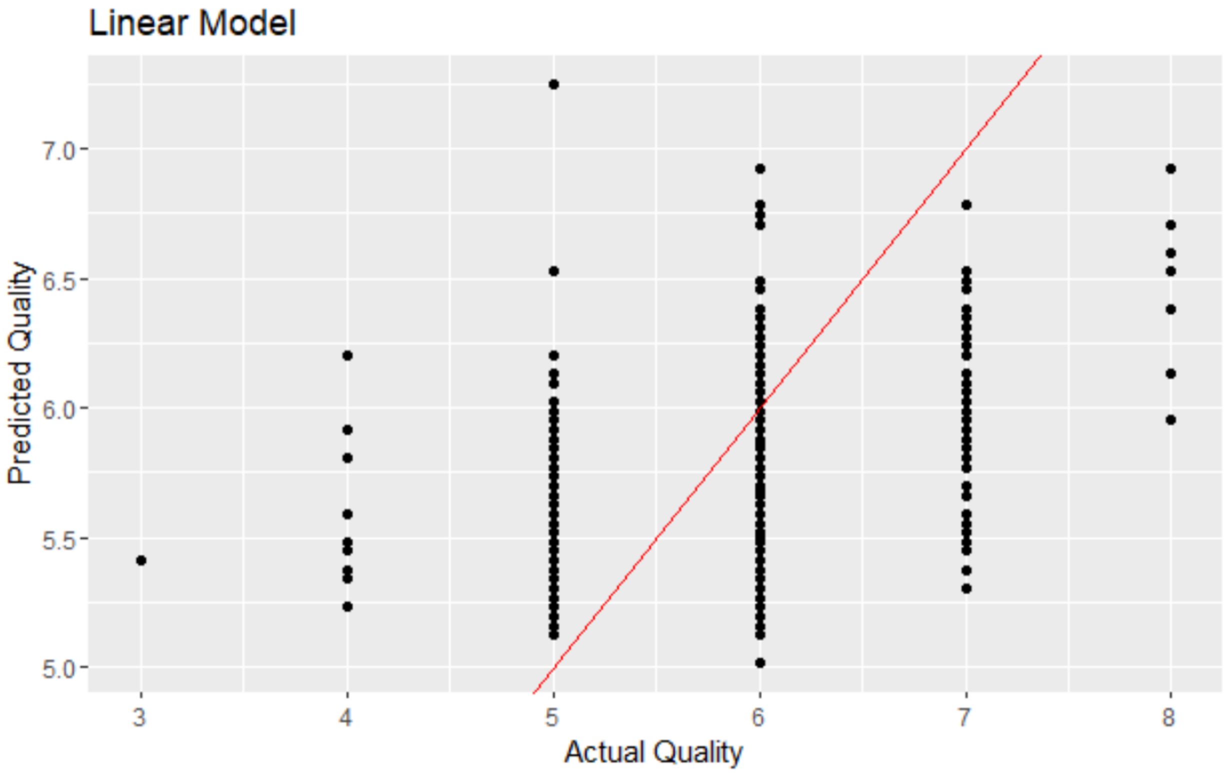
Part 1: Regression

Complete the following objectives utilizing the data set you selected as ideal for:

Linear Regression

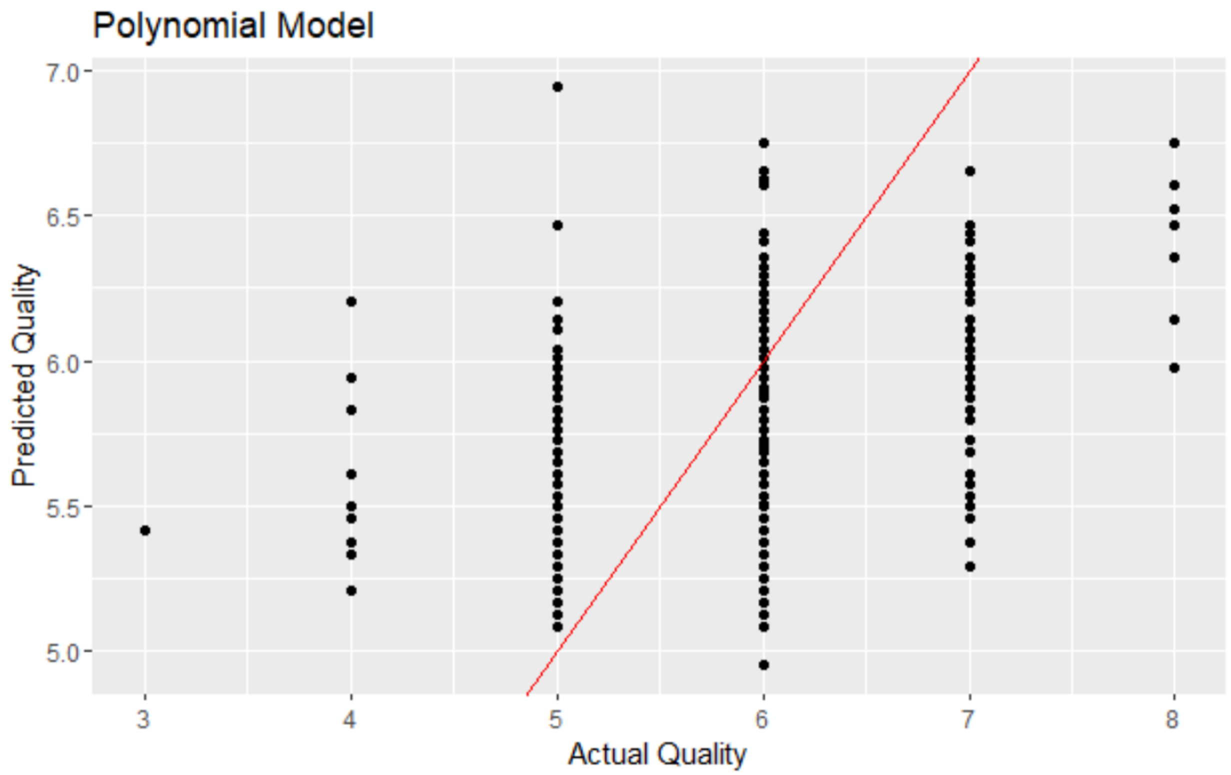
a)



```
"Linear Model MSE:  0.459945869270605"
```

The linear regression model uses only the alcohol content to predict the quality of the wine. The model has an MSE of about 0.460 on the test data.

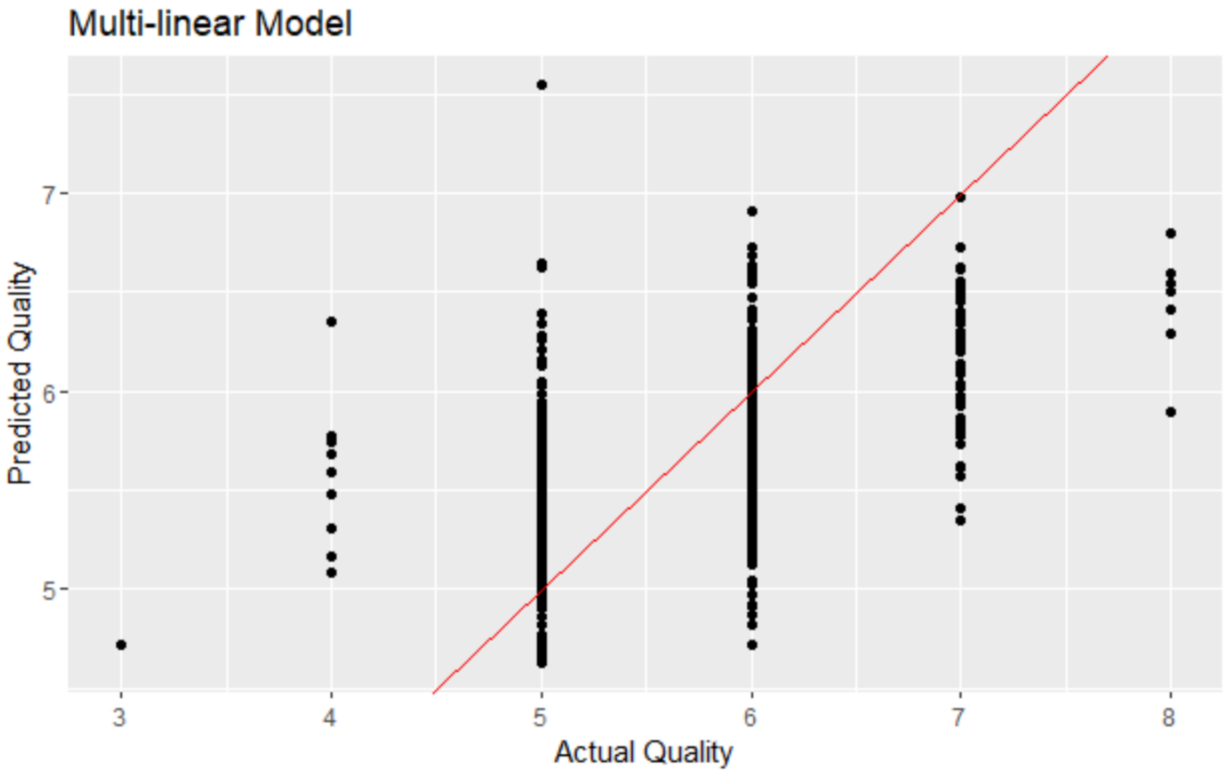
b)



```
Polynomial Model MSE:  0.458923441001458
```

This model uses a quadratic term (degree 2) for the alcohol content to predict wine quality. It has a slightly lower MSE of about 0.459 on the test data.

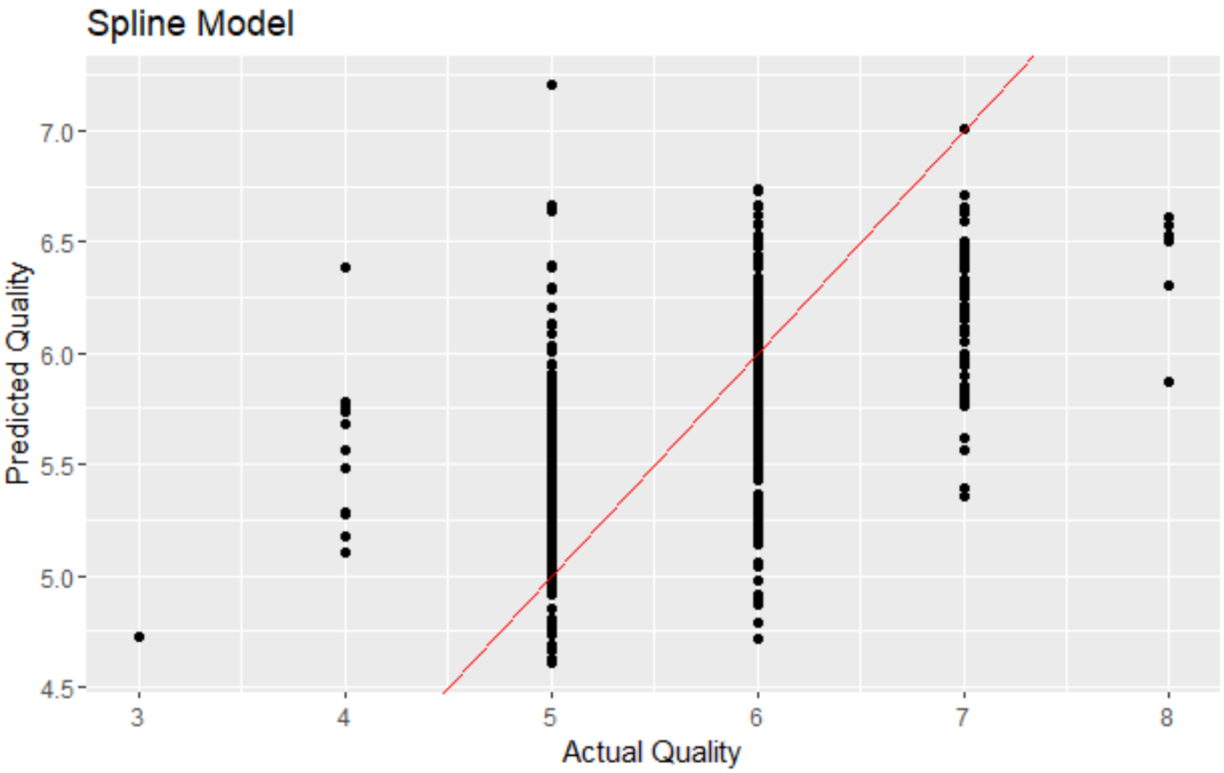
c)



```
Multi-linear Model MSE:  0.426564653304327
```

This model uses all available features in the dataset to predict wine quality. It has a noticeably lower MSE of about 0.427 on the test data.

d)

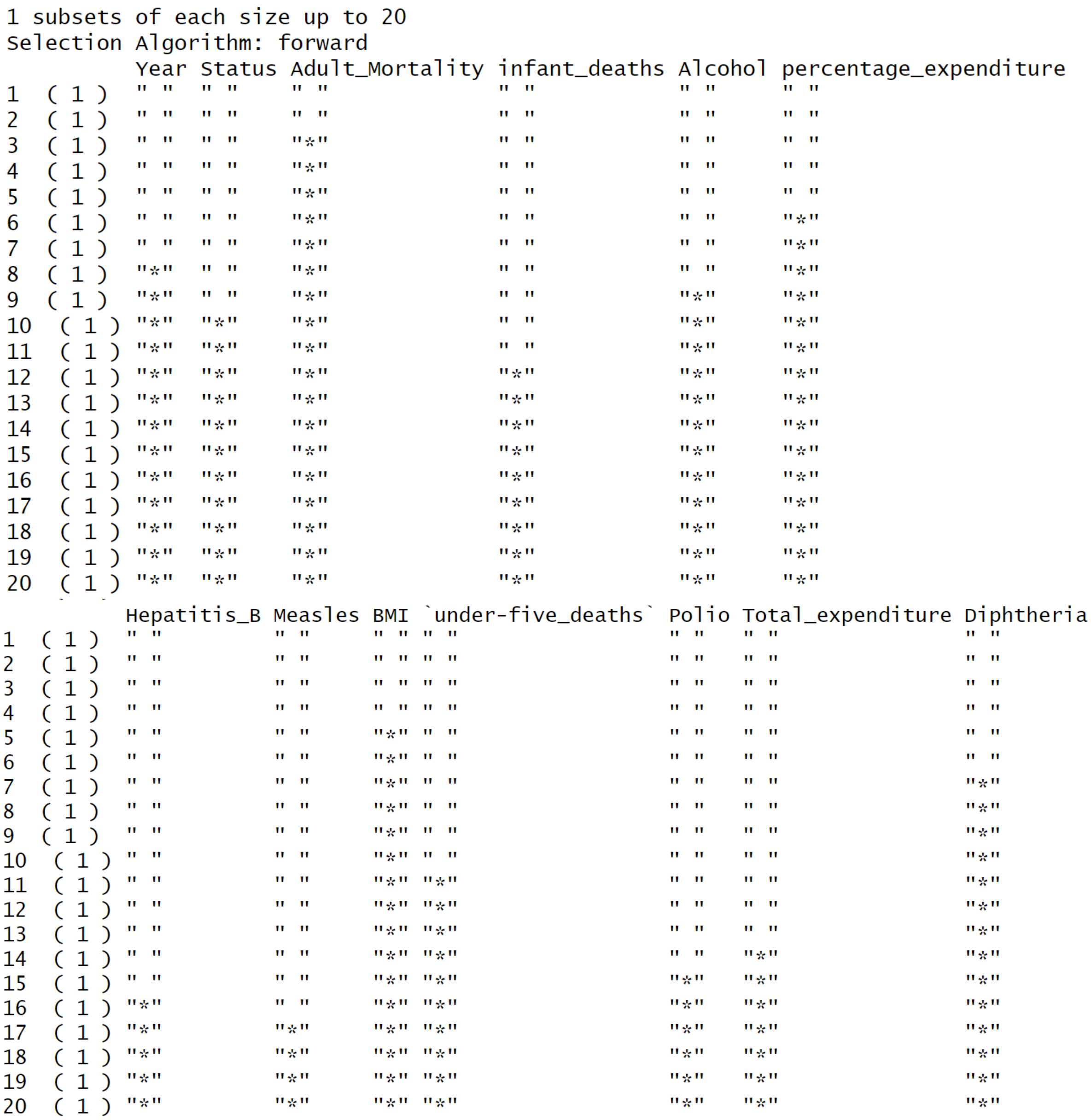


```
Spline Model MSE:  0.423194625548574
```

This model uses a natural spline transformation of the alcohol content, along with all other features in the dataset, to predict wine quality. The model encountered a warning about potential issues with the rank-deficient fit, which suggests that some of the predictors may be highly correlated. Despite this, it has the lowest MSE of about 0.423 on the test data.

Part2: Feature Selection / Model Optimization Methods

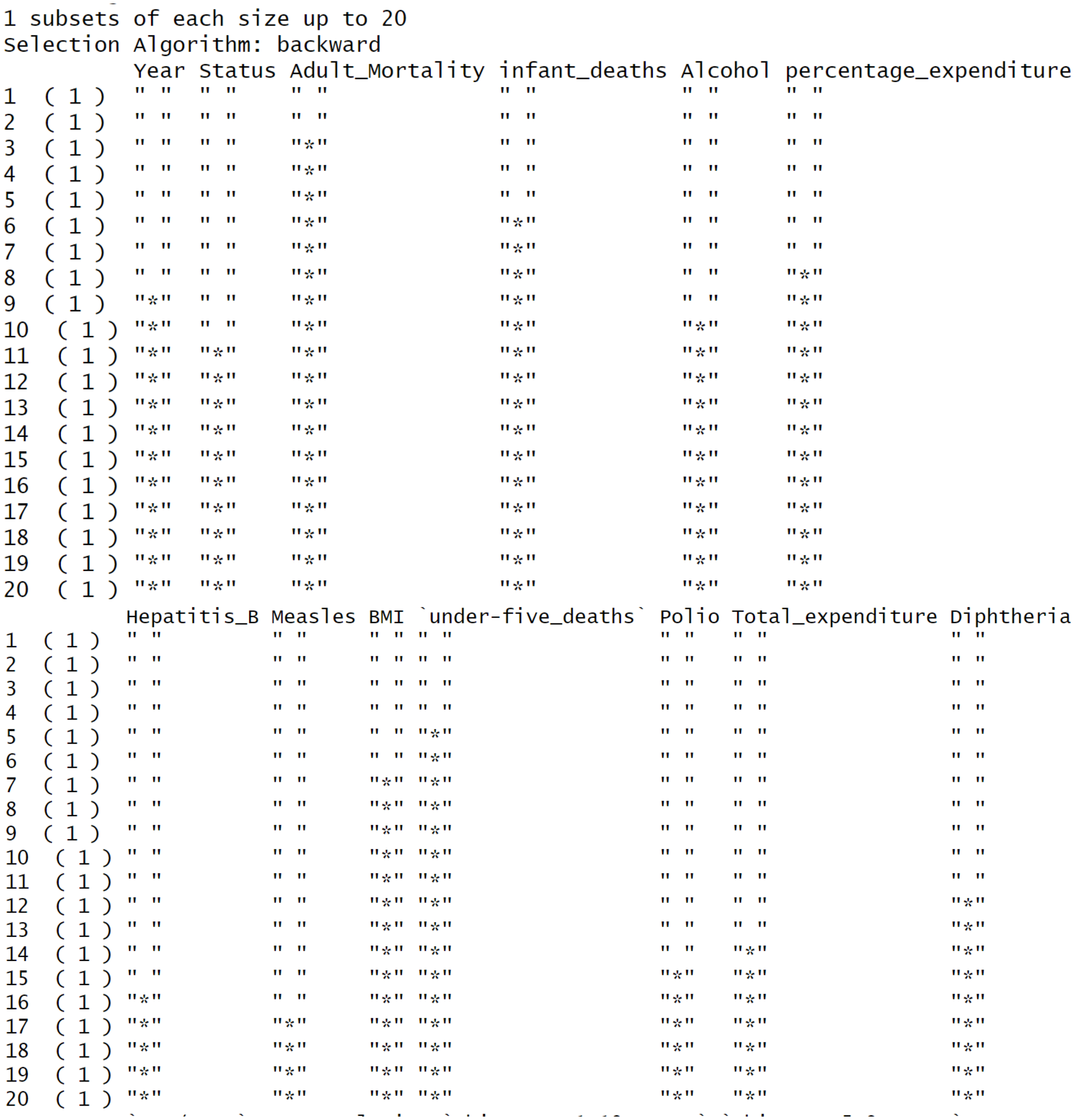
1) Feature Selection
    a. Perform a Forward Stepwise Selection



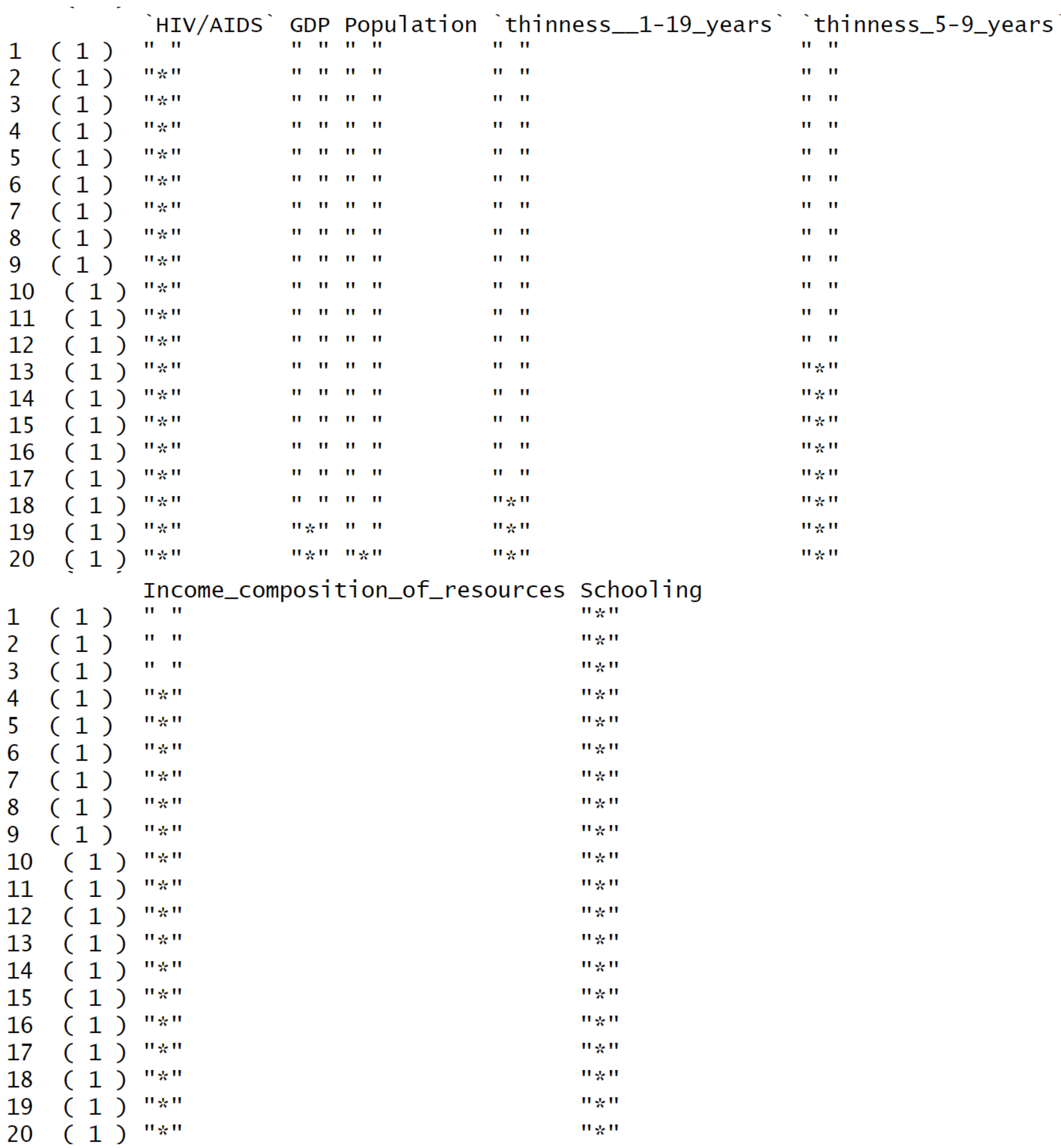
```
1 subsets of each size up to 20
Selection Algorithm: forward
          Year Status Adult_Mortality infant_deaths Alcohol percentage_expenditure
1  ( 1 )  " "  " "    " "             " "           " "     " "                   
2  ( 1 )  " "  " "    " "             " "           " "     " "                   
3  ( 1 )  " "  " "    "*"             " "           " "     " "                   
4  ( 1 )  " "  " "    "*"             " "           " "     " "                   
5  ( 1 )  " "  " "    "*"             " "           " "     " "                   
6  ( 1 )  " "  " "    "*"             " "           " "     "*"                   
7  ( 1 )  " "  " "    "*"             " "           " "     "*"                   
8  ( 1 )  "*"  " "    "*"             " "           " "     "*"                   
9  ( 1 )  "*"  " "    "*"             " "           "*"     "*"                   
10  ( 1 ) "*"  "*"    "*"             " "           "*"     "*"                   
11  ( 1 ) "*"  "*"    "*"             " "           "*"     "*"                   
12  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
13  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
14  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
15  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
16  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
17  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
18  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
19  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
20  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"                   
          Hepatitis_B Measles BMI `under-five_deaths` Polio Total_expenditure Diphtheria
1  ( 1 )  " "         " "     " " " "                 " "   " "               " "       
2  ( 1 )  " "         " "     " " " "                 " "   " "               " "       
3  ( 1 )  " "         " "     " " " "                 " "   " "               " "       
4  ( 1 )  " "         " "     " " " "                 " "   " "               " "       
5  ( 1 )  " "         " "     "*" " "                 " "   " "               " "       
6  ( 1 )  " "         " "     "*" " "                 " "   " "               " "       
7  ( 1 )  " "         " "     "*" " "                 " "   " "               "*"       
8  ( 1 )  " "         " "     "*" " "                 " "   " "               "*"       
9  ( 1 )  " "         " "     "*" " "                 " "   " "               "*"       
10  ( 1 ) " "         " "     "*" " "                 " "   " "               "*"       
11  ( 1 ) " "         " "     "*" "*"                 " "   " "               "*"       
12  ( 1 ) " "         " "     "*" "*"                 " "   " "               "*"       
13  ( 1 ) " "         " "     "*" "*"                 " "   " "               "*"       
14  ( 1 ) " "         " "     "*" "*"                 " "   "*"               "*"       
15  ( 1 ) " "         " "     "*" "*"                 "*"   "*"               "*"       
16  ( 1 ) "*"         " "     "*" "*"                 "*"   "*"               "*"       
17  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"       
18  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"       
19  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"       
20  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"       
```

```
          `HIV/AIDS` GDP Population `thinness__1-19_years` `thinness_5-9_years`
1  ( 1 )  " "        " " " "        " "                    " "
2  ( 1 )  "*"        " " " "        " "                    " "
3  ( 1 )  "*"        " " " "        " "                    " "
4  ( 1 )  "*"        " " " "        " "                    " "
5  ( 1 )  "*"        " " " "        " "                    " "
6  ( 1 )  "*"        " " " "        " "                    " "
7  ( 1 )  "*"        " " " "        " "                    " "
8  ( 1 )  "*"        " " " "        " "                    " "
9  ( 1 )  "*"        " " " "        " "                    " "
10  ( 1 ) "*"        " " " "        " "                    " "
11  ( 1 ) "*"        " " " "        " "                    " "
12  ( 1 ) "*"        " " " "        " "                    " "
13  ( 1 ) "*"        " " " "        " "                    "*"
14  ( 1 ) "*"        " " " "        " "                    "*"
15  ( 1 ) "*"        " " " "        " "                    "*"
16  ( 1 ) "*"        " " " "        " "                    "*"
17  ( 1 ) "*"        " " " "        " "                    "*"
18  ( 1 ) "*"        " " " "        "*"                    "*"
19  ( 1 ) "*"        "*" " "        "*"                    "*"
20  ( 1 ) "*"        "*" "*"        "*"                    "*"
          Income_composition_of_resources Schooling
1  ( 1 )  "*"                             " "
2  ( 1 )  "*"                             " "
3  ( 1 )  "*"                             " "
4  ( 1 )  "*"                             "*"
5  ( 1 )  "*"                             "*"
6  ( 1 )  "*"                             "*"
7  ( 1 )  "*"                             "*"
8  ( 1 )  "*"                             "*"
9  ( 1 )  "*"                             "*"
10  ( 1 ) "*"                             "*"
11  ( 1 ) "*"                             "*"
12  ( 1 ) "*"                             "*"
13  ( 1 ) "*"                             "*"
14  ( 1 ) "*"                             "*"
15  ( 1 ) "*"                             "*"
16  ( 1 ) "*"                             "*"
17  ( 1 ) "*"                             "*"
18  ( 1 ) "*"                             "*"
19  ( 1 ) "*"                             "*"
20  ( 1 ) "*"                             "*"
```

b. Perform a backward Stepwise Selection



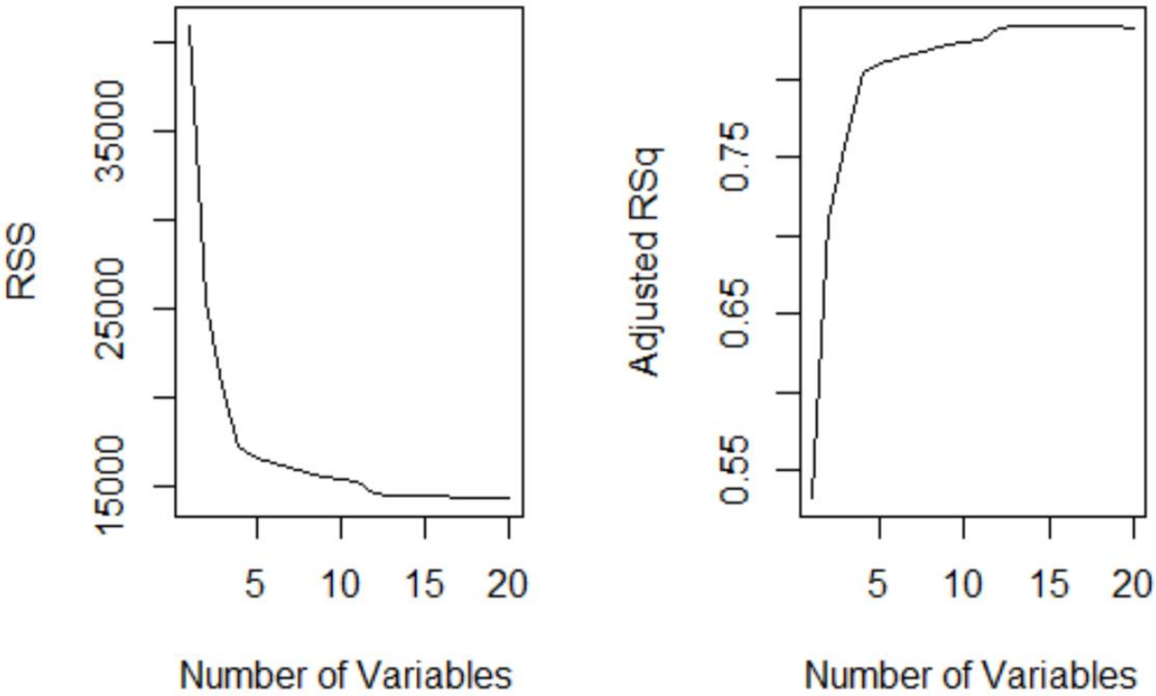
```
1 subsets of each size up to 20
Selection Algorithm: backward
          Year Status Adult_Mortality infant_deaths Alcohol percentage_expenditure
1  ( 1 )  " "  " "    " "             " "           " "     " "
2  ( 1 )  " "  " "    " "             " "           " "     " "
3  ( 1 )  " "  " "    "*"             " "           " "     " "
4  ( 1 )  " "  " "    "*"             " "           " "     " "
5  ( 1 )  " "  " "    "*"             " "           " "     " "
6  ( 1 )  " "  " "    "*"             "*"           " "     " "
7  ( 1 )  " "  " "    "*"             "*"           " "     " "
8  ( 1 )  " "  " "    "*"             "*"           " "     "*"
9  ( 1 )  "*"  " "    "*"             "*"           " "     "*"
10  ( 1 ) "*"  " "    "*"             "*"           "*"     "*"
11  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
12  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
13  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
14  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
15  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
16  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
17  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
18  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
19  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
20  ( 1 ) "*"  "*"    "*"             "*"           "*"     "*"
          Hepatitis_B Measles BMI `under-five_deaths` Polio Total_expenditure Diphtheria
1  ( 1 )  " "         " "     " " " "                 " "   " "               " "
2  ( 1 )  " "         " "     " " " "                 " "   " "               " "
3  ( 1 )  " "         " "     " " " "                 " "   " "               " "
4  ( 1 )  " "         " "     " " " "                 " "   " "               " "
5  ( 1 )  " "         " "     " " "*"                 " "   " "               " "
6  ( 1 )  " "         " "     " " "*"                 " "   " "               " "
7  ( 1 )  " "         " "     "*" "*"                 " "   " "               " "
8  ( 1 )  " "         " "     "*" "*"                 " "   " "               " "
9  ( 1 )  " "         " "     "*" "*"                 " "   " "               " "
10  ( 1 ) " "         " "     "*" "*"                 " "   " "               " "
11  ( 1 ) " "         " "     "*" "*"                 " "   " "               " "
12  ( 1 ) " "         " "     "*" "*"                 " "   " "               "*"
13  ( 1 ) " "         " "     "*" "*"                 " "   " "               "*"
14  ( 1 ) " "         " "     "*" "*"                 " "   "*"               "*"
15  ( 1 ) " "         " "     "*" "*"                 "*"   "*"               "*"
16  ( 1 ) "*"         " "     "*" "*"                 "*"   "*"               "*"
17  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"
18  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"
19  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"
20  ( 1 ) "*"         "*"     "*" "*"                 "*"   "*"               "*"
```



```
          `HIV/AIDS` GDP Population `thinness__1-19_years` `thinness_5-9_years`
1  ( 1 )  " "        " " " "        " "                    " "
2  ( 1 )  "*"        " " " "        " "                    " "
3  ( 1 )  "*"        " " " "        " "                    " "
4  ( 1 )  "*"        " " " "        " "                    " "
5  ( 1 )  "*"        " " " "        " "                    " "
6  ( 1 )  "*"        " " " "        " "                    " "
7  ( 1 )  "*"        " " " "        " "                    " "
8  ( 1 )  "*"        " " " "        " "                    " "
9  ( 1 )  "*"        " " " "        " "                    " "
10  ( 1 ) "*"        " " " "        " "                    " "
11  ( 1 ) "*"        " " " "        " "                    " "
12  ( 1 ) "*"        " " " "        " "                    " "
13  ( 1 ) "*"        " " " "        " "                    "*"
14  ( 1 ) "*"        " " " "        " "                    "*"
15  ( 1 ) "*"        " " " "        " "                    "*"
16  ( 1 ) "*"        " " " "        " "                    "*"
17  ( 1 ) "*"        " " " "        " "                    "*"
18  ( 1 ) "*"        " " " "        "*"                    "*"
19  ( 1 ) "*"        "*" " "        "*"                    "*"
20  ( 1 ) "*"        "*" "*"        "*"                    "*"
          Income_composition_of_resources Schooling
1  ( 1 )  " "                             "*"
2  ( 1 )  " "                             "*"
3  ( 1 )  " "                             "*"
4  ( 1 )  "*"                             "*"
5  ( 1 )  "*"                             "*"
6  ( 1 )  "*"                             "*"
7  ( 1 )  "*"                             "*"
8  ( 1 )  "*"                             "*"
9  ( 1 )  "*"                             "*"
10  ( 1 ) "*"                             "*"
11  ( 1 ) "*"                             "*"
12  ( 1 ) "*"                             "*"
13  ( 1 ) "*"                             "*"
14  ( 1 ) "*"                             "*"
15  ( 1 ) "*"                             "*"
16  ( 1 ) "*"                             "*"
17  ( 1 ) "*"                             "*"
18  ( 1 ) "*"                             "*"
19  ( 1 ) "*"                             "*"
20  ( 1 ) "*"                             "*"
```

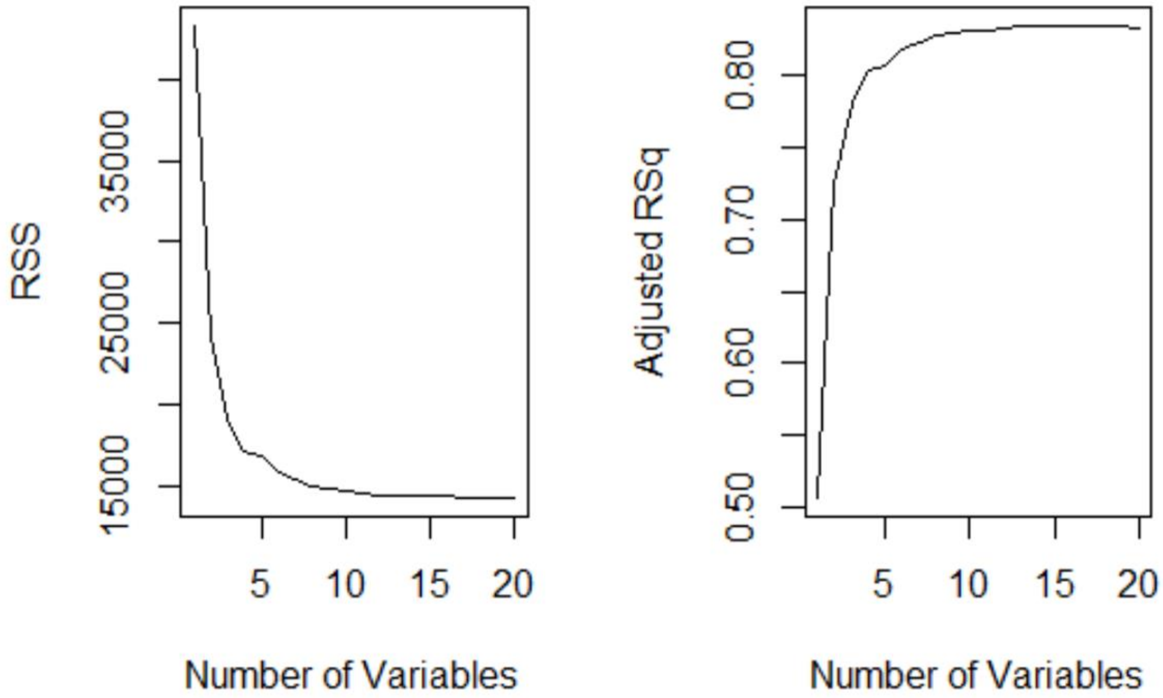
2) Using the models generated for the feature selection, generate the plots of RSS and Adjusted R2

   a. Forward Features



Forward selected features have a huge improvement in the RSS and adjusted R squared up to 4 features. There is continued improvement up 11 or 12 components. Additional features saw little to no improvement.

b. Backward Features



Backward selected features have a huge improvement in the RSS and adjusted R squared up to 4 features. There is continued improvement up 10 or 11 components. Additional features saw little to no improvement.

3) PCR

```
Data:     X dimension: 1156 20
          Y dimension: 1156 1
Fit method: svdpc
Number of components considered: 20

VALIDATION: RMSEP
Cross-validated using 10 random segments.
       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
CV           8.722    8.718    8.035    7.947    7.938    7.483    5.639    5.486
adjCV        8.722    8.717    7.982    7.944    7.935    7.497    5.637    5.483
       8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps  15 comps
CV       5.322    5.071     5.056     4.980     4.865     4.446     4.424     4.243
adjCV    5.341    5.068     5.053     4.976     4.890     4.440     4.420     4.238
       16 comps  17 comps  18 comps  19 comps  20 comps
CV        4.243     3.779     3.776     3.767     3.603
adjCV     4.239     3.776     3.773     3.763     3.598

TRAINING: % variance explained
                  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
X               100.00000    100.0   100.00   100.00   100.00   100.00   100.00   100.00
Life_expectancy   0.09701     15.8    17.83    18.14    28.11    58.72    61.05    63.38
                9 comps  10 comps  11 comps  12 comps  13 comps  14 comps  15 comps
X                100.00    100.00    100.00     100.0    100.00    100.00    100.00
Life_expectancy   66.79     67.16     68.23      70.9     74.87     75.14     77.16
                16 comps  17 comps  18 comps  19 comps  20 comps
X                 100.00    100.00    100.00    100.00    100.00
Life_expectancy    77.17     81.77     81.83     81.99     83.64
```

This is the output of a Principal Component Regression (PCR) analysis, which is a technique used to predict a dependent variable (in this case, life expectancy) using multiple independent variables. The analysis was performed with 20 components, and the root mean square error of prediction (RMSEP) decreased as more components were used, indicating an improvement in prediction accuracy. The variance explained by the model for life expectancy increased with each component, reaching a maximum of 83.64% with 20 components, which implies that 83.64% of the variability in life expectancy can be explained by the independent variables used in the model.

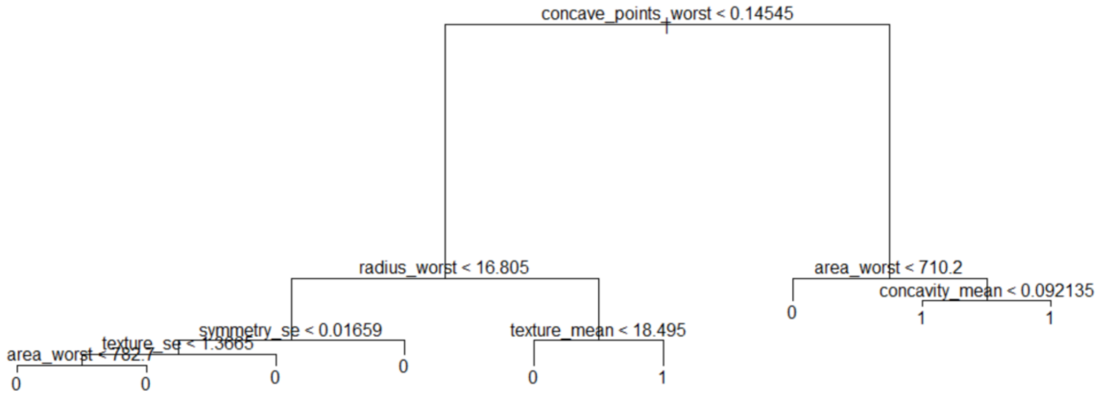
Part 3: Classification

1) Generate two Classification Models for based on your given data.
   These models will include Logistic Regression, Linear Discriminant Analysis, as given in the chapter 4 lab exercise.

```
Logistic_predictions
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 94  4
         1  4 69
                                          
               Accuracy : 0.9532          
                 95% CI : (0.9099, 0.9796)
    No Information Rate : 0.5731          
    P-Value [Acc > NIR] : <2e-16          
                                          
                  Kappa : 0.9044          
                                          
 Mcnemar's Test P-Value : 1               
                                          
            Sensitivity : 0.9592          
            Specificity : 0.9452          
         Pos Pred Value : 0.9592          
         Neg Pred Value : 0.9452          
             Prevalence : 0.5731          
         Detection Rate : 0.5497          
   Detection Prevalence : 0.5731          
      Balanced Accuracy : 0.9522          
                                          
       'Positive' Class : 0               

lda_predictions
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 97  8
         1  1 65
                                          
               Accuracy : 0.9474          
                 95% CI : (0.9024, 0.9757)
    No Information Rate : 0.5731          
    P-Value [Acc > NIR] : <2e-16          
                                          
                  Kappa : 0.8911          
 Mcnemar's Test P-Value : 0.0455

            Sensitivity : 0.9898
            Specificity : 0.8904
         Pos Pred Value : 0.9238
         Neg Pred Value : 0.9848
             Prevalence : 0.5731
         Detection Rate : 0.5673
   Detection Prevalence : 0.6140
      Balanced Accuracy : 0.9401

       'Positive' Class : 0
```

These are the confusion matrices and associated statistics for two different predictive models: logistic regression and linear discriminant analysis (LDA). The logistic regression model achieved an accuracy of 95.32% with a kappa statistic of 0.9044, indicating high agreement between predicted and actual values. The LDA model's accuracy was slightly lower at 94.74%, with a kappa statistic of 0.8911, but it had a higher sensitivity, meaning it was more effective at correctly identifying positive instances of the class labeled '0'.

2) Generate a tree classifier for the classes and predictors used above.

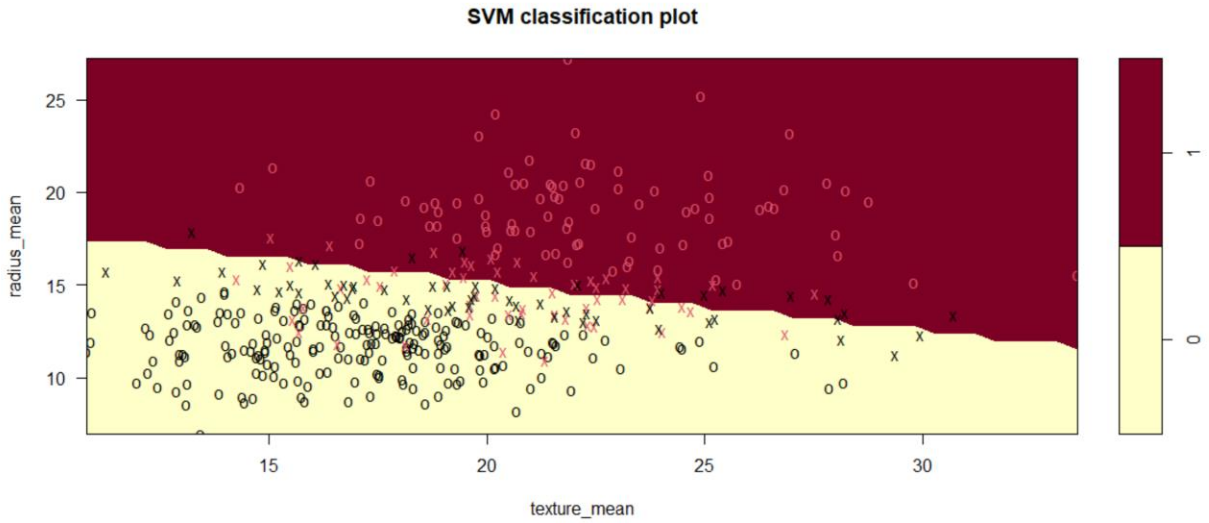


```
tree_predictions
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 97  8
         1  1 65

               Accuracy : 0.9474
                 95% CI : (0.9024, 0.9757)
    No Information Rate : 0.5731
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.8911
```

```
 Mcnemar's Test P-Value : 0.0455

            Sensitivity : 0.9898
            Specificity : 0.8904
         Pos Pred Value : 0.9238
         Neg Pred Value : 0.9848
             Prevalence : 0.5731
         Detection Rate : 0.5673
   Detection Prevalence : 0.6140
      Balanced Accuracy : 0.9401

       'Positive' Class : 0
```

This is the confusion matrix and associated statistics for a predictive model, likely a decision tree given the name "tree_predictions". The model has an accuracy of 94.74%, and a kappa statistic of 0.8911, indicating a high level of agreement between the model predictions and the actual values. The model demonstrates high sensitivity (98.98%), meaning it correctly identified most positive instances of the class labeled '0'.

3) Construct a Support Vector Classifier for some set of classes.



This output represents the process and results of training a Support Vector Machine (SVM) model to predict the 'diagnosis' based on 'radius_mean' and 'texture_mean'. In the hyperparameter tuning stage, various cost values were tested for the SVM's regularization parameter. The best performance, an error rate of approximately 0.1106, was achieved with a cost value of 5. The final model, trained with the optimal cost, used a linear kernel and resulted in 113 support vectors split almost evenly between the two classes, 0 and 1.

Part 4: Models

a) For the first scenario, you might consider using a Multiple Linear Regression model. This model is used to understand the relationship between two or more variables and an outcome. The model could help your friend determine how each factor (like total inventory, number of employees, annual operation budget) contributes to the company's success (total profits). The coefficients of the regression model will tell you the degree of impact each predictor variable has on the outcome variable.

b) In this scenario I would try to use a Classification model, such as logistic regression, decision trees, or even ensemble methods like random forest or gradient boosting. These methods can be used to predict a binary outcome (like whether a household will use the coupon or not), and they can handle a mix of different types of variables. This approach would allow you to predict the probability of each postal code's households using the coupon, and you could then target the ones with the highest probabilities.

c) A Dimensionality Reduction technique like Principal Component Analysis (PCA) could be a good starting point. This technique can reduce the thousands of searches and behavior features into a smaller set of new variables (called principal components) that still capture most of the information in the original features. This can make subsequent analyses more manageable and less resource intensive.

d) In the last scenario, a Support Vector Machine (SVM) or a Random Forest classifier might be suitable. These are powerful machine learning models that can handle high-dimensional data and are capable of modeling complex decision boundaries, which seems necessary given the significant overlap between classes. SVM is particularly good when classes are overlapping and works well in high-dimensional space, while Random Forest can model non-linear decision boundaries and provide feature importance.