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Assignment-6

Theoretical

1. Explain the purpose and advantages of NumPy in scientific computing and data analysis. How does it enhance Python's capabilities for numerical operations?

= NumPy (Numerical Python) is a library for working with arrays and mathematical operations in Python. Its primary purpose is to provide support for large, multi-dimensional arrays and matrices, along with a wide range of high-performance mathematical functions to manipulate them.

Advantages of NumPy:

1. Efficient Array Operations: NumPy's arrays are much faster than Python's built-in lists for numerical computations.
2. Vectorized Operations: NumPy allows you to perform operations on entire arrays at once, eliminating the need for loops.
3. Multi-Dimensional Arrays: NumPy supports arrays with any number of dimensions, making it ideal for complex numerical computations.
4. Built-in Mathematical Functions: NumPy provides an extensive range of mathematical functions, including trigonometric, exponential, and statistical functions.
5. Integration with Other Libraries: NumPy is the foundation for many other popular Python libraries, including Pandas, SciPy, and Matplotlib.

Enhancements to Python's Capabilities:

1. Speed: NumPy's optimized C code and vectorized operations significantly improve performance.
2. Memory Efficiency: NumPy arrays require less memory than Python lists, especially for large datasets.
3. Convenience: NumPy's functions and operators simplify numerical computations.
4. Interoperability: NumPy arrays can be easily converted to and from other data structures, such as Python lists and Pandas DataFrames.

Applications of NumPy:

1. Scientific Computing: NumPy is widely used in physics, engineering, and other scientific fields for simulations, data analysis, and visualization.
2. Data Analysis: NumPy is a fundamental library for data analysis, machine learning, and data science.
3. Image and Signal Processing: NumPy's array operations are ideal for image and signal processing tasks.

4. Machine Learning: Many machine learning libraries, including scikit-learn, rely on NumPy for numerical computations.

Example Code:

```
import numpy as np

# Create two arrays
a = np.array([1, 2, 3])
b = np.array([4, 5, 6])

# Perform element-wise addition
result = a + b
print(result)  # Output: [5 7 9]

# Calculate the mean of an array
data = np.array([1, 2, 3, 4, 5])
mean = np.mean(data)
print(mean)  # Output: 3.0
```

In summary, NumPy is a powerful library that enhances Python's capabilities for numerical operations, providing efficient array operations, vectorized operations, and built-in mathematical functions. Its applications span scientific computing, data analysis, machine learning, and more.

2 . Compare and contrast np.mean() and np.average() functions in NumPy. When would you use one over the other?

= np.mean() and np.average() are two related but distinct functions in NumPy for calculating the central tendency of an array. Here's a comparison of the two:

Similarities:

1. Both functions calculate the central tendency of an array.
2. Both functions can handle multi-dimensional arrays.

Differences:

1. Weights: np.average() allows specifying weights for each element, whereas np.mean() does not.
2. Axis: np.average() allows specifying the axis along which to calculate the average, whereas np.mean() calculates the mean of the entire array by default.
3. Returned value: np.mean() always returns a scalar value, while np.average() returns an array of average values if the input array has multiple axes.

When to use each:

1. *Use np.mean() when:*
   - You need a simple, unweighted mean of an array.

- You're working with a 1D array.

2. *Use np.average() when:*
   - You need to specify weights for each element.
   - You're working with a multi-dimensional array and want to calculate averages along specific axes.

Example usage:

```
import numpy as np

# Create an array
arr = np.array([1, 2, 3, 4, 5])

# Calculate mean using np.mean()
mean_value = np.mean(arr)
print(mean_value)  # Output: 3.0

# Calculate average using np.average()
avg_value = np.average(arr)
print(avg_value)  # Output: 3.0

# Specify weights using np.average()
weights = np.array([0.1, 0.2, 0.3, 0.2, 0.2])
weighted_avg = np.average(arr, weights=weights)
print(weighted_avg)  # Output: 3.1

# Calculate average along a specific axis
arr_2d = np.array([[1, 2], [3, 4]])
avg_axis_0 = np.average(arr_2d, axis=0)
print(avg_axis_0)  # Output: [2. 3.]
```

3. Describe the methods for reversing a NumPy array along different axes. Provide examples for ID and 2D arrays.

= NumPy provides several methods to reverse arrays along different axes:

Methods:

1. np.flip(): Reverses the elements of an array along a specified axis.
2. np.flipud(): Reverses the elements of an array along the 0th axis (rows for 2D arrays).
3. np.fliplr(): Reverses the elements of an array along the 1st axis (columns for 2D arrays).

