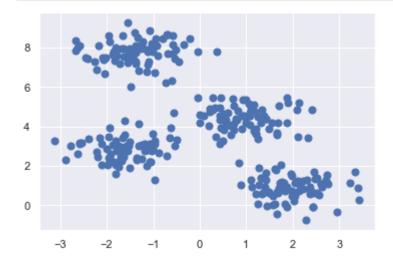
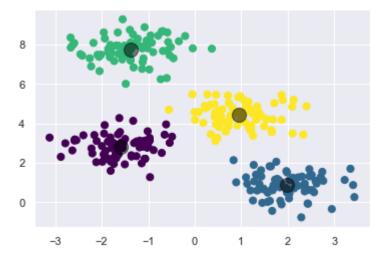
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns; sns.set() # for plot styling
import numpy as np
```



```
In [11]:
    from sklearn.cluster import KMeans
    kmeans = KMeans(n_clusters=4)
    kmeans.fit(X)
    y_kmeans = kmeans.predict(X)
    plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=50, cmap='viridis')

    centers = kmeans.cluster_centers_
    plt.scatter(centers[:, 0], centers[:, 1], c='black', s=200, alpha=0.5);
```



```
from sklearn.datasets import make_moons
X, y = make_moons(200, noise=.05, random_state=0)
```

```
In [15]: plt.scatter(X[:, 0], X[:, 1], s=50);
```

```
1.00

0.75

0.50

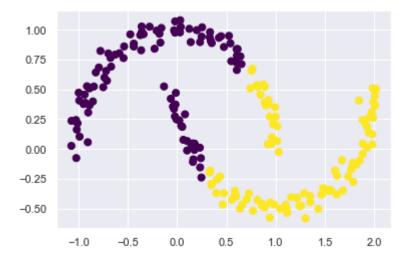
0.25

0.00

-0.25

-0.50

-1.0 -0.5 0.0 0.5 1.0 1.5 2.0
```

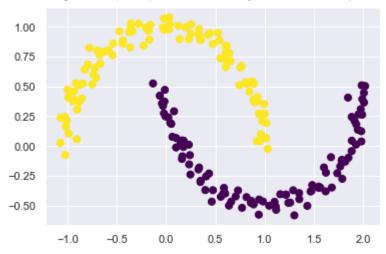


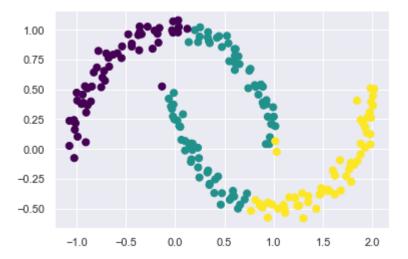
#This situation is reminiscent of the discussion in In-Depth: Support Vector Machines, #where we used a kernel transformation to project the data into a higher dimension wher #We might imagine using the same trick to allow k-means to discover non-linear boundari

In [19]: #SpectralClustering estimator is an expanded version on K-means.
#It uses the graph of nearest neighbors to compute a higher-dimensional representation #and then assigns labels using a k-means algorithm

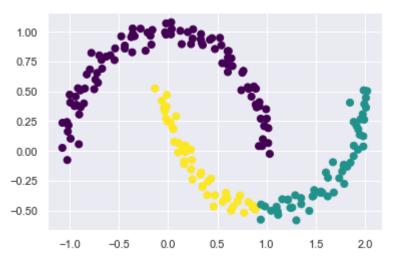
C:\Users\tabkh\anaconda3\lib\site-packages\sklearn\manifold\ spectral embedding.py:245:

UserWarning: Graph is not fully connected, spectral embedding may not work as expected. warnings.warn("Graph is not fully connected, spectral embedding"





C:\Users\tabkh\anaconda3\lib\site-packages\sklearn\manifold\\_spectral\_embedding.py:245:
UserWarning: Graph is not fully connected, spectral embedding may not work as expected.
warnings.warn("Graph is not fully connected, spectral embedding"



In []: