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This assignment consists of 2 parts which analyse two different datasets. Part 1 analyses the confidence intervals of the results of different football matches. Part 2 analyzes the number of Covid-19 cases, deaths, and income level in different countries.

Part 1: Football Matches

Abstract

In this part, the dataset "results.csv" is used. The data shows the results of different matches between the men's national teams, starting from the year 1872 till 2019. The data consists of 43,170 match results. This big number of matches helps in reaching valid statistical conclusions about the results of different countries.

First, the confidence intervals of winning, losing, draw will be analysed when teams are playing in their home country. Also, 5 different Arab (Egypt, Saudi Arabia, Kuwait, Tunisia, and Morocco) countries' confidence intervals of winning in their home countries will be analyzed and compared.

It was concluded (using the confidence intervals) that when playing in the home country, the team had the highest probability of winning, then losing, then draw. Also, out of the 5 countries mentioned above, Egypt was the one with the highest confidence interval of winning.

General interpretation of home/away matches

```
import pandas as pd
```

```
df= pd.read_csv('results.csv')
df
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral
0	1872-11-30	Scotland	England	0	0	Friendly	Glasgow	Scotland	False
1	1873-03-08	England	Scotland	4	2	Friendly	London	England	False
2	1874-03-07	Scotland	England	2	1	Friendly	Glasgow	Scotland	False
3	1875-03-06	England	Scotland	2	2	Friendly	London	England	False
4	1876-03-04	Scotland	England	3	0	Friendly	Glasgow	Scotland	False
...	...	...	...	...	...	...	...	...	...
43183	2/1/2022	Suriname	Guyana	2	1	Friendly	Paramaribo	Suriname	False
43184	2/2/2022	Burkina Faso	Senegal	1	3	African Cup of Nations	Yaoundé	Cameroon	True
43185	2/3/2022	Cameroon	Egypt	0	0	African Cup of Nations	Yaoundé	Cameroon	False
43186	2/5/2022	Cameroon	Burkina Faso	3	3	African Cup of Nations	Yaoundé	Cameroon	False
43187	2/6/2022	Senegal	Egypt	0	0	African Cup of Nations	Yaoundé	Cameroon	True

43188 rows × 9 columns

First, we want to see how many countries are analyzed in the dataset. Then, it is important to find out the number of games each country contributed in. That is because a country must have participated in at least 200 matches, in order to include it in the statistical analysis.

```python
df['home_team'].value_counts()+ df['away_team'].value_counts() #This table would be useful when choosing which countries will be anal
```

```python
x=df['home_score']-df['away_score']
```

```python
x
```

```python
conditions= [(x<0),(x>0),(x==0)] # If the result is negative: The home team has lost. If it is positive: The home team has won. If the
values=['lose','win','draw']
```

```python
import numpy as np
```

```python
df['result_home']=np.select(conditions,values)
```

```python
df # This is the data with the new column (results_home)
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result_home
0	1872-11-30	Scotland	England	0	0	Friendly	Glasgow	Scotland	False	draw
1	1873-03-08	England	Scotland	4	2	Friendly	London	England	False	win
2	1874-03-07	Scotland	England	2	1	Friendly	Glasgow	Scotland	False	win
3	1875-03-06	England	Scotland	2	2	Friendly	London	England	False	draw
4	1876-03-04	Scotland	England	3	0	Friendly	Glasgow	Scotland	False	win
...	...	...	...	...	...	...	...	...	...	...
43183	2/1/2022	Suriname	Guyana	2	1	Friendly	Paramaribo	Suriname	False	win
43184	2/2/2022	Burkina Faso	Senegal	1	3	African Cup of Nations	Yaoundé	Cameroon	True	lose
43185	2/3/2022	Cameroon	Egypt	0	0	African Cup of Nations	Yaoundé	Cameroon	False	draw
43186	2/5/2022	Cameroon	Burkina Faso	3	3	African Cup of Nations	Yaoundé	Cameroon	False	draw
43187	2/6/2022	Senegal	Egypt	0	0	African Cup of Nations	Yaoundé	Cameroon	True	draw

43188 rows × 10 columns

```python
df['result_home'][0:3]
```

```python
df['result_home'].value_counts() # This shows the number of mtaches won, lost, and draw by the home team.
```

```python
df['result_home'].value_counts(normalize=True) # Thi converts the above information into percentages.
```

```python
r=df['result_home'].value_counts()
```

```python
r=np.array(r)
```

```
r
```

```
R=r.sum()
```

```
R # The number of matches played are 43188
```

```
43188
```

```
df.head()
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result_home
0	1872-11-30	Scotland	England	0	0	Friendly	Glasgow	Scotland	False	draw
1	1873-03-08	England	Scotland	4	2	Friendly	London	England	False	win
2	1874-03-07	Scotland	England	2	1	Friendly	Glasgow	Scotland	False	win
3	1875-03-06	England	Scotland	2	2	Friendly	London	England	False	draw
4	1876-03-04	Scotland	England	3	0	Friendly	Glasgow	Scotland	False	win

The home team wins around 48.7% of matches. This is almost double the probability for the home team to lose or be in a draw. This might suggest that a team playing in their home country would affect the results of the match, and lead to a bigger chance for the away team to win. However, this conclusion cannot be finalized yet. That is because these probabilities include neutral matches (which didn't take place in the country of the home team OR away team). Therefore, the same process must be repeated for the matches which are not neutral, to see the impact of a match being played in the country of one of the teams.

```
df_noneutral= df[df['neutral']==False]
```

```
df_noneutral.shape #a new dataset with only non-neutral matches. According to the output, there are 32481 non-neutral matches.
```

```
(32481, 10)
```

```
df_noneutral
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result_home
0	1872-11-30	Scotland	England	0	0	Friendly	Glasgow	Scotland	False	draw
1	1873-03-08	England	Scotland	4	2	Friendly	London	England	False	win
2	1874-03-07	Scotland	England	2	1	Friendly	Glasgow	Scotland	False	win
3	1875-03-06	England	Scotland	2	2	Friendly	London	England	False	draw
4	1876-03-04	Scotland	England	3	0	Friendly	Glasgow	Scotland	False	win
...	...	...	...	...	...	...	...	...	...	...
43181	2/1/2022	Nepal	Mauritius	1	0	Friendly	Kathmandu	Nepal	False	win
43182	2/1/2022	Nicaragua	Belize	1	1	Friendly	Managua	Nicaragua	False	draw
43183	2/1/2022	Suriname	Guyana	2	1	Friendly	Paramaribo	Suriname	False	win
43185	2/3/2022	Cameroon	Egypt	0	0	African Cup of Nations	Yaoundé	Cameroon	False	draw
43186	2/5/2022	Cameroon	Burkina Faso	3	3	African Cup of Nations	Yaoundé	Cameroon	False	draw

32481 rows × 10 columns

```
y=df_noneutral['result_home'].value_counts()
```

```
y
```

```
df_noneutral['result_home'].value_counts(normalize=True)
```

After removing all the neutral matches from the data, we can now correctly analyze the effect of teams playing in their home countries on the match results. Without the neutral matches, the probability of a team winning if they are playing at their home stadium has increased from 49% to 51%. This infers that this variable (matches being non-neutral) affects the match results. According to the above output, there is a much higher probability (almost double) for a home team to win a match, rather than lose it or draw. This means that a team playing in their home stadium would increase their chance of wining.

```
n=np.array(y)
n
```

```
N=n.sum()# N would be used for the calculation of the confidence interval
N
```

```
32481
```

Now, we want to find the confidence interval (95%) for the win, loss, and draw of a match by the home team.

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
```

```
CIwin=proportion_confint(count=n[0],nobs=N,alpha=(1-.95))
CIwin
```

```
(0.4995656452847087, 0.5104402042888881)
```

```
CIlose=proportion_confint(count=n[1],nobs=N,alpha=(1-.95))
CIlose
```

```
(0.25890067381105686, 0.2684845667911413)
```

```
CIdraw=proportion_confint(count=n[2],nobs=N,alpha=(1-.95))
CIdraw
```

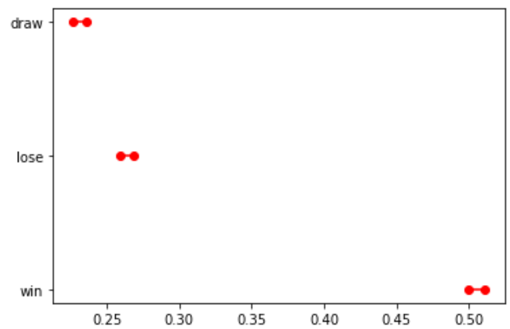
```
(0.22671878725859246, 0.23589012256561248)
```

```
CIhomewin = {}
CIhomewin['result_home'] = ['win','lose','draw']
CIhomewin['lb'] = [CIwin[0],CIlose[0],CIdraw[0]]
CIhomewin['ub'] = [CIwin[1],CIlose[1],CIdraw[1]]
CIhomewin
df_ci= pd.DataFrame(CIhomewin)
df_ci
```

	result_home	lb	ub
0	win	0.499566	0.510440
1	lose	0.258901	0.268485
2	draw	0.226719	0.235890

```
import matplotlib.pyplot as plt
for lb,ub,y in zip(df_ci['lb'],df_ci['ub'],range(len(df_ci))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci)),list(df_ci['result_home']))
```

```
([<matplotlib.axis.YTick at 0x7f190fd1dfd0>,
  <matplotlib.axis.YTick at 0x7f190fd1d850>,
  <matplotlib.axis.YTick at 0x7f190fd187c0>],
 [Text(0, 0, 'win'), Text(0, 1, 'lose'), Text(0, 2, 'draw')])
```



From the above graph, we can see that the probability of the home team winning (with 95% confidence) is the highest. whereas the probability of a draw is the lowest, and the probability of losing is slightly higher than that of the draw. There are no overlaps between any of the outcomes; this means that the difference between win/loss/draw is statistically significant. Also, the intervals are extremely narrow, meaning that there is high precision in the data and that is a good representation of the population.

Teams who play in their home stadiums believe that they have an advantage over the away team, as there are fans cheering for them. This explains why nowadays matches are played twice (once in each country) and the scores are added up in leagues, in order to ensure fair play.

Arab home/away results

The importance of an Arab team playing in their home stadium will be analyzed. Countries included: Egypt, Saudi Arabia, Kuwait Tunisia, and Morocco.

1) EGYPT

```
dfNoneutralEGY=df_noneutral[df_noneutral['country']=='Egypt']
```

```
dfNoneutralEGY
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result_home
1463	2/19/1932	Egypt	Hungary	0	0	Friendly	Cairo	Egypt	False	draw
1661	3/16/1934	Egypt	Israel	7	1	FIFA World Cup qualification	Cairo	Egypt	False	win
1895	6/19/1936	Egypt	Greece	3	1	Friendly	Cairo	Egypt	False	win
2927	12/24/1948	Egypt	Norway	1	1	Friendly	Cairo	Egypt	False	draw
3080	2/17/1950	Egypt	Greece	2	0	Friendly	Cairo	Egypt	False	win
...	...	...	...	...	...	...	...	...	...	...
42165	3/29/2021	Egypt	Comoros	4	0	African Cup of Nations qualification	Cairo	Egypt	False	win
42590	9/1/2021	Egypt	Angola	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
42758	9/30/2021	Egypt	Liberia	2	0	Friendly	Alexandria	Egypt	False	win
42812	10/8/2021	Egypt	Libya	1	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
43040	11/16/2021	Egypt	Gabon	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win

258 rows × 10 columns

```
dfNoneutralEGY['result_home'].value_counts(normalize=True) #This shows the nupercentage of mtaches won, lost, and draw by the home tea
```

From the above output, we can see that there is a 66.3% chance of the Egyptian football team to win if they play in their country, which is around 4 times the probability of Egypt losing or having a draw. The probability of draw and loss are very close (17%). when comparing the probability of Egypt winning (in their home country) and the world average probability, we can see that it is much higher for Egypt. There is a difference of 17.6 %. This means that the Egyptian fans cheering have a great impact on Egyptian match results.

However, in order to make this conclusion, we have to make sure that the probability of Egypt winning is not also around 66% in its away matches. This conclusion would only be valid if the probability of Egypt winning in its opposer's country is less than 66% (The probability of Egypt winning in its home country). Therefore, we must now find out this probability.

```
dfNoneutralEGYaway=df_noneutral[df_noneutral['away_team']=='Egypt'] # creating a data with all non-neutral matches, where Egypt is the
dfNoneutralEGYaway['result_home'].value_counts(normalize=True) # finding the probability of the home team winning (NOT Egypt)
```

In order to analyse the above output in terms of the away team (Egypt), we should switch the percentages. Win would mean Egypt losing, and lose would mean Egypt winning.

Therefore:
Draw:0.367924,
Lose:0.349057
Win:0.283019

This means that the probability of Egypt winning when it is the away team is 28.3%, which is less than 66.3%. Now we can safely conclude that the Egyptian fans cheering do have a great effect on Egyptian match results.

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
```

```
y=dfNoneutralEGY['result_home'].value_counts() #Now we want to find the confidence interval of Egypt winning in its home country
y=np.array(y)
y
```

```
N=y.sum()
N
```

```
258
```

```
CIegy=proportion_confint(count=y[0],nobs=N,alpha=(1-.95))
CIegy
```

```
(0.6051039288730269, 0.7204774664758102)
```

The same will be repeated for the other 4 Arab countries, in order to compare their confidence intervals of winning at their home country.

2) Saudi Arabia

```
dfNoneutralSA=df_noneutral[df_noneutral['country']=='Saudi Arabia']
dfNoneutralSA['result_home'].value_counts(normalize=True) #This shows the nupercentage of mtaches won, lost, and draw by the home team
```

The result is close to that of Egypt.

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
```

```
y=dfNoneutralSA['result_home'].value_counts() #Now we want to find the confidence interval of Saudi Aarbia winning in its home country
y=np.array(y)
y
```

```
N=y.sum()
N
```

```
269
```

```
CIsa=proportion_confint(count=y[0],nobs=N,alpha=(1-.95))
CIsa
```

```
(0.5437421740284505, 0.6607187925143005)
```

3) Kuwait

```
dfNoneutralKUW=df_noneutral[df_noneutral['country']=='Kuwait']
dfNoneutralKUW['result_home'].value_counts(normalize=True)
```

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
y=dfNoneutralKUW['result_home'].value_counts()
y=np.array(y)
y
```

```
N=y.sum()
N
```

```
230
```

```
CIkuw=proportion_confint(count=y[0],nobs=N,alpha=(1-.95))
CIkuw
```

```
(0.40506693786952574, 0.534063496913083)
```

4) Tunisia

```
dfNoneutralTUN=df_noneutral[df_noneutral['country']=='Tunisia']
dfNoneutralTUN['result_home'].value_counts(normalize=True)
```

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
y=dfNoneutralTUN['result_home'].value_counts()
y=np.array(y)
y
```

```
N=y.sum()
N
```

```
272
```

```
CItun=proportion_confint(count=y[0],nobs=N,alpha=(1-.95))
CItun
```

```
(0.5222448180850877, 0.6395198877972653)
```

5) Oman

```
dfNoneutralOMAN=df_noneutral[df_noneutral['country']=='Oman']
dfNoneutralOMAN['result_home'].value_counts(normalize=True)
```

```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
y=dfNoneutralOMAN['result_home'].value_counts()
y=np.array(y)
y
```

```
N=y.sum()
CIoman=proportion_confint(count=y[0],nobs=N,alpha=(1-.95))
CIoman
```

```
(0.4307048087825161, 0.5692951912174838)
```

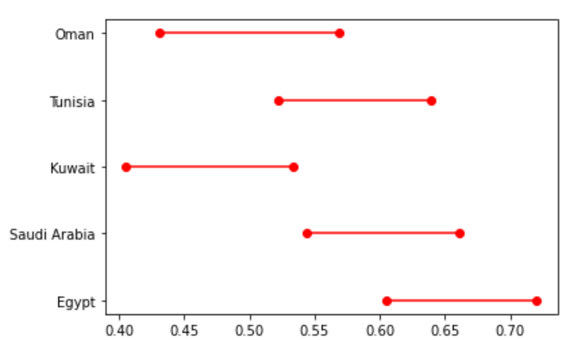
6) Comparing the Arab countries

```
CIhomewinarab = {}
CIhomewinarab['country'] = ['Egypt','Saudi Arabia','Kuwait','Tunisia','Oman']
CIhomewinarab['lb'] = [CIegy[0],CIsa[0],CIkuw[0],CItun[0],CIoman[0]]
CIhomewinarab['ub'] = [CIegy[1],CIsa[1],CIkuw[1],CItun[1],CIoman[1]]
CIhomewinarab
df_ci= pd.DataFrame(CIhomewinarab)
df_ci
```

	country	lb	ub
0	Egypt	0.605104	0.720477
1	Saudi Arabia	0.543742	0.660719
2	Kuwait	0.405067	0.534063
3	Tunisia	0.522245	0.639520
4	Oman	0.430705	0.569295

```
import matplotlib.pyplot as plt
for lb,ub,y in zip(df_ci['lb'],df_ci['ub'],range(len(df_ci))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci)),list(df_ci['country']))
```

```
([<matplotlib.axis.YTick at 0x7f190fc97970>,
  <matplotlib.axis.YTick at 0x7f190fc971f0>,
  <matplotlib.axis.YTick at 0x7f190fc91130>,
  <matplotlib.axis.YTick at 0x7f190fc4c1f0>,
  <matplotlib.axis.YTick at 0x7f190fc4c940>],
 [Text(0, 0, 'Egypt'),
  Text(0, 1, 'Saudi Arabia'),
  Text(0, 2, 'Kuwait'),
  Text(0, 3, 'Tunisia'),
  Text(0, 4, 'Oman')])
```



The above graph gives a visualization of the 95% confidence intervals of the 5 Arab countries (Egypt, Saudi Arabia, Kuwait, Tunisia, and Oman). It can help us compare the probabilities of these teams winning matches in their home country. It can be seen that the intervals have close wideness, which means that the countries have a close amount of variation in the data.