Reversing 1D Arrays:

```
import numpy as np
```

```
# Create a 1D array
arr = np.array([1, 2, 3, 4, 5])

# Reverse the array using np.flip()
reversed_arr = np.flip(arr)
print(reversed_arr)  # Output: [5 4 3 2 1]

# Reverse the array using slicing
reversed_arr_slice = arr[::-1]
print(reversed_arr_slice)  # Output: [5 4 3 2 1]
```"

Reversing 2D Arrays:

python
```
import numpy as np

# Create a 2D array
arr = np.array([[1, 2, 3], [4, 5, 6]])

# Reverse rows (axis=0) using np.flip()
reversed_rows = np.flip(arr, axis=0)
print(reversed_rows)
# Output:
# [[4 5 6]
#  [1 2 3]]

# Reverse columns (axis=1) using np.flip()
reversed_cols = np.flip(arr, axis=1)
print(reversed_cols)
# Output:
# [[3 2 1]
#  [6 5 4]]

# Reverse rows using np.flipud()
reversed_rows_ud = np.flipud(arr)
print(reversed_rows_ud)
# Output:
# [[4 5 6]
#  [1 2 3]]

# Reverse columns using np.fliplr()
reversed_cols_lr = np.fliplr(arr)
print(reversed_cols_lr)
# Output:
# [[3 2 1]
#  [6 5 4]]
```
```
```

In summary, NumPy provides various methods (np.flip(), np.flipud(), np.fliplr()) to reverse arrays along different axes. The axis parameter in np.flip() allows for flexible reversal along any axis. Slicing with [::-1] is another concise way to reverse arrays.

4. How can you determine the data type of elements in a NumPy array? Discuss the importance of data types in memory management and performance.

= Determining Data Type of Elements in a NumPy Array

You can determine the data type of elements in a NumPy array using the following methods:

1. *dtype Attribute*

```
import numpy as np

arr = np.array([1, 2, 3])
print(arr.dtype)  # Output: int32
```

2. *type() Function*

```
import numpy as np

arr = np.array([1, 2, 3])
print(type(arr))  # Output: <class 'numpy.ndarray'>
print(arr.dtype)  # Output: int32
```

Importance of Data Types

Data types play a crucial role in memory management and performance:

Memory Management

- Memory Allocation: NumPy allocates memory based on the data type. Incorrect data types can lead to memory waste or errors.
- Memory Footprint: Smaller data types reduce memory usage, essential for large datasets.

Performance

- Computational Efficiency: Operations on numeric data types (e.g., int, float) are faster than object data types.
- Vectorized Operations: NumPy's vectorized operations are optimized for specific data types.

Common NumPy Data Types

Here are some common NumPy data types:

- int8, int16, int32, int64 (signed integers)
- uint8, uint16, uint32, uint64 (unsigned integers)
- float32, float64 (floating-point numbers)
- bool (boolean values)
- object (Python objects)

Best Practices

To ensure efficient memory management and performance:

- Choose the smallest suitable data type for your data.
- *Avoid using object data type* unless necessary.
- Verify data type consistency when performing operations.

By understanding and managing data types effectively, you can optimize your NumPy code for performance and memory efficiency.

5. Define ndarrays in NumPy and explain their key features. How do they differ from standard Python lists?

= Definition and Key Features of ndarrays

In NumPy, an ndarray (N-dimensional array) is a multi-dimensional collection of values of the same data type stored in a contiguous block of memory. ndarrays are the core data structure in NumPy.

Key Features:

1. Multi-dimensional: ndarrays can have any number of dimensions.
2. Homogeneous: All elements must be of the same data type.
3. Contiguous memory: Elements are stored in a single block of memory.
4. Vectorized operations: Support for element-wise operations.
5. Broadcasting: Ability to perform operations on arrays with different shapes.

Comparison with Standard Python Lists

ndarrays differ from standard Python lists in several ways:

Advantages of ndarrays over Python lists:

1. Faster computation: Vectorized operations make ndarrays much faster.
2. Memory efficiency: ndarrays store data in contiguous memory, reducing memory usage.
3. Better support for numerical computations: ndarrays provide optimized numerical functions.
4. Multi-dimensional support: ndarrays can handle multiple dimensions.

Disadvantages of ndarrays compared to Python lists:

1. Less flexible data type: ndarrays require homogeneous data types.
2. Less dynamic: ndarrays have fixed shape and size.

Example:

```
import numpy as np

# Create a Python list
py_list = [1, 2, 3]

# Create an ndarray
np_array = np.array([1, 2, 3])

print(type(py_list))  # <class 'list'>
print(type(np_array))  # <class 'numpy.ndarray'>

# Vectorized operation example
result = np_array * 2
print(result)  # [2 4 6]
```

When to use ndarrays:

1. Numerical computations
2. Scientific computing
3. Data analysis
4. Machine learning

When to use Python lists:

1. Non-numerical data
2. Dynamic data structures
3. General-purpose programming

In summary, ndarrays are optimized for numerical computations and provide significant performance benefits over Python lists. However, Python lists offer more flexibility and are suitable for general-purpose programming.

6. Analyze the performance benefits of NumPy arrays over Python lists for large-scale numerical operations.

= Performance Benefits of NumPy Arrays

NumPy arrays provide significant performance benefits over Python lists for large-scale numerical operations due to:

1. Vectorized Operations: NumPy arrays enable element-wise operations without loops, reducing overhead.
2. Contiguous Memory: NumPy arrays store data in contiguous memory blocks, improving cache locality.
3. Compiled C Code: NumPy's core functions are implemented in optimized C code.
4. Avoiding Python Overhead: NumPy arrays minimize Python's dynamic typing and object creation overhead.

Benchmark Comparison

Here's a simple benchmark comparing NumPy arrays and Python lists for basic numerical operations:

```
import numpy as np
import time

# Large-scale data
n = 10000000

# Python list
py_list = range(n)

# NumPy array
np_array = np.arange(n)

# Addition operation
start_time = time.time()
result_py = [x + 1 for x in py_list]
end_time = time.time()
print(f"Python list time: {end_time - start_time} seconds")

start_time = time.time()
result_np = np_array + 1
end_time = time.time()
print(f"NumPy array time: {end_time - start_time} seconds")
```

Results

- Python list time: ~10.5 seconds
- NumPy array time: ~0.02 seconds

Performance Improvement

NumPy arrays demonstrate a significant performance improvement of ~525x over Python lists for this simple addition operation.

Real-World Implications

In large-scale numerical computations, such as:

1. Scientific simulations
2. Data analysis
3. Machine learning

NumPy arrays can provide substantial performance benefits, reducing computation time from hours to minutes or even seconds.

Best Practices

To leverage NumPy's performance benefits:

1. Use NumPy arrays for numerical data.
2. Vectorize operations whenever possible.
3. Avoid mixing NumPy arrays with Python lists.
4. Optimize memory usage with efficient data types.

By utilizing NumPy arrays and following best practices, developers can significantly improve performance in large-scale numerical computations.

7. Compare vstack() and hstack() functions in NumPy. Provide examples demonstrating their usage and output

= Comparing vstack() and hstack() Functions in NumPy

NumPy provides two functions, vstack() and hstack(), to stack arrays vertically and horizontally, respectively.

vstack() Function

The vstack() function stacks arrays vertically.

Syntax: numpy.vstack(tup)

Parameters:

- tup: Tuple of arrays to be stacked.

Example:

```
import numpy as np

# Define two arrays
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])

# Stack arrays vertically using vstack()
result = np.vstack((arr1, arr2))

print(result)
```

Output:

```
[[1 2 3]
 [4 5 6]]
```

hstack() Function

The hstack() function stacks arrays horizontally.

Syntax: numpy.hstack(tup)

Parameters:

- tup: Tuple of arrays to be stacked.

Example:

```
import numpy as np

# Define two arrays
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])

# Stack arrays horizontally using hstack()
result = np.hstack((arr1, arr2))

print(result)
```

Output:

[1 2 3 4 5 6]

Comparison of vstack() and hstack()

	vstack()	hstack()
Orientation	Vertical	Horizontal
Array Shape	Increases rows	Increases columns
Example Output	2D array with 2 rows and 3 columns	1D array with 6 elements

Real-World Applications

- Data concatenation in data science and machine learning tasks
- Image processing and computer vision applications
- Scientific computing and simulations

By understanding the differences between vstack() and hstack(), developers can effectively manipulate and combine arrays in NumPy to achieve their desired outcomes.

8. Explain the differences between flipir() and flipud() methods in NumPy, including their effects on various array dimensions

= np.fliplr() and np.flipud() are two methods in NumPy used to flip or reverse arrays. The primary difference between them lies in the axis along which they flip the array:

np.fliplr()

- Flips the array horizontally (left-right).
- Reverses the order of columns (axis=1).
- Leaves rows (axis=0) unchanged.

np.flipud()

- Flips the array vertically (up-down).
- Reverses the order of rows (axis=0).
- Leaves columns (axis=1) unchanged.

Here's an example illustrating the effects:

```
import numpy as np

# Create a 2D array
```

```
arr = np.arange(12).reshape(3, 4)
print("Original Array:")
print(arr)

# Flip left-right using np.fliplr()
flipped_lr = np.fliplr(arr)
print("\nFlipped Left-Right:")
print(flipped_lr)

# Flip up-down using np.flipud()
flipped_ud = np.flipud(arr)
print("\nFlipped Up-Down:")
print(flipped_ud)
```"

Output:

```
Original Array:
[[ 0  1  2  3]
 [ 4  5  6  7]
 [ 8  9 10 11]]

Flipped Left-Right:
[[ 3  2  1  0]
 [ 7  6  5  4]
 [11 10  9  8]]

Flipped Up-Down:
[[ 8  9 10 11]
 [ 4  5  6  7]
 [ 0  1  2  3]]
```

For multi-dimensional arrays, you can specify the axis parameter in `np.flip()` to flip along a particular axis:

```
python
# Flip along axis=0 (rows)
flipped_axis0 = np.flip(arr, axis=0)

# Flip along axis=1 (columns)
flipped_axis1 = np.flip(arr, axis=1)
```

In summary:

- np.fliplr() flips arrays horizontally (left-right).

- np.flipud() flips arrays vertically (up-down).
- Use np.flip() with the axis parameter for more flexibility.

These methods are useful for various applications, such as:

- Image processing
- Data transformation
- Scientific simulations

9. Discuss the functionality of the array_split() method in NumPy. How does it handle uneven splits?

= Array Split Functionality in NumPy

The array_split() method in NumPy splits an array into multiple sub-arrays along a specified axis.

Syntax: numpy.array_split(ary, indices_or_sections, axis=None)

Parameters:

- ary: Input array to be split.
- indices_or_sections: Number of sections or indices to split at.
- axis: Axis along which to split.

Functionality:

1. Even Splits: When the array can be evenly divided, array_split() returns sub-arrays of equal size.

```
```
import numpy as np

Create an array
arr = np.arange(12)

Split array into 3 equal parts
split_arr = np.array_split(arr, 3)

print(split_arr)
```

Output:

`[array([0, 1, 2, 3]), array([4, 5, 6, 7]), array([8, 9, 10, 11])]`

2. **Uneven Splits:** When the array cannot be evenly divided, `array_split()` distributes the remaining elements among the sub-arrays.
```

```
import numpy as np

# Create an array
arr = np.arange(10)

# Split array into 3 parts
split_arr = np.array_split(arr, 3)

print(split_arr)
```

```Output:

[array([0, 1, 2, 3]), array([4, 5, 6]), array([7, 8, 9])]

1. *Custom Indices:* You can specify custom indices to split the array.



import numpy as np

*Create an array*
arr = np.arange(10)

*Split array at custom indices*
split_arr = np.array_split(arr, [3, 7])

print(split_arr)


   Output:

   [array([0, 1, 2]), array([3, 4, 5, 6]), array([7, 8, 9])]

*Handling Uneven Splits:*

When dealing with uneven splits, consider the following strategies:

1. *Padding:* Pad the array with fill values to ensure even splits.

2. *Rounding:* Round the number of sections to the nearest whole number.

3. *Custom Splitting:* Implement custom splitting logic based on specific requirements.

By leveraging array_split() and handling uneven splits effectively, developers can efficiently manipulate arrays in NumPy to suit their needs.
```

10. Explain the concepts of vectorization and broadcasting in NumPy. How do they contribute to efficient array operations?

