Statistical Analysis and Comparison of Winning Nations in Football Matches Around the World

Abstract

In this part I will tackle and analyze the following points along with the interpretation behind them: The probability of winning, losing, and drawing along with their confidence intervals of all matches in the dataset; probability of winning, losing, and drawing in a neutral venue of all matches in the dataset; probability of winning, losing, and drawing in a non-neutral venue of all matches in the dataset; the probability of Egypt winning in all tournaments under all conditions; the probability of Egypt winning, Losing, and having a draw in The FIFA World cup qualifications; the probability of Egypt winning a match in The FIFA World cup qualifications; the probability of Egypt Losing a match in The FIFA World cup qualifications; the probability of Egypt drawing a match in The FIFA World cup qualifications; the probability of Egypt winning in all tournaments vs. in World Cup Qualifications; the probability of Egypt Winning, Losing, having a draw in a Friendly match vs. an Offical match; the confidence Interval of Probability of Egypt Winning a Friendly Match; the Confidence Interval of Probability of Egypt Winning an Official Match; the Confidence Interval of Probability of Egypt Winning a Friendly Match vs an Official Match; the Probability of Egypt Winning at Home vs Winning Away; the Probability of Egypt Winning at Home; the Probability of Egypt Winning Away; the Confidence Interval of Probability of Egypt Winning at home vs away; and the probability of Egypt Winning, Losing, and Drawing a match in Non-Neutral Conditions.

Discussion

```
import pandas as pd
```

```
import numpy as np
```

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

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

Imports the data set into the workspace

```
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

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

```
x[0:3]
```

```
0    0
1    2
2    1
dtype: int64
```

```
conditions=[(x<0),(x>0),(x==0)]
```

```
values=['lose','win','draw']
```

This code subtracts the away score from the home score and assigns the result to the variable x. Next, it assigns 3 conditions to 3 statuses. This means that when the difference between the home score and the away score is below zero then the team lost; when the difference between the home score and the away score is more than zero then the team won, and when the difference is zero the this means that there was a draw.

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

```
df['result'][0:5]
```

```
0    draw
1     win
2     win
3    draw
4     win
Name: result, dtype: object
```

```
df['result'].value_counts()
```

```
win     21009
lose    12224
draw     9955
Name: result, dtype: int64
```

The probability of winning/losing

```
df['result'].value_counts(normalize=True)
```

```
win     0.486455
lose    0.283042
draw    0.230504
Name: result, dtype: float64
```

This code calculates the percentage of wins,losses, and draws.

```
df
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
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

```
x=df['result'].value_counts()
```

```
x=np.array(x)
```

```
x
```

```
array([21009, 12224,  9955])
```

```
N=x.sum()
N
```

```
43188
```

```
x[1]
```

```
12224
```

Confidence Intervals of Wins/Losses/Draws

We would anticipate the population mean to be found within 95% of the CI if many samples were chosen from the same population and a 95 percent CI calculated for each sample.

Here this means that the probaility of winning or the mean of the probability of winnning of all matches of all nations in the data lies in between the interval (0.481740705905987, 0.49116843552218753). In fact, if we observe the output of the command **df['result'].value_counts(normalize=True)**, we would see that the mean probability of wins of this sample of data specifically does indeed lie within this confidence interval.

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

```
(0.481740705905987, 0.49116843552218753)
```

Here this means that the probaility of losses or the mean of the probability of losses of all matches of all nations in the data lies in between the interval (0.27879305599044235, 0.28729011526083115). In fact, if we observe the output of the command **df['result'].value_counts(normalize=True)**, we would see that the mean probability of losses of this sample of data specifically does indeed lie within this confidence interval.

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

```
(0.27879305599044235, 0.28729011526083115)
```

Here this means that the probaility of a draw or the mean of the probability of a draw of all matches of all nations in the data lies in between the interval (0.2265318471530234, 0.23447584016752862). In fact, if we observe the output of the command **df['result'].value_counts(normalize=True)**, we would see that the mean probability of draws of this sample of data specifically does indeed lie within this confidence interval.

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

```
(0.2265318471530234, 0.23447584016752862)
```

```
df.head()
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
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

Probability of Winning/losing/drawing in a Neutral venue

```
df_neutral=df[df['neutral']==True]
```

```
df_neutral['result'].value_counts()
```

```
win     4606
lose    3659
draw    2442
Name: result, dtype: int64
```

```
df_neutral['result'].value_counts(normalize=True)
```

```
win     0.430186
lose    0.341739
draw    0.228075
Name: result, dtype: float64
```

This code shows the probability of winning, losing, drawing a match in a neutral venue. This shows that teams have a probability 0.430186 of winning, a probability 0.341739 of losing, a probability 0.228075 of drawing in a neutral venue. The higher probability of winning could be explained by the fact that if the venue played in is in good conditions this might impact the result of winning for the better.

Probability of Winning/losing/drawing in a Non-neutral venue

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

```
df_noneutral.shape
```

```
(32481, 10)
```

```
x=df_noneutral['result'].value_counts()
```

```
x
```

```
win     16403
lose     8565
draw     7513
Name: result, dtype: int64
```

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

```
win     0.505003
lose    0.263693
draw    0.231304
Name: result, dtype: float64
```

```
df['neutral'].value_counts()
```

```
False    32481
True     10707
Name: neutral, dtype: int64
```

This code shows the probability of winning, losing, drawing a match in a non-neutral venue. This shows that teams have a probability 0.505003 of winning, a probability 0.263693 of losing, a probability 0.231304 of drawing in a non-neutral venue. This shows that the venue has no significance on the resulting score, since the probability of winning in a non-neutral venue is higher than that of a eutral venue, which is illogical. Or, as shown in the output of the code directly above, the number of matches played in a non-neutral venue is significantly greater than the ones played in a neutral venue and this could explain the higer probability of winning in a non-neutral venue, since most of the winning matches are going to lie in the non-neutral group.

```
df['home_team'].value_counts().loc[lambda x : x>300]
```

```
Brazil                  586
Argentina               561
Mexico                  529
Germany                 521
England                 516
Sweden                  501
France                  496
South Korea             489
Hungary                 470
Italy                   461
United States           438
Austria                 434
Netherlands             433
Belgium                 425
Switzerland             418
Denmark                 418
Norway                  409
Chile                   403
Poland                  397
Egypt                   393
Scotland                391
Malaysia                389
Japan                   388
Saudi Arabia            381
Kenya                   375
Spain                   372
Uruguay                 355
Malawi                  344
China PR                343
Kuwait                  342
Indonesia               340
Finland                 340
Romania                 338
Portugal                336
Thailand                335
Wales                   333
Qatar                   330
Northern Ireland        321
Republic of Ireland     319
Tunisia                 315
Costa Rica              313
Russia                  311
Zambia                  310
Trinidad and Tobago     310
United Arab Emirates    310
Bulgaria                307
Bahrain                 306
Name: home_team, dtype: int64
```

Through this code we identify the most repeated countries meaning the countries that played the most matches in this data.

Egypt Analysis

Through the last code, we find out that Egypt is one of the most repeated countries, with a total of 393 home matches, therefore I chose to analyze it.

```
Egypt=df[df['country']=='Egypt']
Egypt['tournament'].unique()
```

```
array(['Friendly', 'FIFA World Cup qualification',
       'African Cup of Nations qualification', 'African Cup of Nations',
       'Nile Basin Tournament', 'African Nations Championship',
       'UEFA Euro qualification'], dtype=object)
```

In this data, Egypt participated in the following tournaments: Friendlies, FIFA World Cup qualifications, African Cup of Nations qualifications, African Cup of Nations, Nile Basin Tournament, African Nations Championship, and UEFA Euro qualifications.

The probability of Egypt winning in all tournaments and under all conditions

```
Egypt['result'].value_counts(normalize=True)
```

```
win     0.584767
lose    0.226044
draw    0.189189
Name: result, dtype: float64
```

```
p=Egypt['result'].value_counts()
```

```
p=np.array(p)
```

```
N=p.sum()
```

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

```
(0.5368938422372662, 0.6326393272959032)
```

This code shows us that Egypt had a 0.584767 probability of winning in all matches and all the tournaments it participated in this dataset. Moreover, by computing the confidence interval of Egypt winning, we are able to generalize the result on a larger scale. Evidently, the probability of egypt winning in the matches in this dataset does lie in the confidence interval.

```
Egypt
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
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
...	...	...	...	...	...	...	...	...	...	...
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
42958	11/12/2021	Djibouti	Algeria	0	4	FIFA World Cup qualification	Cairo	Egypt	True	lose
43040	11/16/2021	Egypt	Gabon	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win

407 rows × 10 columns

```
k=Egypt['tournament'].value_counts()
k
```

```
Friendly                                181
African Cup of Nations                  117
FIFA World Cup qualification             51
African Cup of Nations qualification     42
Nile Basin Tournament                    14
African Nations Championship              1
UEFA Euro qualification                   1
Name: tournament, dtype: int64
```

```
k[2]
```

```
51
```

This sample contains 51 matches that Egypt played part of the FIFA World Cup Qualifications.

Probability of Egypt Winning/Losing/having a draw in The FIFA World cup qualifications

```
Egypt_WC=Egypt[Egypt['tournament']=='FIFA World Cup qualification']
Egypt_WC
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
1661	3/16/1934	Egypt	Israel	7	1	FIFA World Cup qualification	Cairo	Egypt	False	win
3587	11/13/1953	Egypt	Italy	1	2	FIFA World Cup qualification	Cairo	Egypt	False	lose
8508	12/8/1972	Egypt	Tunisia	2	1	FIFA World Cup qualification	Cairo	Egypt	False	win
10000	10/29/1976	Egypt	Ethiopia	3	0	FIFA World Cup qualification	Cairo	Egypt	False	win
10133	2/27/1977	Egypt	Kenya	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
10294	7/15/1977	Egypt	Zambia	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
10413	10/21/1977	Egypt	Nigeria	3	1	FIFA World Cup qualification	Cairo	Egypt	False	win
10459	11/25/1977	Egypt	Tunisia	3	2	FIFA World Cup qualification	Cairo	Egypt	False	win
11897	5/8/1981	Egypt	Morocco	0	0	FIFA World Cup qualification	Cairo	Egypt	False	draw
13310	8/28/1984	Egypt	Zimbabwe	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
13746	4/5/1985	Egypt	Madagascar	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
13941	7/12/1985	Egypt	Morocco	0	0	FIFA World Cup qualification	Cairo	Egypt	False	draw
15414	1/6/1989	Egypt	Liberia	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
15813	8/12/1989	Egypt	Malawi	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
15835	8/26/1989	Egypt	Kenya	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
15969	11/17/1989	Egypt	Algeria	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
17335	10/11/1992	Egypt	Angola	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
17553	1/31/1993	Egypt	Togo	3	0	FIFA World Cup qualification	Cairo	Egypt	False	win
20130	11/8/1996	Egypt	Namibia	7	1	FIFA World Cup qualification	Cairo	Egypt	False	win
20665	6/8/1997	Egypt	Tunisia	0	0	FIFA World Cup qualification	Cairo	Egypt	False	draw
20863	8/17/1997	Egypt	Liberia	5	0	FIFA World Cup qualification	Cairo	Egypt	False	win
22927	4/20/2000	Egypt	Mauritius	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
22945	4/23/2000	Egypt	Mauritius	4	2	FIFA World Cup qualification	Alexandria	Egypt	False	win
23662	1/28/2001	Egypt	Morocco	0	0	FIFA World Cup qualification	Cairo	Egypt	False	draw
23794	3/11/2001	Egypt	Algeria	5	2	FIFA World Cup qualification	Cairo	Egypt	False	win
24027	5/6/2001	Egypt	Senegal	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
24269	7/13/2001	Egypt	Namibia	8	2	FIFA World Cup qualification	Alexandria	Egypt	False	win
26811	6/20/2004	Egypt	Ivory Coast	1	2	FIFA World Cup qualification	Alexandria	Egypt	False	lose
27030	9/5/2004	Egypt	Cameroon	3	2	FIFA World Cup qualification	Cairo	Egypt	False	win
27558	3/27/2005	Egypt	Libya	4	1	FIFA World Cup qualification	Cairo	Egypt	False	win
27678	6/5/2005	Egypt	Sudan	6	1	FIFA World Cup qualification	Cairo	Egypt	False	win
27923	9/4/2005	Egypt	Benin	4	1	FIFA World Cup qualification	Cairo	Egypt	False	win
30337	6/1/2008	Egypt	DR Congo	2	1	FIFA World Cup qualification	Cairo	Egypt	False	win
30538	6/22/2008	Egypt	Malawi	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
30752	9/6/2008	Sudan	Chad	1	2	FIFA World Cup qualification	Cairo	Egypt	True	lose
30773	9/10/2008	Chad	Sudan	1	3	FIFA World Cup qualification	Cairo	Egypt	True	lose
30892	10/12/2008	Egypt	Djibouti	4	0	FIFA World Cup qualification	Cairo	Egypt	False	win
31550	7/5/2009	Egypt	Rwanda	3	0	FIFA World Cup qualification	Cairo	Egypt	False	win
31881	11/14/2009	Egypt	Algeria	2	0	FIFA World Cup qualification	Cairo	Egypt	False	win
34183	6/1/2012	Egypt	Mozambique	2	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
35201	3/26/2013	Egypt	Zimbabwe	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win
35640	9/10/2013	Egypt	Guinea	4	2	FIFA World Cup qualification	el-Gouna	Egypt	False	win
35836	11/19/2013	Egypt	Ghana	2	1	FIFA World Cup qualification	Cairo	Egypt	False	win
37697	11/17/2015	Egypt	Chad	4	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
38626	11/13/2016	Egypt	Ghana	2	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
39347	9/5/2017	Egypt	Uganda	1	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
39437	10/8/2017	Egypt	Congo	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win
42590	9/1/2021	Egypt	Angola	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win
42812	10/8/2021	Egypt	Libya	1	0	FIFA World Cup qualification	Alexandria	Egypt	False	win
42958	11/12/2021	Djibouti	Algeria	0	4	FIFA World Cup qualification	Cairo	Egypt	True	lose
43040	11/16/2021	Egypt	Gabon	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win

```
Egypt_WC['result'].value_counts(normalize=True)
```

```
win     0.823529
lose    0.098039
draw    0.078431
Name: result, dtype: float64
```

```
Egypt_WC_Proba=Egypt_WC['result'].value_counts(normalize=True)
```

Probability of Egypt Winning a match in The FIFA World cup qualifications

```
Egypt_WC_Proba[0]
```

```
0.8235294117647058
```

```
f=Egypt_WC['result'].value_counts()
```

```
f=np.array(f)
f
```

```
array([42,  5,  4])
```

```
N=f.sum()
N
```

```
51
```

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

```
(0.7189036274158941, 0.9281551961135176)
```

As evident here, the mean probability of the Egyptian National Team winning a world cup qualification match is 0.823529. By computing the confidence interval too, it can be said that if applied on other future samples/matches, Egypt has a probability between (0.7189036274158941, 0.9281551961135176) of winning a match in The world cup qualifications. This might be due to the fact that Egypt is one of the most powerful African nations, therefore when The world cup qualifications are constructed Egypt usually has to face an African team after the drawing of lots, so, it occupies a high probability of winning.

Probability of Egypt Losing a match in The FIFA World cup qualifications

```
Egypt_WC_Proba[1]
```

```
0.0980392156862745l
```

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

```
(0.016426703796684955, 0.17965172757586406)
```

As evident here, the mean probability of the Egyptian National Team losing a world cup qualification match is 0.09803921568627451. By computing the confidence interval too, it can be said that if applied on other future samples/matches, Egypt has a probability between (0.016426703796684955, 0.17965172757586406) of losing a match in The world cup qualifications.

Probability of Egypt drawing a match in The FIFA World cup qualifications

```
Egypt_WC_Proba[2]
```

```
0.0784313725490196
```

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

```
(0.004645749045858988, 0.15221699605218023)
```

As evident here, the mean probability of the Egyptian National Team having a draw in a world cup qualification match is 0.0784313725490196. By computing the confidence interval too, it can be said that if applied on other future samples/matches, Egypt has a probability between (0.004645749045858988, 0.15221699605218023) of drawing a match in The World cup qualifications.

Egypt Winning in all tournaments vs. in World Cup Qualifications

```
ci_egywin = {}
ci_egywin['Tournaments']=['All Tournaments','FIFA World Cup Qualifications']
ci_egywin['lb'] = [CI_Egypt_Win[0],CI_Egypt_WC_Win[0]]
ci_egywin['ub'] = [CI_Egypt_Win[1],CI_Egypt_WC_Win[1]]
df_ci= pd.DataFrame(ci_egywin)
df_ci
```

	Tournaments	lb	ub
0	All Tournaments	0.536894	0.632639
1	FIFA World Cup Qualifications	0.718904	0.928155

```
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['Tournaments']))
```

```
([<matplotlib.axis.YTick at 0x7f7eba5e47c0>,
  <matplotlib.axis.YTick at 0x7f7eba5e4040>],
 [Text(0, 0, 'All Tournaments'), Text(0, 1, 'FIFA World Cup Qualifications')])
```

As shown in the graph above, Egypt has a higher/greater and long confidence interval therefore a greater probability of winning in FIFA World Cup Qualifications. Unlike in the world cup qualifications, in all tournaments all together, egypt has a lower and shorter confidence interval therefore a lower probability than that of the world cup qualifications but still higher than 0.5 which is not very low. The high probability of winning in the world cup qualifications could be explained by the fact that Egypt already occupies a high probability of winning a world cup qualification match; however, the number of world cup qualifications alone is insignificant compared to the number of matches Egypt played in all other tournaments, and, logically, when the number of matches is greater this means that the number of losses increases which impacts the overall probability of winning.

Probability of Egypt Winning/Losing/having a draw in a Friendly match vs. an Offical match

```
Egypt.head()
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
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

```
conditions = [
    (Egypt['tournament']=='Friendly'),
    (Egypt['tournament']!='Friendly') ]
```

```
values=['Friendly','Official']
```

```
Egypt_typematch=Egypt['typematch'] = np.select(conditions, values)
print(Egypt_typematch)
```

```
['Friendly' 'Official' 'Friendly' 'Friendly' 'Friendly' 'Friendly' 'Friendly'
[illegible]
 'Official']
/var/folders/9q/f13yp71d2v509vam_rdzy_8r0000gn/T/ipykernel_1060/169254995.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  Egypt_typematch=Egypt['typematch'] = np.select(conditions, values)
```

```
Egypt['typematch'].value_counts()
```

```
Official    226
Friendly    181
Name: typematch, dtype: int64
```

```
x=pd.crosstab(Egypt['typematch'],Egypt['result'],margins=True)
x
```

result	draw	lose	win	All
typematch				
Friendly	37	45	99	181
Official	40	47	139	226
All	77	92	238	407

```
x=np.array(x)
x
```

```
array([[ 37,  45,  99, 181],
       [ 40,  47, 139, 226],
       [ 77,  92, 238, 407]])
```

Confidence Interval of Probability of Egypt Winning a Friendly Match

```
CI_Egypt_Win_Friendly=proportion_confint(count=x[0,2],nobs=x[0,3],alpha=(1-.95))
CI_Egypt_Win_Friendly
```

```
(0.4744419341319208, 0.619480817801781)
```

When applied on future data, Egypt has a probability between (0.4744418341319208, 0.619480817801781) of winning a friendly match.

Confidence Interval of Probability of Egypt Winning an Official Match

```
CI_Egypt_Win_Official=proportion_confint(count=x[1,2],nobs=x[1,3],alpha=(1-.95))
CI_Egypt_Win_Official
```

```
(0.5516058130564923, 0.6784826825187289)
```

When applied on future data, Egypt has a probability between (0.5516058130564923, 0.6784826825187289) of winning an official match.

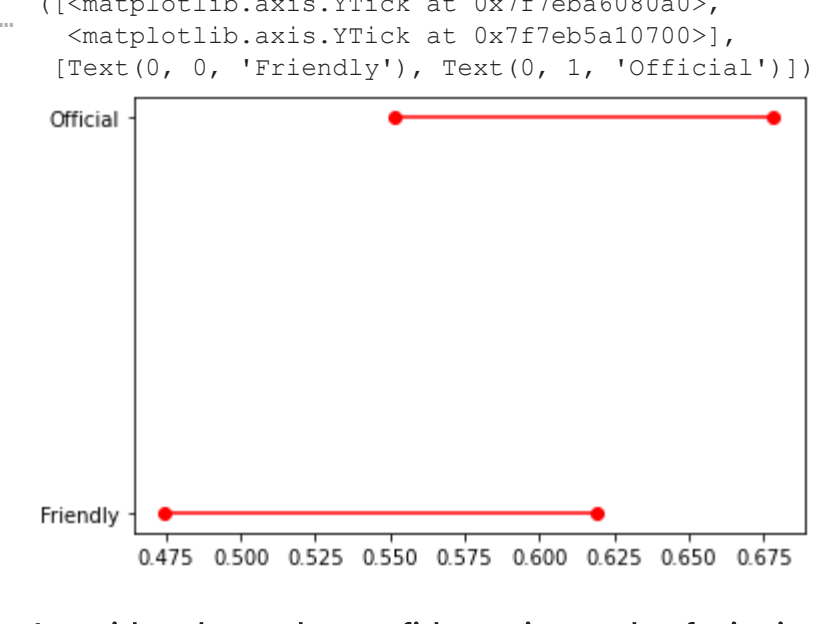
Confidence Interval of Probability of Egypt Winning a Friendly Match vs an Official Match

```
ci_egywin = {}
ci_egywin['Typematch'] = ['Friendly','Official']
ci_egywin['lb'] = [CI_Egypt_Win_Friendly[0],CI_Egypt_Win_Official[0]]
ci_egywin['ub'] = [CI_Egypt_Win_Friendly[1],CI_Egypt_Win_Official[1]]
df_ci= pd.DataFrame(ci_egywin)
df_ci
```

	Typematch	lb	ub
0	Friendly	0.474442	0.619481
1	Official	0.551606	0.678483

```
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['Typematch']))
```

```
([<matplotlib.axis.YTick at 0x7f7eba6080a0>,
  <matplotlib.axis.YTick at 0x7f7eb5a10700>],
 [Text(0, 0, 'Friendly'), Text(0, 1, 'Official')])
```



As evident here, the confidence intervals of winning an official match and a friendly match intersect. This means that there is a high chance of Egypt having the same probability in both winning an official match and a friendly match. The only difference is that Egypt may have a chance higher than approximately 0.619480817801781 of winning an official match until 0.6784826825187289, while the probability of winning a friendly match has a max of 0.619480817801781; and the minimum probability of winning an official match has a minimum of 0.5516058130564923, while the minimum probability of winning a friendly match is 0.4744418341319208. In conclusion, this basically means that Egypt occupies a higher probability of winning an official match than a friendly match. The reason why Egypt might have a higher probability of winning an official match is that official matches most of the time are taken more seriously than friendly matches since the score matters the most in real tournaments. Added to that, the team captain usually experiments with different lineups during friendly matches and that might cause a decline in performance than the usual performance with the usual lineup.

Probabilitiy of Egypt Winning at Home vs Winning Away

```
Egypt['home']=(Egypt['home_team']=='Egypt')
```

```
/var/folders/9q/f13yp71d2v509vxm_rdry_8r0000gn/T/ipykernel_1060/955588134.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  Egypt['home']=(Egypt['home_team']=='Egypt')
```

```
Egypt['home'].value_counts()
```

```
True     258
False    149
Name: home, dtype: int64
```

```
Egypt
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result	typematch
1463	2/19/1932	Egypt	Hungary	0	0	Friendly	Cairo	Egypt	False	draw	Friendly
1661	3/16/1934	Egypt	Israel	7	1	FIFA World Cup qualification	Cairo	Egypt	False	win	Official
1895	6/19/1936	Egypt	Greece	3	1	Friendly	Cairo	Egypt	False	win	Friendly
2927	12/24/1948	Egypt	Norway	1	1	Friendly	Cairo	Egypt	False	draw	Friendly
3080	2/17/1950	Egypt	Greece	2	0	Friendly	Cairo	Egypt	False	win	Friendly
...	...	...	...	...	...	...	...	...	...	...	...
42590	9/1/2021	Egypt	Angola	1	0	FIFA World Cup qualification	Cairo	Egypt	False	win	Official
42758	9/30/2021	Egypt	Liberia	2	0	Friendly	Alexandria	Egypt	False	win	Friendly
42812	10/8/2021	Egypt	Libya	1	0	FIFA World Cup qualification	Alexandria	Egypt	False	win	Official
42958	11/12/2021	Djibouti	Algeria	0	4	FIFA World Cup qualification	Cairo	Egypt	True	lose	Official
43040	11/16/2021	Egypt	Gabon	2	1	FIFA World Cup qualification	Alexandria	Egypt	False	win	Official

407 rows × 12 columns

```
x=pd.crosstab(Egypt['home'],Egypt['result'],margins=True)
x
```

result	draw	lose	win	All
home				
False	33	49	67	149
True	44	43	171	258
All	77	92	238	407

```
u=np.array(x)
```

```
u
```

```
array([[ 33,  49,  67, 149],
       [ 44,  43, 171, 258],
       [ 77,  92, 238, 407]])
```

Probability of Egypt Winning at Home

```
CI_Egy_Win_Home=proportion_confint(count=u[1,2],nobs=u[1,3],alpha=(1-.95))
CI_Egy_Win_Home
```

```
(0.6051039288730269, 0.7204774664758102)
```

This confidence interval shows that the probability of Egypt winning a match at home lies between (0.6051039288730269, 0.7204774664758102).

Probability of Egypt Winning Away

```
CI_Egy_Win_Away=proportion_confint(count=u[0,2],nobs=u[0,3],alpha=(1-.95))
CI_Egy_Win_Away
```

```
(0.3697890350639206, 0.5295398239964821)
```

This confidence interval shows that the probability of Egypt winning a match away lies between (0.3697890350639206, 0.5295398239964821).

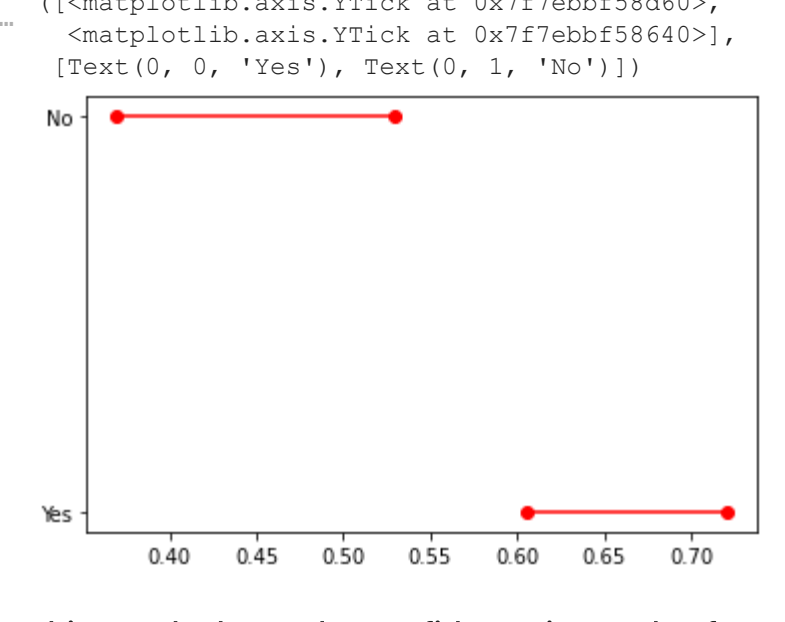
Confidence Interval of Probability of Egypt Winning at home vs away

```
ci_egywin = {}
ci_egywin['home'] = ['Yes','No']
ci_egywin['lb'] = [CI_Egy_Win_Home[0],CI_Egy_Win_Away[0]]
ci_egywin['ub'] = [CI_Egy_Win_Home[1],CI_Egy_Win_Away[1]]
df_ci= pd.DataFrame(ci_egywin)
df_ci
```

	home	lb	ub
0	Yes	0.605104	0.720477
1	No	0.369789	0.529540

```
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['home']))
```

```
([<matplotlib.axis.YTick at 0x7f7ebbf58d60>,
  <matplotlib.axis.YTick at 0x7f7ebbf58640>],
 [Text(0, 0, 'Yes'), Text(0, 1, 'No')])
```



This graph shows the confidence intervals of Egypt winning at home and away. As evident and shown in the graph, Egypt has a higher probability of winning a match at home. This could be explained by the fact that traveling distances to away lands are likely to cause fatigue, a decrease in sleep quality, and hydration. Moreover, Referees have been proven to subconsciously favor the home side. The atmosphere can be hostile when a team is away from its people. Also, the change in weather may be a huge factor, since a player's body is usually accustomed to the weather of his homeland or the place he lives in.

Non-neutral and Neutral Venues Egypt

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

```
df_Noneutral_Egypt
```

	date	home_team	away_team	home_score	away_score	tournament	city	country	neutral	result
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

Probability of Egypt Winning/Losing/Drawing a match in Neutral Conditions

```
df_Neutral_Egypt=df_neutral[df_neutral['country']=='Egypt']
```

```
df_Neutral_Egypt['result'].value_counts(normalize=True)
```

```
win     0.449664
lose    0.328859
draw    0.221477
Name: result, dtype: float64
```

```
x=df_Neutral_Egypt['result'].value_counts()
x=np.array(x)
x
```

```
array([67, 49, 33])
```

```
N=x.sum()
N
```

```
149
```

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

```
(0.3697890350639206, 0.5295398239964821)
```

This code means that Egypt has a probability of winning on a neutral venue that lies in the (0.3697890350639206, 0.5295398239964821) interval.

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

```
(0.25342513144684364, 0.40429298935852553)
```

This code means that Egypt has a probability of losing on a neutral venue that lies in the (0.25342513144684364, 0.40429298935852553) interval.

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

```
(0.15480279527394458, 0.28815022486028363)
```

This code means that Egypt has a probability of drawing on a neutral venue that lies in the (0.15480279527394458, 0.28815022486028363) interval.

Probability of Egypt Winning/Losing/Drawing a match in Non-Neutral Conditions

```
df_Noneutral_Egypt['result'].value_counts(normalize=True)
```

```
win     0.662791
draw    0.170543
lose    0.166667
Name: result, dtype: float64
```

```
x=df_Noneutral_Egypt['result'].value_counts()
x=np.array(x)
x
```

```
array([171,  44,  43])
```

```
N=x.sum()
N
```

```
258
```

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

```
(0.6051039288730269, 0.7204774664758102)
```

This code means that Egypt has a probability of winning on a non-neutral venue that lies in the (0.6051039288730269, 0.7204774664758102) interval.

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

```
(0.12464907466317304, 0.2164361966546564)
```

This code means that Egypt has a probability of losing on a non-neutral venue that lies in the (0.12464907466317304, 0.2164361966546564) interval.

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

```
(0.12119174183927744, 0.21214159149405587)
```

This code means that Egypt has a probability of drawing on a neutral venue that lies in the (0.12119174183927744, 0.21214159149405587) interval.

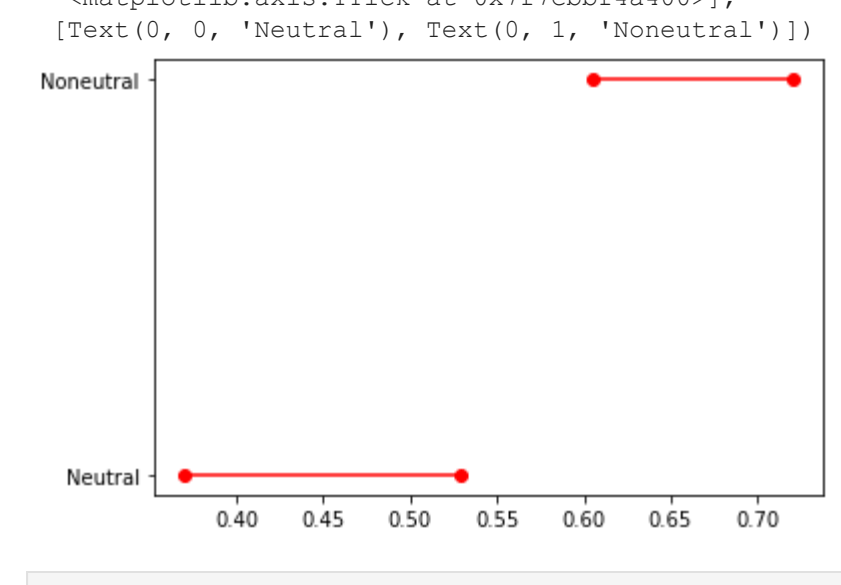
Probability of Egypt Winning on a Neutral vs. Non-neutral Venue

```
ci_egy_win_venue = {}
ci_egy_win_venue['Venue'] = ['Neutral','Noneutral']
ci_egy_win_venue['lb'] = [CI_Egypt_Win_Neutral[0],CI_Egypt_Win_Noneutral[0]]
ci_egy_win_venue['ub'] = [CI_Egypt_Win_Neutral[1],CI_Egypt_Win_Noneutral[1]]
df_ci_venue= pd.DataFrame(ci_egy_win_venue)
df_ci_venue
```

	Venue	lb	ub
0	Neutral	0.369789	0.529540
1	Noneutral	0.605104	0.720477

```
for lb,ub,y in zip(df_ci_venue['lb'],df_ci_venue['ub'],range(len(df_ci_venue))):
    plt.plot((lb,ub),(y,y),'ro-')
plt.yticks(range(len(df_ci_venue)),list(df_ci_venue['Venue']))
```

```
([<matplotlib.axis.YTick at 0x7f7ebc2caa60>,
  <matplotlib.axis.YTick at 0x7f7ebbf4a400>],
 [Text(0, 0, 'Neutral'), Text(0, 1, 'Noneutral')])
```




```
Egypt['neutral'].value_counts()
```

```
False    258
True     149
Name: neutral, dtype: int64
```

The graph above shows the confidence intervals of winning in a non-neutral venue vs in a neutral venue. What is logical and expected is the probability of winning in a neutral venue to be higher than that of in a non-neutral venue. However, as shown in the graph, Egypt has a higher probability of winning in a non-neutral venue.This might show that the venue has no significance on the resulting score, since the probability of winning in a non-neutral venue is higher than that of a neutral venue, which is illogical. Or, as shown in the output of the code directly above, the number of matches played in a non-neutral venue is greater than the ones played in a neutral venue and this could explain the higher probability of winning in a non-neutral venue.

Conclusion

Egypt participated in the following tournaments: Friendlies, FIFA World Cup qualifications, African Cup of Nations qualifications, African Cup of Nations, Nile Basin Tournament, African Nations Championship, and UEFA Euro qualifications. Egypt had a 0.584767 probability of winning in all matches and all the tournaments it participated in this dataset. Egypt has a probability between (0.7189036274158941, 0.9281551961135176) of winning a match in The world cup qualifications. This might be due to the fact that Egypt is one of the most powerful African nations, therefore when The world cup qualifications are constructed Egypt usually has to face an African team after the drawing of lots, so, it occupies a high probability of winning. Egypt has a greater probability of winning in FIFA World Cup Qualifications than that in all tournaments. The high probability of winning in the world cup qualifications could be explained by the fact that Egypt already occupies a high probability of winning a world cup qualification match; however, the number of world cup qualifications alone is insignificant compared to the number of matches Egypt played in all other tournaments, and, logically, when the number of matches is greater this means that the number of losses increases which impacts the overall probability of winning. Egypt occupies a higher probability of winning an official match than a friendly match. The reason why Egypt might have a higher probability of winning an official match is that official matches most of the time are taken more seriously than friendly matches since the score matters the most in real tournaments. Added to that, the team captain usually experiments with different lineups during friendly matches and that might cause a decline in performance than the usual performance with the usual lineup. Egypt has a higher probability of winning a match at home than away. This could be explained by the fact that traveling distances to away lands are likely to cause fatigue, a decrease in sleep quality, and hydration. Moreover, Referees have been proven to subconsciously favor the home side. The atmosphere can be hostile when a team is away from its people. Also, the change in weather may be a huge factor, since a player's body is usually accustomed to the weather of his homeland or the place he lives in. Egypt has a higher probability of winning in a non-neutral venue. This might show that the venue has no significance on the resulting score, since the probability of winning in a non-neutral venue is higher than that of a neutral venue, which is illogical. Or, the number of matches played in a non-neutral venue is greater than the ones played in a neutral venue and this could explain the higher probability of winning in a non-neutral venue.

Analysis of Corona Virus and Factors Impacting it

Abstract

In this part I will compute the Case Fatality Rate for all countries. I will compute the Case Fatality Rate in Egypt and compare between 2020 and 2021. I will form a comparison between countries in different regions and find whether the region impacts the case fatality rate. I will examine whether a country's income level and population number impacts the case fatality rate.

Discussion

Computing Case fatality rate

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

```
df.columns
```

```
Index(['date', 'iso3c', 'country', 'income', 'region', 'continent', 'dcases',
       'ddeaths', 'population', 'weekdays', 'month'],
      dtype='object')
```

```
df['totcases'] = df.groupby(['iso3c'])['dcases'].cumsum()
```

```
df['totdeaths'] = df.groupby(['iso3c'])['ddeaths'].cumsum()
```

```
df['totdeaths'].loc[df['iso3c']=='EGY']
```

```
34049        0
34050        0
34051        0
34052        0
34053        0
         ...
34731    21639
34732    21667
34733    21695
34734    21727
34735    21752
Name: totdeaths, Length: 687, dtype: int64
```

```
df['cfr']=df['totdeaths']/df['totcases']
```

```
df
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	totcases	totdeaths
0	2020-02-24	AFG	Afghanistan	Low income	South Asia	Asia	5	0	38041754	Mon	Feb	5	0
1	2020-02-25	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Tue	Feb	5	0
2	2020-02-26	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Wed	Feb	5	0
3	2020-02-27	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Thu	Feb	5	0
4	2020-02-28	AFG	Afghanistan	Low income	South Asia	Asia	0	0	38041754	Fri	Feb	5	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
122838	2021-12-27	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	1098	17	14645468	Mon	Dec	205455	4908
122839	2021-12-28	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	2099	32	14645468	Tue	Dec	207554	4940
122840	2021-12-29	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	0	0	14645468	Wed	Dec	207554	4940
122841	2021-12-30	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	4180	57	14645468	Thu	Dec	211734	4997
122842	2021-12-31	ZWE	Zimbabwe	Lower middle income	Sub-Saharan Africa	Africa	1530	7	14645468	Fri	Dec	213264	5004

122843 rows × 14 columns

Egypt

```
df_egy=df.loc[df['iso3c']=='EGY']
df_egy
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	totcases	totdeaths	
34049	2020-02-14	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	1	0	100388073	Fri	Feb	1	0	0.000
34050	2020-02-15	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	0	0	100388073	Sat	Feb	1	0	0.000
34051	2020-02-16	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	0	0	100388073	Sun	Feb	1	0	0.000
34052	2020-02-17	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	0	0	100388073	Mon	Feb	1	0	0.000
34053	2020-02-18	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	0	0	100388073	Tue	Feb	1	0	0.000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
34731	2021-12-27	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	851	31	100388073	Mon	Dec	382194	21639	0.056
34732	2021-12-28	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	809	28	100388073	Tue	Dec	383003	21667	0.056
34733	2021-12-29	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	854	28	100388073	Wed	Dec	383857	21695	0.056
34734	2021-12-30	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	871	32	100388073	Thu	Dec	384728	21727	0.056
34735	2021-12-31	EGY	Egypt	Lower middle income	Middle East & North Africa	Africa	847	25	100388073	Fri	Dec	385575	21752	0.056

687 rows × 14 columns

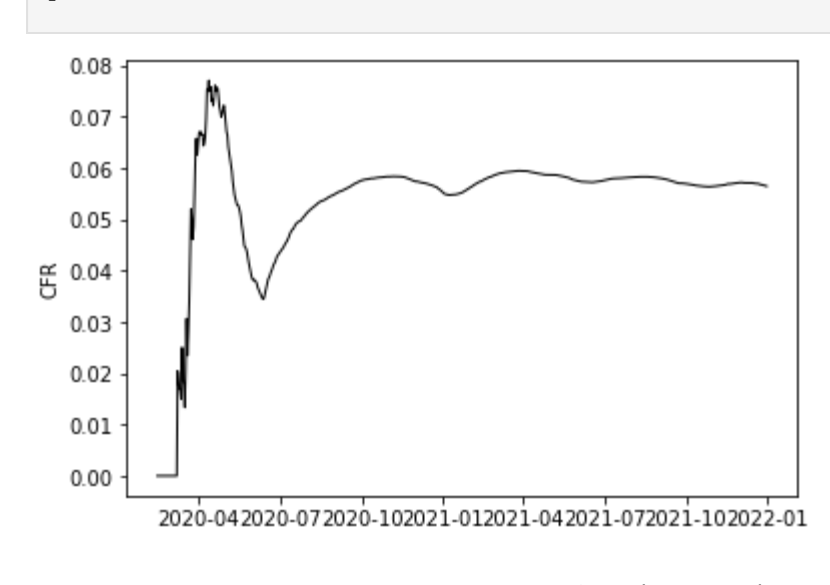
```
import matplotlib.pyplot as plt
```

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

```
/var/folders/9q/f13yp71d2v509vxm_rdry_8r0000gn/T/ipykernel_1060/3233637083.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df_egy['date'] = pd.to_datetime(df_egy['date'],format='%Y-%m-%d')
```

```
plt.plot( 'date', 'cfr', data=df_egy,  color='black', markersize=4,     linewidth=1)
plt.xlabel("")
plt.ylabel("CFR")
plt.show()
```



The graph above portrays the case fatality rate in Egypt. Starting at the beginning of year 2020, Egypt had a 0% case fatality rate, meaning that no deaths were reported at that time and no cases as well, since at that time it was still the period before the beginning of covid. Then, starting 03-2020 there was a rise in the case fatality rate until it reached until nearly 06-2020. This is in fact true since in Egypt the number of cases at that time was very high and as a result the number of deaths too. At that time, the virus was still new so controlling the numbers was an issue, which explains the deaths. The highest value reached was between 0.07 and 0.08. Then, starting the end of june till July, there was a slight decrease in the rate. This could be explained by the implementation of a proper quarantine at that time, which somewhat controlled the number of cases and the number of deaths as a result. Then, starting the end of the year 2020 towards the beginning of the year 2021, there has been a somewhat steady rate of cases and deaths. This could be explained by the emergence of the Omicron Variant and the end of the quarantine period, which cause the rise in cases and deaths.Ever since, there has been a somewhat steady rate of cases and deaths.

```
from pandas.api.types import CategoricalDtype
cats=['Jan', 'Feb', 'Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
cat_type = CategoricalDtype(categories=cats, ordered=True)
df["month"] = df["month"].astype(cat_type)
```

```
dfegy=df[df['country']=='Egypt']
```

```
import numpy as np
```

```
stats=dfegy.groupby("month").agg({"dcases": [np.mean, np.std, np.size]})
```

```
stats=pd.DataFrame(stats)
```

```
stats.columns=['mean','std','size']
```

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

```
s=dfegy['dcases']
```

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

```
ci_dcases=statm=dfegy.groupby("month").agg({"dcases": [np.mean, np.std, np.size,get_ci_lb,get_ci_ub]})
```

```
statm.columns=['mean','std','size','lb','ub']
```

```
statm["month"]=statm.index
```

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

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

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

```
statsdcases=df.groupby(['country','year','month']).agg({"dcases": [np.mean, np.std, np.size,get_ci_lb,get_ci_u
```

```
statsdcases=statsdcases.reset_index()
```

```
statsEgy=statsdcases[(statsdcases['country']=='Egypt') & (statsdcases['year']==2021)]
```

```
statsEgy.columns=['country','year','month','mean','std','size','lb','ub']
```

```
ci_lb_ub=[statsEgy['lb'],statsEgy['ub']]
```

```
err = np.abs(ci_lb_ub - statsEgy['mean'].to_numpy())
```

```
statsEgy21=statsdcases[(statsdcases['country']=='Egypt')
                       & (statsdcases['year']==2021)]
```

```
statsEgy20=statsdcases[(statsdcases['country']=='Egypt')
                       & (statsdcases['year']==2020)]
```

```
statsEgy20.columns=['country','year','month','mean','std','size','lb','ub']
```

```
statsEgy21.columns=['country','year','month','mean','std','size','lb','ub']
```

```
x=statsEgy20["month"]
```

```
y1=statsEgy20["mean"]
```

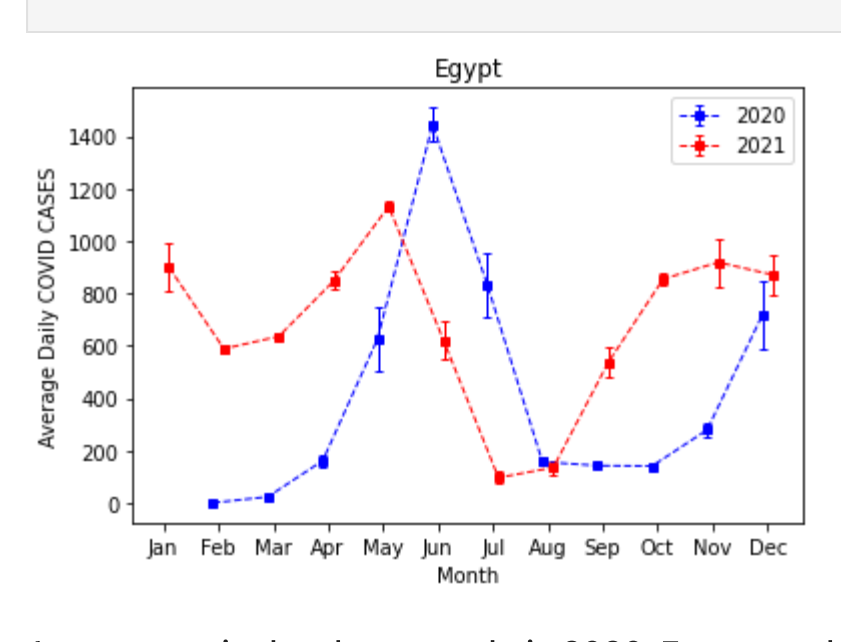
```
y2=statsEgy21["mean"]
```

```
ci_lb_ub20=[statsEgy20['lb'],statsEgy20['ub']]
err20 = np.abs(ci_lb_ub20 - statsEgy20['mean'].to_numpy())
```

```
ci_lb_ub21=[statsEgy21['lb'],statsEgy21['ub']]
err21 = np.abs(ci_lb_ub21 - statsEgy21['mean'].to_numpy())
```

```
from matplotlib.transforms import Affine2D
```

```
fig, ax = plt.subplots()
trans1 = Affine2D().translate(-0.1, 0.0) + ax.transData
trans2 = Affine2D().translate(+0.1, 0.0) + ax.transData
plt.errorbar('month', 'mean', yerr=err20, data=statsEgy20,marker='s', capsize=2,
             color='blue', markersize=4, linewidth=1, linestyle='--',transform=trans1)
plt.errorbar('month', 'mean', yerr=err21, data=statsEgy21,marker='s', capsize=2,
             color='red', markersize=4, linewidth=1, linestyle='--',transform=trans2)
plt.legend(['2020','2021'])
plt.xlabel("Month")
plt.ylabel("Average Daily COVID CASES")
plt.title("Egypt")
plt.show()
```



As apparent in the above graph, in 2020, Egypt reached its peak and experienced the highest number of daily covid cases, during the months may until mid july. However, during the other months the cases were low. In 2021, the cases were much higher all year long with a decrease only during june, july, and august, which is ironic since people during summer are usually always in contact with lots of other people.

Comparison Between Countries in Different Regions

```
df_hungary=df.loc[df['country']=='Hungary']
```

```
df_hungary
```

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	totcases	totdeaths	
48775	2020-03-04	HUN	Hungary	High income	Europe & Central Asia	Europe	2	0	9769949	Wed	Mar	2	0	0.00
48776	2020-03-05	HUN	Hungary	High income	Europe & Central Asia	Europe	0	0	9769949	Thu	Mar	2	0	0.00
48777	2020-03-06	HUN	Hungary	High income	Europe & Central Asia	Europe	0	0	9769949	Fri	Mar	2	0	0.00
48778	2020-03-07	HUN	Hungary	High income	Europe & Central Asia	Europe	2	0	9769949	Sat	Mar	4	0	0.00
48779	2020-03-08	HUN	Hungary	High income	Europe & Central Asia	Europe	3	0	9769949	Sun	Mar	7	0	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
49438	2021-12-27	HUN	Hungary	High income	Europe & Central Asia	Europe	7989	436	9769949	Mon	Dec	1245319	38743	0.03
49439	2021-12-28	HUN	Hungary	High income	Europe & Central Asia	Europe	1370	151	9769949	Tue	Dec	1246689	38894	0.03
49440	2021-12-29	HUN	Hungary	High income	Europe & Central Asia	Europe	3005	115	9769949	Wed	Dec	1249694	39009	0.03
49441	2021-12-30	HUN	Hungary	High income	Europe & Central Asia	Europe	3361	95	9769949	Thu	Dec	1253055	39104	0.03
49442	2021-12-31	HUN	Hungary	High income	Europe & Central Asia	Europe	3360	82	9769949	Fri	Dec	1256415	39186	0.03

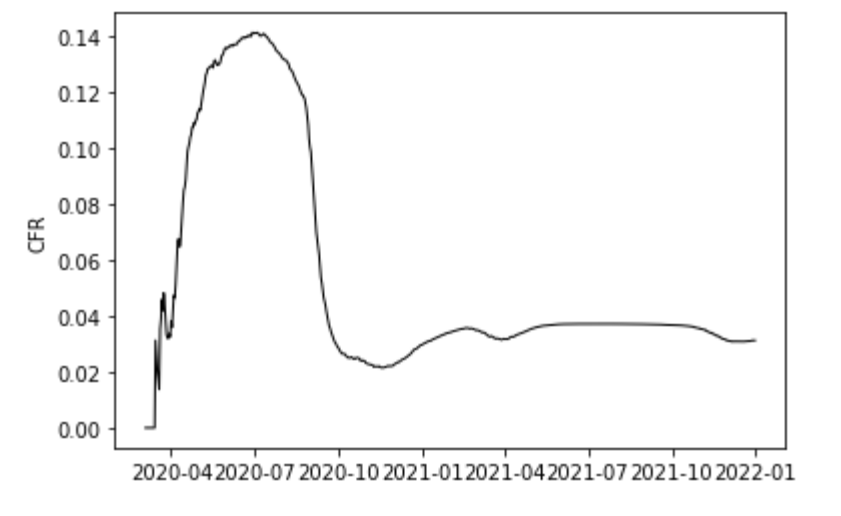
668 rows × 15 columns

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

```
/var/folders/9q/f13yp71d2v509vxm_rdry_8r0000gn/T/ipykernel_1060/3269099244.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df_hungary['date'] = pd.to_datetime(df_hungary['date'],format='%Y-%m-%d')
```

```
plt.plot( 'date', 'cfr', data=df_hungary,  color='black', markersize=4,     linewidth=1)
plt.xlabel("")
plt.ylabel("CFR")
plt.show()
```



Starting 04-2020, Hungary started expriencing a rise in covid cases until 07-2020. It reached a 0.14 case fatality rate. Starting 07-2020 till 10-2020, there was a significant decrease to a 0.3 case fatality rate. Then, there was a slight rise till 0.4 that is constant until 01-2022. This all could be explained by the fact that starting 03-2020, the hungarian government ordered the gradual easing of lockdown measures. However, a month and a half later, the government lifted all coronavirus restrictions and officially ended a state of emergency, which didnt control the cases and tha fatalities. The hungarian government had a dissmissive attitude towards the conflict and when there was a rise in cases the government did not introduce measures to protect people and there there was no mask mandate and no mass testing.

In [239…
```
df_china=df.loc[df['country']=='China']
df_china
```

Out[239…

	date	iso3c	country	income	region	continent	dcases	ddeaths	population	weekdays	month	totcases	totdeaths	
21405	2020-01-22	CHN	China	Upper middle income	East Asia & Pacific	Asia	548	17	1397715000	Wed	Jan	548	17	0.03
21406	2020-01-23	CHN	China	Upper middle income	East Asia & Pacific	Asia	95	1	1397715000	Thu	Jan	643	18	0.02
21407	2020-01-24	CHN	China	Upper middle income	East Asia & Pacific	Asia	277	8	1397715000	Fri	Jan	920	26	0.02
21408	2020-01-25	CHN	China	Upper middle income	East Asia & Pacific	Asia	486	16	1397715000	Sat	Jan	1406	42	0.02
21409	2020-01-26	CHN	China	Upper middle income	East Asia & Pacific	Asia	669	14	1397715000	Sun	Jan	2075	56	0.02
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
22110	2021-12-27	CHN	China	Upper middle income	East Asia & Pacific	Asia	371	0	1397715000	Mon	Dec	114164	4852	0.04
22111	2021-12-28	CHN	China	Upper middle income	East Asia & Pacific	Asia	203	0	1397715000	Tue	Dec	114367	4852	0.04
22112	2021-12-29	CHN	China	Upper middle income	East Asia & Pacific	Asia	221	0	1397715000	Wed	Dec	114588	4852	0.04
22113	2021-12-30	CHN	China	Upper middle income	East Asia & Pacific	Asia	208	0	1397715000	Thu	Dec	114796	4852	0.04
22114	2021-12-31	CHN	China	Upper middle income	East Asia & Pacific	Asia	248	0	1397715000	Fri	Dec	115044	4852	0.04

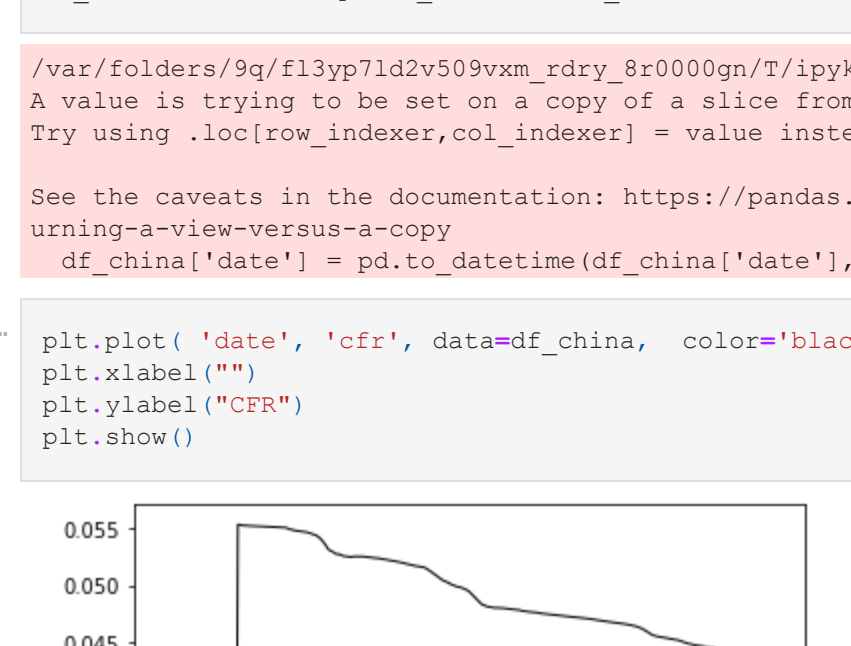
710 rows × 15 columns

In [239…
```
df_china['date'] = pd.to_datetime(df_china['date'],format='%Y-%m-%d')
```

```
/var/folders/9q/f13yp71d2v509vxm_rdry_8r0000gn/T/ipykernel_1060/942122686.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df_china['date'] = pd.to_datetime(df_china['date'],format='%Y-%m-%d')
```

In [239…
```
plt.plot( 'date', 'cfr', data=df_china,  color='black', markersize=4,     linewidth=1)
plt.xlabel("")
plt.ylabel("CFR")
plt.show()
```



Starting 01-2020, China was the only country with a case this early. The case fatality rate started increasing from 02-2020 till 05-2020, to a rate of nearly 0.055 Then starting 05-2020 till 01-2022 there was a contant decrease to a rate of 0.040. This rate is pretty low compared to other countries. Despite it being the origin country for the virus, China has managed to keep the death rates down. China was placed under a strict lockdown that lasted 76 days and public transport was suspended. Only one member of each household was permitted to leave the home every couple of days to collect necessary supplies. The level of strict measures prevented the virus from spreading so easily.

The conclusion reached is that despite china, a country in Asia, being the primary source of the virus, however, its case fatality rate compared to Hungary, a country in Europe, is significantly lower, implying that the region doesn't hold much significance as much as the implemented measures.

Does a country's income level impact the case fatality rate?

In [239…
```
df_china['income']
```

Out[239…
```
21405    Upper middle income
21406    Upper middle income
21407    Upper middle income
21408    Upper middle income
21409    Upper middle income
                ...
22110    Upper middle income
22111    Upper middle income
22112    Upper middle income
22113    Upper middle income
22114    Upper middle income
Name: income, Length: 710, dtype: object
```

In [239…
```
df_hungary['income']
```

Out[239…
```
48775    High income
48776    High income
48777    High income
48778    High income
48779    High income
            ...
49438    High income
49439    High income
49440    High income
49441    High income
49442    High income
Name: income, Length: 668, dtype: object
```

As evident in the outputs above, China has an upper middle income while Hungary has a high income; however, china has managed to better control the virus. Therefore, the income level of a country isn't a primary factor as much as the implemented measures are. Of course, income is important, however, a country can have a very high income level and still fail to control the situation.

Does the population number impact the case fatality rate?

In [239…
```
df_china['population']
```

Out[239…
```
21405    1397715000
21406    1397715000
21407    1397715000
21408    1397715000
21409    1397715000
            ...
22110    1397715000
22111    1397715000
22112    1397715000
22113    1397715000
22114    1397715000
Name: population, Length: 710, dtype: int64
```

In [239…
```
df_UK=df.loc[df['country']=='United Kingdom']
```

In [239…
```
df_UK['population']
```

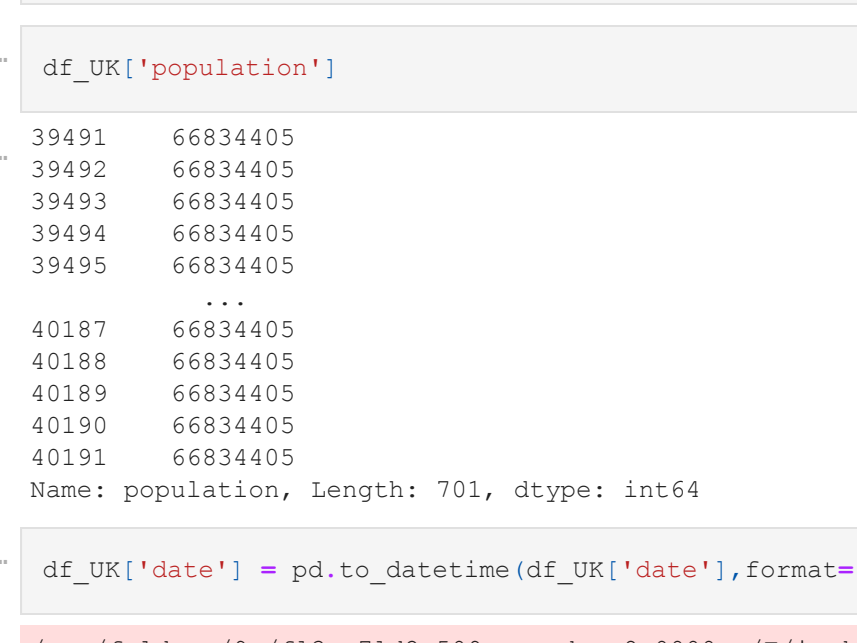
Out[239…
```
39491    66834405
39492    66834405
39493    66834405
39494    66834405
39495    66834405
           ...
40187    66834405
40188    66834405
40189    66834405
40190    66834405
40191    66834405
Name: population, Length: 701, dtype: int64
```

In [240…
```
df_UK['date'] = pd.to_datetime(df_UK['date'],format='%Y-%m-%d')
```

```
/var/folders/9q/f13yp71d2v509vxm_rdry_8r0000gn/T/ipykernel_1060/108896636.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  df_UK['date'] = pd.to_datetime(df_UK['date'],format='%Y-%m-%d')
```

In [240…
```
plt.plot( 'date', 'cfr', data=df_UK,  color='black', markersize=4,     linewidth=1)
plt.xlabel("")
plt.ylabel("CFR")
plt.show()
```



Despite the population of the UK being 20 times smaller than China, the UK has 30 times as many Covid deaths. The UK reached a 0.16 case fatality rate while the maximum china reached was near 0.055. This shows that population size has no significance and effect on the case fatality rate as much as the effectiveness of the implemented measures and how the country deals with the conflict.

Conclusion

The conclusion reached is that despite china, a country in Asia, being the primary source of the virus, however, its case fatality rate compared to Hungary, a country in Europe, is significantly lower, implying that the region doesn't hold much significance as much as the implemented measures. China has an upper middle income while Hungary has a high income; however, China has managed to better control the virus. Therefore, the income level of a country isn't a primary factor as much as the implemented measures are. Of course, income is important, however, a country can have a very high-income level and still fail to control the situation. Despite the population of the UK being 20 times smaller than China, the UK has 30 times as many Covid deaths. The UK reached a 0.16 case fatality rate while the maximum china reached was near 0.055. This shows that population size has no significance and effect on the case fatality rate as much as the effectiveness of the implemented measures and how the country deals with the conflict.