

# STATS 415 - Homework 9 - Support Vector Machines

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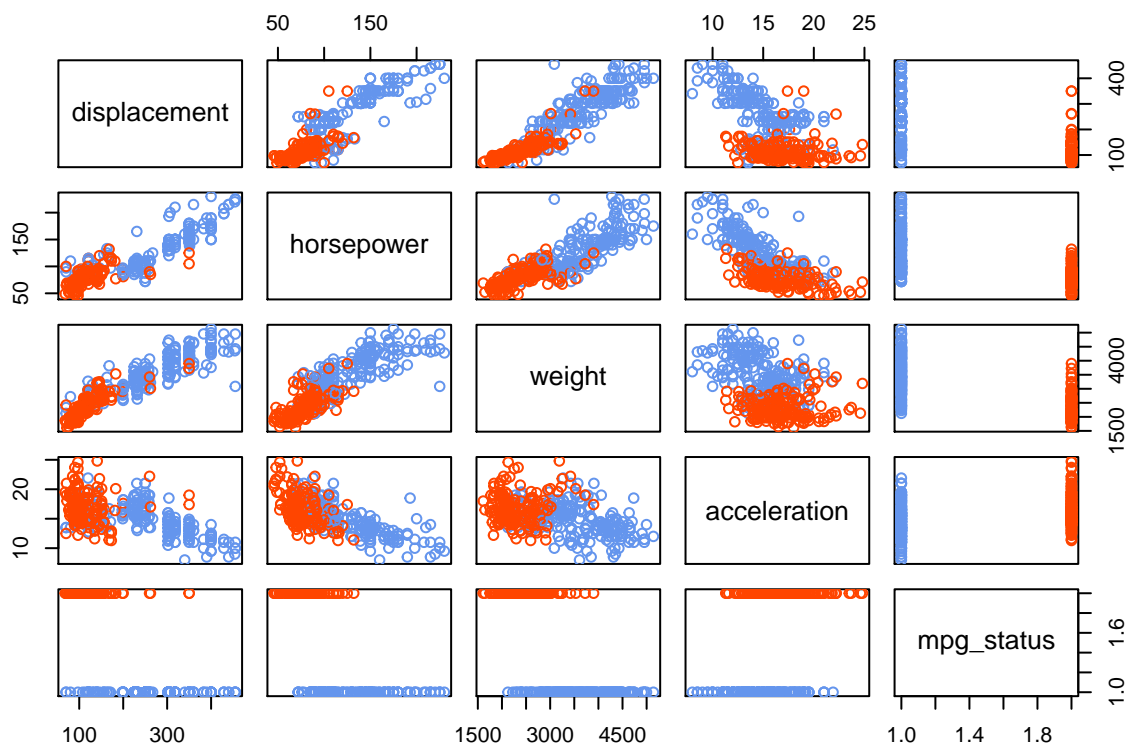
April 5, 2016

1. In this problem, you will use support vector approaches in order to predict whether a given car gets high or low gas mileage based on the Auto data set.

(a) Create a binary variable that takes on a 1 for cars with gas mileage above the median, and a 0 for cars with gas mileage below the median.

```
mpg_status <- ifelse(mpg > median(mpg), 1, 0)
Auto$mpg_status <- as.factor(mpg_status)
auto_data <- select(Auto, c(displacement, horsepower, weight, acceleration, mpg_status))
```

```
plot(auto_data, col = (cols))
```



(b) Fit a support vector classifier to the data with various values of cost, in order to predict whether a car gets high or low gas mileage. Report the cross-validation errors associated with different values of this parameter. Comment on your results.

```
set.seed(1)
### divide into equal sets of testing and training data
train <- sample(1:dim(auto_data)[1], dim(auto_data)[1] / 2)
test <- -train
train_auto <- auto_data[train, ]
test_auto <- auto_data[test, ]
# Run the SVM
```

