Project 2

CS 5/7394 - Applied Machine Learning

- **Due** - March 11 @ 11:59 pm pushed to Github repo
- **Teams** - You can do this project solo or in pairs. Not 3, not 4 not 5... Max of 2. If a 5394 student pairs with a 7394 student, the pair needs to do the 7394 work.

Below are 6 Kaggle Datasets. You will choose 1 to work with for this project.

- Airfare Prediction Dataset
- Chinese Rest Holiday Dataset
- Jigsaw Toxic Comment Classification Challenge
- Latest Covid 19 Dataset Worldwide
- Trains
- Football Data top 5 Leagues

Merging disparate datasets is a staple of the data exploration process. Therefore, for which ever data set above that you choose, you will need to independently find **an additional** dataset to merge with your selection. The only requirement is that it add to the richness of the original dataset. Students in the 7000-level version of the class need to find two additional data sets to merge with the original selection.

Note: If you want to start with a different data set, you need to get Fontenot's OK first.

Your Tasks

Below, there are cells that provide directions on what to do for the project.

You can insert as many cells between the ones below as you'd like, but please **Do NOT** change the cells already provided.

Part 1 - Getting Started

- Import libraries
- Load original Data (which ever one you chose from the provided list) into a data frame.
- Load your additional data set(s) into a data frame.
- In a markdown cell, provide a brief description of your the data sets you've chosen to work with.
- Develop a list of 3 - 4 questions that you hope to be able to answer after the exploration of the data and write them in this section.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
import matplotlib as mpl
covidRaw = pd.read_csv("archive/owid-covid-data.csv")
vaccineRaw = pd.read_csv("Manufacturers/country_vaccinations_by_manufacturer.csv")
```

Original Dataset: Latest Covid 19 Dataset Worldwide

This dataset provides a summary of COVID-19 cases, vaccination rates, hospitalization rates, and more from Jan 28, 2020 to Jan 8, 2022.

Second Dataset: COVID-19 World Vaccinations By Manufacturer

This dataset is a record of the number of each type of COVID-19 vaccine that was administered each day in each country.

Questions to answer:

- Which countries had the highest total death rates the quickest?
- Which COVID-19 vaccine manufacturer is the most popular in the world?
- Did the popularity of the Johnson & Johnson vaccine decrease worldwide after negative side effects were reported?

Part 2 - Data Inspection

Write some code to summarize the datasets. Think about the following questions:

- What type of data is each variable? (think like a data scientist here, not a computer scientist)
- What is the total size of the data sets?
- What time boundaries are there in the dataset? IOW, what time frame do they span?
- Are there any missing values in any of the variables?

Do this with Intentionality. Don't skimp.

Initial Dataset

In [2]:

```
covidRaw.info() #This line of code provides an excellent summary of the dataset. For th
# most of the columns will not be necessary.
# There is a total of 153172 entries across 67 columns.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153172 entries, 0 to 153171
Data columns (total 67 columns):
 #   Column                                      Non-Null Count   Dtype
---  ------                                      --------------   -----
 0   iso_code                                    153172 non-null  object
 1   continent                                   143944 non-null  object
 2   location                                    153172 non-null  object
 3   date                                        153172 non-null  object
 4   total_cases                                 150522 non-null  float64
 5   new_cases                                   150431 non-null  float64
 6   new_cases_smoothed                          149280 non-null  float64
 7   total_deaths                                133279 non-null  float64
```

```
8   new_deaths                                    133441 non-null  float64
9   new_deaths_smoothed                           133309 non-null  float64
10  total_cases_per_million                       149820 non-null  float64
11  new_cases_per_million                         149729 non-null  float64
12  new_cases_smoothed_per_million                148583 non-null  float64
13  total_deaths_per_million                      132590 non-null  float64
14  new_deaths_per_million                        132752 non-null  float64
15  new_deaths_smoothed_per_million               132620 non-null  float64
16  reproduction_rate                             114970 non-null  float64
17  icu_patients                                  19330 non-null   float64
18  icu_patients_per_million                      19330 non-null   float64
19  hosp_patients                                 21303 non-null   float64
20  hosp_patients_per_million                     21303 non-null   float64
21  weekly_icu_admissions                         4339 non-null    float64
22  weekly_icu_admissions_per_million             4339 non-null    float64
23  weekly_hosp_admissions                        8696 non-null    float64
24  weekly_hosp_admissions_per_million            8696 non-null    float64
25  new_tests                                     60733 non-null   float64
26  total_tests                                   62146 non-null   float64
27  total_tests_per_thousand                      62146 non-null   float64
28  new_tests_per_thousand                        60733 non-null   float64
29  new_tests_smoothed                            74236 non-null   float64
30  new_tests_smoothed_per_thousand               73535 non-null   float64
31  positive_rate                                 69318 non-null   float64
32  tests_per_case                                68655 non-null   float64
33  tests_units                                   75706 non-null   object
34  total_vaccinations                            39438 non-null   float64
35  people_vaccinated                             37767 non-null   float64
36  people_fully_vaccinated                       34895 non-null   float64
37  total_boosters                                12431 non-null   float64
38  new_vaccinations                              32684 non-null   float64
39  new_vaccinations_smoothed                     71698 non-null   float64
40  total_vaccinations_per_hundred                39438 non-null   float64
41  people_vaccinated_per_hundred                 37767 non-null   float64
42  people_fully_vaccinated_per_hundred           34895 non-null   float64
43  total_boosters_per_hundred                    12431 non-null   float64
44  new_vaccinations_smoothed_per_million         71698 non-null   float64
45  new_people_vaccinated_smoothed                70460 non-null   float64
46  new_people_vaccinated_smoothed_per_hundred    70460 non-null   float64
47  stringency_index                              119510 non-null  float64
48  population                                    152153 non-null  float64
49  population_density                            136343 non-null  float64
50  median_age                                    127234 non-null  float64
51  aged_65_older                                 125852 non-null  float64
52  aged_70_older                                 126551 non-null  float64
53  gdp_per_capita                                127647 non-null  float64
54  extreme_poverty                               84258 non-null   float64
55  cardiovasc_death_rate                         126237 non-null  float64
56  diabetes_prevalence                           132708 non-null  float64
57  female_smokers                                97777 non-null   float64
58  male_smokers                                  96369 non-null   float64
59  handwashing_facilities                        63222 non-null   float64
60  hospital_beds_per_thousand                    114047 non-null  float64
61  life_expectancy                               142953 non-null  float64
62  human_development_index                       125712 non-null  float64
63  excess_mortality_cumulative_absolute          5234 non-null    float64
64  excess_mortality_cumulative                   5234 non-null    float64
65  excess_mortality                              5234 non-null    float64
66  excess_mortality_cumulative_per_million       5234 non-null    float64
```

```
dtypes: float64(62), object(5)
memory usage: 78.3+ MB
```

In [3]:
```
# For the sake of this project, most of the columns will not be necessary.
# Rather than deleting each column I don't want one by one, I'll be making a new datafr
covid = covidRaw[['date','iso_code', 'location', 'total_cases', 'new_cases', 'new_death
```

In [4]:
```
covid.head() #Here we can see that there are quite a few missing values. These don't re
# especially since they are numerical variables (you don't say that there are NaN total
# This is a problem we'll address quickly.
```

Out[4]:

	date	iso_code	location	total_cases	new_cases	new_deaths	total_deaths	gdp_per_capita	total_
0	2020-02-24	AFG	Afghanistan	5.0	5.0	NaN	NaN	1803.987	
1	2020-02-25	AFG	Afghanistan	5.0	0.0	NaN	NaN	1803.987	
2	2020-02-26	AFG	Afghanistan	5.0	0.0	NaN	NaN	1803.987	
3	2020-02-27	AFG	Afghanistan	5.0	0.0	NaN	NaN	1803.987	
4	2020-02-28	AFG	Afghanistan	5.0	0.0	NaN	NaN	1803.987	

In [5]:
```
covid = covid.fillna(0) #This is now a much cleaner dataset to work with, but there's s
```

In [6]:
```
covid.info() # This dataset now has 20 columns of 153172 instances, and there is no lon
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153172 entries, 0 to 153171
Data columns (total 20 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   date                      153172 non-null  object
 1   iso_code                  153172 non-null  object
 2   location                  153172 non-null  object
 3   total_cases               153172 non-null  float64
 4   new_cases                 153172 non-null  float64
 5   new_deaths                153172 non-null  float64
 6   total_deaths              153172 non-null  float64
 7   gdp_per_capita            153172 non-null  float64
 8   total_tests               153172 non-null  float64
 9   new_vaccinations          153172 non-null  float64
 10  positive_rate             153172 non-null  float64
 11  human_development_index   153172 non-null  float64
 12  icu_patients              153172 non-null  float64
 13  hosp_patients             153172 non-null  float64
 14  new_tests                 153172 non-null  float64
 15  people_vaccinated         153172 non-null  float64
 16  people_fully_vaccinated   153172 non-null  float64
```

```
 17  population                153172 non-null  float64
 18  total_vaccinations        153172 non-null  float64
 19  aged_65_older             153172 non-null  float64
dtypes: float64(17), object(3)
memory usage: 23.4+ MB
```

In [7]:

```
covid.location.unique()
```

Out[7]:

```
array(['Afghanistan', 'Africa', 'Albania', 'Algeria', 'Andorra', 'Angola',
       'Anguilla', 'Antigua and Barbuda', 'Argentina', 'Armenia', 'Aruba',
       'Asia', 'Australia', 'Austria', 'Azerbaijan', 'Bahamas', 'Bahrain',
       'Bangladesh', 'Barbados', 'Belarus', 'Belgium', 'Belize', 'Benin',
       'Bermuda', 'Bhutan', 'Bolivia', 'Bonaire Sint Eustatius and Saba',
       'Bosnia and Herzegovina', 'Botswana', 'Brazil',
       'British Virgin Islands', 'Brunei', 'Bulgaria', 'Burkina Faso',
       'Burundi', 'Cambodia', 'Cameroon', 'Canada', 'Cape Verde',
       'Cayman Islands', 'Central African Republic', 'Chad', 'Chile',
       'China', 'Colombia', 'Comoros', 'Congo', 'Cook Islands',
       'Costa Rica', "Cote d'Ivoire", 'Croatia', 'Cuba', 'Curacao',
       'Cyprus', 'Czechia', 'Democratic Republic of Congo', 'Denmark',
       'Djibouti', 'Dominica', 'Dominican Republic', 'Ecuador', 'Egypt',
       'El Salvador', 'Equatorial Guinea', 'Eritrea', 'Estonia',
       'Eswatini', 'Ethiopia', 'Europe', 'European Union',
       'Faeroe Islands', 'Falkland Islands', 'Fiji', 'Finland', 'France',
       'French Polynesia', 'Gabon', 'Gambia', 'Georgia', 'Germany',
       'Ghana', 'Gibraltar', 'Greece', 'Greenland', 'Grenada',
       'Guatemala', 'Guernsey', 'Guinea', 'Guinea-Bissau', 'Guyana',
       'Haiti', 'High income', 'Honduras', 'Hong Kong', 'Hungary',
       'Iceland', 'India', 'Indonesia', 'International', 'Iran', 'Iraq',
       'Ireland', 'Isle of Man', 'Israel', 'Italy', 'Jamaica', 'Japan',
       'Jersey', 'Jordan', 'Kazakhstan', 'Kenya', 'Kiribati', 'Kosovo',
       'Kuwait', 'Kyrgyzstan', 'Laos', 'Latvia', 'Lebanon', 'Lesotho',
       'Liberia', 'Libya', 'Liechtenstein', 'Lithuania', 'Low income',
       'Lower middle income', 'Luxembourg', 'Macao', 'Madagascar',
       'Malawi', 'Malaysia', 'Maldives', 'Mali', 'Malta',
       'Marshall Islands', 'Mauritania', 'Mauritius', 'Mexico',
       'Micronesia (country)', 'Moldova', 'Monaco', 'Mongolia',
       'Montenegro', 'Montserrat', 'Morocco', 'Mozambique', 'Myanmar',
       'Namibia', 'Nauru', 'Nepal', 'Netherlands', 'New Caledonia',
       'New Zealand', 'Nicaragua', 'Niger', 'Nigeria', 'Niue',
       'North America', 'North Macedonia', 'Northern Cyprus', 'Norway',
       'Oceania', 'Oman', 'Pakistan', 'Palau', 'Palestine', 'Panama',
       'Papua New Guinea', 'Paraguay', 'Peru', 'Philippines', 'Pitcairn',
       'Poland', 'Portugal', 'Qatar', 'Romania', 'Russia', 'Rwanda',
       'Saint Helena', 'Saint Kitts and Nevis', 'Saint Lucia',
       'Saint Pierre and Miquelon', 'Saint Vincent and the Grenadines',
       'Samoa', 'San Marino', 'Sao Tome and Principe', 'Saudi Arabia',
       'Senegal', 'Serbia', 'Seychelles', 'Sierra Leone', 'Singapore',
       'Sint Maarten (Dutch part)', 'Slovakia', 'Slovenia',
       'Solomon Islands', 'Somalia', 'South Africa', 'South America',
       'South Korea', 'South Sudan', 'Spain', 'Sri Lanka', 'Sudan',
       'Suriname', 'Sweden', 'Switzerland', 'Syria', 'Taiwan',
       'Tajikistan', 'Tanzania', 'Thailand', 'Timor', 'Togo', 'Tokelau',
       'Tonga', 'Trinidad and Tobago', 'Tunisia', 'Turkey',
       'Turkmenistan', 'Turks and Caicos Islands', 'Tuvalu', 'Uganda',
       'Ukraine', 'United Arab Emirates', 'United Kingdom',
       'United States', 'Upper middle income', 'Uruguay', 'Uzbekistan',
       'Vanuatu', 'Vatican', 'Venezuela', 'Vietnam', 'Wallis and Futuna',
       'World', 'Yemen', 'Zambia', 'Zimbabwe'], dtype=object)
```

In [8]:
```
covid.date.head() # This dataset begins on Feb. 24th, 2020
```

Out[8]:
```
0    2020-02-24
1    2020-02-25
2    2020-02-26
3    2020-02-27
4    2020-02-28
Name: date, dtype: object
```

In [9]:
```
covid.date.tail() # This is consistent with the dataset's description: "The dataset con
```

Out[9]:
```
153167    2022-01-04
153168    2022-01-05
153169    2022-01-06
153170    2022-01-07
153171    2022-01-08
Name: date, dtype: object
```

In [10]:
```
covid.head() # Our data looks much better now.
```

Out[10]:

	date	iso_code	location	total_cases	new_cases	new_deaths	total_deaths	gdp_per_capita	total_
0	2020-02-24	AFG	Afghanistan	5.0	5.0	0.0	0.0	1803.987	
1	2020-02-25	AFG	Afghanistan	5.0	0.0	0.0	0.0	1803.987	
2	2020-02-26	AFG	Afghanistan	5.0	0.0	0.0	0.0	1803.987	
3	2020-02-27	AFG	Afghanistan	5.0	0.0	0.0	0.0	1803.987	
4	2020-02-28	AFG	Afghanistan	5.0	0.0	0.0	0.0	1803.987	

Secondary dataset: vaccine data

In [11]:
```
vaccineRaw.info() #This is a much smaller dataset, but it luckily won't take as much ef
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28833 entries, 0 to 28832
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   location            28833 non-null  object
 1   date                28833 non-null  object
 2   vaccine             28833 non-null  object
 3   total_vaccinations  28833 non-null  int64 
dtypes: int64(1), object(3)
memory usage: 901.2+ KB
```

In [12]:
```
vaccineRaw.head()
```

Out[12]:

	location	date	vaccine	total_vaccinations
0	Austria	2021-01-08	Johnson&Johnson	0
1	Austria	2021-01-08	Moderna	0
2	Austria	2021-01-08	Oxford/AstraZeneca	0
3	Austria	2021-01-08	Pfizer/BioNTech	31632
4	Austria	2021-01-15	Johnson&Johnson	0

In [13]:
```
vaccineRaw.location.unique()
```

Out[13]:
```
array(['Austria', 'Belgium', 'Bulgaria', 'Chile', 'Croatia', 'Cyprus',
       'Czechia', 'Denmark', 'Ecuador', 'Estonia', 'Finland', 'France',
       'Germany', 'Hong Kong', 'Hungary', 'Iceland', 'Ireland', 'Italy',
       'Japan', 'Latvia', 'Liechtenstein', 'Lithuania', 'Luxembourg',
       'Malta', 'Nepal', 'Netherlands', 'Norway', 'Peru', 'Poland',
       'Portugal', 'Romania', 'Slovakia', 'Slovenia', 'South Korea',
       'Spain', 'Sweden', 'Switzerland', 'Ukraine', 'United States',
       'Uruguay', 'European Union'], dtype=object)
```

In [14]:
```
# Ideally I want to switch the columns around to consolidate each day for each country
# I want each of the vaccines to have a column with their count for that day.
vaccineRaw.vaccine.unique()
```

Out[14]:
```
array(['Johnson&Johnson', 'Moderna', 'Oxford/AstraZeneca',
       'Pfizer/BioNTech', 'Sinovac', 'CanSino', 'Sputnik V',
       'Sinopharm/Beijing', 'Novavax'], dtype=object)
```

In [15]:
```
vaccineRaw.date.describe #This dataset spans Jan 8th, 2021 to Feb 24th, 2022. That's no
# time that we should be able to get meaningful analysis from comparing the two.
```

Out[15]:
```
<bound method NDFrame.describe of 0        2021-01-08
1        2021-01-08
2        2021-01-08
3        2021-01-08
4        2021-01-15
            ...
28828    2022-02-24
28829    2022-02-24
28830    2022-02-24
28831    2022-02-24
28832    2022-02-24
Name: date, Length: 28833, dtype: object>
```

In [16]:
```
# I want to make each of these vaccine types into a column and make the corresponding '
vaccinePivot= vaccineRaw.pivot(index=['location','date'],columns='vaccine')['total_vacc
# It took a while to figure out but now we have a presentable dataset that will be comp
```

In [17]:
```
vaccineClean = vaccinePivot.fillna(0)  #Since we're counting the number of each vaccine
```

In [18]:
```
vaccineClean
```

Out[18]:

	vaccine	location	date	CanSino	Johnson&Johnson	Moderna	Novavax	Oxford/AstraZeneca	Pfizer/B
0		Austria	2021-01-08	0.0	0.0	0.0	0.0	0.0	
1		Austria	2021-01-15	0.0	0.0	97.0	0.0	0.0	
2		Austria	2021-01-22	0.0	0.0	341.0	0.0	0.0	
3		Austria	2021-01-29	0.0	0.0	4340.0	0.0	0.0	
4		Austria	2021-02-05	0.0	0.0	6056.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
7950		Uruguay	2022-02-20	0.0	0.0	0.0	0.0	89635.0	2
7951		Uruguay	2022-02-21	0.0	0.0	0.0	0.0	89635.0	2
7952		Uruguay	2022-02-22	0.0	0.0	0.0	0.0	89635.0	2
7953		Uruguay	2022-02-23	0.0	0.0	0.0	0.0	89635.0	2
7954		Uruguay	2022-02-24	0.0	0.0	0.0	0.0	89635.0	2

7955 rows × 11 columns

In [19]:

