Problem_Set_4

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Section One:

Part A:

```
library(tm)
## Loading required package: NLP
library(tidyverse)
## ── Attaching packages ─────────────────────────────────────── tidyverse
1.3.1 ──
## ✓ ggplot2 3.4.2     ✓ purrr   1.0.1
## ✓ tibble  3.2.1     ✓ dplyr   1.1.1
## ✓ tidyr   1.3.0     ✓ stringr 1.5.0
## ✓ readr   2.1.2     ✓ forcats 0.5.1
## Warning: package 'ggplot2' was built under R version 4.1.2
## Warning: package 'tibble' was built under R version 4.1.2
## Warning: package 'tidyr' was built under R version 4.1.2
## Warning: package 'readr' was built under R version 4.1.2
## Warning: package 'purrr' was built under R version 4.1.2
## Warning: package 'dplyr' was built under R version 4.1.2
## Warning: package 'stringr' was built under R version 4.1.2
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✕ ggplot2::annotate() masks NLP::annotate()
## ✕ dplyr::filter()     masks stats::filter()
## ✕ dplyr::lag()        masks stats::lag()
texts <-
file.path("~/Downloads/Machine_Learning/Problem_Set_Four/SimpleText_auto")

docs <- VCorpus(DirSource(texts))
```

Part B:

```
clean_corpus <- function(corpus) {
  corpus <- tm_map(corpus, content_transformer(tolower))

  corpus <- tm_map(corpus, removePunctuation)

  corpus <- tm_map(corpus, removeNumbers)
```

```
  corpus <- tm_map(corpus, removeWords, stopwords("english"))

  academic_words <- c(
    "table", "figure", "results", "analyze",
    "concept", "construct", "data", "define", "evidence", "framework",
    "hypothesis", "interpret", "methodology", "perspective", "principle",
    "quantitative", "research", "significant", "theory", "variable",
    "validity", "conclude", "critique", "figure", "model", "analysis", "can",
    "since", "therefore", "first", "state", "within", "use", "using",
"similar",
    "used", "shown", "shows", "however", "give", "given", "also", "compared",
    "found", "fig", "two", "present", "well", "may", "time", "different",
"one",
    "study", "show", "will", "due", "thus", "let", "see", "number", "based",
    "set", "left"
  )

  corpus <- tm_map(corpus, removeWords, academic_words)

  corpus <- tm_map(corpus, stripWhitespace)

  return(corpus)
}

cleaned_docs <- clean_corpus(docs)
```

In Part B, I transformed all the words to lowercase to help standardize the document. Then, I removed all punctuation, numbers, and stopwords. Additionally, I created a set of custom words to filter out. I repeatedly ran the code and generated word clouds to visualize the non-necessary words that were appearing. I would then take those words and further filter them out through a cyclical process. These words are common academic jargon that, in my opinion, do not contribute to distinguishing the stem topic. Lastly, I removed all whitespace and executed the function to clean the words in the documents.

Part C:

```
library(wordcloud)
## Loading required package: RColorBrewer
## Warning: package 'RColorBrewer' was built under R version 4.1.2
word_matrix <- DocumentTermMatrix(cleaned_docs)

freq_words <- findFreqTerms(word_matrix, 50)

freq_table <- data.frame(
  word = freq_words,
  freq = colSums(as.matrix(word_matrix[, freq_words]))
)
```

```r
freq_table <- freq_table[order(freq_table$freq, decreasing = TRUE), ]

wordcloud(freq_table$word, freq_table$freq, scale = c(2, 0.1), max.words =
50, random.order = FALSE, rot.per = 0.2)
```


```
freq_table %>% head(50)
##                          word freq
## flow                     flow  893
## cells                   cells  853
## energy                 energy  830
## section               section  808
## case                     case  806
## values                 values  781
## high                     high  774
## system                 system  758
## soil                     soil  753
## surface               surface  744
## lower                   lower  696
## observed             observed  691
## temperature       temperature  665
## field                   field  651
## order                   order  627
## wind                     wind  624
```

```
## higher              higher  615
## low                    low  594
## conditions      conditions  556
## large                large  551
## region              region  537
## size                  size  529
## increase          increase  516
## value                value  508
## three                three  500
## velocity          velocity  499
## level                level  493
## levels              levels  485
## work                  work  478
## samples            samples  469
## electron          electron  454
## rate                  rate  454
## small                small  454
## cell                  cell  452
## species            species  452
## power                power  451
## approach          approach  450
## function          function  443
## control            control  441
## density            density  441
## network            network  441
## studies            studies  441
## respectively respectively  437
## nodes                nodes  427
## particles        particles  426
## possible          possible  426
## algorithm        algorithm  424
## performance    performance  424
## following        following  422
## increased        increased  421
```

Part D:

```
library(topicmodels)
## Warning: package 'topicmodels' was built under R version 4.1.2
k_values <- c(2, 3, 5, 8, 10)

for (k in k_values) {
  lda_model <- LDA(word_matrix, k)
  cat("LDA Model with k = ", k, "\n")

  top_freq_words <- terms(lda_model, 10)

  for (i in 1:k) {
    cat("Topic", i, ": ")
```

```r
    cat(paste(top_freq_words[i, ], collapse = ", "))
    cat("\n")
  }

  cat("------------------------\n\n")
}
## LDA Model with k =  2
## Topic 1 : cells, flow
## Topic 2 : system, energy
## ------------------------
##
## LDA Model with k =  3
## Topic 1 : energy, cells, soil
## Topic 2 : temperature, flow, nodes
## Topic 3 : surface, cell, wind
## ------------------------
##
## LDA Model with k =  5
## Topic 1 : energy, cells, wind, soil, case
## Topic 2 : electron, cell, turbine, algorithm, order
## Topic 3 : flow, expression, particles, nodes, temperature
## Topic 4 : electrons, gene, high, memory, theorem
## Topic 5 : field, human, power, algorithms, section
## ------------------------
##
## LDA Model with k =  8
## Topic 1 : surface, temperature, cells, memory, network, cells, electron,
flow
## Topic 2 : film, particles, neurons, clusters, nodes, surface, energy, wind
## Topic 3 : temperature, energy, expression, cluster, tephra, cell,
electrons, soil
## Topic 4 : flows, atmosphere, mitochondrial, nodes, connectivity, culture,
field, depth
## Topic 5 : lddos, heating, cell, algorithm, area, tinnitus, turbine, beach
## Topic 6 : approach, solar, levels, system, cost, human, theorem, surface
## Topic 7 : layer, observations, mutation, program, cafrep, hipscs, soil,
concentration
## Topic 8 : samples, thermosphere, patients, module, scaling, rpe, power,
velocity
## ------------------------
##
## LDA Model with k =  10
## Topic 1 : nodes, particles, surface, turbine, energy, area, energy,
clusters, soil, cells
## Topic 2 : maximal, temperature, film, power, electron, network, region,
cluster, root, cell
## Topic 3 : order, wind, layer, algorithm, approach, soil, electron, flow,
elements, expression
## Topic 4 : module, epoxy, mitochondrial, performance, electrons, values,
plasma, beach, values, gene
```

```
## Topic 5 : node, atmosphere, rpe, turbines, flow, tephra, field, coherent,
operators, genes
## Topic 6 : system, observations, mtdna, memory, flows, flow, observed,
pressure, soils, culture
## Topic 7 : output, polymer, devices, speed, lddos, scaling, thermosphere,
dependence, concentration, human
## Topic 8 : clock, models, sediment, algorithms, feature, cost, wake,
program, theorem, neurons
## Topic 9 : input, heating, samples, work, features, vertical, electrons,
surface, roots, differentiation
## Topic 10 : lemma, particle, high, java, normal, equations, density, sets,
case, growth
## ------------------------
```

LDA Model with k = 2:

Topic 1: This topic indicates a correlation with biological and ecological terms, such as flow and cells.

Topic 2: This topic includes words like systems and energy, representing a potential correlation with numerical or quantitative terminology related to energy.

LDA Model with k = 3:

Topic 1: This topic mentions words such as soil, energy, and cells, possibly indicating a focus on biological systems or dynamics.

Topic 2: This topic involves words like temperature, flow, and nodes, suggesting a correlation with thermal science and case studies related to energy.

Topic 3: This topic includes words such as surface, cell, and wind, which indicates a correlation related to topics such as experimental measurements, sections in scientific papers, and electron-related phenomena.

LDA Model with k = 5:

Topic 1: This topic includes words like energy, cells, wind, soil, and case which could indicate a relationship to energy systems, cellular biology, and mathematical theorems.

Topic 2: This topic involves words like electron, cell, turbine, algorithm, and order suggesting a correlation to topics such as fluid flow, cellular biology, and mathematical lemmas.

Topic 3: This topic includes words such as flow, expression, particles, nodes, and temperature indicating a potential focus on scientific topics related to network systems, human factors, and ordered structures.

Topic 4: This topic involves words like electrons, gene, high, memory, and theorem suggesting a focus on topics such as temperature effects, gene expression, plant biology, and performance evaluation.

Topic 5: This topic includes words such as field, human, power, algorithms, and section which might correlate to topic areas related to fluid velocity, cultural aspects, modular systems, and maximum values.

LDA models with topic sizes 8 and 10 both yield similar topic selections, and the distribution of words is identical to that of smaller LDA sizes. They do not generate unique or distinct word patterns that help distinguish the topic theme or subject matter.

Based on my opinion, a k-size of 5 yields the most meaningful coherence for each topic. This is because k-sizes 2 and 3 are too small and do not reveal significant information regarding word meaning or the context of word distribution. On the other hand, k-sizes 8 and 10 provide too much information and overwhelm the reader with noisy words. Thus, a k-size of 5 is an effective measure to distinguish between each topic theme and the quantity of words that each topic encompasses.

Part E:

```
set.seed(123)

k_values <- c(2, 3, 5, 8, 10)
fold <- 10

best_model <- NULL

best_perplexity <- Inf

for (k in k_values) {
  fold_perplexities <- c()

  for (i in 1:fold) {

    # Creating training and testing sets

    set.seed(123)
    train_indices <- sample(seq_len(nrow(word_matrix)),
      size = floor((fold - 1) / fold * nrow(word_matrix)), replace = FALSE
    )

    training_data <- word_matrix[train_indices, ]
    test_data <- word_matrix[-train_indices, ]

    # Training the LDA model

    lda_model.cv <- LDA(training_data, k)

    # Calculating the perplexity on test set

    perplexity <- perplexity(lda_model.cv, newdata = test_data)
```

```r
    fold_perplexities <- c(fold_perplexities, perplexity)
  }

  avg_perplexity <- mean(fold_perplexities)

  if (avg_perplexity < best_perplexity) {
    best_perplexity <- avg_perplexity
    best_model <- LDA(word_matrix, k)
  }
}

# Presenting the topics from the best model

cat("Best LDA Model:\n")
cat("Number of Topics (k):", best_model$k, "\n")
cat("Perplexity:", best_perplexity, "\n")

top_freq_words <- terms(best_model, 10)

for (i in 1:best_model$k) {
  cat("Topic", i, ": ")
  cat(paste(top_freq_words[i, ], collapse = ", "))
  cat("\n")
}
```

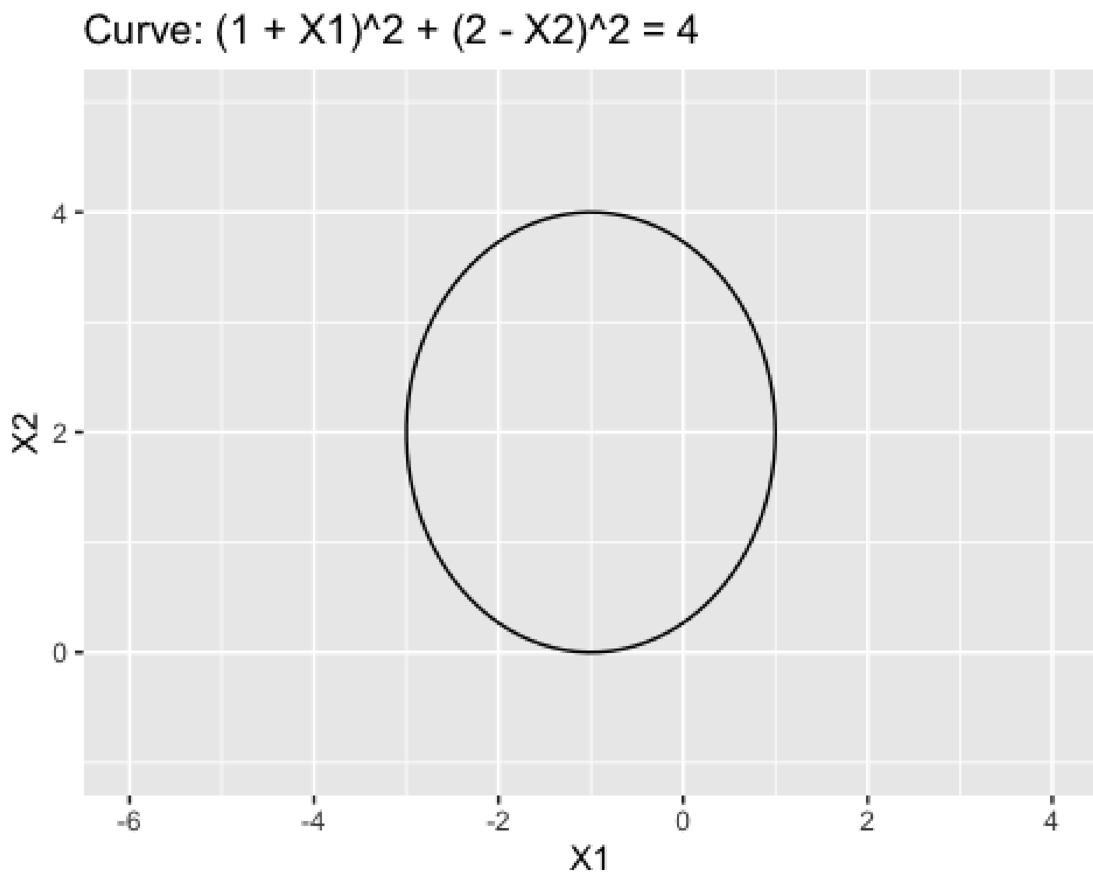
This code was to computationally extensive and took too long to run in R. Therefore, I did not provide the output. I did include the code however, to demonstrate the different steps in achieving the optimization of the hyperparameters of the LDA model using 10-fold cross-validation.

Section Two

Part A:

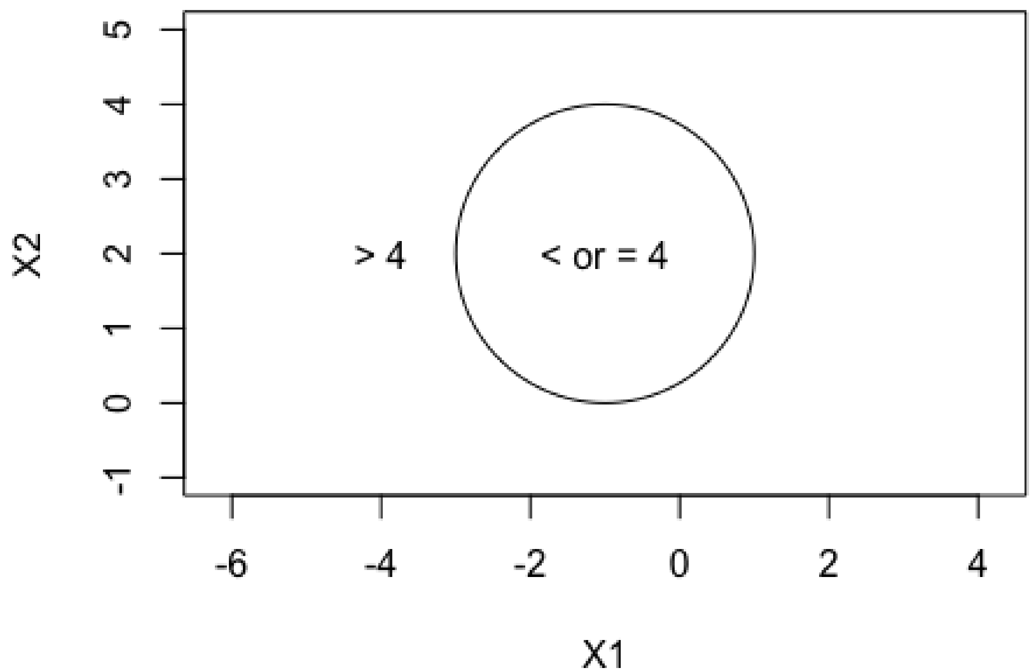
```r
library(ggplot2)

theta <- seq(0, 2 * pi, length.out = 100)
X1 <- -1 + 2 * cos(theta)
X2 <- 2 + 2 * sin(theta)

plot_one <- data.frame(X1, X2)

ggplot(plot_one, aes(X1, X2)) +
  geom_path() +
  xlim(-6, 4) +
  ylim(-1, 5) +
  xlab("X1") +
```

```
  ylab("X2") +
  ggtitle("Curve: (1 + X1)^2 + (2 - X2)^2 = 4")
```



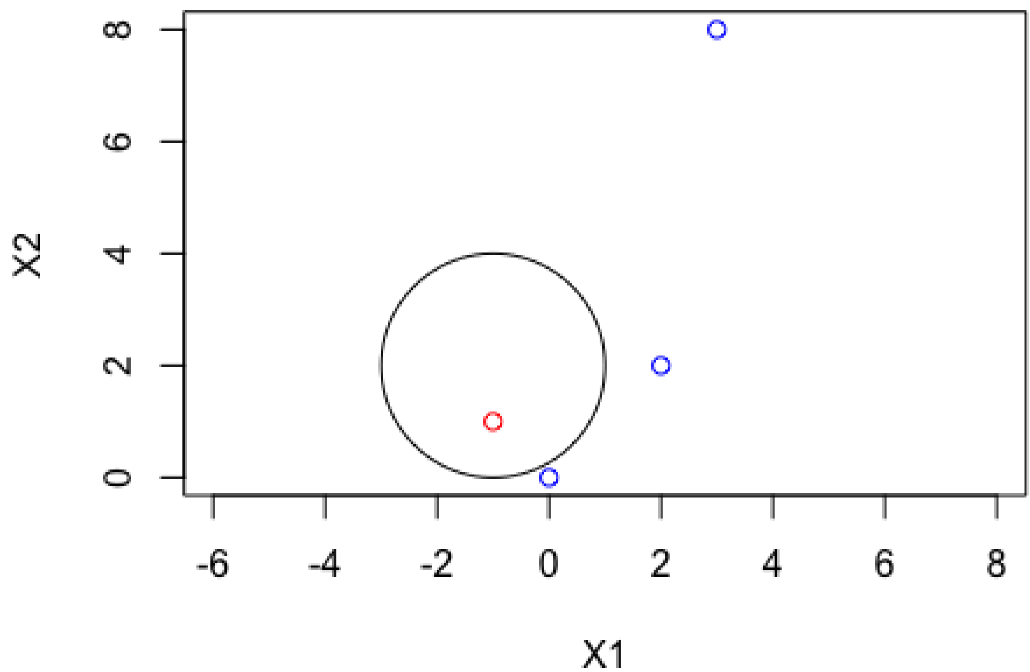
Part B:

```
plot(NA, NA,
  type = "n", xlim = c(-6, 4), ylim = c(-1, 5), asp = 1,
  xlab = "X1", ylab = "X2"
)

symbols(c(-1), c(2), circles = c(2), add = TRUE, inches = FALSE)

text(c(-1), c(2), "< or = 4")
text(c(-4), c(2), "> 4")
```



Part C:

```
plot(c(0, -1, 2, 3), c(0, 1, 2, 8),
  col = c("blue", "red", "blue", "blue"),
  type = "p", asp = 1, xlab = "X1", ylab = "X2"
)
symbols(c(-1), c(2), circles = c(2), add = TRUE, inches = FALSE)
```



(0, 0) would be classified blue since it is outside the circle.

(-1, 1) would be classified red since it is inside the circle.
(2, 2) would be classified blue since it is outside of the circle.

(3, 8) would be classified blue since it is outside of the circle.

Part D:

By expanding the equation of the decision boundary, $(1 + X1)^2 + (2 - X2)^2 = 4$, we can obtain:

$$(1 + X1)^2 + (2 - X2)^2 = 4$$

$$1 + 2X1 + X1^2 + 4 - 4X2 + X2^2 = 4$$

$$X1^2 + X2^2 + 2X1 - 4X2 + 1 = 0$$

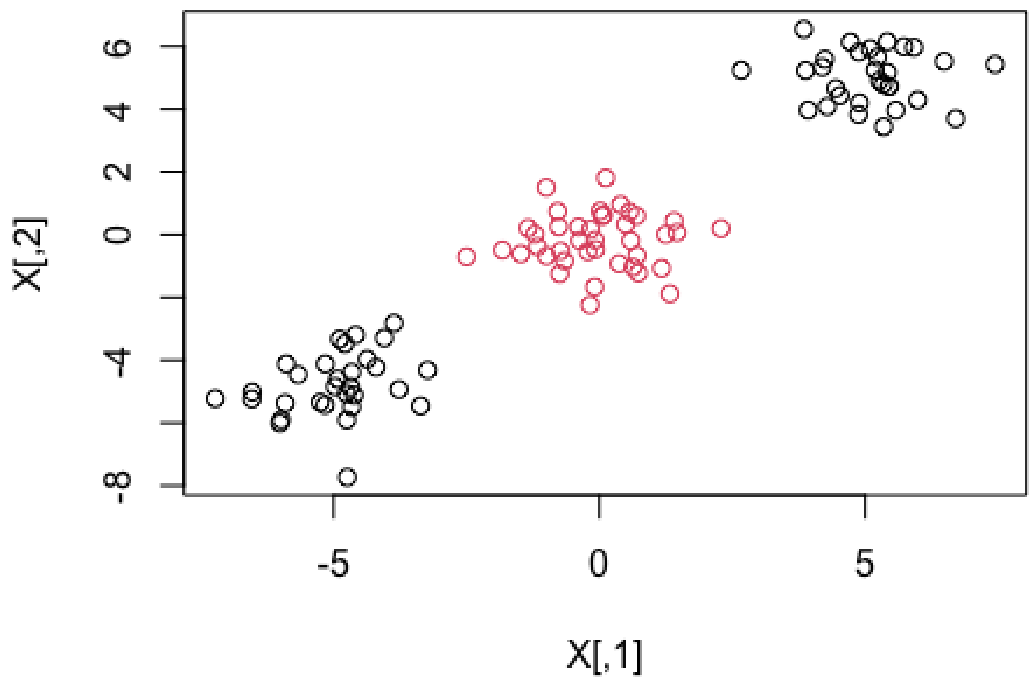
This is a quadratic equation in terms of X1 and X2. However, when we introduce the additional variables $Y1 = X1^2$ and $Y2 = X2^2$, we can rewrite the equation as:

$$Y1 + Y2 + 2X1 - 4X2 + 1 = 0$$

When we expand the equation to this form, it becomes linear in terms of X1, $X1^2$, X2, and $X2^2$. The linear coefficients are 2 and -4, multiplying X1 and X2, respectively, while Y1 and Y2 serve as additional terms.

Section Three:

```
library(e1071)
## Warning: package 'e1071' was built under R version 4.1.2
library(mlbench)
## Warning: package 'mlbench' was built under R version 4.1.2
set.seed(321)

shift <- 5

X <- matrix(rnorm(100 * 2), ncol = 2)

X[1:30, ] <- X[1:30, ] + shift

X[31:60, ] <- X[31:60, ] - shift

y <- c(rep(0, 60), rep(1, 40))

simulated_data <- data.frame(Feature1 = X[, 1], Feature2 = X[, 2], Class =
as.factor(y))

plot(X, col = y + 1)
```




```
train_function <- sample(100, 80)

training_data <- simulated_data[train_function, ]

test_data <- simulated_data[-train_function, ]

# Fitting the data with a Support Vector Classifier

svm_linear <- svm(Class ~ .,
  data = training_data, kernel = "linear",
  scale = FALSE
)

plot(svm_linear, data = training_data)
```


```
summary(svm_linear)
##
## Call:
## svm(formula = Class ~ ., data = training_data, kernel = "linear",
##     scale = FALSE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##
## Number of Support Vectors:  70
##
##  ( 33 37 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
table(predicted = svm_linear$fitted, truth = training_data$Class)
```

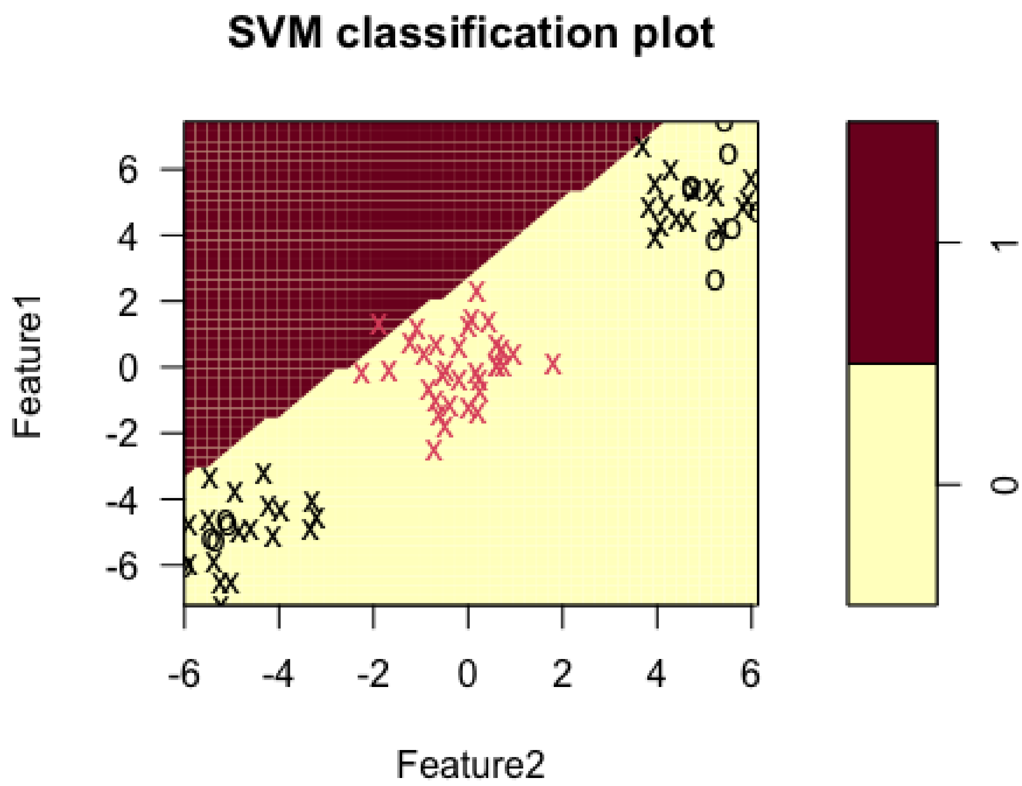
```
##           truth
## predicted  0  1
##          0 47 33
##          1  0  0
```

Error rate = Number of incorrect predictions / Total number of predictions
33/80 = .4125 or 41.25%

The support vector classifier labels all training points as class zero, indicating its inability to distinguish between the different classes in the training set. Consequently, it assigns all instances to class zero, disregarding their actual class labels.

This observation implies that the support vector classifier fails to capture the underlying patterns and characteristics of the data. It suggests that the classifier struggles to identify an appropriate decision boundary or effectively separate the classes. As a result, the model is deemed ineffective on this specific training set as it fails to provide meaningful predictions or accurate classification.

```
# Fitting the data with polynomial kernel

svm_poly <- svm(Class ~ .,
  data = training_data, kernel = "polynomial",
  scale = FALSE
)

plot(svm_poly, data = training_data)
```

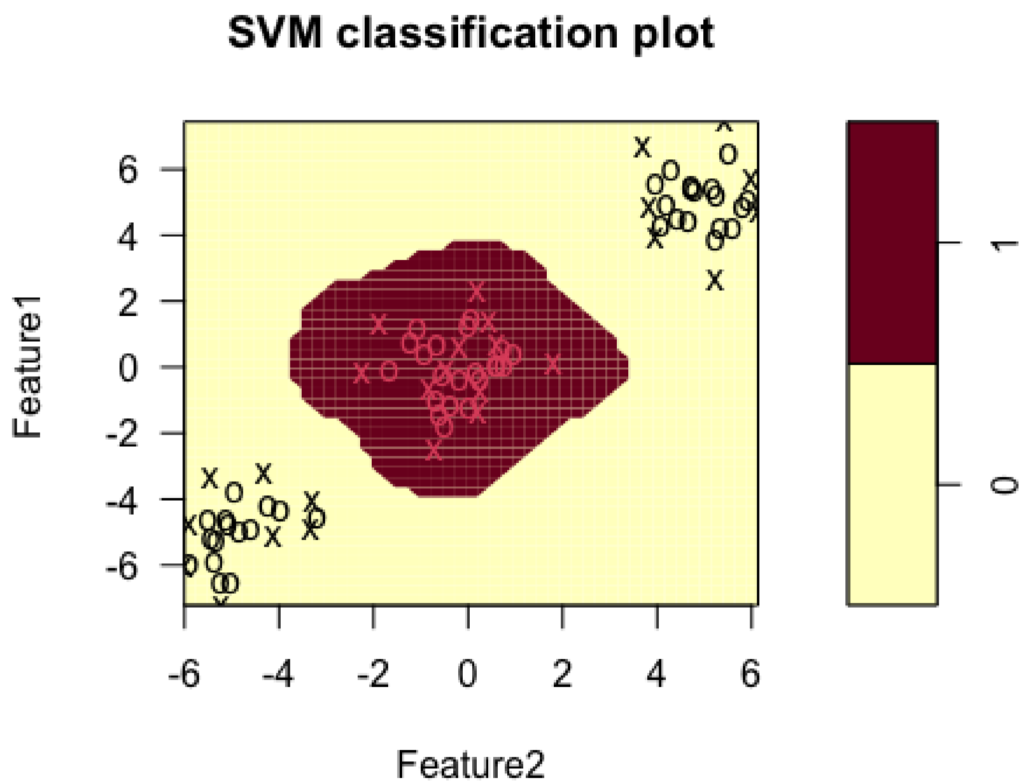



```
table(predicted = svm_poly$fitted, truth = training_data$Class)
##          truth
## predicted  0  1
##         0 47 32
##         1  0  1
```

Error rate = Number of incorrect predictions / Total number of predictions
32/80 = .40 or 40%

The error rate corrects for one observation using the polynomial kernel model

```
# Fitting the data with radial kernel

svm_radial <- svm(Class ~ .,
  data = training_data, kernel = "radial",
  scale = FALSE
)

plot(svm_radial, data = training_data)
```




```
table(predicted = svm_radial$fitted, truth = training_data$Class)
##           truth
## predicted  0  1
##         0 47  0
##         1  0 33
```

Error rate = Number of incorrect predictions / Total number of predictions
0/80 = 0%

The error rate for the radial kernel model is much lower than the svm and polynomial models. In fact, the error rate for the radial kernel is 0.

```
# Comparing the test errors for the 3 kernels:

linear_pred <- predict(svm_linear, test_data)

table(predicted = linear_pred, truth = test_data$Class)
##           truth
## predicted  0  1
##         0 13  7
##         1  0  0
```

Error rate = Number of incorrect predictions / Total number of predictions
7/20 = .35 or 35%

```
poly_pred <- predict(svm_poly, test_data)

table(predicted = poly_pred, truth = test_data$Class)
##            truth
## predicted  0  1
##          0 12  7
##          1  1  0
```

Error rate = Number of incorrect predictions / Total number of predictions
8/20 = .4 or 40%

```
radial_pred <- predict(svm_radial, test_data)

table(predicted = radial_pred, truth = test_data$Class)
##            truth
## predicted  0  1
##          0 13  0
##          1  0  7
```

Error rate = Number of incorrect predictions / Total number of predictions
0/20 = 0%

The Radial Kernel model generates lower error rates for both the training data and the test data.

Section Four

Part A:

```
library(ISLR)

data(Auto)

median_mpg <- median(Auto$mpg)

Auto$mpg_binary <- ifelse(Auto$mpg > median_mpg, 1, 0)

Auto$mpg_binary <- as.factor(Auto$mpg_binary)
```

Part B:

```
library(e1071)

set.seed(10)

cost_tune <- tune(svm, mpg_binary ~ ., data = Auto, kernel = "linear", ranges
= list(cost = c(.001, 0.01, 0.1, 1, 10, 100, 1000)))

summary(cost_tune)
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##     1
##
## - best performance: 0.007628205
##
## - Detailed performance results:
##    cost       error dispersion
## 1 1e-03 0.091730769 0.03990003
## 2 1e-02 0.073974359 0.03067293
## 3 1e-01 0.050897436 0.03153169
## 4 1e+00 0.007628205 0.01228382
## 5 1e+01 0.020384615 0.02019157
## 6 1e+02 0.033205128 0.01737168
## 7 1e+03 0.033205128 0.01737168
```

In the linear model, the lowest error of 0.007628205 was achieved when the cost parameter was set to 1, indicating that this parameter value yielded the best performance for the support vector (SVM) machine. The dispersion represents the variability or spread of errors across different cost values.

Part C:

```
# For the radial basis kernel (rbf):

set.seed(09)

cost_tune_rbf <- tune(svm, mpg_binary ~ .,
  data = Auto, kernel = "radial",
  ranges = list(
    cost = c(.001, 0.01, 0.1, 1, 10),
```

```r
    gamma = c(0.01, 0.1, 1, 5, 10, 100)
  )
)
summary(cost_tune_rbf)
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost gamma
##    10  0.01
##
## - best performance: 0.02301282
##
## - Detailed performance results:
##     cost gamma      error dispersion
## 1  1e-03 1e-02 0.51096154 0.13709174
## 2  1e-02 1e-02 0.51096154 0.13709174
## 3  1e-01 1e-02 0.08929487 0.05558189
## 4  1e+00 1e-02 0.07147436 0.04312562
## 5  1e+01 1e-02 0.02301282 0.02549182
## 6  1e-03 1e-01 0.51096154 0.13709174
## 7  1e-02 1e-01 0.16839744 0.08975786
## 8  1e-01 1e-01 0.07653846 0.05100638
## 9  1e+00 1e-01 0.05615385 0.04294734
## 10 1e+01 1e-01 0.02551282 0.02076457
## 11 1e-03 1e+00 0.51096154 0.13709174
## 12 1e-02 1e+00 0.51096154 0.13709174
## 13 1e-01 1e+00 0.51096154 0.13709174
## 14 1e+00 1e+00 0.06128205 0.05274896
## 15 1e+01 1e+00 0.06134615 0.05006757
## 16 1e-03 5e+00 0.54596154 0.03201429
## 17 1e-02 5e+00 0.54596154 0.03201429
## 18 1e-01 5e+00 0.54596154 0.03201429
## 19 1e+00 5e+00 0.48205128 0.04602804
## 20 1e+01 5e+00 0.47692308 0.05114030
## 21 1e-03 1e+01 0.54596154 0.03201429
## 22 1e-02 1e+01 0.54596154 0.03201429
## 23 1e-01 1e+01 0.54596154 0.03201429
## 24 1e+00 1e+01 0.50506410 0.03662576
## 25 1e+01 1e+01 0.49743590 0.03803299
## 26 1e-03 1e+02 0.54846154 0.02632839
## 27 1e-02 1e+02 0.54846154 0.02632839
## 28 1e-01 1e+02 0.54846154 0.02632839
## 29 1e+00 1e+02 0.54846154 0.02632839
## 30 1e+01 1e+02 0.54846154 0.02632839

# For the polynomial basis kernel (poly):
```

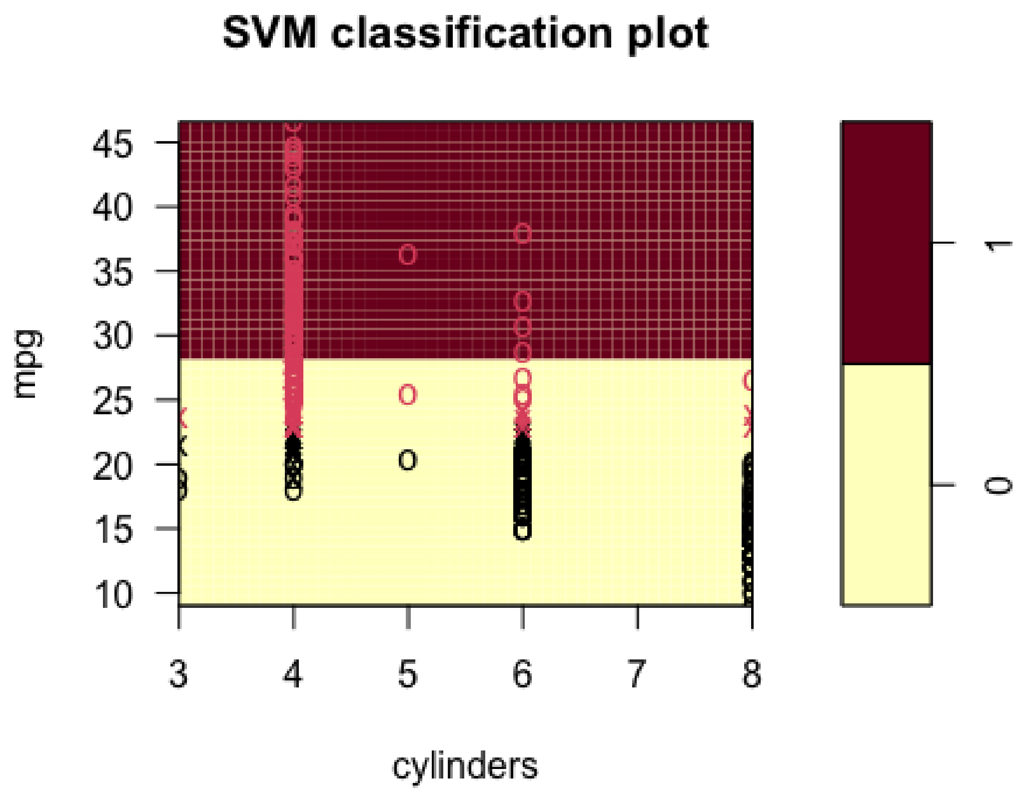
```r
set.seed(08)

cost_tune_poly <- tune(svm, mpg_binary ~ ., data = Auto, kernel =
"polynomial", ranges = list(cost = c(.001, 0.01, 0.1, 1, 10), degree = c(1,
2, 3, 4, 5)))

summary(cost_tune_poly)
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost degree
##    10      1
##
## - best performance: 0.06371795
##
## - Detailed performance results:
##      cost degree      error dispersion
## 1  1e-03      1 0.56378205 0.05004495
## 2  1e-02      1 0.56378205 0.05004495
## 3  1e-01      1 0.16525641 0.10934527
## 4  1e+00      1 0.08160256 0.03553445
## 5  1e+01      1 0.06371795 0.04355118
## 6  1e-03      2 0.56378205 0.05004495
## 7  1e-02      2 0.56378205 0.05004495
## 8  1e-01      2 0.56378205 0.05004495
## 9  1e+00      2 0.56378205 0.05004495
## 10 1e+01      2 0.50224359 0.12621940
## 11 1e-03      3 0.56378205 0.05004495
## 12 1e-02      3 0.56378205 0.05004495
## 13 1e-01      3 0.56378205 0.05004495
## 14 1e+00      3 0.56378205 0.05004495
## 15 1e+01      3 0.56378205 0.05004495
## 16 1e-03      4 0.56378205 0.05004495
## 17 1e-02      4 0.56378205 0.05004495
## 18 1e-01      4 0.56378205 0.05004495
## 19 1e+00      4 0.56378205 0.05004495
## 20 1e+01      4 0.56378205 0.05004495
## 21 1e-03      5 0.56378205 0.05004495
## 22 1e-02      5 0.56378205 0.05004495
## 23 1e-01      5 0.56378205 0.05004495
## 24 1e+00      5 0.56378205 0.05004495
## 25 1e+01      5 0.56378205 0.05004495
```

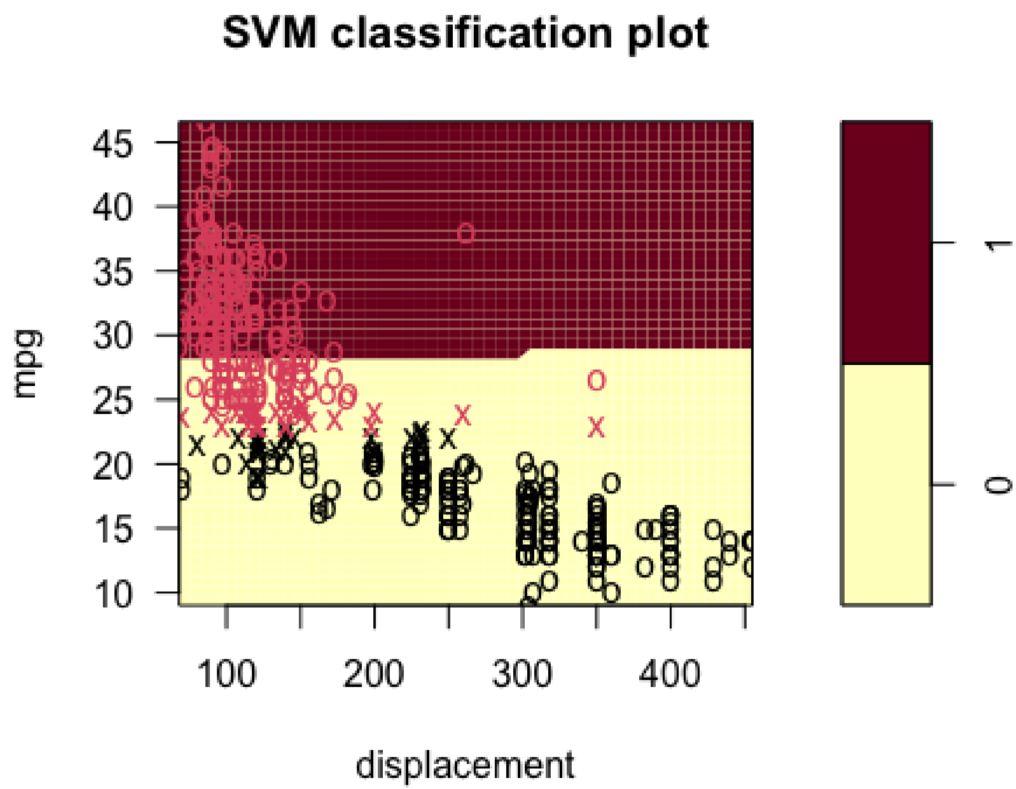
The parameter tuning process for the radial basis kernel model suggests that the SVM model performs best when the cost parameter is set to 10 and the gamma parameter is set to 0.01. This yields the lowest error of 0.02301282. The dispersion represents the variability or spread of errors across different cost and gamma values. It appears that the parameter combinations with lower values of cost and gamma generally result in higher error rates.

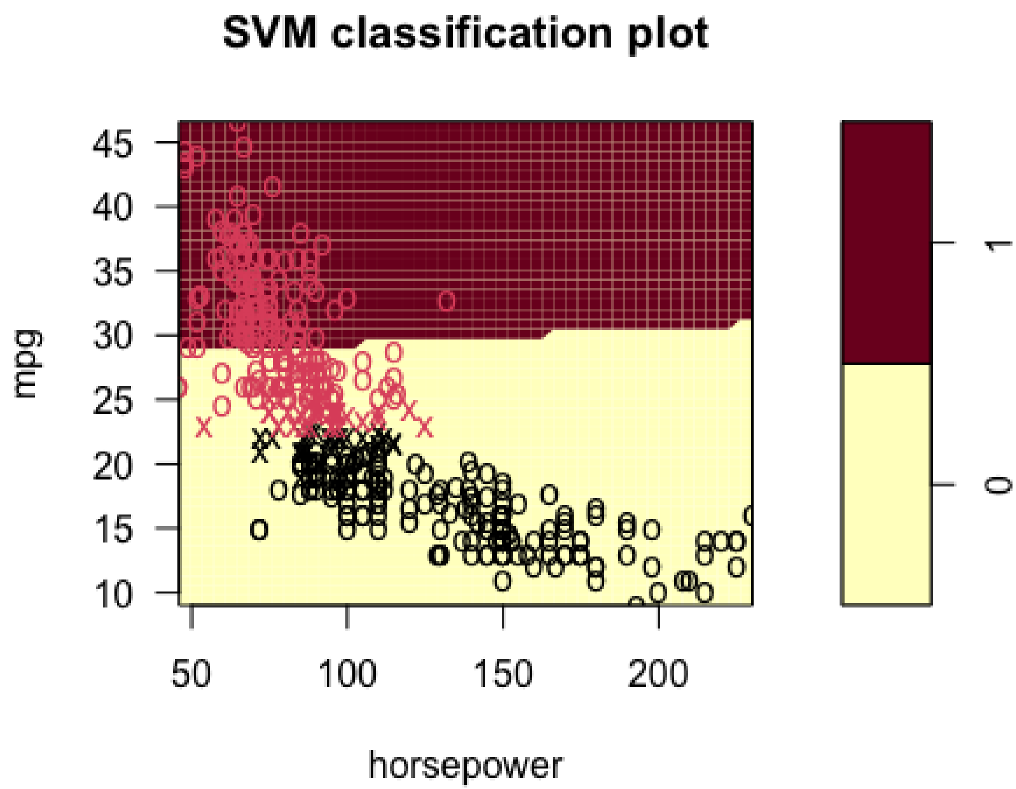
The parameter tuning process for the polynomial basis kernel model suggests that the SVM model performs best when the cost parameter is set to 10 and the degree parameter is set to 1. This yields the lowest error of 0.06371795. The dispersion represents the variability or spread of errors across different cost and degree values.

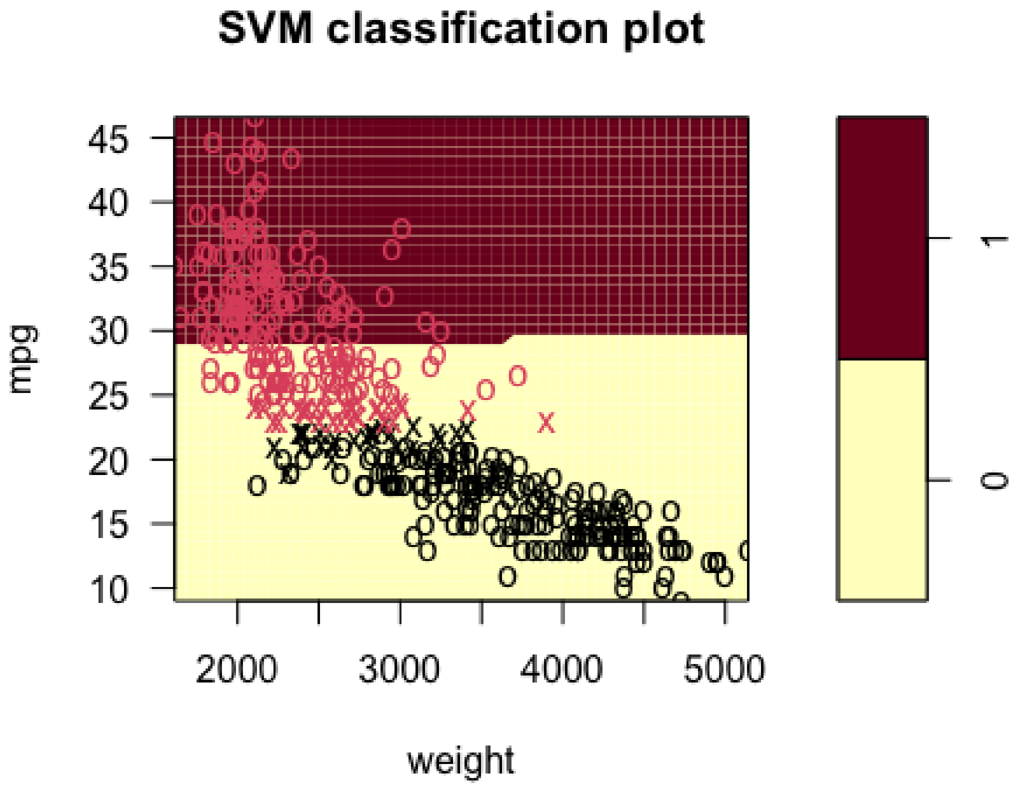
Part D:

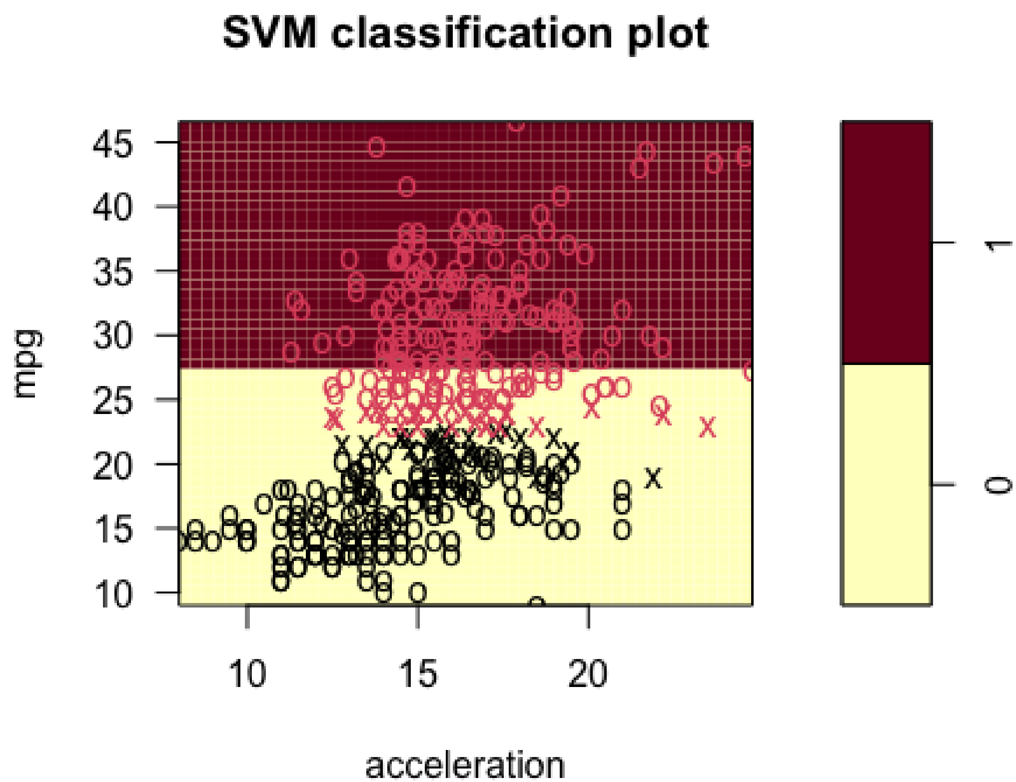
```
svm_linear <- svm(mpg_binary ~ ., data = Auto, kernel = "linear", cost = 1)

svm_poly <- svm(mpg_binary ~ .,
  data = Auto, kernel = "polynomial", cost = 10,
  degree = 1
)

svm_radial <- svm(mpg_binary ~ .,
  data = Auto, kernel = "radial", cost = 10,
  gamma = 0.01
)

plotpairs <- function(fit) {
  for (name in names(Auto)[!(names(Auto) %in% c("mpg", "mpg_binary",
"name"))])
  {
    plot(fit, Auto, as.formula(paste("mpg~", name, sep = "")))
  }
}

plotpairs(svm_linear)
```

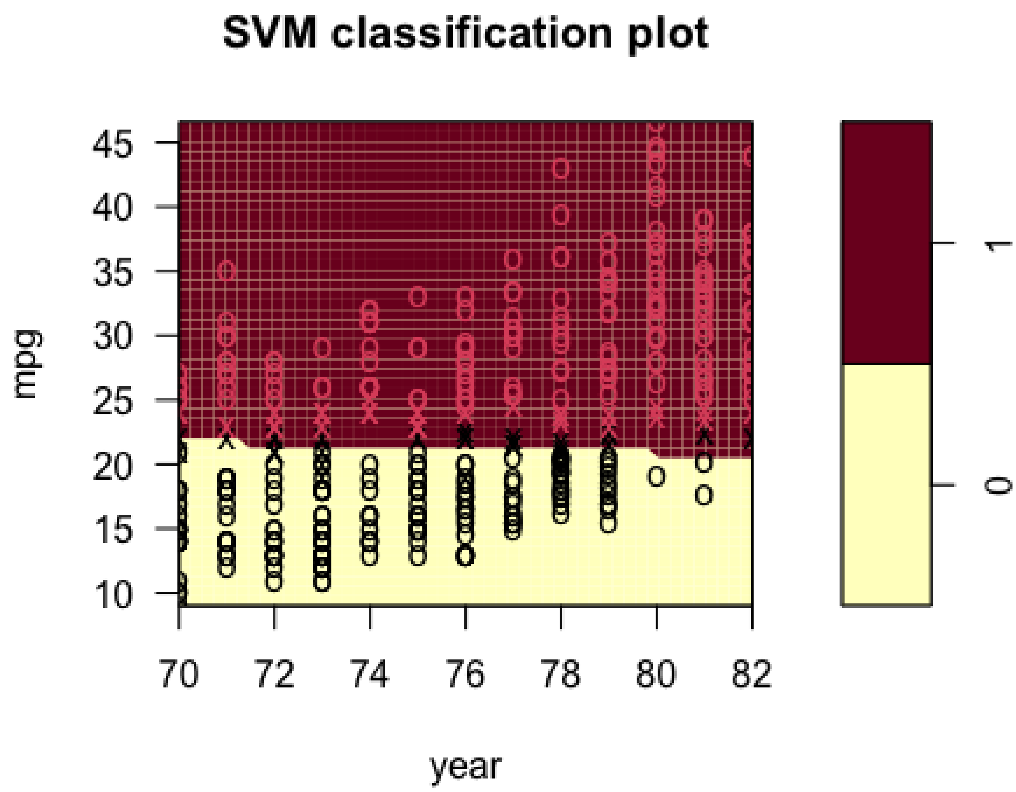

SVM classification plot
mpg
45
40
35
30
25
20
15
10
3
4
5
6
7
8
cylinders
1
0

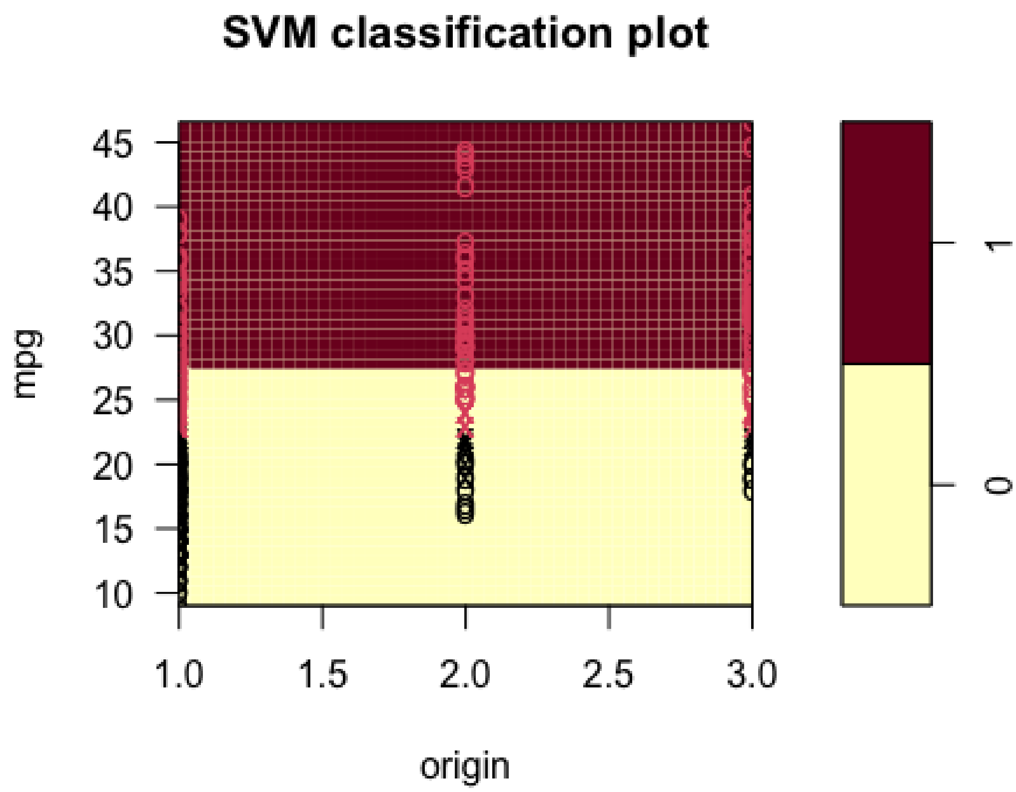

SVM classification plot
mpg
45
40
35
30
25
20
15
10
100
200
300
400
displacement
1
0


SVM classification plot
mpg
horsepower
45
40
35
30
25
20
15
10
50
100
150
200
1
0

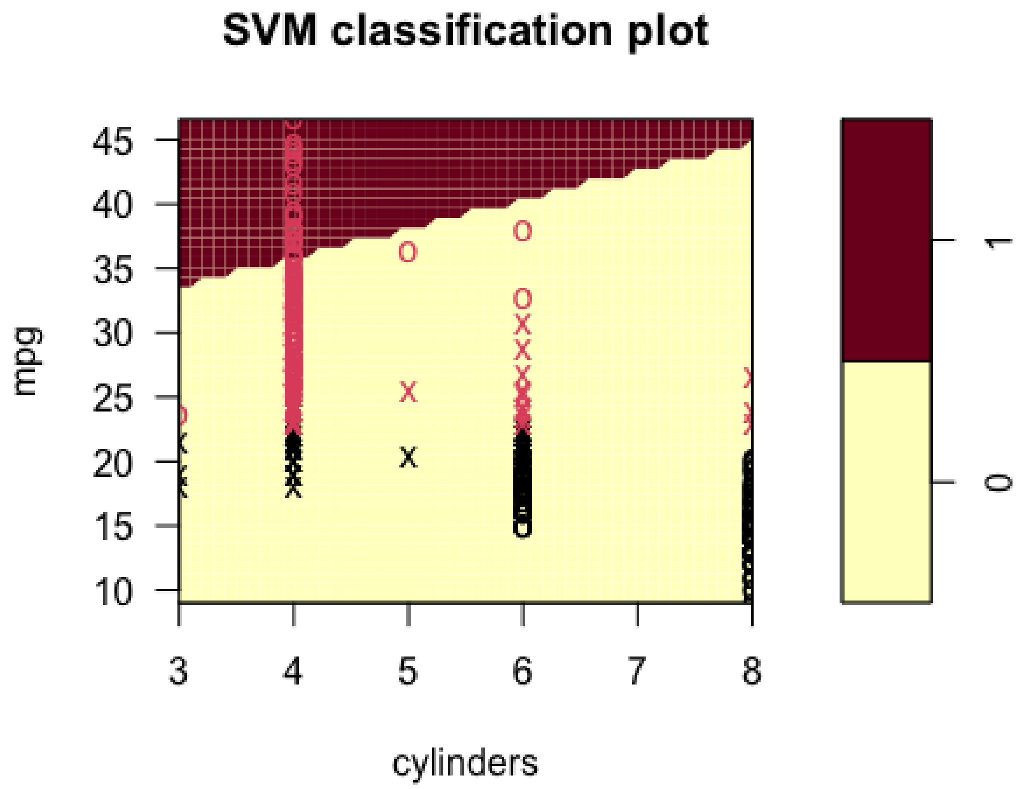

SVM classification plot
mpg
weight
45
40
35
30
25
20
15
10
2000
3000
4000
5000
1
0

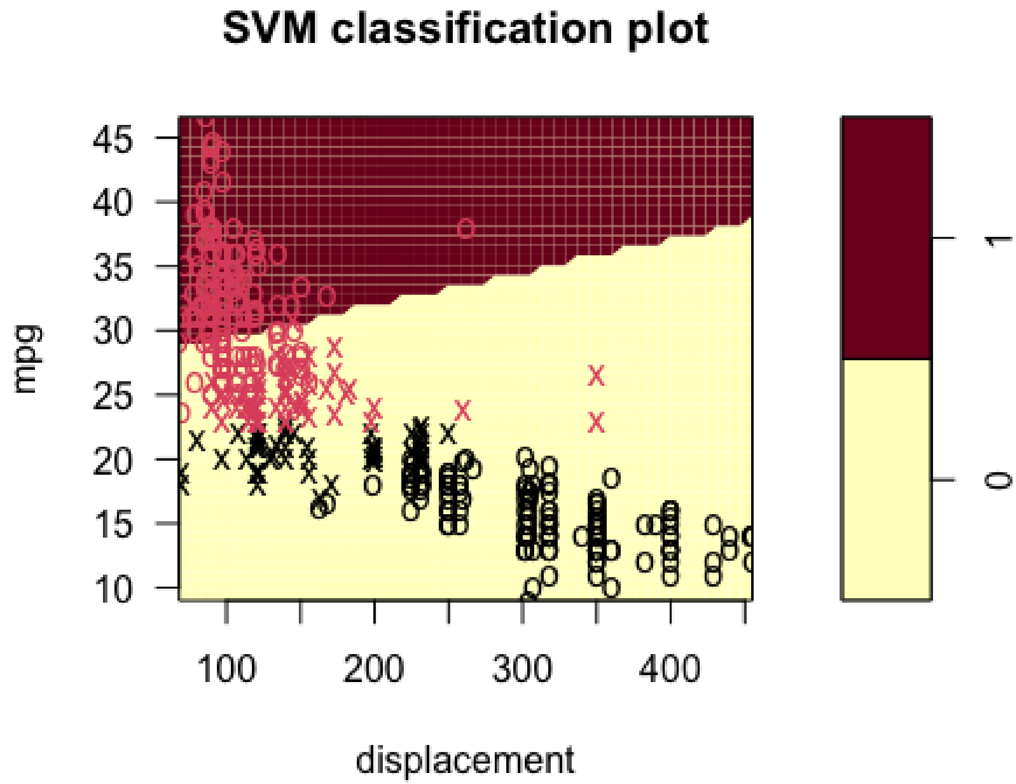

SVM classification plot
mpg
acceleration
45
40
35
30
25
20
15
10
10
15
20
1
0

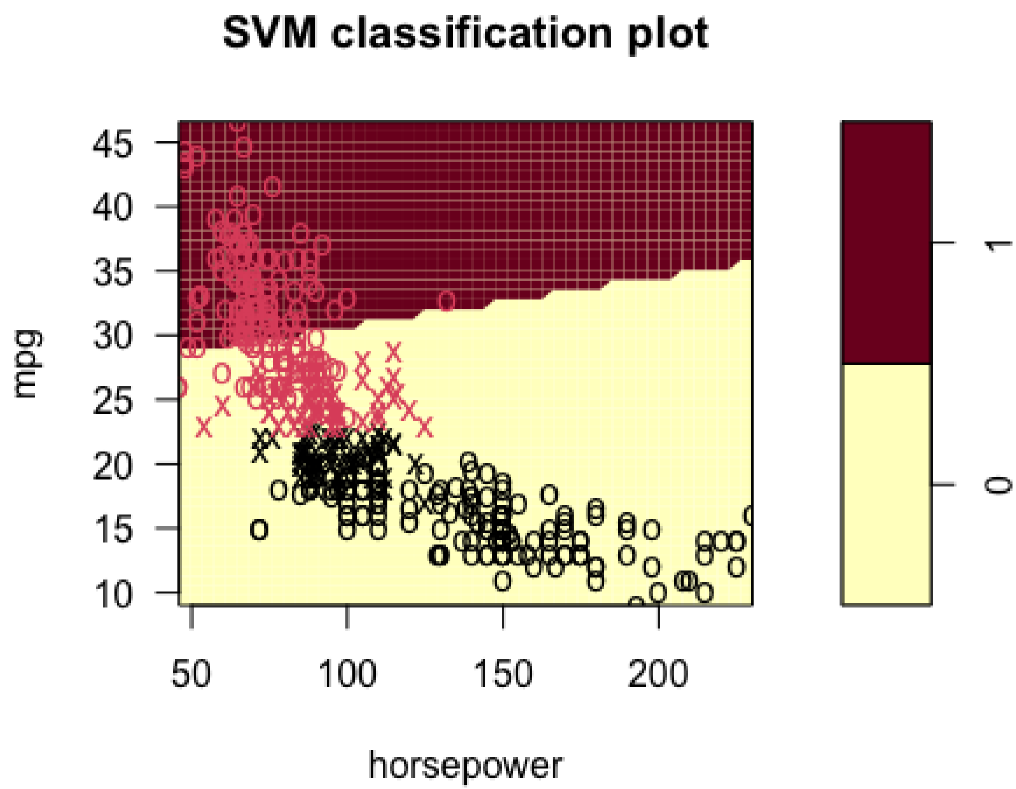

SVM classification plot
mpg
year
45
40
35
30
25
20
15
10
70
72
74
76
78
80
82
1
0

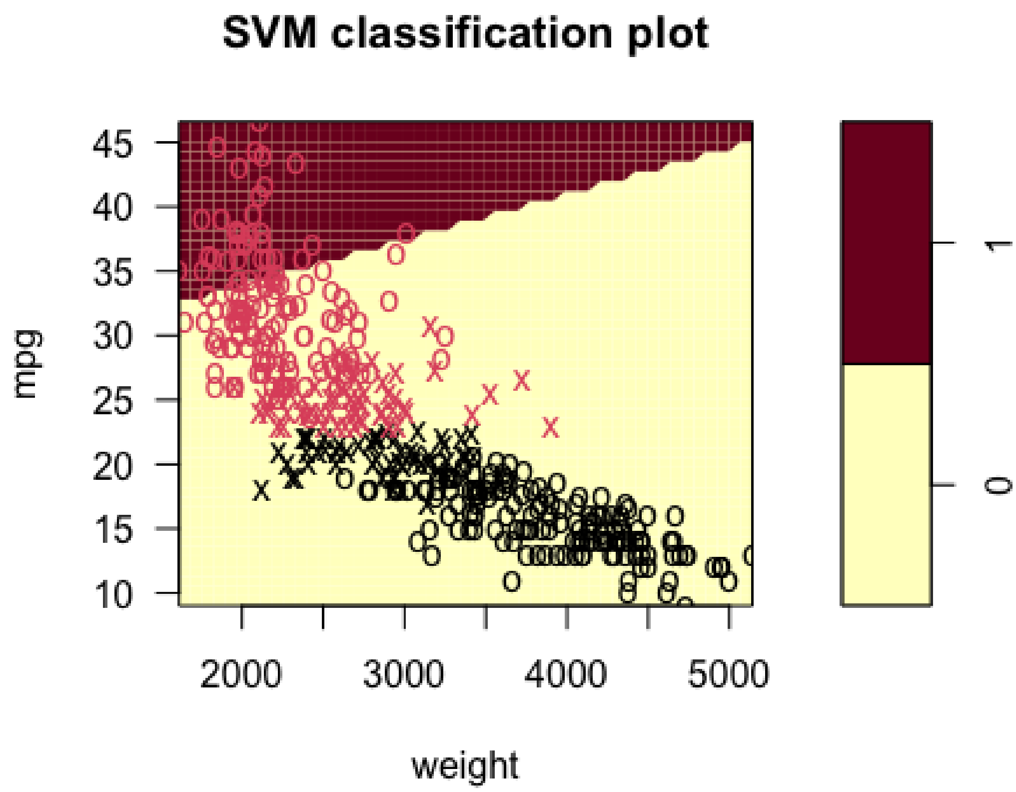


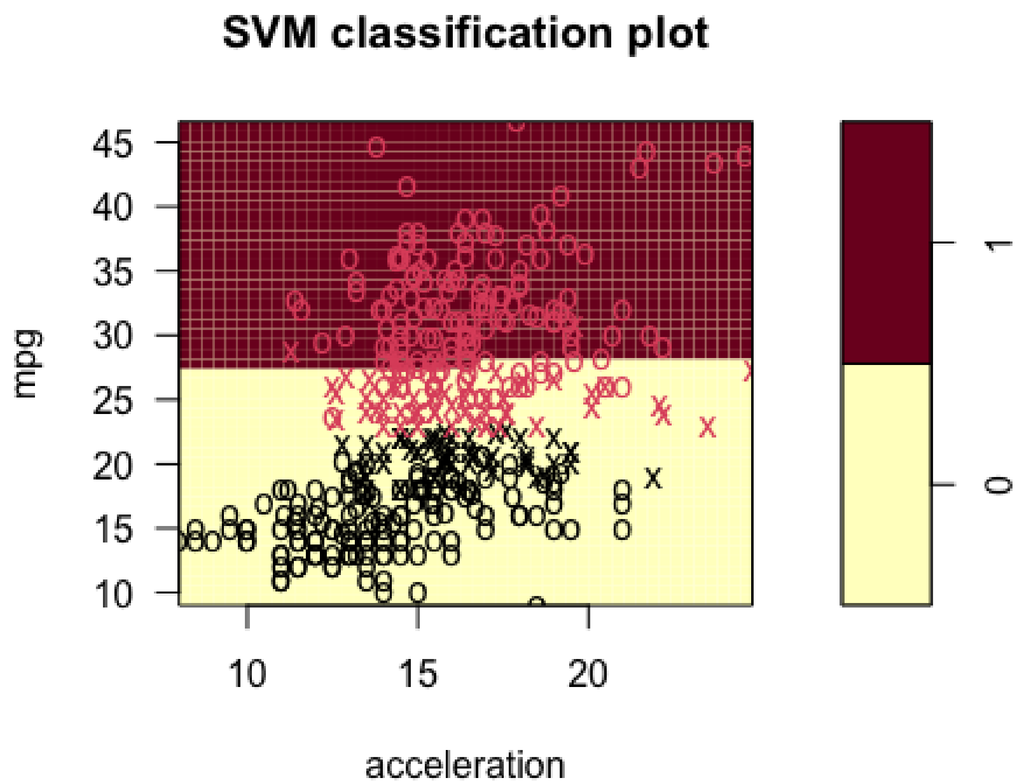

```r
plotpairs(svm_poly)
```


SVM classification plot
mpg
45
40
35
30
25
20
15
10
3
4
5
6
7
8
cylinders
1
0

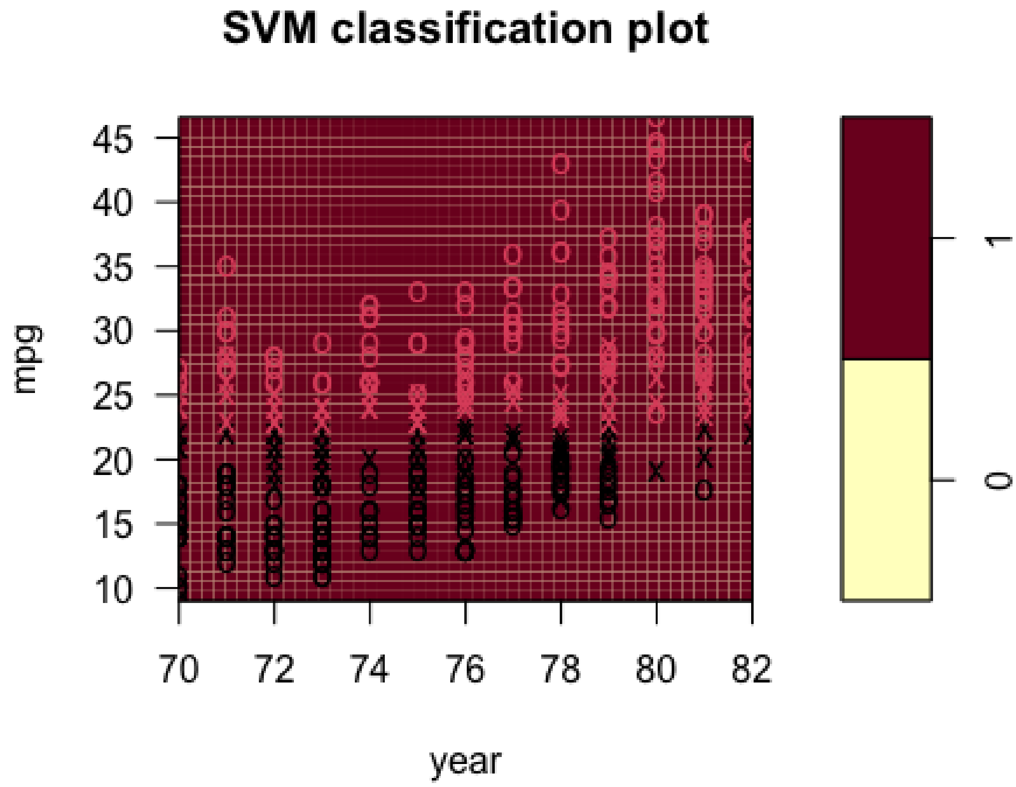

SVM classification plot
mpg
45
40
35
30
25
20
15
10
100
200
300
400
displacement
1
0

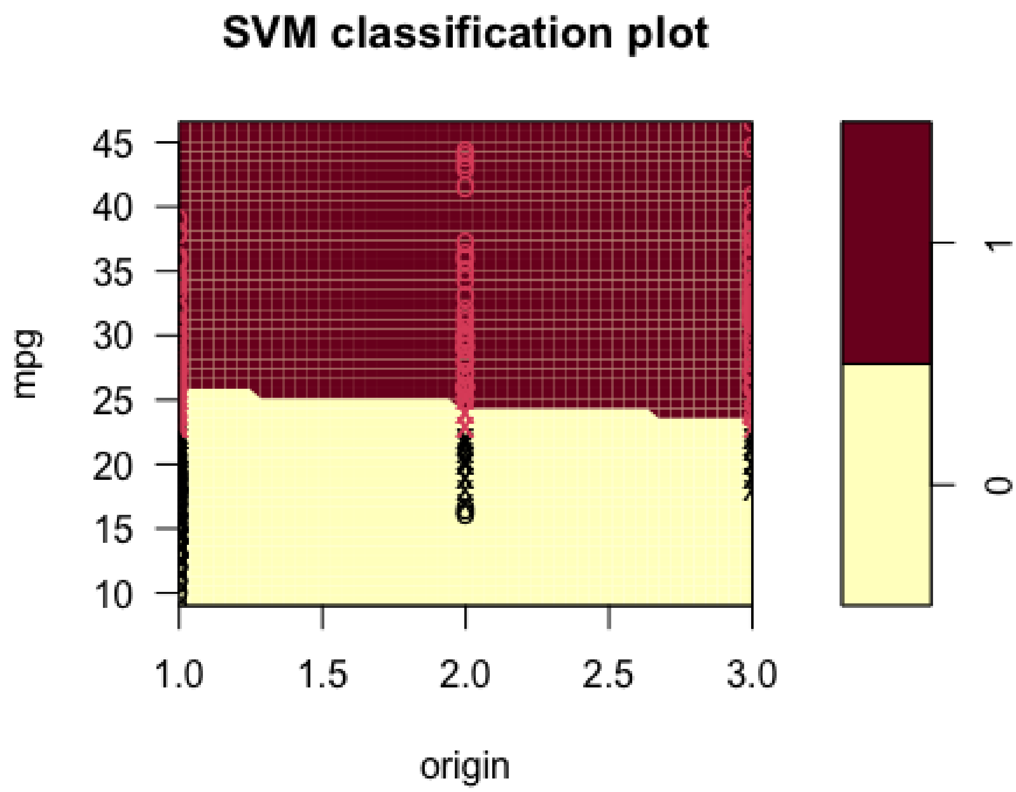

SVM classification plot
mpg
horsepower
45
40
35
30
25
20
15
10
50
100
150
200
1
0


SVM classification plot
mpg
weight
45
40
35
30
25
20
15
10
2000
3000
4000
5000
1
0

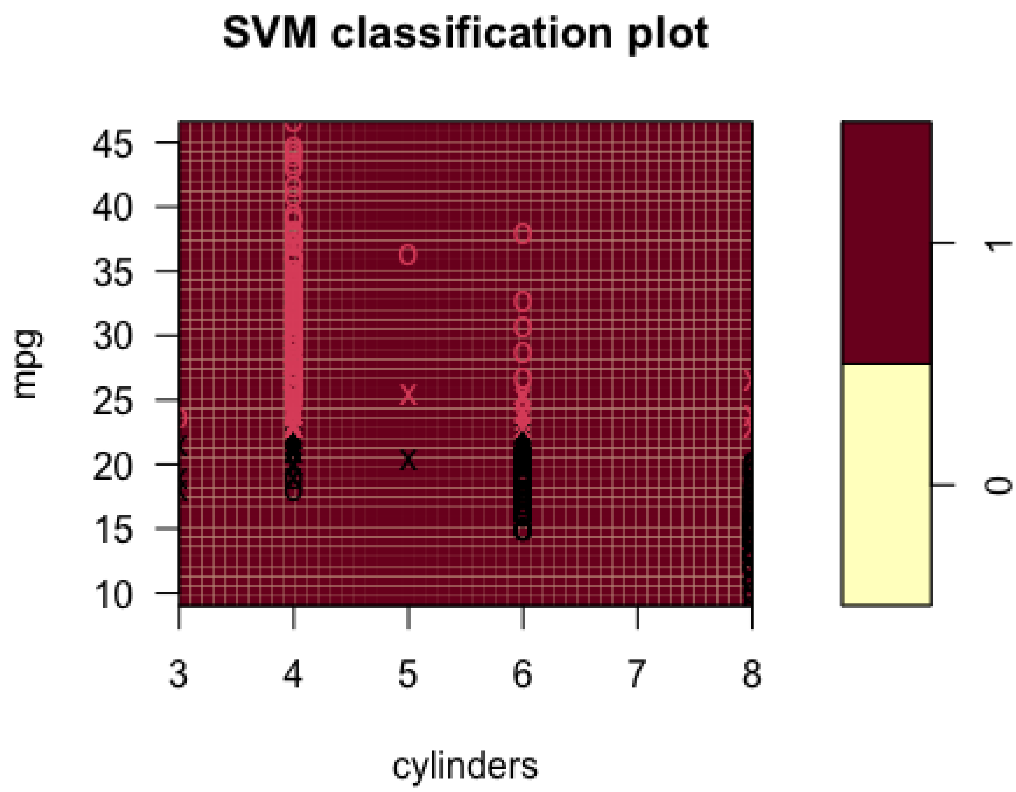


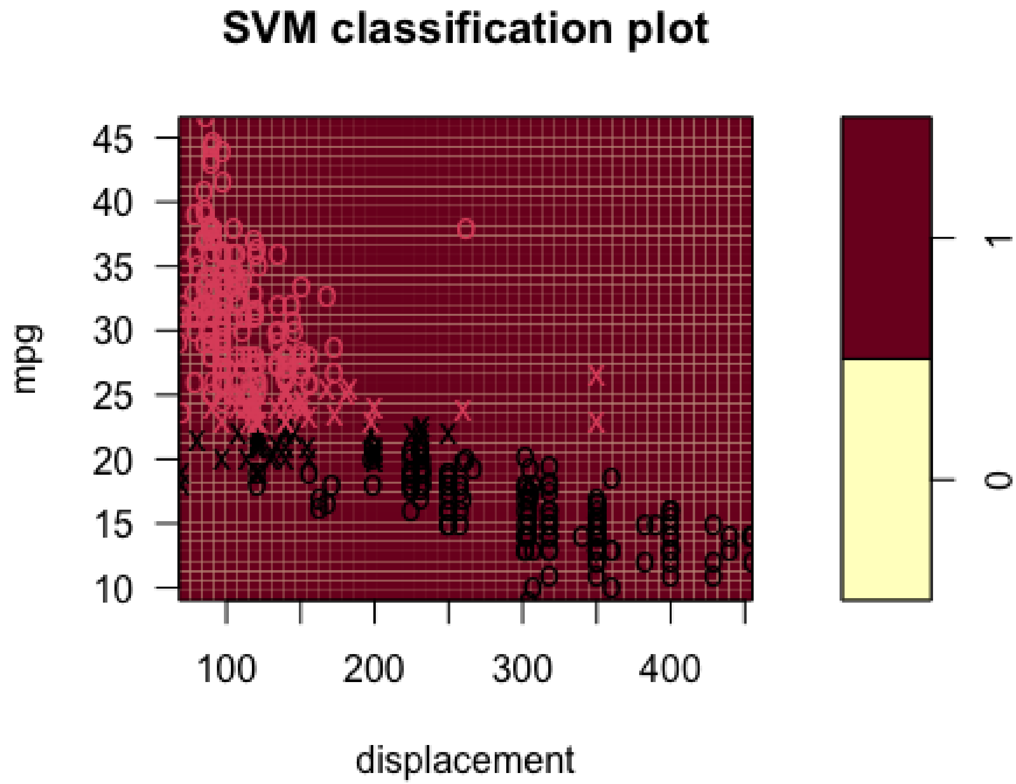
SVM classification plot
mpg
45
40
35
30
25
20
15
10
10
15
20
acceleration
1
0

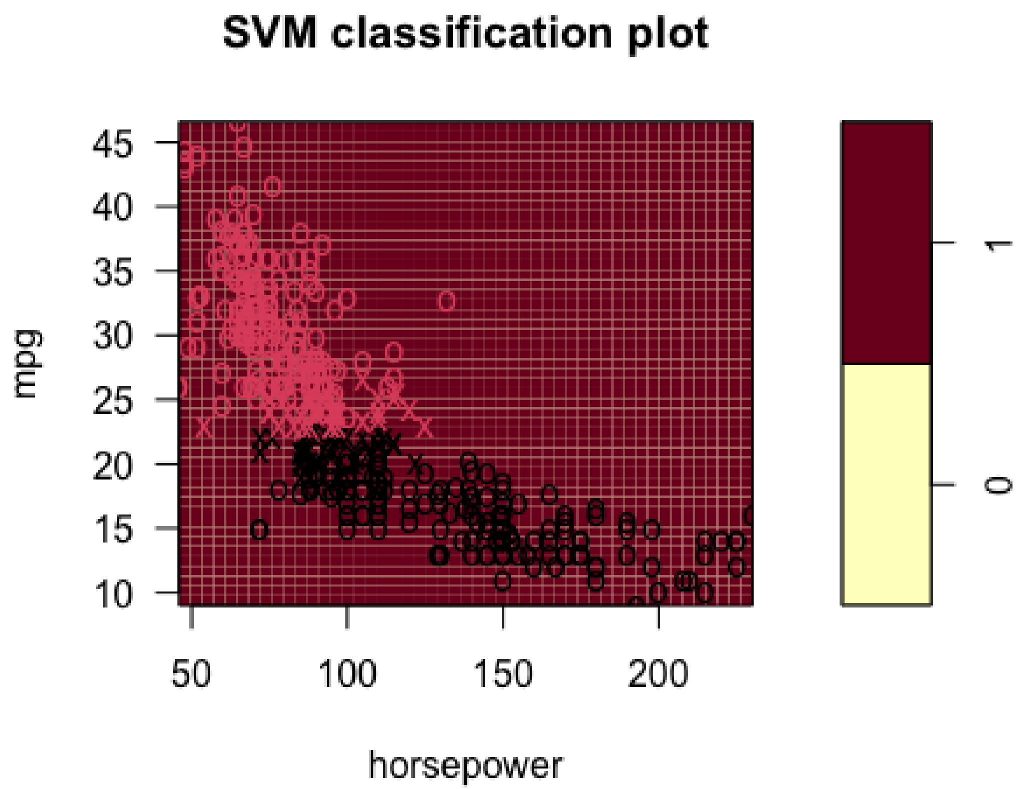

SVM classification plot
mpg
45
40
35
30
25
20
15
10
70
72
74
76
78
80
82
year
1
0

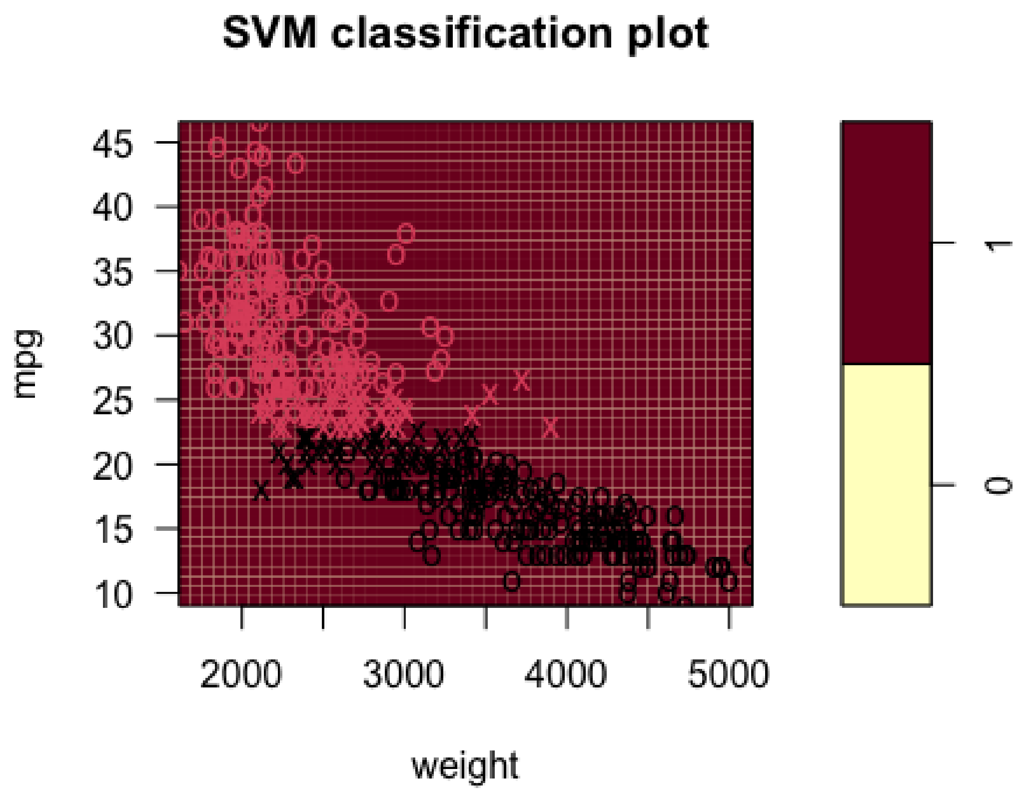



```
plotpairs(svm_radial)
```

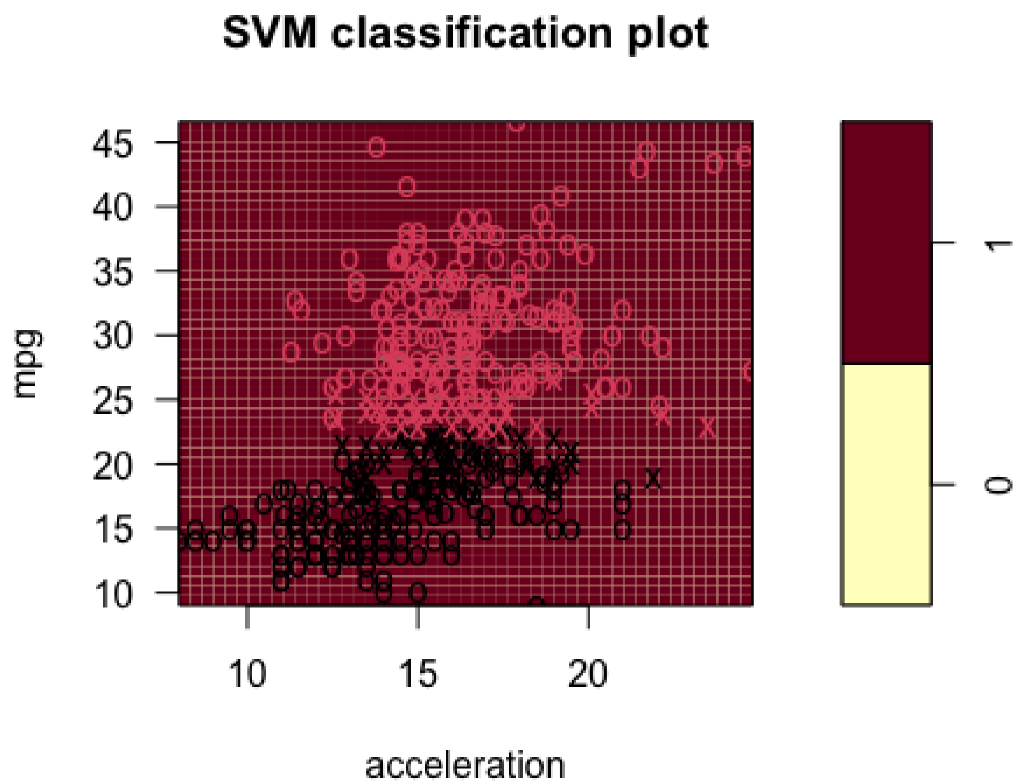

SVM classification plot
mpg
45
40
35
30
25
20
15
10
3
4
5
6
7
8
cylinders
1
0

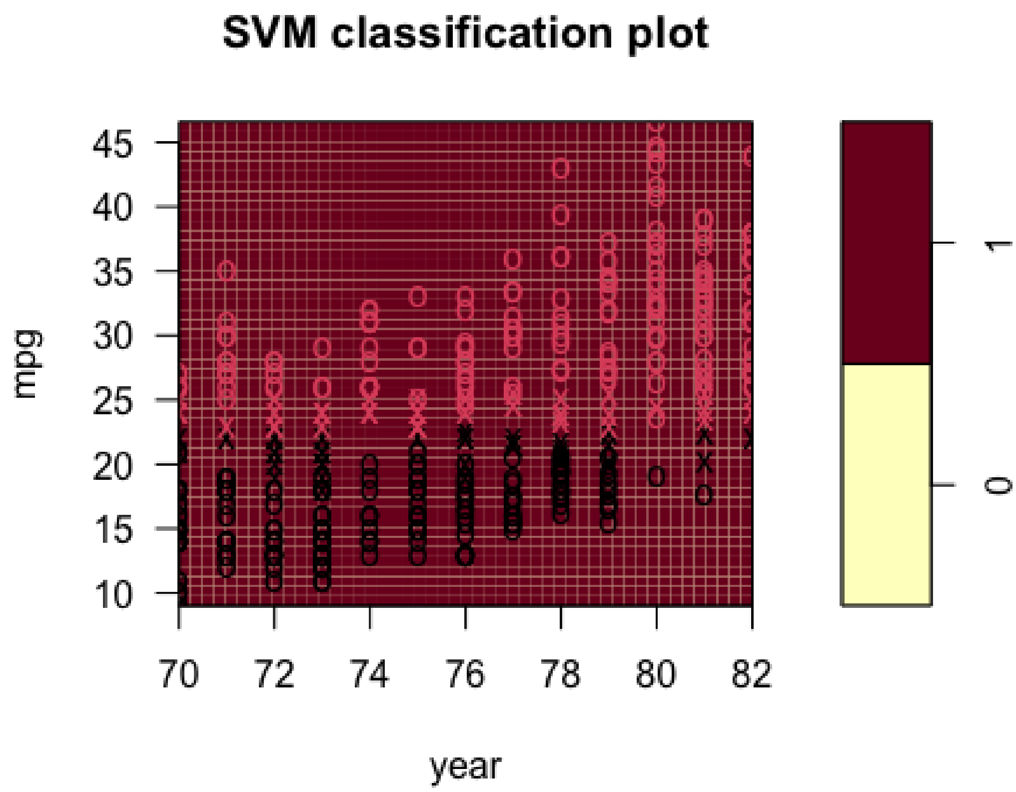

SVM classification plot
mpg
45
40
35
30
25
20
15
10
100
200
300
400
displacement
1
0

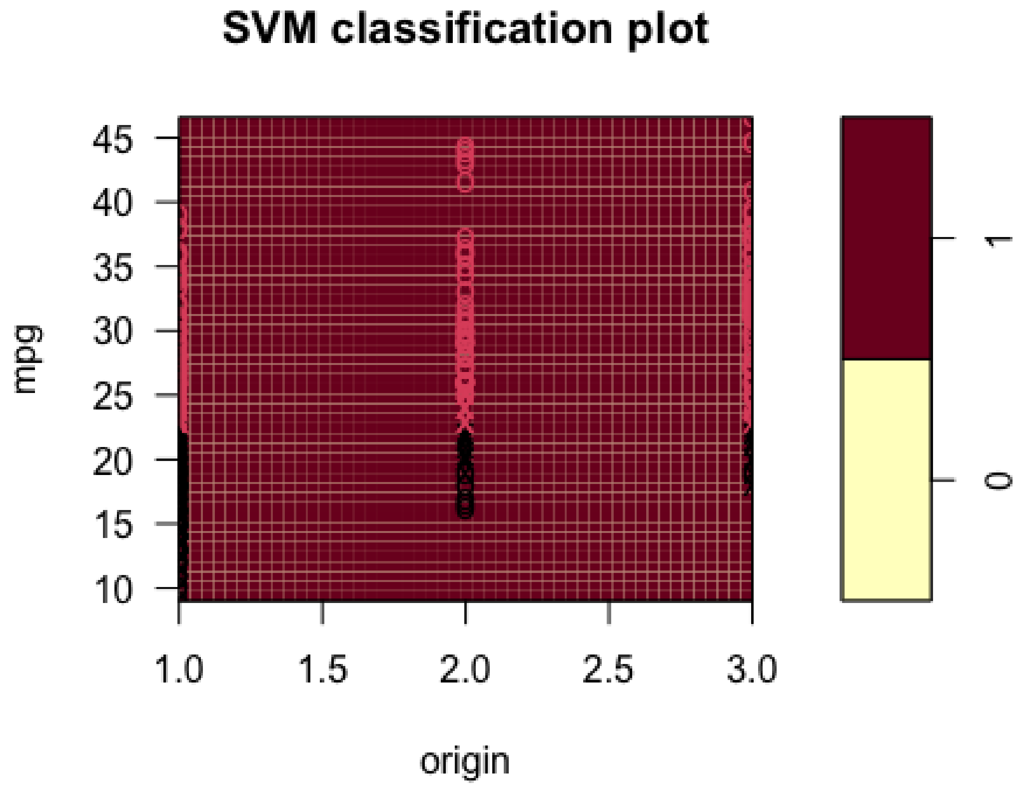

SVM classification plot
mpg
45
40
35
30
25
20
15
10
50
100
150
200
horsepower
1
0



SVM classification plot
mpg
45
40
35
30
25
20
15
10
2000
3000
4000
5000
weight
1
0


SVM classification plot
45
40
35
30
25
20
15
10
mpg
10
15
20
acceleration
1
0


SVM classification plot
mpg
45
40
35
30
25
20
15
10
70
72
74
76
78
80
82
year
1
0


SVM classification plot
mpg
45
40
35
30
25
20
15
10
1.0
1.5
2.0
2.5
3.0
origin
1
0