Programming Assignment № 2

Evangelia Panourgia, Athens University of Economics and Business University

27/03/2025

Intoduction

In the scope of this assignment, we will use the Apache Spark framework and the Apache Cassandra NoSQL database in order to create a structured streaming Spark process that consumes Kafka messages and uses Cassandra as a sink to persist information.

Part I

The python script for the first part.

The provided Python script is an asynchronous Kafka producer designed to simulate real-time movie rating events. It uses the Faker library to generate synthetic user names and reads actual movie titles from a CSV file using pandas. Each generated user rates a randomly selected movie with a random rating between 1 and 10, along with a current timestamp. These events are serialized to JSON and sent to a Kafka topic named "test" using the aiokafka library. The process runs continuously, with each user producing one rating per minute, making it ideal for streaming applications such as those built with Apache Spark Structured Streaming. Additionally, the script appends a specific user name, "Evangelia Panourgia", to ensure consistent personal data inclusion for testing or filtering.

Listing 1: python-kafka-example

```
1
2
  Async Kafka Producer: Fake Movie Ratings Generator
3
4 Overview:
  -----
6 This script continuously generates **fake movie rating events** and sends ←
      them to a Kafka topic ("test").
7 It simulates users rating random movies with timestamps, mimicking real-\leftarrow
      time data.
8
9 Components:
10 -----
11 1. Faker: Generates fake human names.
12 2. Pandas: Loads real movie titles from a CSV file.
13 3. aiokafka: Asynchronous Kafka producer library.
```

```
14 4. Kafka: Acts as the message broker for event streaming.
15
16 Use Case:
17 -----
18 Run this script to simulate live rating data for a Spark Structured \leftarrow
       Streaming application to consume and process.
19
20 import json
21 import asyncio
22 import random
23 from datetime import datetime
24
25 import pandas as pd
26 from faker import Faker
27 from aiokafka import AIOKafkaProducer
28
29 # Load movie titles
30 movies_df = pd.read_csv('data/movies.csv', header=None, names=["←
      movie_title"])
31 movie_titles = movies_df['movie_title'].dropna().tolist()
32
33 # Generate names
34 fake = Faker()
35 names = [fake.name() for _ in range(10)]
36 names.append("Evangelia Panourgia") # add my own name
37
38 # Kafka settings
39 KAFKA_TOPIC = "test"
40 KAFKA_BOOTSTRAP_SERVERS = "localhost:29092"
41
42 # JSON serializer
43 def serializer(data):
44
       return json.dumps(data).encode()
45
46 # Producer logic
   async def produce():
47
       producer = AIOKafkaProducer(
48
           bootstrap_servers=KAFKA_BOOTSTRAP_SERVERS,
49
50
           value_serializer=serializer,
51
           compression_type="gzip"
52
       )
53
54
       await producer.start()
55
       try:
56
           while True:
57
               for name in names:
58
                   movie = random.choice(movie_titles)
```

```
rating = random.randint(1, 10)
59
                    timestamp = datetime.now().isoformat()
60
61
62
                    message = {
63
                        "name": name,
64
                         "movie": movie,
65
                         "timestamp": timestamp,
                         "rating": rating
66
67
                    }
68
                    print(f"Sending: {message}")
69
                    await producer.send(KAFKA_TOPIC, message)
70
71
                    await asyncio.sleep(60) # One message per user per minute
        finally:
72
73
            await producer.stop()
74
75
   # Run it (no deprecation warning)
   if __name__ == "__main__":
76
        loop = asyncio.new_event_loop()
77
78
       asyncio.set_event_loop(loop)
79
        loop.run_until_complete(produce())
```

The image Figure 1 depicts the output of Kafka producer running in the first terminal.

```
| Genomb | Programmer | Program
```

Figure 1: Terminal 1: Kafka Producer.

An additional modification was applied to the console script located in the examples directory, specifically to the file named console-spark-streaming-example.py. This adjust-

ment was necessary to tailor the script to the project's requirements and ensure compatibility with the streaming architecture.

The Figures 2, 3 below depict the console output helping us to debug the kafka producer real-time data. It runs in another terminal.

Figure 2: Terminal 2: Console for Kafka Producer.

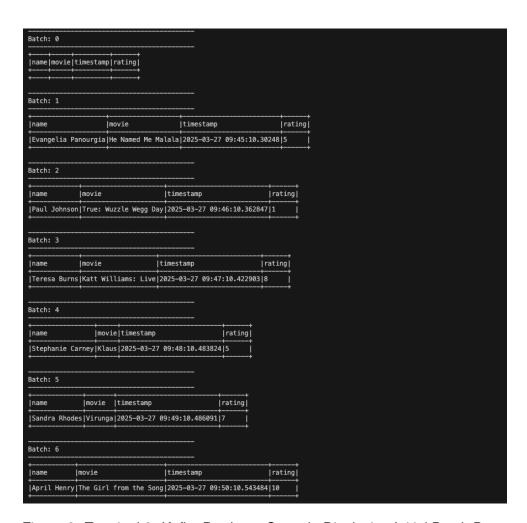


Figure 3: Terminal 2: Kafka Producer Console Displaying Initial Batch Data.

Note: The second terminal was executed a few minutes after the first, resulting in the initial data produced in the first terminal not appearing in the console output of the second.

Part 2

The pyspark script for the second part.

This PySpark application establishes a real-time data pipeline that reads movie rating events from a Kafka topic, enriches them with metadata from a static Netflix dataset, and writes the processed results into a Cassandra database (that is the **sink**). The script defines two schemas: one for parsing JSON-encoded rating messages received from Kafka, and another for reading static metadata from a CSV file. It converts timestamps to proper TimestampType, and groups data by hourly buckets for time-based aggregations. Ratings are joined with metadata on the movie title to create an enriched DataFrame, which is then written to Cassandra using the for eachBatch method in micro-batch mode. This architecture enables structured streaming analysis and time-windowed queries for individual users and movies.

To improve performance and avoid repeated disk reads, the static Netflix metadata is cached in memory, ensuring it remains efficiently accessible during each micro-batch operation within the streaming query.

Listing 2: cassandra-spark-streaming-example.py.

```
1 from pyspark.sql import SparkSession
2 from pyspark.sql.types import StructType, StructField, StringType, ←
       IntegerType, TimestampType
3 from pyspark.sql.functions import from_json, col, to_timestamp, ←
       date_format
 4
5 # Schema for Kafka messages (movie ratings)
   ratingSchema = StructType([
6
7
       StructField("name", StringType(), False),
8
       StructField("movie", StringType(), False),
       StructField("timestamp", StringType(), False),
9
       StructField("rating", IntegerType(), False)
10
   ])
11
12
13 # Schema for Netflix CSV
   netflixSchema = StructType([
14
       StructField("show_id", StringType(), True),
15
       StructField("title", StringType(), False),
16
       StructField("director", StringType(), True),
17
18
       StructField("country", StringType(), True),
       StructField("release_year", StringType(), True),
19
       StructField("rating", StringType(), True),
20
21
       StructField("duration", StringType(), True)
22 ])
```

```
23
24 # Initialize Spark session
25 \text{ spark} = (
       SparkSession.builder
26
27
        .appName("MovieRatingStreamer")
28
        .config("spark.jars.packages", "org.apache.spark:spark-sql-kafka-0-10↔
           _2.12:3.5.0,com.datastax.spark:spark-cassandra-connector_2←
           .12:3.4.1")
        .config("spark.cassandra.connection.host", "localhost")
29
        .getOrCreate()
30
31
   )
32
   spark.sparkContext.setLogLevel("ERROR")
33
34
35 # Read Netflix CSV with renamed rating column to avoid conflict with "\leftarrow
       rating" in Kafka schema
   netflix_df = (
36
37
        spark.read.schema(netflixSchema)
             .option("header", True)
38
39
             .csv("data/netflix.csv")
             .withColumnRenamed("rating", "rating_category") # Rename avoids ←
40
                conflict
             .cache()
41
42 )
43
44 # Read streaming data from Kafka
45 \, df = (
       spark.readStream.format("kafka")
46
             .option("kafka.bootstrap.servers", "localhost:29092")
47
             .option("subscribe", "test")
48
             .option("startingOffsets", "latest")
49
             .load()
50
51 )
52
53 # Parse JSON from Kafka messages
   ratings df = (
54
       df.selectExpr("CAST(value AS STRING)")
55
          .select(from_json(col("value"), ratingSchema).alias("data"))
56
          .select("data.*")
57
          .withColumn("timestamp", to_timestamp("timestamp"))  # Convert \leftarrow
58
             string timestamp to TimestampType
          .withColumn("hour_bucket", date_format("timestamp", "yyyy-MM-dd HH \leftarrow
59
             :00")) # Grouping by hour
60 )
61
62 # Join ratings with static Netflix metadata
63 \text{ enriched\_df} = (
```

```
ratings_df.join(netflix_df, ratings_df.movie == netflix_df.title, "←
64
           left")
                  .drop("title")
65
66 )
67
68
   # Optional: Print schema for debugging (can be removed later)
69
   enriched_df.printSchema()
70
71 # Define Cassandra write logic
   def writeToCassandra(writeDF, _):
72
73
       (
74
            writeDF.select(
                "name", "movie", "timestamp", "rating", "hour_bucket",
75
                "show_id", "director", "country", "release_year", "↔
76
                   rating_category", "duration"
77
            )
78
            .write
79
            .format("org.apache.spark.sql.cassandra")
            .mode('append')
80
81
            .options(table="movie_ratings", keyspace="netflix_ks")
82
            .save()
83
       )
84
85 # Write to Cassandra in a streaming loop
86 result = None
   while result is None:
87
88
       try:
89
            result = (
                enriched_df.writeStream
90
91
                    .foreachBatch(writeToCassandra)
92
                    .outputMode("update")
                    .option("checkpointLocation", "/tmp/checkpoints/movie")
93
94
                    .trigger(processingTime="30 seconds")
95
                    .start()
                    .awaitTermination()
96
97
            )
       except Exception as e:
98
            print(f"Streaming error: {e}")
99
```

The figure below 4 illustrates the third terminal associated with Spark.

Details about your Cassandra data model.

The Cassandra data model was carefully designed to optimize query performance for the specific requirement of aggregating movie ratings by user and hour. The primary key is composed of a composite partition key (name, hour_bucket), ensuring that all ratings provided by a spe-

cific user within a given hour are stored in the same partition. This design eliminates the need for inefficient filtering operations and allows for fast, targeted queries such as retrieving all movies rated by a user during a specific hour or calculating the average rating and duration of those movies. The clustering columns (timestamp, movie) further organize the data chronologically within each partition, enabling efficient range queries and ordered retrieval. Crucially, the fields rating and duration are stored as integers, allowing native support for aggregation functions like AVG(), which would not be possible with text fields. Overall, this schema supports the core analytical tasks required by the application while adhering to Cassandra's best practices for scalability and performance.

Listing 3: Cassandra schema for movie ratings

```
CREATE KEYSPACE IF NOT EXISTS netflix_ks
   WITH replication = {'class': 'SimpleStrategy', 'replication_factor': 1};
2
3
4
   CREATE TABLE IF NOT EXISTS netflix_ks.movie_ratings (
5
       name text,
6
       hour_bucket text,
7
       timestamp timestamp,
8
       movie text,
9
       rating int,
10
       show_id text,
11
       director text,
12
       country text,
13
       release_year int,
                             -- changed from text : int
       rating_category text,
14
15
       duration int,
                                  -- changed from text : int
       PRIMARY KEY ((name, hour_bucket), timestamp, movie)
16
17
   );
```



Figure 4: Terminal 3: Spark pre-process, enrich with metadata...

A sample of persisted lines (around 50) of your Cassandra table.

To inspect the data stored in the movie_ratings table of the netflix_ks keyspace, we can use the cqlsh shell interface provided by Apache Cassandra. The following query retrieves approximately 50 rows that were previously persisted by the streaming pipeline:

```
SELECT * FROM netflix_ks.movie_ratings LIMIT 50;
```

This query provides a representative snapshot of the data ingested into Cassandra, including key fields such as name, movie, timestamp, rating, and duration. Analyzing these records ensures data integrity, validates the correctness of the ingestion pipeline, and confirms that the schema design supports the desired querying capabilities. Figure 5 depicts the aforementioned sample.



Figure 5: A sample output of the Cassandra table with 50 persisted entries.

Two CQL queries and their results in your database about your own name and a particular hour that generate the average runtime of the movies that you've rated during this hour, and the names of the movies, respectively.

To support time-based analytics in our Cassandra data model, we designed the schema to partition data by name and hour_bucket, allowing efficient access to all ratings a specific user made during a given hour. The first query retrieves the titles of movies rated by the user *Evangelia Panourgia* during the hour of 2025-03-27 09:00 using a direct lookup on the partition key. The second query, which includes the ALLOW FILTERING clause, calculates the average duration of those rated movies within the same hour. While Cassandra does not natively support aggregations without filtering, our schema minimizes performance issues by narrowing queries to a specific partition, ensuring practical execution even with the filtering clause. Figures 6, 7 depict the respective queries and their outputs.

Figure 6: Names of the movies you rated during a particular hour SELECT movie.

Figure 7: Average duration of the movies you rated during the same hour SELECT avg(duration).

Furthermore, after allowing the real-time streaming process to run for an additional hour, we re-executed the following queries—this time updating the hour_bucket value from 09:00 to **10:00** to reflect the new time window. The Figures 8, 9 depict the respective queries and their outputs.

```
cqlsh:netflix_ks> SELECT movie FROM netflix_ks.movie_ratings
... WHERE name = 'Evangelia Panourgia' AND hour_bucket = '2025-03-27 10:00';

movie

Little Lunch: The Nightmare Before Graduation
Rezeta
Baby Dolls
Clair Obscur
Deadly Scholars

(5 rows)
```

Figure 8: Names of the movies you rated during a particular hour SELECT movie.

```
cqlsh:netflix_ks> SELECT avg(duration) FROM netflix_ks.movie_ratings WHERE name = 'Evangelia Panourgia' AND hour_bucket = '2025-03-27 10:00';

system.avg(duration)

84

(1 rows)
```

Figure 9: Average duration of the movies you rated during the same hour SELECT avg(duration).

Note: It is not necessary to explicitly include conditions such as IS NOT NULL in the CQL queries, as Cassandra automatically excludes null values from aggregation functions like AVG(). Therefore, rows with missing values for the targeted column are implicitly ignored during com-

Hosted on GitHub Repository - Deploy Instructions.

The complete implementation of this project is hosted on GitHub and is publicly accessible at https://github.com/e-panourgia/large-data-kafka-cassandra. The repository contains all necessary components, including Kafka producers, Spark Structured Streaming jobs, and Cassandra schemas. To execute the project, clone the repository using git clone https://github.com/e-panourgia/large-data-kafka-cassandra, then follow the instructions in the README file to set up Docker containers, start Kafka and Cassandra services, and run the streaming application using spark-submit. Ensure that you have installed Docker, Docker Compose, and Spark locally or are running within the provided Vagrant virtual machine for a consistent and reproducible development environment.

Important note, this implementation was designed to run on mac m4 pc.

Open source software (OSS): Contribution to Faker

As part of the Applied Software Engineering course during my BSc studies, I had the opportunity to contribute to the open-source project Faker, a Python library widely used for generating synthetic data. My contribution focused on enhancing the tag-handling functionality, which plays a critical role in structured data generation. Specifically, I improved the way tags are processed within data pipelines, enabling more accurate and flexible population of fields with fake data. This work was incorporated through a merged pull request on GitHub, addressing limitations in tag parsing and significantly improving Faker's usability in scenarios involving automated testing and data anonymization. This contribution was relevant, as Faker was used in our project to auto-generate event data for a producer component.

Acknowledgements

I would like to sincerely thank **Professor Liakos Panayiotis** for his invaluable guidance, support, and dedication throughout the entire teaching process. His insightful lectures and continuous encouragement greatly contributed to the successful completion of this project.