CloudWatch Logs Transformation and Querying Workflow Report

Objective

The goal of this task was to build an automated workflow to extract, clean, and transform raw CloudWatch logs into a structured format that enables easy querying and analysis in Amazon Athena.

This involved:

- 1. Using AWS Glue (PySpark) for ETL (Extract, Transform, Load).
- 2. Storing cleaned logs in S3.
- 3. Querying structured logs with Amazon Athena.

Raw Input

The raw dataset was a CSV file exported from CloudWatch Logs into a S3 Bucket in this format:

timestamp, message

1757511342804,"INFO 2025-09-10T13:35:42,804 10153 org.apache.spark.metrics.source.StageSkewness [Thread-10] 29 [Observability] Skewness metric using Skewness Factor = 5"

The challenge with this raw data:

- The message column contained multiple attributes mixed together (timestamp, log level, class name, thread, etc.).
- The structure was not suitable for querying (e.g., filtering by ERROR, aggregating by date).

Feature Engineering & Transformations

To make the logs query able, we applied **regex-based parsing** inside an AWS Glue PySpark job.

Steps Taken

1. Regex Extraction

Extracted key components from the message field:

- o **timestamp_raw** → extracted event timestamp string.
- o **log_level** → captured INFO, ERROR, DEBUG, etc.
- thread → extracted thread name (e.g., Thread-10).

- class → Java/Python class that logged the event.
- \circ line \rightarrow line number in source file.
- o message_clean → actual log message text.

2. Type Conversion

- o Converted timestamp_raw → timestamp column (timestamp type).
- Extracted date (date type) from timestamp for partitioning and easy filtering.

3. Filtering Noise

 Removed rows where message_clean was empty or null (avoided blank entries).

Final Schema

After transformations, the structured dataset contained the following columns:

Column	Туре	Description
timestamp	timestamp	Event timestamp with full precision.
log_level	string	Log level (INFO, ERROR, DEBUG, WARN, TRACE).
thread	string	Thread name that produced the log.
class	string	Class/package name of the log source.
line	int	Line number in the source file.
message_clean	string	Cleaned human-readable log message.
date	date	Event date (extracted from timestamp).

Workflow Overview

Extract

Source: CloudWatch logs exported to S3 (log-events-viewer-result.csv).

Format: CSV.

Transform (Glue Job / PySpark)

- o Parsed message using regex.
- o Added structured fields (log_level, class, etc.).
- Converted timestamps into proper types.
- Removed empty rows.

Load

- Saved cleaned data as CSV in S3 under s3://cloudwatch-cleaned-logs-aip-71/cleaned-logs/.
- o Ensured single file output (part-0000*.csv).

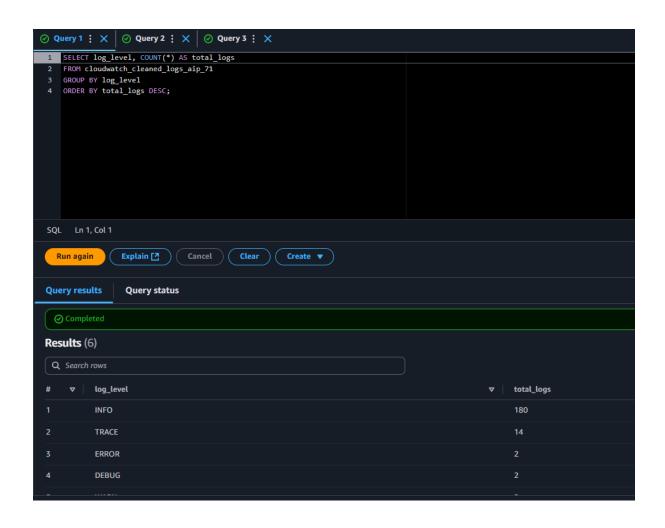
Query (Athena)

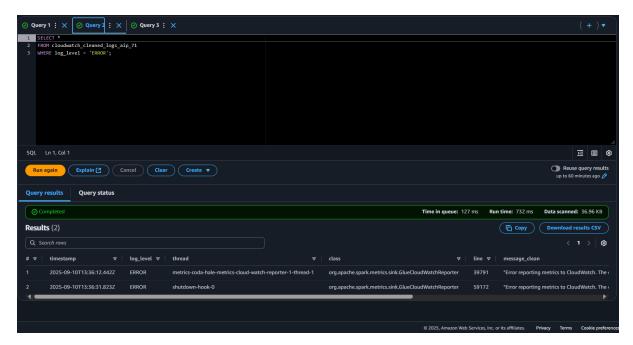
- Created Athena external table over the cleaned logs.
- Queried logs by date, log_level, and keywords.

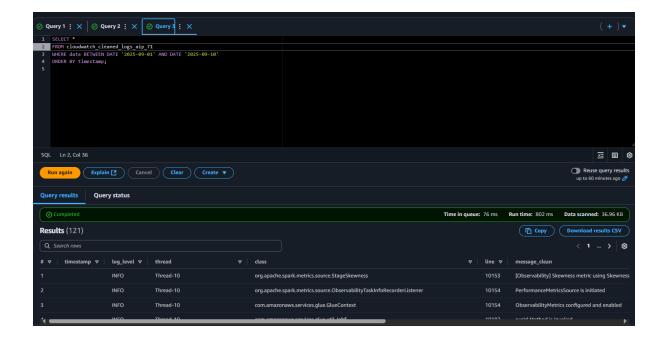
Why These Features Were Created

- **timestamp** → Enables time-series queries (e.g., logs per hour/day).
- date → Optimized partitioning in Athena, allows fast date filtering.
- log_level → Separates ERROR/INFO logs for reliability monitoring.
- thread → Useful for debugging concurrency or thread-specific issues.
- class → Helps trace which component of the system generated logs.
- line → Assists in pinpointing exact code lines for debugging.
- message_clean → Human-readable message for deeper insights and keyword search.

Example Athena Queries







Conclusion

By engineering new features from the unstructured message column, we converted raw CloudWatch logs into a structured dataset suitable for analytical querying. This workflow:

- · Improves log observability.
- Enables faster debugging and monitoring via Athena.
- Provides flexibility for future extensions (e.g., partitioning by log_level or date for performance).