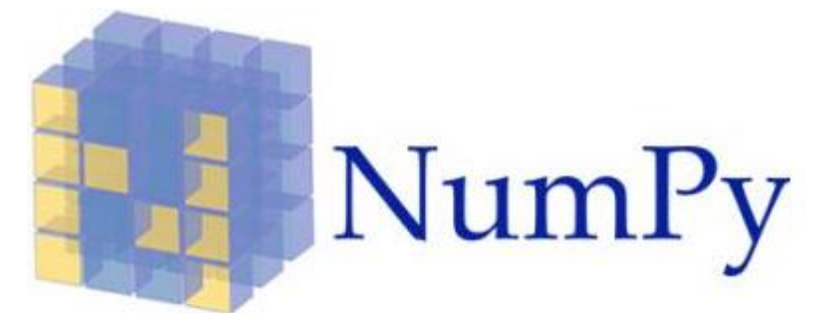


The SciPy Stack

A Python ecosystem for Scientific Computation



Michael Colaresi

SciPy



- Is both a **library** containing numerical computing tools and distribution
- And a **collection** of related tools that build on each other

- NumPy



- matplotlib



- pandas



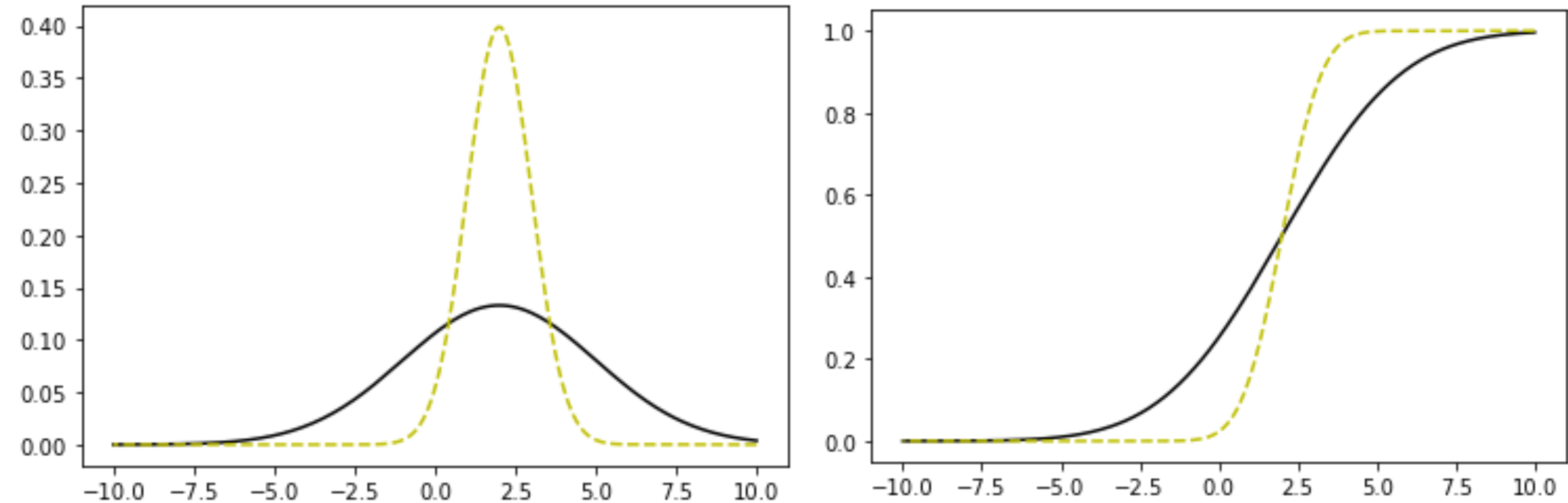
- sklearn



There are others, like SymPy for symbolic math (it can do your algebra homework for you)

SciPy

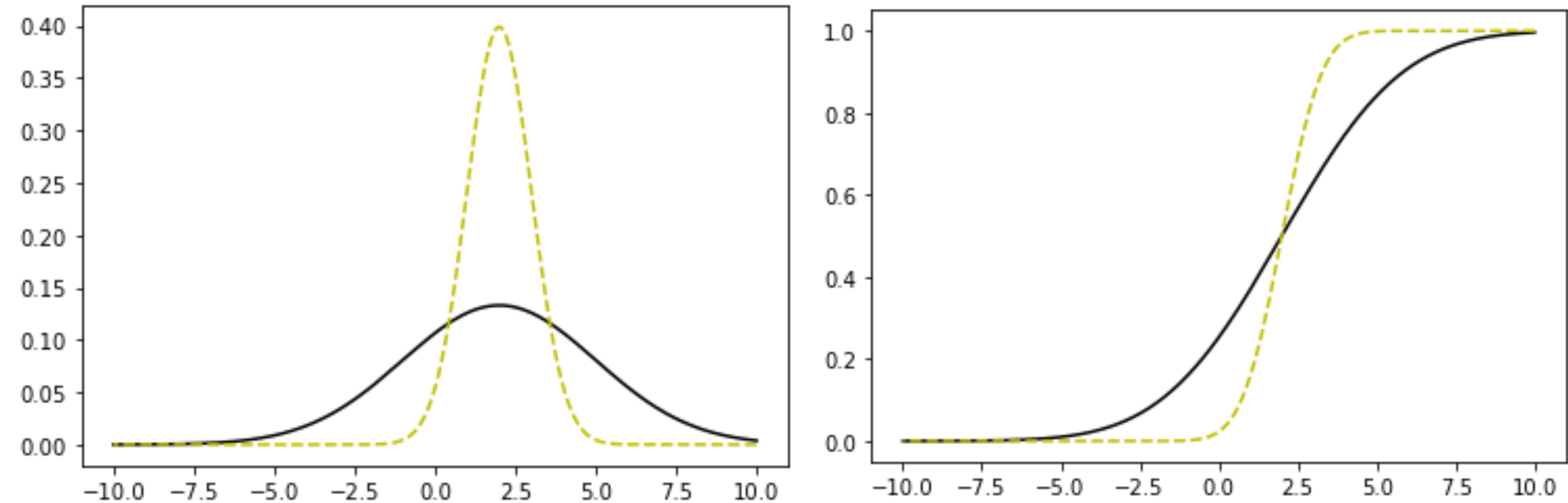
Distributions



- `scipy.stats.DISTRIBUTION(params)`
 - methods:
 - `pdf(x)` — probability density function (or pmf for discrete distribution) at x
 - `cdf(x)` — cumulative density function at x ($\text{pr}(y \leq x)$)
 - `ppf(P)` — percentile function, returns the x that makes $\text{pr}(x \leq x) = P$ true
 - `rvs(n)` — generate random variates from distribution

SciPy

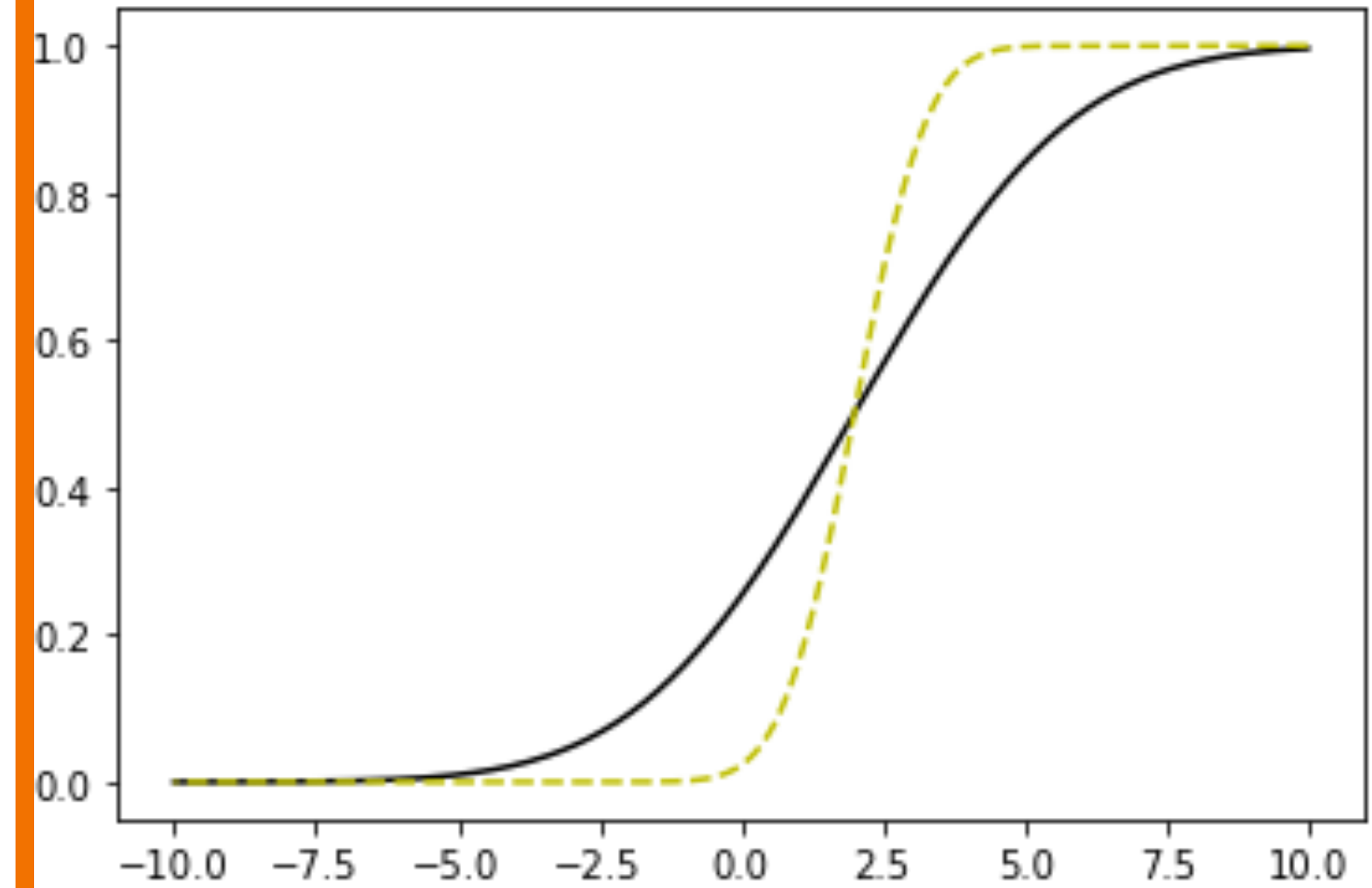
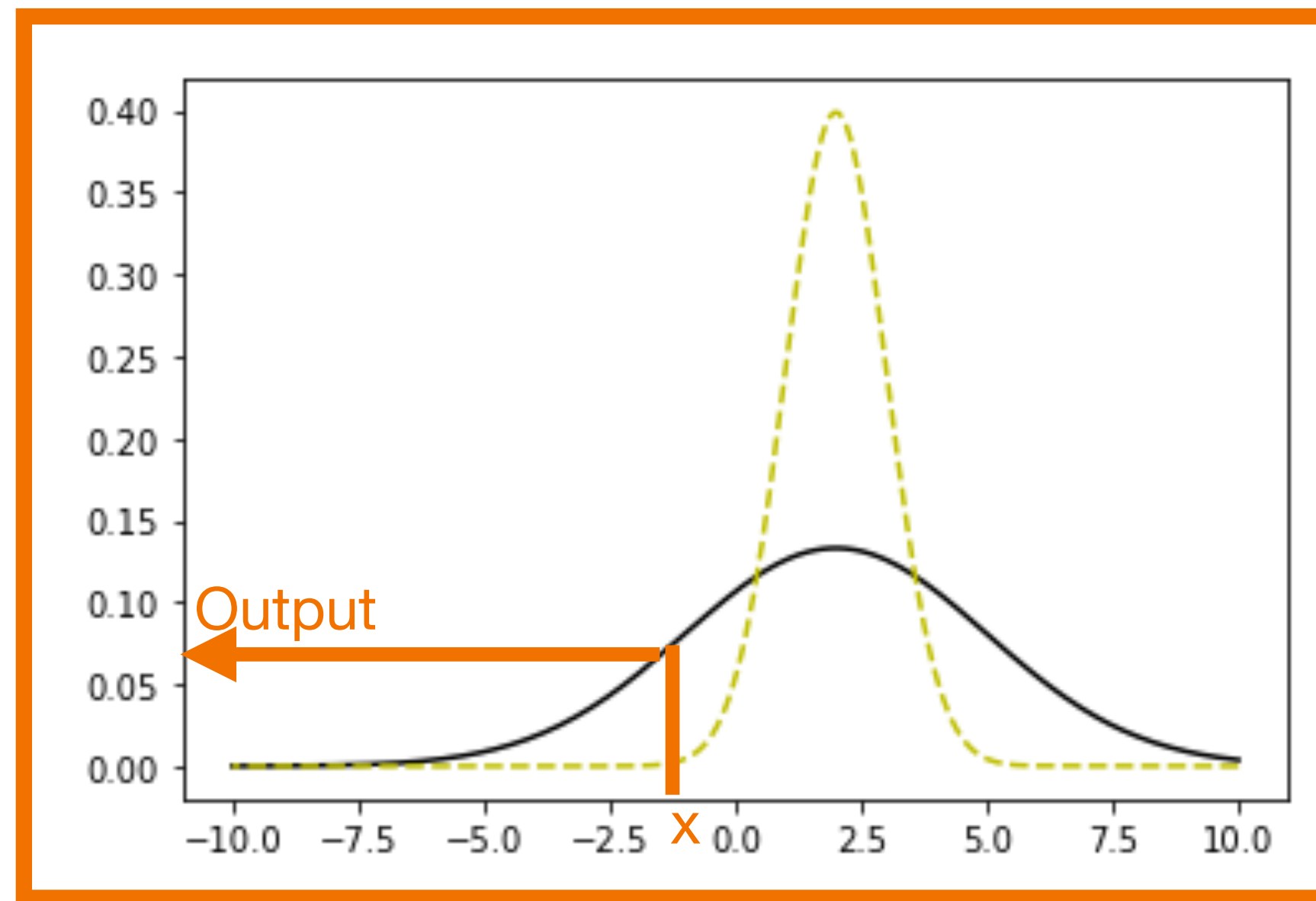
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SciPy