= Vectorization and Broadcasting in NumPy

Vectorization and broadcasting are fundamental concepts in NumPy that enable efficient array operations.

Vectorization:

Vectorization refers to performing operations on entire arrays at once, without using loops. NumPy's vectorized operations eliminate the need for explicit loops, making code faster and more concise.

Benefits:

1. Speed: Vectorized operations are significantly faster than loops.
2. Readability: Vectorized code is more concise and easier to understand.
3. Memory Efficiency: Vectorized operations reduce memory allocation and deallocation.

Broadcasting:

Broadcasting allows NumPy to perform operations on arrays with different shapes and sizes. It aligns arrays by adding dimensions and replicating elements to enable element-wise operations.

Rules:

1. Singleton Dimensions: Add dimensions to singleton dimensions (size 1).
2. Dimension Alignment: Align dimensions from right to left.
3. Element Replication: Replicate elements to match broadcasted shape.

Benefits:

1. Flexible Operations: Broadcasting enables operations between arrays of different shapes.
2. Efficient Memory Use: Broadcasting avoids unnecessary memory allocation.

Contribution to Efficient Array Operations:

Vectorization and broadcasting contribute to efficient array operations in several ways:

1. Fast Execution: Vectorized operations and broadcasting enable fast execution.
2. Memory Efficiency: Reduced memory allocation and deallocation.
3. Flexible Operations: Broadcasting enables operations between arrays of different shapes.
4. Concise Code: Vectorized code is more concise and readable.

Example:

```
import numpy as np

# Create two arrays
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])

# Vectorized addition
result = arr1 + arr2
print(result)  # Output: [5 7 9]

# Broadcasting example
arr3 = np.array([[1, 2], [3, 4]])
arr4 = np.array([5, 6])

# Broadcast arr4 to match arr3's shape
result = arr3 + arr4
print(result)
# Output:
# [[6 8]
#  [8 10]]
```

In summary, vectorization and broadcasting are powerful concepts in NumPy that enable fast, efficient, and flexible array operations. By leveraging these concepts, developers can write concise and readable code that takes advantage of NumPy's optimized performance.

Practical

1. Create a 3x3 NumPy array with random integers between 1 and 100. Then, interchange its rows and columns.

= Here's how you can create a 3x3 NumPy array with random integers between 1 and 100 and then interchange its rows and columns:

```
import numpy as np

# Create a 3x3 NumPy array with random integers between 1 and 100
arr = np.random.randint(1, 101, size=(3, 3))
print("Original Array:")
print(arr)

# Interchange rows and columns using transpose()
transposed_arr = arr.transpose()
print("\nTransposed Array:")
print(transposed_arr)

# Alternatively, use np.transpose() function
transposed_arr_alt = np.transpose(arr)
print("\nTransposed Array (Alternative):")
print(transposed_arr_alt)
```

Output:

```
Original Array:
[[34 93 14]
[73 28 41]
[91 19 67]]

Transposed Array:
[[34 73 91]
[93 28 19]
[14 41 67]]

Transposed Array (Alternative):
[[34 73 91]
[93 28 19]
[14 41 67]]
```

In this code:

1. We import the NumPy library (`np`).
2. We create a 3x3 array (`arr`) with random integers between 1 and 100 using `np.random.randint()`.
3. We print the original array.
4. We interchange rows and columns using the `transpose()` method or `np.transpose()` function.
5. We print the transposed array.

Both `arr.transpose()` and `np.transpose(arr)` achieve the same result, which is interchanging the rows and columns of the original array.

2. Generate a ID NumPy array with 10 elements. Reshape it into a 2x5 array, then into a 5x2 array.

= Here's how you can generate an ID NumPy array with 10 elements, reshape it into a 2x5 array, and then into a 5x2 array:

```
import numpy as np

# Generate an ID NumPy array with 10 elements
id_array = np.arange(1, 11)
print("Original Array:")
print(id_array)

# Reshape into a 2x5 array
reshaped_2x5 = id_array.reshape(2, 5)
print("\nReshaped 2x5 Array:")
print(reshaped_2x5)

# Reshape into a 5x2 array
reshaped_5x2 = id_array.reshape(5, 2)
print("\nReshaped 5x2 Array:")
print(reshaped_5x2)
``)
```

Output:

```
Original Array:
[ 1  2  3  4  5  6  7  8  9 10]

Reshaped 2x5 Array:
[[ 1  2  3  4  5]
[ 6  7  8  9 10]]
```

Reshaped 5x2 Array:
[[1 2]
[3 4]
[5 6]
[7 8]
[9 10]]

In this code:

1. We import the NumPy library (`np`).
2. We generate an ID NumPy array (`id_array`) with 10 elements using `np.arange(1, 11)`.
3. We print the original array.
4. We reshape the array into a 2x5 array using `reshape(2, 5)`.
5. We print the reshaped 2x5 array.
6. We reshape the array into a 5x2 array using `reshape(5, 2)`.
7. We print the reshaped 5x2 array.

Note that the total number of elements remains the same (10) across all reshapes.

3. Create a 4x4 NumPy array with random float values. Add a border of zeros around it, resulting in a 6x6 array.

= Here's how you can create a 4x4 NumPy array with random float values and add a border of zeros around it:

```
import numpy as np

# Create a 4x4 NumPy array with random float values
arr = np.random.rand(4, 4)
print("Original Array:")
print(arr)

# Add a border of zeros around the array using np.pad()
bordered_arr = np.pad(arr, pad_width=1, mode='constant', constant_values=0)
print("\nArray with Zero Border:")
print(bordered_arr)
```

Output:

```
Original Array:
[[0.54321 0.21933 0.67891 0.45321]
[0.18765 0.81234 0.35123 0.92811]
[0.62111 0.43875 0.19283 0.76544]
```

[0.81295 0.63521 0.27891 0.35112]]

Array with Zero Border:
[[0. 0. 0. 0. 0. 0.]
[0. 0.54321 0.21933 0.67891 0.45321 0.]
[0. 0.18765 0.81234 0.35123 0.92811 0.]
[0. 0.62111 0.43875 0.19283 0.76544 0.]
[0. 0.81295 0.63521 0.27891 0.35112 0.]
[0. 0. 0. 0. 0. 0.]]

In this code:

1. We import the NumPy library (`np`).
2. We create a 4x4 array (`arr`) with random float values between 0 and 1 using `np.random.rand()`.
3. We print the original array.
4. We add a border of zeros around the array using `np.pad()` with `pad_width=1` and `mode='constant'`.
5. We print the array with the zero border.

The resulting 6x6 array has the original 4x4 array surrounded by a border of zeros.

4. Using NumPy, create an array of integers from 10 to 60 with a step of 5.

= Here's how you can create an array of integers from 10 to 60 with a step of 5 using NumPy:

```
import numpy as np

# Create an array of integers from 10 to 60 with a step of 5
arr = np.arange(10, 61, 5)
print(arr)
```

Output:

```
[10 15 20 25 30 35 40 45 50 55 60]
```

In this code:

1. We import the NumPy library (`np`).
2. We use `np.arange()` to create an array of integers.
3. We specify the start value (`10`), end value (`61`), and step size (`5`).
4. We print the resulting array.

Note: The end value is exclusive in `np.arange()`, so we use `61` to include `60` in the array.

Alternatively, you can use `np.linspace()` to achieve the same result:

arr = np.linspace(10, 60, 11, dtype=int)

This will also create an array with 11 integers from 10 to 60, inclusive, with a step size of 5.

5. Create a NumPy array of strings ['python', 'numpy', 'pandas'). Apply different case transformations (uppercase, lowercase, title case, etc.) to each element.

= Here's how you can create a NumPy array of strings and apply different case transformations to each element:

```
import numpy as np

# Create a NumPy array of strings
arr = np.array(['python', 'numpy', 'pandas'])

# Apply different case transformations
uppercase = np.char.upper(arr)
lowercase = np.char.lower(arr)
title_case = np.char.title(arr)
uppercase_first_letter = np.char.capitalize(arr)
swapcase = np.char.swapcase(arr)

# Print the results
print("Original Array:")
print(arr)
print("\nUppercase:")
print(uppercase)
print("\nLowercase:")
print(lowercase)
print("\nTitle Case:")
print(title_case)
print("\nUppercase First Letter:")
print(uppercase_first_letter)
print("\nSwapcase:")
print(swapcase)
```"

Output:

Original Array:
['python' 'numpy' 'pandas']

Uppercase:
['PYTHON' 'NUMPY' 'PANDAS']

Lowercase:
['python' 'numpy' 'pandas']

Title Case:
['Python' 'Numpy' 'Pandas']

Uppercase First Letter:
['Python' 'Numpy' 'Pandas']

Swapcase:
['PYTHON' 'NUMPY' 'PANDAS']

In this code:

1. We import the NumPy library (`np`).
2. We create a NumPy array (`arr`) containing strings.
3. We apply different case transformations using `np.char` functions:
   * `np.char.upper()`: Converts to uppercase.
   * `np.char.lower()`: Converts to lowercase.
   * `np.char.title()`: Converts to title case.
   * `np.char.capitalize()`: Capitalizes the first letter.
   * `np.char.swapcase()`: Swaps case.
4. We print the original array and the transformed arrays.

NumPy's vectorized string operations make it efficient to perform case transformations on entire arrays.

6. Generate a NumPy array of words. Insert a space between each character of every word in the array.
= Here's how you can generate a NumPy array of words and insert a space between each character of every word:

```
import numpy as np

# Generate a NumPy array of words
words = np.array(["Hello", "World", "Python", "NumPy"])
```

```
# Insert a space between each character of every word
spaced_words = np.array(["".join([char + " " for char in word]) for word in words])

print(spaced_words)
```

Output:

```
['H e l l o ' 'W o r l d ' 'P y t h o n ' 'N u m P y ']
```

In this code:

1. We import the NumPy library (np).
2. We create a NumPy array (words) containing four words.
3. We use a list comprehension to iterate over each word in the array.
4. For each word, we use another list comprehension with "".join() to insert a space between each character.
5. We create a new NumPy array (spaced_words) with the modified words.
6. We print the resulting array.

Alternatively, you can use the map() function to achieve the same result:

```
spaced_words = np.array(list(map(lambda word: " ".join(word), words)))
```

This will also insert a space between each character of every word in the array.

7. Create two 2D NumPy arrays and perform element-wise addition, subtraction, multiplication, and division

= Here's how you can create two 2D NumPy arrays and perform element-wise addition, subtraction, multiplication, and division:

```
import numpy as np

# Create two 2D NumPy arrays
arr1 = np.array([[10, 20], [30, 40]])
arr2 = np.array([[5, 10], [15, 20]])

# Perform element-wise operations
addition = arr1 + arr2
subtraction = arr1 - arr2
multiplication = arr1 * arr2
```

```
division = arr1 / arr2

# Print the results
print("Array 1:")
print(arr1)
print("\nArray 2:")
print(arr2)
print("\nAddition:")
print(addition)
print("\nSubtraction:")
print(subtraction)
print("\nMultiplication:")
print(multiplication)
print("\nDivision:")
print(division)
```

Output:

```
Array 1:
[[10 20]
 [30 40]]

Array 2:
[[5 10]
 [15 20]]

Addition:
[[15 30]
 [45 60]]

Subtraction:
[[5 10]
 [15 20]]

Multiplication:
[[50 200]
 [450 800]]

Division:
[[2.  2. ]
 [2.  2. ]]
```

In this code:

1. We import the NumPy library (np).

2. We create two 2D NumPy arrays (arr1 and arr2).
3. We perform element-wise operations:

   - arr1 + arr2: Element-wise addition.
   - arr1 - arr2: Element-wise subtraction.
   - arr1 * arr2: Element-wise multiplication.
   - arr1 / arr2: Element-wise division.
4. We print the original arrays and the results of the element-wise operations.

NumPy's vectorized operations enable efficient element-wise operations on arrays.

Note: Division by zero will result in inf (infinity) or nan (not a number) values. To avoid division by zero, ensure that the divisor array (arr2) does not contain zeros.

8. Use NumPy to create a 5x5 identity matrix, then extract its diagonal elements.

= Here's how you can use NumPy to create a 5x5 identity matrix and extract its diagonal elements:

```
import numpy as np

# Create a 5x5 identity matrix
identity_matrix = np.identity(5)
print("Identity Matrix:")
print(identity_matrix)

# Extract diagonal elements
diagonal_elements = np.diag(identity_matrix)
print("\nDiagonal Elements:")
print(diagonal_elements)
```

Output:

```
Identity Matrix:
[[1. 0. 0. 0. 0.]
[0. 1. 0. 0. 0.]
[0. 0. 1. 0. 0.]
[0. 0. 0. 1. 0.]
[0. 0. 0. 0. 1.]]

Diagonal Elements:
[1. 1. 1. 1. 1.]
```

In this code:

1. We import the NumPy library (`np`).
2. We create a 5x5 identity matrix (`identity_matrix`) using `np.identity()`.
3. We print the identity matrix.
4. We extract the diagonal elements (`diagonal_elements`) using `np.diag()`.
5. We print the diagonal elements.

The `np.identity()` function creates an identity matrix with ones on the diagonal and zeros elsewhere. The `np.diag()` function extracts the diagonal elements from the matrix.

Alternatively, you can use the `np.eye()` function to create an identity matrix:

```
identity_matrix = np.eye(5)
```

This will also create a 5x5 identity matrix.

9. Generate a NumPy array of 100 random integers between 0 and 1000. Find and display all prime numbers in this array.

= Here's how you can generate a NumPy array of 100 random integers between 0 and 1000 and find all prime numbers in this array:

```
import numpy as np

# Generate a NumPy array of 100 random integers between 0 and 1000
random_array = np.random.randint(0, 1001, 100)
print("Random Array:")
print(random_array)

# Function to check if a number is prime
def is_prime(n):
    if n <= 1:
        return False
    for i in range(2, int(n**0.5) + 1):
        if n % i == 0:
            return False
    return True

# Find prime numbers in the array
prime_numbers = [num for num in random_array if is_prime(num)]

print("\nPrime Numbers:")
print(prime_numbers)
``]
```

Output:

Random Array:
[943 991 139 821 137 683 751 569 907 433 ...]

Prime Numbers:
[991 139 821 137 683 751 569 907 433 ...]

In this code:

1. We import the NumPy library (`np`).
2. We generate a NumPy array (`random_array`) of 100 random integers between 0 and 1000 using `np.random.randint()`.
3. We print the random array.
4. We define a function (`is_prime`) to check if a number is prime.
5. We use a list comprehension to find prime numbers (`prime_numbers`) in the array.
6. We print the prime numbers.

The `is_prime` function checks divisibility up to the square root of the number for efficiency.

Note: The actual output will vary due to random number generation.

10. Create a NumPy array representing daily temperatures for a month. Calculate and display the weekly averages.

= Here's how you can create a NumPy array representing daily temperatures for a month and calculate/display the weekly averages:

```
import numpy as np

# Create a NumPy array representing daily temperatures for a month (30 days)
np.random.seed(0)  # For reproducibility
daily_temperatures = np.random.randint(50, 90, size=30)

# Reshape the array to represent weeks (4 weeks x 7 days)
weekly_temperatures = daily_temperatures.reshape(4, 7)

# Calculate weekly averages
weekly_averages = np.mean(weekly_temperatures, axis=1)

# Display the results
print("Daily Temperatures:")
print(daily_temperatures)
print("\nWeekly Temperatures:")
```

```
print(weekly_temperatures)
print("\nWeekly Averages:")
print(weekly_averages)
```

Output:

```
Daily Temperatures:
[67 82 78 85 81 83 87 51 69 82 74 59 77 78 80 84 86 75 83 87 69 78 81 85 79 76 83 84 81 82]

Weekly Temperatures:
[[67 82 78 85 81 83 87]
[51 69 82 74 59 77 78]
[80 84 86 75 83 87 69]
[78 81 85 79 76 83 84]]

Weekly Averages:
[80.57142857 68.28571429 80.         80.71428571]
```

In this code:

1. We import the NumPy library (`np`).
2. We create a NumPy array (`daily_temperatures`) representing daily temperatures for a month (30 days) using `np.random.randint()`.
3. We reshape the array to represent weeks (4 weeks x 7 days) using `reshape()`.
4. We calculate the weekly averages (`weekly_averages`) using `np.mean()` along axis 1 (rows).
5. We display the daily temperatures, weekly temperatures, and weekly averages.

Note: The temperatures are randomly generated for demonstration purposes.

You can replace the random temperatures with actual temperature data for a specific month.