Campaigns and Elementary Text Analysis

GOV 1347 Lab: Week XII

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Check-In

Any questions? Ponderings? Holiday recollections?

Agenda

- Processing Text Data
- Methods for Text Content Analysis
    - Topic Models
    - LLMs

Section 1

Processing Text Data

Quantitative Text Analysis Basics

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- Visualizing quantitative representations of text using word clouds, keyness plots, and feature correspondence network plots.
- How to ultimately apply textual data analysis to simplify the intensive process of manual coding undertaken by Vavreck (2009) in her work on the 2008 election.

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- *Reduce complexity:* Language is extraordinarily complex, with subtlety and nuance. We need to represent documents as straightforward mathematical objects.
- (Traditional) *Pre-processing:* What can be simplified? Which complexity can be removed?
    - Tokenize (using whitespace)
    - Remove grammatical structure: *bag of words* assumption
    - Remove punctuation
    - Remove capitalization
    - Remove stop words (e.g., a, it, the, would . . .)
    - Stemming (e.g., radicalize, radical $\rightsquigarrow$ radic)

Using Quanteda in R

```
harris_1028_tokens_processed <- tokens(harris_1028_enos$text,
                                       remove_symbols = TRUE,
                                       remove_numbers = TRUE,
                                       remove_punct = TRUE,
                                       remove_separators = TRUE) |>
  tokens_tolower() |>
  tokens_remove(pattern = c("joe", "biden", "donald", "trump", "president",
                           "kamala", "harris")) |>
  tokens_remove(pattern = stopwords("en")) |>
  tokens_select(min_nchar = 3)
```

Document-Feature Matrix

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```
harris_1028_dfm <- dfm(harris_1028_tokens_processed)
head(harris_1028_dfm, 10)
```

```
## Document-feature matrix of: 1 document, 710 features (0.00% sparse) and
##                    features
## docs                 can hear michelle obama good afternoon michigan we're
##   Harris_10_28.txt  13    3        3     2    3         2        6     8
##                    features
## docs                 okay
##   Harris_10_28.txt    8
## [ reached max_nfeat ... 700 more features ]
```

Word-Frequency Matrix

- *Word-frequency matrix:* Quantitative summarization of text corpus.

```r
# Summarize word frequncies.
freq_harris_dfm <- textstat_frequency(harris_dfm)
head(freq_harris_dfm, 10)
```

```
##     feature frequency rank docfreq group
## 1    people       656    1      34   all
## 2   freedom       479    2      22   all
## 3    that's       403    3      30   all
## 4    states       392    4      34   all
## 5   country       357    5      34   all
## 6    united       349    6      34   all
## 7   america       349    6      33   all
## 8   speaker       316    8      22   all
## 9  audience       304    9      17   all
## 10  believe       254   10      31   all
```

Word-Frequency Matrix

```r
freq_trump_dfm <- textstat_frequency(trump_dfm)
head(freq_trump_dfm, 10)
```

```
##     feature frequency rank docfreq group
## 1    people      4472    1      54   all
## 2   country      3166    2      54   all
## 3   they're      2805    3      53   all
## 4    that's      2510    4      53   all
## 5    you're      1522    5      53   all
## 6    really      1211    6      54   all
## 7    didn't      1140    7      53   all
## 8   america      1138    8      54   all
## 9    border      1063    9      51   all
## 10 american       928   10      54   all
```

Word Cloud

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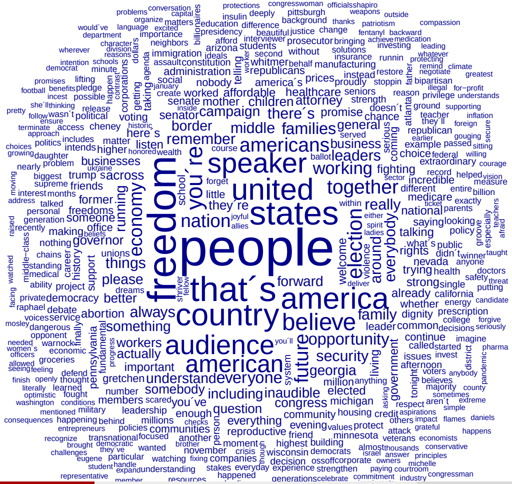
```
textplot_wordcloud(harris_dfm)
```



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textplot_wordcloud(trump_dfm)
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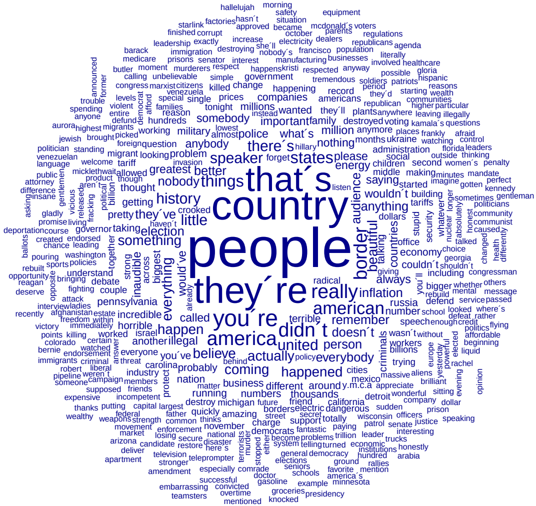
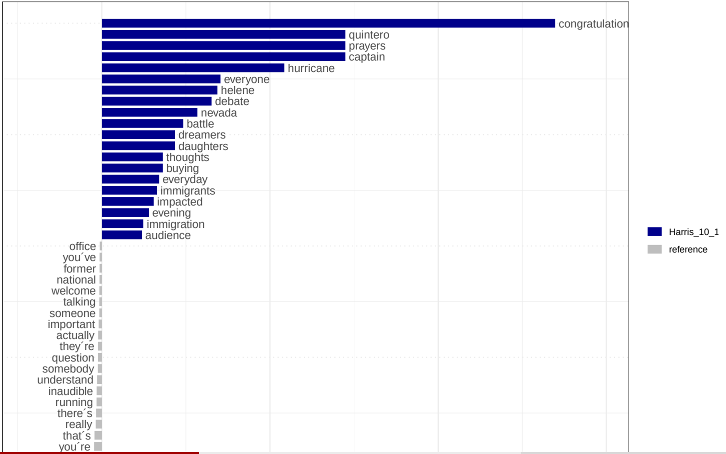


Keyness Plot

- *Word "keyness"* for specific group of documents:

```
harris_keyness <- textstat_keyness(harris_dfm)
textplot_keyness(harris_keyness)
```



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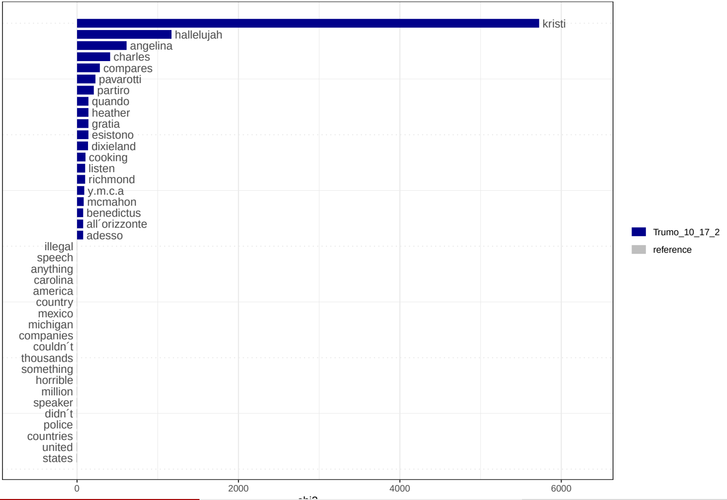

Section 2

Text Content Analysis

Analyzing Speech Text Data for Content

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Instead, let's try two methods of text content analysis: *structural topic modelling* and *large language model (LLM) classification*.

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- It's purpose is to uncover latent topics in text and, in more advanced settings, model the relatinoships between topics and metadata like document date, author, etc.

Structural Topic Modelling in R

- `RStudio live coding!`

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But, I ~~was too lazy to do this last night~~ may have found a more efficient way to do text analysis in the modern day using LLMs!

LLM Classification with Gemini!

Google Gemini

LLM Classification in R

- RStudio live coding!

Section 3

Course Conclusion

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Wow! That's a lot!

Thank You!!!!!!!!!

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- It was an honor and a pleasure to be your TF and get to know you this semester.
- Please feel free to reach out to me about anything in the future!