Introduction to Data Wrangling IV

Summer Institute in Data Science

Rolando J. Acosta

HARVARD
SCHOOL OF PUBLIC HEALTH

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@RJANunez

What to expected today

- Today we will use some of the functions we have learned this week in a case study
    - Join functions
    - *regex*
- Specifically, we are going to conduct a *sentiment analysis* on Trump tweets
- Sentiment analysis is the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information

Case Study: Trump Tweets

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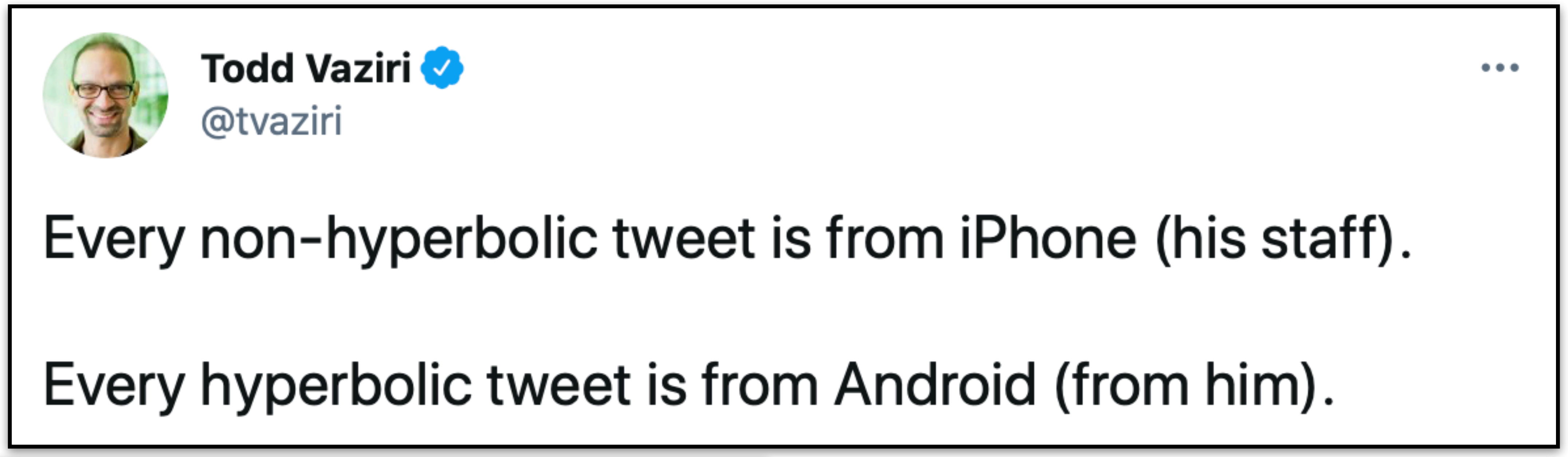
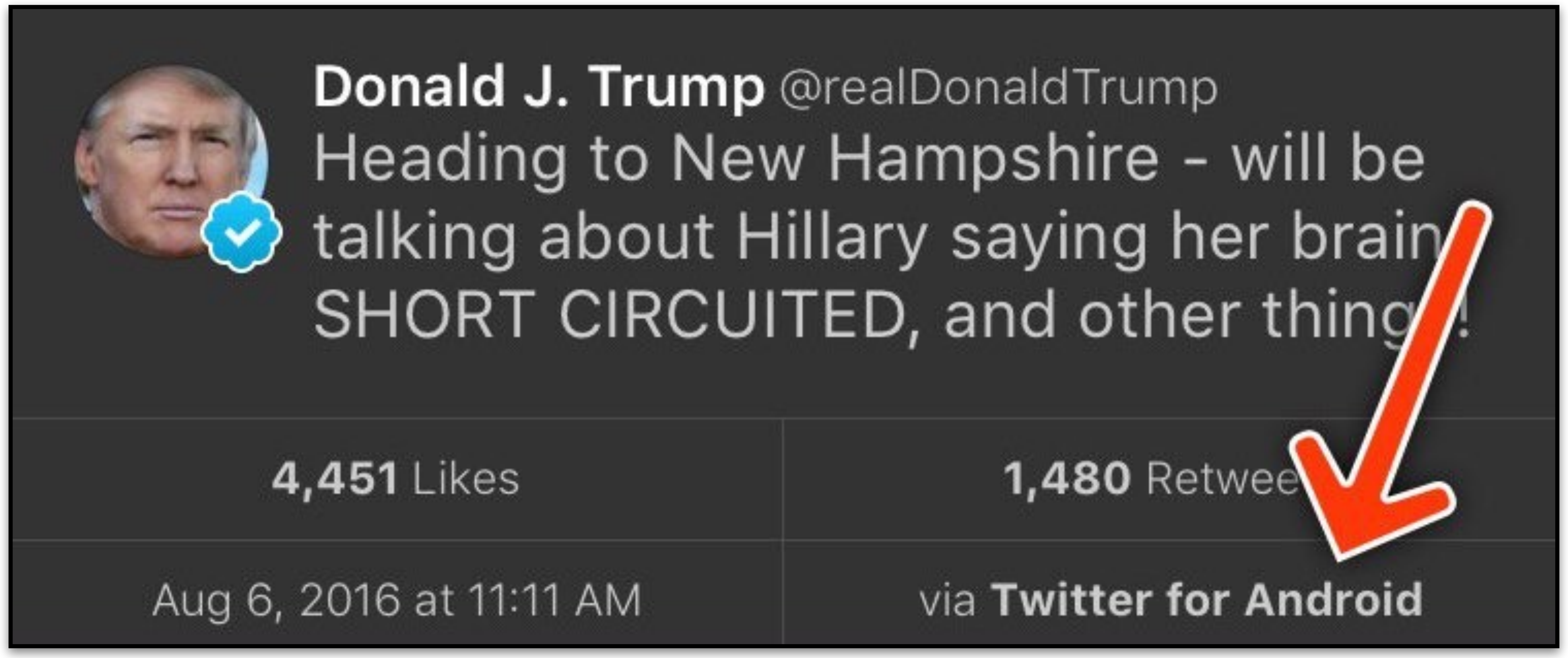
- During the 2016 US presidential election, Donald Trump used his twitter account to, among other things, communicate with potential voters
- On August 2016, Todd Vaziri tweeted:





https://twitter.com/tvaziri/status/762005541388378112

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- David Robinson, a data scientist, conducted an analysis to check if the data supports this claim

http://varianceexplained.org/r/trump-tweets/

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- Here is the set up

```
library(tidyverse)
library(lubridate)
library(tidytext)
library(textdata)
library(dslabs)
library(scales)

data("trump_tweets")
```

	source	id_str	text	created_at	retweet_count	in_reply_to_user_id_str	favorite_count	is_retweet
1	Twitter Web Client	6971079756	From Donald Trump: Wishing everyone a wonderful h...	2009-12-23 12:38:18	28	NA	12	FALSE
2	Twitter Web Client	6312794445	Trump International Tower in Chicago ranked 6th tall...	2009-12-03 14:39:09	33	NA	6	FALSE
3	Twitter Web Client	6090839867	Wishing you and yours a very Happy and Bountiful Th...	2009-11-26 14:55:38	13	NA	11	FALSE
4	Twitter Web Client	5775731054	Donald Trump Partners with TV1 on New Reality Serie...	2009-11-16 16:06:10	5	NA	3	FALSE
5	Twitter Web Client	5364614040	--Work has begun, ahead of schedule, to build the gr...	2009-11-02 09:57:56	7	NA	6	FALSE

tweets/

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- Thus, we have to do some wrangling:

```
campaign_tweets <- trump_tweets %>%
  extract(source, "source", "Twitter for (.*)") %>%
  filter(source %in% c("Android", "iPhone") &
           created_at >= ymd("2015-06-17") &
           created_at < ymd("2016-11-08")) %>%
  filter(!is_retweet) %>%
  arrange(created_at) %>%
  as_tibble()
```

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- Note that the `extract` function is similar to the `separate` function that permits the use of *regex*
- ymd is a date format function from the ***lubridate*** package

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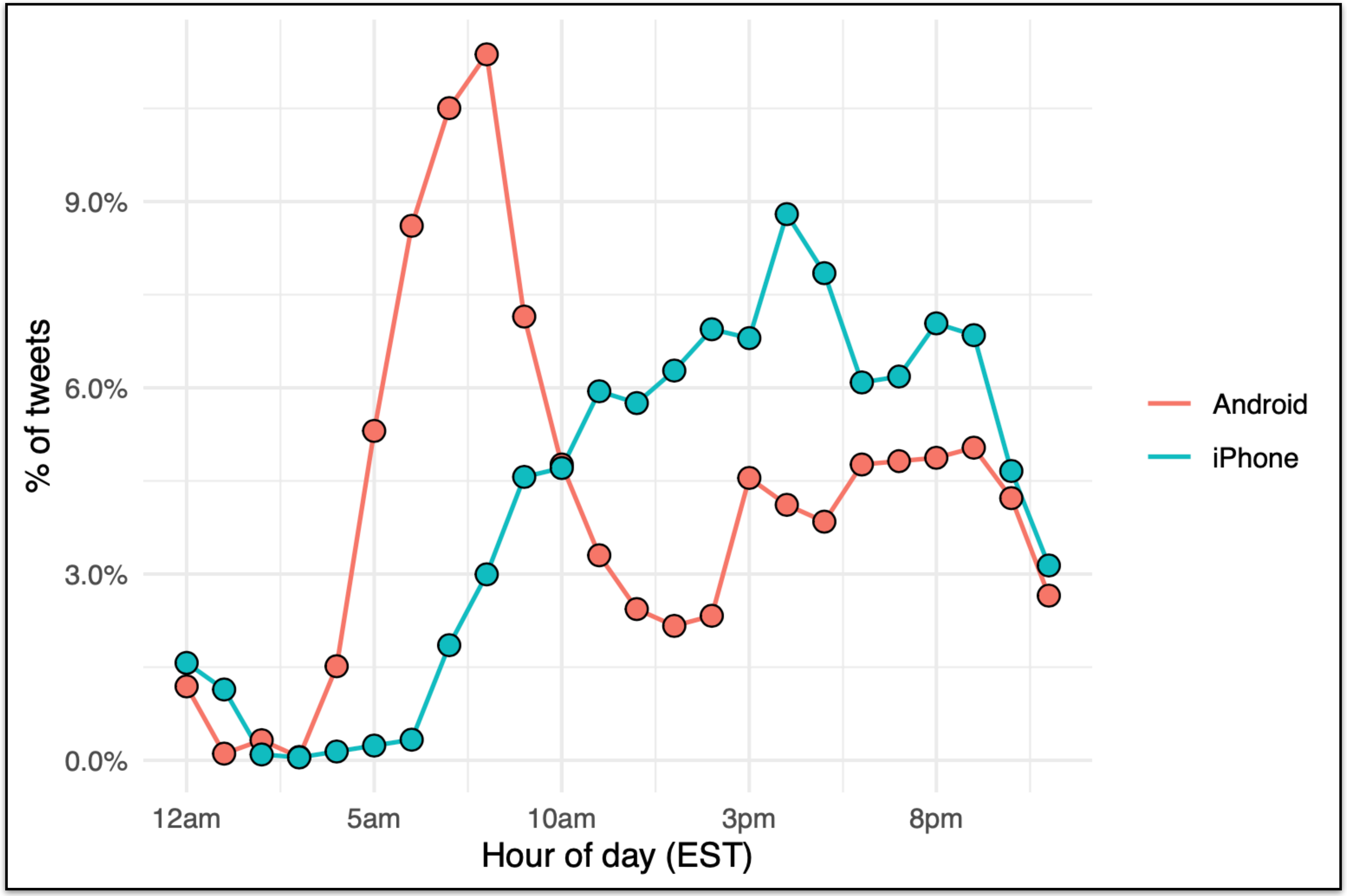
```
campaign_tweets %>%
  mutate(hour = hour(with_tz(created_at, "EST"))) %>%
  count(source, hour) %>%
  group_by(source) %>%
  mutate(percent = n / sum(n)) %>%
  ungroup() %>%
  ggplot(aes(hour, percent, fill = source, color = source)) +
  geom_line(size = 0.70) +
  geom_point(shape       = 21,
             color       = "black",
             size        = 3,
             show.legend = FALSE) +
  scale_y_continuous(labels = percent_format()) +
  scale_x_continuous(breaks = seq(0, 20, by = 5),
                     labels = c("12am", "5am", "10am", "3pm", "8pm")) +
  labs(x = "Hour of day (EST)", y = "% of tweets", color = "") +
  theme_minimal()
```

Case Study: Trump Tweets



- Comments?

Quick detour: The `unnest_tokens` function

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- The function to do this is the `unnest_tokens` function
- Here is a quick example:

```
poem <- c("Roses are red,", "Violets are blue,",
          "Sugar is sweet,", "And so are you.")

example <- tibble(line = c(1, 2, 3, 4),
                  text = poem)

example_token <- example %>% unnest_tokens(word, text)
```

Quick detour: The `unnest_tokens` function

example

	line	text
1	1	Roses are red,
2	2	Violets are blue,
3	3	Sugar is sweet,
4	4	And so are you.

example_token

	line	word
1	1	roses
2	1	are
3	1	red
4	2	violets
5	2	are
6	2	blue
7	3	sugar
8	3	is
9	3	sweet
10	4	and
11	4	so
12	4	are
13	4	you

Quick detour: The `unnest_tokens` function

- Now let us look at an example from the tweets

```
i <- 3008
campaign_tweets$text[i] %>% str_wrap(width = 65) %>% cat()
Great to be back in Iowa! #TBT with @JerryJrFalwell joining me in
Davenport- this past winter. #MAGA https://t.co/A5IF0QHnic

campaign_tweets[i,] %>%
  unnest_tokens(word, text) %>%
  pull(word)
 [1] "great"          "to"             "be"             "back"           "in"
 [6] "iowa"           "tbt"            "with"           "jerryjrfalwell" "joining"
[11] "me"             "in"             "davenport"      "this"           "past"
[16] "winter"         "maga"           "https"          "t.co"           "a5if0qhnic"
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```

- Note that the function strips characters that are important in the context of Twitter (*e.g.*, @JerryJrFalwell)
- A *token* in the context of Twitter is not the same as in the context of spoken or written English

Quick detour: The `unnest_tokens` function

- Let us fix this:

```
campaign_tweets[i,] %>%
  unnest_tokens(word, text, token = “tweets”) %>%
  pull(word)
[1] "great"                          "to"                           "be"
[4] "back"                           "in"                           "iowa"
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```

- Another minor adjustment, let us remove the links to photos

```
links <- "https://t.co/[A-Za-z\\d]+|&amp;"
campaign_tweets[i,] %>%
  mutate(text = str_replace_all(text, links, "")) %>%
  unnest_tokens(word, text, token = “tweets”) %>%
  pull(word)
```

Case Study: Trump Tweets

- Now we are ready to extract the words for all our tweets

```
tweet_words <- campaign_tweets %>%
  mutate(text = str_replace_all(text, links, ""))  %>%
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	source	id_str	created_at	retweet_count	in_reply_to_user_id_str	favorite_count	is_retweet	word
1	Android	612063082186174464	2015-06-19 20:03:05	166	NA	348	FALSE	why
2	Android	612063082186174464	2015-06-19 20:03:05	166	NA	348	FALSE	did
3	Android	612063082186174464	2015-06-19 20:03:05	166	NA	348	FALSE	@danaperino
4	Android	612063082186174464	2015-06-19 20:03:05	166	NA	348	FALSE	beg
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- What are the most commonly used words?

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tweet_words %>%
  count(word) %>%
  arrange(desc(n))
```

Case Study: Trump Tweets

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  count(word) %>%
  arrange(desc(n))
```

	word	n
1	the	2329
2	to	1410
3	and	1239
4	in	1185
5	i	1143
6	a	1112
7	you	999
8	of	982
9	is	942
10	on	874

- Comments?

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- The top words are not very informative!

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- This is common in text analysis. Luckily, the ***tidytext*** package has a database of commonly used words called *stop_words*

```
tweet_words <- campaign_tweets %>%
  mutate(text = str_replace_all(text, links, "")) %>%
  unnest_tokens(word, text, token = "tweets") %>%
  filter(!word %in% stop_words$word)
```

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  unnest_tokens(word, text, token = "tweets") %>%
  filter(!word %in% stop_words$word)

tweet_words %>%
  count(word) %>%
  top_n(10, n) %>%
  mutate(word = reorder(word, n)) %>%
  arrange(desc(n))
```

Case Study: Trump Tweets

	word	n
1	#trump2016	414
2	hillary	405
3	people	303
4	#makeamericagreatagain	294
5	america	254
6	clinton	237
7	poll	217
8	crooked	205
9	trump	195
10	cruz	159

- Much better!

