

Preliminaries

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Linear algebra

Scalars and vectors

▸ Scalars

- integers, real numbers, rational numbers, etc.
- usually denoted by lowercase letters

▸ Vectors

- 1-D array of elements (scalars)

$$\mathbf{x} \in \mathbb{R}^n$$

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

Norms

▸ Functions that measure the **magnitude** (“length”) of a vector

- **strictly positive**, except for the zero vector
- think about the distance between zero and the point represented by the vector

$$f(\mathbf{x}) = 0 \Rightarrow \mathbf{x} = \mathbf{0}$$

$$f(\mathbf{x} + \mathbf{y}) \leq f(\mathbf{x}) + f(\mathbf{y}) \text{ (triangle inequality)}$$

$$\forall \alpha \in \mathbb{R}, f(\alpha \mathbf{x}) = |\alpha| f(\mathbf{x})$$

Norms

$$\ell_1\text{-norm: } \|\mathbf{x}\|_1 = \sum_{i=1}^n |x_i|$$

$$\ell_2\text{-norm: } \|\mathbf{x}\|_2 = \left(\sum_{i=1}^n x_i^2 \right)^{\frac{1}{2}}$$

$$\text{max norm: } \|\mathbf{x}\|_\infty = \max_i |\mathbf{x}_i|$$

Matrices and tensors

Matrices

- 2-D array of elements

$$\begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix}_{m \times n} \quad A \in \mathbb{R}^{m \times n}$$

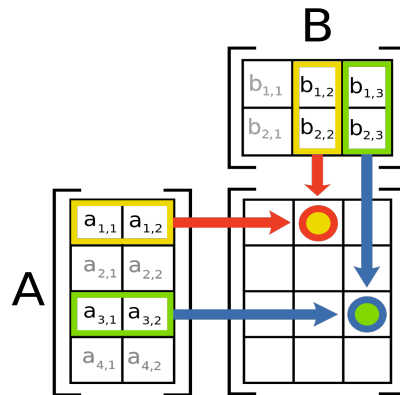
Tensors

- homogeneous arrays that may have **zero or more** dimensions

Matrix multiplication

$$C = AB$$

$$C_{i,j} = \sum_k A_{i,k} B_{k,j}$$



Number of columns in A must be equal to the number of rows in B

https://en.wikipedia.org/wiki/Matrix_multiplication

Dot product

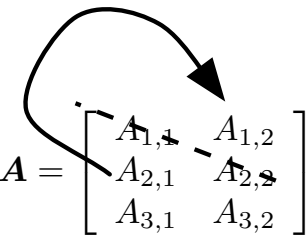
$$\begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$\mathbf{x}^T \mathbf{y} = \sum_{i=1}^n x_i y_i$$

$$\mathbf{x}^T \mathbf{y} = \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta$$

$$\mathbf{x}^T \mathbf{y} \in \mathbb{R}$$

Matrix transpose


$$\mathbf{A} = \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \\ A_{3,1} & A_{3,2} \end{bmatrix} \Rightarrow \mathbf{A}^T = \begin{bmatrix} A_{1,1} & A_{2,1} & A_{3,1} \\ A_{1,2} & A_{2,2} & A_{3,2} \end{bmatrix}$$

$$(\mathbf{A}^T)_{i,j} = A_{j,i} \quad (\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T$$

Identity matrix

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\forall x \in \mathbb{R}^n, \mathbf{I}_n x = x$$

$$\mathbf{A}^{-1} \mathbf{A} = \mathbf{I}_n$$

Special matrices and vectors

▸ Unit vector

$$\|\mathbf{x}\|_2 = 1$$

▸ Symmetric matrix

$$\mathbf{A} = \mathbf{A}^T$$

▸ Orthogonal matrix

$$\mathbf{A}^T \mathbf{A} = \mathbf{A} \mathbf{A}^T = \mathbf{I}$$

$$\mathbf{A}^{-1} = \mathbf{A}^T$$

Python and Tensors

Python basics (must know)

▸ Basic data types

- booleans, integers, floating point values, strings

▸ Control flow

▸ Built-in data structures

- lists, tuples, dictionaries, sets
- iterators

▸ Functions

- functions can be assigned, passed, returned, and stored
- lambda functions (inline and anonymous)

▸ Classes

Numpy

▸ Library for scientific computing

- provides a **high-performance** multidimensional array object and routines for fast operations on these arrays

▸ The **ndarray** object encapsulates n-dimensional arrays of homogeneous data types

- many operations performed as “compiled code” for higher performance
- have a fixed size at creation
- changing the size of an **ndarray** will create a new array and delete the original

```
def dot_python(x, y):
    sum = 0
    for i in range(len(x)):
        sum += x[i] * y[i]
    return sum

def dot_numpy(x, y):
    return np.dot(x, y)

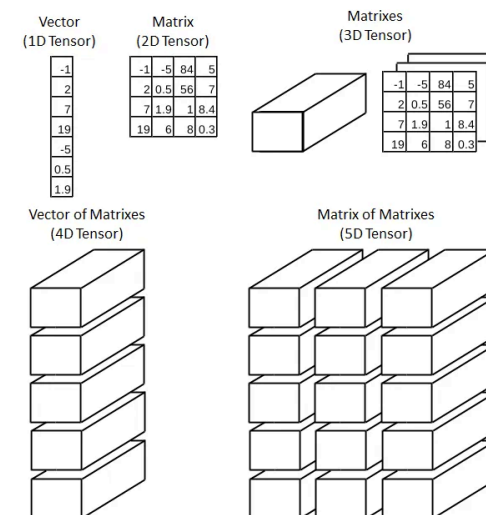
n = 100000000
array1 = np.random.rand(n)
array2 = np.random.rand(n)

time_taken = timeit.timeit(lambda: dot_numpy(array1, array2), number=1)
print(f'Numpy Time: {time_taken} seconds')
Numpy Time: 0.05994947799996453 seconds

array1 = array1.tolist()
array2 = array2.tolist()
time_taken = timeit.timeit(lambda: dot_python(array1, array2), number=1)
print(f'Python Time: {time_taken} seconds')
Python Time: 8.325287125999978 seconds
```

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Tensors



<https://towardsdatascience.com/deep-learning-introduction-to-tensors-tensorflow-36ce3663528f>

The following figures are from “NumPy Illustrated: The Visual Guide to NumPy” by Lev Maximov

<https://betterprogramming.pub/numpy-illustrated-the-visual-guide-to-numpy-3b1d4976de1d>

Elegant code

```
In [3]: a = [1, 2, 3]
        [q*2 for q in a]
```

Out[3]: [2, 4, 6]

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

Out[4]: array([2, 4, 6])

```
In [1]: a = [1, 2, 3]
        b = [4, 5, 6]
        [q+r for q, r in zip(a, b)]
```

Out[1]: [5, 7, 9]

```
In [2]: a = np.array([1, 2, 3])
        b = np.array([4, 5, 6])
        a + b
```

Out[2]: array([5, 7, 9])

Homogeneous and fixed-length

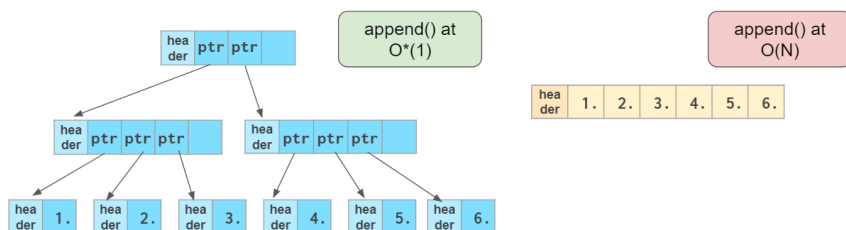
python list

1.	2.	3.
4.	5.	6.

vs

numpy array

1.	2.	3.
4.	5.	6.



Creating numpy arrays

`a = np.array([1., 2., 3.])` →

1.	2.	3.
----	----	----

`.dtype == np.float64`
`.shape == (3,)`

`np.zeros(3)` →

0.	0.	0.
----	----	----

`np.zeros_like(a)` →

0	0	0
---	---	---

`np.ones(3)` →

1.	1.	1.
----	----	----

`np.ones_like(a)` →

1	1	1
---	---	---

`np.empty(3)` →

5e-296	7e-297	1e-296
--------	--------	--------

`np.empty_like(a)` →

54087	1630432036429	6897
398	426	

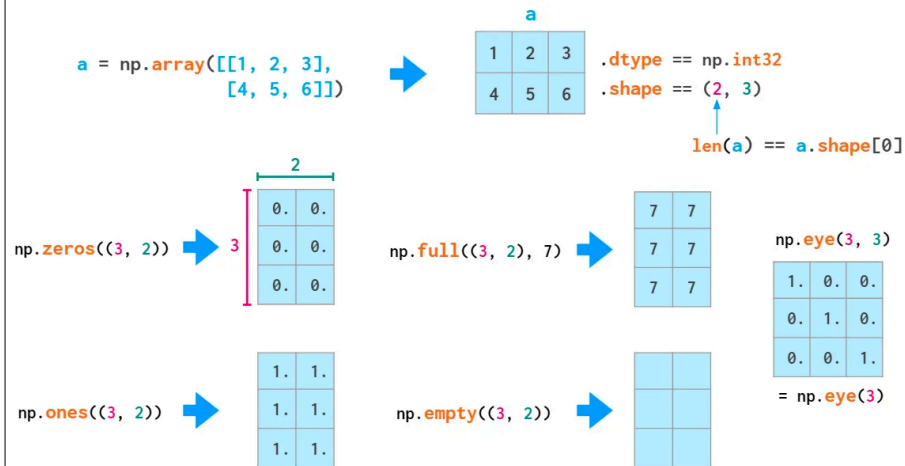
`np.full(3, 7.)` →

7.	7.	7.
----	----	----

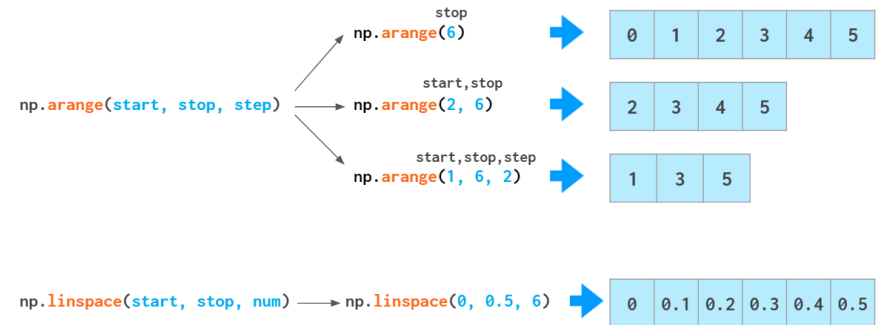
`np.full_like(a, 7)` →

7	7	7
---	---	---

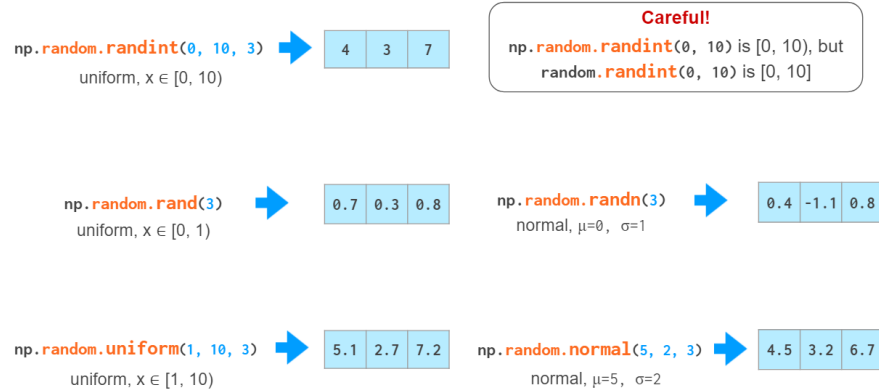
Creating numpy arrays



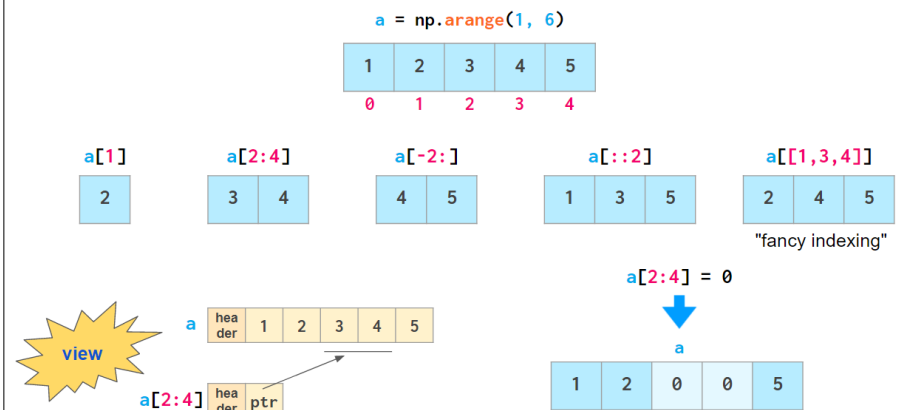
Creating numpy arrays



Creating numpy arrays



Indexing



Careful when making copies

python list	vs	numpy array
<code>a = [1, 2, 3]</code>		<code>a = np.array([1, 2, 3])</code>
<code>b = a</code> # no copy		<code>b = a</code> # no copy
<code>c = a[:]</code> # copy		<code>c = a[:]</code> # no copy!!!
<code>d = a.copy()</code> # copy		<code>d = a.copy()</code> # copy

Boolean indexing

a

1	2	3	4	5	6	7	6	5	4	3	2	1
---	---	---	---	---	---	---	---	---	---	---	---	---

a > 5

False	False	False	False	False	True	True	True	False	False	False	False	False
-------	-------	-------	-------	-------	------	------	------	-------	-------	-------	-------	-------

`np.any(a > 5)` → True

`a[a > 5]`

6	7	6
---	---	---

`np.all(a > 5)` → False

`a[a > 5] = 0`

a

1	2	3	4	5	0	0	0	5	4	3	2	1
---	---	---	---	---	---	---	---	---	---	---	---	---

`a[(a >= 3) & (a <= 5)] = 0`

a

1	2	0	0	0	6	7	6	0	0	0	2	1
---	---	---	---	---	---	---	---	---	---	---	---	---

& and
| or
^ xor
~ not

Vector operations

Element-wise operations

`1 2 + 4 8 = 5 10`

`1 2 - 4 8 = -3 -6`

`4 8 * 2 5 = 8 40`

`4 8 / 2 5 = 2.0 1.6` np.float64

`4 8 // 2 5 = 2 1` np.int32

`3 4 ** 2 3 = 9 64`

Math functions

a^2 = `2 3 ** 2 = 4 9`

\sqrt{a} = `np.sqrt(4 9) = 2. 3.`

e^a = `np.exp(1 2) = 2.72 7.39`

$\ln a$ = `np.log(np.e np.e**2) = 1. 2.`

$\vec{a} \cdot \vec{b}$ = `np.dot(1 2, 3 4) = 11`

$\vec{a} \times \vec{b}$ = `np.cross(2 0 0, 0 3 0) = 0 0 6`

Element-wise operations

Broadcasting scalars

`1 2 + 3 = 4 5`

`1 2 - 3 = -2 -1`

`1 2 * 3 = 3 6`

`1 2 / 3 = 0.33 0.67` np.float64

`1 2 // 2 = 0 1` np.int32

`3 4 ** 2 = 9 16`

`np.max(1 2 3) = 3`

`np.floor(1.1 1.5 1.9 2.5) = 1. 1. 1. 2.`

`np.ceil(1.1 1.5 1.9 2.5) = 2. 2. 2. 3.`

`np.round(1.1 1.5 1.9 2.5) = 1. 2. 2. 2.`

`1 2 3 .max() = 3`

`1 2 3 .min() = 1`

`1 2 3 .sum() = 6`

`1 2 3 .var() = 0.67`

`1 2 3 .argmax() = 2`

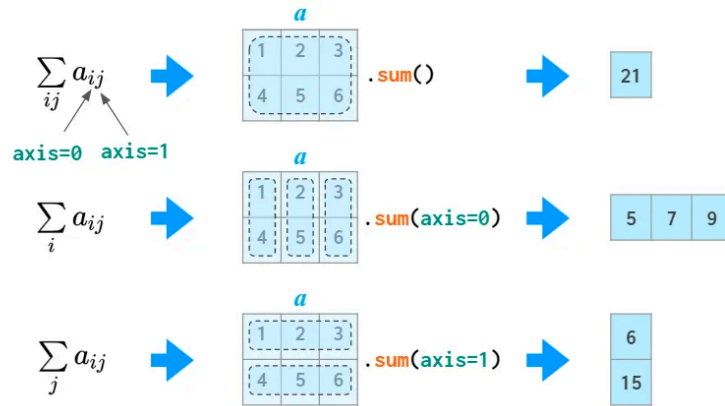
`1 2 3 .argmin() = 0`

`1 2 3 .mean() = 2`

`1 2 3 .std() = 0.82`

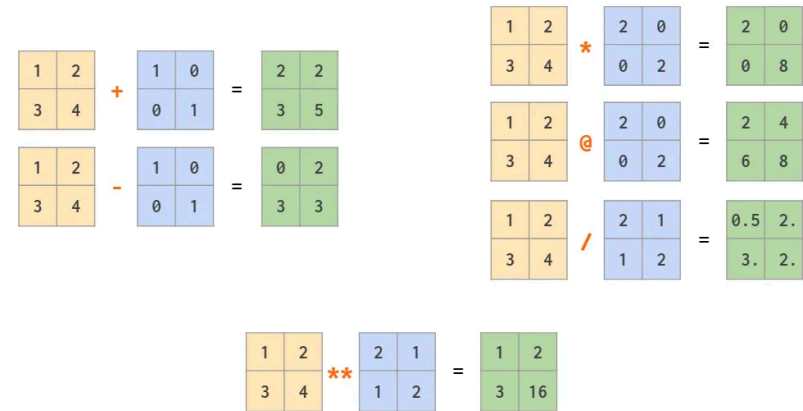
$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ $\bar{x}^2 = \frac{1}{n} \sum_{i=1}^n x_i^2$ $s^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$ $s = \sqrt{s^2}$

The axis



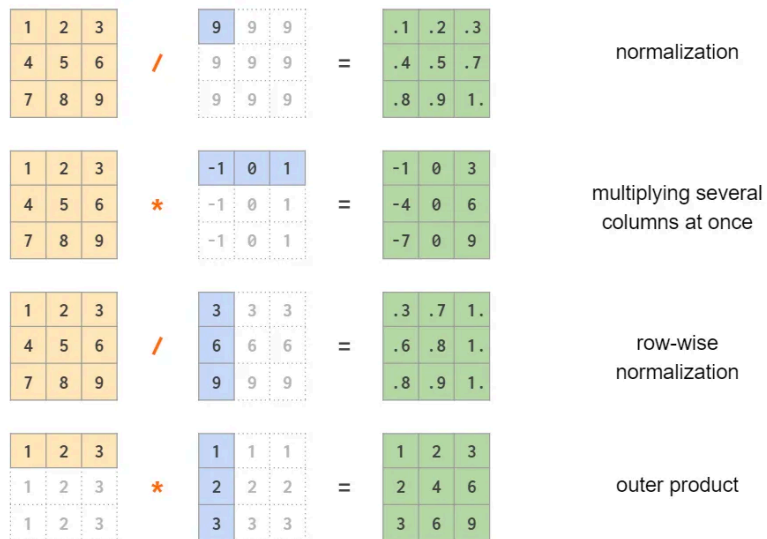
By specifying the **axis** parameter you can apply an operation along the specified axis of an array

Matrix operations



Not every operator or operation in NumPy is element-wise

Broadcasting



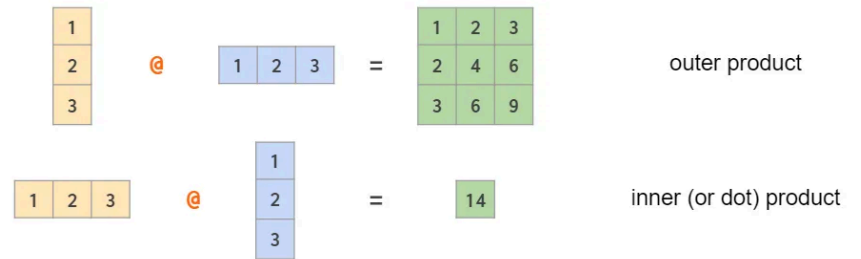
General broadcasting rules

- ▶ Numpy follows a [set of rules](#) to determine how the smaller array is **broadcasted** to match the shape of the larger array
 - if the arrays have a different number of dimensions, **pad the smaller array's shape** with ones on its left
 - start with the rightmost dimension and **work backwards**
 - two dimensions are **compatible** if they are equal, or one of them is 1
 - otherwise throw a ValueError exception: "operands could not be broadcast together"
- ▶ Resulting array will have the same number of dimensions as the input array with the greatest number of dimensions
 - the size of each dimension is the largest size of the corresponding dimension among the input arrays

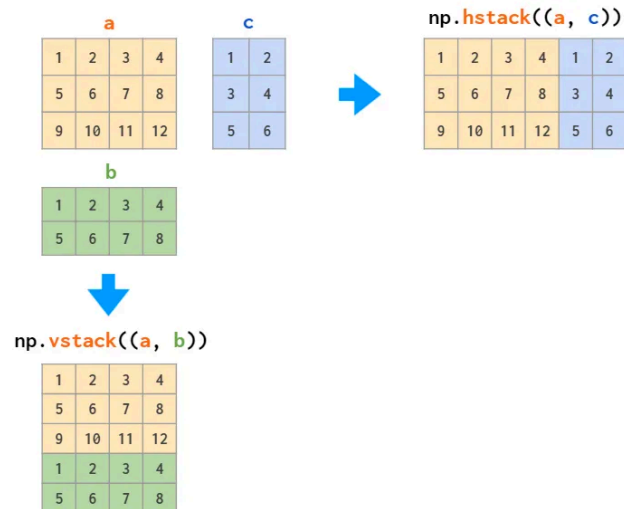
Practice

Arrays	Result	Arrays	Result
$8 \times 1 \times 6 \times 1$ $7 \times 1 \times 5$	$8 \times 7 \times 6 \times 5$	4×3 3	
5×4 1	5×4	$5 \times 4 \times 3$ 1×3	
5×4 4	5×4	$8 \times 1 \times 6$ 7×1	
$15 \times 3 \times 5$ $15 \times 1 \times 5$	$15 \times 3 \times 5$	5×2 5	
$15 \times 3 \times 5$ 3×5	$15 \times 3 \times 5$	3×1 3×5	
$15 \times 3 \times 5$ 3×1	$15 \times 3 \times 5$	$2 \times 4 \times 1$ 8	
3 4	mismatch	6×3 3×1	
2×1 $8 \times 4 \times 3$	mismatch	$3 \times 5 \times 2$ 3	

Must know your shapes ...



Concatenation



Practice

Task

- given n data points, find the nearest neighbor to a query data point q

Input:

- input vector (vector_dim)
- data (num_vectors, vector_dim)

Output:

- nearest_neighbor_idx

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^d (x_i - y_i)^2}$$

Hint:

- use euclidean distance for distance calculations
- use vectorized and broadcasting operations