# STATS790HW1

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### Question 1

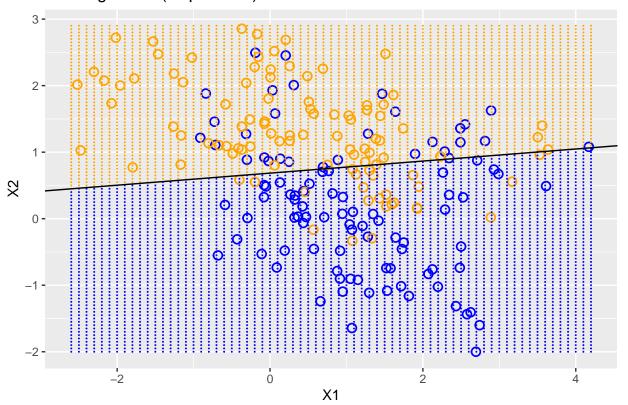
In the last two sections of the article, Professor Breiman pointed out that algorithmic models usually give better accuracy than data models and are able to discover some relation behind data that data models may not discover. Also, higher accuracy usually means a more reliable relation behind data is discovered. Do algorithmic models or focusing on accuracy always be a good choice? I think data models can also give some useful information that algorithmic can not give. For instance, Model-based clustering can give a mixture distribution underlining data and soft assignment where each data observation has a probability of belonging to each cluster. Latent variable analysis can discover hidden components which most other algorithmic models can not discover.

### Question 2

```
library("ggplot2")
library(dplyr)
#read and process data
load(file = "ESL.mixture.rda")
df.q2.x <- as.matrix(ESL.mixture$x)</pre>
df.q2.y <- as.matrix(ESL.mixture$y)</pre>
df.q2 <- as.data.frame(matrix(nrow = length(df.q2.y), ncol = 3))</pre>
df.q2[,1:2] \leftarrow df.q2.x
df.q2[,3] \leftarrow df.q2.y
df.q2 <- df.q2 %>%
  mutate(Color = ifelse(V3 == 0, "blue",
                          ifelse(V3 == 1, "orange", "none")))
xnew <- as.matrix(ESL.mixture$xnew)</pre>
#df.xnew <- as.data.frame(xnew)
#Linear regression
#Add column of 1 for beta 0
df.q2.x \leftarrow cbind(rep(1,nrow(df.q2.x)), df.q2.x)
#Train
#Coefficients
```

```
beta.q2 <- (solve(t(df.q2.x) %*% df.q2.x) %*% t(df.q2.x)) %*% df.q2.y
#Test
xnew <- cbind(rep(1,nrow(xnew)), xnew)</pre>
y.xnew <- xnew %*% beta.q2</pre>
#Change color
y.xnew \leftarrow ifelse(y.xnew < 0.5, 0, 1)
xynew <- as.data.frame(cbind(xnew,y.xnew))</pre>
xynew <- xynew %>%
  mutate(Color = ifelse(xynew[,4] == 0, "blue",
                         ifelse(xynew[,4] == 1, "orange", "none")))
#Create Figure
ggplot() + geom_point(data = df.q2,aes(x=V1,y=V2,col=Color),shape = 1, size = 2.5, stroke=0.9) +
  geom_point(data = xynew, aes(x=x1,y=x2,col=Color),size = 0.01) +
  geom_abline(slope = -beta.q2[2]/beta.q2[3],
              intercept = (0.5 - beta.q2[1])/beta.q2[3]) +
  scale_color_identity() +
  ggtitle("ESL Figure 2.1(Replication)") +
  xlab("X1") + ylab("X2")
```

# ESL Figure 2.1(Replication)



#### Question 6

```
#ESL 2.8
df.train <- read.table("zip.train")</pre>
df.train <- as.data.frame(df.train)</pre>
df.train <- df.train[df.train$V1==2 | df.train$V1==3,]</pre>
df.test <- read.table("zip.test")</pre>
df.test <- as.data.frame(df.test)</pre>
df.test <- df.test[df.test$V1==2 | df.test$V1==3,]</pre>
#Create a table to store acurracy:
acc.table <- as.data.frame(matrix(nrow = 6,ncol = 2))</pre>
#linear regression:
y.zip.train <- as.matrix(df.train[,1])</pre>
y.zip.train01 <- ifelse(y.zip.train==2, 0, 1)</pre>
x.zip.train <- as.matrix(cbind(rep(1,nrow(df.train)), df.train[,-1]))</pre>
y.zip.test <- as.matrix(df.test[,1])</pre>
x.zip.test <- as.matrix(cbind(rep(1,nrow(df.test)), df.test[,-1]))</pre>
#Coefficients
beta <- (solve(t(x.zip.train) %*% x.zip.train) %*% t(x.zip.train)) %*% y.zip.train01
#training error
pred.zip.train <- x.zip.train %*% beta</pre>
pred.zip.train <- ifelse(pred.zip.train < 0.5,2,3)</pre>
acc.table[1,1] <- 1 - mean(pred.zip.train == y.zip.train)</pre>
#test error
pred.zip.test <- x.zip.test %*% beta</pre>
pred.zip.test <- ifelse(pred.zip.test < 0.5,2,3)</pre>
acc.table[1,2] <- 1 - mean(pred.zip.test == y.zip.test)</pre>
#k-nearest neighbour
df.train.zip <- df.train[,-1]</pre>
v1.train <- df.train[,1]</pre>
df.test.zip <- df.test[,-1]</pre>
v1.test <- df.test[,1]</pre>
library(FNN)
\#k = 1
knn.zip1.train <- knn(</pre>
```

```
train = df.train.zip,
 test = df.train.zip,
 v1.train,
 k = 1
#train error
acc.table[2,1] <- 1 - mean(knn.zip1.train == v1.train)</pre>
knn.zip1.test <- knn(</pre>
 train = df.train.zip,
 test = df.test.zip,
 v1.train,
 k = 1
)
#test error
acc.table[2,2] <- 1 - mean(knn.zip1.test == v1.test)</pre>
colnames(acc.table) <- c("Training Error", "Test Error")</pre>
rownames(acc.table) <- c("Linear Regression", "KNN k=1", "KNN k=3", "KNN k=5", "KNN k=7", "KNN k=15")
#k = 3
knn.zip3.train <- knn(</pre>
train = df.train.zip,
 test = df.train.zip,
 v1.train,
 k = 3
#train error
acc.table[3,1] <- 1 - mean(knn.zip3.train == v1.train)</pre>
knn.zip3.test <- knn(</pre>
 train = df.train.zip,
 test = df.test.zip,
 v1.train,
 k = 3
)
#test error
acc.table[3,2] <- 1 - mean(knn.zip3.test == v1.test)</pre>
#k = 5
knn.zip5.train <- knn(</pre>
train = df.train.zip,
```

```
test = df.train.zip,
 v1.train,
  k = 5
)
#train error
acc.table[4,1] <- 1 - mean(knn.zip5.train == v1.train)</pre>
knn.zip5.test <- knn(</pre>
 train = df.train.zip,
 test = df.test.zip,
 v1.train,
  k = 5
#test error
acc.table[4,2] \leftarrow 1 - mean(knn.zip5.test == v1.test)
#k = 7
knn.zip7.train <- knn(</pre>
 train = df.train.zip,
 test = df.train.zip,
 v1.train,
  k = 7
#train error
acc.table[5,1] <- 1 - mean(knn.zip7.train == v1.train)</pre>
knn.zip7.test <- knn(</pre>
 train = df.train.zip,
  test = df.test.zip,
 v1.train,
 k = 7
)
#test error
acc.table[5,2] <- 1 - mean(knn.zip7.test == v1.test)</pre>
#k = 15
knn.zip15.train <- knn(</pre>
 train = df.train.zip,
  test = df.train.zip,
  v1.train,
```

```
k = 15
)

#train error
acc.table[6,1] <- 1 - mean(knn.zip15.train == v1.train)

knn.zip15.test <- knn(
    train = df.train.zip,
    test = df.test.zip,
    v1.train,
    k = 15
)

#test error
acc.table[6,2] <- 1 - mean(knn.zip15.test == v1.test)

library(knitr)

kable(acc.table,caption = "Accuracy table")</pre>
```

Table 1: Accuracy table

	Training Error	Test Error
Linear Regression	0.0057595	0.0412088
KNN $k=1$	0.0000000	0.0247253
KNN k=3	0.0050396	0.0302198
KNN $k=5$	0.0057595	0.0302198
KNN $k=7$	0.0064795	0.0329670
KNN k=15	0.0093593	0.0384615