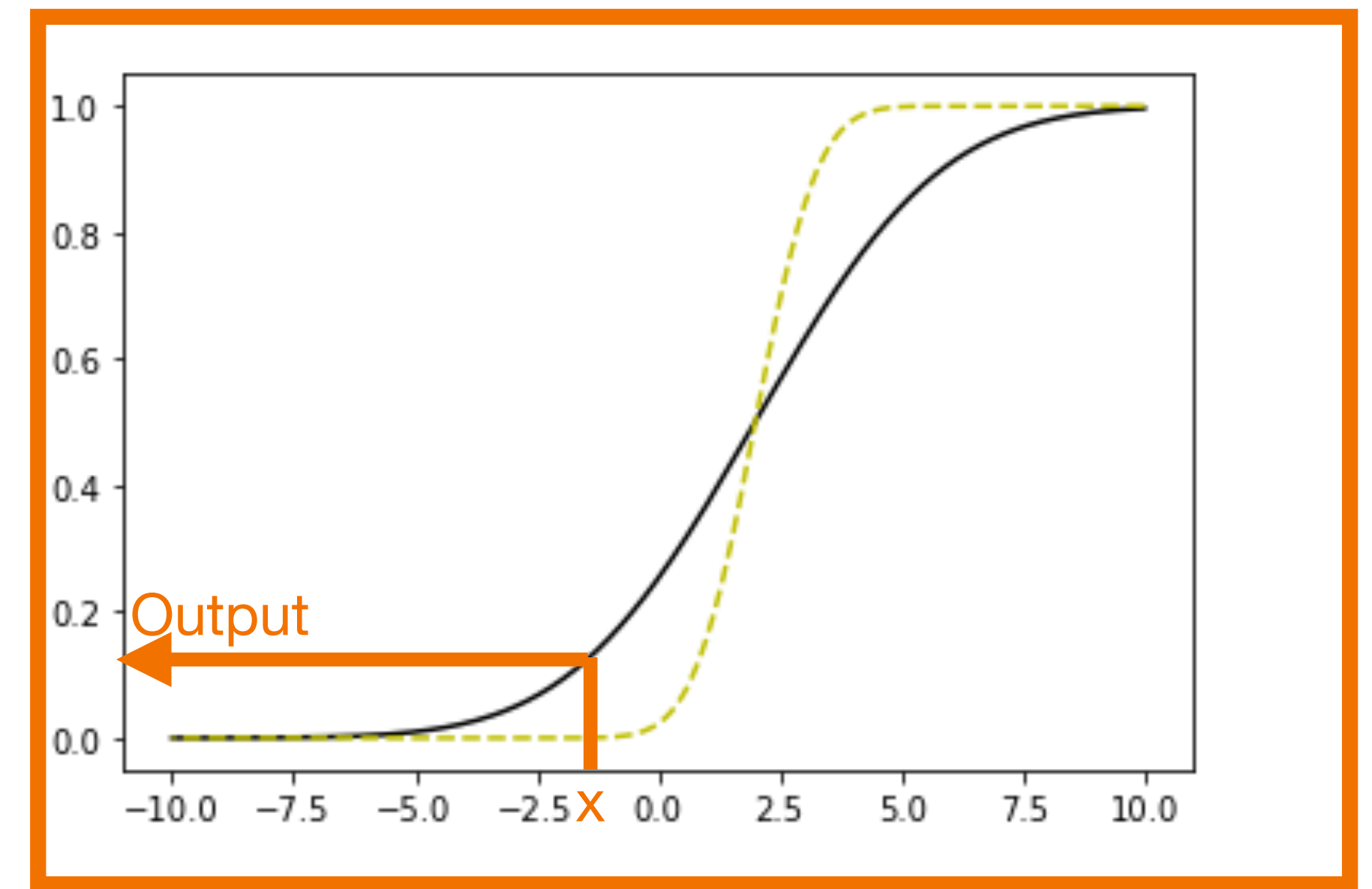
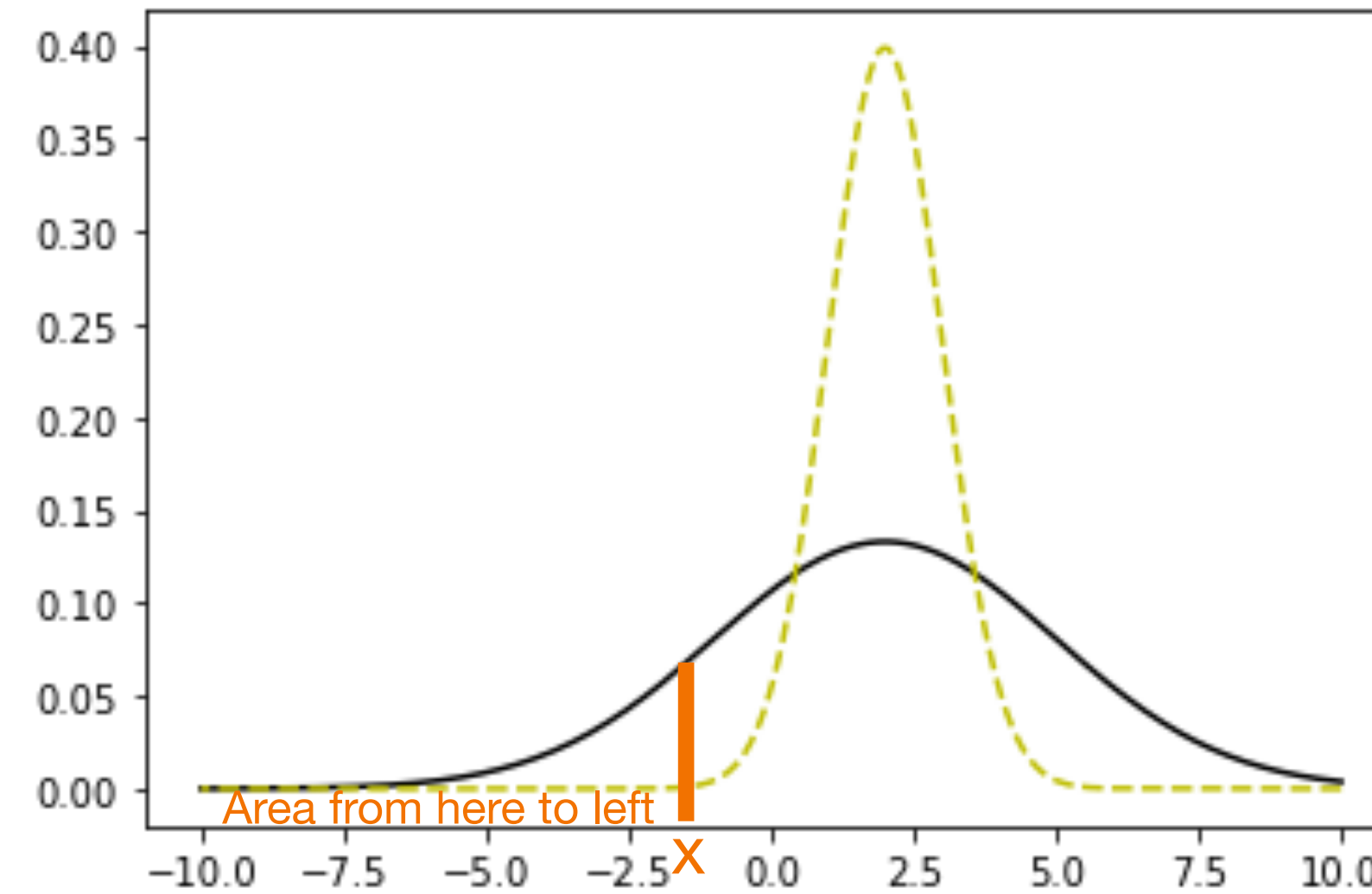
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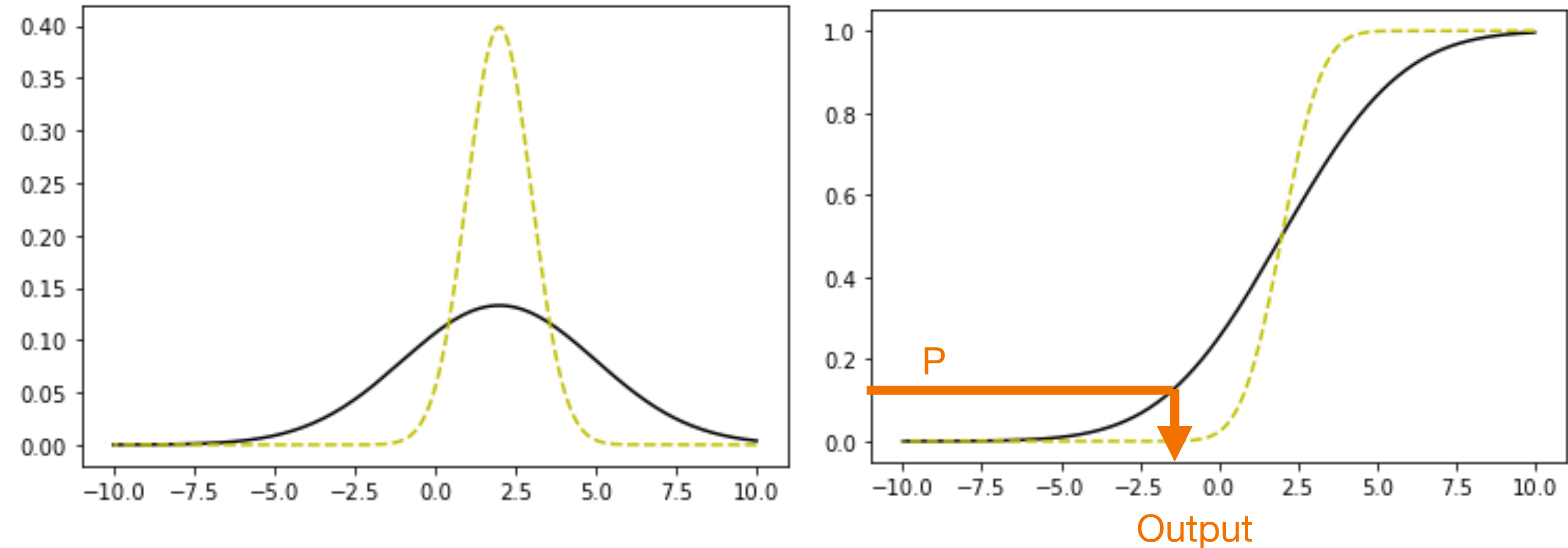
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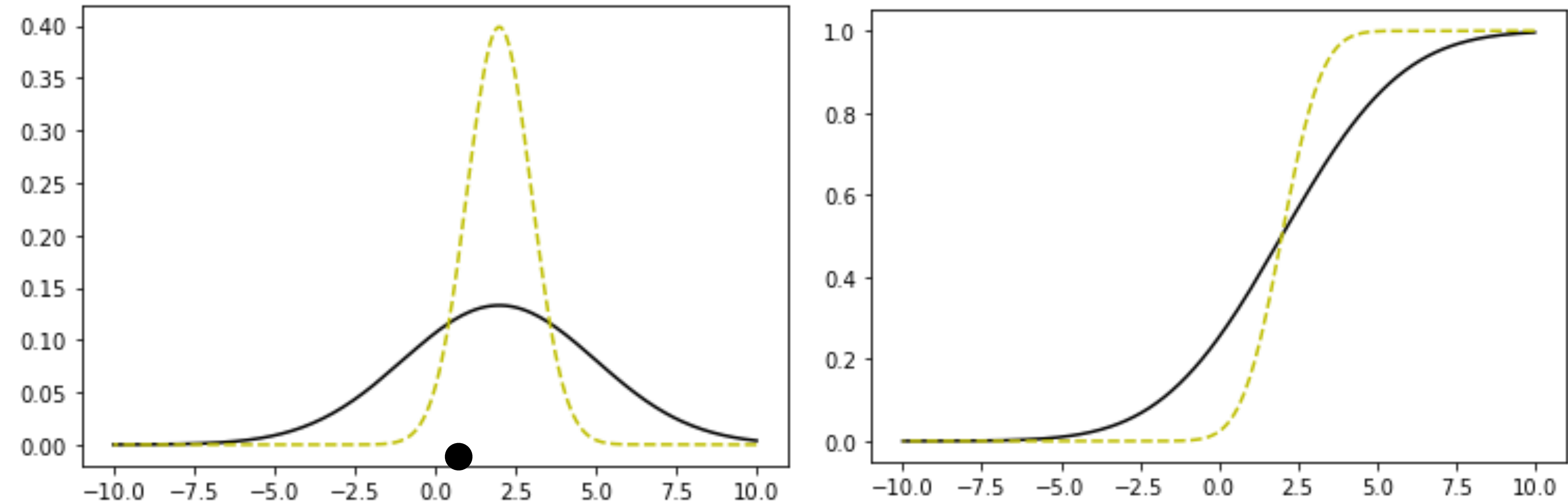
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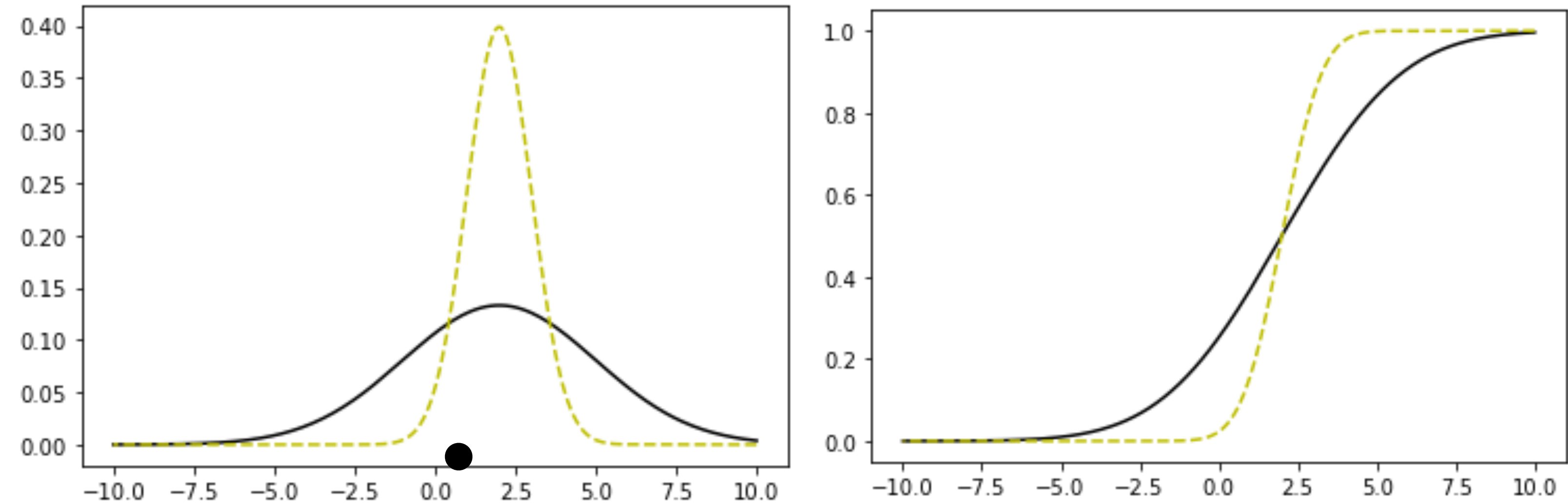
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SciPy

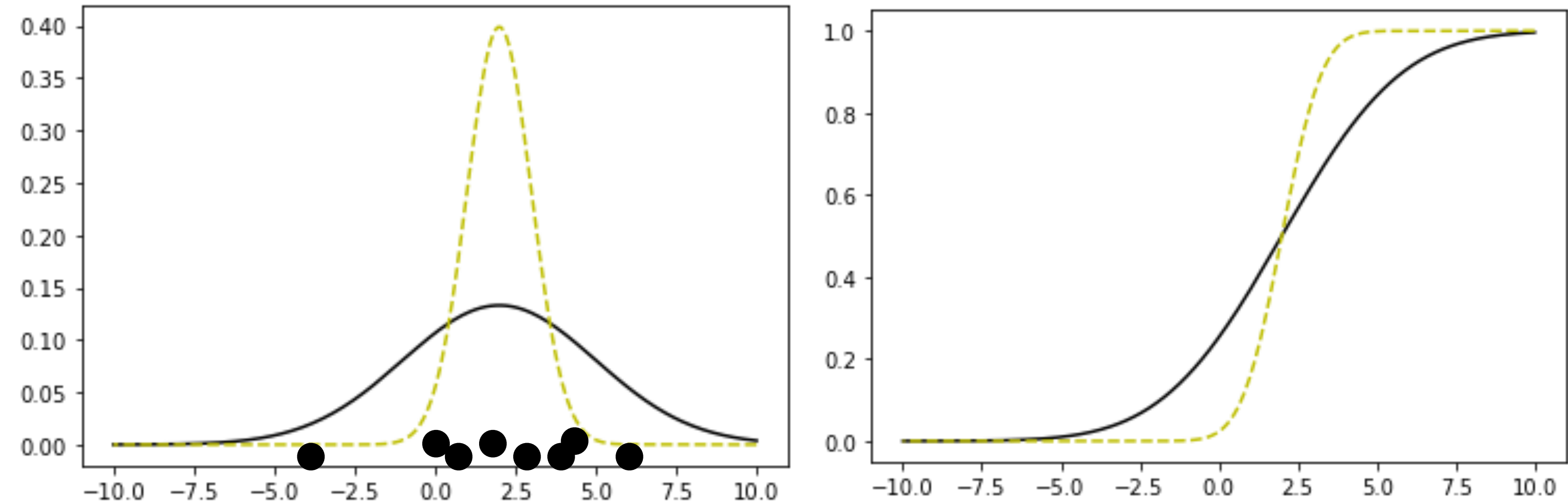
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SciPy

Distributions

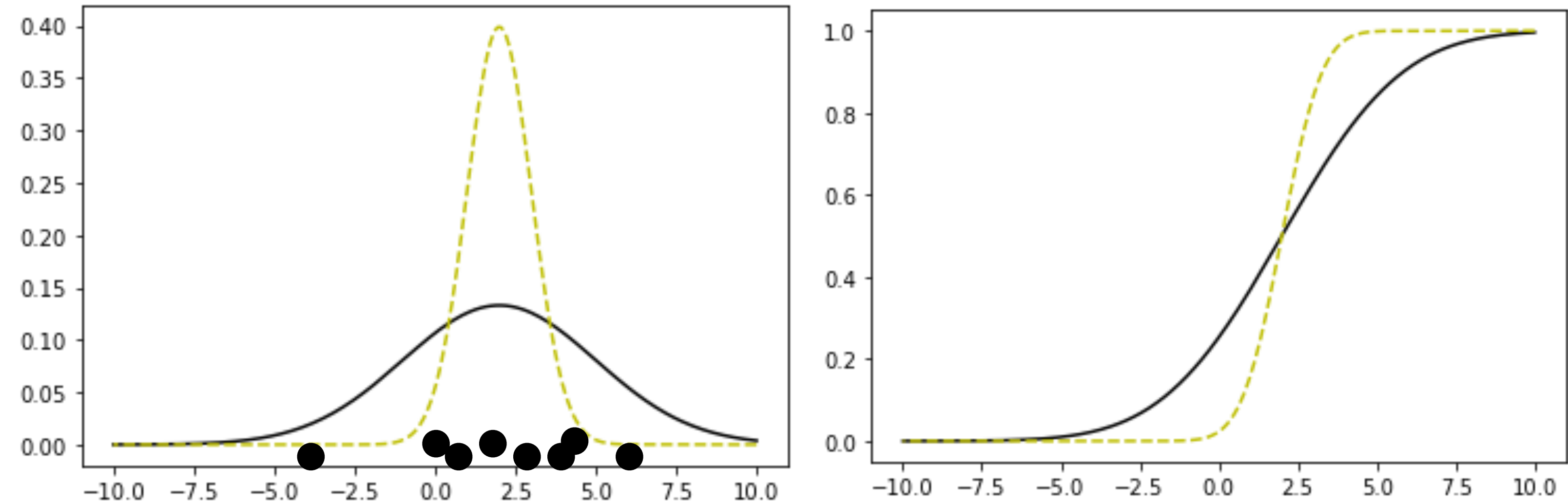


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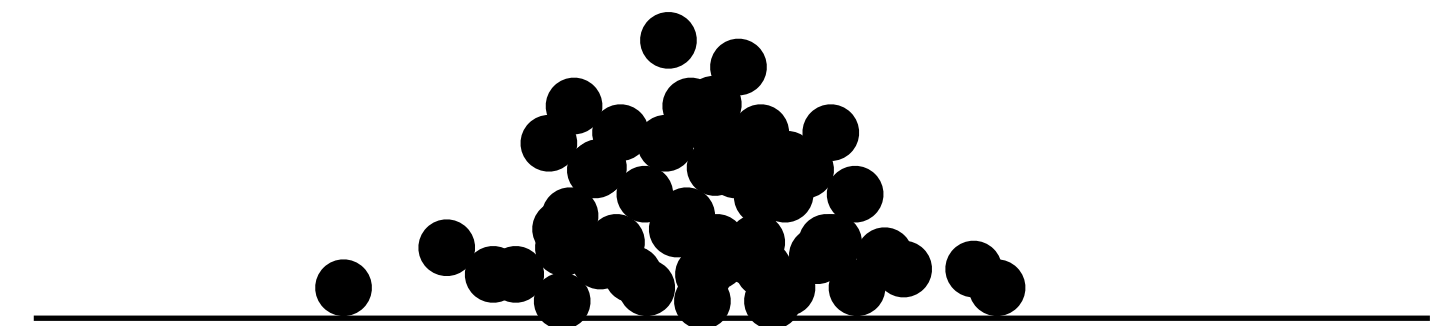


SciPy

Distributions



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 - `rvs(n)` — generate random variates from distribution



NumPy indexing

Basic

```
>>> a[0, 3:5]
array([3, 4])

>>> a[4:, 4:]
array([[44, 55],
       [54, 55]])

>>> a[:, 2]
a([2, 12, 22, 32, 42, 52])

>>> a[2::2, ::2]
array([[20, 22, 24],
       [40, 42, 44]])
```

np.ndarray

.shape= (6, 6)

0	1	2	3	4	5
10	11	12	13	14	15
20	21	22	23	24	25
30	31	32	33	34	35
40	41	42	43	44	45
50	51	52	53	54	55

NumPy indexing

Basic

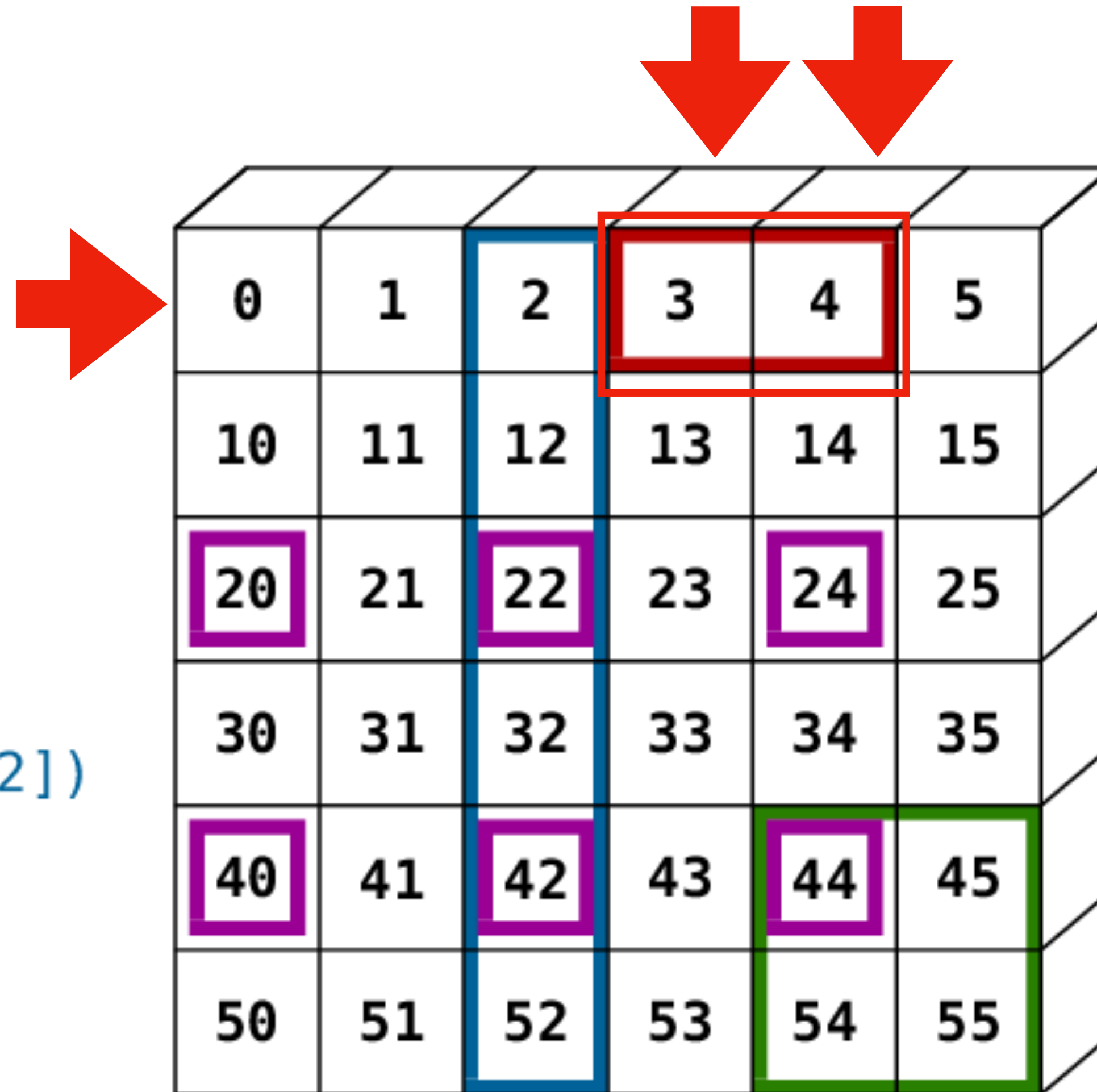
Row Cols

```
>>> a[0, 3:5]  
array([3, 4])
```

```
>>> a[4:, 4:]  
array([[44, 55],  
       [54, 55]])
```

```
>>> a[:, 2]  
a([2, 12, 22, 32, 42, 52])
```

```
>>> a[2::2, ::2]  
array([[20, 22, 24],  
       [40, 42, 44]])
```



NumPy indexing

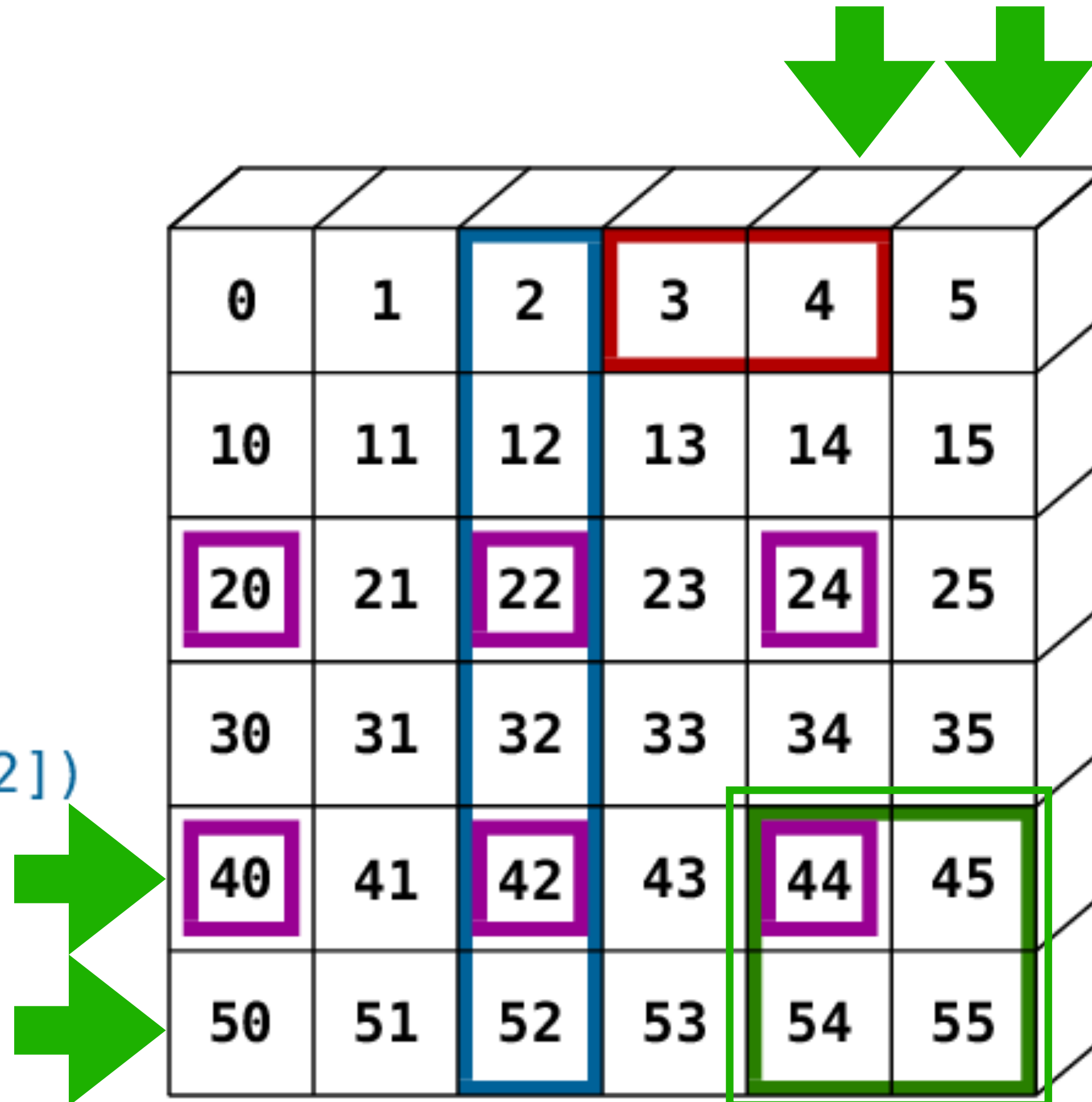
Basic

```
>>> a[0, 3:5]  
array([3, 4])
```

```
>>> a[4:, 4:]  
array([[44, 55],  
       [54, 55]])
```

```
>>> a[:, 2]  
a([2, 12, 22, 32, 42, 52])
```

```
>>> a[2::2, ::2]  
array([[20, 22, 24],  
       [40, 42, 44]])
```



NumPy indexing

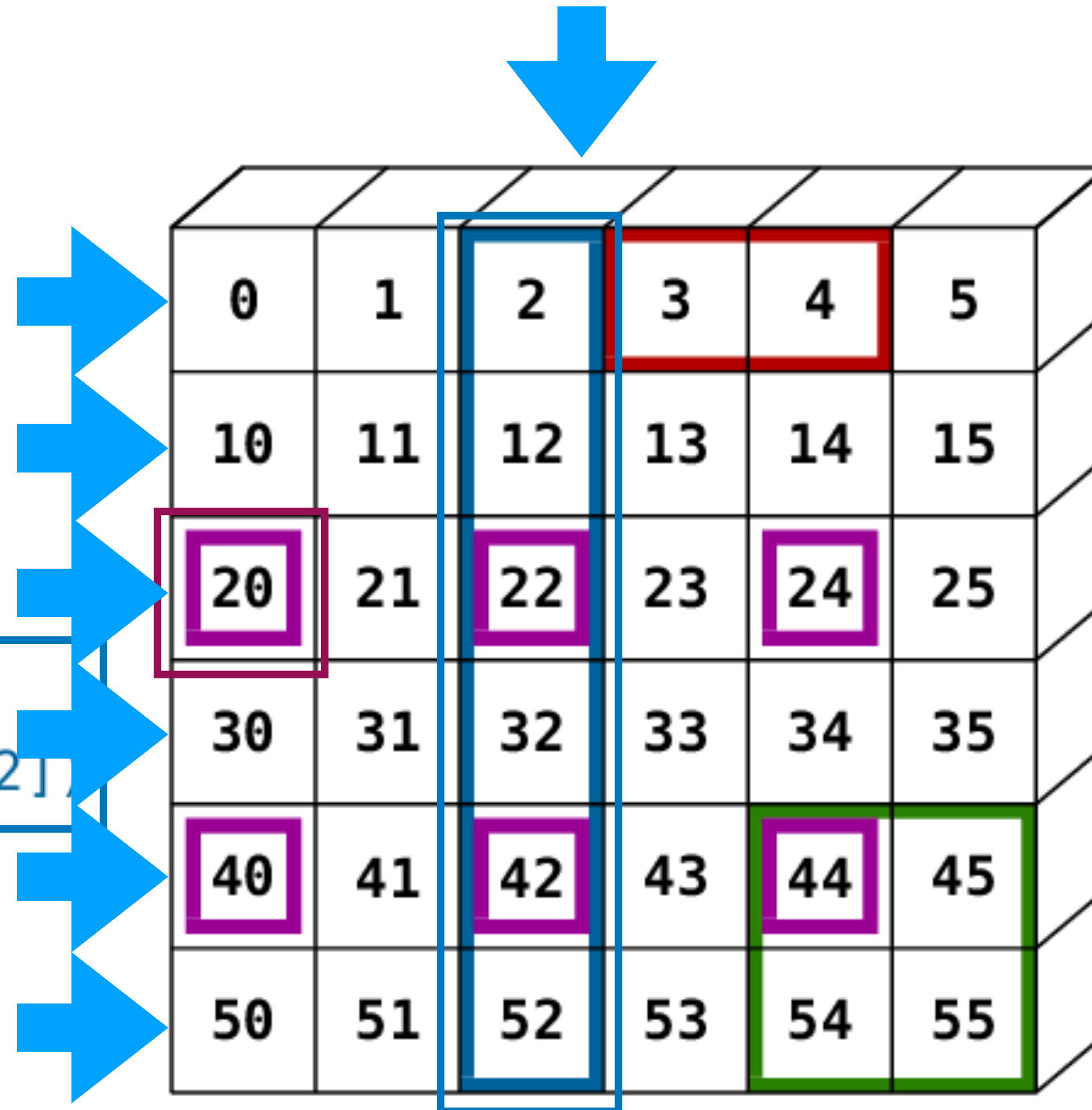
Basic

```
>>> a[0, 3:5]  
array([3, 4])
```

```
>>> a[4:, 4:]  
array([[44, 55],  
       [54, 55]])
```

```
>>> a[:, 2]  
a([2, 12, 22, 32, 42, 52])
```

```
>>> a[2::2, ::2]  
array([[20, 22, 24],  
       [40, 42, 44]])
```



NumPy indexing

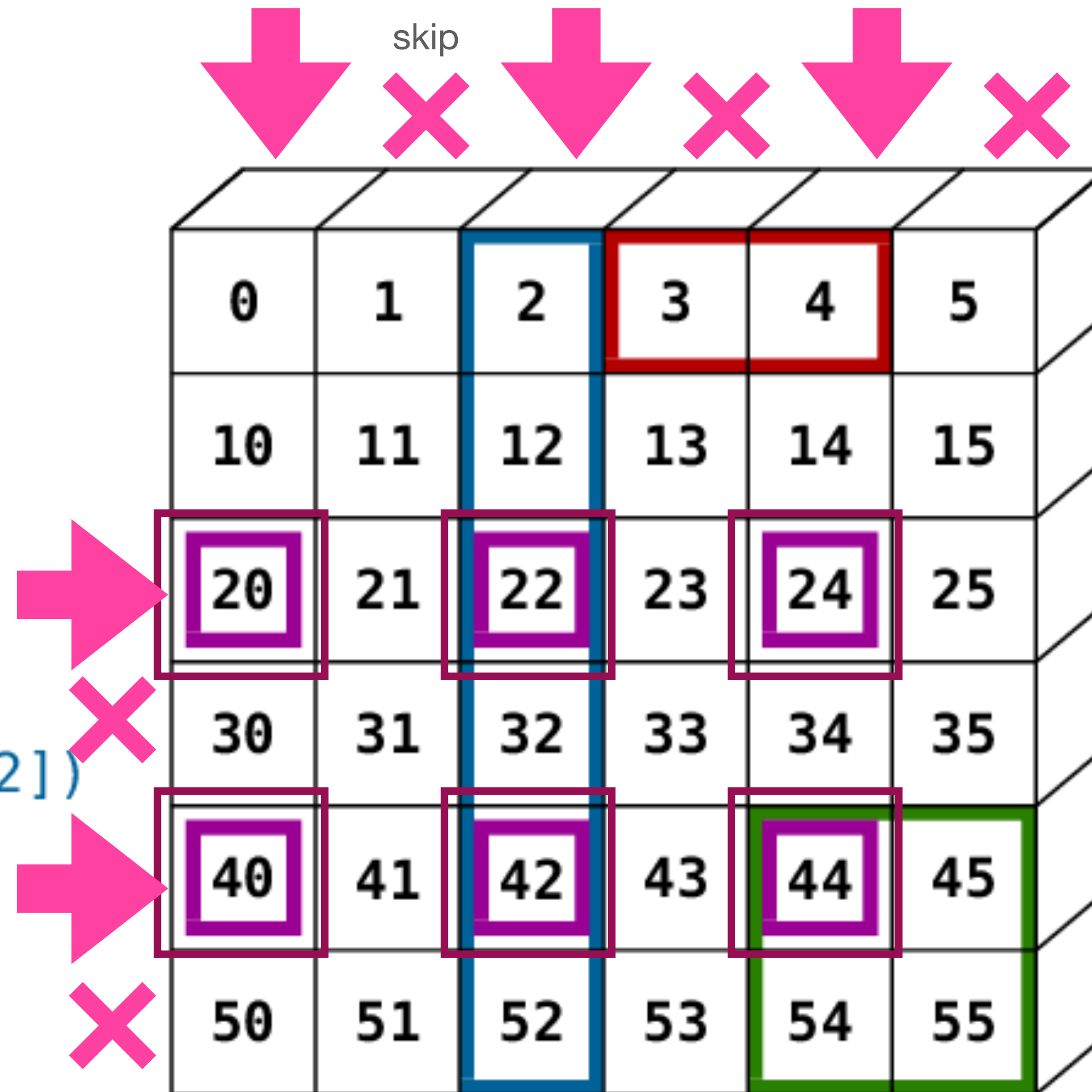
Basic

```
>>> a[0, 3:5]  
array([3, 4])
```

```
>>> a[4:, 4:]  
array([[44, 55],  
       [54, 55]])
```

```
>>> a[:, 2]  
a([2, 12, 22, 32, 42, 52])
```

```
>>> a[2::2, ::2]  
array([[20, 22, 24],  
       [40, 42, 44]])
```



start:stop before:step

NOTE: These are VIEWS on the original data, not copies
Remember discussion of lists of lists and pointers (and deep copy)

NumPy indexing

Basic

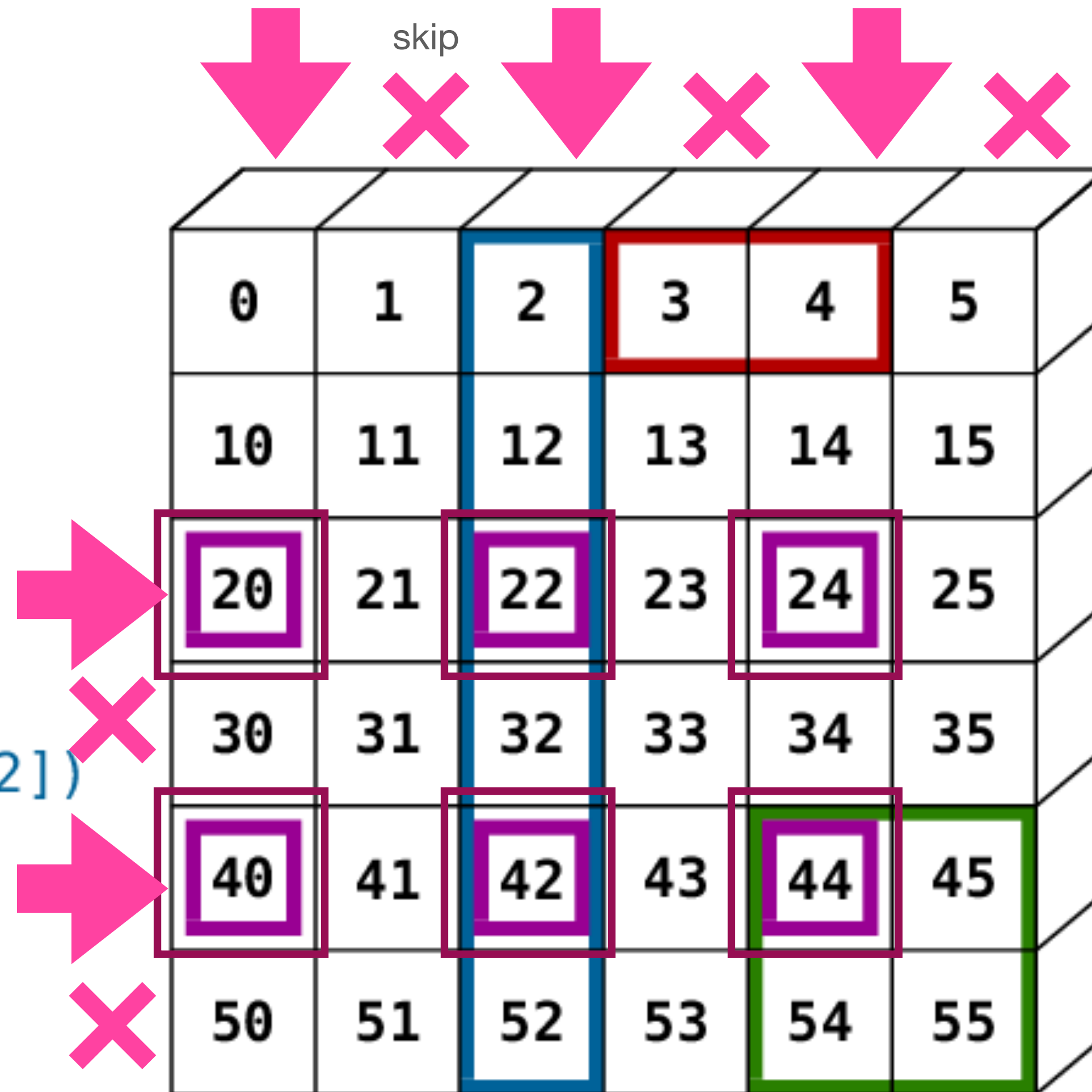
```
>>> a[0, 3:5]  
array([3, 4])
```

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>>> a[4:, 4:]  
array([[44, 55],  
       [54, 55]])
```

```
>>> a[:, 2]  
a([2, 12, 22, 32, 42, 52])
```

```
>>> a[2::2, ::2]  
array([[20, 22, 24],  
       [40, 42, 44]])
```

Rows Cols



start:stop before:step

NumPy *fancy* indexing

Basic

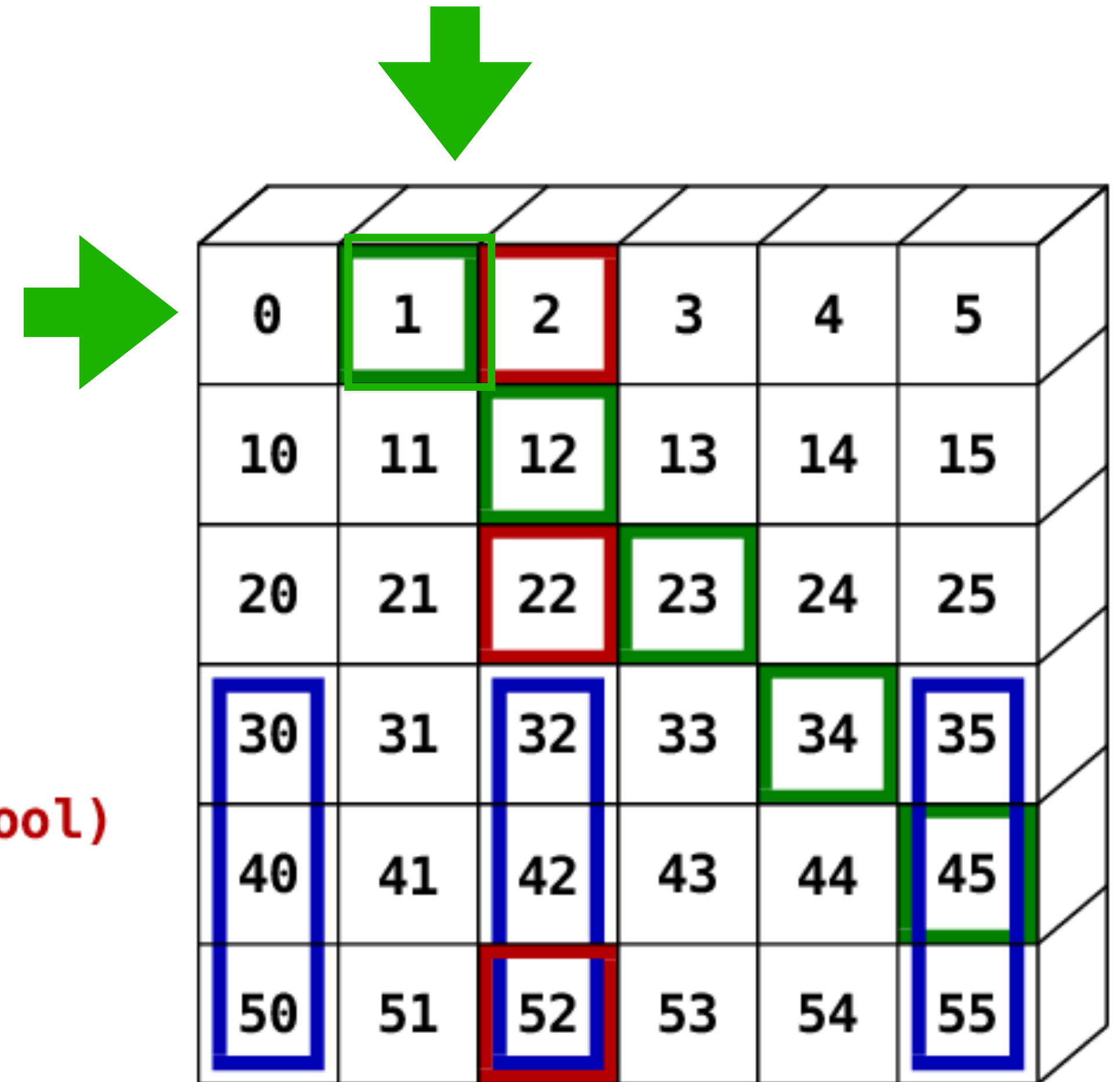
NOTE: These are COPIES, not VIEWS

Rows Cols

```
>>> a[(0,1,2,3,4), (1,2,3,4,5)]  
array([1, 12, 23, 34, 45])
```

```
>>> a[3:5, [0,2,5]]  
array([[30, 32, 35],  
       [40, 42, 45],  
       [50, 52, 55]])
```

```
>>> mask = np.array([1,0,1,0,0,1], dtype=bool)  
>>> a[mask, 2]  
array([2, 22, 52])
```



NumPy *fancy* indexing

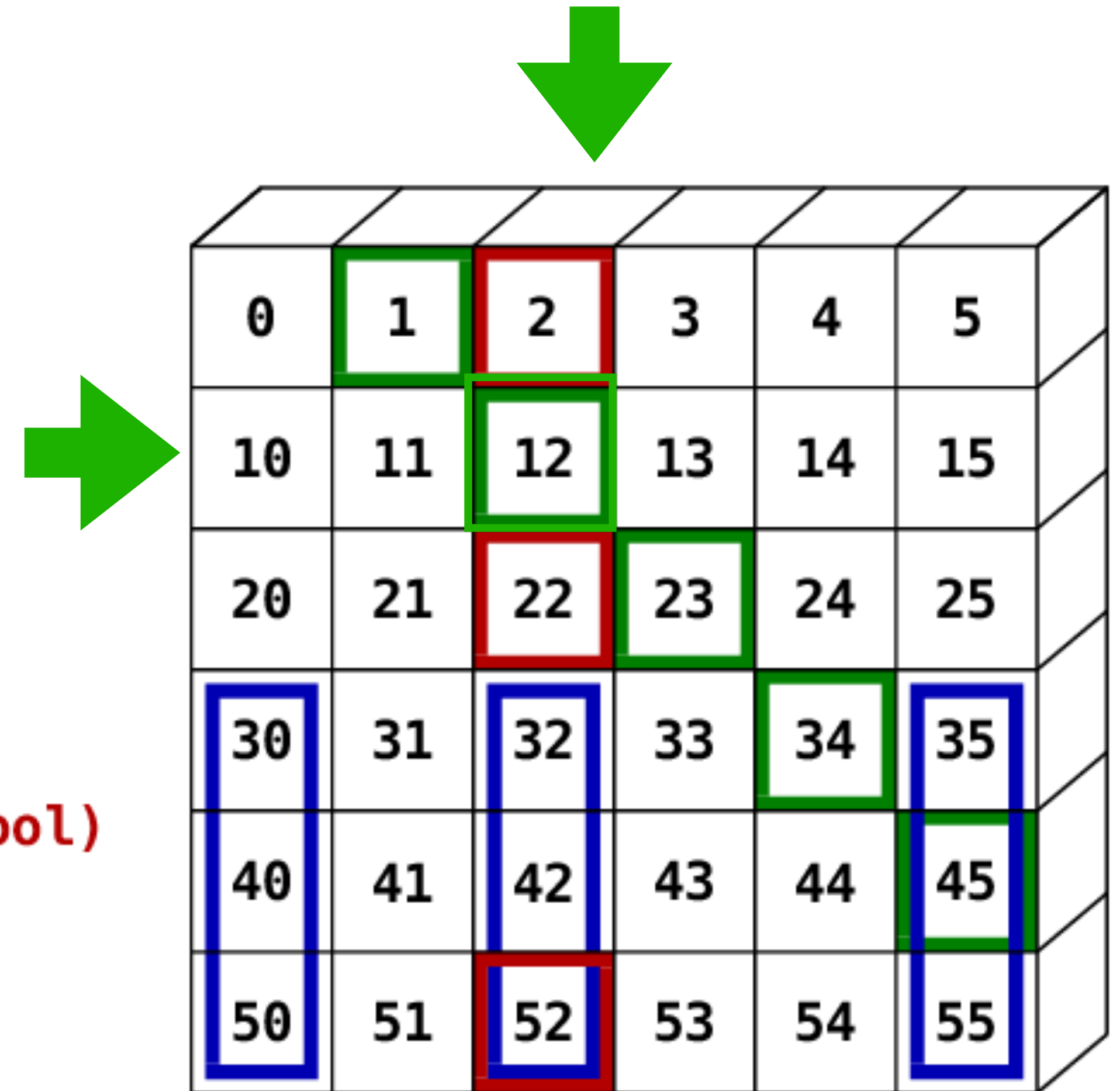
Basic

Rows Cols

```
>>> a[(0,1,2,3,4), (1,2,3,4,5)]  
array([1, 12, 23, 34, 45])
```

```
>>> a[3:., [0,2,5]]  
array([[30, 32, 35],  
       [40, 42, 45],  
       [50, 52, 55]])
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```
>>> mask = np.array([1,0,1,0,0,1], dtype=bool)  
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```



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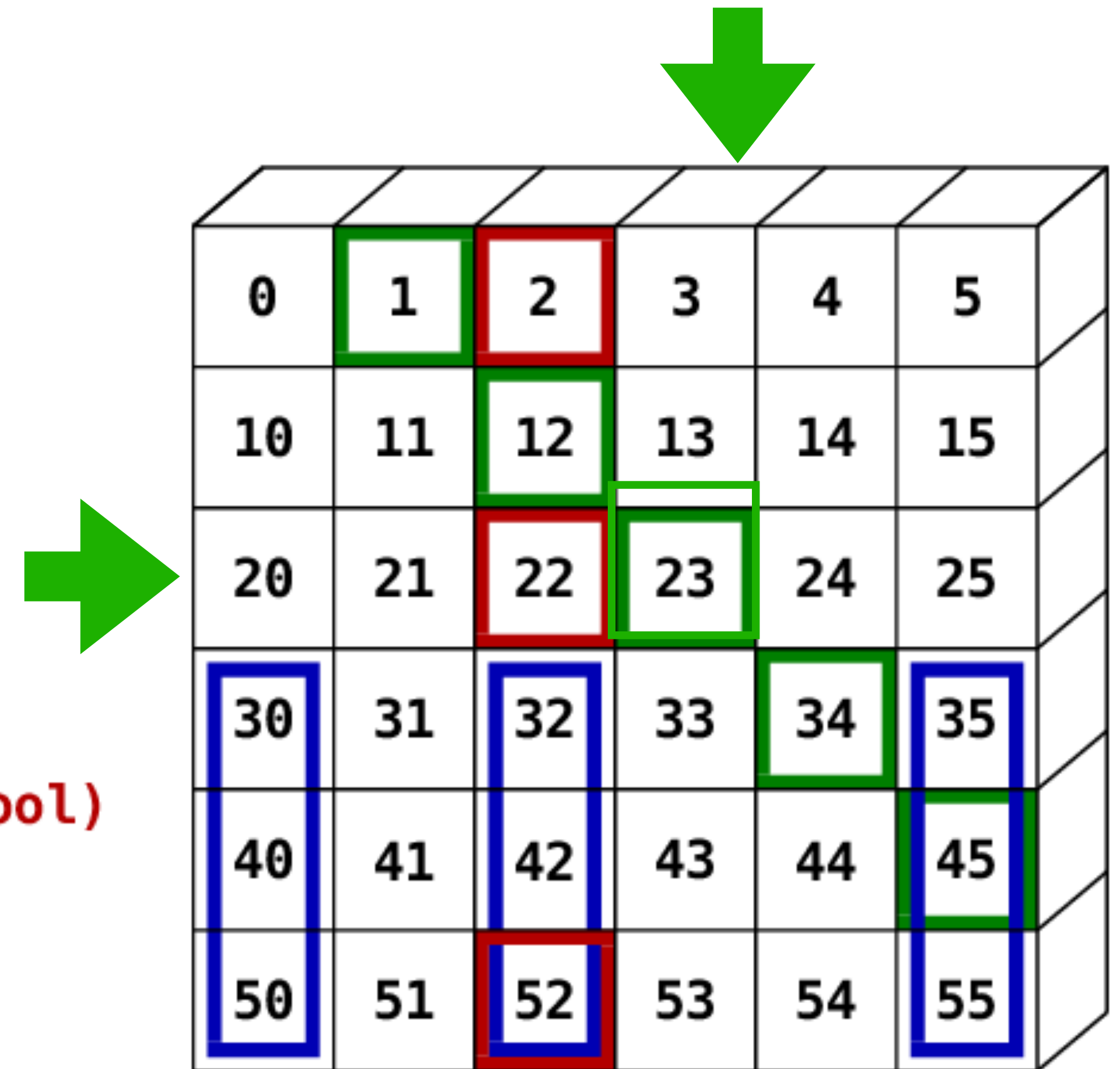
Basic

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```
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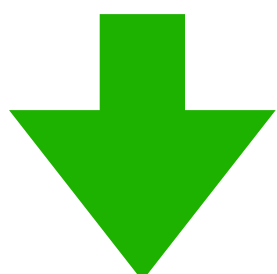
Basic

Rows Cols

```
>>> a[(0,1,2,3,4), (1,2,3,4,5)]  
array([1, 12, 23, 34, 45])
```

```
>>> a[3:5, [0,2,5]]  
array([[30, 32, 35],  
       [40, 42, 45],  
       [50, 52, 55]])
```

```
>>> mask = np.array([1,0,1,0,0,1], dtype=bool)  
>>> a[mask, 2]  
array([2, 22, 52])
```



0	1	2	3	4	5
10	11	12	13	14	15
20	21	22	23	24	25
30	31	32	33	34	35
40	41	42	43	44	45
50	51	52	53	54	55

NumPy *fancy* indexing

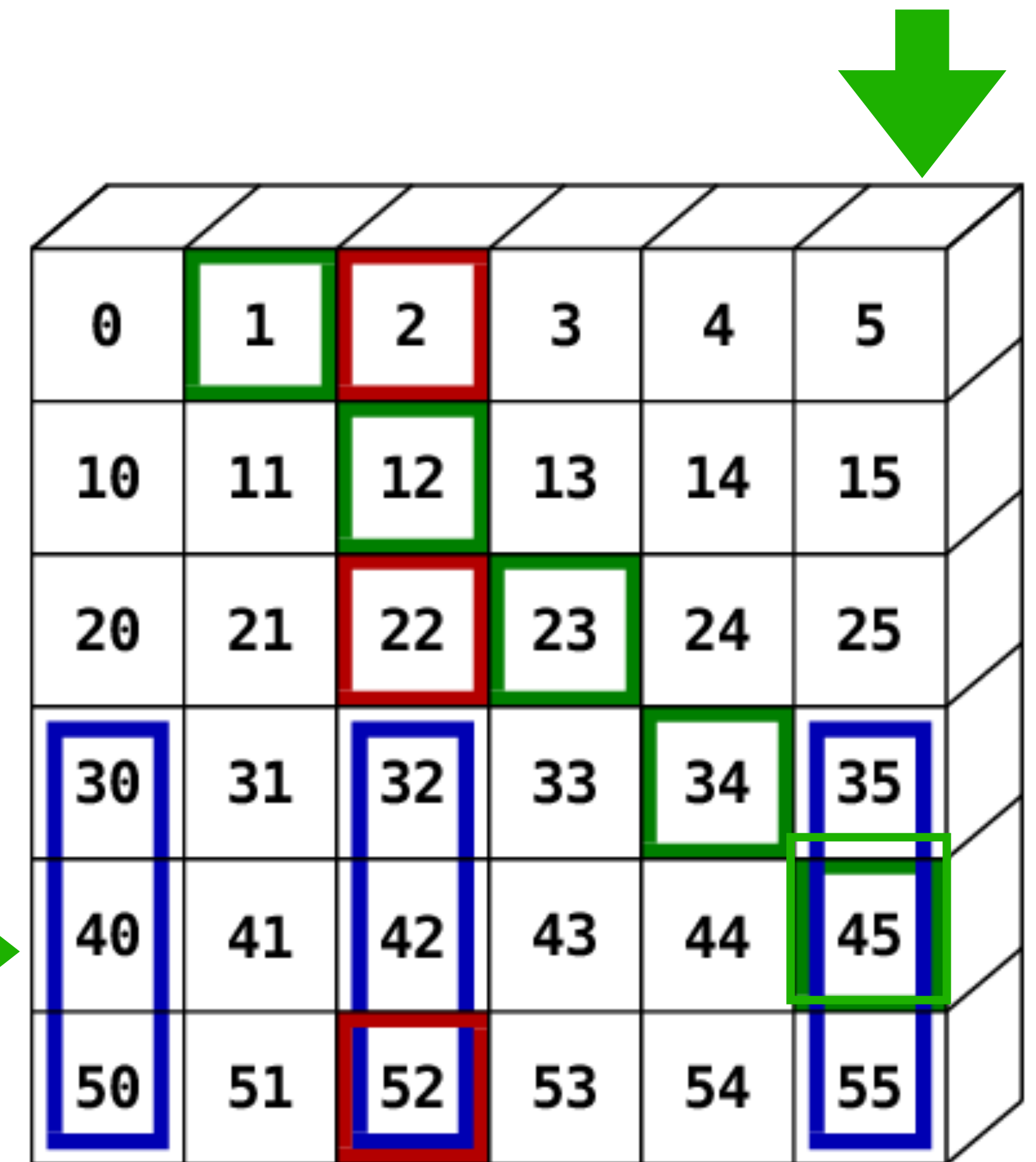
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NumPy *fancy* indexing

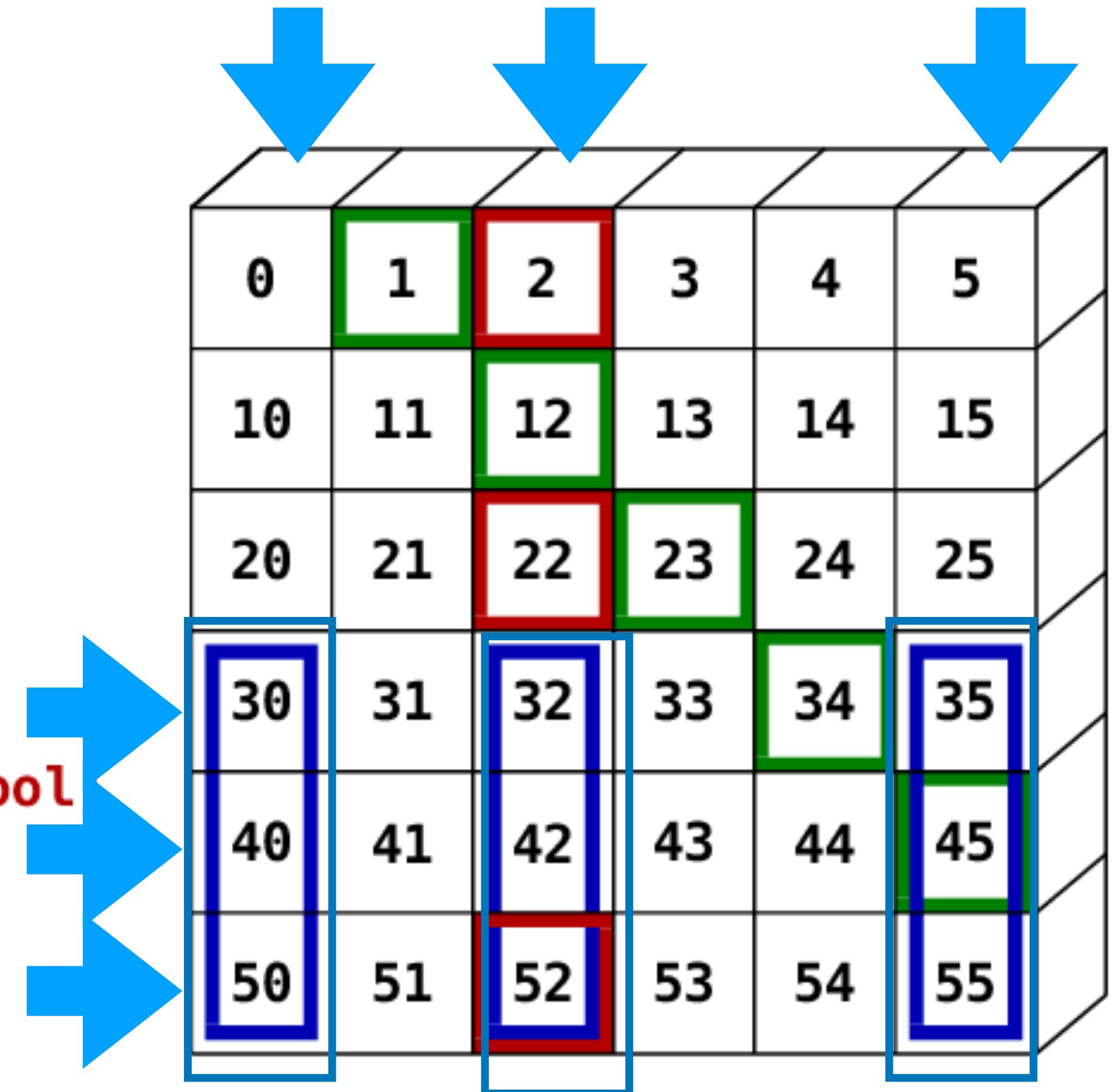
Basic

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Rows Cols

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NumPy *fancy* indexing

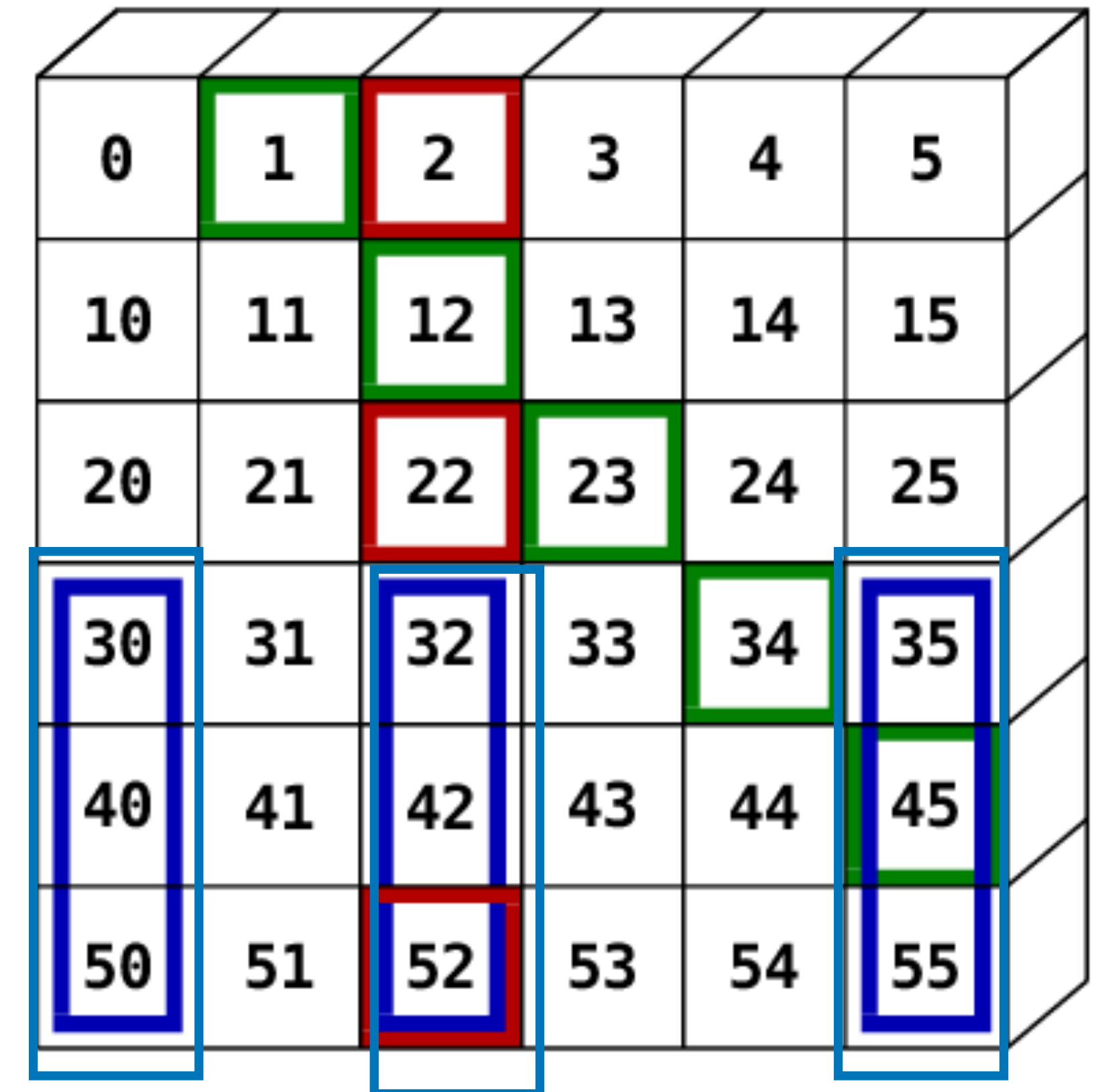
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Rows Cols

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NumPy *fancy* indexing

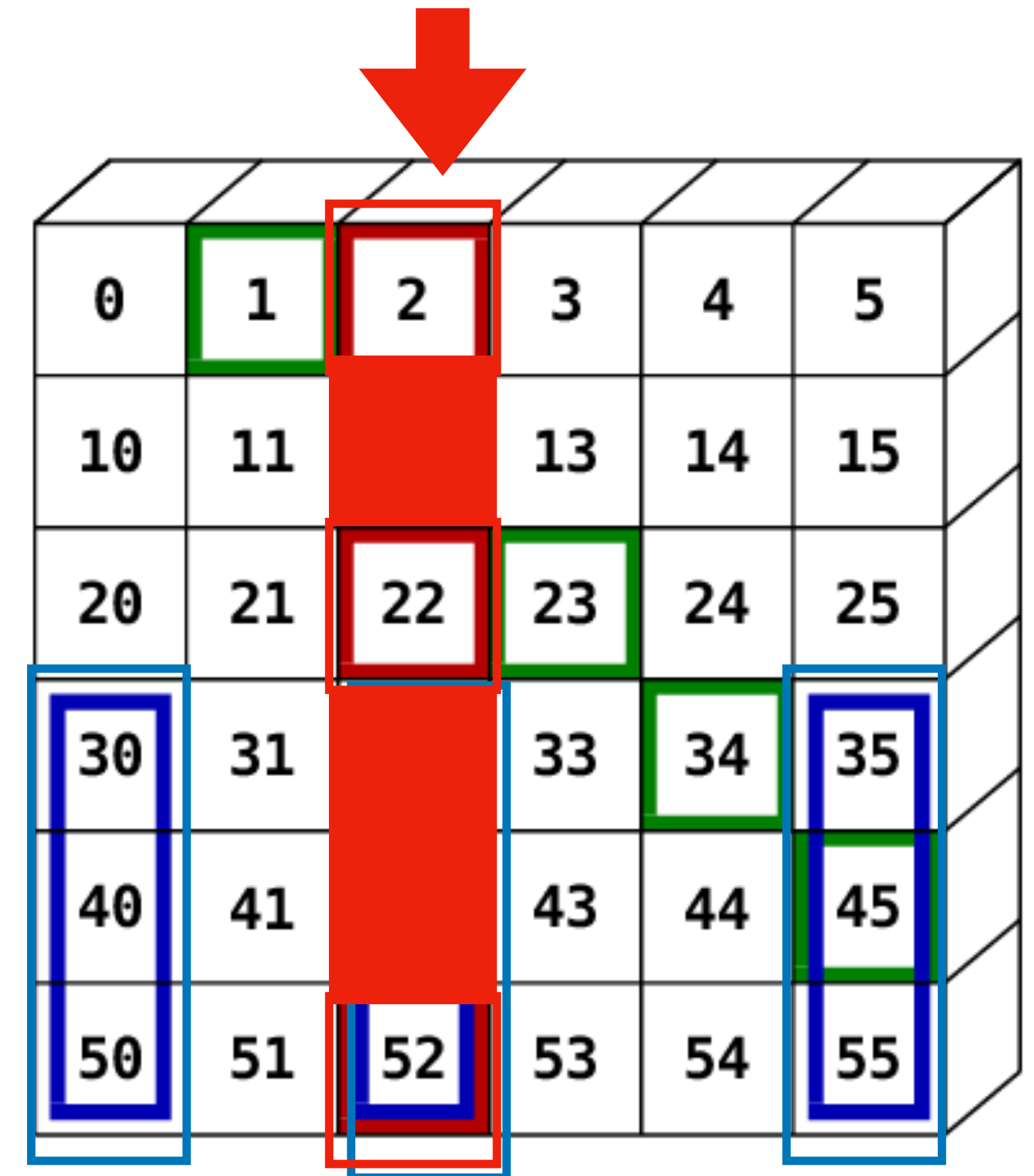
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NumPy *fancy* indexing

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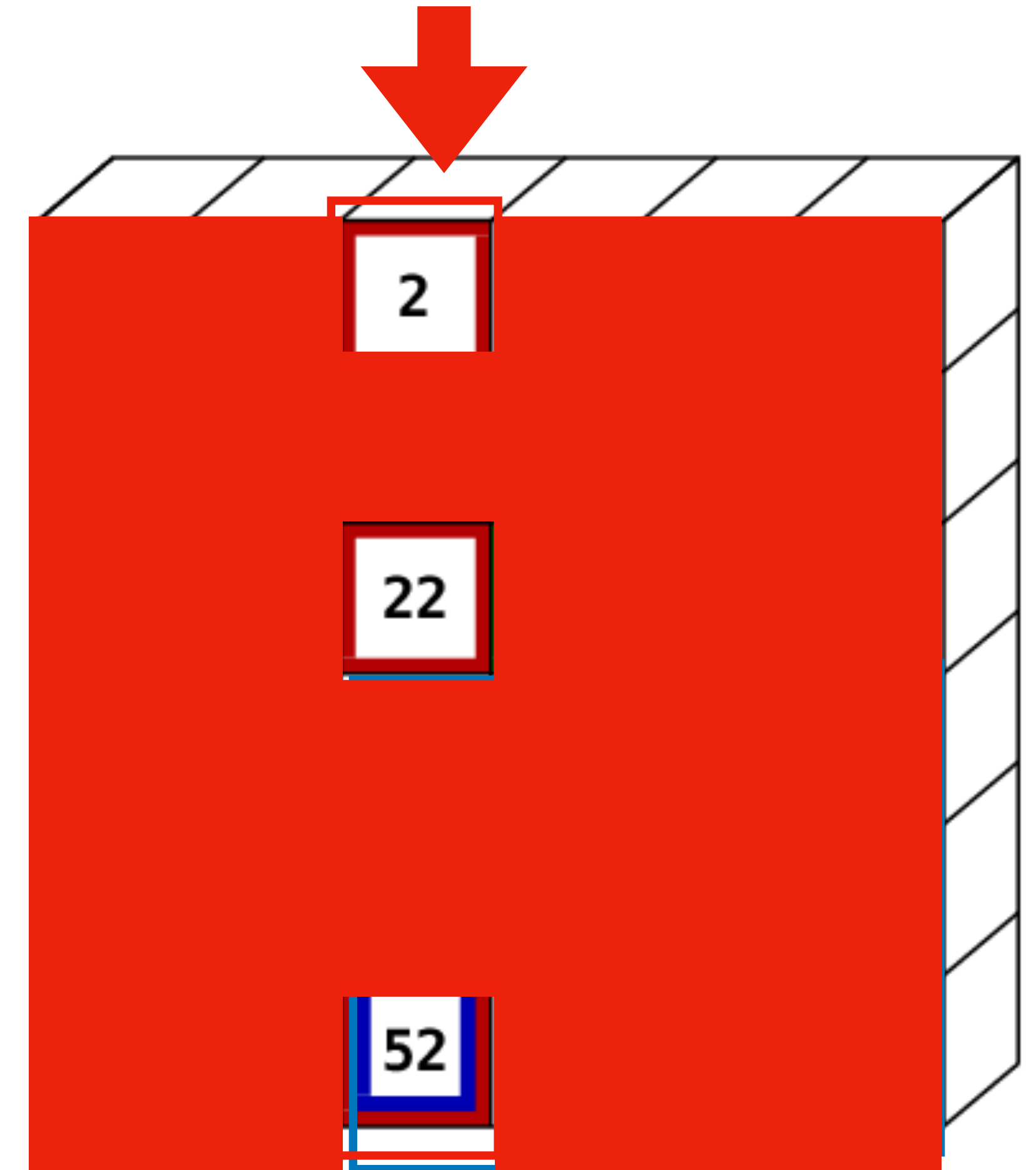
Rows Cols

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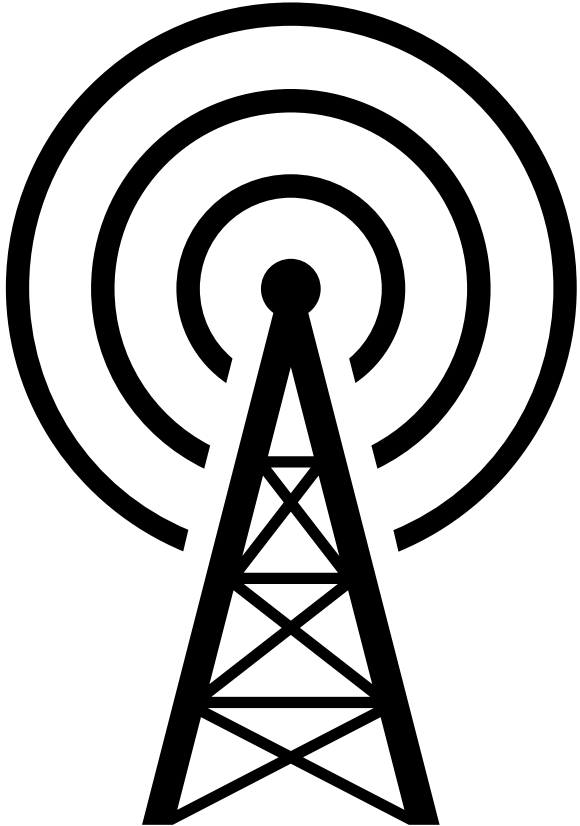


So fancy indexing copies!
And is done by either a sequence of slices (notice the lists/tuples of indices)
or a boolean mask

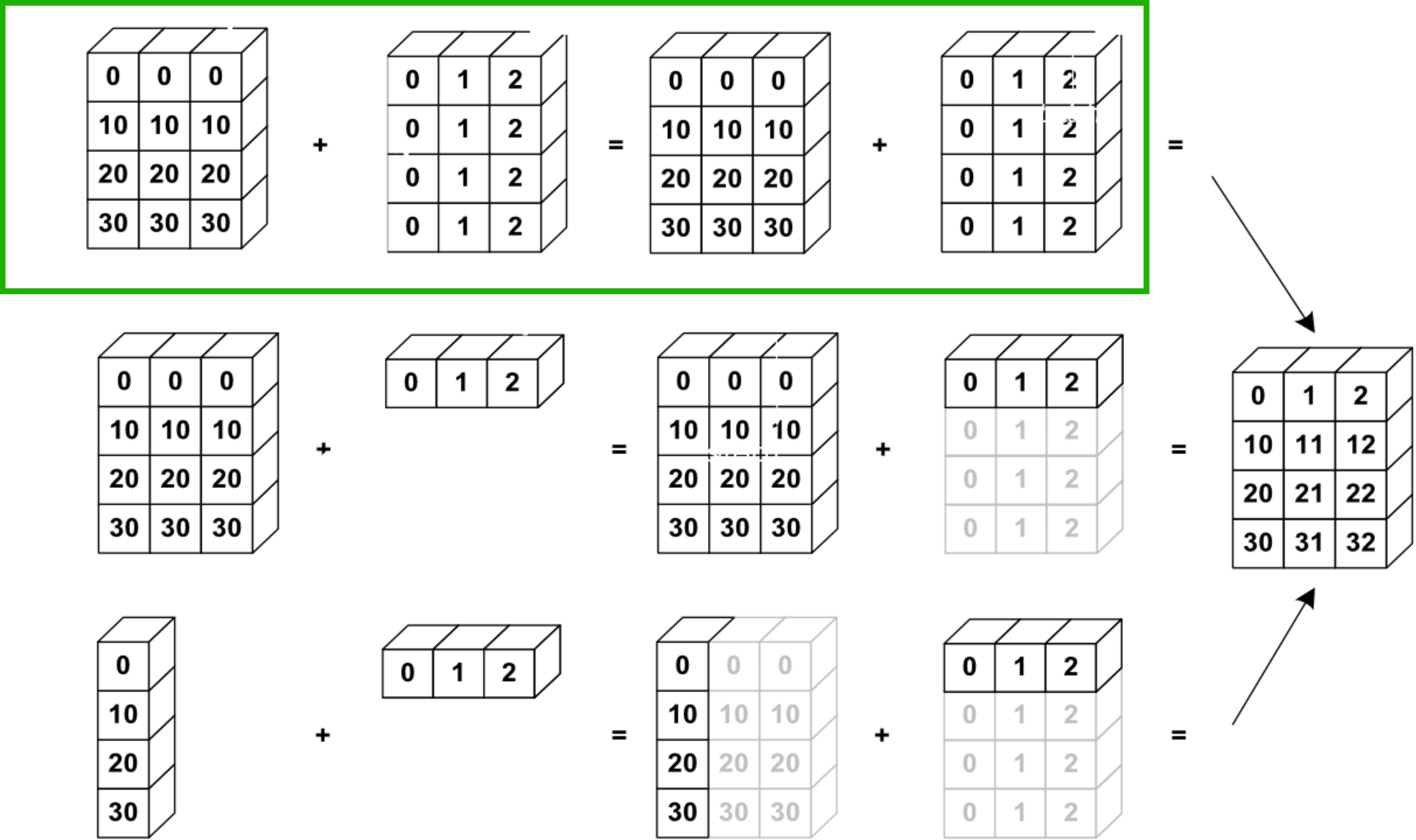


Graphic from
<https://github.com/scipy-lectures/scipy-lecture-notes>

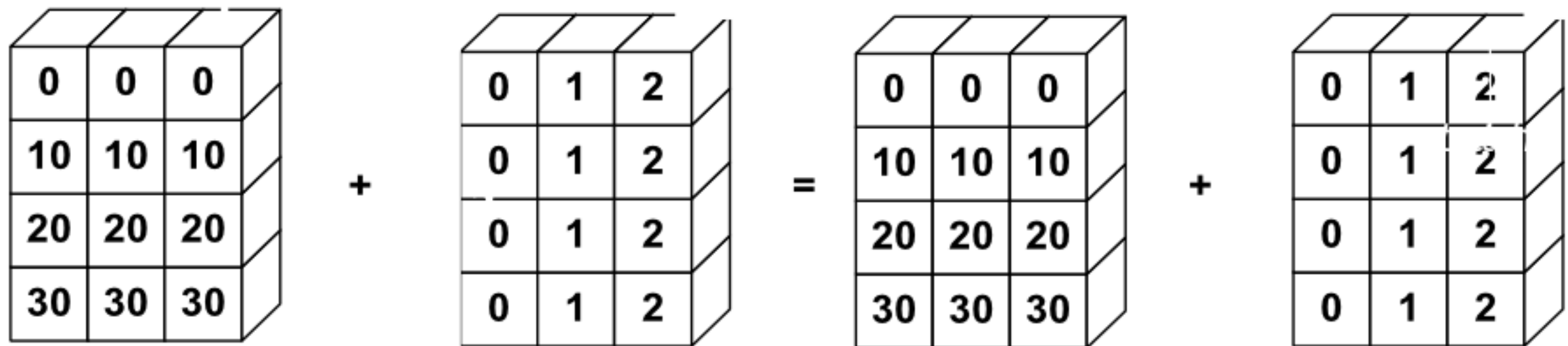
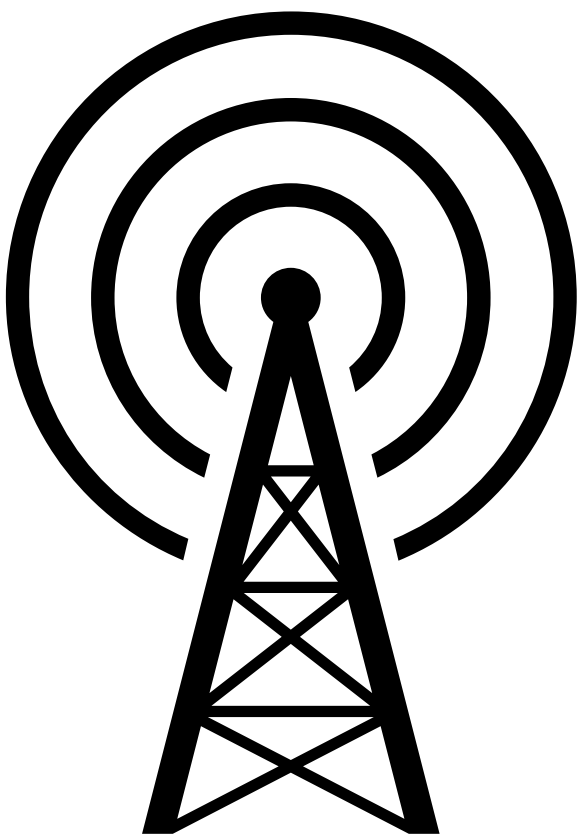
NumPy Broadcasting Example



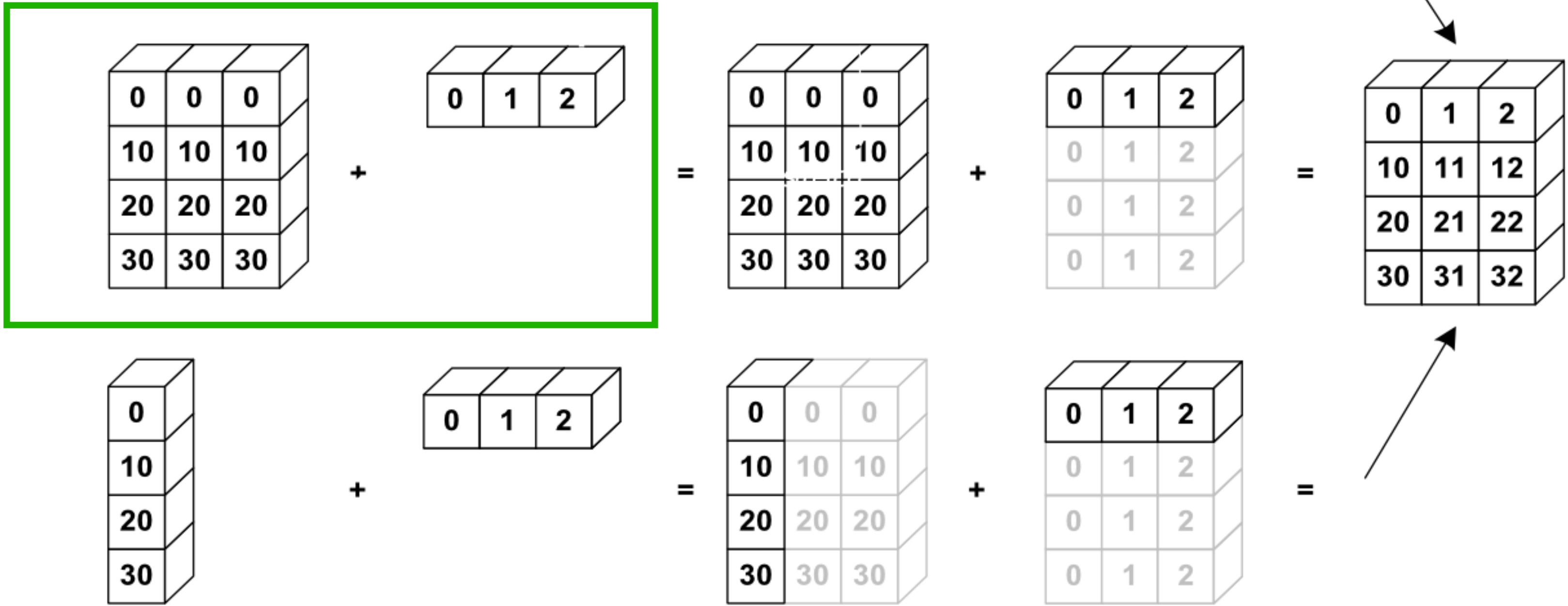
coherent shapes for action (addition here)



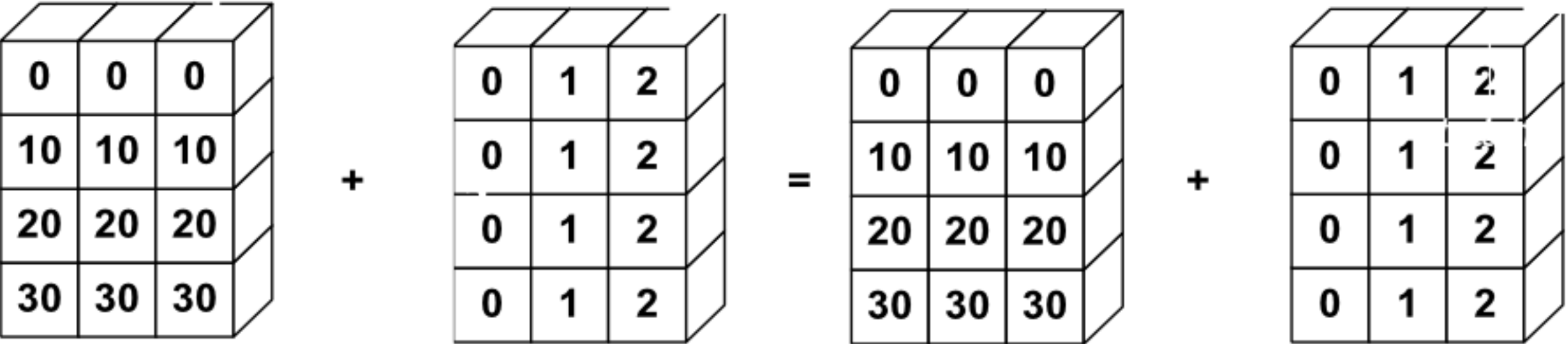
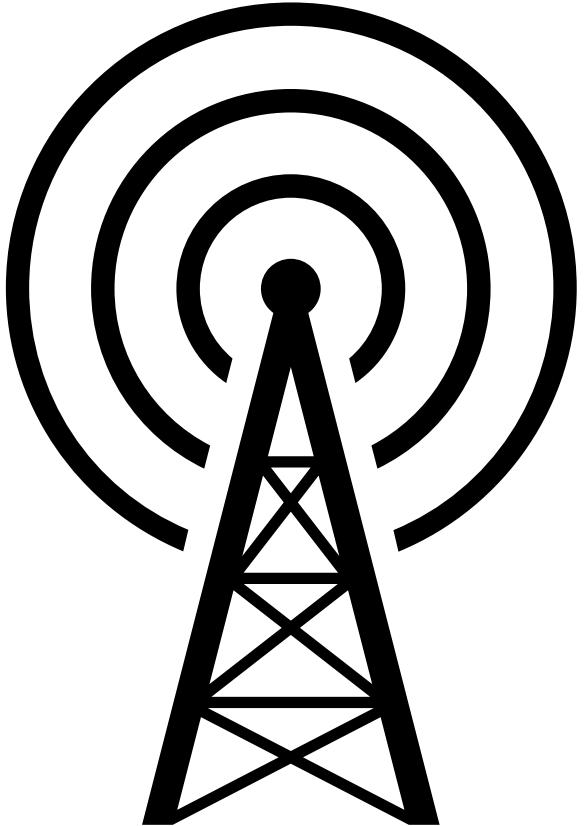
NumPy Broadcasting Example



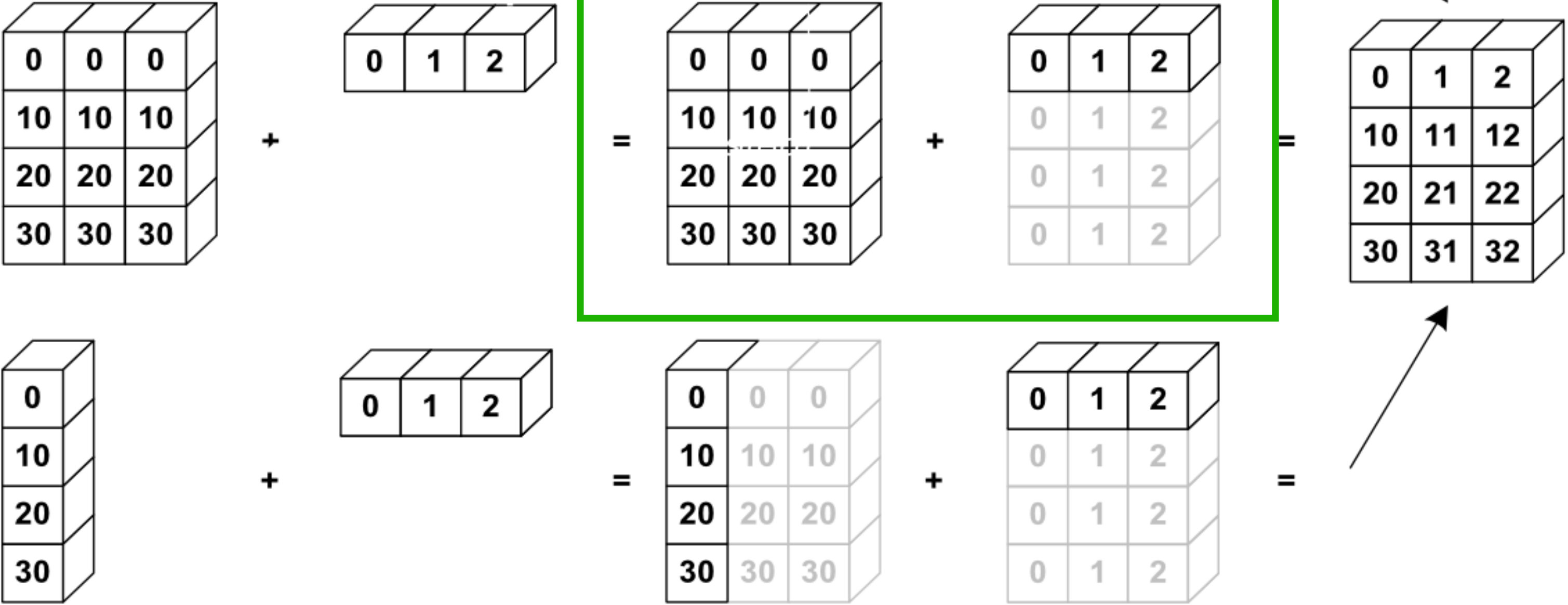
Not coherent but the second smaller object can be broadcasted to coherence



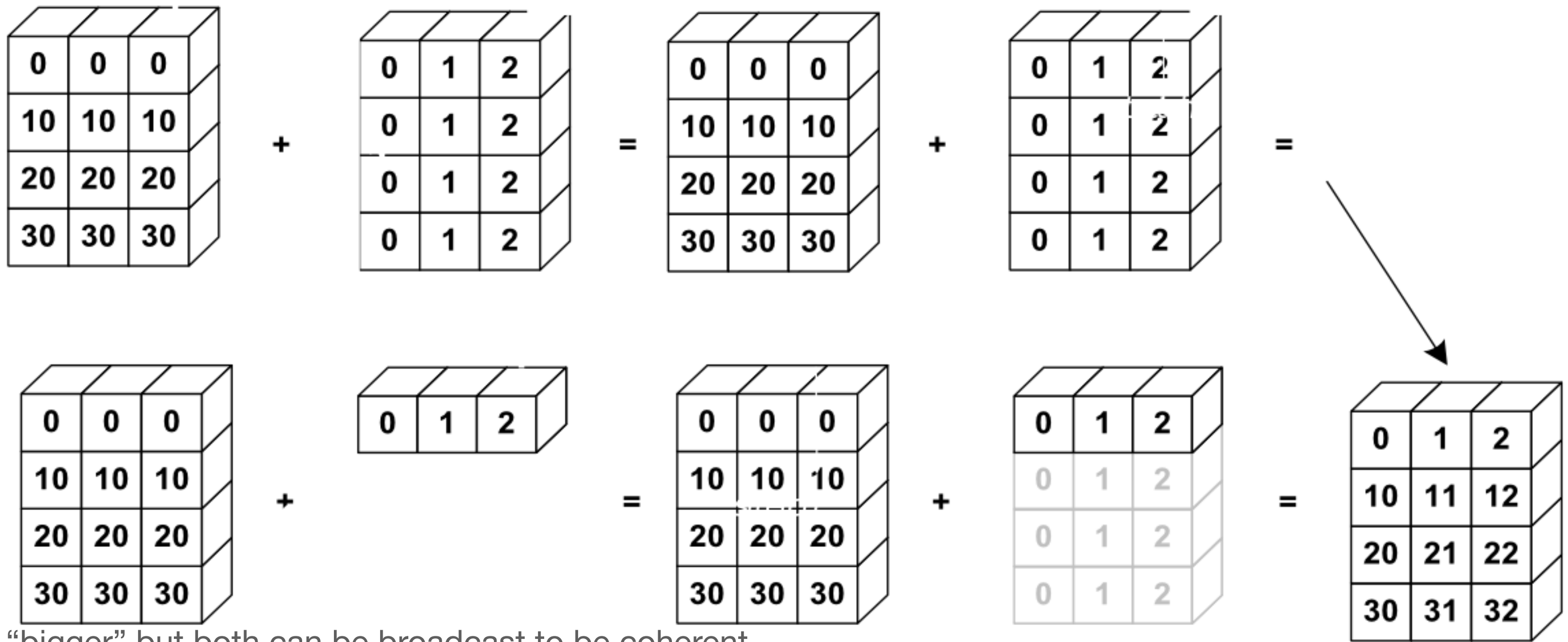
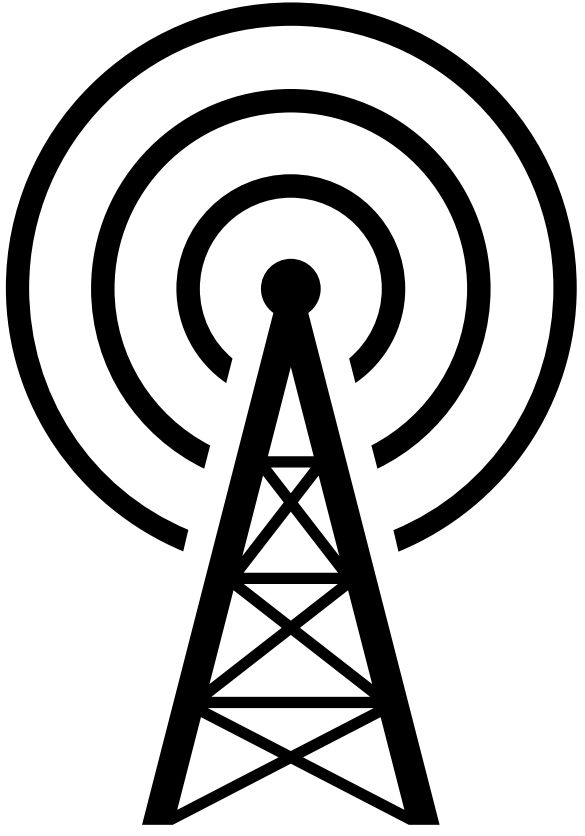
NumPy Broadcasting Example



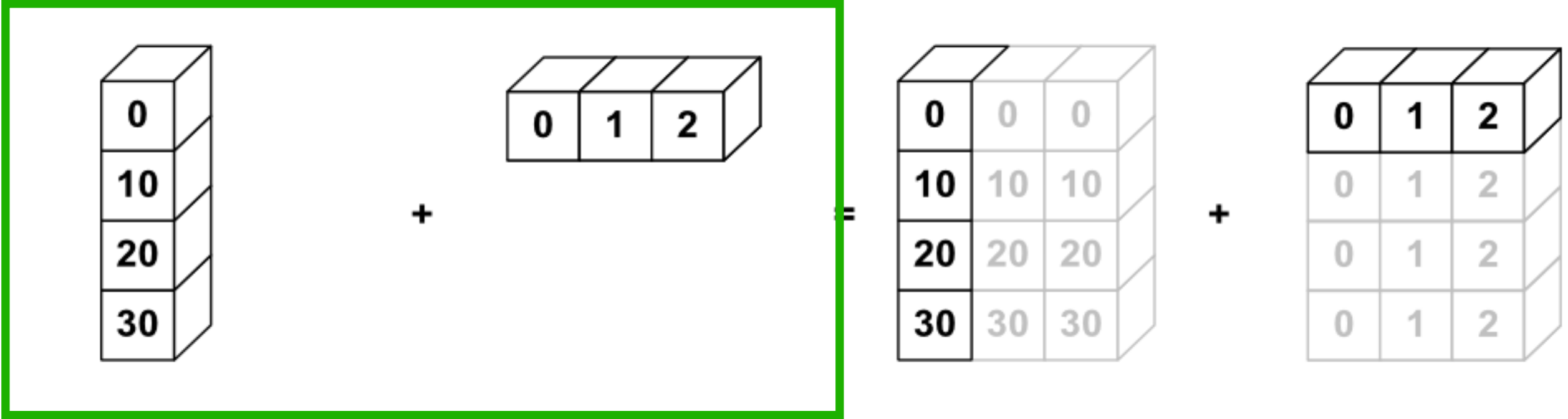
Not coherent but the second smaller object can be broadcasted to coherence



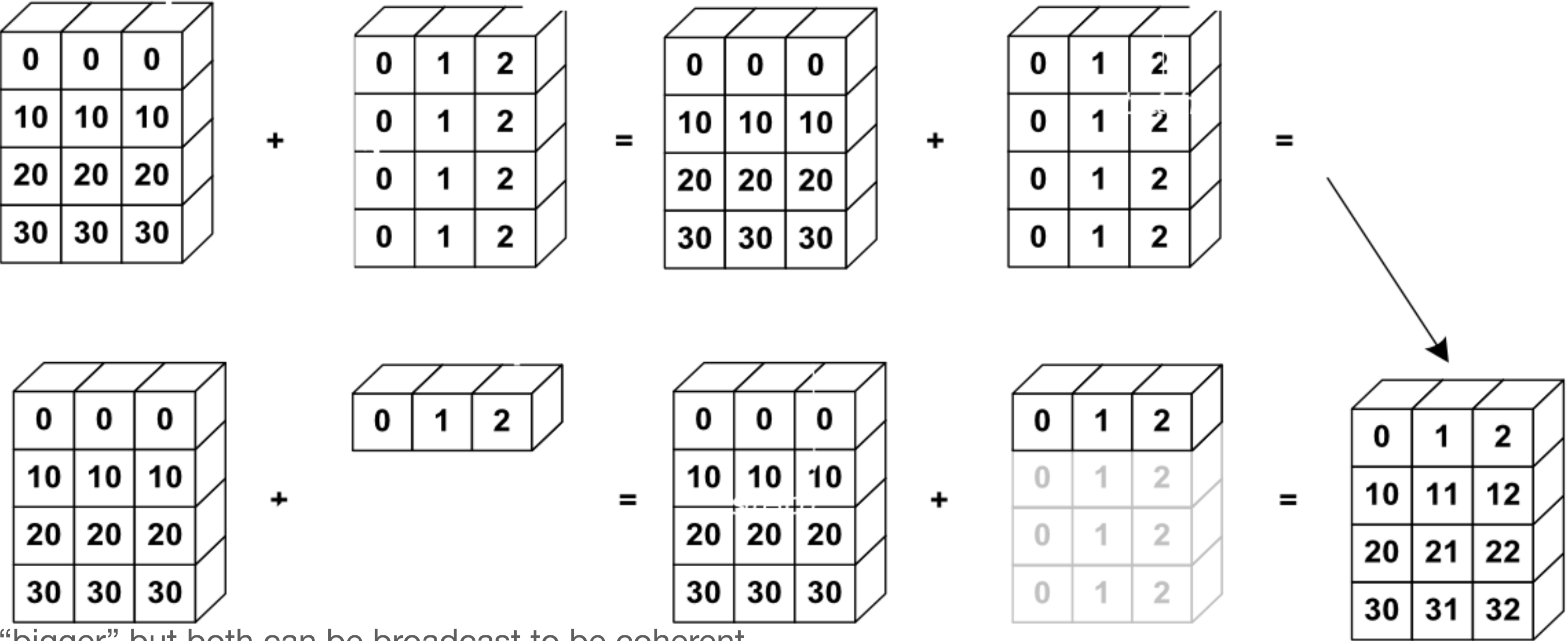
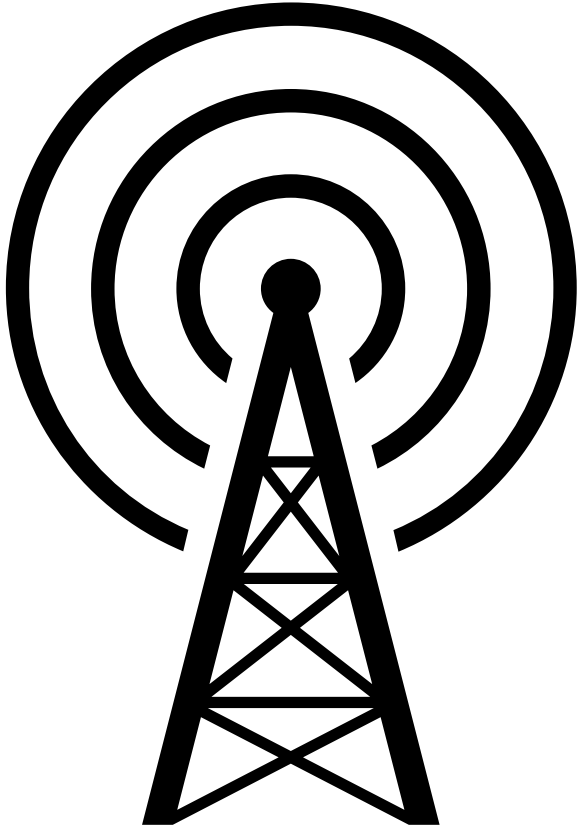
NumPy Broadcasting Example



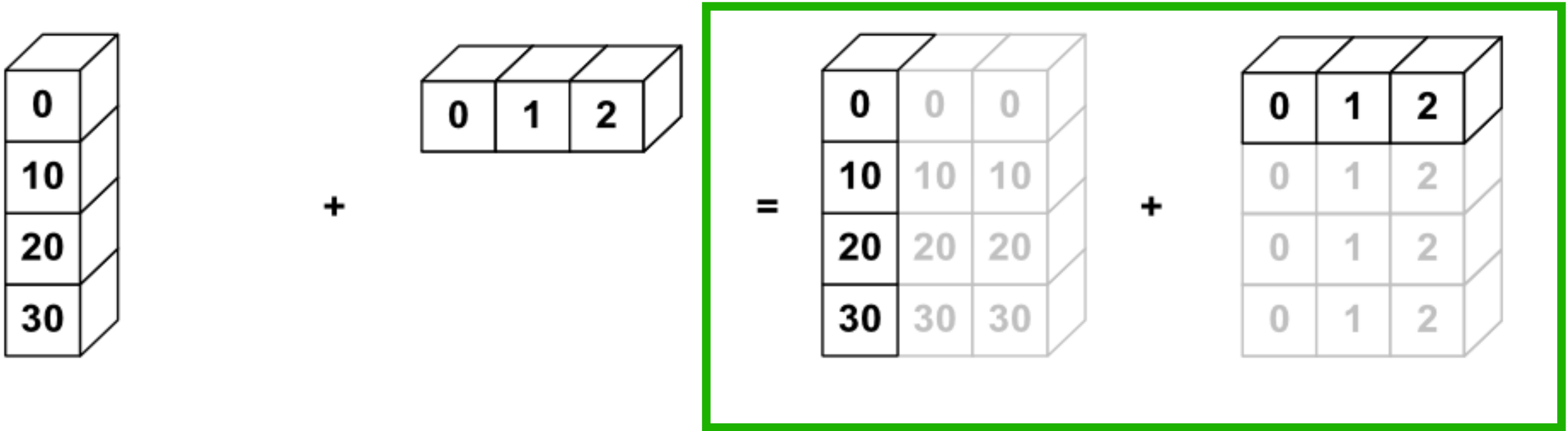
Here neither shape is “bigger” but both can be broadcast to be coherent



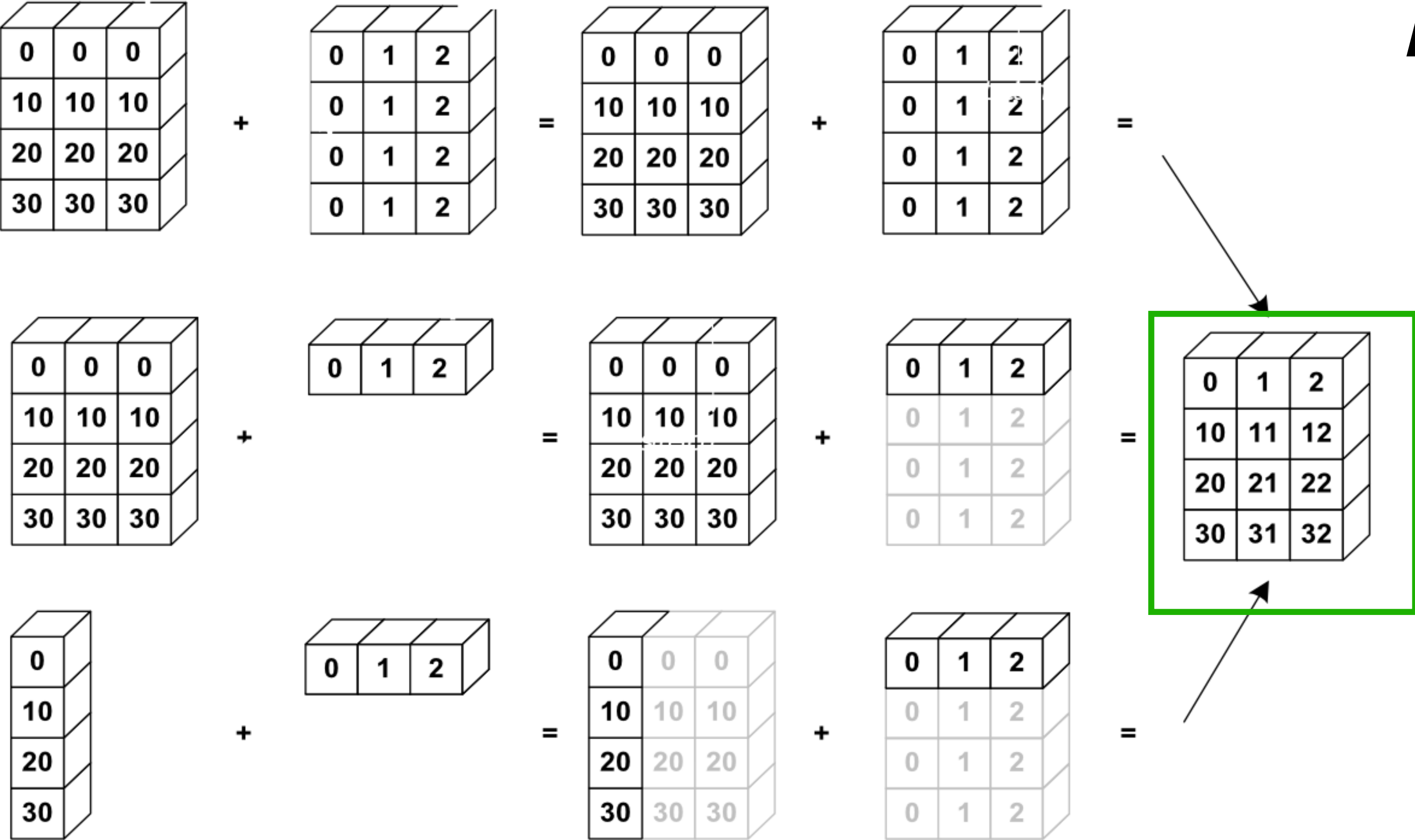
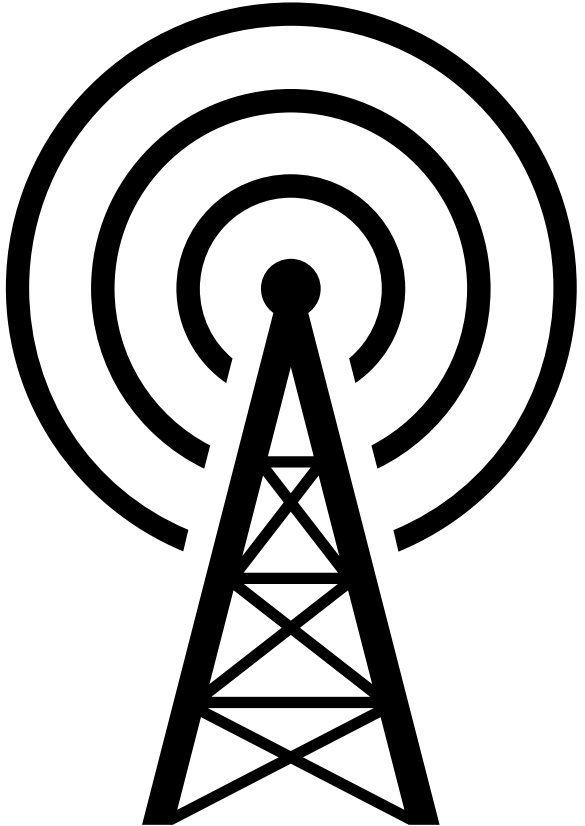
NumPy Broadcasting Example



Here neither shape is “bigger” but both can be broadcast to be coherent



NumPy Broadcasting Example



All 3 give the same answer

NumPy type checking

See <https://numpy.org/devdocs/reference/typing.html>

- Numpy has a number of helper functions for type checking
 - `import np.typing as npt`
 - `npt.ArrayLike` — Union of array-like objects
 - `npt.dtype` — can be used as output to change data type

NumPy *shape shifting*

ravel and reshape

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

Un-ravel the (2, 3) array into a (6,) vector
Row-major order by default, like C

```
>>> np.ravel(x, order='F')  
array([1, 4, 2, 5, 3, 6])
```

order='F' uses Fortran order, column-major

Can also use .reshape and scrap axis

```
>>> x.reshape(-1)  
array([1, 2, 3, 4, 5, 6])
```

Other useful NumPy array operations

- See:
 - <http://scipy-lectures.org/intro/numpy/operations.html>
 - Code here: <https://github.com/scipy-lectures/scipy-lecture-notes/blob/master/intro/numpy/operations.rst>

Pandas

Built on top of and extended from numpy

- `pd.Series` — like a `np.array`
 - Can be used for vectors/columns of one type of feature across instances (usually one type or a general type)
 - eg. “count: [1, 12, 15, 0, 3]”
 - dtype is an object type (`np.float64`, `np.str`, `np.object`)
 - Can also be used for vectors that represent instances/rows across multiple features (then usually multiple types across these features/columns)
 - This about a `pd.Series` like a item in a dictionary “name: Vals”

Pandas

Built on top of and extended from numpy

- **pd.DataFrame** — like a collection of **pd.Series** objects
 - Multiple columns are named series, for features
 - {"color": ["red", "brown", "green"], "animal": ["panda", "fox", "turtle"]}
 - Can also think about this as multiple rows for instances
 - [["red", "panda"], ["brown", "fox"], ["green", "turtle"]]
 - In either case we get a rectangular DataFrame

	color	animal
row0	red	panda
row1	brown	fox
row2	green	Turtle

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Pandas

Subsetting columns, many flavors

TRY PASSING IN NAMES WHEN YOU CAN
INCREASES READABILITY (first 3)

- `my_DataFrame["col_name"]`
 - `my_DataFrame[["col_name1", "col_name2"]]` (notice list of names as index)
- `my_DataFrame.col_name`
- `my_DataFrame.loc[:, ["col_name1", "col_name2"]]`
- `my_DataFrame.iloc[:, [1, 7, -1]]` COLUMN NUMBERS (ints)
- Old documents will say you can pass in integers for column positions
 - Like: `my_DataFrame[[1, 7, -1]]`
 - This behavior was deprecated circa pandas 0.20

Pandas

Subsetting rows, many flavors

TRY PASSING IN NAMES WHEN YOU CAN
INCREASES READABILITY (loc)

- `my_DataFrame.loc[0]`
 - `my_Data.loc[[0, 2, 8]]` ROW NAMES! Ints by default, but can change
 - `my_Data.loc[[0, 2, 8], :]`
- `my_DataFrame.iloc[0]`
 - `my_DataFrame.iloc[[0, 2, -1]]` ROW NUMBERS (ints)
 - `my_DataFrame.iloc[[0, 2, -1], :]`
- Back in the day, you could use `.ix` to do either, this was confusing and has been deprecated circa pandas .20

More Pandas

See munging with pandas for more...



Matplotlib



See IntroSciPy.ipynb and SC:P3H4MJ book

Imperative plotting, Seaborn wrapper

Also useful: <http://scipy-lectures.org/intro/matplotlib/index.html>

with code here: <https://github.com/scipy-lectures/scipy-lecture-notes/blob/master/intro/matplotlib/index.rst>