UNIVERSITÀ DEGLI STUDI DI MILANO

FACOLTÀ DI SCIENZE POLITICHE,
ECONOMICHE E SOCIALI

Political communication and populist rhetoric, an analysis of Italian politicians in the digital arena.

By

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in partial fulfillment of the requirement
for the degree of ...
in Political, Economic and Social Sciences

07/22

Abstract

(the spacing is set to 1.5)

no more than 250 words for the abstract

- a description of the research question/knowledge gap – what we know and what we don't know
- how your research has attempted to fill this gap
- a brief description of the methods
- brief results
- key conclusions that put the research into a larger context

Contents

1 Data cleaning

1.1 Import the dataset and check variables

```
# import the data
tw <-  read_csv("data/large_files/politicians_final_corrected.csv", show_col_types =

kable(colnames(tw), col.names = "variables")
```

variables
tw_screen_name
nome
tweet_testo
creato_il
creato_il_code
url
party_id
genere
chamber
status

1.2 Adjust date.time format

```
# RUN IN THIS ORDER !!
Sys.setlocale("LC_TIME", "C")
tw$date <- as.Date(strptime(tw$creato_il,"%a %b %d %H:%M:%S %z %Y", tz = "CET"))
tw$date <- na.replace(tw$date, as.Date(tw$creato_il))
```

1.2.1 Check the conversion

```r
check_dates <- tw %>% select(creato_il,date)
kable(head(check_dates), col.names = c("Old date", "New date"))
```

Old date	New date
2021-02-13	2021-02-13
2021-02-09	2021-02-09
2021-02-07	2021-02-07
2021-01-21	2021-01-21
2021-01-21	2021-01-21
2021-01-20	2021-01-20

```r
kable(tail(check_dates), col.names = c("Old date", "New date"))
```

Old date	New date
Mon Dec 28 09:51:35 +0000 2020	2020-12-28
Tue Jul 20 11:15:44 +0000 2021	2021-07-20
Thu Nov 26 13:46:51 +0000 2020	2020-11-26
Fri Oct 15 17:28:57 +0000 2021	2021-10-15
Wed Jun 03 12:22:31 +0000 2020	2020-06-03
Fri Dec 03 21:01:20 +0000 2021	2021-12-03

1.3 Create the week variable

```r
tw <- tw %>% mutate(week = cut.Date(date, breaks = "1 week", labels = FALSE))
```

1.3.1 Check the variable

Inspect the first and the last dates and check if the number of weeks is correct

```
max(tw$date)
```

```
## [1] "2022-04-18"
```

```
min(tw$date)
```

```
## [1] "2020-01-01"
```

```
difftime(max(tw$date), min(tw$date), units = "weeks")
```

```
## Time difference of 119.7143 weeks
```

1.4 Create the month variable

```
tw <- tw %>% mutate(month = cut.Date(date, breaks = "1 month", labels = FALSE))
```

1.4.1 Check the number of month

```
max(tw$month)
```

```
## [1] 28
```

```
length(seq(from = min(tw$date), to = max(tw$date), by = 'month'))
```

```
## [1] 28
```

1.5 Count the number of missing values

```
sum(is.na(tw))
```

```
## [1] 154672
```

1.5.1 Inspect where are the missings

```
missings <- c(
sum(is.na(tw$tw_screen_name)),
sum(is.na(tw$nome)),
sum(is.na(tw$tweet_testo)),
sum(is.na(tw$creato_il)),
sum(is.na(tw$creato_il_code)),
sum(is.na(tw$url)),
sum(is.na(tw$party_id)),
sum(is.na(tw$genere)),
sum(is.na(tw$chamber)),
sum(is.na(tw$status)),
sum(is.na(tw$date)),
sum(is.na(tw$week)),
sum(is.na(tw$month)) )


missing_df <- data.frame(colnames(tw), missings)
kable(missing_df)
```

colnames.tw.	missings
tw__screen__name	0
nome	0
tweet__testo	6494
creato__il	0
creato__il__code	0
url	148178
party__id	0
genere	0
chamber	0
status	0
date	0
week	0
month	0

From that analysis i obtain 148178 url missing, this is because the url is collected only when the tweets has an external link to other sources, for our analysis we can ignore those missings, with this check also results 6494 tweets missing those are the cases when someone post only images or video without text, so the extraction is correct.

1.5.2 Remove rows with missing tweets

```
sum(is.na(tw$tweet_testo))
```

```
## [1] 6494
```

```
tw <- tw %>% drop_na(tweet_testo)
```

1.6 Check that the variables make sense

```
unique(tw$party_id)
```

```
##  [1] "PD"           "FDI"          "M5S"          "FI"           "REG_LEAGUES"
##  [6] "MISTO"        "LEGA"         "IV"           "INDIPENDENTE" "CI"
## [11] "LEU"
```

```
unique(tw$genere)
```

```
## [1] "male"   "female" "male "
```

```
unique(tw$chamber)
```

```
## [1] "NotParl" "Senate"  "Camera"
```

```
unique(tw$status)
```

```
## [1] "sottosegretario" "presregione"     "viceministro"    "ministro"
## [5] "segretario"      "Parl"
```

1.6.1 Adjust the variable genere

```
# Remove space from genere variable [RUN ONLY ONCE!]
a <- unique(tw$genere)
a[3]
```

```
## [1] "male "
```

```
which(tw$genere == a[3])
```

```
## [1] 33300 33301 33302 33303 33304
```

```
tw$genere <- gsub(a[3],"male",tw$genere)
```

1.6.2 Verify the substitution

```
which(tw$genere == a[3])
```

```
## integer(0)
```

```
unique(tw$genere)
```

```
## [1] "male"   "female"
```

Now all the variables are ready for next steps

1.7 Create a new dataset selecting only necessary informations

```
# Select variables for the analysis
dataset <- tw %>% select(nome, tweet_testo, genere, party_id,chamber,status, date, w
colnames(dataset)
```

```
## [1] "nome"        "tweet_testo" "genere"      "party_id"    "chamber"
## [6] "status"      "date"        "week"        "month"
```

1.8 Create the corpus

```
corpus <- corpus(dataset, text = "tweet_testo")
ndoc(corpus)
```

```
## [1] 391197
```

1.9 Create the DFM

```
# Split the corpus into single tokens (remain positional)
doc.tokens <- tokens(corpus,
                                remove_punct = TRUE,
                                remove_numbers = TRUE,
                                remove_symbols = TRUE,
                                remove_url = TRUE)

# Import my stopwords
my_word <- as.list(read_csv("data/it_stopwords_new_list.csv",
                           show_col_types = FALSE))

# Attach unrecognized symbols
my_list <- c(" ","c'è","+"," ", my_word$stopwords, stopwords('italian'), stopwords("

# Save my_list
#save(my_list,file="data/my_list.Rda")

doc.tokens <- tokens_select(doc.tokens, my_list, selection='remove')
```

```r
DFM <- dfm(doc.tokens, tolower = TRUE)
```

1.10 Trim the data

Only words that occur in the top 20% of the distribution and in less than 30% of documents. Very frequent but document specific words.

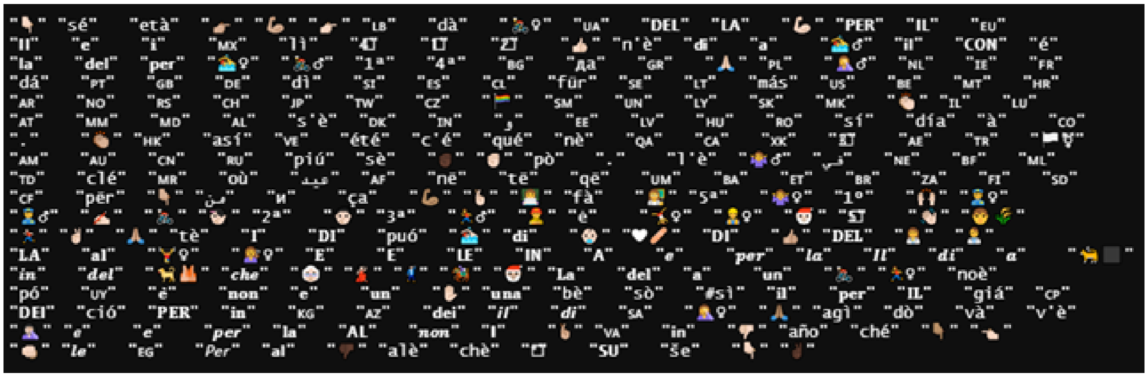
```r
DFM_trimmed <- dfm_trim(DFM, min_termfreq = 0.80, termfreq_type = "quantile",
                        max_docfreq = 0.3, docfreq_type = "prop")

# Check the topfeatures
topfeatures(DFM_trimmed,15)
```

```
##    governo     grazie     lavoro      paese       anni presidente     grande
##      26036      20835      18314      16473      16317      14258      13656
##   italiani     italia   l'italia        via   politica  cittadini       bene
##      12011      11980      11752      11504       9964       9360       9311
##      forza
##       8505
```

1.11 Remove the emoji

```r
# Create a copy of the dfm
test <- DFM_trimmed
# Remove from the copy all the non ASCII carachters
test@Dimnames$features <- gsub("[^\x01-\x7F]", "", test@Dimnames$features)
```

```r
# Check the difference from the list of features before and after apply gsub
a <- unique(test@Dimnames$features)
b <- unique(DFM_trimmed@Dimnames$features)
setdiff(b,a) #I have selected also words that cannot be removed

# Create an object with the features after remove non ASCII characters
c <- test@Dimnames$features
# Create an object with the original features
d <- DFM_trimmed@Dimnames$features

# Create the list of the removed features
diff <- setdiff(d,c)
emoji <- diff[diff %>% nchar() < 4]
emoji <- list(emoji)
emoji
# Now i can remove this list from the dfm
DFM_trimmed <- dfm_remove(DFM_trimmed, emoji)

#save(DFM_trimmed,file="data/dfm_trimmed.Rda")
```



```
"👇" "sé" "età" "👉" "💪" "👉" "LB" "dà" "🚴‍♀" "UA" "DEL" "LA" "💪" "PER" "IL" "EU"
"II" "e" "i" "MX" "lì" "4T" "LT" "ZT" "👍" "n'è" "di" "a" "🏊‍♂" "il" "CON" "é"
"la" "del" "per" "🏊‍♀" "🚴‍♂" "1ª" "4ª" "BG" "Дa" "GR" "🙏" "PL" "🙎‍♂" "NL" "IE" "FR"
"dá" "PT" "GB" "DE" "dì" "SI" "ES" "CL" "für" "SE" "LT" "más" "US" "BE" "MT" "HR"
"AR" "NO" "RS" "CH" "JP" "TW" "CZ" "🏳‍🌈" "SM" "UN" "LY" "SK" "MK" "👏" "IL" "LU"
"AT" "MM" "MD" "AL" "s'è" "DK" "IN" "," "EE" "LV" "HU" "RO" "sí" "día" "à" "CO"
"." "👏" "HK" "así" "VE" "été" "c'é" "qué" "nè" "QA" "CA" "XK" "ST" "AE" "TR" "🏳⚧"
"AM" "AU" "CN" "RU" "piú" "sè" "🏿" "🏻" "pò" "." "l'è" "🙆‍♂" "في" "NE" "BF" "ML"
"TD" "clé" "MR" "où" "هيد" "AF" "nè" "tè" "që" "UM" "BA" "ET" "BR" "ZA" "FI" "SD"
"CF" "për" "👇" "من" "и" "ça" "💪" "👆" "🧖" "fà" "👩‍🏫" "5ª" "🙆‍♀" "1º" "🎧" "👮‍♀"
"👮‍♂" "🍰" "🚴" "🧑" "2ª" "🧑" "3ª" "🏃‍♂" "👷" "è" "🤸‍♀" "👷‍♀" "🎅" "ST" "👋" "👦🌽"
"🏃" "✌" "🙏" "tè" "I" "DI" "puó" "🏊" "di" "😷" "🤍🩹" "DI" "👍" "DEL" "👨‍⚕" "👨‍⚕"
"LA" "al" "🤸‍♀" "💁‍♀" "E" "E" "LE" "IN" "A" "e" "per" "la" "Il" "di" "a" "🐈‍⬛"
"in" "del" "🐕‍🦺" "che" "👵" "💃" "🚶" "🏇" "🎅" "La" "del" "a" "un" "🚴" "🏃‍♀" "noè"
"pó" "UY" "é" "non" "e" "un" "👂" "una" "bè" "sò" "#sì" "il" "per" "IL" "giá" "CP"
"DEI" "ció" "PER" "in" "KG" "AZ" "dei" "il" "di" "SA" "🙎‍♀" "🙏" "agì" "dò" "và" "v'è"
"🙍" "e" "e" "per" "la" "AL" "non" "I" "🖕" "VA" "in" "👎" "año" "ché" "👇" "👈"
"✊" "le" "EG" "Per" "al" "👎" "alè" "chè" "ST" "SU" "še" "👇" "✌"
```

Figure 1: Emoji removed

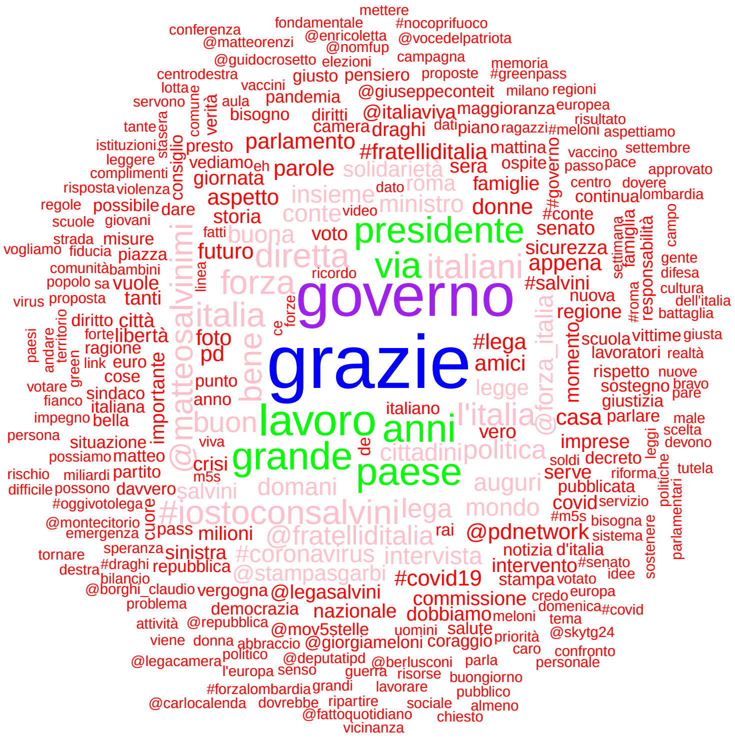
1.12 Take the proportion of the frequencies

```r
# Weight the frequency
dfm_weight <- DFM_trimmed %>%
  dfm_weight(scheme = "prop")
```

