

HOMEWORK4_Q4 – Sadiya Amreen

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

```
##
## Attaching package: "dplyr"
## The following objects are masked from "package:stats":
##
##   filter, lag
## The following objects are masked from "package:base":
##
##   intersect, setdiff, setequal, union
```

```
library(caret)
library(tidyverse)
```

```
##... Attaching packages.....tidyverse 1.3.2 ....
## v tibble 3.1.8      v purrr 0.3.4
## v tidyr 1.2.1      v stringr 1.4.1
## v readr 2.1.2      v forcats 0.5.2
##.....Conflicts.....tidyverse_conflicts() .....
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x purrr::lift()    masks caret::lift()
```

```
library(stats)
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
library(cluster)
```

4. Back to the Starwars data from a previous assignment! Remember that the variable that lists the actual names and the variables that are actually lists will be a problem, so remove them (name, films, vehicles, starships). Make sure to double check the types of the variables, i.e., that they are numerical or factors as you expect.

```
#Importing the starwars data into the playground.
head(starwars)
```

```
## # A tibble: 6 x 14
##   name      height  mass hair_~1 skin_~2 eye_c~3 birth~4 sex  gender homew~5
##   <chr>      <int> <dbl> <chr>   <chr>   <chr>   <dbl> <chr> <chr>   <chr>
```

```
## 1 Luke Skywalker      172    77 blond    fair    blue      19    male    mascu~ Tatooi~
## 2 C-3PO                167    75 <NA>    gold    yellow   112    none    mascu~ Tatooi~
## 3 R2-D2                 96    32 <NA>    white,~ red      33    none    mascu~ Naboo~
## 4 Darth Vader          202   136 None     white    yellow   41.9   male    mascu~ Tatooi~
## 5 Leia Organa          150    49 brown    light    brown     19    fema~  femin~ Aldera~
## 6 Owen Lars            178   120 brown,~ light    blue     52    male    mascu~ Tatooi~
## # ... with 4 more variables: species <chr>, films <list>, vehicles <list>,
## #   starships <list>, and abbreviated variable names 1: hair_color,
## #   2: skin_color, 3: eye_color, 4: birth_year, 5: homeworld
```

```
starwars <- na.omit(starwars)
data_star <- starwars
data_star <- data_star[, -c(1, 12, 13, 14)] #removing the names, height
str(data_star)
```

```
## tibble [29 x 10] (S3: tbl_df/tbl/data.frame)
## $ height      : int [1:29] 172 202 150 178 165 183 182 188 228 180 ...
## $ mass        : num [1:29] 77 136 49 120 75 84 77 84 112 80 ...
## $ hair_color: chr [1:29] "blond" "none" "brown" "brown, grey" ...
## $ skin_color: chr [1:29] "fair" "white" "light" "light" ...
## $ eye_color  : chr [1:29] "blue" "yellow" "brown" "blue" ...
## $ birth_year: num [1:29] 19 41.9 19 52 47 24 57 41.9 200 29 ...
## $ sex        : chr [1:29] "male" "male" "female" "male" ...
## $ gender     : chr [1:29] "masculine" "masculine" "feminine" "masculine" ...
## $ homeworld  : chr [1:29] "Tatooine" "Tatooine" "Alderaan" "Tatooine" ...
## $ species    : chr [1:29] "Human" "Human" "Human" "Human" ...
## - attr(*, "na.action")= "omit" Named int [1:58] 2 3 8 12 15 16 18 19 22 27 ...
## ..- attr(*, "names")= chr [1:58] "2" "3" "8" "12" ...
```

#creating dummies for the data processing of the data.

```
dummydata <- dummyVars(gender ~ ., data=data_star)
dummies_data <- as.data.frame(predict(dummydata, newdata = data_star))
dum_dat_g <- dummies_data
dum_dat_g$gender <- starwars$gender
str(dum_dat_g)
```

```
## "data.frame":    29 obs. of  67 variables:
## $ height      : num  172 202 150 178 165 183 182 188 228 180 ...
## $ mass        : num  77 136 49 120 75 84 77 84 112 80 ...
## $ hair_colorauburn, white: Num  0 0 0 0 0 0 1 0 0 0 ...
## $ hair_colorblack      : Num  0 0 0 0 0 1 0 0 0 0 ...
## $ hair_colorblond      : Num  1 0 0 0 0 0 0 1 0 0 ...
## $ hair_colorbrown      : Num  0 0 1 0 1 0 0 0 1 1 ...
## $ hair_colorbrown, grey : Num  0 0 0 1 0 0 0 0 0 0 ...
## $ hair_colorgrey       : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ hair_colornone       : Num  0 1 0 0 0 0 0 0 0 0 ...
## $ hair_colorwhite      : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorblue       : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorbrown      : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorbrown mottle : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colordark       : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorfair       : Num  1 0 0 0 0 0 1 1 0 1 ...
## $ skin_colorgreen      : Num  0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorlight      : Num  0 0 1 1 1 1 0 0 0 0 ...
## $ skin_colororange     : Num  0 0 0 0 0 0 0 0 0 0 ...
```

```

## $ skin_colorpale      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorred       : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colortan       : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ skin_colorunknown   : Num 0 0 0 0 0 0 0 0 1 0 ...
## $ skin_colorwhite     : Num 0 1 0 0 0 0 0 0 0 0 ...
## $ skin_coloryellow    : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ eye_colorblack      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ eye_colorblue       : Num 1 0 0 1 1 0 0 1 1 0 ...
## $ eye_colorblue-gray  : Num 0 0 0 0 0 0 1 0 0 0 ...
## $ eye_colorbrown      : Num 0 0 1 0 0 1 0 0 0 1 ...
## $ eye_colorhazel      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ eye_colororange     : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ eye_colorred        : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ eye_coloryellow     : Num 0 1 0 0 0 0 0 0 0 0 ...
## $ birth_year          : num 19 41.9 19 52 47 24 57 41.9 200 29 ...
## $ sexfemale           : Num 0 0 1 0 1 0 0 0 0 0 ...
## $ sexmale             : Num 1 1 0 1 0 1 1 1 1 1 ...
## $ homeworldAlderaan   : Num 0 0 1 0 0 0 0 0 0 0 ...
## $ homeworldBespin     : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldCerea      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldConcord Dawn : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldCorellia   : Num 0 0 0 0 0 0 0 0 0 1 ...
## $ homeworldDathomir   : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldDorin      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldEndor      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldHaruun Kal : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldKamino     : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldKashyyyk   : Num 0 0 0 0 0 0 0 0 1 0 ...
## $ homeworldMirial     : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldMon Cala   : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldNaboo      : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldRyloth     : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldSerenno    : Num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldSocorro    : num 0 0 0 0 0 0 0 0 0 0 ...
## $ homeworldStewjon    : num 0 0 0 0 0 0 1 0 0 0 ...
## $ homeworldTatooine   : num 1 1 0 1 1 1 0 1 0 0 ...
## $ homeworldTrandosha  : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesCerean       : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesEwok         : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesGungan       : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesHuman        : num 1 1 1 1 1 1 1 1 0 1 ...
## $ speciesKel Dor      : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesMirialan     : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesMon Calamari : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesTrandoshan   : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesTwilek       : num 0 0 0 0 0 0 0 0 0 0 ...
## $ speciesWookiee      : num 0 0 0 0 0 0 0 0 1 0 ...
## $ speciesZabrak       : num 0 0 0 0 0 0 0 0 0 0 ...
## $ gender              : chr "masculine" "masculine" "feminine" "masculine" ...
dum_dat_g <- na.omit(dum_dat_g)
dist_mat <- daisy(dummies_data, metric = "gower")#Using the daisy from cluster to find the dist_mat.

## Warning in daisy(dummies_data, metric = "gower"): binary variable(s) 3, 4, 5, 6,
## 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27,

```

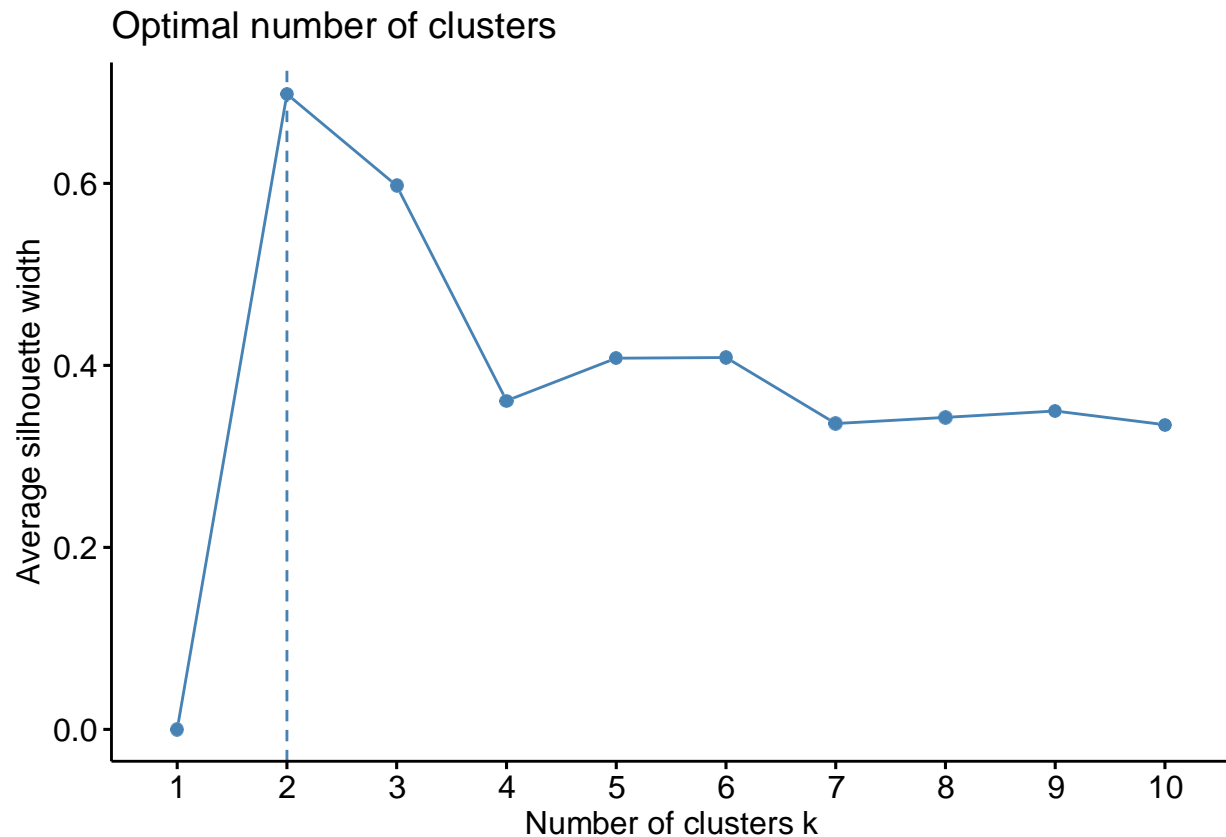
```
## 28, 29, 30, 31, 32, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48,  
## 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66 treated  
## as interval scaled
```

4.A. Use hierarchical agglomeration clustering to cluster the Star wars data. This time we can leave the categorical variables in place, because we will use the gower metric from daisy in the cluster library to get the distances. Use average linkage. Determine the best number of clusters.

Now we have to perform the preprocess and predict for the k-means plotting by using the silhouette.

```
preproc <- preProcess(data_star, method=c("center", "scale"))  
predictors <- predict(preproc, data_star)  
fviz_nbclust(data_star, FUN = hcut, method = "silhouette")
```

```
## Warning in stats::dist(x): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion  
## Warning in stats::dist(x, method = method, ...): NAs introduced by coercion
```



To find the best number of clusters

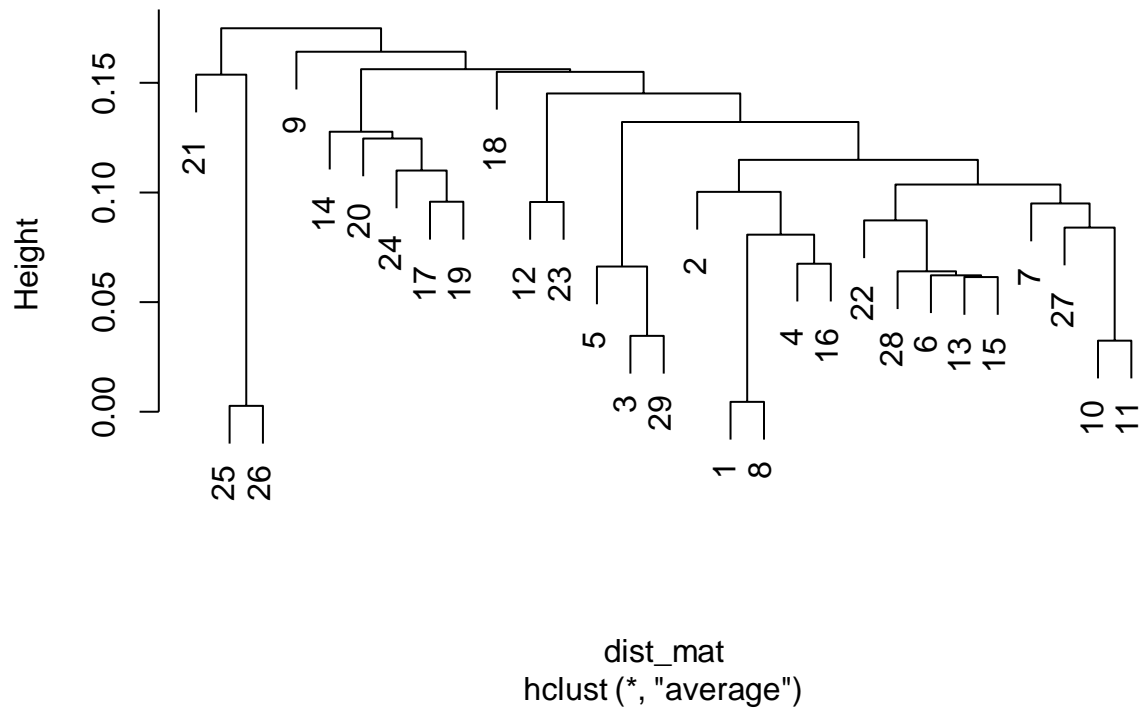
```
best_number_cluster <- hclust(dist_mat, method = "average")
cluster_star <- cutree(best_number_cluster, k=2)
summary(cluster_star)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  1.000   1.000   1.000   1.103   1.000   2.000
```

4.B. Produce the dendrogram for (a). How might an anomaly show up in a dendrogram? Do you see a Starwars character who does not seem to fit in easily? What is the advantage of considering anomalies this way as opposed to looking for unusual values relative to the mean and standard deviations, as we considered earlier in the course? Disadvantages?

```
dendrogram <- hclust(dist_mat, method = "average")
plot(dendrogram)
```

Cluster Dendrogram



The anomalies can be easily found by the dendrogram by the height of the nodes, however we can only predict the anomalies by the looks of the dendrogram but they can have similar characteristics so we have to be careful with the similarities too.

4.C. Use dummy variables to make this data fully numeric and then use k-means to cluster. Choose the best number of clusters.

```
head(dum_dat_g)
```

```
## height mass hair_colorauburn, white hair_colorblack hair_colorblond
## 1 172 77 0 0 1
## 2 202 136 0 0 0
## 3 150 49 0 0 0
## 4 178 120 0 0 0
## 5 165 75 0 0 0
## 6 183 84 0 1 0
## hair_colorbrown hair_colorbrown, grey hair_colorgrey hair_colornone
## 1 0 0 0 0
## 2 0 0 0 1
## 3 1 0 0 0
## 4 0 1 0 0
## 5 1 0 0 0
## 6 0 0 0 0
## hair_colorwhite skin_colorblue skin_colorbrown skin_colorbrown mottle
## 1 0 0 0 0
## 2 0 0 0 0
## 3 0 0 0 0
## 4 0 0 0 0
## 5 0 0 0 0
```

## 6	0	0	0	0	0
##	skin_color	dark	skin_color	fair	skin_color
## 1	0	1	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	1	0
## 4	0	0	0	1	0
## 5	0	0	0	1	0
## 6	0	0	0	1	0
##	skin_color	orange	skin_color	pale	skin_color
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	skin_color	white	skin_color	yellow	eye_color
## 1	0	0	0	1	0
## 2	1	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	1	0
## 5	0	0	0	1	0
## 6	0	0	0	0	0
##	eye_color	blue-gray	eye_color	brown	eye_color
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	1	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	1	0	0	0
##	eye_color	yellow	birth_year	sexfemale	sexmale
## 1	0	19.0	0	1	0
## 2	1	41.9	0	1	0
## 3	0	19.0	1	0	1
## 4	0	52.0	0	1	0
## 5	0	47.0	1	0	0
## 6	0	24.0	0	1	0
##	homeworld	Bespin	homeworld	Cerea	homeworld
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	homeworld	Dathomir	homeworld	Dorin	homeworld
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	homeworld	Kamino	homeworld	Kashyyyk	homeworld
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0

```

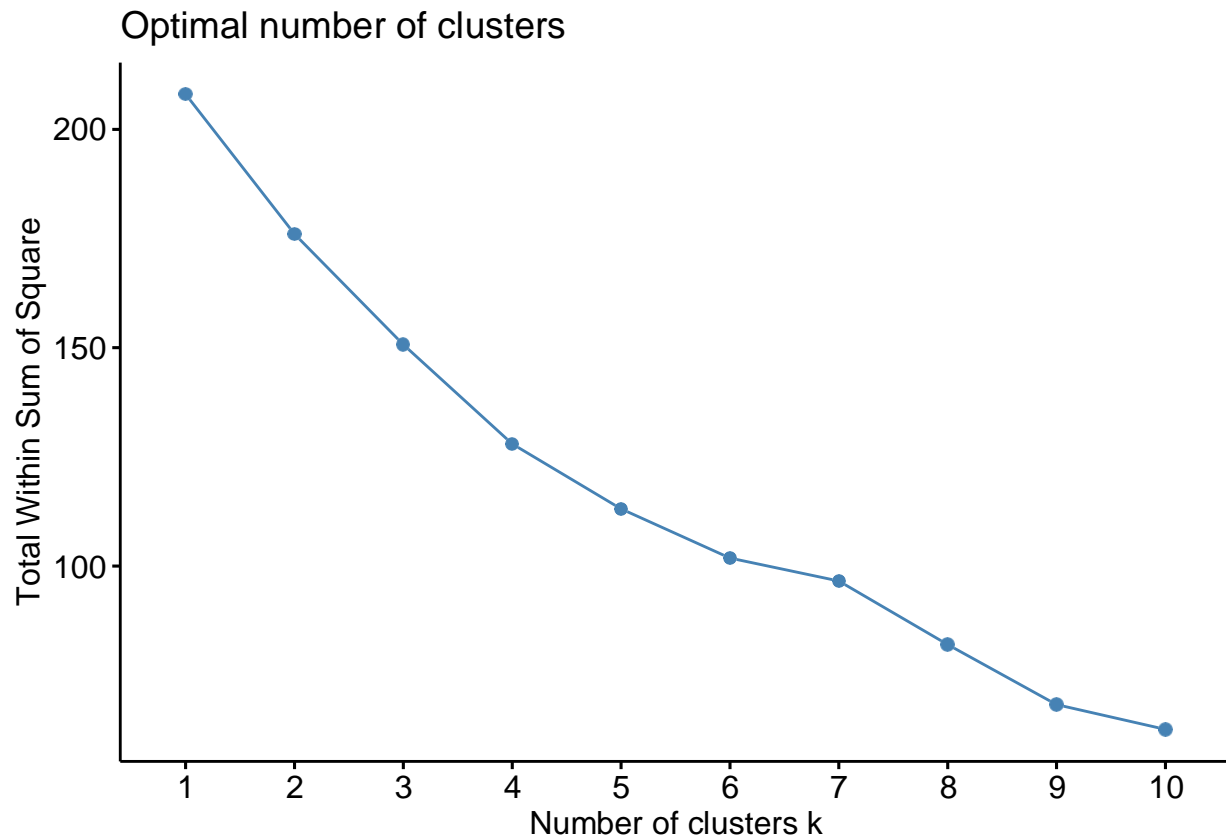
## 4      0      0      0      0
## 5      0      0      0      0
## 6      0      0      0      0
## homeworldNaboo homeworldRyloth homeworldSerenno homeworldSocorro
## 1      0      0      0      0
## 2      0      0      0      0
## 3      0      0      0      0
## 4      0      0      0      0
## 5      0      0      0      0
## 6      0      0      0      0
## homeworldStewjon homeworldTatooine homeworldTrandoshia speciesCerean
## 1      0      1      0      0
## 2      0      1      0      0
## 3      0      0      0      0
## 4      0      1      0      0
## 5      0      1      0      0
## 6      0      1      0      0
## speciesEwok speciesGungan speciesHuman speciesKel Dor speciesMirialan
## 1      0      0      1      0      0
## 2      0      0      1      0      0
## 3      0      0      1      0      0
## 4      0      0      1      0      0
## 5      0      0      1      0      0
## 6      0      0      1      0      0
## speciesMon Calamari speciesTrandoshan speciesTwilek speciesWookiee
## 1      0      0      0      0
## 2      0      0      0      0
## 3      0      0      0      0
## 4      0      0      0      0
## 5      0      0      0      0
## 6      0      0      0      0
## speciesZabrak gender
## 1      0 masculine
## 2      0 masculine
## 3      0 feminine
## 4      0 masculine
## 5      0 feminine
## 6      0 masculine

