Special Tasks

Keshav Padiyar Manuru

03/01/2021

Assignment 1. Variable selection with randomized LASSO

1. Reading data excluding *total_UPDRS*, scaling to zero and unit variance.

```
park <- read.csv("parkinsons.csv")
park <- park %>% select(-total_UPDRS) %>% scale() %>% data.frame()
lambda <- seq(0.05,1,by=0.05)
```

2. Defining function to implement randomized lasso.

In the function *f1* glmnet package is used to implement lasso regression with weakness parameter $\alpha = 0.5$

$$\hat{\beta}^{\lambda,W} = arg\ min(||Y - X\beta||_2^2 + \lambda \sum_{k=1}^{p} \frac{|\beta_k|}{W_k})$$
$$W_k\ be\ IID\ random\ variables\ in [\alpha, 1]$$

```
f1 <- function(data,ind,lambda,alpha){

  data1 <- data[ind,]

  x_train <- as.matrix(data1 %>%select(-motor_UPDRS))

  y_train <- data1$motor_UPDRS

  # generating w_k
  w <- runif(ncol(x_train),alpha,1)

  m1 <- glmnet(x=x_train,y=y_train,lambda=lambda,alpha=1,
              family = "gaussian", panalty.factor = 1/w)

  return(matrix(as.vector(t(coef(m1))),ncol=ncol(x_train)+1,nrow=1))

}
```

3 Executing the model for different values of lambda and on bootstrap samples

```r
for (l in 1:length(lambda)){

  m2 <- boot(park, f1, R =100,lambda=lambda[l],alpha=0.5)

  coefs<-m2$t

  if (l ==1){

    max_probabilities <- matrix(colSums
                                (apply(coefs,2
                                    ,function(x) ifelse(x!=0,1,0)))/100,nrow=1)

  }else{

    max_probabilities <- rbind(max_probabilities
                               ,matrix(colSums(apply(coefs,2
                              ,function(x) ifelse(x!=0,1,0)))/100,nrow=1))
  }

}

max_probabilities <- max_probabilities[,-1]

rownames(max_probabilities) <- lambda

colnames(max_probabilities) <- colnames(park %>% select(-motor_UPDRS ))
```

Table 1: Probabilities of Vairable Significance for different Lambda values

	subject	age	sex	test_time	Jitter...	Jitter.Abs.	Jitter.RAP	Jitter.PPQ5	Jitter.DDP	Shimmer	Shimmer.dB.	Shimmer.APQ3	Shimmer.APQ5	Shimmer.APQ11	Shimmer.DDA	NHR	HNR	RPDE	DFA	PPE
0.05	1.00	1.00	1	0.91	0	0	0	0	0	0	0	0	0	0.02	0	0	0.57	0.08	1.00	1
0.1	1.00	1.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.18	0.03	0.97	1
0.15	1.00	1.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.2	1.00	1.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.25	0.62	1.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.3	0.00	0.04	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.35	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.4	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.45	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.5	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.55	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.6	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.65	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.7	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.75	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.8	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.85	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.9	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0
0.95	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0

	subject.	age	sex	test_time	Jitter...	Jitter.Abs.	Jitter.RAP	Jitter.PPQ5	Jitter.DDP	Shimmer	Shimmer.dB.	Shimmer.APQ3	Shimmer.APQ5	Shimmer.APQ11	Shimmer.DDA	NHR	HNR	RPDE	DFA	PPE
1	0.00	0.00	0	0.00	0	0	0	0	0	0	0	0	0	0.00	0	0	0.00	0.00	0.00	0

```r
max_probabilities <- matrix(apply(max_probabilities,2,max),nrow=1,
                            dimnames = list("probability",colnames(park %>% select(-motor_UPDRS ))))

stable <- max_probabilities[,which(apply(max_probabilities,2,function(x) x>0.7))]

kable(t(stable), caption = "Stable Variable Set and their Probabilities")
```

Table 2: Stable Variable Set and their Probabilities

subject.	age	sex	test_time	DFA	PPE
1	1	1	0.91	1	1

Assignment 3. Neural networks

Implementation of Neural networks using back propagation algorithm. The NN has single input and output units with 10 hidden units. Sigmoid $h(a) = \frac{1}{1+e^{-a}}$ and Tanh $h(a) = \tanh(a)$ functions are used as activation functions.

```
Nnet <- function(a_function){

  set.seed(1234567890)
  Var <- runif(50, 0, 10)
  trva <- data.frame(Var, Sin=sin(Var))
  tr <- trva[1:25,] # Training
  va <- trva[26:50,] # Validation


  # plot(trva)
  # plot(tr)
  # plot(va)

  ##  Initializing Variables

  w_j <- runif(10, -1, 1) # Input weight
  b_j <- runif(10, -1, 1) # Input Bias
  w_k <- runif(10, -1, 1) # Output weight
  b_k <- runif(1, -1, 1)  # Output bias
  l_rate <- 1/nrow(tr)^2  # learning rate
  n_ite = 25000           # Number of Iterations
  error <- rep(0, n_ite)  # Error in Training
  error_va <- rep(0, n_ite) # Error in Validation

  for(i in 1:n_ite) {
  # error computation: Your code here

  ## Error Computation for Test

  a_j <- (as.matrix(tr$Var))%*% (w_j) +
    matrix(rep(b_j,nrow(tr)),ncol=length(b_j),byrow=T) # Activations: aj

  ## Condition to switch the activation functions
  if (a_function == "sigmoid"){

        z_j <- 1/(1+exp(-a_j)) # Equation of Sigmoid function

    }else{

        z_j <- tanh(a_j) # Equation of Tanh function

    }

  a_k <- (z_j %*% w_k) +
    matrix(rep(b_k,nrow(tr)),ncol=length(b_k),byrow=T) # Output Activations: ak

  error[i] <- sum((tr$Sin - as.numeric(a_k))^2) # Least Square Error in test
```

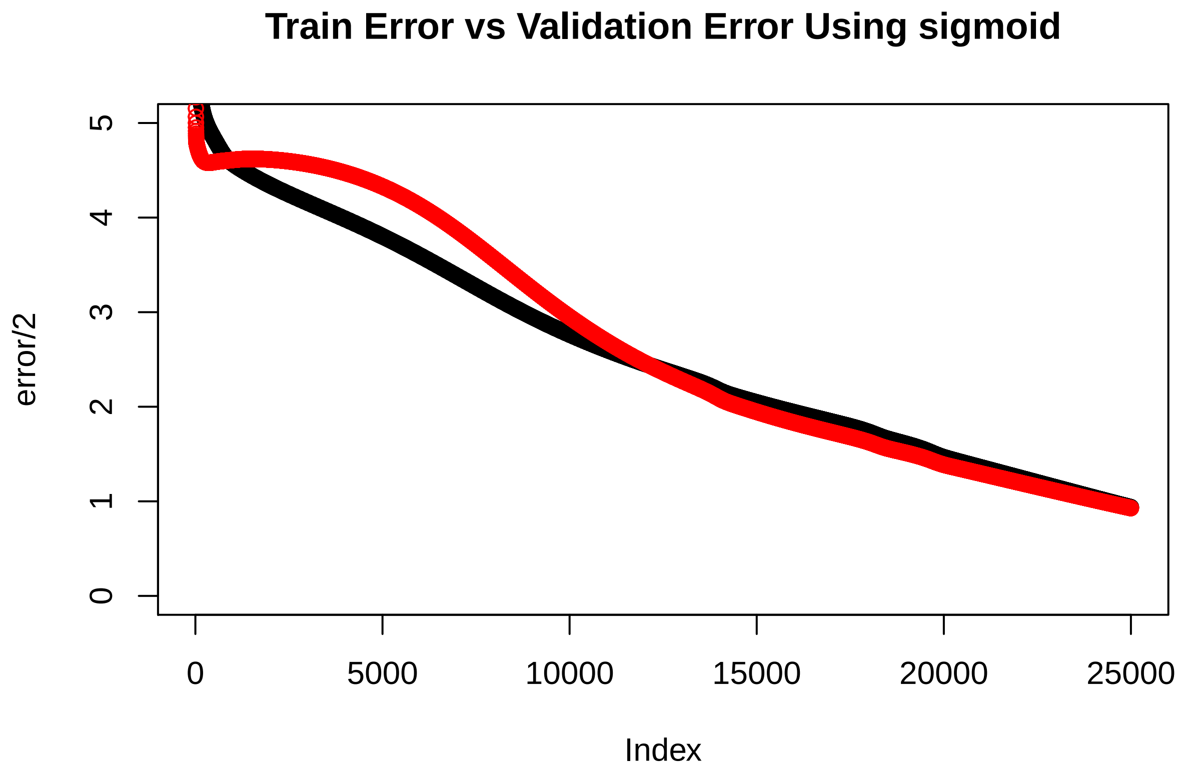
```r
## Error Computation for validation (Same steps as test, used data set va)

a_j <- (as.matrix(va$Var))%*% (w_j) + matrix(rep(b_j,nrow(va)),ncol=length(b_j),byrow=T)

if (a_function == "sigmoid"){

      z_j <- 1/(1+exp(-a_j))

  }else{

      z_j <- tanh(a_j)

  }

a_k <- (z_j %*% w_k) + matrix(rep(b_k,nrow(va)),ncol=length(b_k),byrow=T)

error_va[i] <- sum((va$Sin - as.numeric(a_k))^2)

#cat("i: ", i, ", error: ", error[i]/2, ", error_va: ", error_va[i]/2, "\n")

#flush.console()

for(n in 1:nrow(tr)) {

  # forward propagation: Your code here

      # Renaming Variables for ease of understanding

      w_i <- w_j # Input weight

      w_o <- w_k # Output weight

      b_i <- b_j  # Input Bias

      b_o <- b_k # Output Bias

      x <- tr[n,1] # Training data

      a_j <-(w_i * x)+ b_i #Input Activations


    ## Condition to switch the activation functions
    if (a_function == "sigmoid"){

          z_j <- 1/(1+exp(-a_j))

      }else{

          z_j <- tanh(a_j)

      }

      a_k <- (z_j %*% w_o) + b_o # Output activations
```

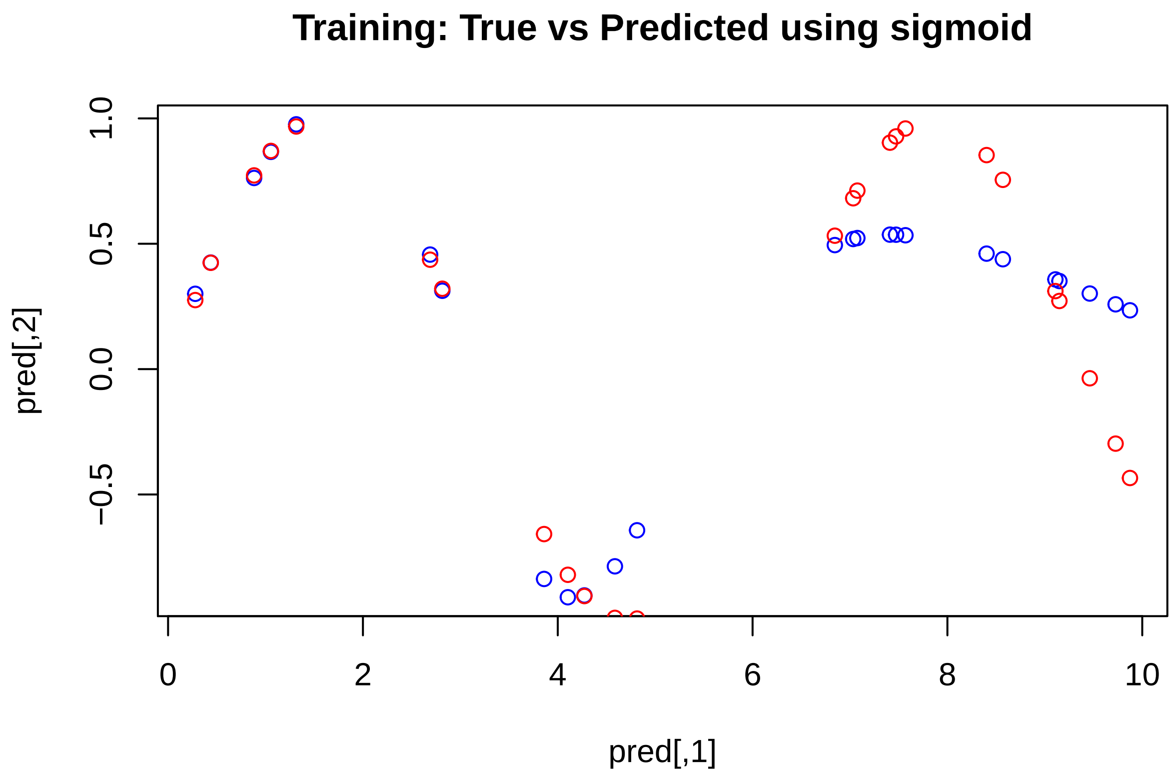
```r
  ## End of  Forward Propagation

  # backward propagation: Your code here

      y_k <- as.vector(a_k) # For regression output activation is target

      delta_k <- (as.numeric(y_k-tr[n,2])) # partial derivative wrt output activation

        if (a_function == "sigmoid"){

             # Incase of sigmoid function - derivative
             delta_j <-  (z_j * (1-z_j)) *  (w_o * delta_k) # Partial derivative wrt input autivation

        }else{

            # Incase of sigmoid function - derivative
            delta_j <-  (1-z_j^2) *  (w_o * delta_k)

        }


      E_wi <-delta_j * x # gradient of input weights

      E_wo <- z_j * delta_k # gradient of output weights

      w_ni <- w_j - (l_rate * E_wi) # new input weights using stochastic gradient descent method

      w_no <- w_k - (l_rate * E_wo) # new output weights

      w_j <- w_ni # replace old weights with new weights

      w_k <- w_no

      b_j <- b_i - (l_rate * delta_j) # new input bias using stochastic gradient descent

      b_k <- b_o - (l_rate * delta_k) # new output bias


 }

}

  # print final weights and errors
cat("Converged Weights and Biases Using ",a_function,"\n")
cat("Input Weight: ", w_j,"\n")
cat("Input Bias: ",b_j, "\n")
cat("Output Weight: ",w_k,"\n")
cat("Output Bias: ",b_k,"\n")

plot(error/2, ylim=c(0, 5), main = paste0("Train Error vs Validation Error Using ",a_function))
points(error_va/2, col = "red")
```

```r
  # plot prediction on training data

  ## predicting the target values using converged weights and biases for training data

  a_j <- (as.matrix(tr$Var))%*% (w_j) + matrix(rep(b_j,nrow(tr)),ncol=length(b_j),byrow=T)

  if (a_function == "sigmoid"){

        z_j <- 1/(1+exp(-a_j))

    }else{

        z_j <- tanh(a_j)

    }

  y_k <- (z_j %*% w_k) + matrix(rep(b_k,nrow(tr)),ncol=length(b_k),byrow=T)

  pred <- cbind(tr$Var,y_k)

  plot(pred,col="blue",main=paste0("Training: True vs Predicted using ", a_function))

  points(tr, col = "red")

  # plot prediction on validation data

  ## predicting the target values using converged weights and biases for validation data
  a_j <- (as.matrix(va$Var))%*% (w_j) + matrix(rep(b_j,nrow(va)),ncol=length(b_j),byrow=T)

  if (a_function == "sigmoid"){

        z_j <- 1/(1+exp(-a_j))

    }else{

        z_j <- tanh(a_j)

    }

  y_k <- (z_j %*% w_k) + matrix(rep(b_k,nrow(va)),ncol=length(b_k),byrow=T)

  pred <- cbind(va$Var,y_k)

  plot(pred,col="blue",main=paste0("Validation: True vs Predicted using ", a_function))

  points(va, col = "red")


}
```

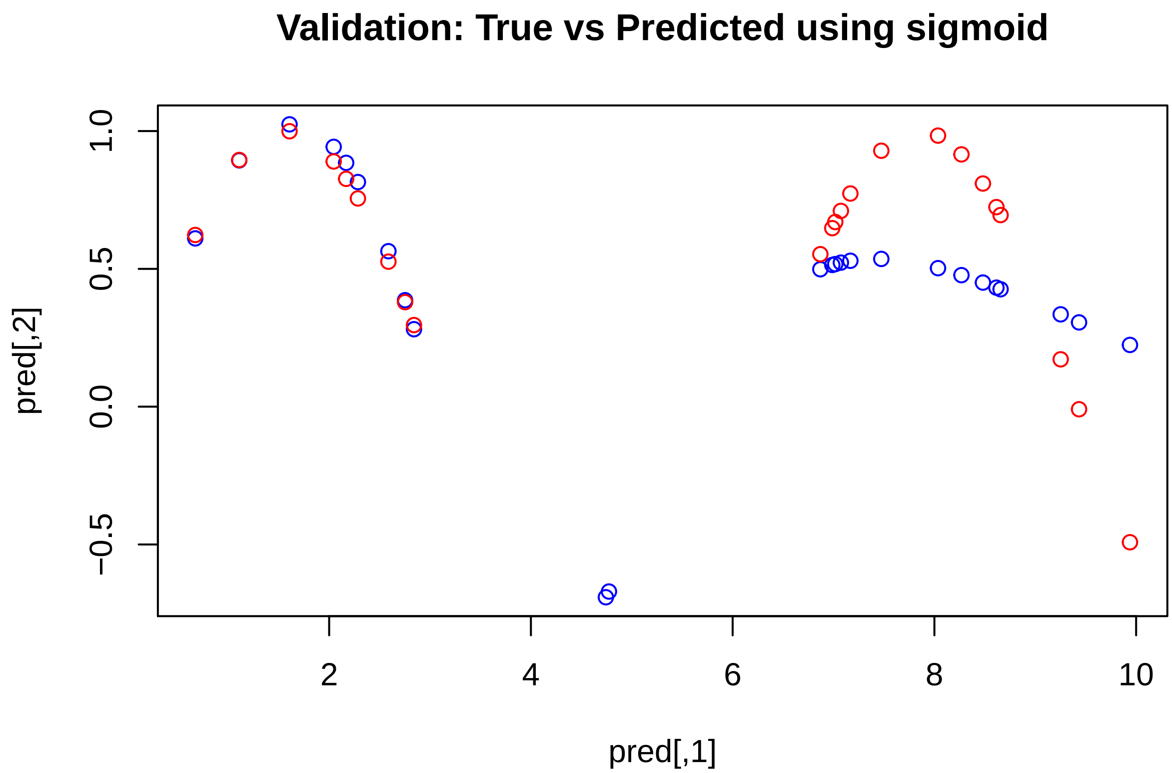
```r
## NN using Sigmoid activation function
Nnet("sigmoid")
```

```
## Converged Weights and Biases Using  sigmoid
## Input Weight:  0.629252 1.814546 -0.1810731 1.163563 0.1878194 -1.183294 1.799135 0.886882 0.597502 -
## Input Bias:  0.6264243 -5.865782 0.3065285 -1.560954 -0.4227426 5.739419 -0.9978777 -2.636683 0.74835
## Output Weight:  0.3252505 -4.34645 1.309957 -1.301127 -1.51287 -3.678236 2.464523 2.444056 0.2505412
## Output Bias:  0.8377446
```



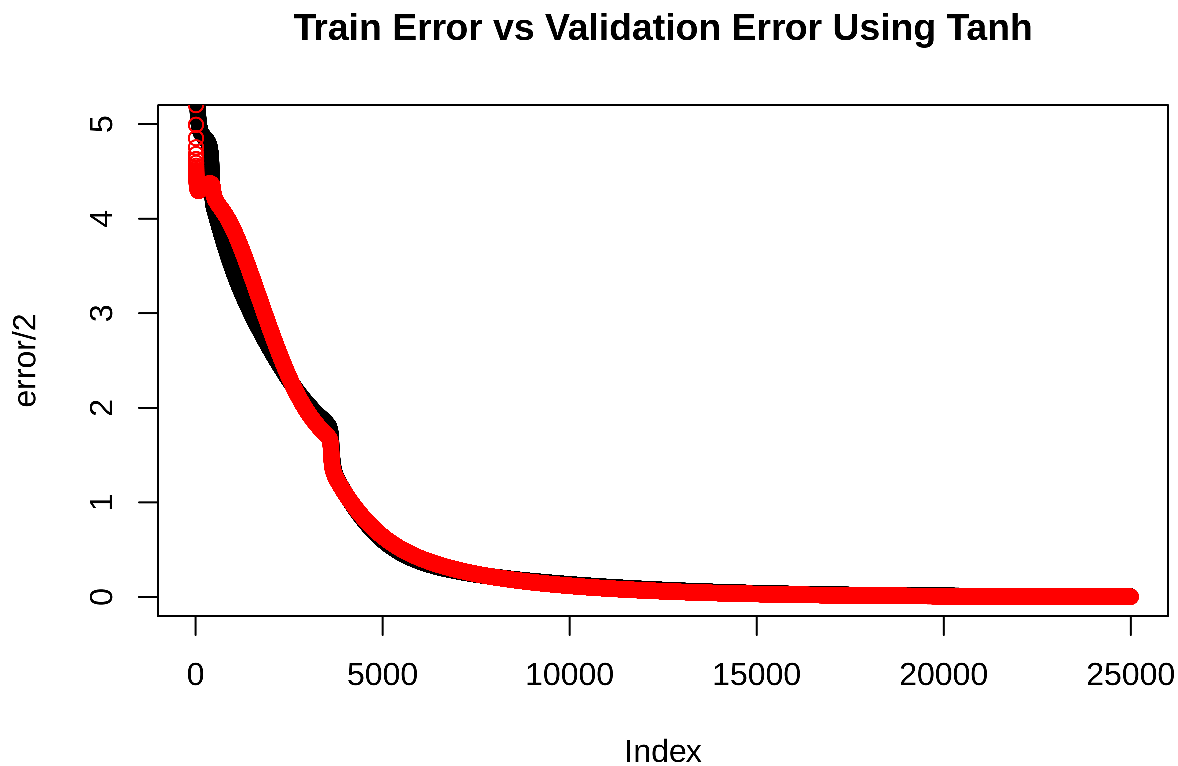


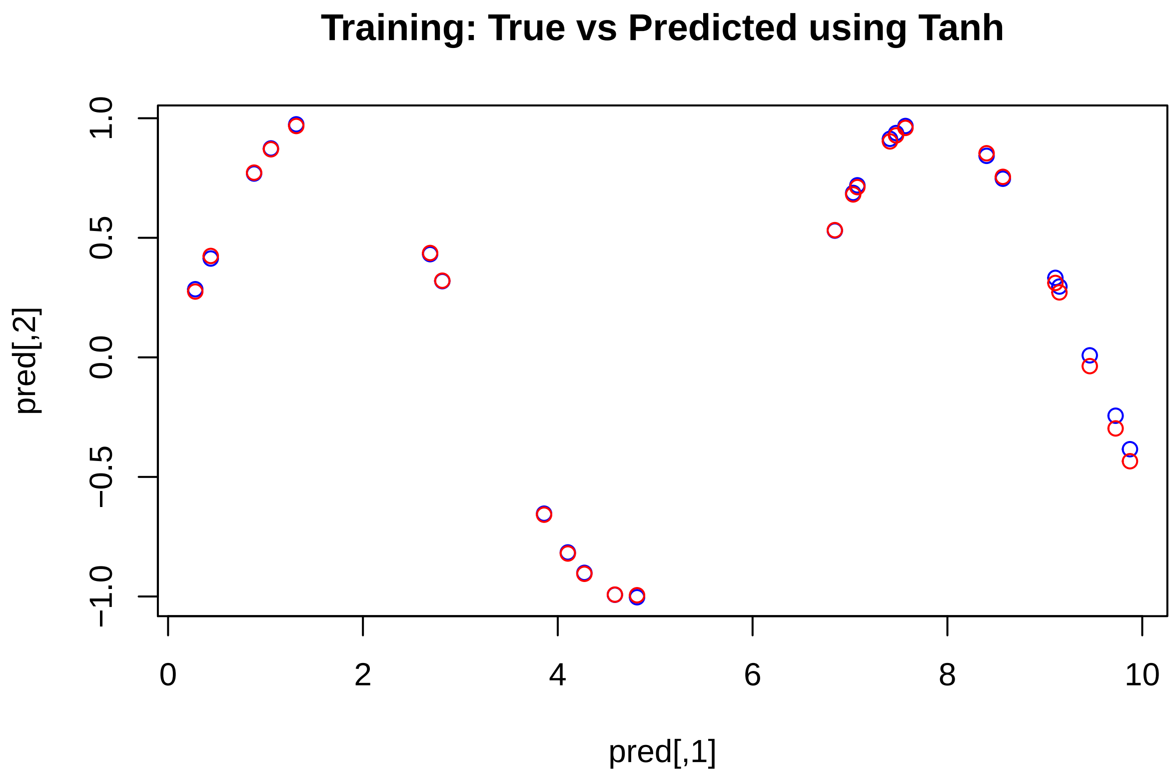
Training: True vs Predicted using sigmoid
pred[,2]
1.0
0.5
0.0
−0.5
0
2
4
6
8
10
pred[,1]

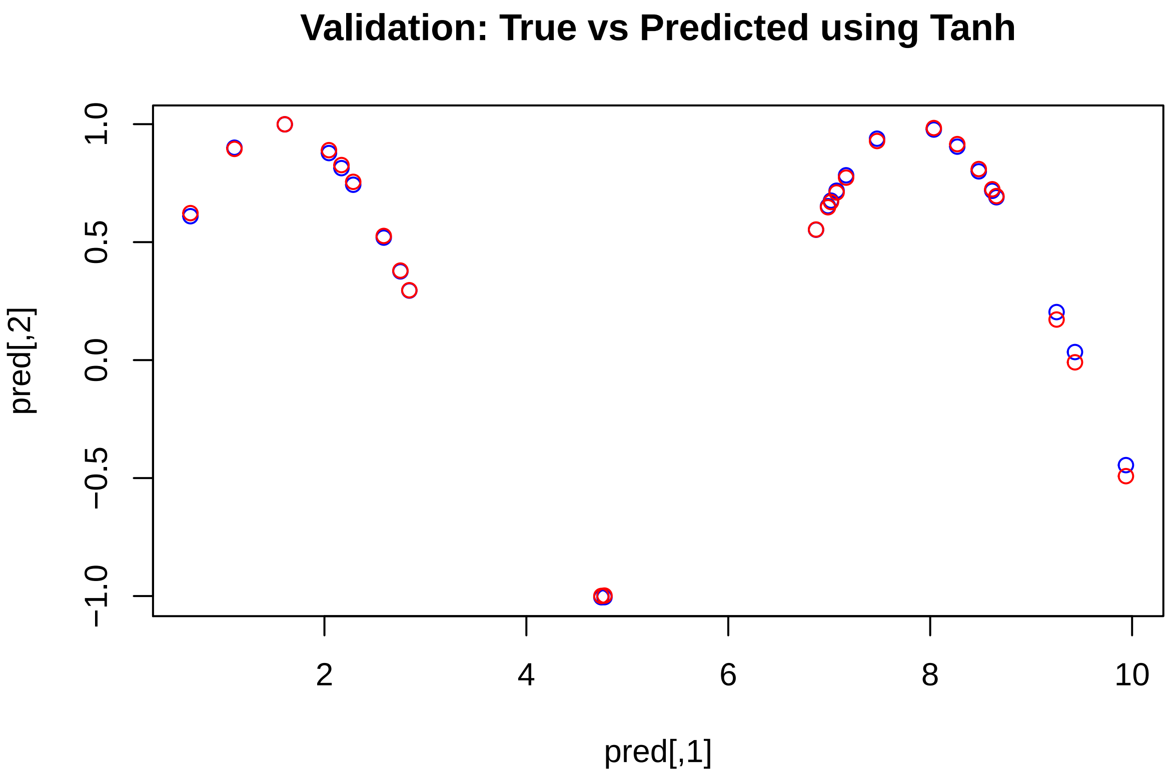



```r
## NN using Tanh activation function
Nnet("Tanh")
```

```
## Converged Weights and Biases Using  Tanh
## Input Weight:  0.4541394 0.6569828 -0.5023898 0.3908682 0.7952875 -1.067047 1.102249 0.5989191 0.379
## Input Bias:  0.6370998 -2.154366 -0.4000872 -3.589061 0.6077995 0.8259108 -0.1052611 -3.889978 0.746
## Output Weight:  -0.2002968 -1.593744 0.3063093 -2.877745 -0.8697115 -0.696131 1.00758 2.575853 -0.30
## Output Bias:  0.3143672
```


Train Error vs Validation Error Using Tanh
error/2
0
1
2
3
4
5
0
5000
10000
15000
20000
25000
Index


Training: True vs Predicted using Tanh
pred[,2]
pred[,1]
1.0
0.5
0.0
−0.5
−1.0
0
2
4
6
8
10



Validation: True vs Predicted using Tanh
pred[,2]
pred[,1]
1.0
0.5
0.0
−0.5
−1.0
2
4
6
8
10