Mini Project

AIM: Finding Bias in Political News and Blog Websites

Introduction

Quantifying political bias of online news media based on the media-sharing habits of US lawmakers on Twitter. Here, the focus is on a more streamlined (and multi-threaded) approach to resolving shortened URLs via the quicknews package. The unsupervised methods for visualizing media bias in two-dimensional space via tSNE are presented, and compare results to the manually curated fact and bias checking online resource, Media Bias/Fact Check (MBFC), with some fairly nice results.

```
library(tidyverse)
localdir <- '/home/jtimm/jt_work/GitHub/data_sets'
##  devtools::install_github("jaytimm/quicknews")
```

Tweet-set

The tweet-set used here was accessed via the GWU Library, and subsequently "hydrated" using the Hydrator desktop application. Tweets were generated by members of the 116th House from 3 Jan 2019 to 7 May 2020. Subsequent analyses are based on a sample of 500 tweets/lawmaker containing shared URLs.

```
setwd(localdir)
house_tweets <- readRDS('house116-sample-urls.rds') %>%
  filter(urls != '')
```

Media bias data set

Media Bias/Fact Check is a fact-checking organization that classifies online news sources along two dimensions: (1) political bias and (2) factuality. These two scores (for ~850 sources) have been extracted by Baly et al. (2020), and made available in tabular format here.

```
setwd('/home/jtimm/jt_work/GitHub/packages/quicknews/data-raw')
## emnlp18 <- read.csv('emnlp18-corpus.tsv', sep = '\t')
acl2020 <- read.csv('acl2020-corpus.tsv', sep = '\t')
```

A sample of this data set is presented below.

```
set.seed(221)
acl2020 %>%
  group_by(fact, bias) %>%
  sample_n(1) %>%
  # ungroup() %>%
  select(source_url_normalized, fact, bias) %>%
  # spread(bias, source_url_normalized) %>%
  knitr::kable()
```

source_url_normalized	fact	bias
wn.com	high	center
dailydot.com	high	left
yellowhammernews.com	high	right
freakoutnation.com	low	left
christianaction.org	low	right
wionews.com	mixed	center
extranewsfeed.com	mixed	left
lifenews.com	mixed	right

Resolving shortened URLs

The quicknews package is a collection of tools for navigating the online news landscape; here, we detail a simple workflow for researchers to use for multi-threaded URL un-shortening. As a three step process: (1) identify URLs that have been shortened via qnews_clean_urls, (2) split vector of URLs into multiple batches via qnews_split_batches for distribution across multiple cores, and (3) resolve shortened URLs via qnews_unshorten_urls.

```
## step 1
shortened_urls <- quicknews::qnews_clean_urls(url = house_tweets$urls) %>%
  filter(is_short == 1)

## step 2
batch_urls <- shortened_urls %>% quicknews::qnews_split_batches(n = 12)

## step 3
unshortened_urls <- parallel::mclapply(lapply(batch_urls, "[[", 1),
                                       quicknews::qnews_unshorten_urls,
                                       seconds = 10,
                                       mc.cores = 12)

unshortened_urls1 <- data.table::rbindlist(unshortened_urls)
```

Shared news media sources

Next, we update the original tweet-set with the resolved URLs from above; we also extract domain information from each shared link in our data set.

```
full_tweets <- house_tweets %>%
  left_join(unshortened_urls1, by = c('urls' = 'short_url')) %>%
  mutate(long_url = ifelse(is.na(long_url), urls, long_url),
         source = gsub('(http)(s)?(://)(www\\.)?', '', long_url),
         source = gsub('/.*$', '', source),
         user_screen_name = toupper(user_screen_name))  ###
```

The list below details some less useful domains that we can remove from the data frame of shared URLs.

```
junks <-  c('facebook', 'lnkd.in',
            'twitter', 'youtube',
            'youtu\\.be', 'instagram',
            'twimg', 'tumblr',
            'google', 'medium',
            'vimeo', '\\.gov',
            'actblue\\.com', 'bit\\.ly',
            'ow\\.ly', 'timeout',
            'myemail', 'apple.news',
            'trib.al')

filt.tweets <- full_tweets %>%
  filter(!grepl(paste0(junks, collapse = '|'), long_url))
```

The table below summarizes some of the more frequently shared news media domains among lawmakers during the 116th congress. For good measure, domains are ranked by % coverage, which is the percentage of lawmakers that have shared a news link from a given domain in our data set. So, 94% (or 403/429) of House members shared content from The Hill, which compares to 49% for Fow News and only 15% for Breitbert.

```
share.summary <- filt.tweets %>%
  mutate(source = tolower(source)) %>%
  group_by(source) %>%
  summarize(n = n(), tweeters = length(unique(user_screen_name))) %>%
  ungroup() %>%
  mutate(cover = round(tweeters/429*100,1)) %>%
  #left_join(acl2020, by = c('source' = 'source_url_normalized')) %>%
  arrange(desc(tweeters)) %>%
  filter(tweeters > 10)
```

source	n	tweeters	cover
thehill.com	2977	403	93.9
washingtonpost.com	4853	384	89.5
politico.com	1782	354	82.5
c-span.org	1488	346	80.7
nytimes.com	4717	342	79.7
cnn.com	1802	323	75.3
usatoday.com	889	311	72.5
cnbc.com	973	309	72.0
nbcnews.com	1086	282	65.7
wsj.com	1043	277	64.6

Media bias & tSNE

Build matrix

To aggregate these data, we build a simple domain-lawmaker matrix, in which each domain/news organization is represented by the number of times each lawmaker has shared one of its news stories.

```
ft1 <- filt.tweets %>%
  group_by(user_screen_name, source) %>%
  count() %>%
  filter(source %in% share.summary$source) %>%
  tidytext::cast_sparse(row = 'source',
                        column = 'user_screen_name',
                        value = n)

ft2 <- as.matrix(ft1) #%>% Rtsne::normalize_input()
```

Matrix top-left::

```
t2[1:5, 1:5]
#                  AUSTINSCOTTGA08 BENNIEGTHOMPSON BETTYMCCOLLUM04 BILLPASCRELL
# abcnews.go.com                 1               4               0            3
# airforcetimes.com              1               0               0            0
# ajc.com                        6               0               0            0
# bloomberg.com                  2               3               0            5
# c-span.org                     2               1               4            3
#                  BOBBYSCOTT
# abcnews.go.com             0
# airforcetimes.com          0
# ajc.com                    0
# bloomberg.com              2
# c-span.org                 1
```

TSNE

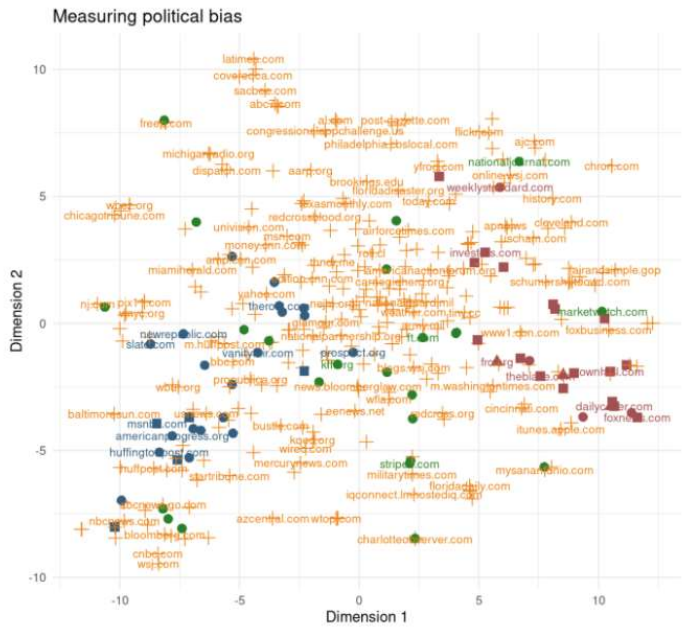
```
set.seed(77) ## 9
tsne <- Rtsne::Rtsne(X = ft2, check_duplicates = FALSE)
tsne_clean <- data.frame(descriptor_name = rownames(ft1), tsne$Y) %>%
  #mutate(screen_name = toupper(descriptor_name)) %>%
  left_join(acl2020, by = c('descriptor_name' = 'source_url_normalized')) %>%
  replace(is.na(.), 'x')
```

Plot

Per figure below, the first dimension of the tSNE plot does a fairly nice job capturing differences in bias classifications as presented by Media Bias/Fact Check, and results are generally intuitive. Factors underlying variation along the second dimension, however, are less clear, and do not appear to be capturing factuality in this case. Note: news organizations indicated by orange Xs are not included in the MB/FC data set.

```
split_pal <- c('#3c811a',
               '#395f81', '#9e5055',
               '#e37e00')

tsne_clean %>%
  ggplot(aes(X1, X2)) +
  geom_point(aes(col = bias,
                 shape = fact),
             size = 3) +
  geom_text(aes(label = descriptor_name,
                col = bias,
                shape = fact), #
            size = 3,
            check_overlap = TRUE) +
  theme_minimal() +
  theme(legend.position = "bottom") +
  scale_color_manual(values = split_pal) +
  xlab('Dimension 1') + ylab('Dimension 2')+
  labs(title = "Measuring political bias")
```



Bias score distributions

```
tsne_clean %>%
  ggplot() +
  geom_density(aes(X1, fill = bias),
               alpha = .4) +
  theme_minimal() +
  theme(legend.position = "bottom") +
  scale_fill_manual(values = split_pal) +
  ggtitle('Media bias scores by MB/FC bias classification')
```