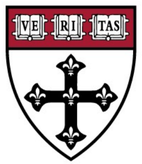
Introduction to Data Wrangling IV

Summer Institute in Data Science

Rolando J. Acosta



HARVARD
SCHOOL OF PUBLIC HEALTH

July 01, 2021

@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

- During the 2016 US presidential election, Donald Trump used his twitter account to, among other things, communicate with potential voters

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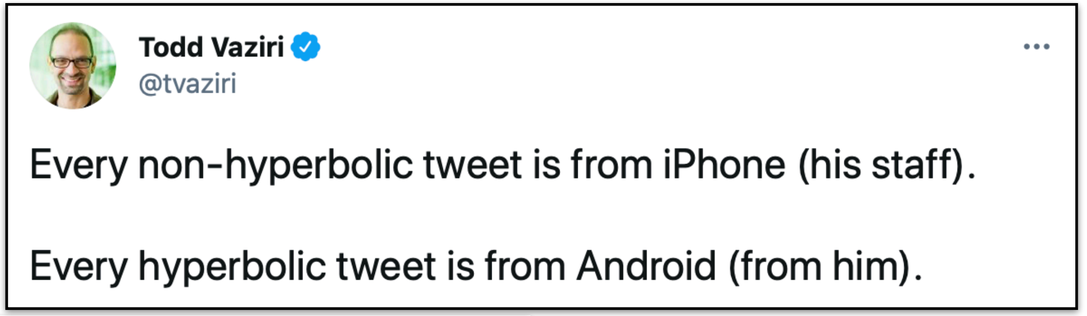
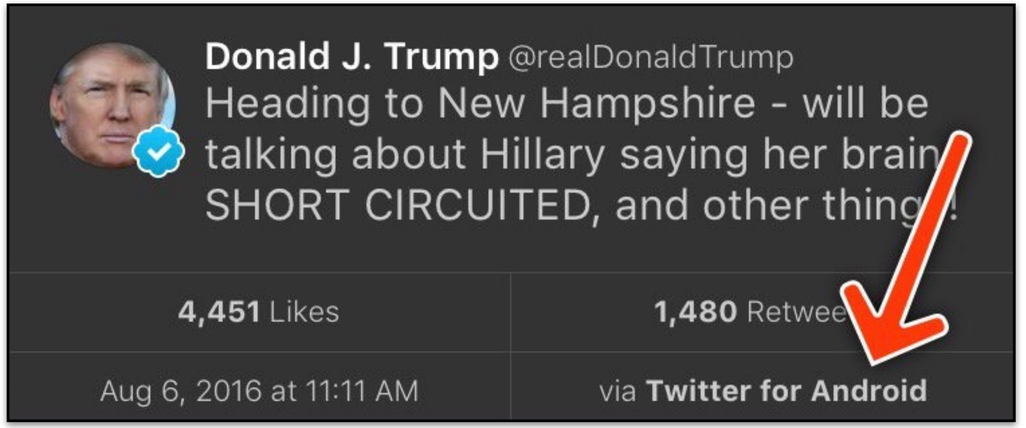
- During the 2016 US presidential election, Donald Trump used his twitter account to, among other things, communicate with potential voters
- On August 2016, Todd Vaziri tweeted:





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

Case Study: Trump Tweets

- 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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Case Study: 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/

Case Study: Trump 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

Case Study: Trump Tweets

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- For each tweet, let us extract the hour it was tweeted and then plot proportion of tweets by device

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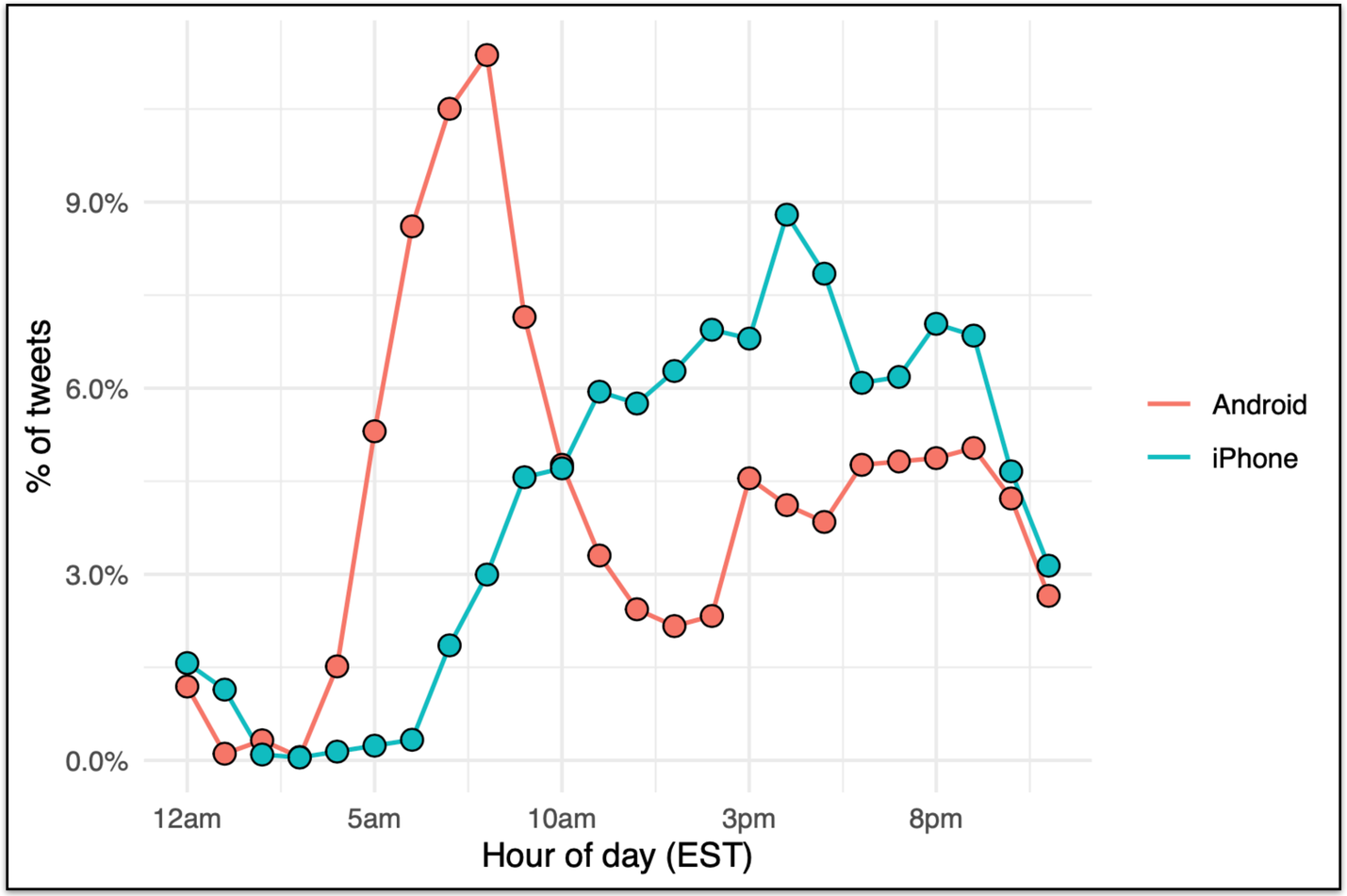
```
campaign_tweets %>%
  mutate(hour = hour(with_tz(created_at, "EST"))) %>%
  count(source, hour) %>%
  group_by(source) %>%
  mutate(percent = n / sum(n)) %>%
  ungroup() %>%
  ggplot(aes(hour, percent, fill = source, color = source)) +
  geom_line(size = 0.70) +
  geom_point(shape       = 21,
             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

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

example

	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

example_token

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
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3	Android	612063082186174464	2015-06-19 20:03:05	166	*NA*	348	FALSE	@danaperino
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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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```

	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?

Case Study: Trump Tweets

- 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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  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$word &
           !str_detect(word, "^\\d+$")) %>%
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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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- We are ready to perform an analysis comparing Android v iPhone sentiments
- 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
5	joy	688	535
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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

- Suppose you are interested in two events **A** and **B**

Brief introduction to odds ratio

- Suppose you are interested in two events **A** and **B**
- For example, **A** can be the event that it rains tomorrow and B the event that its sunny tomorrow

Brief introduction to odds ratio

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- For example, **A** can be the event that it rains tomorrow and B the event that its sunny tomorrow
- We define the odds of **A** with:

$$\text{Odds of A} = \frac{\text{Chances that A happens}}{\text{Chances that A does not happen}}$$

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

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- 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

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

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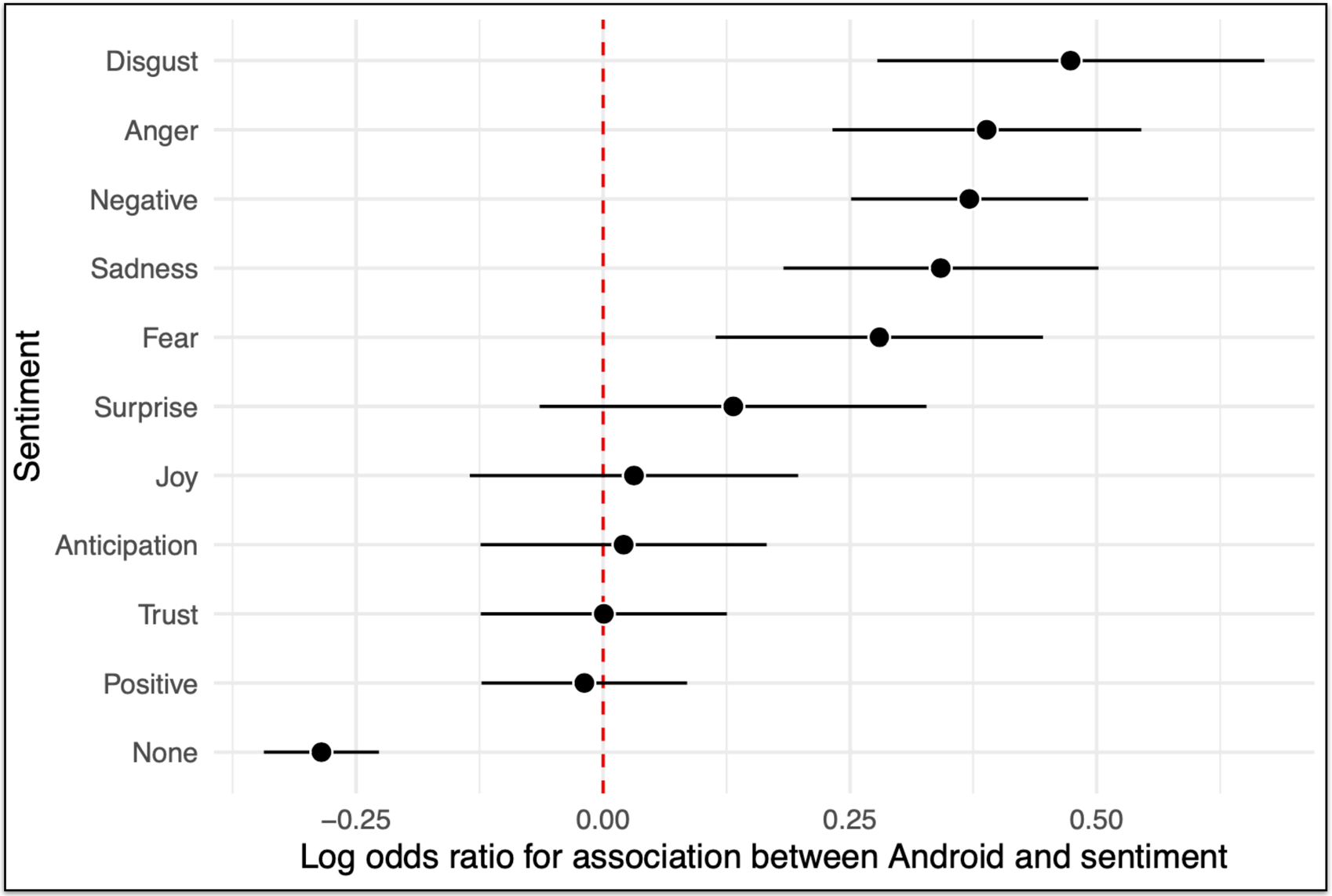
- Some interesting differences
- Perhaps there is meaning in the order of the sentiments
- Are these differences due to chance? (note that we are venturing into inference land)
- Let us compute confidence intervals for each sentiment

Sentiment analysis (SA)

```
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()
```

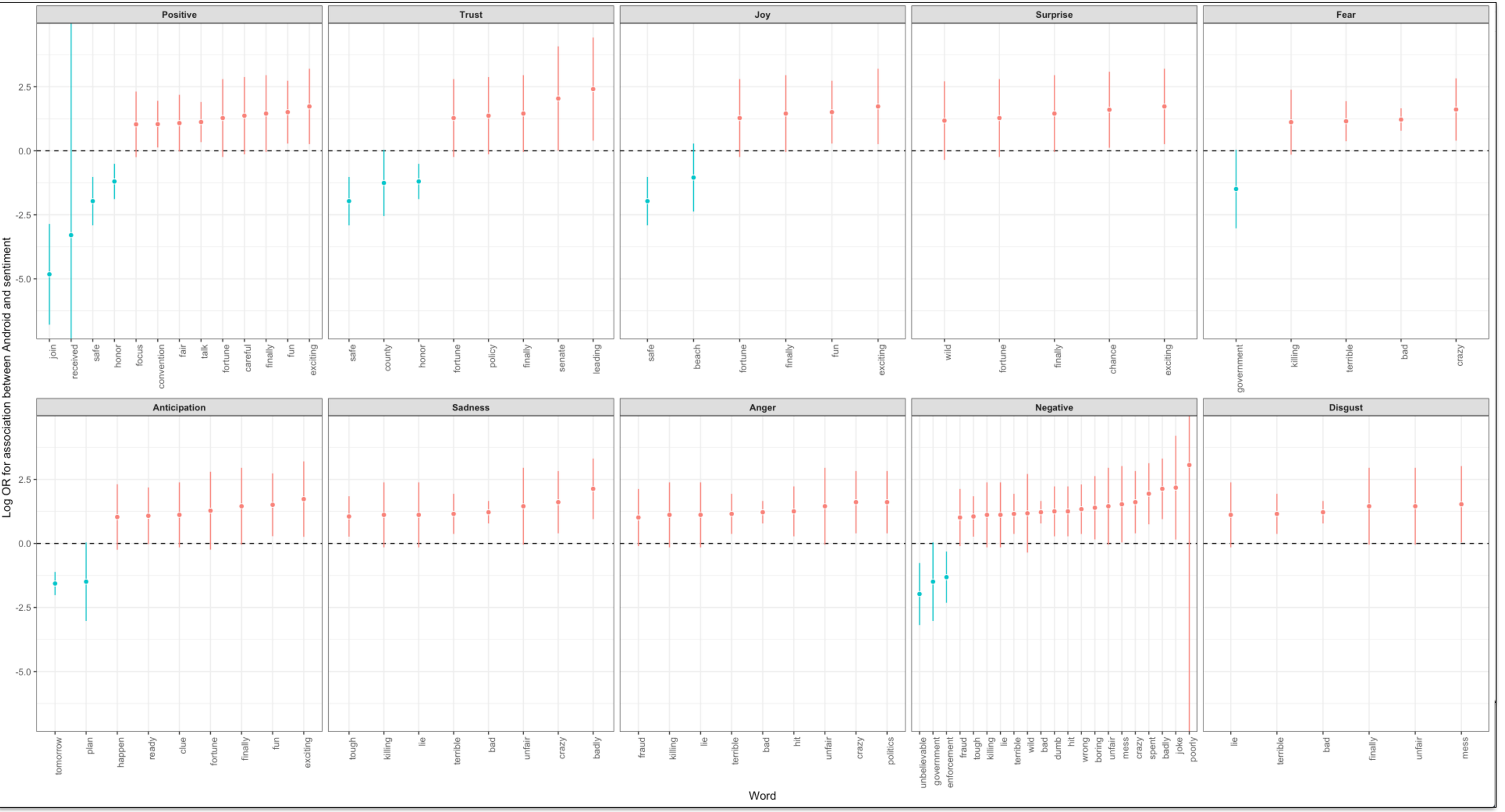
Sentiment analysis (SA)



Sentiment analysis (SA)

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

```
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"))
```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received
safe
honor
focus
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talk
fortune
careful
finally
fun
exciting
safe
county
honor
fortune
policy
finally
senate
leading
safe
beach
fortune
finally
fun
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wild
fortune
finally
chance
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tomorrow
plan
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wild
bad
dumb
hit
wrong
boring
unfair
mess
crazy
spent
badly
joke
poorly
lie
terrible
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finally
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Word

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!

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