

FINAL PROJECT Option #1:

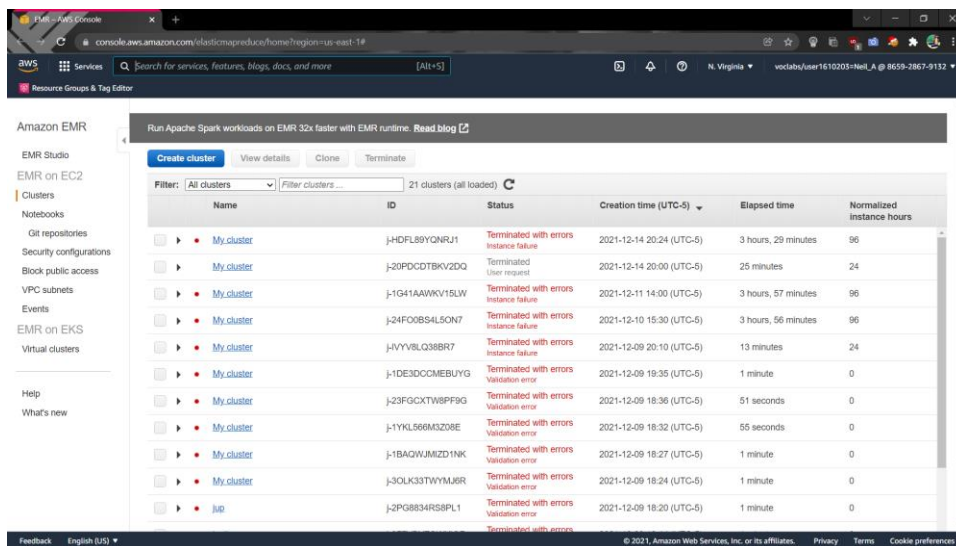
GEO-LOCATION CLUSTERING USING THE k-MEANS ALGORITHM

Introduction and Motivation:

Clustering is a process where a similar kind of data is within a same cluster, but distinct kinds of data are within different clusters. In a regular basis, we can use clustering in business, marketing, logistics, data documentation etc. In this project we used k-means clustering in geo-location.

Data Preparation

1. MAKE AN EMR CLUSTER



Name	ID	Status	Creation time (UTC-5)	Elapsed time	Normalized instance hours
My cluster	j-HDFL8BYQNRJ1	Terminated with errors Instance failure	2021-12-14 20:24 (UTC-5)	3 hours, 29 minutes	96
My cluster	j-20PDCDTBKV2DQ	Terminated User request	2021-12-14 20:00 (UTC-5)	25 minutes	24
My cluster	j-1G41AAWV15LW	Terminated with errors Instance failure	2021-12-11 14:00 (UTC-5)	3 hours, 57 minutes	96
My cluster	j-24FO0BS4L5ON7	Terminated with errors Instance failure	2021-12-10 15:30 (UTC-5)	3 hours, 56 minutes	96
My cluster	j-VYVBLQ38BR7	Terminated with errors Instance failure	2021-12-09 20:10 (UTC-5)	13 minutes	24
My cluster	j-1DE3DCMMEBUYG	Terminated with errors Validation error	2021-12-09 19:35 (UTC-5)	1 minute	0
My cluster	j-23FGCXTW8PF9G	Terminated with errors Validation error	2021-12-09 18:36 (UTC-5)	51 seconds	0
My cluster	j-1YKL566M3Z08E	Terminated with errors Validation error	2021-12-09 18:32 (UTC-5)	55 seconds	0
My cluster	j-1BAQWUMZD1NK	Terminated with errors Validation error	2021-12-09 18:27 (UTC-5)	1 minute	0
My cluster	j-3OLK33TWYJM6R	Terminated with errors Validation error	2021-12-09 18:24 (UTC-5)	1 minute	0
juj	j-2PG8834R58PL1	Terminated with errors Validation error	2021-12-09 18:20 (UTC-5)	1 minute	0

2. Name your EMR cluster along with hardware config as m4.xlarge and software config as spark

Create Cluster - Quick Options [Go to advanced options](#)

General Configuration

Cluster name:

☒ Logging [?](#)

S3 folder:

Launch mode: ☒ Cluster [?](#) ☐ Step execution [?](#)

Software configuration

Release: [?](#)

Applications:

- ☐ Core Hadoop: Hadoop 2.10.1, Hive 2.3.8, Hue 4.9.0, Mahout 0.13.0, Pig 0.17.0, and Tez 0.9.2
- ☐ HBase: HBase 1.4.13, Hadoop 2.10.1, Hive 2.3.8, Hue 4.9.0, Phoenix 4.14.3, and ZooKeeper 3.4.14
- ☐ Presto: Presto 0.261 with Hadoop 2.10.1 HDFS and Hive 2.3.8 Metastore
- ☒ Spark: Spark 2.4.8 on Hadoop 2.10.1 YARN and Zeppelin 0.10.0
- ☐ Use AWS Glue Data Catalog for table metadata [?](#)

Hardware configuration

Instance type: The selected instance type adds 64 GiB of GP2 EBS storage per instance by default. [Learn more](#)

Number of instances: (1 master and 2 core nodes)

3. Choose your key pair

Hardware configuration

Instance type: The selected instance type adds 64 GiB of GP2 EBS storage per instance by default. [Learn more](#)

Number of instances: (1 master and 2 core nodes)

Cluster scaling: ☐ scale cluster nodes based on workload

Auto-termination: ☒ Enable auto-termination [Learn more](#)

Terminate cluster when it is idle after: hours minutes

Security and access

EC2 key pair: [Learn how to create an EC2 key pair](#)

Permissions: ☒ Default ☐ Custom

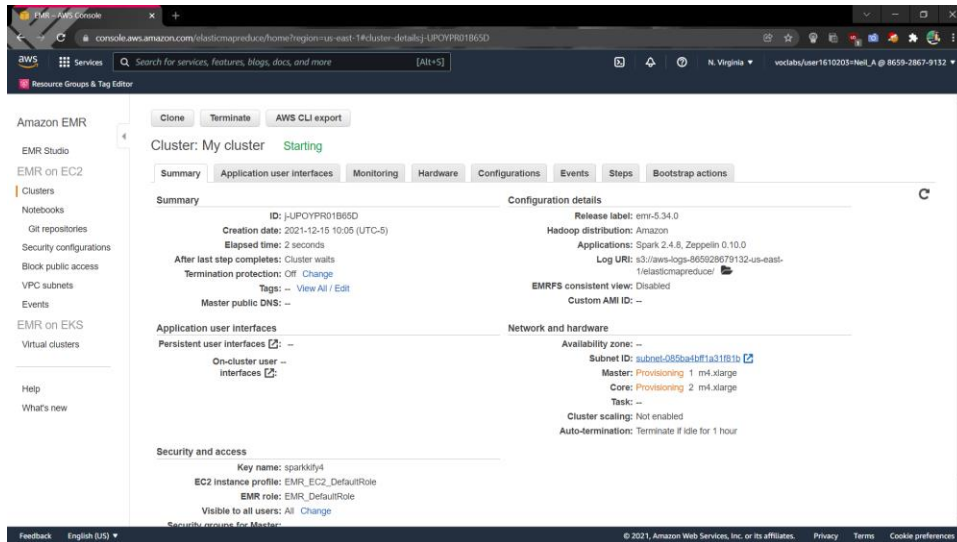
Use default IAM roles. If roles are not present, they will be automatically created for you with managed policies for automatic policy updates.

EMR role: [?](#) ☐ Use EMR_DefaultRole_V2 [?](#)

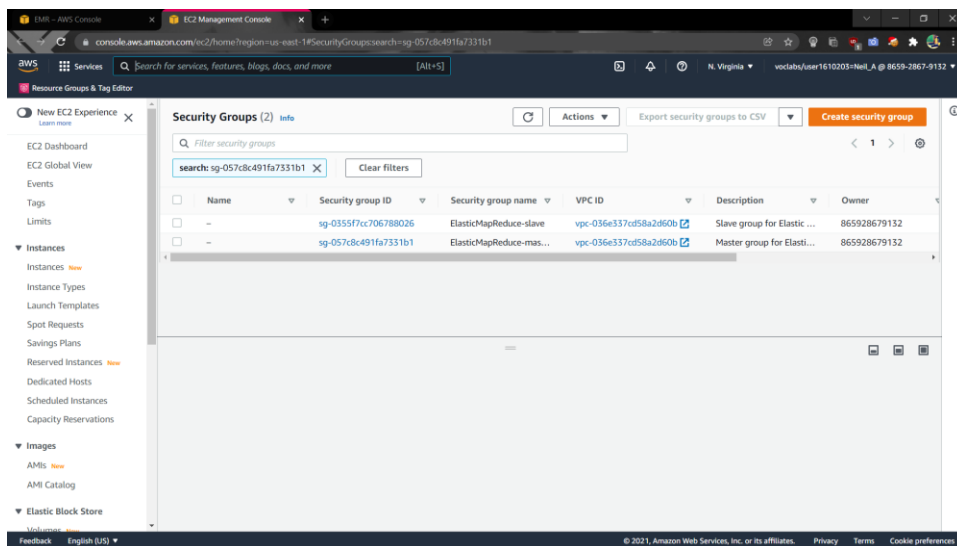
EC2 instance profile: [?](#)

[Cancel](#) [Create cluster](#)

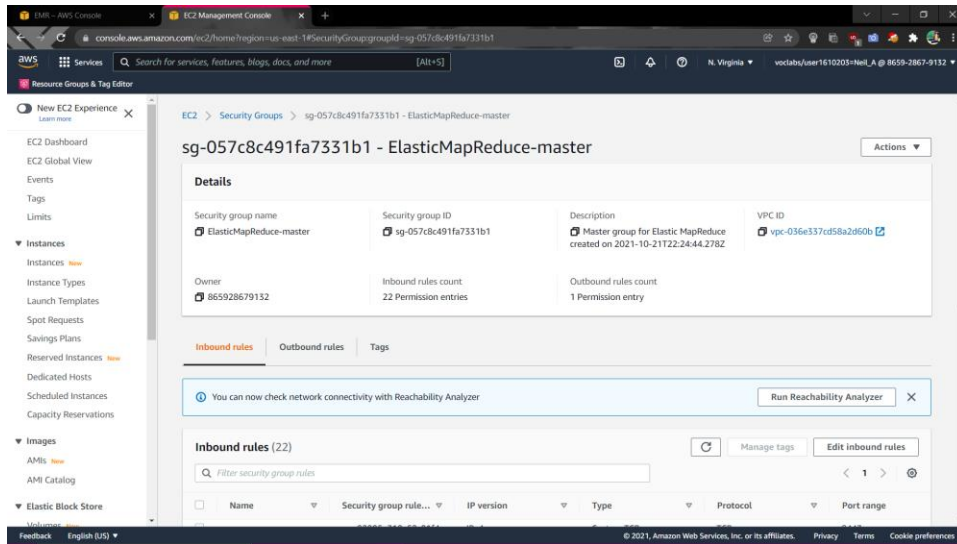
4. Click on create cluster



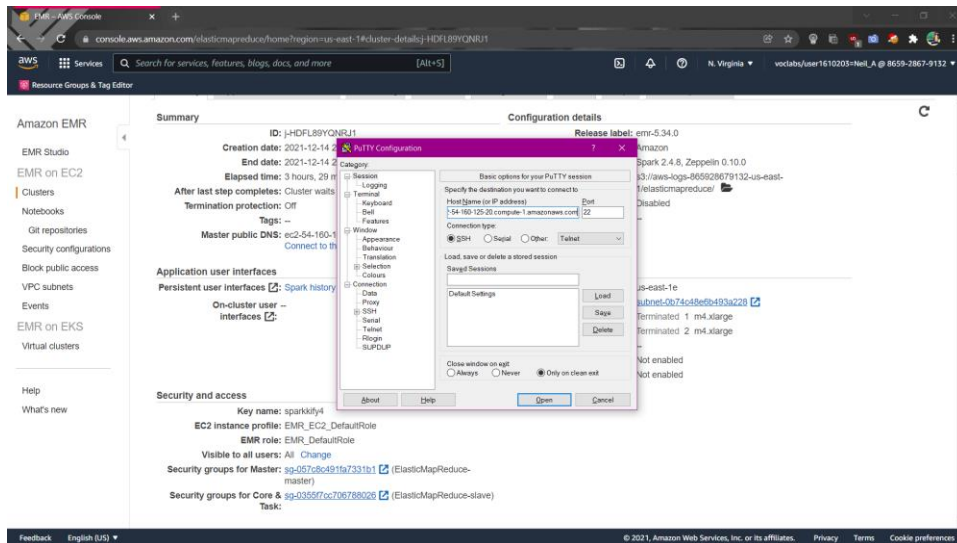
5. Goto security and access and click on master group



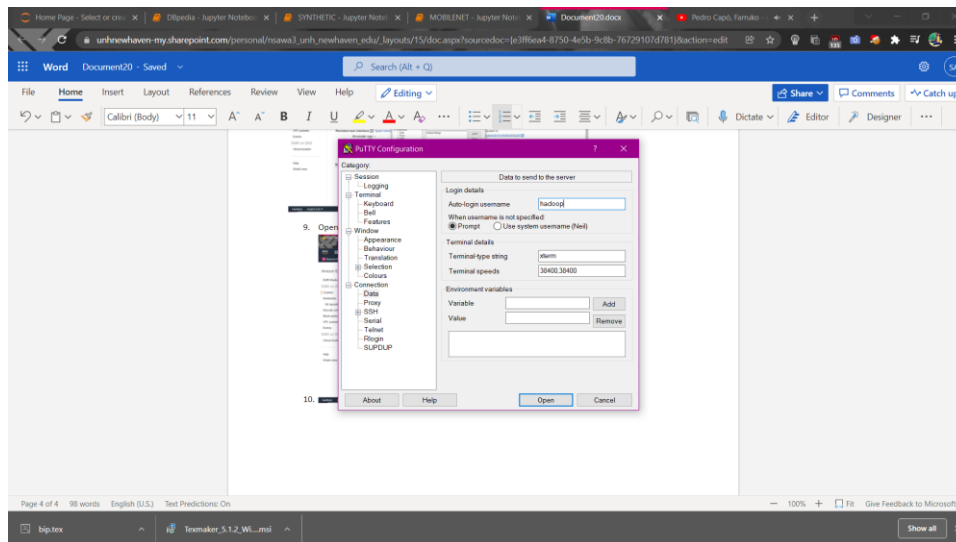
6. Open the master group and click on edit inbound rules



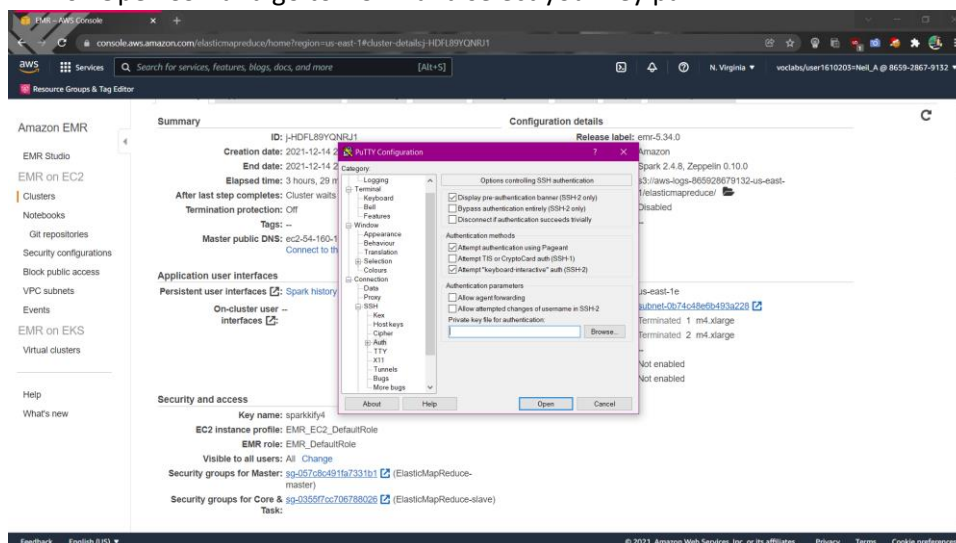
7. Create rules with ports 22 as SSH and 8888 as custom
8. Open putty for windows users and hostname as "hadoop@your Master public DNS address"



9. Open data in connection and write "hadoop" in auto login username



10. Open SSH and go to AUTH and select your key pair

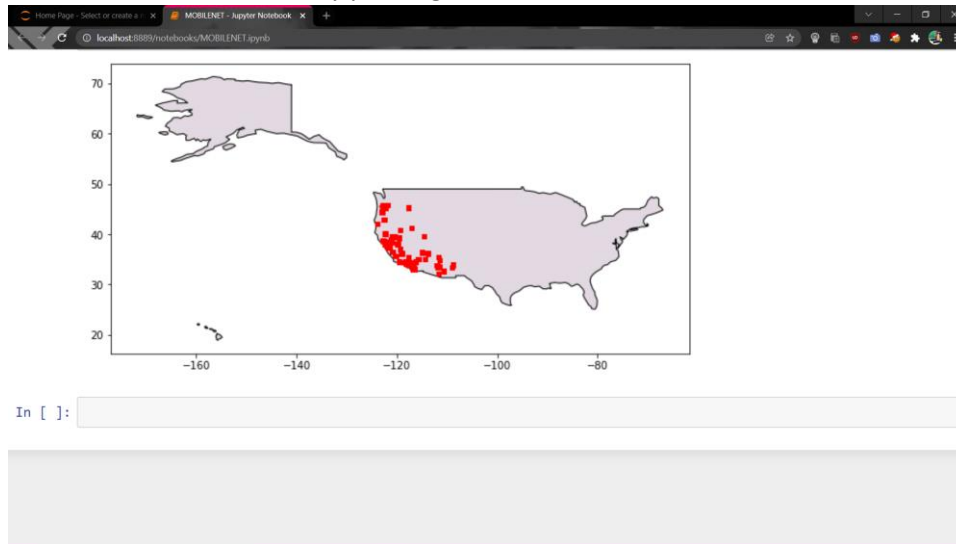


11. You will see your putty opened now type the below commands

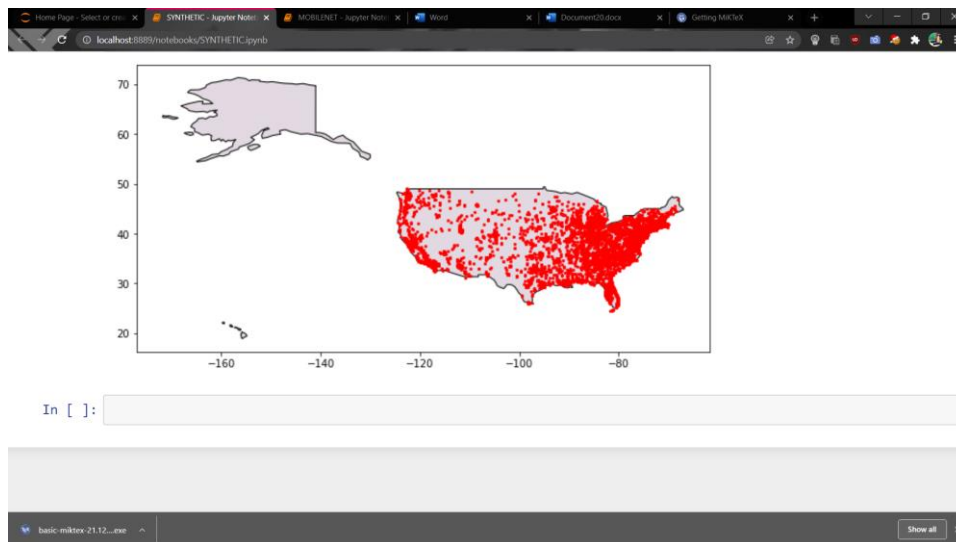
- `sudo su`
- `Python3 -m pip install pyyaml ipython jupyter ipyparallel pandas boto -U`
- `Type exit`
- `export PYSPARK_DRIVER_PYTHON=/usr/local/bin/jupyter`
- `export PYSPARK_DRIVER_PYTHON_OPTS="notebook --no-browser --ip=0.0.0.0 --port=8888"`
- `Source ~/.bashrc`
- `pyspark`

12. You will see your address to run jupyter notebook now copy paste the address in your browser

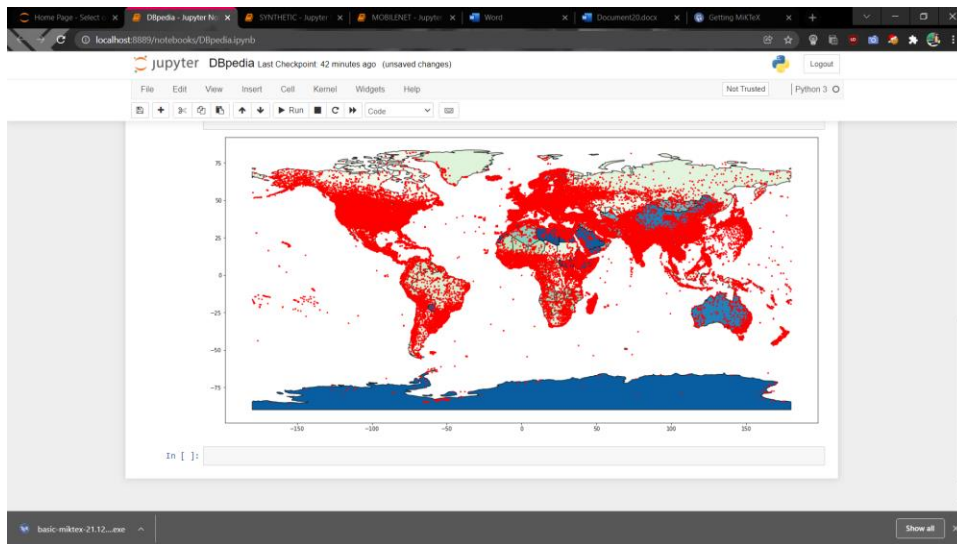
13. Now replace the part of your address that is before port number in my case “:8888” with your EMR cluster Public DNS
14. Now open a new jupyter notebook python file
15. We have 4 in total jupyter notebook files
16. Name the first file MOBILENET and use the data from device_status
17. We created a data frame to see the required coloumnns
18. Visualize the data by plotting it



19. In a new jupyter notebook named Synthetic use data from file sample geo
20. We created a dataframe
21. Visualize the data



22. Again in a new jupyter notebook named DBpedia use data from Lat_long file
23. We created new dataframe
24. Visualize it



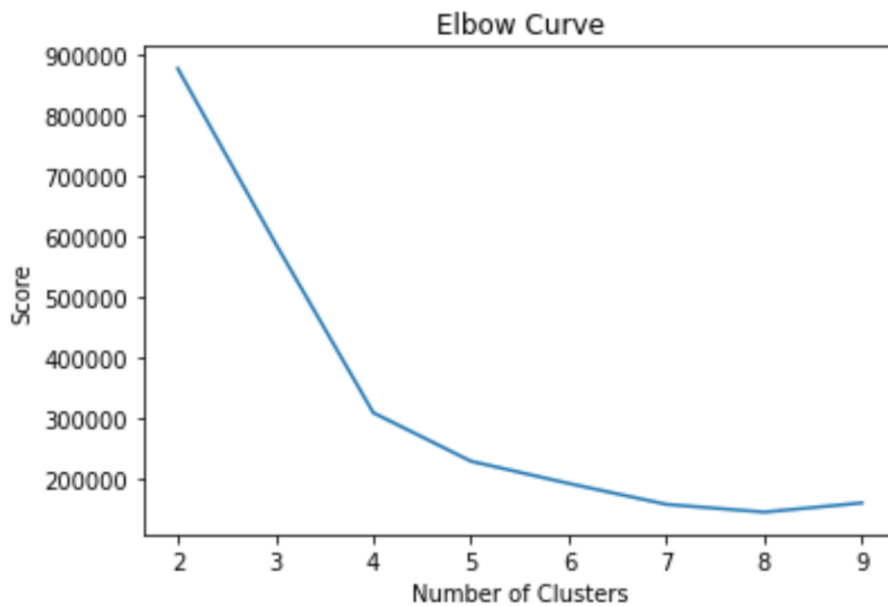
Clustering Big Data – k-means in Spark

k-means

1. K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. Typically, unsupervised algorithms make inferences from datasets using only input vectors without referring to known, or labelled, outcomes.
2. To process the learning data, the K-means algorithm in data mining starts with a first group of randomly selected centroids, which are used as the beginning points for every cluster, and then performs iterative (repetitive) calculations to optimize the positions of the centroids
 - It halts creating and optimizing clusters when either:
 - The centroids have stabilized — there is no change in their values because the clustering has been successful.
 - The defined number of iterations has been achieved

Implementation

Since the data is big, so in order to execution of the model faster, we used AWS. Create an S3 bucket and upload all three folders. Then create an EMR cluster and run spark in browser using putty. Convert latitude and longitude coordinates to vector using vector assembler from pyspark. Combines all columns with features together. Done before the model cause the data has to be in vector form. To find the best K possible use elbow curve. Plot the curve against number of clusters and score. Now we find K means



Results

1.Device location data:

Cluster and k=4 and seed = 1

```
%time prediction_df, centers = kmeans_model(df=device_status_df, k=4, seed=1)
```

Silhouette with squared euclidean distance = 0.7540828544162818

Within Set Sum of Squared Errors = 309322.4486914122

Cluster Centers:

```
[ 34.30404014 -117.8032879 ]
```

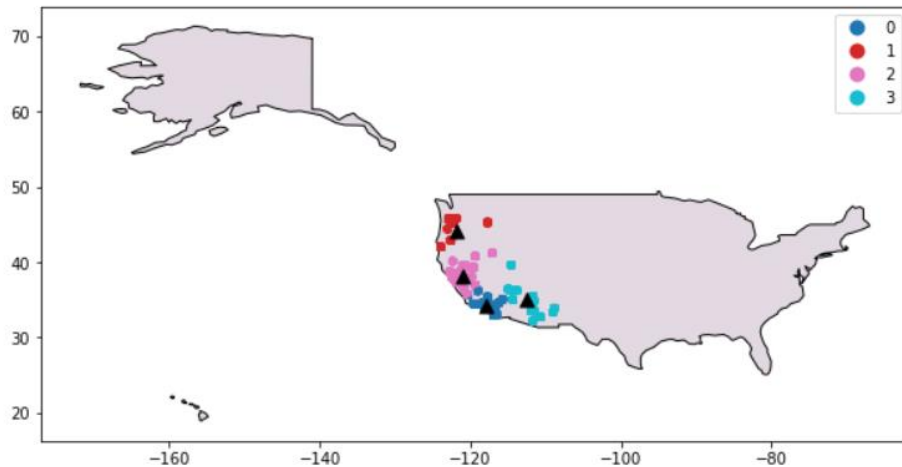
```
[ 44.23926087 -121.79580631]
```

```
[ 38.19538776 -121.08051278]
```

```
[ 35.08461054 -112.57140921]
```

CPU times: user 37.3 ms, sys: 4.27 ms, total: 41.6 ms

Wall time: 2.86 s



CPU times: user 16.9 s, sys: 163 ms, total: 17.1 s
Wall time: 17.2 s

3. K=5 and distance method is euclidean method

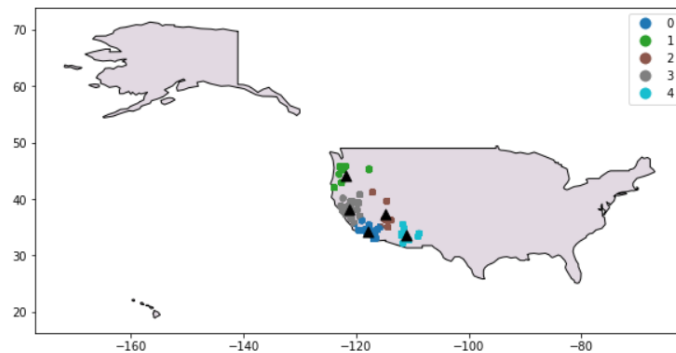
```
In [23]: # Step 3: Compute and Visualize Clusters

# Calculate the k-means clusters for the device location data using k = 5.

%time prediction_df, centers = kmeans_model(df=device_status_df, k=5, seed=1)

%time plot_data(prediction_df, a=0, after_prediction=True)
```

Silhouette with squared euclidean distance = 0.7911724452946861
Within Set Sum of Squared Errors = 229329.08140511927
Cluster Centers:
[34.29368632 -117.81213281]
[44.23926087 -121.79580631]
[37.33148137 -114.84963868]
[38.0957093 -121.19758985]
[33.68736796 -111.04079699]
CPU times: user 53.3 ms, sys: 451 µs, total: 53.7 ms
Wall time: 2.83 s



CPU times: user 15.6 s, sys: 156 ms, total: 15.7 s
Wall time: 16 s

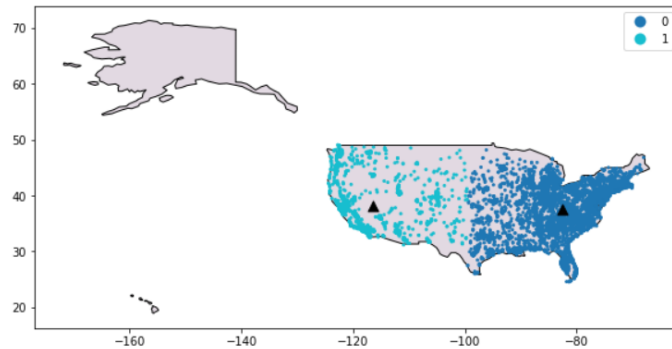
Synthetic location data

1. When k=2 distance is euclidean

In [24]: `# Calculate the k-means clusters for the synthetic location data using k = 2 and k = 4.`

```
print("Calculating the k-means clusters for the synthetic location data using k = 2")  
  
# calculate for sample geo data  
%time prediction_df, centers = kmeans_model(df=sample_geo_log_df, k=2, seed=1)  
  
%time plot_data(prediction_df, a=0, after_prediction=True)
```

Calculating the k-means clusters for the synthetic location data using k = 2
Silhouette with squared euclidean distance = 0.8525189358156998
Within Set Sum of Squared Errors = 704244.7373775935
Cluster Centers:
[37.5647472 -82.55711082]
[38.07161548 -116.43342043]
CPU times: user 41.8 ms, sys: 197 μ s, total: 42 ms
Wall time: 1.15 s



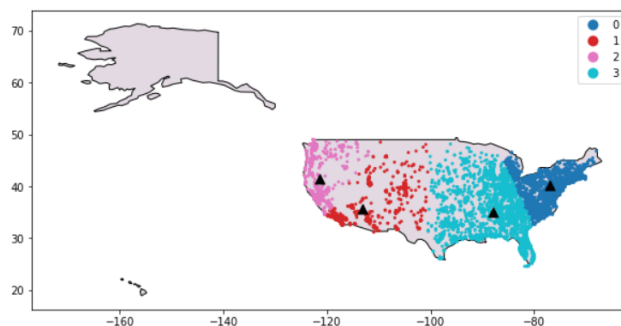
CPU times: user 1.87 s, sys: 140 ms, total: 2.01 s
Wall time: 1.91 s

2. When k=4 and distance is euclidean

In [25]: `print("Calculating the k-means clusters for the synthetic location data using k = 4")`

```
%time prediction_df, centers = kmeans_model(df=sample_geo_log_df, k=4, seed=1)  
  
%time plot_data(prediction_df, a=0, after_prediction=True)
```

Calculating the k-means clusters for the synthetic location data using k = 4
Silhouette with squared euclidean distance = 0.5548689033882502
Within Set Sum of Squared Errors = 365558.3934312812
Cluster Centers:
[40.14836238 -76.96598964]
[35.57495009 -113.07189577]
[41.49405835 -121.33793416]
[35.11449774 -87.93102449]
CPU times: user 41.1 ms, sys: 375 μ s, total: 41.5 ms
Wall time: 1.18 s



CPU times: user 2.48 s, sys: 120 ms, total: 2.6 s
Wall time: 2.41 s

3. K=5 and distance is euclidean

```
In [26]: print("Calculating the k-means clusters for the synthetic location data using k = 5")
```

```
%time prediction_df, centers = kmeans_model(df=sample_geo_log_df, k=5, seed=1)
```

```
%time plot_data(prediction_df, a=0, after_prediction=True)
```

Calculating the k-means clusters for the synthetic location data using k = 5

Silhouette with squared euclidean distance = 0.579380126122293

Within Set Sum of Squared Errors = 276292.5761643455

Cluster Centers:

```
[ 38.03380474 -82.91911996]
```

```
[ 38.08274514 -116.98428691]
```

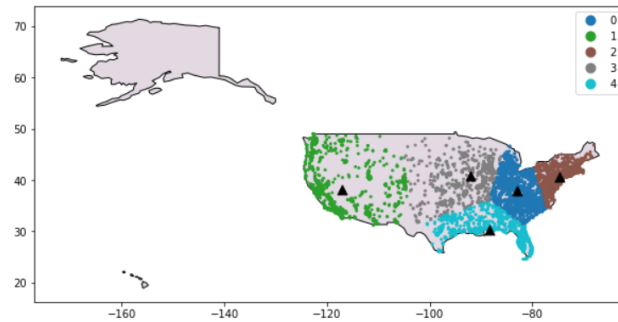
```
[ 40.689765   -74.77185746]
```

```
[ 40.76409505 -91.99226496]
```

```
[ 30.22653902 -88.43888705]
```

CPU times: user 36.5 ms, sys: 8.14 ms, total: 44.6 ms

Wall time: 1.59 s



CPU times: user 1.94 s, sys: 104 ms, total: 2.04 s

Wall time: 1.9 s

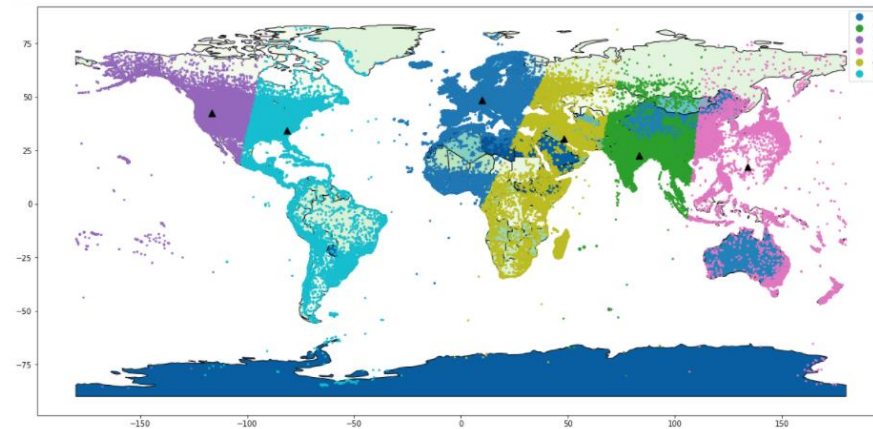
DBpedia Location data

1. When k=6 and euclidean distance

```
print("Calculating the k-means clusters for the synthetic location data using k = 6")
# calculate for long lat data
%time prediction_df, centers = kmeans_model(df=long_lats_log_df, k=6, seed=1)
%time plot_data(prediction_df, a=1, after_prediction=True)
```

Calculating the k-means clusters for the synthetic location data using k = 6

Silhouette with squared euclidean distance = 0.7199107240404778
 Within Set Sum of Squared Errors = 121593903.3697077
 Cluster Centers:
 [48.59554363 9.7731195]
 [22.591739 83.18051205]
 [42.38381357 -116.64759113]
 [17.2112931 134.06313631]
 [30.47517672 48.12423989]
 [34.19284121 -81.42496763]
 CPU times: user 43.7 ms, sys: 4.31 ms, total: 48 ms
 Wall time: 4.89 s



CPU times: user 1min 14s, sys: 453 ms, total: 1min 15s
 Wall time: 1min 16s

Runtime Analysis:

Dataset	K	Measure	Runtime
Device location	5	Euclidean distance	53.7 ms
Synthetic location	2	Euclidean distance	42 ms
Synthetic location	4	Euclidean distance	41.5 ms
Synthetic location	5	Euclidean distance	44.6 ms
DBpedia location	6	Euclidean distance	48 ms

Conclusion:

The project was built in AWS EMR, S3 bucket, pyspark and jupyter notebook. I uploaded all the dataset to S3 bucket and then the data was extracted to Jupyter notebook from the log file. I used geopandas for visualization in jupyter notebook. K means clustering was applied to the dataset. Then cluster all the three datasets by preprocessing, extracting and then splitting and then storing it in pyspark dataframe. Apply k means clustering to find centroid and cluster the data as per k values. Use different k values for better output results. Geopandas visualized the perfect output of clusters and centroids.

