Linear Support Vector Machines

SUPPORT VECTOR MACHINES IN R

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Instructor

Split into training and test sets

- The dataset generated in previous chapter is in dataframe `df`.
- Split dataset into training and test sets
- Random 80/20 split

```
# Set seed for reproducibility
set.seed(1)
# Set the upper bound for the number of rows to be in the training set
sample_size <- floor(0.8 * nrow(df))
# Assign rows to training/test sets randomly in 80/20 proportion
train <- sample(seq_len(nrow(df)), size = sample_size)
# Separate training and test sets
trainset <- df[train, ]
testset <- df[-train, ]
```

Decision boundaries and kernels

- Decision boundaries can have different shapes - lines, polynomials or more complex functions.
- Type of decision boundary is called a **kernel**.
- Kernel must be specified upfront.
- This chapter focuses on linear kernels.

SVM with linear kernel

- We'll use the svm function from the `e1071` library.
- The function has a number of parameters. We'll set the following explicitly:
  - **formula** - a formula specifying the dependent variable. y in our case.
  - **data** - dataframe containing the data - i.e. trainset.
  - **type** - set to C-classification (classification problem).
  - **kernel** - this is the form of the decision boundary, linear in this case.
  - **cost** and **gamma** - these are parameters that are used to tune the model.
  - **scale** - Boolean indicating whether to scale data.

Building a linear SVM

- Load e1071 library and invoke `svm()` function

```
library(e1071)
```

```
svm_model<- svm(y ~ .,
                data = trainset,
                type = "C-classification",
                kernel = "linear",
                scale = FALSE)
```

Overview of model

- Entering `svm_model` gives:
  - an overview of the model including classification and kernel type
  - tuning parameter values

```
svm_model
```

```
Call:
svm(formula = y ~ .,
    data = trainset,
    type = "C-classification",
    kernel = "linear",
    scale = FALSE)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  1
      gamma:  0.5
Number of Support Vectors:  55
```

```r
# Index of support vectors in training dataset
svm_model$index
# Support vectors
svm_model$SV
# Negative intercept (unweighted)
svm_model$rho
# Weighting coefficients for support vectors
svm_model$coefs
```

```
4   8  10  11  18  37  38  39  47  59  60  74  76  77  78  80  83 ...
             x1          x2
5   0.519095949 0.44232464
-0.1087075
            [,1]
 [1,]  1.0000000
```

- Obtain class predictions for training and test sets.
- Evaluate the training and test set accuracy of the model.

```
# Training accuracy
pred_train <- predict(svm_model, trainset)
mean(pred_train == trainset$y)
```

```
1
```

```
# Test accuracy
pred_test <- predict(svm_model, testset)
mean(pred_test == testset$y)
```

```
1
# Perfect!!
```

Time to practice!

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Visualizing linear SVMs

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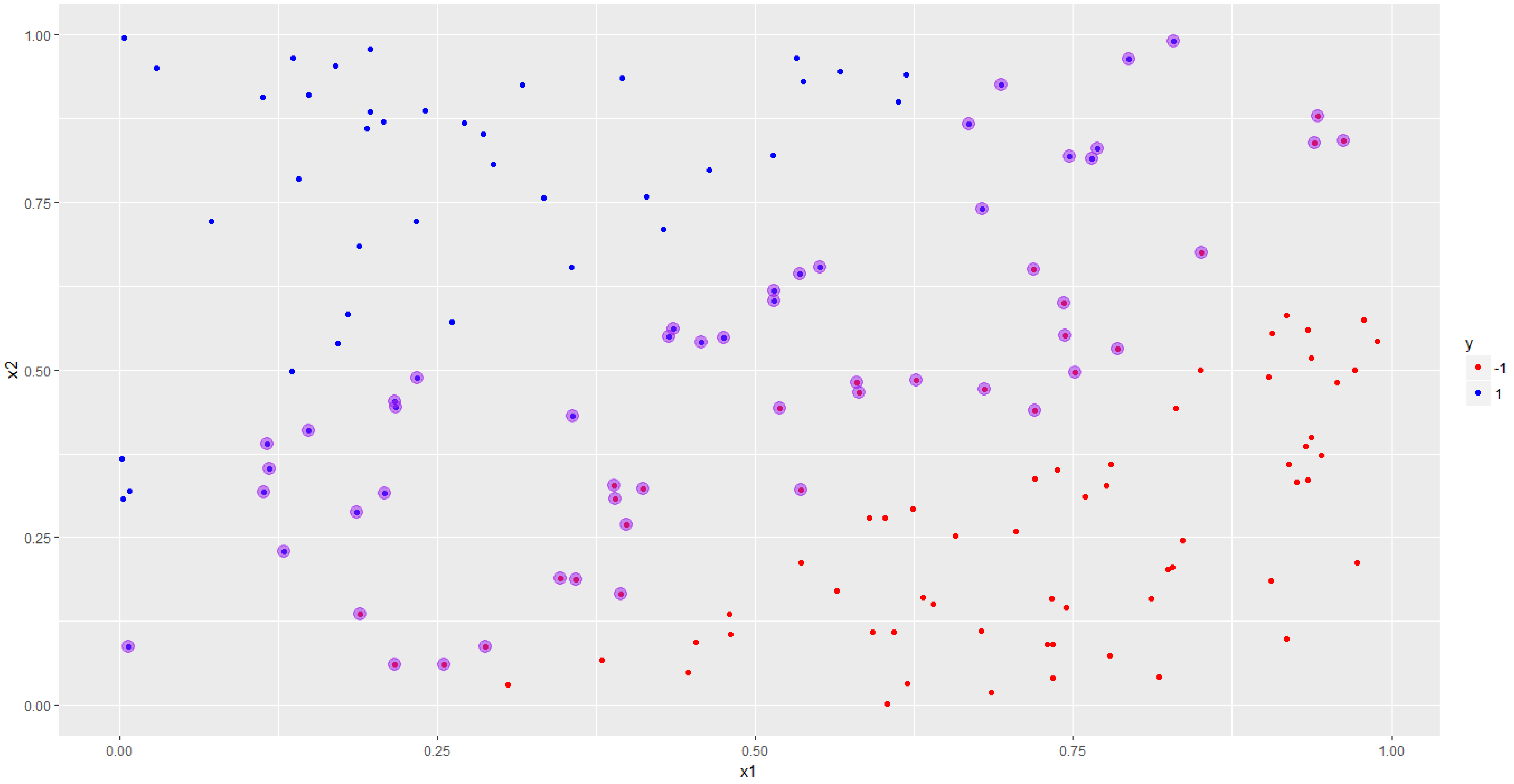
- Plot the training data using `ggplot()`.

```
# Visualize training data, distinguish classes using color
p <- ggplot(data = trainset, aes(x = x1, y = x2, color = y)) +
     geom_point() +
     scale_color_manual(values = c("red", "blue"))
# Render plot
p
```

- Mark out the support vectors using `index` from `svm_model`.

```
# Identify support vectors
df_sv <- trainset[svm_model$index, ]
# Mark out support vectors in plot
p <- p + geom_point(data = df_sv,
                    aes(x = x1, y = x2),
                    color = "purple",
                    size = 4, alpha = 0.5)
# Display plot
p
```



1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

Find slope and intercept of the boundary:

- Build the weight vector, `w`, from `coefs` and `SV` elements of `svm_model`.

```
# Build weight vector
w <- t(svm_model$coefs) %*% svm_model$SV
```

- slope = `-w[1] / w[2]`

```
# Calculate slope and save it to a variable
slope_1 <- -w[1] / w[2]
```

- intercept = `svm_model$rho / w[2]`

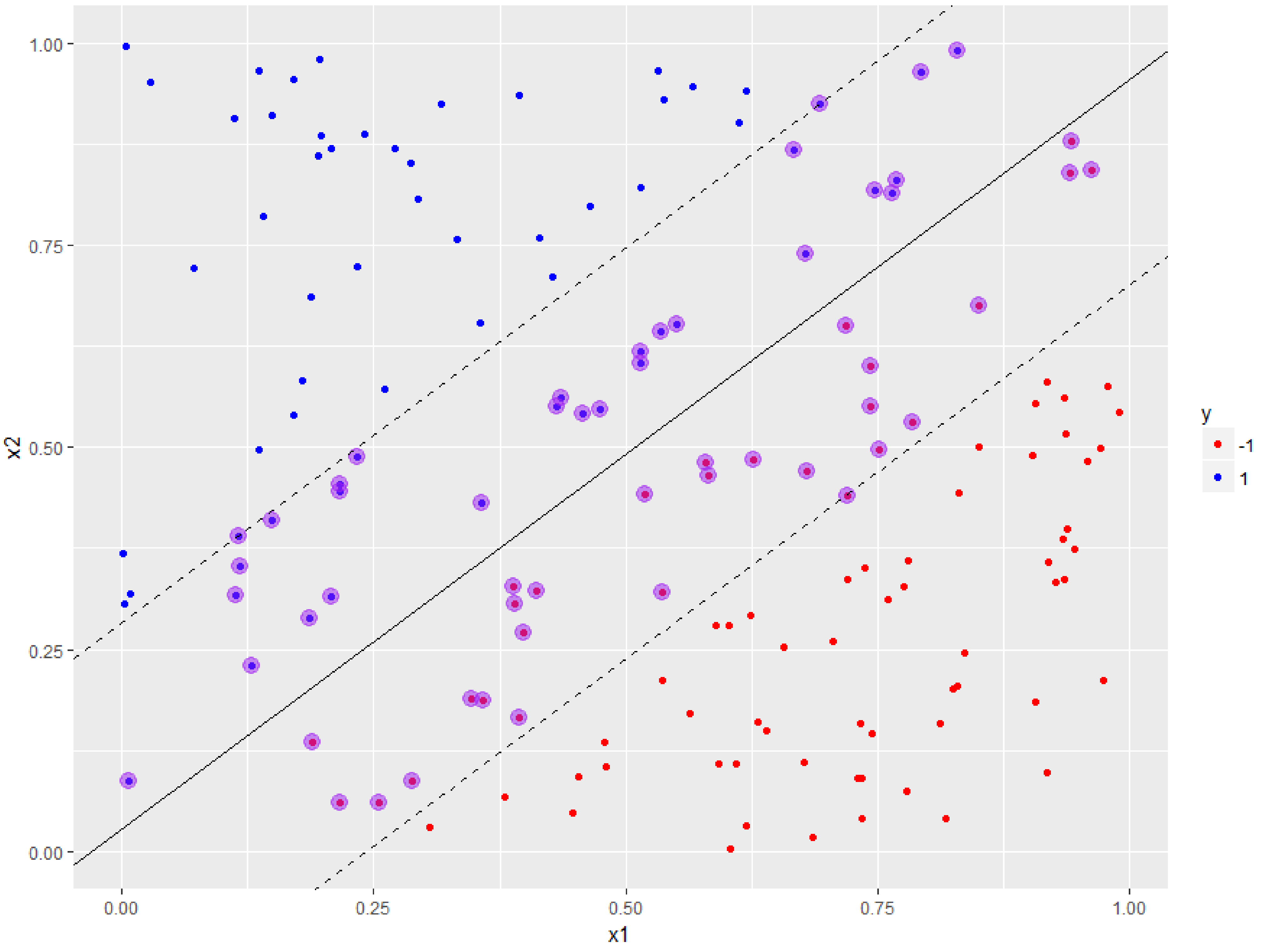
```
# Calculate intercept and save it to a variable
intercept_1 <- svm_model$rho / w[2]
```

- Add **decision boundary** using slope and intercept calculated in previous slide.
- We use `geom_abline()` to add the decision boundary to the plot.

```
# Plot decision boundary based on calculated slope and intercept
p <- p + geom_abline(slope = slope_1,
                     intercept = intercept_1)
```

- **Margins** parallel to decision boundary, offset by `1 / w[2]` on either side of it.

```
# Add margins to plot
p <- p +
    geom_abline(slope = slope_1,
                intercept = intercept_1 - 1 / w[2],
                linetype = "dashed") +
    geom_abline(slope = slope_1,
                intercept = intercept_1 + 1 / w[2],
                linetype = "dashed")
# Display plot
p
```



1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

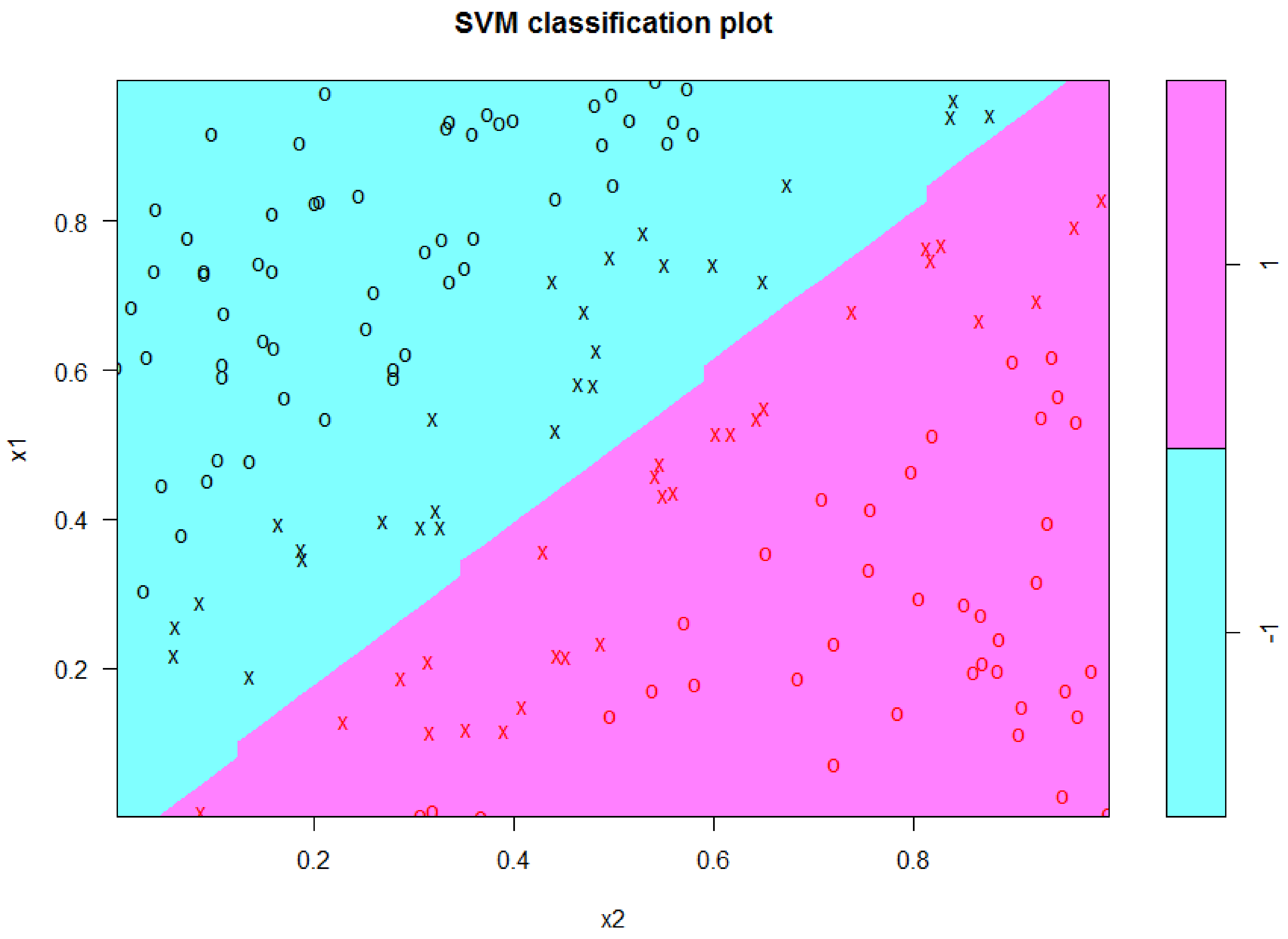
Soft margin classifiers

- Allow for uncertainty in location / shape of boundary
  - Never perfectly linear
  - Usually unknown
- Our decision boundary is linear, so we can reduce margin

Visualizing the decision boundary using the svm plot() function

- The svm `plot()` function in `e1071` offers an easy way to plot the decision boundary.

```
# Visualize decision boundary using built in plot function
plot(x = svm_model,
     data = trainset)
```



SVM classification plot
x1
x2
0.2
0.4
0.6
0.8
1
-1

Time to practice!

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Tuning linear SVMs

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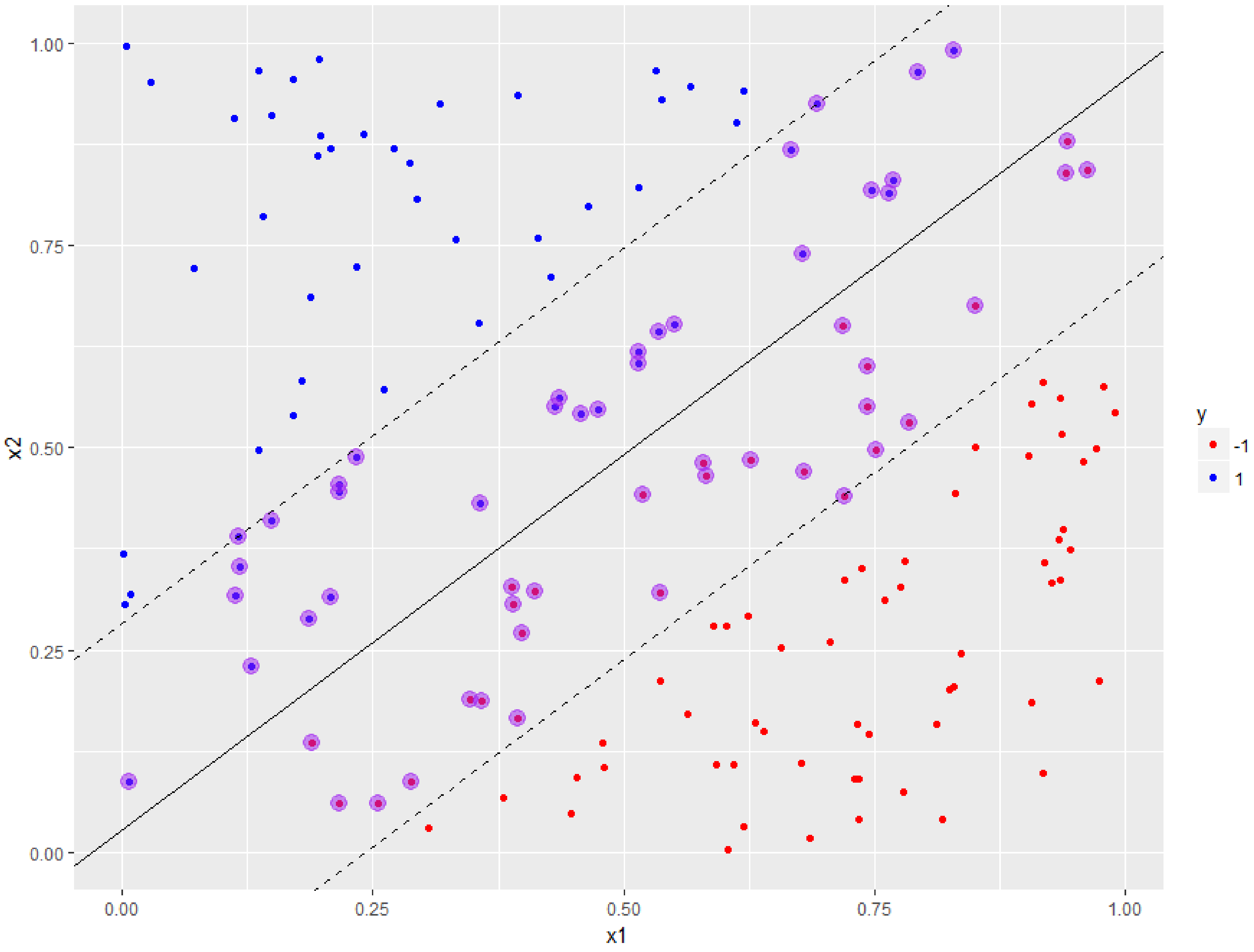
Linear SVM, default cost

```r
library(e1071)
svm_model <- svm(y ~ .,
                data = trainset,
                type = "C-classification",
                kernel = "linear",
                scale = FALSE)
# Print model summary
svm_model
```

```
Call:
svm(formula = y ~ .,
    data = trainset,
    type = "C-classification",
    kernel = "linear",
    scale = FALSE)

Parameters:
SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  1
      gamma:  0.5
Number of Support Vectors:  55
```



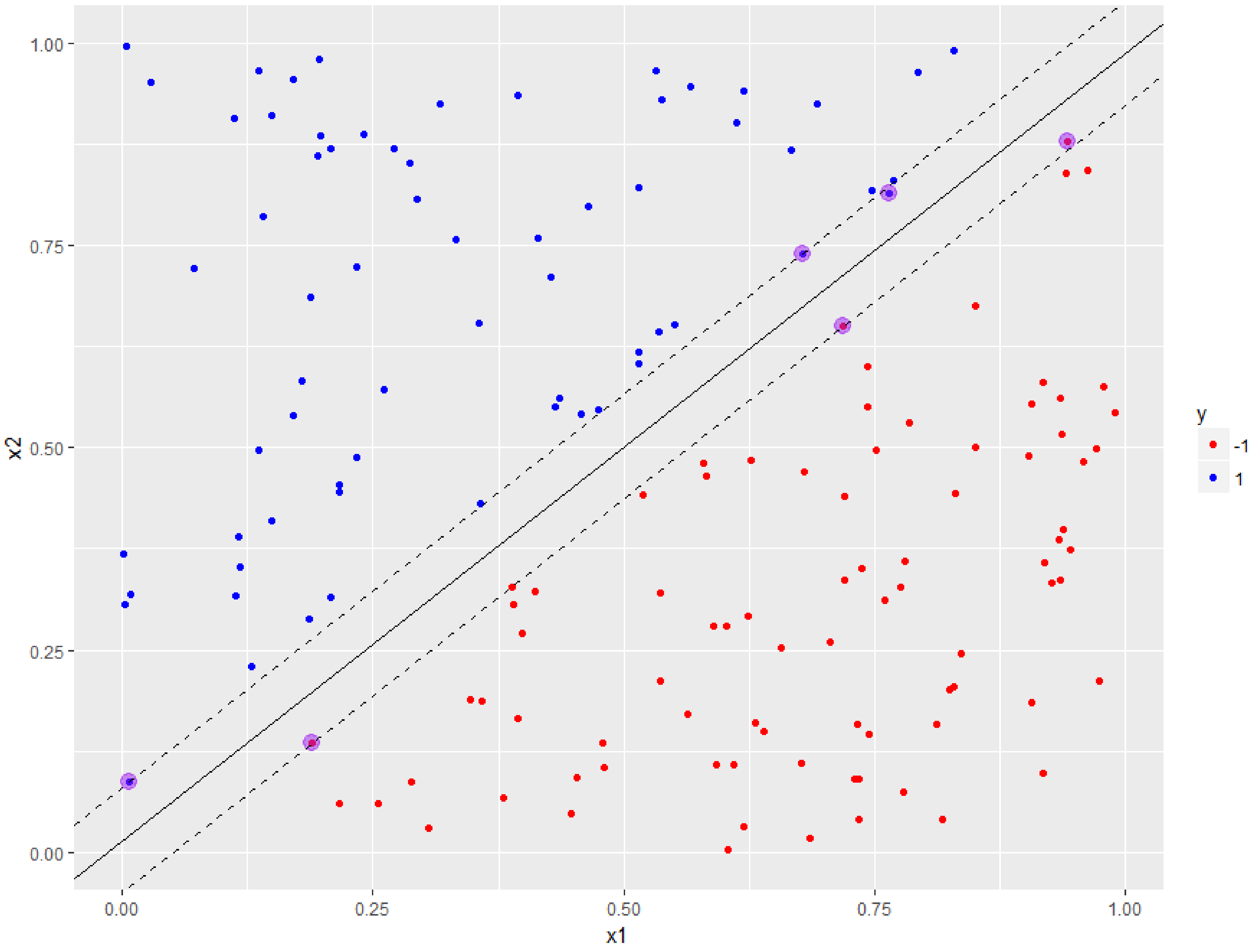
1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

Linear SVM with cost = 100

```r
library(e1071)
svm_model <- svm(y ~ .,
                data = trainset,
                type = "C-classification",
                kernel = "linear",
                cost = 100,
                scale = FALSE)
# Print model summary
svm_model
```

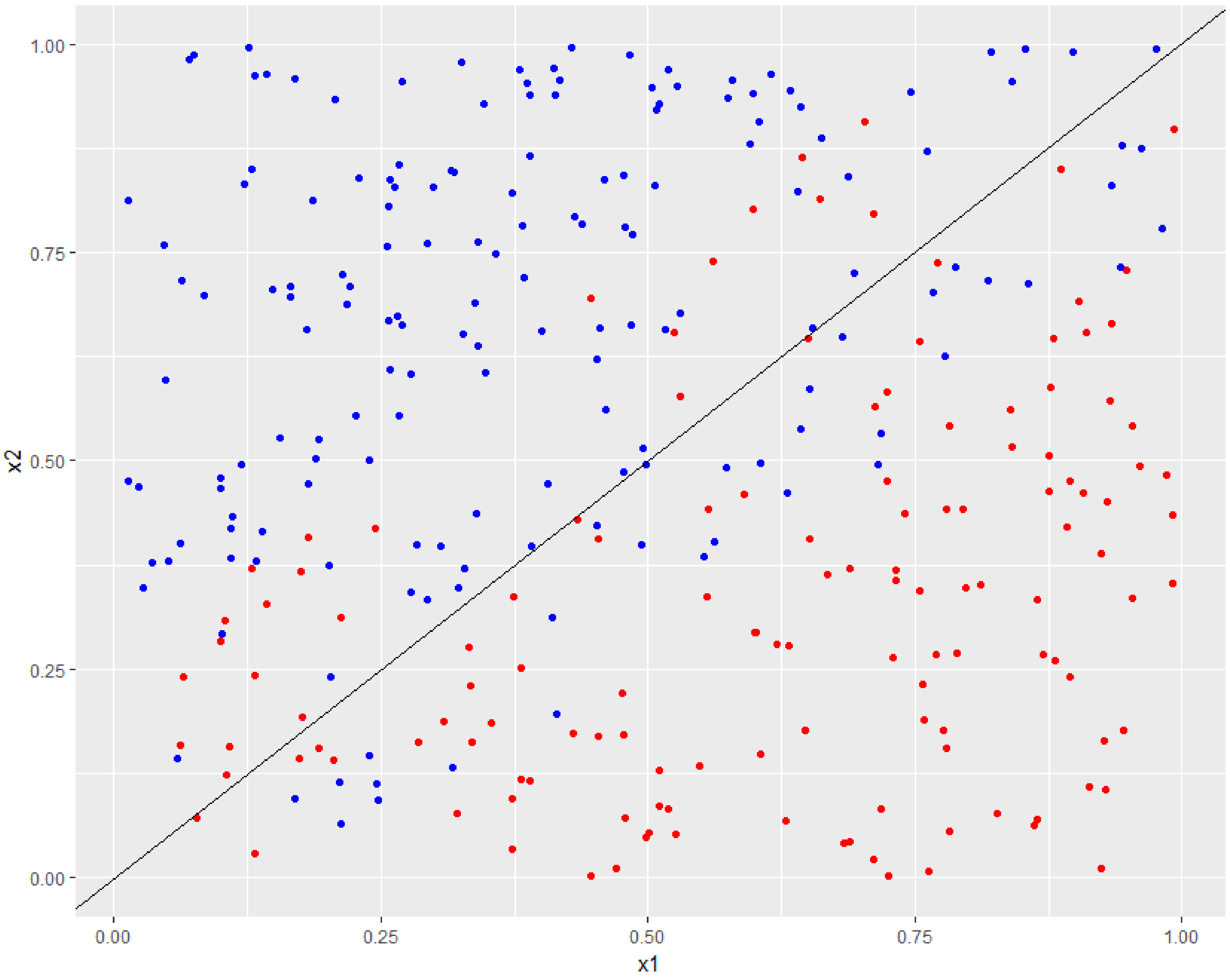
```
Call:
svm(formula = y ~ .,
    data = trainset,
    type = "C-classification",
    kernel = "linear",
    cost = 100,
    scale = FALSE)

Parameters:
SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  100
      gamma:  0.5
Number of Support Vectors:  6
```


1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

Implication

- Can be useful to reduce margin if decision boundary is known to be linear
- ...but this is rarely the case in real life



1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1

Nonlinear dataset, linear SVM (cost = 100)

- Build cost=100 model using training set composed of 80% of data

```
# Build model
library(e1071)
svm_model<- svm(y ~ .,
                data = trainset,
                type = "C-classification",
                kernel = "linear",
                cost = 100,
                scale = FALSE)
```

- Calculate accuracy

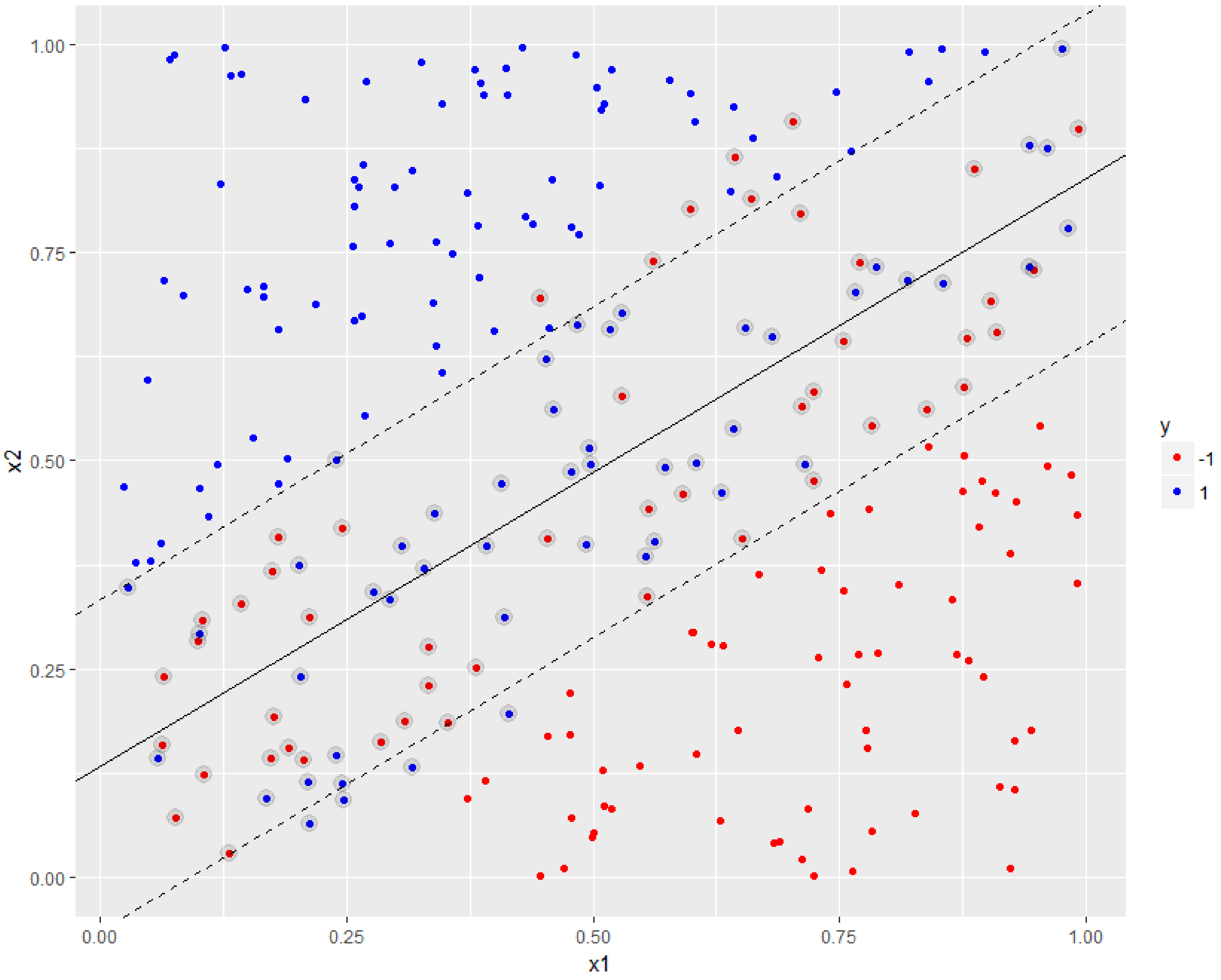
```
# Train and test accuracy
pred_train <- predict(svm_model, trainset)
mean(pred_train == trainset$y)
```

```
0.8208333
```

```
pred_test <- predict(svm_model, testset)
mean(pred_test == testset$y)
```

```
0.85
```

- Average test accuracy over 50 random train/test splits: 82.9%



1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

Nonlinear dataset, linear SVM (cost = 1)

- Rebuild model setting cost =1

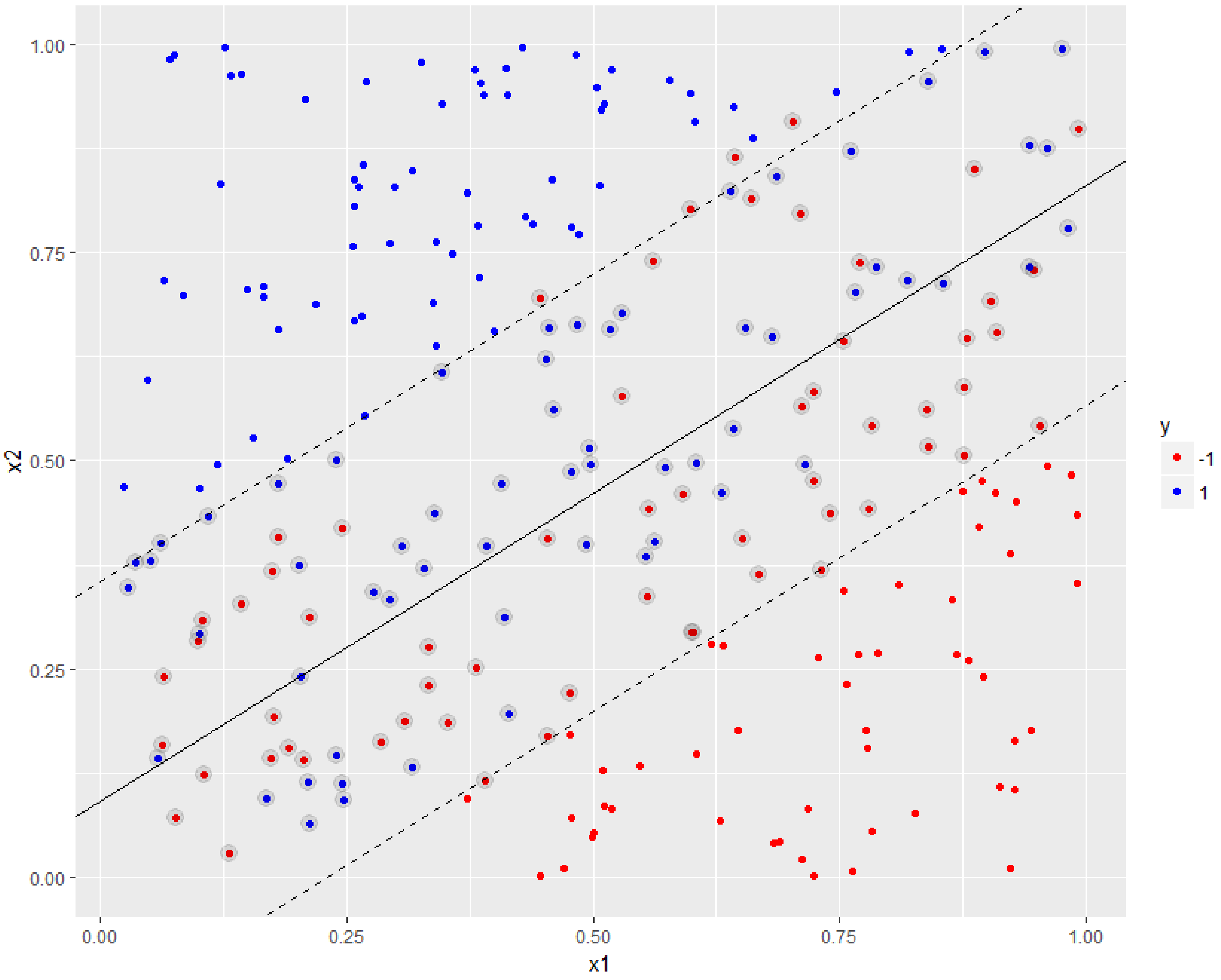
```
# Trainset contains 80% of data
# Same train/test split as before.
# Build model
svm_model <- svm(y ~ .,
                 data = trainset,
                 type = "C-classification",
                 kernel = "linear",
                 cost = 1,
                 scale = FALSE)
```

- Calculate test accuracy

```
# Test accuracy
pred_test <- predict(svm_model, testset)
mean(pred_test == testset$y)
```

```
0.8666667
```

- Average test accuracy over 50 random train/test splits: 83.7%



1.00
0.75
0.50
0.25
0.00
x2
0.00
0.25
0.50
0.75
1.00
x1
y
-1
1

Time to practice!

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Multiclass problems

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The iris dataset - an introduction

- 150 measurements of 5 attributes
  - Petal width and length - number (predictor variables)
  - Sepal width and length - number (predictor variables)
  - Species - category: setosa, virginica or versicolor (predicted variable)
- Dataset available from **UCI ML repository**

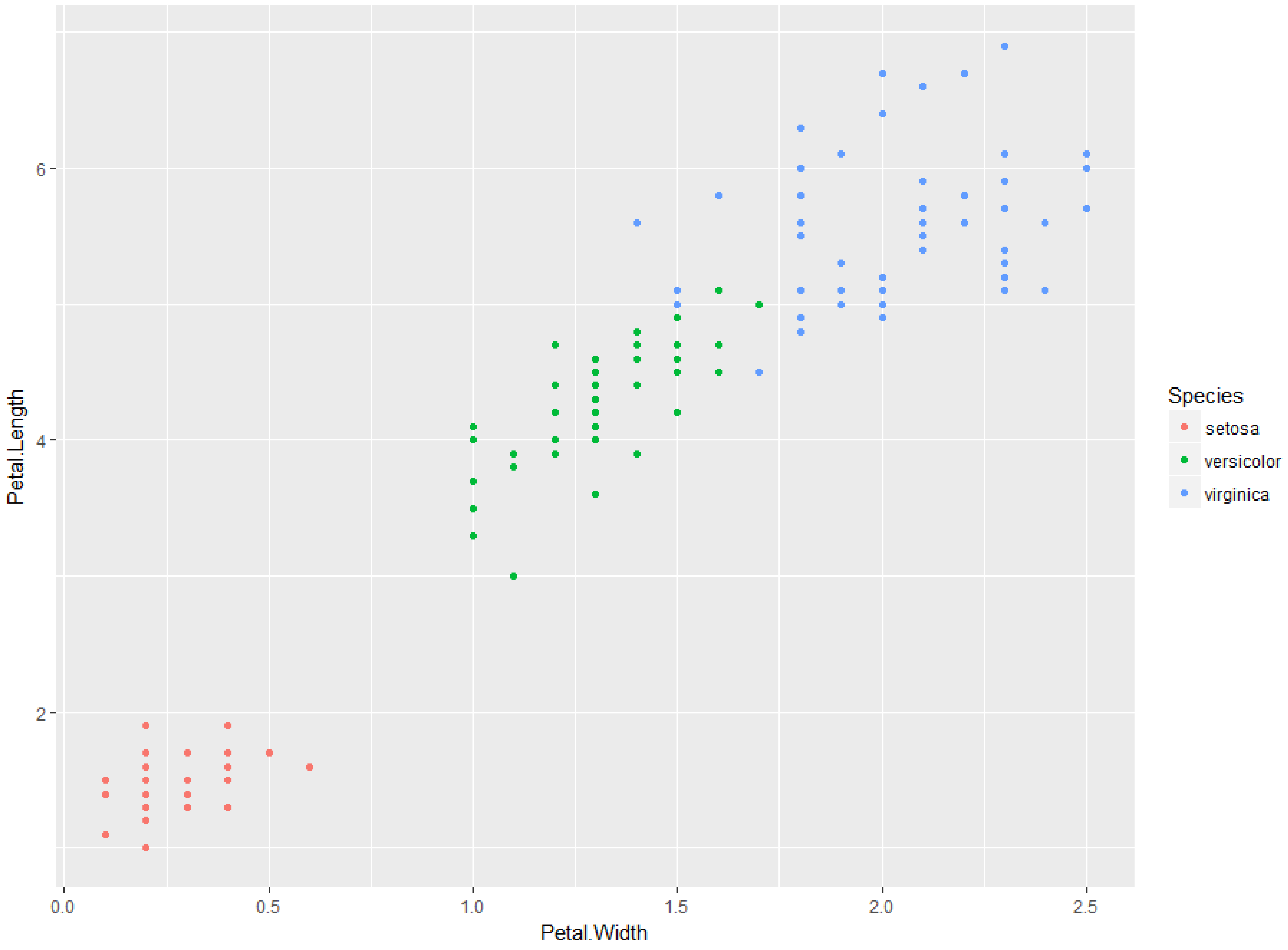
Visualizing the iris dataset

- Plot petal length vs petal width.

```
library(ggplot2)

# Plot petal length vs width for dataset, distinguish species by color
p <- ggplot(data = iris,
            aes(x = Petal.Width,
                y = Petal.Length,
                color = Species)) +
     geom_point()

# Display plot
p
```


Petal.Length
6
4
2
0.0
0.5
1.0
1.5
2.0
2.5
Petal.Width
Species
setosa
versicolor
virginica

How does the SVM algorithm deal with multiclass problems?

- SVMs are essentially binary classifiers.
- Can be applied to multiclass problems using the following voting strategy:
  - Partition the data into subsets containing two classes each.
  - Solve the binary classification problem for each subset.
  - Use majority vote to assign a class to each data point.
- Called **one-against-one** classification strategy.

Building a multiclass linear SVM

- Build a linear SVM for the iris dataset
  - 80/20 training / test split (seed 10), default cost

```
library(e1071)

# Build model
svm_model <- svm(Species ~ .,
                 data = trainset,
                 type = "C-classification",
                 kernel = "linear")
```

- Calculate accuracy

```
pred_train <- predict(svm_model, trainset)
mean(pred_train == trainset$Species)
```

```
0.9756098
```

```
pred_test <- predict(svm_model, testset)
mean(pred_test == testset$Species)
```

```
0.962963
```

Time to practice!

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