Lab 04: Streaming Data Processing with Spark

CSC14118 Introduction to Big Data 20KHMT1

Contents

1	Lab	04: Streaming Data Processing with Spark	1
	1.1	Lab requirements	1
	1.2	Get the Twitter tweets	1
	1.3	Stream tweets to Apache Spark	5
	1.4	Conclusion	2
		1.4.1 What have we learned?	2
		1.4.2 How well did we do?	2
		1.4.3 What could we have done better?	3
		1.4.4 Self-evaluation	3
	1.5	References	3

1 Lab 04: Streaming Data Processing with Spark

1.1 Lab requirements

The main purpose of this lab is to learn how to use Spark to process streaming data. In this lab, we will use Spark to process streaming data from a Kafka topic. The data is a stream of tweets from Twitter. We will use Spark to process the data and perform sentiment analysis on the tweets.

First, we need the Twitter tweets data.

1.2 Get the Twitter tweets

We will use crawled data of tweets in ChatGPT-Tweets. The easiest way to download the date is using wget command.

!wget -0 tweets.parquet https://huggingface.co/datasets/deberain/ChatGPT-Tweets/resolve/main/data/train-00000-of-00001_-c77acc9ef8da1d50.parquet

Now we have the tweets data in tweets.parquet file. Let's store it in MongoDB. But we need to install mongodb first.

!apt install -qq mongodb
!service mongodb start

We will use pymongo to connect to MongoDB and store the tweets data.

!pip install pymongo

Let's create a dummy datebase to test (refer to Instructor Doan Dinh Toan's strategy).

```
from pymongo import MongoClient
client = MongoClient()

db = client['dummy']
db['chunks'].insert_many([{'Banh xeo': 'Rat ngon'},{'Banh bao': 'Cung ngon'}])
client.list_database_names()
```

```
from pymongo import MongoClient

client = MongoClient()

db = client['dummy']
   db['chunks'].insert_many([{'Banh xeo': 'Rat ngon'},{'Banh bao': 'Cung ngon'}])

client.list_database_names()

['admin', 'config', 'dummy', 'local']
```

Figure 1.1: MongoDB Test

Now let's install Spark and PySpark.

```
!apt-get install openjdk-8-jdk-headless -qq > /dev/null
!wget https://downloads.apache.org/spark/spark-3.4.0/spark-3.4.0-bin-hadoop3.tgz
!tar -xf spark-3.4.0-bin-hadoop3.tgz
!pip install findspark
```

Set the environment variables.

In PYSPARK_SUBMIT_ARGS variable, we have added three different packages:

- org.apache.spark:spark-sql-kafka-0-10_2.12:3.4.0 and org.apache.kafka:kafka-clients:3.4.0 are used to connect to Kafka.
- org.mongodb.spark:mongo-spark-connector_2.12:10.1.1 is used to connect to MongoDB.

Now let's import Spark and start a Spark session.

```
import findspark
findspark.init()
import pyspark

from pyspark.shell import spark
from pyspark import SparkContext, SparkConf

uri = "mongodb://localhost:27017/dummy"
from pyspark.sql import SparkSession

my_spark = SparkSession \
    .builder \
    .appName("csc14112") \
    .config("spark.mongodb.read.connection.uri", uri) \
    .config("spark.mongodb.write.connection.uri", uri) \
    .getOrCreate()
```

Figure 1.2: Start Spark

Let's read the tweets data from tweets.parquet file.

```
tweets_df = my_spark.read.parquet("tweets.parquet")
tweets_df.head()
```

```
[11] tweets_df = my_spark.read.parquet("tweets.parquet")
tweets_df.head()

Row(Date='2023-02-24 07:59:26+00:00', Tweet='How to hire 100x more productive team members for Free? We just interviewed and hired #chatgpt for free
as a team member. \nhttps://t.co/JwlXXKGWKt', Url='https://twitter.com/smnishad/status/1629028212914245632', User='smnishad', UserCreated='2009-03-04
15:50:52+00:00', UserVerified='FALSE', UserFollowers='2524', UserFriends='4966', Retweets='0', Likes='0', Location='New Delhi, India',
UserDescription='Account Planning at Adfactors Advertising')

root
|-- Date: string (nullable = true)
|-- User: string (nullable = true)
|-- User: string (nullable = true)
|-- UserCreated: string (nullable = true)
|-- UserFollowers: string (nullable = true)
|-- UserFriends: string (nullable = true)
|-- UserFriends: string (nullable = true)
|-- UserFriends: string (nullable = true)
|-- Likes: string (nullable = true)
|-- Location: string (nullable = true)
|-- UserDescription: string (nullable = true)
```

Figure 1.3: Read Date

Finnaly, let's store the tweets data in MongoDB.

```
tweets_df.write \
.format("mongodb") \
.option("database", "lab4") \
.option("collection", "tweets") \
.mode("overwrite") \
.save()
```

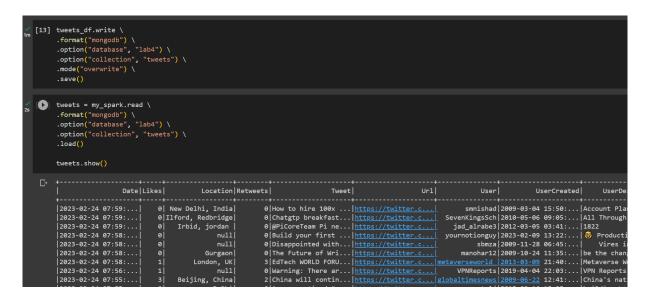


Figure 1.4: Store data in MongoDB

Next, meet Spark's old friend, Kafka.

1.3 Stream tweets to Apache Spark

Install Kafka and kafka-python.

```
!wget https://downloads.apache.org/kafka/3.4.0/kafka_2.12-3.4.0.tgz
!tar -xf kafka_2.12-3.4.0.tgz
!pip install kafka-python
```

Run the instances

```
!./kafka_2.12-3.4.0/bin/zookeeper-server-start.sh -daemon
- ./kafka_2.12-3.4.0/config/zookeeper.properties
!./kafka_2.12-3.4.0/bin/kafka-server-start.sh -daemon
- ./kafka_2.12-3.4.0/config/server.properties
!echo "Waiting for 10 secs until kafka and zookeeper services are up and running"
!sleep 10
```

Figure 1.5: Run Kafka

Create a topic named tweets.

```
!./kafka_2.12-3.4.0/bin/kafka-topics.sh --create --bootstrap-server 127.0.0.1:9092
--replication-factor 1 --partitions 1 --topic tweets
```

```
[18] 1./kafka_2.12-3.4.0/bin/kafka-topics.sh --create --bootstrap-server 127.0.0.1:9092 --replication-factor 1 --partitions 1 --topic tweets

Created topic tweets.

[19] 1./kafka_2.12-3.4.0/bin/kafka-topics.sh --describe --bootstrap-server 127.0.0.1:9092 --topic tweets

Topic: tweets TopicId: oYv7LSDbSHaKnu23xcqPnQ PartitionCount: 1 ReplicationFactor: 1 Configs:

Topic: tweets Partition: 0 Leader: 0 Replicas: 0 Isr: 0
```

Figure 1.6: Create a kafka topic

Now let's set up our Kafka producer.

In the code above, we have created a thread to stream data from MongoDB and push to Kafka. Why do we need to use a thread? Because the date should be pushed to Kafka and processed in parallel. Now let's see how we can consume the data from Kafka.

```
# Define the Kafka topic to read from
KAFKA_TOPIC = "tweets"

# Create a streaming DataFrame that reads from Kafka

df = my_spark \
    .readStream \
    .format("kafka") \
    .option("kafka.bootstrap.servers", "localhost:9092") \
    .option("subscribe", KAFKA_TOPIC) \
    .option("startingOffsets", "earliest") \
    .load()
```

If we print the schema of the DataFrame, we can see that it has 7 different columns.

```
root
|-- key: binary (nullable = true)
|-- value: binary (nullable = true)
|-- topic: string (nullable = true)
|-- partition: integer (nullable = true)
|-- offset: long (nullable = true)
|-- timestamp: timestamp (nullable = true)
|-- timestampType: integer (nullable = true)
```

Figure 1.7: Kafka Schema

But we only need the value column. And in this column, we only want the tweet and date fields. So we need to extract these fields from the value column.

Figure 1.8: Extract fields

It looks good. Now let's see how we can perform sentiment analysis on the tweets. First, let's create a global dateframe to store the result.

Figure 1.9: Global dataframe

This dataframe will store the date, the sum of the scores, the number of tweets, and the average score of the tweets. Now let's create a function to perform sentiment analysis on the tweets.

```
from textblob import TextBlob

def sentiment_analysis(text):
    return TextBlob(text).sentiment.polarity
```

We use the textblob library to perform sentiment analysis. Now let's create a function to process the tweets.

```
convertUDF = udf(lambda z: sentiment_analysis(z), FloatType())

def foreach_batch_function(df, epoch_id):
    global GLOBAL_DF
    temp_df = (
        df.select(col("date"), convertUDF(col("tweet")).alias("score"))
        .groupBy(window("date", "1 day"))
        .agg(
            count("score").alias("score_count"),
            sum("score").alias("score_sum"),
            avg("score").alias("score_avg"),
    )
        .select(
            col("window").start.cast(DateType()).alias("date"),
            col("score_sum"),
```

What the code does is that it takes our dataframe, performs sentiment analysis on each tweet, then group the tweets by date, and calculate the sum, count, and average of the scores. Finally, it combines the result with the global dataframe. Now we can start the stream. But wait, we also need to visualize the result. So let's install dash and plotly, or more accurately, jupyter-dash for Google Colab.

```
!pip install jupyter-dash
```

Set up our dashboard.

In the code above, we have created a dashboard with a Scatter plot. The plot uses the data from the global dataframe and updates every 1 minute. Now let's actually run the job.

First, our dash server's running on port 8081 in Google Colab.

```
app.run_server(port=8081, debug=True, mode='inline') # dash server
```

Second, our producer's thread.

```
p.start() # producer
```

Last, our stream.

```
query = a.writeStream.foreachBatch(foreach_batch_function).start() # consumer and analysis
query.awaitTermination(1200) # run for 20 mins
```

Here is the result.

```
+----+
      date
             score_sum|score_count|
                                          score_avg|
|2022-11-30|13.659312244970351|
                                    80 0.1707414030621294
2022-12-01 227.76981028774753
                                 1533 0.14857782797635194
|2022-12-02| 488.6751429014839|
                                 3533 | 0.13831733453197959 |
2022-12-03 405.1867597522214
                                 3001 0.1350172475015733
2022-12-04 560.2814430227736
                                 4072 0.13759367461266542
2022-12-05 744.2909653562238
                                 5801 | 0.12830390714639264 |
|2022-12-06| 843.0127569913166|
                                 6267 0.13451615717110524
2022-12-07 611.344178639818
                                  4729 0.12927557171491183
|2022-12-08| 648.1176630014088|
                                 4895 | 0.13240401695636544 |
|2022-12-09| 624.5475762507413|
                                 4601 | 0.13574170316251713 |
2022-12-10 431.6898907672148
                                 3306 0.13057770440629607
2022-12-11 356.0624272071291
                                 2857 0.1246280809265415
|2022-12-12|377.93522490165196|
                                 2886 0.13095468638310878
2022-12-13 384.3298166455352
                                  2765 | 0.13899812536909048 |
|2022-12-14| 345.5603205021471|
                                 2658 | 0.13000764503466783 |
2022-12-15 340.2394986238214
                                 2512 0.13544566028018368
2022-12-16 330.8948772518197
                                  2440 0.1356126546114015
2022-12-17 212.17916162637994
                                 1718 | 0.12350358651128052 |
|2022-12-18|151.68795004254207|
                                 1445 0.10497435989103257
2022-12-19 259.63001460745
                                  1791 0.14496371558204912
only showing top 20 rows
```

Figure 1.10: Result

And our plot.

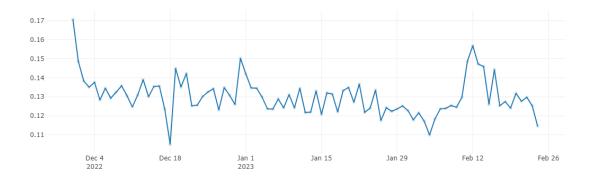


Figure 1.11: Plot

1.4 Conclusion

1.4.1 What have we learned?

- We have learned how to set up MongoDB, Kafka, and Spark.
- We have learned how to push data from MongoDB to Kafka.
- We have learned how to consume data from Kafka and perform sentiment analysis on the data.
- We have learned how to visualize the result using Dash and Plotly.

1.4.2 How well did we do?

We did really well. We have completed all the requirements of the lab. Setting up the environment, getting the data, pushing the data to Kafka, consuming the data from Kafka, performing sentiment analysis on the data, and visualizing the result.

Of course, we encountered a lot of problems during the lab. We could not connect PySpark and Kafka because of the incompatible versions. We didn't know what version to choose, what packages to install. We also didn't know how to visualize the result in Google Colab. But the most difficult problem is that we didn't know how to consume the data in Kafka correctly ('cause it didn't print anything to console). We had to try a lot of different ways and finally, we found the solution.

1.4.3 What could we have done better?

We could have done better if we had more time. We could have analyzed the data more efficient, and tried to visualize the result in different ways. But the main point of this lab is to learn how to use Spark to process streaming data, and we have done that. So we guess it's okay.

1.4.4 Self-evaluation

Here is result that we have done in this lab:

- [100%] Get Twitter tweets
- [100%] Stream tweets to Apache Spark
- [100%] Perform sentiment analysis on the tweets
- [100%] Visualize the analytic results

1.5 References

- Kafka and Spark Streaming in Colab
 - https://colab.research.google.com/github/recohut/notebook/blob/master/_notebooks/2021-06-25-kafka-spark-streaming-colab.ipynb
- Structured Streaming Programming Guide
 - https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html
- Live Graphs with Events Data Visualization GUIs with Dash and Python
 - https://pythonprogramming.net/live-graphs-data-visualization-application-dashpython-tutorial/
- MapReduce Word Count Example
 - https://www.javatpoint.com/mapreduce-word-count-example
- Lab 3: Apache Spark with MongoDB
- All of StackOverflow link related.