Preparing Wide Form Time Data

Learning Objectives:

- Recognize wide-form vs long-form dataframes.
- Use panda's melt function to convert wide form to long form.
- Navigate a MultiIndex
- Combine groupby and resample to process time series in a group-wise manner

1. Preparing Time Series from Wide-Form data

```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import os
# set random seed
SEED = 321
np.random.seed(SEED)
```

```
## Customization Options
# plt.style.use(['fivethirtyeight'])#'seaborn-talk'])#,
plt.rcParams['figure.facecolor']='white'
plt.rcParams['figure.figsize']=(12,4)
#import tick customization tools
import matplotlib.ticker as mticks
import matplotlib.dates as mdates
sns.set_context("talk", font_scale=0.9)
```

```
def format_xdates(ax, fig=None, xtick_fontweight='bold',
                  title= None):
    """Formats x-axis with minor ticks every 3 months, and major
    ticks every year. Includes different grid options for visibility"""
    # create the locator to place ticks every 3 months.
    loc_3months = mdates.MonthLocator(interval=3)
    fmt_months = mdates.DateFormatter("%b")
    ## for major year ticks
    loc_year = mdates.YearLocator()
    fmt_year = mdates.DateFormatter("%Y")

    ## Change the font of the major ticks to stand out
    ax.set_xticks(ax.get_xticks())
    ax.set_xticklabels(ax.get_xticklabels(),
                       fontweight=xtick_fontweight)

    ## customize minor ticks
    ax.xaxis.set_minor_locator(loc_3months)
    ax.xaxis.set_minor_formatter(fmt_months)
    ## customize major ticks
    ax.xaxis.set_major_locator(loc_year)
    ax.xaxis.set_major_formatter(fmt_year)
    ## Making major/minor gridlines visually distince
    ax.grid(which='minor',axis='x',ls=":")
    ax.grid(which='major',axis='x',color='k')
    if fig is None:
        fig = ax.get_figure()
    ## rotate the dates
    fig.autofmt_xdate(which='major',rotation=90,ha='center')
    return fig,ax
```

Wide vs Long-Form Data

- Thus far with pandas, we have been using dataframes that have al formatted where the ROWS are the time steps. This is called Long-Form.
- It is very common to receive time series data where each COLUMN is a time step. This is "Wide-Form" data.

- Below we will walk through converting covid19 data from wide-form to long-form using `pd.melt`

Corona Virus Time Series - Cases

The data set below is an example of a "Wide-Form" data set from the Novel Covid-19 Kaggle Data Set.

```
url = "https://docs.google.com/spreadsheets/d/e/2PACX-1vRtZ3XGbdzViSOsO6Gam4LQAQTSrFMXSAz_CIcBmmQYBv9uuggbGcxUuqXtMeUPiHR9NyI6At3apf5d/pub?output=csv"
df = pd.read_csv(url)
df
```

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	...	6/23/22	6/24/22	6/25/22	6/26/22	6/27/22	6/28/22	6/29/22	6/30/22	7/1/22	7/2/22
0	NaN	Afghanistan	33.939110	67.709953	0	0	0	0	0	0	...	181987	182033	182072	182149	182228	182324	182403	182528	182594	182643
1	NaN	Albania	41.153300	20.168300	0	0	0	0	0	0	...	278211	278504	278793	279077	279077	279167	280298	280851	281470	282141
2	NaN	Algeria	28.033900	1.659600	0	0	0	0	0	0	...	266015	266025	266030	266038	266049	266062	266073	266087	266105	266115
3	NaN	Andorra	42.506300	1.521800	0	0	0	0	0	0	...	43774	43774	43774	43774	43774	43774	43774	43774	44177	44177
4	NaN	Angola	-11.202700	17.873900	0	0	0	0	0	0	...	99761	99761	99761	99761	99761	101320	101320	101320	101320	101320
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
280	NaN	West Bank and Gaza	31.952200	35.233200	0	0	0	0	0	0	...	658503	658503	658503	658503	659853	659853	659853	659853	659853	659853
281	NaN	Winter Olympics 2022	39.904200	116.407400	0	0	0	0	0	0	...	535	535	535	535	535	535	535	535	535	535
282	NaN	Yemen	15.552727	48.516388	0	0	0	0	0	0	...	11824	11824	11824	11824	11824	11824	11824	11824	11824	11824
283	NaN	Zambia	-13.133897	27.849332	0	0	0	0	0	0	...	324922	325110	325110	325110	325348	325498	325498	325857	325857	325857
284	NaN	Zimbabwe	-19.015438	29.154857	0	0	0	0	0	0	...	255136	255309	255309	255355	255383	255383	255520	255586	255586	255586

285 rows × 897 columns

- We can see that we have many countries in this dataset, each with its own row and that we have a separate column for each day in the dataset.
- We need to convert this to long-form before we are able to use it as a time series with pandas.
- Note also, that the values given for each date are the cumulative number of confirmed cases of covid.

`pd.melt`

- Pandas has a function called pd.melt which is designed to turn wide-form data into long-form, but to let us keep some id columns intact. Its easier to understand once demonstrated.
- The columns we want to keep associated with each timestamp will be our `id_vars` .
  - If we want EVERY other column to be converted to rows, that's all we need!
  - If we wanted only SOME columns converted to rows, we would use the `value_vars` argument.

Let's take a look at the existing columns:

```
df.columns
```

```
Index(['Province/State', 'Country/Region', 'Lat', 'Long', '1/22/20', '1/23/20',
       '1/24/20', '1/25/20', '1/26/20', '1/27/20',
       ...
       '6/23/22', '6/24/22', '6/25/22', '6/26/22', '6/27/22', '6/28/22',
       '6/29/22', '6/30/22', '7/1/22', '7/2/22'],
      dtype='object', length=897)
```

We want to keep several columns including the Province/State, Country/Region, Lat, and Long. We will include these in our list of id_vars. What do you think the result will be when we use the pd.melt function?

```
melted = pd.melt(df,id_vars=['Province/State', 'Country/Region', 'Lat', 'Long'] )
melted
```

	Province/State	Country/Region	Lat	Long	variable	value
0	NaN	Afghanistan	33.939110	67.709953	1/22/20	0
1	NaN	Albania	41.153300	20.168300	1/22/20	0
2	NaN	Algeria	28.033900	1.659600	1/22/20	0
3	NaN	Andorra	42.506300	1.521800	1/22/20	0
4	NaN	Angola	-11.202700	17.873900	1/22/20	0
...	...	...	...	...	...	...
254500	NaN	West Bank and Gaza	31.952200	35.233200	7/2/22	659853
254501	NaN	Winter Olympics 2022	39.904200	116.407400	7/2/22	535
254502	NaN	Yemen	15.552727	48.516388	7/2/22	11824
254503	NaN	Zambia	-13.133897	27.849332	7/2/22	325857
254504	NaN	Zimbabwe	-19.015438	29.154857	7/2/22	255586

254505 rows × 6 columns

Is this the result you expected?

Notice how all of the previous date columns have now been compressed into rows. Do you see the new column that includes the date? It is titled "variable". The corresponding original value in that column is in the "value" column. Take some time to compare the original df with the melted df to ensure you understand the transformation!

- We can also provide the names we want to use for these 2 new columns. Since these values are confirmed cases of Covid, we will name this column "Confirmed".
- To simplify our output, we also decided to drop the "Lat" and "Long" values here.

```
melted = pd.melt(df.drop(columns=['Lat','Long']),
                 id_vars=['Province/State', 'Country/Region'],
                value_name='Confirmed',var_name="Date")
melted
```

	Province/State	Country/Region	Date	Confirmed
0	NaN	Afghanistan	1/22/20	0
1	NaN	Albania	1/22/20	0
2	NaN	Algeria	1/22/20	0
3	NaN	Andorra	1/22/20	0
4	NaN	Angola	1/22/20	0
...	...	...	...	...
254500	NaN	West Bank and Gaza	7/2/22	659853
254501	NaN	Winter Olympics 2022	7/2/22	535
254502	NaN	Yemen	7/2/22	11824
254503	NaN	Zambia	7/2/22	325857
254504	NaN	Zimbabwe	7/2/22	255586

254505 rows × 4 columns

- Now that we have our melted dataframe, we can slice out the countries of interest and begin preparing our datetime index.

First, we will convert the 'Date' column values to datetime objects.

```
melted['Date'] = pd.to_datetime(melted['Date'])
melted.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 254505 entries, 0 to 254504
Data columns (total 4 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
0   Province/State  79477 non-null   object
1   Country/Region  254505 non-null  object
2   Date            254505 non-null  datetime64[ns]
3   Confirmed       254505 non-null  int64
dtypes: datetime64[ns](1), int64(1), object(2)
memory usage: 7.8+ MB
```

Notice that in this dataset, we have the same dates repeated many times, one for each country in the dataset.

We will need to set Date as our index, but we will NOT resample just yet

```
melted = melted.set_index("Date")
melted
```

Date	Province/State	Country/Region	Confirmed
2020-01-22	NaN	Afghanistan	0
2020-01-22	NaN	Albania	0
2020-01-22	NaN	Algeria	0
2020-01-22	NaN	Andorra	0
2020-01-22	NaN	Angola	0
...	...	...	...
2022-07-02	NaN	West Bank and Gaza	659853
2022-07-02	NaN	Winter Olympics 2022	535
2022-07-02	NaN	Yemen	11824
2022-07-02	NaN	Zambia	325857
2022-07-02	NaN	Zimbabwe	255586

254505 rows × 3 columns

What do you think will happen if we resample the data at this point?

Let's give it a try and inspect the results.

```
# take a look at what happens when we resample
melted.resample("D").sum()
```

Date	Confirmed
2020-01-22	557
2020-01-23	657
2020-01-24	944
2020-01-25	1437
2020-01-26	2120
...	...
2022-06-28	545535742
2022-06-29	546470126
2022-06-30	547500950
2022-07-01	548474889
2022-07-02	548826605

893 rows × 1 columns

We now have the sum of all cases for each day, BUT what information have we lost? We did have data broken down by country, but when we resampled, all the data for each day were combined into a single result. We will explore how can we resample while maintaining the original granularity of our data in the next section.

2. Combining .groupby and .resample for groupwise-time series processing

Our data is broken down by country. Let's take a look at how many countries are included.

```
## There are 199 unique countries included
melted['Country/Region'].nunique()
```

```
199
```

- We can combine a groupby by for Country/Region with a .resample("D") to resample the data in a group-wise manner.
    - The only caveat/complexity that this introduces is that we will now have 2 columns for our index: a MultiIndex
    - Note that when we use .resample, we must include a method to aggregate. Since we only have one value per day per country, you may have thought .asfreq() would work, but this will not work with groupby. It does not make a difference which aggregation method we use because the mathematical result is the same. For example, we could aggregate by using .last(), .first(), or .mean(). We used .sum() in the code below. Try the other methods to confirm they give the same results!

```
df_ts = melted.groupby('Country/Region').resample("D").sum()
df_ts
```

		Confirmed
Country/Region	**Date**	
Afghanistan	**2020-01-22**	0
	2020-01-23	0
	2020-01-24	0
	2020-01-25	0
	2020-01-26	0
...	**...**	...
Zimbabwe	**2022-06-28**	255383
	2022-06-29	255520
	2022-06-30	255586
	2022-07-01	255586
	2022-07-02	255586

177707 rows × 1 columns

```
df_ts.head().index
```

```
MultiIndex([('Afghanistan', '2020-01-22'),
            ('Afghanistan', '2020-01-23'),
            ('Afghanistan', '2020-01-24'),
            ('Afghanistan', '2020-01-25'),
            ('Afghanistan', '2020-01-26')],
           names=['Country/Region', 'Date'])
```

Notice, though, that we have maintained our ability to locate information for particular countries!

```
df_ts.loc['Afghanistan']
```

Filtering by Date with a MultiIndex using pd.IndexSlice

While we can easily filter by country, we now have altered how we must filter by date.

Let's say we wanted to limit our data to just the year 2020. If you try the method that we would use with a single index, you will get an error.

```
# This will not work with our multiIndex
# df_ts.loc['2020']
```

Instead, we can use pd.IndexSlice with .loc to filter for all values in 2020.

```
df_ts.loc[pd.IndexSlice[:, '2020'],:]
```

		Confirmed
Country/Region	**Date**	
Afghanistan	**2020-01-22**	0
	2020-01-23	0
	2020-01-24	0
	2020-01-25	0
	2020-01-26	0
...	**...**	...
Zimbabwe	**2020-12-27**	13077
	2020-12-28	13148
	2020-12-29	13325
	2020-12-30	13625
	2020-12-31	13867

68655 rows × 1 columns

We can also filter by both date and country. For example, if we just want the countries from Afghanistan to Algeria (alphabetically) and the data for 2020:

```
df_ts.loc[pd.IndexSlice['Afghanistan':'Algeria','2020'],:]
```

		Confirmed
Country/Region	**Date**	
Afghanistan	**2020-01-22**	0
	2020-01-23	0
	2020-01-24	0
	2020-01-25	0
	2020-01-26	0
...	...	...
Algeria	**2020-12-27**	98249
	2020-12-28	98631
	2020-12-29	98988
	2020-12-30	99311
	2020-12-31	99610

1035 rows × 1 columns

Plotting with a MultiIndex

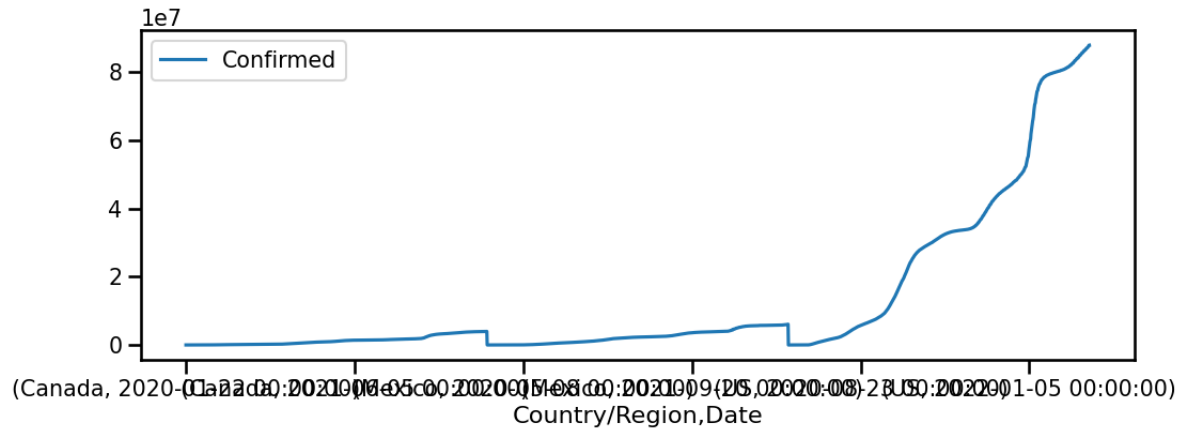
- Let's go ahead and visualize the time series data! Specifically, let's plot the number of Confirmed Cases for several countries in North America (US, Mexico, Canada).

```
countries = ['Canada','Mexico','US']
plot_df = df_ts.loc[countries].copy()
plot_df
```

		Confirmed
Country/Region	**Date**	
Canada	**2020-01-22**	0
	2020-01-23	2
	2020-01-24	3
	2020-01-25	3
	2020-01-26	3
...	...	...
US	**2022-06-28**	87296327
	2022-06-29	87490815
	2022-06-30	87627486
	2022-07-01	87821971
	2022-07-02	87838623

2679 rows × 1 columns

```
plot_df.plot(figsize=(12,4));
```



Oh, no! What happened?!

