer to normal in Figure 5. Finally, the normal Q-Q plots are shown in Figure 6. It shows that the data is more consistent with what we would expect from normal data. To further support these findings, the Shapiro-Wilk Normality Test is performed on both these log transformed samples. We see the p-values in Table 3 are large and we do not reject the null hypothesis indicating that the transformed data possibly follows a normal distribution. The R code is also shown below.

Table 3 Shapiro-Wilk test result on log transformed samples

Log(word_count) for Book	Log(word_count) for Article
Shapiro-Wilk normality test data: ledf1 W = 0.98875, p-value = 0.9024	Shapiro-Wilk normality test data: ledf2 W = 0.98531, p-value = 0.8573

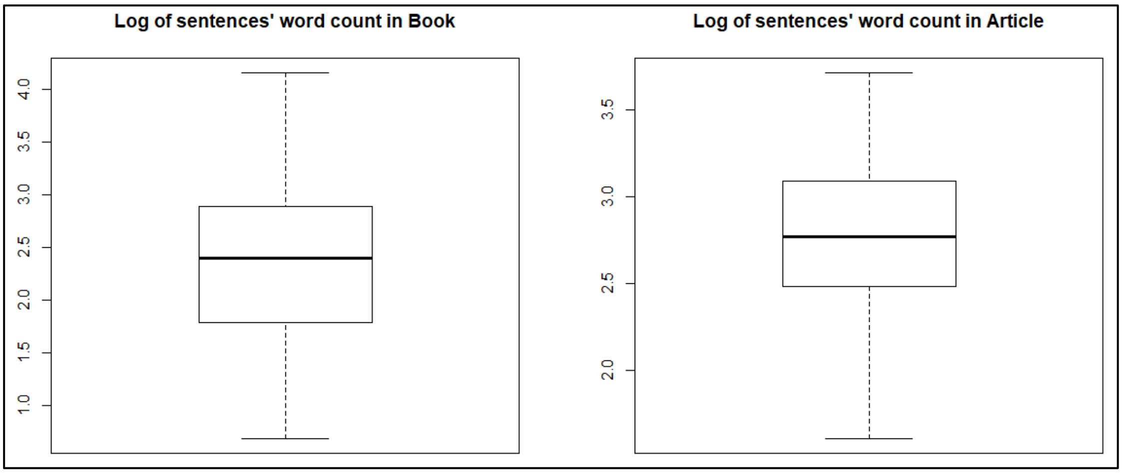

Figure 4 Boxplot of Logarithm of sentences' word count for Book and Article

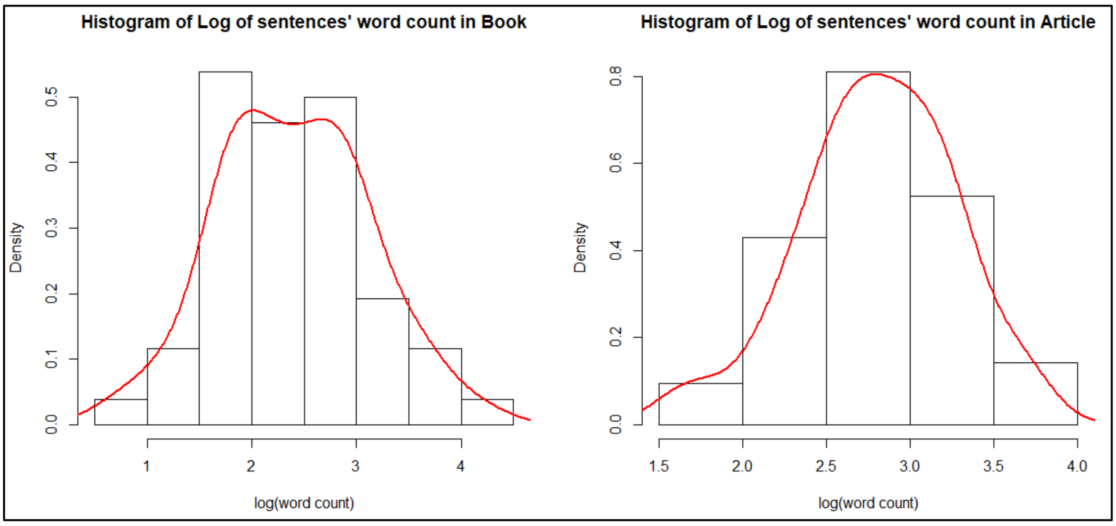

Figure 5 Histogram of Logarithm of sentences' word count for Book and Article

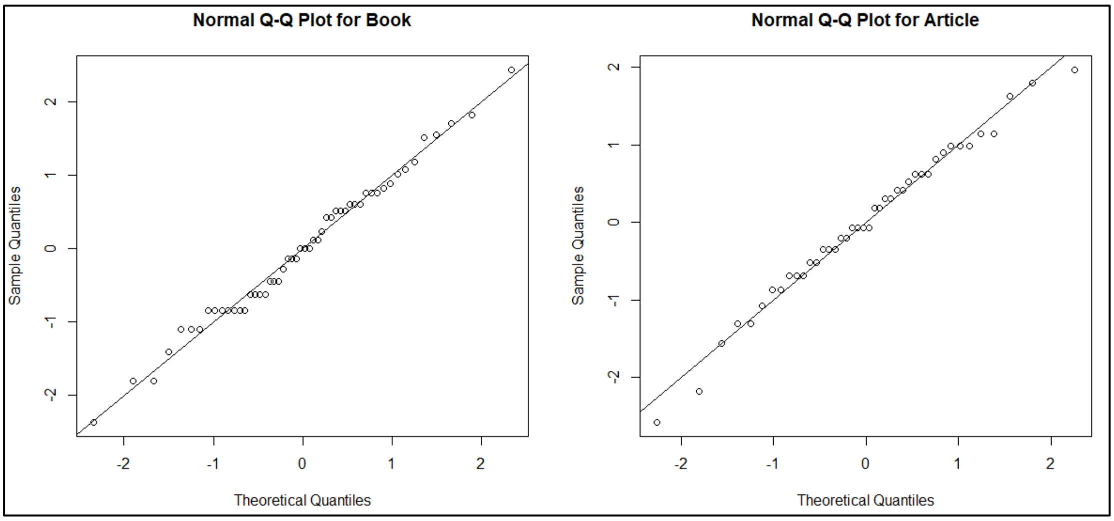

Figure 6 Normal Q-Q Plot of Logarithm of sentences' word count for Book and Article

```
# Log transformation of samples
ledf1 = log(df1) # book
ledf2 = log(df2) # article

# Creating Boxplots
par(mfrow=c(1,2))
boxplot(ledf1, main = "Log of sentences' word count in Book")
boxplot(ledf2, main = "Log of sentences' word count in Article")

# Creating Histograms
par(mfrow=c(1,2))
hist(ledf1, freq = FALSE, main = "Histogram of Log of sentences' word count in Book",
     xlab = "log(word count)")
lines(density(ledf1), lwd = 2, col = 'red')
hist(ledf2, freq = FALSE, main = "Histogram of Log of sentences' word count in Article",
     xlab = "log(word count)")
lines(density(ledf2), lwd = 2, col = 'red')

# Drawing the QQ-plot (drawn for standardized data)
par(mfrow=c(1,2))
qqnorm((ledf1-mean(ledf1))/sd(ledf1), main = "Normal Q-Q Plot for Book")
abline(0,1) # drawing a 45-degree reference line
qqnorm((ledf2-mean(ledf2))/sd(ledf2), main = "Normal Q-Q Plot for Article")
abline(0,1) # drawing a 45-degree reference line

# Performing Shapiro-Wilk test on log transformed samples
shapiro.test(ledf1) # book
shapiro.test(ledf2) # article
```

There is strong evidence that the logarithm of the sentences' word count data for both samples more closely resembles a normal distribution then does the raw word count data. For that reason, all the analysis that follows will be for the logarithm of the word count data for both the book and article.

One of the most common tests in statistics is the *t*-test, which is used to determine whether the means of two groups are equal. The assumption for the test is that both groups are independent, sampled from normal distributions with equal variances. Let us now check various assumption before performing appropriate hypothesis test procedure to compare the differences in the two samples.

Check Assumption 1: Are these samples independent?
Yes, the two data samples are independent since they come from distinct populations and the samples do not affect each other.

Check Assumption 2: Are these samples normally distributed?
Yes, we just checked that these log transformed samples can be approximated as normally distributed based on the above analysis.

