correlaid_text_analysis

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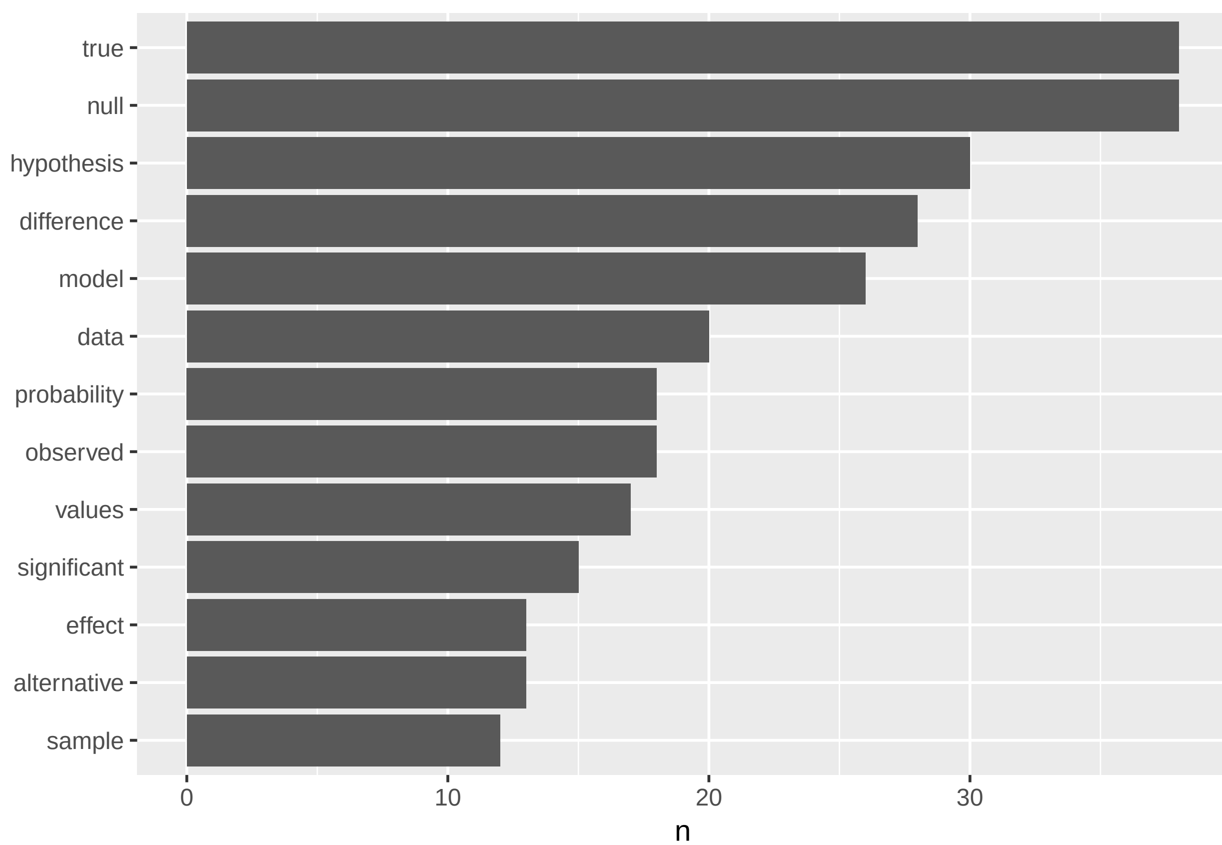
Scraping webpages

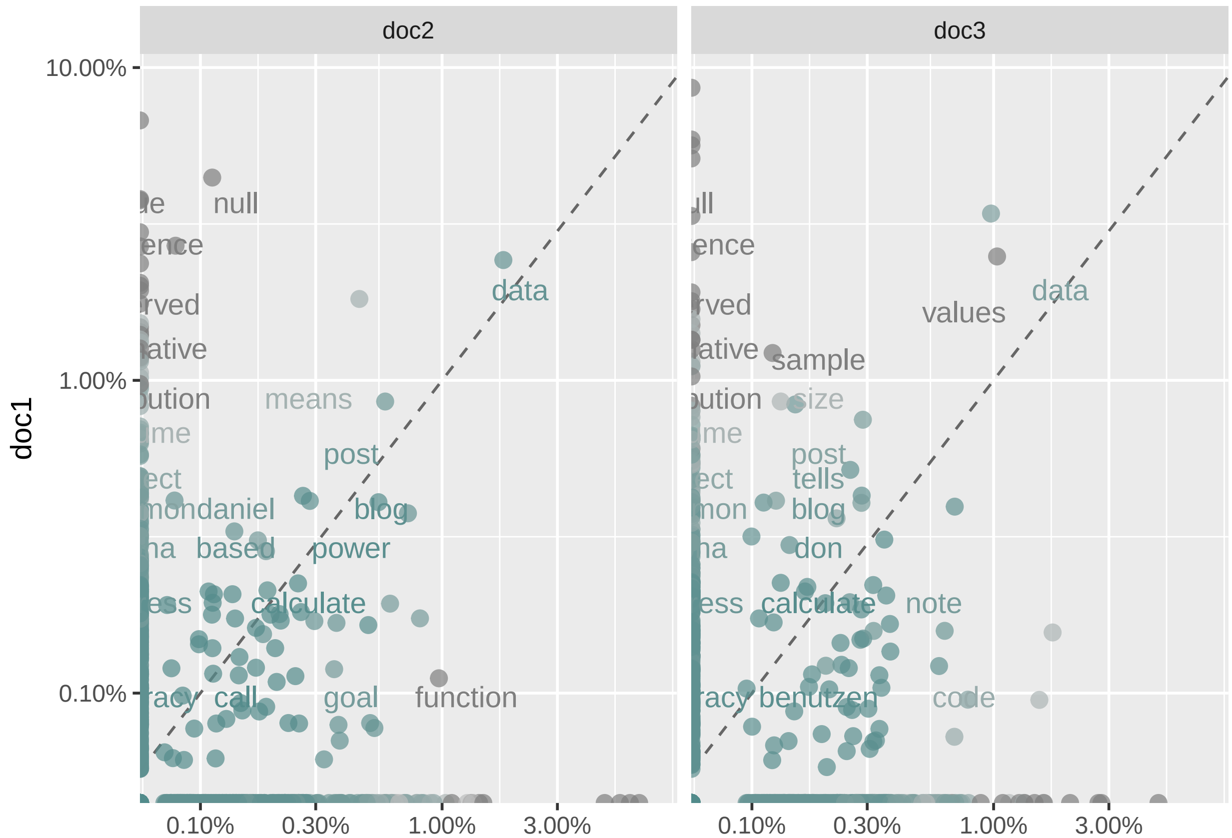
tidy text

look at single word frequency and visualize

first at doc1



plotting and comparing the three articles



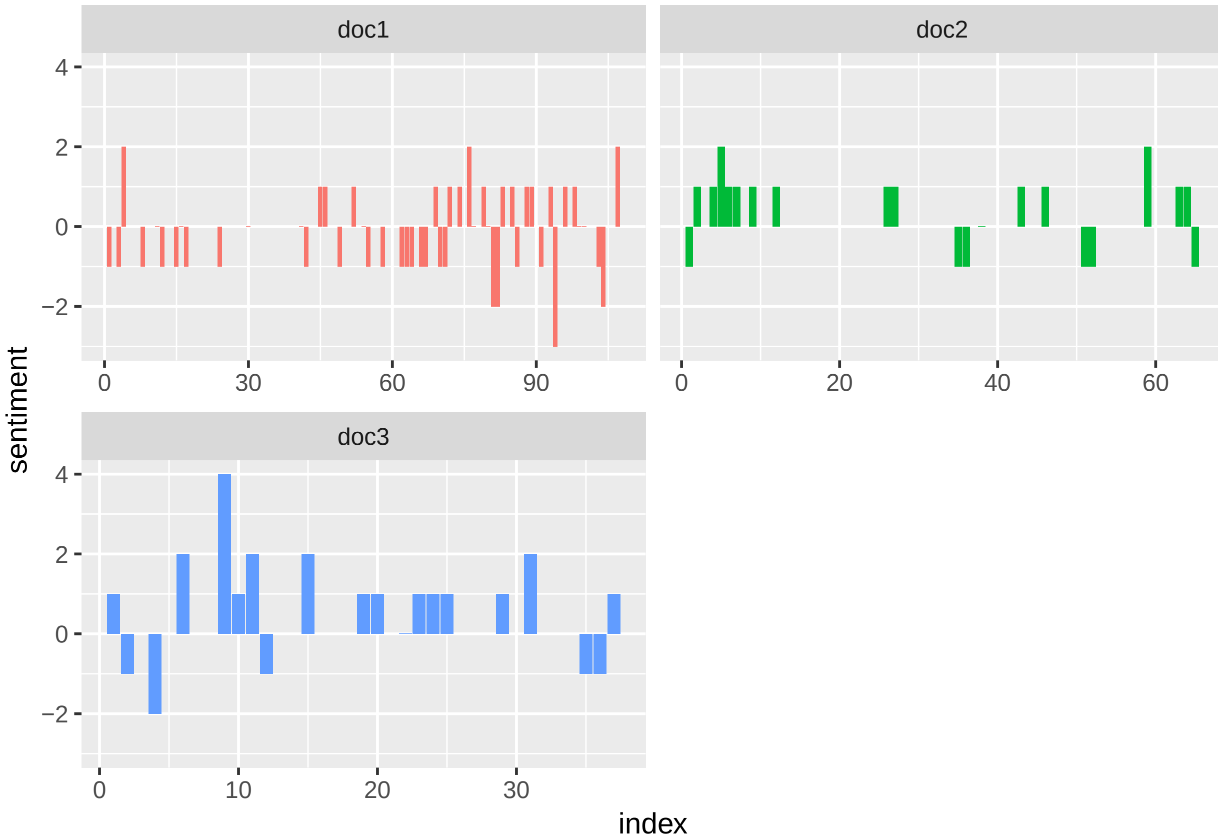

```
##
##  Pearson's product-moment correlation
##
## data:  proportion and doc1
## t = -0.90635, df = 800, p-value = 0.365
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.10103135  0.03728257
## sample estimates:
##         cor
## -0.03202772
```

```
##
##  Pearson's product-moment correlation
##
## data:  proportion and doc1
## t = -1.3419, df = 800, p-value = 0.18
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.11623528  0.02191054
## sample estimates:
##         cor
## -0.04738898
```

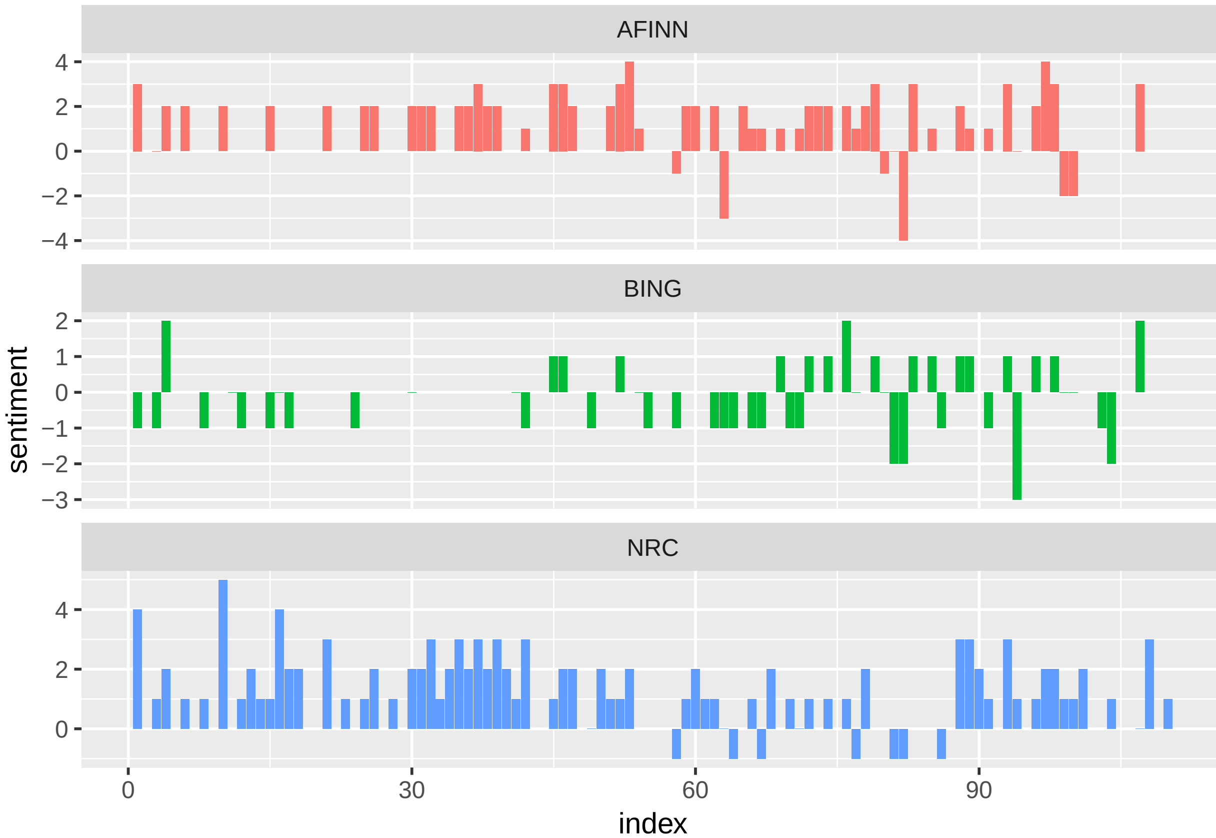
As we saw in the plots, the word frequencies have little frequencies in three articles.

Sentiment analysis

bing sentiment analysis

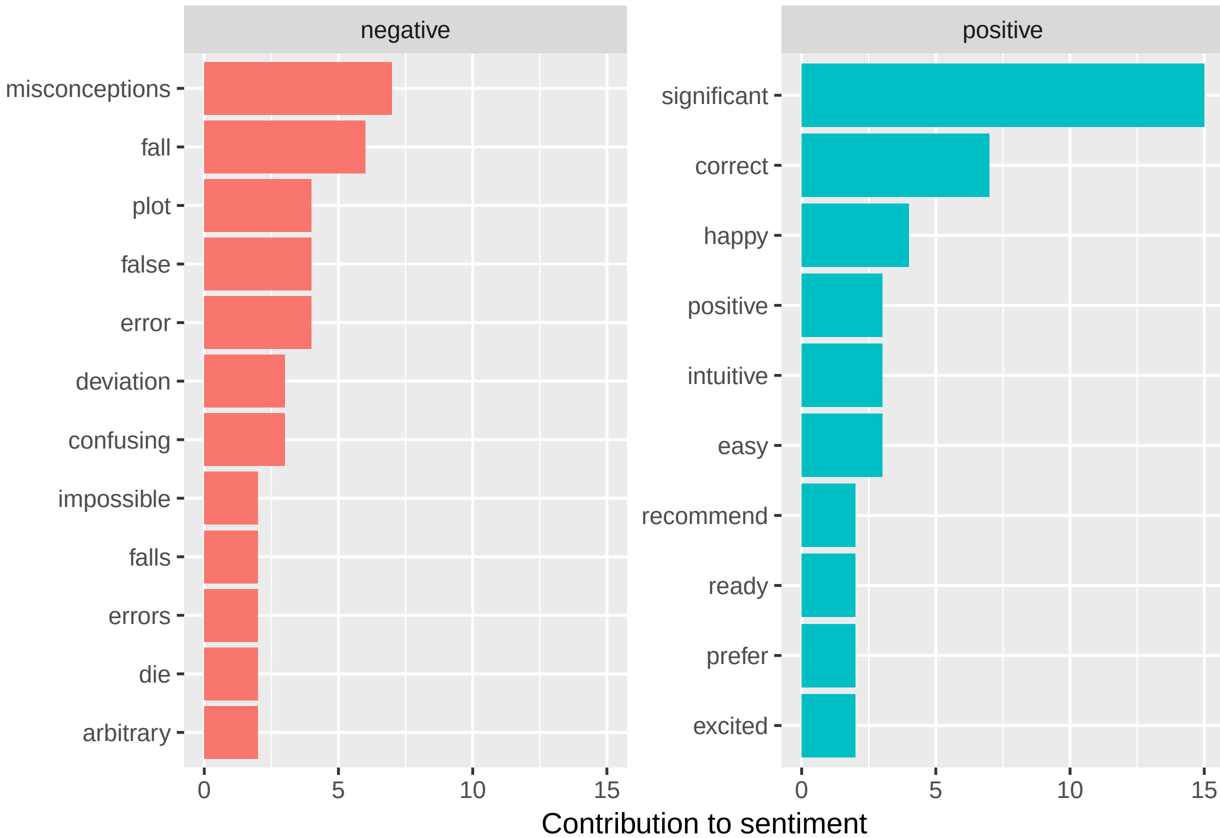


Comparing the three sentiment dictionaries

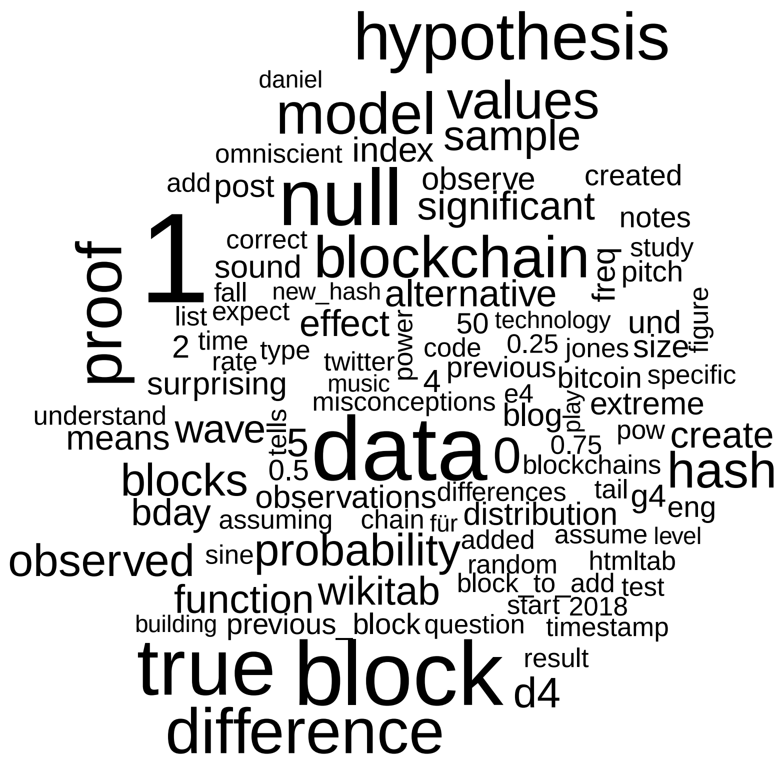


Most common sentiment words

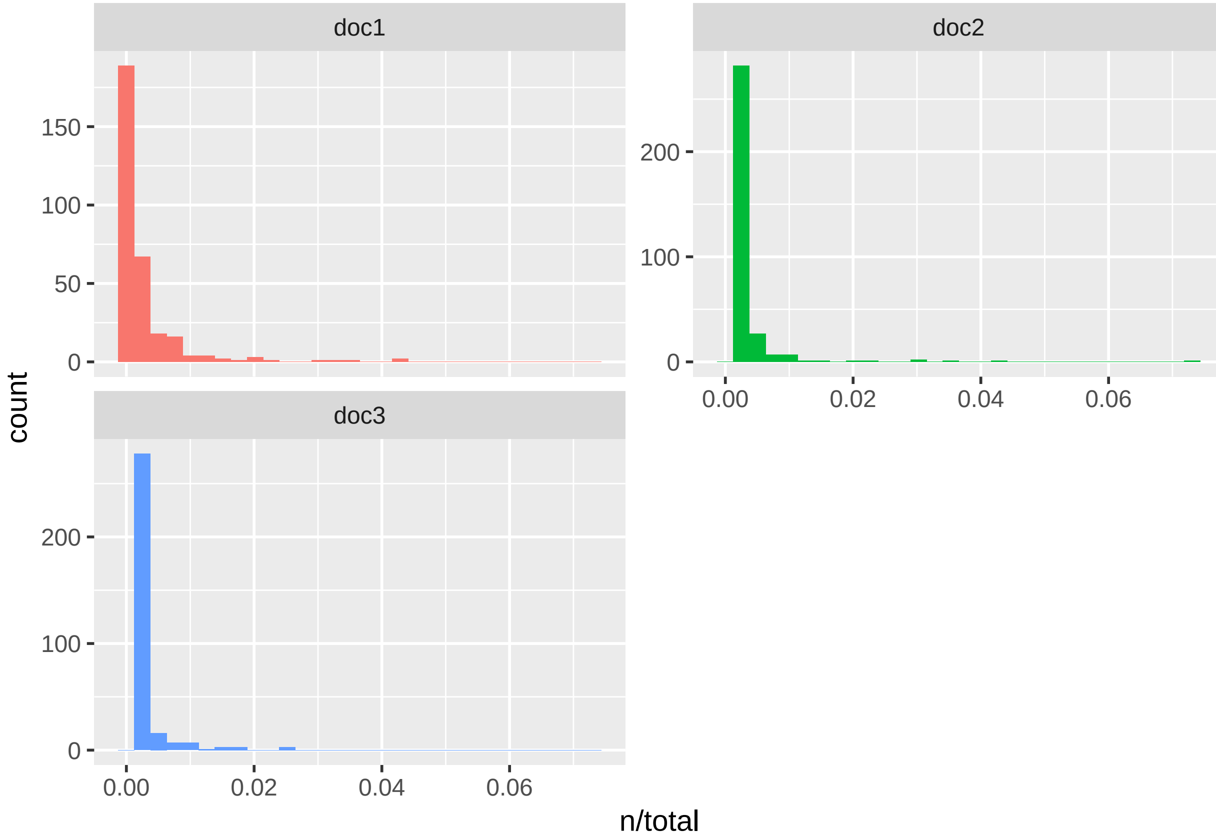
```
## # A tibble: 79 x 3
##    word           sentiment     n
##    <chr>          <chr>     <int>
##  1 significant    positive     15
##  2 correct        positive      7
##  3 misconceptions negative      7
##  4 fall           negative      6
##  5 error          negative      4
##  6 false          negative      4
##  7 happy          positive      4
##  8 plot           negative      4
##  9 confusing      negative      3
## 10 deviation      negative      3
## # ... with 69 more rows
```


negative
positive
misconceptions
fall
plot
false
error
deviation
confusing
impossible
falls
errors
die
arbitrary
significant
correct
happy
positive
intuitive
easy
recommend
ready
prefer
excited
0
5
10
15
Contribution to sentiment

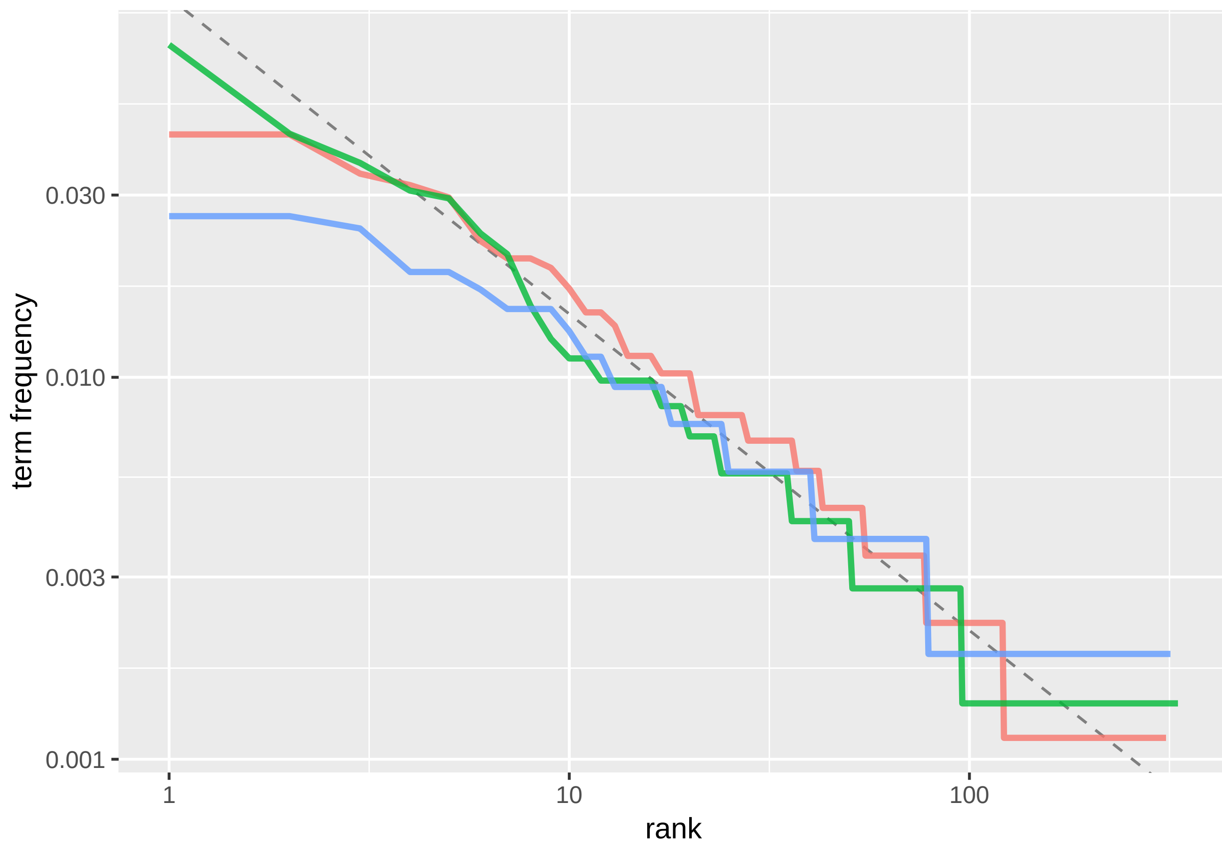
Wordclouds


hypothesis
daniel
model values
sample
omniscient index
add post null observe created
significant notes
1
proof
correct
blockchain study
sound freq pitch
fall new_hash alternative
list expect figure
effect 50 technology und
2 time power 0.25 jones size
rate type twitter code
surprising music 4 previous bitcoin specific
e4
understand misconceptions blog play extreme
means wave tells 5 data 0 0.75 pow create
0.5 blockchains hash
blocks
observations differences tail g4
bday assuming chain für distribution eng
assume level
observed sine probability added
random htmltab
function wikitab block_to_add test
start 2018
building previous_block question timestamp
result
true block d4
difference

negative
misconceptions
significant
illiterate
sneaky
loose
wrong
crazy
object
hype
broken
evil
reject
disrupt
impossible
falls
fallen
unfamiliar
difficulty
die
critical
confusing
deviation
plot
errors
odd
misconception
complaining
confusion
fall
arbitrary
misunderstand
lose
error
false
hard
correct
imaginative
handy
excited
clearer
conveniently
happy
intuitive
grateful
modern
incredibly
positive
easy
congratulate
nicely
genius
prefer
fair
accurate
enjoy
versatile
recommend
ready
easier
trust
intriguing
capable
brilliant
efficient
leading
correctly
complement
supported
realistic
insightful
dedicated
intelligence
master
pretty
meaningful
promise
sufficient
secure
successfully
positive

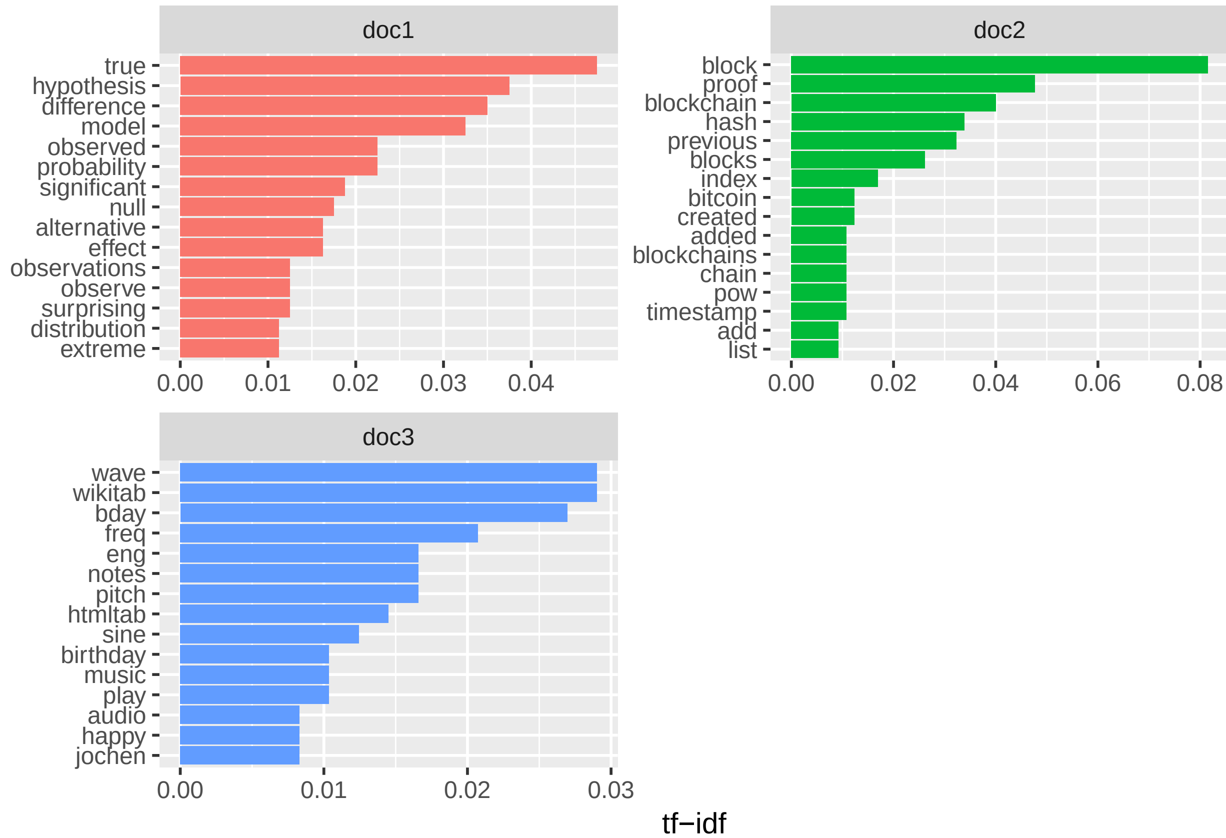



```
## (Intercept) log10(rank)
##  -1.0057750  -0.8284333
```



tf-idf function

```
## # A tibble: 960 x 6
##    article word           n     tf   idf tf_idf
##    <chr>   <chr>      <int>  <dbl> <dbl>  <dbl>
##  1 doc2    block         53 0.0742  1.10 0.0815
##  2 doc2    proof         31 0.0434  1.10 0.0477
##  3 doc1    true          38 0.0432  1.10 0.0475
##  4 doc2    blockchain    26 0.0364  1.10 0.0400
##  5 doc1    hypothesis    30 0.0341  1.10 0.0375
##  6 doc1    difference    28 0.0319  1.10 0.0350
##  7 doc2    hash          22 0.0308  1.10 0.0339
##  8 doc1    model         26 0.0296  1.10 0.0325
##  9 doc2    previous      21 0.0294  1.10 0.0323
## 10 doc3    wave          14 0.0264  1.10 0.0290
## # ... with 950 more rows
```



Chapter 4 n-grams and correlations

We use `unnest_tokens` function to tokenize the articles into consecutive sequences of words, called n-grams. Here we focus on bigrams, aka two consecutive words.

As one might expect, a lot of the most common bigrams are pairs of common (uninteresting) words, such as of the and to be: what we call "stop-words" . This is a useful time to use tidyr's `separate()` and `unite()`, which splits a column into multiple based on a delimiter and reunite them. In this process we can remove cases where either is a stop-word.

Also, we clean the bigrams by `str_extract()` and `filter()` function to remove cases where either is NA, space or non-letter word.

Then we look at tf_idf of bigrams and visualize them.

```
## # A tibble: 10 x 6
##    article bigram                   n     tf   idf tf_idf
##    <chr>   <chr>                <int>  <dbl> <dbl>  <dbl>
##  1 doc1    null hypothesis         21 0.0843  1.10 0.0927
##  2 doc1    null model              15 0.0602  1.10 0.0662
##  3 doc2    previous block          13 0.0478  1.10 0.0525
##  4 doc1    alternative model        7 0.0281  1.10 0.0309
##  5 doc2    previous hash            7 0.0257  1.10 0.0283
##  6 doc1    omniscient jones         6 0.0241  1.10 0.0265
##  7 doc1    sample size              6 0.0241  1.10 0.0265
##  8 doc1    significant result       6 0.0241  1.10 0.0265
```

```
##  9 doc3    wikitab eng                 6 0.0231  1.10 0.0254
## 10 doc1    alternative hypothesis      5 0.0201  1.10 0.0221
```

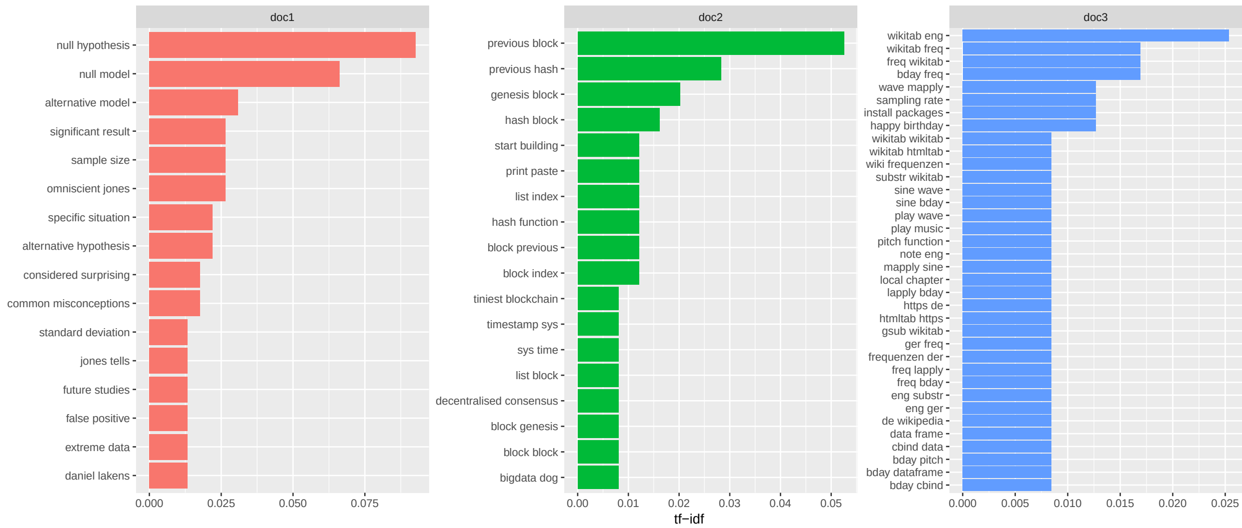


Figure: The 12 bigrams with the highest tf-idf

There are advantages and disadvantages to examining the tf-idf of bigrams rather than individual words. Pairs of consecutive words might capture structure that isn't present when one is just counting single words, and may provide context that makes tokens more understandable . However, the per-bigram counts are also sparser: a typical two-word pair is rarer than either of its component words. Thus, bigrams can be more useful when we have a larger text dataset.

- Using bigrams to provide context in sentiment analysis

```
## # A tibble: 0 x 4
## # ... with 4 variables: word1 <chr>, word2 <chr>, score <int>, nn <int>
```

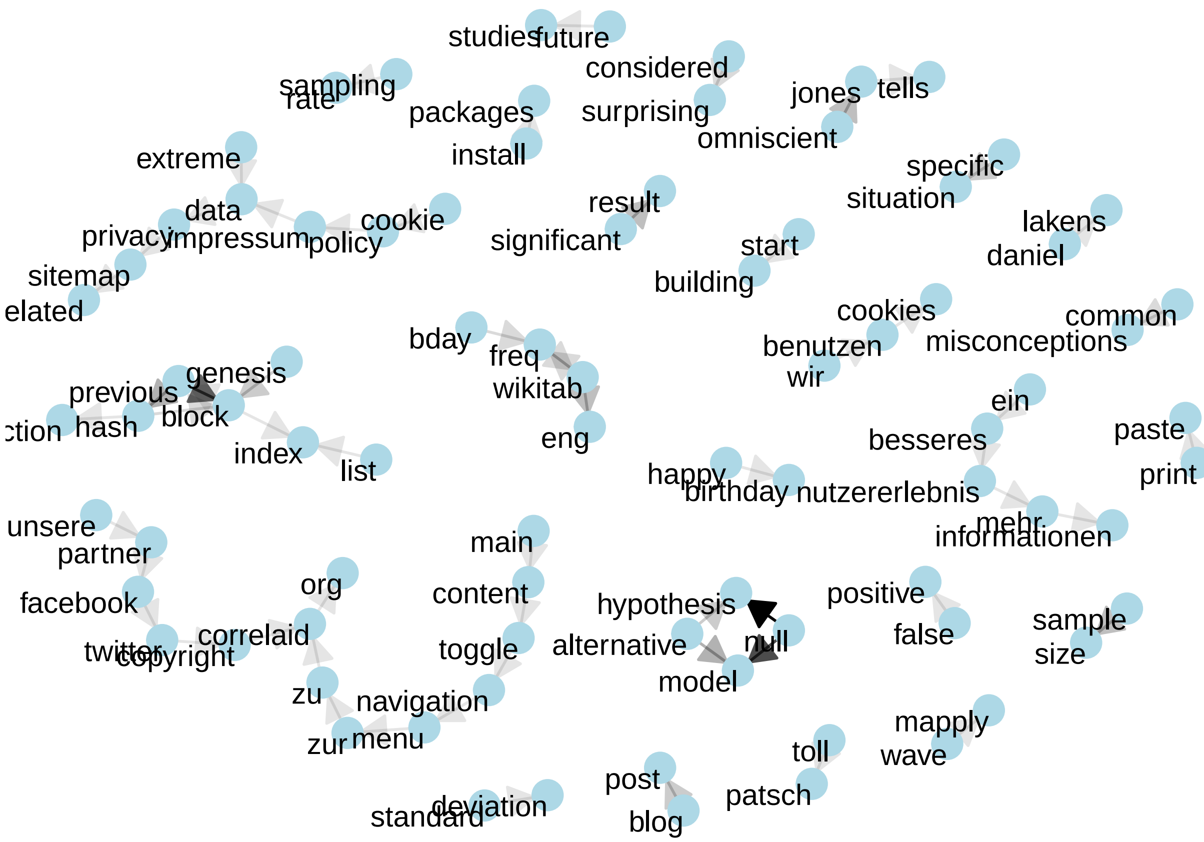
For these are three academic articles and there are not many bigrams with negative terms. So we can skip this part.

- Visualizing a network of bigrams with ggraph

```
## # A tibble: 6 x 3
##   word1       word2          n
##   <chr>       <chr>      <int>
## 1 null        hypothesis    21
## 2 null        model         15
## 3 previous    block         13
## 4 alternative model          7
## 5 previous    hash           7
## 6 omniscient  jones          6
```

```
## IGRAPH b9a6b53 DN-- 82 62 --
## + attr: name (v/c), n (e/n)
## + edges from b9a6b53 (vertex names):
##  [1] null       ->hypothesis     null       ->model
##  [3] previous   ->block          alternative->model
##  [5] previous   ->hash           omniscient ->jones
##  [7] sample     ->size           significant->result
##  [9] wikitab    ->eng            alternative->hypothesis
## [11] blog       ->post           genesis    ->block
```

```
## [13] specific   ->situation      bday       ->freq
## [15] common     ->misconceptions considered ->surprising
## + ... omitted several edges
```



- Counting and correlating pairs of words

```
##   article       word
## 1    doc1       skip
## 2    doc1       main
## 3    doc1    content
## 4    doc1     toggle
## 5    doc1 navigation
## 6    doc1       menu
```

```
## # A tibble: 294,912 x 3
##    item1      item2     n
##    <chr>      <chr> <dbl>
##  1 main       skip      3
##  2 content    skip      3
##  3 toggle     skip      3
##  4 navigation skip      3
##  5 menu       skip      3
##  6 zur        skip      3
##  7 zu         skip      3
##  8 correlaid  skip      3
##  9 blog       skip      3
## 10 values     skip      3
```

```
## # ... with 294,902 more rows
```

- Pairwise correlation

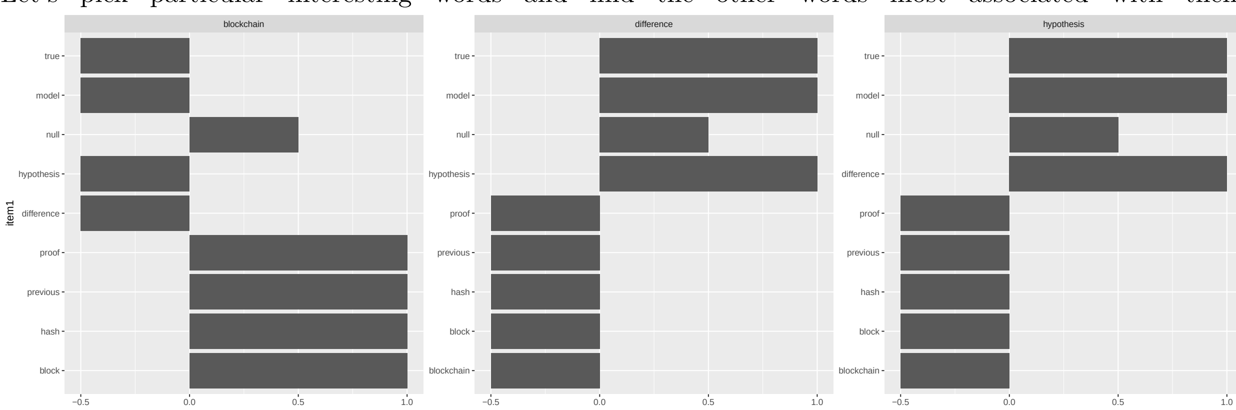
Find the phi coefficient between words based on how often they appear in the same article.

```
## # A tibble: 132 x 3
##    item1      item2      correlation
##    <chr>      <chr>            <dbl>
##  1 true       hypothesis       1.000
##  2 difference hypothesis       1.000
##  3 model      hypothesis       1.000
##  4 hypothesis true             1.000
##  5 difference true             1.000
##  6 model      true             1.000
##  7 hypothesis difference       1.000
##  8 true       difference       1.000
##  9 model      difference       1.000
## 10 hypothesis model            1.000
## # ... with 122 more rows
```

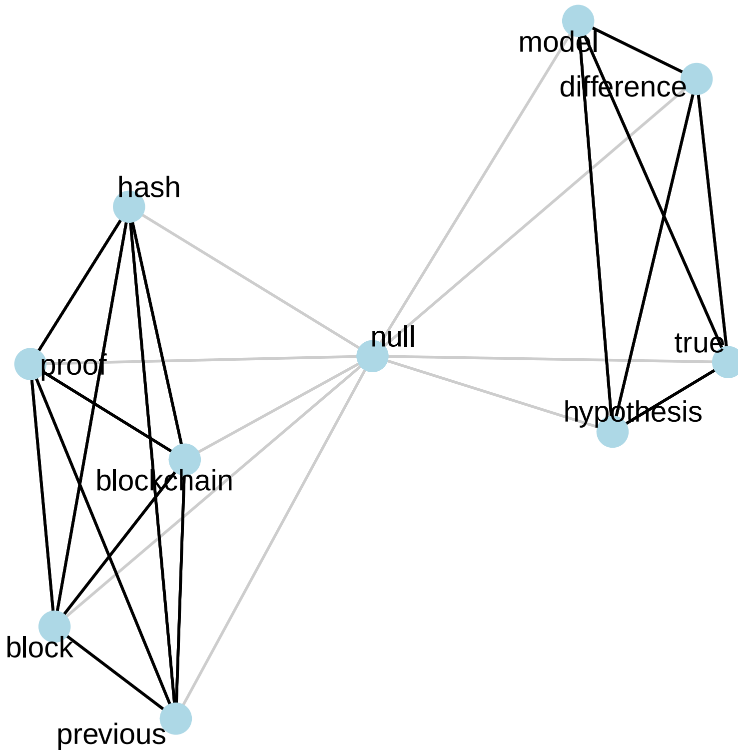
```
##  [1] "true"       "difference" "model"      "hypothesis" "block"
##  [6] "previous"   "hash"       "proof"      "blockchain" "null"
## [11] "data"       "values"
```

```
##  [1] "hypothesis" "true"       "difference" "model"      "blockchain"
##  [6] "block"      "previous"   "hash"       "proof"      "null"
## [11] "values"     "data"
```

Let's pick particular interesting words and find the other words most associated with them.



Visualize the correlations and clusters of words.


model
difference
hash
null
true
proof
hypothesis
blockchain
block
previous