- When we have a multi-index, creating visualizations becomes more complex. Pandas is confused about what should be considered a group, and it has lumped all of the data together into 1 line.
- In order to visualize each country as a separate line, we will have to modify our multi-index (temporarily). We need Pandas to consider each country as its own separate column so that we get a line for each country.

- To do so, we can leverage the `.unstack()` method.

Using `unstack()` for Plotting with a MultiIndex

Understanding Index Levels

- Right now, we have a multi-index with 2 levels.
  - Level 0 (the outer-most index on the left): Country
  - Level 1 (the next/inner index): Date
- To demonstrate, let's use the `df.index.get_level_values()` function to get the values from 1 index at a time.

```
# level 0 is Country/Region
plot_df.index.get_level_values(0)
```

```
Index(['Canada', 'Canada', 'Canada', 'Canada', 'Canada', 'Canada', 'Canada',
       'Canada', 'Canada', 'Canada',
       ...
       'US', 'US', 'US', 'US', 'US', 'US', 'US', 'US', 'US', 'US'],
      dtype='object', name='Country/Region', length=2679)
```

```
# level 1 is Date
plot_df.index.get_level_values(1)
```

```
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',
               ...
               '2022-06-23', '2022-06-24', '2022-06-25', '2022-06-26',
               '2022-06-27', '2022-06-28', '2022-06-29', '2022-06-30',
               '2022-07-01', '2022-07-02'],
              dtype='datetime64[ns]', name='Date', length=2679, freq=None)
```

- According to the [Pandas documentation for .unstack()](), it will "pivot a level of the (necessarily hierarchical) index labels."
- So `.unstack()` will allow us to pivot our data in a way that we can keep our Date as the index and convert our outer index (Country/Region) into columns, which is exactly what we need.

Applying `unstack()` for Our Visualization

- Unstack accepts a "level" argument for which level of our multi-index should be converted into columns.
- Since we want the outermost index (level 0) to become the columns, we will need to specify `level=0`.

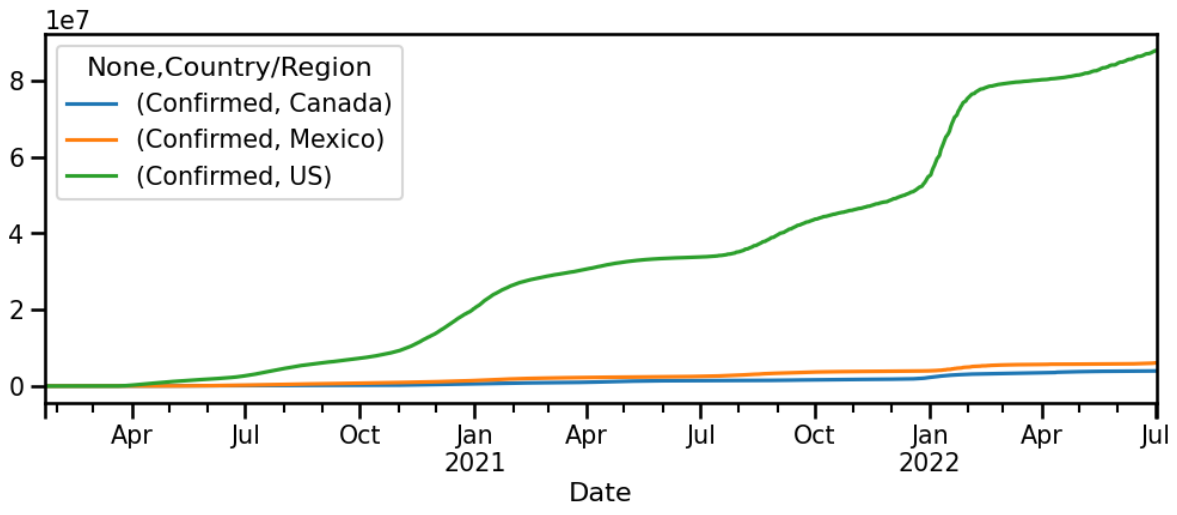
```
unstacked = plot_df.unstack(level=0)
unstacked
```

	Confirmed		
Country/Region	Canada	Mexico	US
Date			
2020-01-22	0	0	1
2020-01-23	2	0	1
2020-01-24	3	0	2
2020-01-25	3	0	2
2020-01-26	3	0	5
...	...	...	...
2022-06-28	3945493	5986917	87296327
2022-06-29	3948112	5986917	87490815
2022-06-30	3954275	6034602	87627486
2022-07-01	3955704	6058689	87821971
2022-07-02	3956897	6058689	87838623

893 rows × 3 columns

- Now that we have our DataFrame unstacked, we have a separate column for each country.

```
ax = unstacked.plot()
```



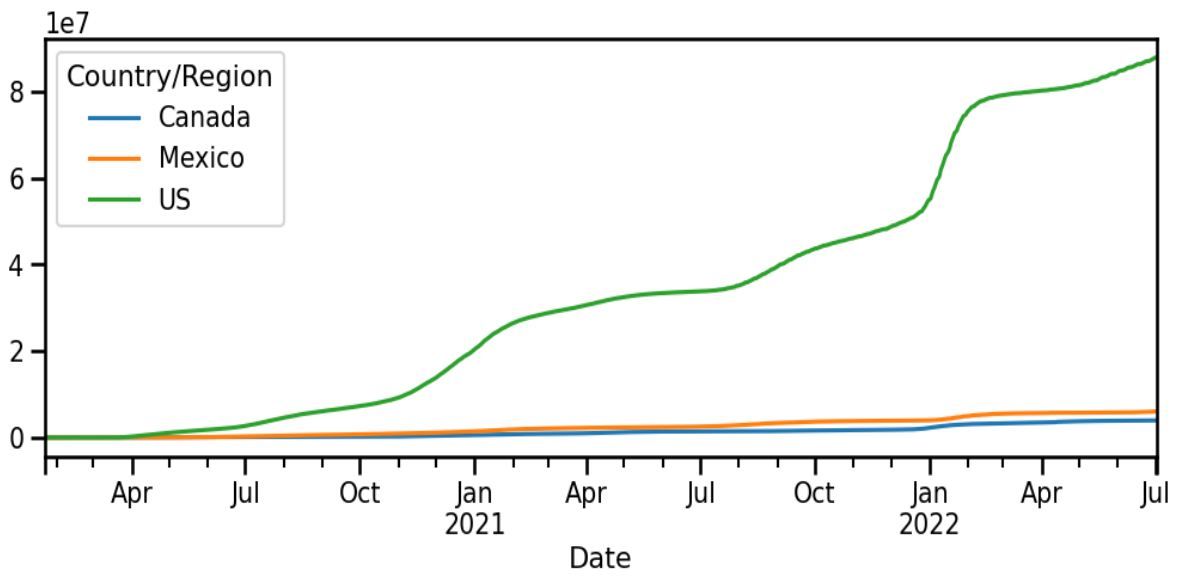
- And there we go! We were able to plot each country as a separate line.
- The one remaining issue is our legend.
  - Why do we now have (Confirmed, CountryName) for all of the countries?
- If we take a look at the columns of our unstacked dataframe, we will see that we have now created a MultiIndex.

```
unstacked.columns
```

```
MultiIndex([('Confirmed', 'Canada'),
            ('Confirmed', 'Mexico'),
            ('Confirmed',     'US')],
           names=[None, 'Country/Region'])
```

- By slicing out the "Confirmed" column from our multi-index before we plot, we will have bypassed the outer level of our MultiIndex, so we will not see the "Confirmed" column name appear in our legend.

```
ax = unstacked['Confirmed'].plot()
```



And there we go!

Additional Resources

To learn more about the .unstack() method, check out these resources:

- Towards Data Science: Reshaping a DataFrame with Pandas Stack and Unstack
- Article: Fun with Pandas Groupby, Aggregate, Multi-Index and Unstack
- Article: Making Plots with Pandas Groupby

Selecting 1 Country to Analyze

To continue our exploration of the data, let's separate the US from the rest of the datasets (but keep all the dates).

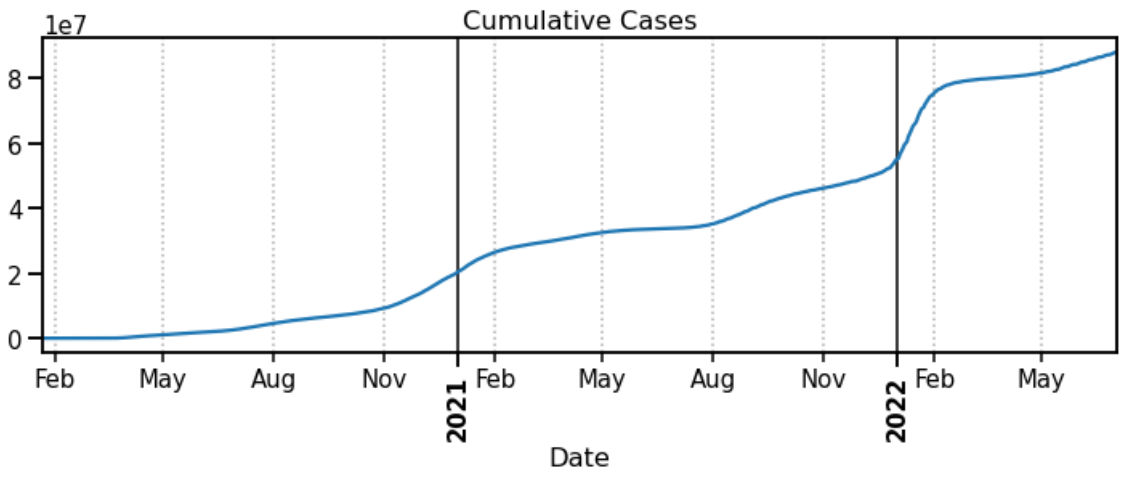
```
ts_us = df_ts.loc['US', 'Confirmed']
ts_us.index
```

```
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',
               ...
               '2022-06-23', '2022-06-24', '2022-06-25', '2022-06-26',
               '2022-06-27', '2022-06-28', '2022-06-29', '2022-06-30',
               '2022-07-01', '2022-07-02'],
              dtype='datetime64[ns]', name='Date', length=893, freq='D')
```

> *As we can see, we have a successfully created our time series for the use with a proper datetime index.*

Now we can plot our time series data.

```
ax = ts_us.plot(style='-',title="Cumulative Cases");
format_xdates(ax);
```



Drilling Down into the US

We want to get a more detailed view of what happening in specific states in the U.S.

- Slice out just values for the US into a new dataframe.
- Check the Province/State column for us states

```
## check for states
df_us = melted[melted['Country/Region']=='US']
df_us
```

Date	Province/State	Country/Region	Confirmed
2020-01-22	NaN	US	1
2020-01-23	NaN	US	1
2020-01-24	NaN	US	2
2020-01-26	NaN	US	5
...	...	...	...
2022-06-28	NaN	US	87296327
2022-06-29	NaN	US	87490815
2022-06-30	NaN	US	87627486
2022-07-01	NaN	US	87821971
2022-07-02	NaN	US	87838623

893 rows × 3 columns

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