Università di Pisa

SCUOLA DI INGEGNERIA

Corso di Laurea in Artificial Intelligence and Data Engineering

Cloud Computing project: The k-means Clustering Algorithm in MapReduce

Candidati Alice Nannini Fabio Malloggi Marco Parola Stefano Poleggi Relatore

Dr. Nicola Tonellotto

Contents

1	Introduction	1
2	Dataset	1
3	MapReduce pseudo-code	2
4	Hadoop Implementation and Tests	3
5	Spark Implementation and Tests	3
6	Conclusions	3

1 Introduction

This project presents the implementation of the k-means algorithm based on a MapReduce version, using both the Hadoop framework both the Spark framework.

The two implementations of the k-means algorithm developed must be performed with the following inputs:

- Name of the input file containing the dataset
- Number of centroids/clusters
- Output directory
- Number of total samples in the input dataset (the algorithm can be run assuming that you know this value)

The algorithm exit can occur due to two events:

- The maximum number of possible iteration has been reached
- The centroids calculated at i-th step and i+1-th step do not deviate beyond a certain threshold (Euclidean norm)

2 Dataset

The datasets for the final tests were generated with a python script, shown below and having the following format: 'dataset numPoints kClusters dimPoints'.

We tested our implementations with different number of dimensions for the point (d), different number of clusters to find (k), and different dimension of the input datasets (n).

```
import random
# inputs: n (records), k (clusters), d (dimensions)
numPoints = [1000,10000,100000]
kClusters = [7,13]
dimPoints = [3,7]
for n in numPoints:
    for k in kClusters:
        for d in dimPoints:
            # open a new file
            f = open("data/dataset_"+str(n)+"_"+str(k)+"_"+str(d)+".txt", "a")
            # compute the interval for creating the clusters
            interval = round(n/k)
            count = 0
            print("dataset_"+str(n)+"_"+str(k)+"_"+str(d)+"; int: "+str(interval))
            # compute each point
            for i in range(n):
                if( (i%interval) == 0 and i!= 0):
                    count = count + 4
                x = ""
                for j in range(d):
```

```
x = x + str( interval*count + random.random()*interval )
    if(j < d-1):
        x = x + " "

x = x + "\n"
    # write the new point coordinates in the file
    f.write(x)

f.close()</pre>
```

List of files generated from the previous code:

- $\bullet \ dataset_100000_13_3.txt$
- $\bullet \ dataset_100000_13_7.txt$
- $\bullet \ dataset_100000_7_3.txt$
- $\bullet \ dataset_100000_7_7.txt$
- $\bullet \ dataset_10000_13_3.txt$
- dataset_10000_13_7.txt
- $\bullet \ dataset_10000_7_3.txt$
- $\bullet \ dataset_10000_7_7.txt$
- dataset 1000 13 3.txt
- dataset 1000 13 7.txt
- \bullet dataset 1000 7 3.txt
- dataset 1000 7 7.txt

3 MapReduce pseudo-code

The following pseudo-code shows the basic functioning of the Mapper and Reducer, implemented in this project:

```
class MAPPER
  method MAP(sample_id id, sample_list 1)
    for all sample s in sample_list 1 do
        dist <- MAX_VALUE
        for all center c in cluster_centers cc do
            newDist <- computeDistance(s, c)
        if (newDist < dist) then
            dist <- newDist
            clusterIndex <- c.index
        EMIT(index clusterIndex, sample s)

class REDUCER
    method REDUCE(index clusterIndex, samples [s1, s2,...])
    count <- 0
    center <- cluster_centers[clusterIndex]</pre>
```

```
for all sample s in samples [s1, s2,...] do
  count <- count + 1
  for i in [0:size(s)] do
    newCenter[i] <- newCenter[i] + s[i]
for i in [0:size(newCenter)] do
  newCenter[i] <- newCenter[i] / count
EMIT(index clusterIndex, sample newCenter)</pre>
```

4 Hadoop Implementation and Tests

This implementation of the k-means algorithm is developed in a Maven project written in Java language, using the **org.apache.hadoop** library.

The first version consists in a Mapper class and a Reducer class. Each dataset has been tested initially with a single reducer, and then with k reducers. The results of our tests are shown below. In the following version, a Combiner class is added to test improvements in the performance. Finally, we tryed different values for the threshold of the stop condition.

5 Spark Implementation and Tests

The Spark implementation is developed in Python language, using the **pyspark** library. The exploited transformations are:

- map: takes as input the RDD created from the dataset file and gives as output an RDD of (K, V), in which the key is a cluster index and the value is the coordinates of a point.
- reduce ByKey: takes the (K, V) pairs RDD, created by the mapping, and returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function computeNewCenter, which is of type (V,V)=>V. This transformation is executed with different number of reduce tasks, to test improvements in the performance.

The results of our tests are shown below.

6 Conclusions