Data Science Assignment (2)

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Theoretical Group: B

1) What did you learn from the assigned reading?

This section of the book introduces the foundational object for all data science in Python: the **NumPy array** (ndarray). The key takeaway is that NumPy provides a high-performance data structure that is far more efficient and powerful than standard Python lists for numerical calculations.

The main topics covered are:

- **Array Creation:** How to create arrays from scratch. This includes:
  - np.array(): Converting existing Python lists or tuples.
  - np.arange(): Creating arrays with regularly spaced values (like Python's range but for arrays).
  - np.linspace(): Creating arrays with a specific number of points between a start and end value.
  - np.zeros(), np.ones(), np.empty(): Creating arrays filled with zeros, ones, or uninitialized data, which is useful for reserving memory.
- **Array Attributes:** Inspecting the properties of an array, such as:
  - .shape: The dimensions of the array (e.g., (3, 4) for a 3x4 matrix).
  - .ndim: The number of dimensions (e.g., 2 for a matrix).
  - .size: The total number of elements in the array.
  - .dtype: The data type of the elements (e.g., float64, int32), which is crucial for memory efficiency.
- **Indexing and Slicing:** This is a major topic. It explains how to access and modify parts of an array. This goes far beyond Python lists and includes:

    - **Basic Slicing:** Accessing rows, columns, or sub-regions (e.g., `arr[0:2, 5:10]`).
    - **Boolean Indexing:** Using an array of `True`/`False` values to filter and select elements that meet a condition (e.g., `arr[arr > 50]`). This is extremely powerful.
    - **"Fancy" Indexing:** Using an array of integers to pick out specific elements in any order.
- **Vectorization:** This is the most important concept. NumPy allows you to perform batch operations on entire arrays without writing `for` loops. For example, to add 5 to every number in an array, you just write `arr + 5`. This "vectorized" code is not only cleaner to read but also hundreds or thousands of times faster, as the loops are executed in highly optimized, pre-compiled C code.

2) Can your learning help you solve real-life problems?
A) If yes, describe how (Write approximately 200–300 words):

Yes, this learning is not just helpful—it is absolutely essential for solving almost any real-life data-driven problem.

NumPy is the bedrock of the entire scientific Python ecosystem (which includes Pandas, SciPy, Matplotlib, and scikit-learn). The reason it's so critical is speed and scale. Real-world problems involve datasets that are far too large and complex for standard Python lists and loops.

For example, a high-definition color image is just a 3D NumPy array (Height x Width x 3 channels). To increase its brightness, you don't loop through millions of pixels; you simply multiply the entire array by 1.2. This is a single, vectorized operation.

In data science, you might have a file with 10 million temperature readings. With NumPy, you can find the average, maximum, and minimum temperatures, or identify all readings above a certain threshold, in a fraction of a second.

In finance, analysts model stock market fluctuations using massive arrays of price data to run simulations. In scientific research, complex physical systems, from brain activity to climate patterns, are modeled using multi-dimensional arrays representing space and time.

The "vectorization" and "indexing" techniques from this reading are the high-performance tools that make these large-scale tasks feasible. They allow you to express complex mathematical operations clearly and have them execute with incredible speed.

B) If you are able to answer question A, provide an example with a clear explanation and include Python code to support your answer.

Example: Filtering Sensor Data

Here is a practical example that directly uses the concepts of array creation, vectorization, and boolean indexing.

A) The Problem: Imagine you are monitoring a network of 100 environmental sensors. You receive their temperature readings every minute. Your data comes in as a large list. You need to perform two tasks quickly:

1. **Convert all readings from Celsius to Fahrenheit.**
2. **Count how many of those readings are "critical" (e.g., over 90°F).**

If you have millions of readings, looping through a Python list is extremely slow.

B) The NumPy Solution: Using NumPy, you can perform these tasks almost instantly.

1. **First, create a sample NumPy array (in a real app, you'd load this from a file).**
2. **Use a vectorized operation to convert all temperatures at once.**
3. **Use a boolean mask to find all critical temperatures.**
4. **Use np.sum() on the boolean mask to count them (since True equals 1 and False equals 0).**

C) Python Code:

```python
import random

print("Running standard Python loop...")
celsius_list = [random.uniform(15.0, 40.0) for _ in range(1_000_000)]
fahrenheit_list = []
critical_count = 0

for temp in celsius_list:
    f_temp = (temp * 9/5) + 32
    fahrenheit_list.append(f_temp)
    if f_temp > 90:
        critical_count += 1

print(f"Standard Python: Found {critical_count} critical readings.\n")
import numpy as np

print("Running vectorized NumPy solution...")

celsius_arr = np.array(celsius_list)

fahrenheit_arr = (celsius_arr * 9/5) + 32
critical_mask = fahrenheit_arr > 90

num_critical = np.sum(critical_mask)

print(f"NumPy: Found {num_critical} critical readings.")
```

Explanation: The Python for loop has to individually check one million items. The NumPy solution ((celsius_arr * 9/5) + 32 and fahrenheit_arr > 90) runs a single command on the entire dataset at C-language speed. For large datasets, the NumPy version isn't just a little faster; it can be **100x to 10,000x faster**, making it the only practical choice for real-world data analysis.