There are many overlaps in the graph. This means that the confidence intervals that overlap do not have a statistically significant difference. For instance, Saudi Arabia and Tunis almost fully overlap, with Saudi Arabia having slightly larger upper and lower bounds. we can infer that the chance of these 2 countries winning as home teams would be extremely close.

The same can also be said about Kuwait and Oman. They both have the lowest intervals, and a big part of the interval overlaps (less than the overlap of Saudi Arabia and Tunisia). Which also means that there is a low statistical significance between the chances of both countries winning. Lastly, Egypt shows

an overlap with Tunisia and Saudi Arabia.

The only 2 countries which do not slightly overlap are Egypt and Kuwait. This suggests that there is a significant statistical difference between both intervals and that Egypt has a higher probability of winning a match as a home team.

Conclusion:

Egypt seems to have the highest upper and lower bounds. This means that from these 5 Arab countries, Egypt has the highest probability of winning matches where it's the home team. Following Egypt is Saudi Arabia, then Tunisia, then Oman, then Kuwait because both the upper and lower bounds decrease in that order of countries. We can conclude that Egypt has the highest probability of winning (from these Arab countries), whereas Kuwait has the least probability.

Generally, in order for a country to have advantage over the opposing team in football matches, it should play as the home team. That is because the home team fans will certainly surpass the number of away team fans; and the players get positive influence from the presence of their fans. Also, playing at home eliminates the fatigue of players traveling to another country and it leaves the players playing in a familiar condition, which would also improve the team's performance and score. Explaining why countries have a higher probability of winning when playing in their home country.

Part 2: Covid-19 cases

Abstract

In this part, the dataset "Covid_data.csv" is used. The data shows the daily number of Covid cases and deaths in 187 countries for the years 2020 and 2021. It also shows the income level of each country along with its region and continent. First, how the number of cases and deaths changed in the world as time passed. Then, the death to cases ratio (fatality rate) will be analyzed in the 187 countries and in China, as it is the source of the pandemic. Also, it was attempted to analyze the effect of the region, income, and continent on the daily Covid cases and deaths in 2020 and 2021.

It was concluded that there were 4 waves (increases) of Covid-19 cases followed by 3 waves of increases in the number of deaths, and the number of cases was almost always more than the number of deaths. The fatality rate was around 2.5 to 3 percent worldwide. The average daily cases are higher in high income countries, Europe, and North America. There are more Covid-19 cases in 2021 than in 2020.


```
import pandas as pd
df= pd.read_csv('covid_data.csv',encoding='latin-1')
```

```
df
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month
0	2020-02-24	AFG	Afghanistan	Low income	South Asia	Asia	5	0	38041754	Mon	Feb
1	2020-02-25	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Tue	Feb
2	2020-02-26	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Wed	Feb
3	2020-02-27	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Thu	Feb
4	2020-02-28	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Fri	Feb
...	...	...	...	...	...	...	...	...	...	...	...
122838	2021-12-27	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	1098	17	14645468	Mon	Dec
122839	2021-12-28	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	2099	32	14645468	Tue	Dec
122840	2021-12-29	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	0	0	14645468	Wed	Dec
122841	2021-12-30	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	4180	57	14645468	Thu	Dec
122842	2021-12-31	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	1530	7	14645468	Fri	Dec

122843 rows × 11 columns

We want to first create a function that can find the upper and lower bounds of confidence intervals, in order to facilitate the process.

```python
from scipy import stats
from scipy.stats import norm,t
```

```python
def get_ci_lb(x, alpha=0.05):
    sample_s=np.std(x)
    sample_mean=np.mean(x)
    sample_size=len(x)
    margin_of_error = t.ppf(1 - alpha/2,sample_size-1)*sample_s/np.sqrt(sample_size-1)
    return sample_mean - margin_of_error
```

```python
def get_ci_ub(x, alpha=0.05):
    sample_s=np.std(x)
    sample_mean=np.mean(x)
    sample_size=len(x)
    margin_of_error = t.ppf(1 - alpha/2,sample_size-1)*sample_s/np.sqrt(sample_size-1)
    return sample_mean + margin_of_error
```

1. Statistical analysis of changes in the total number of cases and deaths as time passes in 187 countries.

```python
import numpy as np
import pandas as pd
```

```python
statsDATE=df.groupby("date").agg({"dcases": [np.sum, np.mean, np.std, np.size,]}) # Creating the data that will help us plot a graph t
statsDATE # This is the data which has the total daily number of cases
```

	dcases			
	sum	mean	std	size
date				
2020-01-22	556	111.200000	244.181695	5
2020-01-23	100	12.500000	33.346664	8
2020-01-24	285	31.666667	92.002717	9
2020-01-25	493	44.818182	146.328274	11
2020-01-26	682	56.833333	192.787133	12
...	...	...	...	...
2021-12-27	1281192	6851.294118	41261.650149	187
2021-12-28	1330998	7117.636364	32216.866272	187
2021-12-29	1724167	9220.144385	43179.093930	187
2021-12-30	1940432	10376.641711	49932.947023	187
2021-12-31	1714926	9170.727273	44126.962602	187

710 rows × 4 columns

```python
statsDATEdf=pd.DataFrame(statsDATE['dcases'])
statsDATEdf.columns=['total', 'mean','std','size']
statsDATEdf['date']=statsDATEdf.index
```

```python
statsDATEdf['date']=statsDATEdf.index
```

```python
statsDATEdf
```

	total	mean	std	size	date
date					
2020-01-22	556	111.200000	244.181695	5	2020-01-22
2020-01-23	100	12.500000	33.346664	8	2020-01-23
2020-01-24	285	31.666667	92.002717	9	2020-01-24
2020-01-25	493	44.818182	146.328274	11	2020-01-25
2020-01-26	682	56.833333	192.787133	12	2020-01-26
...	...	...	...	...	...
2021-12-27	1281192	6851.294118	41261.650149	187	2021-12-27
2021-12-28	1330998	7117.636364	32216.866272	187	2021-12-28
2021-12-29	1724167	9220.144385	43179.093930	187	2021-12-29
2021-12-30	1940432	10376.641711	49932.947023	187	2021-12-30
2021-12-31	1714926	9170.727273	44126.962602	187	2021-12-31

710 rows × 5 columns

```
statsDATE2=df.groupby("date").agg({"ddeaths": [np.sum, np.mean, np.std, np.size,]}) # The data that has the average daily number of de
```

```
statsDATE2df=pd.DataFrame(statsDATE2['ddeaths'])
statsDATE2df.columns=['total','mean','std','size']
statsDATE2df['date']=statsDATE2df.index
```

```
statsDATE2df
```

	total	mean	std	size	date
date					
2020-01-22	17	3.400000	7.602631	5	2020-01-22
2020-01-23	1	0.125000	0.353553	8	2020-01-23
2020-01-24	8	0.888889	2.666667	9	2020-01-24
2020-01-25	16	1.454545	4.824182	11	2020-01-25
2020-01-26	14	1.166667	4.041452	12	2020-01-26
...	...	...	...	...	...
2021-12-27	6726	35.967914	161.704293	187	2021-12-27
2021-12-28	7478	39.989305	195.229614	187	2021-12-28
2021-12-29	8037	42.978610	197.903663	187	2021-12-29
2021-12-30	7572	40.491979	149.155053	187	2021-12-30
2021-12-31	6593	35.256684	113.666454	187	2021-12-31

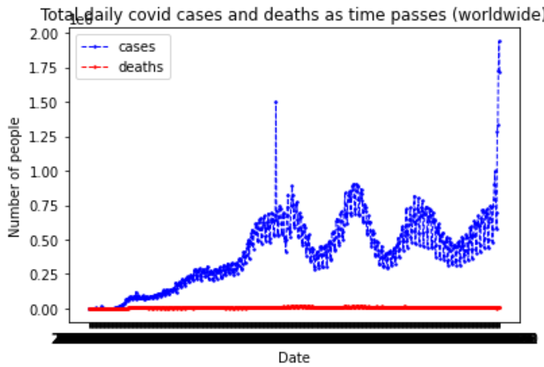
710 rows × 5 columns

We now have the two datasets that would help us create a scatter plot to understand the pattern of the changes in the number of Covid cases and deaths

```
import matplotlib.pyplot as plt
```

```
plt.plot( 'date', 'total', data=statsDATEdf, marker='.', color='blue', markersize=3,     linewidth=1, linestyle='--')
plt.plot( 'date', 'total', data=statsDATE2df, marker='.', color='red', markersize=3,     linewidth=1, linestyle='--')

plt.xlabel("Date")
plt.ylabel("Number of people")
plt.title("Total daily covid cases and deaths as time passes (worldwide)")
plt.legend(['cases','deaths'])
plt.show()
```



The above graph is a scatter plot which represents the daily number of Covid-19 cases and deaths. The blue plot represents the cases, whereas the red one represents the number of deaths.

When observing the average number of daily cases (blue), it can be seen that as the 2 years (from 2020 till the end of 2021) passed, there have been variations in the daily number of reported cases. 4 different maximum points can be seen; these 4 curves shown suggest that there were 4 waves of Covid-19. A wave represents a time when the spread of Covid was rapid, which leads to the increase in the number of daily cases. The 4th wave seems to start at the beginning of the year 2022, which explains why only the half of the wave is shown in the graph, as the data collection ended by the end of 2021. It can be seen that the time between each wave is consistent (when a certain amount of time passes after a wave, a new one starts).

It is important to note that these numbers are surely an inaccurate representation of the number of cases and deaths. That is because not all cases are reported and recorded; which implies that the data is underestimating the total number of daily cases.

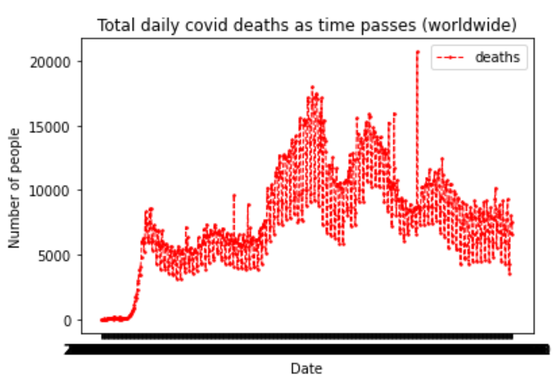
When looking at the number of daily deaths and comparing it to the number of cases, the number of daily deaths is much smaller, which may suggest that a relatively small proportion of people included in the number of cases has died from the virus.

Lastly, it seems like the daily number of deaths caused by Covid-19 is consistent because the red plot looks like a straight line with no (or minimal) variations and curves. However, this conclusion cannot be made without having a closer look on the plot of the number of deaths.

```
#creating a plot with noly the daily death number to see the graph up close and understand the trend.

plt.plot( 'date', 'total', data=statsDATE2df, marker='.', color='red', markersize=3,     linewidth=1, linestyle='--')

plt.xlabel("Date")
plt.ylabel("Number of people")
plt.title("Total daily covid deaths as time passes (worldwide)")
plt.legend(['deaths'])
plt.show()
```



After having a closer look, we can see that there were actually variations in the number of deaths. The plot looked straight in the previous graph because it was compared to another one with much higher measurements (the number of daily cases). However, the variation present in the plot of the daily number of deaths is not extreme, like the plot of the number of cases.

It can be seen that there were 3 maximum points (representing a high number of deaths). When comparing the three waves in the red curve with the blue one, it is noticed that the increases in deaths (red plot waves) follow the increases in the number of cases (blue plot waves) with respect of time. Meaning that an effect of the increase in the number of Covid cases is an increase in the number of deaths.

2. The worldwide (187 countries) fatality rate vs Chinese fatality rate

The worldwide fatality rate

the fatality rate can be calculated by dividing the number of deaths over the number of cases. After dividing the 2 numbers, the rate would be in form of decimals. Where, for example, 0.25 would mean that 25% of cases on that day die.

```
statsCDR= statsDATE2df['total']/ statsDATEdf['total'] #craeting a data which represents the ratio between deaths and cases
statsCDRdf=pd.DataFrame(statsCDR)
statsCDRdf.columns=['total']
statsCDRdf['date']=statsCDRdf.index
statsCDRdf
```

	total	date
date		
2020-01-22	0.030576	2020-01-22
2020-01-23	0.010000	2020-01-23
2020-01-24	0.028070	2020-01-24
2020-01-25	0.032454	2020-01-25
2020-01-26	0.020528	2020-01-26
...	...	...
2021-12-27	0.005250	2021-12-27
2021-12-28	0.005618	2021-12-28
2021-12-29	0.004661	2021-12-29
2021-12-30	0.003902	2021-12-30
2021-12-31	0.003844	2021-12-31

710 rows × 2 columns

The visualize and statistics options in the above output will also be used to find specific values in the data, as they would help in the statistical analysis.

In this visualize option, we can zoom in on the graph created below and see the dates of the exact points.

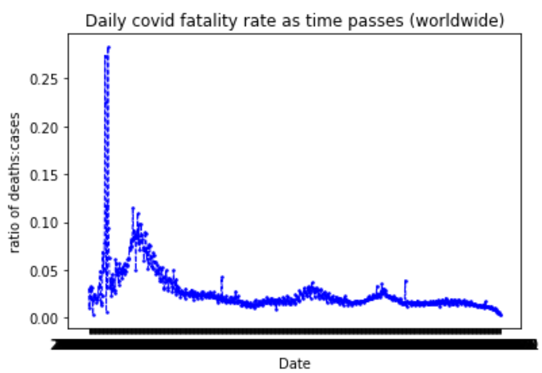
```
statsCDRdf.describe()
```

	total
count	710.000000
mean	0.026519
std	0.023149
min	0.003396
25%	0.015884
50%	0.019335
75%	0.026644
max	0.282686

```
import matplotlib.pyplot as plt
```

```
plt.plot('date', 'total', data= statsCDRdf, marker='.', color='blue', markersize=3, linewidth=1, linestyle='--')

plt.xlabel("Date")
plt.ylabel("ratio of deaths:cases")
plt.title("Daily covid fatality rate as time passes (worldwide)")
plt.show()
```



It is seen that in the beginning of the pandemic, the fatality rate was the highest. There are two major spikes that represent increases in the rate. For 20 days, the rate has been increasing till it reached 28% on the 24th of February (this represents the 1st obvious spike in the plot). However, this rate increase did not last for long, and the next day the rate decreased back to around 3%.

The rate increased again until the 2nd spike was reached with a maximum of 11.5% in April of 2020. The rate then decreased and was relatively steady between 1% to 5% with some fluctuations till the end of 2021. 75 percent of the days from 2020 till the end of 2021 had a rate less than or equal to 2.7%

Chinese Covid fatality rate

```
dfCHI=df[df['country']=='China'] # data taken from china only
dfCHI
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month
21405	2020-01-22	CHN	China	Upper middle income	East Asia & Pacific	Asia	548	17	1397715000	Wed	Jan
21406	2020-01-23	CHN	China	Upper middle income	East Asia & Pacific	Asia	95	1	1397715000	Thu	Jan
21407	2020-01-24	CHN	China	Upper middle income	East Asia & Pacific	Asia	277	8	1397715000	Fri	Jan
21408	2020-01-25	CHN	China	Upper middle income	East Asia & Pacific	Asia	486	16	1397715000	Sat	Jan
21409	2020-01-26	CHN	China	Upper middle income	East Asia & Pacific	Asia	669	14	1397715000	Sun	Jan
...	...	...	...	...	...	...	...	...	...	...	...
22110	2021-12-27	CHN	China	Upper middle income	East Asia & Pacific	Asia	371	0	1397715000	Mon	Dec
22111	2021-12-28	CHN	China	Upper middle income	East Asia & Pacific	Asia	203	0	1397715000	Tue	Dec
22112	2021-12-29	CHN	China	Upper middle income	East Asia & Pacific	Asia	221	0	1397715000	Wed	Dec
22113	2021-12-30	CHN	China	Upper middle income	East Asia & Pacific	Asia	208	0	1397715000	Thu	Dec
22114	2021-12-31	CHN	China	Upper middle income	East Asia & Pacific	Asia	248	0	1397715000	Fri	Dec

710 rows × 11 columns

```
statsDATEchi=dfCHI.groupby("date").agg({"dcases": [np.sum,]})
statsDATEchidf=pd.DataFrame(statsDATEchi['dcases'])
statsDATEchidf.columns=['total']
statsDATEchidf['date']=statsDATEchidf.index
statsDATEchidf
```

	total	date
date		
2020-01-22	548	2020-01-22
2020-01-23	95	2020-01-23
2020-01-24	277	2020-01-24
2020-01-25	486	2020-01-25
2020-01-26	669	2020-01-26
...	...	...
2021-12-27	371	2021-12-27
2021-12-28	203	2021-12-28
2021-12-29	221	2021-12-29
2021-12-30	208	2021-12-30
2021-12-31	248	2021-12-31

710 rows × 2 columns

```
statsDATE2chi=dfCHI.groupby("date").agg({"ddeaths": [np.sum,]})
statsDATE2chidf=pd.DataFrame(statsDATE2chi['ddeaths'])
statsDATE2chidf.columns=['total']
statsDATE2chidf['date']=statsDATE2chidf.index
statsDATE2chidf # same as above but with the number of daily deaths
```

	total	date
date		
2020-01-22	17	2020-01-22
2020-01-23	1	2020-01-23
2020-01-24	8	2020-01-24
2020-01-25	16	2020-01-25
2020-01-26	14	2020-01-26
...	...	...
2021-12-27	0	2021-12-27
2021-12-28	0	2021-12-28
2021-12-29	0	2021-12-29
2021-12-30	0	2021-12-30
2021-12-31	0	2021-12-31

710 rows × 2 columns

```
statsCDRchi= statsDATE2chidf['total']/ statsDATEchidf['total']
statsCDRchidf=pd.DataFrame(statsCDRchi)
statsCDRchidf.columns=['total']
statsCDRchidf['date']=statsCDRchidf.index
statsCDRchidf #The ratio of the chinese fatality rate
```

	total	date
date		
2020-01-22	0.031022	2020-01-22
2020-01-23	0.010526	2020-01-23
2020-01-24	0.028881	2020-01-24
2020-01-25	0.032922	2020-01-25
2020-01-26	0.020927	2020-01-26
...	...	...
2021-12-27	0.000000	2021-12-27
2021-12-28	0.000000	2021-12-28
2021-12-29	0.000000	2021-12-29
2021-12-30	0.000000	2021-12-30
2021-12-31	0.000000	2021-12-31

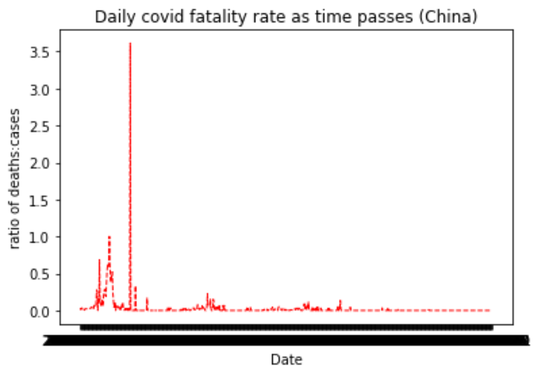
710 rows × 2 columns

```
statsCDRchidf.describe()
```

	total
count	704.000000
mean	0.028869
std	0.159220
min	0.000000
25%	0.000000
50%	0.000000
75%	0.014311
max	3.613445

```
plt.plot('date', 'total', data= statsCDRchidf, color='red', markersize=3, linewidth=1, linestyle='--')

plt.xlabel("Date")
plt.ylabel("ratio of deaths:cases")
plt.title("Daily covid fatality rate as time passes (China)")
plt.show()
```



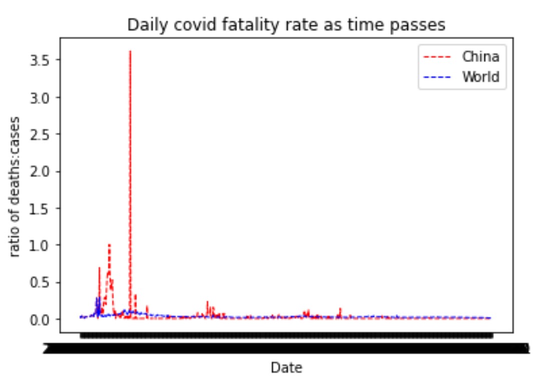
From the above graph, we can see that there were several spikes. In March of 2020, the fatality rate reached 100%. There is also an outlier on the 17th of April 2020, where the rate reached 360%. Which means that the number of deaths on that day was three and a half times the number of cases. However, this rate was only reached once and it is an outlier, so it will not be used in the statistical analysis. After ignoring this outlier, the new maximum would be at a rate of 1 (100%).

After the month of May in 2020, there were several variations in the rate ranging from 0 to 0.23 (23%). 75 percent of the days from 2020 till the end of 2021 had a rate less than or equal to 1.4%

China vs worldwide fatality rate

```
plt.plot('date', 'total', data= statsCDRchidf, color='red', markersize=3, linewidth=1, linestyle='--')
plt.plot('date', 'total', data= statsCDRdf, color='blue', markersize=3, linewidth=1, linestyle='--')

plt.xlabel("Date")
plt.ylabel("ratio of deaths:cases")
plt.title("Daily covid fatality rate as time passes")
plt.legend(['China','World'])
plt.show()
```



We put the worldwide and Chinese plot for the fatality rate in one graph, in order to compare them. Just by looking at the graph, it can be seen that the Chinese rate surpasses the world rate several times. This might lead us to conclude that the general rate in China is higher than the world rate. However, both averages are very close (World:0.027, China: 0.029). Also, Q3 in China is less (World:0.027, China: 0.014). This might actually mean that the world fatality rate is close to that of China.

3. Confidence interval of average daily Covid cases comparisons between two different incomes (low & high) by year

We first want to create a column that divides the data into the two years 2020 and 2021

```
df['date'] = pd.to_datetime(df['date'],format='%Y-%m-%d')
df['date'][0]
```

```
Timestamp('2020-02-24 00:00:00')
```

```
df['year'] = pd. DatetimeIndex(df['date']). year
df['year'][0]
```

```
2020
```

```
#creating the data in terms of income
statsINC=df.groupby(['income','year']).agg({"dcases": [np.mean, np.std, np.size,get_ci_lb,get_ci_ub]})
statsINCdf=statsINC.reset_index()
statsINCdf
```

	income	year	dcases				
			mean	std	size	get_ci_lb	get_ci_ub
0	High income	2020	2321.685027	12494.070695	17865	2138.462037	2504.908017
1	High income	2021	4520.954339	18317.784729	20937	4272.818827	4769.089852
2	Low income	2020	77.125254	283.402922	8351	71.046059	83.204450
3	Low income	2021	168.681058	657.105911	10585	156.161537	181.200579
4	Lower middle income	2020	1214.800373	6871.170940	12879	1096.120084	1333.480661
5	Lower middle income	2021	2550.449589	17762.604302	16653	2280.650760	2820.248417
6	Upper middle income	2020	1643.653786	8259.918227	15863	1515.106084	1772.201487
7	Upper middle income	2021	3368.106393	8585.182602	19710	3248.244540	3487.968246

```
# Creating the data for high income
statsHIGH20df=statsINCdf[(statsINCdf['income']=='High income') & (statsINCdf['year']==2020)]
statsHIGH21df=statsINCdf[(statsINCdf['income']=='High income') & (statsINCdf['year']==2021)]
```

```
# Creating the data for low income
statsLOW20df=statsINCdf[(statsINCdf['income']=='Low income') & (statsINCdf['year']==2020)]
statsLOW21df=statsINCdf[(statsINCdf['income']=='Low income') & (statsINCdf['year']==2021)]
```

```
statsLOW21df
```

	income	year	dcases				
			mean	std	size	get_ci_lb	get_ci_ub
3	Low income	2021	168.681058	657.105911	10585	156.161537	181.200579

```
statsLOW21df.iloc[0,5]
```

```
156.16153742238862
```

```python
df[(df['income']=='Low income') & (df['date']=='2020-04-27 00:00:00')] # To know the number of low income countries
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	year
63	2020-04-27	AFG	Afghanistan	Low income	South Asia	Asia	68	1	38041754	Mon	Apr	2020
7444	2020-04-27	BDI	Burundi	Low income	Sub-Saharan Africa	Africa	0	0	11530580	Mon	Apr	2020
8797	2020-04-27	BEN	Benin	Low income	Sub-Saharan Africa	Africa	0	0	11801151	Mon	Apr	2020
9459	2020-04-27	BFA	Burkina Faso	Low income	Sub-Saharan Africa	Africa	3	0	20321378	Mon	Apr	2020
18728	2020-04-27	CAF	Central African Republic	Low income	Sub-Saharan Africa	Africa	0	0	4745185	Mon	Apr	2020
23489	2020-04-27	COD	Congo - Kinshasa	Low income	Sub-Saharan Africa	Africa	17	0	86790567	Mon	Apr	2020
36155	2020-04-27	ETH	Ethiopia	Low income	Sub-Saharan Africa	Africa	1	0	112078730	Mon	Apr	2020
41570	2020-04-27	GIN	Guinea	Low income	Sub-Saharan Africa	Africa	167	0	12771246	Mon	Apr	2020
42225	2020-04-27	GMB	Gambia	Low income	Sub-Saharan Africa	Africa	0	0	2347706	Mon	Apr	2020
42872	2020-04-27	GNB	Guinea-Bissau	Low income	Sub-Saharan Africa	Africa	20	0	1920922	Mon	Apr	2020
48161	2020-04-27	HTI	Haiti	Low income	Latin America & Caribbean	North America(continent)	0	0	11263077	Mon	Apr	2020
63248	2020-04-27	LBR	Liberia	Low income	Sub-Saharan Africa	Africa	4	1	4937374	Mon	Apr	2020
71197	2020-04-27	MDG	Madagascar	Low income	Sub-Saharan Africa	Africa	4	0	26969307	Mon	Apr	2020
74286	2020-04-27	MLI	Mali	Low income	Sub-Saharan Africa	Africa	19	0	19658031	Mon	Apr	2020
77563	2020-04-27	MOZ	Mozambique	Low income	Sub-Saharan Africa	Africa	0	0	30366036	Mon	Apr	2020
79514	2020-04-27	MWI	Malawi	Low income	Sub-Saharan Africa	Africa	2	0	18628747	Mon	Apr	2020
81531	2020-04-27	NER	Niger	Low income	Sub-Saharan Africa	Africa	5	0	23310715	Mon	Apr	2020
84913	2020-04-27	NPL	Nepal	Low income	South Asia	Asia	0	0	28608710	Mon	Apr	2020
95128	2020-04-27	RWA	Rwanda	Low income	Sub-Saharan Africa	Africa	16	0	12626950	Mon	Apr	2020
98922	2020-04-27	SLE	Sierra Leone	Low income	Sub-Saharan Africa	Africa	0	0	7813215	Mon	Apr	2020
100903	2020-04-27	SOM	Somalia	Low income	Sub-Saharan Africa	Africa	44	3	15442905	Mon	Apr	2020
102205	2020-04-27	SSD	South Sudan	Low income	Sub-Saharan Africa	Africa	0	0	11062113	Mon	Apr	2020
107496	2020-04-27	SYR	Syria	Low income	Middle East & North Africa	Asia	0	0	17070135	Mon	Apr	2020
108149	2020-04-27	TCD	Chad	Low income	Sub-Saharan Africa	Africa	0	0	15946876	Mon	Apr	2020
108815	2020-04-27	TGO	Togo	Low income	Sub-Saharan Africa	Africa	0	0	8082366	Mon	Apr	2020
113428	2020-04-27	TZA	Tanzania	Low income	Sub-Saharan Africa	Africa	0	0	58005463	Mon	Apr	2020
114079	2020-04-27	UGA	Uganda	Low income	Sub-Saharan Africa	Africa	0	0	44269594	Mon	Apr	2020
120256	2020-04-27	YEM	Yemen	Low income	Middle East & North Africa	Asia	0	0	29161922	Mon	Apr	2020

```python
df[(df['income']=='High income') & (df['date']=='2020-04-27 00:00:00')] # To know the number of high income countries
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	year
2048	2020-04-27	AND	Andorra	High income	Europe & Central Asia	Europe	5	0	77142	Mon	Apr	2020
2751	2020-04-27	ARE	United Arab Emirates	High income	Middle East & North Africa	Asia	490	6	9770529	Mon	Apr	2020
4750	2020-04-27	ATG	Antigua & Barbuda	High income	Latin America & Caribbean	North America(continent)	0	0	97118	Mon	Apr	2020
5456	2020-04-27	AUS	Australia	High income	East Asia & Pacific	Oceania	7	0	25364307	Mon	Apr	2020
6132	2020-04-27	AUT	Austria	High income	Europe & Central Asia	Europe	49	7	8877067	Mon	Apr	2020
8141	2020-04-27	BEL	Belgium	High income	Europe & Central Asia	Europe	553	113	11484055	Mon	Apr	2020
11464	2020-04-27	BHR	Bahrain	High income	Middle East & North Africa	Asia	76	0	1641172	Mon	Apr	2020
12120	2020-04-27	BHS	Bahamas	High income	Latin America & Caribbean	North America(continent)	0	0	389482	Mon	Apr	2020
16100	2020-04-27	BRB	Barbados	High income	Latin America & Caribbean	North America(continent)	1	0	287025	Mon	Apr	2020
16763	2020-04-27	BRN	Brunei	High income	East Asia & Pacific	Asia	0	0	433285	Mon	Apr	2020
19437	2020-04-27	CAN	Canada	High income	North America(region)	North America(continent)	1656	164	37589262	Mon	Apr	2020
20113	2020-04-27	CHE	Switzerland	High income	Europe & Central Asia	Europe	103	20	8574832	Mon	Apr	2020
20791	2020-04-27	CHL	Chile	High income	Latin America & Caribbean	South America(continent)	482	9	18952038	Mon	Apr	2020
28063	2020-04-27	CYP	Cyprus	High income	Europe & Central Asia	Asia	7	0	1198575	Mon	Apr	2020
28734	2020-04-27	CZE	Czechia	High income	Europe & Central Asia	Europe	41	3	10669709	Mon	Apr	2020
29439	2020-04-27	DEU	Germany	High income	Europe & Central Asia	Europe	988	150	83132799	Mon	Apr	2020

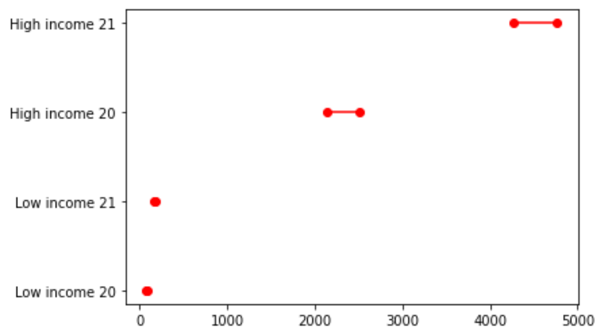
29439	2020-04-27	DEU	Germany	High income	Europe & Central Asia	Europe	988	150	83132799	Mon	Apr	2020
31417	2020-04-27	DNK	Denmark	High income	Europe & Central Asia	Europe	123	5	5818553	Mon	Apr	2020
34822	2020-04-27	ESP	Spain	High income	Europe & Central Asia	Europe	1831	331	47076781	Mon	Apr	2020
35496	2020-04-27	EST	Estonia	High income	Europe & Central Asia	Europe	4	1	1326590	Mon	Apr	2020
36858	2020-04-27	FIN	Finland	High income	Europe & Central Asia	Europe	73	5	5520314	Mon	Apr	2020
38219	2020-04-27	FRA	France	High income	Europe & Central Asia	Europe	3686	437	67059887	Mon	Apr	2020
39578	2020-04-27	GBR	United Kingdom	High income	Europe & Central Asia	Europe	4707	323	66834405	Mon	Apr	2020
44204	2020-04-27	GRC	Greece	High income	Europe & Central Asia	Europe	17	2	10716322	Mon	Apr	2020
47509	2020-04-27	HRV	Croatia	High income	Europe & Central Asia	Europe	9	4	4067500	Mon	Apr	2020
48829	2020-04-27	HUN	Hungary	High income	Europe & Central Asia	Europe	83	8	9769949	Mon	Apr	2020
50873	2020-04-27	IRL	Ireland	High income	Europe & Central Asia	Europe	386	15	4941444	Mon	Apr	2020
52905	2020-04-27	ISL	Iceland	High income	Europe & Central Asia	Europe	0	0	361313	Mon	Apr	2020
53585	2020-04-27	ISR	Israel	High income	Middle East & North Africa	Asia	128	4	9053300	Mon	Apr	2020
54286	2020-04-27	ITA	Italy	High income	Europe & Central Asia	Europe	1739	333	60297396	Mon	Apr	2020
56326	2020-04-27	JPN	Japan	High income	East Asia & Pacific	Asia	171	22	126264931	Mon	Apr	2020
59878	2020-04-27	KNA	St. Kitts & Nevis	High income	Latin America & Caribbean	North America(continent)	0	0	52834	Mon	Apr	2020
60588	2020-04-27	KOR	South Korea	High income	East Asia & Pacific	Asia	14	1	51709098	Mon	Apr	2020
61265	2020-04-27	KWT	Kuwait	High income	Middle East & North Africa	Asia	213	2	4207083	Mon	Apr	2020
65222	2020-04-27	LIE	Liechtenstein	High income	Europe & Central Asia	Europe	0	0	38019	Mon	Apr	2020
67197	2020-04-27	LTU	Lithuania	High income	Europe & Central Asia	Europe	12	1	2786844	Mon	Apr	2020
67869	2020-04-27	LUX	Luxembourg	High income	Europe & Central Asia	Europe	6	0	619896	Mon	Apr	2020
68539	2020-04-27	LVA	Latvia	High income	Europe & Central Asia	Europe	6	1	1912789	Mon	Apr	2020
69881	2020-04-27	MCO	Monaco	High income	Europe & Central Asia	Europe	1	0	38964	Mon	Apr	2020
74951	2020-04-27	MLT	Malta	High income	Middle East & North Africa	Europe	2	0	502653	Mon	Apr	2020
83531	2020-04-27	NLD	Netherlands	High income	Europe & Central Asia	Europe	171	43	17332850	Mon	Apr	2020
84206	2020-04-27	NOR	Norway	High income	Europe & Central Asia	Europe	72	4	5347896	Mon	Apr	2020
85586	2020-04-27	NZL	New Zealand	High income	East Asia & Pacific	Oceania	3	0	4917000	Mon	Apr	2020
86263	2020-04-27	OMN	Oman	High income	Middle East & North Africa	Asia	51	0	4974986	Mon	Apr	2020
87601	2020-04-27	PAN	Panama	High income	Latin America & Caribbean	North America(continent)	242	2	4246439	Mon	Apr	2020
90421	2020-04-27	POL	Poland	High income	Europe & Central Asia	Europe	285	27	37970874	Mon	Apr	2020
91091	2020-04-27	PRT	Portugal	High income	Europe & Central Asia	Europe	163	25	10269417	Mon	Apr	2020
93094	2020-04-27	QAT	Qatar	High income	Middle East & North Africa	Asia	957	0	2832067	Mon	Apr	2020
95798	2020-04-27	SAU	Saudi Arabia	High income	Middle East & North Africa	Asia	1289	5	34268528	Mon	Apr	2020
97835	2020-04-27	SGP	Singapore	High income	East Asia & Pacific	Asia	799	2	5703569	Mon	Apr	2020
100247	2020-04-27	SMR	San Marino	High income	Europe & Central Asia	Europe	25	1	33860	Mon	Apr	2020
104164	2020-04-27	SVK	Slovakia	High income	Europe & Central Asia	Europe	2	0	5454073	Mon	Apr	2020
104831	2020-04-27	SVN	Slovenia	High income	Europe & Central Asia	Europe	6	1	2087946	Mon	Apr	2020
105531	2020-04-27	SWE	Sweden	High income	Europe & Central Asia	Europe	563	80	10285453	Mon	Apr	2020
106846	2020-04-27	SYC	Seychelles	High income	Sub-Saharan Africa	Africa	0	0	97625	Mon	Apr	2020
111443	2020-04-27	TTO	Trinidad & Tobago	High income	Latin America & Caribbean	North America(continent)	1	0	1394973	Mon	Apr	2020
115407	2020-04-27	URY	Uruguay	High income	Latin America & Caribbean	South America(continent)	14	0	3461734	Mon	Apr	2020
116117	2020-04-27	USA	United States	High income	North America(region)	North America(continent)	24629	1480	328239523	Mon	Apr	2020

```
CIcovidINC = {}
CIcovidINC['income'] = ['Low income 20','Low income 21','High income 20','High income 21']
CIcovidINC['lb'] = [statsLOW20df.iloc[0,5],statsLOW21df.iloc[0,5],statsHIGH20df.iloc[0,5],statsHIGH21df.iloc[0,5]]
CIcovidINC['ub'] = [statsLOW20df.iloc[0,6],statsLOW21df.iloc[0,6],statsHIGH20df.iloc[0,6],statsHIGH21df.iloc[0,6]]
df_ci= pd.DataFrame(CIcovidINC)
df_ci
```

	income	lb	ub
0	Low income 20	71.046059	83.204450
1	Low income 21	156.161537	181.200579
2	High income 20	2138.462037	2504.908017
3	High income 21	4272.818827	4769.089852

```
#plotting the confidence intervals of average daily covid cases per year and income
import matplotlib.pyplot as plt
for lb,ub,y in zip(df_ci['lb'],df_ci['ub'],range(len(df_ci))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci)),list(df_ci['income']))
```

```
([<matplotlib.axis.YTick at 0x7f190ef51d30>,
  <matplotlib.axis.YTick at 0x7f190f57cf40>,
  <matplotlib.axis.YTick at 0x7f190f57c0d0>,
  <matplotlib.axis.YTick at 0x7f190ef1f670>],
 [Text(0, 0, 'Low income 20'),
  Text(0, 1, 'Low income 21'),
  Text(0, 2, 'High income 20'),
  Text(0, 3, 'High income 21')])
```



The above graph gives a visualization of the 95% confidence intervals of daily confirmed Covid cases in high and low income countries, in the years 2020 and 2021.

Firstly, it can be seen that all 4 groups are relatively narrow; which means that there is little variation in the number of daily cases within each group. However, the low income groups' intervals (both 2020 and 2021) are much narrower than the high income groups. Meaning that there is less variation in the low income groups. This might be because the low income group consists of only 28 countries, whereas the high income group consists of 57 countries. The high income interval has more countries, which means that there is more room for variation within the daily number of cases.

It can also be seen that in both groups (low income & high income) the confidence interval is higher in 2021 than 2020. This means that the overall worldwide daily cases were much more in 2021 than in 2020. However, the confidence interval of the low income countries in 2021 does not exceed 2020 by a very large proportion (unlike the high confidence interval).

There are no overlaps between any of the 4 groups' confidence intervals. This simply means that there is a significant statistical difference between the intervals.

The intervals increase in the following order: low income 2020, low income 2021, high income 2020, high income 2021. It was already established that the intervals in 2021 are higher than 2020, but we can also infer from the graph that the average daily cases in high income countries are more than in low income countries. This is due to the fact that high income countries are more developed; thus they have better medical resources and infrastructure in larger quantities than low income countries. This means that higher income countries have access to more Covid-19 tests, which increases the possibility of having positive cases. This does not necessarily mean that there are more daily cases in high income countries. It only means that there are more reported cases.

4. Confidence interval of average daily Covid cases comparisons between two different Continents (Arfrica & Europe) by year

```
statsCONT=df.groupby(['continent','year']).agg({"dcases": [np.mean, np.std, np.size,get_ci_lb,get_ci_ub]})
statsCONT
```

		dcases				
		mean	std	size	get_ci_lb	get_ci_ub
continent	year					
Africa	2020	179.989695	812.148803	15332	167.133318	192.846071
	2021	361.298423	1454.828779	19345	340.796114	381.800733
Asia	2020	1448.863760	9560.899804	14313	1292.218142	1605.509379
	2021	3835.418999	18090.729958	16790	3561.759742	4109.078257
Europe	2020	1783.304743	5020.494465	13408	1698.317882	1868.291605
	2021	4145.443007	10270.295699	15695	3984.754849	4306.131166
North America(continent)	2020	3390.453029	19128.794001	6834	2936.850853	3844.055205
	2021	4976.624658	25708.743737	8395	4426.601186	5526.648129
Oceania	2020	21.459072	73.945973	1466	17.670683	25.247461
	2021	151.743598	1082.525697	3280	114.683230	188.803965
South America(continent)	2020	3669.935090	8827.038998	3605	3381.693677	3958.176504
	2021	6067.011416	14054.616405	4380	5650.669546	6483.353286

```
statsCONTdf=statsCONT.reset_index()
statsCONTdf
```

	continent	year	dcases				
			mean	std	size	get_ci_lb	get_ci_ub
0	Africa	2020	179.989695	812.148803	15332	167.133318	192.846071
1	Africa	2021	361.298423	1454.828779	19345	340.796114	381.800733
2	Asia	2020	1448.863760	9560.899804	14313	1292.218142	1605.509379
3	Asia	2021	3835.418999	18090.729958	16790	3561.759742	4109.078257
4	Europe	2020	1783.304743	5020.494465	13408	1698.317882	1868.291605
5	Europe	2021	4145.443007	10270.295699	15695	3984.754849	4306.131166
6	North America(continent)	2020	3390.453029	19128.794001	6834	2936.850853	3844.055205
7	North America(continent)	2021	4976.624658	25708.743737	8395	4426.601186	5526.648129
8	Oceania	2020	21.459072	73.945973	1466	17.670683	25.247461
9	Oceania	2021	151.743598	1082.525697	3280	114.683230	188.803965
10	South America(continent)	2020	3669.935090	8827.038998	3605	3381.693677	3958.176504
11	South America(continent)	2021	6067.011416	14054.616405	4380	5650.669546	6483.353286

```
# Creating the data for Africa
statsAFR20df=statsCONTdf[(statsCONTdf['continent']=='Africa') & (statsCONTdf['year']==2020)]
statsAFR21df=statsCONTdf[(statsCONTdf['continent']=='Africa') & (statsCONTdf['year']==2021)]
```

```
statsAFR20df
```

	continent	year	dcases				
			mean	std	size	get_ci_lb	get_ci_ub
0	Africa	2020	179.989695	812.148803	15332	167.133318	192.846071

```
# Creating the data for Europe
statsEUR20df=statsCONTdf[(statsCONTdf['continent']=='Europe') & (statsCONTdf['year']==2020)]
statsEUR21df=statsCONTdf[(statsCONTdf['continent']=='Europe') & (statsCONTdf['year']==2021)]
```

```
statsAFR20df.iloc[0,5]
```

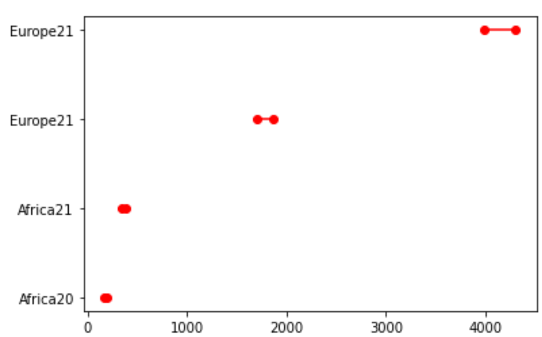
```
167.1333182485662
```

```
CIcovidAfrEur = {}
CIcovidAfrEur['continent'] = ['Africa20','Africa21','Europe21','Europe21']
CIcovidAfrEur['lb'] = [statsAFR20df.iloc[0,5],statsAFR21df.iloc[0,5],statsEUR20df.iloc[0,5],statsEUR21df.iloc[0,5]]
CIcovidAfrEur['ub'] = [statsAFR20df.iloc[0,6],statsAFR21df.iloc[0,6],statsEUR20df.iloc[0,6],statsEUR21df.iloc[0,6]]
df_ci= pd.DataFrame(CIcovidAfrEur)
df_ci
```

	continent	lb	ub
0	Africa20	167.133318	192.846071
1	Africa21	340.796114	381.800733
2	Europe21	1698.317882	1868.291605
3	Europe21	3984.754849	4306.131166

```
#plotting the confidence intervals of average daily covid cases per year and continent
import matplotlib.pyplot as plt
for lb,ub,y in zip(df_ci['lb'],df_ci['ub'],range(len(df_ci))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci)),list(df_ci['continent']))
```

```
([<matplotlib.axis.YTick at 0x7f19115172e0>,
  <matplotlib.axis.YTick at 0x7f19115a01c0>,
  <matplotlib.axis.YTick at 0x7f190f59b3a0>,
  <matplotlib.axis.YTick at 0x7f190f9c3040>],
 [Text(0, 0, 'Africa20'),
  Text(0, 1, 'Africa21'),
  Text(0, 2, 'Europe21'),
  Text(0, 3, 'Europe21')])
```



The above graph gives a visualization of the 95% confidence intervals of daily confirmed Covid cases in the continents of Africa and Europe in the years 2020 and 2021.

Firstly, it can be seen that all 4 groups (Africa20, Africa21, Europe20, Europe21) are relatively narrow; which means that there is little variation in the number of daily cases within each group. However, the intervals of Africa (both 2020 and 2021) are slightly narrower than those of Europe. Meaning that there is less variation in the daily Covid cases in Africa.

It can also be seen that in both continents (Africa & Europe) the confidence interval is higher in 2021 than 2020. This means that the overall worldwide daily cases were much more in 2021 than in 2020. However, the confidence interval of the African countries in 2021 does not exceed 2020 by a very large proportion (unlike the European confidence interval). This is very similar to the low income and high income comparison explained in the previous part

There are no overlaps between any of the confidence intervals. This simply means that there is a significant statistical difference between the intervals.

The intervals increase in the following order: Africa 2020, Africa 2021, Europe 2020, Europe 2021. We can infer from the graph and the order of the intervals that the average daily cases in European countries are more than in African countries. This might be caused by the same reason mentioned in the previous part. Africa consists of countries with lower incomes than Europe; which means that Africa could be classified as a low income continent, while Europe is a high income one. Therefore, due to the fact that high income countries are more developed, they have better medical resources and infrastructure in larger quantities than low income countries. This means that higher income countries have access to more Covid-19 tests, which increases the possibility of having positive cases. This explains why Europe has more reported Covid-19 cases.

5. Confidence interval of average daily Covid cases comparisons between two different regions (North America and South Asia) by year

```
df['region'].unique()
```

```
#creating the data in terms of regions
statsREG=df.groupby(['region','year']).agg({"dcases": [np.mean, np.std, np.size,get_ci_lb,get_ci_ub]})
statsREGdf=statsREG.reset_index()
statsREGdf
```

	region	year	dcases				
			mean	std	size	get_ci_lb	get_ci_ub
0	East Asia & Pacific	2020	309.256309	896.313605	6301	287.120939	331.391678
1	East Asia & Pacific	2021	1902.043518	4625.905443	8755	1805.131683	1998.955353
2	Europe & Central Asia	2020	1721.858350	8132.391315	15743	1594.813810	1848.902890
3	Europe & Central Asia	2021	4023.235026	9943.233979	18615	3880.387583	4166.082468
4	Latin America & Caribbean	2020	1601.753333	5688.858753	9750	1488.819296	1714.687371
5	Latin America & Caribbean	2021	2665.195766	9032.505081	12045	2503.872669	2826.518863
6	Middle East & North Africa	2020	762.715511	1430.243017	6415	727.709585	797.721436
7	Middle East & North Africa	2021	1620.897326	3832.749549	7665	1535.080777	1706.713874
8	North America(region)	2020	30164.552975	53111.710028	689	26191.782753	34137.323198
9	North America(region)	2021	49657.521918	73271.501688	730	44333.456360	54981.587475
10	South Asia	2020	4586.009052	14809.626669	2541	4009.910388	5162.107715
11	South Asia	2021	9507.577055	41050.751055	2920	8018.017440	10997.136669
12	Sub-Saharan Africa	2020	135.919003	789.508946	13519	122.609196	149.228810
13	Sub-Saharan Africa	2021	304.006762	1452.606156	17155	282.268178	325.745346

```
# Creating the data for North America
statsNAr20df=statsREGdf[(statsREGdf['region']=='North America(region)') & (statsREGdf['year']==2020)]
statsNAr21df=statsREGdf[(statsREGdf['region']=='North America(region)') & (statsREGdf['year']==2021)]
```

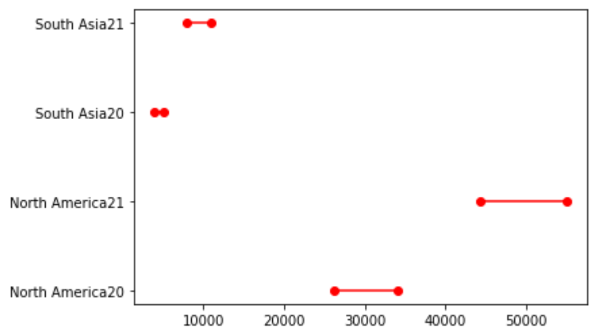
```
# Creating the data for South Asia
statsSAr20df=statsREGdf[(statsREGdf['region']=='South Asia') & (statsREGdf['year']==2020)]
statsSAr21df=statsREGdf[(statsREGdf['region']=='South Asia') & (statsREGdf['year']==2021)]
```

```
CIcovidNaSa = {}
CIcovidNaSa['region'] = ['North America20','North America21','South Asia20','South Asia21']
CIcovidNaSa['lb'] = [statsNAr20df.iloc[0,5],statsNAr21df.iloc[0,5],statsSAr20df.iloc[0,5],statsSAr21df.iloc[0,5]]
CIcovidNaSa['ub'] = [statsNAr20df.iloc[0,6],statsNAr21df.iloc[0,6],statsSAr20df.iloc[0,6],statsSAr21df.iloc[0,6]]
df_ci= pd.DataFrame(CIcovidNaSa)
df_ci
```

	region	lb	ub
0	North America20	26191.782753	34137.323198
1	North America21	44333.456360	54981.587475
2	South Asia20	4009.910388	5162.107715
3	South Asia21	8018.017440	10997.136669

```python
#plotting the confidence intervals of average daily covid cases per year and region
import matplotlib.pyplot as plt
for lb,ub,y in zip(df_ci['lb'],df_ci['ub'],range(len(df_ci))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci)),list(df_ci['region']))
```

```
([<matplotlib.axis.YTick at 0x7f190f5a2040>,
  <matplotlib.axis.YTick at 0x7f190f3c0f40>,
  <matplotlib.axis.YTick at 0x7f190f3c0100>,
  <matplotlib.axis.YTick at 0x7f190facda00>],
 [Text(0, 0, 'North America20'),
  Text(0, 1, 'North America21'),
  Text(0, 2, 'South Asia20'),
  Text(0, 3, 'South Asia21')])
```



The above graph gives a visualization of the 95% confidence intervals of daily confirmed Covid cases in the regions of North America and South Asia in the years 2020 and 2021.

Firstly, it can be seen that the interval od the region of South Asia is narrow, which means that there is little variation in the number of daily cases within the countries of this region. On the other hand, the intervals of North America are not relatively wide, meaning that there are many variations in the average daily cases within this region's countries and that the data is less precise. However, the interval of North America in 2020 is slightly narrower than 2021; this suggests that there were more variations in 2021 than in 2020 (The same also applies to South Asia)

It can also be seen that in both regions, the confidence interval is higher in 2021 than 2020 (similarly as the 2 previous parts). This means that the overall worldwide daily cases were much more in 2021 than in 2020. However, the confidence interval of North America in 2021 exceeds 2020 by a much larger proportion than the proportion between South Asia in 2021 and 2020.

There are no overlaps between any of the confidence intervals. This means that there is a significant statistical difference between the intervals.

The intervals increase in the following order: South Asia 2020, South Asia 2021, North America 2020, North America 2021. We can infer from the graph and the order of the intervals that the average daily cases in the countries of North America are more than in European countries. This might be because North America has countries with higher average daily cases. For instance, North America has the country of the US, which is the country with the most Covid-19 cases in the world and is a country with a very large population. This means that the number of daily cases in the US must have affected the average number of daily cases in North America (causing it to increase). This might also explain why the intervals of North America are wide; because it has one of the countries with the most Covid cases (causing a lot of variations within this region)

Conclusion:

There were 4 waves (increases) of Covid-19 cases followed by 3 waves of increases in the number of deaths, and the number of cases was almost always more than the number of deaths. The fatality rate was around 2.5 to 3 percent worldwide. The average daily cases are higher in high income countries, Europe, and North America. There are more Covid-19 cases in 2021 than in 2020.