

Lecture 4-3

More NumPy

Week 5 Friday

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Based on Python Data Science Handbook by Jake VanderPlas

```
In [1]: import numpy as np
```

Concatenating Arrays

Concatenating Arrays

In [2]:

```
x = np.arange(4)
y = np.arange(100, 104)
print(x)
print(y)
```

```
[0 1 2 3]
```

```
[100 101 102 103]
```

Concatenating Arrays

In [2]:

```
x = np.arange(4)
y = np.arange(100, 104)
print(x)
print(y)
```

```
[0 1 2 3]
[100 101 102 103]
```

In [3]:

```
np.concatenate([x,y])
```

Out[3]: array([0, 1, 2, 3, 100, 101, 102, 103])

Concatenating Arrays

In [2]:

```
x = np.arange(4)
y = np.arange(100, 104)
print(x)
print(y)
```

```
[0 1 2 3]
[100 101 102 103]
```

In [3]:

```
np.concatenate([x,y])
```

Out[3]: array([0, 1, 2, 3, 100, 101, 102, 103])

`np.concatenate` has an argument for `axis`. The axes are 0-indexed.

Concatenating Arrays

In [2]:

```
x = np.arange(4)
y = np.arange(100, 104)
print(x)
print(y)
```

```
[0 1 2 3]
[100 101 102 103]
```

In [3]:

```
np.concatenate([x,y])
```

Out[3]: array([0, 1, 2, 3, 100, 101, 102, 103])

`np.concatenate` has an argument for `axis`. The axes are 0-indexed.

In [4]:

```
np.concatenate([x,y], axis = 0)
```

Out[4]: array([0, 1, 2, 3, 100, 101, 102, 103])

Let's try to concatenate in the other direction. We specify `axis = 1`

Let's try to concatenate in the other direction. We specify axis = 1

```
In [5]: np.concatenate([x,y], axis = 1) # throws an error
```

```
-----  
-  
AxisError                                Traceback (most recent call las  
t)  
~\AppData\Local\Temp\ipykernel_25452\1729112478.py in <module>  
----> 1 np.concatenate([x,y], axis = 1) # throws an error  
  
<__array_function__ internals> in concatenate(*args, **kwargs)  
  
AxisError: axis 1 is out of bounds for array of dimension 1
```


Let's try to concatenate in the other direction. We specify axis = 1

```
In [5]: np.concatenate([x,y], axis = 1) # throws an error
```

```
-----  
-  
AxisError                                Traceback (most recent call las  
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<__array_function__ internals> in concatenate(*args, **kwargs)  
  
AxisError: axis 1 is out of bounds for array of dimension 1
```

```
In [6]: x.shape # you can't use axis with index 1, because axis index 1 does not exist
```

```
Out[6]: (4,)
```

Let's try to concatenate in the other direction. We specify axis = 1

```
In [5]: np.concatenate([x,y], axis = 1) # throws an error
```

```
-----  
-  
AxisError                                Traceback (most recent call las  
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<__array_function__ internals> in concatenate(*args, **kwargs)  
  
AxisError: axis 1 is out of bounds for array of dimension 1
```

```
In [6]: x.shape # you can't use axis with index 1, because axis index 1 does not exist
```

```
Out[6]: (4,)
```

```
In [7]: np.vstack([x,y]) # vstack will vertically stack unidimensional arrays
```

```
Out[7]: array([[ 0,  1,  2,  3],  
              [100, 101, 102, 103]])
```

```
In [8]: x.reshape(1,4)
```

```
Out[8]: array([[0, 1, 2, 3]])
```

```
In [8]: x.reshape(1,4)
```

```
Out[8]: array([[0, 1, 2, 3]])
```

```
In [9]: y.reshape(1,4)
```

```
Out[9]: array([[100, 101, 102, 103]])
```

```
In [8]: x.reshape(1,4)
```

```
Out[8]: array([[0, 1, 2, 3]])
```

```
In [9]: y.reshape(1,4)
```

```
Out[9]: array([[100, 101, 102, 103]])
```

```
In [10]: np.concatenate([x.reshape(1,4), y.reshape(1,4)], axis = 0)
```

```
Out[10]: array([[ 0,  1,  2,  3],  
                [100, 101, 102, 103]])
```

```
In [8]: x.reshape(1,4)
```

```
Out[8]: array([[0, 1, 2, 3]])
```

```
In [9]: y.reshape(1,4)
```

```
Out[9]: array([[100, 101, 102, 103]])
```

```
In [10]: np.concatenate([x.reshape(1,4), y.reshape(1,4)], axis = 0)
```

```
Out[10]: array([[ 0,  1,  2,  3],  
                [100, 101, 102, 103]])
```

note that when I concatenate along axis 0 for a 2-dimensional array, it concatenates by rows. In a 2D array, index 0 is for rows, and index 1 is for columns.

```
In [8]: x.reshape(1,4)
```

```
Out[8]: array([[0, 1, 2, 3]])
```

```
In [9]: y.reshape(1,4)
```

```
Out[9]: array([[100, 101, 102, 103]])
```

```
In [10]: np.concatenate([x.reshape(1,4), y.reshape(1,4)], axis = 0)
```

```
Out[10]: array([[ 0,  1,  2,  3],  
                [100, 101, 102, 103]])
```

note that when I concatenate along axis 0 for a 2-dimensional array, it concatenates by rows. In a 2D array, index 0 is for rows, and index 1 is for columns.

```
In [11]: np.concatenate([x.reshape(1,4), y.reshape(1,4)], axis = 1)
```

```
Out[11]: array([[ 0,  1,  2,  3, 100, 101, 102, 103]])
```

In [12]:

```
xm = np.arange(6).reshape((2,3))  
ym = np.arange(100,106,1).reshape((2,3))  
print(xm)  
print(ym)
```

```
[[0 1 2]  
 [3 4 5]]  
[[100 101 102]  
 [103 104 105]]
```



```
In [12]: xm = np.arange(6).reshape((2,3))  
ym = np.arange(100,106,1).reshape((2,3))  
print(xm)  
print(ym)
```

```
[[0 1 2]  
 [3 4 5]]  
[[100 101 102]  
 [103 104 105]]
```

```
In [13]: xm.shape
```

```
Out[13]: (2, 3)
```

```
In [12]: xm = np.arange(6).reshape((2,3))  
ym = np.arange(100,106,1).reshape((2,3))  
print(xm)  
print(ym)
```

```
[[0 1 2]  
 [3 4 5]]  
[[100 101 102]  
 [103 104 105]]
```

```
In [13]: xm.shape
```

```
Out[13]: (2, 3)
```

```
In [14]: ym.shape
```

```
Out[14]: (2, 3)
```

```
In [15]: print(np.concatenate([xm,ym])) # default behavior concatenates on axis 0
```

```
[[ 0  1  2]
 [ 3  4  5]
 [100 101 102]
 [103 104 105]]
```

```
In [15]: print(np.concatenate([xm,ym])) # default behavior concatenates on axis 0
```

```
[[ 0  1  2]
 [ 3  4  5]
 [100 101 102]
 [103 104 105]]
```

```
In [16]: print(np.concatenate([xm,ym], axis = 0))
# axes are reported as rows, then columns.
# concatenating along axis 0 will concatenate along rows
```

```
[[ 0  1  2]
 [ 3  4  5]
 [100 101 102]
 [103 104 105]]
```

```
In [15]: print(np.concatenate([xm,ym])) # default behavior concatenates on axis 0
```

```
[[ 0  1  2]
 [ 3  4  5]
 [100 101 102]
 [103 104 105]]
```

```
In [16]: print(np.concatenate([xm,ym], axis = 0))
# axes are reported as rows, then columns.
# concatenating along axis 0 will concatenate along rows
```

```
[[ 0  1  2]
 [ 3  4  5]
 [100 101 102]
 [103 104 105]]
```

```
In [17]: print(np.concatenate([xm,ym], axis = 1))
# concatenating along axis 1 will concatenate along columns
```

```
[[ 0  1  2 100 101 102]
 [ 3  4  5 103 104 105]]
```

```
In [18]: np.vstack([xm, ym])
```

```
Out[18]: array([[ 0,  1,  2],
                [ 3,  4,  5],
                [100, 101, 102],
                [103, 104, 105]])
```

```
In [18]: np.vstack([xm, ym])
```

```
Out[18]: array([[ 0,  1,  2],  
                [ 3,  4,  5],  
                [100, 101, 102],  
                [103, 104, 105]])
```

```
In [19]: np.hstack([xm, ym])
```

```
Out[19]: array([[ 0,  1,  2, 100, 101, 102],  
                [ 3,  4,  5, 103, 104, 105]])
```

```
In [18]: np.vstack([xm, ym])
```

```
Out[18]: array([[ 0,  1,  2],  
                [ 3,  4,  5],  
                [100, 101, 102],  
                [103, 104, 105]])
```

```
In [19]: np.hstack([xm, ym])
```

```
Out[19]: array([[ 0,  1,  2, 100, 101, 102],  
                [ 3,  4,  5, 103, 104, 105]])
```

You can always use `vstack` and `hstack` for 2D arrays.

Math Operators with numpy arrays

Math Operators with numpy arrays

In [20]:

```
print(x)  
print(y)
```

```
[0 1 2 3]
```

```
[100 101 102 103]
```

Math Operators with numpy arrays

In [20]:

```
print(x)  
print(y)
```

```
[0 1 2 3]  
[100 101 102 103]
```

In [21]:

```
x + 5
```

Out[21]: array([5, 6, 7, 8])

Math Operators with numpy arrays

In [20]:

```
print(x)  
print(y)
```

```
[0 1 2 3]  
[100 101 102 103]
```

In [21]:

```
x + 5
```

Out[21]: array([5, 6, 7, 8])

In [22]:

```
x + y # elementwise addition
```

Out[22]: array([100, 102, 104, 106])

Math Operators with numpy arrays

In [20]:

```
print(x)  
print(y)
```

```
[0 1 2 3]  
[100 101 102 103]
```

In [21]:

```
x + 5
```

Out[21]: array([5, 6, 7, 8])

In [22]:

```
x + y # elementwise addition
```

Out[22]: array([100, 102, 104, 106])

In [23]:

```
x * y
```

Out[23]: array([0, 101, 204, 309])

Math Operators with numpy arrays

In [20]:

```
print(x)  
print(y)
```

```
[0 1 2 3]  
[100 101 102 103]
```

In [21]:

```
x + 5
```

Out[21]: array([5, 6, 7, 8])

In [22]:

```
x + y # elementwise addition
```

Out[22]: array([100, 102, 104, 106])

In [23]:

```
x * y
```

Out[23]: array([0, 101, 204, 309])

In [24]:

```
np.sum(x * y)
```

Out[24]: 614

In [25]: `np.dot(x,y)` *# 0 * 100 + 1 * 101 + 2 * 102 + 3 * 103*

Out[25]: 614

```
In [25]: np.dot(x,y)    # 0 * 100 + 1 * 101 + 2 * 102 + 3 * 103
```

```
Out[25]: 614
```

```
In [26]: x @ y # matrix multiplication
```

```
Out[26]: 614
```


In [27]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [27]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [28]:

```
xm + 5
```

Out[28]:

```
array([[ 5,  6,  7],
       [ 8,  9, 10]])
```

In [27]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [28]:

```
xm + 5
```

Out[28]:

```
array([[ 5,  6,  7],
       [ 8,  9, 10]])
```

In [29]:

```
xm + ym # elementwise addition
```

Out[29]:

```
array([[100, 102, 104],
       [106, 108, 110]])
```

In [30]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [30]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [31]:

```
xm * ym # element-wise multiplication
```

Out[31]:

```
array([[ 0, 101, 204],
       [309, 416, 525]])
```

```
In [30]: print(xm)
         print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

```
In [31]: xm * ym # element-wise multiplication
```

```
Out[31]: array([[ 0, 101, 204],
               [309, 416, 525]])
```

```
In [32]: np.multiply(xm, ym) # element-wise multiplication
```

```
Out[32]: array([[ 0, 101, 204],
               [309, 416, 525]])
```

In [33]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [33]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [34]:

```
np.dot(xm, ym.T)
```

Out[34]:

```
array([[ 305,  314],
       [1214, 1250]])
```


In [33]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [34]:

```
np.dot(xm, ym.T)
```

Out[34]:

```
array([[ 305,  314],
       [1214, 1250]])
```

In [35]:

```
xm.dot(ym.T)
```

Out[35]:

```
array([[ 305,  314],
       [1214, 1250]])
```

In [33]:

```
print(xm)
print(ym)
```

```
[[0 1 2]
 [3 4 5]]
[[100 101 102]
 [103 104 105]]
```

In [34]:

```
np.dot(xm, ym.T)
```

Out[34]:

```
array([[ 305,  314],
       [1214, 1250]])
```

In [35]:

```
xm.dot(ym.T)
```

Out[35]:

```
array([[ 305,  314],
       [1214, 1250]])
```

In [36]:

```
xm @ ym.T
```

Out[36]:

```
array([[ 305,  314],
       [1214, 1250]])
```

Basic Math

Basic Math

In [37]:

```
x = np.arange(4)
print(x)
```

```
[0 1 2 3]
```

Basic Math

In [37]:

```
x = np.arange(4)  
print(x)
```

```
[0 1 2 3]
```

In [38]:

```
print(x + 4)
```

```
[4 5 6 7]
```

Basic Math

In [37]:

```
x = np.arange(4)  
print(x)
```

```
[0 1 2 3]
```

In [38]:

```
print(x + 4)
```

```
[4 5 6 7]
```

In [39]:

```
print(x - 5)
```

```
[-5 -4 -3 -2]
```

Basic Math

In [37]:

```
x = np.arange(4)  
print(x)
```

```
[0 1 2 3]
```

In [38]:

```
print(x + 4)
```

```
[4 5 6 7]
```

In [39]:

```
print(x - 5)
```

```
[-5 -4 -3 -2]
```

In [40]:

```
print(x * 2)
```

```
[0 2 4 6]
```

In [41]:

```
print(x / 2)
```

```
[0.  0.5 1.  1.5]
```


In [41]:

```
print(x / 2)
```

```
[0.  0.5 1.  1.5]
```

In [42]:

```
print(-x)
```

```
[ 0 -1 -2 -3]
```

In [41]:

```
print(x / 2)
```

```
[0.  0.5 1.  1.5]
```

In [42]:

```
print(-x)
```

```
[ 0 -1 -2 -3]
```

In [43]:

```
print(x ** 2)
```

```
[0 1 4 9]
```

In [41]:

```
print(x / 2)
```

```
[0.  0.5 1.  1.5]
```

In [42]:

```
print(-x)
```

```
[ 0 -1 -2 -3]
```

In [43]:

```
print(x ** 2)
```

```
[0 1 4 9]
```

In [44]:

```
print(x % 2) # modulo division
```

```
[0 1 0 1]
```

In [41]:

```
print(x / 2)
```

```
[0.  0.5 1.  1.5]
```

In [42]:

```
print(-x)
```

```
[ 0 -1 -2 -3]
```

In [43]:

```
print(x ** 2)
```

```
[0 1 4 9]
```

In [44]:

```
print(x % 2) # modulo division
```

```
[0 1 0 1]
```

In [45]:

```
print(abs(x)) # abs
```

```
[0 1 2 3]
```

Trig functions

note that the functions are preceded by np.

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In [46]:

```
theta = np.linspace(0, np.pi, 5)  
print(theta)
```

```
[0.          0.78539816 1.57079633 2.35619449 3.14159265]
```

Trig functions

note that the functions are preceeded by np.

In [46]:

```
theta = np.linspace(0, np.pi, 5)  
print(theta)
```

```
[0.          0.78539816  1.57079633  2.35619449  3.14159265]
```

In [47]:

```
print(np.sin(theta))
```

```
[0.00000000e+00  7.07106781e-01  1.00000000e+00  7.07106781e-01  
 1.22464680e-16]
```

Trig functions

note that the functions are preceeded by np.

```
In [46]: theta = np.linspace(0, np.pi, 5)  
         print(theta)
```

```
[0.          0.78539816 1.57079633 2.35619449 3.14159265]
```

```
In [47]: print(np.sin(theta))
```

```
[0.00000000e+00  7.07106781e-01  1.00000000e+00  7.07106781e-01  
 1.22464680e-16]
```

```
In [48]: print(np.cos(theta))
```

```
[ 1.00000000e+00  7.07106781e-01  6.12323400e-17 -7.07106781e-01  
 -1.00000000e+00]
```


Trig functions

note that the functions are preceeded by np.

```
In [46]: theta = np.linspace(0, np.pi, 5)  
         print(theta)
```

```
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```

```
In [47]: print(np.sin(theta))
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```
[0.00000000e+00  7.07106781e-01  1.00000000e+00  7.07106781e-01  
 1.22464680e-16]
```

```
In [48]: print(np.cos(theta))
```

```
[ 1.00000000e+00  7.07106781e-01  6.12323400e-17 -7.07106781e-01  
 -1.00000000e+00]
```

```
In [49]: print(np.tan(theta))
```

```
[ 0.00000000e+00  1.00000000e+00  1.63312394e+16 -1.00000000e+00  
 -1.22464680e-16]
```

Log and Exp

Log and Exp

In [50]:

```
x = np.array([1, 10, 100])
print(np.log(x))    # natural log
print(np.log10(x))  # common log
```

```
[0.          2.30258509  4.60517019]
```

```
[0.  1.  2.]
```

Log and Exp

In [50]:

```
x = np.array([1, 10, 100])
print(np.log(x))    # natural log
print(np.log10(x))  # common log
```

```
[0.          2.30258509  4.60517019]
[0.  1.  2.]
```

In [51]:

```
y = np.arange(3)
print(np.exp(y))    #  $e^y$ 
```

```
[1.          2.71828183  7.3890561 ]
```

Log and Exp

In [50]:

```
x = np.array([1, 10, 100])
print(np.log(x))    # natural log
print(np.log10(x))  # common log
```

```
[0.          2.30258509  4.60517019]
[0.  1.  2.]
```

In [51]:

```
y = np.arange(3)
print(np.exp(y))    #  $e^y$ 
```

```
[1.          2.71828183  7.3890561 ]
```

In [52]:

```
print(np.exp2(y))   #  $2^y$ 
```

```
[1.  2.  4.]
```

Log and Exp

In [50]:

```
x = np.array([1, 10, 100])
print(np.log(x))    # natural log
print(np.log10(x))  # common log
```

```
[0.          2.30258509  4.60517019]
[0.  1.  2.]
```

In [51]:

```
y = np.arange(3)
print(np.exp(y))    #  $e^y$ 
```

```
[1.          2.71828183  7.3890561 ]
```

In [52]:

```
print(np.exp2(y))   #  $2^y$ 
```

```
[1.  2.  4.]
```

In [53]:

```
print(np.power(3, y)) #  $power^y$ 
```

```
[1 3 9]
```

Aggregates

you can use `sum()`

or `np.sum()`

`np.sum()` is faster than `sum`, but doesn't always behave the same way

Aggregates

you can use `sum()`

or `np.sum()`

`np.sum()` is faster than `sum`, but doesn't always behave the same way

In [54]:

```
x = np.arange(100)
print(x)
```

```
[ 0  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 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95
 96 97 98 99]
```


Aggregates

you can use `sum()`

or `np.sum()`

`np.sum()` is faster than `sum`, but doesn't always behave the same way

In [54]:

```
x = np.arange(100)
print(x)
```

```
[ 0  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 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95
 96 97 98 99]
```

In [55]:

```
print(sum(x))
```

```
4950
```

Aggregates

you can use `sum()`

or `np.sum()`

`np.sum()` is faster than `sum`, but doesn't always behave the same way

In [54]:

```
x = np.arange(100)
print(x)
```

```
[ 0  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 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95
 96 97 98 99]
```

In [55]:

```
print(sum(x))
```

4950

In [56]:

```
print(np.sum(x))
```

4950

```
In [ ]: big_array = np.random.rand(10000)
        %timeit sum(big_array)
        %timeit np.sum(big_array)  # the np version is much faster
```

min and max

min and max

```
In [ ]: print(min(big_array))  
        print(max(big_array))
```

min and max

```
In [ ]: print(min(big_array))  
        print(max(big_array))
```

```
In [ ]: print(np.min(big_array))  
        print(np.max(big_array))
```

min and max

```
In [ ]: print(min(big_array))  
        print(max(big_array))
```

```
In [ ]: print(np.min(big_array))  
        print(np.max(big_array))
```

```
In [ ]: %timeit min(big_array)  
        %timeit np.min(big_array) # the np version is much faster
```

summaries for matrices

summaries for matrices

In []:

```
np.random.seed(1)
# M = np.random.random((3, 4))
M = np.arange(12)
np.random.shuffle(M)
M = np.reshape(M, (3, 4))
print(M)
```

summaries for matrices

```
In [ ]: np.random.seed(1)
# M = np.random.random((3, 4))
M = np.arange(12)
np.random.shuffle(M)
M = np.reshape(M, (3,4))
print(M)
```

```
In [ ]: sum(M) # regular sum function
```

summaries for matrices

```
In [ ]: np.random.seed(1)
        # M = np.random.random((3, 4))
        M = np.arange(12)
        np.random.shuffle(M)
        M = np.reshape(M, (3,4))
        print(M)
```

```
In [ ]: sum(M) # regular sum function
```

```
In [ ]: np.sum(M) # np.sum function
```

In []: `print(M)`

```
In [ ]: print(M)
```

```
In [ ]: np.sum(M, axis = 0)  # np.sum function with axis specified  
# matrices have two dimensions  
# 0 is rows, 1 is columns  
# np.sum axis = 0, will sum over rows, so you end up getting column totals
```

```
In [ ]: print(M)
```

```
In [ ]: np.sum(M, axis = 0)  # np.sum function with axis specified  
      # matrices have two dimensions  
      # 0 is rows, 1 is columns  
      # np.sum axis = 0, will sum over rows, so you end up getting column totals
```

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

```
In [ ]: print(M)
```

```
In [ ]: np.sum(M, axis = 0)  # np.sum function with axis specified  
# matrices have two dimensions  
# 0 is rows, 1 is columns  
# np.sum axis = 0, will sum over rows, so you end up getting column totals
```

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

```
In [ ]: np.min(M, axis = 0)
```

In []: `print(M)`


```
In [ ]: print(M)
```

```
In [ ]: np.std(M)
```

```
In [ ]: print(M)
```

```
In [ ]: np.std(M)
```

```
In [ ]: np.std(M, axis = 0)
```

```
In [ ]: print(M)
```

```
In [ ]: np.std(M)
```

```
In [ ]: np.std(M, axis = 0)
```

```
In [ ]: np.mean(M, axis = 1)
```

Summaries for higher dimensional arrays

Summaries for higher dimensional arrays

In []:

```
np.random.seed(1)
A = np.ones(24)
np.random.shuffle(A)
A = np.reshape(A, (2, 3, 4)) # two sheets, 3 rows, 4 columns
print(A)
```

Summaries for higher dimensional arrays

```
In [ ]: np.random.seed(1)
A = np.ones(24)
np.random.shuffle(A)
A = np.reshape(A, (2, 3, 4)) # two sheets, 3 rows, 4 columns
print(A)
```

```
In [ ]: np.sum(A, axis = 0) # sum across "sheets"
```

Summaries for higher dimensional arrays

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```
In [ ]: np.sum(A, axis = 0) # sum across "sheets"
```

```
In [ ]: np.sum(A, axis = 1) # sum across rows
```

Summaries for higher dimensional arrays

```
In [ ]: np.random.seed(1)
A = np.ones(24)
np.random.shuffle(A)
A = np.reshape(A, (2, 3, 4)) # two sheets, 3 rows, 4 columns
print(A)
```

```
In [ ]: np.sum(A, axis = 0) # sum across "sheets"
```

```
In [ ]: np.sum(A, axis = 1) # sum across rows
```

```
In [ ]: np.sum(A, axis = 2) # sum across columns
```


dealing with nan

nan is the float value for something that is not a number. We often use it in the place of a missing value. nan only exists in float type.

dealing with nan

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```
In [ ]: x = float("nan") # direct creation of nan  
        print(x)  
        print(type(x))
```

dealing with nan

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```
In [ ]: x = float("nan")  # direct creation of nan
        print(x)
        print(type(x))
```

```
In [ ]: y = float("inf")  # y is the float representation of infinity
        print(y / y)      # these calculations will yield a nan result
        print(y - y)
```

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```

```
In [ ]: np.sum([x, 2])
```

dealing with nan

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```

```
In [ ]: y = float("inf")  # y is the float representation of infinity
        print(y / y)  # these calculations will yield a nan result
        print(y - y)
```

```
In [ ]: np.sum([x, 2])
```

```
In [ ]: np.nansum([x, 2])  # in R you have the option na.rm = TRUE
```

The following table provides a list of useful aggregation functions available in NumPy:

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

Broadcasting

This is a similar concept to recycling values in R, but only works when the dimensions are compatible

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This is a similar concept to recycling values in R, but only works when the dimensions are compatible

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


Broadcasting

This is a similar concept to recycling values in R, but only works when the dimensions are compatible

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

```
In [ ]: c = np.array([7,8])  
        print(a + c)  # doesn't work
```

```
In [ ]: print(a)
```

```
In [ ]: print(a)
```

```
In [ ]: e = np.ones([3,3])  
print(e)
```

```
In [ ]: print(a)
```

```
In [ ]: e = np.ones([3,3])  
print(e)
```

```
In [ ]: print(e + a)  # the array a gets 'broadcast' across all three rows
```

```
In [ ]: print(a)
```

```
In [ ]: e = np.ones([3,3])  
print(e)
```

```
In [ ]: print(e + a)  # the array a gets 'broadcast' across all three rows
```

```
In [ ]: print(a.reshape([3,1]))  # we reshape a to be a 3x1 array
```

```
In [ ]: print(a)
```

```
In [ ]: e = np.ones([3,3])  
print(e)
```

```
In [ ]: print(e + a)  # the array a gets 'broadcast' across all three rows
```

```
In [ ]: print(a.reshape([3,1]))  # we reshape a to be a 3x1 array
```

```
In [ ]: print(e + a.reshape([3,1]))  # the reshaped array is broadcast across columns
```

```
In [ ]: d = np.vstack([a,b])  # we stack the arrays a and b vertically
        print(d)
```

```
In [ ]: d = np.vstack([a,b])  # we stack the arrays a and b vertically  
        print(d)
```

```
In [ ]: a
```



```
In [ ]: d = np.vstack([a,b])  # we stack the arrays a and b vertically  
        print(d)
```

```
In [ ]: a
```

```
In [ ]: print(d + a)  # a is broadcast across row
```

In []: `print(c)`

```
In [ ]: print(c)
```

```
In [ ]: print(d)
```

```
In [ ]: print(c)
```

```
In [ ]: print(d)
```

```
In [ ]: print(d + c)  # c does not have compatible dimensions
```

```
In [ ]: print(c)
```

```
In [ ]: print(d)
```

```
In [ ]: print(d + c)  # c does not have compatible dimensions
```

```
In [ ]: print(d + c.reshape([2,1]))  # after we reshape c to be a column, we can broadcast it
```

```
In [ ]: e = np.arange(10).reshape((10, 1))  
        f = np.arange(11)  
        print(e)  
        print(f)
```

```
In [ ]: e = np.arange(10).reshape((10, 1))  
        f = np.arange(11)  
        print(e)  
        print(f)
```

```
In [ ]: print(e + f)  ## e and f are broadcast into compatible matrices and then added
```

```
In [ ]: print(e * f)  ## e and f are broadcast into compatible matrices and then multiplied eleme
```



```
In [ ]: print(e * f)  ## e and f are broadcast into compatible matrices and then multiplied eleme
```

```
In [ ]: print(d)
```

```
In [ ]: print(e * f)  ## e and f are broadcast into compatible matrices and then multiplied eleme
```

```
In [ ]: print(d)
```

```
In [ ]: d.reshape((1,6)) + d.reshape((6,1))
```

Boolean Operators in NumPy

Boolean Operators in NumPy

In []:

```
x = np.arange(6)  
print(x)
```

Boolean Operators in NumPy

```
In [ ]: x = np.arange(6)  
        print(x)
```

```
In [ ]: print(x < 3)
```

Boolean Operators in NumPy

```
In [ ]: x = np.arange(6)  
        print(x)
```

```
In [ ]: print(x < 3)
```

```
In [ ]: print(x >= 3)
```

Boolean Operators in NumPy

```
In [ ]: x = np.arange(6)  
        print(x)
```

```
In [ ]: print(x < 3)
```

```
In [ ]: print(x >= 3)
```

```
In [ ]: print(x == 3)
```

```
In [ ]: # the results can then be used to subset  
print(x[x >= 3])
```



```
In [ ]: # the results can then be used to subset  
print(x[x >= 3])
```

```
In [ ]: np.sum(x >= 3) # True = 1, False = 0, so sum counts how many are true
```

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```
In [ ]: np.mean(x >= 3) # finds the proportion that is True
```

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In [ ]: # the results can then be used to subset  
print(x[x >= 3])
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```
In [ ]: np.sum(x >= 3) # True = 1, False = 0, so sum counts how many are true
```

```
In [ ]: np.mean(x >= 3) # finds the proportion that is True
```

```
In [ ]: print(~(x == 3)) # use the tilde for negation of boolean values
```

In []: `print(~x == 3) # be careful if you leave off parenthesis`

```
In [ ]: print(~x == 3) # be careful if you leave off parenthesis
```

```
In [ ]: ~x
```

Working with matrices

Working with matrices

```
In [ ]: y = np.arange(12).reshape([3,4])  
        print(y)
```

Working with matrices

```
In [ ]: y = np.arange(12).reshape([3,4])  
        print(y)
```

```
In [ ]: print(y >= 6)
```


Working with matrices

```
In [ ]: y = np.arange(12).reshape([3,4])  
        print(y)
```

```
In [ ]: print(y >= 6)
```

```
In [ ]: np.sum(y >= 6)
```

Working with matrices

```
In [ ]: y = np.arange(12).reshape([3,4])  
        print(y)
```

```
In [ ]: print(y >= 6)
```

```
In [ ]: np.sum(y >= 6)
```

```
In [ ]: np.sum(y >= 6, axis = 0)  # you can perform sums and other aggregate functions axis-wise
```

Working with matrices

```
In [ ]: y = np.arange(12).reshape([3,4])  
        print(y)
```

```
In [ ]: print(y >= 6)
```

```
In [ ]: np.sum(y >= 6)
```

```
In [ ]: np.sum(y >= 6, axis = 0)  # you can perform sums and other aggregate functions axis-wise
```

```
In [ ]: np.sum(y >= 6, axis = 1)
```

Bitwise (element-wise) Boolean operators

Bitwise (element-wise) Boolean operators

In []:

```
a = np.array([True, True, False, False])  
b = np.array([True, False, True, False])  
print(a)  
print(b)
```

Bitwise (element-wise) Boolean operators

```
In [ ]: a = np.array([True, True, False, False])  
        b = np.array([True, False, True, False])  
        print(a)  
        print(b)
```

```
In [ ]: print(a & b) # bitwise and
```

Bitwise (element-wise) Boolean operators

```
In [ ]: a = np.array([True, True, False, False])  
        b = np.array([True, False, True, False])  
        print(a)  
        print(b)
```

```
In [ ]: print(a & b) # bitwise and
```

```
In [ ]: print(a | b) # bitwise or
```

Bitwise (element-wise) Boolean operators

```
In [ ]: a = np.array([True, True, False, False])  
        b = np.array([True, False, True, False])  
        print(a)  
        print(b)
```

```
In [ ]: print(a & b) # bitwise and
```

```
In [ ]: print(a | b) # bitwise or
```

```
In [ ]: print(a ^ b) # bitwise xor (exclusive or)
```



```
In [ ]: print(~a)  # bitwise not
```

```
In [ ]: print(~a)  # bitwise not
```

```
In [ ]: np.any(a)
```

```
In [ ]: print(~a)  # bitwise not
```

```
In [ ]: np.any(a)
```

```
In [ ]: np.all(a)
```

fancy indexing

Regular lists in python do not support fancy indexing, but NumPy does!

fancy indexing

Regular lists in python do not support fancy indexing, but NumPy does!

In []:

```
np.random.seed(1)
x = np.random.randint(100, size = 10)
print(x)
```

fancy indexing

Regular lists in python do not support fancy indexing, but NumPy does!

```
In [ ]: np.random.seed(1)
x = np.random.randint(100, size = 10)
print(x)
```

```
In [ ]: index = [0, 1, 5]
print(x[index])
```

In []:

```
a = [1, 4, 7]
b = [2, 3, 8]
ind = np.vstack([a,b])
print(ind)
```

```
In [ ]: a = [1, 4, 7]
        b = [2, 3, 8]
        ind = np.vstack([a,b])
        print(ind)
```

```
In [ ]: print(x[ind])
```



```
In [ ]: a = [1, 4, 7]
        b = [2, 3, 8]
        ind = np.vstack([a,b])
        print(ind)
```

```
In [ ]: print(x[ind])
```

```
In [ ]: x = np.arange(12).reshape((3, 4))
        print(X)
```

```
In [ ]: a = [1, 4, 7]
        b = [2, 3, 8]
        ind = np.vstack([a,b])
        print(ind)
```

```
In [ ]: print(x[ind])
```

```
In [ ]: X = np.arange(12).reshape((3, 4))
        print(X)
```

```
In [ ]: row = np.array([0, 1, 2])
        col = np.array([2, 1, 3])
        X[row, col]
```

- `np.sort()`
- `np.argsort()` gives the indexes of the values to have the proper sorting

- `np.sort()`
- `np.argsort()` gives the indexes of the values to have the proper sorting

In []:

```
np.random.seed(2)
x = np.arange(5)
np.random.shuffle(x)
print(x)
```

- `np.sort()`
- `np.argsort()` gives the indexes of the values to have the proper sorting

```
In [ ]: np.random.seed(2)
        x = np.arange(5)
        np.random.shuffle(x)
        print(x)
```

```
In [ ]: x.sort() # sorts x in place
        print(x)
```

- `np.sort()`
- `np.argsort()` gives the indexes of the values to have the proper sorting

```
In [ ]: np.random.seed(2)
        x = np.arange(5)
        np.random.shuffle(x)
        print(x)
```

```
In [ ]: x.sort() # sorts x in place
        print(x)
```

```
In [ ]: y = np.array([5, 2, 1, 4])
        print(y)
        print(y.argsort())
```

- `np.sort()`
- `np.argsort()` gives the indexes of the values to have the proper sorting

```
In [ ]: np.random.seed(2)
        x = np.arange(5)
        np.random.shuffle(x)
        print(x)
```

```
In [ ]: x.sort() # sorts x in place
        print(x)
```

```
In [ ]: y = np.array([5, 2, 1, 4])
        print(y)
        print(y.argsort())
```

```
In [ ]: d = y.argsort()
        y[d]
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the `axis` argument. For example:

Sorting along rows or columns

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```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

```
In [ ]: # sort each row of X
np.sort(X, axis=1)
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

```
In [ ]: # sort each row of X
np.sort(X, axis=1)
```

```
In [ ]: x[0,:] # selecting a row
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

```
In [ ]: # sort each row of X
np.sort(X, axis=1)
```

```
In [ ]: X[0,:] # selecting a row
```

```
In [ ]: print(X)
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

```
In [ ]: # sort each row of X
np.sort(X, axis=1)
```

```
In [ ]: X[0,:] # selecting a row
```

```
In [ ]: print(X)
```

```
In [ ]: X[:,1].argsort() # the argsort for the column index 1
```

Sorting along rows or columns

A useful feature of NumPy's sorting algorithms is the ability to sort along specific rows or columns of a multidimensional array using the axis argument. For example:

```
In [ ]: np.random.seed(1)
X = np.random.randint(0, 10, (4, 6))
print(X)
```

```
In [ ]: # sort each column of X
# np.sort returns a copy of X after sorted. It does not modify X
np.sort(X, axis=0)
```

```
In [ ]: # sort each row of X
np.sort(X, axis=1)
```

```
In [ ]: X[0,:] # selecting a row
```

```
In [ ]: print(X)
```

```
In [ ]: X[:,1].argsort() # the argsort for the column index 1
```

```
In [ ]: print(X[X[:,1].argsort(), :]) # 'subset' X by the argsort to arrange X by the column
```