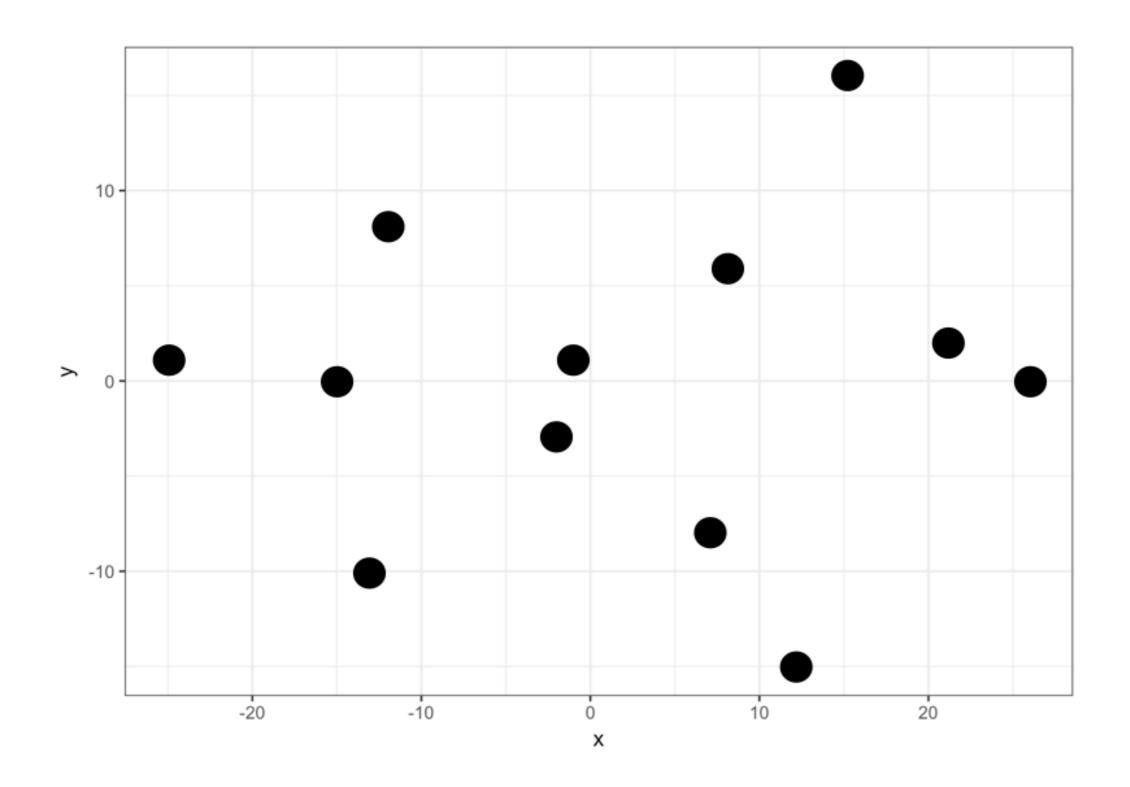
# Introduction to K-means

**CLUSTER ANALYSIS IN R** 

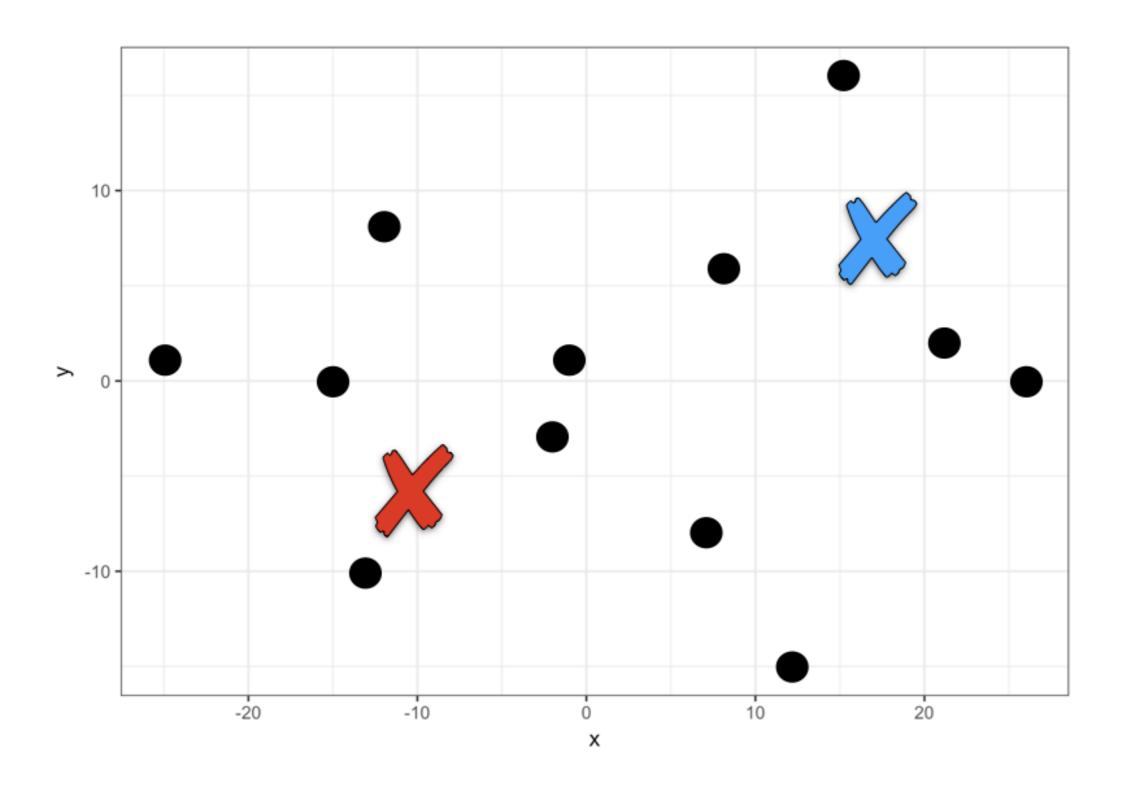


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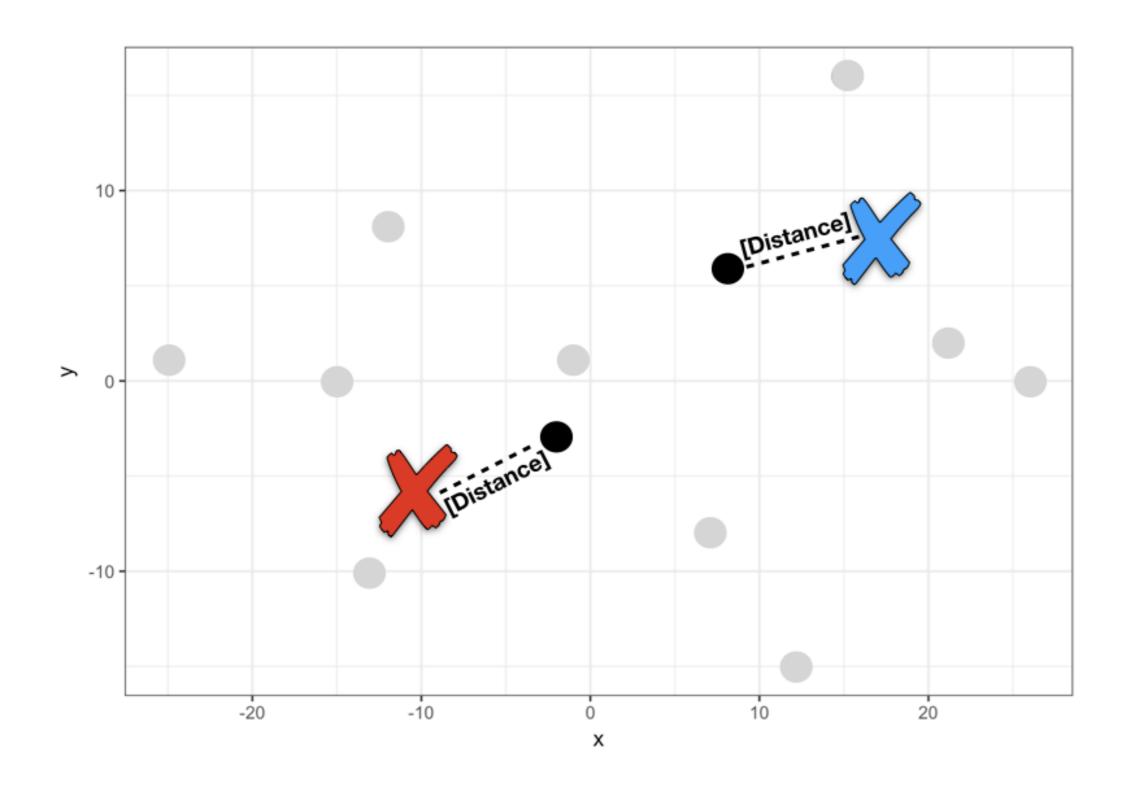




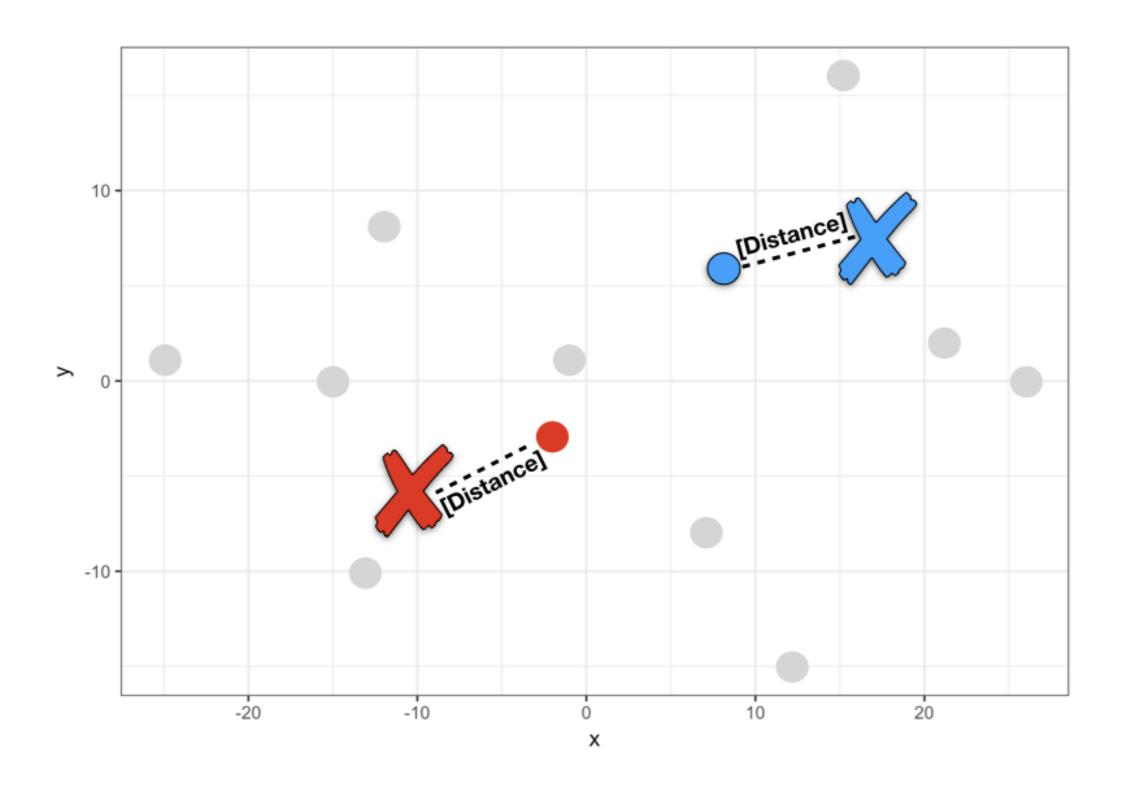




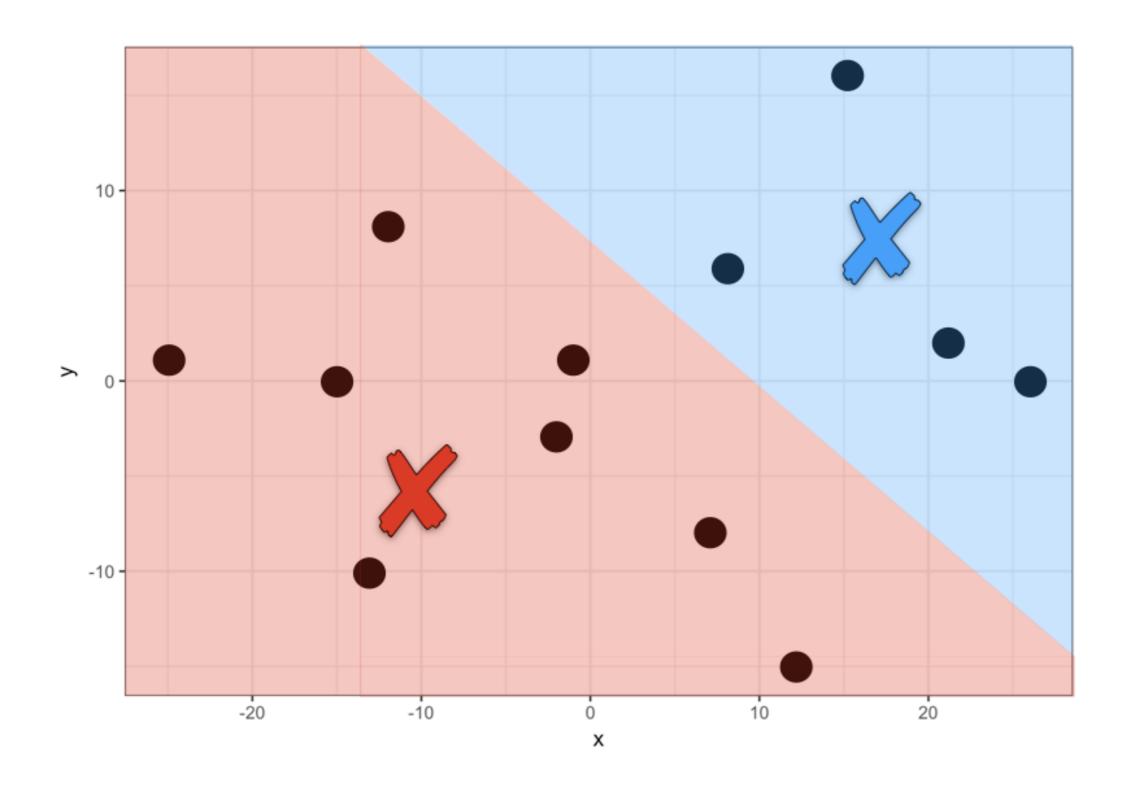


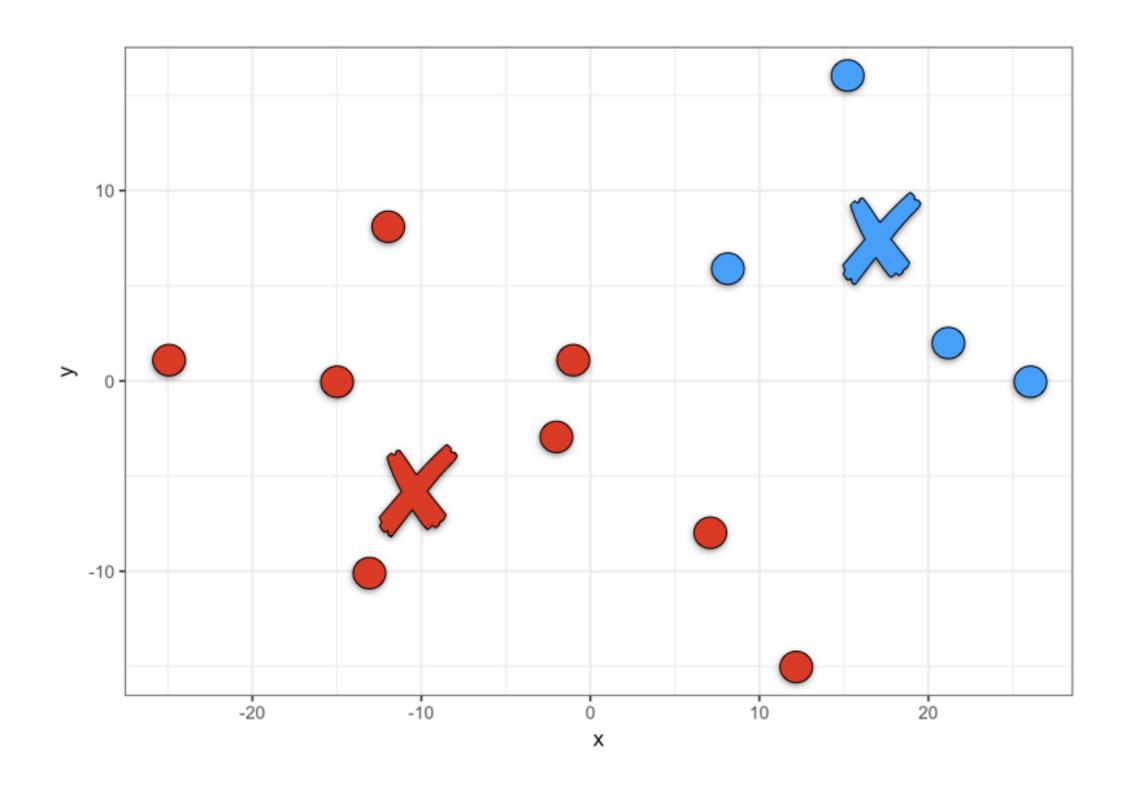


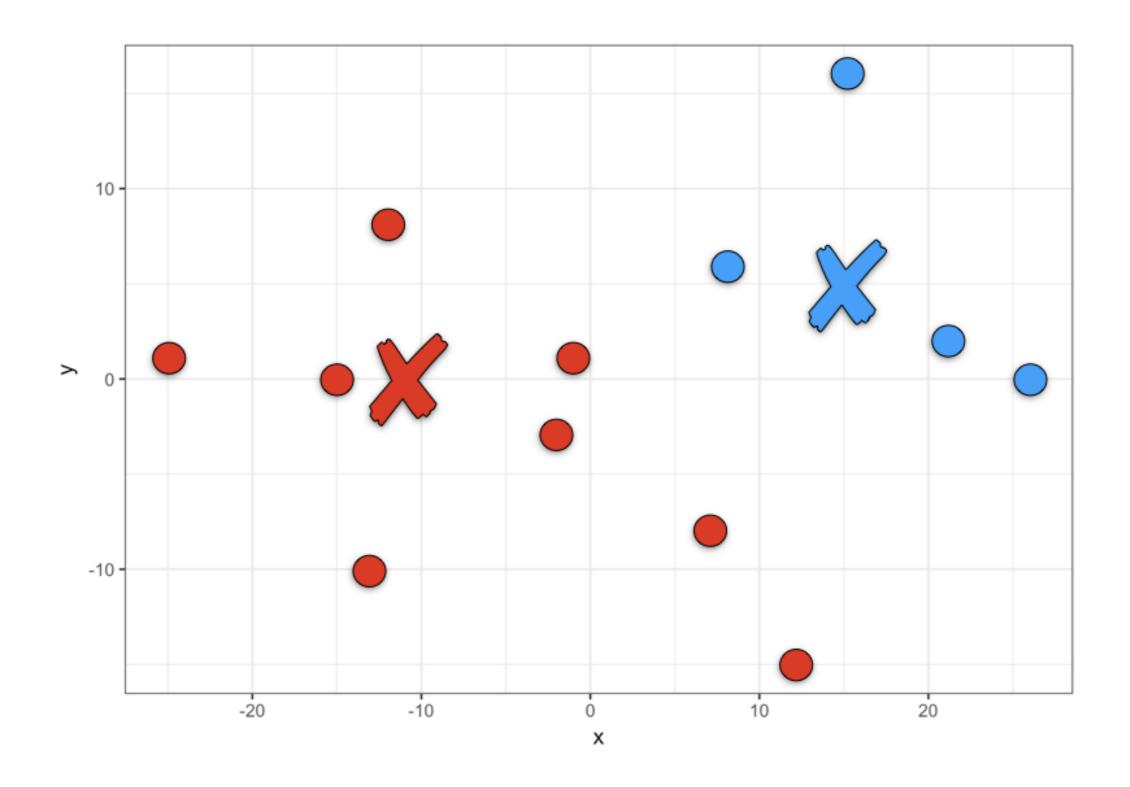