```
vaccineClean = vaccineClean.rename(columns={"Johnson&Johnson":"JJ", "Oxford/AstraZeneca
# Here I've renamed the column to JJ
# Additionally, a few other columns have the same issue. I've gone ahead and just added
```

We now have both of our datasets in a position where we could merge them.

Part 3 - Data Description

- Create a data description (data dictionary) for your data sets.
  - Describe each variable
  - If categorical, what levels are present? If the levels are encoded, what do the codes mean?
  - If numeric, provide min, max, median and any other univariate stats you'd like to add in.
- Where appropriate, provide histograms or other visualizations to characterize each variable.

Initial Dataset:

Categorical:

- date: the date of the observation (different day for each day in the span of the dataset (from Jan 8 2021 - Jan 8 2022)
- iso_code: 3 letter country code
- location: country name

Numeric:

- total_cases: the total confirmed cases of COVID-19 (cumulative) (min: 0, max: 3.051916e+08, mean: 2.103392e+06)
- new_cases: new confirmed cases of COVID-19 (min: 0, max: 2.879121e+06, mean: 8.362585e+03)
- new_deaths: new deaths attributed to COVID-19 (min: 0, max: 18062, mean: 148.549102)
- total_deaths: total deaths attributed to COVID-19 (min: 0, max: 5.484782e+06, mean: 4.599508e+04)
- gdp_per_capita: GDP at purchasing power parity (constant 2011 international dollars), from the most recent year available (min: 0, max: 116935.60, mean: 16404.527025)
- human_development_index: composite index measuring average achievement in 3 basic dimensions of human development (long healthy life, knowledge, standard of living) (min: 0, max: 0.957, mean: 0.595734)
- icu_patients: number of COVID-19 patients in intensive care units on a given day (min: 0, max: 28891, mean: 118.789596)
- hosp_patients: number of COVID-19 patients in the hospital on a given day (min: 0, max: 133268, 559.981805)
- new_tests: new tests for COVID-19 (min: 0, max: 3.740296e+06, mean: 2.443949e+04)
- people_vaccinated: total number of people who received at least one vaccine dose (cumulative) (min: 0, max: 4.655633e+09, mean: 1.823795e+07)
- people_fully_vaccinated: total number of people who received all doses prescribed (cumulative) (min: 0, max: .934990e+09, mean: 1.256051e+07)
- population: latest available value of population (min: 1.002197e+06, max: 7.874966e+09, mean: 1.474617e+08)
- total_vaccinations: total number of COVID-19 vaccination doses administered (cumulative) (min: 0, max: 9.421129e+09, mean: 3.611898e+07)
- aged_65_older: % share of the population that is 65+ according to the most recent info (min: 0, max: 27.049000, 7.208174)

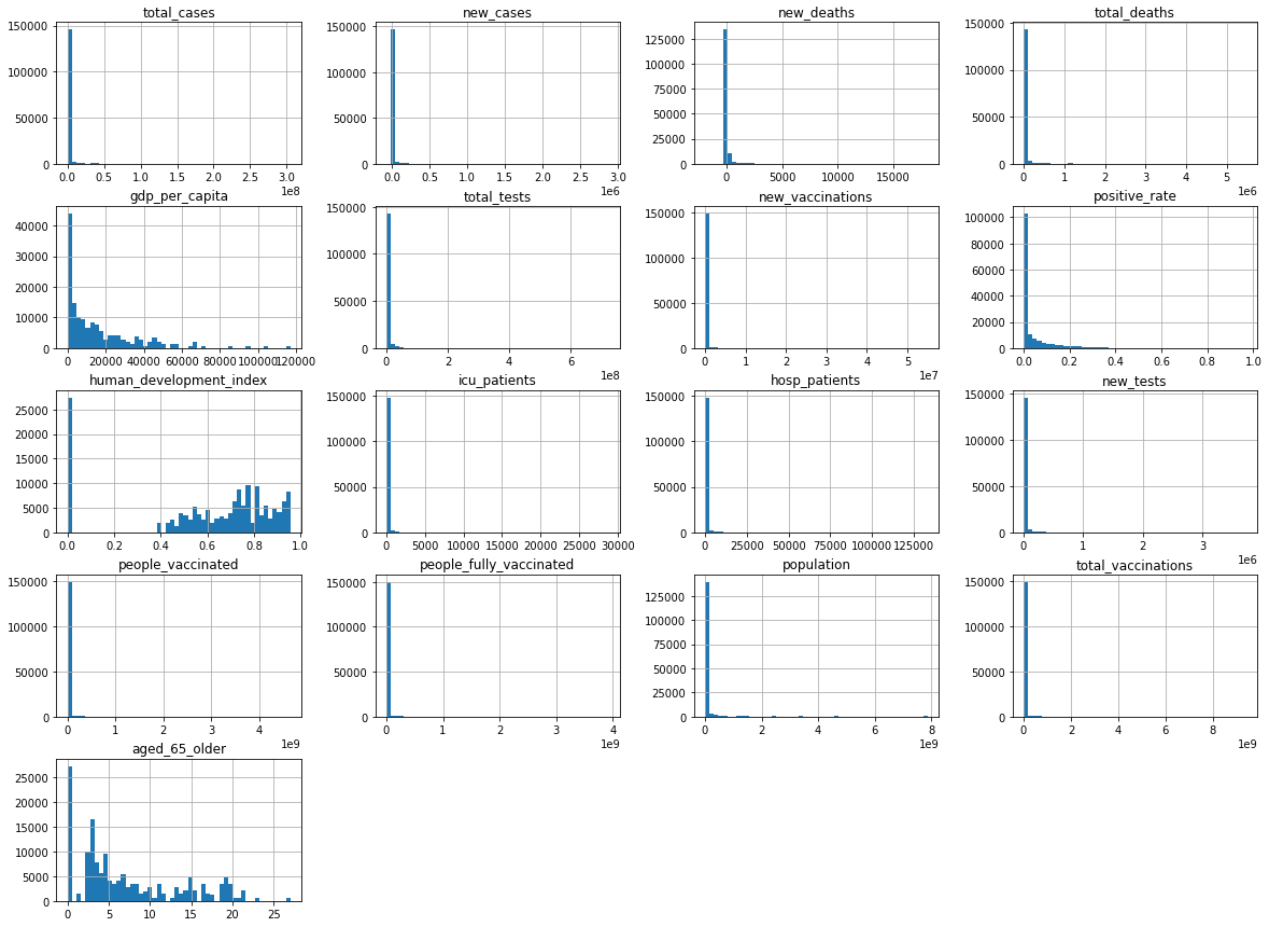
Secondary Dataset: (omitting data that will be overlapped in merge: location, date)

Numerical:

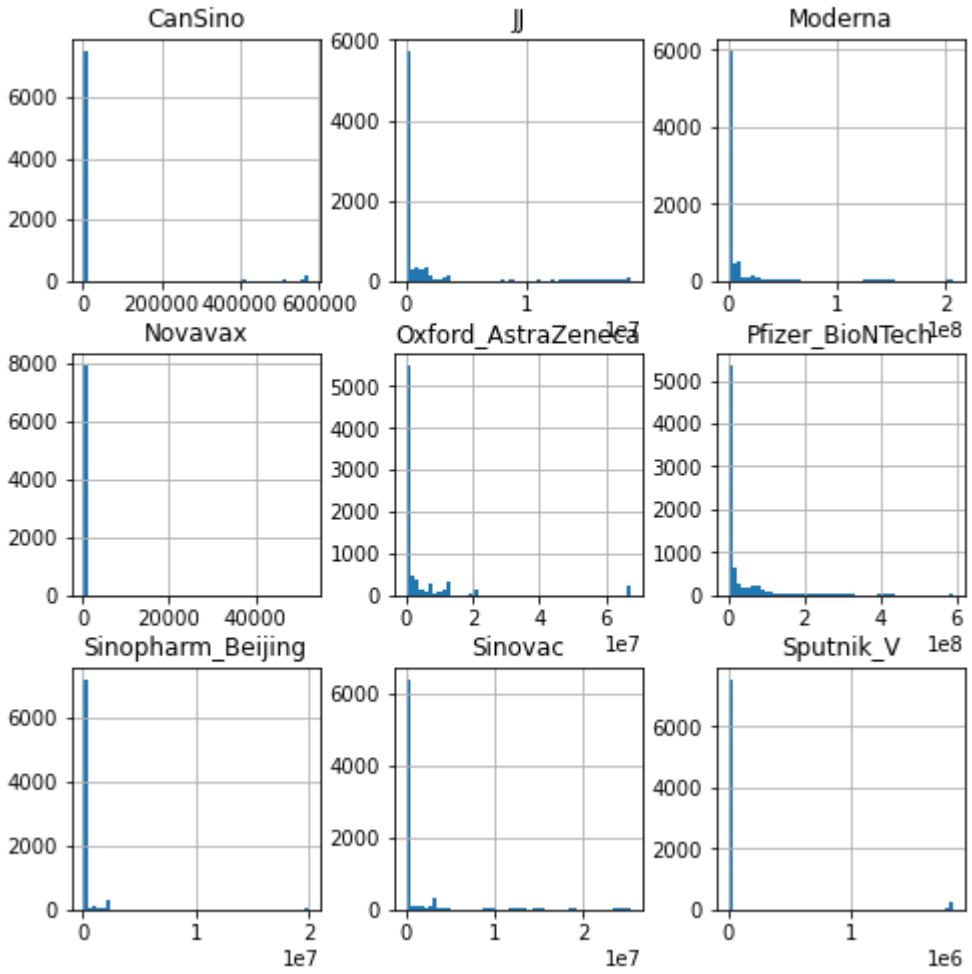
- CanSino: total # of vaccinations that day (min: 0, max: 574208, mean: 25312.205531)
- JJ: (Johnson&Johnson) total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 1.850264e+07, mean: 1.352508e+06)

- Moderna: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 2.079438e+08, mean: 1.083511e+07)
- Novavax: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 52306, mean: 41.710371)
- Oxford_AstraZeneca: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 6.739285e+07, mean: 4.605971e+06)
- Pfizer_BioNTech: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 5.924887e+08, mean: 3.712610e+07)
- Sinopharm_Beijing: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 1.996166e+07, mean: 4.884539e+05)
- Sinovac: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 2.537591e+07, mean: 1.557454e+06)
- Sputnik_V: total # of vaccination doses administered that day for this particular vaccine (min: 0, max: 1.845103e+06, mean: 7.973871e+04)

In [20]:
```
import matplotlib.pyplot as plt
covid.hist(bins=50, figsize=(20,15));
```



In [21]:
```
vaccineClean.hist(bins=50, figsize=(8,8)); # All of the plots have a significant number
# the vaccines weren't available everywhere at first.
```



Part 4 - Merge the data

Now that you have a better feel for each of your two (or three, for the 7394 students) data sets, it is time to merge them. Describe your strategy for merging the data sets and then actually perform the merge.

Develop a strategy for verifying that the data is properly merged (hoping and finger-crossing are not valid strategies).

In [22]:
```
#I've already cleaned up the data and specifically formatted it. This was strategic-- e
#the vaccineClean dataset with the original dataset on location and date, so that we ca
merged = covid.merge(vaccineClean, on=['location','date'])
merged.location.unique() #This shows that we merged the locations correctly: we only wa
# The first dataset has many more countries, so the second dataset was the limiter
```

Out[22]:
```
array(['Austria', 'Belgium', 'Bulgaria', 'Chile', 'Croatia', 'Cyprus',
       'Czechia', 'Denmark', 'Ecuador', 'Estonia', 'European Union',
       'Finland', 'France', 'Germany', 'Hong Kong', 'Hungary', 'Iceland',
       'Ireland', 'Italy', 'Japan', 'Latvia', 'Liechtenstein',
       'Lithuania', 'Luxembourg', 'Malta', 'Netherlands', 'Norway',
       'Peru', 'Poland', 'Portugal', 'Romania', 'Slovakia', 'Slovenia',
       'South Korea', 'Spain', 'Sweden', 'Switzerland', 'Ukraine',
       'United States', 'Uruguay'], dtype=object)
```

In [23]:
```
merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7063 entries, 0 to 7062
Data columns (total 29 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   date                      7063 non-null   object 
 1   iso_code                  7063 non-null   object 
 2   location                  7063 non-null   object 
 3   total_cases               7063 non-null   float64
 4   new_cases                 7063 non-null   float64
 5   new_deaths                7063 non-null   float64
 6   total_deaths              7063 non-null   float64
 7   gdp_per_capita            7063 non-null   float64
 8   total_tests               7063 non-null   float64
 9   new_vaccinations          7063 non-null   float64
 10  positive_rate             7063 non-null   float64
 11  human_development_index   7063 non-null   float64
 12  icu_patients              7063 non-null   float64
 13  hosp_patients             7063 non-null   float64
 14  new_tests                 7063 non-null   float64
 15  people_vaccinated         7063 non-null   float64
 16  people_fully_vaccinated   7063 non-null   float64
 17  population                7063 non-null   float64
 18  total_vaccinations        7063 non-null   float64
 19  aged_65_older             7063 non-null   float64
 20  CanSino                   7063 non-null   float64
 21  JJ                        7063 non-null   float64
 22  Moderna                   7063 non-null   float64
 23  Novavax                   7063 non-null   float64
 24  Oxford_AstraZeneca        7063 non-null   float64
 25  Pfizer_BioNTech           7063 non-null   float64
 26  Sinopharm_Beijing         7063 non-null   float64
 27  Sinovac                   7063 non-null   float64
 28  Sputnik_V                 7063 non-null   float64
dtypes: float64(26), object(3)
memory usage: 1.6+ MB
```

In [24]:

```
merged.date.describe # This makes sense and shows that we merged the dates correctly. T
# and that is the time spanned in our new merged set
```

Out[24]:

```
<bound method NDFrame.describe of 0       2021-01-08
1       2021-01-15
2       2021-01-22
3       2021-01-29
4       2021-02-05
           ...
7058    2022-01-04
7059    2022-01-05
7060    2022-01-06
7061    2022-01-07
7062    2022-01-08
Name: date, Length: 7063, dtype: object>
```

In [25]:

```
merged.Moderna.describe()
```

Out[25]:

```
count    7.063000e+03
mean     9.232086e+06
std      2.887680e+07
```

```
min       0.000000e+00
25%       0.000000e+00
50%       2.445330e+05
75%       2.894582e+06
max       1.974213e+08
Name: Moderna, dtype: float64
```

In [26]:
```
pd.to_datetime(merged['date'])
merged['month'] = pd.DatetimeIndex(merged['date']).month
merged.head()
```

Out[26]:

	date	iso_code	location	total_cases	new_cases	new_deaths	total_deaths	gdp_per_capita	total_tes
0	2021-01-08	AUT	Austria	376793.0	2063.0	73.0	6641.0	45436.686	3871527
1	2021-01-15	AUT	Austria	390788.0	1528.0	66.0	6987.0	45436.686	7459608
2	2021-01-22	AUT	Austria	401886.0	2088.0	42.0	7330.0	45436.686	8593891
3	2021-01-29	AUT	Austria	411730.0	1500.0	51.0	7658.0	45436.686	9160616
4	2021-02-05	AUT	Austria	421189.0	1388.0	37.0	7973.0	45436.686	9940634

5 rows × 30 columns

In [27]:
```
merged[(merged['date']=="2021-01-08") & (merged['location']=="Austria")]
# Here I just wanted to make sure that the data was consistent with the separate datase
```

Out[27]:

	date	iso_code	location	total_cases	new_cases	new_deaths	total_deaths	gdp_per_capita	total_tes
0	2021-01-08	AUT	Austria	376793.0	2063.0	73.0	6641.0	45436.686	3871527

1 rows × 30 columns

In [28]:
```
covid[(covid['date']=="2021-01-08") & (covid['location']=="Austria")]
```

Out[28]:

	date	iso_code	location	total_cases	new_cases	new_deaths	total_deaths	gdp_per_capita	total
9241	2021-01-08	AUT	Austria	376793.0	2063.0	73.0	6641.0	45436.686	387

In [29]:
```
vaccineClean[(vaccineClean['date']=="2021-01-08")& (vaccineClean['location']=="Austria"
```

Out[29]:

vaccine	location	date	CanSino	JJ	Moderna	Novavax	Oxford_AstraZeneca	Pfizer_BioNTech	Sinop

vaccine	location	date	CanSino	JJ	Moderna	Novavax	Oxford_AstraZeneca	Pfizer_BioNTech	Sinop
0	Austria	2021-01-08	0.0	0.0	0.0	0.0	0.0	31632.0	

Part 5 - Explore Bivariate relationships

- Choose a reasoned set of variables to explore further. You don't have to explore all possible pairs of variables, nor do we want to grade that much. Choose 7 - 9 variables. One should be a variable that you'd like to predict (target variable) using the others (predictor variables).
- List your predictor variables
- List your target variable
- Briefly describe why you have chosen these.

Use any of the available visualizations from Seaborn to explore the relationships between the variables. Explore the relationships among the predictor variables as well as the relationship between each predictor variable and the target variable. Which of the predictor variables are most strongly related? Are there any interesting relationships between categorical predictors and numeric predictors? If there are any dichotomous variables, does that influence any of the relationships? Are the relationships positive or negative?

Below each plot, you should provide a description and interpretation of the plot. Make sure to include why the variables in that plot were chosen and what you hope the reader would gain from it as well.

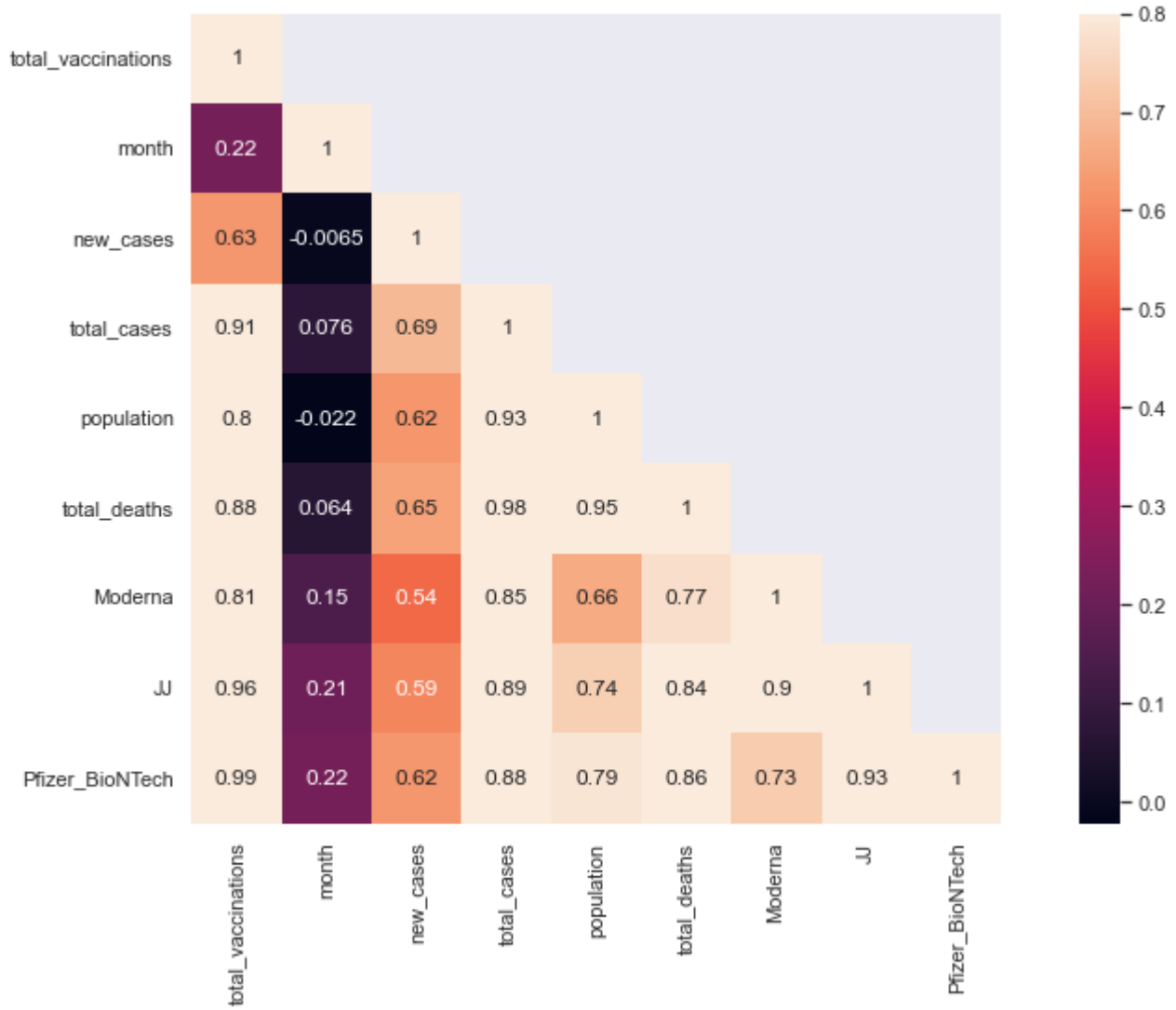
Chosen Variables:

- date (predictor)
- month (predictor)
- location (predictor)
- new_cases (predictor)
- total_cases (predictor)
- population (predictor)
- total_deaths (predictor)
- total_vaccinations (predictor)
- Moderna (can be predictor or target depending on question)
- JJ (can be predictor or target depending on question)
- Pfizer_BioNTech (can be predictor or target depending on question) My goal with choosing these two datasets was to draw conclusions about the number of each type of vaccine administered through the dataset's time frame. I chose to focus on the Johnson and Johnson, Moderna and Pfizer/BioNTech vaccines. Since we're not building a model right now, it's also safe to use each of the vaccines as predictors for the other vaccine types.

None of my variables are dichotomous. However, there were some still unexpected relationships between variables.

In [30]:
```
import seaborn as sn
corrMatt = merged[["total_vaccinations","location","month",
                   "new_cases","total_cases",
                   "population","total_deaths", "Moderna", "JJ", "Pfizer_BioNTech"]].c
mask = np.array(corrMatt)
mask[np.tril_indices_from(mask)] = False
sn.set(rc = {'figure.figsize':(15,8)})
sn.heatmap(corrMatt, mask=mask,
           vmax=.8, square=True,annot=True)
```

Out[30]: <AxesSubplot:>

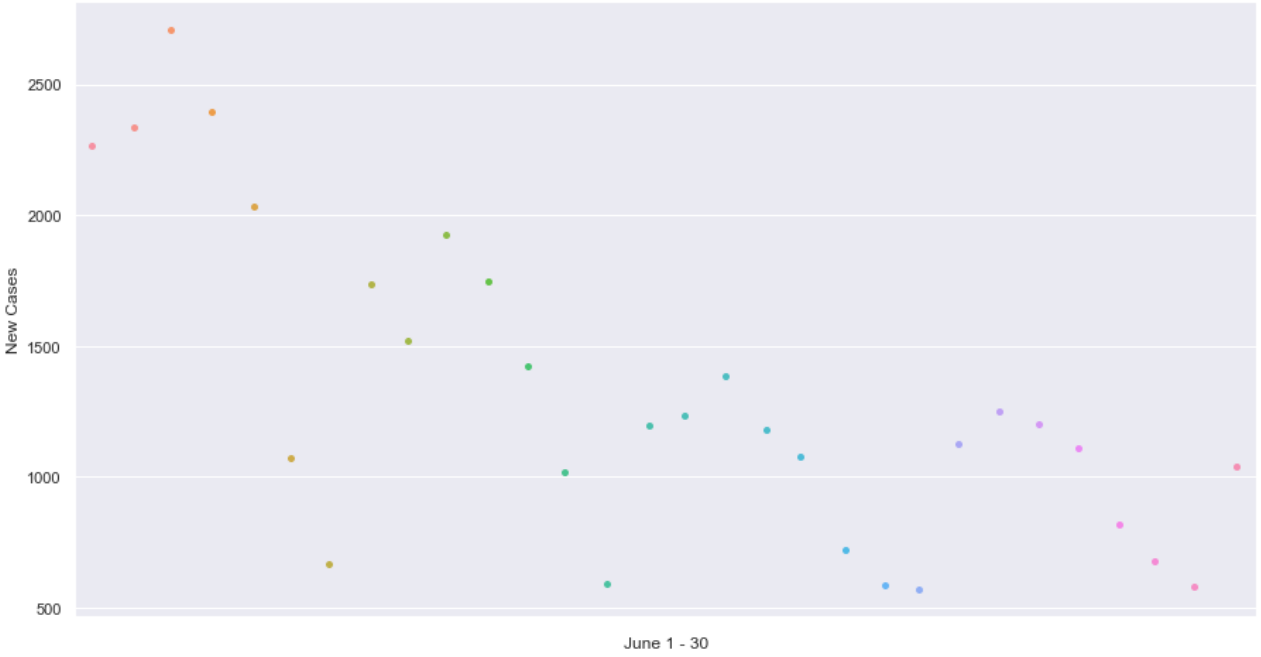


This graph shows the correlations between every possible pair of variables (except for the location variable, which is categorical and would not be comparable to the other variables). As you can see, there are quite a few positive correlations and very few negative. Most of the correlations are fairly strong, in fact, with the majority being over 0.5. I was surprised to see that there were such high

correlation values between the vaccine types. However, I want to know more about each country. Let's explore Ukraine's experience with COVID-19.

In [110…

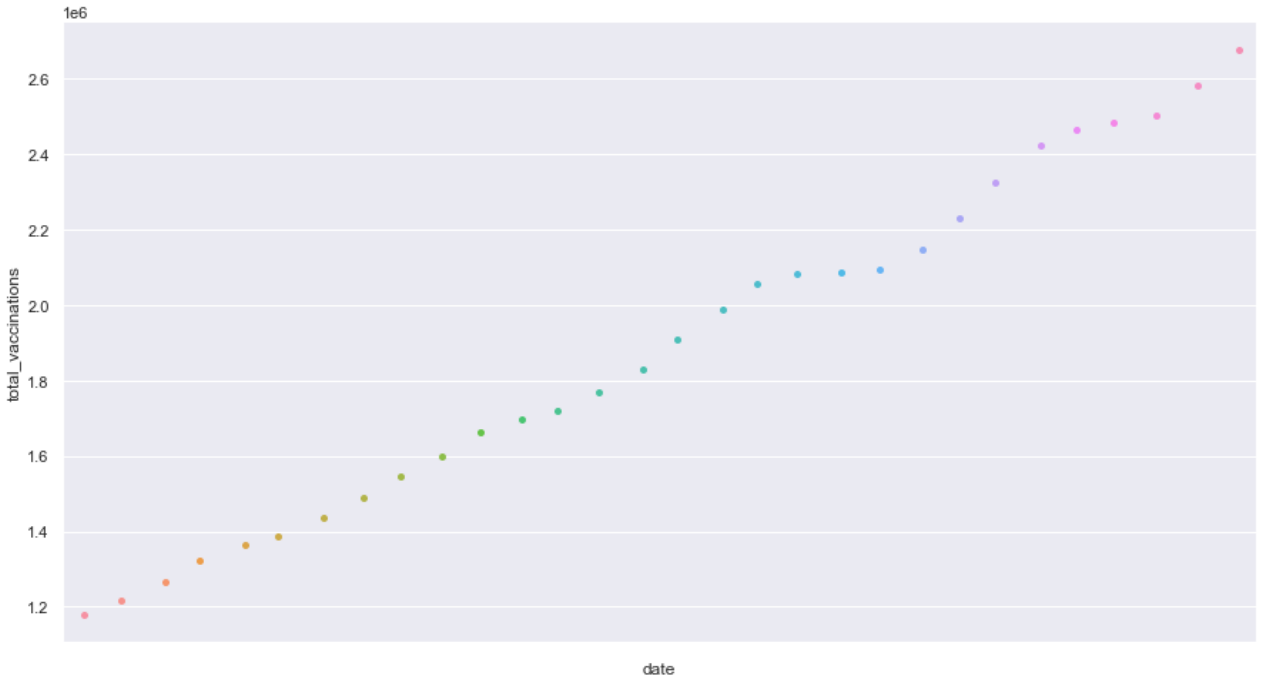
```
#Let's see what Ukraine's June 2021 looked like.
ukraineDf = merged[(merged['location']=="Ukraine") & (merged['month']==6)]
graph = sns.stripplot(x='date', y ='new_cases', data=ukraineDf, alpha=0.9)
graph.set(xticklabels=[]);
graph.set(xlabel="June 1 - 30");
graph.set(ylabel="New Cases");
```



Interesting. As June went on, the number of new cases tended to go down, then would spike up again. This happened over what looks like weekly intervals. However, as the month went on, the number of new cases declined. Now let's see if that correlates at all with vaccination rates.

In [112…

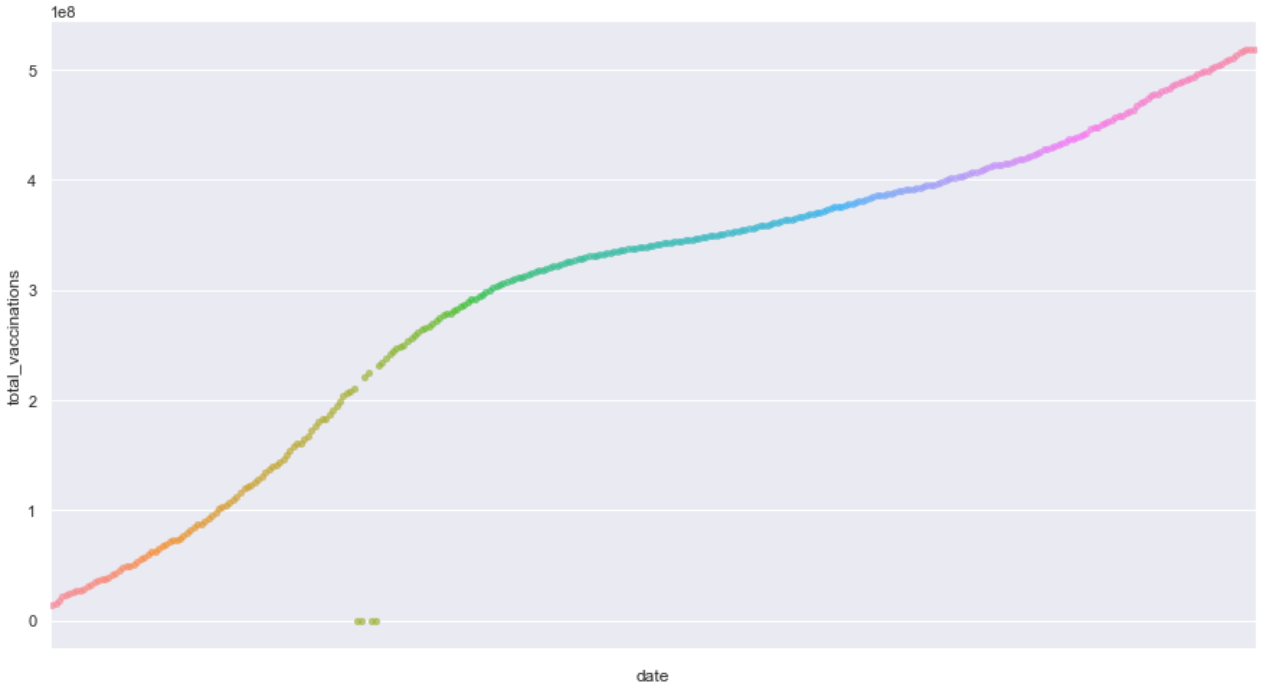
```
graph = sns.stripplot(x='date', y ='total_vaccinations', data=ukraineDf, alpha=0.9)
graph.set(xticklabels=[]);
```



Cool! It looks like the number of total vaccinations administered in Ukraine consistently rose throughout the month of June. This trend makes sense with the downward slope of the number of new cases.

In [114…

```
# I want to try the same thing with the US, except for the entire year.
usDf= merged[["date","total_vaccinations","location","month",
                    "new_cases","total_cases",
                    "population","total_deaths", "Moderna", "JJ", "Pfizer_BioNTech"]]
usDf = usDf[(usDf['location']=="United States")]
graph = sns.stripplot(x='date', y ='total_vaccinations', data=usDf, alpha=0.7)
graph.set(xticklabels=[]);
```

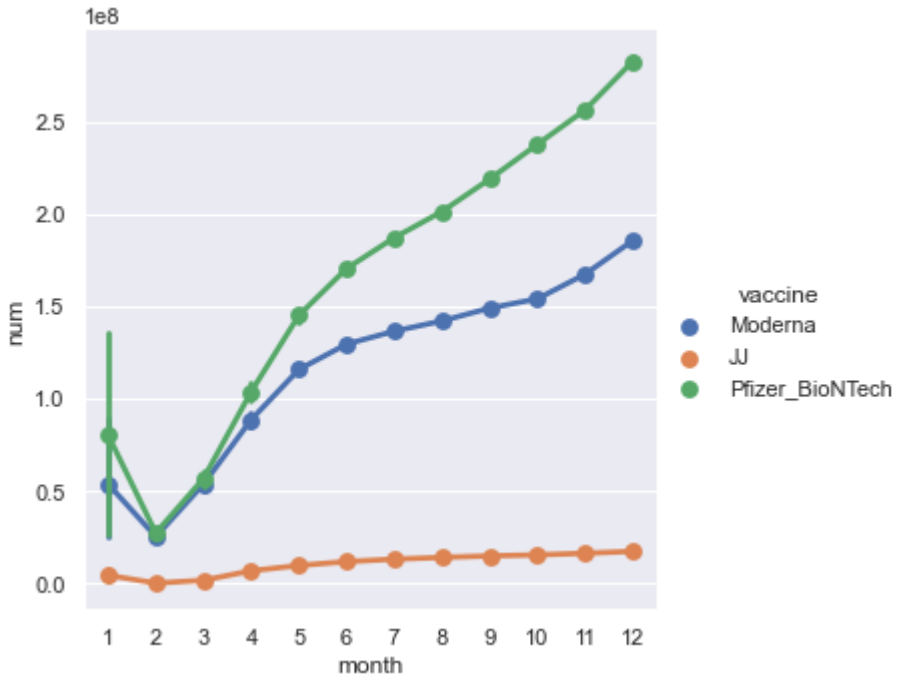


This is great. Over the entire time span of the dataset, the US has a fairly steady upward trend of

vaccinations. Let's see if there was a favorite.

In [104…
```
#Here I'm creating a dataset to use for the plot that will allow me to separate the val
usDfMelt = usDf.melt(id_vars=["date","total_vaccinations","location","month",
                    "new_cases","total_cases",
                    "population","total_deaths"], var_name='vaccine', value_name='num')
sns.catplot(x='month', y='num', hue = 'vaccine', data=usDfMelt, kind='point')
```

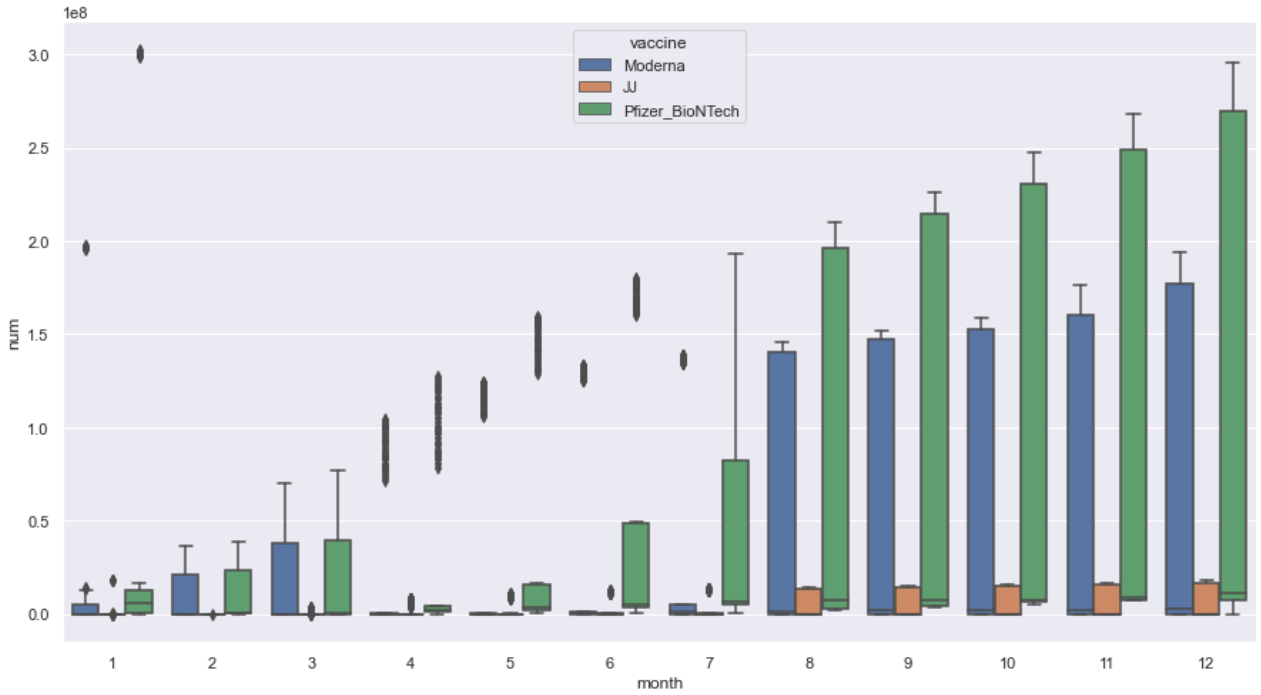
Out[104…
```
<seaborn.axisgrid.FacetGrid at 0x21d10703d90>
```



It appears that Pfizer/BioNTech was the most popular vaccine in the US during 2021, followed by Moderna. Overall, the number of vaccinations for each different type was an upward trend (except for JJ, which appears slightly flat).

In [137…
```
#I liked the last visualization so much that I decided to do it again, but for a few co
mergedMelt= merged[["date","total_vaccinations","location","month",
                    "new_cases","total_cases",
                    "population","total_deaths", "Moderna", "JJ", "Pfizer_BioNTech"]]
mergedMelt = mergedMelt[(mergedMelt['location']=="United States") |(merged['location']=
mergedMelt = mergedMelt.melt(id_vars=["date","total_vaccinations","location","month",
                    "new_cases","total_cases",
                    "population","total_deaths"], var_name='vaccine', value_name='num')
sns.boxplot(x='month', y='num', hue = 'vaccine',data=mergedMelt)
```

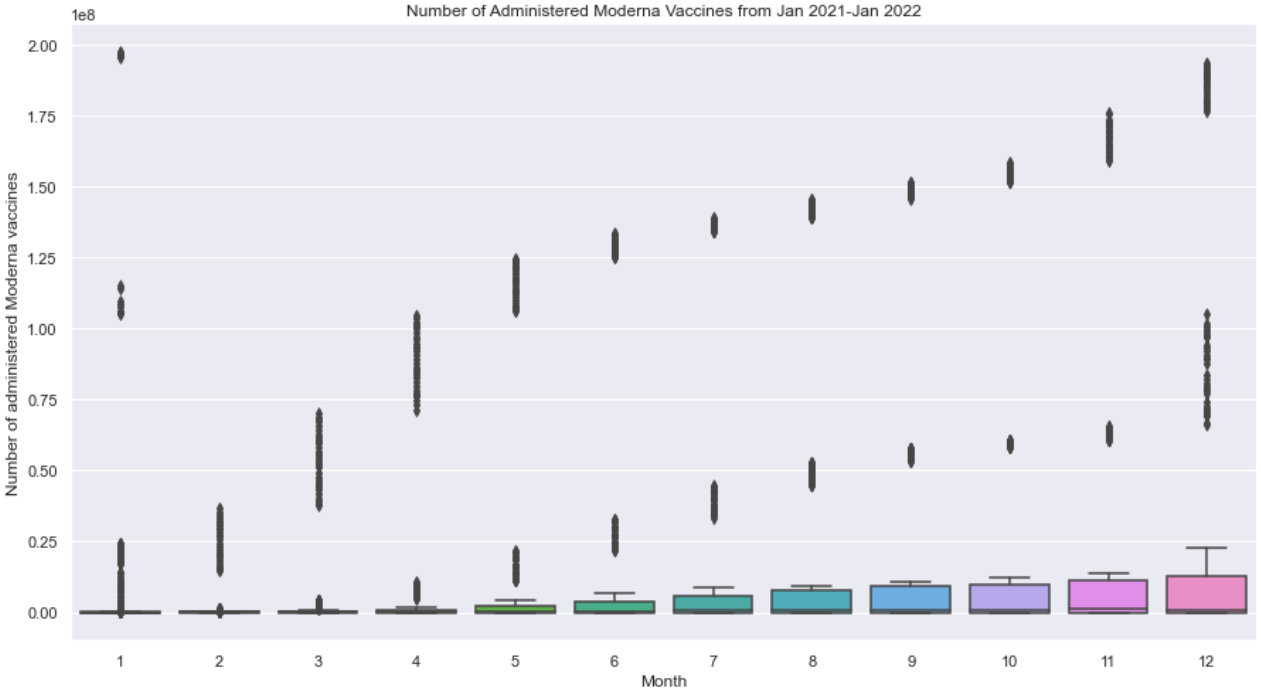
Out[137…
```
<AxesSubplot:xlabel='month', ylabel='num'>
```



From this visualization it appears that Pfizer was still the most popular in the countries I included, and that the trend of increased numbers of vaccines being administered as the year went on wasn't exclusive to the US.

In [36]:
```
boxPlot2 = sn.boxplot(data=merged[['month',
                                   'Moderna']],
                      x="month",y="Moderna").set(title="Number of Administered Moderna Vaccines
plt.xlabel("Month")
plt.ylabel("Number of administered Moderna vaccines")
```

Out[36]:
```
Text(0, 0.5, 'Number of administered Moderna vaccines')
```



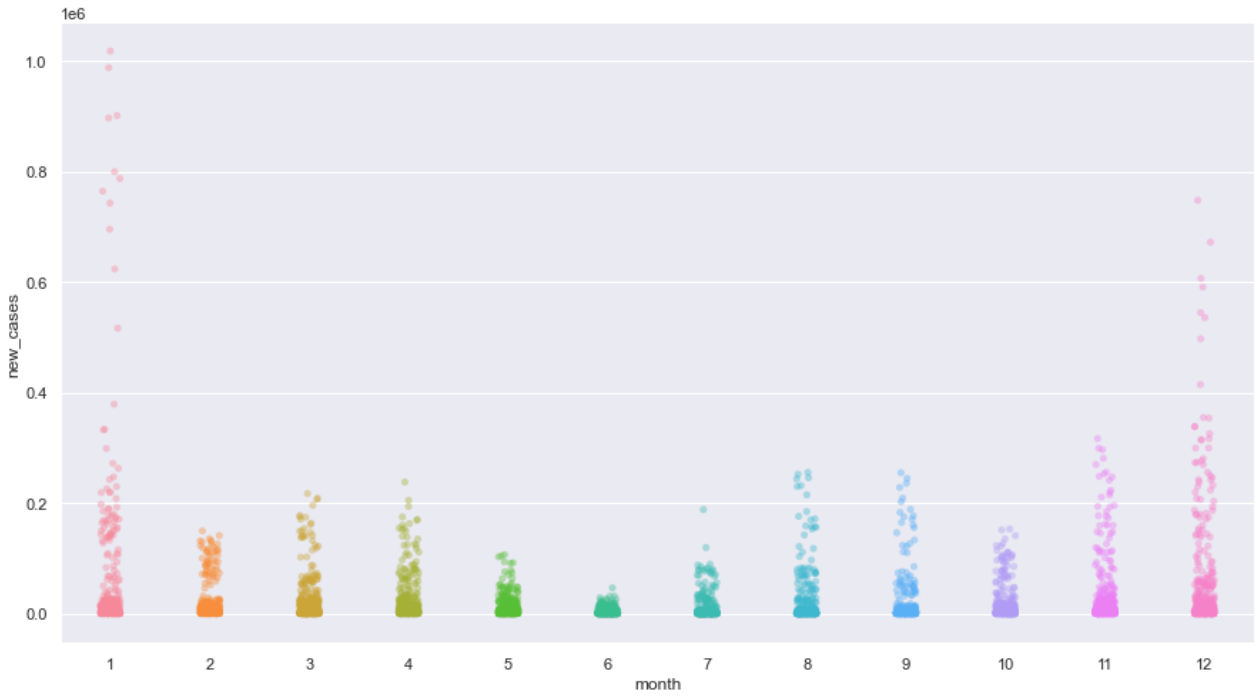
Here we can see how many Moderna vaccines were administered in the world from January 2021 to

January 2022. It appears that the number of Moderna vaccines administered had an upward trend.

In [115…
```
import matplotlib.pyplot as plt
```

In [43]:
```
sns.stripplot(x='month', y='new_cases', data=merged, alpha=0.4)
```

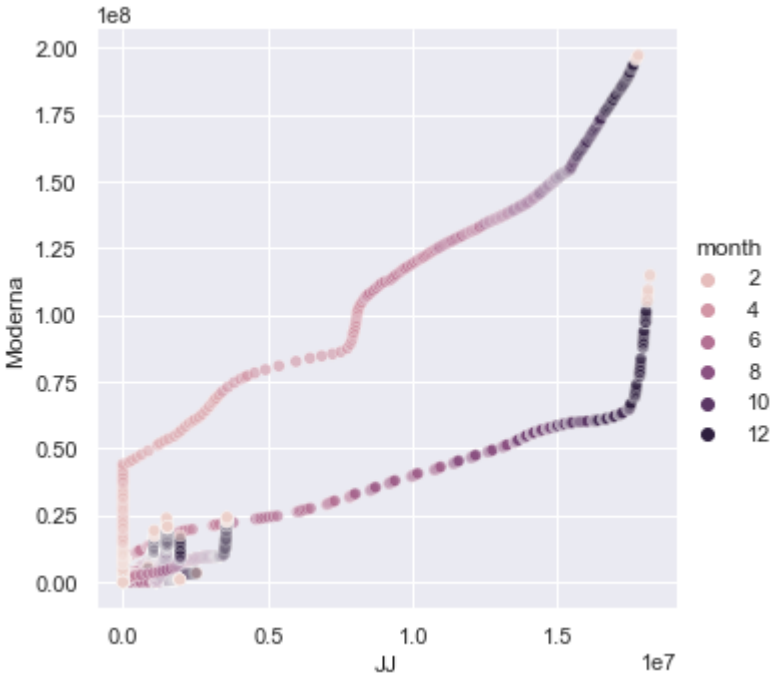
Out[43]:
```
<AxesSubplot:xlabel='month', ylabel='new_cases'>
```



This data makes a lot of sense-- as the year went on, more people in different countries were exposed to COVID-19 and its different variants.

In [119…
```
sns.relplot(x='JJ', y='Moderna', data=merged,alpha=0.6, hue="month")
```

Out[119…
```
<seaborn.axisgrid.FacetGrid at 0x21db109d2b0>
```



This graph shows an interesting trend-- at the beginning of the year, Moderna was much more popular than JJ. However, it seems like JJ gained popularity as the year went on (most of the darkest hues are in JJ's higher value region).