```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt
```

Data used for this tutorial:

Air quality data

```
In [3]: air_quality = pd.read_csv("data/air_quality_no2_long.csv")

In [4]: air_quality = air_quality.rename(columns={"date.utc": "datetime"})

In [5]: air_quality.head()
Out[5]:
    city country                   datetime location parameter  value   unit
0  Paris      FR  2019-06-21 00:00:00+00:00  FR04014       no2   20.0  µg/m³
1  Paris      FR  2019-06-20 23:00:00+00:00  FR04014       no2   21.8  µg/m³
2  Paris      FR  2019-06-20 22:00:00+00:00  FR04014       no2   26.5  µg/m³
3  Paris      FR  2019-06-20 21:00:00+00:00  FR04014       no2   24.9  µg/m³
4  Paris      FR  2019-06-20 20:00:00+00:00  FR04014       no2   21.4  µg/m³
```

```
In [6]: air_quality.city.unique()
Out[6]: array(['Paris', 'Antwerpen', 'London'], dtype=object)
```

How to handle time series data with ease

Using pandas datetime properties

I want to work with the dates in the column `datetime` as datetime objects instead of plain text

```
In [7]: air_quality["datetime"] = pd.to_datetime(air_quality["datetime"])

In [8]: air_quality["datetime"]
Out[8]:
0      2019-06-21 00:00:00+00:00
1      2019-06-20 23:00:00+00:00
2      2019-06-20 22:00:00+00:00
3      2019-06-20 21:00:00+00:00
4      2019-06-20 20:00:00+00:00
                  ...
2063   2019-05-07 06:00:00+00:00
2064   2019-05-07 04:00:00+00:00
2065   2019-05-07 03:00:00+00:00
2066   2019-05-07 02:00:00+00:00
2067   2019-05-07 01:00:00+00:00
Name: datetime, Length: 2068, dtype: datetime64[ns, UTC]
```

Initially, the values in `datetime` are character strings and do not provide any datetime operations (e.g. extract the year, day of the week,...). By applying the `to_datetime` function, pandas interprets the strings and convert these to datetime (i.e. `datetime64[ns, UTC]`) objects. In pandas we call these datetime objects similar to `datetime.datetime` from the standard library

Note

As many data sets do contain datetime information in one of the columns, pandas input function like `pandas.read_csv()` and `pandas.read_json()` can do the transformation to dates when reading the data using the `parse_dates` parameter with a list of the columns to read as Timestamp:

```
pd.read_csv("../data/air_quality_no2_long.csv", parse_dates=["datetime"])
```

Why are these `pandas.Timestamp` objects useful? Let's illustrate the added value with some example cases.

> What is the start and end date of the time series data set we are working with?

```
In [9]: air_quality["datetime"].min(), air_quality["datetime"].max()
Out[9]:
(Timestamp('2019-05-07 01:00:00+0000', tz='UTC'),
 Timestamp('2019-06-21 00:00:00+0000', tz='UTC'))
```

Using `pandas.Timestamp` for datetimes enables us to calculate with date information and make them comparable. Hence, we can use this to get the length of our time series:

```
In [10]: air_quality["datetime"].max() - air_quality["datetime"].min()
Out[10]: Timedelta('44 days 23:00:00')
```

The result is a `pandas.Timedelta` object, similar to `datetime.timedelta` from the standard Python library and defining a time duration.

To user guide The various time concepts supported by pandas are explained in the user guide section on time related concepts.

I want to add a new column to the `DataFrame` containing only the month of the measurement

```
In [11]: air_quality["month"] = air_quality["datetime"].dt.month

In [12]: air_quality.head()
Out[12]:
    city country                  datetime  ... value   unit  month
0  Paris      FR 2019-06-21 00:00:00+00:00  ...  20.0  µg/m³      6
1  Paris      FR 2019-06-20 23:00:00+00:00  ...  21.8  µg/m³      6
2  Paris      FR 2019-06-20 22:00:00+00:00  ...  26.5  µg/m³      6
3  Paris      FR 2019-06-20 21:00:00+00:00  ...  24.9  µg/m³      6
4  Paris      FR 2019-06-20 20:00:00+00:00  ...  21.4  µg/m³      6

[5 rows x 8 columns]
```

By using `Timestamp` objects for dates, a lot of time-related properties are provided by pandas. For example the `month`, but also `year`, `quarter`,... All of these properties are accessible by the `dt` accessor.

To user guide An overview of the existing date properties is given in the time and date components overview table. More details about the `dt` accessor to return datetime like properties are explained in a dedicated section on the dt accessor.

Skip to main content

What is the average NO_2 concentration for each day of the week for each of the measurement locations?

```
In [13]: air_quality.groupby(
   ....:     [air_quality["datetime"].dt.weekday, "location"])["value"].mean()
   ....: 
Out[13]: 
datetime  location          
0         BETR801               27.875000
          FR04014               24.856250
          London Westminster    23.969697
1         BETR801               22.214286
          FR04014               30.999359
                                  ...    
5         FR04014               25.266154
          London Westminster    24.977612
6         BETR801               21.896552
          FR04014               23.274306
          London Westminster    24.859155
Name: value, Length: 21, dtype: float64
```

Remember the split-apply-combine pattern provided by `groupby` from the tutorial on statistics calculation? Here, we want to calculate a given statistic (e.g. mean NO_2) **for each weekday** and **for each measurement location**. To group on weekdays, we use the datetime property `weekday` (with Monday=0 and Sunday=6) of pandas `Timestamp`, which is also accessible by the `dt` accessor. The grouping on both locations and weekdays can be done to split the calculation of the mean on each of these combinations.

Danger

As we are working with a very short time series in these examples, the analysis does not provide a long-term representative result!

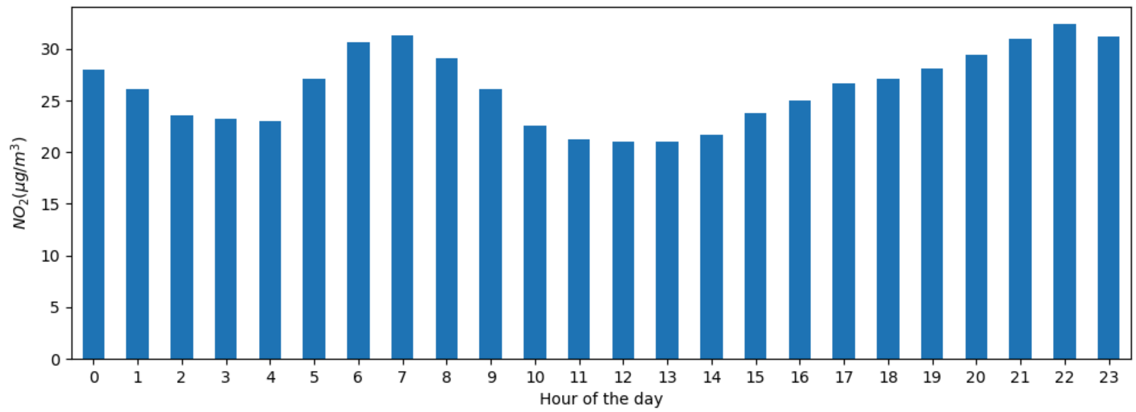
Plot the typical NO_2 pattern during the day of our time series of all stations together. In other words, what is the average value for each hour of the day?

```
In [14]: fig, axs = plt.subplots(figsize=(12, 4))

In [15]: air_quality.groupby(air_quality["datetime"].dt.hour)["value"].mean().plot(
   ....:     kind='bar', rot=0, ax=axs
   ....: )
   ....: 
Out[15]: <Axes: xlabel='datetime'>

In [16]: plt.xlabel("Hour of the day");  # custom x label using Matplotlib

In [17]: plt.ylabel("$NO_2 (µg/m^3)$");
```



Similar to the previous case, we want to calculate a given statistic (e.g. mean NO_2) **for each hour of the day** and we can use the split-apply-combine approach again. For this case, we use the datetime property `hour` of pandas `Timestamp`, which is also accessible by the `dt` accessor.

Datetime as index

In the tutorial on reshaping, `pivot()` was introduced to reshape the data table with each of the measurements locations as a separate column:

```
In [18]: no_2 = air_quality.pivot(index="datetime", columns="location", values="value")

In [19]: no_2.head()
Out[19]: 
location                   BETR801  FR04014  London Westminster
datetime                                                       
2019-05-07 01:00:00+00:00     50.5     25.0                23.0
2019-05-07 02:00:00+00:00     45.0     27.7                19.0
2019-05-07 03:00:00+00:00      NaN     50.4                19.0
2019-05-07 04:00:00+00:00      NaN     61.9                16.0
2019-05-07 05:00:00+00:00      NaN     72.4                 NaN
```

Note

By pivoting the data, the datetime information became the index of the table. In general, setting a column as an index can be achieved by the `set_index` function.

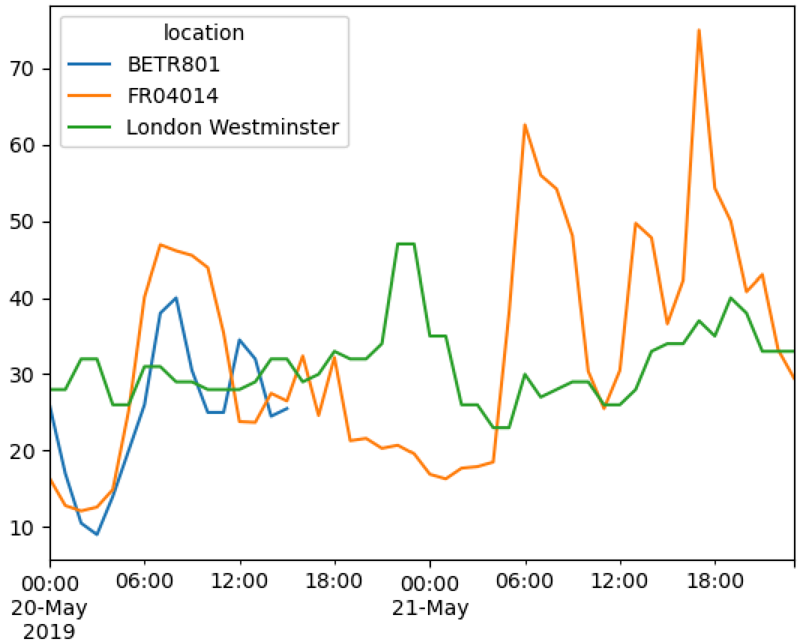
Working with a datetime index (i.e. `DatetimeIndex`) provides powerful functionalities. For example, we do not need the `dt` accessor to get the time series properties, but have these properties available on the index directly:

```
In [20]: no_2.index.year, no_2.index.weekday
Out[20]: 
(Index([2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019,
        ...
        2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019],
       dtype='int32', name='datetime', length=1033),
 Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        ...
        3, 3, 3, 3, 3, 3, 3, 3, 3, 4],
       dtype='int32', name='datetime', length=1033))
```

Some other advantages are the convenient subsetting of time period or the adapted time scale on plots. Let's apply this on our

Create a plot of the NO_2 values in the different stations from the 20th of May till the end of 21st of May

```
In [21]: no_2["2019-05-20":"2019-05-21"].plot();
```



By providing a **string that parses to a datetime**, a specific subset of the data can be selected on a `DatetimeIndex`.

To user guide More information on the `DatetimeIndex` and the slicing by using strings is provided in the section on time series indexing.

Resample a time series to another frequency

Aggregate the current hourly time series values to the monthly maximum value in each of the stations.

```
In [22]: monthly_max = no_2.resample("ME").max()

In [23]: monthly_max
Out[23]: 
location                   BETR801  FR04014  London Westminster
datetime                                                       
2019-05-31 00:00:00+00:00     74.5     97.0                97.0
2019-06-30 00:00:00+00:00     52.5     84.7                52.0
```

A very powerful method on time series data with a datetime index, is the ability to `resample()` time series to another frequency (e.g., converting secondly data into 5-minutely data).

The `resample()` method is similar to a groupby operation:

- it provides a time-based grouping, by using a string (e.g. `M`, `5H`,…) that defines the target frequency
- it requires an aggregation function such as `mean`, `max`,…

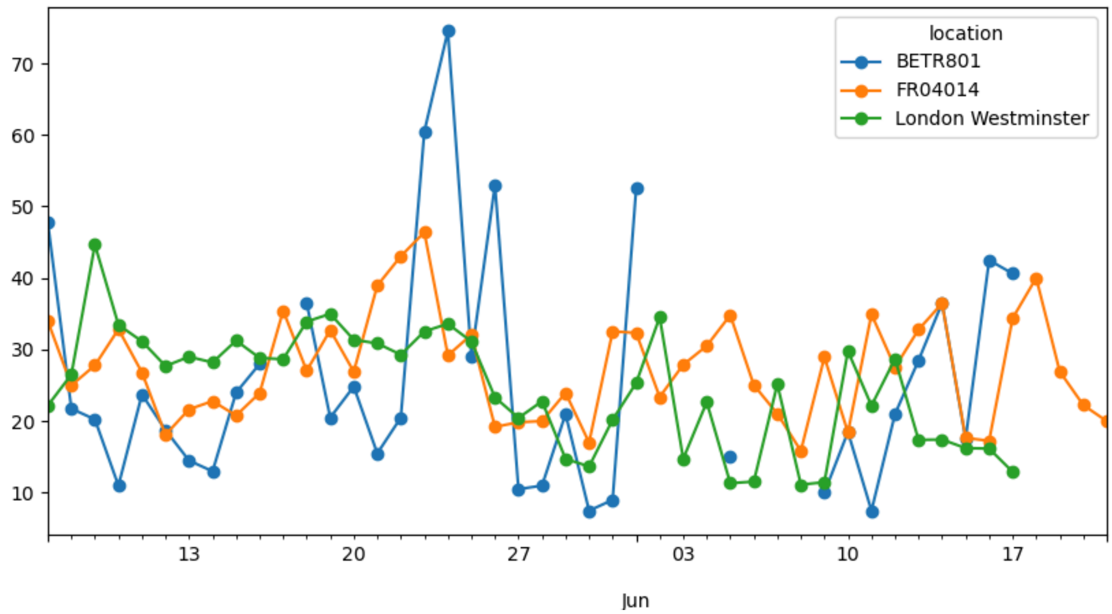
To user guide An overview of the aliases used to define time series frequencies is given in the offset aliases overview table

When defined, the frequency of the time series is provided by the `freq` attribute:

```
In [24]: monthly_max.index.freq
Out[24]: <MonthEnd>
```

Make a plot of the daily mean NO_2 value in each of the stations.

```
In [25]: no_2.resample("D").mean().plot(style="-o", figsize=(10, 5));
```



To user guide More details on the power of time series `resampling` is provided in the user guide section on resampling.

REMEMBER

- Valid date strings can be converted to datetime objects using `to_datetime` function or as part of read functions.

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