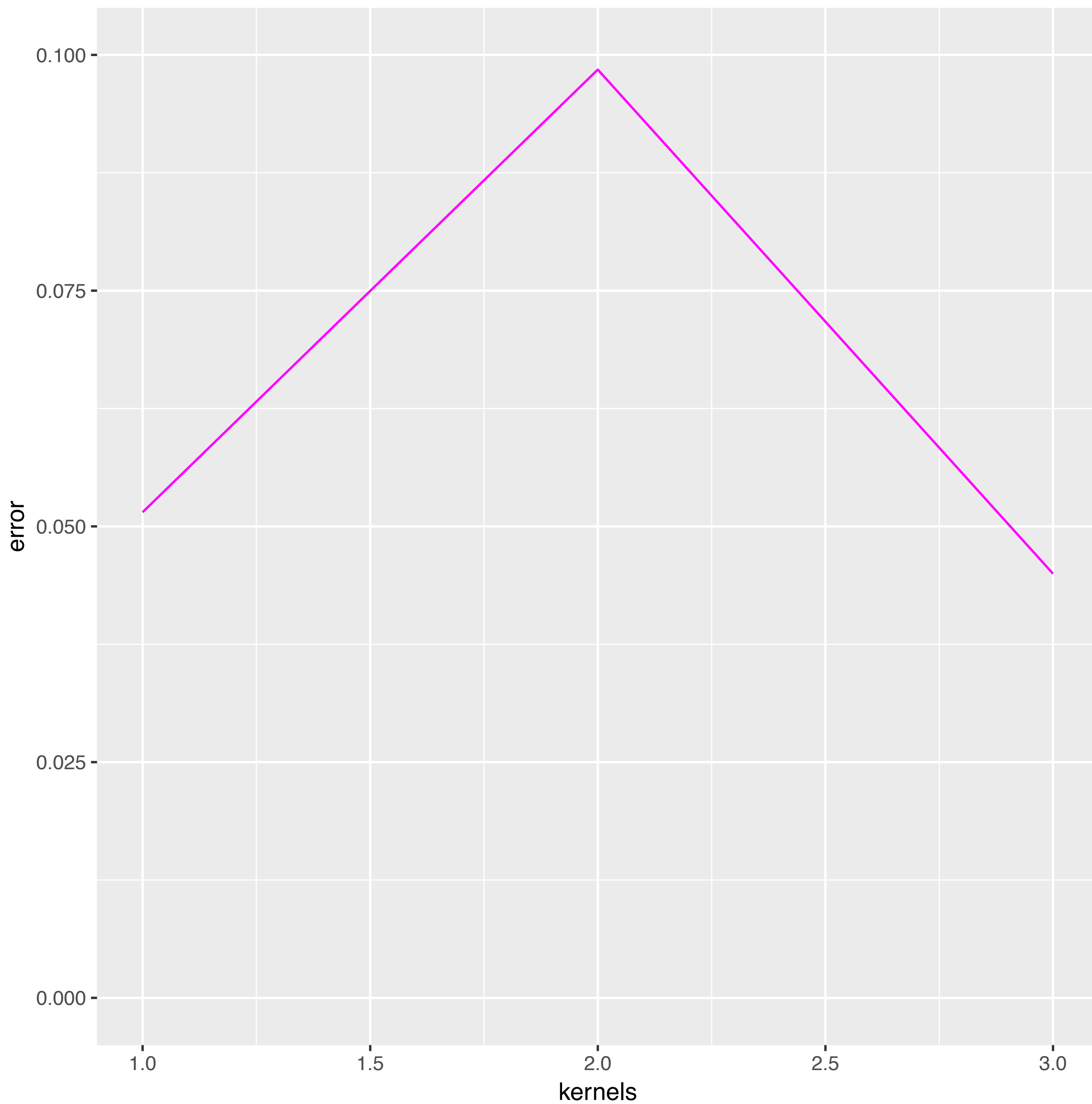
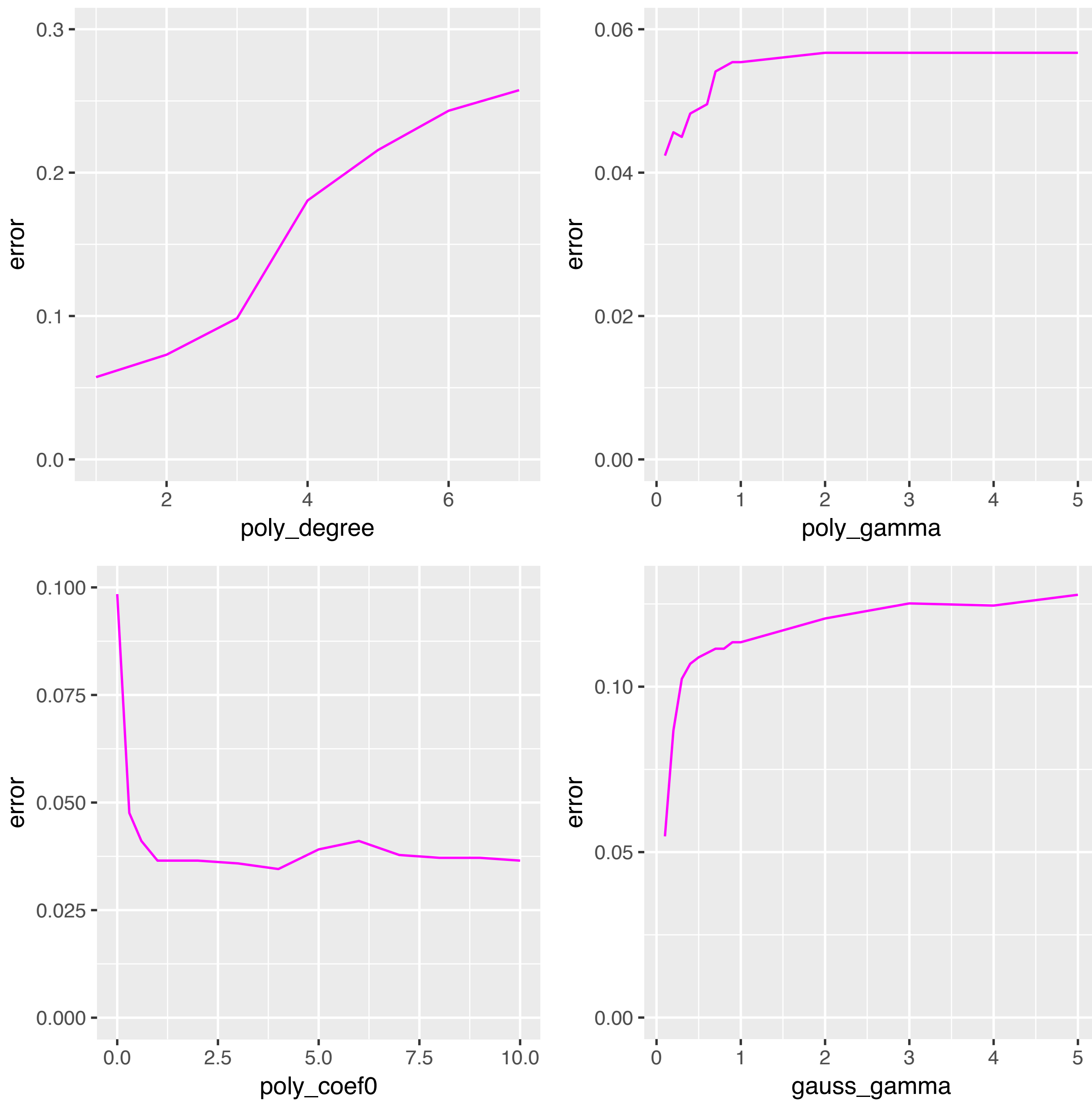
```r
setwd("/Users/tong/Desktop/R")
test=read.table("spam-test.txt",sep=",")
train=read.table("spam-train.txt",sep=",")
require(ggplot2)

## Loading required package:  ggplot2

require(e1071)

## Loading required package:  e1071

require(gridExtra)

## Loading required package:  gridExtra

require(neuralnet)

## Loading required package:  neuralnet

require(reshape)

## Loading required package:  reshape

test=data.frame(log(1+test[, -58]), spam=factor(test[,58]))
train=data.frame(log(1+train[,-58]), spam=factor(train[,58]))

################Choice of kernels (linear, polynomial, Gaussian)
#Since the test data is given and no special requirement of CV here, we use test error to compare
#sensitiveness of parameters and kernels.
#For the comparison of kernels I use the default set of parameters.
errors=c()
spam_svm=svm(spam~.,data=train,kernel="linear",cost=1)
errors[1]=sum(predict(spam_svm, test)!=test$spam)/length(test[,1])
spam_svm1=svm(spam~.,data=train,kernel="polynomial",cost=1)
errors[2]=sum(predict(spam_svm1, test)!=test$spam)/length(test[,1])
spam_svm2=svm(spam~.,data=train,kernel="radial",cost=1)
errors[3]=sum(predict(spam_svm2, test)!=test$spam)/length(test[,1])
errors=as.data.frame(cbind(seq(3),errors))
colnames(errors)=c("kernels","error")
#The three points in the plot is linear, poly and gaussian respectively.
ggplot(data=errors,aes(x=kernels,y=error))+geom_line(color="Magenta")+
  scale_y_continuous(limits=c(0, 0.1))
```



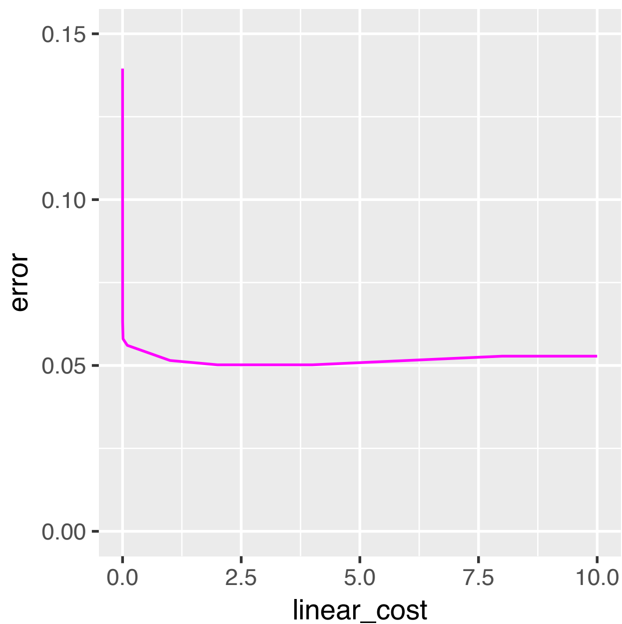

```
###############Choice tuning parameters (polynomial(degree, gamma, coef0), Gaussian(gamma))
#I have ajusted the grid to capture more important features of the curve.
gam=c(seq(0.1,1,0.1),seq(2,5))
deg=seq(1,7)
coef=c(0,0.3,0.6,seq(1,10))
```

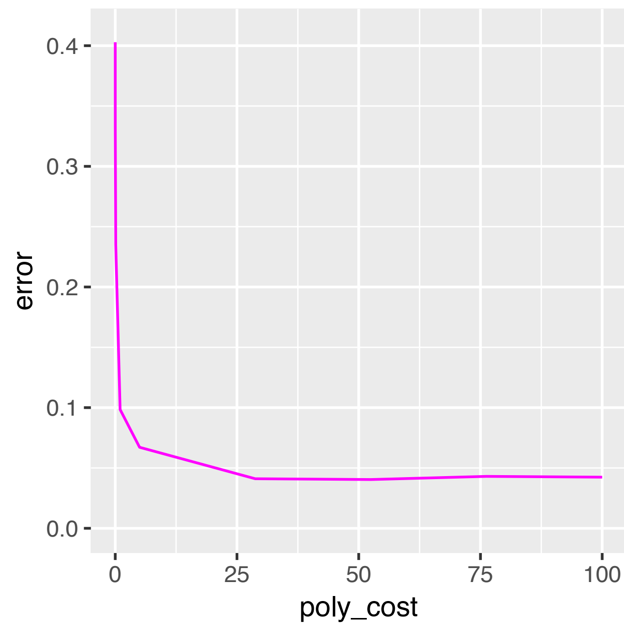
```
errors=c()
for(i in seq(length(deg))){
  spam_svm1=svm(spam~.,data=train,kernel="polynomial",cost=1, degree=deg[i])
  errors[i]=sum(predict(spam_svm1, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(deg,errors))
colnames(errors)=c("poly_degree","error")
x=ggplot(data=errors,aes(x=poly_degree,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0
errors=c()
for(i in seq(length(gam))){
  spam_svm1=svm(spam~.,data=train,kernel="polynomial",cost=1, gamma=gam[i])
  errors[i]=sum(predict(spam_svm1, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(gam,errors))
colnames(errors)=c("poly_gamma","error")
y=ggplot(data=errors,aes(x=poly_gamma,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0,
errors=c()
for(i in seq(length(coef))){
  spam_svm1=svm(spam~.,data=train,kernel="polynomial",cost=1, coef0=coef[i])
  errors[i]=sum(predict(spam_svm1, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(coef,errors))
colnames(errors)=c("poly_coef0","error")
z=ggplot(data=errors,aes(x=poly_coef0,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0,
errors=c()
for(i in seq(length(gam))){
  spam_svm2=svm(spam~.,data=train,kernel="radial",cost=1, gamma=gam[i])
  errors[i]=sum(predict(spam_svm2, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(gam,errors))
colnames(errors)=c("gauss_gamma","error")
t=ggplot(data=errors,aes(x=gauss_gamma,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0
grid.arrange(x,y,z,t,ncol=2)
```

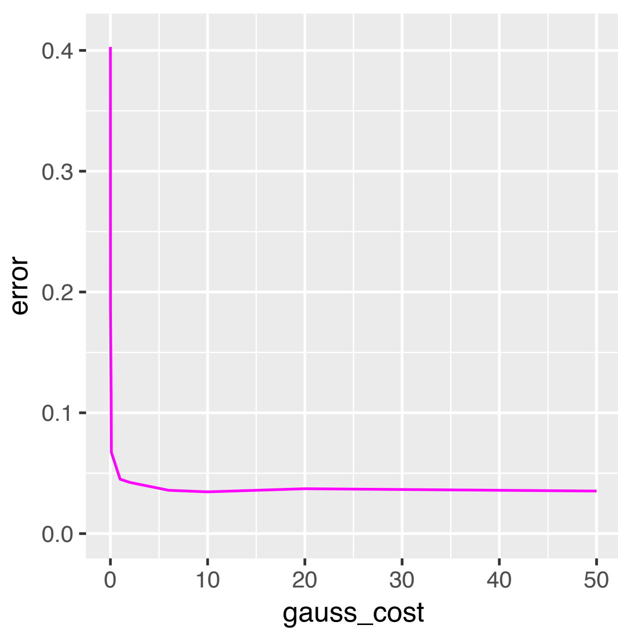



```
###############Choice of cost (Linear, polynomial, Gaussian respectively)
#For different kernels, the allowed range of cost are different. I have adjusted the grids.
co=c(10^(-4:0),seq(2,10,2))
errors=c()
for(i in seq(length(co))){
```

```
  spam_svm=svm(spam~.,data=train,kernel="linear",cost=co[i])
  errors[i]=sum(predict(spam_svm, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(co,errors))
colnames(errors)=c("linear_cost","error")
x=ggplot(data=errors,aes(x=linear_cost,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0

co=c(10^(-4:0),seq(5,100,length.out = 5))
errors=c()
for(i in seq(length(co))){
  spam_svm1=svm(spam~.,data=train,kernel="polynomial",cost=co[i])
  errors[i]=sum(predict(spam_svm1, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(co,errors))
colnames(errors)=c("poly_cost","error")
y=ggplot(data=errors,aes(x=poly_cost,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0,

co=c(10^(-4:0),seq(2,10,4),20,50)
errors=c()
for(i in seq(length(co))){
  spam_svm=svm(spam~.,data=train,kernel="radial",cost=co[i])
  errors[i]=sum(predict(spam_svm, test)!=test$spam)/length(test[,1])
}
errors=as.data.frame(cbind(co,errors))
colnames(errors)=c("gauss_cost","error")
z=ggplot(data=errors,aes(x=gauss_cost,y=error))+geom_line(color="Magenta")+scale_y_continuous(limits=c(0,
grid.arrange(x,y,z,ncol=2)
```



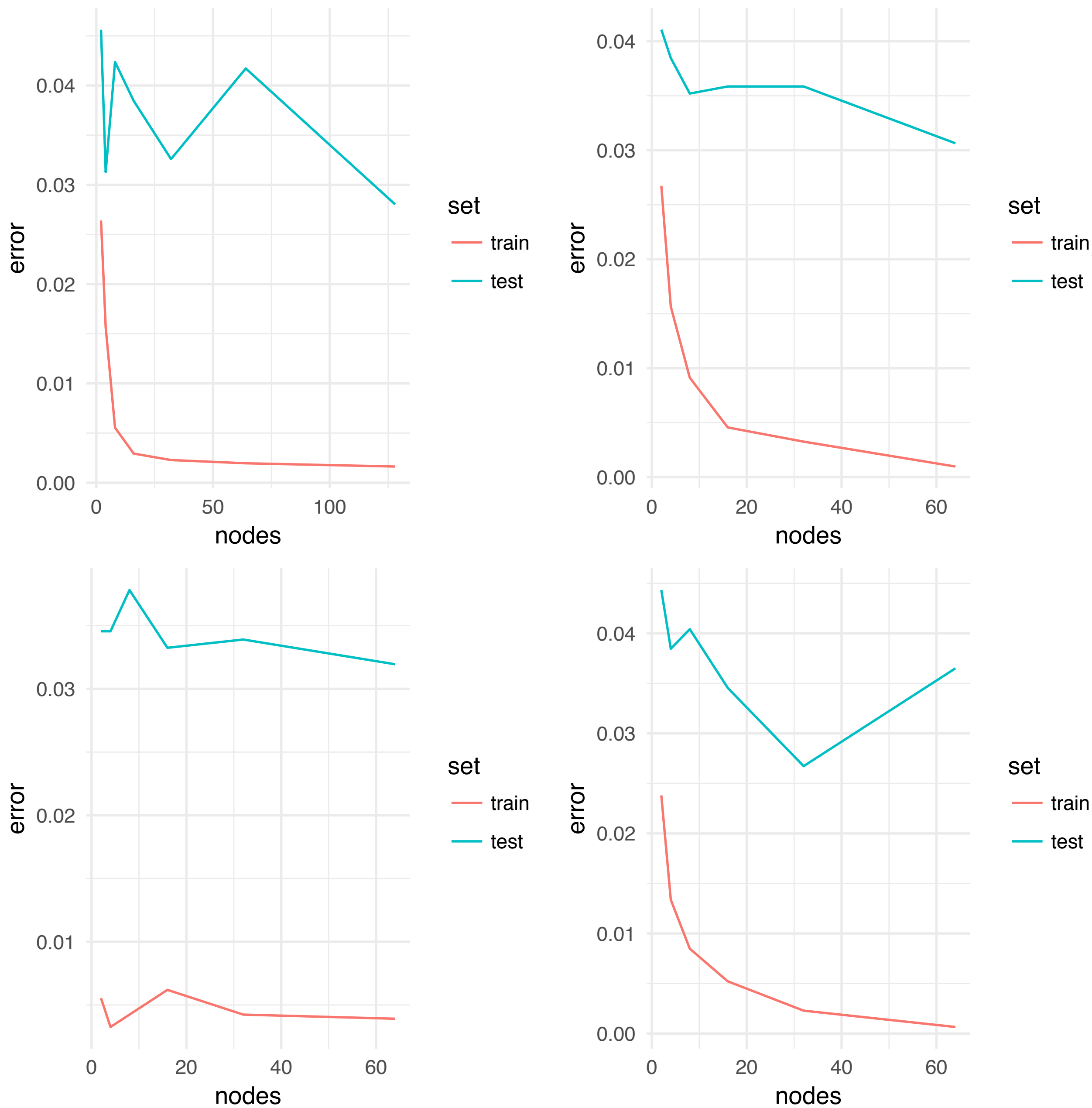





```
################Neural Network
###One layer, different nodes
train_nn=data.frame(train[,-58], model.matrix(~train$spam-1))
colnames(train_nn)[58:59]=c("no","yes")
pred=function(nn, dat){
```

```r
  yhat = compute(nn, dat)$net.result
  yhat = apply(yhat, 1, which.max)-1
  return(yhat)
}
set.seed(123)
nodes=2^(1:7)
errors=c()
errors_t=c()
for(i in seq(length(nodes))){
  nn = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=nodes[i],
  linear.output=F)   #To reduce the computing time, no smoothing here
  errors[i]=mean(pred(nn, train[-58]) != train$spam)
  errors_t[i]=mean(pred(nn, test[-58]) != test$spam)
}
errors=data.frame(nodes=nodes, train=errors, test=errors_t)
errors=melt(errors, id.vars = 1)
colnames(errors)=c("nodes", "set", "error")
x=ggplot(data=errors,aes(x=nodes,y=error,color=set))+geom_line()+theme_minimal()
###Two layers, and two layers' nodes change symchronously
set.seed(666)
nodes=2^(1:6)
errors=c()
errors_t=c()
for(i in seq(length(nodes))){
  nn = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=c(nodes[i], nodes[i]),
  linear.output=F)
  errors[i]=mean(pred(nn, train[-58]) != train$spam)
  errors_t[i]=mean(pred(nn, test[-58]) != test$spam)
}
errors=data.frame(nodes=nodes, train=errors, test=errors_t)
errors=melt(errors, id.vars = 1)
colnames(errors)=c("nodes", "set", "error")
y=ggplot(data=errors,aes(x=nodes,y=error,color=set))+geom_line()+theme_minimal()
###Two layers, and fix the first layer as 20 nodes, change the second layer
set.seed(123)
nodes=2^(1:6)
errors=c()
errors_t=c()
for(i in seq(length(nodes))){
```

```
  nn = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=c(20, nodes[i]),
  linear.output=F)
  errors[i]=mean(pred(nn, train[-58]) != train$spam)
  errors_t[i]=mean(pred(nn, test[-58]) != test$spam)
}
errors=data.frame(nodes=nodes, train=errors, test=errors_t)
errors=melt(errors, id.vars = 1)
colnames(errors)=c("nodes", "set", "error")
z=ggplot(data=errors,aes(x=nodes,y=error,color=set))+geom_line()+theme_minimal()
###Two layers, and fix the second layer as 20 nodes, change the first layer
nodes=2^(1:6)
errors=c()
errors_t=c()
for(i in seq(length(nodes))){
  nn = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=c(nodes[i], 20),
  linear.output=F)
  errors[i]=mean(pred(nn, train[-58]) != train$spam)
  errors_t[i]=mean(pred(nn, test[-58]) != test$spam)
}
errors=data.frame(nodes=nodes, train=errors, test=errors_t)
errors=melt(errors, id.vars = 1)
colnames(errors)=c("nodes", "set", "error")
t=ggplot(data=errors,aes(x=nodes,y=error,color=set))+geom_line()+theme_minimal()
grid.arrange(x,y,z,t,ncol=2)
```




```
################Choose the roughly better performance models for each method by performance curves
