numpy-intro

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1 Numpy Intro

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2 numpy

- In machine learning you will work *a lot* with matrices
- numpy is the de facto standard for matrices in python
- Many other libraries have adopted and extended the API of numpy
  - scipy
  - pandas
  - many deep learning libraries

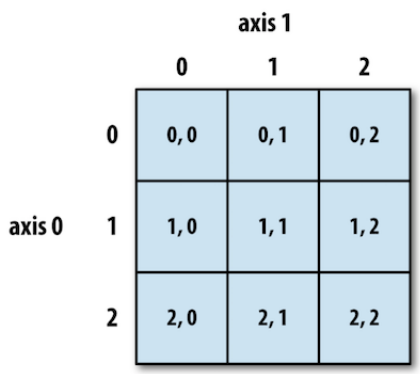
3 numpy is fast

```
In [174]: my_list = list(range(1000000))
          %timeit [x * 2 for x in my_list]

117 ms ś 18.8 ms per loop (mean ś std. dev. of 7 runs, 10 loops each)
```

```
In [2]: import numpy as np
        np.random.seed(0)  # seed for reproducibility
        my_arr = np.arange(1000000)
        %timeit my_arr * 2

668 ţs ś 79.2 ţs per loop (mean ś std. dev. of 7 runs, 1000 loops each)
```

4 Creating Arrays

```
In [4]: np.array([1, 4, 2, 5, 3])

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



Array indexing

4.1 Specifying data types at array creation time

```
In [8]: np.array([1, 2, 3, 4], dtype='float32')

Out[8]: array([1., 2., 3., 4.], dtype=float32)
```

4.2 Creating two-dimensional arrays

```
In [14]: two_d_data = [list(range(i, i + 3)) for i in [2, 4, 6]]
         two_d_data

Out[14]: [[2, 3, 4], [4, 5, 6], [6, 7, 8]]

In [15]: np.array(two_d_data)

Out[15]: array([[2, 3, 4],
                [4, 5, 6],
                [6, 7, 8]])
```

4.3 Creating Arrays from Scratch

```
In [16]: np.zeros(10, dtype=int)

Out[16]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])

In [28]: # Create a 3x5 floating-point array filled with ones
         np.ones((2, 3), dtype=float)

Out[28]: array([[1., 1., 1.],
                [1., 1., 1.]])

In [19]: # something like builtin range function
         np.arange(0, 20, 2)

Out[19]: array([ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18])
```

```
In [20]: # Create an array of five values evenly spaced between 0 and 1
         np.linspace(0, 1, 5)
```

```
Out[20]: array([0.  , 0.25, 0.5 , 0.75, 1.  ])
```

```
In [39]: # Create a 3x3 array of values uniformly distributed between 0 and 1
         np.random.random((2, 3))
```

```
Out[39]: array([[0.5488135 , 0.71518937, 0.60276338],
                [0.54488318, 0.4236548 , 0.64589411]])
```

```
In [41]: # Create a 3x3 array of random integers in the interval [0, 10)
         np.random.randint(0, 10, (2, 3))
```

```
Out[41]: array([[8, 1, 5],
                [9, 8, 9]])
```

4.4 Array Indexing and Slicing

Arrays are indexed like this:

`x[index]`

and sliced like this:

`x[start:stop:step]`

With defaults `start=0`, `stop=`*`size of dimension`*, `step=1`.
Slices are *views* not *copies* (as for Lists)

4.4.1 Two Dimensional Arrays

Items can be accessed using a comma-separated tuple of indices:

```
In [54]: x2
```

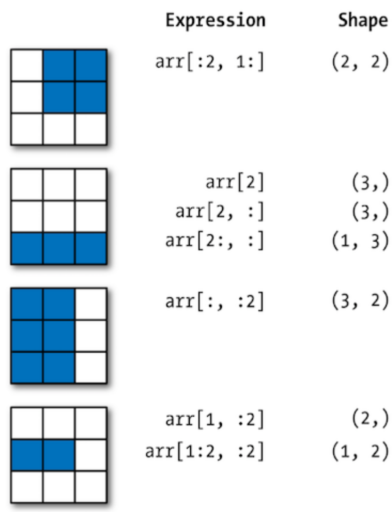
```
Out[54]: array([[1, 5, 3, 9],
                [7, 2, 9, 8],
                [5, 0, 2, 8]])
```

```
In [55]: x2[0, 0]
```

```
Out[55]: 1
```

```
In [56]: x2[2,-1]
```

```
Out[56]: 8
```



Array indexing

4.4.2 Slicing Two Dimensional Arrays

Same as with lists and one-dimensional arrays:

```
In [57]: x2

Out[57]: array([[1, 5, 3, 9],
                [7, 2, 9, 8],
                [5, 0, 2, 8]])

In [58]: x2[0,:] # entire first row

Out[58]: array([1, 5, 3, 9])

In [59]: x2[0] # same as x2[0, :]

Out[59]: array([1, 5, 3, 9])

In [60]: x2[:,0] # entire first column

Out[60]: array([1, 7, 5])
```

4.5 Boolean Indexing

You can efficiently index arrays using boolean masks

```
In [116]: grid = np.arange(1, 10)
          grid

Out[116]: array([1, 2, 3, 4, 5, 6, 7, 8, 9])

In [115]: grid > 5

Out[115]: array([False, False, False, False, False,  True,  True,  True,  True])

In [117]: grid[grid > 5]

Out[117]: array([6, 7, 8, 9])
```

4.6 Fancy Indexing

Can give you arbitrary subsets of arrays given a set of indices

```
In [118]: x = np.random.randint(100, size=10)
          print(x)

[24 80 66 27 81 70 35 67 65 88]


In [119]: [x[1], x[4]]

Out[119]: [80, 81]

In [123]: ind = [1,4]
          x[ind]

Out[123]: array([80, 81])
```

5 Reshaping

Often you need to change the shape of an array; this is done with `reshape`

```
In [67]: grid = np.arange(1, 10)
         grid

Out[67]: array([1, 2, 3, 4, 5, 6, 7, 8, 9])

In [68]: grid = grid.reshape((3, 3))
         grid

Out[68]: array([[1, 2, 3],
                [4, 5, 6],
                [7, 8, 9]])

In [69]: row_vector = np.arange(3).reshape((1, 3))
         row_vector

Out[69]: array([[0, 1, 2]])

In [70]: column_vector = np.arange(3).reshape((3, 1))
         column_vector

Out[70]: array([[0],
                [1],
                [2]])
```

6 Broadcasting

In [5]:
```
# elementwise addition
a = np.array([0, 1, 2])
a + 5
```

Out[5]:
```
array([5, 6, 7])
```

In [6]:
```
# elementwise addition
b = np.array([5, 5, 5])
a + b
```

Out[6]:
```
array([5, 6, 7])
```

In [7]:
```
M = np.ones((3, 3))
M
```

Out[7]:
```
array([[1., 1., 1.],
       [1., 1., 1.],
       [1., 1., 1.]])
```

In [8]:
```
M + a
```

Out[8]:
```
array([[1., 2., 3.],
       [1., 2., 3.],
       [1., 2., 3.]])
```

In [10]:
```
b = np.array([5, 5, 5]).reshape((3,1))
b
```

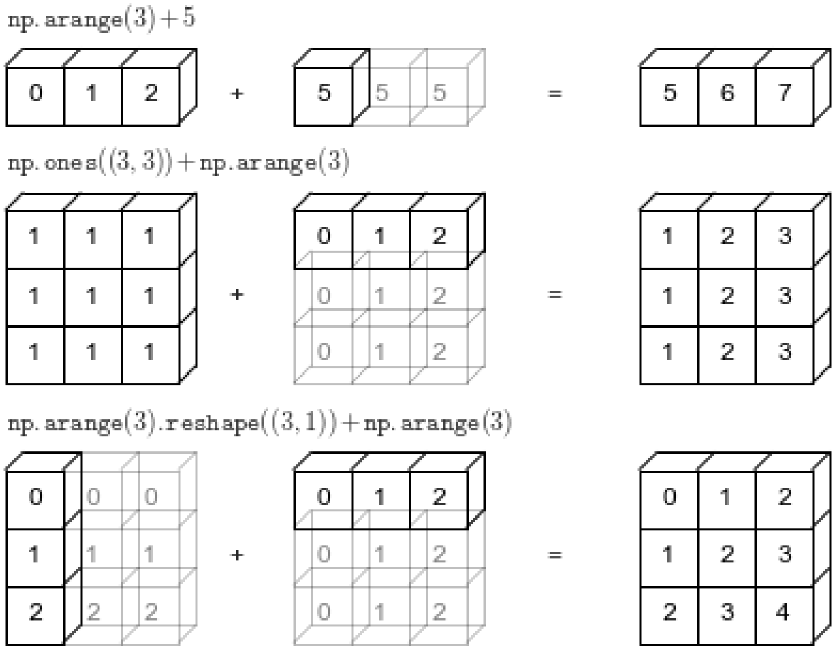
Out[10]:
```
array([[5],
       [5],
       [5]])
```

In [13]:
```
a + b
```

Out[13]:
```
array([[5, 6, 7],
       [5, 6, 7],
       [5, 6, 7]])
```

In [15]:
```
c = np.array([2,3])
a + c
```

```
---------------------------------------------------------------------------

ValueError                                Traceback (most recent call last)

<ipython-input-15-ce668e4220e4> in <module>
  1 c = np.array([2,3])
```



Broadcasting Visual

```
----> 2 a + c


    ValueError: operands could not be broadcast together with shapes (3,) (2,)
```

```
In [17]: a.reshape((3,1))

Out[17]: array([[0],
                [1],
                [2]])

In [18]: a.reshape((3,1)) + c

Out[18]: array([[2, 3],
                [3, 4],
                [4, 5]])
```

7 Fast Vectorized Computations with UFuncs

- Python's defacult implementation CPython is slow for repeated executions
- This is mostly due to the fact that it's not compiled down to bytecode
- Major Bottlenecks are: type-checking and function dispatches
- `numpy` is fast since it allows to *vectorize* operations through NumPy's *universal functions* (ufuncs)
- For many tasks you can use plain python and `numpy` for efficient computations

7.1 `ufunc` Arithmetic Operators and Shortcuts

Operator	Equivalent ufunc	Description
`+`	`np.add`	Addition (e.g., `1 + 1 = 2`)
`-`	`np.subtract`	Subtraction (e.g., `3 - 2 = 1`)
`-`	`np.negative`	Unary negation (e.g., `-2`)
`*`	`np.multiply`	Multiplication (e.g., `2 * 3 = 6`)
`/`	`np.divide`	Division (e.g., `3 / 2 = 1.5`)
`//`	`np.floor_divide`	Floor division (e.g., `3 // 2 = 1`)
`**`	`np.power`	Exponentiation (e.g., `2 ** 3 = 8`)
`%`	`np.mod`	Modulus/remainder (e.g., `9 % 4 = 1`)

8 Aggregation Functions

When working with large data sets, aggregations help to understand your data:

- Summing all values
- Min/Max
- Quantiles
- Mean/Median

Again, python itself is slow at that, but `numpy` is fast

```
In [86]: L = np.arange(10)
         L
```

```
Out[86]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
In [87]: sum(L)
```

```
Out[87]: 45
```

```
In [88]: np.sum(L)
```

```
Out[88]: 45
```

Function Name	NaN-safe Version	Description
`np.sum`	`np.nansum`	Compute sum of elements
`np.prod`	`np.nanprod`	Compute product of elements
`np.mean`	`np.nanmean`	Compute mean of elements
`np.std`	`np.nanstd`	Compute standard deviation
`np.var`	`np.nanvar`	Compute variance
`np.min`	`np.nanmin`	Find minimum value
`np.max`	`np.nanmax`	Find maximum value
`np.argmin`	`np.nanargmin`	Find index of minimum value
`np.argmax`	`np.nanargmax`	Find index of maximum value
`np.median`	`np.nanmedian`	Compute median of elements
`np.percentile`	`np.nanpercentile`	Compute rank-based statistics of elements
`np.any`	N/A	Evaluate whether any elements are true
`np.all`	N/A	Evaluate whether all elements are true

8.0.1 Multi dimensional aggregates

```
In [100]: M = np.ones((3, 4))
          M
```

```
Out[100]: array([[1., 1., 1., 1.],
                 [1., 1., 1., 1.],
                 [1., 1., 1., 1.]])
```

```
In [101]: M.sum()
```

```
Out[101]: 12.0
```

```
In [102]: M.sum(axis=0)
```

```
Out[102]: array([3., 3., 3., 3.])
```

```
In [103]: M.sum(axis=1)
```

```
Out[103]: array([4., 4., 4.])
```

8.1 Fast Sorting in NumPy: `np.sort` and `np.argsort`

```
In [124]: np.sort(heights)
```

```
Out[124]: array([163, 168, 168, 170, 170, 171, 173, 173, 173, 173, 174, 175, 175,
                 177, 178, 178, 178, 178, 179, 180, 182, 182, 182, 182, 183, 183,
                 183, 183, 183, 183, 183, 183, 185, 185, 185, 188, 188, 188, 189,
                 189, 193, 193])
```

```
In [125]: heights[heights.argsort()]
```

```
Out[125]: array([163, 168, 168, 170, 170, 171, 173, 173, 173, 173, 174, 175, 175,
                 177, 178, 178, 178, 178, 179, 180, 182, 182, 182, 182, 183, 183,
                 183, 183, 183, 183, 183, 183, 185, 185, 185, 188, 188, 188, 189,
                 189, 193, 193])
```

9 Saving and Loading Arrays

```
In [126]: arr = np.arange(10)
          np.save('some_array', arr)
          loaded_arr = np.load('some_array.npy')
          loaded_arr
```

```
Out[126]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

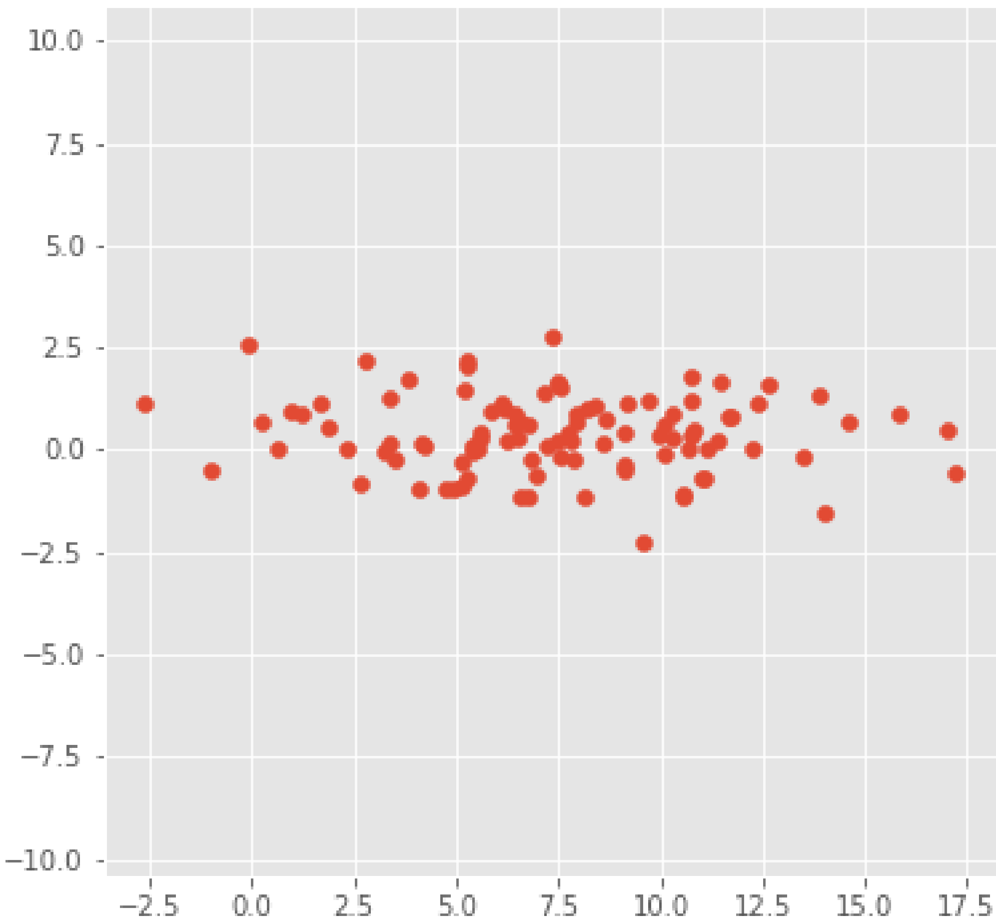
9.1 Matrix Multiplication

```
In [167]: A = np.array([[1,1],[1,1]])
          B = np.array([[2,3],[4,5]])
          A.dot(B)

Out[167]: array([[6, 8],
                 [6, 8]])

In [168]: A @ B

Out[168]: array([[6, 8],
                 [6, 8]])

In [169]: (A @ B).T

Out[169]: array([[6, 6],
                 [8, 8]])
```

10 Visualization

Let's create some toy data:
$X \in R^{100,2} \sim \mathcal{N}(0,1)$

```
In [4]: %matplotlib inline
        import matplotlib.pyplot as plt
        # set some other plotting style
        plt.style.use('ggplot')

        plt.figure(figsize=(6,6))
        X = np.random.randn(100,2)
        # add some offset
        X += np.array([2,.5])
        # scale the first dimension
        X[:,0] *= 4
        plt.scatter(X[:,0],X[:,1]);
        plt.axis('equal');
```


10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5