# Covid19AndWbIndicators(LaTeX)

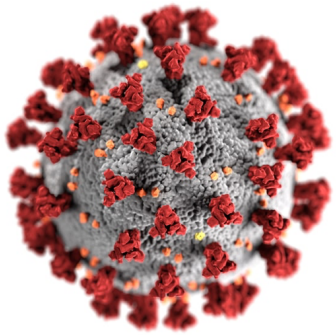
November 6, 2020

**Universidad Oberta de Catalunya**

Tipología y Ciclo de vida de los datos

*WebScrapping*

# Detección de patrones existentes en diferentes indicadores con respecto a datos de la COVID-19

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# Contents

# 1 Contexto

El contexto con el que está enfocado esta práctica, es tratar de realizar un análisis sobre la relación existente entre diferentes indicadores de los diferentes países del mundo (así como la expectancia de vida, la fertilidad, acceso a la electricidad…) y el número de muertes causadas por la pandemia COVID-19 en los mismos.

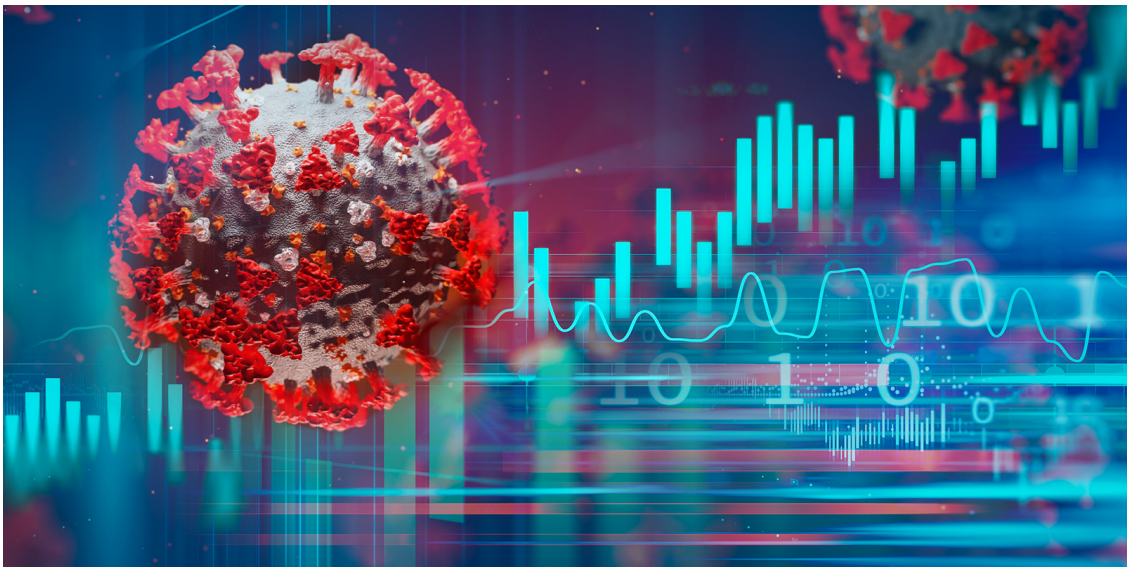
Para conseguir el fin descrito anteriormente, se han elegido dos fuentes de datos: - a) Por un lado, la **página https://www.worldometers.info/coronavirus/** que corresponde con la fuente de datos que proporciona información sobre la pandemia en los diferentes países, para obtener la información de la misma se ha utilizado la técnica de Web Scrapping - b) Por otro lado, la **librería wbdata**, que corresponde con la fuente de datos que proporciona información sobre los valores de los distintos indicadores de cada país. Dicha librería, realmente permite obtener información de la página del Banco Mundial de datos abiertos: https://databank.worldbank.org/home de una manera sencilla y parametrizada

La razón por la que se han elegido estas fuentes es porque se consideran fuentes de datos fiables y además de uso público que incluso normalmente se publican con el fin de que se puedan realizar estudios de investigación sobre los mismos, por lo que resulta más sencillo que obtenerlo de páginas que realmente no los publican con este fin.

# 2 Título del dataset

Debido a que el dataset que se quiere conseguir fusiona información de la pandemia COVID-19 en los diferentes países y de los valores de los diferentes indicadores que se consideren a simple vista que pueden llegar a tener una relación con las muertes ocasionadas por la pandemia, el nombre que hemos elegido para el dataset que se va a generar es: **covid19AndWbIndicators**

# 3 Representación gráfica



# 4 Código

[1]:
```
import wbdata
import requests
from bs4 import BeautifulSoup
import pandas as pd
import numpy as np
import datetime
import matplotlib.pyplot as plt
from pylab import rcParams
from sklearn.ensemble import ExtraTreesClassifier
import statistics
from geopy.geocoders import Nominatim
import math
import folium
from folium.plugins import HeatMap
from sklearn import preprocessing
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.cluster import KMeans
import seaborn as sns
```

## 4.1 Extracción de datos

[2]:
```
url = 'https://www.worldometers.info/coronavirus/'
requests.get(url)
wdweb = requests.get(url)
```

[3]:
```
wdweb
```

[3]:
```
<Response [200]>
```

[4]:
```
wdwebsoup = BeautifulSoup(wdweb.text, 'lxml')
```

[5]:
```
wdwebtable_data = wdwebsoup.find('table', id = 'main_table_countries_yesterday')
```

[6]:
```
headers = []
for i in wdwebtable_data.find_all('th'):
    title = i.text
    headers.append(title)
```

[ ]:
```

```

[7]:
```
covid = pd.DataFrame(columns = headers)
```

[8]:
```
for j in wdwebtable_data.find_all('tr')[1:]:
        row_data = j.find_all('td')
        row = [td.text for td in row_data]
```

```
        length = len(covid)
        covid.loc[length] = row
```

[9]:
```
covid.columns =␣
↪['ID','country','TotalCases','NewCases','TotalDeaths','NewDeaths','TotalRecov','NewRecov','
covid.set_index('country', inplace=True, drop=True)
```

[10]:
```
covid.shape
```

[10]:
```
(234, 18)
```

[11]:
```
covid.index
```

[11]:
```
Index(['\nAsia\n', '\nNorth America\n', '\nSouth America\n', '\nEurope\n',
       '\nAfrica\n', '\nOceania\n', '\n\n', 'World', 'China', 'USA',
       …
       'Marshall Islands', 'Wallis and Futuna', 'Total:', 'Total:', 'Total:',
       'Total:', 'Total:', 'Total:', 'Total:', 'Total:'],
      dtype='object', name='country', length=234)
```

[12]:
```
pd.set_option('display.max_rows', None)
covid.index=covid.index.str.replace("\n","")
covid=covid.rename(index={'USA': 'United States'})
```

[13]:
```
data_date = datetime.datetime(2018, 12, 31), datetime.datetime(2018, 12, 31)
# countries = [i['id'] for i in wbdata.get_country(incomelevel='HIC')]
indicators = {"EG.ELC.ACCS.ZS":"AccessElectricity", "NY.GDP.MKTP.CD":"GDP",
              "NY.GDP.PCAP.CD":"GDPperCap", "SH.XPD.CHEX.PC.CD":
↪"HealthExpenseperCap",
               "IT.NET.USER.ZS":"IndividUsingInternet", "SP.DYN.LE00.IN":
↪"LifeExpect",
               "SH.MED.PHYS.ZS":"DrsPer1k", "GB.XPD.RSDV.GD.ZS":"RDExpen",
               "SH.HIV.INCD":"NewInfecHIV", "SP.DYN.TFRT.IN":"FertilityRate",
              "per_si_allsi.cov_pop_tot":"CovSocialInsurance",
              "SP.URB.TOTL":"UrbanPopulation", "SP.URB.TOTL.IN.ZS":
↪"UrbanPopulationPerc"}
wbdf = wbdata.get_dataframe(indicators, country="all", data_date=data_date)
```

