NumPy

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What is NumPy?

- It is a Python module/library

  import numpy as np

- It is useful for computing with numeric vectors, matrices, and multi-dimensional arrays in general
- Standard Python lists could be used, but +, -, *, /, etc. cannot be used with numeric lists:

```
>>> a = [1,3,5,7,9]
>>> print(a[2:4])
[5, 7]
>>> b = [[1, 3, 5, 7, 9], [2, 4, 6, 8, 10]]
>>> print(b[0])
[1, 3, 5, 7, 9]
>>> print(b[1][2:4])
[6, 8]
```

```
>>> a = [1,3,5,7,9]
>>> b = [3,5,6,7,9]
>>> c = a + b
>>> print c
[1, 3, 5, 7, 9, 3, 5, 6, 7, 9]
```

Creating NumPy arrays

- One-dimension vectors:

```
# From lists
>>> a = np.array([1,3,5,7,9])
>>> b = np.array([3,5,6,7,9])
>>> c = a + b
>>> print c
[4, 8, 11, 14, 18]

>>> type(c)
(<type 'numpy.ndarray'>)

>>> c.shape
(5,)
```

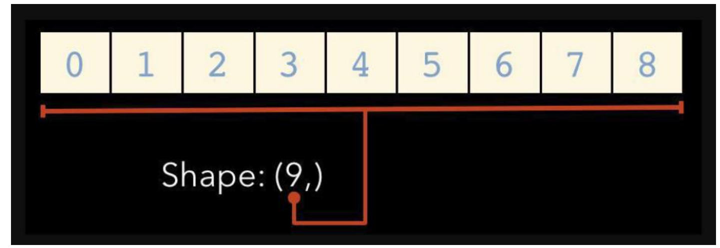
Creating NumPy arrays

- Matrices:

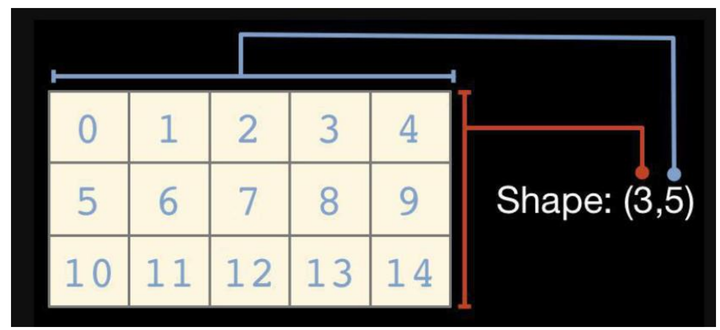
```
>>> # convert a list to an array
>>> a = np.array([[1, 2, 3], [3, 6, 9], [2, 4, 6]])
>>>print(a)
[[1 2 3]
 [3 6 9]
 [2 4 6]]
>>> a.shape
(3, 3)
```

Shape of NumPy arrays

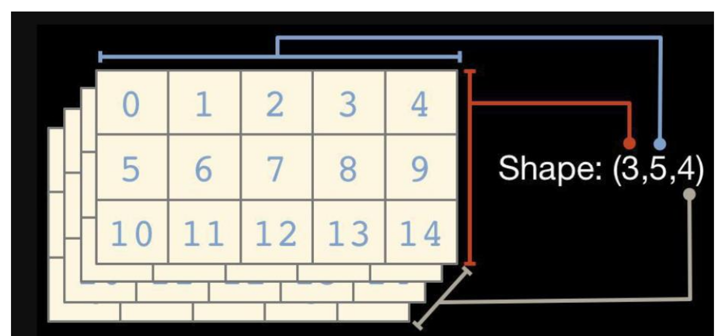
- 1-dimensional arrays



- 2-dimensional arrays (matrices)



- 3-dimensional arrays



Shape of NumPy arrays

- Important: a 1-dimensional vector is different from a matrix with 1 row (or 1 column)

```
vector_1d = np.array([1,2,3,4])
print(vector_1d)
print(vector_1d.shape)
```

```
[1 2 3 4]
(4,)
```

```
matrix_1row = np.array([[1,2,3,4]])
print(matrix_1row)
print(matrix_1row.shape)
```

```
[[1 2 3 4]]
(1, 4)
```

```
matrix_1col = np.array([[1],[2],[3],[4]])
print(matrix_1col)
print(matrix_1col.shape)
```

```
[[1]
 [2]
 [3]
 [4]]
(4, 1)
```

Types of NumPy arrays

- All elements in a NumPy array **must belong to the same type** (dtype)
- dtypes are inferred automatically
- But dtypes can also be stated explicitely
- Available dtypes

```
a = np.array([1,2,3])
print(a.dtype)
```

```
int32
```

```
b = np.array([1,2,3.141516])
print(b.dtype)
```

```
float64
```

```
c = np.array([1,2,3], dtype=np.float32)
print(c.dtype)
```

```
float32
```

```
np.sctypes
```

```
{'int': [numpy.int8, numpy.int16, numpy.int32, numpy.int64],
 'uint': [numpy.uint8, numpy.uint16, numpy.uint32, numpy.uint64],
 'float': [numpy.float16, numpy.float32, numpy.float64],
 'complex': [numpy.complex64, numpy.complex128],
 'others': [bool, object, bytes, str, numpy.void]}
```

Beware! (NumPy types)

- A NumPy array belongs to a single type

```
>>> d = np.arange(5)
>>> print(d.dtype)
>>> print(d)
int32
[0 1 2 3 4]

# We try to assign a real number to an integer array
# but the value is converted to integer
>>> d[1] = 9.7
print(d)
[0 9 2 3 4]
```

Creating NumPy vectors with functions

- arange(x) is similar to list(range(x)), but it generates NumPy vectors, rather than Python vectors

```
>>> x = np.arange(0, 10, 1) # arguments: start, stop, step
>>> x
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> x.dtype
dtype('int32')

# Real-valued (float) vectors can also be created
>>> d = np.arange(5, dtype=numpy.float)
>>> print(d)
[ 0.  1.  2.  3.  4.]

# arbitrary start, stop and step
>>> np.arange(3, 7, 0.5)
array([ 3. , 3.5, 4. , 4.5, 5. , 5.5, 6. , 6.5])
```

Creating NumPy vectors with functions

- linspace is useful for generating n real-valued vectors within an interval

```
>>> np.linspace(0, 10, 25)
array([  0.        ,   0.41666667,   0.83333333,   1.25      ,
         1.66666667,   2.08333333,   2.5       ,   2.91666667,
         3.33333333,   3.75      ,   4.16666667,   4.58333333,
         5.        ,   5.41666667,   5.83333333,   6.25      ,
         6.66666667,   7.08333333,   7.5       ,   7.91666667,
         8.33333333,   8.75      ,   9.16666667,   9.58333333,  10.
])
```

Creating NumPy vectors with functions

- diag: diagonal matrices

```
# a diagonal matrix
>>> np.diag([1,2,3])
array([[1, 0, 0],
       [0, 2, 0],
       [0, 0, 3]])

# An identity matrix
>>> np.eye(3)
array([[1., 0., 0.],
      [0., 1., 0.],
      [0., 0., 1.]])
```

- arrays of zeros or ones

```
# A vector of zeros
>>> b = np.zeros(5)
>>> print(b)
[ 0.  0.  0.  0.  0.]

# A matrix of ones
>>> c = np.ones((3,3))
>>> print(c)
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])
```

Creating NumPy vectors with functions

- Generating **random real numbers** from a **uniform** distribution in [0,1)

```
>>> np.random.rand(5,5)
array([[ 0.51531133,  0.74085206,  0.99570623,  0.97064334,  0.5819413 ],
       [ 0.2105685 ,  0.86289893,  0.13404438,  0.77967281,  0.78480563],
       [ 0.62687607,  0.51112285,  0.18374991,  0.2582663 ,  0.58475672],
       [ 0.72768256,  0.08885194,  0.69519174,  0.16049876,  0.34557215],
       [ 0.93724333,  0.17407127,  0.1237831 ,  0.96840203,  0.52790012]])
```

- randn(a,b) returns a axb matrix with **random real numbers** from the standard **normal** distribution
- randint(low, high, size=(a,b)) returns **uniform random integers** in the low-high interval

Creating NumPy matrices from vectors

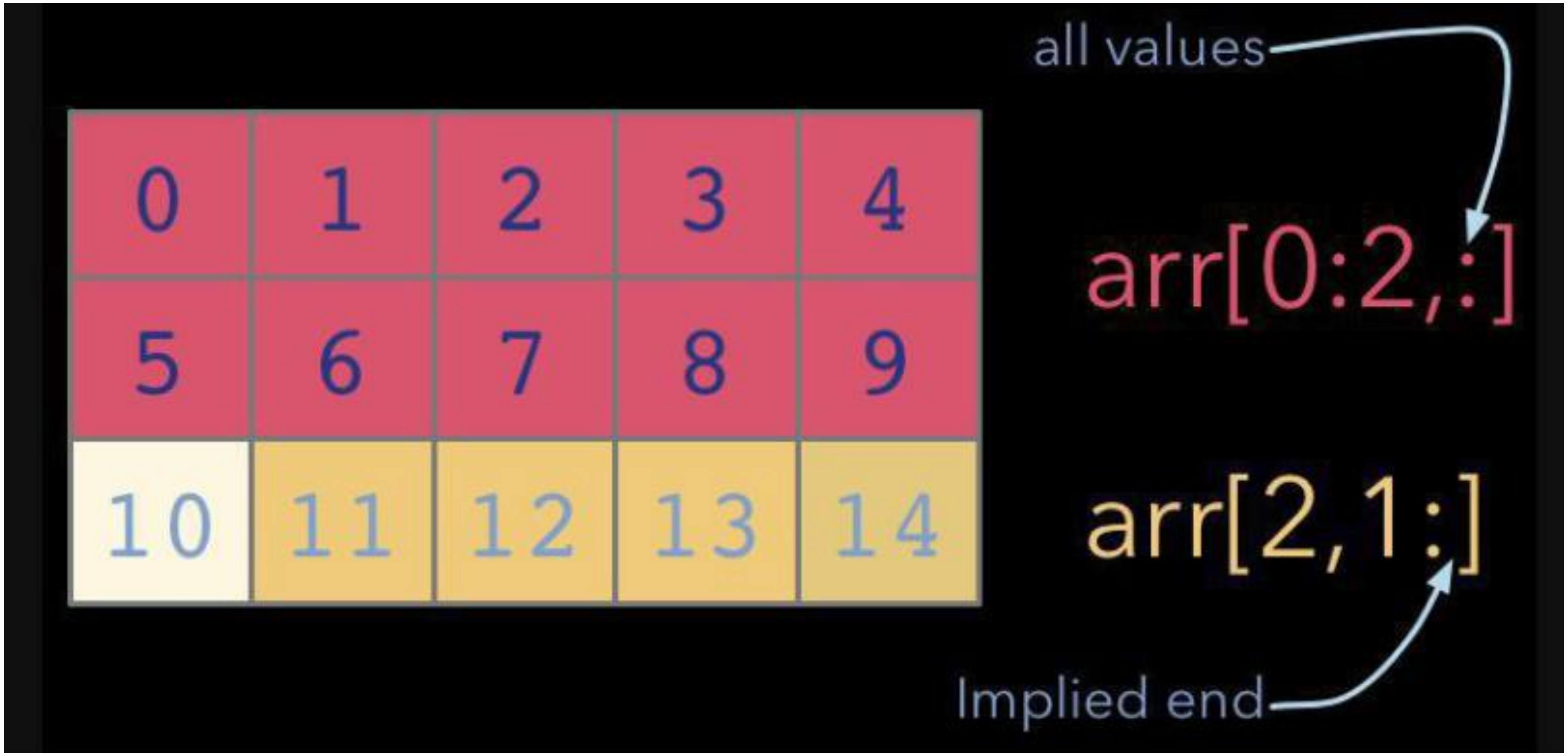
- Using reshape

```
In []: a = np.arange(10)
In []: a
Out[]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
In []: a.shape
Out[]: (10,)

In []: a = a.reshape((2,5))
In []: a
Out[]:
array([[0, 1, 2, 3, 4],
       [5, 6, 7, 8, 9]])

In []: a.shape
Out[]: (2, 5)
```

Indexing and setting

- Indexing: accessing element within a vector or matrix
  - Using slices (or ranges)
  - Using conditions (boolean indexing)
- Setting: modifying elements within a vector or matrix (usually, first we index the elements to be modified, then they are modified)

Using NumPy matrices: indexing with slices (ranges)



Slicing (indexing with slices)

```
>>> print(a)
[[1 2 3]
 [3 6 9]
 [2 4 6]]

# this is just like a list of lists
>>> print(a[0])
[1 2 3]

# arrays can be given comma separated indices
>>> print(a[1, 2])
9

# and slices
>>> print(a[1, 1:3])
[6 9]
>>> print(a[:,1])
[2 6 4]
```

```
  0 1 2
[[1 2 3]  0
 [3 6 9]  1
 [2 4 6]] 2
```

```
[[1 2 3]  0
 [3 6 9]  1
 [2 4 6]] 2
```

```
[[1 2 3]  0
 [3 6 9]  1
 [2 4 6]] 2
```

```
[[1 2 3]  0
 [3 6 9]  1
 [2 4 6]] 2
```

Modification (setting)

```
# We can modify a single element in the matrix
>>> a[1, 2] = 7
>>> print(a)
[[1 2 3]
 [3 6 7]
 [2 4 6]]

# We can also modify whole columns
>>> a[:, 0] = [0, 9, 8]
>>> print(a)
[[0 2 3]
 [9 6 7]
 [8 4 6]]

# And whole rows
>>> a[0, :] = [1, 1, 1]
>>> print(a)
[[1 1 1]
 [9 6 7]
 [8 4 6]]
```

Modification (setting)

- Important, for arrays, a = 0 is not the same as a[:]=0 (or a[0:] = 0)

```
In [18]: a = np.array(np.arange(10))
In [19]: a
Out[19]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [20]: a[:] = 0
In [21]: a
Out[21]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])

In [22]: a = 0
In [23]: a
Out[23]: 0
```

Indexing and setting with Booleans (conditions)

```
In [99]: a = np.array([[0, np.nan], [np.nan, 3], [4, np.nan]])
In [100]: a
Out[100]:
array([[ 0., nan],
       [nan, 3.],
       [ 4., nan]])

In [101]: a<4
# This array of booleans shows where a<4 is true
Out[101]:
array([[ True, False],
       [False, True],
       [False, False]])
# Here, we can see what elements in the array are < 4
In [103]: a[a<4]
Out[103]: array([0., 3.])
```

```
# This array of booleans shows where a contains nan

In [104]: np.isnan(a)
Out[104]:
array([[False, True],
       [ True, False],
       [False, True]])

# Here we transform nan's into 0
In [106]: a[np.isnan(a)] = 0
In [107]: a
Out[107]:
array([[0., 0.],
       [0., 3.],
       [4., 0.]])
```

Views (references)

- **b=a** does not copy a’s content into b. Rather, it creates a reference (**view**). We already saw this behavior with base Python datatypes (lists, dictionaries, ...).

```
In [10]: import numpy as np
In [11]: a = np.array(np.arange(10))

In [12]: a
Out[12]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [13]: b = a
In [14]: b[0] = 1000

In [15]: a
Out[15]: array([1000, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [16]: b
Out[16]: array([1000, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

The way to making copies is:
b = a.copy()

Views (references)

- Beware, indexing also creates a view (reference)!

```
In [26]: a = np.array(np.arange(10))
In [27]: a
Out[27]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [28]: # This is a view into a
In [29]: b = a[2:4]
In [30]: b
Out[30]: array([2, 3])

In [31]: # If we modify the view, we modify the original variable
In [32]: b[:] = -1
In [33]: b
Out[33]: array([-1, -1])
In [34]: a
# a is modified aswell!!
Out[34]: array([ 0, 1, -1, -1, 4, 5, 6, 7, 8, 9])

# We can print owndata to distinguish views from copies
In [35]: a.flags.owndata
Out[35]: True
In [36]: b.flags.owndata
Out[36]: False
```

Views (references)

- We can use copy() to actually copy the object

```
In [58]: a = np.array(np.arange(10))
In [59]: a
Out[59]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])


In [60]: b = a[2:4].copy()
In [61]: b[:] = -1

In [62]: a
Out[62]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
In [63]: b
Out[63]: array([-1, -1])

In [64]: a.flags.owndata
Out[64]: True
In [65]: b.flags.owndata
Out[65]: True
```

Exercise

1. Create a 3x5 matrix of normal random numbers named *my_matrix.* Print it.
2. Now, we are going to introduce some NA's into the matrix (in Python NA's are represented as numpy.nan = not a number)
   1. x = [0,2]
   2. y = [3,1]
   3. We are going to use x and y to introduce NA's into my_matrix, at positions (0,3) and (2,1) by doing this: *my_matrix[x,y] = np.nan.*
   4. Print the result.
3. Now, use boolean indexing and *isna()* for replacing all NA's by zero, and print the result

Solution

```
In []: my_matrix = np.random.randn(3,5)
In []: my_matrix
array([[-1.48413505, -0.23568385, -1.22030818, -0.81259558,  1.68216758],
       [-0.24242369, -2.51793289,  1.70739294,  1.30946991, -1.74124409],
       [-0.17144277, -1.42001248, -0.23261268,  1.08373964,  1.41257598]])

In []: x = [0,2]
In []: y = [3,1]

In []: my_matrix
array([[-1.48413505, -0.23568385, -1.22030818,         nan,  1.68216758],
       [-0.24242369, -2.51793289,  1.70739294,  1.30946991, -1.74124409],
       [-0.17144277,         nan, -0.23261268,  1.08373964,  1.41257598]])

In []: my_matrix[np.isnan(my_matrix)] = 0
In []: print(my_matrix)
[[-1.48413505 -0.23568385 -1.22030818  0.          1.68216758]
 [-0.24242369 -2.51793289  1.70739294  1.30946991 -1.74124409]
 [-0.17144277  0.         -0.23261268  1.08373964  1.41257598]]
```

Universal functions

- They are functions that operate **element-wise** on one or more arrays

```
In [69]: a = np.arange(10)
In [70]: a
Out[70]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

# Universal function sqrt
In [71]: a = np.sqrt(a)
In [72]: a
Out[72]:
array([0. , 1. , 1.41421356, 1.73205081, 2. , 2.23606798, 2.44948974, 2.64575131, 2.82842712, 3. ])
```

```
In [73]: b = np.arange(10)*8.7

In [75]: c = a + b
In [76]: c
Out[76]:
array([ 0. , 9.7 , 18.81421356, 27.83205081, 36.8 , 45.73606798, 54.64948974, 63.54575131, 72.42842712,
81.3 ])
```

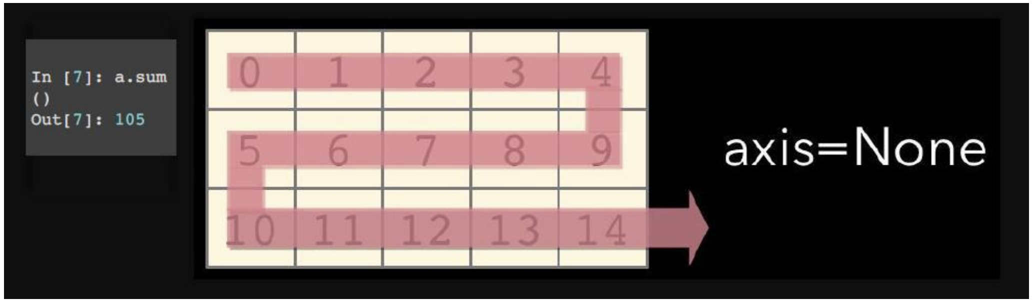
Available universal functions

https://docs.scipy.org/doc/numpy/reference/ufuncs.html#available-ufuncs

- comparison: <, <=, ==, !=, >=, >
- arithmetic: +, -, *, /, reciprocal, square
- exponential: exp, expm1, exp2, log, log10, log1p, log2, power, sqrt
- trigonometric: sin, cos, tan, acsin, arccos, atctan
- hyperbolic: sinh, cosh, tanh, acsinh, arccosh, atctanh
- bitwise operations: &, |, ~, ^, left_shift, right_shift
- logical operations: and, logical_xor, not, or
- predicates: isfinite, isinf, isnan, signbit
- other: abs, ceil, floor, mod, modf, round, sinc, sign, trunc

Reduction functions

- Reduction functions allow to transform an array to a single number:
  - sum, mean, ...




```
In [10]: a = np.arange(10)
In [11]: a
Out[11]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [12]: a.sum()
Out[12]: 45

In [13]: a.mean()
Out[13]: 4.5
```

```
In [14]: a = np.array([[0, 1, 2, 3],
                       [4, 5, 6, 7],
                       [8, 9, 10, 11]])
In [15]: a
Out[15]:
array([[0, 1, 2, 3, 4],
       [5, 6, 7, 8, 9],
       [10, 11, 12, 13, 14]])

In [16]: a.sum()
Out[16]: 105
```

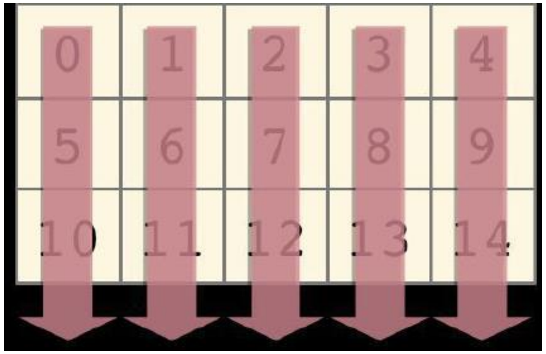
Reduction functions

- In general, reduction functions transform arrays into arrays of smaller dimensionality by reducing along an axis
- A 1-dimensional array has one axis, axis=0
- A 2-dimensional array (matrix) has two axis, axis=0 (rows), axis=1(columns)
- We could, for instance, sum the columns of a matrix (sum along the 0-axis)

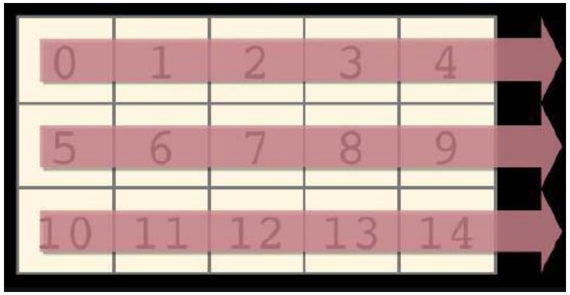
Reduction functions

```
# Sum along axis 0 / rows (sum all rows elements in a column)
In [19]: a.sum(axis=0)
Out[19]: array([15, 18, 21, 24, 27])
# Sum along axis 1 / columns (sum all column elements in a row)
In [20]: a.sum(axis=1)
Out[20]: array([ 6, 22, 38])
```

Axis 0



Axis 1




```
# Sum along axis 0 / rows
In [21]: np.sum(a, axis=0)
Out[21]: array([12, 15, 18, 21])
# Sum along axis 1
In [22]: np.sum(a, axis=1)
Out[22]: array([ 6, 22, 38])
```

Reduction functions

- Other reduction functions: max, min, mean, ...

Broadcasting

- Why does this work?

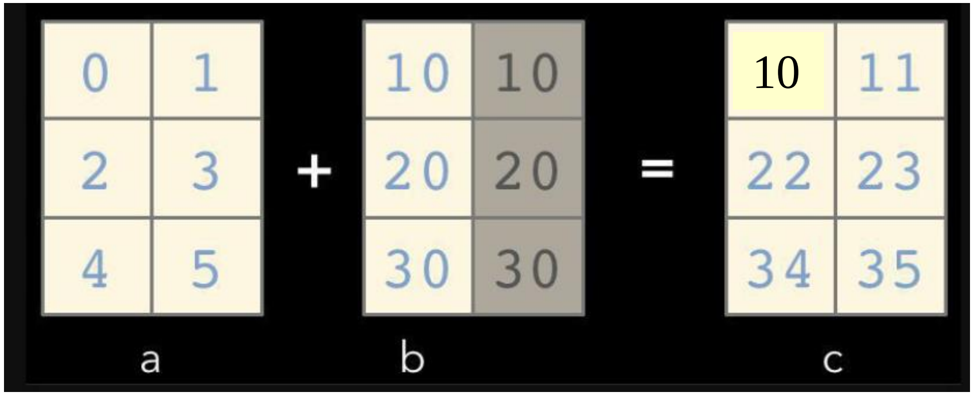
```
In []: a = np.array([0, 1, 2, 3, 4, 5])
In []: b = np.array([10])

In []: a
Out[]: array([0, 1, 2, 3, 4, 5])
In []: b
Out[]: array([10])

In [48]: c = a+b
In [49]: c
Out[49]: array([10, 11, 12, 13, 14, 15])
```

- Broadcasting allows to have operations between arrays with different sizes

Broadcasting

- Broadcast requires all dimensions to be 1 or equal.

```
In []: a = np.array([[0, 1], [2, 3], [4, 5]])
In []: b = np.array([[10], [20], [30]])
In []: a
Out[]:
array([[0, 1],
       [2, 3],
       [4, 5]])
In []: b
Out[]:
array([[10],
       [20],
       [30]])

In [61]: c = a + b
In [62]: c
Out[62]:
array([[10, 11],
       [22, 23],
       [34, 35]])
```



a.shape = (3,2)
b.shape = (3,1) => (3,2)

Exercise: normalization (scaling features to a range)

1. Create a 3x5 matrix of normal random numbers named *my_matrix*. Print it.
2. Now, use reduction functions (*max* and *min*) to compute two vectors *maxima* and *minima* with the máximum and minimum values (respectively) of the columns of *my_matrix*
3. Now, compute new matrix *normalized_matrix*, so that columns of *my_matrix* become normalized between zero and one.
    1. Definition of normalization: $x'_{ij} = (x_{ij} - \min(x_{.j}))/(\max(x_{.j})-\min(x_{.j}))$
4. Check that all values of normalized_matrix are >= 0, and <= 1
5. Finally, compute *standarized_matrix* (mean removal/variance scaling)
    1. Def of standarization: $x'_{ij} = (x_{ij} - \text{mean}(x_{.j}))/\text{std}(x_{.j})$
6. Verify that the mean of all columns is zero, and the standard deviation is 1 (approximately)

```
In [201]: my_matrix = np.random.randn(3,5)
In [202]: maxima = my_matrix.max(axis=0)
In [203]: print(maxima)
[ 2.19405637 0.54857877 -0.77583136 -0.75875882 1.22463799]

In [204]: minima = my_matrix.min(axis=0)
In [205]: print(minima)
[ 1.03488226 -0.82966138 -1.55133288 -1.46959842 -0.76071212]

In [206]: normalized_matrix = (my_matrix - minima) / (maxima-minima)
In [207]: print(normalized_matrix)
[[0.28223942 0. 0.37006178 1. 1. ]
[1. 1. 0. 0. 0. ]
[0. 0.14074337 1. 0.64842885 0.40670394]]

In [208]: normalized_matrix >= 0
Out[208]:
array([[ True, True, True, True, True],
[ True, True, True, True, True],
[ True, True, True, True, True]])

In [209]: normalized_matrix <= 1
Out[209]:
array([[ True, True, True, True, True],
[ True, True, True, True, True],
[ True, True, True, True, True]])

In [210]: standarized_matrix = (my_matrix - my_matrix.mean(axis=0))/(my_matrix.std(axis=0))
In [211]: print(standarized_matrix)
[[-0.34486633 -0.86032467 -0.20983943 1.08769345 1.29343692]
[ 1.36020436 1.40221228 -1.10626795 -1.32659331 -1.14196153]
[-1.01533803 -0.54188761 1.31610738 0.23889987 -0.15147539]]

In [212]: standarized_matrix.mean(axis=0)
Out[212]:
array([ 2.22044605e-16, 3.70074342e-17, 3.70074342e-16, -3.88578059e-16,
4.62592927e-17])

In [213]: standarized_matrix.std(axis=0)
Out[213]: array([1., 1., 1., 1., 1.])
```

Loading and saving numpy arrays to files

- Reading files: np.genfromtxt("BodyTemperature.txt", skip_header=True)
  - np.loadtxt is faster, but allows for less user control (header, handling NA's)
- Writing to text files: np.savetxt(filename, data)
- For pickle (binary format, faster):
  - np.save(filename, data)
  - my_array = np.load(filename, data)

```
Gender Age HeartRate Temperature
0 33 69 97
0 32 72 98.8
0 42 68 96.2
1 33 75 97.8
1 26 68 98.8
0 37 79 101.3
1 32 71 97.8
1 45 73 97.4
1 31 77 99.2
0 49 81 99.2
```

```python
print(an_array)
```

OUTPUT

```
[[0 1]
 [2 3]
 [4 5]
 [6 7]]
```

```python
a_file = open("test.txt", "w")
for row in an_array:
    np.savetxt(a_file, row)

a_file.close()
```

close `a_file`

TEST.TXT

```
0.000000000000000000e+00
1.000000000000000000e+00
2.000000000000000000e+00
3.000000000000000000e+00
4.000000000000000000e+00
5.000000000000000000e+00
6.000000000000000000e+00
7.000000000000000000e+00
```

Exercise

