

NumPy Review



لاتنسونا من دعواتكم

الله يوفقنا ويوفقكم وبإذن الله نتقابل في الصيفية

لو عندكم اي سؤال او اقتراح
هذا حسابتنا في X

Muath Sara Ice

Why NumPy? Beyond Standard Python Lists

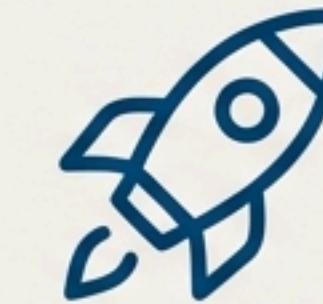
Slow & Verbose



```
# Adding elements of two lists
list_a = [1, 2, 3]
list_b = [4, 5, 6]
result = []
for i in range(len(list_a)):
    result.append(list_a[i] + list_b[i])
```

- Requires explicit, slow loops for element-wise operations.
- Inefficient memory usage for numerical data.
- Lacks a rich library of mathematical functions.

Fast & Concise

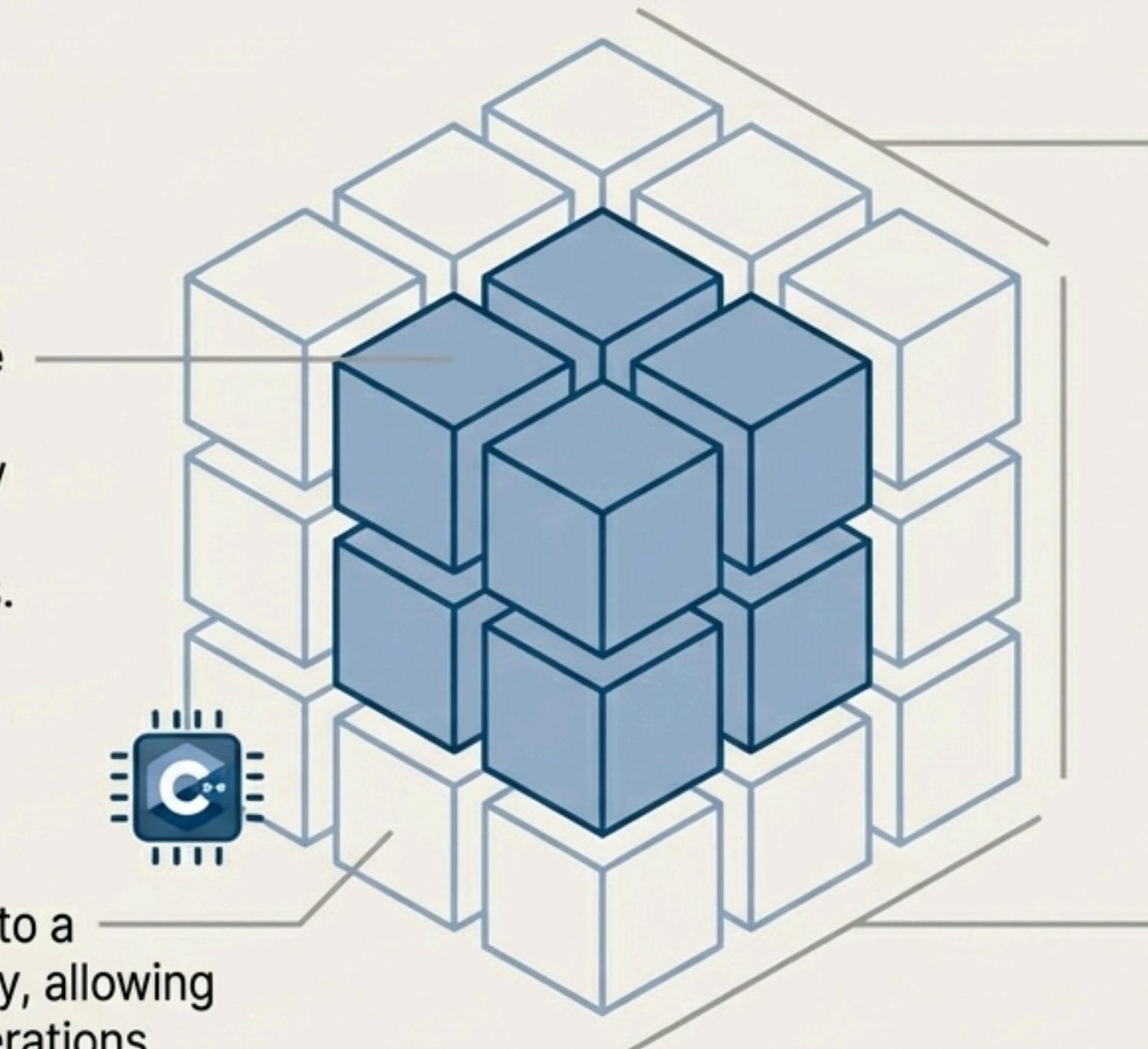


```
# Adding elements of two NumPy arrays
import numpy as np
array_a = np.array([1, 2, 3])
array_b = np.array([4, 5, 6])
result = array_a + array_b
```

- Performs vectorized operations using highly optimized C code.
- Stores data in a contiguous block of memory for performance.
- The foundation for Pandas, Scikit-learn, and the entire data science ecosystem.

The Core Object: The N-Dimensional Array (ndarray)

Homogeneous: All elements must be the same data type (e.g., int64, float64), ensuring memory efficiency. This is a key difference from Python lists.



High-Performance: Points to a contiguous block of memory, allowing for optimized C/Fortran operations without Python's overhead.

N-Dimensional: A grid of values that can have any number of dimensions.

Fixed-Size: The size of an array is determined at creation.

Array Creation I: From Existing Data & Placeholders

From a List

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

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
|---|---|---|---|

Ones

```
np.ones((2, 3))
```

| | | |
|----|----|----|
| 1. | 1. | 1. |
| 1. | 1. | 1. |

Zeros

```
np.zeros((2, 3))
```

| | | |
|----|----|----|
| 0. | 0. | 0. |
| 0. | 0. | 0. |

shape: 2 rows, 3 columns

Identity Matrix

```
np.eye(3)
```

| | | |
|----|----|----|
| 1. | 0. | 0. |
| 0. | 1. | 0. |
| 0. | 0. | 1. |

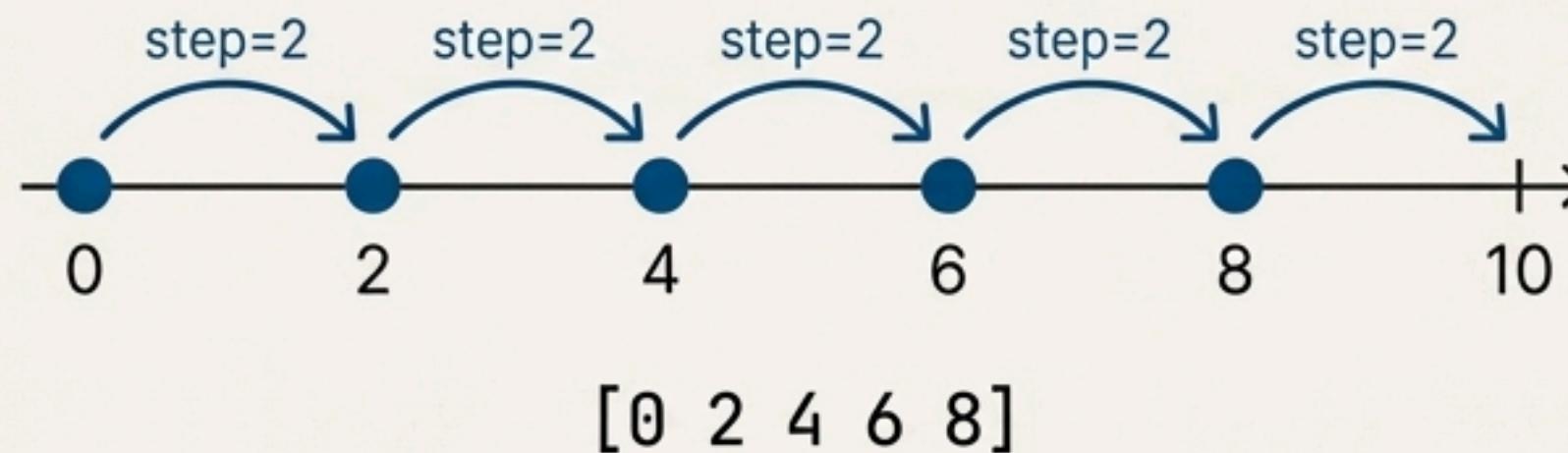
Array Creation II: Generating Numerical Sequences

`np.arange()`

Create values with a defined *step size*.

`np.arange(start, stop, step)`

`np.arange(0, 10, 2)`



`np.linspace()`

Create a specific *number* of evenly spaced values.

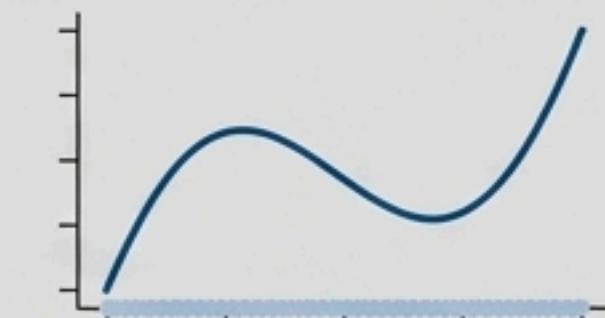
`np.linspace(start, stop, num_points)`

`np.linspace(0, 1, 5)`



Pro-Tip: Plotting

Essential for generating X-coordinates for plotting functions. To draw a smooth curve, you might generate 1000 points between your min and max X-values using `linspace`.

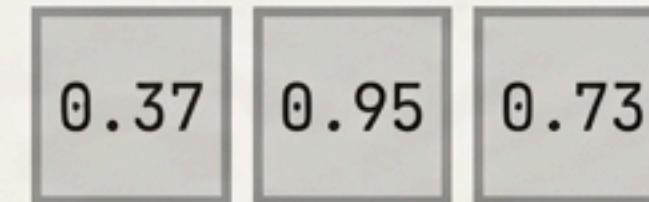


A Critical Best Practice: Ensuring Reproducibility with `np.random.seed()`

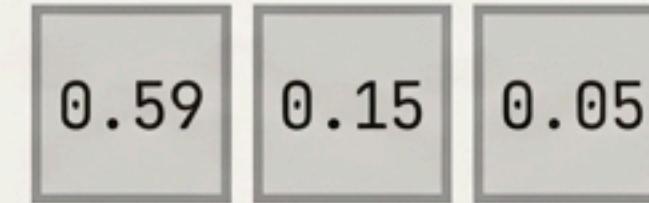
Pseudo-random number generators are deterministic. A 'seed' initializes the generator. Using the same seed guarantees the same sequence of 'random' numbers, which is essential for debugging, sharing results, and scientific validity.

Without a Seed

```
# Run 1  
np.random.rand(3)
```



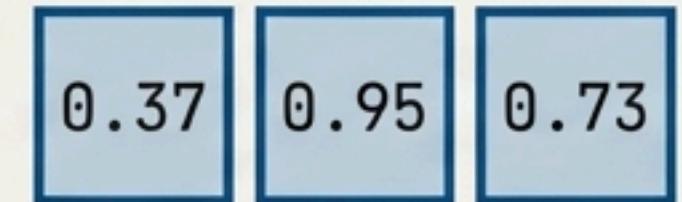
```
# Run 2  
np.random.rand(3)
```



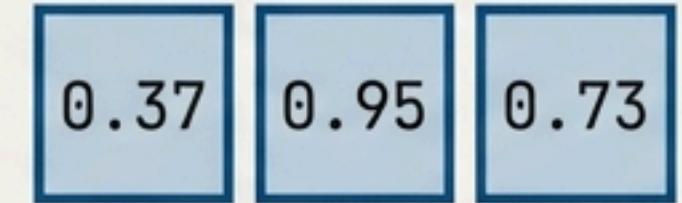
Results are different each time.

With `np.random.seed(42)`

```
# Run 1  
np.random.seed(42) →  
np.random.rand(3)
```



```
# Run 2  
np.random.seed(42) →  
np.random.rand(3)
```



Results are identical every time.

Knowing and Shaping Your Array

```
arr = np.arange(12).reshape(3, 4)
```

Inspection

arr.shape → (3, 4) The dimensions

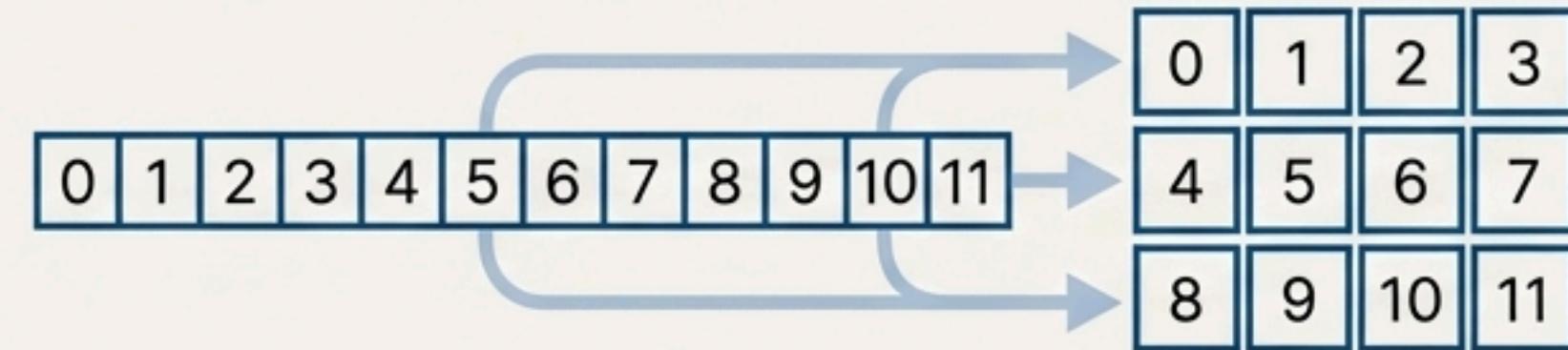
arr.ndim → 2 The number of dimensions

arr.size → 12 The total number of elements

arr.dtype → int64 The data type of the elements

Reshaping

arr.reshape(new_shape) changes the shape without changing the data.



```
a = np.arange(12)  
b = a.reshape(3, 4)
```

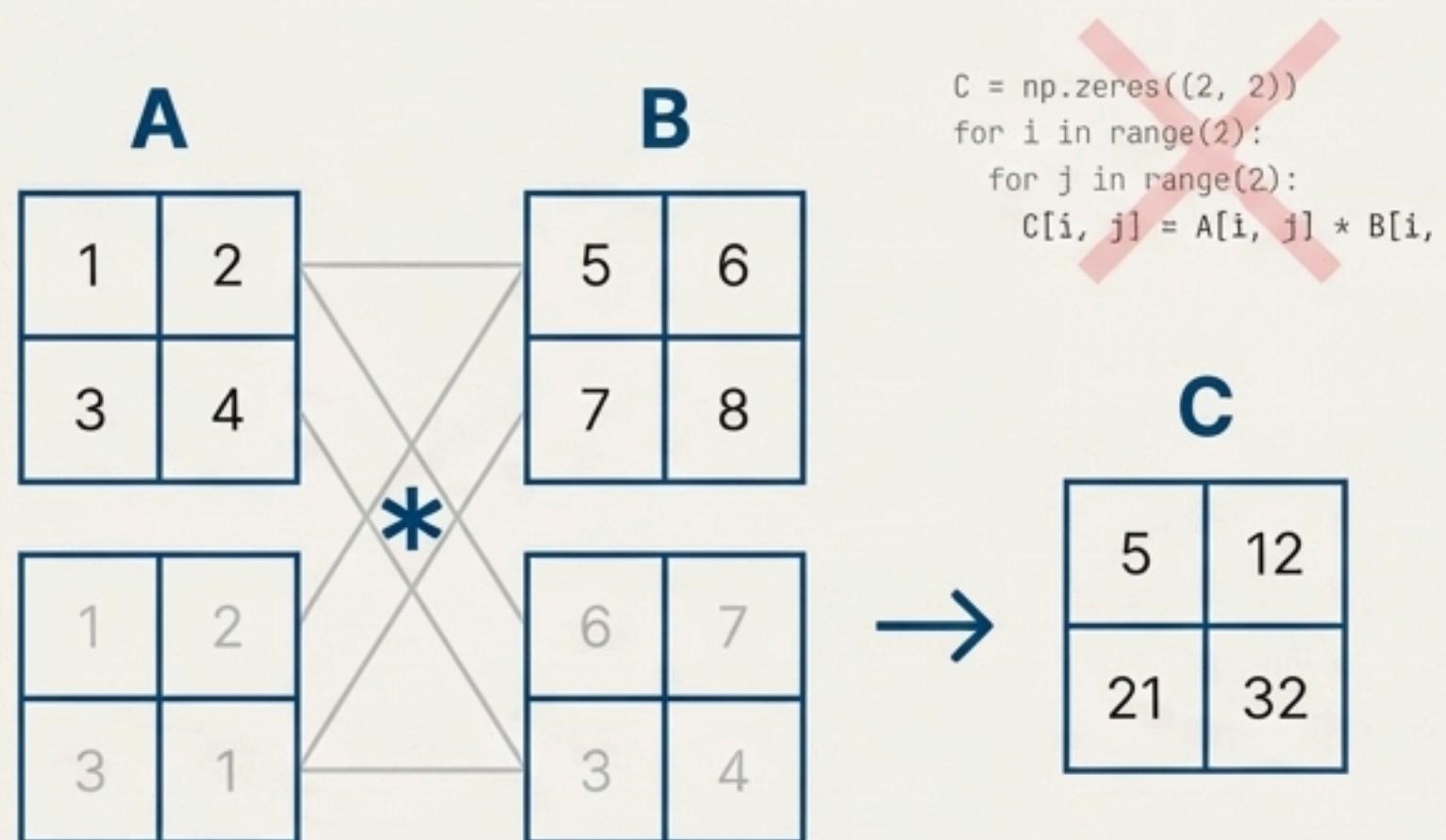
Pro-Tip: Infer Dimension

Use -1 to have NumPy automatically infer a dimension.
a.reshape(6, -1) will create a 6x2 array.

NumPy's Superpowers: Vectorization and Broadcasting

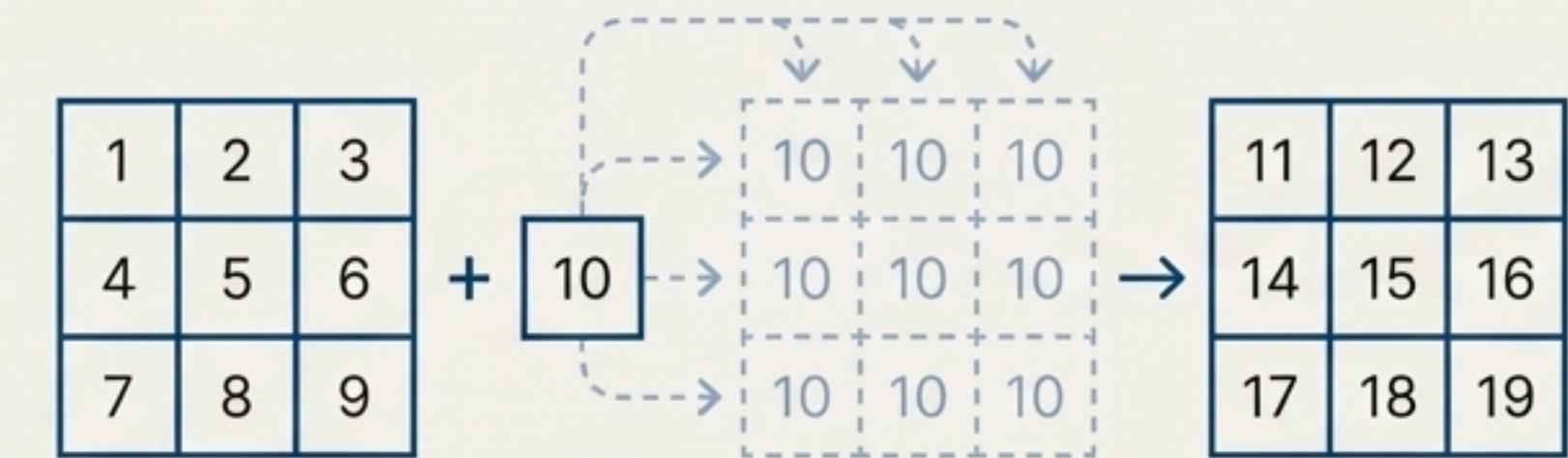
Vectorization

Operations are applied element-by-element without writing explicit Python loops.



Broadcasting

NumPy's ability to stretch smaller arrays to match the shape of larger arrays for element-wise operations.



Broadcasting works when dimensions are compatible (either equal, or one of them is 1).

Accessing Data with Precision: Multi-Dimensional Slicing

`array[row_slice, column_slice]`

Select a single element
`arr[0, 1]`

| | | | | |
|----|----|----|----|----|
| 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 |

Select a single row
`arr[2, :]`

| | | | | | |
|---|----|----|----|----|----|
| 0 | 0 | 1 | 2 | 3 | 4 |
| 1 | 5 | 6 | 7 | 8 | 9 |
| 2 | 10 | 11 | 12 | 13 | 14 |
| 3 | 15 | 16 | 17 | 18 | 19 |
| 4 | 20 | 21 | 22 | 23 | 24 |

Select a single column
`arr[:, 3]`

| | | | | |
|----|----|----|----|----|
| 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 |

Select a sub-grid
`arr[1:4, 0:2]`

Aggregating Data Across Dimensions with `axis`

"Imagine an array where rows are **students** and columns are **exam scores**."

| | | grades | | | | |
|-----------|---|--------|----|----|----|---|
| | | Exams: | 0 | 1 | 2 | 3 |
| Students: | 0 | 85 | 92 | 78 | 90 | |
| | 1 | 76 | 88 | 80 | 85 | |
| | 2 | 90 | 82 | 89 | 93 | |

Aggregate over the entire array

`grades.sum()`

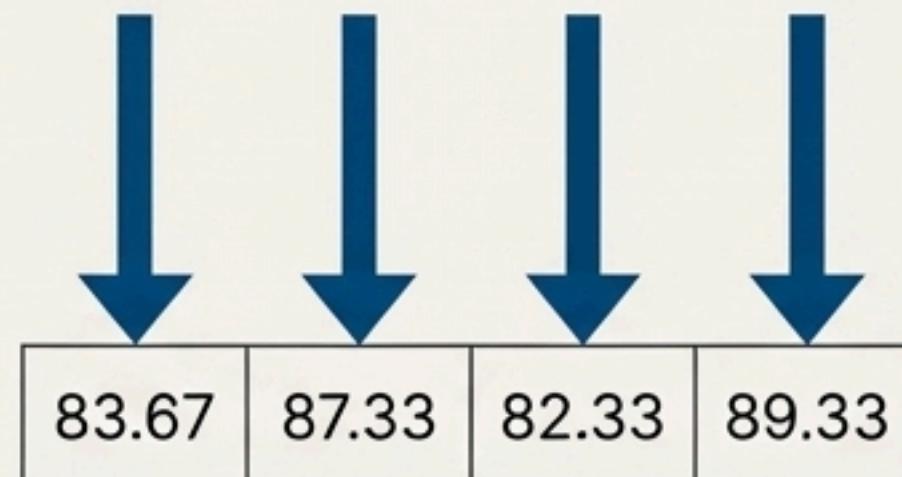
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| | | | |
|----|----|----|----|
| 85 | 92 | 78 | 90 |
| 76 | 88 | 80 | 85 |
| 90 | 82 | 89 | 93 |

Aggregate down the columns (`axis=0`)

`grades.mean(axis=0)`

Calculates the average score for each exam (column).



Aggregate across the rows (`axis=1`)

`grades.mean(axis=1)`

Calculates the average score for each student (row).

| |
|-------|
| 86.25 |
| 82.25 |
| 88.50 |

Advanced Selection: Filtering with Boolean Masking

Use a conditional expression inside indexing brackets to create a temporary boolean array (a "mask"). Only elements corresponding to `True` are returned.

1. Original Array

```
arr = np.array([10, 2, 8, 25, 17])
```

| | | | | |
|----|---|---|----|----|
| 10 | 2 | 8 | 25 | 17 |
|----|---|---|----|----|

2. Create Condition

```
arr > 10
```



3. Resulting Boolean Mask

| | | | | |
|-------|-------|-------|------|------|
| False | False | False | True | True |
|-------|-------|-------|------|------|

4. Apply Mask to Array

```
arr[arr > 10]
```



5. Final Filtered Array

| | |
|----|----|
| 25 | 17 |
|----|----|

This is a highly efficient way to select data based on complex conditions without writing loops.

A Tale of Two Multiplications: Element-wise vs. Matrix

Element-wise Product



Multiplies corresponding elements in two arrays of the same shape. This is the default behavior.

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} \times \begin{bmatrix} E & F \\ G & H \end{bmatrix} \rightarrow \begin{bmatrix} A*E & B*F \\ C*G & D*H \end{bmatrix}$$

Arrays must have the **same shape** (or be broadcastable).

Matrix Product



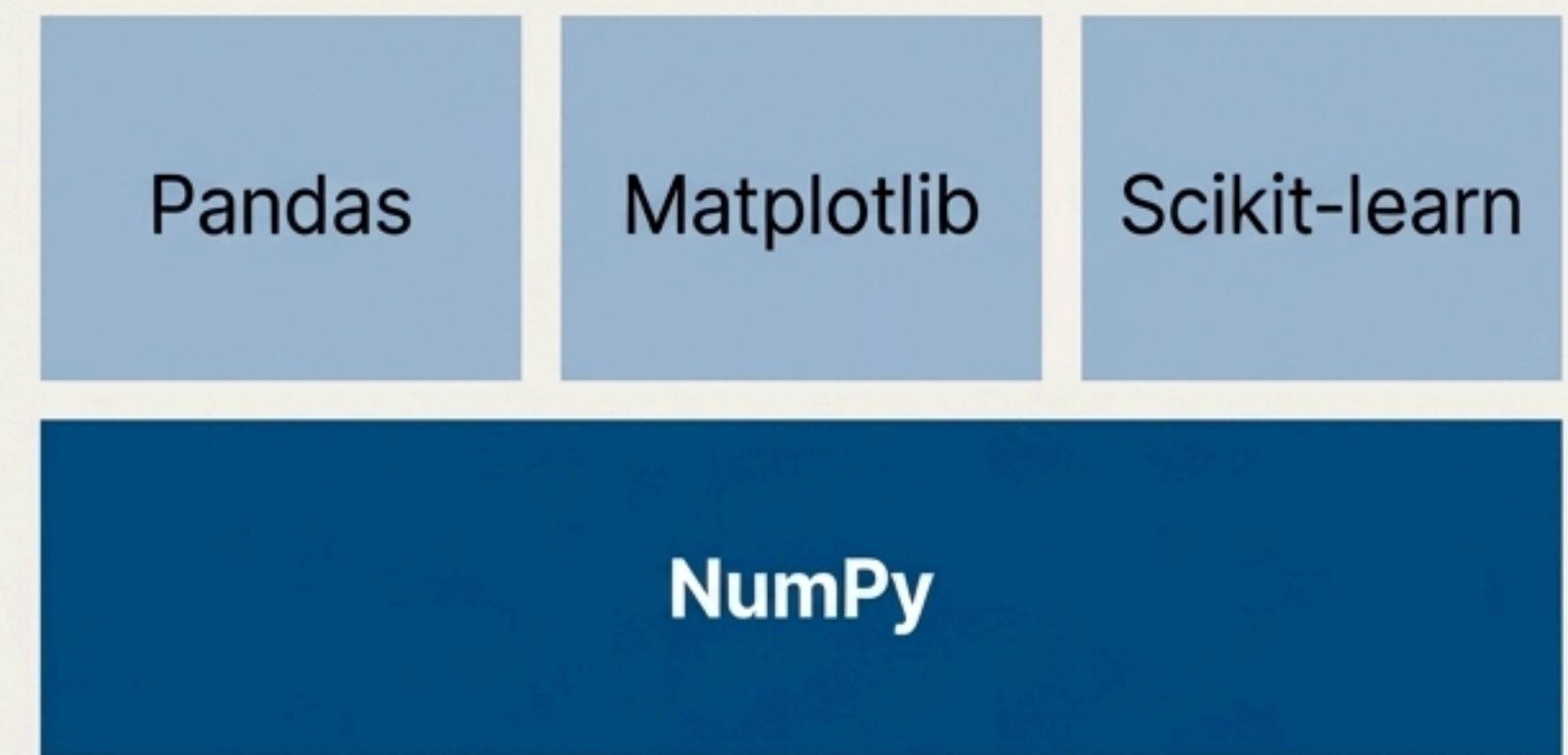
Performs the dot product (true linear algebra matrix multiplication).

$$\begin{bmatrix} r1_c1 & r1_c2 & r1_c3 \\ r2_c1 & r2_c2 & r2_c3 \end{bmatrix} \times \begin{bmatrix} c1_r1 & c2_r1 \\ c1_r2 & c2_r2 \\ c1_r3 & c2_r3 \end{bmatrix} = \begin{bmatrix} r1_c1*c1_r1 & r1_c2*c2_r1 \\ r1_c3*c1_r3 & r1_c3*c2_r3 \end{bmatrix}$$

The inner dimensions must match (e.g., $(M, K) @ (K, N)$). The matching **K** dimensions are highlighted.

NumPy: The Bedrock of the Data Science Stack

- The ndarray is the high-performance heart of numerical computing in Python.
- Vectorized operations and broadcasting provide unmatched speed and code elegance, eliminating slow Python loops.
- Mastery of multi-dimensional slicing and axis-based aggregations is key to effective data manipulation.



Understanding NumPy is the first and most critical step in mastering data science in Python. It is the language that all other data libraries speak.