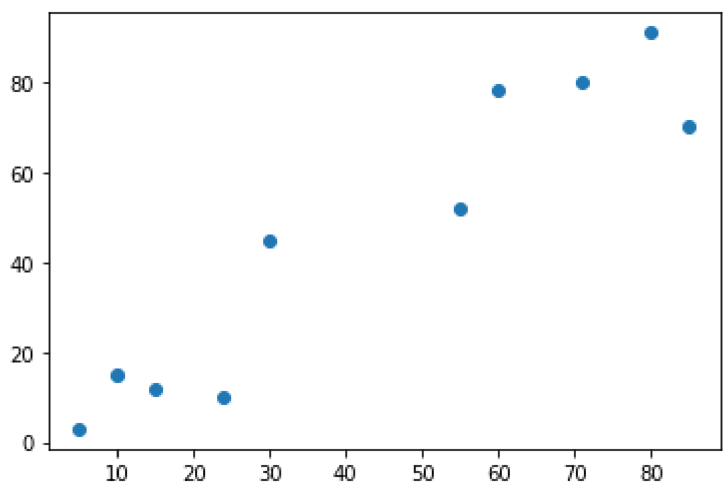
Simple Kmeans example with scikit-learn

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.cluster import KMeans
```

In [2]:
```
X = np.array([[5,3],
     [10,15],
     [15,12],
     [24,10],
     [30,45],
     [85,70],
     [71,80],
     [60,78],
     [55,52],
     [80,91],])
```

In [3]:
```
plt.scatter(X[:,0],X[:,1])
```

Out[3]:
```
<matplotlib.collections.PathCollection at 0x1a1be19810>
```

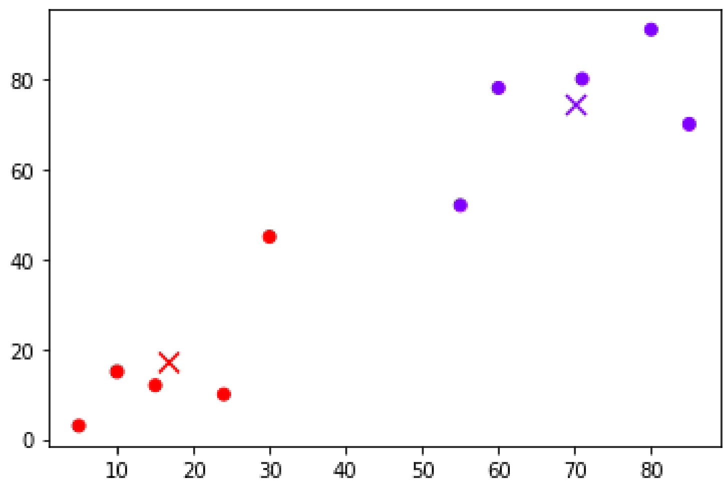


In [4]:
```
##Fitting the kMeans algorithm with k=2 clusters
kmeans = KMeans(n_clusters=2)
kmeans.fit(X)
print(kmeans.cluster_centers_)
print(kmeans.labels_)
```

```
[[70.2 74.2]
 [16.8 17. ]]
[1 1 1 1 1 0 0 0 0 0]
```

In [5]:
```
#Building a function that will color the datapoints in X according to where
#and plot the centroids.
def plot_kmeans(X, kmeans, ax=None):
    if ax is None:
        ax = plt.gca()
    ax.scatter(X[:,0],X[:,1], c=kmeans.labels_, cmap='rainbow')
    centers = kmeans.cluster_centers_
    ax.scatter(centers[:,0], centers[:,1], c=np.arange(centers.shape[0]),
               marker='x', s=100, cmap='rainbow')
```

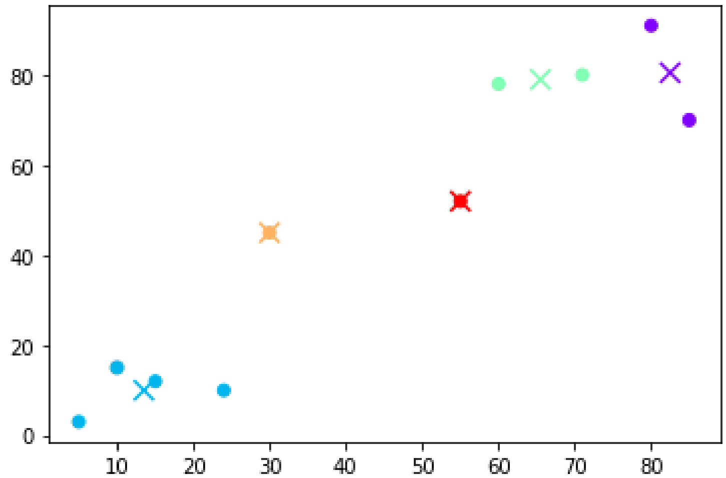
In [6]:
```
plot_kmeans(X, kmeans)
```



In [7]:
```
##Now let's change kmeans to use k=5 clusters instead of k=2
kmeans = KMeans(n_clusters=5)
kmeans.fit(X)
print(kmeans.cluster_centers_)
print(kmeans.labels_)
```

```
[[82.5 80.5]
 [13.5 10. ]
 [65.5 79. ]
 [30.  45. ]
 [55.  52. ]]
[1 1 1 1 3 0 2 2 4 0]
```

In [8]:
```
#The result looks overfitted, with two of the clusters only having one data
#in our choice of k!
plot_kmeans(X, kmeans)
```

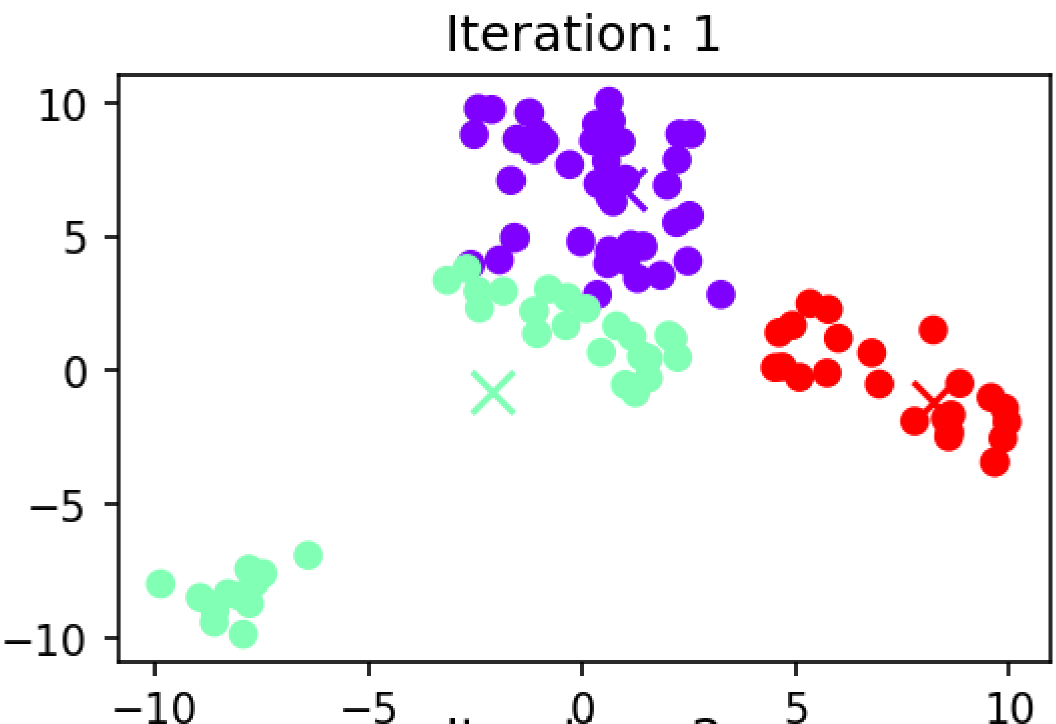


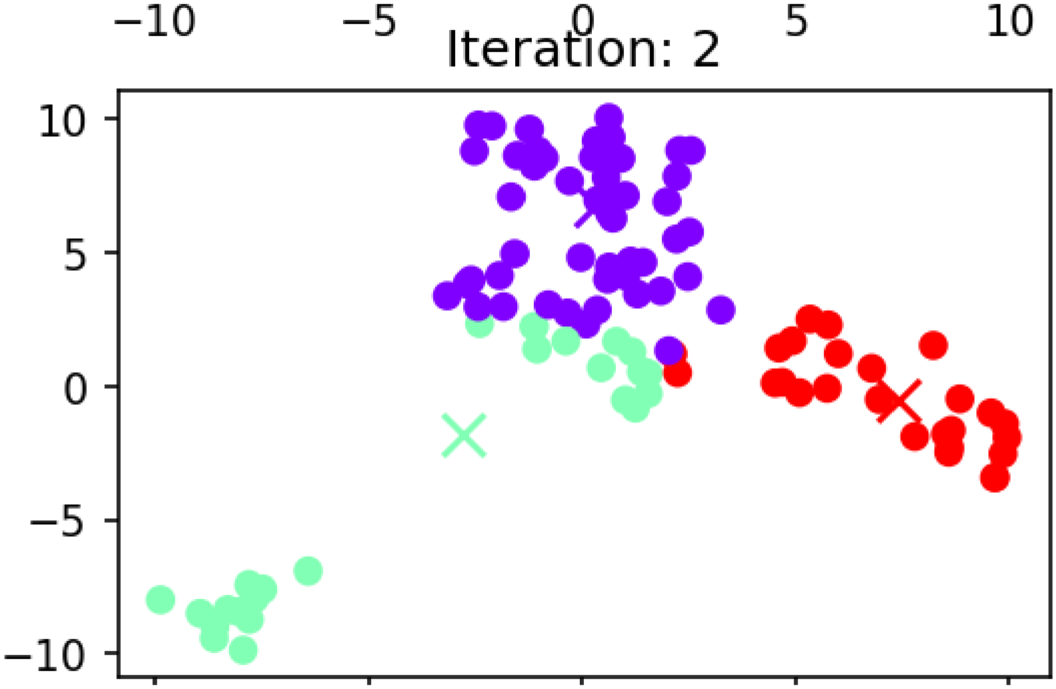
Show progression of kmeans algorithm

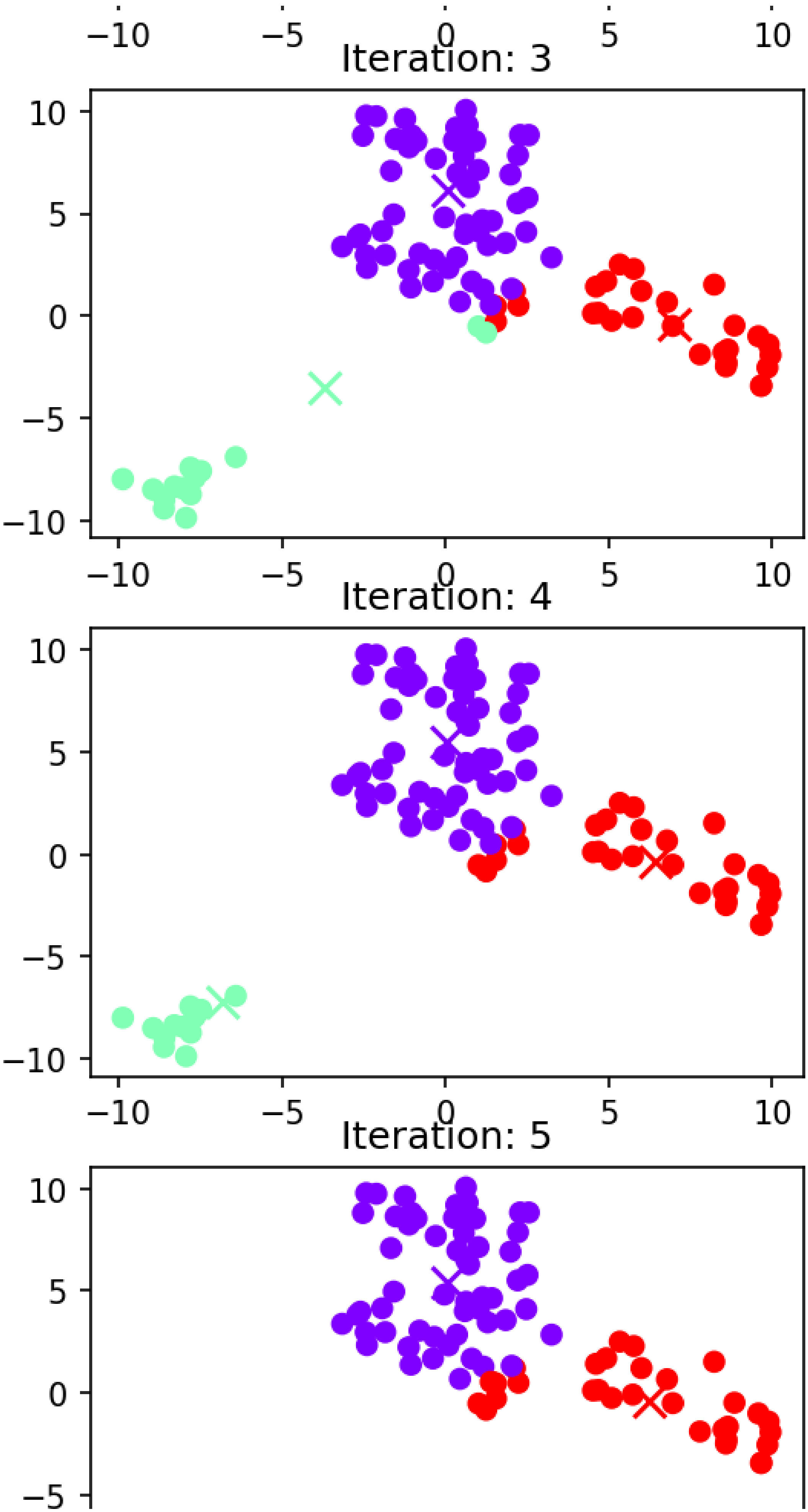
In [9]:
```python
from sklearn.datasets import make_blobs
X2, _ = make_blobs(centers=8, random_state=0)

# Setup plots
show_iters = np.arange(5) + 1
_, axes = plt.subplots(len(show_iters), 1,
                       figsize=(4, 3*len(show_iters)), dpi=150)

# Show plot for each iteration
for max_iter, ax in zip(show_iters, axes):
    kmeans = KMeans(n_clusters=3,  max_iter=max_iter,
                    n_init=1, init='random', random_state=0)
    kmeans.fit(X2)
    plot_kmeans(X2, kmeans, ax=ax)
    ax.set_title(f'Iteration: {max_iter}')
```



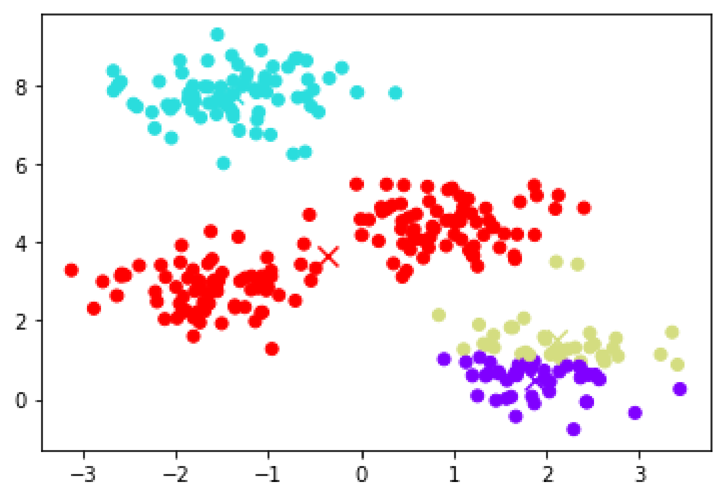



−10
−5
0
5
10
Iteration: 3
10
5
0
−5
−10
−10
−5
0
5
10
Iteration: 4
10
5
0
−5
−10
−10
−5
0
5
10
Iteration: 5
10
5
0
−5

Examples below taken Python handbook [https://jakevdp.github.io/PythonDataScienceHandbook/05.1 k-means.html (https://jakevdp.github.io/PythonDataScienceHandbook/05.1 k-means.html)](https://jakevdp.github.io/PythonDataScienceHandbook/05.1)

Clustering may not converge to optimal solution

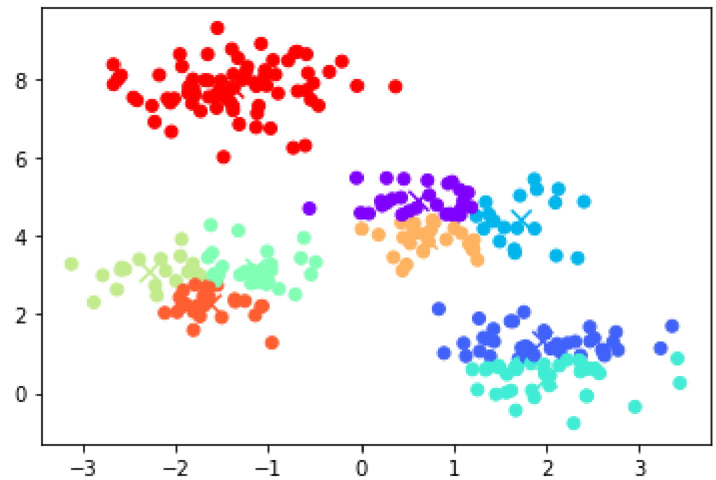
In [10]:
```
X2, _ = make_blobs(n_samples=300, centers=4,
                   cluster_std=0.60, random_state=0)
kmeans = KMeans(n_clusters=4, init='random',
                n_init=1, random_state=104) # 104 gives bad seeding
kmeans.fit(X2)
plot_kmeans(X2, kmeans)
```



Choosing the number of clusters is not obvious

In [11]:
```
# Example from Python handbook
X2, _ = make_blobs(n_samples=300, centers=4,
                       cluster_std=0.60, random_state=0)

kmeans = KMeans(n_clusters=9, init='random', n_init=1, random_state=0)
kmeans.fit(X2)
plot_kmeans(X2, kmeans)
```



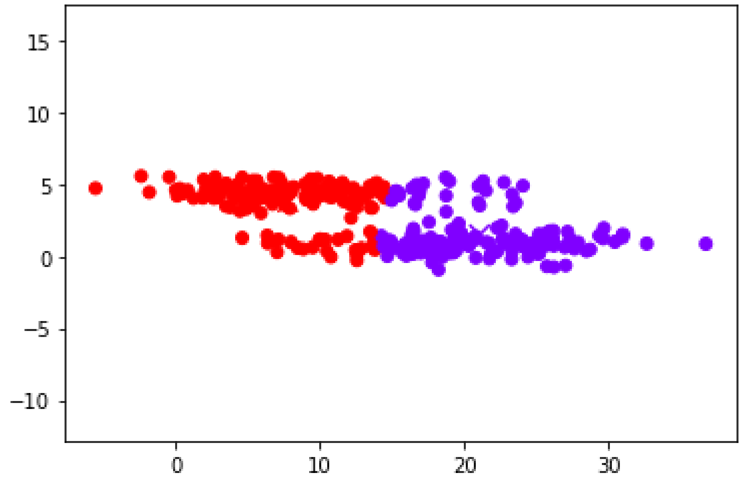
Axis scaling matters for k-means (one motivation for GMMs)

In [12]:
```
X3, y_true = make_blobs(n_samples=300, centers=2,
                        cluster_std=0.60, random_state=0)
X3[:, 0] = X3[:, 0]*10

kmeans = KMeans(n_clusters=2, random_state=0).fit(X3)

plot_kmeans(X3, kmeans)
plt.axis('equal')
```

Out[12]:
```
(-7.679357622326382, 38.85413904249712, -1.2688240342438202, 5.8812849055
65782)
```



In [10]:
```
np.arange(kmeans.cluster_centers_.shape[0])
```

Out[10]:
```
array([0, 1, 2, 3, 4])
```

In [ ]:
```

```