```

```

predictors <- dummies_data
set.seed(125)
prproc <- preProcess(predictors, method=c("center", "scale"))
predictors <- predict(prproc, predictors)
fviz_nbclust(predictors, kmeans, method = "wss")

```

Fit of the Kmeans is 4.

```
w_fit_d <- kmeans(predictors, centers = 4, nstart = 25) #fit the data
w_fit_d
```

```
## K-means clustering with 4 clusters of sizes 1, 1, 21, 6
##
## Cluster means:
##      height      mass hair_colorauburn, white hair_colorblack hair_colorblond
## 1  2.2232870  1.4826220      0.00000000      0.00000000      0.00000000
## 2 -3.9976263 -2.5025035      0.00000000      0.00000000      0.00000000
## 3  0.2406354  0.3299884      0.04761905      0.1904762      0.0952381
## 4 -0.5465006 -0.9849792      0.00000000      0.3333333      0.0000000
##  hair_colorbrown hair_colorbrown, grey hair_colorgrey hair_colornone
## 1      1.0000000      0.00000000      0.00000000      0.0000000
## 2      1.0000000      0.00000000      0.00000000      0.0000000
## 3      0.0952381      0.04761905      0.04761905      0.3809524
## 4      0.5000000      0.00000000      0.00000000      0.1666667
##  hair_colorwhite skin_colorblue skin_colorbrown skin_colorbrown mottle
## 1      0.0000000      0.0000000      0      0.00000000
## 2      0.0000000      0.0000000      1      0.00000000
## 3      0.0952381      0.0000000      0      0.04761905
## 4      0.0000000      0.1666667      0      0.00000000
##  skin_colordark skin_colorfair skin_colorgreen skin_colorlight
## 1      0.0000000      0.0000000      0.00000000      0.0000000
## 2      0.0000000      0.0000000      0.00000000      0.0000000
## 3      0.0952381      0.3333333      0.04761905      0.1428571
## 4      0.0000000      0.0000000      0.00000000      0.5000000
```

##	skin_colororange	skin_colorpale	skin_colorred	skin_colortan	skin_colorunknown
## 1	0.0000000	0.0000000	0.00000000	0.00000000	1
## 2	0.0000000	0.0000000	0.00000000	0.00000000	0
## 3	0.0952381	0.0952381	0.04761905	0.04761905	0
## 4	0.0000000	0.0000000	0.00000000	0.00000000	0
##	skin_colorwhite	skin_coloryellow	eye_colorblack	eye_colorblue	
## 1	0.00000000	0.0000000	0.00000000	1.0000000	
## 2	0.00000000	0.0000000	0.00000000	0.0000000	
## 3	0.04761905	0.0000000	0.04761905	0.1904762	
## 4	0.00000000	0.3333333	0.00000000	0.5000000	
##	eye_colorblue-gray	eye_colorbrown	eye_colorhazel	eye_colororange	eye_colorred
## 1	0.00000000	0.0000000	0.00000000	0.0000000	0.00000000
## 2	0.00000000	1.0000000	0.00000000	0.0000000	0.00000000
## 3	0.04761905	0.3333333	0.04761905	0.0952381	0.04761905
## 4	0.00000000	0.3333333	0.16666667	0.0000000	0.00000000
##	eye_coloryellow	birth_year	sexfemale	sexmale	homeworldAlderaan
## 1	0.0000000	4.12053386	0	1	0.0000000
## 2	0.0000000	-1.19936609	0	1	0.0000000
## 3	0.1904762	-0.07350532	0	1	0.0000000
## 4	0.0000000	-0.22959266	1	0	0.1666667
##	homeworldBespin	homeworldCerea	homeworldConcord Dawn	homeworldCorellia	
## 1	0.00000000	0.00000000	0.00000000	0.0000000	
## 2	0.00000000	0.00000000	0.00000000	0.0000000	
## 3	0.04761905	0.04761905	0.04761905	0.0952381	
## 4	0.00000000	0.00000000	0.00000000	0.0000000	
##	homeworldDathomir	homeworldDorin	homeworldEndor	homeworldHaruun Kal	
## 1	0.00000000	0.00000000	0	0.00000000	
## 2	0.00000000	0.00000000	1	0.00000000	
## 3	0.04761905	0.04761905	0	0.04761905	
## 4	0.00000000	0.00000000	0	0.00000000	
##	homeworldKamino	homeworldKashyyyk	homeworldMirial	homeworldMon Cala	
## 1	0.00000000	1	0.0000000	0.00000000	
## 2	0.00000000	0	0.0000000	0.00000000	
## 3	0.04761905	0	0.0000000	0.04761905	
## 4	0.00000000	0	0.3333333	0.00000000	
##	homeworldNaboo	homeworldRyloth	homeworldSerenno	homeworldSocorro	
## 1	0.0000000	0.0000000	0.00000000	0.00000000	
## 2	0.0000000	0.0000000	0.00000000	0.00000000	
## 3	0.0952381	0.0000000	0.04761905	0.04761905	
## 4	0.1666667	0.1666667	0.00000000	0.00000000	
##	homeworldStewjon	homeworldTatooine	homeworldTrandosha	speciesCerean	
## 1	0.00000000	0.0000000	0.00000000	0.00000000	
## 2	0.00000000	0.0000000	0.00000000	0.00000000	
## 3	0.04761905	0.2380952	0.04761905	0.04761905	
## 4	0.00000000	0.1666667	0.00000000	0.00000000	
##	speciesEwok	speciesGungan	speciesHuman	speciesKel Dor	speciesMirialan
## 1	0	0.00000000	0.0000000	0.00000000	0.0000000
## 2	1	0.00000000	0.0000000	0.00000000	0.0000000
## 3	0	0.04761905	0.7142857	0.04761905	0.0000000
## 4	0	0.00000000	0.5000000	0.00000000	0.3333333
##	speciesMon Calamari	speciesTrandoshan	speciesTwi'lek	speciesWookiee	
## 1	0.00000000	0.00000000	0.0000000	1	
## 2	0.00000000	0.00000000	0.0000000	0	
## 3	0.04761905	0.04761905	0.0000000	0	

```
## 4      0.00000000      0.00000000      0.1666667      0
## speciesZabrak
## 1      0.00000000
## 2      0.00000000
## 3      0.04761905
## 4      0.00000000
##
## Clustering vector:
## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
## 3 3 4 3 4 3 3 3 1 3 3 3 3 3 3 3 3 2 3 3 4 3 3 3 4 4
## 27 28 29
## 3 3 4
##
## Within cluster sum of squares by cluster:
## [1] 0.0000 0.0000 101.6367 21.8729
## (between_SS / total_SS = 40.6 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"      "withinss"    "tot.withinss"
## [6] "betweenss"    "size"        "iter"      "ifault"
```

4.D. Compare the HAC and k-means clusterings with a crosstabulation.

#Creating new fit for the Kmenas by using the dummies data.

```
set.seed(123)
preproc <- preProcess(dummies_data, method=c("center", "scale"))
predictors <- predict(preproc, dummies_data)
dist_mat_4 <- dist(predictors, method = "euclidean")
hfit_4 <- hclust(dist_mat_4, method = "average")
h1 <- cutree(hfit_4, k=2)
fit <- kmeans(dummies_data, centers = 4, nstart = 25)
summary(cluster_star)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.000   1.000   1.000   1.103   1.000   2.000

results <- data.frame(Gender = dum_dat_g$gender, HAC_Star_Wars = h1, Kmeans = fit$cluster)
best_number_cluster

##
## Call:
## hclust(d = dist_mat, method = "average")
##
## Cluster method      : average
## Number of objects: 29

results %>% group_by(HAC_Star_Wars) %>% select(HAC_Star_Wars, Gender) %>% table()

##
##      Gender
## HAC_Star_Wars feminine masculine
##      1         6         22
##      2         0         1

results %>% group_by(Kmeans) %>% select(Kmeans, Gender) %>% table()

##      Gender
```

```
## Kmeans  feminine masculine
##      1         6         13
##      2         0          1
##      3         0          1
##      4         0          8
```