Week 10: Clustering

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AGGLOMERATIVE HIERARCHICAL CLUSTERING

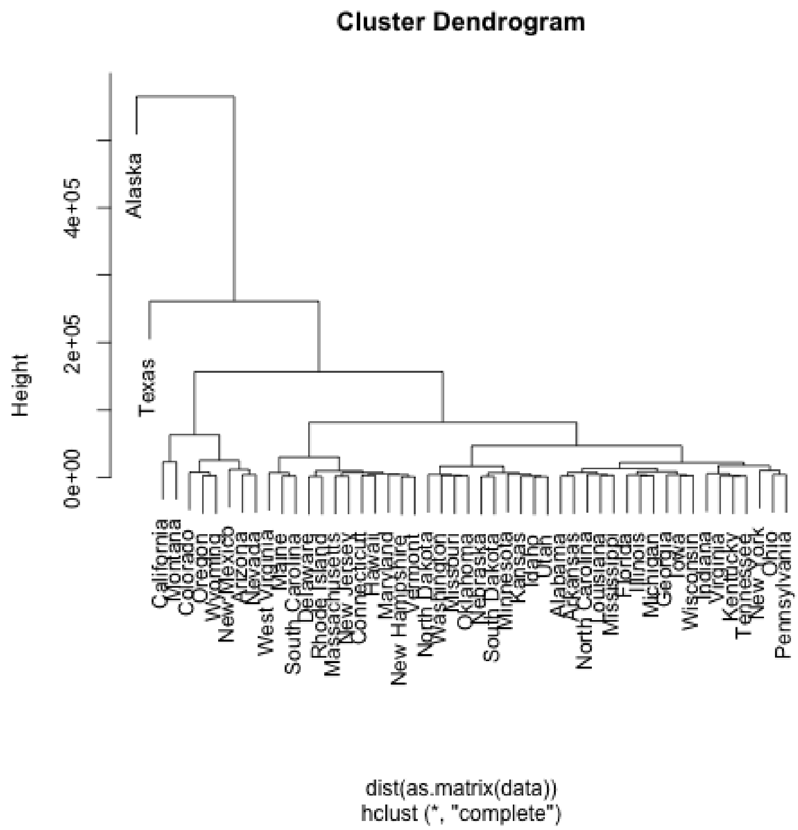
Step 1

Completed

```
# Load the dataset
library(datasets)
library(cluster)
data = state.x77
```

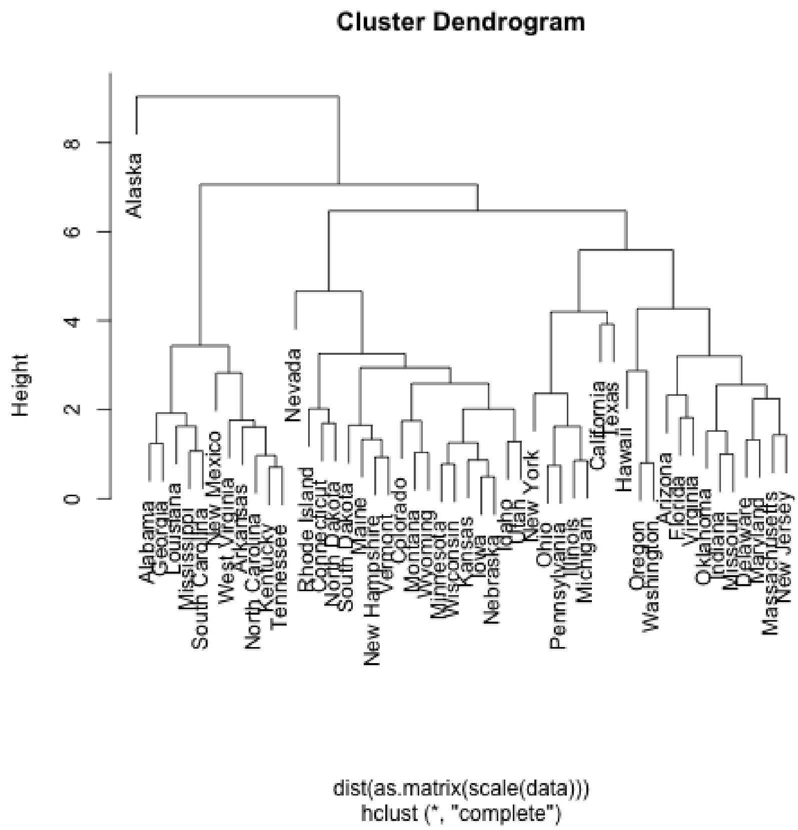
Step 2

```
# Use hierarchical clustering to cluster the data on all attributes and produce a dendr
png(filename="hclust-all-attri-no-scale.png")
plot(hclust(dist(as.matrix(data))))
```



