

▼ COVID19 EXPLORATORY DATA ANALYSIS WITH PYTHON

This notebook contains an Exploratory Data Analysis of the pandemic Covid19 based on the data from the University of Oxford (<https://github.com/CSSEGISandData/COVID-19>). I have made no statistical or predictive sensitivity of the situation and some problems that predictions can create.

The main reasons for using the JHU data are:

JHU is already a trusted and respected institution, They cite many sources, which are themselves provided directly in the github repository (.csv in a github repository).

▼ Exploratory data analysis and visualization using Python

▼ Imports and data

Let's import the necessary packages from the SciPy stack and get [the data](#).

```
# Import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Set style & figures inline
sns.set()
%matplotlib inline
```

```
↳ /usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning
import pandas.util.testing as tm
```

```
# Data urls
base_url = 'https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19'
confirmed_cases_data_url = base_url + 'time_series_covid19_confirmed_global.csv'
death_cases_data_url = base_url + 'time_series_covid19_deaths_global.csv'
recovery_cases_data_url = base_url + 'time_series_covid19_recovered_global.csv'

# Import datasets as pandas dataframes
raw_confirmed_df = pd.read_csv(confirmed_cases_data_url)
raw_deaths_df = pd.read_csv(death_cases_data_url)
raw_recovered_df = pd.read_csv(recovery_cases_data_url)
```

▼ Analysing the Confirmed cases of COVID-19

```
raw_confirmed_df.head()
```



	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20
0	NaN	Afghanistan	33.0000	65.0000	0	0	0	0
1	NaN	Albania	41.1533	20.1683	0	0	0	0
2	NaN	Algeria	28.0339	1.6596	0	0	0	0
3	NaN	Andorra	42.5063	1.5218	0	0	0	0
4	NaN	Angola	-11.2027	17.8739	0	0	0	0

5 rows × 85 columns

Using .info() and .describe()

```
raw_confirmed_df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
```


```
RangeIndex: 264 entries, 0 to 263
```

```
Data columns (total 85 columns):
```

#	Column	Non-Null Count	Dtype
0	Province/State	82 non-null	object
1	Country/Region	264 non-null	object
2	Lat	264 non-null	float64
3	Long	264 non-null	float64
4	1/22/20	264 non-null	int64
5	1/23/20	264 non-null	int64
6	1/24/20	264 non-null	int64
7	1/25/20	264 non-null	int64
8	1/26/20	264 non-null	int64
9	1/27/20	264 non-null	int64
10	1/28/20	264 non-null	int64
11	1/29/20	264 non-null	int64
12	1/30/20	264 non-null	int64
13	1/31/20	264 non-null	int64
14	2/1/20	264 non-null	int64
15	2/2/20	264 non-null	int64
16	2/3/20	264 non-null	int64
17	2/4/20	264 non-null	int64
18	2/5/20	264 non-null	int64
19	2/6/20	264 non-null	int64
20	2/7/20	264 non-null	int64
21	2/8/20	264 non-null	int64
22	2/9/20	264 non-null	int64
23	2/10/20	264 non-null	int64
24	2/11/20	264 non-null	int64
25	2/12/20	264 non-null	int64
26	2/13/20	264 non-null	int64
27	2/14/20	264 non-null	int64
28	2/15/20	264 non-null	int64
29	2/16/20	264 non-null	int64
30	2/17/20	264 non-null	int64
31	2/18/20	264 non-null	int64
32	2/19/20	264 non-null	int64
33	2/20/20	264 non-null	int64
34	2/21/20	264 non-null	int64
35	2/22/20	264 non-null	int64
36	2/23/20	264 non-null	int64
37	2/24/20	264 non-null	int64
38	2/25/20	264 non-null	int64
39	2/26/20	264 non-null	int64
40	2/27/20	264 non-null	int64
41	2/28/20	264 non-null	int64
42	2/29/20	264 non-null	int64
43	3/1/20	264 non-null	int64
44	3/2/20	264 non-null	int64
45	3/3/20	264 non-null	int64
46	3/4/20	264 non-null	int64
47	3/5/20	264 non-null	int64
48	3/6/20	264 non-null	int64
49	3/7/20	264 non-null	int64
50	3/8/20	264 non-null	int64
51	3/9/20	264 non-null	int64
52	3/10/20	264 non-null	int64
53	3/11/20	264 non-null	int64
54	3/12/20	264 non-null	int64
55	3/13/20	264 non-null	int64

```
56 3/14/20      264 non-null    int64
57 3/15/20      264 non-null    int64
58 3/16/20      264 non-null    int64
59 3/17/20      264 non-null    int64
60 3/18/20      264 non-null    int64
61 3/19/20      264 non-null    int64
62 3/20/20      264 non-null    int64
63 3/21/20      264 non-null    int64
64 3/22/20      264 non-null    int64
65 3/23/20      264 non-null    int64
66 3/24/20      264 non-null    int64
67 3/25/20      264 non-null    int64
68 3/26/20      264 non-null    int64
69 3/27/20      264 non-null    int64
70 3/28/20      264 non-null    int64
71 3/29/20      264 non-null    int64
72 3/30/20      264 non-null    int64
73 3/31/20      264 non-null    int64
74 4/1/20       264 non-null    int64
75 4/2/20       264 non-null    int64
76 4/3/20       264 non-null    int64
77 4/4/20       264 non-null    int64
78 4/5/20       264 non-null    int64
79 4/6/20       264 non-null    int64
80 4/7/20       264 non-null    int64
81 4/8/20       264 non-null    int64
82 4/9/20       264 non-null    int64
83 4/10/20      264 non-null    int64
84 4/11/20      264 non-null    int64
dtypes: float64(2), int64(81), object(2)
memory usage: 175.4+ KB
```

```
raw_confirmed_df.describe()
```



	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20
count	264.000000	264.000000	264.000000	264.000000	264.000000	264.000000	264.000000
mean	21.317326	22.168315	2.102273	2.477273	3.564394	5.431818	8.022727
std	24.734994	70.669996	27.382118	27.480921	34.210982	47.612615	66.537778
min	-51.796300	-135.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	6.969250	-20.026050	0.000000	0.000000	0.000000	0.000000	0.000000
50%	23.488100	20.535638	0.000000	0.000000	0.000000	0.000000	0.000000
75%	41.166075	78.750000	0.000000	0.000000	0.000000	0.000000	0.000000
max	71.706900	178.065000	444.000000	444.000000	549.000000	761.000000	1058.000000

8 rows × 83 columns

▼ Number of confirmed cases by country

```
raw_confirmed_df.tail()
```



	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20
259	Saint Pierre and Miquelon	France	46.885200	-56.315900	0	0	0
260	NaN	South Sudan	6.877000	31.307000	0	0	0
261	NaN	Western Sahara	24.215500	-12.885800	0	0	0
262	NaN	Sao Tome and Principe	0.186360	6.613081	0	0	0
263	NaN	Yemen	15.552727	48.516388	0	0	0

5 rows × 85 columns

```
raw_confirmed_df.head()
```



	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20
0	NaN	Afghanistan	33.0000	65.0000	0	0	0	
1	NaN	Albania	41.1533	20.1683	0	0	0	
2	NaN	Algeria	28.0339	1.6596	0	0	0	
3	NaN	Andorra	42.5063	1.5218	0	0	0	
4	NaN	Angola	-11.2027	17.8739	0	0	0	

5 rows × 85 columns

From the head and tail observations, its visible that each entry contains the data belonging to the f

We will take all the rows (*regions/provinces*) that correspond to that country and add up the number of cases. In other words, we want to **group by** the country column and sum up all the values for the other columns.

```
# Group by region (we'll also drop 'Lat', 'Long' as it doesn't make sense to sum them here)
confirmed_df = raw_confirmed_df.groupby(['Country/Region']).sum().drop(["Lat", "Long"], axis=1)
confirmed_df.head()
```



	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	1/28/20	1/29/20
Country/Region								
Afghanistan	0	0	0	0	0	0	0	(
Albania	0	0	0	0	0	0	0	(
Algeria	0	0	0	0	0	0	0	(
Andorra	0	0	0	0	0	0	0	(
Angola	0	0	0	0	0	0	0	(

5 rows × 81 columns

So each row of our new dataframe `confirmed_df` is a time series of the number of confirmed cases over time, indexed by the index of our dataframe.

```
confirmed_df.index
```

```
Index(['Afghanistan', 'Albania', 'Algeria', 'Andorra', 'Angola',
      'Antigua and Barbuda', 'Argentina', 'Armenia', 'Australia', 'Austria',
      ...,
      'United Kingdom', 'Uruguay', 'Uzbekistan', 'Venezuela', 'Vietnam',
      'West Bank and Gaza', 'Western Sahara', 'Yemen', 'Zambia', 'Zimbabwe'],
      dtype='object', name='Country/Region', length=185)
```

It's indexed by `Country/Region`. That's all good **but** if we index by date **instead**, it will allow us to plot more easily.

To make the index the set of dates, notice that the column names are the dates. To turn column names into the index, we can use `confirmed_df.T` to make the columns the rows and vice versa. This corresponds to taking the transpose of the dataframe.

```
confirmed_df = confirmed_df.transpose()
confirmed_df.head()
```

```
↩
```

Now, let's have a look at our index to see whether it actually consists of DateTimes or not

```
confirmed_df.index
```

```
Index(['1/22/20', '1/23/20', '1/24/20', '1/25/20', '1/26/20', '1/27/20',
      '1/28/20', '1/29/20', '1/30/20', '1/31/20', '2/1/20', '2/2/20',
      '2/3/20', '2/4/20', '2/5/20', '2/6/20', '2/7/20', '2/8/20', '2/9/20',
      '2/10/20', '2/11/20', '2/12/20', '2/13/20', '2/14/20', '2/15/20',
      '2/16/20', '2/17/20', '2/18/20', '2/19/20', '2/20/20', '2/21/20',
      '2/22/20', '2/23/20', '2/24/20', '2/25/20', '2/26/20', '2/27/20',
      '2/28/20', '2/29/20', '3/1/20', '3/2/20', '3/3/20', '3/4/20', '3/5/20',
      '3/6/20', '3/7/20', '3/8/20', '3/9/20', '3/10/20', '3/11/20', '3/12/20',
      '3/13/20', '3/14/20', '3/15/20', '3/16/20', '3/17/20', '3/18/20',
      '3/19/20', '3/20/20', '3/21/20', '3/22/20', '3/23/20', '3/24/20',
      '3/25/20', '3/26/20', '3/27/20', '3/28/20', '3/29/20', '3/30/20',
      '3/31/20', '4/1/20', '4/2/20', '4/3/20', '4/4/20', '4/5/20', '4/6/20',
      '4/7/20', '4/8/20', '4/9/20', '4/10/20', '4/11/20'],
      dtype='object')
```

Note that `dtype='object'` which means that these are strings, not DateTimes. We will use `pandas`

```
# Set index as DateTimeIndex
datetime_index = pd.DatetimeIndex(confirmed_df.index)
confirmed_df.set_index(datetime_index, inplace=True)
# Check out index
confirmed_df.index
```

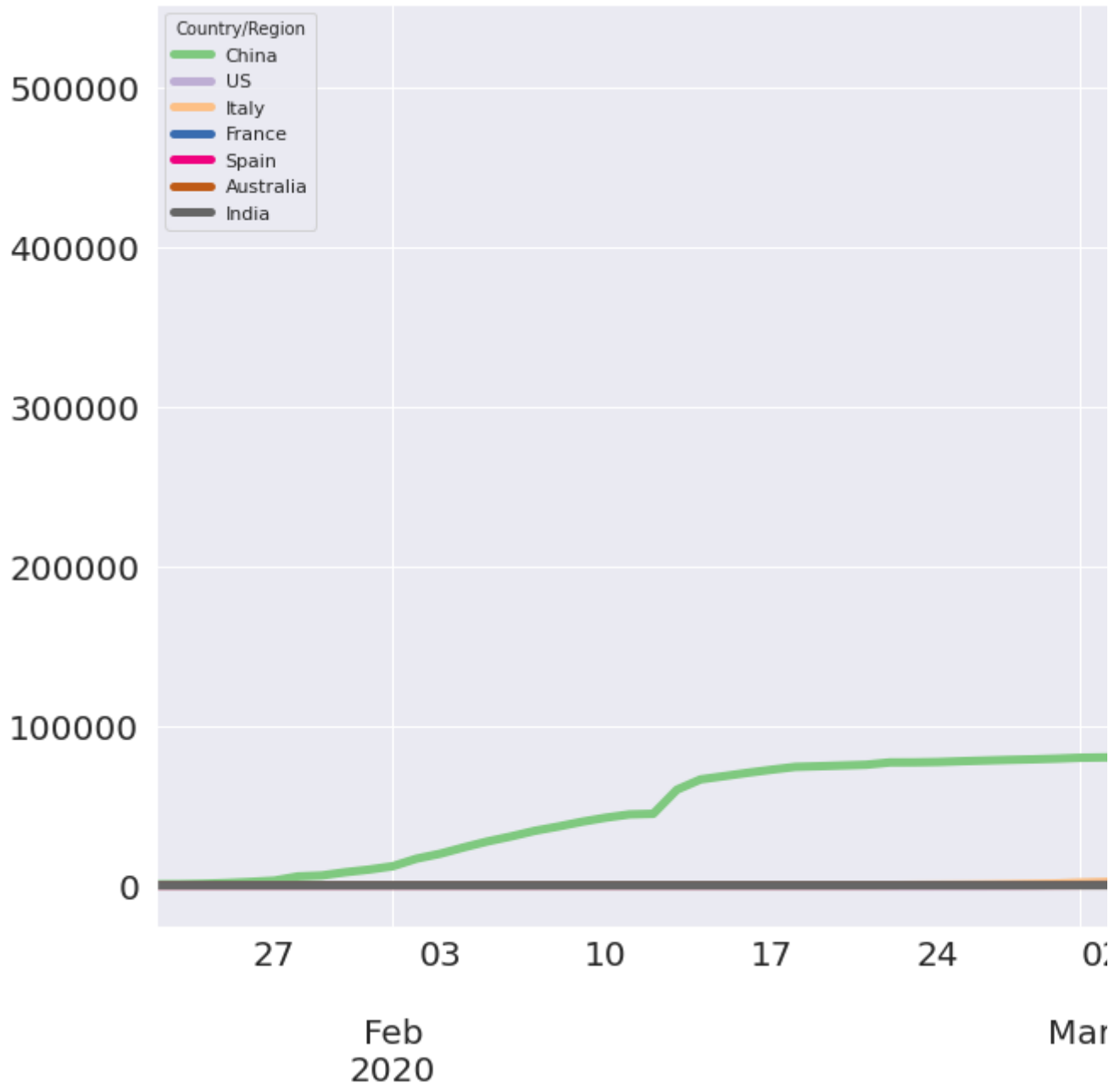
```
DatetimeIndex(['2020-01-22', '2020-01-23', '2020-01-24', '2020-01-25',
              '2020-01-26', '2020-01-27', '2020-01-28', '2020-01-29',
              '2020-01-30', '2020-01-31', '2020-02-01', '2020-02-02',
              '2020-02-03', '2020-02-04', '2020-02-05', '2020-02-06',
              '2020-02-07', '2020-02-08', '2020-02-09', '2020-02-10',
              '2020-02-11', '2020-02-12', '2020-02-13', '2020-02-14',
              '2020-02-15', '2020-02-16', '2020-02-17', '2020-02-18',
              '2020-02-19', '2020-02-20', '2020-02-21', '2020-02-22',
              '2020-02-23', '2020-02-24', '2020-02-25', '2020-02-26',
              '2020-02-27', '2020-02-28', '2020-02-29', '2020-03-01',
              '2020-03-02', '2020-03-03', '2020-03-04', '2020-03-05',
              '2020-03-06', '2020-03-07', '2020-03-08', '2020-03-09',
              '2020-03-10', '2020-03-11', '2020-03-12', '2020-03-13',
              '2020-03-14', '2020-03-15', '2020-03-16', '2020-03-17',
              '2020-03-18', '2020-03-19', '2020-03-20', '2020-03-21',
              '2020-03-22', '2020-03-23', '2020-03-24', '2020-03-25',
              '2020-03-26', '2020-03-27', '2020-03-28', '2020-03-29',
              '2020-03-30', '2020-03-31', '2020-04-01', '2020-04-02',
              '2020-04-03', '2020-04-04', '2020-04-05', '2020-04-06',
              '2020-04-07', '2020-04-08', '2020-04-09', '2020-04-10',
              '2020-04-11'],
              dtype='datetime64[ns]', freq=None)
```

