Practical Business Python

Lecture 4: NumPy Basics: Arrays and Vectorized Computation.

Iegor Vyshnevskyi

Woosong University

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Agenda

1. NumPy Intro
2. Your first NumPy array
3. NumPy data types
4. Selecting and Updating Data
5. Array Mathematics
6. Array Transformations

1. NumPy Intro

Intro

NumPy, short for ***Numerical Python***, is one of the most important foundational packages for numerical computing in Python.

Many computational packages providing scientific functionality use NumPy's array objects as one of the standard interface for data exchange.

TensorFlow and scikit-learn use NumPy arrays as inputs, and pandas and Matplotlib are built on top of NumPy.

Source: Wes McKinney (2022); Introduction to NumPy. Izzy Weber. Rpubs

Intro

Here are some of the things you'll find in NumPy:

- ndarray, an efficient multidimensional array providing fast array-oriented arithmetic operations and flexible broadcasting capabilities
- Mathematical functions for fast operations on entire arrays of data without having to write loops
- Tools for reading/writing array data to disk and working with memory-mapped files
- Linear algebra, random number generation, and Fourier transform capabilities
- a C API for connecting NumPy with libraries written in C, C++, or FORTRAN

Source: Wes McKinney (2022)

Intro

While NumPy by itself does not provide modeling or scientific functionality, having an *understanding of NumPy arrays and array-oriented computing* will *help you use tools with array computing semantics, like pandas*, much more effectively.

One of the reasons NumPy is so important for numerical computations in Python is because it is designed for efficiency on large arrays of data.

Source: Wes McKinney (2022)

Application

For most data analysis applications, the main NumPy areas of functionality are:

- Fast array-based operations for data munging and cleaning, subsetting and filtering, transformation, and any other kind of computation
- Common array algorithms like sorting, unique, and set operations
- Efficient descriptive statistics and aggregating/summarizing data
- Data alignment and relational data manipulations for merging and joining heterogeneous datasets
- Expressing conditional logic as array expressions instead of loops with *'if-elif-else'* branches
- Group-wise data manipulations (aggregation, transformation, and function application)

Source: Wes McKinney (2022)

2. Your first NumPy array

Our First NumPy Array

We create NumPy array (*sudoku_array*) from the list. In this case *sudoku_list* is a Python list containing a sudoku game:

```
# sudoku_list is a Python list containing a sudoku game
sudoku_list =  [[0, 0, 4, 3, 0, 0, 2, 0, 9],
                [0, 0, 5, 0, 0, 9, 0, 0, 1],
                [0, 7, 0, 0, 6, 0, 0, 4, 3],
                [0, 0, 6, 0, 0, 2, 0, 8, 7],
                [1, 9, 0, 0, 0, 7, 4, 0, 0],
                [0, 5, 0, 0, 8, 3, 0, 0, 0],
                [6, 0, 0, 0, 0, 0, 1, 0, 5],
                [0, 0, 3, 5, 0, 8, 6, 9, 0],
                [0, 4, 2, 9, 1, 0, 3, 0, 0]]


# Import NumPy
import numpy as np

# Convert sudoku_list into an array
sudoku_array = np.array(sudoku_list)

# Print the type of sudoku_array
print(type(sudoku_array))
```

```
>>> # sudoku_list is a Python list containing a sudoku game
>>> sudoku_list =  [[0, 0, 4, 3, 0, 0, 2, 0, 9],
...                 [0, 0, 5, 0, 0, 9, 0, 0, 1],
...                 [0, 7, 0, 0, 6, 0, 0, 4, 3],
...                 [0, 0, 6, 0, 0, 2, 0, 8, 7],
...                 [1, 9, 0, 0, 0, 7, 4, 0, 0],
...                 [0, 5, 0, 0, 8, 3, 0, 0, 0],
...                 [6, 0, 0, 0, 0, 0, 1, 0, 5],
...                 [0, 0, 3, 5, 0, 8, 6, 9, 0],
...                 [0, 4, 2, 9, 1, 0, 3, 0, 0]]
>>>
>>>
>>> # Import NumPy
>>> import numpy as np
>>>
>>> # Convert sudoku_list into an array
>>> sudoku_array = np.array(sudoku_list)
>>>
>>> # Print the type of sudoku_array
>>> print(type(sudoku_array))
<class 'numpy.ndarray'>
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Let's Create Our Own NP Array From Scratch

1. We create and print an array filled with zeros called *zero_array*, which has two rows and four columns.
2. We create and print an array of random floats between *0* and *1* called *random_array*, which has three rows and six columns.

```
# Create an array of zeros which has four columns and two rows
zero_array = np.zeros((2, 4))
print(zero_array)

# Create an array of random floats which has six columns and three rows
random_array = np.random.random((3, 6))
print(random_array)
```

```
>>> # Create an array of zeros which has four columns and two rows
>>> zero_array = np.zeros((2, 4))
>>> print(zero_array)
[[0. 0. 0. 0.]
 [0. 0. 0. 0.]]
>>>
>>> # Create an array of random floats which has six columns and three rows
>>> random_array = np.random.random((3, 6))
>>> print(random_array)
[[0.56611979 0.127742   0.85030863 0.99050974 0.67661321 0.7466267 ]
 [0.99208374 0.52878452 0.78842089 0.31176378 0.33288376 0.96392977]
 [0.17946211 0.11692052 0.59033335 0.27838068 0.52408142 0.3130792 ]]
```

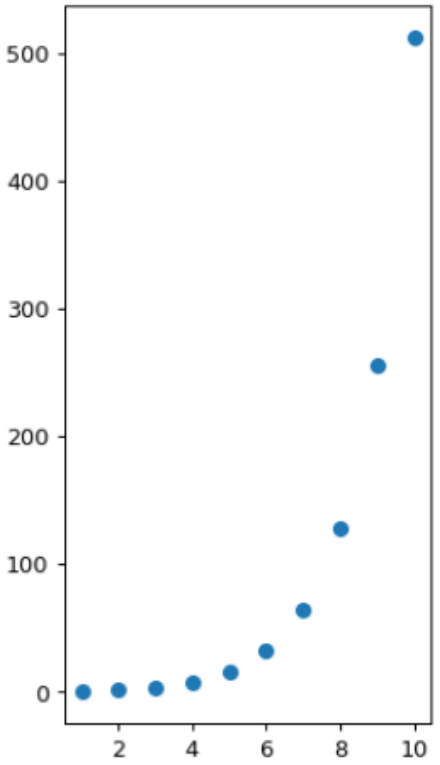
Source: Introduction to NumPy. Izzy Weber. Rpubs

Let's Create a Range Array

1. np.arange() has especially useful applications in graphing.
2. We create a scatter plot with the values from doubling_array on the y-axis, but we need values for the x-axis, which we can create with *np.arange()*.

```
# get plt + edited/added
!pip install matplotlib
from matplotlib import pyplot as plt
doubling_array = [1, 2, 4, 8, 16, 32, 64, 128, 256, 512]

# Create an array of integers from one to ten
one_to_ten = np.arange(1, 11)
one_to_ten

# Create your scatterplot
plt.scatter(one_to_ten, doubling_array)
plt.show()
```

```
>>> from matplotlib import pyplot as plt
>>>
>>> doubling_array = [1, 2, 4, 8, 16, 32, 64, 128, 256, 512]
>>>
>>> # Create an array of integers from one to ten
>>> one_to_ten = np.arange(1, 11)
>>> one_to_ten
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10])
>>>
>>> # Create your scatterplot
>>> plt.scatter(one_to_ten, doubling_array)
<matplotlib.collections.PathCollection object at 0x0000020A99EC7890>
>>> plt.show()
```



Source: Introduction to NumPy. Izzy Weber. Rpubs

Array Dimensionality: 3D

Recall the *sudoku_array*. It's actually 2D array. Now, let's assume we have many games and we want to add the solution of the games. Hence, we add one more dimension to get 3D array.

```
# check the current working directory
import os
print(os.getcwd())
# change the current working directory
import os
print(os.getcwd())
os.chdir('[path]')
print(os.getcwd())
```

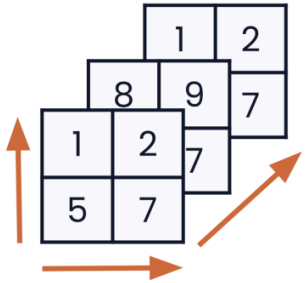
```
For Google Colab:
1. Upload the file.
2.
import numpy as np
np.load('/tree_census.npy')
```

```
# edited/added
sudoku_solution = np.load('sudoku_solution.npy')
sudoku_list = np.load('sudoku_game.npy')
sudoku_game = np.array(sudoku_list)

# Create the game_and_solution 3D array
game_and_solution = np.array([sudoku_game, sudoku_solution])

# Print game_and_solution
print(game_and_solution)
```

```
>>> print(game_and_solution)
[[[0 0 5 0 0 9 0 0 1]
  [0 7 0 0 6 0 0 4 3]
  [0 0 6 0 0 2 0 8 7]
  [1 9 0 0 0 7 4 0 0]
  [0 5 0 0 8 3 0 0 0]
  [6 0 0 0 0 0 1 0 5]
  [0 0 3 5 0 8 6 9 0]
  [0 4 2 9 1 0 3 0 0]]

 [[3 2 5 8 4 9 7 6 1]
  [9 7 1 2 6 5 8 4 3]
  [4 3 6 1 9 2 5 8 7]
  [1 9 8 6 5 7 4 3 2]
  [2 5 7 4 8 3 9 1 6]
  [6 8 9 7 3 4 1 2 5]
  [7 1 3 5 2 8 6 9 4]
  [5 4 2 9 1 6 3 7 8]]]
```

Explanation: We have two 2D arrays, 8 Rows per array, and 9 Columns.

Note: Whenever you see a "*Set of numbers*" closed in double brackets from both ends. Consider it as a "*set*". And 3D and 3D+ arrays are always built on these "sets".



Source: Introduction to NumPy. Izzy Weber. Rpubs

Flattening and Reshaping

We can change not only array shape but also the number of dimensions that an array has.

We change *sudoku_array* from a 2D array to a 1D array and back again.

```
# Import NumPy
import numpy as np

# edited/added
sudoku_game = np.load('sudoku_game.npy')

# Flatten sudoku_game
flattened_game = sudoku_game.flatten()

# Print the shape of flattened_game
print(flattened_game.shape)

# Reshape flattened_game back to a nine by nine array
reshaped_game = flattened_game.reshape((8, 9))

# Print sudoku_game and reshaped_game
print(sudoku_game)
print(reshaped_game)
```

```
>>> print(sudoku_game)
[[0 0 5 0 0 9 0 0 1]
 [0 7 0 0 6 0 0 4 3]
 [0 0 6 0 0 2 0 8 7]
 [1 9 0 0 0 7 4 0 0]
 [0 5 0 0 8 3 0 0 0]
 [6 0 0 0 0 0 1 0 5]
 [0 0 3 5 0 8 6 9 0]
 [0 4 2 9 1 0 3 0 0]]
>>> print(reshaped_game)
[[0 0 5 0 0 9 0 0 1]
 [0 7 0 0 6 0 0 4 3]
 [0 0 6 0 0 2 0 8 7]
 [1 9 0 0 0 7 4 0 0]
 [0 5 0 0 8 3 0 0 0]
 [6 0 0 0 0 0 1 0 5]
 [0 0 3 5 0 8 6 9 0]
 [0 4 2 9 1 0 3 0 0]]
```

Explanation:

- Flatten *sudoku_game* so that it is a 1D array, and save it as *flattened_game*.
- *Print* the .shape of *flattened_game*.
- *Reshape* the *flattened_game* back to its original shape of nine rows and nine columns; save the new array as *reshaped_game*.

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3. NumPy data types

The dtype Argument

One way to control the data type of a NumPy array is to declare it when the array is created using the *dtype* keyword argument.

```
# Create an array of zeros with three rows and two columns
zero_array = np.zeros((3, 2))

# Print the data type of zero_array
print(zero_array.dtype)

# Create an array of zeros with three rows and two columns
zero_array = np.zeros((3, 2))

# Print the data type of zero_array
print(zero_array.dtype)

# Create a new array of int32 zeros with three rows and two columns
zero_int_array = np.zeros((3, 2), dtype=np.int32)

# Print the data type of zero_int_array
print(zero_int_array.dtype)
```

```
>>> # Create an array of zeros with three rows and two columns
>>> zero_array = np.zeros((3, 2))
>>>
>>> # Print the data type of zero_array
>>> print(zero_array.dtype)
float64
>>>
>>> # Create an array of zeros with three rows and two columns
>>> zero_array = np.zeros((3, 2))
>>>
>>> # Print the data type of zero_array
>>> print(zero_array.dtype)
float64
>>>
>>> # Create a new array of int32 zeros with three rows and two columns
>>> zero_int_array = np.zeros((3, 2), dtype=np.int32)
>>>
>>> # Print the data type of zero_int_array
>>> print(zero_int_array.dtype)
int32
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Numpy Data Types

NumPy offers a wider range of numerical data types than what is available in Python. Here's the list of most commonly used numeric data types in NumPy:

1. `int8`, `int16`, `int32`, `int64` - signed integer types with different bit sizes
2. `uint8`, `uint16`, `uint32`, `uint64` - unsigned integer types with different bit sizes
3. `float32`, `float64` - floating-point types with different precision levels
4. `complex64`, `complex128` - complex number types with different precision levels

Source: Learn NumPy Interactively. Programiz.

Example: Check Data Type of NumPy Array

```
# create an array of  integers
int_array = np.array([-3, -1, 0, 1])

# create an array of floating-point numbers
float_array = np.array([0.1, 0.2, 0.3])

# create an array of complex numbers
complex_array = np.array([1+2j, 2+3j, 3+4j])

# check the data type of int_array
print(int_array.dtype)  # prints int64

# check the data type of float_array
print(float_array.dtype)  # prints float64

# check the data type of complex_array
print(complex_array.dtype)  # prints complex128
```

```
>>> print(int_array.dtype)  # prints int64
int32
>>>
>>> # check the data type of float_array
>>> print(float_array.dtype)  # prints float64
float64
>>>
>>> # check the data type of complex_array
>>> print(complex_array.dtype)  # prints complex128
complex128
```

Source: Learn NumPy Interactively. Programiz.

Anticipating Data Types

Anticipating what data type an array will have is very important since some NumPy functionality only works with certain data types.

```
# A string data type
print(np.array([78.988, "NumPy", True]).dtype)
print(np.array([9, 1.12, True]).astype("<U5").dtype)

# An integer data type
print(np.array([34.62, 70.13, 9]).astype(np.int64).dtype)
print(np.array([45.67, True], dtype=np.int8).dtype)

# A float data type
print(np.array([[6, 15.7], [True, False]]).dtype)
print(np.random.random((4, 5)).dtype)
```

```
>>> print(np.array([78.988, "NumPy", True]).dtype)
<U32
>>>
>>> print(np.array([9, 1.12, True]).astype("<U5").dtype)
<U5
>>>
>>> print(np.array([34.62, 70.13, 9]).astype(np.int64).dtype)
int64
>>>
>>> print(np.array([45.67, True], dtype=np.int8).dtype)
int8
>>>
>>> print(np.array([[6, 15.7], [True, False]]).dtype)
float64
>>>
>>> print(np.random.random((4, 5)).dtype)
float64
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Change Data Type

NumPy data types, which emphasize speed, are more specific than Python data types, which emphasize flexibility.

When working with large amounts of data in NumPy, it's good practice to check the data type and consider whether a smaller data type is large enough for your data, since smaller data types use less memory.

```
# edited/added
sudoku_game = np.load('sudoku_game.npy')

# Print the data type of sudoku_game
print(sudoku_game.dtype)

# Change the data type of sudoku_game to int8
small_sudoku_game = sudoku_game.astype(np.int8)

# Print the data type of small_sudoku_game
print(small_sudoku_game.dtype)
```

We make *sudoku game* more memory-efficient.

