Audience Segmentation

Read fake data

This data is simulated for a client proposal

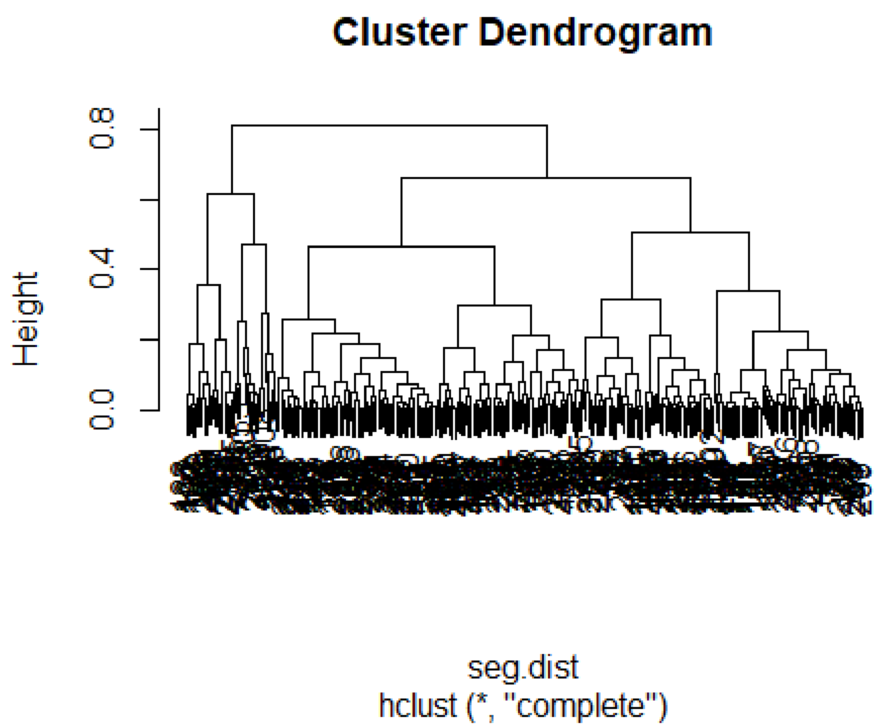
```
seg.raw <- read.csv("http://goo.gl/qw303p")
seg.df  <- seg.raw[ , -7]     # a copy without the known segment assignments

summary(seg.df)

##       age           gender        income            kids        ownHome
##  Min.   :19.26   Female:157   Min.   : -5183   Min.   :0.00   ownNo :159
##  1st Qu.:33.01   Male  :143   1st Qu.: 39656   1st Qu.:0.00   ownYes:141
##  Median :39.49                Median : 52014   Median :1.00
##  Mean   :41.20                Mean   : 50937   Mean   :1.27
##  3rd Qu.:47.90                3rd Qu.: 61403   3rd Qu.:2.00
##  Max.   :80.49                Max.   :114278   Max.   :7.00
##   subscribe
##  subNo :260
##  subYes: 40
##
##
##
##

str(seg.df)

## 'data.frame':    300 obs. of  6 variables:
##  $ age      : num  47.3 31.4 43.2 37.3 41 ...
##  $ gender   : Factor w/ 2 levels "Female","Male": 2 2 2 1 1 2 2 2 1 1 ...
##  $ income   : num  49483 35546 44169 81042 79353 ...
##  $ kids     : int  2 1 0 1 3 4 3 0 1 0 ...
##  $ ownHome  : Factor w/ 2 levels "ownNo","ownYes": 1 2 2 1 2 2 1 1 1 2 ...
##  $ subscribe: Factor w/ 2 levels "subNo","subYes": 1 1 1 1 1 1 1 1 1 1 ...
```

Build clustering solution

```
# now the real hclust() work
library(cluster)                  # daisy works with mixed data types
seg.dist <- daisy(seg.df)
# inspect some of the results
as.matrix(seg.dist)[1:5, 1:5]

##           1         2         3         4         5
## 1 0.0000000 0.2532815 0.2329028 0.2617250 0.4161338
## 2 0.2532815 0.0000000 0.0679978 0.4129493 0.3014468
## 3 0.2329028 0.0679978 0.0000000 0.4246012 0.2932957
```

```
## 4 0.2617250 0.4129493 0.4246012 0.0000000 0.2265436
## 5 0.4161338 0.3014468 0.2932957 0.2265436 0.0000000
```

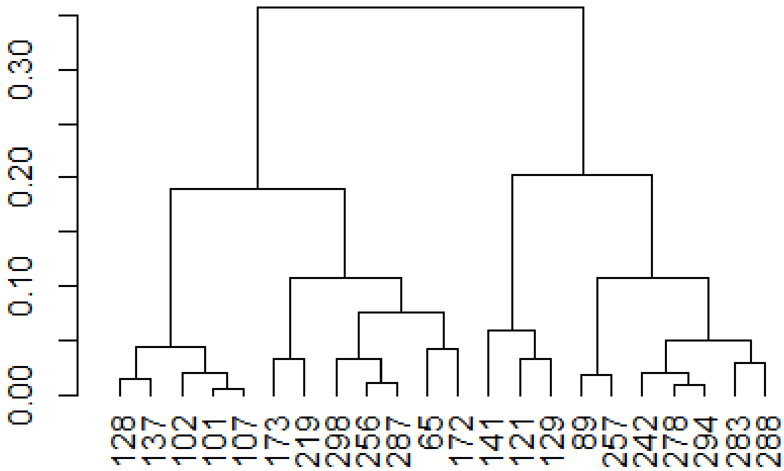
```r
seg.hc <- hclust(seg.dist, method="complete")

plot(seg.hc)
```



A hierarchical dendrogram is interpreted primarily by height and where observations are joined. The height represents the dissimilarity between elements that are joined.

Let us zoom into one section of the chart

```r
plot(cut(as.dendrogram(seg.hc), h=0.5)$lower[[1]])
```



Check the proposed similarities

```r
# check some of the proposed similarities
seg.df[c(101, 107), ]  # similar

##          age gender   income kids ownHome subscribe
## 101 24.73796   Male 18457.85    1   ownNo    subYes
## 107 23.19013   Male 17510.28    1   ownNo    subYes

seg.df[c(278, 294), ]  # similar

##          age gender   income kids ownHome subscribe
## 278 36.23860 Female 46540.88    1   ownNo    subYes
## 294 35.79961 Female 52352.69    1   ownNo    subYes

seg.df[c(173, 141), ]  # less similar

##          age gender   income kids ownHome subscribe
## 173 64.70641   Male 45517.15    0   ownNo    subYes
## 141 25.17703 Female 20125.80    2   ownNo    subYes
```

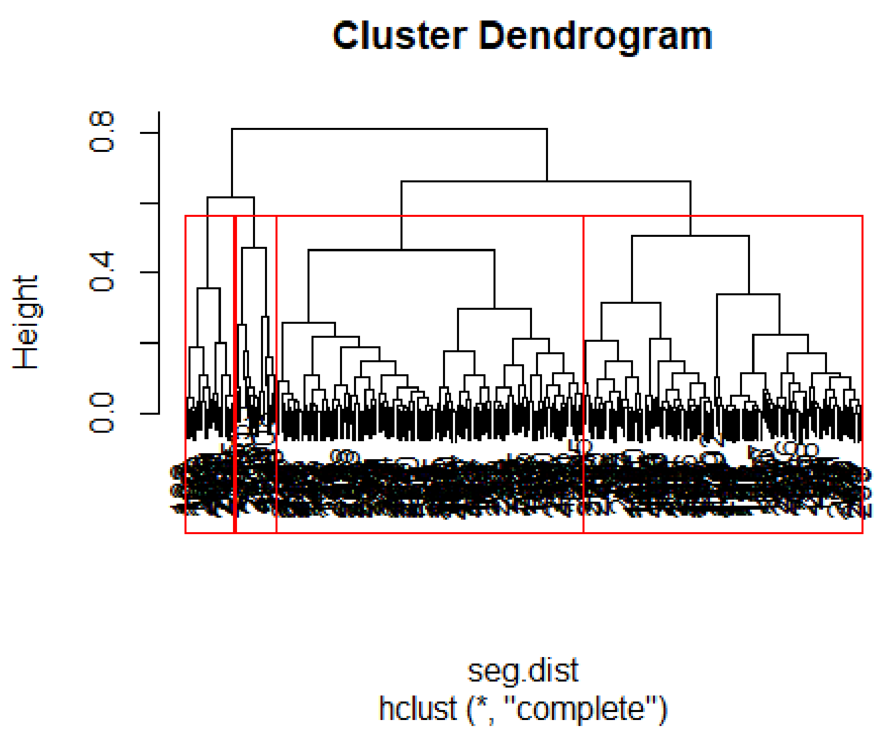
As you can see, these segments seem quite similar.

```r
# examine cophenetic correlation
cor(cophenetic(seg.hc), seg.dist)

## [1] 0.7682436
```

CPCC > 0.7 indicates a relatively strong fit, meaning that the hierarchical tree represents the distances between customers well.

Let us try to cut the dendrogram such that we get 4 clusters

```
plot(seg.hc)
rect.hclust(seg.hc, k=4, border="red")
```




```
# actually get 4 groups
seg.hc.segment <- cutree(seg.hc, k=4)     # membership vector for 4 groups
table(seg.hc.segment)

## seg.hc.segment
##   1   2   3   4
## 124 136  18  22
```

We see that groups 1 and 2 dominate the assignment. Note that the class labels (1, 2, 3, 4) are in arbitrary order and are not meaningful in themselves. seg.hc.segment is the vector of group assignments.

```
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
```

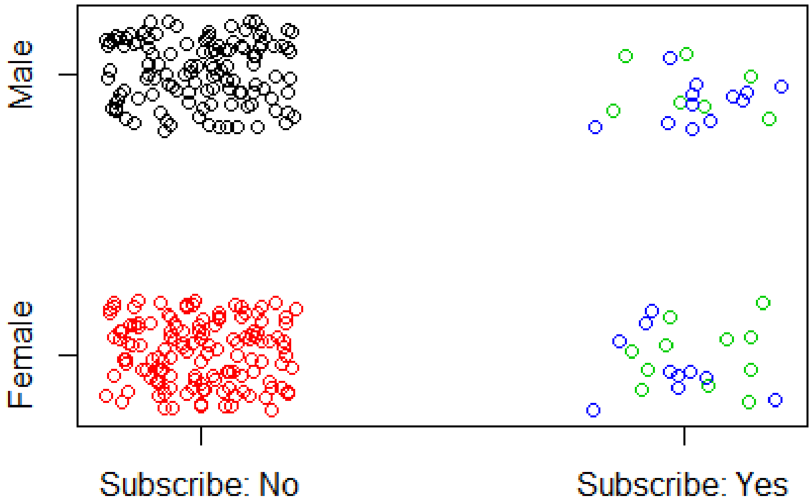
```
seg.df$seg.hc.segment = seg.hc.segment
seg.summ <- function(data, groups) {
  aggregate(data, list(groups), function(x) mean(as.numeric(x)))
}

numeric_mean <- function(col){
  return (mean(as.numeric(col)))
}
seg.df %>% group_by(seg.hc.segment) %>% summarize_each(funs(numeric_mean))
```

```
## `summarise_each()` is deprecated.
## Use `summarise_all()`, `summarise_at()` or `summarise_if()` instead.
## To map `funs` over all variables, use `summarise_all()`
```

```
## # A tibble: 4 x 7
##   seg.hc.segment   age gender income  kids ownHome subscribe
##            <int> <dbl>  <dbl>  <dbl> <dbl>   <dbl>     <dbl>
## 1              1  40.8   2.00 49454.  1.31    1.47        1.
## 2              2  42.0   1.00 53760.  1.24    1.48        1.
## 3              3  44.3   1.39 52628.  1.39    2.00        2.
## 4              4  35.8   1.55 40456.  1.14    1.00        2.
```

```
#seg.summ(data = seg.df,groups = seg.hc.segment)
```

```
# plot this
plot(jitter(as.numeric(seg.df$gender)) ~
jitter(as.numeric(seg.df$subscribe)),
     col=seg.hc.segment, yaxt="n", xaxt="n", ylab="", xlab="")
axis(1, at=c(1, 2), labels=c("Subscribe: No", "Subscribe: Yes"))
axis(2, at=c(1, 2), labels=levels(seg.df$gender))
```



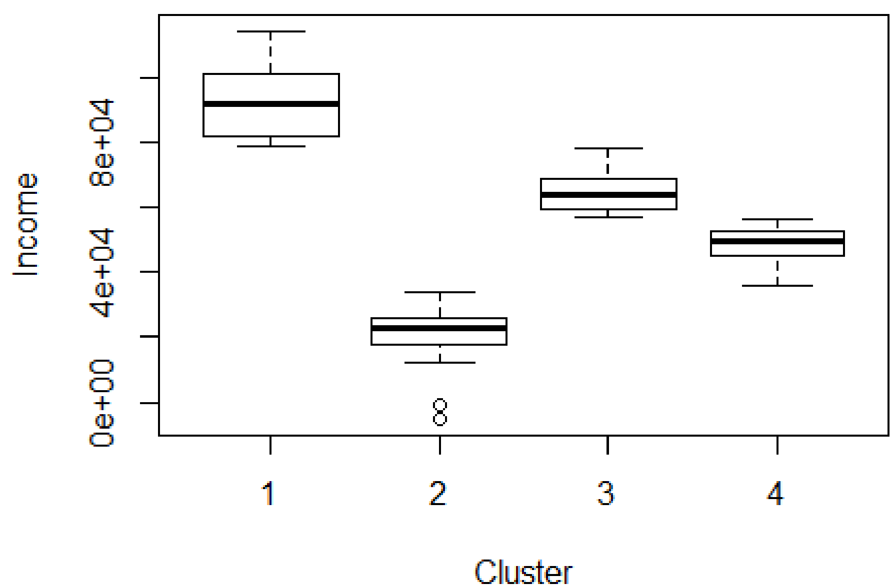
Perform k-means clustering

```
# convert factor variables to numeric (kmeans requires). OK b/c all are
binary.
seg.df.num <- seg.df
seg.df.num$gender    <- ifelse(seg.df$gender=="Male", 0, 1)
seg.df.num$ownHome   <- ifelse(seg.df$ownHome=="ownNo", 0, 1)
seg.df.num$subscribe <- ifelse(seg.df$subscribe=="subNo", 0, 1)
summary(seg.df.num)

##       age            gender           income            kids
##  Min.   :19.26   Min.   :0.0000   Min.   : -5183   Min.   :0.00
##  1st Qu.:33.01   1st Qu.:0.0000   1st Qu.: 39656   1st Qu.:0.00
##  Median :39.49   Median :1.0000   Median : 52014   Median :1.00
##  Mean   :41.20   Mean   :0.5233   Mean   : 50937   Mean   :1.27
##  3rd Qu.:47.90   3rd Qu.:1.0000   3rd Qu.: 61403   3rd Qu.:2.00
##  Max.   :80.49   Max.   :1.0000   Max.   :114278   Max.   :7.00
##     ownHome        subscribe      seg.hc.segment
##  Min.   :0.00   Min.   :0.0000   Min.   :1.000
##  1st Qu.:0.00   1st Qu.:0.0000   1st Qu.:1.000
##  Median :0.00   Median :0.0000   Median :2.000
##  Mean   :0.47   Mean   :0.1333   Mean   :1.793
##  3rd Qu.:1.00   3rd Qu.:0.0000   3rd Qu.:2.000
##  Max.   :1.00   Max.   :1.0000   Max.   :4.000

set.seed(96743)
seg.k <- kmeans(seg.df.num, centers=4)
```

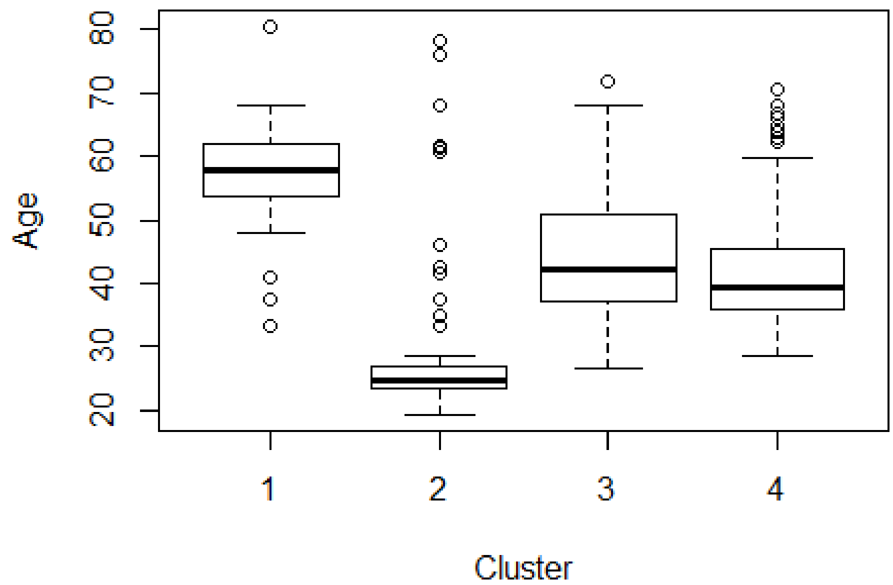
```r
# inspect it
seg.summ(seg.df, seg.k$cluster)
```

```
##   Group.1      age   gender   income      kids  ownHome subscribe
## 1       1 56.37245 1.428571 92287.07 0.4285714 1.857143  1.142857
## 2       2 29.58704 1.571429 21631.79 1.0634921 1.301587  1.158730
## 3       3 44.42051 1.452632 64703.76 1.2947368 1.421053  1.073684
## 4       4 42.08381 1.454545 48208.86 1.5041322 1.528926  1.165289
##   seg.hc.segment
## 1       1.809524
## 2       1.809524
## 3       1.694737
## 4       1.859504
```

```r
# plot one of the variables
boxplot(seg.df.num$income ~ seg.k$cluster, ylab="Income", xlab="Cluster")
```




```r
boxplot(seg.df.num$age ~ seg.k$cluster, ylab="Age", xlab="Cluster")
```



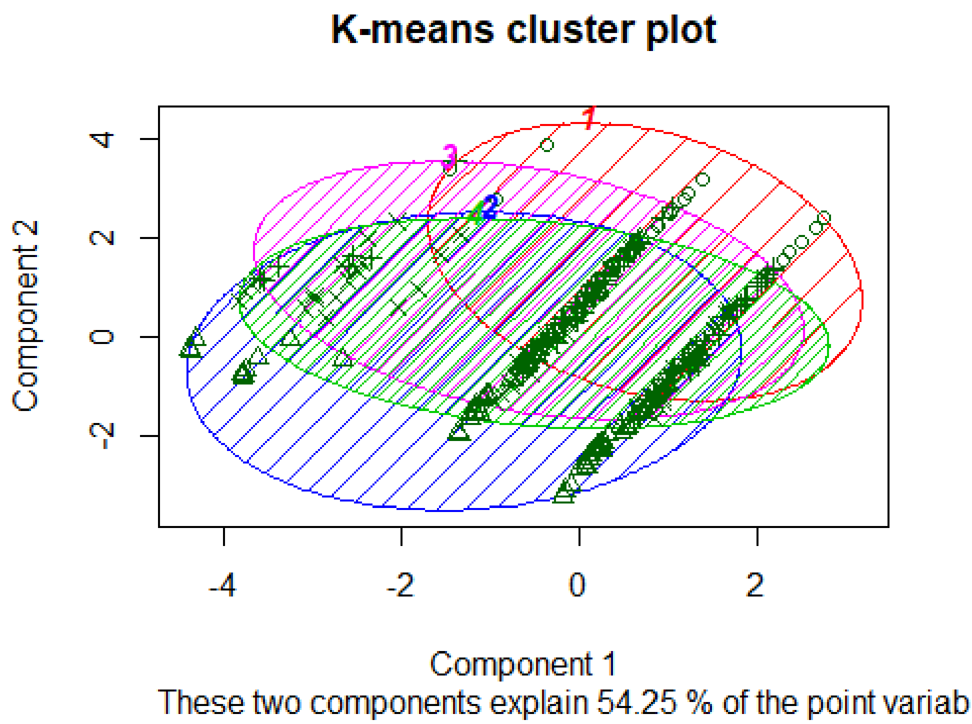
Scree Plot

Draw a scree plot to determine the number of clusters.

```
wssplot <- function(data, nc=15, seed=1234){
  wss <- (nrow(data)-1)*sum(apply(data,2,var))
  for (i in 2:nc){
    set.seed(seed)
    wss[i] <- sum(kmeans(data, centers=i)$withinss)}
  plot(1:nc, wss, type="b", xlab="Number of Clusters",
       ylab="Within groups sum of squares")}

wssplot(seg.df.num, nc=6)
```

Plot the results

```
# plot the result
library(cluster)
clusplot(seg.df, seg.k$cluster, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="K-means cluster plot")
```



Overall, this is a far more interesting cluster solution for our segmentation data than the hclust() proposal. The groups here are clearly differentiated on key variables such as age and income.With this information, an analyst might cross-reference the group membership with key variables (as we did using our seg.summ() function and then look at the relative differentiation of the groups.

This may suggest a business strategy. In the present case, for instance, we see that group 1 is modestly well differentiated, and has the highest average income. That may make it a good target for a potential campaign. Many other strategies are possible, too; the key point is that the analysis provides interesting options to consider. A limitation of k-means analysis is that it requires specifying the number of clusters, and it can be difficult to determine whether one solution is better than another. If we were to use k-means for the present problem, we would repeat the analysis for k =3, 4, 5, and so forth, and determine which solution gives the most useful result for our business goals. One might wonder whether the algorithm itself can suggest how many clusters are in the data. Yes! To see that, we turn next to model-based clustering.

Model Based Clustering (MCLUST)

The key idea for model-based clustering is that observations come from groups with different statistical distributions (such as different means and variances). The algorithms try to find the best set of such underlying distributions to explain the observed data. We use the mclust package to demonstrate this. Such models are also known as “mixture models” because it is assumed that the data reflect a mixture of observations drawn from different populations, although we don’t know which population each observation was drawn from. We are trying to estimate the underlying population parameters and the mixture proportion. mclust models such clusters as being drawn from a mixture of normal (also known as Gaussian) distributions. As you might guess, because mclust models data with normal distributions, it uses only numeric data. We use the numeric data frame seg.df.num that we adapted for kmeans(). The model is estimated with Mclust()

```
# do mclust for segments
library(mclust)

## Package 'mclust' version 5.4
## Type 'citation("mclust")' for citing this R package in publications.

###
# convert factor variables to numeric (mclust requires). OK b/c all are
binary.
# these lines are the same as above for k-means [not repeated in book]
seg.df.num <- seg.df
seg.df.num$gender    <- ifelse(seg.df$gender=="Male", 0, 1)
seg.df.num$ownHome   <- ifelse(seg.df$ownHome=="ownNo", 0, 1)
seg.df.num$subscribe <- ifelse(seg.df$subscribe=="subNo", 0, 1)
summary(seg.df.num)

##       age            gender           income            kids
##  Min.   :19.26   Min.   :0.0000   Min.   : -5183   Min.   :0.00
##  1st Qu.:33.01   1st Qu.:0.0000   1st Qu.: 39656   1st Qu.:0.00
##  Median :39.49   Median :1.0000   Median : 52014   Median :1.00
##  Mean   :41.20   Mean   :0.5233   Mean   : 50937   Mean   :1.27
##  3rd Qu.:47.90   3rd Qu.:1.0000   3rd Qu.: 61403   3rd Qu.:2.00
##  Max.   :80.49   Max.   :1.0000   Max.   :114278   Max.   :7.00
##     ownHome        subscribe      seg.hc.segment
##  Min.   :0.00   Min.   :0.0000   Min.   :1.000
##  1st Qu.:0.00   1st Qu.:0.0000   1st Qu.:1.000
##  Median :0.00   Median :0.0000   Median :2.000
##  Mean   :0.47   Mean   :0.1333   Mean   :1.793
##  3rd Qu.:1.00   3rd Qu.:0.0000   3rd Qu.:2.000
##  Max.   :1.00   Max.   :1.0000   Max.   :4.000

###


# fit the model
seg.mc <- Mclust(seg.df.num)
summary(seg.mc)

## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VEV (ellipsoidal, equal shape) model with 2 components:
##
##  log.likelihood   n df       BIC       ICL
```

```
##       -5079.071 300 65 -10528.89 -10528.89
##
## Clustering table:
##   1   2
## 124 176
```

```r
# what if we estimate 4 clusters?
seg.mc4 <- Mclust(seg.df.num, G=4)
summary(seg.mc4)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VII (spherical, varying volume) model with 4 components:
##
##  log.likelihood   n df       BIC      ICL
##       -19420.54 300 35 -39040.71 -39043.4
##
## Clustering table:
##  1  2  3  4
## 86 89 59 66
```

Develop a 3 cluster model

```r
# fit the model
seg.mc3 <- Mclust(seg.df.num, G=3)
summary(seg.mc3)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust EEE (ellipsoidal, equal volume, shape and orientation) model with 3
components:
##
##  log.likelihood   n df       BIC       ICL
##       -5304.038 300 51 -10898.97 -10901.88
##
## Clustering table:
##   1   2   3
##  66 163  71
```

Compare the two models

```r
# compare the three models
logLik(seg.mc, seg.mc3, seg.mc4)
```

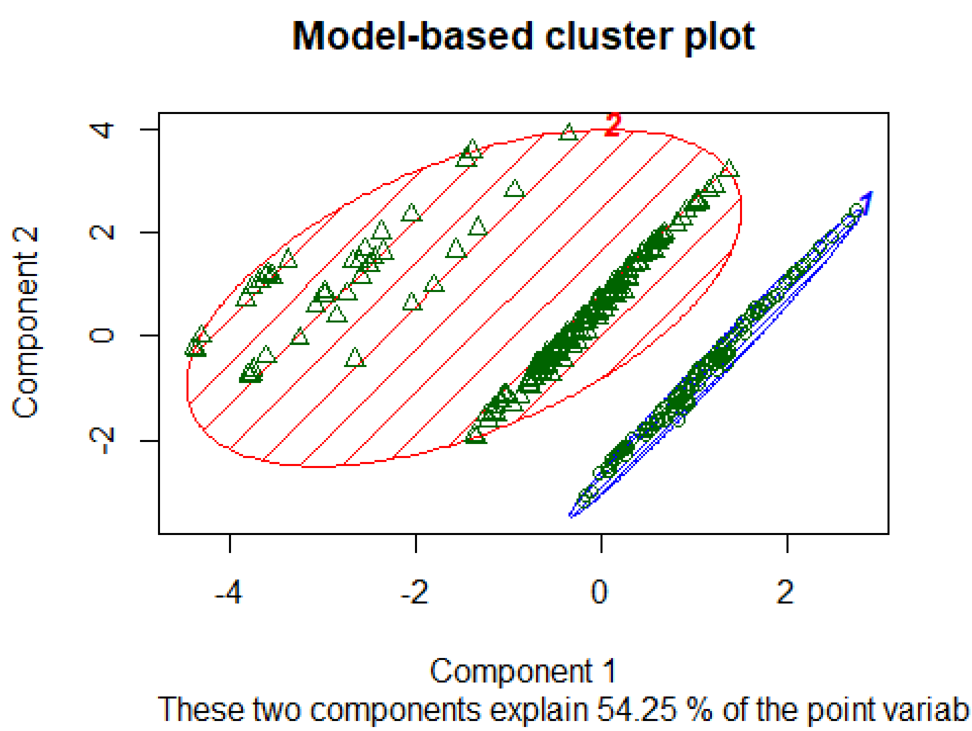
```
## 'log Lik.' -5079.071 (df=65)
```

```
# examine the 3-cluster model
seg.summ(seg.df, seg.mc3$class)
```

```
##   Group.1      age   gender   income     kids  ownHome subscribe
## 1       1 36.02187 2.000000 45227.51 1.348485 1.000000  1.000000
## 2       2 44.68018 1.472393 52980.52 1.171779 1.865031  1.245399
## 3       3 38.02229 1.000000 51550.98 1.422535 1.000000  1.000000
##   seg.hc.segment
## 1        1.00000
## 2        2.02454
## 3        2.00000
```

Plot the 2-cluster model

```
# plot the 3-cluster model
library(cluster)
clusplot(seg.df, seg.mc$class, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="Model-based cluster plot")
```



Latent Class Analysis: poLCA()

Latent class analysis (LCA) is similar to mixture modeling in the assumption that differences are attributable to unobserved groups that one wishes to uncover. In this section we take a look at the poLCA package for polytomous (i.e., categorical) LCA. Whereas mclust and kmeans() work with numeric data, and hclust() depends on the distance measure, poLCA uses only categorical variables. To demonstrate it here, we adopt an opposite strategy from our procedure with k-means and mclust and convert our data seg.df to be all categorical data before analyzing it.

There are several approaches to convert numeric data to factors, but for purposes here we simply recode everything as binary with regard to a specified cutting point (for instance, to recode as 1 for income below some cutoff and 2 above that). In the present case, we split each variable at the median() and recode using ifelse() and factor(). We use with() to save typing, and ~1 to specify a formula with intercepts only:

```
seg.df.cut <- seg.df
seg.df.cut$age    <- factor(ifelse(seg.df$age < median(seg.df$age), 1, 2))
seg.df.cut$income <- factor(ifelse(seg.df$income < median(seg.df$income),
                                   1, 2))
seg.df.cut$kids   <- factor(ifelse(seg.df$kids < median(seg.df$kids), 1, 2))
summary(seg.df.cut)
```

```
##   age        gender     income   kids      ownHome     subscribe
##   1:150   Female:157   1:150   1:121   ownNo :159   subNo :260
##   2:150   Male  :143   2:150   2:179   ownYes:141   subYes: 40
##
##
##
##
##   seg.hc.segment
##   Min.   :1.000
##   1st Qu.:1.000
##   Median :2.000
##   Mean   :1.793
##   3rd Qu.:2.000
##   Max.   :4.000
```

```
# create a model formula
seg.f <- with(seg.df.cut,
              cbind(age, gender, income, kids, ownHome, subscribe)~1)
```

With the data in place, we specify the model that we want to fit. poLCA can estimate complex models with covariates, but for the present analysis we only wish Segmentation: Clustering and Classification to examine the effect of cluster membership alone. Thus, we model the dependent variables (all the observed columns) with respect to the model intercepts (i.e., the cluster positions).

```
# fit the model
library(poLCA)
```

```
## Loading required package: scatterplot3d
```

```
## Loading required package: MASS
```

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```
set.seed(02807)
seg.LCA3 <- poLCA(seg.f, data=seg.df.cut, nclass=3)
```

```
## Conditional item response (column) probabilities,
##  by outcome variable, for each class (row)
##
## $age
##                 1      2
## class 1:  1.0000 0.0000
## class 2:  0.0000 1.0000
## class 3:  0.6555 0.3445
##
## $gender
##           Female   Male
## class 1:  0.4211 0.5789
## class 2:  0.4681 0.5319
## class 3:  0.6079 0.3921
##
## $income
##                 1      2
## class 1:  1.0000 0.0000
## class 2:  0.3803 0.6197
## class 3:  0.3746 0.6254
##
## $kids
##                 1      2
## class 1:  0.2818 0.7182
## class 2:  0.8065 0.1935
## class 3:  0.1575 0.8425
##
## $ownHome
##            ownNo ownYes
## class 1:  0.7289 0.2711
## class 2:  0.2338 0.7662
## class 3:  0.6638 0.3362
##
## $subscribe
##            subNo subYes
## class 1:  0.7496 0.2504
## class 2:  0.8948 0.1052
## class 3:  0.8960 0.1040
##
## Estimated class population shares
##  0.1974 0.341 0.4616
##
## Predicted class memberships (by modal posterior prob.)
```

```
##  0.2333 0.3467 0.42
##
## =========================================================
## Fit for 3 latent classes:
## =========================================================
## number of observations: 300
## number of estimated parameters: 20
## residual degrees of freedom: 43
## maximum log-likelihood: -1092.345
##
## AIC(3): 2224.691
## BIC(3): 2298.767
## G^2(3): 42.77441 (Likelihood ratio/deviance statistic)
## X^2(3): 38.47647 (Chi-square goodness of fit)
##
```

```
seg.LCA4 <- poLCA(seg.f, data=seg.df.cut, nclass=4)
```

```
## Conditional item response (column) probabilities,
##  by outcome variable, for each class (row)
##
## $age
##                  1      2
## class 1:  0.6823 0.3177
## class 2:  0.0000 1.0000
## class 3:  1.0000 0.0000
## class 4:  1.0000 0.0000
##
## $gender
##            Female   Male
## class 1:  0.5853 0.4147
## class 2:  0.4810 0.5190
## class 3:  0.8466 0.1534
## class 4:  0.3277 0.6723
##
## $income
##                  1      2
## class 1:  0.4137 0.5863
## class 2:  0.3701 0.6299
## class 3:  0.5850 0.4150
## class 4:  1.0000 0.0000
##
## $kids
##                  1      2
## class 1:  0.0000 1.0000
## class 2:  0.8114 0.1886
## class 3:  1.0000 0.0000
## class 4:  0.2506 0.7494
##
## $ownHome
```

```
##              ownNo ownYes
## class 1:  0.6540 0.3460
## class 2:  0.2688 0.7312
## class 3:  0.6537 0.3463
## class 4:  0.7721 0.2279
## 
## $subscribe
##              subNo subYes
## class 1:  0.8746 0.1254
## class 2:  0.8965 0.1035
## class 3:  1.0000 0.0000
## class 4:  0.7203 0.2797
## 
## Estimated class population shares 
##  0.4101 0.3697 0.0643 0.1559 
## 
## Predicted class memberships (by modal posterior prob.) 
##  0.41 0.3733 0.0667 0.15 
## 
## ========================================================= 
## Fit for 4 latent classes: 
## ========================================================= 
## number of observations: 300 
## number of estimated parameters: 27 
## residual degrees of freedom: 36 
## maximum log-likelihood: -1088.021 
## 
## AIC(4): 2230.041
## BIC(4): 2330.043
## G^2(4): 34.12473 (Likelihood ratio/deviance statistic) 
## X^2(4): 31.50696 (Chi-square goodness of fit) 
## 
```

```
seg.LCA4$bic
```

```
## [1] 2330.043
```

```
seg.LCA3$bic
```

```
## [1] 2298.767
```

The 3-cluster model shows a lower BIC by 32 and thus a substantially stronger fit to the data. As we’ve seen, that is not entirely conclusive as to business utility, so we also examine some other indicators such as the quick summary function and cluster plots:

```
# examine the solutions
# 3 clusters
seg.summ(seg.df, seg.LCA3$predclass)
```

```
##   Group.1      age   gender   income      kids  ownHome subscribe
## 1       1 28.22385 1.685714 30075.32 1.1285714 1.285714  1.271429
```

```
## 2        2 54.44407 1.576923 60082.47 0.3846154 1.769231  1.105769
## 3        3 37.47652 1.277778 54977.08 2.0793651 1.325397  1.079365
##   seg.hc.segment
## 1       1.900000
## 2       1.634615
## 3       1.865079
```

```
seg.summ(seg.df, seg.LCA4$predclass)
```

```
##   Group.1      age   gender   income      kids  ownHome subscribe
## 1       1 36.62554 1.349593 52080.13 2.1951220 1.349593  1.113821
## 2       2 53.64073 1.535714 60534.17 0.5178571 1.785714  1.098214
## 3       3 30.22575 1.050000 41361.81 0.0000000 1.350000  1.000000
## 4       4 27.61506 1.866667 28178.70 1.1777778 1.066667  1.333333
##   seg.hc.segment
## 1       1.829268
## 2       1.660714
## 3       1.950000
## 4       1.955556
```

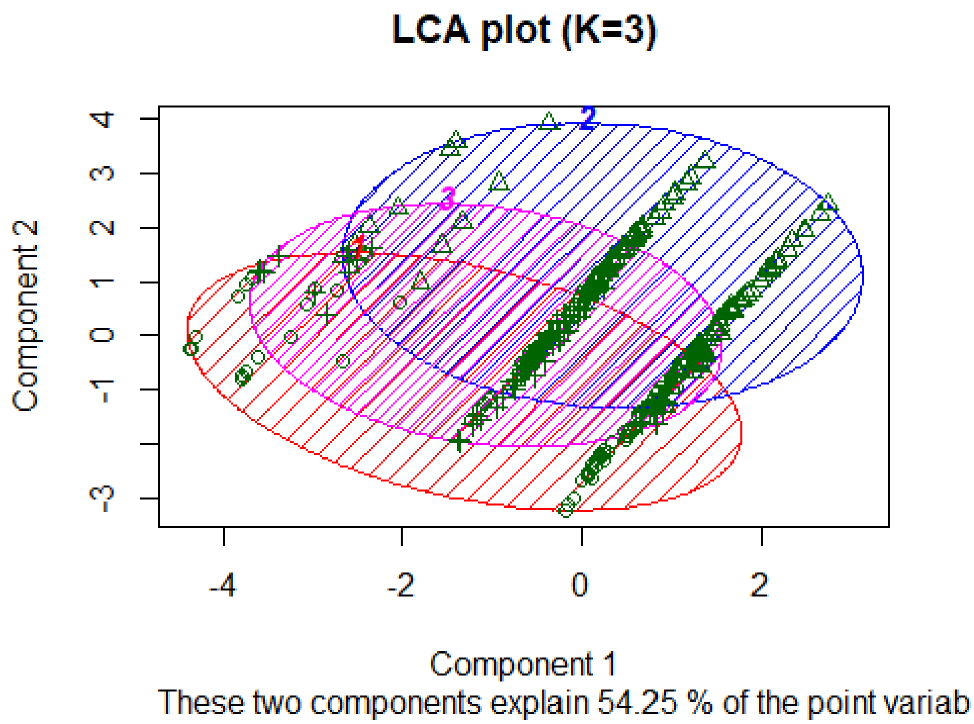
```
table(seg.LCA3$predclass)
```

```
## 
##   1   2   3 
##  70 104 126
```

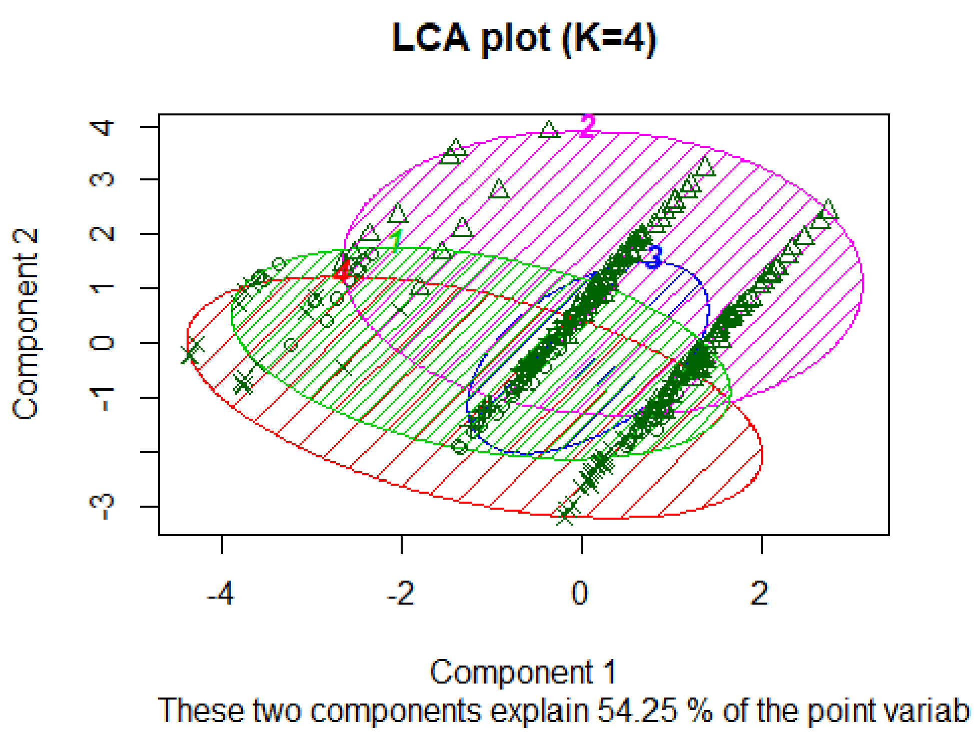
```
table(seg.LCA4$predclass)
```

```
## 
##   1   2   3   4 
## 123 112  20  45
```

```
clusplot(seg.df, seg.LCA3$predclass, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="LCA plot (K=3)")
```




```
clusplot(seg.df, seg.LCA4$predclass, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="LCA plot (K=4)")
```



At a high level, it appears that “Group 2” is similar in both solutions. The primary difference is that “Group 3” buried inside the overlapping ellipses in the 4-cluster solution could be viewed as being largely carved out of two larger groups (Groups “2” and “3” as labeled in the 3-cluster solution). This is an approximate interpretation of the data visualization, not a perfect correspondence.

Does the additional group in the 4-cluster solution add anything to our interpretation? Turning to the quick summary from seg.summ() in the code block, we see good differentiation of groups in both models. One argument in favor of the 4-cluster solution is that Group 3 has no subscribers (as shown by the mean in the seg.summ() results) and is relatively well identified (mostly younger women with no kids); that might make it an appealing group either for targeting or exclusion, depending on one’s strategy.

Comparing Cluster Solutions

mapClass() solves the matching problem. It examines all permutations of how two sets of class assignments might be related and selects a mapping that maximizes agreement between the two assignment schemes. adjustedRandIndex() likewise matches two assignment schemes and then computes the degree of agreement over and above what might be attributed to “chance” by simply assigning all observations to the largest group [81, 131]. Its magnitude may be interpreted similarly to a standard r correlation coefficient.

We use table() to look at the cross-tabs between the LCA 3-cluster and 4-cluster solutions found above:

```
# compare 3-cluster and 4-cluster solutions
table(seg.LCA3$predclass, seg.LCA4$predclass)

##
##       1   2   3   4
##   1  13   0  12  45
##   2   0 104   0   0
##   3 110   8   8   0
```

It would appear that observations assigned to “Group 1” in the 3-cluster solution are split between Groups 1, 3, and 4 in the 4-cluster solution, while “Group 3” maps closely to “Group 1” (in the 4 class solution) and “Group 2” is predominantly the same in both. However, matching groups manually is sometimes unclear and generally error-prone. Instead, we use mapClass (a, b) and adjustedRandIndex(a, b) to compare agreement between the two solutions:

```
library(mclust)
mapClass(seg.LCA3$predclass, seg.LCA4$predclass)

## $aTOb
## $aTOb$`1`
## [1] 4
##
## $aTOb$`2`
## [1] 2
```

```
##
## $aTOb$`3`
## [1] 1
##
##
## $bTOa
## $bTOa$`1`
## [1] 3
##
## $bTOa$`2`
## [1] 2
##
## $bTOa$`3`
## [1] 1
##
## $bTOa$`4`
## [1] 1
```

```
adjustedRandIndex(seg.LCA3$predclass, seg.LCA4$predclass)
```

```
## [1] 0.7288822
```

This tells us that "1" in the LCA3 model (a) maps best to "4" in the LCA4 model (b), and so forth. The adjusted Rand index of 0.729 indicates that the match between the two assignment lists is much better than chance. From a business perspective, it also tells us that the 3-cluster and 4-cluster differ modestly from one another, which provides another perspective on choosing between them.

```
# compare random assignment to LCA4
set.seed(11021)
random.data <- sample(4, length(seg.LCA4$predclass), replace=TRUE)
adjustedRandIndex(random.data, seg.LCA4$predclass)
```

```
## [1] 0.002292031
```

In this case, the adjusted Rand index is near zero, because the match between the clusters is no better than random chance.

Finally we compare the LCA 4-cluster solution to the true segments in seg.raw:

```
# compare to known segments
table(seg.raw$Segment, seg.LCA4$predclass)
```

```
##
##               1  2  3  4
##   Moving up  50  4  8  8
##   Suburb mix 62 29  2  7
##   Travelers   0 79  1  0
##   Urban hip  11  0  9 30
```

```
adjustedRandIndex(seg.raw$Segment, seg.LCA4$predclass)
```

```
## [1] 0.3513031
```

With a Rand index of 0.35, the LCA solution matches the true segment assignments moderately better than chance alone. In many cases, of course, one would not have identified clusters for comparison; but when they are available from other projects or previous efforts, it is helpful to examine correspondence in this way.

Using CLASSIFICATION

First, we will use Naive Bayes.

```
set.seed(04625)
train.prop  <- 0.65
train.cases <- sample(nrow(seg.raw), nrow(seg.raw)*train.prop)
seg.df.train <- seg.raw[train.cases, ]
seg.df.test  <- seg.raw[-train.cases, ]
library(e1071)
(seg.nb <- naiveBayes(Segment ~ ., data=seg.df.train))

##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##  Moving up Suburb mix  Travelers  Urban hip
##  0.2512821  0.3025641  0.2615385  0.1846154
##
## Conditional probabilities:
##             age
## Y                [,1]     [,2]
##   Moving up  36.09168 4.167010
##   Suburb mix 40.14240 5.173803
##   Travelers  57.47194 8.126370
##   Urban hip  23.95040 1.798332
##
##             gender
## Y               Female      Male
##   Moving up  0.6530612 0.3469388
##   Suburb mix 0.4576271 0.5423729
##   Travelers  0.4705882 0.5294118
##   Urban hip  0.3333333 0.6666667
##
##             income
## Y                [,1]      [,2]
##   Moving up  52880.45  9836.682
##   Suburb mix 54124.75 11429.940
##   Travelers  63547.20 23862.123
```

```
##   Urban hip  21285.99  5141.259
##
##            kids
## Y               [,1]     [,2]
##   Moving up  2.102041 1.489476
##   Suburb mix 1.694915 1.249196
##   Travelers  0.000000 0.000000
##   Urban hip  1.166667 1.108409
##
##            ownHome
## Y               ownNo    ownYes
##   Moving up  0.6734694 0.3265306
##   Suburb mix 0.5932203 0.4067797
##   Travelers  0.2156863 0.7843137
##   Urban hip  0.8611111 0.1388889
##
##            subscribe
## Y                subNo     subYes
##   Moving up  0.79591837 0.20408163
##   Suburb mix 0.93220339 0.06779661
##   Travelers  0.92156863 0.07843137
##   Urban hip  0.77777778 0.22222222
```

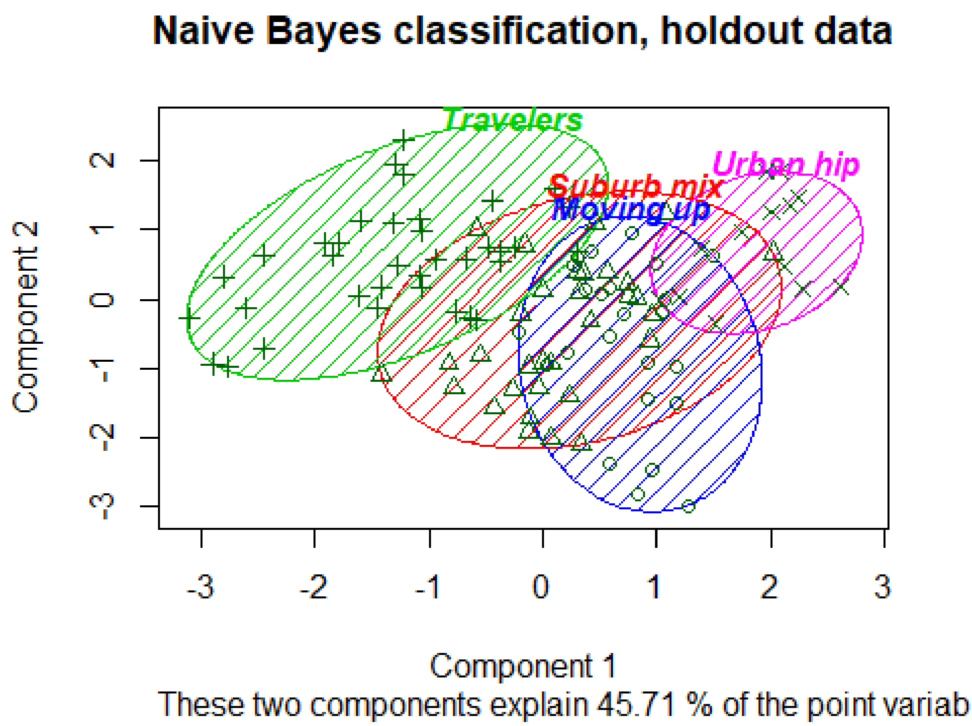
```
(seg.nb.class <- predict(seg.nb, seg.df.test))
```

```
##   [1] Suburb mix Travelers  Suburb mix Suburb mix Suburb mix Suburb mix
##   [7] Moving up  Suburb mix Suburb mix Suburb mix Travelers  Moving up
##  [13] Moving up  Moving up  Suburb mix Moving up  Moving up  Suburb mix
##  [19] Suburb mix Suburb mix Moving up  Suburb mix Suburb mix Moving up
##  [25] Suburb mix Suburb mix Moving up  Suburb mix Suburb mix Suburb mix
##  [31] Suburb mix Suburb mix Suburb mix Moving up  Suburb mix Suburb mix
##  [37] Suburb mix Suburb mix Suburb mix Suburb mix Suburb mix Urban hip
##  [43] Urban hip  Urban hip  Urban hip  Urban hip  Urban hip  Urban hip
##  [49] Urban hip  Urban hip  Urban hip  Moving up  Urban hip  Urban hip
##  [55] Urban hip  Travelers  Travelers  Travelers  Travelers  Travelers
##  [61] Travelers  Travelers  Travelers  Travelers  Travelers  Travelers
##  [67] Travelers  Travelers  Travelers  Travelers  Travelers  Travelers
##  [73] Travelers  Travelers  Travelers  Travelers  Travelers  Travelers
##  [79] Travelers  Travelers  Travelers  Travelers  Travelers  Travelers
##  [85] Suburb mix Moving up  Moving up  Travelers  Moving up  Travelers
##  [91] Suburb mix Moving up  Suburb mix Travelers  Moving up  Travelers
##  [97] Moving up  Moving up  Moving up  Moving up  Moving up  Moving up
## [103] Moving up  Travelers  Moving up
## Levels: Moving up Suburb mix Travelers Urban hip
```

```
# frequencies in predicted data
prop.table(table(seg.nb.class))
```

```
## seg.nb.class
##  Moving up Suburb mix  Travelers  Urban hip
##  0.2285714  0.3047619  0.3428571  0.1238095
```

```
# plot it
clusplot(seg.df.test[, -7], seg.nb.class, color=TRUE, shade=TRUE,
         labels=4, lines=0,
         main="Naive Bayes classification, holdout data")
```




```
# compare to known segments (which we can do with this test data)
mean(seg.df.test$Segment==seg.nb.class)

## [1] 0.8

# adjusted for chance
library(mclust)
adjustedRandIndex(seg.nb.class, seg.df.test$Segment)

## [1] 0.5626787

table(seg.nb.class, seg.df.test$Segment)

##
## seg.nb.class Moving up Suburb mix Travelers Urban hip
##   Moving up         13         10         0         1
##   Suburb mix         3         29         0         0
##   Travelers          5          2        29         0
##   Urban hip          0          0         0        13

# summary data for proposed segments in the test data
seg.summ(seg.df.test, seg.nb.class)
```

```
##      Group.1      age   gender   income      kids  ownHome subscribe
## 1  Moving up 34.29258 1.125000 51369.52 2.2916667 1.416667  1.250000
## 2 Suburb mix 41.24653 1.562500 58095.10 2.1875000 1.562500  1.000000
## 3  Travelers 55.08669 1.444444 58634.10 0.0000000 1.666667  1.166667
## 4  Urban hip 23.36047 1.461538 22039.69 0.8461538 1.307692  1.153846
##    Segment
## 1 1.541667
## 2 1.906250
## 3 2.666667
## 4 4.000000
```

```
# summary data for the known segments in the test data
seg.summ(seg.df.test, seg.df.test$Segment)
```

```
##      Group.1      age   gender   income      kids  ownHome subscribe
## 1  Moving up 36.88989 1.190476 53582.16 1.4761905 1.333333  1.190476
## 2 Suburb mix 39.61984 1.487805 56341.99 2.2439024 1.585366  1.048780
## 3  Travelers 58.57245 1.448276 59869.24 0.0000000 1.689655  1.206897
## 4  Urban hip 23.71537 1.428571 22700.06 0.9285714 1.357143  1.142857
##   Segment
## 1       1
## 2       2
## 3       3
## 4       4
```

```
# predict raw probabilities
predict(seg.nb, seg.df.test, type="raw")
```

```
##           Moving up   Suburb mix    Travelers     Urban hip
##   [1,] 4.070780e-01 5.928052e-01 4.848358e-05  6.832328e-05
##   [2,] 2.715183e-04 2.422066e-03 9.973064e-01  6.143554e-32
##   [3,] 2.671393e-01 7.326897e-01 1.710510e-04  2.844967e-40
##   [4,] 2.237216e-01 7.746457e-01 1.632613e-03  7.568258e-37
##   [5,] 2.255663e-01 7.740280e-01 4.057610e-04  9.030641e-11
##   [6,] 2.051011e-01 7.948047e-01 9.422156e-05  1.554167e-33
##   [7,] 6.226983e-01 3.772938e-01 7.952188e-06  1.250892e-24
##   [8,] 1.429048e-01 8.565200e-01 5.751660e-04  2.667936e-36
##   [9,] 2.282427e-01 7.716462e-01 1.111296e-04  6.476270e-22
##  [10,] 1.881606e-01 8.114632e-01 3.762108e-04  2.155829e-33
##  [11,] 1.409837e-03 3.908209e-03 9.946820e-01  4.248292e-33
##  [12,] 8.812766e-01 1.187179e-01 5.530903e-06  1.315135e-13
##  [13,] 9.363446e-01 6.188859e-02 1.766807e-03  2.521926e-19
##  [14,] 5.935200e-01 4.064759e-01 2.932670e-06  1.210546e-06
##  [15,] 4.725188e-01 5.274249e-01 5.631135e-05  5.870878e-25
##  [16,] 7.963638e-01 2.035722e-01 6.404062e-05  1.030205e-20
##  [17,] 6.477085e-01 3.522871e-01 4.456907e-06  9.790789e-19
##  [18,] 1.715141e-03 9.840527e-01 1.423214e-02  2.993688e-73
##  [19,] 1.179409e-01 8.812472e-01 8.119052e-04  1.001008e-39
##  [20,] 2.893329e-01 7.106172e-01 4.987617e-05  3.384453e-30
##  [21,] 5.585618e-01 4.413705e-01 6.533428e-05  2.374933e-06
##  [22,] 3.337822e-01 6.660742e-01 1.436054e-04  9.311995e-32
```

```
##  [23,] 8.249975e-02 9.172824e-01 2.178072e-04  3.649129e-44
##  [24,] 5.008053e-01 4.991899e-01 4.757632e-06  1.371772e-15
##  [25,] 4.442623e-01 5.555204e-01 2.172838e-04  3.746701e-33
##  [26,] 3.586398e-01 6.411569e-01 2.032695e-04  4.374357e-34
##  [27,] 9.864036e-01 1.331108e-02 2.852760e-04  7.920841e-20
##  [28,] 4.791363e-01 5.201146e-01 7.491095e-04  6.306240e-32
##  [29,] 1.719093e-01 8.274102e-01 6.805144e-04  4.384449e-39
##  [30,] 2.792319e-01 7.207143e-01 5.377341e-05  3.945087e-32
##  [31,] 4.444809e-01 5.555000e-01 1.902410e-05  6.186405e-23
##  [32,] 4.317279e-01 5.682500e-01 2.207835e-05  4.243505e-31
##  [33,] 1.988075e-01 8.011554e-01 3.716906e-05  3.770192e-28
##  [34,] 6.826468e-01 3.172864e-01 6.680345e-05  6.263200e-15
##  [35,] 3.656168e-01 6.343525e-01 3.075380e-05  8.154635e-29
##  [36,] 1.409983e-02 9.597235e-01 2.617663e-02  1.705685e-65
##  [37,] 1.474668e-01 8.518188e-01 7.143783e-04  6.036608e-42
##  [38,] 4.107278e-01 5.892610e-01 1.121548e-05  8.009665e-12
##  [39,] 1.097242e-01 8.895641e-01 7.116990e-04  3.640361e-41
##  [40,] 1.584013e-01 7.947219e-01 4.687685e-02  4.328512e-50
##  [41,] 3.505440e-02 9.606926e-01 4.252956e-03  6.290196e-55
##  [42,] 1.122555e-05 2.586008e-05 2.070450e-09  9.999629e-01
##  [43,] 2.708565e-06 5.002437e-06 8.813820e-09  9.999923e-01
##  [44,] 2.012864e-06 6.344218e-06 8.237494e-04  9.991679e-01
##  [45,] 2.618790e-05 5.683791e-05 6.829390e-08  9.999169e-01
##  [46,] 5.290098e-05 8.357094e-05 4.181535e-02  9.580482e-01
##  [47,] 5.528166e-06 1.352741e-05 1.234177e-03  9.987468e-01
##  [48,] 1.505269e-04 1.307232e-04 1.121059e-08  9.997187e-01
##  [49,] 9.840399e-05 1.124898e-04 7.933819e-09  9.997891e-01
##  [50,] 4.141680e-05 2.133260e-05 1.691168e-09  9.999372e-01
##  [51,] 4.846737e-06 9.321986e-06 3.083240e-09  9.999858e-01
##  [52,] 5.073755e-01 3.176407e-01 3.414710e-05  1.749497e-01
##  [53,] 6.285033e-06 1.992342e-05 4.122520e-09  9.999738e-01
##  [54,] 5.617880e-04 6.110798e-04 1.523376e-01  8.464896e-01
##  [55,] 1.585677e-04 1.260877e-04 5.471530e-03  9.942438e-01
##  [56,] 3.848736e-12 4.426424e-08 1.000000e+00 2.158109e-114
##  [57,] 7.589320e-16 2.151421e-09 1.000000e+00 6.591408e-136
##  [58,] 2.180764e-03 1.399840e-02 9.838208e-01  1.973439e-34
##  [59,] 1.453951e-04 1.172650e-03 9.986820e-01  1.997596e-41
##  [60,] 5.165052e-13 5.590014e-08 9.999999e-01 9.545166e-118
##  [61,] 1.036906e-17 4.096307e-10 1.000000e+00 7.010506e-154
##  [62,] 3.486228e-07 7.350485e-05 9.999261e-01  1.723402e-66
##  [63,] 1.779764e-12 7.979504e-08 9.999999e-01 1.151915e-108
##  [64,] 6.556751e-10 1.532494e-06 9.999985e-01  6.536369e-81
##  [65,] 8.515440e-09 6.959245e-06 9.999930e-01  2.837008e-81
##  [66,] 2.052778e-15 3.492683e-10 1.000000e+00 2.393598e-138
##  [67,] 5.688381e-05 1.289988e-03 9.986531e-01  1.425667e-55
##  [68,] 1.838440e-15 4.026445e-09 1.000000e+00 3.379407e-140
##  [69,] 1.798857e-06 8.038892e-05 9.999178e-01  5.958005e-55
##  [70,] 2.076097e-06 1.326329e-04 9.998653e-01  6.508037e-62
##  [71,] 4.656512e-11 2.093391e-07 9.999998e-01 1.881985e-106
##  [72,] 3.626703e-14 3.847436e-09 1.000000e+00  5.646380e-97
```

```
##  [73,] 1.605414e-11 7.846866e-08 9.999999e-01 2.853606e-113
##  [74,] 4.409435e-16 1.604309e-09 1.000000e+00 2.010348e-151
##  [75,] 5.821964e-19 1.476104e-11 1.000000e+00 1.988381e-169
##  [76,] 1.681580e-11 3.428651e-07 9.999997e-01  1.122044e-90
##  [77,] 1.204774e-06 1.381948e-04 9.998606e-01  1.868316e-73
##  [78,] 8.299835e-13 3.707382e-08 1.000000e+00  4.592253e-99
##  [79,] 5.965582e-26 3.845277e-15 1.000000e+00 1.662621e-199
##  [80,] 6.230834e-05 1.976800e-03 9.979609e-01  1.249634e-53
##  [81,] 2.172137e-09 2.501661e-06 9.999975e-01  1.545993e-83
##  [82,] 2.948970e-18 8.801702e-12 1.000000e+00 1.907937e-155
##  [83,] 4.223935e-14 1.605263e-09 1.000000e+00 7.259005e-127
##  [84,] 2.087288e-14 2.251596e-08 1.000000e+00 1.373288e-130
##  [85,] 2.799951e-01 7.195106e-01 4.942965e-04  8.053513e-37
##  [86,] 6.455032e-01 3.544805e-01 1.631816e-05  3.333431e-12
##  [87,] 8.770655e-01 1.229329e-01 1.643295e-06  1.032652e-17
##  [88,] 9.124913e-02 6.023881e-02 8.485121e-01  3.476815e-21
##  [89,] 8.125672e-01 1.874132e-01 1.963252e-05  2.173069e-23
##  [90,] 1.880513e-03 7.330164e-03 9.907893e-01  2.953075e-43
##  [91,] 4.978976e-01 5.020053e-01 9.703109e-05  2.455250e-31
##  [92,] 6.512389e-01 3.487564e-01 4.661974e-06  5.535521e-20
##  [93,] 4.071302e-01 5.928361e-01 3.377476e-05  3.364233e-12
##  [94,] 3.936946e-02 5.920812e-02 9.014224e-01  5.525953e-24
##  [95,] 7.131613e-01 2.868359e-01 2.722473e-06  2.914527e-14
##  [96,] 1.981632e-04 1.915729e-03 9.978861e-01  2.559204e-30
##  [97,] 5.536556e-01 4.463331e-01 1.132570e-05  2.656886e-17
##  [98,] 8.656092e-01 1.343837e-01 7.053256e-06  2.362430e-13
##  [99,] 8.003381e-01 1.988422e-01 8.196091e-04  6.861077e-22
## [100,] 5.230366e-01 4.769470e-01 1.638791e-05  7.947511e-14
## [101,] 8.540672e-01 1.459302e-01 2.573149e-06  1.778876e-15
## [102,] 5.469917e-01 4.529987e-01 9.673663e-06  1.779996e-24
## [103,] 5.725079e-01 4.274841e-01 8.013238e-06  3.155921e-23
## [104,] 3.270015e-03 6.079785e-03 9.906502e-01  5.581108e-30
## [105,] 8.618555e-01 1.381424e-01 2.119364e-06  1.540710e-17
```

```
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

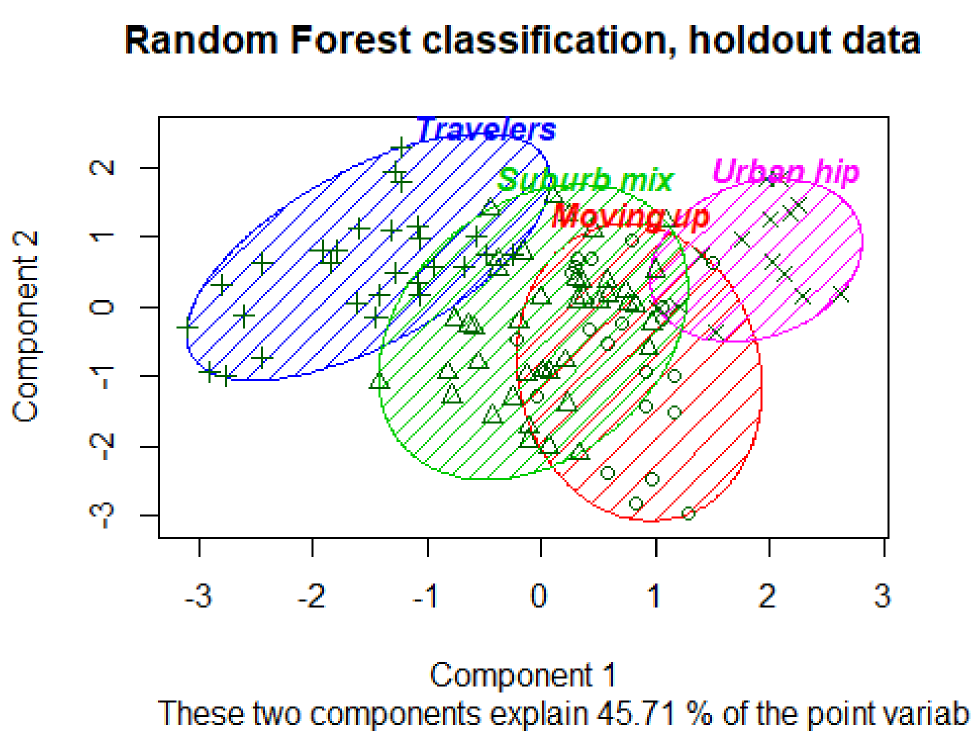
```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
set.seed(98040)
```

```
(seg.rf <- randomForest(Segment ~ ., data=seg.df.train))
```

```
##
## Call:
##  randomForest(formula = Segment ~ ., data = seg.df.train)
##               Type of random forest: classification
##                     Number of trees: 500
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 23.08%
## Confusion matrix:
##             Moving up Suburb mix Travelers Urban hip class.error
## Moving up          30         17         0         2  0.38775510
## Suburb mix         18         36         4         1  0.38983051
## Travelers           0          3        48         0  0.05882353
## Urban hip           0          0         0        36  0.00000000

# predict the test data for random forest
seg.rf.class <- predict(seg.rf, seg.df.test)

# plot the solution
library(cluster)

clusplot(seg.df.test[, -7], seg.rf.class, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="Random Forest classification, holdout
data")
```




```
# get the individual prediction distribution
seg.rf.class.all <- predict(seg.rf, seg.df.test, predict.all=TRUE)
```

```r
# look at the distribution for the first 5 test data cases
apply(seg.rf.class.all$individual[1:5, ], 1, table)
```

```
## $`2`
##
##  Moving up Suburb mix  Travelers  Urban hip
##        197        226         24         53
##
## $`3`
##
##  Moving up Suburb mix  Travelers
##         44        245        211
##
## $`4`
##
##  Moving up Suburb mix  Travelers  Urban hip
##         91        350         58          1
##
## $`6`
##
##  Moving up Suburb mix  Travelers
##         55        437          8
##
## $`7`
##
##  Moving up Suburb mix  Travelers  Urban hip
##        105        167         24        204
```

```r
# summaries for the proposed and actual segments
seg.summ(seg.df.test, seg.rf.class)
```

```
##      Group.1      age   gender   income       kids  ownHome subscribe
## 1  Moving up 34.63061 1.136364 51885.37 2.45454545 1.454545  1.272727
## 2 Suburb mix 40.66557 1.487805 57737.61 1.63414634 1.536585  1.000000
## 3  Travelers 59.26118 1.464286 59812.04 0.03571429 1.714286  1.214286
## 4  Urban hip 24.37450 1.500000 21842.73 1.00000000 1.285714  1.142857
##    Segment
## 1 1.636364
## 2 1.829268
## 3 2.892857
## 4 3.857143
```

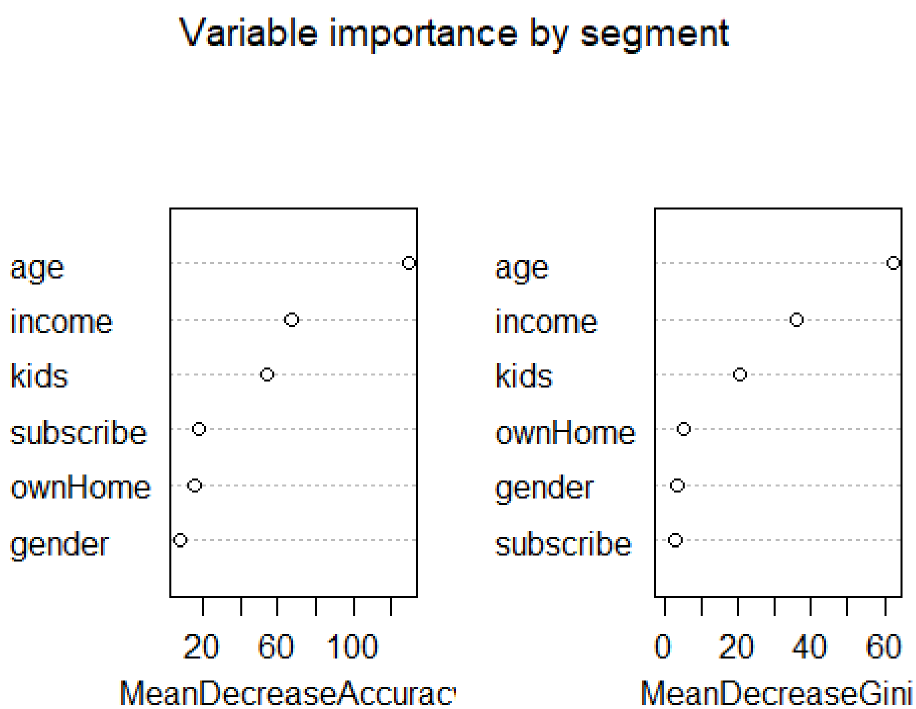
```r
seg.summ(seg.df.test, seg.df.test$Segment)
```

```
##      Group.1      age   gender   income      kids  ownHome subscribe
## 1  Moving up 36.88989 1.190476 53582.16 1.4761905 1.333333  1.190476
## 2 Suburb mix 39.61984 1.487805 56341.99 2.2439024 1.585366  1.048780
## 3  Travelers 58.57245 1.448276 59869.24 0.0000000 1.689655  1.206897
## 4  Urban hip 23.71537 1.428571 22700.06 0.9285714 1.357143  1.142857
##   Segment
```

```
## 1       1
## 2       2
## 3       3
## 4       4

# confusion matrix in test data
mean(seg.df.test$Segment==seg.rf.class)

## [1] 0.7333333

table(seg.df.test$Segment, seg.rf.class)

##               seg.rf.class
##                Moving up Suburb mix Travelers Urban hip
##   Moving up           10         10         1         0
##   Suburb mix          11         28         1         1
##   Travelers            0          3        26         0
##   Urban hip            1          0         0        13

library(mclust)
adjustedRandIndex(seg.df.test$Segment, seg.rf.class)

## [1] 0.4587587

### random forest variable importance
set.seed(98040)
(seg.rf <- randomForest(Segment ~ ., data=seg.df.train, ntree=3000,
                        importance=TRUE))

##
## Call:
##  randomForest(formula = Segment ~ ., data = seg.df.train, ntree = 3000,
importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 3000
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 23.59%
## Confusion matrix:
##              Moving up Suburb mix Travelers Urban hip class.error
## Moving up           29         19         0         1  0.40816327
## Suburb mix          19         36         3         1  0.38983051
## Travelers            0          3        48         0  0.05882353
## Urban hip            0          0         0        36  0.00000000

importance(seg.rf)

##           Moving up Suburb mix   Travelers Urban hip MeanDecreaseAccuracy
## age       59.926151  44.013275 122.6900323 86.496891           129.354271
## gender    13.161197  -3.690088  -3.6665717  9.174039             7.757333
## income    22.259442  17.992316  15.8721495 78.262846            67.554326
## kids      18.263661  14.264086  55.5604028  6.410428            53.827310
```

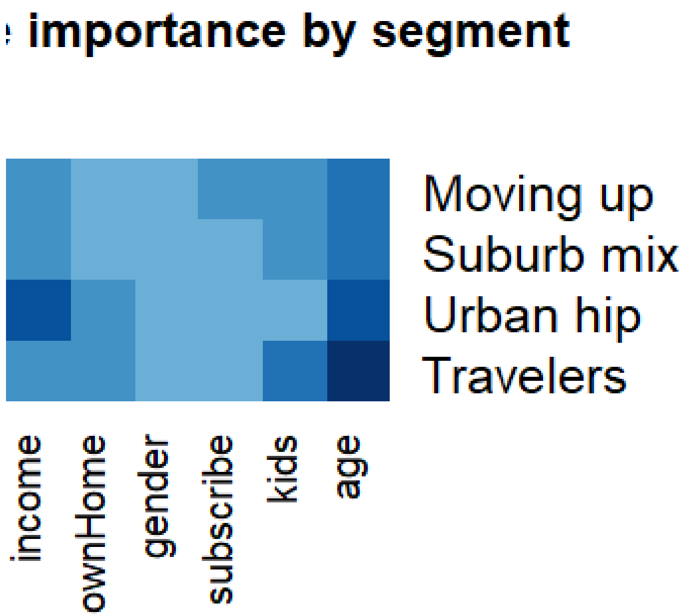
```
## ownHome    4.124127  -9.036638  22.6148866 19.842501            15.964989
## subscribe 18.588573   9.460176   0.4312472 -4.130187            17.858784
##           MeanDecreaseGini
## age              62.321942
## gender            3.356217
## income           36.212893
## kids             20.634224
## ownHome           4.941645
## subscribe         3.010284
```

```
varImpPlot(seg.rf, main="Variable importance by segment")
```

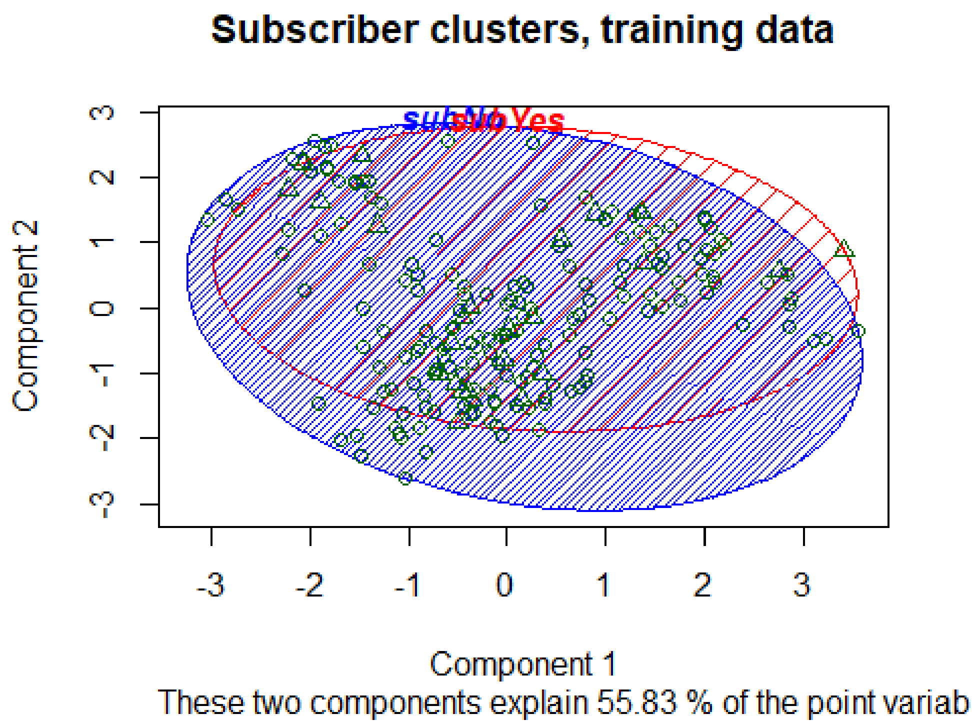



```
library(gplots)

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

library(RColorBrewer)


heatmap.2(t(importance(seg.rf)[ , 1:4]),
          col=brewer.pal(9, "Blues"),
          dend="none", trace="none", key=FALSE,
```

```
          margins=c(10, 10),
          main="Variable importance by segment"
          )
```




```
#### predict subscription status

#### using random forest

set.seed(92118)
train.prop  <- 0.65
train.cases <- sample(nrow(seg.df), nrow(seg.df)*train.prop)
sub.df.train <- seg.raw[train.cases, ]
sub.df.test  <- seg.raw[-train.cases, ]


# see how differentiated the subscribers are, in the training data

clusplot(sub.df.train[, -6], sub.df.train$subscribe, color=TRUE, shade=TRUE,
         labels=4, lines=0, main="Subscriber clusters, training data")
```



Prediction: Identifying potential Customers*

We now turn to another use for classification: to predict potential customers. An important business question-especially in high-churn categories such as mobile subscriptions-is how to reach new customers. If we have data on past prospects that includes potential predictors such as demographics, and an outcome such as purchase, we can develop a model to identify customers for whom the outcome is most likely among new prospects. In this section, we use a random forest model and attempt to predict subscription status from our data set seg.df. As usual with classification problems, we split the data into a training sample and a test sample:

```
library(randomForest)
set.seed(11954)
(sub.rf <- randomForest(subscribe ~ ., data=sub.df.train, ntree=3000))

##
## Call:
##  randomForest(formula = subscribe ~ ., data = sub.df.train, ntree = 3000)
##                Type of random forest: classification
##                      Number of trees: 3000
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 14.87%
## Confusion matrix:
##        subNo subYes class.error
```

```
## subNo    166      4  0.02352941
## subYes    25      0  1.00000000
```

```r
# try again with more trees, and balanced classes using sampsize
set.seed(11954)
(sub.rf <- randomForest(subscribe ~ ., data=sub.df.train, ntree=3000,
                       sampsize=c(25, 25)) )
```

```
##
## Call:
##  randomForest(formula = subscribe ~ ., data = sub.df.train, ntree = 3000,
sampsize = c(25, 25))
##                Type of random forest: classification
##                      Number of trees: 3000
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 29.74%
## Confusion matrix:
##        subNo subYes class.error
## subNo    128     42   0.2470588
## subYes    16      9   0.6400000
```

```r
# predict the holdout data
sub.rf.sub <- predict(sub.rf, sub.df.test)
# confusion matrix
table(sub.rf.sub, sub.df.test$subscribe)
```

```
##
## sub.rf.sub subNo subYes
##     subNo     79      9
##     subYes    11      6
```

```r
library(mclust)
adjustedRandIndex(sub.rf.sub, sub.df.test$subscribe)
```

```
## [1] 0.1928668
```

```r
library(psych)
```

```
##
## Attaching package: 'psych'

## The following object is masked from 'package:randomForest':
##
##     outlier

## The following object is masked from 'package:mclust':
##
##     sim
```

```r
cohen.kappa(cbind(sub.rf.sub, sub.df.test$subscribe))
```

```
## Call: cohen.kappa1(x = x, w = w, n.obs = n.obs, alpha = alpha, levels =
levels)
##
## Cohen Kappa and Weighted Kappa correlation coefficients and confidence
boundaries
##                    lower estimate upper
## unweighted kappa 0.025     0.26   0.5
## weighted kappa   0.025     0.26   0.5
##
##  Number of subjects = 105
```

With an adjusted Rand Index = 0.19 and Cohen's kappa = 0.26 (confidence interval 0.025-0.50), the model identifies subscribers in the test data modestly better than chance.

How could we further improve prediction? We would expect to improve predictive ability if we had more data: additional observations of the subscriber group and additional predictor variables. We have described prediction using a random forest model, but there are many other approaches such as logistic regression and other machine learning algorithms

With a difficult problem-predicting a low incidence group, in data where the groups are not well-differentiated, and with a small sample-the random forest model performs modestly yet perhaps surprisingly well. There are no magic bullets in predictive modeling, but if you use the many tools available in R, avoid pitfalls such as class imbalance, and interpret results in terms of the business action, you will have good odds to achieve positive results.