In [1]:
```
# Question 1 - Import and Explore Data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
from sklearn import metrics
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
from sklearn.preprocessing import MinMaxScaler

os.chdir('C:\\Users\\micha\\Documents\\DAAN862')

seeds = pd.read_csv('seeds_dataset.csv')
display(seeds)

# As we can see, the csv file doesn't have column names
# lets fix that

colnames = ['Area', 'Perimeter', 'Compactness', 'Kernel Length',
            'Kernel Width', 'Asymmetry', 'Groove Length', 'Species']

seeds = pd.read_csv('seeds_dataset.csv', names=colnames)
display(seeds)
```

	15.26	14.84	0.871	5.763	3.312	2.221	5.22	1
0	14.88	14.57	0.8811	5.554	3.333	1.018	4.956	1
1	14.29	14.09	0.9050	5.291	3.337	2.699	4.825	1
2	13.84	13.94	0.8955	5.324	3.379	2.259	4.805	1
3	16.14	14.99	0.9034	5.658	3.562	1.355	5.175	1
4	14.38	14.21	0.8951	5.386	3.312	2.462	4.956	1
...	...	...	...	...	...	...	...	...
204	12.19	13.20	0.8783	5.137	2.981	3.631	4.870	3
205	11.23	12.88	0.8511	5.140	2.795	4.325	5.003	3
206	13.20	13.66	0.8883	5.236	3.232	8.315	5.056	3
207	11.84	13.21	0.8521	5.175	2.836	3.598	5.044	3
208	12.30	13.34	0.8684	5.243	2.974	5.637	5.063	3

209 rows × 8 columns

	Area	Perimeter	Compactness	Kernel Length	Kernel Width	Asymmetry	Groove Length	Species
0	15.26	14.84	0.8710	5.763	3.312	2.221	5.220	1
1	14.88	14.57	0.8811	5.554	3.333	1.018	4.956	1
2	14.29	14.09	0.9050	5.291	3.337	2.699	4.825	1
3	13.84	13.94	0.8955	5.324	3.379	2.259	4.805	1
4	16.14	14.99	0.9034	5.658	3.562	1.355	5.175	1
...	...	...	...	...	...	...	...	...
205	12.19	13.20	0.8783	5.137	2.981	3.631	4.870	3
206	11.23	12.88	0.8511	5.140	2.795	4.325	5.003	3
207	13.20	13.66	0.8883	5.236	3.232	8.315	5.056	3
208	11.84	13.21	0.8521	5.175	2.836	3.598	5.044	3
209	12.30	13.34	0.8684	5.243	2.974	5.637	5.063	3

210 rows × 8 columns

In [2]:
```
# Question 1 Cont - Explore data
display(seeds.describe())
display(seeds.corr())
```

	Area	Perimeter	Compactness	Kernel Length	Kernel Width	Asymmetry	Groove Length
count	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000	210.00000
mean	14.847524	14.559286	0.870999	5.628533	3.258605	3.700201	5.408071
std	2.909699	1.305959	0.023629	0.443063	0.377714	1.503557	0.49148
min	10.590000	12.410000	0.808100	4.899000	2.630000	0.765100	4.51900
25%	12.270000	13.450000	0.856900	5.262250	2.944000	2.561500	5.04500
50%	14.355000	14.320000	0.873450	5.523500	3.237000	3.599000	5.22300
75%	17.305000	15.715000	0.887775	5.979750	3.561750	4.768750	5.87700
max	21.180000	17.250000	0.918300	6.675000	4.033000	8.456000	6.55000

	Area	Perimeter	Compactness	Kernel Length	Kernel Width	Asymmetry	Groov Lengt
Area	1.000000	0.994341	0.608288	0.949985	0.970771	-0.229572	0.86369
Perimeter	0.994341	1.000000	0.529244	0.972422	0.944829	-0.217340	0.89078
Compactness	0.608288	0.529244	1.000000	0.367915	0.761635	-0.331471	0.22682
Kernel Length	0.949985	0.972422	0.367915	1.000000	0.860415	-0.171562	0.93280
Kernel Width	0.970771	0.944829	0.761635	0.860415	1.000000	-0.258037	0.74913
Asymmetry	-0.229572	-0.217340	-0.331471	-0.171562	-0.258037	1.000000	-0.01107
Groove Length	0.863693	0.890784	0.226825	0.932806	0.749131	-0.011079	1.00000
Species	-0.346058	-0.327900	-0.531007	-0.257269	-0.423463	0.577273	0.02430

In [58]:
```
# Question 2 - Use K-Means Clustering to Group

# First, convert to scaler
scaler = MinMaxScaler()
X = scaler.fit_transform(seeds.iloc[:, 0:7])
y = seeds.Species
```

In [61]:
```
# K-Means, set n_clusters to 3 since we have 3 known species
kmeans = KMeans(n_clusters=3, random_state=100, n_init=10)
y_pred = kmeans.fit_predict(X)
```

In [88]:
```
# Print Scores
print('Homogenity:     ', metrics.homogeneity_score(y, y_pred))
print('Completeness:   ', metrics.completeness_score(y, y_pred))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, y_pred))
print('Silhouette:     ', metrics.silhouette_score(X, y_pred, metric='euclidean'))
```

```
Homogenity:      0.6734021033886654
Completeness:    0.6751899081752645
Adjusted Rand:  0.7048605249026285
Silhouette:      0.4221052568124793
```

In [63]:
```
centers = kmeans.cluster_centers_
```

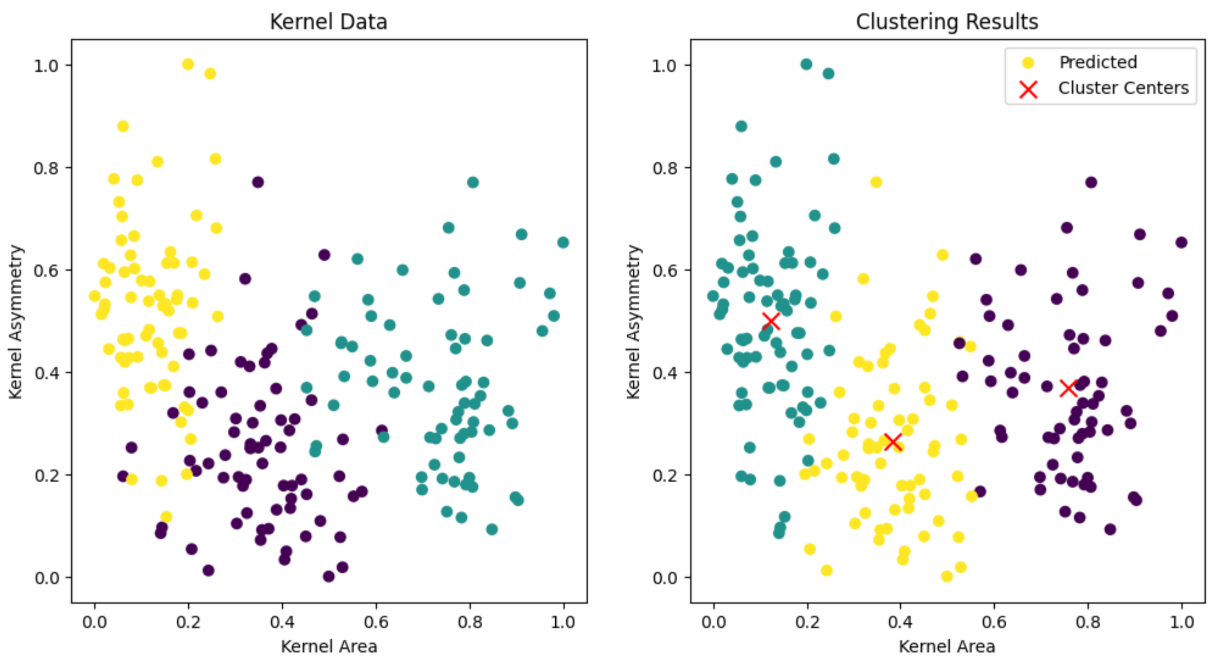
In [89]:
```
print(centers)

# For example, we can view clusters in the form of scatter plots
# We will experiment with Area and Asymmetry
c_area = centers[:, 0]
c_asymm = centers[:, 5]
```

```
[[0.75733298 0.79374354 0.69419238 0.73003765 0.76950062 0.36757645
  0.75709318]
 [0.1233337  0.17513685 0.37817899 0.18671025 0.16252742 0.49856915
  0.27928792]
 [0.38349003 0.4198407  0.67120387 0.36468534 0.46849918 0.26417688
  0.31838389]]
```

