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Numpy

Import Convention

Import numpy as np

Why Numpy ?

- Supports element wise operation + Vectorization
  - arr = np.array([1, 2, 3, 4])
    - Output: array([1, 2, 3, 4])
  - arr * 2
    - output: array([2, 4, 6, 8])

- Faster Execution speed
  - Python list (took **300 milli sec** for squaring elements)

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

```
%timeit [i**2 for i in l]
```

```
339 ms ± 14.8 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

  - Numpy array (took **2 ms**)
    - Numpy internally uses C arrays.

```
l = np.array(range(1000000))
```

```
%timeit l**2
```

```
2.92 ms ± 418 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

Initializing Array

Initializing array using python list	arr1= np.array([4, 11, 53, 2, 9,]) type(arr1) > numpy.ndarray
Creates 2-D array of float data type array([1., 2., 3.],	arr2 = np.array([[2, 7 , 11], [4, 8 , 2]], dtype= float)

[4., 5., 6.]])	
Initializing numpy array range. Similar to python range(). Step size can be float.	arr3 = np.arange(stop= 5) # array([0, 1, 2, 3, 4]) arr4 = np.arange(start = 2, stop = 10,step = 1.5) # array([2. , 3.5, 5. , 6.5, 8. , 9.5])
Returns evenly spaced numbers over specified interval	np.linspace(start = 0, stop = 100,num =5) # array([0, 25., 50. , 75., 100.]) np.linspace(0, 10, 5) # array([0. , 2.5, 5. , 7.5, 10.])
Creates an array with all elements as 0 similar func: np.ones()	zero_arr = np.zeros(3) # [0., 0., 0.] zero_arr_2d= np.zeros((2,3)) # [[0., 0., 0.], [0., 0., 0.]]

Generates array with elements belonging to continuous uniform distribution
Range: [0, 1)
	np.random.rand(3, 2)
	
	# array([[0.81595852, 0.59222987],
	  [0.30536743, 0.27175429],
	  [0.03835455, 0.27976716]])

Properties of Array

number of dimensions of the array.	**arr.ndim** arr1.ndim # returns 1 arr2.ndim # returns 2
shape of array	**arr.shape** arr1.shape # returns (5,) arr2.shape # returns (2, 3)
datatype of array.	**arr.dtype** arr1.dtype # returns int64

Accessing Elements

Accessing Single element (Indexing)

access element present at that index. Index start from 0	arr1[2] # returns 53 arr2[1, 2] # returns 6
Negative index based indexing	arr1[-1] # returns 6

Accessing Sequence(Slicing)

Slice out and get part of the numpy array. Can use negative indexes for slicing as well. Slicing returns View not copy.	arr1[3:] # returns [2, 9] arr1[:4] # returns [4, 11, 53, 2] arr[1: 4: 2] #returns array([11, 2]) arr1[-4: -1] # returns [11, 53, 2]
	arr2[:1, :] # fetches first row # [[2., 7. , 11.]] arr2[:, 2:] # fetches third column # [[11.], [2.]]

Accessing based on condition (Masking)

Indexing based on condition. Masking creates a copy of the array not a view.	arr1[arr1 > 8] # returns [11, 53, 9] arr1[(arr1 >5) & (arr1 <=11)] # returns [11, 9]

Operations

Arithmetic

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

Element wise Addition	a + b [or np.add (a, b)] # [2, 3, 5, 6]

Element wise Subtraction	a - b [or np.subtract(a,b)] # [0, 1, 1, 2]
Element wise Multiplication	a * b [or np.multiply(a, b)] # [1, 2, 6, 8]
Element wise Division	a/b [pr np.divide(a, b)] # [1., 2., 1.5., 2.]

Comparison

Element wise comparison Returns bool array	a==b, a>=b, a<=b
Array wise equality Returns True/False	np.array_equal(a, b)

Matrix Multiplication

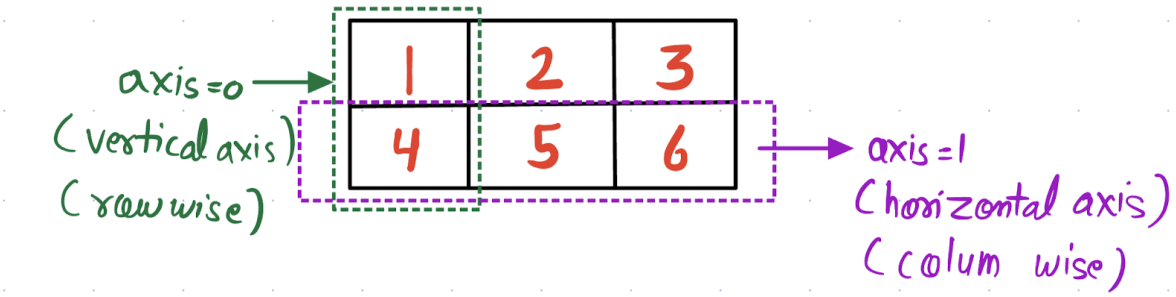
mat1 = np.array([[2], [1]])
mat2 = np.array([[2, 4]])

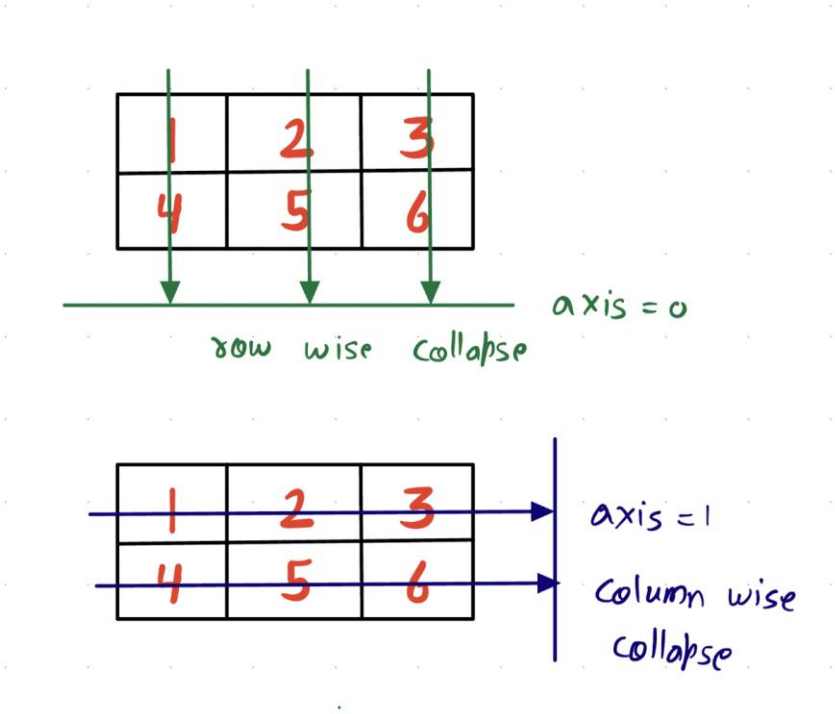
Returns matrix mul. of arrays provided the condition for matrix multiplication is satisfied.	**np.matmul**(mat1, mat2) # array([[4, 8], [2, 4]])
	mat1 @ mat2 # array([[4, 8], [2, 4]])
Performs matrix multiplication if both	**np.dot()**

inputs are 2D. Other cases for np.dot(): **Case1:** It performs dot product if both inputs are scalar **Case2:** Perform simple multiplication if both inputs are scalars	np.dot(mat1, mat2) # returns ([[4, 8], [2, 4]] np.dot(a, b) # [2, 4, 6] =< 1*2 + 2*2 + 3*2 np.dot(2, 3) # returns 6

Axis

Diagram ref: [Cheat sheet Numpy Python copy.indd]





Universal Functions

Aggregate

Sums all the elements of array Sums the elements along the vertical axis(rowwise). We can also take sum along horizontal axis (axis =1)	**np.sum()** np.sum(arr2) # retuns 34.0 np.sum(arr2, axis = 0) # returns [6., 15., 3.]
Takes mean of all the elements of array Takes mean along the horizontal axis (column wise)	np.mean(arr2) # returns 5.666667 np.mean(arr2, axis = 1) # [6.6667, 4.66667]
Returns element with minimum value. Can also find mean row wise/ column	np.min(arr2) # returns 2.0

wise using axis 0/1 Other similar func: np.max()	

Logical

Returns True if the any of the corresponding elements in the array follow provided condition	np.any(arr1 < arr3) # returns True
Returns True only if the all of the corresponding elements in the array follow provided condition	np.all(arr1 < arr3) # returns False
Function signature: np.where(condition, [x, y]) Vectorized if else over an array. Returns an array where value = x if the condition is True else y.	np.where(arr1 > 2, 1, 0) # array([1, 1, 1, 0, 1])

Array Manipulation

Reshaping

```
array3d = np.array([[[1 , 2]],
                    [[5, 6]]])
```

Reshapes the array Can use -ve index in reshape	array3d.reshape(2, 2) # returns [[1, 2], [5, 6]] arr5.reshape(2, -1) # [[1, 2], [5, 6]]

Returns a flattened array i.e. 1D array. Returns copy of array	array3d.flatten() # returns array([1, 2, 5, 6])
Returns a flattened array. Returns view of array	array3d.ravel()
Transposes the array	reshaped_arr.T np.transpose(array3d, axis = [2, 1, 0]) # array([[[1, 5]], [[2, 6]]])

Sorting

Sorts original array. Doesn't return anything	arr2.sort()
Returns sorted array. Doesn't make changes to original array	np.sort(arr) # array([[2., 7., 11.], [2., 4., 8.]])
Sorts array row wise i.e. along the vertical axis Sorts array along the horizontal axis i.e. column wise	np.sort(arr, axis = 0) # array([[2., 7., 2.], [4., 8., 11.]]) np.sort(arr, axis = 1) # array([[2., 7., 11.], [2., 4., 8.]])
Returns indices that would sort the array	np.argsort(arr) # [4, 0, 3, 1, 2]

Splitting

Split array into multiple sub arrays	np.split(arr, indices_or_sections= 2) # [array([1, 2]), array([3, 4])]

	np.split(arr, indices_or_sections = [1, 3]) # `[array([1]), array([2, 3]), array([4])]`
Split along horizontal axis i.e. column wise	np.hsplit(arr2, [1, 2]) `# [array([[2.], [4.]]), array([[7.], [8.]]), array([[11.], [ 2.]])]`
Split along vertical axis i.e. row wise	np.vsplit(arr2, 2) `# [array([[ 2., 7., 11.]]), array([[4., 8., 2.]])]`

Merging

Stacks array vertically ie. row wise append (axis = 0)	**np.vstack()** np.vstack((arr, arr, arr)) # [[1, 2, 3, 4], [1, 2, 3, 4], [1, 2, 3, 4]]
Stacks array horizontally i.e. column wise append (axis = 1)	**np.hstack()** arr = arr.reshape(4,1) # [[0], [1], [2]] np.hstack((arr, arr, arr)) # [[0, 0, 0], [1, 1, 1], [2, 2, 2], [3, 3, 3]]
Concatenate two or more array along the given axis	np.concatenate([arr, arr]) # [1, 2, 3, 4, 1, 2, 3, 4]

	arr_2d = arr.reshape(1,-1) np.concatenate([arr, arr], axis = 0) #[[1, 2, 3, 4], [1, 2, 3, 4]] np.concatenate([arr, arr], axis = 1) array([[1, 2, 3, 4, 1, 2, 3, 4]])

Argument based function

Get indices of non zero elements	np.argwhere(arr1)
	
	# array([[0],
	  [1],
	  [2],
	  [3]
	  [4]])

Get indices minimum value. Other similar func: np.argmax()	np.argmin(arr1) # returns 3 np.argmin(arr2) # array([0, 0, 1])
Returns indices that would sort the array	np.argsort(arr) # array([3, 0, 4, 1, 2])

Broadcasting

For each dimension (going from right side)
  1. The size of each dimension should be same OR
  2. The size of one dimension should be 1
 	
Rule 1 : If two arrays differ in the number
	Shape of arr1= (1, 2)
	Shape of arr2 = (2, 2)
	
	Shape of [arr1 + arr2] = (2, 2) # **Rule 2**
	
	arr1 shape = (2, 1)
	arr2 shape = (2, 2)

of dimensions, the shape of one with fewer dimensions is padded with ones on its leading(Left Side). **Rule 2 :** If the shape of two arrays does not match in any dimensions, the array with shape equal to 1 is stretched to match the other shape i.e. broadcasted. **Rule 3 :** If in any dimension the sizes disagree and neither equal to 1 , then Error is raised.	arr1 + arr2 shape = (2,2) # **Rule 2** arr1 shape = (2, 4) arr2 shape = (4, 4) arr1 - arr2 shape = Error # **Rule 3** arr1 shape = (15, 3, 5) arr2 shape = (3, 1) arr1 + arr2 shape = (15, 3, 5) # **Rule1 + Rule2**

Copying Array

Creates a copy of an array. Masking and array op creates copy.	copy = arr1.copy()
Creates View of an array. Slicing creates view	view = arr1.view()

Misc

Change the datatype of an array	arr.astype(int)