correlaid_text_analysis

Xiang XU, Jing(Mira) Tang, Ningze(Summer) ZU, Jianhao(Miller) Yan

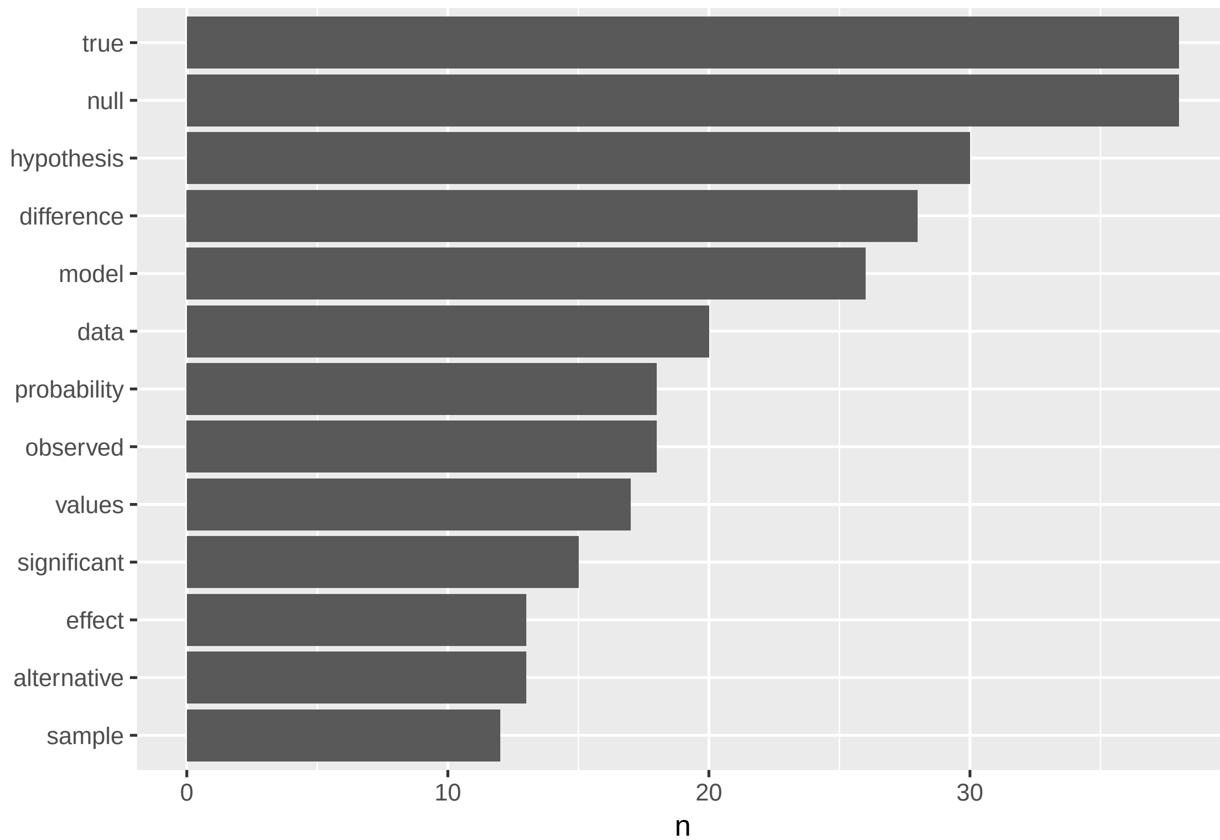
November 3, 2018

Scraping webpages

tidy text

look at single word frequency and visualize

first at doc1



plotting and comparing the three articles

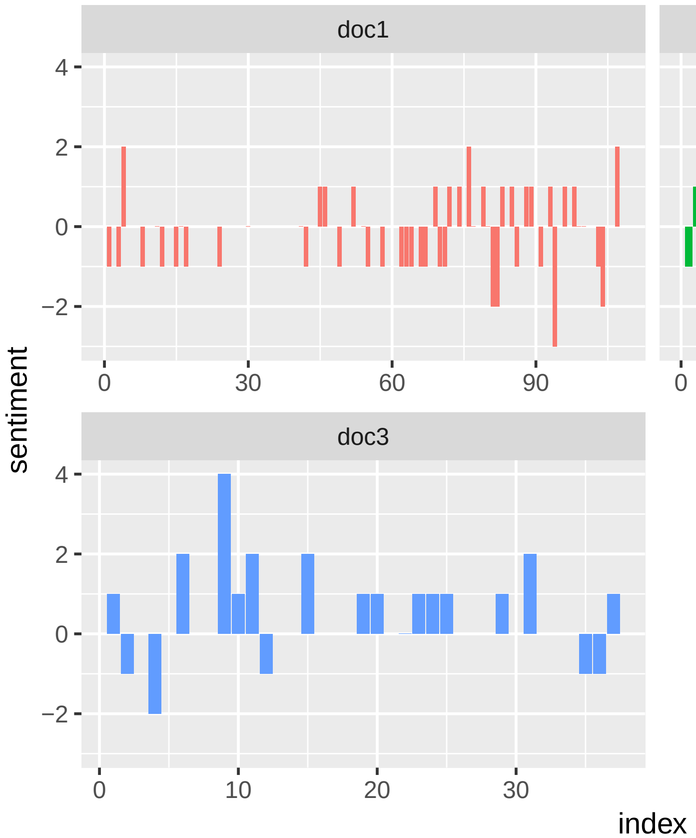

```
##
##  Pearson's product-moment correlation
##
## data:  proportion and doc1
## t = -0.90635, df = 800, p-value = 0.365
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.10103135  0.03728257
## sample estimates:
##         cor
## -0.03202772
```

```
##
##  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
```

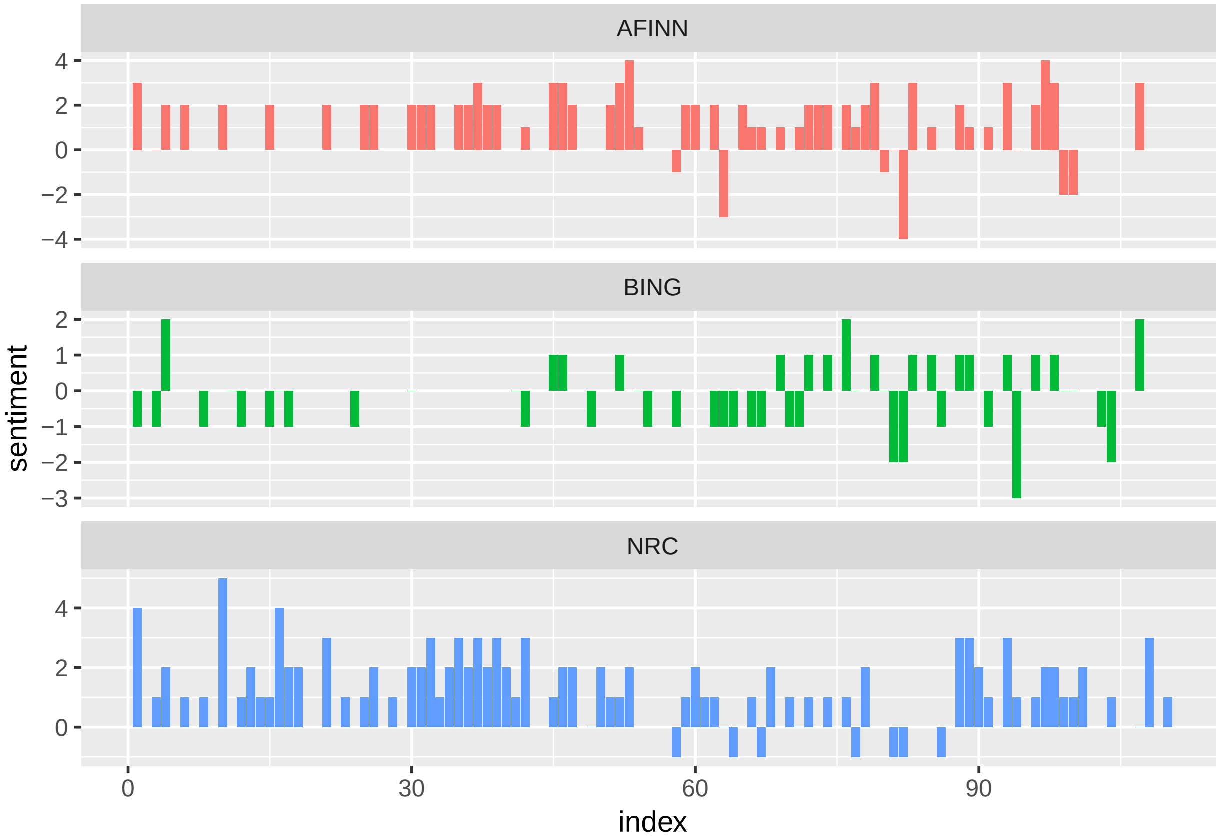
As we saw in the plots, the word frequencies have little frequencies in three articles.

Sentiment analysis

bing sentiment analysis

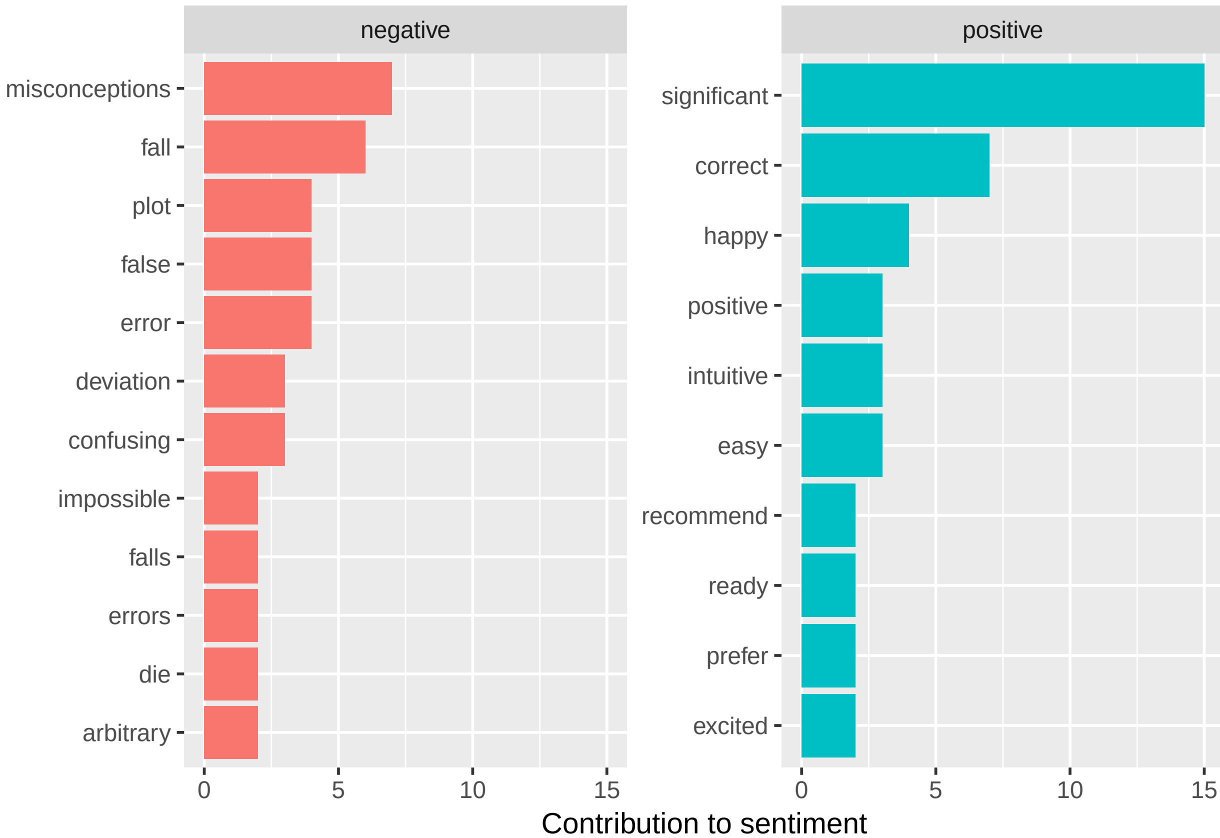


Comparing the three sentiment dictionaries

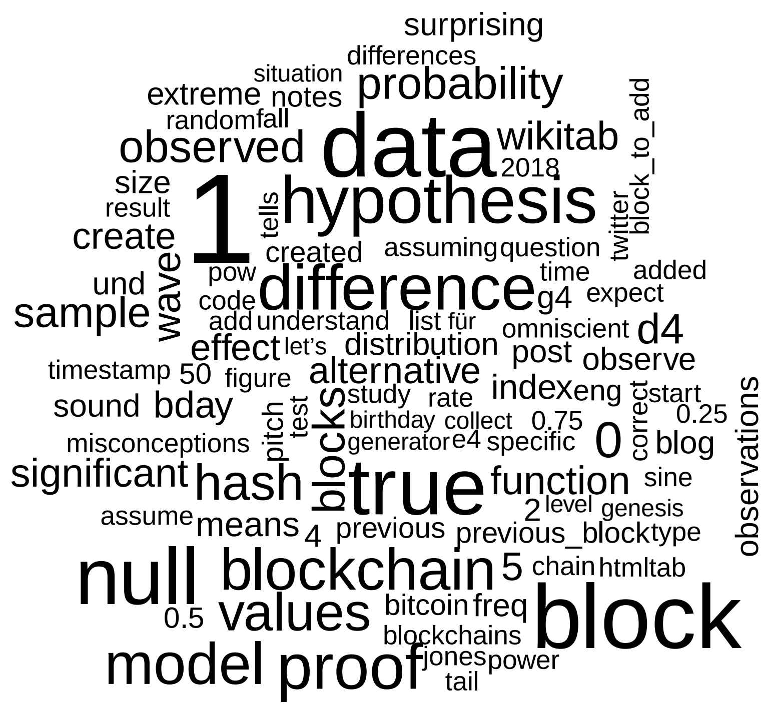


Most common sentiment words

```
## # 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
```

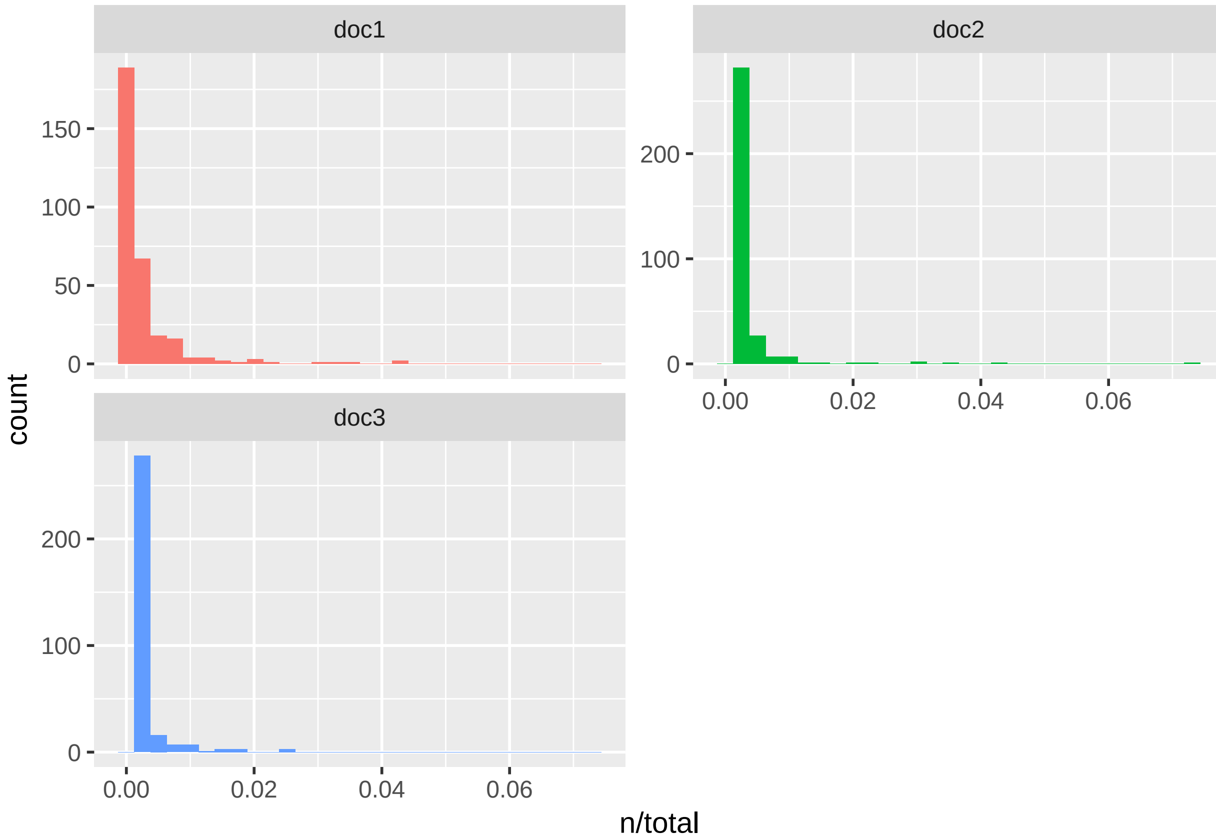

negative
positive
misconceptions
fall
plot
false
error
deviation
confusing
impossible
falls
errors
die
arbitrary
significant
correct
happy
positive
intuitive
easy
recommend
ready
prefer
excited
0
5
10
15
Contribution to sentiment

Wordclouds

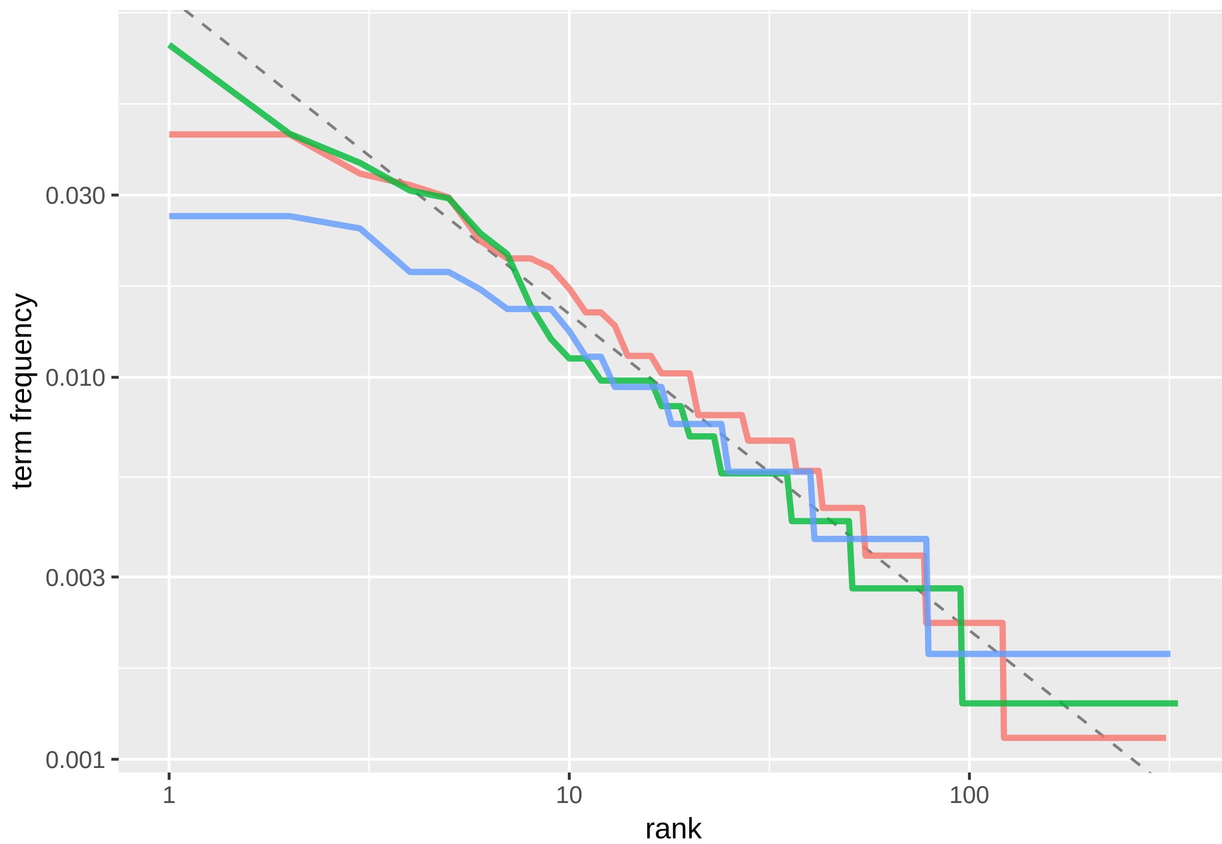


surprising
differences
situation
probability
extreme
notes
randomfall
data
wikitab
observed
2018
block_to_add
size
1
hypothesis
result
tells
twitter
create
created
assuming
question
pow
time
added
und
difference
g4
expect
wave
code
sample
add
understand
list
für
omniscient
d4
effect
let's
distribution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


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

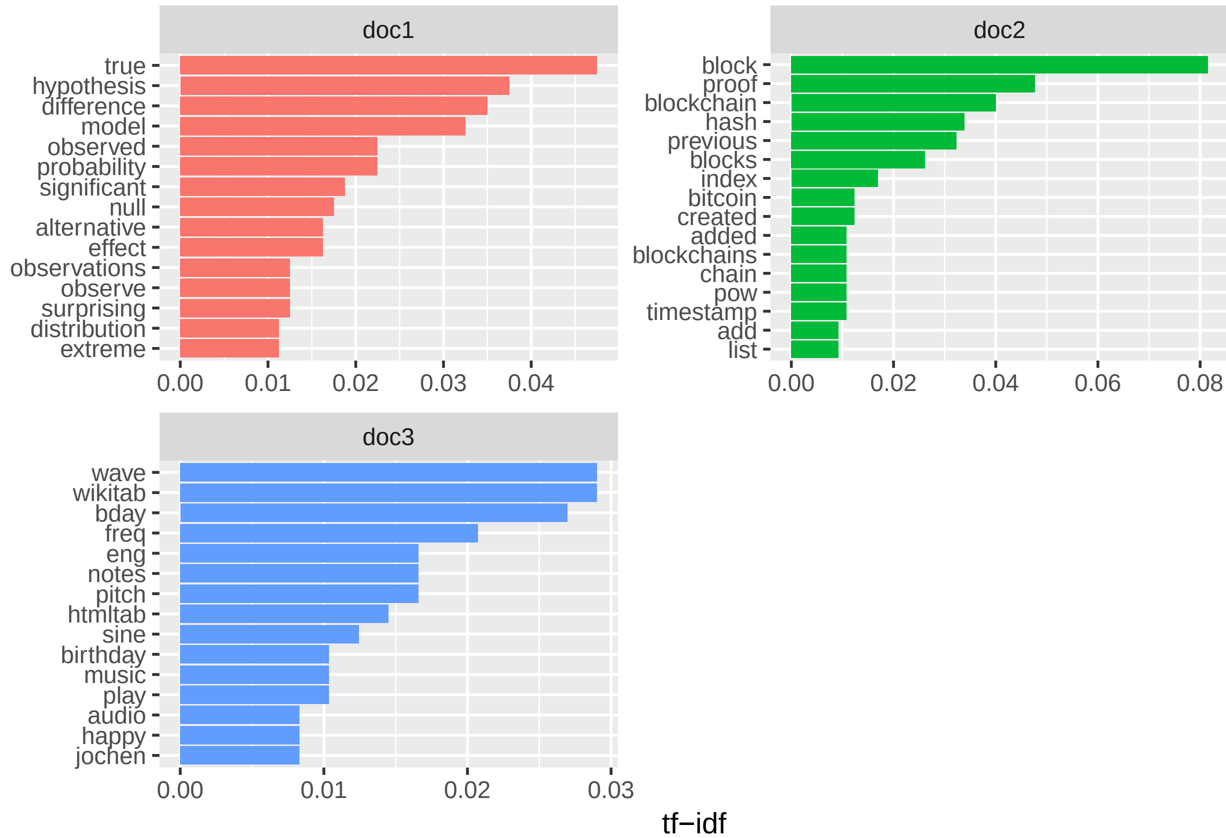



```
## (Intercept) log10(rank)
##  -1.0057750  -0.8284333
```



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
```

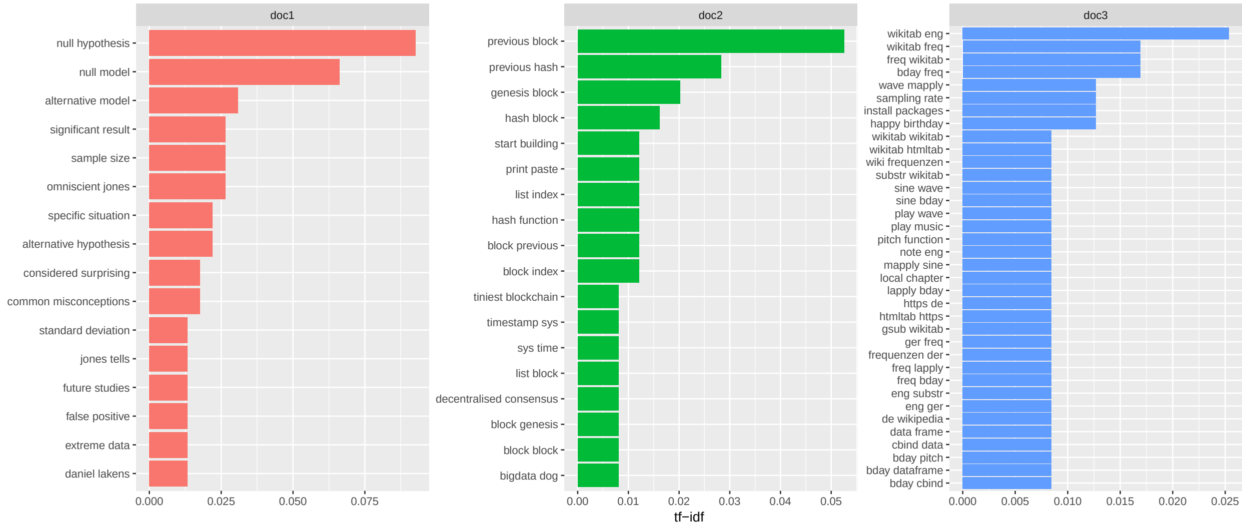


Figure: The 12 bigrams with the highest tf-idf

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>
```

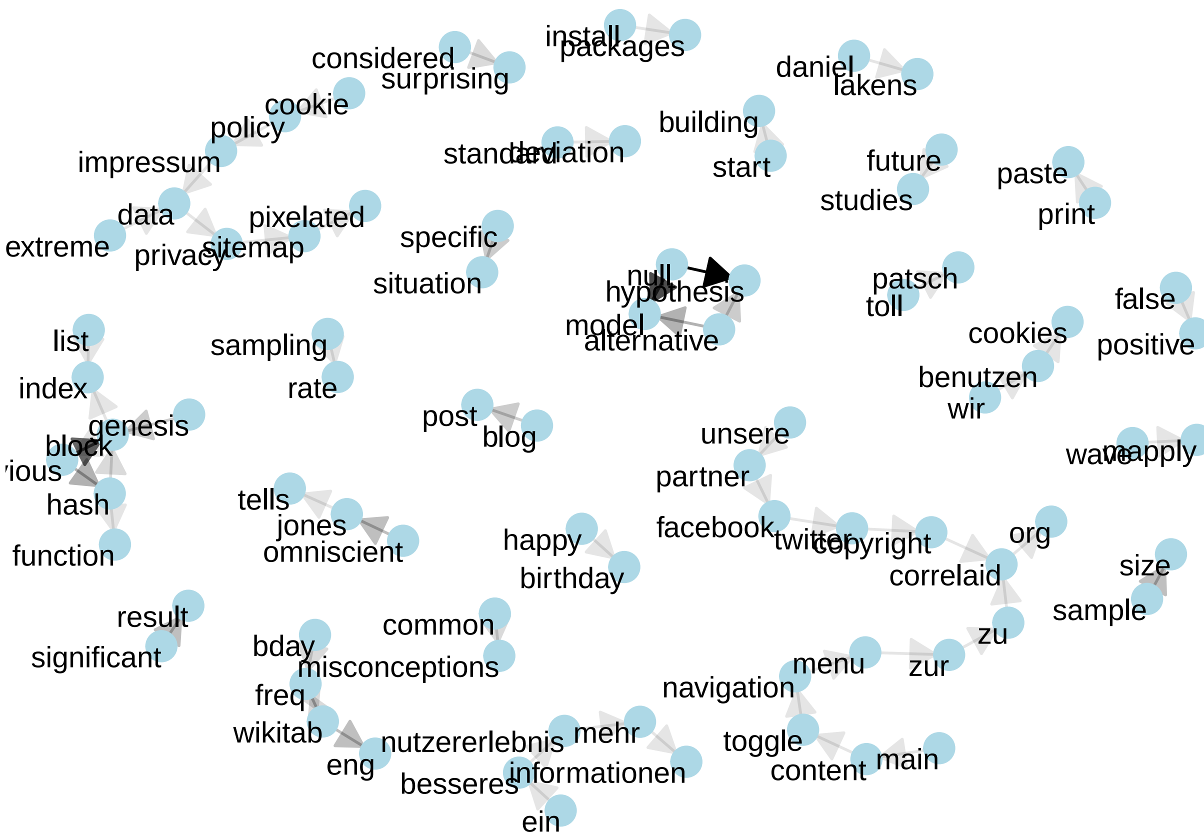
For these are three academic articles and there are not many bigrams with negative terms. So we can skip this part.

- 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 194f07f DN-- 82 62 --
## + attr: name (v/c), n (e/n)
## + edges from 194f07f (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

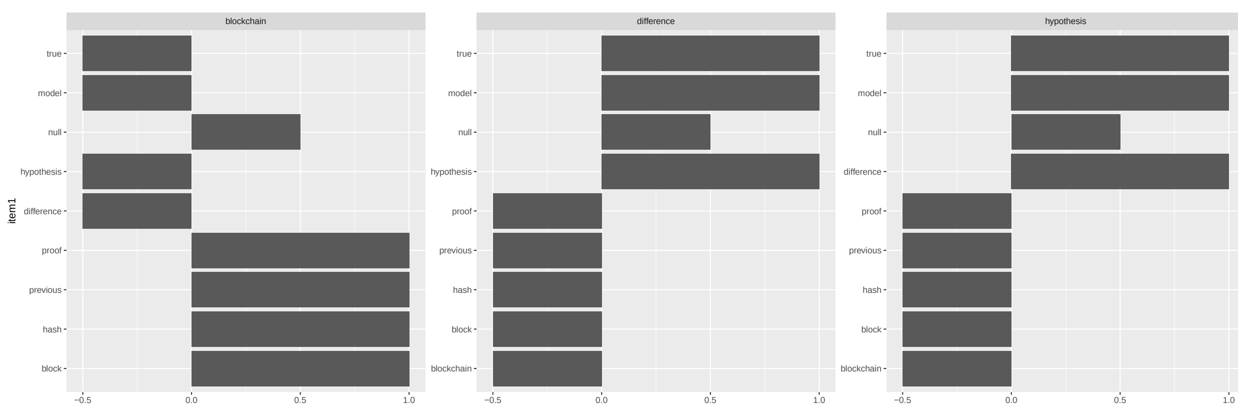
Find the phi coefficient between words based on how often they appear in the same article.

```
## # 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
```

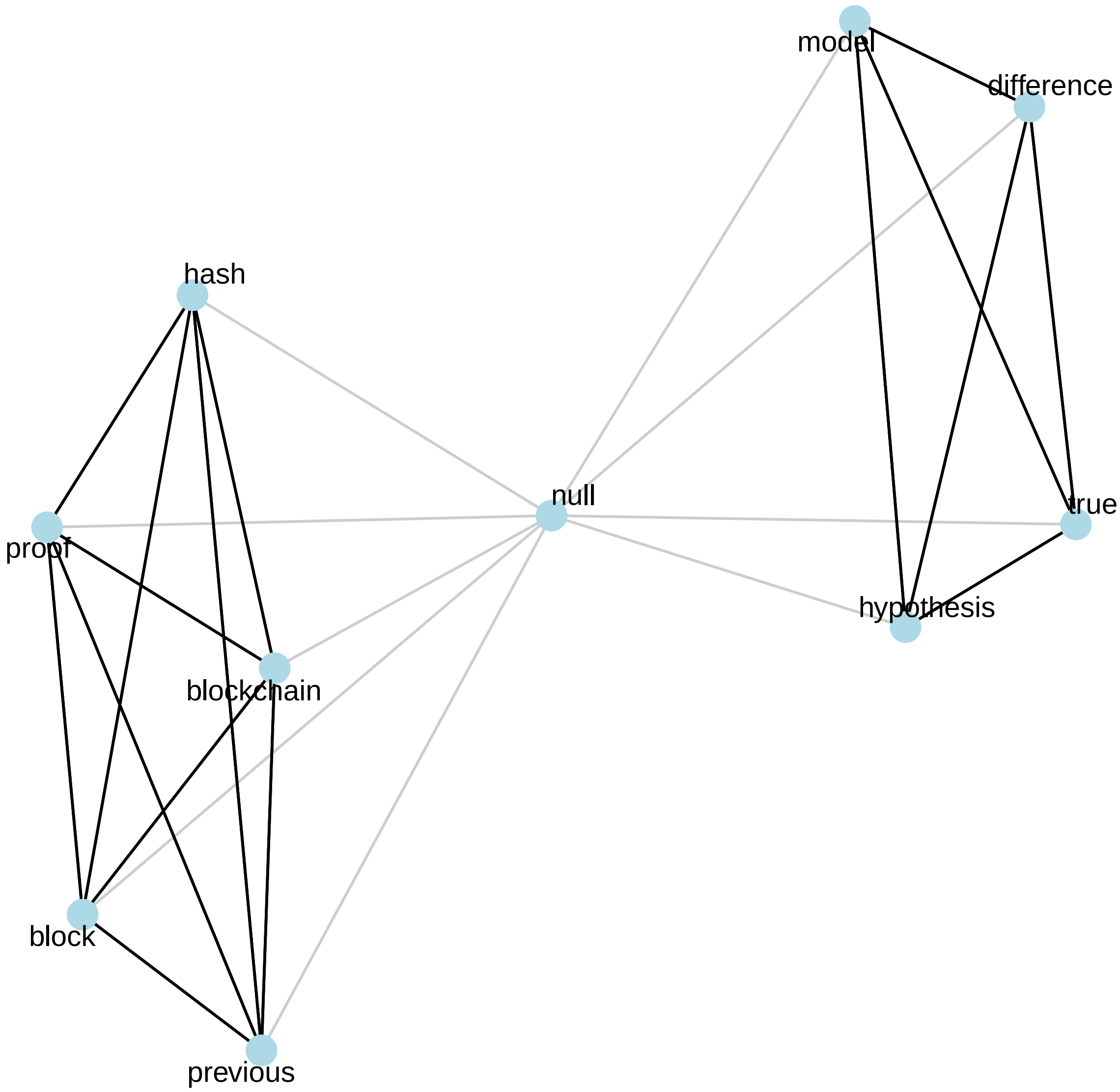
```
##  [1] "true"       "difference" "model"      "hypothesis" "block"
##  [6] "previous"   "hash"       "proof"      "blockchain" "null"
## [11] "data"       "values"
```

```
##  [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