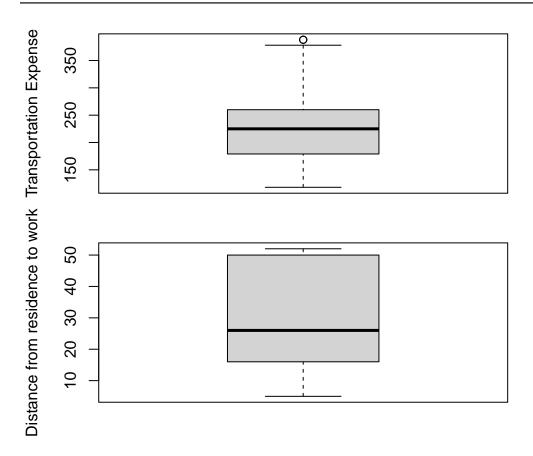
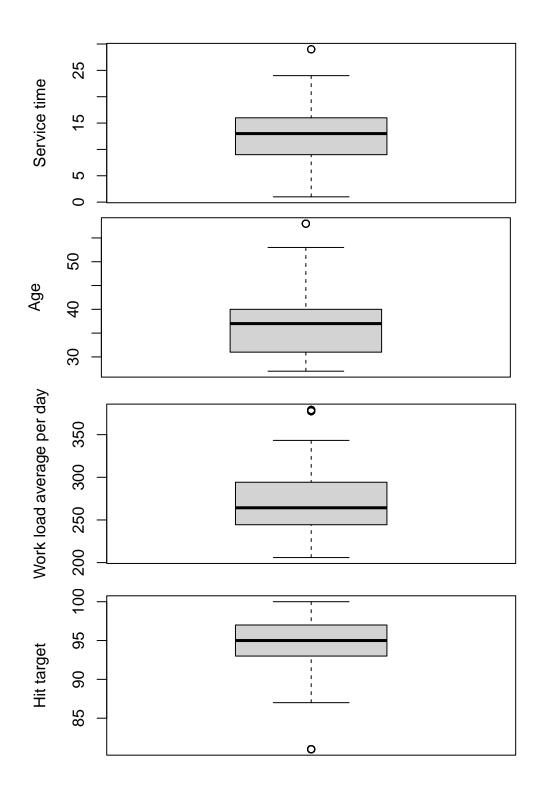
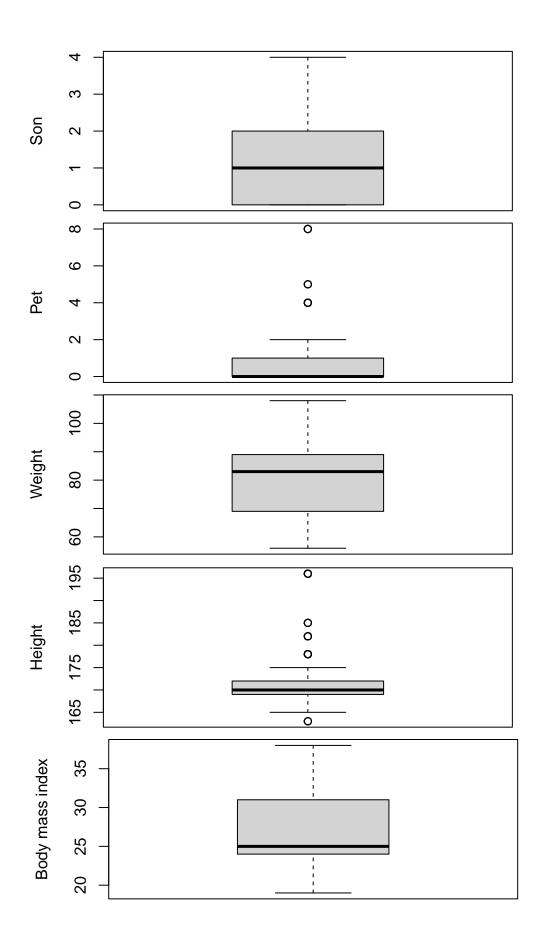
# STATS/CSE 780 Assignment 3

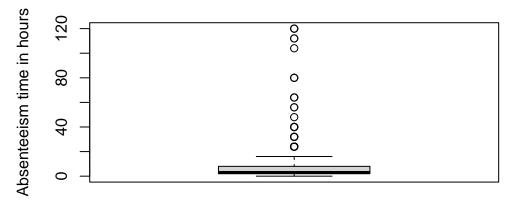
Pao Zhu Vivian Hsu (Student Number: 400547994) 2023-11-06

	data_type	min	max	nulls_blanks
Transportation.expense	integer	118.000	388.000	0
${\bf Distance. from. Residence. to. Work}$	integer	5.000	52.000	0
Service.time	integer	1.000	29.000	0
Age	integer	27.000	58.000	0
Work.load.Average.day	numeric	205.917	378.884	0
Hit.target	integer	81.000	100.000	0
Son	integer	0.000	4.000	0
Pet	integer	0.000	8.000	0
Weight	integer	56.000	108.000	0
Height	integer	163.000	196.000	0
Body.mass.index	integer	19.000	38.000	0
Absenteeism.time.in.hours	integer	0.000	120.000	0

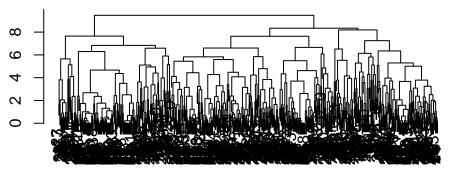




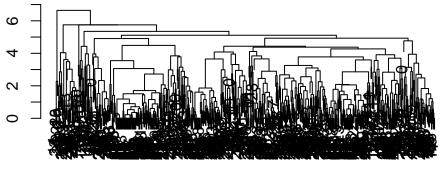




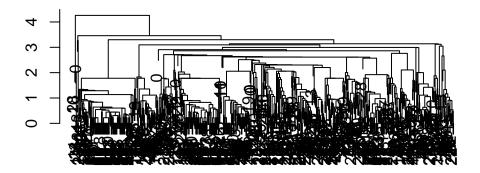
## **Complete Linkage**

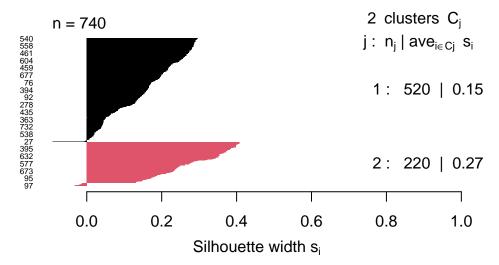


Average Linkage

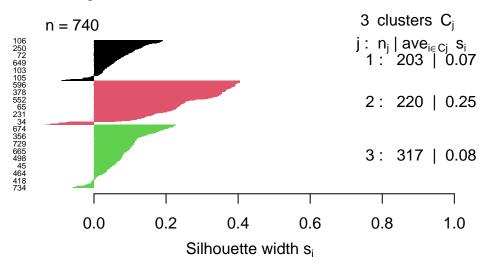


Single Linkage

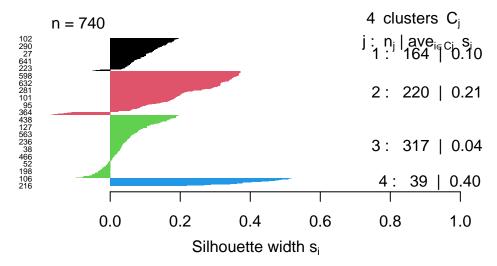




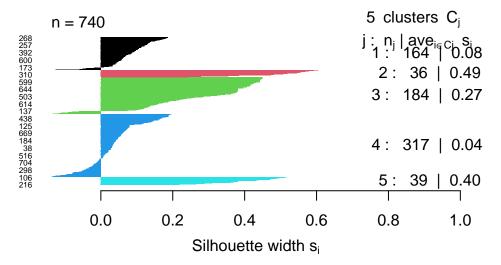
Average silhouette width: 0.19



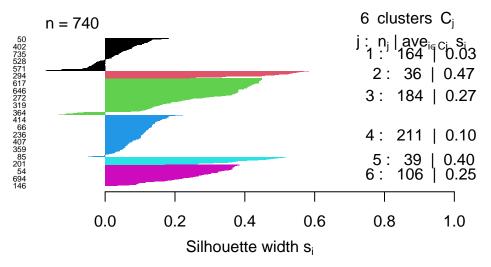
Average silhouette width: 0.13



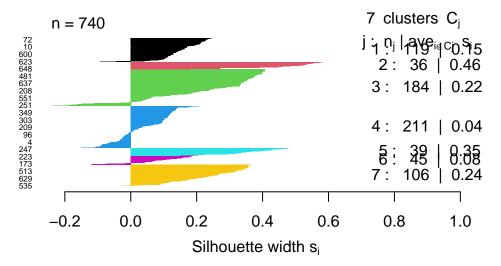
Average silhouette width: 0.12



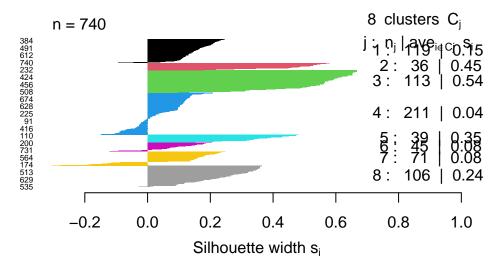
Average silhouette width: 0.15



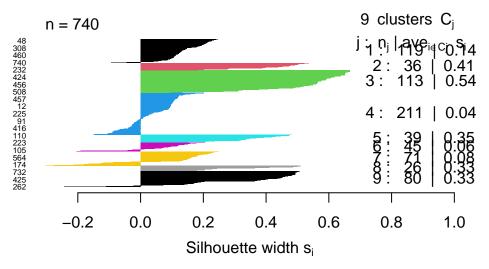
Average silhouette width: 0.18



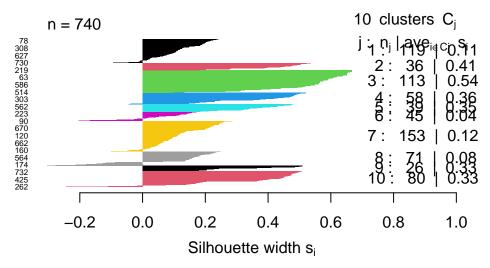
Average silhouette width: 0.17



