

Numpy-I Notes

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Installation Using %pip

In []:

```
1 !pip install numpy
```

Importing Numpy

In [3]:

```
1 import numpy as np
```

Use case Introduction: Fitbit

#date	step_count	mood	calories_burned	hours_of_sleep	bool_of_active	weight_kg
06-10-2017	5464	200	181	5	0	66
07-10-2017	6041	100	197	8	0	66
08-10-2017	25	100	0	5	0	66
09-10-2017	5461	100	174	4	0	66
10-10-2017	6915	200	223	5	500	66
11-10-2017	4545	100	149	6	0	66
12-10-2017	4340	100	140	6	0	66
13-10-2017	1230	100	38	7	0	66
14-10-2017	61	100	1	5	0	66
15-10-2017	1258	100	40	6	0	65
16-10-2017	3148	100	101	8	0	65
17-10-2017	4687	100	152	5	0	65
18-10-2017	4732	300	150	6	500	65
19-10-2017	3519	100	113	7	0	65
20-10-2017	1580	100	49	5	0	65
21-10-2017	2822	100	86	6	0	65
22-10-2017	181	100	6	8	0	65
23-10-2017	3158	200	99	5	0	65

Every row is called a record or data point and every column is a feature

What kind of questions can we answer using this data?

- How many records and features are there in the dataset?
- What is the **average step count**?
- On which day the **step count was highest/lowest**?
- What's the **most frequent mood**?

We will try finding

- How daily activity affects mood?

Why use Numpy?

In [2]:

```
1 a = [1,2,3,4,5]
```

In [3]:

```
1 a = [i**2 for i in a]
2 print(a)
```

```
[1, 4, 9, 16, 25]
```

Lets try the same operation with NumPy

In [4]:

```
1 a = np.array([1,2,3,4,5])
2 print(a**2)
```

```
[ 1  4  9 16 25]
```

But is the clean syntax and ease in writing the only benefit we are getting here?

In [1]:

```
1 l = range(1000000)
```

In [2]:

```
1 %timeit [i**3 for i in l]
```

```
305 ms ± 8.66 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [4]:

```
1 l = np.arange(1000000)
```

In [5]:

```
1 %timeit l**3
```

2.24 ms ± 77.2 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [6]:

```
1 # Want more examples
2 l1 = range(10000)
3 l2 = [i**2 for i in range(10000)]
```

In [7]:

```
1 %timeit list(map(lambda x, y: x*y, l1, l2))
```

1.32 ms ± 45.3 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

In [8]:

```
1 a1 = np.array(l1)
2 b1 = np.array(l2)
```

In [9]:

```
1 %timeit a1*b1
```

9.36 µs ± 568 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)

Takeaway ?

- NumPy provides clean syntax for providing element-wise operations
- Per loop time for numpy to perform operation is much lesser than list

In []:

```
1
```

Basic arrays in NumPy

array()

In [6]:

```
1 # Let's create a 1-D array
2 arr1 = np.array([1, 2, 3])
3 print(arr1)
4 print(arr1 * 2)
```

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

What will be the dimension of this array?

In [7]:

```
1 arr1.ndim
```

Out[7]:

```
1
```

Shape of array

In [9]:

```
1 arr1.shape
2
```

```
-----
NameError                                Traceback (most recent call last)
C:\Users\SHELEN~1\AppData\Local\Temp\ipykernel_14276\3738189820.py in <module>
----> 1 arr1.shape

NameError: name 'arr1' is not defined
```

Sequences in Numpy

From a range and stepsize - arange()

- `arange(start, end, step)`

In [2]:

```
1 import numpy as np
```

In [4]:

```
1 arr2 = np.arange(1, 5)
2 arr2
```

Out[4]:

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

In [7]:

```
1 arr2_stepsize = np.arange(1, 5, 2)
2 arr2_stepsize
```

Out[7]:

```
array([1, 3])
```

- In `np.arange()`, we can pass a **floating point number** as **step-size**

In [18]:

```
1 arr3 = np.arange(1, 5, 0.5)
2 arr3
```

Out[18]:

```
array([1. , 1.5, 2. , 2.5, 3. , 3.5, 4. , 4.5])
```

What if we want to generate equally spaced points?

=> `linspace()`

In [14]:

```
1 np.linspace(0, 10, 11)
```

Out[14]:

```
array([ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10.])
```

Note: The `end` value is included in the array.

In [16]:

```
1 start, end, flag_count = 0, 100, 25
2 np.linspace(start, end, flag_count)
```

Out[16]:

```
array([ 0.          ,  4.16666667,  8.33333333, 12.5          ,
        16.66666667, 20.83333333, 25.          , 29.16666667,
        33.33333333, 37.5          , 41.66666667, 45.83333333,
        50.          , 54.16666667, 58.33333333, 62.5          ,
        66.66666667, 70.83333333, 75.          , 79.16666667,
        83.33333333, 87.5          , 91.66666667, 95.83333333,
        100.         ])
```

Processing math: 100%

Lets check the type of a Numpy array

In [17]:

```
1 type(arr1)
```

Out[17]:

numpy.ndarray

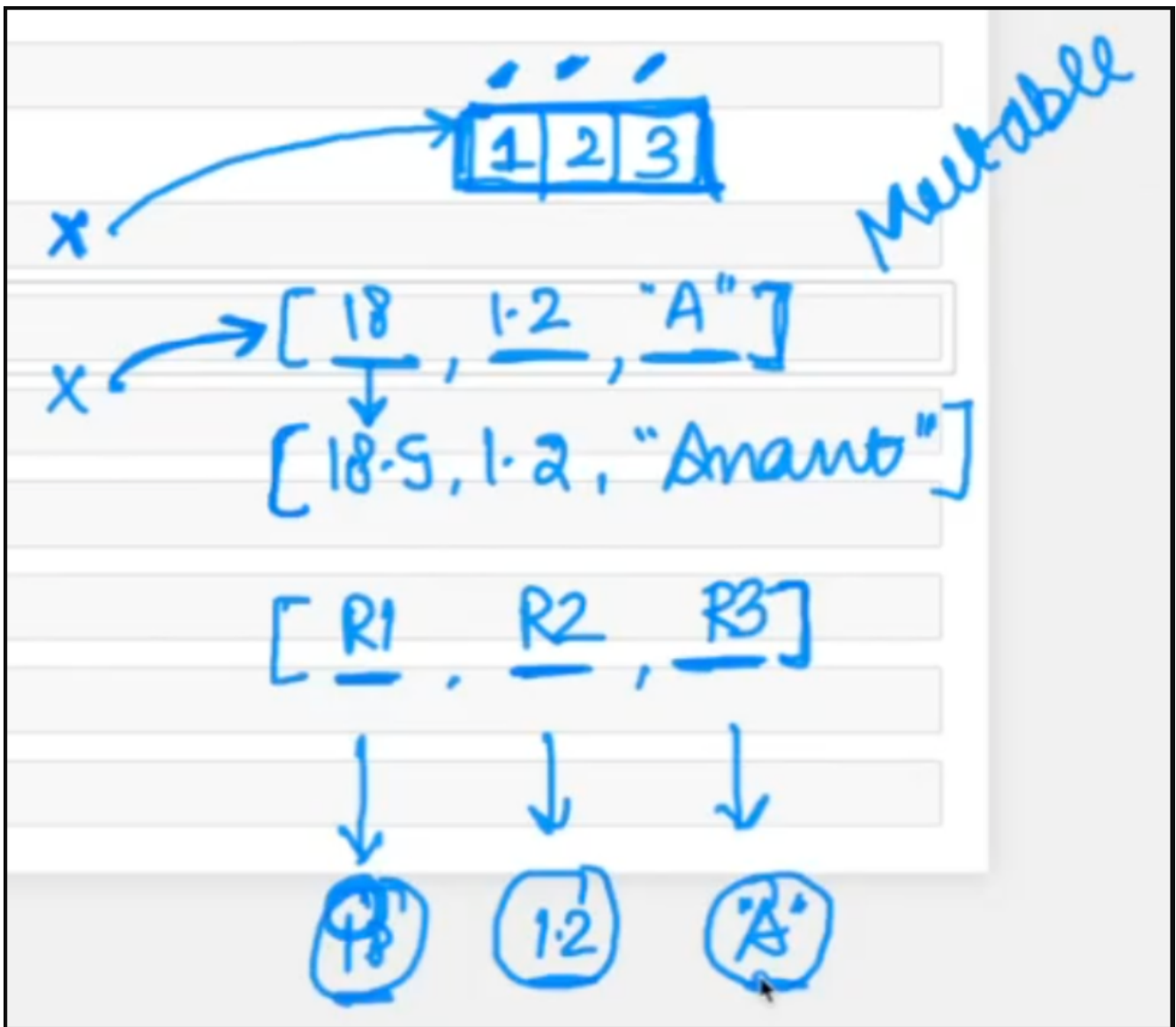
How numpy works under the hood?

- It's a **Python Library**, we will **write code in Python** to use numpy

However, numpy itself is written in C

Allows numpy to **manage memory very efficiently**

But why is C arrays more efficient or faster than Python Lists?



- In **Python List**, we can **store objects of different types together** - int, float, string, etc.
- The **actual values** of objects are **stored somewhere else in the memory**
- Only **References to those objects** (R1, R2, R3, ...) are stored in the Python List.
- So, when we have to access an element in Python List, we **first access the reference** to that element and then that **reference allows us to access the value** of element stored in memory

C array does all this in one step

- C array stores objects of same data type together**
- Actual values are stored in same contiguous memory**
- So, when we have to access an element in C array, we **access it directly using indices**.

Processing math: 100%

This makes NumPy array lose the flexibility to store heterogenous data

==> Unlike Python lists, NumPy array can only hold contiguous data

- So numpy arrays are **NOT** really **Python lists**
- They are basically **C arrays**

C type behaviour of Numpy

In [18]:

```
1 arr4 = np.array([1, 2, 3, 4])
2 arr4
```

Out[18]:

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

In [19]:

```
1 arr4 = np.array([1, 2, 3, 4.0])
2 arr4
```

Out[19]:

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

- Because **one single C array** can store values of **only one data type** i.e. homogenous data
- We can specify the datatype of array at time of initialization using `dtype` parameter
 - `**` by default set to `None`

In [20]:

```
1 arr5 = np.array([1, 2, 3, 4])
2 arr5
```

Out[20]:

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

In [21]:

```
1 arr5 = np.array([1, 2, 3, 4], dtype="float")
2 arr5
```

Out[21]:

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

Another way np array behaves like C arrays and not Python lists

- In Python lists, number values can be **arbitrarily large or small**
- There's **usually no overflow of number values**

However, in C, C++ and Java, there's overflow of values

- As soon as a **number crosses the max possible** value for a data-type, the number gets **wrapped around to a smaller value**

In [22]:

```
1 100**10 # no overflow
```

Out[22]:

```
10000000000000000000
```

In [28]:

```
1 arr6 = np.array([0, 100])
2 arr6 ** 10 # 100^10 will overflow
```

Out[28]:

```
array([      0, 1661992960], dtype=int32)
```

Working with 2-D arrays (Matrices)

In [29]:

```
1 m1 = np.array([[1,2,3],[4,5,6]])
2 m1
3 # Nicely printing out in a Matrix form
```

Out[29]:

```
array([[1, 2, 3],
       [4, 5, 6]])
```

How can we check shape of a numpy array?

In [30]:

```
1 m1.shape # arr1 has 3 elements
```

Out[30]:

```
(2, 3)
```

What is the type of this result of `arr1.shape` ? Which data structure is this?

Tuple

Now, What is the dimension of this array?

In [31]:

```
1 m1.ndim
```

Out[31]:

```
2
```

How can we create high dimensional arrays using `reshape()` ?

In [32]:

```
1 m2 = np.arange(1, 13)
2 m2
```

Out[32]:

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12])
```

Can we make `m2` a 4×4 array?

In [33]:

```
1 m2 = np.arange(1, 13)
2 m2.reshape(4, 4)
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-33-fc70b006b379> in <module>
      1 m2 = np.arange(1, 13)
----> 2 m2.reshape(4, 4)
```

ValueError: cannot reshape array of size 12 into shape (4,4)

So, What are the ways in which we can reshape it?

- 4×3
- 3×4
- 6×2
- 2×6
- 1×12
- 12×1

In [34]:

```
1 m2 = np.arange(1, 13)
2 m2.reshape(4, 3)
```

Out[34]:

```
array([[ 1,  2,  3],
       [ 4,  5,  6],
       [ 7,  8,  9],
       [10, 11, 12]])
```

In [42]:

```
1 m2 = np.arange(1, 13)
2 m2
```

Out[42]:

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12])
```

In [43]:

```
1 m2.shape
```

Out[43]:

```
(12,)
```

In [44]:

```
1 m2.reshape(12, 1)
```

Out[44]:

```
array([[ 1],
       [ 2],
       [ 3],
       [ 4],
       [ 5],
       [ 6],
       [ 7],
       [ 8],
       [ 9],
       [10],
       [11],
       [12]])
```

In [45]:

```
1 # no change in original array
2 m2
```

Out[45]:

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12])
```

- (12,) means its a **1D array**
- (12, 1) means its a **2D array** with 12 rows and 1 column

Resize

In [48]:

```
1 c = np.arange(4)
2 c.resize((2,2))
3 c
```

Out[48]:

```
array([[0, 1],
       [2, 3]])
```

In [49]:

```
1 a = np.arange(4)
2 a.resize((2,4))
3 a
```

Out[49]:

```
array([[0, 1, 2, 3],
       [0, 0, 0, 0]])
```

difference between **resize** and **reshape**?

The difference is that it'll add extra zeros to it if shape exceeds number of elements. However, there is a catch: it'll throw an error if array is referenced somewhere and you try resizing it

In [50]:

```
1 b = a
2 a.resize((10,))
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-50-6e04a2659d2b> in <module>
      1 b = a
----> 2 a.resize((10,))
```

ValueError: cannot resize an array that references or is referenced by another array in this way.
Use the np.resize function or refcheck=False

In [13]:

```
1 a = np.array([2,4,5,6])
2 a.resize((10,2))
3 a
```

Out[13]:

```
array([[2, 4],
       [5, 6],
       [0, 0],
       [0, 0],
       [0, 0],
       [0, 0],
       [0, 0],
       [0, 0],
       [0, 0],
       [0, 0]])
```

Transpose

- Change rows into columns and columns into rows

In [51]:

```
1 a = np.arange(3)
2 a
```

Out[51]:

```
array([0, 1, 2])
```

In [52]:

```
1 a.T
```

Out[52]:

```
array([0, 1, 2])
```

Why did Transpose did not work?

- numpy sees `a` as a vector (3,), NOT a matrix.

In [53]:

```
1 a = np.arange(3).reshape(1, 3) #reshape vector to a matrix
2 a
3 # Now a has dimensions (1, 3) instead of just (3,)
4 # It has 1 row and 3 columns
```

Out[53]:

```
array([[0, 1, 2]])
```

In [54]:

```
1 a.T
2 # It has 3 rows and 1 column
```

Out[54]:

```
array([[0],
       [1],
       [2]])
```

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Flattening of an array

In [55]:

```
1 A = np.arange(12).reshape(3, 4)
2 A
```

Out[55]:

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [56]:

```
1 A.flatten()
```

Out[56]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

In [57]:

```
1 A
```

Out[57]:

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

convert a matrix to 1D array using reshape()

What should I pass in A.reshape() if I want to use it to convert A to 1D vector?

- (1, 1)?

In [58]:

```
1 A.reshape(1, 1)
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-58-902e5c35e0d3> in <module>
----> 1 A.reshape(1, 1)
```

ValueError: cannot reshape array of size 12 into shape (1,1)

- So, (1, 12)?

In [59]:

```
1 A.reshape(1, 12)
```

Out[59]:

```
array([[ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]])
```

- We need a vector of dimension (12,). So, we need to pass only 1 dimension.

In [60]:

```
1 A.reshape(12)
```

Out[60]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

What will happen if we pass a negative integer in reshape() ?

In [61]:

```
1 A.reshape(6, -1)
```

Out[61]:

```
array([[ 0,  1],
       [ 2,  3],
       [ 4,  5],
       [ 6,  7],
       [ 8,  9],
       [10, 11]])
```

- Since **no. of elements in our matrix is 12** and **we passed 6 as no. of rows**, it is **able to figure out** that **no. of columns should be 2**

In [62]:

```
1 A.reshape(-1, 6)
```

Out[62]:

```
array([[ 0,  1,  2,  3,  4,  5],
       [ 6,  7,  8,  9, 10, 11]])
```

Special arrays using Numpy

numpy array with all zeros

In [63]:

```
1 np.zeros(3)
2 # Pass in how many values you need in array
3 # All values will be zeroes
```

Out[63]:

```
array([0., 0., 0.])
```

In [64]:

```
1 np.zeros((2, 3))
```

Out[64]:

```
array([[0., 0., 0.],
       [0., 0., 0.]])
```

numpy array with all ones

In [65]:

```
1 # Just like np.zeros, but initialize all values to 1
2 np.ones(3)
```

Out[65]:

```
array([1., 1., 1.])
```

In [66]:

```
1 # 2D
2 np.ones((2,3))
```

Out[66]:

```
array([[1., 1., 1.],
       [1., 1., 1.]])
```

Now, do we need np.twos(), np.threes(), np.fours(), np.hundreds() ?

- We can just create array using np.ones() and multiply with required value

In [67]:

```
1 np.ones((2, 3)) * 5
```

Out[67]:

```
array([[5., 5., 5.],
       [5., 5., 5.]])
```

Datatype of special arrays

In [68]:

```
1 a = np.zeros((2,2))
2 a
```

Out[68]:

```
array([[0., 0.],
       [0., 0.]])
```

In [69]:

```
1 a.dtype
```

Out[69]:

```
dtype('float64')
```

It by defaults creates array with dtype float

Diagonal matrices

In [70]:

```
1 np.diag([1, 2, 3])
2 # We pass values for diagonal elements as a List
3 # ALL other elements are zero
```

Out[70]:

```
array([[1, 0, 0],
       [0, 2, 0],
       [0, 0, 3]])
```

Identity matrix

square matrix where all diagonal values are 1 and All non-diagonal values are 0

In [71]:

```
1 np.identity(3)
2 # Pass in the single dimension of required square identity matrix
```

Out[71]:

```
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

Indexing and Slicing upon Numpy arrays

In [72]:

```
1 m1 = np.arange(12)
2 m1
```

Out[72]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

Indexing in np arrays

In [73]:

```
1 m1[0] # gives first element of array
```

Out[73]:

```
0
```

In [74]:

```
1 m1[12] # out of index Error
```

```
-----
IndexError                                Traceback (most recent call last)
<ipython-input-74-24d969f9df5e> in <module>
----> 1 m1[12] # out of index Error
```

IndexError: index 12 is out of bounds for axis 0 with size 12

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In [75]:

```
1 m1 = np.arange(1,10).reshape((3,3))
```

In [76]:

```
1 m1
```

Out[76]:

```
array([[1, 2, 3],
       [4, 5, 6],
       [7, 8, 9]])
```

In [77]:

```
1 m1[1][2]
```

Out[77]:

6

In [78]:

```
1 m1[1, 2] #m1[row, column] (another way of indexing using comma)
```

Out[78]:

6

list of indexes in numpy

In [79]:

```
1 m1 = np.array([100,200,300,400,500,600])
```

In [81]:

```
1 m1[[2,3,4,1,2,2]]
```

Out[81]:

```
array([300, 400, 500, 200, 300, 300])
```

List of indexes in 2D array

In [82]:

```
1 import numpy as np
```

In [83]:

```
1 m1 = np.arange(9).reshape((3,3))
```

In [84]:

```
1 m1
```

Out[84]:

```
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

In [85]:

```
1 m1[[0,1,2],[0,1,2]] # picking up element (0,0), (1,1) and (2,2)
```

Out[85]:

```
array([0, 4, 8])
```

Slicing

In [86]:

```
1 m1 = np.arange(12)
2 m1
```

Out[86]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

Processing math: 100%

In [87]:

```
1 m1[:5]
```

Out[87]:

```
array([0, 1, 2, 3, 4])
```

Can we just get this much of our array m1 ?

```
[[5, 6],  
 [9, 10]]
```

Remember our m1 is:

```
m1 = [[0, 1, 2, 3],  
      [4, 5, 6, 7],  
      [8, 9, 10, 11]]
```

In [88]:

```
1 m1 = np.arange(12).reshape(3,4)
```

In [89]:

```
1 # First get rows 1 to all  
2 # Then get columns 1 to 3 (not included)  
3 m1[1:, 1:3]
```

Out[89]:

```
array([[ 5,  6],  
       [ 9, 10]])
```

What if I want this much part?

```
[[2, 3],  
 [6, 7],  
 [10,11]]
```

In [90]:

```
1 # First get all rows  
2 # Then get columns 2 to all  
3  
4 m1[:, 2:]
```

Out[90]:

```
array([[ 2,  3],  
       [ 6,  7],  
       [10, 11]])
```

What if I need 1st and 3rd column?

```
[[1, 3],  
 [5, 7],  
 [9,11]]
```

In [91]:

```
1 # Get all rows  
2 # Then get columns from 1 to all with step of 2  
3  
4 m1[:, 1::2]
```

Out[91]:

```
array([[ 1,  3],  
       [ 5,  7],  
       [ 9, 11]])
```

In [92]:

```

1 # Get all rows
2 # Then get columns 1 and 3
3
4 m1[:, (1,3)] #can also pass indices of required columns as a tuple to get the sam result

```

Out[92]:

```

array([[ 1,  3],
       [ 5,  7],
       [ 9, 11]])

```

Fancy indexing (Masking)

- Numpy arrays can be indexed with boolean arrays (masks).
- It creates copies not views.

In [93]:

```

1 m1 = np.arange(12).reshape(3, 4)
2 m1 < 6

```

Out[93]:

```

array([[ True,  True,  True,  True],
       [ True,  True, False, False],
       [False, False, False, False]])

```

In [94]:

```

1 m1[m1 < 6]
2 # Value corresponding to True is retained
3 # Value corresponding to False is filtered out

```

Out[94]:

```
array([0, 1, 2, 3, 4, 5])
```

In [95]:

```
1 m1
```

Out[95]:

```

array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

```

In [96]:

```
1 m1[m1%2 == 0]
```

Out[96]:

```
array([ 0,  2,  4,  6,  8, 10])
```

Takeaway?

Matrix gets converted into a 1D array after masking because the filtering operation **implicitly converts high-dimensional array into 1D array** as it **cannot retain its 3×4 with lesser number of elements**

Multiple filter conditions

In [97]:

```
1 a = np.arange(11)
```

In [98]:

```
1 a[(a %2 == 0) | (a%5 == 0)] # filter elements which are multiple of 2 or 3
```

Out[98]:

```
array([ 0,  2,  4,  5,  6,  8, 10])
```

Aggregate / Universal Functions (ufunc)

Numpy universal functions are objects that belongs to `numpy.ufunc` class.

• Some ufuncs are called automatically when the corresponding "arithmetic operator" is used on arrays.

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For example:

- When **addition of two array** is performed **element-wise** using **+** operator, then **np.add()** is called internally.

In [99]:

```
1 a = np.array([1,2,3,4])
2 b = np.array([5,6,7,8])
3 a+b # ufunc `np.add()` called automatically
```

Out[99]:

```
array([ 6,  8, 10, 12])
```

In [100]:

```
1 np.add(a,b)
```

Out[100]:

```
array([ 6,  8, 10, 12])
```

Aggregate Functions/ Reduction functions

np.sum()

In [101]:

```
1 a = np.arange(12).reshape(3, 4)
2 a
```

Out[101]:

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [102]:

```
1 np.sum(a) # sums all the values present in array
```

Out[102]:

```
66
```

We can do row-wise and column-wise sum by setting axis parameter

- **axis = 0** ---> **Changes will happen along the vertical axis**
- Summing of values happen **in the vertical direction**

In [103]:

```
1 np.sum(a, axis=0)
```

Out[103]:

```
array([12, 15, 18, 21])
```

- **axis = 1** ---> **Changes will happen along the horizontal axis**
- Summing of values happen **in the horizontal direction**

In [104]:

```
1 np.sum(a, axis=1)
```

Out[104]:

```
array([ 6, 22, 38])
```

np.mean()

In [105]:

```
1 np.mean(a)
```

Out[105]:

5.5

In [106]:

```
1 np.mean(a, axis=0)
```

Out[106]:

array([4., 5., 6., 7.])

In [107]:

```
1 np.mean(a, axis=1)
```

Out[107]:

array([1.5, 5.5, 9.5])

np.min()

In [108]:

```
1 a
```

Out[108]:

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [109]:

```
1 np.min(a)
```

Out[109]:

0

In [110]:

```
1 np.min(a, axis = 1 )
```

Out[110]:

array([0, 4, 8])

np.max()

In [111]:

```
1 a
```

Out[111]:

```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [112]:

```
1 np.max(a) # maximum value
```

Out[112]:

11

In [113]:

```
1 np.max(a, axis = 0) # column wise max
```

Out[113]:

array([8, 9, 10, 11])

Logical functions

In [114]:

```
1 a = np.array([1,2,3,4])
2 a
```

Out[114]:

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

np.any()

- any() returns True if **any of the elements** in the argument array is **non-zero**.

In [115]:

```
1 np.any([True, True, False])
```

Out[115]:

```
True
```

In [116]:

```
1 a = np.array([1,2,3,4]) # at least 1 element is non-zero
2 np.any(a)
```

Out[116]:

```
True
```

In [117]:

```
1 a = np.array([1,0,0,0]) # at least 1 element is non-zero
2 np.any(a)
```

Out[117]:

```
True
```

In [118]:

```
1 a = np.zeros(4) # all elements are zero
2 np.any(a)
```

Out[118]:

```
False
```

- any() returns True if **any of the corresponding elements** in the argument arrays follow the **provided condition**.

In [119]:

```
1 a = np.array([1,2,3,4])
2 b = np.array([4,3,2,1])
3 np.any(a<b) # At least 1 element in a < corresponding element in b
```

Out[119]:

```
True
```

In [120]:

```
1 a = np.array([4,5,6,7])
2 b = np.array([4,3,2,1])
3 np.any(a<b) # ALL elements in a >= corresponding elements in b
```

Out[120]:

```
False
```

np.all()

In [121]:

```
1 a = np.array([1,2,3,4])
2 b = np.array([4,3,2,1])
3 a, b
```

Out[121]:

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

Processing math: 100%

In [122]:

```
1 np.all(a<b) # Not all elements in a < corresponding elements in b
```

Out[122]:

False

In [123]:

```
1 a = np.array([1,0,0,0])
2 b = np.array([4,3,2,1])
3 np.all(a<b) # All elements in a < corresponding elements in b
```

Out[123]:

True

Multiple conditions for .all() function

In [124]:

```
1 a = np.array([1, 2, 3, 2])
2 b = np.array([2, 2, 3, 2])
3 c = np.array([6, 4, 4, 5])
4 ((a <= b) & (b <= c)).all()
```

Out[124]:

True

Sorting Arrays

- Default axis for sorting is the last axis of the array.

np.sort()

- Returns a **sorted copy of an array**.

In [125]:

```
1 a = np.array([2,30,41,7,17,52])
2 a
```

Out[125]:

array([2, 30, 41, 7, 17, 52])

In [126]:

```
1 np.sort(a)
```

Out[126]:

array([2, 7, 17, 30, 41, 52])

In [127]:

```
1 a
```

Out[127]:

array([2, 30, 41, 7, 17, 52])

In [128]:

```
1 arr = np.arange(12,0,-1).reshape(4,3)
```

In [129]:

```
1 arr
```

Out[129]:

```
array([[12, 11, 10],
       [ 9,  8,  7],
       [ 6,  5,  4],
       [ 3,  2,  1]])
```

In [130]:

```
1 np.sort(arr)
```

Out[130]:

```
array([[10, 11, 12],
       [ 7,  8,  9],
       [ 4,  5,  6],
       [ 1,  2,  3]])
```

np.argsort()

- Returns the **indices** that would sort an array.

In [131]:

```
1 a = np.array([2,30,41,7,17,52])
2 a
```

Out[131]:

```
array([ 2, 30, 41,  7, 17, 52])
```

In [132]:

```
1 np.argsort(a)
```

Out[132]:

```
array([0, 3, 4, 1, 2, 5], dtype=int64)
```

Use Case: Fitness data analysis

In [133]:

```
1 !gdown 1kXqcJo4YzmfF1G2BPoA17CI49TZVHANF
```

'gdown' is not recognized as an internal or external command,
operable program or batch file.

In [134]:

```
1 data = np.loadtxt('fitness.txt', dtype='str')
```

In [135]:

```
1 data[:5]
```

Out[135]:

```
array([[ '06-10-2017', '5464', '200', '181', '5', '0', '66'],
       [ '07-10-2017', '6041', '100', '197', '8', '0', '66'],
       [ '08-10-2017', '25', '100', '0', '5', '0', '66'],
       [ '09-10-2017', '5461', '100', '174', '4', '0', '66'],
       [ '10-10-2017', '6915', '200', '223', '5', '500', '66']],
      dtype='<U10')
```

What's the shape of the data?

In [136]:

```
1 data.shape
```

Out[136]:

```
(96, 7)
```

There are 96 records and each record has 7 features. These features are:

- Date
- Step count
- Mood
- Calories Burned
- Hours of sleep
- activity status
- weight

In [137]:

```
1 data[0]
```

Out[137]:

```
array(['06-10-2017', '5464', '200', '181', '5', '0', '66'], dtype='<U10')
```

Whats the way to change columns to rows and rows to columns?

Transpose

In [138]:

```
1 data.T[0]
```

Out[138]:

```
array(['06-10-2017', '07-10-2017', '08-10-2017', '09-10-2017',
      '10-10-2017', '11-10-2017', '12-10-2017', '13-10-2017',
      '14-10-2017', '15-10-2017', '16-10-2017', '17-10-2017',
      '18-10-2017', '19-10-2017', '20-10-2017', '21-10-2017',
      '22-10-2017', '23-10-2017', '24-10-2017', '25-10-2017',
      '26-10-2017', '27-10-2017', '28-10-2017', '29-10-2017',
      '30-10-2017', '31-10-2017', '01-11-2017', '02-11-2017',
      '03-11-2017', '04-11-2017', '05-11-2017', '06-11-2017',
      '07-11-2017', '08-11-2017', '09-11-2017', '10-11-2017',
      '11-11-2017', '12-11-2017', '13-11-2017', '14-11-2017',
      '15-11-2017', '16-11-2017', '17-11-2017', '18-11-2017',
      '19-11-2017', '20-11-2017', '21-11-2017', '22-11-2017',
      '23-11-2017', '24-11-2017', '25-11-2017', '26-11-2017',
      '27-11-2017', '28-11-2017', '29-11-2017', '30-11-2017',
      '01-12-2017', '02-12-2017', '03-12-2017', '04-12-2017',
      '05-12-2017', '06-12-2017', '07-12-2017', '08-12-2017',
      '09-12-2017', '10-12-2017', '11-12-2017', '12-12-2017',
      '13-12-2017', '14-12-2017', '15-12-2017', '16-12-2017',
      '17-12-2017', '18-12-2017', '19-12-2017', '20-12-2017',
      '21-12-2017', '22-12-2017', '23-12-2017', '24-12-2017',
      '25-12-2017', '26-12-2017', '27-12-2017', '28-12-2017',
      '29-12-2017', '30-12-2017', '31-12-2017', '01-01-2018',
      '02-01-2018', '03-01-2018', '04-01-2018', '05-01-2018',
      '06-01-2018', '07-01-2018', '08-01-2018', '09-01-2018'],
      dtype='<U10')
```

In [42]:

```
1 #x = np.ones((5,5))
2 x = np.array([[2,6,4,9,6],[2,3,4,5,6],[2,3,4,5,6],[2,3,4,5,6],[2,8,4,7,6]])
3 x[1:-1,1:-1]
```

Out[42]:

```
array([[3, 4, 5],
      [3, 4, 5],
      [3, 4, 5]])
```

In [44]:

```
1 import numpy as np
2
3 def update_height(height,delta):
4
5     height = np.array(height)
6
7     delta = np.array(delta)
8
9     new_height = height+delta
10
11     return new_height
12 height = [3,4,5,6]
13 delta = [4,5,6,6]
14 update_height(height,delta)
```

Out[44]:

```
array([ 7,  9, 11, 12])
```

In [46]:

```
1 def update_height(hight, delta):
2     new_height=[]
3     for i in range(len(height)):
4         new_height.append(height[i]+delta[i])
5     return new_height
6
7 height = [3,4,5,6]
8 delta = [4,5,6,6]
9 update_height(height,delta)
```

Out[46]:

```
[7, 9, 11, 12]
```

In [143]:

```
1 (data.T)
```

[illegible]

In [139]:

```
1 date, step_count, mood, calories_burned, hours_of_sleep, activity_status, weight = data.T
```

In [144]:

```
1 step_count
```

Out[144]:

```
array(['5464', '6041', '25', '5461', '6915', '4545', '4340', '1230', '61',  
      '1258', '3148', '4687', '4732', '3519', '1580', '2822', '181',  
      '3158', '4383', '3881', '4037', '202', '292', '330', '2209',  
      '4550', '4435', '4779', '1831', '2255', '539', '5464', '6041',  
      '4068', '4683', '4033', '6314', '614', '3149', '4005', '4880',  
      '4136', '705', '570', '269', '4275', '5999', '4421', '6930',  
      '5195', '546', '493', '995', '1163', '6676', '3608', '774', '1421',  
      '4064', '2725', '5934', '1867', '3721', '2374', '2909', '1648',  
      '799', '7102', '3941', '7422', '437', '1231', '1696', '4921',  
      '221', '6500', '3575', '4061', '651', '753', '518', '5537', '4108',  
      '5376', '3066', '177', '36', '299', '1447', '2599', '702', '133',  
      '153', '500', '2127', '2203'], dtype='<U10')
```

In [145]:

```
1 step_count.dtype
```

Out[145]:

```
dtype('<U10')
```

Because Numpy type-casted all the data to strings. It's a string type where U means Unicode String. and 10 means 10 bytes.

Step Count

In [146]:

```
1 step_count = np.array(step_count, dtype = 'int')  
2 step_count.dtype
```

Out[146]:

```
dtype('int32')
```

In [147]:

```
1 step_count
```

Out[147]:

```
array([5464, 6041, 25, 5461, 6915, 4545, 4340, 1230, 61, 1258, 3148,  
      4687, 4732, 3519, 1580, 2822, 181, 3158, 4383, 3881, 4037, 202,  
      292, 330, 2209, 4550, 4435, 4779, 1831, 2255, 539, 5464, 6041,  
      4068, 4683, 4033, 6314, 614, 3149, 4005, 4880, 4136, 705, 570,  
      269, 4275, 5999, 4421, 6930, 5195, 546, 493, 995, 1163, 6676,  
      3608, 774, 1421, 4064, 2725, 5934, 1867, 3721, 2374, 2909, 1648,  
      799, 7102, 3941, 7422, 437, 1231, 1696, 4921, 221, 6500, 3575,  
      4061, 651, 753, 518, 5537, 4108, 5376, 3066, 177, 36, 299,  
      1447, 2599, 702, 133, 153, 500, 2127, 2203])
```

Calories Burned

In [148]:

```
1 calories_burned = np.array(calories_burned, dtype = 'int')  
2 calories_burned.dtype
```

Out[148]:

```
dtype('int32')
```

Hours of Sleep

In [149]:

```
1 hours_of_sleep = np.array(hours_of_sleep, dtype = 'int')  
2 hours_of_sleep.dtype
```

Out[149]:

```
dtype('int32')
```

Weight

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In [150]:

```
1 weight = np.array(weight, dtype = 'int')
2 weight.dtype
```

Out[150]:

dtype('int32')

Mood

Mood is a categorical data type

In [151]:

```
1 mood
```

Out[151]:

```
array(['200', '100', '100', '100', '200', '100', '100', '100', '100',
       '100', '100', '100', '300', '100', '100', '100', '100', '200',
       '200', '200', '200', '200', '200', '300', '200', '300', '300',
       '300', '300', '300', '300', '300', '200', '300', '300', '300',
       '300', '300', '300', '300', '300', '300', '300', '200', '300',
       '300', '300', '300', '300', '300', '300', '300', '200',
       '100', '300', '300', '300', '300', '300', '300', '300', '100',
       '200', '200', '100', '100', '200', '200', '300', '200', '200',
       '100', '200', '100', '200', '200', '100', '100', '100', '100',
       '300', '200', '300', '200', '100', '100', '100', '200', '200',
       '100', '100', '300', '200', '200', '300'], dtype='<U10')
```

In [152]:

