

Chapter 7 Code

Xi Liang

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Example 1. Modeling the strength of concrete with ANNs

Exploring and preparing the data

```
concrete <- read.csv('data/concrete.csv')
```

```
str(concrete)
```

```
## 'data.frame':  1030 obs. of  9 variables:
## $ cement      : num  540 540 332 332 199 ...
## $ slag        : num   0  0 142 142 132 ...
## $ ash         : num   0  0  0  0  0  0  0  0  0 ...
## $ water       : num  162 162 228 228 192 228 228 228 228 ...
## $ superplastic: num   2.5 2.5  0  0  0  0  0  0  0 ...
## $ coarseagg   : num 1040 1055 932 932 978 ...
## $ fineagg     : num  676 676 594 594 826 ...
## $ age         : int   28 28 270 365 360 90 365 28 28 28 ...
## $ strength    : num   80 61.9 40.3 41 44.3 ...
```

Normalizing the data.

```
normalize <- function(x) {
  return ((x-min(x)) / (max(x) - min(x)))
}
```

```
concrete_norm <- as.data.frame(lapply(concrete, normalize))
```

```
summary(concrete_norm$strength)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.0000  0.2664  0.4001  0.4172  0.5457  1.0000
```

training a model on the data

```
concrete_train <- concrete_norm[1:773, ]
concrete_test  <- concrete_norm[774:1030, ]
```

```
library(neuralnet)
```

```
set.seed(10)
```

```
concrete_model <- neuralnet(strength ~ cement + slag + ash + water + superplastic + coarseagg + fineagg)
```

```
plot(concrete_model)
```

evaluating model performance

```
model_results <- compute(concrete_model, concrete_test[1:8])
predicted_strength <- model_results$net.result
```

```
cor(predicted_strength, concrete_test$strength)
```

```
##           [,1]
## [1,] 0.7218542561
```

improving model performance

```
set.seed(10)
concrete_model2 <- neuralnet(strength ~ cement + slag + ash + water + superplastic + coarseagg + fineagg,
                             data = concrete_train, hidden = 5)
```

```
plot(concrete_model2)
```

```
model_results2 <- compute(concrete_model2, concrete_test[1:8])
predicted_strength2 <- model_results2$net.result
cor(predicted_strength2, concrete_test$strength)
```

```
##           [,1]
## [1,] 0.8111905868
```

Example 2. Performing OCR with SVMs

Exploring and preparing the data

```
letters <- read.csv("data/letterdata.csv")
```

```
str(letters)
```

```
## 'data.frame':  20000 obs. of  17 variables:
## $ letter: Factor w/ 26 levels "A","B","C","D",...: 20 9 4 14 7 19 2 1 10 13 ...
## $ 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 ...
## $ yedgey: int  8 10 9 8 10 7 10 7 7 8 ...
```

Training a model on the data

```
library(kernlab)

letters_train <- letters[1:16000, ]
letters_test <- letters[16001:20000, ]

letter_classifier <- ksvm(letter ~., data = letters_train,
                          kernal = "vanilladot")

letter_classifier

## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc (classification)
## parameter : cost C = 1
##
## Gaussian Radial Basis kernel function.
## Hyperparameter : sigma = 0.0460515263229448
##
## Number of Support Vectors : 8705
##
## Objective Function Value : -43.7045 -34.2373 -59.9812 -27.5964 -35.1291 -47.6352 -68.0306 -39.7344 -
## Training error : 0.053375
```

Evaluating model performance

```
letter_predictions <- predict(letter_classifier, letters_test)
head(letter_predictions)

## [1] U C E G R L
## 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
##                   A 545    1    0    0    0    0    0    0    1    2    0    0    1    0
##                   B   0 522    0    7    6    2    1   11    1    0    1    0   10    2
##                   C   1   0 483    0    1    0    1    0    1    0    3    2    0    0
##                   D   1   5   0 521    0    2   10   18    3    3    5    0    0    5
##                   E   0   3   11   0 506    1    2    0    0    1    1   14    0    0
##                   F   0   0   0   0   1 531    1    0    6    1    0    0    0    0
##                   G   0   0   8   0   19   0 500    7    0    0    0   11    5    0
##                   H   0   2   1   8   0   3   0 410    0    2    5    1    4    3
##                   I   0   0   0   0   0   1   0   0 474    9    0    0    0    0
##                   J   0   0   0   0   0   0   0   0 18 474    0    0    0    0
##                   K   1   0   1   0   1   0   1   8   0   0 468    1    0    0
##                   L   0   0   0   0   0   0   1   1   0   0   0 499    0    0
##                   M   4   0   1   0   0   0   0   0   0   0   1   0 532    2
##                   N   0   0   0   3   0   1   0   1   0   2   0   0   2 508
##                   O   0   0   8   3   0   1   7   5   0   2   0   1   1   10
##                   P   0   0   0   0   0   3   0   1   1   0   0   0   0   0
##                   Q   0   0   0   0   2   0   4   3   0   0   0   1   0   0
```

```

##           R    0    7    1    5    3    0    3   26    0    0   22    3    0    7
##           S    0    2    0    0    1    1    0    0    2    6    0    4    0    0
##           T    0    0    0    0    0    9    0    0    0    0    0    0    0    0
##           U    0    0    0    2    0    0    0    3    0    0    1    0    0    0
##           V    0    0    0    0    0    0    1    0    0    0    0    0    0    0
##           W    0    0    0    0    0    0    2    0    0    0    1    0    2    1
##           X    0    1    0    0    1    1    0    0    4    2    7    4    0    0
##           Y    1    0    0    0    0    0    0    0    0    0    0    0    0    0
##           Z    0    0    0    0    2    0    0    0    1    1    0    0    0    0
##
## letter_predictions  O    P    Q    R    S    T    U    V    W    X    Y    Z
##           A    0    0    0    1    1    0    1    0    0    0    1    0
##           B    0    1    2   19    5    2    0   18    3    1    0    0
##           C    0    0    0    0    0    0    0    0    0    0    0    0
##           D    8    1    0    3    0    1    0    0    0    4    0    0
##           E    0    3    3    0    3    0    0    1    0    7    0    5
##           F    0   23    0    0    4    4    0    1    0    1    1    0
##           G    2    6    2    2    0    2    0    1    1    0    0    0
##           H    1    3    0    3    1    7    1    1    2    0    1    0
##           I    0    0    0    0    0    0    0    0    0    1    0    0
##           J    0    0    0    0    0    0    0    0    0    0    0    1
##           K    0    0    0    5    0    2    2    0    0    7    0    0
##           L    0    0    0    0    0    0    0    0    0    0    0    0
##           M    0    0    0    0    0    0    5    1    8    0    1    0
##           N    0    0    0    2    0    0    0    1    0    0    0    0
##           O  510    2    9    0    0    0    2    0    0    2    0    0
##           P    0  505    0    0    0    0    0    0    0    0    0    0
##           Q    6    1  527    1    1    0    0    0    0    1    0    7
##           R    4    0    1  498    1    1    0    2    1    1    0    0
##           S    0    0    2    0  484    0    0    0    0    0    0    5
##           T    0    0    0    0    0  544    0    0    0    0    1    0
##           U    2    0    0    0    0    1  559    0    3    0    1    0
##           V    0    0    0    0    0    0    2  517    0    0    2    0
##           W    9    0    1    0    0    0    3    6  537    0    0    0
##           X    0    0    0    1    1    3    0    0    0  517    0    1
##           Y    0    6    0    0    0    0    0    0    0    1  559    0
##           Z    0    0    0    0    2    0    0    0    0    0    0  495

```

```

agreement <- letter_predictions == letters_test$letter
prop.table(table(agreement))

```

```

## agreement
##           FALSE           TRUE
## 0.05549207256 0.94450792744

```

Improving model performance

```

letter_classifier_rbf <- ksvm(letter ~., data = letters_train,
                             kernel = "rbfdot")

letter_predictions_rbf <- predict(letter_classifier_rbf, letters_test)

agreement_rbf <- letter_predictions_rbf == letters_test$letter
table(agreement_rbf)

```

```
## agreement_rbf
## FALSE TRUE
## 750 13252
prop.table(table(agreement_rbf))
```

```
## agreement_rbf
## FALSE TRUE
## 0.0535637766 0.9464362234
```