nrcm-kmeans-1-1

August 28, 2023

```
[]: #import the numpy, matlot, pandas libery's import numpy as np import pandas as pd import matplotlib.pyplot as plt
```

##Name:Manohar Goud ##Roll No:21X05A6706 ##Branch:IV year cse(data science) ##College:Narsimha Reddy Engineering College ##Github:

##Project Title: Analysis and prediction of "small customers.csv" American Mall market called as phonix small. To find out how may customers are visited to a particular shop on the basis of this prediction of annual income vs spending scores

###Disclaimer: In this particular dataset we assume annual income as a centroid and spending score from the range 1to 100 called as data node s of the cluster

##problem statement: The americak finance market as per the gdp of 2011 The american finance market 'PHONIX_TRILLIUMS MALL" as in the first range out of 5. The owner of the mall is want to be exact which particular shop or product search in different kinds of clusters in entire mall ##2) As a Datascience engineer predict the futuristic finacial market for upcoming gdp rate based on no:of clusters. The client wants at least top 5 cluster in shops.

<IPython.core.display.HTML object>

Male

Male

2

0

1

Saving Mall_Customers.csv to Mall_Customers.csv

19

21

```
[]: dataset=pd.read_csv('Mall_Customers.csv')
dataset.head()

[]: CustomerID Genre Age Annual Income (k$) Spending Score (1-100)
```

15

15

39

81

```
2
                  3 Female
                               20
                                                     16
                                                                                6
     3
                  4 Female
                               23
                                                     16
                                                                               77
     4
                     Female
                                                                               40
                               31
                                                     17
[]: dataset.shape
[]: (200, 5)
[]: x=dataset.iloc[:,[3,4]].values
[]: array([[ 15,
                    39],
             [ 15,
                    81],
             [ 16,
                     6],
             [ 16,
                    77],
             [ 17,
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             [ 17,
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             [ 29,
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             [ 30,
                     4],
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                    4],
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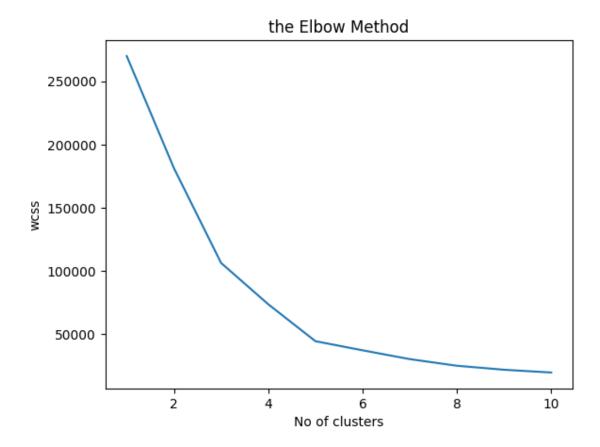
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- [87,
- 10], [87, 92],
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- [88, 86],
- 15], [88,

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[ 97,
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[120, 16],
[120, 79],
[126, 28],
[126, 74],
[137, 18],
[137, 83]])
```

```
[]: ## <THE ELBOW METHOD>
     #from sklearn used "sklearn.cluster" attribute and import KMeans
     from sklearn.cluster import KMeans
     #Take a distance from from centroid to cluster point with WrapsColumnExpression.
     # Assume you have 10 cluster and iterate the for up to range 10 with iterater
      ⇒kmeans++.
     for i in range(1,11):
      kmeans=KMeans(n_clusters=i, init='k-means++', random_state= 42)
      kmeans.fit(x)
      wcss.append(kmeans.inertia_)
     plt.plot(range(1,11),wcss)
     plt.title('the Elbow Method')
     plt.xlabel('No of clusters')
     plt.ylabel('wcss')
     plt.show()
     # Fit the model if value comes too samlla in range.
     #For clustering in wcss ,inertia is adding / appending is required. (kmeans.
     ⇔inertia_)#defalut usecase.
     #Plot the poarticular graph along with the wcss and your range which you taken_
      ⇔as input variable.
```

```
#Add title "The Elbow Method".
#Lable x variable as "No of Customers".
#Lable y variable as "WCSS".
#Plot the graph using plt.show().
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
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```



```
[]: for i in range(1,11):
    kmeans=KMeans(n_clusters=5,init='k-means++',random_state=42)
    y_predict=kmeans.fit_predict(x)
```

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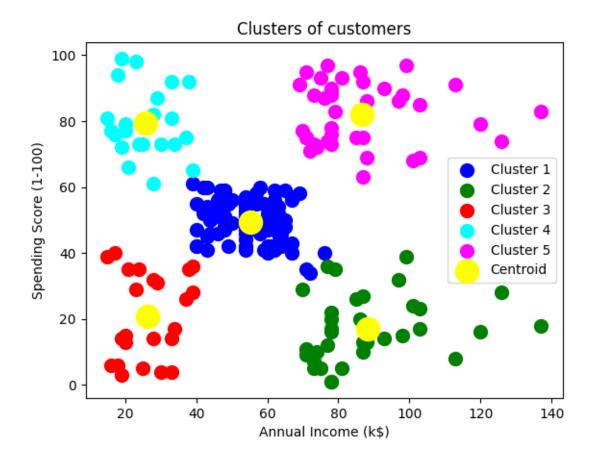
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```
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    1.4. Set the value of `n_init` explicitly to suppress the warning
      warnings.warn(
[]: plt.scatter(x[y_predict == 0,0],x[y_predict == 0,1], s = 100, c = 'blue', labelu
     →= 'Cluster 1') #for first cluster
     plt.scatter(x[y_predict == 1,0], x[y_predict == 1,1], s = 100, c = 'green', __
      ⇔label = 'Cluster 2') #for second cluster
     plt.scatter(x[y_predict== 2,0], x[y_predict == 2,1], s = 100, c = 'red', labelu
     ⇒= 'Cluster 3') #for third cluster
     plt.scatter(x[y_predict == 3,0], x[y_predict == 3,1], s = 100, c = 'cyan', u
      ⇒label = 'Cluster 4') #for fourth cluster
     plt.scatter(x[y_predict == 4,0], x[y_predict == 4,1], s = 100, c = 'magenta', u
      →label = 'Cluster 5') #for fifth cluster
     plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = __
      ⇒300, c = 'yellow', label = 'Centroid')
     plt.title('Clusters of customers')
     plt.xlabel('Annual Income (k$)')
     plt.ylabel('Spending Score (1-100)')
     plt.legend()
     plt.show()
```



##CONCLUSION: According to the model basics prediction using machine learning algorithm k_means clustering we found that cluster one which consists of blue color is the highest color which attached more than 50 datanodes.

##REFERENCES:THe model building algorithm devolop for all kinds of cluteration values.THE YELLOW Ssquads represents centroids which is max to max only 5.

[]: