Assignment 6 Walkthrough

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Outputting the Datasets

- It can be helpful to output the datasets so you can manually view them.

```
data("swiss") # Load the data frame into memory
write.csv(swiss, # <rite it out as-is to your working directory
          file = "swiss.csv",
          row.names = TRUE)   # keeps the canton names as the first column
```

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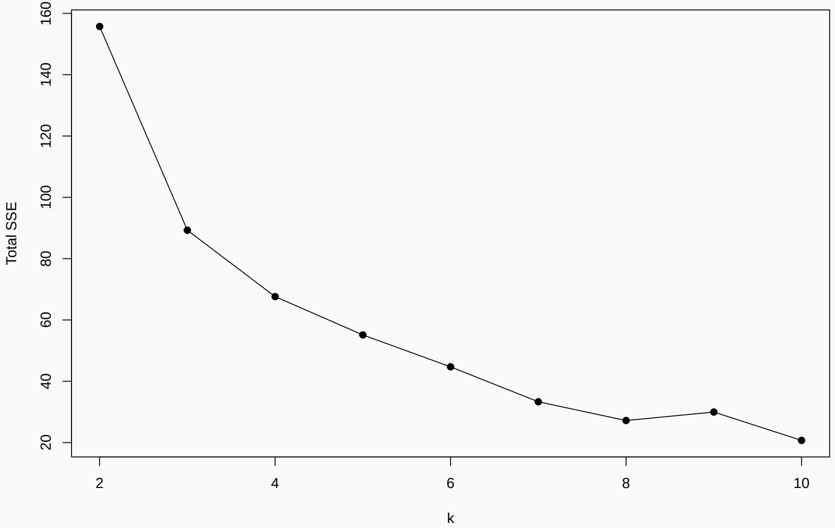
- With the pins moved, some dots now find a nearer pin, so they switch groups; pins then move again.
- These "reassign dots, move pins" steps repeat until no dot wants to switch—or switches only a tiny amount—leaving you with tight, coherent clusters and pins sitting at their centers.

K-Means Finding Best K Code

```r
library(tidyverse) # load data tools
df <- read.csv('State_Parks_Recreation.csv') # read csv
num <- df %>% select(-state) # keep numeric cols
scaled <- scale(num) # standardize values
set.seed(31) # make results repeatable
tot_sse <- c() # hold total SSE for each k
for(k in 2:10){ # test k from 2 to 10
  km <- kmeans(scaled, centers=k, nstart=25) # run k-means
  tot_sse[k] <- km$tot.withinss # save total SSE
}
plot(2:10, tot_sse[2:10], type='o', pch=19, # elbow plot
     xlab='k', ylab='Total SSE') # visualize WSS drop
```

```r
tot_tbl <- tibble(k=2:10, SSE=tot_sse[2:10]) # build table
tot_tbl <- tot_tbl %>% # add gains and fixed-base %
  mutate(gain=lag(SSE)-SSE) %>% # drop from k-1 to k
  mutate(base_gain=gain[which(!is.na(gain))[1]]) %>% # first gain
  mutate(gain_pct=round(100*gain/base_gain,2)) %>% # % of first gain
  select(-base_gain) # tidy up
knitr::kable(tot_tbl, caption='SSE, marginal gain, gain % of first') # show
```

K-Means Finding Best K Chart



K-Means Finding Best K Table

Table 1: SSE, marginal gain, gain % of first

k	SSE	gain	gain_pct
2	155.72898	NA	NA
3	89.26688	66.462100	100.00
4	67.62224	21.644645	32.57
5	55.12050	12.501741	18.81
6	44.71120	10.409299	15.66
7	33.31720	11.393999	17.14
8	27.19758	6.119623	9.21
9	29.96890	-2.771322	-4.17
10	20.71428	9.254613	13.92

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- From the table, we see that k=4 only benefited 32% of what k=3 benefited.
- We will likely choose k=3.
- If you had extra domain knowledge, or the app really need k=4, you could argue for k=4.

K-Means Cluster Code

```r
set.seed(31) # reproducible clustering
best_k <- 3
k3 <- kmeans(scaled, centers=best_k, nstart=25) # final model
df$cluster <- k3$cluster # add labels to original data
cent <- data.frame(k3$centers) # get scaled centroids
cent$cluster <- 1:nrow(cent) # tag centroid rows
print(cent) # view centroid profile
target <- cent %>% # find cluster with highest spend + air quality
  arrange(desc(outdoor_spending), desc(air_quality_index)) %>%
  slice(1) %>% pull(cluster) # extract cluster id
states_high <- df %>% # list states in that cluster
  filter(cluster == target) %>% pull(state) # pull state names
print(states_high) # show result
```

K-Means Cluster Results

```
[1] "New York"     "Florida"      "Washington"   "California"   "Pennsylvania"
[6] "Texas"
```

Interpretation of K-Means Cluster Results

- **Shared profile** – K-means grouped all 50 states into three clusters using every numeric column (park_count, park_acres, acres_per_park, outdoor_spending, air_quality_index). These six states landed in the same cluster, meaning their overall park-system and recreation metrics are more similar to each other than to the rest of the country.

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- **Not an absolute ranking** – A state outside this list might still outshine one of these on an individual metric. The list simply reflects which states are nearest the cluster center that scores best on both spending and air quality after scaling all features.
- **Actionable takeaway** – If you're studying funding strategies or environmental quality for state park systems, these six states form a peer group worth comparing, benchmarking, or investigating further.

K-Means Cluster Code (k=8)

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set.seed(31) # reproducible clustering
best_k <- 8
k3 <- kmeans(scaled, centers=best_k, nstart=25) # final model
df$cluster <- k3$cluster # add labels to original data
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[1] "Florida"    "California" "Texas"
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- **Lesson for class** – A lower SSE looks good numerically, but past the elbow you trade interpretability and stable peer groups for noise fitting; k = 3 still offers the clearest, policy-relevant clusters.