# **Public Opinion of COVID Policies**

**Using Twitter Sentiment and Policy Data Elena Stein** 

1. Read in the tweets JSON and process 2. Investigate word use in the text

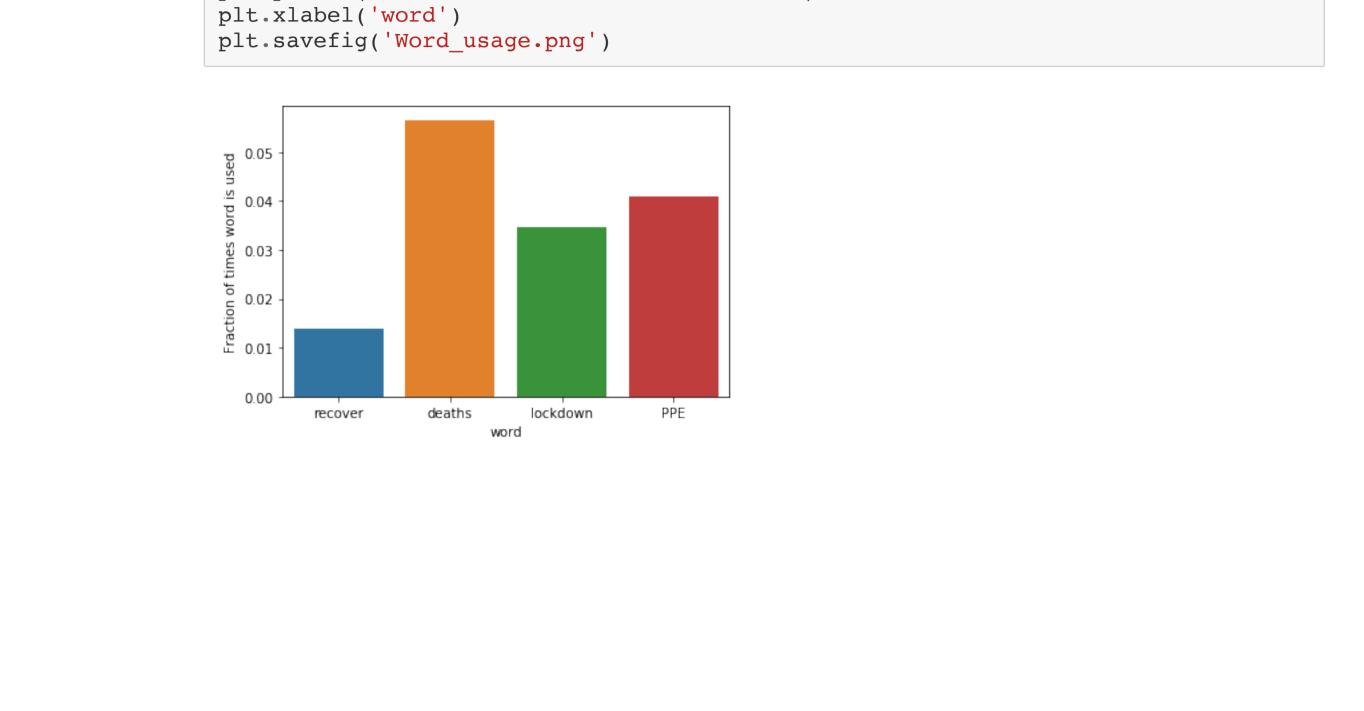
In [58]: fig = sns.barplot(words,words\_use\_frac)

plt.ylabel('Fraction of times word is used')

**Covid Tweets EDA** 

The tasks for this EDA are to:

- 3. Look and word use and sentiment over time
- 4. Investigate which fields to use for Geographical analysis later on



Investigating the use of the word "recovery" versus "death" over time

plt.scatter(mean\_death.index.minute, mean\_death)

Looking at sentiment over time for the 6th of May

plt.xlabel('Time (minute)')

plt.ylabel('Sentiment')

plt.show()

Tasks:

sentiment\_covid = sentiment.resample('1 min').mean()

plt.title('Sentiment with time for COVID tweets')

plt.scatter(sentiment\_covid.index.minute, sentiment\_covid, )

plt.scatter(mean\_recover.index.minute, mean\_recover)

In [8]:

In [10]:

```
plt.xlabel('Minute')
plt.ylabel('Frequency')
plt.title('Mentions per Minute')
plt.legend(('deaths', 'recovery'))
plt.show()
                  Mentions per Minute
          deaths
          recovery
  0.12
  0.10
Frequency
90.0
  0.02
  0.00
                                 19
       14
            15
                 16
                                      20
                        Minute
```

```
Sentiment with time for COVID tweets
    0.00
   -0.02
Sentiment
Po.o-
   -0.06
   -0.08
          14
                 15
                         16
                                17
                                        18
                                               19
                                                      20
                                                             21
                               Time (minute)
```

## 3. Plot selected countries to see the affect of death toll on stringency

plt.title('Deaths over time', fontweight='semibold')

1. Fill the df with json data

import matplotlib.pyplot as plt

plt.xlim('2020-03-01','2020-04-24')

Deaths over time

['stringency','deaths']) df\_pivot.plot(y='deaths')

plt.xlabel('Date')

(18322, 18376)

50000 -

40000

30000 20000

Out[15]:

plt.ylabel('Deaths')

country\_code — CHN DEU

> — ESP — GBR

— ITA — SWE --- USA

16

09

23

30

Date

Apr

02

Mar 2020

In [45]: fig

Time Series Analysis of Policy Data

df\_pivot = df\_selected.pivot(index='date\_value', columns='country\_code', values=

This analysis investigates the evolution of Stringency Index in different countries over

time, with the death rate. For information of how it is calculated see the link

https://covidtracker.bsg.ox.ac.uk, we use the API data instead of the csv files.

2. Plot deaths and the stringency index over time for March and April

```
10000
                            16
                                 23
                                                     20
                                                13
                Mar
2020
                                       Apr
                                    Date
In [16]:
           df_pivot.plot(y='stringency')
           plt.xlabel('Date')
           plt.ylabel('Stringency of measures')
           plt.xlim('2020-03-01','2020-04-24')
           plt.legend(loc=4)
           plt.title('Stringency over time', fontweight='bold')
           Text(0.5, 1.0, 'Stringency over time')
Out[16]:
                           Stringency over time
              80
           Stringency of measures S 8
```

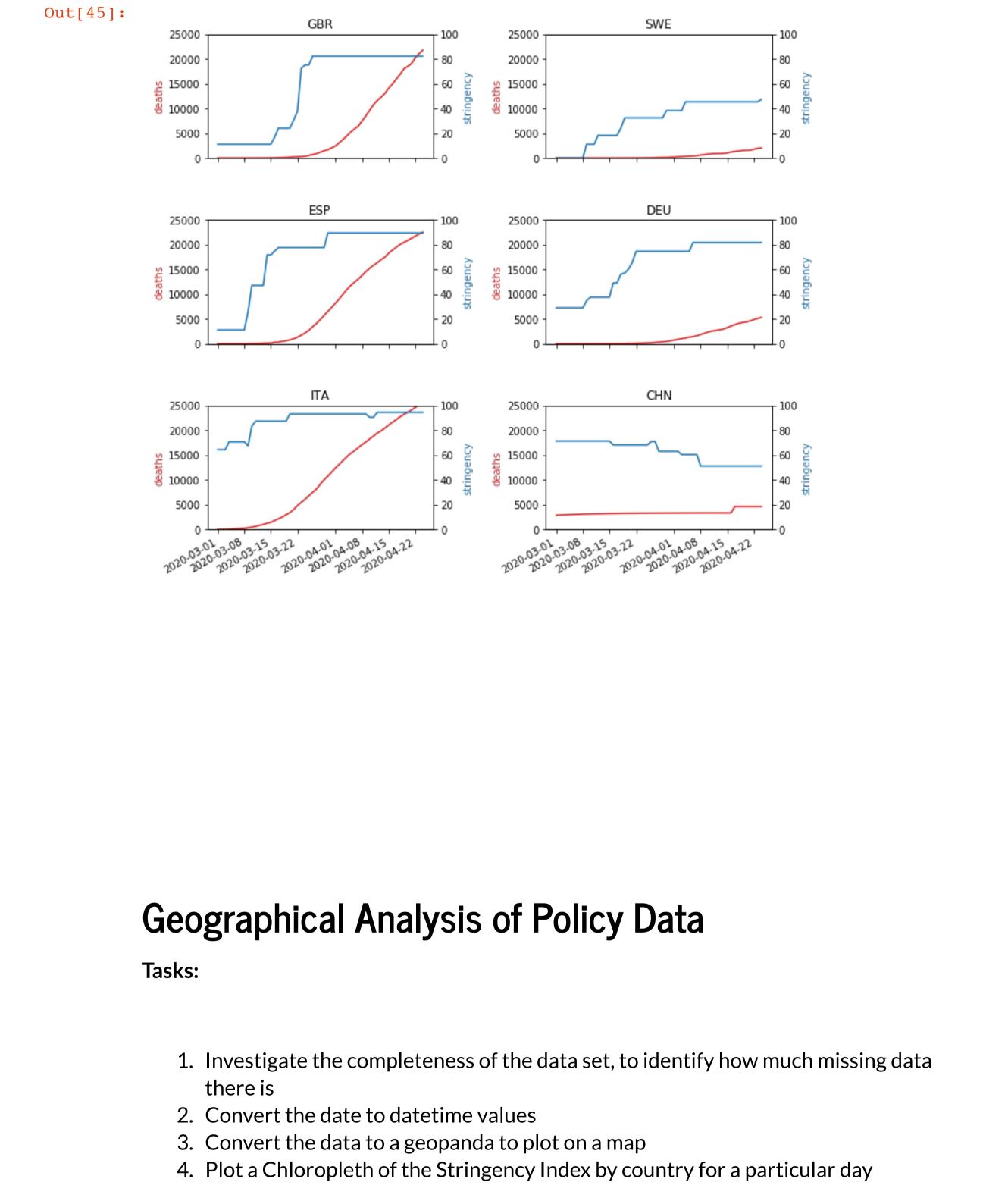
CHN

DEU ESP

GBR — ITA SWE USA

20

13

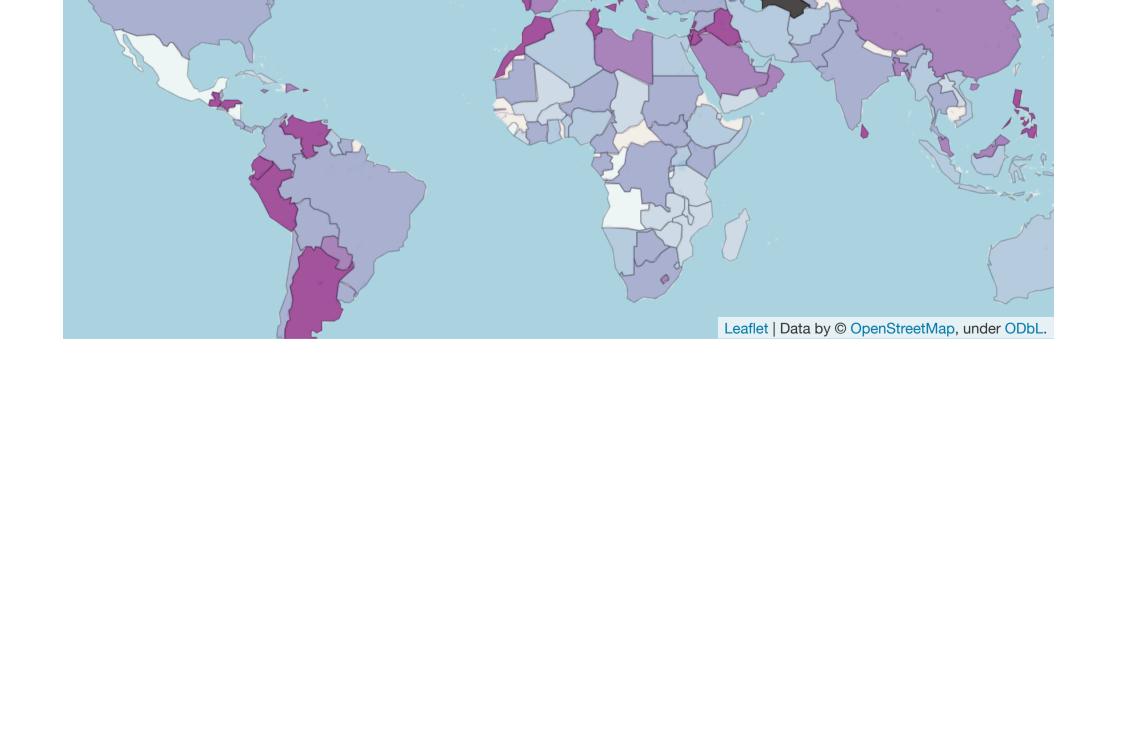


### We plot the Stringency Index of each country on a map, shaded according to the level of Stringency

19

Stringency Index

100



#### **Geographical Analysis of Tweets** Tasks: 1. Import may 5th tweets

2. Carry out sentiment analysis of the tweets 3. Geocode the tweets based on user location 4. Plot them on a map based on Sentiment

In [49]: m

Out[49]:

