correlaid_text_analysis

November 3, 2018

Scraping webpages

```r
url1 <- "https://correlaid.org/blog/posts/understand-p-values"
url2 <- "https://correlaid.org/blog/posts/blockchain-explained"
url3 <- "https://correlaid.org/blog/posts/music-with-r"

doc1 <- gettxt(url1)
# doc11 <- getURL(url1)
# dic11 <- htmlTreeParse(doc11)
# doc1111 <- readLines(url1)
doc2 <- gettxt(url2)
doc3 <- gettxt(url3)

raw.text <- as.data.frame(rbind(cbind("doc1",doc1),
                                cbind("doc2",doc2),
                                cbind("doc3",doc3)))
colnames(raw.text)  <-  c("article", "text")
raw.text$article <- as.character(raw.text$article)
raw.text$text <- as.character(raw.text$text)
str(raw.text)
```

```
## 'data.frame':    3 obs. of  2 variables:
##  $ article: chr  "doc1" "doc2" "doc3"
##  $ text   : chr  "Skip to main content\n\nToggle navigation Menu\n\n•\n• Zurück zu Correlaid.org\n• 
```

tidy text

```r
tidy_webtext <- raw.text %>%
  # unnest_tokens(sentence, text, token = "sentences") %>%
  unnest_tokens(word, text)%>%
  mutate(word = str_extract(word , "[a-z'\\s]+")) %>%
  anti_join(stop_words, by= "word") %>%
  filter(!word %in% "[\\s]+",
         !word %in% "",
         !word %in% NA)
```

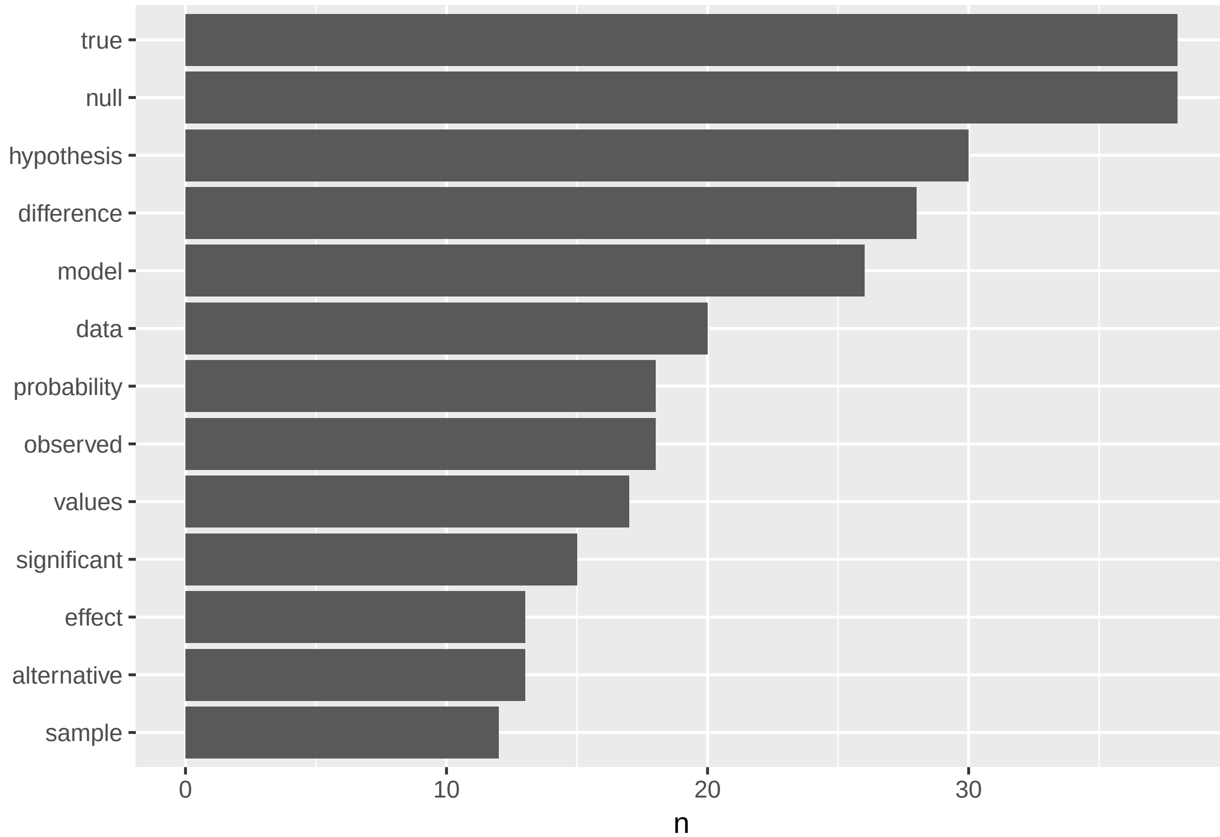
Chapter 1

look at single word frequency and visualize

first at doc1

```r
text1_count <- tidy_webtext %>%
  filter(article == "doc1" )%>%
```

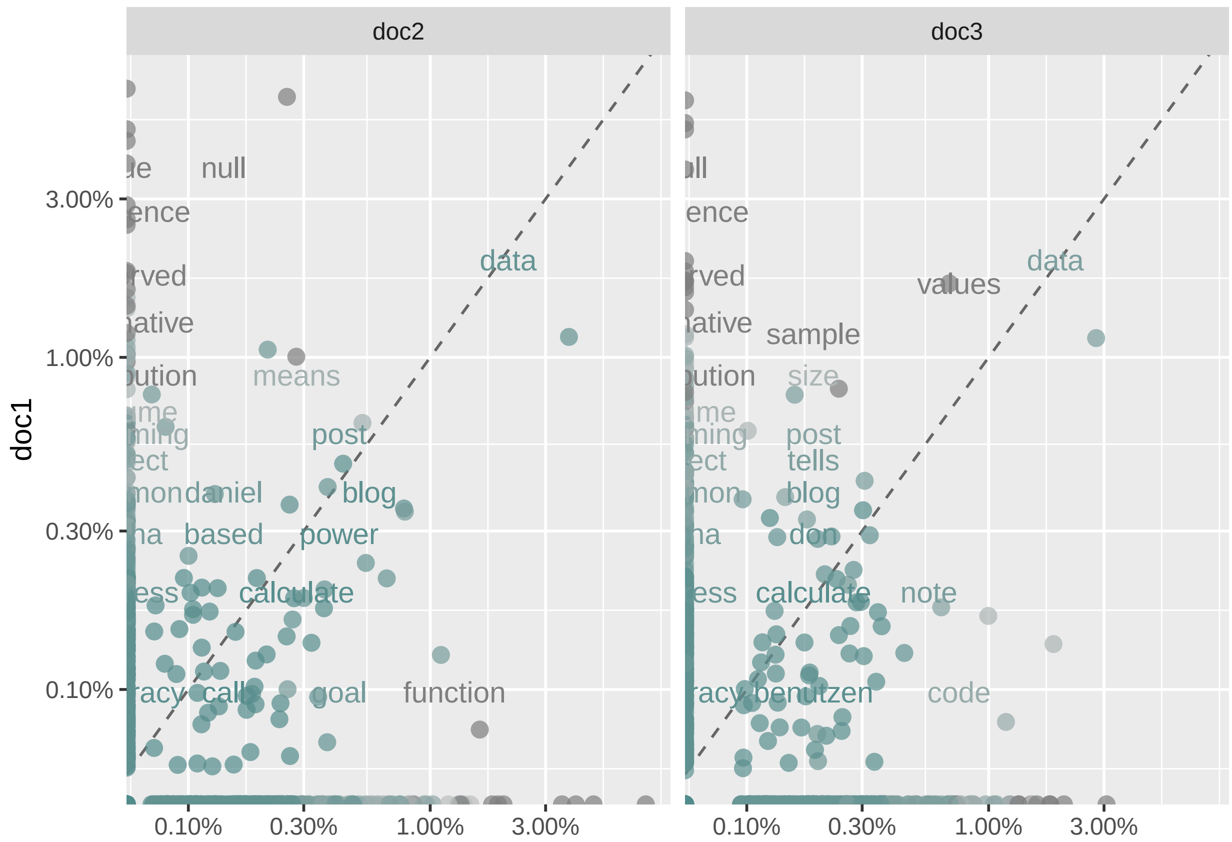
```
  count(word, sort = TRUE)

text1_count %>%
  filter(n > 10) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n)) +
  geom_col() +
  xlab(NULL) +
  coord_flip()
```