#For SVM, choose the Gaussian with gamma 0.2; single layer NN with 15 nodes; double layer NN with
#first layer 60, second layer 20.
spam_svm=svm(spam~.,data=train,kernel="radial", gamma=0.2)
a=table(test$spam, predict(spam_svm, test))
```

```r
nn = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=15,
  linear.output=F)
b=table(test$spam, pred(nn, test[,-58]))
set.seed(9999)
nn2 = neuralnet(
  paste("no+yes ~", paste(colnames(train)[-58], collapse=" + ")),
  data=train_nn,
  hidden=c(60, 20),
  linear.output=F)
c=table(test$spam, pred(nn2, test[,-58]))
d=table(train$spam, predict(spam_svm, train))
e=table(train$spam, pred(nn, train[,-58]))
f=table(train$spam, pred(nn2, train[,-58]))
m_svm=array(c(d[1,2]/sum(d[1,]),a[1,2]/sum(a[1,]),d[2,1]/sum(d[2,]),a[2,1]/sum(a[2,])),c(2,2))
rownames(m_svm)=c("train","test")
colnames(m_svm)=c("0","1")
m_one=array(c(e[1,2]/sum(e[1,]),b[1,2]/sum(b[1,]),e[2,1]/sum(e[2,]),b[2,1]/sum(b[2,])),c(2,2))
rownames(m_one)=c("train","test")
colnames(m_one)=c("0","1")
m_two=array(c(f[1,2]/sum(f[1,]),c[1,2]/sum(c[1,]),f[2,1]/sum(f[2,]),c[2,1]/sum(c[2,])),c(2,2))
rownames(m_two)=c("train","test")
colnames(m_two)=c("0","1")
m_svm

##                     0             1
## train 0.0005408328826 0.01149425287
## test  0.0076419213974 0.20388349515

m_one

##                    0              1
## train 0.003244997296 0.005747126437
## test  0.026200873362 0.042071197411

m_two

##                    0              1
## train 0.001622498648 0.004926108374
## test  0.027292576419 0.046925566343

#Comment: From the result of picked models for each method, the overal performance of svm is the
#worst; one-layer NN is similar to two layer. SVM has very bad performance of class 1 in test. The
#two-layer doesn't have too much overfit compared to one-layer, since I choose the model by test
#error. Both SVM and one-layer NN have very small train-error for class 0, so I feel they have
```

```
#some overfit, and SVM can also be regarded as one-layer NN, so sometimes they have similar
#features. And based on the result, I feel there's a trade-off of the errors for different
#classes. And the trade-off can be realized by changing parameters and models.
```

The SGD introduces much randomness to the result.