Final Project Report

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Spring 2020 – Distributed and Scalable Data

Objective: Complete the tasks given in project final assignment, plot meaningful graphs and produce compiling time analysis. The order of the headings will correspond to the assignment.

Problem 2

Step 1

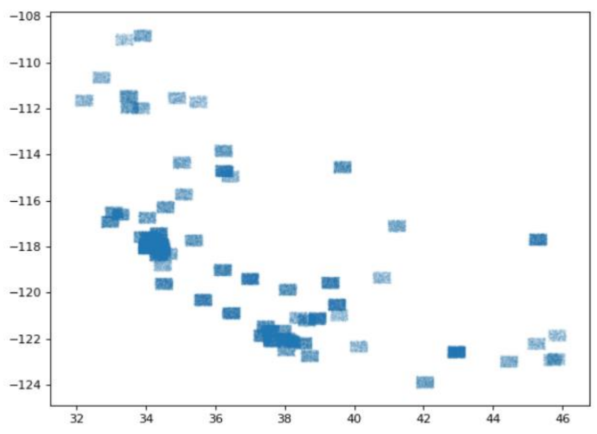
Data from devicestatus.txt required data scrubbing since (1) there were multiple delimiters such as |, comma, and forward slash, (2) the number of features varied among the samples. The following steps were taken:

1. We import the data from the S3 bucket
2. Use .flatMap and split the data on \n to separate the samples
3. Use regular expression library method re.sub and replace and of the delimiters with a comma
4. Use .split() on commas
5. Filter for the first two features and last two features. Conventionally this is where date, model, latitude, and longitude would be stored if correct.
6. Filter samples where the last two features are of type float. OR if it's still consider a string, consider using re.sub() and capture any patterns matching digits with a floating point and use backreference to return the value. Then check for float type.
7. We map attempt to cast the latitude and longitude to floats.
8. Filter entries where latitude or longitude are equal to 0
9. Split model into manufacturer and model_device using .split()[0] and .split()[1]
10. We use rdd.coalesce(1).saveAsTextFile() to save it to the bucket.

Step 2

Using the sample_geo.txt data, a bit of preprocessing was required since the incoming data was considered a string rather than numerical values. We use similarly the same steps of splitting on newlines, discarding the header line, splitting the features on \t and casting all features to numeric, floats or integer.

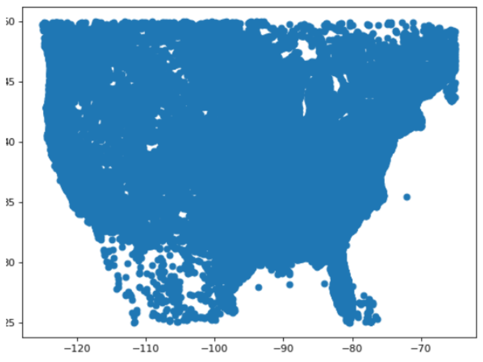
We use matplotlib.pyplot to plot our data, so we have to collect the data from the rdd using .collect(), though in practice, a finite number with .take() is better.

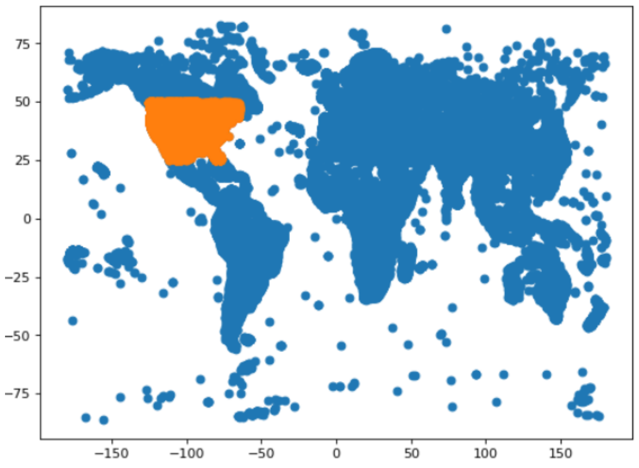


Visually this is a bit bizarre and I cannot recognize it as a continent; however, by evaluating a single sample, we can see that this is California State.

Step 3

Similarly for geo_sample.txt, we process the string latitude and longitude to numerics again and plot. We filtered out the longitude and latitude regions of the continuous United States.





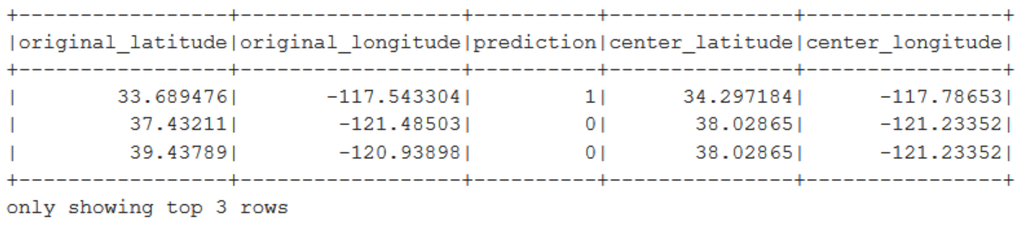
Problem 3

Step 2

The documentation here: https://spark.apache.org/docs/latest/mllib-clustering.html#k-means describes that the parameter epsilon is the Convergence threshold; however, with KMeans from pyspark.mllib.clustering, it is not required to be set. The alternative conclusion is that it is calculated internally. Still, considering the distribution of points and many outliers, we should expect by running kmeans first and calculating the distance metrics, then consider the standard deviation of the distance metrics. Then, take the standard deviation and divide it by the sum of the distance metric to get a small value less than 1. This is would be our proportional epsilon to the sum of the distance metric which we may attempt to apply to other k-clusters.

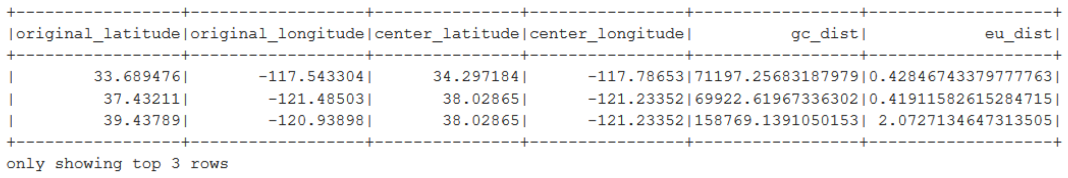
Step 3

Using the **device location data** and clustering for 5 groups we get a column called predictions. Then, we use the prediction as positional values to obtain the center cluster's longitude and latitude:



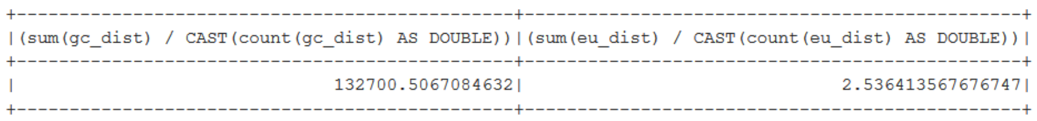
```
+-----------------+------------------+----------+---------------+----------------+
|original_latitude|original_longitude|prediction|center_latitude|center_longitude|
+-----------------+------------------+----------+---------------+----------------+
|        33.689476|       -117.543304|         1|      34.297184|      -117.78653|
|         37.43211|        -121.48503|         0|       38.02865|      -121.23352|
|         39.43789|        -120.93898|         0|       38.02865|      -121.23352|
+-----------------+------------------+----------+---------------+----------------+
only showing top 3 rows
```

We manually calculated the great circle distance and Euclidean distance through creating a column from aggregating the latitude and longitude columns.



```
+-----------------+------------------+---------------+----------------+----------------+------------------+
|original_latitude|original_longitude|center_latitude|center_longitude|         gc_dist|           eu_dist|
+-----------------+------------------+---------------+----------------+----------------+------------------+
|        33.689476|       -117.543304|      34.297184|      -117.78653|71197.25683187979|0.42846743379777763|
|         37.43211|        -121.48503|       38.02865|      -121.23352|69922.61967336302|0.41911582615284715|
|         39.43789|        -120.93898|       38.02865|      -121.23352|158769.1391050153| 2.0727134647313505|
+-----------------+------------------+---------------+----------------+----------------+------------------+
only showing top 3 rows
```

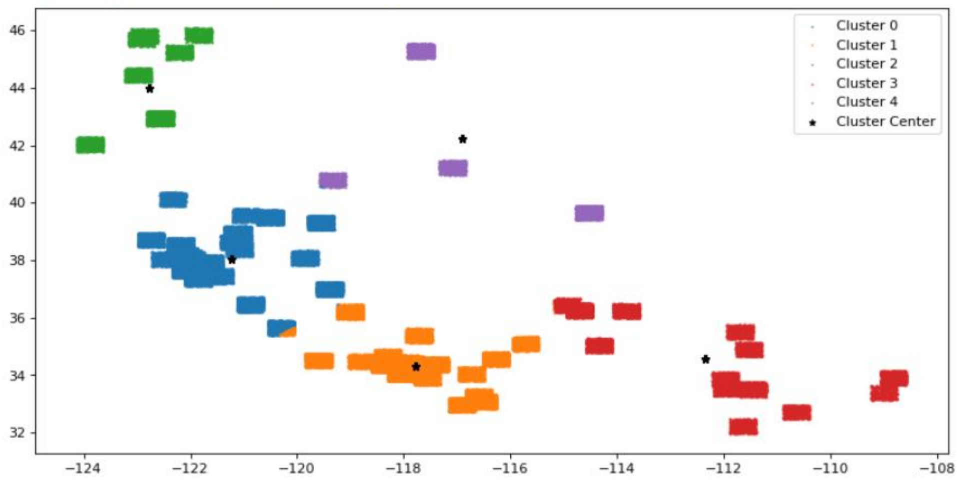
We can use spark SQL commands to aggregate the average of the distance mtetrics.



```
+--------------------------------------------+--------------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+--------------------------------------------+--------------------------------------------+
|                           132700.5067084632|                           2.536413567676747|
+--------------------------------------------+--------------------------------------------+
```

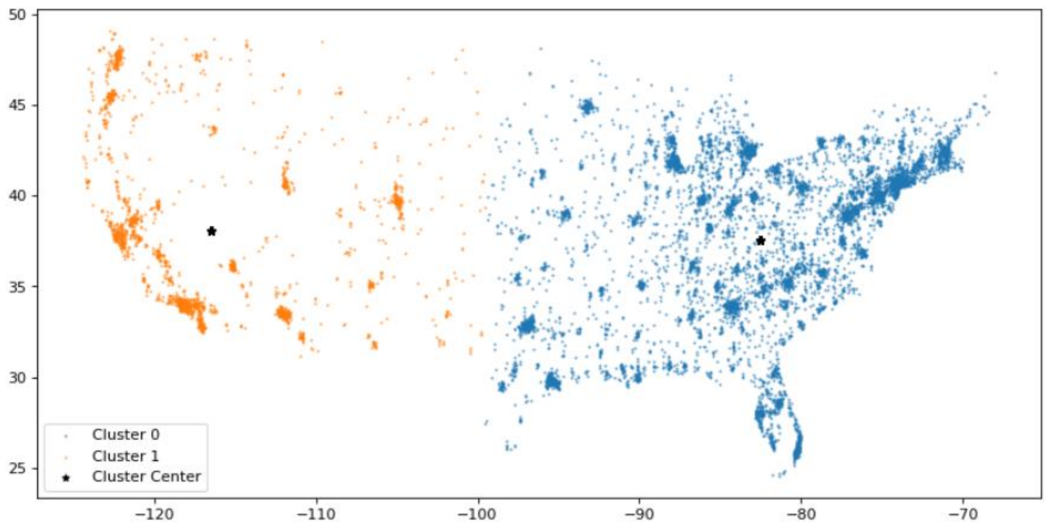
We can also plot the original coordinates and plot them by color based on their prediction classification.

```
[illegible]
```



Using the **synthetic location data** and clustering for 2 and 4 groups:

K=2:

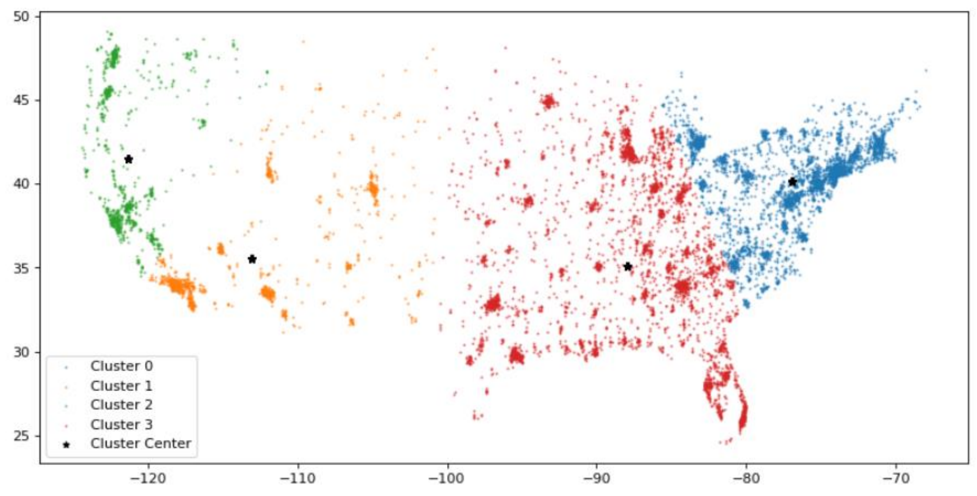


```
+-----------------+------------------+---------------+----------------+------------------+------------------+
|original_latitude|original_longitude|center_latitude|center_longitude|           gc_dist|           eu_dist|
+-----------------+------------------+---------------+----------------+------------------+------------------+
|         37.77254|         -77.49955|      37.564747|       -82.55711|445697.46533880796|25.622129831521306|
|        42.090134|        -87.689156|      37.564747|       -82.55711| 667018.4268019216|46.816980165967834|
|         39.56342|         -75.58753|      37.564747|       -82.55711| 645216.0229611602|52.569759438571054|
+-----------------+------------------+---------------+----------------+------------------+------------------+
only showing top 3 rows
```

Mean distance metrics:

```
+------------------------------------------+------------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+------------------------------------------+------------------------------------------+
|                         730104.5231404818|                         70.63638292632837|
+------------------------------------------+------------------------------------------+
```

K=4:

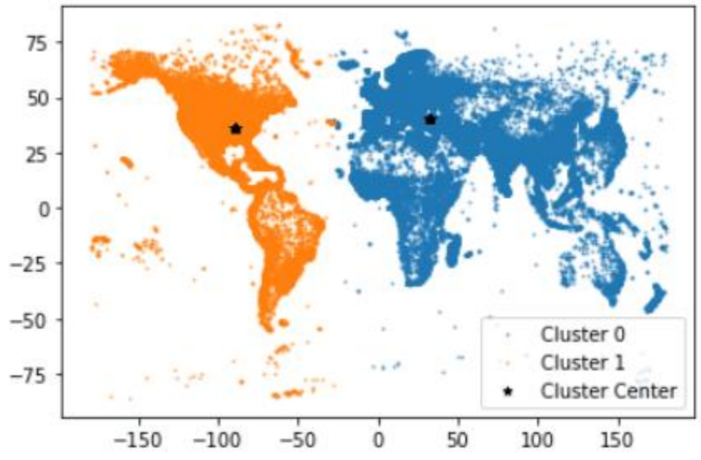


```
+-----------------------------------------+-----------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+-----------------------------------------+-----------------------------------------+
|                          532013.1570450937|                         36.665836915395765|
+-----------------------------------------+-----------------------------------------+
```

We see that many of the clusterings are recognizibly similar to how we'd partition the United States. Eg. Northeast, Southeast, the Middle West, and West Coast.

Using the **DBpedia** data for 2,4,6 clusters:

K=2:



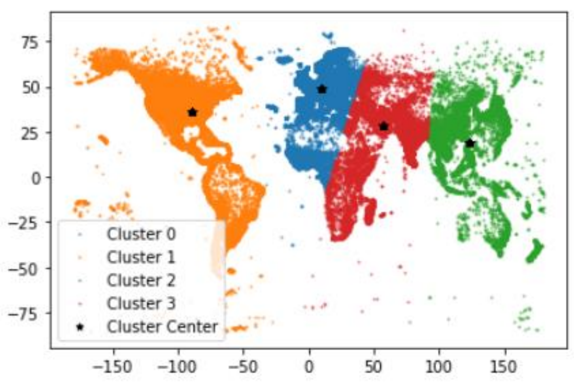
Metrics:

```
+-----------------+------------------+---------------+----------------+------------------+-----------------+
|original_latitude|original_longitude|center_latitude|center_longitude|           gc_dist|          eu_dist|
+-----------------+------------------+---------------+----------------+------------------+-----------------+
|             36.7|         3.2166667|      40.182056|       32.483273|2566289.6920982013|868.6589019522216|
|             42.5|         1.5166667|      40.182056|       32.483273|2583587.1626723097|964.3035582459561|
|        12.516666|         -70.03333|      35.941673|       -88.83209| 3214123.721362224|902.1243039452966|
+-----------------+------------------+---------------+----------------+------------------+-----------------+
only showing top 3 rows
```

Mean distances:

```
+-------------------------------------------+-------------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+-------------------------------------------+-------------------------------------------+
|                         2526786.4716782477|                         1242.8234952762402|
+-------------------------------------------+-------------------------------------------+
```

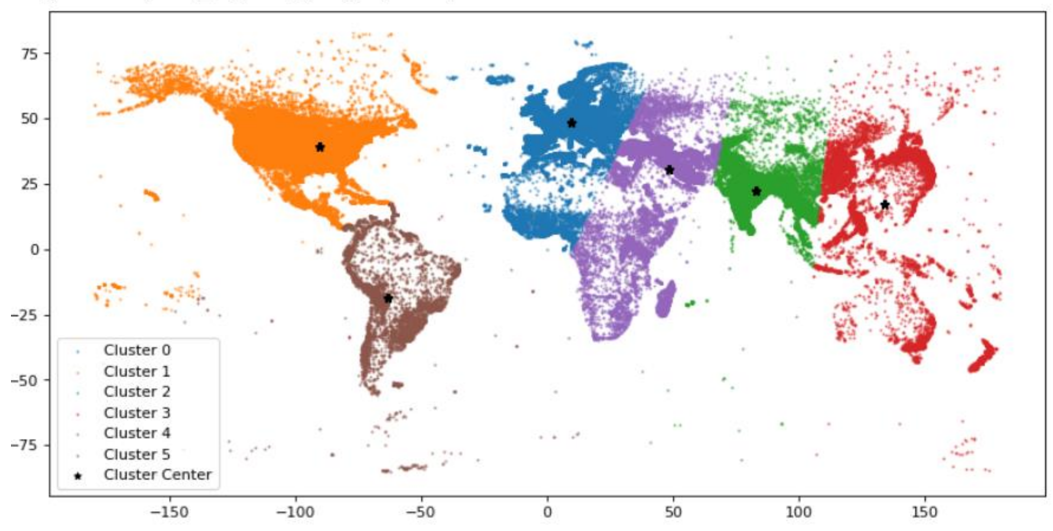
K=4:

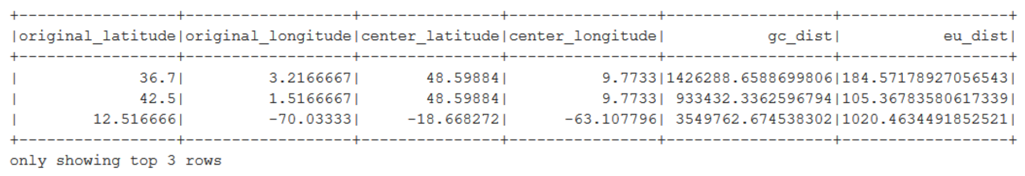


```
+-----------------+------------------+---------------+----------------+------------------+------------------+
|original_latitude|original_longitude|center_latitude|center_longitude|           gc_dist|           eu_dist|
+-----------------+------------------+---------------+----------------+------------------+------------------+
|             36.7|         3.2166667|      48.436523|        9.999369|1416923.7066886013|183.75101049274076|
|             42.5|         1.5166667|      48.436523|        9.999369| 933439.1195545978|107.19854807519368|
|        12.516666|         -70.03333|      35.934708|      -88.915085| 3218406.521958237| 904.9252141390025|
+-----------------+------------------+---------------+----------------+------------------+------------------+
only showing top 3 rows
```

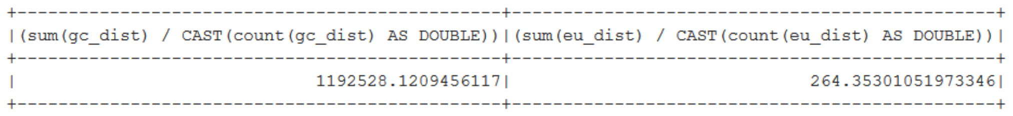
```
+-------------------------------------------+-------------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+-------------------------------------------+-------------------------------------------+
|                         1431525.8149716915|                          385.8855322130194|
+-------------------------------------------+-------------------------------------------+
```

K=6:



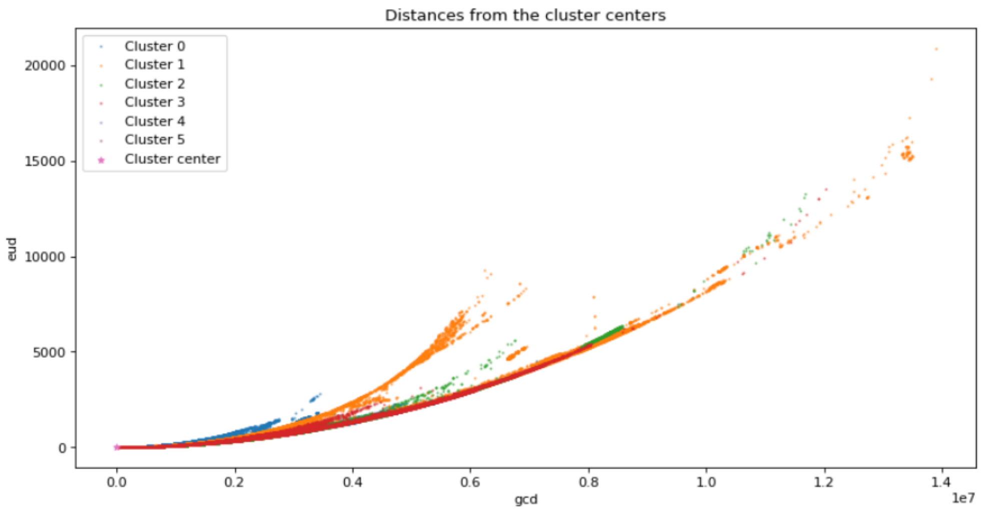


```
+-----------------+------------------+---------------+----------------+------------------+------------------+
|original_latitude|original_longitude|center_latitude|center_longitude|           gc_dist|           eu_dist|
+-----------------+------------------+---------------+----------------+------------------+------------------+
|             36.7|         3.2166667|       48.59884|          9.7733|1426288.6588699806|184.57178927056543|
|             42.5|         1.5166667|       48.59884|          9.7733| 933432.3362596794|105.36783580617339|
|        12.516666|         -70.03333|     -18.668272|      -63.107796| 3549762.674538302|1020.4634491852521|
+-----------------+------------------+---------------+----------------+------------------+------------------+
only showing top 3 rows
```



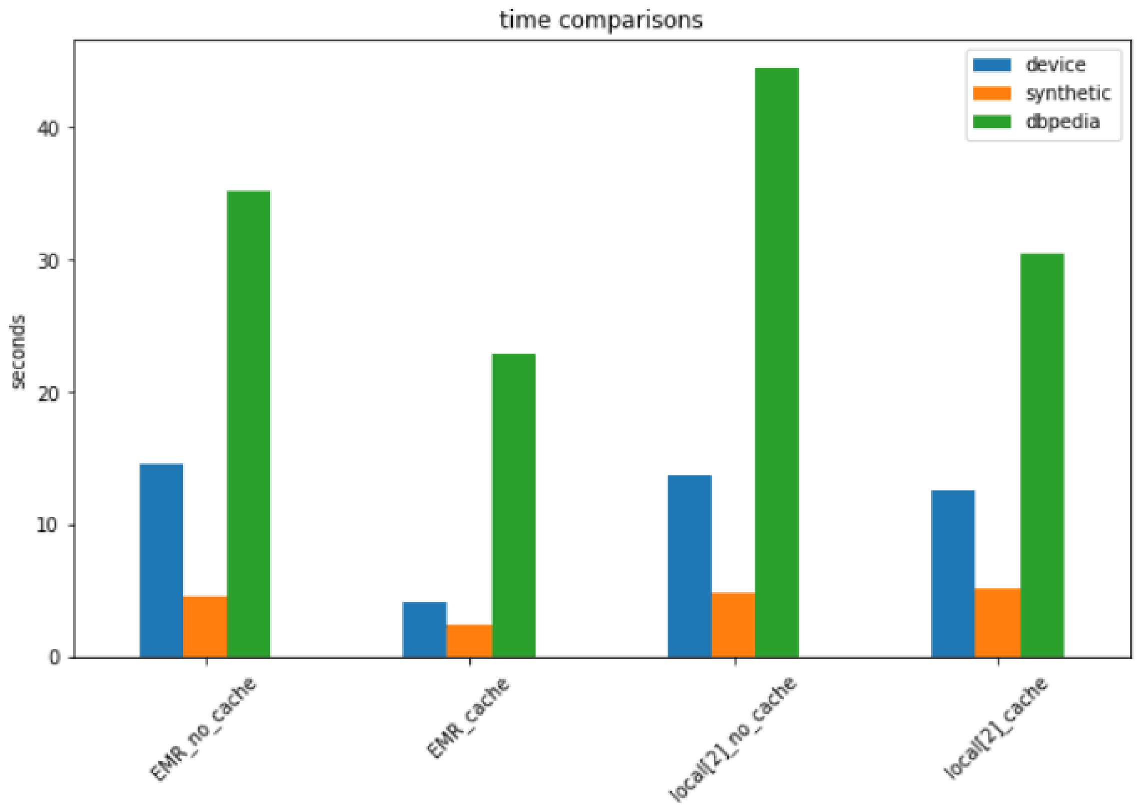
```
+--------------------------------------------+--------------------------------------------+
|(sum(gc_dist) / CAST(count(gc_dist) AS DOUBLE))|(sum(eu_dist) / CAST(count(eu_dist) AS DOUBLE))|
+--------------------------------------------+--------------------------------------------+
|                          1192528.1209456117|                          264.35301051973346|
+--------------------------------------------+--------------------------------------------+
```

Recognizibly we see that with lower k clusters, more points partitioned by their longitude value than latitude. This generally makes sense since longitude contains the most variance out of the two coordinates. It seems that grouping by 4 or 6 clusters represents generally our continents and it's amazing that, as people with pattern recognition, we've established continents as such before being able to compute clusters numerically.



This is a graph of the 6-mean cluster distance metrics. We can see that certain clusters contain more outliers than others. The reason we should consider this plot is because any 2D plot of the Earth is a manifold, a flat representation of the dimensions in Euclidean distance despite having a curve to the topology; however, since longitude and latitude are treated orthogonal from one another, our clustering suffers from being unable to estimate the true distances from the clusters using Euclidean distance. Instead, by looking the comparison between Euclidean and great circle distance from their cluster center located at 0,0 on the graph above, we get a better idea of where Euclidean distance falls short in representing the distance. Eg. Many of the plots in orange have higher Euclidean distance, but only finitely few have higher great circle distance. This is probably due to Euclidean distance's incapability to represent fundamental regions of the Earth's topology. Both distances agree that outliers like islands are numerically further away from their centers.

Step 4:



Here is a graph that compares four different environments for running the kmeans clustering for all three datasets, respectively K=5, K=2,4 and K=2,4,6. As we can see, there is an exponential relationship to time when able to cache/persist the rdds and have a distributed system for parallel computation. Of course, this supports that non-pseudo clusters are better because pseudo-clusters are sequential, and caching reduces the time taken assuming some repetition.

This part of the assignment could've done through spark—submit where the times would've been appended to a textfile, which would've made the process more documentary from the Cluster Manager page and extra statistics; however it wasn't until after doing it manually did I realize that would've been a better option. (The ipynb could easily be converted to a spark-submit job since the ipynbs are modified to run using the runall option.) Still, the task was completed and since I didn't use spark-submit, the times recorded are more accurate to the time taken to run the kmean models separately from the preprocessing steps.