plotting and comparing the three articles

```
frequency <- tidy_webtext %>%
  count(article, word) %>%
  group_by(article) %>%
  mutate(proportion = n/sum(n) )%>%
  select(-n) %>%
  spread(article, proportion) %>%
  gather(article, proportion, 'doc2' : 'doc3')
#fill all NA (word proporton) with zero
frequency[is.na(frequency)] <- 0


ggplot(frequency, aes(x = proportion, y = `doc1`, color = abs(`doc1` - proportion))) +
  geom_abline(color = "gray40", lty = 2) +
```

```
  geom_jitter(alpha = .7, size = 2.5, width = 0.3, height = 0.3) +
  geom_text(aes(label = word), check_overlap = TRUE, vjust = 1.5) +
  scale_x_log10(labels = percent_format()) +
  scale_y_log10(labels = percent_format()) +
  scale_color_gradient(limits = c(0, 0.01), low = "darkslategray4", high = "gray75") +
  facet_wrap(~ article, ncol = 2) +
  theme(legend.position="none") +
  labs(y = "doc1", x = NULL)
```




```
cor.test(data = frequency[frequency$article == "doc2",],
         ~ proportion + `doc1`)
```

```
##
##  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
```

```
cor.test(data = frequency[frequency$article == "doc3",],
         ~ proportion + `doc1`)
```

```
##
```

```
##  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
```

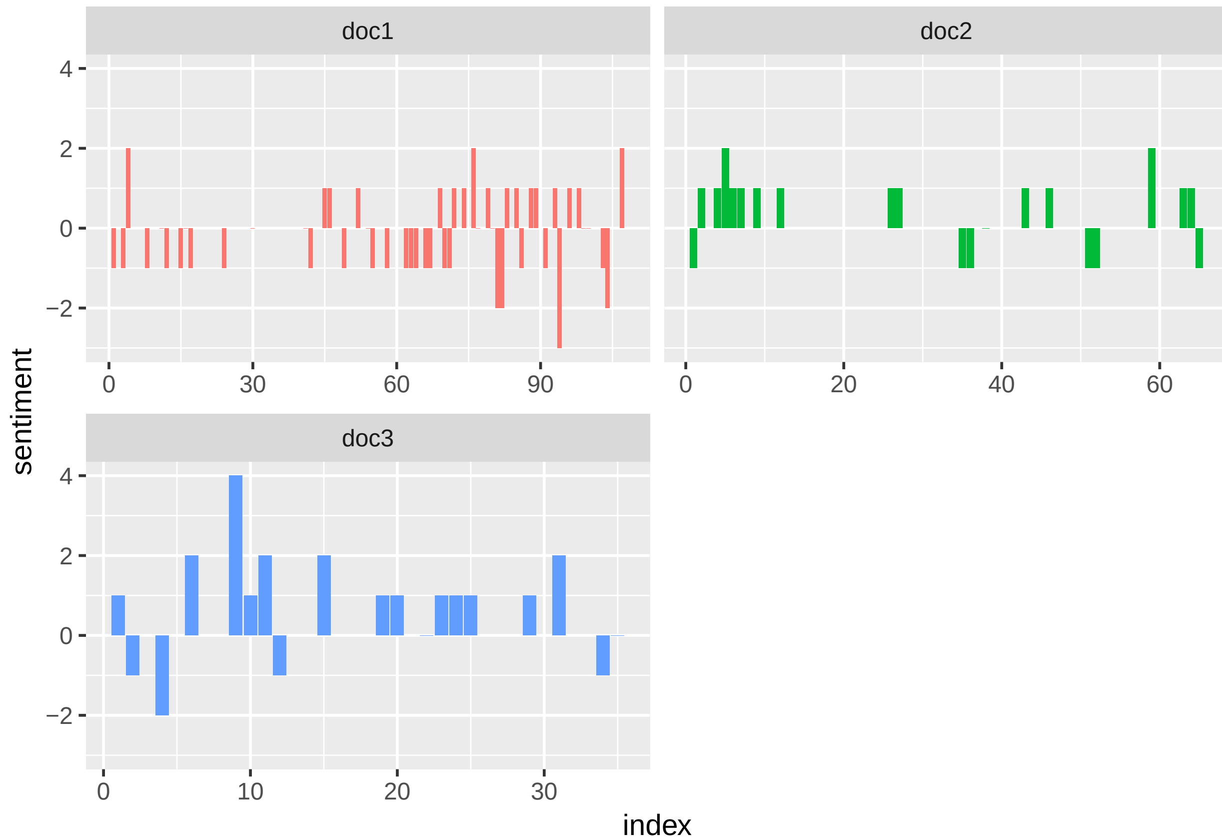
As we saw in the plots, the word frequencies have little frequencies in three articles.

Chapter 2 Sentiment analysis

```
afinn <- get_sentiments("afinn")
bing <- get_sentiments("bing")
nrc <- get_sentiments("nrc")
```

bing sentiment analysis

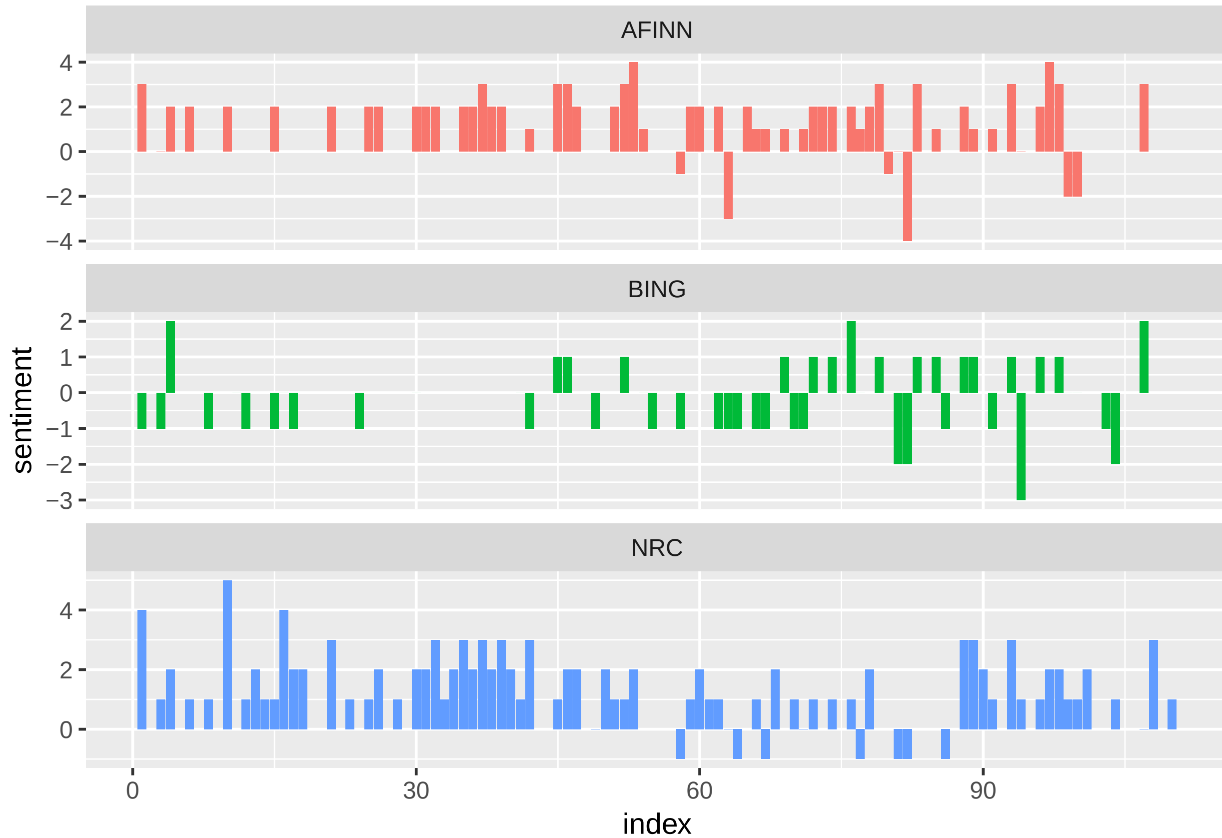
```
sentitext <-  raw.text %>%
  unnest_tokens(sentence, text, token = "sentences") %>%
  group_by(article) %>%
  mutate(linenumber = row_number()) %>%
  ungroup() %>%
  unnest_tokens(word, sentence) %>%
  anti_join(stop_words, by = "word")

bing_analysis <- sentitext %>%
  inner_join(bing, by = "word") %>%
  count(article, index = linenumber , sentiment)%>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)

ggplot(bing_analysis, aes(index, sentiment, fill = article)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ article, ncol = 2, scales = "free_x")
```



Comparing the three sentiment dictionaries

```
sentidoc1 <-  sentitext %>%
  filter(article == "doc1")

afinnsenti <- sentidoc1 %>%
  inner_join(afinn, by = "word") %>%
  group_by(index = linenumber ) %>%
  summarise(sentiment = sum(score)) %>%
  mutate(method = "AFINN")

bingnrcsenti <- bind_rows(sentidoc1 %>%
                            inner_join(bing) %>%
                            mutate(method = "BING"),
                          sentidoc1 %>%
                            inner_join(nrc %>%
                                         filter(sentiment %in% c("positive",
                                                                 "negative"))) %>%
                            mutate(method = "NRC")) %>%
  count(method, index = linenumber, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)

bind_rows(afinnsenti,
          bingnrcsenti) %>%
```

```r
  ggplot(aes(index, sentiment, fill = method)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~method, ncol = 1, scales = "free_y")
```



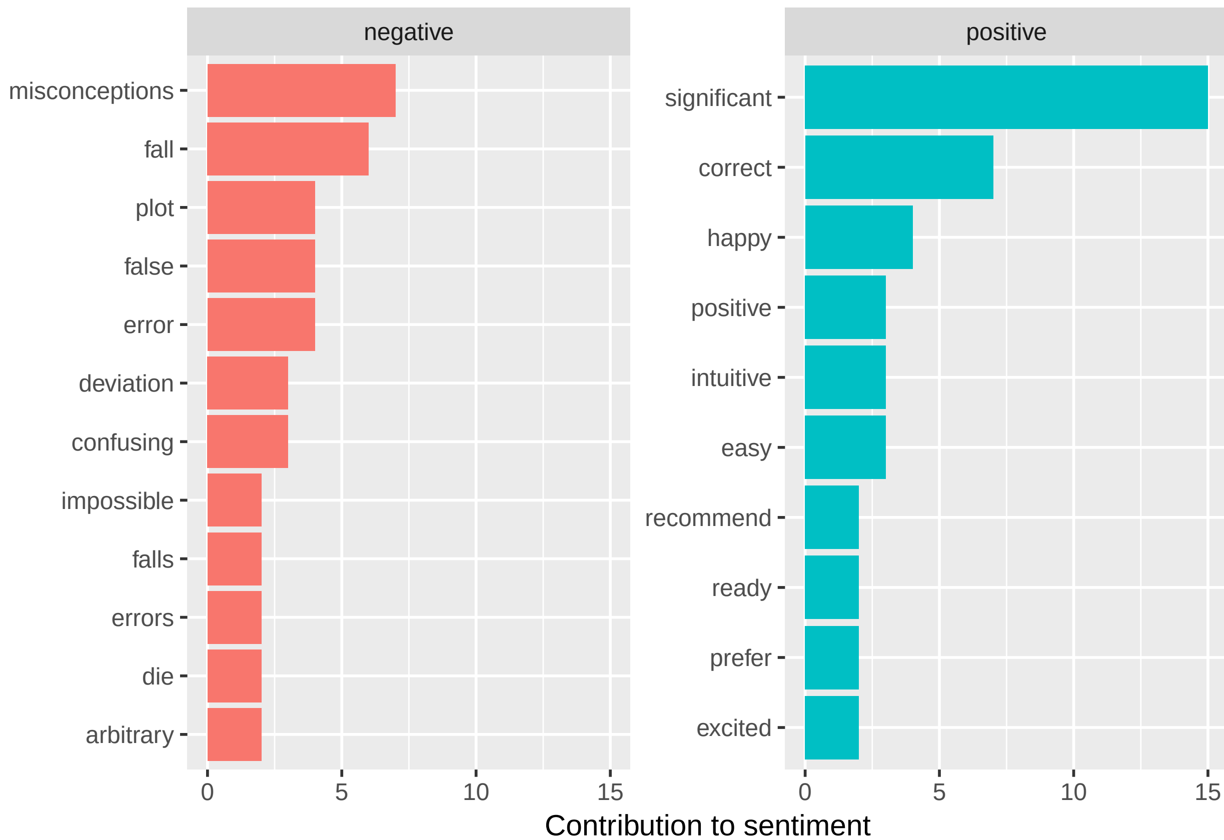
Most common sentiment words

```r
bing_counts <- sentitext %>%
  inner_join(bing) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()
bing_counts
```

```
## # 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
```

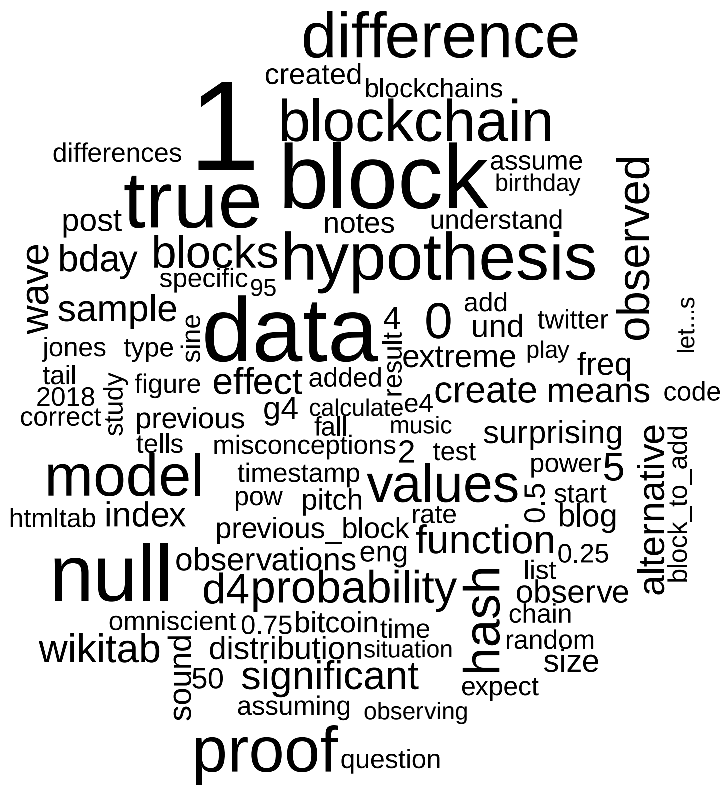
```
## # ... with 69 more rows
```

```
bing_counts %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment",
       x = NULL) +
  coord_flip()
```



Wordclouds

```
sentitext %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 100))
```

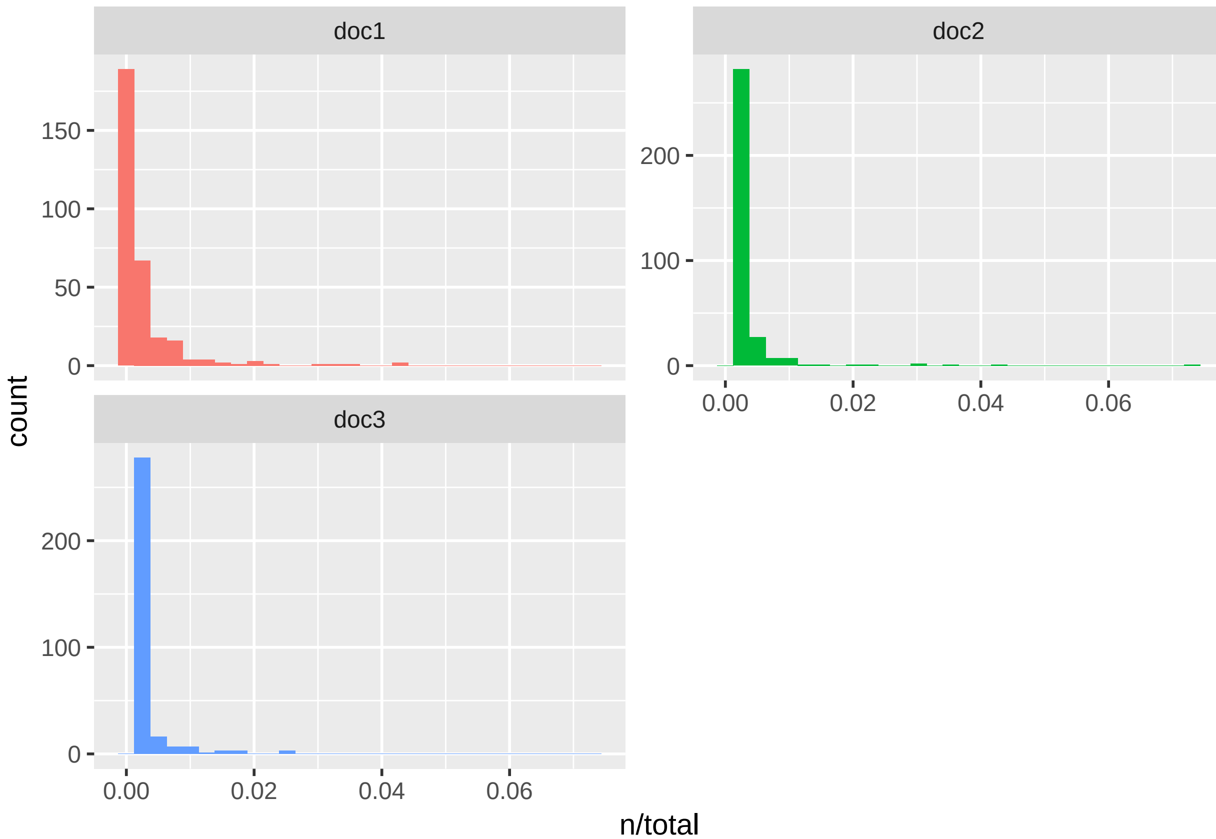



```r
library(reshape2)

sentitext %>%
  inner_join(bing) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("pink", "gray20"),
                   max.words = 100)
```

Chapter 3 tf-idf

```
wordcount <- tidy_webtext %>%
  group_by(article) %>%
  count(article, word) %>%
  summarise(total = sum(n))

tidy.text <- left_join(tidy_webtext %>%
  group_by(article) %>%
  count(article, word)%>%
  ungroup(),
  wordcount)
```

```
ggplot(tidy.text, aes(n/total, fill = article)) +
  geom_histogram(show.legend = FALSE) +
  #xlim(NA, 0.01) +
  facet_wrap(~ article, ncol = 2, scales = "free_y")
```



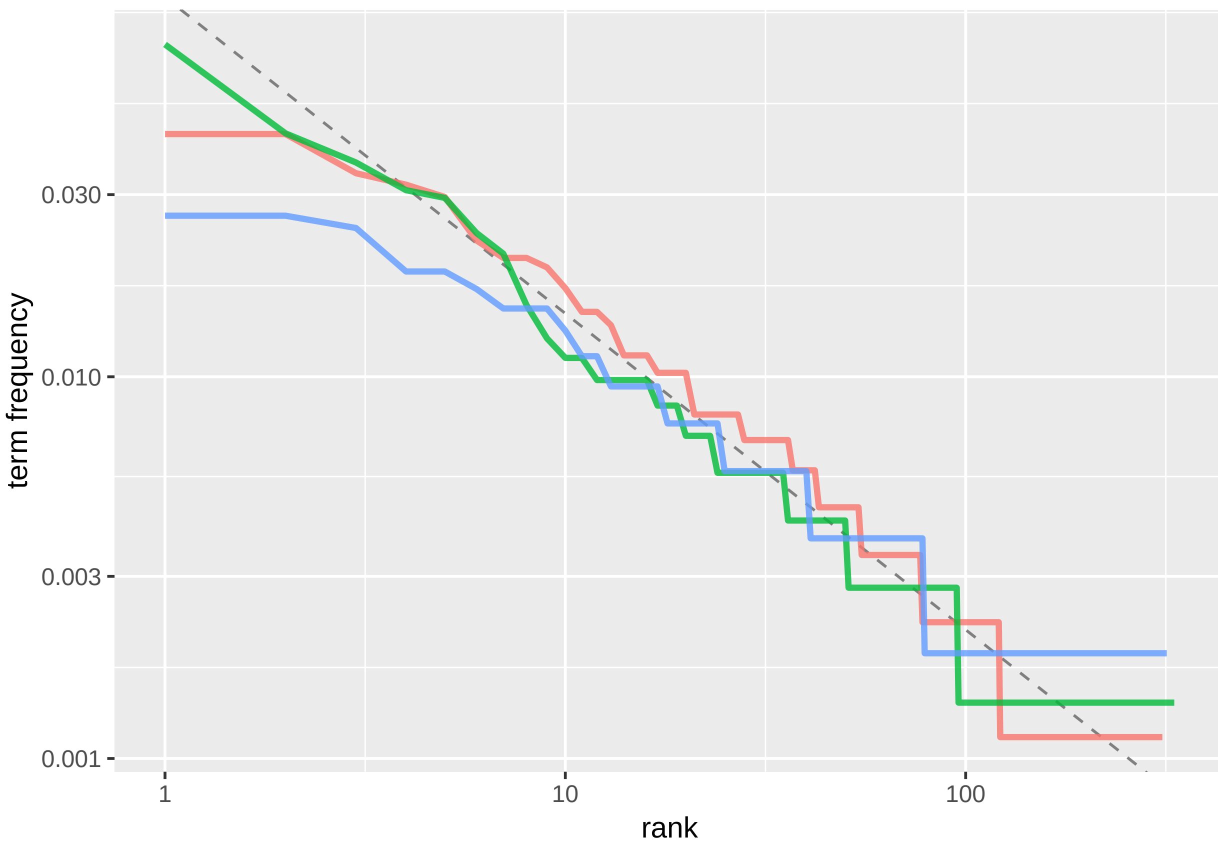

```
# freq_by_rank <- tidy.text %>%
#   group_by(article) %>%
#   mutate(rank = row_number(),
#          `term frequency` = n/total) %>%
#   arrange(desc(`term frequency`))

freq_by_rank <- tidy.text %>%
  group_by(article) %>%
  mutate(`term frequency` = n/total) %>%
```

```
  arrange(desc(`term frequency`)) %>%
  mutate(rank = row_number())
```

```
rank_subset <- freq_by_rank %>%
  filter(rank < 100,
         rank > 10)

rankreg <- lm(log10(`term frequency`) ~ log10(rank), data = rank_subset)
rankreg$coef
```

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

```
freq_by_rank %>%
  ggplot(aes(rank, `term frequency`, color = article)) +
  geom_abline(intercept = rankreg$coef[1], slope =rankreg$coef[2], color = "gray50", linetype = 2) +
  geom_line(size = 1.1, alpha = 0.8, show.legend = FALSE) +
  scale_x_log10() +
  scale_y_log10()
```



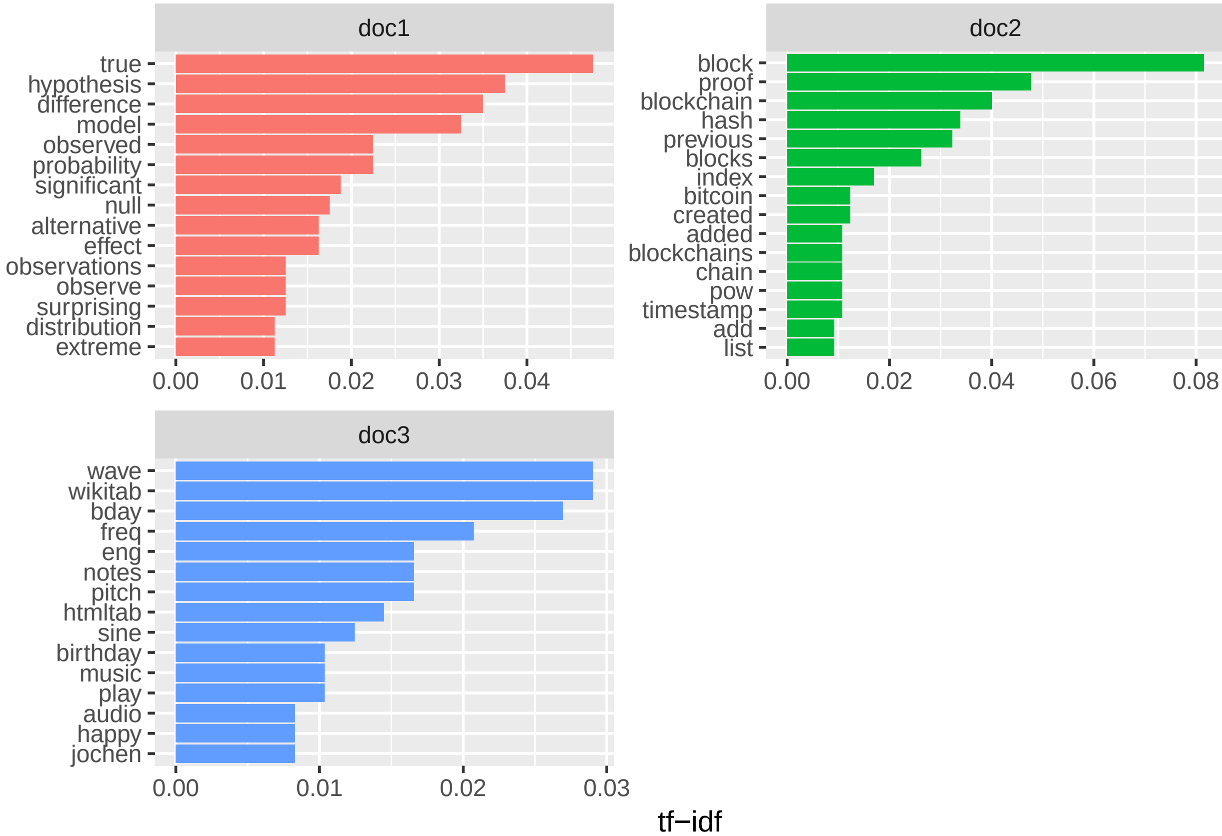
tf-idf function

```
tidytext <- tidy.text %>%
  bind_tf_idf(word, article, n) %>%
  select(-total) %>%
  arrange(desc(tf_idf))
```

```r
tidytext
```

```
## # 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
```

```r
tidytext %>%
  arrange(desc(tf_idf)) %>%
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  group_by(article) %>%
  top_n(15) %>%
  ungroup %>%
  ggplot(aes(word, tf_idf, fill = article)) +
  geom_col(show.legend = FALSE) +
  labs(x = NULL, y = "tf-idf") +
  facet_wrap(~article, ncol = 2, scales = "free") +
  coord_flip()
```


doc1
true
hypothesis
difference
model
observed
probability
significant
null
alternative
effect
observations
observe
surprising
distribution
extreme
0.00
0.01
0.02
0.03
0.04
doc2
block
proof
blockchain
hash
previous
blocks
index
bitcoin
created
added
blockchains
chain
pow
timestamp
add
list
0.00
0.02
0.04
0.06
0.08
doc3
wave
wikitab
bday
freq
eng
notes
pitch
htmltab
sine
birthday
music
play
audio
happy
jochen
0.00
0.01
0.02
0.03
tf−idf