```
>>> print(sudoku_game.dtype)
int64
>>>
>>> print(small_sudoku_game.dtype)
int8
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

4. Selecting and Updating Data

Slicing and Indexing Trees

- We'll be working specifically with the second column, representing block IDs.
- We will select specific city blocks for further analysis using NumPy slicing and indexing.

```
# edited/added
tree_census = np.load('tree_census.npy')

# Select all rows of block ID data from the second column
block_ids = tree_census[:, 1]

# Print the first five block_ids
print(block_ids[:5])

# Select the tenth block ID from block_ids
tenth_block_id = block_ids[9]
print(tenth_block_id)

# Select five block IDs from block_ids starting with the tenth ID
block_id_slice = block_ids[9:14]
print(block_id_slice)
```

```
>>> print(block_ids[:5])
[501451 501451 501911 501911 501911]
>>>
>>> print(tenth_block_id)
501911
>>>
>>> print(block_id_slice)
[501911 501911 501911 501909 501909]
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Slicing and Indexing Trees

- We create an array called *hundred_diameters* which contains the first 100 trunk diameters (from column 3) in *tree_census*.
- We create an array, *every_other_diameter*, which contains only trunk diameters for trees with even row indices from 50 to 100, inclusive.

```
# Create an array of the first 100 trunk diameters from tree_census
hundred_diameters = tree_census[:100, 2]
print(hundred_diameters)

# Create an array of trunk diameters with even row indices from 50 to 1(
every_other_diameter = tree_census[50:101:2, 2]
print(every_other_diameter)
```

```
>>> print(hundred_diameters)
[24 20  3  3  4  4  4  4  4  3  3  4  2  2  3  4  4  4  0 14  3  4  7  8
  7  8  7  5  6  5  5 17  0 19 21 18  4  5  3  4  3  4 13 13 13  5  4  4
  4 11  5  4  5  8 51  7  4 15  3  8  6  6  3  4  3  2  3  3  6  5  5  5
  5  9  4  4  7  7  6  5  4  4  5  5  5  7  3  5  3  3  6  6  8  7  4  5
  4  4  4  4]
>>>
>>> print(every_other_diameter)
[ 5  5 51  4  3  6  3  3  3  6  5  5  4  7  6  4  5  5  3  3  6  8  4  4
  4  6]
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Sorting Trees

- Create an array called *sorted_trunk_diameters* which selects only the trunk diameter column from *tree_census* and sorts it so that the smallest trunk diameters are at the top of the array and the largest at the bottom.

```
# Extract trunk diameters information and sort from smallest to largest
sorted_trunk_diameters = np.sort(tree_census[:, 2])
print(sorted_trunk_diameters)
```

```
>>> print(sorted_trunk_diameters)
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  1  1  1  1  1  2  2  2  2  2  2
  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2
  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2
  2  2  2  2  2  2  2  2  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3
  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3
  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3
  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  4  4  4  4
  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4
  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4
  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4
  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4  4
  4  4  4  4  4  4  4  4  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5
  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5
  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5
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  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7
  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  7  8  8  8  8
  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8  8
  8  8  8  8  8  8  8  8  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9
  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9
  9 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10
 10 10 10 10 10 10 10 11 11 11 11 11 11 11 11 11 11 11 11 11 11 11 11
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 23 24 24 24 24 24 24 24 25 25 25 25 25 25 25 25 25 26 26 26 26
 26 26 27 27 27 28 28 28 30 30 33 34 38 39 44 51]
>>>
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Filtering with Masks

- We'll use fancy indexing to return the row of data representing the largest tree in *tree_census*.
- Using Boolean indexing, we create an array, *largest_tree_data*, which contains the row of data on the largest tree in *tree_census* corresponding to the tree with a diameter of 51.

```
# Create an array which contains row data on the largest tree in tree_census
largest_tree_data = tree_census[tree_census[:, 2] == 51]
print(largest_tree_data)

# Slice largest_tree_data to get only the block id
largest_tree_block_id = largest_tree_data[:, 1]
print(largest_tree_block_id)

# Create an array which contains row data on all trees with largest_tree_block_id
trees_on_largest_tree_block = tree_census[tree_census[:, 1] == largest_tree_block_id]
print(trees_on_largest_tree_block)
```

```
>>> print(largest_tree_data)
[[    61 501882     51      0]]
>>>
>>> print(largest_tree_block_id)
[501882]
>>>
>>> print(trees_on_largest_tree_block)
[[    60 501882      8      0]
 [    61 501882     51      0]
 [    62 501882      7      0]
 [    63 501882      4      0]
 [    64 501882     15      0]
 [    65 501882      3      0]
 [    66 501882      8      0]
 [    67 501882      6      0]
 [    68 501882      6      0]
 [    69 501882      3      0]]
>>>
```

Source: Introduction to NumPy. Izzy Weber. Rpubs

Fancy Indexing vs. np.where()

- You've been assigned to check the data for trees on block *313879*, and you'd like to make a small array of just the tree data that relates to your work.

```
# Create the block_313879 array containing trees on block 313879
block_313879 = tree_census[tree_census[:, 1] == 313879]
print(block_313879)

# Create an array of row_indices for trees on block 313879
row_indices = np.where(tree_census[:, 1] == 313879)

# Create an array which only contains data for trees on block 313879
block_313879 = tree_census[row_indices]
print(block_313879)
```

```
>>> block_313879 = tree_census[tree_census[:, 1] == 313879]
>>> print(block_313879)
[[  1115 313879      3      0]
 [  1116 313879     17      0]]
>>>
>>> # Create an array of row_indices for trees on block 313879
>>> row_indices = np.where(tree_census[:, 1] == 313879)
>>>
>>> # Create an array which only contains data for trees on block 313879
>>> block_313879 = tree_census[row_indices]
>>> print(block_313879)
[[  1115 313879      3      0]
 [  1116 313879     17      0]]
```

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Creating Arrays From Conditions

- Create and print a 1D array called *trunk_stump_diameters*, which replaces a tree's trunk diameter with its stump diameter if the trunk diameter is zero.

```
# Create and print a 1D array of tree and stump diameters
trunk_stump_diameters = np.where(tree_census[:, 2] == 0, tree_census[:, 3], tree_census[:, 2])
print(trunk_stump_diameters)
```

```
>>> print(trunk_stump_diameters)
[24 20  3  3  4  4  4  4  3  3  4  2  2  3  4  4  4  3 14  3  4  7  8
  7  8  7  5  6  5  5 17 31 19 21 18  4  5  3  4  3  4 13 13 13  5  4  4
  4 11  5  4  5  8 51  7  4 15  3  8  6  6  3  4  3  2  3  3  6  5  5  5
  5  9  4  4  7  7  6  5  4  4  5  5  5  7  3  5  3  3  6  6  8  7  4  5
  4  4  4  4  6  5  3  4 12 12 12  5  6  6  6  6  6  5  5  6  7  7 25  5
  5  4  6  6  7 11  6 17 13 14 14 20 15 13  7  7 10 17 14  4  6  7  8  7
  7  6  7  5  2  2  2  2 26 25  2 15  6 20  5  9 15 13 15  3  2 13  6 12
 15 18 22 18 18 15 17  7  3  7  8  4 12 11 12  3  9 12 11 10  8  6  6  7
  7  3 15 12 12  4  5  5  5  4  4  5  4  9  2  4  4  6  5  5  2  5  5  4
  4  5  5  6 11  4  5  7  3 14 11 10  7 15 10  5  6 10 10  6  5  4  4  3
  5  4 14 12 11  8 14 12  9 12 11  7  8 10 10 12 11 12  5  5  6  9  9  8
  5  5  5  6  6 12 12 11 12  8  9  5  5  5  8  2  2  2 14 18 14 14 22 15
 19 14 18  7  7  7  8  8  5 10 14  2  2  2  2 11 12 12  3  3  3  3  3  6
  6  8  2  2 11 11 11  9 11 12 13  9 11  6  4  5  5  2  2  8 10  7  9 11
 11  1  2 26  4 13  2  4  3  4  4  4  4  3  4  2  2 12 13  5  4  2  3  3
 25 11 11 14 22  2  3 10  2  2 13 19 26 21 19 14 14  5 19 15 11 15  6 19
 17 12 13 15 12  2 16  2  2  2 25  2 21  2 15 16 14 13 11  8 11 13 12  7
 24 19  3  3  4  6 11 17 19 19 17 15 13 15 27 16 15 20 17 16  4 10  9 14
 11 12  8  9  9 13 14  7 11 14  3  7 16 17 13 14 16 12  4  5  3 16 11  9
  9 10  8 10 11 11  8 11 11 11  9 11 10  9  5 12 11 13  9 15 16 12  7 10
  6  9  5  9  6  6  3  3  5  4  4  4  4  6  4  7  6  7  6  5  7  8 20  9
 11 11 10  9 11 12 10 18  7  4  4  4  4  3 19 12  3  4  5  4  4 17 15  8
  4  5  6 25  6 11  3  3 15  4 14 12 15  2  3  2 11 11 14 12 15 12  8  9
  9  8  7 12 15  4 11 10  6  7  9 38  6  3 15 11  5  4  2 13 21 26  4 18
 10 17 20 19 21 19 18 18 17 24 27 22 21  9 17 17 19 28 21 11 23 28  7 33
 30  5 26 27 22  2  2  2  3  4  3  3 12 17 15  2  3  3  6  6  6  6 18 13
 25 25 22 25 21 19  3  3  3  4  4 19  4  4 24 27 20  3 19  5 12 26 13  7
 13  4 20  5 14 20 11  3  4 19  4 17 22 24 15  7  5  4  5  5  4  4  4  8
  4  4  7  6 10  8 11  2  9  8  4  3  3  2  2 22 22 24 23 20 21  5  6  7
  4  2 15 19 20  4  4  7  2 17 10  3 11  2 10 11  4  4  3 13  3  3  3  3
  4  3  3  3 14  3  9  9  9 10 20 14 19 16 22 22 17 18  9  9  7  9  3 14
 13 15 16 18 21  3  8  3  9  8 11  9 10  5  5 11 16  3  4  3  4  5  4 10
 10 12  9  9 13 11 10  3  3  3  4  3  4  4 10 25  5  5  1 34  1  1  1 15
 11 11 13  7  7 12 13  3 17 14 18 15 17 14 13 20  9 11  4  9 13  9 19 20
  8  8 20 19 13 44 17 25 14 12 14 15  6  6  7  5  5  5  5  3  9  9 17 13
  3 13 20 20 18 18 21 20 19 22 18 21 25 21 21 18 20 18 23 23 23 18 24 22
  2  7  2 11 19 21 14 20 13  2 18  2  2 31 25 31 25 11 22  2 18 17 18 21
 22 16 16 18 15 23  5  6 13 19  7 16 16 20 15 18  1 15 10 24 18  2  3  2
 17 12 14 17 23 18 12 13 23  3 17  8  8  8  4  9 22  2 14 23 20 23  3  7
  3  6  4 12  4  4  2  6  4  3 17 19  4 19 15 14 17 20  2 16  3 12 10 11
  4 11  4 30  8  4 39  3  7 11 18 22 19 21  7 21  2 16 11 20 21 22  8 16
  2 23 14 14 13 20 21 15 19 28 17 16 12 11 11  6]
>>>
```

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Adding Rows

- We add rows containing the data for two new trees to the end of the *tree_census* array. The new trees' data is saved in a 2D array called *new_trees*

```
# edited/added
new_trees = np.array([[1211, 227386, 20, 0], [1212, 227386, 8, 0]])

# Print the shapes of tree_census and new_trees
print(tree_census.shape, new_trees.shape)

# Add rows to tree_census which contain data for the new trees
updated_tree_census = np.concatenate((tree_census, new_trees))
print(updated_tree_census)
```

```
>>> print(tree_census.shape, new_trees.shape)
(1000, 4) (2, 4)
>>>
>>> print(updated_tree_census)
[[     3 501451     24      0]
 [     4 501451     20      0]
 [     7 501911      3      0]
 ...
 [  1210 227386      6      0]
 [  1211 227386     20      0]
 [  1212 227386      8      0]]
>>>
```

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Adding Columns

- We'll add *trunk_stump_diameters* 1D array as a column to the *tree_census* array.

```
# Print the shapes of tree_census and trunk_stump_diameters
print(trunk_stump_diameters.shape, tree_census.shape)

# Reshape trunk_stump_diameters
reshaped_diameters = trunk_stump_diameters.reshape((1000, 1))

# Concatenate reshaped_diameters to tree_census as the last column
concatenated_tree_census = np.concatenate((tree_census, reshaped_diameters), axis=1)
print(concatenated_tree_census)
```

```
>>> print(trunk_stump_diameters.shape, tree_census.shape)
(1000,) (1000, 4)
>>>
>>> print(concatenated_tree_census)
[[     3 501451     24      0     24]
 [     4 501451     20      0     20]
 [     7 501911      3      0      3]
 ...
 [  1198 227387     11      0     11]
 [  1199 227387     11      0     11]
 [  1210 227386      6      0      6]]
```

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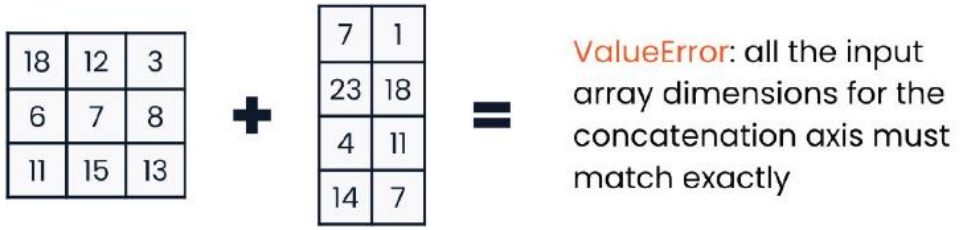
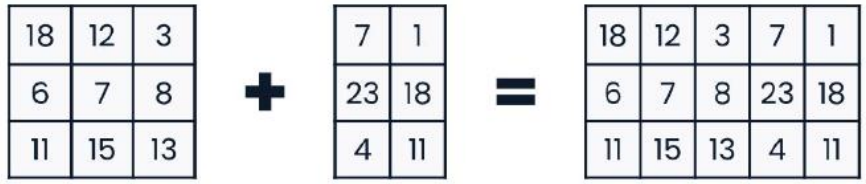
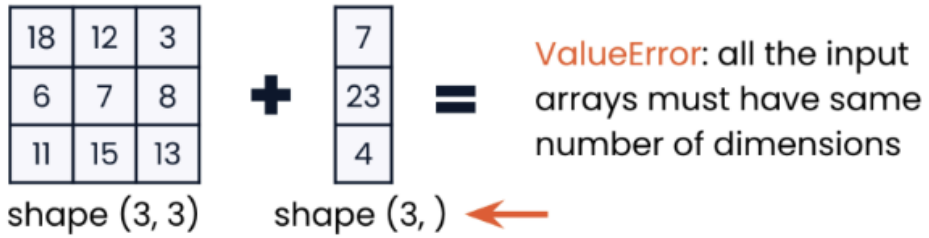
Compatibility for Concatenation

- Arrays must have the same shape along all axes except the one being concatenated along.





- Two arrays must also have the same number of dimension.



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Deleting with np.delete()

- It might be helpful to delete some unneeded data.

```
# Delete the stump diameter column from tree_census
tree_census_no_stumps = np.delete(tree_census, 3, axis=1)

# Save the indices of the trees on block 313879
private_block_indices = np.where(tree_census[:,1] == 313879)

# Delete the rows for trees on block 313879 from tree_census_no_stumps
tree_census_clean = np.delete(tree_census_no_stumps, private_block_indices, axis=0)

# Print the shape of tree_census_clean
print(tree_census_clean.shape)
```

Explanation:

- *np.delete()* function takes three arguments: the original array, the index or indices to be deleted, and the axis to delete along. *np.where()* returns an array of indices where a condition is met

```
>>> # Delete the stump diameter column from tree_census
>>> tree_census_no_stumps = np.delete(tree_census, 3, axis=1)
>>>
>>> # Save the indices of the trees on block 313879
>>> private_block_indices = np.where(tree_census[:,1] == 313879)
>>>
>>> # Delete the rows for trees on block 313879 from tree_census_no_stumps
>>> tree_census_clean = np.delete(tree_census_no_stumps, private_block_indices, axis=0)
>>>
>>> # Print the shape of tree_census_clean
>>> print(tree_census_clean.shape)
(998, 3)
```

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5. Array Mathematics

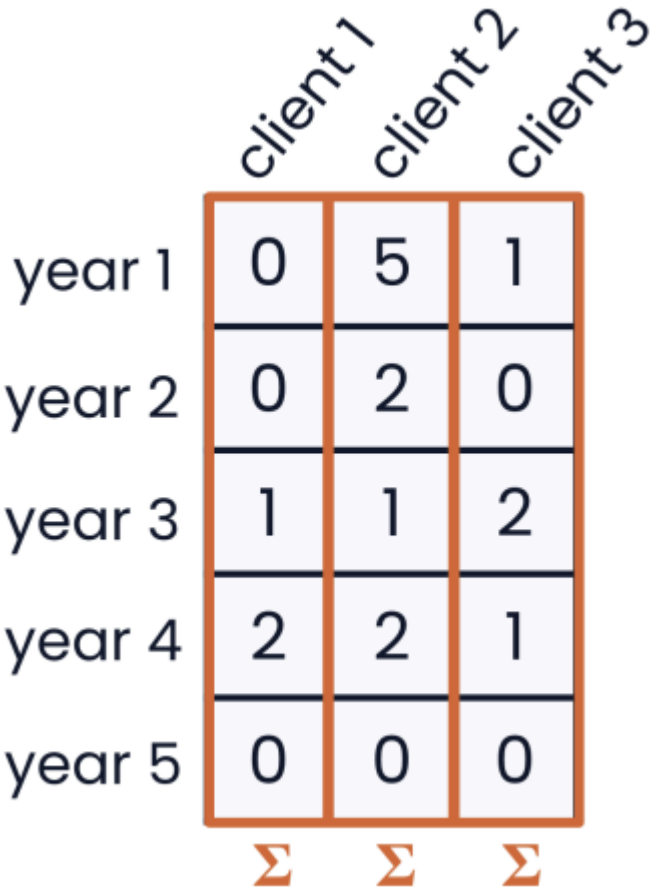
Summarizing Data

- To have an aggregate picture about our data we may use:
  - .sum()
  - .min()
  - .max()
  - .mean()
  - .cumsum()

Our data:

- *Security breaches of 3 clients per year.*

```
# data
security_breaches = np.array([[0,5,1],
                              [0,2,0],
                              [1,1,2],
                              [2,2,1],
                              [0,0,0]])
security_breaches
```



Source: Kaggle. Intro to Numpy. https://www.kaggle.com/code/sharifulislams/introduction-to-numpy/notebook

Summarizing Data (2)

- Let's work with *Security breaches* data:

```
# Summing Data
security_breaches.sum()

# sum the values of all rows in each column to create column totals
security_breaches.sum(axis=0)

# Find the minimum value of each column
security_breaches.min(axis=0)

# Find the maximum value of each column
security_breaches.max(axis=0)

# Find the mean of each column
security_breaches.mean(axis=0)

# Cumulative sum
security_breaches.cumsum(axis=0) # column sum
security_breaches.cumsum(axis=1) # raw sum
```

```
>>> # Summing Data
>>> security_breaches.sum()
17
>>>
>>> # sum the values of all rows in each column to create column totals
>>> security_breaches.sum(axis=0)
array([ 3, 10,  4])
>>>
>>> # Find the minimum value of each column
>>> security_breaches.min(axis=0)
array([0, 0, 0])
>>>
>>> # Find the maximum value of each column
>>> security_breaches.max(axis=0)
array([2, 5, 2])
>>>
>>> # Find the mean of each column
>>> security_breaches.mean(axis=0)
array([0.6, 2. , 0.8])
>>>
>>> # Cumulative sum
>>> security_breaches.cumsum(axis=0) # column sum
array([[ 0,  5,  1],
       [ 0,  7,  1],
       [ 1,  8,  3],
       [ 3, 10,  4],
       [ 3, 10,  4]])
>>> security_breaches.cumsum(axis=1) # raw sum
array([[0, 5, 6],
       [0, 2, 2],
       [1, 2, 4],
       [2, 4, 5],
       [0, 0, 0]])
```

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Vectorized operations

- Extension of the laws of elementary algebra to vectors. They include addition, subtraction, and three types of multiplication.

```
array = np.array([[1, 2, 3], [4, 5, 6]])
array + 3 # adding 3 to all elements in array

array * 2 # multiplying by 2 to all elements in array

# Adding two arrays together
array_a = np.array([[1, 2, 3], [4, 5, 6]])
array_b = np.array([[0, 1, 0], [1, 0, 1]])
array_a + array_b

# Multiplying two arrays together
array_a = np.array([[1, 2, 3], [4, 5, 6]])
array_b = np.array([[0, 1, 0], [1, 0, 1]])
array_a * array_b
```

```
>>> array = np.array([[1, 2, 3], [4, 5, 6]])
>>> array + 3 # adding 3 to all elements in array
array([[4, 5, 6],
       [7, 8, 9]])
>>>
>>> array * 2 # multiplying by 2 to all elements in array
array([[ 2,  4,  6],
       [ 8, 10, 12]])
>>>
>>> # Adding two arrays together
>>> array_a = np.array([[1, 2, 3], [4, 5, 6]])
>>> array_b = np.array([[0, 1, 0], [1, 0, 1]])
>>> array_a + array_b
array([[1, 3, 3],
       [5, 5, 7]])
>>>
>>> # Multiplying two arrays together
>>> array_a = np.array([[1, 2, 3], [4, 5, 6]])
>>> array_b = np.array([[0, 1, 0], [1, 0, 1]])
>>> array_a * array_b
array([[0, 2, 0],
       [4, 0, 6]])
```

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Vectorized operations (2)

- *np.vectorize()* is used to vectorize Python methods and functions on array elements in NumPy. Vectorized operations are much faster and more efficient than a for loop
- Make all the letters of every word in the array uppercase/lowercase by using *np.vectorize()*

```
array = np.array(["NumPy", "is", "awesome"])
vectorized_len = np.vectorize(len)
vectorized_len(array) > 2

vectorized_upper = np.vectorize(str.upper)
vectorized_upper(array)

vectorized_lower = np.vectorize(str.lower)
vectorized_lower(array)
```

```
>>> array = np.array(["NumPy", "is", "awesome"])
>>> vectorized_len = np.vectorize(len)
>>> vectorized_len(array) > 2
array([ True, False,  True])
>>>
>>> vectorized_upper = np.vectorize(str.upper)
>>> vectorized_upper(array)
array(['NUMPY', 'IS', 'AWESOME'], dtype='<U7')
>>>
>>> vectorized_lower = np.vectorize(str.lower)
>>> vectorized_lower(array)
array(['numpy', 'is', 'awesome'], dtype='<U7')
```

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6. Array Transformations

Loading Arrays

- *Let's* load *rgb_array.npy* from the folder

```
# loading data
with open("rgb_array.npy","rb") as f:
    logo_rgb_array = np.load(f)
logo_rgb_array

# Display the array as image
!pip install matplotlib
import matplotlib.pyplot as plt
plt.imshow(logo_rgb_array)
plt.show()
```

```
>>> # loading data
>>> with open("rgb_array.npy","rb") as f:
...     logo_rgb_array = np.load(f)
... logo_rgb_array
array([[[117, 141, 175],
        [120, 145, 176],
        [121, 146, 177],
        ...,
        [116, 147, 168],
        [117, 145, 167],
        [117, 145, 166]],
```

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Getting help

- Return NumPy's documentation text for *.astype()*

```
# Display the documentation for .astype()
help(np.ndarray.astype)
```

```
astype(...)
    a.astype(dtype, order='K', casting='unsafe', subok=True, copy=True)

    Copy of the array, cast to a specified type.

    Parameters
    ----------
    dtype : str or dtype
        Typecode or data-type to which the array is cast.
    order : {'C', 'F', 'A', 'K'}, optional
        Controls the memory layout order of the result.
        'C' means C order, 'F' means Fortran order, 'A'
        means 'F' order if all the arrays are Fortran contiguous,
        'C' order otherwise, and 'K' means as close to the
        order the array elements appear in memory as possible.
        Default is 'K'.
    casting : {'no', 'equiv', 'safe', 'same_kind', 'unsafe'}, optional
        Controls what kind of data casting may occur. Defaults to 'unsafe'
        for backwards compatibility.
```

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Updating Array

- *Let's* update *logo_rgb_array*

```
# Reduce every value in logo_rgb_array by 50 percent
darker_rgb_array = logo_rgb_array * 0.5
print(darker_rgb_array)
```

```
>>> # Reduce every value in logo_rgb_array by 50 percent
>>> darker_rgb_array = logo_rgb_array * 0.5
>>> print(darker_rgb_array)
[[[ 58.5  70.5  87.5]
  [ 60.   72.5  88. ]
  [ 60.5  73.   88.5]
  ...
  [ 58.   73.5  84. ]
  [ 58.5  72.5  83.5]
  [ 58.5  72.5  83. ]]

 [[ 63.   75.5  91. ]
  [ 59.   71.5  87. ]
  [ 59.   71.5  87. ]
  ...
  [ 59.   74.5  85. ]
  [ 58.   73.5  84. ]
  [ 58.5  72.5  83.5]]
```

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Saving Array

- *Let's* save *darker_rgb_array*

```
# Save darker_rgb_int_array to an .npy file called darker_monet.npy
with open("darker_monet.npy", "wb") as f:
    np.save(f, darker_rgb_array)
```

- Check your folder for the new file in there.

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Flipping Array

- Reverse the order of elements in an array along the given axis.

```
# Flipping
array = np.array([[1.1, 1.2, 1.3],
                  [2.1, 2.2, 2.3],
                  [3.1, 3.2, 3.3],
                  [4.1, 4.2, 4.3]])
np.flip(array)
np.flip(array, axis = 0) # raws bottom -> top
np.flip(array, axis = 1) # column right -> left
```

```
>>> # Flipping
>>> array = np.array([[1.1, 1.2, 1.3],
...                   [2.1, 2.2, 2.3],
...                   [3.1, 3.2, 3.3],
...                   [4.1, 4.2, 4.3]])
>>> np.flip(array)
array([[4.3, 4.2, 4.1],
       [3.3, 3.2, 3.1],
       [2.3, 2.2, 2.1],
       [1.3, 1.2, 1.1]])
>>> np.flip(array, axis = 0) # raws bottom -> top
array([[4.1, 4.2, 4.3],
       [3.1, 3.2, 3.3],
       [2.1, 2.2, 2.3],
       [1.1, 1.2, 1.3]])
>>> np.flip(array, axis = 1) # column right -> left
array([[1.3, 1.2, 1.1],
       [2.3, 2.2, 2.1],
       [3.3, 3.2, 3.1],
       [4.3, 4.2, 4.1]])
```

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Transposing Array

- This function permutes or reserves the dimension of the given array and returns the modified array.

```
array

np.transpose(array)
```

```
>>> array
array([[1.1, 1.2, 1.3],
       [2.1, 2.2, 2.3],
       [3.1, 3.2, 3.3],
       [4.1, 4.2, 4.3]])
>>>
>>> np.transpose(array)
array([[1.1, 2.1, 3.1, 4.1],
       [1.2, 2.2, 3.2, 4.2],
       [1.3, 2.3, 3.3, 4.3]])
```

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7. In-class Assignment