# Week 5: Assignment 4: Word relationship analysis

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## Load Libraries

```
packages=c("tidyr",
           "pdftools",
           "lubridate",
           "tidyverse",
           "tidytext",
           "readr",
           "quanteda",
           "readtext",
           "quanteda.textstats",
           "quanteda.textplots",
           "ggplot2",
           "forcats",
           "stringr",
           "quanteda.textplots",
           "widyr",
           "igraph",
           "ggraph",
           "here")

for (i in packages) {
  if (require(i,character.only=TRUE)==FALSE) {
    install.packages(i,repos='http://cran.us.r-project.org')
  }
  else {
    require(i,character.only=TRUE)
  }
}
```

## Read in data

```
#filepath to data
files <- list.files(path = here("data/week5_data/"),
                    pattern = "*pdf$",
                    full.names = TRUE)

#renders all textboxes on a text canvas and returns a character vector of equal length to the number of
ej_reports <- lapply(files, pdf_text)
```

```r
#read texts and (if any) associated document-level meta-data from one or more source files - makes a df
ej_pdf <- readtext(file = here("data/week5_data/*.pdf"),
                   docvarsfrom = "filenames",
                   docvarnames = c("type", "subj", "year"),
                   sep = "_")

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

#return details of the corpus
summary(epa_corp) %>%
  knitr::kable()
```

| Text | Types | Tokens | Sentences | type | subj | year |
|---|---|---|---|---|---|---|
| EPA_EJ_2015.pdf | 2136 | 8944 | 263 | EPA | EJ | 2015 |
| EPA_EJ_2016.pdf | 1599 | 7965 | 176 | EPA | EJ | 2016 |
| EPA_EJ_2017.pdf | 2774 | 16658 | 447 | EPA | EJ | 2017 |
| EPA_EJ_2018.pdf | 3973 | 30564 | 653 | EPA | EJ | 2018 |
| EPA_EJ_2019.pdf | 3773 | 22648 | 672 | EPA | EJ | 2019 |
| EPA_EJ_2020.pdf | 4493 | 30523 | 987 | EPA | EJ | 2020 |

```r
#I'm adding some additional, context-specific stop words to stop word lexicon
more_stops <-c("2015","2016", "2017", "2018",
               "2019", "2020", "www.epa.gov", "https")

#add the additional stopwords to the stop word lexicon
add_stops <- tibble(word = c(stop_words$word, more_stops))

stop_vec <- as_vector(add_stops)
```

```r
#convert to tidy format and apply my stop words
raw_text <- tidy(epa_corp)

#Distribution of most frequent words across documents
raw_words <- raw_text %>%
  mutate(year = as.factor(year)) %>%
  unnest_tokens(word, text) %>%
  anti_join(add_stops, by = 'word') %>%
  count(year, word, sort = TRUE)

#number of total words by document
total_words <- raw_words %>%
  group_by(year) %>%
  summarize(total = sum(n))

report_words <- left_join(raw_words, total_words)
```

```
## Joining, by = "year"
```

```r
par_tokens <- unnest_tokens(raw_text,
                            output = paragraphs,
                            input = text,
                            token = "paragraphs")
```

```
par_tokens <- par_tokens %>%
 mutate(par_id = 1:n())

par_words <- unnest_tokens(par_tokens,
                           output = word,
                           input = paragraphs,
                           token = "words")
```

## Part 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?

```
tokens <- tokens(epa_corp, remove_punct = TRUE) #list of character vectors - takes each document and sp

toks1<- tokens_select(tokens, min_nchar = 3)

toks1 <- tokens_tolower(toks1)

toks1 <- tokens_remove(toks1, pattern = (stop_vec))

dfm <- dfm(toks1) #create document feature matrix - rows are number of occurances of each word within e

#first the basic frequency stat
tstat_freq <- textstat_frequency(dfm, n = 5, groups = year)

head(tstat_freq, 10) %>%
  knitr::kable()
```

| feature | frequency | rank | docfreq | group |
|---|---|---|---|---|
| environmental | 127 | 1 | 1 | 2015 |
| communities | 99 | 2 | 1 | 2015 |
| epa | 92 | 3 | 1 | 2015 |
| justice | 84 | 4 | 1 | 2015 |
| community | 47 | 5 | 1 | 2015 |
| environmental | 109 | 1 | 1 | 2016 |
| communities | 85 | 2 | 1 | 2016 |
| justice | 71 | 3 | 1 | 2016 |
| epa | 48 | 4 | 1 | 2016 |
| federal | 31 | 5 | 1 | 2016 |

```
toks2 <- tokens_ngrams(toks1, n = 3)

dfm2 <- dfm(toks2)

dfm2 <- dfm_remove(dfm2, pattern = c(stop_vec))
#gives more coherent terms - power of chunking at a different token level

freq_words2 <- textstat_frequency(dfm2, n = 20)

freq_words2$token <- rep("trigram", 20)
#tokens1 <- tokens_select(tokens1,pattern = stopwords("en"), selection = "remove")

head(freq_words2, 5) %>%
  knitr::kable()
```

| feature | frequency | rank | docfreq | group | token |
|---|---|---|---|---|---|
| justice_fy2017_progress | 51 | 1 | 1 | all | trigram |
| fy2017_progress_report | 51 | 1 | 1 | all | trigram |
| environmental_public_health | 50 | 3 | 6 | all | trigram |
| environmental_justice_fy2017 | 50 | 3 | 1 | all | trigram |

| feature | frequency | rank | docfreq | group | token |
| --- | --- | --- | --- | --- | --- |
| national_environmental_justice | 37 | 5 | 6 | all | trigram |

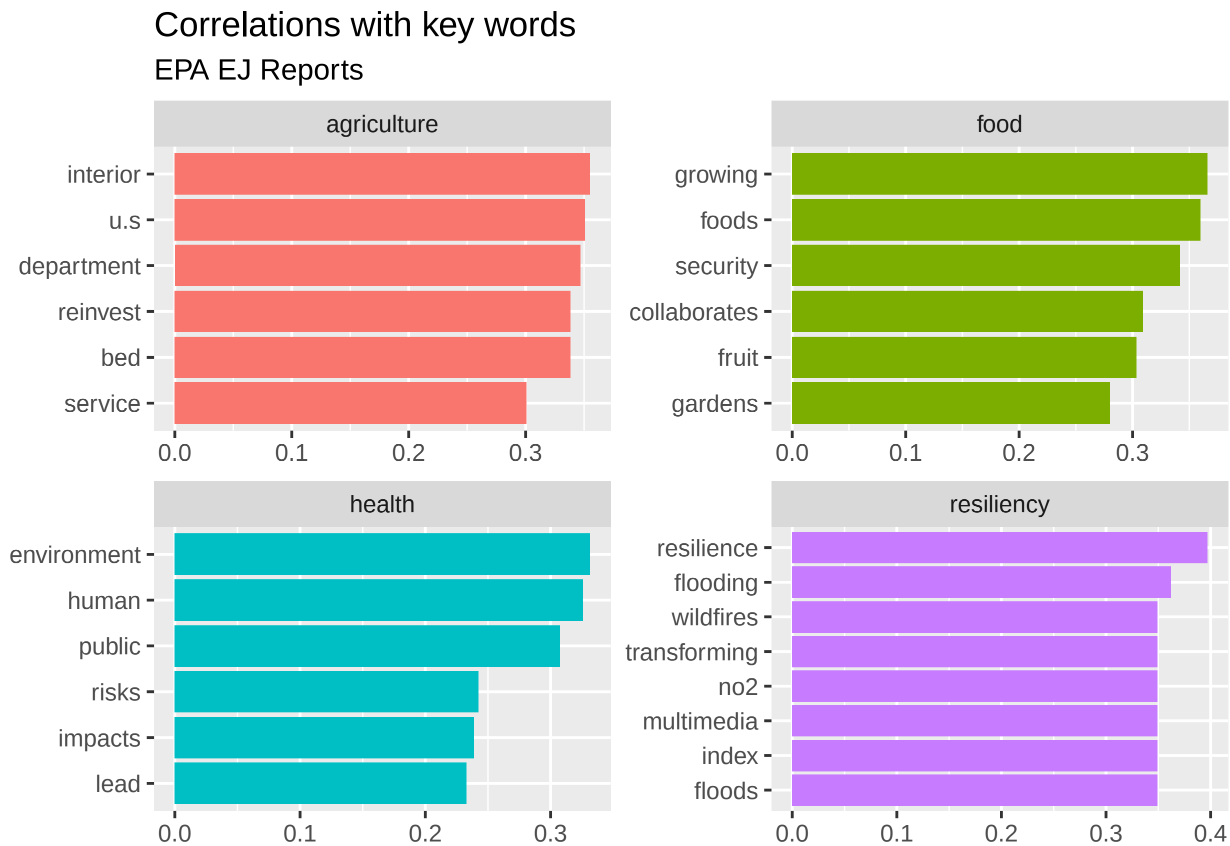
The most frequent trigrams in the dataset are shown in the table above, with justice_fy2017_progress as the most frequently occurring trigram.

## Part 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!

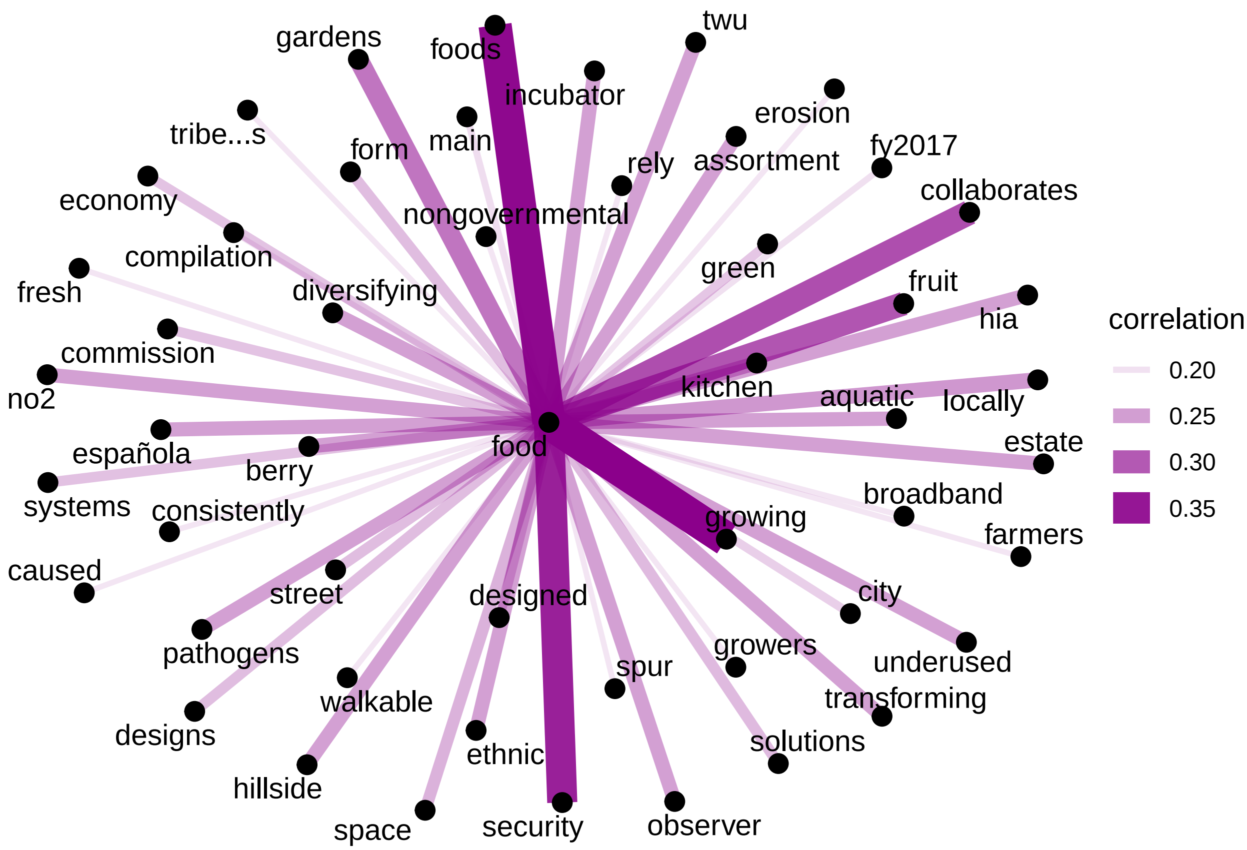
```
#correlation between co-occuring words
word_cors <- par_words %>%
  add_count(par_id) %>%
  filter(n >= 50) %>%
  select(-n) %>%
  pairwise_cor(word, par_id, sort = TRUE)

#now we can select words cooccurring with the word justice and get correlation coefficients
food_cors <- word_cors %>%
  filter(item1 == "food")

  word_cors %>%
  filter(item1 %in% c("food", "agriculture", "health", "resiliency")) %>%
  group_by(item1) %>%
  top_n(6) %>%
  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")+
  scale_y_reordered() +
  labs(y = NULL,
       x = NULL,
       title = "Correlations with key words",
       subtitle = "EPA EJ Reports")
```

```
## Selecting by correlation
```




```
#let's zoom in on just one of our key terms
 food_cors <- word_cors %>%
filter(item1 == "food") %>%
 mutate(n = 1:n())
```

```
food_cors  %>%
  filter(n <= 50) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation,
                     edge_width = correlation),
                 edge_colour = "darkmagenta") +
  geom_node_point(size = 3) +
  geom_node_text(aes(label = name),
                 repel = TRUE,
                 point.padding = unit(0.2,
                                      "lines")) +
  theme_void()
```



twu
gardens
foods
incubator
erosion
tribe...s
main
form
rely
assortment
fy2017
economy
nongovernmental
collaborates
compilation
green
fresh
diversifying
fruit
hia
commission
kitchen
no2
aquatic
locally
food
estate
española
berry
systems
broadband
consistently
growing
farmers
caused
city
street
designed
pathogens
growers
underused
spur
walkable
transforming
designs
ethnic
solutions
hillside
space
security
observer
correlation
0.20
0.25
0.30
0.35

## Part 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.

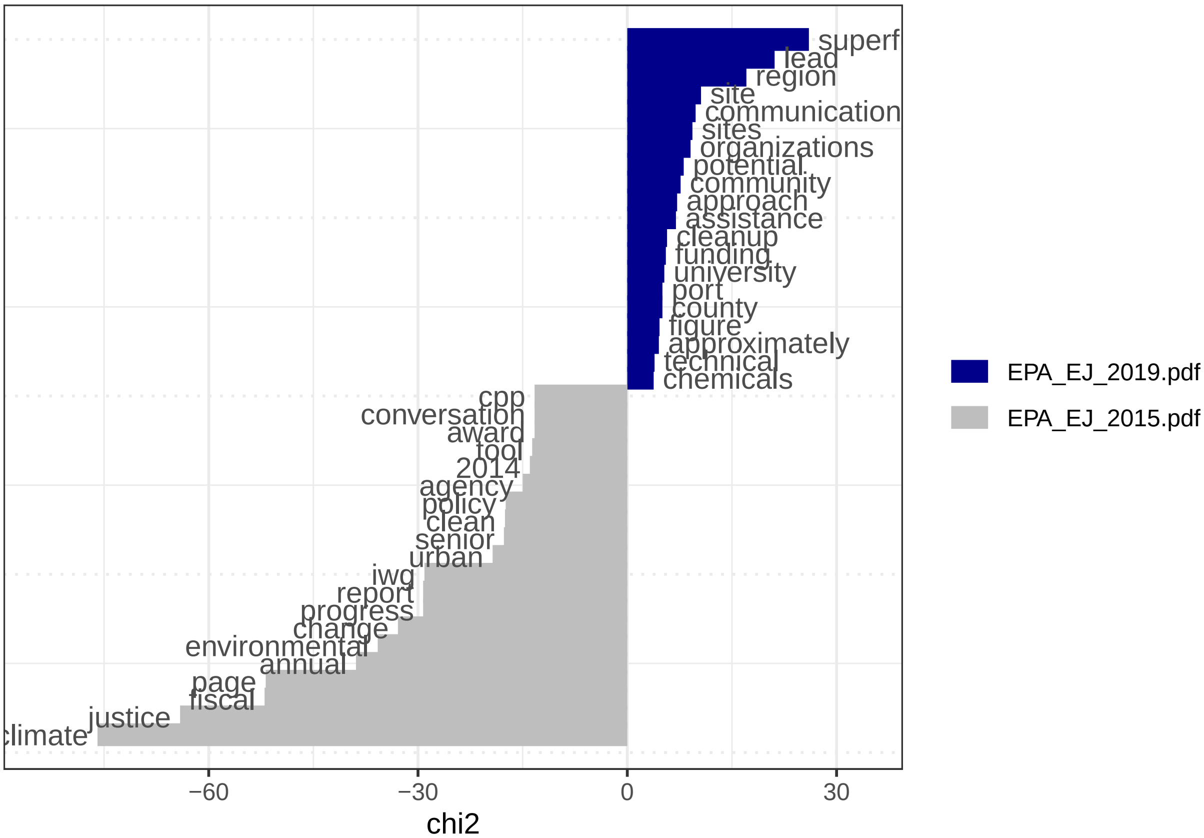
```
#test function
dfm_subset <- corpus_subset(epa_corp, grepl("2018|2019", docnames(epa_corp)))
```

```
#write function
keyness_comparison <- function(text1_year, text2_year) {

  #subset the corpus
  corpus_subset <- corpus_subset(epa_corp, grepl(paste0(text1_year, "|", text2_year), docnames(epa_corp

  #tokenize corpus
  tokens <- tokens(corpus_subset, remove_punct = TRUE) #list of character vectors - takes each document
  toks<- tokens_select(tokens, min_nchar = 3)
  toks <- tokens_tolower(toks)
  toks <- tokens_remove(toks, pattern = (stop_vec))
  dfm <- dfm(toks) #create document feature matrix - rows are number of occurances of each word within

  keyness <- textstat_keyness(dfm, target = 2)

  textplot_keyness(keyness)

}
```

### Keyness plot 1

Test running the function on 2015 and 2019

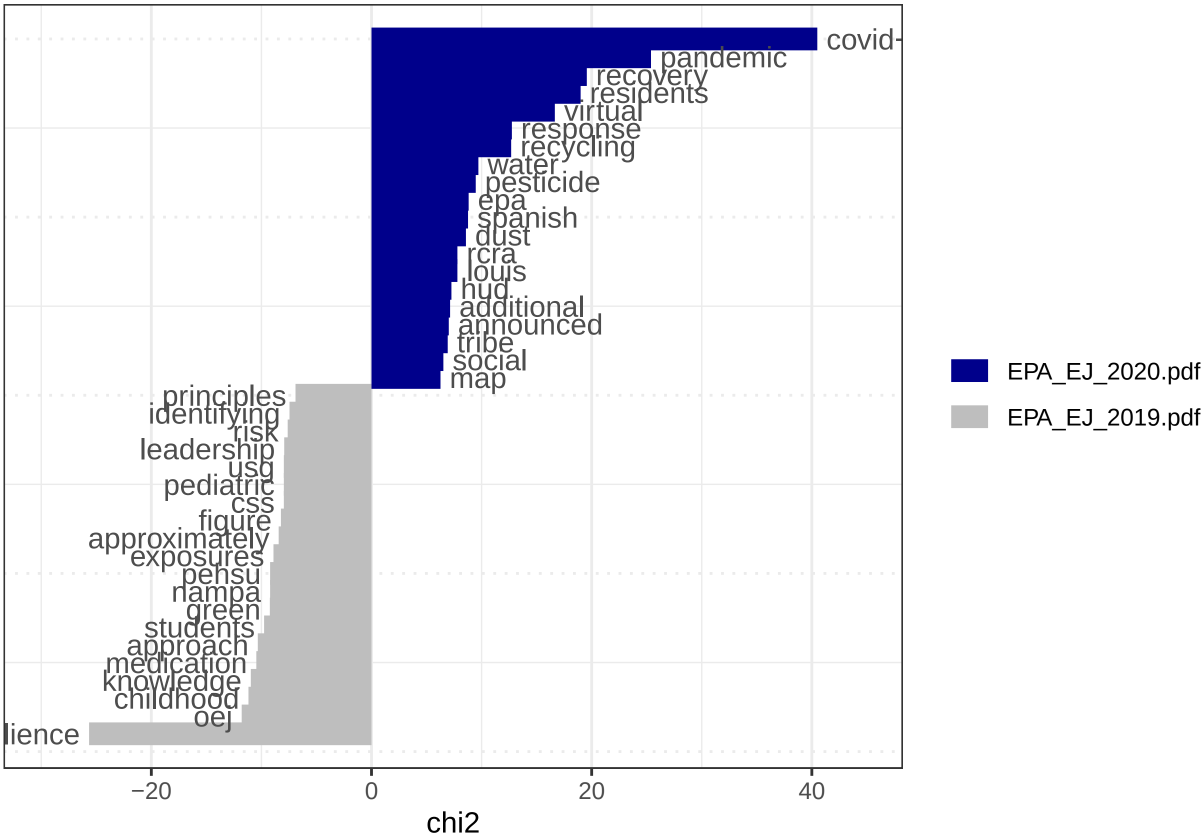
```
keyness_comparison(text1_year = 2015, text2_year = 2019)
```



### Keyness plot 2

Test running the function on 2019 and 2020

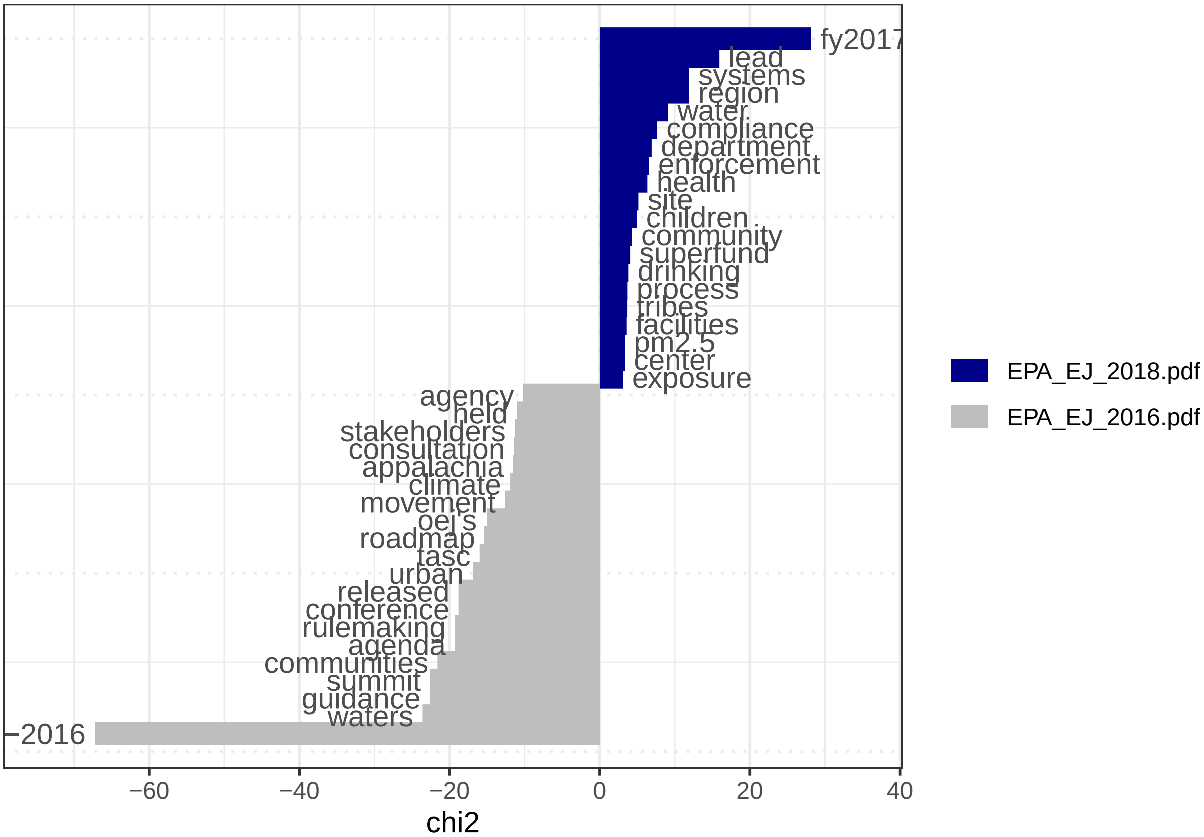
```
keyness_comparison(text1_year = 2019, text2_year = 2020)
```



### Keyness plot 3

Test running the function on 2016 and 2018:

```
keyness_comparison(text1_year = 2016, text2_year = 2018)
```



# Part 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 two 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

**food systems**

Create an object containing all words occurring within a 10 word window of **food systems**.

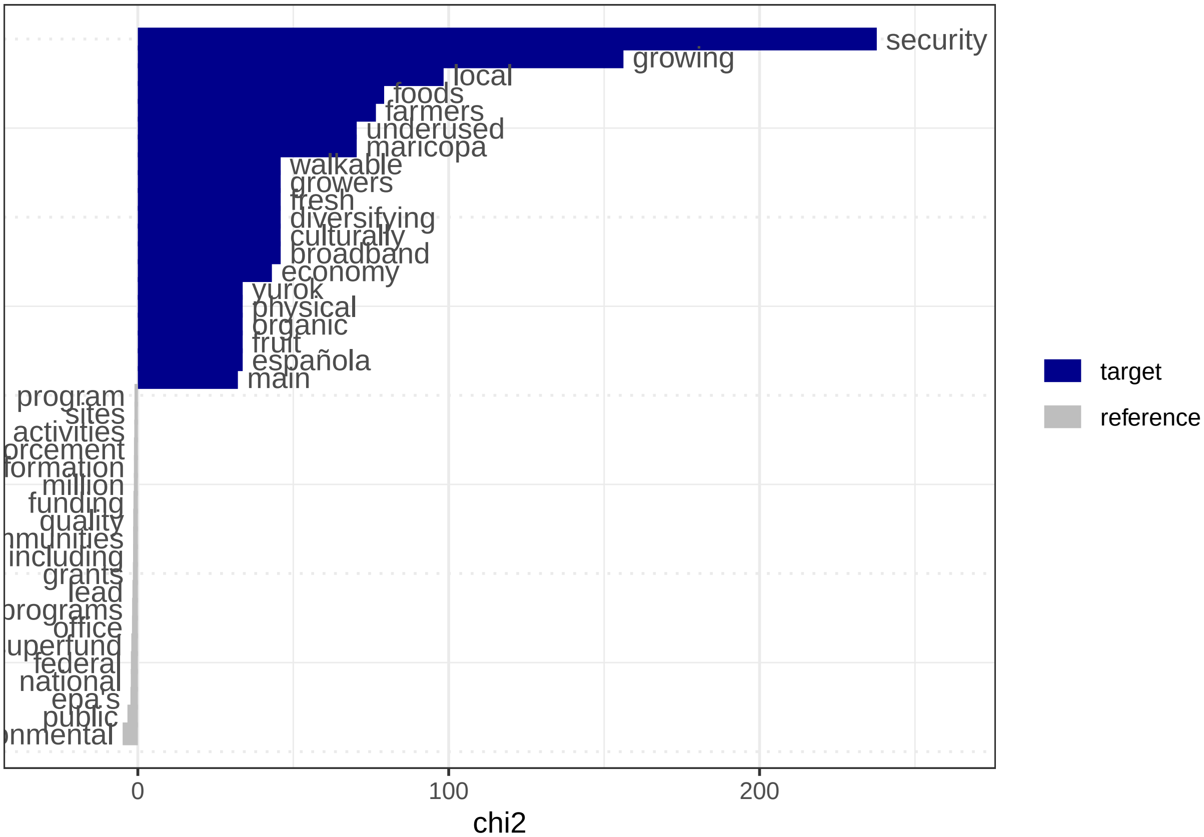
```
term = "food"

toks_inside <- tokens_keep(toks1,
                          pattern = term,
                          window = 10)

toks_inside <- tokens_remove(toks_inside,
                            pattern = term)
```

Create an object containing all other words:

```
toks_outside <- tokens_remove(toks1,
                             pattern = term,
                             window = 10)
```

Run a keyness comparison of the objects:

```
dfmat_inside <- dfm(toks_inside)
dfmat_outside <- dfm(toks_outside)

tstat_key_inside <- textstat_keyness(rbind(dfmat_inside, dfmat_outside),
                                     target = seq_len(ndoc(dfmat_inside)))

textplot_keyness(tstat_key_inside)
```




`toks_inside` is the target, and `toks_outside` is the reference.