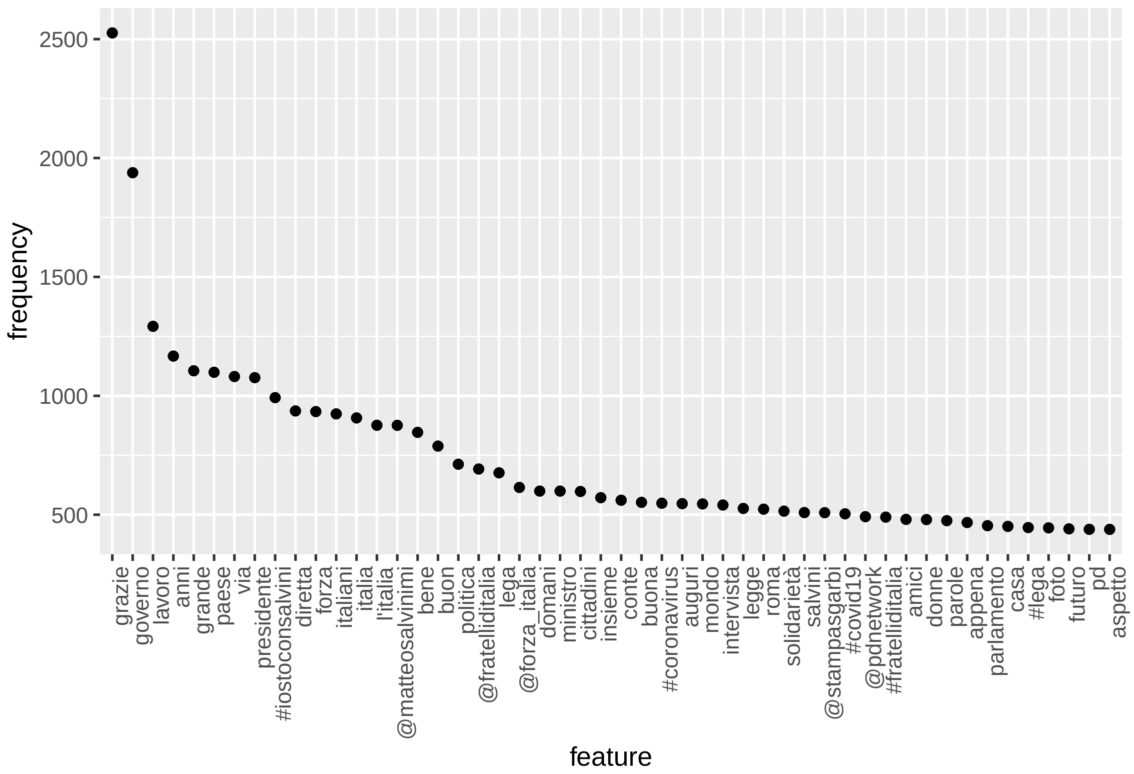
1.12.1 Now the data are ready for the next analysis

2 Preliminar analysis

2.1 Topfeatures frquency



```
# Plot frequency of the topfeatures in the DFM
features_dfm <- textstat_frequency(dfm_weight, n = 50)

# Sort by reverse frequency order
features_dfm$feature <- with(features_dfm, reorder(feature, -frequency))

ggplot(features_dfm, aes(x = feature, y = frequency)) +
  geom_point() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

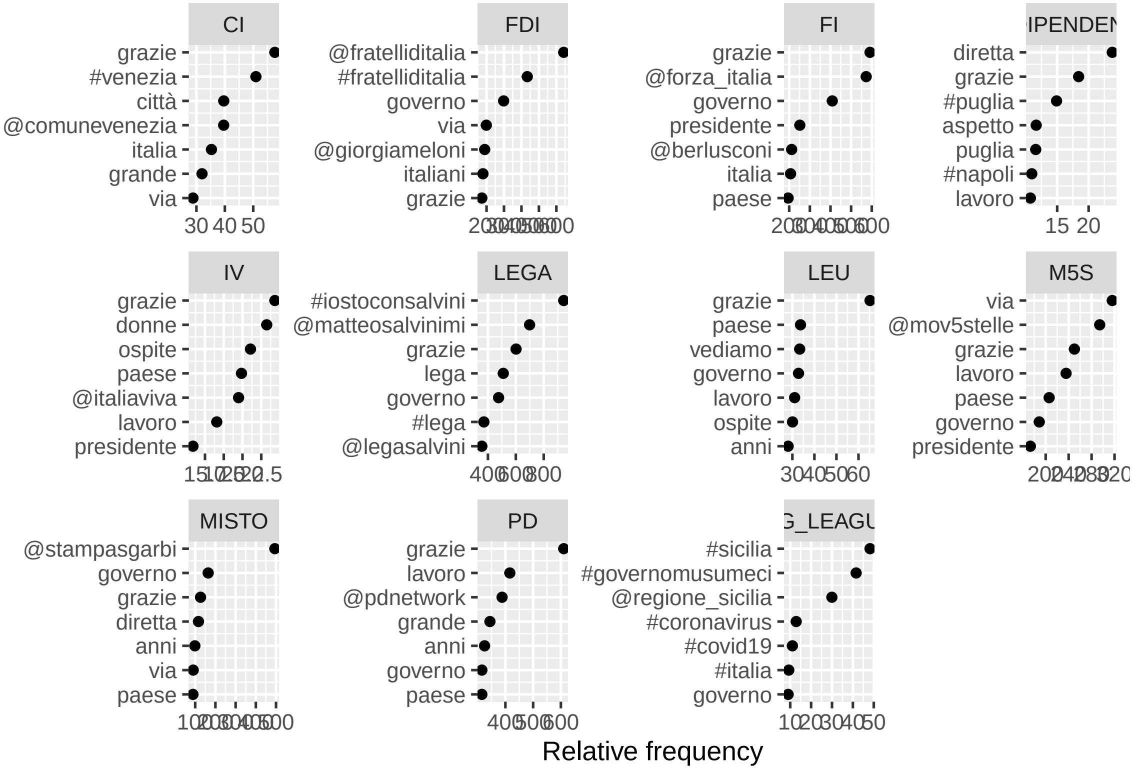


2.1.1 Relative frequency of the topfeatures by Party ID

```
kable(unique(DFM_trimmed$party_id),col.names = "Party")
```

Party
PD
FDI
M5S
FI
REG_LEAGUES
MISTO
LEGA
IV
INDIPENDENTE
CI
LEU

```r
# Plot relative frequency by party_id
freq_weight <- textstat_frequency(dfm_weight, n = 7,
                                  groups = dfm_weight$party_id)

ggplot(data = freq_weight, aes(x = nrow(freq_weight):1, y = frequency)) +
     geom_point() +
     facet_wrap(~ group, scales = "free") +
     coord_flip() +
     scale_x_continuous(breaks = nrow(freq_weight):1,
                        labels = freq_weight$feature) +
     labs(x = NULL, y = "Relative frequency")
```

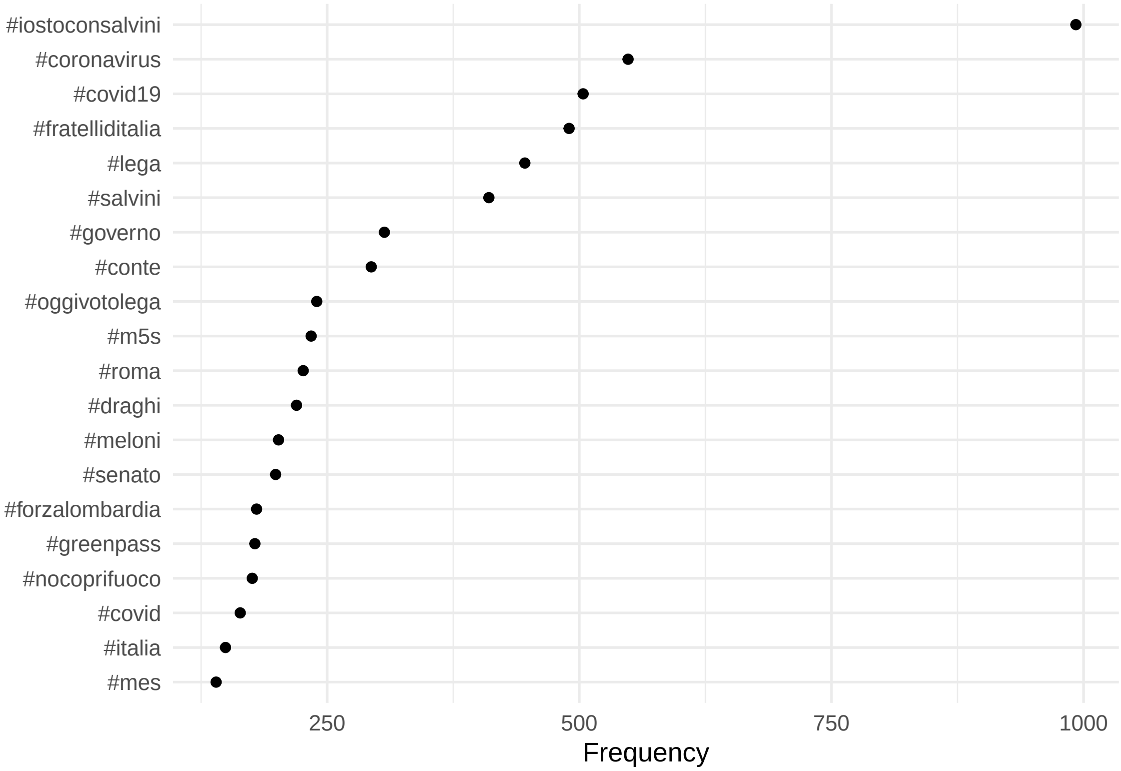


2.2 Most common hashtag

```
tag_dfm <- dfm_select(dfm_weight, pattern = "#*")
toptag <- names(topfeatures(tag_dfm, 20))
toptag
```

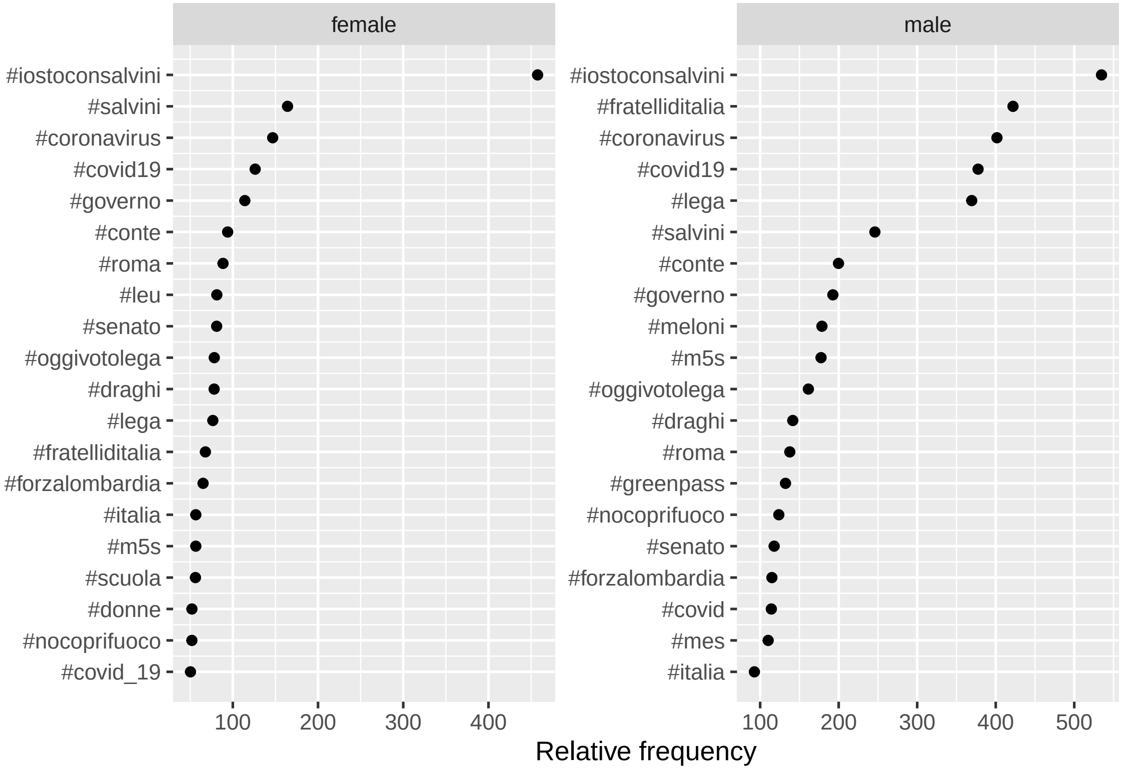
```
##  [1] "#iostoconsalvini" "#coronavirus"     "#covid19"         "#fratelliditalia"
##  [5] "#lega"            "#salvini"         "#governo"         "#conte"
##  [9] "#oggivotolega"    "#m5s"             "#roma"            "#draghi"
## [13] "#meloni"          "#senato"          "#forzalombardia"  "#greenpass"
## [17] "#nocoprifuoco"    "#covid"           "#italia"          "#mes"
```

```r
tag_dfm %>%
  textstat_frequency(n = 20) %>%
  ggplot(aes(x = reorder(feature, frequency), y = frequency)) +
  geom_point() +
  coord_flip() +
  labs(x = NULL, y = "Frequency") +
  theme_minimal()
```



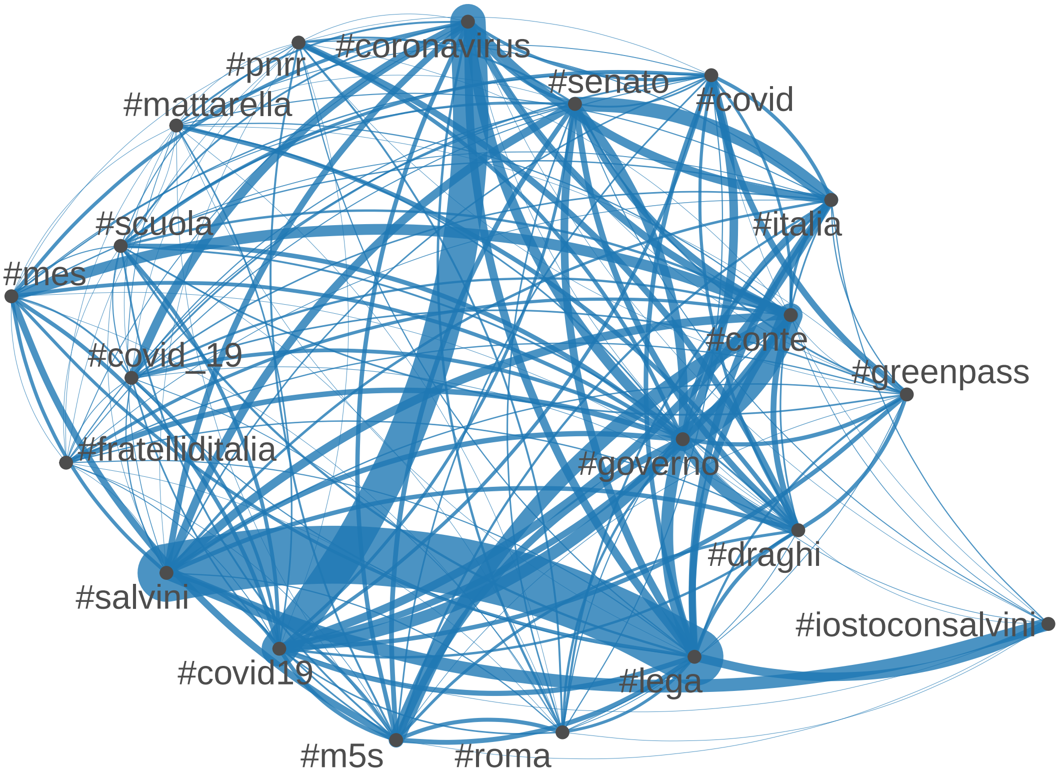
2.2.1 Most common hashtag by Gender

```r
tstat_freq <- textstat_frequency(tag_dfm, n = 20,
                                groups = dfm_weight$genere)
```

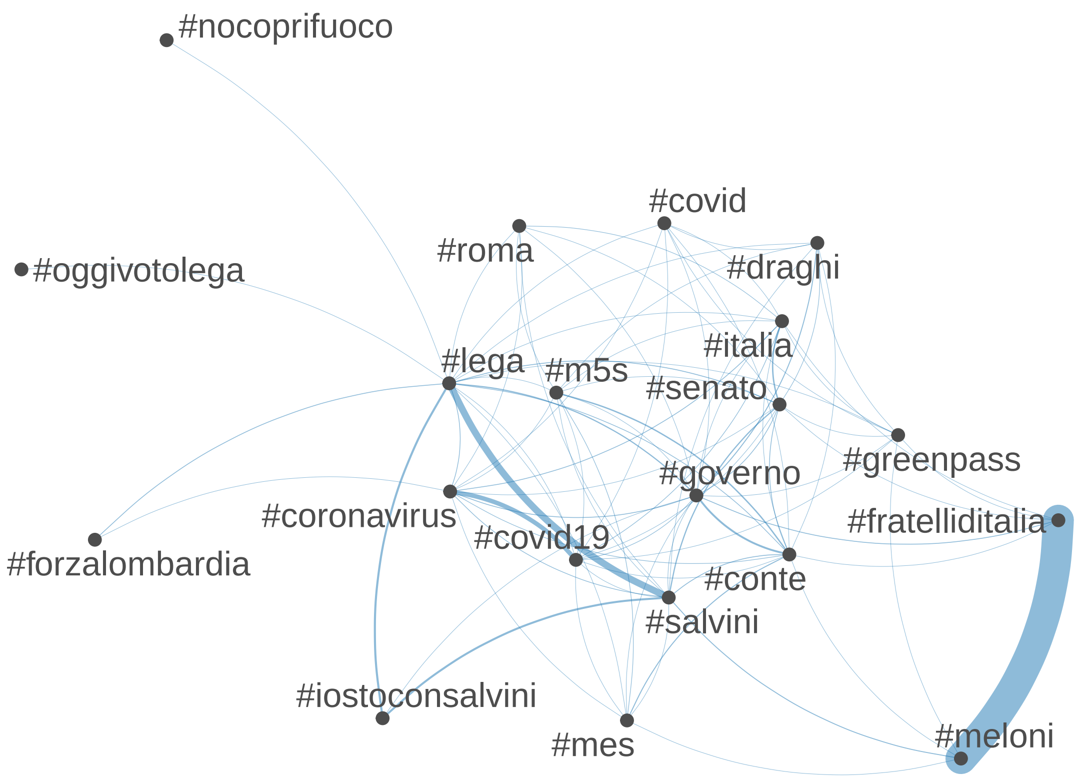


2.2.2 Co-occurrence Plot of hashtags

```
# NOT WEIGHTED
tag_dfm_NOT_W <- dfm_select(DFM, pattern = "#*")
toptag_NOT <- names(topfeatures(tag_dfm_NOT_W, 20))


tag_fcm_NOT <- fcm(tag_dfm_NOT_W)
set.seed(666)
topgat_fcm_NOT <- fcm_select(tag_fcm_NOT, pattern = toptag_NOT)
textplot_network(topgat_fcm_NOT, min_freq = 0.1, edge_alpha = 0.8, edge_size = 5)
```



```
# WEIGHTED
tag_fcm <- fcm(tag_dfm)
set.seed(123)
topgat_fcm <- fcm_select(tag_fcm, pattern = toptag)
textplot_network(topgat_fcm)#, min_freq = 0.1, edge_alpha = 0.8, edge_size = 5)
```



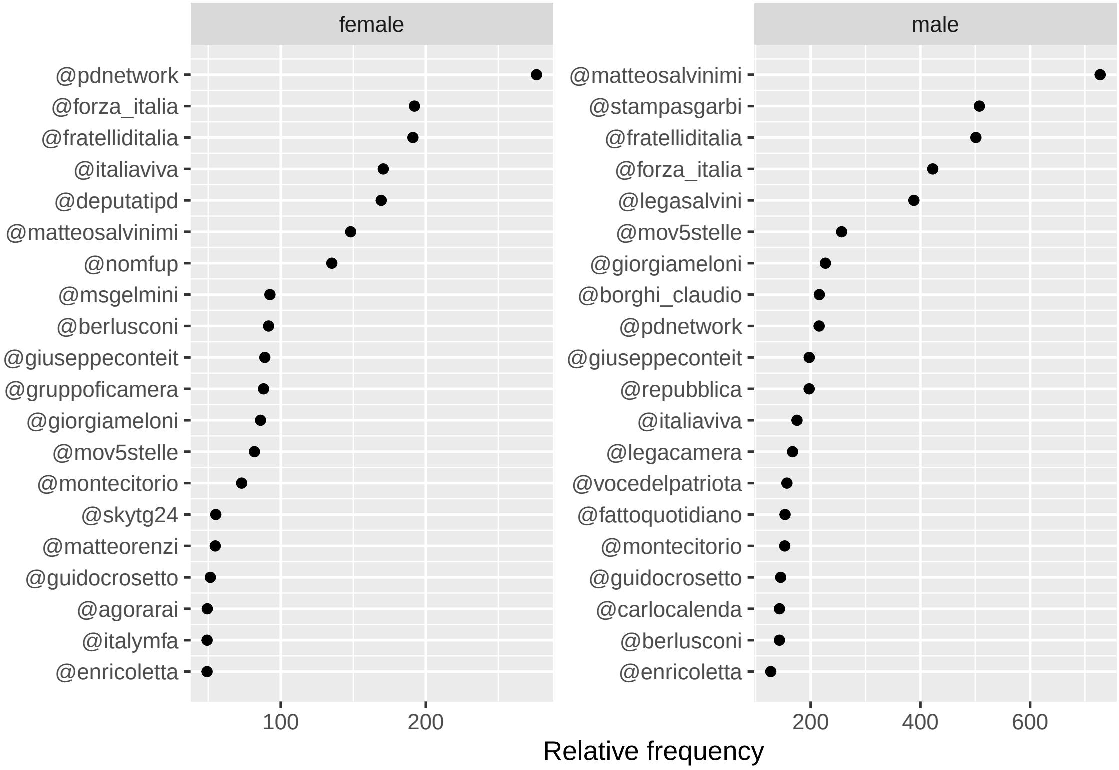
2.3 Most frequently mentioned usernames

```
user_dfm <- dfm_select(dfm_weight, pattern = "@*")
topuser <- names(topfeatures(user_dfm, 20, scheme = "docfreq"))
kable(topuser, col.names = "Most mentioned username")
```

Most mentioned username
@matteosalvinimi
@fratelliditalia
@forza_italia
@pdnetwork
@stampasgarbi
@mov5stelle
@legasalvini
@italiaviva
@giuseppeconteit
@giorgiameloni
@montecitorio
@deputatipd
@repubblica
@vocedelpatriota
@legacamera
@berlusconi
@matteorenzi
@fattoquotidiano
@enricoletta
@borghi_claudio

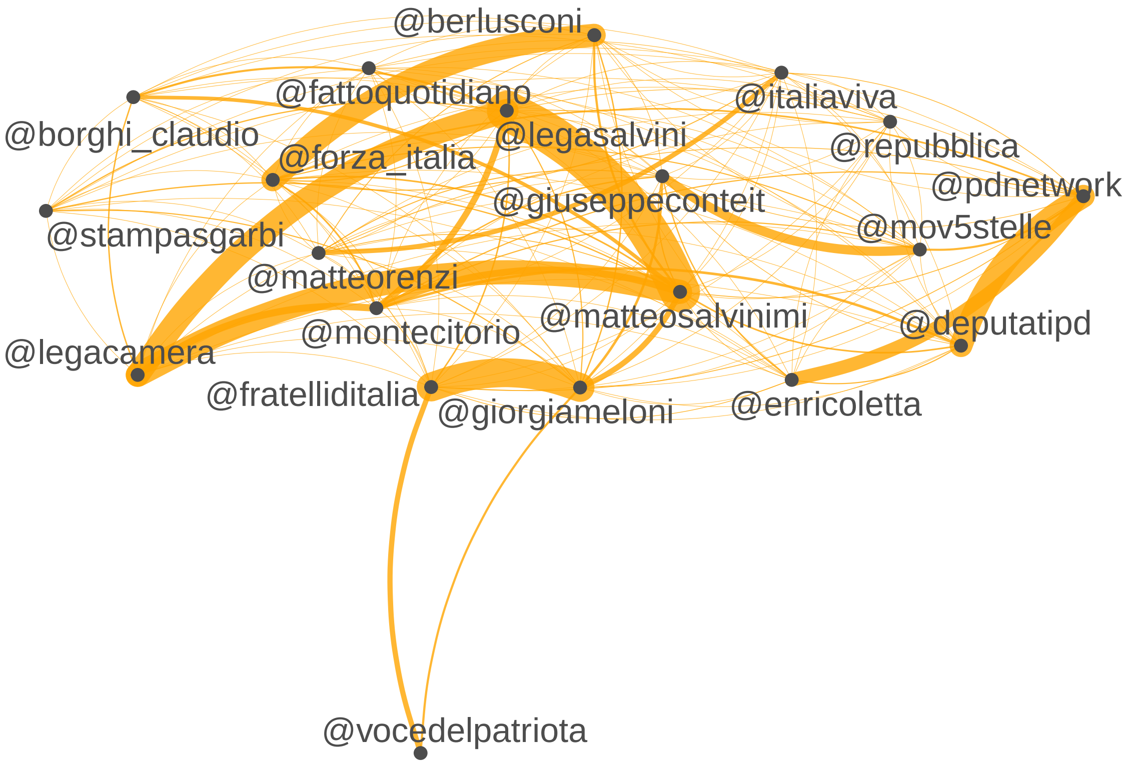
2.3.1 Most frequently mentioned usernames by gender

```
user_tstat_freq <- textstat_frequency(user_dfm, n = 20,
                                      groups = dfm_weight$genere)
```

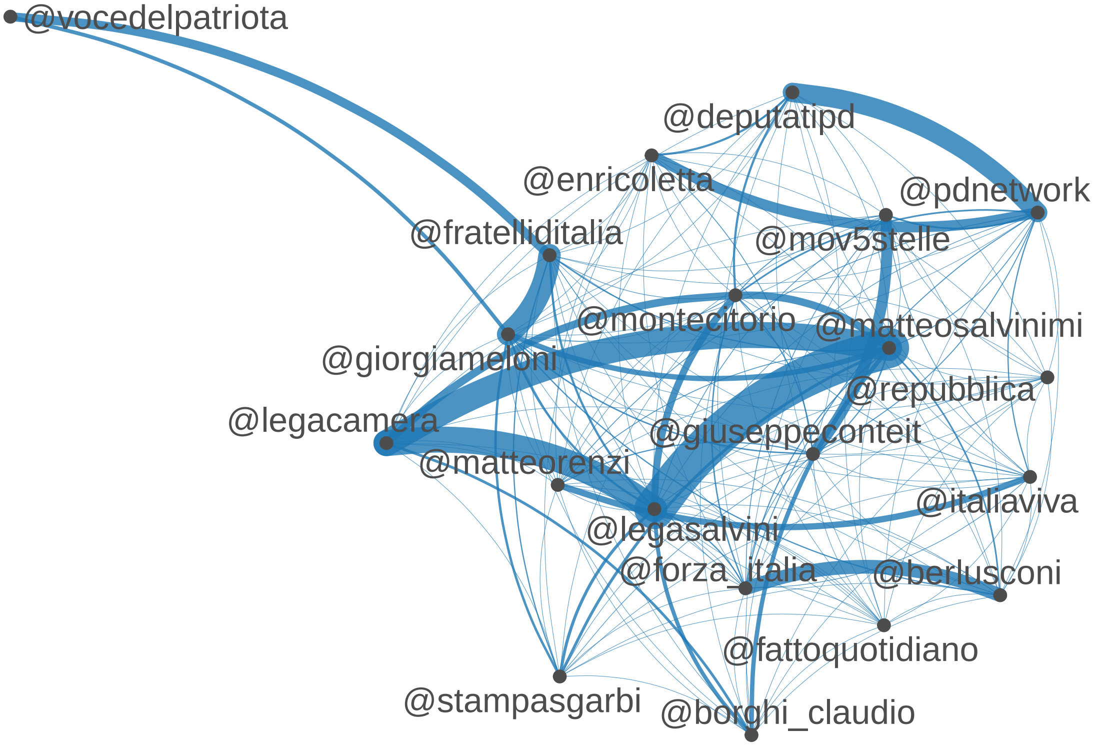


2.3.2 Co-occurrence plot of usernames

```
# WEIGHTED
user_fcm <- fcm(user_dfm)
set.seed(123)
user_fcm <- fcm_select(user_fcm, pattern = topuser)
textplot_network(user_fcm, min_freq = 0.1, edge_color = "orange", edge_alpha = 0.8,
```



```
# NOT WEIGHTED
user_dfm_NOT_W <- dfm_select(DFM, pattern = "@*")
topuser_NOT <- names(topfeatures(user_dfm_NOT_W, 20, scheme = "docfreq"))

user_fcm_NOT <- fcm(user_dfm_NOT_W)
set.seed(6)
topuser_fcm_NOT <- fcm_select(user_fcm_NOT, pattern = topuser_NOT)
textplot_network(topuser_fcm_NOT, min_freq = 0.1, edge_alpha = 0.8, edge_size = 5)
```


@vocedelpatriota
@deputatipd
@enricoletta
@pdnetwork
@fratelliditalia
@mov5stelle
@montecitorio
@matteosalvinimi
@giorgiameloni
@repubblica
@legacamera
@giuseppeconteit
@matteorenzi
@italiaviva
@legasalvini
@forza_italia
@berlusconi
@fattoquotidiano
@stampasgarbi
@borghi_claudio

3 Dictionary analysis

At the level of political parties, which ones make most use of populist rhetoric?

At the level of individual politicians, which ones make most use of populist rhetoric?

I use 3 dictionary to perform the analysis

- Rooduijn & Pauwels: Rooduijn, M., and T. Pauwels. 2011. “Measuring Populism: Comparing Two Methods of Content Analysis.” West European Politics 34 (6): 1272–1283.
- Decadri & Boussalis: Decadri, S., & Boussalis, C. (2020). Populism, party membership, and language complexity in the Italian chamber of deputies. Journal of Elections, Public Opinion and Parties, 30(4), 484-503.
- Grundl: Gründl J. Populist ideas on social media: A dictionary-based measurement of populist communication. New Media & Society. December 2020.
- Decadri & Boussalis + Grundl: this is simply a more extended version of the D&B dictionary, which also contains some terms taken from Grundl.

3.1 Create the dictionary

```r
# import dictionaries file
dict <-  read_excel("data/populism_dictionaries.xlsx")
variable.names(dict)
```

```
## [1] "Rooduijn_Pauwels_Italian"
## [2] "Grundl_Italian_adapted"
## [3] "Decadri_Boussalis"
## [4] "Decadri_Boussalis_Grundl_People"
## [5] "Decadri_Boussalis_Grundl_Common Will"
## [6] "Decadri_Boussalis_Grundl_Elite"
```

```r
# create the dictionary
Rooduijn_Pauwels_Italian <-
  dictionary(list(populism =
                    (dict$Rooduijn_Pauwels_Italian
                     [!is.na(dict$Rooduijn_Pauwels_Italian)])))

Grundl_Italian_adapted <-
  dictionary(list(populism =
                    dict$Grundl_Italian_adapted
                  [!is.na(dict$Grundl_Italian_adapted)]))

Decadri_Boussalis <-
  dictionary(list(populism =
                    dict$Decadri_Boussalis
                  [!is.na(dict$Decadri_Boussalis)]))

Decadri_Boussalis_Grundl <-
  dictionary(list(people =
                    dict$Decadri_Boussalis_Grundl_People
                  [!is.na(dict$Decadri_Boussalis_Grundl_People)],
                  common_will =
                    dict$`Decadri_Boussalis_Grundl_Common Will`
                  [!is.na(dict$`Decadri_Boussalis_Grundl_Common Will`)],
                  elite =
                    dict$Decadri_Boussalis_Grundl_Elite
                  [!is.na(dict$Decadri_Boussalis_Grundl_Elite)]))
```

3.2 Apply dictionary

3.3 Decadri_Boussalis_Grundl

3.3.1 Level of sparsity

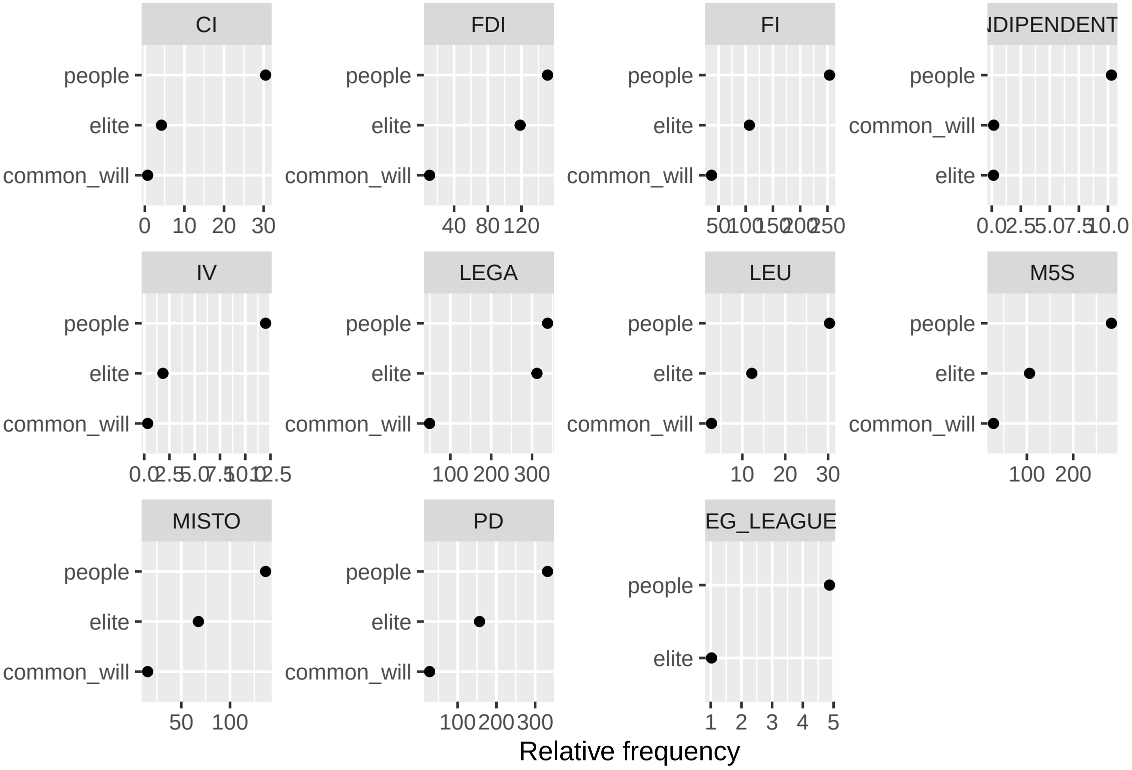
daily: 12.08%

weekly: 0.55%

monthly: 0%

```
# Daily Dictionary analysis with Decadri_Boussalis_Grundl on the whole dataset
dfm_dict1  <- dfm_lookup(dfm_weight, dictionary = Decadri_Boussalis_Grundl)
# Group by date
dfm_by_date1 <- dfm_group(dfm_dict1, groups= date)
#dfm_by_date1
# Group by week
dfm_by_week1 <- dfm_group(dfm_dict1, groups= week)
#dfm_by_week1
# Group by month
dfm_by_month1 <- dfm_group(dfm_dict1, groups= month)

kable(dfm_by_month1)
```

doc_id	people	common_will	elite
1	63.08421	6.7206174	30.07071
2	51.95882	3.5324477	36.73581
3	59.69107	3.0654092	26.04866
4	51.97619	1.9757148	38.92381
5	49.45054	1.0127899	35.60162
6	43.57187	1.7857503	39.61004
7	56.55317	3.7960223	29.79968
8	53.00149	9.5933176	28.46625
9	85.44455	20.3706540	29.07701
10	59.49955	2.7737546	39.66205
11	49.73316	3.7235276	37.89949
12	49.94546	0.6535908	40.42253
13	55.60681	3.8602075	54.16762
14	40.04550	0.9839938	22.10838
15	45.56965	2.5438049	24.07726
16	55.96528	10.9229303	39.12011
17	56.86530	2.7511473	32.82973
18	48.81594	9.1557063	21.42126
19	59.91423	15.9431835	24.08967
20	52.91074	7.2841548	33.03036
21	89.42553	17.8845192	24.03434
22	89.60724	10.1613697	44.03908
23	62.27881	6.8619658	38.56875
24	46.69026	4.8762916	30.41294
25	62.78604	4.6705967	30.18396
26	60.27223	12.2456079	27.17848
27	48.96990	2.6807170	16.48902
28	32.12638	0.8460317	12.31448



Looking at the populist rhetoric for each party divided into the 3 components people-centrism, anti-elitism and common-will, we note that the most frequent components is People-centrism.

3.4 Rooduijn_Pauwels_Italian

3.4.1 Level of sparsity

daily: 0.60%

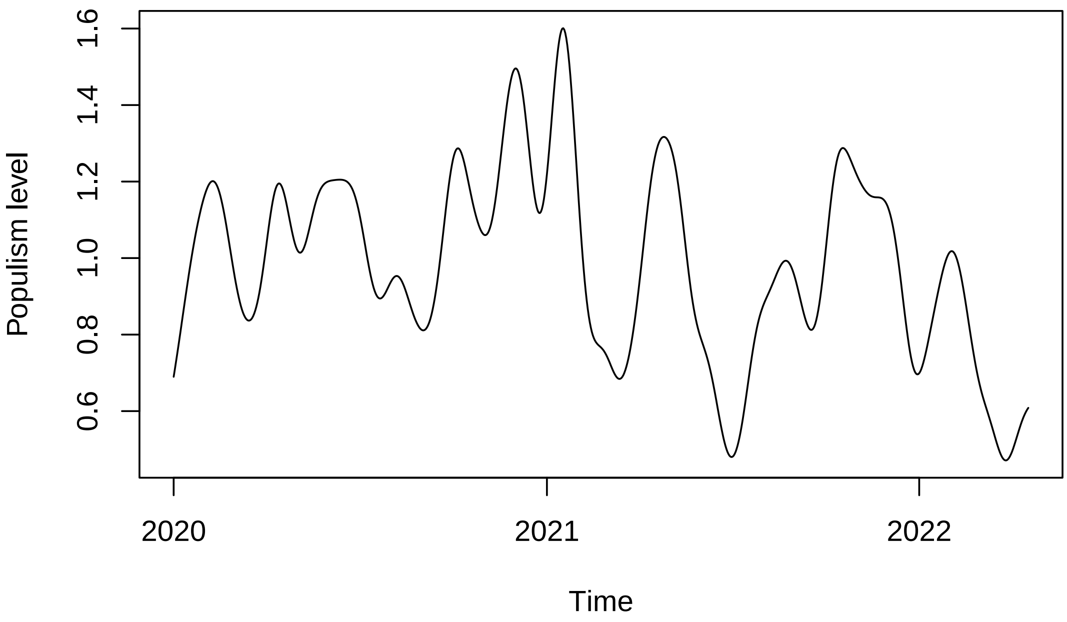
weekly: 0.%

monthly: 0%

```
# Daily Dictionary analysis with Rooduijn_Pauwels_Italian on the whole dataset
dfm_dict2  <- dfm_lookup(dfm_weight, dictionary = Rooduijn_Pauwels_Italian)
# Group by date
dfm_by_date2 <- dfm_group(dfm_dict2, groups= date)
#dfm_by_date2
# Group by week
dfm_by_week2 <- dfm_group(dfm_dict2, groups= week)
#dfm_by_week2
# Group by month
dfm_by_month2 <- dfm_group(dfm_dict2, groups= month)

kable(dfm_by_month2)
```

doc_id	populism
1	28.10591
2	34.76596
3	24.91863
4	37.43421
5	32.79228
6	37.74417
7	28.35085
8	27.36380
9	28.08691
10	38.72625
11	36.03047
12	38.57222
13	51.75047
14	20.10344
15	23.24975
16	36.54012
17	31.14446
18	20.58931
19	22.07645
20	30.04277
21	22.06137
22	41.01336
23	35.59173
24	25.65097
25	27.54361
26	25.97639
27	15.44186
28	11.47281

3.4.2 General level of populism in time



3.4.3 Most populist party

```r
# Most populist party
dfm_dict2_tstat_party <- textstat_frequency(dfm_dict2, groups = party_id)
kable(dfm_dict2_tstat_party %>% slice_max(frequency, n = 20))
```

	feature	frequency	rank	docfreq	group
6	populism	303.9474786	1	1919	LEGA
10	populism	149.7512641	1	1671	PD
2	populism	113.7388243	1	1124	FDI
3	populism	98.6906136	1	941	FI
8	populism	87.6625041	1	1119	M5S
9	populism	60.9720255	1	669	MISTO
7	populism	11.7023384	1	175	LEU
1	populism	3.7116701	1	45	CI
5	populism	1.8540424	1	26	IV
11	populism	1.0264294	1	11	REG_LEAGUES
4	populism	0.0833333	1	1	INDIPENDENTE

3.4.4 Most populist politician

```
dict2_tstat_nome <- textstat_frequency(dfm_dict2, groups = nome)


kable(dict2_tstat_nome %>% slice_max(frequency, n = 20))
```

	feature	frequency	rank	docfreq	group
194	populism	42.115152	1	146	FERRERO Roberta
472	populism	15.910436	1	160	SGARBI Vittorio
341	populism	14.112659	1	77	MORANI Alessia
24	populism	13.999694	1	52	BALDELLI Simone
179	populism	13.821584	1	48	FAGGI Antonella
271	populism	13.095709	1	149	LANNUTTI Elio
217	populism	12.884799	1	39	FREGOLENT Sonia
450	populism	12.806346	1	64	RUSPANDINI Massimo
326	populism	12.518396	1	192	MELONI Giorgia
427	populism	12.257891	1	40	RIVOLTA Erica
106	populism	10.788399	1	68	CECCHETTI Fabrizio
283	populism	10.783981	1	108	LOLLOBRIGIDA Francesco
260	populism	10.778644	1	76	IEZZI Igor Giancarlo
230	populism	10.648954	1	155	GARNERO SANTANCHE' Daniela
303	populism	10.133849	1	78	MALAN Lucio
447	populism	9.885108	1	29	RUFA Gianfranco
455	populism	9.561830	1	93	SALVINI Matteo
360	populism	9.110910	1	105	NOBILI Luciano
35	populism	8.689617	1	57	BAZZARO Alex
501	populism	8.495460	1	32	TONELLI Gianni

3.5 Grundl_Italian_adapted

3.5.1 Level of sparsity

daily: 0.24%

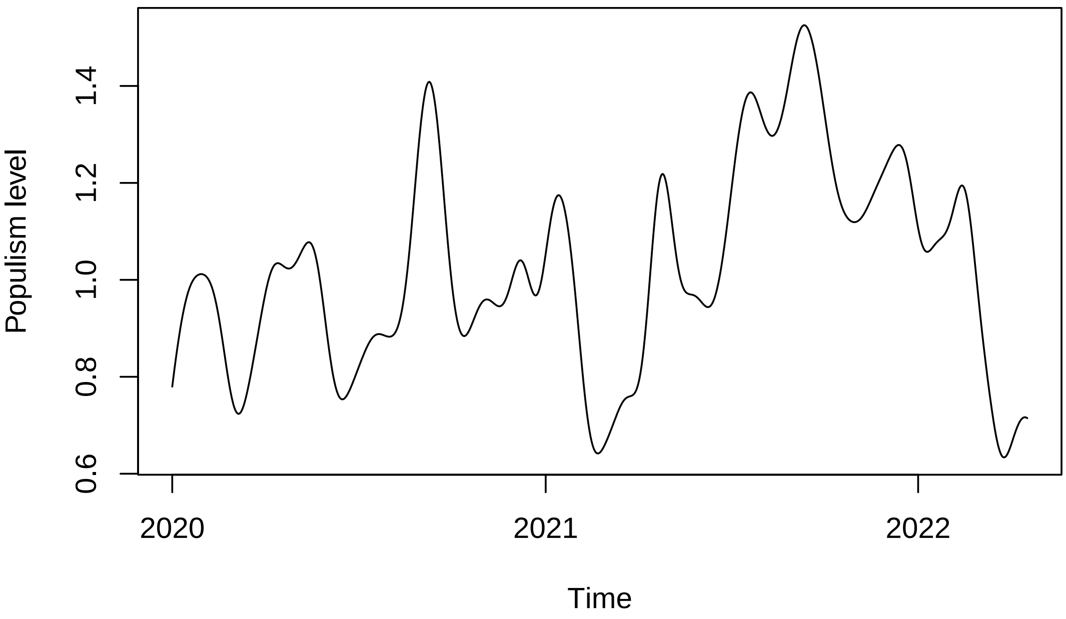
weekly: 0.0%

monthly: 0%

```r
# Daily Dictionary analysis with Grundl_Italian_adapted on the whole dataset
dfm_dict3  <- dfm_lookup(dfm_weight, dictionary = Grundl_Italian_adapted)
# Group by date
dfm_by_date3<- dfm_group(dfm_dict3, groups= date)
#dfm_by_date3
# Group by week
dfm_by_week3 <- dfm_group(dfm_dict3, groups= week)
#dfm_by_week3
# Group by month
dfm_by_month3 <- dfm_group(dfm_dict3, groups= month)

kable(dfm_by_month3)
```

doc_id	populism
1	30.09665
2	26.23980
3	22.99661
4	32.36833
5	33.50214
6	21.44168
7	27.84302
8	28.97910
9	42.01900
10	26.10592
11	27.73779
12	30.11849
13	38.82232
14	18.62336
15	23.43787
16	34.35922
17	27.47914
18	28.23726
19	44.51744
20	37.22778
21	47.97110
22	36.88430
23	34.36299
24	40.02462
25	30.90143
26	33.14042
27	22.64935
28	13.13454

3.5.2 General level of populism in time



3.5.3 Most populist party

```
# Most populist party
dict_3_tstat_party <- textstat_frequency(dfm_dict3, groups = party_id)
kable(dict_3_tstat_party %>% slice_max(frequency, n = 20))
```

	feature	frequency	rank	docfreq	group
6	populism	225.678708	1	2075	LEGA
10	populism	153.269683	1	2017	PD
8	populism	133.053746	1	1724	M5S
3	populism	131.838292	1	1524	FI
2	populism	99.425177	1	1087	FDI
9	populism	86.092041	1	997	MISTO
7	populism	15.213765	1	231	LEU
1	populism	10.602522	1	157	CI
5	populism	2.559005	1	40	IV
4	populism	1.983671	1	31	INDIPENDENTE
11	populism	1.505044	1	22	REG_LEAGUES

3.5.4 Most populist politician

```r
dict_3_tstat_nome <- textstat_frequency(dfm_dict3, groups = nome)

kable(dict_3_tstat_nome %>% slice_max(frequency, n = 20))
```

	feature	frequency	rank	docfreq	group
287	populism	23.033031	1	240	LANNUTTI Elio
210	populism	19.501980	1	110	FERRERO Roberta
562	populism	19.042283	1	131	VITO Elio
275	populism	16.483870	1	120	IEZZI Igor Giancarlo
494	populism	15.974269	1	184	SGARBI Vittorio
341	populism	11.063928	1	159	MELONI Giorgia
15	populism	10.731212	1	120	ANZALDI Michele
298	populism	10.659433	1	98	LOLLOBRIGIDA Francesco
74	populism	10.645964	1	97	BORGHI Claudio
476	populism	9.238862	1	122	SALVINI Matteo
248	populism	9.004085	1	139	GARNERO SANTANCHE' Daniela
96	populism	8.438949	1	103	CANGINI Andrea
546	populism	8.339166	1	106	URSO Adolfo
224	populism	8.162373	1	101	FONTANA Lorenzo
472	populism	7.850014	1	68	RUSPANDINI Massimo
44	populism	7.832168	1	120	BERGESIO Giorgio Maria
165	populism	7.565932	1	92	DE MARTINI Guido
141	populism	7.036558	1	43	CROSETTO Guido
446	populism	7.000320	1	47	RIVOLTA Erica
359	populism	6.861311	1	73	MORELLI Alessandro

3.6 Decadri_Boussalis

3.6.1 Level of sparsity

daily: 0%

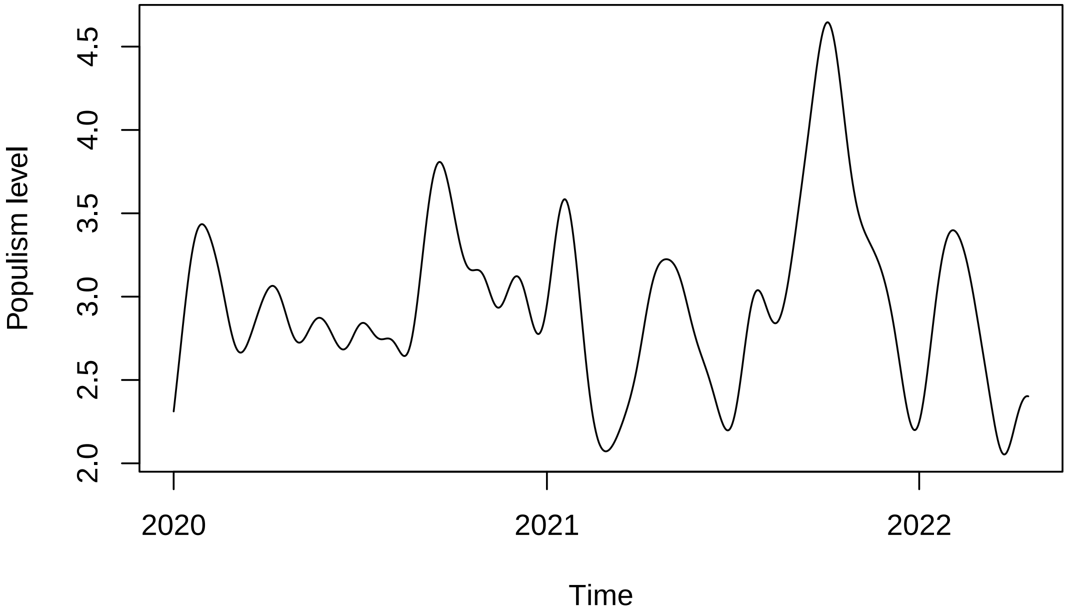
weekly: 0.0%

monthly: 0%

```r
# Daily Dictionary analysis with Decadri_Boussalis on the whole dataset
dfm_dict4  <- dfm_lookup(dfm_weight, dictionary = Decadri_Boussalis)
# Group by date
dfm_by_date4<- dfm_group(dfm_dict4, groups= date)
#dfm_by_date4
# Group by week
dfm_by_week4 <- dfm_group(dfm_dict4, groups= week)
#dfm_by_week4
# Group by month
dfm_by_month4 <- dfm_group(dfm_dict4, groups= month)

kable(dfm_by_month4)
```

doc_id	populism
1	93.79618
2	88.79620
3	85.17899
4	90.99191
5	83.84470
6	82.69573
7	86.64935
8	81.95542
9	115.45515
10	99.27498
11	87.54297
12	89.72799
13	110.94629
14	62.65329
15	70.34687
16	94.13414
17	90.03489
18	71.30863
19	89.16969
20	85.12252
21	120.57959
22	134.28306
23	100.48658
24	74.25601
25	91.93483
26	90.76021
27	64.69319
28	46.01515

3.6.2 General level of populism in time



3.6.3 Most populist party

```
# Most populist party
dict_4_tstat_party <- textstat_frequency(dfm_dict4, groups = party_id)
kable(dict_4_tstat_party %>% slice_max(frequency, n = 20))
```

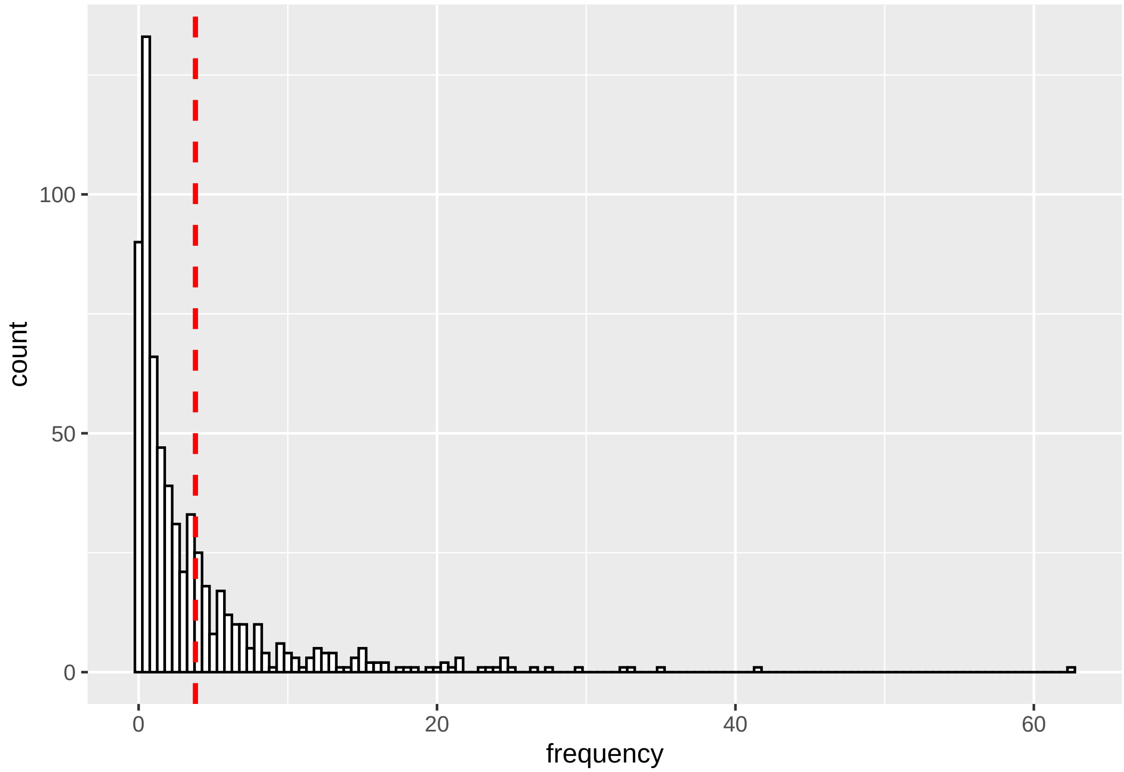
	feature	frequency	rank	docfreq	group
6	populism	651.348390	1	5672	LEGA
10	populism	493.532735	1	6417	PD
8	populism	376.966170	1	5178	M5S
3	populism	376.609606	1	4532	FI
2	populism	270.814483	1	2960	FDI
9	populism	202.466904	1	2463	MISTO
7	populism	44.919508	1	659	LEU
1	populism	35.105322	1	506	CI
5	populism	14.132863	1	197	IV
4	populism	10.615825	1	153	INDIPENDENTE
11	populism	6.122696	1	93	REG_LEAGUES

3.6.4 Most populist politician

```r
dict_4_tstat_nome <- textstat_frequency(dfm_dict4, groups = nome)

kable(dict_4_tstat_nome %>% slice_max(frequency, n = 20))
```

	feature	frequency	rank	docfreq	group
236	populism	62.66405	1	282	FERRERO Roberta
560	populism	41.70723	1	443	SGARBI Vittorio
329	populism	34.85565	1	397	LANNUTTI Elio
391	populism	33.15912	1	496	MELONI Giorgia
344	populism	32.36912	1	358	LOLLOBRIGIDA Francesco
540	populism	29.61242	1	368	SALVINI Matteo
27	populism	27.44810	1	135	BALDELLI Simone
280	populism	26.74696	1	372	GARNERO SANTANCHE' Daniela
530	populism	24.85093	1	184	ROTONDI Gianfranco
68	populism	24.50676	1	252	BONACCINI Stefano
220	populism	24.35617	1	122	FAGGI Antonella
317	populism	24.31241	1	207	IEZZI Igor Giancarlo
128	populism	23.82148	1	195	CECCHETTI Fabrizio
585	populism	23.63509	1	327	TAJANI Antonio
80	populism	22.82617	1	240	BORGHI Claudio
161	populism	21.54784	1	158	CROSETTO Guido
39	populism	21.35229	1	202	BAZZARO Alex
47	populism	21.29380	1	318	BERGESIO Giorgio Maria
535	populism	20.92822	1	140	RUSPANDINI Massimo
365	populism	20.38171	1	185	MALAN Lucio

```
# TEST
ggplot(dict_4_tstat_nome, aes(x=frequency)) +
  geom_histogram(binwidth=.5, colour="black", fill="white") +
    geom_vline(aes(xintercept=mean(frequency, na.rm=T)),   # Ignore NA values for m
                   color="red", linetype="dashed", size=1)
```



4 Sentiment analysis

http://saifmohammad.com/WebPages/lexicons.html

4.1 Inspect the dictionary

```
head(get_sentiment_dictionary(dictionary = "nrc", language = "italian"),15)
```

```
##       lang         word sentiment value
## 1  italian         abba  positive     1
## 2  italian     capacità  positive     1
## 3  italian sopra citato  positive     1
## 4  italian     assoluto  positive     1
## 5  italian  assoluzione  positive     1
## 6  italian    assorbito  positive     1
## 7  italian   abbondanza  positive     1
## 8  italian   abbondante  positive     1
## 9  italian   accademico  positive     1
## 10 italian    accademia  positive     1
## 11 italian  accettabile  positive     1
## 12 italian accettazione  positive     1
## 13 italian  accessibile  positive     1
## 14 italian      encomio  positive     1
## 15 italian     alloggio  positive     1
```

4.1.1 Clean text from dataframe

Define function to make the text extracted from dataframe suitable for analysis

```r
# Define function to make the text suitable for analysis
clean.text = function(x)
{
  # tolower
  x = tolower(x)
  # remove rt
  x = gsub("rt", "", x)
  # remove at
  x = gsub("@\\w+", "", x)
  # remove punctuation
  x = gsub("[[:punct:]]", "", x)
  # remove numbers
  x = gsub("[[:digit:]]", "", x)
  # remove links http
  x = gsub("http\\w+", "", x)
  # remove tabs
  x = gsub("[ |\t]{2,}", "", x)
  # remove blank spaces at the beginning
  x = gsub("^ ", "", x)
  # remove blank spaces at the end
  x = gsub(" $", "", x)
  return(x)
}
```

4.2 Create the filtered dataframes

```r
# Create filtered dataframes
MELONI <- dataset %>% filter(nome  == "MELONI Giorgia")
CONTE <- dataset %>% filter(nome  == "CONTE Giuseppe")
RENZI <- dataset %>% filter(nome  == "RENZI Matteo")
SALVINI <- dataset %>% filter(nome  == "SALVINI Matteo")
LETTA <- dataset %>% filter(nome  == "LETTA Enrico")
BERLUSCONI <- dataset %>% filter(nome  == "BERLUSCONI Silvio")
SPERANZA <- dataset %>% filter(nome  == "SPERANZA Roberto")
```

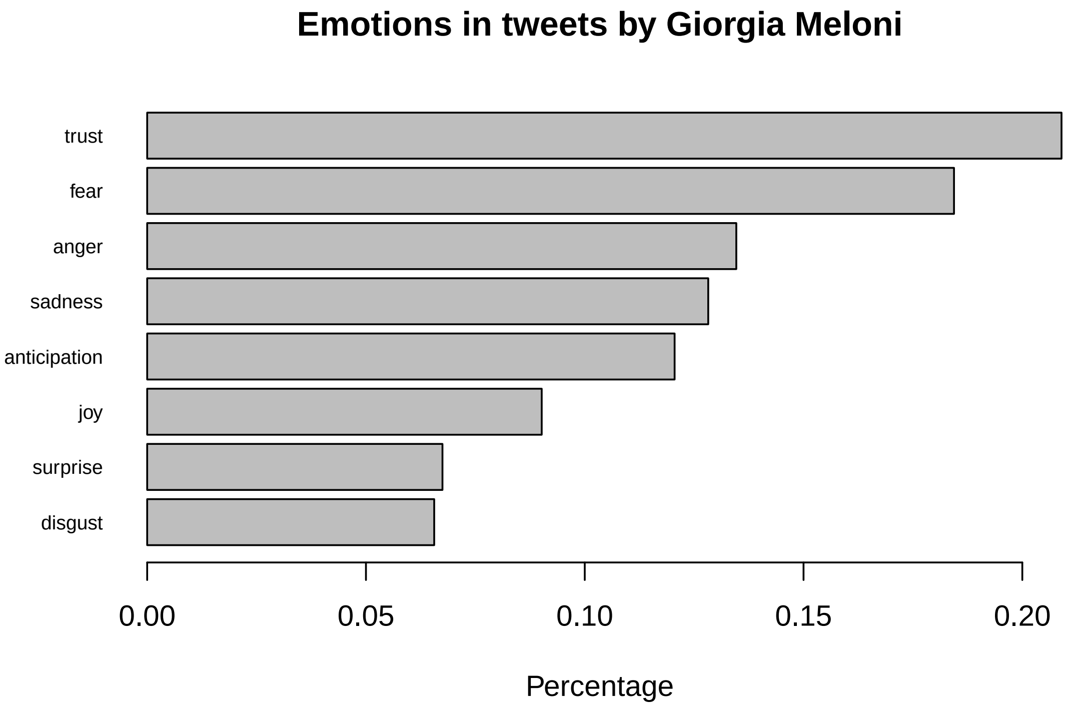
4.3 Create nrc objects

```r
# Create the nrc object
nrc_meloni <- get_nrc_sentiment(MELONI$tweet_testo, language="italian")
save(nrc_meloni,file="data/nrc_meloni.Rda")

nrc_conte <- get_nrc_sentiment(CONTE$tweet_testo, language="italian")
save(nrc_conte,file="data/nrc_conte.Rda")

nrc_renzi <- get_nrc_sentiment(RENZI$tweet_testo, language="italian")
save(nrc_renzi,file="data/nrc_renzi.Rda")

nrc_salvini <- get_nrc_sentiment(SALVINI$tweet_testo, language="italian")
save(nrc_salvini,file="data/nrc_salvini.Rda")

nrc_letta <- get_nrc_sentiment(LETTA$tweet_testo, language="italian")
save(nrc_letta,file="data/nrc_letta.Rda")

nrc_berlusconi <- get_nrc_sentiment(BERLUSCONI$tweet_testo, language="italian")
```

```r
save(nrc_berlusconi, file="data/nrc_berlusconi.Rda")

nrc_speranza <- get_nrc_sentiment(SPERANZA$tweet_testo, language="italian")
save(nrc_speranza,file="data/nrc_speranza.Rda")
```

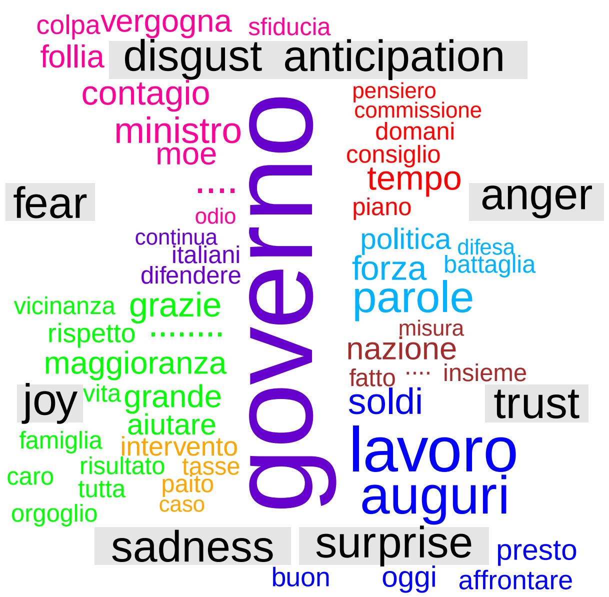
4.4 Giorgia Meloni

4.4.1 Proportion of the emotion



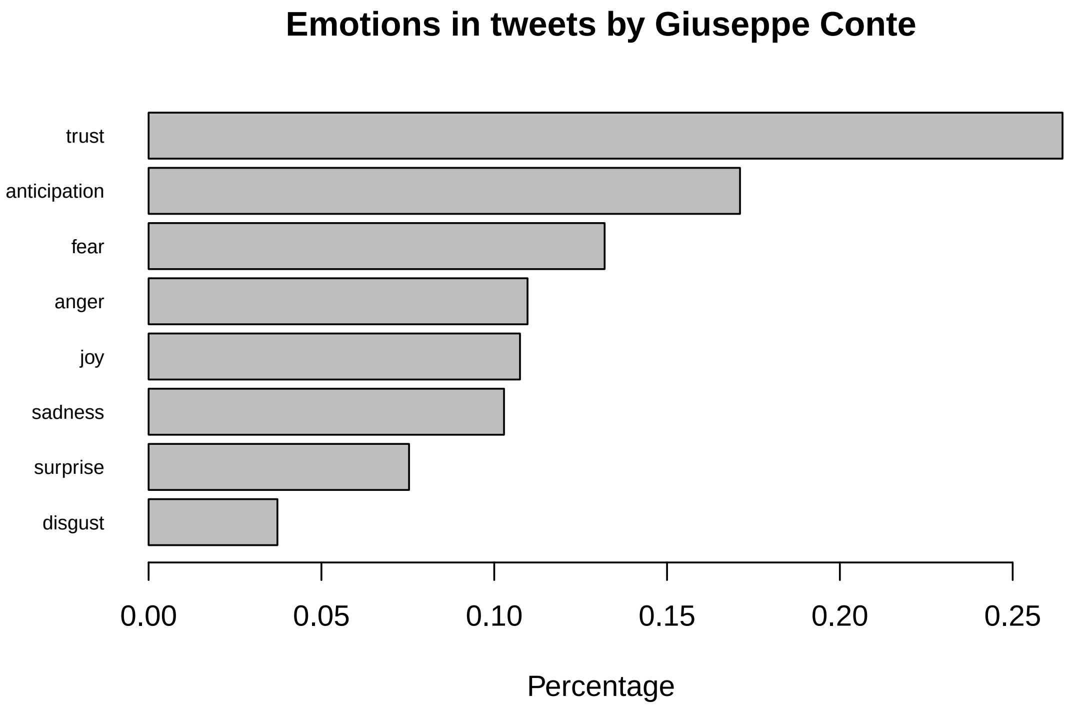
4.4.2 Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Giorgia Meloni



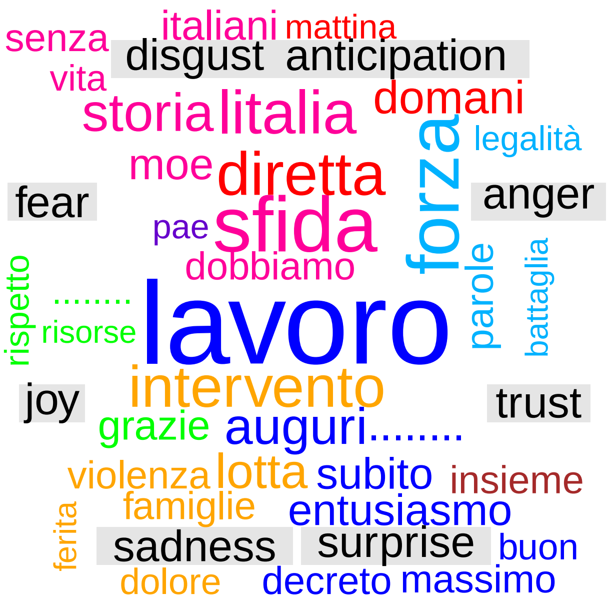
4.5 Giuseppe Conte

4.5.1 Proportion of the emotion



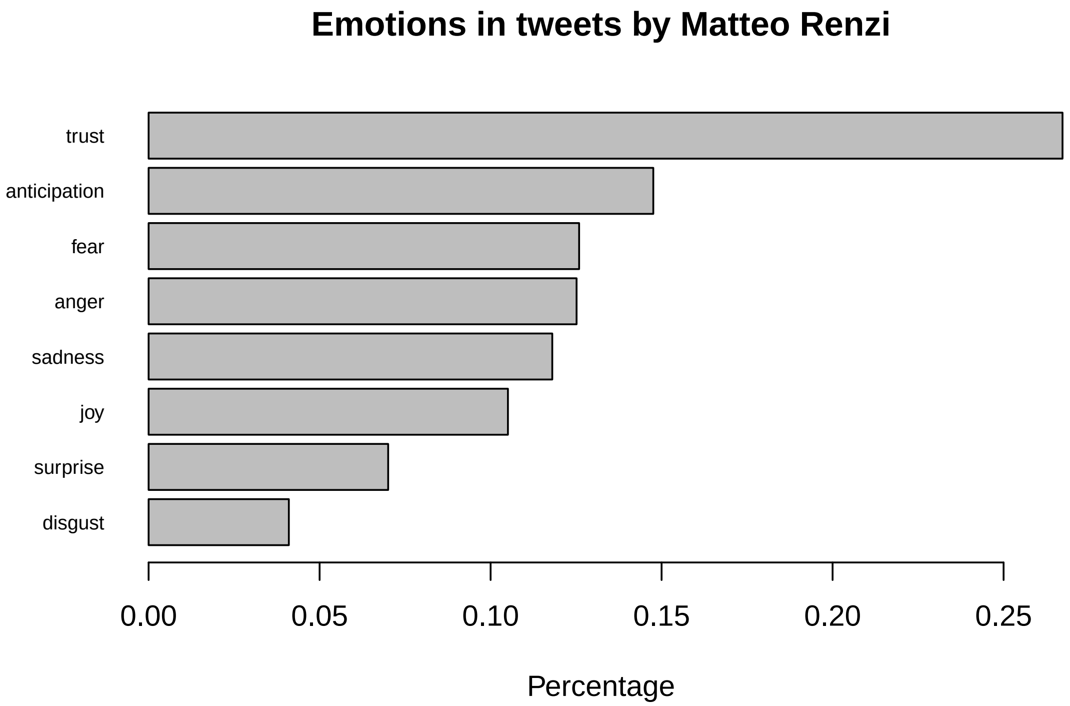
### Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Giuseppe Conte



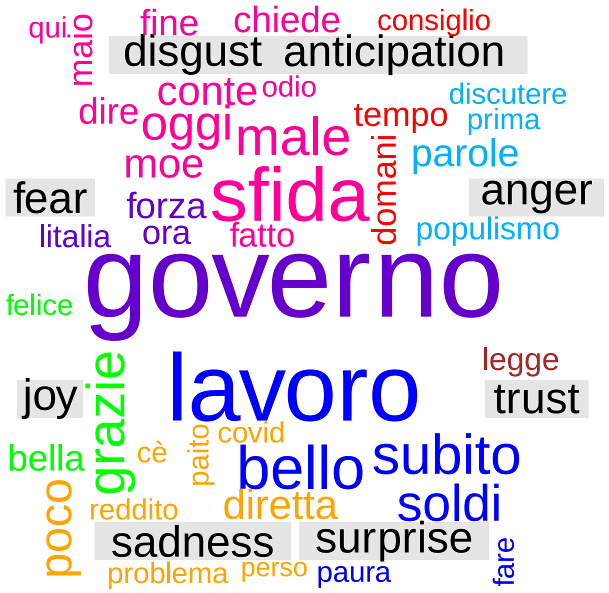
4.6 Matteo Renzi

4.6.1 Proportion of the emotion



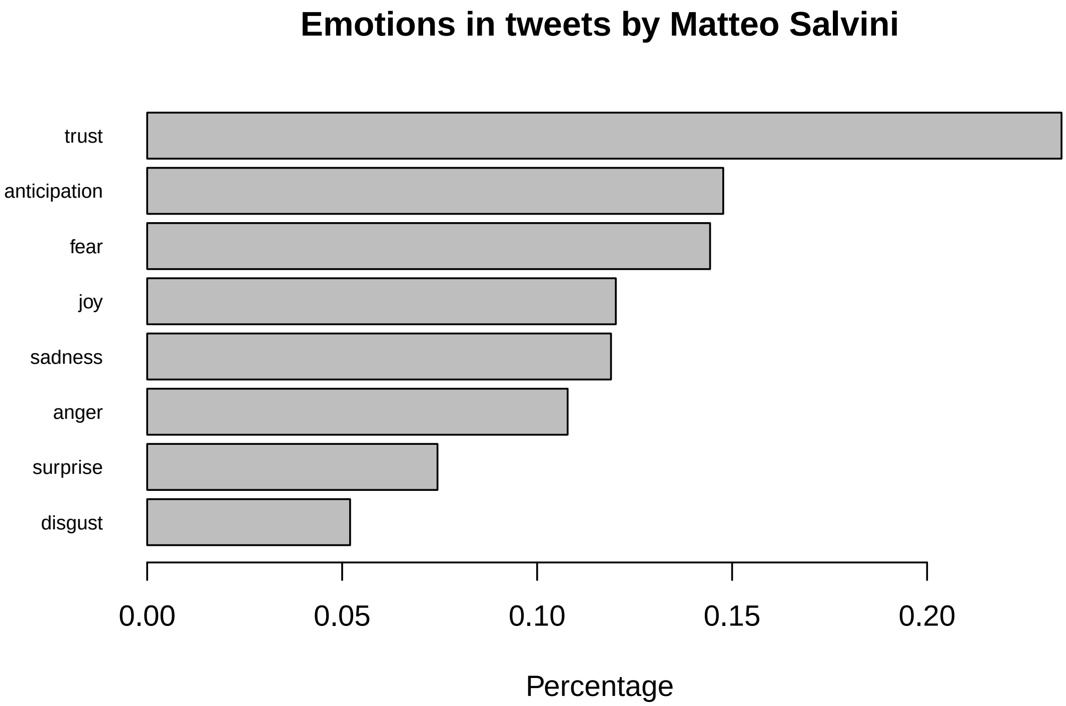
4.6.2 Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Matteo Renzi



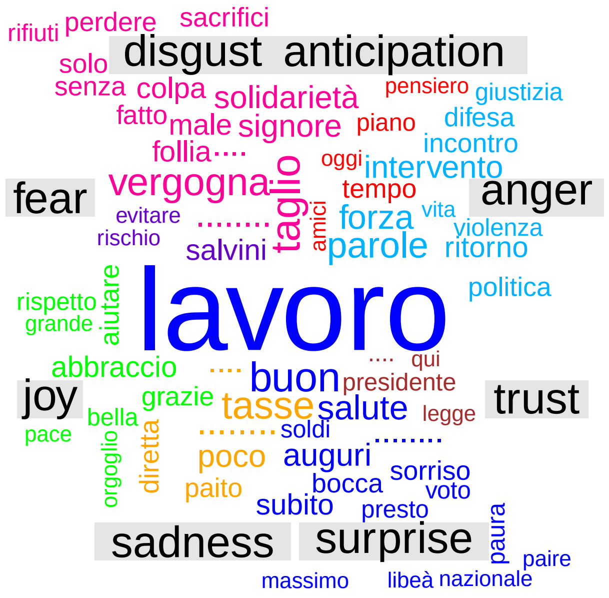
4.7 Matteo Salvini

4.7.1 Proportion of the emotion



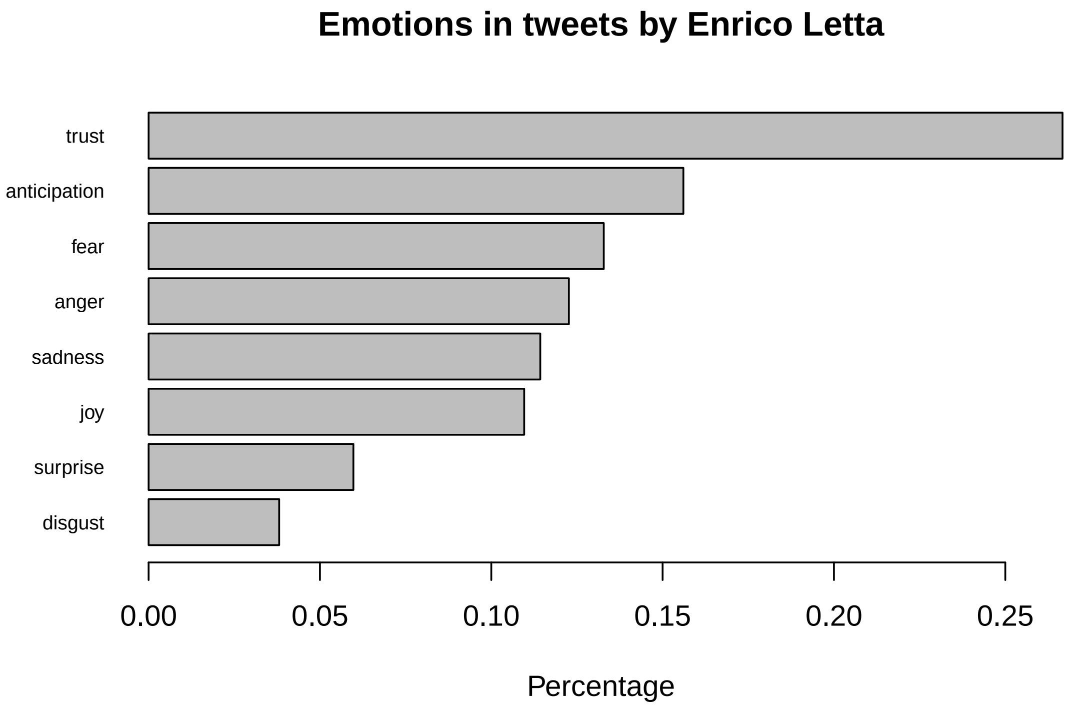
4.7.2 Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Matteo Salvini



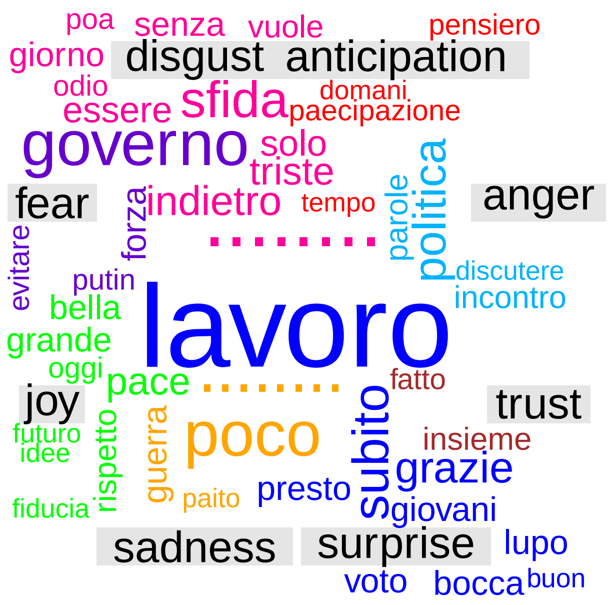
4.8 Enrico Letta

4.8.1 Proportion of the emotion



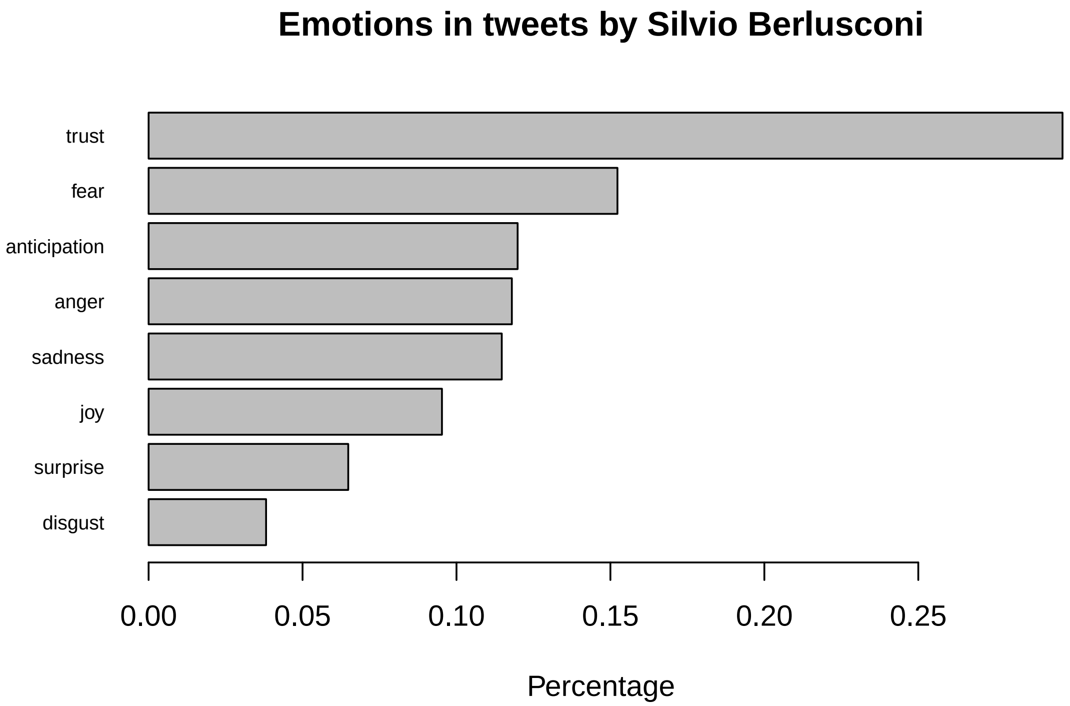
4.8.2 Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Enrico Letta



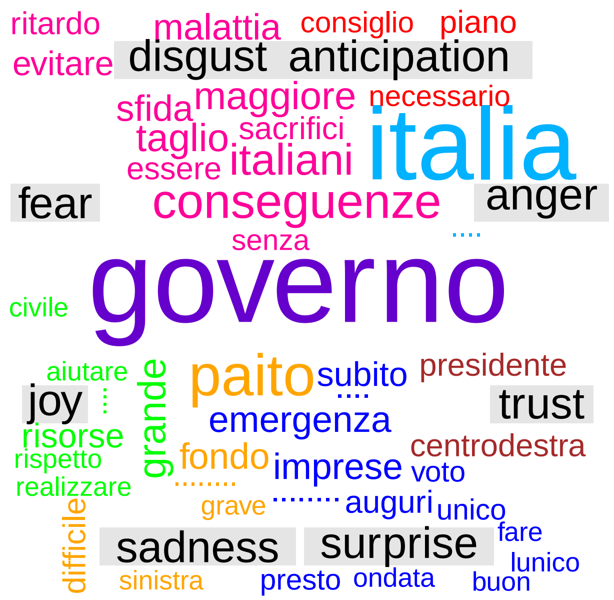
4.9 Silvio Berlusconi

4.9.1 Proportion of the emotion



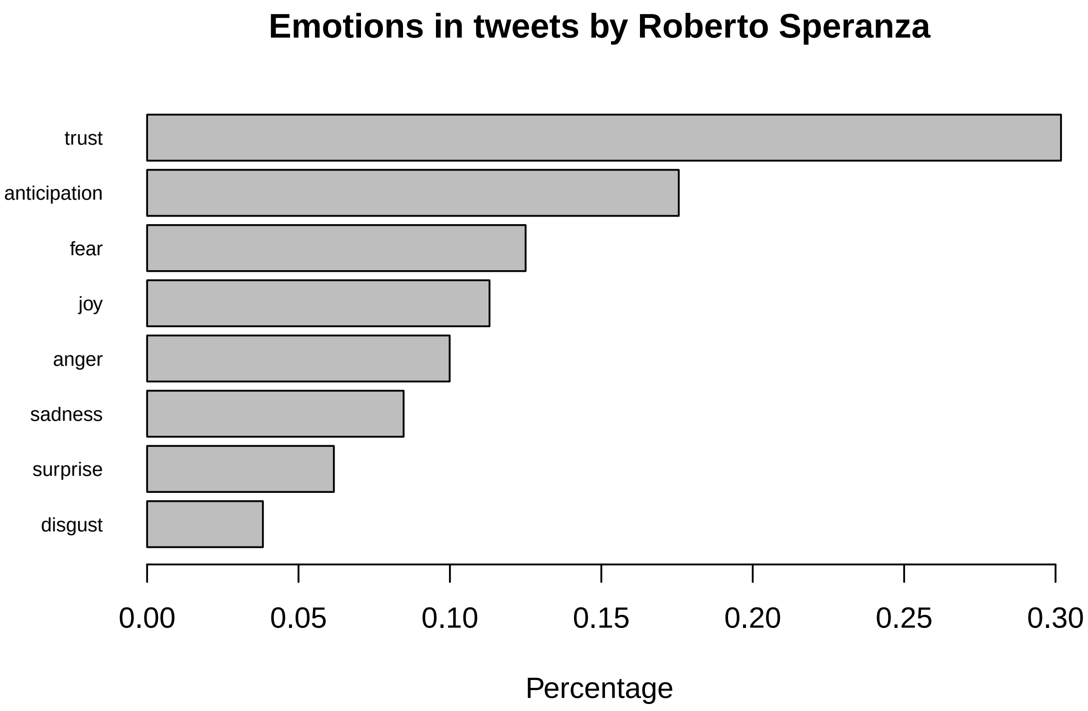
4.9.2 Wordcloud of emotions

Emotion Comparison Word Cloud for tweets by Silvio Berlusconi

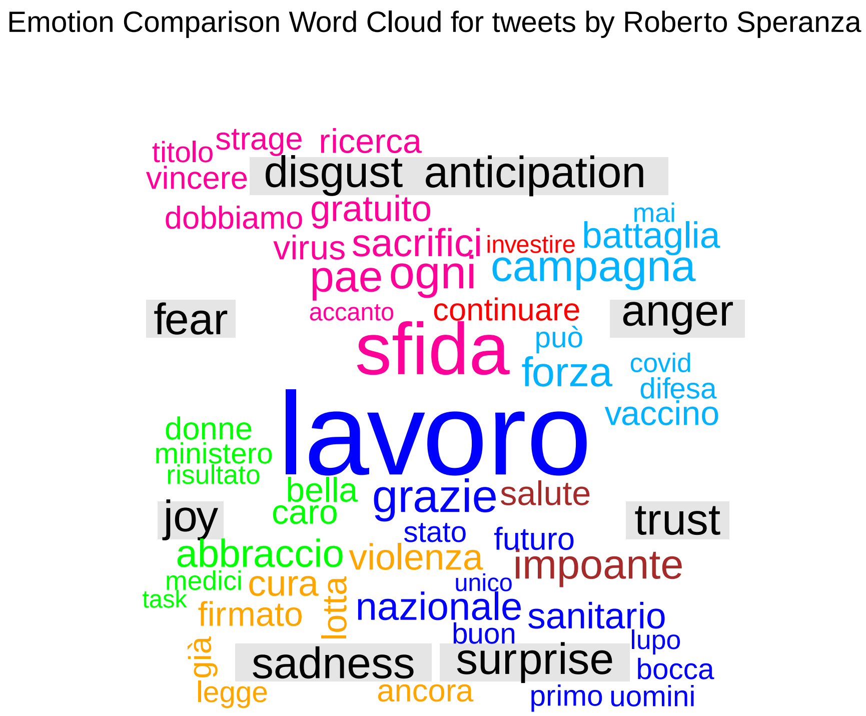


4.10 Roberto Speranza

4.10.1 Proportion of the emotion



4.10.2 Wordcloud of emotions



5 LDA Topic model analysis

5.1 CREATE THE DTM

5.1.1 Remove all the account's mentions

```
DFM_trimmed@Dimnames$features <- gsub("^@", "", DFM_trimmed@Dimnames$features)
```

###Convert the Document Feature Matrix (Dfm) in a Topic Model (Dtm)

```
dtm <- quanteda::convert(DFM_trimmed, to = "topicmodels")
```

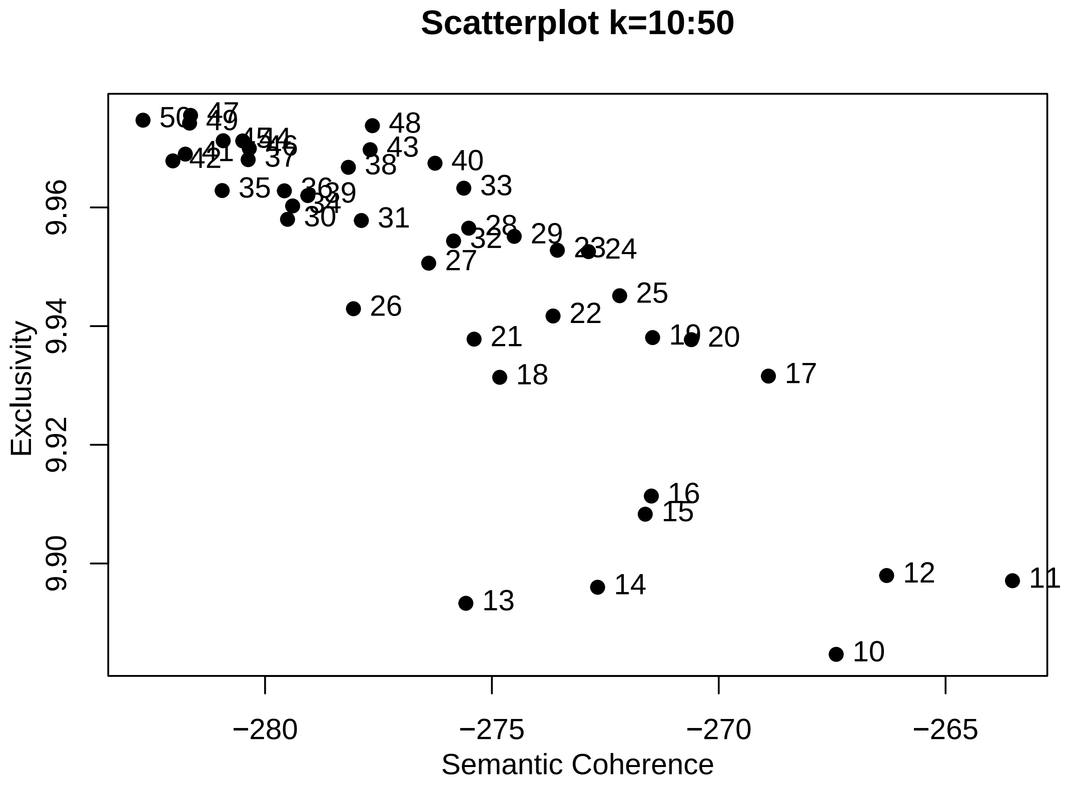
5.2 FIND THE BEST NUMBER OF TOPICS K

5.2.1 Search the best number of Topics comparing coherence and exclusivity values

K = 10:50

```
# 10 : 50 iter 1000
top1 <- c(10:50)

## let's create an empty data frame
risultati <- data.frame(first=vector(), second=vector(), third=vector())

system.time(
  for (i  in top1)
  {
    set.seed(123)
    lda_test <- LDA(dtm, method= "Gibbs", k = (i),  control=list(verbose=50L, iter=
    topic <- (i)
    coherence_test <- mean(topic_coherence(lda_test, dtm))
    exclusivity_test <- mean(topic_exclusivity(lda_test))
    risultati <- rbind(risultati , cbind(topic, coherence_test, exclusivity_test ))
  }
)
# save(risultati,file="data/results_K_10-50.Rda")
```

5.2.2 Plot the values of coherence and exclusivity in order to find the best K



Interpreting those data i can state that K= 22 has the best values of coherence and exclusivity.

5.3 ANALISYS OF THE TOPICS

5.3.1 Repeat the analysis selecting k = 22

```
system.time(lda_22 <- LDA(dtm, method= "Gibbs", k = 22, control = list(seed = 123)))
# save(lda, file = "data/lda_k_22.Rda")
```

5.3.2 The most important terms from the model, for each topic

Top terms 01	Top terms 02	Top terms 03	Top terms 04	Top terms 05	Top terms 06
vaccini	guerra	#draghi	grazie	#referendumgiustizia	#tokyo2020
aprile	#ucraina	draghi	mondo	luglio	#afghanistan
vaccinale	ucraina	governo	insieme	giustizia	talebani
pandemia	pace	#governodraghi	presidente	#ddlzan	agosto
@fratelliditalia	putin	lavoro	lavoro	gazebo	afghanistan
buon	marzo	paese	solidarietà	#primalitalia	medaglia
draghi	russia	@fratelliditalia	donne	giugno	oro
#draghi		presidente	paese	riforma	@fattoquotidiano
covid	popolo	buon	grande	firme	kabul
@pdnetwork	ucraino	vaccini	nazionale	#euro2020	medaglie

Top terms 7	Top terms 8	Top terms 9	Top terms 10	Top terms 11	Top terms 12
#coronavirus	maggio	sindaco	#iostoconsalvini	#iostoconsalvini	conte
misure	#ddlzan	ottobre	#oggivotolega	luglio	governo
momento	coprifuoco	pass	salvini	paese	crisi
coronavirus	@stampasgarbi	roma	#borgonzonipresidente	#salvini	#crisidigoverno
emergenza	vaccinale	@forza__italia	governo	giugno	#conte
grazie	#fratelliditalia	green	#salvini	#conte	maggioranza
l'emergenza	lavoro	città	#prescrizione	rilancio	paese
#covid19	#meloni	candidato	@fratelliditaiia	conte	presidente
casa	#coprifuoco	#roma	#m5s	#2giugno	gennaio
medici	sinistra	elettorale	#emiliaromagna	#recoveryfund	fiducia

Top terms 13	Top terms 14	Top terms 15	Top terms 16	Top terms 17	Top terms 18
#dpcm	#fase2	presidente	draghi	the	natale
#iostoconsalvini	maggio	#quirinale	pass	@fratelliditalia	dicembre
ottobre	#mes	repubblica	green	to	bilancio
#mes	lavoro	#presidentedellarepubblica	covid	of	anno
jole	ripartire	#mattarella	via	and	#atreju21
covid	aprile	#quirinale2022	#greenpass	bilancio	@fattoquotidiano
contagi	imprese	quirinale	@fratelliditalia	covid	#natale
@fratelliditalia	liquidità	gennaio	vaccinati	#mes	euro
#conte	#forzalombardia	mattarella	@stampasgarbi	natale	buon
de	#recoveryfund	david	pandemia	#covid	auguri

Top terms 19	Top terms 20	Top terms 21	Top terms 22
governo	settembre	novembre	grazie
italiani	#iovotono	de	lavoro
#covid19	elettorale	violenza	anni
paese	@fratelliditalia	pass	politica
#governo	#referendum	@fattoquotidiano	governo
imprese	scuola	donne	grande
conte	parlamentari	reddito	bene
l'italia	#iostoconsalvini	et	l'italia
crisi	referendum	@theskeptical_	forza
decreto	#processateancheme	renzi	via

```r
titles_22 <- c("1", "2", "3", "4", "5","6",
                 "7", "8", "9", "10", "11","12",
                 "13", "14", "15", "16","17","18",
                 "19", "20", "21", "22")


table_titles_22 <- rbind (titles_22, terms)



t22.1 <- table_titles_22[,1:6]

t22.2 <- table_titles_22[,7:12]

t22.3 <- table_titles_22[,13:18]

t22.4 <- table_titles_22[,19:22]


kable(t22.1)%>%
  kable_styling(latex_options = c("HOLD_position","scale_down"))
```

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
titles_22	1	2	3	4	5	6
	vaccini	guerra	#draghi	grazie	#referendumgiustizia	#tokyo2020
	aprile	#ucraina	draghi	mondo	luglio	#afghanistan
	vaccinale	ucraina	governo	insieme	giustizia	talebani
	pandemia	pace	#governodraghi	presidente	#ddlzan	agosto
	@fratelliditalia	putin	lavoro	lavoro	gazebo	afghanistan
	buon	marzo	paese	solidarietà	#primalitalia	medaglia
	draghi	russia	@fratelliditalia	donne	giugno	oro
	#draghi		presidente	paese	riforma	@fattoquotidiano
	covid	popolo	buon	grande	firme	kabul
	@pdnetwork	ucraino	vaccini	nazionale	#euro2020	medaglie

```r
kable(t22.2)%>%
  kable_styling(latex_options = c("HOLD_position","scale_down"))
```

	Topic 7	Topic 8	Topic 9	Topic 10	Topic 11	Topic 12
titles_22	7	8	9	10	11	12
	#coronavirus	maggio	sindaco	#iostoconsalvini	#iostoconsalvini	conte
	misure	#ddlzan	ottobre	#oggivotolega	luglio	governo
	momento	coprifuoco	pass	salvini	paese	crisi
	coronavirus	@stampasgarbi	roma	#borgonzonipresidente	#salvini	#crisidigoverno
	emergenza	vaccinale	@forza_italia	governo	giugno	#conte
	grazie	#fratelliditalia	green	#salvini	#conte	maggioranza
	l'emergenza	lavoro	città	#prescrizione	rilancio	paese
	#covid19	#meloni	candidato	@fratelliditaiia	conte	presidente
	casa	#coprifuoco	#roma	#m5s	#2giugno	gennaio
	medici	sinistra	elettorale	#emiliaromagna	#recoveryfund	fiducia

```r
kable(t22.3)%>%
  kable_styling(latex_options = c("HOLD_position","scale_down"))
```

	Topic 13	Topic 14	Topic 15	Topic 16	Topic 17	Topic 18
titles_22	13	14	15	16	17	18
	#dpcm	#fase2	presidente	draghi	the	natale
	#iostoconsalvini	maggio	#quirinale	pass	@fratelliditalia	dicembre
	ottobre	#mes	repubblica	green	to	bilancio
	#mes	lavoro	#presidentedellarepubblica	covid	of	anno
	jole	ripartire	#mattarella	via	and	#atreju21
	covid	aprile	#quirinale2022	#greenpass	bilancio	@fattoquotidiano
	contagi	imprese	quirinale	@fratelliditalia	covid	#natale
	@fratelliditalia	liquidità	gennaio	vaccinati	#mes	euro
	#conte	#forzalombardia	mattarella	@stampasgarbi	natale	buon
	de	#recoveryfund	david	pandemia	#covid	auguri

```r
kable(t22.4)%>%
  kable_styling(latex_options = c("HOLD_position","scale_down"))
```

	Topic 19	Topic 20	Topic 21	Topic 22
titles_22	19	20	21	22
	governo	settembre	novembre	grazie
	italiani	#iovotono	de	lavoro
	#covid19	elettorale	violenza	anni
	paese	@fratelliditalia	pass	politica
	#governo	#referendum	@fattoquotidiano	governo
	imprese	scuola	donne	grande
	conte	parlamentari	reddito	bene
	l'italia	#iostoconsalvini	et	l'italia
	crisi	referendum	@theskeptical_	forza
	decreto	#processateancheme	renzi	via

6 FER: Facial Emotion Recognition Analysis

6.1 Report on the analysis made with FER Puthon package

The package use the FER-2013 dataset created by Pierre Luc Carrier and Aaron Courville.

The dataset was created using the Google image search API to search for images of faces that match a set of 184 emotion-related keywords like “blissful”, “enraged,” etc. These keywords were combined with words related to gender, age or ethnicity, to obtain nearly 600 strings which were used as facial image search queries. The first 1000 images returned for each query were kept for the next stage of processing. OpenCV face recognition was used to obtain bounding boxes around each face in the collected images. Human labelers than rejected incorrectly labeled images, corrected the cropping if necessary, and filtered out some duplicate images. Approved, cropped images were then resized to 48x48 pixels and converted to grayscale. Mehdi Mirza and Ian Goodfellow prepared a subset of the images for this contest,and mapped the fine-grained emotion keywords into the same seven broad categories used in the Toronto Face Database [Joshua Susskind, Adam Anderson, and Geoffrey E. Hinton. The Toronto face dataset. Technical Report UTML TR 2010-001, U. Toronto, 2010.]. The resulting dataset contains 35887 images, with 4953 “Anger” images, 547 “Disgust” images, 5121 “Fear” images, 8989 “Happiness” images, 6077 “Sadness” images, 4002 “Surprise” images, and 6198 “Neutral” images. FER-2013 could theoretical suffer from label errors due to the way it was collected, but Ian Goodfellow found that human accuracy on FER-2013 was 65±5%.

66% ACCURACY REPORTED BY OCTAVIO ARRIAGA, Matias Valdenegro-Toro, Paul Plöger (Real-time Convolutional Neural Networks for Emotion and Gender Classification)