WSJ Op-Ed Comment Analysis

12/15/2020

 $\label{lem:taken from: https://github.com/domrussel/wsj_comment_analysis/blob/main/wsj_comment_analysis.Rm\ d$

This is an RMarkdown document with code to analyze the online comments on the Wall Street Journal opinion piece 'Is There a Doctor in the White House? Not if You Need an MD.'

Setup

```
library(tidyverse)
library(gender)
library(cleanNLP)
library(glmnet)
library(ggpubr)
library(grid)
library(gridExtra)
library(wesanderson)
# Read in the comments
# dat_in <- read_csv("cleaned_wsj_comments_1214_noon.csv")</pre>
dat_in <- read_csv("https://raw.githubusercontent.com/domrussel/wsj_comment_analysis/main/cleaned_wsj_c</pre>
# Proxy for gender using SSA recrods for individuals born from 1932 - 2002
dat_in2 <- dat_in %>%
  mutate(first_name = tolower(str_extract(name, "([^\\s]+)"))) %>%
  mutate(
    birth_year_min = "1932",
    birth_year_max = "2002")
name_gender_probs <- gender_df(</pre>
  dat_in2,
  name_col = "first_name",
  year_col = c("birth_year_min", "birth_year_max"),
  method="ssa") %>%
  distinct(name, proportion_female)
dat_final <- dat_in2 %>%
  left_join(name_gender_probs, by=c("first_name"="name")) %>%
  select(name, first_name, prob_name_female=proportion_female, comment)
```

Comment Summary 1

```
# Summary table of the raw comments dat_final %>%
```

```
mutate(words = sapply(strsplit(comment, " "), length)) %>%
summarise(
   `Total Comments` = n(),
   `Total Words` = sum(words),
   `25th Percentile Words` = quantile(words, .25),
   `Median Words` = quantile(words, .5),
   `75th Percentile Words` = quantile(words, .75)
) %>%
gather(key="Measure", value="Value") %>%
mutate(Value = prettyNum(Value, big.mark=",")) %>%
ggtexttable(rows = NULL, theme = ttheme("blank")) %>%
tab_add_hline(at.row = 1:2, row.side = "top", linewidth = 4)
```

Measure	Value
Total Comments	3,771
Total Words	176,634
25th Percentile Words	16
Median Words	33
75th Percentile Words	64

Comment Summary 2

```
# Many authors comment more than once. Here we make each observation a
# unique author (first name / last name combination)
dat_by_author <- dat_final %>%
 group_by(name) %>%
  summarise(
   first_name = first(first_name),
   prob_name_female = first(prob_name_female),
   comment = paste(comment, collapse = " "),
   num_comments = n()) %>%
  # Only use individuals where we are >= 75% sure about their gender
  mutate(gender = case_when(
   prob_name_female >= 0.75 ~ "F",
   prob_name_female <= 0.25 ~ "M",</pre>
   TRUE ~ "Unknown"
  ))
dat_by_author %>%
  group_by(gender) %>%
  summarise(
    N = n(),
    `Median Comments Per Poster` = median(num_comments),
   `Avg. Comments Per Poster` = mean(num_comments),
  ) %>%
  mutate(
    `N Posters` = prettyNum(`N Posters`, big.mark=","),
    `Avg. Comments Per Poster` = round(`Avg. Comments Per Poster`, 2)) %>%
  rename(`Gender` = gender) %>%
```

```
ggtexttable(rows = NULL, theme = ttheme("blank")) %>%
tab_add_hline(at.row = 1:2, row.side = "top", linewidth = 4)
```

Gender	N Posters	Median Comments Per Poster	Avg. Comments Per Poster
F	629	1	1.75
M	1,306	1	1.83
Unknown	152	1	1.88

Annotate the Data

```
# Filter out unknown gender
dat_by_author <- dat_by_author %>%
filter(gender != "Unknown")

# Start up the udpipe init of cleanNLP.
# cleanLP will tokenize the text data, allowing us to limit
# to certain parts of speech and lemmatise each word.
# See: https://statsmaths.github.io/cleanNLP/
cnlp_init_udpipe()

# Final preparations for the annotation
dat_to_anno <- dat_by_author %>%
    rename(text=comment) %>%
    mutate(doc_id = 1:n())

# This annotation step takes somewhat long to run
anno <- cnlp_annotate(dat_to_anno)</pre>
```

Find Marginal Effects

Here, we use a simple Lasso regression model, loosely basing our methodology on Wu, 2018. Specifically, letting w_i denote a vector of indicators for whether each of the lemmatised verbs, adjectives, and nouns used by at least 25 commenters is used by commenter i, we estimate a Lasso linear regression model for the probability that the post is authored by a Female, as follows:

```
\hat{\beta_{\lambda}} = argmin_{\beta} \sum_{i} (Female_{i} - \beta_{0} - w'_{i}\beta)^{2} + \lambda ||\beta||_{1}
where ||\beta||_{1} = \sum_{j \geq 1} |\beta^{j}|
```

The marginal effect of word k on the probability that an author is Female is estimated by $\hat{\beta}_{\lambda}^{k}$, the coefficient on the regressor w_{i}^{k} . We select an optimal tuning parameter λ^{*} through 10-fold cross validation. Importantly, Lasso regression's functional form helps identify words without over-fitting our model. There are 425 words used by at least 25 commenters.

```
# Set a seed for reproducibility
set.seed(21)

# Filter to Nouns, Adjectives, and Verbs
df <- anno$token %>%
    left_join(anno$document, by="doc_id") %>%
    filter(upos %in% c("NOUN", "ADJ", "VERB"))

# Build the term-frequency matrix.
```

```
# We use binary (0/1 - does this author use the word?).
# min_df is the minimum share of documents the word must be used in to be used,
# we will set is so that a word needs to be in 25 documents.
min_docs_used <- 25
# Build the term frequency matrix
mat <- cnlp_utils_tf(df, doc_var = "doc_id", "binary", min_df=min_docs_used/max(df$doc_id))</pre>
# Make the vector of outcome variables as 0/1
gender <- df %>%
  distinct(doc_id, gender) %>%
 mutate(gender_F = as.numeric(gender == "F"))
# Use 10-fold cross validation to set the lambda tuning parameter
cv <- cv.glmnet(mat, gender$gender_F, alpha = 1, family = "gaussian", nfolds=10)
# Now use that lambda to predict
model <- glmnet(mat, gender$gender_F, alpha = 1, lambda = cv$lambda.min, family = "gaussian")</pre>
# Get the betas
beta <- coef(model)[-1]
# Get the non-zero betas
final <- tibble(</pre>
  word = colnames(mat)[beta != 0],
  coef = beta[beta != 0]
```

Most Predictive Words

```
# Most female predictive
female <- final %>%
  arrange(desc(coef)) %>%
  slice(1:20) %>%
 mutate(coef = round(coef, 3)) %>%
 rename(Word=word, `Marginal Effect`=coef)
# Most male predictive
male <- final %>%
  arrange(coef) %>%
  slice(1:20) %>%
 mutate(coef = round(coef, 3)) %>%
 rename(Word=word, `Marginal Effect`=coef)
female_p <- ggtexttable(female, rows = NULL, theme = ttheme("blank")) %>%
  tab_add_hline(at.row = 1:2, row.side = "top", linewidth = 4)
male_p <- ggtexttable(male, rows = NULL, theme = ttheme("blank")) %>%
 tab_add_hline(at.row = 1:2, row.side = "top", linewidth = 4)
grid.arrange(
```

Words Most Predictive of Male/Female Commenters

Most Female Most Male

Word	Marginal Effect
disappoint	0.165
woman	0.147
offensive	0.113
female	0.102
accomplished	0.076
complete	0.073
white	0.070
drop	0.060
man	0.060
ignorance	0.060
subscription	0.058
sexist	0.054
educator	0.042
grant	0.041
kiddo	0.038
choose	0.036
community	0.033
show	0.031
enough	0.028
stop	0.026

Make a simple bar chart

```
# Words about sexism/misogyny
numer_sexist <- dat_by_author %>%
  mutate(comment = tolower(comment)) %>%
  filter(
    grepl("sexism", comment) |
      grepl("sexist", comment) |
      grepl("misogyny", comment) |
      grepl("misogynistic", comment) |
      grepl("misogynist", comment)) %>%
  group_by(gender) %>%
  summarise(n_sexist = n())
denom <- dat_by_author %>%
  group_by(gender) %>%
  summarise(n_total = n())
numer_sexist %>%
  inner_join(denom, by="gender") %>%
  mutate(
    share = n_sexist/n_total,
    gender = if_else(gender == "M", "Male", "Female")) %>%
  ggplot() +
  geom_bar(aes(y=share, x=gender, fill=gender), stat="identity") +
  theme_classic() +
  scale_fill_manual(values = wes_palette("Darjeeling2", 2)) +
  labs(x="", y="Share of Commenters", title="Commenters using the words 'sexism', 'sexist', \n 'misogyn
  theme(legend.position = "none")
```

Commenters using the words 'sexism', 'sexist', 'misogyny', 'misogynistic', or 'misogynist'

