

```
In [1]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.cluster import KMeans
from scipy.spatial.distance import cdist
from sklearn.datasets import make_blobs
```

```
In [3]: #import the dataset (data file needs to be in the same folder as notebook)
#missing data points removed
data = pd.read_csv("clustering1.csv")
print("Input Data and Shape")
print(data.shape)
data.head()
```

Input Data and Shape  
(115, 37)

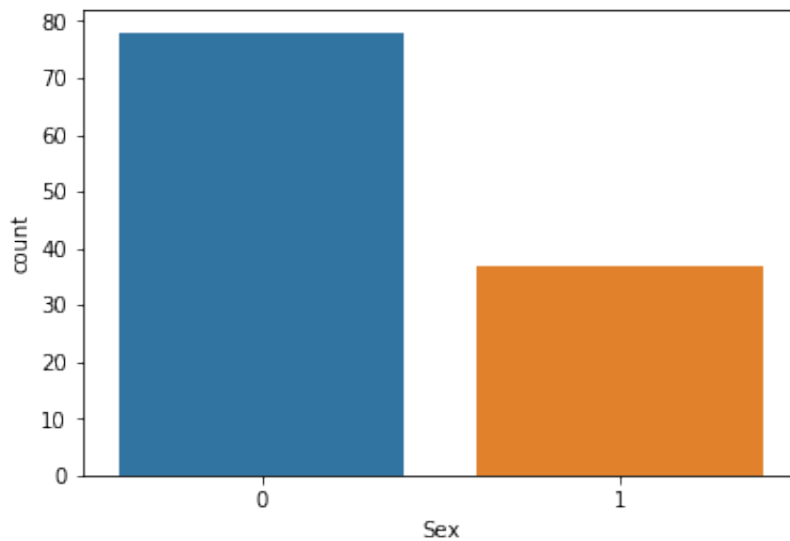
Out[3]:

	Unnamed: 0	Sex	BMI	Stroop_Accuracy	GDT_Risky_Dice_Percentage	WSCT_Accuracy
0	S0001	0	16.184275	0.991667	0.222222	0.8167
1	S0004	0	25.390219	0.991667	0.000000	0.8833
2	S0005	0	19.146722	1.000000	0.055556	0.8167
3	S0006	1	20.761246	0.966667	0.166667	0.8833
4	S0009	0	23.533043	0.991667	0.444444	0.8500

5 rows × 37 columns

```
In [102]: print(data['Sex'].unique())  
print(data.groupby('Sex').size())  
  
import seaborn as sns  
sns.countplot(data['Sex'], label="Count")  
plt.savefig('Sex_Difference.png')  
plt.show()
```

```
[0 1]  
Sex  
0    78  
1    37  
dtype: int64
```



```

In [99]: m_Openness = np.mean(data['Openness'])
sem_Openness = np.std(data['Openness'])/np.sqrt(115)
m_Conscientious = np.mean(data['Conscientious'])
sem_Conscientious = np.std(data['Conscientious'])/np.sqrt(115)
m_Extraversion = np.mean(data['Extraversion'])
sem_Extraversion = np.std(data['Extraversion'])/np.sqrt(115)
m_Agreeable = np.mean(data['Agreeable'])
sem_Agreeable = np.std(data['Agreeable'])/np.sqrt(115)
m_Neuroticism = np.mean(data['Neuroticism'])
sem_Neuroticism = np.std(data['Neuroticism'])/np.sqrt(115)

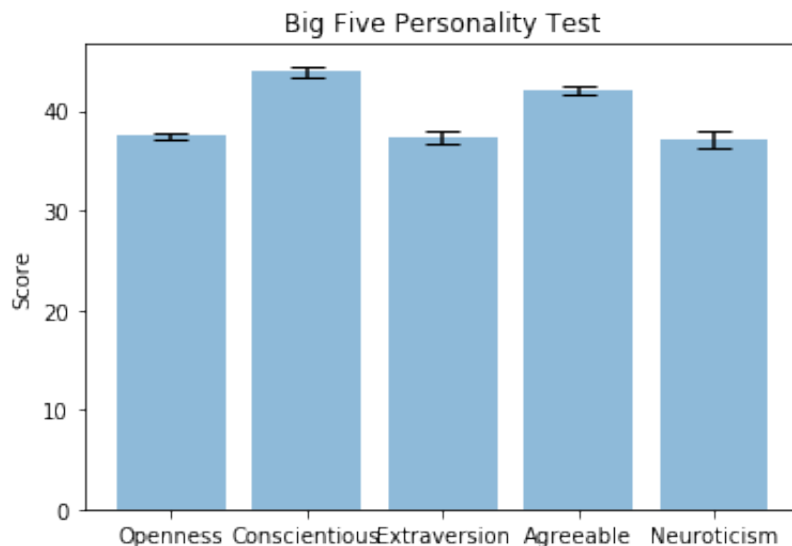
means = [m_Openness, m_Conscientious, m_Extraversion, m_Agreeable, m_Neuroticism]
errorbars = [sem_Openness, sem_Conscientious, sem_Extraversion, sem_Agreeable, sem_Neuroticism]

Group=['Openness', 'Conscientious', 'Extraversion', 'Agreeable', 'Neuroticism']
x_pos = np.arange(len(Group))

fig, ax= plt.subplots()

ax.bar(x_pos, means, yerr=errorbars, align='center', alpha=0.5, ecolor='black')
ax.set_ylabel('Score')
ax.set_xticks(x_pos)
ax.set_xticklabels(Group)
ax.set_title('Big Five Personality Test')
plt.savefig('big5.png')

```



```

In [100]: m_Stroop = np.mean(data['Stroop_Accuracy'])
sem_Stroop = np.std(data['Stroop_Accuracy'])/np.sqrt(115)
m_GoNoGo = np.mean(data['GoNoGo_Accuracy'])
sem_GoNoGo = np.std(data['GoNoGo_Accuracy'])/np.sqrt(115)
m_WCST = np.mean(data['WCST_Accuracy'])
sem_WCST = np.std(data['WCST_Accuracy'])/np.sqrt(115)
m_ZeroBack = np.mean(data['NBack_ZeroBack_Accuracy'])
sem_ZeroBack = np.std(data['NBack_ZeroBack_Accuracy'])/np.sqrt(115)
m_OneBack = np.mean(data['NBack_OneBack_Accuracy'])
sem_OneBack = np.std(data['NBack_OneBack_Accuracy'])/np.sqrt(115)
m_TwoBack = np.mean(data['NBack_TwoBack_Accuracy'])
sem_TwoBack = np.std(data['NBack_TwoBack_Accuracy'])/np.sqrt(115)

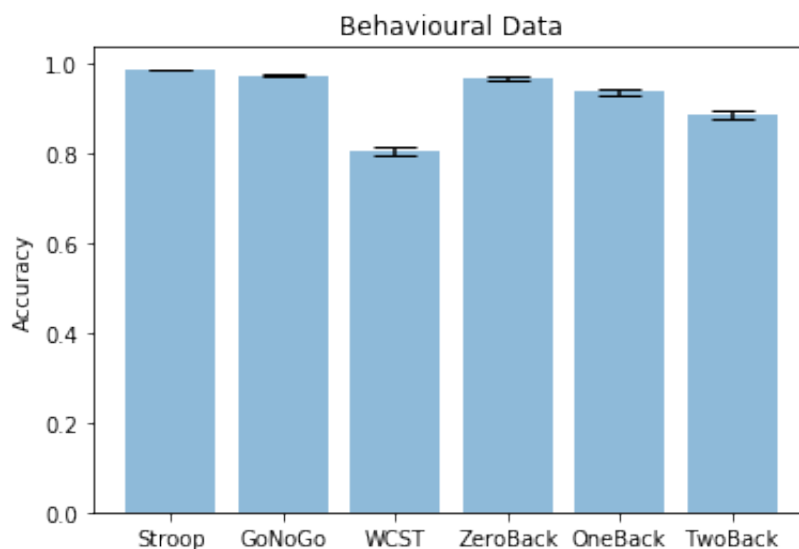
means = [m_Stroop, m_GoNoGo, m_WCST, m_ZeroBack, m_OneBack, m_TwoBack]
errorbars = [sem_Stroop, sem_GoNoGo, sem_WCST, sem_ZeroBack, sem_OneBack, sem_TwoBack]

Group=['Stroop', 'GoNoGo', 'WCST', 'ZeroBack', 'OneBack', 'TwoBack']
x_pos = np.arange(len(Group))

fig, ax= plt.subplots()

ax.bar(x_pos, means, yerr=errorbars, align='center', alpha=0.5, ecolor='black')
ax.set_ylabel('Accuracy')
ax.set_xticks(x_pos)
ax.set_xticklabels(Group)
ax.set_title('Behavioural Data')
plt.savefig('accuracy.png')

```



```
In [51]: data['BMI'].describe()
```

```
Out[51]: count      115.000000  
mean        21.503261  
std         3.449098  
min         16.184275  
25%         19.472274  
50%         20.829995  
75%         23.068114  
max         36.203614  
Name: BMI, dtype: float64
```

```
In [54]: data['Stroop_Accuracy'].describe()
```

```
Out[54]: count      115.000000  
mean         0.985217  
std          0.018406  
min          0.908333  
25%          0.983333  
50%          0.991667  
75%          1.000000  
max          1.000000  
Name: Stroop_Accuracy, dtype: float64
```

```
In [58]: data['GoNoGo_Accuracy'].describe()
```

```
Out[58]: count      114.000000  
mean         0.971754  
std          0.028634  
min          0.860000  
25%          0.960000  
50%          0.980000  
75%          1.000000  
max          1.000000  
Name: GoNoGo_Accuracy, dtype: float64
```

```
In [62]: data['WSCT_Accuracy'].describe()
```

```
Out[62]: count      115.000000  
mean         0.806230  
std          0.104633  
min          0.216700  
25%          0.783300  
50%          0.833300  
75%          0.858350  
max          0.916700  
Name: WSCT_Accuracy, dtype: float64
```

```
In [64]: data['NBack_ZeroBack_Accuracy'].describe()
```

```
Out[64]: count      115.000000
mean         0.967633
std          0.047107
min          0.638889
25%          0.972222
50%          0.972222
75%          1.000000
max          1.000000
Name: NBack_ZeroBack_Accuracy, dtype: float64
```

```
In [65]: data['NBack_OneBack_Accuracy'].describe()
```

```
Out[65]: count      115.000000
mean         0.936473
std          0.088895
min          0.250000
25%          0.916667
50%          0.944444
75%          0.972222
max          1.000000
Name: NBack_OneBack_Accuracy, dtype: float64
```

```
In [66]: data['NBack_TwoBack_Accuracy'].describe()
```

```
Out[66]: count      115.000000
mean         0.886473
std          0.111267
min          0.333333
25%          0.847222
50%          0.916667
75%          0.944444
max          1.000000
Name: NBack_TwoBack_Accuracy, dtype: float64
```

```
In [57]: data['GDT_Risky_Dice_Percentage'].describe()
```

```
Out[57]: count      115.000000
mean         0.182126
std          0.240652
min          0.000000
25%          0.000000
50%          0.111111
75%          0.222222
max          1.000000
Name: GDT_Risky_Dice_Percentage, dtype: float64
```

```
In [71]: data['IGT_B'].describe()
```

```
Out[71]: count      115.000000  
mean         0.380174  
std          0.182848  
min          0.010000  
25%         0.262500  
50%         0.355000  
75%         0.467500  
max          0.900000  
Name: IGT_B, dtype: float64
```

```
In [72]: data['Neuroticism'].describe()
```

```
Out[72]: count      115.000000  
mean        37.182609  
std         9.187694  
min        13.000000  
25%        31.000000  
50%        37.000000  
75%        45.000000  
max        59.000000  
Name: Neuroticism, dtype: float64
```

```
In [73]: data['Extraversion'].describe()
```

```
Out[73]: count      115.000000  
mean        37.304348  
std         6.852038  
min        18.000000  
25%        33.000000  
50%        37.000000  
75%        41.000000  
max        55.000000  
Name: Extraversion, dtype: float64
```

```
In [74]: data['Openness'].describe()
```

```
Out[74]: count      115.000000  
mean        37.469565  
std         4.323177  
min        26.000000  
25%        35.000000  
50%        38.000000  
75%        41.000000  
max        46.000000  
Name: Openness, dtype: float64
```

```
In [75]: data['Agreeable'].describe()
```

```
Out[75]: count      115.000000  
mean        42.147826  
std         4.507778  
min         30.000000  
25%        39.500000  
50%        43.000000  
75%        45.000000  
max         52.000000  
Name: Agreeable, dtype: float64
```

```
In [76]: data['Conscientious'].describe()
```

```
Out[76]: count      115.000000  
mean        43.895652  
std         6.343077  
min         27.000000  
25%        40.000000  
50%        45.000000  
75%        48.000000  
max         59.000000  
Name: Conscientious, dtype: float64
```

```
In [77]: data['BART'].describe()
```

```
Out[77]: count      115.000000  
mean        27.986297  
std        13.406352  
min         4.500000  
25%        18.214286  
50%        26.000000  
75%        36.550000  
max        60.750000  
Name: BART, dtype: float64
```

```
In [79]: data['IGT Score'].describe()
```

```
Out[79]: count      115.000000  
mean        -0.678261  
std        77.193258  
min       -188.000000  
25%       -54.000000  
50%        -4.000000  
75%        53.000000  
max       194.000000  
Name: IGT Score, dtype: float64
```



```
In [80]: data['DDT_AUC'].describe()
```

```
Out[80]: count      115.000000  
mean         0.615548  
std          0.274932  
min          0.192761  
25%          0.384512  
50%          0.568013  
75%          0.898990  
max          1.000000  
Name: DDT_AUC, dtype: float64
```

```
In [81]: data['PDT_AUC'].describe()
```

```
Out[81]: count      115.000000  
mean         0.459350  
std          0.140894  
min          0.180135  
25%          0.343939  
50%          0.461616  
75%          0.544613  
max          0.837037  
Name: PDT_AUC, dtype: float64
```

```
In [82]: data['BAS_D'].describe()
```

```
Out[82]: count      115.000000  
mean        11.652174  
std         2.106979  
min         8.000000  
25%        11.000000  
50%        12.000000  
75%        13.000000  
max        16.000000  
Name: BAS_D, dtype: float64
```

```
In [83]: data['BAS_FS'].describe()
```

```
Out[83]: count      115.000000  
mean        11.930435  
std         1.931828  
min         7.000000  
25%        11.000000  
50%        12.000000  
75%        13.000000  
max        16.000000  
Name: BAS_FS, dtype: float64
```

```
In [84]: data['BAS_RR'].describe()
```

```
Out[84]: count      115.000000  
mean        17.113043  
std         1.927480  
min         12.000000  
25%        15.500000  
50%        17.000000  
75%        19.000000  
max         20.000000  
Name: BAS_RR, dtype: float64
```

```
In [85]: data['BIS'].describe()
```

```
Out[85]: count      115.000000  
mean        21.208696  
std         3.406639  
min         14.000000  
25%        19.000000  
50%        21.000000  
75%        24.000000  
max         28.000000  
Name: BIS, dtype: float64
```

```
In [86]: data['PANAS_PA'].describe()
```

```
Out[86]: count      115.000000  
mean        27.573913  
std         6.260515  
min         14.000000  
25%        23.000000  
50%        26.000000  
75%        32.000000  
max         46.000000  
Name: PANAS_PA, dtype: float64
```

```
In [87]: data['PANAS_NA'].describe()
```

```
Out[87]: count      115.000000  
mean        23.643478  
std         7.925300  
min         10.000000  
25%        19.000000  
50%        22.000000  
75%        27.500000  
max         50.000000  
Name: PANAS_NA, dtype: float64
```

```
In [88]: data['DividedAttention'].describe()
```

```
Out[88]: count      115.000000  
mean         0.100894  
std          0.088469  
min          0.000000  
25%         0.035714  
50%         0.091429  
75%         0.129286  
max          0.631429  
Name: DividedAttention, dtype: float64
```

```
In [89]: data['SPAI_10'].describe()
```

```
Out[89]: count      115.000000  
mean        24.173913  
std         4.935125  
min         11.000000  
25%         21.000000  
50%         24.000000  
75%         28.000000  
max         38.000000  
Name: SPAI_10, dtype: float64
```

```
In [90]: data['CIAS'].describe()
```

```
Out[90]: count      115.000000  
mean        55.043478  
std        11.505446  
min        30.000000  
25%        47.000000  
50%        54.000000  
75%        63.000000  
max        89.000000  
Name: CIAS, dtype: float64
```

```
In [91]: data['PMGQ'].describe()
```

```
Out[91]: count      115.000000  
mean        11.947826  
std         9.723225  
min         0.000000  
25%         0.000000  
50%         14.000000  
75%         20.000000  
max         32.000000  
Name: PMGQ, dtype: float64
```

```
In [92]: data['IGD'].describe()
```

```
Out[92]: count      115.000000  
mean         1.000000  
std          1.611363  
min          0.000000  
25%          0.000000  
50%          0.000000  
75%          2.000000  
max          6.000000  
Name: IGD, dtype: float64
```

```
In [103]: data['Stress'].describe()
```

```
Out[103]: count      115.000000  
mean        12.600000  
std         3.028519  
min         7.000000  
25%        10.000000  
50%        13.000000  
75%        14.000000  
max        22.000000  
Name: Stress, dtype: float64
```

```

In [19]: #value input for each column
f0 = data['Sex'].values
f1 = data['BMI'].values
f2 = data['Stroop_Accuracy'].values
f3 = data['GDT_Risky_Dice_Percentage'].values
f4 = data['WSCT_Accuracy'].values
f5 = data['GoNoGo_Accuracy'].values
f6 = data['NBack_ZeroBack_Accuracy'].values
f7 = data['NBack_OneBack_Accuracy'].values
f8 = data['NBack_TwoBack_Accuracy'].values
f9 = data['IGT_A'].values
f10 = data['IGT_B'].values
f11 = data['IGT_C'].values
f12 = data['IGT_D'].values
f13 = data['IGT_Score'].values
f14 = data['DDT_AUC'].values
f15 = data['PDT_AUC'].values
f16 = data['BART'].values
f17 = data['Stress'].values
f18 = data['Neuroticism'].values
f19 = data['Extraversion'].values
f20 = data['Openness'].values
f21 = data['Agreeable'].values
f22 = data['Conscientious'].values
f23 = data['BAS_D'].values #BAS Drive
f24 = data['BAS_FS'].values #BAS Fun Seeking
f25 = data['BAS_RR'].values # BAS Reward Response
f26 = data['BAS'].values
f27 = data['BIS'].values
f28 = data['PANAS_PA'].values
f29 = data['PANAS_NA'].values
f30 = data['DividedAttention'].values
f31 = data['SPAI_10'].values #smartphone addiction scores
f32 = data['CIAS'].values #chen's internet addiction scales
f33 = data['PMGQ'].values #problematic mobile gaming questionnaires
f34 = data['IGD'].values #internet gaming disorder

```

```

In [16]: #Focused research topic 1: technology addiction
#Smartphone & Internet addiction
A = np.array(list(zip(f31,f32)))

```

```

In [17]: #elbow plot
##### cluster data into k=1....10 clusters #####
K_range=range(1,10)
distortions = []

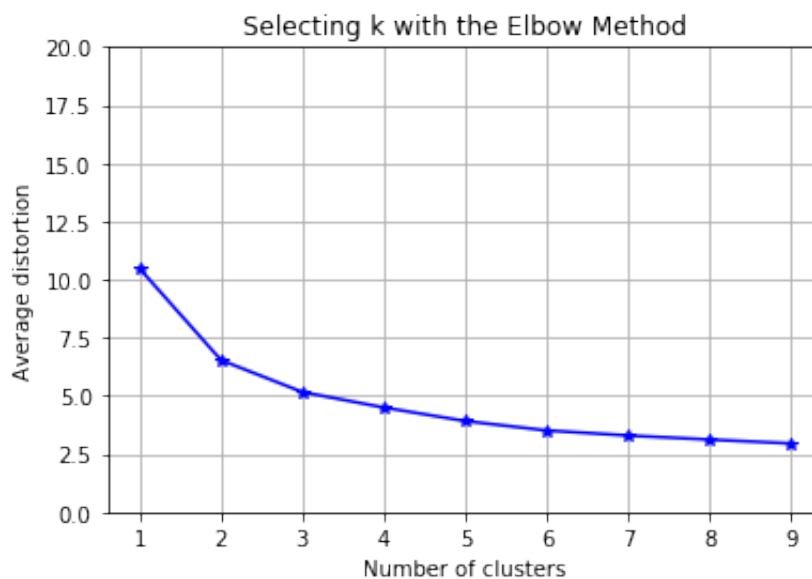
for i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(A)
    distortions.append(sum(np.min(cdist(A, kmModel.cluster_centers_, 'euclidean', axis=1), axis=0)))

fig1 = plt.figure()
ex = fig1.add_subplot(111)
ex.plot(K_range, distortions, 'b*-')
#mark the elboq
#ex.plot(K_range[2], distortions[2], marker='o', markersize=12, markercolor='r')

plt.grid(True)
#plt.xlim([0,20])
plt.ylim([0, 20])
plt.xlabel('Number of clusters')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')

```

Out[17]: Text(0.5,1,'Selecting k with the Elbow Method')



```

In [41]: ##Nuber of clusters
k=4

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)

```

```

#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

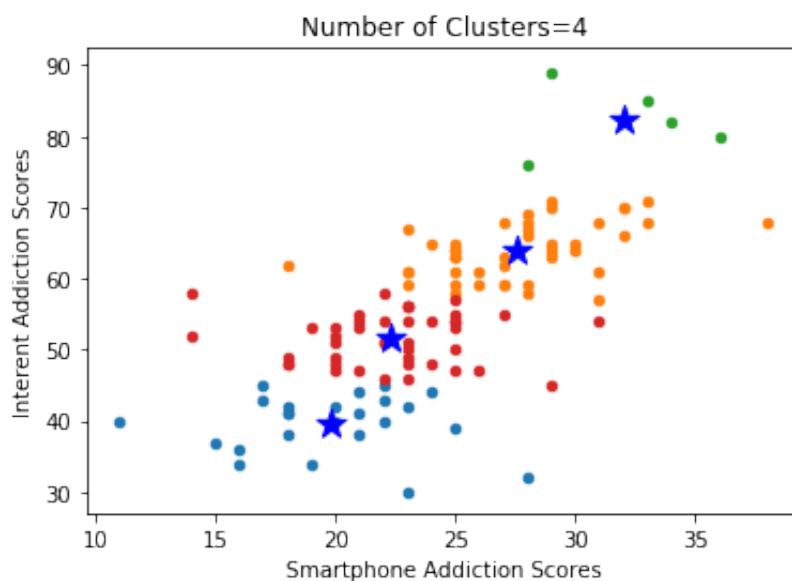
#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(A)
#Getting the cluster labels
labels = kmeans.predict(A)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

for i in range(k):
    points = np.array([A[j] for j in range(len(A)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('Smartphone Addiction Scores')
plt.ylabel('Internet Addiction Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('A_Clustering.png')

```

Final Centroids  
centroids



```

In [20]: #Internet addiction & Internet Gaming addiction
B = np.array(list(zip(f32,f34)))

```

```

In [21]: #elbow plot
##### cluster data into k=1....10 clusters #####
K_range=range(1,10)
distortions = []

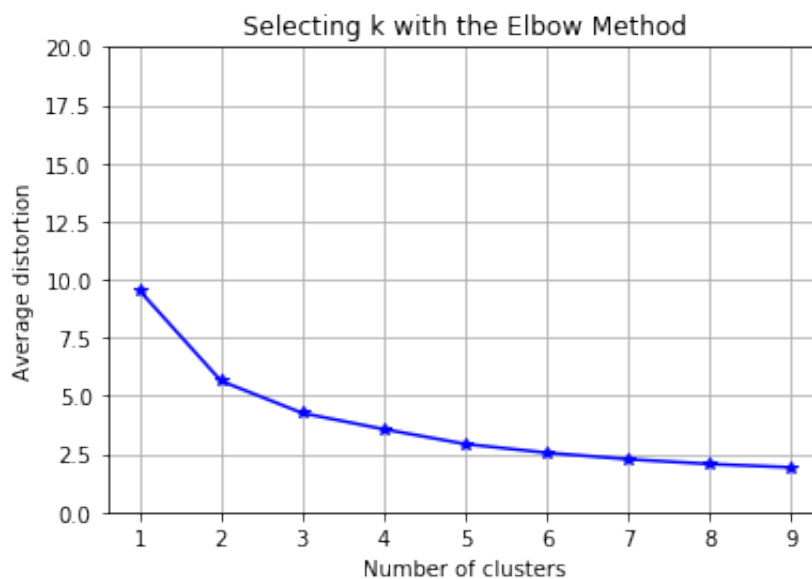
for i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(B)
    distortions.append(sum(np.min(cdist(B, kmModel.cluster_centers_, 'euclidean')
                                , axis=1) * B.shape[0]) / B.shape[0])

fig1 = plt.figure()
ex = fig1.add_subplot(111)
ex.plot(K_range, distortions, 'b*-')
#mark the elboq
#ex.plot(K_range[2], distortions[2], marker='o', markersize=12, markercolor='red')

plt.grid(True)
#plt.xlim([0,20])
plt.ylim([0, 20])
plt.xlabel('Number of clusters')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')

```

Out[21]: Text(0.5,1,'Selecting k with the Elbow Method')



```

In [43]: ##Nuber of clusters
k=4

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)

```



```

#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

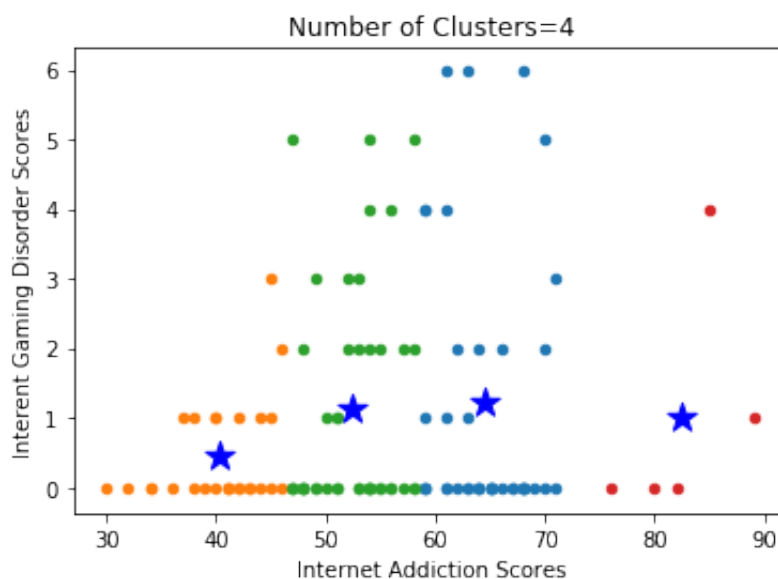
#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(B)
#Getting the cluster labels
labels = kmeans.predict(B)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

for i in range(k):
    points = np.array([B[j] for j in range(len(B)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('Internet Addiction Scores')
plt.ylabel('Internet Gaming Disorder Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('B_clustering.png')

```

Final Centroids  
centroids



```

In [24]: #Smartphone addiction & Problematic Smartphone Gaming
C = np.array(list(zip(f31,f33)))

```

```

In [26]: #elbow plot
##### cluster data into k=1....10 clusters #####
K_range=range(1,10)
distortions = []

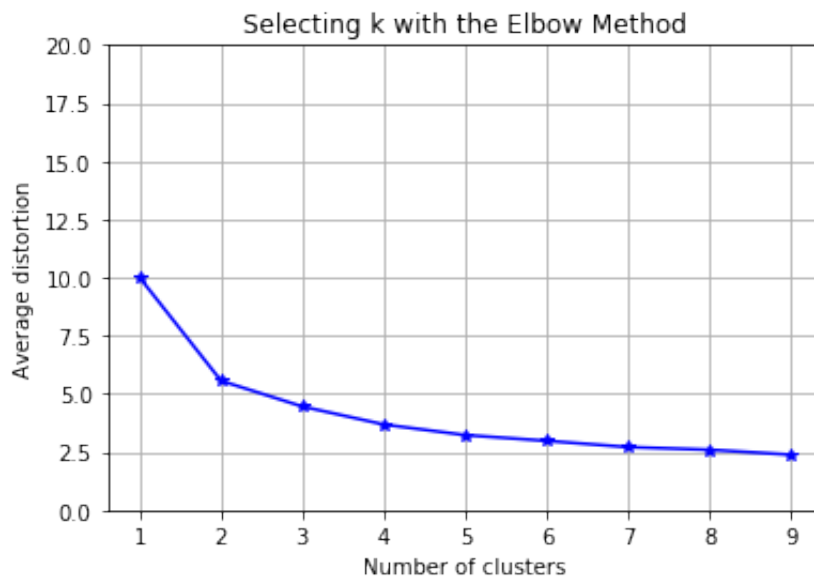
for i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(C)
    distortions.append(sum(np.min(cdist(C, kmModel.cluster_centers_, 'euclidean', axis=2), axis=1) * C.shape[0]) / C.shape[0])

fig1 = plt.figure()
ax = fig1.add_subplot(111)
ax.plot(K_range, distortions, 'b*-')
#mark the elbow
#ax.plot(K_range[2], distortions[2], marker='o', markersize=12, markeredgewidth=2)

plt.grid(True)
#plt.xlim([0,20])
plt.ylim([0, 20])
plt.xlabel('Number of clusters')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')

```

Out[26]: Text(0.5,1,'Selecting k with the Elbow Method')



```

In [28]: ##Nuber of clusters
k=4

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)

```

```

#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(C)
#Getting the cluster labels
labels = kmeans.predict(C)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

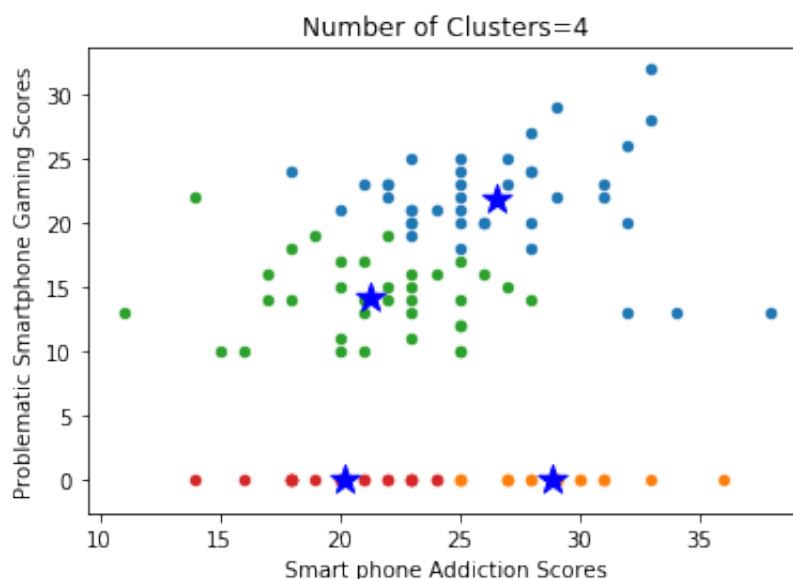
for i in range(k):
    points = np.array([C[j] for j in range(len(C)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('Smartphone Addiction Scores')
plt.ylabel('Problematic Smartphone Gaming Scores')
plt.title('Number of Clusters={}'.format(k))

```

Final Centroids  
centroids

Out[28]: Text(0.5,1,'Number of Clusters=4')



In [47]: ##Nuber of clusters  
k=3

```

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)
#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

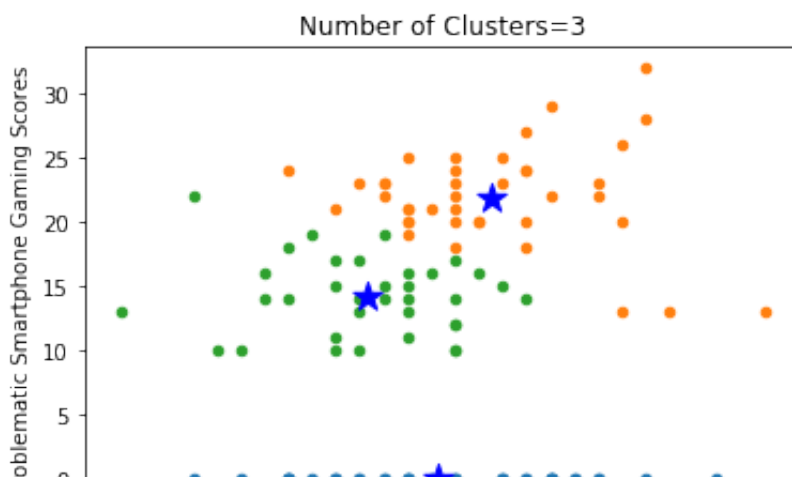
#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(C)
#Getting the cluster labels
labels = kmeans.predict(C)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

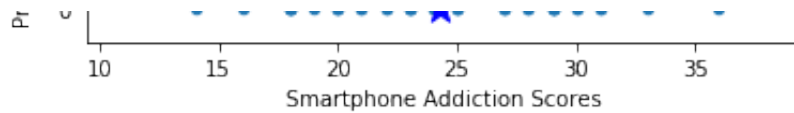
for i in range(k):
    points = np.array([C[j] for j in range(len(C)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('Smartphone Addiction Scores')
plt.ylabel('Problematic Smartphone Gaming Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('C_clustering.png')

```

Final Centroids  
centroids





```
In [29]: #Internet Gaming Disorder & Problematic Smartphone Gaming
D = np.array(list(zip(f33,f34)))
```

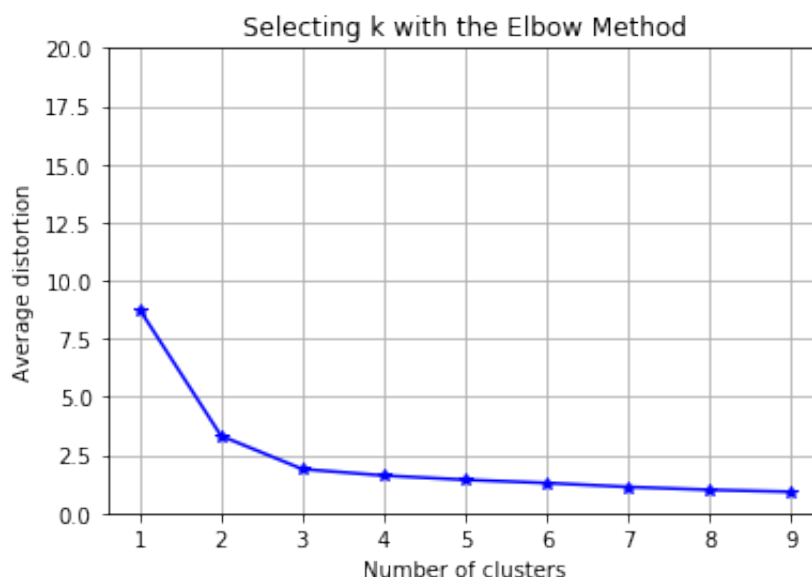
```
In [30]: #elbow plot
##### cluster data into k=1....10 clusters #####
K_range=range(1,10)
distortions = []

for i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(D)
    distortions.append(sum(np.min(cdist(D, kmModel.cluster_centers_, 'euclidean', axis=1), axis=0)))

fig1 = plt.figure()
ex = fig1.add_subplot(111)
ex.plot(K_range, distortions, 'b*-')
#mark the elbow
#ex.plot(K_range[2], distortions[2], marker='o', markersize=12, markercolor='red')

plt.grid(True)
#plt.xlim([0,20])
plt.ylim([0, 20])
plt.xlabel('Number of clusters')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')
```

```
Out[30]: Text(0.5,1,'Selecting k with the Elbow Method')
```



```
In [44]: ##Nuber of clusters
k=4

##X coordinates of random centroids
```

```

##### COORDINATES OF RANDOM CENTROIDS
#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)
#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(D)
#Getting the cluster labels
labels = kmeans.predict(D)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

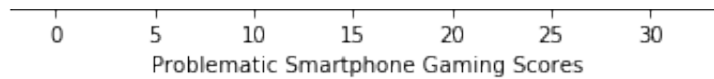
for i in range(k):
    points = np.array([D[j] for j in range(len(D)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('Problematic Smartphone Gaming Scores')
plt.ylabel('Internet Gaming Disorder Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('D_clustering.png')

```

Final Centroids  
centroids





```
In [32]: #BAS fun seeking & smartphone addiction
E = np.array(list(zip(f24,f31)))
```

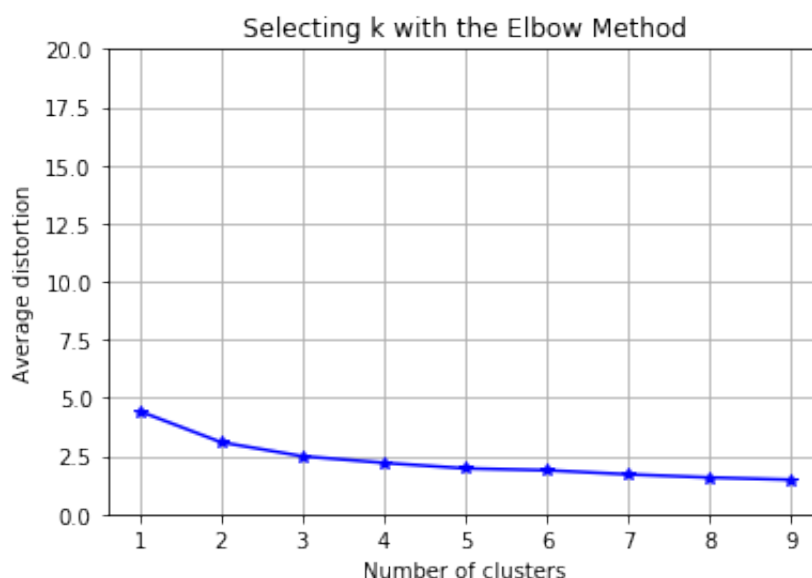
```
In [33]: #elbow plot
##### cluster data into k=1....10 clusters #####
K_range=range(1,10)
distortions = []

for i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(E)
    distortions.append(sum(np.min(cdist(E, kmModel.cluster_centers_, 'euclidean')
                                for c in kmModel.cluster_centers_)))

fig1 = plt.figure()
ex = fig1.add_subplot(111)
ex.plot(K_range, distortions, 'b*-')
#mark the elboq
#ex.plot(K_range[2], distortions[2], marker='o', markersize=12, markercolor='red')

plt.grid(True)
#plt.xlim([0,20])
plt.ylim([0, 20])
plt.xlabel('Number of clusters')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')
```

```
Out[33]: Text(0.5,1,'Selecting k with the Elbow Method')
```



```
In [45]: ##Nuber of clusters
k=4

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
```

```

#C_x = np.random.randint(0, np.max(X), size=k)
##Y coordinates of random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)
#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

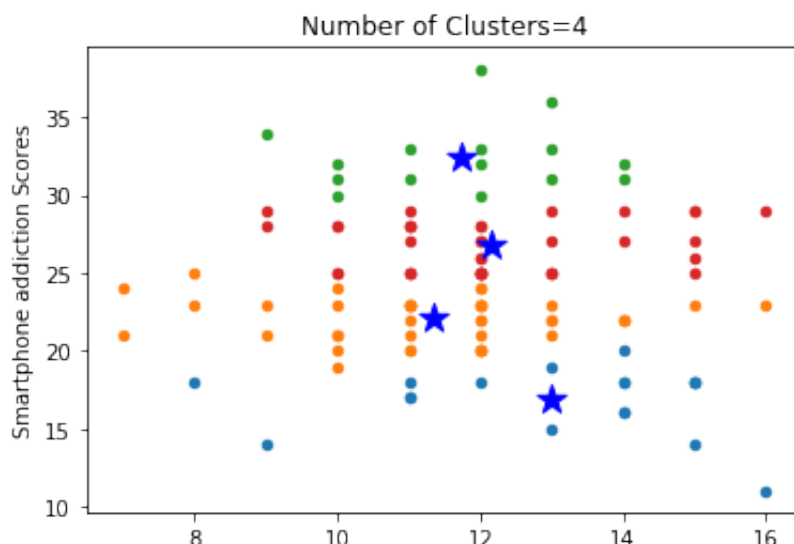
#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(E)
#Getting the cluster labels
labels = kmeans.predict(E)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

for i in range(k):
    points = np.array([E[j] for j in range(len(E)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('BAS Fun Seeking')
plt.ylabel('Smartphone addiction Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('E_clustering.png')

```

Final Centroids  
centroids





## BAS Fun Seeking

```
In [36]: #BAS fun seeking & Problematic smartphone Gaming
F = np.array(list(zip(f24, f33)))
```

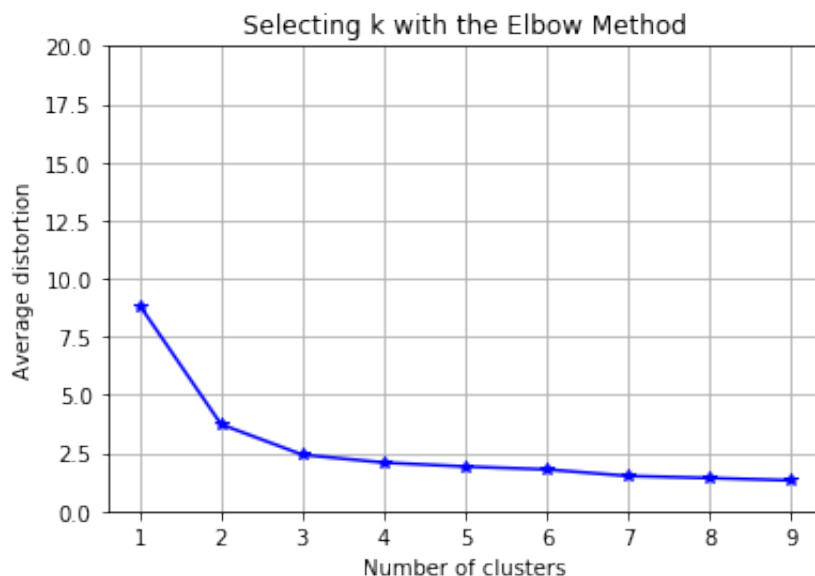
```
In [37]: bow plot
## cluster data into k=1....10 clusters #####
ange=range(1,10)
tortions = []

i in K_range:
    kmModel = KMeans(n_clusters=i)
    kmModel.fit(F)
    distortions.append(sum(np.min(cdist(F, kmModel.cluster_centers_, 'eucl

l = plt.figure()
= fig1.add_subplot(111)
plot(K_range, distortions, 'b*-')
rk the elboq
.plot(K_range[2], distortions[2], marker='o', markersixe=12, markeredge

.grid(True)
t.xlim([0,20])
.ylim([0, 20])
.xlabel('Number of clusters')
.ylabel('Average distortion')
.title('Selecting k with the Elbow Method')
```

```
Out[37]: Text(0.5,1,'Selecting k with the Elbow Method')
```



```
In [46]: ##Nuber of clusters
k=4

##X coordinates of random centroids
#C_x = np.random.randint(0, np.max(X), size=k)
"""
```

```

##Y coordinates or random centroids
#C_y = np.random.randint(0, np.max(X), size=k)
#C = np.array(list(zip(C_x, C_y)), dtype=np.float32)

##plotting along with the Centroids
#plt.scatter(f1, f2, c='#050505', s=20)
#plt.scatter(C_x, C_y, marker='*', s=200, c='g')
#plt.xlabel('IGD')
#plt.ylabel('PMG')
#plt.title('Internet Gaming & Mobile Gaming')

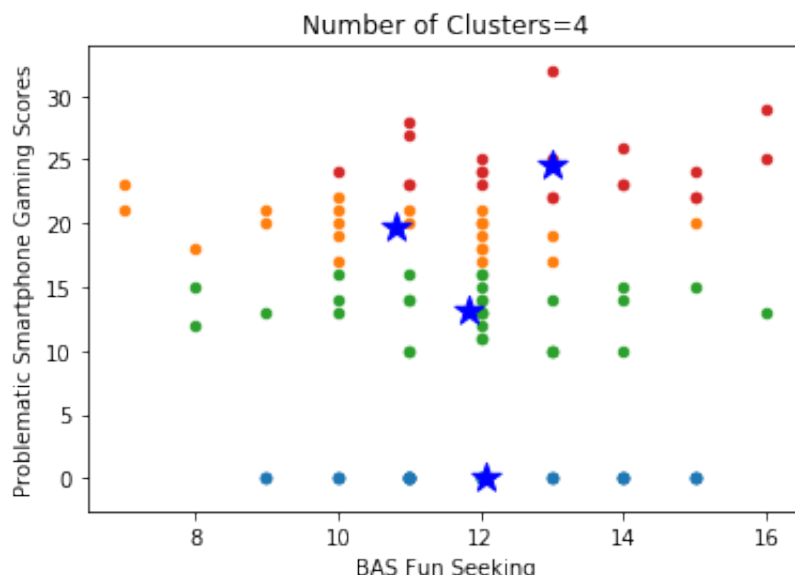
#cluster plot
kmeans = KMeans(n_clusters=k)
#Fitting the input data
kmeans = kmeans.fit(F)
#Getting the cluster labels
labels = kmeans.predict(F)
#Centroid values
centroids = kmeans.cluster_centers_
colors = ['r', 'g', 'y', 'm', 'o', 'w']
fig2 = plt.figure()
kg = fig2.add_subplot(111)

for i in range(k):
    points = np.array([F[j] for j in range(len(F)) if labels[j] == i])
    kg.scatter(points[:,0], points[:,1], s=20, cmap='rainbow')

kg.scatter(centroids[:,0], centroids[:,1], marker='*', s=200, c='b')
print('Final Centroids')
print('centroids')
plt.xlabel('BAS Fun Seeking')
plt.ylabel('Problematic Smartphone Gaming Scores')
plt.title('Number of Clusters={}'.format(k))
plt.savefig('F_clustering.png')

```

Final Centroids  
centroids



In [ ]: