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.

Open in Colab

Setup

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

In [1]:

```
import pandas as pd
```

`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.

Creating a `Series`

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

In [2]:

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

Out[2]:

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

Similar to a 1D `ndarray`

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

In [3]:

```
import numpy as np
np.exp(s)
```

Out[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 `ndarray`s:

In [4]:

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

Out[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*:

In [5]:

```
s + 1000
```

Out[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:

In [6]:

```
s < 0
```

Out[6]:

```
0    False
1     True
2    False
3    False
dtype: bool
```

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:

In [7]:

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

Out[7]:

```
alice       68
bob         83
charles    112
```

```
charles     112
darwin       68
dtype: int64
```

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

In [8]:

```
s2["bob"]
```

Out[8]:

```
83
```

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

In [9]:

```
s2[1]
```

Out[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:

In [10]:

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

Out[10]:

```
83
```

In [11]:

```
s2.iloc[1]
```

Out[11]:

```
83
```

Slicing a `Series` also slices the index labels:

In [12]:

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

Out[12]:

```
bob          83
charles     112
dtype: int64
```

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

In [13]:

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

Out[13]:

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

In [14]:

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

Out[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:

In [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:

In [16]:

```
surprise_slice.iloc[0]
```

Out[16]:

```
1002
```

Init from `dict`

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

In [17]:

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

Out[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`:

In [18]:

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

Out[18]:

```
colin    86
alice    68
dtype: int64
```

Automatic alignment

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

In [19]:

```
print(s2.keys())
print(s3.keys())

s2 + s3
```

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

Out[19]:

```
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:

In [20]:

```
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]
```

Out[20]:

```
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.

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.

In [21]:

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

Out[21]:

```
life          42
universe      42
everything    42
```

```
dtype: int64
```

`Series` name

A `Series` can have a `name`:

In [22]:

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

Out[22]:

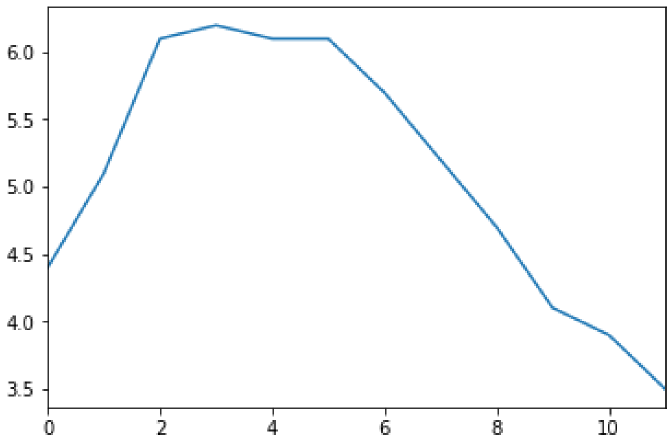
```
bob      83
alice    68
Name: weights, dtype: int64
```

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:

In [23]:

```
%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.

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.

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.

datetime per hour for 12 hours starting on October 29th 2016 at 5:30pm.

In [24]:

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

Out[24]:

```
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`:

In [25]:

```
temp_series = pd.Series(temperatures, dates)
temp_series
```

Out[25]:

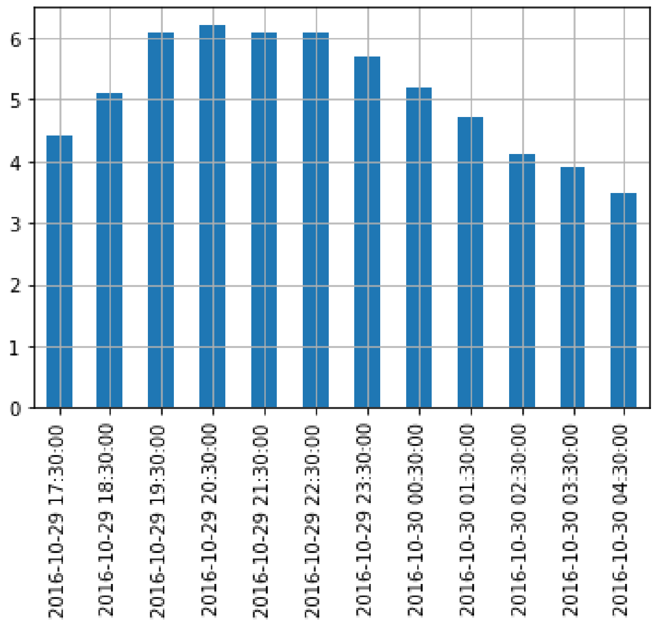
```
2016-10-29 17:30:00    4.4
2016-10-29 18:30:00    5.1
2016-10-29 19:30:00    6.1
2016-10-29 20:30:00    6.2
2016-10-29 21:30:00    6.1
2016-10-29 22:30:00    6.1
2016-10-29 23:30:00    5.7
2016-10-30 00:30:00    5.2
2016-10-30 01:30:00    4.7
2016-10-30 02:30:00    4.1
2016-10-30 03:30:00    3.9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

Let's plot this series:

In [26]:

```
temp_series.plot(kind="bar")

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



Resampling

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

In [27]:

```
temp_series_freq_2H = temp_series.resample("2H")
temp_series_freq_2H
```

Out[27]:

```
DatetimeIndexResampler [freq=<2 * Hours>, axis=0, closed=left, label=left, convention=sta
rt, base=0]
```

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:

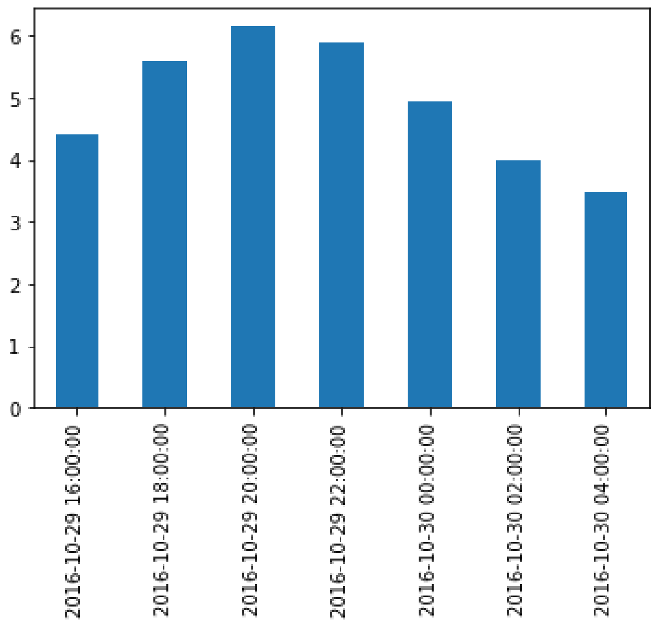
In [28]:

```
temp_series_freq_2H = temp_series_freq_2H.mean()
```

Let's plot the result:

In [29]:

```
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:

In [30]:

```
temp_series_freq_2H = temp_series.resample("2H").min()
temp_series_freq_2H
```

Out[30]:

```
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 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:

In [31]:

```
temp_series_freq_2H = temp_series.resample("2H").apply(np.min)
temp_series_freq_2H
```

Out[31]:

```
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
```

Upsampling and interpolation

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

In [32]:

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

Out[32]:

```
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:

In [33]:

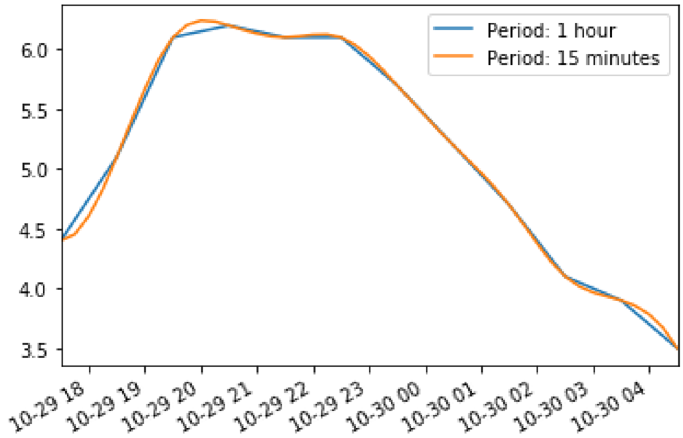
```
temp_series_freq_15min = temp_series.resample("15Min").interpolate(method="cubic")
temp_series_freq_15min.head(n=10)
```

Out[33]:

```
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
```

In [34]:

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



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:

In [35]:

```
temp_series_ny = temp_series.tz_localize("America/New_York")
temp_series_ny
```

Out[35]:

```
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
Freq: H, 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:

In [36]:

```
temp_series_paris = temp_series_ny.tz_convert("Europe/Paris")
temp_series_paris
```

Out[36]:

```
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 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
Freq: H, 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):

In [37]:

```
temp_series_paris_naive = temp_series_paris.tz_localize(None)
temp_series_paris_naive
```

Out[37]:

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

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

In [38]:

```
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 Timestamp('2016-10-30 02:30:00'), try using the 'ambiguous' ar
gument
```

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:

In [39]:

```
temp_series_paris_naive.tz_localize("Europe/Paris", ambiguous="infer")
```

Out[39]:

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

Periods

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

In [40]:

```
quarters = pd.period_range('2016Q1', periods=8, freq='Q')
quarters
```

Out[40]:

```
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:

In [41]:

```
quarters + 3
```

Out[41]:

```
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):

In [42]:

```
quarters.asfreq("M")
```

Out[42]:

```
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:

In [43]:

```
quarters.asfreq("M", how="start")
```

Out[43]:

```
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:

In [44]:

```
quarters.asfreq("A")
```

Out[44]:

```
PeriodIndex(['2016', '2016', '2016', '2016', '2017', '2017', '2017', '2017'], dtype='peri
od[A-DEC]', freq='A-DEC')
```

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

In [45]:

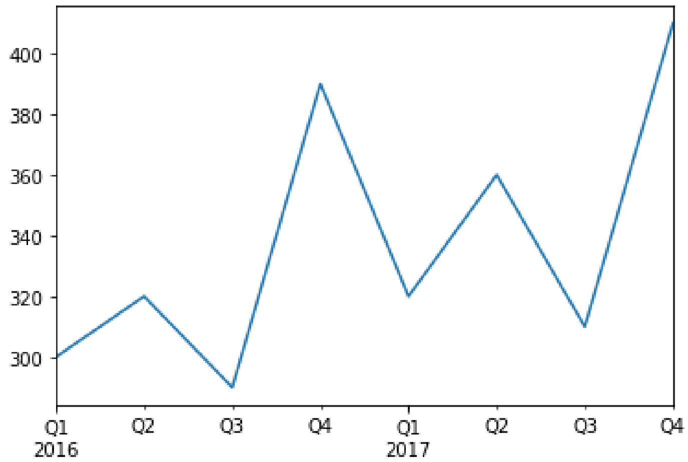
```
quarterly_revenue = pd.Series([300, 320, 290, 390, 320, 360, 310, 410], index = quarters
)
quarterly_revenue
```

Out[45]:

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

In [46]:

```
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:

In [47]:

```
last_hours = quarterly_revenue.to_timestamp(how="end", freq="H")
last_hours
```

Out[47]:

```
2016-03-31 23:00:00    300
2016-06-30 23:00:00    320
2016-09-30 23:00:00    290
2016-12-31 23:00:00    390
2017-03-31 23:00:00    320
2017-06-30 23:00:00    360
2017-09-30 23:00:00    310
2017-12-31 23:00:00    410
Freq: Q-DEC, dtype: int64
```

And back to periods by calling `to_period`:

In [48]:

```
last_hours.to_period()
```

Out[48]:

```
2016Q1    300
2016Q2    320
2016Q3    290
2016Q4    390
```

```
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:

In [49]:

```
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
```

Out[49]:

```
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')
```

`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`.

Creating a `DataFrame`

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

In [50]:

```
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
```

Out[50]:

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

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:

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

In [51]:

```
people["birthyear"]
```

Out[51]:

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

You can also get multiple columns at once:

In [52]:

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

Out[52]:

	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:

In [53]:

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

Out[53]:

	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:

In [54]:

```
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
```

Out[54]:

	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:

In [55]:

```
masked_array = np.ma.asarray(values, dtype=np.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
```

Out[55]:

	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:

In [56]:

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

Out[56]:

	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):

In [57]:

```
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
```

Out[57]:

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

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:

In [58]:

```
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
```

Out[58]:

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

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

In [59]:

```
d5["public"]
```

Out[59]:

		birthyear	hobby
London	charles	1992	NaN
Paris	alice	1985	Biking
	bob	1984	Dancing

In [60]:

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

Out[60]:

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

Dropping a level

Let's look at `d5` again:

In [61]:

```
d5
```

Out[61]:

Out[61]:

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

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):

In [62]:

```
d5.columns = d5.columns.droplevel(level = 0)
d5
```

Out[62]:

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

Transposing

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

In [63]:

```
d6 = d5.T
d6
```

Out[63]:

	London	Paris	
	charles	alice	bob
children	0	NaN	3
weight	112	68	83
birthyear	1992	1985	1984
hobby	NaN	Biking	Dancing

Stacking and unstacking levels

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

In [64]:

```
d7 = d6.stack()
d7
```

Out[64]:

		London	Paris
children	bob	NaN	3
	charles	0	NaN
weight	alice	NaN	68

		London	Paris
weight	alice	NaN	68
	bob	NaN	83
	charles	112	NaN
birthyear	alice	NaN	1985
	bob	NaN	1984
	charles	1992	NaN
hobby	alice	NaN	Biking
	bob	NaN	Dancing

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.

In [65]:

```
d8 = d7.unstack()
d8
```

Out[65]:

	London			Paris		
	alice	bob	charles	alice	bob	charles
children	None	NaN	0	None	3	NaN
weight	NaN	NaN	112	68	83	NaN
birthyear	NaN	NaN	1992	1985	1984	NaN
hobby	NaN	NaN	None	Biking	Dancing	None

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

In [66]:

```
d9 = d8.unstack()
d9
```

Out[66]:

```
London  alice    children        None
                 weight           NaN
                 birthyear        NaN
                 hobby            NaN
        bob      children         NaN
                 weight           NaN
                 birthyear        NaN
                 hobby            NaN
        charles  children           0
                 weight           112
                 birthyear       1992
                 hobby           None
Paris   alice    children        None
                 weight            68
                 birthyear       1985
                 hobby         Biking
        bob      children           3
                 weight            83
                 birthyear       1984
                 hobby        Dancing
        charles  children         NaN
                 weight           NaN
                 birthyear        NaN
                 hobby           None
dtype: object
```

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

In [67]:

```
d10 = d9.unstack(level = (0,1))
d10
```

Out[67]:

	London			Paris		
	alice	bob	charles	alice	bob	charles
children	None	NaN	0	None	3	NaN
weight	NaN	NaN	112	68	83	NaN
birthyear	NaN	NaN	1992	1985	1984	NaN
hobby	NaN	NaN	None	Biking	Dancing	None

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.

Accessing rows

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

In [68]:

```
people
```

Out[68]:

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

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:

In [69]:

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

Out[69]:

```
birthyear    1992
children        0
hobby         NaN
weight        112
Name: charles, dtype: object
```

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

In [70]:

```
people.iloc[2]
```

Out[70]:

```
birthyear    1992
children        0
hobby         NaN
weight        112
Name: charles, dtype: object
```

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

In [71]:

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

Out[71]:

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

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

In [72]:

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

Out[72]:

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

This is most useful when combined with boolean expressions:

In [73]:

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

Out[73]:

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

Adding and removing columns

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

In [74]:

```
people
```

Out[74]:

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

In [75]:

```
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
```

Out[75]:

	hobby	weight	age	over 30
alice	Biking	68	33	True
bob	Dancing	83	34	True
charles	NaN	112	26	False

In [76]:

```
birthyears
```

Out[76]:

```
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:

In [77]:

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

Out[77]:

	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:

In [78]:

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

Out[78]:

	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

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:

In [79]:

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

Out[79]:

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

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

In [80]:

```
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:

In [81]:

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

Out[81]:

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

In [82]:

```
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:

In [83]:

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

Out[83]:

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

Problem solved!

Evaluating an expression

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

In [84]:

```
people.eval("weight / (height/100) ** 2 > 25")
```

Out[84]:

```
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:

In [85]:

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

Out[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

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

In [86]:

```
overweight_threshold = 30
people.eval("overweight = body_mass_index > @overweight_threshold", inplace=True)
people
```

Out[86]:

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

Querying a `DataFrame`

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

In [87]:

```
people.query("age > 30 and pets == 0")
```

Out[87]:

	hobby	height	weight	age	over 30	pets	body_mass_index	overweight
bob	Dancing	181	83	34	True	0.0	25.335002	False

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:

In [88]:

```
people.sort_index(ascending=False)
```

Out[88]:

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

In [89]:

```
people.sort_index(axis=1, inplace=True)
people
```

Out[89]:

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

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

In [90]:

```
people.sort_values(by="age", inplace=True)
people
```

Out[90]:

	age	body_mass_index	height	hobby	over 30	overweight	pets	weight
charles	26	32.724617	185	NaN	False	True	5.0	112
alice	33	22.985398	172	Biking	True	False	NaN	68

bob	age 34	body_mass_index 25.335002	height 181	hobby Dancing	over 30 True	overweight False	pets 0.0	weight 83

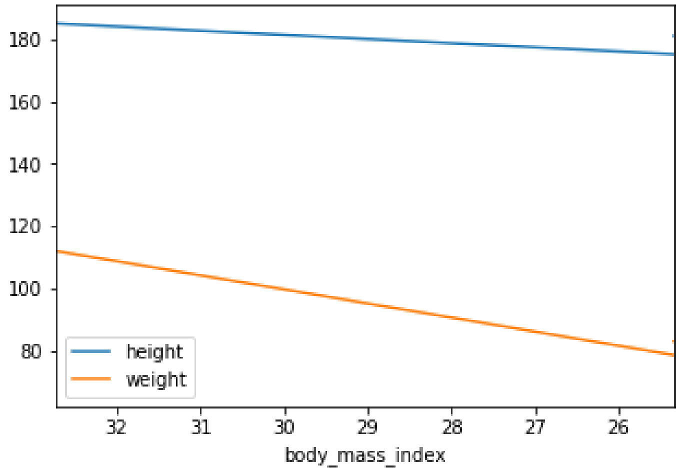
Plotting a `DataFrame`

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:

In [91]:

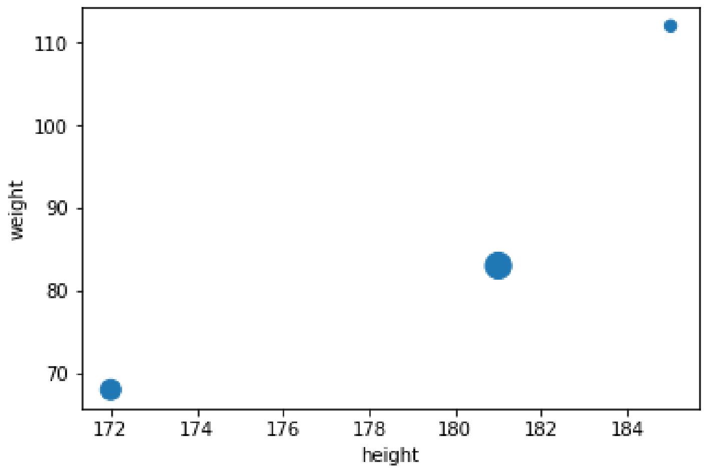
```
people.plot(kind = "line", x = "body_mass_index", y = ["height", "weight"])
plt.show()
```



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:

In [92]:

```
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.

Operations on `DataFrame`s

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

In [93]:

```
grades_array = np.array([[8,8,9],[10,9,9],[4, 8, 2], [9, 10, 10]])
```

```
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
```

Out[93]:

	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:

In [94]:

```
np.sqrt(grades)
```

Out[94]:

	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*:

In [95]:

```
grades + 1
```

Out[95]:

	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:

In [96]:

```
grades >= 5
```

Out[96]:

	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:

In [97]:

```
grades.mean()
```

Out[97]:

```
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`:

In [98]:

```
(grades > 5).all()
```

Out[98]:

```
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`:

In [99]:

```
(grades > 5).all(axis = 1)
```

Out[99]:

```
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:

In [100]:

```
(grades == 10).any(axis = 1)
```

Out[100]:

```
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 `DataFrame`s rows. For example, let's subtract the `mean` of the `DataFrame` (a `Series` object) from the `DataFrame`:

In [101]:

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

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

Out[101]:

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

In [102]:

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

Out[102]:

	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 subtract the global mean from every grade, here is one way to do it:

In [103]:

```
grades - grades.values.mean() # subtracts the global mean (8.00) from all grades
```

Out[103]:

	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

Automatic alignment

Similar to `Series`, when operating on multiple `DataFrame`s, 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:

In [104]:

```
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","co
lin", "darwin", "charles"])
bonus_points
```

Out[104]:

	oct	nov	dec
bob	0.0	NaN	2.0
colin	NaN	1.0	0.0

	oct	nov	dec
darwin	0.0	1.0	0.0
charles	3.0	3.0	0.0

In [105]:

```
grades + bonus_points
```

Out[105]:

	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 `DataFrame`s, 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.

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:

In [106]:

```
(grades + bonus_points).fillna(0)
```

Out[106]:

	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:

In [107]:

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

Out[107]:

	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

charles	NaN	5.0	11.0	4.0
	dec	nov	oct	sep
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:

In [108]:

```
bonus_points
```

Out[108]:

	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`).

In [109]:

```
bonus_points.interpolate(axis=1)
```

Out[109]:

	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.

In [110]:

```
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
```

Out[110]:

	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:

In [111]:

```
grades + better_bonus_points
```

Out[111]:

	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:

In [112]:

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

Out[112]:

	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:

In [113]:

```
final_grades_clean = final_grades.dropna(how="all")
final_grades_clean
```

Out[113]:

	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`:

In [114]:

```
final_grades_clean = final_grades_clean.dropna(axis=1, how="all")
```

```
final_grades_clean
```

Out[114]:

	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

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:

In [115]:

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

Out[115]:

	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:

In [116]:

```
grouped_grades = final_grades.groupby("hobby")
grouped_grades
```

Out[116]:

```
<pandas.core.groupby.DataFrameGroupBy object at 0x10b680e10>
```

We are ready to compute the average grade per hobby:

In [117]:

```
grouped_grades.mean()
```

Out[117]:

	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.

Pivot tables

Pandas supports spreadsheet-like [pivot tables](https://en.wikipedia.org/wiki/Pivot_table) that allow quick data summarization. To illustrate this, let's create a simple `DataFrame`:

In [118]:

```
bonus_points
```

Out[118]:

	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

In [119]:

```
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
```

Out[119]:

	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:

In [120]:

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

Out[120]:

	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:

In [121]:

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

Out[121]:

	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`:

In [122]:

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

Out[122]:

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:

In [123]:

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

Out[123]:

		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

		bonus	grade
name	month		
	oct	1.000	10.00
	sep	0.000	9.00
All		1.125	8.75

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`:

In [124]:

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

Out[124]:

	A	B	C	some_text	D	E	F	G	H	I	...	Q	R	S	T	U	V	W
0	NaN	11.0	44.0	Blabla	99.0	NaN	88.0	22.0	165.0	143.0	...	11.0	NaN	11.0	44.0	99.0	NaN	88.0
1	11.0	22.0	55.0	Blabla	110.0	NaN	99.0	33.0	NaN	154.0	...	22.0	11.0	22.0	55.0	110.0	NaN	99.0
2	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0
3	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0
4	44.0	55.0	88.0	Blabla	143.0	33.0	132.0	66.0	22.0	NaN	...	55.0	44.0	55.0	88.0	143.0	33.0	132.0
5	55.0	66.0	99.0	Blabla	154.0	44.0	143.0	77.0	33.0	11.0	...	66.0	55.0	66.0	99.0	154.0	44.0	143.0
6	66.0	77.0	110.0	Blabla	165.0	55.0	154.0	88.0	44.0	22.0	...	77.0	66.0	77.0	110.0	165.0	55.0	154.0
7	77.0	88.0	121.0	Blabla	NaN	66.0	165.0	99.0	55.0	33.0	...	88.0	77.0	88.0	121.0	NaN	66.0	165.0
8	88.0	99.0	132.0	Blabla	NaN	77.0	NaN	110.0	66.0	44.0	...	99.0	88.0	99.0	132.0	NaN	77.0	NaN
9	99.0	110.0	143.0	Blabla	11.0	88.0	NaN	121.0	77.0	55.0	...	110.0	99.0	110.0	143.0	11.0	88.0	NaN
10	110.0	121.0	154.0	Blabla	22.0	99.0	11.0	132.0	88.0	66.0	...	121.0	110.0	121.0	154.0	22.0	99.0	11.0
11	121.0	132.0	165.0	Blabla	33.0	110.0	22.0	143.0	99.0	77.0	...	132.0	121.0	132.0	165.0	33.0	110.0	22.0
12	132.0	143.0	NaN	Blabla	44.0	121.0	33.0	154.0	110.0	88.0	...	143.0	132.0	143.0	NaN	44.0	121.0	33.0
13	143.0	154.0	NaN	Blabla	55.0	132.0	44.0	165.0	121.0	99.0	...	154.0	143.0	154.0	NaN	55.0	132.0	44.0
14	154.0	165.0	11.0	Blabla	66.0	143.0	55.0	NaN	132.0	110.0	...	165.0	154.0	165.0	11.0	66.0	143.0	55.0
15	165.0	NaN	22.0	Blabla	77.0	154.0	66.0	NaN	143.0	121.0	...	NaN	165.0	NaN	22.0	77.0	154.0	66.0
16	NaN	NaN	33.0	Blabla	88.0	165.0	77.0	11.0	154.0	132.0	...	NaN	NaN	NaN	33.0	88.0	165.0	77.0
17	NaN	11.0	44.0	Blabla	99.0	NaN	88.0	22.0	165.0	143.0	...	11.0	NaN	11.0	44.0	99.0	NaN	88.0
18	11.0	22.0	55.0	Blabla	110.0	NaN	99.0	33.0	NaN	154.0	...	22.0	11.0	22.0	55.0	110.0	NaN	99.0
19	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0
20	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0
21	44.0	55.0	88.0	Blabla	143.0	33.0	132.0	66.0	22.0	NaN	...	55.0	44.0	55.0	88.0	143.0	33.0	132.0
22	55.0	66.0	99.0	Blabla	154.0	44.0	143.0	77.0	33.0	11.0	...	66.0	55.0	66.0	99.0	154.0	44.0	143.0
23	66.0	77.0	110.0	Blabla	165.0	55.0	154.0	88.0	44.0	22.0	...	77.0	66.0	77.0	110.0	165.0	55.0	154.0
24	77.0	88.0	121.0	Blabla	NaN	66.0	165.0	99.0	55.0	33.0	...	88.0	77.0	88.0	121.0	NaN	66.0	165.0
25	88.0	99.0	132.0	Blabla	NaN	77.0	NaN	110.0	66.0	44.0	...	99.0	88.0	99.0	132.0	NaN	77.0	NaN
26	99.0	110.0	143.0	Blabla	11.0	88.0	NaN	121.0	77.0	55.0	...	110.0	99.0	110.0	143.0	11.0	88.0	NaN
27	110.0	121.0	154.0	Blabla	22.0	99.0	11.0	132.0	88.0	66.0	...	121.0	110.0	121.0	154.0	22.0	99.0	11.0

	A	B	C	some_text	D	E	F	G	H	I	...	Q	R	S	T	U	V	W
28	121.0	132.0	165.0	Blabla	33.0	110.0	22.0	143.0	99.0	77.0	...	132.0	121.0	132.0	165.0	33.0	110.0	22.0
29	132.0	143.0	NaN	Blabla	44.0	121.0	33.0	154.0	110.0	88.0	...	143.0	132.0	143.0	NaN	44.0	121.0	33.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9970	88.0	99.0	132.0	Blabla	NaN	77.0	NaN	110.0	66.0	44.0	...	99.0	88.0	99.0	132.0	NaN	77.0	NaN
9971	99.0	110.0	143.0	Blabla	11.0	88.0	NaN	121.0	77.0	55.0	...	110.0	99.0	110.0	143.0	11.0	88.0	NaN
9972	110.0	121.0	154.0	Blabla	22.0	99.0	11.0	132.0	88.0	66.0	...	121.0	110.0	121.0	154.0	22.0	99.0	11.0
9973	121.0	132.0	165.0	Blabla	33.0	110.0	22.0	143.0	99.0	77.0	...	132.0	121.0	132.0	165.0	33.0	110.0	22.0
9974	132.0	143.0	NaN	Blabla	44.0	121.0	33.0	154.0	110.0	88.0	...	143.0	132.0	143.0	NaN	44.0	121.0	33.0
9975	143.0	154.0	NaN	Blabla	55.0	132.0	44.0	165.0	121.0	99.0	...	154.0	143.0	154.0	NaN	55.0	132.0	44.0
9976	154.0	165.0	11.0	Blabla	66.0	143.0	55.0	NaN	132.0	110.0	...	165.0	154.0	165.0	11.0	66.0	143.0	55.0
9977	165.0	NaN	22.0	Blabla	77.0	154.0	66.0	NaN	143.0	121.0	...	NaN	165.0	NaN	22.0	77.0	154.0	66.0
9978	NaN	NaN	33.0	Blabla	88.0	165.0	77.0	11.0	154.0	132.0	...	NaN	NaN	NaN	33.0	88.0	165.0	77.0
9979	NaN	11.0	44.0	Blabla	99.0	NaN	88.0	22.0	165.0	143.0	...	11.0	NaN	11.0	44.0	99.0	NaN	88.0
9980	11.0	22.0	55.0	Blabla	110.0	NaN	99.0	33.0	NaN	154.0	...	22.0	11.0	22.0	55.0	110.0	NaN	99.0
9981	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0
9982	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0
9983	44.0	55.0	88.0	Blabla	143.0	33.0	132.0	66.0	22.0	NaN	...	55.0	44.0	55.0	88.0	143.0	33.0	132.0
9984	55.0	66.0	99.0	Blabla	154.0	44.0	143.0	77.0	33.0	11.0	...	66.0	55.0	66.0	99.0	154.0	44.0	143.0
9985	66.0	77.0	110.0	Blabla	165.0	55.0	154.0	88.0	44.0	22.0	...	77.0	66.0	77.0	110.0	165.0	55.0	154.0
9986	77.0	88.0	121.0	Blabla	NaN	66.0	165.0	99.0	55.0	33.0	...	88.0	77.0	88.0	121.0	NaN	66.0	165.0
9987	88.0	99.0	132.0	Blabla	NaN	77.0	NaN	110.0	66.0	44.0	...	99.0	88.0	99.0	132.0	NaN	77.0	NaN
9988	99.0	110.0	143.0	Blabla	11.0	88.0	NaN	121.0	77.0	55.0	...	110.0	99.0	110.0	143.0	11.0	88.0	NaN
9989	110.0	121.0	154.0	Blabla	22.0	99.0	11.0	132.0	88.0	66.0	...	121.0	110.0	121.0	154.0	22.0	99.0	11.0
9990	121.0	132.0	165.0	Blabla	33.0	110.0	22.0	143.0	99.0	77.0	...	132.0	121.0	132.0	165.0	33.0	110.0	22.0
9991	132.0	143.0	NaN	Blabla	44.0	121.0	33.0	154.0	110.0	88.0	...	143.0	132.0	143.0	NaN	44.0	121.0	33.0
9992	143.0	154.0	NaN	Blabla	55.0	132.0	44.0	165.0	121.0	99.0	...	154.0	143.0	154.0	NaN	55.0	132.0	44.0
9993	154.0	165.0	11.0	Blabla	66.0	143.0	55.0	NaN	132.0	110.0	...	165.0	154.0	165.0	11.0	66.0	143.0	55.0
9994	165.0	NaN	22.0	Blabla	77.0	154.0	66.0	NaN	143.0	121.0	...	NaN	165.0	NaN	22.0	77.0	154.0	66.0
9995	NaN	NaN	33.0	Blabla	88.0	165.0	77.0	11.0	154.0	132.0	...	NaN	NaN	NaN	33.0	88.0	165.0	77.0
9996	NaN	11.0	44.0	Blabla	99.0	NaN	88.0	22.0	165.0	143.0	...	11.0	NaN	11.0	44.0	99.0	NaN	88.0
9997	11.0	22.0	55.0	Blabla	110.0	NaN	99.0	33.0	NaN	154.0	...	22.0	11.0	22.0	55.0	110.0	NaN	99.0
9998	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0
9999	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0

10000 rows × 27 columns

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

In [125]:

```
large_df.head()
```

Out[125]:

	A	B	C	some_text	D	E	F	G	H	I	...	Q	R	S	T	U	V	W	X	Y
0	NaN	11.0	44.0	Blabla	99.0	NaN	88.0	22.0	165.0	143.0	...	11.0	NaN	11.0	44.0	99.0	NaN	88.0	22.0	165.0
1	11.0	22.0	55.0	Blabla	110.0	NaN	99.0	33.0	NaN	154.0	...	22.0	11.0	22.0	55.0	110.0	NaN	99.0	33.0	NaN
2	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0	44.0	NaN

	A	B	C	some_text	D	E	F	G	H	I	...	Q	R	S	T	U	V	W	X	Y
3	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0	55.0	11.0
4	44.0	55.0	88.0	Blabla	143.0	33.0	132.0	66.0	22.0	NaN	...	55.0	44.0	55.0	88.0	143.0	33.0	132.0	66.0	22.0

5 rows × 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:

In [126]:

```
large_df.tail(n=2)
```

Out[126]:

	A	B	C	some_text	D	E	F	G	H	I	...	Q	R	S	T	U	V	W	X	Y
9998	22.0	33.0	66.0	Blabla	121.0	11.0	110.0	44.0	NaN	165.0	...	33.0	22.0	33.0	66.0	121.0	11.0	110.0	44.0	NaN
9999	33.0	44.0	77.0	Blabla	132.0	22.0	121.0	55.0	11.0	NaN	...	44.0	33.0	44.0	77.0	132.0	22.0	121.0	55.0	11.0

2 rows × 27 columns

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

In [127]:

```
large_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
A            8823 non-null float64
B            8824 non-null float64
C            8824 non-null float64
some_text    10000 non-null object
D            8824 non-null float64
E            8822 non-null float64
F            8824 non-null float64
G            8824 non-null float64
H            8822 non-null float64
I            8823 non-null float64
J            8823 non-null float64
K            8822 non-null float64
L            8824 non-null float64
M            8824 non-null float64
N            8822 non-null float64
O            8824 non-null float64
P            8824 non-null float64
Q            8824 non-null float64
R            8823 non-null float64
S            8824 non-null float64
T            8824 non-null float64
U            8824 non-null float64
V            8822 non-null float64
W            8824 non-null float64
X            8824 non-null float64
Y            8822 non-null float64
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**

- `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

In [128]:

```
large_df.describe()
```

Out[128]:

	A	B	C	D	E	F	G	H	I
count	8823.000000	8824.000000	8824.000000	8824.000000	8822.000000	8824.000000	8824.000000	8822.000000	8823.000000
mean	87.977559	87.972575	87.987534	88.012466	87.983791	88.007480	87.977561	88.000000	88.022441
std	47.535911	47.535523	47.521679	47.521679	47.535001	47.519371	47.529755	47.536879	47.535911
min	11.000000	11.000000	11.000000	11.000000	11.000000	11.000000	11.000000	11.000000	11.000000
25%	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000
50%	88.000000	88.000000	88.000000	88.000000	88.000000	88.000000	88.000000	88.000000	88.000000
75%	132.000000	132.000000	132.000000	132.000000	132.000000	132.000000	132.000000	132.000000	132.000000
max	165.000000	165.000000	165.000000	165.000000	165.000000	165.000000	165.000000	165.000000	165.000000

8 rows × 26 columns

Saving & loading

Pandas can save `DataFrame`s 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:

In [129]:

```
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
```

Out[129]:

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

Saving

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

In [130]:

```
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:

In [131]:

```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:

In [132]:

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

```
No module named 'openpyxl'
```

Loading

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

In [133]:

```python
my_df_loaded = pd.read_csv("my_df.csv", index_col=0)
my_df_loaded
```

Out[133]:

	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 the top 1,000 U.S. cities from github:

In [134]:

```
us_cities = None
try:
    csv_url = "https://raw.githubusercontent.com/plotly/datasets/master/us-cities-top-1k.
csv"
    us_cities = pd.read_csv(csv_url, index_col=0)
    us_cities = us_cities.head()
except IOError as e:
    print(e)
us_cities
```

Out[134]:

	State	Population	lat	lon
City				
Marysville	Washington	63269	48.051764	-122.177082
Perris	California	72326	33.782519	-117.228648
Cleveland	Ohio	390113	41.499320	-81.694361
Worcester	Massachusetts	182544	42.262593	-71.802293
Columbia	South Carolina	133358	34.000710	-81.034814

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

Combining `DataFrame`s

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:

In [135]:

```
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
```

Out[135]:

	state	city	lat	lng
0	CA	San Francisco	37.781334	-122.416728

	state	city	lat	lng
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

In [136]:

```
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
```

Out[136]:

	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:

In [137]:

```
pd.merge(left=city_loc, right=city_pop, on="city")
```

Out[137]:

	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"`:

In [138]:

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

Out[138]:

	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

	state_x	city	lat	lng	population	state_y
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:

In [139]:

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

Out[139]:

	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:

In [140]:

```
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")
```

Out[140]:

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

Concatenation

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

In [141]:

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

Out[141]:

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

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:

In [142]:

```
result_concat.loc[3]
```

Out[142]:

	city	lat	lng	population	state
3	Cleveland	41.473508	-81.739791	NaN	OH
3	San Francisco	NaN	NaN	808976.0	California

Or you can tell pandas to just ignore the index:

In [143]:

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

Out[143]:

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

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* `DataFrame`s are returned:

In [144]:

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

Out[144]:

	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 `DataFrame`s horizontally instead of vertically by setting `axis=1`:

In [145]:

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

Out[145]:

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

In [146]:

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

Out[146]:

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

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:

In [147]:

```
city_loc.append(city_pop)
```

Out[147]:

	city	lat	lng	population	state
0	San Francisco	37.781334	-122.416728	NaN	CA
1	New York	40.705649	-74.008344	NaN	NY
2	Miami	25.791100	-80.320733	NaN	FL
3	Cleveland	41.473508	-81.739791	NaN	OH
4	Salt Lake City	40.755851	-111.896657	NaN	UT
3	San Francisco	NaN	NaN	808976.0	California
4	New York	NaN	NaN	8363710.0	New-York

	city	lat	lng	population	state
5	Miami	NaN	NaN	413201.0	Florida
6	Houston	NaN	NaN	2242193.0	Texas

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

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:

In [148]:

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

Out[148]:

	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_code`s:

In [149]:

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

Out[149]:

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

Now we can give each category a meaningful name:

In [150]:

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

Out[150]:

	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:

In [151]:

```
city_eco.sort_values(by="economy", ascending=False)
```

```
city_eco.sort_values(by='economy', ascending=False)
```

Out[151]:

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

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]().

In [ ]:

```
```