Queen Mary
University of London

ECS765 Big Data Processing
Coursework 1: Twitter Analysis with Map Reduce

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MSc Big Data Science, ECS765

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1.1. MapReduce

1.1.1. Mapper

```
String[] fields = value.toString().split(";");


  if (fields.length == 4){
      tweetLen = fields[2].length();
      if ((tweetLen >= 1) && (tweetLen <= 140)){
          double val = (double) tweetLen;
          data.set((int) Math.ceil(tweetLen/5));
          context.write(data, one);

   }
```

Figure 1: Snippet from Message Length Mapper code

The Mapper job processes the Olympic tweets (input data) that's stored on the Hadoop Distributed File System (HDFS). It takes the input data line by line, computing the correct bin for each tweet.

As shown in the first line of code in fig. 1, the split method was used to divide the input data into the tweet elements (epoch_time, tweet ID, tweet message and device type) on the delimiter ";". The divided elements were stored in an array. An if statement was used to iterate over the divided elements and retrieve the four elements that form the tweet.

The "tweetLen" variable in fig. 1 stored the extracted 3rd element of every 4 with length method applied. The 3rd element (index 2 of the array) was the tweet message and the length method computed the total number of characters in the message. An if statement nested within the first if statement filtered out any tweet message without a valid length (of 1, 140 or any value in between. When the if condition was met the correct bin was calculated.

The bins for each valid tweet was calculated by dividing the message length by the class width 5. This simplified the problem and assigned each tweet with a bin between 1 and 28. The ceil function was applied to round up the tweet length/5 float point to the nearest integer value. This ensured that each tweet was assigned to the correct bin (e.g. message length 136 was assigned to bin 28).

The processed data is emitted through context.write() to the reducer, as smaller chunks of key/value pairs in a serialised fashion. The first argument K2 and second argument V2 of the context.write() function represented the bin and one respectively.

1.1.2. Reducer

```
int len = 0;

for (IntWritable value : values) {

    len += value.get();

}

result.set(len);
context.write(key, result);
```

Figure 2: Snippet from Message Length Reducer code

After the shuffle and sort phase, the Reducer job receives K2/V2 pairs from the mapper as its inputs. A for loop is executed for each K2/V2 pair. The for loop simply sums the frequency of each bin with a counter that increments by 1 for each occurrence.

The context.write function emits K3 and V3 as a list, where K3 is the bins and V3 is the frequency of the corresponding bin. The list of K3/V3 pairs is saved on the Hadoop Distributed File System (HDFS).

1.2. Results: Frequency of Message Length

The MapReduce job aggregated the bins, which was saved in a text file. Excel was used to import the data in the text file and sort by bins in ascending order. Labels was then assigned to each corresponding bin e.g. bin 28 was labelled "136 – 140".

Bins	Class (Tweet Lengths)	Frequency
1	1 - 5	11200
2	6 - 10	7645
3	11 - 15	26024
4	16 - 20	73461
5	21 - 25	181833
6	26 - 30	309019
7	31 - 35	345659
8	36 - 40	386889
9	41 - 45	428841
10	46 - 50	481598
11	51 - 55	497100
12	56 - 60	587357
13	61 - 65	610618
14	66 - 70	709109
15	71 - 75	683743
16	76 - 80	746501
17	81 - 85	806405
18	86 - 90	875538
19	91 - 95	918900
20	96 - 100	923181
21	101 - 105	917333
22	106 - 110	959870
23	111 - 115	1023777
24	116 - 120	1076193
25	121 - 125	1181781
26	126 - 130	1337609
27	131 - 135	2021925
28	136 - 140	6411788

1.3. Histogram Plot

Excel was used to generate the histogram for the aggregated bins. It represents the distribution of the tweet message lengths, ready to support deeper data analysis.

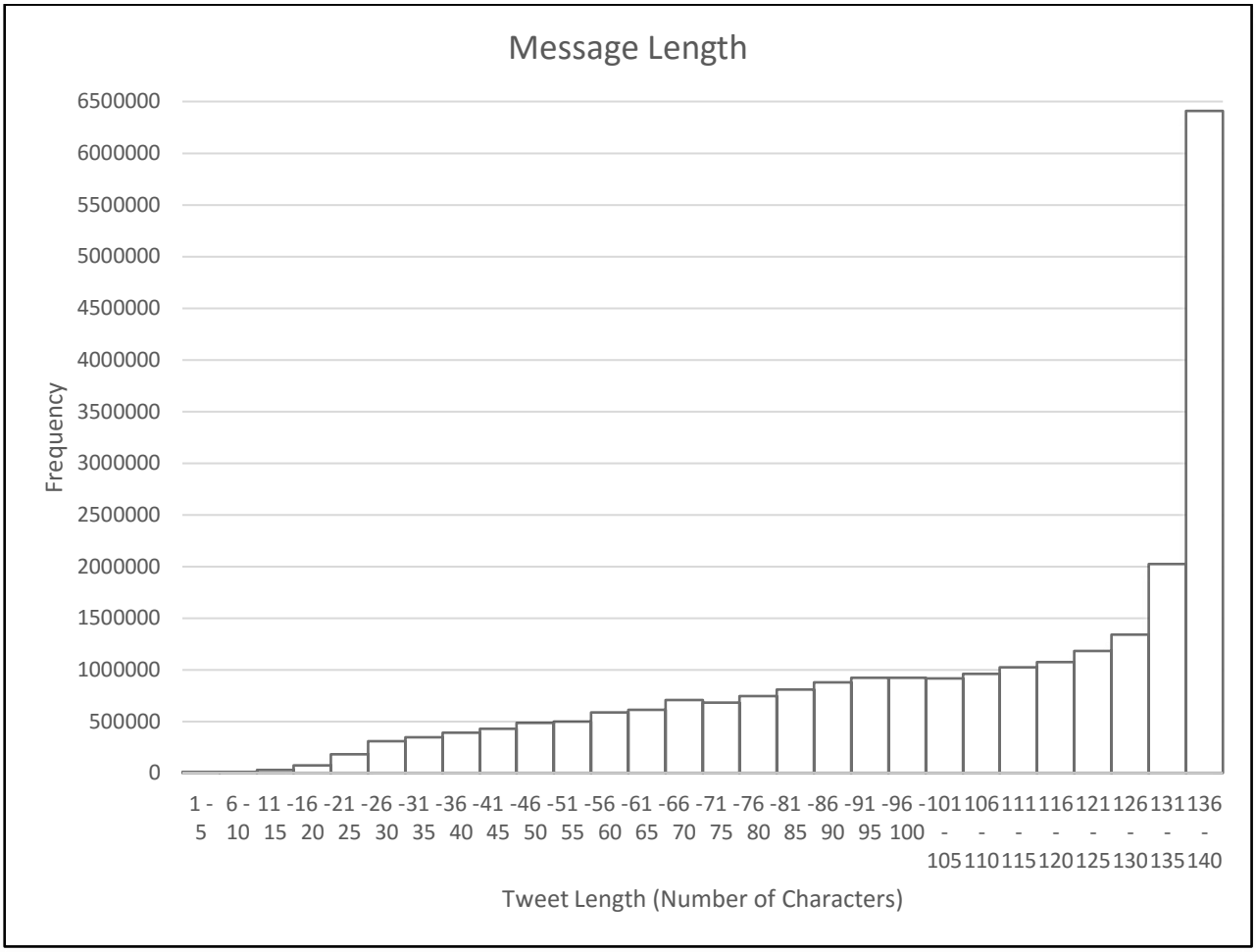


Figure 3: Histogram for distribution of tweet message lengths

2. Part B: Time Analysis

2.1. MapReduce

2.1.1. Mapper

```
try{
      String[] fields = value.toString().split(";");

      if (fields.length == 4){


          long epochTime =  Long.parseLong(fields[0]);
          LocalDateTime dateTime = LocalDateTime.ofEpochSecond(epochTime/1000, 0, ZoneOffset.UTC);
          hours = dateTime.getHour();


          if (hours == 1){
            Pattern hashtag = Pattern.compile("(#\\w+)\\b");
            Matcher mat = hashtag.matcher(fields[2].toLowerCase());

            while (mat.find()){
              data.set(mat.group());
              context.write(data, one);


            }
          }

        }

       }
  catch(Exception e) {

  }
}
```

Figure 4: Snippet from Time Analysis Mapper code

The Mapper job processes the Olympic tweets (input data) that's stored on the Hadoop Distributed File System (HDFS). It takes the input data line by line, computing number of tweets that were posted each hour of the event. It then filtered the tweet messages that occurred at 1am (the most popular hour of the Olympic games) leaving only the hashtags used.

As shown as the first try statement in fig. 4, the split method was used to divide the input data into the tweet elements (epoch_time, tweet ID, tweet message and device type) on the delimiter ";". The divided elements were stored in an array. An if statement was used to iterate over the divided elements and retrieve the four elements that form the tweet.

The "epochTime" variable in fig. 4 stored the extracted 1st element of every 4. The 1st element (index 0 of the array) contained the epoch time expressed in milliseconds. The epoch time in each tweet is declared as a float point data type and then divided by 1000 to convert the units to seconds.

The "ofEpochSecond" function is used to compute the data and time since 01/01/1970. This was used to convert the epoch time of each tweet into a date and time, in the format YYYY-MM-DD HH:MM:SS. The time zone was set to UTC for outputting the local time in the UK. The "getHour" method was used to get the specific hour for each tweet, based on the output of the "ofEpochSecond".

An if statement nested within the first if statement filtered out tweets, excepts the tweets that occurred at 1am (the most popular hour of the games). The Pattern.compile function is used to define any hashtag (pattern), characterised by a hash symbol and the subsequent characters before a space. The matcher method matches the defined hashtag to the tweet message (index 2 of the tweet array). The find and group methods are used to search for occurrences of the defined pattern and repeats the process for each tweet message in the input data.

The processed data is emitted through context.write() to the reducer, as smaller chunks of key/value pairs in a serialised fashion. The first argument K2 and second argument V2 of the context.write() function represented the hashtags found and one respectively.

2.1.2. Reducer

```
int count = 0;

for (IntWritable value : values) {

    count += value.get();

}

    result.set(count);
    context.write(key, result);
```

Figure 5: Snippet from Time Analysis Reducer code

After the shuffle and sort phase, the Reducer job receives K2/V2 pairs from the mapper as its inputs. A for loop is executed for each K2/V2 pair. The for loop simply sums the frequency of the tweets or each hashtag with a counter that increments by 1 for each occurrence.

The context.write function emits K3 and V3 as a list, where K3 is the hashtags and V3 is the frequency of the corresponding hashtags. The list of K3/V3 pairs is saved on the Hadoop Distributed File System (HDFS).

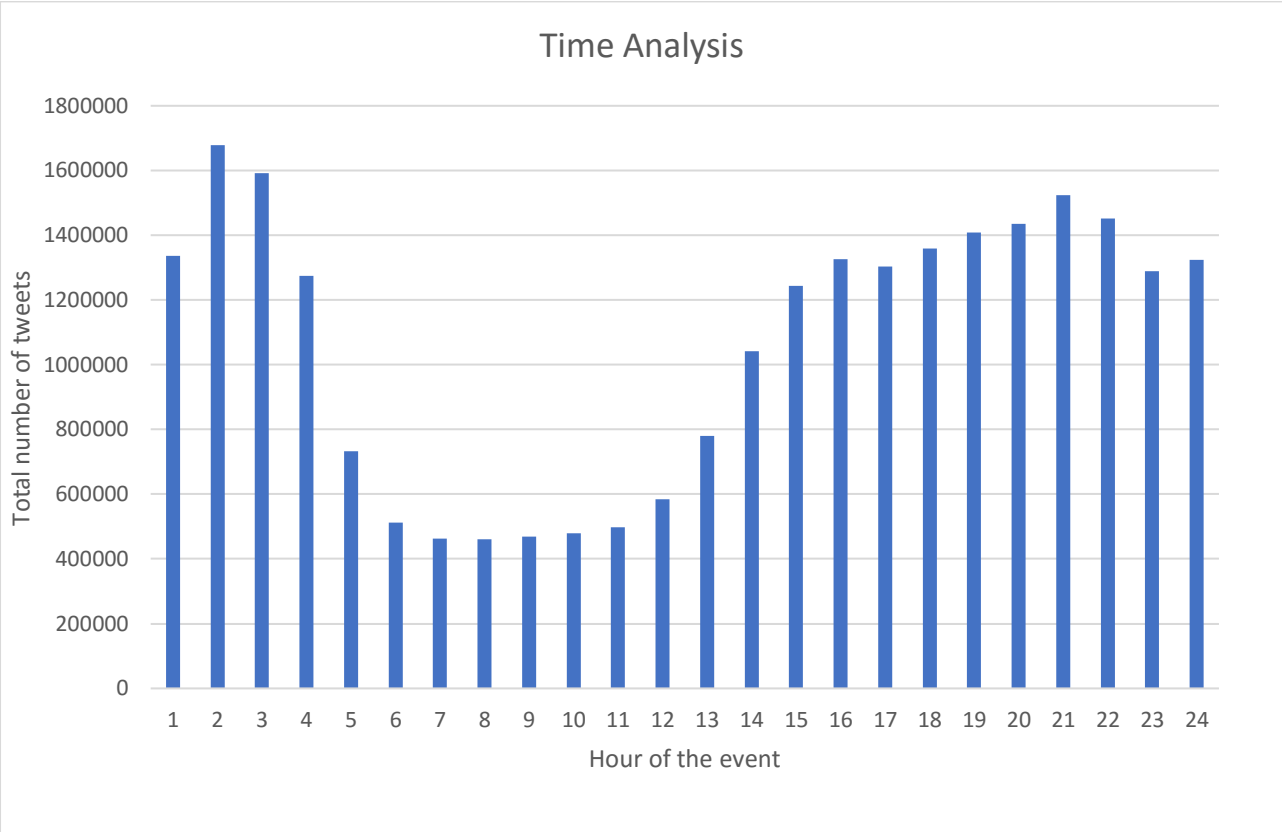
2.2. Results: Frequency of Tweets each Hour

The MapReduce job aggregated together all the messages sent at the same hour, which was saved in a text file. Excel was used to import the data in the text file and sort by hours in ascending order.

Hours	Total number of tweets
0	1335522
1	1677571
2	1592418
3	1274876
4	733462
5	512754
6	463271
7	460629
8	469869
9	479094
10	497403
11	584556
12	780445
13	1041557
14	1244185
15	1325675
16	1304166
17	1359317
18	1408453
19	1434978
20	1522919
21	1451945
22	1288767
23	1324717

2.3. Bar plot

Excel was used to generate the bar plot for the frequency of tweets each hour. This allows us to make quick and accurate conclusions about the data, including that the prime time of tweets about the events was between 1am and 2am (UK time).



2.4. Results: Top Ten Hash Tags

The MapReduce job aggregated together all the hashtags used within tweet messages between 1am and 2am, which was saved in a text file. Excel was used to import the data in the text file and sort by frequency in descending order. The table below shows the top ten hashtags of the hour.

Hash Tag	Frequency
#rio2016	1449246
#olympics	91756
#gold	68144
#bra	50263
#futebol	49365
#usa	42754
#oro	40899
#swimming	36649
#cerimoniadeabertura	36499
#openingceremony	35974

3. Part C: Support Analysis

3.1. MapReduce

3.1.1. Mapper

```
String[] fields = value.toString().split(";");

if (fields.length == 4){

    for (String athlete : companyInfo.keySet()){
                    //tweet containing athlete names
                    if (fields[2].contains(athlete)) {
                        data.set(athlete);
                        context.write(data, one);
                    }
            }
    }
```

Figure 6: Snippet from Support Analysis Mapper code

The Mapper job processes the Olympic tweets (input data) that's stored on the Hadoop Distributed File System (HDFS). It takes the input data line by line, computing number of mentions for athlete names or sports in the tweet message.

The split method was used to divide the input data into the tweet elements (epoch_time, tweet ID, tweet message and device type) on the delimiter ";". The divided elements was stored in an array. An if statement was used to iterate over the divided elements and retrieve the four elements that form the tweet. A nested for loop was used iterate over the rows in the second dataset medalistrio.csv. The required columns name (index 1) and sport (index 7) was selected with the put method, as shown in fig. 7. The if statement nested within the for loop was used emit all athlete names or sports mentioned in the tweet message.

The processed data is emitted through context.write() to the reducer, as smaller chunks of key/value pairs in a serialised fashion. The first argument K2 and second argument V2 of the context.write() function represented the athlete names or sports mentioned and one respectively.

```
// Fields are: 0:id 1:name 2:nationality 3:sex 4:dob 5:height 6:weight 7:sport 8:gold 9:silver 10:bronze
if (fields.length == 11)
    companyInfo.put(fields[1], fields[0]);
```

Figure 7: Extracting required columns in medalistrio.csv

3.1.2. Reducer

```
int count = 0;

for (IntWritable value : values) {

    count += value.get();

}

result.set(count);
context.write(key, result);
```

Figure 8: Snippet from Support Analysis Reducer code

After the shuffle and sort phase, the Reducer job receives K2/V2 pairs from the mapper as its inputs. A for loop is executed for each K2/V2 pair. The for loop simply sums the frequency of mentions for athlete names or sport with a counter that increments by 1 for each occurrence.

The context.write function emits K3 and V3 as a list, where K3 is the hashtags and V3 is the frequency of the corresponding athlete names or sport. The list of K3/V3 pairs is saved on the Hadoop Distributed File System (HDFS).

3.2. Results: Top 30 Athletes Mentioned

The MapReduce job aggregated together all the athletes mentioned within tweet messages, which was saved in a text file. Excel was used to import the data in the text file and sort by total mentions in descending order. The table below shows the top 30 athletes based on mentions.

Athletes	Total Mentions
Michael Phelps	181167
Usain Bolt	170647
Neymar	100853
Simone Biles	79300
William	53262
Ryan Lochte	40773
Katie Ledecky	37885
Yulimar Rojas	34443
Simone Manuel	27367
Joseph Schooling	26467
Sakshi Malik	24644
Rafaela Silva	22805
Andy Murray	21776
Kevin Durant	21263
Tontowi Ahmad	20428
Liliyana Natsir	19905
Wayde van Niekerk	18343
Penny Oleksiak	17575
Monica Puig	17208
Rafael Nadal	16120
Laura Trott	16098
Ruth Beitia	14930
Teddy Riner	13995
Lilly King	13279
Shaunae Miller	12250
Jason Kenny	12140
Elaine Thompson	12111
Caster Semenya	11675
Almaz Ayana	11092
Allyson Felix	11066

3.3. Results: Top 20 Sports Mentioned

The MapReduce job aggregated together all the sports mentioned within tweet messages, which was saved in a text file. Excel was used to import the data in the text file and sort by total mentions in descending order. The table below shows the top 20 sports based on mentions.

Sports	Total Mentions
badminton	325781
volleyball	280069
basketball	188228
judo	141142
gymnastics	140805
tennis	135169
football	130891
hockey	107961
handball	93221
cycling	79909
rowing	59023
wrestling	57560
golf	55657
athletics	53799
boxing	49316
fencing	39338
shooting	38820
weightlifting	36684
triathlon	28888
sailing	21579