

# Chapter 5

## Numeric Computing with Numpy



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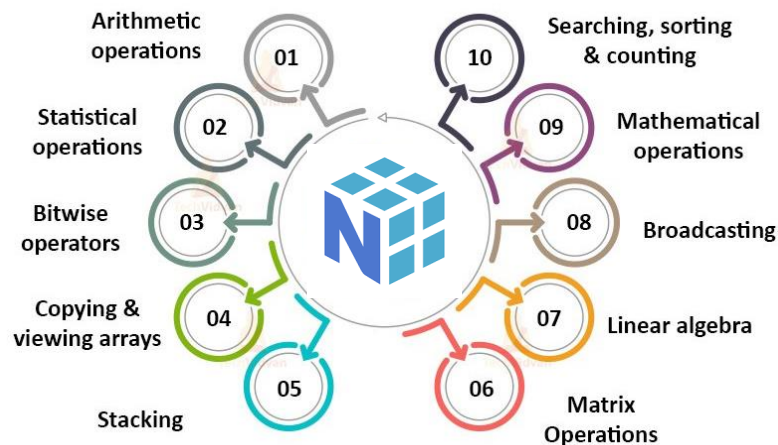
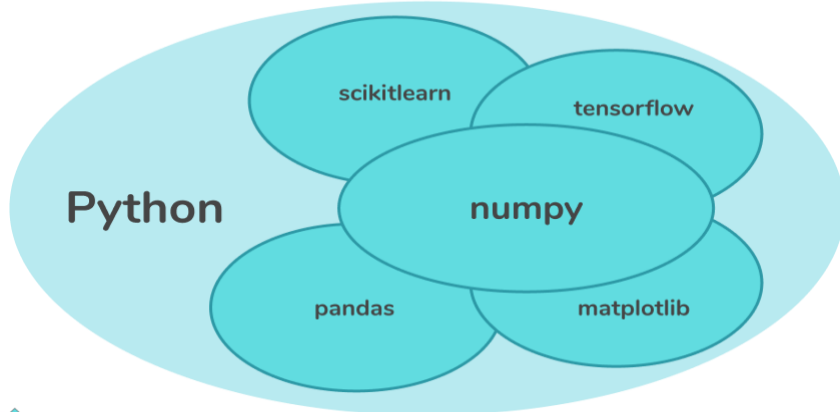
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- Introduction to NumPy
- Why should use Numpy?
- Numpy Array
- Numpy Linear Algebra
- Numpy Matrix Library [matlib](#)
- I/O with Numpy

# Introduction to NumPy

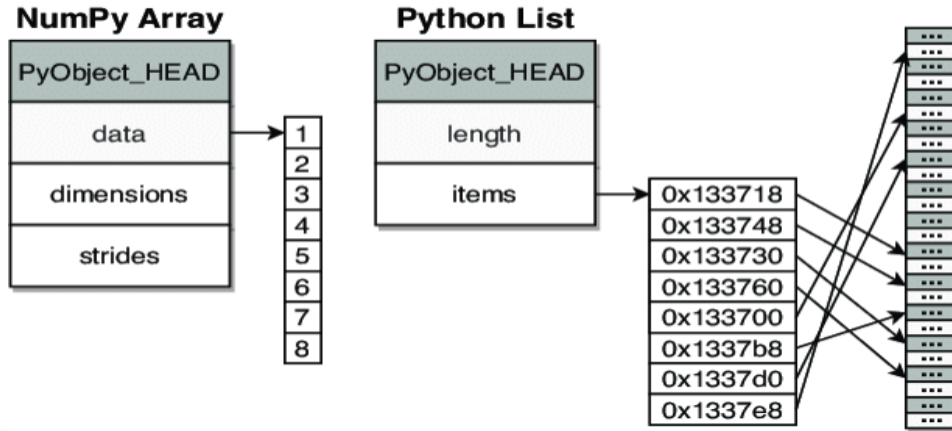


- NumPy is short for *Numerical Python*
- Array oriented computing
- Efficiently implemented multi-dimensional arrays
- Used for *scientific computing*.



# Why should we use Numpy?

- Convenient interface for working with multi-dimensional array data structures efficiently (`ndarray`).
- Less memory to store the data.
- High computational efficiency



# Numpy Getting Started



- Installing Numpy: `pip install numpy`
- Import Numpy: `import numpy`
- Alias of Numpy: `import numpy as np`
- Check Numpy version: `np.__version__`

# Numpy Data Types

→ supports a much greater variety of numerical types than Python does

Boolean	bool_
Integer	int_, intc, intp, int8, int16, int32, int64
Unsigned Integer	uint8, uint16, uint32, uint64
Float	float_, float 16, float32, float 64
Complex	complex_, complex64, complex128

# Numpy Array



→ `ndarray` (*N-Dimensional array*)

## 0-D Array

1
---

`np.array(1)`

## 1-D Array

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

**Vector**

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

## 2-D Array

Axis 0

1	2	3
4	5	6
7	8	9

**Matrix**

Axis 1

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

## 3-D Array

Axis 0

			19	20	21
		10	11	12	23
1	2	3		15	24
4	5	6		18	26
7	8	9			27

Axis 2

Axis 1

`np.array([[[1, 2, 3],  
[4, 5, 6],  
[7, 8, 9]],  
[[10, 11, 12],  
[13, 14, 15],  
[16, 17, 18]],  
[[19, 20, 21],  
[22, 23, 24],  
[25, 26, 27]]])`



# Numpy Array

- ✓ Numpy Array Creation
- ✓ Numpy Array Indexing
- ✓ Numpy Array Slicing
- ✓ Numpy Arithmetic Operations
- ✓ Numpy Arithmetic Functions
- ✓ Numpy Array Manipulation Functions
- ✓ Numpy Broadcasting
- ✓ Numpy Statistical Operations

# Numpy Array Creation



→ Using the function `array()`

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5])
```

→ Converting from lists, tuples.

```
list1 = [1, 2, 3, 4, 5]
arr = np.array(list1)
```

```
tuple1 = (1, 2, 3, 4, 5)
arr = np.array(tuple1)
```

→ Using special Numpy functions: `empty(shape, dtype)`, `ones(shape, dtype)`, `zeros(shape, dtype)`, `arange(start, stop, step, dtype)`, `random.random(size)`, `full(shape, fill_value, dtype)`, `eyes(nrow, [ncol], dtype)`.

```
Ex: arr = np.empty(2, dtype=int)
      arr = np.zeros(2, dtype=int)
```

# Numpy Array Attributes

**ndarray.shape**

return the size of array

(3,3)

**ndarray.ndim**

return number of array dimension

2

**ndarray.dtype**

return data type of elements in the array

int64

1	2	3
4	5	6
7	8	9

**ndarray.size**

return number of elements in the array

9

**ndarray.itemsize**

return the size (in bytes) of elements in the array

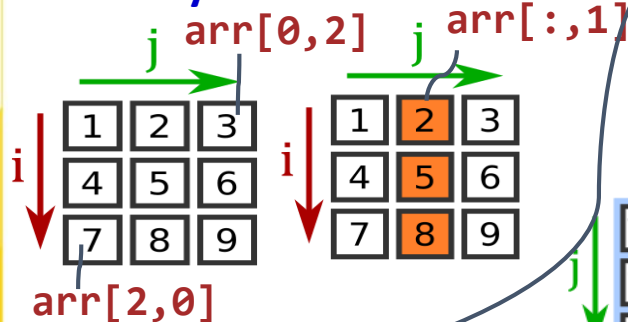
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# Numpy Array Indexing

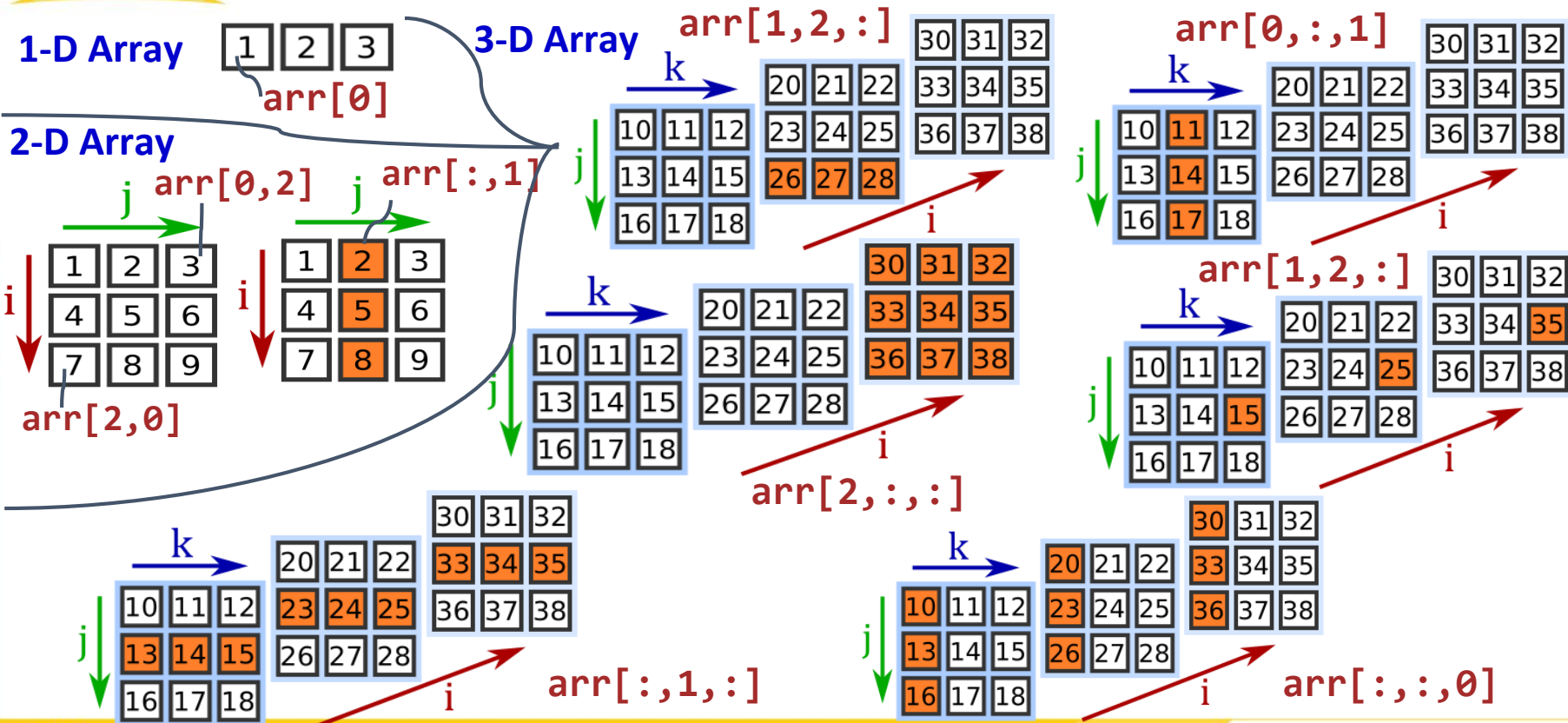
1-D Array



2-D Array



3-D Array



# Numpy Array Slicing

**1-D Array**

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

`arr[:1]`

*[start:end]*

**2-D Array**

*j* →

10	11	12	13	14
15	16	17	18	19
20	21	22	23	24
25	26	27	28	29

*i* ↓

`arr[1:,2:4]`

**3-D Array**

`arr[:2,1:,:2]`

*k* →

*j* ↓

10	11	12	20	21	22	30	31	32
13	14	15	23	24	25	33	34	35
16	17	18	26	27	28	36	37	38

*i* ↗

# Numpy Arithmetic Operations

```
import numpy as np
a = np.arange(9, dtype = np.float_).reshape(3,3)
b = np.array([10,10,10])
```

$\longrightarrow$

	<code>[[ 0, 1, 2]</code>
	<code>[ 3, 4, 5 ]</code>
	<code>[ 6, 7, 8 ]]</code>

$\longrightarrow$

<code>[10, 10, 10]</code>	
---------------------------	--

`np.add (a,b)`

$\longrightarrow$

<code>[[ 10, 11, 12 ]</code>
<code>[ 13, 14, 15 ]</code>
<code>[ 16, 17 18 ]]</code>

`np.subtract (a,b)`

$\longrightarrow$

<code>[[ 10, 11, 12]</code>
<code>[ 13, 14, 15]</code>
<code>[ 16, 17, 18]]</code>

`np.multiply (a,b)`

$\longrightarrow$

<code>[[ -10, -9, -8]</code>
<code>[ -7, -6, -5]</code>
<code>[ -4, -3, -2]]</code>

`(a,b)`

`np.divide`

$\longrightarrow$

<code>[[ 0, 0.1, 0.2]</code>
<code>[ 0.3, 0.4, 0.5]</code>
<code>[ 0.6, 0.7, 0.8]]</code>

# Numpy Arithmetic Functions

```
import numpy as np  
a = np.array([7,3,4,5,1])  
b = np.array([3,4,5,6,7])
```

```
np.remainder (a,b)  
⇒ [1, 3, 4, 5, 1]
```

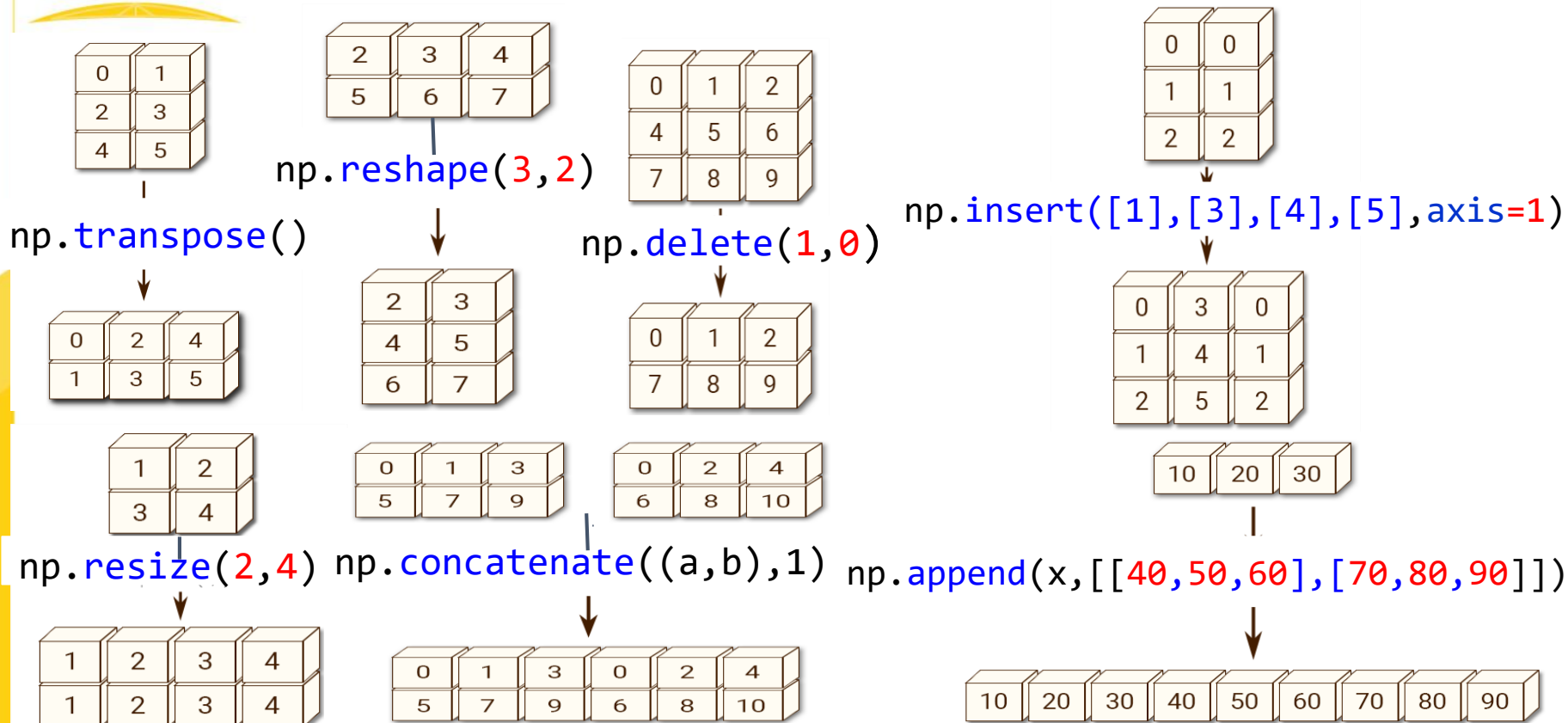
```
np.mod (a,b)  
⇒ [1, 3, 4, 5, 1]
```

```
np.power (a,b)  
⇒ [343, 81, 1024, 15625, 1]
```

```
np.reciprocal (a)  
⇒ [0, 0, 0, 0, 1]
```



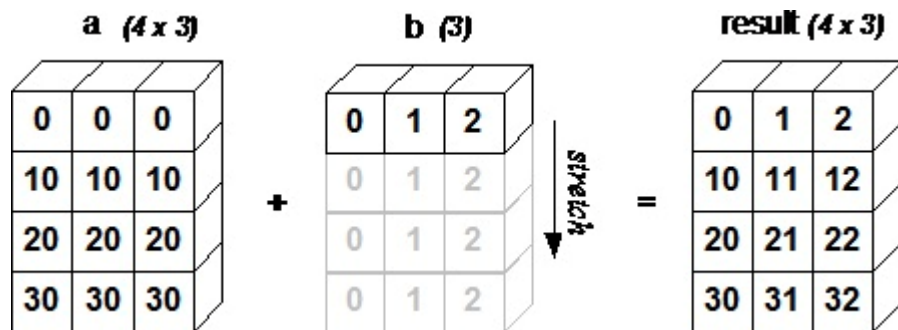
# Numpy Array Manipulation Functions





# Numpy Broadcasting

→ **Broadcasting** refers to how **numpy** treats arrays with different dimension during arithmetic operations which lead to certain constraints, the smaller array is broadcast across the larger array so that they have compatible shapes.

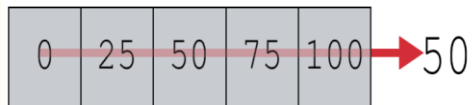


## → Broadcasting Rules:

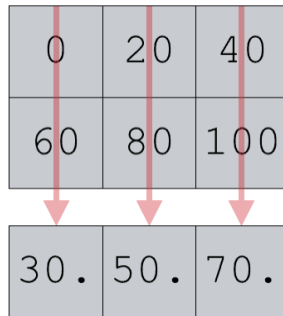
- ◆ If the arrays don't have the same rank then prepend the shape of the lower rank array with 1s until both shapes have the same length.
- ◆ The two arrays are compatible in a dimension if they have the same size in the dimension or if one of the arrays has size 1 in that dimension.
- ◆ The arrays can be broadcast together iff they are compatible with all dimensions.
- ◆ After broadcasting, each array behaves as if it had shape equal to the element-wise maximum of shapes of the two input arrays.
- ◆ In any dimension where one array had size 1 and the other array had size greater than 1, the first array behaves as if it were copied along

# Numpy Statistical Operations

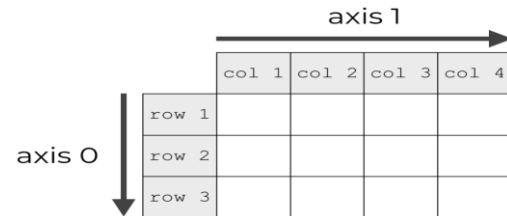
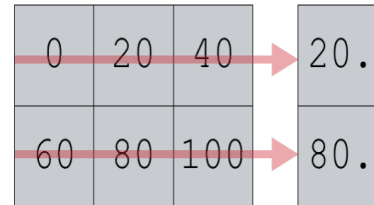
→ `np.median(array, [axis], ...)`



axis=0



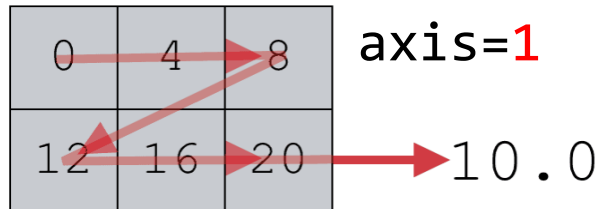
axis=1



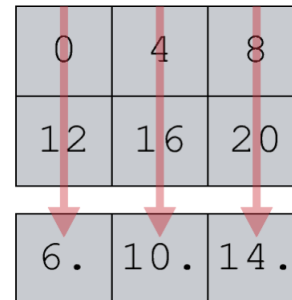
→ `np.mean(array, [axis], ...)`



axis=1



axis=0



# Numpy Statistical Operations

→ `np.std(array, [axis], ...)` # standard deviation

axis=0

4	12	0	4
6	11	8	4
18	14	13	7
6.18	1.25	5.35	1.41

axis=1

4	12	0	4	4.36
6	11	8	4	2.59
18	14	13	7	3.94

→ `np.var(array, [axis], ...)` # variance

axis=0

4	12	0	4
6	11	8	4
18	14	13	7
38.2	1.56	28.7	2.0

axis=1

4	12	0	4	19.
6	11	8	4	6.69
18	14	13	7	15.5

→ `Linalg` : the package in NumPy for Linear Algebra

→ `dot()` : product of two arrays

`vdot()` : Complex-conjugating dot product

Example : `a = [[1, 0], [0, 1]]`

```
>>> b = [[4, 1], [2, 2]]
```

```
>>> np.dot(a, b)  
array([[4, 1], [2, 2]])
```

→ `inner()`: product of two arrays

- `numpy.inner(a, b, /)`

- **a, b: array\_like**

If *a* and *b* are non-scalar, their last dimensions must match

- **Returns: out: ndarray**

If *a* and *b* are both scalars or both 1-D arrays then a scalar is returned; otherwise an array is returned. `out.shape = (*a.shape[:-1], *b.shape[:-1])`

→ **outer()**: compute the outer product of two vectors

**numpy.outer(a, b, out=None)**

**Parameters:**

- **a** : (M,) array\_like

First input vector. Input is flattened if not already 1-dimensional.

- **b** : (N,) array\_like

Second input vector. Input is flattened if not already 1-dimensional.

- **out** : (M, N) ndarray, optional

A location where the result is stored

→ **matmul(): Matrix product of two arrays**

```
numpy.matmul(x1, x2, /, out=None, *, casting='same_kind',  
order='K', dtype=None, subok=True[, signature, extobj, axes, axis])  
= <ufunc 'matmul'>
```

**Parameters: x1, x2: array\_like**

Input arrays, scalars not allowed.

**Out: ndarray, optional**

If provide allocation, it must have a shape that matches the signature  $(n,k),(k,m) \rightarrow (n,m)$ . If not provided or None, a freshly-allocated array is returned.



Another linear algebra functions

- `det()`
- `inv()`
- `trace()`
- `rank()`

→ has functions that return **matrices** instead of **ndarray** objects.

```
import numpy as np
import numpy.matlib
# with the specified shape and type without initializing entries
mat_e = np.matlib.empty((3, 2), dtype = int)
# filled with 0
mat_zeros = np.matlib.zeros(5, 3)
# filled with 1
mat_ones = np.matlib.ones(4, 3)
# diagonal elements filled with 1, others with 0
mat_ones = np.matlib.eye(3,5)
# create square matrix with 0, diagonal filled with 1, others with 0
mat_zeros = np.matlib.identity(5)
# filled with random data
mat_e = np.matlib.empty(3, 2))
```

→ What are the I/O functions of NumPy?

The I/O functions provided by NumPy are:

- `load()` and `save()` functions handle numPy binary files (with `npyextension`)
- `loadtxt()` and `savetxt()` functions handle normal text files

→ `numpy.save()`: The input array is stored in a disk file with the `numpy.save()` file and with an `np` extension.

**Ex:**

```
#The input array is stored in a disk file with  
the numpy.save() file and with an npy extension.  
import numpy as np  
a = np.array([1,2,3,4,5])  
np.save('outfile',a)  
# use load() function to reconstruct  
import numpy as np  
b = np.load('outfile.npy')  
print b
```

```
#The output as:  
array([1, 2, 3, 4, 5])
```

→ `numpy.savetxt()` and `numpy.loadtxt()` functions help in storage and retrieval of the array data in simple text file format.

Ex:

```
import numpy as np
a = np.array([1,2,3,4,5])
np.savetxt('out.txt',a)
b = np.loadtxt('out.txt')
print b
```

The output produced appears as: [ 1. 2. 3. 4. 5.]