Detecting Fake News Using Sentiment Analysis

Andrea Boskovic and Peter Cho 12/18/2018

```
# Loading the dataset
fake <- read_csv("fake.csv") #all fake
## Parsed with column specification:
## cols(
##
     .default = col_character(),
##
     ord_in_thread = col_integer(),
     published = col_datetime(format = ""),
##
     crawled = col_datetime(format = ""),
##
     domain_rank = col_integer(),
##
     spam_score = col_double(),
##
     replies_count = col_integer(),
##
     participants_count = col_integer(),
     likes = col_integer(),
     comments = col_integer(),
##
##
     shares = col_integer()
## )
## See spec(...) for full column specifications.
real <- read_csv("Articles.csv") #all real</pre>
## Parsed with column specification:
## cols(
##
     Article = col character(),
##
     Date = col_character(),
     Heading = col_character(),
##
     NewsType = col_character()
## )
new_ds <- read_csv("data.csv") #combination of real and fake</pre>
## Parsed with column specification:
## cols(
    URLs = col_character(),
##
    Headline = col_character(),
##
     Body = col_character(),
##
    Label = col_integer()
## )
fake_type <- c("fake", "satire", "bias", "bs", "conspiracy", "state", "junksci", "hate")</pre>
real_type <- c("sports", "business")</pre>
# Merging the datasets and removing unnecessary columns
real <- real %>%
  mutate(binary_type = ifelse(NewsType %in% fake_type, 0, 1)) #now fake = 0 and real = 1
fake <- fake %>%
  mutate(binary_type = ifelse(type %in% fake_type, 0, 1)) #now fake = 0 and real = 1
new_ds <- new_ds %>%
 filter(Label == 1)
```

```
real <- full_join(real, new_ds, by = c("Heading" = "Headline", "Article" = "Body", "binary_type" = "Lab
real <- real %>%
  mutate(id = as.character(seq(1:4564))) %>%
  mutate(realtype = "real")
# Making a combined dataset with both fake and real articles and selecting only for the unid (unique id
combined <- full_join(fake, real, by = c("text" = "Article", "title" = "Heading", "uuid" = "id", "binar
  select(uuid, binary_type, type, title, text)
# Making a tidy dataset where we have the the words in their own column for facilitated data analysis a
tidy_combined <- combined %>%
  unnest_tokens(word, text)
# Basic Data Exploration:
# This allows us to see how many observations are in each type of fake news.
combined %>%
  group_by(type) %>%
summarize(n = n())
## # A tibble: 9 x 2
    type
##
     <chr>>
                <int>
## 1 bias
                  443
## 2 bs
                11492
## 3 conspiracy
                  430
## 4 fake
                  19
## 5 hate
                  246
## 6 junksci
                  102
## 7 real
                 4564
## 8 satire
                 146
## 9 state
                  121
typetotals <- combined %>%
 group_by(type) %>%
summarize(n = n())
# What are the most common words for each basic emotion?
# We will use the nrc lexicon to categorize each documented word into on of the basic human emotions ca
# Anger
nrc_anger <- get_sentiments("nrc") %>%
 filter(sentiment == "anger")
tidy_combined %>%
  inner_join(nrc_anger) %>%
  count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 1,220 x 2
##
     word
                   n
##
      <chr>>
               <int>
## 1 vote
                4969
## 2 money
                4835
## 3 force
                3189
```

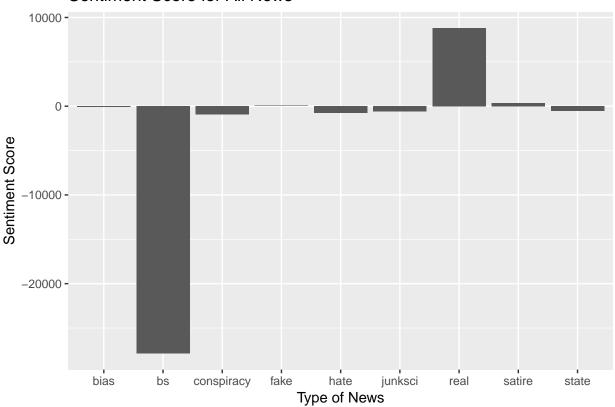
```
## 4 court
               2721
## 5 attack
               2548
## 6 defense 2242
## 7 death
               2176
## 8 bad
                2175
## 9 politics 2058
## 10 fight
                2054
## # ... with 1,210 more rows
# Fear
nrc_fear <- get_sentiments("nrc") %>%
  filter(sentiment == "fear")
tidy_combined %>%
  inner_join(nrc_fear) %>%
  count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 1,430 x 2
##
      word
                     n
##
      <chr>
                 <int>
## 1 government 11656
## 2 war
                 9845
## 3 military
                 5880
## 4 police
                 4902
## 5 change
                 4442
## 6 case
                 4177
## 7 force
                 3189
## 8 court
                 2721
                 2548
## 9 attack
## 10 problem
                 2381
## # ... with 1,420 more rows
# Anticipation
nrc_anticipation <- get_sentiments("nrc") %>%
  filter(sentiment == "anticipation")
tidy_combined %>%
  inner_join(nrc_anticipation) %>%
  count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 816 x 2
##
     word
                       n
##
      <chr>
                   <int>
## 1 time
                    14159
## 2 white
                     6547
## 3 public
                     6039
## 4 good
                     5802
## 5 long
                     5706
## 6 vote
                     4969
## 7 money
                     4835
## 8 investigation 3968
## 9 top
                     3822
## 10 continue
                     3439
```

```
## # ... with 806 more rows
# Trust
nrc_trust <- get_sentiments("nrc") %>%
 filter(sentiment == "trust")
tidy_combined %>%
  inner_join(nrc_trust) %>%
  count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 1,191 x 2
##
     word
                   n
##
      <chr>
               <int>
## 1 president 12344
## 2 united
               7803
## 3 white
                6547
## 4 good
                5802
## 5 law
                5181
## 6 system
                5088
## 7 vote
                4969
## 8 police
                4902
## 9 money
                4835
## 10 fact
                4673
## # ... with 1,181 more rows
# Surprise
nrc_surprise <- get_sentiments("nrc") %>%
 filter(sentiment == "surprise")
tidy_combined %>%
  inner_join(nrc_surprise) %>%
 count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 518 x 2
##
     word
##
      <chr> <int>
## 1 trump 23953
## 2 good
           5802
## 3 vote
           4969
## 4 money 4835
## 5 deal 2802
## 6 death 2176
## 7 leave 2080
## 8 hope 1902
## 9 young 1859
## 10 shot 1604
## # ... with 508 more rows
# Sadness
nrc_sadness <- get_sentiments("nrc") %>%
 filter(sentiment == "sadness")
tidy_combined %>%
```

```
inner_join(nrc_sadness) %>%
  count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 1,151 x 2
##
     word
##
      <chr>
              <int>
              4969
## 1 vote
## 2 black
              4196
## 3 case
              4177
## 4 problem 2381
## 5 lost
              2260
## 6 tax
               2211
## 7 death
               2176
## 8 bad
               2175
## 9 leave
               2080
## 10 violence 1955
## # ... with 1,141 more rows
# Joy
nrc_joy <- get_sentiments("nrc") %>%
 filter(sentiment == "joy")
tidy combined %>%
  inner_join(nrc_joy) %>%
 count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 668 x 2
##
     word
      <chr> <int>
## 1 white 6547
## 2 good 5802
## 3 vote
           4969
## 4 money 4835
## 5 found 4192
## 6 share 3090
## 7 deal 2802
## 8 food 2756
## 9 pay
            2339
## 10 true
            2234
## # ... with 658 more rows
# Disqust
nrc_disgust <- get_sentiments("nrc") %>%
 filter(sentiment == "disgust")
tidy_combined %>%
  inner_join(nrc_disgust) %>%
 count(word, sort = TRUE)
## Joining, by = "word"
## # A tibble: 1,023 x 2
##
   word
```

```
##
      <chr>>
                 <int>
## 1 john
                  3108
## 2 congress
                  2473
## 3 death
                  2176
## 4 bad
                  2175
## 5 criminal
                  1805
## 6 illegal
                  1756
## 7 powerful
                  1611
## 8 corruption 1571
## 9 finally
                  1442
## 10 remains
                  1244
## # ... with 1,013 more rows
# Find net sentiment for each type of fake news documented in the dataset using the bing lexicon. The b
# Note that some types, such as bs (> 400,000), have more corresponding observations than other types,
combined_sentiment <- tidy_combined %>%
  inner_join(get_sentiments("bing")) %>%
  count(type, sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
## Joining, by = "word"
combined_sentiment
## # A tibble: 9 x 4
     type
                negative positive sentiment
##
                            <dbl>
                                       <dbl>
     <chr>>
                   <dbl>
## 1 bias
                    5422
                             5322
                                        -100
## 2 bs
                                      -27855
                  247391
                           219536
## 3 conspiracy
                             3851
                                        -954
                    4805
## 4 fake
                     148
                              199
                                          51
## 5 hate
                    8765
                             7998
                                        -767
## 6 junksci
                    3070
                             2469
                                        -601
## 7 real
                   45896
                                        8794
                            54690
## 8 satire
                    1148
                             1487
                                        339
## 9 state
                    1215
                              704
                                        -511
# Plot of the sentiment score for each type of news
ggplot(combined_sentiment, aes(x = type, y = sentiment)) + geom_col() + labs(title = "Sentiment Score f
```

Sentiment Score for All News



```
# We can also get the sentiment score on a scale of -5 to 5 from the AFINN lexicon. The AFINN lexicon h
afinn <- tidy_combined %>%
  inner_join(get_sentiments("afinn")) %>%
 group_by(type) %>%
 summarise(sentiment = sum(score)) %>%
 mutate(method = "AFINN")
## Joining, by = "word"
afinn
## # A tibble: 9 x 3
##
    type
              sentiment method
##
     <chr>>
                  <int> <chr>
## 1 bias
                   -1507 AFINN
## 2 bs
                   -62021 AFINN
## 3 conspiracy
                   -1846 AFINN
## 4 fake
                      108 AFINN
## 5 hate
                   -1625 AFINN
## 6 junksci
                       41 AFINN
## 7 real
                    28457 AFINN
## 8 satire
                      868 AFINN
                   -1089 AFINN
## 9 state
# It may be useful to investigate the basic contents of the lexicons.
\# Positive and negative words in nrc lexicon
get_sentiments("nrc") %>%
    filter(sentiment %in% c("positive",
```

```
"negative")) %>%
 count(sentiment)
## # A tibble: 2 x 2
     sentiment n
##
     <chr>
             <int>
## 1 negative 3324
## 2 positive
              2312
# Positive and negative words in bing lexicon
get_sentiments("bing") %>%
 count(sentiment)
## # A tibble: 2 x 2
## sentiment n
##
   <chr>
             <int>
## 1 negative 4782
              2006
## 2 positive
# Both lexicons have more negative words than positive words, but the bing lexicon has a higher ratio o
# Counting the most frequently appearing words and which sentiment they correspond to (positive or nega
bing_word_counts <- tidy_combined %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()
## Joining, by = "word"
bing_word_counts
## # A tibble: 5,552 x 3
##
     word sentiment
      <chr> <chr>
##
                       <int>
## 1 trump positive 23953
## 2 like positive 14612
## 3 well positive 8250
## 4 right positive 7530
## 5 good positive 5802
## 6 work
                      5544
             positive
## 7 support positive
                       5504
## 8 free
             positive
                        4327
## 9 great
                        4007
             positive
## 10 strong positive
                        3862
## # ... with 5,542 more rows
bing_word_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") +
  ggtitle("Positive and Negative Word Frequency") +
 labs(y = "Frequency of Word",
```

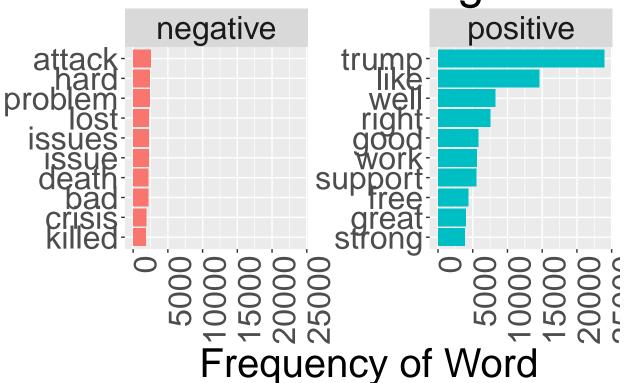
x = NULL) +

Selecting by n

for <e2>

for <80>

Positive and Negative V



```
# Wordcloud with most frquently appearing words
tidy_combined %>%
  anti_join(stop_words) %>%
  count(word) %>%
  with(wordcloud(words = word, freq = n, max.words = 100, min.freq = 1, random.order=FALSE, rot.per = 0
## Joining, by = "word"
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'it's' in 'mbcsToSbcs': dot substituted for <e2>
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'it's' in 'mbcsToSbcs': dot substituted for <80>
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'it's' in 'mbcsToSbcs': dot substituted for <99>
```

Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
rotWord * : conversion failure on 'it's' in 'mbcsToSbcs': dot substituted

Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
rotWord * : conversion failure on 'it's' in 'mbcsToSbcs': dot substituted

```
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on 'it's' in 'mbcsToSbcs': dot substituted
## for <99>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : font metrics unknown for Unicode character U+2019
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'don't' in 'mbcsToSbcs': dot substituted for <e2>
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'don't' in 'mbcsToSbcs': dot substituted for <80>
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## 'don't' in 'mbcsToSbcs': dot substituted for <99>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on 'don't' in 'mbcsToSbcs': dot substituted
## for <e2>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on 'don't' in 'mbcsToSbcs': dot substituted
## for <80>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on 'don't' in 'mbcsToSbcs': dot substituted
## for <99>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : font metrics unknown for Unicode character U+2019
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : presidential could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : washington could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : international could not be fit on page. It will not be plotted.
## Warning in strwidth(words[i], cex = size[i], ...): conversion failure on
## ' ' in 'mbcsToSbcs': dot substituted for <d0>
## Warning in strwidth(words[i], cex = size[i], \dots): conversion failure on
## ' ' in 'mbcsToSbcs': dot substituted for <b2>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on ' ' in 'mbcsToSbcs': dot substituted for
## <d0>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : conversion failure on ' ' in 'mbcsToSbcs': dot substituted for
## <b2>
## Warning in text.default(x1, y1, words[i], cex = size[i], offset = 0, srt =
## rotWord * : font metrics unknown for Unicode character U+0432
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : investigation could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : democratic could not be fit on page. It will not be plotted.
```

```
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : control could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : york could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : days could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : economic could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : strong could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : story could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : china could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : countries could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : human could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : history could not be fit on page. It will not be plotted.
## Warning in wordcloud(words = word, freq = n, max.words = 100, min.freq =
## 1, : team could not be fit on page. It will not be plotted.
                  article black email police
     includingoctober
global
   national
toreign
                                      party change
                  russian support
```

security

```
# Wordcloud faceted into positive and negative with color (blue corresponds to a negative sentiment whi
tidy_combined %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("blue", "orange"),
                       max.words = 100)
## Joining, by = "word"
          opposition concerns
protest cold concerns
dangerousworse wrong of difficult risk false of fell corruption
        difficult risk false a fell corruption breaklack & killed crisisbad attacks conflictoriminal lost death debt cancer threat issues problem fear blest distributions and the standard problem fear willed a standard problem.
                         attack hard illegal >
     breakingfailedissue
                                          fraud
dead
     loss lose fall
                                           crime 5
  clearlywin g
pretty clear
     love top
 interes
      leading good free \Phi
supremeprotect SUPPORT
                                gold peace
                     better
                             r victory Epositive
        intelligence.
# Now, it is time to start the machine learning aspect of the project.
# Using the AFINN lexicon to append the sentiment score of each word to a new dataset called tidy_combi
tidy_combined_a <- tidy_combined %>%
  inner_join(get_sentiments("afinn"))
## Joining, by = "word"
# Categorize article as positive or negative overall based on the average of the AFINN score of the wor
tidy_combined_final <- tidy_combined_a %>%
  select(uuid, score, binary_type) %>%
  group_by(uuid) %>%
  summarise(n_words = n(), avgscore = sum(score) / n_words,
              type = mean(binary_type),
              positive_score = sum(score[score > 0]),
              negative_score = sum(score[score < 0]),</pre>
              n_{positive} = sum(score > 0),
              n_negative = sum(score < 0)</pre>
              ) %>%
  mutate(articlesent = ifelse(avgscore < 0, "Negative", "Positive")) %>%
  mutate(txt_type = as.factor(type)) %>%
  select(-type)
tidy_combined_final
## # A tibble: 16,693 x 9
##
       uuid n_words avgscore positive_score negative_score n_positive
##
       <chr>
                 <int>
                            <dbl>
                                              <int>
                                                                <int>
                                                                              <int>
    1 0005~
                    21
                            0.286
                                                  19
                                                                   -13
                                                                                  13
```

```
2 0020~
                       -0.667
                                                          -28
                                                                        7
##
                  24
                                           12
                                          109
## 3 0021~
                  87
                        0.379
                                                          -76
                                                                       49
   4 002d~
##
                  88
                        0.261
                                           99
                                                          -76
                                                                       50
  5 0033~
                  9
                                            8
                                                                        5
##
                        0
                                                           -8
##
    6 0033~
                  58
                       -0.759
                                           36
                                                          -80
                                                                       20
   7 0037~
                        0.714
                                           16
                                                                        8
##
                  14
                                                           -6
##
   8 0038~
                  30
                       -0.667
                                           20
                                                          -40
                                                                        9
                                                                        7
## 9 003d~
                        0.7
                                           14
                                                           -7
                  10
## 10 0048~
                  58
                        0.172
                                           50
                                                          -40
                                                                       34
## # ... with 16,683 more rows, and 3 more variables: n_negative <int>,
       articlesent <chr>, txt_type <fct>
tidy_combined_final %>%
  filter(txt_type == 0) %>%
  summarise(n_negative = n())
## # A tibble: 1 x 1
##
     n_negative
##
          <int>
## 1
          12248
# Decision tree training process
n <- nrow(tidy_combined_final)</pre>
train_id <- sample(1:n, size = round(n * 0.8))</pre>
train <- tidy_combined_final[train_id,]</pre>
test <- tidy_combined_final[-train_id,]</pre>
tree <- rpart(txt_type ~ avgscore + n_words + n_positive + n_negative + negative_score + positive_score
plot(as.party(tree))
                             Node 1 (n = 13354)
                                                                              1
0
                                                                             - 0.8
                                                                             - 0.6
                                                                            - 0.4
                                                                            - 0.2
                                                                             - 0
```

```
## n= 13354
##
## node), split, n, loss, yval, (yprob)
         * denotes terminal node
##
## 1) root 13354 3550 0 (0.7341620 0.2658380) *
saveRDS(tree, file = "tree.rds")
saveRDS(train, file = "train.rds")
prediction <- predict(tree, test)</pre>
test <- test %>%
  mutate(prediction = prediction[1])
roc_obj <- roc(test$txt_type, test$prediction)</pre>
auc(roc_obj)
## Area under the curve: 0.5
plot(roc_obj)
    0.8
    9.0
Sensitivity
    0.4
    0.2
    0.0
                                              0.5
                        1.0
                                                                    0.0
                                          Specificity
# Based on this tree, we can see that none of the predictors (average score, number of words, number of
# Why is this true? Below, we will do some exploration using visualizations to display the poor relatio
# Histogram of Average Sentiment Score by News Type (Real and Fake)
```

tree

ggplot(tidy_combined_final, aes(x = avgscore, fill = txt_type)) +

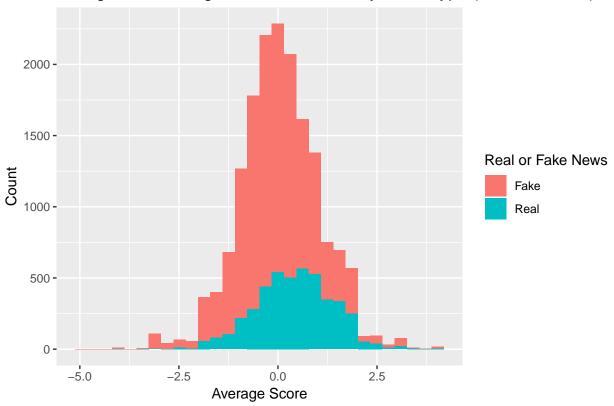
geom_histogram() +
xlab("Average Score") +

ylab("Count") +

```
ggtitle("Histogram of Average Sentiment Score by News Type (Real and Fake)") +
scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

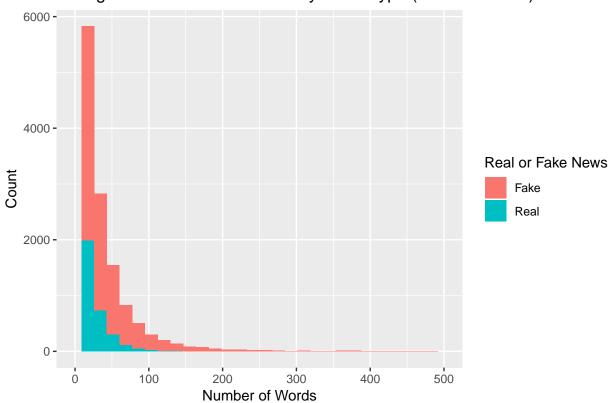
Histogram of Average Sentiment Score by News Type (Real and Fake)



```
# Histogram of Number of Words by News Type (Real and Fake)
ggplot(tidy_combined_final, aes(x = n_words, fill = txt_type)) +
   geom_histogram() +
   xlim(0, 500) +
   xlab("Number of Words") +
   ylab("Count") +
   ggtitle("Histogram of Number of Words by News Type (Real and Fake)") +
   scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

- ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
- ## Warning: Removed 25 rows containing non-finite values (stat_bin).
- ## Warning: Removed 4 rows containing missing values (geom_bar).

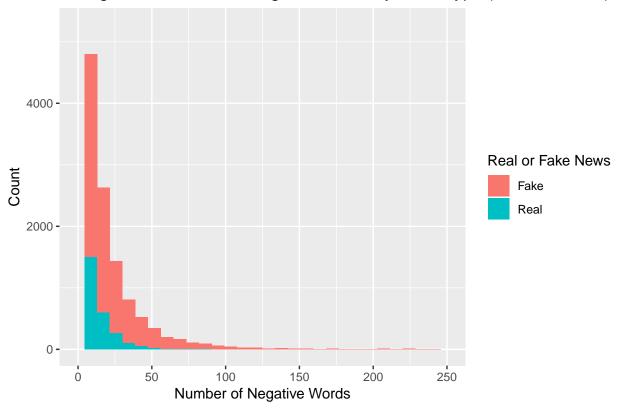
Histogram of Number of Words by News Type (Real and Fake)



```
# Histogram of Number of Negative Words by News Type (Real and Fake)
ggplot(tidy_combined_final, aes(x = n_negative, fill = txt_type)) +
  geom_histogram() +
  xlim(0, 250) +
  xlab("Number of Negative Words") +
  ylab("Count") +
  ggtitle("Histogram of Number of Negative Words by News Type (Real and Fake)") +
  scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

- ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
- ## Warning: Removed 27 rows containing non-finite values (stat_bin).
- ## Warning: Removed 4 rows containing missing values (geom_bar).

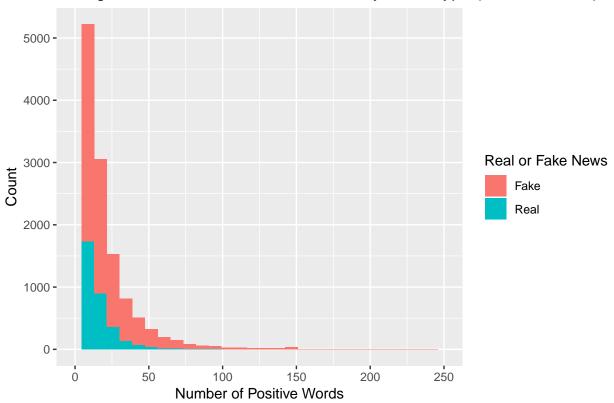
Histogram of Number of Negative Words by News Type (Real and Fake)



```
# Histogram of Number of Positive Words by News Type (Real and Fake
ggplot(tidy_combined_final, aes(x = n_positive, fill = txt_type)) +
  geom_histogram() +
  xlim(0, 250) +
  xlab("Number of Positive Words") +
  ylab("Count") +
  ggtitle("Histogram of Number of Positive Words by News Type (Real and Fake)") +
  scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

- ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
- ## Warning: Removed 27 rows containing non-finite values (stat_bin).
- ## Warning: Removed 4 rows containing missing values (geom_bar).

Histogram of Number of Positive Words by News Type (Real and Fake)



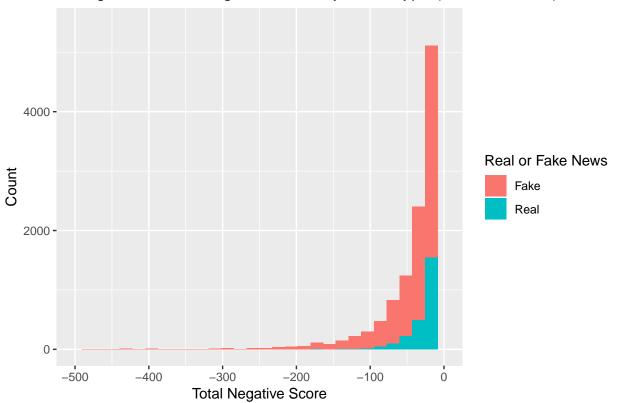
```
# Histogram of Total Negative Score by News Type (Real and Fake)
ggplot(tidy_combined_final, aes(x = negative_score, fill = txt_type)) +
    geom_histogram() +
    xlim(-500, 0) +
    xlab("Total Negative Score") +
    ylab("Count") +
    ggtitle("Histogram of Total Negative Score by News Type (Real and Fake)") +
    scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

^{##} Warning: Removed 25 rows containing non-finite values (stat_bin).

^{##} Warning: Removed 4 rows containing missing values (geom_bar).

Histogram of Total Negative Score by News Type (Real and Fake)



```
# Histogram of Total Positive Score by News Type (Real and Fake)
ggplot(tidy_combined_final, aes(x = positive_score, fill = txt_type)) +
  geom_histogram() +
  xlim(0, 500) +
  xlab("Total Positive Score") +
  ylab("Count") +
  ggtitle("Histogram of Total Positive Score by News Type (Real and Fake)") +
  scale_fill_discrete(name = "Real or Fake News", labels = c("Fake", "Real"))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

^{##} Warning: Removed 21 rows containing non-finite values (stat_bin).

^{##} Warning: Removed 4 rows containing missing values (geom_bar).

