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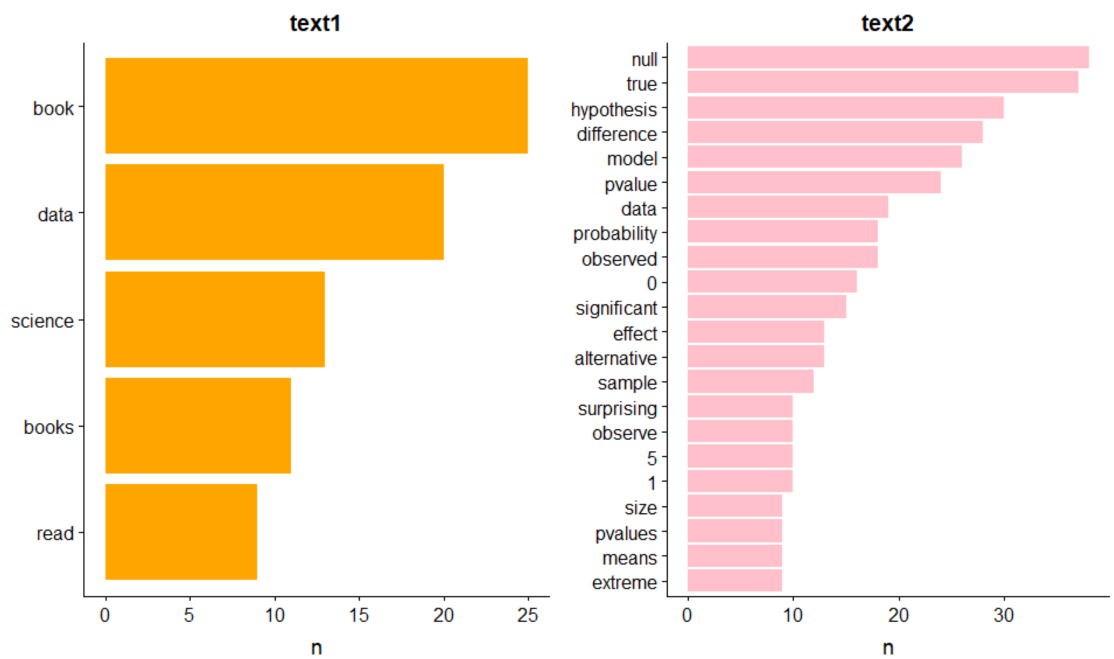
Introduction

We scraped two articles from https://www.correlaid.org/bog. "DATA SCIENCE IS NOT JUST ABOUT DATA SCIENCE", and "ABOUT P-VALUES". Based on these two articles, we analyzed tidy format, frequency, sentiment, relationships between words, and topics.

Words frequency



Words that occur over 9 times in each text

The barplot shows words that occur over 9 times in each text. We can see that the they both have "data"

number of words about trust in text1

word	n

machine	4
system	4
found	3
related	3
architecture	2
calls	2
crucial	2
hope	2
influential	2
statistical	2
account	1
communicate	1
doubt	1
economy	1
guide	1
inspired	1
level	1
policy	1
professor	1
rational	1
scientific	1
understanding	1
wealth	1

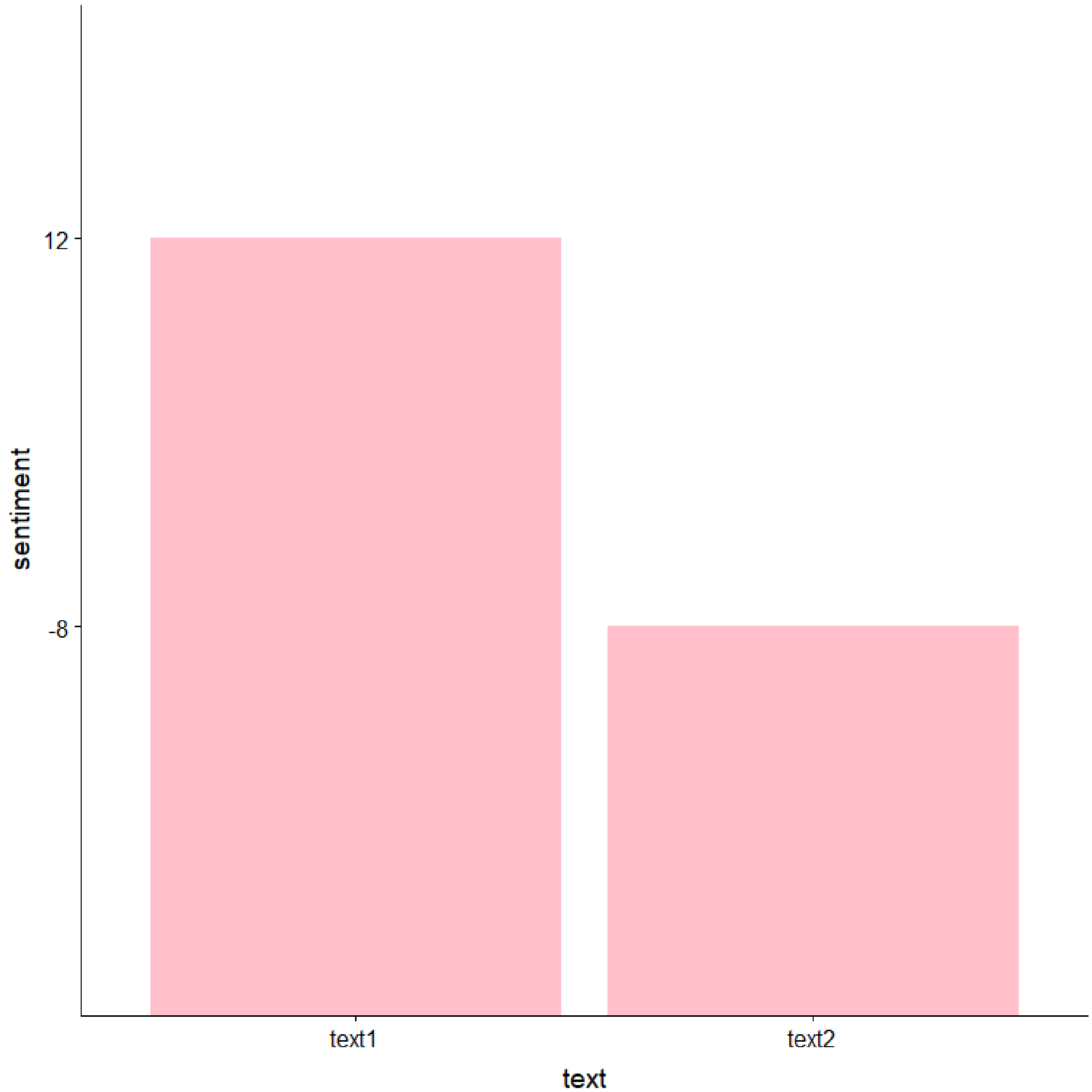
number of words about trust in text2

word	n
true	37
expect	7
omniscient	6
level	4
statement	4
explain	3
larger	3
theory	3
grammar	2
prefer	2
provide	2

complement	1
enable	1
finally	1
inform	1
label	1
recommend	1
series	1
statistical	1

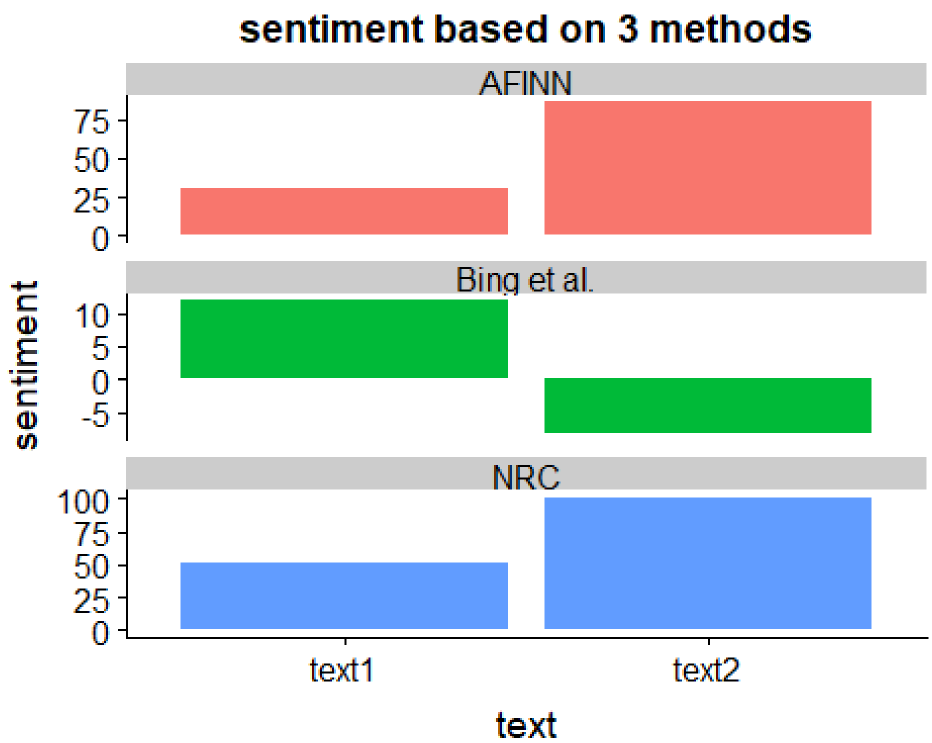
Sentiment

Overall sentiment



The plot shows the sentiment score of two texts, the text1 has higher score so that it has a better sentiment.

Sentiment based on 3 methods



sentiment based on 3 methods

The plot shows that sentiment of text2 based on Bing sentiment dasaset has different result with other two sentiment dataset.

Top10 positive and negative words

top 10 positive and negative words for text1

word	sentiment	n
popular	positive	3
critical	negative	2
criticism	negative	2
enjoyed	positive	2
fascinating	positive	2
fast	positive	2
influential	positive	2
master	positive	2
pessimistic	negative	2
bad	negative	1
beautiful	positive	1

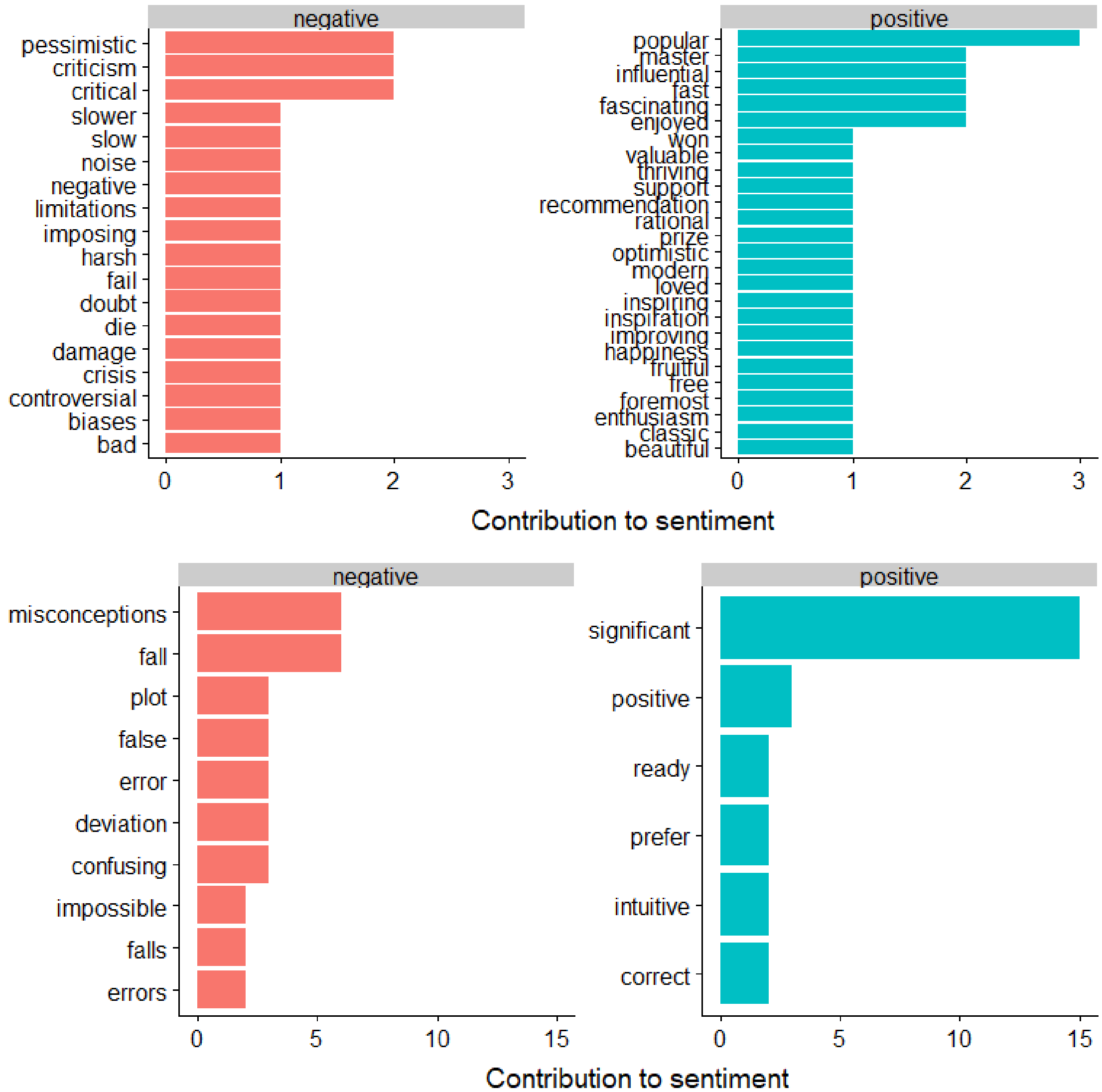
biases	negative	1
classic	positive	1
controversial	negative	1
crisis	negative	1
damage	negative	1
die	negative	1
doubt	negative	1
enthusiasm	positive	1
fail	negative	1
foremost	positive	1
free	positive	1
fruitful	positive	1
happiness	positive	1
harsh	negative	1
imposing	negative	1
improving	positive	1
inspiration	positive	1
inspiring	positive	1
limitations	negative	1
loved	positive	1
modern	positive	1
negative	negative	1
noise	negative	1
optimistic	positive	1
prize	positive	1
rational	positive	1
recommendation	positive	1
slow	negative	1
slower	negative	1
support	positive	1
thriving	positive	1
valuable	positive	1
won	positive	1

top 10 positive and negative words for text2

word	sentiment	n
significant	positive	15

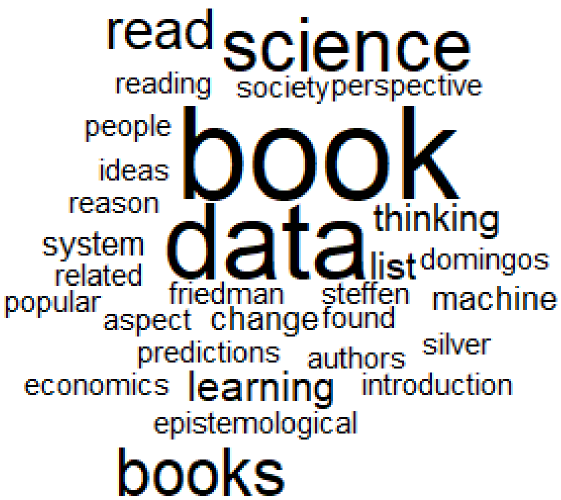
fall	negative	6
misconceptions	negative	6
confusing	negative	3
deviation	negative	3
error	negative	3
false	negative	3
plot	negative	3
positive	positive	3
correct	positive	2
errors	negative	2
falls	negative	2
impossible	negative	2
intuitive	positive	2
prefer	positive	2
ready	positive	2

Words that contribute to positive and negative sentiment



The plot shows positive and negative words on both texts.

Wordscloud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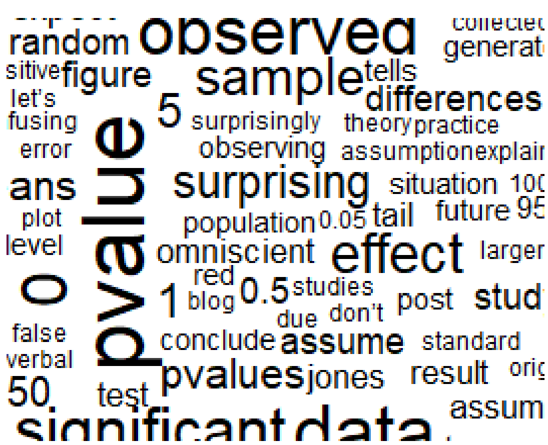
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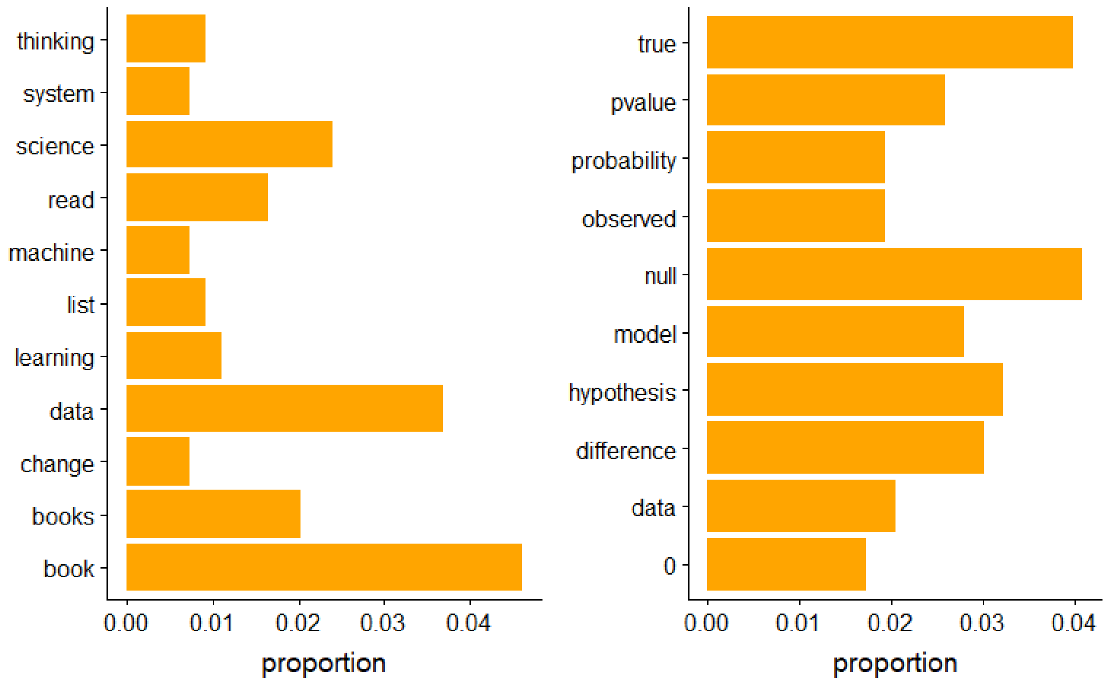
result
50
test

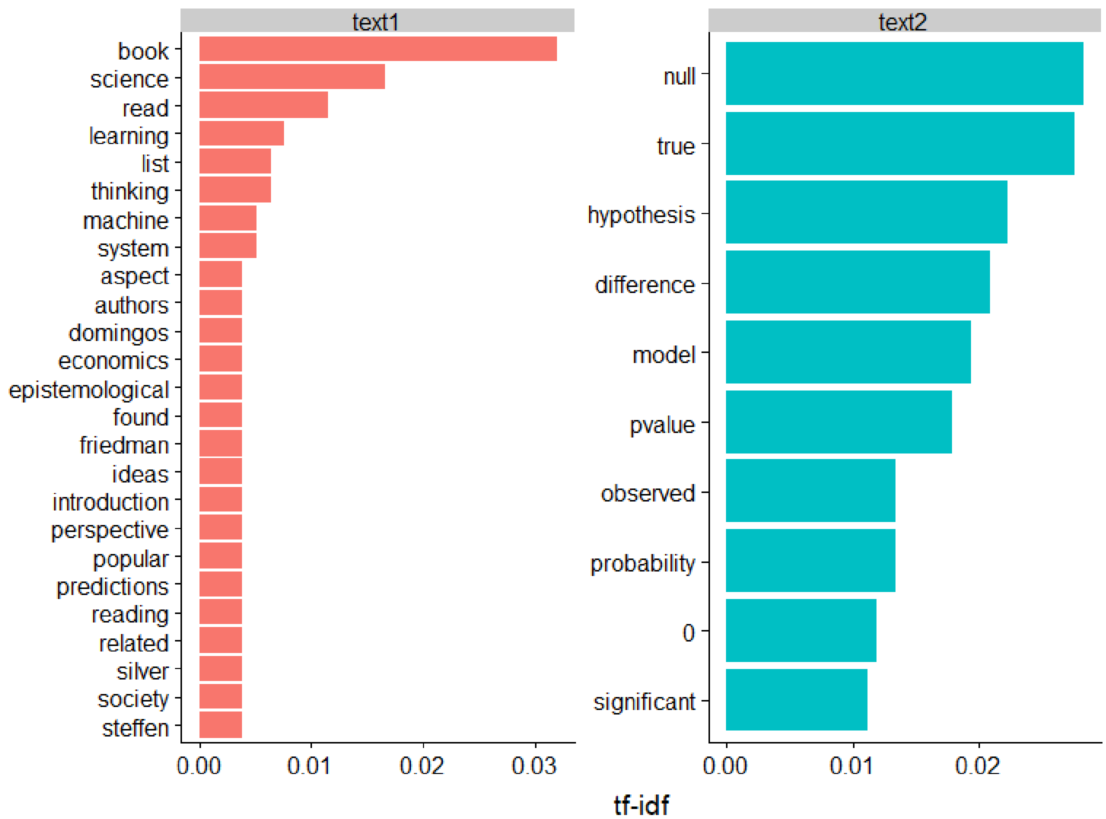
The wordscloud shows that "book","science","data","read" are the most frequent in text1; "true","hypothesis","pvalue","model","data","effect"."probability" are the most frequent in text2.

Word and document frequency



Term Frequency Distribution

The plot shows term frequency of top 10 frequent words of each text.



how important a word is to a document in 2 documents

The plot shows term frequency based on tf_idf of top 10 frequent words of both text. We can see that the result is almost same with the result of term frequency based on simple term frequency(tf).

Relationships between words: n-grams and correlations

tokenize into consecutive sequences of words(token = "ngrams")

Counting and filtering n-grams

```
## # A tibble: 6 x 2
##   bigram                   n
##   <chr>                <int>
## 1 data science             9
## 2 machine learning         3
## 3 choice architecture      2
## 4 data analysts            2
## 5 enjoyed reading          2
## 6 learning techniques      2

## # A tibble: 6 x 2
##   bigram                  n
```

```
##   <chr>              <int>
## 1 null hypothesis       21
## 2 null model            15
## 3 alternative model      7
## 4 omniscient jones       6
## 5 sample size            6
## 6 significant result     6
```

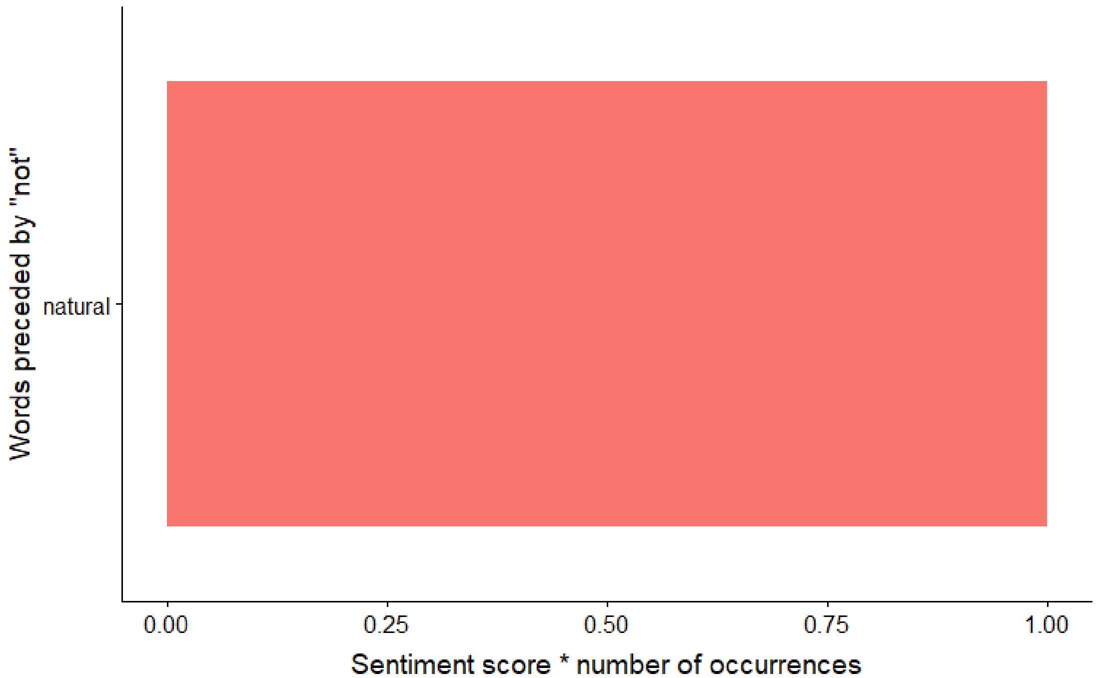
We can see that "data science" and "null hypothesis" are the most common pairs in the two books seperately, which are close to the topic of books.

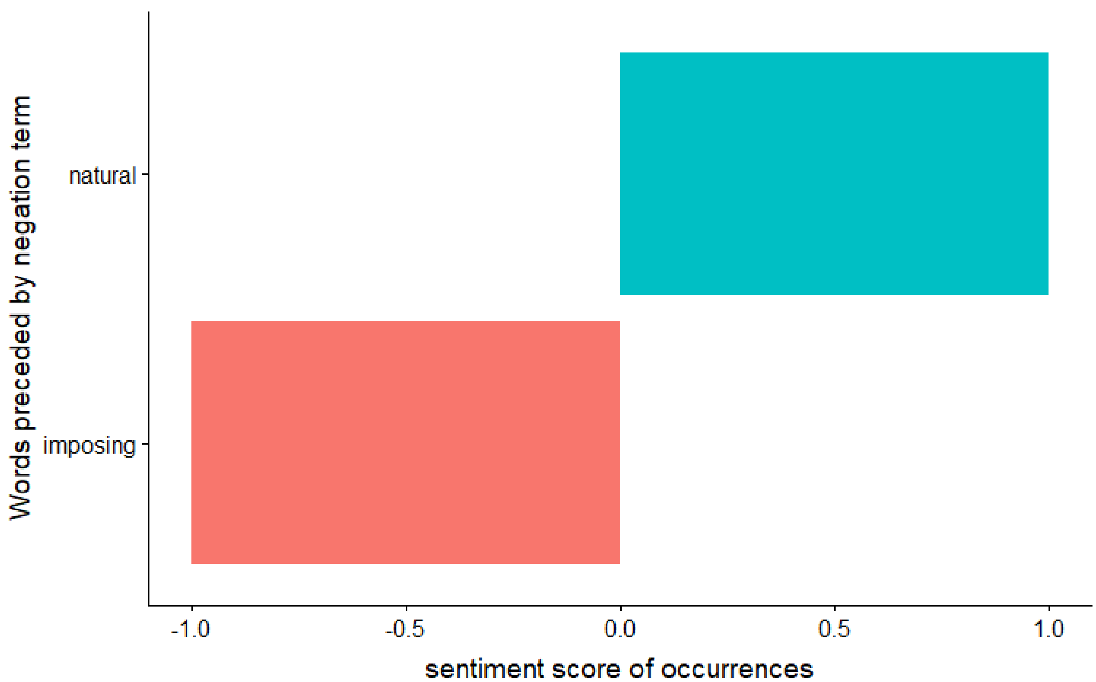
Analyzing bigrams

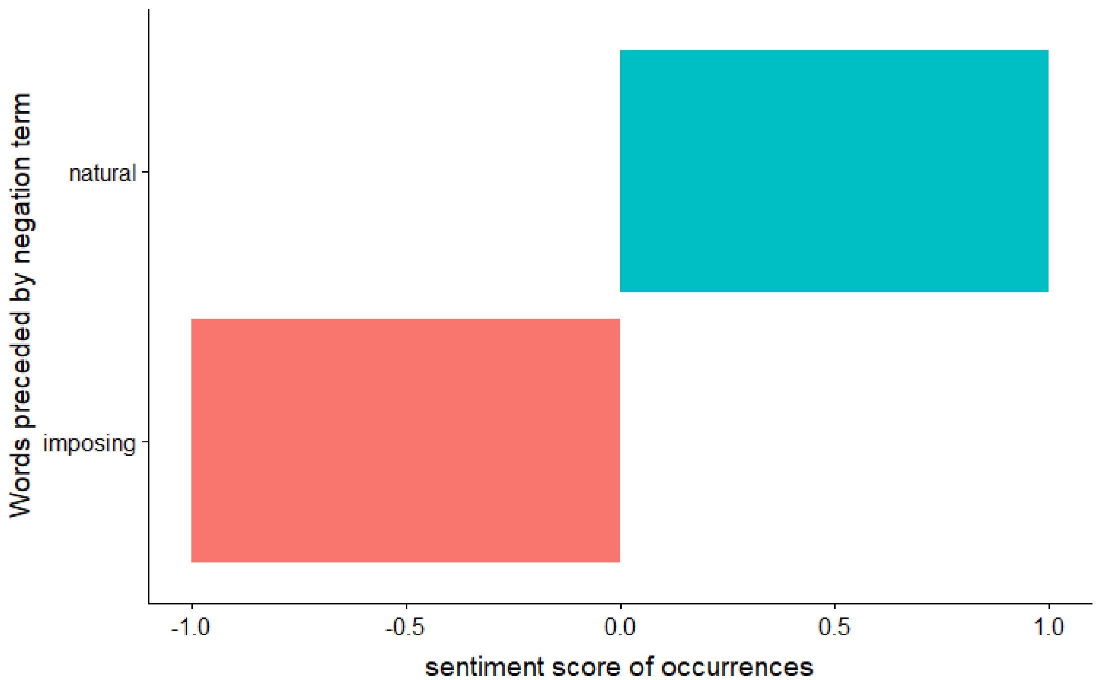
```
## # A tibble: 3 x 3
##   word1   word2       n
##   <chr>   <chr>   <int>
## 1 data    science     9
## 2 popular science     2
## 3 social  science     1

## # A tibble: 3 x 3
##   word1   word2      nn
##   <chr>   <chr>   <int>
## 1 data    science     1
## 2 popular science     1
## 3 social  science     1
```

We can see that for both two books, the word1(s) are the same corresponding to word2 "science", but with different frequencies.

Using bigrams to provide context in sentiment analysis

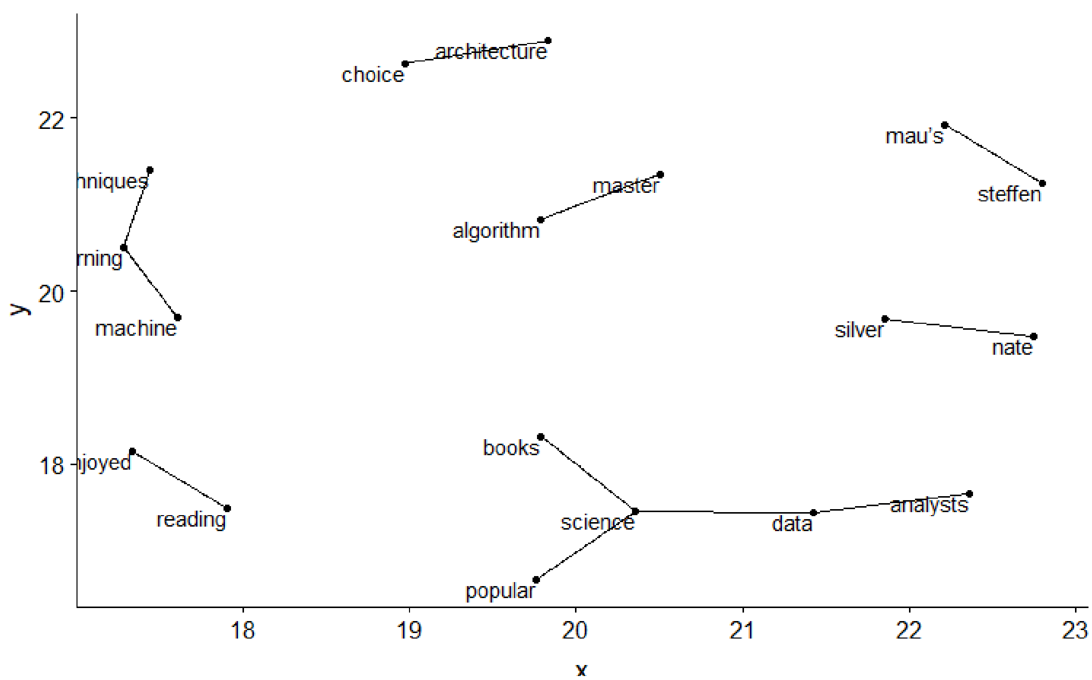






We can see the sentiment scores of occurrences of Words preceded by negation term are the same in the two books. Maybe because the two texts are both downloaded from the same blog.

Visualizing a network of bigrams with ggraph



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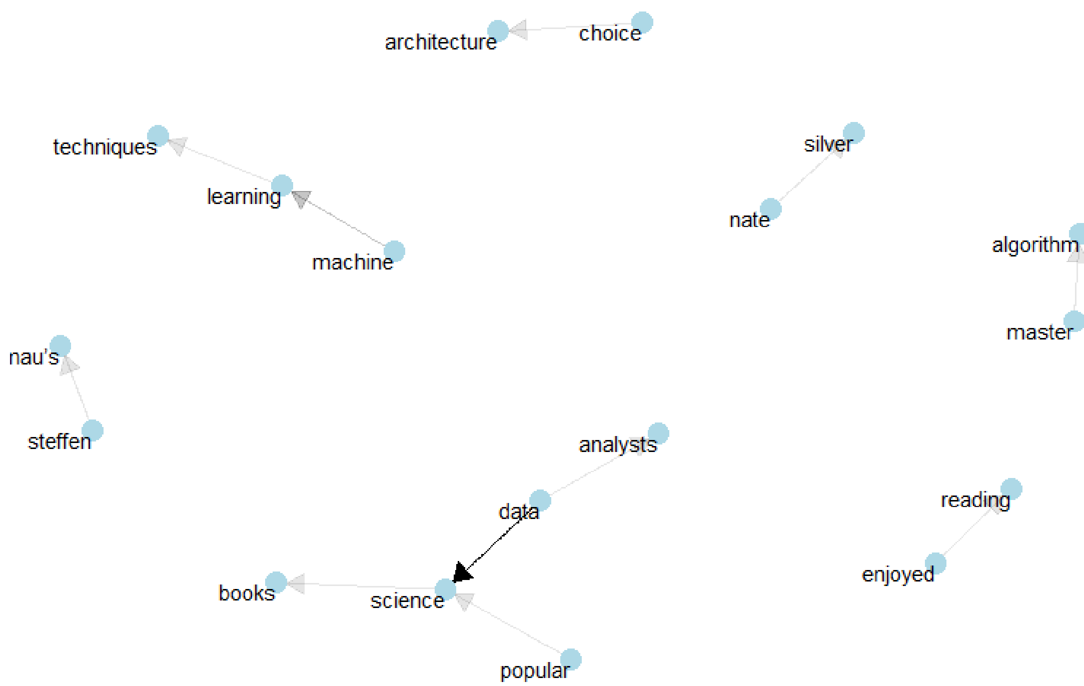

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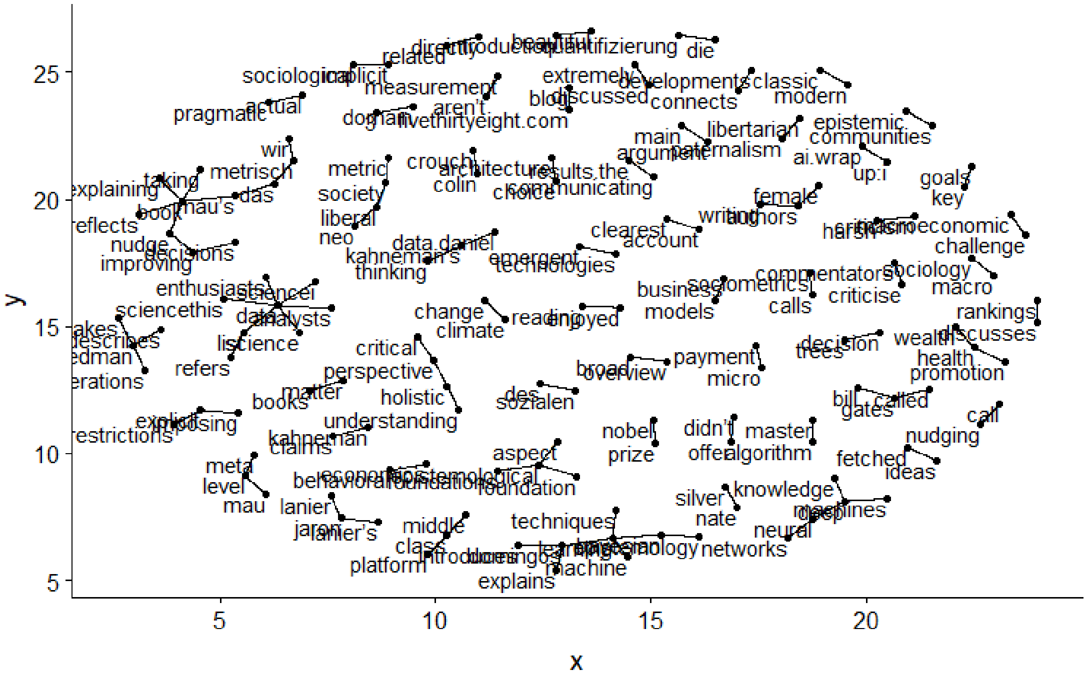


Counting and correlating pairs of words with the widyr package

Counting and correlating among sections

```
## # A tibble: 351 x 3
##    item1 item2       n
##    <chr> <chr>   <dbl>
##  1 data  day         1
##  2 data  list        1
##  3 data  books       1
##  4 data  read        1
##  5 data  half        1
##  6 data  noticed     1
##  7 data  popular     1
##  8 data  science     1
##  9 data  related     1
## 10 data  found       1
## # ... with 341 more rows
```

```
## # A tibble: 302 x 3
##    item1 item2           n
##    <chr> <chr>       <dbl>
##  1 data  pvalue          1
##  2 data  probability     1
##  3 data  observed        1
##  4 data  extreme         1
##  5 data  assumption      1
##  6 data  null            1
##  7 data  hypothesis      1
```

```
##   8 data  true            1
##   9 data  goal            1
## 10 data  blog            1
## # ... with 292 more rows
```

We can easily find the words that occur with "data" in the two texts

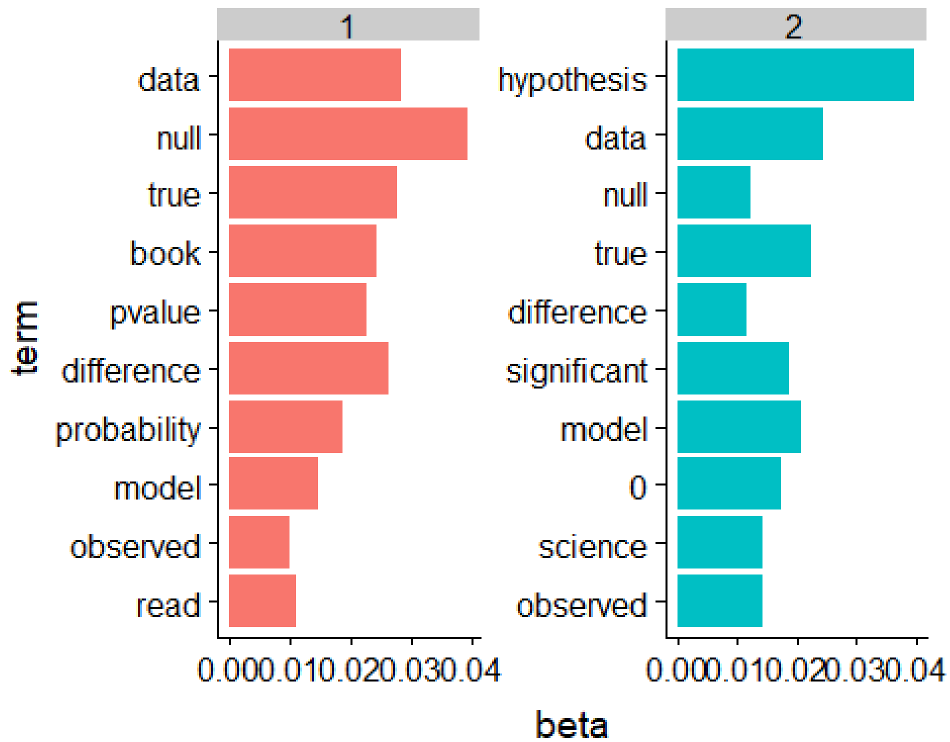
5 Latent Dirichlet allocation

```
## A LDA_VEM topic model with 2 topics.

## # A tibble: 1,264 x 3
##    topic term              beta
##    <int> <chr>            <dbl>
##  1     1 1             0.00653
##  2     2 1             0.00976
##  3     1 2             0.00343
##  4     2 2             0.00198
##  5     1 3             0.00129
##  6     2 3             0.00142
##  7     1 accelerations 0.000560
##  8     2 accelerations 0.000798
##  9     1 account       0.000928
## 10     2 account       0.000425
## # ... with 1,254 more rows
```

The model computes the probability of each term generated by each topic. For example, the term accelerations has 5.598958e-04 probability of being generated from topic 1, but a 7.975985e-04 probability of being generated from topic 2.

Word-topic probabilities



We use top_n function to find the 10 most common terms for each topic. The most common words in topic 1 include "probability", "model", "pvalue" and so on, which shows that it maybe related to statistics. Those most common in topic 2 include "data", "null", and "significant", also suggeting that this topic is related to statistics.

```
## # A tibble: 364 x 4
##    term     topic1    topic2 log_ratio
##    <chr>     <dbl>     <dbl>     <dbl>
##  1 0      0.00457   0.0172       1.91
##  2 0.01   0.00117   0.00154      0.398
##  3 0.05   0.00340   0.000648    -2.39
##  4 0.35   0.00112   0.00160      0.518
##  5 0.5    0.00714   0.00232     -1.62
##  6 05     0.000652  0.00207      1.67
##  7 1      0.00653   0.00976      0.581
##  8 1.5    0.000228  0.00113      2.32
##  9 100    0.00245   0.00161     -0.603
## 10 150    0.0000746 0.00129      4.11
## # ... with 354 more rows
```

We can see that the words more common in topic 1 include bayesian, which seems more theoretical. Topic 2 has more word like error, errors, centered, key, interpretation seems much more practical.

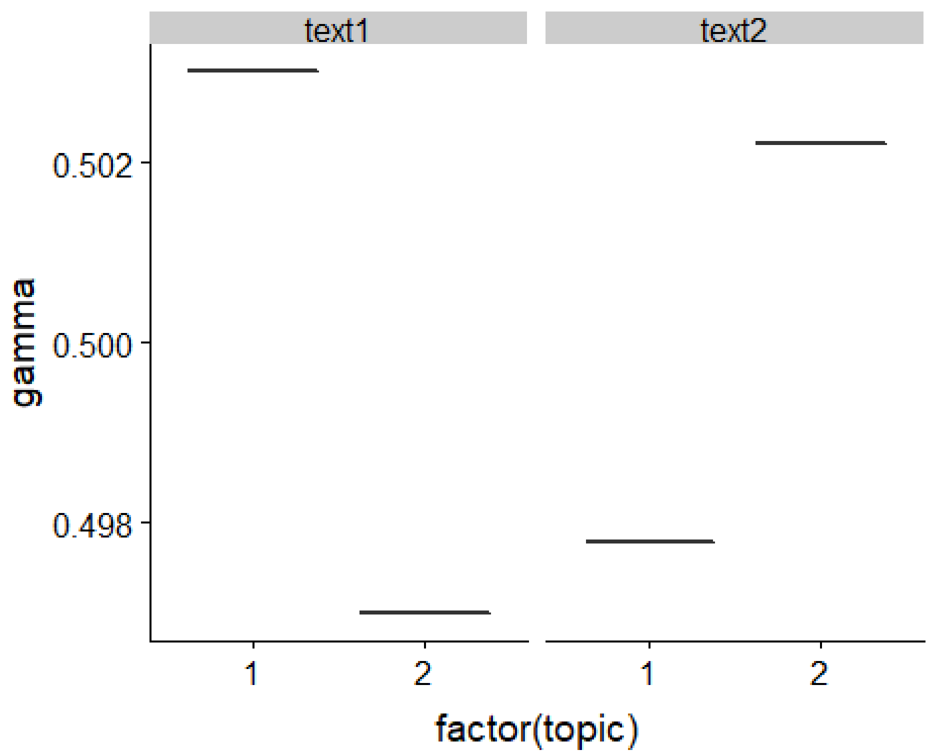
Document-topic probabilities

```
## # A tibble: 4 x 3
##   document topic gamma
##   <chr>    <int> <dbl>
## 1 text1        1 0.503
## 2 text2        1 0.498
## 3 text1        2 0.497
## 4 text2        2 0.502
```

```
## # A tibble: 4 x 4
##   title chapter topic gamma
##   <chr> <lgl>   <int> <dbl>
## 1 text1 NA          1 0.503
## 2 text2 NA          1 0.498
## 3 text1 NA          2 0.497
## 4 text2 NA          2 0.502
```

We can see the proportion of words from that document that are generated from that topic. For example, the model estimates that nearly more than half of the words in document 1 were generated from topic 1. Nearly more than half of the words in document 2 were generated from topic 2 we how topics are associated with each document.However, these articles does not have chapters so that their values are NA.

Per-document classification



```
## # A tibble: 2 x 4
##   title chapter topic gamma
##   <chr> <lgl>   <int> <dbl>
## 1 text1 NA          1 0.503
## 2 text2 NA          2 0.502
```

```
## # A tibble: 0 x 5
## # ... with 5 variables: title <chr>, chapter <lgl>, topic <int>,
## #   gamma <dbl>, consensus <chr>
```

```
## # A tibble: 2 x 4
##   title chapter topic gamma
##   <chr> <lgl>   <int> <dbl>
## 1 text1 NA          1 0.503
## 2 text2 NA          2 0.502
```

We visualize the gamma probabilities by using box plot.We notice that these two articles were uniquely identified as a single topic each.

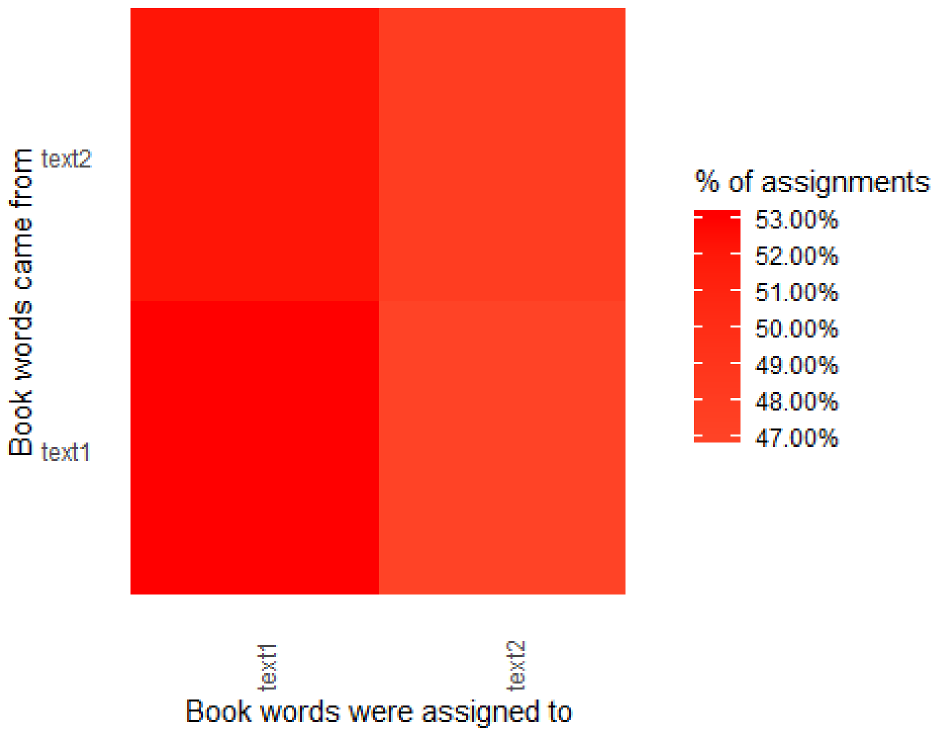
By word assignments: augment

```
## # A tibble: 655 x 4
##    document term          count .topic
##    <chr>    <chr>         <dbl>  <dbl>
##  1 text1    1                 2      2
##  2 text2    1                10      2
##  3 text1    2                 2      1
##  4 text2    2                 2      1
##  5 text1    3                 1      2
##  6 text2    3                 1      2
##  7 text1    accelerations     1      2
##  8 text1    account           1      1
##  9 text1    actual            1      1
## 10 text1    age               2      2
## # ... with 645 more rows
```

```
## # A tibble: 655 x 6
##    title chapter term          count .topic consensus
##    <chr> <lgl>   <chr>         <dbl>  <dbl> <chr>
##  1 text1 NA      1                 2      2 text2
##  2 text2 NA      1                10      2 text2
##  3 text1 NA      2                 2      1 text1
##  4 text2 NA      2                 2      1 text1
##  5 text1 NA      3                 1      2 text2
##  6 text2 NA      3                 1      2 text2
##  7 text1 NA      accelerations     1      2 text2
##  8 text1 NA      account           1      1 text1
##  9 text1 NA      actual            1      1 text1
## 10 text1 NA      age               2      2 text2
## # ... with 645 more rows
```

This script returns a tidy data frame for the counts of words. combine this assignments table with the consensus book titles so that we can find incorrect classified words. We can see in the list, the incoorrect classified words have been counted.

visualize a confusion matrix



By visualizing a confusion matrix, we can find how often words from one book were assigned to another. We can find that words are slightly more often assigned to text1.

Find out and count mistaken words

```
## # A tibble: 327 x 6
##    title chapter term          count .topic consensus
##    <chr> <lgl>   <chr>         <dbl>  <dbl> <chr>
##  1 text1 NA      1                 2      2 text2
##  2 text2 NA      2                 2      1 text1
##  3 text1 NA      3                 1      2 text2
##  4 text1 NA      accelerations     1      2 text2
##  5 text1 NA      age               2      2 text2
##  6 text1 NA      agnostic          1      2 text2
##  7 text1 NA      algorithm         2      2 text2
##  8 text1 NA      analysts          2      2 text2
##  9 text1 NA      architecture      2      2 text2
## 10 text1 NA      aren�t            1      2 text2
## # ... with 317 more rows
```

```
## # A tibble: 327 x 4
##    title consensus term            n
##    <chr> <chr>     <chr>       <dbl>
##  1 text2 text1     null           38
##  2 text2 text1     true           37
##  3 text2 text1     difference     28
##  4 text2 text1     pvalue         24
##  5 text2 text1     data           19
##  6 text2 text1     probability    18
##  7 text1 text2     science        13
##  8 text2 text1     alternative    13
##  9 text2 text1     effect         13
## 10 text2 text1     extreme         9
## # ... with 317 more rows
```

We find the commonly mistaken words, such as null, true, difference and pvalue which are more than 20.