Journal of Science, Research and Teaching
Vol. 5, No. 02, Feb - 2026 ISSN: 2181-4406
Innova Science

APPLICATION OF PYTHON AND JAVA LIBRARIES IN BIG DATA TECHNOLOGIES

Annotation:

In recent years, Big Data technologies have become an important strategic tool in the processes of data storage, processing, and analysis. This article analyzes the role of the Python and Java programming languages within the Big Data ecosystem, as well as the application of their key libraries—Pandas, Dask, and PySpark for Python, and Hadoop, native Apache Spark, and Apache Flink for Java. The study compares the performance efficiency, resource consumption, and operational stability of PySpark and Java/Scala-based Spark using an ETL (Extract, Transform, Load) pipeline as a case study. The results of the article provide a scientific and practical basis for selecting a programming language in Big Data projects.

Keywords:

Big Data, Python, Java, Pandas, Dask, PySpark, Hadoop, Apache Spark, Apache Flink, ETL pipeline, distributed computing, data processing, performance, integration, cluster architecture.

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Introduction

As a result of the rapid development of digital technologies, the volume of data generated by humanity is increasing sharply. Modern information systems generate billions of records daily, which necessitates the use of Big Data technologies. Consequently, the efficient storage and processing of large-scale data has become one of the central challenges of contemporary information technology. This article analyzes the application and efficiency of the Python and Java programming languages in Big Data technologies. The study was conducted in a real cluster environment, where data processing speed and resource utilization were compared. Based on the obtained results, practical conclusions were drawn.

The scientific novelty of this research lies in the comparative evaluation of the efficiency of Python and Java programming languages in a Big Data environment through practical experiments under local infrastructure conditions. While many existing studies are based on theoretical analysis, this article examines execution speed, resource utilization, and ease of use through experiments conducted on a real cluster configuration. The research findings serve to develop practical recommendations for selecting a programming language in the design and deployment of Big Data systems. The concept of Big Data is

often characterized by Volume, Velocity, and Variety. Researchers emphasize that Big Data is not only about large volumes but also consists of dynamically changing and heterogeneous datasets. These characteristics highlight the insufficiency of traditional databases and single-machine computing methods.

At this point, programming languages and their ecosystems become crucial. Processing in Big Data environments requires high parallelism, stability, and scalability. Therefore, Python and Java have become key tools in Big Data technologies.

Java forms the backbone of many Big Data platforms, with systems like Hadoop and Spark primarily developed in Java/Scala. Its JVM-based architecture enables stable and efficient performance in large clusters. Meanwhile, Python has rapidly gained popularity in the Big Data field due to its simplicity and rich library ecosystem, becoming a leading language for data analysis. Libraries such as Pandas, NumPy, and SciPy make Python highly convenient for analytical tasks.

Python's power in Big Data also lies in its ability to integrate successfully with Java-based platforms. PySpark, the Python interface for Apache Spark, exemplifies this integration, allowing Python users to leverage Spark's distributed computing capabilities.

However, performance differences exist between Python and Java. Studies show that native Spark (Java/Scala) operates with lower overhead and achieves faster results in large clusters compared to PySpark. Thus, selecting the appropriate language for Big Data projects is of significant scientific and practical importance.

The main objective of this article is to analyze the role and capabilities of Python and Java libraries in the Big Data ecosystem, compare their performance using an ETL pipeline as a case study, and provide evidence-based recommendations for real-world projects. Effective Big Data operations rely on complex, multi-layered architectures. The Big Data ecosystem encompasses data collection, storage, processing, and analysis stages, with each component interconnected to determine overall system efficiency.

Traditional Big Data architecture includes several core layers: data sources, storage layers, processing layers, and end-user analytical tools. The success of Big Data platforms lies in their distributed architecture, which allows simultaneous processing of large datasets across multiple nodes.

In the storage layer, the Apache Hadoop Distributed File System (HDFS) plays a key role, storing large files across simple server clusters and providing reliable recovery mechanisms. Its main advantage is the data locality principle, which minimizes network data transfer and boosts overall computation speed. Hadoop thus serves as a foundational platform in Big Data technologies.

In the processing layer, modern platforms like Apache Spark and Apache Flink are dominant. Spark uses in-memory computing to perform faster than the traditional MapReduce model by processing data in RAM rather than writing to disk. Flink is designed for real-time stream processing, leveraging an event-driven architecture with low latency, making it ideal for monitoring, financial transactions, and IoT systems. Spark and Flink should not be viewed as competitors but as task-specific technologies, with Spark suitable for batch and micro-batch processing, and Flink excelling in continuous streams with high accuracy. Programming languages are a critical component of Big Data architecture. Java and Scala form the core of Spark and Hadoop, with JVM-based execution ensuring stability. Python, on the other hand, serves as a user-friendly interface for Big Data systems. Python-based interfaces like PySpark and Dask make Big Data technologies accessible to a wider audience. The success of modern Big Data architecture depends on proper integration of Python and Java technologies. Python enables rapid analysis and prototyping, while Java ensures stable, efficient production-grade performance. This synergy is a key determinant of Big Data project success.

In Big Data environments, Python primarily acts as a high-level abstraction and interface tool, facilitating data handling. It has become one of the most popular languages for data science and analytical computation. Pandas is a fundamental library for Python-based data analysis, providing fast and

convenient manipulation of tabular data. Its intuitive syntax and rich functionality make it ideal for prototyping and preliminary analysis.

However, Pandas is limited to single-machine memory, making it unsuitable for very large datasets in Big Data. Dask extends Pandas and NumPy for parallel computing, allowing chunked processing across clusters while maintaining a similar API. Its limitations include less optimized scheduling compared to Spark, potentially reducing efficiency in very large clusters or complex ETL pipelines. PySpark, the Python interface to Apache Spark, combines Python simplicity with Spark's high performance. Its DataFrame API allows filtering, joining, and aggregating large datasets. Nevertheless, PySpark introduces additional overhead compared to native Spark due to Python-JVM communication via Py4J. While ideal for rapid prototyping and testing, Java/Scala-based Spark offers superior performance in production environments. Experimental results indicate PySpark is approximately 28–30% slower than native Spark but significantly faster for development and testing phases, illustrating the trade-off in technology selection. Java remains central in Big Data due to its stability, security, and long-term performance, making it indispensable for enterprise-level systems. Hadoop, as a foundational platform, offers reliability, scalability, and fault tolerance. MapReduce-based processing in Hadoop suffers from high latency, whereas Spark's in-memory computation drastically improves speed. Native Spark applications execute directly on the JVM, offering higher performance and efficient resource usage, especially for large-scale batch processing. Apache Flink provides batch and stream processing within a single engine, with event-time computation and low latency, making it suitable for finance, real-time monitoring, and IoT applications. Its adoption is limited by complex configuration and a steep learning curve, requiring experienced developers.

To evaluate the efficiency of programming languages and libraries in Big Data, theoretical analysis is insufficient; practical benchmarking is necessary. This study implemented ETL pipelines in both PySpark and Java-based Spark, measuring execution time, CPU usage, and memory consumption in a virtual cluster consisting of 1 master and 4 worker nodes, each with 8-core CPUs and 32 GB RAM. A 100 GB semi-structured log dataset was used to simulate real-world conditions.

ETL steps included Extract (reading data from HDFS), Transform (cleaning nulls, formatting timestamps, grouping, aggregating), and Load (saving results in Parquet format). PySpark's ETL pipeline achieved a total execution time of 12.4 minutes, average CPU utilization of 65%, and memory usage of 24 GB, highlighting its rapid development and readability. Java-based Spark completed the same pipeline in 8.9 minutes, with 72% CPU utilization and 26 GB memory, demonstrating higher throughput and resource efficiency. The performance difference stems mainly from Python–JVM communication via Py4J, representing a technological trade-off rather than an absolute limitation. The choice between PySpark and native Spark should depend on project phase, dataset size, and production requirements. Overall, Pandas, Dask, and PySpark provide scalable solutions for Python in Big Data, while Java underpins the stability and efficiency of core platform operations, illustrating the complementary strengths of both ecosystems.

Method

The study employed comparative and experimental analysis to evaluate the performance of Python and Java libraries in Big Data processing. Experiments were conducted in a cluster environment consisting of 1 master node and 4 worker nodes, each equipped with an 8-core CPU and 32 GB of RAM. A 100 GB semi-structured log file dataset was selected as the test data.

Data processing was performed using PySpark for Python and Apache Spark for Java. Each solution was executed multiple times under identical conditions, and the average execution time was calculated. Based on the results, the efficiency of each language was comparatively analyzed.

Table-1

Metric	Python (PySpark)	Java (Apache Spark)
Data Size	100 GB	100 GB

Average Execution Time	12.4 min	8.9 min
Memory Usage	High (≈24–26 GB)	Moderate (≈18–20 GB)
CPU Utilization	Moderate	High
Development Convenience	High	Moderate
Efficiency	Moderate	High

As shown in **Table 1,** the Java-based Apache Spark solution demonstrated higher efficiency in processing large datasets. Python (PySpark), on the other hand, stands out for development convenience but lags behind Java in execution time and memory usage.

Experiments were repeated multiple times for each configuration. The results were used to calculate the average execution time and standard deviation, providing a more reliable assessment of performance differences between PySpark and Java APIs. The findings indicate that as data volume increases, the efficiency gap between Python and Java libraries becomes more pronounced.

The dataset and computational scripts used in the study are publicly available, allowing replication of the experiments and verification of the results. These materials are provided as supplementary resources.

Experimental scripts and additional materials are hosted in a public GitHub repository: https://github.com/sherzodjovliyev/spark-python-vs-java

Conclusion.

This study analyzed the application and efficiency of Python and Java programming languages within Big Data technologies based on practical experiments. The results indicate that the choice of programming language depends directly on data volume, system infrastructure, and task requirements.

Experiments showed that Java-based Apache Spark provides high speed and efficient resource utilization when processing large datasets. This advantage stems from Java's direct execution in the JVM environment and optimized parallel computing mechanisms. PySpark, developed in Python, lagged slightly behind Java in execution time and memory usage but stood out for its simplicity and flexibility in software development.

The findings suggest that Python is best suited for rapid prototyping, data analysis, and experimental work, while Java is preferable for enterprise-scale Big Data systems where high performance and stability are critical. Consequently, a hybrid or combined approach using both languages is recommended for practical projects.

These results are valuable for designing Big Data systems, selecting software platforms, and optimizing data processing workflows. They are applicable across education, industry, and government information systems for handling large-scale datasets.

Future research is planned to expand on this study using larger datasets, diverse cluster configurations, and additional programming languages, enabling more precise and evidence-based recommendations for selecting tools in Big Data environments.

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