

SAGAR CHOUKSEY											
<u>Numpy</u>											
Stand for Numerical Python.	Created by Travis Oliphant in 2005 to make the otherwise slow Python loops fast and memory efficient.										
Features :-	Speed in (50-100x faster than normal Python lists) Less Memory Occupying Easy Math Operations :- (almost every column)										
List vs Numpy Arrays	<table border="1"><thead><tr><th>List</th><th>Np Arrays</th></tr></thead><tbody><tr><td>Slow</td><td>Fast (50-100x)</td></tr><tr><td>Memory - Usage More</td><td>Less Memory used</td></tr><tr><td>Operations -</td><td>Large Dataset</td></tr><tr><td>Uses -</td><td>Smaller Level Lists</td></tr></tbody></table>	List	Np Arrays	Slow	Fast (50-100x)	Memory - Usage More	Less Memory used	Operations -	Large Dataset	Uses -	Smaller Level Lists
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Install in your local Machine:											
! pip install numpy											
! pip install numpy Installed in .ipynb											
Pre installed in Google Colab.											

solutions near you simply by

The Academic Industry Gap

what Industry Demands

- Messy data and ambiguous problems
- Hands on tools
- Relevant things and projects

what Academia Teaches

- Theoretical foundations and algorithms
- clean datasets and controlled environments
- Individual assignments with clear objectives
- Emphasis on accuracy metrics

Framework → ~~Making Academic~~

```

python_list = [1, 2, 3, 4, 5]
print(python_list)

```

```

import numpy as np
arr_1d = np.array([1, 2, 3, 4, 5]) ← Array in Numpy

```

1D Array in Numpy =

```

2D Array in Numpy →
    (Elements)

```

```

import numpy as np
arr_2d = np.array([
    [1, 2, 3],
    [4, 5, 6],
    [7, 8, 9]
])
print(arr_2d)

```

Pythonic lists to Numpy Arrays

```

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

```

+ Creating Arrays with ones

as default values

```

import numpy as np
o_arr = np.ones(3)
print(o_arr) → [1. 1. 1.]

```

NOTE = WE CAN ALSO DO THE SAME

with a 2D System

```

import numpy as np
ones_array = np.ones((2, 3))
print(ones_array)
[[1. 1. 1.]
 [1. 1. 1.]]

```

Creating Identity Matrices

+ Eye Method i.e eye(num)

- import numpy as np

if i1 = np.eye(3)

print(i1)

creating Array with default values

```

import numpy as np
z_arr = np.zeros(3)
print(z_arr)
[0. 0. 0.]

```

Creating specific VALUE

(Full Function)

Full(shape, value)

import numpy as np

np.full((2, 2), 7)

Creating SEQUENCE OF Numbers in Numpy

use → range(start, stop, step)

import numpy as np

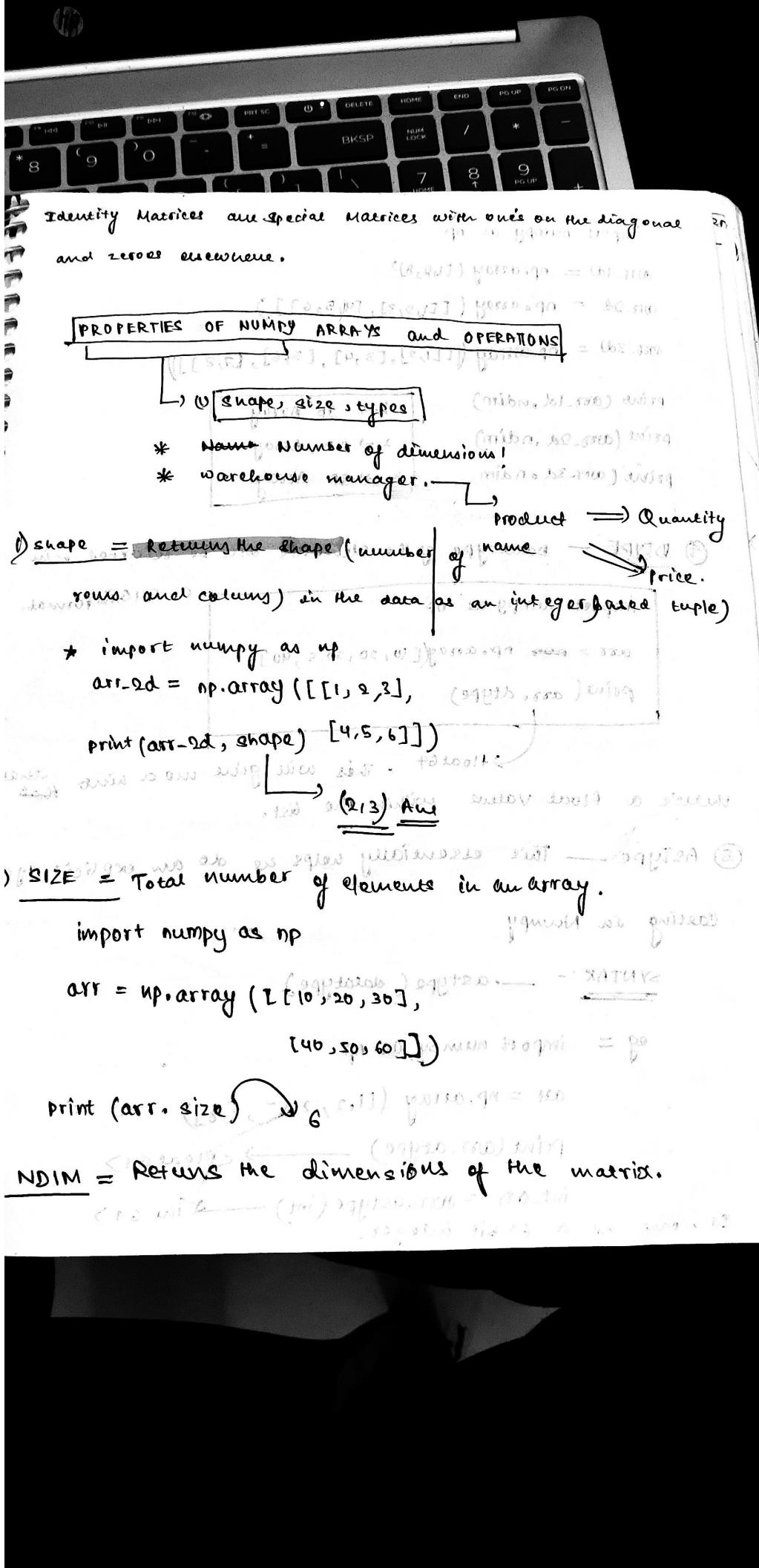
arr = np.arange(1, 10, 2)

print(arr)

```

[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]

```



Identity Matrices are special Matrices with one's on the diagonal and zeros elsewhere.

PROPERTIES OF NUMPY ARRAYS and OPERATIONS

- * shape, size, types
- * Name: Number of dimensions!
- * warehouse manager.

Product \Rightarrow Quantity

) shape = Returns the shape (number of rows and columns) in the data as an integer packed tuple.

```
* import numpy as np  
arr_2d = np.array([[1, 2, 3],  
                   [4, 5, 6]])  
print(arr_2d, shape) [4,5,6]
```

Erstellen eines 2D Arrays mit 3 Zeilen und 3 Spalten.

Ergebnis: (2,3). Ausgabe ist ein 2D-Array.

) SIZE = Total number of elements in an array.

```
import numpy as np  
arr = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])  
print(arr, size) [40,50,60]
```

Ergebnis: 10

NDIM = Returns the dimensions of the matrix.

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

Ergebnis: 3



import numpy as np

arr_1d = np.array([1, 2, 3, 4, 5, 6, 7, 8])

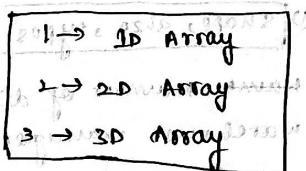
arr_2d = np.array([[1, 2, 3], [4, 5, 6]])

arr_3d = np.array([[[1, 2], [3, 4], [5, 6], [7, 8]]])

print(arr_1d.ndim)

print(arr_2d.ndim)

print(arr_3d.ndim)



④ DTYPE — Datatype of the elements will be returned in

eg:- import numpy as np

arr = np.array([10, 20, 30.5, 40])

print(arr.dtype)

64 bit format.

([10, 20, 30.5, 40])

→ float64 — This will give me a hint that there's a float value within the list.

⑤ ASTYPE — This essentially helps us do an explicit type conversion of elements of an array.

Creating in Numpy

SYNTAX:- arr.astype(datatype)

eg = import numpy as np

arr = np.array([1.2, 2.5, 3.8])

print(arr.dtype)

→ <float64>

int_arr = arr.astype(int)

→ int64 means as a 64 bit integer.

MATHEMATICAL OPERATIONS THAT CAN BE PERFORMED ON THE SAID ARRAYS

Import All Arithmetic options that we can perform on arrays can be achieved on Numpy.

maths.py \Rightarrow import numpy as np

```
arr = np.array([10, 20, 30])
print(arr + 5)  $\rightarrow$  [15, 25, 35]
print(arr * 2)  $\rightarrow$  [20, 40, 60]
print(arr ** 2)  $\rightarrow$  [100, 400, 900]
```

ACQUAERATION FUNCTIONS IN THE NUMPY LIBRARY

FUNCTION	WHAT IT DOES
np.sum(array)	Add all Elements
np.mean(array)	Returns the Average of All Elements
np.std(array)	Returns the Standard Deviation of all Arrays
np.min(array)	Returns the Minimum of the Array Elements
np.max(array)	Returns the Maximum Value of the Array Elements
np.var(array)	Returns the Variance of the Array Elements

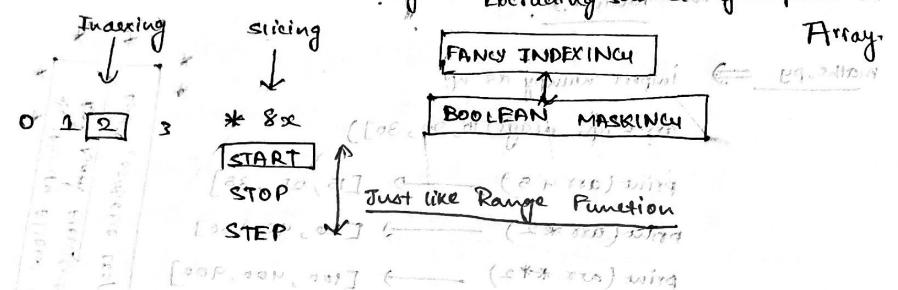
e.g. import numpy as np

```
arr = np.array([10, 20, 30, 40, 50])
print(np.sum(arr))
print(np.mean(arr))
print(np.min(arr))
print(np.max(arr))
print(np.std(arr))
print(np.var(arr))
```



④ **INDEXING + SLICING** → we can access any particular element at any particular position of the array — that is known as Slicing.

Slicing → Extracting subsets of a parent array.



* Fancy Indexing = It is a method of using an array (or list) of indices to select multiple, non-contiguous elements.

How to use these? This process involves two main steps:

- (1) Select the desired subset of data using an index array or a boolean mask.
- (2) Apply an Aggregation Function that can then be used.

import numpy as np
data = np.array([10, 20, 30, 40, 50])

indices = np.array([1, 4, 7, 8])

selected_elements = data[indices]

print("Selected Elements : ", selected_elements)

avg_value = np.mean(selected_elements)

print("Average of selected elements is : ", avg_value)

BOOLEAN MASKING → It's a powerful Numpy Technique for filtering, selecting, modifying, or counting elements in an array based on specific conditions.

SYNTAX → `array[index]` # 1D Array
`array [row][column]` # 2D Array

eg - import numpy as np
`arr = np.array([10, 20, 30, 40, 50])`

`print(arr[0])` → 10 (first element)
`print(arr[2])` → 30 (third element)
`print(arr[-1])` → 50 (last element)

Index Number as well
call it "0" as
uses '0' based indexing
Uses -ve indexing as well

arr[start, stop]
goes from start to end -1

eg - import numpy as np
`arr = np.array([10, 20, 30, 40, 50, 60])`

`print(arr[1:5])` → 20, 30, 40, 50
`print(arr[:4])` → 10, 20, 30, 40
`print(arr[1:-2])` → 20, 30, 40
`print(arr[::-1])` → 60, 50, 40, 30, 20, 10

REFERRING DATA

BOOLEAN MASKING → eg :- `arr > 25`

`import numpy as np`

`arr = np.array([10, 20, 30, 40, 50])`

`print(arr[arr > 25])`



(ii) RESHAPING AND MANIPULATING → Reshaping is changing the

dimensions of data without modifying its metadata (elements)

eg- 1D Array → 2D "

2D " → 3D "

* The total number of elements (even after reshaping/conversion remains the same)

SYNTAX = arr.reshape()

* It doesn't create a copy, rather creates a view, (original array)

Two arguments are taken i.e. rows and columns.

* Note = This can only be done if and only if the dimensions match otherwise you can't reshape it.

i.e. rows * columns

([10, 20, 30, 40, 50]) → 5x10

e.g - import numpy as np

```
arr = np.array([10, 20, 30, 40, 50])  
arr.reshape(5, 1)
```

reshapedArr = arr.reshape(2, 5)

```
print(reshapedArr)
```

Output → [[1 2 3]
[4 5 6]]

FLATTENING ARRAYS

ravel()

flatten()

Used for -

→ multidimensional

→ 1D array

→ 1D array

ravel()

flatten()

Both work in similar ways

* Difference → ravel() just changes the view only but flatten changes the



but flatten creates a copy of the table.

```
import numpy as np
```

```
arr_2d = np.array([[1, 2, 3],  
                  [4, 5, 6]])
```

```
print(arr_2d.ravel())
```

```
Print(arr_2d.flatten())
```

RESHAPING AND MANIPULATING ARRAYS

Dimension Change

Element
Add, Remove, Stack, Split

ARRAY C without Modifying

Syntax = np.insert(

(1, 2, 3, 4), 3, 5)

Array

Index

Value

axis = None

Axis = 0 (For Row-Wise)

NUM (For Flattened Array)

by Default

1 (For column wise)

If axis none then
inserted into flat
ed array

eg - import numpy as np

```
arr = np.array([10, 20, 30, 40, 50, 60])
```

```
Print("Original Array: {arr}")
```

```
new_arr = np.insert(arr, 2, 100)
```

[10, 20, 30, 40, 50, 60]

```
Print("New Array: {new_arr}")
```

Now HOW TO DO THIS IN 2D

CONV

```

import numpy as np
arr_2d = np.array([[1, 2], [3, 4]])
print(arr_2d)
# Inserted at Position ①

```

new_arr_2d = np.insert(arr_2d, 1, [5, 6], axis=None)

print(new_arr_2d)

APPEND IN NUMPY ARRAYS

(Inserts at The End of the Particular Numpy Array) ②

```

import numpy as np
arr = np.array([10, 20, 30])
new_array = np.append(arr, [40, 50, 60])

```

Print(new_array)

'ONCATENATE 2 ARRAYS' ③

NP. CONCATENATE ((Array1, Array2), axis=0)

- import numpy as np

arr1 = np.array([1, 2, 3])

arr2 = np.array([4, 5, 6])

new_array = np.concatenate((arr1, arr2))

Print(new_array)



new_arr = DELETE ARRAY

Syntax: `np.delete(array, index, axis=None)`

flatten array

* import numpy as np
`arr = np.array([10, 20, 30, 40, 50, 60])`
`print(arr) → [10, 20, 30, 40, 50, 60]`

`new_arr = np.delete(arr, 2, axis=None)`
`print(new_arr) → [10, 20, 40, 50, 60]`

How to do this in the 2D Array?

