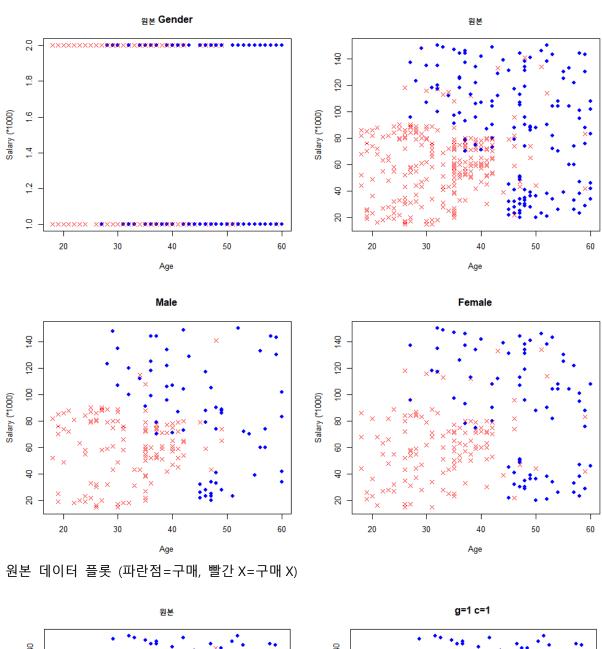
```
3. SVM SN
```

```
rm(list=ls())
graphics.off()
setwd("~/Tobigs/homework_0801/SVM")
library(e1071)
library(kernlab)
library(caret)
SN=read.csv('SN_ad.csv')
str(SN)
#ID 제거
SN=SN[-1]
SN$Purchased=as.factor(SN$Purchased)
#남성 여성 분리
SN.male=subset(SN,Gender=='Male')
SN.female=subset(SN,Gender=='Female')
summary(SN$Age)
summary(SN$EstimatedSalary)
#구매함 = blue, 구매안함 = red
#어떤 물건인지는 몰라도 Gender 에 대해서는 구매 여부에 상관이 없음
#영향을 주는 변수는 Age 와 Salary
while(1){
   par(mfrow=c(2,2))
   plot(SN\$Age,SN\$Gender,pch=c(4,19)[SN\$Purchased],
            col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(1,2),xlab='Age',ylab='Salary
(*1000)',main='원본 Gender')
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN$Purchased],
col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='원본')
   plot(SN.male$Age,SN.male$EstimatedSalary/1000,pch=c(4,19)[SN.male$Purchased],
col=c('red','blue')[SN.male$Purchased], xlim=c(18,60), ylim=c(15,150), xlab='Age', ylab='Salary for the context of the conte
(*1000)',main='Male')
   plot(SN.female$Age,SN.female$EstimatedSalary/1000,pch=c(4,19)[SN.female$Purchased],
col=c('red','blue')[SN.female$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Sala
ry (*1000)', main='Female')
   break
}
#svm
svm.model<- svm(Purchased~., data=SN, gamma=1, cost=1)</pre>
addmargins(table(SN$Purchased, svm.model$fitted))
while(1){
   par(mfrow=c(2,2))
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN$Purchased],
col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='원본')
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[svm.model$fitted],
col=c('red','blue')[svm.model$fitted],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='g=1 c=1')
   break
sum(SN$Purchased==svm.model$fitted)/length(SN$Purchased) #0.9175
#polvnomial 커널
kpar = list(degree = 4), C = 10,
                               prob.model = TRUE)
SN.poly=predict(SN.model1, subset(SN,select=-c(Purchased)))
while(1){
```

```
par(mfrow=c(2,2))
    plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN$Purchased],
col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='원본')
    plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN.poly],
             col=c('red', 'blue')[SN.poly], xlim=c(18,60), ylim=c(15,150), xlab='Age', ylab='Salary
(*1000)', main='poly 4th order g=10')
}
sum(SN$Purchased==SN.poly)/length(SN$Purchased) #0.9175
#rbf 커널
kpar = list(sigma = 100), C = 10,
                                   prob.model = TRUE)
SN.rbf=predict(SN.model2, subset(SN,select=-c(Purchased)))
while(1){
   par(mfrow=c(2,2))
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN$Purchased],
col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='원본')
    plot(SN$Age, SN$EstimatedSalary/1000, pch=c(4,19)[SN.rbf],
             \label{localization} $$ \operatorname{col=c('red','blue')[SN.rbf],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary | Color |
(*1000)',main='rbf g=100 C=10')
   break
sum(SN$Purchased==SN.rbf)/length(SN$Purchased) #0.9975
#Hyperbolic 커널
SN.model3 \leftarrow ksvm(Purchased \sim ., data = SN,
                                   type = "C-bsvc", kernel = "tanhdot",
                                   kpar = list(scale = 0.005), C = 100,
                                   prob.model = TRUE)
SN.tanh=predict(SN.model3, subset(SN,select=-c(Purchased)))
while(1){
    par(mfrow=c(2,2))
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN$Purchased],
col=c('red','blue')[SN$Purchased],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='원본')
   plot(SN$Age,SN$EstimatedSalary/1000,pch=c(4,19)[SN.tanh],
             col=c('red','blue')[SN.tanh],xlim=c(18,60),ylim=c(15,150),xlab='Age',ylab='Salary
(*1000)',main='tanh scale=0.005 C=100')
   break
}
sum(SN$Purchased==SN.tanh)/length(SN$Purchased) #0.83
#rbf 모델이 0.9975 로 가장 높았다.
#rbf > poly 4th > tanh
```

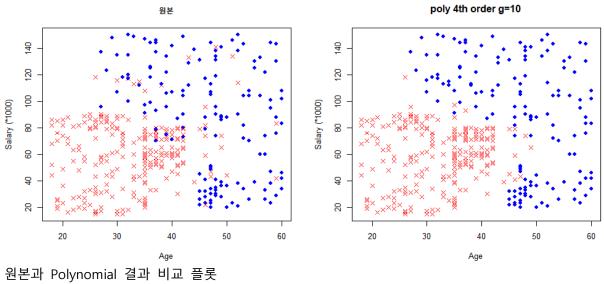


Salary (*1000) Salary (*1000)

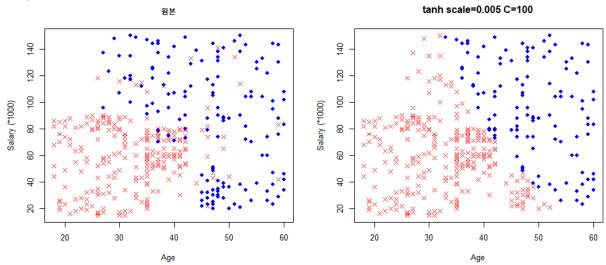
Age

원본과 SVM 결과 비교 플롯 정확도 0.9175

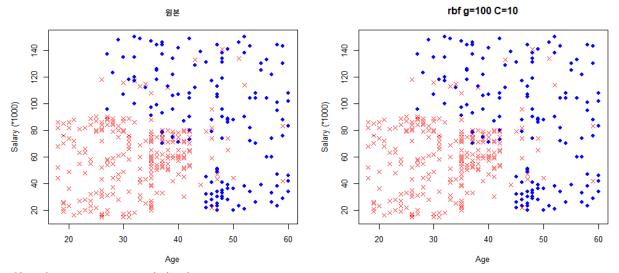
Age



원본과 Polynomial 결과 비교 플롯 정확도 0.9175



원본과 Hyperbolic 결과 비교 플롯 정확도 0.83



원본과 Gaussian RBF 결과 비교 플롯 정확도 0.9975

RBF 가 가장 정확도가 높다.