Check Assumption 3: Are the two sample variances equal?
It is necessary to evaluate the sample variances of the two groups, using a Fisher's F-test to verify the homogeneity of variances. We can use var.test() method in R to perform this test as shown below.

```
> var.test(ledf1,ledf2)

        F test to compare two variances

data:  ledf1 and ledf2
F = 2.4201, num df = 51, denom df = 41, p-value = 0.004196
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 1.330407 4.319475
sample estimates:
ratio of variances
          2.420134
```

We obtain a p-value smaller than 0.05 (assumed significance level), thus we cannot assume that the two variances are homogeneous. Indeed we can compare the value of F obtained with the tabulated value of F for alpha = 0.05, degrees of freedom of numerator = 51, and degrees of freedom of denominator = 41, using the function qf() in R. We see that the value of F computed (i.e. 2.42) is greater than the tabulated value of F (i.e.1.65), which leads us to reject the null hypothesis of homogeneity of variances.

```
> qf(0.95, 51, 41)
[1] 1.649979
```

Since the assumption of equal variances is not tenable, we can invoke Welch's variance approximation which is believed to provide a more robust *t*-test procedure where the assumption of equal population variances is not required. Welch's *t*-test that adjusts the number of degrees of freedom. We can compute the two sided *t*-test using Welch's approximation by setting var.equal=FALSE in t.test() method of R as demonstrated in the following line of code.

Note that when we are conducting a t-test on log transformed data, we are conducting a hypothesis test on the ratio of the medians and not a hypothesis about the difference of the means. As a result, we are testing the hypothesis of ratio of the medians against a two-sided alternative.

```
> # Performing Welch's t-test
> t.test(ledf1, ledf2, var.equal=FALSE, alternative = "two.sided")

        Welch Two Sample t-test

data:  ledf1 and ledf2
t = -3.2836, df = 87.91, p-value = 0.001472
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.6486549 -0.1595252
sample estimates:
mean of x mean of y
 2.398352  2.802442
```

We observe that the p-value is very less compared to 0.05, which indicates that we should reject the null hypothesis and conclude that there are differences in the *median* (as expressed by a ratio) of sentences' word count of the book and the article.

Let us now interpret the 95% CI that we obtain from performing the above test. This CI is in terms of log of median ratio. Suppose X and Y represents the raw data of sentences' word count for the book and the article, respectively. Then, the 95% CI obtained is,

$$-0.64865 \leq \log\left(\frac{median(X)}{median(Y)}\right) \leq -0.15952$$

We can back-transform this CI in terms of the original raw data and make interpretation about the ratio of the medians (without log) of the two samples. We can back-transform by taking the exponent (e-to-the-power) of above CI. Thus, we obtain a new 95% CI,

$$e^{-0.64865} \leq \frac{median(X)}{median(Y)} \leq e^{-0.15952}$$

$$0.52275 \leq \frac{median(X)}{median(Y)} \leq 0.85255$$

$$0.52275 \cdot median(Y) \leq median(X) \leq 0.85255 \cdot median(Y)$$

Thus, we are 95% confident that X's median is between 0.52275 and 0.85255 times that of sample Y, i.e., we are 95% confident that the median sentences' word count for the book is between 52.28% and 85.26% that of the article.

b) Comparing words' length for book vs article: (i.e. Table 2 samples)

The initial analysis in comparing words' length for the book and the article will be very similar to that of part (a). The files containing samples of words' length are first read in R, and a summary of the center and spread of the data is obtained. The R code and summary statistics of words' length for both the book and the article are shown below.

```
# Importing the samples of words' length for book and article
df3 = as.numeric(read.table("LifeOfPi.csv", nrows=1, skip=1, header = FALSE))
df4 = as.numeric(read.table("SpaceX.csv", nrows=1, skip=1, header = FALSE))
# Sample size
n3 = length(df3) # Book
n4 = length(df4) # Article
# Summary Statistics
summary(df3) # Book
summary(df4) # Article
```

```
# Summary Statistics
summary(df3) # Book
 Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.000   2.000   4.000   4.153   5.000  14.000
summary(df4) # Article
 Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.000   3.000   4.000   4.604   6.000  15.000
```

Both these samples appear to be skewed. The spread between the third quartile and the max is greater than the spread between the min and the first quartile for both samples. A boxplot is shown in Figure 7 which shows that the data appears to be skewed with median of words' length being almost the same for both samples. Also, both these boxplots show several outliers. Further, histograms in Figure 8 confirms positive skewness of data in both samples.

Finally, a normal Q-Q plot is shown in Figure 9. The plots show several steps indicating that the distribution of both these samples is discrete. Also, the points do not fall closely on the identity line with greater departure from normal in the tails. Thus, the data of both samples does not appear to be normal. The R implementation is also shown.

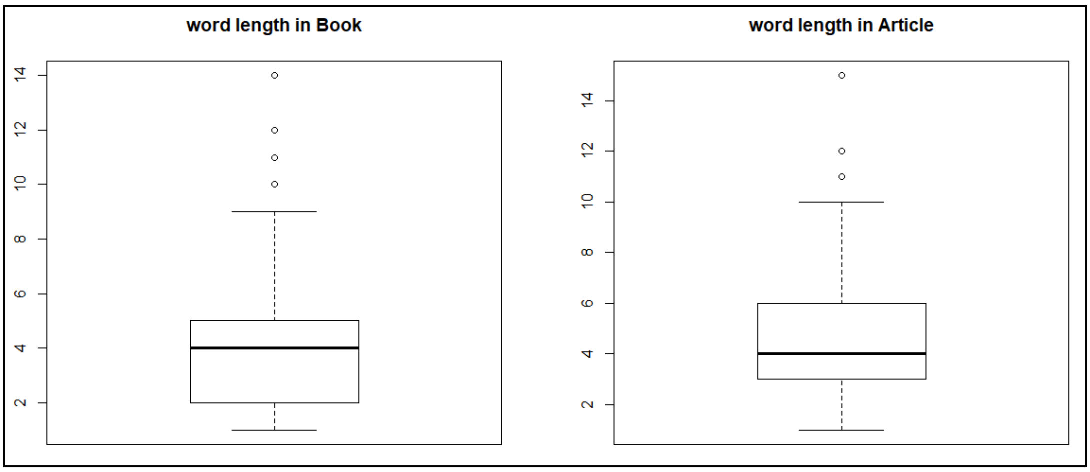

Figure 7 Boxplot of words' length for Book and Article

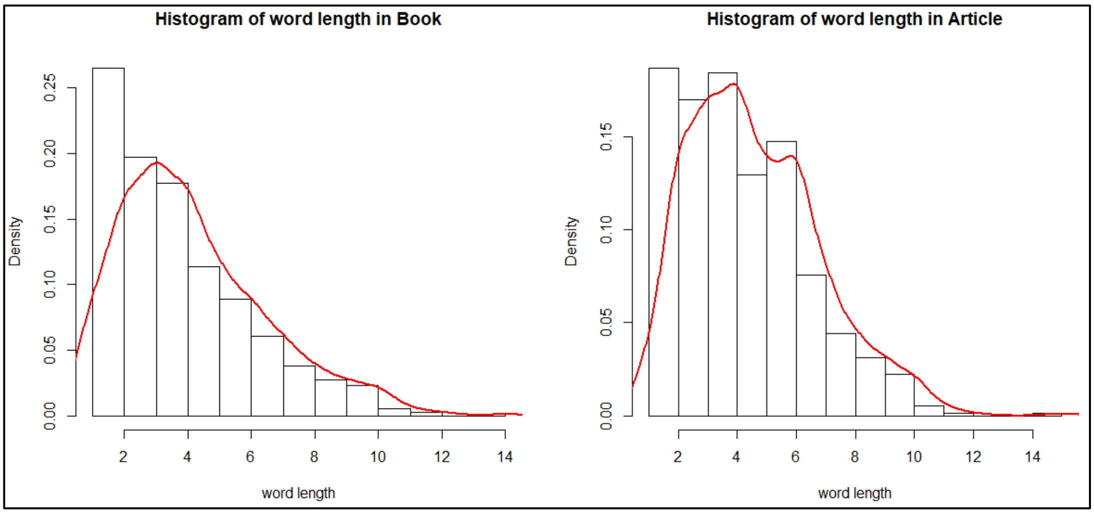

Figure 8 Histogram of words' length for Book and Article

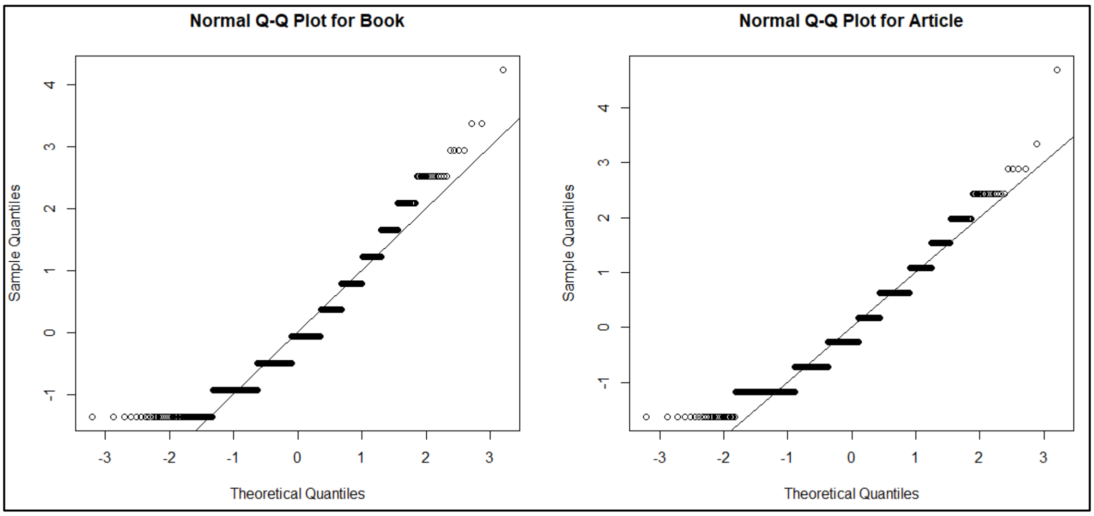

Figure 9 Normal Q-Q Plot of words' length for Book and Article

```
# Creating Boxplots
par(mfrow=c(1,2))
boxplot(df3, main = "Word length in Book")
boxplot(df4, main = "Word length in Article")

# Creating Histograms
par(mfrow=c(1,2))
hist(df3, freq = FALSE, main = "Histogram of word length in Book",
     xlab = "Word length")
lines(density(df3), lwd = 2, col = 'red')
hist(df4, freq = FALSE, main = "Histogram of word length in Article",
     xlab = "Word length")
lines(density(df4), lwd = 2, col = 'red')

# Drawing the QQ-plot (drawn for standardized data)
par(mfrow=c(1,2))
qqnorm((df3-mean(df3))/sd(df3), main = "Normal Q-Q Plot for Book")
abline(0,1) # drawing a 45-degree reference line
qqnorm((df4-mean(df4))/sd(df4), main = "Normal Q-Q Plot for Article")
abline(0,1) # drawing a 45-degree reference line
```

Let us now check various assumption before performing appropriate hypothesis test procedure to compare the differences in the two samples.

Check Assumption 1: Are these samples independent?
Yes, the two data samples are independent since they come from distinct populations and the samples do not affect each other.

Check Assumption 2: Are these samples normally distributed?
Logarithm and square root transformations were examined for the two samples (similar to the log transformation in part (a)). However, assumption of normality wasn't achieved with either of the transformations for both samples. Even the Shapiro-Wilk test resulted in extremely small p-value, thus normality assumption was not conceivable. (The R implementation isn't being shown here so as to keep the report short.)

Check Assumption 3: Are the two sample variances equal?
Using a Fisher's F-test, the homogeneity of variances of the two samples is verified as shown below using var.test() method in R.

```
> var.test(df3,df4)

        F test to compare two variances

data:  df3 and df4
F = 1.0961, num df = 739, denom df = 764, p-value = 0.2084
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.9500402 1.2648974
sample estimates:
ratio of variances
          1.096128
```

We obtain a p-value greater than 0.05 (assumed significance level), thus we can assume that the two variances are homogeneous. Indeed we can compare the value of F obtained with the tabulated value of F for alpha = 0.05, degrees of freedom of numerator

= 739, and degrees of freedom of denominator = 764, using the function qf() in R. We see that the value of F computed (i.e. 1.096) is less than the tabulated value of F (i.e.1.128), thus we do not reject the null hypothesis of homogeneity of variances.

```
> qf(0.95,739,764)
[1] 1.127526
```

Since, from above we concluded that the samples of words' length of the book and the article are not normally distributed, we must solve this problem using certain non-parametric test. Non-parametric tests are often called distribution free tests and can be used instead of their parametric equivalent. Non-parametric tests such as bootstrap or permutation test procedures can be used. Let us use bootstrap procedure to test the null hypothesis that the two sampling distributions are identical.

Bootstrapping is resampling with replacement which allows a wider range of values than may be possible from the statistical sample. The illustration is shown in Figure 10. Consider samples of size 4 and 3, respectively as shown. Also, let us suppose that the statistic of interest is difference of two sample means. Firstly, all the data from both samples is grouped into one big pool, then randomly split (with replacement) into two groups of the same sizes as the original samples. We then simulate this multiple time and compute the statistic of interest on every bootstrapped sample, which forms the null hypothesis. The p-value obtained is the probability of obtaining a difference in parameter (e.g. means) at least as large as observed at random, if the two samples did come from the same population.

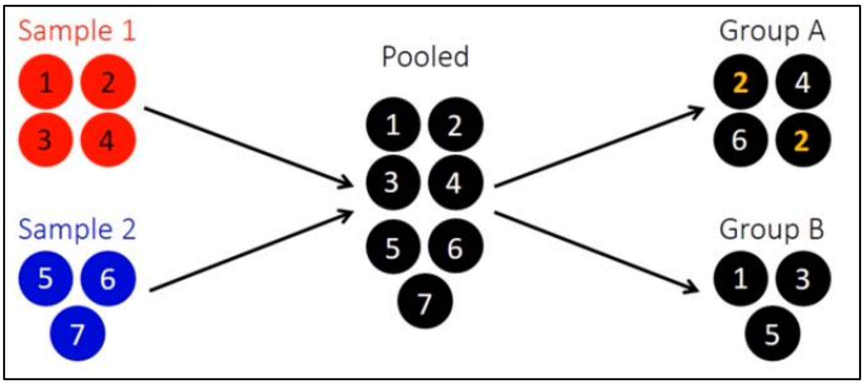

Figure 10 Illustration of bootstrap test procedure

Let us now implement bootstrap test procedure on the sample of words' length of the book and the article to test the hypothesis that the two population means are equal against an alternative that they are not equal.

Since we have two independent samples, we resample each group separately. This mimics the original sampling scheme when resampling the data. We have 740 words in the book sample and 765 words in the article sample. The bootstrap code for the words' length data, using 2000 resamplings is shown. The histogram of expected differences in means of words' length of the two samples is shown in Figure 11 and it shows to approximate a normal distribution.

```r
# Performing bootstrap test
boot <- rep(0,2000)
for(i in 1:2000)
{
  a <- sample(df4, 765, replace=T)
  b <- sample(df3, 740, replace=T)
  boot[i] <- mean(a)-mean(b)
}

# Histogram of expected difference in means
hist(boot, freq = FALSE, main = "Expected difference between
     means of words' length", xlab = "Difference in means")
lines(density(boot), lwd = 2, col = 'red')
```

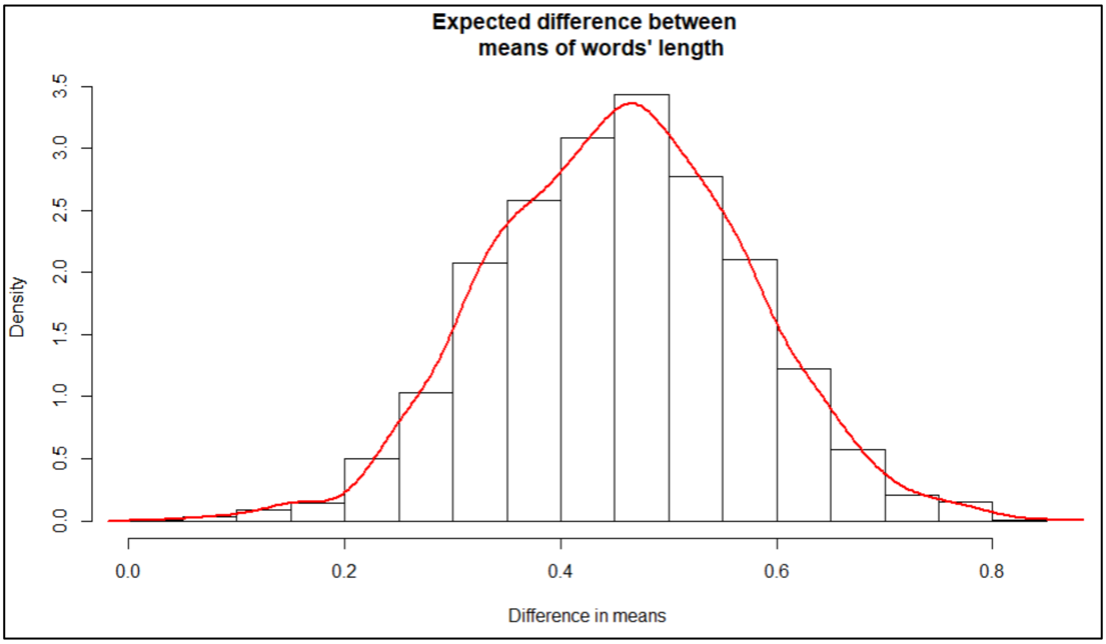

Figure 11 Histogram of difference between the means

The 95% confidence interval for the difference between the means is (0.23687, 0.68468) as shown by the following line of code.

```
> quantile(boot,c(.025,.975))
     2.5%     97.5%
0.2368707 0.6846759
```

```
> # Observed value of test statistic
> mean(df4)-mean(df3)
[1] 0.4512189
```

We see the observed value of difference in the two sample means lies in the 95% CI. Also, the 95% CI does not include 0, implying that the means of the two samples are not equal and thus we reject the null hypothesis.

- **Attach copies of the original pages from the book and the article. Describe how you drew the sample pages from them.**

  The book, Life of Pi, by Yann Martel is a 326-page book. To pick a page, I generated a uniform random number between 1 and 326 using `round(runif(1, 1, 326))` in R. The random number generated was 133, and accordingly I picked page 133 from the book.

  For the news article, I searched 'SpaceX Falcon Heavy Launch News' on Google and picked a random number between 1 and 10 using `round(runif(1, 1, 10))`, which resulted in 5. So, I clicked link 5 from the top of the results displayed by Google. The reference is shown on the copy of the article attached.

Yann Martel: Life of Pi

I thought of sustenance for the first time. I had not had a drop to drink or a bite to eat or a minute of sleep in three days. Finding this obvious explanation for my weakness brought me a little strength.

Richard Parker was still on board. In fact, he was directly beneath me. Incredible that such a thing should need consent to be true, but it was only after much deliberation, upon assessing various mental items and points of view, that I concluded that it was not a dream or a delusion or a misplaced memory or a fancy or any other such falsity, but a solid, true thing witnessed while in a weakened, highly agitated state. The truth of it would be confirmed as soon as I felt well enough to investigate.

How I had failed to notice for two and a half days a 450-pound Bengal tiger in a lifeboat twenty-six feet long was a conundrum I would have to try to crack later, when I had more energy. The feat surely made Richard Parker the largest stowaway, proportionally speaking, in the history of navigation. From tip of nose to tip of tail he took up over a third of the length of the ship he was on.

You might think I lost all hope at that point. I did. And as a result I perked up and felt much better. We see that in sports all the time, don't we? The tennis challenger starts strong but soon loses confidence in his playing. The champion racks up the games. But in the final set, when the challenger has nothing left to lose, he becomes relaxed again, insouciant, daring. Suddenly he's playing like the devil and the champion must work hard to get those last points. So it was with me. To cope with a hyena seemed remotely possible, but I was so obviously outmatched by Richard Parker that it wasn't even worth worrying about. With a tiger aboard, my life was over. That being settled, why not do something about my parched throat?

I believe it was this that saved my life that morning, that I was quite literally dying of thirst. Now that the word had popped into my head I couldn't think of anything else, as if the word itself were salty and the more I thought of it, the worse the effect. I have heard that the hunger for air exceeds as a compelling sensation the thirst for water. Only for a few minutes, I say. After a few minutes you die and the discomfort of asphyxiation goes away. Whereas thirst is a drawn-out affair. Look: Christ on the Cross died of suffocation, but His only complaint was of thirst. If thirst can be so taxing that even God Incarnate complains about it, imagine the effect on a regular human. It was enough to make me go raving mad. I have never known a worse physical hell than this putrid taste and pasty feeling in the mouth, this unbearable pressure at the back of the throat, this sensation that my blood was turning to a thick syrup that barely flowed. Truly, by comparison, a tiger was nothing.

And so I pushed aside all thoughts of Richard Parker and fearlessly went exploring for fresh water.

The divining rod in my mind dipped sharply and a spring gushed water when I remembered that I was on a genuine, regulation lifeboat and that such a lifeboat was surely outfitted with supplies. That seemed like a perfectly reasonable proposition. What captain would fail in so elementary a way to ensure the safety of his crew? What ship chandler would not think of making a little extra money under the noble guise of saving lives? It was settled. There was water aboard. All I had to do was find it.

Which meant I had to move.

I made it to the middle of the boat, to the edge of the tarpaulin. It was a hard crawl. I felt I was climbing the side of a volcano and I was about to look over the rim into a boiling cauldron of orange lava. I lay flat. I carefully brought my head over. I did not look over any more than I had to. I did not see Richard Parker. The hyena was plainly visible, though. It was back behind what was left of the zebra. It was looking at me.

[ref] https://www.scollingsworthenglish.com/uploads/3/8/4/2/38422447/_life_of_pi_full_text_pdf.pdf

SpaceX launches Falcon Heavy, the world's most powerful rocket

SpaceX has done it again. The pioneering rocket firm just pulled off the unexpected, and carried out what appears to be a seamless first-ever launch of its massive new rocket, called Falcon Heavy. That makes SpaceX, the game-changing company helmed by billionaire Tesla CEO Elon Musk, the owner of the world's most powerful operational rocket. Falcon Heavy took flight Tuesday around 3:45 pm ET from Kennedy Space Center in Florida.

"I'm still trying to absorb everything that happened because it's still kind of surreal to me," Musk told reporters after the launch.

Thousands of onlookers in Florida could be heard cheering on the company's livestream, which was viewed by about 3 million people. In the run up to launch, it wasn't at all clear that the rocket would work. "People came from all around the world to see what will either be a great rocket launch or the best fireworks display they've ever seen," Musk said in an interview with CNN's Rachel Crane Monday.

The rocket's smooth takeoff wasn't the only stunning thing about this launch. In a never-before-seen feat, SpaceX also managed to guide at least two of the Falcon Heavy's first-stage rocket boosters to land upright back on Earth. They cut back through the Earth's atmosphere and landed in unison at a Kennedy Space Center landing pad. "That was probably the most exciting thing I've ever seen literally ever," Musk said. The third booster was supposed to land on a sea-faring platform called a droneship but just as it was about to land, the livestream cut out. Musk confirmed after the launch that the booster crashed.

On board the rocket that's now headed deeper into space is Musk's personal Tesla (TSLA) roadster. At the wheel is a dummy dressed in a spacesuit. Musk said in December the car would play David Bowie's "Space Oddity" on repeat. Cameras on board the car show it cruising by Earth, which appears as a big blue orb in the background. Musk plans to send the car into orbit around the sun. He announced last year he planned to put his car on the inaugural Falcon Heavy flight. When asked on Twitter why he wanted to throw away a $100,000 vehicle, he replied, "I love the thought of a car drifting apparently endlessly through space and perhaps being discovered by an alien race millions of years in the future".

Tuesday's success marked a huge step forward for a company that's already managed to shake up the rocket industry with its ground breaking technology. The company made the world take notice when it proved it can safely return first-stage rocket boosters to Earth with its Falcon 9 rocket, which the company has used for more than 40 missions dating back to 2012. Those rockets have a single first-stage booster, and SpaceX has safely recaptured them after 21 Falcon 9 launches. Now, SpaceX routinely puts used boosters back to work. In fact, the inaugural Falcon Heavy flight actually used two pre-flown Falcon 9 boosters (the center booster was new). Reusing hardware is part of SpaceX's plan to drive down the cost of launches. Before SpaceX came along, companies just discarded rockets after each mission.

Note the Falcon Heavy is not the most powerful rocket in history. That honor belongs to NASA's Saturn V rocket, which was used for the Apollo moon landings and was retired in the 1970s.

Falcon Heavy is big, Musk said, but SpaceX needs a rocket "way bigger than that". SpaceX's idea of exactly how it will get humans to Mars has evolved over the years. Musk revealed his most recent plan at a conference in Australia last year. It involves a truly enormous launch vehicle, called BFR or Big Falcon Rocket, that would give off more than 11 million pounds of thrust at liftoff. That's more than double the Falcon Heavy's thrust. BFR needs enough power to vault a 160-foot long spacecraft (loaded with humans and all their cargo) into space before it can begin the months-long trek to Mars.

In the near future, "most of our engineering resources will be dedicated to BFR, and I think that will make things go quite quickly," Musk said. A first test flight for BFR could happen in "three or four years". SpaceX and the space community in general is notoriously loose with deadlines. When Falcon Heavy was first announced back in 2011, Musk said it could fly within the next couple of years. It ended up taking nearly seven. And SpaceX does have one more thing to check off its to-do list before it can focus on BFR.

[ref] http://money.cnn.com/2018/02/06/technology/future/spacex-falcon-heavy-launch-mainbar/index.html