Covid-19 Vaccination World – EDA

About the Data Set

The data set is about the vaccination details of the current Covid-19 pandemic all over the world.

The attributes in the data set include the daily count of vaccinations as well as the percentage from the beginning of the year 2021 (Some Dec 2020 also). It also includes the type of vaccine used by each country and that will be really useful to analyze and visualize to have a good idea about the vaccines recommended most. Some of the other attributes are the dates and source of each feature. Here in this project I cleaned the data for the exploratory data analysis of my dataset and then visualized them to highlight some general features of the data set.

The data set for this project was collected from https://www.kaggle.com/datasets.

Initial Plan for the Exploration

Key Features to be used

- Data cleaning and feature engineering
- Key findings and insights
- Visualizing in a useful manner
- Hypothesis testing
- Next moves

Exploring the data

```
import numpy as np

import pandas as pd

import seaborn as sb

from scipy import stats

import matplotlib.pyplot as plt


%matplotlib inline


vd = pd.read_csv("country_vaccinations.csv")
```

Let's navigate to the top five rows of the dataframe.

```
vd.head()
```

Out[230]:

	country	iso_code	date	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations	total_vaccinations_per_
0	Afghanistan	AFG	2021-02-22	0.0	0.0	NaN	NaN	NaN	
1	Afghanistan	AFG	2021-02-23	NaN	NaN	NaN	NaN	1367.0	
2	Afghanistan	AFG	2021-02-24	NaN	NaN	NaN	NaN	1367.0	
3	Afghanistan	AFG	2021-02-25	NaN	NaN	NaN	NaN	1367.0	
4	Afghanistan	AFG	2021-02-26	NaN	NaN	NaN	NaN	1367.0	

Here we have to select the columns we need for the analysis. The unuseful columns should be dropped from the DataFrame. So Let us drop these columns in order to clean our dataset. Below mentioned data is only sufficient for our analysis.

1. iso_code
2. date
3. total_vaccinations
4. daily_vaccinations
5. total_vaccinations_per_hundred
6. daily_vaccinations_per_million
7. vaccines

We can rename the data in the attribute 'date' as follows.

```
vd['date'] = vd.date.str.replace('2021-', '')

vd['date'] = vd.date.str.replace('2020-', '')

vd.head()
```

	country	iso_code	date	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations	total_vaccinations_per
0	Afghanistan	AFG	02-22	0.0	0.0	NaN	NaN	NaN	
1	Afghanistan	AFG	02-23	NaN	NaN	NaN	NaN	1367.0	
2	Afghanistan	AFG	02-24	NaN	NaN	NaN	NaN	1367.0	
3	Afghanistan	AFG	02-25	NaN	NaN	NaN	NaN	1367.0	
4	Afghanistan	AFG	02-26	NaN	NaN	NaN	NaN	1367.0	

```
vd = vd.rename(columns={'iso_code' : 'countryCode', 'total_vaccinations' : 'totalCount', 'daily_vaccinations' : 'dailyCount', 'total_vaccinations_per_hundred' : 'totalPercentage', 'daily_vaccinations_per_million' : 'dailyCountPerMillion'})

vd.head()
```

ions_raw	dailyCount	totalPercentage	people_vaccinated_per_hundred	people_fully_vaccinated_per_hundred	dailyCountPerMillion	vaccines	source_nam
NaN	NaN	0.0	0.0	NaN	NaN	Oxford/AstraZeneca	Governmer of Afghanista
NaN	1367.0	NaN	NaN	NaN	35.0	Oxford/AstraZeneca	Governmer of Afghanista
NaN	1367.0	NaN	NaN	NaN	35.0	Oxford/AstraZeneca	Governmer of Afghanista
NaN	1367.0	NaN	NaN	NaN	35.0	Oxford/AstraZeneca	Governmer of Afghanista
NaN	1367.0	NaN	NaN	NaN	35.0	Oxford/AstraZeneca	Governmer of Afghanista