```
Gender Age HeartRate Temperature
0 33 69 97
0 32 72 98.8
0 42 68 96.2
1 33 75 97.8
1 26 68 98.8
0 37 79 101.3
1 32 71 97.8
1 45 73 97.4
1 31 77 99.2
0 49 81 99.2
```

1) Look inside the file BodyTemperature.txt (0=MALE, 1=FEMALE)

[redacted]

3) Read the file in numpy using the command np.genfromtxt() and put it into a numpy 2Darray (have a look at the manual for the correct options)

4) Create a function to extract the number of Males and Female in the dataset

5) Compute the overall mean for Age, HeartRate and Temperature

6) Compute the mean, max and min of Age, HeartRate and Temperature for Male and Females separately and write the results on the file BD_results.txt in a table format.

[redacted]

```
Gender Age HeartRate Temperature
0 33 69 97
0 32 72 98.8
0 42 68 96.2
1 33 75 97.8
1 26 68 98.8
0 37 79 101.3
1 32 71 97.8
1 45 73 97.4
1 31 77 99.2
0 49 81 99.2
```

```
# Read textdatafile, ignore the header
# The header is Gender Age HeartRate Temperature
In [313]: data = np.genfromtxt("BodyTemperature.txt" , skip_header=True )

# Any nan?
In [315]: np.any(np.isnan(data))
Out[315]: False

# Number of males
In [317]: np.sum(data[:,0] == 0)
Out[317]: 49

# Number of females
In [319]: np.sum(data[:,0] == 1)
Out[319]: 51

# Ignoring gender, the remaining columns are averages for:
# Age HeartRate Temperature

In [322]: data.mean(axis=0)[1:]
Out[322]: array([37.62, 73.66, 98.33])
```

```
In [323]: males = data[data[:,0] == 0]
In [324]: females = data[data[:,0] == 1]
In [325]: males_mean = males.mean(axis=0)[1:]
In [326]: males_max = males.max(axis=0)[1:]
In [327]: males_min = males.min(axis=0)[1:]
In [328]: females_mean = females.mean(axis=0)[1:]
In [329]: females_max = females.max(axis=0)[1:]
In [330]: females_min = females.min(axis=0)[1:]
In [331]: table = np.array([males_mean, males_max, males_min, females_mean, females_max, females_min])

In [332]: table
Out[332]:
array([[ 37.81632653, 73.91836735, 98.19795918],
[ 50. , 87. , 101.3 ],
[ 22. , 61. , 96.2 ],
[ 37.43137255, 73.41176471, 98.45686275],
[ 49. , 87. , 100.8 ],
[ 21. , 67. , 96.8 ]])

In [333]: np.savetxt("BD_results.txt", table)
```

CONCATENATING MATRICES

```
import numpy as np

a1 = np.array([[0, 1, 2],
               [3, 4, 5],
               [6, 7, 8]])

a2 = np.array([[10, 11, 12],
               [13, 14, 15],
               [16, 17, 18]])

b = np.concatenate((a1,a2))
b

c = np.concatenate((a1,a2), axis=1)
c
```

np.vstack

np.hstack

```
In [31]: a1 = np.array([[0, 1, 2],
    ...:                [3, 4, 5],
    ...:                [6, 7, 8]])
    ...:

In [32]: a2 = np.array([[10, 11, 12],
    ...:                [13, 14, 15],
    ...:                [16, 17, 18]])
    ...:

In [33]: b = np.concatenate((a1,a2))

In [34]: b
Out[34]:
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [10, 11, 12],
       [13, 14, 15],
       [16, 17, 18]])

In [35]: c = np.concatenate((a1,a2), axis=1)

In [36]: c
Out[36]:
array([[ 0,  1,  2, 10, 11, 12],
       [ 3,  4,  5, 13, 14, 15],
       [ 6,  7,  8, 16, 17, 18]])
```

STACKING VECTORS

```
v1 = np.arange(0,4)
v2 = np.arange(5,9)
v1
v2

# Vertical stacking of vectors
vv = np.vstack((v1,v2))
vv

# Horizontal stacking of vectors
ww = np.vstack((v1, v2)).T
ww
```

```
In [61]: v1 = np.arange(0,4)

In [62]: v2 = np.arange(5,9)

In [63]: v1
Out[63]: array([0, 1, 2, 3])

In [64]: v2
Out[64]: array([5, 6, 7, 8])

In [65]: # Vertical stacking of vectors

In [66]: vv = np.vstack((v1,v2))

In [67]: vv
Out[67]:
array([[0, 1, 2, 3],
       [5, 6, 7, 8]])

In [68]: # Horizontal stacking of vectors

In [69]: ww = np.vstack((v1, v2)).T

In [70]: ww
Out[70]:
array([[0, 5],
       [1, 6],
       [2, 7],
       [3, 8]])
```

Pandas

by Ricardo Aler

PANDAS

- Pandas is the Python library to work with dataframes (similar to R data.frames)

  import pandas as **pd**

- An advantage of Pandas over numpy is that all elements in a numpy array must belong to the same type, while Pandas allows to have different columns with different types (integers, reals, strings, ...)

PANDAS data structures

- Pandas library contains two data structures:
  - Series: a series is like a vector, but with an index
    - A series is made of:
      - index
      - values
  - Dataframes: it is similar to R dataframes (a matrix with column names. Each column may belong to different data types: integer, real numbers, strings, ...)
    - A dataframe is made of:
      - index
      - column names
      - values

Example of series

```
# Using the default index 0, 1, ...


s = pd.Series(np.random.randn(5))



In [224]: s
Out[224]:
0  1.037685
1  0.403077
2  -1.814123
3  -0.005181
4  1.692980
   dtype: float64

# We can get the values of a series as a numpy array
In [225]: s.values
Out[225]: array([ 1.03768522, 0.40307685, -1.81412276, -0.005181 ,
1.69298038])



In [226]: s.index
Out[226]: RangeIndex(start=0, stop=5, step=1)
```

```
# Using a custom index
In [228]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [229]: s
Out[229]:
a 0.226183
b -0.564569
c -1.058691
d 0.970553
e -0.857780
dtype: float64

In [230]: s.values
Out[230]: array([ 0.22618273, -0.564569 , -1.05869052, 0.97055338, -
0.85777957])

In [231]: s.index
Out[231]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
```

Note: although indices can be useful in some cases (time series, ...), this tutorial will not focus on them

Reading files as dataframes

In [121]: import pandas as pd

Read file in csv format into a Pandas dataframe

In [122]: flights = pd.read_csv("flights.csv")

In [124]: flights.shape

Out[124]: (336776, 19)

head: print the first rows

```
In [22]: flights.head(
    ...: )
Out[22]:
   year  month  day         ...           hour  minute            time_hour
0  2013      1    1         ...              5      15  2013-01-01 05:00:00
1  2013      1    1         ...              5      29  2013-01-01 05:00:00
2  2013      1    1         ...              5      40  2013-01-01 05:00:00
3  2013      1    1         ...              5      45  2013-01-01 05:00:00
4  2013      1    1         ...              6       0  2013-01-01 06:00:00

[5 rows x 19 columns]
```

Column names

Values

Index (by default 0, 1, 2, ...)

In []: flights.index

Out[]: RangeIndex(start=0, stop=336776, step=1)

Getting the names of the columns

In [130]: list(flights.columns)

Out[130]:

['year', 'month', 'day', 'dep_time', 'sched_dep_time', 'dep_delay', 'arr_time', 'sched_arr_time', 'arr_delay', 'carrier', 'flight', 'tailnum', 'origin', 'dest', 'air_time', 'distance', 'hour', 'minute', 'time_hour']

Describing the dataframe

- describe and info

```
In [23]: flights.describe()
Out[23]:
            year          month      ...           hour         minute
count   336776.0  336776.000000      ...  336776.000000  336776.000000
mean      2013.0       6.548510      ...      13.180247      26.230100
std          0.0       3.414457      ...       4.661316      19.300846
min       2013.0       1.000000      ...       1.000000       0.000000
25%       2013.0       4.000000      ...       9.000000       8.000000
50%       2013.0       7.000000      ...      13.000000      29.000000
75%       2013.0      10.000000      ...      17.000000      44.000000
max       2013.0      12.000000      ...      23.000000      59.000000

[8 rows x 14 columns]
```

```
In [24]: flights.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 336776 entries, 0 to 336775
Data columns (total 19 columns):
year              336776 non-null int64
month             336776 non-null int64
day               336776 non-null int64
dep_time          328521 non-null float64
sched_dep_time    336776 non-null int64
dep_delay         328521 non-null float64
arr_time          328063 non-null float64
sched_arr_time    336776 non-null int64
arr_delay         327346 non-null float64
carrier           336776 non-null object
flight            336776 non-null int64
tailnum           334264 non-null object
origin            336776 non-null object
dest              336776 non-null object
air_time          327346 non-null float64
distance          336776 non-null int64
hour              336776 non-null int64
minute            336776 non-null int64
time_hour         336776 non-null object
dtypes: float64(5), int64(9), object(5)
memory usage: 48.8+ MB
```

Setting the index

- By default: 0, 1, 2, ...

In [**12**]: flights.index

Out[**12**]: RangeIndex(start=0, stop=336776, step=1)

- In most cases, this is what you need
- We can set one of the columns as the index:

flights.set_index("month")

Setting the index

- New index. We could also use dates ...

```
In [21]: flights.index = np.arange(10, 336776+10)

In [22]: flights
Out[22]:
    year  month  day       ...        hour  minute           time_hour
10  2013      1    1       ...           5      15 2013-01-01 05:00:00
11  2013      1    1       ...           5      29 2013-01-01 05:00:00
12  2013      1    1       ...           5      40 2013-01-01 05:00:00
13  2013      1    1       ...           5      45 2013-01-01 05:00:00
14  2013      1    1       ...           6       0 2013-01-01 06:00:00
15  2013      1    1       ...           5      58 2013-01-01 05:00:00
16  2013      1    1       ...           6       0 2013-01-01 06:00:00
17  2013      1    1       ...           6       0 2013-01-01 06:00:00
18  2013      1    1       ...           6       0 2013-01-01 06:00:00
19  2013      1    1       ...           6       0 2013-01-01 06:00:00
20  2013      1    1       ...           6       0 2013-01-01 06:00:00
21  2013      1    1       ...           6       0 2013-01-01 06:00:00
22  2013      1    1       ...           6       0 2013-01-01 06:00:00
23  2013      1    1       ...           6       0 2013-01-01 06:00:00
24  2013      1    1       ...           6       0 2013-01-01 06:00:00
25  2013      1    1       ...           5      59 2013-01-01 05:00:00
26  2013      1    1       ...           6       0 2013-01-01 06:00:00
27  2013      1    1       ...           6       0 2013-01-01 06:00:00
28  2013      1    1       ...           6       0 2013-01-01 06:00:00
29  2013      1    1       ...           6       0 2013-01-01 06:00:00
30  2013      1    1       ...           6      10 2013-01-01 06:00:00
31  2013      1    1       ...           6       5 2013-01-01 06:00:00
32  2013      1    1       ...           6      10 2013-01-01 06:00:00
33  2013      1    1       ...           6      10 2013-01-01 06:00:00
34  2013      1    1       ...           6       7 2013-01-01 06:00:00
35  2013      1    1       ...           6       0 2013-01-01 06:00:00
36  2013      1    1       ...           6       0 2013-01-01 06:00:00
37  2013      1    1       ...           6      10 2013-01-01 06:00:00
38  2013      1    1       ...           6      15 2013-01-01 06:00:00
```

Terminal de IPython   Historial de comandos

Permisos: RW   Fin de lín

Note: although indices can be useful in some cases (time series, ...), this tutorial will not focus on them

Extracting the values from a Pandas dataframe or series to a numpy matrix / array

```
In [39]: flights.values
Out[39]:
array([[2013, 1, 1, ..., 5, 15, '2013-01-01 05:00:00'],
[2013, 1, 1, ..., 5, 29, '2013-01-01 05:00:00'],
[2013, 1, 1, ..., 5, 40, '2013-01-01 05:00:00'],
...,
[2013, 9, 30, ..., 12, 10, '2013-09-30 12:00:00'],
[2013, 9, 30, ..., 11, 59, '2013-09-30 11:00:00'],
[2013, 9, 30, ..., 8, 40, '2013-09-30 08:00:00']], dtype=object)
```

Creating dataframes from Python dictionaries

```
import pandas as pd

# intialise data of lists.
data = {'Name':['Tom', 'nick', 'krish', 'jack'],
        'Age':[20, 21, 19, 18]}

# Create DataFrame
df = pd.DataFrame(data)

# Print the output.
print(df)
```

```
In [100]: import pandas as pd

In [101]: # intialise data of lists.

In [102]: data = {'Name':['Tom', 'nick', 'krish', 'jack'],
     ...:         'Age':[20, 21, 19, 18]}
     ...:

In [103]: df = pd.DataFrame(data)

In [104]: print(df)
    Name  Age
0    Tom   20
1   nick   21
2  krish   19
3   jack   18
```

Writing dataframes to text files

```
import pandas as pd

# intialise data of lists.
data = {'Name':['Tom', 'nick', 'krish', 'jack'],
        'Age':[20, 21, 19, 18]}

# Create DataFrame
df = pd.DataFrame(data)

# Write to file.
df.to_csv('names_ages.csv', index=False)
```

Selecting rows and columns (indexing)

- Label selection: both rows and columns can have labels: **loc**
  - the labels of the rows are the indices (index)
  - the labels of the columns are the column names
- Position (integer) selection: **iloc**
  - Rows: e.g. select rows from 0 to 10
  - Columns: e.g. select rows from 3 to 7
- Boolean selection: selecting rows that satisfy a condition
  - E.g.: Select all rows where age > 35

Selecting rows and columns (indexing)

- Label selection: both rows and columns can have labels: **loc**
  - the labels of the rows are the indices (index)
  - the labels of the columns are the column names
- Position (integer) selection: **iloc**
  - Rows: select rows from 0 to 10
  - Columns: select rows from 3 to 7
- Boolean selection: selecting rows that satisfy a condition
  - E.g.: Select all rows where age > 35

Label selection: rows .loc

```
In [22]: flights.head(
    ...: )
Out[22]:
   year  month  day      ...       hour  minute           time_hour
0  2013      1    1      ...          5      15 2013-01-01 05:00:00
1  2013      1    1      ...          5      29 2013-01-01 05:00:00
2  2013      1    1      ...          5      40 2013-01-01 05:00:00
3  2013      1    1      ...          5      45 2013-01-01 05:00:00
4  2013      1    1      ...          6       0 2013-01-01 06:00:00

[5 rows x 19 columns]
```

In [25]: flights.loc[2:4]

Out[25]:

year month day ... hour minute time_hour

2 2013 1 1 ... 5 40 2013-01-01 05:00:00

3 2013 1 1 ... 5 45 2013-01-01 05:00:00

4 2013 1 1 ... 6 0 2013-01-01 06:00:00

Beware, this is not a range/slice, but row names '2', '3', and '4'. 4 is **not** excluded! Equivalent to;

flights.loc[[2,3,4]]

Label selection: columns .loc

List of columns

```
In [26]: flights.loc[:, ['month', 'day', 'time_hour']]
Out[26]:
        month  day            time_hour
0           1    1  2013-01-01 05:00:00
1           1    1  2013-01-01 05:00:00
2           1    1  2013-01-01 05:00:00
3           1    1  2013-01-01 05:00:00
4           1    1  2013-01-01 06:00:00
5           1    1  2013-01-01 05:00:00
6           1    1  2013-01-01 06:00:00
7           1    1  2013-01-01 06:00:00
8           1    1  2013-01-01 06:00:00
9           1    1  2013-01-01 06:00:00
10          1    1  2013-01-01 06:00:00
11          1    1  2013-01-01 06:00:00
12          1    1  2013-01-01 06:00:00
13          1    1  2013-01-01 06:00:00
14          1    1  2013-01-01 06:00:00
15          1    1  2013-01-01 05:00:00
16          1    1  2013-01-01 06:00:00
17          1    1  2013-01-01 06:00:00
18          1    1  2013-01-01 06:00:00
19          1    1  2013-01-01 06:00:00
20          1    1  2013-01-01 06:00:00
```

Range of columns

```
In [30]: flights.loc[:, 'year':'dep_time']
Out[30]:
        year  month  day  dep_time
0       2013      1    1     517.0
1       2013      1    1     533.0
2       2013      1    1     542.0
3       2013      1    1     544.0
4       2013      1    1     554.0
5       2013      1    1     554.0
6       2013      1    1     555.0
7       2013      1    1     557.0
8       2013      1    1     557.0
9       2013      1    1     558.0
10      2013      1    1     558.0
11      2013      1    1     558.0
12      2013      1    1     558.0
13      2013      1    1     558.0
14      2013      1    1     559.0
15      2013      1    1     559.0
16      2013      1    1     559.0
17      2013      1    1     600.0
18      2013      1    1     600.0
19      2013      1    1     601.0
20      2013      1    1     602.0
```

Labels: rows and columns .loc

```
In [31]: flights.loc[2:4, ['month', 'day', 'time_hour']]
Out[31]:
   month  day           time_hour
2      1    1 2013-01-01 05:00:00
3      1    1 2013-01-01 05:00:00
4      1    1 2013-01-01 06:00:00
```

Beware! series vs. dataframe

This returns a dataframe

In []: flights.loc[:,['month']]
Out[]:

```
   month
0 1
1 1
2 1
3 1
4 1
5 1
6 1
7 1
8 1
9 1
```

This returns a series!

In [35]: flights.loc[:,'month']
Out[35]:

```
0 1
1 1
2 1
3 1
4 1
5 1
6 1
7 1
8 1
9 1
10 1
```

In []: type(flights.loc[:,['month']])
Out[]: pandas.core.frame.**DataFrame**

In []: type(flights.loc[:,'month'])
Out[]: pandas.core.series.**Series**

Selecting single columns (series)

This returns a series!

```
In [35]: flights.loc[:,'month']
Out[35]:
0 1
1 1
2 1
3 1
4 1
5 1
6 1
7 1
8 1
9 1
10 1
```

The same, with dot notation

```
In [42]: flights.month
Out[42]:
0 1
1 1
2 1
3 1
4 1
5 1
6 1
7 1
8 1
9 1
10 1
```

Note: we can get the values as a numpy array

```
In [43]: flights.month.values
Out[43]: array([1, 1, 1, ..., 9, 9, 9], dtype=int64)
```

Shorthand for column selection

- flights.loc[:,'month'] is equivalent to flights['month']
  - (and also flights.month)
- flighs.loc[:,['year', 'month']] is equivalent to flights[['year', 'month']]

Selecting rows and columns (indexing)

- Label selection: both rows and columns can have labels: **loc**
  - the labels of the rows are the indices (index)
  - the labels of the columns are the column names
- Position (integer) selection: **iloc**
  - Rows: select rows from 0 to 10
  - Columns: select rows from 3 to 7
- Boolean selection: selecting rows that satisfy a condition
  - E.g.: Select all rows where age > 35

Position (integer) selection: iloc

```
In [22]: flights.head(
    ...: )
Out[22]:
   year  month  day         ...          hour  minute           time_hour
0  2013      1    1         ...             5      15 2013-01-01 05:00:00
1  2013      1    1         ...             5      29 2013-01-01 05:00:00
2  2013      1    1         ...             5      40 2013-01-01 05:00:00
3  2013      1    1         ...             5      45 2013-01-01 05:00:00
4  2013      1    1         ...             6       0 2013-01-01 06:00:00

[5 rows x 19 columns]
```

```
In [41]: flights.iloc[2:4, 1:3]
Out[41]:
  month day
2 1      1
3 1      1
```

Beware, those are ranges/slices. Last element is excluded

Combining iloc for rows and loc for columns

- What if we want to select rows by position but columns by name?

```
# Just one column
In [51]: flights.iloc[2:4, flights.columns.get_loc('month')]
Out[51]:
2 1
3 1
Name: month, dtype: int64

# Several columns
In [53]: flights.iloc[2:4, flights.columns.get_indexer(['month','day'])]
Out[53]:
   month day
2 1        1
3 1        1
```

Selecting rows and columns (indexing)

- Label selection: both rows and columns can have labels: **loc**
  - the labels of the rows are the indices (index)
  - the labels of the columns are the column names
- Position (integer) selection: **iloc**
  - Rows: select rows from 0 to 10
  - Columns: select rows from 3 to 7
- Boolean selection: selecting rows that satisfy a condition
  - E.g.: Select all rows where age > 35

Boolean indexing: selecting rows on condition

- Both loc and iloc can be used, but **loc** is recommended
- List of flights for January the first?

```
In []: flights.loc[(flights.month == 1) & (flights.day == 1)]
Out[]:
      year   month day ... hour minute time_hour
0     2013   1       1   ... 5     15      2013-01-01 05:00:00
1     2013   1       1   ... 5     29      2013-01-01 05:00:00
2     2013   1       1   ... 5     40      2013-01-01 05:00:00
3     2013   1       1   ... 5     45      2013-01-01 05:00:00
4     2013   1       1   ... 6      0      2013-01-01 06:00:00
```

- Note: we can also write (**flights.loc[:,"month"] == 1)**

Boolean indexing: selecting rows on condition

- Same thing in two lines (clearer code)
- List of flights for January the first?

```
In []: condition = (flights.month == 1) & (flights.day == 1)
In []: flights.loc[condition]
Out[]:
      year   month day ... hour minute time_hour
0     2013   1       1   ... 5     15      2013-01-01 05:00:00
1     2013   1       1   ... 5     29      2013-01-01 05:00:00
2     2013   1       1   ... 5     40      2013-01-01 05:00:00
3     2013   1       1   ... 5     45      2013-01-01 05:00:00
4     2013   1       1    ... 6     0      2013-01-01 06:00:00
```

Boolean indexing: selecting rows on condition

- List of flights for January the first?
  - A shorter version

```
•In []: flights.query("month == 1 & day == 1")
Out[]:
     year  month day ... hour minute time_hour
0    2013  1     1   ... 5    15     2013-01-01 05:00:00
1    2013  1     1   ... 5    29     2013-01-01 05:00:00
2    2013  1     1   ... 5    40     2013-01-01 05:00:00
3    2013  1     1   ... 5    45     2013-01-01 05:00:00
4    2013  1     1   ... 6     0     2013-01-01 06:00:00
```

Boolean conditions

- In order to create conditions, we can use:
  - <, >, ==, <=, >=, !=
  - &: and
  - |: or
  - ~: not
  - isin: is value in a list of values?
  - isnull: is value nan?

Boolean selection: selecting rows on condition

- What flights start at EWR or JFK airports?

```
In [61]: flights.loc[flights.origin.isin(['EWR', 'JFK']), ['origin', 'dest']]
Out[61]:
   origin dest
0   EWR   IAH
2   JFK   MIA
3   JFK   BQN
5   EWR   ORD
6   EWR   FLL
8   JFK   MCO
10  JFK   PBI
```

- Note: we are also selecting origin and dest columns

Creating new columns

- Compute speed for every flight
  - speed = distance / airtime

- Two ways:
  - First: **flights.loc[:,'speed'] =**
    - flights.loc[:,'speed'] = flights.distance / flights.air_time
    - flights.loc[:,'speed'] = flights.loc[:,'distance'] / flights.loc[:,'air_time']
    - flights.loc[:,'speed'] = flights['distance'] / flights['air_time']
  - Shorthand: **flights['speed'] =**
    - flights['speed'] = flights['distance'] / flights['air_time']

Creating new columns

```
In [74]: flights['speed'] = flights['distance'] / flights['air_time']

In [75]: flights
Out[75]:
        year  month  day  ...    minute           time_hour   speed
0       2013      1    1  ...        15 2013-01-01 05:00:00  1173.0
1       2013      1    1  ...        29 2013-01-01 05:00:00  1189.0
2       2013      1    1  ...        40 2013-01-01 05:00:00   929.0
3       2013      1    1  ...        45 2013-01-01 05:00:00  1393.0
4       2013      1    1  ...         0 2013-01-01 06:00:00   646.0
5       2013      1    1  ...        58 2013-01-01 05:00:00   569.0
6       2013      1    1  ...         0 2013-01-01 06:00:00   907.0
7       2013      1    1  ...         0 2013-01-01 06:00:00   176.0
8       2013      1    1  ...         0 2013-01-01 06:00:00   804.0
9       2013      1    1  ...         0 2013-01-01 06:00:00   595.0
10      2013      1    1  ...         0 2013-01-01 06:00:00   879.0
11      2013      1    1  ...         0 2013-01-01 06:00:00   847.0
12      2013      1    1  ...         0 2013-01-01 06:00:00  2130.0
13      2013      1    1  ...         0 2013-01-01 06:00:00  2204.0
14      2013      1    1  ...         0 2013-01-01 06:00:00  1132.0
15      2013      1    1  ...        59 2013-01-01 05:00:00   143.0
16      2013      1    1  ...         0 2013-01-01 06:00:00  1890.0
17      2013      1    1  ...         0 2013-01-01 06:00:00   924.0
18      2013      1    1  ...         0 2013-01-01 06:00:00   628.0
19      2013      1    1  ...         0 2013-01-01 06:00:00   876.0
20      2013      1    1  ...        10 2013-01-01 06:00:00   850.0
21      2013      1    1  ...         5 2013-01-01 06:00:00   397.0
22      2013      1    1  ...        10 2013-01-01 06:00:00   933.0
23      2013      1    1  ...        10 2013-01-01 06:00:00   632.0
24      2013      1    1  ...         7 2013-01-01 06:00:00   928.0
```

Modifying subsets of the dataframe (setting)

- Let's put *nan* on the first three rows and columns 'year', 'month' and 'day'

```
# Let's create a copy first
In [81]: flights_copy = flights.copy()
# Let's see the content of the first three rows and the first three columns
In [83]: flights_copy.iloc[0:4, flights.columns.get_indexer(['year', 'month', 'day'])]
Out[83]:
year month day
0 2013 1 1
1 2013 1 1
2 2013 1 1
3 2013 1 1
```

```
# Now, we do the assignment
In [85]: flights_copy.iloc[0:4, flights.columns.get_indexer(['year', 'month', 'day'])] = np.nan
In [86]: flights_copy
Out[86]:
  year month day ... minute time_hour speed
0 NaN NaN NaN ... 15 2013-01-01 05:00:00 1173.0
1 NaN NaN NaN ... 29 2013-01-01 05:00:00 1189.0
2 NaN NaN NaN ... 40 2013-01-01 05:00:00 929.0
3 NaN NaN NaN ... 45 2013-01-01 05:00:00 1393.0
4 2013.0 1.0 1.0 ... 0 2013-01-01 06:00:00 646.0
5 2013.0 1.0 1.0 ... 58 2013-01-01 05:00:00 569.0
6 2013.0 1.0 1.0 ... 0 2013-01-01 06:00:00 907.0
7 2013.0 1.0 1.0 ... 0 2013-01-01 06:00:00 176.0
```

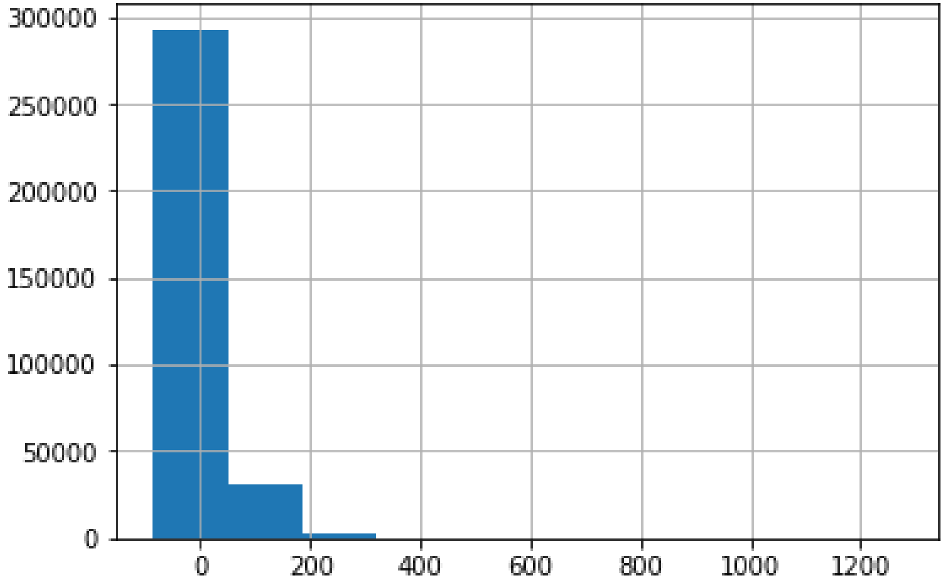
Setting (modification) with boolean indexing

- Let's create a column 'satisfaction' with 'good' if arrival delay <= 75, and 'bad' otherwise

```
In [107]: flights['satisfaction'] = 'bad'

In [108]: flights.loc[flights.arr_delay <= 75, 'satisfaction'] = 'good'

In [109]: flights.loc[:, ['arr_delay', 'satisfaction']].head()
Out[109]:
arr_delay satisfaction
0 11.0 good
1 20.0 good
2 33.0 good
3 -18.0 good
4 -25.0 good
```

- Let's visualize arrival delays

```
In [93]: flights.arr_delay.hist()
Out[93]: <matplotlib.axes._subplots.AxesSubplot at 0x15ceff93e10>
```



- https://towardsdatascience.com/3-methods-to-create-conditional-columns-with-python-pandas-and-numpy-a6cd4be9da53