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BCA Honours | Semester VI | BCA6EJ303(4)

Advanced Python for Data Science

Module 3 Comprehensive Notes

Module 3: Data Visualization and Scientific Computing Libraries

Communicating insights from analytical pipelines requires structured visual plots with Matplotlib and Seaborn, coupled with scientific computation modules from SciPy.

3.1 The Matplotlib Figure and Axes Architecture

Matplotlib uses an object-oriented plotting hierarchy:

- **Figure:** The top-level bounding canvas holding all subplots, titles, legends, and colorbars.
- **Axes:** The actual plotting area with coordinate systems (x-axis, y-axis) where data lines, bars, and points are drawn.

```
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(x_data, y_data, label='Signal Waveform', color='#1F3A5F', linewidth=2)
ax.set_title("Time-Domain Telemetry Analysis")
ax.set_xlabel("Time (seconds)")
ax.set_ylabel("Amplitude (Volts)")
ax.legend()
ax.grid(True, linestyle='--', alpha=0.6)
```

3.2 Statistical Data Visualization with Seaborn

Seaborn provides high-level statistical plotting interfaces integrated with Pandas DataFrames:

- **Distributions:** `sns.histplot()` (histograms with kernel density estimates KDE).
- **Categorical Distributions:** `sns.boxplot()` (quartiles and outliers) and `sns.violinplot()` (combining boxplots with rotated KDE curves).
- **Correlation Heatmaps:** `sns.heatmap(df.corr(), annot=True, cmap='coolwarm')` to visualize correlation matrices.

3.3 Scientific Computing with SciPy and Web Scraping

- **`scipy.optimize`:** Minimizes loss functions using algorithms such as BFGS, Nelder-Mead, and conjugate gradient.
- **`scipy.integrate`:** Evaluates definite integrals numerically via adaptive Gaussian quadrature (`quad`).
- **Web Scraping with BeautifulSoup:** Parses HTML/XML documents to extract tabular web data:

```
 from bs4 import BeautifulSoup
import requests

response = requests.get("https://example.com/data")
soup = BeautifulSoup(response.text, 'html.parser')
rows = soup.find_all('tr')
```

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1. Architectural Trade-offs and Computational Complexity

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- **Time Complexity Optimization versus Spatial Footprint:** In high-throughput algorithmic pipelines handling Module 3 Core Concepts and Methods, pre-computing intermediate lookup tables, spatial indices, and hashing structures achieves near-instantaneous $O(1)$ query latency, but inflates the physical memory footprint. Conversely, in-place algorithms minimize RAM utilization at the cost of higher CPU cycle counts. Modern architectures dynamically calibrate memory allocations using memory-mapped files and cache-aware structures.
- **Concurrency Scalability versus Thread Contention:** While multi-core hardware allows horizontal execution, concurrent modifications to shared state structures create severe lock contention, thread synchronization bottlenecks, and cache line invalidation storms. High-performance frameworks deploy lock-free algorithms, optimistic concurrency control, and atomic compare-and-swap (CAS) primitives.
- **Algorithmic Determinism versus Heuristic Scalability:** Exact mathematical algorithms frequently encounter NP-hard combinatorial barriers as problem dimensions scale. Contemporary systems bridge this gap by deploying bounded approximation algorithms and meta-heuristics that produce near-optimal solutions within guaranteed execution time windows.

2. Empirical Comparative Framework

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