covid19_vacc_prog

December 31, 2023

1 World Vaccination Progress EDA

Okay, we have a vaccine; that's exciting news! But how are we doing? Is the vaccination progressing quick enough? This lecture, we will explore a dataset downloaded from `kaggle`, you can follow this link to learn more about this dataset. The dataset is collected by the organization Our World in Data that publish papers about solutions to world issues.

[1]:
```
# list of imports
import scipy as sp
import numpy as np
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

import pandas as pd
import datascience
import matplotlib.pyplot as plt
%matplotlib inline
from datascience import Table
import seaborn as sns
```

We very briefly walked through how to interact with an API (it's very simple!) If you are interested, you can look at more in the official `github` page: https://github.com/Kaggle/kaggle-api

[2]:
```
# kaggle API
! kaggle datasets list -s "covid vaccination" --sort-by 'hottest' | head -10
```

```
ref                                                 title
size  lastUpdated          downloadCount  voteCount  usabilityRating
-------------------------------------------------
------------------------------------------------  -----  -------------------
-------------  ---------  ---------------
gpreda/covid-world-vaccination-progress             COVID-19 World Vaccination
Progress                101KB  2021-03-01 08:15:06          19482         888  1.0
fedesoriano/coronavirus-covid19-vaccinations-data  COVID-19 World Vaccination
Progress Data             3MB  2021-01-27 06:37:50            186           7  1.0
keplaxo/twitter-vaccination-dataset                 Twitter Vaccination Dataset
305MB  2020-04-15 17:33:37             346         13  0.9411765
padmajabuggaveeti/covid-vaccination-dataset-2021   COVID VACCINATION DATASET -
2021                    29KB  2021-01-27 11:04:44             75           5
```

```
0.5882353
mpwolke/cusersmarildownloadsvaccinationcsv         Covid-19 Vaccination Doses
Administered            681B  2020-12-28 21:06:44              7           2  1.0
teesoong/covid-vaccination-forecast                Covid Vaccination forecast
2KB  2021-02-27 14:33:03             10          2  0.47058824
alechelyar/facebook-antivaccination-dataset        Facebook Anti-Vaccination
Dataset                  53MB  2019-04-02 17:24:22            206          8
0.3529412
rtatman/animal-bites                               Animal Bites
95KB  2017-09-15 17:21:38           3496         60  0.85294116
```

[4]:
```
# find the files in dataset
! kaggle datasets files gpreda/covid-world-vaccination-progress -v
```

[7]:
```
# download the file in csv format
! kaggle datasets download -f country_vaccinations.csv -p "./data" gpreda/
↪covid-world-vaccination-progress
! echo ">>> check if data is there"
! ls "./data"
```

```
country_vaccinations.csv: Skipping, found more recently modified local copy (use
--force to force download)
>>> check if data is there
country_vaccinations.csv
```

Data wrangling and EDA are the most initial steps in our data science lifecyle. Most often than not in research, the data is newly collected or simulated; no one has had time to write up extensive descriptions of the data. Therefore, an important step is getting to know our data.

[9]:
```
# read data in
path = "./data/"
filename = "country_vaccinations.csv"
read_path = path + filename
vax = pd.read_csv(read_path)
# what columns does it have
# what are data types
vax.dtypes
```

[9]:
```
country                                object
iso_code                               object
date                                   object
total_vaccinations                    float64
people_vaccinated                     float64
people_fully_vaccinated               float64
daily_vaccinations_raw                float64
```

```
daily_vaccinations                        float64
total_vaccinations_per_hundred            float64
people_vaccinated_per_hundred             float64
people_fully_vaccinated_per_hundred       float64
daily_vaccinations_per_million            float64
vaccines                                   object
source_name                                object
source_website                             object
dtype: object
```

Now that we have the data, let's load it in and look at what it has to offer. To learn more about this dataset, it is often helpful to look at its `README` file or just directly go to `kaggle` and read the descriptions. https://www.kaggle.com/gpreda/covid-world-vaccination-progress

The description of columns is usually called a **`data dictionary`**. By reading the documentation we learn that this data is directly sourced from John Hopkins University: https://github.com/owid/covid-19-data/tree/master/public/data. This is sometimes important to know because different organizations, institutions, or even individuals often collect and record data following different conventions (how are `NA` values represented, how are categorical values stored, etc.). You can explore the data source's description a little more closely: https://ourworldindata.org/coronavirus-source-data.

[10]:
```python
# how much space does this dataset take?
display(vax.memory_usage())
# how many kilobytes?
print("{} kB".format(np.round(vax.memory_usage().sum()/2**10, 2)))
```

```
Index                                    128
country                                35480
iso_code                               35480
date                                   35480
total_vaccinations                     35480
people_vaccinated                      35480
people_fully_vaccinated                35480
daily_vaccinations_raw                 35480
daily_vaccinations                     35480
total_vaccinations_per_hundred         35480
people_vaccinated_per_hundred          35480
people_fully_vaccinated_per_hundred    35480
daily_vaccinations_per_million         35480
vaccines                               35480
source_name                            35480
source_website                         35480
dtype: int64
```

```
519.85 kB
```

A more comprehensive description of the data types is `df.info` function.

[11]:
```
vax.info();
# vax.dim, vix.shape, vix.dtypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4435 entries, 0 to 4434
Data columns (total 15 columns):
country                               4435 non-null object
iso_code                              4131 non-null object
date                                  4435 non-null object
total_vaccinations                    2916 non-null float64
people_vaccinated                     2483 non-null float64
people_fully_vaccinated               1662 non-null float64
daily_vaccinations_raw                2467 non-null float64
daily_vaccinations                    4281 non-null float64
total_vaccinations_per_hundred        2916 non-null float64
people_vaccinated_per_hundred         2483 non-null float64
people_fully_vaccinated_per_hundred   1662 non-null float64
daily_vaccinations_per_million        4281 non-null float64
vaccines                              4435 non-null object
source_name                           4435 non-null object
source_website                        4435 non-null object
dtypes: float64(9), object(6)
memory usage: 519.9+ KB
```

```
'b'       boolean 'i'       (signed) integer 'u'       unsigned integer 'f'
floating-point 'c'       complex-floating point 'O'       (Python) objects 'S',
'a'  (byte-)string 'U'       Unicode 'V'       raw data (void)
```

[13]:
```
# what are these "object" values, let's look at "country" for example
countries = vax['country']
countries.dtype # probably not very helpful
```

[13]: `dtype('O')`

[14]:
```
type(countries[0])
```

[14]: `str`

Now that we know what the columns are and (roughly) what they represent, let's also look at the table as a whole.

1.0.1 Q: What is the granularity of this dataset?

Discussion: Is it better to have more granularity, or less granularity?

[15]:
```
vax.head()
```

[15]:
```
   country iso_code        date  total_vaccinations  people_vaccinated  \
0  Albania      ALB  2021-01-10                 0.0                0.0
1  Albania      ALB  2021-01-11                 NaN                NaN
2  Albania      ALB  2021-01-12               128.0              128.0
3  Albania      ALB  2021-01-13               188.0              188.0
4  Albania      ALB  2021-01-14               266.0              266.0

   people_fully_vaccinated  daily_vaccinations_raw  daily_vaccinations  \
0                      NaN                     NaN                 NaN
1                      NaN                     NaN                64.0
2                      NaN                     NaN                64.0
3                      NaN                    60.0                63.0
4                      NaN                    78.0                66.0

   total_vaccinations_per_hundred  people_vaccinated_per_hundred  \
0                            0.00                           0.00
1                             NaN                            NaN
2                            0.00                           0.00
3                            0.01                           0.01
4                            0.01                           0.01

   people_fully_vaccinated_per_hundred  daily_vaccinations_per_million  \
0                                  NaN                             NaN
1                                  NaN                            22.0
2                                  NaN                            22.0
3                                  NaN                            22.0
4                                  NaN                            23.0

          vaccines         source_name  \
0  Pfizer/BioNTech  Ministry of Health
1  Pfizer/BioNTech  Ministry of Health
2  Pfizer/BioNTech  Ministry of Health
3  Pfizer/BioNTech  Ministry of Health
4  Pfizer/BioNTech  Ministry of Health

                                    source_website
0  https://shendetesia.gov.al/covid19-ministria-e…
1  https://shendetesia.gov.al/covid19-ministria-e…
2  https://shendetesia.gov.al/covid19-ministria-e…
3  https://shendetesia.gov.al/covid19-ministria-e…
4  https://shendetesia.gov.al/covid19-ministria-e…
```

We have quite a few numerical features, such as `people_vaccinated`, `daily_vaccinations` … We may be generally interested in some statistics.

[20]:
```python
# compute mean
sum(vax['daily_vaccinations'])/len(vax['daily_vaccinations']) # comments?
```

```python
vax['daily_vaccinations'].mean()
```

[20]: 55316.880168185

We have some NaN values, this can be due to a few different reasons depending on context. But remember: **If there is no data, it does not mean that there is no problem**.

1.0.2 Q: Is getting rid of data points that contain NaN's a good idea?

Now that we know in general: * the (physical) size of data * the dimensions of data * what each row / column represents * the data types contained in this data * analmolies

Now we can dive into the data values themselves and find out what properties this dataset has.

[24]:
```python
# what happens if we get rid of NaN's
vax_clean = vax.dropna()
vax_clean = vax_clean.sort_values(by="date", ascending=False).reset_index()
display(vax_clean.head())
print(vax_clean.shape)

# so getting rid of NaN's may not always be the best idea
```

```
   index        country iso_code        date  total_vaccinations  \
0   4342  United States      USA  2021-02-27          72806180.0
1   3417        Romania      ROU  2021-02-27           1521737.0
2    580         Brazil      BRA  2021-02-27           8322042.0
3   1981      Indonesia      IDN  2021-02-27           2598535.0
4   2794        Morocco      MAR  2021-02-27           3597903.0

   people_vaccinated  people_fully_vaccinated  daily_vaccinations_raw  \
0         48435536.0               23698627.0               2352116.0
1           905142.0                 616595.0                 15704.0
2          6437836.0                1884206.0                220255.0
3          1616165.0                 982370.0                149084.0
4          3435997.0                 161906.0                173608.0

   daily_vaccinations  total_vaccinations_per_hundred  \
0           1645240.0                           21.77
1             24351.0                            7.91
2            215553.0                            3.92
3             91687.0                            0.95
4            162387.0                            9.75

   people_vaccinated_per_hundred  people_fully_vaccinated_per_hundred  \
0                          14.48                                 7.09
1                           4.71                                 3.21
2                           3.03                                 0.89
3                           0.59                                 0.36
4                           9.31                                 0.44
```

```
   daily_vaccinations_per_million  \
0                          4919.0
1                          1266.0
2                          1014.0
3                           335.0
4                          4399.0

                                       vaccines  \
0                        Moderna, Pfizer/BioNTech
1  Moderna, Oxford/AstraZeneca, Pfizer/BioNTech
2                     Oxford/AstraZeneca, Sinovac
3                                         Sinovac
4         Oxford/AstraZeneca, Sinopharm/Beijing

                                     source_name  \
0   Centers for Disease Control and Prevention
1                          Government of Romania
2  Regional governments via Coronavirus Brasil
3                             Ministry of Health
4                             Ministry of Health

                                      source_website
0  https://covid.cdc.gov/covid-data-tracker/#vacc…
1  https://vaccinare-covid.gov.ro/wp-content/uplo…
2                https://coronavirusbra1.github.io/
3                         https://www.kemkes.go.id/
4  http://www.covidmaroc.ma/Documents/BULLETIN/27…
(1316, 16)
```

How many countries are represented?

[28]:
```python
np.unique(vax['country'])
```

[28]:
```
array(['Albania', 'Algeria', 'Andorra', 'Anguilla', 'Argentina',
       'Australia', 'Austria', 'Azerbaijan', 'Bahrain', 'Bangladesh',
       'Barbados', 'Belarus', 'Belgium', 'Bermuda', 'Bolivia', 'Brazil',
       'Bulgaria', 'Cambodia', 'Canada', 'Cayman Islands', 'Chile',
       'China', 'Colombia', 'Costa Rica', 'Croatia', 'Cyprus', 'Czechia',
       'Denmark', 'Dominican Republic', 'Ecuador', 'Egypt', 'El Salvador',
       'England', 'Estonia', 'Faeroe Islands', 'Falkland Islands',
       'Finland', 'France', 'Germany', 'Gibraltar', 'Greece', 'Greenland',
       'Guernsey', 'Guyana', 'Hungary', 'Iceland', 'India', 'Indonesia',
       'Iran', 'Ireland', 'Isle of Man', 'Israel', 'Italy', 'Japan',
       'Jersey', 'Kazakhstan', 'Kuwait', 'Latvia', 'Lebanon',
       'Liechtenstein', 'Lithuania', 'Luxembourg', 'Macao', 'Maldives',
       'Malta', 'Mauritius', 'Mexico', 'Monaco', 'Montenegro', 'Morocco',
```

```
'Myanmar', 'Nepal', 'Netherlands', 'New Zealand',
'Northern Cyprus', 'Northern Ireland', 'Norway', 'Oman',
'Pakistan', 'Panama', 'Paraguay', 'Peru', 'Poland', 'Portugal',
'Qatar', 'Romania', 'Russia', 'Saint Helena', 'Saudi Arabia',
'Scotland', 'Senegal', 'Serbia', 'Seychelles', 'Singapore',
'Slovakia', 'Slovenia', 'South Africa', 'South Korea', 'Spain',
'Sri Lanka', 'Sweden', 'Switzerland', 'Trinidad and Tobago',
'Turkey', 'Turks and Caicos Islands', 'Ukraine',
'United Arab Emirates', 'United Kingdom', 'United States',
'Venezuela', 'Wales', 'Zimbabwe'], dtype=object)
```

How much data do we have on each country, are they equal?

[30]:
```
vax['country'].value_counts()
```

[30]:
```
Lithuania          82
Scotland           76
United Kingdom     76
Wales              76
England            76
                   ..
Senegal             5
South Korea         3
Ukraine             3
Saint Helena        1
Greenland           1
Name: country, Length: 112, dtype: int64
```

What is the range of dates?

[33]:
```
# these achieves the same goal
print("the dates are from {} to {}".format(np.amin(vax['date']), np.
 ↪amax(vax['date'])))
# or you can do this
(vax['date'].min(), vax['date'].max())
# so, about 3 months worth of data
```

```
the dates are from 2020-12-08 to 2021-02-27
```

[33]:
```
('2020-12-08', '2021-02-27')
```

How is the world vaccination progressing? Namely, on average, how many people get vaccinated everyday?

[34]:
```
# these achieves the same goal
print("daily vaccination average: {}".format(vax['daily_vaccinations'].mean()))
# or you can do this
```

```
print("daily vaccination average: {}".format(np.
 ↪mean(vax['daily_vaccinations'])))
# that's a bit slow, but we are making progress
```

```
daily vaccination average: 55316.880168185
daily vaccination average: 55316.880168185
```

[ ]:
```
# you can do numerical computations on pd.Series directly
vax['people_fully_vaccinated'] / vax['']
```

Here is a quick way: `df.describe` gives you some quick statistics of your numerical data. It has a few advantages, but need to be careful about interpretability.

[35]:
```
vax.describe()
```

[35]:
```
       total_vaccinations  people_vaccinated  people_fully_vaccinated  \
count        2.916000e+03       2.483000e+03             1.662000e+03
mean         1.709487e+06       1.481442e+06             4.888581e+05
std          5.774372e+06       4.646374e+06             1.899838e+06
min          0.000000e+00       0.000000e+00             1.000000e+00
25%          3.154575e+04       2.799900e+04             1.119425e+04
50%          2.049345e+05       1.822800e+05             5.062800e+04
75%          8.565680e+05       7.471645e+05             2.607428e+05
max          7.280618e+07       4.843554e+07             2.369863e+07

       daily_vaccinations_raw  daily_vaccinations  \
count            2.467000e+03        4.281000e+03
mean             7.517774e+04        5.531688e+04
std              2.111072e+05        1.744120e+05
min             -5.001200e+04        1.000000e+00
25%              2.282000e+03        1.121000e+03
50%              1.183300e+04        5.857000e+03
75%              5.366500e+04        2.704700e+04
max              2.352116e+06        1.916190e+06

       total_vaccinations_per_hundred  people_vaccinated_per_hundred  \
count                     2916.000000                    2483.000000
mean                         7.078261                       5.751832
std                         13.147480                       9.446641
min                          0.000000                       0.000000
25%                          0.620000                       0.600000
50%                          2.735000                       2.530000
75%                          6.675000                       5.200000
max                        106.530000                      67.410000

       people_fully_vaccinated_per_hundred  daily_vaccinations_per_million
count                          1662.000000                     4281.000000
```

```
mean                           2.262515                2404.288951
std                            5.501138                4378.201585
min                            0.000000                   0.000000
25%                            0.212500                 321.000000
50%                            0.840000                1064.000000
75%                            1.935000                2190.000000
max                           39.110000               54264.000000
```

Now we understand better the numerical properties of our data. We can start to ask some more complex questions.

1.1 Q: Who's not vaccinated?

$$\text{(Total number of people vaccinated per hundred)} = \frac{\text{(Total number of people fully vaccinated)}}{\text{(Total population up to the date in the country)}} \times 100\%$$

[37]:
```python
vax['total_population'] = vax['people_fully_vaccinated'] /␣
↪(vax['total_vaccinations_per_hundred'] / 100)
vax[['country', 'total_population']].dropna()
```

[37]:
```
      country  total_population
23    Albania      5.000000e+03
30    Albania      1.095000e+06
38    Albania      1.018333e+06
39    Albania      5.554545e+05
43    Albania      2.847826e+05
…       …               …
4420    Wales      1.705384e+05
4421    Wales      1.993241e+05
4422    Wales      2.296220e+05
4423    Wales      2.569384e+05
4424    Wales      2.792505e+05

[1654 rows x 2 columns]
```

Now we can see who's not vaccinated in each country.

[38]:
```python
vax['people_unvaccinated'] = vax['total_population'] -␣
↪vax['people_fully_vaccinated']
vax[['country', 'people_unvaccinated']].dropna()
```

[38]:
```
      country  people_unvaccinated
23    Albania         4.999000e+03
30    Albania         1.094562e+06
38    Albania         1.017722e+06
39    Albania         5.548435e+05
43    Albania         2.841276e+05
…       …                  …
```

```
4420     Wales          1.208094e+05
4421     Wales          1.400451e+05
4422     Wales          1.597710e+05
4423     Wales          1.768764e+05
4424     Wales          1.901975e+05

[1654 rows x 2 columns]
```

We can even ask further questions as to which country is most recently, most vaccinated, and most un-vaccinated?

[39]:
```python
# let's move to the same recorded day
vax_curr = vax[vax['date'] == '2021-02-26']
```

[40]:
```python
vax.iloc[vax_curr['people_fully_vaccinated'].idxmax]
```

[40]:
```
country
United States
iso_code
USA
date
2021-02-26
total_vaccinations
7.04541e+07
people_vaccinated
4.71842e+07
people_fully_vaccinated
2.26134e+07
daily_vaccinations_raw
2.17995e+06
daily_vaccinations
1.55272e+06
total_vaccinations_per_hundred
21.07
people_vaccinated_per_hundred
14.11
people_fully_vaccinated_per_hundred
6.76
daily_vaccinations_per_million
4643
vaccines                                                              Moderna,
Pfizer/BioNTech
source_name                                     Centers for Disease Control and
Prevention
source_website                           https://covid.cdc.gov/covid-data-
tracker/#vacc…
total_population
```

```
1.07325e+08
people_unvaccinated
8.47116e+07
Name: 4341, dtype: object
```

[41]:
```python
vax.iloc[vax_curr['people_fully_vaccinated'].idxmin]
```

[41]:
```
country
Isle of Man
iso_code
IMN
date
2021-02-26
total_vaccinations
19884
people_vaccinated
13600
people_fully_vaccinated
6284
daily_vaccinations_raw
1089
daily_vaccinations
391
total_vaccinations_per_hundred
23.38
people_vaccinated_per_hundred
15.99
people_fully_vaccinated_per_hundred
7.39
daily_vaccinations_per_million
4598
vaccines                                              Oxford/AstraZeneca,
Pfizer/BioNTech
source_name                                                       Isle of Man
Government
source_website                             https://covid19.gov.im/general-
information/cov…
total_population
26877.7
people_unvaccinated
20593.7
Name: 2084, dtype: object
```

There are many more topics we can explore (feel free to try to answer these on your own: How effective are vaccines? What's the busiest day, is there a pattern?). Notice that all we are doing are just computing simple statistics, but the key is to learn about our data in that: (1) get familiar with manipulating this dataset and (2) explore the **scope** and **temporality** of this dataset.

2 Visualizing Our Data

Depending on our needs and whether the data is categorical / numerical, we can have different ways to look at data. We can understand the dataset in a much more direct and intuitive way by visualizing. We will discuss more in the upcoming lectures.

Today, we will be working with `datascience` which provides some useful visualization tools, and see a few examples of more standard packages such as `pandas`, `matplotlib` and `seaborn`.

2.1 Q: Is the vaccination rate in the United States looking up?

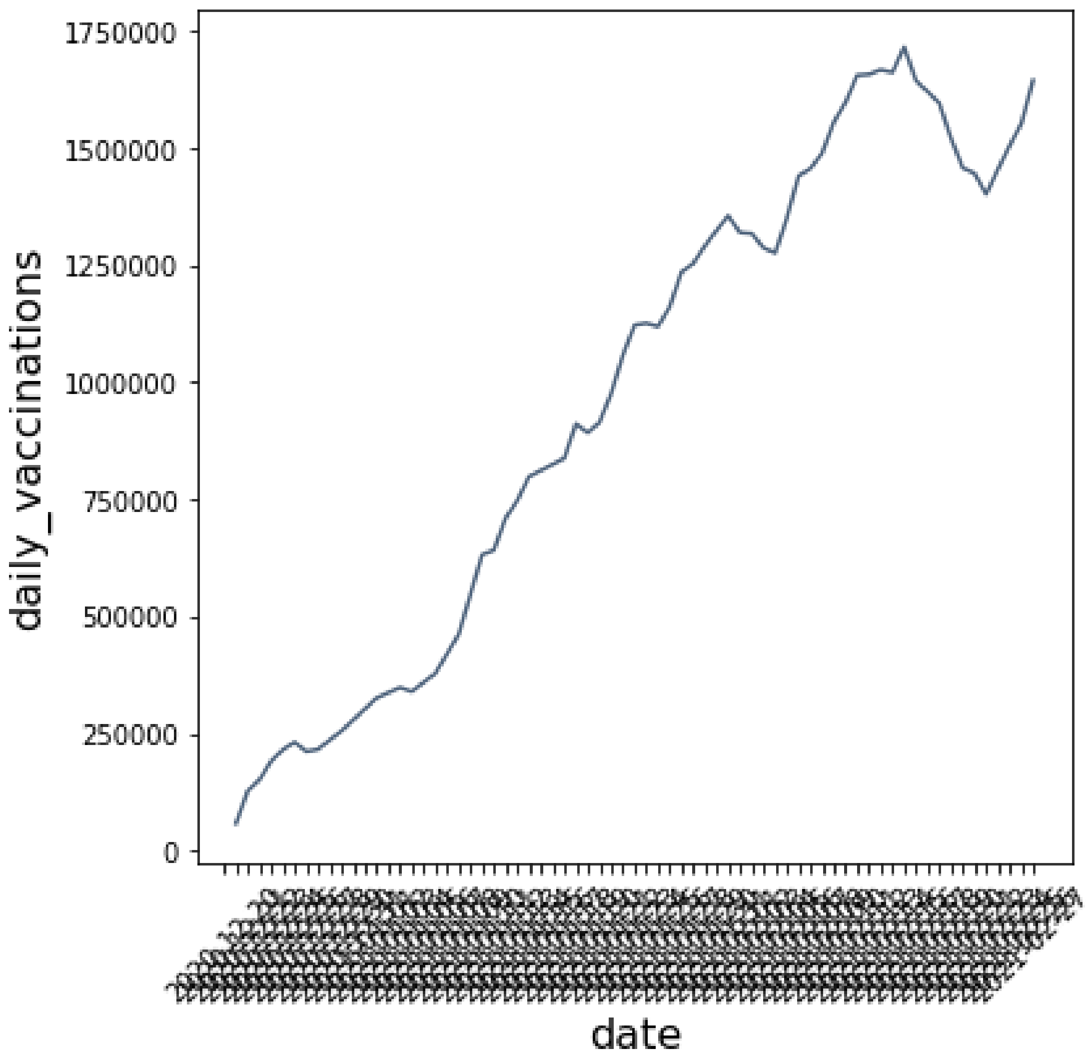
[43]:
```
# focus on the US
us_vax = vax[vax['country'] == "United States"]
us_vax.shape
```

[43]:
```
(70, 17)
```

What is a good way to understand the temporal trend of a numerical value?

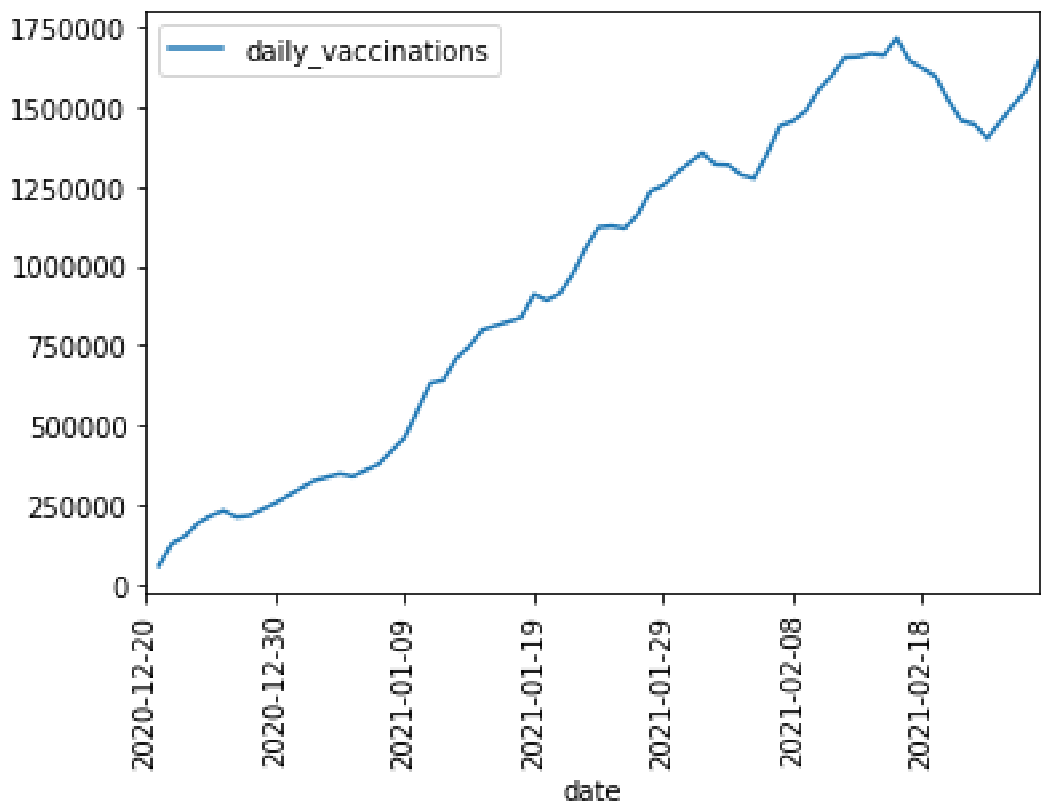
[44]:
```
us_daily_trend = Table().with_columns([
    'date', us_vax['date'],
    'daily_vaccinations', us_vax['daily_vaccinations']
])

# plot
#help(us_daily_trend.plot)
us_daily_trend.plot('date');
plt.xticks(rotation = 45);
```



How to do this in `pandas`? Look at `pd.DataFrame().plot`.

```
[49]: us_vax.plot('date', 'daily_vaccinations', rot=90);
```



We can get even more detailed plots with `matplotlib`.

Here are a few `stackexchange` posts I consulted. Most often than not, your question has been answered.

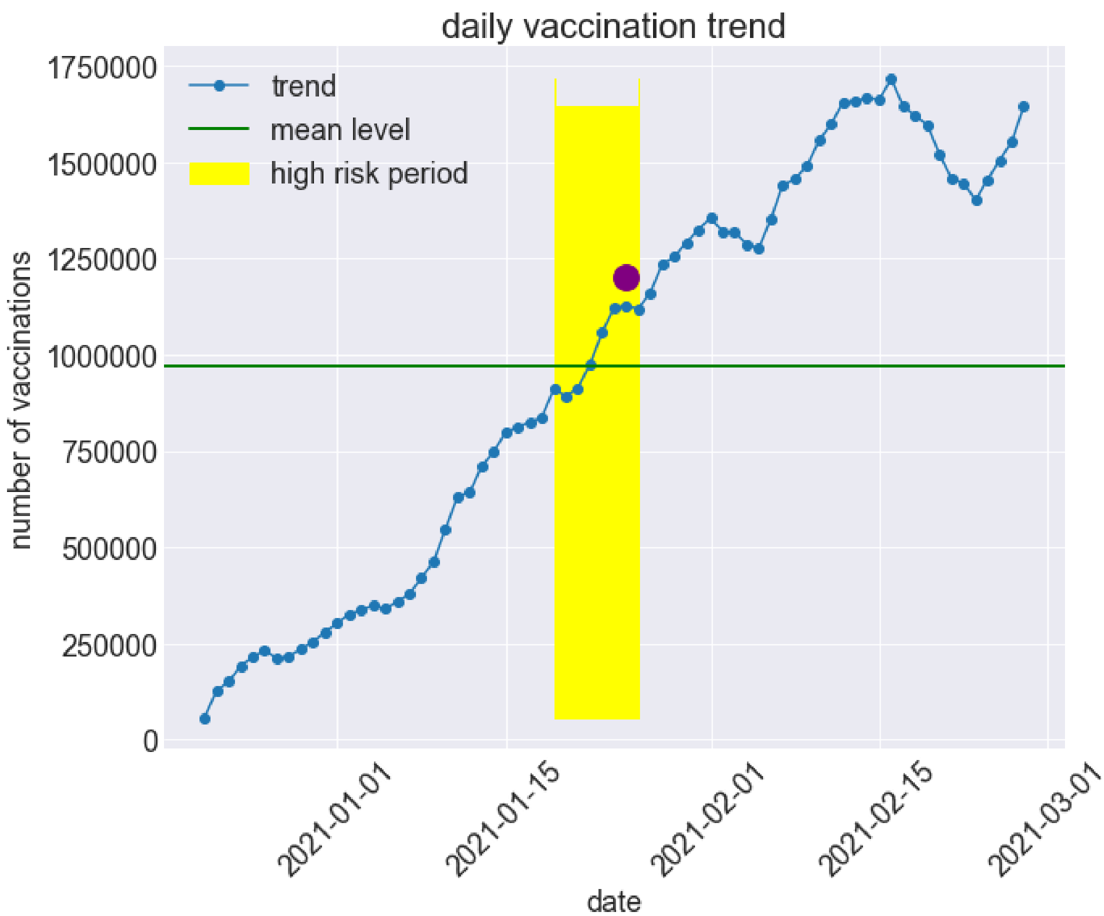
- https://stackoverflow.com/questions/33382619/plot-a-horizontal-line-using-matplotlib
- https://stackoverflow.com/questions/23248435/fill-between-two-vertical-lines-in-matplotlib
- https://stackoverflow.com/questions/18089667/how-to-estimate-how-much-memory-a-pandas-dataframe-will-need/47751572
- https://stackoverflow.com/questions/20625582/how-to-deal-with-settingwithcopywarning-in-pandas

The documentations are also good places to go to, they usually contain useful examples.

[53]:
```
plt.figure(figsize=(10, 8))
plt.xlabel('date'); plt.ylabel('number of vaccinations'); plt.title('daily␣
↪vaccination trend');
# change date to datetime
plt.plot(pd.to_datetime(us_vax['date'], format = '%Y-%m-%d').dt.date,␣
↪us_vax['daily_vaccinations'], \
        marker='o', label='trend');
plt.xticks(rotation = 45); plt.legend(loc='upper left'); plt.grid();
```

```
plt.axhline(np.mean(us_vax['daily_vaccinations']), color='green', lw=2,␣
↪label="mean level");

plt.fill_betweenx(us_vax['daily_vaccinations'],␣
↪sorted(list(us_vax['date']))[30], \
                    sorted(list(us_vax['date']))[37], color='yellow', label='high␣
↪risk period');
plt.scatter(sorted(list(us_vax['date']))[36], 1200000, s=250, color="purple",␣
↪marker='o');
plt.style.use('seaborn-dark'); plt.legend();
plt.rcParams.update({'font.size': 18})
```




```
[ ]:
```