SUPPORT VECTOR MACHINES

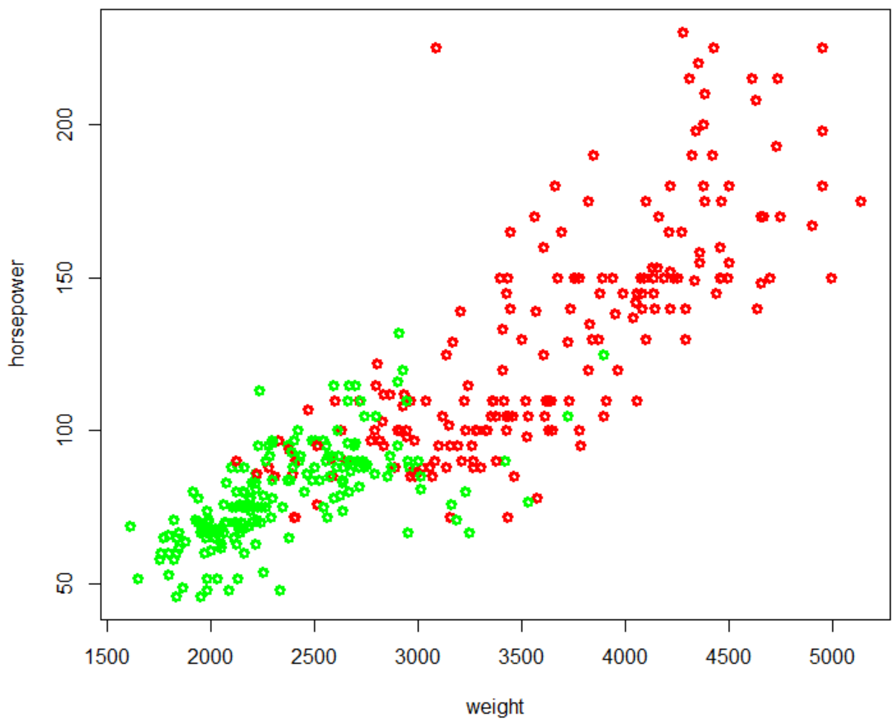
1. SVM with various kernels

The SVM command is in package called e1071.

> install.packages("e1071");
> library(e1071)

Let's use support vector machines to classify cars into Economy and Consuming classes.

> ECO = ifelse(mpg > 22.75, "Economy", "Consuming")
> Color = ifelse(mpg > 22.75, "green", "red")
> plot(weight, horsepower, lwd=3, col=Color)



The two classes cannot be separated by a hyperplane, but the SVM method is surely applicable.

> S = svm(ECO ~ weight + horsepower, data=Auto, kernel = "linear")
Error in svm.default(x, y, scale = scale, ..., na.action = na.action) :
  Need numeric dependent variable for regression.

Error? There are other, unused variables in dataset Auto that prevent R from doing this SVM analysis. We'll create a reduced dataset.

> d = data.frame(ECO, weight, horsepower)

> S = svm(ECO ~ weight + horsepower, data=d, kernel="linear")
> summary(S)

Parameters:
SVM-Type: C-classification
SVM-Kernel: linear
cost: 1
gamma: 0.5

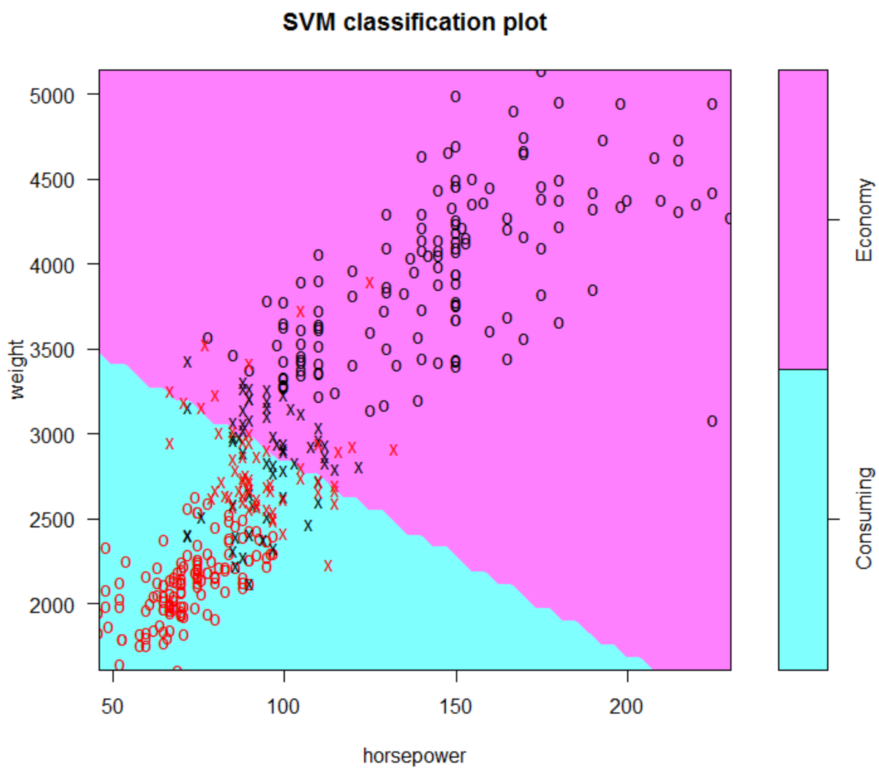
Number of Support Vectors: 120
(60 60)

So, there are 120 points violating the separating hyperplane or the margin, 60 in each class.

> plot(S, data=Auto)
Error in plot.svm(S, data = Auto) : missing formula.

Same story. We need to use a reduced dataset that contains only the needed variables.

> plot(S, data=d)

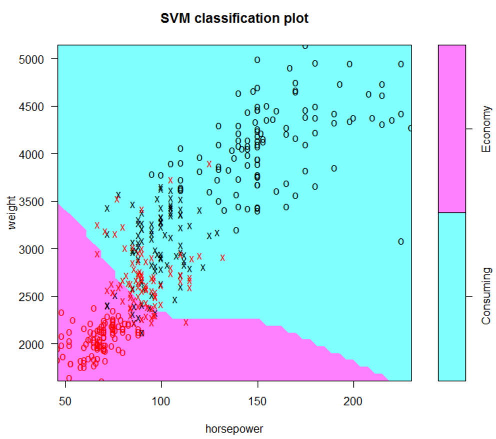


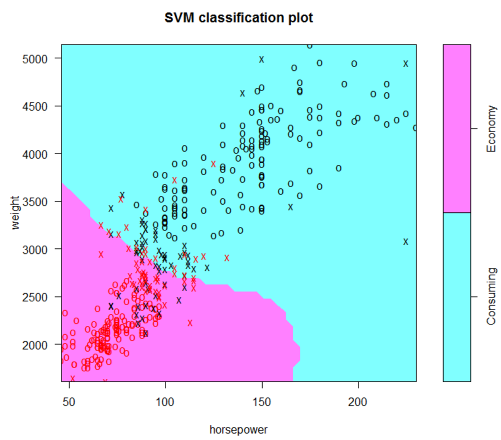
This is the final classification with a linear kernel and therefore, a linear boundary. Support vectors are marked as "x", other points as "o".

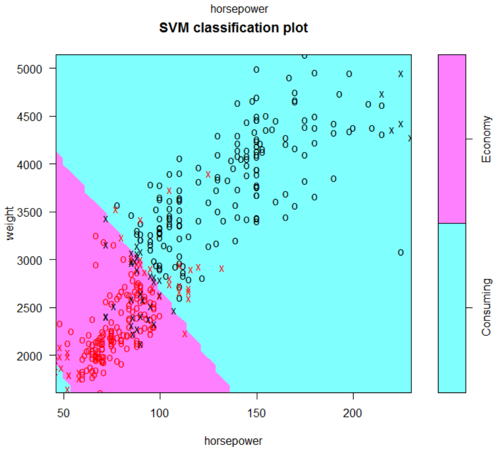
We can look at other types of kernels and boundaries – polynomial, radial, and sigmoid.

> S = svm(ECO ~ weight + horsepower, data=d, kernel="polynomial")
> summary(S); plot(S,d)
Number of Support Vectors: 176

```
> S = svm( ECO ~ weight + horsepower, data=d, kernel="radial" )
> summary(S); plot(S,d)
Number of Support Vectors:  121

> S = svm( ECO ~ weight + horsepower, data=d, kernel="sigmoid" )
> summary(S); plot(S,d)
Number of Support Vectors:  74
```







Adding more variables should give a better fit – to the *training* data.

```
> S = svm( factor(ECO) ~ weight + horsepower + displacement + cylinders, data=Auto, kernel="linear" )
> summary(S)
Number of Support Vectors:  99
```

We can identify the support vectors:

```
> S$index
 [1]  16  17  18  25  33  45  46  48  60  61  71  76  77  78  80 100 107 108 109
[20] 110 111 112 113 119 120 123 153 154 162 173 178 199 206 208 209 210 240 241
[39] 242 253 258 262 269 273 274 275 280 281 384  24  31  49  84 101 114 122 131
[58] 149 170 177 179 192 205 218 233 266 270 271 296 297 298 299 305 306 313 314
[77] 318 322 326 327 331 337 338 353 355 356 357 358 360 363 365 368 369 375 381
[96] 382 383 385 387

> Auto[S$index,]
    mpg cylinders displacement horsepower weight acceleration year origin
```

```
16  22.0      6      198      95  2833      15.5  70    1
17  18.0      6      199      97  2774      15.5  70    1
18  21.0      6      200      85  2587      16.0  70    1
25  21.0      6      199      90  2648      15.0  70    1
          < truncated >
```

2. Tuning and cross-validation

The “cost” option specifies the cost of violating the margin. We can try costs 0.001, 0.01, 0.1, 1, 10, 100, 1000:

```
> Stuned = tune( svm, ECO ~ weight + horsepower, data=d, kernel="linear", ranges=list(cost=10^seq(-3,3)) )
> summary(Stuned)
- sampling method: 10-fold cross validation

- best parameters:
 cost
  0.1

- best performance: 0.1173718

- Detailed performance results:
   cost     error dispersion
1 1e-03 0.2478205 0.10663023
2 1e-02 0.1432051 0.05485355
3 1e-01 0.1173718 0.04208311
```

 # This cost yielded the lowest cross-validation error of classification.

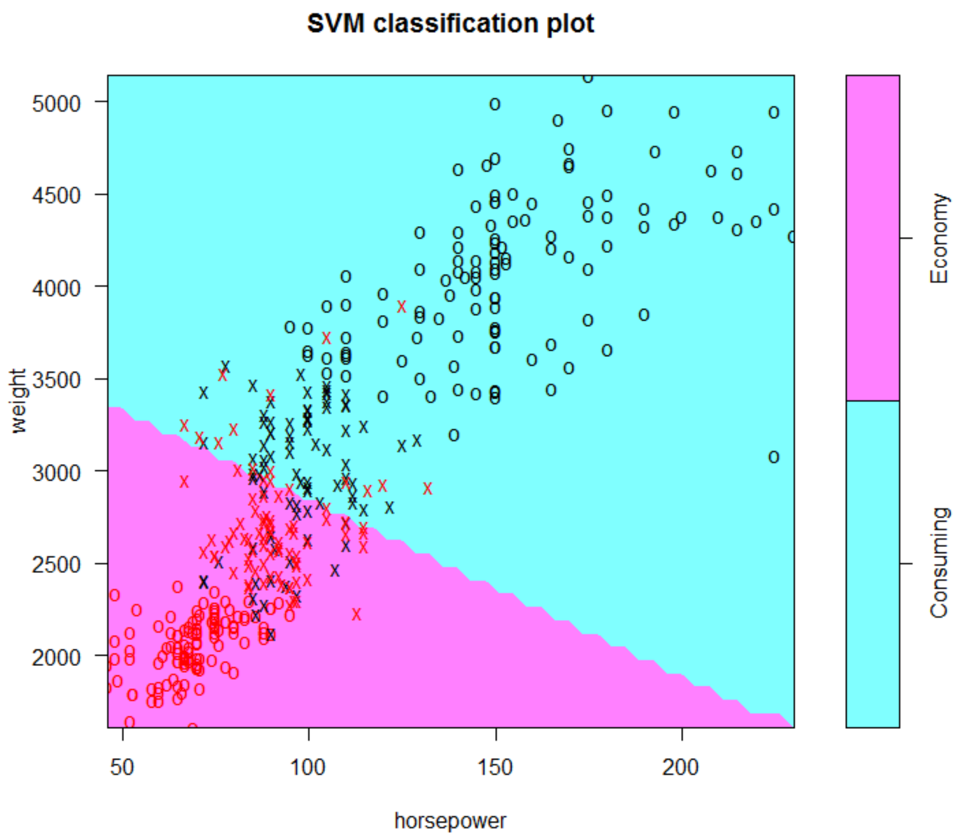
```
4 1e+00 0.1326282 0.04461101
5 1e+01 0.1351923 0.04819639
6 1e+02 0.1351923 0.04819639
7 1e+03 0.1351923 0.04819639
```

We can also find the optimal kernel.

```
> Stuned = tune( svm, ECO ~ weight + horsepower, data=d, ranges=list(cost=10^seq(-3,3),
kernel=c("linear","polynomial","radial","sigmoid")) )
> summary(Stuned)

Parameter tuning of ‘svm’:

- sampling method: 10-fold cross validation

- best parameters:
 cost  kernel
  0.1 sigmoid

- best performance: 0.1046154

- Detailed performance results:
    cost     kernel      error dispersion
1  1e-03     linear 0.2164744 0.10501351
2  1e-02     linear 0.1326282 0.05074006
```

```
3  1e-01      linear 0.1096154 0.04330918
4  1e+00      linear 0.1172436 0.03813782
5  1e+01      linear 0.1223718 0.04775672
6  1e+02      linear 0.1223718 0.04775672
7  1e+03      linear 0.1223718 0.04775672
8  1e-03 polynomial 0.3720513 0.08274072
9  1e-02 polynomial 0.2601282 0.06438244
10 1e-01 polynomial 0.1987821 0.07443903
11 1e+00 polynomial 0.1784615 0.05328633
12 1e+01 polynomial 0.1580769 0.04909157
13 1e+02 polynomial 0.1555128 0.04999836
14 1e+03 polynomial 0.1504487 0.04722372
15 1e-03      radial 0.5816026 0.05687780
16 1e-02      radial 0.1301282 0.05190241
17 1e-01      radial 0.1198077 0.05104329
18 1e+00      radial 0.1223718 0.04118608
19 1e+01      radial 0.1096795 0.04835338
20 1e+02      radial 0.1198718 0.04184981
21 1e+03      radial 0.1146795 0.04354410
22 1e-03     sigmoid 0.5816026 0.05687780
23 1e-02     sigmoid 0.1530769 0.04517581
24 1e-01     sigmoid 0.1046154 0.03711533          # The best kernel and cost.
25 1e+00     sigmoid 0.1173718 0.04715638
26 1e+01     sigmoid 0.1530769 0.06159616
27 1e+02     sigmoid 0.1582051 0.06489946
28 1e+03     sigmoid 0.1582051 0.06489946
```

```
> Soptimal = svm( ECO ~ weight + horsepower, data=d, cost=0.1, kernel="sigmoid" )
> summary(Soptimal); plot(Soptimal,data=d)
Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  sigmoid
       cost:  0.1
      gamma:  0.5

Number of Support Vectors:  164          # We know that more support vectors imply a lower variance
 ( 82 82 )

Number of Classes:  2
Levels:   Consuming Economy
```



Let’s use the validation set method to estimate the classification rate of this optimal SVM.

```
> n = length(mpg);   Z = sample(n,n/2)
> Strain = svm( ECO ~ weight + horsepower, data=d[Z,], cost=0.1, kernel="sigmoid" )
> Yhat = predict( Strain, data=d[-Z,] )
> table( Yhat, ECO[Z] )

Yhat        Consuming Economy
  Consuming        82       9
  Economy          17      88

> table( Yhat, ECO[Z] )
> mean( Yhat==ECO[Z] )
[1] 0.8673469
```

3. More than two classes

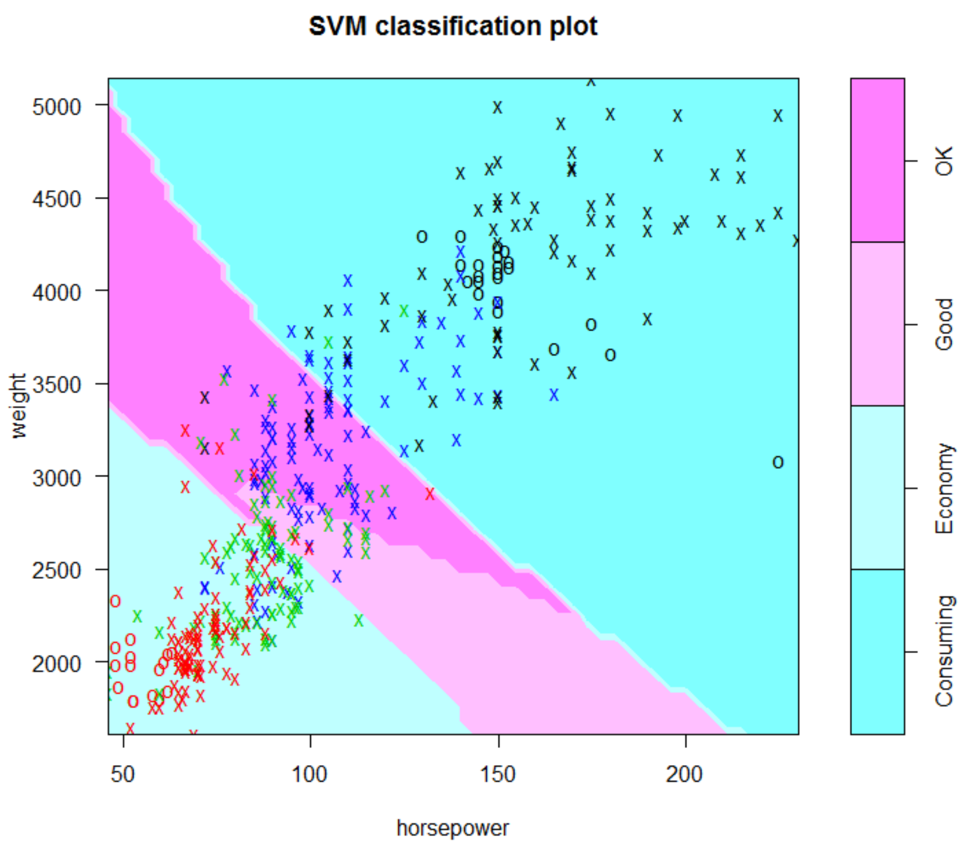
Let’s create more categories of ECO. The same tool svm( ) can handle multiple classes.

```
> summary(mpg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   9.00   17.00   22.75   23.45   29.00   46.60

> ECO4 = rep("Economy",n)
> ECO4[mpg < 29] = "Good"
```

```
> ECO4[mpg < 22.75] = "OK"
> ECO4[mpg < 17] = "Consuming"

> table(ECO4)
ECO4
Consuming   Economy      Good        OK
       92       103        93       104

> S4 = svm( ECO4 ~ weight + horsepower, data=d, cost=0.1, kernel="sigmoid" )
Error in svm.default(x, y, scale = scale, ..., na.action = na.action) :
  Need numeric dependent variable for regression.
```

R was trying to do regression SVM but realized that ECO4 is not numerical. We can direct R to do classification by replacing ECO4 with factor(ECO4).

```
> S4 = svm( factor(ECO4) ~ weight + horsepower, data=d, cost=0.1, kernel="sigmoid" )
> plot(S4, data=d)
```




```
> Yhat = predict( S4, data.frame(Auto) )
> table( Yhat, ECO4 )

           ECO4
Yhat        Consuming Economy Good OK
  Consuming        88       0    2 33
  Economy           0      96   58 15
  Good              0       2    9  5
  OK                4       5   24 51

> mean( Yhat == ECO4 )
[1] 0.622449
```

It’s more difficult to predict finer classes correctly