Large Scale Parallel Data Processing – Spring 2019

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GitHub repo: <https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing>

Submission for : HW1

**Hadoop Map-Reduce Implementation**

**Source code :** https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/MR-Demo

**Psuedo Code:**

**Step 1**:

Take input file and output file dir as input from the user:

FileInputFormat.*addInputPath*(job, **new** Path(args[0]));

**Step 2: Mapper phase**

The mapper implementation via map method, processes one line at a time, as provide in the file

It then splits the line into two tokens separated by "," and selects the first word(User ID) and emits a key-value pair as <User-ID,1>

**public** **void** map(**final** Object key, **final** Text value, **final** Context context) **throws** IOException, InterruptedException {

**final** StringTokenizer itr = **new** StringTokenizer(value.toString());

**while** (itr.hasMoreTokens()) {

// Split each line of the csv by "," and take the first word as the input

word.set(itr.nextToken().split(",")[0]);

context.write(word, ***one***);

}

}

**Step 3: Combiner phase**:

We have also specified a combiner. Hence, the output of each map is passed through the local combiner for local aggregation, after being sorted on the keys.

job.setCombinerClass(IntSumReducer.**class**);

**Step 4: Reducer phase:**

The Reducer implementation, via the reduce method just sums up the values, which are the occurrence counts for each key.

@Override

**public** **void** reduce(**final** Text key, **final** Iterable<IntWritable> values, **final** Context context) **throws** IOException, InterruptedException {

**int** sum = 0;

**for** (**final** IntWritable val : values) {

sum += val.get();

}

result.set(sum);

context.write(key, result);}

**Step 5: Output:**

Once jobs are completed the result is saved as output in the directory specified by the user.

FileOutputFormat.*setOutputPath*(job, **new** Path(args[1]));

**General Idea:**

* My program assumes the its output is a csv file in the format of userid, follow’s userid.
* It takes input as a csv file.
* The TokenizerMapper helps to read the input line by line.
* Each line is then split by “,” using the set function and the first word is selected to be the key
* the map function spits out a <userid, id> after reading each line.
* The output of the local mapper then goes to the local combiner for sorting.
* The local combiner sorts the value of the map based on the key.
* The reduce method is use to sum up the occurrence of each key emitted by all the map.
* This way we can find all the occurences of the userids in edges.csv and we can find how many followers each user has.

**Spark Scala Implementation**

**Source :** https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/Spark-Demo

Note : I have used RDD APIs for the implementation.

**Psuedo Code:**

1) Reads the input from the text file and tokenises

**val** textFile = sc.textFile(args(0))

2) Each token(Each line) is split by “,” and we select the first word(userID).

**val** counts = textFile.map(line => line.split(",")(0))

3) The mapping phase just takes the userID as input and spits out <userID, 1> as a key value pair

.map(word => (word, 1))

4) In the reduce phase the number of occurrences of userid key is stored as

<userid, number of occurences>

.reduceByKey(\_ + \_)

5) We save the sparks RDD’s logical exectution plan by the following snippet of code

**val** file = **new** File("log.txt")

**val** bw = **new** BufferedWriter(**new** FileWriter(file))

bw.write(counts.toDebugString)

bw.close()

counts.saveAsTextFile(args(1))

The output is as follows:

(40) ShuffledRDD[4] at reduceByKey at WordCount.scala:30 []

+-(40) MapPartitionsRDD[3] at map at WordCount.scala:29 []

| MapPartitionsRDD[2] at map at WordCount.scala:28 []

| input/edges.csv MapPartitionsRDD[1] at textFile at WordCount.scala:27 []

| input/edges.csv HadoopRDD[0] at textFile at WordCount.scala:27 []

**Running Time Measurements**

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**Logs for map reduce run 1**

[**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/blob/master/Important%20logs/hadoop%201/syslog**](https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/blob/master/Important logs/hadoop 1/syslog)

**Logs for map reduce run 2**

[**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/blob/master/Important%20logs/hadoop2/syslog**](https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/blob/master/Important logs/hadoop2/syslog)

**Output :**

[**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/MR-Demo/output**](https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/MR-Demo/output)

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**Logs for spark scala run 1**

[**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/Important%20logs/spark%201**](https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/Important logs/spark 1)

**Logs for spark scala run 2**

**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/Important%20logs/spark%202**

**Output :**

**https://github.ccs.neu.edu/vaibhavdave5/parallelDataProcessing/tree/master/Spark-Demo/output**

**Question**

Measure the running time of each program. Repeat the time measurements one more time, starting each program from scratch as a new job. Report all 2 programs \* 2 independent runs = 4 running times you measured

1) Runtime for run 1 – Map-Reduce - 1.6 min

Total time spent by all maps in occupied slots (ms)=55838448

Total time spent by all reduces in occupied slots (ms)=13295904

Total time spent by all map tasks (ms)=1163301

Total time spent by all reduce tasks (ms)=138499

Total vcore-milliseconds taken by all map tasks=1163301

Total vcore-milliseconds taken by all reduce tasks=138499

Total megabyte-milliseconds taken by all map tasks=1786830336

Total megabyte-milliseconds taken by all reduce tasks=425468928

2) Runtime for run 2 – Map-Reduce – 1.7 min

Total time spent by all maps in occupied slots (ms)=54659760

Total time spent by all reduces in occupied slots (ms)=12879744

Total time spent by all map tasks (ms)=1138745

Total time spent by all reduce tasks (ms)=134164

Total vcore-milliseconds taken by all map tasks=1138745

Total vcore-milliseconds taken by all reduce tasks=134164

Total megabyte-milliseconds taken by all map tasks=1749112320

Total megabyte-milliseconds taken by all reduce tasks=412151808

1) Runtime for run 1 – Spark-scala – 1.1 min

2) Runtime for run 2 – Spark-scala – 1.1 min

**Question:**

**Report the amount of data transferred to the Mappers, from Mappers to Reducers, and from Reducers to output. There should be 3 numbers. (3 points)**

**For map reduce run -1**

Date transferred to mappers -1319507620

Mappers to reducers – 955121298

Reducers to Output - 87376129

**For map reduce run - 2**

Date transferred to mappers -1319487591

Mappers to reducers – 955121298

Reducers to Output - 87376129

**Question**

Argue briefly, why or why not your MapReduce program is expected to have good speedup. Make sure you discuss (i) how many tasks were executed in each stage and (ii) if there is a part of your program that is inherently sequential (see discussion of Amdahl’s Law in the module.)

Conceptually:

Speedup = sequentialTime / parallelTime

1) Number of Map task - 20

2) Number of reduce task - 9