
First iteration of K-Means clustering algorithm using MapReduce

Assignment 2

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1 Hadoop Installation

As far as the installation of Hadoop, we decided to use Hadoop through a Virtual Machine. We chose to download Bitnami's Virtual Machine image for Hadoop [1], because it is lightweight and easy to use. Then, we launched a Virtual Machine by importing the downloaded image to the Oracle VirtualBox [2] virtualization application. Once the startup process was completed, we logged in using the login prompt shown in the image below in order to access the console. Afterwards, we installed git (command: `sudo apt install git`) at the Virtual Machine through the console, in order to clone our Github repository containing the code. Finally, we also installed pip3 (command: `sudo apt install python3-pip`) in order to install the dependencies used in our code which are listed in the requirements.txt file (command: `pip3 install -r requirements.txt`).

```
*** You can access the application at http://192.168.1.11 ***
*** The default username and password is 'user' and '40B1SL3MU7To'. ***
*** You can find out more at https://docs.bitnami.com/virtual-machine/apps/hadoop/ ***

*****
To access the console, please use login 'bitnami'
and password 'bitnami'
*****

debian login: bitnami
Password:
Last login: Sat Apr  9 11:38:42 UTC 2022 on tty1
Linux debian 4.19.0-18-amd64 #1 SMP Debian 4.19.208-1 (2021-09-29) x86_64

The programs included with the Debian GNU/Linux system are free software;
the exact distribution terms for each program are described in the
individual files in /usr/share/doc/*/copyright.

Debian GNU/Linux comes with ABSOLUTELY NO WARRANTY, to the extent
permitted by applicable law.

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 | _ | _ | _ |
 | _ | _ | _ |

*** Welcome to the Hadoop packaged by Bitnami 3.3.2-4 ***
*** Documentation: https://docs.bitnami.com/virtual-machine/apps/hadoop/ ***
*** https://docs.bitnami.com/virtual-machine/ ***
*** Bitnami Forums: https://community.bitnami.com/ ***

#####
### For frequently used commands, please run: ###
### sudo /opt/bitnami/bnhelper-tool ###
#####

bitnami@debian:~$ _
```

Figure 1: Install Bitnami

2 Dataset Creation

The script `generate_data.py` was written for generating data-points in the form (x, y) . Specifically, it reads centroids in the form (x, y) from a csv file `(-i)` and generates the specified amount of data-points around each centroid `(-n)`, which is then written to the specified file `(-o)`. The argument `-d` is optional, but if provided it generates the graphical representation of the points in an image `(points.png)`.

```
usage: generate_data.py [-h] -i I -o O [-n [N]] [-d]

optional arguments:
  -h, --help  show this help message and exit
  -i I        path to the file containing the centroids
  -o O        path to the file where the points will be written
  -n [N]      number of points to be generated around each centroid
  -d          draw points
```

Figure 2: Script arguments.

For our assignment needs, the script described above was used with the command shown below to read three centroids from the `centroids.csv` file and generate 600.000 data-points around each one of them, that was then written to the `points.csv` file. Also the `points.png` image was produced since the argument `-d` was provided.

```
python3 generate_data.py -i centroids.csv -o points.csv -n 600000 -d
```

Figure 3: Dataset generation command.

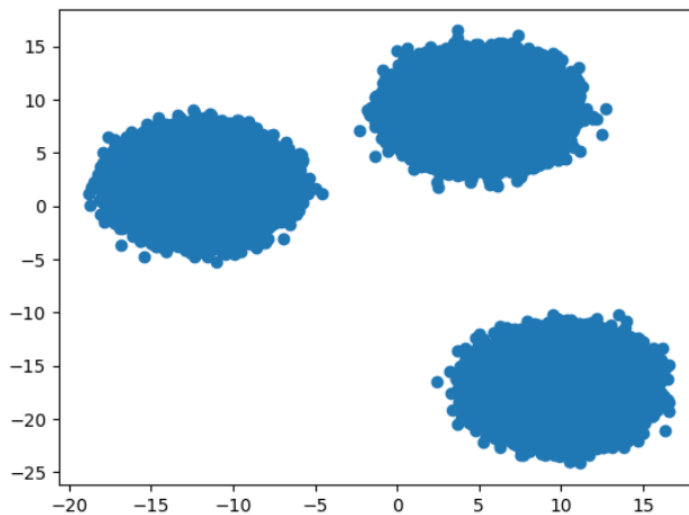


Figure 4: Dataset graphical representation.

```

1  import csv
2  import random
3  import argparse
4  from scipy.stats import skewnorm
5  from matplotlib import pyplot as plt
6
7  def read_centroids(centroids_file_path):
8      centroids = []
9      with open(centroids_file_path) as centroids_file:
10         for centroid in csv.reader(centroids_file):
11             centroids.append(centroid)
12     return centroids
13
14 def generate_points_around_centroids(centroids, num_of_points):
15     points = []
16     for x_centroid, y_centroid in centroids:
17         # When a = 0 the distribution is identical to normal distribution
18         x_skews = skewnorm.rvs(a=0, scale=1.5, size=num_of_points)
19         y_skews = skewnorm.rvs(a=0, scale=1.5, size=num_of_points)
20         for x_skew, y_skew in zip(x_skews, y_skews):
21             x = float(x_centroid) + x_skew
22             y = float(y_centroid) + y_skew
23             points.append((x, y))
24     return points
25
26 def write_points(points_file_path, points):
27     with open(points_file_path, 'w') as points_file:
28         for point in points:
29             csv.writer(points_file).writerow(point)
30
31 def draw_points(points):
32     x, y = zip(*points)
33     plt.scatter(x, y)
34     plt.savefig('points')
35

```

Figure 5: generate_data.py source code.

```

36 if __name__ == '__main__':
37     parser = argparse.ArgumentParser()
38     parser.add_argument("-i", required=True,
39         help="path to the file containing the centroids")
40     parser.add_argument("-o", required=True,
41         help="path to the file where the points will be written")
42     parser.add_argument("-n", nargs='?', const=400000, type=int,
43         help="number of points to be generated around each centroid")
44     parser.add_argument("-d", action="store_true", help="draw points")
45     args = parser.parse_args()
46
47     centroids_file_path, points_file_path, num_of_points = args.i, args.o, args.n
48
49     centroids = read_centroids(centroids_file_path)
50     points = generate_points_around_centroids(centroids, num_of_points)
51     write_points(points_file_path, points)
52
53     if args.d:
54         draw_points(points)

```

Figure 6: generate_data.py source code.

3 K-Means Clustering Algorithm

The script `kmeans.py` was written to implement the first iteration of the K-Means clustering algorithm [6] using MapReduce. To write the MapReduce job we used the Python library `mrjob` [3].

The `configure_args` method is used to add a file argument that allows the user to specify the path to the file containing the initial centroids:

```
def configure_args(self):
    super(KMeans, self).configure_args()

    self.add_file_arg(
        '--centroids-file',
        dest='centroids_file',
        help='path to the file containing the centroids.'
    )
```

Figure 7: `configure_args` method

The `load_centroids` method is used to broadcast the initial centroids to the mappers:

```
# This method is executed before mappers process any input.
def load_centroids(self):
    self.__centroids = []

    with open(self.options.centroids_file) as centroids_file:
        for line in centroids_file:
            x, y = line.strip().split(',')
            centroid = (float(x), float(y))
            self.__centroids.append(centroid)
```

Figure 8: `load_centroids` method

The mapper method is used to map each point to its closest centroid based on euclidean distance:

```
def __calculate_euclidean_dist(self, point, centroid):
    x1, y1 = point
    x2, y2 = centroid
    return sqrt((x2 - x1)**2 + (y2 - y1)**2)

# The line will be a raw line of the input file, with newline (\n) stripped.
def mapper(self, _, line):
    x, y = line.split(',')
    point = (float(x), float(y))

    min_euclidean_dist = float('inf')
    closest_centroid = None
    for centroid in self.__centroids:
        euclidean_dist = self.__calculate_euclidean_dist(point, centroid)
        if euclidean_dist < min_euclidean_dist:
            min_euclidean_dist = euclidean_dist
            closest_centroid = centroid

    yield closest_centroid, point
```

Figure 9: mapper method

The reducer method is used to compute the new centroids based on the data points that were mapped to each centroid:

```
def reducer(self, centroid, points):
    n, sum_x, sum_y = 0, 0, 0
    for x, y in points:
        sum_x += x
        sum_y += y
        n += 1
    mean_x = sum_x / n
    mean_y = sum_y / n

    yield centroid, (mean_x, mean_y)
```

Figure 10: reducer method


```
python3 kmeans.py -r hadoop < points.csv --centroids-file centroids.csv > new_centroids.csv
```

Figure 11: MapReduce job execution command

```
[-12.0, 2.0]    [-11.998412456771415, 2.003507904965915]  
[5.0, 9.0]    [5.000860165963167, 9.003015553446247]  
[10.0, -17.0] [10.001930427993857, -16.99727203388207]
```

Figure 12: MapReduce job results

We observe that the deviation between the initial and the new centroids is small, which is normal since the data points were generated around the initial centroids using normal distribution.

```

1  from math import sqrt
2  from mrjob.job import MRJob
3  from mrjob.step import MRStep
4
5  class KMeans(MRJob):
6
7      def configure_args(self):
8          super(KMeans, self).configure_args()
9
10         self.add_file_arg(
11             '--centroids-file',
12             dest='centroids_file',
13             help='path to the file containing the centroids.'
14         )
15
16     def steps(self):
17         return[
18             MRStep(mapper_init=self.load_centroids,
19                   mapper=self.mapper,
20                   reducer=self.reducer)
21         ]
22
23     # This method is executed before mappers process any input.
24     def load_centroids(self):
25         self.__centroids = []
26
27         with open(self.options.centroids_file) as centroids_file:
28             for line in centroids_file:
29                 x, y = line.strip().split(',')
30                 centroid = (float(x), float(y))
31                 self.__centroids.append(centroid)
32
33

```

Figure 13: kmeans.py source code.

```

32
33     def __calculate_euclidean_dist(self, point, centroid):
34         x1, y1 = point
35         x2, y2 = centroid
36         return sqrt((x2 - x1)**2 + (y2 - y1)**2)
37
38     # The line will be a raw line of the input file, with newline (\n) stripped.
39     def mapper(self, _, line):
40         x, y = line.split(',')
41         point = (float(x), float(y))
42
43         min_euclidean_dist = float('inf')
44         closest_centroid = None
45         for centroid in self.__centroids:
46             euclidean_dist = self.__calculate_euclidean_dist(point, centroid)
47             if euclidean_dist < min_euclidean_dist:
48                 min_euclidean_dist = euclidean_dist
49                 closest_centroid = centroid
50
51         yield closest_centroid, point
52
53     def reducer(self, centroid, points):
54         n, sum_x, sum_y = 0, 0, 0
55         for x, y in points:
56             sum_x += x
57             sum_y += y
58             n += 1
59         mean_x = sum_x / n
60         mean_y = sum_y / n
61
62         yield centroid, (mean_x, mean_y)
63
64 if __name__ == "__main__":
65     KMeans.run()

```

Figure 14: kmeans.py source code.

References

- [1] Hadoop packaged by Bitnami, [*https://bitnami.com/stack/hadoop/virtual-machine*](https://bitnami.com/stack/hadoop/virtual-machine)
- [2] Oracle VirtualBox, [*https://www.virtualbox.org/*](https://www.virtualbox.org/)
- [3] mrjob, [*https://pypi.org/project/mrjob/*](https://pypi.org/project/mrjob/)
- [4] skewnorm, [*https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.skewnorm.html*](https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.skewnorm.html)
- [5] matplotlib, [*https://matplotlib.org/*](https://matplotlib.org/)
- [6] MapReduce Algorithms for k-means Clustering , title = MapReduce Algorithms for k-means Clustering, author = Max Bodoia, note = [*https://stanford.edu/~rezab/classes/cme323/S16/projects_reports/bodoia.pdf*](https://stanford.edu/~rezab/classes/cme323/S16/projects_reports/bodoia.pdf), note = Accessed: 10-4-2022,