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APPLICATION OF MACHINE LEARNING ALGORITHMS IN INTELLIGENT ANALYSIS OF LARGE-SCALE DATA

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Abstract. The rapid expansion of digital information has increased the need for analytical methods capable of extracting reliable knowledge from large-scale, heterogeneous and continuously changing datasets. This thesis critically examines the application of supervised, unsupervised and deep learning algorithms to intelligent big data analysis. Particular attention is given to Random Forest, XGBoost, clustering and neural models, together with distributed processing, data quality, computational efficiency and model interpretability. Based on established research, a methodological framework is proposed for selecting and evaluating algorithms under realistic data and resource constraints. The discussion is theoretical and does not present unverified experimental improvements.

Keywords: big data; machine learning; intelligent data analysis; Random Forest; XGBoost; clustering; distributed computing; concept drift; explainable artificial intelligence.

INTRODUCTION. Large-scale data are produced by digital transactions, industrial sensors, communication networks, public services and scientific systems. Their value depends not merely on volume but on whether useful patterns can be identified and translated into defensible decisions. Conventional analysis may become insufficient when data are high-dimensional, heterogeneous, incomplete or generated too rapidly for manual examination. Machine learning provides adaptable techniques for discovering relationships, classifying observations, estimating numerical outcomes and detecting deviations. Nevertheless, larger datasets do not automatically yield better models: redundant records, measurement errors, biased samples and weak analytical design may increase both cost and uncertainty.

The aim of this thesis is to examine the opportunities and limitations of machine learning algorithms in intelligent large-scale data analysis and to formulate a practical evaluation

approach. The discussion combines a comparative review of established methods with a critical assessment of scalability, generalization and interpretability. Its central proposition is that algorithm selection should be driven by the analytical task, characteristics of the data and operational constraints rather than by model complexity alone.

MACHINE LEARNING APPROACHES TO INTELLIGENT ANALYSIS. Supervised learning is used when observations contain known target values. Classification models can distinguish transactions, events or document categories, whereas regression models estimate quantities such as demand, energy consumption or system performance. Random Forest combines multiple decision trees and can capture nonlinear associations while reducing some sources of variance [1]. Its flexibility makes it relevant to structured records containing numerous interacting predictors. However, extremely large ensembles require substantial memory, and variable importance estimates may be misleading when predictors are correlated. An apparently accurate classifier can also perform poorly on the rare cases that matter most if the training data are imbalanced.

Gradient-boosted decision trees, including XGBoost, construct successive models that correct errors from earlier iterations. The XGBoost framework introduced computational strategies for sparse information and scalable tree learning [2]. Such approaches are often suitable for heterogeneous tabular data, but their effectiveness depends on feature design, hyperparameter selection and representative training examples. Increasing the number or depth of trees may improve performance on historical samples without improving predictions for new data. Furthermore, computational scalability should be evaluated against actual hardware and data configurations rather than inferred from an algorithm’s reputation.

Unsupervised learning extends analysis to datasets without labeled outcomes. K-means and density-based clustering can reveal groups of similar observations, while anomaly detection may identify unusual transactions, equipment measurements or network behavior. Yet clusters are sensitive to preprocessing, distance metrics, dimensionality and the assumed structure of the data. In high-dimensional settings, distances may become less informative, and statistically

unusual cases are not necessarily operationally significant. For this reason, the validity of identified groups should be assessed using stability checks, domain knowledge and, when possible, independent evidence.

Deep learning techniques offer further possibilities for unstructured text, images, sequential observations and other complex inputs. Neural networks can learn hierarchical representations and reduce some manual feature-engineering requirements. Their use, however, introduces additional challenges related to training time, hardware resources, data requirements and reproducibility. When labeled examples are scarce or noisy, increased model capacity can intensify overfitting instead of improving generalization. Simpler models therefore remain essential benchmarks, especially when the additional predictive gain of deep learning is small relative to its deployment costs.

SCALABILITY, RELIABILITY AND INTERPRETABILITY. At large scale, a model is only one component of the analytical system. Data ingestion, preprocessing, storage, feature generation and repeated training may dominate computational expenditure. Distributed frameworks such as Apache Spark support processing across multiple machines and integrate several analytical workloads [3]. However, distributed execution does not eliminate bottlenecks caused by data transfer, partition imbalance or poorly designed workflows. A distributed solution may even introduce unnecessary complexity for workloads that fit efficiently on one machine. Consequently, end-to-end execution time, memory usage and infrastructure cost should be considered alongside conventional prediction metrics.

Another critical issue is the assumption that future observations resemble historical data. Economic changes, evolving user behavior and changes in measurement procedures may alter the relationship between input variables and desired outputs. This phenomenon, known as concept drift, can degrade previously successful models. Gama and colleagues describe adaptive approaches to detecting and responding to such changes [4]. In practical analysis, continuous monitoring, periodic reassessment and transparent retraining rules are more defensible than treating the initial accuracy score as permanent proof of model quality.

Interpretability is equally important when automated findings inform consequential decisions. Complex algorithms may return plausible predictions without making their underlying reasoning apparent. Local explanation methods, including LIME, have been proposed to clarify individual model outputs [5]. Nevertheless, an explanation of a prediction is not proof of a causal relationship or evidence that a model is free from bias. Data governance, privacy safeguards and traceability must therefore remain part of the analytical process. As Sculley and colleagues emphasize, machine learning systems can accumulate maintenance difficulties through hidden dependencies and feedback effects [6].

PROPOSED METHODOLOGICAL FRAMEWORK. A rigorous comparative study should begin by defining the target decision, the unit of observation and the available data sources. The dataset should then be audited for missing values, duplicates, inconsistent labels, imbalance and potential information leakage. Baseline statistical or rule-based procedures should be established before training Random Forest, gradient boosting, clustering or neural models. If observations are time-dependent, chronological train–validation–test separation is required; otherwise, appropriate group-aware or stratified procedures should be selected. Hyperparameters must be adjusted without using final test results, and repeated experiments should record software versions, resource budgets and random seeds.

Evaluation must match the task. For classification, precision, recall, F1-score and precision–recall curves can be more informative than accuracy under severe class imbalance. Regression requires suitable error measures and checks for systematic bias; clustering requires stability and substantive assessment rather than reliance on a single internal index. Alongside analytical quality, the study should report training and inference time, peak memory demand and sensitivity to corrupted or shifted data. This integrated protocol would allow the usefulness of sophisticated models to be judged by their practical contribution rather than by isolated benchmark scores.

CONCLUSION. Machine learning algorithms provide significant opportunities to transform large-scale data into structured knowledge through prediction, classification,

clustering and anomaly detection. The reviewed literature nevertheless indicates that success depends on data quality, workload characteristics, reliable evaluation and the capacity to maintain models as conditions change. Random Forest and XGBoost offer strong options for many structured-data problems, while deep learning can be valuable for complex unstructured inputs; none should be regarded as universally optimal. A research agenda combining reproducible experiments, resource-aware benchmarking, drift monitoring and explainable outputs is therefore recommended. The proposed framework is conceptual and requires empirical verification on real datasets before any claims of superior performance can be made.

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