22P-9252-Assignment-01

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3 BAI-4A

[1]:
```
import pandas as pd
data = pd.read_csv('total_data_na.csv')
data.head()
```

[1]:

	PLAYER	Mat.x	Inns.x	NO	Runs.x	HS	Avg.x	BF	SR.x	X100	\
0	Aaron Finch	10	9	1	134	46	16.75	100	134.00	0	
1	AB de Villiers	12	11	2	480	90	53.33	275	174.54	0	
2	Abhishek Sharma	3	3	2	63	46	63	33	190.90	0	
3	Ajinkya Rahane	15	14	1	370	65	28.46	313	118.21	0	
4	Alex Hales	6	6	0	148	45	24.66	118	125.42	0	

	…	Ov	Runs.y	Wkts	BBI	Avg.y	Econ	SR.y	X4w	X5w	y
0	…	0.0	0	0	0	0	0.0	0	0	0	0
1	…	0.0	0	0	0	0	0.0	0	0	0	0
2	…	0.0	0	0	0	0	0.0	0	0	0	0
3	…	0.0	0	0	0	0	0.0	0	0	0	0
4	…	0.0	0	0	0	0	0.0	0	0	0	0

[5 rows x 25 columns]

[5]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.preprocessing import LabelEncoder
import numpy as np


# Select relevant features for clustering
features = data[['Runs.x', 'HS', 'Avg.x', 'BF', 'SR.x', 'X100', 'X50', 'Runs.
 ↪y', 'Wkts', 'BBI', 'Avg.y', 'Econ', 'SR.y']]
```

```
features = features.replace('-', np.nan)
# Impute missing values with the mean of the column
imputer = SimpleImputer(strategy='mean')
features = pd.DataFrame(imputer.fit_transform(features), columns=features.
 ↪columns)


# Scale the features
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

features_scaled
```

[5]:
```
array([[ 0.00943771,  0.40323538, -0.03937894, …, -1.08126244,
        -1.3206071 , -1.1344344 ],
       [ 1.98807763,  1.78437691,  2.14671767, …, -1.08126244,
        -1.3206071 , -1.1344344 ],
       [-0.39658378,  0.40323538,  2.72461691, …, -1.08126244,
        -1.3206071 , -1.1344344 ],
       …,
       [-0.75685636, -1.04068531, -1.04039365, …, -0.04270068,
         0.36491249,  0.11820146],
       [-0.75685636, -1.04068531, -1.04039365, …,  0.53372595,
         2.31419659, -0.23128002],
       [-0.75685636, -1.04068531, -1.04039365, …,  0.42191906,
         0.23624687,  0.82894469]])
```

[6]:
```
k_means = KMeans(n_clusters=3, random_state= 42, n_init=10)
k_means.fit(features_scaled)

centroids = k_means.cluster_centers_
identified_clusters = k_means.fit_predict(features_scaled)

data['Cluster'] = identified_clusters

data.head()
```

[6]:

	PLAYER	Mat.x	Inns.x	NO	Runs.x	HS	Avg.x	BF	SR.x	X100	\
0	Aaron Finch	10	9	1	134	46	16.75	100	134.00	0	
1	AB de Villiers	12	11	2	480	90	53.33	275	174.54	0	
2	Abhishek Sharma	3	3	2	63	46	63	33	190.90	0	
3	Ajinkya Rahane	15	14	1	370	65	28.46	313	118.21	0	
4	Alex Hales	6	6	0	148	45	24.66	118	125.42	0	

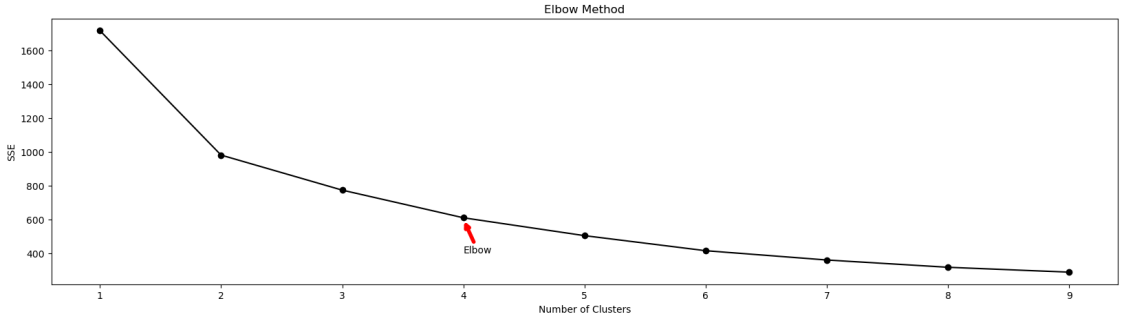
	…	Runs.y	Wkts	BBI	Avg.y	Econ	SR.y	X4w	X5w	y	Cluster
0	…	0	0	0	0	0.0	0	0	0	0	1
1	…	0	0	0	0	0.0	0	0	0	0	2

```
2  …       0     0    0      0   0.0     0    0    0  0       1
3  …       0     0    0      0   0.0     0    0    0  0       1
4  …       0     0    0      0   0.0     0    0    0  0       1

[5 rows x 26 columns]
```

[9]:
```
#Visualization
import matplotlib.pyplot as plt

fig = plt.figure(figsize=(10,3))

plt.subplots_adjust(left=0.125, right=0.9, bottom=0.1, top=0.9)

labels = k_means.labels_
print("\nLabels:")
print(labels)

data_with_clusters = data.copy()

data_with_clusters['Clusters'] = identified_clusters

# index as x
plt.scatter(data_with_clusters.index, data_with_clusters['Clusters'],␣
 ↪c=identified_clusters, cmap='viridis')
plt.title('Clusters of Players')
plt.xlabel('Players')
plt.ylabel('Clusters')

plt.show()
```

```
Labels:
[1 2 1 1 1 2 0 0 0 0 0 0 1 0 2 2 0 0 0 1 0 1 0 1 0 0 2 0 1 1 1 0 0 0 0 1 1
 1 0 0 2 0 2 1 1 1 0 0 2 0 1 1 1 0 0 1 0 0 0 0 0 2 1 1 0 1 1 0 1 0 0 0 1 2
 1 1 1 2 1 0 2 0 2 0 1 0 2 1 0 0 2 2 0 0 0 2 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

[38]:
```
# Elbow Method
sse = []
for k in range(1,10):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10, max_iter=1000)
    kmeans.fit(features_scaled)
    sse.append(kmeans.inertia_)

number_clusters = range(1,10)
plt.figure(figsize=(20,5))
plt.plot(number_clusters, sse, marker='o', color='black')
plt.annotate('Elbow', xy=(4,600), xytext=(4, 400), arrowprops={'arrowstyle':␣
 ↪'->', 'color': 'red', 'lw': 4})
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')


plt.show()
```



[39]:
```
k_means = KMeans(n_clusters=4, random_state= 42, n_init=1000)
k_means.fit(features_scaled)

centroids = k_means.cluster_centers_
identified_clusters = k_means.fit_predict(features_scaled)

data['Cluster'] = identified_clusters

data.head()
```

[39]:

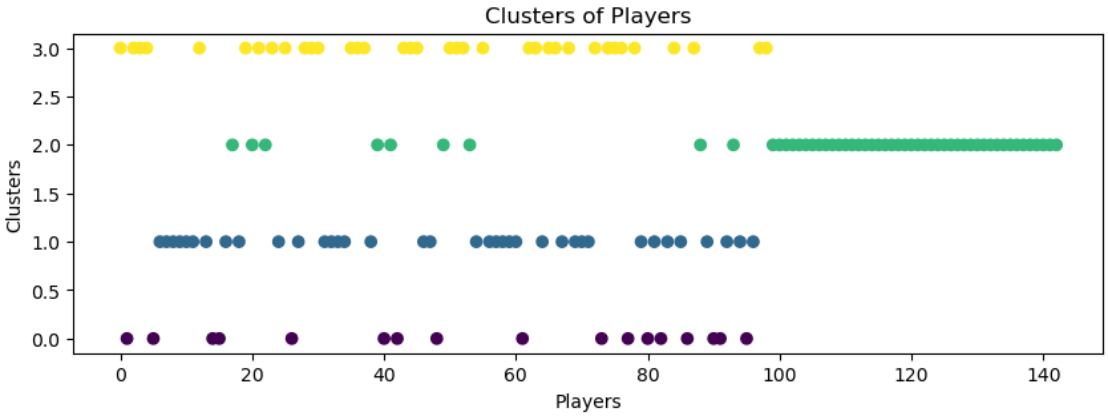
	PLAYER	Mat.x	Inns.x	NO	Runs.x	HS	Avg.x	BF	SR.x	X100	\
0	Aaron Finch	10	9	1	134	46	16.75	100	134.00	0	
1	AB de Villiers	12	11	2	480	90	53.33	275	174.54	0	
2	Abhishek Sharma	3	3	2	63	46	63	33	190.90	0	
3	Ajinkya Rahane	15	14	1	370	65	28.46	313	118.21	0	
4	Alex Hales	6	6	0	148	45	24.66	118	125.42	0	

	…	Runs.y	Wkts	BBI	Avg.y	Econ	SR.y	X4w	X5w	y	Cluster
0	…	0	0	0	0	0.0	0	0	0	0	3
1	…	0	0	0	0	0.0	0	0	0	0	0
2	…	0	0	0	0	0.0	0	0	0	0	3
3	…	0	0	0	0	0.0	0	0	0	0	3
4	…	0	0	0	0	0.0	0	0	0	0	3

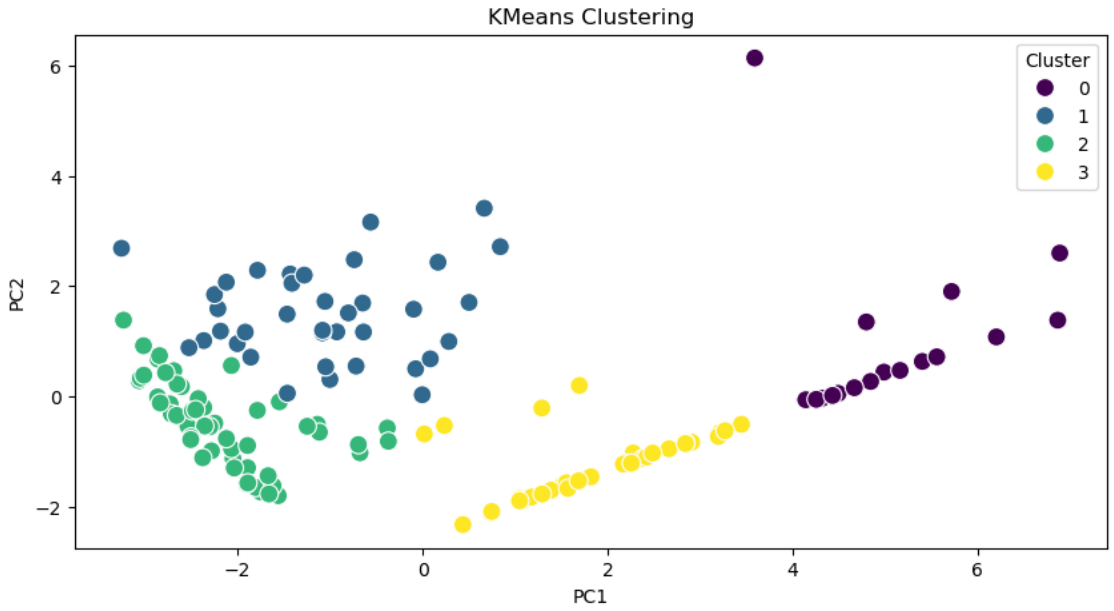
[5 rows x 26 columns]

[40]:
```
fig = plt.figure(figsize=(10,3))

plt.subplots_adjust(left=0.125, right=0.9, bottom=0.1, top=0.9)

labels = k_means.labels_
print("\nLabels:")
print(labels)

data_with_clusters = data.copy()

data_with_clusters['Clusters'] = identified_clusters

# index as x
plt.scatter(data_with_clusters.index, data_with_clusters['Clusters'],␣
 ↪c=identified_clusters, cmap='viridis')
plt.title('Clusters of Players')
plt.xlabel('Players')
plt.ylabel('Clusters')

plt.show()
```

```
Labels:
[3 0 3 3 3 0 1 1 1 1 1 1 3 1 0 0 1 2 1 3 2 3 2 3 1 3 0 1 3 3 3 1 1 1 1 3 3
 3 1 2 0 2 0 3 3 3 1 1 0 2 3 3 3 2 1 3 1 1 1 1 1 0 3 3 1 3 3 1 3 1 1 1 3 0
 3 3 3 0 3 1 0 1 0 1 3 1 0 3 2 1 0 0 1 2 1 0 1 3 3 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```



[43]:
```
# Visualizing the clusters
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import seaborn as sns

pca = PCA(n_components=2)
principal_components = pca.fit_transform(features_scaled)
principal_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])
principal_df['Cluster'] = identified_clusters

plt.figure(figsize=(10, 5))
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', data=principal_df,␣
 ↪palette='viridis', s=100)
plt.title('KMeans Clustering')
plt.show()
```



[58]:
```
num_top_order = 3
num_middle_order = 2
num_all_rounders = 3
num_bowlers = 4

''' from the clusters, we can see that cluster 0 is for top order batsmen,
cluster 1 is for all rounders ,cluster 2 is for bowlers
and cluster 3 is for middle order batsmen and iam considering 3 top order␣
 ↪batsmen(with highest  runs and strike rate),
 2 middle order batsmen(with highest runs and average rate),
   3 all rounders(with highest runs and wickets)
     and 4 bowlers(highest wickets and economy rate)'''

'''The performance of top batsmen is generally measured by using several␣
 ↪different criteria,
including the total number of runs scored (Runs.x), the highest score achieved␣
 ↪(HS), the average score (Avg.x),
 and the strike rate (SR.x).

    Higher Runs.x are better, as they indicate the batsman's ability to score␣
 ↪runs effectively.
    Higher HS is better, as it shows the batsman's capacity to make significant␣
 ↪contributions to the team's total score.
    Higher Avg.x is better, as it reflects the batsman's consistency in scoring␣
 ↪runs.
```

```
    Higher SR.x is better, as it shows the batsman's efficiency in scoring runs␣
 ↪per ball faced.
'''

top_order = data_with_clusters[data_with_clusters['Cluster'] == 0].
 ↪sort_values(by=['Runs.x', 'HS', 'Avg.x', 'SR.x'],ascending=False).
 ↪head(num_top_order)

'''The performance of middle-order batsmen is generally measured by using␣
 ↪several different criteria,
  including the total number of runs scored (Runs.x), the average score (Avg.
 ↪x), and the strike rate (SR.x).

    Higher Runs.x are better, as they indicate the batsman's ability to score␣
 ↪runs effectively.
    Higher Avg.x is better, as it reflects the batsman's consistency in scoring␣
 ↪runs.
    Higher SR.x is better, as it shows the batsman's efficiency in scoring runs␣
 ↪per ball faced.
 '''


middle_order = data_with_clusters[data_with_clusters['Cluster'] == 3].
 ↪sort_values(by=['Runs.x', 'Avg.x','SR.x'], ascending=False).
 ↪head(num_middle_order)

'''The performance of all-rounders is generally measured by using two different␣
 ↪criteria,
  i.e. the total number of runs scored (Runs.x) and the total number of wickets␣
 ↪taken (Wkts).

      Higher Runs.x are better, as they indicate the all-rounder's ability to␣
 ↪score runs effectively.
      Higher Wkts are better, as they indicate the all-rounder's effectiveness␣
 ↪in removing batsmen from the crease.
  '''

all_rounders = data_with_clusters[data_with_clusters['Cluster'] == 1].
 ↪sort_values(by=['Runs.x', 'Wkts'], ascending=False).head(num_all_rounders)


'''The performance of bowlers is generally measured by using three different␣
 ↪criteria, i.e.
the average number of runs conceded per wicket taken (A), the economy rate (E),
which is the average number of runs conceded per over bowled, and the strike␣
 ↪rate (S),
```

```
which is the average number of balls bowled per wicket taken.'''

'''
    Higher wickets are better, as they indicate the bowler's effectiveness in␣
 ↪removing batsmen from the crease.
    Lower A (runs conceded per wicket) is better, as it indicates the bowler is␣
 ↪economical.
    Lower E (economy rate) is better, as it indicates the bowler is able to␣
 ↪restrict runs without needing to bowl too many overs.
    Lower S (strike rate) is better, as it indicates the bowler is able to take␣
 ↪wickets without needing to bowl too many balls.
'''
bowlers = data_with_clusters[data_with_clusters['Cluster'] == 2].
 ↪sort_values(by=['Wkts', 'Avg.y', 'Econ', 'SR.y'], ascending=[False, True,␣
 ↪True, True]).head(num_bowlers)

print("\nTop Order Batsmen:")
print(top_order[['PLAYER', 'Runs.x', 'HS', 'SR.x']])
print("\nMiddle Order Batsmen:")
print(middle_order[['PLAYER', 'Runs.x', 'Avg.x']])
print("\nAll Rounders:")
print(all_rounders[['PLAYER', 'Runs.x', 'Wkts']])
print("\nBowlers:")
print(bowlers[['PLAYER', 'Wkts', 'Econ']])
```

```
Top Order Batsmen:
              PLAYER  Runs.x   HS    SR.x
42  Kane Williamson      735   84  142.44
73      Rishabh Pant     684  128  173.60
48      Lokesh Rahul     659   95  158.41

Middle Order Batsmen:
            PLAYER  Runs.x  Avg.x
28      Evin Lewis     382  29.38
3   Ajinkya Rahane     370  28.46

All Rounders:
           PLAYER  Runs.x  Wkts
89    Sunil Orine     357    17
6   Andre Russell     316    13
33  Hardik Pandya     260    18

Bowlers:
             PLAYER  Wkts  Econ
138   Siddarth Kaul    21  8.28
140     Umesh Yadav    20  7.86
```

```
139     Trent Boult    18  8.84
115  Jasprit Bumrah    17  6.88
```

[59]:
```
# Team Creation

team = pd.concat([top_order, middle_order, all_rounders, bowlers])
team.reset_index(drop=True, inplace=True)
print("\nTeam:")
print(team[['PLAYER', 'Runs.x', 'HS', 'SR.x', 'Wkts', 'Econ']])
```

```
Team:
              PLAYER  Runs.x   HS    SR.x  Wkts  Econ
0   Kane Williamson     735   84  142.44     0  0.00
1       Rishabh Pant     684  128  173.60     0  0.00
2       Lokesh Rahul     659   95  158.41     0  0.00
3         Evin Lewis     382   65  138.40     0  0.00
4     Ajinkya Rahane     370   65  118.21     0  0.00
5        Sunil Orine     357   75  189.89    17  7.65
6      Andre Russell     316   88  184.79    13  9.38
7      Hardik Pandya     260   50  133.33    18  8.92
8      Siddarth Kaul       0    0    0.00    21  8.28
9        Umesh Yadav       0    0    0.00    20  7.86
10       Trent Boult       0    0    0.00    18  8.84
11    Jasprit Bumrah       0    0    0.00    17  6.88
```

[60]:
```
# Justification for the team selection
print("\nJustification:")
print("\nTop Order Batsmen:")
print("Top order batsmen are selected based on highest runs and strike rate.")
print("\nMiddle Order Batsmen:")
print("Middle order batsmen are selected based on highest runs and average rate.
 ↪")
print("\nAll Rounders:")
print("All rounders are selected based on highest runs and wickets.")
print("\nBowlers:")
print("Bowlers are selected based on highest wickets and economy rate.")
print("\nTeam:")
print("The team is selected based on the best players from each cluster.")
print("The team consists of 3 top order batsmen, 2 middle order batsmen, 3 all␣
 ↪rounders and 4 bowlers.")
```

```
Justification:

Top Order Batsmen:
Top order batsmen are selected based on highest runs and strike rate.
```

Middle Order Batsmen:
Middle order batsmen are selected based on highest runs and average rate.

All Rounders:
All rounders are selected based on highest runs and wickets.

Bowlers:
Bowlers are selected based on highest wickets and economy rate.

Team:
The team is selected based on the best players from each cluster.
The team consists of 3 top order batsmen, 2 middle order batsmen, 3 all rounders and 4 bowlers.

[ ]: