COEN 242 Big Data

Project 2

Movie Review Analysis and Twitter Emerging Topic Detector using Apache Spark

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Commands to Run

Part 1

Both Scala applications for Part 1 were run on the Hadoop cluster in client mode. Although the JAR files execute in both client and cluster mode, we specifically chose client mode as it gave more detailed information about CPU time. This information was important for our performance analysis discussed later. The JAR files can be executed on the Hadoop cluster with the following commands.

```
For Query 1:

spark-submit --class Popularity --master yarn-client spark1.jar

<movie_path> <reviews_path> <output_path>

For Query 2:

spark-submit --class Reviews --master yarn-client spark2.jar

<movie_path> <reviews_path> <output_path>
```

Part 2

We ran into issues executing the JAR file for the Twitter emerging topics detector on the Hadoop cluster. When trying both client and cluster mode, YARN was unable to open the class. Thus, we executed the Spark program locally in the Intellij IDE. Our project has the same settings as the example described in the Part 2 help document on semantic analysis. All Intellij project files are included in the submission.

Execution on the Hadoop cluster can be called with the following command.

```
spark-submit --class TwitterAnalyzer --master yarn-client twitter.jar
<consumer_key> <consumer_secret> <access_token> <access_token_secret>
```

Methodology

Movie Reviews

For both queries we used the Spark RDD approach. We verified that both of these queries produced the same results as Project 1.

For Query 1 we first mapped the movie data as a collection of tuples in the form (movieId, movieTitle). We then mapped the review data as a collection in the form of (movieId, 1). We called reduceByKey to aggregate the keys and calculate a reviewCount for output in the form (movieId, reviewCount). To get the movie name in addition to the review count, we joined the mapped reviews and movieIds on the movieId and sorted it in ascending order.

For Query 2 we first mapped the reviews as a tuple (movieId, rating). We then grouped by the key movieId which returns a tuple where the first element is movieId and the second is an array of movie reviews associated with the movieId. Then we mapped that result in the format of (movieId, (averageRating, reviewCount)). We were able to then filter the RDD to remove any movies with 10 or fewer ratings or an average rating before 4.0.

Twitter Semantic Analysis

For the second part of the project, we used a DStream of tweets and stateful streaming to detect emerging topics. Topics are defined as unique hashtags that may appear in tweets. We used sliding windows in order to determine the frequency of topics in different subsets of the Twitter data stream. We used a window duration of 45 seconds and a sliding duration of 15 seconds.

To determine the emerging topic, all the hashtags in the window of tweets were read, mapped, and reduced to calculate the count of unique topics. The data stream is then sorted and the topic with the largest positive difference between states was defined as the emerging topic. To calculate the difference between two windows, we used mapWithState in order to keep a record of the topics counts in the previous window. For a given Twitter topic, the previous count is stored as the state. However, our StateSpec function to update our state also returns a value, the difference in counts. This output from our mapWithState function gives us the data stream to sort and pick the most emergent topic.

Tweets not written in English, as determined by checking the language field of the tweet metadata, or not containing hashtags were not included in our emerging topic windows. Semantic analysis of non-English tweets is less accurate and topics cannot be determined without any hashtags by our given definition.

Code Snippet

The code snippet below provides our implementation of the StateSpec function used for mapWithState and how the topics are mapped and reduced to determine emerging topics. The final statement extracts the emergent topic from the topics data stream.

```
// This function updates the state with the new count
// and returns the difference between the windows in terms of topic frequency
def updateTopicCounts(key: String,
                     value: Option[Int],
                     state: State[Int]): (String, Int) =
 val existingCount: Int =
   state
     .getOption()
     .getOrElse(₀)
 val newCount = value.getOrElse(0)
 state.update(newCount)
 (key, newCount - existingCount)
// Define our StateSpec function to be called by mapWithState
val stateSpec = StateSpec.function(updateTopicCounts _)
// map and count the frequency of topics in the hashtags, sort in descending order by count
val topics = window.flatMap(t => t("hashtags").asInstanceOf[Array[String]])
    .map(h => (h, 1))
    .reduceByKey(_+_)
    .mapWithState(stateSpec)
    .map{case (topic, count) => (count, topic)}
    .transform(_.sortByKey(false))
var emergingTopic = ""
// use rdd.take to extract the first topic which is the one with the highest difference
topics.foreachRDD(rdd => {
 val top = rdd.take(1)
 top.foreach{case (count, topic) => emergingTopic = topic}
})
```

Results

Query 1 Output

```
## Montry Python and the Holy Grail (1975)

## Montry Python and the Holy Grail (1975)

## Good Will Hunting (1997)

## Oark Knight, The (2008)**

## Took Knight, The (2008)**

## Oark Knight, The (2008)**

## Oark Knight, The (2008)**

## Oark For Holy William (1975)*

## Oark Holy William (1975)*

## Oark Hold William (1975)*

## Oark Holy William (1976)*

## Oa
                                                                                                                                                                                                                                                                                Redemption, The (1994)'
```

Query 2 Output

```
Query 2 Output

Patrix, The (1997)* 4, 154698255515649 77969

Worthy Python and the Holy Gen'l (1975) 4, 15513873726253 39058

Memento (2006) 4, 157077887986335 49769

Touch of Evil (1988) 4, 15727887986335 49769

To Kill a Mockinghird (1962) 4, 157694981114388 17374

Chintonan (1974) 4, 15771931944245 18377

Inception (2019) 4, 167559578596878 35297

M (1931) 4, 1655547867842 4873

Taception (2019) 4, 1655547867842 4873

Taception (2019) 4, 1655547867842 4873

Tale (1984) 4, 1675557666869 5468

Notorious (1946) 4, 16715575666869 5468

Notorious (1946) 4, 16715575766869 5468

Notorious (1946) 4, 167157575766869 5478

Notorious (1946) 4, 1878367574689 5489

Notorious (1946) 4, 18783675786789891 4, 187836786972772 13994

Notorious (1946) 4, 187836757878 1896

Notorious (1946) 4, 18783677878 1896

Notorious (1946) 4, 187836778778 1896

Notorious (1946) 4, 187836778778 1896

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Notorious (1946) 4, 187836787788 1896

Notorious (1946) 4, 187836778778 1896

Notorious (
```

Twitter Emerging Topic Output

As evidenced in this output for #ForniteE3, many of the tweets share the same content. It appears there was a sweepstakes that required a tweet for entry, with an easily available auto-generated message. However, you will notice that since the hashtags array of strings is not printed out, they're memory locations are printed instead, showing these are in fact unique tweets even though they share the same content. To make this more obvious, we reintroduced the user field to our mapped tweets so it is more obvious. An example of the new option can be found below for topic #BTSxCorden.

```
Map(sentiment → NEUTRAL, text → RT @aegyotaetae: baby boy culture  #BTSxCorden https://t.co/8UJe4PcNEf, language → en, user → BTSmusicNsujin, hashtags → [Ljava.lang.String;@6e757c79]
Map(sentiment → NEGATIVE, text → Jimin didn't open the door to green room HE OPENED IT TO HELL #BTSxCorden, language → en, user → jinddicted, hashtags → [Ljava.lang.String;@509259f]
Map(sentiment → NEUTRAL, text → RT @latelateshow: BTS HAVE ARRIVED TO THE #LATELATESHOW! #BTSxCorden https://t.co/9qcklZ0eZ, language → en, user → kymmb11, hashtags → [Ljava.lang.String;@307cf944]
Map(sentiment → NEUTRAL, text → #BTSxCorden MY BABES LOOK AMAZINGGG, language → en, user → Isabellaxvy, hashtags → [Ljava.lang.String;@13125ab3)
Map(sentiment → NEUTRAL, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NEUTRAL, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #Map(sentiment → NECATIVE, text → RT @btsvotingteam: #BTSxCorden in few minutes!  #BTSxCorden in few minu
```

Performance Analysis

Below are the times recorded to run both queries from Part 1 in our MapReduce implementation, as well as our Spark RDD implementation. The programs were run on the large dataset. We used real time as a comparison because it is the most obvious measure of performance experienced by the programmer. Real time measurements for the MapReduce jobs were extracted from the counters Hadoop tracks. For Spark, real time was calculated using the Linux time command.

| Framework | Query | Real Time |
|-----------|---------|-----------|
| MapReduce | Query 1 | 343.130s |
| | Query 2 | 305.740s |
| Charle | Query 1 | 55.496s |
| Spark | Query 2 | 46.015s |

It is clear, the Spark implementations greatly outperform the MapReduce jobs. This difference in execution time is due largely to Spark storing intermediate data representations in memory and limiting the amount of I/O calls. This allows Spark to finish jobs much faster since I/O is the largest bottleneck.

To further document the Spark behavior, we also recorded the amount of CPU time spent on all tasks for the Spark programs. These times are divided into time spent on computations in tasks, time spent sorting intermediate results, and total execution time.

| Query | Computations | Sorting | Total |
|---------|--------------|---------|----------|
| Query 1 | 51.305s | 50.665s | 101.970s |
| Query 2 | 70.002s | 40.125s | 110.127s |

From this table, we can see significant time was spent on sorting the results. In query 1 for instance, almost half of the total execution time is spent sorting results. This highlights just how intensive sorting results is for a given program. Query 2 uses a smaller portion of its total execution time for sorting. This result conforms to expectations since there are significantly fewer records produced for query 2 than query 1; 387 records compared to 45,115 records.