Data Acces Capstone: Google Trends Project

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1 INTRODUCTION

1.1 Questions research

Inspired by a Rovetta A. study published on JMIR, the aim of this project is testing the hypothesis claiming that the volume of researches on Google Italia about right-wing topics, actors, websites and news has raised during the pandemic.

This project tries to answer a few questions:

1. Crossing date and hits variables, will we observe a positive linear trend?
2. Is there a seasonality to the queries?
3. Overall, how effective can be Google Trends on following socio-political movements?

- My research about the topic suggests me that lockdown and, more generally, COVID-19 Pandemic, have raised internet traffic and extremism has gained popularity among world citizens, therefore it's likely that my plot visualization will show a positive linear trend.

- No prediction could be made for the first question, since that the answer could be affected by important socio-political events occurred during the pandemic or even changes in the lockdowns severity.
- Last question is a secondary quest I added for a more personal curiosity, so the answer will be more subjective and won't be answered with a statistical approach but rather with a researcher point of view that is testing RStudio's package *gtrendsR* and GoogleTrends for my socio-political studies!

1.2 Data and tool:*gtrendsR*

To test the hypotheses, I create a dataset that contains as many right-wing related keywords as possible. In order to do it, I start from a scraped list of organizations and people linked to right-wing parties and then look for related queries trying to identify the trending keywords among users.

The starting list is obtained by scraping an already existing map made by patriaindipendente.it. The best way to import a dataset with all trending searches on Google is by using Google Trends and, since I'm exclusively using RStudio to work on this project, I employ gtrendsR package (more info...). This package allows us to get a dataset with different variables: geo, time, keywords and onlyInterest (a boolean that allows to call ONLY the interest_over_time or not).

```
library(tidyverse)
library(rvest)
library(stringr)
library(rio)
library(gtrendsR)
```

2 DATA IMPORT AND PREPARATION

2.1 First dataset

Firstly I imported the dataset by scraping a website (see the reference) and running the *gtrendsR* API to obtain the complete dataframe of the Google Trends statistics about a keyword. After I scraped the list, I had to replace all the keywords inside the gtrendsR argument *keyword*, set the *geo* variable as *"IT"* (Italy) and the period of time chosen for the study: *"2020-01-01 2022-02-28"*.

The first problem I encountered was the fact that the package's argument *keyword* allows just 5 words at a time; to solve that issue, I created a function called *divideR* that allows me to divide the list in several groups of 5 so that I could automatically run one group of five at the time.

```
divideR <- function(x,n) split(x, cut(seq_along(x), n, labels = FALSE))

dvd_listaNera <- divideR(scrap_listaNera, 7)

test1_listaNera <- gtrends(keyword = dvd_listaNera$'1',
                           geo = "IT",
                           time = "2020-01-01 2022-02-28"
)
test2_listaNera <- gtrends(keyword = dvd_listaNera$'2',
                           geo = "IT",
                           time = "2020-01-01 2022-02-28"
)
test3_listaNera <- gtrends(keyword = dvd_listaNera$'3',
                           geo = "IT",
```

```
                            time = "2020-01-01 2022-02-28"
)
test4_listaNera <- gtrends(keyword = dvd_listaNera$'4',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28"
)
test5_listaNera <- gtrends(keyword = dvd_listaNera$'5',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28"
)
test6_listaNera <- gtrends(keyword = dvd_listaNera$'6',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28"
)
test7_listaNera <- gtrends(keyword = dvd_listaNera$'7',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28"
)
test8_listaNera <- gtrends(keyword = c("8chan","8kun","pillola rossa","olocausto italiano","grande sost
                            geo = "IT",
                            time = "2020-01-01 2022-02-28"
)
```

After that, to enlarge my dataset, and to recreate the environment of a right-wing user that surfs the Internet binge-searching the related topics that the Google algorithm provides them, I create a first dataframe with the *related queries* that *gtrendsR* package found.

```
list_1 <- test1_listaNera$related_queries$value
list_2 <- test2_listaNera$related_queries$value
list_3 <- test3_listaNera$related_queries$value
list_4 <- test4_listaNera$related_queries$value
list_5 <- test5_listaNera$related_queries$value
list_6 <- test6_listaNera$related_queries$value
list_7 <- test7_listaNera$related_queries$value

LIST <- c(list_1, list_2, list_3,list_4,list_5,list_6,list_7)

DATASET <- unique(LIST)
DATASET <- DATASET[-c(2,3,6,32,39,41,44,46,48,49,57,58,61,64:110)]
```

After some cleanings, I had my first list of *queries*. Then, I runned again *gtrendsR* but this time I only asked for *interest_over_time* by adding the argument *interestOnly=T*

```
DATASET <- divideR(DATASET, 10)


group_1_onlytime <- gtrends(keyword = DATASET$'1',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)
```

```
group_2_onlytime <- gtrends(keyword = DATASET$'2',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_3_onlytime <- gtrends(keyword = DATASET$'3',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_4_onlytime <- gtrends(keyword = DATASET$'4',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_5_onlytime <- gtrends(keyword = DATASET$'5',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_6_onlytime <- gtrends(keyword = DATASET$'6',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_7_onlytime <- gtrends(keyword = DATASET$'7',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)
group_8_onlytime <- gtrends(keyword = DATASET$'8',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE

)

group_9_onlytime <- gtrends(keyword = DATASET$'9',
                            geo = "IT",
                            time = "2020-01-01 2022-02-28",
                            onlyInterest = TRUE
```

```
)

group_10_onlytime <- gtrends(keyword = DATASET$'10',
                             geo = "IT",
                             time = "2020-01-01 2022-02-28",
                             onlyInterest = TRUE

)
```

2.2 Second dataset

Following the method above, I did the same for the second dataset, scraped from another list of keywords found online (see references). This time, my list was quite longer than the first so I had to use a for loop.

```
download.file(url = nuova_lista,
              destfile = here::here("nuovaLista.html"))

scrap_nuovaLista <- read_html(here::here("nuovaLista.html")) %>%
  html_elements(css = "a") %>%
  html_text(trim = TRUE)

new_list <- unique(scrap_nuovaLista)
new_list <- new_list[-c(1)]

DATASET_2 <- vector()
v <- vector()

for (i in 1:446) {
  tryCatch({v <- gtrendsR::gtrends(keyword = new_list[i], geo = "IT", time = "2020-01-01 2022-02-28", o
            error = function(e){})
  cat(i, " ")
  v <- as.data.frame(v$interest_over_time)
  DATASET_2 <- rbind(DATASET_2, v)
}
```

Before merging the two dataset to create the final one, I had to clean the datasets with regex to delete the most general keywords and the other unrelated keywords that fell into the dataframe due to weird outcomes of the Google Algorithm. For the sake of the next regression, I had to cut all the values that fall below the *hits* = 5, and in the next part we'll see what does it mean.

3 TEST AND VISUALIZATION

3.1 Is there a seasonality to the queries?

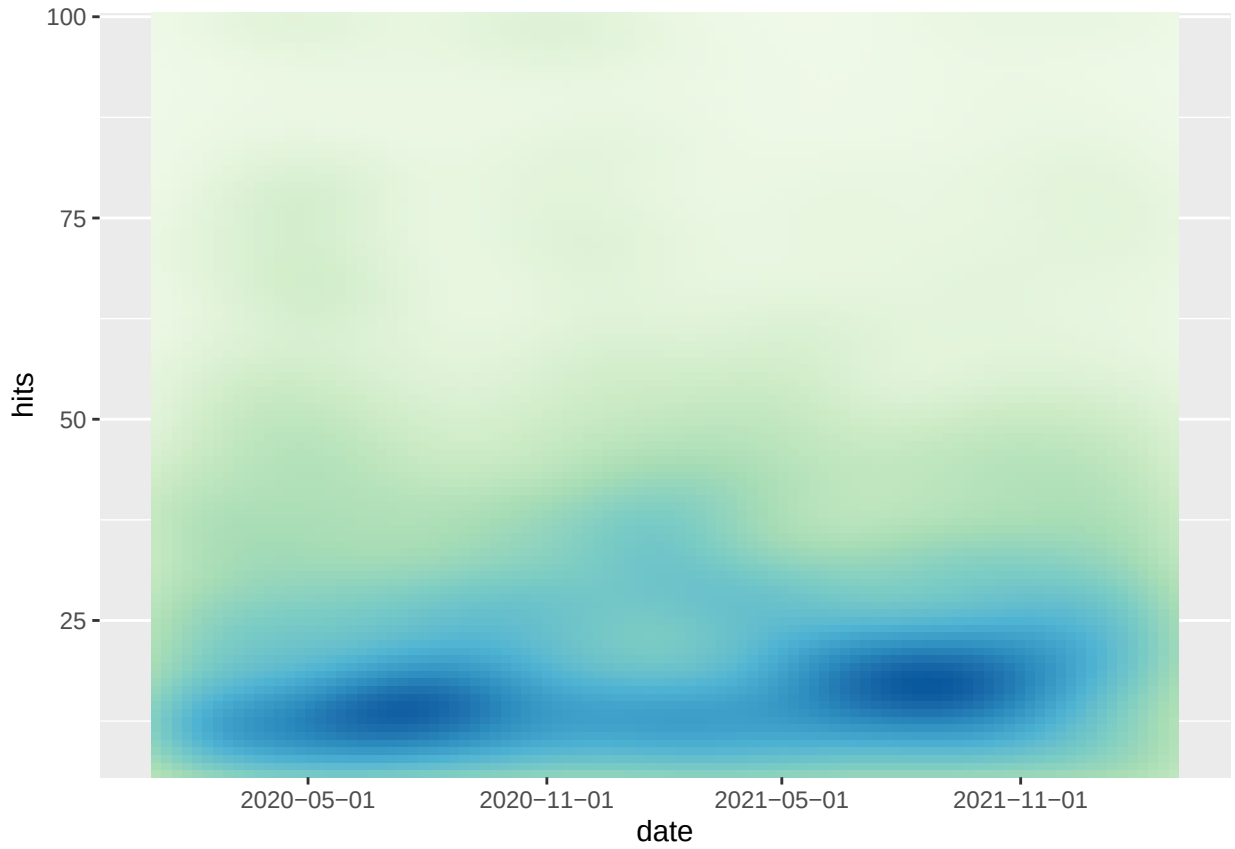
Having the full dataset for testing my hypothesis, I started with the first: is there a seasonality of the queries? Having the opportunity to cross *hits* that it's a value that express the level of popularity of the term; when it's 100 is the peak of popularity, whilst a value of 50 means that the term is half as popular. Scores of 0 mean that a sufficient amount of data was not available for the selected term.

To answer the first question, I did a density plot with *ggplot2*

```r
COMPLETE_DATASET_regex <- import("Complete_dataset(cleanedREGEXS).csv")


density_plot <- ggplot(COMPLETE_DATASET_regex, aes(x=date, y=hits) ) +
  stat_density_2d(aes(fill = ..density..), geom = "raster", contour = FALSE) +
  scale_fill_distiller(palette=4, direction=1) +
  scale_x_datetime(date_breaks = "6 months") +
  scale_y_continuous(expand = c(0, 0)) +
  theme(
    legend.position='none'
  )

density_plot
```



As we can see, the plot shows that the first peak has been reached during the summer of 2020, between June and August 2020, while the seconds occurred between August and October 2021. Therefore, even if there isn't a precise pattern that we can notice and can helps us making a prediction model, we can observe that the trending occurred just once a year; furthermore we can spot a little "cloud" during January-February 2021 that indicate a cluster of very trending queries.

3.2 Crossing date and hits: a positive linear trend?

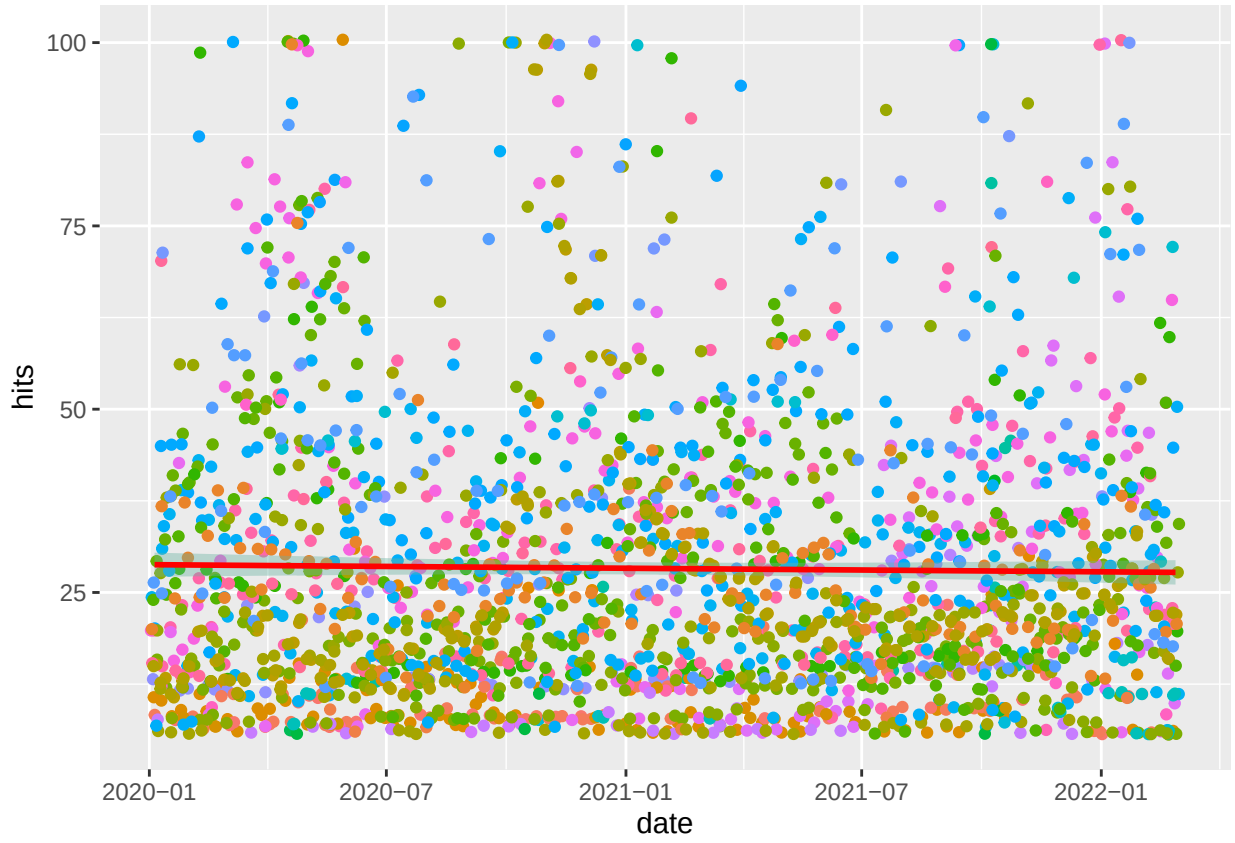
For the second question, let's have a look at the linear trend plot:

```
COMPLETE_DATASET_regex <- import("Complete_dataset(cleanedREGEXS).csv")

linear_plot<- ggplot(COMPLETE_DATASET_regex, aes(x=date, y=hits) ) +
  geom_point(aes(date, hits,color = keyword), position = 'jitter') +
  geom_smooth(method=lm , color="red", fill="#69b3a2", se=TRUE) +
  theme(
    legend.position ='none')

linear_plot
```

```
## `geom_smooth()` using formula 'y ~ x'
```



It's clear that, even if I removed all the *hits* below a certain value, the majority of the queries is condensed in at the bottom of the plot and, even if the linear trend shows a slight negative slope, the results it's not statistically significant.

4 Conclusion and personal considerations

4.1 Results comment

Although the two peaks spotted while testing the presence of a seasonality about the queries, eventually I had to conclude that we can't reject the null hypotheses for both questions therefore our two alternative hypotheses are rejected since the results are statistically irrelevant.

There are several critical issues in my project, starting from the richness of the data to the statistical methods applied for testing the hypotheses that could be implemented with further studies about the topic and the tools involved. For these reason, I would rather focus on my *journey* and the impressions I had during my capstone research and the skills/tools involved. That's why I wrote the next and last paragraph.

4.2 Third question research: opinion about *gtrendsR* and Google Trends

When I started my project I asked myself: I've always wondered if Google Trends could be used to observe mass opinion and its shifting and I started looking for an API so I found *gtrendsR*. Given that I had just learnt to scrape from websites, I decided to enter the black galaxy of right-wing forums and social pages to obtain the largest dataframe possibile about slogans, topic, recurring keywords related to extreme right parties, organizations and communities. For example, I decided to scrap from Stormfront,a famous forum populated by right-sympathizers.

```
stormfront <- read_html(here::here("Stormfront.html")) %>%
  html_elements(css = "#posts .alt1 a") %>%
  html_text(trim = TRUE)
view(stormfront)

stormfront <- c("Der Strumer in italiano", "ebrei nemico occulto", "giudeo bolscevismo","piano giudaico
                "der ewidge jude","forces occultes 1943","suss l'ebreo ","banche ebraiche sovietici","el
                "movimento omosessuale ebrei","il dividendo dei Rothschilds Waterloo","mario monti ebrei
                "contro il filoislamismo","progetto grande califfato","bibbia dell'antislamismo","il pe
                "difendere identità biologica","diffondere identità razziale","nazionalismo bianco","W.
                "invasione allogeni","rhodesia paradiso a inferno","11 settembre la verità","critiche g
                "gilberto oneto bugie immigrati","pericolo rom","druido verità piccone", "giorno memori
                "protocolli sion falsi","miracolo economico hitler","the colour of crime italiano","rus
                "teorie Armand Marie Leroi","verità meticciato","Jared Tayler razza","Genius Seculi","G
                "American Dissident Voices ita","piano giudaico kalergi italiano","savitri devi femmini
```

I was very positive about the list I was creating, but then I had to give up because of Google Trends: the API was giving me back results about just the ~5% of the list of keywords due to lack of available data. This is one of the most critical issues about my research method, Google Trends is really sensitive and works better with maximum 2 words and preferably *non specific*.

Overall, I can consider myself quite satisfied about my personal progress achieved during this project. Finally I had the chance to try my scraping skills and I found very challenging the fact that I had to face several critical issues solved with regular expressions, new packages, for loops and a lot of data cleaning and preparation.

Despite the scarce results obtained, I believe that this research could be a starting point for further analysis and a nice capstone from which starting my data science and analysis carrier.