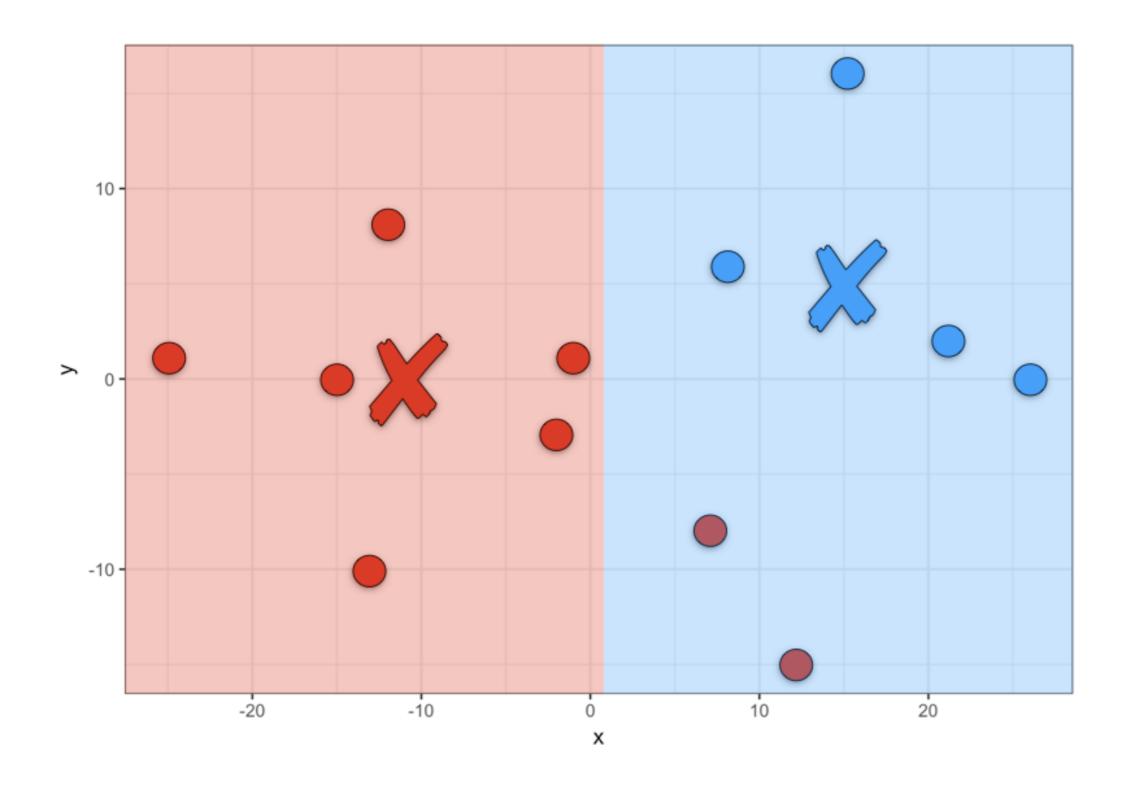


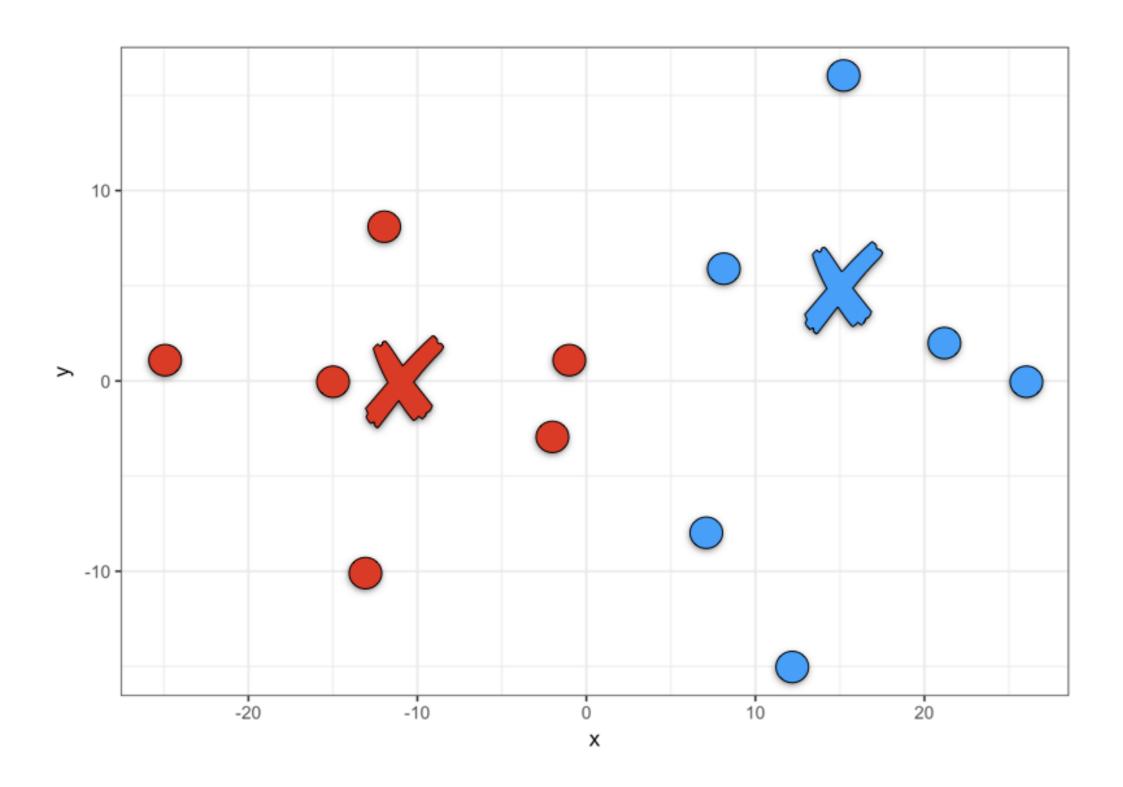




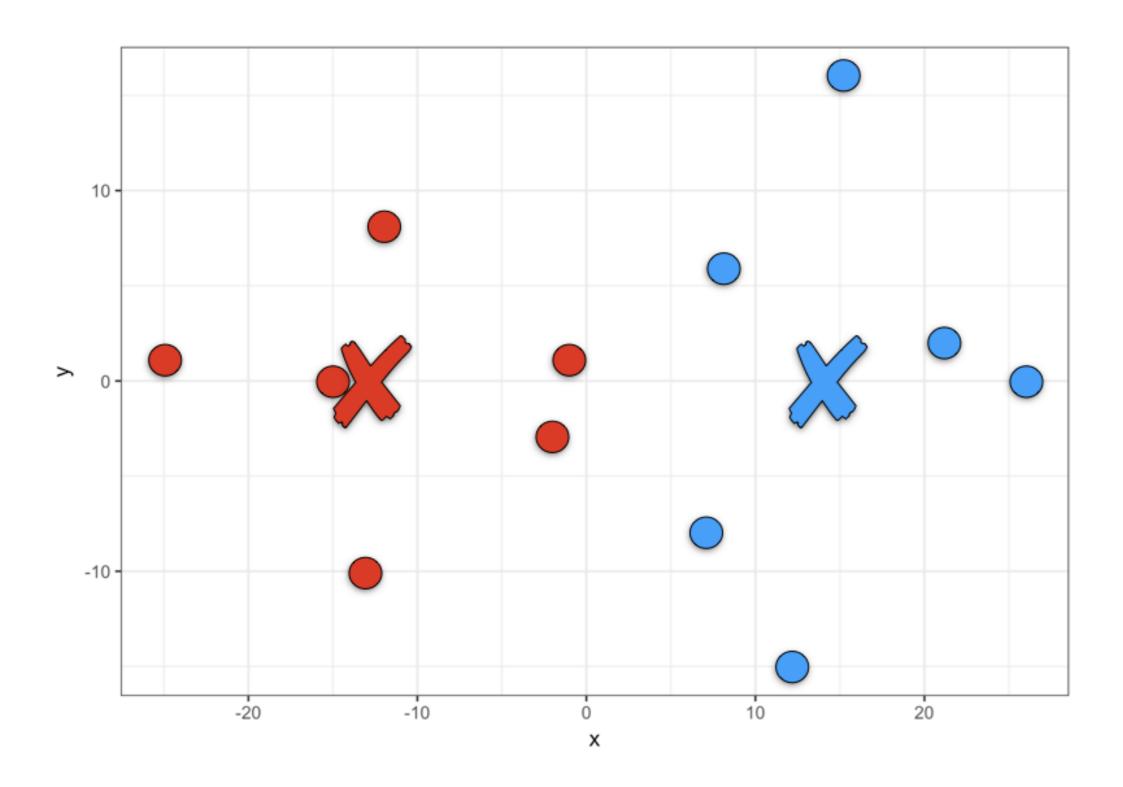














# kmeans()

## Assigning clusters

```
print(model$cluster)
1 1 2 2 1 1 1 2 2 2 1 2
lineup_clustered <- mutate(lineup, cluster = model$cluster)</pre>
print(lineup_clustered)
             y cluster
   <dbl> <dbl> <int>
```

# Let's practice!

**CLUSTER ANALYSIS IN R** 



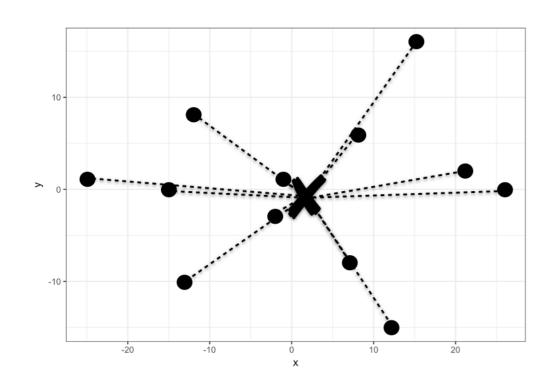
# Evaluating different values of K by eye

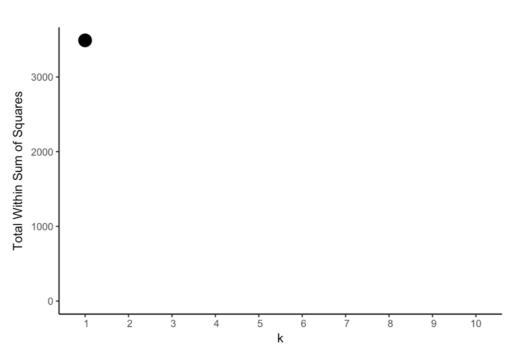
**CLUSTER ANALYSIS IN R** 

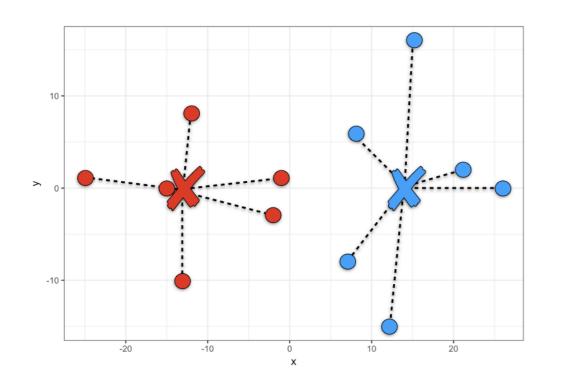


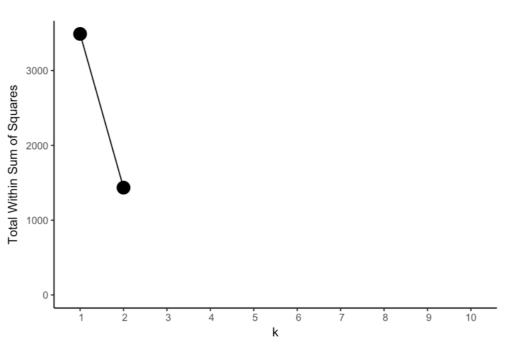
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Kettering Cancer Center

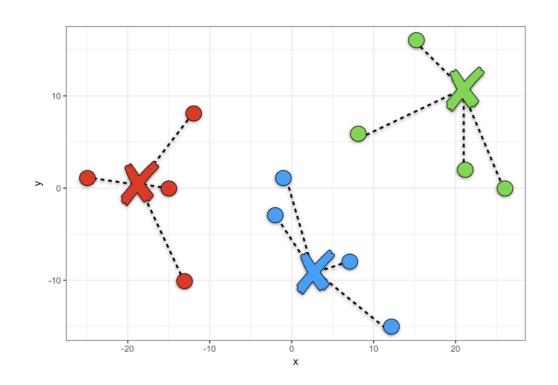


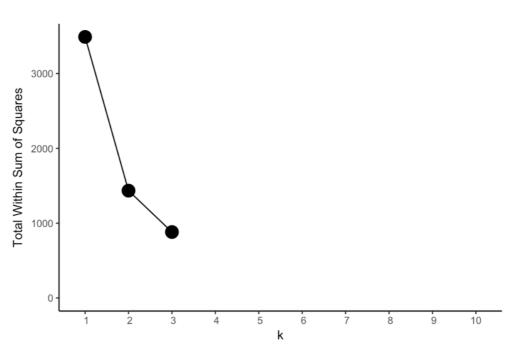


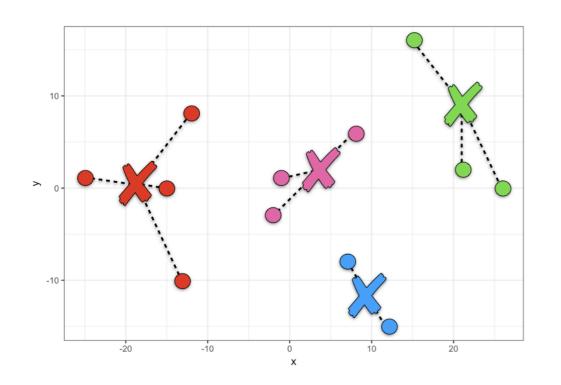


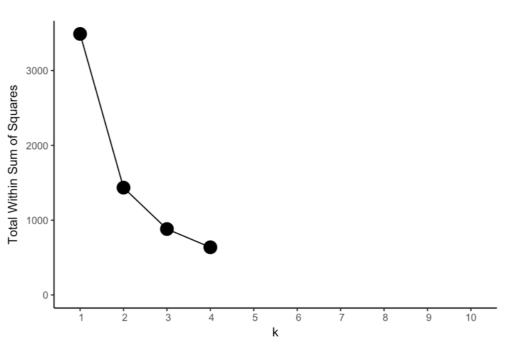




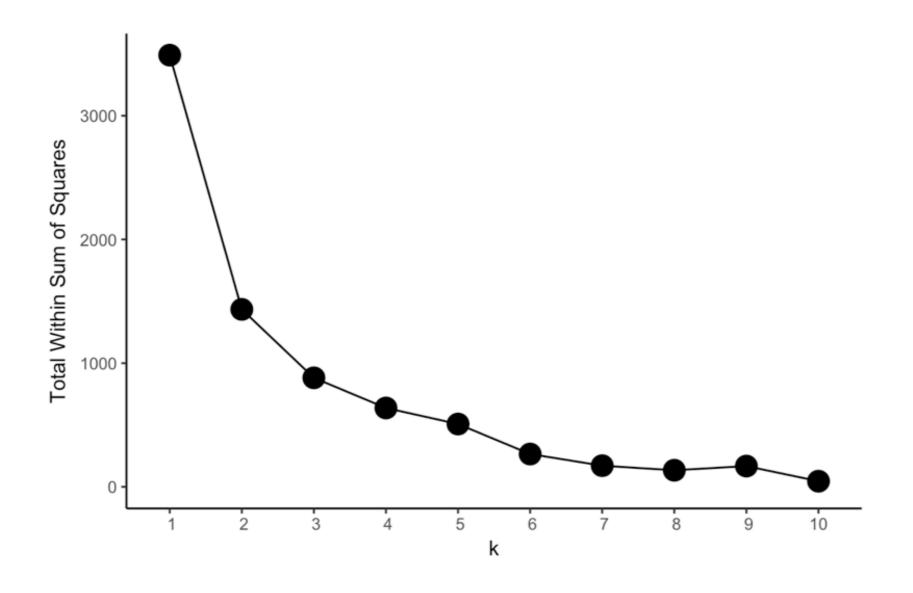






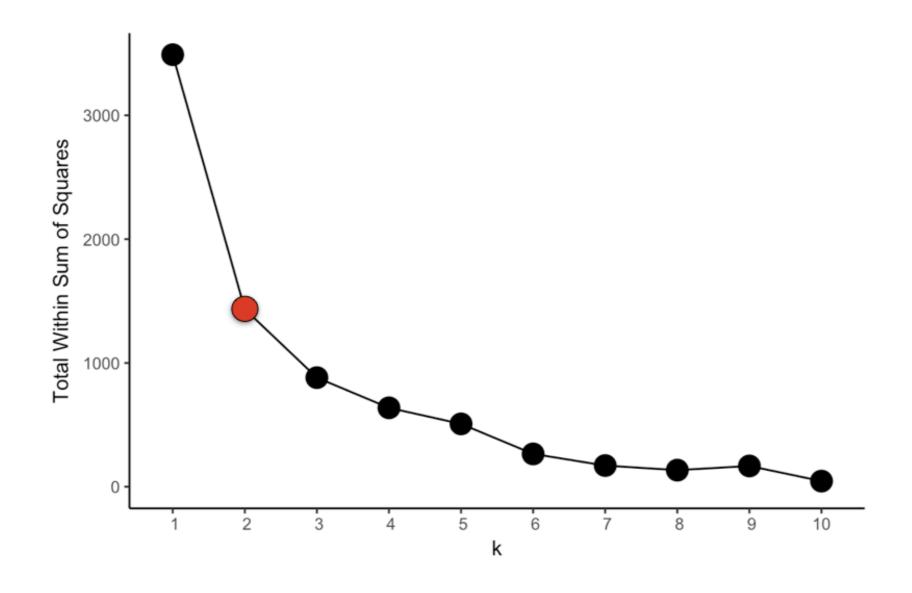


# Elbow plot





# Elbow plot





# Generating the elbow plot

```
model <- kmeans(x = lineup, centers = 2)
model$tot.withinss
[1] 1434.5</pre>
```



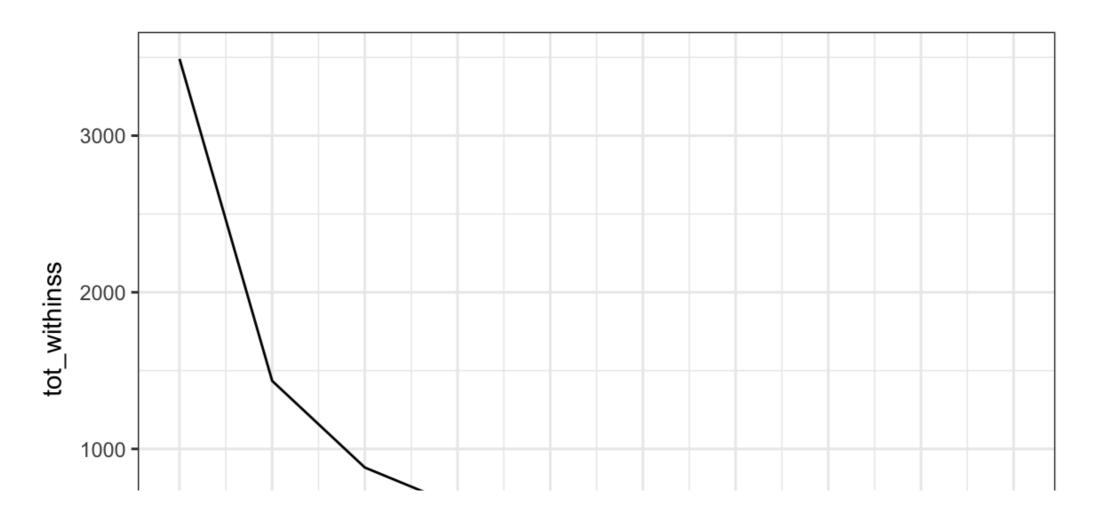
# Generating the elbow plot

```
library(purrr)
tot_withinss <- map_dbl(1:10, function(k){</pre>
  model <- kmeans(x = lineup, centers = k)</pre>
  model$tot.withinss
})
elbow_df <- data.frame(</pre>
  k = 1:10,
  tot_withinss = tot_withinss
print(elbow_df)
    k tot_withinss
         3489.9167
   2 1434.5000
    3 881.2500
    4 637.2500
```



# Generating the elbow plot

```
ggplot(elbow_df, aes(x = k, y = tot_withinss)) +
  geom_line() +
  scale_x_continuous(breaks = 1:10)
```





# Let's practice!

**CLUSTER ANALYSIS IN R** 



# Silhouette analysis: observation level performance

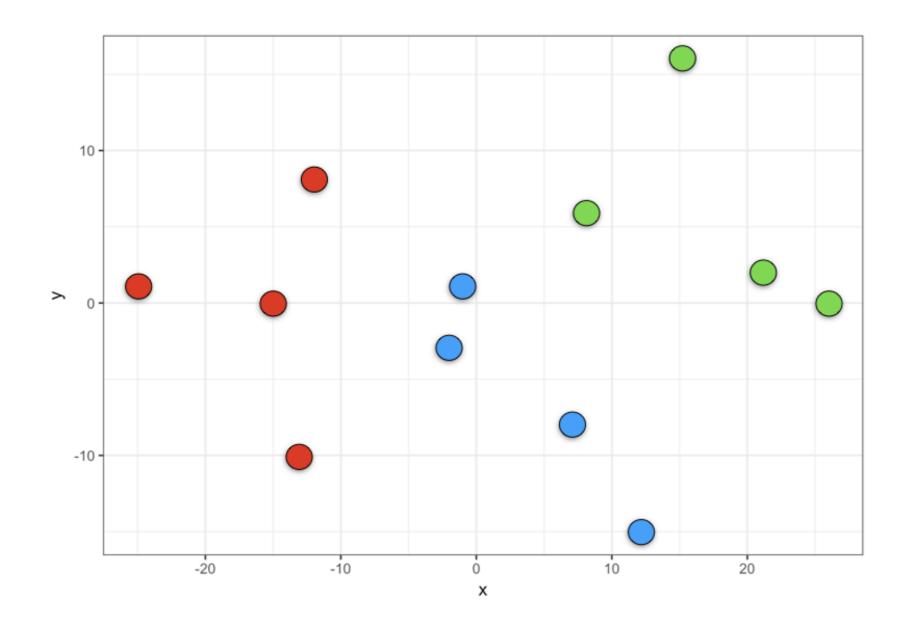
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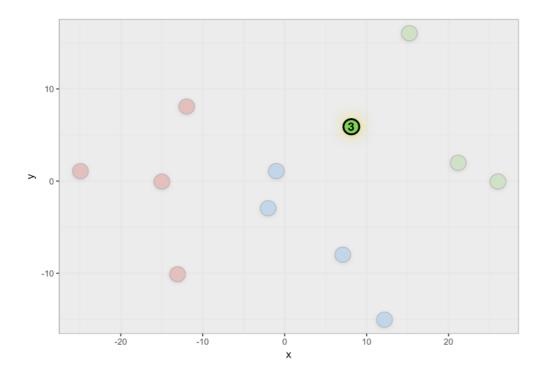


# Soccer lineup with K = 3



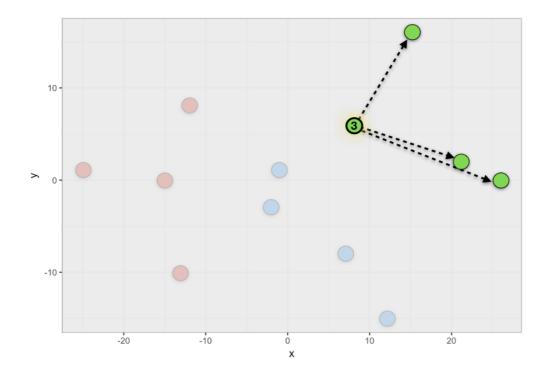


Within Cluster Distance: C(i)



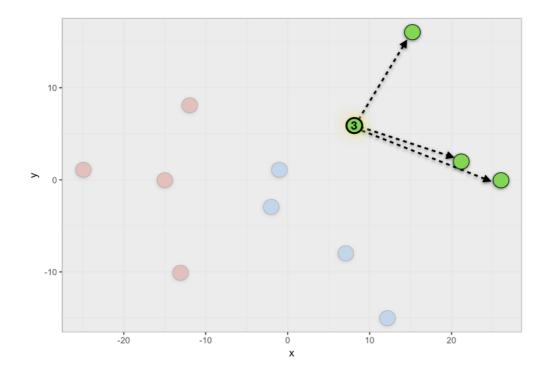
Closest Neighbor Distance: N(i)

Within Cluster Distance: C(i)



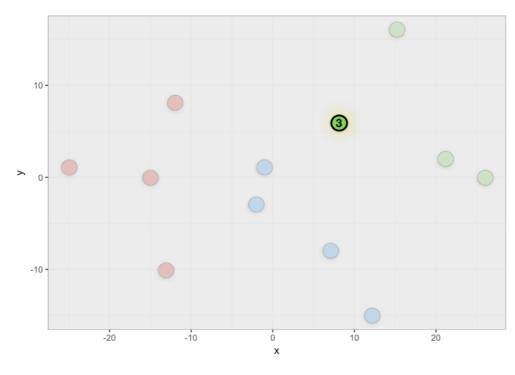
Closest Neighbor Distance: N(i)

#### Within Cluster Distance: C(i)

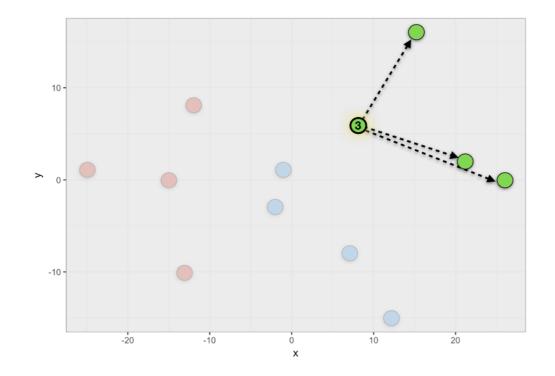


#### **Closest Neighbor Distance:**

N(i)

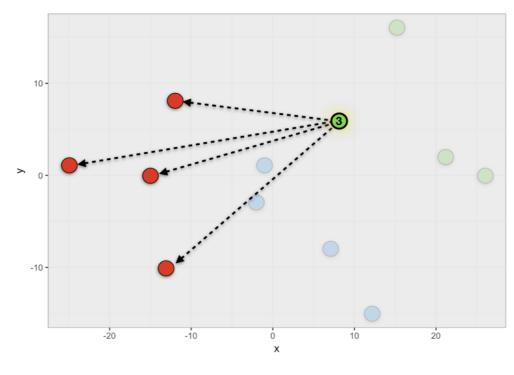


#### Within Cluster Distance: C(i)

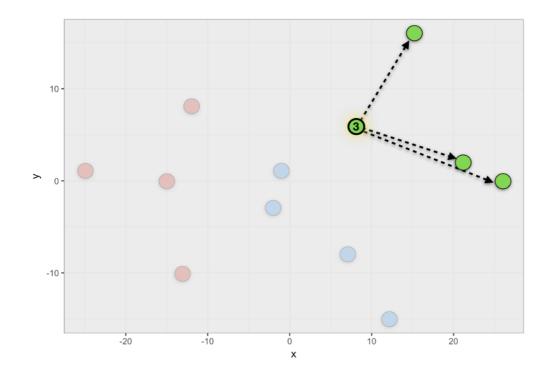


#### **Closest Neighbor Distance:**

N(i)

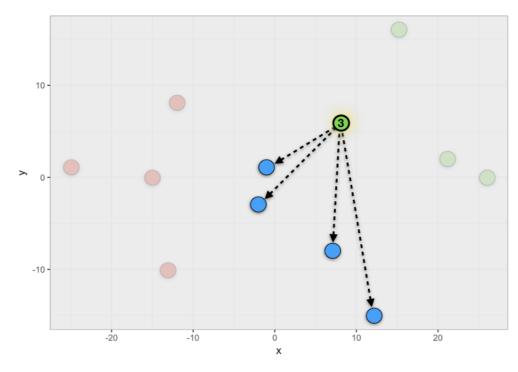


#### Within Cluster Distance: C(i)

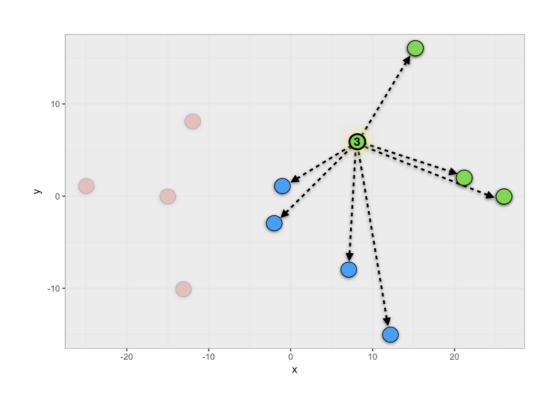


#### **Closest Neighbor Distance:**

N(i)

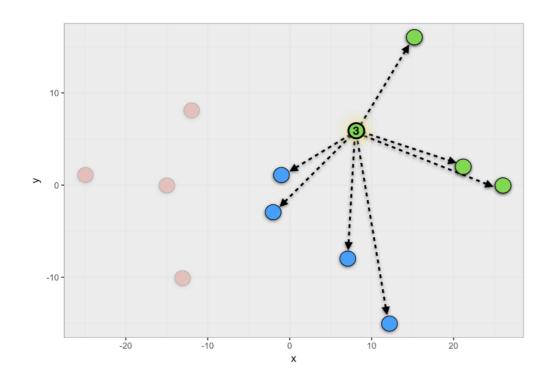


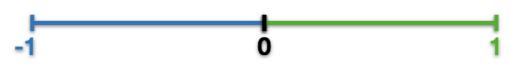
# Silhouette width: S(i)



$$s(i) = \begin{cases} 1 - C(i)/N(i), & \text{if } C(i) < N(i) \\ 0, & \text{if } C(i) = N(i) \\ N(i)/C(i) - 1, & \text{if } C(i) > N(i) \end{cases}$$

# Silhouette width: S(i)





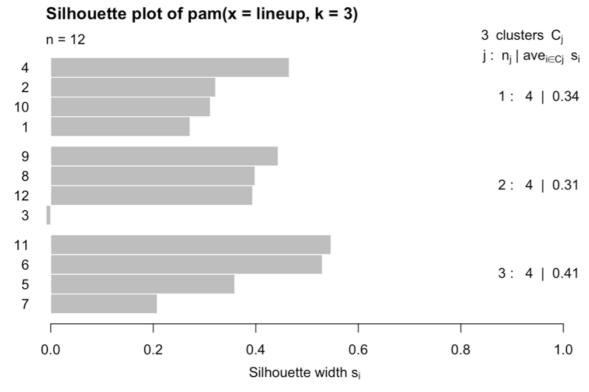
- 1: Well matched to cluster
- **0:** On border between two clusters
- -1: Better fit in neighboring cluster

# Calculating S(i)

```
library(cluster)
pam_k3 \leftarrow pam(lineup, k = 3)
pam_k3$silinfo$widths
   cluster neighbor sil_width
                  2 0.465320054
4
                  3 0.321729341
10
                  2 0.311385893
                  3 0.271890169
                  1 0.443606497
```

### Silhouette plot

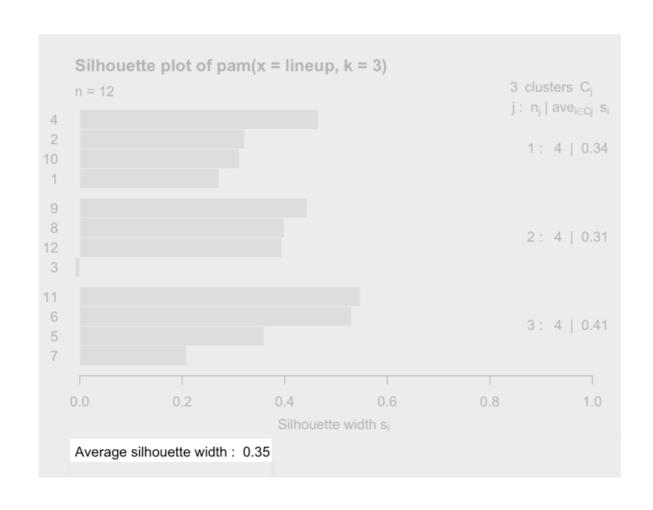
```
sil_plot <- silhouette(pam_k3)
plot(sil_plot)</pre>
```



Average silhouette width: 0.35

### Silhouette plot

```
sil_plot <- silhouette(pam_k3)
plot(sil_plot)</pre>
```





### Average silhouette width

```
pam_k3$silinfo$avg.width
[1] 0.353414
```

- 1: Well matched to each cluster
- 0: On border between clusters
- -1: Poorly matched to each cluster

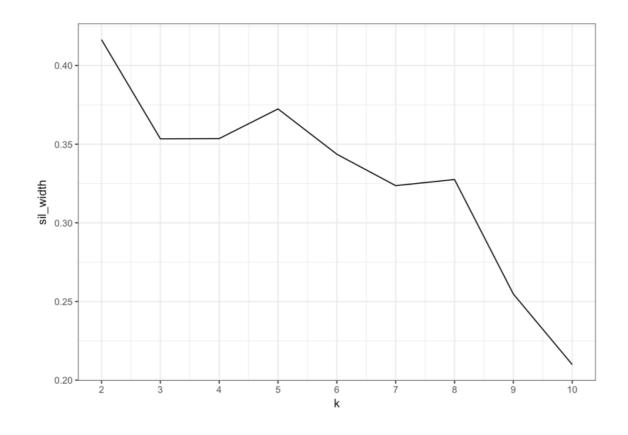
### Highest average silhouette width

```
library(purrr)
sil_width <- map_dbl(2:10, function(k){</pre>
  model <- pam(x = lineup, k = k)
  model$silinfo$avg.width
})
sil_df <- data.frame(</pre>
  k = 2:10,
  sil_width = sil_width
print(sil_df)
         sil_width
        0.4164141
    3 0.3534140
   4 0.3535534
        0.3724115
```



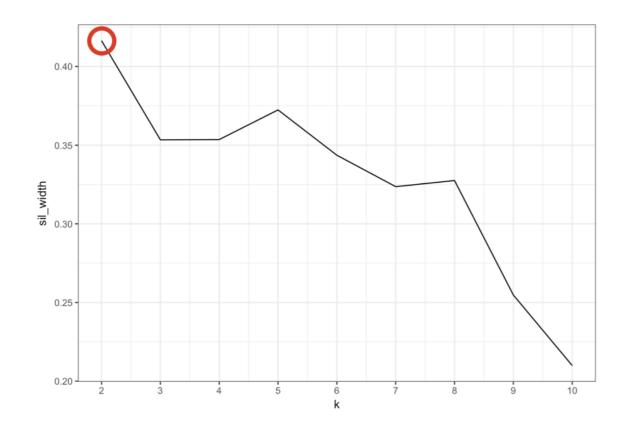
### Choosing K using average silhouette width

```
ggplot(sil_df, aes(x = k, y = sil_width)) +
  geom_line() +
  scale_x_continuous(breaks = 2:10)
```



### Choosing K using average silhouette width

```
ggplot(sil_df, aes(x = k, y = sil_width)) +
  geom_line() +
  scale_x_continuous(breaks = 2:10)
```



## Let's practice!

**CLUSTER ANALYSIS IN R** 



# Making sense of the K-means clusters

**CLUSTER ANALYSIS IN R** 



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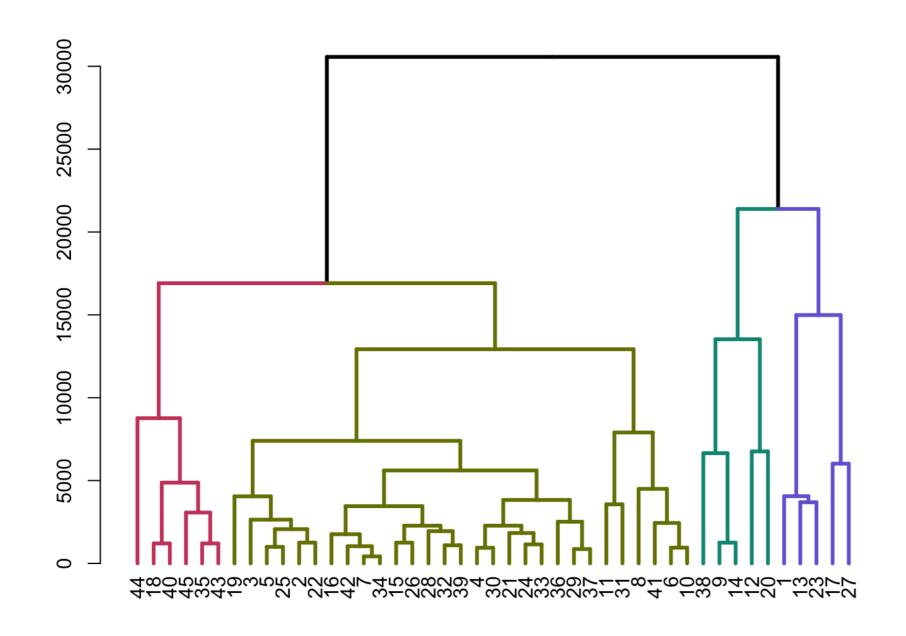


#### Wholesale dataset

- 45 observations
- 3 features:
  - Milk Spending
  - Grocery Spending
  - Frozen Food Spending

```
print(customers_spend)
    Milk Grocery Frozen
   11103
           12469
                     902
                     909
    2013
            6550
    1897
            5234
                     417
    1304
                    3045
            3643
5
    3199
            6986
                    1455
```

### Segmenting with hierarchical clustering





### Segmenting with hierarchical clustering

cluster	Milk	Grocery	Frozen	cluster size
1	16950	12891	991	5
2	2512	5228	1795	29
3	10452	22550	1354	5
4	1249	3916	10888	6

### Segmenting with K-means

- Estimate the "best" k using average silhouette width
- Run k-means with the suggested k
- Characterize the spending habits of these clusters of customers

### Let's cluster!

**CLUSTER ANALYSIS IN R** 