[14]:
```
covidandwb_merged = pd.merge(covid,wbdf, on=["country"])
```

[15]:
```
covidandwb_merged.head()
```

[15]:

| country | ID | TotalCases | NewCases | TotalDeaths | NewDeaths | TotalRecov | \ |
|---|---|---|---|---|---|---|---|
| North America | | 11,676,256 | +120,709 | 357,960 | +1,815 | 7,697,604 | |
| World | | 48,419,186 | +574,691 | 1,230,109 | +9,057 | 34,667,040 | |
| China | 1 | 86,087 | +17 | 4,634 | | 81,061 | |

```
United States  2   9,801,355  +108,389    239,829     +1,201   6,292,019
India          3   8,363,412   +50,465    124,354       +704   7,710,630

               NewRecov ActiveCases SeriousCritical TotalCases1M  …  \
country                                                           …
North America   +67,890   3,620,692          21,731              …
World          +320,758  12,522,037          89,292        6,212  …
China              +16         392               9           60  …
United States   +55,849   3,269,507          18,045       29,551  …
India           +55,873     528,428           8,944        6,040  …

              HealthExpenseperCap IndividUsingInternet LifeExpect DrsPer1k  \
country
North America                None            88.498903  78.886891      NaN
World                        None                  NaN  72.563274      NaN
China                        None                  NaN  76.704000      NaN
United States                None            88.498903  78.539024      NaN
India                        None            20.081300  69.416000   0.8571

               RDExpen NewInfecHIV FertilityRate CovSocialInsurance  \
country
North America  2.739569         NaN      1.706032               NaN
World          2.273640   1400000.0      2.414975               NaN
China          2.185680         NaN      1.690000               NaN
United States  2.837660     33000.0      1.729500               NaN
India          0.649980         NaN      2.222000               NaN

               UrbanPopulation  UrbanPopulationPerc
country
North America     2.989531e+08            82.173045
World             4.195080e+09            55.270426
China             8.238276e+08            59.152000
United States     2.687201e+08            82.256000
India             4.602957e+08            34.030000

[5 rows x 31 columns]
```

[16]:
```
covidandwb_merged.shape
```

[16]:
```
(172, 31)
```

[17]:
```
covidandwb = covidandwb_merged
```

### 4.2 Procesamiento de los datos obtenidos

[18]:
```
covidandwb = covidandwb.drop(["NewCases", "NewDeaths", "TotalRecov", "NewRecov",
                              "ActiveCases", "SeriousCritical"], axis=1)
covidandwb = covidandwb.drop(["World"], axis=0)
covidandwb = covidandwb.drop(["North America"], axis=0)
```

[19]:
```
covidandwb.head()
```

[19]:

| country | ID | TotalCases | TotalDeaths | TotalCases1M | TotalDeaths1M | \ |
|---|---|---|---|---|---|---|
| China | 1 | 86,087 | 4,634 | 60 | 3 | |
| United States | 2 | 9,801,355 | 239,829 | 29,551 | 723 | |
| India | 3 | 8,363,412 | 124,354 | 6,040 | 90 | |
| Brazil | 4 | 5,590,941 | 161,170 | 26,238 | 756 | |
| France | 6 | 1,543,321 | 38,674 | 23,626 | 592 | |

| country | TotalTests | TotalTests1M | Population | Continent | \ |
|---|---|---|---|---|---|
| China | 160,000,000 | 111,163 | 1,439,323,776 | Asia | |
| United States | 152,050,414 | 458,433 | 331,674,530 | North America | |
| India | 112,998,959 | 81,607 | 1,384,678,624 | Asia | |
| Brazil | 21,900,000 | 102,777 | 213,081,672 | South America | |
| France | 16,819,377 | 257,477 | 65,323,720 | Europe | |

| country | 1CaseEvery | … | HealthExpenseperCap | IndividUsingInternet | \ |
|---|---|---|---|---|---|
| China | 16,719 | … | None | NaN | |
| United States | 34 | … | None | 88.498903 | |
| India | 166 | … | None | 20.081300 | |
| Brazil | 38 | … | None | 70.434283 | |
| France | 42 | … | None | 82.043187 | |

| country | LifeExpect | DrsPer1k | RDExpen | NewInfecHIV | FertilityRate | \ |
|---|---|---|---|---|---|---|
| China | 76.704000 | NaN | 2.18568 | NaN | 1.6900 | |
| United States | 78.539024 | NaN | 2.83766 | 33000.0 | 1.7295 | |
| India | 69.416000 | 0.8571 | 0.64998 | NaN | 2.2220 | |
| Brazil | 75.672000 | 2.1643 | NaN | NaN | 1.7300 | |
| France | 82.724390 | 3.2672 | 2.20002 | NaN | 1.8800 | |

| country | CovSocialInsurance | UrbanPopulation | UrbanPopulationPerc |
|---|---|---|---|
| China | NaN | 823827650.0 | 59.152 |
| United States | NaN | 268720071.0 | 82.256 |
| India | NaN | 460295677.0 | 34.030 |
| Brazil | 30.869548 | 181335507.0 | 86.569 |
| France | NaN | 53870058.0 | 80.444 |

```
[5 rows x 25 columns]
```

[20]:
```
TotalDeathsindex = covidandwb[covidandwb['TotalDeaths'].str.match(' ')].index
covidandwb.loc[TotalDeathsindex, 'TotalDeaths'] = 0
covidandwb['TotalDeaths']=covidandwb['TotalDeaths'].str.replace(",","").
 ↪astype(float)
covidandwb.loc[TotalDeathsindex, 'TotalDeaths1M'] = 0
covidandwb['TotalDeaths1M']=covidandwb['TotalDeaths1M'].str.replace(",","").
 ↪astype(float)
covidandwb['TotalCases1M']=covidandwb['TotalCases1M'].str.replace(",","").
 ↪astype(float)
covidandwb['TotalCases']=covidandwb['TotalCases'].str.replace(",","").
 ↪astype(float)
```

[21]:
```
covidandwb.head()
```

[21]:

| country | ID | TotalCases | TotalDeaths | TotalCases1M | TotalDeaths1M | \ |
|---|---|---|---|---|---|---|
| China | 1 | 86087.0 | 4634.0 | 60.0 | 3.0 | |
| United States | 2 | 9801355.0 | 239829.0 | 29551.0 | 723.0 | |
| India | 3 | 8363412.0 | 124354.0 | 6040.0 | 90.0 | |
| Brazil | 4 | 5590941.0 | 161170.0 | 26238.0 | 756.0 | |
| France | 6 | 1543321.0 | 38674.0 | 23626.0 | 592.0 | |

| country | TotalTests | TotalTests1M | Population | Continent | \ |
|---|---|---|---|---|---|
| China | 160,000,000 | 111,163 | 1,439,323,776 | Asia | |
| United States | 152,050,414 | 458,433 | 331,674,530 | North America | |
| India | 112,998,959 | 81,607 | 1,384,678,624 | Asia | |
| Brazil | 21,900,000 | 102,777 | 213,081,672 | South America | |
| France | 16,819,377 | 257,477 | 65,323,720 | Europe | |

| country | 1CaseEvery | … | HealthExpenseperCap | IndividUsingInternet | \ |
|---|---|---|---|---|---|
| | | … | | | |
| China | 16,719 | … | None | NaN | |
| United States | 34 | … | None | 88.498903 | |
| India | 166 | … | None | 20.081300 | |
| Brazil | 38 | … | None | 70.434283 | |
| France | 42 | … | None | 82.043187 | |

| country | LifeExpect | DrsPer1k | RDExpen | NewInfecHIV | FertilityRate | \ |
|---|---|---|---|---|---|---|
| China | 76.704000 | NaN | 2.18568 | NaN | 1.6900 | |
| United States | 78.539024 | NaN | 2.83766 | 33000.0 | 1.7295 | |
| India | 69.416000 | 0.8571 | 0.64998 | NaN | 2.2220 | |
| Brazil | 75.672000 | 2.1643 | NaN | NaN | 1.7300 | |

```
France          82.724390    3.2672  2.20002         NaN         1.8800

               CovSocialInsurance  UrbanPopulation  UrbanPopulationPerc
country
China                         NaN      823827650.0               59.152
United States                 NaN      268720071.0               82.256
India                         NaN      460295677.0               34.030
Brazil                  30.869548      181335507.0               86.569
France                        NaN       53870058.0               80.444

[5 rows x 25 columns]
```

[22]:
```
covidandwb.dtypes
```

[22]:
```
ID                      object
TotalCases             float64
TotalDeaths            float64
TotalCases1M           float64
TotalDeaths1M          float64
TotalTests              object
TotalTests1M            object
Population              object
Continent               object
1CaseEvery              object
1DeathEvery             object
1TestEvery              object
AccessElectricity      float64
GDP                    float64
GDPperCap              float64
HealthExpenseperCap     object
IndividUsingInternet   float64
LifeExpect             float64
DrsPer1k               float64
RDExpen                float64
NewInfecHIV            float64
FertilityRate          float64
CovSocialInsurance     float64
UrbanPopulation        float64
UrbanPopulationPerc    float64
dtype: object
```

[23]:
```
covidandwb['1DeathEvery']= covidandwb['1DeathEvery'].str.replace(",","")
covidandwb['1DeathEvery']=covidandwb['1DeathEvery'].str.replace(r'^\s*$','NaN')
covidandwb['1DeathEvery']=covidandwb['1DeathEvery'].astype(float)
```

[24]:
```
covidandwb['TotalTests']= covidandwb['TotalTests'].str.replace(",","")
covidandwb['TotalTests']=covidandwb['TotalTests'].str.replace(r'^\s*$','NaN')
```

```
covidandwb['TotalTests']=covidandwb['TotalTests'].astype(float)
```

[25]:
```
covidandwb['TotalTests1M']= covidandwb['TotalTests1M'].str.replace(",","")
covidandwb['TotalTests1M']=covidandwb['TotalTests1M'].str.
 ↪replace(r'^\s*$','NaN')
covidandwb['TotalTests1M']=covidandwb['TotalTests1M'].astype(float)
```

[26]:
```
covidandwb['Population']= covidandwb['Population'].str.replace(",","")
covidandwb['Population']=covidandwb['Population'].str.replace(r'^\s*$','NaN')
covidandwb['Population']=covidandwb['Population'].astype(float)
```

[27]:
```
covidandwb['1CaseEvery']= covidandwb['1CaseEvery'].str.replace(",","")
covidandwb['1CaseEvery']=covidandwb['1CaseEvery'].str.replace(r'^\s*$','NaN')
covidandwb['1CaseEvery']=covidandwb['1CaseEvery'].astype(float)
```

[28]:
```
covidandwb['HealthExpenseperCap']= covidandwb['HealthExpenseperCap'].str.
 ↪replace(",","")
covidandwb['HealthExpenseperCap']=covidandwb['HealthExpenseperCap'].str.
 ↪replace(r'^\s*$','NaN')
covidandwb['HealthExpenseperCap']=covidandwb['HealthExpenseperCap'].
 ↪astype(float)
```

[29]:
```
covidandwb['1TestEvery']= covidandwb['1TestEvery'].str.replace(",","")
covidandwb['1TestEvery']=covidandwb['1TestEvery'].str.replace(r'^\s*$','NaN')
covidandwb['1TestEvery']=covidandwb['1TestEvery'].astype(float)
```

[30]:
```
covidandwb.dtypes
```

[30]:
```
ID                      object
TotalCases             float64
TotalDeaths            float64
TotalCases1M           float64
TotalDeaths1M          float64
TotalTests             float64
TotalTests1M           float64
Population             float64
Continent               object
1CaseEvery             float64
1DeathEvery            float64
1TestEvery             float64
AccessElectricity      float64
GDP                    float64
GDPperCap              float64
HealthExpenseperCap    float64
IndividUsingInternet   float64
LifeExpect             float64
DrsPer1k               float64
```

```
RDExpen                 float64
NewInfecHIV             float64
FertilityRate           float64
CovSocialInsurance      float64
UrbanPopulation         float64
UrbanPopulationPerc     float64
dtype: object
```

[31]:
```
covidandwb.shape
```

[31]:
```
(170, 25)
```

[32]:
```
covidandwb.isnull().sum()
```

[32]:
```
ID                       0
TotalCases               0
TotalDeaths             13
TotalCases1M             0
TotalDeaths1M           13
TotalTests              13
TotalTests1M            13
Population               0
Continent                0
1CaseEvery               0
1DeathEvery             13
1TestEvery              13
AccessElectricity        1
GDP                     12
GDPperCap               12
HealthExpenseperCap    170
IndividUsingInternet    97
LifeExpect              10
DrsPer1k               114
RDExpen                110
NewInfecHIV             66
FertilityRate            9
CovSocialInsurance     164
UrbanPopulation          1
UrbanPopulationPerc      1
dtype: int64
```

[33]:
```
covidandwb.columns
```

[33]:
```
Index(['ID', 'TotalCases', 'TotalDeaths', 'TotalCases1M', 'TotalDeaths1M',
       'TotalTests', 'TotalTests1M', 'Population', 'Continent', '1CaseEvery',
       '1DeathEvery', '1TestEvery', 'AccessElectricity', 'GDP', 'GDPperCap',
       'HealthExpenseperCap', 'IndividUsingInternet', 'LifeExpect', 'DrsPer1k',
```

```
       'RDExpen', 'NewInfecHIV', 'FertilityRate', 'CovSocialInsurance',
       'UrbanPopulation', 'UrbanPopulationPerc'],
      dtype='object')
```

Eliminamos: * **CovSocialInsurance** * **RDExpen** * **HealthExpenseperCap** * **IndividUsing-Internet**

Debido a que todas ellas cuentan con más de un 60% de datos nulos

[34]:
```
columns_acceptables = ['ID', 'TotalCases', 'TotalDeaths', 'TotalCases1M',␣
↪'TotalDeaths1M',
      'TotalTests', 'TotalTests1M', 'Population', 'Continent', '1CaseEvery',
      '1DeathEvery', '1TestEvery', 'AccessElectricity', 'GDP', 'GDPperCap',␣
↪'LifeExpect','DrsPer1k', 'NewInfecHIV', 'FertilityRate',
      'UrbanPopulation', 'UrbanPopulationPerc']
```

[35]:
```
covidandwb = covidandwb[columns_acceptables]
covidandwb.isnull().sum()
```

[35]:
```
ID                     0
TotalCases             0
TotalDeaths           13
TotalCases1M           0
TotalDeaths1M         13
TotalTests            13
TotalTests1M          13
Population             0
Continent              0
1CaseEvery             0
1DeathEvery           13
1TestEvery            13
AccessElectricity      1
GDP                   12
GDPperCap             12
LifeExpect            10
DrsPer1k             114
NewInfecHIV           66
FertilityRate          9
UrbanPopulation        1
UrbanPopulationPerc    1
dtype: int64
```

[36]:
```
def imputationFunct(x, indexColumn):
    if math.isnan(x.iloc[indexColumn]):
        x.iloc[indexColumn] = statistics.median(covidandwb.
↪loc[covidandwb['Continent'] == x.iloc[8]].iloc[:, indexColumn].dropna())
    return x.iloc[indexColumn]
```

[37]:
```
columnsWithNaN = [2,4,5,6,10,11,12,13,14,15,16,17,18,19,20]
```

### 4.2.1 Imputation Data

[38]:
```
for column in columnsWithNaN:
    covidandwb.iloc[:,[column]] = covidandwb.
↪apply(imputationFunct,axis=1,args=(column,))
```

[39]:
```
covidandwb.isnull().sum()
```

[39]:
```
ID                    0
TotalCases            0
TotalDeaths           0
TotalCases1M          0
TotalDeaths1M         0
TotalTests            0
TotalTests1M          0
Population            0
Continent             0
1CaseEvery            0
1DeathEvery           0
1TestEvery            0
AccessElectricity     0
GDP                   0
GDPperCap             0
LifeExpect            0
DrsPer1k              0
NewInfecHIV           0
FertilityRate         0
UrbanPopulation       0
UrbanPopulationPerc   0
dtype: int64
```

[40]:
```
covidandwb.head()
```

[40]:

| country | ID | TotalCases | TotalDeaths | TotalCases1M | TotalDeaths1M | TotalTests | TotalTests1M | Population | Continent |
|---|---|---|---|---|---|---|---|---|---|
| China | 1 | 86087.0 | 4634.0 | 60.0 | 3.0 | 160000000.0 | 111163.0 | 1.439324e+09 | Asia |
| United States | 2 | 9801355.0 | 239829.0 | 29551.0 | 723.0 | 152050414.0 | 458433.0 | 3.316745e+08 | North America |
| India | 3 | 8363412.0 | 124354.0 | 6040.0 | 90.0 | | | | |
| Brazil | 4 | 5590941.0 | 161170.0 | 26238.0 | 756.0 | | | | |
| France | 6 | 1543321.0 | 38674.0 | 23626.0 | 592.0 | | | | |

```
India          112998959.0       81607.0  1.384679e+09           Asia
Brazil          21900000.0      102777.0  2.130817e+08  South America
France          16819377.0      257477.0  6.532372e+07         Europe

               1CaseEvery  …  1TestEvery  AccessElectricity           GDP  \
country                    …
China             16719.0  …         9.0         100.000000  1.389482e+13
United States        34.0  …         2.0         100.000000  2.052905e+13
India               166.0  …        12.0          95.235855  2.713165e+12
Brazil               38.0  …        10.0         100.000000  1.885483e+12
France               42.0  …         4.0         100.000000  2.787864e+12

                  GDPperCap  LifeExpect  DrsPer1k  NewInfecHIV  FertilityRate  \
country
China           9976.676822   76.704000    0.9186       1050.0         1.6900
United States  62840.020239   78.539024    1.9357      33000.0         1.7295
India           2005.863005   69.416000    0.8571       1050.0         2.2220
Brazil          9001.234249   75.672000    2.1643       2300.0         1.7300
France         41631.090739   82.724390    3.2672        500.0         1.8800

               UrbanPopulation  UrbanPopulationPerc
country
China            823827650.0               59.152
United States    268720071.0               82.256
India            460295677.0               34.030
Brazil           181335507.0               86.569
France            53870058.0               80.444

[5 rows x 21 columns]
```

[41]:
```
geolocator = Nominatim(user_agent='myapplication')
```

[42]:
```
def getLatitude(x):
    return geolocator.geocode(x[0]).latitude
```

[43]:
```
def getLongitude(x):
    return geolocator.geocode(x[0]).longitude
```

[44]:
```
covidandwb.head()
```

[44]:
```
                ID  TotalCases  TotalDeaths  TotalCases1M  TotalDeaths1M  \
country
China            1     86087.0       4634.0          60.0            3.0
United States    2   9801355.0     239829.0       29551.0          723.0
India            3   8363412.0     124354.0        6040.0           90.0
Brazil           4   5590941.0     161170.0       26238.0          756.0
France           6   1543321.0      38674.0       23626.0          592.0
```

```
                TotalTests  TotalTests1M    Population      Continent  \
country
China          160000000.0      111163.0  1.439324e+09           Asia
United States  152050414.0      458433.0  3.316745e+08  North America
India          112998959.0       81607.0  1.384679e+09           Asia
Brazil          21900000.0      102777.0  2.130817e+08  South America
France          16819377.0      257477.0  6.532372e+07         Europe

                1CaseEvery  …  1TestEvery  AccessElectricity           GDP  \
country                     …
China              16719.0  …         9.0         100.000000  1.389482e+13
United States         34.0  …         2.0         100.000000  2.052905e+13
India                166.0  …        12.0          95.235855  2.713165e+12
Brazil                38.0  …        10.0         100.000000  1.885483e+12
France                42.0  …         4.0         100.000000  2.787864e+12

                  GDPperCap  LifeExpect  DrsPer1k  NewInfecHIV  FertilityRate  \
country
China           9976.676822   76.704000    0.9186       1050.0         1.6900
United States  62840.020239   78.539024    1.9357      33000.0         1.7295
India           2005.863005   69.416000    0.8571       1050.0         2.2220
Brazil          9001.234249   75.672000    2.1643       2300.0         1.7300
France         41631.090739   82.724390    3.2672        500.0         1.8800

                UrbanPopulation  UrbanPopulationPerc
country
China             823827650.0               59.152
United States     268720071.0               82.256
India             460295677.0               34.030
Brazil            181335507.0               86.569
France             53870058.0               80.444

[5 rows x 21 columns]
```

[45]:
```
covidandwb = covidandwb.reset_index()
covidandwb.head()
```

[45]:
```
          country ID  TotalCases  TotalDeaths  TotalCases1M  TotalDeaths1M  \
0           China  1     86087.0       4634.0          60.0            3.0
1   United States  2   9801355.0     239829.0       29551.0          723.0
2           India  3   8363412.0     124354.0        6040.0           90.0
3          Brazil  4   5590941.0     161170.0       26238.0          756.0
4          France  6   1543321.0      38674.0       23626.0          592.0

    TotalTests  TotalTests1M    Population      Continent  …  1TestEvery  \
0  160000000.0      111163.0  1.439324e+09           Asia  …         9.0
```

```
1  152050414.0      458433.0  3.316745e+08  North America  …         2.0
2  112998959.0       81607.0  1.384679e+09           Asia  …        12.0
3   21900000.0      102777.0  2.130817e+08  South America  …        10.0
4   16819377.0      257477.0  6.532372e+07         Europe  …         4.0

   AccessElectricity           GDP     GDPperCap  LifeExpect  DrsPer1k  \
0         100.000000  1.389482e+13   9976.676822   76.704000    0.9186
1         100.000000  2.052905e+13  62840.020239   78.539024    1.9357
2          95.235855  2.713165e+12   2005.863005   69.416000    0.8571
3         100.000000  1.885483e+12   9001.234249   75.672000    2.1643
4         100.000000  2.787864e+12  41631.090739   82.724390    3.2672

   NewInfecHIV  FertilityRate  UrbanPopulation  UrbanPopulationPerc
0       1050.0         1.6900      823827650.0               59.152
1      33000.0         1.7295      268720071.0               82.256
2       1050.0         2.2220      460295677.0               34.030
3       2300.0         1.7300      181335507.0               86.569
4        500.0         1.8800       53870058.0               80.444

[5 rows x 22 columns]
```

[46]:
```
covidandwb['Latitude'] = covidandwb.apply(getLatitude,axis=1)
```

[47]:
```
covidandwb['Longitude'] = covidandwb.apply(getLongitude,axis=1)
```

[48]:
```
covidandwb.head()
```

[48]:
```
         country ID  TotalCases  TotalDeaths  TotalCases1M  TotalDeaths1M  \
0          China  1     86087.0       4634.0          60.0            3.0
1  United States  2   9801355.0     239829.0       29551.0          723.0
2          India  3   8363412.0     124354.0        6040.0           90.0
3         Brazil  4   5590941.0     161170.0       26238.0          756.0
4         France  6   1543321.0      38674.0       23626.0          592.0

    TotalTests  TotalTests1M    Population      Continent  …           GDP  \
0  160000000.0      111163.0  1.439324e+09           Asia  …  1.389482e+13
1  152050414.0      458433.0  3.316745e+08  North America  …  2.052905e+13
2  112998959.0       81607.0  1.384679e+09           Asia  …  2.713165e+12
3   21900000.0      102777.0  2.130817e+08  South America  …  1.885483e+12
4   16819377.0      257477.0  6.532372e+07         Europe  …  2.787864e+12

      GDPperCap  LifeExpect  DrsPer1k  NewInfecHIV  FertilityRate  \
0   9976.676822   76.704000    0.9186       1050.0         1.6900
1  62840.020239   78.539024    1.9357      33000.0         1.7295
2   2005.863005   69.416000    0.8571       1050.0         2.2220
3   9001.234249   75.672000    2.1643       2300.0         1.7300
4  41631.090739   82.724390    3.2672        500.0         1.8800
```

```
   UrbanPopulation  UrbanPopulationPerc   Latitude   Longitude
0      823827650.0                59.152  35.000074  104.999927
1      268720071.0                82.256  39.783730 -100.445882
2      460295677.0                34.030  22.351115   78.667743
3      181335507.0                86.569 -10.333333  -53.200000
4       53870058.0                80.444  46.603354    1.888334

[5 rows x 24 columns]
```

## 4.3 Representaciones gráficas de los datos

### 4.3.1 HeatMap

[49]:
```
map_hooray = folium.Map([40.4166359,-3.7059988], zoom_start=3)
```

[50]:
```
HeatMap(data=covidandwb[['Latitude','Longitude','TotalCases1M']].
↪groupby(['Latitude','Longitude']).sum().reset_index().values.tolist()).
↪add_to(map_hooray)
```

[50]:
```
<folium.plugins.heat_map.HeatMap at 0x199a394f9d0>
```

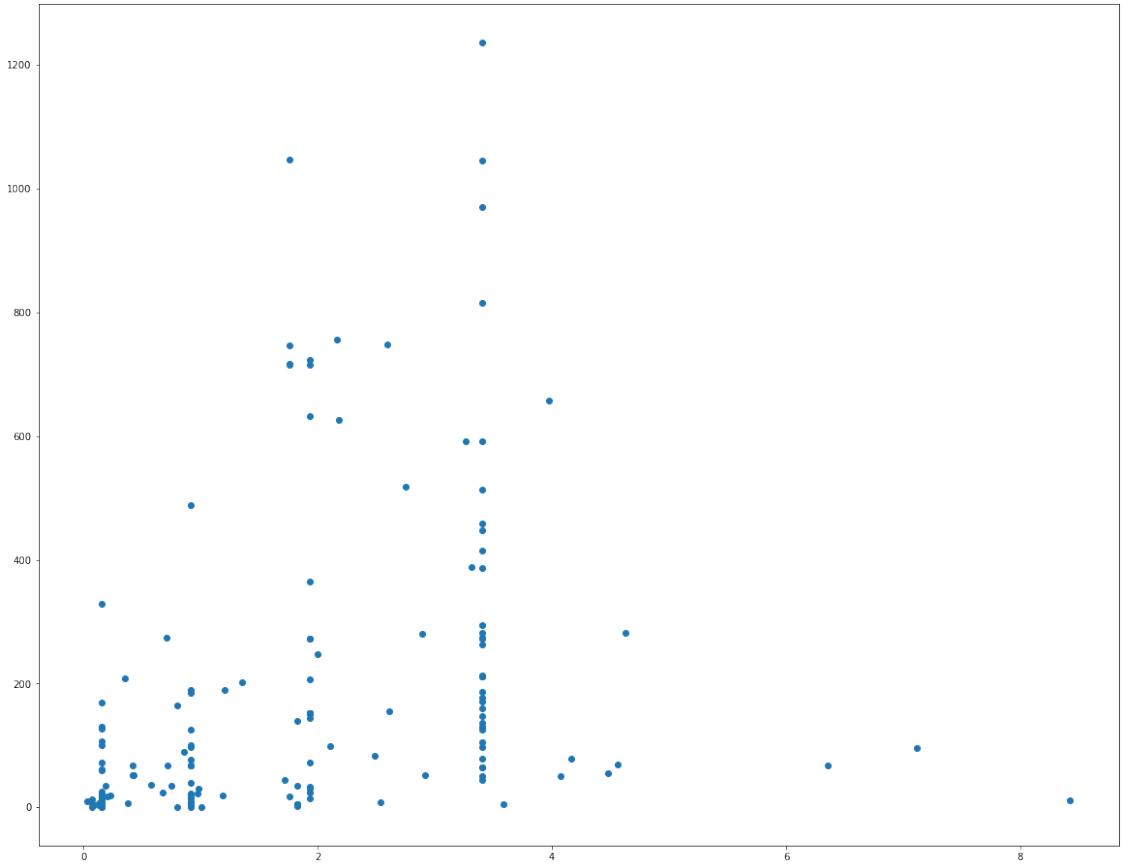
[51]:
```
map_hooray
```

[51]:
```
<folium.folium.Map at 0x199a38f8760>
```

[52]:
```
covidandwb.set_index('country', inplace=True, drop=True)
```

### 4.3.2 Plots of relations

[53]:
```
%matplotlib inline
rcParams['figure.figsize'] = 20,16
plt.scatter(covidandwb['DrsPer1k'], covidandwb['TotalDeaths1M'])
plt.show()
```




[54]:
```
# Recreamos el campo UrbanPopulationPerc
```

[55]:
```
covidandwb['UrbanPopulationPerc'].head()
```

[55]:
```
country
China            59.152
United States    82.256
India            34.030
Brazil           86.569
France           80.444
Name: UrbanPopulationPerc, dtype: float64
```

[56]:
```
def fx(x, y):
    return x*100/y
covidandwb['UrbanPopulationPerc'] = np.
 ↪vectorize(fx)(covidandwb['UrbanPopulation'], covidandwb['Population'])
```

[57]:
```
covidandwb['UrbanPopulationPerc'].head()
```

[57]:
```
country
China            57.237132
United States    81.019206
India            33.242058
Brazil           85.101410
France           82.466305
Name: UrbanPopulationPerc, dtype: float64
```

[58]:
```
# Exportamos el Datframe final a CSV
```

[59]:
```
csv_path='./covidandwb.csv'
covidandwb.to_csv(csv_path, index=False, header=True)
```

### 4.3.3 Clusterización con KMeans

[60]:
```
covidkmeans_cols=['TotalDeaths1M', 'TotalTests1M', 'GDPperCap',␣
↪'LifeExpect','DrsPer1k', 'NewInfecHIV', 'FertilityRate',
      'UrbanPopulation']
covidkmeans=covidandwb[covidkmeans_cols]
covidkmeans.head()
```

[60]:

| country | TotalDeaths1M | TotalTests1M | GDPperCap | LifeExpect | DrsPer1k | NewInfecHIV | FertilityRate | UrbanPopulation |
|---|---|---|---|---|---|---|---|---|
| China | 3.0 | 111163.0 | 9976.676822 | 76.704000 | 0.9186 | 1050.0 | 1.6900 | 823827650.0 |
| United States | 723.0 | 458433.0 | 62840.020239 | 78.539024 | 1.9357 | 33000.0 | 1.7295 | 268720071.0 |
| India | 90.0 | 81607.0 | 2005.863005 | 69.416000 | 0.8571 | 1050.0 | 2.2220 | 460295677.0 |
| Brazil | 756.0 | 102777.0 | 9001.234249 | 75.672000 | 2.1643 | 2300.0 | 1.7300 | 181335507.0 |
| France | 592.0 | 257477.0 | 41631.090739 | 82.724390 | 3.2672 | 500.0 | 1.8800 | 53870058.0 |

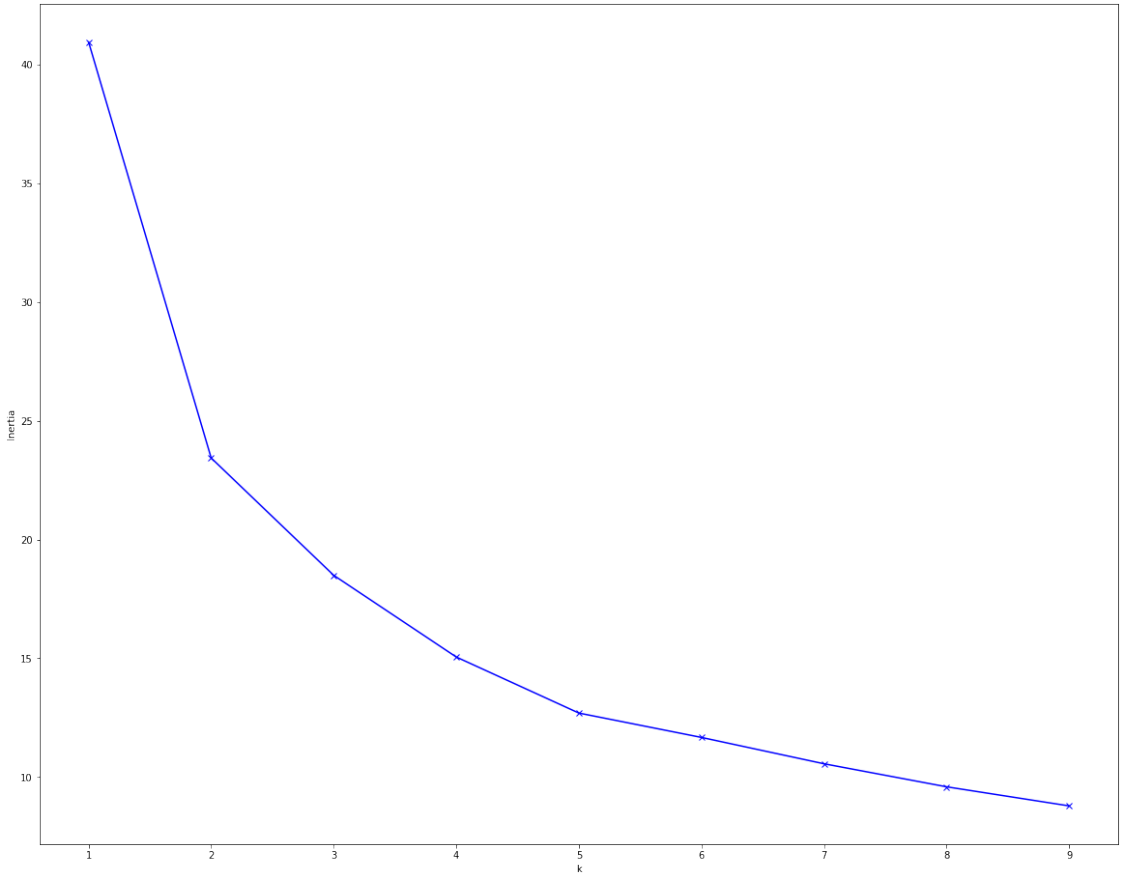
[61]:
```
scaler = preprocessing.MinMaxScaler()
features_normal = scaler.fit_transform(covidkmeans)
```

[62]:
```
features_normal
```

[62]:
```
array([[2.36070239e-03, 5.43155082e-02, 5.23015077e-02, …,
        5.00263296e-03, 9.52710896e-02, 1.00000000e+00],
       [5.84451703e-01, 2.24249349e-01, 3.37191152e-01, …,
        1.73249078e-01, 1.02113286e-01, 3.26180371e-01],
       [7.26966983e-02, 3.98525123e-02, 9.34542203e-03, …,
        5.00263296e-03, 1.87424216e-01, 5.58725212e-01],
```

```
       …,
       [1.22821201e-01, 9.46446397e-02, 2.92088828e-01, …,
        5.00263296e-03, 1.48969340e-01, 5.24397124e-05],
       [3.97762183e-03, 0.00000000e+00, 1.00558641e-02, …,
        2.63296472e-03, 5.65217391e-01, 1.81605931e-04],
       [3.97762183e-03, 2.68252461e-02, 1.89505462e-02, …,
        2.63296472e-03, 1.43772735e-01, 4.80200695e-05]])
```

[63]:
```
inertia = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k).fit(features_normal)
    kmeanModel.fit(features_normal)
    inertia.append(kmeanModel.inertia_)
plt.plot(K, inertia, 'bx-')
plt.xlabel('k')
plt.ylabel('Inertia')
plt.show()
```



[64]:
```
kmeans = KMeans(n_clusters=5).fit(features_normal)
```

[65]:
```
covidkmeans.head()
```

[65]:

| country | TotalDeaths1M | TotalTests1M | GDPperCap | LifeExpect | DrsPer1k | NewInfecHIV | FertilityRate | UrbanPopulation |
|---|---|---|---|---|---|---|---|---|
| China | 3.0 | 111163.0 | 9976.676822 | 76.704000 | 0.9186 | 1050.0 | 1.6900 | 823827650.0 |
| United States | 723.0 | 458433.0 | 62840.020239 | 78.539024 | 1.9357 | 33000.0 | 1.7295 | 268720071.0 |
| India | 90.0 | 81607.0 | 2005.863005 | 69.416000 | 0.8571 | 1050.0 | 2.2220 | 460295677.0 |
| Brazil | 756.0 | 102777.0 | 9001.234249 | 75.672000 | 2.1643 | 2300.0 | 1.7300 | 181335507.0 |
| France | 592.0 | 257477.0 | 41631.090739 | 82.724390 | 3.2672 | 500.0 | 1.8800 | 53870058.0 |

[66]:
```
labels = pd.DataFrame(kmeans.labels_) #This is where the label output of the␣
↪KMeans we just ran lives. Make it a dataframe so we can concatenate back to␣
↪the original data
covidkmeans=covidkmeans.assign(Country=covidkmeans.index.
↪get_level_values('country'))
covidkmeans.reset_index(drop=True, inplace=True)
labeledcovidkmeans = pd.concat((covidkmeans,labels), axis=1)
labeledcovidkmeans = labeledcovidkmeans.rename({0:'labels'},axis=1)
```

[67]:
```
labeledcovidkmeans.head()
```

[67]:

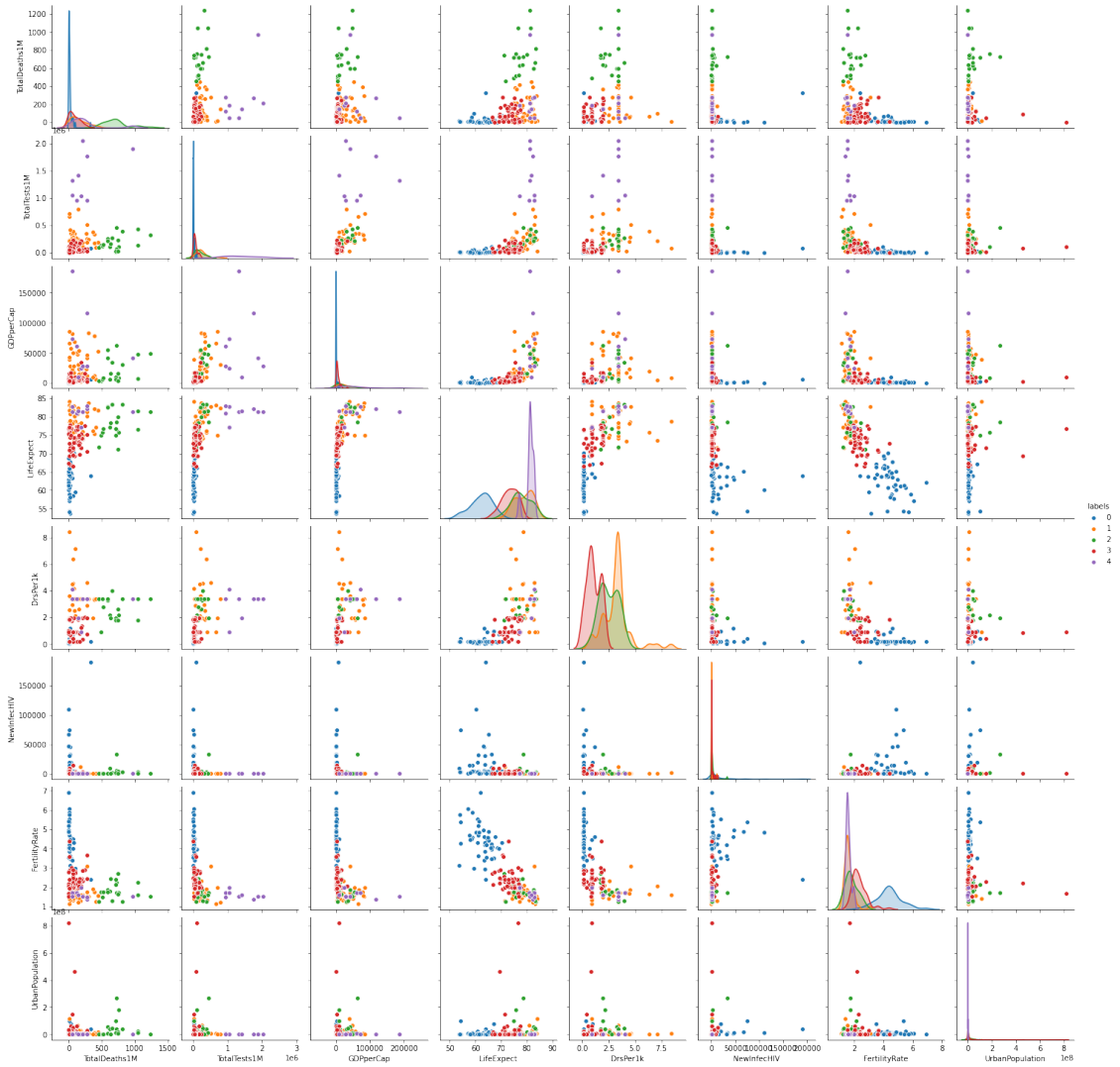
| | TotalDeaths1M | TotalTests1M | GDPperCap | LifeExpect | DrsPer1k | NewInfecHIV | FertilityRate | UrbanPopulation | Country | labels |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 3.0 | 111163.0 | 9976.676822 | 76.704000 | 0.9186 | 1050.0 | 1.6900 | 823827650.0 | China | 3 |
| 1 | 723.0 | 458433.0 | 62840.020239 | 78.539024 | 1.9357 | 33000.0 | 1.7295 | 268720071.0 | United States | 2 |
| 2 | 90.0 | 81607.0 | 2005.863005 | 69.416000 | 0.8571 | 1050.0 | 2.2220 | 460295677.0 | India | 3 |
| 3 | 756.0 | 102777.0 | 9001.234249 | 75.672000 | 2.1643 | 2300.0 | 1.7300 | 181335507.0 | Brazil | 2 |
| 4 | 592.0 | 257477.0 | 41631.090739 | 82.724390 | 3.2672 | 500.0 | 1.8800 | 53870058.0 | France | 2 |

[68]:
```
sns.pairplot(labeledcovidkmeans,hue='labels')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:369:
```

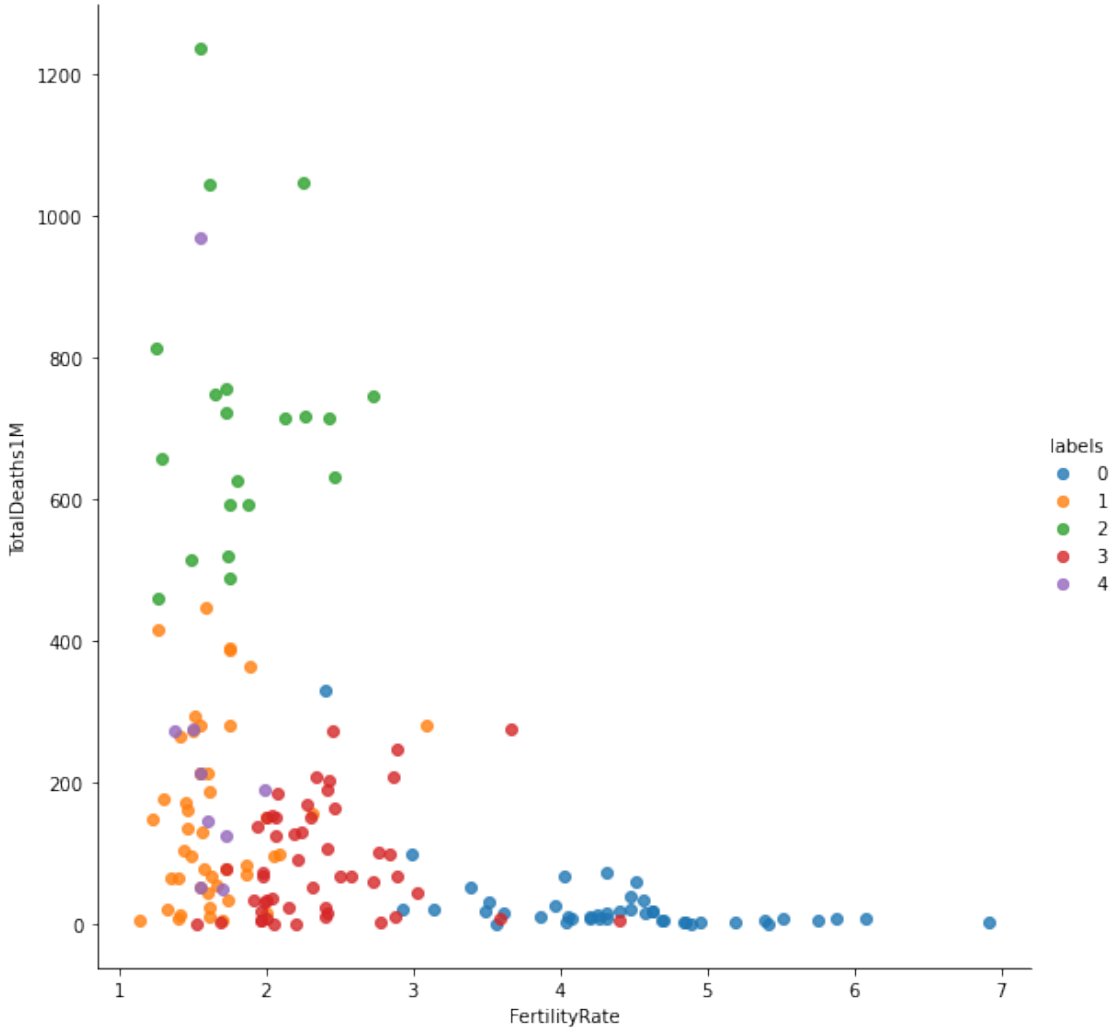
```
UserWarning: Default bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:369:
UserWarning: Default bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:369:
UserWarning: Default bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
```

[68]: `<seaborn.axisgrid.PairGrid at 0x199a41112b0>`



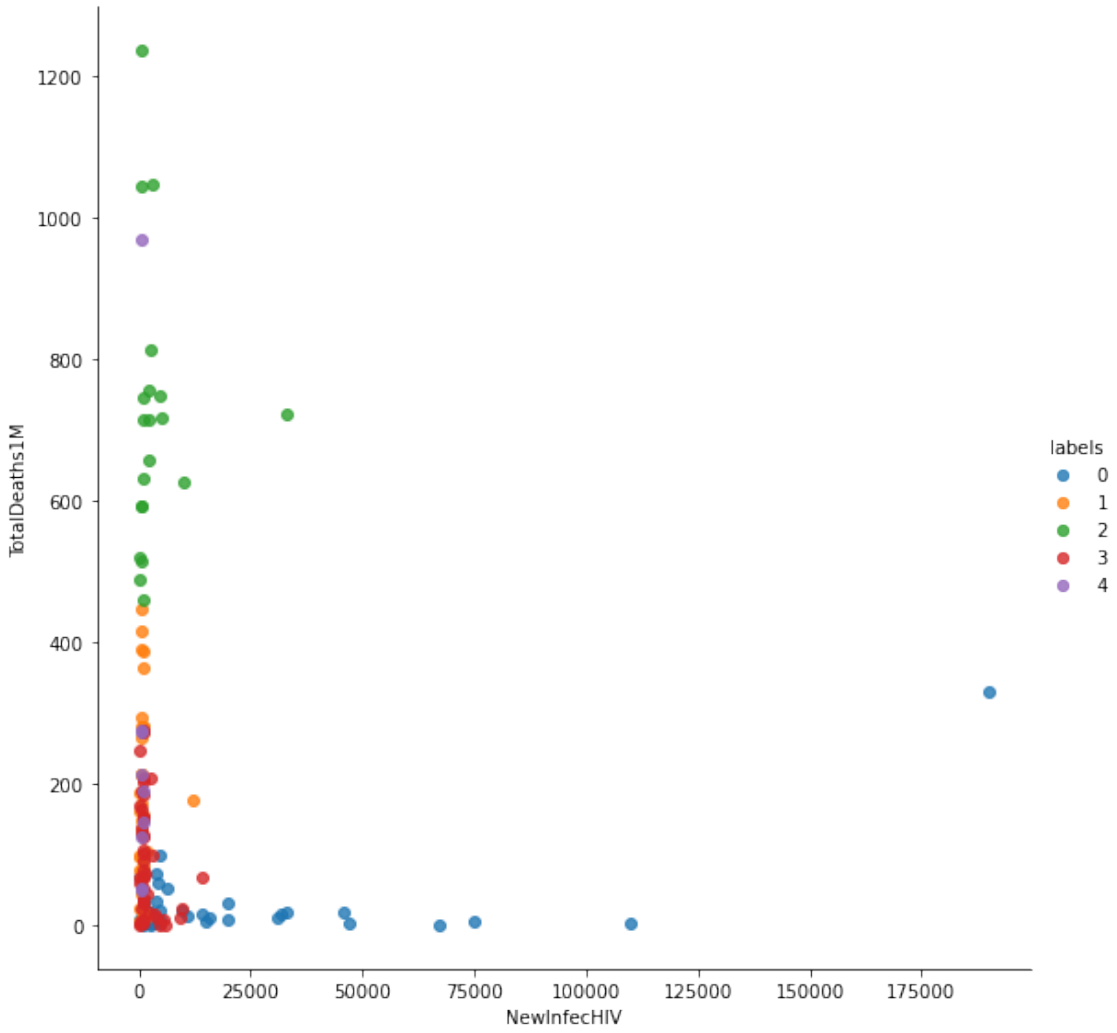

[69]:
```
sns.
↪lmplot(x='FertilityRate',y='TotalDeaths1M',data=labeledcovidkmeans,hue='labels',fit_reg=Fal
↪height=8)
```

[69]: <seaborn.axisgrid.FacetGrid at 0x199a8f2b190>



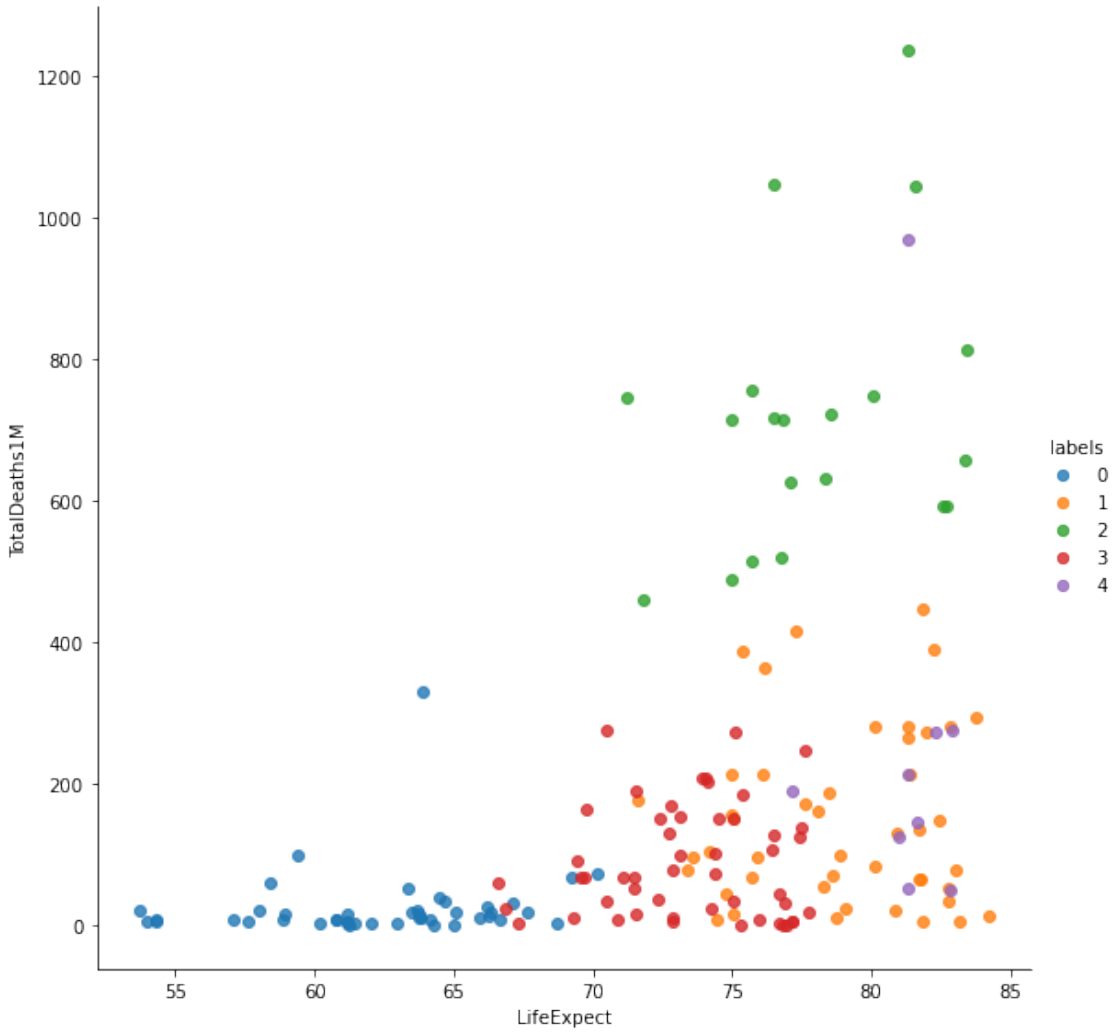

[70]:
```
sns.
↪lmplot(x='NewInfecHIV',y='TotalDeaths1M',data=labeledcovidkmeans,hue='labels',fit_reg=False
```

[70]: <seaborn.axisgrid.FacetGrid at 0x199a6a40880>



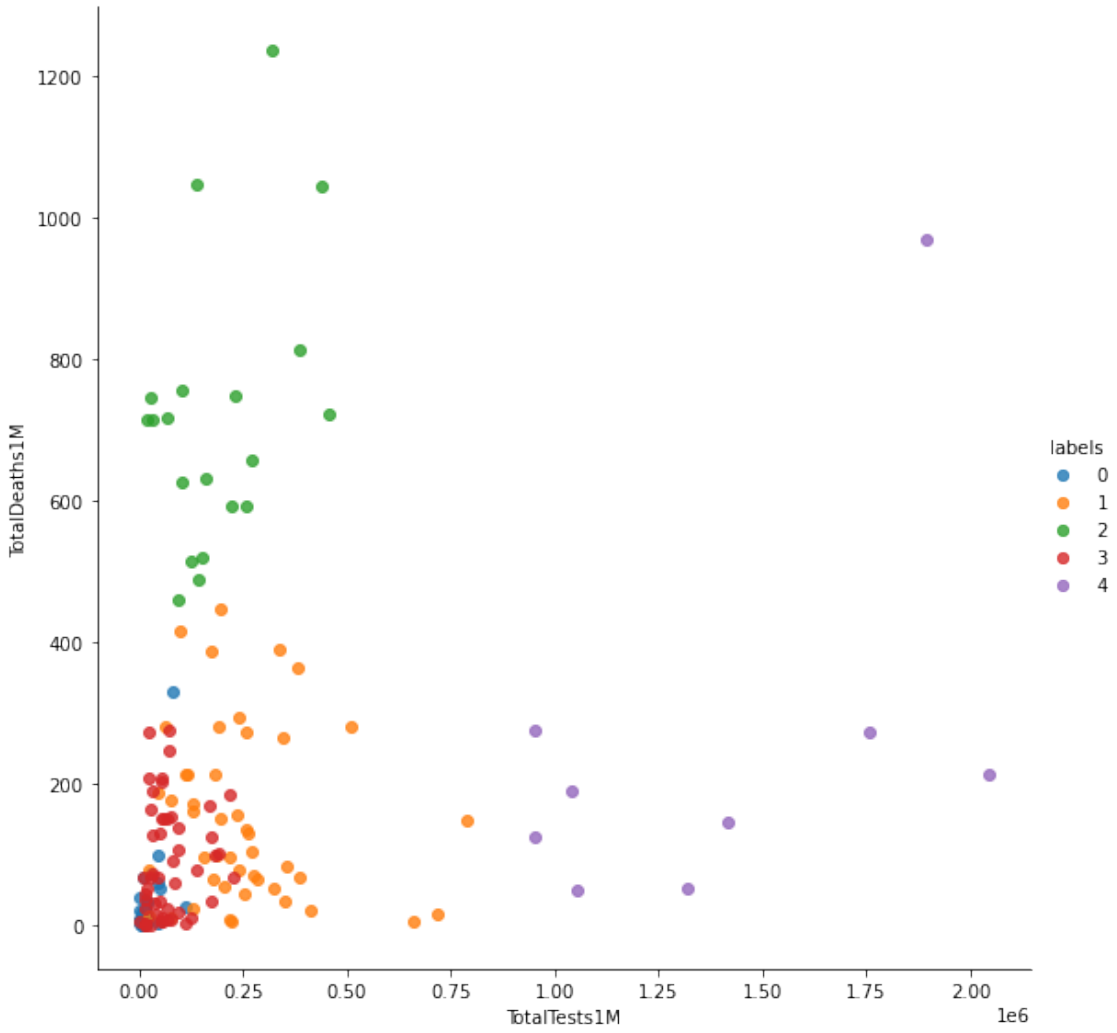

[71]:
```
sns.
↪lmplot(x='LifeExpect',y='TotalDeaths1M',data=labeledcovidkmeans,hue='labels',fit_reg=False,
↪height=8)
```

[71]: <seaborn.axisgrid.FacetGrid at 0x199aa40d9a0>

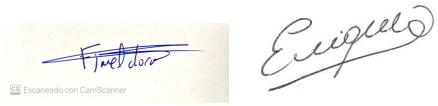
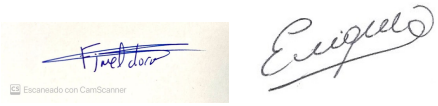
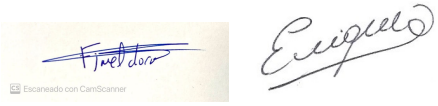
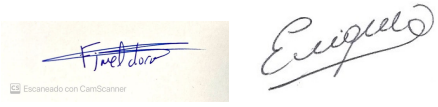
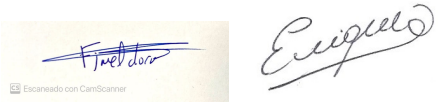
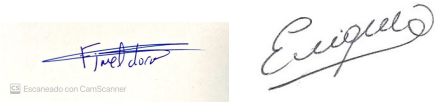
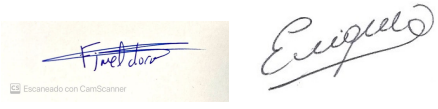
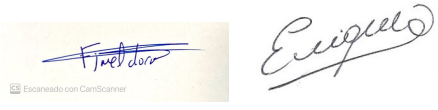
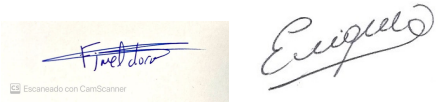



[72]:
```
sns.
↪lmplot(x='TotalTests1M',y='TotalDeaths1M',data=labeledcovidkmeans,hue='labels',fit_reg=Fals
↪height=8)
```

[72]: <seaborn.axisgrid.FacetGrid at 0x199aa48c640>




Finalmente, atendiendo a los clustering obtenidos por el modelo, se detecta que hay un grupo de países donde los parámetros parecen indicar que son países subdesarrollados, en los cuales se detectan un menor número de muertes debido a la pandemia de la COVID-19

| Contribuciones | Firma |
| --- | --- |
| Investigación Inicial |  |
| Análisis de herramientas Scrappping |  |
| Codigo python Scrapping y app |  |
| Investigación de Indicadores WorldBank |  |
| Obtención de datos Covid y WorldBank |  |
| Procesado y limpieza de Datos |  |
| Análisis ejemplo Clustering |  |
| Export de DataSet |  |
| Documentacion |  |