AWS Glue vs Spark on EMR for UPSERT Operations

Technical Architecture Decision Document

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1 Executive Summary

This document compares two AWS-based Apache Spark solutions for handling UPSERT (merge) operations from S3 to multiple target databases including MSSQL, Apache Iceberg, and potentially Clickhouse:

- 1. AWS Glue: A managed Apache Spark service
- 2. Apache Spark on Amazon EMR: A more configurable Spark deployment

Note

Both solutions use Apache Spark as their processing engine. The key differences lie in management, configuration, and operational aspects rather than core processing capabilities.

2 Understanding the Options

AWS Glue

AWS Glue provides a managed Apache Spark environment with:

- Built-in Apache Spark engine (same as EMR)
- AWS-specific optimizations and tooling
- Both Spark SQL and PySpark interfaces
- Additional features like DynamicFrames

• Managed infrastructure and scaling

Spark on EMR

Amazon EMR provides a more traditional Spark deployment with:

- Full Apache Spark ecosystem
- Complete configuration control
- Custom cluster management
- Direct access to Spark internals
- Infrastructure flexibility

3 Cost Analysis

3.1 AWS Glue Costs

3.1.1 Pricing Structure

- \$0.44 per DPU-Hour (1 DPU = 4 vCPU, 16GB memory)
- Minimum 10-minute billing
- Development endpoints additional cost

3.1.2 Hidden Savings

- No cluster management costs
- Includes Spark optimization
- Less operational overhead

3.1.3 Considerations

- More expensive per compute hour
- Less granular scaling
- Simplified cost model

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3.2 EMR Costs

3.2.1 Direct Costs

- EC2 instance costs
- EMR service charges
- Storage and data transfer

3.2.2 Optimization Options

- Spot instance usage
- More granular scaling
- Resource optimization

3.2.3 Hidden Costs

- Operational overhead
- Management complexity
- Required expertise

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4 Performance Comparison

4.1 AWS Glue Performance

```
# Example Glue Spark UPSERT implementation
from awsglue.context import GlueContext
from pyspark.context import SparkContext

# Initialize Glue Spark context
glueContext = GlueContext(SparkContext.getOrCreate())
spark = glueContext.spark_session

# Read from S3 (using standard Spark)
source_df = spark.read.parquet("s3://bucket/path")

# MSSQL UPSERT
def perform_mssql_upsert(df):
```

```
# Write to staging table using Spark JDBC

df.write \
     .format("jdbc") \
     .option("url", jdbc_url) \
     .option("dbtable", "staging_table") \
     .mode("overwrite") \
     .save()

# Execute MERGE using Spark SQL

spark.sql("""

MERGE INTO target_table t

USING staging_table s

ON t.key = s.key

WHEN MATCHED THEN UPDATE...

WHEN NOT MATCHED THEN INSERT...

""")
```

? Glue Performance Strengths

- Pre-configured Spark optimizations
- AWS service-specific tuning
- Auto-scaling built in
- Warm pools reduce startup time

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