Average silhouette width: 0.21

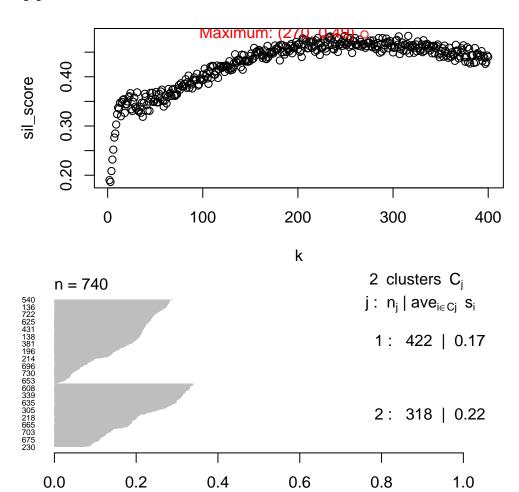


Average silhouette width: 0.21

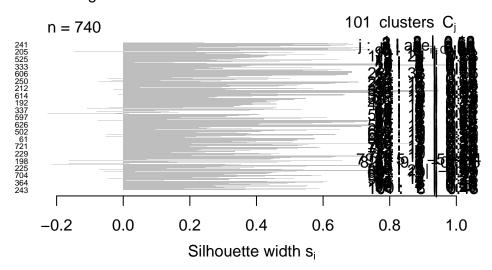


Average silhouette width: 0.25

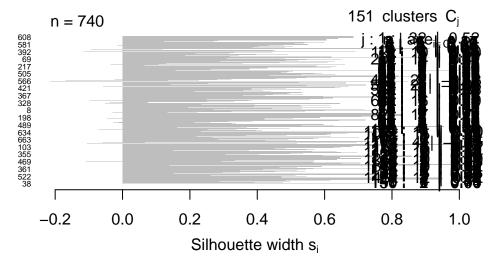
#### [1] 0.556248

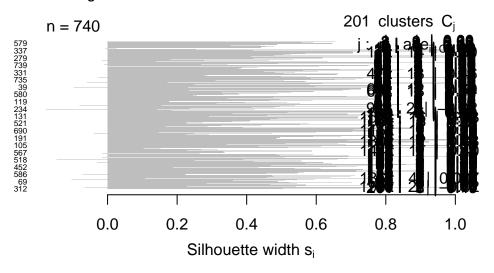


Average silhouette width: 0.19

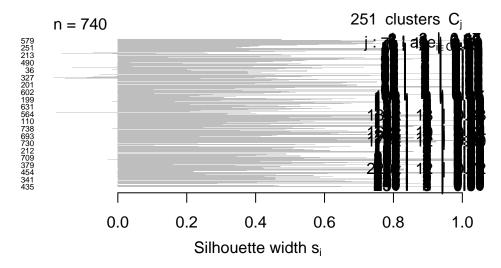


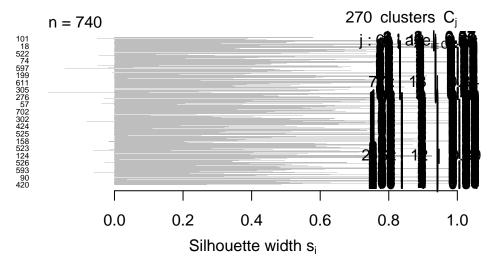
Silhouette width si

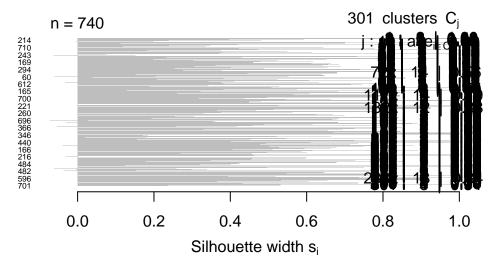




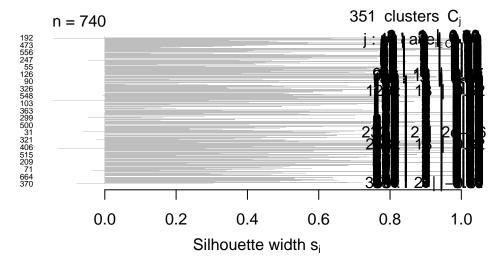
Average silhouette width: 0.47



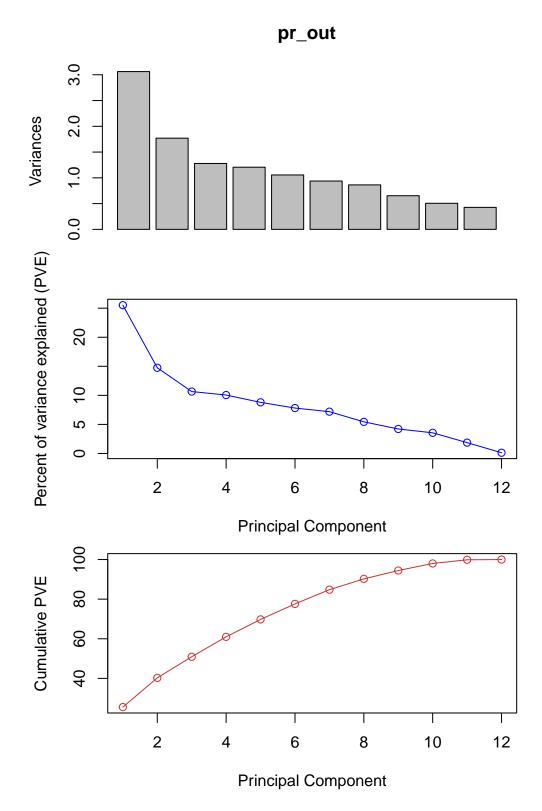


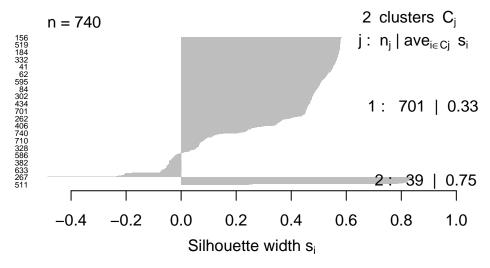


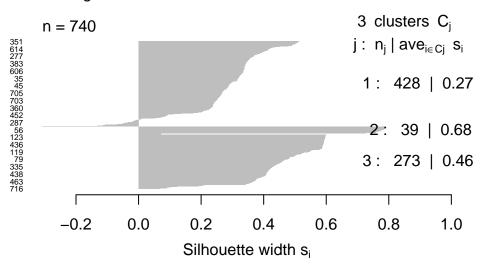
Average silhouette width: 0.46



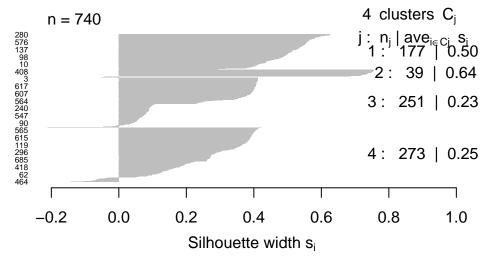
- [1] 0.9047654
- [1] 0.02523856

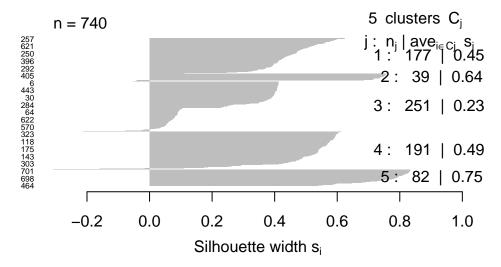


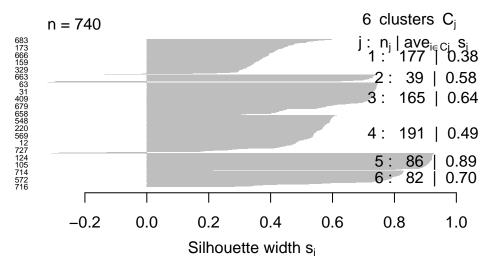




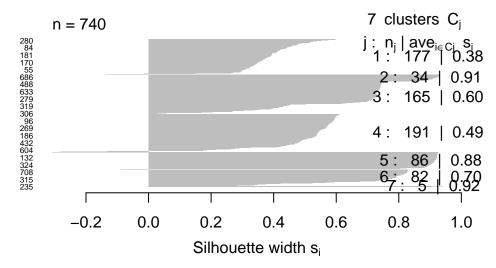
Average silhouette width: 0.36

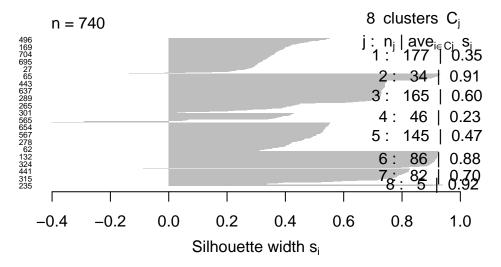




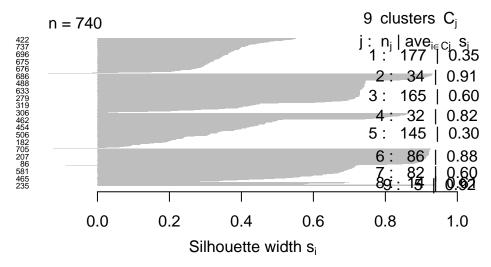


Average silhouette width: 0.57

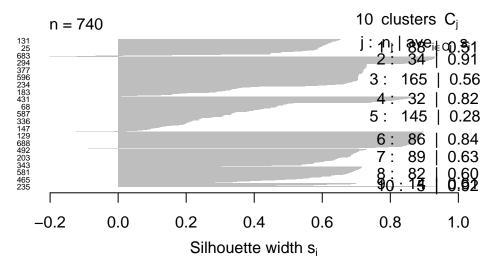




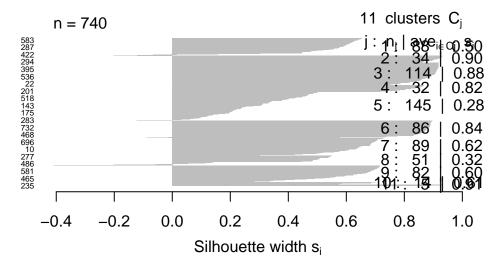
Average silhouette width: 0.55

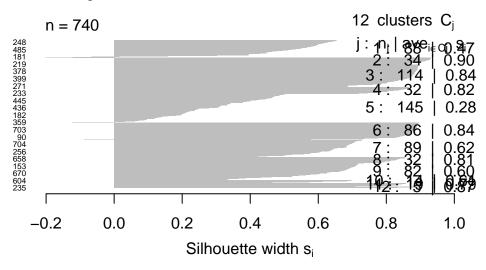


Average silhouette width: 0.54

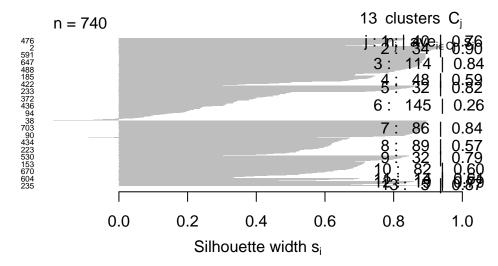


Average silhouette width: 0.58





Average silhouette width: 0.63



[1] 0.171699

Introduction

Methods

Discussion

#### Supplementary material

```
# ---- SETUP ---- #
# Load packages
packages <- c("knitr", "tidyverse", "ggplot2", "cluster", "fossil")</pre>
lapply(packages, library, character.only = TRUE)
# Read data, extract labels, and keep only quantitative data
absentData_raw <- read.csv("Absenteeism_at_work.csv", sep = ";")</pre>
absentData_lab <- absentData_raw$`Reason.for.absence`</pre>
absentData <- absentData_raw %>%
  select(-c("Reason.for.absence","ID","Month.of.absence","Day.of.the.week","Seasons",
            "Disciplinary.failure", "Education", "Social.drinker", "Social.smoker"))
# ---- DATA EXPLORATION ---- #
# Check data types, min, max, and missing data
data_type <- sapply(absentData,class)</pre>
min <- sapply(absentData, function(col){min(col,na.rm=TRUE)})</pre>
max <- sapply(absentData, function(col){max(col,na.rm=TRUE)})</pre>
nulls <- sapply(absentData, function(col){sum(is.na(col))})</pre>
blanks <- sapply(absentData,
                 function(col){ifelse(is.na(sum(col == "")), 0, sum(col == ""))})
data_summary <- data.frame(row.names = names(nulls), data_type=data_type,</pre>
                            min=min, max=max, nulls_blanks=nulls+blanks)
kable(data_summary)
# Create box plots to check for outliers
b01 <- boxplot(absentData$Transportation.expense, ylab = "Transportation Expense")
b02 <- boxplot(absentData$Distance.from.Residence.to.Work,
               ylab = "Distance from residence to work")
b03 <- boxplot(absentData$Service.time, ylab = "Service time")
b04 <- boxplot(absentData$Age, ylab = "Age")
b05 <- boxplot(absentData$Work.load.Average.day, ylab = "Work load average per day")
```

```
b06 <- boxplot(absentData$Hit.target, ylab = "Hit target")
b07 <- boxplot(absentData$Son, ylab = "Son")
b08 <- boxplot(absentData$Pet, ylab = "Pet")
b09 <- boxplot(absentData$Weight, ylab = "Weight")
b10 <- boxplot(absentData$Height, vlab = "Height")
b11 <- boxplot(absentData$Body.mass.index, ylab = "Body mass index")
b12 <- boxplot(absentData$Absenteeism.time.in.hours, ylab = "Absenteeism time in hours")
# ---- DATA CLEANSING ----
# Handle outliers by capping them using interquartile range
cap <- function(val, bplot) {</pre>
  lower_fence <- bplot$stats[2]-(1.5*(bplot$stats[4]-bplot$stats[2])) #Q1-1.5*IQR</pre>
 upper_fence <- bplot$stats[4]+(1.5*(bplot$stats[4]-bplot$stats[2])) #Q3+1.5*IQR
 val <- ifelse(val < lower_fence, lower_fence, val)</pre>
 val <- ifelse(val > upper_fence, upper_fence, val)
 val
}
absentData <- absentData %>%
 mutate(Transportation.expense = cap(val=Transportation.expense, bplot=b01),
         Service.time = cap(val=Service.time, bplot=b03),
         Age = cap(val=Age, bplot=b04),
         Work.load.Average.day = cap(val=Work.load.Average.day, bplot=b05),
         Hit.target = cap(val=Hit.target, bplot=b06),
         Pet = cap(val=Pet, bplot=b08),
         Height = cap(val=Height, bplot=b10),
         Absenteeism.time.in.hours = cap(val=Absenteeism.time.in.hours, bplot=b12))
# ---- AGGLOMERATIVE HIERARCHICAL CLUSTERING ---- #
# Compare linkage types
absentData_sd <- scale(absentData)</pre>
absentData_dist <- dist(absentData_sd)</pre>
```

```
plot(hclust(absentData_dist), xlab = "", sub = "", ylab = "",
     labels = absentData_lab, main = "Complete Linkage")
plot(hclust(absentData_dist, method = "average"),
     labels = absentData_lab, main = "Average Linkage",
     xlab = "", sub = "", ylab = "")
plot(hclust(absentData_dist, method = "single"),
     labels = absentData_lab, main = "Single Linkage",
     xlab = "", sub = "", ylab = "")
# Choose k using goodness-of-clustering
set.seed(780)
plotHeirSilK <- function(k){</pre>
  hc_out <- hclust(dist(absentData_sd))</pre>
  hc_clusters <- cutree(hc_out, k)</pre>
  sil <- silhouette(hc clusters, dist(absentData sd))</pre>
  plot(sil, nmax= 800, cex.names=0.5, main = "", col=1:k, border=NA)
}
plotHeirSilK(2)
plotHeirSilK(3)
plotHeirSilK(4)
plotHeirSilK(5)
plotHeirSilK(6)
plotHeirSilK(7)
plotHeirSilK(8)
plotHeirSilK(9)
plotHeirSilK(10)
# Perform hierarchical clustering using k=2
set.seed(780)
hc_out <- hclust(dist(absentData_sd))</pre>
adj.rand.index(cutree(hc_out, k = 2), as.numeric(as.factor(absentData_lab)))
```

```
# ---- K-MEANS CLUSTERING ---- #
# Functions to get silhouette and plot for a k value
set.seed(780)
silK <- function(k){</pre>
  x_k <- kmeans(absentData_sd, k, nstart = 20)</pre>
  silhouette(x_k$cluster, dist(absentData_sd))
plotSil <- function(sil){</pre>
  plot(sil, nmax= 800, cex.names=0.5, main = "", border=NA)
}
# Choose k using goodness-of-clustering
k < -c(2:400)
sil_k <- lapply(k, silK)</pre>
sil_score <- sapply(sil_k, function(x) {mean(x[,"sil_width"])})</pre>
sil_max <- max(sil_score)</pre>
sil_max_k <- match(sil_max, sil_score)+min(k)-1</pre>
plot(x=k, y=sil_score, col=ifelse(sil_score==sil_max, "red", "black"))
text(x=sil_max_k, y=sil_max, pos=2, col="red",
     labels= c(paste0("Maximum: (",sil_max_k,", ",round(sil_max,2), ")")))
# Plot some of the silhouettes
plotSil(sil_k[[1]])
plotSil(sil_k[[100]])
plotSil(sil_k[[150]])
plotSil(sil_k[[200]])
plotSil(sil_k[[250]])
plotSil(sil_k[[sil_max_k-1]])
plotSil(sil_k[[300]])
plotSil(sil_k[[350]])
```

```
# Perform k-means clustering with best k value
set.seed(780)
km_out <- kmeans(absentData, sil_max_k, nstart = 20)</pre>
km_clusters <- km_out$cluster</pre>
# Compare the k-means clusters with the given labels.
# Compute the rand index between the labels and k-means clustering.
rand.index(km_clusters, as.numeric(as.factor(absentData_lab)))
adj.rand.index(km_clusters, as.numeric(as.factor(absentData_lab)))
# ---- K-MEANS CLUSTERING AFTER PCA ---- #
# Principal component analysis (PCA)
pr_out <- prcomp(absentData, scale = TRUE)</pre>
# Proportion of variance explained
plot(pr_out)
pve <- 100 * pr_out$sdev^2 / sum(pr_out$sdev^2)</pre>
plot(pve, type = "o",
xlab = "Principal Component", col = "blue", ylab = "Percent of variance explained (PVE)")
plot(cumsum(pve), type = "o", ylab = "Cumulative PVE",
     xlab = "Principal Component", col = "brown3")
# Choose k using goodness-of-clustering
plotPCAHeirSilK <- function(k){</pre>
  hc out <- hclust(dist(dist(pr out$x[, 1:2])))</pre>
 hc_clusters <- cutree(hc_out, k)</pre>
  sil <- silhouette(hc_clusters, dist(pr_out$x[, 1:2]))</pre>
 plot(sil, nmax= 800, cex.names=0.5, main = "", border=NA)
}
```

```
plotPCAHeirSilK(2)
plotPCAHeirSilK(3)
plotPCAHeirSilK(4)
plotPCAHeirSilK(5)
plotPCAHeirSilK(6)
plotPCAHeirSilK(7)
plotPCAHeirSilK(8)
plotPCAHeirSilK(9)
plotPCAHeirSilK(10)
plotPCAHeirSilK(11)
plotPCAHeirSilK(12)
plotPCAHeirSilK(13)
hc_out <- hclust(dist(dist(pr_out$x[, 1:2])))
hc_clusters <- cutree(hc_out, 11)
adj.rand.index(hc_clusters, as.numeric(as.factor(absentData_lab)))</pre>
```

### References

R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/