Homework 2

```
library(pacman)
library(gam); data("kyphosis")
```

```
## Loading required package: splines

## Loading required package: foreach

## Loaded gam 1.20
```

```
require(caTools)
```

```
## Loading required package: caTools
```

```
library(glmnet)
```

```
## Loading required package: Matrix

## Loaded glmnet 4.1-2
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(psych)
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v stringr 1.4.0
## v tidyr   1.1.3     v forcats 0.5.1
## v readr   2.0.1
```

```
## -- Conflicts ---------------------------------------- tidyverse_conflicts() --
## x ggplot2::%+%()      masks psych::%+%()
## x purrr::accumulate() masks foreach::accumulate()
## x ggplot2::alpha()    masks psych::alpha()
## x tidyr::expand()     masks Matrix::expand()
## x dplyr::filter()     masks stats::filter()
## x dplyr::lag()        masks stats::lag()
## x tidyr::pack()       masks Matrix::pack()
## x tidyr::unpack()     masks Matrix::unpack()
## x purrr::when()       masks foreach::when()
```

```
library(caret)
```

```
## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(pls)
```

```
##
## Attaching package: 'pls'

## The following object is masked from 'package:caret':
##
##     R2

## The following object is masked from 'package:stats':
##
##     loadings
```

```
library(e1071)
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

```
library(klaR)
library(nnet)
library(sigmoid)
```

```
##
## Attaching package: 'sigmoid'
```

```
## The following object is masked from 'package:e1071':
##
##     sigmoid

## The following objects are masked from 'package:psych':
##
##     logistic, logit
```

```
library(nnet)
library(fastDummies)
head(kyphosis)
```

```
##   Kyphosis Age Number Start
## 1   absent  71      3     5
## 2   absent 158      3    14
## 3  present 128      4     5
## 4   absent   2      5     1
## 5   absent   1      4    15
## 6   absent   1      2    16
```

Q1: Based on the formulas we derived in class, derive the decision boundary between the two classes given the distribution parameters below.

LDA.png

```
#Splitting Data into Training and Testing Data
set.seed(11)
training.samples <- kyphosis$Kyphosis %>%
  createDataPartition(p = 0.75, list = FALSE)
train.data  <- kyphosis[training.samples, ]
train.data = data.frame(train.data)
test.data <- kyphosis[-training.samples, ]
test.data = data.frame(test.data)


#Proving the proper split
SizeOriginal <- nrow(kyphosis)
SizeTraining <- nrow(train.data)
SizeTest <- nrow(test.data)
PercentageTraining <- (SizeTraining/SizeOriginal)*100
PercentageTest <- (SizeTest/SizeOriginal)*100

sprintf('Percent of Testing Data = %f', PercentageTest)
```

Q2: Use data set kyphosis from R package "gam", randomly divide the data into training (75%) and testing (25%) set.

```
## [1] "Percent of Testing Data = 24.691358"
```

```
sprintf('Percent of Training Data = %f', PercentageTraining)
```

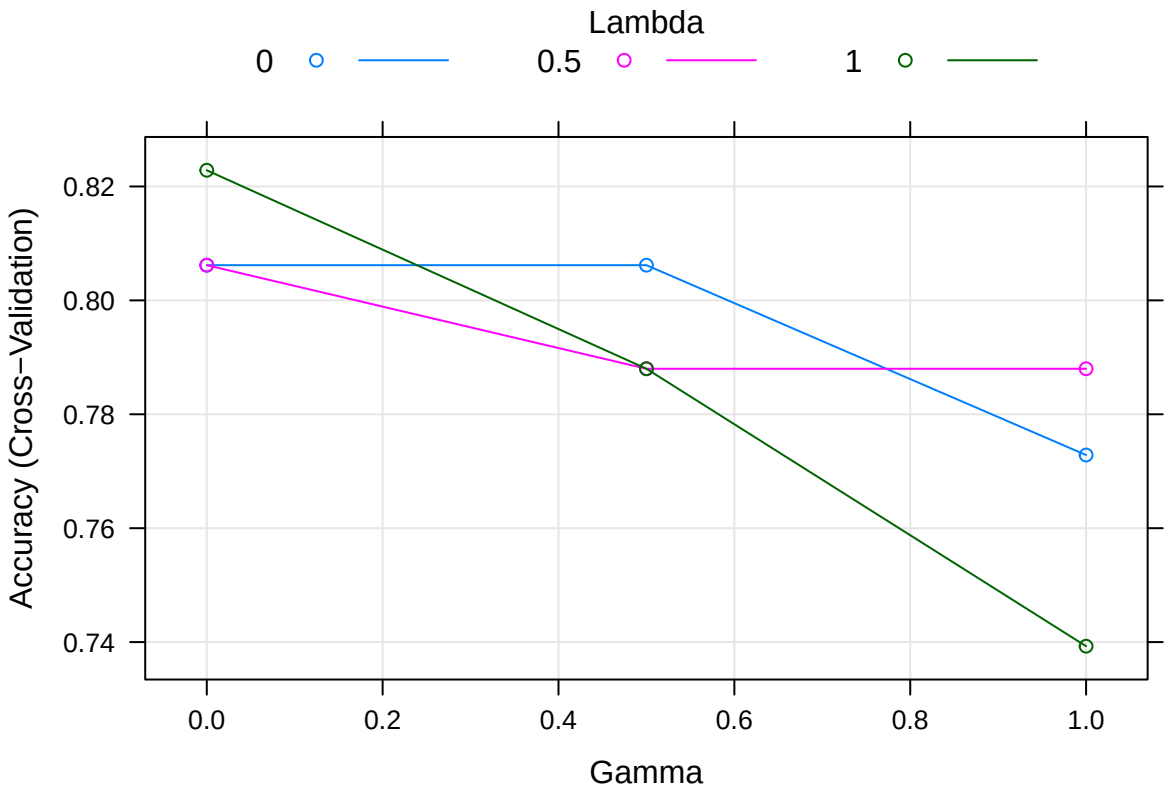
```
## [1] "Percent of Training Data = 75.308642"
```

```
set.seed(11)
model.rda <- rda(Kyphosis~.,data=train.data)
grid = trainControl(method = "cv", number = 5)
fit_rda_grid = train(Kyphosis ~ ., data = train.data, method = "rda", trControl = grid)

fit_rda_grid
```

2.1 Fit a regularized discriminant analysis model, find the best tuning parameter combination, and evaluate the model using the testing set and report the confusion matrix

```
## Regularized Discriminant Analysis
##
## 61 samples
##  3 predictor
##  2 classes: 'absent', 'present'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 48, 48, 49, 50, 49
## Resampling results across tuning parameters:
##
##   gamma  lambda  Accuracy   Kappa
##   0.0    0.0     0.8061772   0.22056650
##   0.0    0.5     0.8061772   0.27339669
##   0.0    1.0     0.8228438   0.34268241
##   0.5    0.0     0.8061772   0.17413793
##   0.5    0.5     0.7879953   0.00000000
##   0.5    1.0     0.7879953   0.00000000
##   1.0    0.0     0.7728438   0.12136015
##   1.0    0.5     0.7879953   0.00000000
##   1.0    1.0     0.7392774  -0.07608696
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were gamma = 0 and lambda = 1.
```

```
plot(fit_rda_grid)
```




```
predictions.rda = predict(model.rda, test.data)
confusionM.rda<-confusionMatrix(predictions.rda$class,test.data$Kyphosis)
print(confusionM.rda$table)
```

```
##           Reference
## Prediction absent present
##    absent      16       4
##    present      0       0
```

```
print(confusionM.rda)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction absent present
##    absent      16       4
##    present      0       0
##
##                Accuracy : 0.8
##                  95% CI : (0.5634, 0.9427)
##     No Information Rate : 0.8
##     P-Value [Acc > NIR] : 0.6296
##
##                   Kappa : 0
```

```
##
##  Mcnemar's Test P-Value : 0.1336
##
##             Sensitivity : 1.0
##             Specificity : 0.0
##          Pos Pred Value : 0.8
##          Neg Pred Value : NaN
##              Prevalence : 0.8
##          Detection Rate : 0.8
##    Detection Prevalence : 1.0
##       Balanced Accuracy : 0.5
##
##        'Positive' Class : absent
##
```

```
#Best Tuning Parameters are Gamma and Lambda
```

```
# Fit the model
model.lReg <- nnet::multinom(Kyphosis ~., data = train.data)
```

2.2 Fit a logistic regression model, and interpret the coefficients you estimated

```
## # weights:  5 (4 variable)
## initial  value 42.281978
## iter  10 value 25.720280
## final  value 25.720273
## converged
```

```
predicted.lReg <- model.lReg %>% predict(test.data)
accuracy.lReg <- mean(predicted.lReg == test.data$Kyphosis)
sprintf('Model Accuracy = %f', accuracy.lReg)
```

```
## [1] "Model Accuracy = 0.850000"
```

```
confusionM.lReg<-confusionMatrix(predicted.lReg, test.data$Kyphosis)
print(confusionM.lReg)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction absent present
##    absent      16       3
##    present      0       1
##
##                Accuracy : 0.85
##                  95% CI : (0.6211, 0.9679)
##     No Information Rate : 0.8
##     P-Value [Acc > NIR] : 0.4114
##
```

```
##                   Kappa : 0.3478
##
##  Mcnemar's Test P-Value : 0.2482
##
##             Sensitivity : 1.0000
##             Specificity : 0.2500
##          Pos Pred Value : 0.8421
##          Neg Pred Value : 1.0000
##              Prevalence : 0.8000
##          Detection Rate : 0.8000
##    Detection Prevalence : 0.9500
##       Balanced Accuracy : 0.6250
##
##        'Positive' Class : absent
##
```

```
summary(model.lReg)
```

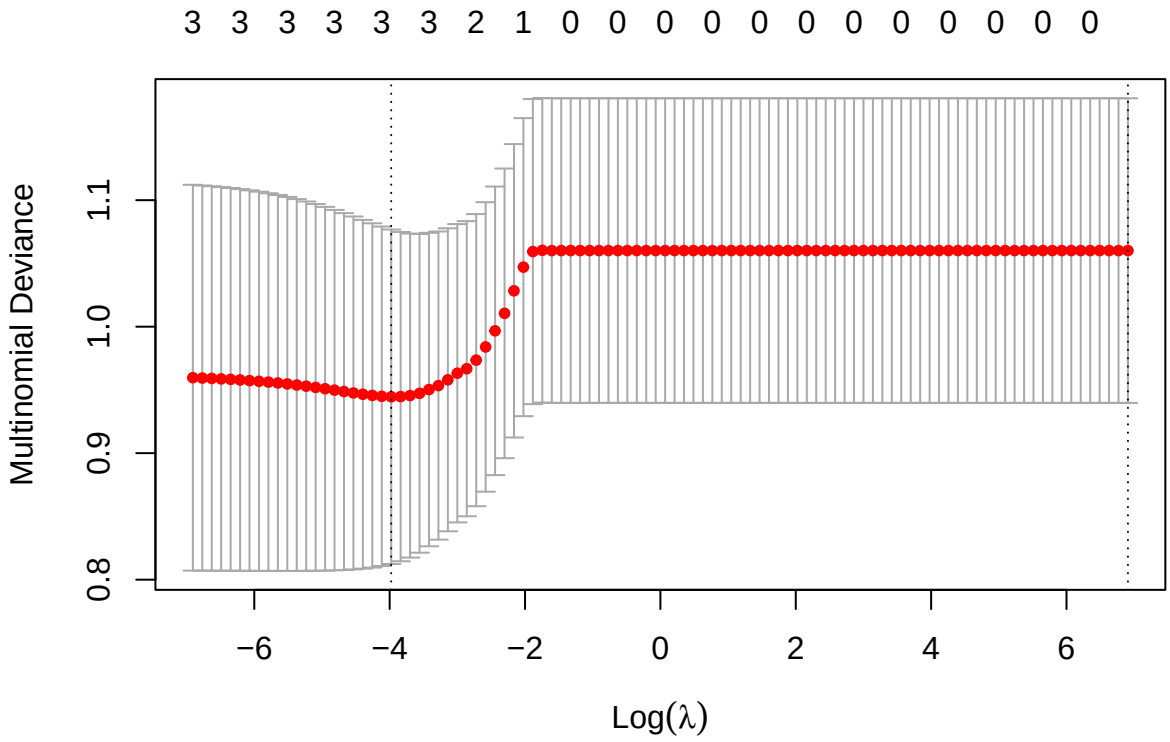
```
## Call:
## nnet::multinom(formula = Kyphosis ~ ., data = train.data)
##
## Coefficients:
##                    Values   Std. Err.
## (Intercept) -2.802845551 1.651499825
## Age          0.008487559 0.006541321
## Number       0.452436071 0.241935524
## Start       -0.116142793 0.077015622
##
## Residual Deviance: 51.44055
## AIC: 59.44055
```

```
# Based off the results,
# Age has little effect to if kyphosis is found in the child,
# Start(which vertebrae the surgeon started on) has a negative correlation,
# Number of operations has a positive correlation to finding the kyphosis.
```

```
x <- train.data[,2:4] %>% as.matrix()
y <- train.data[,1] %>% as.matrix()

y_dummy <- dummy_columns(y)
colnames(y_dummy)[colnames(y_dummy) == "V_absent"] <- "absent"
colnames(y_dummy)[colnames(y_dummy) == "V_present"] <- "present"


y_dummy1 <- y_dummy[,2:3] %>% as.matrix()

# Perform 10-fold cross-validation to select lambda ----------------------------
lambdas_to_try <- 10^seq(-3, 3, length.out = 100)

# Setting alpha = 1 implements lasso regression
```

```
lasso_cv <- cv.glmnet(x, y_dummy1, family="multinomial", alpha = 1, lambda = lambdas_to_try,
                      standardize = TRUE, nfolds = 10)
plot(lasso_cv)
```

2.3 Fit a regularized logistic regression model, and find the best model from your regularization




```
lasso_model<-glmnet(x, y_dummy1, family="multinomial", alpha = 1,  lambda=lasso_cv$lambda.min, standardi
test_class_hat<-as.factor(predict(lasso_model, newx = as.matrix(test.data[,2:4]),type="class"))
```

```
# Training Data
set.seed(100)

cmatrix = cbind(c(1, 0.8),c(0.8, 1.5))
mu = c(0,0)
mu = as.matrix(mu)
mu = t(mu)

cmatrix2 = cbind(c(0.5, 0.4),c(0.4, 1))

mu2 = c(0.5,0.5)
mu2 = as.matrix(mu2)
mu2 = t(mu2)
nrows = 50
```

```
x1 = data.frame(mvrnorm(n = 50, mu = mu , Sigma = cmatrix))
x2 = data.frame(mvrnorm(n = 50, mu = mu2, Sigma = cmatrix2))
x_train = rbind(x1,x2)

Y_train = rep(c(1,-1), c(50,50))

Y = as.factor(Y_train)
dat = cbind(x_train, Y)
dat = data.frame(dat)
```

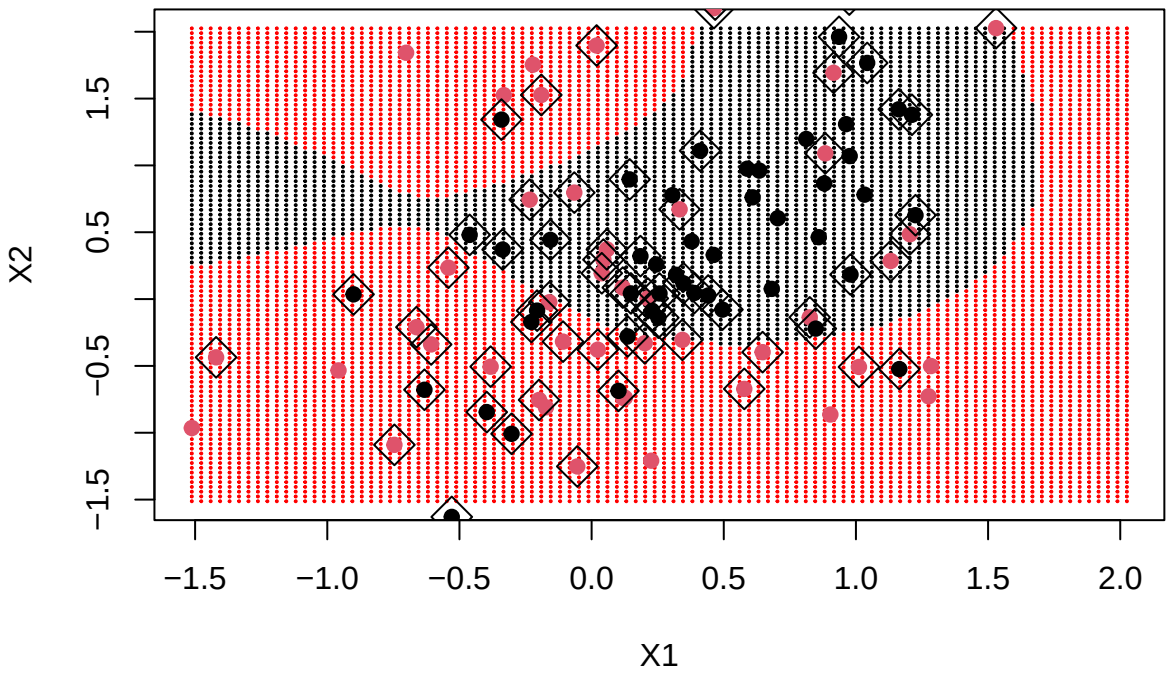
3.1 Use mvrnorm function to generate the training data set below (use seed(100)):

```
svmfit = svm(Y ~ ., data = dat, kernel = "radial", cost = 10, scale = FALSE, type = 'C-classification')
print(svmfit)
```

3.2 Fit a nonlinear SVM model (using radial kernel) based on the training data generated in 3.1, and make a plot to visualize the decision boundary (set cost=10).

```
##
## Call:
## svm(formula = Y ~ ., data = dat, kernel = "radial", cost = 10, type = "C-classification",
##     scale = FALSE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  10
##
## Number of Support Vectors:  68
```

```
dat.svm<-predict(svmfit,data=dat)


make.grid = function(x_train, n = 100) {
  grange = apply(x_train, 2, range)
  x1 = seq(from = grange[1,1], to = grange[2,1], length = n)
  x2 = seq(from = grange[2,1], to = grange[1,1], length = n)
  expand.grid(X1 = x1, X2 = x2)
}
xgrid = make.grid(x_train)

ygrid = predict(svmfit, xgrid)
plot(xgrid, col = c("black","red")[as.numeric(ygrid)], pch = 20, cex = .2)
points(x_train, col = Y , pch = 19)
points(x_train[svmfit$index,], pch = 5, cex = 2)
```



3.3 Use the same approach in 3.1 to generate the testing data set with 100 samples (use seed(123)).a) Evaluate the classification performance using the classification accuracy based on the testing data set.b) Specify the number of type I errors and type II errors based on the confusion matrix.

```
# Testing data
set.seed(123)


Sigma = cbind(c(1, 0.8),c(0.8, 1.5))
mu = c(0,0)
mu = as.matrix(mu)
mu = t(mu)

Sigma2 = cbind(c(0.5, 0.4),c(0.4, 1))

mu2 = c(0.5,0.5)
mu2 = as.matrix(mu2)
mu2 = t(mu2)
nrows = 50

x1 = data.frame(mvrnorm(n = 50, mu = mu , Sigma = Sigma))
x2 = data.frame(mvrnorm(n = 50, mu = mu2, Sigma = Sigma2))
x_test = rbind(x1,x2)

Y_test = rep(c(1,-1), c(50,50))

Y_test2 = as.factor(Y_test)
```

```r
dat.test = cbind(x_test, Y_test2)
dat.test = data.frame(dat.test)

results = predict(svmfit, dat.test)
results = as.factor(results)

ConfusionM.svm<-confusionMatrix(results, dat.test$Y)
print(ConfusionM.svm)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction -1  1
##         -1 26 22
##         1  24 28
##
##                Accuracy : 0.54
##                  95% CI : (0.4374, 0.6402)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : 0.2421
##
##                   Kappa : 0.08
##
##  Mcnemar's Test P-Value : 0.8828
##
##             Sensitivity : 0.5200
##             Specificity : 0.5600
##          Pos Pred Value : 0.5417
##          Neg Pred Value : 0.5385
##              Prevalence : 0.5000
##          Detection Rate : 0.2600
##    Detection Prevalence : 0.4800
##       Balanced Accuracy : 0.5400
##
##        'Positive' Class : -1
##
```

3.4 (Bonus 2 points) Use a for-loop to test the performance of the SVM model using radial kernel when using cost = 1, 10, 100, 1000, and report the performance based on the testing set by plotting the classification accuracy vs log10(cost).

```r
# Generating the training data
set.seed(100)
x1_train = data.frame(rnorm(100, mean = 0, sd = 1))
set.seed(101)
x2_train = data.frame(rnorm(100, mean = 0, sd = 1))

x_train = cbind(x1_train,x2_train)
colnames(x_train) = c('x1', 'x2')
x_train2 = matrix(as.numeric(unlist(x_train)),nrow=nrow(x_train))
```

```r
a1 = c(3,3)
a2 = c(3,-3)

a1 = matrix(a1)
a2 = matrix(a2)

Y_train = sigmoid(x_train2 %*% a1) + sigmoid(x_train2 %*% a2)


# Generating the testing data
set.seed(102)
x1_test = data.frame(rnorm(10000, mean = 0, sd = 1))
set.seed(103)
x2_test = data.frame(rnorm(10000, mean = 0, sd = 1))

x_test = cbind(x1_test,x2_test)
colnames(x_test) = c('x1', 'x2')
x_test2 = matrix(as.numeric(unlist(x_test)),nrow=nrow(x_test))


Y_test = sigmoid(x_test2 %*% a1) + sigmoid(x_test2 %*% a2)
```

```r


# Developing Neural Network


AvgError = c()
Size = c(1,2,3,4,5,6,7,8,9,10)


# Standard Weight Decay

for (i in seq(Size)){
  ran.nn <- nnet(x_train, Y_train, size = i, rang = 0.1, decay = .005, maxit = 200)
  predic = predict(ran.nn, x_test2)
  TestError = (Y_test - predic)^2
  AvgError = c(AvgError,TestError)
}
```

Read section 11.6 of the textbook "Elements of Statistical Learning". Follow the steps in the textbook and recreate the Figure 11.6, 11.7, and 11.8 for the Sum of sigmoids only. The objective of this question is helping you better understand the effect of parameter selection on the accuracy of the trained neural network.

```
## # weights:  5
## initial  value 54.509940
## iter  10 value 31.485646
## iter  20 value 17.816070
## final  value 17.812993
## converged
## # weights:  9
## initial  value 52.005357
```

```
## iter  10 value 31.446865
## iter  20 value 17.804562
## iter  30 value 16.367286
## iter  40 value 16.173539
## iter  50 value 16.168836
## final  value 16.168819
## converged
## # weights:  13
## initial  value 51.680582
## iter  10 value 31.504967
## iter  20 value 17.755042
## iter  30 value 16.640062
## iter  40 value 16.112864
## iter  50 value 16.104923
## iter  60 value 16.101990
## iter  70 value 16.101956
## iter  70 value 16.101956
## iter  70 value 16.101956
## final  value 16.101956
## converged
## # weights:  17
## initial  value 53.445620
## iter  10 value 31.549499
## iter  20 value 19.877531
## iter  30 value 16.620749
## iter  40 value 16.109660
## iter  50 value 16.095710
## iter  60 value 16.091725
## iter  70 value 16.090594
## iter  80 value 16.088429
## iter  90 value 16.087972
## iter 100 value 16.087891
## iter 110 value 16.087886
## iter 110 value 16.087885
## iter 110 value 16.087885
## final  value 16.087885
## converged
## # weights:  21
## initial  value 56.318426
## iter  10 value 31.607473
## iter  20 value 17.789134
## iter  30 value 17.529717
## iter  40 value 16.106014
## iter  50 value 16.085010
## iter  60 value 16.082394
## iter  70 value 16.082164
## iter  80 value 16.082128
## iter  90 value 16.082117
## final  value 16.082112
## converged
## # weights:  25
## initial  value 50.529298
## iter  10 value 31.567234
## iter  20 value 17.954000
```

```
## iter  30 value 17.418806
## iter  40 value 16.132203
## iter  50 value 16.098089
## iter  60 value 16.095189
## iter  70 value 16.094144
## iter  80 value 16.093524
## iter  90 value 16.092831
## iter 100 value 16.091950
## iter 110 value 16.089699
## iter 120 value 16.088523
## iter 130 value 16.088403
## iter 140 value 16.088383
## iter 150 value 16.088334
## iter 160 value 16.088249
## iter 170 value 16.087993
## iter 180 value 16.087873
## iter 190 value 16.087828
## iter 200 value 16.087785
## final  value 16.087785
## stopped after 200 iterations
## # weights:  29
## initial  value 56.469064
## iter  10 value 31.683340
## iter  20 value 23.861415
## iter  30 value 17.724133
## iter  40 value 16.166619
## iter  50 value 16.110420
## iter  60 value 16.087716
## iter  70 value 16.056101
## iter  80 value 16.040768
## iter  90 value 16.038221
## iter 100 value 16.037412
## iter 110 value 16.036970
## iter 120 value 16.036724
## iter 130 value 16.036608
## iter 140 value 16.036522
## iter 150 value 16.036441
## iter 160 value 16.036416
## iter 170 value 16.036401
## iter 180 value 16.036394
## final  value 16.036393
## converged
## # weights:  33
## initial  value 56.590796
## iter  10 value 31.719995
## iter  20 value 24.456594
## iter  30 value 17.607185
## iter  40 value 16.182188
## iter  50 value 16.126185
## iter  60 value 16.120386
## iter  70 value 16.117074
## iter  80 value 16.112329
## iter  90 value 16.103749
## iter 100 value 16.077739
```

```
## iter 110 value 16.060549
## iter 120 value 16.052117
## iter 130 value 16.046351
## iter 140 value 16.043270
## iter 150 value 16.039841
## iter 160 value 16.038253
## iter 170 value 16.037364
## iter 180 value 16.037020
## iter 190 value 16.036951
## iter 200 value 16.036889
## final  value 16.036889
## stopped after 200 iterations
## # weights:  37
## initial  value 57.354939
## iter  10 value 31.758972
## iter  20 value 19.066724
## iter  30 value 17.512933
## iter  40 value 16.223262
## iter  50 value 16.130901
## iter  60 value 16.128156
## iter  70 value 16.122384
## iter  80 value 16.107778
## iter  90 value 16.081420
## iter 100 value 16.064107
## iter 110 value 16.055016
## iter 120 value 16.050982
## iter 130 value 16.049044
## iter 140 value 16.043675
## iter 150 value 16.042281
## iter 160 value 16.041608
## iter 170 value 16.041012
## iter 180 value 16.039789
## iter 190 value 16.037185
## iter 200 value 16.036269
## final  value 16.036269
## stopped after 200 iterations
## # weights:  41
## initial  value 51.591646
## iter  10 value 31.696476
## iter  20 value 26.065030
## iter  30 value 17.680911
## iter  40 value 16.413951
## iter  50 value 16.148072
## iter  60 value 16.140534
## iter  70 value 16.130118
## iter  80 value 16.105469
## iter  90 value 16.082572
## iter 100 value 16.067754
## iter 110 value 16.056964
## iter 120 value 16.051836
## iter 130 value 16.048630
## iter 140 value 16.041588
## iter 150 value 16.037989
## iter 160 value 16.036759
```

```
## iter 170 value 16.036612
## iter 180 value 16.036579
## final  value 16.036571
## converged
```

```
AvgError2 = c()
Size = c(1,2,3,4,5,6,7,8,9,10)

# No Weight Decay

for (i in seq(Size)){
  ran.nn <- nnet(x_train, Y_train, size = i, rang = 0.1, decay = 0, maxit = 200)
  predic = predict(ran.nn, x_test2)
  TestError = (Y_test - predic)^2
  AvgError2 = c(AvgError2,TestError)
}
```

```
## # weights:  5
## initial  value 53.845462
## final  value 31.314791
## converged
## # weights:  9
## initial  value 54.617091
## final  value 31.314791
## converged
## # weights:  13
## initial  value 58.985732
## final  value 31.314791
## converged
## # weights:  17
## initial  value 53.578982
## final  value 31.314791
## converged
## # weights:  21
## initial  value 56.111726
## final  value 31.314791
## converged
## # weights:  25
## initial  value 54.527393
## final  value 31.314791
## converged
## # weights:  29
## initial  value 54.396699
## final  value 31.314791
## converged
## # weights:  33
## initial  value 51.916905
## final  value 31.314791
## converged
## # weights:  37
## initial  value 48.968696
## final  value 31.314791
## converged
## # weights:  41
```

```
## initial  value 53.549527
## final  value 31.314791
## converged
```

```
AvgError3 = c()
Size = c(1,2,3,4,5,6,7,8,9,10)

# Large Weight Decay

for (i in Size){
  ran.nn <- nnet(x_train, Y_train, size = i, rang = 0.1, decay = .1, maxit = 200)
  predic = predict(ran.nn, x_test2)
  TestError = (Y_test - predic)^2
  AvgError3 = c(AvgError3,TestError)
}
```

```
## # weights:  5
## initial  value 55.683961
## iter  10 value 22.094028
## final  value 21.977936
## converged
## # weights:  9
## initial  value 58.015376
## iter  10 value 21.330001
## iter  20 value 21.198894
## iter  30 value 21.162559
## final  value 21.161211
## converged
## # weights:  13
## initial  value 56.154658
## iter  10 value 22.841612
## iter  20 value 20.965897
## iter  30 value 20.954946
## iter  40 value 20.928246
## final  value 20.927823
## converged
## # weights:  17
## initial  value 56.460262
## iter  10 value 28.227609
## iter  20 value 20.889193
## iter  30 value 20.870339
## iter  40 value 20.861566
## iter  50 value 20.861311
## final  value 20.861310
## converged
## # weights:  21
## initial  value 56.009776
## iter  10 value 22.854209
## iter  20 value 20.871062
## iter  30 value 20.869216
## iter  40 value 20.858595
## iter  50 value 20.858360
## final  value 20.858352
## converged
```

```
## # weights:  25
## initial  value 54.616355
## iter  10 value 22.062540
## iter  20 value 20.887458
## iter  30 value 20.887314
## final  value 20.887291
## converged
## # weights:  29
## initial  value 55.926462
## iter  10 value 28.214186
## iter  20 value 20.874802
## iter  30 value 20.483845
## iter  40 value 20.422788
## iter  50 value 20.419362
## iter  60 value 20.419043
## iter  70 value 20.419006
## iter  80 value 20.418998
## final  value 20.418996
## converged
## # weights:  33
## initial  value 52.628270
## iter  10 value 22.073983
## iter  20 value 20.968316
## iter  30 value 20.966475
## iter  40 value 20.965575
## iter  50 value 20.965355
## iter  60 value 20.965331
## iter  60 value 20.965331
## iter  60 value 20.965331
## final  value 20.965331
## converged
## # weights:  37
## initial  value 56.487233
## iter  10 value 30.619576
## iter  20 value 21.017713
## iter  30 value 21.016278
## iter  40 value 21.011923
## iter  50 value 20.804991
## iter  60 value 20.490845
## iter  70 value 20.485849
## iter  80 value 20.456066
## iter  90 value 20.411320
## iter 100 value 20.408850
## iter 110 value 20.407698
## final  value 20.407629
## converged
## # weights:  41
## initial  value 54.159894
## iter  10 value 30.276730
## iter  20 value 21.071312
## iter  30 value 21.021683
## iter  40 value 20.465060
## iter  50 value 20.401725
## iter  60 value 20.393408
```

```
## iter  70 value 20.391526
## final  value 20.391511
## converged
```

```
AvgError4 = c()
Weights = c(.00,.01,.02,.03,.04,.05,.06,.07,.08,.09,.10,.11,.12,.13,.14,.15)

# Changing Weights

for (i in Weights){
  ran.nn <- nnet(x_train, Y_train, size = 10, rang = 0.1, decay = i, maxit = 200)
  predic = predict(ran.nn, x_test2)
  TestError = (Y_test - predic)^2
  AvgError4 = c(AvgError4,TestError)
}
```

```
## # weights:  41
## initial  value 51.298925
## final  value 31.314791
## converged
## # weights:  41
## initial  value 51.930212
## iter  10 value 32.109423
## iter  20 value 18.437373
## iter  30 value 17.878109
## iter  40 value 16.640589
## iter  50 value 16.616303
## iter  60 value 16.547563
## iter  70 value 16.500867
## iter  80 value 16.469441
## iter  90 value 16.456466
## iter 100 value 16.451083
## iter 110 value 16.447488
## iter 120 value 16.445113
## iter 130 value 16.444451
## iter 140 value 16.443309
## iter 150 value 16.440287
## iter 160 value 16.438040
## iter 170 value 16.437130
## iter 180 value 16.437053
## iter 190 value 16.437020
## final  value 16.437013
## converged
## # weights:  41
## initial  value 59.479822
## iter  10 value 31.412097
## iter  20 value 18.556990
## iter  30 value 17.447754
## iter  40 value 17.286057
## iter  50 value 17.150792
## iter  60 value 17.124781
## iter  70 value 17.115050
## iter  80 value 17.110719
## iter  90 value 17.110537
```

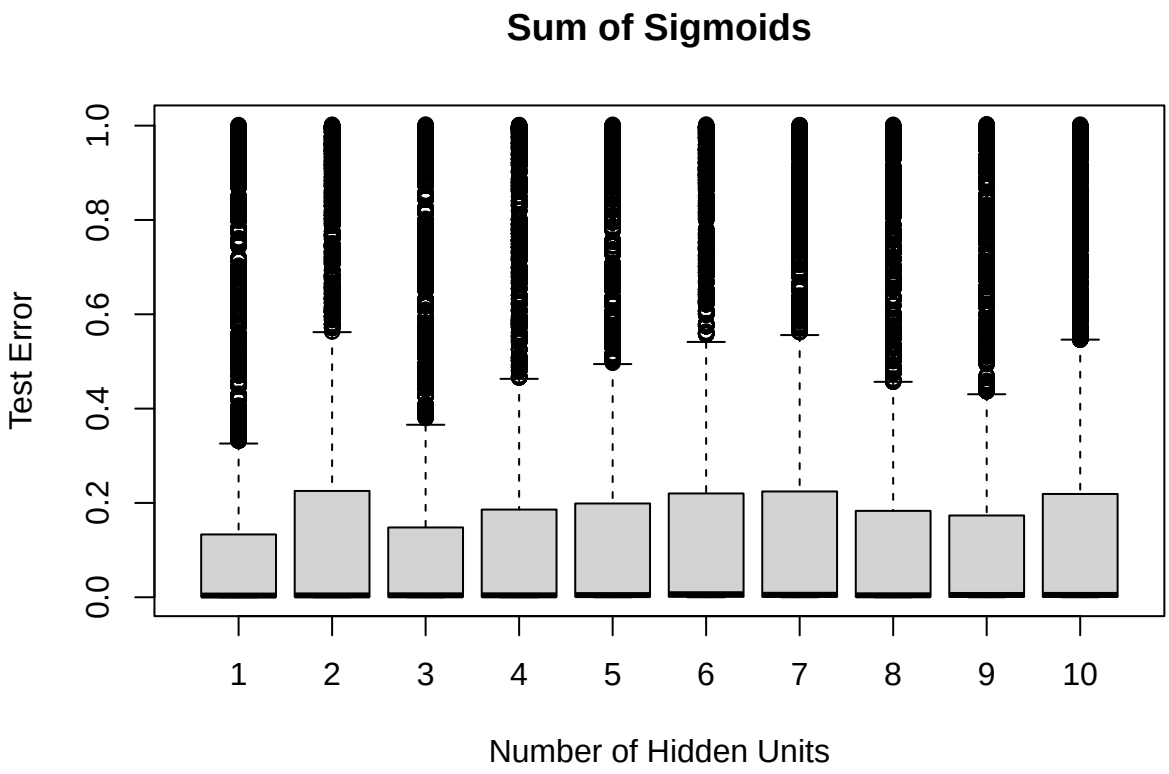
```
## iter 100 value 17.110475
## iter 110 value 17.110461
## final  value 17.110457
## converged
## # weights:  41
## initial  value 59.228373
## iter  10 value 30.918532
## iter  20 value 18.784356
## iter  30 value 17.975044
## iter  40 value 17.793047
## iter  50 value 17.709413
## iter  60 value 17.698757
## iter  70 value 17.696262
## iter  80 value 17.695575
## iter  90 value 17.693411
## iter 100 value 17.692946
## iter 110 value 17.692874
## iter 120 value 17.692861
## final  value 17.692856
## converged
## # weights:  41
## initial  value 52.031884
## iter  10 value 28.829994
## iter  20 value 19.174106
## iter  30 value 18.705870
## iter  40 value 18.481004
## iter  50 value 18.263090
## iter  60 value 18.216124
## iter  70 value 18.210629
## iter  80 value 18.209093
## iter  90 value 18.208862
## iter 100 value 18.208798
## iter 110 value 18.208792
## final  value 18.208790
## converged
## # weights:  41
## initial  value 58.200773
## iter  10 value 30.705347
## iter  20 value 19.506468
## iter  30 value 18.829242
## iter  40 value 18.714442
## iter  50 value 18.678250
## iter  60 value 18.673069
## iter  70 value 18.671235
## iter  80 value 18.670805
## iter  90 value 18.670740
## final  value 18.670738
## converged
## # weights:  41
## initial  value 53.310712
## iter  10 value 31.100024
## iter  20 value 20.605774
## iter  30 value 19.303462
## iter  40 value 19.110908
```

```
## iter  50 value 19.093935
## iter  60 value 19.093129
## iter  70 value 19.092996
## iter  80 value 19.090630
## iter  90 value 19.089847
## iter 100 value 19.089508
## iter 110 value 19.089379
## iter 120 value 19.089326
## iter 130 value 19.089319
## iter 140 value 19.089315
## final  value 19.089311
## converged
## # weights:  41
## initial  value 54.689681
## iter  10 value 29.662445
## iter  20 value 20.203682
## iter  30 value 19.896981
## iter  40 value 19.523230
## iter  50 value 19.474852
## iter  60 value 19.470363
## iter  70 value 19.470169
## iter  80 value 19.470087
## iter  90 value 19.470060
## final  value 19.470059
## converged
## # weights:  41
## initial  value 58.109008
## iter  10 value 28.392050
## iter  20 value 20.482258
## iter  30 value 19.951956
## iter  40 value 19.830922
## iter  50 value 19.818275
## iter  60 value 19.817025
## iter  70 value 19.816568
## iter  80 value 19.816357
## final  value 19.816355
## converged
## # weights:  41
## initial  value 57.860424
## iter  10 value 28.302282
## iter  20 value 20.520155
## iter  30 value 20.264316
## iter  40 value 20.143725
## iter  50 value 20.128036
## iter  60 value 20.125328
## iter  70 value 20.124327
## iter  80 value 20.124050
## iter  90 value 20.123994
## iter 100 value 20.123961
## iter 110 value 20.123926
## iter 120 value 20.123879
## iter 130 value 20.123365
## iter 140 value 20.122786
## iter 150 value 20.122572
```

```
## final  value 20.122570
## converged
## # weights:  41
## initial  value 55.202224
## iter  10 value 30.412381
## iter  20 value 21.067838
## iter  30 value 20.840104
## iter  40 value 20.501118
## iter  50 value 20.455578
## iter  60 value 20.403070
## iter  70 value 20.399356
## iter  80 value 20.395222
## iter  90 value 20.394685
## iter 100 value 20.393234
## iter 110 value 20.392899
## iter 120 value 20.392883
## iter 130 value 20.392869
## iter 140 value 20.392856
## final  value 20.392855
## converged
## # weights:  41
## initial  value 56.467194
## iter  10 value 30.691138
## iter  20 value 21.301161
## iter  30 value 20.745675
## iter  40 value 20.638514
## iter  50 value 20.629589
## iter  60 value 20.628845
## final  value 20.628823
## converged
## # weights:  41
## initial  value 51.002946
## iter  10 value 30.103847
## iter  20 value 21.607866
## iter  30 value 21.328097
## iter  40 value 20.858589
## iter  50 value 20.852971
## iter  60 value 20.852811
## final  value 20.852811
## converged
## # weights:  41
## initial  value 54.725368
## iter  10 value 28.557309
## iter  20 value 21.869006
## iter  30 value 21.757791
## iter  40 value 21.124883
## iter  50 value 21.069910
## iter  60 value 21.069517
## final  value 21.069512
## converged
## # weights:  41
## initial  value 53.623676
## iter  10 value 30.413325
## iter  20 value 22.118523
```

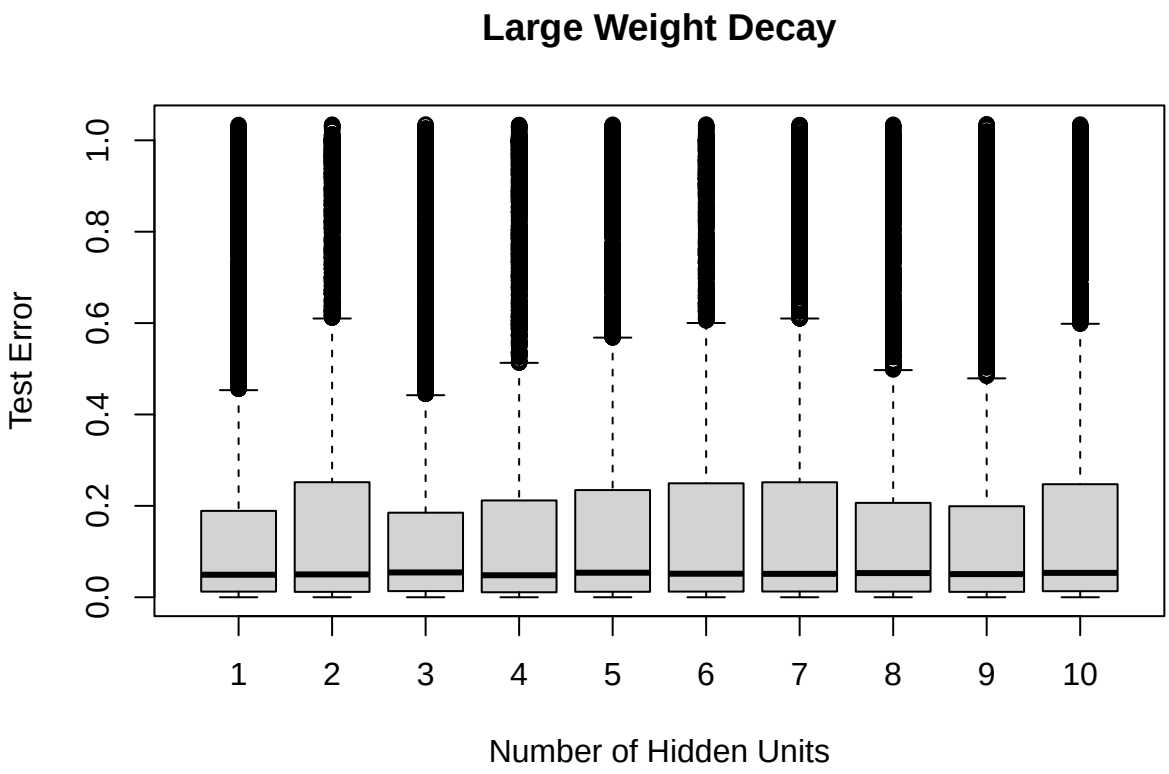
```
## iter  30 value 21.907641
## iter  40 value 21.419460
## iter  50 value 21.417561
## iter  60 value 21.417467
## final  value 21.417466
## converged
## # weights:  41
## initial  value 59.488878
## iter  10 value 29.991913
## iter  20 value 22.360891
## iter  30 value 22.282816
## iter  40 value 21.684877
## iter  50 value 21.634728
## iter  60 value 21.631715
## iter  70 value 21.631624
## final  value 21.631623
## converged
```

```
# Making the Box plots

Size = data.frame(Size)
Weights = data.frame(Weights)
Error1 = data.frame(AvgError)
Error2 = data.frame(AvgError2)
Error3 = data.frame(AvgError3)
Error4 = data.frame(AvgError4)

Error1 = cbind.data.frame(Size, Error1)
Error2 = cbind.data.frame(Size, Error2)
Error3 = cbind.data.frame(Size, Error3)
Error4 = cbind.data.frame(Weights, Error4)



boxplot(AvgError~Size, data = Error1, main = "Sum of Sigmoids", xlab = "Number of Hidden Units", ylab =
```

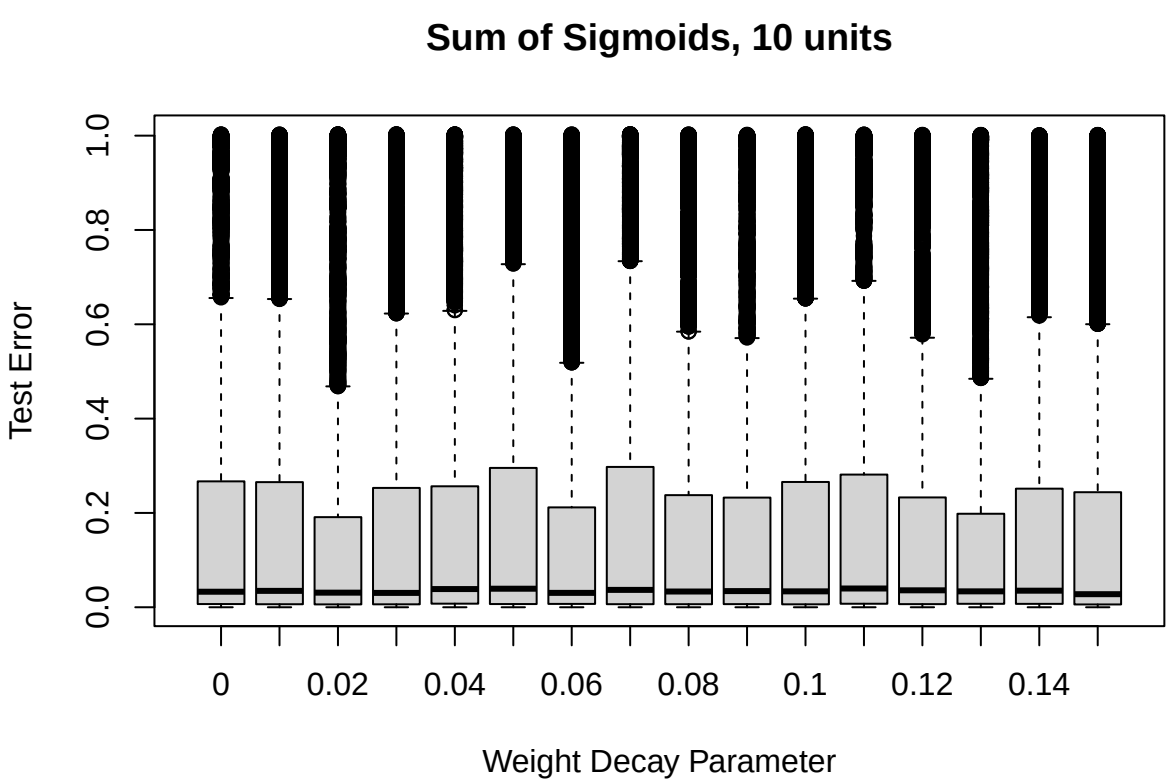



```
boxplot(AvgError2~Size, data = Error2, main = "No Weight Decay", xlab = "Number of Hidden Units", ylab =
```


```
boxplot(AvgError3~Size, data = Error3, main = "Large Weight Decay", xlab = "Number of Hidden Units", yla
```




```
boxplot(AvgError4~Weights, data = Error4, main = "Sum of Sigmoids, 10 units", xlab = "Weight Decay Para
```


Sum of Sigmoids, 10 units
Test Error
0.0
0.2
0.4
0.6
0.8
1.0
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
Weight Decay Parameter