2. Hadoop and Spark Setup

2.1 Hadoop Setup

Command:

hadoop jar /usr/lib/hadoop-mapreduce/hadoop-mapreduce-examples.jar grep input output 'dfs[a-z.]+'

```
Output 'dfs[a-z.]+'

[hodopspir-17-3:1-5e-22 hadops] bin/hodop jar /usr/lib/hadop-mapreduce/hadoop-mapreduce-examples.jar grep input output 'dfs[a-z.]+'
17/04/81 is:19:19 lNF0 inpl. imeline(lientImpl: Timeline service address: http://ip-172-31-56-22.ec2.internal:8188/ms/v1/timeline/
17/04/81 is:51:19 lNF0 inpl. imeline(lientImpl: Timeline service address: http://ip-172-31-56-22.ec2.internal/172.31.56.22:8032
17/04/81 is:51:20 lNF0 inpl. tileInputFonours: Total input paths to process: s
17/04/81 is:51:20 lNF0 izo.CPUNctiveCodeLoader: Loaded native gpl library
17/04/81 is:51:20 lNF0 izo.Codec: Successfully loaded & initialized native-lzo library [hadoop-lzo rev 30eccced8ce8c483445f0ao3175ce725831ff06b]
17/04/81 is:51:20 lNF0 mapreduce.Job/sumitter: number of splits:8
17/04/81 is:51:20 lNF0 impl. varnCitentImpl: Submitted application application.1491245129359_0001
17/04/81 is:51:20 lNF0 impl. varnCitentImpl: Submitted application application.1491245129359_0001
17/04/81 is:51:21 lNF0 mapreduce.Job: The unit to track the job: http://pi-172-31-56-22.ec2.internal:20888/groxy/application_1491245129359_0001
17/04/81 is:51:21 lNF0 mapreduce.Job: mp job.ju-1491245129359_0001
17/04/81 is:51:22 lNF0 mapreduce.Job: mp job.ju-1491245129359_0001
17/04/81 is:51:29 lNF0 mapreduce.Job: mp job.ju-1491245129359_0001
17/04/81 is:51:29 lNF0 mapreduce.Job: mp job.ju-1491245129359_0001
17/04/81 is:51:40 lNF0 mapreduce.Job: mp job.ju-1491245129359_0001
17/04/81 is:51:51 lNF0 mapreduce.Job: mp job.ju-14912451293
```

```
[hadoop@ip-172-31-56-22 hadoop]$ hdfs dfs -cat output/part-r-00000
2
        dfs.hosts.exclude
        dfs.datanode.available
1
        dfs.namenode.https
1
        dfsadmin
1
        dfs.namenode.plugins
1
        dfs.datanode.max.xcievers
1
        dfs.permissions.superusergroup
1
        dfs.namenode.handler.count
        dfs.datanode.plugins
        dfs.replication
1
        dfs.data.dir
1
        dfs.namenode.safemode.extension
1
        dfs.encryption.key.provider.uri
1
        dfs.server.datanode.fsdataset.
1
        dfs.datanode.du.reserved
1
        dfs.namenode.name.dir
1
        dfs.name.dir
1
        dfs.webhdfs.enabled
1
        dfs.namenode.http
1
        dfs.datanode.fsdataset.volume.choosing.policy
1
        dfs.datanode.data.dir
        dfs.namenode.rpc
```

Explanation:

This command extracts strings that match a regular expression from input files and counts how many times they occurred, sorts matching strings by their frequency and writes the output in output file.

The argument input identifies input directory path and output identifies output directory path. Argument 'dfs[a-z.]+' is a regular expression that matches the character sequence 'dfs' (case sensitive) followed by any characters in the range between a and z and '.' one or more times.

The program runs map and reduce jobs in sequence. Map job takes a line as input and matches the regex against the line, with output as (matching string, 1). Reducer job takes the output from mapper and sums the frequency of each matching string and the output is (matching string, frequency).

2.2 Spark Setup

Command:

```
>>> rdd=sc.parallelize(range(10000000))
>>> rdd.takeSample(False,10)
[Stage 0:> (0 + 0) / 4]17/04/03 19:03:12 WARN TaskSetManager: Stage 0 contains a t ask of very large size (12130 KB). The maximum recommended task size is 100 KB.
17/04/03 19:03:13 WARN TaskSetManager: Stage 1 contains a task of very large size (12130 KB). The maximum recommended task size is 100 KB.
[8643435, 6704656, 2380813, 6520879, 7053948, 4182820, 7147427, 7767040, 1886445, 6780719]
```

Explanation:

sc means SparkContext, which tells Spark how and where to access a cluster. We should use SparkContext to create RDDs. We don't have to initialize it in pyspark shell because it automatically create SparkContext for us.

3. MapReduce Programming for Finding Degree Distribution in Graphs Undirected graph

3.1

The mapper takes each line (nodeX -- nodeY) as input and produces output as (nodeX, 1) and (nodeY, 1). The reducer takes the output from mapper and sums the frequency based on key. The output would be (node, frequency).

3.2

Mapper output:

- (1, 1)(2, 1)
- (1, 1)(3, 1)
- (3, 1)(4, 1)
- (1, 1)(4, 1)
- (9, 1)(7, 1)
- (5, 1)(6, 1)
- (7, 1)(5, 1)
- (7, 1)(6, 1)

- (1, 1)(9, 1)
- (8, 1)(9, 1)

Reducer output:

- (1,4)
- (2,1)
- (3,2)
- (4,2)
- (5,2)
- (6,2)
- (7,3)
- (8,1)
- (9,3)

Directed graph

3.3

The mapper takes each line (node $X \rightarrow$ node Y) as input and produces output as (node Y, 1). The reducer takes (node Y, 1) as input and sums the frequency based on node Y, the output is (node Y, frequency).

3.4

Mapper output:

- (2,1)
- (3,1)
- (4,1)
- (4,1)
- (7,1)
- (6,1)
- (5,1)
- (6,1)
- (9,1)
- (9,1)

Reducer output:

- (2,1)
- (3,1)
- (4,2)
- (5,1)
- (6,2)
- (7,1)
- (9,2)

4. Computing Degree Distribution in Hadoop

4.1

```
[hadoop@ip-172-31-24-108 hadoop]$ hdfs dfs -moveFromLocal /localinput/com-friendster.ungraph.txt input [hadoop@ip-172-31-24-108 hadoop]$ hdfs dfs -ls /input ls: `/input': No such file or directory [hadoop@ip-172-31-24-108 hadoop]$ hdfs dfs -ls input Found 1 items -rw-r--r- 2 hadoop hadoop 32364651652 2017-04-04 13:43 input/com-friendster.ungraph.txt [hadoop@ip-172-31-24-108 hadoop]$
```

4.2

Both moveFromLocal and put commands copy files from local file system to HDFS. The difference is that put command copies the file and keeps the original one while moveFromLocal command moves the file to HDFS and deletes the original one.

4.3

See code at BlackBoard.

4.4

It sorted the id of nodes (key) in ascending order.

4.5

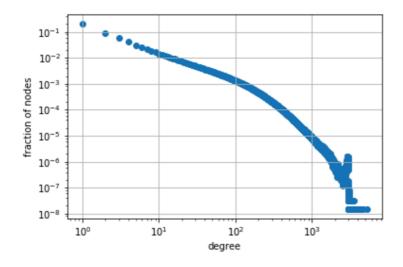
See code at BlackBoard.

4.6

```
1 71768986,5214
 2 54083823,4667
 3 54118654,4488
 4 89750075,4406
 5 54085211,4333
 6 54118345,4214
7 7688909,4006
 8 19713658,3897
9 54086114,3891
10 10278129,3829
11 106212071,3722
12 7123984,3707
13 45360334,3570
14 6879541,3562
15 20366275,3561
16 45032137,3553
17 25849922,3553
18 34557675,3544
19 33529861,3525
20 59858810,3507
21 41937494,3458
22 76883100,3440
23 57394902,3430
24 13701967,3426
25 81272200,3423
26 28596706,3392
27 52736481,3377
28 59033707,3346
29 52736401,3336
30 113966763,3316
31 44632351,3316
32 49787738,3306
33 63715953,3289
34 6821999,3286
35 3653464,3286
36 31742320,3280
```

```
37 29364051,3279
38 25722722,3247
39 85554090,3235
40 37384478,3225
41 24605639,3224
42 79188771,3223
43 20943522,3219
44 46191989,3217
45 35364707,3214
46 12628503,3208
47 32892161,3206
48 8046960,3197
49 35393926,3196
50 27830575,3192
51 44848860,3189
52 25265623,3183
53 23382015,3180
54 11304056,3176
55 12132865,3176
56 68344538,3171
57 18419444,3171
58 37491512,3170
59 36291316,3166
60 73976135,3164
61 37872400,3159
62 52840255,3156
63 14008201,3150
64 24307738,3141
65 64782691,3141
66 36542244,3132
67 62168417,3129
68 16324321,3127
69 76056267,3127
70 37748346,3124
71 63915702,3121
72 33961320,3120
73 30139434,3119
74 38906012,3117
75 94826493,3116
76 35018189,3115
77 76358513,3111
78 61429407,3111
79 46598206,3109
80 36947798,3105
81 90608504,3103
82 27089370,3102
83 26388641,3102
84 16209345,3099
85 49203749,3097
86 35816339,3096
87 39171857,3094
88 76461293,3094
89 45338224,3094
90 43571592,3094
91 37883265,3093
92 40203014,3092
93 65925160,3091
94 55704705,3090
95 44014655,3089
96 13085298,3088
97 66911524,3084
98 117227284,3084
99 21594966,3084
.00 6261933,3081
```

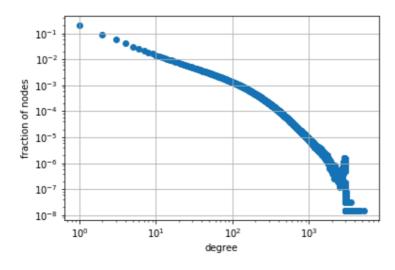
4.7 **Plot:**



5. Computing Degree Distribution in Spark

See code at BlackBoard.

Plot:



6. About Hadoop and Spark

6.1 Explain the concept of lazy evaluation employed by Apache Spark. How does it allow Spark to optimize the execution of code?

Lazy evaluation means Spark remembers the operation we tell it to do on the dataset, but it absolutely evaluates nothing until we take an action operation.

This allows Spark to optimize the memory and disk usage. Spark will understand the entire instruction chain as a whole, figure out the final answer it needs to evaluate and how much work it has to do, and "does the right thing" based on the information. However, if Spark does evaluation step by step explicitly as the instructions we give, it will hold a lot of intermediate datasets and results in memory which will increase GC costs.

6.2 Explain how you can pin an RDD in main memory in Spark using an RDD function. Describe a simple programming use case where such explicit pinning of an RDD in main memory will improve runtime execution.

We can use rdd.cache() to store the computed result of rdd in memory thus we don't need to re-compute it every time. For example, if we want to do sentiment analysis where the label of dataset is either positive or negative. Then after we load the dataset using sc.textFile() and split the line by flatMap(), we are going to count the number of positive instances and that of negative instances. If we do not cache, Spark will reload the data for both posCount and negCount operation. However, if we do cache after RDD is created in flatMap step, the processing done previously will be stored and reused.

6.3 During a Spark program execution, one of the slaves died and partitions of RDDs stored on the slave were lost. Will Spark re-compute the entire RDD or only the partitions? Explain briefly how Spark will carry out this RDD recovery.

Spark will re-compute only the partitions. RDDs are designed to recover from worker failures as they have a long lineage graph and can regain their state by re-computing lost blocks using the prior information based on lineage.

Also, in case of slave failure, if the executor fails it will be re-launched automatically; if the receiver fails it will re-started by the worker and actually the data received by receiver is replicated on another slave.

6.4 Give a simple example of a summary statistic that is difficult to compute using Apache Hadoop MapReduce programming but can be easily computed using Apache Spark. (Hint: MapReduce programming is limited to map and reduce functions, while Spark incorporates many other functions that are calculated over all elements in the RDD.)

For example, we have a sentiment dataset with twitter, sentiment, hashtag as attributes and we want to calculate the difference between the number of positive instances and that of negative ones on each hashtag.

References:

http://www.michael-noll.com/tutorials/writing-an-hadoop-mapreduce-program-in-python/

http://stackoverflow.com/questions/28981359/why-do-we-need-to-call-cache-or-persist-on-a-rdd

https://www.sigmoid.com/fault-tolerant-stream-processing/