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BCA Honours | Semester VI | BCA6EJ303(4)

Advanced Python for Data Science

Module 2 Comprehensive Notes

Module 2: Structured Data Manipulation with Pandas

Pandas provides high-performance, easy-to-use data structures and data analysis tools built on top of NumPy, centered on the `Series` and `DataFrame`.

2.1 Series and DataFrame Data Structures

- **Series:** A one-dimensional labeled array capable of holding any data type. Supports integer and arbitrary label indices.
- **DataFrame:** A two-dimensional tabular data structure with labeled axes (rows and columns). Can be viewed as a dictionary of Series sharing a common index.

2.2 Data Indexing, Selection, and Filtering

Indexing Mechanism	Addressing Syntax	Selection Behavior and Semantics
Label-based (`.loc`)	`df.loc['row_label', 'col_label']`	Selects data strictly by index labels and column names. Slicing endpoints are inclusive: `'A':'C'` includes `'C'`.
Integer-based (`.iloc`)	`df.iloc[0:5, 1:4]`	Selects data strictly by integer coordinate positions (0 to $n-1$). Slicing endpoints are exclusive, matching standard Python slicing.
Boolean Masking	`df[df['age'] >= 21]`	Filters rows based on vectorized boolean predicates combined via bitwise operators (`&`, `|`, `~`).

2.3 Data Cleaning and Missing Value Imputation

- `df.isna()` / `df.notna()`: Returns boolean masks identifying `` / `None` missing entries.
- `df.dropna(axis=0, how='any')`: Drops rows containing missing values.
- `df.fillna(value)`: Imputes missing values with fixed constants or statistical measures (e.g., column mean or median).
- `df.drop_duplicates()`: Removes redundant duplicate rows.

2.4 Split-Apply-Combine with `groupby`

The `groupby` operation splits a DataFrame into groups based on key columns, applies aggregation functions (sum, mean, std) or transformations, and combines results into a new summary table:

```
summary = df.groupby(['department', 'role']).agg({
    'salary': ['mean', 'median', 'std'],
    'bonus': 'sum'
})
```

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Advanced Theoretical Foundations & Industrial Systems Synthesis

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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 2 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

A structured comparative assessment clarifies operational distinctions across conventional paradigms and modern production implementations in Advanced Python for Data Science:

Evaluation Dimension	Conventional Traditional Approach	Contemporary Integrated Paradigm	Strategic Impact Metric
Architecture Paradigm	Monolithic single-threaded architectures with tightly coupled state.	Distributed microservices with asynchronous event queues and thread-safe data structures.	Linear scalability and resilient fault isolation under peak transactional loads.
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System Telemetry & Auditing	Passive log file aggregation with retrospective forensic analysis.	Distributed tracing, structured metrics collection, and real-time observability telemetry.	Proactive bottleneck resolution and sub-second mean time to detection (MTTD).

3. Production Implementation Patterns and Resilience Engineering

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