

Module Seven Lab – Artificial Neural Networks

The dataset that I am going to be working with for this lab consists of 20000 examples of 26 English alphabet capital letters using 20 different randomly distorted and reshaped black-and-white fonts. First, I explored and prepared the data:

I started by importing the data with the following command:

```
> letters <- read.csv("C:\\Users\\toons\\Downloads\\letterdata.csv")
```

And then viewed the data with the following command:

```
> str(letters)
'data.frame': 20000 obs. of 17 variables:
 $ letter: chr "T" "I" "D" "N" ...
 $ xbox : int 2 5 4 7 2 4 4 1 2 11 ...
 $ ybox : int 8 12 11 11 1 11 2 1 2 15 ...
 $ width : int 3 3 6 6 3 5 5 3 4 13 ...
 $ height: int 5 7 8 6 1 8 4 2 4 9 ...
 $ onpix : int 1 2 6 3 1 3 4 1 2 7 ...
 $ xbar : int 8 10 10 5 8 8 8 8 10 13 ...
 $ ybar : int 13 5 6 9 6 8 7 2 6 2 ...
 $ x2bar : int 0 5 2 4 6 6 6 2 2 6 ...
 $ y2bar : int 6 4 6 6 6 9 6 2 6 2 ...
 $ xybar : int 6 13 10 4 6 5 7 8 12 12 ...
 $ x2ybar: int 10 3 3 4 5 6 6 2 4 1 ...
 $ xy2bar: int 8 9 7 10 9 6 6 8 8 9 ...
 $ xedge : int 0 2 3 6 1 0 2 1 1 8 ...
 $ xedgey: int 8 8 7 10 7 8 8 6 6 1 ...
 $ yedge : int 0 4 3 2 5 9 7 2 1 1 ...
 $ yedgex: int 8 10 9 8 10 7 10 7 7 8 ...
```

Because every feature is an integer, I did not need to prepare the data any further. I then created training and testing sets with the following commands. The training set uses 16000 of the 20000 entries:

```
> letters_train <- letters[1:16000, ]
```

And the testing set consists of the remaining data:

```
> letters_test <- letters[16001:20000, ]
```

Next, I installed the kernlab package to use the ksvm() function to specify the linear kernel with the following code:

```
> letter_classifier <- ksvm(letter ~ ., data = letters_train, kernel = "vanilladot")
  Setting default kernel parameters
> letter_classifier
Support Vector Machine object of class "ksvm"

SV type: C-svc (classification)
parameter : cost C = 1

Linear (vanilla) kernel function.

Number of Support Vectors : 7037

Objective Function Value : -14.1746 -20.0072 -23.5628 -6.2009 -7.5524 -32.7694 -49.9786
Training error : 0.130062
> |
```

