In [3]:
```
import pandas as pd
import numpy as np
```

Why Pandas

1. Pandas library provides **high perfromance usable** data structures and **data analysis tools** for managing data tables

2. Supports standard functions to create **pivot tables, column or row groupings, plotting graphs, joining tables like SQL, etc.**

Business UseCase:

Let assume that you are working on an airlines data and you want are recieving data continuously in the form of SQL tables or excel spreadsheets. You have created a detailed report from the data and the management really likes the key insights you are deriving from data. They want you to send this on the weekly level to the entire team.

You can either use SQL or excel spreadsheets to sit and create this every week or you can automate the task with a python script using pandas APIs. You can even automate sending the email with python.

What is Pandas

There are three basic data structures in the pandas library:

1. **DataFrame**: This is the main data structure and it is a 2D table, similar to excel/spreadsheet tables with columns names and row labels.

2. **Series**: It is a 1D array, similar to a column in excel or excel spreadsheet with column name and row labels.
3. **Panel** : It is dictionary of dataframes. It is generally not used in practice and we will not be discussing it in the videos.

Pandas Series

1. Similar to python list for definition purpose.

2. For operations purpose, it behaves similar to numpy one-dimensional ndarrays and can be passed directly to numpy functions.

Creating a Series

In [2]:
```
# Using Python list as series objects
s = pd.Series([-1.,-1,21,5])
```

```
s
```

Out[2]:
```
0    -1.0
1    -1.0
2    21.0
3     5.0
dtype: float64
```

In [3]:
```
# Using python list as index labels and scalar object values

s = pd.Series(40, ["Chuck", "Darwin", "Elijah"])
s
```

Out[3]:
```
Chuck     40
Darwin    40
Elijah    40
dtype: int64
```

In [4]:
```
# Using dictionary with indecies
dict1 = {"Newton": 6, "Chuck": 3, "Darwin": 8, "Elijah": 9}
s = pd.Series(dict1)
s
```

Out[4]:
```
Newton    6
Chuck     3
Darwin    8
Elijah    9
dtype: int64
```

In [5]:
```
#We can also specify the indicies explicity to control what goes into the series
s = pd.Series(dict1, index = ["Chuck", "Elijah"])
s
```

Out[5]:
```
Chuck     3
Elijah    9
dtype: int64
```

In [6]:
```
# Using numpy array
#s = pd.Series(np.array([[1,2],[34,4]]))
s = pd.Series(np.array([1,2,34,4]))
s
```

Out[6]:
```
0     1
1     2
2    34
3     4
dtype: int64
```

In [7]:
```
# Giving name to the series as
s = pd.Series([6, -5.4], index=["Charles", "Chuck"], name="heights")
s
```

Out[7]:
```
Charles    6.0
Chuck     -5.4
Name: heights, dtype: float64
```

Operations on Series

In [8]:
```
# Use a series in numpy functions. Here we take exponential of the series
np.abs(s)
```

Out[8]:
```
Charles    6.0
Chuck      5.4
Name: heights, dtype: float64
```

Elementwise arithmetic operations on pandas Series are similar to numpy ndarray's:

In [9]:
```
s + np.array([1000,2000])
```

Out[9]:
```
Charles    1006.0
Chuck      1994.6
Name: heights, dtype: float64
```

Broadcasting is similar to numpy. If you add a single number to Series, it is broadcasted throughout the series.

In [10]:
```
s + 1000
```

Out[10]:
```
Charles    1006.0
Chuck       994.6
Name: heights, dtype: float64
```

The same is true for all binary operations such as multiplication, division, subtraction or evern conditionals operations

In [11]:
```
s < 0
```

Out[11]:
```
Charles    False
Chuck       True
Name: heights, dtype: bool
```

Accessing elements of Series (Indexing)

1. Each item in a Series object has a unique identifier called the *index label*.

2. By default, it is the rank of the item in the Series (starting at 0) but you can also set the index labels manually

3. You can also use the series as a dictionary with manually set indexing as well as integer index like regular list.

In [12]:
```
s2
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-12-630081a5992e> in <module>
----> 1 s2

NameError: name 's2' is not defined
```

Using as a dictionary

In [13]:
```
s2["Chuck"]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-13-05e1d0e8f3e2> in <module>
```

```
----> 1 s2["Chuck"]

NameError: name 's2' is not defined
```

Using as a list with integer index

In [14]:

```
s2[1]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-14-8755b941c10d> in <module>
----> 1 s2[1]

NameError: name 's2' is not defined
```

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 [15]:

```
s2.loc["Chuck"]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-15-6a9a5ccf47c3> in <module>
----> 1 s2.loc["Chuck"]

NameError: name 's2' is not defined
```

In [16]:

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

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-16-f5692f3bd256> in <module>
----> 1 s2.iloc[1]

NameError: name 's2' is not defined
```

Slicing a Series also slices the index labels. This can lead to **unexpected values being accessed when using the default numeric labels**, so be careful!

In [17]:

```
s3 = s2.iloc[1:3]
print(s3)
s3.loc["Newtown"]
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-17-7aab0de711b6> in <module>
----> 1 s3 = s2.iloc[1:3]
      2 print(s3)
      3 s3.loc["Newtown"]

NameError: name 's2' is not defined
```

In [18]:

```
s2 = pd.Series([1000, 1001, 1002, 1003])
s2
```

Out[18]:

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

In [19]:
```
s2_slice = s2[1:]
s2_slice
```

Out[19]:
```
1    1001
2    1002
3    1003
dtype: int64
```

The first element has index label 1. The element with index label 0 is absent from the slice

In [20]:
```
s2_slice[0]
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-20-e4a7d3f28305> in <module>
----> 1 s2_slice[0]

~/anaconda3/lib/python3.8/site-packages/pandas/core/series.py in __getitem__(self, k
ey)
    866         key = com.apply_if_callable(key, self)
    867         try:
--> 868             result = self.index.get_value(self, key)
    869 
    870             if not is_scalar(result):

~/anaconda3/lib/python3.8/site-packages/pandas/core/indexes/base.py in get_value(sel
f, series, key)
   4372         k = self._convert_scalar_indexer(k, kind='getitem')
   4373         try:
-> 4374             return self._engine.get_value(s, k,
   4375                                           tz=getattr(series.dtype, 'tz', Non
e))
   4376         except KeyError as e1:

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.Int64HashTable.get
_item()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.Int64HashTable.get
_item()

KeyError: 0
```

But we can access elements by integer location using the iloc attribute.

In [21]:
```
s2_slice.iloc[0]
```

Out[21]:
```
1001
```

So, we should **always use loc and iloc** to access Series objects.

Automatic alignment

For operations involving multiple series pandas automatically aligns items by matching the index labels.

In [22]:
```
s2 = pd.Series([231, -23, -99, 100], index=["Newton", "Chuck", "Darwin", "Elijah"])
```

```
s3 = pd.Series([122, -312, 123, -20], index=["Charles", "Darwin", "Chuck", "Elijah"]
print(s2)
print(s3)

s2 + s3
```

```
Newton    231
Chuck     -23
Darwin    -99
Elijah    100
dtype: int64
Charles    122
Darwin    -312
Chuck      123
Elijah     -20
dtype: int64
```

Out[22]:

```
Charles      NaN
Chuck      100.0
Darwin    -411.0
Elijah      80.0
Newton       NaN
dtype: float64
```

Since **Charles** is missing from s2 and **Newton** is missing from s3, these 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 [23]:

```
s5 = pd.Series([100,-10,999,-999])
print("s2 =", s2.values)
print("s5 =", s5.values)

s2 + s5
```

```
s2 = [231 -23 -99 100]
s5 = [ 100  -10  999 -999]
```

Out[23]:

```
0         NaN
1         NaN
2         NaN
3         NaN
Chuck     NaN
Darwin    NaN
Elijah    NaN
Newton    NaN
dtype: float64
```

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

Plotting a Series

Using matplotlib is easy with a **Series.plot()** call

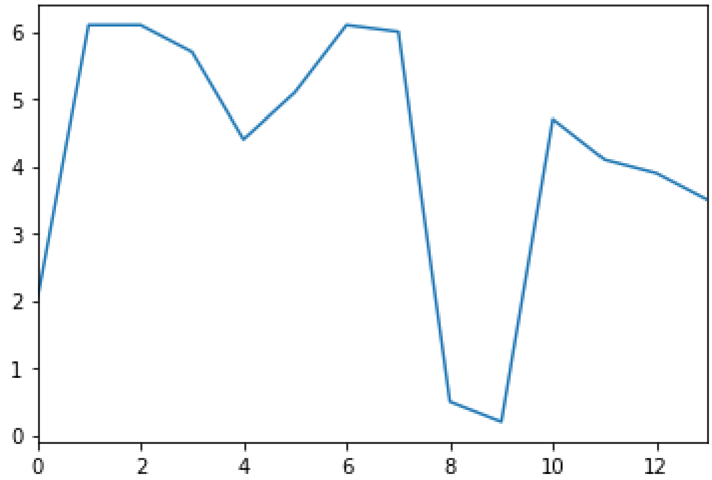
In [24]:

```
%matplotlib inline
import matplotlib.pyplot as plt

pressure = [2,6.1,6.1,5.7,4.4,5.1,6.1,6,.5,.2,4.7,4.1,3.9,3.5]

s7 = pd.Series(pressure, name="Pressure")
```

```
s7.plot()
plt.show()
```



There are a variety of plotting options in pandas and we will visiting those in the visualisation section.

DataFrame objects

A DataFrame object represents a spreadsheet, with cell values, column names and row index labels. We can define expressions to **compute columns based on other columns, create pivot-tables, group rows, draw graphs,** etc.

You can consider DataFrames as dictionaries of Series.

Creating a DataFrame

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

In [25]:

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

Out[25]:

	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

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

In [26]:
```
people["birthyear"]
```

Out[26]:
```
alice      1985
bob        1984
charles    1992
Name: birthyear, dtype: int64
```

You can also get multiple columns at once:

In [27]:
```
people[["birthyear", "hobby"]]
```

Out[27]:

	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 [28]:
```
d2 = pd.DataFrame(
        people_dict,
        columns=["birthyear", "weight", "height"],
        index=["bob", "alice", "eugene"]
     )
d2
```

Out[28]:

	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 [29]:
```
values = np.array([
            [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[29]:

	birthyear	children	hobby	weight

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

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

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

In [30]:
```
d4 = pd.DataFrame(
         d3,
         columns=["hobby", "children"],
         index=["alice", "bob"]
     )
d4
```

Out[30]:

	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 [31]:
```
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[31]:

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

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 [32]:
```
dict1 = {
    ("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}
  }
```

```
print(dict1)
```

```
{('public', 'birthyear'): {('Paris', 'alice'): 1985, ('Paris', 'bob'): 1984, ('Londo
n', 'charles'): 1992}, ('public', 'hobby'): {('Paris', 'alice'): 'Biking', ('Paris',
'bob'): 'Dancing'}, ('private', 'weight'): {('Paris', 'alice'): 68, ('Paris', 'bo
b'): 83, ('London', 'charles'): 112}, ('private', 'children'): {('Paris', 'alice'):
nan, ('Paris', 'bob'): 3, ('London', 'charles'): 0}}
```

In [46]:

```
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[46]:

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

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

In [47]:

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

Out[47]:

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

In [48]:

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

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

Dropping a level

Let's look at `d5` again:

In [44]:

```
d5
```

Out[44]:

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

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):

In [49]:

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

#d5.columns = d5.columns.droplevel(level = 0)
d5.index = d5.index.droplevel(level=10)
d5
```

Out[49]:

	public			private
	birthyear	hobby	weight	children
(1992, nan, 112, 0.0)	1992	NaN	112	0.0
(1985, Biking, 68, nan)	1985	Biking	68	NaN
(1984, Dancing, 83, 3.0)	1984	Dancing	83	3.0

Transposing

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

In [64]:

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

Out[64]:

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

In [51]:

```
d5.transpose()
```

Out[51]:

		(1992, nan, 112, 0.0)	(1985, Biking, 68, nan)	(1984, Dancing, 83, 3.0)
public	birthyear	1992	1985	1984
	hobby	NaN	Biking	Dancing
private	weight	112	68	83

	(1992, nan, 112, 0.0)	(1985, Biking, 68, nan)	(1984, Dancing, 83, 3.0)
children	0	NaN	3

Stacking and unstacking levels

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

In [68]:
```
d6 = d5
d6
```

Out[68]:

		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

In [69]:
```
d7 = d6.stack()
d7
```

Out[69]:

			private	public
Paris	**alice**	**birthyear**	NaN	1985
		hobby	NaN	Biking
		weight	68.0	NaN
	bob	**birthyear**	NaN	1984
		children	3.0	NaN
		hobby	NaN	Dancing
		weight	83.0	NaN
London	**charles**	**birthyear**	NaN	1992
		children	0.0	NaN
		weight	112.0	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.

In [70]:
```
d8 = d7.unstack()
d8
```

Out[70]:

		private				public			
		birthyear	**children**	**hobby**	**weight**	**birthyear**	**children**	**hobby**	**weight**
London	**charles**	NaN	0.0	NaN	112.0	1992	NaN	NaN	NaN

		private				public			
		birthyear	children	hobby	weight	birthyear	children	hobby	weight
Paris	alice	NaN	NaN	NaN	68.0	1985	NaN	Biking	NaN
	bob	NaN	3.0	NaN	83.0	1984	NaN	Dancing	NaN

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

In [72]:

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

Out[72]:

```
private  birthyear  alice    London        NaN
                             Paris         NaN
                    bob      London        NaN
                             Paris         NaN
                    charles  London        NaN
                             Paris         NaN
         children   alice    London        NaN
                             Paris         NaN
                    bob      London        NaN
                             Paris           3
                    charles  London          0
                             Paris         NaN
         hobby      alice    London        NaN
                             Paris         NaN
                    bob      London        NaN
                             Paris         NaN
                    charles  London        NaN
                             Paris         NaN
         weight     alice    London        NaN
                             Paris          68
                    bob      London        NaN
                             Paris          83
                    charles  London        112
                             Paris         NaN
public   birthyear  alice    London        NaN
                             Paris        1985
                    bob      London        NaN
                             Paris        1984
                    charles  London       1992
                             Paris         NaN
         children   alice    London        NaN
                             Paris         NaN
                    bob      London        NaN
                             Paris         NaN
                    charles  London        NaN
                             Paris         NaN
         hobby      alice    London        NaN
                             Paris      Biking
                    bob      London        NaN
                             Paris     Dancing
                    charles  London        NaN
                             Paris         NaN
         weight     alice    London        NaN
                             Paris         NaN
                    bob      London        NaN
                             Paris         NaN
                    charles  London        NaN
                             Paris         NaN
dtype: object
```

In [74]:

```
d9
```

Out[74]:

										private	...		
	birthyear			children			hobby			weight	...	birthyear	
	alice	bob	charles	alice	bob	charles	alice	bob	charles	alice	...	charles	alice
London	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	...	1992	NaN
Paris	NaN	NaN	NaN	NaN	3.0	NaN	NaN	NaN	NaN	68.0	...	NaN	NaN

2 rows × 24 columns

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

In [75]:

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

Out[75]:

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

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 [76]:

```
people
```

Out[76]:

	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:

In [77]:
```
people.loc["charles"]
```

Out[77]:
```
birthyear    1992
hobby         NaN
weight        112
children        0
Name: charles, dtype: object
```

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

In [78]:
```
people.iloc[1]
```

Out[78]:
```
birthyear       1984
hobby        Dancing
weight            83
children           3
Name: bob, dtype: object
```

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

In [79]:
```
people.iloc[1:3]
```

Out[79]:

	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:

In [80]:
```
people[np.array([True, False, True])]
```

Out[80]:

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

In [81]:
```
people
```

Out[81]:

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

In [82]:
```
people["birthyear"] < 1990
```

Out[82]:
```
alice       True
bob         True
charles    False
Name: birthyear, dtype: bool
```

This is most useful when combined with boolean expressions:

In [74]:
```
people[people["birthyear"] < 1990]
```

Out[74]:

	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 [106…

```
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[106…

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

In [107…

```
people["age"] = 2020 - people["birthyear"]  # adds a new column "age"
people["over 30"] = people["age"] > 30      # adds another column "over 30"
birthyears = people.pop("birthyear")        # removes the columns "birthyear"
del people["children"]

people
```

Out[107…

	hobby	weight	age	over 30
alice	Biking	68	35	True
bob	Dancing	83	36	True
charles	NaN	112	28	False

In [108…

```
birthyears
```

Out[108…

```
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 [109…

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

Out[109…

	hobby	weight	age	over 30	pets

	hobby	weight	age	over 30	pets
alice	Biking	68	35	True	NaN
bob	Dancing	83	36	True	0.0
charles	NaN	112	28	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 [110…

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

Out[110…

	hobby	height	weight	age	over 30	pets
alice	Biking	172	68	35	True	NaN
bob	Dancing	181	83	36	True	0.0
charles	NaN	185	112	28	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 [116…

```
people.assign(
    body_mass_index = people["weight"] / (people["height"] / 100) ** 2,
    has_pets = people["pets"] > 0,
    height_gt_25 = people['height']>25
)
```

Out[116…

	hobby	height	weight	age	over 30	pets	body_mass_index	has_pets	height_gt_25
alice	Biking	172	68	35	True	NaN	22.985398	False	True
bob	Dancing	181	83	36	True	0.0	25.335002	False	True
charles	NaN	185	112	28	False	5.0	32.724617	True	True

Evaluating an expression

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

In [117…

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

Out[117…

```
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 [119…
```
people.eval("body_mass_index = weight / (height/100) ** 2", inplace=True)
people
```

Out[119…

	hobby	height	weight	age	over 30	pets	body_mass_index
alice	Biking	172	68	35	True	NaN	22.985398
bob	Dancing	181	83	36	True	0.0	25.335002
charles	NaN	185	112	28	False	5.0	32.724617

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

In [120…
```
overweight_threshold = 30
people.eval("overweight = body_mass_index > @overweight_threshold", inplace=True)
people
```

Out[120…

	hobby	height	weight	age	over 30	pets	body_mass_index	overweight
alice	Biking	172	68	35	True	NaN	22.985398	False
bob	Dancing	181	83	36	True	0.0	25.335002	False
charles	NaN	185	112	28	False	5.0	32.724617	True

Querying a `DataFrame`

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

In [88]:
```
people.query("age > 30 and pets == 0")
```

Out[88]:

	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 [122…
```
people.sort_index(ascending=True)
```

Out[122…

	hobby	height	weight	age	over 30	pets	body_mass_index	overweight
alice	Biking	172	68	35	True	NaN	22.985398	False
bob	Dancing	181	83	36	True	0.0	25.335002	False
charles	NaN	185	112	28	False	5.0	32.724617	True

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 [123…
```
people.sort_index(axis=1, inplace=True)
people
```

Out[123…

	age	body_mass_index	height	hobby	over 30	overweight	pets	weight
alice	35	22.985398	172	Biking	True	False	NaN	68
bob	36	25.335002	181	Dancing	True	False	0.0	83
charles	28	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 [126…
```
people.sort_values(by=["age","height"], inplace=True)
people
```

Out[126…

	age	body_mass_index	height	hobby	over 30	overweight	pets	weight
charles	28	32.724617	185	NaN	False	True	5.0	112
alice	35	22.985398	172	Biking	True	False	NaN	68
bob	36	25.335002	181	Dancing	True	False	0.0	83

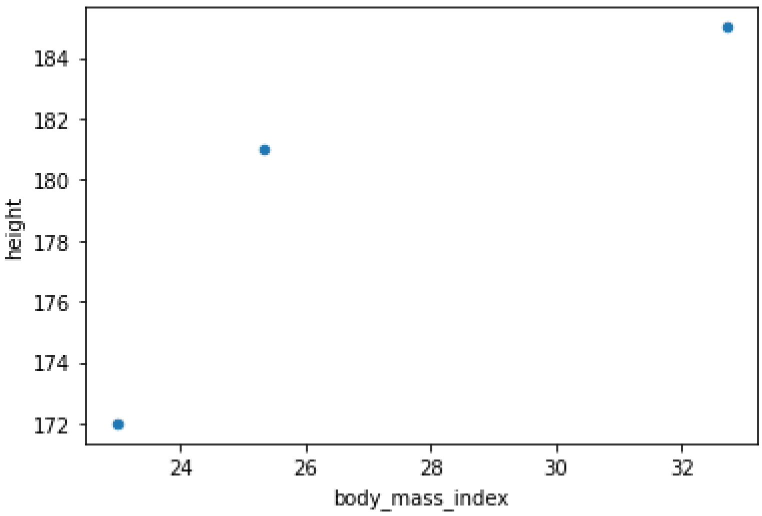
Plotting a `DataFrame`

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 [129…
```
people.plot(kind = "scatter", x = "body_mass_index", y = "height")
#plt.show()
```

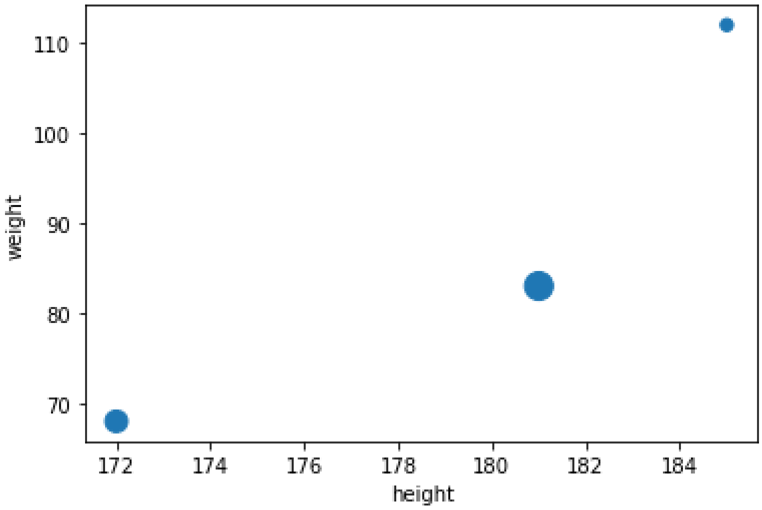
Out[129…
```
<matplotlib.axes._subplots.AxesSubplot at 0x11f6cda90>
```



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 [131…
```
people.plot(kind = "scatter", x = "height", y = "weight", s=[40, 120, 200])
#plt.show()
```

Out[131… <matplotlib.axes._subplots.AxesSubplot at 0x11f85ec70>



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 [132…
```
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","b
grades
```

Out[132…

	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 [133…
```
np.sqrt(grades)
```

Out[133…

	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 [134…

```
grades + 1
```

Out[134…

	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 [137…

```
grades >= 5
```

Out[137…

	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 [138…

```
grades.mean()
```

Out[138…

```
sep     7.75
oct     8.75
nov     7.50
dtype: float64
```

In [139…

```
grades
```

Out[139…

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

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 [99]:

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

Out[99]:
```
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 [100…
```
(grades > 5).all(axis = 1)
```

Out[100…
```
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 [140…
```
(grades == 10).any(axis = 1)
```

Out[140…
```
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 substract the `mean` of the `DataFrame` (a `Series` object) from the `DataFrame` :

In [141…
```
grades
```

Out[141…

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

In [142…
```
grades.mean()
```

Out[142…
```
sep     7.75
oct     8.75
nov     7.50
dtype: float64
```

In [102…
```
grades - grades.mean()  # equivalent to: grades - [7.75, 8.75, 7.50]
```

Out[102…

	sep	oct	nov
alice	0.25	-0.75	1.5

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

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

In [104…

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

Out[104…

	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 [149…

```
grades
```

Out[149…

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

In [144…

```
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"
bonus_points
```

Out[144…

	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 [145…

```
grades
```

Out[145…

	sep	oct	nov

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

In [146…

```
grades + bonus_points
```

Out[146…

	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

Aggregating with `groupby`

Similar to the SQL language, you can group pandas dataframe into by different columns and perform computations.

Lets take the grades dataframe and introduce a column with `NaN` values to understand their handling

In [25]:

```
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","b
grades
```

Out[25]:

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

In [26]:

```
grades["hobby"] = ["Football", np.nan, "Dancing", "Football"]
grades
```

Out[26]:

	sep	oct	nov	hobby
alice	8	8	9	Football
bob	10	9	9	NaN
charles	4	8	2	Dancing
darwin	9	10	10	Football

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

In [31]:
```
grouped_grades = grades.groupby(["hobby"])
grouped_grades
```

Out[31]: `<pandas.core.groupby.generic.DataFrameGroupBy object at 0x11c74a730>`

Now lets compute some statistics on the data

In [32]:
```
grouped_grades.mean()
```

Out[32]:

	sep	oct	nov
hobby			
Dancing	4.0	8.0	2.0
Football	8.5	9.0	9.5

In [36]:
```
grouped_grades.median()
```

Out[36]:

	sep	oct	nov
hobby			
Dancing	4.0	8.0	2.0
Football	8.5	9.0	9.5

Note that the `NaN` values have been skipped when computing the statistics.

Pivot tables

Similar to spreadsheets, you can create pivot tables in pandas for quick data summarization. Let's create a simple `DataFrame` to understand this:

In [37]:
```
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"
bonus_points
```

Out[37]:

	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 [38]:
```
more_grades = bonus_points.stack().reset_index()
more_grades
```

Out[38]:

	level_0	level_1	0
0	bob	oct	0.0

	level_0	level_1	0
1	bob	dec	2.0
2	colin	nov	1.0
3	colin	dec	0.0
4	darwin	oct	0.0
5	darwin	nov	1.0
6	darwin	dec	0.0
7	charles	oct	3.0
8	charles	nov	3.0
9	charles	dec	0.0

In [39]:

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

Out[39]:

	name	month	grade	bonus
0	bob	oct	0.0	NaN
1	bob	dec	2.0	NaN
2	colin	nov	1.0	NaN
3	colin	dec	0.0	0.0
4	darwin	oct	0.0	NaN
5	darwin	nov	1.0	1.0
6	darwin	dec	0.0	3.0
7	charles	oct	3.0	3.0
8	charles	nov	3.0	0.0
9	charles	dec	0.0	1.0

Now we can use the `pd.pivot_table()` function to group by the `name` column. By default, `pivot_table()` computes the mean of each numeric column:

In [40]:

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

Out[40]:

	bonus	grade
name		
bob	NaN	1.000000
charles	1.333333	2.000000
colin	0.000000	0.500000

	bonus	grade
name		
darwin	2.000000	0.333333

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 [41]:
```
pd.pivot_table(more_grades, index="name", values=["grade","bonus"], aggfunc=np.max)
```

Out[41]:

	bonus	grade
name		
bob	NaN	2.0
charles	3.0	3.0
colin	0.0	1.0
darwin	3.0	1.0

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 [42]:
```
pd.pivot_table(more_grades, index="name", values="grade", columns="month", margins=T
```

Out[42]:

month	dec	nov	oct	All
name				
bob	2.0	NaN	0.0	1.000000
charles	0.0	3.000000	3.0	2.000000
colin	0.0	1.000000	NaN	0.500000
darwin	0.0	1.000000	0.0	0.333333
All	0.5	1.666667	1.0	1.000000

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

In [124…
```
pd.pivot_table(more_grades, index=("name", "month"), margins=True)
```

Out[124…

		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

		bonus	grade
name	**month**		
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

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. We will see how to save in csv, html and json format.

Let's start by creating a `DataFrame` :

In [52]:
```
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[52]:

	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 [53]:
```
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 [54]:
```
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},"birt
hyear":{"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 [46]:

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

```
Requirement already satisfied: openpyxl in /Users/himanshusharma/anaconda3/lib/pytho
n3.8/site-packages (3.0.4)

Requirement already satisfied: jdcal in /Users/himanshusharma/anaconda3/lib/python3.
8/site-packages (from openpyxl) (1.4.1)

Requirement already satisfied: et-xmlfile in /Users/himanshusharma/anaconda3/lib/pyt
hon3.8/site-packages (from openpyxl) (1.0.1)
```

Loading

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

In [55]:

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

Out[55]:

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

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. Let's start by creating a couple of simple `DataFrame` s:

In [4]:

```
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[4]:

	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

In [5]:

```
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[5]:

	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 [6]:
```
pd.merge(left=city_loc, right=city_pop, on="city")
```

Out[6]:

	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 [7]:
```
all_cities = pd.merge(left=city_loc, right=city_pop, on="city", how="outer")
all_cities
```

Out[7]:

	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:

In [8]:
```
pd.merge(left=city_loc, right=city_pop, on="city", how="right")
```

Out[8]:

	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 column names differ, you must use `left_on` and `right_on` . For example:

In [9]:
```
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[9]:

	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 [10]:

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

```
<ipython-input-10-7a9b618ffc40>:1: FutureWarning: Sorting because non-concatenation
axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

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

Out[10]:

	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 [11]:

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

Out[11]:

	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 [12]:
```
pd.concat([city_loc, city_pop], ignore_index=True)
```

```
<ipython-input-12-ab7178b112b0>:1: FutureWarning: Sorting because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

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

Out[12]:

	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 [145…
```
pd.concat([city_loc, city_pop], join="inner")
```

Out[145…

	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 [146…
```
pd.concat([city_loc, city_pop], axis=1)
```

Out[146…

	state	city	lat	lng	population	city	state
0	CA	San Francisco	37.781334	-122.416728	NaN	NaN	NaN

	state	city	lat	lng	population	city	state
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 [14]:

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

```
<ipython-input-14-48a737537456>:1: FutureWarning: Sorting because non-concatenation
axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

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

Out[14]:

	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 [15]:

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

```
/Users/himanshusharma/anaconda3/lib/python3.8/site-packages/pandas/core/frame.py:669
0: FutureWarning: Sorting because non-concatenation axis is not aligned. A future ve
rsion
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  return concat(to_concat, ignore_index=ignore_index,
```

Out[15]:

	city	lat	lng	population	state
0	San Francisco	37.781334	-122.416728	NaN	CA

	city	lat	lng	population	state
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

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

In [13]:

```
#Some functions to be kept on the tips

'''
describe()
head()
tail()
info()
'''
```

Out[13]: `'\ndescribe()\nhead()\ntail()\ninfo()\n'`

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 [ ]:

```
```