

HW4

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Question 6

a)

$$\hat{\Pr}(Y = A|X_1, X_2) = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2}} = \frac{e^{-6 + 0.05 \times x_1 + 1 \times x_2}}{1 + e^{-6 + 0.05 \times x_1 + 1 \times x_2}} = \frac{e^{-6 + 0.05 \times 40 + 1 \times 3.5}}{1 + e^{-6 + 0.05 \times 40 + 1 \times 3.5}}$$

Calculated in R:

```
exp(-6+0.05*40+1*3.5)/(1+exp(-6+0.05*40+3.5))
```

```
## [1] 0.3775407
```

As the output shows, the probability is 0.3775407.

b)

When $\hat{Pr}(Y = A|X_2) = 0.5$, $odds = \frac{\hat{Pr}(Y=A|X_2)}{1-\hat{Pr}(Y=A|X_2)} = \frac{0.5}{1-0.5} = 1$.

$\log odds = \log 1 = 0 = -6 + 0.05 \times x_1 + 1 \times 3.5$

$\Rightarrow x_1 = 50$

Therefore, the student needs to study 50 hours.

Question 10

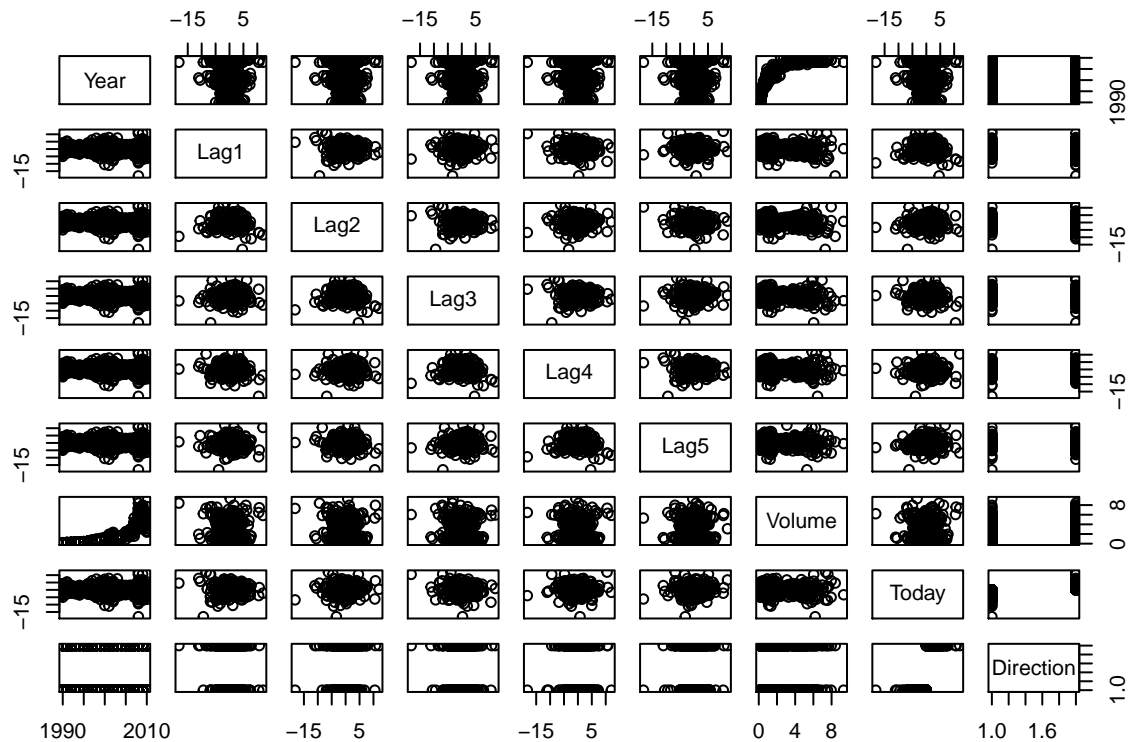
a)

```
library(ISLR)
help(Weekly)
summary(Weekly)
```

```
##      Year      Lag1      Lag2      Lag3
## Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
## 1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
## Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
## Mean   :2000   Mean   :  0.1506   Mean   :  0.1511   Mean   :  0.1472
## 3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
## Max.   :2010   Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
##      Lag4      Lag5      Volume
## Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747
## 1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202
## Median :  0.2380   Median :  0.2340   Median :1.00268
## Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462
## 3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373
## Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821
```

```
##      Today      Direction
## Min.   :-18.1950   Down:484
## 1st Qu.: -1.1540   Up :605
## Median :  0.2410
## Mean   :  0.1499
## 3rd Qu.:  1.4050
## Max.   : 12.0260
```

```
pairs(Weekly)
```



```
cor(Weekly[,1:8])
```

```
##      Year      Lag1      Lag2      Lag3      Lag4
## Year  1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
## Lag1 -0.03228927  1.000000000 -0.07485305  0.05863568 -0.071273876
## Lag2 -0.03339001 -0.074853051  1.00000000 -0.07572091  0.058381535
## Lag3 -0.03000649  0.058635682 -0.07572091  1.00000000 -0.075395865
## Lag4 -0.03112792 -0.071273876  0.05838153 -0.07539587  1.000000000
## Lag5 -0.03051910 -0.008183096 -0.07249948  0.06065717 -0.075675027
## Volume 0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
## Today -0.03245989 -0.075031842  0.05916672 -0.07124364 -0.007825873
##      Lag5      Volume      Today
## Year -0.030519101  0.84194162 -0.032459894
## Lag1 -0.008183096 -0.06495131 -0.075031842
## Lag2 -0.072499482 -0.08551314  0.059166717
## Lag3  0.060657175 -0.06928771 -0.071243639
## Lag4 -0.075675027 -0.06107462 -0.007825873
## Lag5  1.000000000 -0.05851741  0.011012698
## Volume -0.058517414  1.00000000 -0.033077783
## Today  0.011012698 -0.03307778  1.000000000
```

```
#plot(Weekly$Volume~Weekly$Year)
```

According to the output, most of the variables have very small correlations (less than 0.1 or even close to zero). However, the correlation between Year and Volume is noticeably large (0.84194162). As you can see from the scatter plot matrix, there is a strong positive relationship (increasing trend) between Volume and Year.

b)

```
model.fit<-glm(Direction ~ Lag1+Lag2+Lag3+Lag4+Lag5+Volume, data=Weekly, family=binomial)
summary(model.fit)
```

```
##
## Call:
## glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
##      Volume, family = binomial, data = Weekly)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6949  -1.2565   0.9913   1.0849   1.4579
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26686    0.08593   3.106  0.0019 **
## Lag1        -0.04127    0.02641  -1.563  0.1181
## Lag2         0.05844    0.02686   2.175  0.0296 *
## Lag3        -0.01606    0.02666  -0.602  0.5469
## Lag4        -0.02779    0.02646  -1.050  0.2937
## Lag5        -0.01447    0.02638  -0.549  0.5833
## Volume      -0.02274    0.03690  -0.616  0.5377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1496.2  on 1088  degrees of freedom
## Residual deviance: 1486.4  on 1082  degrees of freedom
## AIC: 1500.4
##
## Number of Fisher Scoring iterations: 4
```

According to the output, the only predictor that appears to be significant is lag2 because it has a p-value (0.0296) lower than $\alpha = 0.05$.

c)

```
model.predict<-predict(model.fit, type = "response")
table(Weekly$Direction, model.predict>0.5)
```

```
##
##      FALSE TRUE
## Down    54  430
## Up      48  557
```

According to the output, the overall fraction of correct predictions (accuracy) is $\frac{54+557}{54+48+430+557} = 0.56107$. We have 48 false negative and 430 false positive (suppose Up is positive and Down is negative). The fraction of false positive is $\frac{430}{430+54} = 0.88843$. The specificity is $\frac{54}{430+54} = 0.11157$. The fraction of false negative is $\frac{48}{48+557} = 0.07934$. The sensitivity is $\frac{557}{557+48} = 0.92066$. The rate of missclassification = $\frac{48+430}{54+48+430+557} = 0.43893$ which indicates that the model does not fit very well.

When the model guesses “up”, it has a probability of 0.5643364 ($=\frac{557}{430+557}$) to be correct; when the model guesses “down”, it has a probability of 0.5294118 ($=\frac{54}{54+48}$) to be correct.

d)

```
# fit the logistic regression model using a training data period from 1990 to 2008,
# with Lag2 as the only predictor.
model.fit2<-glm(Direction~Lag2,data=Weekly[Weekly$Year<2009,],family = binomial)
summary(model.fit2)
```

```
##
## Call:
## glm(formula = Direction ~ Lag2, family = binomial, data = Weekly[Weekly$Year <
##     2009, ])
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.536  -1.264   1.021   1.091   1.368
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.20326    0.06428   3.162  0.00157 **
## Lag2         0.05810    0.02870   2.024  0.04298 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1354.7  on 984  degrees of freedom
## Residual deviance: 1350.5  on 983  degrees of freedom
## AIC: 1354.5
##
## Number of Fisher Scoring iterations: 4
```

```
# make predictions based on the held out data (the data from 2009 and 2010)
model.predict2<-predict(model.fit2, Weekly[Weekly$Year>=2009,],type = "response")
# compute the confusion matrix for the held out data (the data from 2009 and 2010).
table(Weekly$Direction[Weekly$Year>=2009],model.predict2>0.5)
```

```
##
##      FALSE TRUE
## Down      9   34
## Up        5   56
```

The overall fraction of correct predictions (accuracy) is $\frac{9+56}{9+34+5+56} = 0.625$ which is higher than the previous model. Its sensitivity is $\frac{56}{5+56} = 0.91803$. Its specificity is $\frac{9}{9+34} = 0.20930$.

Question 13

```
library(MASS)
data(Boston)
help(Boston)
# convert numeric data into binominal: FALSE = 0 and TRUE = 1
Boston$crim01 <- as.numeric(Boston$crim > median(Boston$crim))
# fit a logistic regression with all predictors.
boston.glm<-glm(crim01~. - crim01 - crim, data = Boston, family = binomial)
summary(boston.glm)
```

```
##
## Call:
## glm(formula = crim01 ~ . - crim01 - crim, family = binomial,
##      data = Boston)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3946  -0.1585  -0.0004   0.0023   3.4239
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -34.103704   6.530014  -5.223 1.76e-07 ***
## zn          -0.079918   0.033731  -2.369 0.01782 *
## indus       -0.059389   0.043722  -1.358 0.17436
## chas         0.785327   0.728930   1.077 0.28132
## nox         48.523782   7.396497   6.560 5.37e-11 ***
## rm          -0.425596   0.701104  -0.607 0.54383
## age         0.022172   0.012221   1.814 0.06963 .
## dis         0.691400   0.218308   3.167 0.00154 **
## rad         0.656465   0.152452   4.306 1.66e-05 ***
## tax        -0.006412   0.002689  -2.385 0.01709 *
## ptratio     0.368716   0.122136   3.019 0.00254 **
## black      -0.013524   0.006536  -2.069 0.03853 *
## lstat       0.043862   0.048981   0.895 0.37052
## medv        0.167130   0.066940   2.497 0.01254 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 701.46  on 505  degrees of freedom
## Residual deviance: 211.93  on 492  degrees of freedom
## AIC: 239.93
##
## Number of Fisher Scoring iterations: 9
# get predictions
glm.predict<-predict(boston.glm, type = "response")
# compute the confusion matrix
table(Boston$crim01, glm.predict>0.5)
```

```
##
##      FALSE TRUE
```

```
##    0    234    19
##    1     24   229
```

According to the summary of the model, zn, nox, dis, rad, tax, ptratio, black and medv are statistically significant because their p-values are lower than $\alpha = 0.05$.

According to the confusion matrix, the rate of misclassification is $\frac{24+19}{24+19+234+229} = 0.08498$. The accuracy is $\frac{229+234}{24+19+234+229} = 0.91502$ which indicates a good fit. The sensitivity is $\frac{229}{24+229} = 0.90514$. The specificity is $\frac{234}{19+234} = 0.92490$.

```
# now fit a logistic regression model with another set of predictors
boston.glm<-glm(crim01~zn+nox+dis+rad+tax+ptratio+black+medv, data = Boston, family = binomial)
summary(boston.glm)
```

```
##
## Call:
## glm(formula = crim01 ~ zn + nox + dis + rad + tax + ptratio +
##       black + medv, family = binomial, data = Boston)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.4400  -0.1918  -0.0008   0.0025   3.1885
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -28.347709   5.569863  -5.089 3.59e-07 ***
## zn           -0.074499   0.029975  -2.485 0.01294 *
## nox           44.180443   6.289746   7.024 2.15e-12 ***
## dis           0.489849   0.194930   2.513 0.01197 *
## rad           0.692116   0.137842   5.021 5.14e-07 ***
## tax          -0.007448   0.002428  -3.067 0.00216 **
## ptratio       0.272145   0.107311   2.536 0.01121 *
## black        -0.013484   0.006331  -2.130 0.03317 *
## medv          0.087913   0.030787   2.856 0.00430 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 701.46  on 505  degrees of freedom
## Residual deviance: 221.78  on 497  degrees of freedom
## AIC: 239.78
##
## Number of Fisher Scoring iterations: 9
```

```
# get predictions
glm.predict<-predict(boston.glm, type = "response")
# compute the confusion matrix
table(Boston$crim01, glm.predict>0.5)
```

```
##
##      FALSE TRUE
##    0    229   24
##    1     30  223
```

According to the summary of the model, all the predictors are statistically significant because their p-values are all lower than $\alpha = 0.05$.

According to the confusion matrix, the rate of misclassification is $\frac{30+24}{229+24+30+223} = 0.10672$. The accuracy is $\frac{229+24+223}{229+24+30+223} = 0.89328$ which indicates a good fit. The sensitivity is $\frac{223}{30+223} = 0.88142$. The specificity is $\frac{229}{24+229} = 0.90514$.

```
# Now fit a LDA model
#library(MASS)
boston.lda<-lda(crim01~zn+nox+dis+rad+tax+prratio+black+medv, data = Boston)
# get predictions
glm.predict<-predict(boston.lda, type = "response")
# compute the confusion matrix for the lda model
table(Boston$crim01, glm.predict$class)
```

```
##
##          0    1
##    0 247    6
##    1   59 194
```

According to the confusion matrix, the rate of misclassification is $\frac{59+6}{247+6+59+194} = 0.12846$. The accuracy is $\frac{247+194}{247+6+59+194} = 0.87154$ which indicates a good fit. The sensitivity is $\frac{194}{59+194} = 0.76680$. The specificity is $\frac{247}{6+247} = 0.97628$.

```
# Fit a KNN model by first split data into training and testing set.
set.seed(6)
n <- rnorm(nrow(Boston))
test <- n > quantile(n,0.80)
train <- !test
train.X <- cbind(Boston$zn, Boston$indus, Boston$chas)[train, ]
test.X <- cbind(Boston$zn, Boston$indus, Boston$chas)[test, ]
train.crim01 <- Boston$crim01[train]

# Now fit a KNN model with k = 6
library(class)
boston.knn<-knn(train.X, test.X, train.crim01, k = 6)

# compute the confusion matrix for the lda model
table(boston.knn, Boston$crim01[test])
```

```
##
## boston.knn  0    1
##             0 44    2
##             1   2 53
```

According to the confusion matrix, the rate of misclassification is $\frac{2+2}{44+2+2+53} = 0.03960$. The accuracy is $\frac{44+53}{44+2+2+53} = 0.96040$ which indicates a good fit. The sensitivity is $\frac{53}{2+53} = 0.96364$. The specificity is $\frac{44}{2+44} = 0.95652$.

Image Classification Problem

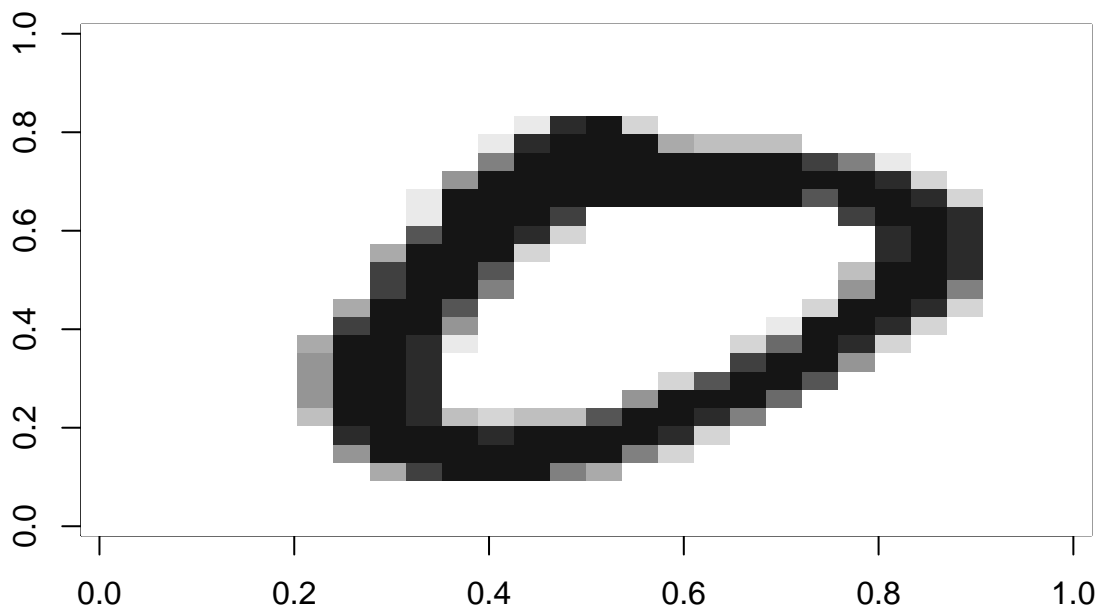
```
load("mnist_data.rdata")
plot_digit <- function(j){
arr784 <- as.numeric(images_df[j,1:784])
col=gray(12:1/12)
image(matrix(arr784, nrow=28)[,28:1], col=col,
      main = paste("this is a ",images_df$labels[j]))
```

```
}
```

A.

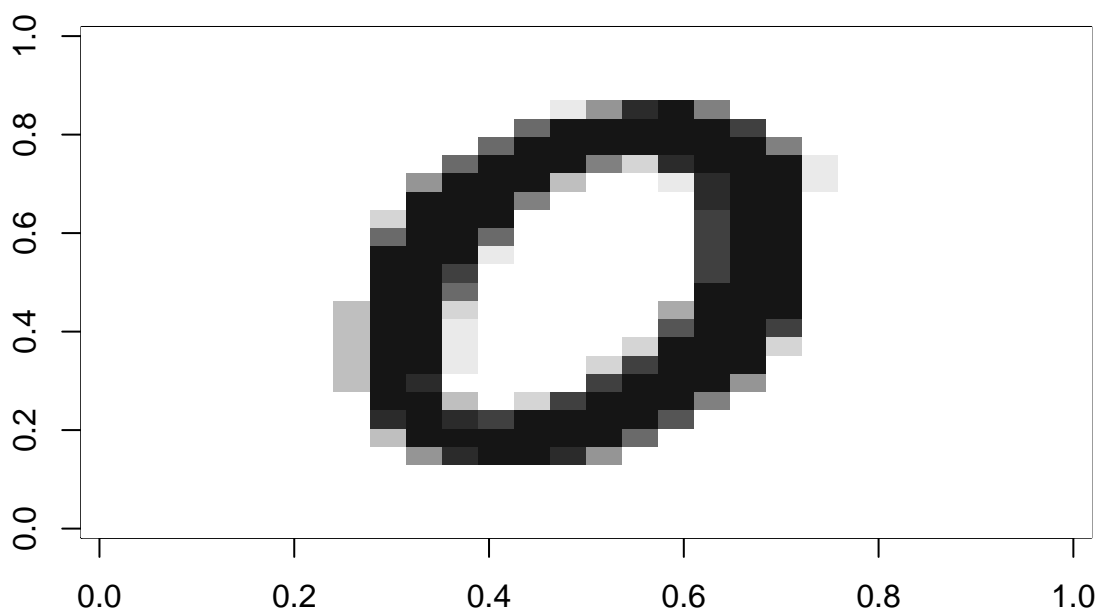
```
# Plot three 0's.  
plot_digit(39)
```

this is a 0



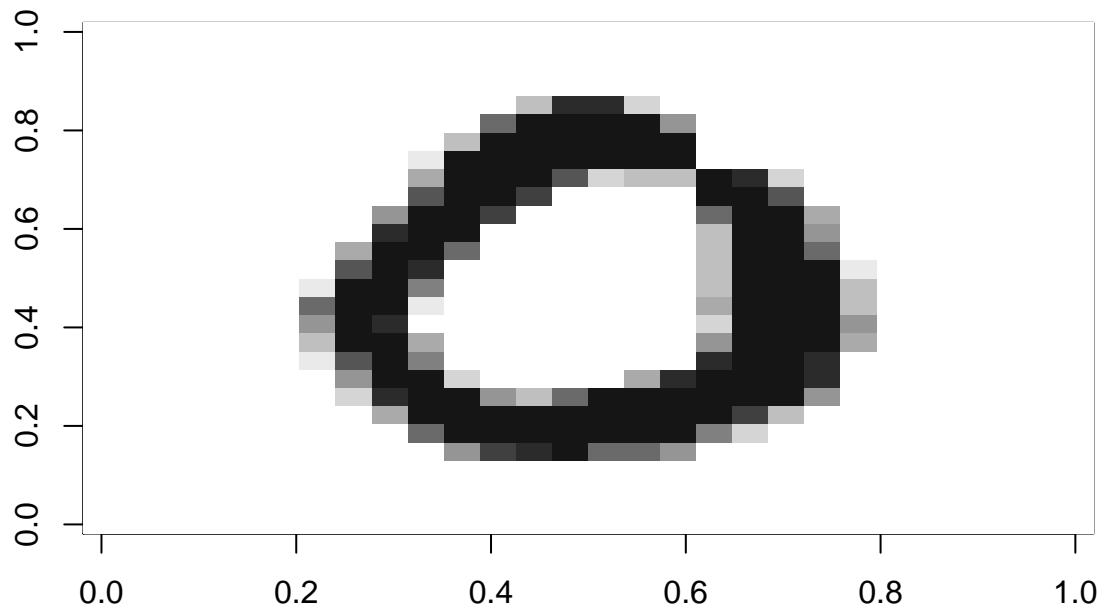
```
plot_digit(49)
```

this is a 0



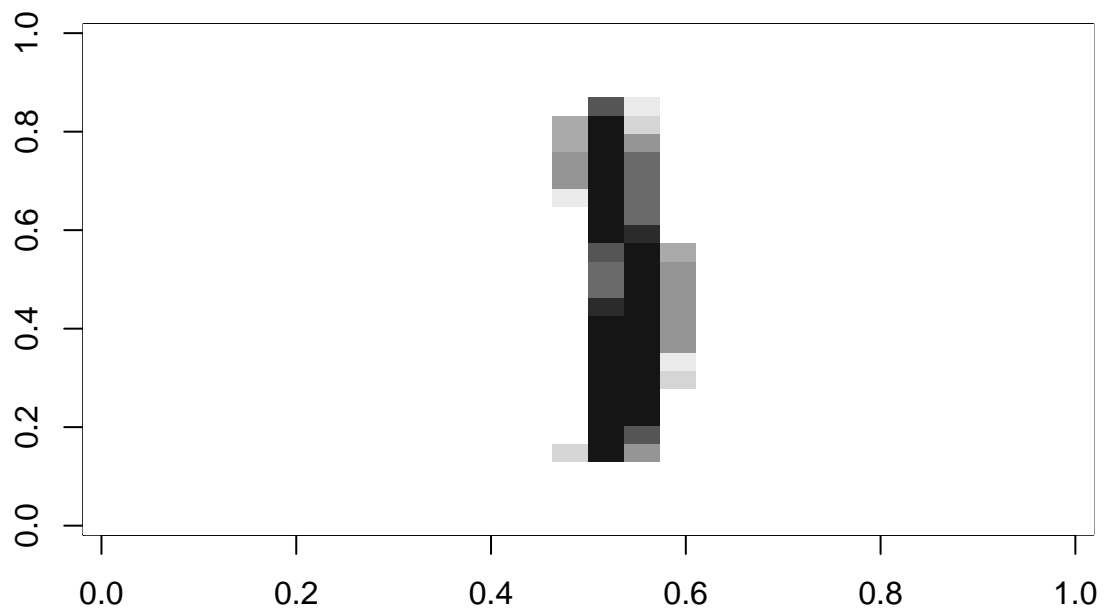

```
plot_digit(58)
```

this is a 0



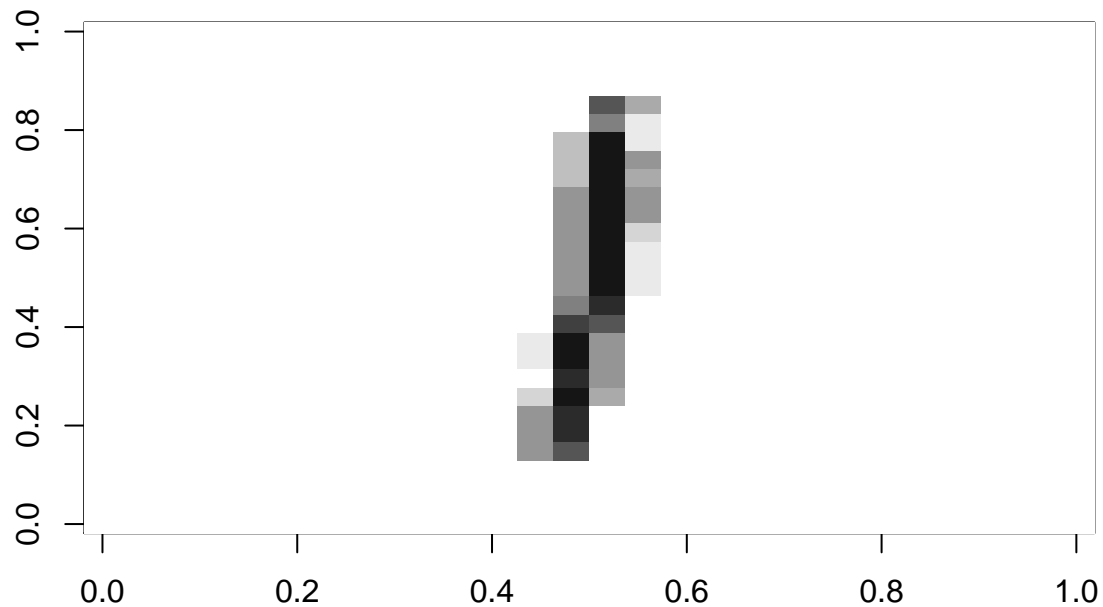
```
# Plot three 1's.  
plot_digit(32)
```

this is a 1



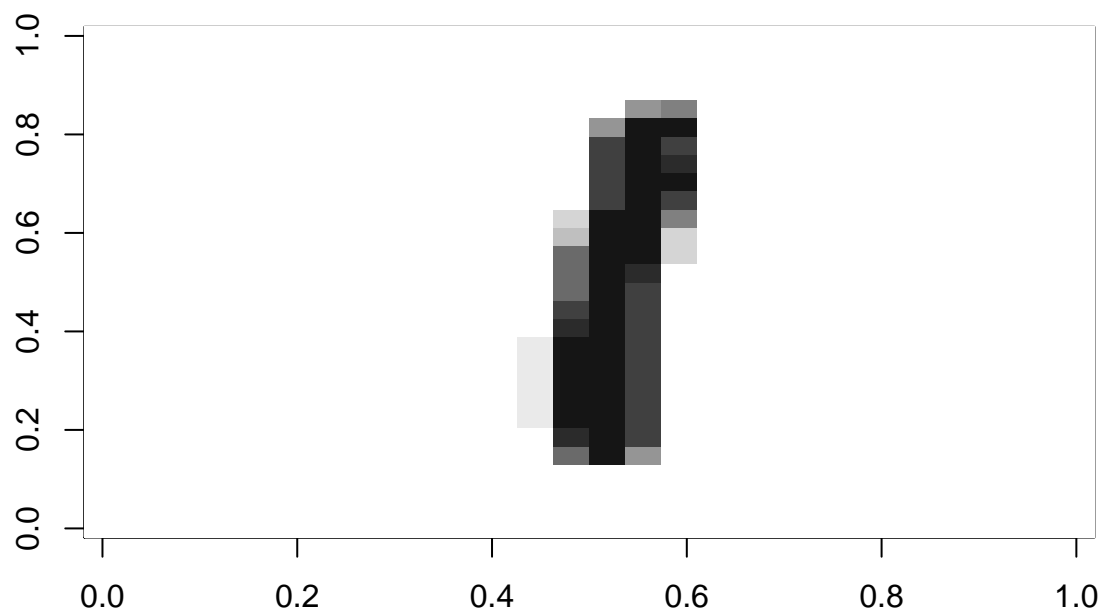
```
plot_digit(35)
```

this is a 1



```
plot_digit(36)
```

this is a 1



B.

(i)

```
# A function to check whether a pixel has a zero variability
isZero<-function(j){
  res = paste("True, pixel",j,"has a zero variability.")
}
```

```

for (i in 1 : 2115){
  if (images_df[i,j]!=0){
    res = paste("False, the variability of pixel",j,"is not zero.")
    break
  }
}
print(res)
}

```

```

# Test to see if pixel 1 has a zero variability.
isZero(1)

```

```
## [1] "True, pixel 1 has a zero variability."
```

```

# Test to see if pixel 2 has a zero variability.
isZero(2)

```

```
## [1] "True, pixel 2 has a zero variability."
```

```

# Test to see if pixel 3 has a zero variability.
isZero(3)

```

```
## [1] "True, pixel 3 has a zero variability."
```

```

# Test to see if pixel 4 has a zero variability.
isZero(4)

```

```
## [1] "True, pixel 4 has a zero variability."
```

```

# Test to see if pixel 5 has a zero variability.
isZero(5)

```

```
## [1] "True, pixel 5 has a zero variability."
```

According to the output, the five features are 1, 2, 3, 4 and 5.

(ii)

```

# Test to see if pixel 100 has a zero variability.
isZero(100)

```

```
## [1] "False, the variability of pixel 100 is not zero."
```

```

# Test to see if pixel 101 has a zero variability.
isZero(101)

```

```
## [1] "False, the variability of pixel 101 is not zero."
```

```

# Test to see if pixel 102 has a zero variability.
isZero(102)

```

```
## [1] "False, the variability of pixel 102 is not zero."
```

```

# Test to see if pixel 103 has a zero variability.
isZero(103)

```

```
## [1] "False, the variability of pixel 103 is not zero."
```

```

# Test to see if pixel 104 has a zero variability.
isZero(104)

```

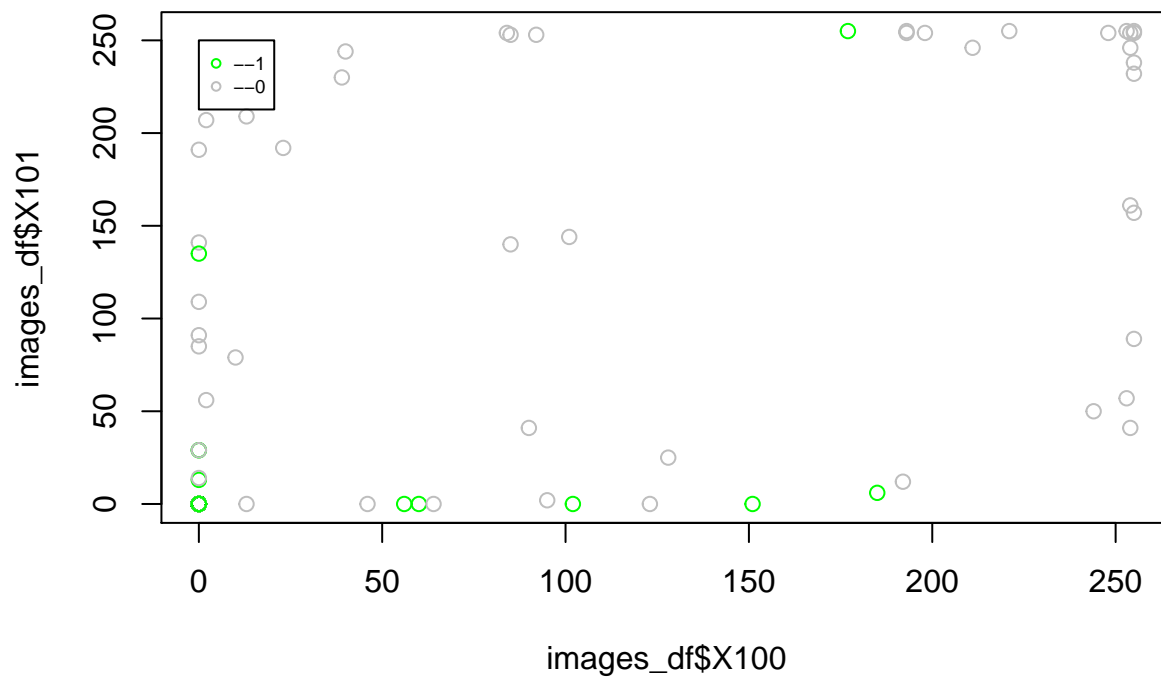
```
## [1] "False, the variability of pixel 104 is not zero."
```

According to the output, the five features are 100, 101, 102, 103 and 104.

(iii)

```
# The two features I pick are 100 and 101.
plot(images_df$X100,images_df$X101,col=ifelse(images_df$labels==1, "green", "grey"),
      main = "Scatter Plot of Feature 101 against 100")
legend(0, 250,pch=c(1,1), col=c("green", "grey"), c("--1", "--0"),cex=.6)
```

Scatter Plot of Feature 101 against 100



C.

```
#install.packages("pROC")
library(pROC)
```

```
## Warning: package 'pROC' was built under R version 3.3.2
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
```

```
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
## cov, smooth, var
```

```
# The three pairs that I choose are 100 & 101, 101 & 102, 102 & 103
```

```

# firstly, fit a logistic regression of labels~X100+X101
c.glm1<-glm(labels~X100+X101, data = images_df, family = binomial)
# take a look at the summary
summary(c.glm1)

##
## Call:
## glm(formula = labels ~ X100 + X101, family = binomial, data = images_df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.257  -1.257   1.100   1.100   2.847
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.184251   0.044137   4.175 2.99e-05 ***
## X100         -0.004841   0.003784  -1.279  0.20076
## X101         -0.013184   0.004752  -2.774  0.00553 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2920.6  on 2114  degrees of freedom
## Residual deviance: 2879.8  on 2112  degrees of freedom
## AIC: 2885.8
##
## Number of Fisher Scoring iterations: 5

# get predictions
glm.predict<-predict(c.glm1, type = "response")

# compute the confusion matrix
table(images_df$labels, glm.predict>0.5)

##
##      FALSE TRUE
##  0      45  935
##  1       9 1126

# compute roc
roc<-roc(images_df$labels, glm.predict)

# compute AUC
auc(roc)

```

```
## Area under the curve: 0.5192
```

According to the summary of the model, the intercept and X101 are statistically significant because their p-values (2.99×10^{-5} and 0.00553 separately) are less than $\alpha = 0.05$. The p-value of X100 is 0.20076 which is much larger than $\alpha = 0.05$ so that X100 is not statistically significant.

According to the confusion matrix, there are 9 false negatives and 935 false positives. The rate of misclassification is $\frac{935+9}{935+9+45+1126} = 0.44634$. The accuracy is $\frac{45+1126}{935+9+45+1126} = 0.55366$. The sensitivity is $\frac{1126}{1126+9} = 0.99207$. The specificity is $\frac{45}{935+45} = 0.04592$.

The AUC is 0.5192.

```

# secondly, fit a logistic regression of labels~X101+X102
c.glm2<-glm(labels~X101+X102, data = images_df, family = binomial)
# take a look at the summary
summary(c.glm2)

##
## Call:
## glm(formula = labels ~ X101 + X102, family = binomial, data = images_df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.291  -1.255   1.102   1.102   2.870
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.1804086  0.0441161   4.089 4.32e-05 ***
## X101         -0.0173091  0.0057676  -3.001  0.00269 **
## X102          0.0009502  0.0036140   0.263  0.79261
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2920.6  on 2114  degrees of freedom
## Residual deviance: 2881.6  on 2112  degrees of freedom
## AIC: 2887.6
##
## Number of Fisher Scoring iterations: 5

# get predictions
glm.predict<-predict(c.glm2, type = "response")

# compute the confusion matrix
table(images_df$labels, glm.predict>0.5)

##
##      FALSE TRUE
##  0      40  940
##  1       4 1131

# compute roc
roc<-roc(images_df$labels, glm.predict)

# compute AUC
auc(roc)

```

```
## Area under the curve: 0.5182
```

According to the summary of the model, the intercept and X101 are statistically significant because their p-values (4.32×10^{-5} and 0.00269 separately) are less than $\alpha = 0.05$. The p-value of X102 is 0.79261 which is much larger than $\alpha = 0.05$ so that X102 is not statistically significant.

According to the confusion matrix, there are 4 false negatives and 940 false positives. The rate of misclassification is $\frac{940+4}{940+4+40+1131} = 0.44634$. The accuracy is $\frac{40+1131}{940+4+40+1131} = 0.55366$. The sensitivity is $\frac{1131}{1131+4} = 0.99648$. The specificity is $\frac{40}{940+40} = 0.04082$.

The AUC is 0.5182.

```

# thirdly, fit a logistic regression of labels~X102+X103
c.glm3<-glm(labels~X102+X103, data = images_df, family = binomial)
# take a look at the summary
summary(c.glm3)

##
## Call:
## glm(formula = labels ~ X102 + X103, family = binomial, data = images_df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.252  -1.252   1.105   1.105   2.074
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.173295   0.044061   3.933 8.39e-05 ***
## X102         -0.008884   0.003065  -2.898  0.00375 **
## X103         -0.001711   0.003101  -0.552  0.58096
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2920.6  on 2114  degrees of freedom
## Residual deviance: 2899.4  on 2112  degrees of freedom
## AIC: 2905.4
##
## Number of Fisher Scoring iterations: 4

# get predictions
glm.predict<-predict(c.glm3, type = "response")

# compute the confusion matrix
table(images_df$labels, glm.predict>0.5)

##
##      FALSE TRUE
##  0      38  942
##  1       9 1126

# compute roc
roc<-roc(images_df$labels, glm.predict)

# compute AUC
auc(roc)

```

```
## Area under the curve: 0.5155
```

According to the summary of the model, the intercept and X102 are statistically significant because their p-values (8.39×10^{-5} and 0.00375 separately) are less than $\alpha = 0.05$. The p-value of X103 is 0.58096 which is much larger than $\alpha = 0.05$ so that X103 is not statistically significant.

According to the confusion matrix, there are 9 false negatives and 942 false positives. The rate of misclassification is $\frac{942+9}{942+9+38+1126} = 0.44965$. The accuracy is $\frac{38+1126}{942+9+38+1126} = 0.55035$. The sensitivity is $\frac{1126}{1126+9} = 0.99207$. The specificity is $\frac{38}{942+38} = 0.03878$.

The AUC is 0.5155.

Among the three models the best model is the first model (c.glm1) because it has the lowest rate of missclassification (0.44634) and the highest AUC value (0.5192).

D.

```
# fit a logistic regression of labels~X100+X101+X102+X103+X104
c.glm3<-glm(labels~X100+X101+X102+X103+X104,data=images_df, family = binomial)

# get predictions
glm.predict<-predict(c.glm3, type = "response")

# compute the confusion matrix
table(images_df$labels, glm.predict>0.5)

##
##      FALSE TRUE
##  0      52  928
##  1      12 1123

# compute roc
roc<-roc(images_df$labels, glm.predict)

# comput AUC
auc(roc)
```

Area under the curve: 0.5228

According to the confusion matrix, there are 12 false negatives and 928 false positives. The rate of missclassification is $\frac{928+12}{928+12+52+1123} = 0.44444$ which is lower than the best model in C. Additionally, the accuracy is $\frac{52+1123}{928+12+52+1123} = 0.55556$ which is better than the best model in C. The sensitivity is $\frac{1123}{1123+12} = 0.98943$. The specificity is $\frac{52}{928+52} = 0.05306$.

The AUC is 0.5228 which is also better than the best model in C.

E.

```
# fit a logistic regression with all features
e.glm<-glm(labels~., data = images_df, family = binomial)

## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

# take a look at the long summary
summary(e.glm)

##
## Call:
## glm(formula = labels ~ ., family = binomial, data = images_df)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.459e-05 -2.110e-08  2.110e-08  4.485e-07  2.148e-05
##
## Coefficients: (286 not defined because of singularities)
```


##	Estimate	Std. Error	z value	Pr(> z)
## (Intercept)	2.903e+00	8.495e+04	0	1
## X1	NA	NA	NA	NA
## X2	NA	NA	NA	NA
## X3	NA	NA	NA	NA
## X4	NA	NA	NA	NA
## X5	NA	NA	NA	NA
## X6	NA	NA	NA	NA
## X7	NA	NA	NA	NA
## X8	NA	NA	NA	NA
## X9	NA	NA	NA	NA
## X10	NA	NA	NA	NA
## X11	NA	NA	NA	NA
## X12	NA	NA	NA	NA
## X13	NA	NA	NA	NA
## X14	NA	NA	NA	NA
## X15	NA	NA	NA	NA
## X16	NA	NA	NA	NA
## X17	NA	NA	NA	NA
## X18	NA	NA	NA	NA
## X19	NA	NA	NA	NA
## X20	NA	NA	NA	NA
## X21	NA	NA	NA	NA
## X22	NA	NA	NA	NA
## X23	NA	NA	NA	NA
## X24	NA	NA	NA	NA
## X25	NA	NA	NA	NA
## X26	NA	NA	NA	NA
## X27	NA	NA	NA	NA
## X28	NA	NA	NA	NA
## X29	NA	NA	NA	NA
## X30	NA	NA	NA	NA
## X31	NA	NA	NA	NA
## X32	NA	NA	NA	NA
## X33	NA	NA	NA	NA
## X34	NA	NA	NA	NA
## X35	NA	NA	NA	NA
## X36	NA	NA	NA	NA
## X37	NA	NA	NA	NA
## X38	NA	NA	NA	NA
## X39	NA	NA	NA	NA
## X40	NA	NA	NA	NA
## X41	NA	NA	NA	NA
## X42	NA	NA	NA	NA
## X43	NA	NA	NA	NA
## X44	NA	NA	NA	NA
## X45	NA	NA	NA	NA
## X46	NA	NA	NA	NA
## X47	NA	NA	NA	NA
## X48	NA	NA	NA	NA
## X49	NA	NA	NA	NA
## X50	NA	NA	NA	NA
## X51	NA	NA	NA	NA
## X52	NA	NA	NA	NA

## X53	NA	NA	NA	NA
## X54	NA	NA	NA	NA
## X55	NA	NA	NA	NA
## X56	NA	NA	NA	NA
## X57	NA	NA	NA	NA
## X58	NA	NA	NA	NA
## X59	NA	NA	NA	NA
## X60	NA	NA	NA	NA
## X61	NA	NA	NA	NA
## X62	NA	NA	NA	NA
## X63	NA	NA	NA	NA
## X64	NA	NA	NA	NA
## X65	NA	NA	NA	NA
## X66	NA	NA	NA	NA
## X67	NA	NA	NA	NA
## X68	2.268e-01	2.738e+04	0	1
## X69	-1.449e-01	2.759e+04	0	1
## X70	1.617e-01	2.108e+04	0	1
## X71	-3.743e-02	5.474e+03	0	1
## X72	NA	NA	NA	NA
## X73	NA	NA	NA	NA
## X74	NA	NA	NA	NA
## X75	NA	NA	NA	NA
## X76	1.101e-01	3.584e+03	0	1
## X77	NA	NA	NA	NA
## X78	NA	NA	NA	NA
## X79	NA	NA	NA	NA
## X80	NA	NA	NA	NA
## X81	NA	NA	NA	NA
## X82	NA	NA	NA	NA
## X83	NA	NA	NA	NA
## X84	NA	NA	NA	NA
## X85	NA	NA	NA	NA
## X86	NA	NA	NA	NA
## X87	NA	NA	NA	NA
## X88	NA	NA	NA	NA
## X89	NA	NA	NA	NA
## X90	NA	NA	NA	NA
## X91	NA	NA	NA	NA
## X92	NA	NA	NA	NA
## X93	NA	NA	NA	NA
## X94	-2.887e-01	2.545e+04	0	1
## X95	9.718e-02	6.589e+03	0	1
## X96	-2.445e-02	5.255e+03	0	1
## X97	-4.224e-02	4.146e+03	0	1
## X98	1.605e-02	2.771e+03	0	1
## X99	-6.050e-03	2.318e+03	0	1
## X100	1.542e-02	1.573e+03	0	1
## X101	-2.892e-02	1.363e+03	0	1
## X102	-5.882e-03	1.620e+03	0	1
## X103	-1.043e-02	1.549e+03	0	1
## X104	8.204e-03	1.877e+03	0	1
## X105	-3.367e-02	2.464e+03	0	1
## X106	1.783e-02	3.973e+03	0	1

## X107	-1.382e-02	5.855e+03	0	1
## X108	1.723e-01	8.893e+03	0	1
## X109	-4.518e-01	1.585e+04	0	1
## X110	NA	NA	NA	NA
## X111	NA	NA	NA	NA
## X112	NA	NA	NA	NA
## X113	NA	NA	NA	NA
## X114	NA	NA	NA	NA
## X115	NA	NA	NA	NA
## X116	2.327e-01	9.938e+03	0	1
## X117	NA	NA	NA	NA
## X118	3.883e-03	3.805e+03	0	1
## X119	1.310e-01	3.768e+03	0	1
## X120	-1.486e-01	1.244e+04	0	1
## X121	-2.502e-02	1.623e+04	0	1
## X122	-1.921e-02	2.893e+03	0	1
## X123	1.005e-02	1.521e+03	0	1
## X124	-1.560e-02	1.126e+03	0	1
## X125	8.021e-03	7.765e+02	0	1
## X126	-8.455e-03	4.745e+02	0	1
## X127	5.466e-03	4.069e+02	0	1
## X128	-1.039e-03	3.446e+02	0	1
## X129	-9.235e-03	3.776e+02	0	1
## X130	6.547e-03	4.050e+02	0	1
## X131	-5.855e-03	4.964e+02	0	1
## X132	-1.031e-02	4.814e+02	0	1
## X133	8.397e-03	6.157e+02	0	1
## X134	-1.060e-02	8.594e+02	0	1
## X135	-7.675e-03	1.272e+03	0	1
## X136	-3.657e-02	2.345e+03	0	1
## X137	2.493e-02	3.020e+03	0	1
## X138	5.464e+01	6.680e+06	0	1
## X139	NA	NA	NA	NA
## X140	NA	NA	NA	NA
## X141	NA	NA	NA	NA
## X142	NA	NA	NA	NA
## X143	NA	NA	NA	NA
## X144	NA	NA	NA	NA
## X145	NA	NA	NA	NA
## X146	-6.702e-01	9.708e+04	0	1
## X147	2.848e-01	4.550e+04	0	1
## X148	-2.479e-03	7.953e+03	0	1
## X149	8.590e-02	3.196e+03	0	1
## X150	-3.101e-02	2.127e+03	0	1
## X151	1.307e-02	1.217e+03	0	1
## X152	-7.081e-03	9.184e+02	0	1
## X153	-7.648e-03	6.075e+02	0	1
## X154	-1.312e-03	4.480e+02	0	1
## X155	-5.251e-03	4.288e+02	0	1
## X156	4.349e-03	3.782e+02	0	1
## X157	-1.411e-02	3.980e+02	0	1
## X158	4.773e-03	3.946e+02	0	1
## X159	3.861e-03	4.400e+02	0	1
## X160	-2.225e-03	4.986e+02	0	1

## X161	1.748e-03	6.230e+02	0	1
## X162	-9.747e-03	9.466e+02	0	1
## X163	6.490e-03	1.209e+03	0	1
## X164	1.845e-03	1.834e+03	0	1
## X165	7.217e-02	4.733e+03	0	1
## X166	4.616e+01	5.516e+06	0	1
## X167	NA	NA	NA	NA
## X168	NA	NA	NA	NA
## X169	NA	NA	NA	NA
## X170	NA	NA	NA	NA
## X171	NA	NA	NA	NA
## X172	NA	NA	NA	NA
## X173	1.730e-01	6.924e+03	0	1
## X174	-1.770e-02	1.618e+04	0	1
## X175	-8.061e-02	1.977e+04	0	1
## X176	1.543e-03	4.157e+03	0	1
## X177	-1.180e-04	2.553e+03	0	1
## X178	1.481e-02	1.338e+03	0	1
## X179	-6.479e-04	1.013e+03	0	1
## X180	-2.236e-02	8.071e+02	0	1
## X181	8.236e-03	6.597e+02	0	1
## X182	-1.329e-02	5.129e+02	0	1
## X183	6.608e-03	4.560e+02	0	1
## X184	-6.164e-03	4.912e+02	0	1
## X185	1.389e-02	4.486e+02	0	1
## X186	-7.114e-03	4.275e+02	0	1
## X187	-1.903e-02	5.159e+02	0	1
## X188	1.149e-02	5.276e+02	0	1
## X189	-7.317e-03	6.661e+02	0	1
## X190	1.421e-02	8.178e+02	0	1
## X191	-4.269e-03	1.007e+03	0	1
## X192	-3.431e-02	2.024e+03	0	1
## X193	-2.843e-02	5.141e+03	0	1
## X194	-3.228e+01	3.858e+06	0	1
## X195	NA	NA	NA	NA
## X196	NA	NA	NA	NA
## X197	NA	NA	NA	NA
## X198	NA	NA	NA	NA
## X199	NA	NA	NA	NA
## X200	NA	NA	NA	NA
## X201	-1.813e+00	5.731e+04	0	1
## X202	-6.315e-02	2.191e+04	0	1
## X203	4.119e-05	4.678e+03	0	1
## X204	-2.200e-02	1.831e+03	0	1
## X205	1.072e-02	1.807e+03	0	1
## X206	-2.026e-02	1.202e+03	0	1
## X207	1.190e-02	9.110e+02	0	1
## X208	7.846e-03	9.129e+02	0	1
## X209	2.299e-02	6.439e+02	0	1
## X210	-5.063e-03	5.254e+02	0	1
## X211	5.123e-03	4.676e+02	0	1
## X212	-1.624e-02	4.395e+02	0	1
## X213	-5.377e-03	4.240e+02	0	1
## X214	6.089e-03	4.800e+02	0	1