Next, I evaluated the model performance to get a better idea about how well the model would perform in the real world. I used the predict() function and was able to get the first six predicted letters U, N, V, X, N, and H. I then compared the predicted letter to the true letter using the data set while using the table() function to get a better visualization:

```

> letter_predictions <- predict(letter_classifier, letters_test)
> head(letter_predictions)
[1] U N V X N H
Levels: A B C D E F G H I J K L M N O P Q R S T U V W X Y Z
> table(letter_predictions, letters_test$letter)

letter_predictions  A  B  C  D  E  F  G  H  I  J  K  L  M  N  O  P  Q  R  S  T  U  V  W
A 144  0  0  0  0  0  0  0  0  1  0  0  1  2  2  0  5  0  1  1  1  0  1
B  0 121  0  5  2  0  1  2  0  0  1  0  1  0  0  2  2  3  5  0  0  2  0
C  0  0 120  0  4  0 10  2  2  0  1  3  0  0  2  0  0  0  0  0  0  0
D  2  2  0 156  0  1  3 10  4  3  4  3  0  5  5  3  1  4  0  0  0  0
E  0  0  5  0 127  3  1  1  0  0  3  4  0  0  0  2  0 10  0  0  0  0
F  0  0  0  0  0 138  2  2  6  0  0  0  0  0  16  0  0  3  0  0  1  0
G  1  1  2  1  9  2 123  2  0  0  1  2  1  0  1  2  8  2  4  3  0  0
H  0  0  0  1  0  1  0 102  0  2  3  2  3  4 20  0  2  3  0  3  0  2
I  0  1  0  0  0  1  0  0 141  8  0  0  0  0  1  0  0  3  0  0  0
J  0  1  0  0  0  1  0  2  5 128  0  0  0  0  1  1  3  0  2  0  0  0
K  1  1  9  0  0  0  2  5  0  0 118  0  0  2  0  1  0  7  0  1  3  0
L  0  0  0  0  2  0  1  1  0  0  0 133  0  0  0  1  0  5  0  0  0  0
M  0  0  1  1  0  0  1  1  0  0  0  0 135  4  0  0  0  0  0  3  0  8
N  0  0  0  0  0  1  0  1  0  0  0  0  0 145  0  0  0  3  0  0  1  0
O  1  0  2  1  0  0  1  2  0  1  0  0  0  1 99  3  3  0  0  3  0  0
P  0  0  0  1  0  2  1  0  0  0  0  0  0  0  2 130  0  0  0  0  0  0
Q  0  0  0  0  0  0  8  2  0  0  0  3  0  0  3  1 124  0  5  0  0  0
R  0  7  0  0  1  0  3  8  0  0  13  0  0  1  1  1  0 138  0  1  0  0
S  1  1  0  0  1  0  3  0  1  1  0  1  0  0  0 14  0 101  3  0  0  0
T  0  0  0  0  3  2  0  0  0  0  1  0  0  0  0  0  0  3 133  1  0  0
U  1  0  3  1  0  0  0  2  0  0  0  0  0  1  0  0  0  0  0 152  0  0
V  0  0  0  0  0  1  3  4  0  0  0  0  1  2  1  0  3  1  0  0 126  1
W  0  0  0  0  0  0  1  0  0  0  0  2  0  0  0  0  0  0  0  4  4 127
X  0  1  0  0  2  0  0  1  3  0  1  6  0  0  1  0  0  0  1  0  0  0
Y  3  0  0  0  0  0  0  1  0  0  0  0  0  0  7  0  0  0  3  0  0  0
Z  2  0  0  0  1  0  0  0  3  4  0  0  0  0  0  0  0  18  3  0  0  0

letter_predictions  X  Y  Z
A  0  0  1
B  1  0  0
C  0  0  0
D  3  3  1
E  2  0  3
F  1  2  0
G  1  0  0
H  0  1  0

```

By returning vector values of true or false (whether the value matches the test data set) I can see that the classifier correctly identified 84 percent of the set:

```

> agreement <- letter_predictions == letters_test$letter
> table(agreement)
agreement
FALSE TRUE
 643 3357
> prop.table(table(agreement))
agreement
FALSE TRUE
0.16075 0.83925
> |

```

To attempt to improve the model performance, I first changed the SVM kernel function with the following code. I began with the Gaussian RBF kernel using the `ksvm()` function:

```

> letter_classifier_rbf <- ksvm(letter ~ ., data = letters_train,
+                               kernel = "rbfdot")
> letter_predictions_rbf <- predict(letter_classifier_rbf,
+                                   letters_test)

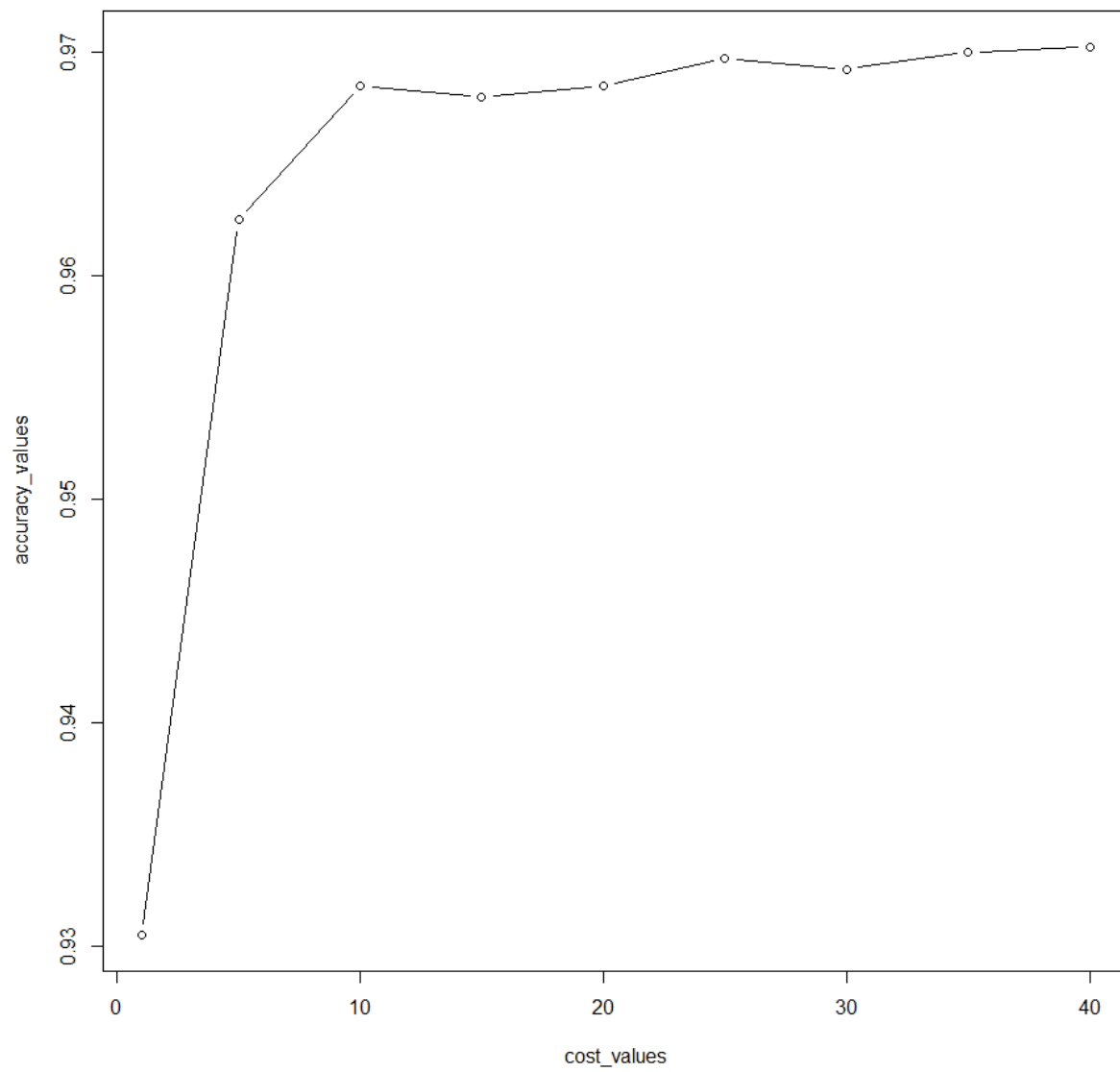
```

Then compared the accuracy with the linear SVM using the following code and I was able to see that by changing the kernel function I was able to increase the accuracy of the model from 84 percent to 93 percent:

```
> agreement_rbf <- letter_predictions_rbf == letters_test$letter
> table(agreement_rbf)
agreement_rbf
FALSE  TRUE
  281   3719
> prop.table(table(agreement_rbf))
agreement_rbf
FALSE  TRUE
0.07025 0.92975
~ |
```

Next, to try and increase the model performance even further, I identified the best SVM cost parameter. I used the `sapply()` function to apply a custom function to a vector of potential cost values. The `seq()` function to generate the vector as a sequence counting from to forty, by five and the `plot()` function to help visualize the result:

```
> cost_values <- c(1, seq(from = 5, to = 40, by = 5))
> accuracy_values <- sapply(cost_values, function(x) {
+   set.seed(12345)
+   m <- ksvm(letter ~ ., data = letters_train,
+             kernel = "rbfdot", C = x)
+   pred <- predict(m, letters_test)
+   agree <- ifelse(pred == letters_test$letter, 1, 0)
+   accuracy <- sum(agree) / nrow(letters_test)
+   return (accuracy)
+ })
```



By identifying the best SVM cost parameter, I was able to increase the accuracy of the model to 97 percent!

References

Lantz, B. (2019). *Machine Learning with R* (3rd ed.). Packt Publishing.

<https://mbsdirect.vitalsource.com/books/9781788291552>