

Basics of Data Science Course - Assignment 2

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Data Set : Covid-19

(For a more complete experience run the notebook as the visualizations are interactive)

Summary :

Most of the visualization we have used are animated over time so this report would just be a quick walkthrough over what has been done, and the main part would be the code for you guys to run and see for yourselves.

Also as the main reason of this exercise is to familiarize with different Visualizations and the respective applications we'll have some plots just for the sake of that purpose only. (e.g. sunburst plot) meaning a lot of the visualizations seen here are actually unnecessary for a concise and fruitful EDA

This is a list of what you will see in code, we'll have a simple output of each here just for introduction, again you need to run the code for more detail

- Spreading of the virus over the globe
- Continent wise cumulative stacked plot over total_cases
- Continent wise percentage based plot over new_cases
- Chronological EDA on different time-stamps over new_cases/new_deaths
- Outlier detection and why we won't be doing that!
- Different choropleths over columns

From now on we'll use a collection of selected countries for more details

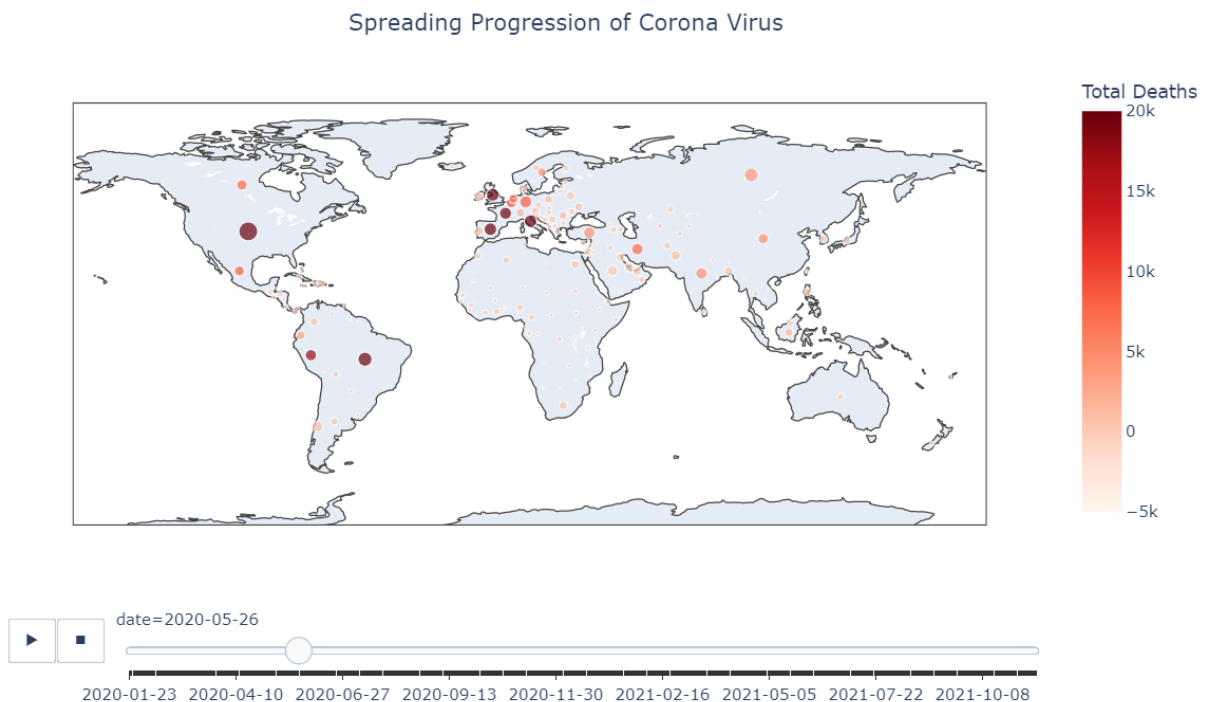
- Weekly differences of new cases
- Recovery rates of each country
- Mortality rate of each country
- Wave counting of countries + world wise

Country specific features such as gdp_per_capita

- Heatmap of all correlations to each other
- Parallel coords of a fraction of these features
- Sunburst and treemap plots

1- How the virus spreaded

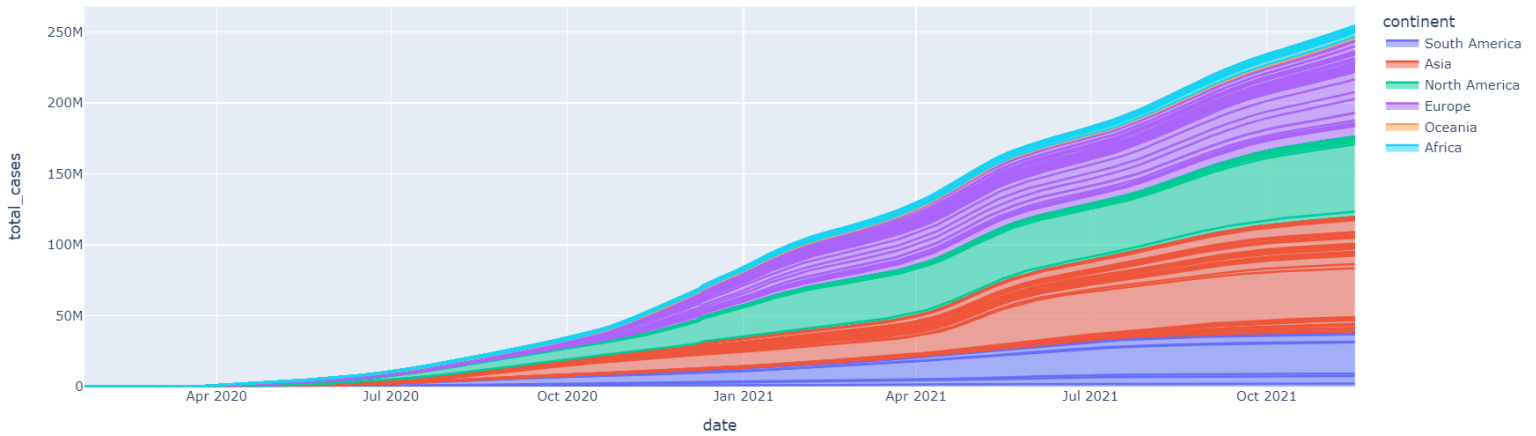
Using a scatter plot on global map (with `plotly.express.scatter_geo`) we can animate through time and watch how the infection started, it is colored over death counts and sized with confirmed cases count, we see it would start and china and just stops there, other countries would get infected with a high number of casualties but china remains the same after the first month of infection



2- Continentwise comulative stacked area plot

Area plots are good for analyzing moments of progression let it be increasing or decreasing, using a stacked area plot let's us to compare each of the continent's total cases over time, the worldwide infection slope would be the last stacked area's slope(here it would be Africa)

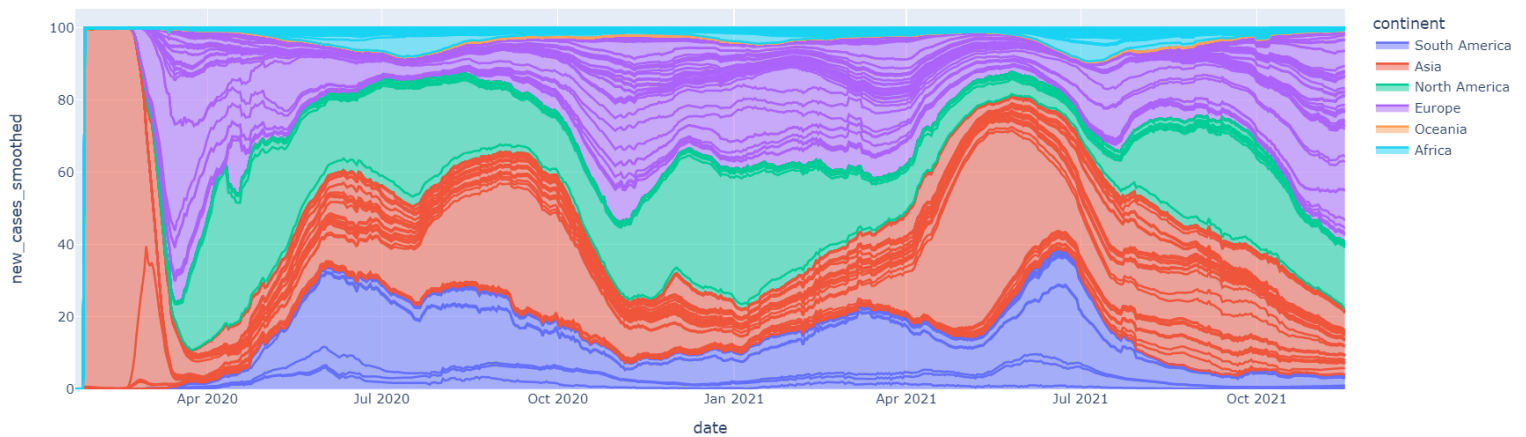
Stacked Area Plot of Total Cases



3- Percentage based stack area plot

In the above plot there's one thing we can't clearly see at times we have very low number of cases, using a percentage based plot solves that issue, now we can compare each continent's new cases and clearly see in which time periods each of the continents were dominating ones in term of having more cases the reasoning above is the same as when we use logarithmic scales when an outlier is overshadowing an slope

Percentage Based Stacked Area Plot Of New Cases



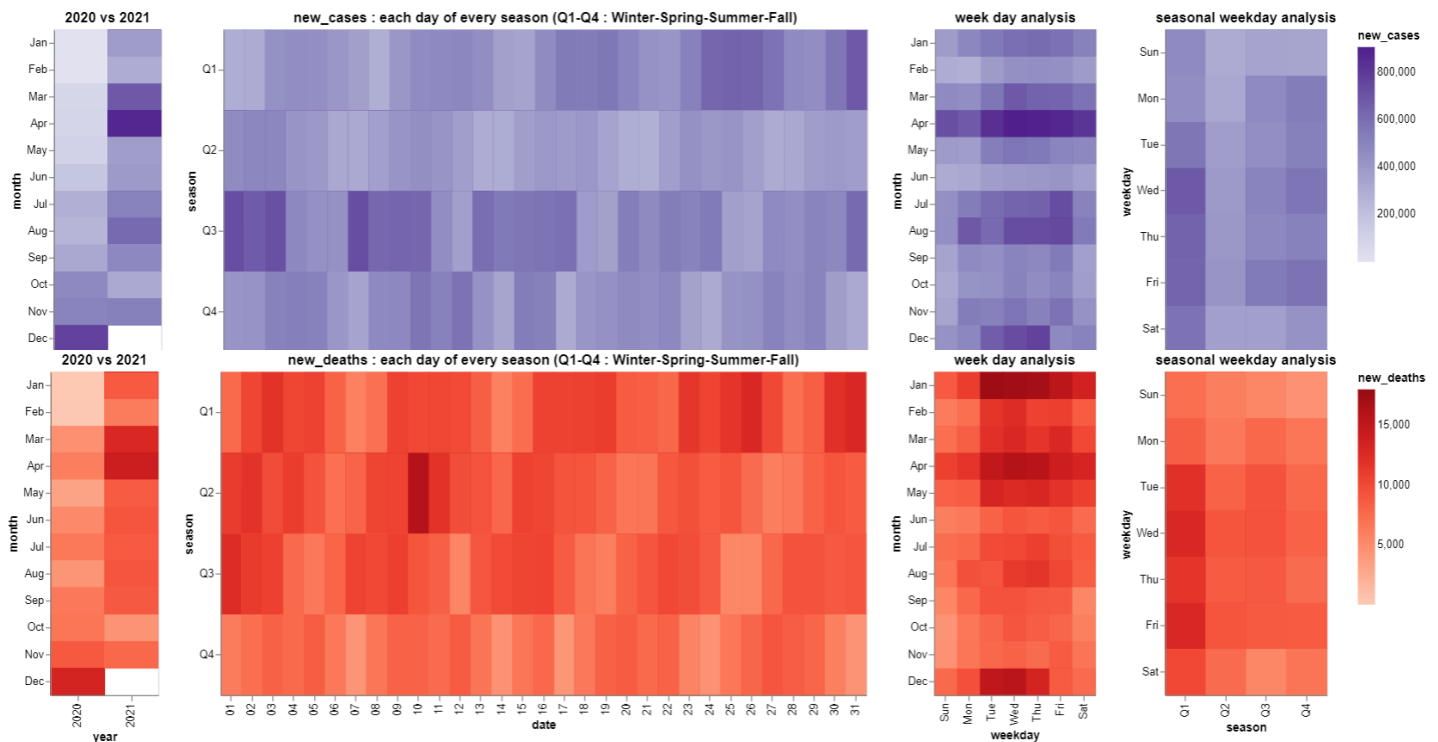
4- Chronological analysis on different time stamps

There are a few insights that could be derived from these heatmaps, each of them has a different time_stamp combination to help us derive different kinds of information

Some of these insights could be :

Week day distinguishment: from the two last chart we observe that as we reach the middle point of our week our cases and deaths increases in number an assumption for this observation could be that as we reach the weekend people tend to be out of their houses more than often thus causing new cases of infection to spread and show itself with a 2-3 day delay (the virus shows symptoms with a 2-3 day delay)

Season distinguishment: we have Q1 as Winter, and clearly has more death and cases submitted in this season, probably one of the main reasons is the tempreture, Spring is the lowest with cases/de



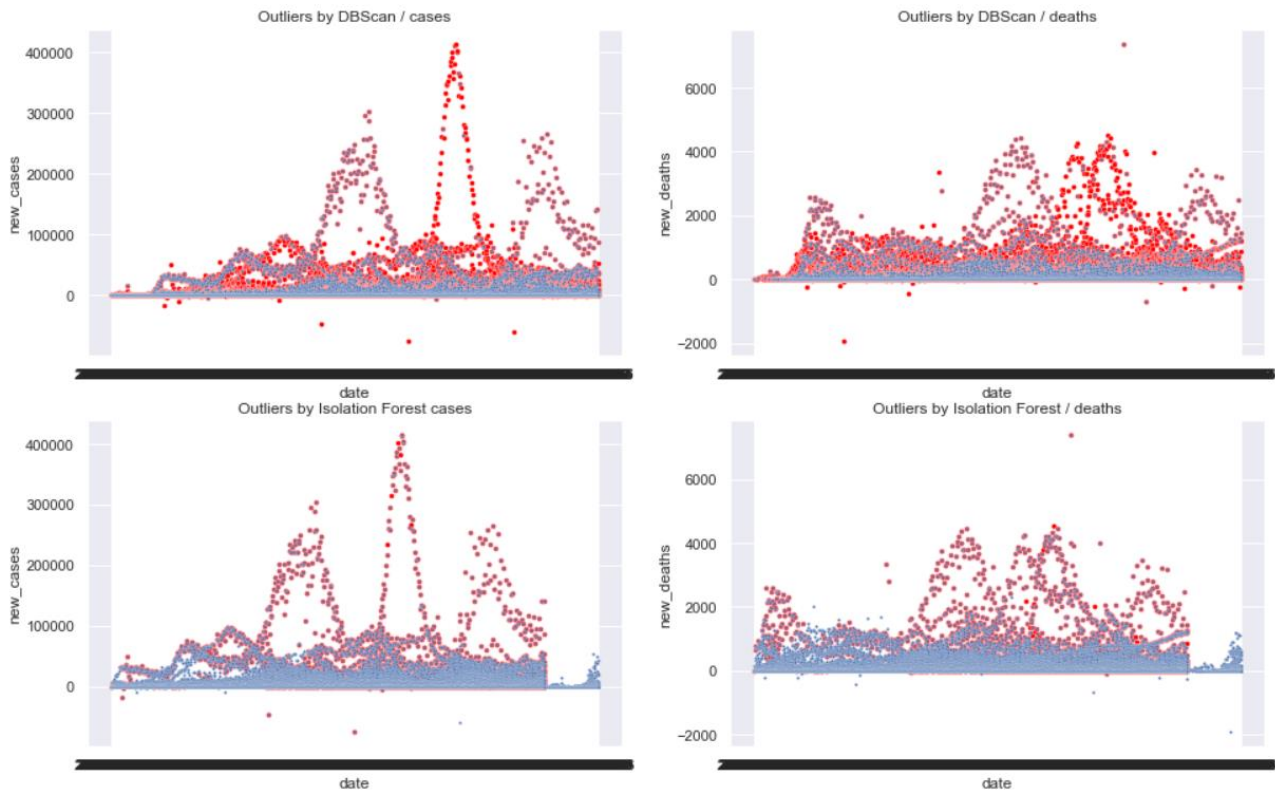
Before we delve into more detailed visualization we would want to know is there any outliers in our data (well ofc we wont be doing any modeling and we wouldnt need anomaly detection)

though as we see below the anomaly detection concept being a challenge in data science itself, there's not an easy path detecting outliers here, the main reason is that we have a lot of features to work with, but if we narrow them to only new/total cases/deaths which this happens :

5- Outlier detection

I have used two methods for detecting outliers including DBScan & Isolation Forest, both were trained over the whole dataframe as a n-dimensional input, but to visualize which of the rows were detected as outliers

I have used new_cases(col1) and new_deaths(col2) and solely to show that removing outliers in this data set means removing all the infection waves which are an extremely important part of the data and we



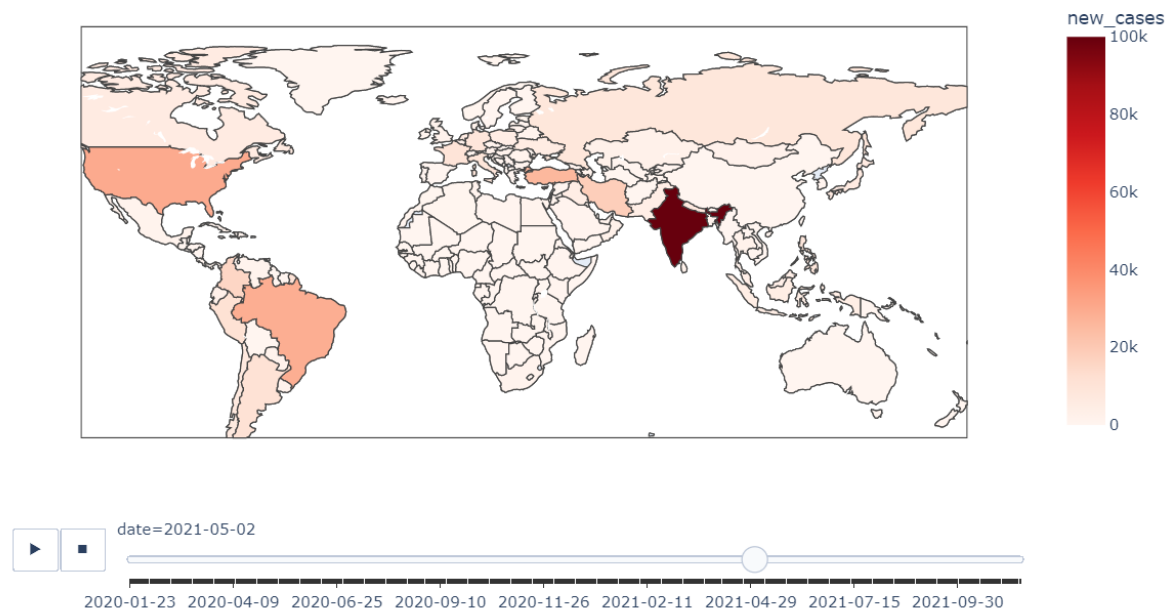
wouldn't want to remove them, also we are not doing any modeling here so we don't need to do anomaly detection either way!

To have a more detailed visualization over our features for some cases we would want to pre select some countries to work with (except choropleths) these are: United States, India, China, United Kingdom, Iran, France, Germany, Brazil, Russia. How did I select these countries to be the our representative ones? Well just sheer geographical/political knowledge (I failed geography course in middle school (miserebaly))

Choropleths are good choices when we want to have an overall view of all the countries but gives us only one dimension (the color) to work with, (although animating over a feature could be applied too, e.g. date) for this purpose we have a choropleth which shows the new_cases of each time_stamp by scrolling over it, I did try to make it more interactive with adding other features as a drop down button in the figure to select from, but that was a burden that made me wish for the apocalypse to happen right away, and failed to do so. Though viewing different features over the choropleth is just the matter of changing one name as the color method which requires you to do if you want to watch the other features as coloring factor.

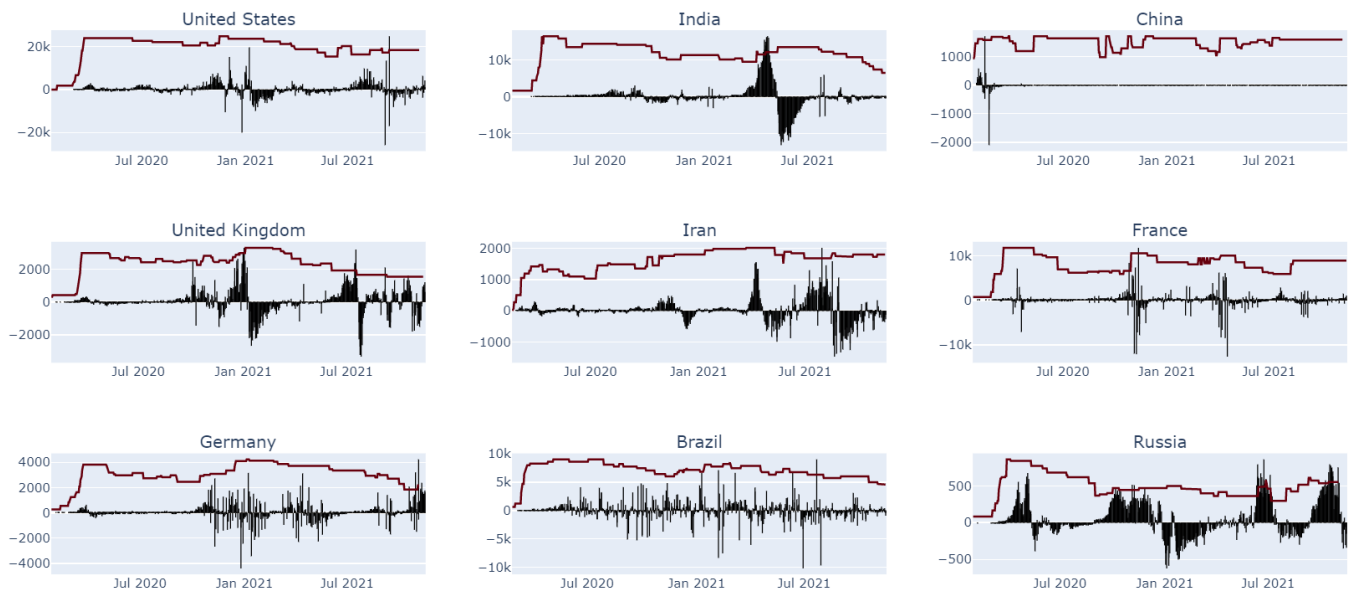
6- Choropleths

new cases of each country over time



7-weekly diffs on new cases and str_index

weekly differences of new cases, the line demonstrates the stringency index(scaled to be seen in the graph)



Something that would catch the eye is the stringency index, seemingly it shows how much a government got serious about the situation and took action to decrease the infection rate, actions like limiting the public gatherings or closing schools, or ...

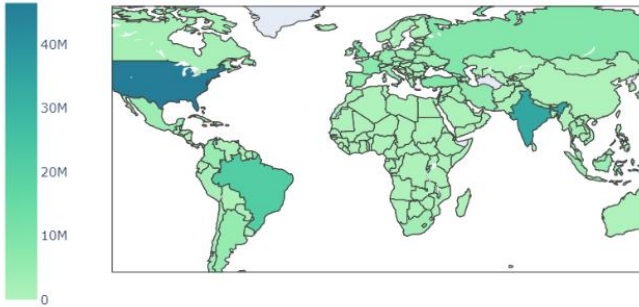
Here we see a chart of each of our selected countries which shows how each day's new cases were comparing to the last day (though smoothed over week to be more stable)

And on top of that we have our stringency index scaled to be seen in the graph

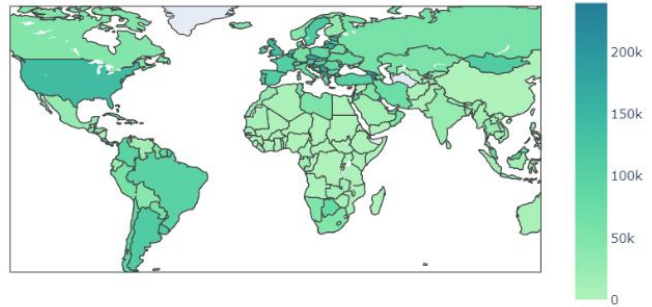
8 -recovs

Revocery number is not something we can confidently know, first we do not have the exact number of cases nor the exact number deaths, beside that we can't decide that how much time it took for each case to be cured so we can't animate this feature over time, though some tries took place to solve this issue which I explained in the code but at last I just used the `total_cases - total_deaths` (left fig) and `total_cases_per_million - total_deaths_per_million` (right fig)

approximate recoveries over the globe



same but per mil



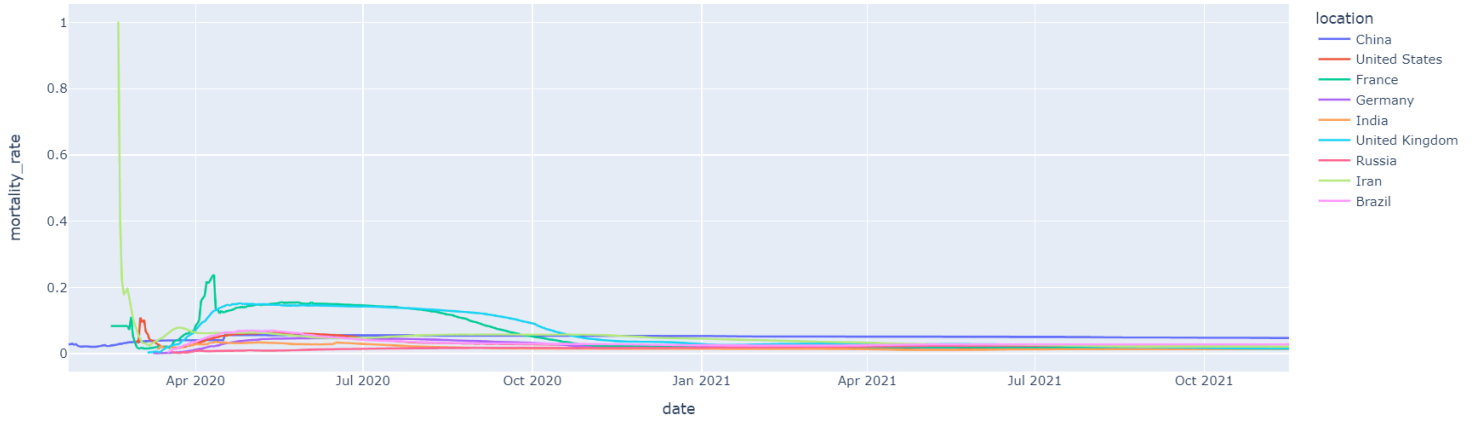
9- excess mortality and mortality rate

One more feature we could add is the death rate of new cases which is defined by the simple formula below :

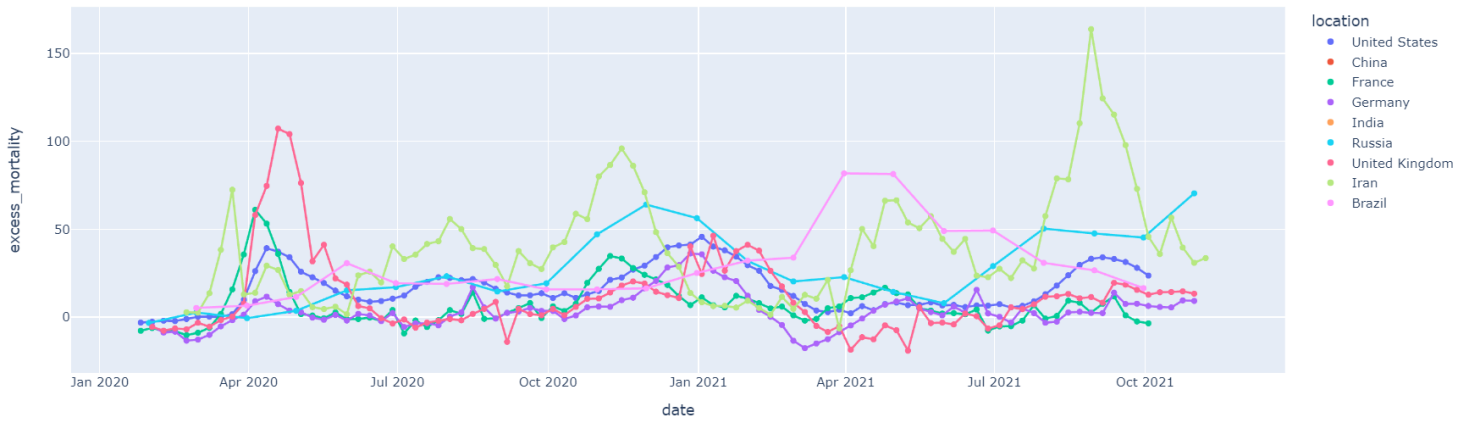
$$df['mortality_rate'] = df['new_deaths'] / df['new_cases']$$

you'll see the above feature in the first figure, the following two are visualizations of Excess_mortality feature which is by definition the number of deaths increased in a country comparing to the normal amount of that country, excess_mortality could be a good alternative to `tota_deaths`, as it is showing since the start of corona virus how was the death rate affected, meaning it is a summation of `corona_deaths + other_corona_related_deaths`

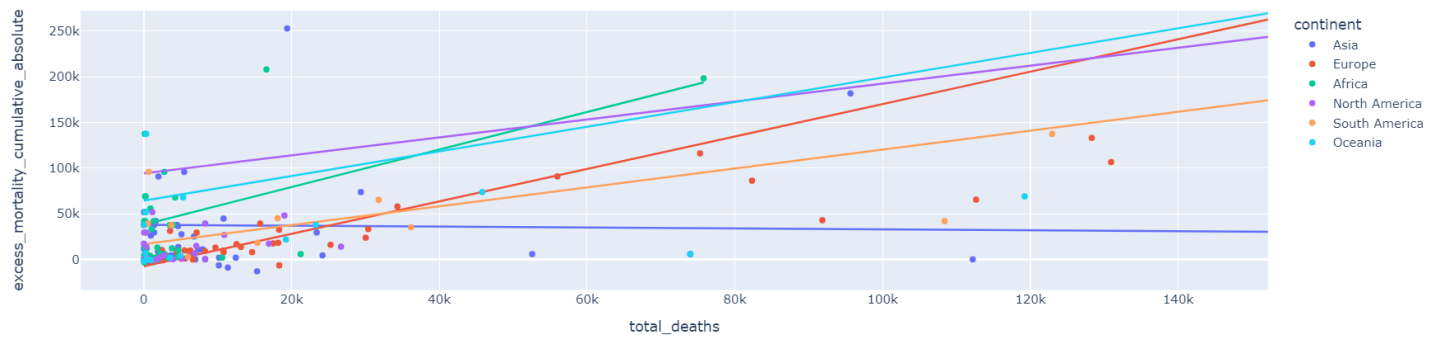
mortality rate of each country over time



excess mortality of each country over time

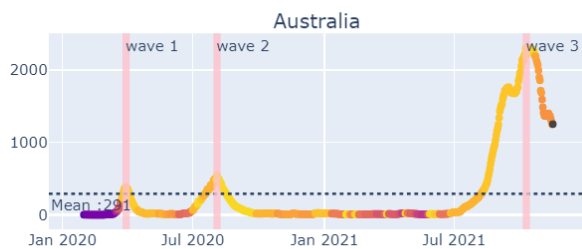
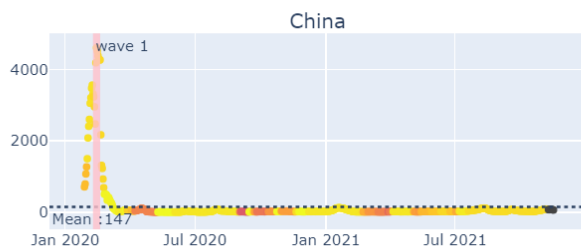
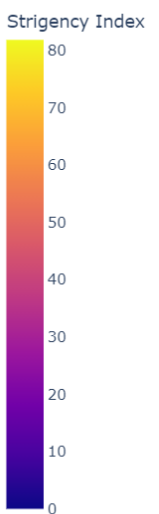
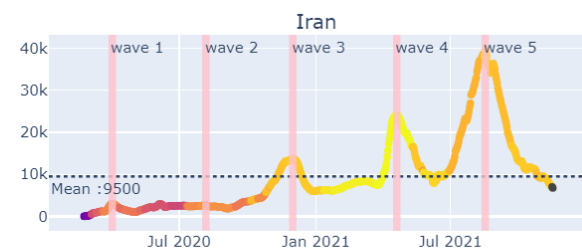
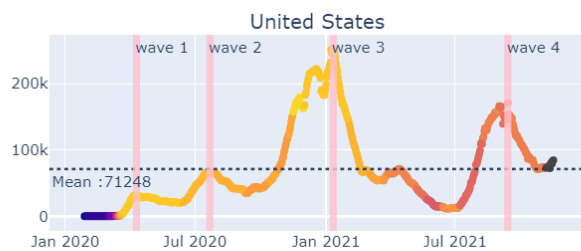


Excess Mortality vs Total Deaths

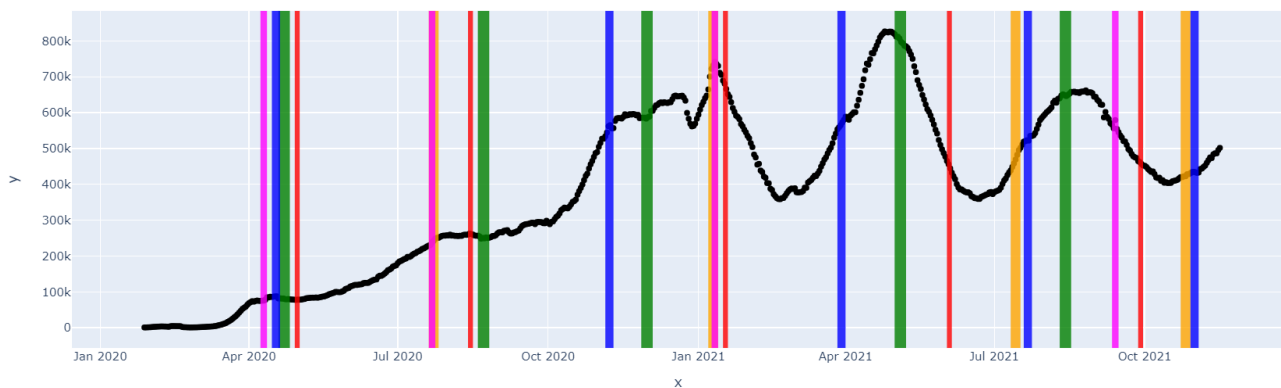


10 – wave counting

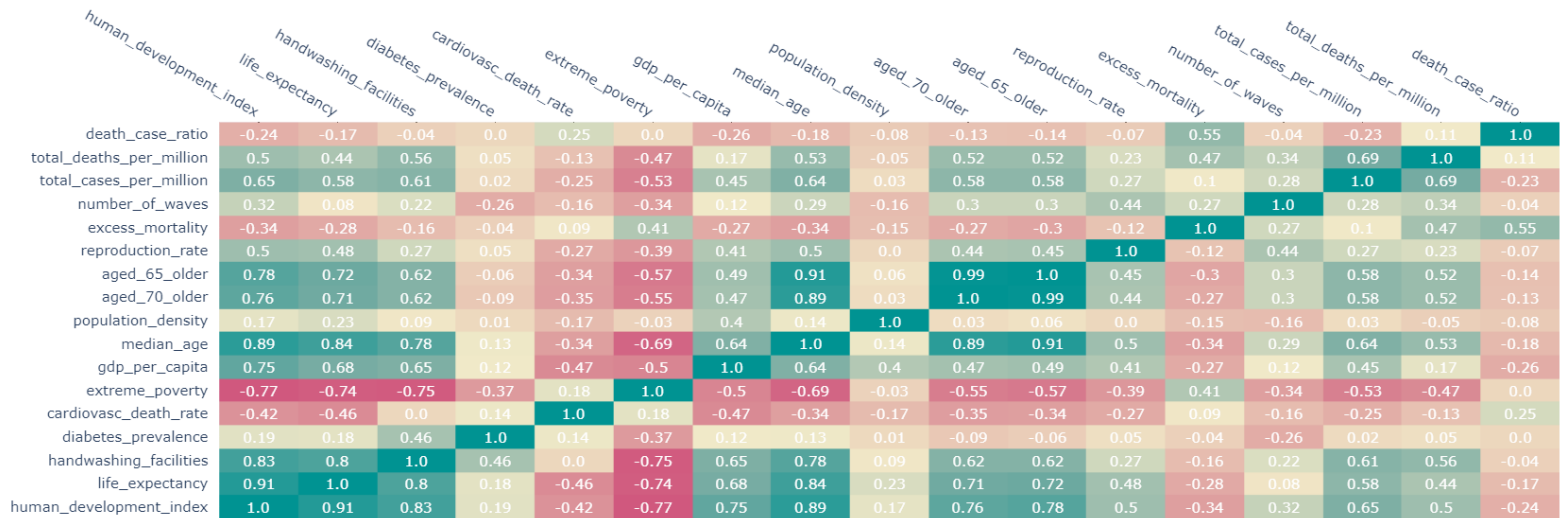
As I tried to add one more feature to our data set, which is the number of infection peaks over each country, for this purpose two algorithms were tested out (both written in sklearn) and after some tuning the model we have the results for United States, Iran, China, Australia (what's up with this china dude, srsly?) I couldn't find a somewhat "useful" application for this feature though we see the continent wise waves affecting the world chart below (in the code I marked down some self-made analysis of this)



Worldwide Waves (Line width is set regarding to the population) (Green:Asia Yellow:Africa Blue:Europe Pink:NA Red:SA)



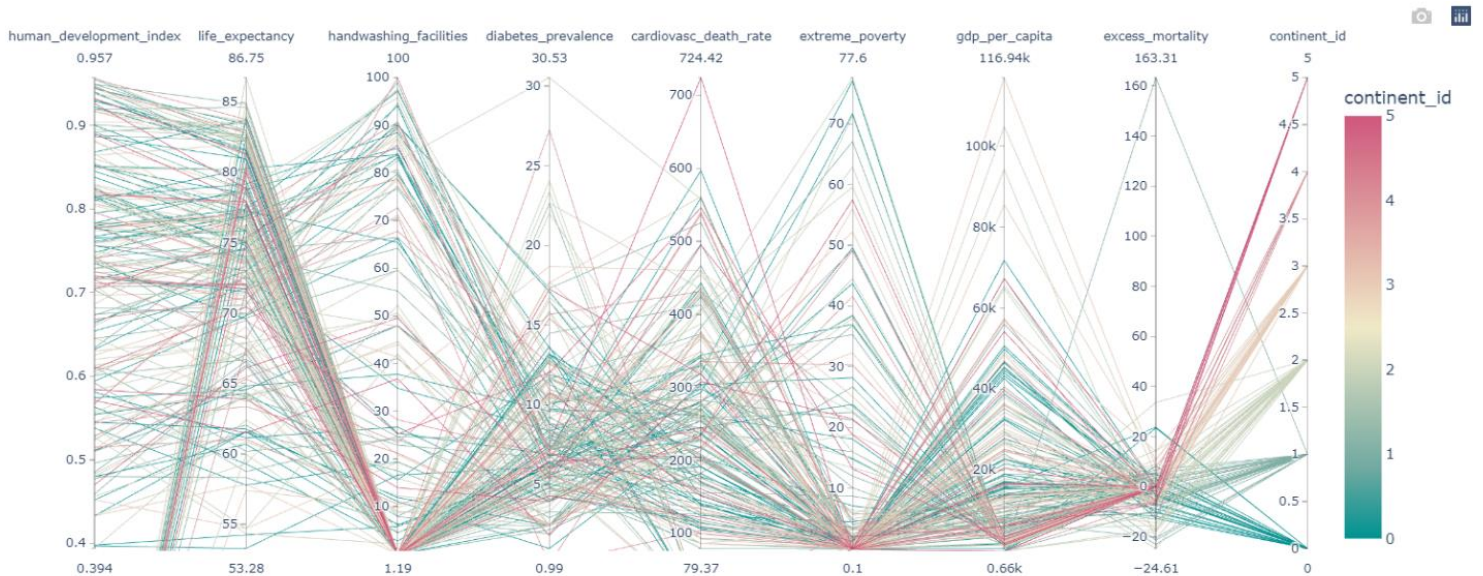
11- heatmap



Heatmaps are a good way to demonstrate a correlation map of a collection of features

12- parallel coordiantes on some features

0 : Africa, 1:Asia, 2:Europe, 3:North America, 4:Oceania, 5:South America



Using a prallel coordinate plot can give us very good relations between features, ofcourse here I couldn't find the best features to use as my plot axis but you get the idea.. the same purpose could be accomplished with a simple scatter plot with connected dots though when we have very different ranges for our features

the most dominant one overshadows all the other features, so we use a parallel coordinate system which solves the issue by using a distinct axis for each feature

13-vaccinations

We'll have 4 different visualizations to see the changes and effects of vaccination to other features, (other features like hospitalization and icu admissions and total_tests_per_hundred Had too much missing values to be meaningfully plotted)