---

```
tune_out_linear <- tune(svm, mpg_status ~ ., data = train_auto, kernel = "linear",
  ranges = list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100)))
best_auto_linear <- tune_out_linear$best.model
summary(best_auto_linear)
```

```
##
## Call:
## best.tune(method = svm, train.x = mpg_status ~ ., data = train_auto,
##   ranges = list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100)),
##   kernel = "linear")
##
##
## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: linear
##     cost:  0.1
##    gamma: 0.25
##
## Number of Support Vectors: 78
##
## ( 39 39 )
##
##
## Number of Classes: 2
##
## Levels:
## 0 1
```

```
y_prediction_linear <- predict(best_auto_linear, test_auto)
linear <- table(predict = y_prediction_linear, truth = test_auto$mpg_status);linear
```

```
##      truth
## predict 0  1
##      0 79  5
##      1 14 98
```

*For a linear kernel, the lowest cross-validation error is obtained for a gamma of 0.25 and a cost of 0.1. The test error rate of this linear kernel is 10.7344633%*

(c) Now repeat (b), this time using SVMs with radial and polynomial kernels, with different values of gamma (radial) and degree (polynomial) and cost (radial + polynomial). Comment on your results.

```
set.seed(1)
tune_out_radial <- tune(svm, mpg_status ~ ., data = train_auto, kernel = "radial",
  ranges = list(cost = c(0.01, 0.1, 1, 5, 10, 100, 1000),
    gamma = c(0.01, 0.1, 1, 5, 10, 100, 1000)))
best_auto_radial <- tune_out_radial$best.model
summary(best_auto_radial)
```

```
##
## Call:
```

---

```
## best.tune(method = svm, train.x = mpg_status ~ ., data = train_auto,
##           ranges = list(cost = c(0.01, 0.1, 1, 5, 10, 100, 1000), gamma = c(0.01,
##           0.1, 1, 5, 10, 100, 1000)), kernel = "radial")
##
##
## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: radial
##       cost:  5
##       gamma: 1
##
## Number of Support Vectors:  66
##
## ( 38 28 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```
y_prediction_radial <- predict(best_auto_radial, test_auto)
radial <- table(predict = y_prediction_radial, truth = test_auto$mpg_status);radial
```

```
##           truth
## predict  0  1
##           0 78 6
##           1 15 97
```

*For a radial kernel, the lowest cross-validation error is obtained for a degree of 3 and a cost of 5. The test error rate of this radial kernel is 12%*

```
set.seed(1)
tune_out_poly <- tune(svm, mpg_status ~ ., data = train_auto, kernel = "polynomial",
                      gamma = 1, coef0=1,
                      ranges = list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100, 1000),
                      degree = c(2, 3, 4, 5, 6)))
best_auto_poly <- tune_out_poly$best.model
summary(best_auto_poly)
```

```
##
## Call:
## best.tune(method = svm, train.x = mpg_status ~ ., data = train_auto,
##           ranges = list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100, 1000),
##           degree = c(2, 3, 4, 5, 6)), kernel = "polynomial", gamma = 1,
##           coef0 = 1)
##
##
## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: polynomial
##       cost:  10
```

```
##      degree: 5
##      gamma: 1
##      coef.0: 1
##
## Number of Support Vectors: 33
##
## ( 14 19 )
##
##
## Number of Classes: 2
##
## Levels:
## 0 1
```

```
y_prediction_poly <- predict(best_auto_poly, test_auto)
poly <- table(predict = y_prediction_poly, truth = test_auto$mpg_status);poly
```

```
##      truth
## predict 0 1
##      0 80 11
##      1 13 92
```

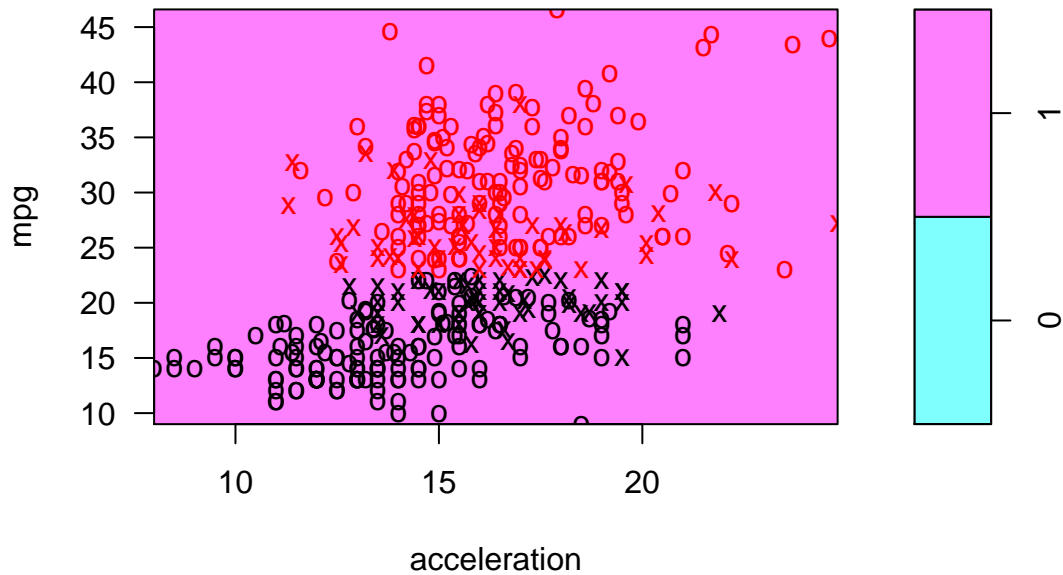
For a polynomial kernel, the lowest cross-validation error is obtained for a degree of 5 and a cost of 10. The test error rate of this polynomial kernel is 13.9534884%

(d) Make some plots to back up your assertions in (b) and (c). Hint: In the lab, we used the `plot()` function for svm objects only in cases with  $p = 2$ . When  $p > 2$ , you can use the `plot()` function to create plots displaying pairs of variables at a time. Essentially, instead of typing `plot(svmfit, dat)` where `svmfit` contains your fitted model and `dat` is a data frame containing your data, you can type `plot(svmfit, dat, x1 ~ x4)` in order to plot just the first and fourth variables. However, you must replace `x1` and `x4` with the correct variable names. To find out more, type “`?plot.svm`”.

*This time we will input all of the data into the models. I have tried hard to change the title and to make the divide between the cyan and pink along the y-axis, instead of the x-axis, to reflect the real support vector classifier. Unfortunately, I was unable to figure this out after a long time.*

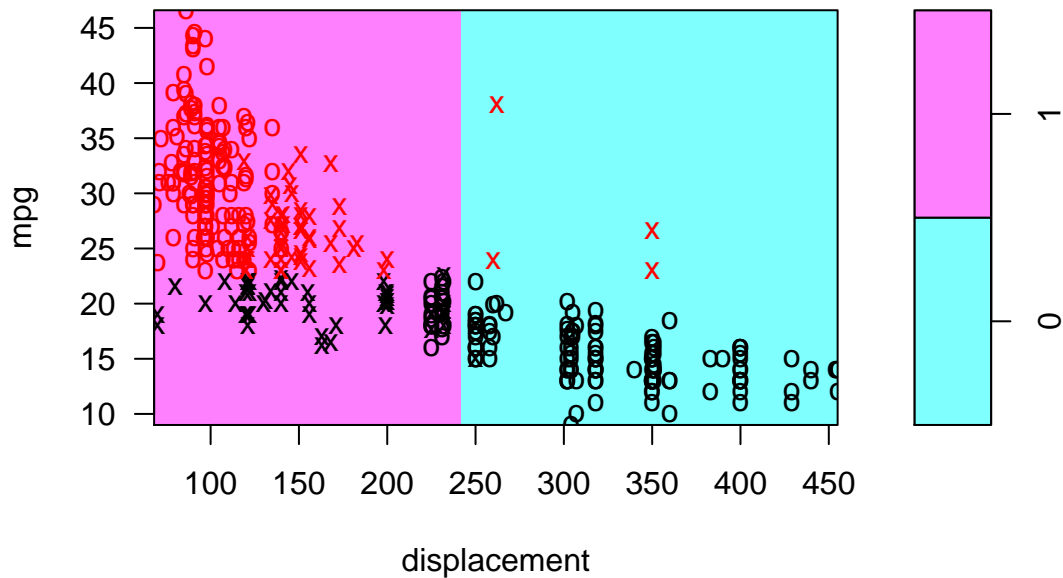
```
svm_linear <- svm(mpg_status ~ ., data = auto_data, kernel = "linear", cost = 1)
svm_radial = svm(mpg_status ~ ., data = auto_data, kernel = "radial", cost = 10, gamma = 0.01)
svm_poly = svm(mpg_status ~ ., data = auto_data, kernel = "polynomial", cost = 0.10, degree = 2,
               gamma = 1, coef0=1)
auto_data$mpg <- Auto$mpg # add mpg back in for plotting
# For slicing the plot variables
mean_acceleration <- mean(auto_data$acceleration); mean_weight <- mean(auto_data$weight)
mean_horsepower <- mean(auto_data$horsepower); mean_displacement <- mean(auto_data$displacement)
mean_mpg <- mean(auto_data$mpg)
# Plot
plot(svm_linear, auto_data, mpg ~ acceleration, main = "Linear: mpg~acceleration",
     slice = list(displacement = mean_displacement, horsepower = mean_horsepower))
```

### SVM classification plot



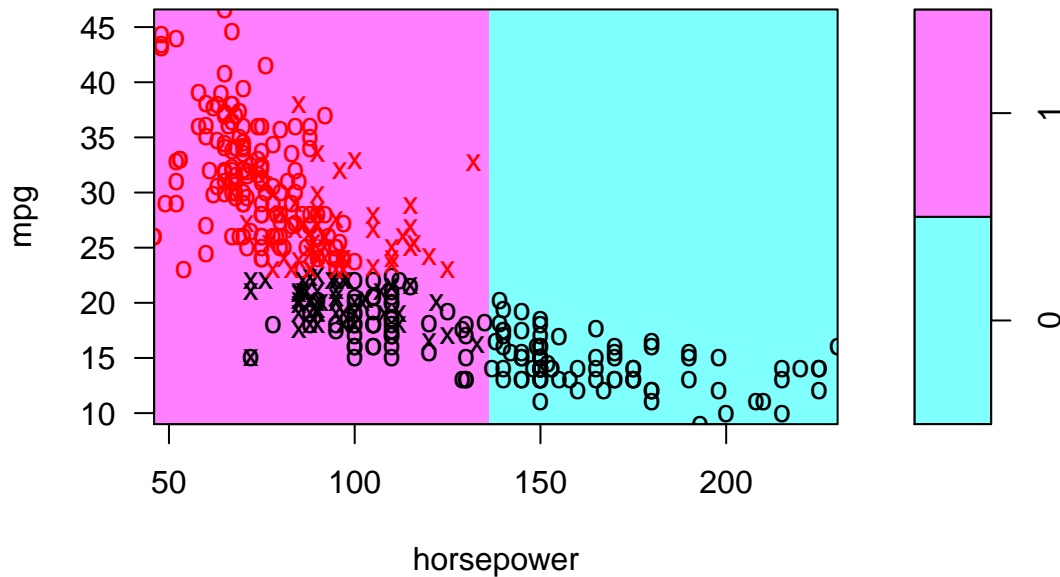
```
plot(svm_linear, auto_data, mpg ~ displacement, main = "Linear: mpg-displacement",  
     slice = list(acceleration = mean_acceleration, horsepower = mean_horsepower))
```

### SVM classification plot



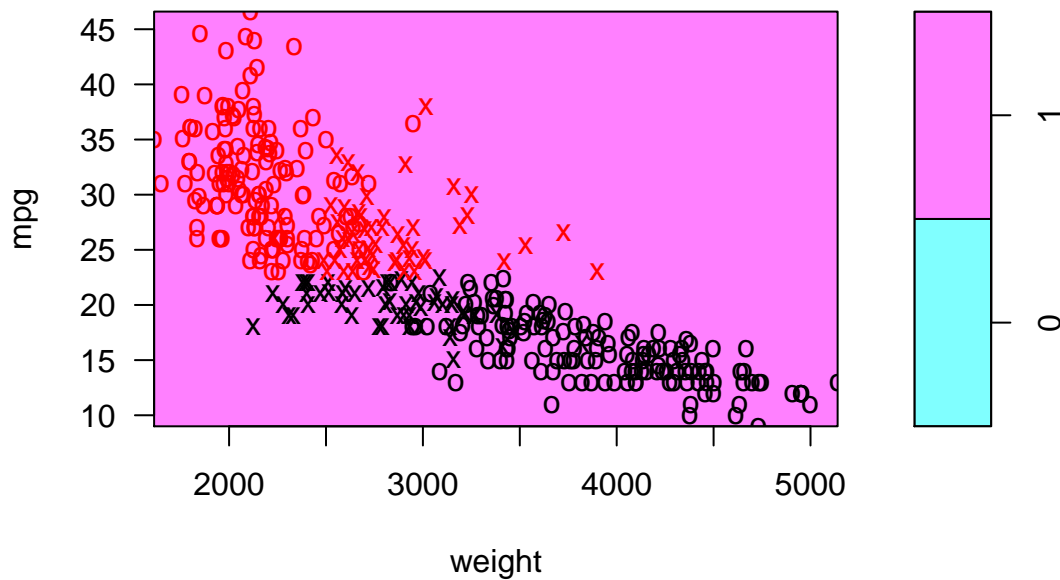
```
plot(svm_linear, auto_data, mpg ~ horsepower, main = "Linear: mpg-horsepower",  
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

### SVM classification plot



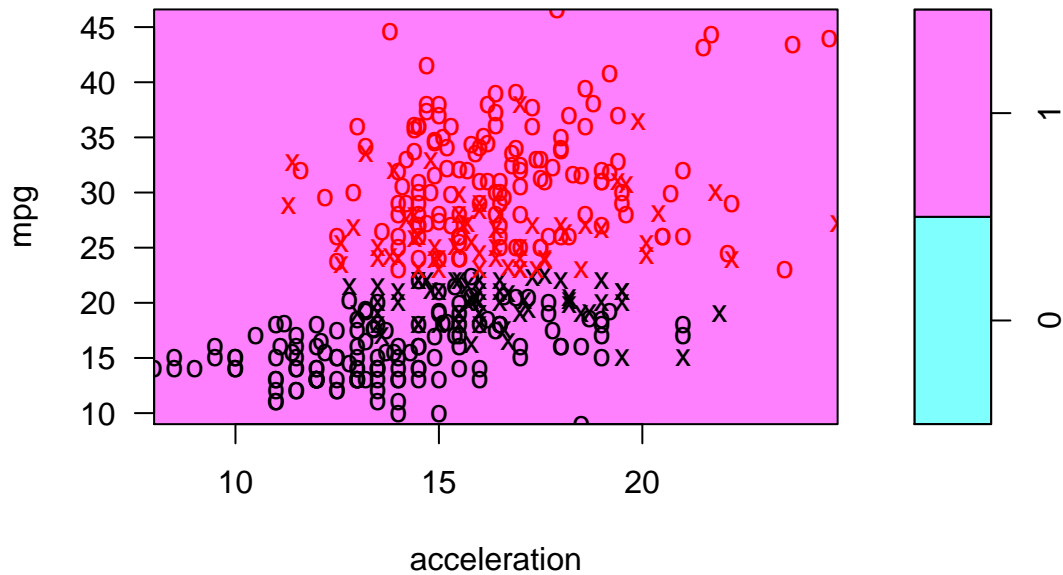
```
plot(svm_linear, auto_data, mpg ~ weight, main = "Linear: mpg~weight",  
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

### SVM classification plot



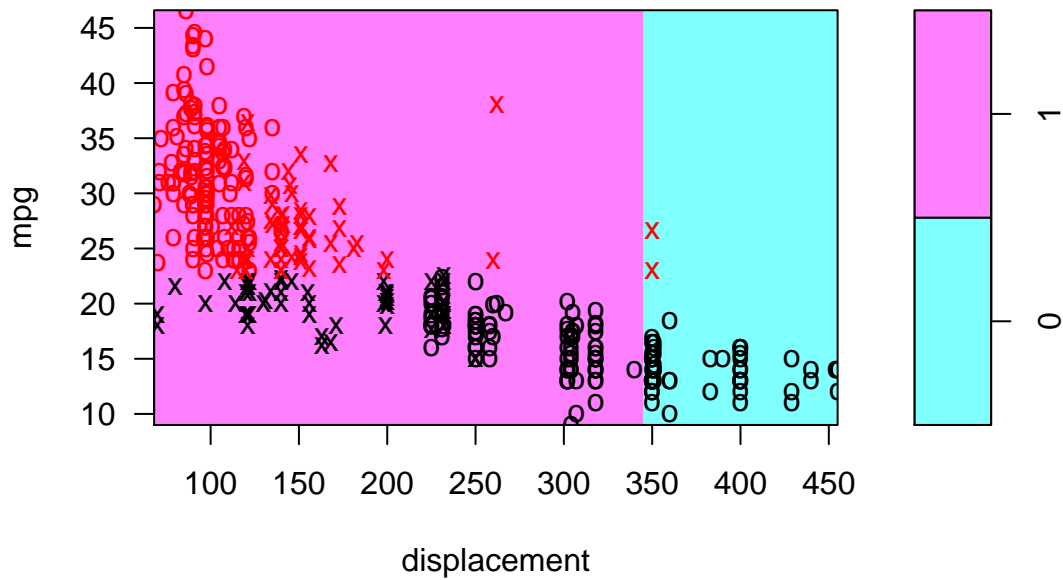
```
# Radial plots  
plot(svm_radial, auto_data, mpg ~ acceleration, main = "Radial: mpg~acceleration",  
     slice = list(displacement = mean_displacement, horsepower = mean_horsepower))
```

### SVM classification plot



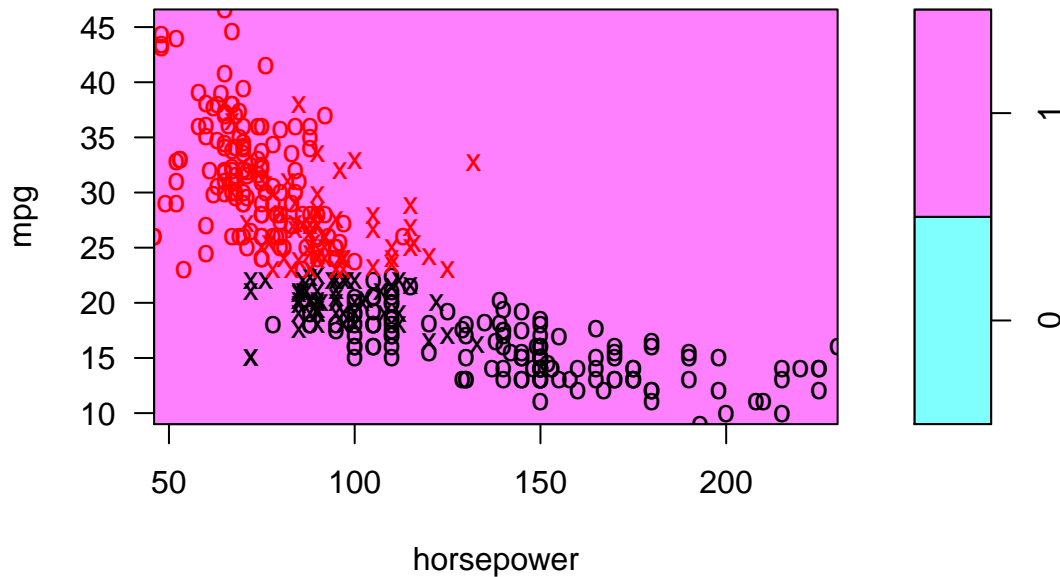
```
plot(svm_radial, auto_data, mpg ~ displacement, main = "Radial: mpg~displacement",  
     slice = list(acceleration = mean_acceleration, horsepower = mean_horsepower))
```

### SVM classification plot



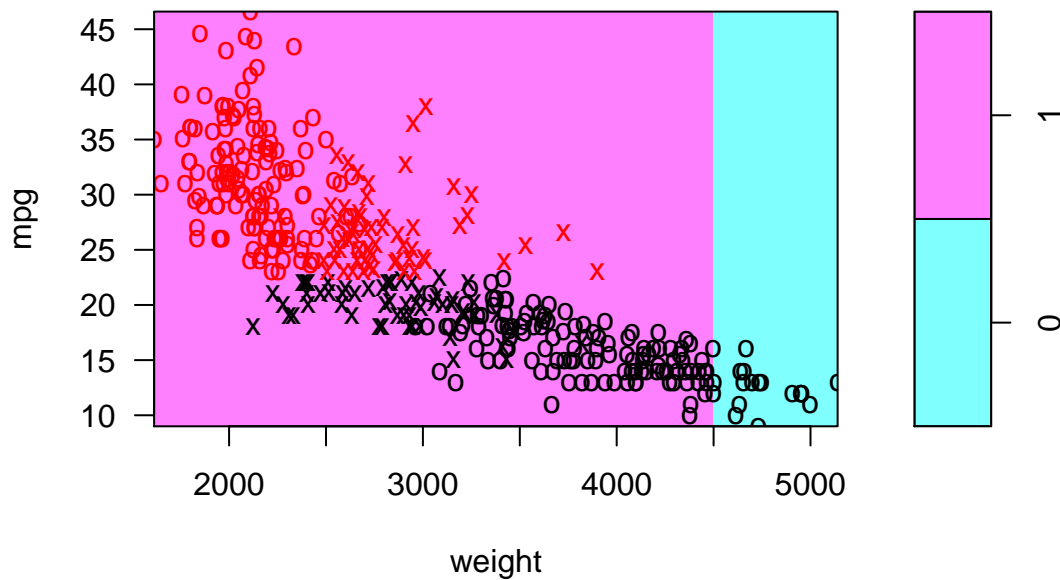
```
plot(svm_radial, auto_data, mpg ~ horsepower, main = "Radial: mpg~horsepower",  
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

### SVM classification plot



```
plot(svm_radial, auto_data, mpg ~ weight, main = "Radial: mpg~weight",
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

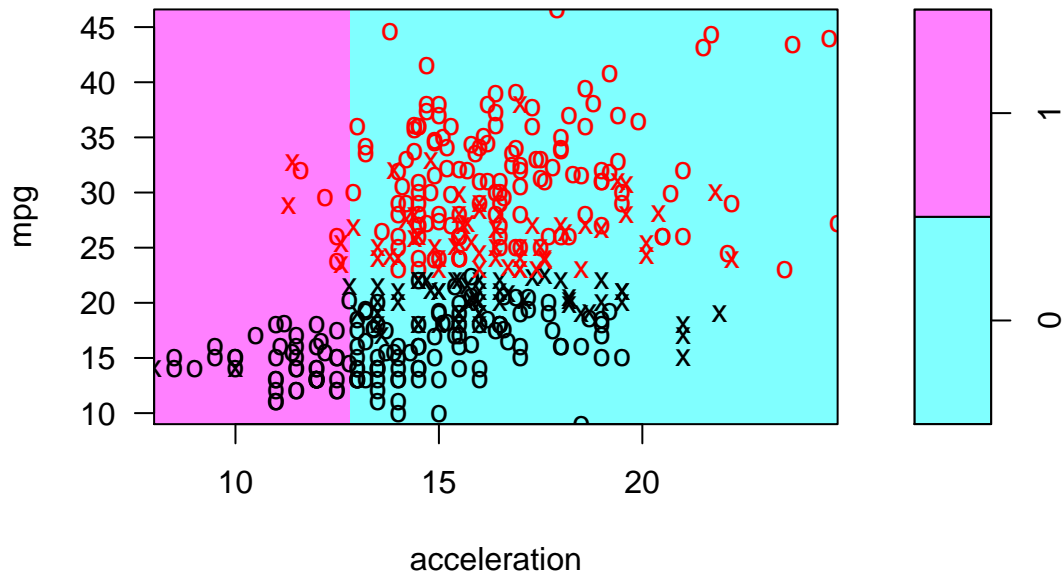
### SVM classification plot



```
# Polynomial
plot(svm_poly, auto_data, mpg ~ acceleration, main = "Polynomial: mpg~acceleration",
     slice = list(displacement = mean_displacement, horsepower = mean_horsepower))
```

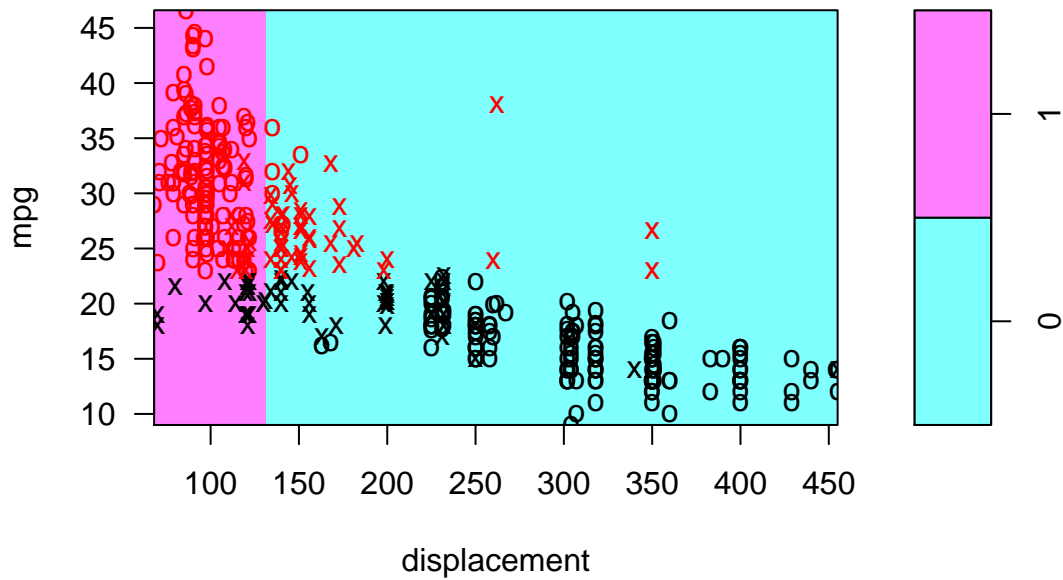


### SVM classification plot



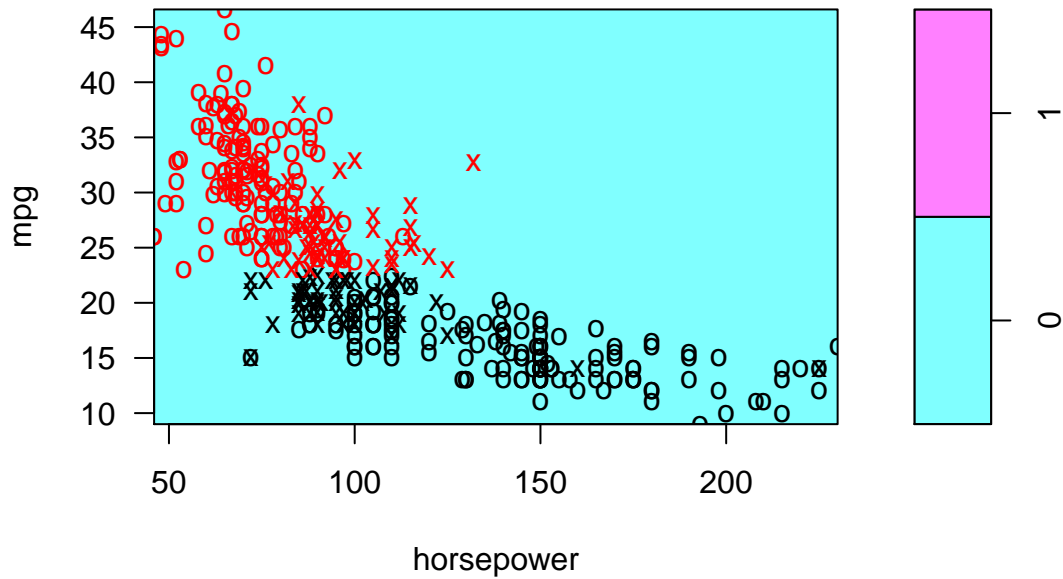
```
plot(svm_poly, auto_data, mpg ~ displacement, main = "Polynomial: mpg~displacement",  
     slice = list(acceleration = mean_acceleration, horsepower = mean_horsepower))
```

### SVM classification plot



```
plot(svm_poly, auto_data, mpg ~ horsepower, main = "Polynomial: mpg~horsepower",  
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

**SVM classification plot**



```
plot(svm_poly, auto_data, mpg ~ weight, main = "Polynomial: mpg~weight",  
     slice = list(acceleration = mean_acceleration, displacement = mean_displacement))
```

**SVM classification plot**