Step 3

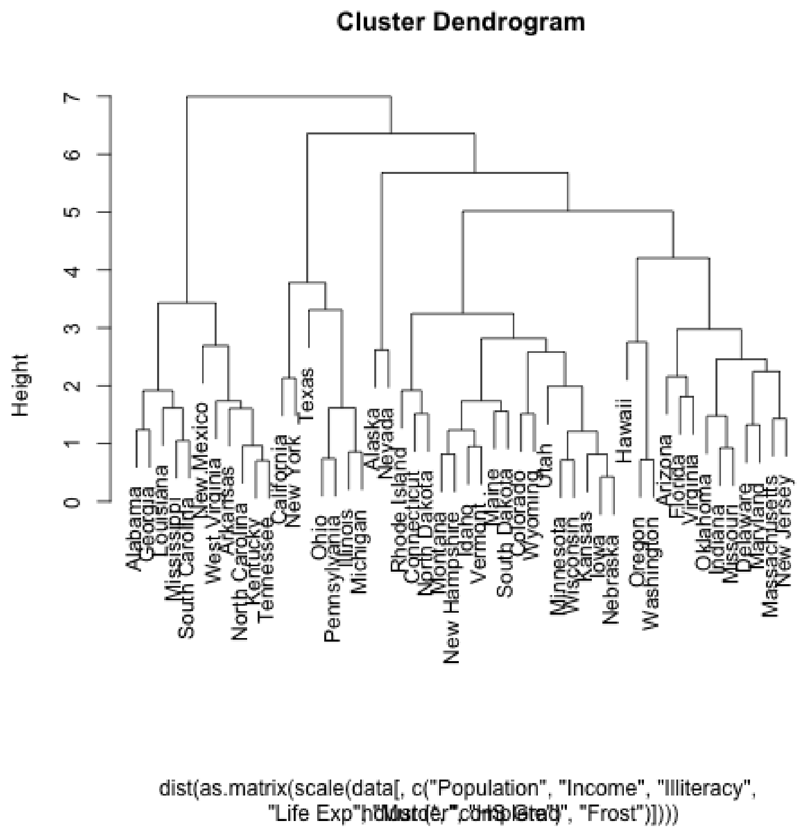
```
# Repeat the previous item with a normalized dataset and note any differences
png(filename="hclust-all-attri-with-scale.png")
plot(hclust(dist(as.matrix(scale(data)))))
```



The scaled clusters seem to do a much better job of creating distinct clusters. A heuristic analysis of the dendogram makes it seem that total area of a the state overpowered nearly all of the other attributes when determining the raw data. By normalizing it, the other attributes were able to have a stronger influence on the clusters.

Step 4

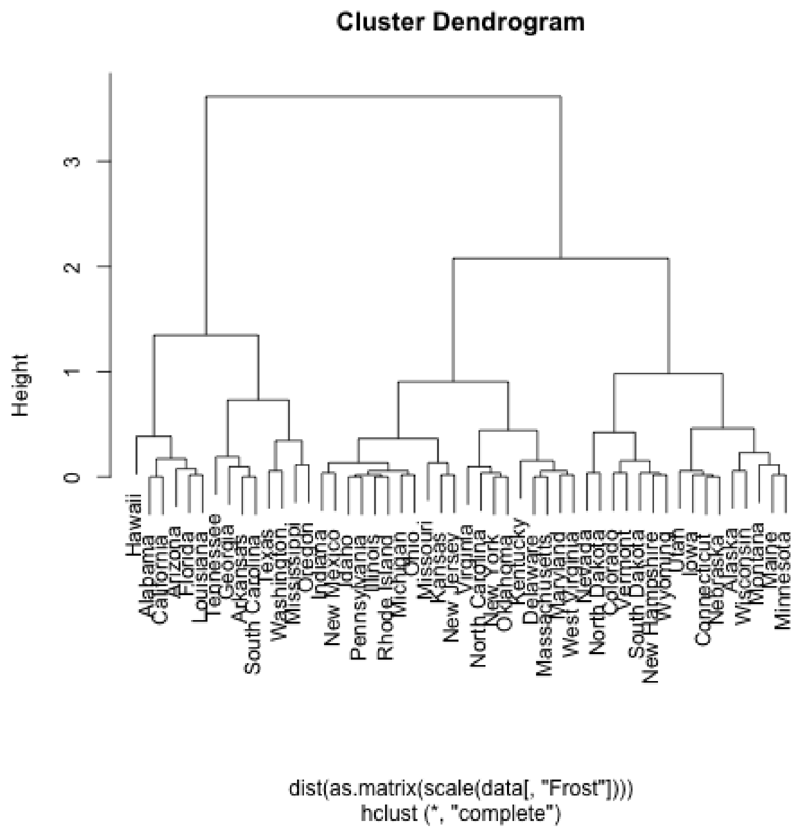
```
# Remove "Area" from the attributes and re-cluster (and note any differences)
png(filename="hclust-no-area-with-scale.png")
plot(hclust(dist(as.matrix(
        scale(data[,c("Population", "Income", "Illiteracy",
                 "Life Exp", "Murder", "HS Grad", "Frost")])))))
```



Without area, the dendogram looks even more balanced. I think this shows just how disproportionate some of the state sizes are. States with very similar attributes in every other respect are grouped differently just because one is much larger than the other. You are now able to see actual regions in the country being grouped together.

Step 5

```
# Cluster only on the Frost attribute and observe the results
png(filename="hclust-only-frost-with-scale.png")
plot(hclust(dist(as.matrix(scale(data[,"Frost"])))))
```



I saw pretty close to what I expected. States with similar weather patterns are grouped together, and often states on similar latitudes are grouped together, even if they are far apart.

USING K-MEANS

Step 1

```
data <- scale(state.x77)
```

Step 2

```
myClusters = kmeans(data, 3)
summary(myClusters)
print(myClusters$centers)
print(myClusters$cluster)
```

Summary

```
# Length Class  Mode
# cluster      50     -none- numeric
# centers      24     -none- numeric
# totss         1     -none- numeric
# withinss      3     -none- numeric
# tot.withinss  1     -none- numeric
# betweenss     1     -none- numeric
# size          3     -none- numeric
# iter          1     -none- numeric
# ifault        1     -none- numeric
```

Mean Values

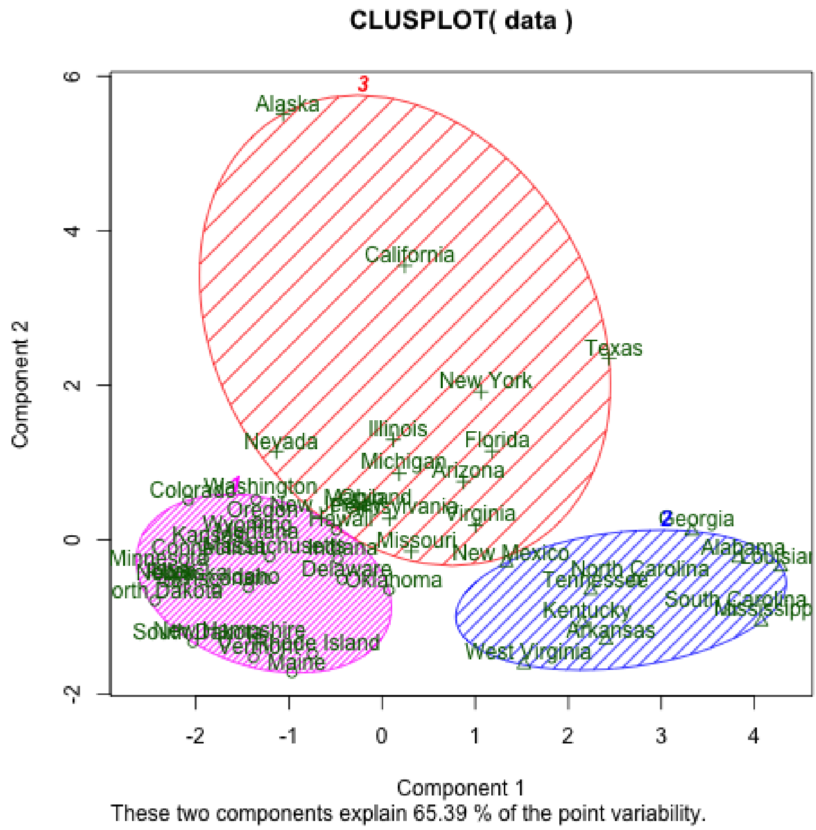
Population	Income	Illiteracy	Life-Exp
-0.2269956	-1.3014617	1.391527063	-1.1773136
-0.4873370	0.1329601	-0.641201154	0.7422562
0.9462026	0.7416690	0.005468667	-0.3242467

Murder	HS-Grad	Frost	Area
1.0919809	-1.4157826	-0.7206500	-0.2340290
-0.8552439	0.5515044	0.4528591	-0.1729366
0.5676042	0.1558335	-0.1960979	0.4483198

Cluster Assignments

Alabama	Alaska	Arizona	Arkansas	California
3	1	1	3	1
Colorado	Connecticut	Delaware	Florida	Georgia
2	2	2	1	3
Hawaii	Idaho	Illinois	Indiana	Iowa
2	2	1	2	2
Kansas	Kentucky	Louisiana	Maine	Maryland
2	3	3	2	1
Massachusetts	Michigan	Minnesota	Mississippi	Missouri
2	1	2	3	1
Montana	Nebraska	Nevada	New-Hampshire	New-Jersey
2	2	1	2	1
New-Mexico	New-York	North-Carolina	North-Dakota	Ohio
3	1	3	2	1
Oklahoma	Oregon	Pennsylvania	Rhode-Island	South-Carolina
2	2	1	2	3
South-Dakota	Tennessee	Texas	Utah	Vermont
2	3	1	2	2
Virginia	Washington	West-Virginia	Wisconsin	Wyoming
1	2	3	2	2

Cluster Assignments Plot

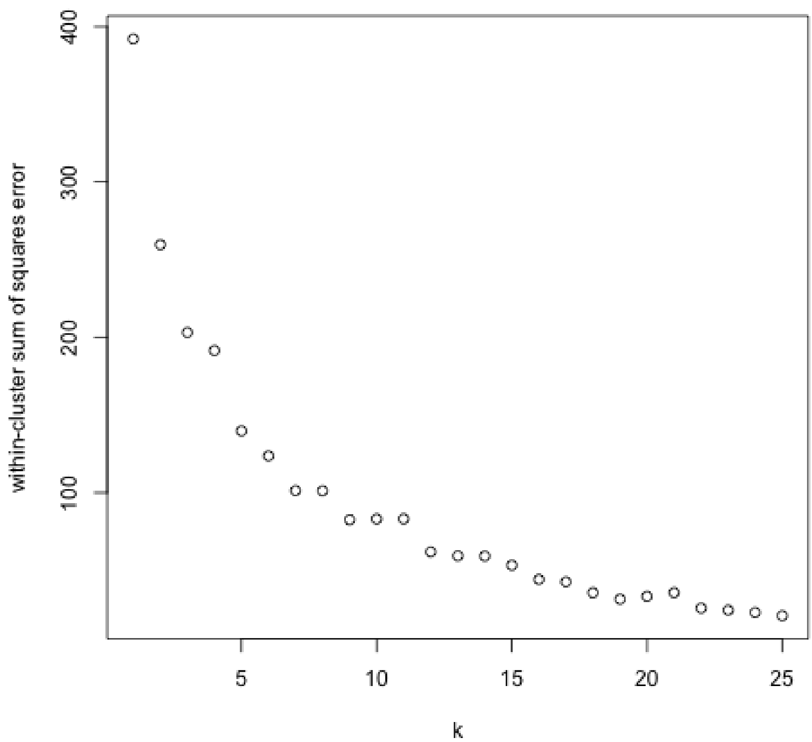


Analysis

My guess is that area and population are the largest factors in these grouping. We can see on the plot that Alaska, California, and Texas are outliers, probably due to their size/population ratios.

Step 3

```
errors <- c()
for (k in 1:25) {
    errors[k] <- kmeans(data, k)$tot.withinss
}
png("kmeans-sum-squares-error.png")
plot(errors, xlab = "k", ylab = "within-cluster sum of squares error")
```



Step 4

I picked 10, as it seems like that is when the rate of error stops decreasing significantly.

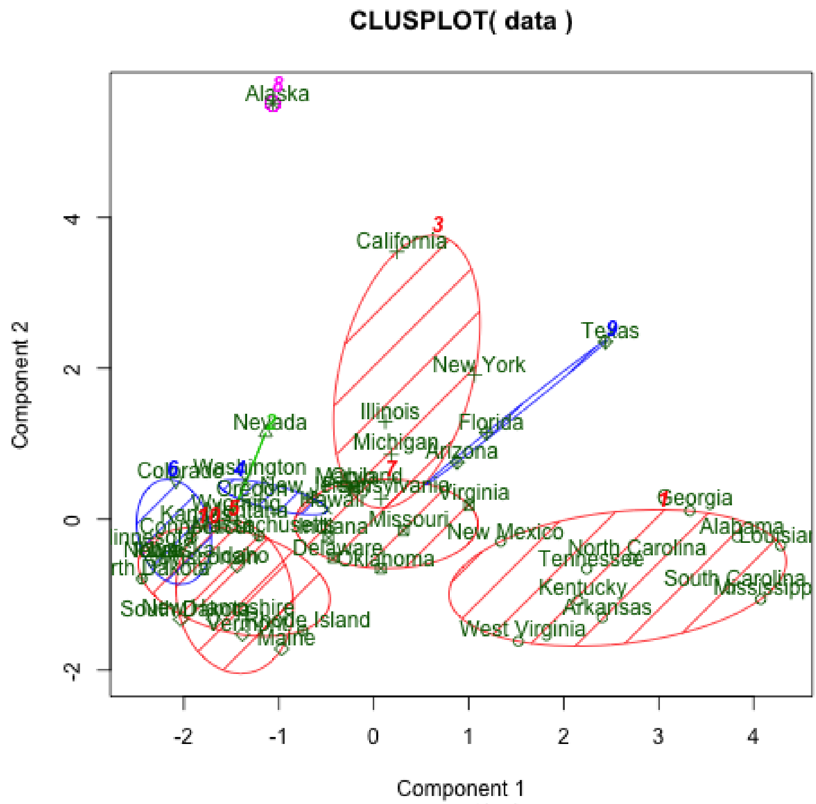
```
k <- 10
```

Step 5

```
print(cluster$cluster)
```

Alabama	Alaska	Arizona	Arkansas	California
4	2	3	4	10
Colorado	Connecticut	Delaware	Florida	Georgia
7	1	8	8	4
Hawaii	Idaho	Illinois	Indiana	Iowa
5	7	8	8	7
Kansas	Kentucky	Louisiana	Maine	Maryland
7	4	4	9	8
Massachusetts	Michigan	Minnesota	Mississippi	Missouri
1	8	7	4	8
Montana	Nebraska	Nevada	New-Hampshire	New-Jersey
6	7	6	9	8
New-Mexico	New-York	North-Carolina	North-Dakota	Ohio
3	10	4	1	8
Oklahoma	Oregon	Pennsylvania	Rhode-Island	South-Carolina
3	5	8	1	4
South-Dakota	Tennessee	Texas	Utah	Vermont
9	4	10	7	9
Virginia	Washington	West-Virginia	Wisconsin	Wyoming
8	5	4	7	6

Step 6



These two components explain 65.39 % of the point variability.

Step 7

Population	Income	Illiteracy	Life-Exp
-0.3499380	0.5656501	-0.7710820	1.2544011
-0.4514893	0.5182516	0.0902330	0.8353735
-0.7660428	-0.5843829	-0.9117048	0.4809958
-0.1667872	-1.3624751	1.8866900	-1.7868083
-0.8429672	0.6862826	-1.0171720	-0.9077815
0.7891560	0.5328170	-0.3117140	-0.2462765
2.8948232	0.4869237	0.6507713	0.1301655
-0.2771693	-1.2506172	0.9788913	-0.6694013
-0.8693980	3.0582456	0.5413980	-1.1685098
-0.3889962	0.1472000	-0.1148420	0.3157792

Murder	HS-Grad	Frost	Area
-1.1080742	0.55150442	0.859258777	-0.058630181
-0.4748696	0.96161967	-1.571925102	-0.001018197
-0.9150653	0.65342525	0.994267293	-0.099820942
1.5933731	-1.55107136	-1.213139113	-0.287006387
0.4935610	1.35471127	1.462846466	0.384520782
0.3093560	-0.19041729	-0.001154271	-0.342772830
1.0172810	0.13932569	-1.131057600	0.992720037
0.6741541	-1.30304191	-0.310242469	-0.189881160
1.0624293	1.68280347	0.914567609	5.809349671

I see that area, income, and population seem to have the greatest deviation among the attributes. This suggests they have the greatest influence on the centers due to the nature of Euclidean distance. The rest of the attributes do not have nearly as much of a range, indicating they do not have a large influence on the centers in comparison.

Summary

D). I completed all of the steps.