k-means-clustering

April 18, 2018

1 Bisecting K-Means Clustering

First, we setup some imports.

```
In [26]: from typing import List, Tuple

         from dataviz import generate_clusters
         from dataviz import plot_clusters
         from kmeans import BisectingKMeans
         from kmeans.kmeans import get_inter_cluster_distances
```

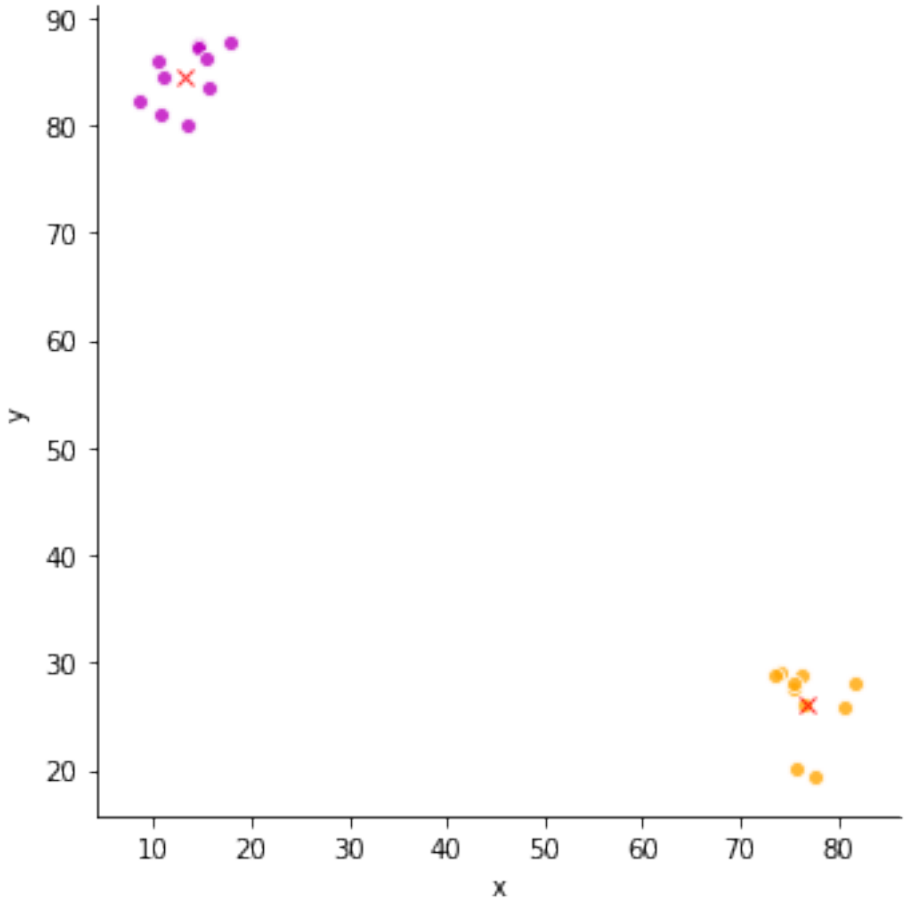
Then we write a function to generate 20 random two-dimensional points in the range [1, 100].

```
In [27]: def generate_data(num_clusters: int, seed=None) -> List[List]:
             num_points = 20
             spread = 7
             bounds = (1, 100)
             return generate_clusters(num_clusters, num_points, spread, bounds, bounds, seed)
```

1.1 k = 2

1.1.1 Euclidean Distance

```
In [28]: num_clusters = 2
         clusters = generate_data(num_clusters, seed=1)
         k_means = BisectingKMeans(num_clusters=num_clusters, seed=1)
         k_means.fit(clusters)
         plot_clusters(clusters, k_means.labels_, k_means.centroids_)
```




```
In [29]: print('Total SSE: {}'.format(k_means.inertia_))

Total SSE: 324.047252480222
```

Let's write a quick helper function to print out the SSE per cluster.

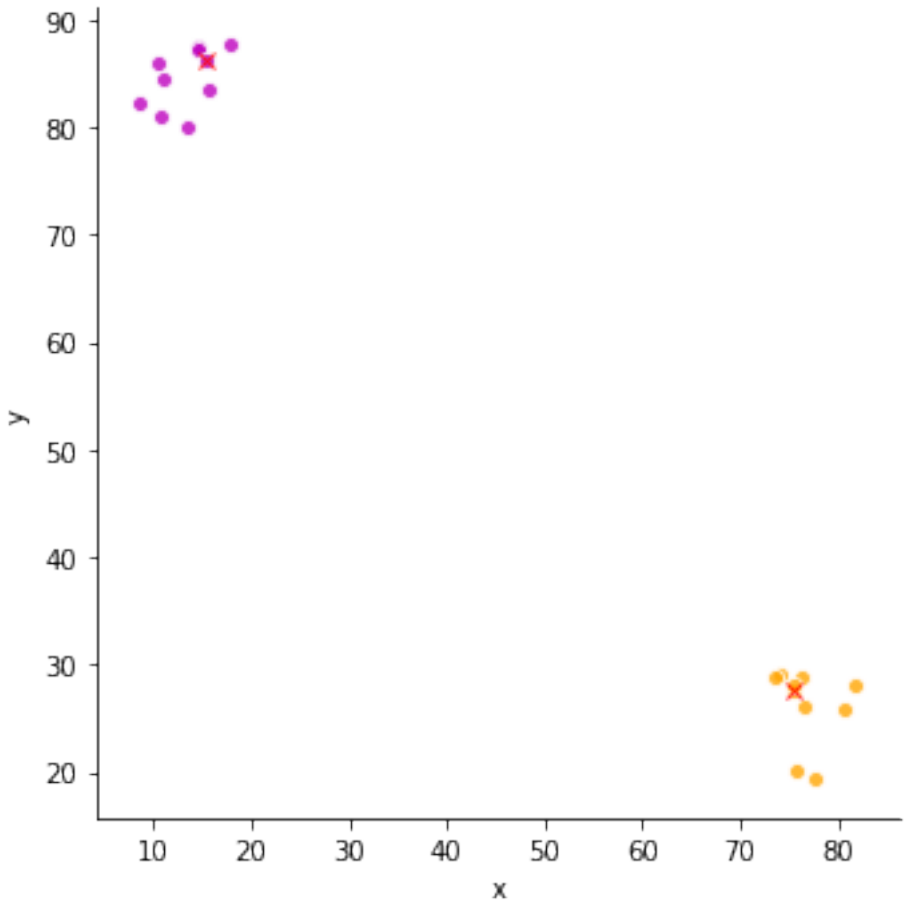
```
In [30]: def print_cluster_sse(cluster_sse: List[float]) -> None:
             for i, sse in enumerate(cluster_sse):
                 print('Cluster {} SSE: {}'.format(i, sse))

In [31]: print_cluster_sse(k_means.inertia_per_cluster_)

Cluster 0 SSE: 177.9374316123801
Cluster 1 SSE: 146.1098208678419
```

Let's also write some helper functions to print out the max and min inter-cluster distances.

```
In [32]: def get_max_and_min_inter_cluster_distances(data,
                                                    labels,
                                                    distance_function='euclidean'):
             args = (data, labels, distance_function)
             inter_cluster_distances = get_inter_cluster_distances(*args)
             return max(inter_cluster_distances), min(inter_cluster_distances)

         def print_max_and_min_inter_cluster_distances(data,
                                                       labels,
                                                       distance_function='euclidean'):
             args = (data, labels, distance_function)
             max_dist, min_dist = get_max_and_min_inter_cluster_distances(*args)
             print('Max inter-cluster distance: {}'.format(max_dist))
             print('Min inter-cluster distance: {}'.format(min_dist))

In [33]: print_max_and_min_inter_cluster_distances(clusters, k_means.labels_)

Max inter-cluster distance: 8939.592569818646
Min inter-cluster distance: 6215.498092277565
```

1.1.2 Manhattan Distance

```
In [34]: num_clusters = 2
         k_means = BisectingKMeans(num_clusters=num_clusters,
                                   distance_function='manhattan',
                                   seed=1)
         k_means.fit(clusters)
         plot_clusters(clusters, k_means.labels_, k_means.centroids_)
```

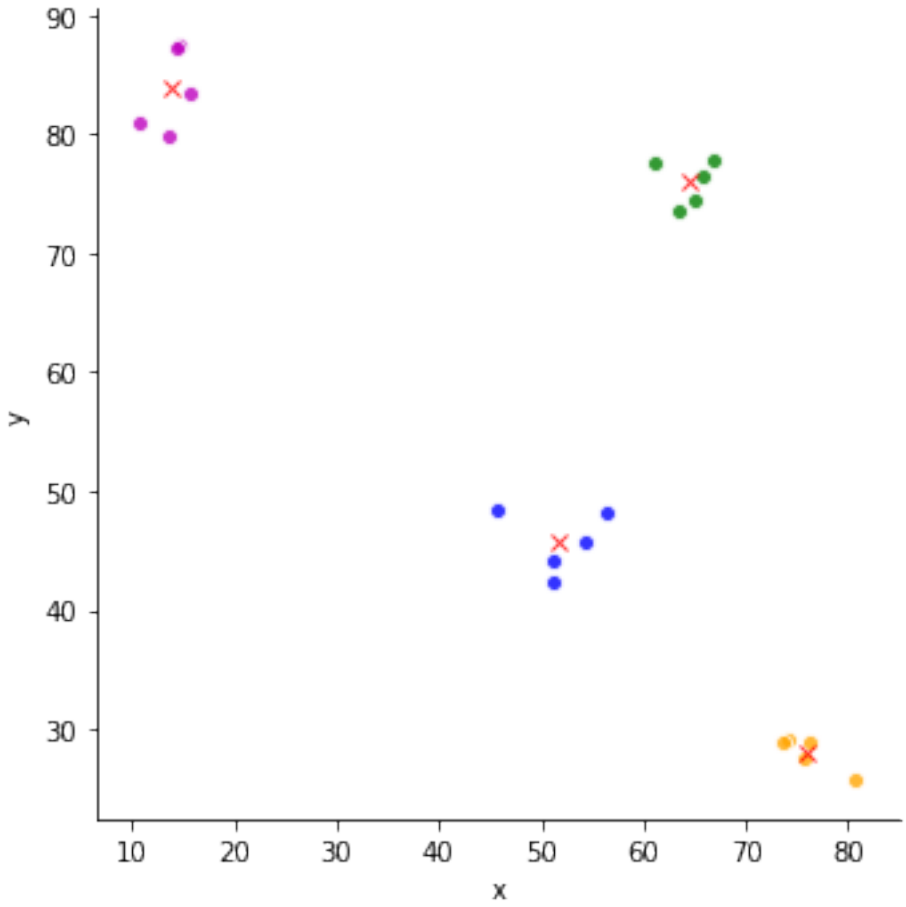



```
In [35]: print('Total SSE: {}'.format(k_means.inertia_))

Total SSE: 94.13626696820376


In [36]: print_cluster_sse(k_means.inertia_per_cluster_)

Cluster 0 SSE: 42.83723671157887
Cluster 1 SSE: 51.29903025662488


In [37]: print_max_and_min_inter_cluster_distances(clusters,
                                                   k_means.labels_,
                                                   distance_function='manhattan')

Max inter-cluster distance: 133.7118537708453
Min inter-cluster distance: 111.1239235786854
```

1.2 k = 4

1.2.1 Euclidean Distance

```
In [38]: num_clusters = 4
         clusters = generate_data(num_clusters, seed=1)
         k_means = BisectingKMeans(num_clusters=num_clusters, seed=4235)
         k_means.fit(clusters)
         plot_clusters(clusters, k_means.labels_, k_means.centroids_)
```




```
In [39]: print('Total SSE: {}'.format(k_means.inertia_))

Total SSE: 230.0880894560679


In [40]: print_cluster_sse(k_means.inertia_per_cluster_)

Cluster 0 SSE: 34.94610880911604
Cluster 1 SSE: 62.05904492709121
```

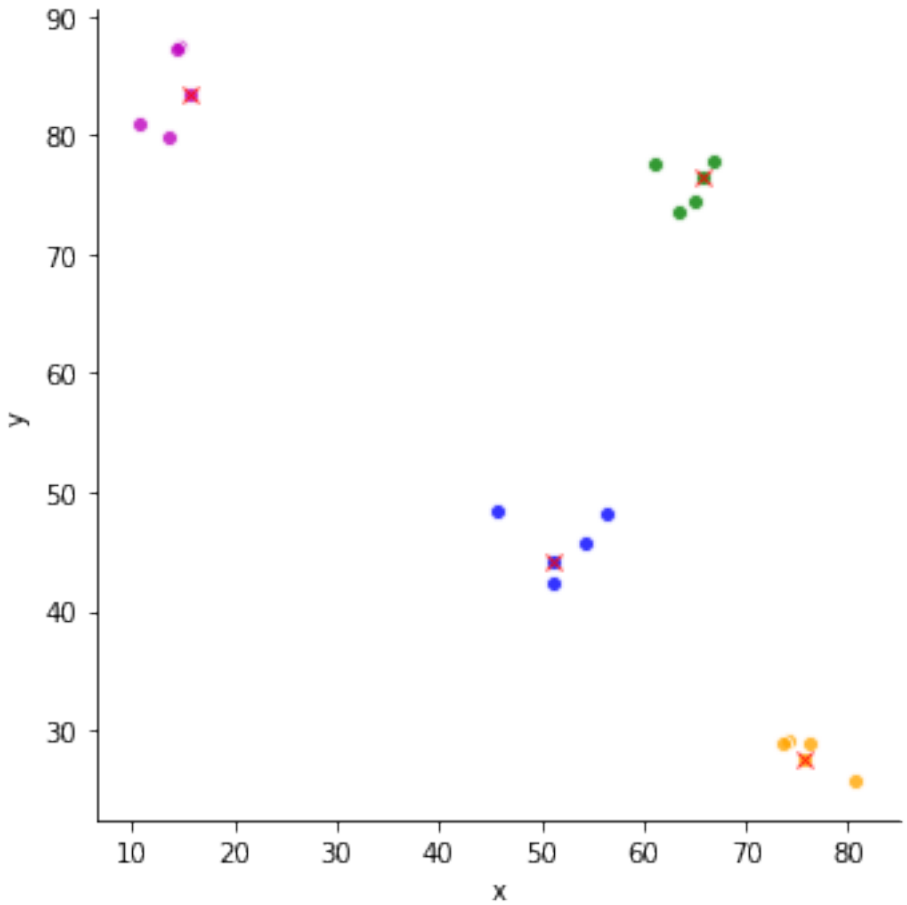
```
Cluster 2 SSE: 92.94168571792414
Cluster 3 SSE: 40.141250001936484
```

```
In [41]: print_max_and_min_inter_cluster_distances(clusters, k_means.labels_)
```

```
Max inter-cluster distance: 8198.125728618705
Min inter-cluster distance: 662.6807115639276
```

1.2.2 Manhattan Distance

```
In [42]: num_clusters = 4
         k_means = BisectingKMeans(num_clusters=num_clusters,
                                   distance_function='manhattan',
                                   seed=4235)
         k_means.fit(clusters)
         plot_clusters(clusters, k_means.labels_, k_means.centroids_)
```



```
In [43]: print('Total SSE: {}'.format(k_means.inertia_))
```

```
Total SSE: 80.04383808675396
```

```
In [44]: print_cluster_sse(k_means.inertia_per_cluster_)
```

```
Cluster 0 SSE: 16.315050448318743
Cluster 1 SSE: 22.784044491106805
Cluster 2 SSE: 25.703033615570583
Cluster 3 SSE: 15.241709531757827
```

```
In [45]: print_max_and_min_inter_cluster_distances(clusters,
                                                  k_means.labels_,
                                                  distance_function='manhattan')
```

```
Max inter-cluster distance: 127.97102541650003
Min inter-cluster distance: 32.41960133088744
```