```
1 np.unique(mood)
```

Out[152]:

```
array(['100', '200', '300'], dtype='<U10')
```

In [153]:

```
1 mood[mood == '300'] = 'Happy'
```

In [154]:

```
1 mood[mood == '200'] = 'Neutral'
```

In [155]:

```
1 mood[mood == '100'] = 'Sad'
```

In [156]:

```
1 mood
```

Out[156]:

```
array(['Neutral', 'Sad', 'Sad', 'Sad', 'Neutral', 'Sad', 'Sad', 'Sad',
       'Sad', 'Sad', 'Sad', 'Sad', 'Sad', 'Happy', 'Sad', 'Sad', 'Sad', 'Sad',
       'Neutral', 'Neutral', 'Neutral', 'Neutral', 'Neutral', 'Neutral',
       'Happy', 'Neutral', 'Happy', 'Happy', 'Happy', 'Happy', 'Happy',
       'Happy', 'Happy', 'Neutral', 'Happy', 'Happy', 'Happy', 'Happy',
       'Happy', 'Happy', 'Happy', 'Happy', 'Happy', 'Happy', 'Neutral',
       'Happy', 'Happy', 'Happy', 'Happy', 'Happy', 'Happy', 'Happy',
       'Happy', 'Happy', 'Neutral', 'Sad', 'Happy', 'Happy', 'Happy',
       'Happy', 'Happy', 'Happy', 'Happy', 'Sad', 'Neutral', 'Neutral',
       'Sad', 'Sad', 'Neutral', 'Neutral', 'Happy', 'Neutral', 'Neutral',
       'Sad', 'Neutral', 'Sad', 'Neutral', 'Neutral', 'Sad', 'Sad', 'Sad',
       'Sad', 'Happy', 'Neutral', 'Happy', 'Neutral', 'Sad', 'Sad', 'Sad',
       'Neutral', 'Neutral', 'Sad', 'Sad', 'Happy', 'Neutral', 'Neutral',
       'Happy'], dtype='<U10')
```

Activity Status

Here 0 means Feeling of inactiveness

500 means Feeling of activeness

In [164]:

```
1 calories_burned[step_count.argmax()]
```

Out[164]:

243

Let's try to get the number of steps on that day as well

In [165]:

```
1 step_count.max()
```

Out[165]:

7422

What's the most frequent mood ?

One approach is for each of the category we get count of record and see which one is the highest

In [166]:

```
1 mood[mood == 'Sad'].shape
```

Out[166]:

(29,)

In [167]:

```
1 mood[mood == 'Neutral'].shape
```

Out[167]:

(27,)

In [168]:

```
1 mood[mood == 'Happy'].shape
```

Out[168]:

(40,)

Another approach:

In [169]:

```
1 np.unique(mood)
```

Out[169]:

```
array(['Happy', 'Neutral', 'Sad'], dtype='<U10')
```

We can get the count by passing in the parameter `return_counts = True`

In [170]:

```
1 np.unique(mood, return_counts = True)
```

Out[170]:

```
(array(['Happy', 'Neutral', 'Sad'], dtype='<U10'),  
 array([40, 27, 29], dtype=int64))
```

The most frequent mood is Happy :)

Comparing step counts on bad mood days and good mood days

Average step count on Sad mood days

In [171]:

```
1 np.mean(step_count[mood == 'Sad'])
```

Out[171]:

2103.0689655172414

In [172]:

```
1 np.sort(step_count[mood == 'Sad'])
```

Out[172]:

```
array([ 25,  36,  61, 133, 177, 181, 221, 299, 518, 651, 702,
       753, 799, 1230, 1258, 1580, 1648, 1696, 2822, 3148, 3519, 3721,
      4061, 4340, 4545, 4687, 5461, 6041, 6676])
```

In [173]:

```
1 np.std(step_count[mood == 'Sad'])
```

Out[173]:

```
2021.2355035376254
```

Average step count on happy days

In [174]:

```
1 np.mean(step_count[mood == 'Happy'])
```

Out[174]:

```
3392.725
```

In [175]:

```
1 np.sort(step_count[mood == 'Happy'])
```

Out[175]:

```
array([ 153,  269,  330,  493,  539,  546,  614,  705,  774,  995, 1421,
      1831, 1867, 2203, 2255, 2725, 3149, 3608, 4005, 4033, 4064, 4068,
      4136, 4275, 4421, 4435, 4550, 4683, 4732, 4779, 4880, 5195, 5376,
      5464, 5537, 5934, 5999, 6314, 6930, 7422])
```

Average step count on sad days - 2103.

Average step count on happy days - 3392

There may be relation between mood and step count

Let's try to check inverse. Mood when step count was greater/lesser

Mood when step count > 4000

In [176]:

```
1 np.unique(mood[step_count > 4000], return_counts = True)
```

Out[176]:

```
(array(['Happy', 'Neutral', 'Sad'], dtype='<U10'),
 array([22,  9,  7], dtype=int64))
```

Out of 38 days when step count was more than 4000, user was feeling happy on 22 days.

Mood when step count <= 2000

In [177]:

```
1 np.unique(mood[step_count < 2000], return_counts = True)
```

Out[177]:

```
(array(['Happy', 'Neutral', 'Sad'], dtype='<U10'),
 array([13,  8, 18], dtype=int64))
```

Out of 39 days, when step count was less than 2000, user was feeling sad on 18 days.

There may be a correlation between Mood and step count