Now we have a `DateTimeIndex` and `Countries` for columns, we can use the dataframe plotting method `number of cases by country`.

Plotting confirmed cases by country

```
# Plotting time series of several countries (as plotting for all the countries will make the plot too crowded)
countries = ['China', 'US', 'Italy', 'France', 'Spain', 'Australia', 'India']
confirmed_df[countries].plot(figsize=(20,10), linewidth=5, colormap='Accent', fontsize=20)
```

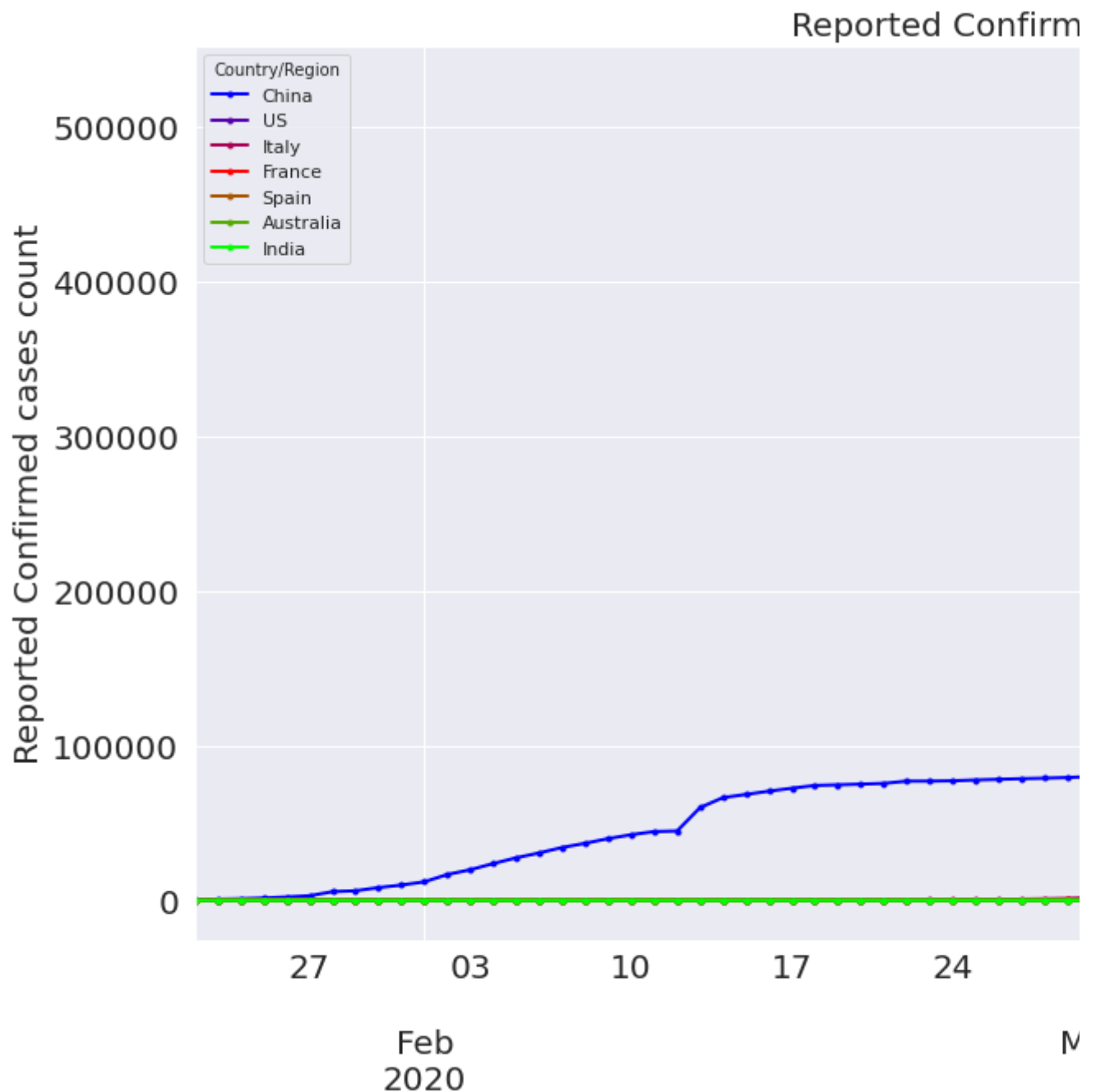
↳ <matplotlib.axes._subplots.AxesSubplot at 0x7f3369fe75c0>



Now, Let's label our axes and give the figure a title. We'll also thin the line and add points for the data.

```
# Plot time series of several countries of interest
confirmed_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', colormap='brg', font=
plt.xlabel('Date', fontsize=20);
plt.ylabel('Reported Confirmed cases count', fontsize=20);
plt.title('Reported Confirmed Cases Time Series', fontsize=20);
```

↳

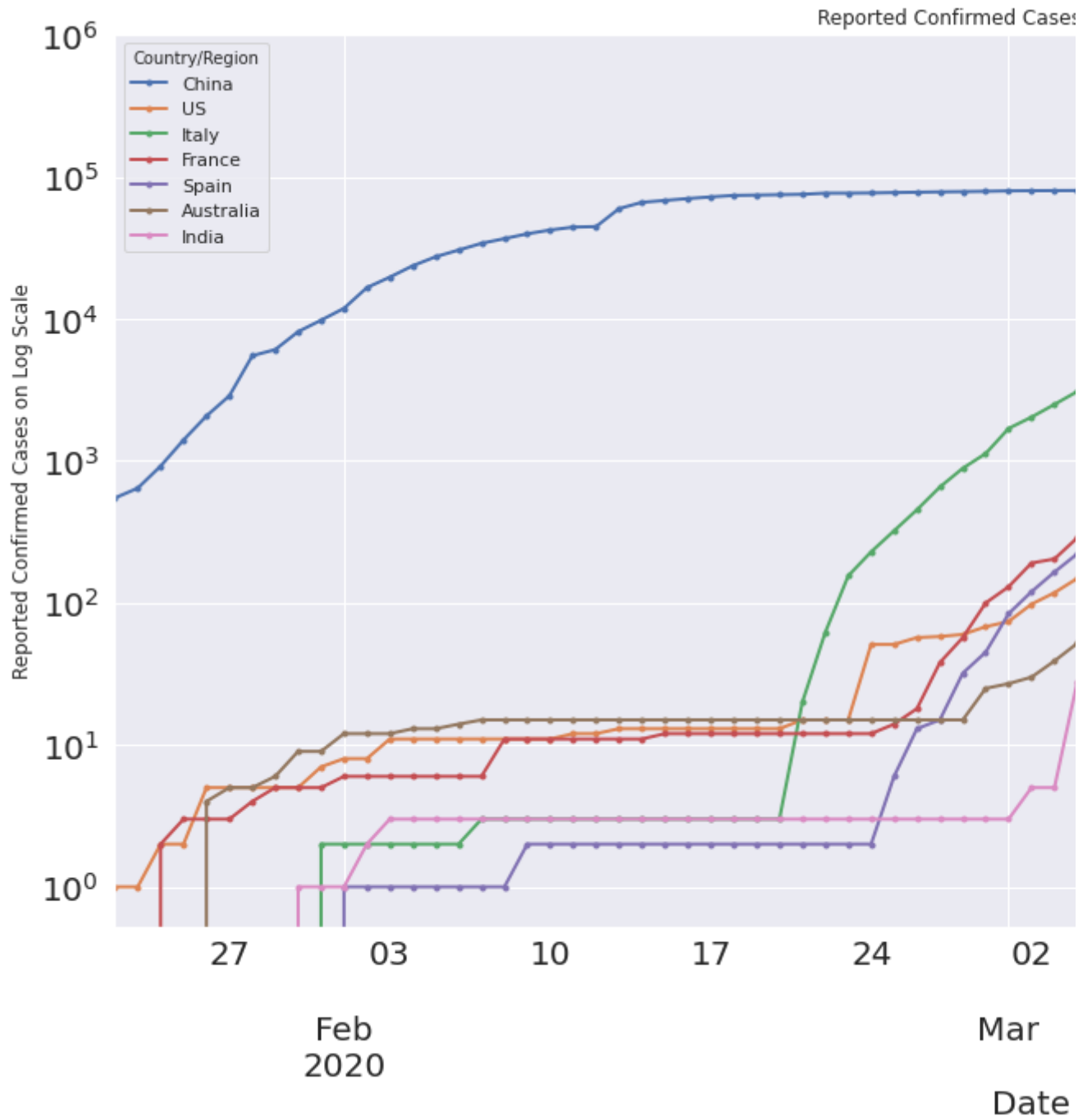


Now, since the US data seems to be going really high. lets take the y-axis on logarithmic scale:

```
# Plot time series of several countries of interest
confirmed_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', fontsize=20, logy =
plt.xlabel('Date', fontsize = 20)
plt.ylabel('Reported Confirmed Cases on Log Scale')
plt.title('Reported Confirmed Cases Time Series Plot')
```



Text(0.5, 1.0, 'Reported Confirmed Cases Time Series Plot')



Till now, we have explored the confirmed cases data and :

- looked at the dataset containing the number of reported confirmed cases for each region,
- wrangled the data to look at the number of reported confirmed cases by country,
- plotted the number of reported confirmed cases by country (both log and semi-log),
- Used log plots for the data.

▼ Number of reported deaths

As we did above for `raw_data_confirmed`, let's check out the head and the info of the `raw_data_deaths`

```
raw_deaths_df.head()
```

raw_deaths_df.info()

↗

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20
0	NaN	Afghanistan	33.0000	65.0000	0	0	0	0
1	NaN	Albania	41.1533	20.1683	0	0	0	0
2	NaN	Algeria	28.0339	1.6596	0	0	0	0
3	NaN	Andorra	42.5063	1.5218	0	0	0	0
4	NaN	Angola	-11.2027	17.8739	0	0	0	0

5 rows × 85 columns

raw_deaths_df.info()



```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 264 entries, 0 to 263
```

```
Data columns (total 85 columns):
```

#	Column	Non-Null Count	Dtype
0	Province/State	82 non-null	object
1	Country/Region	264 non-null	object
2	Lat	264 non-null	float64
3	Long	264 non-null	float64
4	1/22/20	264 non-null	int64
5	1/23/20	264 non-null	int64
6	1/24/20	264 non-null	int64
7	1/25/20	264 non-null	int64
8	1/26/20	264 non-null	int64
9	1/27/20	264 non-null	int64
10	1/28/20	264 non-null	int64
11	1/29/20	264 non-null	int64
12	1/30/20	264 non-null	int64
13	1/31/20	264 non-null	int64
14	2/1/20	264 non-null	int64
15	2/2/20	264 non-null	int64
16	2/3/20	264 non-null	int64
17	2/4/20	264 non-null	int64
18	2/5/20	264 non-null	int64
19	2/6/20	264 non-null	int64
20	2/7/20	264 non-null	int64
21	2/8/20	264 non-null	int64
22	2/9/20	264 non-null	int64
23	2/10/20	264 non-null	int64
24	2/11/20	264 non-null	int64
25	2/12/20	264 non-null	int64
26	2/13/20	264 non-null	int64
27	2/14/20	264 non-null	int64
28	2/15/20	264 non-null	int64
29	2/16/20	264 non-null	int64
30	2/17/20	264 non-null	int64
31	2/18/20	264 non-null	int64
32	2/19/20	264 non-null	int64
33	2/20/20	264 non-null	int64
34	2/21/20	264 non-null	int64
35	2/22/20	264 non-null	int64
36	2/23/20	264 non-null	int64
37	2/24/20	264 non-null	int64
38	2/25/20	264 non-null	int64
39	2/26/20	264 non-null	int64
40	2/27/20	264 non-null	int64
41	2/28/20	264 non-null	int64
42	2/29/20	264 non-null	int64
43	3/1/20	264 non-null	int64
44	3/2/20	264 non-null	int64
45	3/3/20	264 non-null	int64
46	3/4/20	264 non-null	int64
47	3/5/20	264 non-null	int64
48	3/6/20	264 non-null	int64
49	3/7/20	264 non-null	int64
50	3/8/20	264 non-null	int64
51	3/9/20	264 non-null	int64
52	3/10/20	264 non-null	int64
53	3/11/20	264 non-null	int64
54	3/12/20	264 non-null	int64
55	3/13/20	264 non-null	int64

56	3/14/20	264 non-null	int64
57	3/15/20	264 non-null	int64
58	3/16/20	264 non-null	int64
59	3/17/20	264 non-null	int64
60	3/18/20	264 non-null	int64
61	3/19/20	264 non-null	int64
62	3/20/20	264 non-null	int64
63	3/21/20	264 non-null	int64
64	3/22/20	264 non-null	int64
65	3/23/20	264 non-null	int64
66	3/24/20	264 non-null	int64
67	3/25/20	264 non-null	int64
68	3/26/20	264 non-null	int64
69	3/27/20	264 non-null	int64
70	3/28/20	264 non-null	int64
71	3/29/20	264 non-null	int64
72	3/30/20	264 non-null	int64
73	3/31/20	264 non-null	int64
74	4/1/20	264 non-null	int64
75	4/2/20	264 non-null	int64
76	4/3/20	264 non-null	int64
77	4/4/20	264 non-null	int64
78	4/5/20	264 non-null	int64
79	4/6/20	264 non-null	int64
80	4/7/20	264 non-null	int64
81	4/8/20	264 non-null	int64
82	4/9/20	264 non-null	int64
83	4/10/20	264 non-null	int64
84	4/11/20	264 non-null	int64

dtypes: float64(2), int64(81), object(2)

memory usage: 175.4+ KB

The structure of this data is similar to the `raw_confirmed_df`, so we can apply the same steps use

▼ Number of reported deaths by country

```
#group-by countries
deaths_df = raw_deaths_df.groupby(['Country/Region']).sum().drop(['Lat', 'Long'], axis=1)
deaths_df.head()
```



```
# Transpose
deaths_df = deaths_df.transpose()

deaths_df.head()
```



Country/Region	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	A
1/22/20	0	0	0	0	0	0	0	0
1/23/20	0	0	0	0	0	0	0	0
1/24/20	0	0	0	0	0	0	0	0
1/25/20	0	0	0	0	0	0	0	0
1/26/20	0	0	0	0	0	0	0	0

5 rows × 185 columns

```
# Set index as DateTimeIndex
datetime_index = pd.DatetimeIndex(deaths_df.index)
deaths_df.set_index(datetime_index, inplace=True)

# Check out head
deaths_df.head()
```

```
deaths_df.index
```

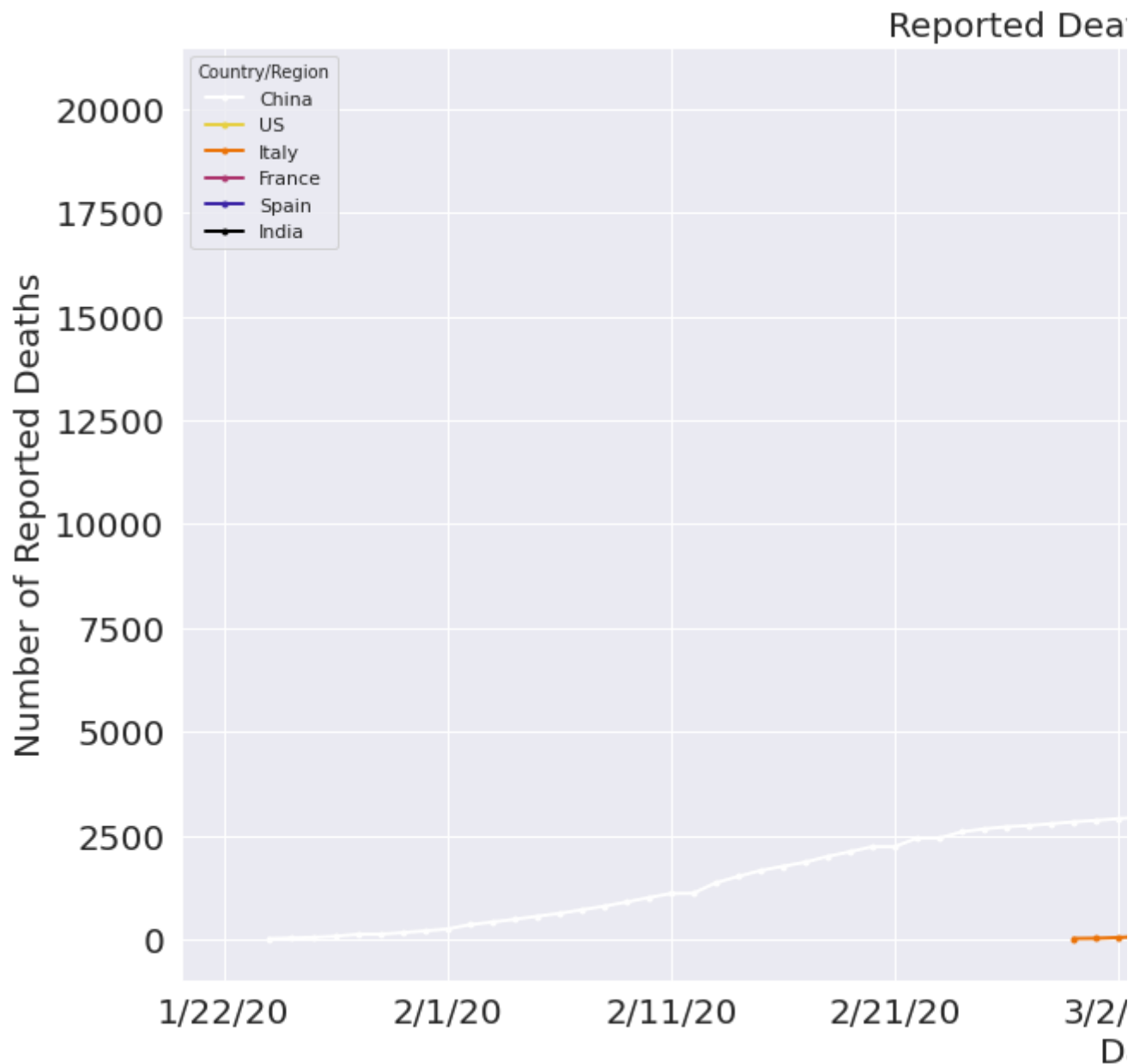
```
Index(['1/22/20', '1/23/20', '1/24/20', '1/25/20', '1/26/20', '1/27/20',
      '1/28/20', '1/29/20', '1/30/20', '1/31/20', '2/1/20', '2/2/20',
      '2/3/20', '2/4/20', '2/5/20', '2/6/20', '2/7/20', '2/8/20', '2/9/20',
      '2/10/20', '2/11/20', '2/12/20', '2/13/20', '2/14/20', '2/15/20',
      '2/16/20', '2/17/20', '2/18/20', '2/19/20', '2/20/20', '2/21/20',
      '2/22/20', '2/23/20', '2/24/20', '2/25/20', '2/26/20', '2/27/20',
      '2/28/20', '2/29/20', '3/1/20', '3/2/20', '3/3/20', '3/4/20', '3/5/20',
      '3/6/20', '3/7/20', '3/8/20', '3/9/20', '3/10/20', '3/11/20', '3/12/20',
      '3/13/20', '3/14/20', '3/15/20', '3/16/20', '3/17/20', '3/18/20',
      '3/19/20', '3/20/20', '3/21/20', '3/22/20', '3/23/20', '3/24/20',
      '3/25/20', '3/26/20', '3/27/20', '3/28/20', '3/29/20', '3/30/20',
      '3/31/20', '4/1/20', '4/2/20', '4/3/20', '4/4/20', '4/5/20', '4/6/20',
      '4/7/20', '4/8/20', '4/9/20', '4/10/20', '4/11/20'],
      dtype='object')
```

▼ Plotting number of reported deaths by country

Visualizing the number of reported deaths:

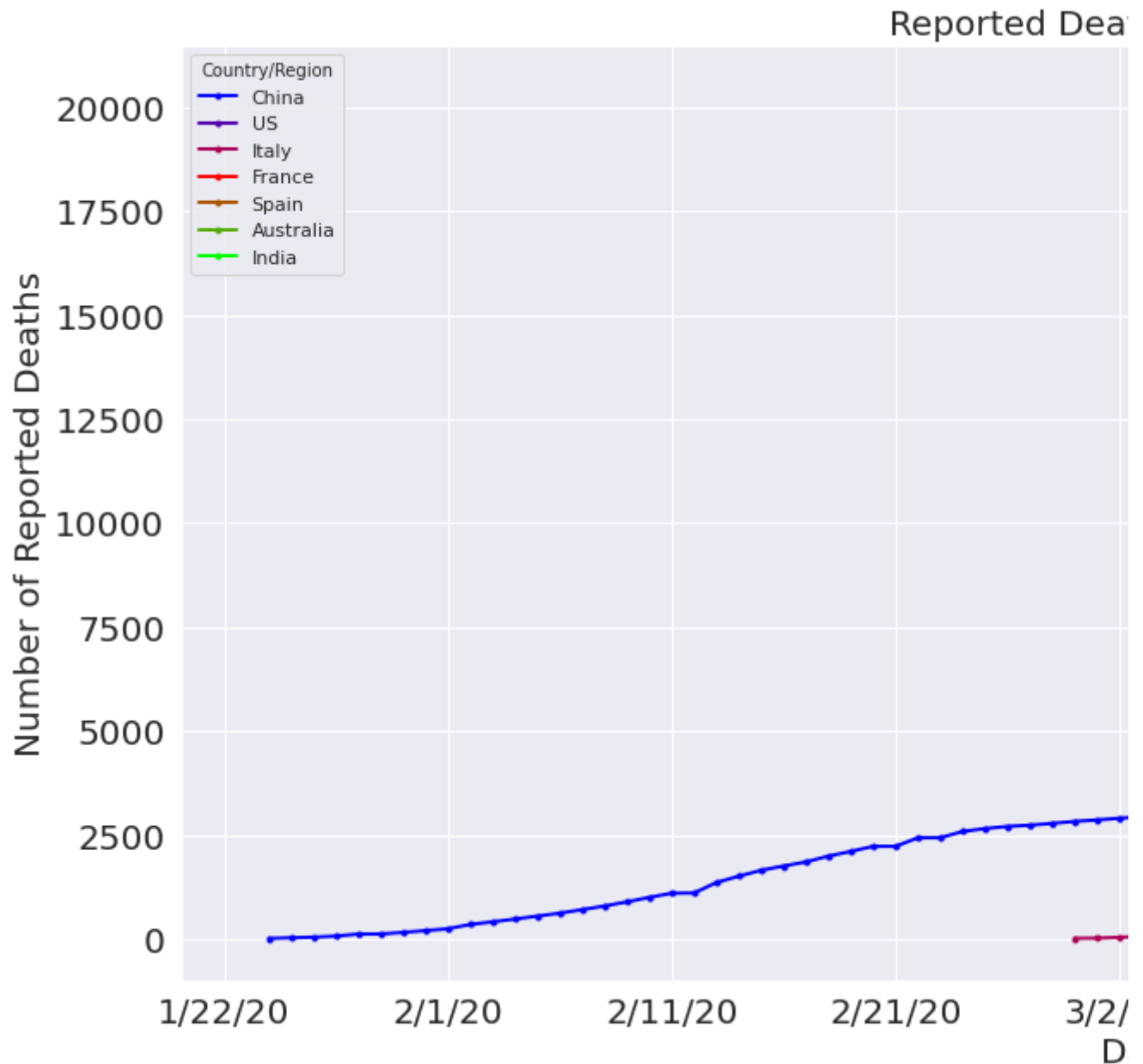
```
# Plot time series of several countries of interest
deaths_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', colormap='CMRmap_r', f
plt.xlabel('Date', fontsize=20))
```

```
plt.xlabel('Date', fontsize=20);
plt.ylabel('Number of Reported Deaths', fontsize=20);
plt.title('Reported Deaths Time Series', fontsize=20);
```



```
# Plot time series of several countries of interest
deaths_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', colormap='brg', fontsi
plt.xlabel('Date', fontsize=20);
plt.ylabel('Number of Reported Deaths', fontsize=20);
plt.title('Reported Deaths Time Series', fontsize=20);
```

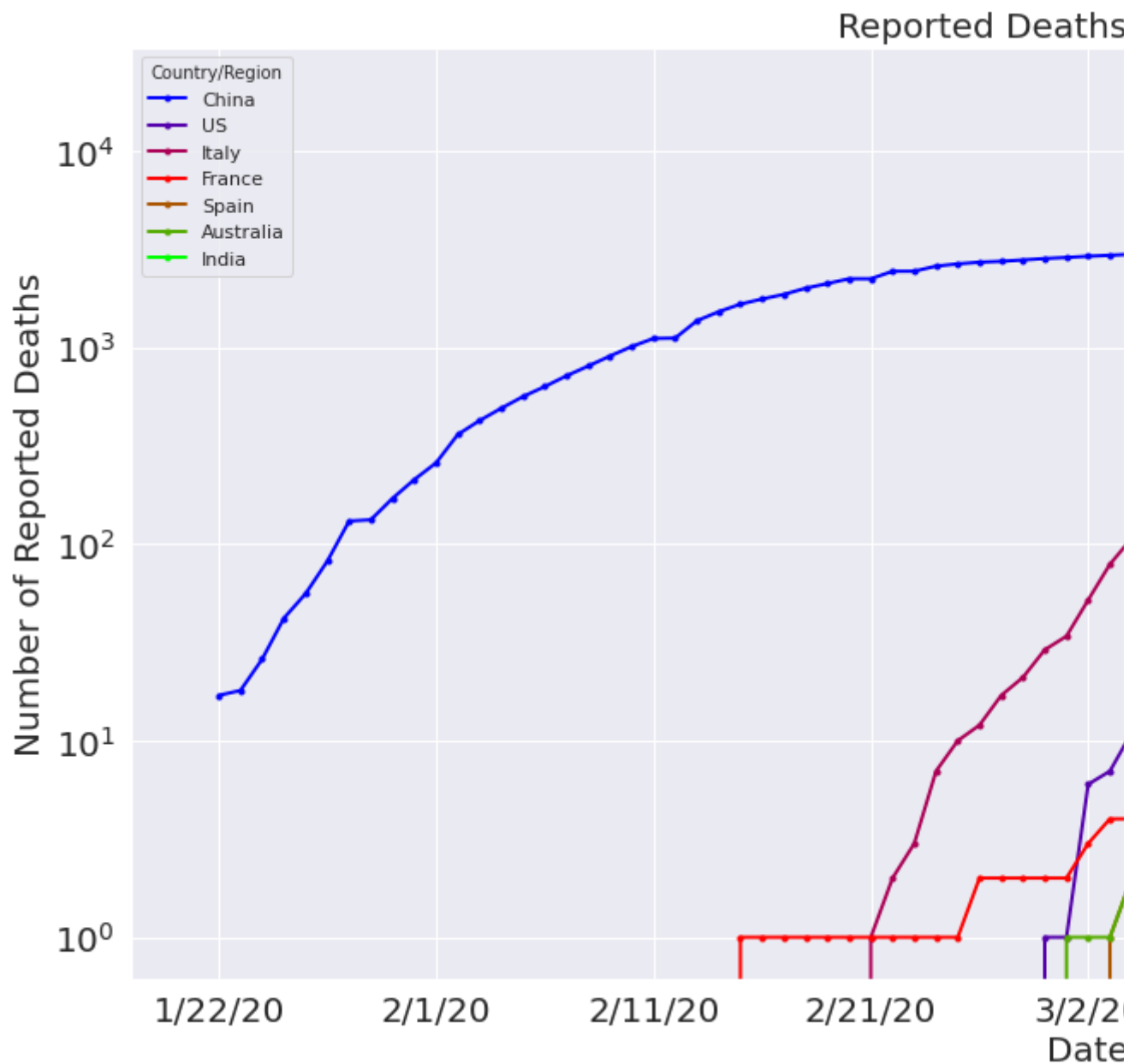




Now on a semi-log plot:

```
# Plot time series of countries on log scale
deaths_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', colormap='brg', fontsi
plt.xlabel('Date', fontsize=20);
plt.ylabel('Number of Reported Deaths', fontsize=20);
plt.title('Reported Deaths Time Series', fontsize=20);
```





▼ Aligning growth curves to start with day of number of known deaths ≥ 25

To compare what's happening in different countries, we can align each country's growth curves to known deaths ≥ 25 , such as reported in the first figure [here](#). To achieve this, first off, let's set all associated data points don't get plotted at all when we visualize the data:

```
# Loop over columns & set values < 25 to None
for col in deaths_df.columns:
    deaths_df.loc[(deaths_df[col] < 25), col] = None

# Check out tail
deaths_df.tail()
```



Country/Region	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	A
4/7/20	NaN	NaN	193.0	NaN	NaN	NaN	56.0	
4/8/20	NaN	NaN	205.0	NaN	NaN	NaN	63.0	
4/9/20	NaN	NaN	235.0	25.0	NaN	NaN	72.0	
4/10/20	NaN	NaN	256.0	26.0	NaN	NaN	82.0	
4/11/20	NaN	NaN	275.0	26.0	NaN	NaN	83.0	

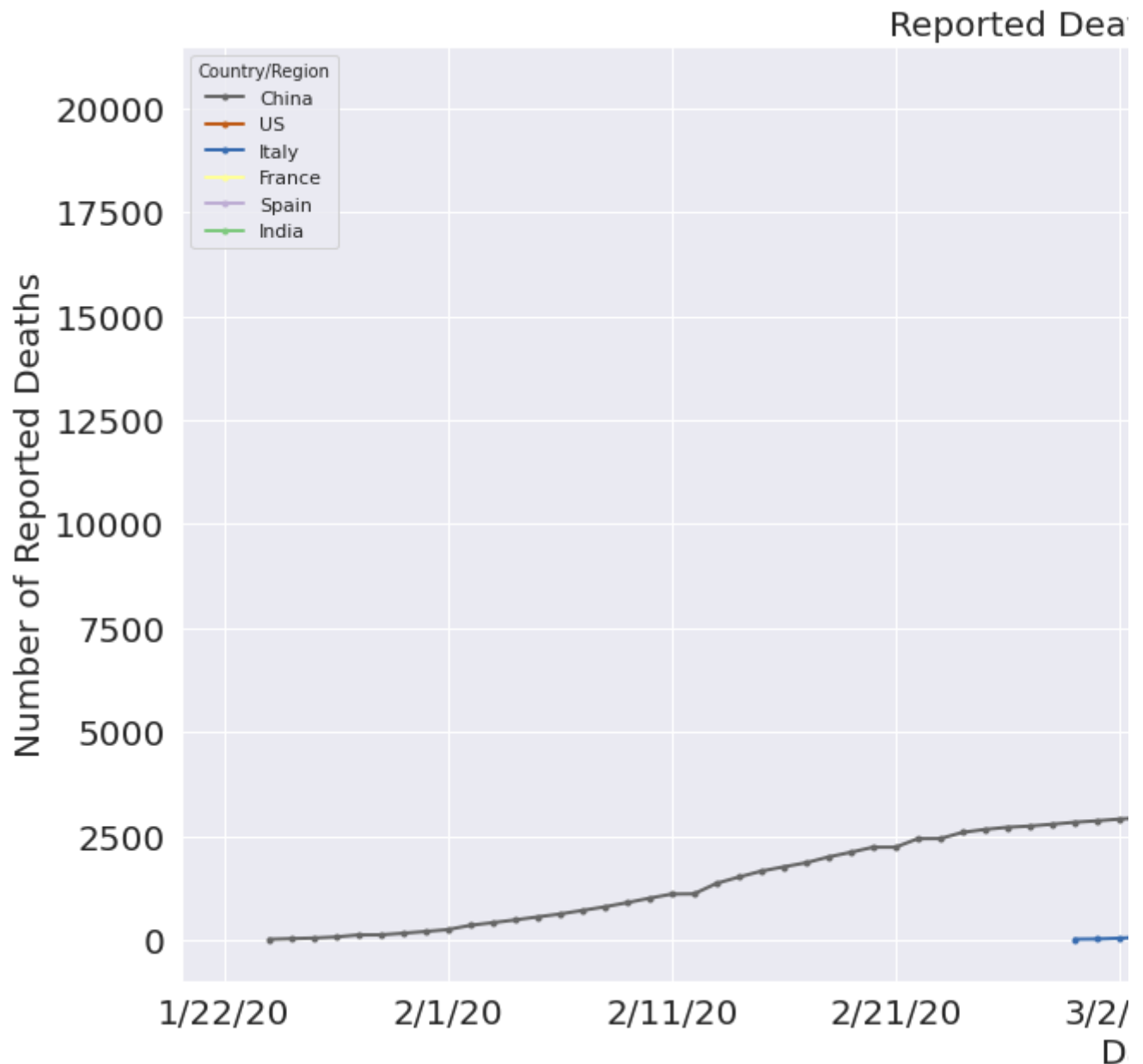
5 rows × 185 columns

Now let's plot as above to make sure we see what we think we should see:

```
# Plot time series of several countries of interest
countries = ['China', 'US', 'Italy', 'France', 'Spain', 'India']
deaths_df[countries].plot(figsize=(20,10), linewidth=2, marker='.', colormap='Accent_r', f
plt.xlabel('Date', fontsize=20)
plt.ylabel('Number of Reported Deaths', fontsize=20)
plt.title('Reported Deaths Time Series', fontsize=20)
```



Text(0.5, 1.0, 'Reported Deaths Time Series')



The countries that have seen less than 25 total deaths will have columns of all NaNs now so let's drop them. We have left:

```
# Drop columns that are all NaNs (i.e. countries that haven't yet reached 25 deaths)
deaths_df.dropna(axis=1, how='all', inplace=True)
deaths_df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 81 entries, 1/22/20 to 4/11/20
```

```
Data columns (total 64 columns):
```

#	Column	Non-Null Count	Dtype
0	Algeria	17 non-null	float64
1	Andorra	3 non-null	float64
2	Argentina	12 non-null	float64
3	Australia	9 non-null	float64
4	Austria	19 non-null	float64
5	Bangladesh	2 non-null	float64
6	Belgium	23 non-null	float64
7	Bosnia and Herzegovina	6 non-null	float64
8	Brazil	21 non-null	float64
9	Bulgaria	2 non-null	float64
10	Burkina Faso	1 non-null	float64
11	Canada	20 non-null	float64
12	Chile	8 non-null	float64
13	China	79 non-null	float64
14	Colombia	9 non-null	float64
15	Czechia	12 non-null	float64
16	Denmark	19 non-null	float64
17	Dominican Republic	15 non-null	float64
18	Ecuador	19 non-null	float64
19	Egypt	16 non-null	float64
20	Finland	8 non-null	float64
21	France	33 non-null	float64
22	Germany	25 non-null	float64
23	Greece	17 non-null	float64
24	Hungary	9 non-null	float64
25	India	14 non-null	float64
26	Indonesia	24 non-null	float64
27	Iran	45 non-null	float64
28	Iraq	19 non-null	float64
29	Ireland	15 non-null	float64
30	Israel	11 non-null	float64
31	Italy	43 non-null	float64
32	Japan	27 non-null	float64
33	Korea, South	41 non-null	float64
34	Luxembourg	11 non-null	float64
35	Malaysia	16 non-null	float64
36	Mexico	12 non-null	float64
37	Moldova	4 non-null	float64
38	Morocco	15 non-null	float64
39	Netherlands	26 non-null	float64
40	North Macedonia	5 non-null	float64
41	Norway	14 non-null	float64
42	Pakistan	12 non-null	float64
43	Panama	12 non-null	float64
44	Peru	12 non-null	float64
45	Philippines	21 non-null	float64
46	Poland	13 non-null	float64
47	Portugal	19 non-null	float64
48	Romania	16 non-null	float64
49	Russia	10 non-null	float64
50	San Marino	13 non-null	float64
51	Saudi Arabia	9 non-null	float64
52	Serbia	11 non-null	float64
53	Slovenia	7 non-null	float64
54	South Africa	1 non-null	float64
55	Spain	34 non-null	float64

```

56 Sweden                20 non-null    float64
57 Switzerland           26 non-null    float64
58 Thailand              6 non-null     float64
59 Tunisia               3 non-null     float64
60 Turkey                21 non-null    float64
61 US                   33 non-null    float64
62 Ukraine               9 non-null     float64
63 United Kingdom       27 non-null    float64
dtypes: float64(64)
memory usage: 43.6+ KB

```

As we're going to align the countries from the day they first had at least 25 deaths, we won't need the date at all. So we can

- Reset the Index, which will give us an ordinal index (which turns the date into a regular column)
- Drop the date column (which will be called 'index') after the reset.

```

# sort index, drop date column
deaths_df_drop = deaths_df.reset_index().drop(['index'], axis=1)
deaths_df_drop.head()

```



Country/Region	Algeria	Andorra	Argentina	Australia	Austria	Bangladesh	Belgium
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Now it's time to shift each column so that the first entry is the first NaN value that it contains! To do this, we need to shift each column by the first valid index of each column. How much do we shift each column, though? The magnitude of the shift is given by the first valid index of each column, which we can retrieve using the `first_valid_index()` method on the column **but** we want to be careful (this is a common convention and perhaps intuition). SO let's do it.

```

# shift
for col in deaths_df_drop.columns:
    deaths_df_drop[col] = deaths_df_drop[col].shift(-deaths_df_drop[col].first_valid_index())
# check out head
deaths_df_drop.head()

```

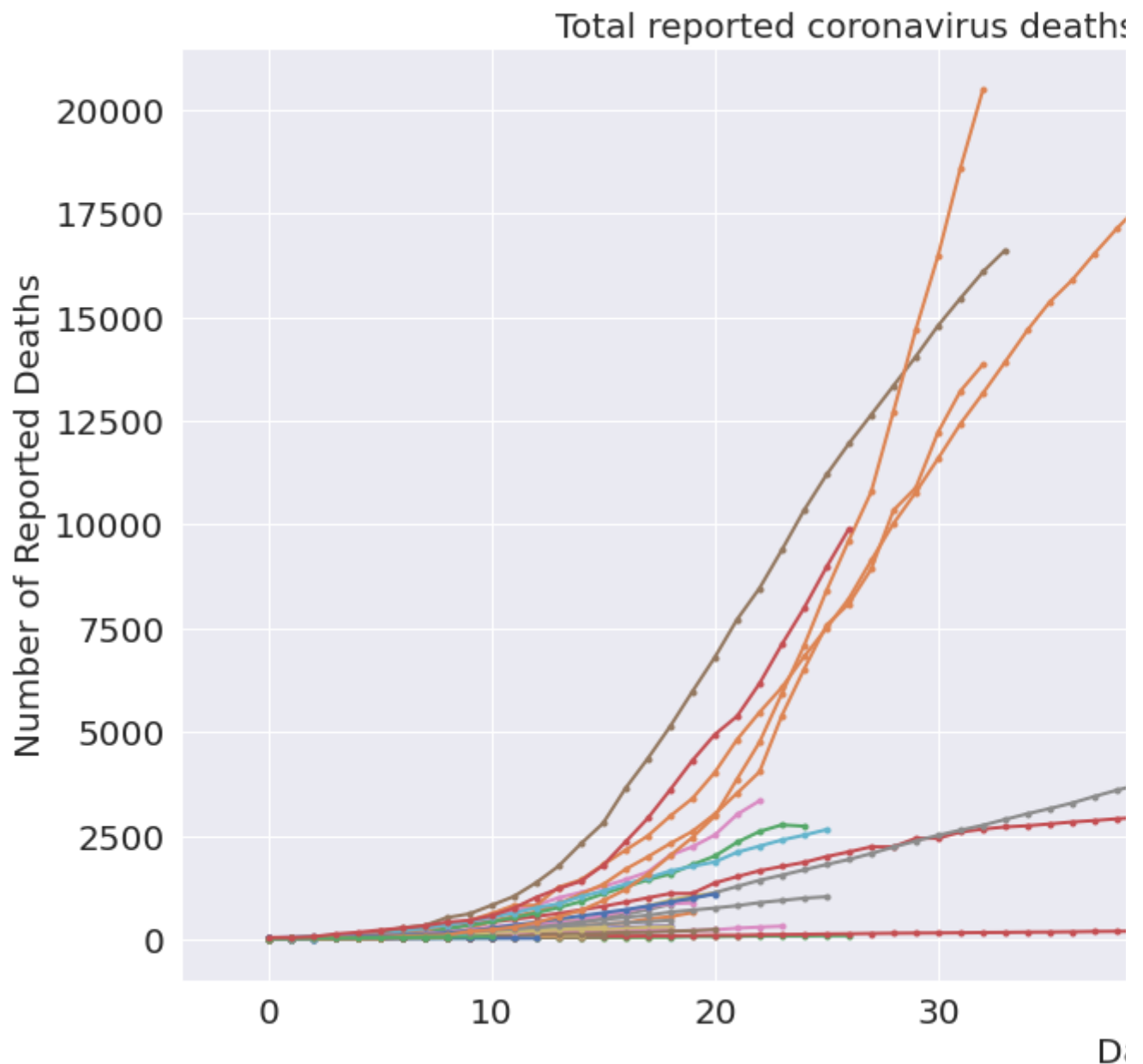


Country/Region	Algeria	Andorra	Argentina	Australia	Austria	Bangladesh	Belgium
0	25.0	25.0	27.0	28.0	28.0	27.0	37.0
1	26.0	26.0	28.0	30.0	30.0	30.0	67.0
2	29.0	26.0	36.0	35.0	49.0	NaN	75.0
3	31.0	NaN	39.0	40.0	58.0	NaN	88.0
4	35.0	NaN	43.0	45.0	68.0	NaN	122.0

Now we get to plot our time series, first with linear axes, then semi-log:

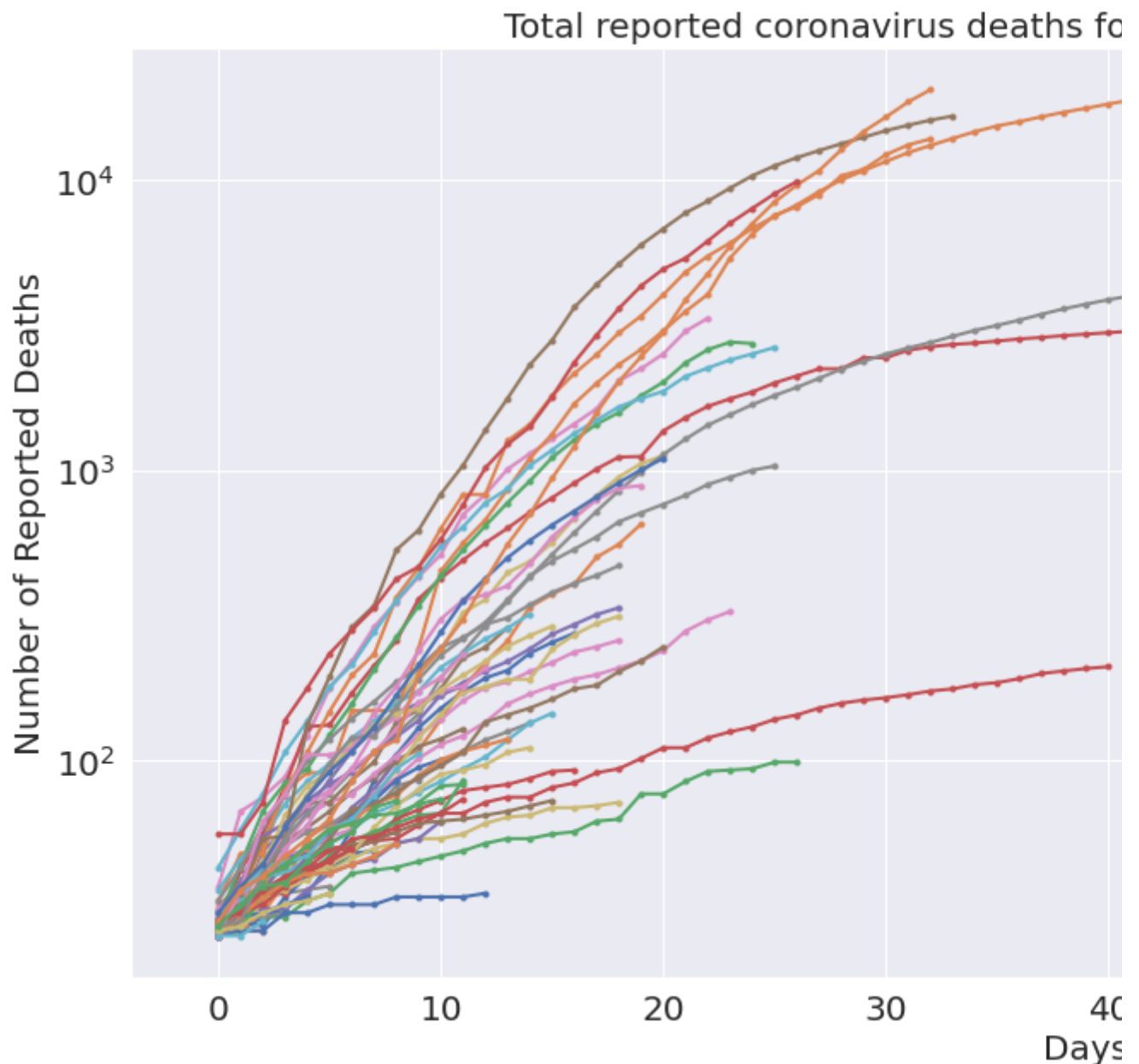
```
# Plot time series
ax = deaths_df_drop.plot(figsize=(20,10), linewidth=2, marker=".", fontsize=20)
ax.legend(ncol=3, loc='upper right')
plt.xlabel('Days', fontsize=20);
plt.ylabel('Number of Reported Deaths', fontsize=20);
plt.title('Total reported coronavirus deaths for places with at least 25 deaths', fontsize
```





```
# Plot time series
ax = deaths_df_drop.plot(figsize=(20,10), linewidth=2, marker=".", fontsize=20, logy=True)
ax.legend(ncol=3, loc='upper right')
plt.xlabel('Days', fontsize=20);
plt.ylabel('Number of Reported Deaths', fontsize=20);
plt.title('Total reported coronavirus deaths for places with at least 25 deaths', fontsize=20);
```

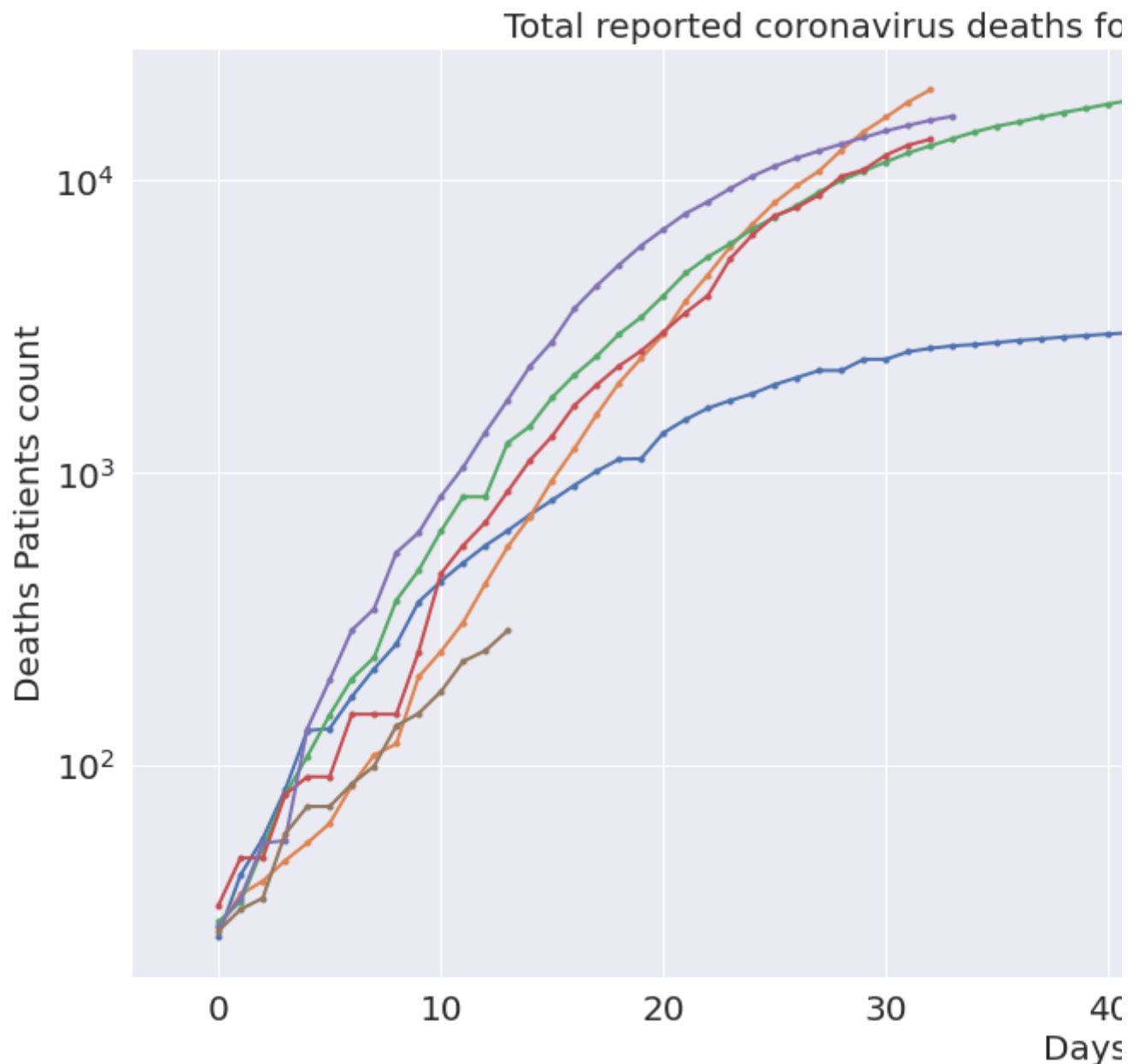




Note: although the plot is what we wanted, the above plots are challenging to retrieve any meaningful growth curves so that it's very crowded **and** too many colours look the same so it's difficult to tell which curve belongs to which country. In the next plot less curves now and further down in the notebook I'll use the python package Altair to introduce

```
# Plot semi log time series
ax = deaths_df_drop[countries].plot(figsize=(20,10), linewidth=2, marker='.', fontsize=20,
ax.legend(ncol=3, loc='upper right')
plt.xlabel('Days', fontsize=20);
plt.ylabel('Deaths Patients count', fontsize=20);
plt.title('Total reported coronavirus deaths for places with at least 25 deaths', fontsize=20)
```





Till Now, We

- looked at the dataset containing the number of reported deaths for each region,
- wrangled the data to look at the number of reported deaths by country,
- plotted the number of reported deaths by country on linear and log scale.
- aligned growth curves to start with day of number of known deaths ≥ 25 .

▼ Plotting number of recovered people

The third dataset in the Hopkins repository is the number of recovered. We want to do similar data *could* copy and paste our code again *but*, if you're writing the same code three times, it's likely time

```
# Function for grouping countries by region
def group_by_country(raw_data):
```

```
# Group by
```

```
# Group by
data = raw_data.groupby(['Country/Region']).sum().drop(['Lat', 'Long'], axis=1)
# Transpose
data = data.transpose()
# Set index as DateTimeIndex
datetime_index = pd.DatetimeIndex(data.index)
data.set_index(datetime_index, inplace=True)
return data
```

Function to align growth curves

```
def align_curves(data, min_val):

    # Loop over columns & set values < min_val to None
    for col in data.columns:
        data.loc[(data[col] < min_val), col] = None
    # Drop columns with all NaNs
    data.dropna(axis=1, how="all", inplace=True)
    # Reset index, drop date
    data = data.reset_index().drop(['index'], axis=1)
    # Shift each column to begin with first valid index
    for col in data.columns:
        data[col] = data[col].shift(-data[col].first_valid_index())
    return data
```

Function to plot time series

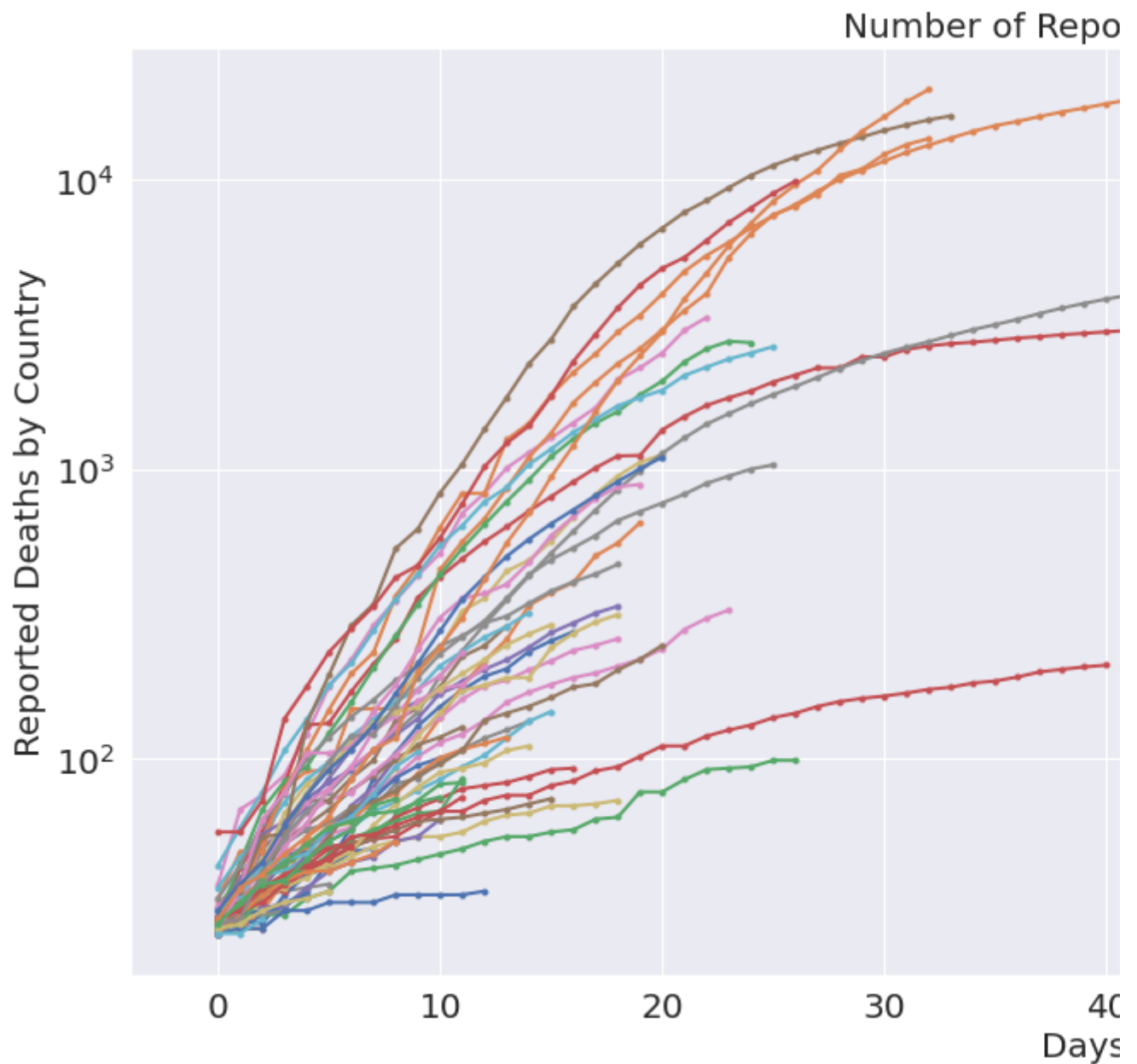
```
def plot_time_series(df, plot_title, x_label, y_label, logy=False):

    ax = df.plot(figsize=(20,10), linewidth=2, marker='.', fontsize=20, logy=logy)
    ax.legend(ncol=3, loc='lower right')
    plt.xlabel(x_label, fontsize=20);
    plt.ylabel(y_label, fontsize=20);
    plt.title(plot_title, fontsize=20);
```

Trying these functions at work on the 'number of deaths' data:

```
deaths_country_drop = (group_by_country(raw_deaths_df))
deaths_country_drop = align_curves(deaths_country_drop, min_val=25)
plot_time_series(deaths_country_drop, 'Number of Reported Deaths', 'Days', 'Reported Death
```





Now let's check use our functions to group, wrangle, and plot the recovered patients data:

```
# group by country and check out tail
recovered_df = group_by_country(raw_recovered_df)
recovered_df.tail()
```



Country/Region	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	A
2020-04-07	18	131	113	39	2	0	338	
2020-04-08	29	154	237	52	2	0	358	
2020-04-09	32	165	347	58	2	0	365	
2020-04-10	32	182	405	71	2	0	375	
2020-04-11	32	197	460	71	4	0	440	

5 rows × 185 columns

```
# align curves and check out head
recovered_df_drop = align_curves(recovered_df, min_val=25)
recovered_df_drop.head()
```



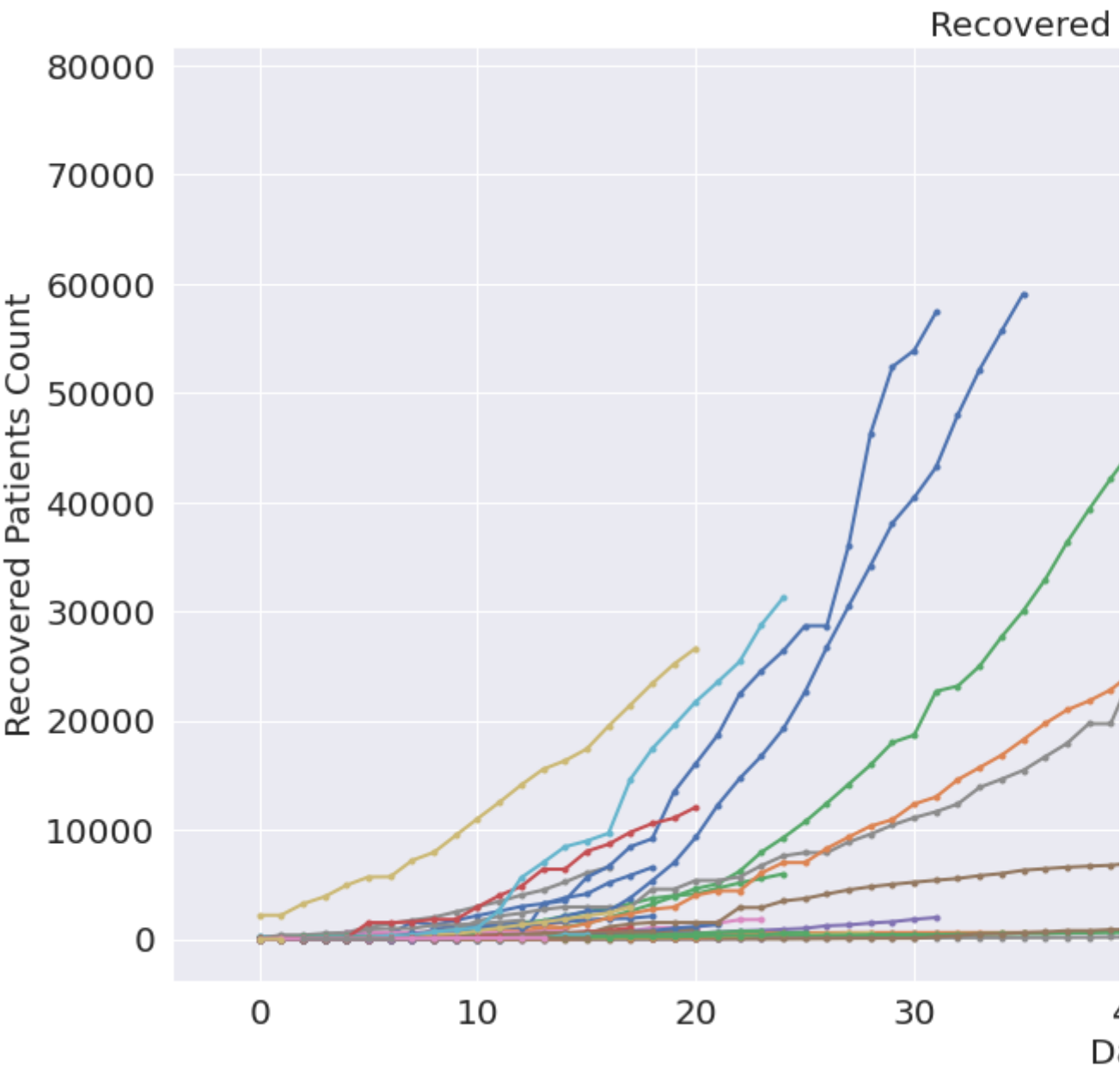
Country/Region	Afghanistan	Albania	Algeria	Andorra	Argentina	Armenia	Australia
0	29.0	31.0	32.0	26.0	52.0	28.0	26.0
1	32.0	31.0	32.0	31.0	52.0	30.0	26.0
2	32.0	33.0	32.0	39.0	63.0	30.0	26.0
3	32.0	44.0	65.0	52.0	72.0	30.0	88.0
4	NaN	52.0	65.0	58.0	72.0	30.0	88.0

5 rows × 109 columns

Plot time series:

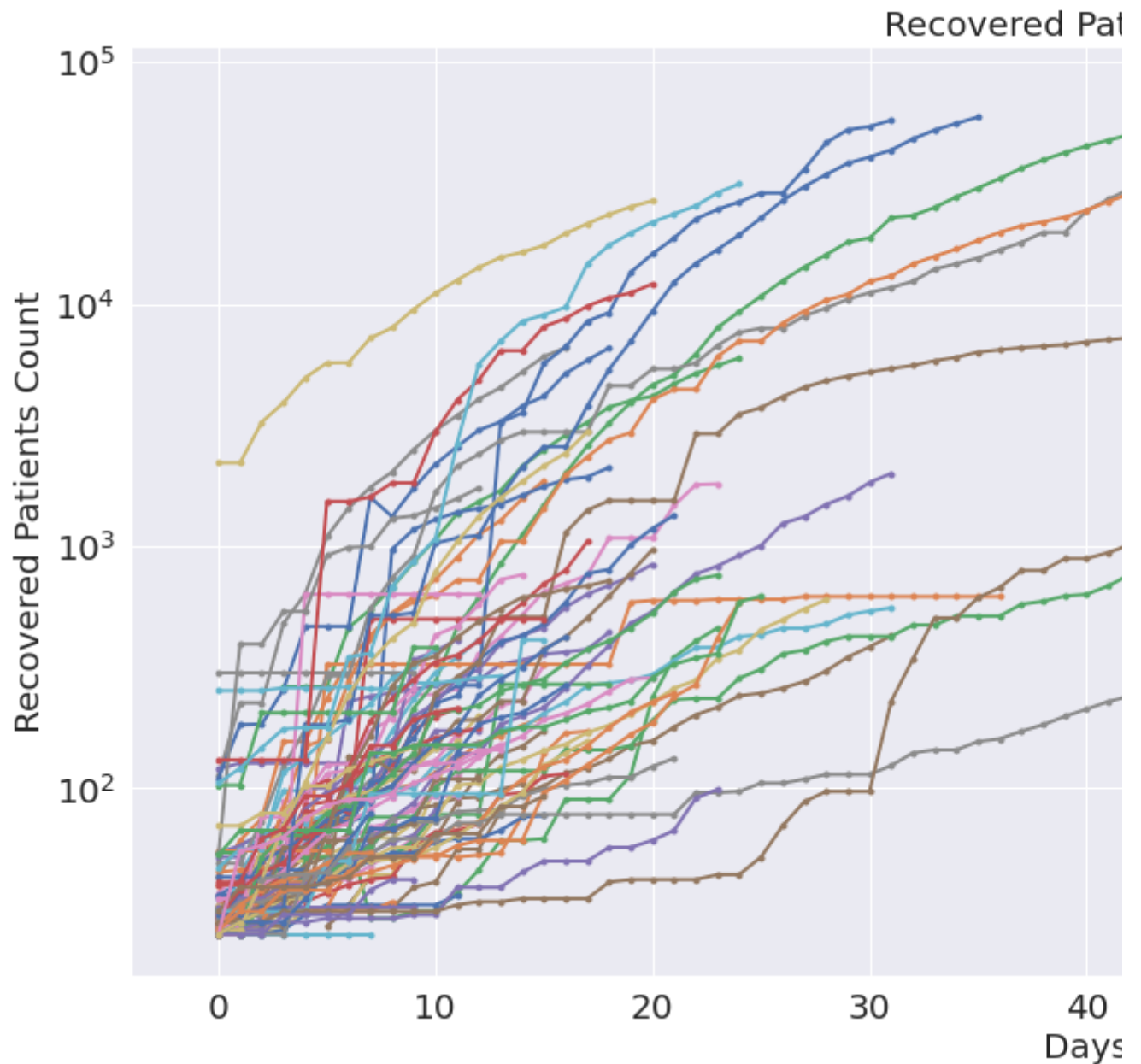
```
plot_time_series(recovered_df_drop, 'Recovered Patients Plot', 'Days', 'Recovered Patients')
```





```
plot_time_series(recovered_df_drop, 'Recovered Patients Plot', 'Days', 'Recovered Patients
```

