

The World of Numpy



Python Mauritius UserGroup (pymug)

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The World of Numpy

⚠ Best to use ***Jupyter*** from ***Anaconda*** to try out the examples

Jupyter Shortcuts

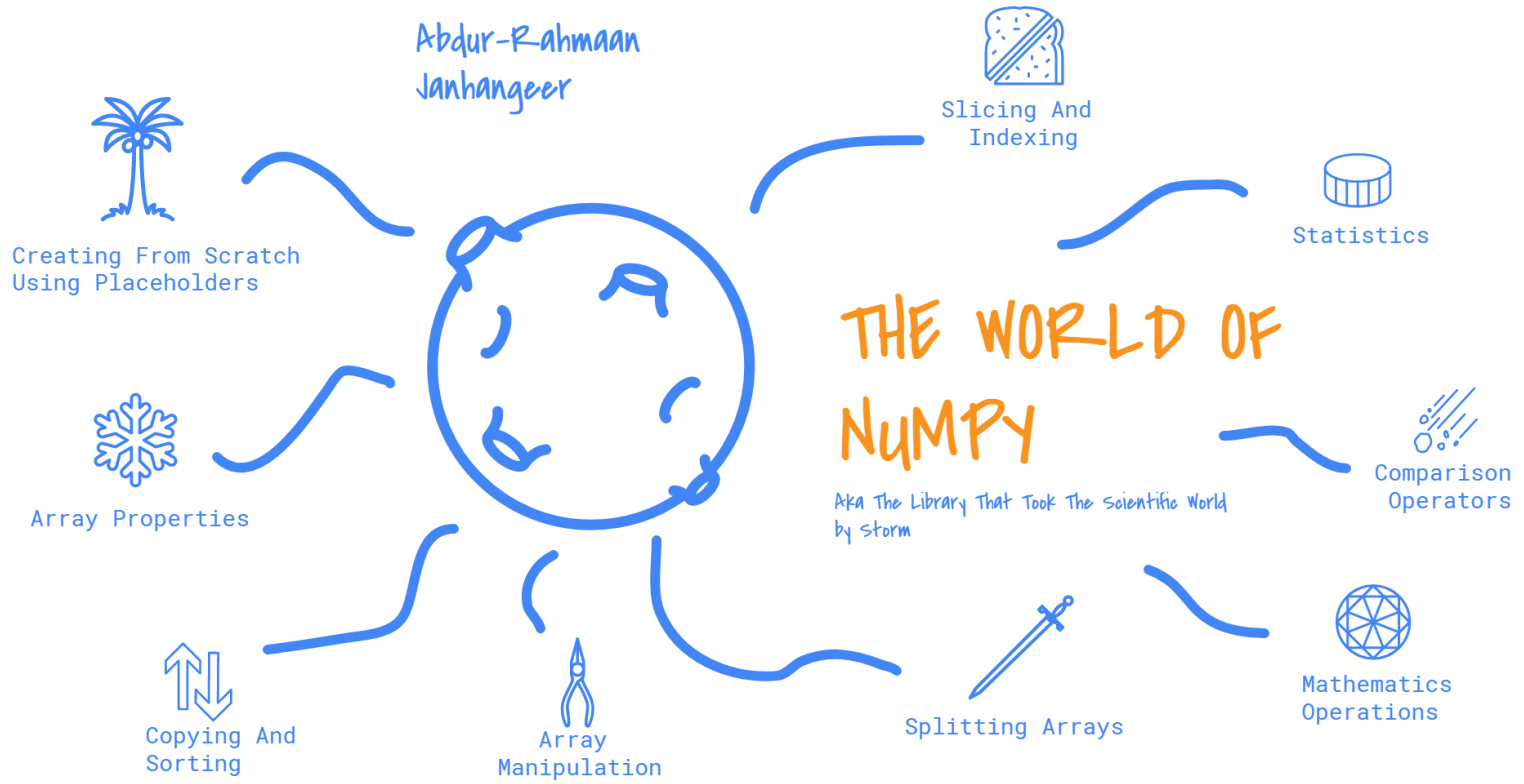
`alt + enter` : run with new cell

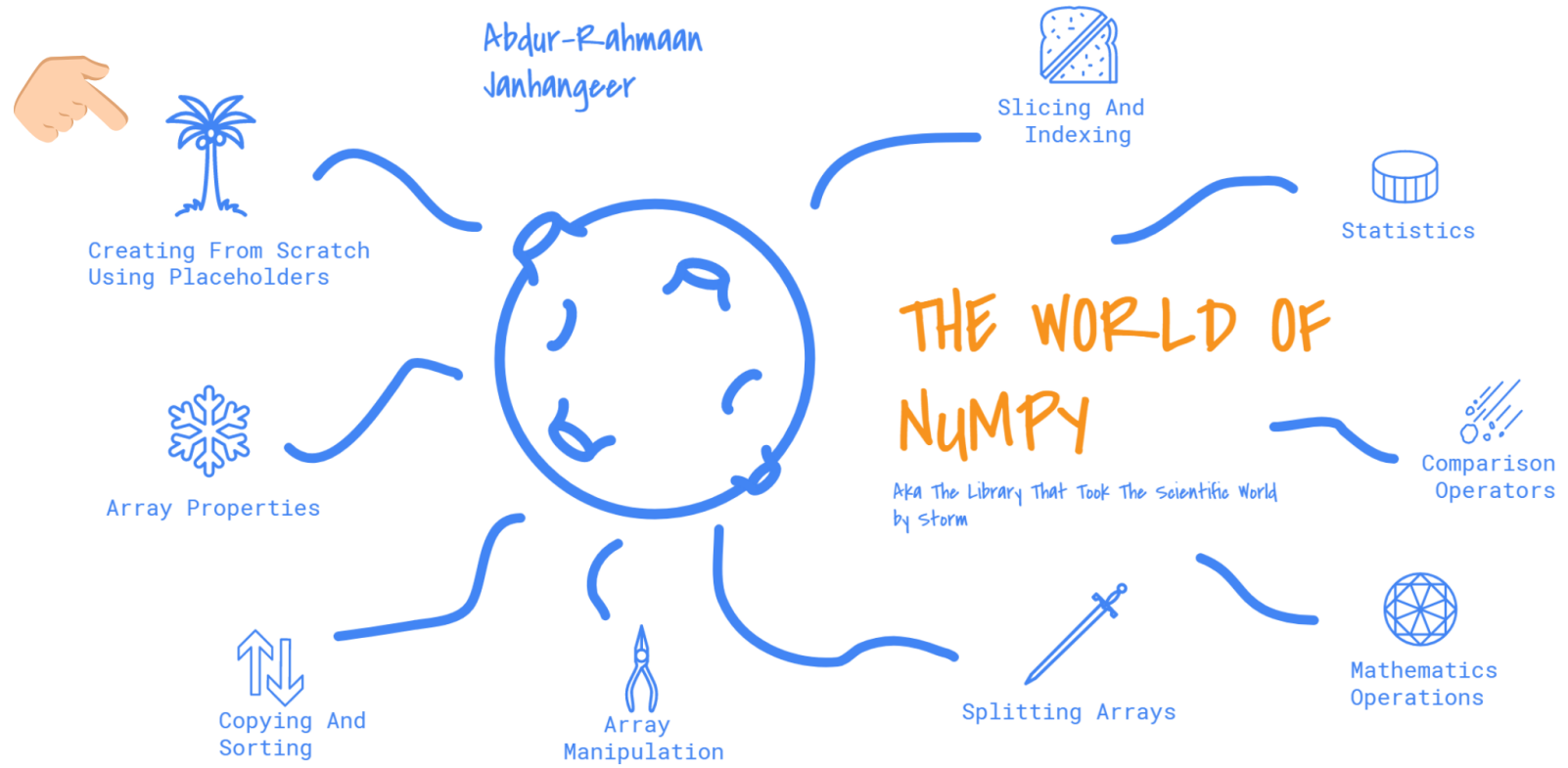
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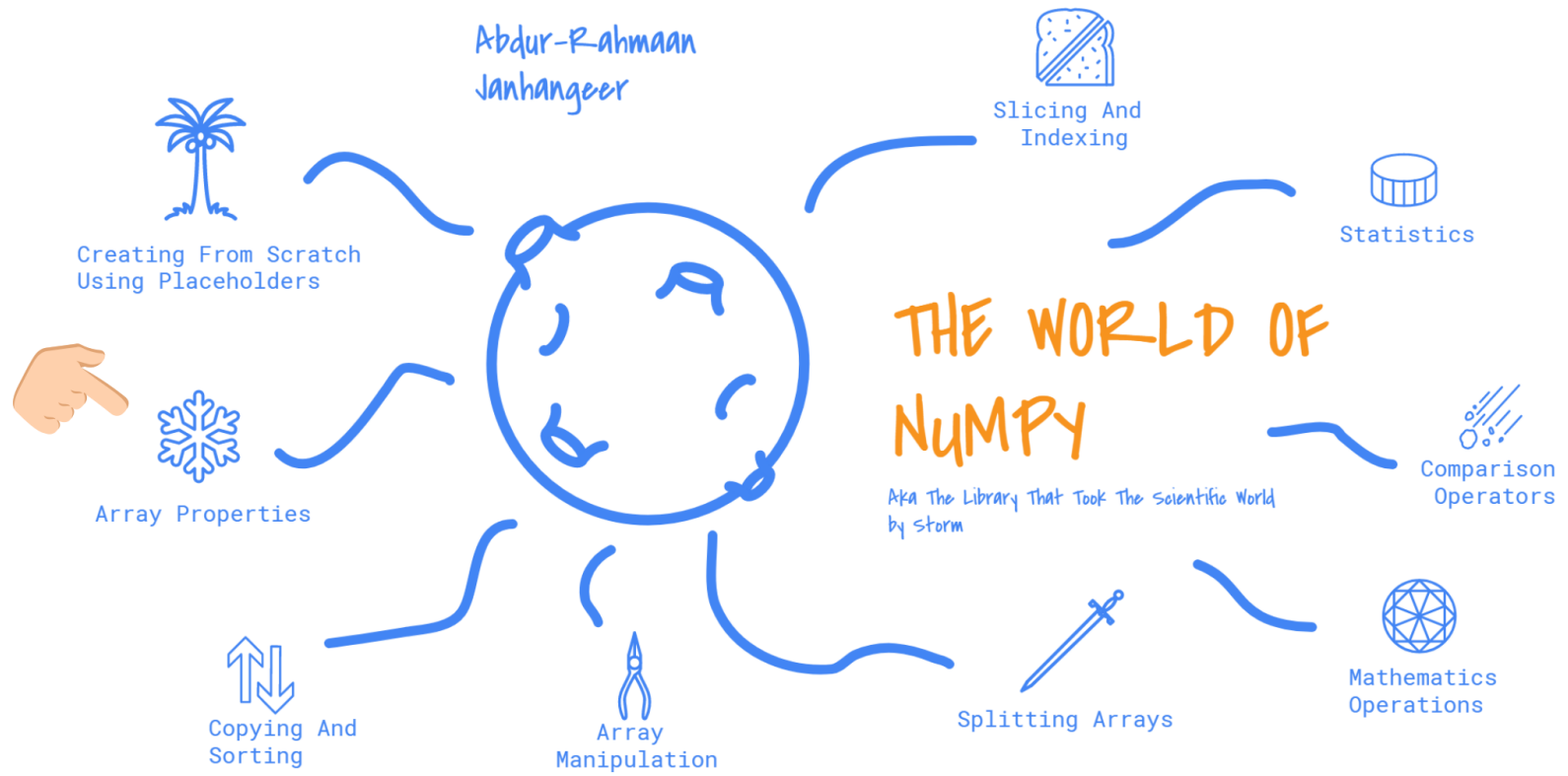
Numpy

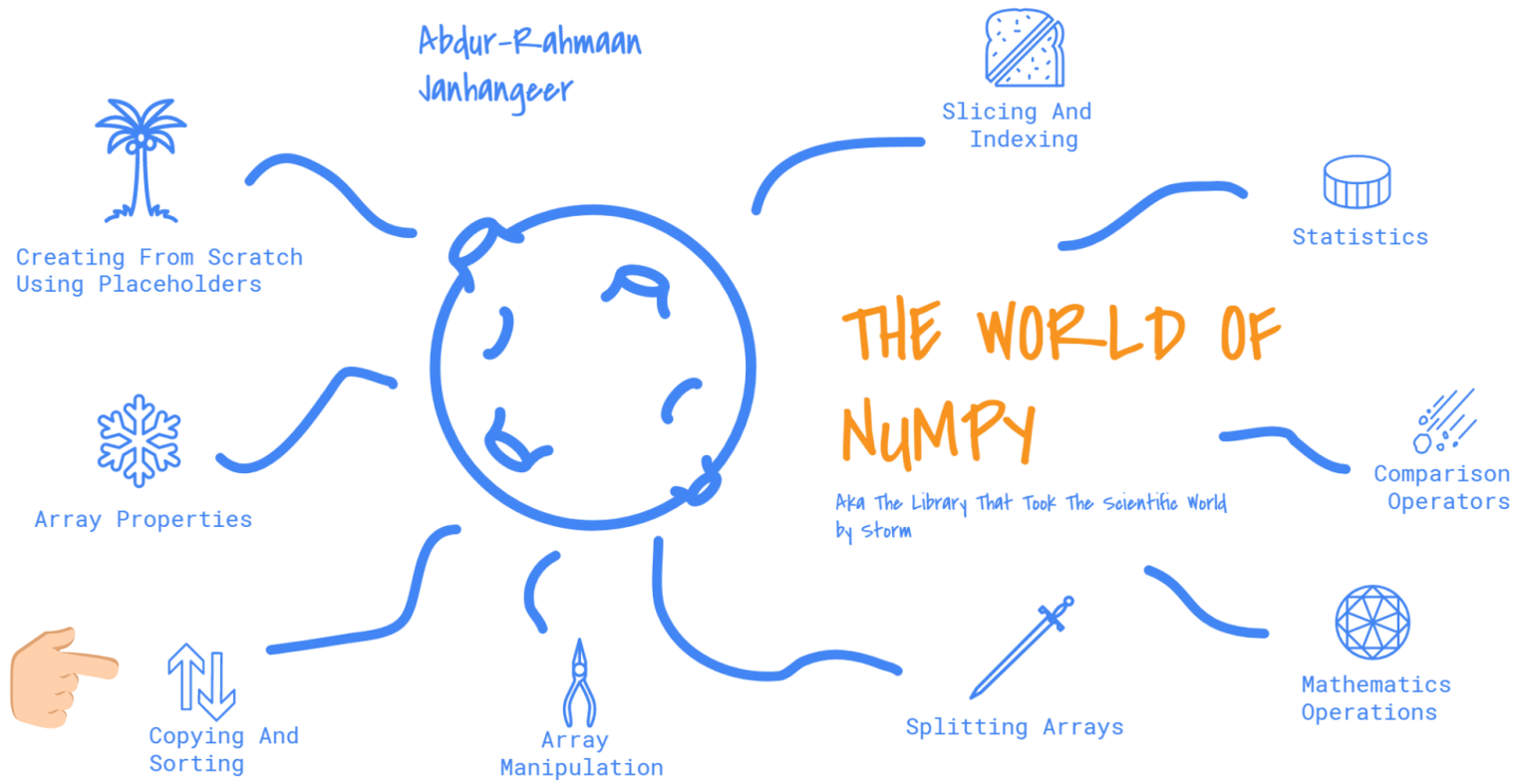
- Top 10 imports, including std lib

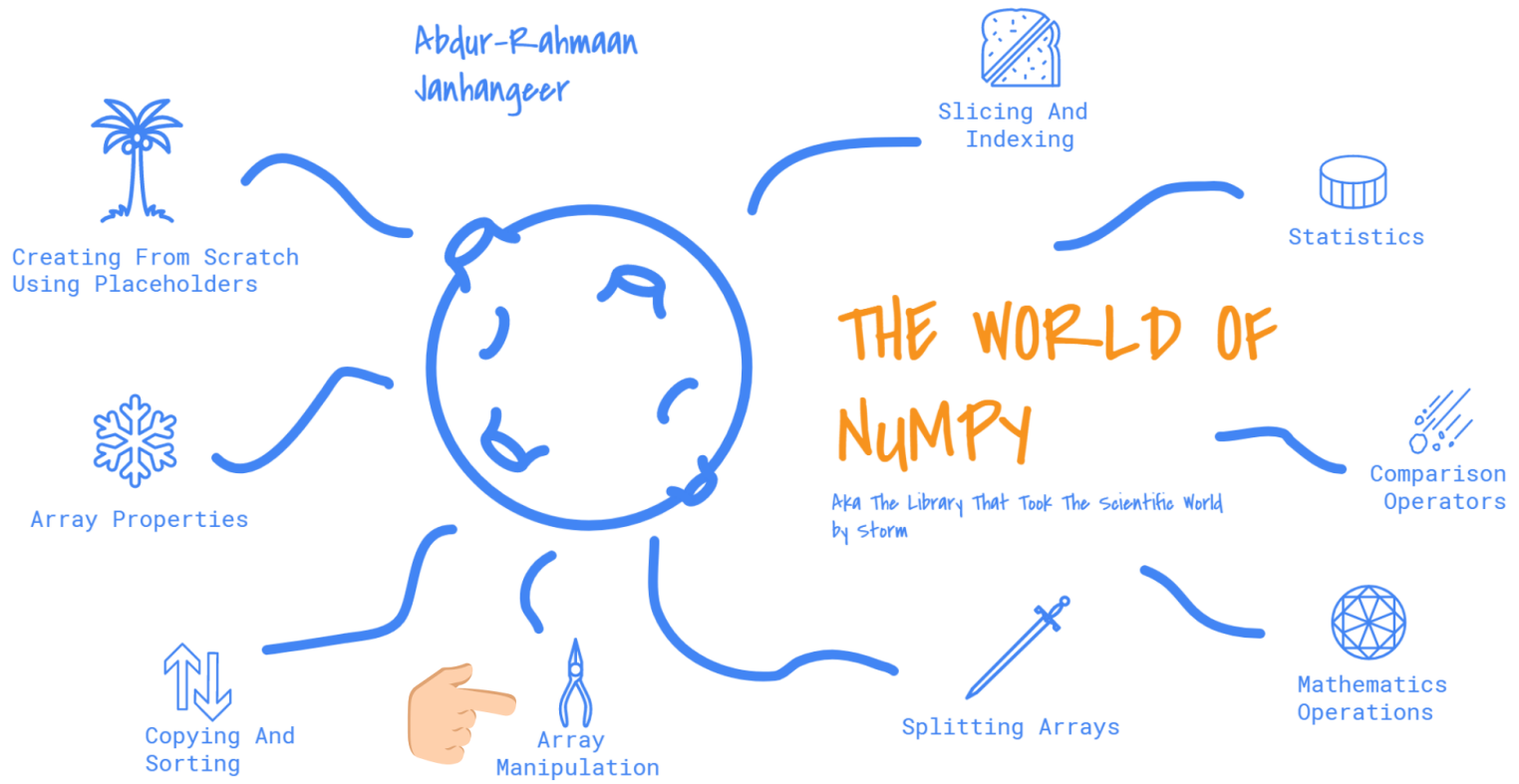


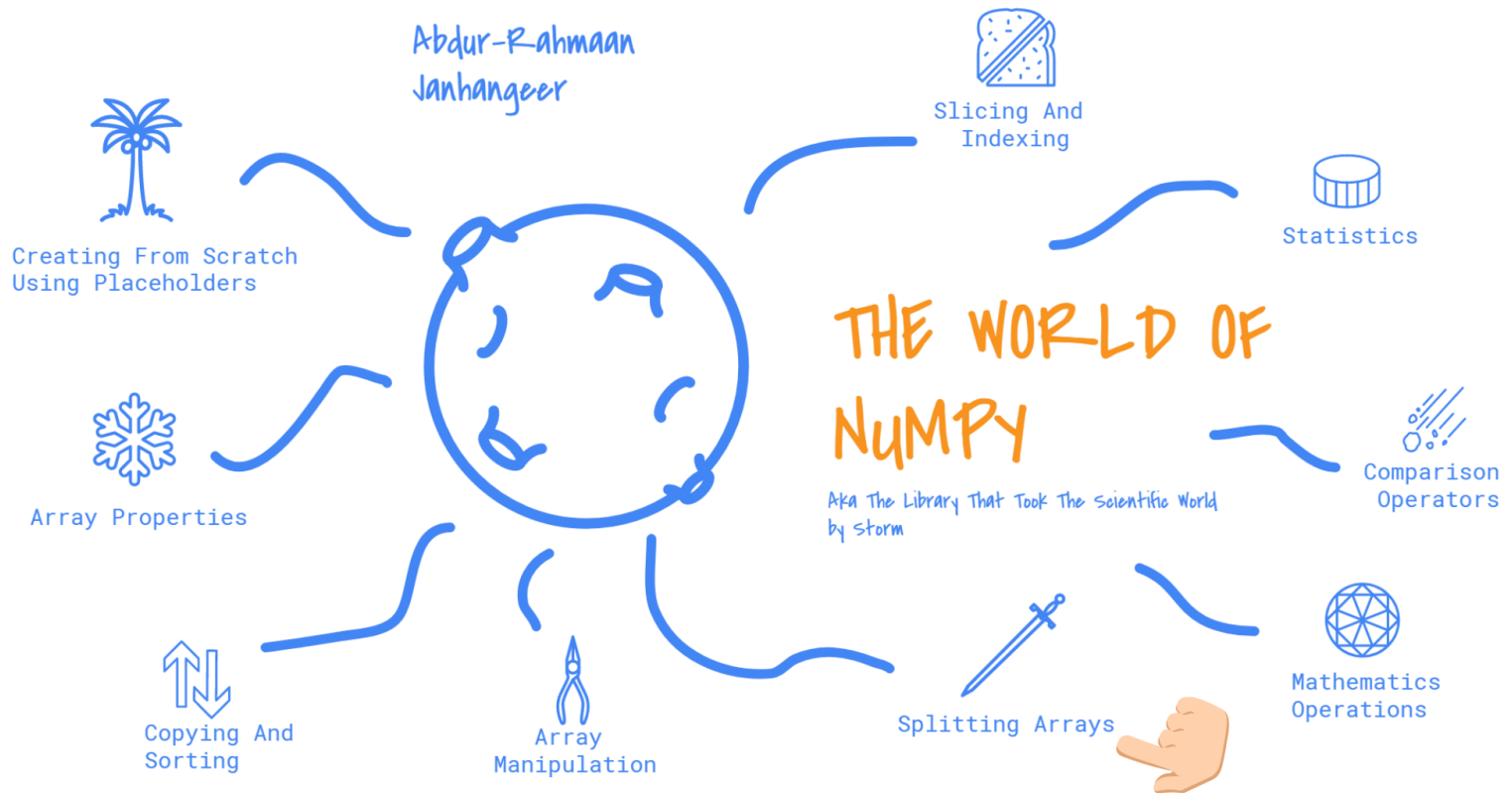


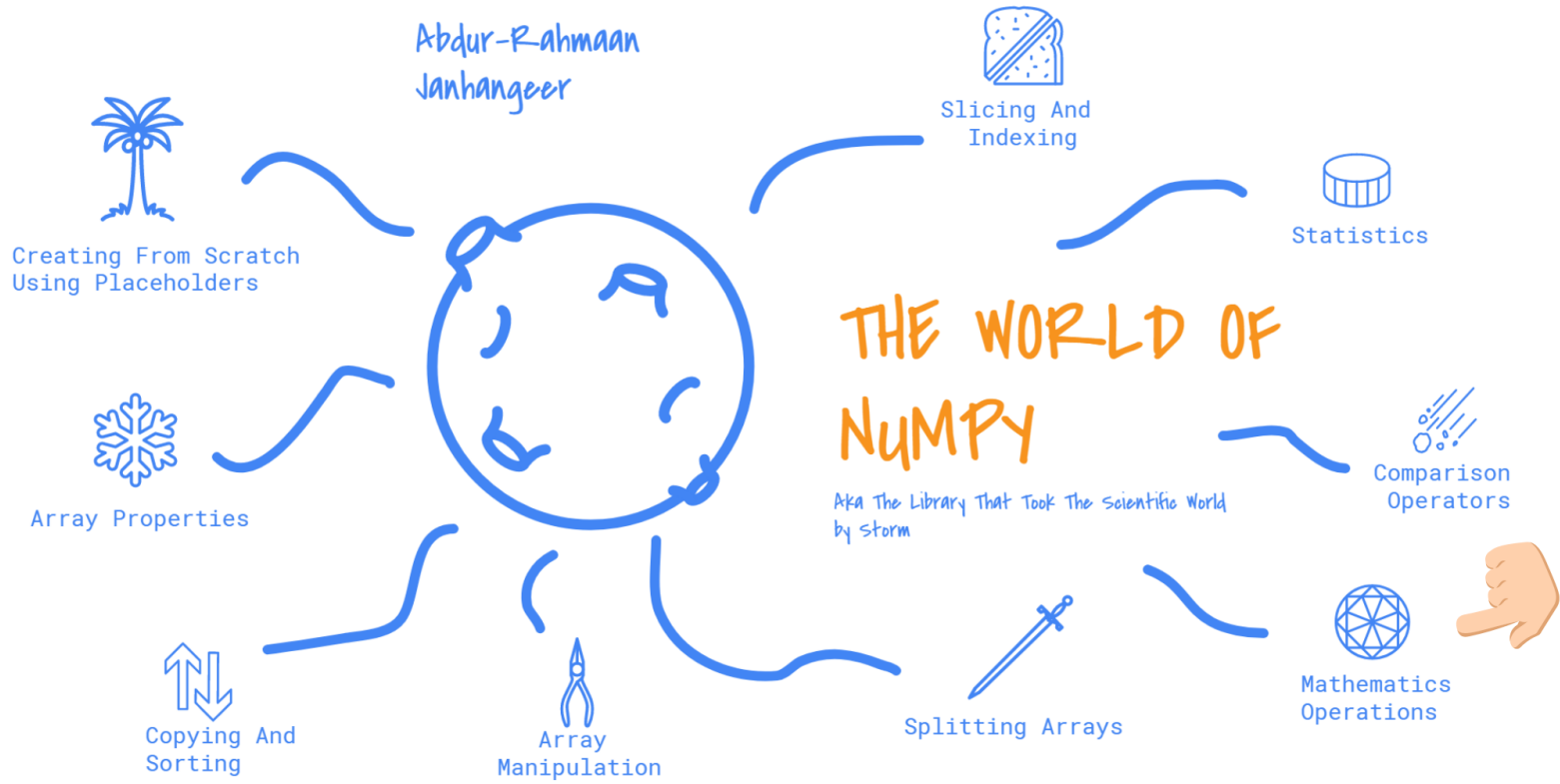


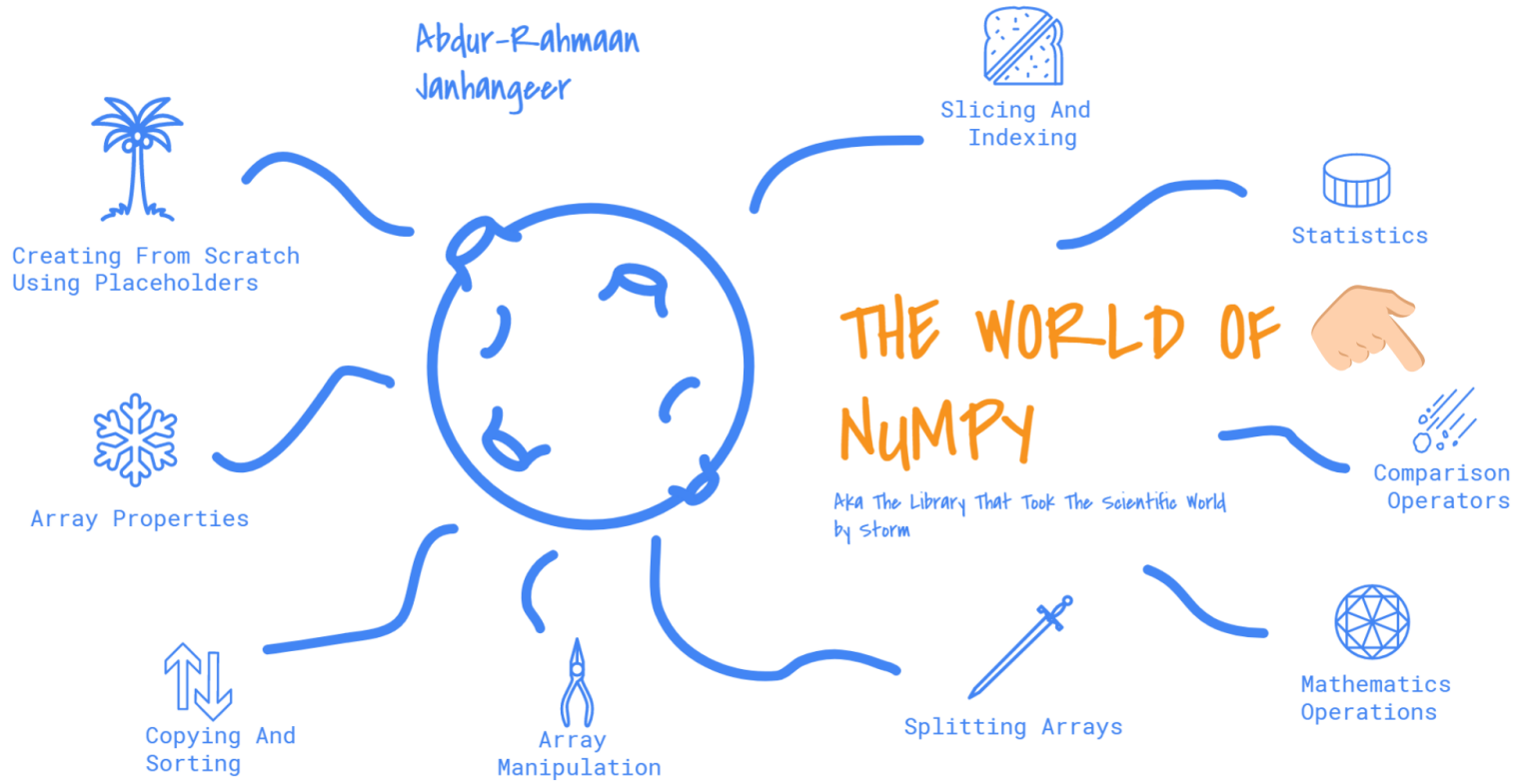


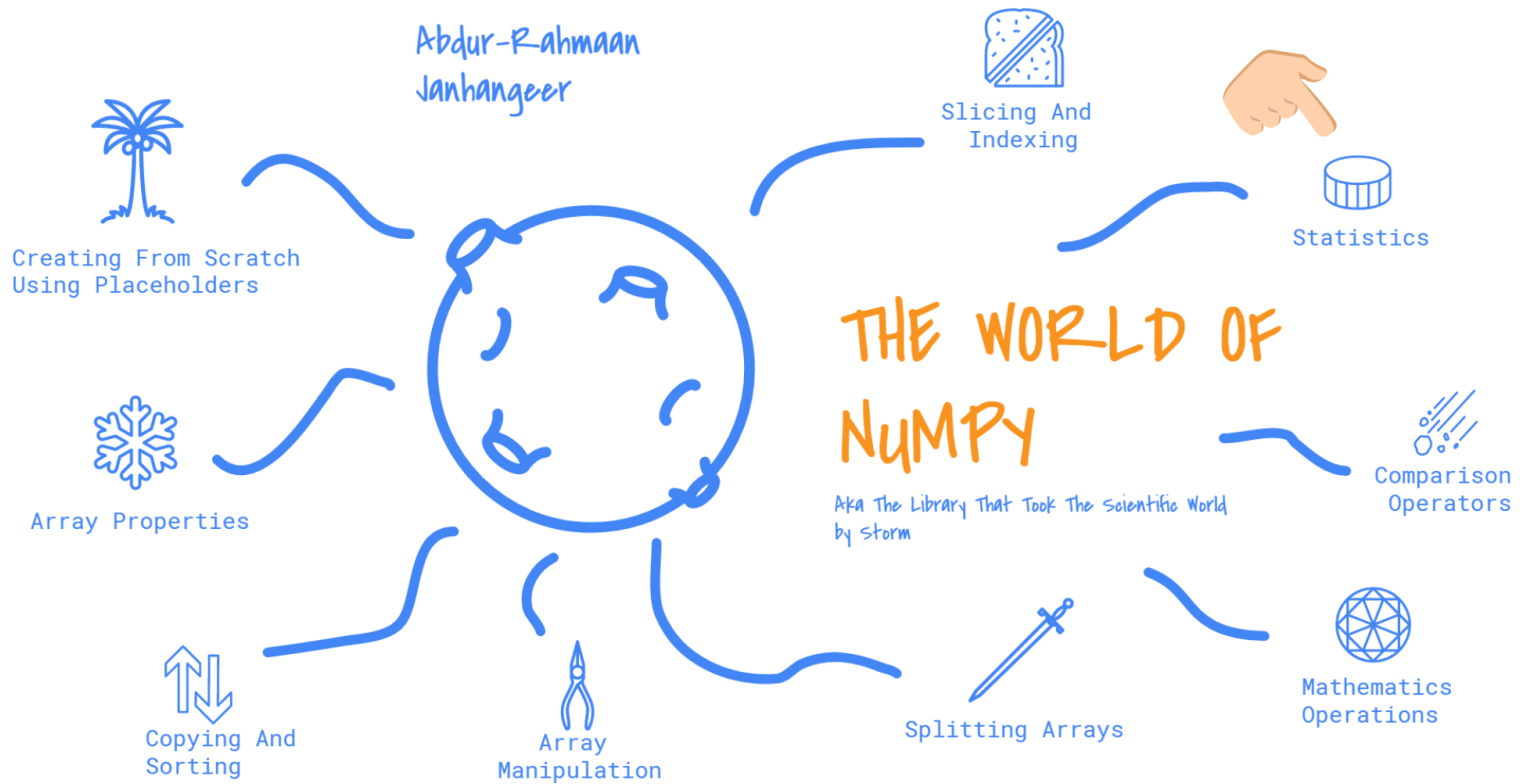


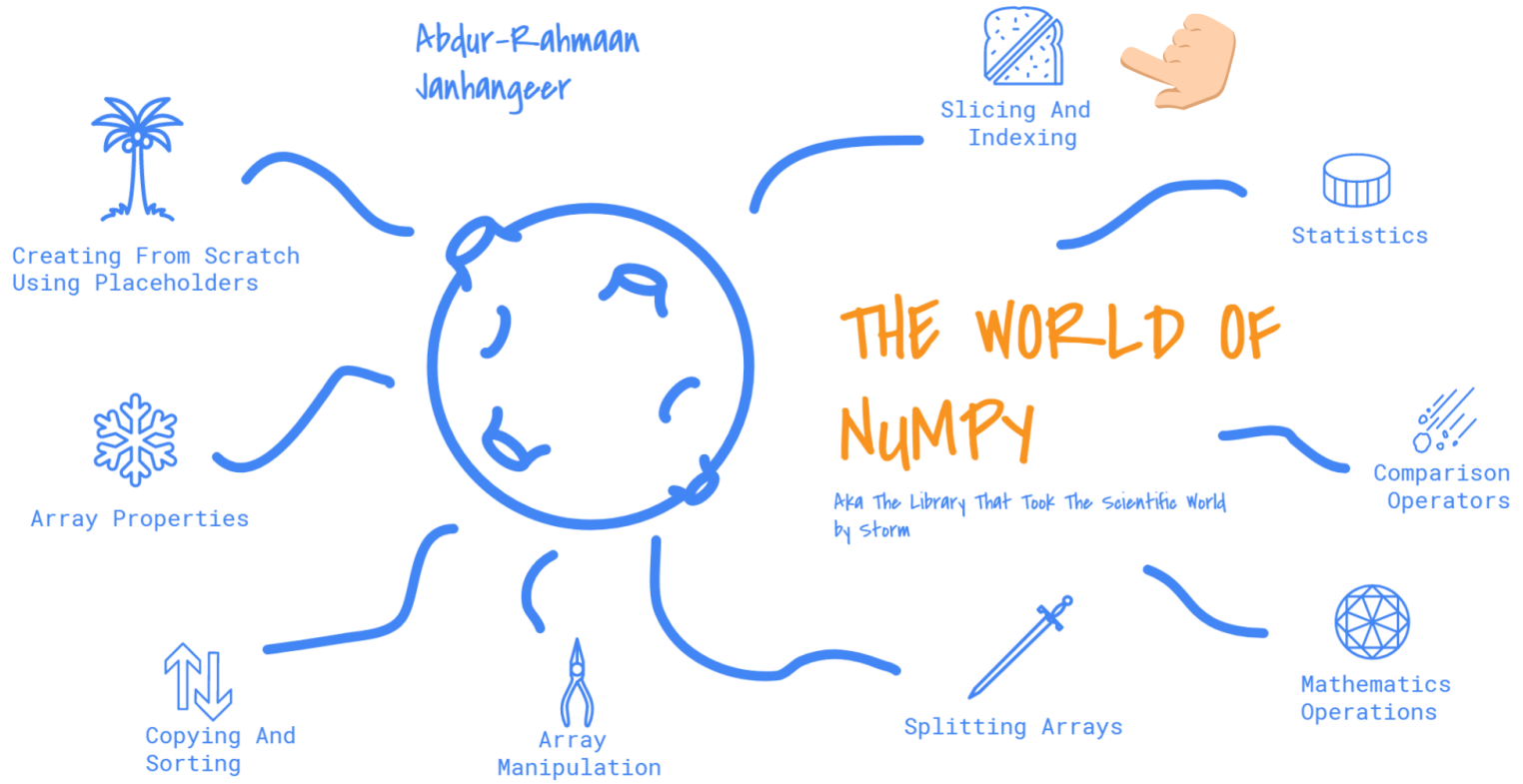












What we need to cover more:

- data types
- loading and saving data from text file

Why Numpy?

n-dimensional array manipulation is just easy and coool

Importing Numpy

```
import numpy as np
```

About numpy arrays

Numpy arrays can only hold one type of data, making them less flexible but more powerful for computation

Numpy Data Types

- `bool_` Boolean (True or False) stored as a byte
- `int_` Default integer type (same as C long; normally either int64 or int32)
- `intc` Identical to C int (normally int32 or int64)
- `intp` Integer used for indexing (same as C `ssize_t`; normally either int32 or int64)
- `int8` Byte (-128 to 127)
- `int16` Integer (-32768 to 32767)
- `int32` Integer (-2147483648 to 2147483647)

- int64 Integer (-9223372036854775808 to 9223372036854775807)
- uint8 Unsigned integer (0 to 255)
- uint16 Unsigned integer (0 to 65535)
- uint32 Unsigned integer (0 to 4294967295)
- uint64 Unsigned integer (0 to 18446744073709551615)
- float_ Shorthand for float64
- float16 Half precision float: sign bit, 5 bits exponent, 10 bits mantissa
- float32 Single precision float: sign bit, 8 bits exponent, 23 bits mantissa

- float64 Double precision float: sign bit, 11 bits exponent, 52 bits mantissa
- complex_ Shorthand for complex128
- complex64 Complex number, represented by two 32-bit floats (real and imaginary components)
- complex128 Complex number, represented by two 64-bit floats (real and imaginary components)

Creating arrays

From Existing Data

```
import numpy as np

x = [3, 4, 5, 6, 2, 4, 2]
y = [10, 30, 15, 16, 32, 76, 23]

np_x = np.array(x)
np_y = np.array(y)
```

We can create np arrays from scratch

```
# creates 3 by 4 matrix filled with zeros  
>>> zeros = np.zeros([3, 4])  
>>> zeros
```

similarly

```
np.ones([3, 3])
```

```
array([[1., 1., 1.],  
       [1., 1., 1.],  
       [1., 1., 1.]])
```

empty()

```
np.empty([2, 2])
```

```
array([[0., 0.],  
       [0., 0.]])
```

random data

```
np.random.random([3, 4])
```

```
array([[0.60905384, 0.07042812, 0.34772305, 0.47484597],  
       [0.63558091, 0.16576978, 0.72063246, 0.93037311],  
       [0.18482108, 0.3001279 , 0.79063717, 0.66592421]])
```

we can also specify the data type when creating

```
np.ones([2, 2], dtype='int')
```

for a normal array we can use a number instead of a list

```
np.ones(5, dtype='int') # here 5
```

```
array([1, 1, 1, 1, 1])
```


To check

- `np.linspace(start, stop, steps)`
- `np.full`
- `np.arange(start, stop, steps)`

Array Properties

Let's have an array, we can see some properties

```
x = np.array([[1, 2, 3, 4], [2, 4, 6, 7]])  
print(x.shape)  
print(x.ndim)  
print(x.dtype)  
print(x.size)
```

```
(2, 4)  
2  
int32  
8
```

Numpy is Powerful

Numpy Maths Operations

with numpy you can do numerical operation with arrays simply!

```
x = np.array([1, 2, 3, 4])  
x + 1
```

```
array([2, 3, 4, 5])
```

+ above is same as `np.add(x)` . Similarly `np.divide`, etc

```
x * 2, x / 2
```

```
(array([2, 4, 6, 8]), array([0.5, 1. , 1.5, 2. ]))
```

```
np.cos(x)
```

```
array([ 0.54030231, -0.41614684, -0.98999925 , -0.65364362])
```

```
np.sin(x + 1)
```

```
array([ 0.90929743,  0.14112001, -0.7568025 , -0.95892427])
```

Rounding

```
np.around(np.cos(x), decimals=1)
```

```
array([ 0.5, -0.4, -1. , -0.7])
```

`np.ceil()` rounds to the top, try it!

Stats and some tidbits

to find min we use

```
np.min(x)
```

```
1
```

```
np.max(x)
```

```
4
```

```
np.mean(x)
```

```
2.5
```

```
np.median(x)
```

```
2.5
```

```
np.std(x)
```

```
1.118033988749895
```

```
np.var(x) # variance
```

```
1.25
```



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

```
10
```

more to look at: `np.percentile(array, percent)`, `a.corrcoef()`,
`b.cumsum(axis=1)`

Numpy Concept: Axis

you might see in many examples axis, `axis=0` means column and `axis=1` means rows

More Fun: Comparing

To compare, just use operators!

```
ages = np.array([21, 22, 23, 26, 20, 30, 22, 21, 40])
```

finding ages greater than 25

```
ages > 25
```

```
array([False, False, False,  True, False,  
       True, False, False,  True])
```

```
ages == 22
```

```
array([False,  True, False, False, False,  
       False,  True, False, False])
```

normal operators work like `!=`, `<=` etc. You can also compare arrays

```
(x * 2) == (x * 3)
```

```
array([False, False, False, False])
```

all and any

```
np.all(ages > 20)
```

False

```
np.any(ages < 30)
```

True

New Arrays

```
ages[ages > 25]
```

```
array([26, 30, 40])
```

any comparison operator can be used

Indexing

Numpy's indexing works same as lists

```
ages[0]
```

```
21
```

```
ages[0:5:1] # start, stop, step
```

```
array([21, 22, 23, 26, 20])
```

```
ages[:, :] # means start from begining till end with step 1
```

```
array([21, 22, 23, 26, 20, 30, 22, 21, 40])
```

```
ages[::-1] # step -1 reverses
```

```
array([40, 21, 22, 30, 20, 26, 23, 22, 21])
```

Now let us see 2D indexing and numpy's flexibility

```
grid = np.array([[20, 22, 34],  
                 [33, 32, 12],  
                 [23, 93, 89]])  
grid[0, 0] # row, column
```

```
20
```



```
grid[:2, :2] #row upto 2, column upto 2
```

```
array([[20, 22],  
       [33, 32]])
```

```
grid[:2, ::-1] # 2 rows, reverse columns
```

```
array([[34, 22, 20],  
       [12, 32, 33]])
```

The Need For Clones (Copies)

let's extract a 2 by 2 grid

```
grid2 = grid[:2, :2]
```

```
grid2
```

```
array([[20, 22],  
       [33, 32]])
```

changing some data

```
grid2[0][0] = 1
```

```
grid2
```

```
array([[ 1, 22],  
       [33, 32]])
```

```
grid
```

```
array([[ 1, 22, 34],  
       [33, 32, 12],  
       [23, 93, 89]])
```

grid 1 also changed. that's why we need copies.
copies achieved by

```
grid2 = grid[:,2, :2].copy()
```

Array Manipulation

splitting is done as

```
np.split(ages, 3)
```

```
[array([21, 22, 23]),  
 array([26, 20, 30]),  
 array([22, 21, 40])]
```

```
ages.reshape((3, 3))
```

```
array([[21, 22, 23],  
       [26, 20, 30],  
       [22, 21, 40]])
```

```
np.concatenate([grid, grid])
```

```
array([[ 1, 22, 34],  
       [33, 32, 12],  
       [23, 93, 89],  
       [ 1, 22, 34],  
       [33, 32, 12],  
       [23, 93, 89]])
```

```
np.sort(grid, axis=0)  
# axis=0 means columns,  
# axis=1 means rows
```

```
array([[ 1, 22, 12],  
       [23, 32, 34],  
       [33, 93, 89]])
```

```
arr = np.array([
    [2, 34, 2],
    [32, 4, 2]])
arr.T # transpose, 2x3 -> 3x2
```

```
array([[ 2, 32],
       [34,  4],
       [ 2,  2]])
```

'vector' manipulations or linear algebra

```
np.linalg.inv(grid)
```

```
array([[ 0.07693674,  0.05348259, -0.0366027 ],  
       [-0.11820362, -0.03078358,  0.04930704],  
       [ 0.10363362,  0.01834577, -0.030828  ]])
```

```
# dot product
```

```
x = np.array([[23, 45, 78], [34, 94, 32]])  
y = np.array([[92, 23, 90], [23, 67, 32], [23, 67, 32]])  
np.dot(x, y)
```

```
array([[4945, 8770, 6006],  
       [6026, 9224, 7092]])
```


Text Files With Numpy

Numpy has can load text files off the bat sing `np.loadtxt` but using pandas

Numpy Concept: broadcasting

Broadcasting simply means when doing operations, arrays are stretched so as to be able to do the operation.

Next: Go Deeper

Find a numpy tuto and see what we did not include XD