In [91]:

```
plt.figure(figsize=(12,6))
plt.subplot(121)
plt.scatter(X[:, 0], X[:, 5], c=y)
plt.title('Kernel Data')
plt.xlabel('Kernel Area')
plt.ylabel('Kernel Asymmetry')
plt.subplot(122)
plt.scatter(X[:, 0], X[:, 5], c=y_pred, label='Predicted')
plt.scatter(c_area, c_asymm, s=100, c='r', marker='x',
            label='Cluster Centers')
plt.title('Clustering Results')
plt.xlabel('Kernel Area')
plt.ylabel('Kernel Asymmetry')
plt.legend()
plt.subplots_adjust(wspace=0.2)
```



In [65]:
```
# Question 3 - Use different linkage types for Hierarchical Clustering
#               Which returns the best results?

# Start by creating three different models, one for each linkage
Hier_y_predavg = AgglomerativeClustering(n_clusters=3,
                                         metric='euclidean',
                                         linkage='average'
                                         ).fit_predict(X)

Hier_y_predward = AgglomerativeClustering(n_clusters=3,
                                          metric='euclidean',
                                          linkage='ward'
                                          ).fit_predict(X)

Hier_y_predcmp = AgglomerativeClustering(n_clusters=3,
                                         metric='euclidean',
                                         linkage='complete'
                                         ).fit_predict(X)
```

In [92]:
```
# We can return the scores for each model and visually compare the results

# Average Results
print('Homogenity:     ', metrics.homogeneity_score(y, Hier_y_predavg))
print('Completeness:   ', metrics.completeness_score(y, Hier_y_predavg))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, Hier_y_predavg))
print('Silhouette:     ', metrics.silhouette_score(X, Hier_y_predavg, metric='euclid
```

```
Homogenity:     0.7016719692947548
Completeness:   0.7098244492986717
Adjusted Rand:  0.7247242716839253
Silhouette:     0.39437476201792854
```

In [93]:
```
# Ward Results
print('Homogenity:     ', metrics.homogeneity_score(y, Hier_y_predward))
print('Completeness:   ', metrics.completeness_score(y, Hier_y_predward))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, Hier_y_predward))
print('Silhouette:     ', metrics.silhouette_score(X, Hier_y_predward, metric='eucli
```

```
Homogenity:     0.6825990188762132
Completeness:   0.6975309670281451
Adjusted Rand:  0.6752090091502835
Silhouette:     0.38103690313150723
```

In [94]:
```
# Complete Results
print('Homogenity:     ', metrics.homogeneity_score(y, Hier_y_predcmp))
print('Completeness:   ', metrics.completeness_score(y, Hier_y_predcmp))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, Hier_y_predcmp))
print('Silhouette:     ', metrics.silhouette_score(X, Hier_y_predcmp, metric='euclid

# As a result, we see that a linkage of Average works the best for this dataset sin
# metric returned is higer than the others.
```

```
Homogenity:     0.6088174496902253
Completeness:   0.6356867819968337
Adjusted Rand:  0.5663819104900444
Silhouette:     0.3637982100400148
```

In [95]:
```
# Question 4 - Use DBSCAN to group, then determine the best parameters

# Create a baseline model using eps=0.2 and min_samples=5
db_y_pred = DBSCAN(eps=0.2, min_samples=5).fit_predict(X)

# Results
print('Homogenity:    ', metrics.homogeneity_score(y, db_y_pred))
print('Completeness:  ', metrics.completeness_score(y, db_y_pred))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, db_y_pred))
print('Silhouette:    ', metrics.silhouette_score(X, db_y_pred, metric='euclidean'))
```

```
Homogenity:     0.46420339686042006
Completeness:   0.45920866716064307
Adjusted Rand:  0.3838628158674018
Silhouette:     0.07937304141396345
```

In [97]:
```
# Now, we will have to manually build models without GridSearchCV
# to determine the best combiniation.
result = []

# Some fine-tuning for this dataset was needed to get a reasonable
# range of parameters. In some cases, not enough unique labels were
# created to calculate silhouette scores
eps = [ 0.15, 0.2, 0.25, 0.3]
min_samples = range(1, 6)

# Loop through the ranges for each combo
for i in eps:
    for j in min_samples:
        print(i, j)
        model = DBSCAN(eps=i, min_samples=j)
        y_pred_tmp = model.fit_predict(X)
        n_clusters = np.unique(model.labels_).size
        score_silh = metrics.silhouette_score(X, y_pred_tmp, metric='euclidean')
        score_homogen = metrics.homogeneity_score(y, y_pred_tmp)
        # Store parameters in array
        result.append((i, j, score_homogen, score_silh, n_clusters))
```

```
0.15 1
0.15 2
0.15 3
0.15 4
0.15 5
0.2 1
0.2 2
0.2 3
0.2 4
0.2 5
0.25 1
0.25 2
0.25 3
0.25 4
0.25 5
0.3 1
0.3 2
0.3 3
0.3 4
0.3 5
```

In [98]:

```
result

# Here, we can visually compare the results and see that, depending on
# exactly which parameters are desired, a few combos work best. It appears
# that an eps=0.2 and min_samples=3 returns the best overall, however higher
# homogenity scores can be observed in other combos but silhouette seems to
# represent the data best so higher weight can be used where a max of silhouette
# score = 0.2617 is likely the best option.
```

Out[98]:

```
[(0.15, 1, 0.9255232183107535, -0.0871698967953067, 69),
 (0.15, 2, 0.6894569537774907, -0.04282907075552252, 17),
 (0.15, 3, 0.6125502269887075, -0.012462484626016769, 9),
 (0.15, 4, 0.5256031865067574, -0.03580746776673375, 7),
 (0.15, 5, 0.4879447754470833, -0.10715870147039122, 6),
 (0.2, 1, 0.5529681063967011, -0.21038821557148724, 21),
 (0.2, 2, 0.5023597544660977, -0.0817995385341649, 9),
 (0.2, 3, 0.4547114189227929, 0.26171136966927827, 4),
 (0.2, 4, 0.46944691568813113, 0.22699171653861017, 4),
 (0.2, 5, 0.46420339686042006, 0.07937304141396345, 5),
 (0.25, 1, 0.04292183887880707, -0.36953735268320786, 9),
 (0.25, 2, 0.0222015140428151 9, -0.025705362437131674, 3),
 (0.25, 3, 0.0015375414298288298, 0.10738522563893668, 2),
 (0.25, 4, 0.0015375414298288298, 0.10738522563893668, 2),
 (0.25, 5, 0.0031411019151860982, 0.10858172504060049, 2),
 (0.3, 1, 0.010854655624153458, -0.05048803705545211, 3),
 (0.3, 2, 0.010854655624153458, -0.05048803705545211, 3),
 (0.3, 3, 0.010854655624153458, -0.05048803705545211, 3),
 (0.3, 4, 0.007113805522111817, 0.057475816359056554, 2),
 (0.3, 5, 0.007113805522111817, 0.057475816359056554, 2)]
```

In [74]:

```
# An additional exercise is to see if reducing the number of attributes
# helps tune some of results. We will rmeove 2 attributes that had the
# lowest correlation to y
X_reduced = scaler.fit_transform(seeds.iloc[:, [0, 1, 2, 4, 5]])
```

In [99]:
```
Reduced_hier = AgglomerativeClustering(n_clusters=3,
                                       metric='euclidean',
                                       linkage='average'
                                       ).fit_predict(X_reduced)

Reduced_dbscan = DBSCAN(eps=0.2, min_samples=3).fit_predict(X_reduced)
```

In [100…
```
print('Homogenity:    ', metrics.homogeneity_score(y, Reduced_hier))
print('Completeness:  ', metrics.completeness_score(y, Reduced_hier))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, Reduced_hier))
print('Silhouette:    ', metrics.silhouette_score(X_reduced, Reduced_hier, metric='
print('\n')
print('Homogenity:    ', metrics.homogeneity_score(y, Reduced_dbscan))
print('Completeness:  ', metrics.completeness_score(y, Reduced_dbscan))
print('Adjusted Rand: ', metrics.adjusted_rand_score(y, Reduced_dbscan))
print('Silhouette:    ', metrics.silhouette_score(X_reduced, Reduced_dbscan, metric

# Overall, these results appear worse than before, and as such can be ignored.
```

```
Homogenity:     0.4186393606442778
Completeness:   0.6153816234672278
Adjusted Rand:  0.44777103855694644
Silhouette:     0.36351443203452477


Homogenity:     0.0
Completeness:   0.0
Adjusted Rand:  -0.000546661146460972
Silhouette:     0.14217516198046135
```

In [ ]: