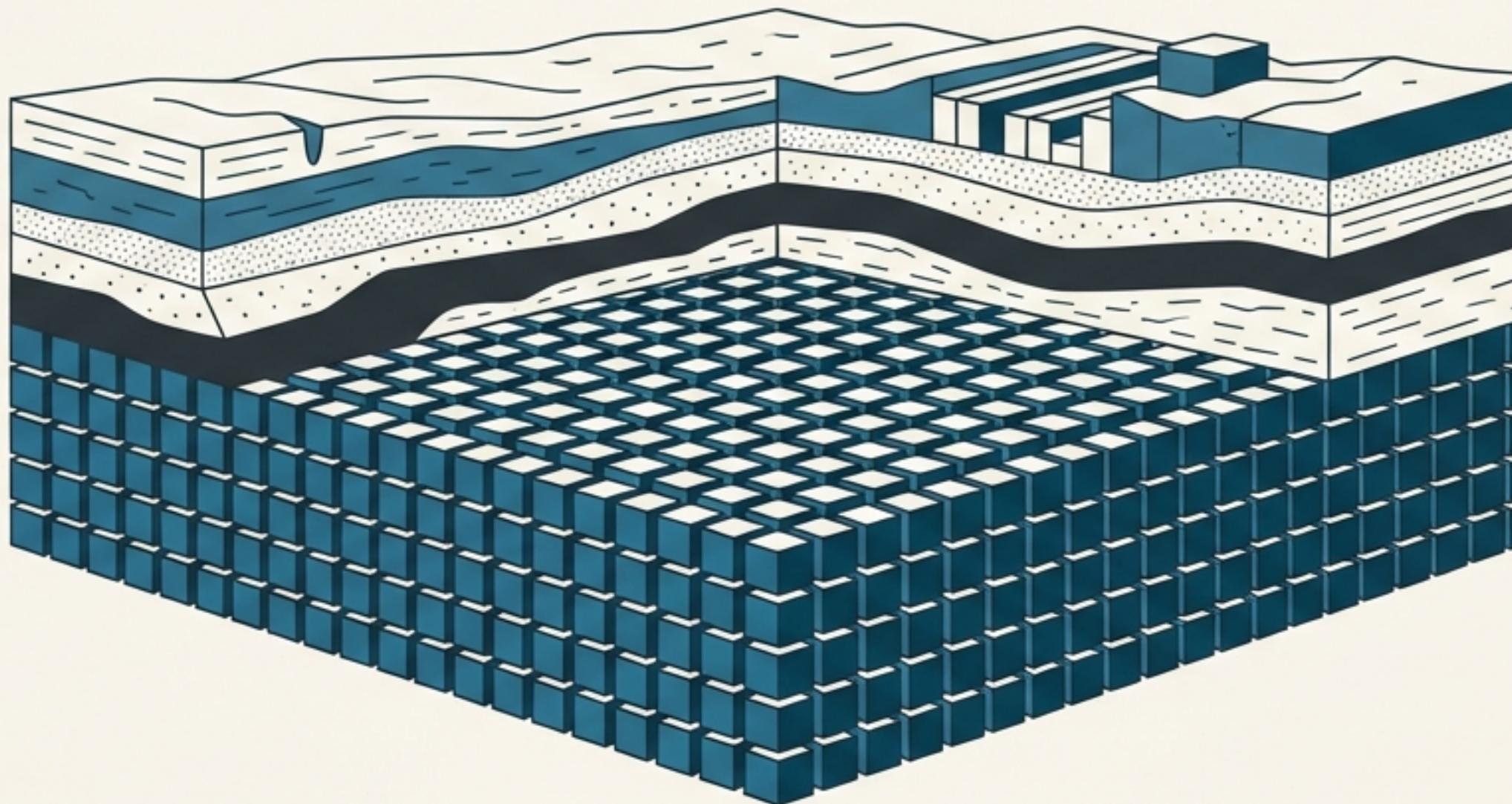


NumPy Fundamentals: The Bedrock of Scientific Computing in Python



Session 13: Data Science Mentorship Program
Unlocking High-Performance Numerical Processing in Python
Your Instructor: Dr. Anya Sharma

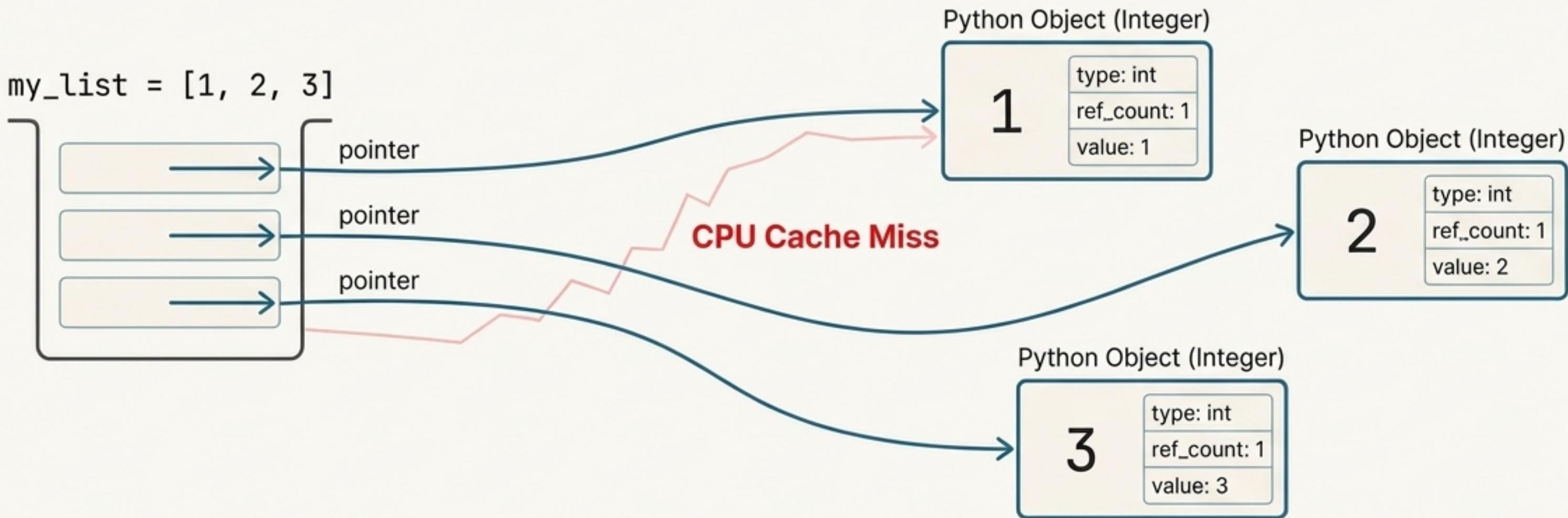
Why Was NumPy Created? A Unifying Force

- **The Creator:** Travis Oliphant, a data scientist and professor.
- **The Time:** 2005. Python's scientific community was fragmented.
- **The Problem:** Two competing array libraries, **Numeric** and **Numarray**, split the community. Code written for one was incompatible with the other.
- **The Vision:** Oliphant created NumPy to unify these efforts, taking the best features from both to create a single, powerful, and flexible standard for array computing in Python.



The Bottleneck: Why Python Lists Are Slow for Math

The Boxed Integer



- **Everything is an Object:** A Python list doesn't store data directly.
- **The 'Boxed Integer':** Each number is a full Python object—a 'box' with the value plus metadata.
- **Pointer Chasing:** The list holds pointers (memory addresses) to these scattered 'boxes'.
- **The Result:** Massive memory overhead and slow processing due to inefficient data layout.

The NumPy Solution: Speed Through Simplicity

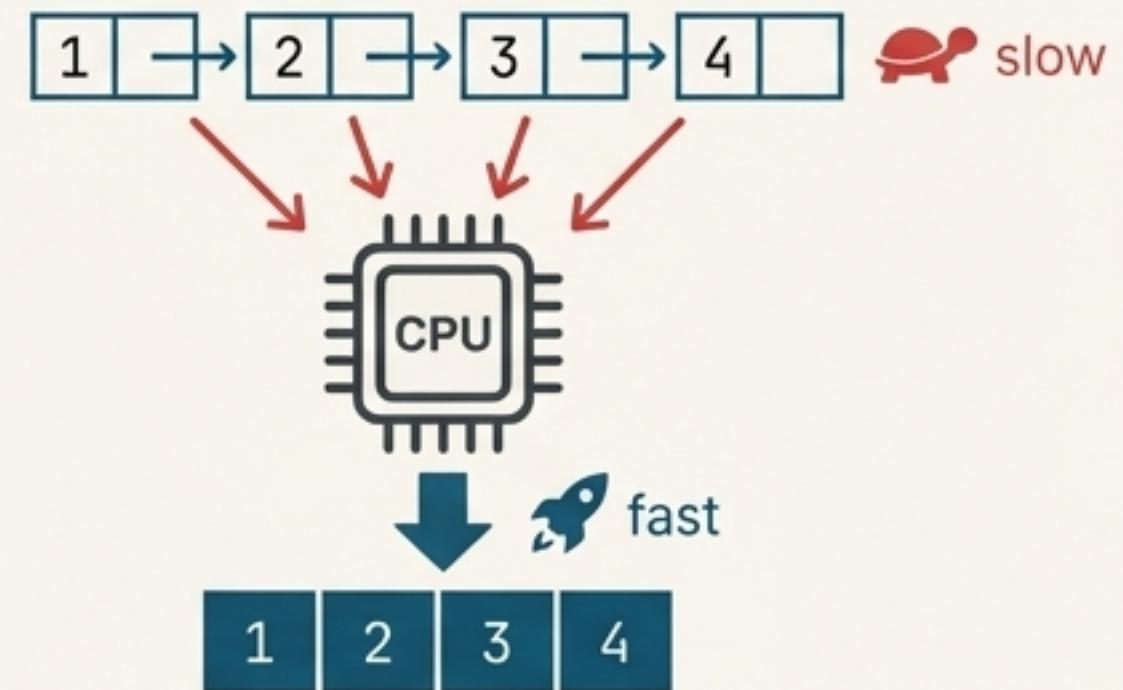
Contiguous & Homogeneous Memory

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



A **dense** block of raw memory. All elements are the same type ('`int64`').

Vectorization (SIMD)



Single Instruction, Multiple Data. The CPU processes entire blocks of data in one clock cycle.

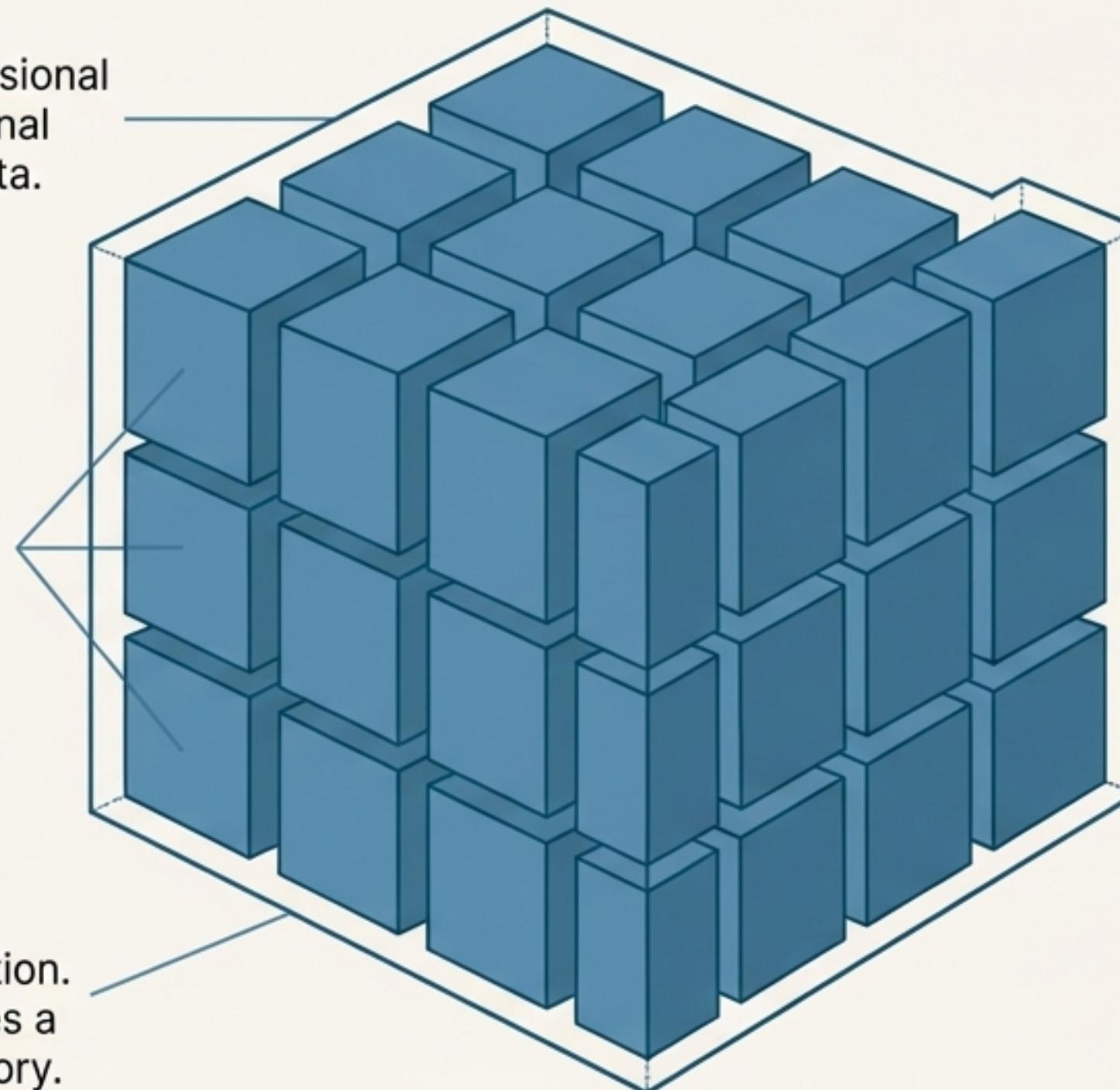
- **Contiguous Memory:** A dense block of raw memory. Values are stored directly. No “boxes,” no pointers.
- **Homogeneity:** All elements must be the same data type, eliminating type-checking during computation.
- **Vectorization (SIMD):** This allows the CPU to process entire blocks of data at once.
- **The Result:** Operations are 50x-100x faster. C-level speed with Python's simple syntax.

The Core Object: The `ndarray`

The `ndarray` (n-dimensional array): A multi-dimensional container for generic data.

Homogeneous: All elements must have the same type (e.g., `float64`).

 **Fixed Size:**
Size is set at creation.
Changing it creates a new array in memory.



- The `ndarray` (n-dimensional array) is the central data structure in NumPy.
- It's an array of **homogeneous** data (all elements have the same type).
- It has a **fixed size** upon creation; you cannot append elements like a Python list.
- It enables powerful **mathematical operations** on entire blocks of data at once.

Your First `ndarray`: Common Creation Routines

```
import numpy as np
```

From a Python List

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

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

Uniform Arrays

```
np.zeros((3, 4))
```

0	0	0	0
0	0	0	0
0	0	0	0

```
np.ones((3, 4))
```

1	1	1	1
1	1	1	1
1	1	1	1

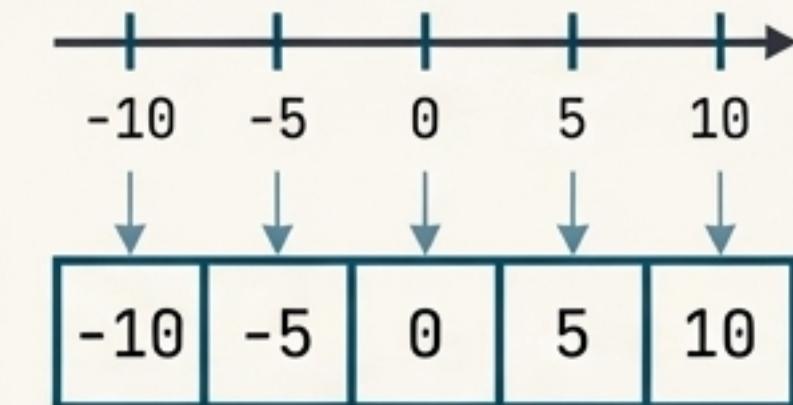
Random Data

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

0.12	0.87	0.54	0.39
0.91	0.02	0.75	0.66
0.43	0.28	0.15	0.98

Evenly Spaced Numbers

```
np.linspace(-10, 10, 5)
```



Inspecting Your Array: Key Attributes

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

- **Dimensions:** a.ndim → 2
 - Dimension 1 (rows)
 - Dimension 2 (columns)
- **Shape:** a.shape → (3, 4)
 - 3 rows
 - 4 columns
- **Total Size:** a.size → 12

A 3x4 grid of numbers from 0 to 11, arranged in 3 rows and 4 columns. The numbers are: Row 1: 0, 1, 2, 3; Row 2: 4, 5, 6, 7; Row 3: 8, 9, 10, 11. A magnifying glass icon is positioned over the number 7.

- **Data Type:** a.dtype → dtype('int64')
 - int64
 - 8 bytes
- **Item Size:** a.itemsize → 8

Accessing Data: Indexing and Slicing

1. 1D & 2D Indexing

- **1D Indexing:**

Same as Python lists.

`a1[5]`, `a1[-1]`

- **2D Indexing:**

Use comma-separated indices.

`arr[row, col]`

a2[1, 2]

2. Slicing Rows & Columns

a2[0, :]

a2	0	1	2	3	4
0	0	1	2	3	4
1	7	8	9	10	12
2	14	15	16	17	28
3	19	20	31	23	40

a2[:, 1]

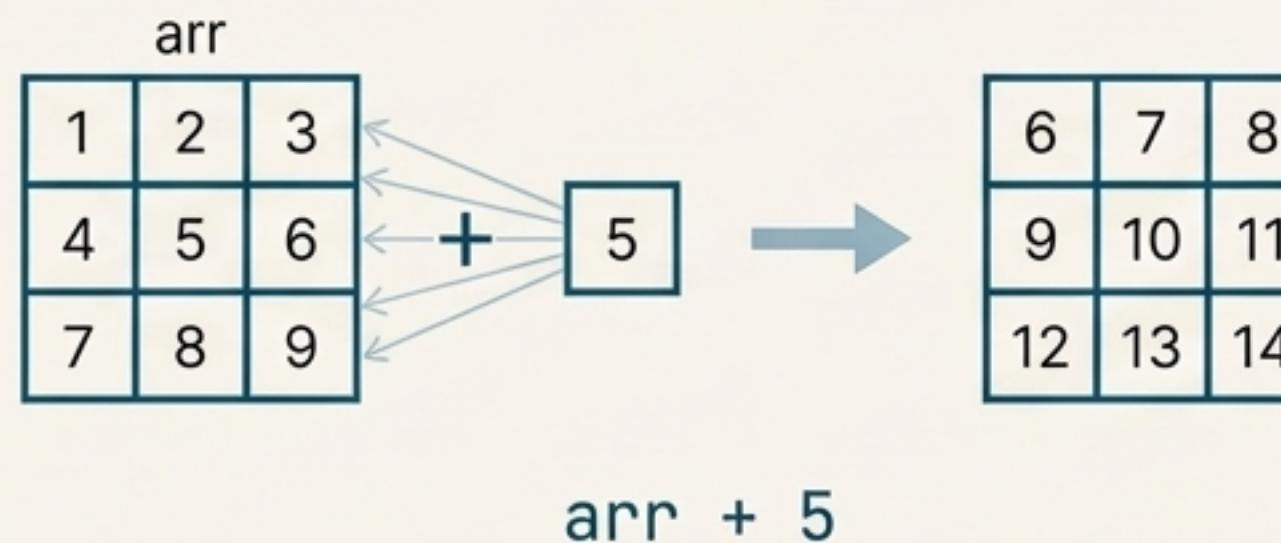
3. Slicing a Sub-matrix

a2[1:, 1:3]

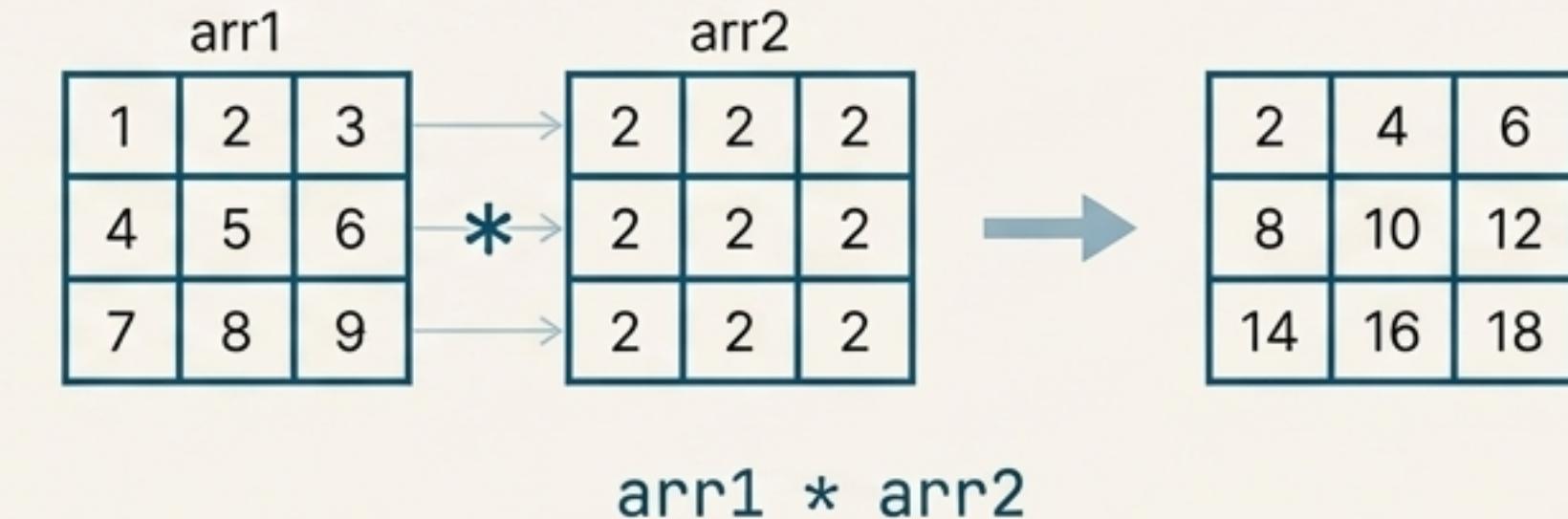
0	1	2	3	4
1	1	8	12	14
2	15	16	17	28
3	14	28	32	40

Universal Functions: Effortless Math

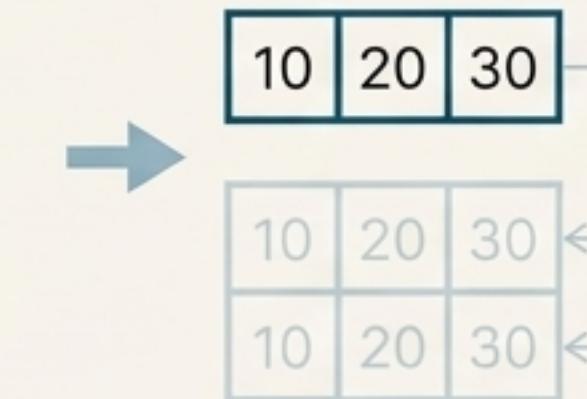
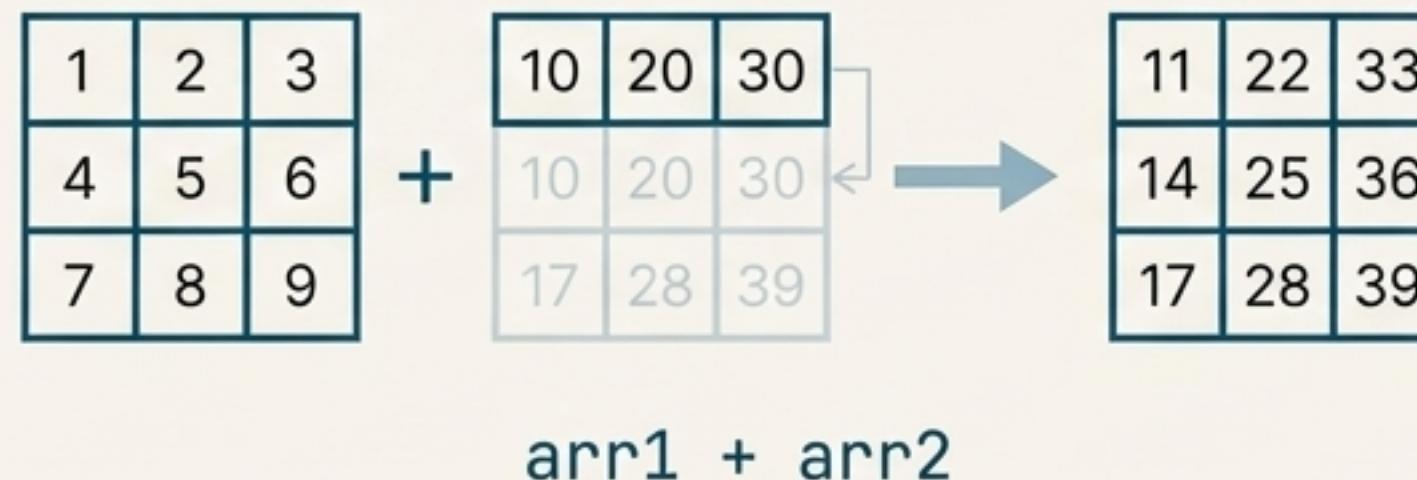
1. Scalar Operations: Array and a single number.



2. Vector Operations: Between two arrays of the same shape.



3. Broadcasting: Operations on arrays of different (but compatible) shapes.



Smaller array is “stretched” to match the shape of the larger one without using more memory.

Aggregations: Summarizing Your Data

- Functions that perform a calculation on an array and return a single value or a smaller array.
- Common Functions:
`np.max()`, `np.min()`,
`np.sum()`, `np.mean()`,
`np.std()`
- The **axis** Parameter: The key to targeted aggregations.

`arr.sum(axis=0)`

1	2	3	4
5	6	7	8
9	10	11	12

↓ ↓ ↓ ↓

15	18	21	24
----	----	----	----

****Sums down the columns****
(collapses the rows)

`arr.sum(axis=1)`

1	2	3	4	→	10
5	6	7	8	→	26
9	10	11	12	→	42

****Sums across the rows****
(collapses the columns)

Shaping and Combining Arrays

Reshaping: Change the shape without changing the data.

```
a.reshape(4, 3)
```

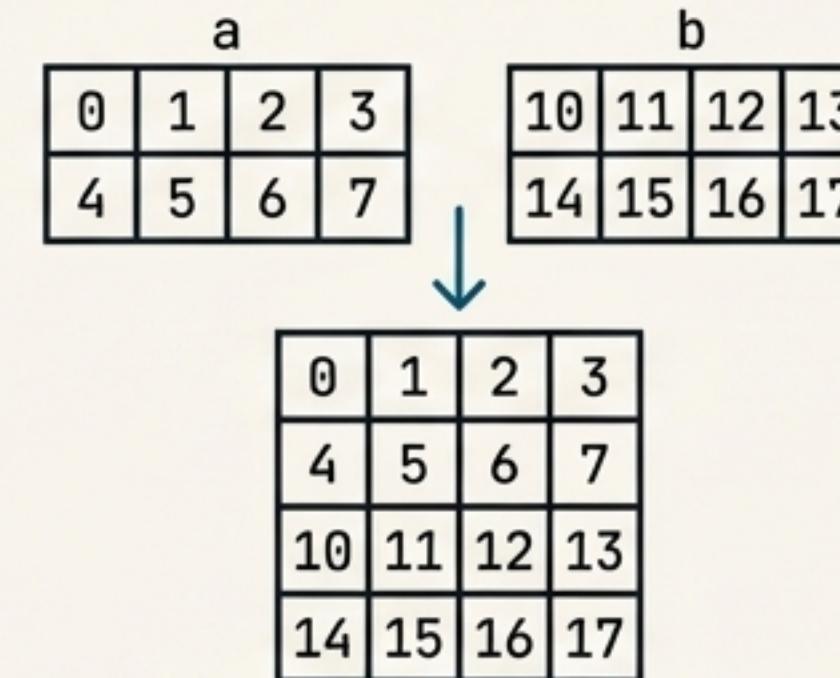
0	1	2	3	4	5	7	8	9	10	11
---	---	---	---	---	---	---	---	---	----	----

A blue curved arrow points from the 1D array above to the 2D array below, indicating the transformation process.

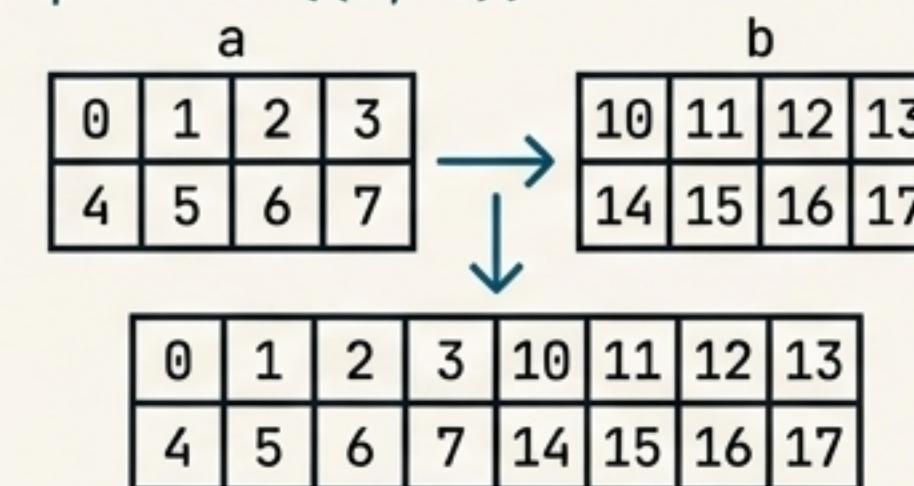
0	1	2
3	4	5
6	7	8
9	10	11

Stacking: Combine multiple arrays into one.

```
np.vstack((a, b))
```

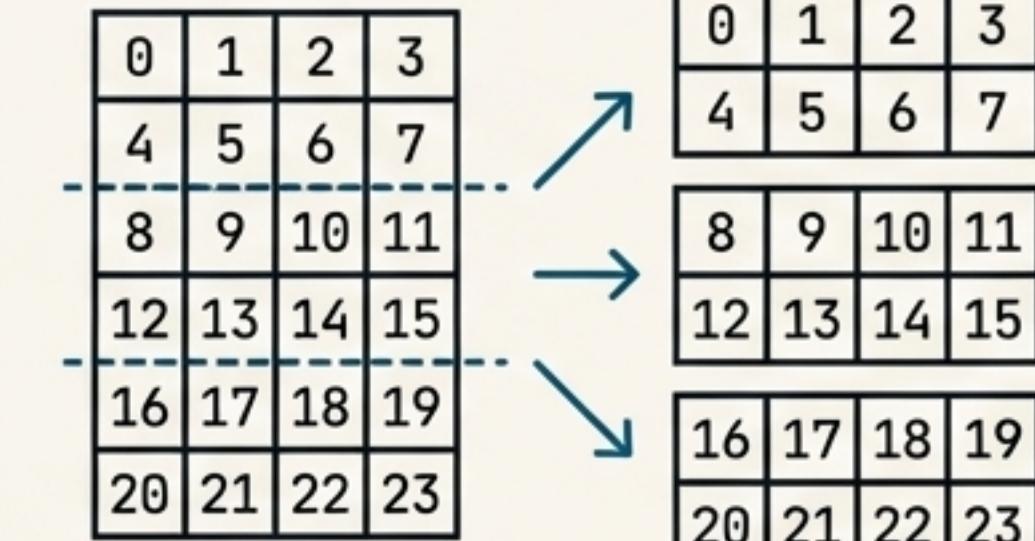


```
np.hstack((a, b))
```

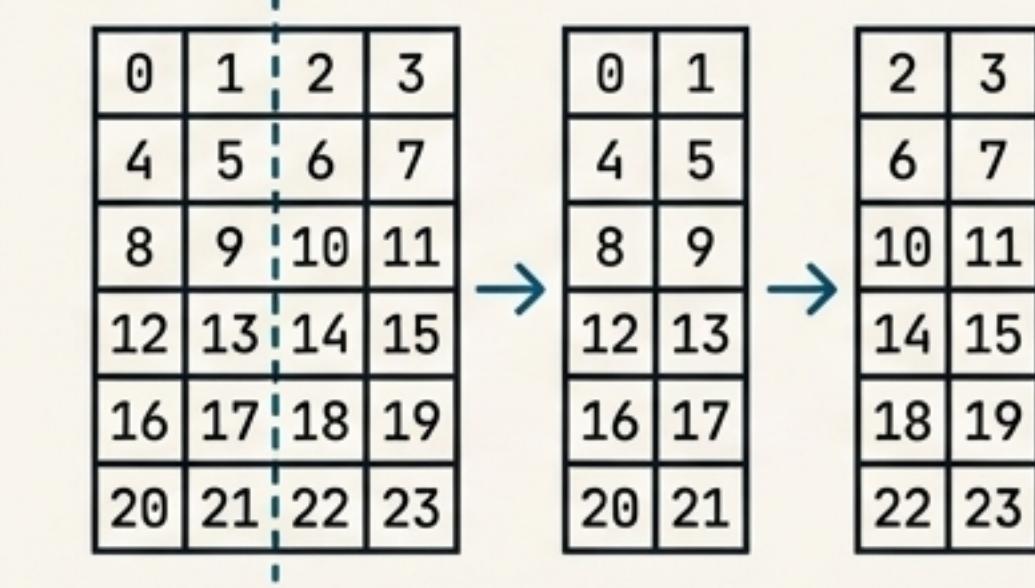


Splitting: Break one array into smaller arrays.

```
np.vsplit(a, 3)
```



```
np.hsplit(a, 2)
```



NumPy: The Foundation You'll Build Upon

- **Why NumPy?** It solves Python's slowness for numerical tasks with contiguous, homogeneous arrays.
- **The Core:** The `ndarray` object enables vectorized, SIMD-powered operations.
- **The Power:** An elegant syntax for complex math, aggregations, and manipulations.
- **The Ecosystem:** Mastering NumPy is the first true step to becoming a professional data scientist.