Case Study: Trump Tweets

- After some exploration, here is the final dataset

```
tweet_words <- campaign_tweets %>%
  mutate(text = str_replace_all(text, links, ""))  %>%
  unnest_tokens(word, text, token = "tweets") %>%
  filter(!word %in% stop_words$word &
           !str_detect(word, "^\\d+$")) %>%
  mutate(word = str_replace(word, "^'", ""))
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5	Android	612063082186174464	2015-06-19 20:03:05	166	NA	348	FALSE	book

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- The ***textdata*** package provides a bevy of lexicons to conduct SA
- We will use the `nrc` (Mohammad and Turney, 2012) lexicon because it provides several different sentiments

```
nrc <- get_sentiments("nrc") %>%
  select(word, sentiment)
```

	word	sentiment
1	suspicious	anger
2	tobacco	negative
3	mum	fear
4	vote	anger
5	irrevocable	negative
6	exquisitely	positive
7	disappear	fear
8	instigate	negative
9	sickness	disgust
10	hag	negative

Sentiment analysis (SA)

- Let us use `inner_join` to explore a random sample of the words in the tweets and their associated sentiment

```
tweet_words %>%
  inner_join(nrc, by = "word") %>%
  select(source, word, sentiment) %>%
  sample_n(10)
```

	source	word	sentiment
1	Android	friend	positive
2	iPhone	invitation	anticipation
3	iPhone	happy	anticipation
4	iPhone	budget	trust
5	iPhone	shatter	fear
6	Android	horrible	negative
7	Android	core	positive
8	Android	president	positive
9	Android	deal	anticipation
10	Android	happy	anticipation

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- Each tweet has several words, hence assigning a sentiment to each tweet is challenging (but possible!)
- We will conduct a simpler analysis. Specifically, we will compare the frequencies of the sentiments appearing in each device
- Time for some wrangling

Sentiment analysis (SA)

```
sentiment_counts <- tweet_words %>%
  left_join(nrc, by = "word") %>%
  count(source, sentiment) %>%
  pivot_wider(names_from = "source", values_from = "n") %>%
  mutate(sentiment = replace_na(sentiment, replace = "none"))
```

	sentiment	Android	iPhone
1	anger	958	528
2	anticipation	910	715
3	disgust	638	322
4	fear	795	486
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6	negative	1641	929
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- Comments? Thoughts?
- Should we compare these counts? Is this a "fair" comparison?
- The count for Android is 21,988, whereas the count for iPhone is 17,624
- We need to use measure of association to compare the two devices.
- Let us use odds ratio

Brief introduction to odds ratio

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- We define the odds of B in a similar way
- Finally, we define the odds ratio of **A** relative to **B** with:

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- Finally, we define the odds ratio of **A** relative to **B** with:

$$\text{OR(A,B)} = \text{Odds of A}\big/\text{Odds of B}$$

- If $OR > 1$, then **A** is more frequent than **B** and if $OR < 1$ the opposite is true
- If $OR = 1$, then the frequency is the same

Sentiment analysis (SA)

```
sentiment_counts %>%
  mutate(Android = Android / (sum(Android) - Android),
         iPhone = iPhone / (sum(iPhone) - iPhone),
         or_android_iphone = Android/iPhone) %>%
  arrange(desc(or_android_iphone))
```

	sentiment	Android	iPhone	or_android_iphone
1	disgust	0.02988290	0.01861057	1.6056957
2	anger	0.04555397	0.03088442	1.4749823
3	negative	0.08065071	0.05564540	1.4493688
4	sadness	0.04238172	0.03010112	1.4079783
5	fear	0.03751239	0.02835803	1.3228133
6	surprise	0.02412669	0.02114839	1.1408288
7	joy	0.03230047	0.03130669	1.0317434
8	anticipation	0.04317298	0.04228517	1.0209956
9	trust	0.05956052	0.05951665	1.0007371
10	positive	0.08948568	0.09120178	0.9811835
11	none	1.18048393	1.56984544	0.7519746

- Comments? Thoughts?

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- Are these differences due to chance? (note that we are venturing into inference land)

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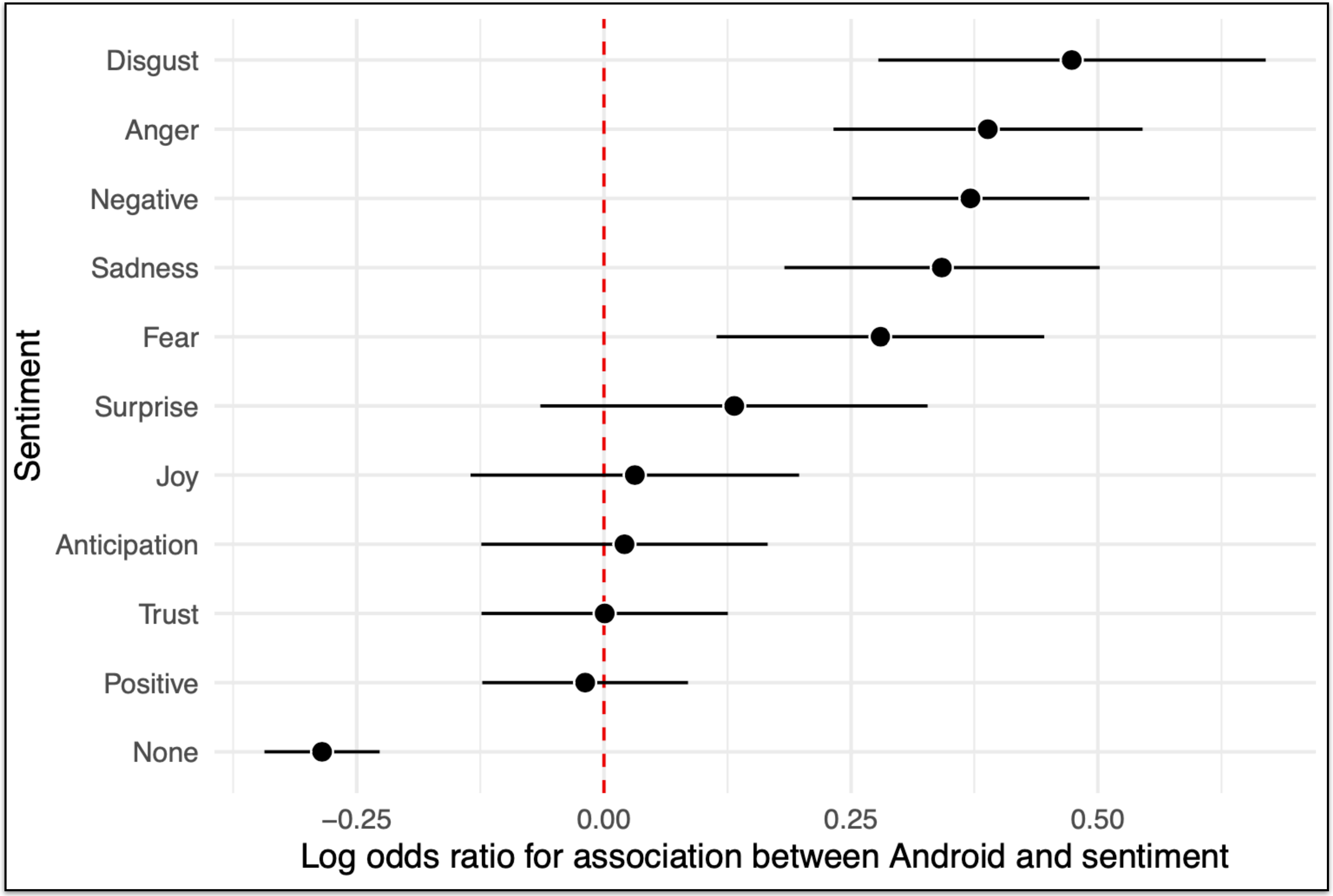
- Comments? Thoughts?
- Some interesting differences
- Perhaps there is meaning in the order of the sentiments
- Are these differences due to chance? (note that we are venturing into inference land)
- Let us compute confidence intervals for each sentiment

Sentiment analysis (SA)

```r
log_or <- sentiment_counts %>%
  mutate(log_or = log((Android / (sum(Android) - Android)) /
                      (iPhone / (sum(iPhone) - iPhone))),
         se = sqrt(1/Android + 1/(sum(Android) - Android) +
                      1/iPhone + 1/(sum(iPhone) - iPhone)),
         conf.low = log_or - qnorm(0.975)*se,
         conf.high = log_or + qnorm(0.975)*se) %>%
  arrange(desc(log_or))

log_or %>%
  mutate(sentiment = str_to_title(sentiment),
         sentiment = reorder(sentiment, log_or)) %>%
  ggplot(aes(x = sentiment, ymin = conf.low, ymax = conf.high)) +
  geom_hline(yintercept = 0, color = "red2", lty = 2) +
  geom_errorbar(width = 0) +
  geom_point(aes(sentiment, log_or),
             shape = 21,
             color = "white",
             fill  = "black",
             size  = 3) +
  labs(x = "Sentiment", y = "Log odds ratio for association between Android and sentiment") +
  coord_flip() +
  theme_minimal()
```

Sentiment analysis (SA)



Sentiment analysis (SA)

- Finally, we can explore which specific words are driving these differences

```r
tweet_words %>%
  count(word, source) %>%
  pivot_wider(names_from = "source", values_from = "n", values_fill = 0) %>%
  mutate(or = (Android + 0.5) / (sum(Android) - Android + 0.5) /
           ( (iPhone + 0.5) / (sum(iPhone) - iPhone + 0.5))) %>%
  inner_join(nrc, by = "word") %>%
  mutate(sentiment = factor(sentiment, levels = log_or$sentiment)) %>%
  mutate(log_or = log(or)) %>%
  mutate(sentiment = str_to_title(sentiment),
         sentiment = reorder(sentiment, log_or)) %>%
  filter(Android + iPhone > 10 & abs(log_or) > 1) %>%
  mutate(word = reorder(word, log_or),
         se = sqrt(1/Android + 1/(sum(Android) - Android) +
                     1/iPhone + 1/(sum(iPhone) - iPhone)),
         conf.low = log_or - qnorm(0.975)*se,
         conf.high = log_or + qnorm(0.975)*se) %>%
  ggplot(aes(word, log_or, fill = log_or < 0, color = log_or < 0, ymin = conf.low, ymax = conf.high)) +
  geom_hline(yintercept = 0, lty = 2) +
  facet_wrap(~sentiment, scales = "free_x", nrow = 2) +
  geom_errorbar(width = 0,
                show.legend = FALSE) +
  geom_point(aes(word, log_or),
             shape = 21,
             color = "white",
             size  = 2,
             show.legend = FALSE) +
  labs(y = "Log OR for association between Android and sentiment",
       x = "Word") +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        strip.text = element_text(face = "bold"))
```


Positive
Trust
Joy
Surprise
Fear
Anticipation
Sadness
Anger
Negative
Disgust
Log OR for association between Android and sentiment
Word
join
received
safe
honor
focus
convention
fair
talk
fortune
careful
finally
fun
exciting
county
policy
senate
leading
beach
wild
chance
government
killing
terrible
bad
crazy
tomorrow
plan
happen
ready
clue
tough
lie
unfair
badly
fraud
hit
politics
unbelievable
enforcement
dumb
wrong
boring
mess
spent
joke
poorly
2.5
0.0
-2.5
-5.0

References

1. Introduction to Data Science: Data analysis and prediction algorithms with R by Rafael A. Irizarry, Chapter 26. https://rafalab.github.io/dsbook/

Referencias en español:

1. Introducción a la Ciencia de Datos: Análisis de datos y algoritmos de predicción con R por Rafael A. Irizarry, Capítulo 26. https://rafalab.github.io/dslibro/

Your turn!

Click here for the class website