Now let's have a description about the data set

```
print('Number of rows: ' + str(vd.shape[0]))

print('Column names: ' + str(vd.columns.tolist()))

print('Number of countries: ' + str(len(vd['countryCode'].unique())))

print('Number of missing values: \n' + str(vd.isnull().sum()))
```

```
Number of rows: 15666
Column names: ['country', 'countryCode', 'date', 'totalCount', 'people_vacc
inated', 'people_fully_vaccinated', 'daily_vaccinations_raw', 'dailyCount',
'totalPercentage', 'people_vaccinated_per_hundred', 'people_fully_vaccinate
d_per_hundred', 'dailyCountPerMillion', 'vaccines', 'source_name', 'source_
website']
Number of countries: 196
Number of missing values:
country                                0
countryCode                            0
date                                   0
totalCount                          6229
people_vaccinated                   6912
people_fully_vaccinated             9164
daily_vaccinations_raw              7738
dailyCount                           201
totalPercentage                     6229
people_vaccinated_per_hundred       6912
people_fully_vaccinated_per_hundred 9164
dailyCountPerMillion                 201
vaccines                               0
source_name                            0
source_website                         0
dtype: int64
```

In [116]:

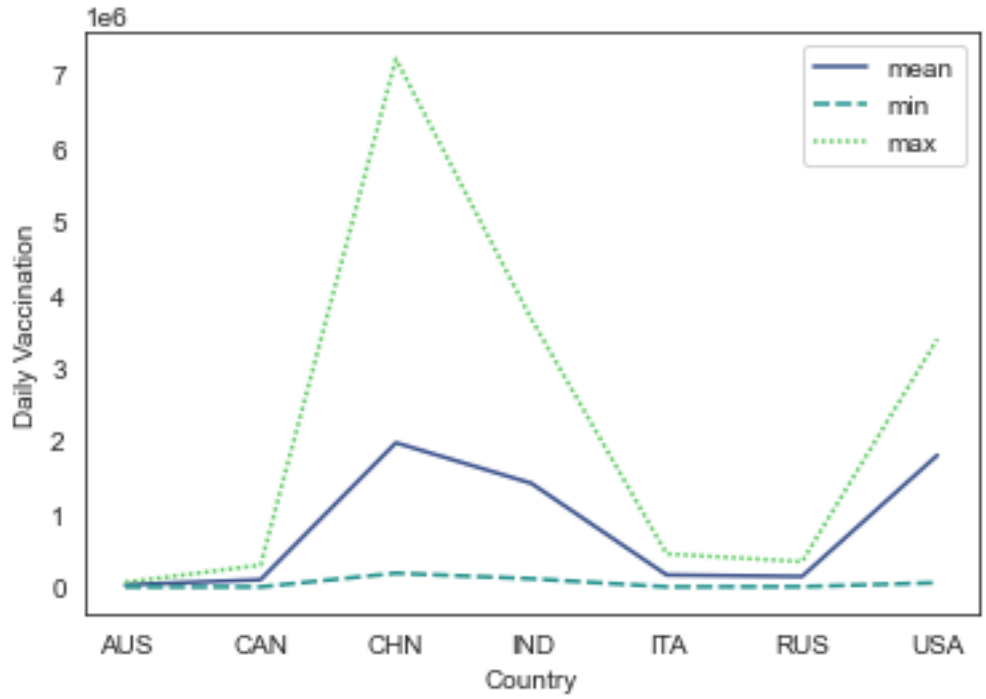
```
sufficient_fields = ['countryCode','date', 'dailyCount', 'dailyCountPerMillion', 'vaccines']

vd = vd[sufficient_fields]

vd.head()
```

Out[116]:

	countryCode	date	dailyCount	dailyCountPerMillion	vaccines
0	AFG	02-22	NaN	NaN	Oxford/AstraZeneca
1	AFG	02-23	1367.0	35.0	Oxford/AstraZeneca
2	AFG	02-24	1367.0	35.0	Oxford/AstraZeneca
3	AFG	02-25	1367.0	35.0	Oxford/AstraZeneca
4	AFG	02-26	1367.0	35.0	Oxford/AstraZeneca

Below is the graph of the mean, min and max of daily vaccination count of some specified countries:

```
spec = vd[(vd['countryCode'] == 'ITA') | (vd['countryCode'] == 'USA') | (vd['countryCode'] == 'IND') | (vd['countryCode'] == 'CHN') | (vd['countryCode'] == 'RUS') | (vd['countryCode'] == 'UK') | (vd['countryCode'] == 'AUS') | (vd['countryCode'] == 'CAN')]

df = spec.groupby('countryCode')['dailyCount'].agg(['mean', 'min', 'max'])

ax = sb.lineplot(data=df, palette="viridis")

ax.set(xlabel='Country', ylabel='Daily Vaccination')
```

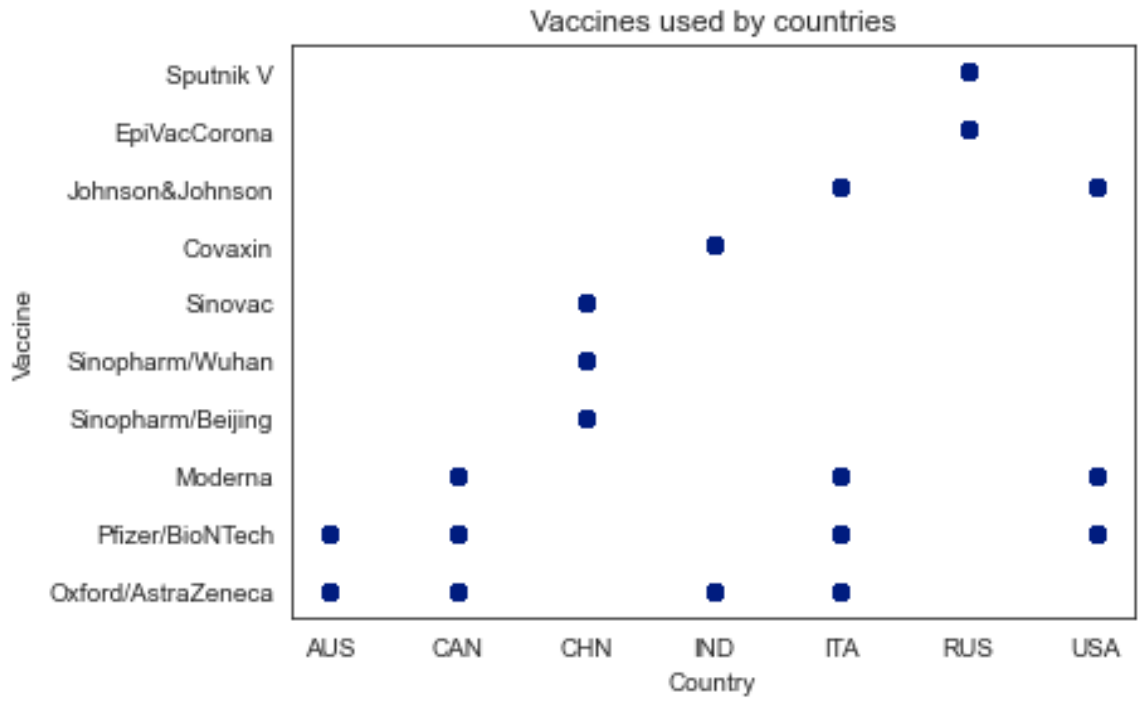


Let's visualize the vaccines used by above mentioned countries.

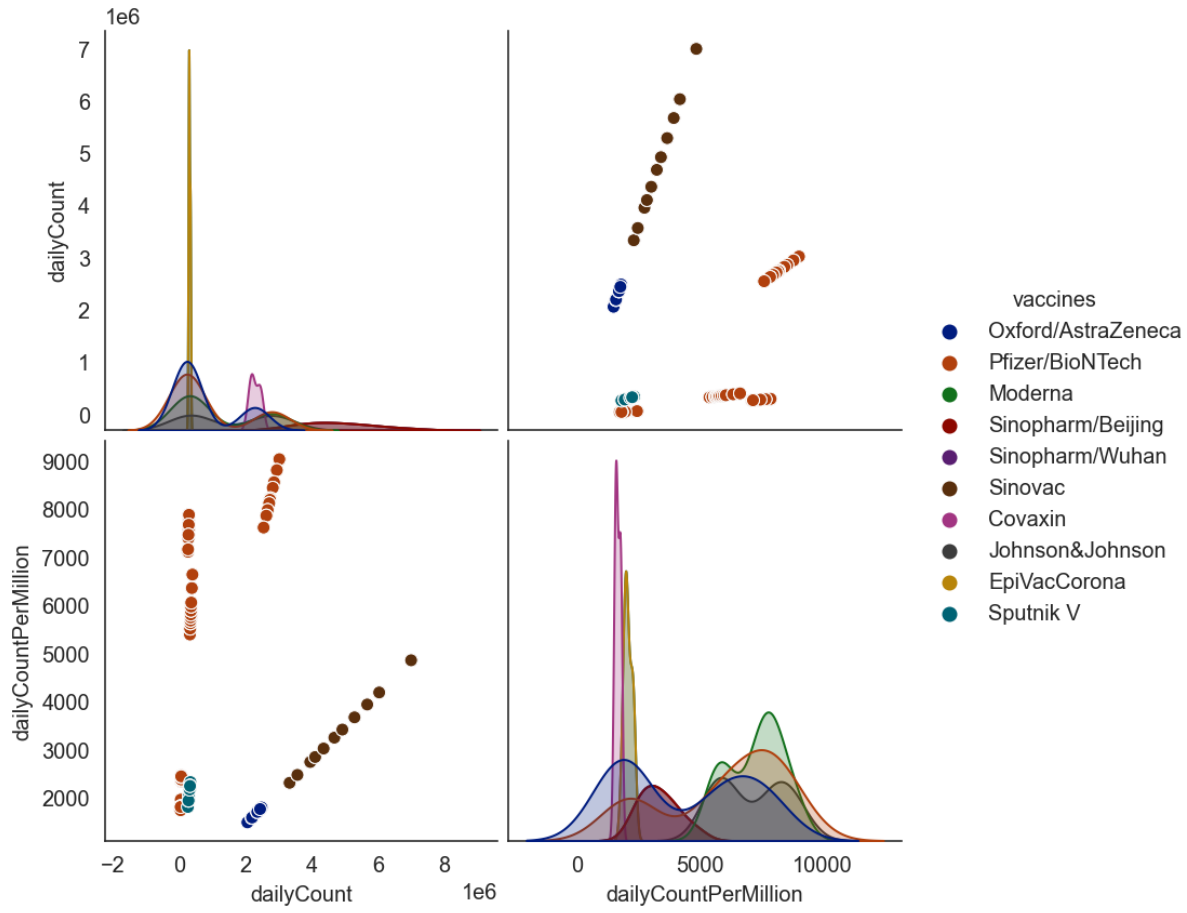
```
lst_col = 'vaccines'

x = vd.assign(**{lst_col:vd[lst_col].str.split(', ')})

vd2 = pd.DataFrame({col:np.repeat(x[col].values, x[lst_col].str.len())

for col in
x.columns.difference([lst_col])}).assign(**{lst_col:np.concatenate(x[lst_col].values)})[x.columns.tolist()]

vd2.vaccines.value_counts()
```

```
Oxford/AstraZeneca    11702
Pfizer/BioNTech        9907
Moderna                4903
Sinopharm/Beijing      2866
Sputnik V              2437
Sinovac                2147
Johnson&Johnson        1749
Sinopharm/Wuhan         265
CanSino                 226
EpiVacCorona            143
Covaxin                 112
Name: vaccines, dtype: int64
```

```
spec = vd2[(vd2['countryCode'] == 'ITA') | (vd2['countryCode'] == 'USA') | (vd2['countryCode'] == 'IND') | (vd2['countryCode'] == 'CHN') | (vd2['countryCode'] == 'RUS') | (vd2['countryCode'] == 'UK') | (vd2['countryCode'] == 'AUS') | (vd2['countryCode'] == 'CAN')]

ax = plt.axes()

ax.scatter(spec.countryCode, spec.vaccines)

ax.set(xlabel='Country',

    ylabel='Vaccine',

    title='Vaccines used by countries');
```



```
sb.pairplot(spec, hue='vaccines', height=3)
```



Feature Engineering

```
vd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15666 entries, 0 to 15665
Data columns (total 5 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   countryCode           15666 non-null  object
 1   date                  15666 non-null  object
 2   dailyCount            15465 non-null  float64
 3   dailyCountPerMillion  15465 non-null  float64
 4   vaccines              15666 non-null  object
dtypes: float64(2), object(3)
memory usage: 612.1+ KB
```

It shows that our data set has only two missing values. So there is no need of dropping any column.

```
num_cols = vd.select_dtypes('number').columns

num_cols
```

```
Index(['dailyCount', 'dailyCountPerMillion'], dtype='object')
```

```
skew_limit = 0.75

skew_vals = vd[num_cols].skew()

skew_vals
```

```
dailyCount              9.954500
dailyCountPerMillion    7.729351
dtype: float64
```

```
skew_cols = skew_vals[abs(skew_vals > skew_limit)].sort_values(ascending=False)

skew_cols
```

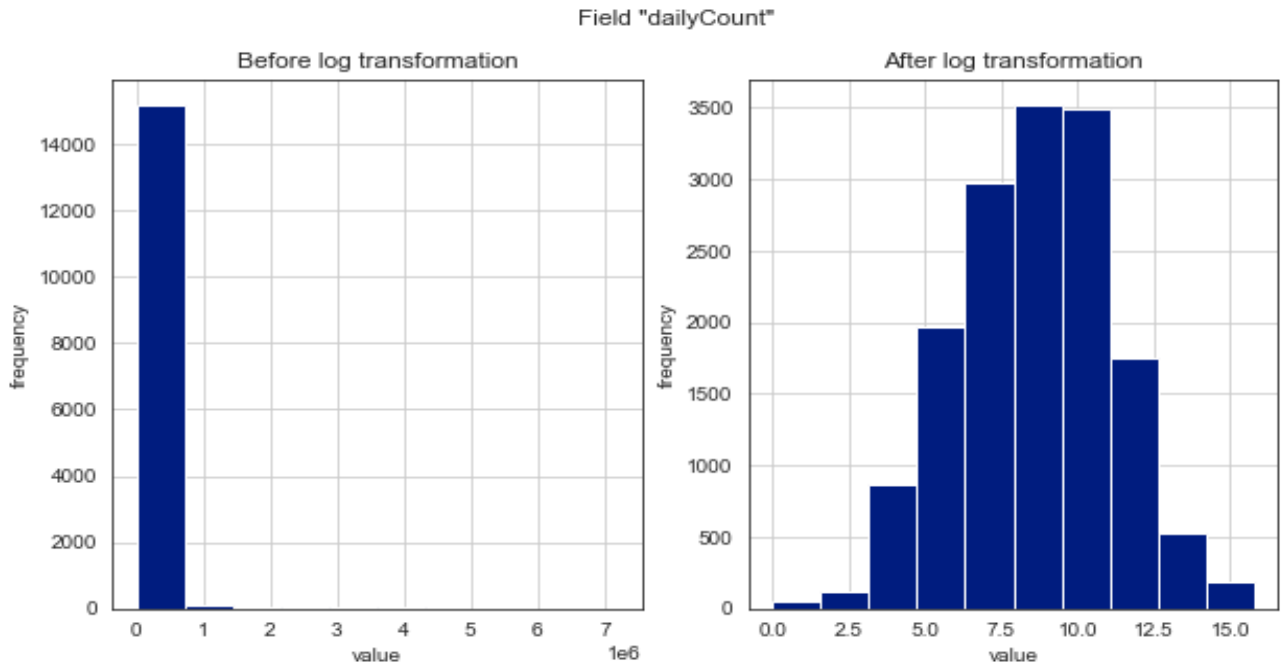
```
dailyCount              9.954500
dailyCountPerMillion    7.729351
dtype: float64
```

Applying logarithmic transformation

Let's select most skewed field, 'dailyCount'

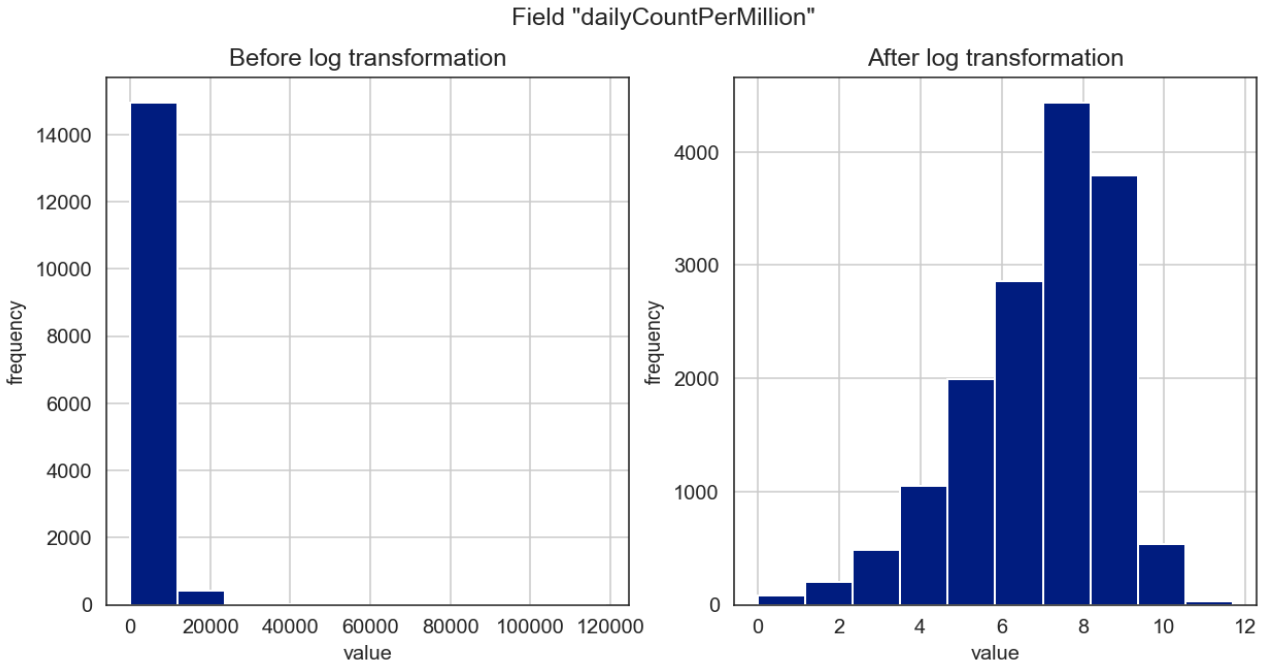
```
field = "dailyCount"


fig, (ax_before,ax_after) = plt.subplots(1,2,figsize=(10,5))

vd[field].hist(ax=ax_before)

vd[field].apply(np.log1p).hist(ax=ax_after)
```

```
ax_before.set(title='Before log transformation', ylabel='frequency', xlabel='value')
ax_after.set(title='After log transformation', ylabel='frequency', xlabel='value')
fig.suptitle('Field "{}"'.format(field));
```



Let's do the same to the dailyCountPerMillion field

```
%config InlineBackend.figure_formats = ['retina']
field = "dailyCountPerMillion"

fig, (ax_before,ax_after) = plt.subplots(1,2,figsize=(10,5))
vd[field].hist(ax=ax_before)
vd[field].apply(np.log1p).hist(ax=ax_after)

ax_before.set(title='Before log transformation', ylabel='frequency', xlabel='value')
ax_after.set(title='After log transformation', ylabel='frequency', xlabel='value')
fig.suptitle('Field "{}"'.format(field));
```



Hypothesis Testing

Let's take the vaccination details from 11/04 to 20/4 and 21/04 to 30/04

```
spec_main = vd[(vd['countryCode'] == 'IND')]

spec_main
```

:

	countryCode	date	dailyCount	dailyCountPerMillion	vaccines
6394	IND	01-15	NaN	NaN	Covaxin, Oxford/AstraZeneca
6395	IND	01-16	191181.0	139.0	Covaxin, Oxford/AstraZeneca
6396	IND	01-17	112150.0	81.0	Covaxin, Oxford/AstraZeneca
6397	IND	01-18	151350.0	110.0	Covaxin, Oxford/AstraZeneca
6398	IND	01-19	168709.0	122.0	Covaxin, Oxford/AstraZeneca
...	...	...	...	...	...
6501	IND	05-02	2146620.0	1556.0	Covaxin, Oxford/AstraZeneca
6502	IND	05-03	1936741.0	1403.0	Covaxin, Oxford/AstraZeneca
6503	IND	05-04	1838788.0	1332.0	Covaxin, Oxford/AstraZeneca
6504	IND	05-05	1839692.0	1333.0	Covaxin, Oxford/AstraZeneca
6505	IND	05-06	1904976.0	1380.0	Covaxin, Oxford/AstraZeneca

112 rows × 5 columns

Hypothesis: The mean value of the mean daily vaccination count of India during the month of March is as same as the month of April

Alternative Hypothesis: There is no relationship between number of vaccinations done in given In two months

Results

As the number of Covid-19 patients increasing and decreasing time by time, the number of vaccinations can be seen as not connected to each other.

Next Moves

After the EDA part, we can either analyse the data further or we can use the data set for future ML model to do a prediction that how many vaccines must be consunmed by each country in future or to predict which of the above vaccines going to be used much or less etc.