0. Import np (3) → `import numpy as np` with `arr_2d = np.array([[1, 2, 3], [4, 5, 6]])`

1. If new, np (3) → `new_arr_2d = np.delete(arr_2d, 0, axis=0)`
`print(new_arr_2d)`

and not integer elements in a multi-dimensional array.

STACKING IN ARRAYS

`arr1 = np.array([1, 2, 3])`
`arr2 = np.array([4, 5, 6])`
`print(np.vstack([arr1, arr2]))` → `[1 2 3
4 5 6]`

SYNTAX: `np.vstack(—, —)`

ROW WISE VERTICALLY STACK

HORIZONTAL STACK

`arr1 = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])`
`arr2 = np.array([[10, 11, 12], [13, 14, 15], [16, 17, 18]])`
`print(np.hstack([arr1, arr2]))` → `[1 2 3 10 11 12
4 5 6 13 14 15
7 8 9 16 17 18]`

COLUMN WISE

TWO ARRAYS



print(np.vstack([arr1, arr2]))

→ VSTACK → HSTACK

★ VSTACK implicitly changes the dimensions without specifying.

[[1 2 3], [4 5 6]] → [[1 2 3 4 5 6]]

[SPLITTING AN ARRAY IN NP INTO SUBARRAYS]

e.g -

import numpy as np

num = np.array([10, 20, 30, 40, 50, 60])

print(np.split(3))

→ Uniformly → ① np.split(3) or 3 will

Horizontally → ② np.hsplit()

Vertically → ③ np.vsplit()

[[10 20 30 40], [50 60]] → [10 20 30] → [40 50 60]

but → [10 20 30 40] → [10 20 30 40] → [10 20 30 40]

otherwise it will cause an ValueError.

BROADCASTING

EPS we perform

operations on entire

array without

using loops.

→ (1) 100 * 100

→ (2) 100 * 100

→ (3) 100 * 100

→ (4) 100 * 100

→ (5) 100 * 100

→ (6) 100 * 100

→ (7) 100 * 100

→ (8) 100 * 100

→ (9) 100 * 100

→ (10) 100 * 100

→ (11) 100 * 100

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→ (206) 100 * 100

→ (20

```
import numpy as np  
prices = np.array([100, 200, 300])  
discount = 10  
final_prices = prices - (prices * discount / 100)  
print(final_prices)  $\Rightarrow$  [this will be a Numpy Array]
```

HOW NUMPY HANDLE ARRAYS OF DIFFERENT SHAPES

1) Matching dimensions := $[1, 2, 3] + [4, 5, 6]$

2) Expanding single dimensions := $[5, 7, 9]$

eg $\rightarrow [1, 2, 3] + 10$
 $= [11, 12, 13]$

(if we add a single element to an array the single element would generally be expanded to operate with each element of the list)

3) INCOMPATIBLE SHAPES := Any other combination (other than ① and ②)

$$\begin{array}{c} [1, 2, 3] + [1, 2] \\ \hline \textcircled{3} \quad \textcircled{2} \end{array}$$

returns an ValueError due to incompatible operand types.

ERROR: $([1, 2, 3]) + 100 = 100$

eg — import numpy as np

arr = np.array([100, 200, 300])

result = arr * 2
print(result) → [200, 400, 600]

eg(2) ⇒ import numpy as np
matrix = np.array([1, 2, 3, 4, 5, 6])
vector = np.array([10, 20, 30])
result = matrix + vector
print(result) → [10 20 30],
[1, 2, 3] + [10, 20, 30] = [11, 21, 31]

eg(3) ⇒ import numpy as np
arr1 = np.array([[1, 2, 3], [4, 5, 6]])
arr2 = np.array([1, 2]) # shape(2, 1)
result = arr1 + arr2
print(result) → [[10, 11, 12], [14, 15, 16]]

VECTORIZATION → Iterating over the loop or the list without loop
is known as Vectorization

→ import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
result = arr1 + arr2
print(result) → [5, 7, 9]



```

import numpy as np
arr = np.array([10, 20, 30])
multiplied = arr * 5
print(multiplied), now [50, 100, 150]

```

↳ [50, 100, 150] is what just doing using?

↳ HANDLING MISSING / INCORRECT VALUES

VECTORIZATION is about loop
Faster than conditional python
loop on the background part is
written in C/C++ for speed.

↳ These are useful

- ↳ Built-in Functions
- * np.isnan = Detect Missing Values
- * np.nan_to_num () => Converts NaN
- * np.isinf () => Detects infinite value.

eg - import numpy as np

```
arr = np.array([1, 2, np.nan, 4, np.nan, 6])
```

```
print(np.isnan(arr))
```

```
cleaned_arr = np.nan_to_num(arr)
```

```
print(cleaned_arr)
```

↳ [1, 2, 0, 4, 0, 6] If we don't specify

↳ handling broken Null,
Empty or NaN values.

↳ What is NaN ?

NAN	NAN is a Javascript
Not A Number	Term which means the adept absence of a Number.

↳ [False False True False True False]

↳ RETURNs a Boolean
Array True for NAN
False otherwise.

↳ Any value then NAN will become replaced with 0

```
clea = np.nan_to_num(arr, nan=0)
```

```
print(clea) → [1, 2, 0, 4, 0, 6]
```

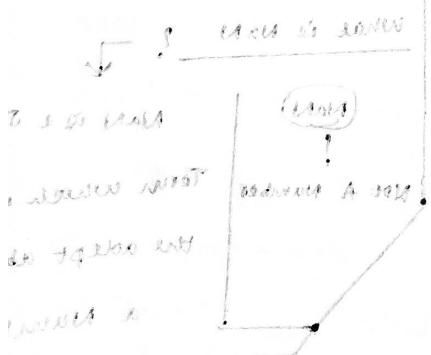


```
import numpy as np
arr = np.array([1, 2, np.inf, 4, -np.inf, 6])
arr<inf> (arr == np.inf) (arr<inf> arr<inf> arr<inf> arr<inf> arr<inf> arr<inf>)
arr<inf> (arr == np.inf) (arr<inf> arr<inf> arr<inf> arr<inf> arr<inf> arr<inf>)
arr<inf> (arr == np.inf) (arr<inf> arr<inf> arr<inf> arr<inf> arr<inf> arr<inf>)
arr<inf> (arr == np.inf) (arr<inf> arr<inf> arr<inf> arr<inf> arr<inf> arr<inf>)
```

so we convert it to some
finite number

cleaned_arr = np.nan_to_num(arr, posinf=1000, neginf=-1000)

print(cleaned_arr)



so we replace infinity with some value (0 by default) → infinity replaced with some value (0 by default)

so we print -p

([1, 2, 1000, 4, -1000, 6])

[1, 2, 1000, 4, -1000, 6] ← (1000, 0) twint

(1000) min - 0.000000 = 100.000000

(100.000000) twint

so we print
 100.000000 ← [0, 100, 1000, 4, -1000, 6] ← (0, 100, 1000, 4, -1000, 6) twint

so we print the full result after printing

(0.000000, 100.000000) min - 0.000000, 0.000000 = 100.000000

[0, 100, 1000, 4, -1000, 6] ← (100.000000) twint