STAT 318/462: Data Mining
Assignment 3
Due Date: 3pm, 14th October, 2019

Your printed assignment must be submitted in the STAT318/462 assignment box on the fourth floor of the Erskine building (by MATH/STAT reception).

You may do the assignment by yourself or with one other person from the same cohort (300-level students cannot work with 400-level students). If you hand in a joint assignment, you will each be given the same mark. Marks will be lost for unexplained, poorly presented and incomplete answers. Whenever you are asked to do computations with data, feel free to do them any way that is convenient. If you use *R* (recommended), please provide your code. All figures and plots must be clearly labelled.

1. **(10 marks)** In this question, you will fit regression trees to predict *sales* using the Carseats data. This dataset has been divided into training and testing sets: `carseatsTrain` and `carseatsTest.csv` (download these sets from Learn). Use the `tree()` and `gbm()` *R* functions to answer this question (see Section 8.3 of the course textbook).

   (a) Fit a regression tree to the training set (do not prune the tree). Plot the tree and interpret the results. What are the test and training MSEs for your tree?

   (b) Use the `cv.tree()` *R* function to prune your tree (use your judgement here). Does the pruned tree perform better?

   (c) Fit a bagged regression tree and a random forest to the training set. What are the test and training MSEs for each model? Was decorrelating trees an effective strategy for this problem?

   (d) Fit a boosted regression tree to the training set. Experiment with different tree depths, shrinkage parameters and the number of trees. What are the test and training MSEs for your best tree? Comment on your results.

   (e) Which model performed best and which predictors were the most important in this model?

```
> tree.fit = tree(Sales~., train)
> summary(tree.fit)

Regression tree:
tree(formula = Sales ~ ., data = train)
Variables actually used in tree construction:
[1] "Price"       "Age"         "CompPrice"   "Education"   "Advertising"
"Income"
Number of terminal nodes:  23
Residual mean deviance:  3.296 = 913 / 277
Distribution of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -4.994  -1.178   0.037   0.000   1.390   4.627

> train.pred = predict(tree.fit, train)
> train.mse = mean((train$Sales-train.pred)^2)
> train.mse
[1] 3.043394
> test.pred = predict(tree.fit, test)
> test.mse = mean((test$Sales-test.pred)^2)
> test.mse
[1] 6.03393
```

(a) Answer : As has been shown in the figure 1.(a) and the code as above,

There are six variables have actually been used, which are "Price", "Age", "CompPrice", "Ed
ucation", "Advertising" and "Income", and the number of terminal nodes are 23.
The train error is **3.043394** and the test error is **6.03393**

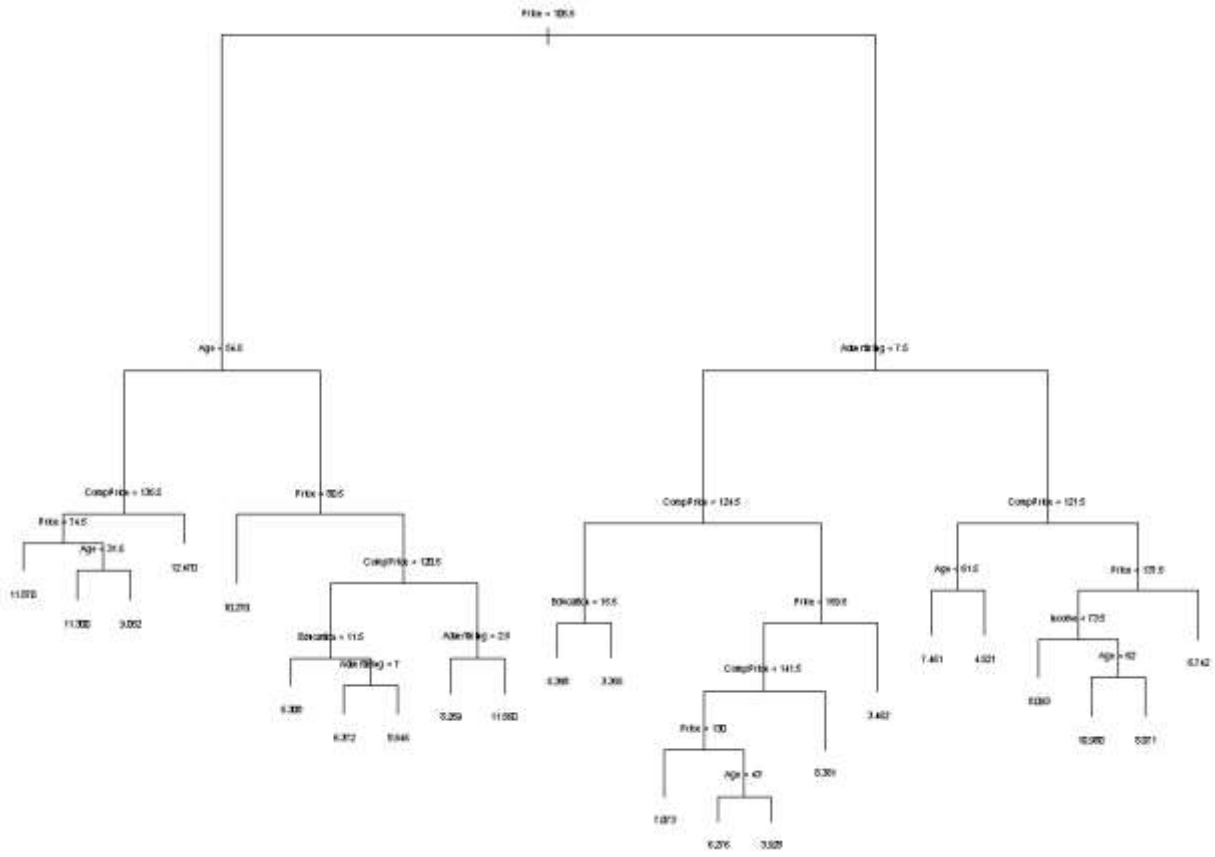


Figure 1.(a) `Regression tree`

(b)

```
> set.seed(10)
> cv.fit=cv.tree(tree.fit)
> plot(cv.fit$size, cv.fit$dev, main = "The relationship between CVdev and
 cvsize",type="b")
```

Answer: From Figure 1 (b), the lowest size is “11”

```
> prune.fit = prune.tree(tree = tree.fit, best = 11)
> plot(prune.fit)
> text(prune.fit, pretty = 0, cex = 0.5)
> #after pruning
> prune.train.pred = predict(prune.fit, train)
> prune.train.mse = mean((train$Sales-prune.train.pred)^2)
> prune.train.mse
[1] 4.38325
> prune.test.pred = predict(prune.fit, test)
> prune.test.mse = mean((test$Sales-prune.test.pred)^2)
> prune.test.mse
[1] 6.05599
```

However, from the code above, after pruning, the train error increase to 4.38325 and test err
or slightly increase to 6.05599, which suggests the pruned tree did not perform better.

