Answer Key: Unsupervised Learning II: Clustering

K-means clustering randomizes the initial values for optimization, so results may vary everytime it is run. This answer key uses a `set.seed(10)` to get consistent results.

Problem statement: A granting agency wants to identify colleges that have high numbers of low-income, and first generation college attendees to give those colleges additional funding.

1. In the clustering tutorial, we used k-means clustering to identify 3 clusters of colleges using these criteria.

   A. Replicate this analysis using the code in the tutorial to generate those 3 clusters and append the cluster levels to the `college_features` dataset.

```
library(dplyr)
library(ggplot2)
```

```
### For reproducible results
set.seed(10)

### Load the colleges datasets on your machine
### colleges = read.delim("colleges.tsv", sep = '\t', header = TRUE)

college_features = colleges %>%
  select(institution_name, first_gen_share, poverty_rate, family_income_median,
     median_earnings, top_ten) %>%
  na.omit() %>%
  distinct()

kmeans_cluster = kmeans(select(college_features, -institution_name, -top_ten), 3)

college_features$cluster = kmeans_cluster$cluster
```

   B. What is the median family income for each cluster (**hint:** see `kmeans_cluster$centers` from the tutorial)?

```
kmeans_cluster$centers
```

```
##   first_gen_share poverty_rate family_income_median median_earnings
## 1       0.4250142     8.579652             40221.74        41790.14
## 2       0.2808411     6.285941             75559.67        46343.79
## 3       0.5483327    12.901803             19231.73        25758.38
```

   C. Subset the colleges_features dataset on the cluster with the lowest `family_income_median`, call this new data grant_candidates. **Note:** in the tutorial, grant_candidates were from Cluster 1, you could find that a different cluster from your analysis has the lowest `family_income_median` when you look at `kmeans_cluster$centers`.

```
grant_candidates = college_features %>% filter(cluster == 3)
```

   D. How many universities are in the cluster of grant receivers?

```
dim(grant_candidates)
```

```
## [1] 2501    7
```

   2,501 are in the lowest family income cluster and would receive grants using this method.

2. Upon review you're informed that there are too many universities receiving grants. The granting agency really likes the cluster approach but suggests you make 5 clusters instead of 3.

   A. Redo the k-means analysis above but create 5 clusters instead of 3. **Note:** If you appended cluster onto your `college_features` dataset, make sure to remove it before redoing the k-means analysis.

```
### re-running this code so the cluster variable isn't included

college_features = colleges %>%
  select(institution_name, first_gen_share, poverty_rate, family_income_median,
     median_earnings, top_ten) %>%
  na.omit() %>%
  distinct()

kmeans_cluster = kmeans(select(college_features, -institution_name, -top_ten), 5)

college_features$cluster = kmeans_cluster$cluster
```

   B. Again subset the data on the cluster with the lowest `family_income_median`. How many universities will receive a grant now? What is the median and range of `family_income_median` of these universities and how does it compare to your answers in Question 1?

```
### instead of printing the cluster results, you can find the minimum family income
### using programmatic methods
grant_candidates = college_features %>%
  filter(cluster == which.min(kmeans_cluster$centers[,"family_income_median"]))

dim(grant_candidates)
```

```
## [1] 31  7
```

   Compared to the 2,501 universities identified in 1D, there are only 31 that are in the cluster now.

   C. You will likely find that there were two clusters out of the five with low but similar `family_income_median`. Among these two clusters, what else determined which cluster these universities were assigned to (**hint:** look at the centers again)? Based on those other variables, do you think we made the correct decision to distribute grants considering only `family_income_median`?

```
kmeans_cluster$centers
```

```
##   first_gen_share poverty_rate family_income_median median_earnings
## 1       0.2478139     5.986602             82779.12        49646.10
## 2       0.2661290     8.406129             14966.27       126393.55
## 3       0.5632721    13.745615             17116.77        23933.89
## 4       0.4682306     9.409572             31499.25        36976.43
## 5       0.3728830     7.410169             55160.78        40199.76
```

   Despite having the lowest median family income at $14,966, our grant cluster has the highest median earnings after graduation among all of the clusters. The cluster with the second lowest median family income ($17,116) has the highest poverty rate and lowest post-graduation earnings, so would seemingly be a better target for a grant program.

3. Hierarchical clustering: Part of the grant is to reformulate curriculums to better match top ten universities.

   A. Subset your colleges dataset using the following code. The !is.na(sat_verbal_quartile_1) removes universities that do not have SAT admission criteria, so we are looking at similar degree-granting universities. What other criteria are we using to subset?

```
grant_colleges =
  colleges %>%
  filter(
    !is.na(sat_verbal_quartile_1) & family_income_median < 40000 & median_earnings < 30000
  )

top_ten_schools = colleges %>% filter(top_ten == TRUE)

heir_analysis_data = rbind(grant_colleges, top_ten_schools)
```

   We are also selecting colleges with median family income less than $40,000 AND median earnings after graduation less than $30,000.

   B. Replicate the heirarchical clustering from the tutorial comparing major percentages using `heir_analysis_data` dataset. Which universities are the most different from the top ten schools in terms of majors?

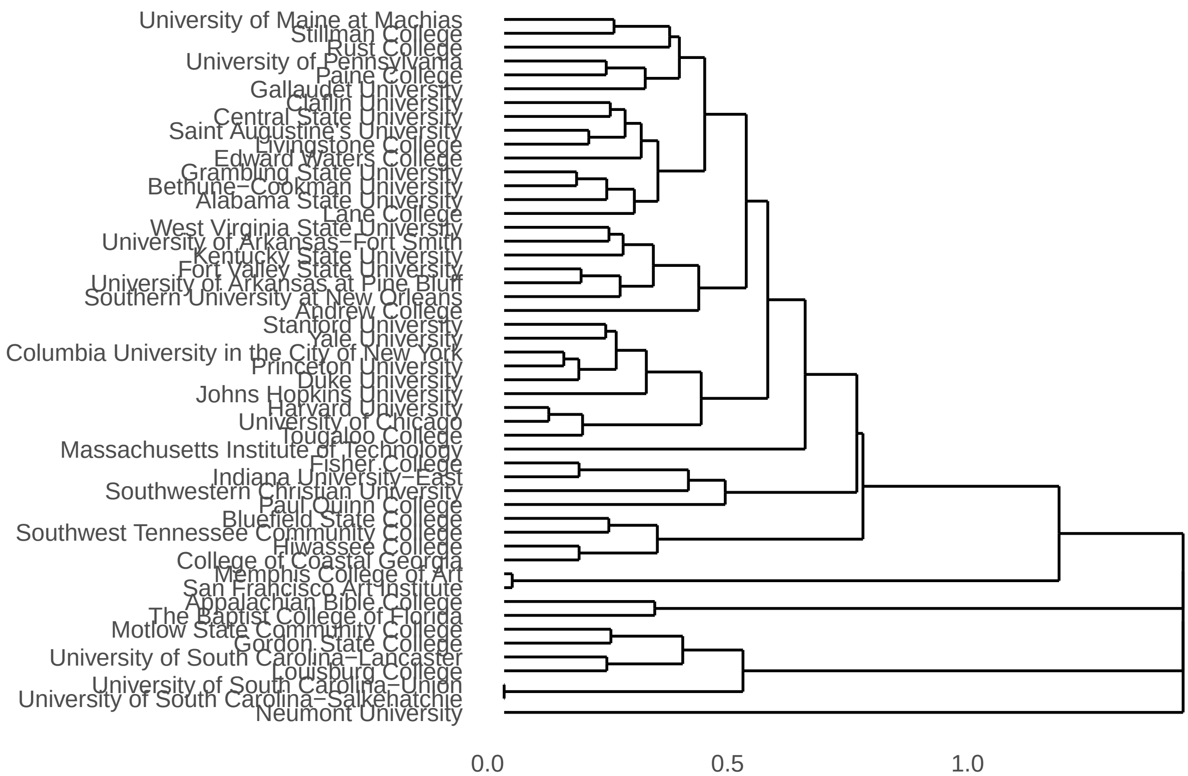
```
major_perc = heir_analysis_data %>%
  select(institution_name, top_ten, contains("_major_perc")) %>%
  na.omit()

### Calculate distances
euclidean = dist(select(major_perc, -institution_name, -top_ten), method = "euclidean")

### hierarchical clustering
hier = hclust(euclidean)

### Relabel the nodes to be institution names
hier$labels = major_perc$institution_name
```

```
### plot using ggdendro
library(ggdendro)
ggdendrogram(hier, rotate = TRUE, size = 2)
```

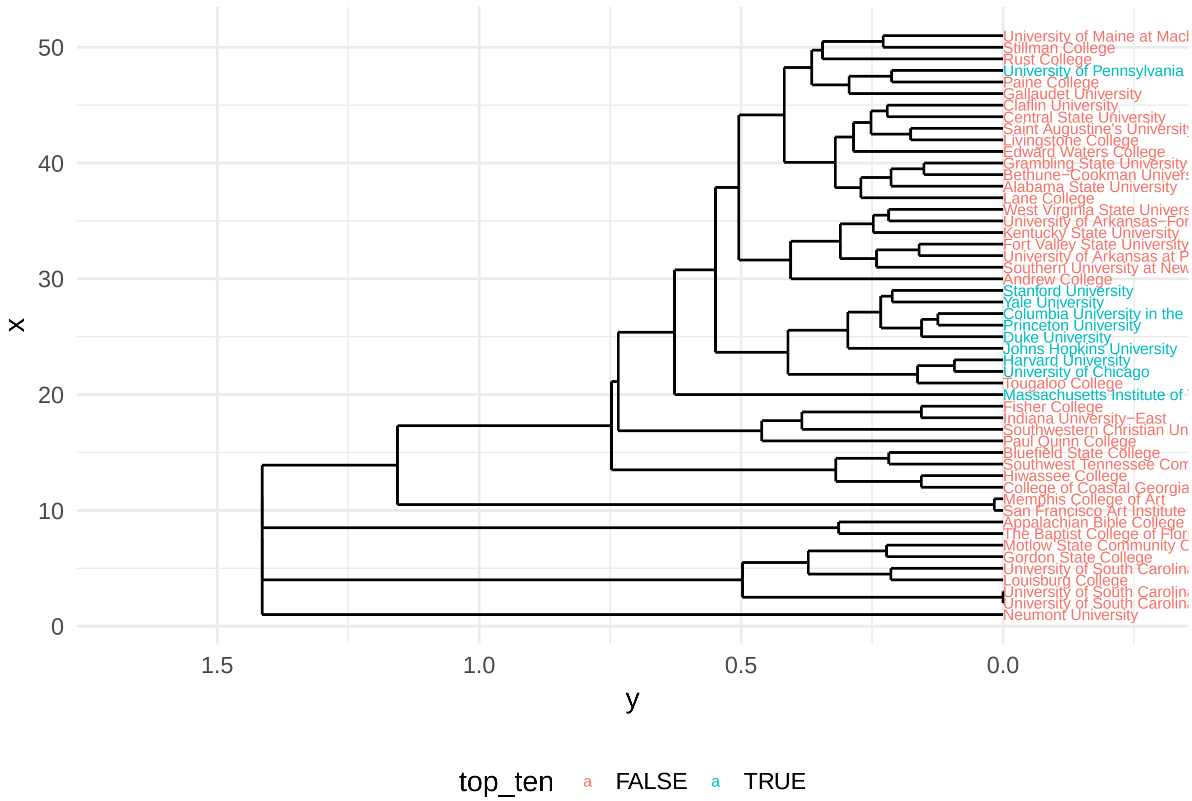



```
### plot using ggplot2

# necessary step for plotting with ggplot2
dendro_data = dendro_data(hier)

# merges on the top_ten variable for plotting
dendro_data$labels = dendro_data$labels %>%
  left_join(select(college_features, institution_name, top_ten),
        by = c("label" = "institution_name"))

ggplot(segment(dendro_data)) +
  geom_segment(aes(x = x, y = y, xend = xend, yend = yend)) +
  geom_text(data = label(dendro_data),
        aes(label = label, x = x, y = 0, hjust = 0, color = top_ten), size = 2) +
  coord_flip() +
  scale_y_reverse(expand = c(0.25, 0)) +
  theme_minimal() +
  theme(legend.position = "bottom")
```



C. How else can we compare the grantee schools to the top ten schools? Explore using any of the methods we learned in this class.

Open question for exploration.