Newspaper coverage of wars in the 21st century

Computational Social Science - 2022

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Introduction

The relationship between the media and wars has always been a controversial one. In such times it is very difficult to get down to the source and the large media companies are most of the time the only ones which have the ability to cover the state of a war since a whole region is in a state of emergency and it is almost impossible for normal citizens to get information otherwise. The media is in a critical position because they have the crucial ability to get the information and it is their determination to distribute it. But from the perspective of the media they are companies with a financial incentive. They earn a lot of money from international crises. The two motives of being a reliable source and attracting a large audience might contradict with each other. In addition have most large media groups a stronger or less strong political agenda which they push and which can have a severe impact on how they cover news. This can result in multiple extremely different portrayals of the same topic. This critical role of the media in times of war has motivated me to have a closer look at how different media sources portray different wars.

Methods

To collect the data I use the “The Guardian” API of the British newspaper and the “New York Times” API of the American Newspaper. After cleaning up the data I will perform three text analysis procedures. First a sentiment analysis to check if there are differences in the positivity score between the wars but also between the two newspapers. Second I will do a word frequency analysis and look at the most used words. And third I will use the ” Lexicoder policy agendas” dictionary to do a topic analysis. I chose to look at three different wars: The war in Afghanistan, the war going on right now in the Ukraine and the civil war in Syria. I have chosen those three because they are all different from each other in the point of how the “West” relates to them. The war in Afghanistan was driven by the USA following the 9/11 terrorist attack in New York. The war in Ukraine is geographically and also politically closer to the “West” but western forces have (not yet) intervened themselves. The war in Syria has been going on for a long time and has had a lot of media coverage in the past, it is geographically and cultural much further away from the “West” but the USA and its allies also have played a controversial role in it.

Limitations

The primary limitation I had to set were the numbers of newspaper and wars I included in the analysis. I initially wanted to also use the “Die Zeit” API to have a newspaper in a different language and from another different country but the service has been stopped due to technical difficulties. Since there are only limited APIs I chose to stick to these two. But it would have been very interesting to also have a newspaper with a potentially right leaning political orientation since these two are both more liberal. I limited myself to those three wars since I don’t think that it would make much of a difference to look at more wars. I think that differences in the reporting of the wars would show when comparing these three. For further studies it would be interesting to look at wars from longer time ago. I’m sure there would be interesting finding when looking at the Vietnam war or even the 2. world war.

Data Collection and Processing

Not all code chunks are run or shown, this is for the reason of illustration and very long time of gathering the data. All the data used is saved in the "Data" folder,

Libraires

```
library(dplyr)
library(quanteda)
library(jsonlite)
library(stringr)
library(tidyverse)
library(ggplot2)
library(rvest)
library(stringr)
library(quanteda.textplots)
```

The Guardian

URL generator for the Guardian API

```
guardian_key = read_lines("guardian_key.txt")

guardian_url = function(search_word, date_from='', date_to='') {
  search_word <- str_replace(search_word, ' ', '%20')

  if (date_from == '' | date_to == '') {
    url <- paste0('http://content.guardianapis.com/search?q=', search_word,
                  '&show-blocks=all&api-key=', guardian_key, sep='')
  } else {
    url <- paste0('http://content.guardianapis.com/search?q=', search_word,
                  '&from-date=', date_from, '&to-date=', date_to,
                  '&show-blocks=all&api-key=', guardian_key, sep='')
  }
  url
}
```

Afghanistan War

```
#There are 63'723 articles which is too much, it exceeds the rate limit of the Guardian API
#that's why I will extract 10% of all the pages of each relevant year.

afgh_list <- vector("list")
counter <- 1

for (year in 1999:2022) {
  base_url <- guardian_url('afghanistan war', paste0(year, '-01-01'),
                           paste0(year, '-12-31'))
  n_results <- fromJSON(base_url) %>% .$response %>% .$total
  max_pages <- ceiling(((n_results[1] / 10)-1))
  random_pages <- sample.int(max_pages, max_pages/10)
  print(year)
```

```
  for(i in 1:(max_pages/10)){
    x=random_pages[i]
    print(i)
    url <- paste0(base_url, "&page=", x, sep='')
      GuardSearch <- fromJSON(url, flatten = TRUE) %>%
        data.frame(.,stringsAsFactors = FALSE)
    afgh_list[[counter]] <- GuardSearch
    counter <- counter + 1
    #Sys.sleep(1)
}
}

afgh_results <- rbind_pages(afgh_list)

save(afgh_results, file = "Data/afgh_results.RData")
```

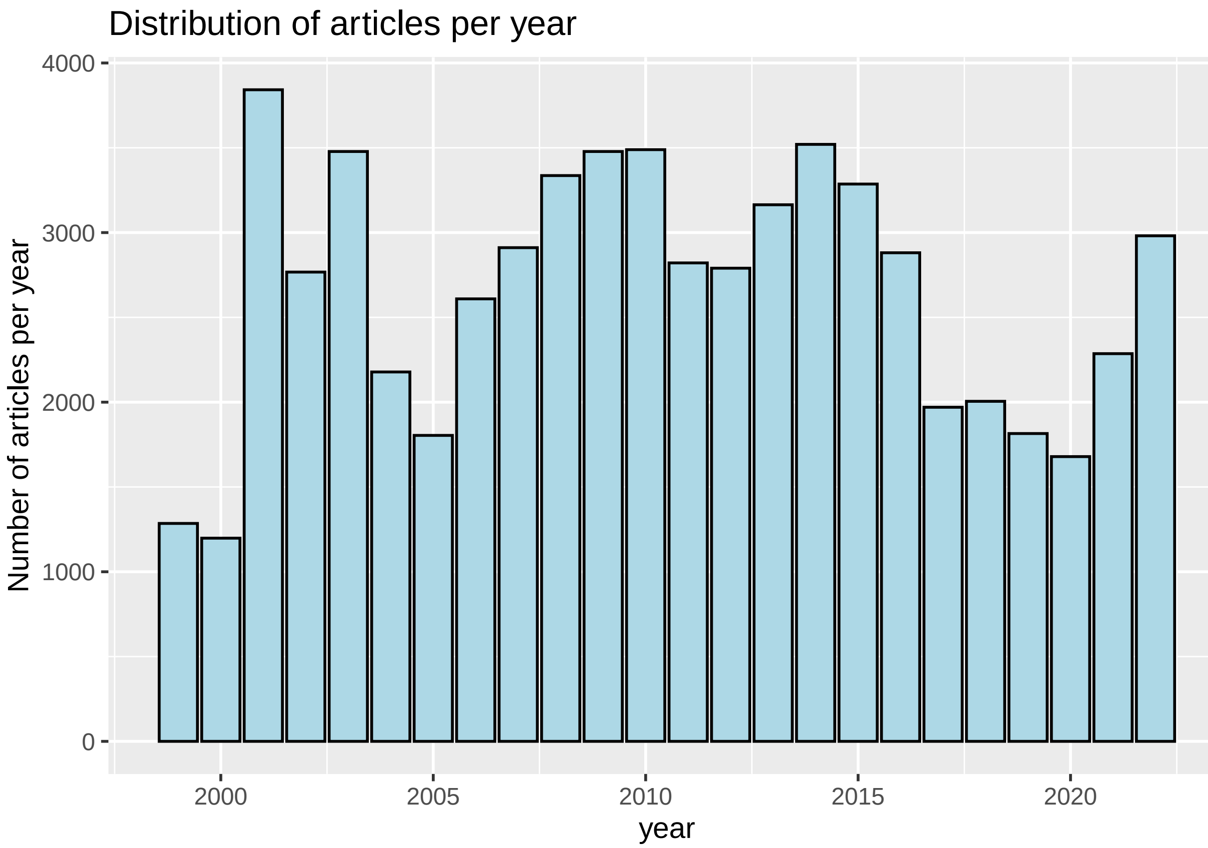
Get Data

```
load('Data/afgh_results.RData')

#Pick filter out the results of the type "article"
afgh_results <- afgh_results %>%
  filter(response.results.type == "article") %>%
  unnest(cols = response.results.blocks.body)

# Make a selection of the important variables

afgh <- afgh_results %>%
  select(id = response.results.id,
         url = response.results.webUrl,
         title = response.results.webTitle,
         text = bodyTextSummary,
         date = response.results.webPublicationDate,
         section = response.results.sectionName,
         total_year = response.total
         )

afgh$text_len <- nchar(afgh$text)
summary(afgh$text_len)

afgh$text[afgh$text_len < 50]

#filter out articles with no significant text
afgh <- afgh %>%
  filter(!text %in% c("", " ", "."))
summary(afgh$text_len)

#extract date and year

afgh$date <- gsub("T.*",
                  "",
                  afgh$date) %>% as.Date()
```

```
afgh$year <- afgh$date %>%
  gsub("([0-9]{4}).*",
       "\\1", .) %>% as.numeric


afgh$total_year <- afgh$total_year %>%
  as.numeric

save(afgh, file = "Data/afgh.RData")
```

Data Cleaning

```
# Create a histogram to show the distribution of articles

load("Data/afgh.RData")
afgh_hist <- ggplot(afgh, aes(x=date))+
  geom_histogram(binwidth = 200, fill='lightblue', color="black")+
  scale_x_date(date_breaks = "3 years", date_labels = "%Y")+
  theme_classic()


afgh_hist_year <- afgh[!duplicated(afgh[ , c("year")]), ] %>%
  select(total_year, year) %>%
  ggplot(aes(x=year, y=total_year))+
  geom_bar(stat='identity', fill = "lightblue", color="black")+
  labs(title = "Distribution of articles per year", y="Number of articles per year")
afgh_hist_year
```



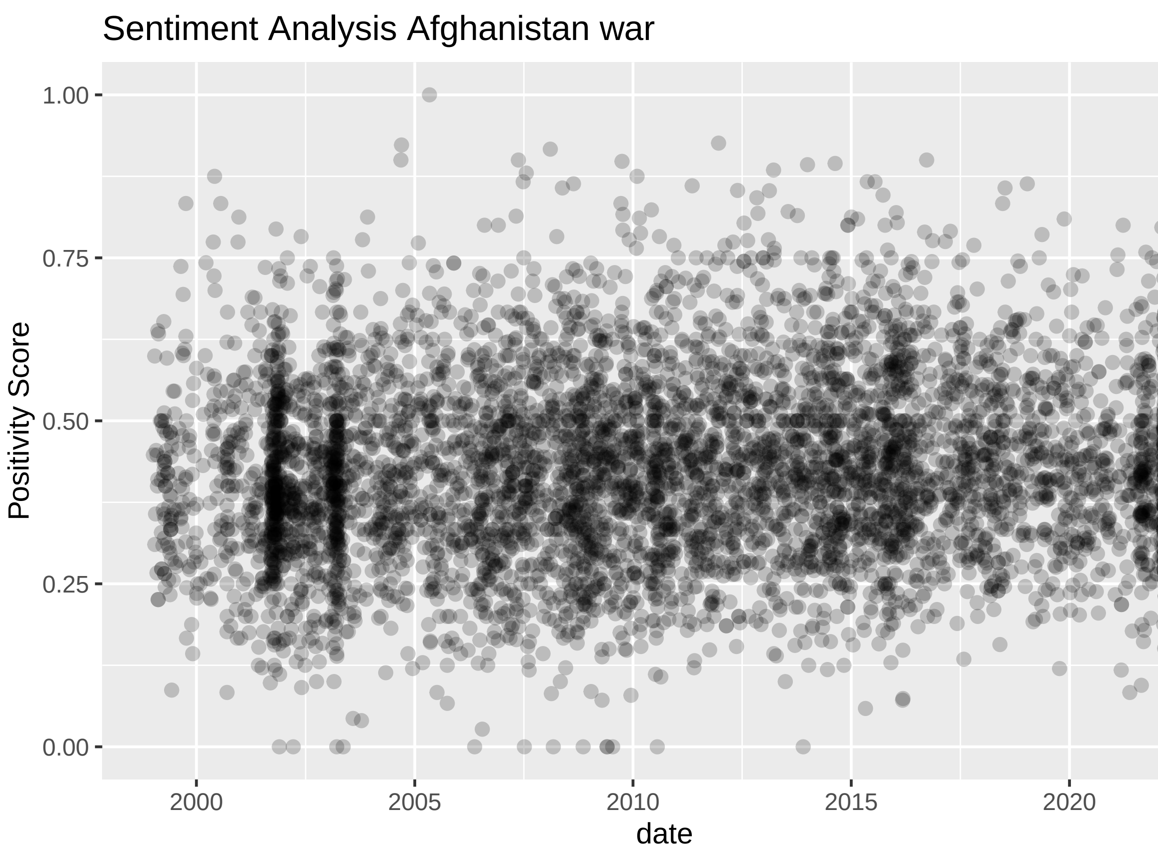
Basic Analysis

```
afgh_corpus <- corpus(afgh,
                      text_field = "text")

summary(afgh_corpus) %>% head
docvars(afgh_corpus) %>%
  head

afgh_corpus[1]


afgh_toks <- tokens(afgh_corpus,
                    what = c("word"),
                    remove_separators = TRUE,
                    include_docvars = TRUE,
                    ngrams = 1L,
                    remove_numbers = FALSE,
                    remove_punct = TRUE,
                    remove_symbols = FALSE,
                    remove_hyphens = FALSE)

afgh_toks %>% head

afgh_toks <- afgh_toks %>%
  tokens_tolower %>%
```

```
  tokens_remove(stopwords("english"), padding = TRUE) %>%
  tokens_remove("") %>%
  tokens_wordstem(language = "english")

save(afgh_toks, file = "Data/afgh_toks.RData")
```

Create a corpus and tokens

```
load("Data/afgh_toks.RData")
load("Data/afgh.RData")

# make a sentiment analysis on the ratio of positive to negative words in each article

afgh_toks_sent <- tokens_lookup(afgh_toks,
                                dictionary =  data_dictionary_LSD2015[1:2])
#afgh_toks_sent %>% head

afgh_dfm_sent <- dfm(afgh_toks_sent)
#afgh_dfm_sent %>% head

afgh_pos_neg <- afgh_dfm_sent %>% convert(.,to = "data.frame") %>%
  mutate(pos_to_neg = (positive / (positive + negative)))

#summary(afgh_pos_neg)
# afgh_pos_neg %>% filter(is.na(afgh_pos_neg$pos_to_neg))
# 1 NA in year 2002
# Row has 0 negative and 0 positive -> NaN -> discard

afgh_sent <- afgh

afgh_sent$pos_neg <- afgh_pos_neg$pos_to_neg
afgh_sent <- afgh_sent %>% filter(!is.na(afgh_sent$pos_neg))

# create plots to show the results

plot_afgh_sent <- ggplot(afgh_sent, aes(x=date, y=pos_neg))+
  geom_point(size=2, alpha=0.2)+
  labs(title = "Sentiment Analysis Afghanistan war", y="Positivity Score")
plot_afgh_sent
```



Sentiment Analysis

```
afgh_by_year <- afgh_sent$pos_neg %>%
  aggregate(by=list(afgh_sent$year), FUN = mean) %>% rename(year = Group.1,
                                                             pos_neg = x)
# afgh_by_year

plot_afgh_pos_by_year <- ggplot(afgh_by_year, aes(x=year, y=pos_neg))+
  geom_line(color="royalblue", size=1)+
  theme_light()+
  ylim(0.35, 0.5)+
  labs(y="Positivity Score", title = "Sentiment Analysis Afghanistan war by year")
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
plot_afgh_pos_by_year
```

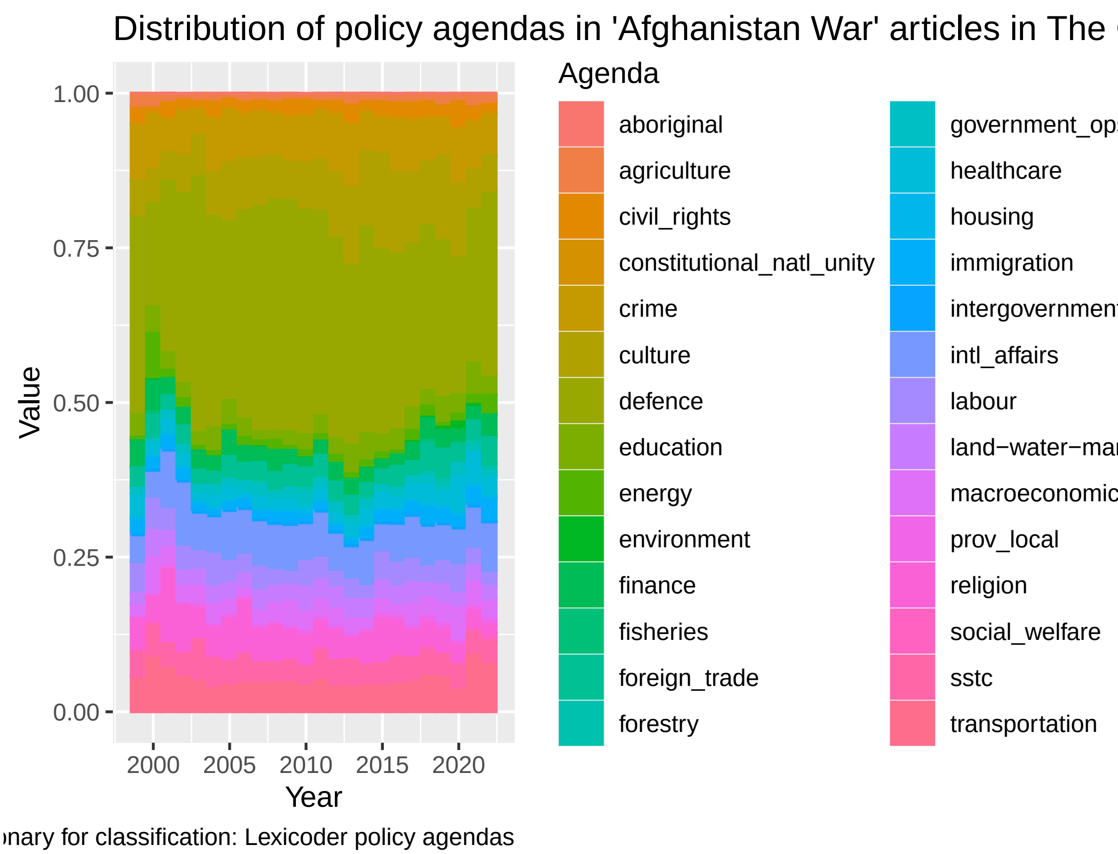

```
load("Data/afgh_toks.RData")


# load list with the most common words in English to remove them from the tokens

common_words <- read.delim("Data/1-1000.txt", header = FALSE) %>%
  head(200) %>%
  as.vector()
common_words <- common_words$V1

# removing the top 200 words from the tokens
afgh_toks_wordcount <- afgh_toks %>%
  tokens_remove(common_words)

afgh_dfm <- dfm(afgh_toks_wordcount)



afgh_topwords <- topfeatures(afgh_dfm, 50) %>%
  data.frame(word=names(.),
             frequency =.,
             row.names = c())

afgh_topwords
```

Word Frequency

```
##             word frequency
## 1            war     18360
## 2          peopl     10797
## 3         govern      8293
## 4        countri      7390
## 5           last      7144
## 6    afghanistan      7094
## 7           forc      6858
## 8           iraq      6277
## 9       militari      6183
## 10          mani      5707
## 11       british      5686
## 12        report      5531
## 13         state      5409
## 14         polit      4988
## 15        nation      4973
## 16        attack      4887
## 17        presid      4816
## 18          week      4814
## 19      american      4783
## 20          kill      4671
## 21       support      4559
## 22         secur      4348
## 23        includ      4306
## 24        intern      4286
## 25          sinc      4041
## 26       taliban      3949
## 27         still      3947
## 28        minist      3874
## 29         month      3832
## 30        public      3809
## 31            mr      3804
## 32         offic      3732
## 33         group      3705
## 34          told      3694
## 35         power      3567
## 36         troop      3539
## 37       soldier      3454
## 38        offici      3366
## 39       foreign      3302
## 40        famili      3301
## 41        leader      3265
## 42         anoth      3236
## 43       britain      3231
## 44            uk      3166
## 45           tri      3158
## 46         chang      3112
## 47          hous      3103
## 48         fight      3074
## 49        believ      3074
## 50        afghan      3052
```

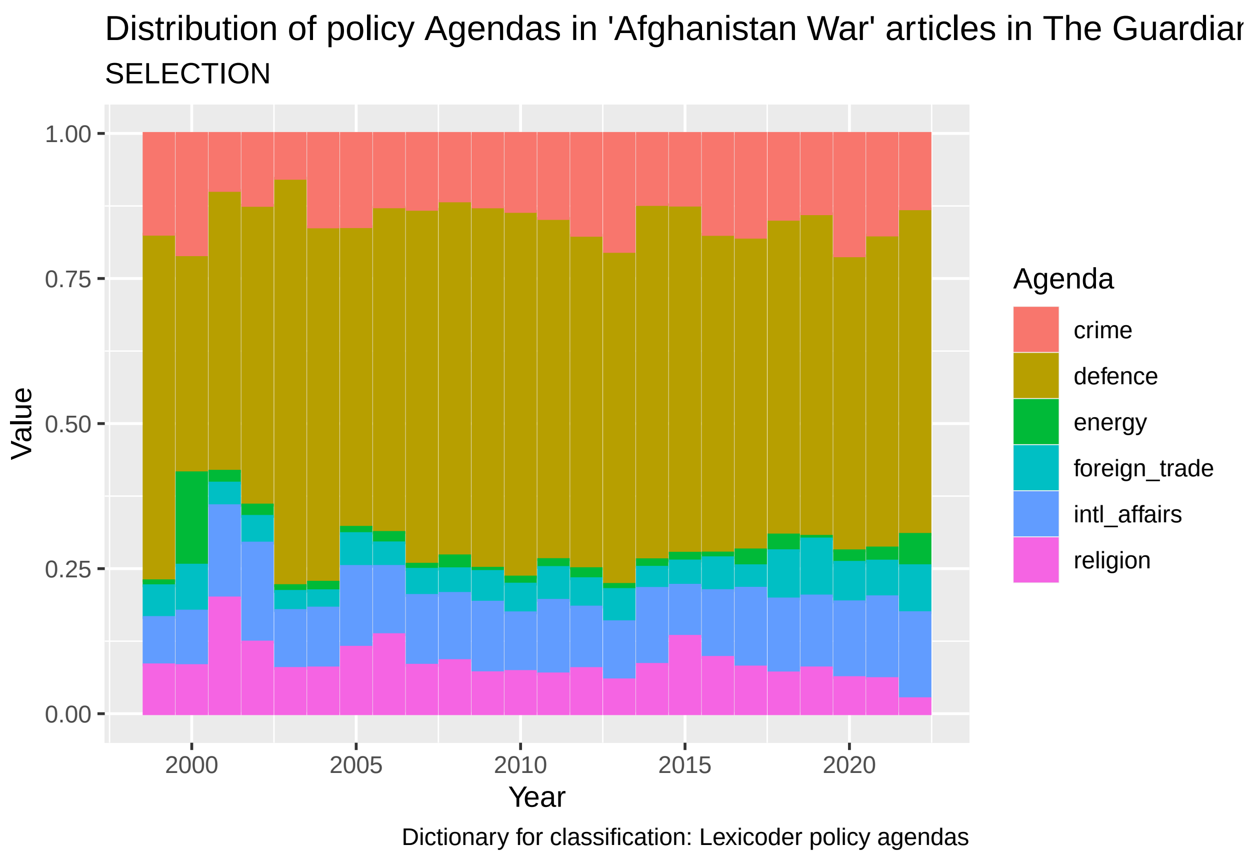
```
save(afgh_dfm, file = "Data/afgh_dfm.RData")
```

```
load("Data/afgh_toks.RData")
load("Data/afgh.RData")

# Load the Lexicoder policy agendas
policyagendas <- dictionary(file = "Data/policy_agendas_english.lcd")

# lookup the policy agendas dictionary and give each article a score
afgh_toks_pol <- tokens_lookup(afgh_toks, dictionary = policyagendas)
afgh_pol <- dfm(afgh_toks_pol) %>%
  convert(to = "data.frame") %>%
  select(-doc_id)

# divide the values for each row through the sum of each row to get relative values for the agendas for
afgh_pol <- afgh_pol / rowSums(afgh_pol)

afgh_pol$year <- afgh$year

afgh_pol <- drop_na(afgh_pol)

# group by year
afgh_pol_by_year <- afgh_pol %>%
  group_by(year) %>%
  summarise_each(funs = sum)

# Plot the results to better inspect them
afgh_pol_by_year_plot1 <- afgh_pol_by_year %>%
  pivot_longer(cols = 2:29, names_to = "Agenda") %>%
  ggplot(aes(x=year, y=value, colour = Agenda, fill = Agenda))+
  geom_bar(position="fill", stat="identity")+
  labs(x="Year", y="Value", title="Distribution of policy agendas in 'Afghanistan War' articles in The G
       caption = "Dictionary for classification: Lexicoder policy agendas")
afgh_pol_by_year_plot1
```



Policy agendas analysis

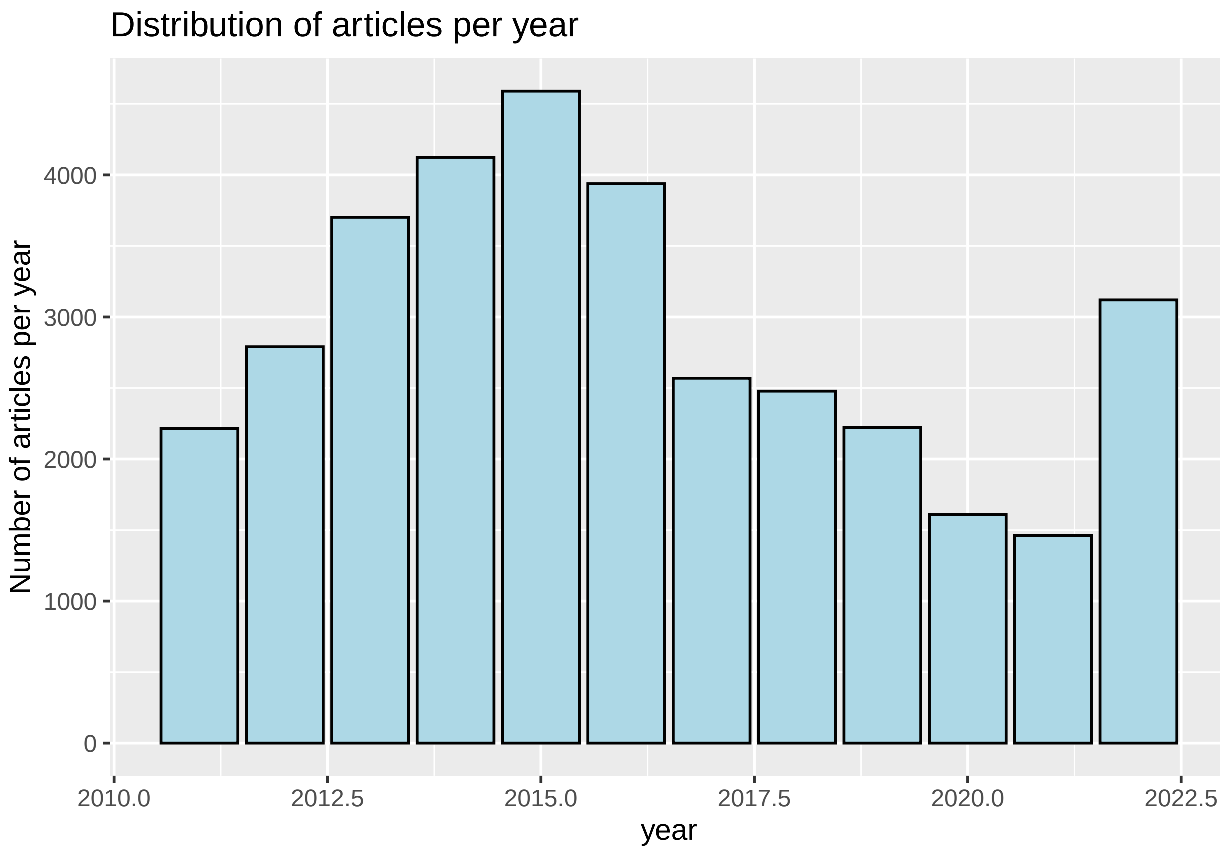
```
# select some agendas which seam important
afgh_pol_by_year_plot_select <- afgh_pol_by_year %>%
  select(year, defence, energy, foreign_trade, intl_affairs, religion, crime) %>%
  pivot_longer(cols = 2:7, names_to = "Agenda") %>%
  ggplot(aes(x=year, y=value, colour = Agenda, fill = Agenda))+
  geom_bar(position="fill", stat="identity")+
  labs(x="Year", y="Value", title="Distribution of policy Agendas in 'Afghanistan War' articles in The
       subtitle = "SELECTION", caption = "Dictionary for classification: Lexicoder policy agendas")
afgh_pol_by_year_plot_select
```



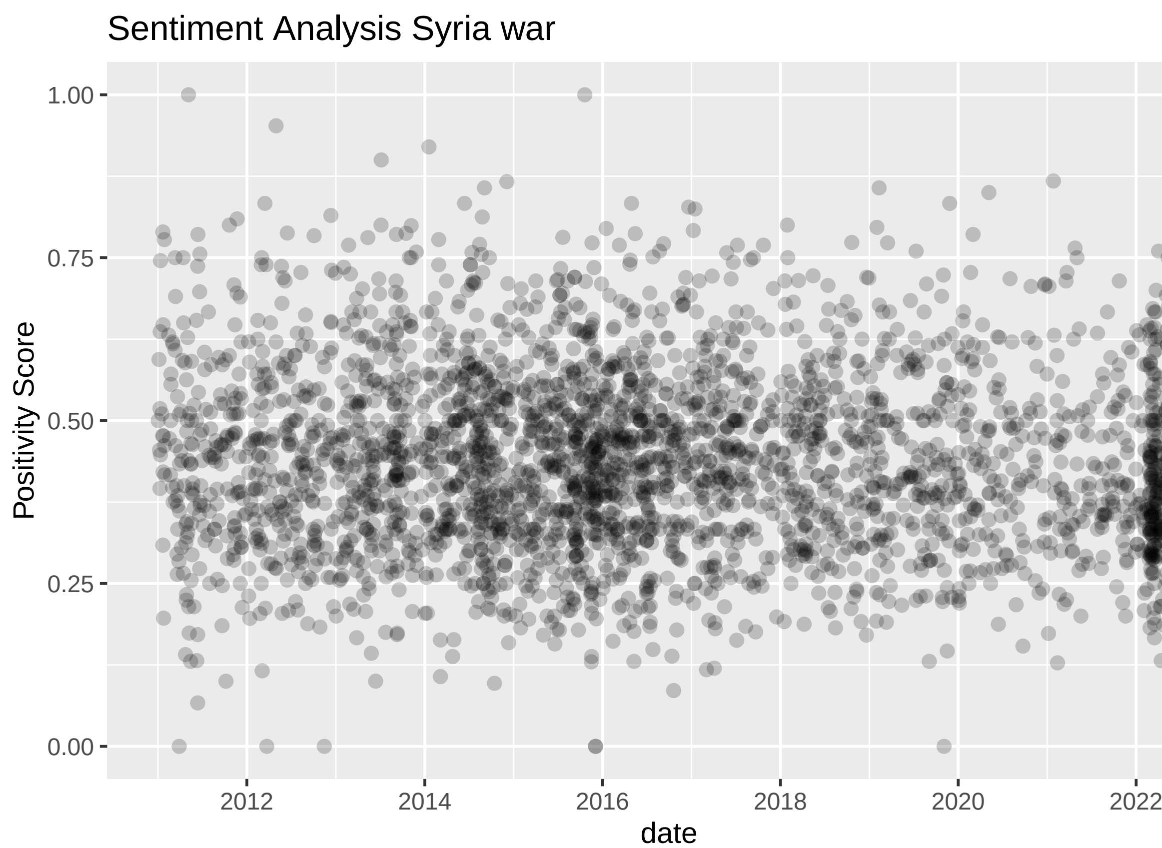

```r
save(afgh_pol, file = "Data/afgh_pol.RData")
```

The code for the other wars are not included in the rendered markdown since they are almost identical to the coverage of the Afghanistan War

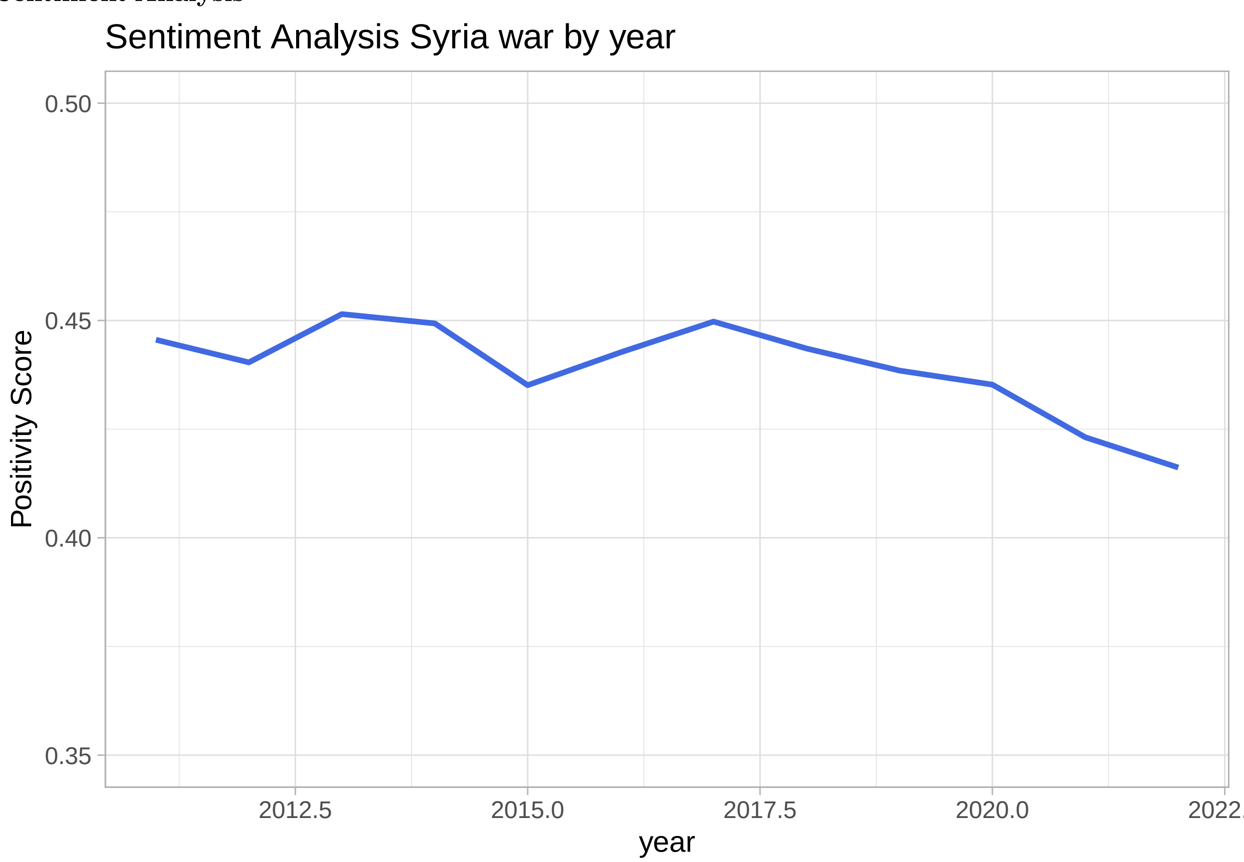
Syria War



Basic Analysis

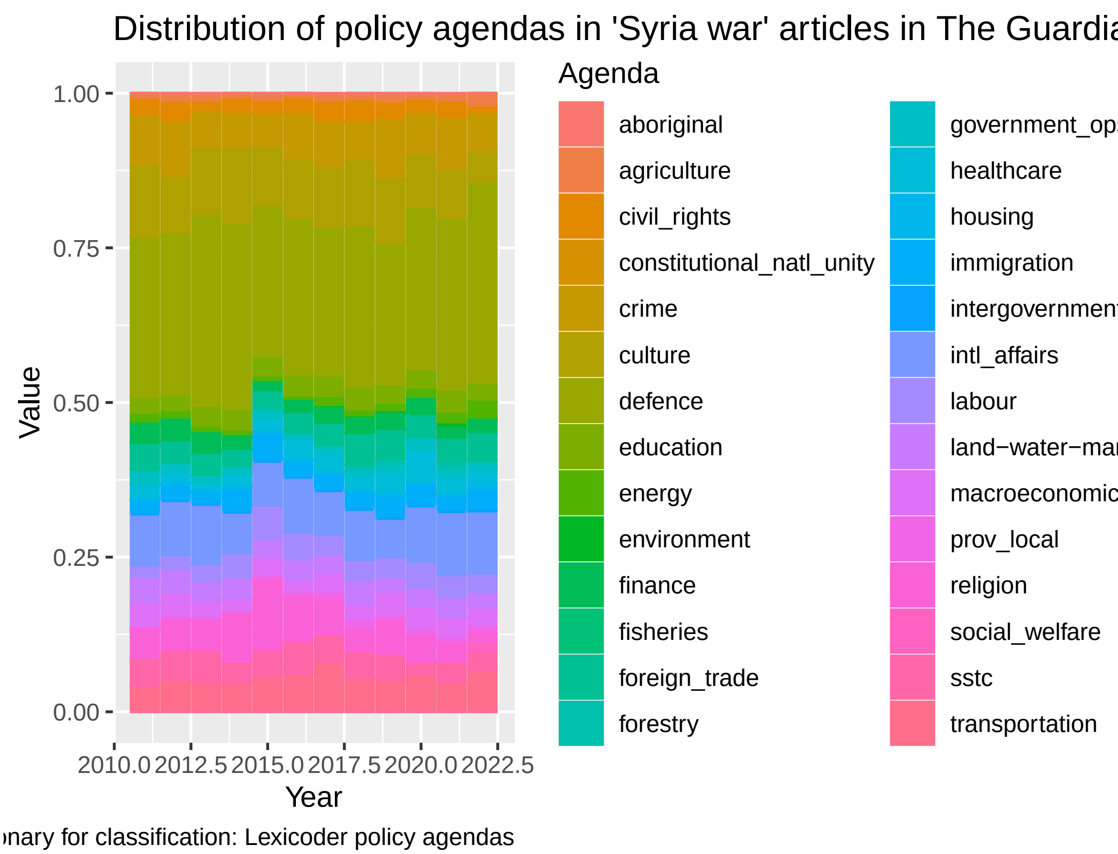


Sentiment Analysis

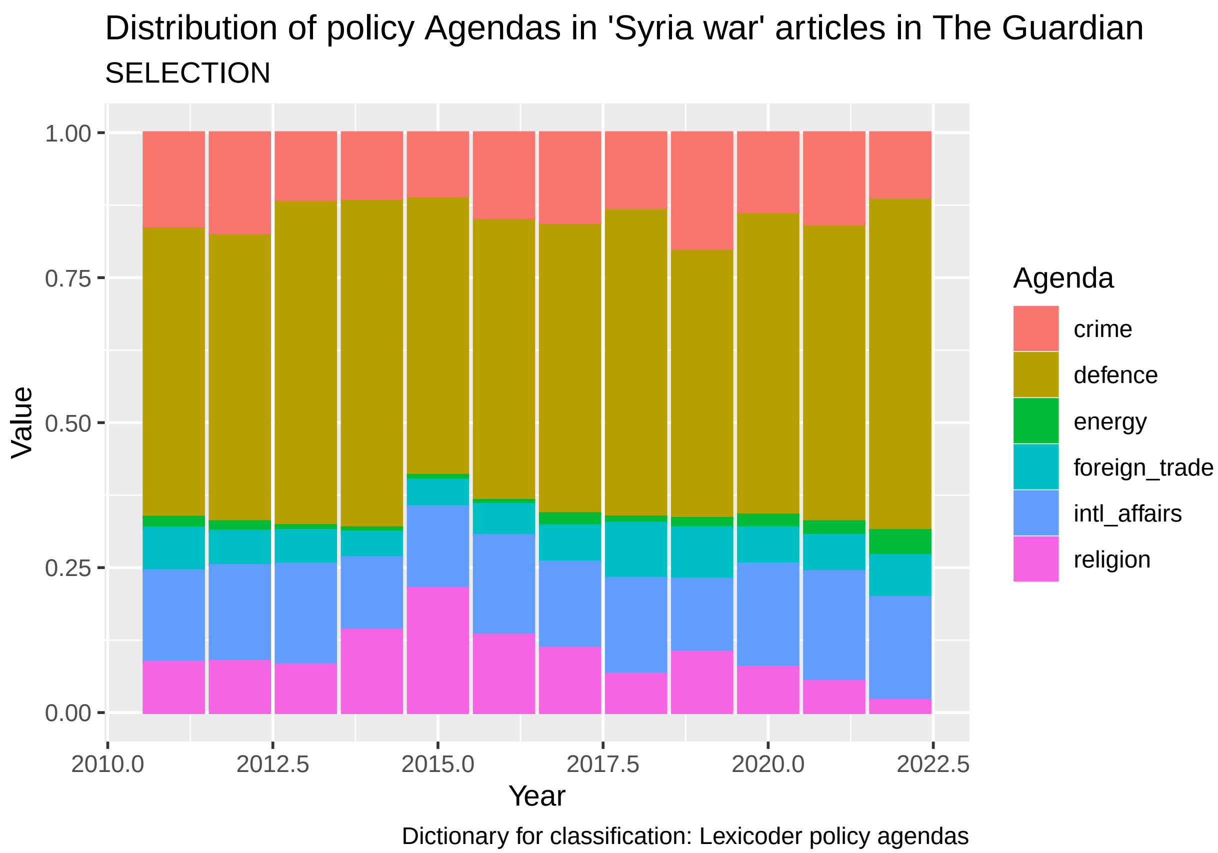


Word Frequency

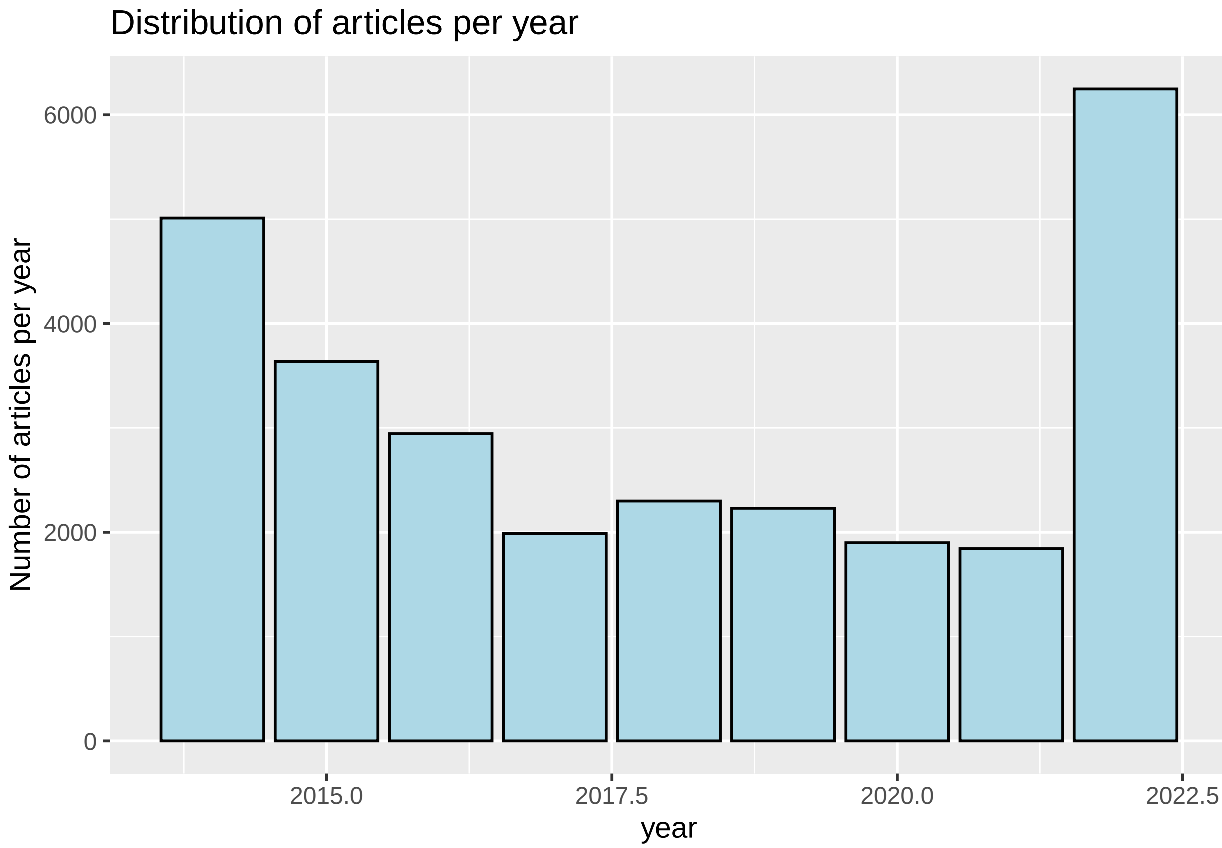
```
##        word frequency
## 1       war      8653
## 2     peopl      6378
## 3    govern      4236
## 4   countri      4181
## 5     syria      4043
## 6     state      3569
## 7      forc      3398
## 8      last      3367
## 9      mani      3014
## 10   report      2909
## 11 militari      2884
## 12    polit      2714
## 13   attack      2683
## 14  support      2617
## 15   nation      2617
## 16   includ      2555
## 17      it'      2545
## 18   presid      2528
## 19     week      2514
## 20   syrian      2465
## 21  russian      2410
## 22     kill      2369
## 23    group      2307
## 24     sinc      2275
## 25    secur      2262
## 26   intern      2243
## 27   famili      2175
## 28   russia      2149
## 29       uk      2146
## 30     told      2092
## 31     iraq      2086
## 32    still      2080
## 33    month      2048
## 34     citi      1992
## 35  british      1985
## 36   minist      1971
## 37   refuge      1912
## 38    power      1899
## 39    chang      1823
## 40  foreign      1788
## 41    fight      1788
## 42      isi      1775
## 43   public      1722
## 44   leader      1713
## 45 children      1698
## 46 conflict      1697
## 47    trump      1696
## 48   offici      1694
## 49      tri      1679
## 50    anoth      1654
```



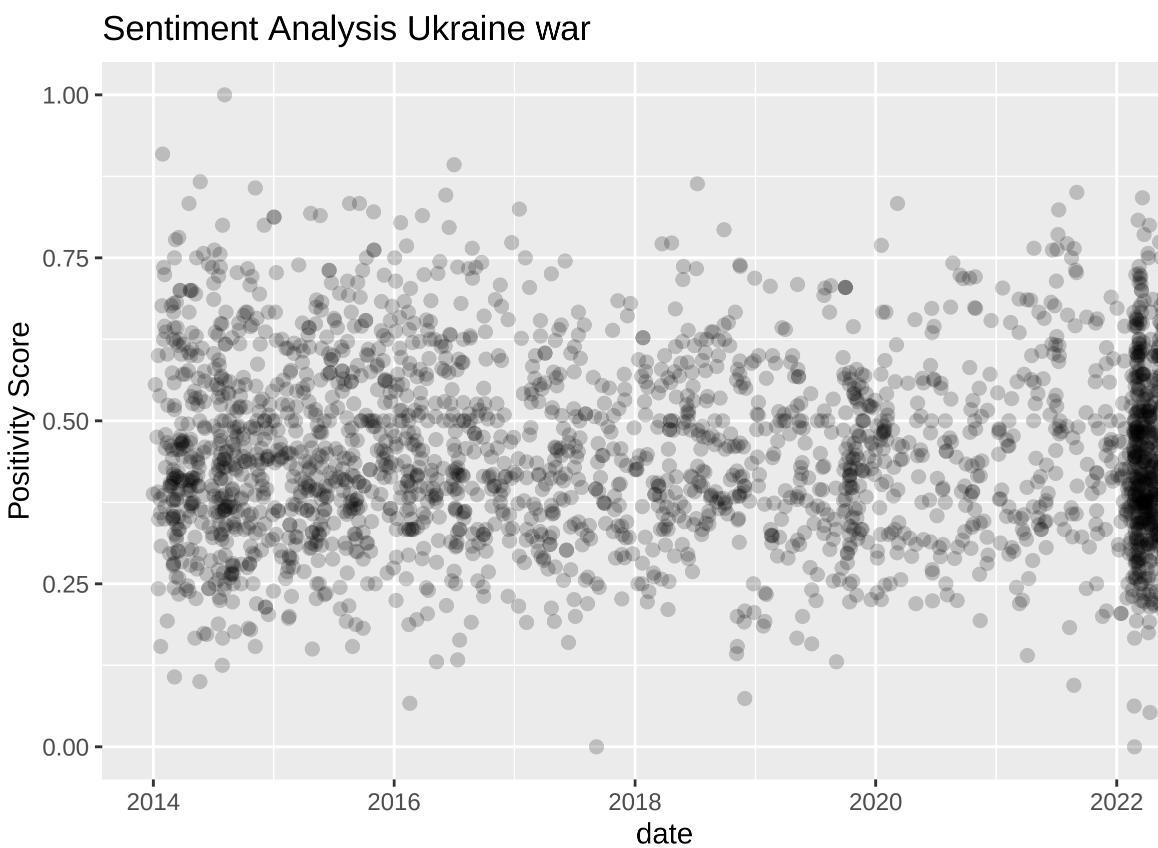
Policy agendas analysis



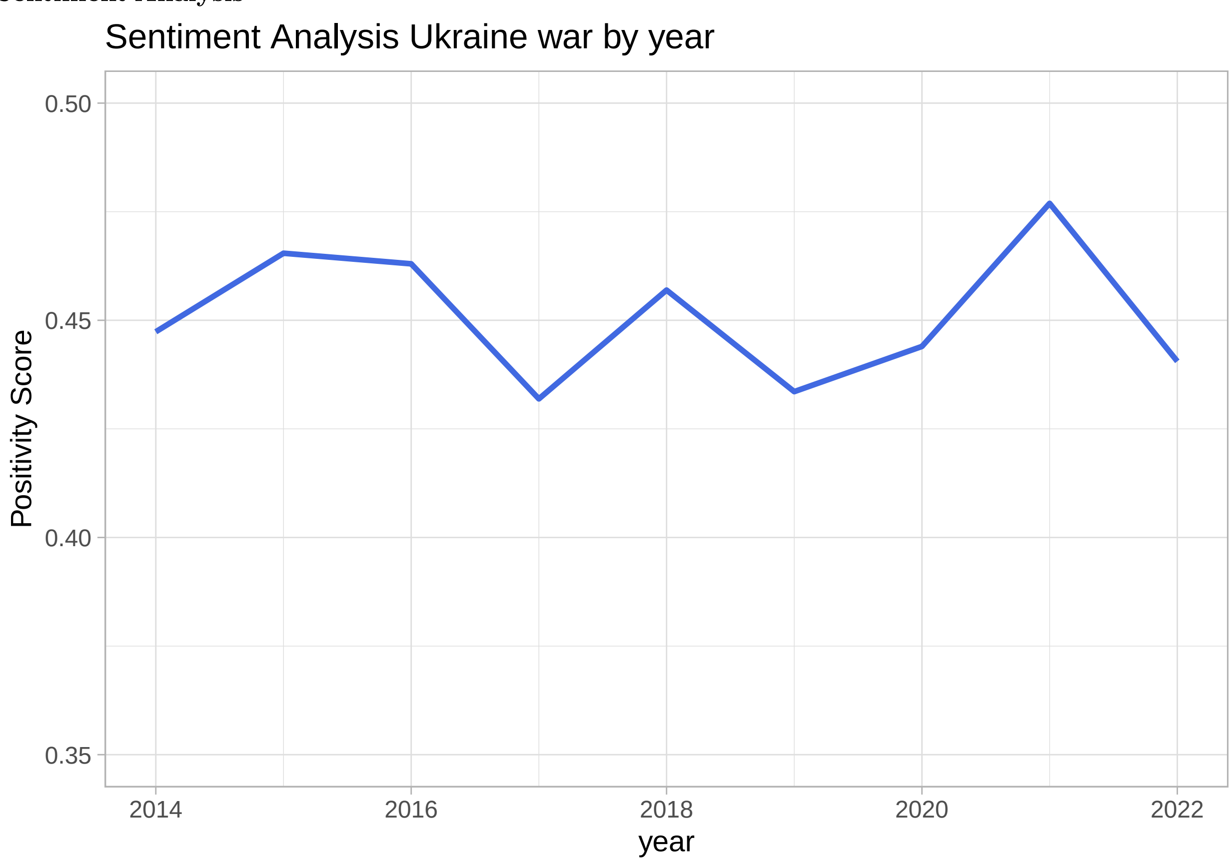
Ukraine War



Basic Analysis

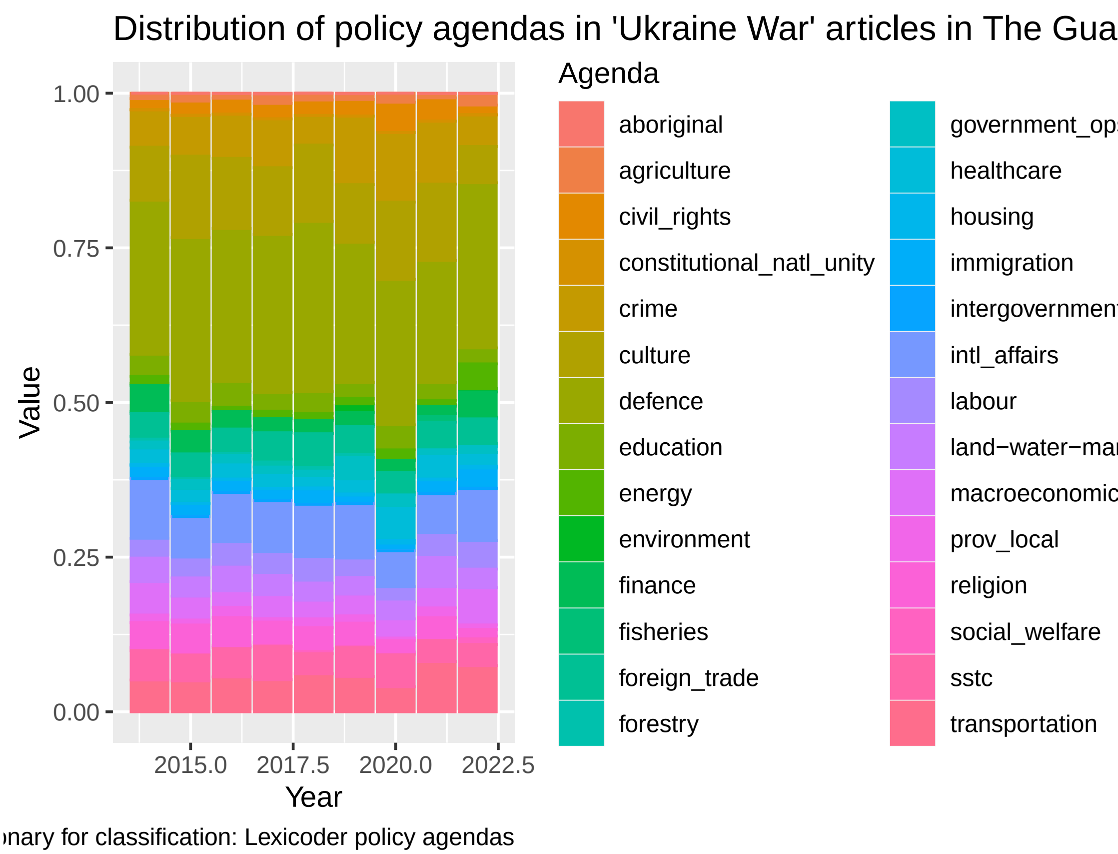


Sentiment Analysis

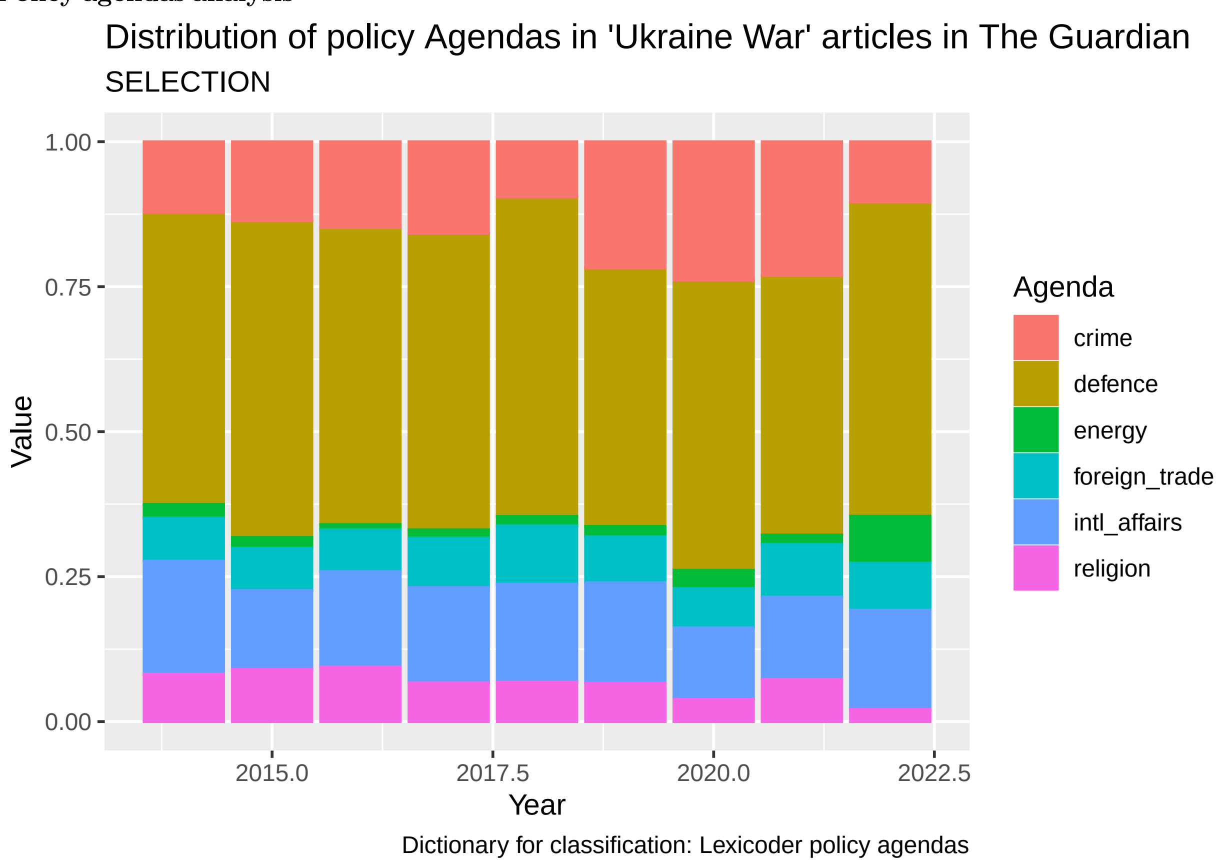


Word Frequency

```
##          word frequency
## 1         war      6385
## 2       peopl      4631
## 3     russian      4139
## 4      ukrain      4133
## 5      russia      3403
## 6     countri      3006
## 7      govern      2988
## 8         it’      2903
## 9        last      2723
## 10     report      2530
## 11      state      2453
## 12     presid      2398
## 13       forc      2390
## 14       mani      2345
## 15     includ      2241
## 16      trump      2226
## 17       week      2149
## 18     nation      2149
## 19      polit      2148
## 20   militari      2064
## 21  ukrainian      2002
## 22    support      1968
## 23         uk      1946
## 24       sinc      1732
## 25      still      1705
## 26      putin      1692
## 27     intern      1646
## 28      group      1631
## 29     minist      1581
## 30      secur      1578
## 31       hous      1578
## 32       told      1577
## 33      power      1563
## 34     public      1547
## 35      month      1543
## 36       citi      1516
## 37     former      1496
## 38     leader      1460
## 39    british      1425
## 40     offici      1420
## 41     attack      1374
## 42     famili      1373
## 43      chang      1373
## 44    foreign      1371
## 45      don’t      1367
## 46      anoth      1328
## 47      start      1320
## 48      parti      1318
## 49       kill      1312
## 50      elect      1301
```



Policy agendas analysis



New York Times

URL generator for the New York Times API

```r
nyt_key = read_lines("nyt_key.txt")

nyt_url <- function(search_word, date_from='', date_to='') {
  search_word <- str_replace(search_word, ' ', '%20')

  if (date_from == '' | date_to == '') {
    url <- paste0('http://api.nytimes.com/svc/search/v2/articlesearch.json?q=', search_word,
                  '&api-key=', nyt_key, sep='')
  } else {
    url <- paste0('http://api.nytimes.com/svc/search/v2/articlesearch.json?q=', search_word,
                  '&begin_date=', date_from, '&end_date=', date_to,
                  '&api-key=', nyt_key, sep='')
  }
  url

}
```

Afghanistan War

```r

nyt_afgh_list <- vector("list")

counter <- 1

# in the NYT API it is only possible to search until page 200

for (year in 1999:2022) {
  Sys.sleep(6)
  base_url <- nyt_url('afghanistan war', paste0(year, '-01-01'),
                           paste0(year, '-12-31'))
  print(base_url)
  n_results <- fromJSON(base_url) %>% .$response %>% .$meta %>% .$hits
  max_pages <-  ceiling(((n_results / 10)-1))

  if (max_pages > 200) {
    max_pages <- 200
  } else {}

  print(year)

  for(i in 1:(max_pages/10)){
      tryCatch({
      print(i)
      url <- paste0(base_url, "&page=", i, sep='')
        NYTSearch <- fromJSON(url, flatten = TRUE) %>%
          data.frame(.,stringsAsFactors = FALSE)
      nyt_afgh_list[[counter]] <- NYTSearch
      counter <- counter + 1
      Sys.sleep(6)
      }, error=function(e){
        message(paste0("Error at ", year, " Page:", i))
```

```
      })
  }

}

nyt_afgh_results <- rbind_pages(nyt_afgh_list)

save(nyt_afgh_results, file = "Data/nyt_afgh_results.RData")
```

Get Data

```
load("Data/nyt_afgh_results.RData")

glimpse(nyt_afgh_results)

# basic data cleaning and selection of important variables

nyt_afgh <- nyt_afgh_results %>%
  filter(response.docs.type_of_material == "News")%>%
  select(abstract = response.docs.abstract,
         date = response.docs.pub_date,
         keywords = response.docs.keywords,
         url = response.docs.web_url,
         word_count = response.docs.word_count,
         headline = response.docs.headline.main,
         id = response.docs._id,
         hits_year = response.meta.hits )

summary(nyt_afgh$word_count)

nyt_afgh <- nyt_afgh %>%
  filter(word_count >=50)

nyt_afgh$date <- nyt_afgh$date %>%
  gsub("T.*",
       "", .) %>%
  as.Date

nyt_afgh$year <- nyt_afgh$date %>%
  gsub("([0-9]{4}).*",
       "\\1", .) %>% as.numeric

glimpse(nyt_afgh)

save(nyt_afgh, file = "Data/nyt_afgh.RData")
```

Data Cleaning

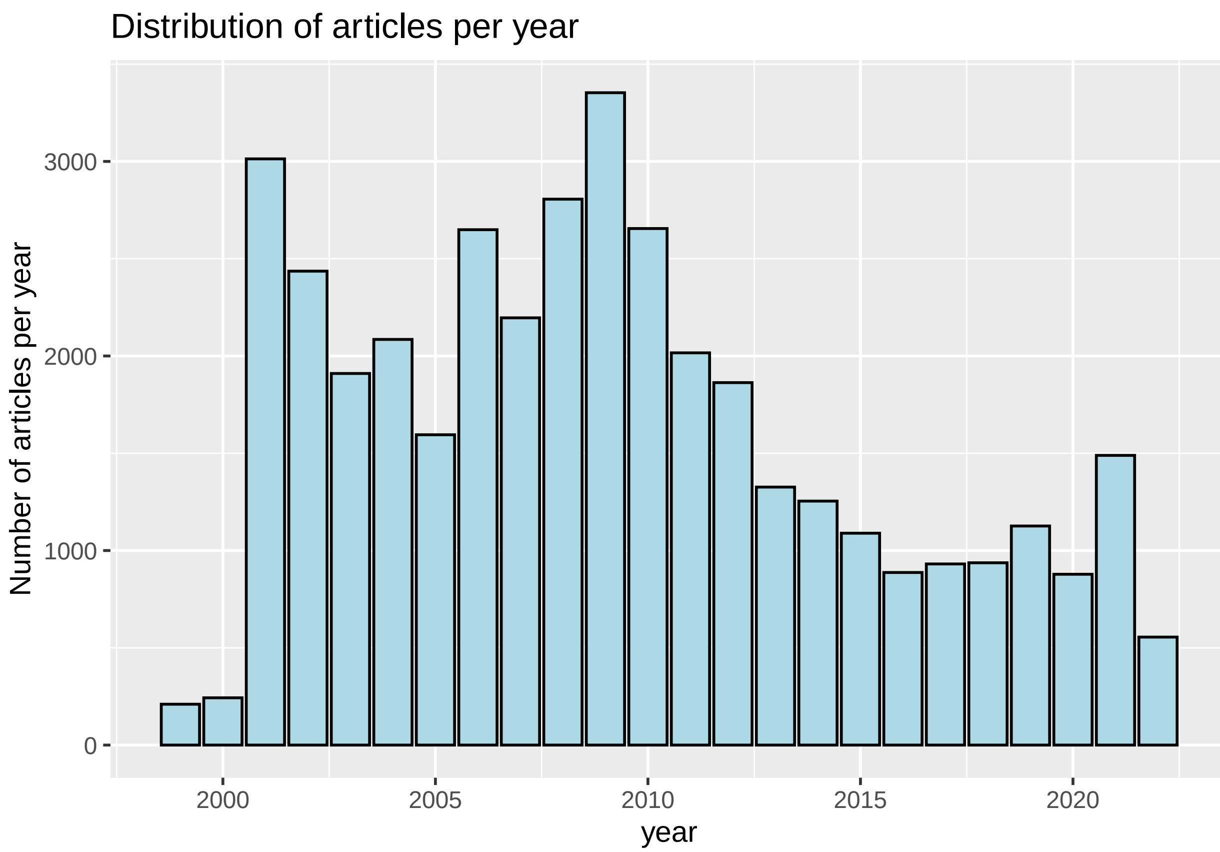
```
load("Data/nyt_afgh.RData")

# the NYT API does not automatically include the article text. That's why I had to write a script to au
```

```
# Some sites are no longer available
# That's why I need to remove the article at position 978

nyt_afgh <- nyt_afgh[-c(978),]

article_text <- vector("list")
count <- 1
error_tries <- 0


while(count <= length(nyt_afgh$url)) {
  tryCatch({
  url = nyt_afgh$url[count]
  raw <- read_html(url)
  text <- html_nodes(raw, "section p") %>% html_text() %>% paste(., collapse=" ")
  article_text[[count]] <- text
  print(count)
  count <- count + 1
  }, error=function(e){
        message(paste0("Error at ", count))
        if (error_tries == 0) {
          error_tries <- error_tries + 1
          Sys.sleep(30)
        } else {
          article_text[[count]] <- NA
          error_tries <- 0
          count <- count + 1
        }
      })
}




nyt_afgh$text <- article_text %>% as.character

glimpse(nyt_afgh)
head(nyt_afgh)

nyt_afgh <- nyt_afgh %>% filter(!is.na(nyt_afgh$text))

save(nyt_afgh, file = "Data/nyt_afgh.RData")
```

Get Full articles

```
load("Data/nyt_afgh.RData")

# Create a histogram to show the distribution of articles

nyt_afgh_hist <- ggplot(nyt_afgh, aes(x=date))+
  geom_histogram(fill="lightblue", color="black", binwidth = 200)
# nyt_afgh_hist
```

```
nyt_afgh_hist_year <- nyt_afgh[!duplicated(nyt_afgh[ , c("hits_year")]), ] %>%
  select(hits_year, year) %>%
  ggplot(aes(x=year, y=hits_year))+
  geom_bar(stat='identity', fill = "lightblue", color="black")+
  labs(title = "Distribution of articles per year", y="Number of articles per year")
nyt_afgh_hist_year
```



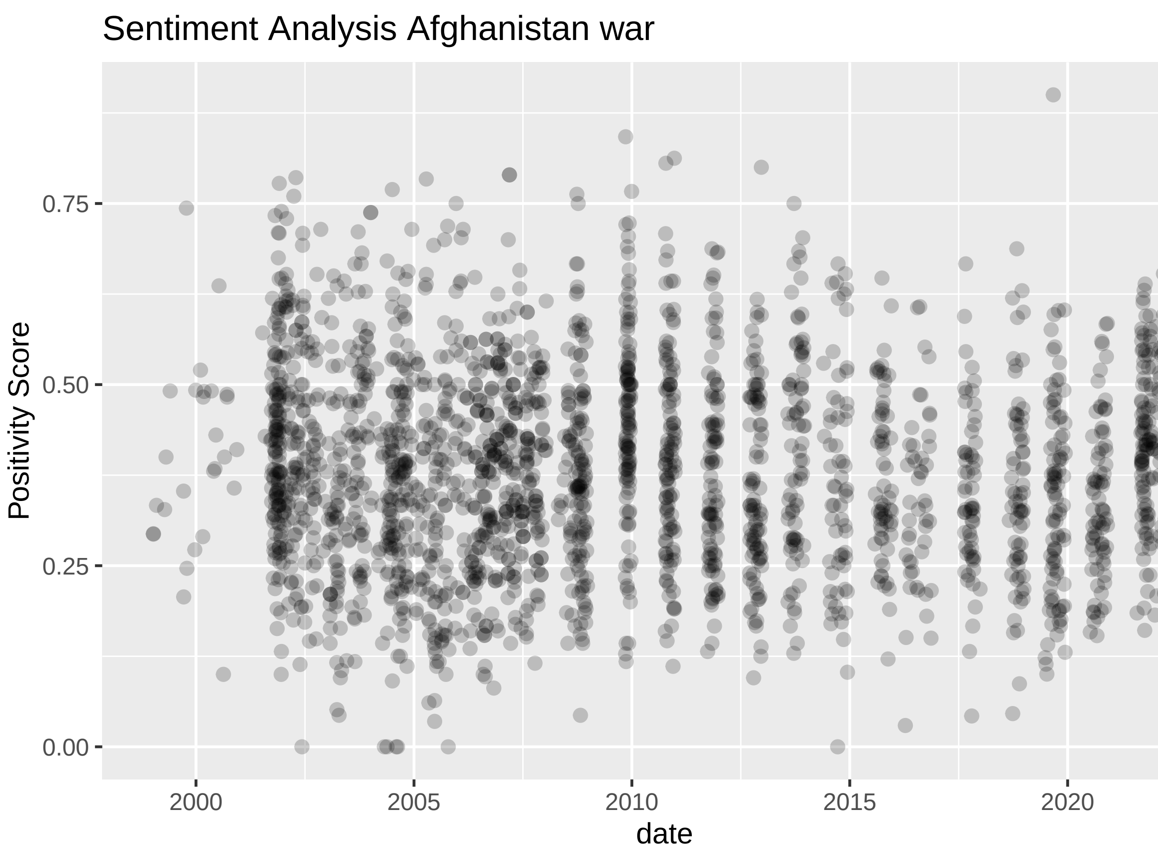
Basic Analysis

```
load("Data/nyt_afgh.RData")

nyt_afgh_corpus <- corpus(nyt_afgh,
                          text_field = "text")

summary(nyt_afgh_corpus) %>% head
docvars(nyt_afgh_corpus) %>%
  head

nyt_afgh_corpus[1]


nyt_afgh_toks <- tokens(nyt_afgh_corpus,
                        what = c("word"),
                        remove_separators = TRUE,
                        include_docvars = TRUE,
                        ngrams = 1L,
```

```r
                    remove_numbers = FALSE,
                    remove_punct = TRUE,
                    remove_symbols = FALSE,
                    remove_hyphens = FALSE)

# nyt_afgh_toks %>% head

nyt_afgh_toks <- nyt_afgh_toks %>%
  tokens_tolower %>%
  tokens_remove(stopwords("english"), padding = TRUE) %>%
  tokens_remove("") %>%
  tokens_wordstem(language = "english")

save(nyt_afgh_toks, file = "Data/nyt_afgh_toks.RData")
```

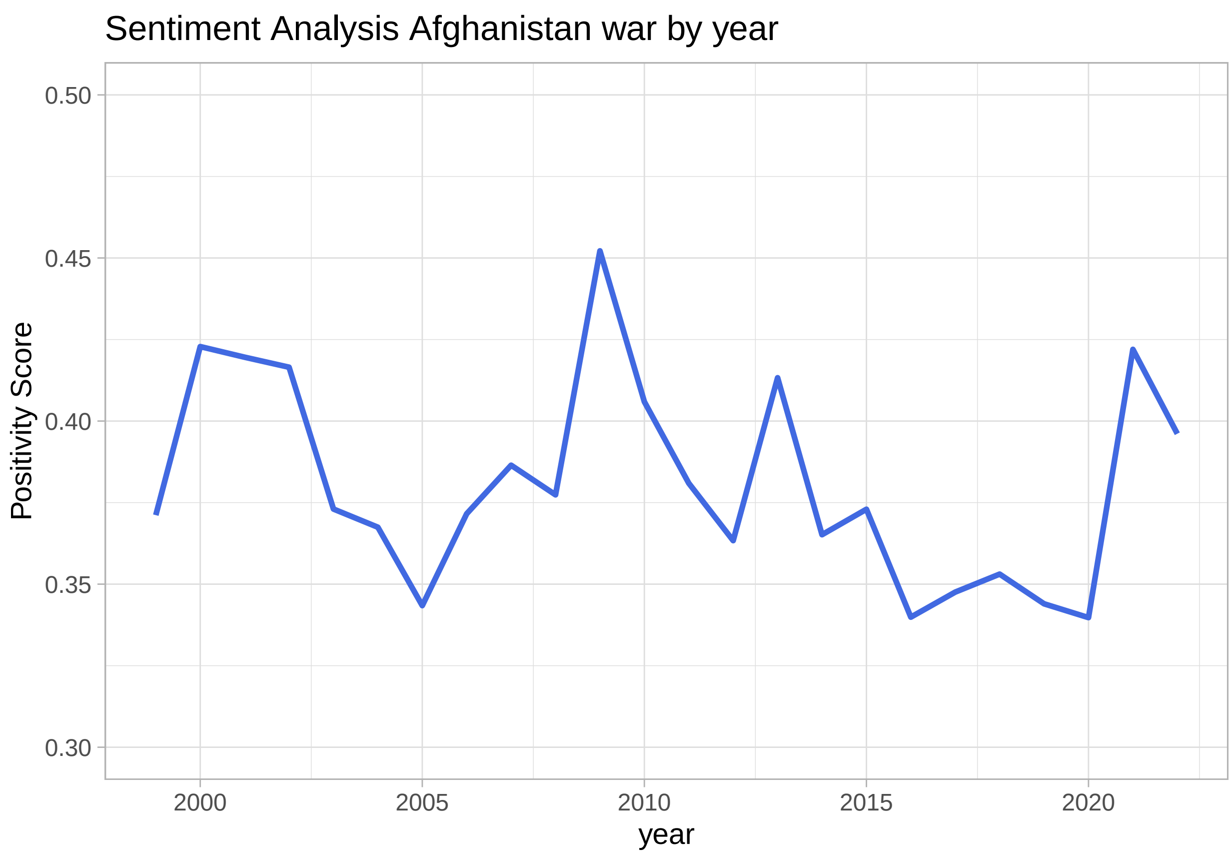
Create a corpus and tokens

```r
load("Data/nyt_afgh_toks.RData")
load("Data/nyt_afgh.RData")

# make a sentiment analysis on the ratio of positive to negative words in each article

nyt_afgh_toks_sent <- tokens_lookup(nyt_afgh_toks,
                                    dictionary =  data_dictionary_LSD2015[1:2])
# nyt_afgh_toks_sent %>% head

nyt_afgh_dfm_sent <- dfm(nyt_afgh_toks_sent)
# nyt_afgh_dfm_sent %>% head

nyt_afgh_pos_neg <- nyt_afgh_dfm_sent %>% convert(.,to = "data.frame") %>%
  mutate(pos_to_neg = positive / (positive + negative))

# summary(nyt_afgh_pos_neg)
#nyt_afgh_pos_neg %>% filter(is.na(nyt_afgh_pos_neg$pos_to_neg))
# 1 NA in year 2002
# Row has 0 negative and 0 positive -> NaN -> discard

nyt_afgh_sent <- nyt_afgh

nyt_afgh_sent$pos_neg <- nyt_afgh_pos_neg$pos_to_neg
nyt_afgh_sent <- nyt_afgh_sent %>% filter(!is.na(nyt_afgh_sent$pos_neg))

plot_nyt_afgh_sent <- ggplot(nyt_afgh_sent, aes(x=date, y=pos_neg))+
  geom_point(size=2, alpha=0.2)+
  labs(title = "Sentiment Analysis Afghanistan war", y="Positivity Score")
plot_nyt_afgh_sent
```



Sentiment Analysis

```
nyt_afgh_by_year <- nyt_afgh_sent$pos_neg %>%
  aggregate(by=list(nyt_afgh_sent$year), FUN = mean) %>% rename(year = Group.1,
                                                                 pos_neg = x)
# nyt_afgh_by_year

plot_nyt_afgh_pos_by_year <- ggplot(nyt_afgh_by_year, aes(x=year, y=pos_neg))+
  geom_line(color="royalblue", size=1, aes(group=1))+
  theme_light()+
  ylim(0.3, 0.5)+
  labs(title = "Sentiment Analysis Afghanistan war by year", y="Positivity Score")
plot_nyt_afgh_pos_by_year
```



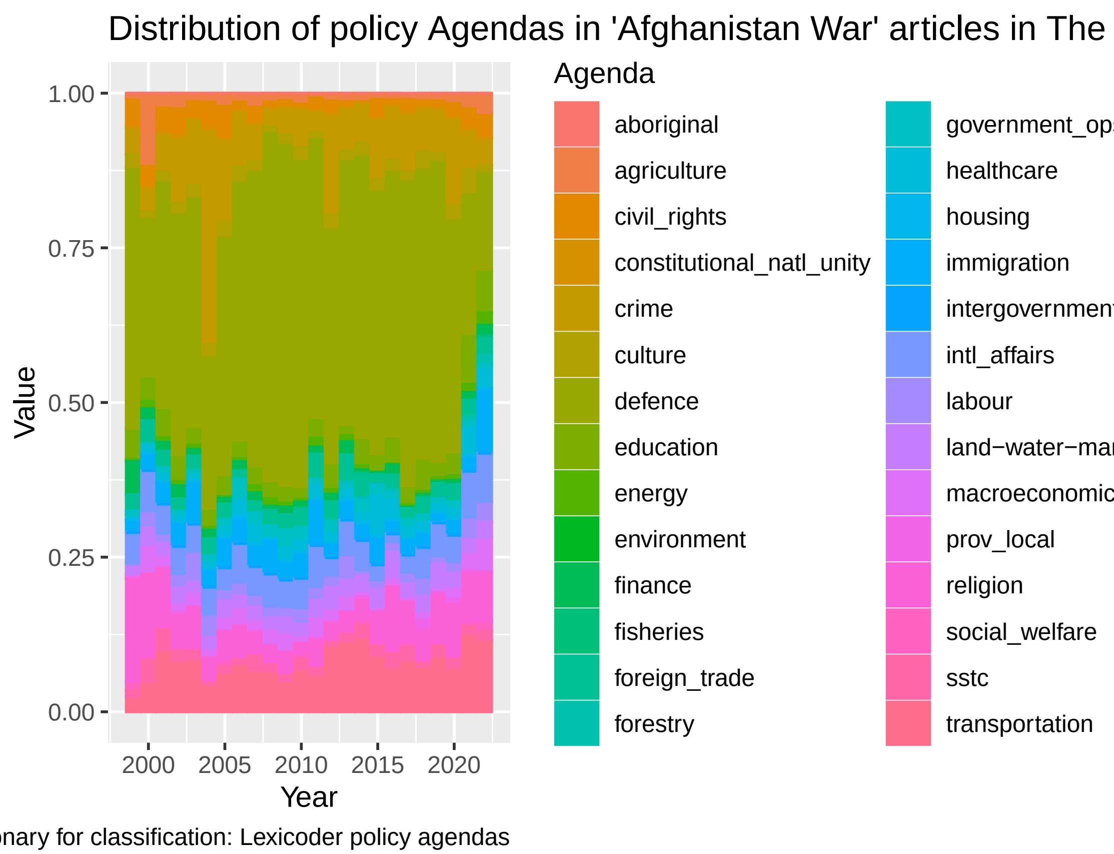

```r
load("Data/nyt_afgh_toks.RData")


# load list with the most common words in English to remove them from the tokens

common_words <- read.delim("Data/1-1000.txt", header = FALSE) %>%
  head(200) %>%
  as.vector()
common_words <- common_words$V1

# removing the top 200 words from the tokens
nyt_afgh_toks_wordcount <- nyt_afgh_toks %>%
  tokens_remove(common_words)

nyt_afgh_dfm <- dfm(nyt_afgh_toks_wordcount)



nyt_afgh_topwords <- topfeatures(nyt_afgh_dfm, 50) %>%
  data.frame(word=names(.),
             frequency =.,
             row.names = c())

nyt_afgh_topwords
```

Word Frequency

```
##            word frequency
## 1  afghanistan     14545
## 2           mr     14062
## 3      taliban     13057
## 4       afghan     12378
## 5     american     11601
## 6         forc      9155
## 7       offici      9132
## 8         kill      8058
## 9     militari      7268
## 10        unit      7096
## 11       state      6519
## 12      govern      6460
## 13      attack      5750
## 14         war      5469
## 15       secur      5239
## 16       troop      5203
## 17     countri      4602
## 18       peopl      4559
## 19       polic      4410
## 20       offic      4392
## 21     soldier      4292
## 22       kabul      4176
## 23     provinc      4101
## 24      presid      3905
## 25     command      3835
## 26      nation      3788
## 27      report      3700
## 28    civilian      3311
## 29        last      3276
## 30        mani      3176
## 31        oper      3119
## 32     general      3081
## 33    pakistan      3080
## 34       month      2875
## 35      member      2862
## 36       fight      2843
## 37      includ      2819
## 38    district      2764
## 39        nato      2758
## 40      karzai      2686
## 41       group      2664
## 42        area      2617
## 43        base      2583
## 44        week      2546
## 45        iraq      2530
## 46      insurg      2471
## 47     support      2401
## 48        bomb      2355
## 49        armi      2352
## 50      leader      2313
```

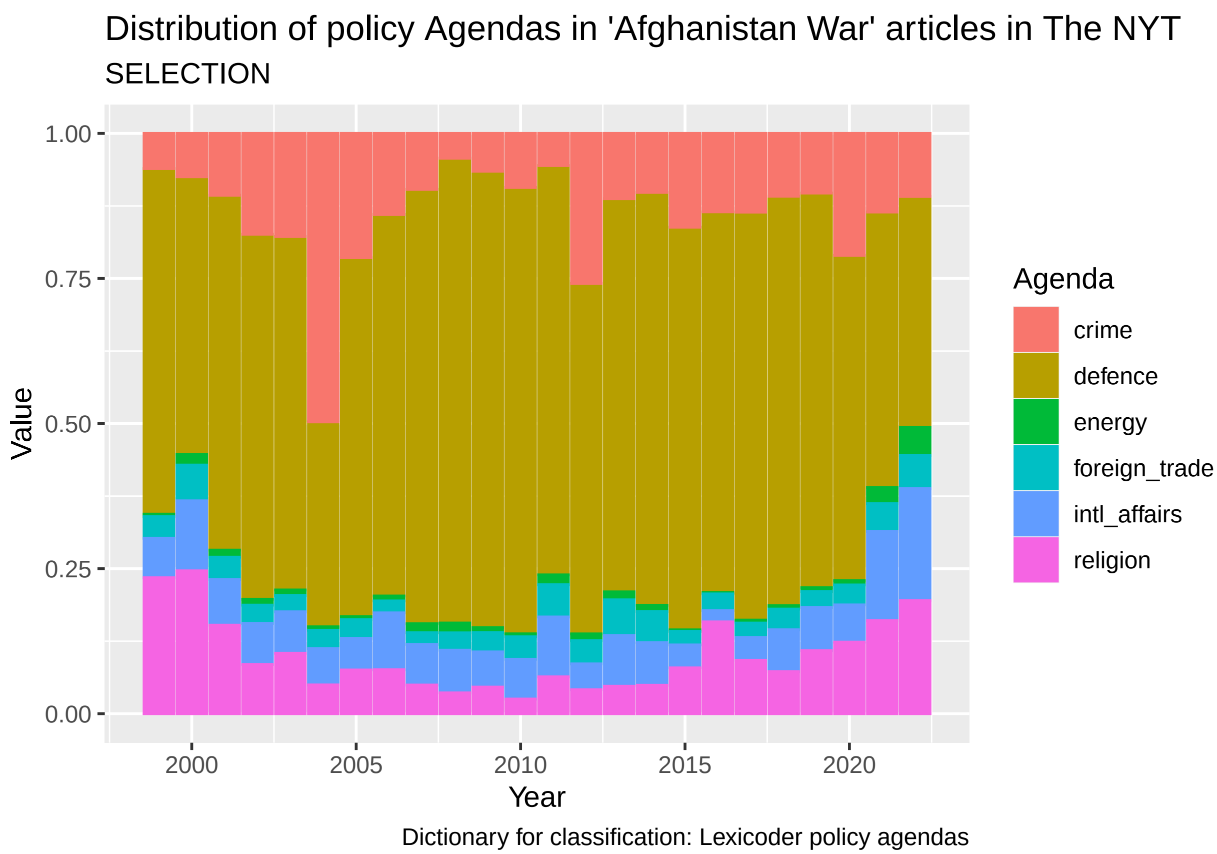
```
save(nyt_afgh_dfm, file = "Data/nyt_afgh_dfm.RData")
```

```

load("Data/nyt_afgh_toks.RData")
load("Data/nyt_afgh.RData")

# Load the Lexicoder policy agendas
policyagendas <- dictionary(file = "Data/policy_agendas_english.lcd")

# lookup the policy agendas dictionary and give each article a score
nyt_afgh_toks_pol <- tokens_lookup(nyt_afgh_toks, dictionary = policyagendas)
nyt_afgh_pol <- dfm(nyt_afgh_toks_pol) %>%
  convert(to = "data.frame") %>%
  select(-doc_id)

# divide the values for each row through the sum of each row to get relative values for the agendas for
nyt_afgh_pol <- nyt_afgh_pol / rowSums(nyt_afgh_pol)

nyt_afgh_pol$year <- nyt_afgh$year

nyt_afgh_pol <- drop_na(nyt_afgh_pol)

nyt_afgh_pol_by_year <- nyt_afgh_pol %>%
  group_by(year) %>%
  summarise_each(funs = sum)

# Plot the results to better inspect them
nyt_afgh_pol_by_year_plot1 <- nyt_afgh_pol_by_year %>%
  pivot_longer(cols = 2:29, names_to = "Agenda") %>%
  ggplot(aes(x=year, y=value, colour = Agenda, fill = Agenda))+
  geom_bar(position="fill", stat="identity")+
  labs(x="Year", y="Value", title="Distribution of policy Agendas in 'Afghanistan War' articles in The N
       caption = "Dictionary for classification: Lexicoder policy agendas")
nyt_afgh_pol_by_year_plot1
```



Policy agendas analysis

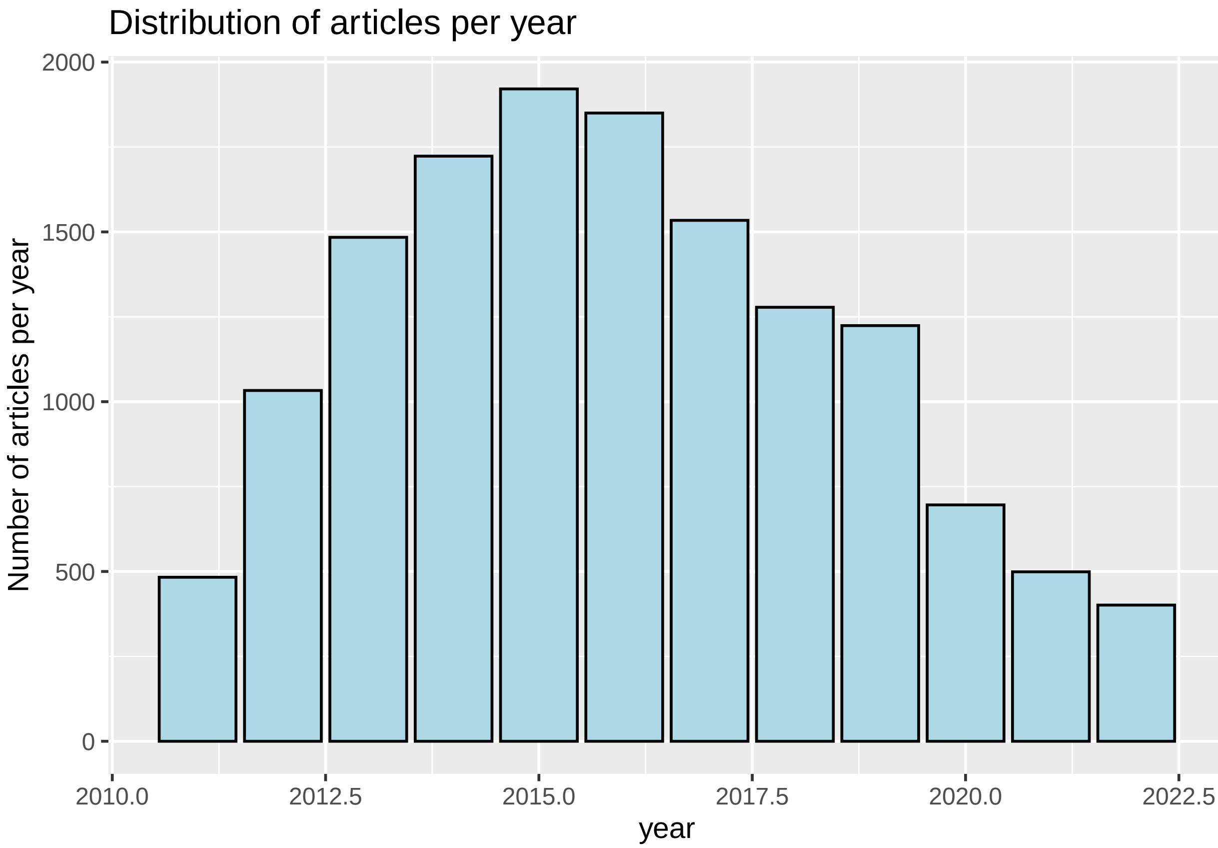
```
# select some agendas which seam important
nyt_afgh_pol_by_year_plot_select <- nyt_afgh_pol_by_year %>%
  select(year, defence, energy, foreign_trade, intl_affairs, religion, crime) %>%
  pivot_longer(cols = 2:7, names_to = "Agenda") %>%
  ggplot(aes(x=year, y=value, colour = Agenda, fill = Agenda))+
  geom_bar(position="fill", stat="identity")+
  labs(x="Year", y="Value", title="Distribution of policy Agendas in 'Afghanistan War' articles in The N
       subtitle = "SELECTION", caption = "Dictionary for classification: Lexicoder policy agendas")
nyt_afgh_pol_by_year_plot_select
```



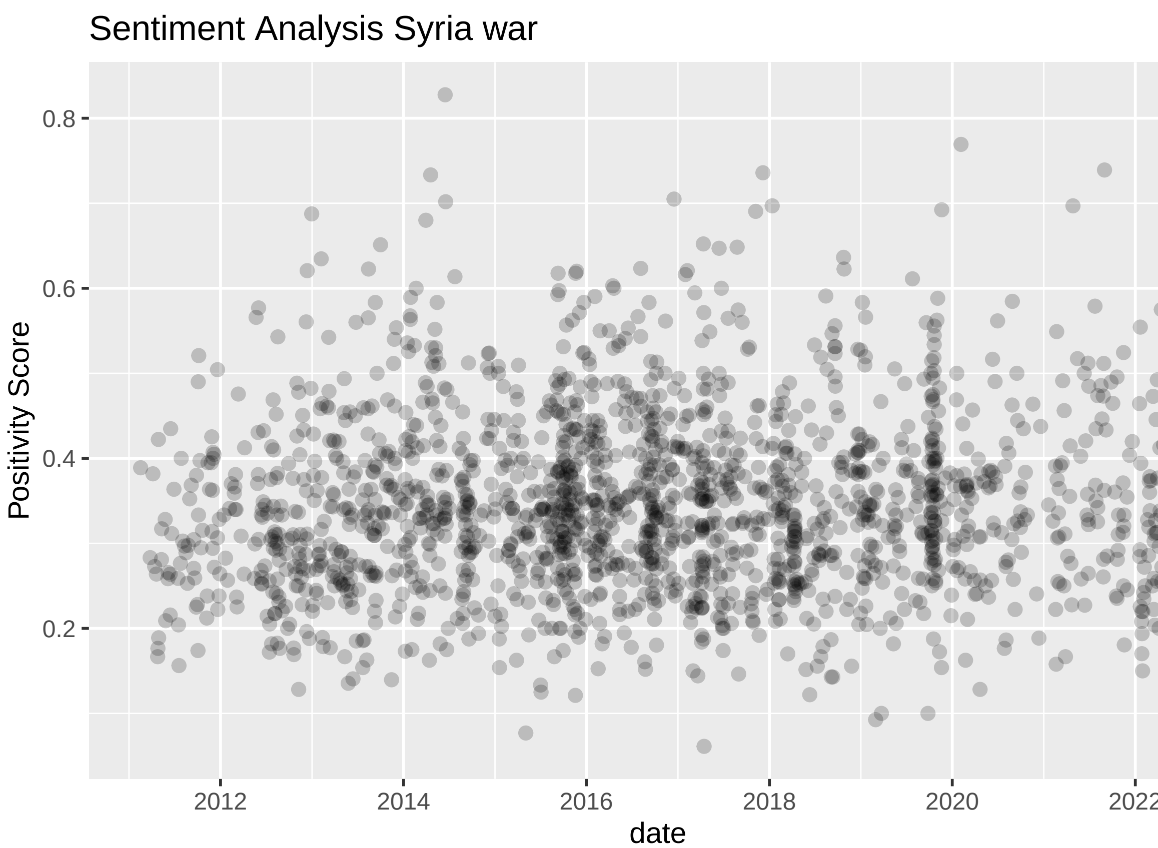

```r
# nyt_afgh_pol_by_year

save(nyt_afgh_pol, file = "Data/nyt_afgh_pol.RData")
```

The code for the other wars are not included in the rendered markdown since they are almost identical to the coverage of the Afghanistan War

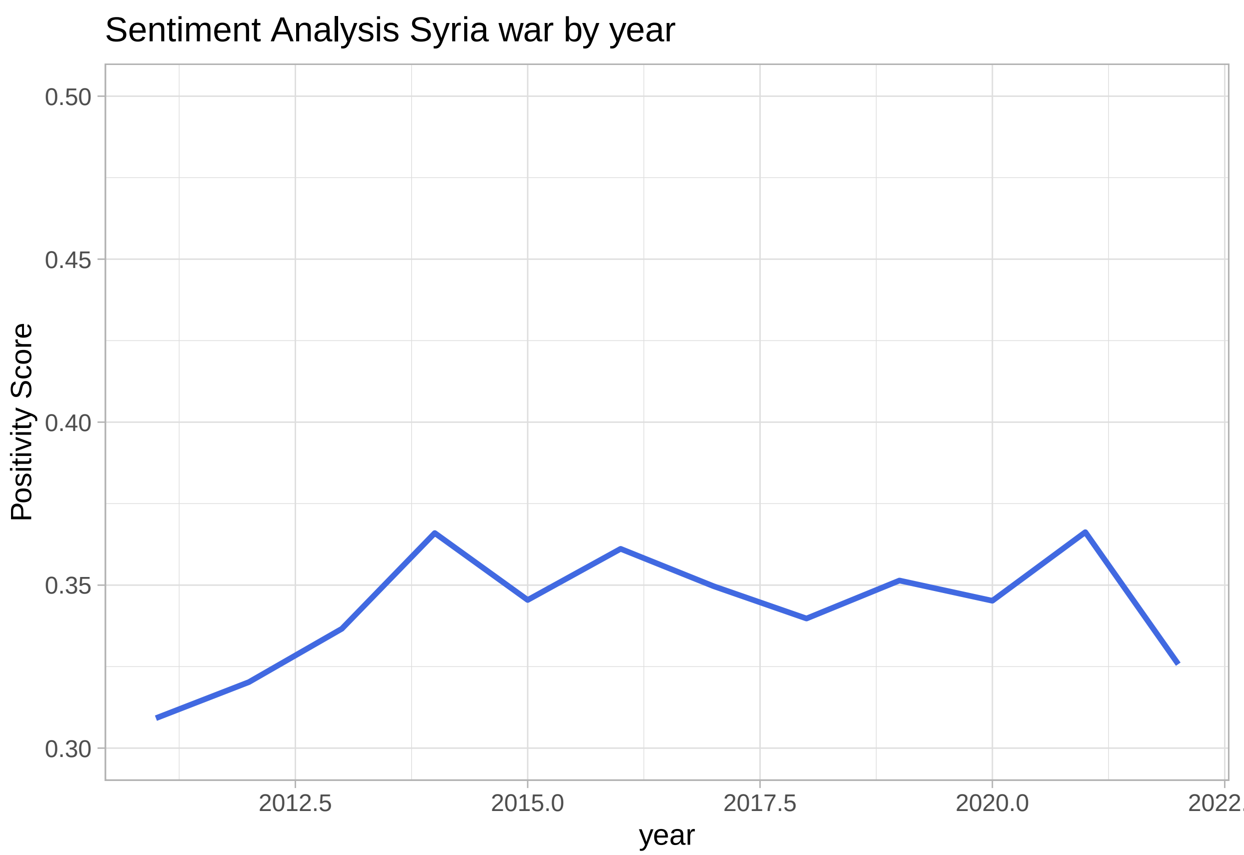
Syria War



Basic Analysis

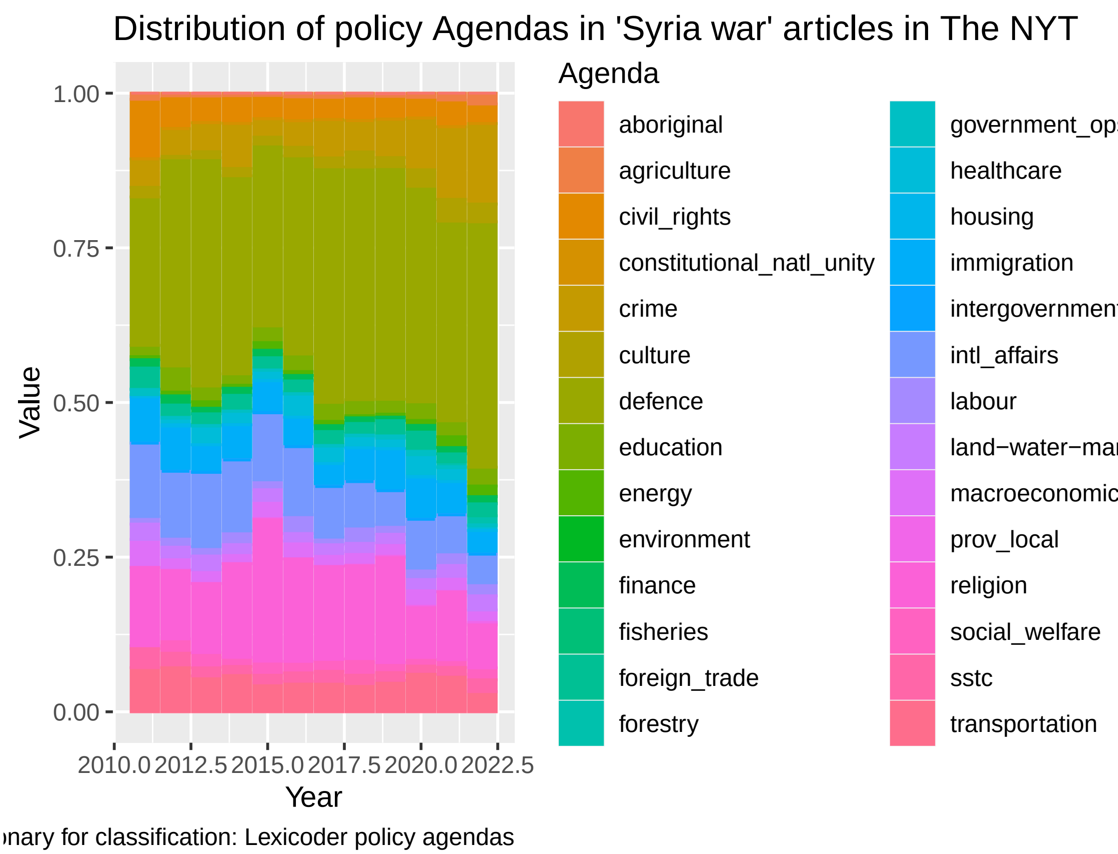


Sentiment Analysis

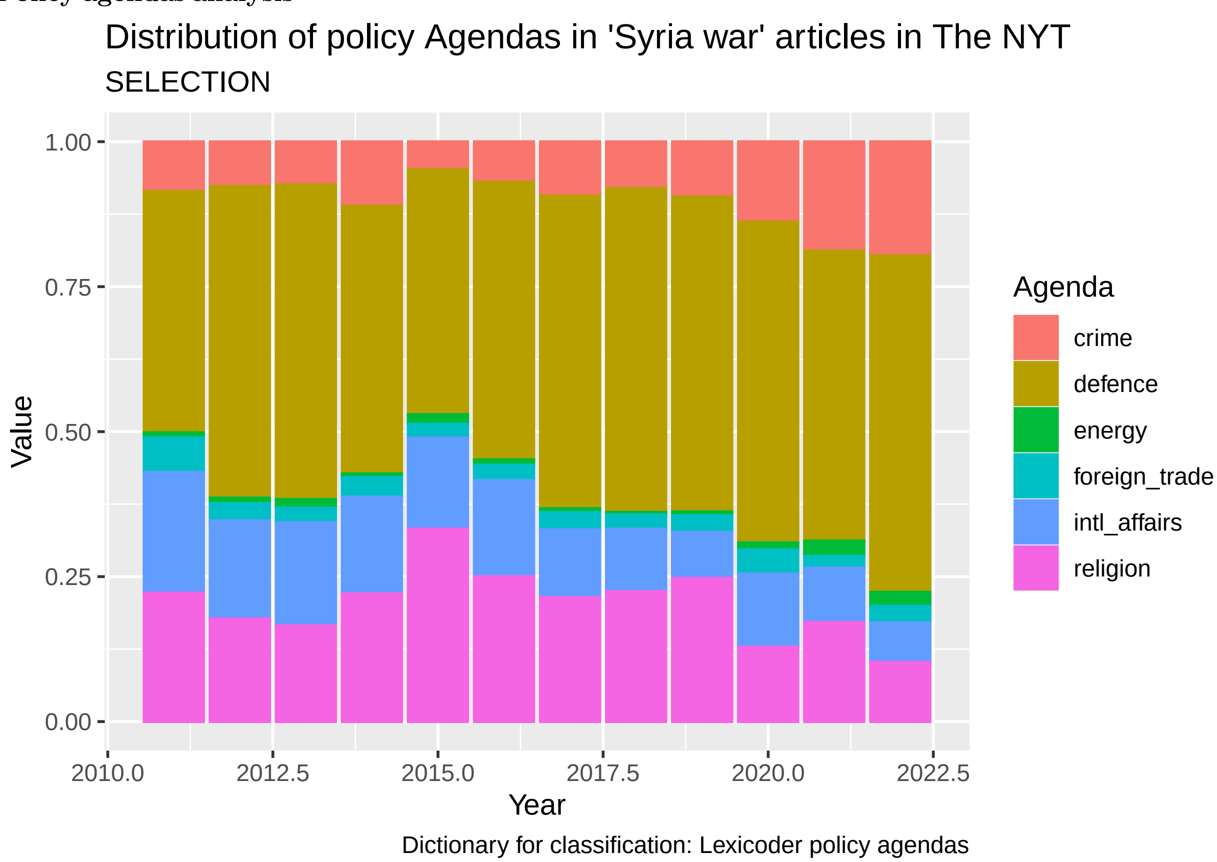


Word Frequency

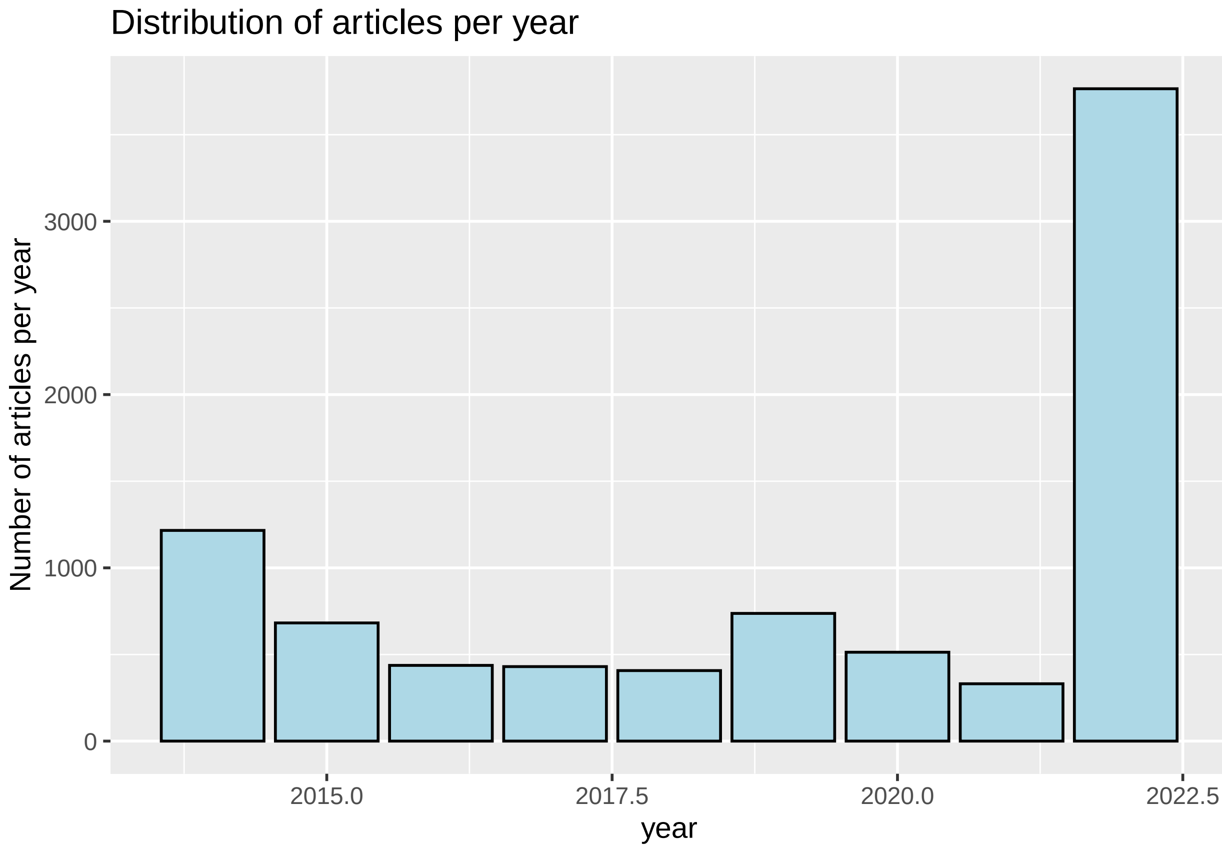
```
##          word frequency
## 1          mr     16331
## 2       syria     13811
## 3      syrian     13380
## 4       state     12456
## 5         war      9061
## 6      govern      8872
## 7        unit      8298
## 8        forc      8062
## 9       group      6747
## 10   american      5466
## 11      islam      5425
## 12      peopl      5089
## 13     offici      4952
## 14   militari      4886
## 15      rebel      4754
## 16     presid      4655
## 17   conflict      4379
## 18     attack      4331
## 19    countri      4244
## 20       kill      4134
## 21     russia      4127
## 22     turkey      3980
## 23      fight      3932
## 24     nation      3922
## 25        arm      3742
## 26     report      3558
## 27    russian      3552
## 28       mani      3514
## 29   al-assad      3414
## 30    support      3346
## 31    kurdish      3265
## 32     weapon      3228
## 33    fighter      3224
## 34       iraq      3163
## 35       took      2977
## 36      secur      2898
## 37       last      2796
## 38      assad      2777
## 39       area      2762
## 40  territori      2687
## 41     includ      2663
## 42       bomb      2643
## 43     syria'      2551
## 44      began      2551
## 45     refuge      2522
## 46       iran      2511
## 47     chemic      2484
## 48    control      2474
## 49    foreign      2466
## 50       citi      2385
```



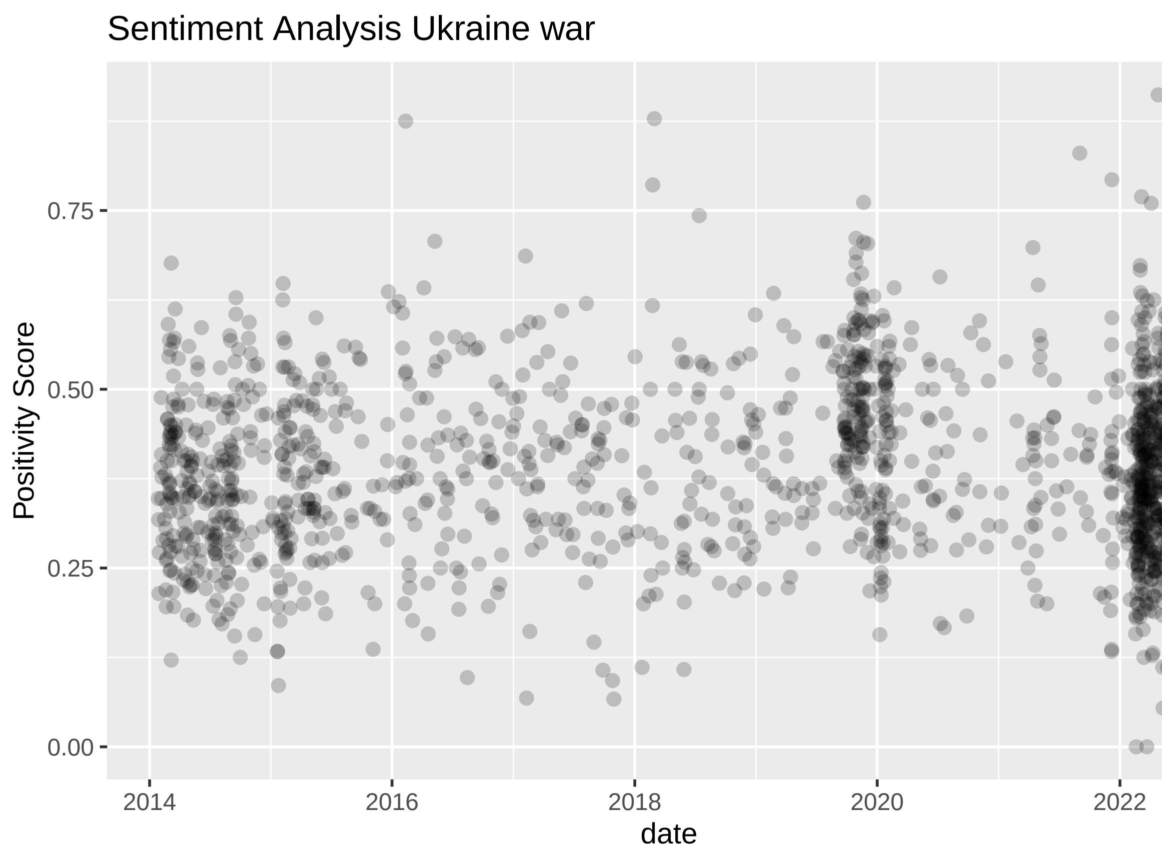
Policy agendas analysis



Ukraine War



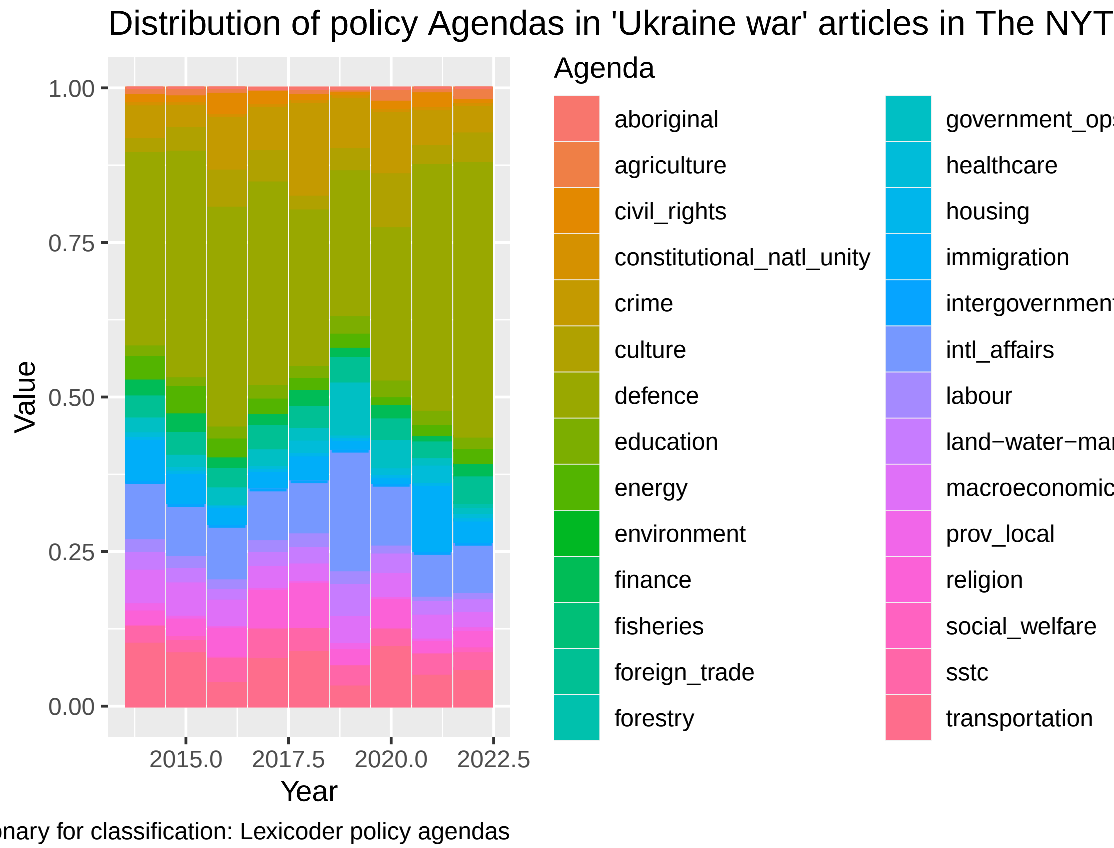
Basic Analysis



Sentiment Analysis

Word Frequency

```
##          word frequency
## 1          mr     17994
## 2      ukrain     12122
## 3     russian     10170
## 4      russia      8335
## 5   ukrainian      7868
## 6         war      6078
## 7      presid      6025
## 8       state      5116
## 9    militari      4427
## 10     offici      4247
## 11       unit      3956
## 12      putin      3557
## 13    countri      3462
## 14       forc      3461
## 15      trump      3247
## 16     govern      3211
## 17      peopl      3171
## 18   american      2771
## 19     nation      2586
## 20      polit      2401
## 21     report      2388
## 22       last      2307
## 23      secur      2269
## 24     includ      2246
## 25   ukraine'      2231
## 26   european      2210
## 27    russia'      2190
## 28       hous      2181
## 29       week      2139
## 30       mani      2109
## 31     leader      2081
## 32    support      2049
## 33     moscow      2025
## 34       citi      1958
## 35   investig      1905
## 36    eastern      1897
## 37      fight      1846
## 38     former      1828
## 39         ms      1799
## 40      month      1735
## 41      troop      1705
## 42       sinc      1685
## 43        tri      1674
## 44    foreign      1635
## 45     region      1617
## 46     attack      1603
## 47      europ      1565
## 48    soldier      1557
## 49      offic      1554
## 50      group      1537
```

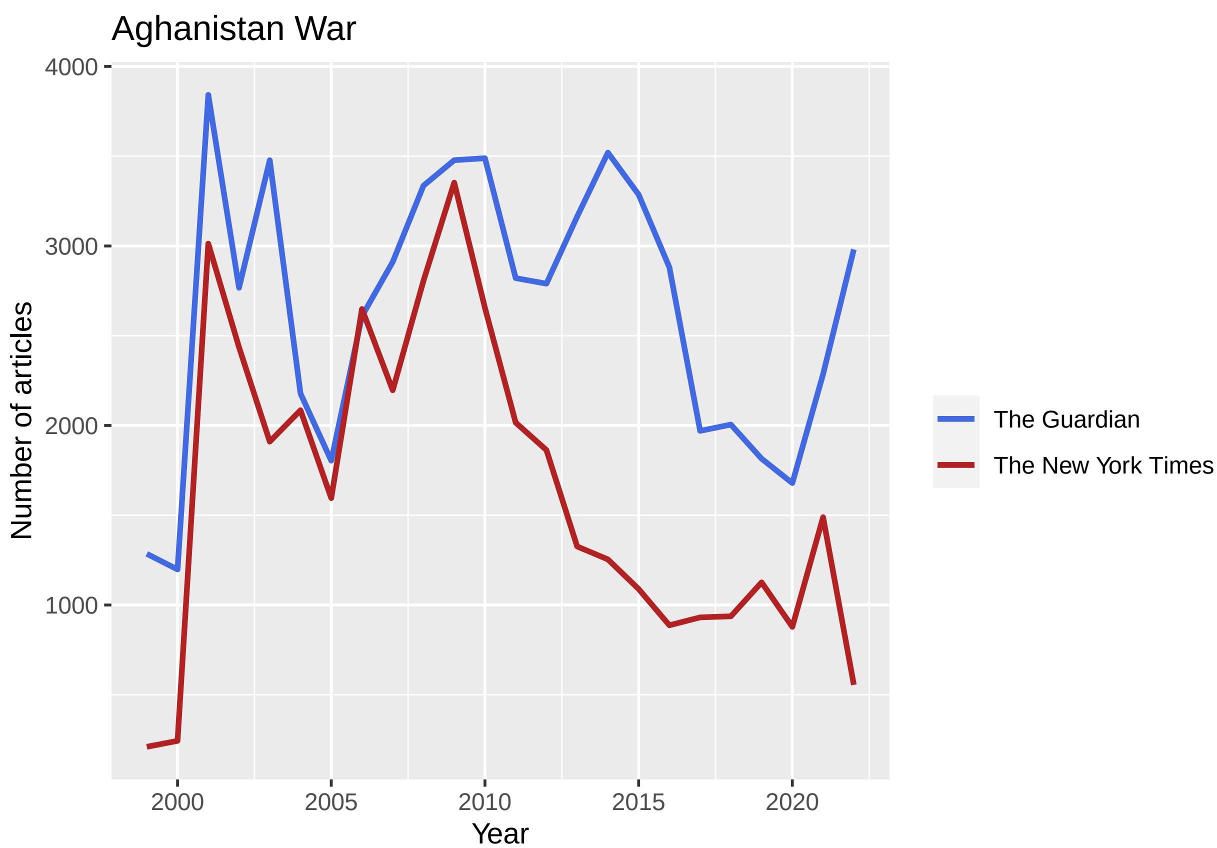


Policy agendas analysis

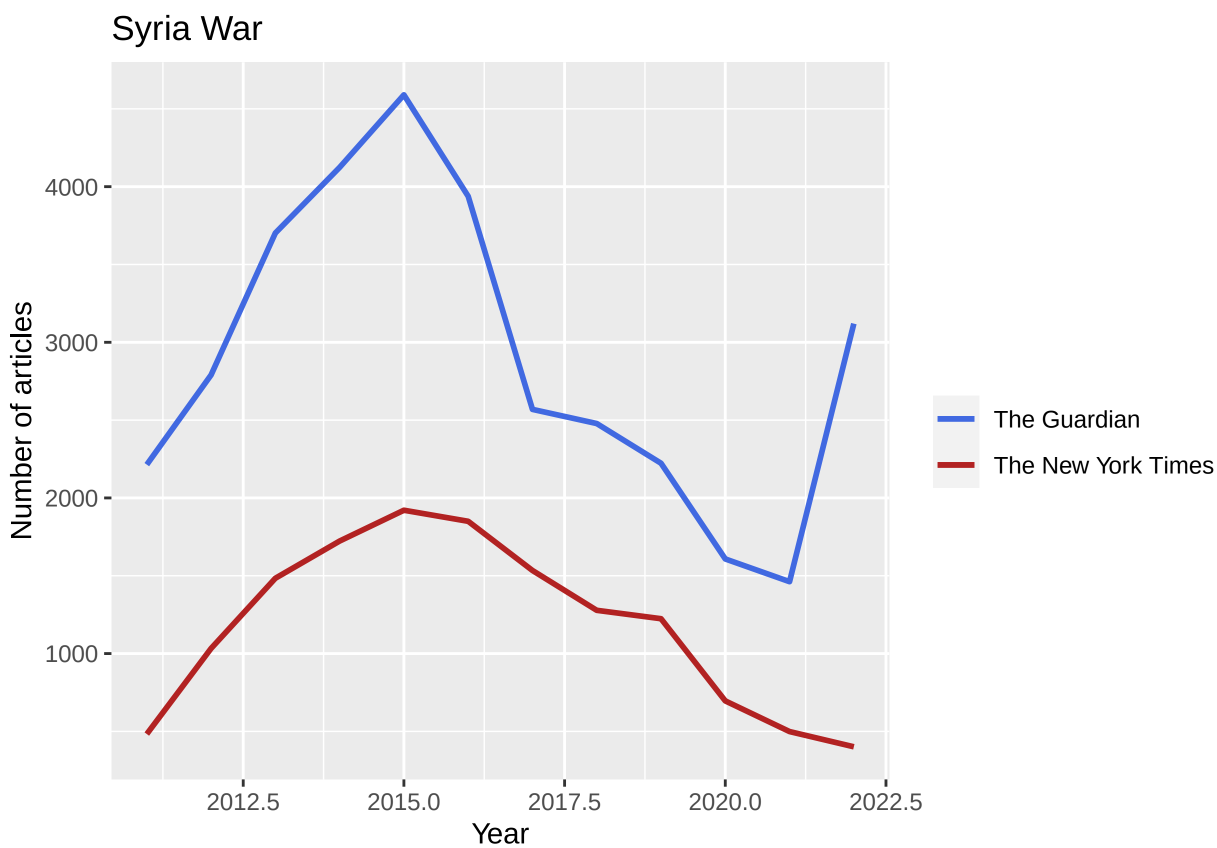
Comparison

Distribution

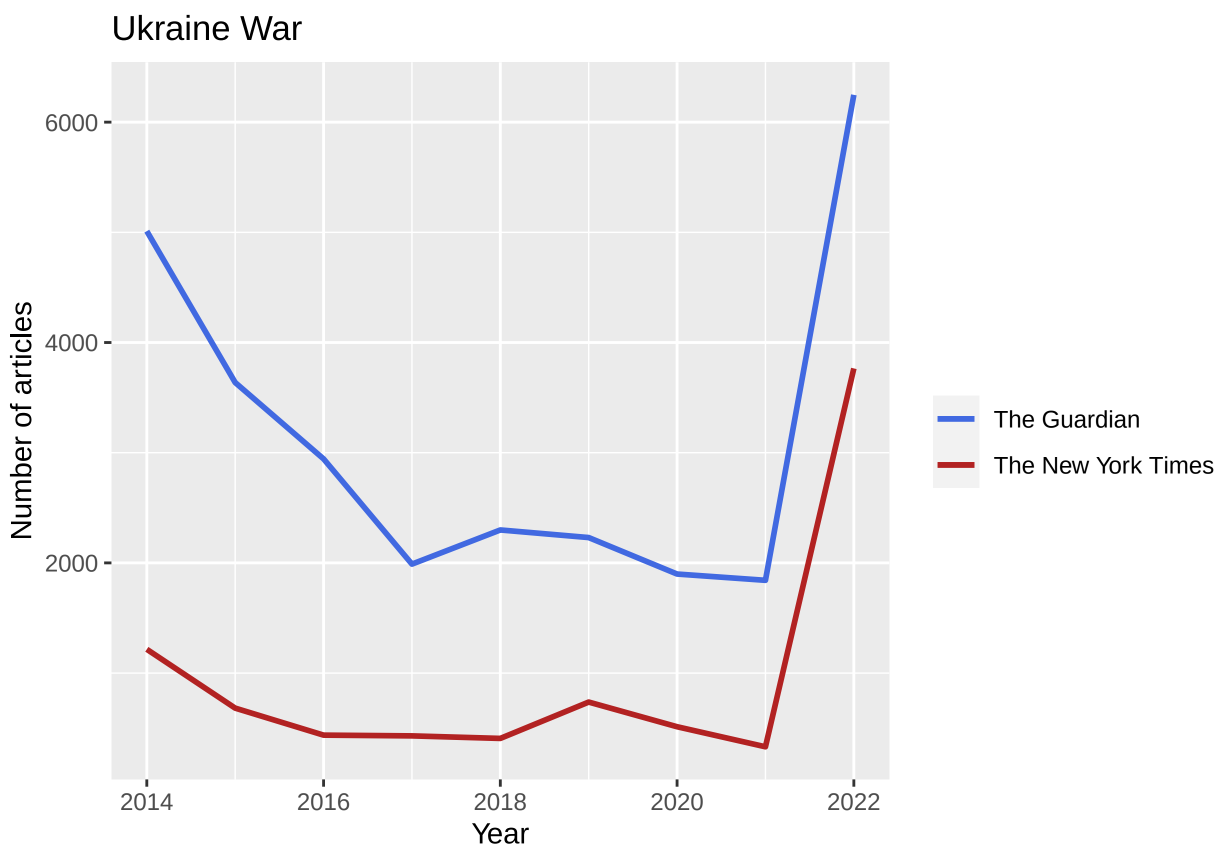
```
afgh_year_total <- afgh[!duplicated(afgh[ , c("year")]), ] %>%
  select(total_year, year)

syria_year_total <- syria[!duplicated(syria[ , c("year")]), ] %>%
  select(total_year, year)

ukraine_year_total <- ukraine[!duplicated(ukraine[ , c("year")]), ] %>%
  select(total_year, year)

nyt_afgh_year_total <- nyt_afgh[!duplicated(nyt_afgh[ , c("year")]), ] %>%
  select(hits_year, year)

nyt_syria_year_total <- nyt_syria[!duplicated(nyt_syria[ , c("year")]), ] %>%
  select(hits_year, year)

nyt_ukraine_year_total <- nyt_ukraine[!duplicated(nyt_ukraine[ , c("year")]), ] %>%
  select(hits_year, year)

afgh_dist_plot <- ggplot()+
  geom_line(afgh_year_total,
            mapping = aes(x=year, y=total_year,
                          color="The Guardian"), size=1)+
  geom_line(nyt_afgh_year_total,
            mapping = aes(x=year, y=hits_year,
                          color="The New York Times"), size=1)+
  scale_color_manual("",
                     values = c("The Guardian"="royalblue",
                                "The New York Times"="firebrick"))+
  labs(title="Aghanistan War", x="Year", y="Number of articles")
afgh_dist_plot
```




```
syria_dist_plot <- ggplot()+
  geom_line(syria_year_total,
            mapping = aes(x=year, y=total_year,
                          color="The Guardian"), size=1)+
  geom_line(nyt_syria_year_total,
            mapping = aes(x=year, y=hits_year,
                          color="The New York Times"), size=1)+
  scale_color_manual("",
                     values = c("The Guardian"="royalblue",
                                "The New York Times"="firebrick"))+
  labs(title="Syria War", x="Year", y="Number of articles")
syria_dist_plot
```




```r
ukraine_dist_plot <- ggplot()+
  geom_line(ukraine_year_total,
            mapping = aes(x=year, y=total_year,
                          color="The Guardian"), size=1)+
  geom_line(nyt_ukraine_year_total,
            mapping = aes(x=year, y=hits_year,
                          color="The New York Times"), size=1)+
  scale_color_manual("",
                     values = c("The Guardian"="royalblue",
                                "The New York Times"="firebrick"))+
  labs(title="Ukraine War", x="Year", y="Number of articles")
ukraine_dist_plot
```

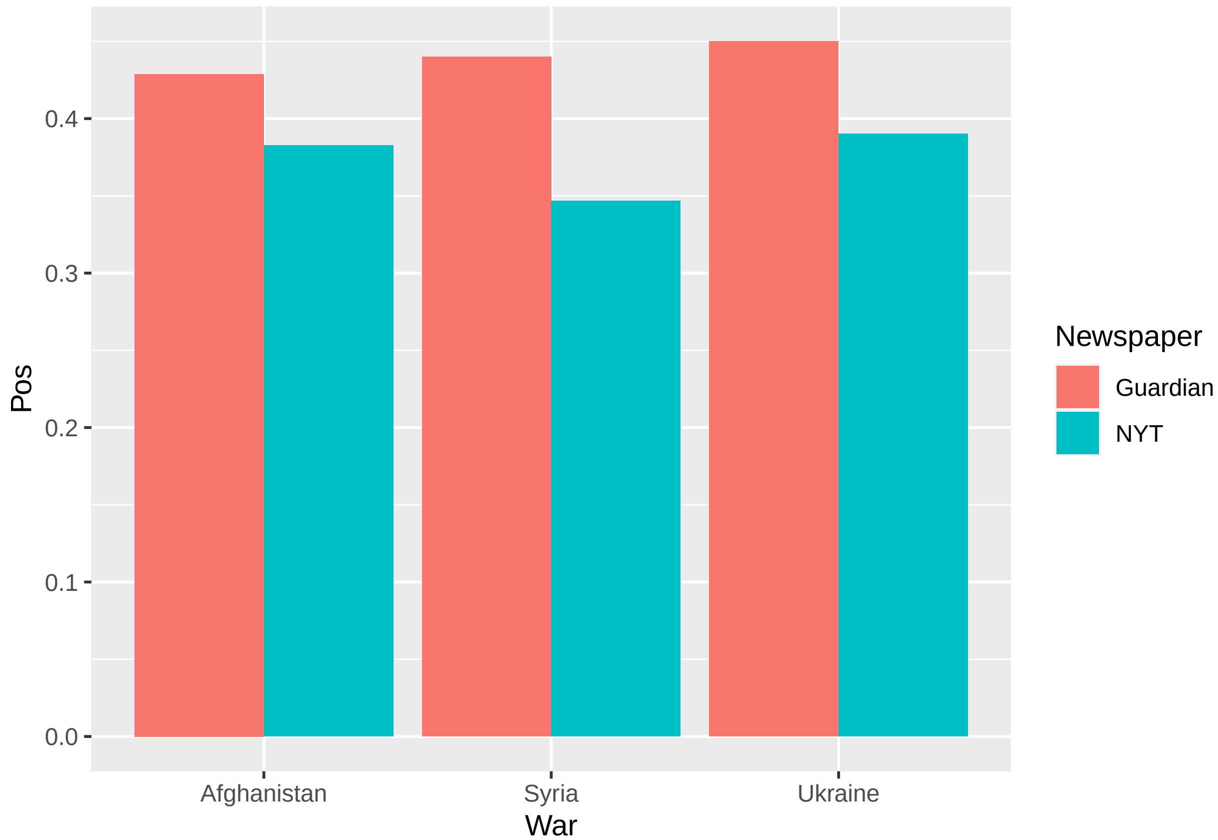


By looking at the distribution of the articles the first noticeable difference between the two newspaper is that the Guardian published more articles almost in every year about every war. But the distance between the two newspaper varies a lot. When comparing the war in Afghanistan and the war in Ukraine it is clearly visible that the difference in the number of published articles is a lot smaller in the Afghanistan war and a lot larger in the Ukraine war. This makes sense since the origin country of the New York Times was involved in the war and the origin country of the Guardian is geographically and politically much closer to the Ukraine. Another noticeable difference is that the number of articles published for the war in Syria peaks again in 2022 in the Guardian but there's no sign of that in the New York Times.

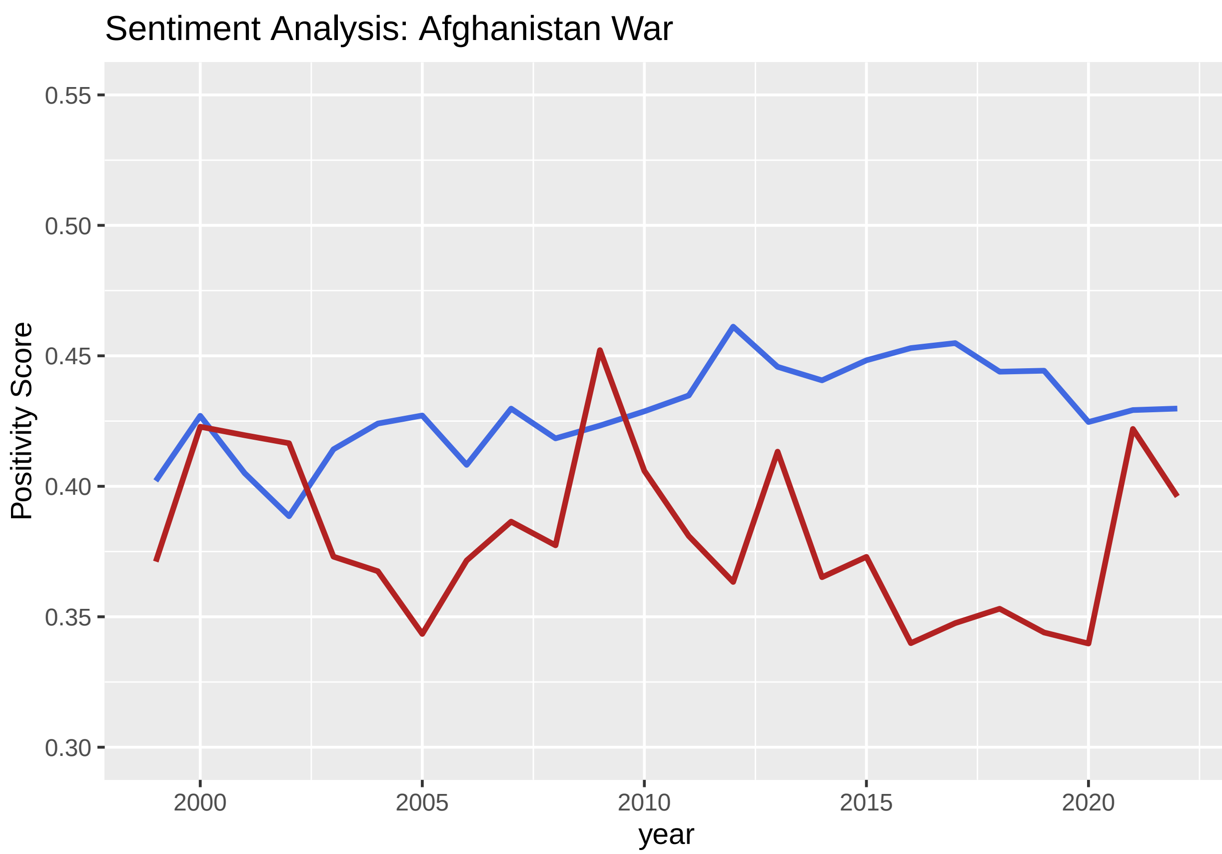
Sentiment Analysis

```
sent_comparison <- data.frame(matrix(nrow = 6, ncol = 3))
colnames(sent_comparison) <- c("Newspaper", "War", "Pos")
sent_comparison$Newspaper <- c("Guardian", "Guardian", "Guardian", "NYT", "NYT", "NYT")
sent_comparison$War <- c("Afghanistan", "Syria", "Ukraine", "Afghanistan", "Syria", "Ukraine")
sent_comparison$Pos <- c(mean(afgh_sent$pos_neg),
                         mean(syria_sent$pos_neg),
                         mean(ukraine_sent$pos_neg),
                         mean(nyt_afgh_sent$pos_neg),
                         mean(nyt_syria_sent$pos_neg),
                         mean(nyt_ukraine_sent$pos_neg))

# sent_comparison

comp_sent_plot <- sent_comparison %>%
  ggplot(aes(x=War, y=Pos, fill = Newspaper))+
```

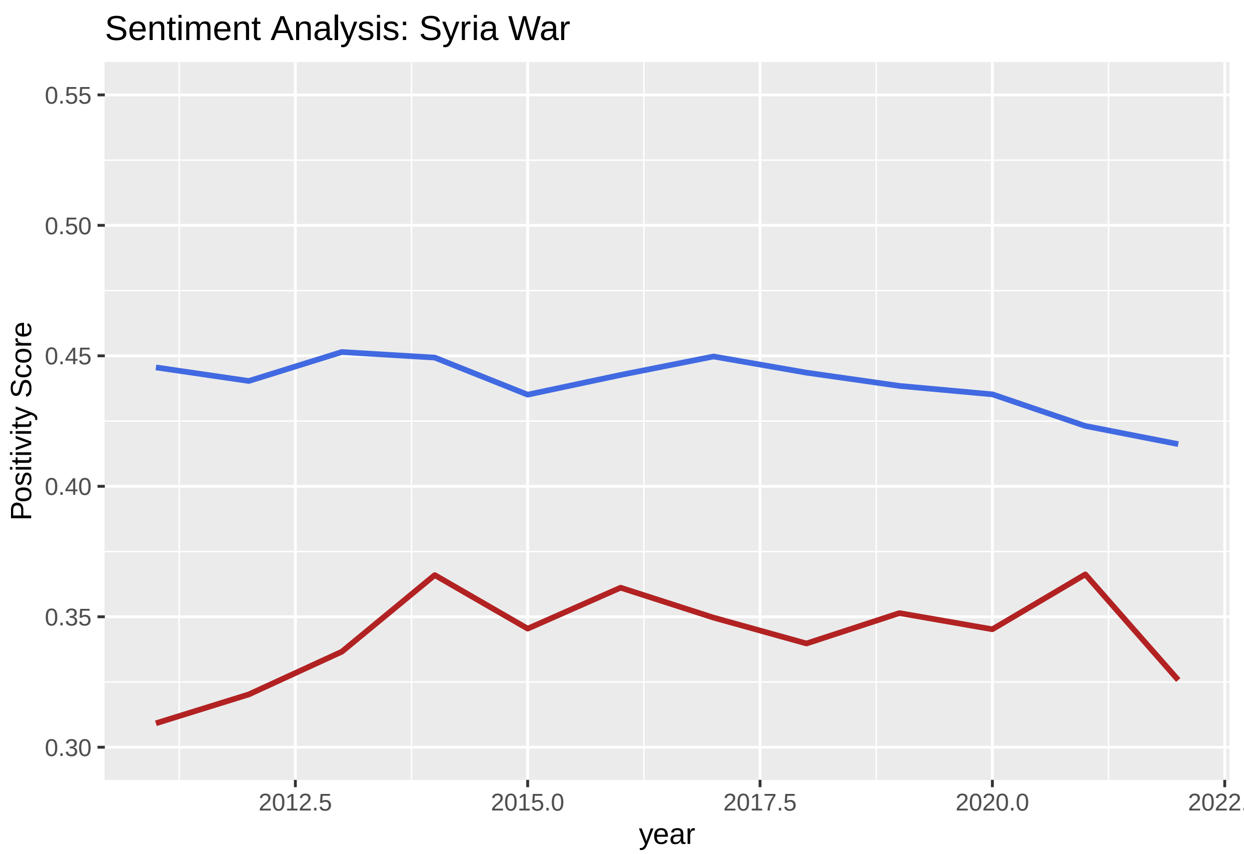
```
  geom_bar(position = "dodge", stat="identity")
comp_sent_plot
```



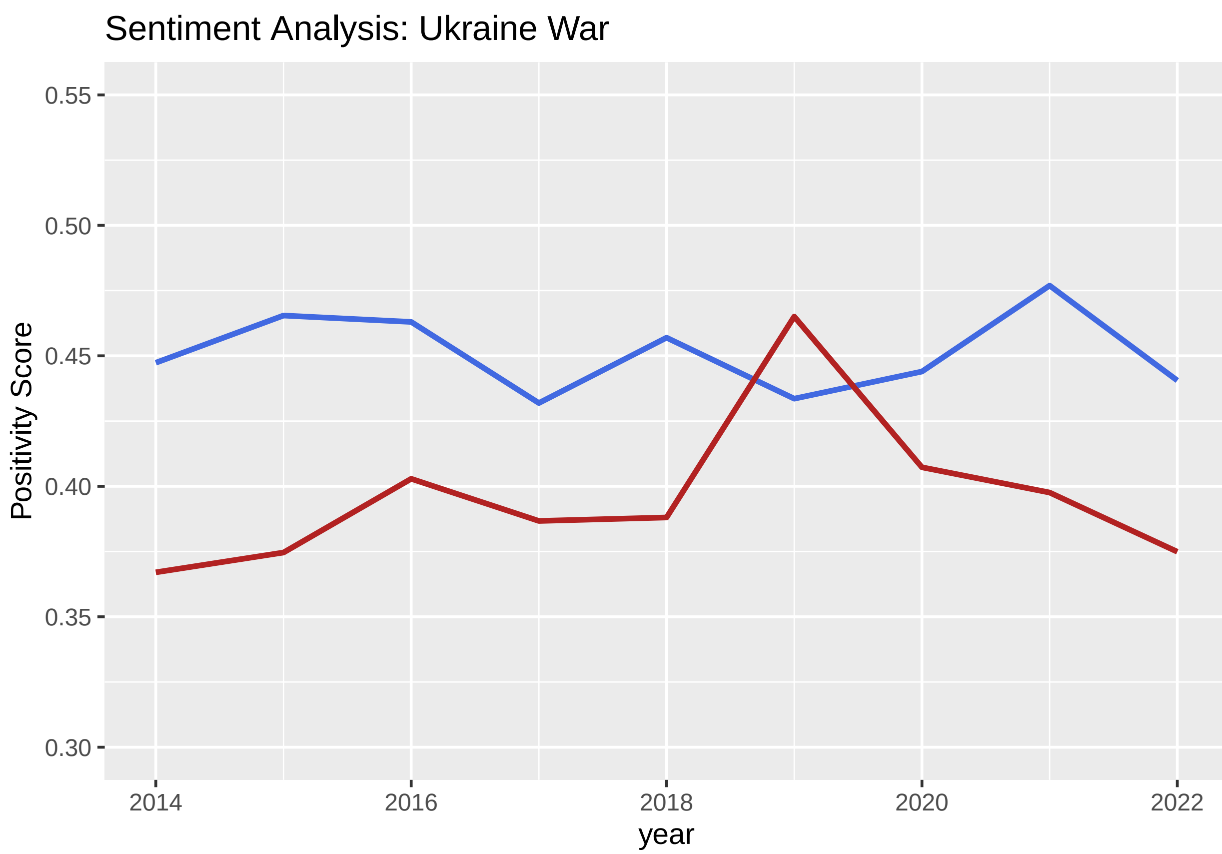

```
afgh_sent_plot <- ggplot()+
  geom_line(afgh_by_year, mapping = aes(x=year, y=pos_neg), size = 1, color = "royalblue")+
  geom_line(nyt_afgh_by_year, mapping = aes(x=year, y=pos_neg, group=1), size = 1, color = "firebrick")
  ylim(0.3, 0.55)+
  labs(title = "Sentiment Analysis: Afghanistan War", y="Positivity Score")
afgh_sent_plot
```




```
syria_sent_plot <- ggplot()+
  geom_line(syria_by_year, mapping = aes(x=year, y=pos_neg), size = 1, color = "royalblue")+
  geom_line(nyt_syria_by_year, mapping = aes(x=as.numeric(year), y=pos_neg, group=1), size = 1, color =
  ylim(0.3, 0.55)+
  labs(title = "Sentiment Analysis: Syria War", y="Positivity Score")
syria_sent_plot
```




```
ukraine_sent_plot <- ggplot()+
  geom_line(ukraine_by_year, mapping = aes(x=year, y=pos_neg), size = 1, color = "royalblue")+
  geom_line(nyt_ukraine_by_year, mapping = aes(x=year, y=pos_neg, group=1), size = 1, color = "firebric
  ylim(0.3, 0.55)+
  labs(title = "Sentiment Analysis: Ukraine War", y="Positivity Score")
ukraine_sent_plot
```



In general one can say that the Guardian has a more positive broadcasting style then the New York Times. This is consistent over all the wars and only in certain years has the New York Times a higher average Sentiment score than the Guardian. But it is noticeable that the difference is larger and even more consistent in the war in Syria. In comparison, in the Afghanistan war (in which the USA was the leading party) the New York Times has in three years a higher positivity score than the Guardian and also the fluctuation is very high. The difference between the newspapers could be a result of a broadcasting style or also of political agendas. The results from the New york Times suggests that there is something to further look into. But the differences could also be the result of language norms in the two different countries.

Word Frequency

```
load("Data/afgh_dfm.RData")
load("Data/syria_dfm.RData")
load("Data/ukraine_dfm.RData")
load("Data/nyt_afgh_dfm.RData")
load("Data/nyt_syria_dfm.RData")
load("Data/nyt_ukraine_dfm.RData")
```

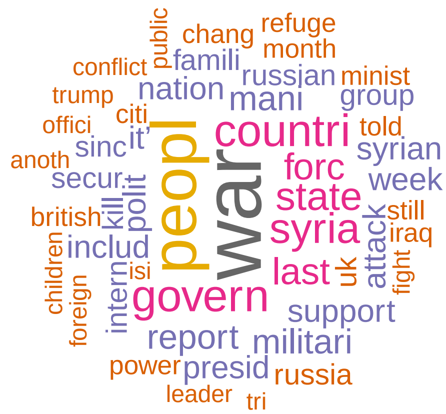
```
afgh_textplot <- textplot_wordcloud(afgh_dfm,
                   max_words = 50,
                   random_order = FALSE,
                   rotation = .3,
                   color = RColorBrewer::brewer.pal(8, "Dark2"))
```

Afghanistan

```
nyt_afgh_textplot <- textplot_wordcloud(nyt_afgh_dfm,
                    max_words = 50,
                    random_order = FALSE,
                    rotation = .3,
                    color = RColorBrewer::brewer.pal(8, "Dark2"))
```

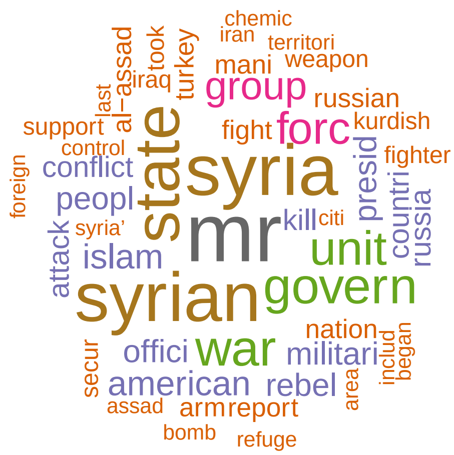
Here is a clear difference noticeable between the two newspapers. The New York Times uses the words "Afghanistan" and especially "Taliban" much more often then the Guardian. This is to be expected since the USA (the origin country of the New York Times) began the war in Afghanistan after the 9/11 terrorist attack executed by the Taliban. This led to the Taliban being the concept of the enemy.

```
syria_textplot <- textplot_wordcloud(syria_dfm,
                    max_words = 50,
                    random_order = FALSE,
                    rotation = .3,
                    color = RColorBrewer::brewer.pal(8, "Dark2"))
```



Syria

```
nyt_syria_textplot <- textplot_wordcloud(nyt_syria_dfm,
                   max_words = 50,
                   random_order = FALSE,
                   rotation = .3,
                   color = RColorBrewer::brewer.pal(8, "Dark2"))
```



There are no real notable differences between the newspapers visible.

```r
ukraine_textplot <- textplot_wordcloud(ukraine_dfm,
                   max_words = 50,
                   random_order = FALSE,
                   rotation = .3,
                   color = RColorBrewer::brewer.pal(8, "Dark2"))
```

Ukraine

```
nyt_ukraine_textplot <- textplot_wordcloud(nyt_ukraine_dfm,
                   max_words = 50,
                   random_order = FALSE,
                   rotation = .3,
                   color = RColorBrewer::brewer.pal(8, "Dark2"))
```

There are no real notable differences between the newspapers visible.

Over all Word Frequencies

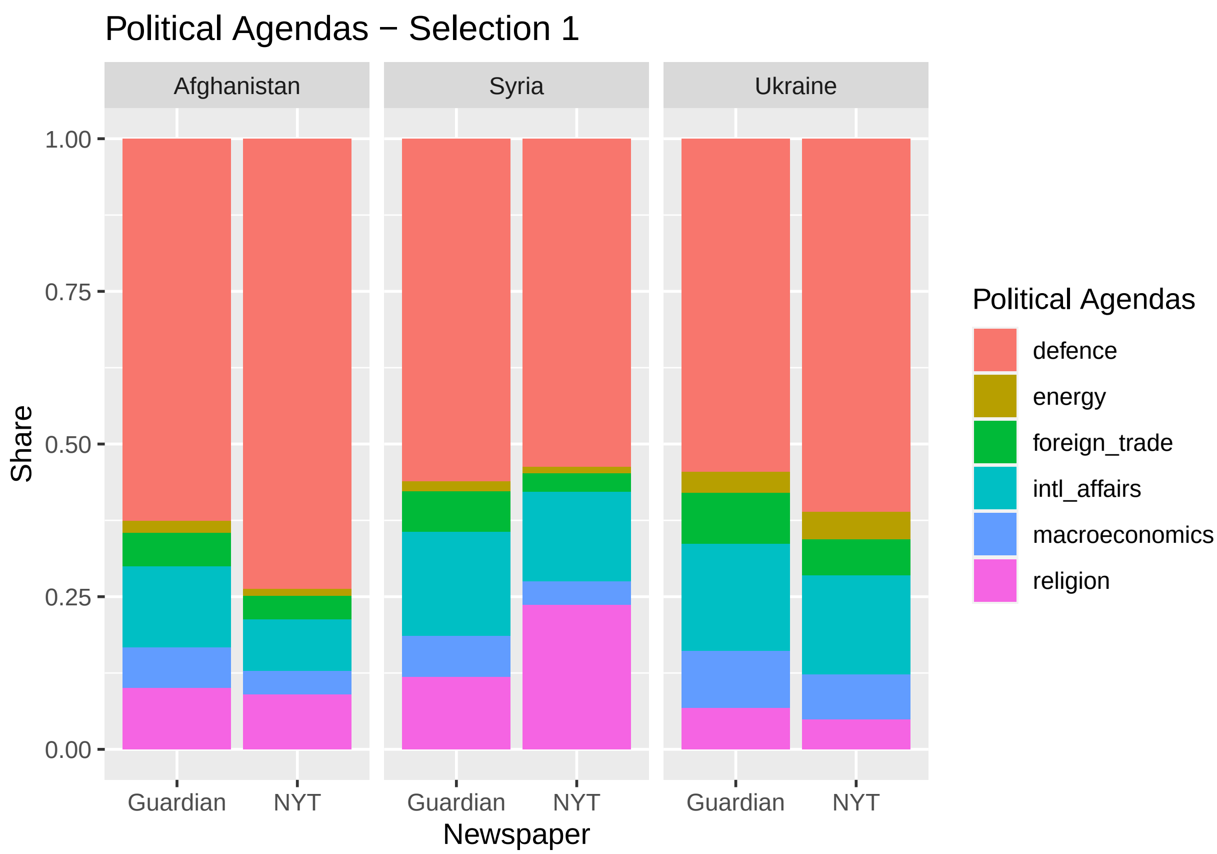
It is difficult here to make a general statement. The noticeable differences between the newspaper could be from the involvement of the country of origin or also from language norms. It is difficult to spot if a difference really comes from a different style of news portrayal. One consistent difference is that the Guardian uses the word "war" much more often then the New York Times. On the other hand it is noticeable that the New York Times very often uses the word "mr" which would suggest a more person-related coverage. But I would argue that that's a result of different language norms in the UK and US.

Policy Agendas

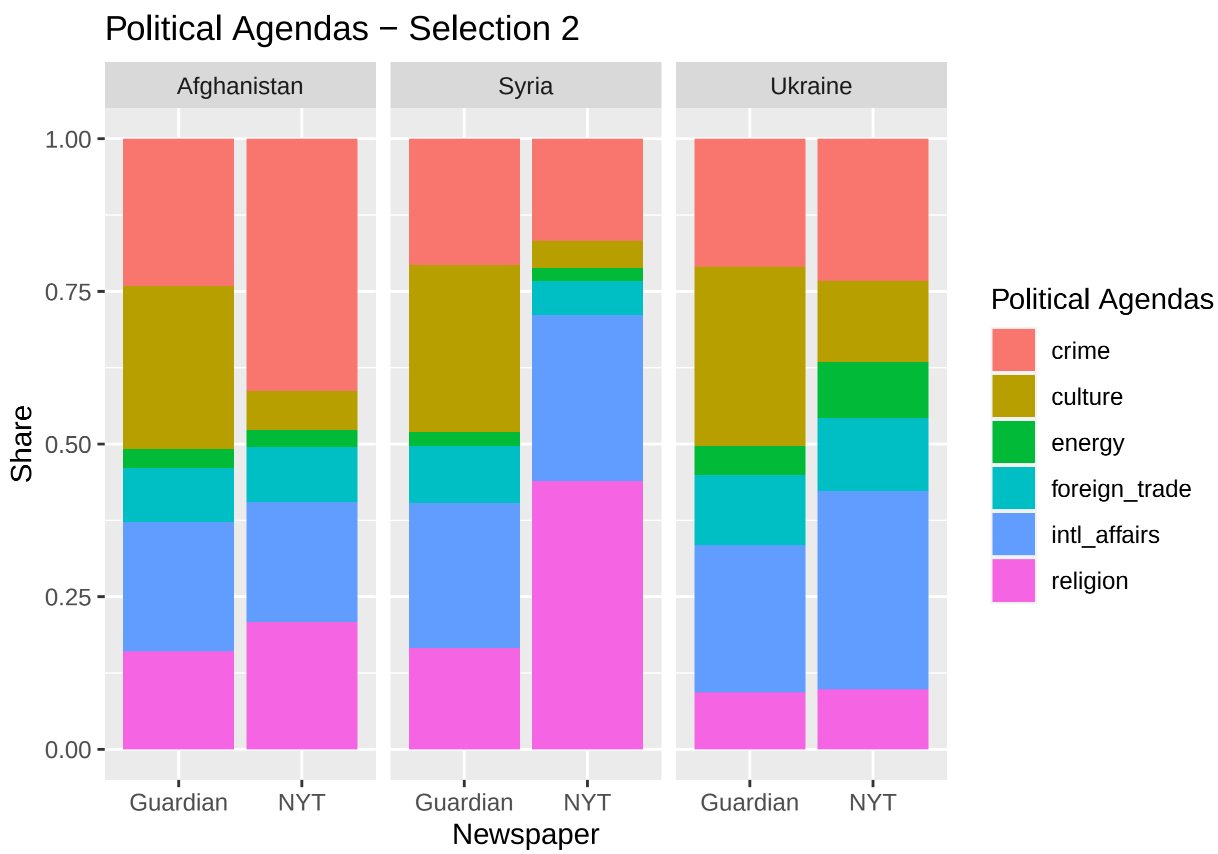
```
load("Data/afgh_pol.RData")
load("Data/syria_pol.RData")
load("Data/ukraine_pol.RData")
load("Data/nyt_afgh_pol.RData")
load("Data/nyt_syria_pol.RData")
load("Data/nyt_ukraine_pol.RData")
```

```
afgh_pol_total <- afgh_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
afgh_pol_total$war <- "Afghanistan"
afgh_pol_total$newspaper <- "Guardian"
```

```
syria_pol_total <- syria_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
syria_pol_total$war <- "Syria"
syria_pol_total$newspaper <- "Guardian"

ukraine_pol_total <- ukraine_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
ukraine_pol_total$war <- "Ukraine"
ukraine_pol_total$newspaper <- "Guardian"

nyt_afgh_pol_total <- nyt_afgh_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
nyt_afgh_pol_total$war <- "Afghanistan"
nyt_afgh_pol_total$newspaper <- "NYT"

nyt_syria_pol_total <- nyt_syria_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
nyt_syria_pol_total$war <- "Syria"
nyt_syria_pol_total$newspaper <- "NYT"

nyt_ukraine_pol_total <- nyt_ukraine_pol %>% select(-year) %>%
  colSums(.) %>%
  enframe()
nyt_ukraine_pol_total$war <- "Ukraine"
nyt_ukraine_pol_total$newspaper <- "NYT"

pol_total <- rbind(afgh_pol_total, syria_pol_total, ukraine_pol_total,
                   nyt_afgh_pol_total, nyt_syria_pol_total, nyt_ukraine_pol_total)


pol_total_plot <- pol_total %>%
  filter(name %in% c("defence", "energy", "foreign_trade", "intl_affairs", "macroeconomics", "religion")
  ggplot(aes(x=newspaper, y=value, fill = name))+
  geom_bar(stat = "identity",
           position = "fill")+
  facet_grid(~ war)+
  labs(title = "Political Agendas - Selection 1", y="Share", x="Newspaper")+
  scale_fill_discrete(name = "Political Agendas")
pol_total_plot
```




```
pol_total_plot_2 <- pol_total %>%
  filter(name %in% c("foreign_trade", "intl_affairs", "crime", "religion", "culture", "energy")) %>%
  ggplot(aes(x=newspaper, y=value, fill = name))+
  geom_bar(stat = "identity",
           position = "fill")+
  facet_grid(~ war)+
  labs(title = "Political Agendas - Selection 2", y="Share", x="Newspaper")+
  scale_fill_discrete(name = "Political Agendas")
pol_total_plot_2
```



The comparison shows that there are some differences between the two newspapers. For the Afghanistan war the New York Times seems to concentrate much more on the "defence" part than the Guardian, the same holds for the war in Ukraine. The second selection shows probably the most consistent difference between the two: culture. Over all three wars the Guardian reports much more about the culture aspect. Other major differences are that the New York Times covers more crime in the Afghanistan war and a lot more religion in the Syrian war.

When comparing the wars there are not many clear differences. The differences get mainly concealed by the differences between the newspapers. Nevertheless there are some notable results. Defence is more covered in the Afghanistan war then in the other two, Energy seems to be more important for the war in Ukraine and religion is a larger part in the Syrian war.

Conclusion

Over all there were some noticeable differences especially between the two newspapers. But one problem is consistent over all the analysis methods. It is very difficult to say if the differences in the result come from the differences between the two publishers or from the differences between the two origin countries. To control for that part I would need to look at other newspapers from the two countries to check how newspaper within a country differ from each other. In further research it would also be interesting to dive deeper into each one of the analysis methods. For example would it be interesting to see how the sentiment changes when filtering out articles which contain specific words like "America" or "Russia".

Another important aspect is the data gathering. I chose to use the simple search terms "Afghanistan war", "Syria war" and "Ukraine war". A completely unrelated difference between the two newspapers could be in the search algorithm of their API. I don't know how broadly they decide if an article matches a search term or not. So one newspaper could include a much broader variety of articles. Such technical differences could change the outcome of this research.

In conclusion, no real interpretive statement can be made. But this work has shown that there is something to look for and it can inspire further research to get to the bottom of the original question of this paper.