## X215	1.606e-02	5.495e+02	0	1
## X216	1.685e-03	5.490e+02	0	1
## X217	-1.567e-02	6.862e+02	0	1
## X218	8.437e-04	6.538e+02	0	1
## X219	-4.870e-03	1.138e+03	0	1
## X220	1.856e-02	1.856e+03	0	1
## X221	1.320e-02	3.109e+03	0	1
## X222	-1.872e-01	3.054e+04	0	1
## X223	NA	NA	NA	NA
## X224	NA	NA	NA	NA
## X225	NA	NA	NA	NA
## X226	NA	NA	NA	NA
## X227	NA	NA	NA	NA
## X228	-1.127e+00	1.308e+05	0	1
## X229	4.245e-01	5.606e+04	0	1
## X230	5.153e-02	1.215e+04	0	1
## X231	-5.483e-02	2.873e+03	0	1
## X232	-1.927e-02	2.256e+03	0	1
## X233	2.442e-02	1.670e+03	0	1
## X234	-7.122e-04	1.105e+03	0	1
## X235	-1.861e-02	8.892e+02	0	1
## X236	-1.209e-02	7.580e+02	0	1
## X237	-9.207e-03	6.698e+02	0	1
## X238	-2.669e-03	5.480e+02	0	1
## X239	-4.627e-04	4.755e+02	0	1
## X240	1.681e-02	4.739e+02	0	1
## X241	-1.556e-02	4.411e+02	0	1
## X242	6.626e-03	5.112e+02	0	1
## X243	-1.302e-02	5.277e+02	0	1
## X244	2.761e-03	5.984e+02	0	1
## X245	2.154e-03	6.789e+02	0	1
## X246	1.881e-02	7.409e+02	0	1
## X247	5.804e-03	1.066e+03	0	1
## X248	-9.846e-03	1.644e+03	0	1
## X249	8.118e-02	2.763e+03	0	1
## X250	5.398e-02	4.774e+04	0	1
## X251	NA	NA	NA	NA
## X252	NA	NA	NA	NA
## X253	NA	NA	NA	NA
## X254	NA	NA	NA	NA
## X255	NA	NA	NA	NA
## X256	NA	NA	NA	NA
## X257	-1.642e-01	4.502e+04	0	1
## X258	6.284e-02	6.799e+03	0	1
## X259	9.554e-03	2.287e+03	0	1
## X260	7.198e-03	1.824e+03	0	1
## X261	2.171e-04	1.128e+03	0	1
## X262	5.713e-04	9.985e+02	0	1
## X263	-6.334e-04	8.437e+02	0	1
## X264	-5.053e-03	7.826e+02	0	1
## X265	-4.283e-03	6.449e+02	0	1
## X266	5.731e-03	5.081e+02	0	1
## X267	6.443e-03	5.364e+02	0	1
## X268	-2.052e-02	5.033e+02	0	1

## X269	2.149e-02	5.304e+02	0	1
## X270	-1.288e-02	5.426e+02	0	1
## X271	-3.607e-03	6.441e+02	0	1
## X272	5.289e-03	5.915e+02	0	1
## X273	-8.320e-04	7.914e+02	0	1
## X274	-2.548e-03	8.364e+02	0	1
## X275	-2.557e-02	1.313e+03	0	1
## X276	2.493e-02	1.583e+03	0	1
## X277	-3.301e-02	2.217e+03	0	1
## X278	-1.142e-01	2.046e+04	0	1
## X279	NA	NA	NA	NA
## X280	NA	NA	NA	NA
## X281	NA	NA	NA	NA
## X282	NA	NA	NA	NA
## X283	NA	NA	NA	NA
## X284	NA	NA	NA	NA
## X285	2.296e-01	1.805e+04	0	1
## X286	3.437e-02	3.122e+03	0	1
## X287	-1.209e-02	2.584e+03	0	1
## X288	9.994e-03	1.633e+03	0	1
## X289	-1.717e-02	1.125e+03	0	1
## X290	4.449e-02	1.000e+03	0	1
## X291	1.686e-02	8.725e+02	0	1
## X292	-9.371e-04	9.658e+02	0	1
## X293	1.310e-02	6.485e+02	0	1
## X294	9.793e-03	4.914e+02	0	1
## X295	-3.174e-03	4.903e+02	0	1
## X296	1.989e-02	6.213e+02	0	1
## X297	-2.511e-02	5.415e+02	0	1
## X298	1.071e-02	6.020e+02	0	1
## X299	1.711e-02	7.212e+02	0	1
## X300	2.737e-03	7.331e+02	0	1
## X301	-2.695e-02	9.544e+02	0	1
## X302	2.881e-03	8.902e+02	0	1
## X303	1.322e-02	1.437e+03	0	1
## X304	-4.868e-02	1.531e+03	0	1
## X305	-4.274e-02	1.900e+03	0	1
## X306	7.985e-02	1.182e+04	0	1
## X307	NA	NA	NA	NA
## X308	NA	NA	NA	NA
## X309	NA	NA	NA	NA
## X310	NA	NA	NA	NA
## X311	NA	NA	NA	NA
## X312	-1.018e-01	9.486e+03	0	1
## X313	-1.409e-01	9.436e+03	0	1
## X314	2.630e-02	3.123e+03	0	1
## X315	-2.191e-02	1.910e+03	0	1
## X316	9.742e-03	1.476e+03	0	1
## X317	-3.289e-03	1.025e+03	0	1
## X318	-1.884e-02	1.056e+03	0	1
## X319	-2.912e-02	1.052e+03	0	1
## X320	-2.584e-03	8.053e+02	0	1
## X321	-1.362e-02	7.068e+02	0	1
## X322	-7.740e-03	5.207e+02	0	1

## X323	1.258e-02	4.996e+02	0	1
## X324	-2.100e-02	6.662e+02	0	1
## X325	1.235e-02	5.196e+02	0	1
## X326	3.430e-03	6.326e+02	0	1
## X327	-2.130e-02	8.298e+02	0	1
## X328	-5.051e-03	8.496e+02	0	1
## X329	1.766e-02	9.275e+02	0	1
## X330	4.007e-03	9.426e+02	0	1
## X331	-3.036e-02	1.288e+03	0	1
## X332	2.314e-03	1.650e+03	0	1
## X333	1.433e-02	1.698e+03	0	1
## X334	-2.464e-02	1.136e+04	0	1
## X335	NA	NA	NA	NA
## X336	NA	NA	NA	NA
## X337	NA	NA	NA	NA
## X338	NA	NA	NA	NA
## X339	NA	NA	NA	NA
## X340	-1.488e-01	5.818e+03	0	1
## X341	-1.892e-02	4.379e+03	0	1
## X342	5.822e-03	2.726e+03	0	1
## X343	-2.256e-02	1.518e+03	0	1
## X344	-9.293e-03	1.082e+03	0	1
## X345	7.306e-03	1.003e+03	0	1
## X346	3.160e-02	1.117e+03	0	1
## X347	3.868e-02	9.489e+02	0	1
## X348	-6.826e-03	8.553e+02	0	1
## X349	-7.193e-03	6.844e+02	0	1
## X350	-1.588e-02	5.680e+02	0	1
## X351	1.725e-02	5.655e+02	0	1
## X352	2.493e-02	7.867e+02	0	1
## X353	-1.664e-02	6.392e+02	0	1
## X354	-2.719e-03	7.623e+02	0	1
## X355	-1.256e-02	9.871e+02	0	1
## X356	2.052e-02	1.028e+03	0	1
## X357	-1.905e-02	1.045e+03	0	1
## X358	-1.465e-02	9.832e+02	0	1
## X359	3.236e-02	1.267e+03	0	1
## X360	2.001e-02	1.891e+03	0	1
## X361	-1.195e-02	1.993e+03	0	1
## X362	-7.502e-03	9.372e+03	0	1
## X363	NA	NA	NA	NA
## X364	NA	NA	NA	NA
## X365	NA	NA	NA	NA
## X366	NA	NA	NA	NA
## X367	NA	NA	NA	NA
## X368	NA	NA	NA	NA
## X369	-8.508e-03	3.469e+03	0	1
## X370	2.577e-03	2.024e+03	0	1
## X371	5.302e-02	1.534e+03	0	1
## X372	1.095e-02	1.422e+03	0	1
## X373	-2.364e-02	1.074e+03	0	1
## X374	-3.081e-02	1.114e+03	0	1
## X375	1.171e-02	1.048e+03	0	1
## X376	-5.214e-03	9.365e+02	0	1

## X377	1.275e-02	6.310e+02	0	1
## X378	3.057e-03	5.830e+02	0	1
## X379	1.552e-02	6.837e+02	0	1
## X380	1.231e-03	7.947e+02	0	1
## X381	6.598e-03	6.831e+02	0	1
## X382	3.058e-02	8.894e+02	0	1
## X383	-2.637e-03	1.108e+03	0	1
## X384	-2.397e-02	1.150e+03	0	1
## X385	-3.775e-03	1.179e+03	0	1
## X386	-1.452e-02	1.177e+03	0	1
## X387	-3.589e-02	1.203e+03	0	1
## X388	-1.669e-02	1.833e+03	0	1
## X389	9.258e-04	1.863e+03	0	1
## X390	1.788e-02	1.071e+04	0	1
## X391	NA	NA	NA	NA
## X392	NA	NA	NA	NA
## X393	NA	NA	NA	NA
## X394	NA	NA	NA	NA
## X395	NA	NA	NA	NA
## X396	NA	NA	NA	NA
## X397	-2.049e-02	2.791e+03	0	1
## X398	-1.619e-02	1.630e+03	0	1
## X399	-4.268e-02	1.605e+03	0	1
## X400	-4.893e-02	1.474e+03	0	1
## X401	3.861e-03	9.924e+02	0	1
## X402	1.507e-03	1.167e+03	0	1
## X403	1.390e-02	1.006e+03	0	1
## X404	-1.406e-02	9.836e+02	0	1
## X405	2.559e-02	6.603e+02	0	1
## X406	-1.759e-02	6.519e+02	0	1
## X407	4.405e-02	8.187e+02	0	1
## X408	-5.560e-03	7.225e+02	0	1
## X409	-1.923e-04	7.457e+02	0	1
## X410	-3.165e-02	1.241e+03	0	1
## X411	-2.356e-02	1.095e+03	0	1
## X412	-6.082e-03	1.025e+03	0	1
## X413	2.631e-02	1.155e+03	0	1
## X414	2.296e-02	1.109e+03	0	1
## X415	2.547e-02	1.299e+03	0	1
## X416	3.516e-02	1.629e+03	0	1
## X417	1.599e-02	1.537e+03	0	1
## X418	-1.810e-02	1.071e+04	0	1
## X419	NA	NA	NA	NA
## X420	NA	NA	NA	NA
## X421	NA	NA	NA	NA
## X422	NA	NA	NA	NA
## X423	NA	NA	NA	NA
## X424	NA	NA	NA	NA
## X425	-1.622e-02	2.124e+03	0	1
## X426	-9.319e-03	1.336e+03	0	1
## X427	2.856e-02	1.652e+03	0	1
## X428	3.291e-02	1.462e+03	0	1
## X429	-7.305e-03	1.125e+03	0	1
## X430	-2.198e-02	1.097e+03	0	1

## X431	-9.451e-03	9.749e+02	0	1
## X432	4.065e-03	8.059e+02	0	1
## X433	-2.089e-02	6.751e+02	0	1
## X434	1.607e-02	6.401e+02	0	1
## X435	1.101e-02	8.542e+02	0	1
## X436	7.526e-03	6.035e+02	0	1
## X437	1.220e-03	8.229e+02	0	1
## X438	2.550e-02	1.218e+03	0	1
## X439	1.043e-02	1.240e+03	0	1
## X440	1.739e-02	9.015e+02	0	1
## X441	-1.657e-02	9.392e+02	0	1
## X442	-5.730e-03	1.029e+03	0	1
## X443	-1.471e-02	1.367e+03	0	1
## X444	-2.652e-02	1.556e+03	0	1
## X445	-2.577e-02	1.739e+03	0	1
## X446	1.416e-01	8.654e+03	0	1
## X447	-8.720e-02	4.907e+03	0	1
## X448	NA	NA	NA	NA
## X449	NA	NA	NA	NA
## X450	8.321e-02	9.721e+03	0	1
## X451	NA	NA	NA	NA
## X452	1.945e-01	2.537e+04	0	1
## X453	1.507e-02	2.441e+03	0	1
## X454	6.605e-04	1.369e+03	0	1
## X455	-3.682e-02	1.307e+03	0	1
## X456	-2.334e-03	1.337e+03	0	1
## X457	-1.287e-02	1.077e+03	0	1
## X458	-2.766e-02	1.035e+03	0	1
## X459	-2.352e-02	8.791e+02	0	1
## X460	-8.006e-03	8.339e+02	0	1
## X461	5.935e-03	7.267e+02	0	1
## X462	7.407e-03	6.838e+02	0	1
## X463	-2.640e-03	6.998e+02	0	1
## X464	-3.426e-03	5.826e+02	0	1
## X465	5.419e-03	7.749e+02	0	1
## X466	-4.465e-03	9.199e+02	0	1
## X467	-2.883e-02	9.327e+02	0	1
## X468	-2.110e-02	1.005e+03	0	1
## X469	-2.143e-03	1.001e+03	0	1
## X470	8.483e-03	9.767e+02	0	1
## X471	-7.994e-03	1.225e+03	0	1
## X472	3.032e-02	1.564e+03	0	1
## X473	-3.245e-02	2.450e+03	0	1
## X474	-2.928e-01	1.383e+04	0	1
## X475	NA	NA	NA	NA
## X476	NA	NA	NA	NA
## X477	NA	NA	NA	NA
## X478	NA	NA	NA	NA
## X479	NA	NA	NA	NA
## X480	-7.513e-01	1.209e+05	0	1
## X481	-1.419e-02	2.364e+03	0	1
## X482	2.265e-02	1.457e+03	0	1
## X483	1.530e-02	1.438e+03	0	1
## X484	-8.629e-03	1.167e+03	0	1

## X485	1.927e-02	8.543e+02	0	1
## X486	1.004e-02	8.906e+02	0	1
## X487	6.914e-03	8.488e+02	0	1
## X488	2.825e-02	7.087e+02	0	1
## X489	7.320e-03	6.668e+02	0	1
## X490	3.433e-03	6.912e+02	0	1
## X491	-2.675e-03	6.182e+02	0	1
## X492	-1.920e-02	6.830e+02	0	1
## X493	-1.243e-02	6.128e+02	0	1
## X494	9.029e-04	8.814e+02	0	1
## X495	1.275e-02	9.432e+02	0	1
## X496	-5.568e-04	9.288e+02	0	1
## X497	2.432e-03	1.073e+03	0	1
## X498	-1.410e-02	1.104e+03	0	1
## X499	-2.544e-02	1.361e+03	0	1
## X500	-4.842e-02	1.831e+03	0	1
## X501	5.101e-02	3.108e+03	0	1
## X502	5.790e-02	2.183e+04	0	1
## X503	NA	NA	NA	NA
## X504	NA	NA	NA	NA
## X505	NA	NA	NA	NA
## X506	NA	NA	NA	NA
## X507	NA	NA	NA	NA
## X508	3.519e-01	7.262e+04	0	1
## X509	-1.435e-02	2.097e+03	0	1
## X510	-2.209e-02	1.279e+03	0	1
## X511	-1.844e-02	1.414e+03	0	1
## X512	-5.933e-03	1.011e+03	0	1
## X513	-1.704e-03	7.840e+02	0	1
## X514	-1.453e-04	7.348e+02	0	1
## X515	-3.628e-03	7.648e+02	0	1
## X516	-1.462e-02	6.398e+02	0	1
## X517	1.552e-02	6.256e+02	0	1
## X518	2.765e-03	5.958e+02	0	1
## X519	1.128e-02	4.964e+02	0	1
## X520	4.699e-03	6.467e+02	0	1
## X521	-3.542e-03	6.421e+02	0	1
## X522	-1.830e-02	9.086e+02	0	1
## X523	-1.430e-02	8.678e+02	0	1
## X524	-6.651e-03	9.682e+02	0	1
## X525	8.793e-03	1.040e+03	0	1
## X526	6.003e-04	1.213e+03	0	1
## X527	3.405e-02	1.454e+03	0	1
## X528	3.536e-02	2.120e+03	0	1
## X529	2.293e-02	4.675e+03	0	1
## X530	4.012e-01	3.001e+04	0	1
## X531	NA	NA	NA	NA
## X532	NA	NA	NA	NA
## X533	NA	NA	NA	NA
## X534	NA	NA	NA	NA
## X535	NA	NA	NA	NA
## X536	NA	NA	NA	NA
## X537	9.707e-03	2.339e+03	0	1
## X538	-9.948e-03	1.152e+03	0	1

## X539	2.460e-02	1.103e+03	0	1
## X540	5.787e-03	8.101e+02	0	1
## X541	3.552e-03	7.600e+02	0	1
## X542	-4.964e-03	5.915e+02	0	1
## X543	-7.306e-04	6.910e+02	0	1
## X544	1.438e-02	5.536e+02	0	1
## X545	-2.548e-02	5.199e+02	0	1
## X546	1.457e-02	5.333e+02	0	1
## X547	1.224e-03	5.072e+02	0	1
## X548	7.234e-03	5.858e+02	0	1
## X549	1.163e-02	6.423e+02	0	1
## X550	-3.253e-04	7.430e+02	0	1
## X551	1.120e-03	8.514e+02	0	1
## X552	-3.503e-02	9.732e+02	0	1
## X553	-8.627e-03	1.067e+03	0	1
## X554	1.181e-03	1.281e+03	0	1
## X555	-6.112e-02	2.532e+03	0	1
## X556	-2.638e-02	2.313e+03	0	1
## X557	2.675e-03	7.238e+03	0	1
## X558	-8.343e-01	6.197e+04	0	1
## X559	-7.513e-01	2.476e+04	0	1
## X560	NA	NA	NA	NA
## X561	NA	NA	NA	NA
## X562	NA	NA	NA	NA
## X563	NA	NA	NA	NA
## X564	1.852e-02	2.728e+04	0	1
## X565	-4.219e-02	2.173e+03	0	1
## X566	3.156e-03	1.171e+03	0	1
## X567	-2.890e-02	1.035e+03	0	1
## X568	7.063e-03	7.814e+02	0	1
## X569	5.807e-04	6.395e+02	0	1
## X570	-2.057e-03	5.606e+02	0	1
## X571	1.033e-02	6.471e+02	0	1
## X572	-9.806e-03	5.242e+02	0	1
## X573	1.228e-02	4.759e+02	0	1
## X574	-2.610e-03	5.026e+02	0	1
## X575	4.497e-03	4.572e+02	0	1
## X576	-1.597e-03	5.822e+02	0	1
## X577	6.507e-03	6.073e+02	0	1
## X578	-8.223e-03	7.979e+02	0	1
## X579	8.688e-03	9.107e+02	0	1
## X580	1.640e-02	1.022e+03	0	1
## X581	-6.681e-03	1.303e+03	0	1
## X582	-1.142e-02	2.097e+03	0	1
## X583	-2.152e-02	2.504e+03	0	1
## X584	5.660e-02	4.123e+03	0	1
## X585	-1.501e-02	2.855e+04	0	1
## X586	NA	NA	NA	NA
## X587	NA	NA	NA	NA
## X588	NA	NA	NA	NA
## X589	NA	NA	NA	NA
## X590	NA	NA	NA	NA
## X591	NA	NA	NA	NA
## X592	1.025e-02	6.842e+03	0	1

## X593	9.289e-02	2.479e+03	0	1
## X594	1.797e-03	1.134e+03	0	1
## X595	4.283e-02	1.026e+03	0	1
## X596	2.983e-03	7.835e+02	0	1
## X597	-1.514e-03	6.272e+02	0	1
## X598	-5.017e-03	6.376e+02	0	1
## X599	-4.652e-03	5.296e+02	0	1
## X600	-6.812e-03	4.817e+02	0	1
## X601	1.238e-02	4.880e+02	0	1
## X602	-1.111e-02	4.823e+02	0	1
## X603	1.230e-02	4.726e+02	0	1
## X604	1.749e-03	5.826e+02	0	1
## X605	-2.944e-03	5.536e+02	0	1
## X606	2.570e-02	7.403e+02	0	1
## X607	2.724e-03	8.623e+02	0	1
## X608	-1.435e-02	1.326e+03	0	1
## X609	7.445e-02	1.338e+03	0	1
## X610	3.745e-02	2.574e+03	0	1
## X611	2.310e-02	3.789e+03	0	1
## X612	-1.015e-01	3.695e+03	0	1
## X613	8.179e-01	4.369e+04	0	1
## X614	NA	NA	NA	NA
## X615	NA	NA	NA	NA
## X616	NA	NA	NA	NA
## X617	NA	NA	NA	NA
## X618	NA	NA	NA	NA
## X619	NA	NA	NA	NA
## X620	-1.333e-01	3.721e+04	0	1
## X621	-1.046e-01	4.095e+03	0	1
## X622	-2.180e-02	1.406e+03	0	1
## X623	-7.354e-03	9.112e+02	0	1
## X624	-5.157e-03	8.384e+02	0	1
## X625	8.268e-03	6.697e+02	0	1
## X626	-2.186e-03	5.907e+02	0	1
## X627	-6.450e-03	4.872e+02	0	1
## X628	5.676e-03	4.733e+02	0	1
## X629	-7.352e-03	4.404e+02	0	1
## X630	1.823e-03	4.325e+02	0	1
## X631	6.319e-04	4.849e+02	0	1
## X632	6.076e-03	5.656e+02	0	1
## X633	-9.979e-03	6.289e+02	0	1
## X634	-1.164e-02	8.703e+02	0	1
## X635	2.198e-02	9.163e+02	0	1
## X636	-1.016e-01	1.802e+03	0	1
## X637	1.340e-02	2.134e+03	0	1
## X638	-3.997e-02	3.491e+03	0	1
## X639	1.852e-02	4.618e+03	0	1
## X640	-4.730e-01	4.905e+04	0	1
## X641	NA	NA	NA	NA
## X642	NA	NA	NA	NA
## X643	NA	NA	NA	NA
## X644	NA	NA	NA	NA
## X645	NA	NA	NA	NA
## X646	NA	NA	NA	NA

## X647	NA	NA	NA	NA
## X648	NA	NA	NA	NA
## X649	1.343e-01	4.653e+03	0	1
## X650	-3.763e-03	1.802e+03	0	1
## X651	1.746e-02	1.124e+03	0	1
## X652	-1.096e-02	7.784e+02	0	1
## X653	1.070e-05	6.224e+02	0	1
## X654	-7.312e-03	5.404e+02	0	1
## X655	5.874e-03	4.452e+02	0	1
## X656	-3.974e-05	4.299e+02	0	1
## X657	-1.070e-02	3.883e+02	0	1
## X658	-3.786e-03	3.835e+02	0	1
## X659	-2.533e-04	4.127e+02	0	1
## X660	-2.951e-02	4.554e+02	0	1
## X661	2.867e-02	6.193e+02	0	1
## X662	-4.598e-03	8.618e+02	0	1
## X663	7.300e-02	1.856e+03	0	1
## X664	-3.461e-03	2.229e+03	0	1
## X665	-5.124e-02	2.833e+03	0	1
## X666	1.533e-01	1.073e+04	0	1
## X667	-1.106e-01	8.462e+04	0	1
## X668	3.561e+00	4.159e+05	0	1
## X669	NA	NA	NA	NA
## X670	NA	NA	NA	NA
## X671	NA	NA	NA	NA
## X672	NA	NA	NA	NA
## X673	NA	NA	NA	NA
## X674	NA	NA	NA	NA
## X675	NA	NA	NA	NA
## X676	NA	NA	NA	NA
## X677	-1.504e-01	1.731e+04	0	1
## X678	1.815e-03	2.677e+03	0	1
## X679	-2.335e-02	1.231e+03	0	1
## X680	1.079e-02	8.901e+02	0	1
## X681	-1.175e-02	6.469e+02	0	1
## X682	1.779e-02	6.037e+02	0	1
## X683	-2.270e-02	6.139e+02	0	1
## X684	3.281e-03	5.648e+02	0	1
## X685	1.013e-02	5.052e+02	0	1
## X686	-1.065e-02	4.503e+02	0	1
## X687	6.623e-03	4.809e+02	0	1
## X688	4.802e-03	5.484e+02	0	1
## X689	-2.401e-02	7.078e+02	0	1
## X690	1.997e-02	9.664e+02	0	1
## X691	-5.122e-02	1.650e+03	0	1
## X692	1.190e-01	7.667e+03	0	1
## X693	-6.088e-02	5.290e+03	0	1
## X694	-1.967e-01	5.054e+04	0	1
## X695	1.169e-01	7.125e+04	0	1
## X696	NA	NA	NA	NA
## X697	NA	NA	NA	NA
## X698	NA	NA	NA	NA
## X699	NA	NA	NA	NA
## X700	NA	NA	NA	NA

## X701	NA	NA	NA	NA
## X702	NA	NA	NA	NA
## X703	NA	NA	NA	NA
## X704	NA	NA	NA	NA
## X705	NA	NA	NA	NA
## X706	NA	NA	NA	NA
## X707	1.214e+00	1.529e+05	0	1
## X708	-1.191e+00	5.316e+04	0	1
## X709	5.589e-01	3.128e+04	0	1
## X710	2.752e-01	1.999e+04	0	1
## X711	-9.701e-02	2.121e+04	0	1
## X712	-9.234e-02	1.272e+04	0	1
## X713	6.354e-02	4.142e+03	0	1
## X714	1.547e-01	7.150e+03	0	1
## X715	-1.231e-01	6.146e+03	0	1
## X716	3.333e-02	3.071e+03	0	1
## X717	1.982e-01	1.581e+04	0	1
## X718	-4.929e-01	4.425e+04	0	1
## X719	1.572e+00	3.762e+05	0	1
## X720	NA	NA	NA	NA
## X721	NA	NA	NA	NA
## X722	NA	NA	NA	NA
## X723	NA	NA	NA	NA
## X724	NA	NA	NA	NA
## X725	NA	NA	NA	NA
## X726	NA	NA	NA	NA
## X727	NA	NA	NA	NA
## X728	NA	NA	NA	NA
## X729	NA	NA	NA	NA
## X730	NA	NA	NA	NA
## X731	NA	NA	NA	NA
## X732	NA	NA	NA	NA
## X733	NA	NA	NA	NA
## X734	NA	NA	NA	NA
## X735	NA	NA	NA	NA
## X736	NA	NA	NA	NA
## X737	NA	NA	NA	NA
## X738	NA	NA	NA	NA
## X739	NA	NA	NA	NA
## X740	NA	NA	NA	NA
## X741	NA	NA	NA	NA
## X742	NA	NA	NA	NA
## X743	NA	NA	NA	NA
## X744	NA	NA	NA	NA
## X745	NA	NA	NA	NA
## X746	NA	NA	NA	NA
## X747	NA	NA	NA	NA
## X748	NA	NA	NA	NA
## X749	NA	NA	NA	NA
## X750	NA	NA	NA	NA
## X751	NA	NA	NA	NA
## X752	NA	NA	NA	NA
## X753	NA	NA	NA	NA
## X754	NA	NA	NA	NA

```

## X755          NA          NA          NA          NA
## X756          NA          NA          NA          NA
## X757          NA          NA          NA          NA
## X758          NA          NA          NA          NA
## X759          NA          NA          NA          NA
## X760          NA          NA          NA          NA
## X761          NA          NA          NA          NA
## X762          NA          NA          NA          NA
## X763          NA          NA          NA          NA
## X764          NA          NA          NA          NA
## X765          NA          NA          NA          NA
## X766          NA          NA          NA          NA
## X767          NA          NA          NA          NA
## X768          NA          NA          NA          NA
## X769          NA          NA          NA          NA
## X770          NA          NA          NA          NA
## X771          NA          NA          NA          NA
## X772          NA          NA          NA          NA
## X773          NA          NA          NA          NA
## X774          NA          NA          NA          NA
## X775          NA          NA          NA          NA
## X776          NA          NA          NA          NA
## X777          NA          NA          NA          NA
## X778          NA          NA          NA          NA
## X779          NA          NA          NA          NA
## X780          NA          NA          NA          NA
## X781          NA          NA          NA          NA
## X782          NA          NA          NA          NA
## X783          NA          NA          NA          NA
## X784          NA          NA          NA          NA
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2.9206e+03  on 2114  degrees of freedom
## Residual deviance: 1.8922e-08  on 1616  degrees of freedom
## AIC: 998
##
## Number of Fisher Scoring iterations: 25

```

The message “glm.fit: algorithm did not convergeglm.fit: fitted probabilities numerically 0 or 1 occurred” implies numerical problems which is caused by too many features or explanatory variables.

The estimated coefficients and standard errors of some features are NA’s such as X1, X20, X10 and so on. This is due to that they have zero variability (so they are not important to the model). Meanwhile, other features have very small estimate coefficients, very large standard errors and p-values of 1 (so they are not statistically significant) such as X100, X109, X69 and so on. The approach fails because we can’t choose all variables, we have to prune or eliminate those with variability of 0.