tools_pandas

June 4, 2021

Tools - pandas

The `pandas` library provides high-performance, easy-to-use data structures and data analysis tools. The main data structure is the `DataFrame`, which you can think of as an in-memory 2D table (like a spreadsheet, with column names and row labels). Many features available in Excel are available programmatically, such as creating pivot tables, computing columns based on other columns, plotting graphs, etc. You can also group rows by column value, or join tables much like in SQL. Pandas is also great at handling time series.

Prerequisites: * NumPy – if you are not familiar with NumPy, we recommend that you go through the NumPy tutorial now.

1 Setup

First, let's import `pandas`. People usually import it as `pd`:

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

2 Series objects

The `pandas` library contains these useful data structures: * `Series` objects, that we will discuss now. A `Series` object is 1D array, similar to a column in a spreadsheet (with a column name and row labels). * `DataFrame` objects. This is a 2D table, similar to a spreadsheet (with column names and row labels). * `Panel` objects. You can see a `Panel` as a dictionary of `DataFrame`s. These are less used, so we will not discuss them here.

2.1 Creating a Series

Let's start by creating our first `Series` object!

[2]:
```
s = pd.Series([2,-1,3,5])
s
```

[2]:
```
0    2
1   -1
2    3
3    5
dtype: int64
```

2.2 Similar to a 1D ndarray

`Series` objects behave much like one-dimensional NumPy `ndarrays`, and you can often pass them as parameters to NumPy functions:

[3]:
```
import numpy as np
np.exp(s)
```

[3]:
```
0      7.389056
1      0.367879
2     20.085537
3    148.413159
dtype: float64
```

Arithmetic operations on `Series` are also possible, and they apply *elementwise*, just like for `ndarrays`:

[4]:
```
s + [1000,2000,3000,4000]
```

[4]:
```
0    1002
1    1999
2    3003
3    4005
dtype: int64
```

Similar to NumPy, if you add a single number to a `Series`, that number is added to all items in the `Series`. This is called * broadcasting*:

[5]:
```
s + 1000
```

[5]:
```
0    1002
1     999
2    1003
3    1005
dtype: int64
```

The same is true for all binary operations such as `*` or `/`, and even conditional operations:

[6]:
```
s < 0
```

[6]:
```
0    False
1     True
2    False
3    False
dtype: bool
```

2.3 Index labels

Each item in a `Series` object has a unique identifier called the *index label*. By default, it is simply the rank of the item in the `Series` (starting at `0`) but you can also set the index labels manually:

[7]:
```
s2 = pd.Series([68, 83, 112, 68], index=["alice", "bob", "charles", "darwin"])
s2
```

[7]:
```
alice       68
bob         83
charles    112
darwin      68
dtype: int64
```

You can then use the `Series` just like a `dict`:

[8]:
```
s2["bob"]
```

[8]:
```
83
```

You can still access the items by integer location, like in a regular array:

[9]:
```
s2[1]
```

[9]:
```
83
```

To make it clear when you are accessing by label or by integer location, it is recommended to always use the `loc` attribute when accessing by label, and the `iloc` attribute when accessing by integer location:

[10]:
```
s2.loc["bob"]
```

[10]:
```
83
```

[11]:
```
s2.iloc[1]
```

[11]:
```
83
```

Slicing a `Series` also slices the index labels:

[12]:
```
s2.iloc[1:3]
```

[12]:
```
bob         83
charles    112
dtype: int64
```

This can lead to unexpected results when using the default numeric labels, so be careful:

[13]:
```
surprise = pd.Series([1000, 1001, 1002, 1003])
surprise
```

[13]:
```
0    1000
1    1001
2    1002
3    1003
dtype: int64
```

[14]:
```
surprise_slice = surprise[2:]
surprise_slice
```

[14]:
```
2    1002
3    1003
dtype: int64
```

Oh look! The first element has index label `2`. The element with index label `0` is absent from the slice:

[15]:
```
try:
    surprise_slice[0]
except KeyError as e:
    print("Key error:", e)
```

```
Key error: 0
```

But remember that you can access elements by integer location using the `iloc` attribute. This illustrates another reason why it's always better to use `loc` and `iloc` to access `Series` objects:

[16]:
```
surprise_slice.iloc[0]
```

[16]:
```
1002
```

2.4 Init from `dict`

You can create a `Series` object from a `dict`. The keys will be used as index labels:

[17]:
```
weights = {"alice": 68, "bob": 83, "colin": 86, "darwin": 68}
s3 = pd.Series(weights)
s3
```

[17]:
```
alice     68
bob       83
colin     86
darwin    68
dtype: int64
```

You can control which elements you want to include in the `Series` and in what order by explicitly specifying the desired `index`:

[18]:
```
s4 = pd.Series(weights, index = ["colin", "alice"])
s4
```

[18]:
```
colin    86
alice    68
dtype: int64
```

[19]:
```
nestor_fruits = {"apple": "red", "mango": "yellow", "pineapple" : "yellow",␣
↪"watermelon" : "pink", "blueberries" : "purple"}
```

```
nestor_f = pd.Series(nestor_fruits)
print('SECOND & THIRD')
print(nestor_f[1:3])
nestor_f2 = nestor_f[1:3]
print('\nILOC SELECTION')
print(nestor_f2.iloc[1])
```

```
SECOND & THIRD
mango        yellow
pineapple    yellow
dtype: object

ILOC SELECTION
yellow
```

2.5 Automatic alignment

When an operation involves multiple `Series` objects, `pandas` automatically aligns items by matching index labels.

[20]:
```
print(s2.keys())
print(s3.keys())

s2 + s3
```

```
Index(['alice', 'bob', 'charles', 'darwin'], dtype='object')
Index(['alice', 'bob', 'colin', 'darwin'], dtype='object')
```

[20]:
```
alice      136.0
bob        166.0
charles      NaN
colin        NaN
darwin     136.0
dtype: float64
```

The resulting `Series` contains the union of index labels from `s2` and `s3`. Since `"colin"` is missing from `s2` and `"charles"` is missing from `s3`, these items have a `NaN` result value. (ie. Not-a-Number means *missing*).

Automatic alignment is very handy when working with data that may come from various sources with varying structure and missing items. But if you forget to set the right index labels, you can have surprising results:

[21]:
```
s5 = pd.Series([1000,1000,1000,1000])
print("s2 =", s2.values)
print("s5 =", s5.values)

s2 + s5
```

```
s2 = [ 68  83 112  68]
s5 = [1000 1000 1000 1000]
```

[21]:
```
alice      NaN
bob        NaN
charles    NaN
darwin     NaN
0          NaN
1          NaN
2          NaN
3          NaN
dtype: float64
```

Pandas could not align the Series, since their labels do not match at all, hence the full NaN result.

2.6 Init with a scalar

You can also initialize a Series object using a scalar and a list of index labels: all items will be set to the scalar.

[22]:
```
meaning = pd.Series(42, ["life", "universe", "everything"])
meaning
```

[22]:
```
life          42
universe      42
everything    42
dtype: int64
```

2.7 Series name

A Series can have a name:

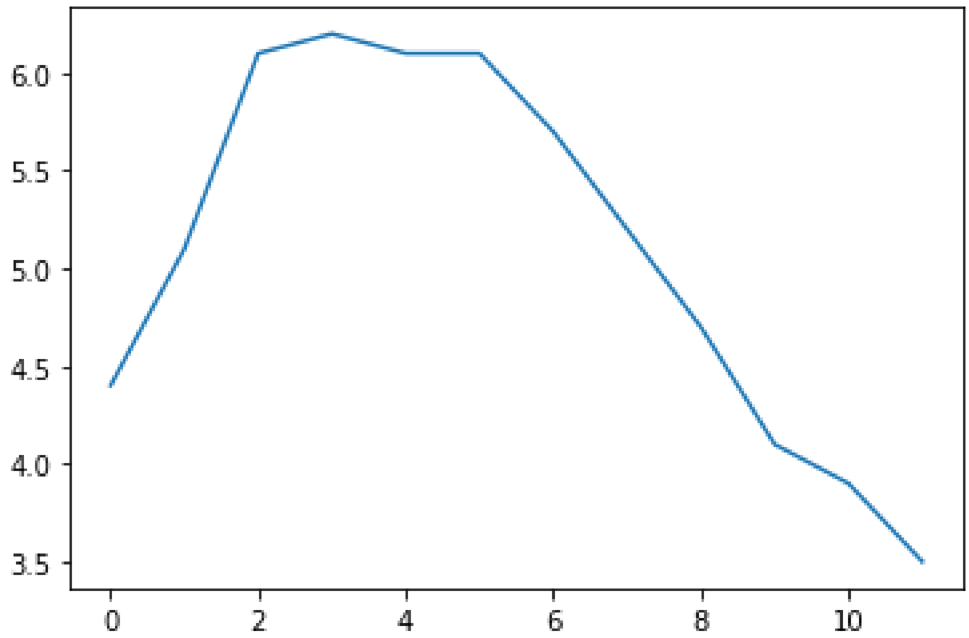
[23]:
```
s6 = pd.Series([83, 68], index=["bob", "alice"], name="weights")
s6
```

[23]:
```
bob      83
alice    68
Name: weights, dtype: int64
```

2.8 Plotting a Series

Pandas makes it easy to plot Series data using matplotlib (for more details on matplotlib, check out the matplotlib tutorial). Just import matplotlib and call the plot() method:

[24]:
```
%matplotlib inline
import matplotlib.pyplot as plt
temperatures = [4.4,5.1,6.1,6.2,6.1,6.1,5.7,5.2,4.7,4.1,3.9,3.5]
s7 = pd.Series(temperatures, name="Temperature")
s7.plot()
plt.show()
```



There are *many* options for plotting your data. It is not necessary to list them all here: if you need a particular type of plot (histograms, pie charts, etc.), just look for it in the excellent Visualization section of pandas' documentation, and look at the example code.

3 Handling time

Many datasets have timestamps, and pandas is awesome at manipulating such data: * it can represent periods (such as 2016Q3) and frequencies (such as "monthly"), * it can convert periods to actual timestamps, and *vice versa*, * it can resample data and aggregate values any way you like, * it can handle timezones.

3.1 Time range

Let's start by creating a time series using `pd.date_range()`. This returns a `DatetimeIndex` containing one datetime per hour for 12 hours starting on October 29th 2016 at 5:30pm.

[25]:
```
dates = pd.date_range('2016/10/29 5:30pm', periods=12, freq='H')
dates
```

[25]:
```
DatetimeIndex(['2016-10-29 17:30:00', '2016-10-29 18:30:00',
               '2016-10-29 19:30:00', '2016-10-29 20:30:00',
               '2016-10-29 21:30:00', '2016-10-29 22:30:00',
               '2016-10-29 23:30:00', '2016-10-30 00:30:00',
               '2016-10-30 01:30:00', '2016-10-30 02:30:00',
               '2016-10-30 03:30:00', '2016-10-30 04:30:00'],
              dtype='datetime64[ns]', freq='H')
```

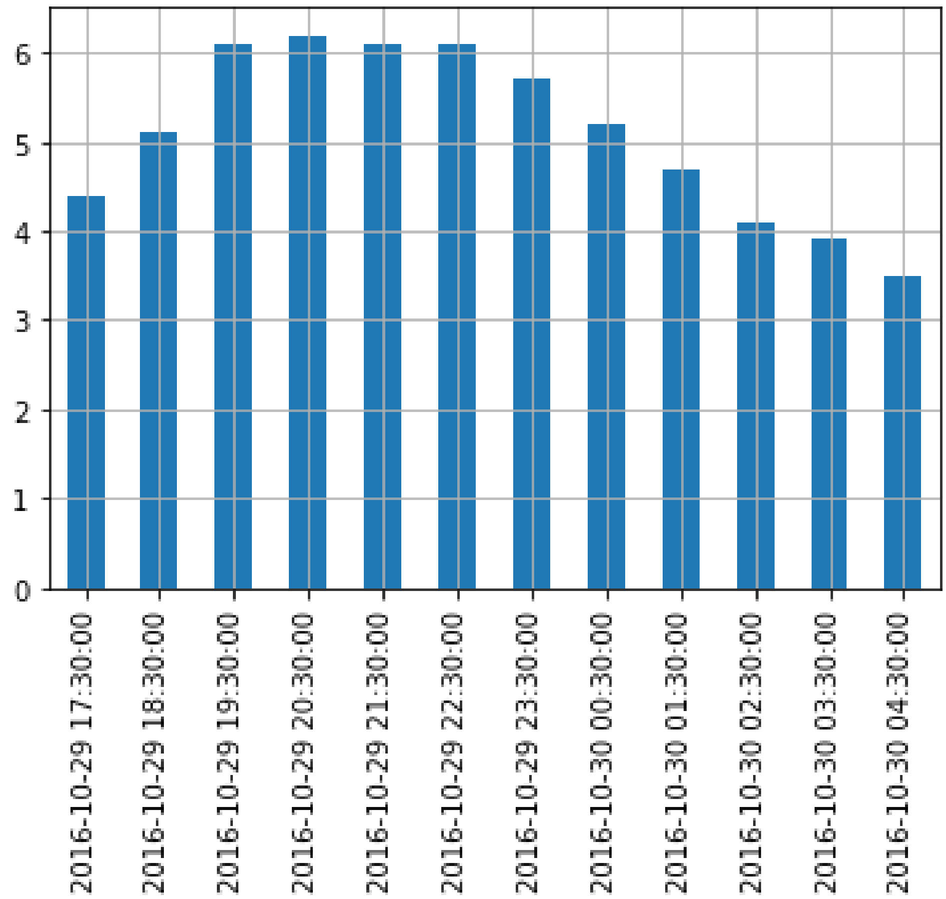
This `DatetimeIndex` may be used as an index in a `Series`:

[26]:
```
temp_series = pd.Series(temperatures, dates)
temp_series
```

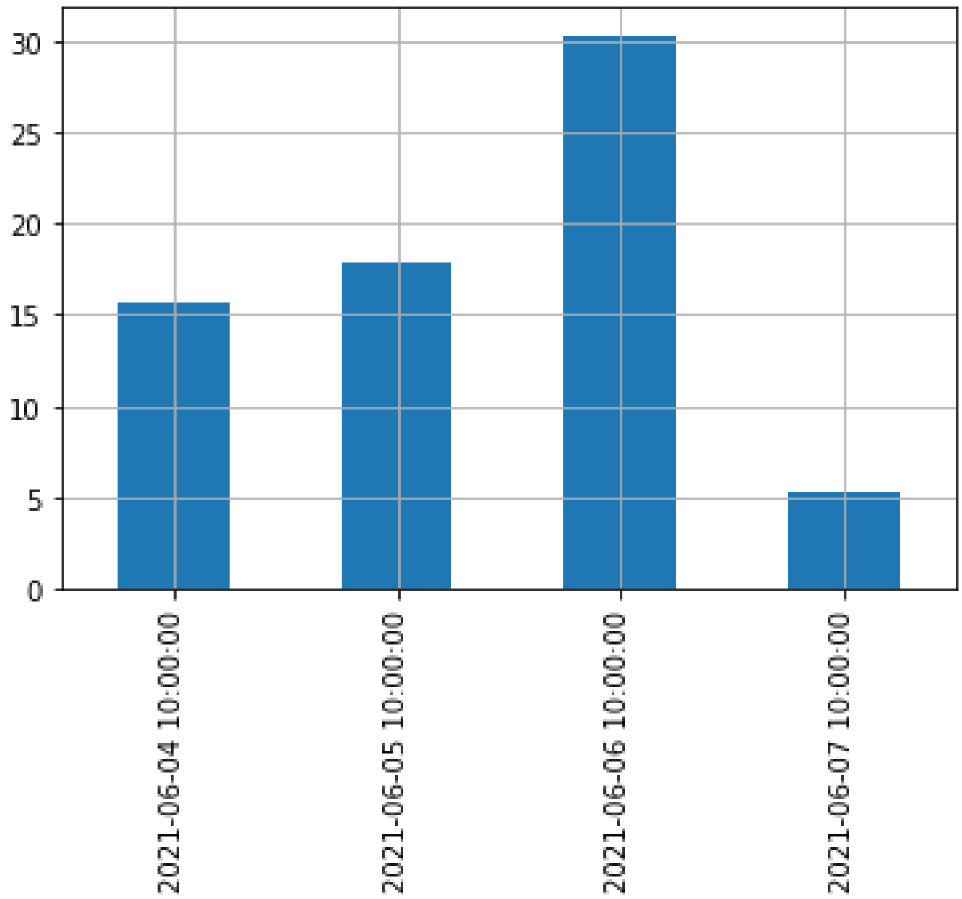
[26]:
```
2016-10-29 17:30:00    4.4
2016-10-29 18:30:00    5.1
2016-10-29 19:30:00    6.1
2016-10-29 20:30:00    6.2
2016-10-29 21:30:00    6.1
2016-10-29 22:30:00    6.1
2016-10-29 23:30:00    5.7
2016-10-30 00:30:00    5.2
2016-10-30 01:30:00    4.7
2016-10-30 02:30:00    4.1
2016-10-30 03:30:00    3.9
2016-10-30 04:30:00    3.5
Freq: H, dtype: float64
```

Let's plot this series:

[27]:
```
temp_series.plot(kind="bar")

plt.grid(True)
plt.show()
```



[28]:
```
nestor_ammounts = [15.6, 17.8, 30.4, 5.3]
nestor_range = pd.date_range('2021/06/04 10:00am', periods=4, freq='D')
nestor_rainfallamounts_today = pd.Series(nestor_ammounts, nestor_range)
nestor_rainfallamounts_today.plot(kind='bar')
plt.grid(True)
plt.show()
```



3.2 Resampling

Pandas lets us resample a time series very simply. Just call the `resample()` method and specify a new frequency:

[29]:
```
temp_series_freq_2H = temp_series.resample("2H")
temp_series_freq_2H
```

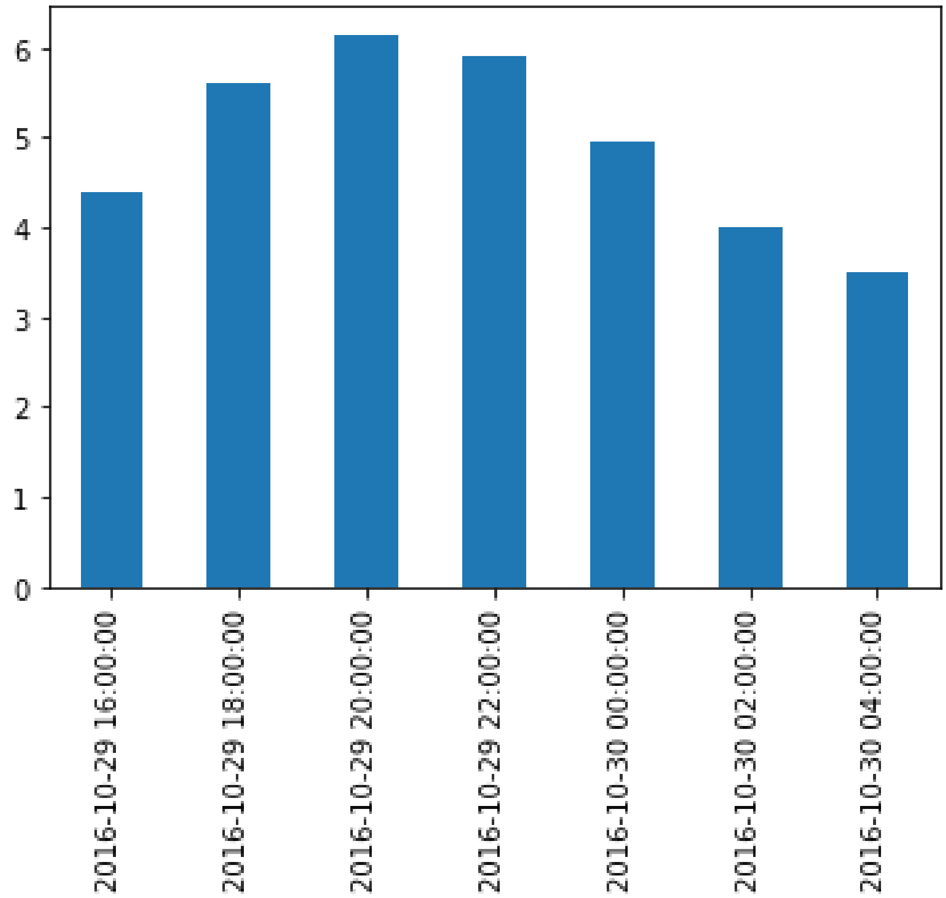
[29]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x0000017A08691340>
```

The resampling operation is actually a deferred operation, which is why we did not get a `Series` object, but a `DatetimeIndexResampler` object instead. To actually perform the resampling operation, we can simply call the `mean()` method: Pandas will compute the mean of every pair of consecutive hours:

[30]:
```
temp_series_freq_2H = temp_series_freq_2H.mean()
```

Let's plot the result:

[31]:
```
temp_series_freq_2H.plot(kind="bar")
plt.show()
```



Note how the values have automatically been aggregated into 2-hour periods. If we look at the 6-8pm period, for example, we had a value of `5.1` at 6:30pm, and `6.1` at 7:30pm. After resampling, we just have one value of `5.6`, which is the mean of `5.1` and `6.1`. Rather than computing the mean, we could have used any other aggregation function, for example we can decide to keep the minimum value of each period:

[32]:
```
temp_series_freq_2H = temp_series.resample("2H").min()
temp_series_freq_2H
```

[32]:
```
2016-10-29 16:00:00    4.4
2016-10-29 18:00:00    5.1
2016-10-29 20:00:00    6.1
2016-10-29 22:00:00    5.7
2016-10-30 00:00:00    4.7
2016-10-30 02:00:00    3.9
2016-10-30 04:00:00    3.5
```

```
Freq: 2H, dtype: float64
```

Or, equivalently, we could use the `apply()` method instead:

[33]:
```
temp_series_freq_2H = temp_series.resample("2H").apply(np.min)
temp_series_freq_2H
```

[33]:
```
2016-10-29 16:00:00    4.4
2016-10-29 18:00:00    5.1
2016-10-29 20:00:00    6.1
2016-10-29 22:00:00    5.7
2016-10-30 00:00:00    4.7
2016-10-30 02:00:00    3.9
2016-10-30 04:00:00    3.5
Freq: 2H, dtype: float64
```

3.3 Upsampling and interpolation

This was an example of downsampling. We can also upsample (ie. increase the frequency), but this creates holes in our data:

[34]:
```
temp_series_freq_15min = temp_series.resample("15Min").mean()
temp_series_freq_15min.head(n=10) # `head` displays the top n values
```

[34]:
```
2016-10-29 17:30:00    4.4
2016-10-29 17:45:00    NaN
2016-10-29 18:00:00    NaN
2016-10-29 18:15:00    NaN
2016-10-29 18:30:00    5.1
2016-10-29 18:45:00    NaN
2016-10-29 19:00:00    NaN
2016-10-29 19:15:00    NaN
2016-10-29 19:30:00    6.1
2016-10-29 19:45:00    NaN
Freq: 15T, dtype: float64
```

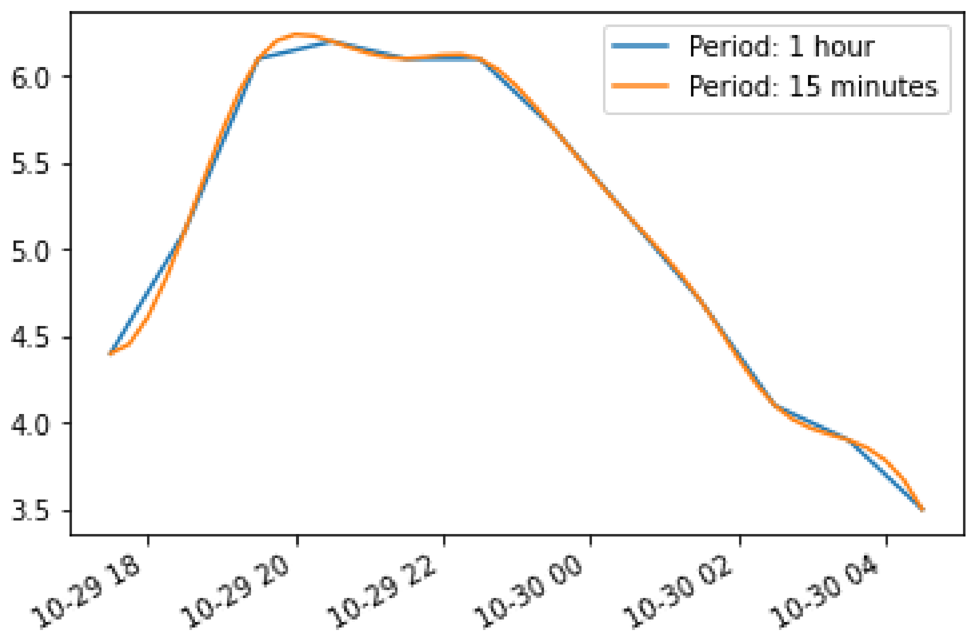
One solution is to fill the gaps by interpolating. We just call the `interpolate()` method. The default is to use linear interpolation, but we can also select another method, such as cubic interpolation:

[35]:
```
temp_series_freq_15min = temp_series.resample("15Min").
 ↪interpolate(method="cubic")
temp_series_freq_15min.head(n=10)
```

[35]:
```
2016-10-29 17:30:00    4.400000
2016-10-29 17:45:00    4.452911
2016-10-29 18:00:00    4.605113
2016-10-29 18:15:00    4.829758
2016-10-29 18:30:00    5.100000
```

```
2016-10-29 18:45:00    5.388992
2016-10-29 19:00:00    5.669887
2016-10-29 19:15:00    5.915839
2016-10-29 19:30:00    6.100000
2016-10-29 19:45:00    6.203621
Freq: 15T, dtype: float64
```

[36]:
```
temp_series.plot(label="Period: 1 hour")
temp_series_freq_15min.plot(label="Period: 15 minutes")
plt.legend()
plt.show()
```



3.4 Timezones

By default datetimes are *naive*: they are not aware of timezones, so 2016-10-30 02:30 might mean October 30th 2016 at 2:30am in Paris or in New York. We can make datetimes timezone *aware* by calling the `tz_localize()` method:

[37]:
```
temp_series_ny = temp_series.tz_localize("America/New_York")
temp_series_ny
```

[37]:
```
2016-10-29 17:30:00-04:00    4.4
2016-10-29 18:30:00-04:00    5.1
2016-10-29 19:30:00-04:00    6.1
2016-10-29 20:30:00-04:00    6.2
2016-10-29 21:30:00-04:00    6.1
```

```
2016-10-29 22:30:00-04:00    6.1
2016-10-29 23:30:00-04:00    5.7
2016-10-30 00:30:00-04:00    5.2
2016-10-30 01:30:00-04:00    4.7
2016-10-30 02:30:00-04:00    4.1
2016-10-30 03:30:00-04:00    3.9
2016-10-30 04:30:00-04:00    3.5
dtype: float64
```

Note that `-04:00` is now appended to all the datetimes. This means that these datetimes refer to UTC - 4 hours.

We can convert these datetimes to Paris time like this:

[38]:
```python
temp_series_paris = temp_series_ny.tz_convert("Europe/Paris")
temp_series_paris
```

[38]:
```
2016-10-29 23:30:00+02:00    4.4
2016-10-30 00:30:00+02:00    5.1
2016-10-30 01:30:00+02:00    6.1
2016-10-30 02:30:00+02:00    6.2
2016-10-30 02:30:00+01:00    6.1
2016-10-30 03:30:00+01:00    6.1
2016-10-30 04:30:00+01:00    5.7
2016-10-30 05:30:00+01:00    5.2
2016-10-30 06:30:00+01:00    4.7
2016-10-30 07:30:00+01:00    4.1
2016-10-30 08:30:00+01:00    3.9
2016-10-30 09:30:00+01:00    3.5
dtype: float64
```

You may have noticed that the UTC offset changes from `+02:00` to `+01:00`: this is because France switches to winter time at 3am that particular night (time goes back to 2am). Notice that 2:30am occurs twice! Let's go back to a naive representation (if you log some data hourly using local time, without storing the timezone, you might get something like this):

[39]:
```python
temp_series_paris_naive = temp_series_paris.tz_localize(None)
temp_series_paris_naive
```

[39]:
```
2016-10-29 23:30:00    4.4
2016-10-30 00:30:00    5.1
2016-10-30 01:30:00    6.1
2016-10-30 02:30:00    6.2
2016-10-30 02:30:00    6.1
2016-10-30 03:30:00    6.1
2016-10-30 04:30:00    5.7
2016-10-30 05:30:00    5.2
2016-10-30 06:30:00    4.7
2016-10-30 07:30:00    4.1
```

```
2016-10-30 08:30:00    3.9
2016-10-30 09:30:00    3.5
dtype: float64
```

Now `02:30` is really ambiguous. If we try to localize these naive datetimes to the Paris timezone, we get an error:

[40]:
```python
try:
    temp_series_paris_naive.tz_localize("Europe/Paris")
except Exception as e:
    print(type(e))
    print(e)
```

```
<class 'pytz.exceptions.AmbiguousTimeError'>
Cannot infer dst time from 2016-10-30 02:30:00, try using the 'ambiguous'
argument
```

Fortunately using the `ambiguous` argument we can tell pandas to infer the right DST (Daylight Saving Time) based on the order of the ambiguous timestamps:

[41]:
```python
temp_series_paris_naive.tz_localize("Europe/Paris", ambiguous="infer")
```

[41]:
```
2016-10-29 23:30:00+02:00    4.4
2016-10-30 00:30:00+02:00    5.1
2016-10-30 01:30:00+02:00    6.1
2016-10-30 02:30:00+02:00    6.2
2016-10-30 02:30:00+01:00    6.1
2016-10-30 03:30:00+01:00    6.1
2016-10-30 04:30:00+01:00    5.7
2016-10-30 05:30:00+01:00    5.2
2016-10-30 06:30:00+01:00    4.7
2016-10-30 07:30:00+01:00    4.1
2016-10-30 08:30:00+01:00    3.9
2016-10-30 09:30:00+01:00    3.5
dtype: float64
```

3.5 Periods

The `pd.period_range()` function returns a `PeriodIndex` instead of a `DatetimeIndex`. For example, let's get all quarters in 2016 and 2017:

[42]:
```python
quarters = pd.period_range('2016Q1', periods=8, freq='Q')
quarters
```

[42]:
```
PeriodIndex(['2016Q1', '2016Q2', '2016Q3', '2016Q4', '2017Q1', '2017Q2',
             '2017Q3', '2017Q4'],
            dtype='period[Q-DEC]', freq='Q-DEC')
```

Adding a number `N` to a `PeriodIndex` shifts the periods by `N` times the `PeriodIndex`'s frequency:

[43]:
```
quarters + 3
```

[43]:
```
PeriodIndex(['2016Q4', '2017Q1', '2017Q2', '2017Q3', '2017Q4', '2018Q1',
             '2018Q2', '2018Q3'],
            dtype='period[Q-DEC]', freq='Q-DEC')
```

The `asfreq()` method lets us change the frequency of the `PeriodIndex`. All periods are lengthened or shortened accordingly. For example, let's convert all the quarterly periods to monthly periods (zooming in):

[44]:
```
quarters.asfreq("M")
```

[44]:
```
PeriodIndex(['2016-03', '2016-06', '2016-09', '2016-12', '2017-03', '2017-06',
             '2017-09', '2017-12'],
            dtype='period[M]', freq='M')
```

By default, the `asfreq` zooms on the end of each period. We can tell it to zoom on the start of each period instead:

[45]:
```
quarters.asfreq("M", how="start")
```

[45]:
```
PeriodIndex(['2016-01', '2016-04', '2016-07', '2016-10', '2017-01', '2017-04',
             '2017-07', '2017-10'],
            dtype='period[M]', freq='M')
```

And we can zoom out:

[46]:
```
quarters.asfreq("A")
```

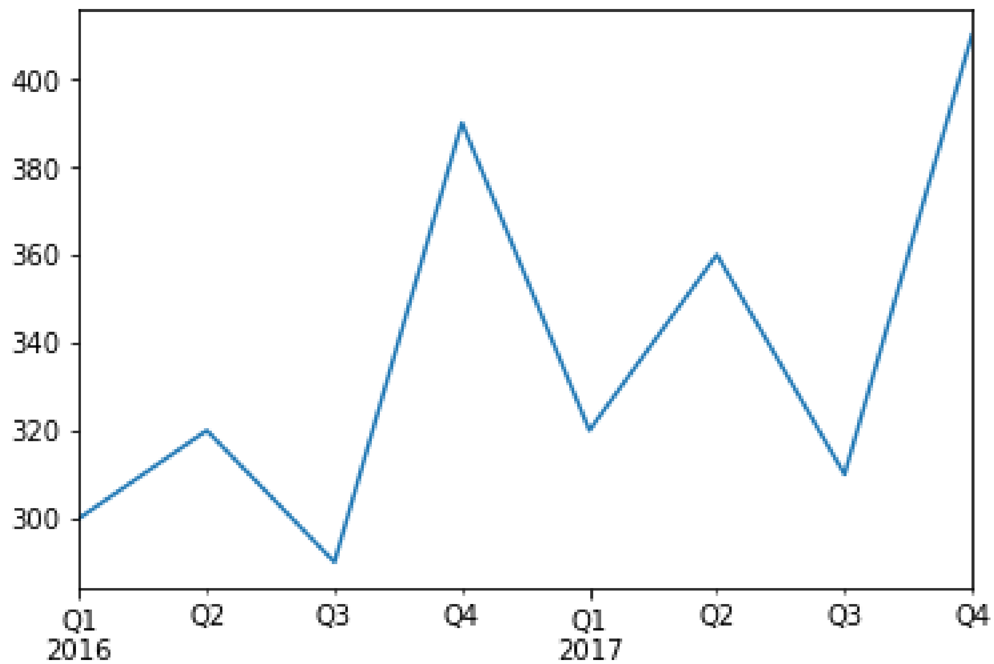
[46]:
```
PeriodIndex(['2016', '2016', '2016', '2016', '2017', '2017', '2017', '2017'],
dtype='period[A-DEC]', freq='A-DEC')
```

Of course we can create a `Series` with a `PeriodIndex`:

[47]:
```
quarterly_revenue = pd.Series([300, 320, 290, 390, 320, 360, 310, 410], index =␣
 ↪quarters)
quarterly_revenue
```

[47]:
```
2016Q1    300
2016Q2    320
2016Q3    290
2016Q4    390
2017Q1    320
2017Q2    360
2017Q3    310
2017Q4    410
Freq: Q-DEC, dtype: int64
```

[48]:
```
quarterly_revenue.plot(kind="line")
plt.show()
```



We can convert periods to timestamps by calling `to_timestamp`. By default this will give us the first day of each period, but by setting `how` and `freq`, we can get the last hour of each period:

[49]:
```
last_hours = quarterly_revenue.to_timestamp(how="end", freq="H")
last_hours
```

[49]:
```
2016-03-31 23:59:59.999999999    300
2016-06-30 23:59:59.999999999    320
2016-09-30 23:59:59.999999999    290
2016-12-31 23:59:59.999999999    390
2017-03-31 23:59:59.999999999    320
2017-06-30 23:59:59.999999999    360
2017-09-30 23:59:59.999999999    310
2017-12-31 23:59:59.999999999    410
dtype: int64
```

And back to periods by calling `to_period`:

[50]:
```
last_hours.to_period()
```

[50]:
```
2016Q1    300
2016Q2    320
2016Q3    290
2016Q4    390
2017Q1    320
2017Q2    360
```

```
2017Q3    310
2017Q4    410
Freq: Q-DEC, dtype: int64
```

Pandas also provides many other time-related functions that we recommend you check out in the documentation. To whet your appetite, here is one way to get the last business day of each month in 2016, at 9am:

[51]:
```
months_2016 = pd.period_range("2016", periods=12, freq="M")
one_day_after_last_days = months_2016.asfreq("D") + 1
last_bdays = one_day_after_last_days.to_timestamp() - pd.tseries.offsets.BDay()
last_bdays.to_period("H") + 9
```

[51]:
```
PeriodIndex(['2016-01-29 09:00', '2016-02-29 09:00', '2016-03-31 09:00',
             '2016-04-29 09:00', '2016-05-31 09:00', '2016-06-30 09:00',
             '2016-07-29 09:00', '2016-08-31 09:00', '2016-09-30 09:00',
             '2016-10-31 09:00', '2016-11-30 09:00', '2016-12-30 09:00'],
            dtype='period[H]', freq='H')
```

4 DataFrame objects

A DataFrame object represents a spreadsheet, with cell values, column names and row index labels. You can define expressions to compute columns based on other columns, create pivot-tables, group rows, draw graphs, etc. You can see `DataFrame`s as dictionaries of `Series`.

4.1 Creating a DataFrame

You can create a DataFrame by passing a dictionary of `Series` objects:

[52]:
```
people_dict = {
    "weight": pd.Series([68, 83, 112], index=["alice", "bob", "charles"]),
    "birthyear": pd.Series([1984, 1985, 1992], index=["bob", "alice",␣
 ↪"charles"], name="year"),
    "children": pd.Series([0, 3], index=["charles", "bob"]),
    "hobby": pd.Series(["Biking", "Dancing"], index=["alice", "bob"]),
}
people = pd.DataFrame(people_dict)
people
```

[52]:

	weight	birthyear	children	hobby
alice	68	1985	NaN	Biking
bob	83	1984	3.0	Dancing
charles	112	1992	0.0	NaN

A few things to note: * the `Series` were automatically aligned based on their index, * missing values are represented as `NaN`, * `Series` names are ignored (the name `"year"` was dropped), * `DataFrame`s are displayed nicely in Jupyter notebooks, woohoo!

You can access columns pretty much as you would expect. They are returned as `Series` objects:

```
[53]: people["birthyear"]
```

```
[53]: alice      1985
      bob        1984
      charles    1992
      Name: birthyear, dtype: int64
```

You can also get multiple columns at once:

```
[54]: people[["birthyear", "hobby"]]
```

```
[54]:          birthyear    hobby
      alice         1985   Biking
      bob           1984  Dancing
      charles       1992      NaN
```

If you pass a list of columns and/or index row labels to the `DataFrame` constructor, it will guarantee that these columns and/or rows will exist, in that order, and no other column/row will exist. For example:

```
[55]: d2 = pd.DataFrame(
              people_dict,
              columns=["birthyear", "weight", "height"],
              index=["bob", "alice", "eugene"]
          )
      d2
```

```
[55]:         birthyear  weight height
      bob        1984.0    83.0    NaN
      alice      1985.0    68.0    NaN
      eugene        NaN     NaN    NaN
```

Another convenient way to create a `DataFrame` is to pass all the values to the constructor as an `ndarray`, or a list of lists, and specify the column names and row index labels separately:

```
[56]: values = [
                  [1985, np.nan, "Biking",   68],
                  [1984, 3,      "Dancing",  83],
                  [1992, 0,      np.nan,    112]
               ]
      d3 = pd.DataFrame(
              values,
              columns=["birthyear", "children", "hobby", "weight"],
              index=["alice", "bob", "charles"]
          )
      d3
```

```
[56]:          birthyear  children    hobby  weight
      alice         1985       NaN   Biking      68
```

```
bob            1984       3.0  Dancing      83
charles        1992       0.0      NaN     112
```

To specify missing values, you can either use `np.nan` or NumPy's masked arrays:

[57]:
```
masked_array = np.ma.asarray(values, dtype=object)
masked_array[(0, 2), (1, 2)] = np.ma.masked
d3 = pd.DataFrame(
        masked_array,
        columns=["birthyear", "children", "hobby", "weight"],
        index=["alice", "bob", "charles"]
     )
d3
```

[57]:
```
        birthyear children    hobby weight
alice        1985      NaN   Biking     68
bob          1984        3  Dancing     83
charles      1992        0      NaN    112
```

Instead of an `ndarray`, you can also pass a `DataFrame` object:

[58]:
```
d4 = pd.DataFrame(
         d3,
         columns=["hobby", "children"],
         index=["alice", "bob"]
     )
d4
```

[58]:
```
         hobby children
alice   Biking      NaN
bob    Dancing        3
```

It is also possible to create a `DataFrame` with a dictionary (or list) of dictionaries (or list):

[59]:
```
people = pd.DataFrame({
    "birthyear": {"alice":1985, "bob": 1984, "charles": 1992},
    "hobby": {"alice":"Biking", "bob": "Dancing"},
    "weight": {"alice":68, "bob": 83, "charles": 112},
    "children": {"bob": 3, "charles": 0}
})
people
```

[59]:
```
         birthyear    hobby  weight  children
alice         1985   Biking      68       NaN
bob           1984  Dancing      83       3.0
charles       1992      NaN     112       0.0
```

4.2 Multi-indexing

If all columns are tuples of the same size, then they are understood as a multi-index. The same goes for row index labels. For example:

[60]:
```
d5 = pd.DataFrame(
  {
    ("public", "birthyear"):
        {("Paris","alice"):1985, ("Paris","bob"): 1984, ("London","charles"):␣
↪1992},
    ("public", "hobby"):
        {("Paris","alice"):"Biking", ("Paris","bob"): "Dancing"},
    ("private", "weight"):
        {("Paris","alice"):68, ("Paris","bob"): 83, ("London","charles"): 112},
    ("private", "children"):
        {("Paris", "alice"):np.nan, ("Paris","bob"): 3, ("London","charles"): 0}
  }
)
d5
```

[60]:
```
                  public          private
               birthyear    hobby  weight children
Paris  alice        1985   Biking      68      NaN
       bob          1984  Dancing      83      3.0
London charles      1992      NaN     112      0.0
```

You can now get a DataFrame containing all the "public" columns very simply:

[61]:
```
d5["public"]
```

[61]:
```
                birthyear    hobby
Paris  alice         1985   Biking
       bob           1984  Dancing
London charles       1992      NaN
```

[62]:
```
d5["public", "hobby"]  # Same result as d5["public"]["hobby"]
```

[62]:
```
Paris   alice       Biking
        bob        Dancing
London  charles        NaN
Name: (public, hobby), dtype: object
```

[63]:
```
nestor_d5 = d5.copy()
print(nestor_d5["private"])
print("\n\n")
print(nestor_d5["private"].T)
```

```
                weight  children
Paris  alice        68       NaN
       bob          83       3.0
```

```
London charles      112       0.0
```

```
         Paris        London
         alice   bob charles
weight    68.0  83.0   112.0
children   NaN   3.0     0.0
```

4.3 Dropping a level

Let's look at `d5` again:

[64]:
```python
d5
```

[64]:
```
                    public           private
                 birthyear    hobby  weight children
Paris  alice          1985   Biking      68      NaN
       bob            1984  Dancing      83      3.0
London charles        1992      NaN     112      0.0
```

There are two levels of columns, and two levels of indices. We can drop a column level by calling `droplevel()` (the same goes for indices):

[65]:
```python
d5.columns = d5.columns.droplevel(level = 0)
d5
```

[65]:
```
                birthyear    hobby  weight  children
Paris  alice         1985   Biking      68       NaN
       bob           1984  Dancing      83       3.0
London charles       1992      NaN     112       0.0
```

4.4 Transposing

You can swap columns and indices using the `T` attribute:

[66]:
```python
d6 = d5.T
d6
```

[66]:
```
            Paris           London
            alice      bob charles
birthyear    1985     1984    1992
hobby      Biking  Dancing     NaN
weight         68       83     112
children      NaN      3.0     0.0
```

4.5 Stacking and unstacking levels

Calling the `stack()` method will push the lowest column level after the lowest index:

[67]:
```
d7 = d6.stack()
d7
```

[67]:
```
                    London    Paris
birthyear alice        NaN     1985
          bob          NaN     1984
          charles     1992      NaN
hobby     alice        NaN   Biking
          bob          NaN  Dancing
weight    alice        NaN       68
          bob          NaN       83
          charles      112      NaN
children  bob          NaN      3.0
          charles      0.0      NaN
```

Note that many `NaN` values appeared. This makes sense because many new combinations did not exist before (eg. there was no `bob` in `London`).

Calling `unstack()` will do the reverse, once again creating many `NaN` values.

[68]:
```
d8 = d7.unstack()
d8
```

[68]:
```
          London                Paris
           alice  bob charles   alice      bob charles
birthyear    NaN  NaN    1992    1985     1984     NaN
children     NaN  NaN     0.0     NaN      3.0     NaN
hobby        NaN  NaN     NaN  Biking  Dancing     NaN
weight       NaN  NaN     112      68       83     NaN
```

If we call `unstack` again, we end up with a `Series` object:

[69]:
```
d9 = d8.unstack()
d9
```

[69]:
```
London  alice    birthyear        NaN
                 children         NaN
                 hobby            NaN
                 weight           NaN
        bob      birthyear        NaN
                 children         NaN
                 hobby            NaN
                 weight           NaN
        charles  birthyear       1992
                 children         0.0
                 hobby            NaN
                 weight           112
Paris   alice    birthyear       1985
                 children         NaN
```

```
              hobby         Biking
              weight            68
bob           birthyear       1984
              children         3.0
              hobby        Dancing
              weight            83
charles       birthyear        NaN
              children         NaN
              hobby            NaN
              weight           NaN
dtype: object
```

The `stack()` and `unstack()` methods let you select the `level` to stack/unstack. You can even stack/unstack multiple levels at once:

[70]:
```
d10 = d9.unstack(level = (0,1))
d10
```

[70]:
```
          London                 Paris
           alice  bob charles    alice      bob charles
birthyear    NaN  NaN    1992     1985     1984     NaN
children     NaN  NaN     0.0      NaN      3.0     NaN
hobby        NaN  NaN     NaN   Biking  Dancing     NaN
weight       NaN  NaN     112       68       83     NaN
```

4.6 Most methods return modified copies

As you may have noticed, the `stack()` and `unstack()` methods do not modify the object they apply to. Instead, they work on a copy and return that copy. This is true of most methods in pandas.

4.7 Accessing rows

Let's go back to the `people` `DataFrame`:

[71]:
```
people
```

[71]:
```
         birthyear    hobby  weight  children
alice         1985   Biking      68       NaN
bob           1984  Dancing      83       3.0
charles       1992      NaN     112       0.0
```

The `loc` attribute lets you access rows instead of columns. The result is a `Series` object in which the `DataFrame`'s column names are mapped to row index labels:

[72]:
```
people.loc["charles"]
```

[72]:
```
birthyear    1992
hobby         NaN
```

```
weight        112
children      0.0
Name: charles, dtype: object
```

You can also access rows by integer location using the `iloc` attribute:

[73]:
```
people.iloc[2]
```

[73]:
```
birthyear    1992
hobby         NaN
weight        112
children      0.0
Name: charles, dtype: object
```

You can also get a slice of rows, and this returns a `DataFrame` object:

[74]:
```
people.iloc[1:3]
```

[74]:

	birthyear	hobby	weight	children
bob	1984	Dancing	83	3.0
charles	1992	NaN	112	0.0

Finally, you can pass a boolean array to get the matching rows:

[75]:
```
people[np.array([True, False, True])]
```

[75]:

	birthyear	hobby	weight	children
alice	1985	Biking	68	NaN
charles	1992	NaN	112	0.0

This is most useful when combined with boolean expressions:

[76]:
```
people[people["birthyear"] < 1990]
```

[76]:

	birthyear	hobby	weight	children
alice	1985	Biking	68	NaN
bob	1984	Dancing	83	3.0

4.8 Adding and removing columns

You can generally treat `DataFrame` objects like dictionaries of `Series`, so the following work fine:

[77]:
```
people
```

[77]:

	birthyear	hobby	weight	children
alice	1985	Biking	68	NaN
bob	1984	Dancing	83	3.0
charles	1992	NaN	112	0.0

```
[78]: people["age"] = 2018 - people["birthyear"]  # adds a new column "age"
      people["over 30"] = people["age"] > 30      # adds another column "over 30"
      birthyears = people.pop("birthyear")
      del people["children"]

      people
```

```
[78]:            hobby  weight  age  over 30
      alice     Biking      68   33     True
      bob      Dancing      83   34     True
      charles      NaN     112   26    False
```

```
[79]: birthyears
```

```
[79]: alice      1985
      bob        1984
      charles    1992
      Name: birthyear, dtype: int64
```

When you add a new colum, it must have the same number of rows. Missing rows are filled with NaN, and extra rows are ignored:

```
[80]: people["pets"] = pd.Series({"bob": 0, "charles": 5, "eugene":1})  # alice is␣
       ↪missing, eugene is ignored
      people
```

```
[80]:            hobby  weight  age  over 30  pets
      alice     Biking      68   33     True   NaN
      bob      Dancing      83   34     True   0.0
      charles      NaN     112   26    False   5.0
```

When adding a new column, it is added at the end (on the right) by default. You can also insert a column anywhere else using the `insert()` method:

```
[81]: people.insert(1, "height", [172, 181, 185])
      people
```

```
[81]:            hobby  height  weight  age  over 30  pets
      alice     Biking     172      68   33     True   NaN
      bob      Dancing     181      83   34     True   0.0
      charles      NaN     185     112   26    False   5.0
```

```
[82]: nestor_people = people.copy()
      nestor_people['diploma'] = pd.Series(['Diploma', 'Masters'], index=["alice",␣
       ↪"bob"])
      nestor_people.loc["alice"]
```

[82]:
```
hobby          Biking
height            172
weight             68
age                33
over 30          True
pets              NaN
diploma       Diploma
Name: alice, dtype: object
```

4.9 Assigning new columns

You can also create new columns by calling the `assign()` method. Note that this returns a new `DataFrame` object, the original is not modified:

[83]:
```python
people.assign(
    body_mass_index = people["weight"] / (people["height"] / 100) ** 2,
    has_pets = people["pets"] > 0
)
```

[83]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index  \
alice     Biking     172      68   33     True   NaN        22.985398
bob      Dancing     181      83   34     True   0.0        25.335002
charles      NaN     185     112   26    False   5.0        32.724617

         has_pets
alice       False
bob         False
charles      True
```

Note that you cannot access columns created within the same assignment:

[84]:
```python
try:
    people.assign(
        body_mass_index = people["weight"] / (people["height"] / 100) ** 2,
        overweight = people["body_mass_index"] > 25
    )
except KeyError as e:
    print("Key error:", e)
```

```
Key error: 'body_mass_index'
```

The solution is to split this assignment in two consecutive assignments:

[85]:
```python
d6 = people.assign(body_mass_index = people["weight"] / (people["height"] /␣
 ↪100) ** 2)
d6.assign(overweight = d6["body_mass_index"] > 25)
```

[85]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index  \
alice     Biking     172      68   33     True   NaN        22.985398
```

```
bob      Dancing     181      83   34     True   0.0          25.335002
charles      NaN     185     112   26    False   5.0          32.724617

        overweight
alice        False
bob           True
charles       True
```

Having to create a temporary variable `d6` is not very convenient. You may want to just chain the assigment calls, but it does not work because the `people` object is not actually modified by the first assignment:

[86]:
```
try:
    (people
         .assign(body_mass_index = people["weight"] / (people["height"] / 100)␣
↪** 2)
         .assign(overweight = people["body_mass_index"] > 25)
    )
except KeyError as e:
    print("Key error:", e)
```

```
Key error: 'body_mass_index'
```

But fear not, there is a simple solution. You can pass a function to the `assign()` method (typically a `lambda` function), and this function will be called with the `DataFrame` as a parameter:

[87]:
```
(people
     .assign(body_mass_index = lambda df: df["weight"] / (df["height"] / 100)␣
↪** 2)
     .assign(overweight = lambda df: df["body_mass_index"] > 25)
)
```

[87]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index  \
alice     Biking     172      68   33     True   NaN        22.985398
bob      Dancing     181      83   34     True   0.0        25.335002
charles      NaN     185     112   26    False   5.0        32.724617

        overweight
alice        False
bob           True
charles       True
```

Problem solved!

4.10 Evaluating an expression

A great feature supported by pandas is expression evaluation. This relies on the `numexpr` library which must be installed.

[88]:
```
people.eval("weight / (height/100) ** 2 > 25")
```

[88]:
```
alice      False
bob         True
charles     True
dtype: bool
```

Assignment expressions are also supported. Let's set `inplace=True` to directly modify the `DataFrame` rather than getting a modified copy:

[89]:
```
people.eval("body_mass_index = weight / (height/100) ** 2", inplace=True)
people
```

[89]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index
alice     Biking     172      68   33     True   NaN        22.985398
bob      Dancing     181      83   34     True   0.0        25.335002
charles      NaN     185     112   26    False   5.0        32.724617
```

You can use a local or global variable in an expression by prefixing it with `'@'`:

[90]:
```
overweight_threshold = 30
people.eval("overweight = body_mass_index > @overweight_threshold",␣
 ↪inplace=True)
people
```

[90]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index  \
alice     Biking     172      68   33     True   NaN        22.985398
bob      Dancing     181      83   34     True   0.0        25.335002
charles      NaN     185     112   26    False   5.0        32.724617

         overweight
alice         False
bob           False
charles        True
```

[91]:
```
people.eval("height < 180")
```

[91]:
```
alice       True
bob        False
charles    False
dtype: bool
```

4.11 Querying a DataFrame

The `query()` method lets you filter a `DataFrame` based on a query expression:

[92]:
```
people.query("age > 30 and pets == 0")
```

[92]:
```
       hobby  height  weight  age  over 30  pets  body_mass_index  overweight
bob  Dancing     181      83   34     True   0.0        25.335002       False
```

[93]:
```
print(nestor_people)
print("\n")
print(nestor_people.query("index == 'alice'"))
```

```
           hobby  height  weight  age  over 30  pets  diploma
alice     Biking     172      68   33     True   NaN  Diploma
bob      Dancing     181      83   34     True   0.0  Masters
charles      NaN     185     112   26    False   5.0      NaN


        hobby  height  weight  age  over 30  pets  diploma
alice  Biking     172      68   33     True   NaN  Diploma
```

4.12 Sorting a DataFrame

You can sort a `DataFrame` by calling its `sort_index` method. By default it sorts the rows by their index label, in ascending order, but let's reverse the order:

[94]:
```
people.sort_index(ascending=False)
```

[94]:
```
           hobby  height  weight  age  over 30  pets  body_mass_index  \
charles      NaN     185     112   26    False   5.0        32.724617
bob      Dancing     181      83   34     True   0.0        25.335002
alice     Biking     172      68   33     True   NaN        22.985398

         overweight
charles        True
bob           False
alice         False
```

Note that `sort_index` returned a sorted *copy* of the `DataFrame`. To modify `people` directly, we can set the `inplace` argument to `True`. Also, we can sort the columns instead of the rows by setting `axis=1`:

[95]:
```
people.sort_index(axis=1, inplace=True)
people
```

[95]:
```
         age  body_mass_index  height    hobby  over 30  overweight  pets  \
alice     33        22.985398     172   Biking     True       False   NaN
bob       34        25.335002     181  Dancing     True       False   0.0
charles   26        32.724617     185      NaN    False        True   5.0

         weight
alice        68
bob          83
charles     112
```

To sort the DataFrame by the values instead of the labels, we can use sort_values and specify the column to sort by:

[96]:
```
people.sort_values(by="age", inplace=True)
people
```

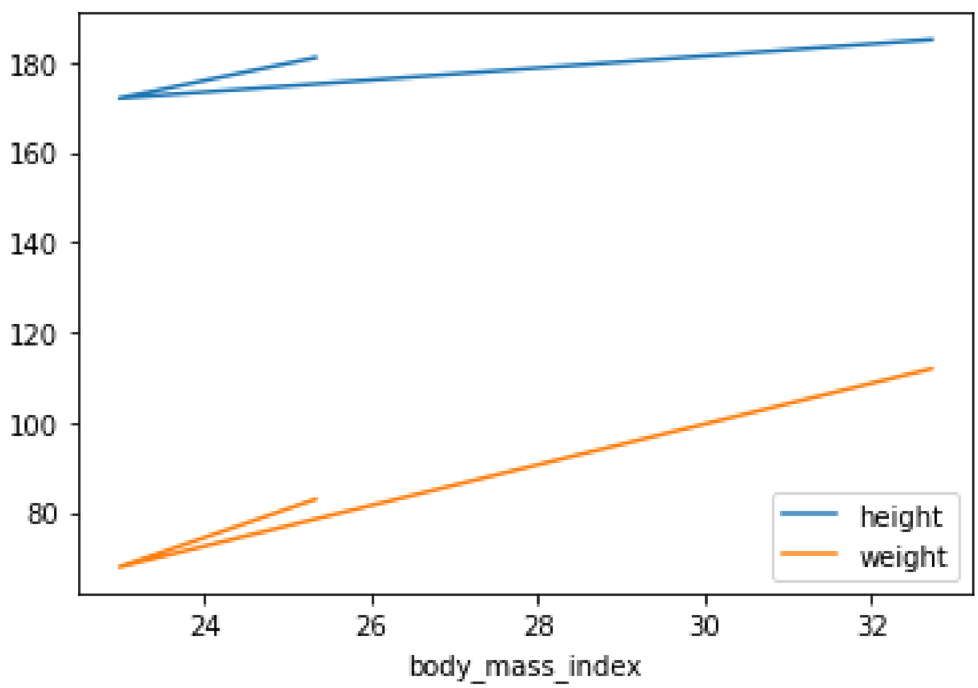
[96]:
```
         age  body_mass_index  height    hobby  over 30  overweight  pets  \
charles   26        32.724617     185      NaN    False        True   5.0
alice     33        22.985398     172   Biking     True       False   NaN
bob       34        25.335002     181  Dancing     True       False   0.0

         weight
charles     112
alice        68
bob          83
```

4.13 Plotting a DataFrame

Just like for Series, pandas makes it easy to draw nice graphs based on a DataFrame.

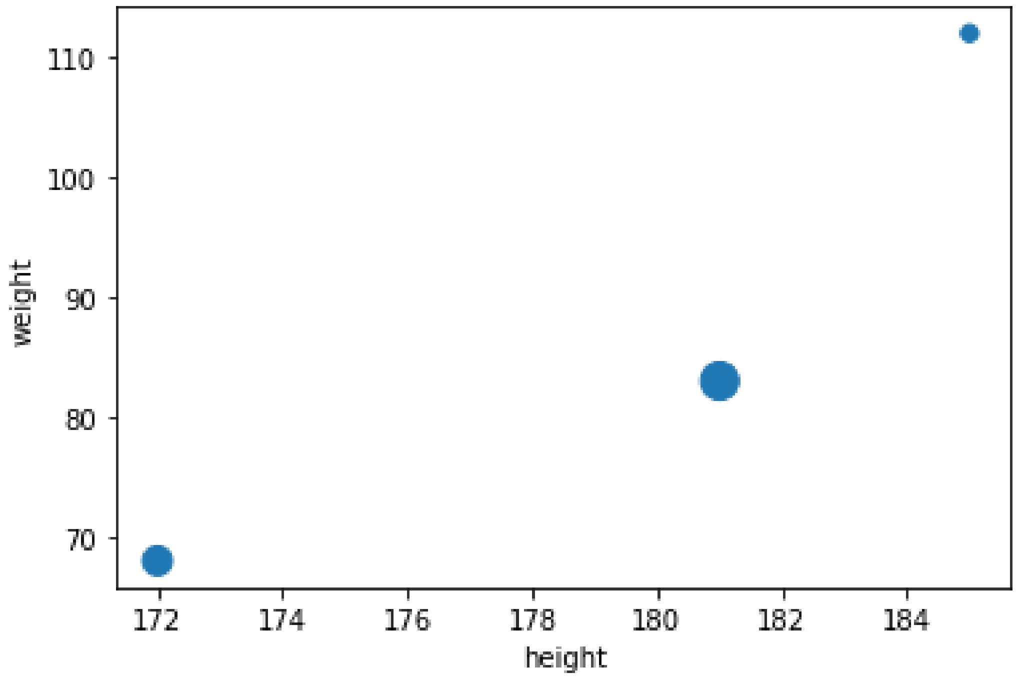
For example, it is trivial to create a line plot from a DataFrame's data by calling its plot method:

[97]:
```
people.plot(kind = "line", x = "body_mass_index", y = ["height", "weight"])
plt.show()
```



You can pass extra arguments supported by matplotlib's functions. For example, we can create scatterplot and pass it a list of sizes using the `s` argument of matplotlib's `scatter()` function:

[98]:
```
people.plot(kind = "scatter", x = "height", y = "weight", s=[40, 120, 200])
plt.show()
```



Again, there are way too many options to list here: the best option is to scroll through the Visualization page in pandas' documentation, find the plot you are interested in and look at the example code.

4.14 Operations on DataFrames

Although `DataFrame`s do not try to mimick NumPy arrays, there are a few similarities. Let's create a `DataFrame` to demonstrate this:

[99]:
```
grades_array = np.array([[8,8,9],[10,9,9],[4, 8, 2], [9, 10, 10]])
grades = pd.DataFrame(grades_array, columns=["sep", "oct", "nov"],␣
↪index=["alice","bob","charles","darwin"])
grades
```

[99]:

	sep	oct	nov
alice	8	8	9
bob	10	9	9
charles	4	8	2
darwin	9	10	10

You can apply NumPy mathematical functions on a `DataFrame`: the function is applied to all values:

[100]:
```
np.sqrt(grades)
```

[100]:
```
                sep       oct       nov
alice    2.828427  2.828427  3.000000
bob      3.162278  3.000000  3.000000
charles  2.000000  2.828427  1.414214
darwin   3.000000  3.162278  3.162278
```

Similarly, adding a single value to a `DataFrame` will add that value to all elements in the `DataFrame`. This is called *broadcasting*:

[101]:
```
grades + 1
```

[101]:
```
         sep  oct  nov
alice      9    9   10
bob       11   10   10
charles    5    9    3
darwin    10   11   11
```

Of course, the same is true for all other binary operations, including arithmetic (`*`,`/`,`**`…) and conditional (`>`, `==`…) operations:

[102]:
```
grades >= 5
```

[102]:
```
           sep   oct    nov
alice     True  True   True
bob       True  True   True
charles  False  True  False
darwin    True  True   True
```

Aggregation operations, such as computing the `max`, the `sum` or the `mean` of a `DataFrame`, apply to each column, and you get back a `Series` object:

[103]:
```
grades.mean()
```

[103]:
```
sep    7.75
oct    8.75
nov    7.50
dtype: float64
```

The `all` method is also an aggregation operation: it checks whether all values are `True` or not. Let's see during which months all students got a grade greater than `5`:

[104]:
```
(grades > 5).all()
```

[104]:
```
sep    False
oct     True
nov    False
```

```
dtype: bool
```

Most of these functions take an optional `axis` parameter which lets you specify along which axis of the `DataFrame` you want the operation executed. The default is `axis=0`, meaning that the operation is executed vertically (on each column). You can set `axis=1` to execute the operation horizontally (on each row). For example, let's find out which students had all grades greater than `5`:

[105]:
```
(grades > 5).all(axis = 1)
```

[105]:
```
alice       True
bob         True
charles    False
darwin      True
dtype: bool
```

The `any` method returns `True` if any value is True. Let's see who got at least one grade 10:

[106]:
```
(grades == 10).any(axis = 1)
```

[106]:
```
alice      False
bob         True
charles    False
darwin      True
dtype: bool
```

If you add a `Series` object to a `DataFrame` (or execute any other binary operation), pandas attempts to broadcast the operation to all *rows* in the `DataFrame`. This only works if the `Series` has the same size as the `DataFrames` rows. For example, let's substract the `mean` of the `DataFrame` (a `Series` object) from the `DataFrame`:

[107]:
```
grades - grades.mean()  # equivalent to: grades - [7.75, 8.75, 7.50]
```

[107]:

	sep	oct	nov
alice	0.25	-0.75	1.5
bob	2.25	0.25	1.5
charles	-3.75	-0.75	-5.5
darwin	1.25	1.25	2.5

We substracted `7.75` from all September grades, `8.75` from October grades and `7.50` from November grades. It is equivalent to substracting this `DataFrame`:

[108]:
```
pd.DataFrame([[7.75, 8.75, 7.50]]*4, index=grades.index, columns=grades.columns)
```

[108]:

	sep	oct	nov
alice	7.75	8.75	7.5
bob	7.75	8.75	7.5
charles	7.75	8.75	7.5
darwin	7.75	8.75	7.5

If you want to substract the global mean from every grade, here is one way to do it:

[109]:
```
grades - grades.values.mean() # substracts the global mean (8.00) from all␣
↪grades
```

[109]:
```
         sep  oct  nov
alice    0.0  0.0  1.0
bob      2.0  1.0  1.0
charles -4.0  0.0 -6.0
darwin   1.0  2.0  2.0
```

[110]:
```
nestor_students = pd.DataFrame({"April": [55,75,40,35],"May":
↪[60,40,30,70],"June":[30,35,20,25],"July":[70,65,70,65]},␣
↪index={"Marie","Irina","Martina","Holly"})
print("ORIGINAL DATAFRAME")
print(nestor_students)
print("\n")
print("AVERAGE GRADE FOR APRIL:",nestor_students["April"].mean())

nestor_students = nestor_students * 1.02
print("\n")
print("ADJUSTED GRADES DATAFRAME(2%)")
print(nestor_students)
print("\n")

print("MAY GRADES HIGHER THAN 50%")
print(nestor_students["May"][nestor_students["May"].apply(lambda g : g>50)])
print("\n")

print("FAILING STUDENTS")
nestor_students["Avg"] = nestor_students.mean(axis=1)
print(nestor_students[nestor_students.mean(axis=1) < 50])
print("\n")
```

```
ORIGINAL DATAFRAME
         April  May  June  July
Irina       55   60    30    70
Martina     75   40    35    65
Marie       40   30    20    70
Holly       35   70    25    65


AVERAGE GRADE FOR APRIL: 51.25


ADJUSTED GRADES DATAFRAME(2%)
         April   May  June  July
Irina     56.1  61.2  30.6  71.4
Martina   76.5  40.8  35.7  66.3
Marie     40.8  30.6  20.4  71.4
```

```
Holly     35.7  71.4  25.5  66.3


MAY GRADES HIGHER THAN 50%
Irina    61.2
Holly    71.4
Name: May, dtype: float64


FAILING STUDENTS
       April   May  June  July     Avg
Marie   40.8  30.6  20.4  71.4  40.800
Holly   35.7  71.4  25.5  66.3  49.725
```

4.15 Automatic alignment

Similar to `Series`, when operating on multiple `DataFrames`, pandas automatically aligns them by row index label, but also by column names. Let's create a `DataFrame` with bonus points for each person from October to December:

[111]:
```
bonus_array = np.array([[0,np.nan,2],[np.nan,1,0],[0, 1, 0], [3, 3, 0]])
bonus_points = pd.DataFrame(bonus_array, columns=["oct", "nov", "dec"],␣
↪index=["bob","colin", "darwin", "charles"])
bonus_points
```

[111]:

	oct	nov	dec
bob	0.0	NaN	2.0
colin	NaN	1.0	0.0
darwin	0.0	1.0	0.0
charles	3.0	3.0	0.0

[112]:
```
grades + bonus_points
```

[112]:

	dec	nov	oct	sep
alice	NaN	NaN	NaN	NaN
bob	NaN	NaN	9.0	NaN
charles	NaN	5.0	11.0	NaN
colin	NaN	NaN	NaN	NaN
darwin	NaN	11.0	10.0	NaN

Looks like the addition worked in some cases but way too many elements are now empty. That's because when aligning the `DataFrames`, some columns and rows were only present on one side, and thus they were considered missing on the other side (`NaN`). Then adding `NaN` to a number results in `NaN`, hence the result.

4.16 Handling missing data

Dealing with missing data is a frequent task when working with real life data. Pandas offers a few tools to handle missing data.

Let's try to fix the problem above. For example, we can decide that missing data should result in a zero, instead of `NaN`. We can replace all `NaN` values by a any value using the `fillna()` method:

[113]:
```
(grades + bonus_points).fillna(0)
```

[113]:
```
         dec   nov   oct  sep
alice    0.0   0.0   0.0  0.0
bob      0.0   0.0   9.0  0.0
charles  0.0   5.0  11.0  0.0
colin    0.0   0.0   0.0  0.0
darwin   0.0  11.0  10.0  0.0
```

It's a bit unfair that we're setting grades to zero in September, though. Perhaps we should decide that missing grades are missing grades, but missing bonus points should be replaced by zeros:

[114]:
```
fixed_bonus_points = bonus_points.fillna(0)
fixed_bonus_points.insert(0, "sep", 0)
fixed_bonus_points.loc["alice"] = 0
grades + fixed_bonus_points
```

[114]:
```
         dec   nov   oct   sep
alice    NaN   9.0   8.0   8.0
bob      NaN   9.0   9.0  10.0
charles  NaN   5.0  11.0   4.0
colin    NaN   NaN   NaN   NaN
darwin   NaN  11.0  10.0   9.0
```

That's much better: although we made up some data, we have not been too unfair.

Another way to handle missing data is to interpolate. Let's look at the `bonus_points` `DataFrame` again:

[115]:
```
bonus_points
```

[115]:
```
         oct  nov  dec
bob      0.0  NaN  2.0
colin    NaN  1.0  0.0
darwin   0.0  1.0  0.0
charles  3.0  3.0  0.0
```

Now let's call the `interpolate` method. By default, it interpolates vertically (`axis=0`), so let's tell it to interpolate horizontally (`axis=1`).

[116]:
```
bonus_points.interpolate(axis=1)
```

[116]:

	oct	nov	dec
bob	0.0	1.0	2.0
colin	NaN	1.0	0.0
darwin	0.0	1.0	0.0
charles	3.0	3.0	0.0

Bob had 0 bonus points in October, and 2 in December. When we interpolate for November, we get the mean: 1 bonus point. Colin had 1 bonus point in November, but we do not know how many bonus points he had in September, so we cannot interpolate, this is why there is still a missing value in October after interpolation. To fix this, we can set the September bonus points to 0 before interpolation.

[117]:
```
better_bonus_points = bonus_points.copy()
better_bonus_points.insert(0, "sep", 0)
better_bonus_points.loc["alice"] = 0
better_bonus_points = better_bonus_points.interpolate(axis=1)
better_bonus_points
```

[117]:

	sep	oct	nov	dec
bob	0.0	0.0	1.0	2.0
colin	0.0	0.5	1.0	0.0
darwin	0.0	0.0	1.0	0.0
charles	0.0	3.0	3.0	0.0
alice	0.0	0.0	0.0	0.0

Great, now we have reasonable bonus points everywhere. Let's find out the final grades:

[118]:
```
grades + better_bonus_points
```

[118]:

	dec	nov	oct	sep
alice	NaN	9.0	8.0	8.0
bob	NaN	10.0	9.0	10.0
charles	NaN	5.0	11.0	4.0
colin	NaN	NaN	NaN	NaN
darwin	NaN	11.0	10.0	9.0

It is slightly annoying that the September column ends up on the right. This is because the `DataFrame`s we are adding do not have the exact same columns (the `grades` `DataFrame` is missing the `"dec"` column), so to make things predictable, pandas orders the final columns alphabetically. To fix this, we can simply add the missing column before adding:

[119]:
```
grades["dec"] = np.nan
final_grades = grades + better_bonus_points
final_grades
```

[119]:

	sep	oct	nov	dec
alice	8.0	8.0	9.0	NaN
bob	10.0	9.0	10.0	NaN
charles	4.0	11.0	5.0	NaN

```
colin      NaN   NaN   NaN  NaN
darwin     9.0  10.0  11.0  NaN
```

There's not much we can do about December and Colin: it's bad enough that we are making up bonus points, but we can't reasonably make up grades (well I guess some teachers probably do). So let's call the `dropna()` method to get rid of rows that are full of `NaN`s:

[120]:
```python
final_grades_clean = final_grades.dropna(how="all")
final_grades_clean
```

[120]:
```
          sep   oct   nov  dec
alice     8.0   8.0   9.0  NaN
bob      10.0   9.0  10.0  NaN
charles   4.0  11.0   5.0  NaN
darwin    9.0  10.0  11.0  NaN
```

Now let's remove columns that are full of `NaN`s by setting the `axis` argument to `1`:

[121]:
```python
final_grades_clean = final_grades_clean.dropna(axis=1, how="all")
final_grades_clean
```

[121]:
```
          sep   oct   nov
alice     8.0   8.0   9.0
bob      10.0   9.0  10.0
charles   4.0  11.0   5.0
darwin    9.0  10.0  11.0
```

4.17 Aggregating with groupby

Similar to the SQL language, pandas allows grouping your data into groups to run calculations over each group.

First, let's add some extra data about each person so we can group them, and let's go back to the `final_grades` `DataFrame` so we can see how `NaN` values are handled:

[122]:
```python
final_grades["hobby"] = ["Biking", "Dancing", np.nan, "Dancing", "Biking"]
final_grades
```

[122]:
```
          sep   oct   nov  dec    hobby
alice     8.0   8.0   9.0  NaN   Biking
bob      10.0   9.0  10.0  NaN  Dancing
charles   4.0  11.0   5.0  NaN      NaN
colin     NaN   NaN   NaN  NaN  Dancing
darwin    9.0  10.0  11.0  NaN   Biking
```

Now let's group data in this `DataFrame` by hobby:

[123]:
```python
grouped_grades = final_grades.groupby("hobby")
grouped_grades
```

[123]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000017A09ECDC70>

We are ready to compute the average grade per hobby:

[124]:
```
grouped_grades.mean()
```

[124]:
```
          sep  oct   nov  dec
hobby
Biking    8.5  9.0  10.0  NaN
Dancing  10.0  9.0  10.0  NaN
```

That was easy! Note that the NaN values have simply been skipped when computing the means.

4.18 Pivot tables

Pandas supports spreadsheet-like pivot tables that allow quick data summarization. To illustrate this, let's create a simple DataFrame:

[125]:
```
bonus_points
```

[125]:
```
         oct  nov  dec
bob      0.0  NaN  2.0
colin    NaN  1.0  0.0
darwin   0.0  1.0  0.0
charles  3.0  3.0  0.0
```

[126]:
```
more_grades = final_grades_clean.stack().reset_index()
more_grades.columns = ["name", "month", "grade"]
more_grades["bonus"] = [np.nan, np.nan, np.nan, 0, np.nan, 2, 3, 3, 0, 0, 1, 0]
more_grades
```

[126]:
```
       name month  grade  bonus
0     alice   sep    8.0    NaN
1     alice   oct    8.0    NaN
2     alice   nov    9.0    NaN
3       bob   sep   10.0    0.0
4       bob   oct    9.0    NaN
5       bob   nov   10.0    2.0
6   charles   sep    4.0    3.0
7   charles   oct   11.0    3.0
8   charles   nov    5.0    0.0
9    darwin   sep    9.0    0.0
10   darwin   oct   10.0    1.0
11   darwin   nov   11.0    0.0
```

Now we can call the pd.pivot_table() function for this DataFrame, asking to group by the name column. By default, pivot_table() computes the mean of each numeric column:

[127]:
```
pd.pivot_table(more_grades, index="name")
```

[127]:

```
            bonus      grade
name
alice         NaN   8.333333
bob      1.000000   9.666667
charles  2.000000   6.666667
darwin   0.333333  10.000000
```

We can change the aggregation function by setting the `aggfunc` argument, and we can also specify the list of columns whose values will be aggregated:

[128]:

```
pd.pivot_table(more_grades, index="name", values=["grade","bonus"], aggfunc=np.
 ↪max)
```

[128]:

```
         bonus  grade
name
alice      NaN    9.0
bob        2.0   10.0
charles    3.0   11.0
darwin     1.0   11.0
```

We can also specify the `columns` to aggregate over horizontally, and request the grand totals for each row and column by setting `margins=True`:

[129]:

```
pd.pivot_table(more_grades, index="name", values="grade", columns="month",␣
 ↪margins=True)
```

[129]:

```
month      nov   oct    sep        All
name
alice     9.00   8.0   8.00   8.333333
bob      10.00   9.0  10.00   9.666667
charles   5.00  11.0   4.00   6.666667
darwin   11.00  10.0   9.00  10.000000
All       8.75   9.5   7.75   8.666667
```

Finally, we can specify multiple index or column names, and pandas will create multi-level indices:

[130]:

```
pd.pivot_table(more_grades, index=("name", "month"), margins=True)
```

[130]:

```
               bonus  grade
name    month
alice   nov      NaN   9.00
        oct      NaN   8.00
        sep      NaN   8.00
bob     nov    2.000  10.00
        oct      NaN   9.00
        sep    0.000  10.00
charles nov    0.000   5.00
        oct    3.000  11.00
        sep    3.000   4.00
```

```
darwin   nov     0.000  11.00
         oct     1.000  10.00
         sep     0.000   9.00
All              1.125   8.75
```

4.19 Overview functions

When dealing with large `DataFrames`, it is useful to get a quick overview of its content. Pandas offers a few functions for this. First, let's create a large `DataFrame` with a mix of numeric values, missing values and text values. Notice how Jupyter displays only the corners of the `DataFrame`:

[131]:
```
much_data = np.fromfunction(lambda x,y: (x+y*y)%17*11, (10000, 26))
large_df = pd.DataFrame(much_data, columns=list("ABCDEFGHIJKLMNOPQRSTUVWXYZ"))␣
↪#26 letters x 10000 rows
large_df[large_df % 16 == 0] = np.nan
large_df.insert(3,"some_text", "Blabla")
large_df
```

[131]:
```
         A     B     C some_text      D      E      F     G      H      I  \
0      NaN  11.0  44.0    Blabla   99.0    NaN   88.0  22.0  165.0  143.0
1     11.0  22.0  55.0    Blabla  110.0    NaN   99.0  33.0    NaN  154.0
2     22.0  33.0  66.0    Blabla  121.0   11.0  110.0  44.0    NaN  165.0
3     33.0  44.0  77.0    Blabla  132.0   22.0  121.0  55.0   11.0    NaN
4     44.0  55.0  88.0    Blabla  143.0   33.0  132.0  66.0   22.0    NaN
…     …     …     …         …      …      …      …     …      …
9995   NaN   NaN  33.0    Blabla   88.0  165.0   77.0  11.0  154.0  132.0
9996   NaN  11.0  44.0    Blabla   99.0    NaN   88.0  22.0  165.0  143.0
9997  11.0  22.0  55.0    Blabla  110.0    NaN   99.0  33.0    NaN  154.0
9998  22.0  33.0  66.0    Blabla  121.0   11.0  110.0  44.0    NaN  165.0
9999  33.0  44.0  77.0    Blabla  132.0   22.0  121.0  55.0   11.0    NaN

      …     Q     R     S     T      U      V      W     X      Y      Z
0     …  11.0   NaN  11.0  44.0   99.0    NaN   88.0  22.0  165.0  143.0
1     …  22.0  11.0  22.0  55.0  110.0    NaN   99.0  33.0    NaN  154.0
2     …  33.0  22.0  33.0  66.0  121.0   11.0  110.0  44.0    NaN  165.0
3     …  44.0  33.0  44.0  77.0  132.0   22.0  121.0  55.0   11.0    NaN
4     …  55.0  44.0  55.0  88.0  143.0   33.0  132.0  66.0   22.0    NaN
…    …   …     …     …     …     …      …      …      …     …      …
9995  …   NaN   NaN   NaN  33.0   88.0  165.0   77.0  11.0  154.0  132.0
9996  …  11.0   NaN  11.0  44.0   99.0    NaN   88.0  22.0  165.0  143.0
9997  …  22.0  11.0  22.0  55.0  110.0    NaN   99.0  33.0    NaN  154.0
9998  …  33.0  22.0  33.0  66.0  121.0   11.0  110.0  44.0    NaN  165.0
9999  …  44.0  33.0  44.0  77.0  132.0   22.0  121.0  55.0   11.0    NaN

[10000 rows x 27 columns]
```

The `head()` method returns the top 5 rows:

```
[132]: large_df.head()
```

```
[132]:
      A     B     C some_text      D     E      F     G      H      I  ...  \
0   NaN  11.0  44.0    Blabla   99.0   NaN   88.0  22.0  165.0  143.0  ...
1  11.0  22.0  55.0    Blabla  110.0   NaN   99.0  33.0    NaN  154.0  ...
2  22.0  33.0  66.0    Blabla  121.0  11.0  110.0  44.0    NaN  165.0  ...
3  33.0  44.0  77.0    Blabla  132.0  22.0  121.0  55.0   11.0    NaN  ...
4  44.0  55.0  88.0    Blabla  143.0  33.0  132.0  66.0   22.0    NaN  ...

      Q     R     S     T      U     V      W     X      Y      Z
0  11.0   NaN  11.0  44.0   99.0   NaN   88.0  22.0  165.0  143.0
1  22.0  11.0  22.0  55.0  110.0   NaN   99.0  33.0    NaN  154.0
2  33.0  22.0  33.0  66.0  121.0  11.0  110.0  44.0    NaN  165.0
3  44.0  33.0  44.0  77.0  132.0  22.0  121.0  55.0   11.0    NaN
4  55.0  44.0  55.0  88.0  143.0  33.0  132.0  66.0   22.0    NaN

[5 rows x 27 columns]
```

Of course there's also a `tail()` function to view the bottom 5 rows. You can pass the number of rows you want:

```
[133]: large_df.tail(n=2)
```

```
[133]:
         A     B     C some_text      D     E      F     G     H      I  ...  \
9998  22.0  33.0  66.0    Blabla  121.0  11.0  110.0  44.0   NaN  165.0  ...
9999  33.0  44.0  77.0    Blabla  132.0  22.0  121.0  55.0  11.0    NaN  ...

         Q     R     S     T      U     V      W     X     Y      Z
9998  33.0  22.0  33.0  66.0  121.0  11.0  110.0  44.0   NaN  165.0
9999  44.0  33.0  44.0  77.0  132.0  22.0  121.0  55.0  11.0    NaN

[2 rows x 27 columns]
```

The `info()` method prints out a summary of each columns contents:

```
[134]: large_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   A          8823 non-null   float64
 1   B          8824 non-null   float64
 2   C          8824 non-null   float64
 3   some_text  10000 non-null  object
 4   D          8824 non-null   float64
 5   E          8822 non-null   float64
 6   F          8824 non-null   float64
```

```
 7   G           8824 non-null   float64
 8   H           8822 non-null   float64
 9   I           8823 non-null   float64
 10  J           8823 non-null   float64
 11  K           8822 non-null   float64
 12  L           8824 non-null   float64
 13  M           8824 non-null   float64
 14  N           8822 non-null   float64
 15  O           8824 non-null   float64
 16  P           8824 non-null   float64
 17  Q           8824 non-null   float64
 18  R           8823 non-null   float64
 19  S           8824 non-null   float64
 20  T           8824 non-null   float64
 21  U           8824 non-null   float64
 22  V           8822 non-null   float64
 23  W           8824 non-null   float64
 24  X           8824 non-null   float64
 25  Y           8822 non-null   float64
 26  Z           8823 non-null   float64
dtypes: float64(26), object(1)
memory usage: 2.1+ MB
```

Finally, the `describe()` method gives a nice overview of the main aggregated values over each column: * `count`: number of non-null (not NaN) values * `mean`: mean of non-null values * `std`: standard deviation of non-null values * `min`: minimum of non-null values * `25%`, `50%`, `75%`: 25th, 50th and 75th percentile of non-null values * `max`: maximum of non-null values

[135]:
```
large_df.describe()
```

[135]:
```
                 A            B            C            D            E  \
count  8823.000000  8824.000000  8824.000000  8824.000000  8822.000000
mean     87.977559    87.972575    87.987534    88.012466    87.983791
std      47.535911    47.535523    47.521679    47.521679    47.535001
min      11.000000    11.000000    11.000000    11.000000    11.000000
25%      44.000000    44.000000    44.000000    44.000000    44.000000
50%      88.000000    88.000000    88.000000    88.000000    88.000000
75%     132.000000   132.000000   132.000000   132.000000   132.000000
max     165.000000   165.000000   165.000000   165.000000   165.000000

                 F            G            H            I            J  …  \
count  8824.000000  8824.000000  8822.000000  8823.000000  8823.000000  …
mean     88.007480    87.977561    88.000000    88.022441    88.022441  …
std      47.519371    47.529755    47.536879    47.535911    47.535911  …
min      11.000000    11.000000    11.000000    11.000000    11.000000  …
25%      44.000000    44.000000    44.000000    44.000000    44.000000  …
50%      88.000000    88.000000    88.000000    88.000000    88.000000  …
75%     132.000000   132.000000   132.000000   132.000000   132.000000  …
```

```
max      165.000000   165.000000   165.000000   165.000000   165.000000  …

                  Q            R            S            T            U  \
count  8824.000000  8823.000000  8824.000000  8824.000000  8824.000000
mean     87.972575    87.977559    87.972575    87.987534    88.012466
std      47.535523    47.535911    47.535523    47.521679    47.521679
min      11.000000    11.000000    11.000000    11.000000    11.000000
25%      44.000000    44.000000    44.000000    44.000000    44.000000
50%      88.000000    88.000000    88.000000    88.000000    88.000000
75%     132.000000   132.000000   132.000000   132.000000   132.000000
max     165.000000   165.000000   165.000000   165.000000   165.000000

                  V            W            X            Y            Z
count  8822.000000  8824.000000  8824.000000  8822.000000  8823.000000
mean     87.983791    88.007480    87.977561    88.000000    88.022441
std      47.535001    47.519371    47.529755    47.536879    47.535911
min      11.000000    11.000000    11.000000    11.000000    11.000000
25%      44.000000    44.000000    44.000000    44.000000    44.000000
50%      88.000000    88.000000    88.000000    88.000000    88.000000
75%     132.000000   132.000000   132.000000   132.000000   132.000000
max     165.000000   165.000000   165.000000   165.000000   165.000000

[8 rows x 26 columns]
```

5 Saving & loading

Pandas can save DataFrames to various backends, including file formats such as CSV, Excel, JSON, HTML and HDF5, or to a SQL database. Let's create a DataFrame to demonstrate this:

[136]:
```
my_df = pd.DataFrame(
    [["Biking", 68.5, 1985, np.nan], ["Dancing", 83.1, 1984, 3]],
    columns=["hobby","weight","birthyear","children"],
    index=["alice", "bob"]
)
my_df
```

[136]:

	hobby	weight	birthyear	children
alice	Biking	68.5	1985	NaN
bob	Dancing	83.1	1984	3.0

5.1 Saving

Let's save it to CSV, HTML and JSON:

[137]:
```
my_df.to_csv("my_df.csv")
my_df.to_html("my_df.html")
my_df.to_json("my_df.json")
```

Done! Let's take a peek at what was saved:

[138]:
```python
for filename in ("my_df.csv", "my_df.html", "my_df.json"):
    print("#", filename)
    with open(filename, "rt") as f:
        print(f.read())
        print()
```

```
# my_df.csv
,hobby,weight,birthyear,children
alice,Biking,68.5,1985,
bob,Dancing,83.1,1984,3.0


# my_df.html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>hobby</th>
      <th>weight</th>
      <th>birthyear</th>
      <th>children</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>alice</th>
      <td>Biking</td>
      <td>68.5</td>
      <td>1985</td>
      <td>NaN</td>
    </tr>
    <tr>
      <th>bob</th>
      <td>Dancing</td>
      <td>83.1</td>
      <td>1984</td>
      <td>3.0</td>
    </tr>
  </tbody>
</table>

# my_df.json
{"hobby":{"alice":"Biking","bob":"Dancing"},"weight":{"alice":68.5,"bob":83.1},"
birthyear":{"alice":1985,"bob":1984},"children":{"alice":null,"bob":3.0}}
```

Note that the index is saved as the first column (with no name) in a CSV file, as `<th>` tags in

HTML and as keys in JSON.

Saving to other formats works very similarly, but some formats require extra libraries to be installed. For example, saving to Excel requires the openpyxl library:

[139]:
```
try:
    my_df.to_excel("my_df.xlsx", sheet_name='People')
except ImportError as e:
    print(e)
```

5.2 Loading

Now let's load our CSV file back into a `DataFrame`:

[140]:
```
my_df_loaded = pd.read_csv("my_df.csv", index_col=0)
my_df_loaded
```

[140]:

	hobby	weight	birthyear	children
alice	Biking	68.5	1985	NaN
bob	Dancing	83.1	1984	3.0

As you might guess, there are similar `read_json`, `read_html`, `read_excel` functions as well. We can also read data straight from the Internet. For example, let's load all U.S. cities from simplemaps.com:

[141]:
```
us_cities = None
try:
    csv_url = "http://simplemaps.com/files/cities.csv"
    us_cities = pd.read_csv(csv_url, index_col=0)
    us_cities = us_cities.head()
except IOError as e:
    print(e)
us_cities
```

```
HTTP Error 403: Forbidden
```

There are more options available, in particular regarding datetime format. Check out the documentation for more details.

6 Combining DataFrames

6.1 SQL-like joins

One powerful feature of pandas is it's ability to perform SQL-like joins on `DataFrame`s. Various types of joins are supported: inner joins, left/right outer joins and full joins. To illustrate this, let's start by creating a couple simple `DataFrame`s:

[142]:
```
city_loc = pd.DataFrame(
    [
        ["CA", "San Francisco", 37.781334, -122.416728],
```

```
        ["NY", "New York", 40.705649, -74.008344],
        ["FL", "Miami", 25.791100, -80.320733],
        ["OH", "Cleveland", 41.473508, -81.739791],
        ["UT", "Salt Lake City", 40.755851, -111.896657]
    ], columns=["state", "city", "lat", "lng"])
city_loc
```

[142]:

	state	city	lat	lng
0	CA	San Francisco	37.781334	-122.416728
1	NY	New York	40.705649	-74.008344
2	FL	Miami	25.791100	-80.320733
3	OH	Cleveland	41.473508	-81.739791
4	UT	Salt Lake City	40.755851	-111.896657

[143]:
```
city_pop = pd.DataFrame(
    [
        [808976, "San Francisco", "California"],
        [8363710, "New York", "New-York"],
        [413201, "Miami", "Florida"],
        [2242193, "Houston", "Texas"]
    ], index=[3,4,5,6], columns=["population", "city", "state"])
city_pop
```

[143]:

	population	city	state
3	808976	San Francisco	California
4	8363710	New York	New-York
5	413201	Miami	Florida
6	2242193	Houston	Texas

Now let's join these `DataFrame`s using the `merge()` function:

[144]:
```
pd.merge(left=city_loc, right=city_pop, on="city")
```

[144]:

	state_x	city	lat	lng	population	state_y
0	CA	San Francisco	37.781334	-122.416728	808976	California
1	NY	New York	40.705649	-74.008344	8363710	New-York
2	FL	Miami	25.791100	-80.320733	413201	Florida

Note that both `DataFrame`s have a column named `state`, so in the result they got renamed to `state_x` and `state_y`.

Also, note that Cleveland, Salt Lake City and Houston were dropped because they don't exist in *both* `DataFrame`s. This is the equivalent of a SQL `INNER JOIN`. If you want a `FULL OUTER JOIN`, where no city gets dropped and `NaN` values are added, you must specify `how="outer"`:

[145]:
```
all_cities = pd.merge(left=city_loc, right=city_pop, on="city", how="outer")
all_cities
```

```
[145]:   state_x            city        lat         lng  population     state_y
       0      CA   San Francisco  37.781334 -122.416728    808976.0  California
       1      NY        New York  40.705649  -74.008344   8363710.0    New-York
       2      FL           Miami  25.791100  -80.320733    413201.0     Florida
       3      OH       Cleveland  41.473508  -81.739791         NaN         NaN
       4      UT  Salt Lake City  40.755851 -111.896657         NaN         NaN
       5     NaN         Houston        NaN         NaN   2242193.0       Texas
```

Of course `LEFT OUTER JOIN` is also available by setting `how="left"`: only the cities present in the left `DataFrame` end up in the result. Similarly, with `how="right"` only cities in the right `DataFrame` appear in the result. For example:

```
[146]: pd.merge(left=city_loc, right=city_pop, on="city", how="right")
```

```
[146]:   state_x           city        lat         lng  population     state_y
       0      CA  San Francisco  37.781334 -122.416728      808976  California
       1      NY       New York  40.705649  -74.008344     8363710    New-York
       2      FL          Miami  25.791100  -80.320733      413201     Florida
       3     NaN        Houston        NaN         NaN     2242193       Texas
```

If the key to join on is actually in one (or both) `DataFrame`'s index, you must use `left_index=True` and/or `right_index=True`. If the key column names differ, you must use `left_on` and `right_on`. For example:

```
[147]: city_pop2 = city_pop.copy()
       city_pop2.columns = ["population", "name", "state"]
       pd.merge(left=city_loc, right=city_pop2, left_on="city", right_on="name")
```

```
[147]:   state_x           city        lat         lng  population           name  \
       0      CA  San Francisco  37.781334 -122.416728      808976  San Francisco
       1      NY       New York  40.705649  -74.008344     8363710       New York
       2      FL          Miami  25.791100  -80.320733      413201          Miami

            state_y
       0  California
       1    New-York
       2     Florida
```

6.2 Concatenation

Rather than joining `DataFrames`, we may just want to concatenate them. That's what `concat()` is for:

```
[148]: result_concat = pd.concat([city_loc, city_pop])
       result_concat
```

```
[148]:         state           city        lat         lng  population
       0           CA  San Francisco  37.781334 -122.416728         NaN
       1           NY       New York  40.705649  -74.008344         NaN
```

```
2          FL           Miami  25.791100  -80.320733         NaN
3          OH       Cleveland  41.473508  -81.739791         NaN
4          UT  Salt Lake City  40.755851 -111.896657         NaN
3  California   San Francisco        NaN        NaN    808976.0
4    New-York        New York        NaN        NaN   8363710.0
5     Florida           Miami        NaN        NaN    413201.0
6       Texas         Houston        NaN        NaN   2242193.0
```

Note that this operation aligned the data horizontally (by columns) but not vertically (by rows). In this example, we end up with multiple rows having the same index (eg. 3). Pandas handles this rather gracefully:

[149]:
```
result_concat.loc[3]
```

[149]:
```
        state           city        lat        lng  population
3          OH      Cleveland  41.473508 -81.739791         NaN
3  California  San Francisco        NaN        NaN    808976.0
```

Or you can tell pandas to just ignore the index:

[150]:
```
pd.concat([city_loc, city_pop], ignore_index=True)
```

[150]:
```
        state            city        lat         lng  population
0          CA   San Francisco  37.781334 -122.416728         NaN
1          NY        New York  40.705649  -74.008344         NaN
2          FL           Miami  25.791100  -80.320733         NaN
3          OH       Cleveland  41.473508  -81.739791         NaN
4          UT  Salt Lake City  40.755851 -111.896657         NaN
5  California   San Francisco        NaN         NaN    808976.0
6    New-York        New York        NaN         NaN   8363710.0
7     Florida           Miami        NaN         NaN    413201.0
8       Texas         Houston        NaN         NaN   2242193.0
```

Notice that when a column does not exist in a `DataFrame`, it acts as if it was filled with `NaN` values. If we set `join="inner"`, then only columns that exist in *both* `DataFrames` are returned:

[151]:
```
pd.concat([city_loc, city_pop], join="inner")
```

[151]:
```
        state            city
0          CA   San Francisco
1          NY        New York
2          FL           Miami
3          OH       Cleveland
4          UT  Salt Lake City
3  California   San Francisco
4    New-York        New York
5     Florida           Miami
6       Texas         Houston
```

You can concatenate `DataFrames` horizontally instead of vertically by setting `axis=1`:

[152]:
```
pd.concat([city_loc, city_pop], axis=1)
```

[152]:
```
  state            city        lat         lng  population            city  \
0    CA   San Francisco  37.781334 -122.416728         NaN             NaN
1    NY        New York  40.705649  -74.008344         NaN             NaN
2    FL           Miami  25.791100  -80.320733         NaN             NaN
3    OH       Cleveland  41.473508  -81.739791    808976.0   San Francisco
4    UT  Salt Lake City  40.755851 -111.896657   8363710.0        New York
5   NaN             NaN        NaN         NaN    413201.0           Miami
6   NaN             NaN        NaN         NaN   2242193.0         Houston

        state
0         NaN
1         NaN
2         NaN
3  California
4    New-York
5     Florida
6       Texas
```

In this case it really does not make much sense because the indices do not align well (eg. Cleveland and San Francisco end up on the same row, because they shared the index label `3`). So let's reindex the `DataFrame`s by city name before concatenating:

[153]:
```
pd.concat([city_loc.set_index("city"), city_pop.set_index("city")], axis=1)
```

[153]:
```
               state        lat         lng  population       state
city
San Francisco     CA  37.781334 -122.416728    808976.0  California
New York          NY  40.705649  -74.008344   8363710.0    New-York
Miami             FL  25.791100  -80.320733    413201.0     Florida
Cleveland         OH  41.473508  -81.739791         NaN         NaN
Salt Lake City    UT  40.755851 -111.896657         NaN         NaN
Houston          NaN        NaN         NaN   2242193.0       Texas
```

This looks a lot like a `FULL OUTER JOIN`, except that the `state` columns were not renamed to `state_x` and `state_y`, and the `city` column is now the index.

The `append()` method is a useful shorthand for concatenating `DataFrame`s vertically:

[154]:
```
city_loc.append(city_pop)
```

[154]:
```
        state            city        lat         lng  population
0          CA   San Francisco  37.781334 -122.416728         NaN
1          NY        New York  40.705649  -74.008344         NaN
2          FL           Miami  25.791100  -80.320733         NaN
3          OH       Cleveland  41.473508  -81.739791         NaN
4          UT  Salt Lake City  40.755851 -111.896657         NaN
3  California   San Francisco        NaN         NaN    808976.0
```

```
4    New-York        New York         NaN          NaN   8363710.0
5     Florida           Miami         NaN          NaN    413201.0
6       Texas         Houston         NaN          NaN   2242193.0
```

As always in pandas, the `append()` method does *not* actually modify `city_loc`: it works on a copy and returns the modified copy.

7 Categories

It is quite frequent to have values that represent categories, for example `1` for female and `2` for male, or `"A"` for Good, `"B"` for Average, `"C"` for Bad. These categorical values can be hard to read and cumbersome to handle, but fortunately pandas makes it easy. To illustrate this, let's take the `city_pop` `DataFrame` we created earlier, and add a column that represents a category:

[155]:
```
city_eco = city_pop.copy()
city_eco["eco_code"] = [17, 17, 34, 20]
city_eco
```

[155]:
```
   population           city       state  eco_code
3      808976  San Francisco  California        17
4     8363710       New York    New-York        17
5      413201          Miami     Florida        34
6     2242193        Houston       Texas        20
```

Right now the `eco_code` column is full of apparently meaningless codes. Let's fix that. First, we will create a new categorical column based on the `eco_codes`:

[156]:
```
city_eco["economy"] = city_eco["eco_code"].astype('category')
city_eco["economy"].cat.categories
```

[156]:
```
Int64Index([17, 20, 34], dtype='int64')
```

Now we can give each category a meaningful name:

[157]:
```
city_eco["economy"].cat.categories = ["Finance", "Energy", "Tourism"]
city_eco
```

[157]:
```
   population           city       state  eco_code  economy
3      808976  San Francisco  California        17  Finance
4     8363710       New York    New-York        17  Finance
5      413201          Miami     Florida        34  Tourism
6     2242193        Houston       Texas        20   Energy
```

Note that categorical values are sorted according to their categorical order, *not* their alphabetical order:

[158]:
```
city_eco.sort_values(by="economy", ascending=False)
```

[158]:
	population	city	state	eco_code	economy
5	413201	Miami	Florida	34	Tourism
6	2242193	Houston	Texas	20	Energy
3	808976	San Francisco	California	17	Finance
4	8363710	New York	New-York	17	Finance

8 What next?

As you probably noticed by now, pandas is quite a large library with *many* features. Although we went through the most important features, there is still a lot to discover. Probably the best way to learn more is to get your hands dirty with some real-life data. It is also a good idea to go through pandas' excellent documentation, in particular the Cookbook.

[159]:
```
import os
print(os.environ['PATH'])
```

```
C:\Dev\ORACLE_19C_HOME\bin;C:\Dev\Installers\ORACLE-
WINDOWS.X64_193000_db_home\bin;C:\Program Files\Common
Files\Oracle\Java\javapath;C:\Program Files (x86)\NVIDIA Corporation\PhysX\Commo
n;C:\Windows\system32;C:\Windows;C:\Windows\System32\Wbem;C:\Windows\System32\Wi
ndowsPowerShell\v1.0\;C:\Windows\System32\OpenSSH\;C:\Program Files\Microsoft
SQL Server\Client SDK\ODBC\130\Tools\Binn\;C:\Program
Files\Java\jdk-16;C:\Dev\eclipse\javafx-sdk-16\lib;C:\Program Files\Microsoft
SQL Server\130\Tools\Binn\;C:\Program Files (x86)\Microsoft SQL
Server\150\DTS\Binn\;C:\Program Files\Azure Data Studio\bin;C:\Program
Files\dotnet\;C:\Program Files\Microsoft SQL Server\Client
SDK\ODBC\170\Tools\Binn\;C:\Program Files (x86)\Microsoft SQL
Server\150\Tools\Binn\;C:\Program Files\Microsoft SQL
Server\150\Tools\Binn\;C:\Program Files\Microsoft SQL
Server\150\DTS\Binn\;C:\Program Files\Calibre2\;C:\Program
Files\Git\cmd;C:\Program Files\Git\mingw64\bin;C:\Program
Files\Git\usr\bin;C:\Program Files\nodejs\;C:\Program Files
(x86)\dotnet\;;C:\Program
Files\Docker\Docker\resources\bin;C:\ProgramData\DockerDesktop\version-bin;C:\De
v\anaconda3;C:\Dev\anaconda3\Library\mingw-w64\bin;C:\Dev\anaconda3\Library\usr\
bin;C:\Dev\anaconda3\Library\bin;C:\Dev\anaconda3\Scripts;C:\Users\romer\AppData
\Local\Microsoft\WindowsApps;C:\Program Files (x86)\Sophos\Sophos SSL VPN Client
\bin;C:\Users\romer\.dotnet\tools;C:\Users\romer\AppData\Local\Programs\Microsof
t VS Code\bin;C:\Users\romer\AppData\Local\GitHubDesktop\bin;C:\Program
Files\Git\bin;C:\Users\romer\AppData\Roaming\npm;C:\Program Files\MongoDB\Server
\4.4\bin;C:\Users\romer\AppData\Local\Programs\MiKTeX\miktex\bin\x64\
```