```
# importing the necessary libraries

from numpy import array
import numpy as np
import pandas as pd
from scipy.cluster.vq import vq, kmeans, whiten
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

```
# let's get the data

from google.colab import files
uploaded = files.upload()
```

Choose files lat_long.csv

- **lat_long.csv**(text/csv) - 11052416 bytes, last modified: 12/02/2022 - 100% done

```
Saving lat_long.csv to lat_long.csv
```

```
import io
df = pd.read_csv(io.StringIO(uploaded['lat_long.csv'].decode('utf-8')))
```

```
# rounding off the lat_long for two reasons 1) it is able to generalise well
# 2) Secondly, importantly, finding optimal number of clusters and then the centroi
# which is heavy (squared and under_roots), rounding off helps in reducing the time

df = df.round(2)
```

```
# removing the Id column, it is not adding any value, except to tell us that data h
del df['Id']
```

```
# confirmation of above operations
# works fine !

df
```

	latitude	longitude
0	87.33	144.48
1	-22.61	143.38
2	-43.53	-78.60

3	-50.79	-8.42
4	-49.27	-62.17
...	...	...
249995	61.70	-115.33
249996	-62.29	160.90
249997	-1.65	27.33
249998	-62.36	5.45

```
# creating a copy of original data to run ML models
x = df[['latitude','longitude']]
x
```

	latitude	longitude
0	87.33	144.48
1	-22.61	143.38
2	-43.53	-78.60
3	-50.79	-8.42
4	-49.27	-62.17
...	...	...
249995	61.70	-115.33
249996	-62.29	160.90
249997	-1.65	27.33
249998	-62.36	5.45
249999	-71.24	99.65

250000 rows × 2 columns

```
# here we use the Kmeans clustering model
# WCSS (Within-Cluster-Sum-of-Squares) is defined as the sum of the squared distanc
# we will run for 15 times (taken randomly) and will check the WCSS score against e
# we will check the no of clusters after which the WCSS is not falling too much
# the marginal benefit of falling WCSS is less compared to the cost of computation,

wcss = {}
run = 15
for i in range(1, run):

    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(x)
    wcss[i] = kmeans.inertia_

# let's see the distance against each number of cluster (which are the keys)
# we can see that after 8 clusters the rate of decrease in WCSS has fallen signific
# currently, it looks like 8 is the optimal number of clusters for our dataset
```

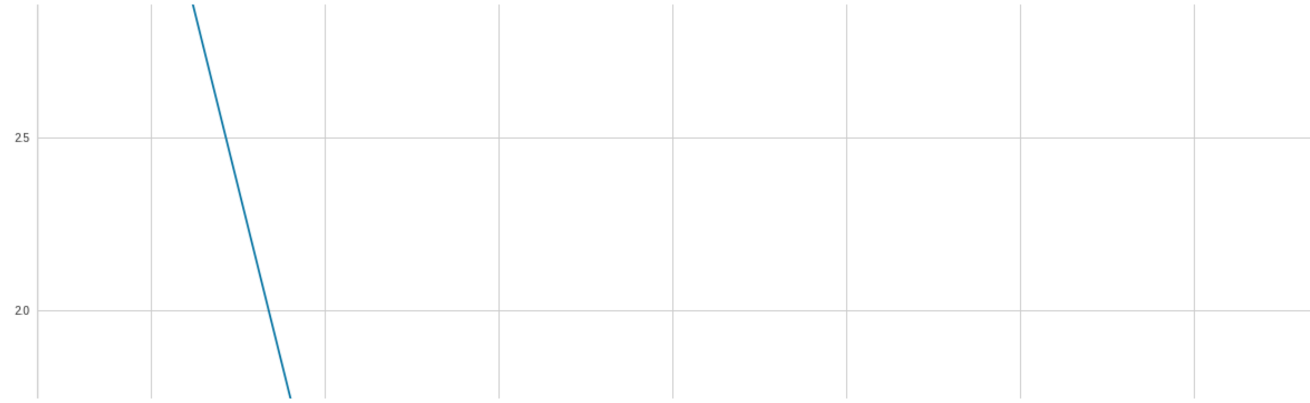
```
# currently, it looks like 8 is the optimal number of clusters for our dataset
# let's verify using couple more methods

wcss
```

```
{1: 3377654434.3883395,
 2: 1349944736.2617295,
 3: 973140398.6754223,
 4: 773706438.2760775,
 5: 602739105.7266858,
 6: 467921197.4666044,
 7: 393623491.98605084,
 8: 337209756.1288835,
 9: 304244904.0239365,
 10: 276643472.9328099,
 11: 254679069.5999413,
 12: 234359542.97107562,
 13: 213821530.34068283,
 14: 194816461.95094115}
```

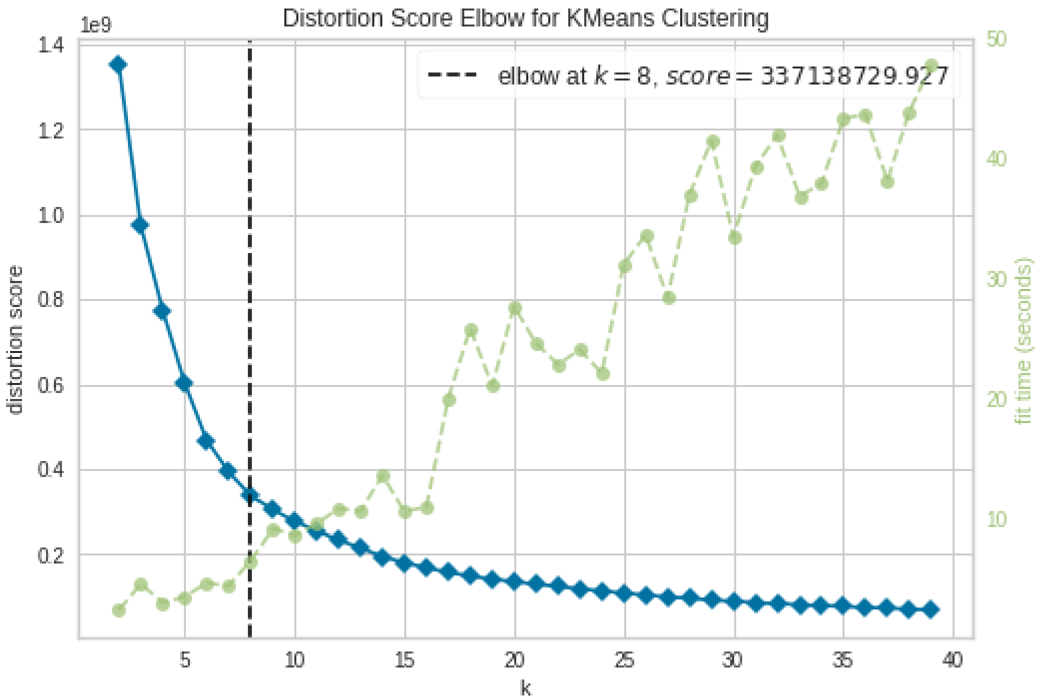
```
# method 1: let's plot #cluster v/s WCSS and check where the 'elbow' of the graph i
# looks like cluter = 6 and cluster = 8 have elbows, it is a bit hard to decide
# but we are on the right track, it is either 8 or 6

xx = [x for x in wcss.keys()]
yy = [x for x in wcss.values()]
plt.figure(figsize = (40,20))
plt.xticks(xx)
plt.plot(xx,yy)
plt.show()
```




```
# Import ElbowVisualizer
# elbow visualiser is a powerful visualising library which gives you a clear cut id
# you can see, it beautifully points at 8 as the optimal number of clusters


from yellowbrick.cluster import KElbowVisualizer
model = KMeans()
# k is range of number of clusters.
visualizer = KElbowVisualizer(model, k=(2,40), timings= True)
visualizer.fit(x)        # Fit data to visualizer
visualizer.show()        # Finalize and render figure
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8d1b4fe210>
```

```
# silhouette score is another very useful way to find optimal no of clusters
# jeremy jordan defines slihouttes score as follows:


'''Silhouette score combines the average within-cluster distance with average neare
A value below zero denotes that the observation is probably in the wrong cluster an
great fit for the cluster and clearly separated from other clusters. This coefficie
neighboring clusters, where it is desirable to be the maximum distance possible fro
```

```
# takes a lot of time to run hence commented out
'''
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import numpy as np

# Use silhouette score to find optimal number of clusters to segment the data
num_clusters = np.arange(2,10)
results = {}
for size in num_clusters:
    model = KMeans(n_clusters = size).fit(x)
    predictions = model.predict(x)
    results[size] = silhouette_score(x, predictions)

best_size = max(results, key=results.get)
'''
```

```
'\nfrom sklearn.cluster import KMeans\nfrom sklearn.metrics import silhouette
_score\nimport numpy as np\n\n# Use silhouette score to find optimal number o
f clusters to segment the data\nnum_clusters = np.arange(2,10)\nresults = {}
\nfor size in num_clusters:\n    model = KMeans(n_clusters = size).fit(x)\n
```

```
# create a new column called clusters in dataframe x
# add cluster number (1 to 8) against each lat_long data point
wcss = {}
run = 9
for i in range(1, run):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(x)
    wcss[i] = kmeans.inertia_
x['clusters'] = 1+kmeans.fit_predict(x)
```

```
x
```

	latitude	longitude	clusters
0	87.33	144.48	7
1	-22.61	143.38	3
2	-43.53	-78.60	8

3	-50.79	-8.42	8
4	-49.27	-62.17	8

```
'''# finding the centroid of these 8 clusters
import scipy
closest, distance = scipy.cluster.vq.vq(model.cluster_centers_,x.values)
print(closest)'''
```

```
[  4504 177419  36216 139091  83287 236293 179050]
```

```
# could not figure out how to do it with GNN although I understoodd the MNIST link
#Classify a set of observations into k clusters with k centroids using the k-means

a = scipy.cluster.vq.kmeans2(x.drop(['clusters'], axis = 1), 8, iter=50)
print("centroids")
a[0]
```

```
centroids
array([[  45.12602101,  -50.93737747],
       [ -44.56652179,  -39.94280761],
       [ -44.78719809,  137.14273947],
       [  45.18933597,  132.47474704],
       [  44.86930168, -137.59582345],
       [ -45.30699006,   50.14715678],
       [ -45.04342201, -133.25611101],
       [  44.48023708,   39.02286876]])
```

```
# cluster mapping

x['clusters'] = 1+kmeans.fit_predict(x)
```

```
x
```

	latitude	longitude	clusters
0	87.33	144.48	2
1	-22.61	143.38	7
2	-43.53	-78.60	1

3	-50.79	-8.42	1
4	-49.27	-62.17	1
...	...	...	...

```
# plotting the clusters for visualisation and verification

plt.figure(figsize = (10,10))
for k in range(1,9):
    data = x[x["clusters"]==k]
    plt.scatter(data["latitude"],data["longitude"], label = "cluster {}".format(k))


plt.xlabel('Latitude')
plt.ylabel('Longitude')
plt.legend(loc='upper right')
```

```
<matplotlib.legend.Legend at 0x7f8d17907a10>
```


```
x
```

	latitude	longitude	clusters

0	87.33	144.48	2
1	-22.61	143.38	7
2	-43.53	-78.60	1
3	-50.79	-8.42	1
4	-49.27	-62.17	1
...	...	...	...
249995	61.70	-115.33	6
249996	-62.29	160.90	7
249997	-1.65	27.33	5
249998	-62.36	5.45	5
249999	-71.24	99.65	7

250000 rows × 3 columns

```
# downloading the CSV

x.to_csv('sample.csv')
from google.colab import files
files.download("sample.csv")
```

✓ 1s completed at 22:29