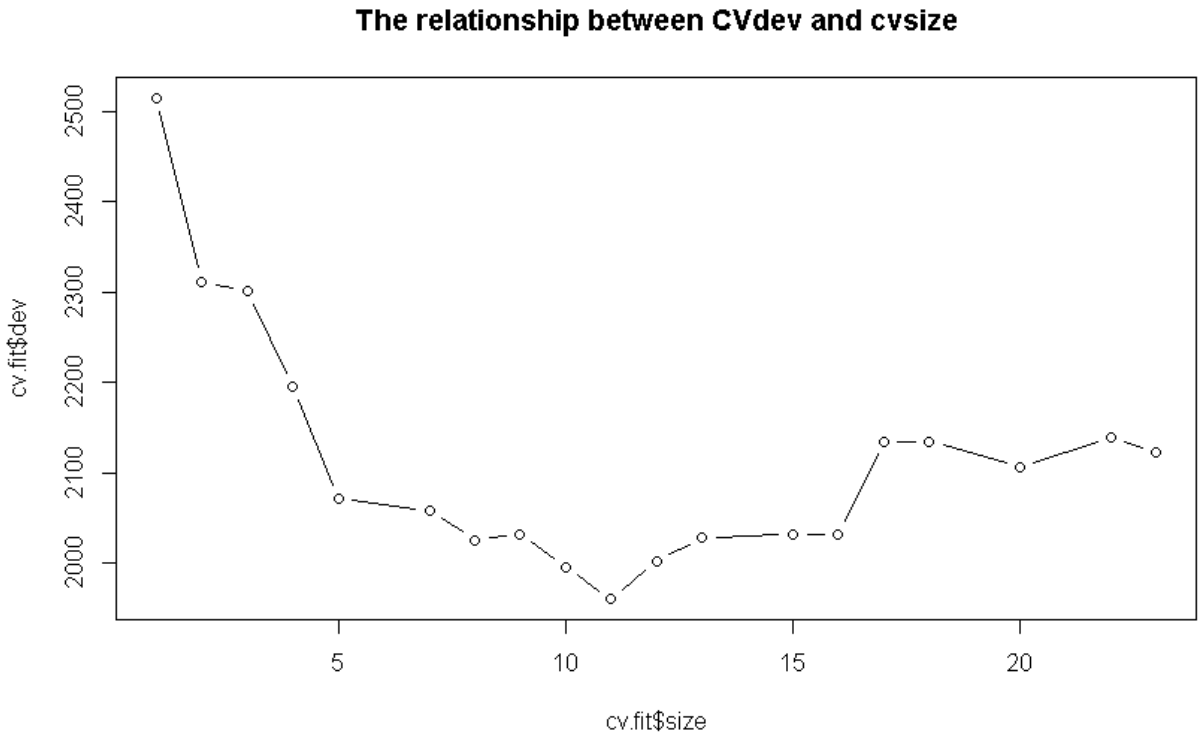


Figure 1.(b) The relationship between CVdev and cvsize

(C)

```
> #Bagging
> library(randomForest)
> bag.fit = randomForest(Sales~., data = train, mtry = 3 , ntree = 1000 ,i
mportance = TRUE)
> bag.fit

Call:
 randomForest(formula = Sales ~ ., data = train, mtry = 3, ntree = 1000,
    importance = TRUE)
               Type of random forest: regression
                     Number of trees: 1000
No. of variables tried at each split: 3

          Mean of squared residuals: 5.27523
                    % Var explained: 34.9
> #after bagging
> bag.train.pred = predict(bag.fit, train)
> bag.train.mse = mean((train$Sales-bag.train.pred)^2)
> bag.train.mse
[1] 1.059408
> bag.test.pred = predict(bag.fit, test)
> bag.test.mse = mean((test$Sales-bag.test.pred)^2)
> bag.test.mse
[1] 4.396091
> #randomForest
> rf.fit = randomForest(Sales~., data = train, importance = TRUE)
> rf.fit

Call:
 randomForest(formula = Sales ~ ., data = train, importance = TRUE)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 3
```

```
          Mean of squared residuals: 5.269197
                    % Var explained: 34.97
> #after rf
> rf.train.pred = predict(rf.fit, train)
> rf.train.mse = mean((train$Sales-rf.train.pred)^2)
> rf.train.mse
[1] 1.058377
> rf.test.pred = predict(rf.fit, test)
> rf.test.mse = mean((test$Sales-rf.test.pred)^2)
> rf.test.mse
[1] 4.426227
```

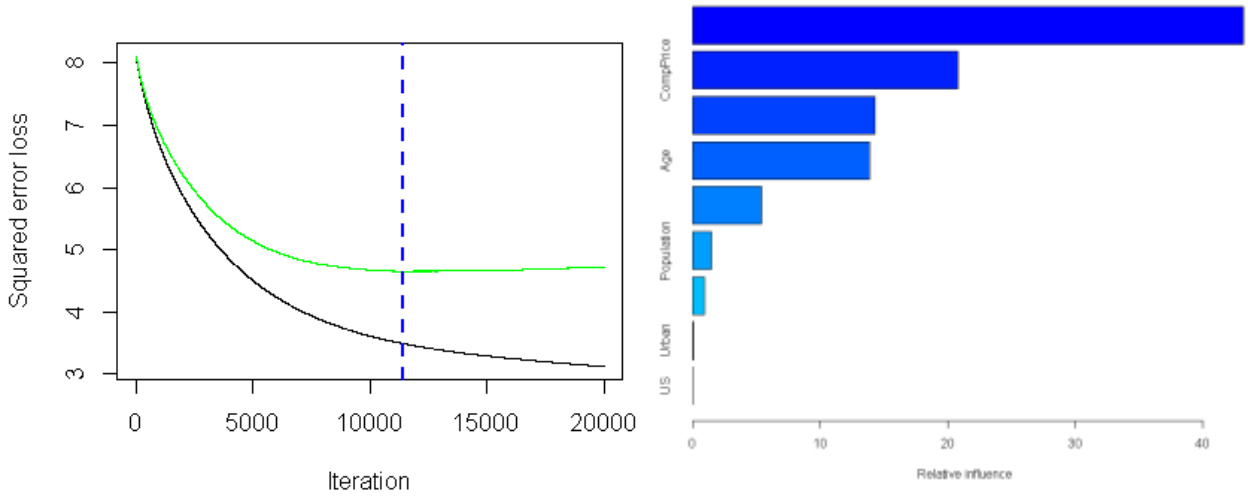
	Train MSE	Test MSE
Bagging	1.059408	4.396091
RF	1.058377	4.426227

From the code above, we can get the lower train MSE and lower test MSE as shown in the Table, which suggests that decorrelating trees was an effective strategy for this problem.

(d)

Using n.trees = 11408, shrinkage = 0.001, we get:

```
> library(gbm)
> set.seed(10)
> boost.fit=gbm(Sales ~ . ,data=train, distribution="gaussian", n.trees =
20000, shrinkage = 0.001, cv.folds=5)
> best.iter = gbm.perf(boost.fit,method='cv')
> best.iter
[1] 11408
> summary(boost.fit)
                     var    rel.inf
Price              Price 39.3538183
CompPrice      CompPrice 20.5270515
Age                  Age 14.2350753
Advertising Advertising 13.0119174
Income            Income  6.9486922
Population    Population  4.0732032
Education      Education  1.5063011
Urban              Urban  0.2056938
US                   US  0.1382473
> boost.fit=gbm(Sales ~ . ,data=train, distribution="gaussian", n.trees =
best.iter, shrinkage = 0.001, interaction.depth = 1)
> summary(boost.fit)
                     var     rel.inf
Price              Price 43.23500051
CompPrice      CompPrice 20.78566958
Advertising Advertising 14.28949436
Age                  Age 13.86266002
Income            Income  5.41494993
Population    Population  1.44733798
Education      Education  0.89838120
Urban              Urban  0.06650642
US                   US  0.00000000
> boost.train.pred = predict(boost.fit, train, n.trees=best.iter)
> boost.train.mse = mean((train$Sales-boost.train.pred)^2)
> boost.train.mse
[1] 3.493034
> boost.test.pred = predict(boost.fit, test, n.trees=best.iter)
> boost.test.mse = mean((test$Sales-boost.test.pred)^2)
> boost.test.mse
[1] 3.775372
```



Answer :
As has shown above, we get test error is 3.775372 for n.trees = 11408 and shrinkage = 0.001. Similarly, when increasing the shrinkage, the n.trees size decreases correspondingly, and we can get different testing error as below table. Obviously, the n=trees is 1585 and shrinkage = 0.01 performs the best with the lowest testing error is 3.726715.

n.trees	**shrinkage**	**train.mse**	**test.mse**
20000(11408)	0.001	3.493034	3.775372
5000(3295)	0.005	3.245314	3.790217
1585	0.01	3.273168	3.726715

(e)

In conclusion, the Boosted regression tree model performs the best, and (n.trees = 11408 and shrinkage = 0.001) one with the lowest test error, which is 3.726715. And the most important predictors from the code are “Price”, “CompPrice”, “Age” and “Advertising”.

2. **(4 marks)** Using the itemset lattice in Figure 1 (on page 3) and the transactions given in Table 1, answer the following questions. Assume *minsup* = 30%.

   (a) Label each node in the itemset lattice with the following letter(s):

   M: if the node is a maximal frequent itemset;
   C: if the node is a closed frequent itemset;
   F: if the node is frequent, but not maximal nor closed;
   I: if the node is infrequent.

Transaction ID	Items Bought	Transaction ID	Items Bought
1	$\{a, d, e\}$	6	$\{a, b, d\}$
2	$\{b, c, d\}$	7	$\{b, d\}$
3	$\{a, d, e\}$	8	$\{a, b\}$
4	$\{a, b, c, d, e\}$	9	$\{a, b, d\}$
5	$\{b, d, e\}$	10	$\{b, d, e\}$

Table 1: Market basket transactions for Question 2.

(a)

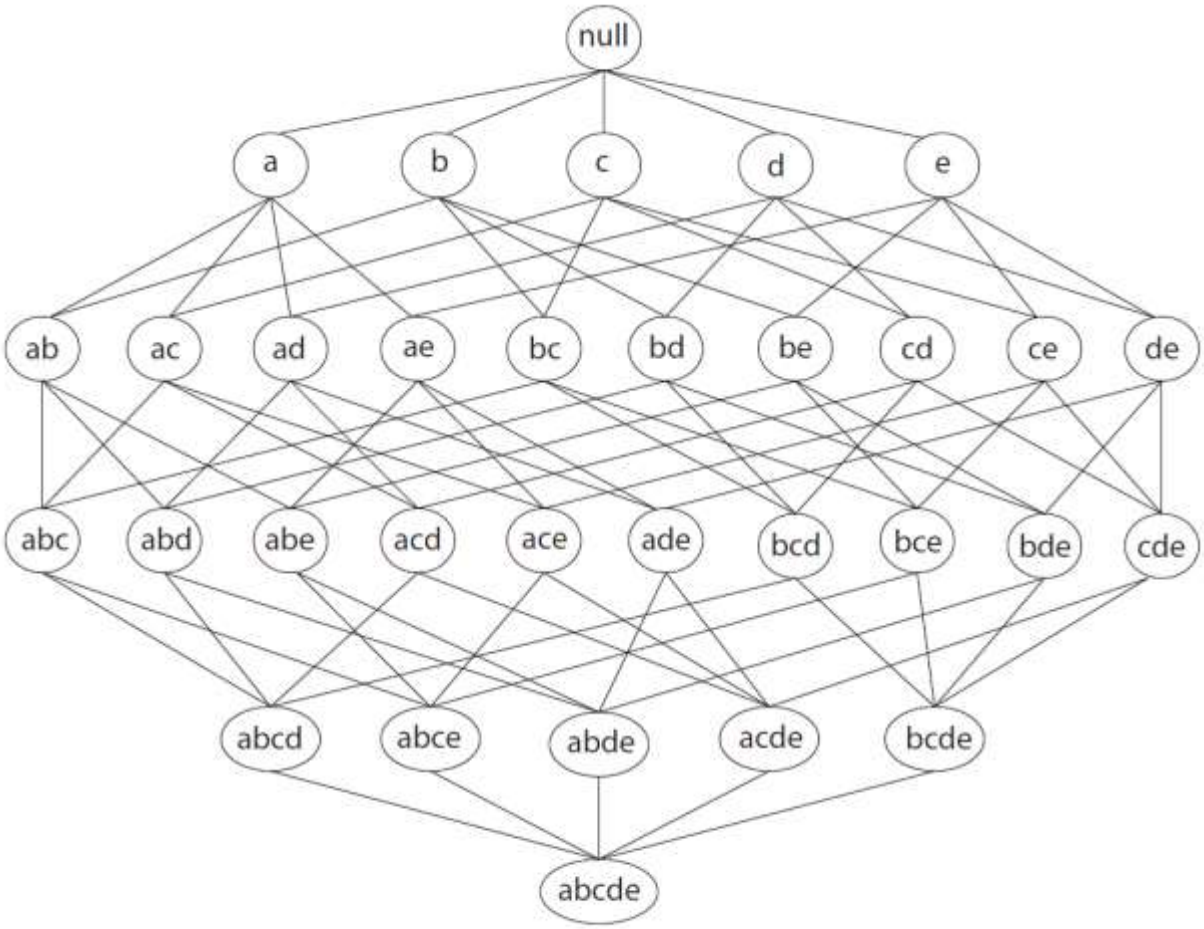


Figure 1: Itemset lattice for Question 3.

(b) Find the confidence and lift for the rule $\{d, e\} \rightarrow \{b\}$. **Comment on what you find.**

In this context, confidence {d,e} → {b} = 60% means there are 60% chance that the customer purchased item {d,e} that also purchased item {b}.

In this context, lift {d,e} → {b} = 0.75 <1, item {d,e} and item {b} are negatively correlated, which means the occurrence of item {d,e} reduces the likelihood of item {b}.

3. **(6 marks)** This question considers clustering the A3data2 data (download from the Learn page). **Use x_1 and x_2 for clustering,** the third variable 'Cluster' is the actual cluster label of each point. This variable is included so that you plot the clusters and assess the performance of each clustering method.

   (a) Perform k-means clustering using $k = 3$. Plot the clustering using a different colour for each cluster.

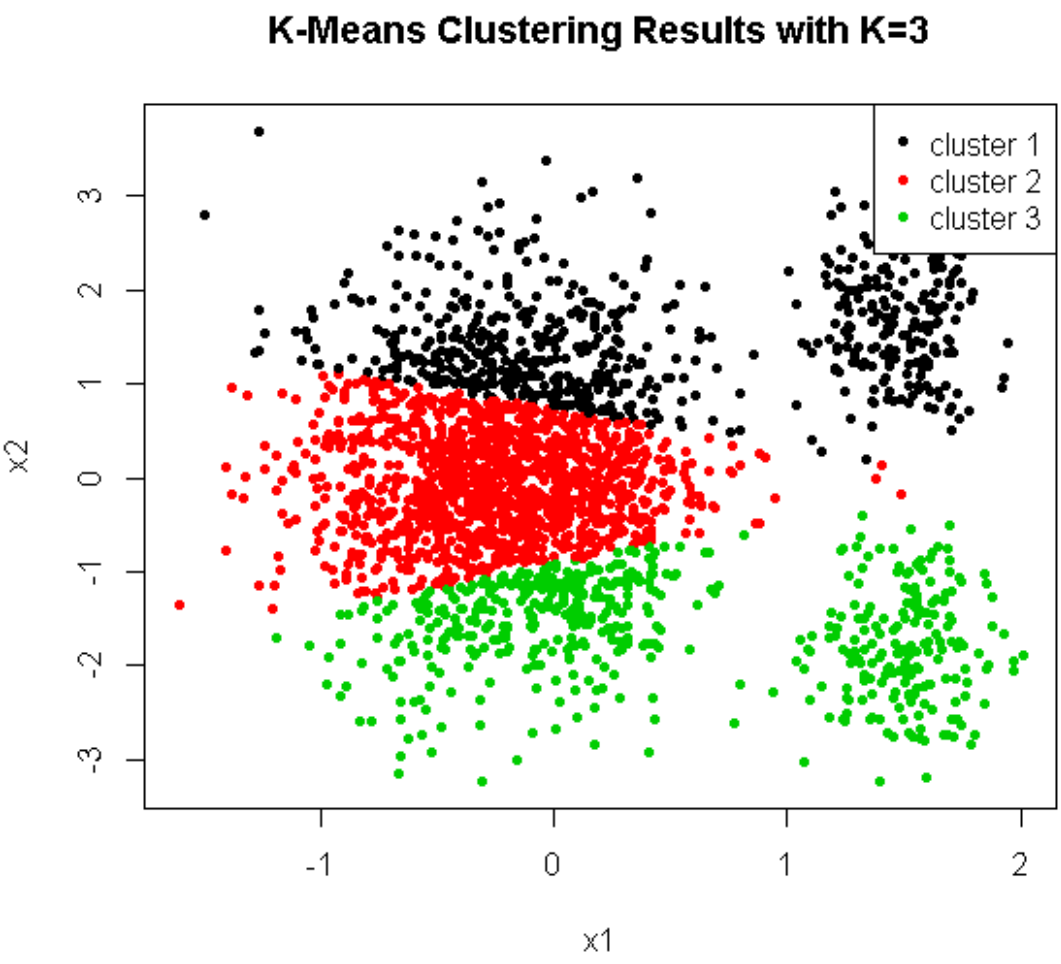
   (b) Using hierarchical clustering with complete linkage and Euclidean distance, cluster the data, provide a dendrogram and plot the clustering with 3 clusters. Repeat using single linkage.

   (c) Comment on your results from parts (a) and (b). Provide possible explanations for each clustering obtained.

   (d) Rescale your data using the R function `scale(Data, center=TRUE, scale=TRUE)` and repeat parts (a) and (b). Does rescaling improve your results? Comment on your results **and** provide possible explanations for each clustering obtained.

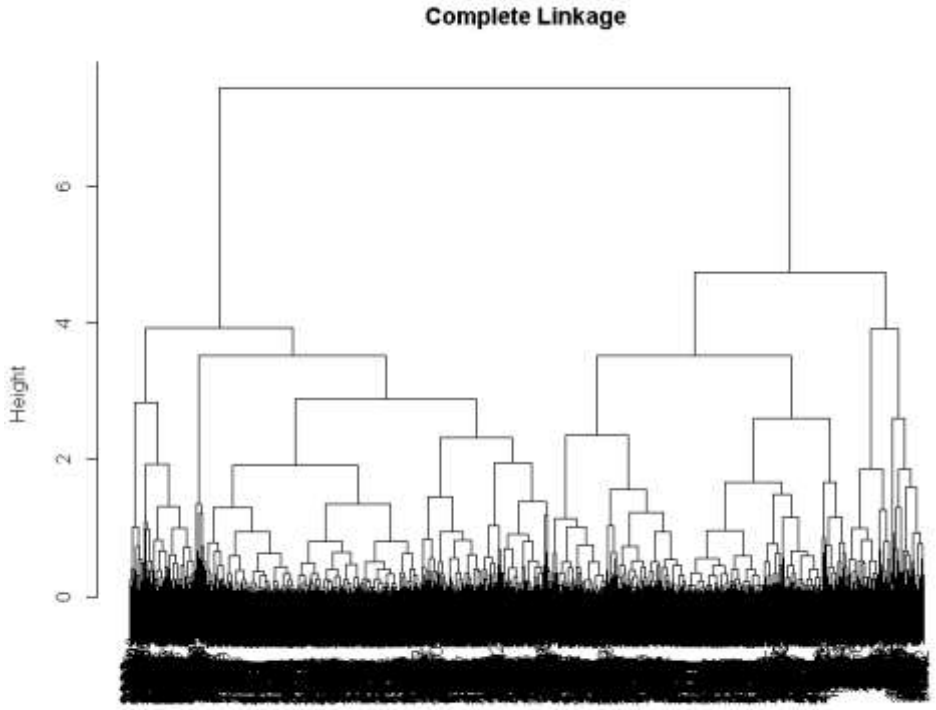
(a)

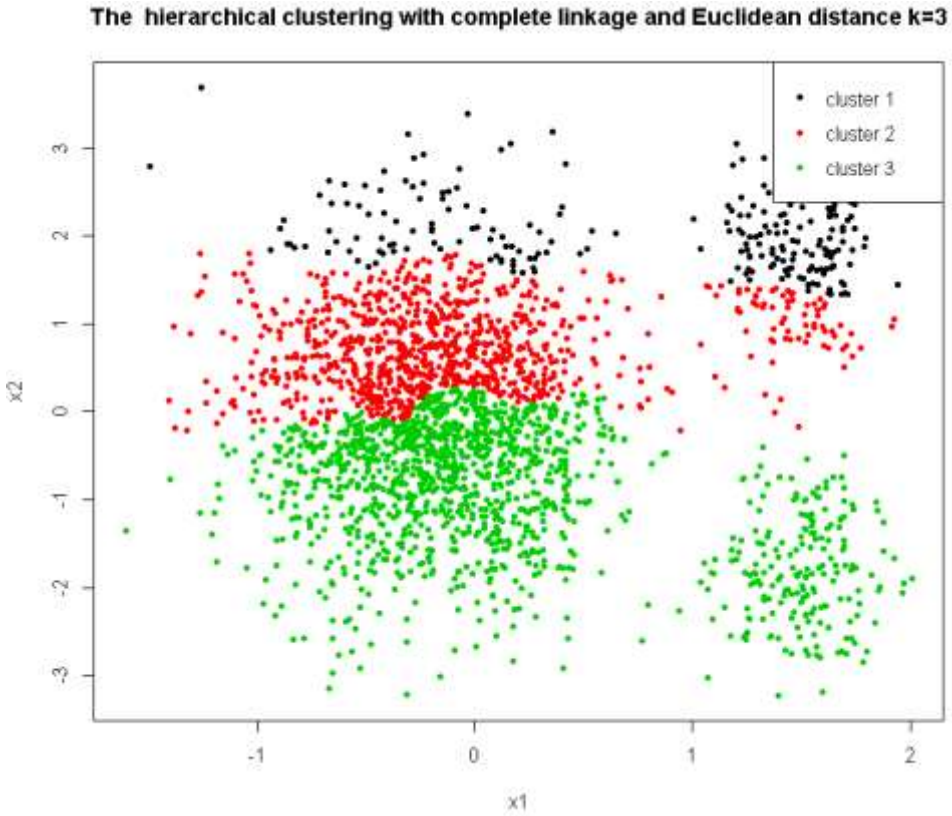
```
> library(cluster)
> A3data = read.csv(file = 'A3data2.csv', header = TRUE)
> km.out = kmeans(A3data[, 1:2], 3, nstart = 100)
> plot(A3data[, 1:2], col=(km.out$cluster), main="K-Means Clustering Resul
ts with K=3", pch =20)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"), col
 =c(1,2,3), pch = 20)
```



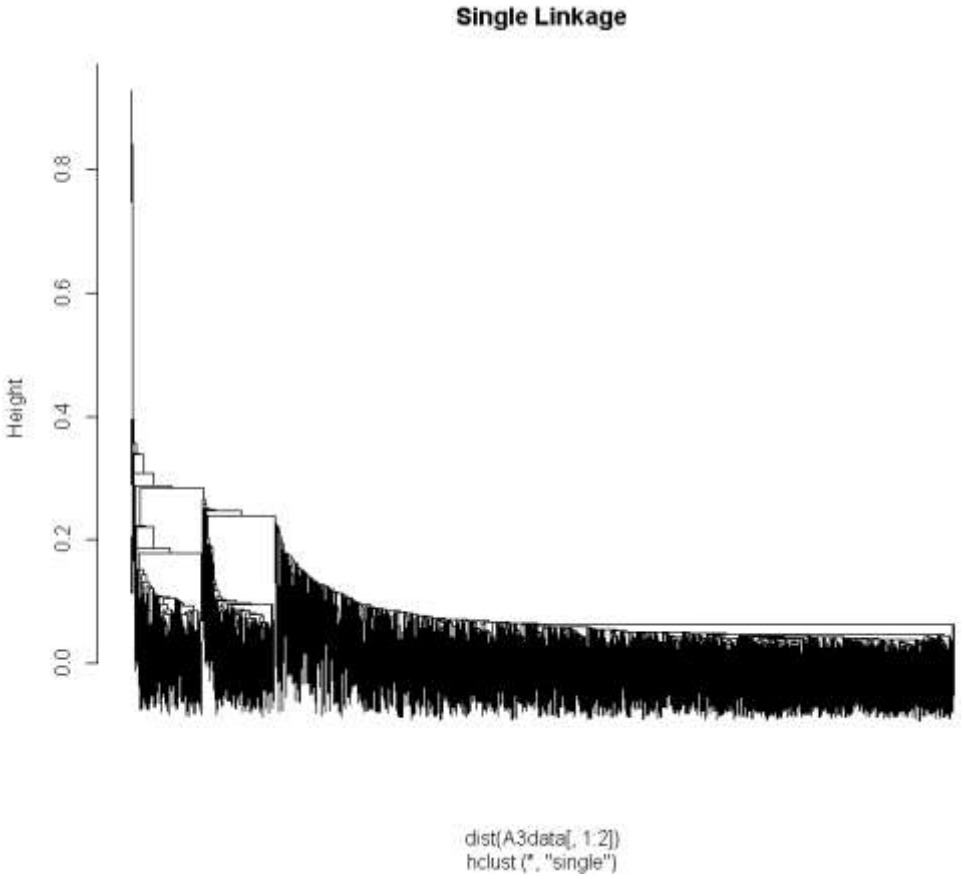
(b)

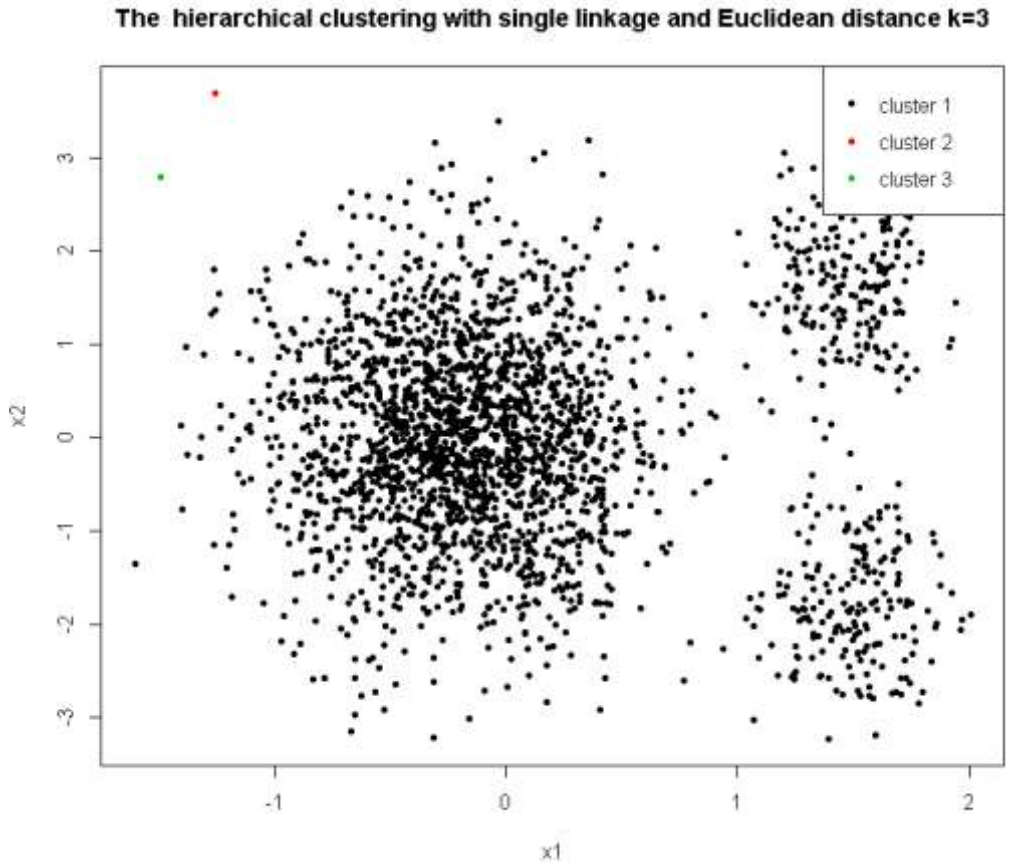
```
> #hc complete
> hc.complete = hclust(dist(A3data[, 1:2]), method="complete")
> plot(hc.complete, main = "Complete Linkage")
> plot(A3data[, 1:2], col=(cutree(hc.complete, 3) ), main="The  hierarchic
al clustering with complete linkage and Euclidean distance k=3", pch =20)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"),
+        col = c(1, 2, 3), pch = 20)
```





```
> #hc single
> hc.single=hclust(dist(A3data[, 1:2]),method="single")
> plot(hc.single, main="Single Linkage", labels=FALSE,cex=0.5)
> plot(A3data[, 1:2], col=(cutree(hc.single, 3) ), main="The  hierarchical
 clustering with single linkage and Euclidean distance k=3", pch =20)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"),
+        col = c(1, 2, 3), pch = 20)
```



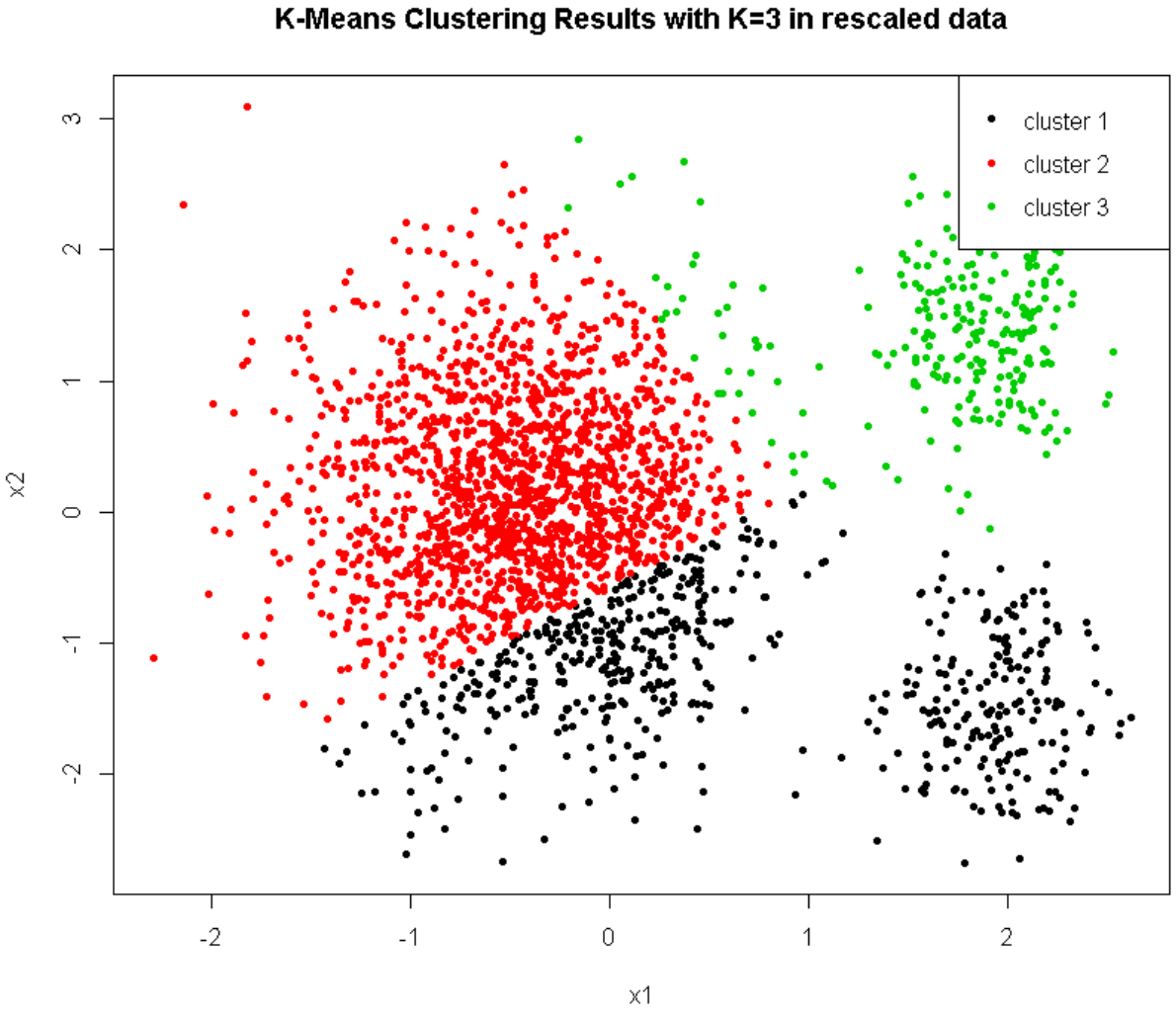


(c)

Answer: From figures above, we can tell the clusters are 3 globular shape with different sizes and densities. After applying K-means model, the largest cluster was split into 3 parts wrongly even though the other two cluster seems to be better classified. After applying complete linkage model, not just the largest one was split into 3 parts, the smaller clusters were also failed to be classified. The single linkage model was totally failed to be classified due to the two outliers, it is clear that the two outliers were classified into two classes and the rest shapes become the whole class. In a word, all three models did a very poor job on this classifying.

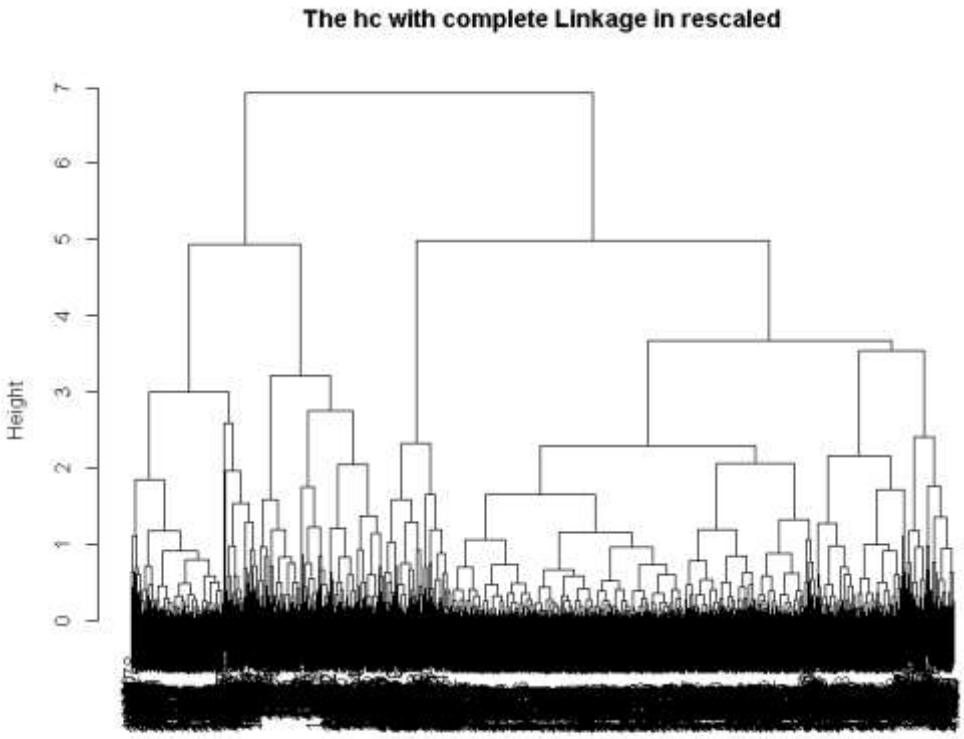
(d)

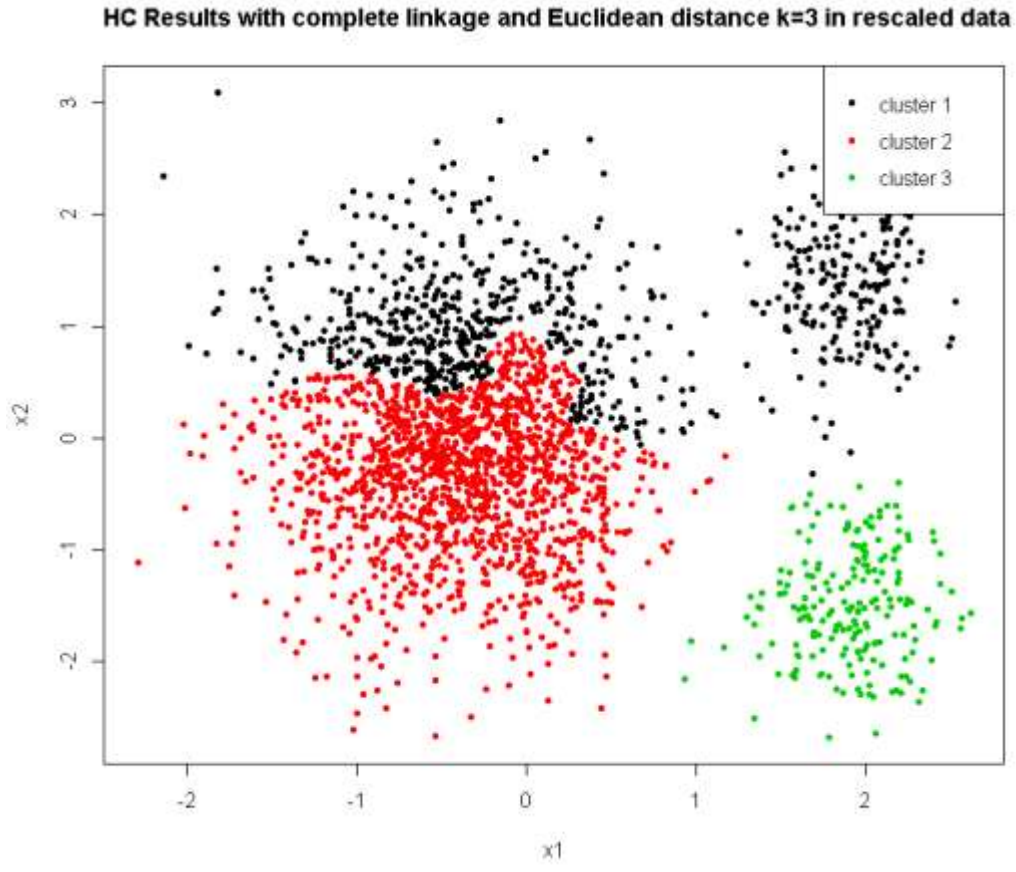
```
> #rescale
> Rescale3=scale(A3data[, 1:2], center=TRUE, scale=TRUE)
> # apply k-means
> set.seed(10)
> Rescale3.km.out=kmeans(Rescale3,3, nstart=20)
> plot(Rescale3, col = (Rescale3.km.out$cluster), main="K-Means Clustering
 Results with K=3 in rescaled data", pch =20)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"), col
 = c(1, 2, 3), pch = 20)
```



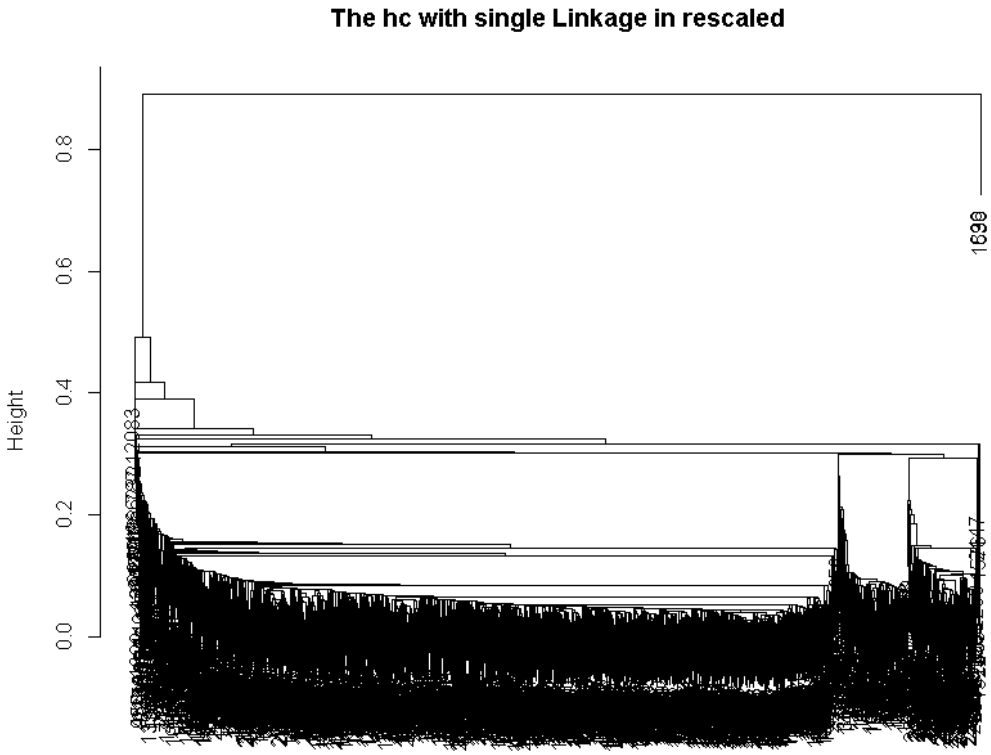

```
> # rescale HC complete
> rescaled.complete = hclust(dist(Rescale3), method="complete")
```

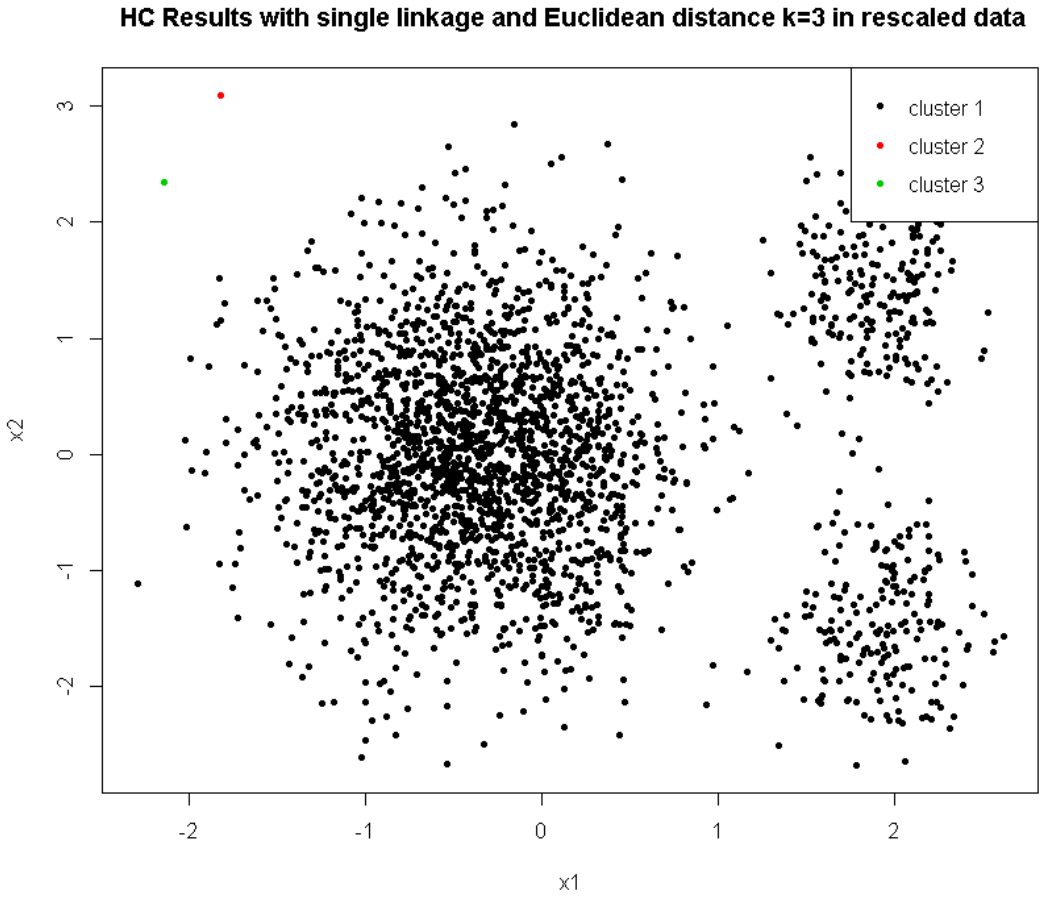
```
> plot(rescaled.complete, main = "The hc with complete Linkage in rescaled
")
> plot(Rescale3, col = (cutree(rescaled.complete, 3) ), main=" HC Results
with complete linkage and Euclidean distance k=3 in rescaled data", pch =2
0)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"),
+        col = c(1, 2, 3), pch = 20)
```





```
# rescale HC single
> rescaled.single = hclust(dist(Rescale3), method="single")
> plot(rescaled.single, main = "The hc with single Linkage in rescaled")
> plot(Rescale3, col = (cutree(rescaled.single, 3) ), main=" HC Results wi
th single linkage and Euclidean distance k=3 in rescaled data", pch =20)
> legend("topright", legend = c("cluster 1", "cluster 2","cluster 3"),
+        col = c(1, 2, 3), pch = 20)
```





Answer: After using recalled data with three models, we can tell the single model was still influenced by the two outliers and did a poor job on classification, however the complete linkage model improved a lot, it was be able to classify the two smaller clusters into right classes whereas the largest cluster was still split into two parts wrongly. The k-means model was better than the un-rescaled one, however the result was still not good in terms of the largest cluster was still split into three parts.

4. (4 marks) In this question, you will fit support vector machines to the Banknote data from Assignment 2 (on the Learn page). **Only use the predictors x_1 and x_3 to fit your classifiers.**

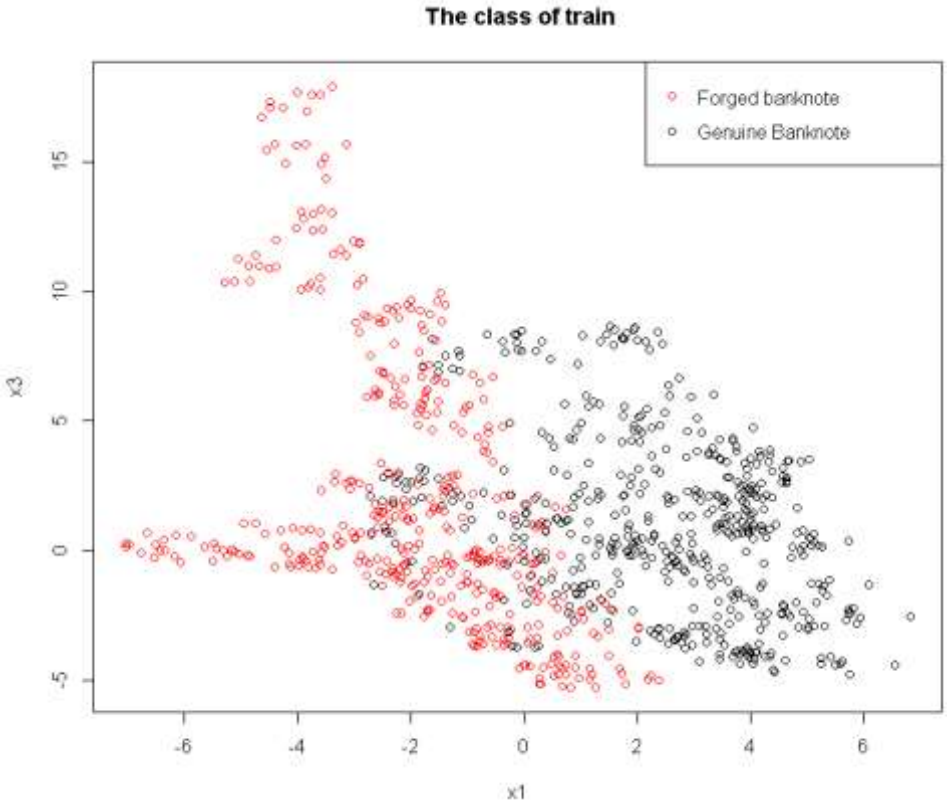
   (a) Is it possible to find a separating hyperplane for the training data? **Explain.**

   (b) Fit a support vector classifier to the training data using `tune()` to find the best `cost` value. Plot the best classifier and produce a confusion matrix for the testing data. **Comment on your results.**

   (c) Fit a support vector machine (SVM) to the training data using the radial kernel. Use `tune()` to find the best `cost` and `gamma` values. Plot the best SVM and produce a confusion matrix for the testing data. **Compare your results with those obtained in part (b).**

(a)

```
  train.bank = read.csv("BankTrain.csv", header = TRUE)[,c("x1","x3","y")]
> train.bank$y=as.factor(train.bank$y)
> test.bank = read.csv("Banktest.csv", header = TRUE)[,c("x1","x3","y")]
> test.bank$y=as.factor(test.bank$y)
> plot(train.bank[, c('x1', 'x3')], col = train.bank$y, main = ' The class
 of train data')
> legend("topright", legend = c("Forged banknote", "Genuine Banknote"), pc
h = c(1, 1), col = c(2, 1), text.col = "black")
```



Answer: For the figure above, it is clear there are some data of these two classes are overlapped, therefore, it is impossible to find a separating hyperplane for the training data.

(b)

```
> library(e1071)
> set.seed(10)
> tune.out = tune(svm, y ~ ., data = train.bank, kernel="linear", ranges=l
ist(cost=c(0.01,0.1,1,10,100,1000)))
> summary(tune.out)

Parameter tuning of ‘svm’:

- sampling method: 10-fold cross validation

- best parameters:
 cost
  0.1

- best performance: 0.1135417


> tune.out$best.parameters
  cost
2  0.1
> bestmodel=tune.out$best.model
> plot(bestmodel, test.bank)

> test.pred = predict(bestmodel, test.bank)
> table(test.pred, test.bank$y)

test.pred   0   1
        0 197  11
        1  39 165
```

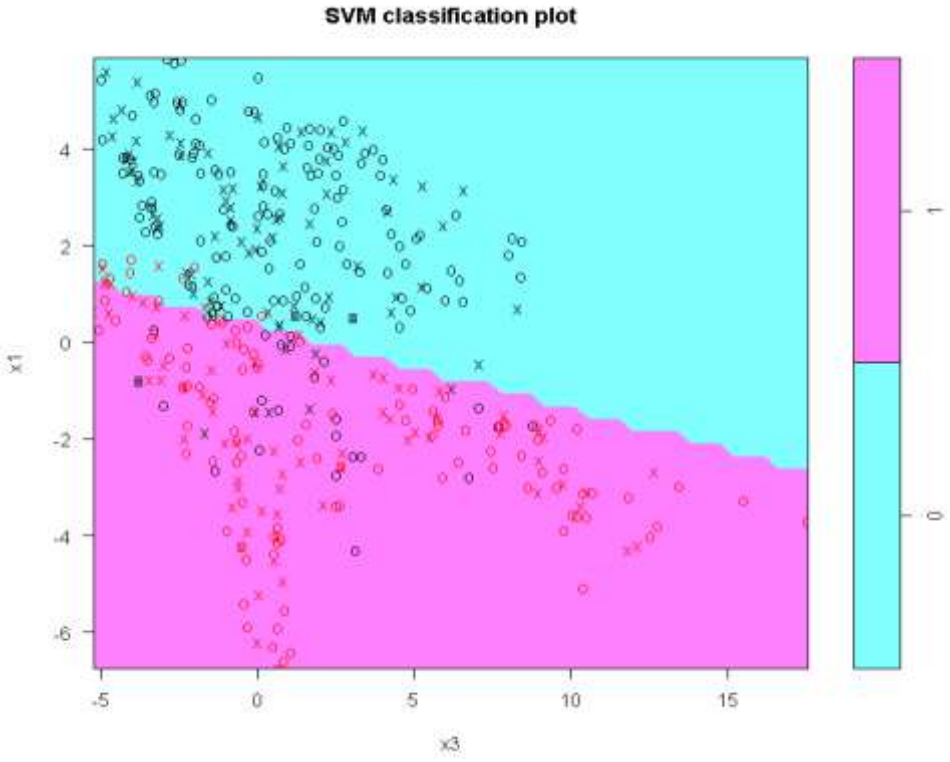


Figure 4.(b)

Answer: From the code above, the test error = (39+11) / 412= 12.14%, Precision is 80.88% ， Specificity is 83.47% and Sensitivity is 93.75%, the test error is very low and Precision is relative high, therefore this model is much useful.

(C)

```
> ##radial
> set.seed(10)
> tune.out = tune(svm, y ~ ., data = train.bank, kernel="radial", ranges=l
ist(cost=c(0.1,1.5,10,50,100,1000), gamma=c(0.5,1,2,3,4)))
> summary(tune.out)

Parameter tuning of 'svm':

- sampling method: 10-fold cross validation

- best parameters:
 cost gamma
   10     4

- best performance: 0.09479167


> tune.out$best.parameters
   cost gamma
27   10     4
> plot(tune.out$best.model, test.bank)

> test.pred.radial = predict(tune.out$best.model, test.bank)
> table(predict=test.pred.radial, truth=test.bank$y)
       truth
predict   0   1
      0 212  12
      1  24 164
```

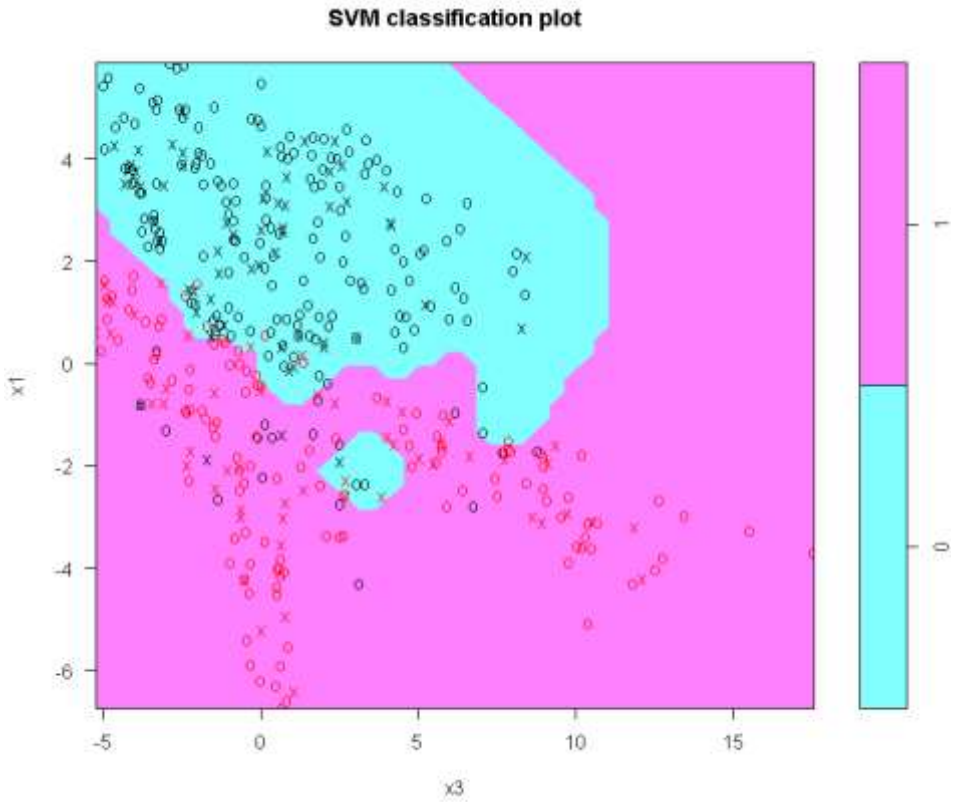


Figure 4.(c)

Answer: From the code above, the test error is 8.74%, Precision is 87.23%, Specificity is 89.83% and Sensitivity is 93.18%. Compare to the previous one, the test error is much lower and Precision is much higher, In a word, the radial kernel model did a better job on classifying the bank data.