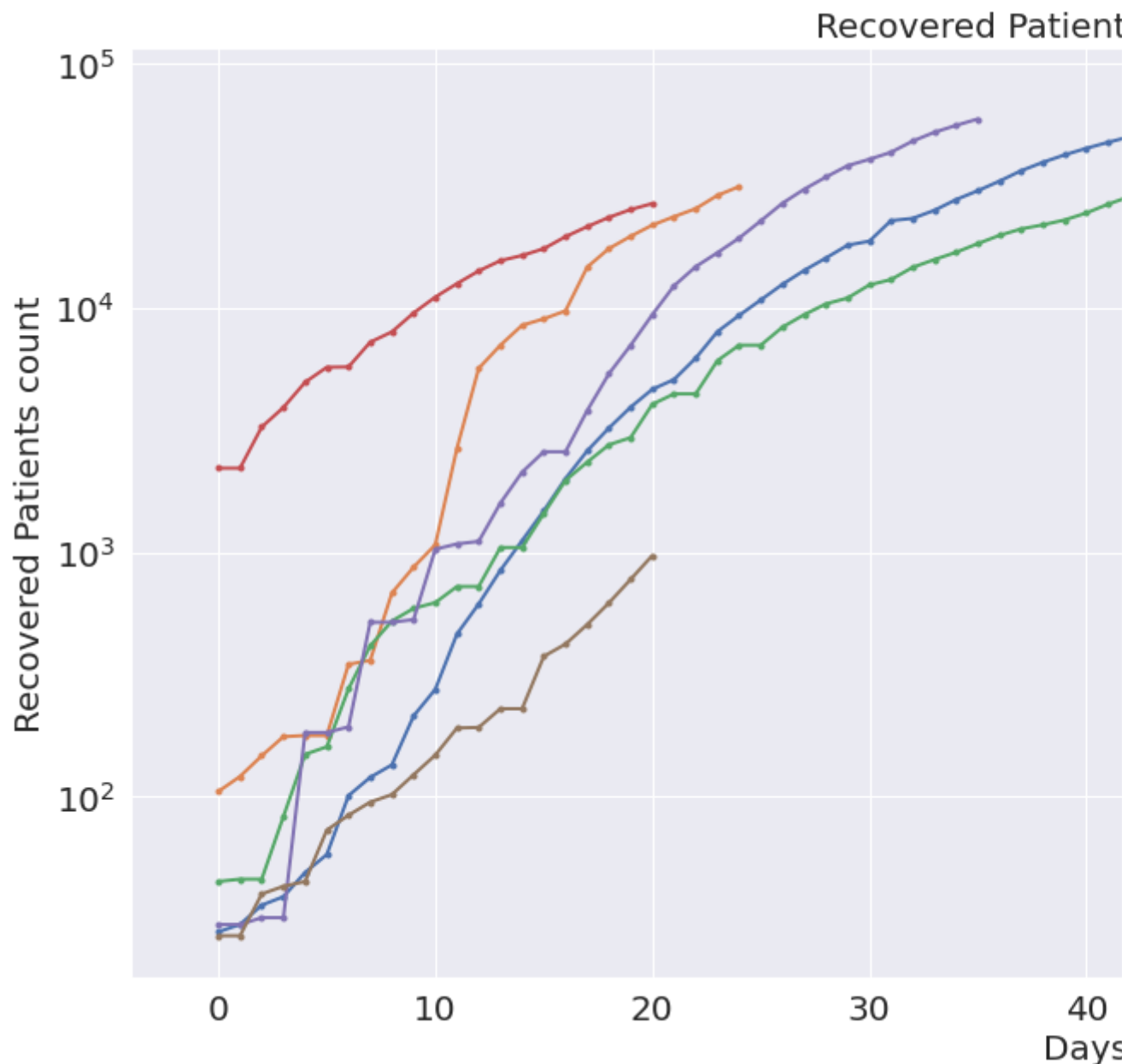




- ▼ Since this plot gets messed up because of the number of countries, I will again

```
plot_time_series(recovered_df_drop[countries], 'Recovered Patients Time Series', 'Days', 'Recovered Patients Count')
```





Now, I looked at the dataset containing the number of reported recoveries for each region, written the data along with using these functions.

▼ Interactive plots with altair

Now for some interactive data visualizations, I will be using Altair which can produce visualization of confirmed number of deaths by country for places with at least 25 deaths, similar to the one above is also really good.

Before going to Altair, I will reshape our `deaths_df` dataset. Notice that it's currently in **wide data** format for each "day" (where day 1 is the first day with over 25 confirmed deaths).

```
# Look at head
deaths_df_drop.head()
```



Country/Region	Algeria	Andorra	Argentina	Australia	Austria	Bangladesh	Belgium
0	25.0	25.0	27.0	28.0	28.0	27.0	37.0
1	26.0	26.0	28.0	30.0	30.0	30.0	67.0
2	29.0	26.0	36.0	35.0	49.0	NaN	75.0
3	31.0	NaN	39.0	40.0	58.0	NaN	88.0
4	35.0	NaN	43.0	45.0	68.0	NaN	122.0

For Altair, we'll want to convert the data into **long data format**. What this will do essentially have a will be 'Day', 'Country', and number of 'Deaths'. We do this using the dataframe method `.melt()` as

```
# create long data for deaths
deaths_long = deaths_df_drop.reset_index().melt(id_vars='index', value_name='Deaths').reorder_index()
deaths_long.head()
```



Day	Country/Region	Deaths
0	Algeria	25.0
1	Algeria	26.0
2	Algeria	29.0
3	Algeria	31.0
4	Algeria	35.0

```
deaths_long.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5184 entries, 0 to 5183
Data columns (total 3 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Day              5184 non-null   int64
1   Country/Region  5184 non-null   object
2   Deaths          1081 non-null   float64
dtypes: float64(1), int64(1), object(1)
memory usage: 121.6+ KB
```

We'll see the power of having long data when using Altair. Now having transformed our data, let's i

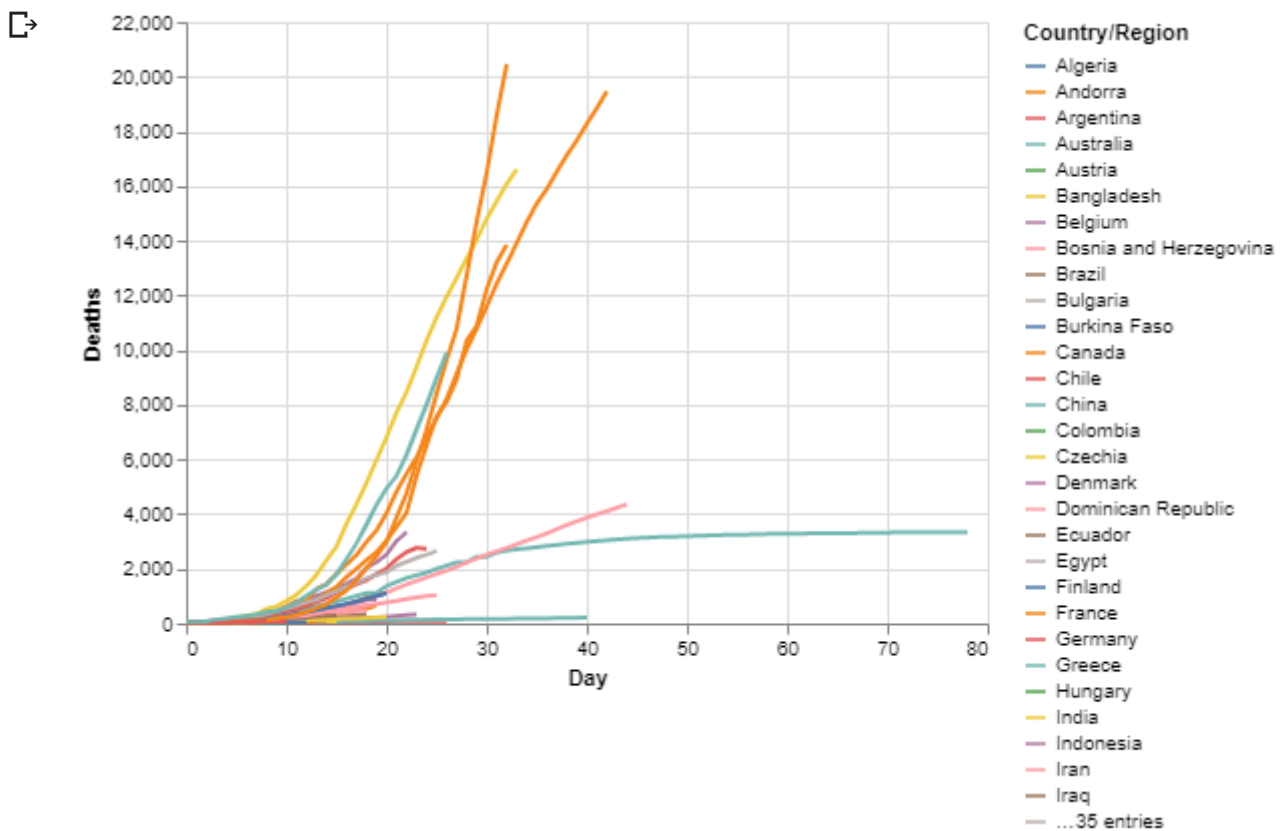
```
import altair as alt
```

```
alt.data_transformers.disable_max_rows()
```

```
#This particular line of code is to be used when we have more than 5000 rows in our dataset
#This limit has just been set to prevent our notebook from growing excessive in size.
```



```
# altair plotting
alt.Chart(deaths_long).mark_line().encode(
    x='Day',
    y='Deaths',
    color='Country/Region')
```



So, we have successfully made the plot.

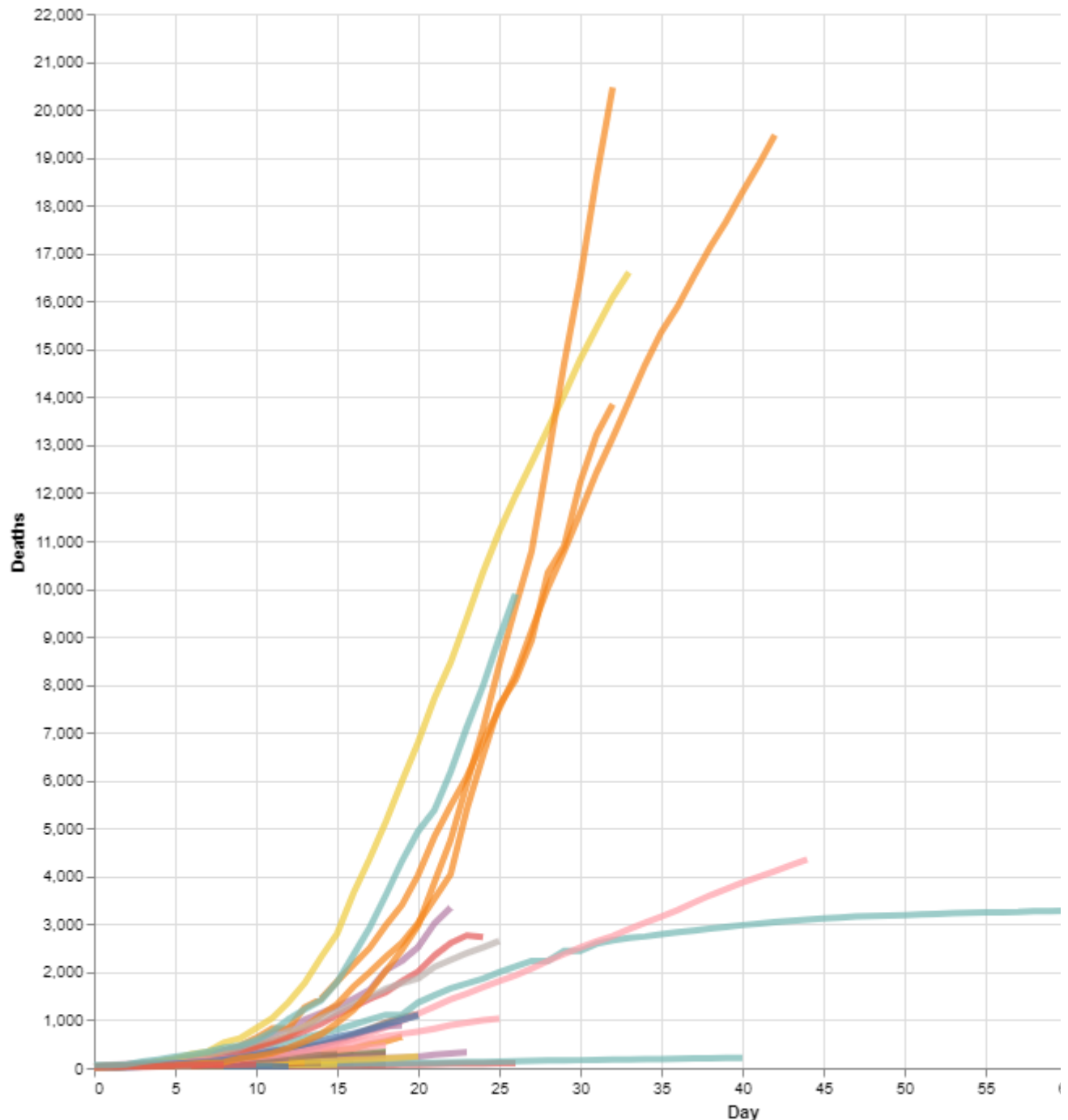
The [Altair documentation states](#),

The key idea is that you are declaring links between *data columns* and *visual encoding channels* etc. The rest of the plot details are handled automatically. Building on this declarative plotting to sophisticated plots and visualizations can be created using a relatively concise grammar.

I can now customize the code to thicken the line width, to alter the opacity, and to make the chart

```
# altair plot
alt.Chart(deaths_long).mark_line(strokeWidth=4, opacity=0.7).encode(
    x='Day',
    y='Deaths',
    color='Country/Region'
).properties(
    width=800, height=650
)
```





We can also add a log y-axis. To do this, The long-form, we express the types using the long-form the [Altair documentation](#)

useful when doing more fine-tuned adjustments to the encoding, such as binning, axis and sc

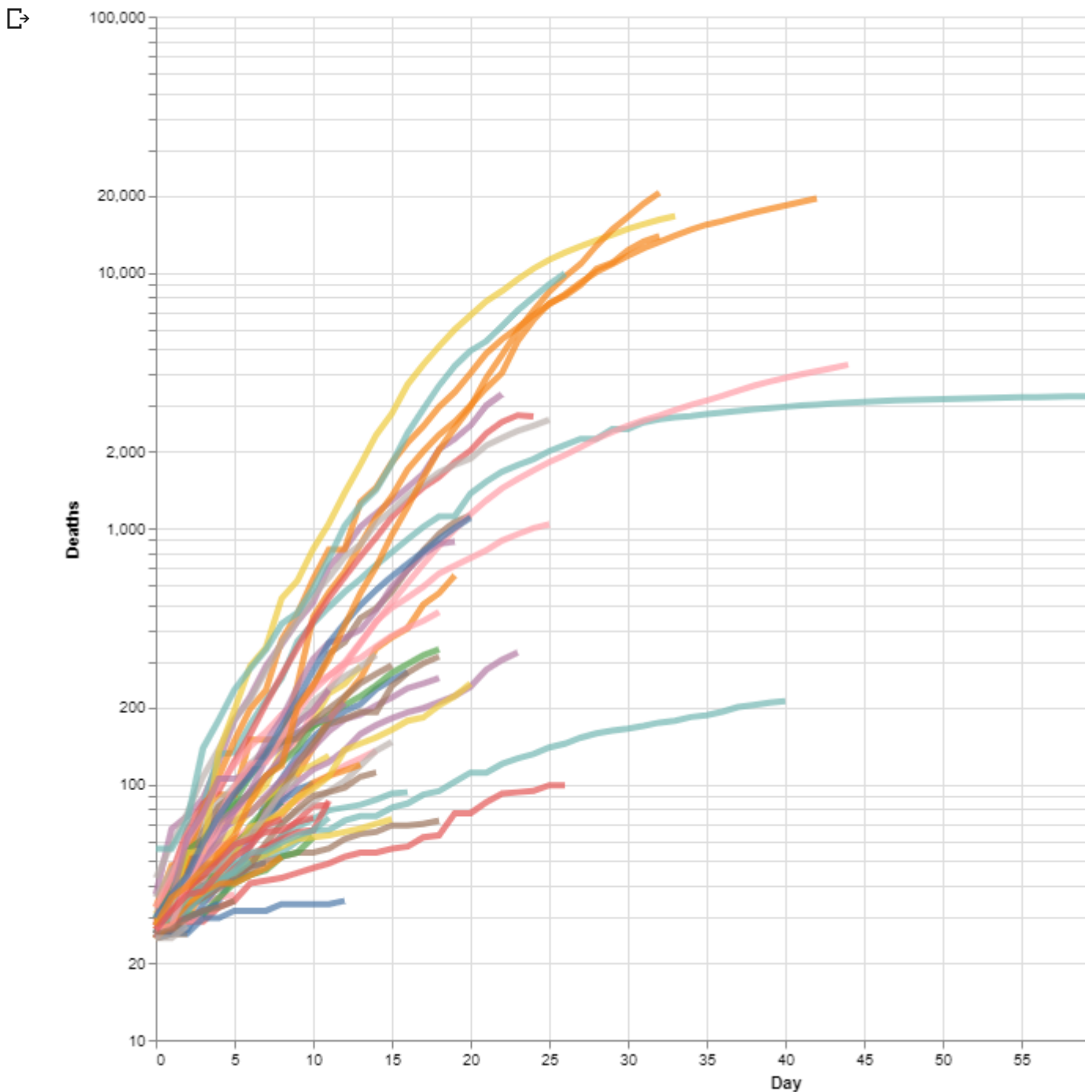
We'll also now add a hover tooltip so that, when we hover our cursor over any point on any of the li the number of 'Deaths'.

```
# altair plot
alt.Chart(deaths_long).mark_line(strokeWidth=4, opacity=0.7).encode(
  x=alt.X('Day'),
  y=alt.Y('Deaths', scale=alt.Scale(type='log')),
  color='Country/Region',
  tooltip=['Country/Region', 'Day', 'Deaths']
```

```

).properties(
  width=800,
  height=650
)

```



It's great that we could add that useful hover tooltip with one line of code `tooltip=['Country/Region']` such information rich interaction to the chart. One useful aspect of the NYTimes chart was that, we made it stand out against the other. We're going to do something similar here: in the resulting chart, we'll use a grey background.

Note: When first attempting to build this chart, I discovered [here](#) that "multiple conditional values in a single spec," which is what Altair uses. For this reason, we build the chart, then an overlay, and then combine them.

```

# Selection tool
selection = alt.selection_single(fields=[ 'Country/Region' ])

```

```
# Color change when clicked
color = alt.condition(selection,
                      alt.Color('Country/Region:N'),
                      alt.value('lightgray'))

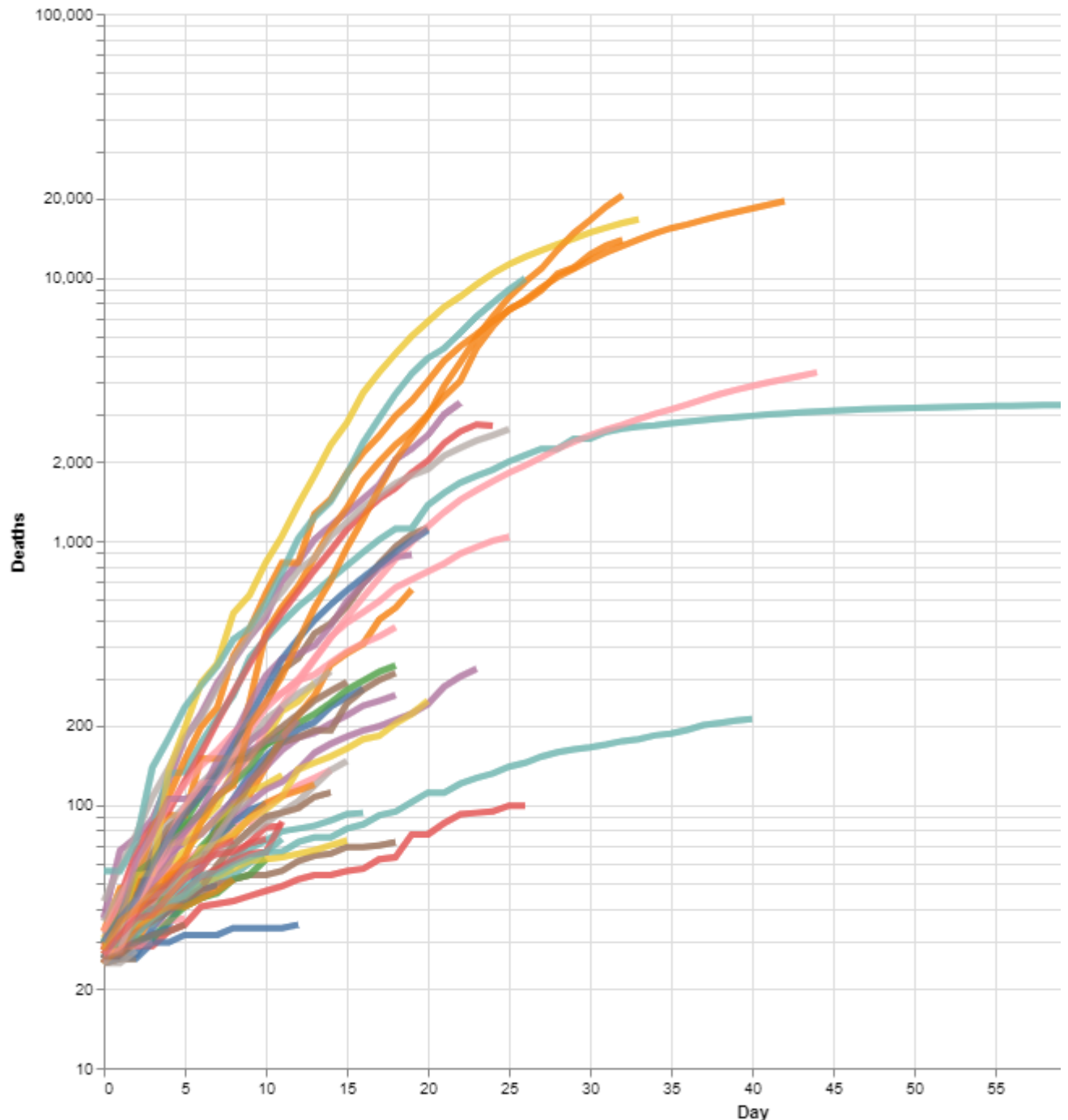
# Base altair plot
base = alt.Chart(deaths_long).mark_line(strokeWidth=4, opacity=0.7).encode(
    x=alt.X('Day'),
    y=alt.Y('Deaths', scale=alt.Scale(type='log')),
    color='Country/Region',
    tooltip=['Country/Region', 'Day', 'Deaths']
).properties(
    width=800,
    height=650
)

# Chart
chart = base.encode(
    color=alt.condition(selection, 'Country/Region:N', alt.value('lightgray'))
).add_selection(
    selection
)

# Overlay
overlay = base.encode(
    color='Country/Region',
    opacity=alt.value(0.5),
    tooltip=['Country/Region:N', 'Name:N']
).transform_filter(
    selection
)

# Sum em up!
chart + overlay
```





It's not super easy to line up the legend with the curves on the chart so let's put the labels on the cl

```
# drop NaNs
deaths_long = deaths_long.dropna()

# Selection tool
selection = alt.selection_single(fields=['Country/Region'])
# Color change when clicked
color = alt.condition(selection,
                       alt.Color('Country/Region:N'),
                       alt.value('lightgray'))

# Base altair plot
base = alt.Chart(deaths_long).mark_line(strokeWidth=4, opacity=0.7).encode(
```

```
x=alt.X('Day'),
y=alt.Y('Deaths', scale=alt.Scale(type='log')),
color=alt.Color('Country/Region', legend=None),
).properties(
    width=800,
    height=650
)

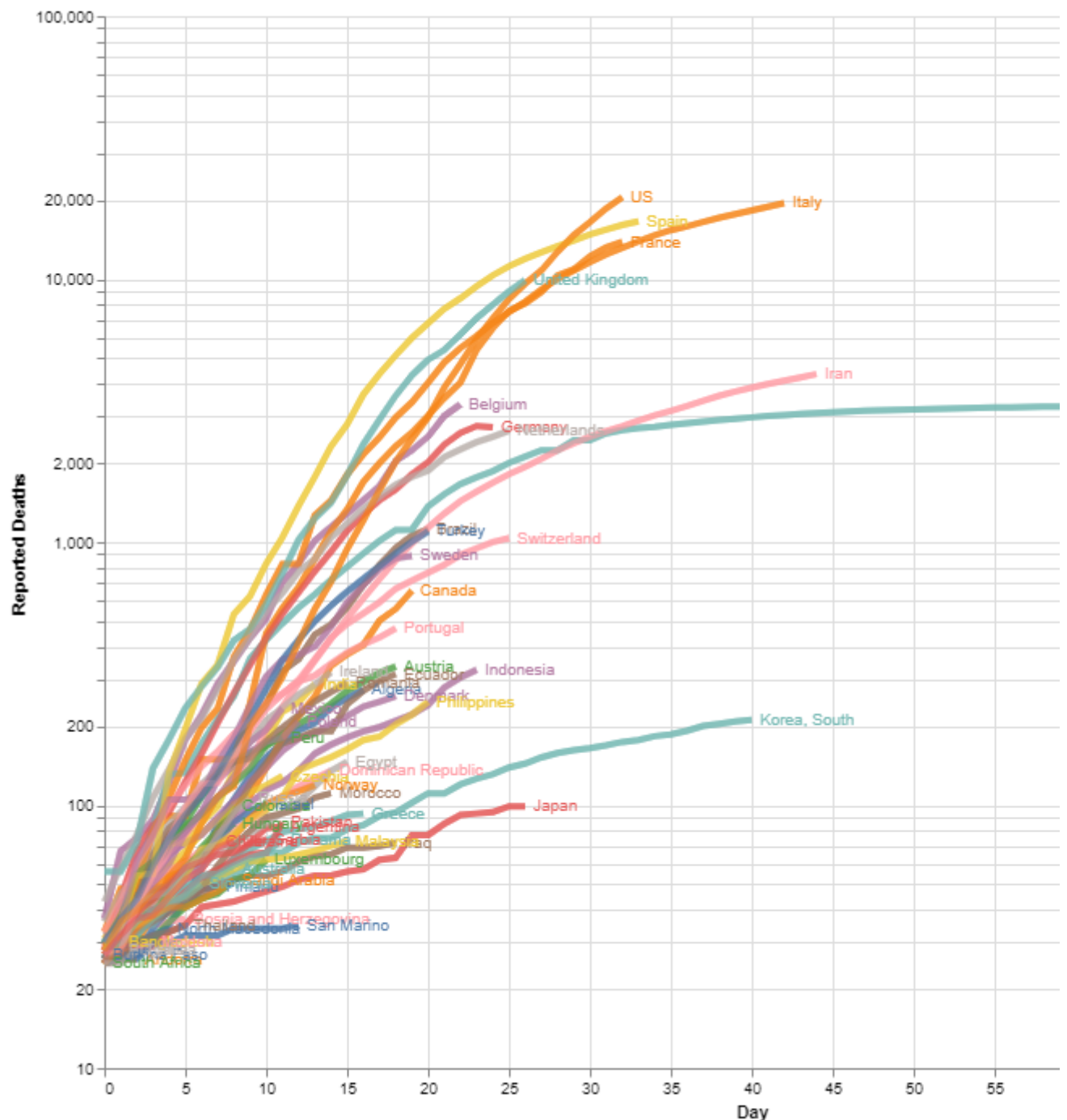
# Chart
chart = base.encode(
    color=alt.condition(selection, 'Country/Region:N', alt.value('lightgray'))
).add_selection(
    selection
)

# Overlay
overlay = base.encode(
    color='Country/Region',
    opacity=alt.value(0.5),
    tooltip=['Country/Region:N', 'Name:N']
).transform_filter(
    selection
)

# Text labels
text = base.mark_text(
    align='left',
    dx=5,
    size=10
).encode(
    x=alt.X('Day', aggregate='max', axis=alt.Axis(title='Day')),
    y=alt.Y('Deaths', aggregate={'argmax': 'Day'}, axis=alt.Axis(title='Reported Deaths')),
    text='Country/Region',
).transform_filter(
    selection
)

# Sum em up!
chart + overlay + text
```





Summary: So, now we have

- melted the data into long format,
- used Altair to make interactive plots of increasing richness,

Thank You! You can check out [my github](https://github.com) for more interesting EDAs and projects.

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