

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns #visualisation
import matplotlib.pyplot as plt #visualisation
from sklearn.preprocessing import LabelEncoder #To Encoding
import missingno as msno #Visualisation Matrix NaNs
```

STEPS

Dataframe about Coronavirus Group D

In [2]:

```
from utils.folders_tb import downloader
world = downloader(url='https://covid.ourworldindata.org/data/owid-covid-data.csv')
world
```

Out[2]:

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	nev
0	AFG	Asia	Afghanistan	2020-02-24	1.0	1.0	NaN	NaN	NaN	
1	AFG	Asia	Afghanistan	2020-02-25	1.0	0.0	NaN	NaN	NaN	
2	AFG	Asia	Afghanistan	2020-02-26	1.0	0.0	NaN	NaN	NaN	
3	AFG	Asia	Afghanistan	2020-02-27	1.0	0.0	NaN	NaN	NaN	
4	AFG	Asia	Afghanistan	2020-02-28	1.0	0.0	NaN	NaN	NaN	
...	
62060	ZWE	Africa	Zimbabwe	2021-01-20	29408.0	733.0	736.000	879.0	54.0	
62061	ZWE	Africa	Zimbabwe	2021-01-21	30047.0	639.0	668.429	917.0	38.0	
62062	ZWE	Africa	Zimbabwe	2021-01-22	30523.0	476.0	630.571	962.0	45.0	
62063	ZWE	Africa	Zimbabwe	2021-01-23	31007.0	484.0	589.429	974.0	12.0	
62064	ZWE	Africa	Zimbabwe	2021-01-24	31320.0	313.0	588.143	1005.0	31.0	

62065 rows × 55 columns



In [5]:

```
#This correlation Matrix of NaNs is showing how many columns have a lot of non-values
msno.matrix(world)
```

Out[5]:

<AxesSubplot:>



In [4]:

```
msno.heatmap(world)
```

```
Out[4]:
```

```
<AxesSubplot:>
```

```
In [6]:
```

```
world.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 62047 entries, 0 to 62046
```

```
Data columns (total 55 columns):
```

#	Column	Non-Null Count	Dtype
0	iso_code	61694 non-null	object
1	continent	61325 non-null	object
2	location	62047 non-null	object
3	date	62047 non-null	object
4	total_cases	61450 non-null	float64
5	new_cases	61443 non-null	float64
6	new_cases_smoothed	60484 non-null	float64
7	total_deaths	52913 non-null	float64
8	new_deaths	52912 non-null	float64
9	new_deaths_smoothed	60484 non-null	float64
10	total_cases_per_million	61097 non-null	float64
11	new_cases_per_million	61090 non-null	float64
12	new_cases_smoothed_per_million	60136 non-null	float64
13	total_deaths_per_million	52573 non-null	float64
14	new_deaths_per_million	52572 non-null	float64
15	new_deaths_smoothed_per_million	60136 non-null	float64
16	reproduction_rate	50035 non-null	float64
17	icu_patients	6856 non-null	float64
18	icu_patients_per_million	6856 non-null	float64
19	hosp_patients	8114 non-null	float64
20	hosp_patients_per_million	8114 non-null	float64
21	weekly_icu_admissions	672 non-null	float64
22	weekly_icu_admissions_per_million	672 non-null	float64
23	weekly_hosp_admissions	991 non-null	float64
24	weekly_hosp_admissions_per_million	991 non-null	float64
25	total_tests	28702 non-null	float64
26	new_tests	28885 non-null	float64
27	total_tests_per_thousand	28702 non-null	float64
28	new_tests_per_thousand	28885 non-null	float64
29	new_tests_smoothed	32573 non-null	float64
30	new_tests_smoothed_per_thousand	32573 non-null	float64
31	positive_rate	30771 non-null	float64
32	tests_per_case	30282 non-null	float64
33	tests_units	33772 non-null	object
34	total_vaccinations	922 non-null	float64
35	new_vaccinations	725 non-null	float64
36	new_vaccinations_smoothed	1196 non-null	float64
37	total_vaccinations_per_hundred	922 non-null	float64
38	new_vaccinations_smoothed_per_million	1196 non-null	float64
39	stringency_index	55360 non-null	float64
40	population	61694 non-null	float64
41	population_density	60390 non-null	float64
42	median_age	59028 non-null	float64
43	aged_65_older	58344 non-null	float64
44	aged_70_older	58694 non-null	float64
45	gdp_per_capita	59064 non-null	float64
46	extreme_poverty	40417 non-null	float64
47	cardiovasc_death_rate	59665 non-null	float64
48	diabetes_prevalence	60368 non-null	float64
49	female_smokers	47084 non-null	float64
50	male_smokers	46439 non-null	float64
51	handwashing_facilities	29886 non-null	float64
52	hospital_beds_per_thousand	54798 non-null	float64
53	life_expectancy	61377 non-null	float64
54	human_development_index	59329 non-null	float64

