

R Notebook

```
#Ex7
library(ISLR)
require(tidyverse)

## Loading required package: tidyverse

## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'tidyverse'

library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

library(e1071)

## Warning: package 'e1071' was built under R version 3.5.2

attach(Auto)

## The following object is masked from package:ggplot2:
##
##      mpg

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

#a
gas_median = median(Auto$mpg)
variation = ifelse(Auto$mpg > gas_median, 1, 0)
Auto$mpglevel = as.factor(variation)

#b
set.seed(1)
library(e1071)

tune_x = tune(svm, mpglevel ~ ., data = Auto, kernel = "linear", ranges =
```

```
list(cost = c(0.01, 0.1, 1, 5, 10, 100)))
summary(tune_x)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##     1
##
## - best performance: 0.01275641
##
## - Detailed performance results:
##   cost      error dispersion
## 1 1e-02 0.07403846 0.05471525
## 2 1e-01 0.03826923 0.05148114
## 3 1e+00 0.01275641 0.01344780
## 4 5e+00 0.01782051 0.01229997
## 5 1e+01 0.02038462 0.01074682
## 6 1e+02 0.03820513 0.01773427
```

*#the best result is achieved when cost = 1. we get an error
of 0.0127*

```
#c
tune_x = tune(svm, mpglevel ~ ., data = Auto, kernel = "polynomial", ranges =
list(cost = c(0.1,
  1, 5, 10), degree = c(2, 3, 4)))
summary(tune_x)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost degree
##   10      2
##
## - best performance: 0.5228205
##
## - Detailed performance results:
##   cost degree      error dispersion
## 1  0.1      2 0.5587179 0.05068311
## 2  1.0      2 0.5587179 0.05068311
## 3  5.0      2 0.5587179 0.05068311
## 4 10.0      2 0.5228205 0.09271988
```

```
## 5  0.1      3 0.5587179 0.05068311
## 6  1.0      3 0.5587179 0.05068311
## 7  5.0      3 0.5587179 0.05068311
## 8 10.0      3 0.5587179 0.05068311
## 9  0.1      4 0.5587179 0.05068311
## 10 1.0      4 0.5587179 0.05068311
## 11 5.0      4 0.5587179 0.05068311
## 12 10.0     4 0.5587179 0.05068311
```

##From the summary we can see that the smallest cross-validation error is obtained for cost=10 and degree=2.

```
tune_x = tune(svm, mpglevel ~ ., data = Auto, kernel = "radial", ranges =
list(cost = c(0.1,
  1, 5, 10), gamma = c(0.01, 0.1, 1, 5, 10, 100)))
summary(tune_x)
```

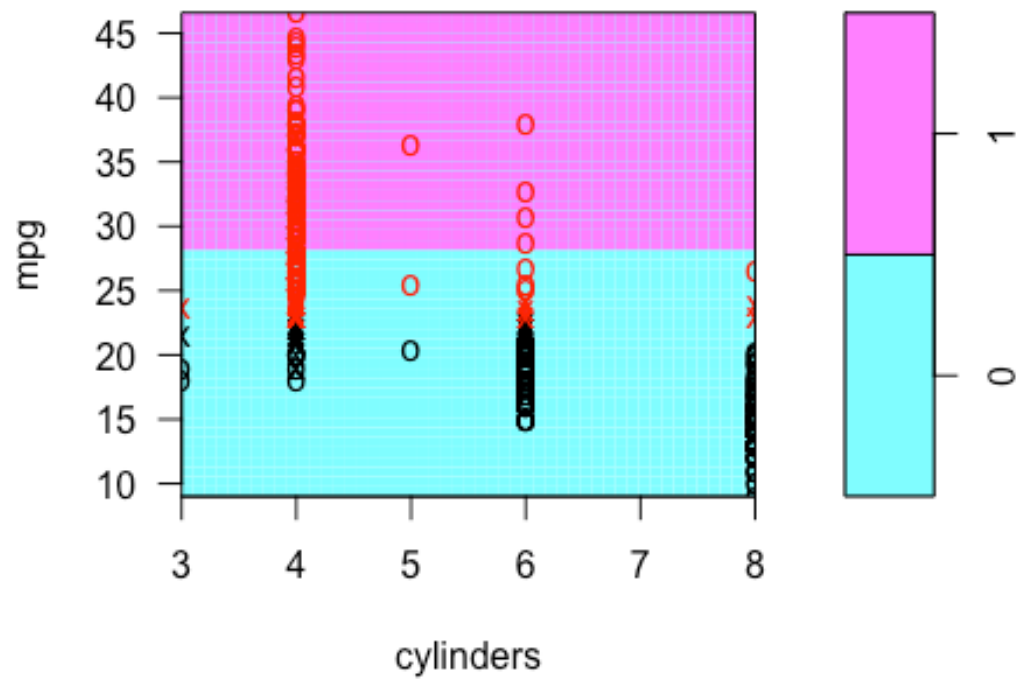
```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost gamma
##   10  0.01
##
## - best performance: 0.02038462
##
## - Detailed performance results:
##   cost gamma      error dispersion
## 1  0.1 1e-02 0.08673077 0.04966103
## 2  1.0 1e-02 0.07147436 0.04638992
## 3  5.0 1e-02 0.04846154 0.03501693
## 4 10.0 1e-02 0.02038462 0.01617396
## 5  0.1 1e-01 0.07660256 0.04674289
## 6  1.0 1e-01 0.05608974 0.03555911
## 7  5.0 1e-01 0.02544872 0.02662645
## 8 10.0 1e-01 0.02544872 0.02662645
## 9  0.1 1e+00 0.58673077 0.03560377
## 10 1.0 1e+00 0.06121795 0.03216114
## 11 5.0 1e+00 0.06115385 0.02720346
## 12 10.0 1e+00 0.06115385 0.02720346
## 13 0.1 5e+00 0.58673077 0.03560377
## 14 1.0 5e+00 0.52032051 0.02994512
## 15 5.0 5e+00 0.51525641 0.03415169
## 16 10.0 5e+00 0.51525641 0.03415169
## 17 0.1 1e+01 0.58673077 0.03560377
## 18 1.0 1e+01 0.55602564 0.03521326
## 19 5.0 1e+01 0.54083333 0.02859746
## 20 10.0 1e+01 0.54083333 0.02859746
```

```
## 21  0.1 1e+02 0.58673077 0.03560377
## 22  1.0 1e+02 0.58673077 0.03560377
## 23  5.0 1e+02 0.58673077 0.03560377
## 24 10.0 1e+02 0.58673077 0.03560377
```

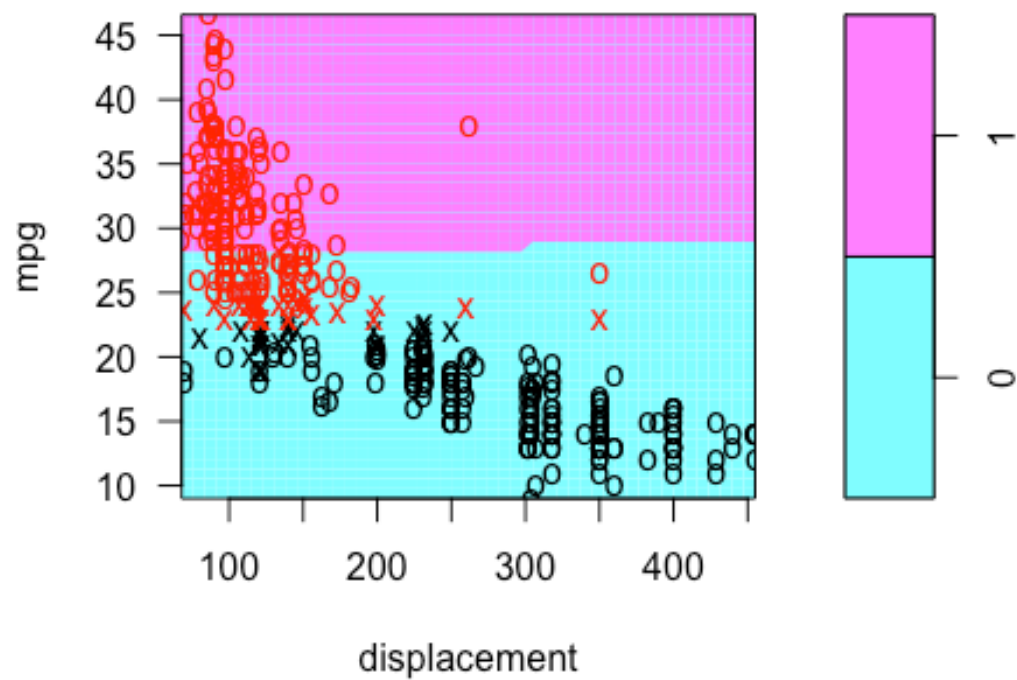
*#with radial the best results are achieved for cost 10
and gamma 0.01*

```
#d
svm_linear_model = svm(mpglevel ~ ., data = Auto, kernel = "linear", cost =
1)
svm_polynomial = svm(mpglevel ~ ., data = Auto, kernel = "polynomial", cost =
10,
  degree = 2)
svm_radial = svm(mpglevel ~ ., data = Auto, kernel = "radial", cost = 10,
gamma = 0.01)
plotpairs = function(fit) {
  for (name in names(Auto)[!(names(Auto) %in% c("mpg", "mpglevel",
"name"))]) {
    plot(fit, Auto, as.formula(paste("mpg~", name, sep = "")))
  }
}
plotpairs(svm_linear_model)
```

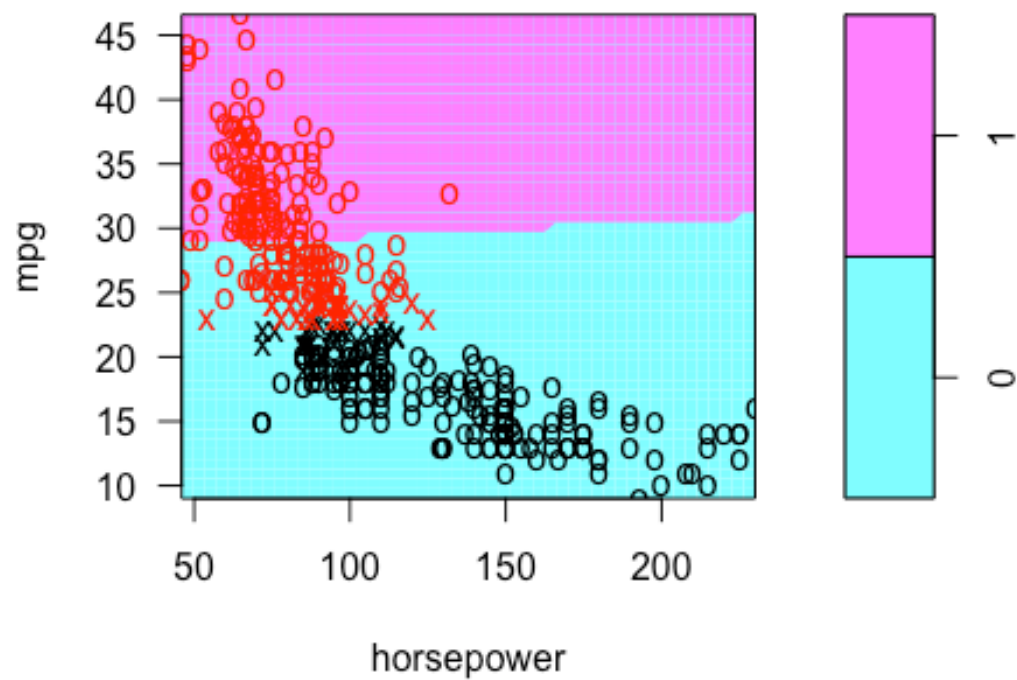
SVM classification plot



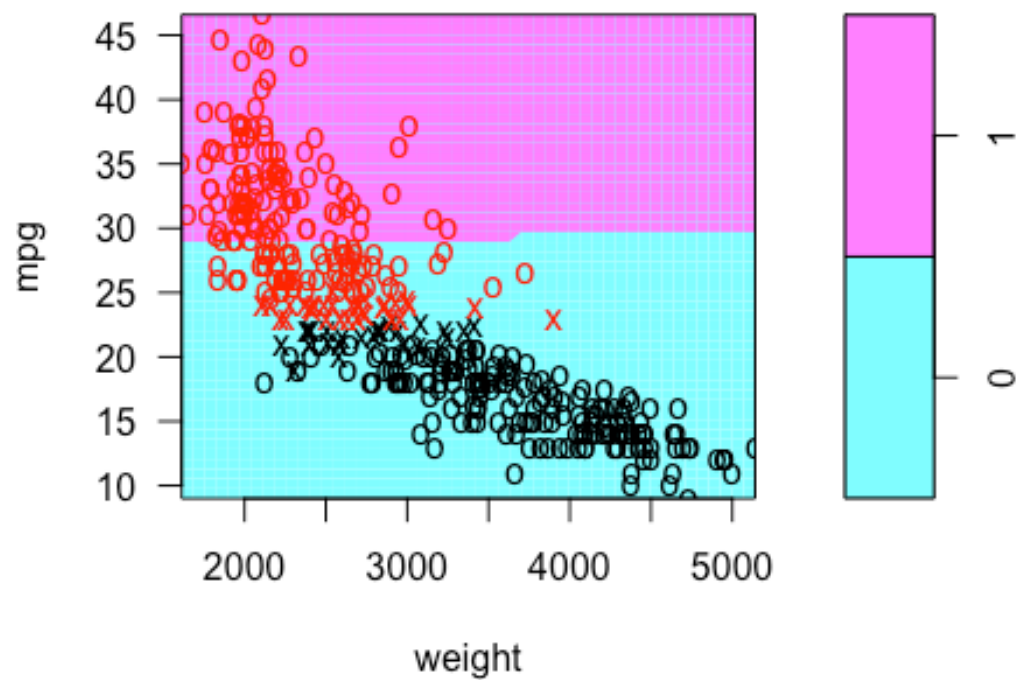
SVM classification plot



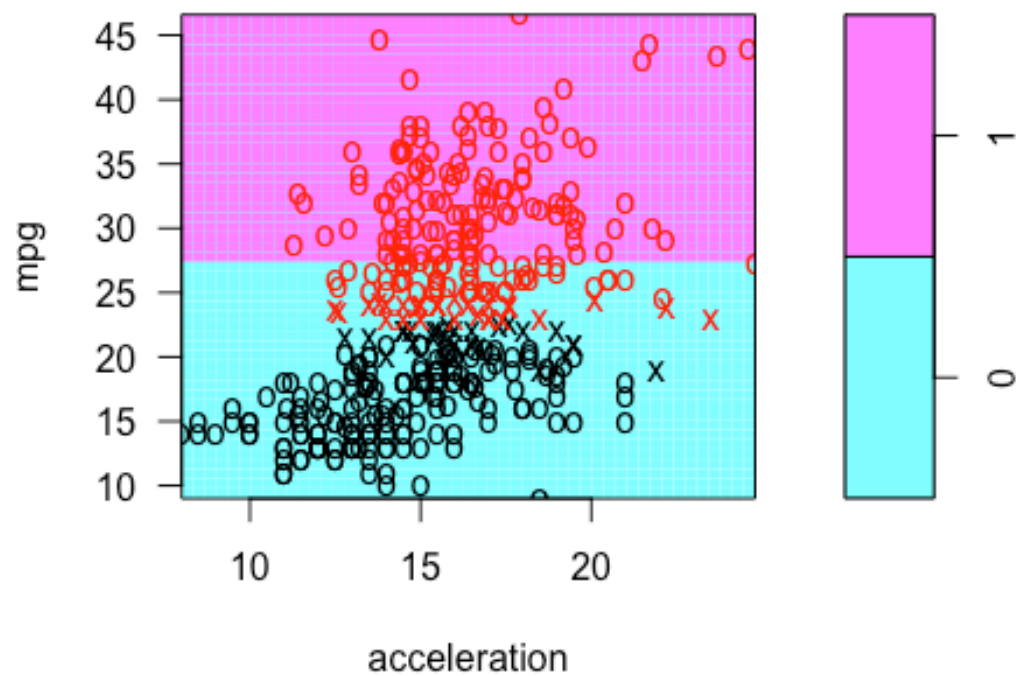
SVM classification plot



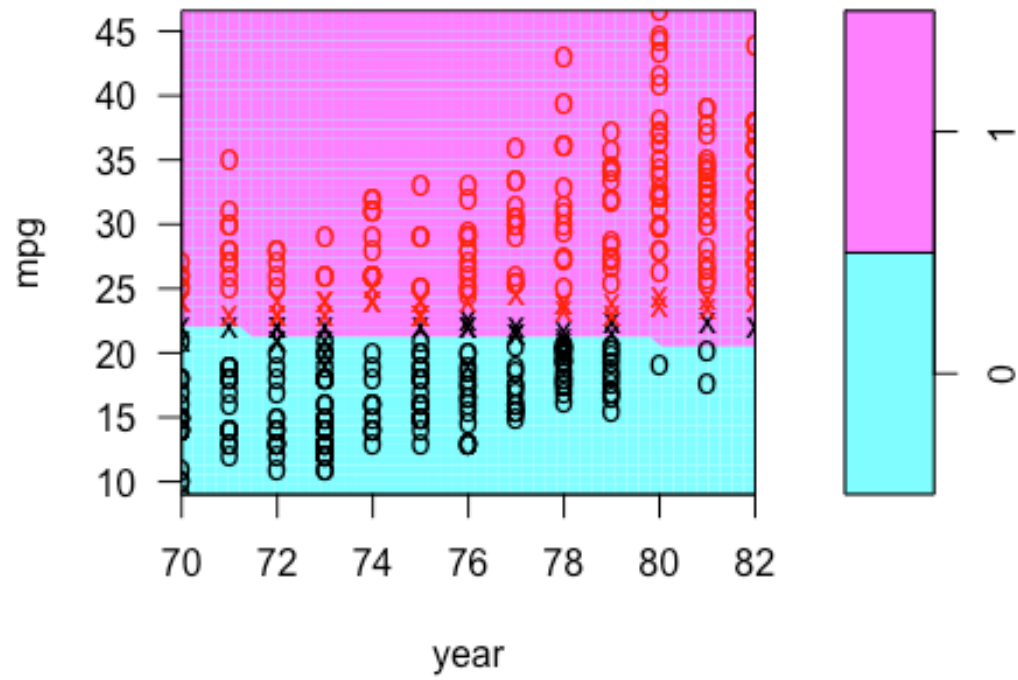
SVM classification plot



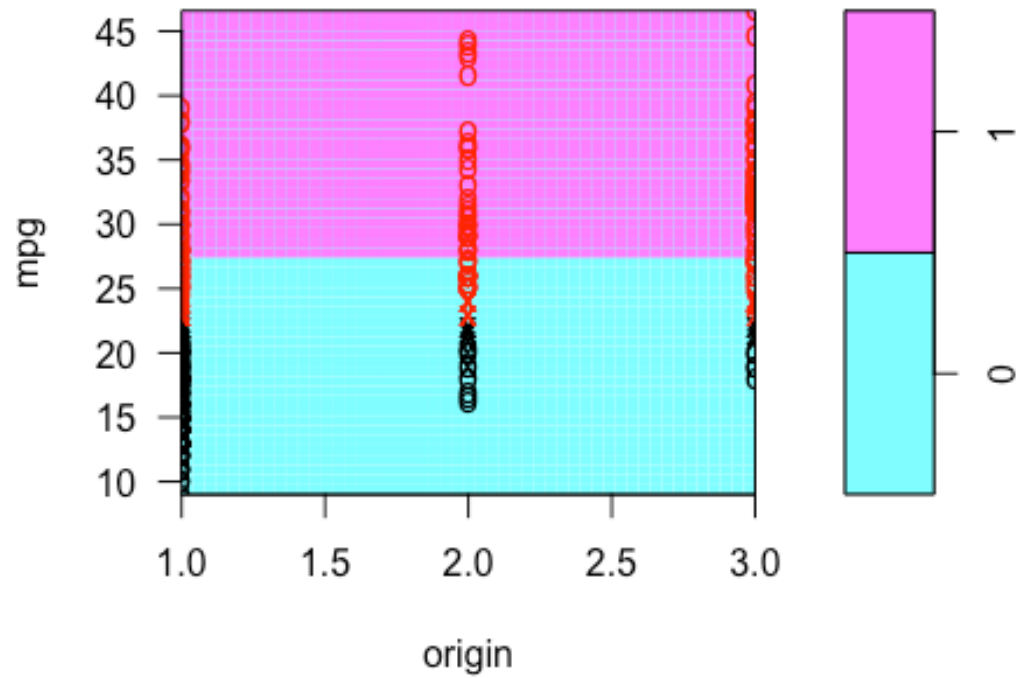
SVM classification plot



SVM classification plot

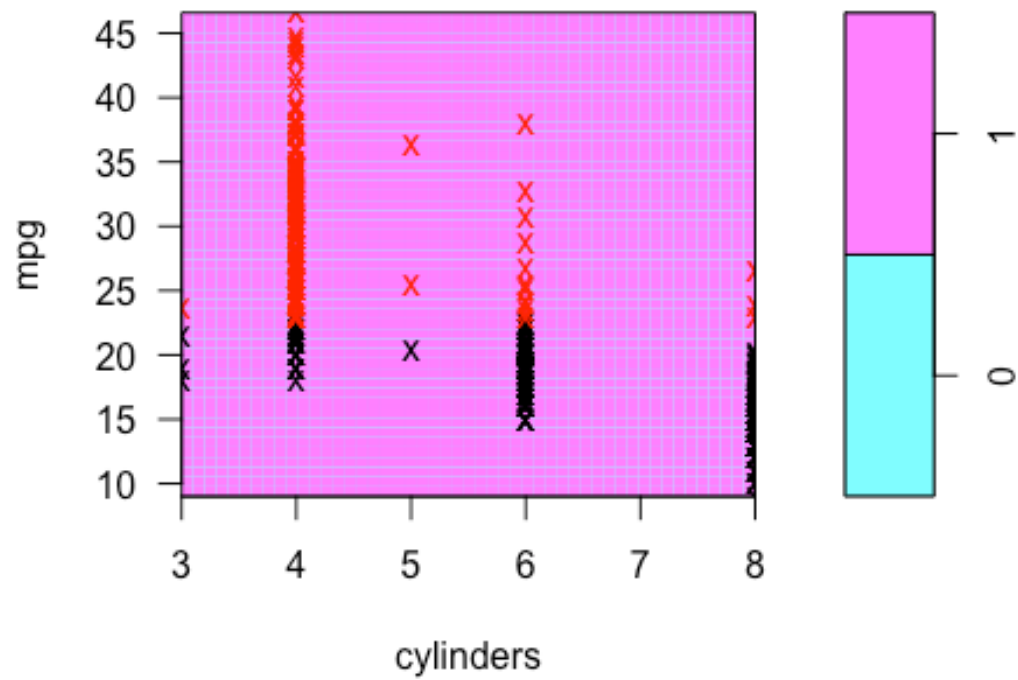


SVM classification plot

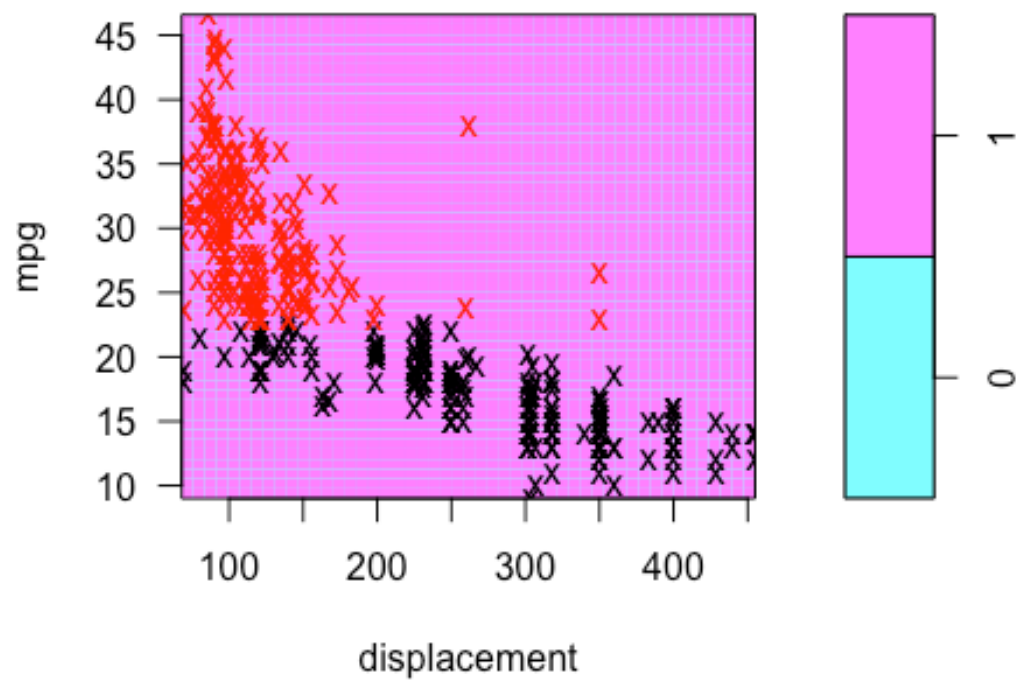


```
plotpairs(svm_polynomial)
```

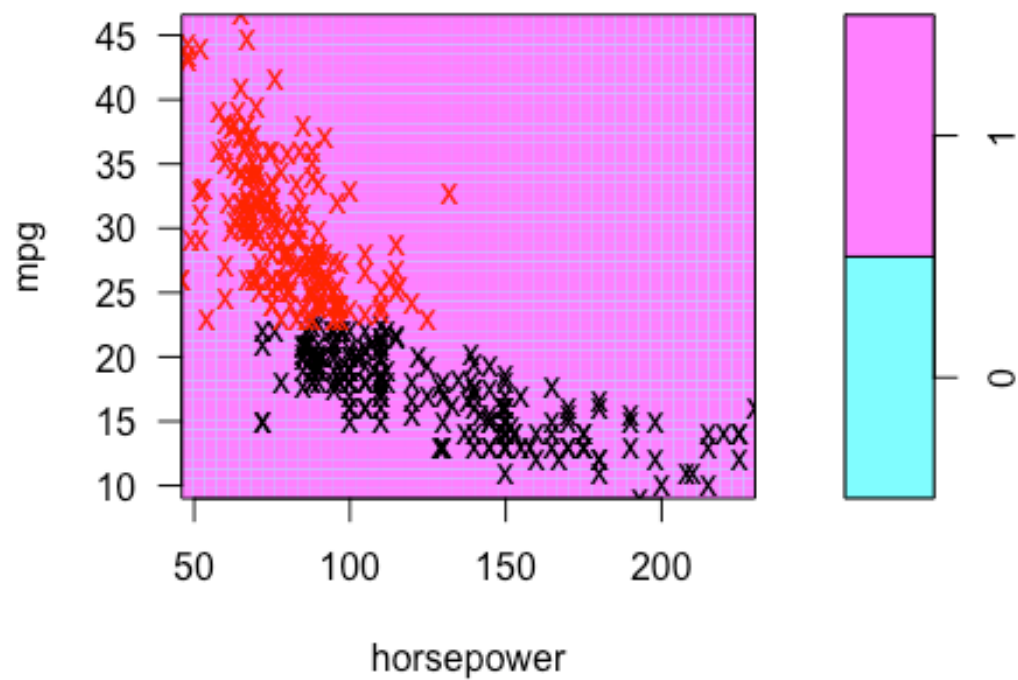
SVM classification plot



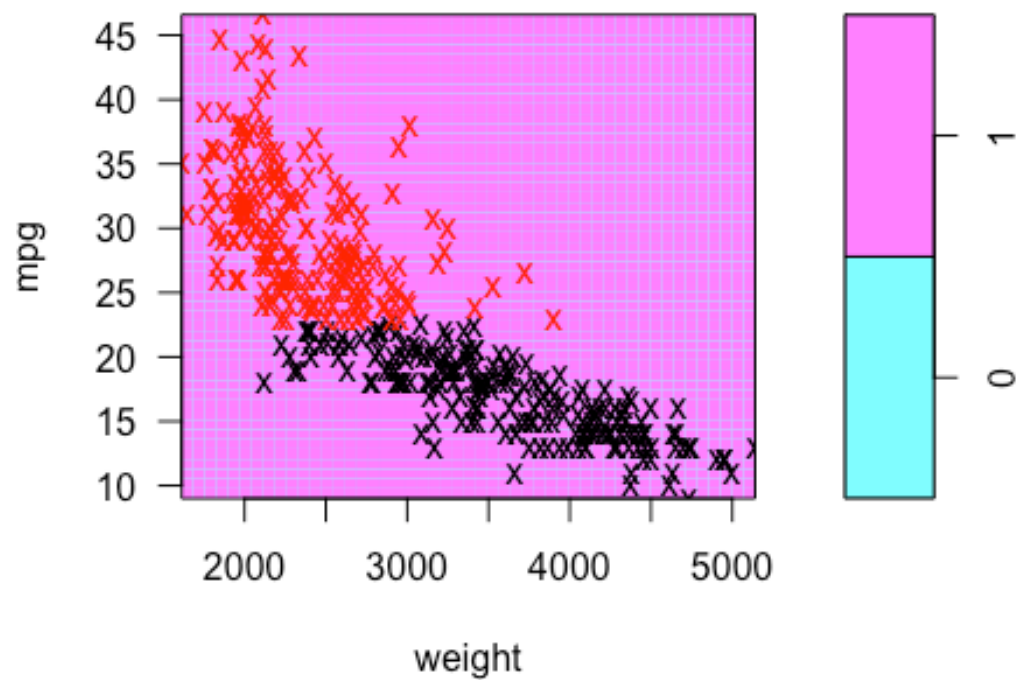
SVM classification plot



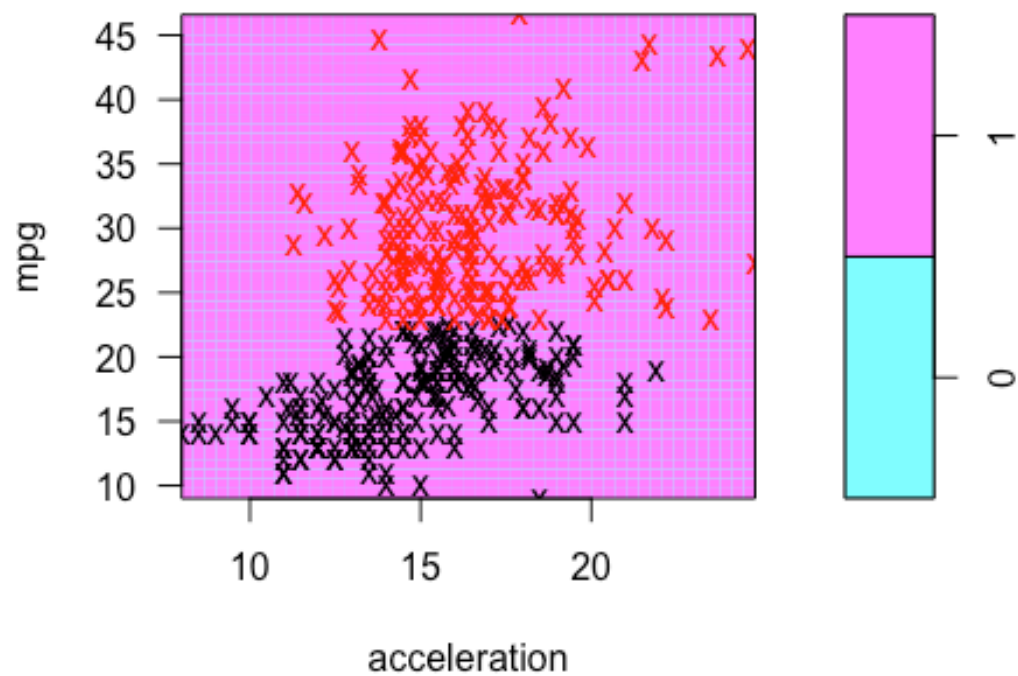
SVM classification plot



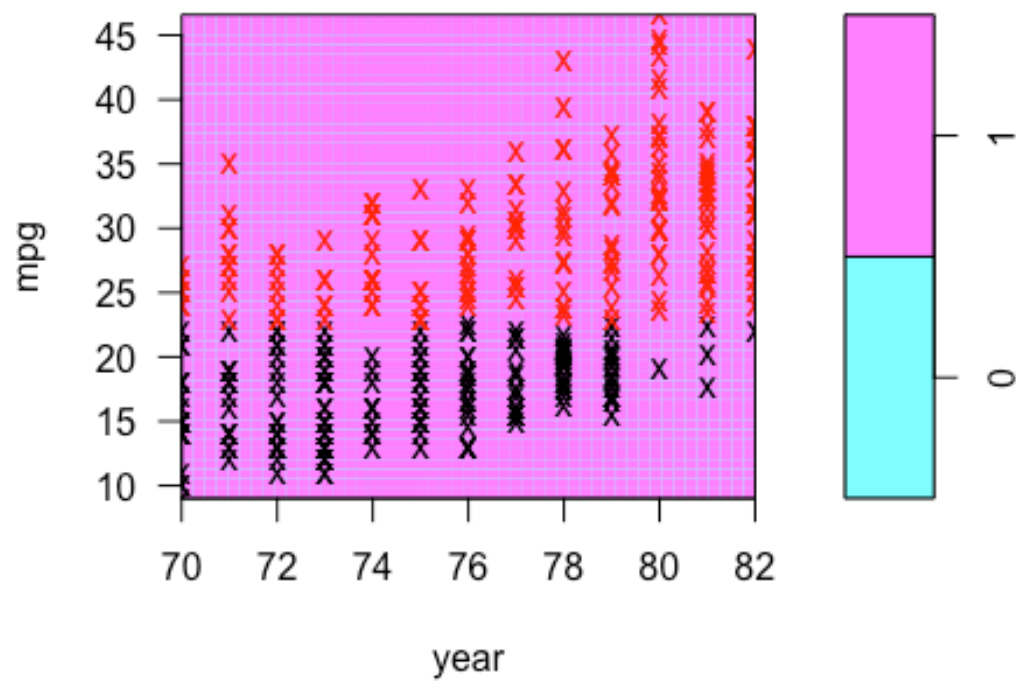
SVM classification plot



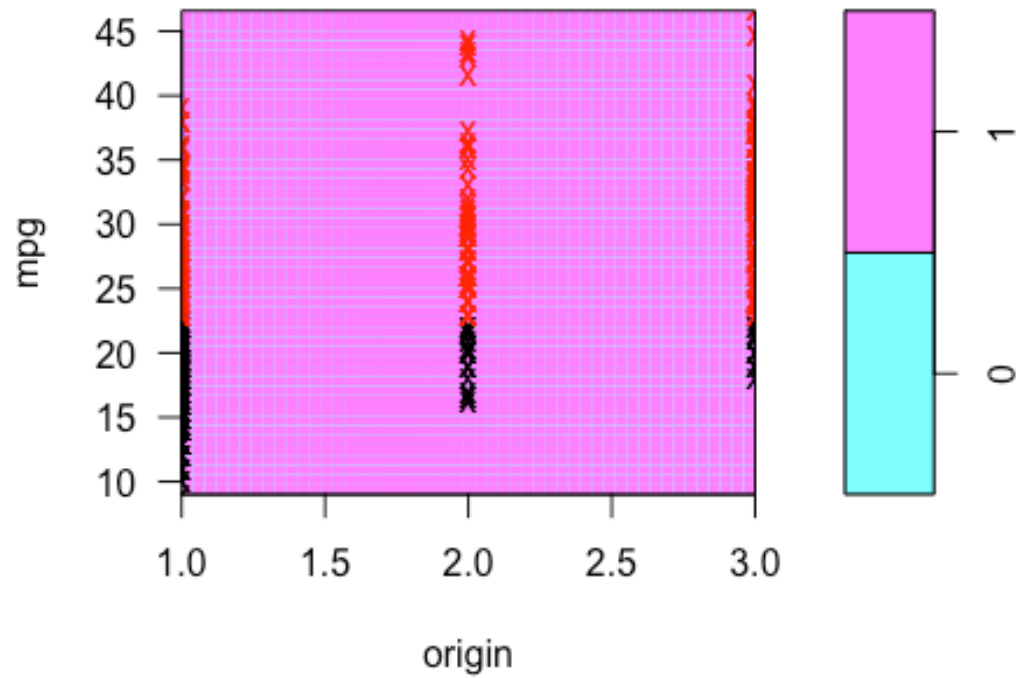
SVM classification plot



SVM classification plot

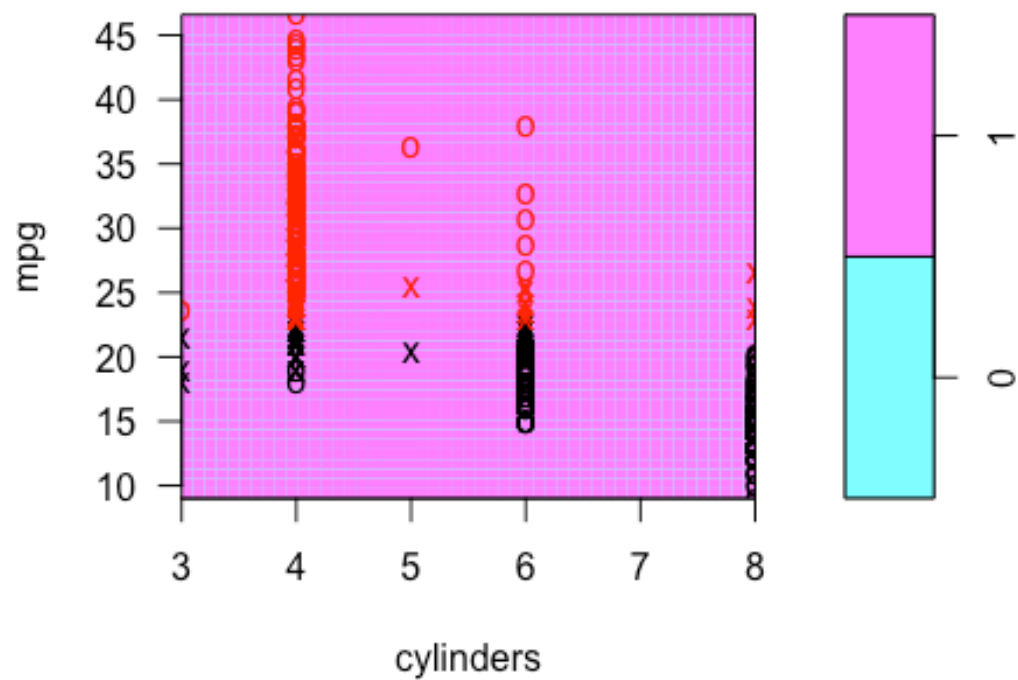


SVM classification plot

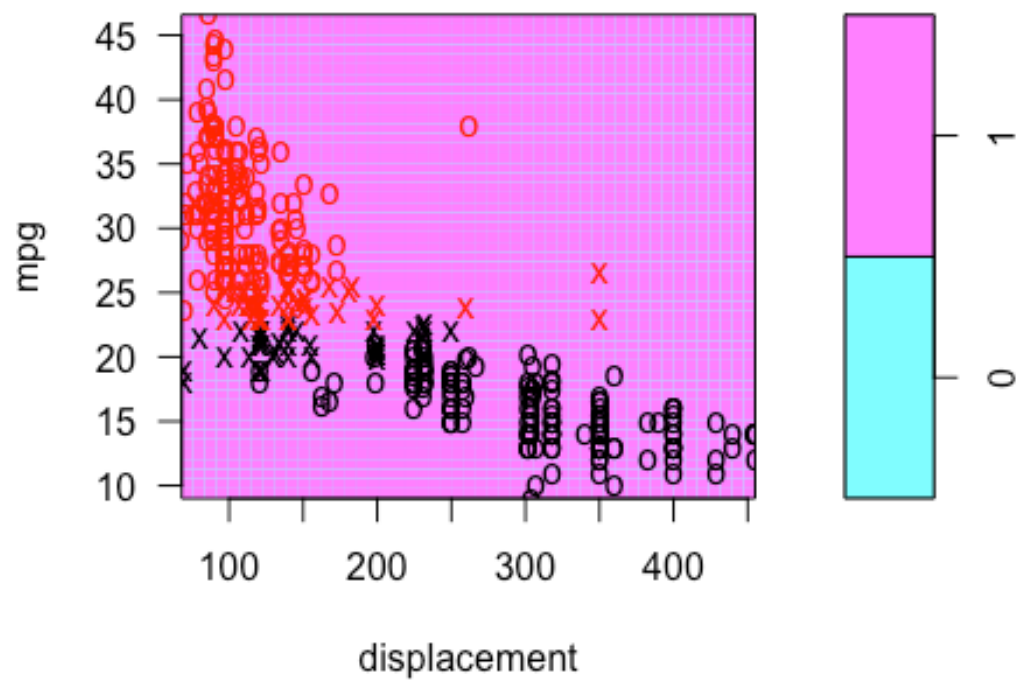


```
plotpairs(svm_radial)
```

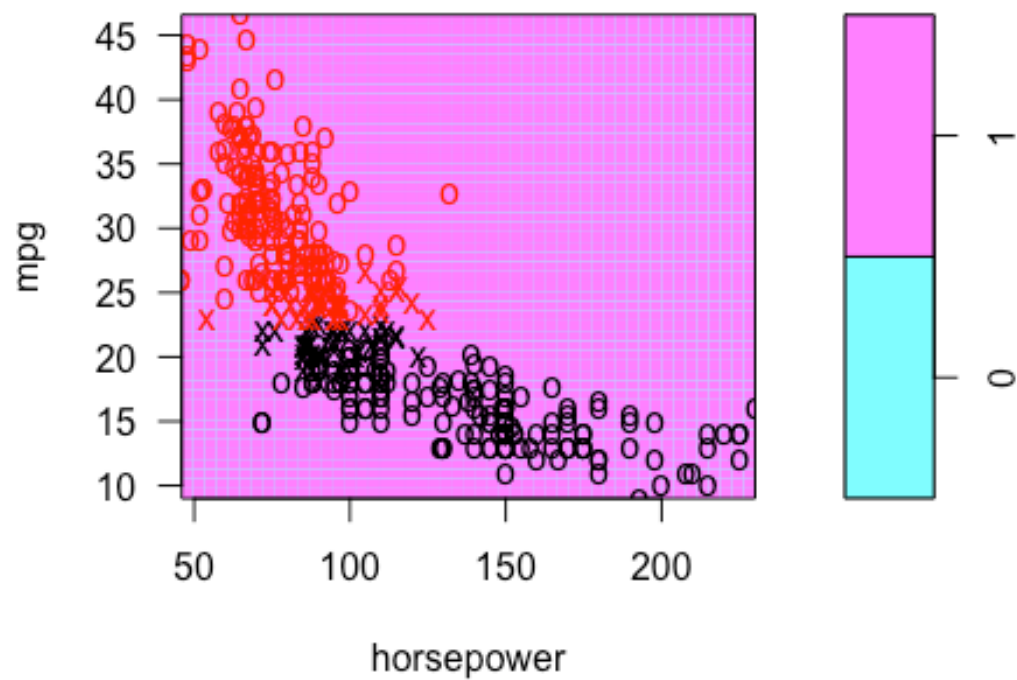
SVM classification plot



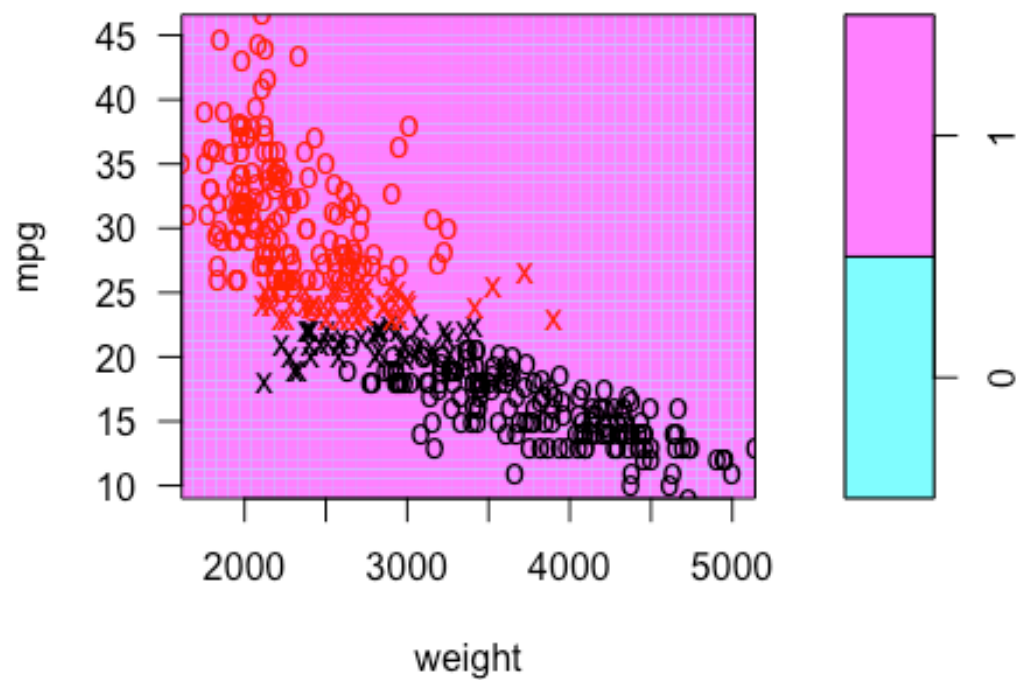
SVM classification plot



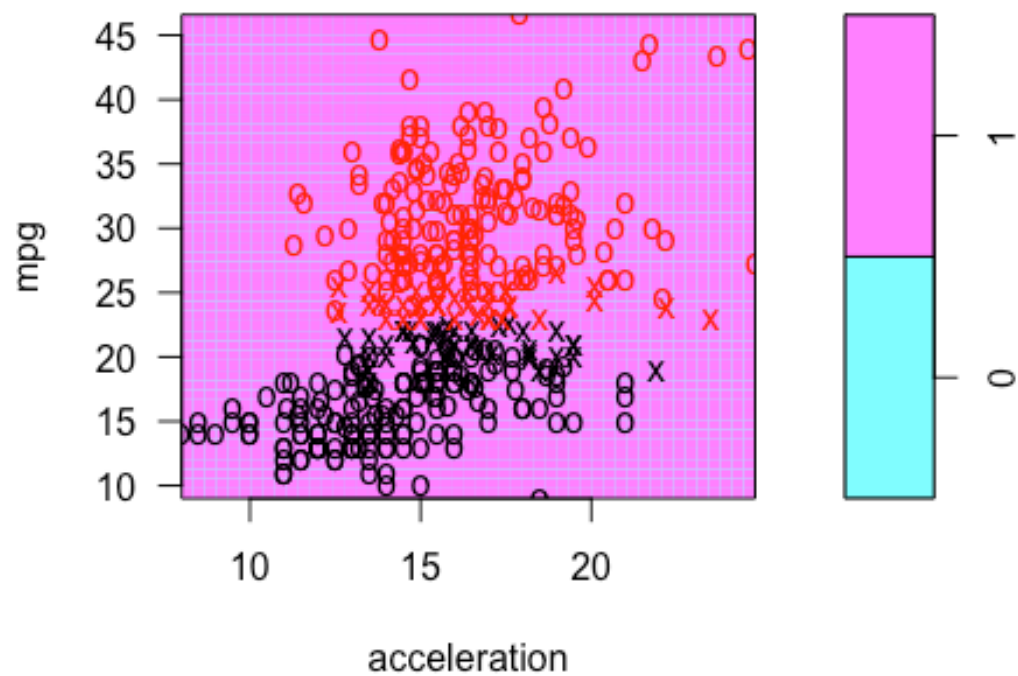
SVM classification plot



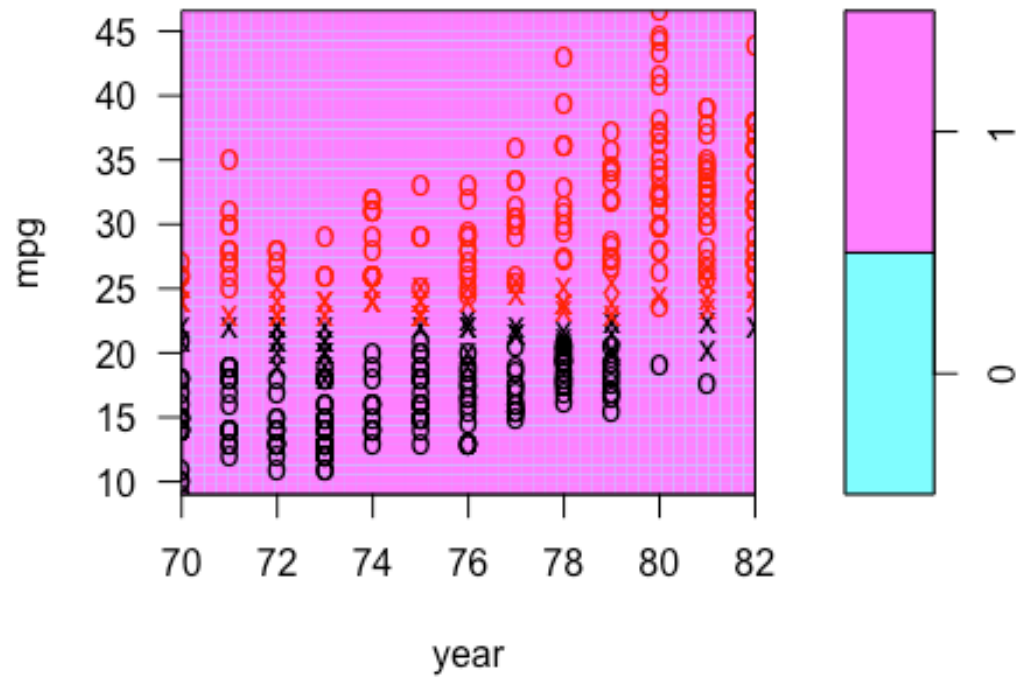
SVM classification plot



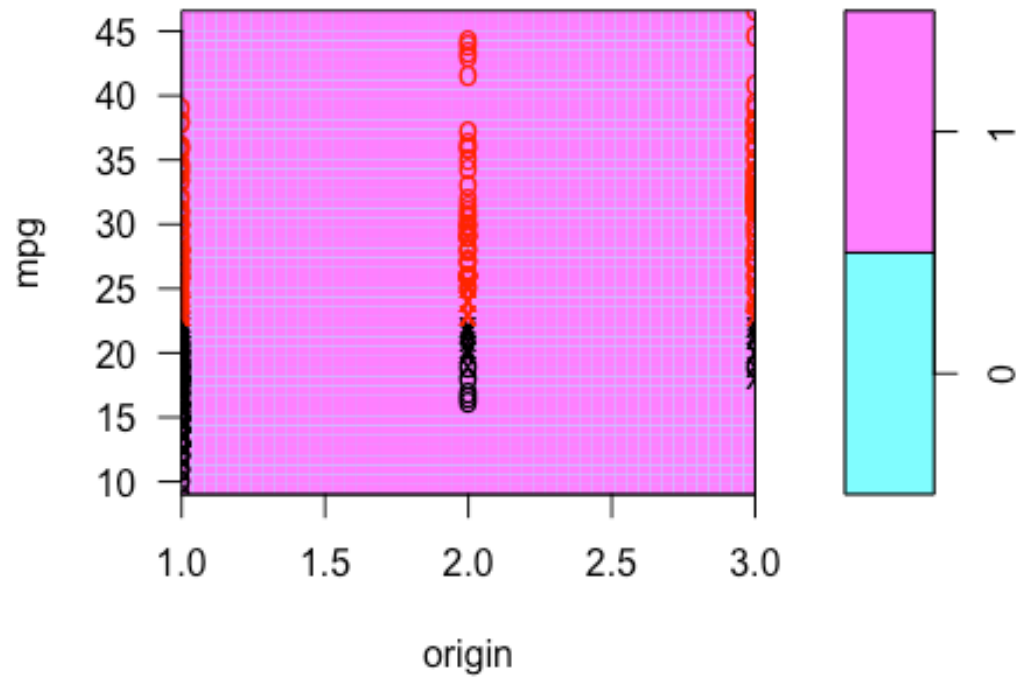
SVM classification plot



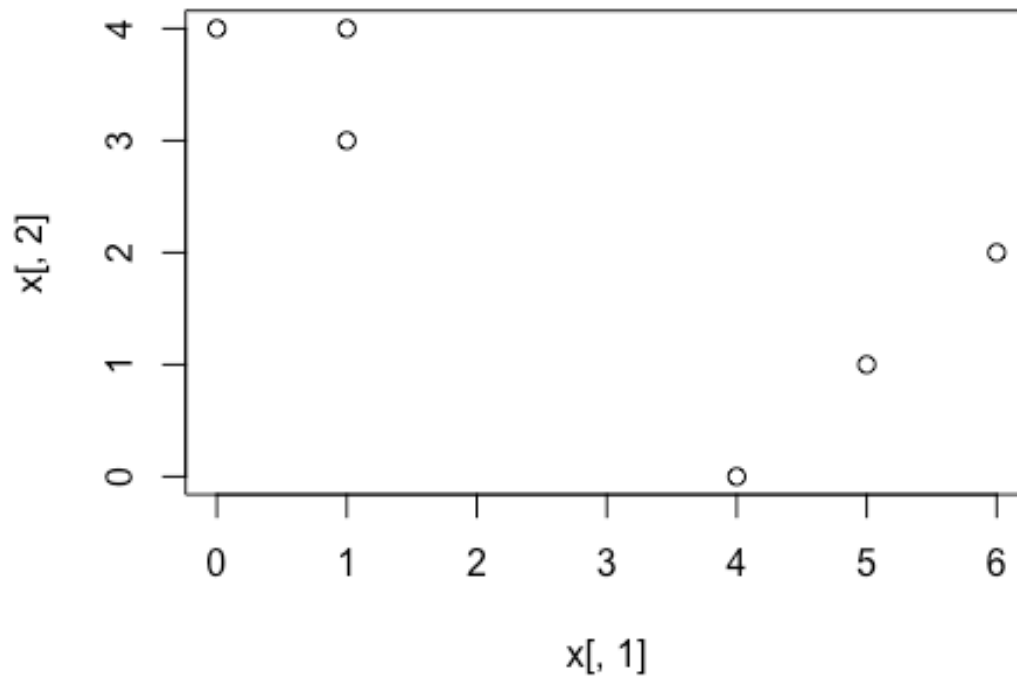
SVM classification plot



SVM classification plot



```
#Ex3
#a
set.seed(1)
x <- cbind(c(1, 1, 0, 5, 6, 4), c(4, 3, 4, 1, 2, 0))
plot(x[,1], x[,2])
```

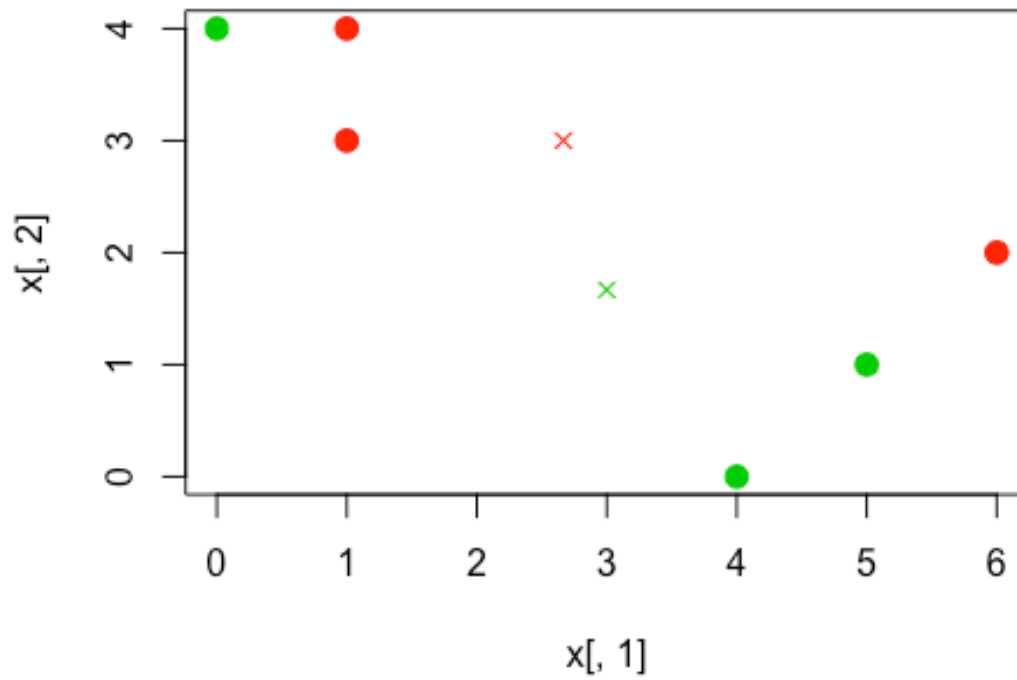


```
#b
set.seed(1)
labels <- sample(2, nrow(x), replace = T)
labels

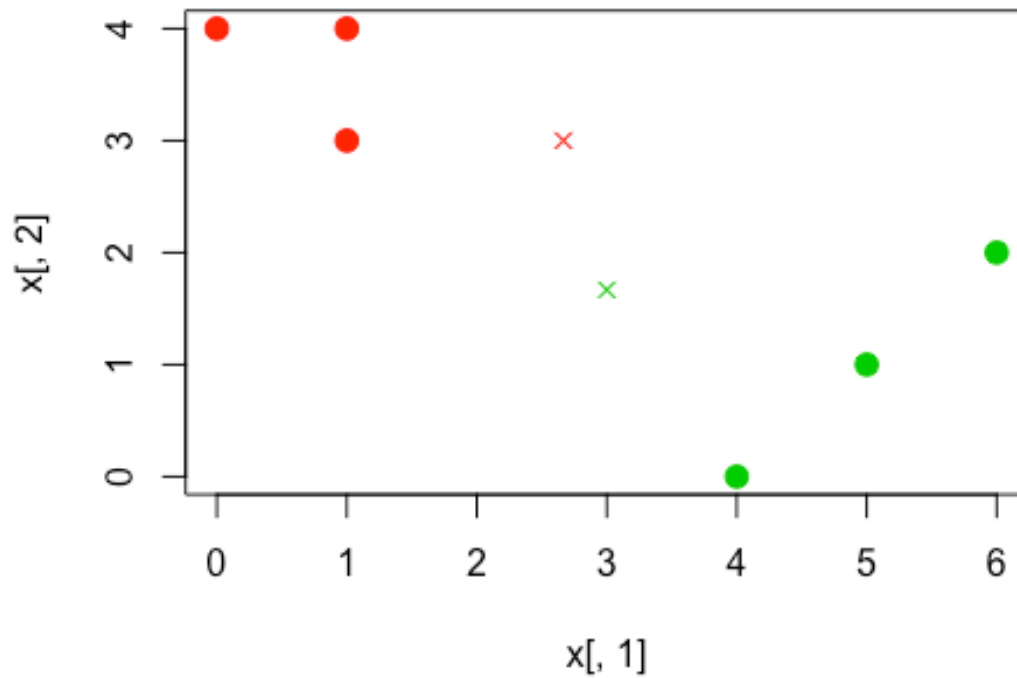
## [1] 1 1 2 2 1 2

plot(x[, 1], x[, 2], col = (labels + 1), pch = 20, cex = 2)

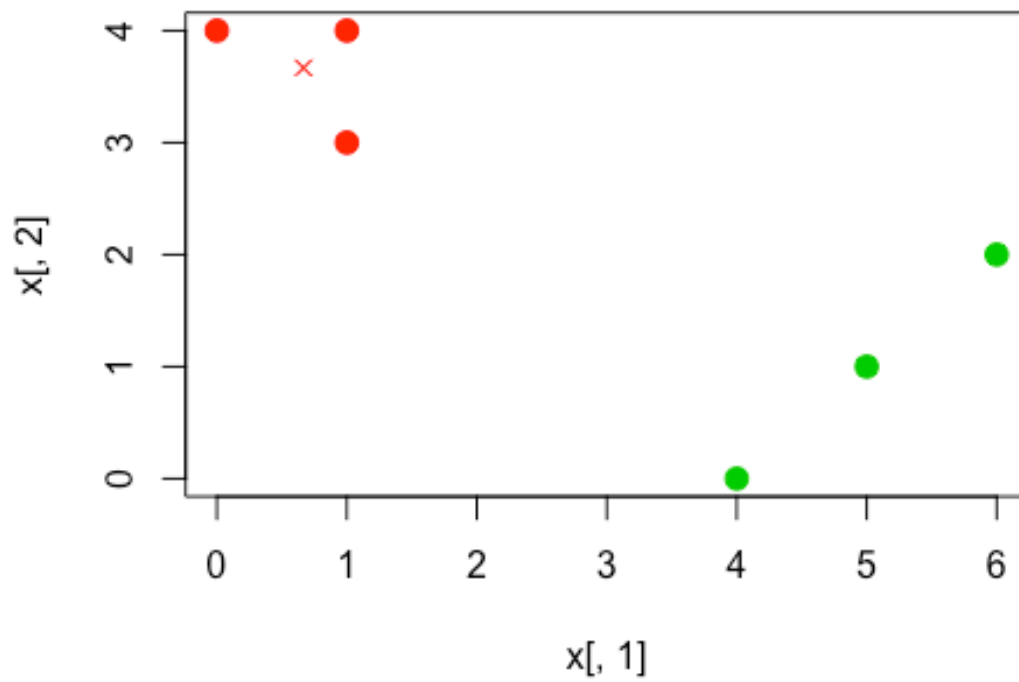
#c
centroid1 <- c(mean(x[labels == 1, 1]), mean(x[labels == 1, 2]))
centroid2 <- c(mean(x[labels == 2, 1]), mean(x[labels == 2, 2]))
plot(x[,1], x[,2], col=(labels + 1), pch = 20, cex = 2)
points(centroid1[1], centroid1[2], col = 2, pch = 4)
points(centroid2[1], centroid2[2], col = 3, pch = 4)
```



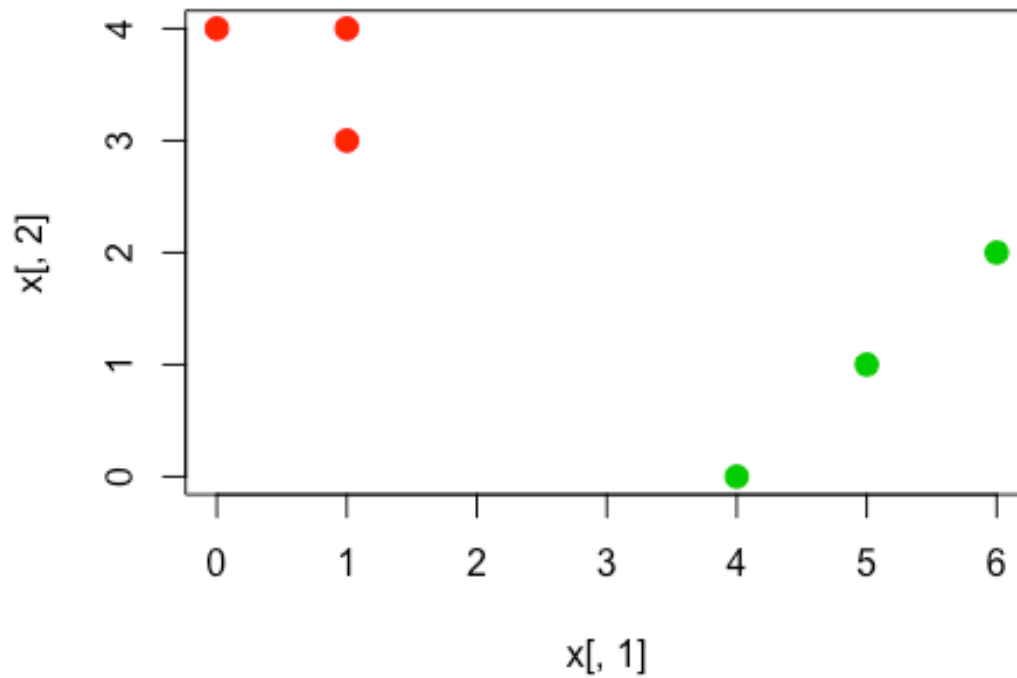
```
#d
labels <- c(1, 1, 1, 2, 2, 2)
plot(x[, 1], x[, 2], col = (labels + 1), pch = 20, cex = 2)
points(centroid1[1], centroid1[2], col = 2, pch = 4)
points(centroid2[1], centroid2[2], col = 3, pch = 4)
```



```
#e
centroid1 <- c(mean(x[labels == 1, 1]), mean(x[labels == 1, 2]))
centroid2 <- c(mean(x[labels == 2, 1]), mean(x[labels == 2, 2]))
plot(x[,1], x[,2], col=(labels + 1), pch = 20, cex = 2)
points(centroid1[1], centroid1[2], col = 2, pch = 4)
points(centroid2[1], centroid2[2], col = 3, pch = 4)
```

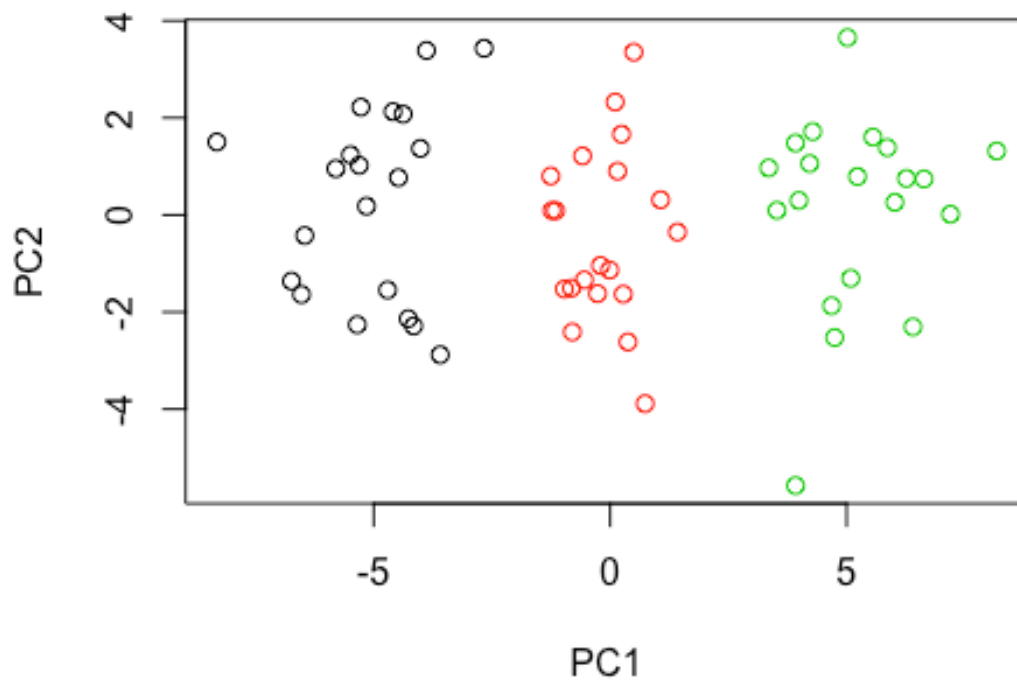


```
#f
plot(x[, 1], x[, 2], col=(labels + 1), pch = 20, cex = 2)
```



```
#Ex 10
#a
set.seed(1)
X <- rbind(matrix(rnorm(20*50, mean = 0), nrow = 20),
            matrix(rnorm(20*50, mean=0.7), nrow = 20),
            matrix(rnorm(20*50, mean=1.4), nrow = 20))

#b
X.pca = prcomp(X)$x
plot(X.pca[,1:2], col=c(rep(1,20), rep(2,20), rep(3,20)))
```



```
#c
res = kmeans(X, centers = 3)
true_class = c(rep(1,20), rep(2,20), rep(3,20))
table(res$cluster, true_class)

##      true_class
##      1  2  3
##  1   0  0 20
##  2   0 20  0
##  3 20  0  0

#class 2 is classified correctly. 1 and 3 classes
# seem to be mixed up when classified.
#d
res = kmeans(X, centers = 2)
true = c(rep(1,20), rep(2,20), rep(3,20))
table(res$cluster, true_class)

##      true_class
##      1  2  3
##  1 20 19  0
##  2   0  1 20
```

*#it seems middle class is grouped in wrong class. Around
#half of classes from group 2 are classified correctly.*

#e

```
res = kmeans(X, centers = 4)
true = c(rep(1,20), rep(2,20), rep(3,20))
table(res$cluster, true_class)
```

```
##      true_class
##      1  2  3
##  1  0  0  7
##  2 20  0  0
##  3  0 20  0
##  4  0  0 13
```

#one of the classes is split into 2 classes

#f

```
res = kmeans(X.pca[,1:2], centers = 3)
true = c(rep(1,20), rep(2,20), rep(3,20))
table(res$cluster, true_class)
```

```
##      true_class
##      1  2  3
##  1  0  0 20
##  2  0 20  0
##  3 20  0  0
```

#g

```
res = kmeans(scale(X), centers = 3)
true = c(rep(1,20), rep(2,20), rep(3,20))
table(res$cluster, true_class)
```

```
##      true_class
##      1  2  3
##  1  0  0 20
##  2 20  0  0
##  3  0 20  0
```

it seems points are now perfectly classified.