Pattern Recognition and Data Mining HW4

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Solution 4(a)

```
transactions <- read.transactions(file = "ratingsAsBasket.txt")
summary(transactions)
```

```
transactions as itemMatrix in sparse format with
 10000 rows (elements/itemsets/transactions) and
 15500 columns (items) and a density of 0.009911529

most frequent items:
M.4712.R.High M.3749.R.High M.5407.R.High M.4275.R.High  M.538.R.High       (Other)
         4729          4610          4162          4152          4010       1514624

element (itemset/transaction) length distribution:
sizes
  20   21   22   23   24   25   26   27   28   29   30   31   32   33   34   35   36   37   38   39   40
  64  110   77   71   81   71   77  100   96   85  108  112   99  100  110   93   83   84   95  115   80  1
  43   44   45   46   47   48   49   50   51   52   53   54   55   56   57   58   59   60   61   62   63
  .
  .
  .
  .


   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   20.0    47.0    92.0   153.6   183.0  2289.0

includes extended item information - examples:
         labels
1  M.1000.R.High
2  M.1000.R.Low
3  M.1000.R.Med
```

- The Number of baskets in the dataset is 10000

-From the Summary above the most frequent item rated high in the datasets is is the Movie 'The Matrix' with a freqency of 4729 in the movie ratings basket. The Second most frequent movie in the basket is "Pulp Fiction" occuring 4610 times in the basket. Third highest rated movie in the basket is "Saving Private Ryan" with a frequency of 4162. "The Silence of the Lambs" comes fourth with a frequency of 4152 which is then followed by "True Lies" with an occurance of 4010 in the dataset.

From the Summary, the number of movies rated by a rater is as follows,
The Minimum number of movies rated by one rater is 20.
The Maximum number of movies rated by one rater is 2289.
The Average number of movies rated by one rater is 153.6

Solution 4(b)

```r
transactions.apriori <- apriori(transactions)
inspect(transactions.apriori[1:10])
```

```
> inspect(transactions.apriori[1:10])

   lhs                 rhs              support confidence     lift
1  {M.3816.R.High} => {M.3749.R.High}  0.1230  0.8698727 1.886926
2  {M.4033.R.High} => {M.4275.R.High}  0.1235  0.8178808 1.969848
3  {M.2175.R.High} => {M.2526.R.High}  0.1405  0.8126084 2.207575
4  {M.2181.R.High,
    M.2434.R.High} => {M.3749.R.High}  0.1017  0.8168675 1.771947
5  {M.2181.R.High,
    M.4275.R.High} => {M.3749.R.High}  0.1119  0.8021505 1.740023
6  {M.1740.R.High,
    M.2526.R.High} => {M.1870.R.High}  0.1026  0.8009368 2.042164
7  {M.2175.R.High,
    M.2936.R.High} => {M.2526.R.High}  0.1011  0.8700516 2.363628
8  {M.2175.R.High,
    M.2749.R.High} => {M.2526.R.High}  0.1106  0.8475096 2.302390
9  {M.1870.R.High,
    M.2175.R.High} => {M.2749.R.High}  0.1031  0.8029595 2.526619
10 {M.2175.R.High,
    M.2250.R.High} => {M.2526.R.High}  0.1057  0.8649755 2.349838
```

Let us consider the 1st association rule which is given by R as,

```
   lhs                 rhs              support confidence     lift
1  {M.3816.R.High} => {M.3749.R.High}  0.1230  0.8698727 1.886926
```

The association rule says that the movie raters who had “Reservoir Dogs” in their basket have a greater chance of having the movie “Pulp Fiction” in the same basket. Support is the ratio of the number of times two or more items occur to the total number of transactions. A Support of 0.1230 for the first association of says that “Reservoir Dogs” and “Pulp Fiction” were in the same basket for 12.3% of the total transactions. The Confidence which is given as 0.8698727 tells that the probablity of the movie “Reservoir Dogs” and “Pulp Fiction” appearing in the same basket is 0.8698727

Solution 4(c)

```
transactions.subset <- subset(transactions.apriori, subset = lift > 3.0)
inspect(transactions.subset)
```

```
> inspect(transactions.subset)

   lhs                   rhs              support  confidence     lift
1  {M.1817.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1026   0.8234350 3.057687
2  {M.2936.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1164   0.8185654 3.039604
3  {M.2250.R.High,
    M.2936.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1025   0.8464079 3.142993
4  {M.2250.R.High,
    M.2749.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1006   0.8293487 3.079646
5  {M.2526.R.High,
    M.2749.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1007   0.8440905 3.134387
6  {M.2250.R.High,
    M.2526.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1158   0.8324946 3.091328
7  {M.2250.R.High,
    M.5407.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1038   0.8166798 3.032602
8  {M.1870.R.High,
    M.2250.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1084   0.8181132 3.037925
9  {M.2250.R.High,
    M.4275.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1157   0.8390138 3.115536
10 {M.2250.R.High,
    M.4712.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1130   0.8242159 3.060586
11 {M.2526.R.High,
    M.5407.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1012   0.8214286 3.050236
12 {M.1870.R.High,
    M.2526.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1072   0.8195719 3.043341
13 {M.2526.R.High,
    M.4275.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1119   0.8369484 3.107866
14 {M.2526.R.High,
    M.4712.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1075   0.8231240 3.056532
15 {M.4275.R.High,
    M.5407.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1066   0.8149847 3.026308
16 {M.1870.R.High,
    M.4275.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1085   0.8238421 3.059198
17 {M.4275.R.High,
    M.4712.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1112   0.8261516 3.067774
```

Let us consider the 1st in the above rule where the lift is greater than 3.0 The association rule states that,

```
   lhs                   rhs              support  confidence     lift
1  {M.1817.R.High,
    M.647.R.High}   => {M.646.R.High}   0.1026   0.8234350 3.057687
```

Lift indicates the strength of an association rule over the random occurance co-occurance of the movie “Aliens”,“Terminator 2: Judgment Day” and the movie “The Terminator”. Lift provides information about the change in the probablity of Item A in the presence of Item B. Lift values greater than 3.0 indicate that transactions containing “The Terminator” has “Aliens” and “Terminator 2: Judgment Day” more often than transactions that do not contain “The Terminator”.

Solultion 5(a)

```r
directory <- c("/home/kevin/DataMining/DataMiningHW4/rec.motorcycles","/home/kevin/DataMining/DataMiningHW4/rec.autos")
dir_source <- DirSource(directory = directory, encoding = "UTF-8")
news.corpus <- VCorpus(dir_source, readerControl = list(reader = reader(dir_source)))
```

```
> news.corpus
> <<VCorpus (documents: 1986, metadata (corpus/indexed): 0/0)>>

> length(news.corpus)
[1] 1986

> news.corpus[[980]]
<<PlainTextDocument (metadata: 7)>>
From: cheekeen@tartarus.uwa.edu.au (Desmond Chan)
Subject: Re: Honda clutch chatter
Organization: The University of Western Australia
Lines: 8
NNTP-Posting-Host: tartarus.uwa.edu.au
X-Newsreader: NN version 6.4.19 #1

     I also experience this kinda problem in my 89 BMW 318. During cold
start ups, the clutch seems to be sticky and everytime i drive out, for
about 5km, the clutch seems to stick onto somewhere that if i depress
the clutch, the whole chassis moves along. But after preheating, it
becomes smooth again. I think that your suggestion of being some
humudity is right but there should be some remedy. I also found out that
my clutch is already thin but still alright for a couple grand more!
```

Solution 5(b)

```r
# Applying the removePunctuation over the news.corpus
news.corpus <- tm_map(news.corpus, removePunctuation)
news.corpus <- VCorpus(VectorSource(news.corpus))
```

```
> news.corpus[[980]]
<<PlainTextDocument (metadata: 7)>>
From cheekeentartarusuwaeduau Desmond Chan
Subject Re Honda clutch chatter
Organization The University of Western Australia
Lines 8
NNTPPostingHost tartarusuwaeduau
XNewsreader NN version 6419 1

     I also experience this kinda problem in my 89 BMW 318 During cold
start ups the clutch seems to be sticky and everytime i drive out for
about 5km the clutch seems to stick onto somewhere that if i depress
the clutch the whole chassis moves along But after preheating it
becomes smooth again I think that your suggestion of being some
humudity is right but there should be some remedy I also found out that
my clutch is already thin but still alright for a couple grand more
```

```r
# Applying removeNumbers over news.corpus
news.corpus <- tm_map(news.corpus, removeNumbers)
news.corpus <- VCorpus(VectorSource(news.corpus))
```

```
> news.corpus[980]
<<PlainTextDocument (metadata: 7)>>
From cheekeentartarusuwaeduau Desmond Chan
Subject Re Honda clutch chatter
Organization The University of Western Australia
Lines
NNTPPostingHost tartarusuwaeduau
XNewsreader NN version

     I also experience this kinda problem in my  BMW  During cold
start ups the clutch seems to be sticky and everytime i drive out for
about km the clutch seems to stick onto somewhere that if i depress
the clutch the whole chassis moves along But after preheating it
becomes smooth again I think that your suggestion of being some
humudity is right but there should be some remedy I also found out that
my clutch is already thin but still alright for a couple grand more
```

```r
# Applying tolower to news.corpus
news.corpus <- tm_map(news.corpus, tolower)
news.corpus <- VCorpus(VectorSource(news.corpus))
```

```
> news.corpus[[980]]
<<PlainTextDocument (metadata: 7)>>
from cheekeentartarusuwaeduau desmond chan
subject re honda clutch chatter
organization the university of western australia
lines
nntppostinghost tartarusuwaeduau
xnewsreader nn version

     i also experience this kinda problem in my  bmw  during cold
start ups the clutch seems to be sticky and everytime i drive out for
```

```
about km the clutch seems to stick onto somewhere that if i depress
the clutch the whole chassis moves along but after preheating it
becomes smooth again i think that your suggestion of being some
humudity is right but there should be some remedy i also found out that
my clutch is already thin but still alright for a couple grand more
```

```
# Applying removeWords stopwords("english")
news.corpus <- tm_map(news.corpus, removeWords, stopwords("english"))
news.corpus <- VCorpus(VectorSource(news.corpus))
```

```
> news.corpus[[980]]
<<PlainTextDocument (metadata: 7)>>
 cheekeentartarusuwaeduau desmond chan
subject re honda clutch chatter
organization  university  western australia
lines
nntppostinghost tartarusuwaeduau
xnewsreader nn version

      also experience  kinda problem    bmw   cold
start ups  clutch seems   sticky  everytime  drive
 km  clutch seems  stick onto somewhere    depress
 clutch  whole chassis moves along   preheating
becomes smooth   think   suggestion
humudity  right      remedy  also found
 clutch  already thin  still alright   couple grand
```

Solution 5(c)

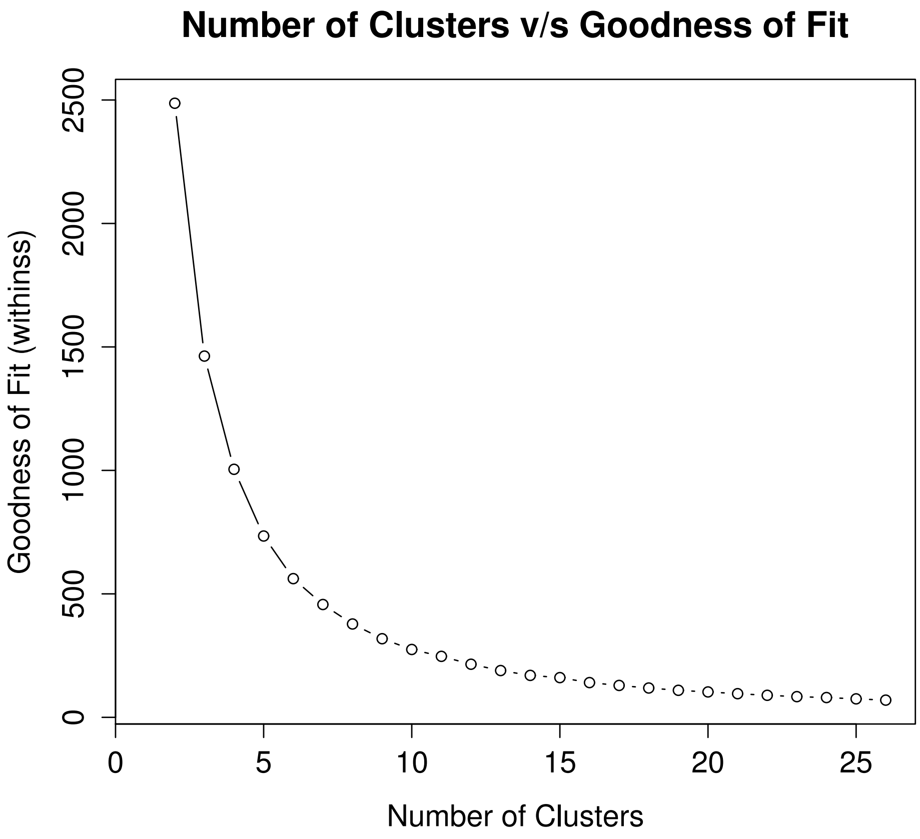
```
dtm <- DocumentTermMatrix(news.corpus, control = list(minWordLength = 1, minDocFreq = 1))
```

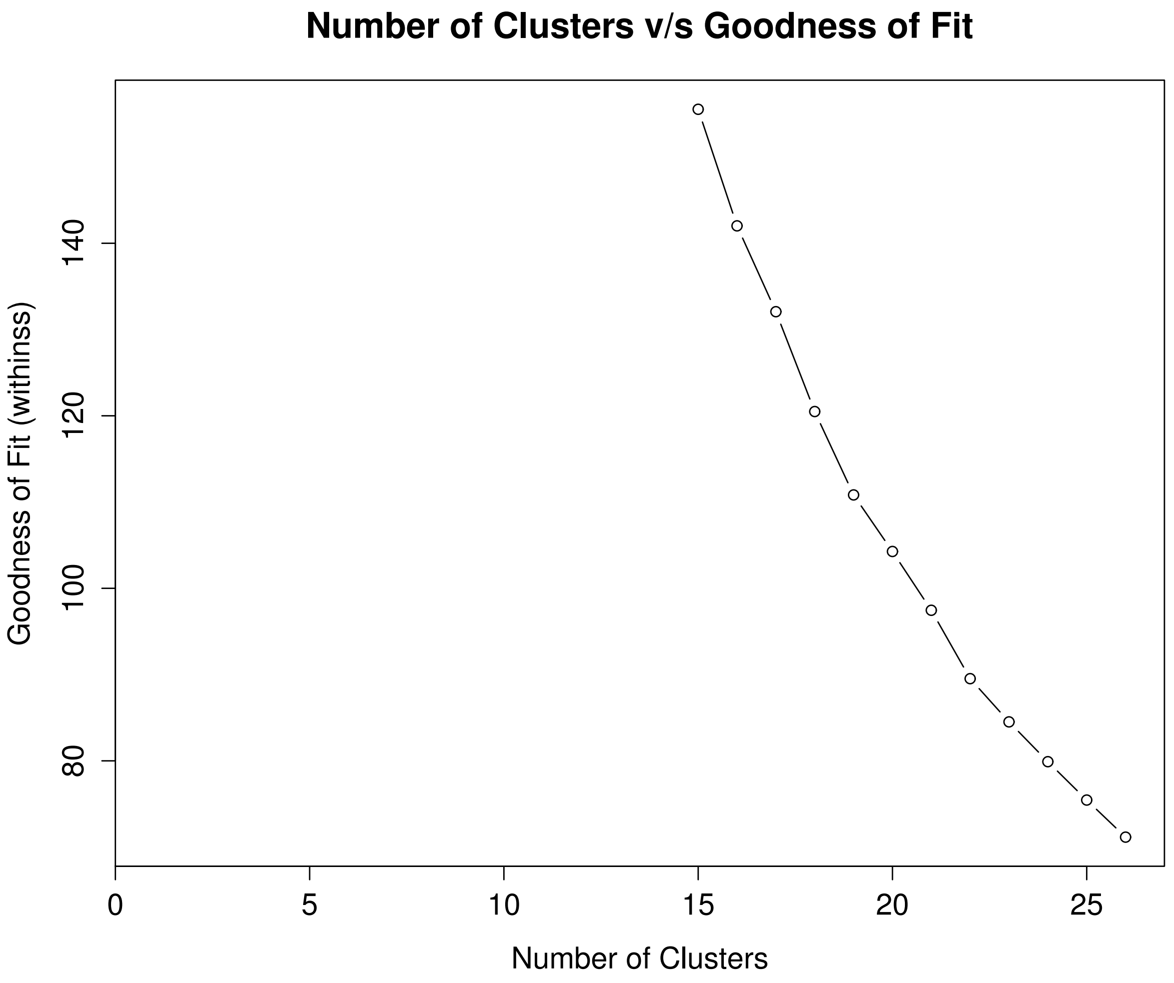
```
> dim(dtm)
[1]  1986 22213

> dtm
<<DocumentTermMatrix (documents: 1986, terms: 22213)>>
Non-/sparse entries: 175981/43939037
Sparsity           : 100%
Maximal term length: 163
Weighting          : term frequency (tf)

> inspect(news.corpus[[980]])
<<VCorpus (documents: 1, metadata (corpus/indexed): 0/0)>>

[[1]]
<<PlainTextDocument (metadata: 7)>>
 cheekeentartarusuwaeduau desmond chan
subject re honda clutch chatter
organization  university  western australia
lines
nntppostinghost tartarusuwaeduau
xnewsreader nn version

      also experience  kinda problem    bmw   cold
start ups  clutch seems   sticky  everytime  drive
 km  clutch seems  stick onto somewhere    depress
 clutch  whole chassis moves along   preheating
becomes smooth   think   suggestion
humudity  right      remedy  also found
 clutch  already thin  still alright   couple grand
```

Solution 2 (a)

```
# Solution(5)
# Kevin Aloysius
# Reading az-5000.txt data
set.seed(1)
char <- read.table("az-5000.txt", header = TRUE)
# Removing the first Column
char <- char[,2:19]
# Applying kmeans() to calculate the number of clusters
fit <- vector()

for (i in 2:26)
{
  output <- kmeans(char, centers = i, iter.max = 26)
  fit[i] <- (1/i)*sum(kmeans(char, centers = i)$withinss)
}
plot(1:26, fit, type = "b", xlab = "Number of Clusters", ylab = "Goodness of Fit (withinss)",
     main = "Number of Clusters v/s Goodness of Fit")

# Applying kmeans from 15 to 26 to calculate the number of clusters
fit2 <- vector()

for (i in 15:26)
{

  fit2[i] <- (1/i)*sum(kmeans(char, centers = i)$withinss)
}
plot(1:26, fit2, type = "b", xlab = "Number of Clusters", ylab = "Goodness of Fit (withinss)",
     main = "Number of Clusters v/s Goodness of Fit")
```

Solution 2 (b)

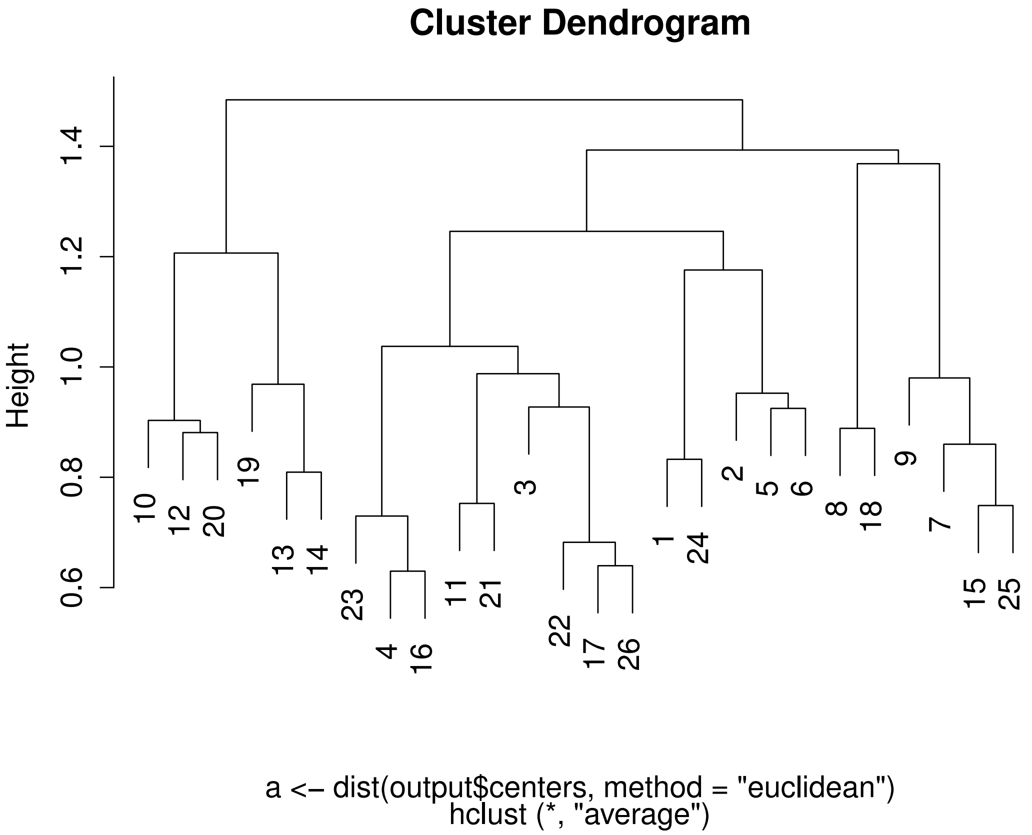




The 23rd letter 'W' suggests the number of natural clusters. This is because after plotting the number of K's from 15 to 26, we could observe a dip at 23 suggesting the number of clusters.

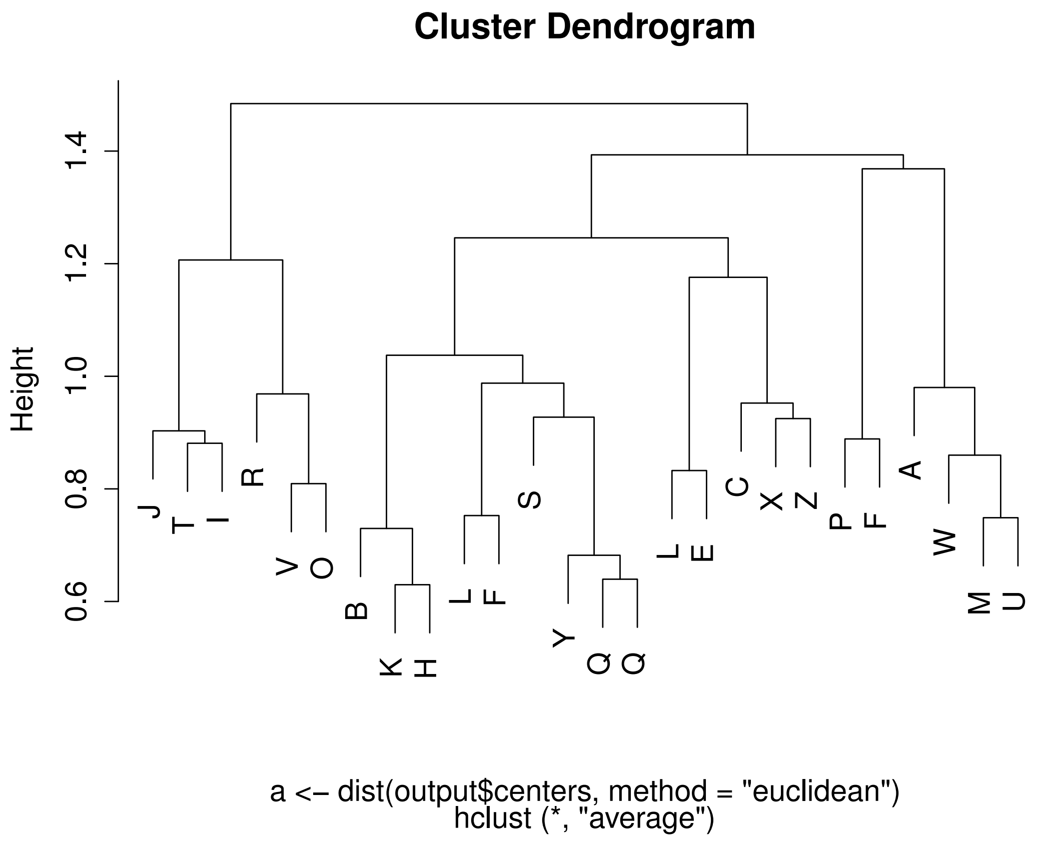
Solution 3 (a)

```
# Hierarchial Clustering
# Kevin Aloysius
set.seed(123)

# Loading the data
character <- read.table("az-5000.txt", header = TRUE)

# Removing the first column
char <- character[,-1]

# Applying kmeans
fit <- vector()
for (i in 2:26)
{
  output <- kmeans(char, centers = i, iter.max = 26)

}

# Hierarchial Clustering
fit <- hclust(a <- dist(output$centers, method = "euclidean"), method="average")
plot(fit)
```



Solution 3 (b)

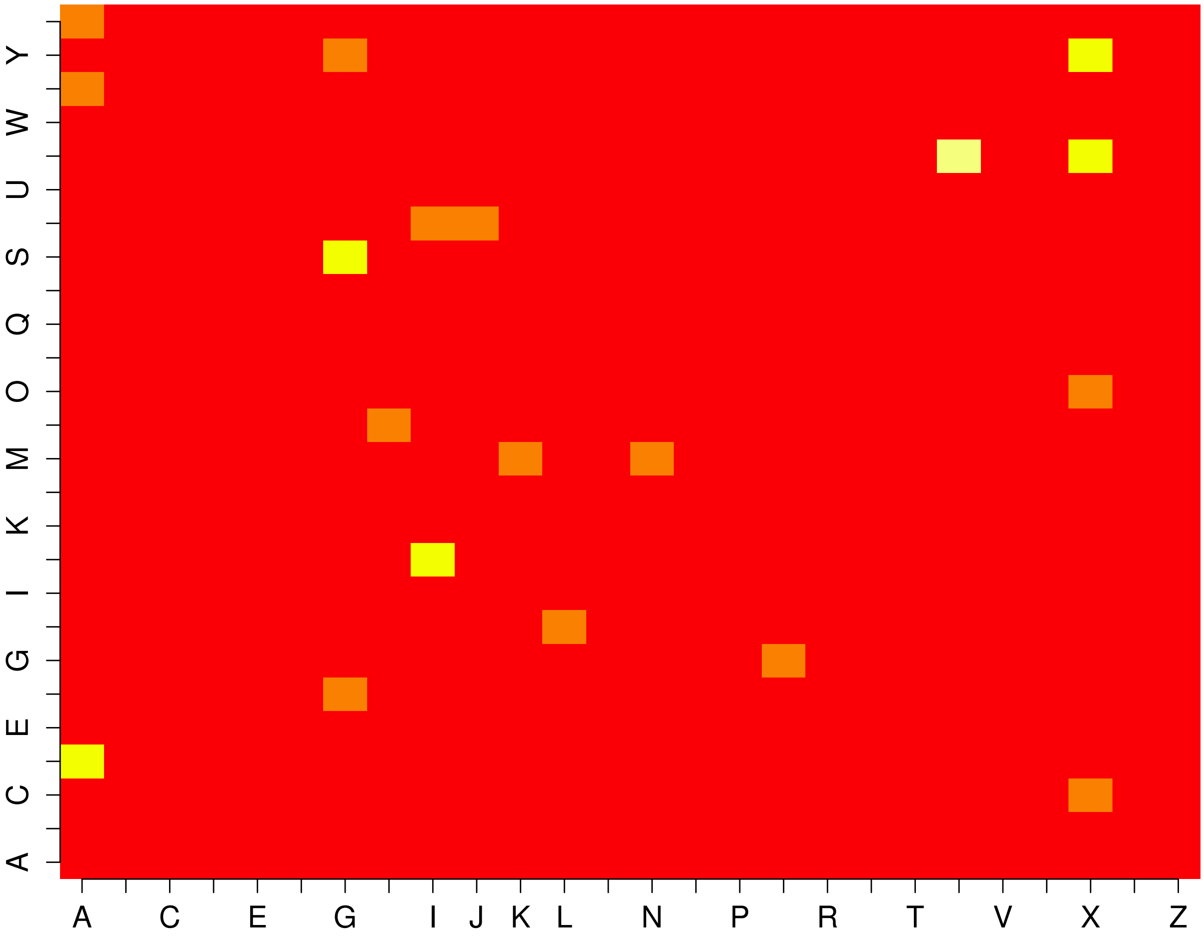
```
# 26x26 Matrix Mapping, Letters vs Cluster numbers

 letter_matrixrix <- character[,1]
num_cluster <- output$cluster
matrix <- matrix(0,26,26)
rownames(matrix) <- LETTERS

for(k in 1:5000)
{
  matrix[letter_matrix[k], num_cluster[k]] <-  matrix[letter_matrix[k], num_cluster[k]] + 1
}

# Replacing Values of Dendograms with Letters
common <- c()
for(i in 1:26)
{
  common[i] <- which.max(matrix[,i])
}

plot(fit, labels=LETTERS[common])
```



Solution 6

```
# Kevin Aloysius
set.seed(123)
#using the letter confusion matrix from HW2 for this question

Chars <- read.table("az-5000.txt", header = TRUE)
dim(Chars)

train <- sample(1:5000, 4000)

table(Chars$char[train])

char.priors <- c(rep(1/26, 26))

Char.lda <- lda(char ~., Chars, subset = train, prior = char.priors)

Char.confusion <- table(Chars[-train, ]$char, predict(Char.lda, Chars[-train, ])$class)

#setting diagonals of the matrix to be 0 and producing image with non-zero entries colored
diag(Char.confusion) <- 0
labelpos <- 0:25
labelpos_std <- labelpos/25
image(Char.confusion, col=heat.colors(4), axes=FALSE)
axis(1, labelpos_std, labels=LETTERS[1:26])
axis(2, labelpos_std, labels=LETTERS[1:26])
```

Solution 6(a)



Solution 6(b)

The Letter pair with the worst confusion matrix from the above diagram is the Letter Pair V,U (Row 'V' and Column 'U'). It is represented in white color and the value of this matrix is 8.