```
31 human_development_index
dtypes: float64(50), object(5)
memory usage: 26.0+ MB
```

In [8]:

```
#In this section only it is showing how "date" columns has been changed from object to da
tetime to can work in future functions.
world_date = downloader(url='https://covid.ourworldindata.org/data/owid-covid-data.csv')
world_date["date"] = pd.to_datetime(world_date["date"])
world_date.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 62047 entries, 0 to 62046
```

```
Data columns (total 55 columns):
```

#	Column	Non-Null Count	Dtype
0	iso_code	61694 non-null	object
1	continent	61325 non-null	object
2	location	62047 non-null	object
3	date	62047 non-null	datetime64[ns]
4	total_cases	61450 non-null	float64
5	new_cases	61443 non-null	float64
6	new_cases_smoothed	60484 non-null	float64
7	total_deaths	52913 non-null	float64
8	new_deaths	52912 non-null	float64
9	new_deaths_smoothed	60484 non-null	float64
10	total_cases_per_million	61097 non-null	float64
11	new_cases_per_million	61090 non-null	float64
12	new_cases_smoothed_per_million	60136 non-null	float64
13	total_deaths_per_million	52573 non-null	float64
14	new_deaths_per_million	52572 non-null	float64
15	new_deaths_smoothed_per_million	60136 non-null	float64
16	reproduction_rate	50035 non-null	float64
17	icu_patients	6856 non-null	float64
18	icu_patients_per_million	6856 non-null	float64
19	hosp_patients	8114 non-null	float64
20	hosp_patients_per_million	8114 non-null	float64
21	weekly_icu_admissions	672 non-null	float64
22	weekly_icu_admissions_per_million	672 non-null	float64
23	weekly_hosp_admissions	991 non-null	float64
24	weekly_hosp_admissions_per_million	991 non-null	float64
25	total_tests	28702 non-null	float64
26	new_tests	28885 non-null	float64
27	total_tests_per_thousand	28702 non-null	float64
28	new_tests_per_thousand	28885 non-null	float64
29	new_tests_smoothed	32573 non-null	float64
30	new_tests_smoothed_per_thousand	32573 non-null	float64
31	positive_rate	30771 non-null	float64
32	tests_per_case	30282 non-null	float64
33	tests_units	33772 non-null	object
34	total_vaccinations	922 non-null	float64
35	new_vaccinations	725 non-null	float64
36	new_vaccinations_smoothed	1196 non-null	float64
37	total_vaccinations_per_hundred	922 non-null	float64
38	new_vaccinations_smoothed_per_million	1196 non-null	float64
39	stringency_index	55360 non-null	float64
40	population	61694 non-null	float64
41	population_density	60390 non-null	float64
42	median_age	59028 non-null	float64
43	aged_65_old	58344 non-null	float64
44	aged_70_old	58694 non-null	float64
45	gdp_per_capita	59064 non-null	float64
46	extreme_poverty	40417 non-null	float64
47	cardiovasc_death_rate	59665 non-null	float64
48	diabetes_prevalence	60368 non-null	float64
49	female_smokers	47084 non-null	float64
50	male_smokers	46439 non-null	float64
51	handwashing_facilities	29886 non-null	float64
52	hospital_beds_per_thousand	54798 non-null	float64
53	life_expectancy	61377 non-null	float64
54	human_development_index	59329 non-null	float64

