sociation-rule-mining-assignment01

October 27, 2024

1 Consider the dataset comprising of 109 cricket players (attached here with assignment), filename is ‘cricketers.csv’. Each row comprises of following details of a cricketer:

matches_played: number of matches played by the player, innings_batted: number of times got the chance to bat, runs_scored: total runs scores across all innings, highest_runs: highest run scored taking all innings in account, ball_faced: total balls faced across all innings, average_runs: average runs scores taking all innings in account, strike_rate: it is computed as (runs_scored / balls_faced) x 100, innings_bowled: number of times got the chance to bowl, overs: number of overs bowled across all innings, runs_given: total run given across all innings, wickets_obtained: total wickets obtained across all innings, average_runs_per_wicket: it is computed as (runs_given / wickets_obtained) bowling_economy: average runs scored per overred per overred per over

[93]:
```
# Importing required packages
import numpy as np
import pandas as pd
import warnings as war
war.filterwarnings("ignore")
```

[94]:
```
# Defining dataset csv Path
dataSetPath="C:\\Users\\ASUS\\jupyterworkspace\\Assignment & Mini␣
 ↪Project\Module_04_Unsupervised Learning and Association Rule␣
 ↪Mining\\Assigments\\cricketers.csv"
# Loading dataSet
dataSetRead=pd.read_csv(dataSetPath)
```

[95]:
```
# Displaying first 5 records to confirming data loading
print("*****************************************************Displaying below␣
 ↪first 5 records**********************************************************")
dataSetRead.head()
```

```
*****************************************************Displaying below first 5
records**********************************************************
```

[95]:
```
            PLAYER  matches_played  innings_batted  runs_scored  highest_runs  \
0     Aaron Finch              10               9          134            46
1   AB de Villiers              12              11          480            90
```

```
2  Abhishek Sharma               3               3          63            46
3   Ajinkya Rahane              15              14         370            65
4       Alex Hales               6               6         148            45

   balls_faced  average_runs  strike_rate  innings_bowled  overs  runs_given  \
0          100         16.75       144.00               0    0.0           0
1          275         53.33       174.54               0    0.0           0
2           33         63.00       190.90               0    0.0           0
3          313         28.46       118.21               0    0.0           0
4          118         24.66       125.42               0    0.0           0

   wickets_obtained  average_runs_per_wicket   bowling_economy
0                 0                      0.0               0.0
1                 0                      0.0               0.0
2                 0                      0.0               0.0
3                 0                      0.0               0.0
4                 0                      0.0               0.0
```

[96]:

```
# Displaying last 5 records to confirming data loading
print("*****************************************************Displaying below␣
 ↪last 5 records**********************************************************")
dataSetRead.tail()
```

```
*****************************************************Displaying below last 5
records**********************************************************
```

[96]:

```
              PLAYER  matches_played  innings_batted  runs_scored  highest_runs  \
104  Anureet Singh               0               0            0             0
105     Avesh Khan               0               0            0             0
106  Barinder Sran               0               0            0             0
107   Basil Thampi               0               0            0             0
108   Ben Laughlin               0               0            0             0

     balls_faced  average_runs  strike_rate  innings_bowled  overs  \
104            0           0.0          0.0               3    4.0
105            0           0.0          0.0               6   19.0
106            0           0.0          0.0               6   22.0
107            0           0.0          0.0               4   10.1
108            0           0.0          0.0               7   21.0

     runs_given  wickets_obtained  average_runs_per_wicket   bowling_economy
104          42                 1                    42.00             10.50
105         204                 4                    51.00             10.73
106         229                 4                    57.25             10.40
107         114                 5                    22.80             10.20
108         212                 9                    22.44             10.04
```

[97]:

```python
# Displaying dimension of dataSet
print("Dimention of Dataset:- {}".format(dataSetRead.shape[0:2]))
print("Total number of rows in Dataset:- {}".format(dataSetRead.shape[0]))
print("Total number of columns in Dataset:- {}".format(dataSetRead.shape[1]))
```

```
Dimention of Dataset:- (109, 14)
Total number of rows in Dataset:- 109
Total number of columns in Dataset:- 14
```

[98]:

```python
# Displaying description & statistcal summary of the dataSet
dataSetRead.describe().T
```

[98]:

```
                         count        mean         std  min     25%     50%  \
matches_played           109.0    9.559633    5.161164  0.0    5.00   10.00
innings_batted           109.0    7.889908    4.982078  0.0    4.00    7.00
runs_scored              109.0  173.633028  182.356522  0.0   36.00   99.00
highest_runs             109.0   43.495413   29.830268  0.0   20.00   40.00
balls_faced              109.0  124.669725  123.670265  0.0   33.00   76.00
average_runs             109.0   22.360092   16.093453  0.0   11.80   21.16
strike_rate              109.0  122.258716   48.576709  0.0  109.09  130.26
innings_bowled           109.0    4.513761    5.449456  0.0    0.00    2.00
overs                    109.0   13.894495   18.395495  0.0    0.00    3.00
runs_given               109.0  119.935780  152.807630  0.0    0.00   27.00
wickets_obtained         109.0    3.926606    5.602094  0.0    0.00    0.00
average_runs_per_wicket  109.0   17.334862   21.910816  0.0    0.00    0.00
bowling_economy          109.0    5.149817    4.773435  0.0    0.00    7.28

                            75%     max
matches_played            14.00   17.00
innings_batted            13.00   17.00
runs_scored              260.00  735.00
highest_runs              62.00  128.00
balls_faced              188.00  516.00
average_runs              30.00   75.83
strike_rate              146.04  300.00
innings_bowled             8.00   17.00
overs                     26.00   68.00
runs_given               223.00  533.00
wickets_obtained           6.00   24.00
average_runs_per_wicket   28.36  108.00
bowling_economy            9.23   16.50
```

[99]:

```python
# Displaying the columns and their respective data types
dataSetRead.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109 entries, 0 to 108
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   PLAYER                   109 non-null    object
 1   matches_played           109 non-null    int64
 2   innings_batted           109 non-null    int64
 3   runs_scored              109 non-null    int64
 4   highest_runs             109 non-null    int64
 5   balls_faced              109 non-null    int64
 6   average_runs             109 non-null    float64
 7   strike_rate              109 non-null    float64
 8   innings_bowled           109 non-null    int64
 9   overs                    109 non-null    float64
 10  runs_given               109 non-null    int64
 11  wickets_obtained         109 non-null    int64
 12  average_runs_per_wicket  109 non-null    float64
 13  bowling_economy          109 non-null    float64
dtypes: float64(5), int64(8), object(1)
memory usage: 12.1+ KB
```

[100]:

```python
# Dropping PLAYER variable from dataset
dataSetRead=dataSetRead.drop('PLAYER',axis='columns')
```

[101]:

```python
# Displaying new dataSet
dataSetRead.head()
```

[101]:

```
   matches_played  innings_batted  runs_scored  highest_runs  balls_faced  \
0              10               9          134            46          100
1              12              11          480            90          275
2               3               3           63            46           33
3              15              14          370            65          313
4               6               6          148            45          118

   average_runs  strike_rate  innings_bowled  overs  runs_given  \
0         16.75       144.00               0    0.0           0
1         53.33       174.54               0    0.0           0
2         63.00       190.90               0    0.0           0
3         28.46       118.21               0    0.0           0
4         24.66       125.42               0    0.0           0

   wickets_obtained  average_runs_per_wicket  bowling_economy
0                 0                      0.0              0.0
1                 0                      0.0              0.0
2                 0                      0.0              0.0
3                 0                      0.0              0.0
4                 0                      0.0              0.0
```

1.1 Question 1:- Given that K-means depends on distance metric, it is a convention to normalize the data attributes so that attributes are on the same scale. So, in this first task, normalize all data attributes. [2 points]

[102]:

```
# Performing MinMax Scaler for perform feature scalling
dataSetRead_Normalize = (dataSetRead - dataSetRead.min()) / (dataSetRead.max()␣
 ↪- dataSetRead.min())
```

[103]:

```
# Displaying first 30 records to confirming data loading
dataSetRead_Normalize.head(30)
```

[103]:

```
    matches_played  innings_batted  runs_scored  highest_runs  balls_faced  \
0         0.588235        0.529412     0.182313      0.359375     0.193798
1         0.705882        0.647059     0.653061      0.703125     0.532946
2         0.176471        0.176471     0.085714      0.359375     0.063953
3         0.882353        0.823529     0.503401      0.507812     0.606589
4         0.352941        0.352941     0.201361      0.351562     0.228682
5         0.941176        0.941176     0.819048      0.781250     0.779070
6         0.941176        0.823529     0.429932      0.687500     0.331395
7         0.823529        0.470588     0.043537      0.109375     0.073643
8         0.529412        0.470588     0.108844      0.148438     0.133721
9         0.529412        0.352941     0.130612      0.289062     0.112403
10        0.764706        0.764706     0.266667      0.351562     0.312016
11        0.705882        0.235294     0.017687      0.054688     0.031008
12        0.352941        0.352941     0.172789      0.335938     0.170543
13        0.235294        0.235294     0.102041      0.335938     0.093023
14        0.647059        0.647059     0.500680      0.812500     0.488372
15        0.941176        0.941176     0.668027      0.578125     0.730620
16        0.235294        0.235294     0.062585      0.210938     0.050388
17        0.294118        0.235294     0.023129      0.085938     0.036822
18        0.529412        0.470588     0.178231      0.312500     0.162791
19        0.294118        0.294118     0.085714      0.257812     0.079457
20        0.176471        0.176471     0.023129      0.117188     0.042636
21        0.411765        0.411765     0.156463      0.343750     0.191860
22        0.235294        0.176471     0.035374      0.101562     0.063953
23        0.176471        0.176471     0.100680      0.203125     0.124031
24        0.705882        0.235294     0.068027      0.304688     0.056202
25        0.529412        0.470588     0.118367      0.250000     0.156977
26        0.941176        0.941176     0.677551      0.406250     0.653101
27        0.941176        0.588235     0.191837      0.531250     0.176357
28        0.764706        0.764706     0.519728      0.507812     0.534884
29        0.352941        0.352941     0.220408      0.523438     0.250000

    average_runs  strike_rate  innings_bowled     overs  runs_given  \
0       0.220889     0.480000        0.000000  0.000000    0.000000
1       0.703284     0.581800        0.000000  0.000000    0.000000
2       0.830806     0.636333        0.000000  0.000000    0.000000
```

```
3       0.375313     0.394033        0.000000  0.000000    0.000000
4       0.325201     0.418067        0.000000  0.000000    0.000000
5       0.567058     0.499167        0.000000  0.000000    0.000000
6       0.378742     0.615967        0.882353  0.551471    0.666041
7       0.070289     0.280700        0.823529  0.823529    0.840525
8       0.175788     0.386467        0.470588  0.382353    0.409006
9       0.316497     0.551700        0.411765  0.250000    0.315197
10      0.215350     0.405767        0.705882  0.544118    0.568480
11      0.085718     0.270833        0.705882  0.677941    0.664165
12      0.279045     0.481033        0.000000  0.000000    0.000000
13      0.329685     0.520833        0.235294  0.148529    0.176360
14      0.539101     0.486767        0.000000  0.000000    0.000000
15      0.431623     0.434100        0.000000  0.000000    0.000000
16      0.606620     0.589733        0.235294  0.205882    0.268293
17      0.112093     0.298233        0.294118  0.267647    0.356473
18      0.345510     0.519833        0.411765  0.220588    0.242026
19      0.166161     0.512167        0.000000  0.000000    0.000000
20      0.074641     0.257567        0.176471  0.123529    0.215760
21      0.216537     0.387200        0.117647  0.044118    0.035647
22      0.171436     0.262600        0.235294  0.169118    0.189493
23      0.487934     0.385400        0.000000  0.000000    0.000000
24      0.219702     0.574700        0.705882  0.560294    0.521576
25      0.286826     0.358000        0.117647  0.044118    0.045028
26      0.656732     0.492567        0.000000  0.000000    0.000000
27      0.464856     0.516467        0.941176  0.783824    1.000000
28      0.387446     0.461333        0.000000  0.000000    0.000000
29      0.427272     0.418600        0.000000  0.000000    0.000000

    wickets_obtained  average_runs_per_wicket   bowling_economy
0           0.000000                  0.000000          0.000000
1           0.000000                  0.000000          0.000000
2           0.000000                  0.000000          0.000000
3           0.000000                  0.000000          0.000000
4           0.000000                  0.000000          0.000000
5           0.000000                  0.000000          0.000000
6           0.541667                  0.252778          0.568485
7           1.000000                  0.172778          0.484848
8           0.125000                  0.672778          0.507879
9           0.083333                  0.777778          0.598788
10          0.333333                  0.350648          0.495758
11          0.375000                  0.364167          0.464242
12          0.000000                  0.000000          0.000000
13          0.208333                  0.174074          0.560000
14          0.000000                  0.000000          0.000000
15          0.000000                  0.000000          0.000000
16          0.125000                  0.441296          0.618788
17          0.333333                  0.219907          0.627879
```

```
18        0.083333              0.597222          0.521212
19        0.000000              0.000000          0.000000
20        0.125000              0.354907          0.803636
21        0.041667              0.175926          0.383636
22        0.166667              0.233796          0.516970
23        0.000000              0.000000          0.000000
24        0.416667              0.257407          0.441212
25        0.000000              0.000000          0.484848
26        0.000000              0.000000          0.000000
27        0.583333              0.352500          0.603636
28        0.000000              0.000000          0.000000
29        0.000000              0.000000          0.000000
```

1.2 Question 2:- Write your own code for K-means algorithm using two attributes namely average_runs and bowling_economy. Take K=2. Plot clusters on a scatter plot with X and Y being the two attributes namely average_runs and bowling_economy, respectively. Color data points belonging to the first cluster with red and the second cluster with blue. Copy the plot diagram in the word document and interpret the output. [2 points]

```
[105]: # Extracting relevant columns: average_runs and bowling_economy
       dataSetRead_kmeans = pd.
        ↪DataFrame(dataSetRead_Normalize,columns=['average_runs','bowling_economy '])
       dataSetRead_kmeans.head(30)
```

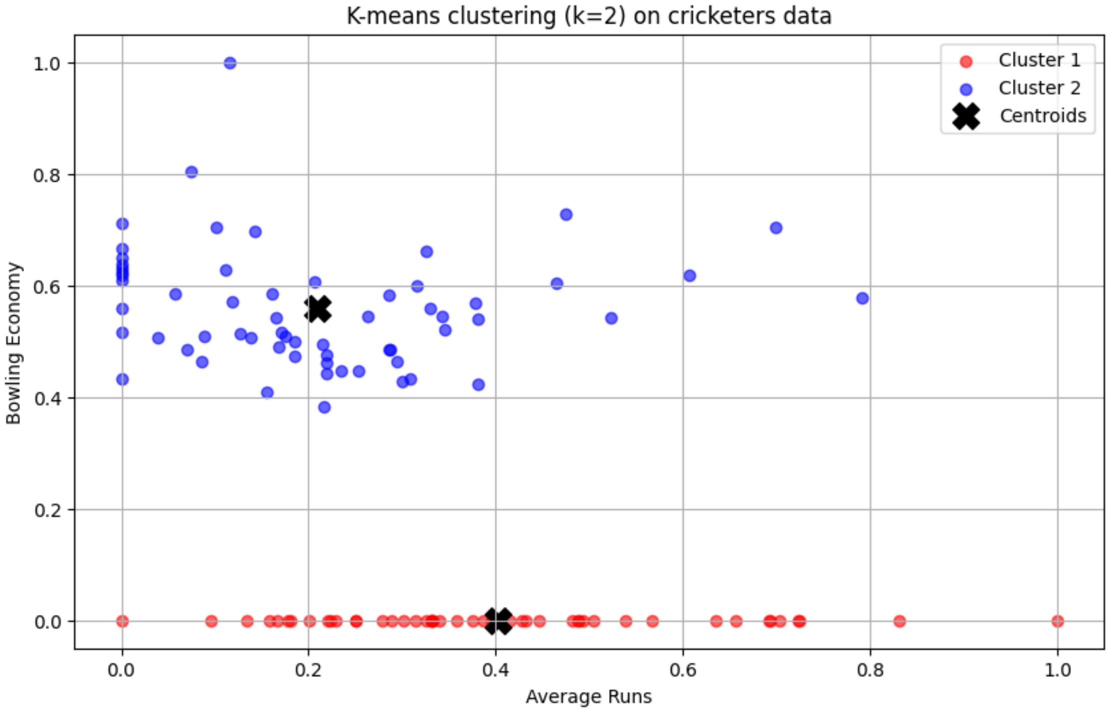
```
[105]:     average_runs  bowling_economy
       0       0.220889         0.000000
       1       0.703284         0.000000
       2       0.830806         0.000000
       3       0.375313         0.000000
       4       0.325201         0.000000
       5       0.567058         0.000000
       6       0.378742         0.568485
       7       0.070289         0.484848
       8       0.175788         0.507879
       9       0.316497         0.598788
       10      0.215350         0.495758
       11      0.085718         0.464242
       12      0.279045         0.000000
       13      0.329685         0.560000
       14      0.539101         0.000000
       15      0.431623         0.000000
       16      0.606620         0.618788
       17      0.112093         0.627879
       18      0.345510         0.521212
       19      0.166161         0.000000
```

```
20      0.074641          0.803636
21      0.216537          0.383636
22      0.171436          0.516970
23      0.487934          0.000000
24      0.219702          0.441212
25      0.286826          0.484848
26      0.656732          0.000000
27      0.464856          0.603636
28      0.387446          0.000000
29      0.427272          0.000000
```

[106]:

```
# # Importing required package
import matplotlib.pyplot as plt
# Converting to numpy array for processing
dataSetRead_numpy = dataSetRead_kmeans.values

# Functioning to initialize centroids randomly
def initialize_centroids(dataSetRead_numpy, k):
    np.random.seed(42)
    indices = np.random.choice(len(dataSetRead_numpy), k, replace=False)
    return dataSetRead_numpy[indices]

# Functioning to assign clusters based on the closest centroid
def assign_clusters(dataSetRead_numpy, centroids):
    distances = np.linalg.norm(dataSetRead_numpy[:, np.newaxis] - centroids,␣
  ↪axis=2)
    return np.argmin(distances, axis=1)

# Functioning to compute new centroids as the mean of assigned points
def compute_centroids(dataSetRead_numpy, labels, k):
    return np.array([dataSetRead_numpy[labels == i].mean(axis=0) for i in␣
  ↪range(k)])

# K-means algorithm
def kmeans(dataSetRead_numpy, k, max_iters=100, tolerance=1e-4):
    centroids = initialize_centroids(dataSetRead_numpy, k)
    for i in range(max_iters):
        labels = assign_clusters(dataSetRead_numpy, centroids)
        new_centroids = compute_centroids(dataSetRead_numpy, labels, k)
        if np.all(np.abs(new_centroids - centroids) < tolerance):
            break
        centroids = new_centroids
    return labels, centroids

# Set number of clusters to 2
k = 2
labels, centroids = kmeans(dataSetRead_numpy, k)
```

```python
# Plotting the clusters
plt.figure(figsize=(10, 6))
for cluster in range(k):
    cluster_points = dataSetRead_numpy[labels == cluster]
    color = 'red' if cluster == 0 else 'blue'
    plt.scatter(cluster_points[:, 0], cluster_points[:, 1], c=color, label=f'Cluster {cluster+1}', alpha=0.6)

# Plot centroids
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', marker='X', s=200, label='Centroids')
plt.xlabel('Average Runs')
plt.ylabel('Bowling Economy')
plt.title('K-means clustering (k=2) on cricketers data')
plt.legend()
plt.grid(True)
plt.show()
```

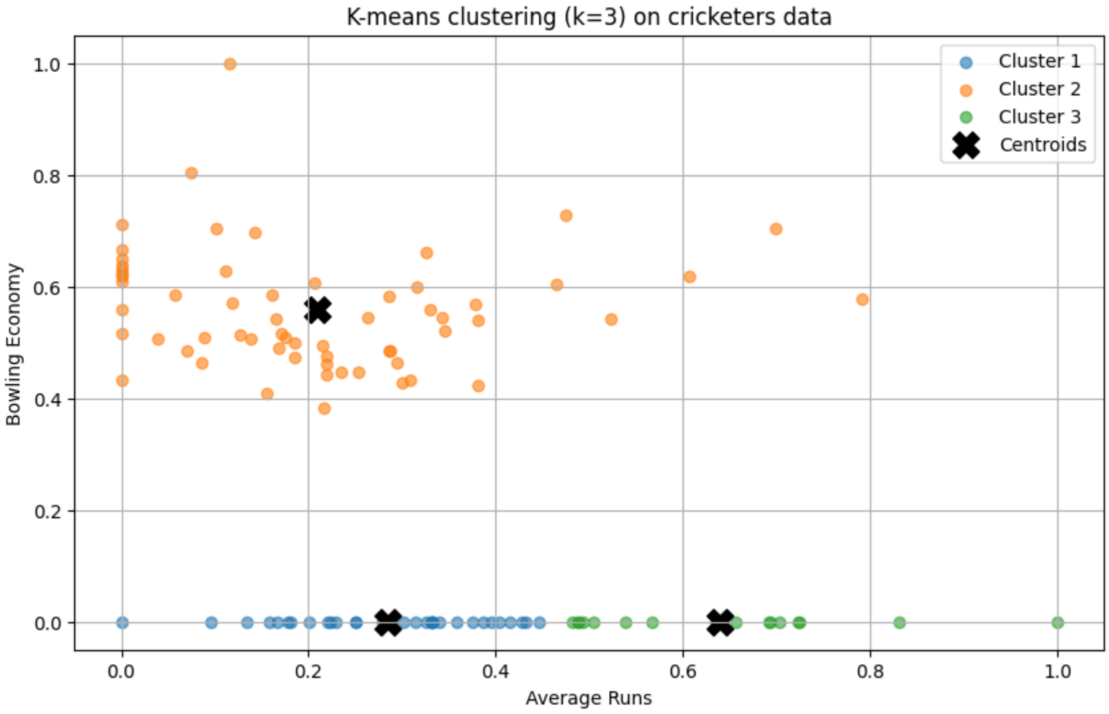


1.3 Question 3: Redo question-2 on different values of K = 2,3,4,5. For each case, draw the plot of clusters as stated above. Visualize these plots, copy the plot diagrams in the word document, and comment on which is better clustering (and reasons) based on visualization only. [1 points]

[107]:

```
# Converting to numpy array for processing
dataSetRead_numpy = dataSetRead_kmeans.values

# Functioning to initialize centroids randomly
def initialize_centroids(dataSetRead_numpy, k):
    np.random.seed(42)
    indices = np.random.choice(len(dataSetRead_numpy), k, replace=False)
    return dataSetRead_numpy[indices]

# Functioning to assign clusters based on the closest centroid
def assign_clusters(dataSetRead_numpy, centroids):
    distances = np.linalg.norm(dataSetRead_numpy[:, np.newaxis] - centroids,␣
 ↪axis=2)
    return np.argmin(distances, axis=1)

# Functioning to compute new centroids as the mean of assigned points
def compute_centroids(dataSetRead_numpy, labels, k):
    return np.array([dataSetRead_numpy[labels == i].mean(axis=0) for i in␣
 ↪range(k)])

# K-means algorithm
def kmeans(dataSetRead_numpy, k, max_iters=100, tolerance=1e-4):
    centroids = initialize_centroids(dataSetRead_numpy, k)
    for i in range(max_iters):
        labels = assign_clusters(dataSetRead_numpy, centroids)
        new_centroids = compute_centroids(dataSetRead_numpy, labels, k)
        if np.all(np.abs(new_centroids - centroids) < tolerance):
            break
        centroids = new_centroids
    return labels, centroids

# Set number of clusters to 3
k = 3
labels, centroids = kmeans(dataSetRead_numpy, k)

# Plotting the clusters
plt.figure(figsize=(10, 6))
for cluster in range(k):
    cluster_points = dataSetRead_numpy[labels == cluster]
    color = plt.cm.tab10(cluster)
    plt.scatter(cluster_points[:, 0], cluster_points[:, 1], c=color,␣
 ↪label=f'Cluster {cluster+1}', alpha=0.6)
```

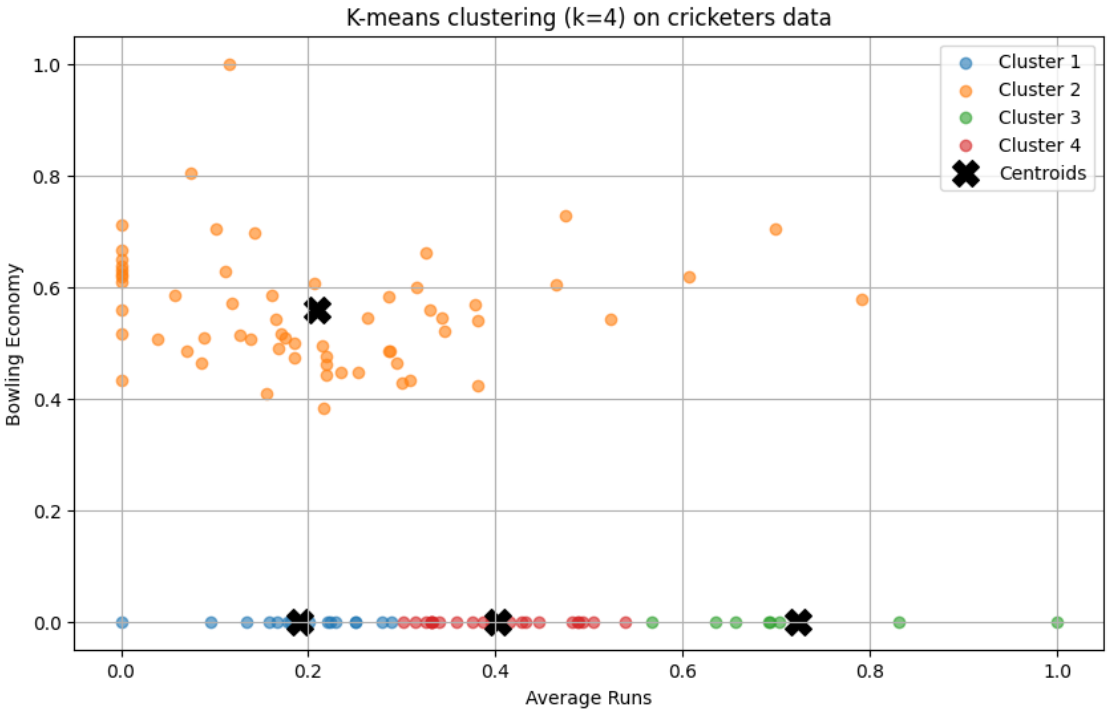
```
# Plot centroids
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', marker='X', s=200,␣
 ↪label='Centroids')
plt.xlabel('Average Runs')
plt.ylabel('Bowling Economy')
plt.title('K-means clustering (k=3) on cricketers data')
plt.legend()
plt.grid(True)
plt.show()
```



[108]:

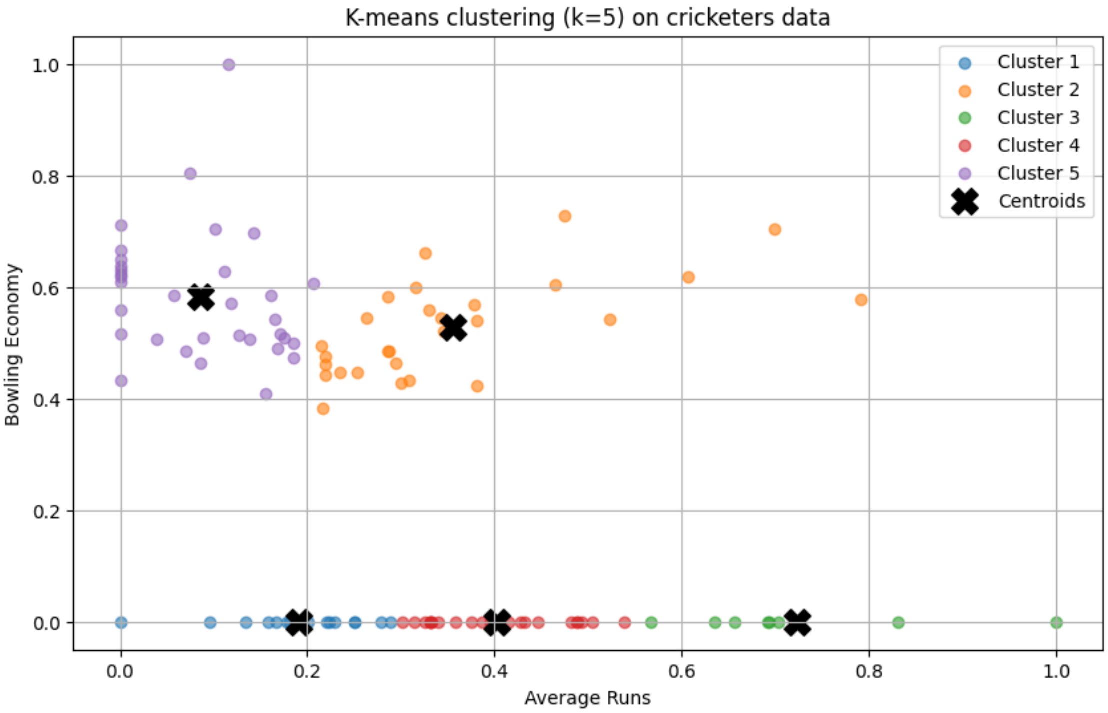
```
# Converting to numpy array for processing
dataSetRead_numpy = dataSetRead_kmeans.values

# Functioning to initialize centroids randomly
def initialize_centroids(dataSetRead_numpy, k):
    np.random.seed(42)
    indices = np.random.choice(len(dataSetRead_numpy), k, replace=False)
    return dataSetRead_numpy[indices]

# Functioning to assign clusters based on the closest centroid
def assign_clusters(dataSetRead_numpy, centroids):
    distances = np.linalg.norm(dataSetRead_numpy[:, np.newaxis] - centroids,␣
 ↪axis=2)
```

```python
    return np.argmin(distances, axis=1)

# Functioning to compute new centroids as the mean of assigned points
def compute_centroids(dataSetRead_numpy, labels, k):
    return np.array([dataSetRead_numpy[labels == i].mean(axis=0) for i in range(k)])

# K-means algorithm
def kmeans(dataSetRead_numpy, k, max_iters=100, tolerance=1e-4):
    centroids = initialize_centroids(dataSetRead_numpy, k)
    for i in range(max_iters):
        labels = assign_clusters(dataSetRead_numpy, centroids)
        new_centroids = compute_centroids(dataSetRead_numpy, labels, k)
        if np.all(np.abs(new_centroids - centroids) < tolerance):
            break
        centroids = new_centroids
    return labels, centroids

# Set number of clusters to 4
k = 4
labels, centroids = kmeans(dataSetRead_numpy, k)

# Plotting the clusters
plt.figure(figsize=(10, 6))
for cluster in range(k):
    cluster_points = dataSetRead_numpy[labels == cluster]
    color = plt.cm.tab10(cluster)
    plt.scatter(cluster_points[:, 0], cluster_points[:, 1], c=color, label=f'Cluster {cluster+1}', alpha=0.6)

# Plot centroids
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', marker='X', s=200, label='Centroids')
plt.xlabel('Average Runs')
plt.ylabel('Bowling Economy')
plt.title('K-means clustering (k=4) on cricketers data')
plt.legend()
plt.grid(True)
plt.show()
```



[109]:

```
# Converting to numpy array for processing
dataSetRead_numpy = dataSetRead_kmeans.values

# Functioning to initialize centroids randomly
def initialize_centroids(dataSetRead_numpy, k):
    np.random.seed(42)
    indices = np.random.choice(len(dataSetRead_numpy), k, replace=False)
    return dataSetRead_numpy[indices]

# Functioning to assign clusters based on the closest centroid
def assign_clusters(dataSetRead_numpy, centroids):
    distances = np.linalg.norm(dataSetRead_numpy[:, np.newaxis] - centroids,␣
  ↪axis=2)
    return np.argmin(distances, axis=1)

# Functioning to compute new centroids as the mean of assigned points
def compute_centroids(dataSetRead_numpy, labels, k):
    return np.array([dataSetRead_numpy[labels == i].mean(axis=0) for i in␣
  ↪range(k)])

# K-means algorithm
def kmeans(dataSetRead_numpy, k, max_iters=100, tolerance=1e-4):
    centroids = initialize_centroids(dataSetRead_numpy, k)
    for i in range(max_iters):
        labels = assign_clusters(dataSetRead_numpy, centroids)
        new_centroids = compute_centroids(dataSetRead_numpy, labels, k)
        if np.all(np.abs(new_centroids - centroids) < tolerance):
            break
        centroids = new_centroids
    return labels, centroids

# Set number of clusters to 5
k = 5
labels, centroids = kmeans(dataSetRead_numpy, k)

# Plotting the clusters
plt.figure(figsize=(10, 6))
for cluster in range(k):
    cluster_points = dataSetRead_numpy[labels == cluster]
    color = plt.cm.tab10(cluster)
    plt.scatter(cluster_points[:, 0], cluster_points[:, 1], c=color,␣
  ↪label=f'Cluster {cluster+1}', alpha=0.6)

# Plot centroids
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', marker='X', s=200,␣
  ↪label='Centroids')
plt.xlabel('Average Runs')
plt.ylabel('Bowling Economy')
plt.title('K-means clustering (k=5) on cricketers data')
plt.legend()
plt.grid(True)
plt.show()
```


K-means clustering (k=5) on cricketers data
Bowling Economy
Average Runs
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Centroids