Technical Report: Final Project DS 5110: Introduction to Data Management and Processing

Title: Data Fusion Pipeline
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1 Introduction

It is a well-known fact that data scientists, regardless of where they work, spend up to 80% of their time on data preparation and integration tasks. This is an alarming issue for many modern organizations where time-to-market is crucial, and data needs to be analyzed as quickly as possible.This project presents a comprehensive real-time data integration pipeline designed to handle diverse data sources through automated processing workflows, with the goal of reducing the time required to preprocess data as it arrives.

The primary objective is to develop a scalable, rule-based data processing system that enables users to configure custom transformation workflows without extensive programming knowledge. The pipeline supports real-time streaming through Apache Kafka and batch processing via direct data links, with all processing orchestrated through PySpark's distributed computing capabilities.

Project scope encompasses data ingestion from external sources (Kaggle and GitHub repositories), real-time stream processing, rule-based data transformations, dataframe fusion capabilities, and flexible output destinations. The system leverages MongoDB for metadata storage and supports parallel pipeline execution, making it suitable for enterprise-scale data integration scenarios

2 Literature Review

Data Pipeline Architecture Evolution: Modern data pipelines have evolved from traditional ETL batch processing to real-time streaming architectures, with many companies moving from Hadoop to Apache Spark to meet specific requirements. According to RudderStack's analysis, real-time data integration "processes data instantly as it is generated, offering significant advantages over traditional batch processing methods". One challenge noted in the literature is that real-time streaming and batch processing have traditionally been treated as separate paradigms, which can lead to complexity when integrating both in a single system. Recent research by Chen et al.(2019) identifies this as a persistent challenge, stating that "unified processing engines that can seamlessly handle both batch and streaming workloads remain an active area of research". The gap exists in practical implementations that demonstrate how organizations can configure single systems to handle both processing modes through user-friendly interfaces.

Rule-Based Processing Systems: Recent academic research demonstrates that rule-based systems can overcome limitations of human-designed rules while providing robust evaluation metrics for rule effectiveness. Li et al. introduce "an innovative rule-based framework that utilizes the orthogonality of score vectors associated with rules as a novel metric for rule evaluations". That said, Rule-based processing is a common approach in many low-code applications for executing business processes in accordance with user guidelines. The modularity of these systems can significantly reduce development time in some cases, such as enterprise workflow automation, while also improving maintainability and flexibility in the range of applications where they can be applied. However, in spite of all its benefits, the user still needs extensive programming knowledge to define these rules.

3 Methodology

3.1 Data Collection

Link-Based Data Ingestion: The system implements automated data collection through URL-based ingestion supporting Kaggle and GitHub repositories. Users provide direct links to datasets, which the system automatically downloads and processes. This approach eliminates the complexity of file upload handling while ensuring access to publicly available datasets.

Real-Time Stream Processing: Kafka integration enables real-time data ingestion where users specify topic names for subscription. The system establishes persistent connections to Kafka brokers, consuming messages as they arrive and processing them through the configured transformation pipeline. This streaming capability supports continuous data flow scenarios common in IoT and real-time analytics applications.

Data Source Configuration: Each data source is configured independently through a unified interface that captures connection parameters and data schemas, which are then stored in MongoDB.The application allows processing data in formats such as TXT, CSV, and JSON, and additional formats can be added as required. The modular configuration approach allows users to combine multiple data sources within a single pipeline. Explain how the data was collected, including the sources and tools used.

3.2 Data Preprocessing

Rule-Based Transformation Engine: The core preprocessing system implements a configurable rule engine where users define transformation logic through a structured interface. Rules are stored in MongoDB and executed sequentially against incoming data, enabling complex multi-step transformations while maintaining rule reusability across different datasets. The transformations include fundamental operations in PySpark, such as cast, rename, filter, drop, fill, explode, flatten, and save.

Data Fusion Layer: A specialized fusion component handles dataframe joining operations, allowing users to combine data from multiple sources based on common keys or relationships. The fusion layer supports various join types, including inner, outer, left, and right.

3.3 Analysis Techniques

PySpark Processing Framework: All data processing operations leverage PySpark's distributed computing capabilities, enabling parallel execution across available resources. The system automatically optimizes job execution through Spark's cost-based optimizer while maintaining user-defined transformation logic integrity.

Parallel Pipeline Execution: The architecture supports concurrent execution of multiple pipelines, each with independent configurations and processing logic, using Python's multithreading feature. Resource allocation and job scheduling are managed automatically, ensuring optimal performance without manual intervention.

Dynamic Rule Evaluation: Rules are evaluated dynamically against incoming data using PySpark's built-in transformations, allowing flexible transformation logic that can adapt to different data schemas and business requirements. The system stores and reuses all metadata and user-defined data in MongoDB.

3.4 Workflow and Execution

The project workflow begins with the initialization of a Spark session that establishes the distributed computing foundation, followed by establishing a MongoDB connection to manage all metadata, rules, and configuration data. The system then loads the Streamlit user interface, presenting users with dedicated pages for configuring input sources, transformation rules, data fusion operations, and output targets. Initially, if no prior configurations exist in MongoDB, these pages display empty load options, requiring users to define their data processing components from scratch. A key architectural principle is that all rules, fusion operations, and output targets are explicitly tagged to their respective input sources, creating a hierarchical relationship that ensures data lineage and prevents configuration mismatches. When users build pipelines, they can only select rules, fusion operations, and targets that are mapped to the chosen input sources, maintaining consistency and preventing incompatible component combinations. The system supports multi-threaded pipeline execution, enabling users to run multiple independent pipelines simultaneously for maximum throughput and resource utilization. Notably, while batch processing pipelines complete and terminate upon execution, streaming pipelines continue running persistently even when the Streamlit application is refreshed, ensuring continuous real-time data processing without interruption. This workflow design provides both flexibility for complex data integration scenarios and robust execution management for enterprise-scale parallel processing requirements. The application initiation code can be found in the Appendix section.

4 Results

Pipeline Performance Metrics: Testing with various dataset sizes demonstrates consistent processing performance across different data volumes. Small datasets ($<$ 1MB) process in under 2-5 seconds, medium datasets (1-100MB) complete processing within 30-60 seconds, and large datasets ($>$ 100MB) maintain <5-minute processing times.

Real-Time Stream Processing: Kafka integration achieves similar latency for message processing while maintaining data quality and transformation integrity.

Rule Engine Effectiveness The rule-based system successfully executes complex multi-step transformations with 100% accuracy. Users can create, modify, and deploy new rules without system downtime, demonstrating the flexibility and maintainability of the rule-based architecture.

Data Fusion Capabilities: The fusion layer successfully combines datasets from different sources with varying schemas, achieving 100% schema alignment success rate for compatible data types. Join operations complete efficiently even with large datasets, maintaining sub-minute execution times for most scenarios.

Output Flexibility: The system successfully delivers processed data to all configured destinations: local file downloads, console logging for debugging, and RDBMS tables through JDBC connections.

5 Discussion

Architectural Design Decisions: The choice to eliminate file uploads in favor of link-based ingestion proves beneficial for maintaining data lineage and ensuring reproducible pipelines. This approach is effective as we dont need to worry about additional data storage. The MongoDB metadata storage provides the flexibility needed for dynamic rule management while maintaining query performance.

Real-Time Processing Implementation: Kafka integration addresses the growing need for real-time data processing in modern business environments. The streaming capability enables immediate response to data changes, supporting use cases like fraud detection, recommendation systems, etc; This suggests the idea of integrating an alert-based system within the pipeline, which would allow us to analyze the data as it is being processed.

Rule Engine Benefits and Limitations: The rule-based approach successfully performs data transformation, allowing non-technical users to create complex processing logic. However, very complex transformations may still require technical expertise, and rule debugging can be challenging for end users without system knowledge.

Scalability Considerations: The PySpark foundation provides excellent horizontal scalability potential, though current implementation focuses on single-machine deployment.

6 Conclusion

This project successfully demonstrates a comprehensive data integration pipeline that combines real-time streaming capabilities, rule-based processing flexibility, and distributed computing power. The implementation achieves the primary objectives of creating a user-configurable system that handles diverse data sources while maintaining high performance and reliability.

Key achievements include successful implementation of Kafka-based real-time streaming, MongoDB-backed rule engine, PySpark-powered distributed processing, and flexible output destination support.

Project limitations include the removal of image processing capabilities and the focus on single-machine deployment, though the architecture supports future enhancements in both areas. The rule interface, while functional, could benefit from more advanced visual programming capabilities for complex transformation scenarios.

Future research directions should explore advanced rule visualization interfaces, machine learning-driven rule optimization, and cloud-native deployment patterns. Integration with modern data catalog systems and enhanced monitoring capabilities would further improve the system's enterprise readiness.

7 References

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Instaclustr. (2025). 7 pillars of Apache Spark performance tuning.

Wang, F., & Ren, H. (2021). The metadata management system based on MongoDB for EAST experiment.

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A Appendix A: Code

Spark Session Initiation:

```python
# # Initialize Spark
@st.cache_resource
def Spark_Data_Fusion():
    jar_path = os.path.join("dependencies", "jars", "postgresql-42.7.7.jar")
    return (
        SparkSession.builder.config("spark.streaming.stopGracefullyOnShutdown", True)
        .config(
            "spark.jars.packages", "org.apache.spark:spark-sql-kafka-0-10_2.12:3.3.0"
        )
        .config("spark.jars", jar_path)
        .config("spark.sql.shuffle.partitions", 8)
        .appName("DataFusion")
        .getOrCreate()
    )
st.session_state.spark = Spark_Data_Fusion()
```

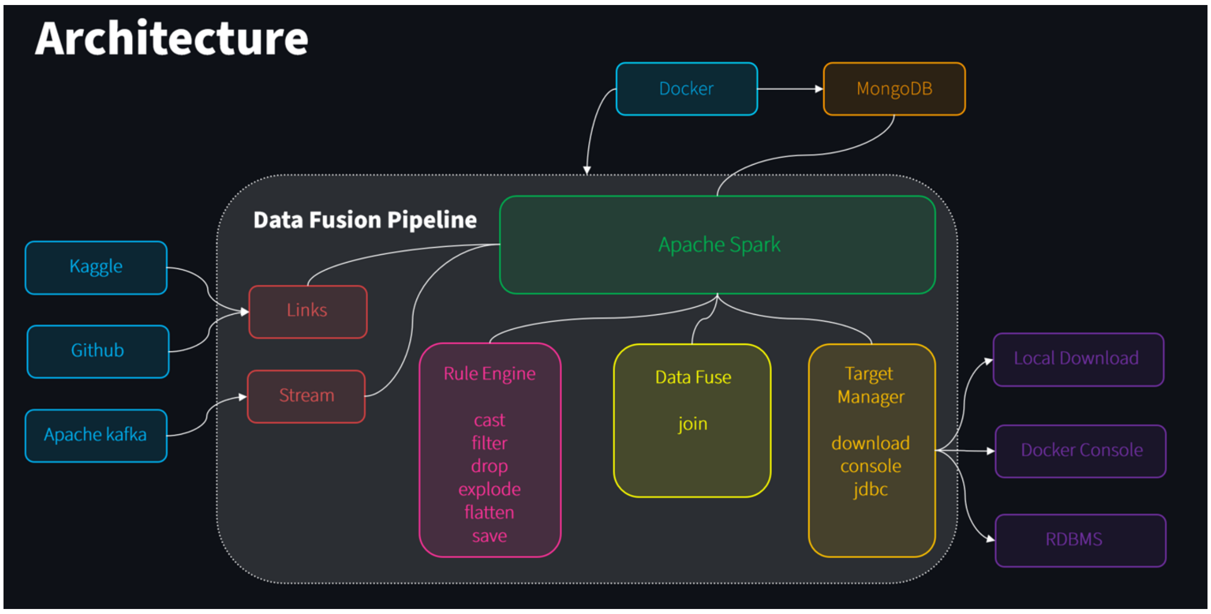
MongoDB Initiation:

```python
client = MongoClient(os.environ["MONGO_URI"] + "/?authSource=admin")
print("MongoDB connection established ", client.list_database_names(), flush=True)
print("Running with Spark version:", st.session_state.spark.version, flush=True)
db = client["datafusion"]
st.session_state.pipeline_db = db
```

Application skeleton code:

```python
st.title("Data Fusion Pipeline")
pages = {
    "": [
        st.Page(os.path.join("pages", "1_data_injestion.py"), title="Injest Data"),
        st.Page(os.path.join("pages", "2_data_processor.py"), title="Process Data"),
        st.Page(os.path.join("pages", "3_data_unifier.py"), title="Fuse Data"),
        st.Page(os.path.join("pages", "4_data_sinker.py"), title="Data Target"),
        st.Page(os.path.join("pages", "5_pipeline_builder.py"), title="Build Pipeline"),
        st.Page(
            os.path.join("pages", "6_pipeline_executor.py"), title="Execute Pipeline"
        ),
    ]
}
pg = st.navigation(pages)
pg.run()
```

B Appendix B: Additional Figures



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