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BCA Honours | Semester VI | BCA6EJ303(4)

Advanced Python for Data Science

Module 4 Comprehensive Notes

Module 4: Machine Learning with Scikit-Learn and Deep Learning Foundations

Scikit-Learn provides consistent APIs for building machine learning workflows, from feature preprocessing to model evaluation and hyperparameter tuning.

4.1 The Scikit-Learn Estimator API

All machine learning algorithms in Scikit-Learn conform to a unified interface design:

- `fit(X, y)` : Trains the estimator on feature matrix X and target vector y.
- `predict(X)` : Generates predictions for new unseen feature samples.
- `transform(X)` : Transforms data (used in preprocessing transformers like `StandardScaler`).
- `fit_transform(X)` : Optimizes fitting and transformation in a single step.

4.2 Feature Engineering and ML Pipelines

- **Feature Scaling:** `StandardScaler` standardizes features to zero mean and unit variance ($z = (x - \mu)/\sigma$). `MinMaxScaler` scales features into the bounded range $[0, 1]$.
- **Categorical Encoding:** `OneHotEncoder` creates binary indicator columns; `LabelEncoder` converts target classes to integers.
- **Pipelines:** `sklearn.pipeline.Pipeline` chains transformers and estimators sequentially, preventing data leakage between training and test sets during cross-validation.

4.3 Hyperparameter Tuning and Cross-Validation

To avoid overfitting, models are evaluated using **K-Fold Cross-Validation** (partitioning training data into K folds, training on $K-1$, and validating on the remaining fold). `GridSearchCV` exhaustively searches specified parameter grids to identify the optimal configuration.

4.4 Introduction to Tensors and Deep Learning with TensorFlow

TensorFlow is an end-to-end open-source machine learning platform developed by Google. Tensors are multidimensional arrays supporting automatic differentiation and hardware acceleration on GPUs and TPUs.

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```
 import tensorflow as tf
from tensorflow.keras import layers, models

# Constructing a Deep Neural Network Sequential Model
model = models.Sequential([
    layers.Dense(128, activation='relu', input_shape=(784,)),
    layers.Dropout(0.2),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

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 4 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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