Queen Mary – University of London

ECS640U/ECS765- Big Data Processing- 2016/17
Coursework 1
Twitter analysis with Map Reduce

Student name: **Ivaylo Shalev**
Programme: **MSc Big Data Science – Part Time**
Student ID: **ec16544**
ECSS user ID: **iss30**

<u>Content of the folder</u>

Files:

- **Ivaylo Shalev - Coursework 1 - Twitter analysis with Map Reduce – Answers.docx** – this document.
- **CourseWork Helper.txt** – helping file containing java compile, Hadoop commands and some results.
- **countries_lookup.csv** – lookup file containing a list of countries used for the final task.

Folders:

- **logs** – contains the latest Hadoop log files from the execution of each job from the cluster.
- **out** – contains the latest output (result) files of the Hadoop jobs of each job from the cluster and xlsx file containing the result tables with data and graphs.
- **src_xxx** – folders containing the java source codes (*.java) for each task.

<u>Explanation of the approaches taken</u>

1) Preparation

Before starting with part A, I decided to first explore the data format, see how to extract the individual fields and evaluate, test the solution. I used the tail and head commands of Hadoop -fs from command line to see some of the rows, however the only way to go through the whole file and extract statistics was by creating a map-reduce job. The source code for it, is inside the src_prep folder and the log and output files are with post-fix "prep".

Based on observation and nature of the data (date, id, text) I found some rules, which can be used to determine if a row from the file is a good example of a row or not. The rules explanation is found in the source code of the mapper.

This job helped me determine these rules and see how many good and bad rows there are. I separated all scenarios into 5 groups:

- **A) Good row** – the row is perfect; all 4 columns exist and are with the expected size and doesn't contain delimiters in the tweet message.
- **B) Invalid row** – the row has 4 columns, but some of them doesn't have the expected size – we can't be 100% sure that the first field contains date information.
- **C) Good row - more than 4** – all fields in the row have the expected format, except that the tweet message column contains delimiter(s). This is OK. The message still can be used, just need to be careful when extracting the whole tweet message.
- **D) More than 4** – the row contains more than 4 fields (more than 3 delimiters) and some of the columns doesn't obey the rules – we can't be 100% sure that the first field contains date information.
- **E) Bad row** – all other scenarios. The row contains less than 3 delimiters. These seems to be rows of tweet messages, with EOL (LF) character in the message, which makes it be processed by Hadoop as new line. There is an option in Hadoop do define a custom class for splitting the data by custom rule and not by LF, but I haven't implemented it as the number of such rows was very small (0.2%) compared with the volume of good ones.

Based on this analysis, I included these rules in all consequent map-reduce jobs and choose to process only the rows from scenarios **A** and **C**, which in total gives **25 697 010** rows.

To make it easier, I kept the names of the source code files the same, but the content is different in each folder.

Results:

bad row	51 093
good row	**25 568 510**
invalid row	39
good row - more than 4	**128 500**
more than 4	2

2) Part A

I split this part into 2 sub tasks A1 and A2. A1 is handling the histogram, A2 is handling the average.

A1

The approach I took was creating a standard map-reduce job with mapper having as key the number of characters (length) of the Tweet message (IntWritable) and as Value the number of encounters (count). The reducer is simply summing the counts per key and outputs the key and count. Because of this format the reducer is used also as combiner to make the whole job faster and more effective.

For the key part, which is aggregating the length of the messages into blocks of 5 I used the round function floor which is rounding to the lower number. In this way by dividing by 5 and rounding and after that multiplying by 5 will round the size of the message to a number exactly dividable by 5.

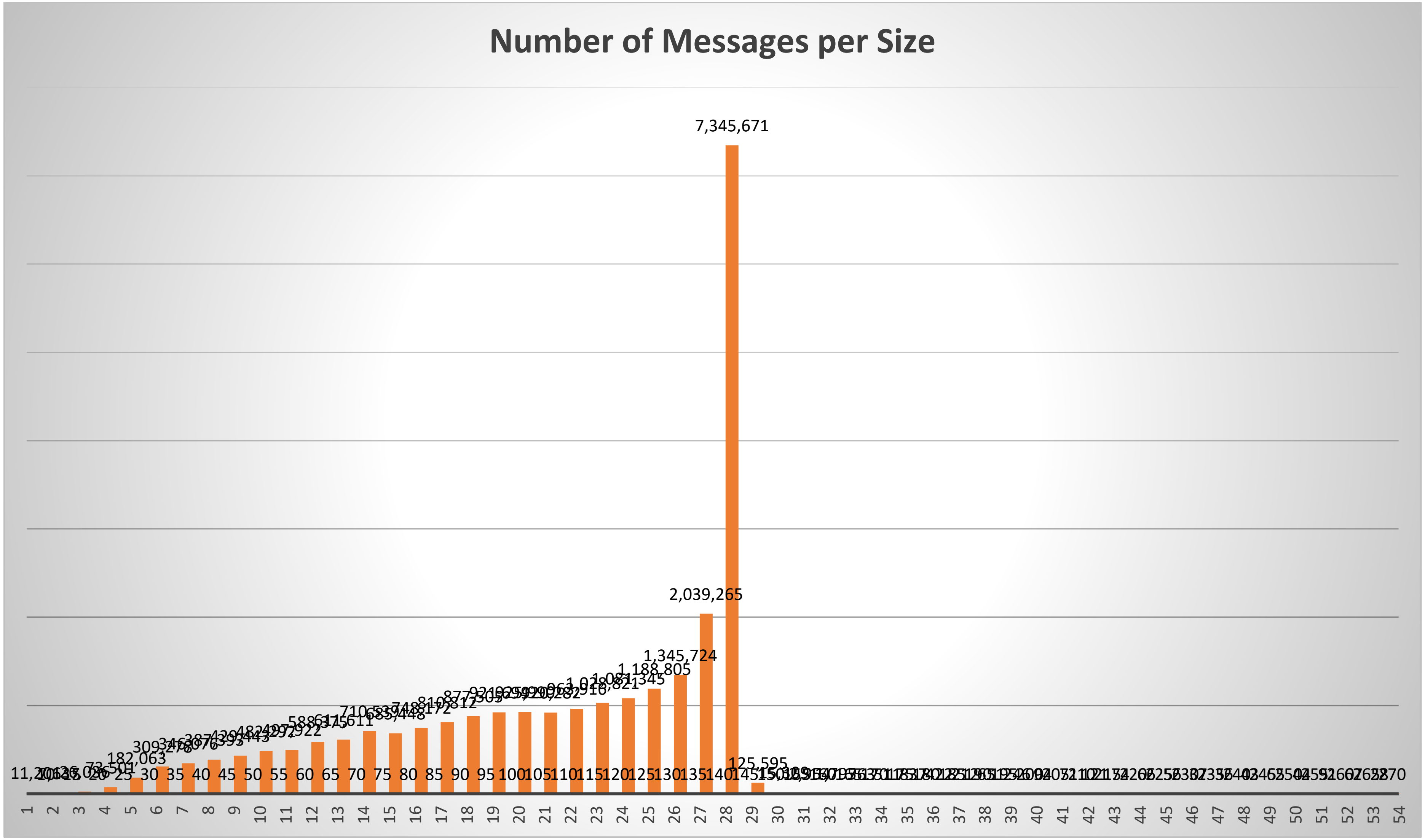
I decided to display the messages with a bit higher amount of data and they are not so much higher and not so many.

Notice, that the total matches the total from the prep job.

Results:

length of the message	number of messages
5	11,201
10	7,637
15	26,036
20	73,501
25	182,063
30	309,278
35	346,076
40	387,393
45	429,443
50	482,292
55	497,922
60	588,375
65	611,611
70	710,539
75	685,448
80	748,172
85	810,812
90	877,505
95	921,694
100	925,990
105	920,282
110	963,916
115	1,028,821
120	1,081,345
125	1,188,805
130	1,345,724
135	2,039,265
140	7,345,671
145	125,595
150	15,309
155	2,954
160	1,795
165	763
170	511
175	837
180	422
185	212
190	651
195	246
200	94
205	71
210	121
215	74
220	66
225	56
230	37
235	36
240	43
245	65

250	44
255	91
260	67
265	28
270	5
Total	**25,697,010**


Number of Messages per Size
7,345,671
2,039,265
1,345,724
1,188,805
125,595

A2

The approach I took for this task was using the IntIntPair custom class as value for the mapper and used Text as key. The key contains just a static text and the IntIntPair will contain the actual size of the message with the count (1). The actual sum and calculation is done inside the reducer. The average is calculated by summing the counts of all lengths and dividing it by the summing of the lengths of all messages.

To make the output more descriptive I choose the key to be "Results:" and added some text in the reducer emit procedure.

The reason to separate this task from the first was, that because the first task is aggregating the length of the messages to 5, when I do an average it will not be accurate using this rounded values (it will be smaller than the real one). In order to get an exact average we have to use the exact length of the messages.

As a validation notice that the total amount of messages is the same as total from A1 task.

Results:

Results	
Total Tweet Messages length	2,817,785,678
Total Number of Tweet Messages	25,697,010
Average Length of Tweet Messages	**109**

3) Part B

The approach I used to this task was similar to the approach of task A1, with the difference that for this task the key is of type Text. In the mapper I extract and convert the epoch_time value to text with UK date format "dd/MM/yyyy" as this is good enough to be used as key for a day. I use the SimpleDateFormat class to transform the date to string.

The reducer is simply summing the counts and is also used as combiner.

You can see the diagram and the data in the xlsx file.

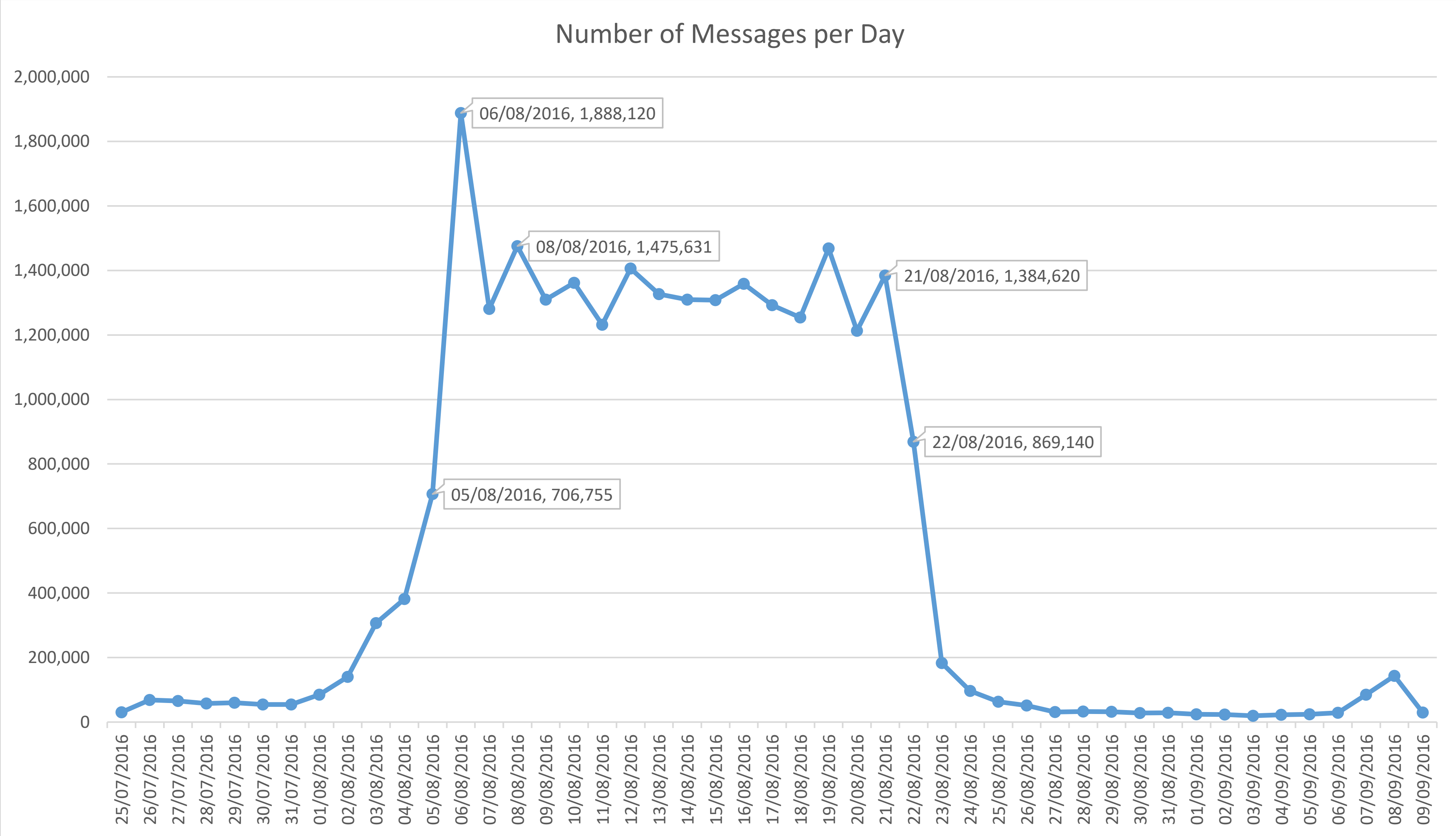
The diagram correctly shows that the peaks of the tweets were during the opening ceremony (05-06/Aug) and all the way until the closing ceremony on 21/Aug.

And again as validation, the total of messages matches the totals from part A.

Results:

Tweet Date	Number Of Messages
25/07/2016	30,254
26/07/2016	68,687
27/07/2016	65,311
28/07/2016	57,263
29/07/2016	59,966
30/07/2016	54,776
31/07/2016	54,618
01/08/2016	85,209
02/08/2016	140,093
03/08/2016	306,930
04/08/2016	381,688

05/08/2016	706,755
06/08/2016	1,888,120
07/08/2016	1,281,008
08/08/2016	1,475,631
09/08/2016	1,309,407
10/08/2016	1,361,399
11/08/2016	1,231,989
12/08/2016	1,405,747
13/08/2016	1,326,582
14/08/2016	1,309,606
15/08/2016	1,308,216
16/08/2016	1,358,456
17/08/2016	1,292,562
18/08/2016	1,254,470
19/08/2016	1,468,455
20/08/2016	1,212,817
21/08/2016	1,384,620
22/08/2016	869,140
23/08/2016	183,314
24/08/2016	96,168
25/08/2016	62,892
26/08/2016	51,510
27/08/2016	31,312
28/08/2016	33,056
29/08/2016	31,999
30/08/2016	28,373
31/08/2016	28,674
01/09/2016	24,277
02/09/2016	23,411
03/09/2016	19,453
04/09/2016	22,722
05/09/2016	24,109
06/09/2016	28,719
07/09/2016	84,473
08/09/2016	143,419
09/09/2016	29,354
Total	**25,697,010**


Number of Messages per Day
2,000,000
1,800,000
1,600,000
1,400,000
1,200,000
1,000,000
800,000
600,000
400,000
200,000
0
06/08/2016, 1,888,120
08/08/2016, 1,475,631
21/08/2016, 1,384,620
22/08/2016, 869,140
05/08/2016, 706,755
25/07/2016
26/07/2016
27/07/2016
28/07/2016
29/07/2016
30/07/2016
31/07/2016
01/08/2016
02/08/2016
03/08/2016
04/08/2016
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27/08/2016
28/08/2016
29/08/2016
30/08/2016
31/08/2016
01/09/2016
02/09/2016
03/09/2016
04/09/2016
05/09/2016
06/09/2016
07/09/2016
08/09/2016
09/09/2016

4) Part C

The output of this task is list of countries and number of encounters: Text and IntWritable.

For this task I used similar IntSumReducer as in the previous jobs, which is just summing-up the number of encounters of a given country, and therefore the it is used as a combiner too.

For this task I also use a replication join using a CSV file as a list of countries with their names in lowercase and in their native language.

The most of the coding and calculation is done inside the mapper. It's doing the following manipulations:

- Caching the lookup data - countries.
- Extracting hashtags data.
- Filtering and formatting hashtags data.
- Executing Normal, Pre and Post key words matching.

Before coming to conclusion what approach to use, my first version of this job was without a lookup, but rather a job that was just extracting the hashtags and formatting them in order to have some idea of additional pre and post key words. I executed these initial tests on the local Hadoop environment using the example file.

Caching phase

This phase is executed once per node in the beginning. To make sure all is good I created also one custom counter to show the total amount of countries read from the CSV file. As the counter is incremented by each mapper this amount becomes high. When executing it on the local, as there is just one mapper it gives the amount of countries: 752. On the cluster as the data is split usually into 44 parts, the counter shows: 33 088.

I decided to use a lookup, as It's more elegant solution, there are small number of rows and gives an option to update it. The other option is to have this list hardcoded into the code, which is never the best solution. The CSV file is UTF-8 decoded as it contains different languages from all countries. This special property is important as it should be in the code when opening the file (otherwise the text from the file will not match those from the input).

Here is the UTF-8 bit: isr = new InputStreamReader(in, "UTF8");

The file has 5 fields. The idea behind it is to gives us ability to match the hashtag by 4 ways:

- English (latin) name of the country - field 3 first 270 rows.
- Native name of the country - field 3 last 270 rows.
- 2 letters code of the country – field 4.
- 3 letters code of the country – field 5.
- Field 1 is ID of the row.
- Field 2 is the Full name of the Country in English – used as output data.

I use 4 hash table variables to store all these pairs of data:

- countryFullName – contains the ID as key and ID concatenated with Full Name as value (this is to make the value unique because the Full Name is repeated few times in the file – one for English and one for the Native).

- countryName – contains the name of the country (enlglish or native) as key (if there isn't one puts empty string) and the ID as value.
- countryISO2 – contains the 2 characters country code as key and the ID as value.
- countryISO3 – contains the 3 characters country code as key and the ID as value.

The first hash table is used as an output at the end when the data is emitted to send the full country name. The other 3 are used for matching with the hashtag.

Extraction phase

There are few methods of extracting hashtags from a string, from which a tempting one is using regular expressions. However, they can be a bit of a black box for even experienced programmers (at least will take a while for one to understand what a given regular expression is exactly doing). That's why I decided to create a function which will parse the whole string and extract the hash tags. The name of the function is **GetAllHashTags**. Basically in there I also declare the definition of a hashtag: A hashtag starts with the symbol # and ends with the symbol space (" ") or beginning of another hashtag (#). This function receives as parameter a string and thus returns a list of hashtags. The list can be of size 0 – if no hashtags are found.

Filtering and formatting phase

As we are after hashtags which represent a country, there should not be any punctuation in the beginning or the end of them. For this task, I use a simple regular expression to remove these and format the hashtag and by this also removing the symbol "#" and at the end formatting it to lower case. Now the hashtags are ready to start matching.

Matching phase

This is the main part of the solution. Based on my observation of the data I decided to use the following methods of detecting a given hashtag which country is supporting:

- if the hashtag is the name of the country in English: #Bulgaria
- if the hashtag is the name of the country in its native language: #българия
- if the hashtag is the 2 or 3 character code of the country: #bg #brg
- if the hashtag starts with a set of key words and then ends with either: the English name, native name, 2 or 3 character code: #GoBulgaria, #Teamбългария, #WeAreBG, #IloveBGR I found few more key words than the suggested "go" and "team" which are used in the tweets (see the source code).
- if the hashtag starts with either: the English name, native name, 2 or 3 character code and then ends with a set of key words: #BulgariaTeam, #българияTeam, #BGteam, #BGRteam

Benefits:

- it's doing a controlled matching, with lower chance of mistakenly match of country with another word.
- It's dynamic as it's using a lookup file.

Cons:

- As it's not a fuzzy match, it might miss scenarios where the country word is in the middle of the hashtag.

- About the key words, most of them I found are in English and few in Portuguese and Spanish. By doing this I miss to match a lot other languages, but it's just a matter of time and effort finding these key words in the other languages. Also this list can be done as a lookup.

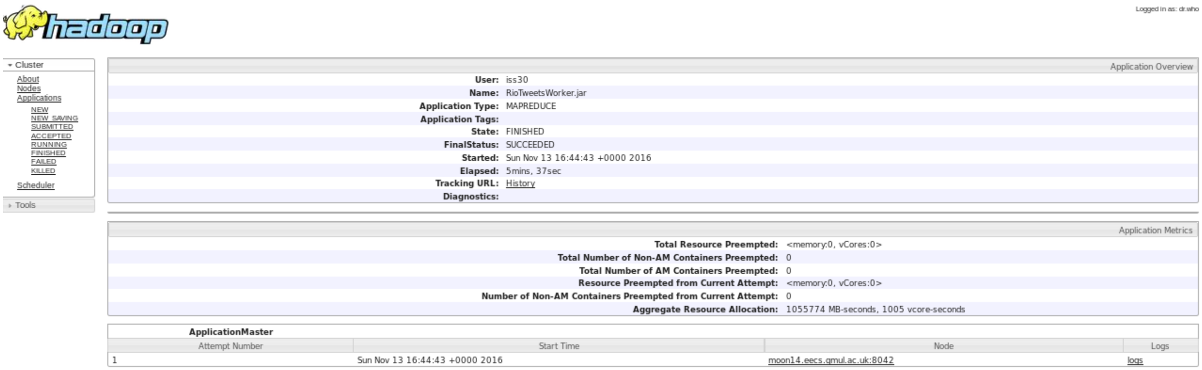
Results:

I had to do few test on the local Hadoop environment. In the source code you will see one block which is commented as one of my tests. This is in order to test my code and see what is missing and what is picked up. In the out folder you'll find 3 txt files (bdp_course_work_c …) with results.

- The USA one is a test one just printing all hashtags picked up as USA.
- The v1 is the first version of the results – there were some duplicated countries.
- The final one is the one I used for the results.

The total number of hashtags decoded as supporting some country is **5.7** million. This is about **23%** compared with the number of rows.

Execution duration of the job: 5min 37sec. (during rush hour)



The stats:

Country	Number Of Hashtags
United States	870,261
Brazil	816,313
Spain	394,759
Argentina	363,033
Great Britain	326,513
Canada	230,042
Italy	219,957
Mexico	190,169
India	174,467
France	165,074
China	147,381
Colombia	138,564
Japan	124,851
Serbia	117,488
Australia	116,476
Venezuela	114,036
Jamaica	111,245
Russian Federation	88,057

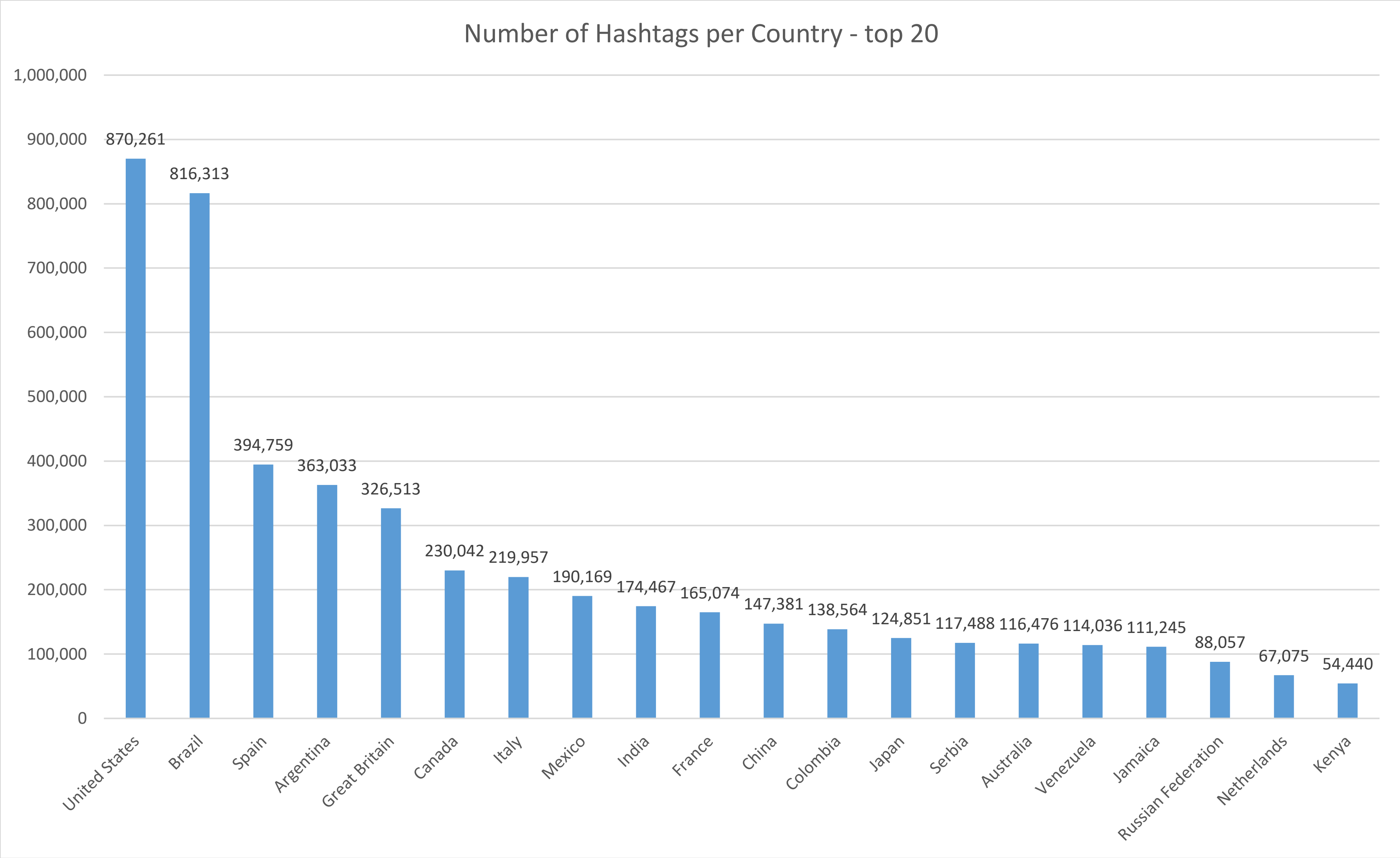
Netherlands	67,075
Kenya	54,440
Refugee Olympic Team	49,266
Poland	40,863
Sweden	40,626
Thailand	40,304
Turkey	39,072
Republic of Korea	34,746
Belgium	32,958
Ireland	28,174
New Zealand	28,072
Ecuador	24,446
Egypt	24,016
Malaysia	23,191
Cuba	21,199
Jordan	18,054
Nigeria	17,337
Ethiopia	13,345
Hungary	12,961
Honduras	12,590
Israel	12,101
Ukraine	11,912
Lithuania	11,547
Austria	11,546
Puerto Rico	10,545
Côte d'Ivoire	10,375
Germany	10,092
Panama	10,020
Iraq	9,678
Bahrain	9,021
Saudi Arabia	9,016
Tonga	8,708
Greece	8,316
Fiji	8,218
Tunisia	7,914
Andorra	7,783
Czech Republic	7,690
Paraguay	7,607
Peru	7,568
Trinidad and Tobago	7,517
Armenia	7,486
Dominican Republic	7,369
Ghana	7,072
Romania	6,924
Cameroon	6,493
Montenegro	6,014
Uzbekistan	5,921
Kazakhstan	5,267
Qatar	5,241
Iran	5,129
Indonesia	4,950
Chile	4,423

Azerbaijan	4,083
Portugal	3,997
Senegal	3,949
Belarus	3,885
Hong Kong (China)	3,870
Norway	3,766
Uganda	3,520
Burundi	3,438
Singapore	3,259
Algeria	3,189
Georgia	2,945
South Africa	2,877
Bulgaria	2,550
Croatia	2,530
Morocco	2,464
British Indian Ocean Territory	2,346
Bolivia	2,125
Finland	2,073
Philippines	2,058
Pakistan	2,045
Estonia	1,896
Grenada	1,828
Macao (China)	1,748
DPR Korea	1,738
Slovakia	1,698
Afghanistan	1,645
Mongolia	1,579
Tuvalu	1,469
Botswana	1,454
Bahamas	1,443
Zimbabwe	1,415
Sudan	1,413
Nepal	1,366
Kuwait	1,363
Haiti	1,344
Denmark	1,338
Cyprus	1,247
Switzerland	1,211
Namibia	1,101
Somalia	1,065
Eritrea	1,060
Lebanon	1,034
Uruguay	1,018
South Sudan	985
Maldives	965
Brunei	934
Sri Lanka	928
Guatemala	905
Rwanda	889
Kyrgyzstan	881
Oman	880
Libya	852

Mali	847
Angola	846
South Georgia and the South Sandwich Islands	814
Kiribati	807
DR Congo	800
Gabon	746
Bosnia and Herzegovina	738
Albania	720
Niger	694
Syria	662
Luxembourg	647
Costa Rica	597
Vietnam	589
Anguilla	585
Barbados	572
Myanmar	545
Moldova	545
Jersey	527
Yemen	526
Djibouti	488
Netherlands Antilles	485
Bermuda	474
Latvia	446
Benin	445
Northern Mariana Islands	425
Suriname	399
Macedonia	382
Nicaragua	379
El Salvador	371
Guyana	370
Guadeloupe	365
Iceland	362
Monaco	350
Micronesia (FS)	350
Saint Barthélemy	347
Papua New Guinea	342
Slovenia	341
Taiwan (ROC)	330
Tajikistan	317
Samoa	315
Sierra Leone	314
Laos	306
Cape Verde	293
Liberia	289
Vatican City	265
Nauru	263
Mozambique	258
Martinique	249
Saint Lucia	249
Belize	241
Togo	226
Marshall Islands	216

Malta	213
Palau	211
Guam	210
Western Sahara	210
Antigua and Barbuda	199
Tanzania	199
Bhutan	191
Lesotho	191
Gambia	180
Bangladesh	170
Central African Republic	169
Chad	169
Guinea	166
Malawi	165
San Marino	163
Dominica	160
American Samoa	158
Cook Islands	154
Comoros	152
Liechtenstein	143
Turkmenistan	142
Zambia	135
Cambodia	132
Aruba	121
Réunion	119
Congo	115
Mauritius	113
Aland Islands	110
Saint Pierre and Miquelon	102
Palestinian Territory, Occupied	98
Madagascar	95
Timor-Leste	93
Saint Vincent and Grenadines	91
Kosovo	88
The Bahamas	88
Montserrat	80
Swaziland	75
Burkina Faso	74
Christmas Island	71
Seychelles	71
Vanuatu	66
Guinea-Bissau	63
Guernsey	61
Mauritania	54
Isle of Man	51
Cayman Islands	46
French Guiana	40
US Virgin Islands	40
Gibraltar	40
Heard Island and Mcdonald Islands	39
Equatorial Guinea	36
The Gambia	36

British Virgin Islands	31
New Caledonia	31
Saint Helena	31
Cocos Islands	29
Sao Tome and Principe	28
Antarctica	27
United Arab Emirates	26
Turks and Caicos Islands	23
Niue	22
Faroe Islands	21
Mayotte	20
Svalbard	20
Tokelau	18
Solomon Islands	17
French Polynesia	16
US Minor Outlying Islands	13
East Timor	12
French Southern Territories	9
Greenland	9
Saint Kitts and Nevis	7
Sahrawi Arab Democratic Republic	6
Saint Martin	6
Norfolk Island	4
Falkland Islands	3
Pitcairn Islands	3
Wallis and Futuna Islands	3
Curaçao	1
Total	**5,723,198**


Number of Hashtags per Country - top 20
1,000,000
900,000
800,000
700,000
600,000
500,000
400,000
300,000
200,000
100,000
0
870,261
816,313
394,759
363,033
326,513
230,042
219,957
190,169
174,467
165,074
147,381
138,564
124,851
117,488
116,476
114,036
111,245
88,057
67,075
54,440
United States
Brazil
Spain
Argentina
Great Britain
Canada
Italy
Mexico
India
France
China
Colombia
Japan
Serbia
Australia
Venezuela
Jamaica
Russian Federation
Netherlands
Kenya

In conclusion

The country with most support was **USA**, but close to it is **Brasil**. If adding more keywords its possible that Brazil will overcome USA in the results.

One of the obvious questions is why there are 253 countries detected if there were just 208 countries in the Olympics present?

There were hashtags supporting countries, which were not officially on the list of countries (at least on the Olympics website). Like Macao (China). There are hashtags gomacao, goma, etc.

But on the other side there are hashtags of other words which gets decoded as countries. Like the 3 character code of “British Indian Ocean Territory” is “iot”, but IOT also can mean Internet Of Things.

I did a check and there are total of 47 countries from this list which are not present on the official Olympics list. This means 253 – 47 = **205 countries detected**. Just 3 countries short.

Map/Reduce is a powerful technique and solution which makes such analysis very easy, effective and very close to the reality. Most of the time I had to spend with cleaning and formatting the input data, lookup data and keywords. The actual coding and execution of the job were the less time consuming. I think the approach I used is a good balance between time invested in cleaning data against receiving good enough approximation of the result.

Sources used

- List of countries and codes – http://www.nationsonline.org/oneworld/country_code_list.htm
- List of countries in their native language – https://en.wikipedia.org/wiki/List_of_countries_and_dependencies_and_their_capitals_in_native_languages
- List of countries in the Olympics - https://www.rio2016.com/en/countries#favorite-countries