Topic 5: Word Relationships

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Import EPA environmental justice data

```
#character of full file paths for each PDF in the data folder
files <- list.files(path = here::here("data"),
                    pattern = "pdf$", full.names = TRUE)

#subset to include only EPA report PDFs
files <- str_subset(files, pattern="EPA")

#list
ej_reports <- lapply(files, pdf_text)

#readtext/df of all 6 PDf reports
ej_pdf <- readtext(file = files,
                   docvarsfrom = "filenames",
                   docvarnames = c("type","year"),
                   sep = "_")

#creating an initial corpus containing the data
epa_corp <- corpus(x = ej_pdf, text_field = "text" )

#check that the corpus contains all 6 reports
#summary(epa_corp)
```

Add additional, context-specific stop words to stop word lexicon

```
more_stops <-c("2015",
               "2016",
               "2017",
               "2018",
               "2019",
               "2020",
               "www.epa.gov",
               "https")
add_stops <- tibble(word = c(stop_words$word, more_stops))
stop_vec <- as_vector(add_stops)
```

Tokenize the data into single words

```
tokens <- tokens(epa_corp, remove_punct = TRUE)

toks1<- tokens_select(tokens, min_nchar = 3)
toks1 <- tokens_tolower(toks1) #lowercase
toks1 <- tokens_remove(toks1, pattern = (stop_vec)) #remove stop words
dfm <- dfm(toks1) #create a data frequency matrix
```

1. What are the most frequent trigrams in the dataset? How does this compare to the most frequent bigrams? Which n-gram seems more informative here, and why?

Calculate the 10 most frequent bigrams

```
toks2 <- tokens_ngrams(toks1, n=2)
dfm2 <- dfm(toks2)
dfm2 <- dfm_remove(dfm2, pattern = c(stop_vec))
freq_words2 <- textstat_frequency(dfm2, n=20)
freq_words2$token <- rep("bigram", 20)

tstat_freq2 <- textstat_frequency(dfm2, n = 5, groups = year)

#display the top 10 rows in a table
tstat_freq2[1:10] %>%
  rename(Bigram = feature,
         "Report Year" = group,
         Frequency = frequency,
         Rank = rank,
         "Document Frequency" = docfreq) %>%
  kbl() %>%
  kable_styling(bootstrap_options = c("striped", "hover"),
                latex_options = "HOLD_position") #hold the table position when knitting
```

Bigram	Frequency	Rank	Document Frequency	Report Year
environmental_justice	82	1	1	2015
progress_report	25	2	1	2015
fiscal_annual	23	3	1	2015
annual_environmental	23	3	1	2015
justice_progress	23	3	1	2015
environmental_justice	63	1	1	2016
progress_report	21	2	1	2016
report_2015-2016	18	3	1	2016
urban_waters	16	4	1	2016
equitable_development	8	5	1	2016

Calculate the most frequent trigrams

```
toks3 <- tokens_ngrams(toks1, n=3)
dfm3 <- dfm(toks3)
dfm3 <- dfm_remove(dfm3, pattern = c(stop_vec))
freq_words3 <- textstat_frequency(dfm3, n=20)
freq_words3$token <- rep("trigram", 20)

tstat_freq3 <- textstat_frequency(dfm3, n = 5, groups = year)

#display the top 10 rows in a table
tstat_freq3[1:10] %>%
  rename(Trigram = feature,
         "Report Year" = group,
         Frequency = frequency,
         Rank = rank,
         "Document Frequency" = docfreq) %>%
  kbl() %>%
  kable_styling(bootstrap_options = c("striped", "hover"),
                latex_options = "HOLD_position")
```

Trigram	Frequency	Rank	Document Frequency	Report Year
fiscal_annual_environmental	23	1	1	2015
annual_environmental_justice	23	1	1	2015
environmental_justice_progress	23	1	1	2015
justice_progress_report	23	1	1	2015
page_fiscal_annual	13	5	1	2015
progress_report_2015-2016	18	1	1	2016
environmental_justice_concerns	6	2	1	2016
epa's_environmental_justice	5	3	1	2016
urban_waters_program	5	3	1	2016
national_environmental_justice	4	5	1	2016

After comparing the 10 most common bigrams and trigrams, the additional third word does not seem to add much more meaning to the results. For example, "environmental_justice" is just as informative as "national_environmental_justice." The third word can even be more confusing. For instance "page_fiscal_annual" is an unclear trigram. Thus, the bigrams seem more informative to me.

2. Choose a new focal term to replace "justice" and recreate the correlation table and network (see corr_paragraphs and corr_network chunks). Explore some of the plotting parameters in the cor_network chunk to see if you can improve the clarity or amount of information your plot conveys. Make sure to use a different color for the ties!

Put the text into tidy format and extract individual words from each paragraph

```r
#convert to tidy format
raw_text <- tidy(epa_corp)

#paragraph tokens (tibble)
par_tokens <- unnest_tokens(raw_text, output = paragraphs, input = text, token = "paragraphs")

#give each paragraph an id number
par_tokens <- par_tokens %>%
 mutate(par_id = 1:n())

#extract individual words from each paragraph
par_words <- unnest_tokens(par_tokens, output = word, input = paragraphs, token = "words")
```

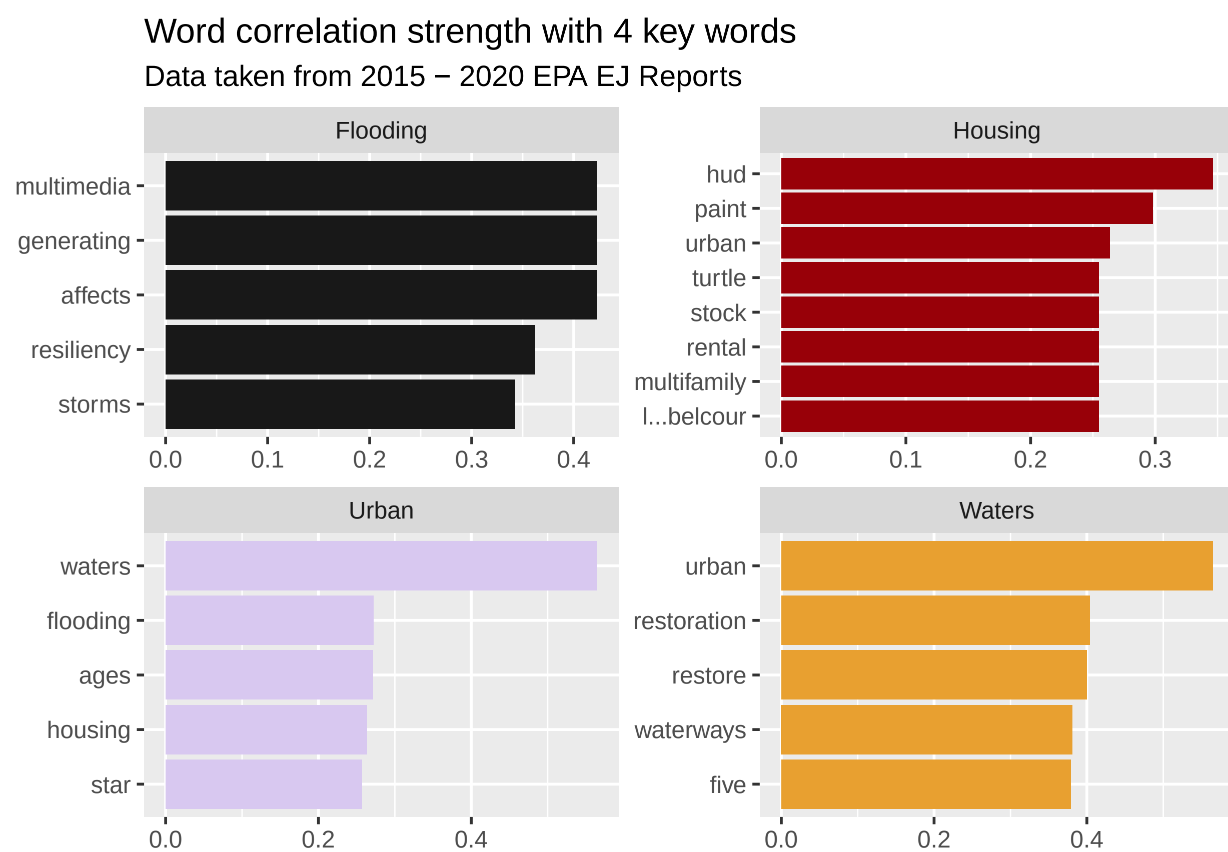
Identify which words tend to occur closely together in the text

```r
word_pairs <- par_words %>%
  pairwise_count(word, par_id, sort = TRUE, upper = FALSE) %>%
  anti_join(add_stops, by = c("item1" = "word")) %>%
  anti_join(add_stops, by = c("item2" = "word"))

#calculate correlation coefficients between words
word_cors <- par_words %>%
  add_count(par_id) %>%
  filter(n >= 50) %>%
  select(-n) %>%
  pairwise_cor(word, par_id, sort = TRUE)
```

Search for and graph words correlated with the term “urban”

```r
#search for words correlated with "urban" (tibble)
urban_cors <- word_cors %>%
  filter(item1 == "urban")

#create facet_wrap labels
supp.labs <- c("Waters",
               "Flooding",
               "Housing",
               "Urban")
names(supp.labs) <- c("waters",
                      "flooding",
                      "housing",
                      "urban")

#graph correlation coefficients for words correlated with 4 key terms based on the correlation coeffici
word_cors %>%
  filter(item1 %in% c("waters",
                      "flooding",
                      "housing",
                      "urban")) %>%
  group_by(item1) %>%
  top_n(5) %>% #display top 5 terms
  ungroup() %>%
  mutate(item1 = as.factor(item1),
```

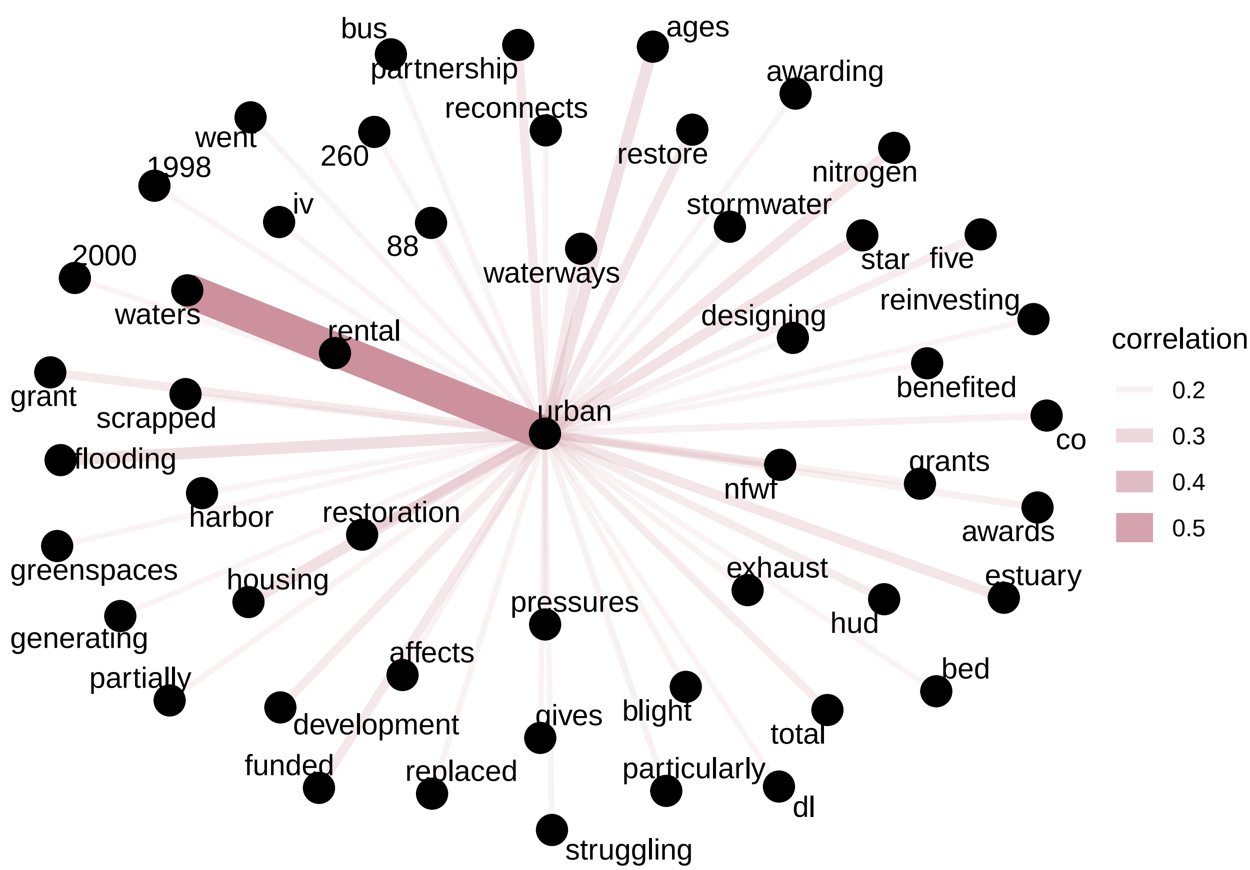
```
  name = reorder_within(item2, correlation, item1)) %>%
  ggplot(aes(y = name, x = correlation, fill = item1)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~item1,
             ncol = 2,
             scales = "free",
             labeller = labeller(item1 = supp.labs))+
  scale_y_reordered() +
  labs(y = NULL,
       x = NULL,
       title = "Word correlation strength with 4 key words",
       subtitle = "Data taken from 2015 - 2020 EPA EJ Reports") +
  palettetown::scale_fill_poke(pokemon = "Beedrill", spread = 4) #select a Pokemon themed color palette
```



Zoom in on just the key term "urban" and the 50 most related words

```
urban_cors <- word_cors %>%
  filter(item1 == "urban") %>%
  mutate(n = 1:n())
urban_cors  %>%
  filter(n <= 50) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation,
                     edge_width = correlation),
                 edge_colour = "pink3") +
```

```
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```



3. Write a function that allows you to conduct a keyness analysis to compare two individual EPA reports (hint: that means target and reference need to both be individual reports). Run the function on 3 pairs of reports, generating 3 keyness plots.

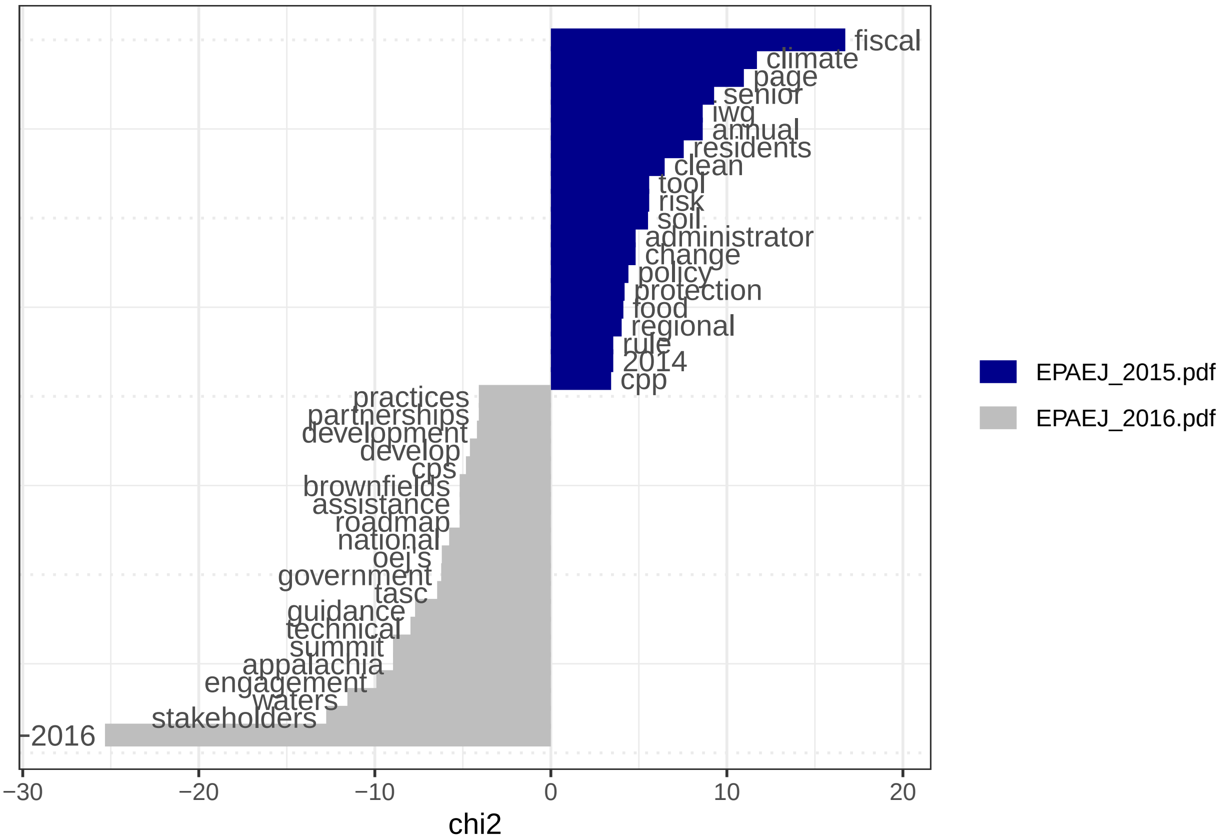
Create the function

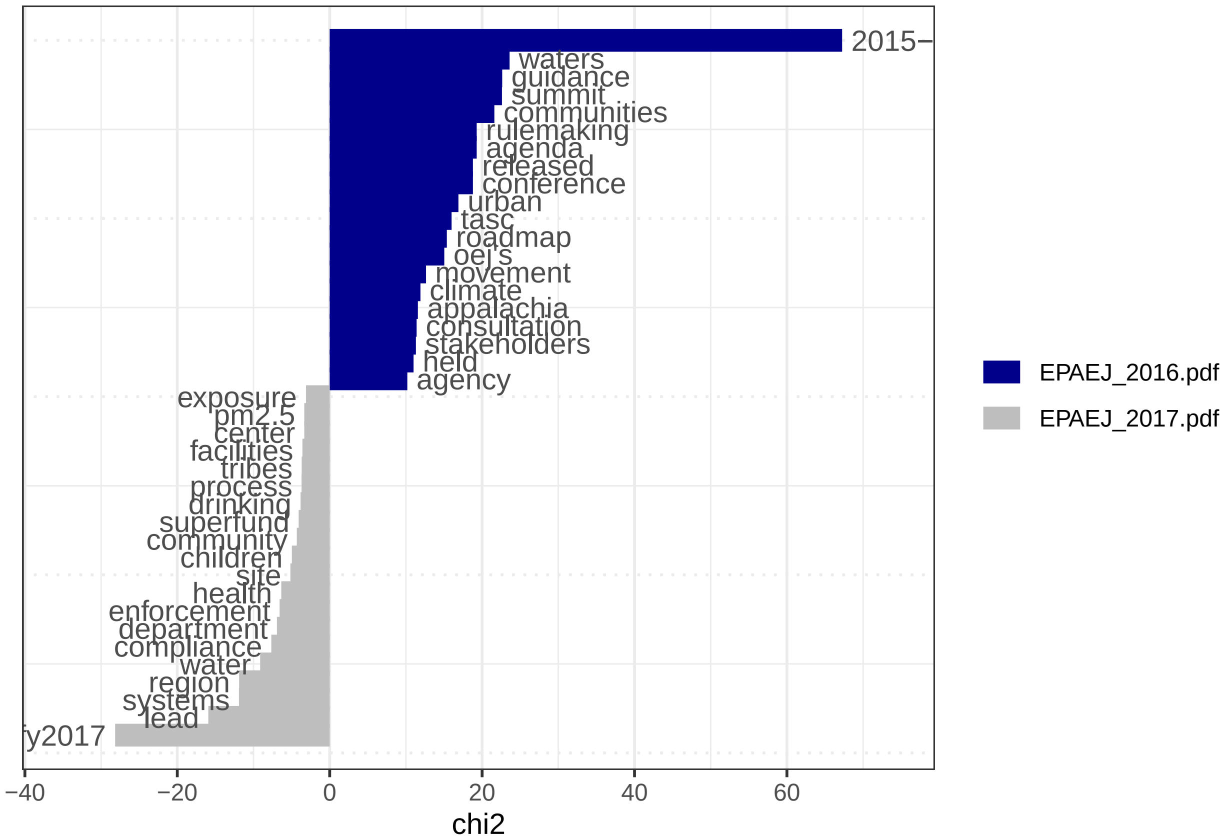
```
keyness_function <- function(report_number) {

  for (i in (1:(length(epa_corp) -1))) { #1:5 to make sure the last list doesn't throw an error
    report_test <- epa_corp[i: (i+1)] #create a list of 2 reports
    #print each list to check that all pairs of reports are accounted for
    #print(report_test)

    #tokenize each list
    tokens_test <- tokens(report_test, remove_punct = TRUE)
    tokens_test <- tokens_select(tokens_test, min_nchar = 3)
```

```
    tokens_test <- tokens_tolower(tokens_test)
    tokens_test <- tokens_remove(tokens_test, pattern = (stop_vec))

    #create a document feature matrix
    dfm_test <- dfm(tokens_test)

    #use the textstat_keyness function where the target is the first report in the list, so the second 
    keyness <- textstat_keyness(dfm_test, target = 1)

    #print the results
    print(textplot_keyness(keyness))

  }

}
```

Test the function

```
keyness_function(report_number = 1)
```




2015–
waters
guidance
summit
communities
rulemaking
agenda
released
conference
urban
tasc
roadmap
oej's
movement
climate
appalachia
consultation
stakeholders
held
agency
exposure
pm2.5
center
facilities
tribes
process
drinking
superfund
community
children
site
health
enforcement
department
compliance
water
region
systems
lead
fy2017
−40
−20
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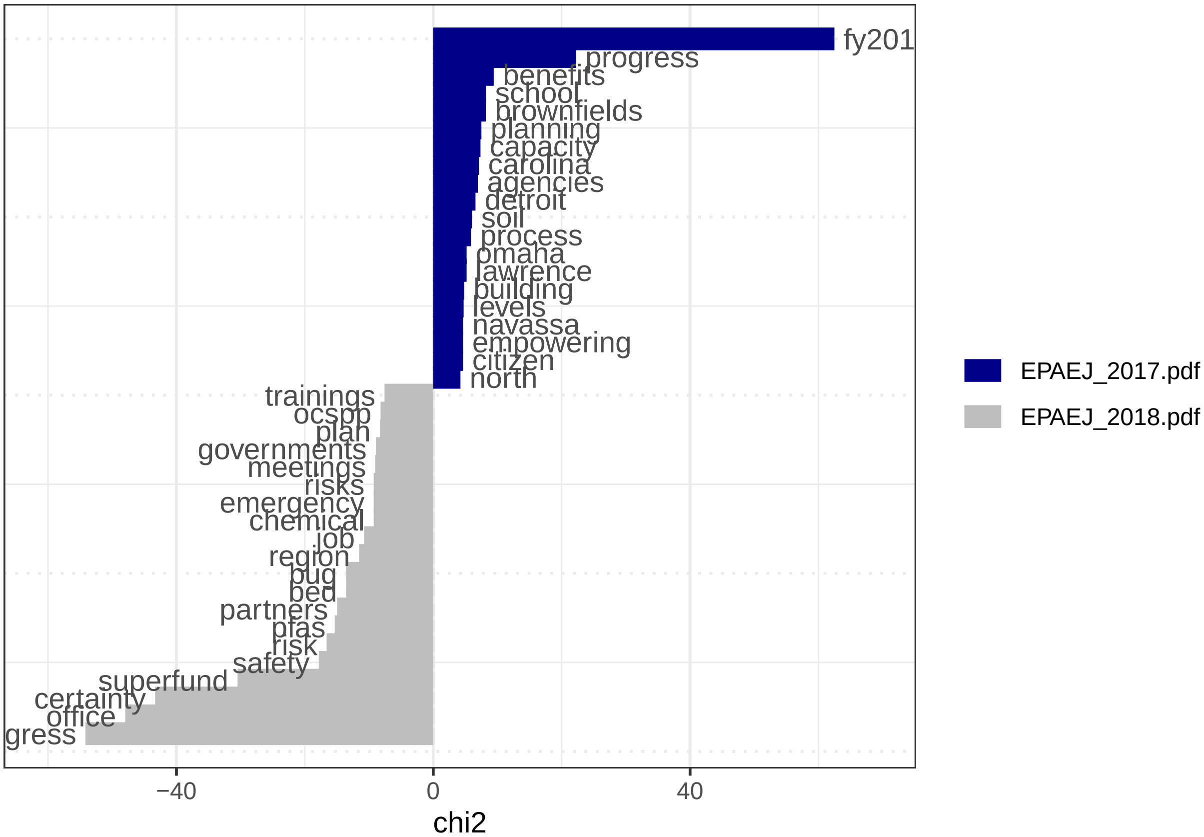
20
40
60
chi2
EPAEJ_2016.pdf
EPAEJ_2017.pdf


fy201
progress
benefits
school
brownfields
planning
capacity
carolina
agencies
detroit
soil
process
omaha
lawrence
building
levels
navassa
empowering
citizen
north
trainings
ocspp
plan
governments
meetings
risks
emergency
chemical
job
region
bug
bed
partners
pfas
risk
safety
superfund
certainty
office
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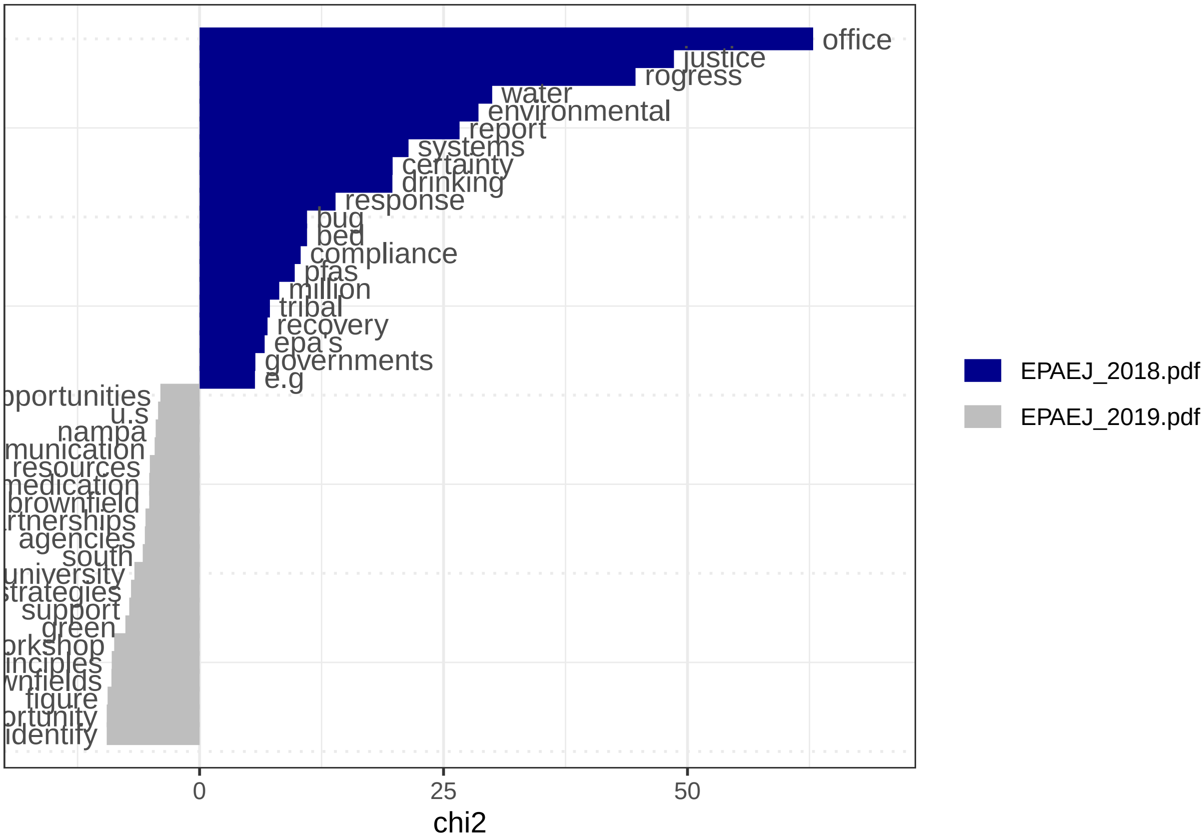
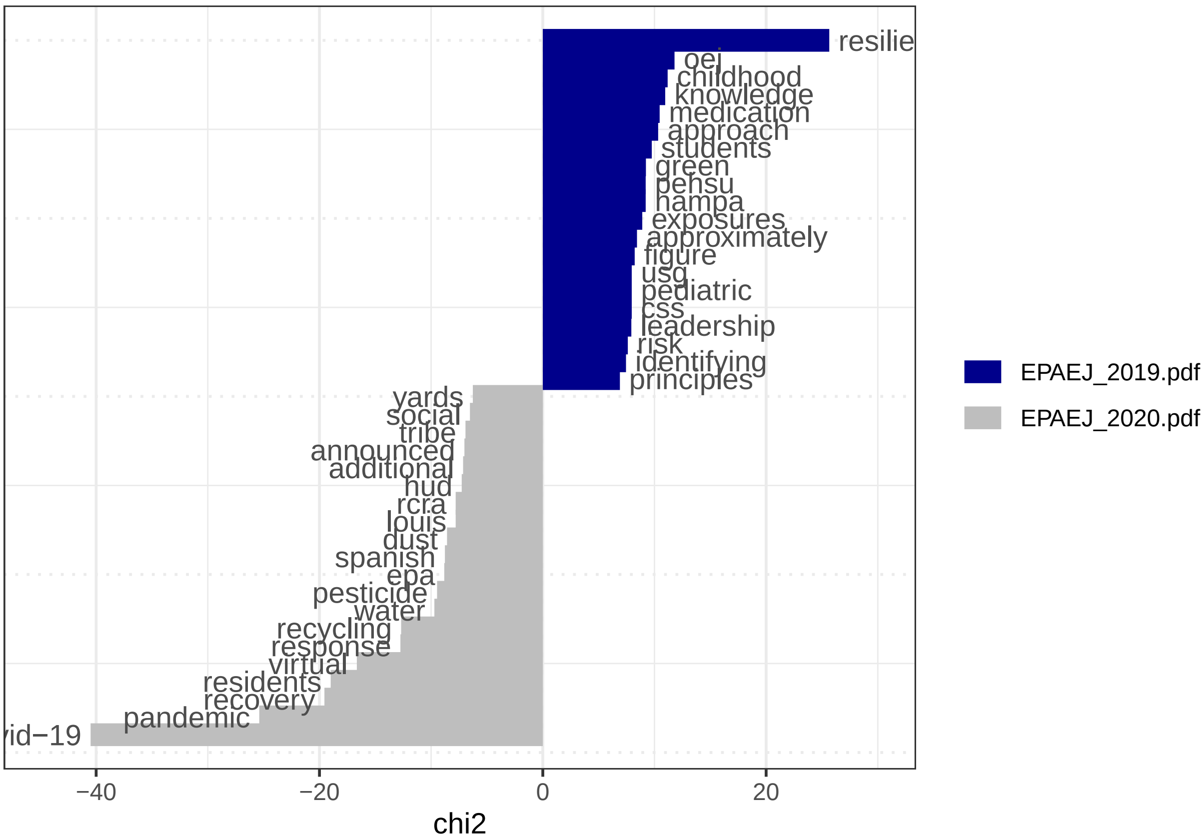
0
40
chi2
EPAEJ_2017.pdf
EPAEJ_2018.pdf


office
justice
rogress
water
environmental
report
systems
certainty
drinking
response
bug
bed
compliance
pfas
million
tribal
recovery
epa's
governments
e.g
pportunities
u.s
nampa
munication
resources
medication
brownfield
rtnerships
agencies
south
university
strategies
support
green
orkshop
inciples
wnfields
figure
ortunity
identify
0
25
50
chi2
EPAEJ_2018.pdf
EPAEJ_2019.pdf



4. Select a word or multi-word term of interest and identify words related to it using windowing and keyness comparison. To do this you will create to objects: one containing all words occurring within a 10-word window of your term of interest, and the second object containing all other words. Then run a keyness comparison on these objects. Which one is the target, and which the reference? Hint

Start with the initial corpus and tokenized words

```
#creating an initial corpus containing the data
epa_corp <- corpus(x = ej_pdf, text_field = "text" )

tokens <- tokens(epa_corp, remove_punct = TRUE)

toks1<- tokens_select(tokens, min_nchar = 3)
toks1 <- tokens_tolower(toks1) #lowercase
toks1 <- tokens_remove(toks1, pattern = (stop_vec)) #remove stop words
#dfm <- dfm(toks1) #create a data frequency matrix
```

Select 2 token objects for words (1) inside vs (2) outside a 10-word window of the keyword "health

```r
#identify keyword
keyword <- c("health")

#1. token object for words inside the 10-word window
toks_inside <- tokens_keep(toks1,
                           pattern = keyword,
                           window = 10)
toks_inside <- tokens_remove(toks_inside,
                             pattern = keyword) # remove the keywords
#create document feature matrix
dfmat_inside <- dfm(toks_inside)

#2. token object for words outside the 10-word window
toks_outside <- tokens_remove(toks1,
                              pattern = keyword, window = 10)
#create document feature matrix
dfmat_outside <- dfm(toks_outside)
```

Display top 10 words most related to "health"

```r
tstat_key_inside <- textstat_keyness(rbind(dfmat_inside, dfmat_outside),
                                     target = seq_len(ndoc(dfmat_inside)))
tstat_key_inside[1:10] %>%
  rename("Related Words" = feature,
         "Chi Squared" = chi2) %>%
  kbl() %>%
  kable_styling(bootstrap_options = c("striped", "hover"),
                latex_options = "HOLD_position")
```

Related Words	Chi Squared	p	n_target	n_reference
environment	187.48080	0	68	40
public	177.92777	0	137	189
human	154.41312	0	44	16
impacts	106.38418	0	55	52
children's	64.90879	0	18	5
care	63.62066	0	24	15
disparities	61.13043	0	21	10
exposures	60.40295	0	22	13
risks	56.07863	0	24	18
childhood	52.03349	0	23	18