```
dtypes: datetime64[ns](1), float64(50), object(4)
```

dtypes: datetime64[ns] (1), float64 (30), object (1)
memory usage: 26.0+ MB

In [4]:

```
from utils.mining_data_tb import countries
gbr = countries(df=world, code= "GBR")
prt = countries(df=world, code= "PRT")
ven = countries(df=world, code= "VEN")
tur = countries(df=world, code= "TUR")
esp = countries(df=world, code= "ESP")
gbr
```

Out[4]:

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	new_d
58315	GBR	Europe	United Kingdom	2020-01-31	2.0	2.0	NaN	NaN	NaN	
58316	GBR	Europe	United Kingdom	2020-02-01	2.0	0.0	NaN	NaN	NaN	
58317	GBR	Europe	United Kingdom	2020-02-02	2.0	0.0	NaN	NaN	NaN	
58318	GBR	Europe	United Kingdom	2020-02-03	8.0	6.0	NaN	NaN	NaN	
58319	GBR	Europe	United Kingdom	2020-02-04	8.0	0.0	NaN	NaN	NaN	
...	
58670	GBR	Europe	United Kingdom	2021-01-20	3515796.0	38992.0	42120.429	93469.0	1826.0	
58671	GBR	Europe	United Kingdom	2021-01-21	3553773.0	37977.0	40573.714	94765.0	1296.0	
58672	GBR	Europe	United Kingdom	2021-01-22	3594094.0	40321.0	38350.286	96166.0	1401.0	
58673	GBR	Europe	United Kingdom	2021-01-23	3627746.0	33652.0	37239.429	97518.0	1352.0	
58674	GBR	Europe	United Kingdom	2021-01-24	3657857.0	30111.0	36016.714	98129.0	611.0	

360 rows x 55 columns



In [5]:

```
from utils.mining_data_tb import column_erraser

gbr_dd = column_erraser(df=gbr, col1="date", col2='new_cases', col3="new_deaths")
prt_dd = column_erraser(df=prt, col1="date", col2='new_cases', col3="new_deaths")
ven_dd = column_erraser(df=ven, col1="date", col2='new_cases', col3="new_deaths")
tur_dd = column_erraser(df=tur, col1="date", col2='new_cases', col3="new_deaths")
esp_dd = column_erraser(df=esp, col1="date", col2='new_cases', col3="new_deaths")
```

In [5]:

```
gbr_dd
```

Out[5]:

	date	new_cases	new_deaths
58315	2020-01-31	2.0	NaN
58316	2020-02-01	0.0	NaN
58317	2020-02-02	0.0	NaN
58318	2020-02-03	6.0	NaN

58319	2020-02-04	0.0	NaN
date new_cases new_deaths			
...
58670	2021-01-20	38992.0	1826.0
58671	2021-01-21	37977.0	1296.0
58672	2021-01-22	40321.0	1401.0
58673	2021-01-23	33652.0	1352.0
58674	2021-01-24	30111.0	611.0

360 rows x 3 columns

In [6]:

```
gbr_dd.dropna(inplace= True)
prt_dd.dropna( inplace= True)
ven_dd.dropna( inplace= True)
tur_dd.dropna( inplace= True)
esp_dd.dropna( inplace= True)
```

In [7]:

```
gbr_dd
```

Out[7]:

	date	new_cases	new_deaths
58350	2020-03-06	79.0	1.0
58351	2020-03-07	55.0	1.0
58352	2020-03-08	54.0	0.0
58353	2020-03-09	147.0	1.0
58354	2020-03-10	259.0	4.0
...
58670	2021-01-20	38992.0	1826.0
58671	2021-01-21	37977.0	1296.0
58672	2021-01-22	40321.0	1401.0
58673	2021-01-23	33652.0	1352.0
58674	2021-01-24	30111.0	611.0

325 rows x 3 columns

In [18]:

```
#Pregunta C8
gbr.corr()
prt.corr()
ven.corr()
tur.corr()
esp.corr()
```

Out[18]:

	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	new_
total_cases	1.000000e+00	5.306517e-01	8.070279e-01	8.793744e-01	5.678626e-02	
new_cases	5.306517e-01	1.000000e+00	6.480925e-01	3.881492e-01	3.449407e-01	
new_cases_smoothed	8.070279e-01	6.480925e-01	1.000000e+00	6.128911e-01	2.063171e-01	
total_deaths	8.793744e-01	3.881492e-01	6.128911e-01	1.000000e+00	-1.186537e-01	
	5.678626e-02	3.449407e-01	2.063171e-01	-1.186537e-01	1.000000e+00	

	new_deaths	5.678626e-02	total_cases	3.449407e-01	new_cases	2.063171e-01	new_cases_smoothed	total_deaths	1.000000e+00	new_deaths	new_deaths_smoothed
	new_deaths_smoothed	1.435459e-01	1.676450e-01			2.996779e-01	-1.084045e-01	7.224396e-01			
	total_cases_per_million	1.000000e+00	5.306517e-01			8.070279e-01	8.793744e-01	5.678626e-02			
	new_cases_per_million	5.306517e-01	1.000000e+00			6.480924e-01	3.881493e-01	3.449407e-01			
	new_cases_smoothed_per_million	8.070280e-01	6.480924e-01			1.000000e+00	6.128912e-01	2.063171e-01			
	total_deaths_per_million	8.793744e-01	3.881493e-01			6.128911e-01	1.000000e+00	-1.186538e-01			
	new_deaths_per_million	5.678975e-02	3.449424e-01			2.063185e-01	-1.186484e-01	1.000000e+00			
	new_deaths_smoothed_per_million	1.435458e-01	1.676428e-01			2.996795e-01	-1.084037e-01	7.224380e-01			
	reproduction_rate	-2.704262e-01	-4.507082e-02			-1.512950e-01	-5.722246e-01	-4.038914e-02			
	icu_patients	7.542774e-01	3.425082e-01			6.763201e-01	6.440188e-01	6.224790e-01			
	icu_patients_per_million	7.542792e-01	3.425099e-01			6.763184e-01	6.440210e-01	6.224782e-01			
	hosp_patients	5.838531e-01	4.455477e-01			8.511182e-01	4.489541e-01	6.179149e-01			
	hosp_patients_per_million	5.838531e-01	4.455474e-01			8.511181e-01	4.489542e-01	6.179150e-01			
	weekly_icu_admissions	-1.034623e-02	3.329079e-01			1.568608e-01	-4.810924e-01	3.140879e-01			
	weekly_icu_admissions_per_million	-1.033943e-02	3.329056e-01			1.568674e-01	-4.810873e-01	3.140857e-01			
	weekly_hosp_admissions	1.560007e-02	4.971079e-01			2.239458e-01	-4.724676e-01	5.053663e-01			
	weekly_hosp_admissions_per_million	1.559985e-02	4.971079e-01			2.239456e-01	-4.724678e-01	5.053663e-01			
	total_tests	9.935334e-01	8.079092e-01			7.706481e-01	9.766989e-01	3.465857e-01			
	new_tests	NaN	NaN			NaN	NaN	NaN			
	total_tests_per_thousand	9.935333e-01	8.079097e-01			7.706486e-01	9.766988e-01	3.465859e-01			
	new_tests_per_thousand	NaN	NaN			NaN	NaN	NaN			
	new_tests_smoothed	8.506193e-01	5.695179e-01			9.376576e-01	7.644713e-01	2.675102e-01			
	new_tests_smoothed_per_thousand	8.506225e-01	5.694967e-01			9.376329e-01	7.644788e-01	2.675182e-01			
	positive_rate	3.259592e-01	3.529368e-01			5.685625e-01	2.010074e-01	2.973048e-01			
	tests_per_case	-3.352373e-01	-2.581484e-01			-4.299592e-01	-2.933662e-01	-1.069640e-01			
	total_vaccinations	9.962167e-01	3.741305e-01			9.846909e-01	9.900327e-01	5.333185e-01			
	new_vaccinations	-1.315952e-01	1.886223e-01			7.621172e-02	-1.466593e-01	-6.665631e-01			
	new_vaccinations_smoothed	6.672829e-01	1.935738e-01			7.559267e-01	6.278346e-01	1.513558e-01			
	total_vaccinations_per_hundred	9.961878e-01	3.744837e-01			9.846397e-01	9.898782e-01	5.339127e-01			
	new_vaccinations_smoothed_per_million	6.673870e-01	1.940945e-01			7.559833e-01	6.279747e-01	1.518692e-01			
	stringency_index	3.689012e-01	2.216712e-01			3.386774e-01	2.378178e-01	3.981147e-01			
	population	NaN	NaN			NaN	NaN	NaN			
	population_density	1.457344e-15	2.342494e-15			1.116635e-15	-3.433818e-15	-4.037768e-16			
	median_age	NaN	NaN			NaN	NaN	NaN			
	aged_65_old	3.290689e-15	2.735455e-18			1.116635e-15	-3.005899e-16	5.467811e-16			
	aged_70_old	4.853011e-15	-1.243446e-15			-1.772436e-16	8.803784e-16	3.148134e-16			
	gdp_per_capita	3.290689e-15	2.735455e-18			-1.772436e-16	-2.557054e-16	4.343872e-16			

	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	new_deaths_smoothed
extreme_poverty	NaN	NaN	NaN	NaN	NaN	NaN
cardiovasc_death_rate	4.271298e-16	1.818611e-15	4.070039e-16	2.007449e-15	6.529491e-16	
diabetes_prevalence	-3.145630e-15	-1.593129e-15	-4.741268e-16	1.404248e-15	6.806264e-16	
female_smokers	3.290689e-15	2.735455e-18	6.255658e-17	1.516406e-15	-3.594241e-16	
male_smokers	3.604038e-15	-1.850639e-15	-1.909256e-15	-3.425526e-15	3.386764e-16	
handwashing_facilities	NaN	NaN	NaN	NaN	NaN	NaN
hospital_beds_per_thousand	2.769411e-15	1.616520e-15	-7.877495e-18	-8.803784e-16	-3.148134e-16	
life_expectancy	3.700407e-15	7.547041e-16	-5.812549e-16	2.667679e-15	4.374249e-16	
human_development_index	-4.853011e-15	1.243446e-15	-8.271370e-16	-3.378236e-15	-2.226180e-16	

50 rows x 50 columns

In [8]:

```
#Pregunta A2
worlda_2 = world.drop(['iso_code', 'continent', 'location', 'date', 'aged_65_older', 'tests_units'], 1)
from utils.mining_data_tb import get_top_abs_correlations
get_top_abs_correlations(df=worlda_2, n=7)
```

Out[8]:

```
new_cases      new_cases_smoothed    0.990950
total_cases     total_deaths         0.977766
new_cases_smoothed total_deaths      0.976873
icu_patients    hosp_patients        0.975158
new_tests       new_tests_smoothed   0.975068
new_deaths      new_deaths_smoothed  0.973488
total_cases     new_cases_smoothed    0.970599
dtype: float64
```

In [9]:

```
worlda_2cor = column_erraser(df= worlda_2, col1='new_cases', col2='new_cases_smoothed',
col3='total_deaths', col4='total_cases', col5='new_tests', col6='new_tests_smoothed', col
7= "icu_patients", col8='hosp_patients', col9='new_deaths', col10='new_deaths_smoothed')
worlda_2cor.corr()
```

Out[9]:

	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	new_deaths_smoothed	icu_p
total_cases	1.000000	0.958567	0.970599	0.977766	0.883569	0.906525	0
new_cases	0.958567	1.000000	0.990950	0.967305	0.933366	0.934160	0
new_cases_smoothed	0.970599	0.990950	1.000000	0.976873	0.922549	0.944571	0
total_deaths	0.977766	0.967305	0.976873	1.000000	0.919862	0.944834	0
new_deaths	0.883569	0.933366	0.922549	0.919862	1.000000	0.973488	0
new_deaths_smoothed	0.906525	0.934160	0.944571	0.944834	0.973488	1.000000	0
icu_patients	0.882391	0.890198	0.909069	0.881514	0.915093	0.962369	1
hosp_patients	0.884858	0.897988	0.915676	0.900303	0.913121	0.956632	0
new_tests	0.883138	0.857692	0.857943	0.846004	0.701788	0.718675	0
new_tests_smoothed	0.902680	0.853262	0.870133	0.847494	0.664222	0.713038	0

In [7]:

```
#Pregunta A.4.b - Ejecutado debajo de este código en la sección Visualization Javi.
from utils.mining_data_tb import A_4_b
gbr1M = A_4_b(df= gbr_dd, column='date', key= "date", freq= '1M')
```

In [8]:

```
gbr10D = A_4_b(df= gbr_dd, column='date', key= "date", freq= '10D')
```

In [25]:

```
prt1M = A_4_b(df= prt_dd, column='date', key= "date", freq= '1M')
```

In [26]:

```
prt10D = A_4_b(df= prt_dd, column='date', key= "date", freq= '10D')
```

In [27]:

```
ven1M = A_4_b(df= ven_dd, column='date', key= "date", freq= '1M')
```

In [28]:

```
ven10D = A_4_b(df= ven_dd, column='date', key= "date", freq= '10D')
```

In [29]:

```
tur1M = A_4_b(df= tur_dd, column='date', key= "date", freq= '1M')
```

In [30]:

```
tur10D = A_4_b(df= tur_dd, column='date', key= "date", freq= '10D')
```

In [31]:

```
esp1M = A_4_b(df= esp_dd, column='date', key= "date", freq= '1M')
```

In [32]:

```
esp10D = A_4_b(df= esp_dd, column='date', key= "date", freq= '10D')
```

Visualization Javi

In [19]:

```
from utils.visualization_tb import b_2_line
gbrb_2_line = b_2_line(df= gbr_dd, x= gbr_dd['date'], y=gbr_dd.columns, title= 'GBR covid deaths')
```

In [20]:

```
from utils.visualization_tb import b_2_bar
gbrb_2_bar = b_2_bar(df= gbr_dd, x= gbr_dd['date'], y=gbr_dd.columns, title= 'GBR covid deaths')
```

In [21]:

```
from utils.visualization_tb import b_2_dots
gbrb_2_dots = b_2_dots(df= gbr_dd, x= gbr_dd['date'], y=gbr_dd.columns, title= 'GBR covid deaths')
```

In [33]:

```
prtb_2_line = b_2_line(df= prt_dd, x= prt_dd['date'], y=prt_dd.columns, title= 'PRT covid deaths')
```



```
In [37]:
```

```
prtb_2_bar = b_2_bar(df= prt_dd, x= prt_dd['date'], y=prt_dd.columns, title= 'PRT covid deaths')
```

```
In [38]:
```

```
prtb_2_dots = b_2_dots(df= prt_dd, x= prt_dd['date'], y=prt_dd.columns, title= 'PRT covid deaths')
```

```
In [39]:
```

```
venb_2_line = b_2_line(df= ven_dd, x= ven_dd['date'], y=ven_dd.columns, title= 'VEN covid deaths')
```

```
In [40]:
```

```
venb_2_bar = b_2_bar(df= ven_dd, x= ven_dd['date'], y=ven_dd.columns, title= 'VEN covid deaths')
```

```
In [42]:
```

```
venb_2_dots = b_2_dots(df= ven_dd, x= ven_dd['date'], y=ven_dd.columns, title= 'VEN covid deaths')
```

```
In [43]:
```

```
turb_2_line = b_2_line(df= tur_dd, x= tur_dd['date'], y=tur_dd.columns, title= 'TUR covid deaths')
```

```
In [44]:
```

```
turb_2_bar = b_2_bar(df= tur_dd, x= tur_dd['date'], y=tur_dd.columns, title= 'TUR covid deaths')
```

```
In [45]:
```

```
turb_2_dots = b_2_dots(df= tur_dd, x= tur_dd['date'], y=tur_dd.columns, title= 'TUR covid deaths')
```

```
In [46]:
```

```
espb_2_line = b_2_line(df= esp_dd, x= esp_dd['date'], y=esp_dd.columns, title= 'ESP covid deaths')
```

```
In [47]:
```

```
espb_2_bar = b_2_bar(df= esp_dd, x= esp_dd['date'], y=esp_dd.columns, title= 'ESP covid deaths')
```

```
In [48]:
```

```
espb_2_dots = b_2_dots(df= esp_dd, x= esp_dd['date'], y=esp_dd.columns, title= 'ESP covid deaths')
```

```
In [13]:
```

```
sns.heatmap(worlda_2cor.corr())
```

```
Out[13]:
```

```
<AxesSubplot:>
```

```
In [32]:
```

```
gbrb1M_line = b_2_line(df= gbr1M, x= gbr1M.index, y=gbr1M.columns, title= 'GBR 1M covid deaths')
```

```
In [22]:
```

```
gbr10D_line = b_2_line(df= gbr10D, x= gbr10D.index, y=gbr10D.columns, title= 'GBR 10D covid deaths')
```

```
In [33]:
```

```
prt1M_line = b_2_line(df= prt1M, x= prt1M.index, y=prt1M.columns, title= 'PRT 1M covid deaths')
```

```
In [34]:
```

```
prt10D_line = b_2_line(df= prt10D, x= prt10D.index, y=prt10D.columns, title= 'PRT 10D covid deaths')
```

```
In [35]:
```

```
ven1M_line = b_2_line(df= ven1M, x= ven1M.index, y=ven1M.columns, title= 'VEN 1M covid deaths')
```

```
In [36]:
```

```
ven10D_line = b_2_line(df= ven10D, x= ven10D.index, y=ven10D.columns, title= 'VEN 10D covid deaths')
```

```
In [37]:
```

```
tur1M_line = b_2_line(df= tur1M, x= tur1M.index, y=tur1M.columns, title= 'TUR 1M covid deaths')
```

```
In [38]:
```

```
tur10D_line = b_2_line(df= tur10D, x= tur10D.index, y=tur10D.columns, title= 'TUR 10D covid deaths')
```

```
In [39]:
```

```
esp1M_line = b_2_line(df= esp1M, x= esp1M.index, y=esp1M.columns, title= 'ESP 1M covid deaths')
```

```
In [40]:
```

```
esp10D_line = b_2_line(df= esp10D, x= esp10D.index, y=esp10D.columns, title= 'ESP 10D covid deaths')
```

Visualization Ariadna

```
In [3]:
```

#Is the second way: this plot is showing that the 75% of the global Countries about total deaths are between 250K and more 500K.

```
from utils.visualization_tb import C10c
```

```
C10c(df=world)
```

<Figure size 432x288 with 0 Axes>

```
In [3]:
```

#In this graphic is representing total cases and total deaths, so this data it's the total since the covid-19 begun. United Kingdom and Spain are in top 10 Ranking of the worst countries that didn't manage very well.

```
from utils.visualization_tb import C10a
```

```
C10a(df=world)
```

<Figure size 432x288 with 0 Axes>

In [3]:

```
"""In this graphic has been thought with new cases and new deaths because they are not ac
cumulative"""
#It is showing the position of our countries: Portugal, Venezuela, Turkey, UK and Spain i
n general ranking in over the world. Venezuela is the first country with less new cases a
nd new deaths being 116 position in new cases and 106 in new deaths respect 190 countries
total. Instead of the last country is United Kingdom in 186 position in new cases and dea
ths. Spain is the second last country being 182/190 and 180/190 in new cases and deaths r
espectively.

from utils.visualization_tb import position

position(df=world, col1="iso_code", col2="date", col3="new_cases", col4="new_deaths", co
l5="continent", col6="location", col7="tests_units")
```

<Figure size 432x288 with 0 Axes>

Visualization Group C's Data - Total Cases

Visualization Ariadna

In [4]:

```
#This graphic from Group C is representing how the cases has gone increased during all Co
ronavirus pandemic.
from utils.visualization_tb import groupC_plot

groupC_plot(df=world)
```

<Figure size 432x288 with 0 Axes>

In []: