Assignment 2

Part 1: Map Reduce Discussion

Data Set

Weather measurements, across the city of Sofia, where collected. The data set consists of the following field names, data types and explanation:

Table 1: Sofia weather data set, field information.

Name	Data Type	Explanation
Unnamed: 0	Integer	Ordered event identifier
senor_id	Integer	Identifier of the weather sensor
location	Integer	Identifier of the sensor's location
lat	Float	Latitude of the sensor
lon	Float	Longitude of the sensor
timestamp	String	Datetime of recording
pressure	Float	Pressure recording from sensor (Pa)
temperature	Float	Temperature recording of sensor $(°C)$
humidity	Float	Humidity recording of sensor $(\%)$

It is assumed that these sensors are used to generate statistics that inform weather information (daily summaries). Therefore, there is a business requirement to create summary statistics of a day's worth of weather information per sensor that can be fed to a dashboard. This dashboard can then show per sensor information about the day's weather of the location, where the sensor occurs.

Approach

A MapReduce algorithm was used to process batches of weather data, that occurs per day. It is assumed that filtering of the collected data has occurred (based on the timestamp) and that this days' worth of batch of data is fed to the MapReduce algorithms. The algorithms will then process the day's batch and produce statistics that can inform a per sensor account of the day's weather.

This approach is demonstrated on the temperature measurement. This can easily be changed and expanded to the pressure and humidity measurements as well.

The following must be considered:

1. The maximum temperature measured per sensor
2. The minimum temperature measured by the sensor
3. The mean temperature measured by the sensor
4. The mode temperature measured by the sensor (to ascertain if the mode and mean are similar, thus a measure of skewness of the distribution of measurements)
5. The standard deviation of measurements (to ascertain if the maximum and minimum values found are outliers and for a measure of variability of the measurement at each location)
6. The skewness of the distribution to understand the measurements' shape
7. In each case the outputs must be ordered so that quick interpretation of results can be ascertained

Each consideration alters a standard MapReduce algorithm:

1. Each sensor (key) is mapped to its measured temperatures (values)
2. For each key the values are summarised (maximum, minimum, mean, mode, standard deviation, and skewness)
3. For all the keys, the outputs are ordered in ascending order

Reasons for this Algorithm:

1. The algorithm does not require dependencies and can be written with standard built-in functions
2. The summary statistics can be used to get daily information, ascertain the validity of that information (via the standard deviation and outliers); ascertain the shape of the distribution of the information and by using ordering – understand the general weather conditions of sensors located in a region
3. The algorithms can easily be transferred to other measurements when considered necessary (pressure and humidity)

Results Generation:

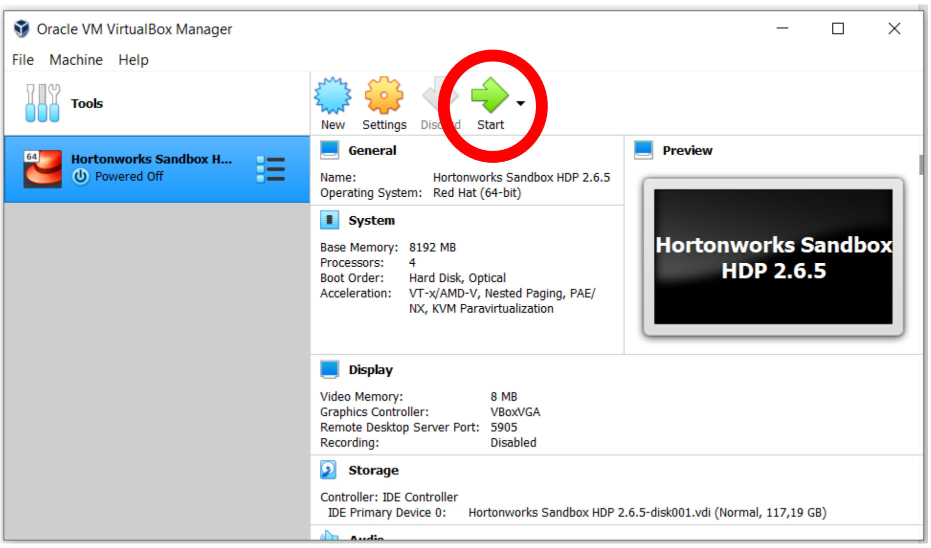
To illustrate the above approach a random day was chosen. In this case the data was filtered for 2017-07-13 as a batch data set used for the MapReduce algorithms to create daily statistics.

A virtual Linux machine was set up using Cloudera's HDP 2.6.5 sandbox. The Hadoop cluster consists of a single node with 8 GB ram.

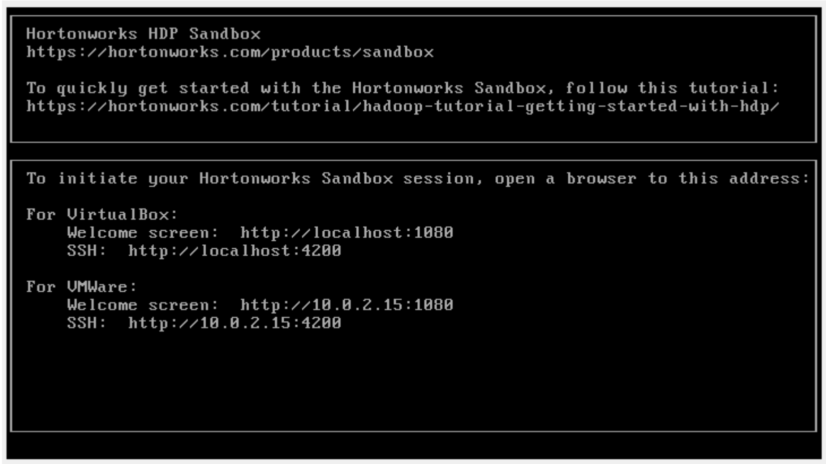
The data set is loaded to the Hadoop File System (HDFS) only with the scripts containing the MapReduce algorithms.

To run the MapReduce algorithm on the machine, one must SSH into the virtual box using puTTY. The user than navigates to the HDFS folder containing the data set and MapReduce code. This is illustrated as follows:

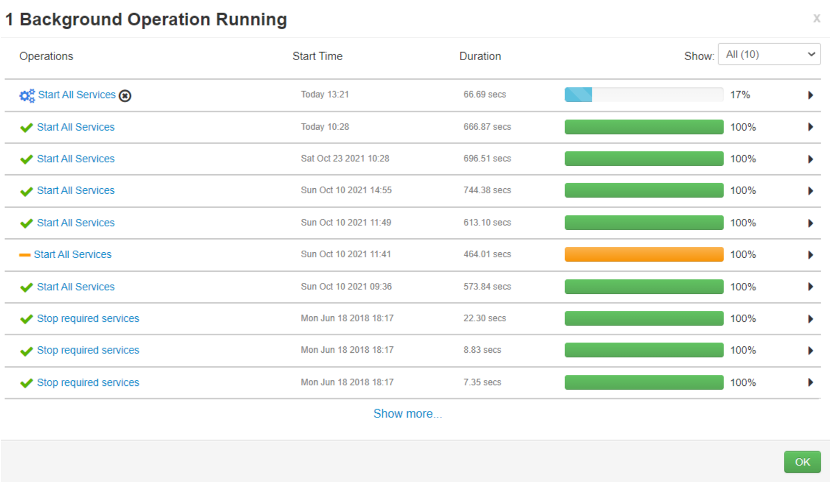
1. Launch the virtual Linux Machine:



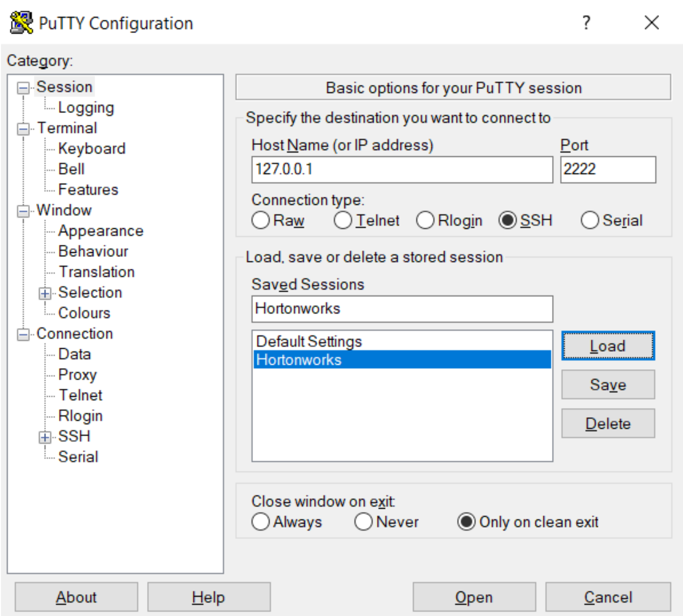
2. Check that all systems are loaded on Ambari by going to the local host specified:



3. Check Ambari and wait for the Hadoop ecosystem to start completely:



4. SSH into the virtual box using puTTY:



5. Ensure the data and MapReduce code are in the same HDFS directory:

maria_dev@sandbox-hdp:~

```
login as: maria_dev
maria_dev@127.0.0.1's password:
Access denied
maria_dev@127.0.0.1's password:
Last failed login: Sun Oct 24 11:36:03 UTC 2021 from 172.18.0.3 on ssh:notty
There was 1 failed login attempt since the last successful login.
Last login: Sun Oct 24 09:20:55 2021 from 172.18.0.3
[maria_dev@sandbox-hdp ~]$ ls
map_reduce.py  map_reduce.py.save  sofia_data.csv
[maria_dev@sandbox-hdp ~]$
```

6. Use the following command to run the script:

```
python MapReduce.py -r hadoop --hadoop-streaming-jar
/usr/hdp/current/hadoop-mapreduce-client/hadoop-streaming.jar
sofia_data.csv
```

7. Here the algorithm used was to find the maximum temperature on a sensor per day. All other MapReduce algorithms are specified in GitHub. The output (keys are sensor IDs and values are maximum temperatures of the sensor on the day) is as follows:

maria_dev@sandbox-hdp:~

```
"1024"  39.79
"2249"  40.15
"1750"  40.82
"2325"  40.99
"1727"  41.06
"1751"  41.09
"1120"  41.16
"1118"  41.79
"2316"  41.81
"925"   41.96
"1172"  42.26
"2005"  42.58
"1123"  42.86
"1140"  43.02
"1025"  43.16
"1154"  43.38
"977"   43.44
"1139"  43.61
"1729"  44.25
"1824"  44.52
"1731"  44.53
"1122"  44.71
"1837"  45.12
"879"   45.28
"1023"  45.69
"1676"  45.91
"1138"  46.07
"976"   46.15
"1313"  46.51
"1114"  46.99
"1556"  47.98
"1732"  48.96
"1155"  49.68
"1561"  49.81
"1660"  49.98
"1933"  51.11
"1793"  51.78
"1770"  52.07
"2250"  52.17
"2291"  52.45
"1764"  53.12
"981"   54.16
"1675"  54.37
"2252"  56.83
"1884"  58.39
"923"   60.47
"2248"  61.17
Removing HDFS temp directory hdfs:///user/maria_dev/tmp/mrjob/map_reduce.maria_dev.20211024.114259.474730...
Removing temp directory /tmp/map_reduce.maria_dev.20211024.114259.474730...
[maria_dev@sandbox-hdp ~]$
```

Results

Table 1: Generated output on temperature per sensor using the map reduce algorithms on a random day (2017-05-18)

Sensor (Keys)	Maximum Temperature	Minimum Temperature	Mean Temperature	Mode Temperature	Percentage Difference	Maximum Outlier	Minimum Outlier	Skewness
1731	30.95	21.55	25.75	25.77	0.08%	31.49	20.01	-0.09
1121	31.55	22.98	27.75	28.01	0.94%	33.41	22.09	-0.05
1120	31.56	21.37	27.75	27.91	0.58%	34.45	21.05	-0.31
1172	31.85	20.17	26.75	26.31	1.64%	34.17	19.33	-0.08
925	32.21	21.15	26.75	27.42	2.50%	34.29	19.21	-0.13
1154	32.92	19.7	26.75	27.11	1.35%	35.09	18.41	-0.2
1024	33.28	23.51	28.75	28.3	1.57%	34.67	22.83	-0.1
2005	33.31	20.94	27.75	27.8	0.18%	34.83	20.67	-0.09
1118	34.6	21.01	28.75	30.01	4.38%	37.33	20.17	-0.24
1558	35.18	23.83	29.75	29.55	0.67%	37.31	22.19	-0.02
1729	35.36	21.14	28.75	28.17	2.02%	37.93	19.57	-0.05
1751	35.83	22.05	28.75	28.77	0.07%	36.03	21.47	-0.03
1998	36.02	23.17	28.75	28.19	1.95%	37.09	20.41	-0.21
1727	36.06	22.76	30.75	31.77	3.32%	37.79	23.71	-0.55
1023	36.42	18.7	26.75	26.3	1.68%	36.33	17.17	-0.09
1750	36.61	21.38	28.75	28.07	2.37%	37.61	19.89	-0.26
1313	37.02	20.02	27.75	28.53	2.81%	36.93	18.57	-0.09
1556	37.02	21.75	27.75	26.85	3.24%	36.03	19.47	-0.22
1138	37.31	20.64	27.75	26.91	3.03%	36.77	18.73	-0.13
1732	37.65	20.03	27.75	27.37	1.37%	39.51	15.99	-0.25
1123	37.66	22.62	29.75	28.81	3.16%	39.65	19.85	-0.27
977	37.81	21.52	29.75	29.37	1.28%	40.37	19.13	-0.05
1140	38	19.18	28.75	29.21	1.60%	39.99	17.51	-0.1
1676	38.04	21.29	24.75	22.96	7.23%	34.67	14.83	-1.88
1139	38.55	22.24	30.75	30.31	1.43%	40.85	20.65	-0.04
976	39.11	19.59	27.75	29.17	5.12%	38.05	17.45	-0.16
1122	39.51	23.21	29.75	29.91	0.54%	39.85	19.65	-0.16
1933	40.23	21.09	28.75	27.39	4.73%	41.17	16.33	-0.45
1824	40.28	21.34	29.75	29.88	0.44%	39.87	19.63	-0.17
1155	40.47	18.52	26.75	24.81	7.25%	38.29	15.21	-0.46
879	40.87	19.57	27.75	26.97	2.81%	39.69	15.81	-0.26
981	41.79	20.73	28.75	27.58	4.07%	40.61	16.89	-0.57
1561	43.08	20.99	30.75	29.95	2.60%	43.91	17.59	-0.2
1764	44.9	21.39	29.75	27.27	8.34%	42.53	16.97	-0.65
1884	45.27	23.02	28.75	28.08	2.33%	38.51	18.99	-1.16
1660	45.59	21.17	28.75	26.46	7.97%	42.33	15.17	-0.76
1770	46.91	20.78	30.75	30.27	1.56%	44.83	16.67	-0.54
923	47.55	19.54	27.75	25.92	6.59%	40.77	14.73	-0.77
1675	52.27	19.45	32.75	28.66	12.49%	48.83	16.67	-1.17
Daily Mean	38.22	21.16	28.52	28.0026				

Table 1 indicates the following:

1. The sensors that read the highest temperatures generally do not also read the lowest temperatures.
2. The mean temperature and mode temperatures generally correspond. However, the percentage difference between these two indicates a correlation with the maximum temperature found.
3. Furthermore, when using $\mu \pm 2 * \sigma$ to detect maximum and minimum outliers, as the temperature increases more of the maximum temperatures found can be considered outliers ($\mu + 2 * \sigma$).
4. Maximum outliers on some sensors indicates that some sensors may have registered unnatural temperatures or are faulty.
5. Most minimum temperatures are within the $\mu - 2 * \sigma$ threshold.
6. Maximum temperatures are more outlier prone compared to minimum temperatures.
7. High percentage differences in mean and mode corresponds to high skewness towards higher temperatures (as expected).

Table 1 indicates that a user can quickly ascertain whether readings are unusual, what the distribution of the readings are, and what the general maximum, minimum, average, and modal temperatures for a day are.

Improvements:

1. This data should incorporate the proximity of sensors so that spatial relationships between readings can be ascertained.