

# Data Science II Final Project Analysis

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```
library(tidymodels)
library(splines)
library(caret)
library(glmnet)
library(table1)
library(kableExtra)
library(summarytools)
library(corrplot)
library(cowplot)

library(vip)
library(pROC)
library(glmnet)
library(tidymodels)
library(mlbench)
library(pROC)
library(pdp)
library(vip)
library(AppliedPredictiveModeling)

library(rpart)
library(rpart.plot)
```

## Background

A research study aims to identify key factors that predict the severity of COVID-19 illness. This study collects demographic information, clinical variables, and disease severity among participants infected with COVID-19 between 2021 and 2023. The goal is to develop a robust prediction model that can accurately predict COVID-19 severity and understand how predictors impact the risk of severe infection.

## Data

The training data in “severity\_training.RData” includes data from 800 participants.

The test data in “severity\_test.RData” includes data from another set of 200 participants.

Here is a description of each variable:

- ID (**id**): Participant ID
- Age (**age**): Age
- Gender (**gender**): 1 = Male, 0 = Female
- Race/ethnicity (**race**): 1 = White, 2 = Asian, 3 = Black, 4 = Hispanic
- Smoking (**smoking**): Smoking status; 0 = Never smoked, 1 = Former smoker, 2 = Current smoker
- Height (**height**): Height (in centimeters)
- Weight (**weight**): Weight (in kilograms)
- BMI (**bmi**): Body Mass Index; BMI = weight (in kilograms) / height (in meters) squared
- Hypertension (**hypertension**): 0 = No, 1 = Yes
- Diabetes (**diabetes**): 0 = No, 1 = Yes
- Systolic blood pressure (**SBP**): Systolic blood pressure (in mm/Hg)
- LDL cholesterol (**LDL**): LDL (low-density lipoprotein) cholesterol (in mg/dL)
- Vaccination status at the time of infection (**vaccine**): 0 = Not vaccinated, 1 = Vaccinated
- Depression score (**depression**): Higher scores indicate higher risk for depression
- Severity of COVID-19 infection (**severity**): **Response variable**; 0 = Not severe, 1 = Severe

## Data Preparation

```
# loading training data
load("data/severity_training.RData")

# making discrete variables factors
training_data = training_data |>
  select(-id) |>
  mutate_at(vars(age, height, weight, bmi, SBP, LDL, depression), as.numeric) |>
  mutate(
    gender = factor(gender,
                    levels = c(0, 1),
                    labels = c("Female", "Male")) |>
    relevel(ref = "Female"),
    race = factor(race,
                  levels = c(1, 2, 3, 4),
                  labels = c("White", "Asian", "Black", "Hispanic")) |>
    relevel(ref = "White"),
    smoking = factor(smoking,
                     levels = c(0, 1, 2),
                     labels = c("Never_smoked", "Former_smoker", "Current_smoker")) |>
    relevel(ref = "Never_smoked"),
    hypertension = factor(hypertension,
                          levels = c(0, 1),
```

```

        labels = c("No", "Yes")) |>
    relevelevel(ref = "No"),
    diabetes = factor(diabetes,
        levels = c(0, 1),
        labels = c("No", "Yes")) |>
    relevelevel(ref = "No"),
    vaccine = factor(vaccine,
        levels = c(0, 1),
        labels = c("Not_vaccinated", "Vaccinated")) |>
    relevelevel(ref = "Not_vaccinated"),
    severity = factor(severity,
        levels = c(0, 1),
        labels = c("Not_severe", "Severe")) |>
    relevelevel(ref = "Not_severe")
) |>
janitor::clean_names()

# checking levels
levels(training_data$race)
levels(training_data$smoking)
levels(training_data$hypertension)
levels(training_data$diabetes)
levels(training_data$vaccine)
levels(training_data$severity)

# matrix of predictors & vector of response for data set exploration
x.train = model.matrix(severity ~ ., training_data)[, -1]
y.train = training_data$severity

# loading testing data
load("data/severity_test.RData")

# making discrete variables factors
test_data = test_data |>
    select(-id) |>
    mutate_at(vars(age, height, weight, bmi, SBP, LDL, depression), as.numeric) |>
    mutate(
        gender = factor(gender,
            levels = c(0, 1),
            labels = c("Female", "Male")) |>
        relevelevel(ref = "Female"),
        race = factor(race,
            levels = c(1, 2, 3, 4),
            labels = c("White", "Asian", "Black", "Hispanic")) |>
        relevelevel(ref = "White"),
        smoking = factor(smoking,
            levels = c(0, 1, 2),
            labels = c("Never_smoked", "Former_smoker", "Current_smoker")) |>
        relevelevel(ref = "Never_smoked"),
        hypertension = factor(hypertension,
            levels = c(0, 1),
            labels = c("No", "Yes")) |>
        relevelevel(ref = "No"),

```

```
diabetes = factor(diabetes,
                  levels = c(0, 1),
                  labels = c("No", "Yes")) |>
  relevel(ref = "No"),
vaccine = factor(vaccine,
                  levels = c(0, 1),
                  labels = c("Not_vaccinated", "Vaccinated")) |>
  relevel(ref = "Not_vaccinated"),
severity = factor(severity,
                  levels = c(0, 1),
                  labels = c("Not_severe", "Severe")) |>
  relevel(ref = "Not_severe")
) |>
janitor::clean_names()

# matrix of predictors and vector of response
x.test = model.matrix(severity ~., test_data)[, -1]
y.test = test_data$severity
```

## Exploratory analysis and data visualization

### Descriptive Statistics of Training Data

```
descriptive_table = table1(~ age + gender + race + smoking + height + weight + bmi + hypertension + dialysis,
                           data = training_data,
                           overall = "Total",
                           caption = "Descriptive Characteristics of Participants, Stratified by Severity")

ds = t1kable(descriptive_table)
ds
```

### Continuous Variable Visualization

```
theme1 <- trellis.par.get()
theme1$plot.symbol$col <- rgb(.2, .4, .2, .5)
theme1$plot.symbol$pch <- 2
theme1$plot.line$col <- rgb(.8, .1, .1, 1)
theme1$plot.line$lwd <- 2
theme1$strip.background$col <- rgb(.0, .2, .6, .2)
trellis.par.set(theme1)

featurePlot(
  x.train[, -c(2, 3, 4, 5, 6, 7, 11, 12, 15)],
  y.train,
  scales = list(x = list(relation = "free"),
               y = list(relation = "free")),
  plot = "box")
```

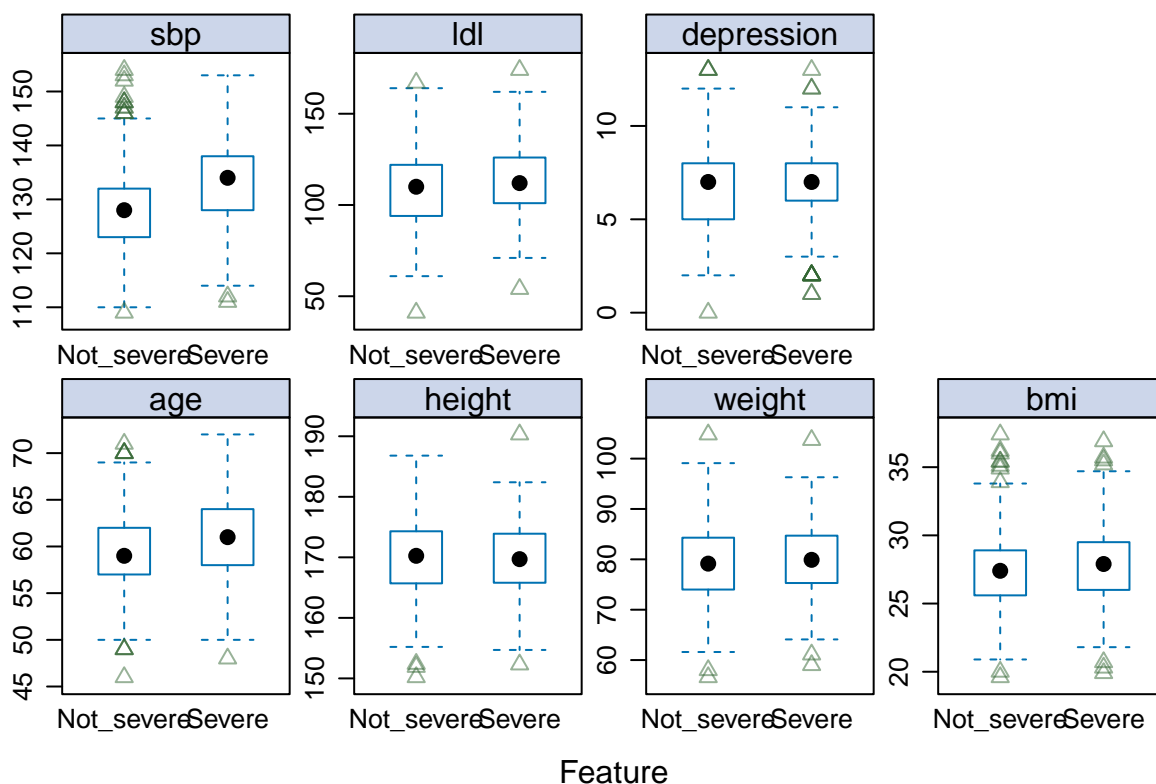


Table 1: Descriptive Characteristics of Participants, Stratified by Severity of COVID-19 Infection

	Not_severe	Severe	Total
	(N=514)	(N=286)	(N=800)
<b>age</b>			
Mean (SD)	59.5 (4.29)	61.0 (4.12)	60.0 (4.30)
Median [Min, Max]	59.0 [46.0, 71.0]	61.0 [48.0, 72.0]	60.0 [46.0, 72.0]
<b>gender</b>			
Female	255 (49.6%)	155 (54.2%)	410 (51.3%)
Male	259 (50.4%)	131 (45.8%)	390 (48.8%)
<b>race</b>			
White	328 (63.8%)	193 (67.5%)	521 (65.1%)
Asian	34 (6.6%)	16 (5.6%)	50 (6.3%)
Black	103 (20.0%)	46 (16.1%)	149 (18.6%)
Hispanic	49 (9.5%)	31 (10.8%)	80 (10.0%)
<b>smoking</b>			
Never_smoked	304 (59.1%)	163 (57.0%)	467 (58.4%)
Former_smoker	157 (30.5%)	91 (31.8%)	248 (31.0%)
Current_smoker	53 (10.3%)	32 (11.2%)	85 (10.6%)
<b>height</b>			
Mean (SD)	170 (6.24)	170 (5.83)	170 (6.09)
Median [Min, Max]	170 [150, 187]	170 [152, 190]	170 [150, 190]
<b>weight</b>			
Mean (SD)	79.0 (7.33)	80.1 (7.09)	79.4 (7.26)
Median [Min, Max]	79.2 [56.6, 105]	79.9 [59.0, 104]	79.3 [56.6, 105]
<b>bmi</b>			
Mean (SD)	27.4 (2.70)	27.9 (2.78)	27.5 (2.74)
Median [Min, Max]	27.4 [19.6, 37.4]	27.9 [19.9, 36.9]	27.6 [19.6, 37.4]
<b>hypertension</b>			
No	332 (64.6%)	100 (35.0%)	432 (54.0%)
Yes	182 (35.4%)	186 (65.0%)	368 (46.0%)
<b>diabetes</b>			
No	437 (85.0%)	242 (84.6%)	679 (84.9%)
Yes	77 (15.0%)	44 (15.4%)	121 (15.1%)
<b>sbp</b>			
Mean (SD)	128 (7.58)	133 (7.62)	130 (7.97)
Median [Min, Max]	128 [109, 154]	134 [111, 153]	130 [109, 154]
<b>ldl</b>			
Mean (SD)	108 (20.5)	113 (18.8)	110 (20.1)
Median [Min, Max]	110 [41.0, 167]	112 [54.0, 174]	111 [41.0, 174]
<b>vaccine</b>			
Not_vaccinated	96 (18.7%)	240 (83.9%)	336 (42.0%)
Vaccinated	418 (81.3%)	46 (16.1%)	464 (58.0%)
<b>depression</b>			
Mean (SD)	6.91 (2.13)	6.90 (2.09)	6.91 (2.12)
Median [Min, Max]	7.00 [0, 13.0]	7.00 [1.00, 13.0]	7.00 [0, 13.0]

Table 2: Descriptive Characteristics of Participants, Stratified by Severity of COVID-19 Infection

	Not_severe	Severe	Total
	(N=514)	(N=286)	(N=800)
<b>gender</b>			
Female	255 (49.6%)	155 (54.2%)	410 (51.3%)
Male	259 (50.4%)	131 (45.8%)	390 (48.8%)
<b>race</b>			
White	328 (63.8%)	193 (67.5%)	521 (65.1%)
Asian	34 (6.6%)	16 (5.6%)	50 (6.3%)
Black	103 (20.0%)	46 (16.1%)	149 (18.6%)
Hispanic	49 (9.5%)	31 (10.8%)	80 (10.0%)
<b>smoking</b>			
Never_smoked	304 (59.1%)	163 (57.0%)	467 (58.4%)
Former_smoker	157 (30.5%)	91 (31.8%)	248 (31.0%)
Current_smoker	53 (10.3%)	32 (11.2%)	85 (10.6%)
<b>hypertension</b>			
No	332 (64.6%)	100 (35.0%)	432 (54.0%)
Yes	182 (35.4%)	186 (65.0%)	368 (46.0%)
<b>diabetes</b>			
No	437 (85.0%)	242 (84.6%)	679 (84.9%)
Yes	77 (15.0%)	44 (15.4%)	121 (15.1%)
<b>vaccine</b>			
Not_vaccinated	96 (18.7%)	240 (83.9%)	336 (42.0%)
Vaccinated	418 (81.3%)	46 (16.1%)	464 (58.0%)

The mean and median ages for both **Severity** groups (Not Severe and Severe) are close, indicating a relatively balanced distribution of age across severity levels. **Height**, **Weight**, and **BMI** have similar mean and median values, suggesting comparable distributions of these variables between the two **severity** groups. The Systolic Blood Pressure (SBP) and LDL cholesterol (LDL) variables show slightly higher mean values in the Severe group compared to the Not Severe group, indicating potential differences in these clinical measures between **severity** levels.

## Descriptive Table of Discrete Variables

```
descriptive_table2 = table1(~ gender + race + smoking + hypertension + diabetes + vaccine | severity,
                             data = training_data,
                             overall = "Total",
                             caption = "Descriptive Characteristics of Participants, Stratified by Severity")

ds_bin = t1kable(descriptive_table2)
ds_bin
```

The distribution of **gender** is relatively balanced in both **severity** groups, with slightly more females in the Not Severe group and slightly more males in the Severe group. The majority of participants in both **severity** groups are White, followed by Black, Asian, and Hispanic participants. The distribution across **race** appears to be consistent between severity levels. The majority of participants in both **severity** groups are non-smokers (Never smoked category), followed by former smokers and current smokers. The distribution of **smoking** status is similar between **severity** levels. The prevalence of **hypertension** and **diabetes** is noticeably higher in the Severe group compared to the Not Severe group, indicating a potential



association between these conditions and COVID-19 **severity**. A significant proportion of participants in the Severe group are not vaccinated, while the majority in the Not Severe group are vaccinated. This suggests a potential protective effect of vaccination against severe COVID-19 infection. The mean and median **depression** scores are similar between **severity** groups, indicating comparable levels of depression risk or severity across severity levels.

## Pre-Processing

Based on the descriptive statistics of the training data, scaling the training data has potential benefits for most of the classification algorithms I plan to use. I will scale the data for the benefits of standardizing the features, model stability, and ensuring that each feature contributes meaningfully to the model training process.

```
# Preprocess the training data by centering and scaling numerical features
t_train = preProcess(training_data,
                      method = c("center", "scale"))
t_train

## Created from 800 samples and 14 variables
##
## Pre-processing:
##   - centered (7)
##   - ignored (7)
##   - scaled (7)

# Apply the preprocessing transformation to the training data to obtain scaled data
scaled_training = predict(t_train, newdata = training_data)

head(scaled_training)

##           age gender  race      smoking      height      weight      bmi
## 1 -0.2402656 Female White Former_smoker  0.04926394 -0.6503925 -0.6351185
## 2 -1.4037793   Male White Former_smoker  0.13130214 -0.5126157 -0.5620324
## 3 -1.1710766   Male Black Former_smoker  0.44304730  1.3887038  0.8996903
## 4 -0.2402656 Female White  Never_smoked  0.27897090 -0.6641702 -0.8178339
## 6  0.9232481   Male White  Never_smoked -0.19685066  1.1682610  1.1920349
## 9  1.6213564 Female White  Never_smoked -0.24607358 -0.4023943 -0.1966017
##  diabetes hypertension      sbp      ldl      vaccine depression
## 1           No              No -1.2354661 -0.7605421      Vaccinated -0.9009419
## 2           Yes              Yes  0.3953052 -1.1594496 Not_vaccinated -2.3169606
## 3           No              No -0.8591342  1.4334492      Vaccinated -0.9009419
## 4           No              No -1.1100221  0.7852245      Vaccinated -1.3729481
## 6           No              Yes  0.2698613 -0.5610883      Vaccinated  0.9870830
## 9           No              Yes  1.0225250 -0.6608152 Not_vaccinated  0.5150768
##      severity
## 1 Not_severe
## 2      Severe
## 3 Not_severe
## 4 Not_severe
## 6 Not_severe
## 9      Severe

# Create the design matrix for training with scaled features, excluding the intercept column
x.train.scaled = model.matrix(severity ~ ., scaled_training)[, -1]

# Extract the scaled target variable (severity) from the scaled training data
y.train.scaled = scaled_training$severity

# Preprocess the test data using the same transformation applied to the training data
t_test = preProcess(test_data,
                    method = c("center", "scale"))
t_test
```

```
## Created from 200 samples and 14 variables
##
## Pre-processing:
##   - centered (7)
##   - ignored (7)
##   - scaled (7)

# Apply the preprocessing transformation to the test data to obtain scaled data
scaled_testing = predict(t_test, newdata = test_data)

# Create the design matrix for testing with scaled features, excluding the intercept column
x.test.scaled = model.matrix(severity ~ ., scaled_testing)[, -1]

# Extract the scaled target variable (severity) from the scaled testing data
y.test.scaled = scaled_training$severity
```

I will compare model performance between scaled and un-scaled data to see if there any benefits from scaling.

## Model training

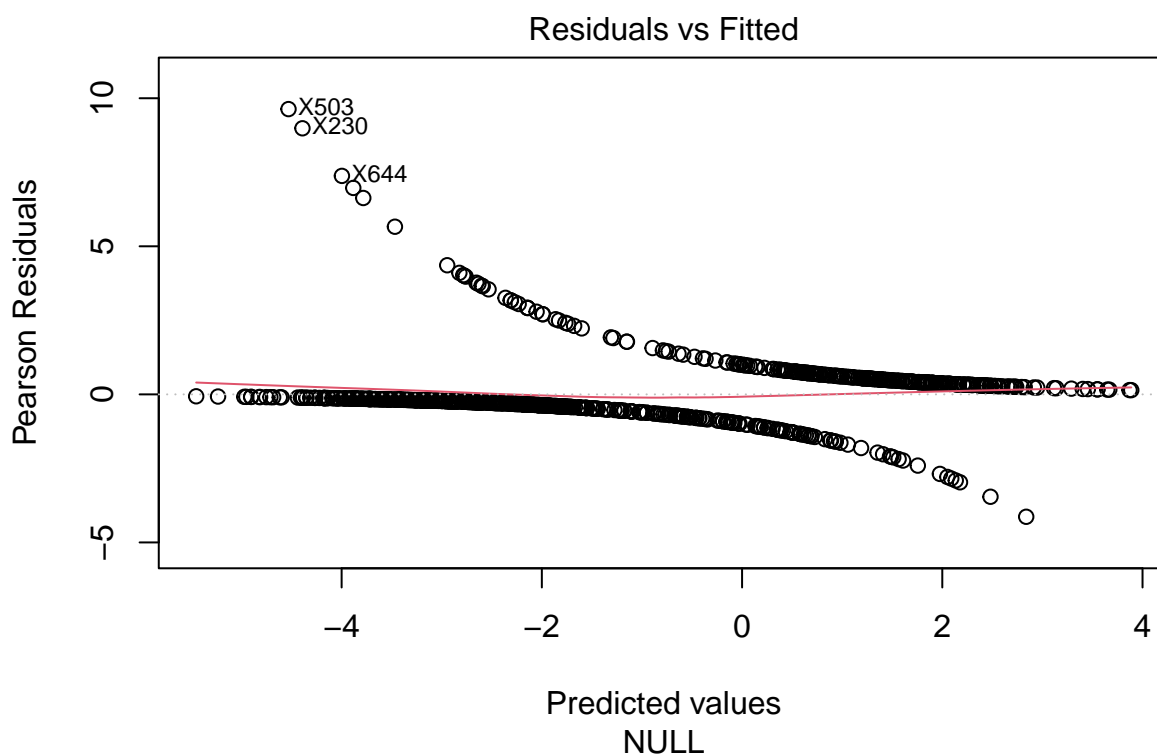
### Logistic Regression

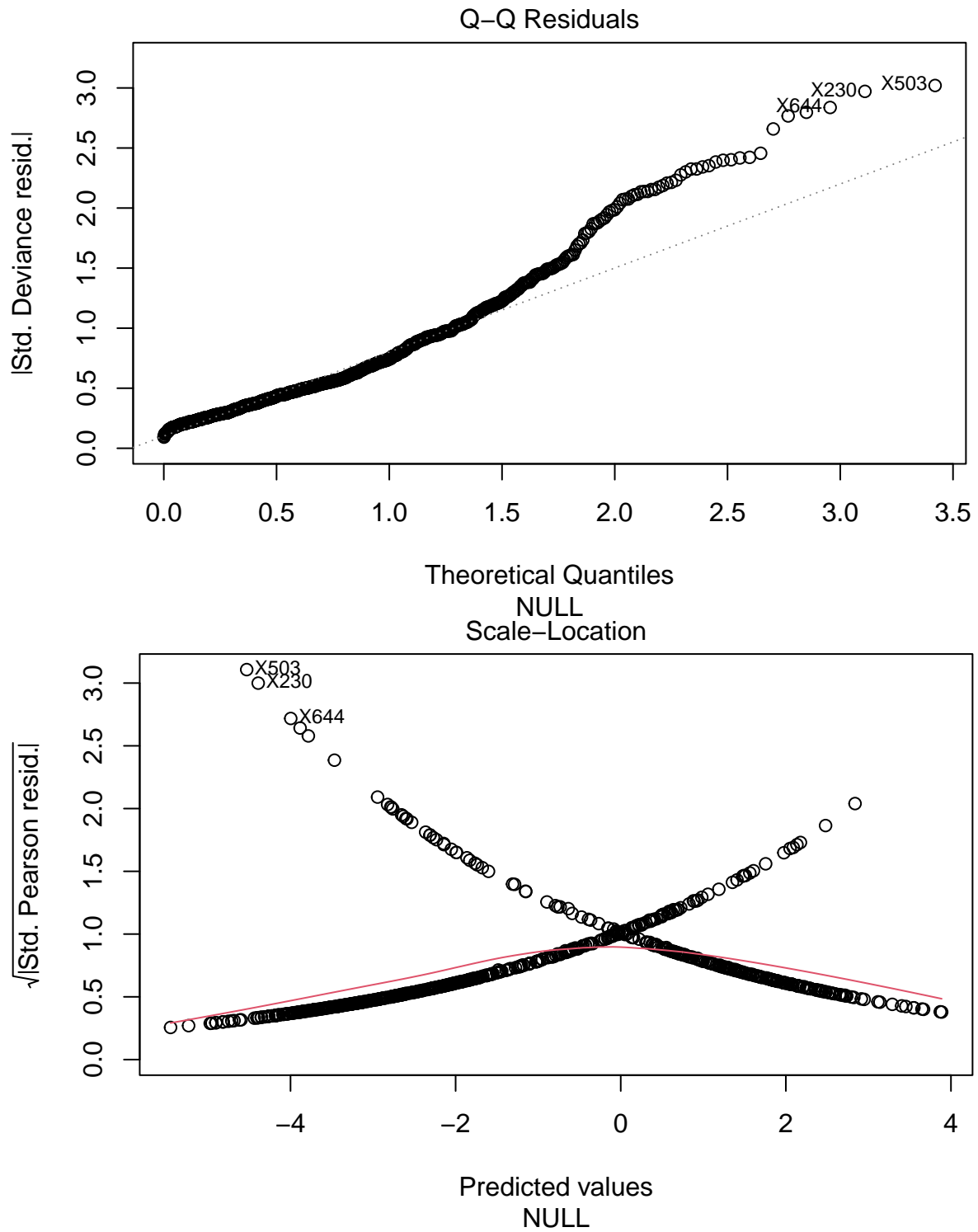
```
# setting a 10-fold cross-validation
ctrl = trainControl(method = "cv", number = 10,
                    summaryFunction = twoClassSummary,
                    classProbs = TRUE)

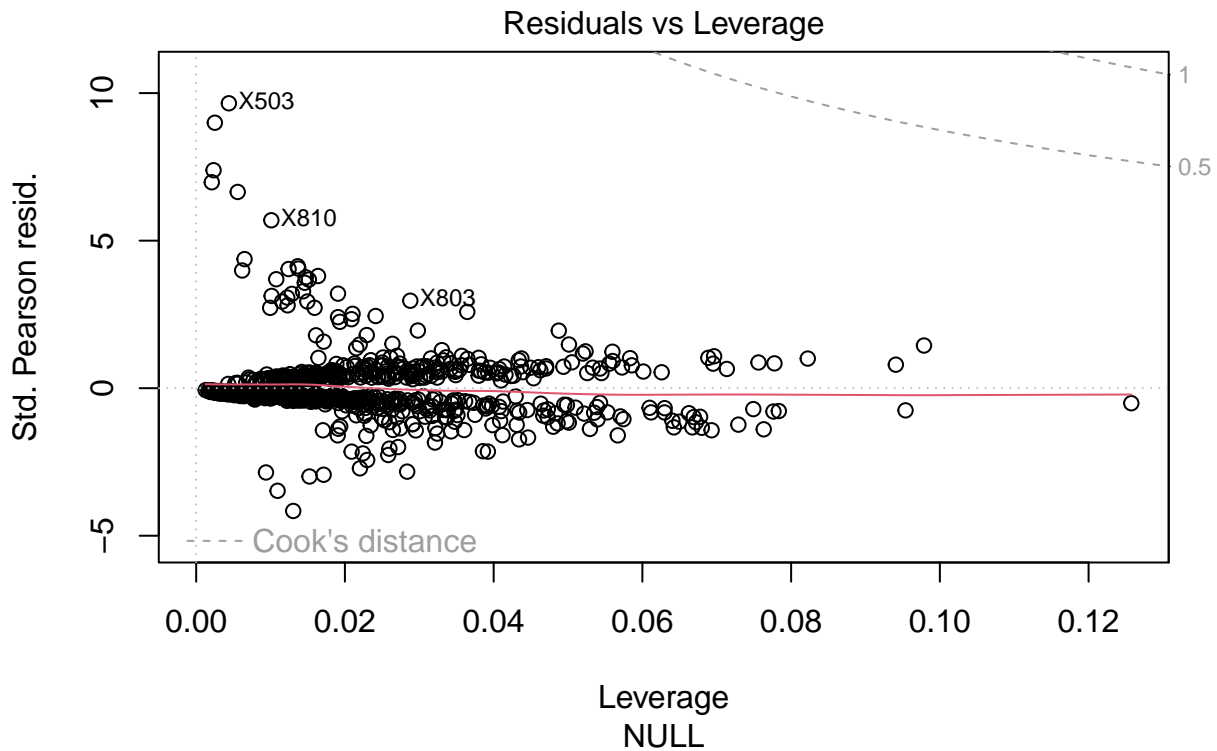
set.seed(2)

# logistic regression
model.glm = train(x = x.train,
                  y = y.train,
                  method = "glm",
                  metric = "ROC",
                  trControl = ctrl)

plot(model.glm$finalModel)
```







```
coef(model.glm$finalModel)
```

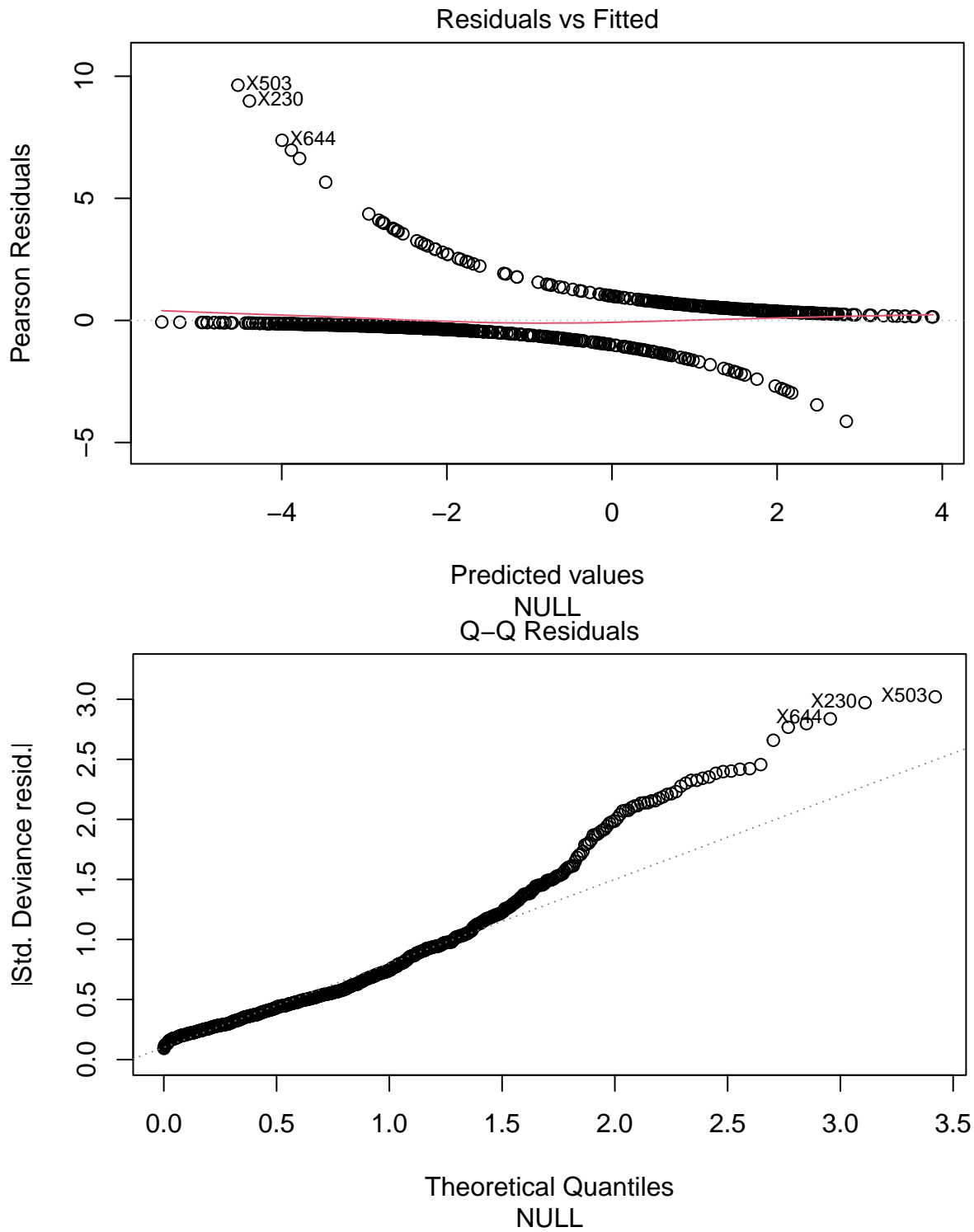
```
##      (Intercept)              age      genderMale
##      -36.14267644      0.06479499      -0.40913157
##      raceAsian      raceBlack      raceHispanic
##      -0.20261995      0.01737165      -0.17462048
##      smokingFormer_smoker smokingCurrent_smoker      height
##      0.02496598      0.49239971      0.11171808
##      weight      bmi      diabetesYes
##      -0.13337473      0.53758507      0.25302775
##      hypertensionYes      sbp      ldl
##      0.38092720      0.07081051      0.01002248
##      vaccineVaccinated      depression
##      -3.61798671      -0.03796927
```

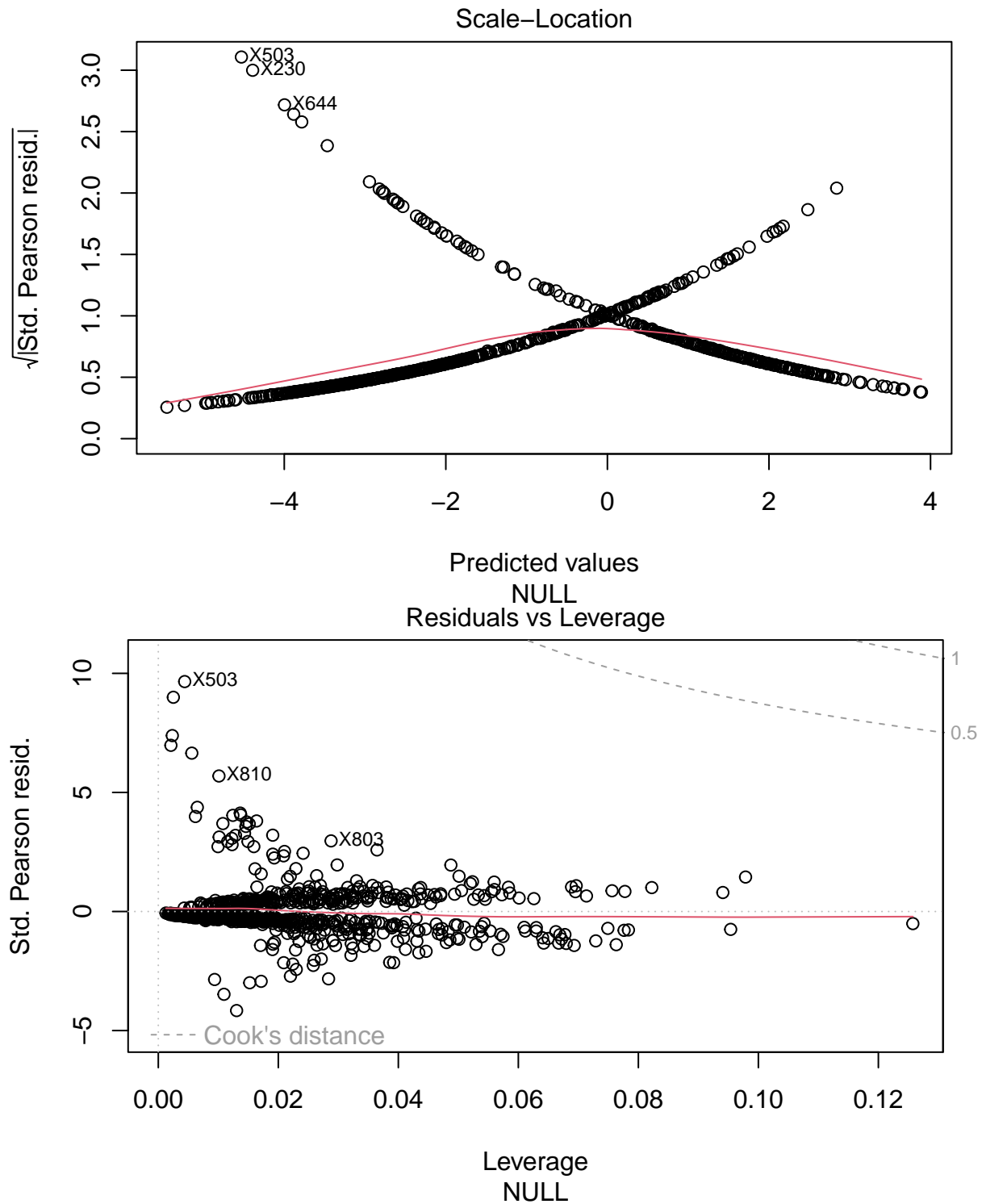
```
set.seed(2)
```

```
# logistic regression scaled
```

```
scaled.model.glm = train(x = x.train.scaled,
                        y = y.train.scaled,
                        method = "glm",
                        metric = "ROC",
                        trControl = ctrl)
```

```
plot(scaled.model.glm$finalModel)
```





```
coef(scaled.model.glm$finalModel)
```

```
##          (Intercept)          age          genderMale
##          0.98782691          0.27844531         -0.40913157
##          raceAsian          raceBlack          raceHispanic
##          -0.20261995          0.01737165         -0.17462048
## smokingFormer_smoker smokingCurrent_smoker          height
```



##	0.02496598	0.49239971	0.68089063
##	weight	bmi	diabetesYes
##	-0.96804941	1.47110001	0.25302775
##	hypertensionYes	sbp	ldl
##	0.38092720	0.56447926	0.20099852
##	vaccineVaccinated	depression	
##	-3.61798671	-0.08044231	

## Penalized Logistic Regression

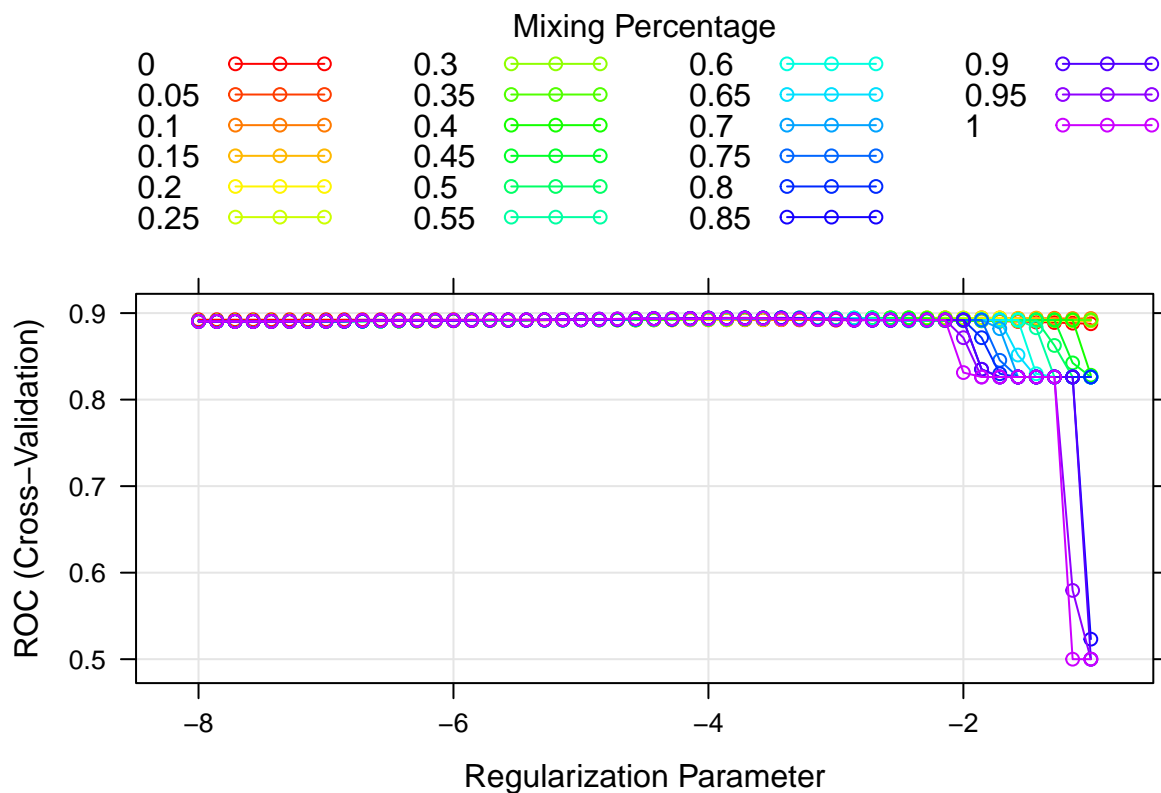
```
# penalized logistic regression - elastic net
glmnetGrid = expand.grid(.alpha = seq(0, 1, length = 21),
                        .lambda = exp(seq(-8, -1, length = 50)))

set.seed(2)
model.glmn = train(x = x.train,
                  y = y.train,
                  method = "glmnet",
                  tuneGrid = glmnetGrid,
                  metric = "ROC",
                  trControl = ctrl)

model.glmn$bestTune

##      alpha      lambda
## 144    0.1 0.156118

myCol = rainbow(25)
myPar = list(superpose.symbol = list(col = myCol),
             superpose.line = list(col = myCol))
plot(model.glmn, par.settings = myPar, xTrans = function(x) log(x))
```

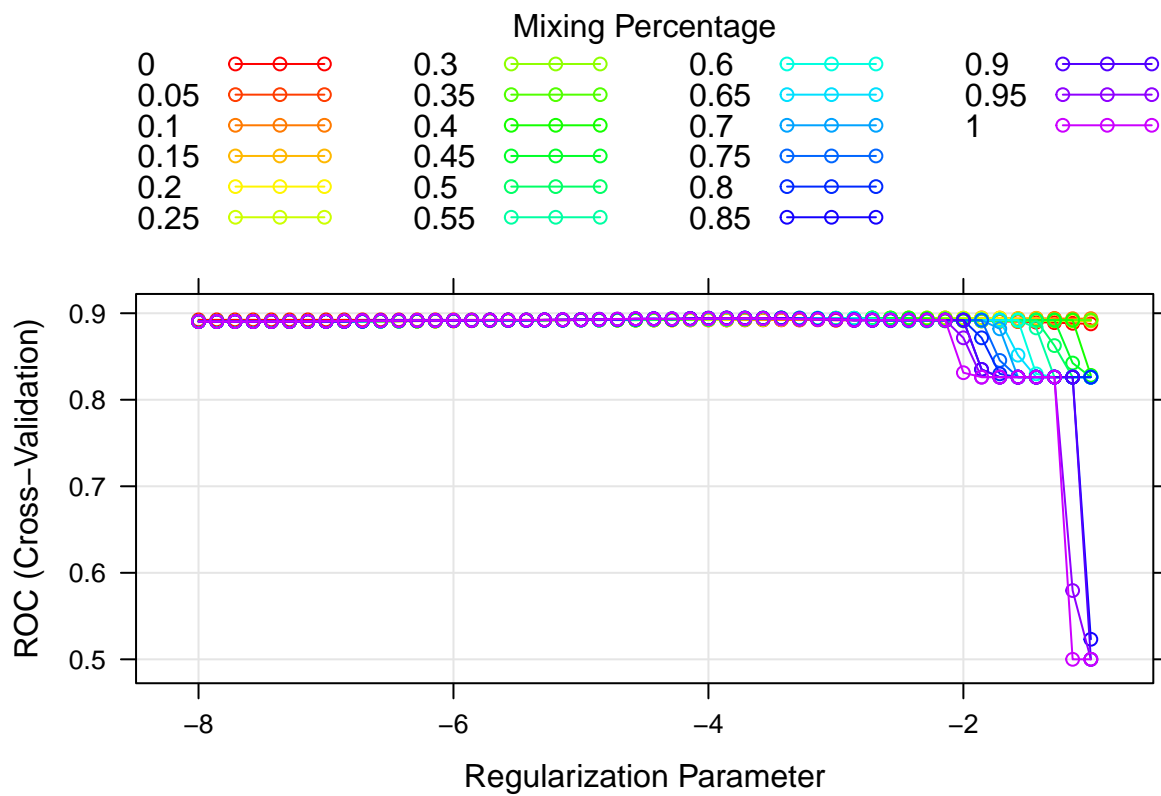


```
# penalized logistic regression - scaled
set.seed(2)
scaled.model.glmn = train(x = x.train.scaled,
                        y = y.train.scaled,
                        method = "glmnet",
                        tuneGrid = glmnetGrid,
                        metric = "ROC",
                        trControl = ctrl)
```

```
scaled.model.glmn$bestTune
```

```
##      alpha  lambda
## 144    0.1 0.156118
```

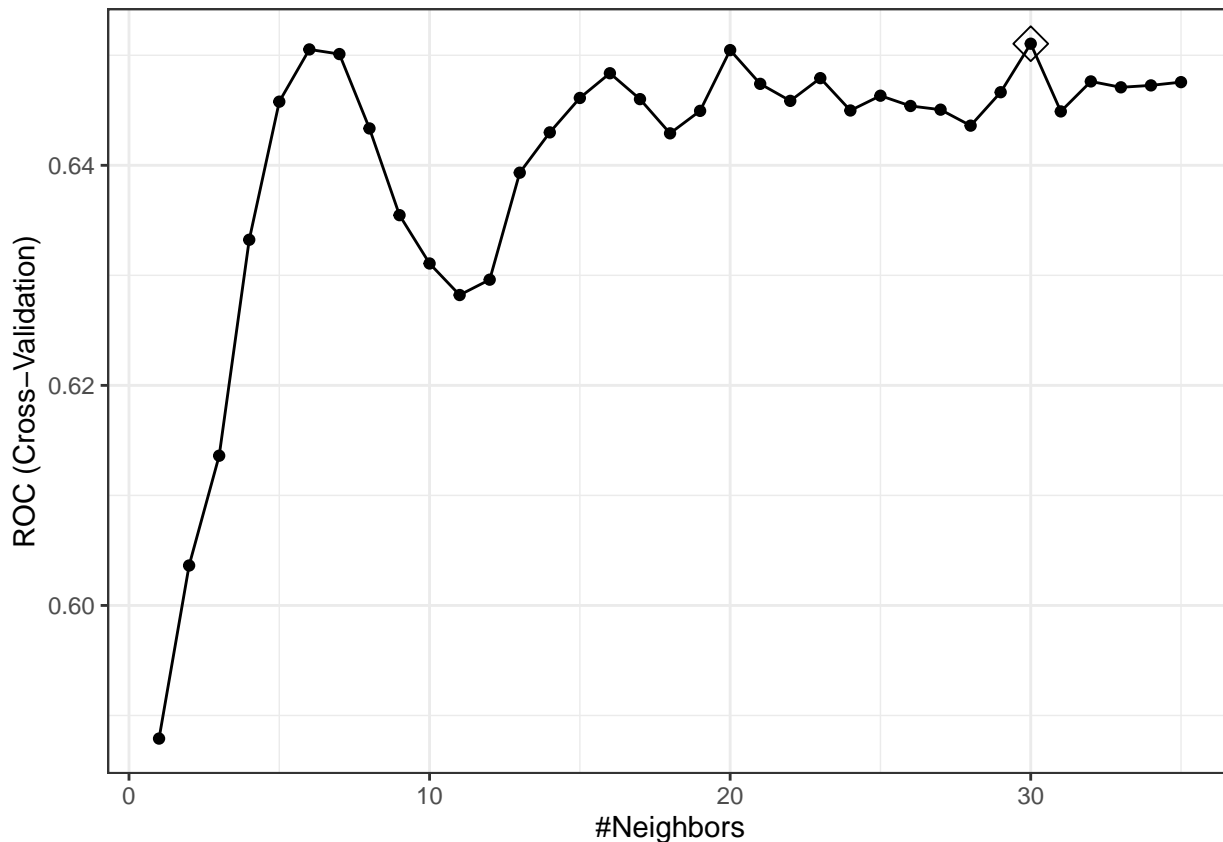
```
myCol = rainbow(25)
myPar = list(superpose.symbol = list(col = myCol),
             superpose.line = list(col = myCol))
plot(scaled.model.glmn, par.settings = myPar, xTrans = function(x) log(x))
```



## KNN - how to tune?

```
# KNN
set.seed(2)
model.knn = train(x.train, y.train,
  method = "knn",
  trControl = ctrl,
  tuneGrid = expand.grid(k = seq(from = 1, to = 35, by = 1)))

ggplot(model.knn, highlight = TRUE) + theme_bw()
```

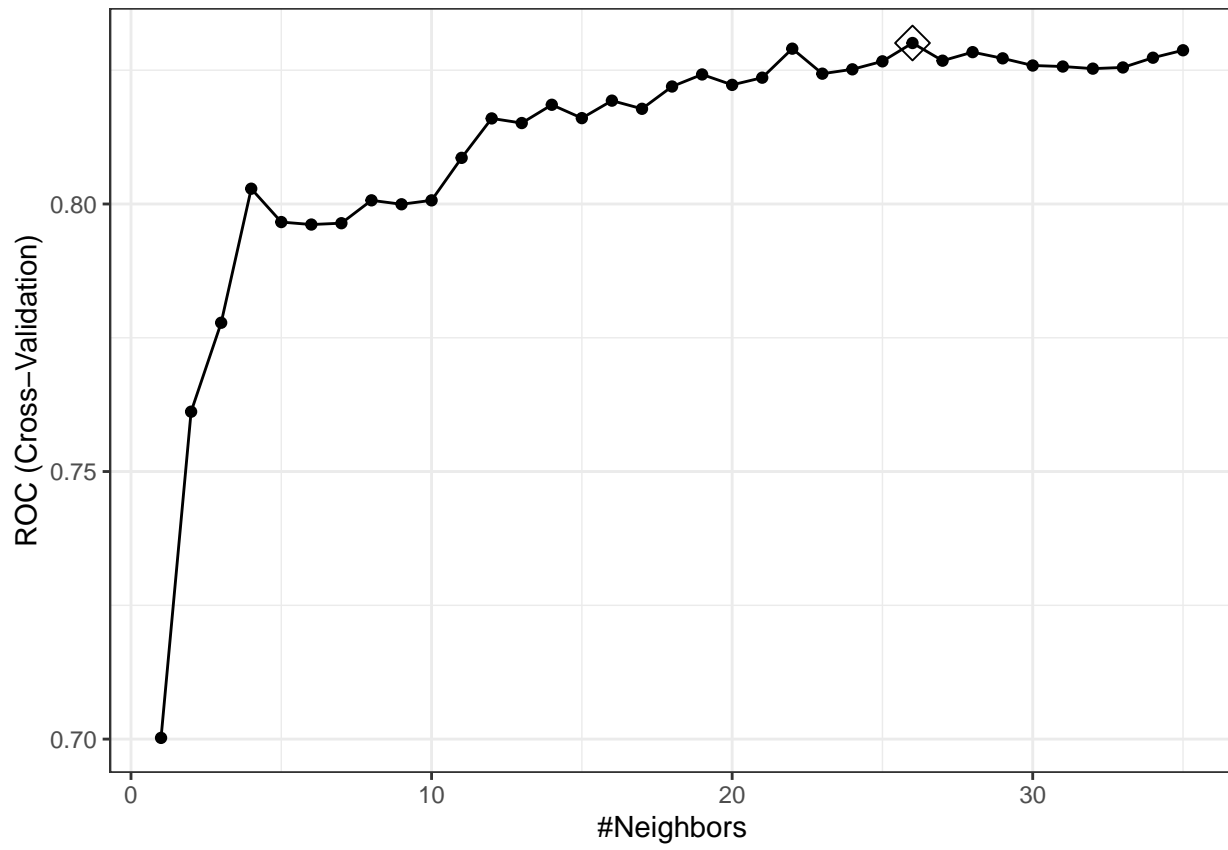


```
model.knn$finalModel
```

```
## 30-nearest neighbor model
## Training set outcome distribution:
##
## Not_severe    Severe
##      514         286
```

```
# KNN scaled
set.seed(2)
scaled.model.knn = train(x.train.scaled, y.train.scaled,
  method = "knn",
  trControl = ctrl,
  tuneGrid = expand.grid(k = seq(from = 1, to = 35, by = 1)))

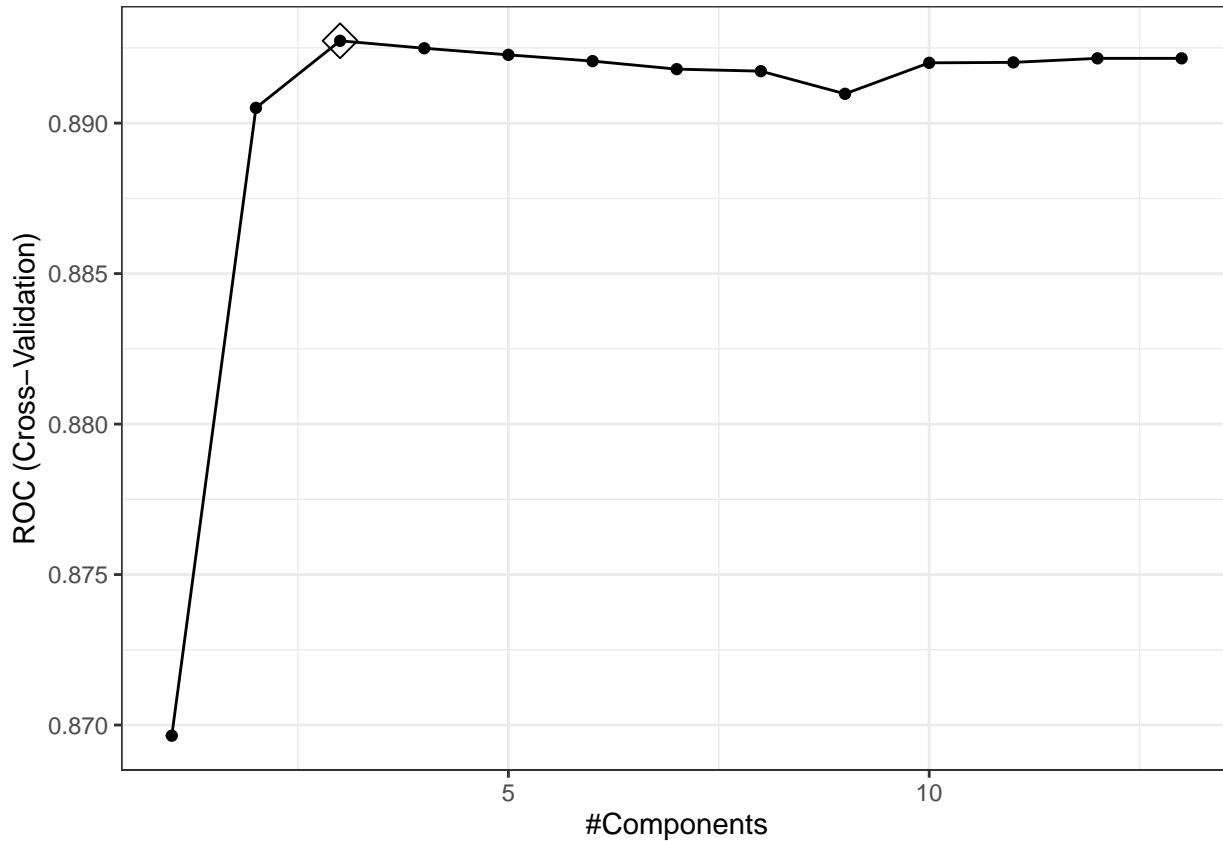
ggplot(scaled.model.knn, highlight = TRUE) + theme_bw()
```



## PLS

```
set.seed(2)
# pls
model.pls = train(x.train, y.train,
  method = "pls",
  tuneGrid = data.frame(ncomp = 1:13),
  trControl = ctrl,
  preProcess = c("center", "scale"))

ggplot(model.pls, highlight = TRUE) + theme_bw()
```



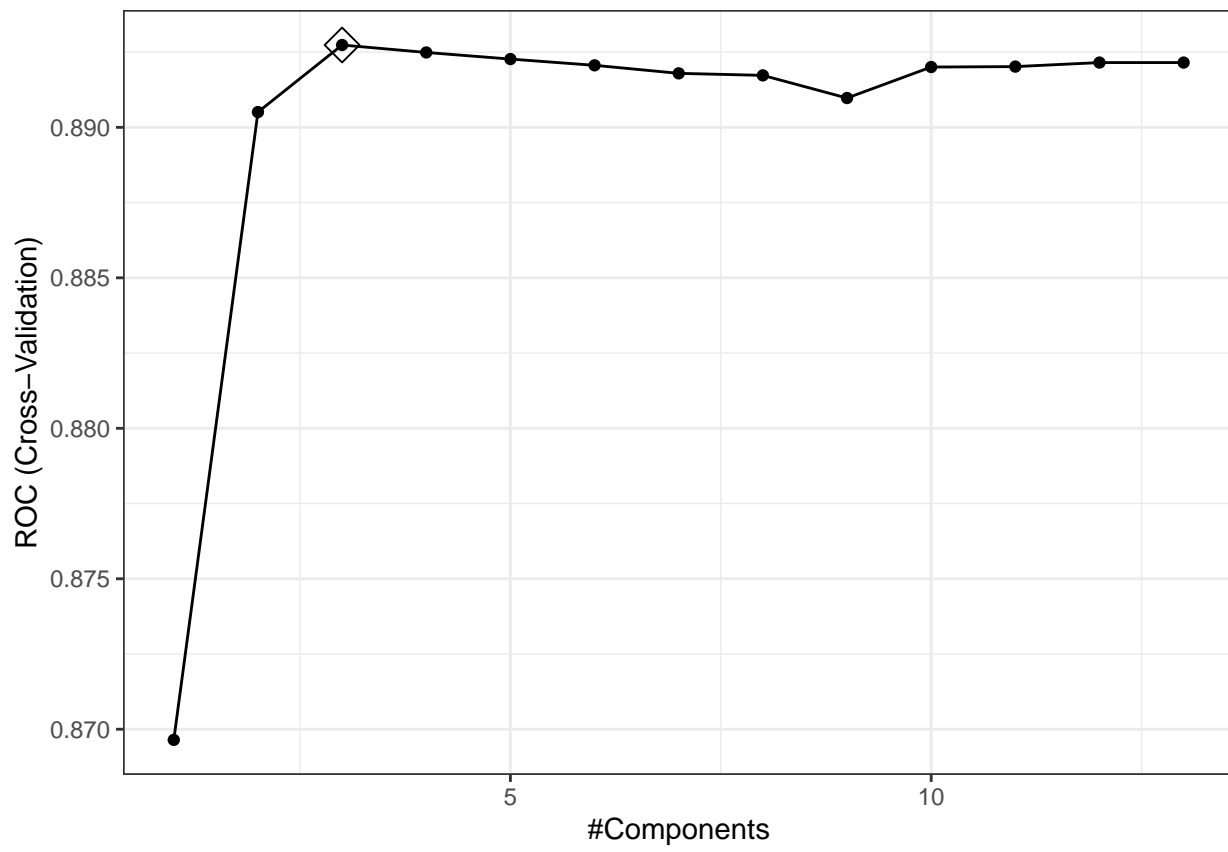
```
model.pls$bestTune
```

```
##  ncomp
##  3      3
```

```
set.seed(2)

# pls scaled
scaled.model.pls = train(x.train.scaled, y.train.scaled,
  method = "pls",
  tuneGrid = data.frame(ncomp = 1:13),
  trControl = ctrl,
  preProcess = c("center", "scale"))

ggplot(scaled.model.pls, highlight = TRUE) + theme_bw()
```



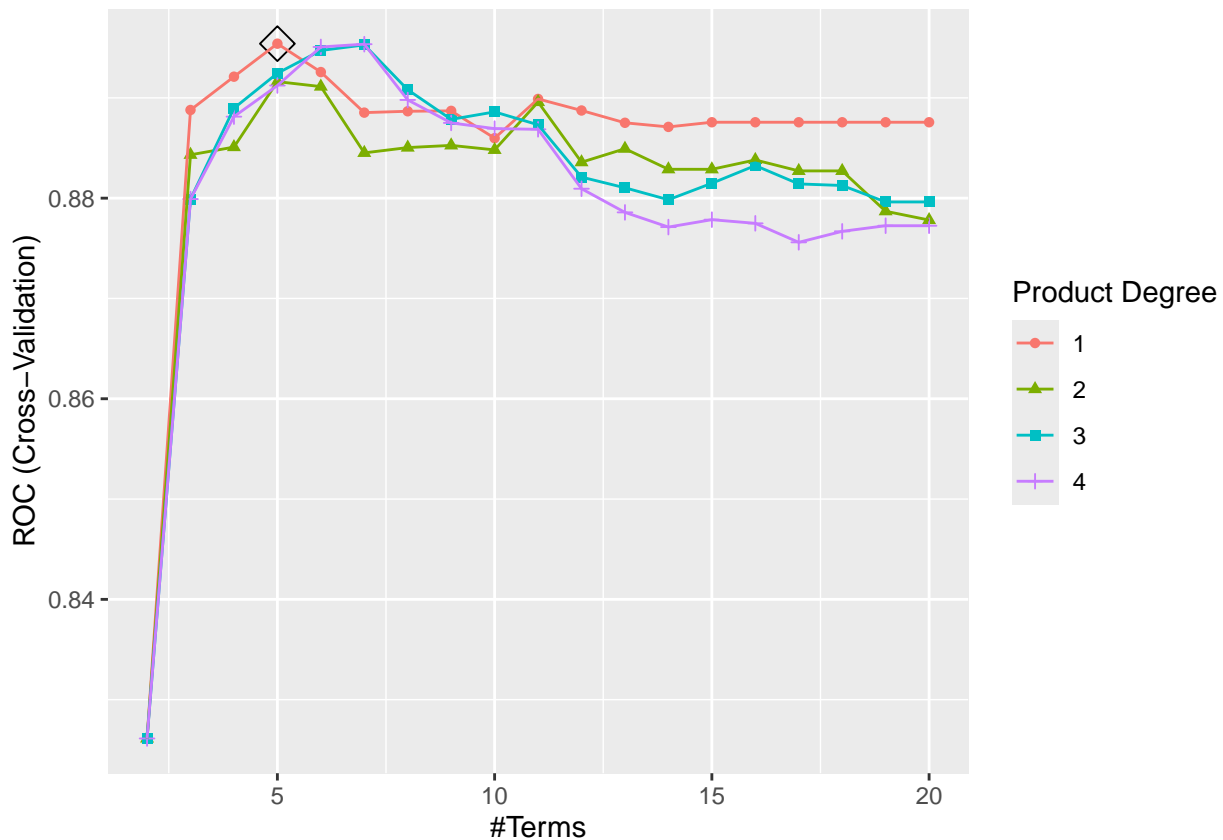
```
model.pls$bestTune
```

```
##   ncomp  
## 3     3
```

## MARS

```
# MARS
set.seed(2)
model.mars = train(x = x.train,
                   y = y.train,
                   method = "earth",
                   tuneGrid = expand.grid(degree = 1:4,
                                         nprune = 2:20),
                   metric = "ROC",
                   trControl = ctrl)

ggplot(model.mars, highlight = TRUE)
```



```
model.mars$bestTune
```

```
##  nprune degree
##  4      5      1
```

```
coef(model.mars$finalModel)
```

```
##      (Intercept) vaccineVaccinated      h(sbp-139)      h(139-sbp)
##      1.98341761      -3.50798169      -0.01515556      -0.13557595
##           h(bmi-27)
##           0.24293455
```

```
# MARS scaled
```

```
set.seed(2)
scaled.model.mars = train(x = x.train.scaled,
```



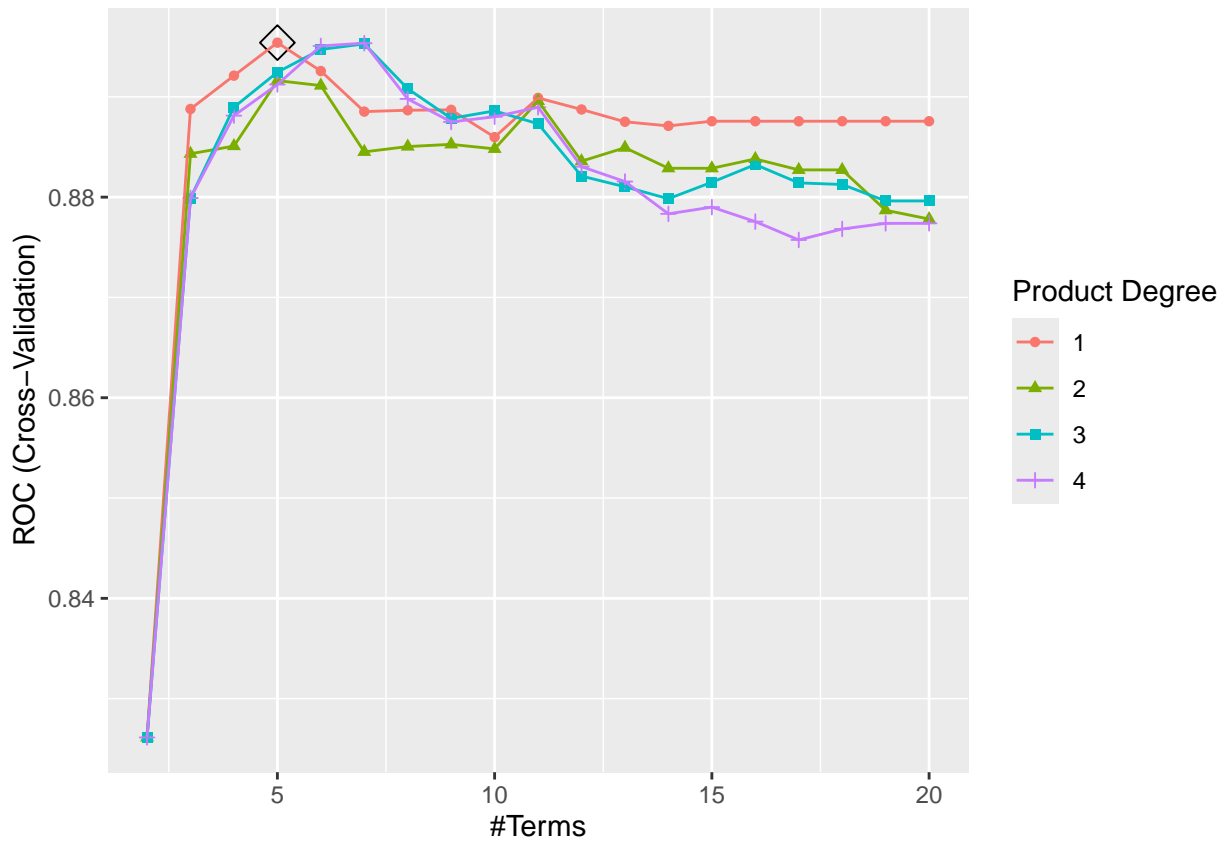
```

y = y.train.scaled,
method = "earth",
tuneGrid = expand.grid(degree = 1:4,
                      nprune = 2:20),

metric = "ROC",
trControl = ctrl)

ggplot(scaled.model.mars, highlight = TRUE)

```



```
scaled.model.mars$bestTune
```

```
##  nprune degree
## 4      5      1
```

```
coef(scaled.model.mars$finalModel)
```

```
##      (Intercept) vaccineVaccinated      h(sbp-1.14797)      h(1.14797-sbp)
##      1.9834176      -3.5079817      -0.1208154      -1.0807692
## h(bmi- -0.196602)
##      0.6647897
```

## GAM

```

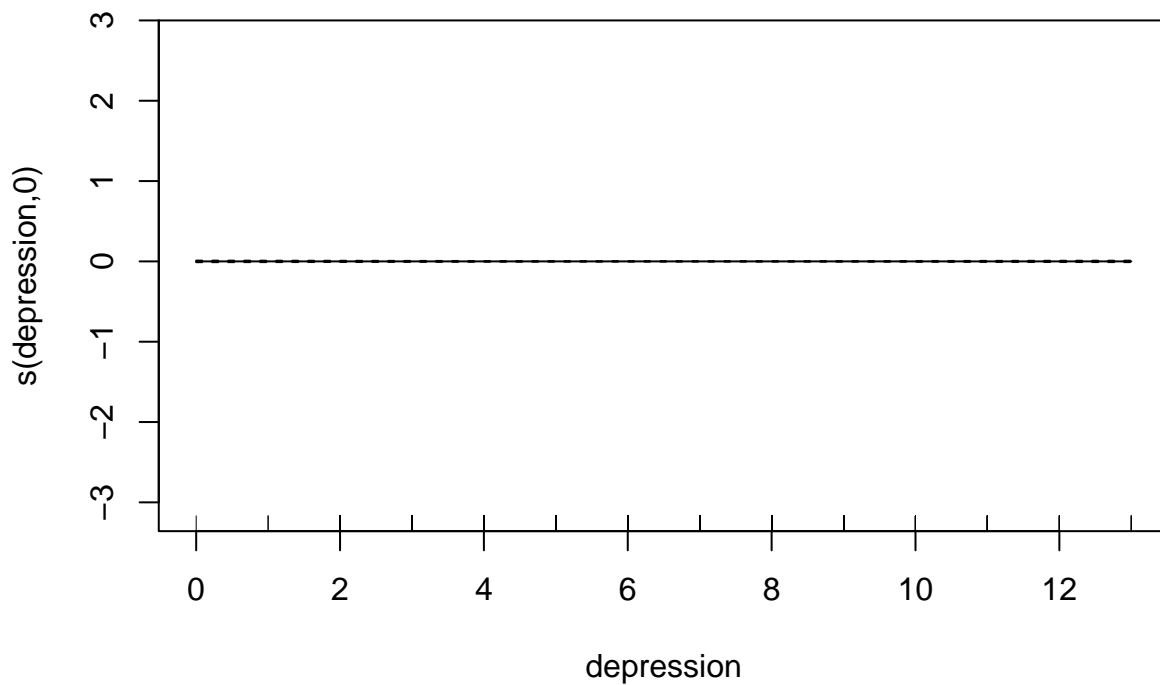
set.seed(2)

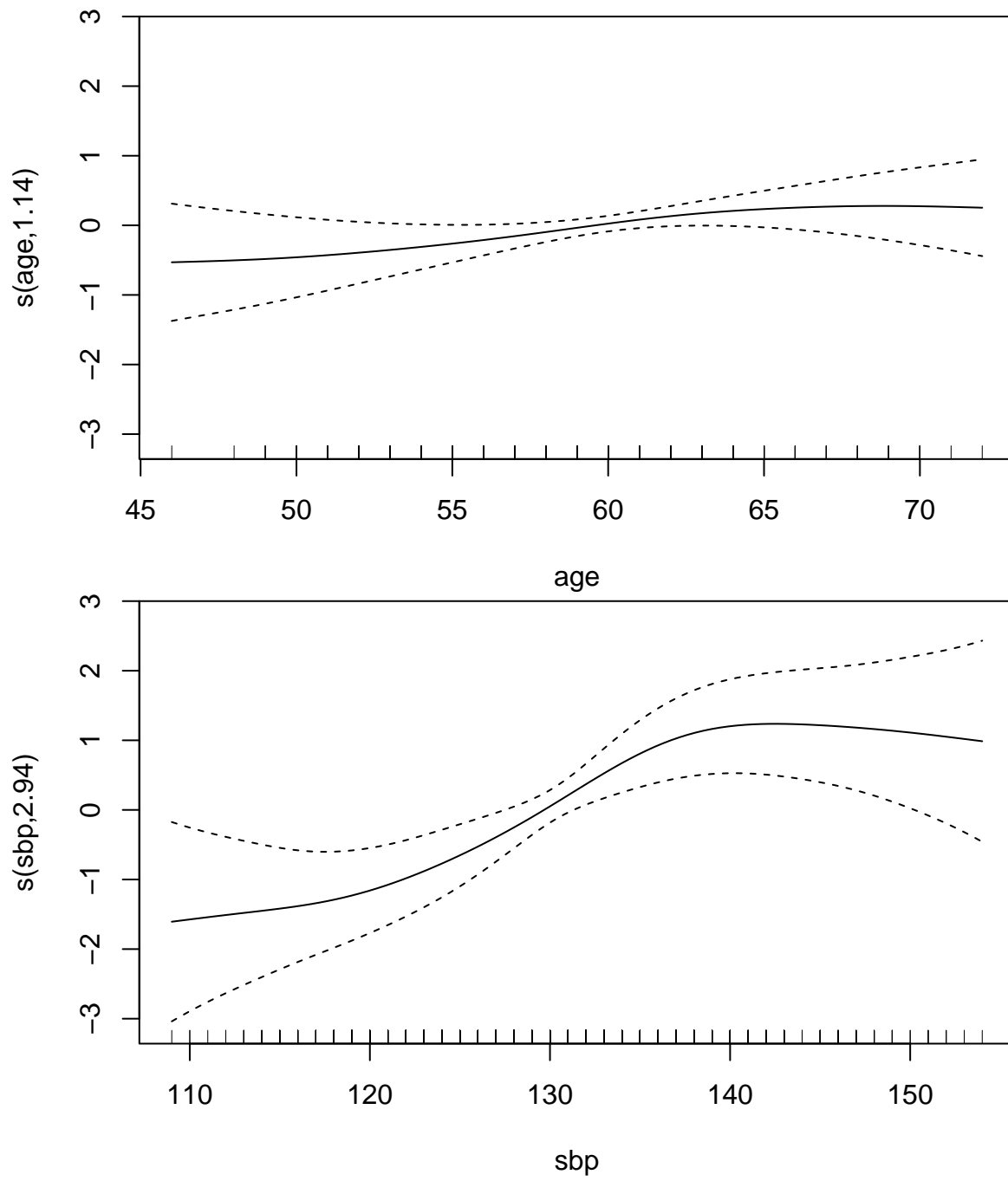
model.gam = train(x = x.train,
                  y = y.train,
                  method = "gam",
                  metric = "ROC",
                  trControl = ctrl)

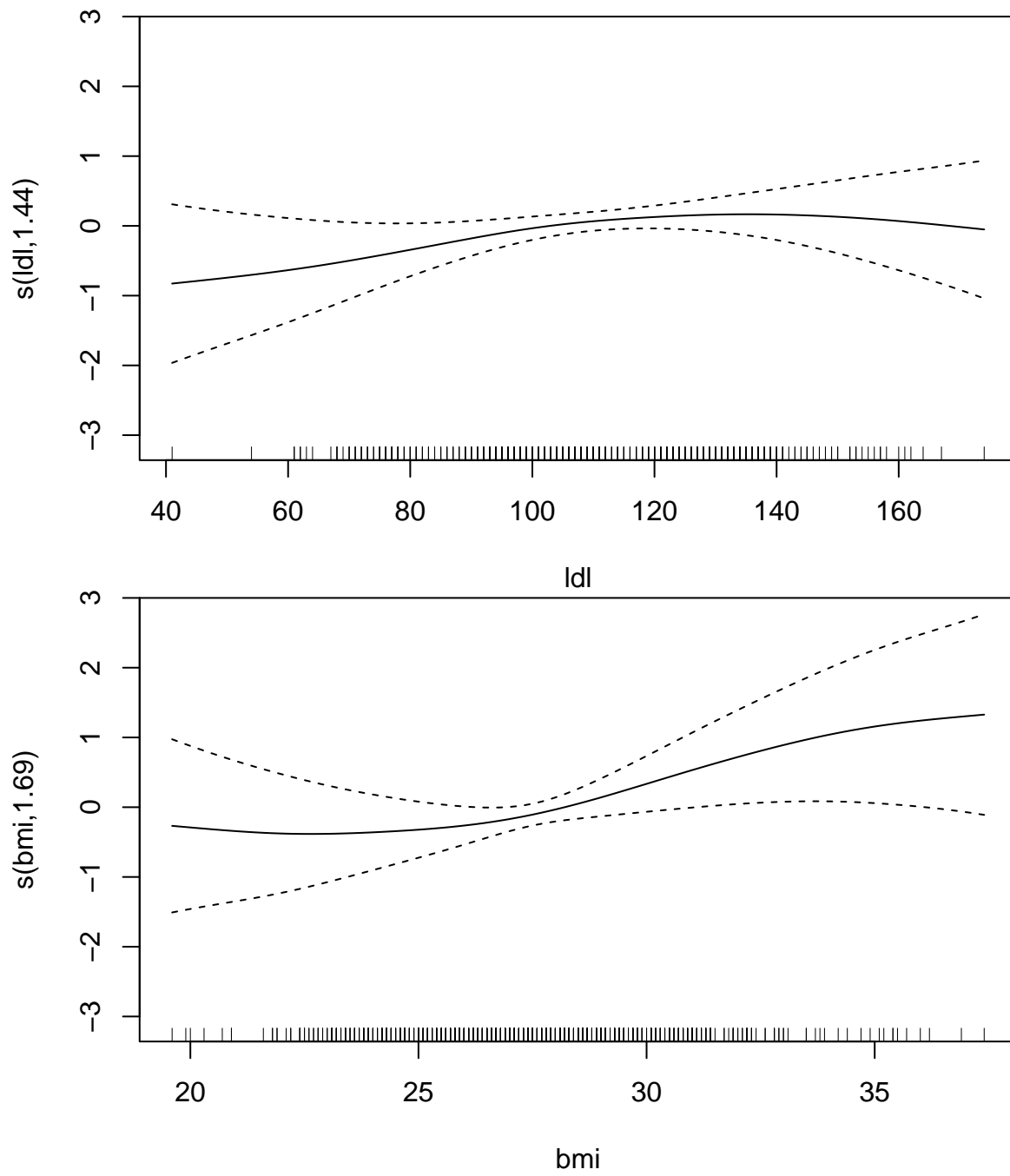
model.gam$finalModel

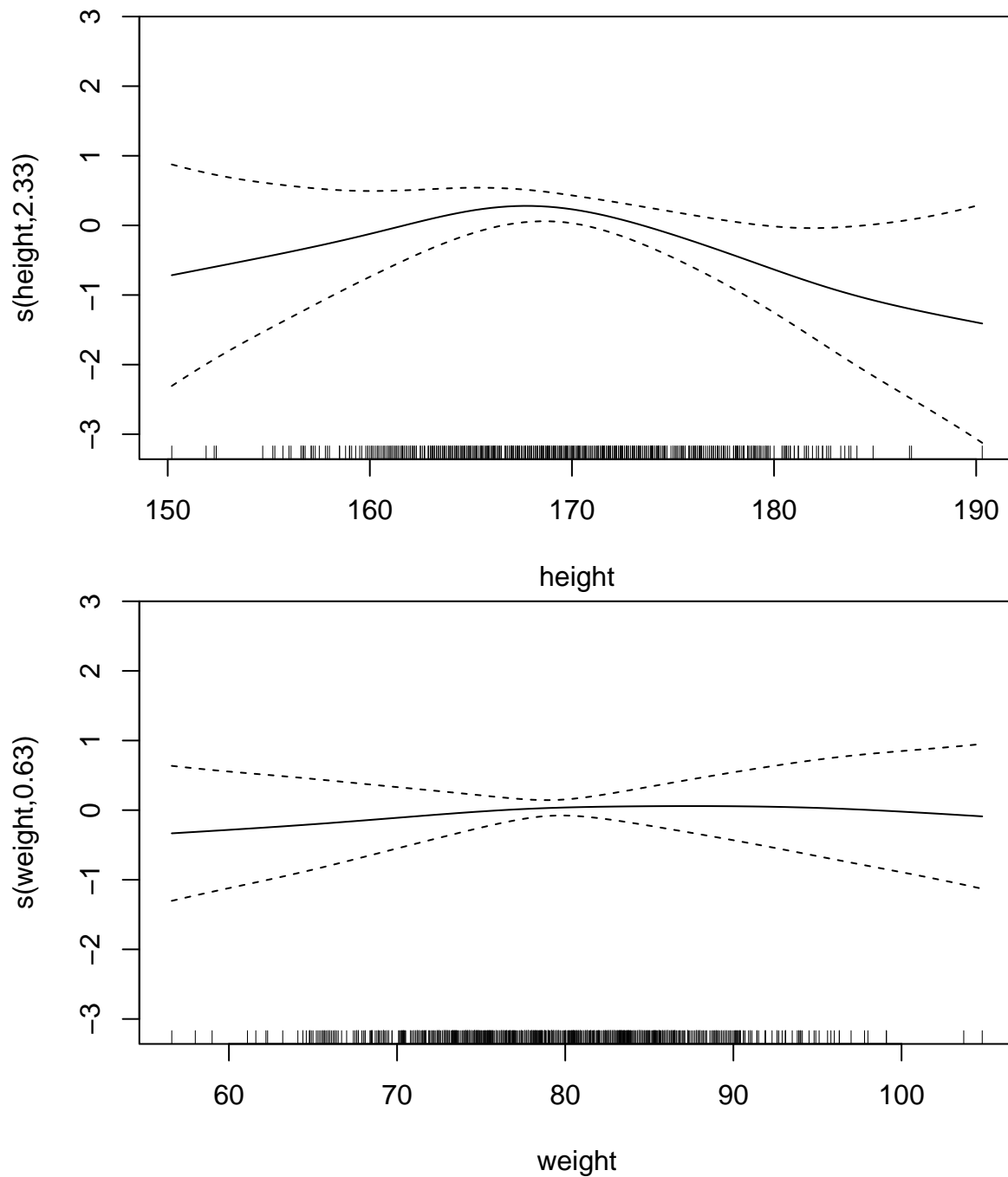
##
## Family: binomial
## Link function: logit
##
## Formula:
## .outcome ~ genderMale + raceAsian + raceBlack + raceHispanic +
##   smokingFormer_smoker + smokingCurrent_smoker + diabetesYes +
##   hypertensionYes + vaccineVaccinated + s(depression) + s(age) +
##   s(sbp) + s(ldl) + s(bmi) + s(height) + s(weight)
##
## Estimated degrees of freedom:
## 0.0003 1.1386 2.9397 1.4411 1.6912 2.3301 0.6288
## total = 20.17
##
## UBRE score: -0.2327168
plot(model.gam$finalModel)

```









```
coef(model.gam)
```

```
## NULL
```

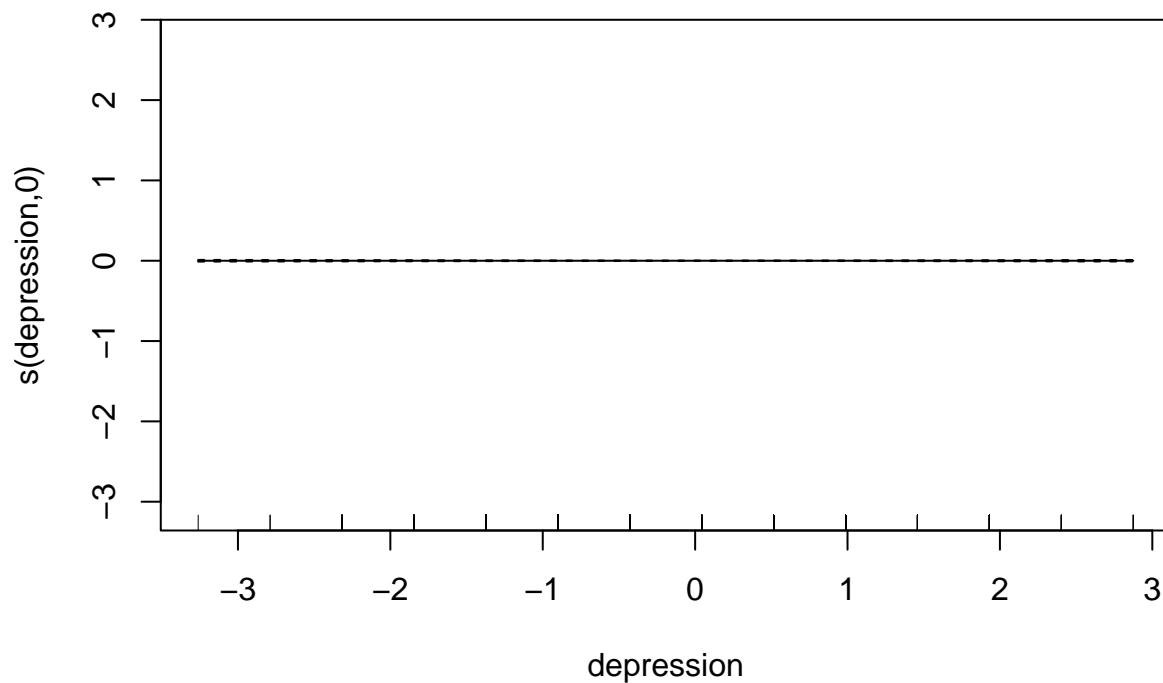
```
# GAM scaled  
set.seed(2)
```

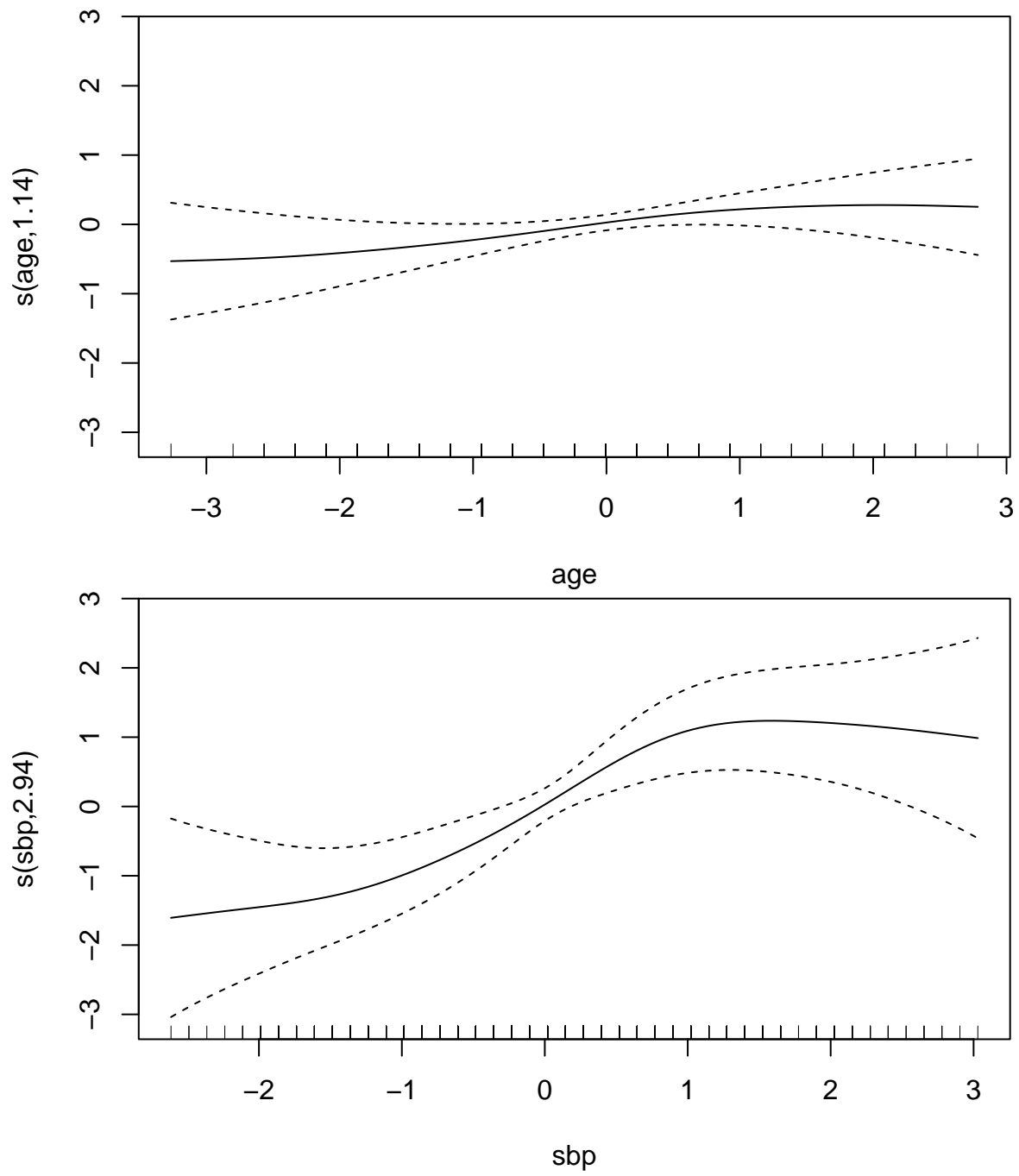
```
scaled.model.gam = train(x = x.train.scaled,  
                          y = y.train.scaled,  
                          method = "gam",  
                          metric = "ROC",  
                          trControl = ctrl)
```

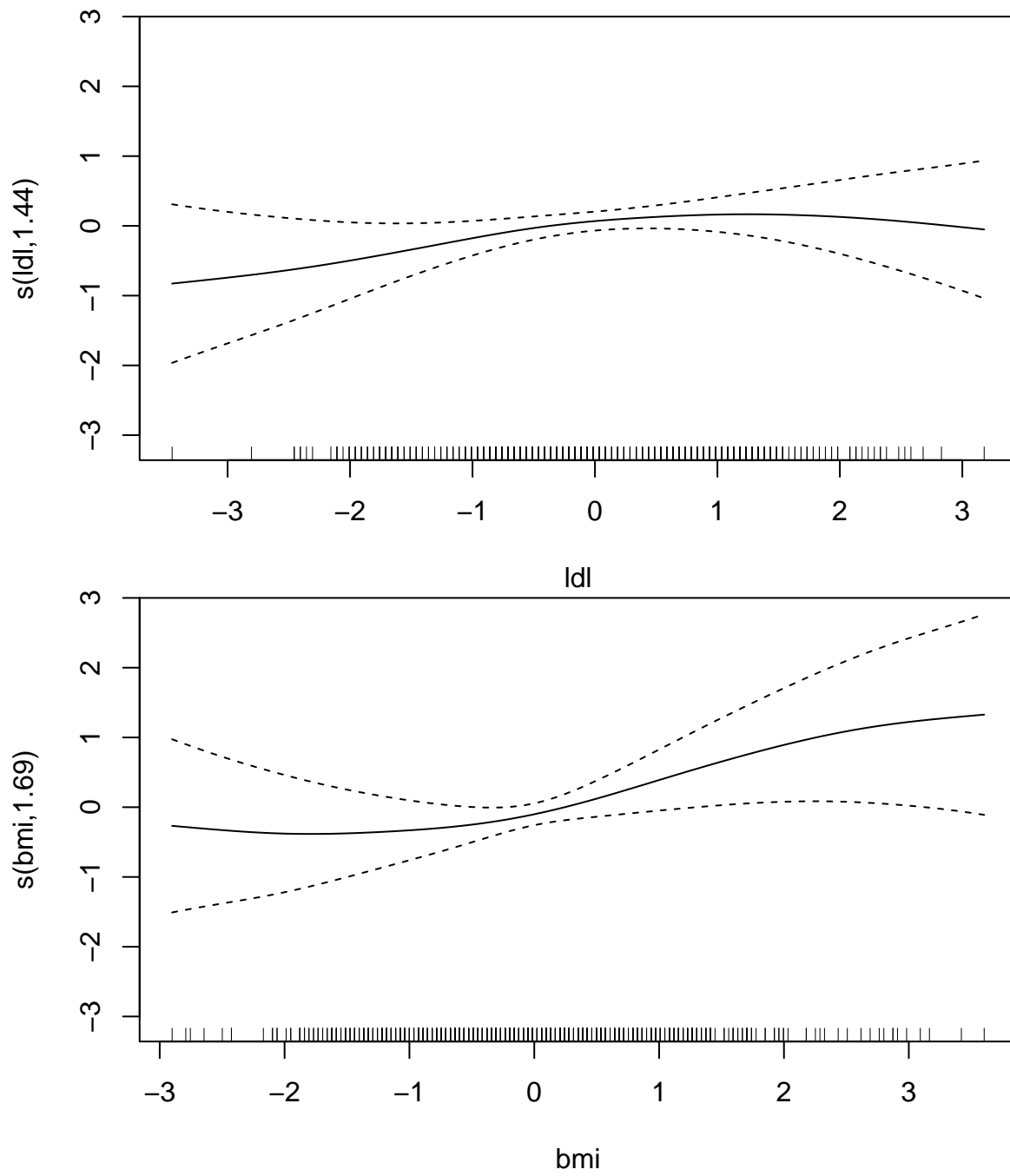
```
scaled.model.gam$finalModel
```

```
##  
## Family: binomial  
## Link function: logit  
##  
## Formula:  
## .outcome ~ genderMale + raceAsian + raceBlack + raceHispanic +  
##   smokingFormer_smoker + smokingCurrent_smoker + diabetesYes +  
##   hypertensionYes + vaccineVaccinated + s(depression) + s(age) +  
##   s(sbp) + s(ldl) + s(bmi) + s(height) + s(weight)  
##  
## Estimated degrees of freedom:  
## 0.0003 1.1386 2.9397 1.4411 1.6912 2.3301 0.6288  
## total = 20.17  
##  
## UBRE score: -0.2327167
```

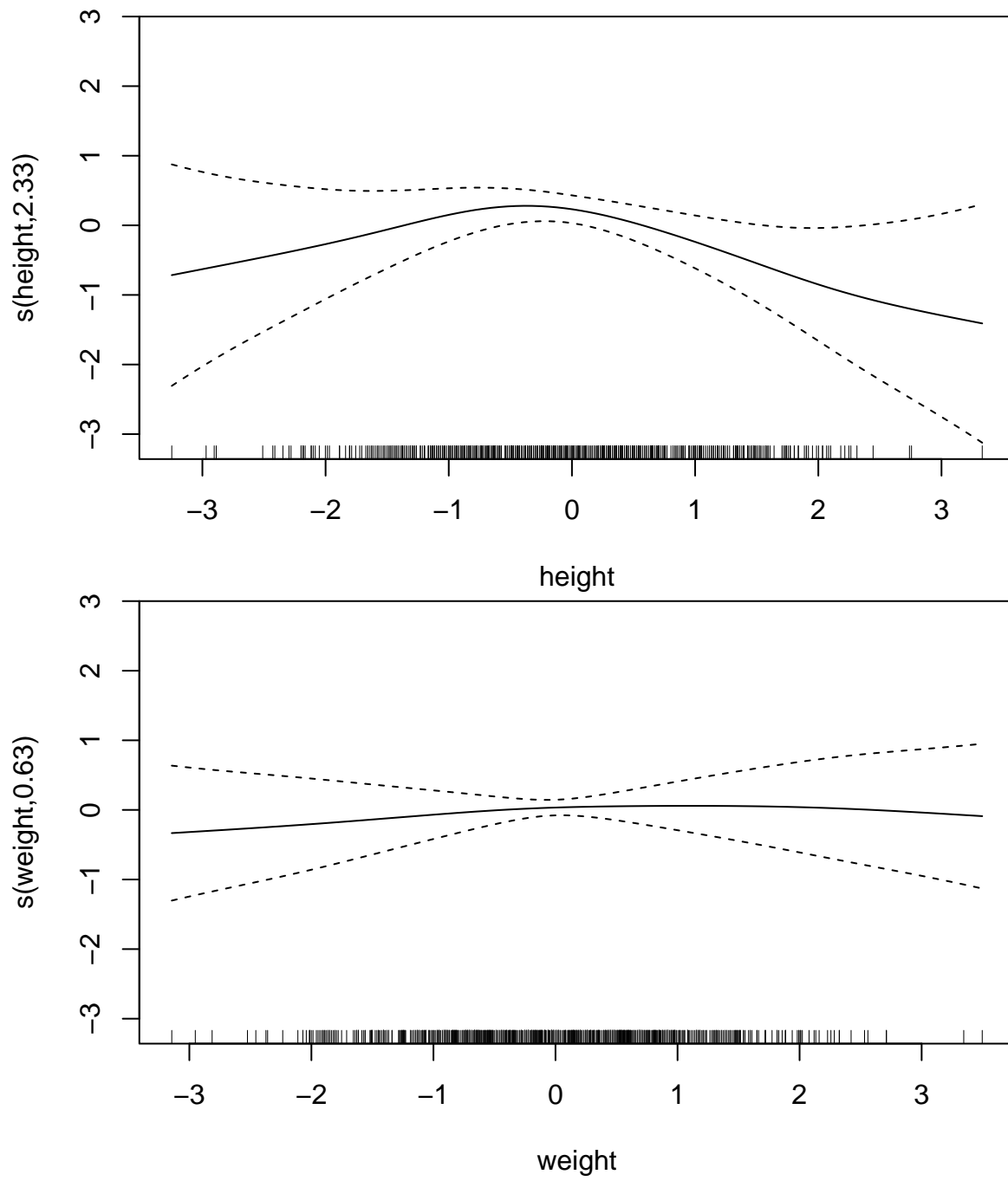
```
plot(scaled.model.gam$finalModel)
```











## LDA

```

set.seed(2)
model.lda = train(x = x.train,
                  y = y.train,
                  method = "lda",
                  metric = "ROC",
                  trControl = ctrl)

model.lda$finalModel

## Call:
## lda(x, grouping = y)
##
## Prior probabilities of groups:
## Not_severe      Severe
##      0.6425      0.3575
##
## Group means:
##              age genderMale  raceAsian raceBlack raceHispanic
## Not_severe  59.46887  0.5038911 0.06614786 0.2003891  0.09533074
## Severe     61.04545  0.4580420 0.05594406 0.1608392  0.10839161
##              smokingFormer_smoker smokingCurrent_smoker  height  weight
## Not_severe              0.3054475              0.1031128 170.1516 79.04125
## Severe              0.3181818              0.1118881 169.7269 80.10245
##              bmi diabetesYes hypertensionYes      sbp      ldl
## Not_severe  27.35331  0.1498054              0.3540856 128.0272 108.4689
## Severe     27.86993  0.1538462              0.6503497 133.1224 113.4580
##              vaccineVaccinated depression
## Not_severe              0.8132296  6.912451
## Severe              0.1608392  6.902098
##
## Coefficients of linear discriminants:
##              LD1
## age              0.034385337
## genderMale       -0.236369596
## raceAsian        -0.126074229
## raceBlack         0.007697045
## raceHispanic     -0.114853112
## smokingFormer_smoker 0.027814955
## smokingCurrent_smoker 0.248324764
## height           0.067561771
## weight          -0.077322293
## bmi              0.301287096
## diabetesYes      0.144018177
## hypertensionYes  0.215120572
## sbp              0.036100853
## ldl              0.004588793
## vaccineVaccinated -2.478676582
## depression       -0.010600382

coef(model.lda)

## NULL

```

```

# LDA scaled
set.seed(2)
scaled.model.lda = train(x = x.train.scaled,
                        y = y.train.scaled,
                        method = "lda",
                        metric = "ROC",
                        trControl = ctrl)

scaled.model.lda$finalModel

## Call:
## lda(x, grouping = y)
##
## Prior probabilities of groups:
## Not_severe      Severe
##      0.6425      0.3575
##
## Group means:
##               age genderMale  raceAsian raceBlack raceHispanic
## Not_severe -0.1311579  0.5038911 0.06614786 0.2003891  0.09533074
## Severe      0.2357173  0.4580420 0.05594406 0.1608392  0.10839161
##               smokingFormer_smoker smokingCurrent_smoker      height      weight
## Not_severe           0.3054475                0.1031128  0.02490785 -0.05226974
## Severe              0.3181818                0.1118881 -0.04476446  0.09393932
##               bmi diabetesYes hypertensionYes      sbp      ldl
## Not_severe -0.06749234   0.1498054            0.3540856 -0.2284977 -0.08893784
## Severe      0.12129743   0.1538462            0.6503497  0.4106568  0.15983934
##               vaccineVaccinated  depression
## Not_severe           0.8132296   0.001747066
## Severe              0.1608392 -0.003139832
##
## Coefficients of linear discriminants:
##               LD1
## age              0.147765068
## genderMale       -0.236369596
## raceAsian        -0.126074229
## raceBlack         0.007697045
## raceHispanic     -0.114853112
## smokingFormer_smoker 0.027814955
## smokingCurrent_smoker 0.248324764
## height           0.411770187
## weight          -0.561214252
## bmi              0.824471272
## diabetesYes       0.144018177
## hypertensionYes   0.215120572
## sbp              0.287784736
## ldl              0.092027205
## vaccineVaccinated -2.478676582
## depression       -0.022458139

```

## QDA

```
set.seed(2)
model.qda = train(x = x.train,
                  y = y.train,
                  method = "qda",
                  metric = "ROC",
                  trControl = ctrl)
model.qda$finalModel
```

```
## Call:
## qda(x, grouping = y)
##
## Prior probabilities of groups:
## Not_severe      Severe
##      0.6425      0.3575
##
## Group means:
##               age genderMale  raceAsian raceBlack raceHispanic
## Not_severe  59.46887  0.5038911 0.06614786 0.2003891  0.09533074
## Severe     61.04545  0.4580420 0.05594406 0.1608392  0.10839161
##               smokingFormer_smoker smokingCurrent_smoker  height  weight
## Not_severe              0.3054475              0.1031128 170.1516 79.04125
## Severe              0.3181818              0.1118881 169.7269 80.10245
##               bmi diabetesYes hypertensionYes      sbp      ldl
## Not_severe  27.35331  0.1498054              0.3540856 128.0272 108.4689
## Severe     27.86993  0.1538462              0.6503497 133.1224 113.4580
##               vaccineVaccinated depression
## Not_severe              0.8132296  6.912451
## Severe              0.1608392  6.902098
```

```
coef(model.qda)
```

```
## NULL
```

```
# QDA scaled
```

```
set.seed(2)
scaled.model.qda = train(x = x.train.scaled,
                        y = y.train.scaled,
                        method = "qda",
                        metric = "ROC",
                        trControl = ctrl)
scaled.model.qda$finalModel
```

```
## Call:
## qda(x, grouping = y)
##
## Prior probabilities of groups:
## Not_severe      Severe
##      0.6425      0.3575
##
## Group means:
##               age genderMale  raceAsian raceBlack raceHispanic
## Not_severe -0.1311579  0.5038911 0.06614786 0.2003891  0.09533074
## Severe     0.2357173  0.4580420 0.05594406 0.1608392  0.10839161
##               smokingFormer_smoker smokingCurrent_smoker  height  weight
```

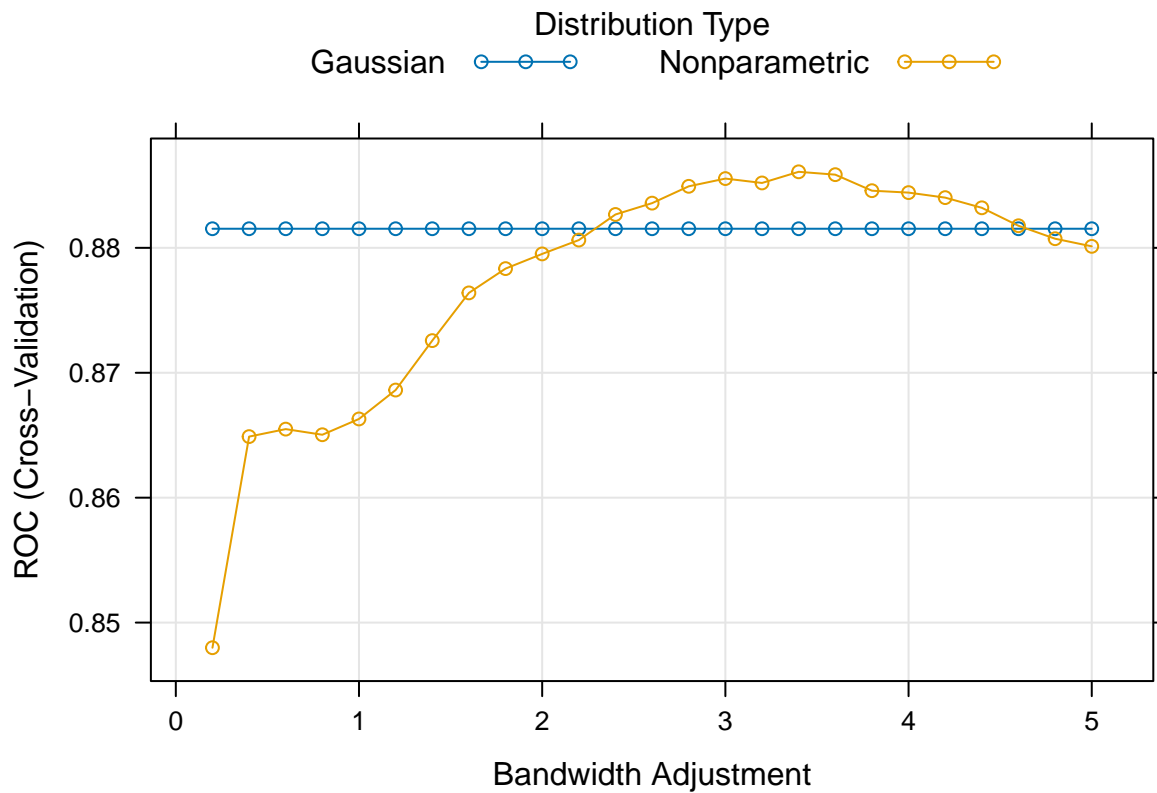
```
## Not_severe      0.3054475      0.1031128  0.02490785 -0.05226974
## Severe          0.3181818      0.1118881 -0.04476446  0.09393932
##                bmi diabetesYes hypertensionYes      sbp      ldl
## Not_severe -0.06749234  0.1498054      0.3540856 -0.2284977 -0.08893784
## Severe      0.12129743  0.1538462      0.6503497  0.4106568  0.15983934
##                vaccineVaccinated  depression
## Not_severe      0.8132296  0.001747066
## Severe          0.1608392 -0.003139832
```

## Naive Bayes (NB)

```
nbGrid = expand.grid(usekernel = c(FALSE, TRUE),
                     fL = 1,
                     adjust = seq(.2, 5, by = .2))

set.seed(2)
model.nb = train(x = x.train,
                 y = y.train,
                 method = "nb",
                 tuneGrid = nbGrid,
                 metric = "ROC",
                 trControl = ctrl)

plot(model.nb)
```



```
model.nb$bestTune
```

```
##      fL usekernel adjust
## 42    1         TRUE   3.4
```

```
model.nb$finalModel
```

```
## $apriori
## grouping
## Not_severe      Severe
##      0.6425      0.3575
##
## $tables
## $tables$age
## $tables$age$Not_severe
##
```

```

## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 3.276
##
##      x      y
## Min.  :36.17  Min.  :3.240e-06
## 1st Qu.:47.34  1st Qu.:5.095e-04
## Median :58.50  Median :8.818e-03
## Mean   :58.50  Mean   :2.237e-02
## 3rd Qu.:69.66  3rd Qu.:4.340e-02
## Max.   :80.83  Max.   :7.341e-02
##
## $tables$age$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 4.071
##
##      x      y
## Min.  :35.79  Min.  :6.120e-06
## 1st Qu.:47.89  1st Qu.:4.830e-04
## Median :60.00  Median :7.734e-03
## Mean   :60.00  Mean   :2.063e-02
## 3rd Qu.:72.11  3rd Qu.:3.977e-02
## Max.   :84.21  Max.   :6.887e-02
##
##
## $tables$genderMale
## $tables$genderMale$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4394
##
##      x      y
## Min.  :-1.3183  Min.  :0.005056
## 1st Qu.: -0.4092  1st Qu.:0.065590
## Median : 0.5000  Median :0.296017
## Mean   : 0.5000  Mean   :0.274341
## 3rd Qu.: 1.4092  3rd Qu.:0.478500
## Max.   : 2.3183  Max.   :0.501583
##
## $tables$genderMale$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4928
##
##      x      y
## Min.  :-1.4783  Min.  :0.004163

```

```

## 1st Qu.: -0.4892 1st Qu.: 0.054802
## Median : 0.5000 Median : 0.249263
## Mean : 0.5000 Mean : 0.252157
## 3rd Qu.: 1.4892 3rd Qu.: 0.451335
## Max. : 2.4783 Max. : 0.503657
##
##
## $tables$raceAsian
## $tables$raceAsian$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2184
##
##      x      y
## Min. : -0.65534 Min. : 0.001356
## 1st Qu.: -0.07767 1st Qu.: 0.058789
## Median : 0.50000 Median : 0.115559
## Mean : 0.50000 Mean : 0.431777
## 3rd Qu.: 1.07767 3rd Qu.: 0.710201
## Max. : 1.65534 Max. : 1.704901
##
## $tables$raceAsian$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.2273
##
##      x      y
## Min. : -0.68188 Min. : 0.001102
## 1st Qu.: -0.09094 1st Qu.: 0.056832
## Median : 0.50000 Median : 0.096677
## Mean : 0.50000 Mean : 0.422084
## 3rd Qu.: 1.09094 3rd Qu.: 0.707112
## Max. : 1.68188 Max. : 1.656538
##
##
## $tables$raceBlack
## $tables$raceBlack$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3518
##
##      x      y
## Min. : -1.0555 Min. : 0.002552
## 1st Qu.: -0.2777 1st Qu.: 0.070360
## Median : 0.5000 Median : 0.244896
## Mean : 0.5000 Mean : 0.320704
## 3rd Qu.: 1.2777 3rd Qu.: 0.517906
## Max. : 2.0555 Max. : 0.910590

```



```

##
## $tables$raceBlack$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3634
##
##      x          y
## Min.   :-1.090   Min.   :0.001981
## 1st Qu.: -0.295   1st Qu.:0.059468
## Median :  0.500   Median :0.203735
## Mean   :  0.500   Mean    :0.313730
## 3rd Qu.:  1.295   3rd Qu.:0.529073
## Max.    :  2.090   Max.    :0.925319
##
##
## $tables$raceHispanic
## $tables$raceHispanic$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2581
##
##      x          y
## Min.   :-0.7743   Min.   :0.001654
## 1st Qu.: -0.1372   1st Qu.:0.077879
## Median :  0.5000   Median :0.143643
## Mean   :  0.5000   Mean    :0.391457
## 3rd Qu.:  1.1372   3rd Qu.:0.651065
## Max.    :  1.7743   Max.    :1.398214
##
## $tables$raceHispanic$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3075
##
##      x          y
## Min.   :-0.9224   Min.   :0.001579
## 1st Qu.: -0.2112   1st Qu.:0.062210
## Median :  0.5000   Median :0.152821
## Mean   :  0.5000   Mean    :0.350712
## 3rd Qu.:  1.2112   3rd Qu.:0.597910
## Max.    :  1.9224   Max.    :1.157318
##
##
## $tables$smokingFormer_smoker
## $tables$smokingFormer_smoker$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)

```

```

##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4048
##
##      x              y
## Min.   :-1.2145   Min.   :0.003377
## 1st Qu.: -0.3572   1st Qu.:0.067287
## Median :  0.5000   Median :0.283394
## Mean   :  0.5000   Mean    :0.290960
## 3rd Qu.:  1.3572   3rd Qu.:0.460554
## Max.    :  2.2145   Max.    :0.699683
##
## $tables$smokingFormer_smoker$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4607
##
##      x              y
## Min.   :-1.382   Min.   :0.003094
## 1st Qu.: -0.441   1st Qu.:0.056076
## Median :  0.500   Median :0.244153
## Mean   :  0.500   Mean    :0.265065
## 3rd Qu.:  1.441   3rd Qu.:0.445425
## Max.    :  2.382   Max.    :0.619975
##
##
## $tables$smokingCurrent_smoker
## $tables$smokingCurrent_smoker$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2673
##
##      x              y
## Min.   :-0.8019   Min.   :0.001728
## 1st Qu.: -0.1509   1st Qu.:0.077124
## Median :  0.5000   Median :0.151115
## Mean   :  0.5000   Mean    :0.383183
## 3rd Qu.:  1.1509   3rd Qu.:0.637338
## Max.    :  1.8019   Max.    :1.338499
##
## $tables$smokingCurrent_smoker$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3118
##
##      x              y
## Min.   :-0.9353   Min.   :0.001607
## 1st Qu.: -0.2177   1st Qu.:0.062239
## Median :  0.5000   Median :0.157377

```

```

## Mean : 0.5000 Mean :0.347555
## 3rd Qu.: 1.2177 3rd Qu.:0.592791
## Max. : 1.9353 Max. :1.137104
##
##
## $tables$height
## $tables$height$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 5.478
##
##      x      y
## Min. :133.8 Min. :2.960e-06
## 1st Qu.:151.1 1st Qu.:3.115e-04
## Median :168.5 Median :5.361e-03
## Mean :168.5 Mean :1.438e-02
## 3rd Qu.:185.9 3rd Qu.:2.806e-02
## Max. :203.2 Max. :4.753e-02
##
## $tables$height$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 5.753
##
##      x      y
## Min. :135.0 Min. :0.0000028
## 1st Qu.:153.2 1st Qu.:0.0002160
## Median :171.3 Median :0.0041101
## Mean :171.3 Mean :0.0137756
## 3rd Qu.:189.4 3rd Qu.:0.0262831
## Max. :207.6 Max. :0.0488791
##
##
## $tables$weight
## $tables$weight$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 6.437
##
##      x      y
## Min. : 37.29 Min. :1.610e-06
## 1st Qu.: 58.99 1st Qu.:1.611e-04
## Median : 80.70 Median :3.327e-03
## Mean : 80.70 Mean :1.151e-02
## 3rd Qu.:102.41 3rd Qu.:2.221e-02
## Max. :124.11 Max. :4.050e-02
##
## $tables$weight$Severe

```

```

##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 6.926
##
##      x              y
## Min.   : 38.22   Min.   :2.520e-06
## 1st Qu.: 59.79   1st Qu.:2.040e-04
## Median : 81.35   Median :3.727e-03
## Mean   : 81.35   Mean    :1.158e-02
## 3rd Qu.:102.91   3rd Qu.:2.215e-02
## Max.   :124.48   Max.    :4.044e-02
##
##
## $tables$bmi
## $tables$bmi$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 2.162
##
##      x              y
## Min.   :13.11   Min.   :5.670e-06
## 1st Qu.:20.81   1st Qu.:6.282e-04
## Median :28.50   Median :9.248e-03
## Mean   :28.50   Mean    :3.246e-02
## 3rd Qu.:36.19   3rd Qu.:6.107e-02
## Max.   :43.89   Max.    :1.176e-01
##
## $tables$bmi$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 2.579
##
##      x              y
## Min.   :12.16   Min.   :1.011e-05
## 1st Qu.:20.28   1st Qu.:7.340e-04
## Median :28.40   Median :1.048e-02
## Mean   :28.40   Mean    :3.076e-02
## 3rd Qu.:36.52   3rd Qu.:5.791e-02
## Max.   :44.64   Max.    :1.075e-01
##
##
## $tables$diabetesYes
## $tables$diabetesYes$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3137

```

```

##
##      x              y
##  Min.   :-0.9410   Min.   :0.002137
##  1st Qu.: -0.2205   1st Qu.:0.073069
##  Median :  0.5000   Median :0.198557
##  Mean   :  0.5000   Mean    :0.346180
##  3rd Qu.:  1.2205   3rd Qu.:0.570623
##  Max.    :  1.9410   Max.    :1.082367
##
## $tables$diabetesYes$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3568
##
##      x              y
##  Min.   :-1.0705   Min.   :0.00193
##  1st Qu.: -0.2853   1st Qu.:0.06001
##  Median :  0.5000   Median :0.19888
##  Mean   :  0.5000   Mean    :0.31763
##  3rd Qu.:  1.2853   3rd Qu.:0.53567
##  Max.    :  2.0705   Max.    :0.94928
##
##
## $tables$hypertensionYes
## $tables$hypertensionYes$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4203
##
##      x              y
##  Min.   :-1.2610   Min.   :0.003773
##  1st Qu.: -0.3805   1st Qu.:0.066342
##  Median :  0.5000   Median :0.289537
##  Mean   :  0.5000   Mean    :0.283276
##  3rd Qu.:  1.3805   3rd Qu.:0.450622
##  Max.    :  2.2610   Max.    :0.635073
##
## $tables$hypertensionYes$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4716
##
##      x              y
##  Min.   :-1.4149   Min.   :0.003319
##  1st Qu.: -0.4574   1st Qu.:0.055554
##  Median :  0.5000   Median :0.246724
##  Mean   :  0.5000   Mean    :0.260511
##  3rd Qu.:  1.4574   3rd Qu.:0.441410

```

```

## Max. : 2.4149 Max. :0.586568
##
##
## $tables$sbp
## $tables$sbp$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 5.897
##
##      x      y
## Min. : 91.31 Min. :3.180e-06
## 1st Qu.:111.40 1st Qu.:3.285e-04
## Median :131.50 Median :4.558e-03
## Mean :131.50 Mean :1.243e-02
## 3rd Qu.:151.60 3rd Qu.:2.358e-02
## Max. :171.69 Max. :4.231e-02
##
## $tables$sbp$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 7.184
##
##      x      y
## Min. : 89.45 Min. :5.770e-06
## 1st Qu.:110.72 1st Qu.:3.990e-04
## Median :132.00 Median :4.851e-03
## Mean :132.00 Mean :1.174e-02
## 3rd Qu.:153.28 3rd Qu.:2.218e-02
## Max. :174.55 Max. :3.895e-02
##
##
## $tables$ldl
## $tables$ldl$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 18.04
##
##      x      y
## Min. : -13.13 Min. :5.520e-07
## 1st Qu.: 45.44 1st Qu.:7.124e-05
## Median :104.00 Median :1.469e-03
## Mean :104.00 Mean :4.265e-03
## 3rd Qu.:162.56 3rd Qu.:8.267e-03
## Max. :221.13 Max. :1.447e-02
##
## $tables$ldl$Severe
##
## Call:

```

```

## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 18.42
##
##      x              y
## Min.   : -1.259   Min.   :1.024e-06
## 1st Qu.: 56.370   1st Qu.:7.066e-05
## Median :114.000   Median :1.353e-03
## Mean   :114.000   Mean   :4.334e-03
## 3rd Qu.:171.630   3rd Qu.:8.271e-03
## Max.   :229.259   Max.   :1.523e-02
##
##
## $tables$vaccineVaccinated
## $tables$vaccineVaccinated$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3425
##
##      x              y
## Min.   : -1.0276   Min.   :0.002442
## 1st Qu.: -0.2638   1st Qu.:0.070760
## Median : 0.5000   Median :0.234795
## Mean   : 0.5000   Mean   :0.326552
## 3rd Qu.: 1.2638   3rd Qu.:0.530281
## Max.   : 2.0276   Max.   :0.950099
##
## $tables$vaccineVaccinated$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3634
##
##      x              y
## Min.   : -1.090   Min.   :0.001981
## 1st Qu.: -0.295   1st Qu.:0.059468
## Median : 0.500   Median :0.203735
## Mean   : 0.500   Mean   :0.313730
## 3rd Qu.: 1.295   3rd Qu.:0.529073
## Max.   : 2.090   Max.   :0.925319
##
##
## $tables$depression
## $tables$depression$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 1.874
##
##      x              y

```

```

## Min.      :-5.6225   Min.      :5.960e-06
## 1st Qu.: 0.4388    1st Qu.:8.031e-04
## Median : 6.5000    Median :1.431e-02
## Mean   : 6.5000    Mean   :4.120e-02
## 3rd Qu.:12.5612    3rd Qu.:7.939e-02
## Max.    :18.6225    Max.    :1.401e-01
##
## $tables$depression$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 1.474
##
##      x              y
## Min.   :-3.421   Min.   :1.343e-05
## 1st Qu.: 1.790   1st Qu.:1.617e-03
## Median : 7.000   Median :1.976e-02
## Mean   : 7.000   Mean   :4.793e-02
## 3rd Qu.:12.210   3rd Qu.:8.962e-02
## Max.    :17.421   Max.    :1.615e-01
##
##
##
## $levels
## [1] "Not_severe" "Severe"
##
## $call
## NaiveBayes.default(x = x, grouping = y, usekernel = TRUE, fL = param$fL,
##      adjust = param$adjust)
##
## $x
##      age genderMale raceAsian raceBlack raceHispanic smokingFormer_smoker
## X1     59          0         0         0           0              1
## X2     54          1         0         0           0              1
## X3     55          1         0         1           0              1
## X4     59          0         0         0           0              0
## X6     64          1         0         0           0              0
## X9     67          0         0         0           0              0
## X10    66          1         0         0           0              0
## X11    50          1         0         0           1              1
## X12    67          0         0         0           0              0
## X13    64          1         0         0           0              0
## X14    63          0         0         0           0              0
## X15    53          0         0         0           1              0
## X17    61          1         0         0           0              0
## X18    62          0         0         0           0              0
## X19    58          0         0         0           1              1
## X21    58          1         0         0           0              0
## X22    63          0         0         1           0              0
## X24    55          0         0         0           0              0
## X25    61          0         0         0           0              1
## X26    64          0         0         1           0              0
## X27    63          0         1         0           0              1

```



## X28	59	0	0	0	0	0
## X29	57	1	0	0	0	1
## X30	61	0	0	1	0	0
## X31	66	0	0	1	0	0
## X33	61	1	1	0	0	0
## X36	56	1	0	1	0	0
## X39	63	1	0	1	0	0
## X40	64	0	0	0	0	0
## X41	65	1	0	0	0	0
## X42	55	0	0	1	0	1
## X45	60	1	0	1	0	0
## X46	62	1	0	0	0	1
## X47	55	1	0	0	0	0
## X49	66	0	0	0	0	0
## X54	60	1	0	1	0	0
## X56	61	1	0	0	0	0
## X57	62	1	1	0	0	1
## X59	62	1	0	0	0	1
## X60	55	1	0	0	0	0
## X61	46	1	0	0	0	0
## X62	63	1	0	0	0	1
## X64	66	0	0	0	0	0
## X65	60	1	1	0	0	0
## X67	58	0	0	0	1	1
## X69	65	0	0	0	0	1
## X70	61	0	0	0	0	1
## X72	57	0	1	0	0	0
## X73	58	0	0	0	1	0
## X74	55	0	0	0	0	0
## X75	59	0	0	0	0	1
## X77	65	0	0	0	1	1
## X78	66	1	0	0	0	1
## X79	64	0	0	1	0	0
## X82	59	1	0	0	0	0
## X85	61	0	0	0	0	0
## X87	56	1	1	0	0	0
## X88	49	0	0	0	0	0
## X89	55	1	0	0	0	0
## X90	57	0	0	0	0	0
## X91	65	1	0	1	0	0
## X92	60	0	0	0	0	0
## X93	64	0	0	0	0	0
## X94	60	1	1	0	0	0
## X95	57	0	0	0	0	0
## X96	51	0	0	0	0	0
## X97	60	0	0	0	0	1
## X98	66	0	0	0	0	1
## X99	64	0	1	0	0	1
## X100	64	0	0	0	0	1
## X101	57	0	0	0	0	0
## X102	59	0	0	0	0	1
## X103	61	1	0	1	0	0
## X104	51	1	0	0	0	0
## X105	62	0	0	1	0	0

## X106	57	1	0	0	0	0
## X108	60	0	1	0	0	0
## X109	51	0	0	0	0	0
## X110	58	0	0	0	0	1
## X112	62	1	0	1	0	1
## X113	53	0	0	0	0	0
## X114	57	1	0	0	0	0
## X115	56	1	1	0	0	0
## X116	62	1	0	0	0	1
## X117	64	1	0	0	1	0
## X119	62	1	0	0	0	0
## X120	60	1	0	1	0	0
## X121	59	0	0	1	0	0
## X122	58	0	0	0	0	1
## X123	54	1	0	0	0	0
## X126	63	1	0	0	0	0
## X127	54	1	0	0	0	0
## X128	61	0	0	0	0	1
## X129	70	1	0	0	0	0
## X130	60	0	0	0	0	0
## X131	56	0	0	0	1	1
## X132	66	1	0	0	1	0
## X133	57	0	1	0	0	1
## X135	66	0	0	0	1	1
## X136	64	1	1	0	0	0
## X137	54	1	0	0	1	0
## X138	67	1	0	0	0	0
## X139	62	0	0	0	0	1
## X142	57	0	0	0	1	0
## X144	67	0	1	0	0	0
## X145	59	0	0	0	0	1
## X146	53	1	0	1	0	0
## X147	64	1	0	0	0	1
## X148	61	0	0	0	1	0
## X149	61	0	0	0	1	0
## X150	58	0	0	1	0	0
## X152	55	0	0	0	0	0
## X154	58	0	0	0	0	1
## X155	63	1	0	0	0	0
## X156	71	0	0	0	0	0
## X157	67	1	0	1	0	0
## X159	60	0	0	0	1	0
## X160	57	0	0	0	1	0
## X161	59	1	0	0	0	0
## X162	57	1	0	0	0	0
## X163	61	0	0	1	0	0
## X164	64	1	0	0	1	0
## X165	62	0	0	0	0	0
## X166	63	1	0	0	0	1
## X167	54	0	0	1	0	1
## X168	59	1	0	0	0	1
## X169	56	0	0	0	0	0
## X170	62	1	0	0	0	0
## X171	56	1	0	0	0	0

##	X172	62	0	0	1	0	0
##	X173	57	0	0	0	0	0
##	X174	58	1	0	1	0	0
##	X175	64	0	0	0	0	0
##	X177	58	0	0	0	0	0
##	X179	57	1	0	0	1	1
##	X180	63	1	0	0	0	1
##	X181	63	1	0	0	0	0
##	X182	53	1	0	0	0	1
##	X183	59	1	0	1	0	0
##	X184	61	1	0	0	0	0
##	X185	62	0	0	0	0	0
##	X186	54	1	0	1	0	0
##	X187	65	0	0	0	0	0
##	X188	49	1	0	1	0	1
##	X189	61	0	0	0	0	0
##	X190	64	0	1	0	0	0
##	X191	63	0	0	0	0	0
##	X192	65	0	0	0	0	1
##	X193	50	1	0	1	0	0
##	X194	72	0	0	0	0	0
##	X195	56	0	0	0	0	0
##	X196	57	0	0	0	0	1
##	X198	62	0	0	0	0	0
##	X200	60	0	0	0	0	0
##	X201	59	1	0	0	0	1
##	X202	52	1	0	0	0	0
##	X204	59	1	0	0	0	0
##	X205	59	0	0	0	0	0
##	X206	57	1	0	0	0	0
##	X207	69	0	0	0	0	0
##	X209	65	0	0	0	1	0
##	X211	59	1	0	1	0	0
##	X212	67	1	1	0	0	1
##	X213	64	1	0	0	0	1
##	X214	60	1	0	1	0	0
##	X215	57	1	0	0	1	0
##	X216	60	0	0	1	0	0
##	X217	59	0	0	1	0	1
##	X218	64	0	0	0	0	0
##	X219	61	0	0	0	0	0
##	X220	60	0	0	0	0	0
##	X221	63	0	0	0	0	0
##	X222	59	1	0	0	1	1
##	X223	60	0	0	0	0	0
##	X224	67	0	0	0	1	1
##	X226	67	1	0	1	0	0
##	X227	66	1	0	1	0	0
##	X228	59	0	0	1	0	0
##	X229	58	1	0	0	0	0
##	X230	60	1	0	0	0	1
##	X231	58	1	0	0	0	0
##	X233	62	1	0	1	0	1
##	X234	55	1	0	0	0	0

##	X235	58	1	0	0	0	0
##	X236	62	0	1	0	0	0
##	X237	60	1	0	0	0	0
##	X238	67	0	0	0	0	0
##	X239	61	0	0	0	0	0
##	X240	56	0	0	0	0	0
##	X241	52	1	0	0	0	0
##	X244	65	1	0	0	0	0
##	X245	63	1	0	0	0	0
##	X246	56	1	0	0	1	1
##	X247	53	0	0	0	0	0
##	X248	67	0	0	0	0	0
##	X249	61	0	0	0	1	0
##	X251	59	1	0	0	0	0
##	X252	60	0	0	0	1	0
##	X254	56	0	0	0	0	0
##	X255	55	1	0	0	0	0
##	X256	54	0	0	1	0	0
##	X257	63	0	0	0	1	1
##	X258	61	0	0	1	0	1
##	X259	61	0	0	0	0	0
##	X260	56	1	0	0	1	0
##	X261	63	1	0	0	0	1
##	X262	63	0	0	0	1	0
##	X264	58	0	0	0	0	0
##	X265	66	1	0	0	0	0
##	X266	62	1	1	0	0	0
##	X267	64	0	0	0	1	0
##	X268	55	1	0	0	0	0
##	X269	60	1	0	0	0	1
##	X270	52	1	0	1	0	1
##	X273	61	1	1	0	0	0
##	X274	64	0	0	0	0	0
##	X275	53	1	0	0	0	0
##	X276	63	0	0	1	0	0
##	X277	51	1	0	0	0	0
##	X278	56	0	0	0	0	0
##	X279	58	0	0	1	0	1
##	X280	61	0	0	1	0	0
##	X282	59	1	0	0	0	0
##	X283	54	1	0	0	0	1
##	X284	64	1	0	0	0	0
##	X286	61	1	0	0	0	0
##	X289	60	1	0	0	0	0
##	X290	56	0	0	0	0	1
##	X292	66	0	0	1	0	0
##	X293	61	1	0	0	0	1
##	X295	58	1	0	0	0	1
##	X296	56	0	0	0	1	0
##	X298	60	0	0	0	0	0
##	X299	59	0	0	0	0	0
##	X300	61	0	0	1	0	0
##	X301	62	1	0	0	1	0
##	X302	58	0	0	0	0	0

## X303	64	0	1	0	0	0
## X305	59	1	0	1	0	1
## X306	61	0	0	0	1	0
## X307	66	0	0	0	0	0
## X311	70	0	0	0	0	0
## X312	59	0	0	0	0	0
## X313	69	1	0	0	0	0
## X314	60	0	0	1	0	0
## X315	65	1	0	0	0	0
## X316	61	0	0	0	1	1
## X317	64	1	0	0	0	0
## X318	55	0	0	0	0	0
## X319	54	1	0	0	0	1
## X321	55	1	0	0	0	0
## X322	60	0	0	1	0	0
## X326	59	0	0	1	0	0
## X327	64	1	0	0	0	0
## X328	57	0	0	0	0	1
## X329	61	0	0	0	1	0
## X330	55	0	0	0	0	0
## X331	57	0	0	0	0	1
## X332	61	1	1	0	0	1
## X333	60	1	0	1	0	0
## X334	62	0	0	0	0	0
## X335	61	0	0	0	0	1
## X336	60	0	0	0	0	1
## X339	60	1	0	0	1	0
## X340	57	1	0	0	0	0
## X341	59	1	0	0	0	0
## X342	56	1	0	0	0	0
## X345	61	1	0	0	0	0
## X347	65	1	1	0	0	0
## X349	60	0	0	0	0	0
## X351	57	0	0	0	0	1
## X353	69	0	0	0	0	0
## X354	56	1	0	0	0	1
## X355	60	0	0	0	0	1
## X356	62	1	0	0	0	0
## X359	60	0	0	0	0	0
## X360	68	1	0	0	0	1
## X361	64	0	0	0	0	0
## X363	57	0	0	0	0	0
## X365	53	1	0	0	0	0
## X366	57	0	0	0	0	0
## X367	60	0	0	0	0	1
## X369	56	1	0	0	0	1
## X371	66	1	0	1	0	0
## X372	59	0	0	0	0	1
## X373	65	0	0	0	0	0
## X374	58	1	0	0	0	1
## X376	59	1	0	0	0	0
## X377	54	0	0	0	0	0
## X378	66	1	0	0	0	0
## X379	52	1	0	0	0	1

## X380	59	0	0	0	0	1
## X382	57	0	0	0	0	0
## X383	56	0	0	0	0	1
## X385	60	0	0	1	0	0
## X386	48	1	1	0	0	0
## X387	60	0	0	0	0	0
## X388	66	1	0	0	0	0
## X389	59	1	0	0	0	0
## X391	52	1	0	0	0	0
## X392	62	1	0	0	0	1
## X393	57	0	0	0	0	1
## X394	65	0	0	0	0	0
## X395	62	0	0	0	0	0
## X396	57	0	0	0	1	0
## X397	59	0	0	1	0	1
## X398	63	1	0	0	0	0
## X399	61	0	0	1	0	1
## X401	62	1	0	0	1	1
## X402	57	1	0	0	0	0
## X405	61	1	0	0	0	0
## X406	62	1	0	0	1	0
## X407	56	1	0	0	1	1
## X408	55	0	0	0	0	1
## X410	67	1	0	0	0	1
## X411	62	1	0	0	1	0
## X412	64	1	0	1	0	0
## X413	61	0	0	0	0	0
## X414	58	0	0	0	1	0
## X415	64	0	0	0	0	0
## X416	61	1	0	0	0	1
## X417	64	1	0	0	0	0
## X418	59	0	0	0	0	0
## X419	60	1	0	0	0	1
## X420	52	1	0	0	0	0
## X421	66	1	0	0	0	0
## X422	59	0	1	0	0	0
## X423	60	0	0	0	1	0
## X424	63	1	0	1	0	0
## X425	55	1	0	1	0	0
## X426	70	0	0	1	0	0
## X427	60	0	0	1	0	1
## X431	60	1	0	1	0	0
## X432	56	1	0	0	0	0
## X434	55	0	0	0	0	1
## X435	58	0	0	0	0	0
## X437	69	0	1	0	0	0
## X438	55	1	0	0	0	0
## X439	69	1	0	0	1	0
## X440	60	0	0	0	0	1
## X441	57	1	0	0	0	1
## X442	67	0	0	0	0	1
## X443	57	1	0	0	0	0
## X444	65	1	0	0	1	0
## X445	57	0	0	0	1	1

##	X448	66	1	0	0	0	1
##	X450	63	0	0	0	1	0
##	X451	61	1	0	1	0	0
##	X453	56	0	0	0	0	1
##	X454	62	0	0	1	0	1
##	X455	60	1	0	0	1	0
##	X456	60	1	0	0	0	1
##	X457	61	0	0	0	0	1
##	X458	56	1	0	0	0	0
##	X459	66	1	0	0	0	1
##	X460	69	1	1	0	0	0
##	X461	57	1	0	1	0	1
##	X464	64	0	0	0	0	0
##	X465	68	0	0	0	1	0
##	X466	59	1	0	0	0	0
##	X468	66	1	0	1	0	1
##	X469	59	0	0	0	1	0
##	X470	61	0	0	0	0	1
##	X472	61	0	0	1	0	1
##	X473	62	0	0	0	0	0
##	X474	63	0	0	0	0	0
##	X475	62	1	0	0	0	0
##	X476	53	1	0	0	1	0
##	X478	62	0	0	0	0	0
##	X480	67	1	0	0	0	1
##	X481	64	0	0	0	0	0
##	X482	58	1	0	0	0	1
##	X483	64	1	1	0	0	0
##	X484	58	1	0	1	0	0
##	X486	70	0	0	0	0	0
##	X487	66	1	0	1	0	1
##	X488	56	0	0	0	0	1
##	X489	70	1	0	0	0	0
##	X490	63	1	0	0	0	0
##	X491	65	0	0	0	0	0
##	X492	57	1	0	0	0	1
##	X493	62	1	0	0	0	0
##	X494	66	1	0	0	0	1
##	X495	62	1	1	0	0	1
##	X496	63	0	0	0	0	0
##	X497	62	0	0	1	0	0
##	X498	57	1	0	0	0	0
##	X499	57	0	0	0	0	0
##	X500	60	1	0	1	0	0
##	X501	62	1	0	1	0	0
##	X502	66	1	0	0	0	0
##	X503	59	0	0	0	0	0
##	X504	61	0	0	0	0	0
##	X507	59	0	0	0	0	0
##	X509	56	1	0	0	0	1
##	X511	58	1	0	0	0	0
##	X512	68	0	0	0	0	0
##	X513	60	0	0	0	0	0
##	X514	57	0	0	0	0	0

##	X515	57	0	0	0	0	0
##	X516	60	1	0	0	0	0
##	X518	58	1	0	0	0	0
##	X520	62	1	0	0	0	0
##	X521	58	1	0	0	0	1
##	X522	61	0	0	0	0	1
##	X523	59	0	0	0	0	1
##	X524	68	1	0	0	0	0
##	X525	59	0	0	0	0	0
##	X527	58	0	0	0	0	0
##	X528	62	1	0	1	0	0
##	X529	62	0	1	0	0	1
##	X530	62	1	0	0	0	0
##	X533	64	1	0	0	0	1
##	X535	61	1	0	0	0	1
##	X536	59	1	0	0	0	1
##	X539	58	0	0	0	0	1
##	X540	63	1	0	1	0	0
##	X541	69	0	0	0	1	0
##	X542	65	1	0	0	0	1
##	X543	64	0	0	0	0	0
##	X545	63	0	0	0	0	0
##	X546	63	0	1	0	0	0
##	X547	67	0	0	0	0	0
##	X548	66	1	0	0	0	1
##	X549	54	1	0	0	0	0
##	X550	54	1	0	1	0	1
##	X551	54	1	0	1	0	1
##	X552	62	0	0	0	0	1
##	X553	66	0	0	0	0	0
##	X554	62	1	0	0	1	0
##	X556	61	0	0	0	0	1
##	X557	58	0	0	0	0	1
##	X558	57	1	0	0	0	0
##	X559	65	1	0	0	0	0
##	X560	57	1	0	0	1	1
##	X561	62	1	0	0	0	1
##	X562	63	0	0	0	0	1
##	X563	58	1	0	0	0	0
##	X564	58	0	0	1	0	0
##	X565	62	1	0	0	0	0
##	X566	53	0	0	0	0	0
##	X567	54	0	0	0	0	0
##	X568	68	1	0	0	0	0
##	X569	62	1	0	1	0	1
##	X571	63	1	0	0	0	1
##	X573	65	1	0	0	1	0
##	X574	59	1	0	0	1	0
##	X575	52	0	0	1	0	0
##	X576	59	1	0	0	0	0
##	X577	61	1	0	0	0	0
##	X579	60	0	0	1	0	1
##	X580	54	0	0	0	1	1
##	X582	62	0	0	0	0	1



## X584	64	1	0	0	0	0
## X587	57	0	0	0	0	0
## X588	63	0	0	0	0	1
## X589	56	1	0	0	0	0
## X591	54	0	0	0	0	0
## X592	60	0	0	1	0	1
## X593	56	1	0	0	0	0
## X594	65	0	0	0	0	0
## X597	56	0	0	0	1	0
## X598	56	0	0	0	0	0
## X600	61	0	0	0	1	1
## X601	65	0	0	0	0	0
## X602	58	0	0	0	0	1
## X603	63	0	0	0	0	1
## X604	52	0	1	0	0	1
## X605	64	1	0	0	0	1
## X606	62	0	0	0	1	1
## X609	63	1	0	0	0	0
## X610	58	1	0	0	0	0
## X611	52	1	0	0	0	1
## X613	63	1	0	1	0	0
## X614	58	0	0	0	0	1
## X615	53	1	1	0	0	0
## X617	57	1	0	0	1	1
## X618	59	1	1	0	0	0
## X619	57	0	0	0	0	1
## X620	55	1	0	0	0	0
## X623	59	0	0	0	0	0
## X624	61	0	0	0	0	0
## X625	56	0	0	0	0	0
## X626	58	0	0	0	0	0
## X628	70	1	0	1	0	0
## X629	59	0	0	0	0	0
## X630	61	0	0	0	0	0
## X631	64	1	0	0	0	1
## X632	59	0	0	0	0	1
## X633	58	1	0	0	0	0
## X634	64	1	0	0	0	0
## X635	55	1	0	0	0	0
## X636	57	1	0	1	0	1
## X637	61	1	0	0	0	1
## X638	56	0	0	1	0	0
## X640	60	0	0	0	0	0
## X641	58	0	0	0	0	0
## X642	60	1	0	1	0	0
## X643	50	1	0	0	1	1
## X644	55	0	0	0	0	0
## X645	54	1	0	0	1	1
## X646	58	1	0	0	0	0
## X648	55	1	0	0	0	0
## X649	57	1	0	0	0	1
## X650	63	0	0	1	0	0
## X652	58	0	0	0	0	0
## X654	64	0	0	0	0	1

##	X655	68	1	0	0	0	1
##	X656	60	0	0	0	0	0
##	X657	56	1	0	0	0	0
##	X658	61	1	0	1	0	1
##	X659	59	0	1	0	0	0
##	X660	66	0	0	1	0	0
##	X661	64	1	0	0	0	1
##	X663	58	0	1	0	0	0
##	X664	61	1	0	0	0	0
##	X665	61	0	0	0	0	1
##	X666	60	0	0	0	0	1
##	X667	69	1	0	1	0	0
##	X668	65	0	0	0	0	1
##	X669	65	1	0	1	0	0
##	X670	61	0	0	0	0	0
##	X673	65	1	0	0	1	0
##	X674	62	0	0	0	0	0
##	X675	52	0	0	0	0	0
##	X676	60	1	0	0	0	0
##	X677	62	1	0	1	0	0
##	X678	59	1	0	0	1	1
##	X679	63	1	0	1	0	0
##	X680	60	0	0	0	0	0
##	X681	64	1	1	0	0	1
##	X682	57	0	0	1	0	1
##	X683	55	1	0	1	0	0
##	X684	64	0	1	0	0	0
##	X685	57	0	0	1	0	0
##	X686	58	0	0	1	0	0
##	X687	62	1	0	0	0	0
##	X688	64	0	0	0	0	1
##	X690	62	1	0	0	0	0
##	X691	52	0	0	0	0	0
##	X692	52	0	0	0	0	0
##	X693	60	0	0	0	0	0
##	X694	62	0	1	0	0	1
##	X697	57	1	0	0	0	0
##	X698	65	1	0	0	0	0
##	X699	56	1	0	0	0	0
##	X700	57	1	0	0	0	0
##	X701	61	1	0	0	0	0
##	X702	58	1	1	0	0	0
##	X703	63	1	0	0	0	0
##	X705	58	0	0	1	0	0
##	X706	63	0	0	0	0	0
##	X707	57	1	0	0	0	0
##	X708	58	0	0	0	1	0
##	X709	63	1	0	1	0	1
##	X710	65	0	0	0	0	1
##	X711	61	1	0	0	0	0
##	X712	58	0	0	0	0	0
##	X713	51	0	1	0	0	0
##	X714	55	0	1	0	0	1
##	X715	56	1	0	0	0	0

##	X716	57	0	0	0	0	0
##	X717	62	1	0	0	0	0
##	X718	59	1	0	0	1	0
##	X719	59	1	0	1	0	0
##	X720	62	0	0	0	0	0
##	X721	57	1	0	1	0	0
##	X722	62	1	0	0	0	0
##	X724	50	0	0	0	0	0
##	X725	56	0	0	1	0	0
##	X726	63	1	0	0	0	0
##	X730	67	0	0	1	0	0
##	X731	61	0	0	0	1	0
##	X732	65	1	0	0	0	0
##	X734	57	1	0	0	0	0
##	X735	52	1	0	0	0	0
##	X737	62	0	0	0	0	0
##	X738	56	0	0	1	0	0
##	X739	59	0	0	0	0	1
##	X740	56	0	0	0	0	1
##	X744	55	1	0	0	0	0
##	X745	62	0	0	0	0	0
##	X746	62	0	0	0	0	0
##	X747	61	1	0	1	0	1
##	X748	54	1	0	0	0	0
##	X749	63	0	0	0	0	0
##	X751	58	0	0	0	0	0
##	X752	66	0	0	0	0	0
##	X753	65	0	0	0	0	1
##	X754	58	1	1	0	0	0
##	X757	64	1	0	0	0	0
##	X758	59	0	0	0	0	0
##	X759	58	1	0	1	0	0
##	X761	65	0	0	1	0	0
##	X762	62	0	0	0	0	0
##	X763	62	0	1	0	0	0
##	X764	67	1	0	0	0	0
##	X765	64	1	0	1	0	0
##	X766	58	1	0	1	0	1
##	X767	62	0	0	0	0	0
##	X768	58	0	0	0	0	1
##	X769	61	1	0	0	0	0
##	X770	65	1	0	0	0	0
##	X772	60	0	0	0	0	1
##	X773	64	0	0	0	0	0
##	X774	68	0	0	0	0	0
##	X775	61	0	0	1	0	0
##	X776	59	0	0	0	0	0
##	X777	61	1	1	0	0	1
##	X778	66	1	0	0	0	0
##	X779	63	1	0	0	0	1
##	X780	61	0	0	0	0	1
##	X781	69	1	0	0	0	0
##	X784	57	1	0	0	0	0
##	X786	63	0	0	1	0	0

## X787	66	1	0	0	0	0
## X788	64	0	0	1	0	0
## X789	56	0	0	1	0	0
## X790	58	0	0	0	0	0
## X791	63	1	0	0	0	1
## X792	67	1	0	0	0	0
## X794	68	0	0	0	0	0
## X795	55	1	0	1	0	0
## X796	61	0	0	0	0	0
## X797	60	1	0	0	0	1
## X798	58	1	0	0	0	0
## X799	58	1	0	0	0	0
## X800	64	1	0	1	0	0
## X801	62	0	0	0	0	1
## X802	50	1	0	0	0	0
## X803	53	0	0	0	1	0
## X804	55	0	0	0	0	1
## X805	55	0	0	0	0	0
## X807	68	0	0	0	0	0
## X808	64	1	0	0	0	0
## X809	58	1	0	0	0	1
## X810	57	0	0	0	0	1
## X812	57	0	0	0	0	1
## X813	64	0	0	1	0	0
## X814	62	1	0	0	0	0
## X815	55	0	0	0	0	0
## X816	63	0	0	1	0	0
## X817	60	1	0	0	0	0
## X818	61	1	0	0	0	1
## X820	61	1	0	0	0	0
## X821	59	1	1	0	0	0
## X822	62	0	0	0	0	0
## X823	67	0	0	0	0	1
## X824	61	0	0	0	1	1
## X825	55	1	0	0	1	0
## X826	64	0	0	1	0	1
## X830	63	1	0	0	0	0
## X831	58	0	1	0	0	1
## X832	55	0	0	0	0	0
## X833	52	1	0	0	0	0
## X834	69	1	0	0	0	1
## X836	56	0	0	1	0	0
## X837	55	1	0	1	0	1
## X838	62	1	0	1	0	1
## X839	53	1	0	0	0	0
## X840	60	1	0	0	0	0
## X841	61	1	0	1	0	0
## X842	56	1	0	0	0	0
## X843	60	0	0	1	0	1
## X844	57	0	0	0	0	0
## X847	70	1	0	0	0	0
## X848	62	0	1	0	0	0
## X849	59	1	0	0	0	0
## X850	58	0	0	0	1	0

##	X851	64	1	0	0	0	1
##	X852	58	0	0	1	0	0
##	X853	54	1	0	0	0	0
##	X854	68	0	0	0	0	0
##	X855	57	1	0	0	0	1
##	X856	49	0	0	1	0	0
##	X857	61	0	0	0	0	0
##	X858	59	1	0	1	0	0
##	X859	61	1	0	1	0	0
##	X860	61	0	0	0	0	0
##	X861	56	0	0	0	0	0
##	X862	53	0	0	0	0	1
##	X864	61	1	0	0	0	0
##	X865	53	0	0	0	0	1
##	X866	64	1	0	1	0	1
##	X867	60	1	0	0	0	0
##	X868	59	1	0	0	0	1
##	X869	60	0	0	0	1	1
##	X870	56	0	0	0	0	0
##	X871	63	0	0	0	0	0
##	X872	54	0	0	0	0	0
##	X873	56	0	0	1	0	0
##	X874	58	1	0	0	0	0
##	X875	57	1	0	1	0	0
##	X877	64	0	0	0	0	0
##	X878	54	0	0	0	0	1
##	X879	59	0	0	0	0	0
##	X880	62	1	0	1	0	0
##	X881	57	0	0	0	0	1
##	X882	60	0	1	0	0	1
##	X883	57	0	0	0	0	1
##	X884	66	0	0	0	0	0
##	X885	59	0	0	1	0	0
##	X886	61	0	0	0	0	0
##	X887	65	1	0	0	0	0
##	X888	65	1	0	0	0	0
##	X889	65	1	0	0	1	0
##	X890	58	1	0	0	0	0
##	X891	58	0	0	0	0	1
##	X892	59	1	0	1	0	1
##	X894	60	0	0	0	1	0
##	X895	64	1	0	1	0	0
##	X897	58	0	0	0	0	1
##	X899	58	1	0	0	0	0
##	X900	57	0	0	1	0	1
##	X901	68	0	0	0	0	1
##	X902	66	0	0	1	0	0
##	X903	61	0	0	0	0	0
##	X904	57	0	0	0	0	1
##	X905	61	0	0	0	0	1
##	X906	52	1	0	0	0	1
##	X907	61	0	1	0	0	0
##	X908	57	1	0	0	0	1
##	X909	58	1	0	0	0	1

## X910	64	0	0	0	0	1
## X911	54	0	0	1	0	0
## X913	59	0	0	0	0	1
## X916	61	1	0	0	1	0
## X917	66	1	0	0	0	0
## X918	55	0	0	0	0	0
## X919	58	1	0	0	0	0
## X920	54	1	0	0	0	1
## X921	70	0	0	0	0	0
## X922	63	1	0	0	0	0
## X924	57	1	0	0	0	0
## X925	55	0	0	0	0	0
## X926	56	0	0	1	0	1
## X927	64	0	0	0	0	0
## X929	61	1	0	0	0	0
## X932	66	1	0	1	0	0
## X933	57	1	0	0	0	1
## X935	65	0	0	0	0	0
## X936	63	1	0	0	0	0
## X937	57	1	1	0	0	0
## X939	64	0	0	0	1	1
## X940	63	1	0	1	0	1
## X941	64	1	0	0	1	0
## X942	59	0	0	1	0	0
## X943	58	1	0	0	0	0
## X945	65	1	0	0	0	0
## X946	63	1	0	1	0	0
## X948	58	0	0	0	0	1
## X949	58	1	0	0	0	0
## X950	50	0	0	0	0	0
## X951	51	0	0	0	0	0
## X953	69	0	0	0	0	0
## X954	69	1	0	0	0	0
## X955	59	0	0	0	0	1
## X956	62	1	0	0	0	0
## X957	55	0	0	0	0	0
## X958	61	0	0	0	0	0
## X959	54	0	0	0	0	0
## X960	51	0	0	0	0	0
## X961	56	0	0	1	0	0
## X962	63	1	0	0	1	1
## X963	63	1	0	0	0	1
## X964	65	1	0	0	0	0
## X965	59	0	0	0	0	0
## X966	56	1	0	1	0	1
## X968	60	1	0	0	1	0
## X969	60	1	0	0	0	1
## X970	57	0	0	0	0	0
## X971	53	0	0	0	0	0
## X972	60	1	0	1	0	1
## X973	55	0	0	0	0	1
## X974	66	1	0	0	0	1
## X975	56	1	0	0	0	1
## X976	58	1	0	0	0	0

##	X977	57	0	0	0	0	0
##	X978	59	1	0	0	0	0
##	X979	67	0	0	0	0	0
##	X980	58	1	0	0	0	1
##	X981	61	1	0	0	0	1
##	X982	56	0	0	1	0	1
##	X983	66	1	0	1	0	1
##	X984	53	0	0	0	0	0
##	X985	59	1	0	1	0	1
##	X986	55	0	0	0	0	1
##	X987	61	0	1	0	0	0
##	X988	51	1	0	1	0	0
##	X989	56	1	0	0	0	0
##	X990	56	0	0	0	1	1
##	X991	55	0	0	1	0	0
##	X992	57	1	0	1	0	0
##	X993	59	0	0	0	0	0
##	X994	63	0	0	0	0	0
##	X995	54	0	0	0	0	0
##	X996	55	0	0	1	0	1
##	X997	57	0	0	0	0	0
##	X998	62	1	0	0	0	1
##	X999	61	1	0	0	0	1
##	smokingCurrent_smoker height weight bmi diabetesYes hypertensionYes sbp						
##	X1		0	170.3	74.7	25.8	0 120
##	X2		0	170.8	75.7	26.0	1 133
##	X3		0	172.7	89.5	30.0	0 123
##	X4		0	171.7	74.6	25.3	0 121
##	X6		0	168.8	87.9	30.8	0 132
##	X9		0	168.5	76.5	27.0	0 138
##	X10		0	170.3	73.0	25.2	0 135
##	X11		0	172.7	93.9	31.5	0 128
##	X12		0	169.9	73.9	25.6	0 143
##	X13		0	181.2	89.6	27.3	1 139
##	X14		1	183.5	78.8	23.4	0 129
##	X15		0	168.6	90.3	31.8	0 131
##	X17		0	160.1	73.3	28.6	0 138
##	X18		0	172.5	83.8	28.1	0 128
##	X19		0	161.6	92.3	35.4	0 133
##	X21		0	173.0	85.8	28.7	0 130
##	X22		0	172.2	77.6	26.2	0 134
##	X24		0	160.6	75.9	29.4	0 124
##	X25		0	170.7	85.6	29.4	0 134
##	X26		0	166.2	79.1	28.7	0 131
##	X27		0	169.7	68.9	23.9	0 140
##	X28		0	156.6	73.4	29.9	0 136
##	X29		0	175.9	78.0	25.2	0 136
##	X30		0	166.7	88.7	31.9	0 134
##	X31		0	165.9	74.9	27.2	0 131
##	X33		0	175.5	80.9	26.3	0 130
##	X36		0	173.1	74.1	24.7	0 140
##	X39		0	163.0	64.6	24.3	0 134
##	X40		0	160.4	69.2	26.9	0 133
##	X41		0	172.2	79.0	26.6	0 124

## X42	0	165.3	84.6	31.0	0	0	122
## X45	0	179.3	82.9	25.8	0	1	135
## X46	0	172.7	85.5	28.7	0	0	128
## X47	0	162.7	85.8	32.4	0	1	131
## X49	0	166.2	85.6	31.0	1	1	134
## X54	0	178.2	73.5	23.2	0	0	127
## X56	0	176.9	104.8	33.5	0	1	133
## X57	0	174.6	84.6	27.8	0	1	137
## X59	0	170.5	82.7	28.5	0	1	131
## X60	1	172.1	65.9	22.2	0	0	121
## X61	0	173.5	77.9	25.9	0	0	125
## X62	0	176.2	83.3	26.8	0	0	124
## X64	0	167.9	73.6	26.1	1	1	153
## X65	1	169.6	70.3	24.4	0	1	136
## X67	0	170.4	85.9	29.6	0	1	133
## X69	0	170.0	81.3	28.1	1	0	125
## X70	0	181.2	77.0	23.5	0	0	121
## X72	0	164.6	80.7	29.8	1	0	119
## X73	0	164.4	78.6	29.1	0	1	132
## X74	0	163.3	67.5	25.3	0	0	124
## X75	0	170.6	67.9	23.3	0	0	116
## X77	0	172.1	71.2	24.0	0	1	133
## X78	0	178.7	91.0	28.5	0	1	135
## X79	1	173.9	81.1	26.8	0	1	150
## X82	0	163.3	78.3	29.4	0	0	114
## X85	0	164.2	82.6	30.6	0	0	124
## X87	0	174.0	80.5	26.6	0	0	117
## X88	0	180.8	88.8	27.2	0	0	117
## X89	0	169.3	81.0	28.3	0	0	120
## X90	0	168.0	76.6	27.1	0	1	131
## X91	0	170.6	78.0	26.8	0	0	128
## X92	0	163.0	76.0	28.6	0	1	133
## X93	0	172.0	77.0	26.0	0	1	148
## X94	0	168.0	76.5	27.1	0	1	136
## X95	0	176.4	85.3	27.4	0	0	130
## X96	1	172.3	77.4	26.1	0	0	121
## X97	0	174.1	78.1	25.8	1	1	136
## X98	0	174.1	83.1	27.4	0	1	140
## X99	0	172.2	85.4	28.8	1	0	119
## X100	0	167.4	72.4	25.9	0	1	132
## X101	0	175.3	84.5	27.5	0	0	126
## X102	0	174.2	84.9	28.0	0	1	138
## X103	0	171.5	82.5	28.1	0	1	141
## X104	0	176.8	87.9	28.1	0	1	135
## X105	0	164.5	72.8	26.9	0	1	132
## X106	0	165.5	87.3	31.9	0	0	122
## X108	0	172.3	81.3	27.4	0	0	122
## X109	0	163.2	79.0	29.7	0	1	135
## X110	0	171.7	80.3	27.3	0	0	128
## X112	0	161.4	75.1	28.9	1	0	128
## X113	0	160.5	74.8	29.0	0	0	122
## X114	0	173.3	75.6	25.2	0	0	114
## X115	0	169.6	83.0	28.9	1	0	126
## X116	0	172.9	84.4	28.2	1	1	134



## X117	0	176.0	89.0	28.7	0	1 143
## X119	0	165.3	75.7	27.7	0	0 128
## X120	0	181.6	98.0	29.7	0	0 128
## X121	0	181.5	77.4	23.5	0	1 146
## X122	0	183.3	88.4	26.3	0	0 127
## X123	0	173.9	67.6	22.4	0	0 116
## X126	0	176.1	94.9	30.6	0	0 128
## X127	0	181.0	83.7	25.6	0	0 124
## X128	0	176.8	89.2	28.5	0	1 151
## X129	0	167.2	77.6	27.7	0	1 145
## X130	0	156.7	67.7	27.6	0	1 131
## X131	0	171.0	84.3	28.8	1	0 122
## X132	0	176.6	88.6	28.4	1	0 118
## X133	0	167.7	70.3	25.0	0	0 124
## X135	0	166.5	80.4	29.0	1	0 126
## X136	0	173.3	83.8	27.9	0	0 126
## X137	0	156.0	76.3	31.4	0	0 126
## X138	0	169.1	76.7	26.8	0	1 154
## X139	0	170.1	86.0	29.7	0	1 131
## X142	0	176.9	81.3	26.0	0	1 141
## X144	0	172.8	88.3	29.6	1	1 134
## X145	0	165.5	92.7	33.8	0	1 134
## X146	0	167.3	83.4	29.8	0	0 125
## X147	0	171.6	70.4	23.9	0	1 131
## X148	0	174.6	88.1	28.9	0	0 120
## X149	0	179.3	89.6	27.9	0	1 143
## X150	0	160.4	72.4	28.1	0	1 133
## X152	0	175.0	84.3	27.5	1	0 130
## X154	0	178.5	71.6	22.5	0	1 131
## X155	0	173.3	77.7	25.9	1	1 132
## X156	0	171.6	82.0	27.9	0	1 131
## X157	1	177.5	72.5	23.0	0	1 143
## X159	0	171.5	84.8	28.8	1	0 128
## X160	0	165.6	83.3	30.4	0	1 132
## X161	1	161.1	80.6	31.0	0	1 131
## X162	0	170.2	83.3	28.8	0	0 117
## X163	1	165.7	75.2	27.4	0	0 126
## X164	0	164.7	79.2	29.2	0	0 126
## X165	1	180.4	86.4	26.6	0	0 125
## X166	0	176.4	84.1	27.0	0	0 128
## X167	0	161.4	85.6	32.8	0	1 135
## X168	0	173.8	83.4	27.6	1	1 131
## X169	0	168.5	74.4	26.2	1	0 118
## X170	0	174.0	78.8	26.0	0	0 124
## X171	0	163.9	75.4	28.1	0	0 125
## X172	0	162.7	82.6	31.2	0	0 130
## X173	0	173.0	89.0	29.7	0	0 120
## X174	0	174.5	78.1	25.7	0	1 131
## X175	0	160.3	72.3	28.1	0	1 132
## X177	0	179.1	80.4	25.0	0	1 134
## X179	0	165.3	96.0	35.1	0	0 127
## X180	0	173.3	83.3	27.7	0	1 149
## X181	0	175.0	82.4	26.9	0	1 143
## X182	0	170.0	83.7	29.0	0	0 116

## X183	0	167.0	68.0	24.4	0	1	131
## X184	0	179.7	79.5	24.6	1	1	145
## X185	0	176.4	75.2	24.2	0	1	137
## X186	0	174.3	89.7	29.5	0	0	125
## X187	0	169.0	67.6	23.7	0	1	140
## X188	0	157.5	79.2	31.9	0	0	115
## X189	1	172.3	82.0	27.6	0	1	132
## X190	0	174.3	79.4	26.1	1	1	142
## X191	0	161.3	78.4	30.1	0	0	130
## X192	0	165.3	77.3	28.3	0	1	148
## X193	0	167.3	84.2	30.1	1	0	124
## X194	1	166.3	81.2	29.4	0	1	149
## X195	0	162.6	93.9	35.5	0	0	117
## X196	0	165.7	64.8	23.6	1	0	123
## X198	0	173.9	95.1	31.4	0	1	134
## X200	1	174.0	81.9	27.0	1	0	122
## X201	0	175.6	86.4	28.0	0	0	129
## X202	0	166.0	85.7	31.1	0	0	130
## X204	0	167.4	76.3	27.2	0	1	132
## X205	0	178.1	89.3	28.2	0	0	119
## X206	0	166.9	78.5	28.2	0	1	134
## X207	0	165.6	85.0	31.0	1	1	138
## X209	0	161.7	76.4	29.2	0	0	121
## X211	1	173.9	72.5	24.0	0	1	134
## X212	0	171.3	86.5	29.5	0	0	128
## X213	0	173.9	83.1	27.5	0	1	147
## X214	0	168.9	71.5	25.1	0	0	116
## X215	0	165.2	79.3	29.1	0	0	125
## X216	0	176.8	80.1	25.6	0	1	135
## X217	0	171.5	85.3	29.0	1	0	124
## X218	0	162.0	72.6	27.6	0	1	138
## X219	1	170.2	74.2	25.6	0	1	134
## X220	0	172.9	74.6	25.0	0	0	122
## X221	0	168.4	84.5	29.8	0	0	122
## X222	0	169.3	87.3	30.5	0	0	125
## X223	0	168.8	71.9	25.2	1	0	121
## X224	0	167.6	79.6	28.3	0	1	137
## X226	0	168.7	74.1	26.0	1	1	141
## X227	0	167.4	87.0	31.0	1	1	142
## X228	0	166.2	78.2	28.3	0	1	132
## X229	0	166.4	80.5	29.1	1	0	126
## X230	0	174.1	71.7	23.7	0	0	121
## X231	0	169.4	85.6	29.8	0	0	129
## X233	0	172.3	75.4	25.4	0	0	124
## X234	0	162.9	82.8	31.2	0	1	139
## X235	0	168.3	82.3	29.1	0	1	133
## X236	0	154.7	85.4	35.7	0	0	127
## X237	0	161.2	71.7	27.6	0	0	129
## X238	1	172.5	75.5	25.4	0	1	140
## X239	0	164.2	71.3	26.4	0	0	122
## X240	0	160.9	79.2	30.6	0	1	131
## X241	0	171.1	79.0	27.0	0	0	120
## X244	0	171.1	80.5	27.5	0	0	128
## X245	1	172.4	77.3	26.0	0	0	130

## X246	0	164.8	85.3	31.4	0	0	130
## X247	0	165.2	79.2	29.0	0	1	132
## X248	0	178.3	73.7	23.2	0	0	115
## X249	0	168.4	65.7	23.2	0	1	138
## X251	0	156.8	88.4	36.0	0	1	133
## X252	0	175.8	87.1	28.2	0	1	142
## X254	0	171.1	79.3	27.1	0	0	128
## X255	0	159.6	72.7	28.6	0	1	134
## X256	0	167.3	87.3	31.2	0	0	115
## X257	0	164.1	82.9	30.8	0	1	141
## X258	0	167.1	81.5	29.2	0	0	129
## X259	1	178.7	71.6	22.4	0	0	127
## X260	0	161.6	72.0	27.6	0	0	128
## X261	0	169.2	79.1	27.6	0	0	126
## X262	1	157.2	68.7	27.8	0	0	126
## X264	0	169.0	74.3	26.0	0	1	132
## X265	0	174.2	75.4	24.8	0	0	123
## X266	0	174.3	85.2	28.1	0	0	125
## X267	0	169.0	80.5	28.2	0	1	138
## X268	0	177.4	90.7	28.8	0	1	133
## X269	0	177.6	88.0	27.9	0	0	128
## X270	0	166.1	87.4	31.7	1	0	114
## X273	0	169.3	79.2	27.6	0	0	123
## X274	1	164.2	69.7	25.9	0	1	134
## X275	0	163.7	65.0	24.3	0	0	125
## X276	0	164.5	88.9	32.9	0	0	127
## X277	0	162.7	75.1	28.4	1	0	123
## X278	0	162.1	64.4	24.5	0	0	122
## X279	0	162.9	66.3	25.0	1	1	133
## X280	0	177.4	84.9	27.0	0	0	126
## X282	1	179.2	76.7	23.9	0	0	122
## X283	0	167.9	66.0	23.4	0	0	121
## X284	0	172.6	79.5	26.7	0	0	123
## X286	0	170.4	91.0	31.3	0	0	120
## X289	1	175.8	88.0	28.5	0	0	122
## X290	0	167.5	81.9	29.2	0	0	120
## X292	1	150.2	58.0	25.7	1	0	122
## X293	0	179.3	85.5	26.6	0	0	126
## X295	0	167.5	68.5	24.4	0	1	135
## X296	0	173.4	78.8	26.2	0	0	125
## X298	0	165.1	71.5	26.2	0	1	131
## X299	0	166.0	74.0	26.9	0	0	129
## X300	0	172.2	86.5	29.2	0	1	134
## X301	0	165.8	76.9	28.0	1	0	129
## X302	0	172.7	85.2	28.6	0	0	125
## X303	0	166.3	74.5	26.9	0	0	126
## X305	0	159.0	82.5	32.6	0	1	131
## X306	0	170.3	81.4	28.1	0	1	131
## X307	0	164.5	82.1	30.3	0	0	119
## X311	0	179.4	82.9	25.8	1	1	141
## X312	0	165.3	78.0	28.6	0	0	130
## X313	1	173.0	91.9	30.7	0	1	141
## X314	0	184.9	82.5	24.1	0	0	126
## X315	0	159.0	78.2	30.9	0	1	138

## X316	0	168.9	72.9	25.6	0	0 129
## X317	0	168.1	64.8	22.9	0	0 125
## X318	0	158.8	72.9	28.9	0	0 119
## X319	0	169.1	74.1	25.9	0	0 128
## X321	1	180.6	84.1	25.8	0	1 133
## X322	0	171.6	89.8	30.5	0	0 121
## X326	0	179.0	91.1	28.4	0	0 119
## X327	0	172.6	96.3	32.3	0	1 135
## X328	0	169.4	86.9	30.3	0	0 113
## X329	0	174.6	81.7	26.8	1	0 120
## X330	0	174.9	83.5	27.3	0	0 116
## X331	0	161.0	72.8	28.1	0	0 119
## X332	0	161.2	74.1	28.5	0	1 138
## X333	0	160.9	69.0	26.6	1	1 133
## X334	0	170.9	77.0	26.4	0	1 139
## X335	0	167.5	73.4	26.1	0	0 127
## X336	0	163.2	74.2	27.9	0	1 136
## X339	0	173.0	87.8	29.3	0	1 139
## X340	1	165.1	76.2	28.0	0	0 129
## X341	0	159.0	80.6	31.9	1	1 135
## X342	0	165.9	68.1	24.7	0	0 130
## X345	0	176.5	72.9	23.4	0	1 133
## X347	0	168.8	66.2	23.2	0	0 126
## X349	0	172.3	86.6	29.2	0	1 146
## X351	0	168.4	81.6	28.8	1	1 140
## X353	0	172.1	81.2	27.4	0	1 134
## X354	0	169.7	82.6	28.7	0	0 128
## X355	0	164.4	65.7	24.3	0	0 125
## X356	1	166.1	70.5	25.6	0	1 133
## X359	0	164.7	56.6	20.9	1	1 132
## X360	0	167.2	80.2	28.7	1	1 148
## X361	0	167.1	80.5	28.8	0	0 123
## X363	0	169.7	80.8	28.1	0	1 138
## X365	0	168.8	91.4	32.1	0	0 128
## X366	0	172.0	72.8	24.6	0	1 135
## X367	0	173.9	91.9	30.4	0	0 121
## X369	0	173.8	87.3	28.9	0	1 138
## X371	0	166.0	73.5	26.7	0	1 133
## X372	0	167.7	103.7	36.9	0	1 139
## X373	0	178.0	84.8	26.8	0	1 135
## X374	0	172.7	70.3	23.6	0	0 123
## X376	0	178.0	75.4	23.8	0	0 121
## X377	1	152.3	65.2	28.1	0	1 134
## X378	0	169.8	68.5	23.8	0	1 137
## X379	0	170.1	78.3	27.1	0	0 119
## X380	0	171.9	92.6	31.4	0	1 146
## X382	1	164.5	74.2	27.4	0	1 131
## X383	0	164.9	85.0	31.2	0	0 121
## X385	0	170.5	66.4	22.8	0	1 131
## X386	1	165.0	77.7	28.5	0	0 114
## X387	0	170.7	81.3	27.9	0	1 135
## X388	0	168.4	77.4	27.3	0	0 117
## X389	0	174.7	70.4	23.1	1	0 120
## X391	0	163.9	74.9	27.9	0	0 118

## X392	0	167.7	79.4	28.2	0	1	135
## X393	0	175.1	80.2	26.2	0	0	121
## X394	0	175.6	82.8	26.9	0	1	137
## X395	0	178.2	78.2	24.6	0	0	124
## X396	1	179.6	89.8	27.8	1	1	133
## X397	0	166.3	78.3	28.3	0	0	125
## X398	0	169.0	74.3	26.0	0	1	131
## X399	0	174.4	75.6	24.8	0	0	129
## X401	0	176.7	68.4	21.9	1	1	141
## X402	0	165.5	67.7	24.7	0	0	122
## X405	0	173.0	79.0	26.4	0	0	129
## X406	0	174.7	79.6	26.1	0	1	136
## X407	0	177.4	86.1	27.4	0	0	119
## X408	0	173.4	75.5	25.1	0	0	122
## X410	0	166.7	73.6	26.5	0	0	128
## X411	0	160.7	84.1	32.6	0	1	134
## X412	0	173.2	76.9	25.7	0	0	125
## X413	1	171.5	76.6	26.1	0	1	134
## X414	0	170.6	75.2	25.9	0	0	126
## X415	0	172.7	83.6	28.0	0	0	130
## X416	0	164.3	65.4	24.2	0	1	140
## X417	0	164.7	77.8	28.7	1	1	132
## X418	0	177.5	86.4	27.4	0	0	129
## X419	0	178.1	90.1	28.4	0	1	131
## X420	0	171.9	78.0	26.4	0	1	132
## X421	0	172.4	78.8	26.5	1	0	128
## X422	0	168.6	72.4	25.5	0	0	123
## X423	0	167.8	85.3	30.3	0	0	129
## X424	0	164.2	79.6	29.5	0	1	133
## X425	0	173.2	77.8	25.9	0	0	115
## X426	0	183.8	85.3	25.3	0	1	134
## X427	0	173.5	65.9	21.9	0	0	130
## X431	0	166.0	77.8	28.2	0	1	135
## X432	0	171.4	73.6	25.1	0	1	136
## X434	0	168.2	73.3	25.9	0	0	122
## X435	0	175.4	75.5	24.5	0	0	118
## X437	0	175.2	61.1	19.9	0	1	144
## X438	0	167.8	87.8	31.2	0	0	130
## X439	0	172.2	82.0	27.7	1	1	144
## X440	0	171.4	83.2	28.3	0	0	123
## X441	0	175.4	81.5	26.5	0	0	121
## X442	0	165.9	69.4	25.2	0	0	130
## X443	0	166.2	72.9	26.4	0	0	119
## X444	1	163.9	61.6	22.9	1	0	130
## X445	0	169.3	85.6	29.9	0	0	127
## X448	0	175.6	77.7	25.2	0	1	140
## X450	0	171.8	87.7	29.7	0	1	133
## X451	0	163.9	76.5	28.5	0	0	125
## X453	0	168.4	73.5	25.9	1	0	122
## X454	0	168.7	83.0	29.1	0	1	134
## X455	0	166.8	77.8	28.0	1	0	127
## X456	0	161.6	74.5	28.5	0	0	124
## X457	0	169.6	78.5	27.3	0	1	131
## X458	0	160.8	83.3	32.2	0	1	131

## X459	0	179.0	77.4	24.2	0	1	135
## X460	0	176.4	79.0	25.4	1	1	137
## X461	0	178.9	80.9	25.3	1	0	126
## X464	0	179.0	79.3	24.7	0	1	147
## X465	0	165.0	83.9	30.8	0	1	152
## X466	0	175.3	72.9	23.7	1	0	127
## X468	0	177.4	78.4	24.9	0	0	124
## X469	0	166.2	80.8	29.2	0	1	132
## X470	0	165.5	74.9	27.4	0	0	123
## X472	0	167.0	82.3	29.5	0	0	128
## X473	0	177.0	75.9	24.2	0	1	131
## X474	1	175.6	94.0	30.5	0	0	128
## X475	1	177.3	84.4	26.8	0	1	134
## X476	1	178.0	83.9	26.5	0	0	120
## X478	0	168.8	78.1	27.4	0	1	137
## X480	0	171.3	88.8	30.2	0	0	130
## X481	0	167.7	80.0	28.4	0	0	129
## X482	0	173.2	99.1	33.0	0	1	132
## X483	0	169.7	71.2	24.7	0	1	132
## X484	0	161.8	72.8	27.8	0	0	125
## X486	0	177.2	84.4	26.9	0	1	138
## X487	0	175.0	83.5	27.3	0	1	137
## X488	0	172.4	69.5	23.4	1	0	127
## X489	0	174.0	80.6	26.6	0	1	138
## X490	0	172.6	70.1	23.5	0	1	146
## X491	0	177.7	78.8	25.0	0	1	136
## X492	0	173.9	81.1	26.8	1	1	138
## X493	0	172.7	79.9	26.8	0	1	140
## X494	0	158.0	71.7	28.7	0	1	142
## X495	0	163.2	68.9	25.9	0	0	129
## X496	1	175.5	76.3	24.8	0	1	133
## X497	1	172.4	84.4	28.4	0	0	127
## X498	0	177.7	90.3	28.6	0	1	131
## X499	0	178.2	81.4	25.6	0	0	123
## X500	0	168.5	75.0	26.4	0	0	123
## X501	0	175.5	86.0	27.9	0	1	133
## X502	0	181.6	76.3	23.1	0	1	138
## X503	0	190.3	83.8	23.1	0	0	118
## X504	0	171.5	75.0	25.5	0	0	120
## X507	1	179.6	76.2	23.6	0	0	126
## X509	0	157.9	75.0	30.1	0	0	130
## X511	0	163.4	85.9	32.2	0	0	121
## X512	1	165.6	69.2	25.2	0	1	134
## X513	0	168.0	82.7	29.3	0	1	133
## X514	0	171.6	72.5	24.6	0	0	125
## X515	0	179.0	83.5	26.0	1	0	130
## X516	0	164.9	74.6	27.5	1	1	131
## X518	0	170.5	78.7	27.1	0	0	123
## X520	0	168.7	80.3	28.2	0	1	147
## X521	0	178.1	83.6	26.4	1	0	121
## X522	0	170.0	80.6	27.9	0	1	133
## X523	0	165.9	82.9	30.1	0	0	125
## X524	1	163.6	83.0	31.0	0	1	136
## X525	0	172.4	72.8	24.5	0	0	115

## X527	1	167.4	76.2	27.2	0	0 124
## X528	0	168.8	59.0	20.7	0	1 136
## X529	0	166.1	77.6	28.1	0	0 126
## X530	0	172.7	76.1	25.5	0	1 131
## X533	0	167.8	76.7	27.2	0	0 126
## X535	0	175.0	89.9	29.3	1	0 123
## X536	0	176.2	84.9	27.3	0	1 131
## X539	0	156.7	71.7	29.2	0	1 135
## X540	0	176.1	69.5	22.4	0	0 121
## X541	0	164.3	84.0	31.1	1	0 128
## X542	0	167.0	82.9	29.7	0	1 151
## X543	0	162.2	77.8	29.6	0	1 135
## X545	0	178.8	70.8	22.2	0	1 138
## X546	0	169.6	86.2	30.0	0	0 129
## X547	0	163.3	76.0	28.5	0	1 139
## X548	0	162.3	75.9	28.8	0	0 130
## X549	1	174.3	87.6	28.8	0	0 122
## X550	0	167.7	63.2	22.5	0	0 123
## X551	0	157.8	66.3	26.6	0	1 131
## X552	0	157.1	73.0	29.6	0	1 137
## X553	0	170.7	86.8	29.8	0	1 137
## X554	0	165.6	76.7	28.0	0	1 138
## X556	0	169.1	71.9	25.1	1	0 124
## X557	0	182.1	74.7	22.5	1	0 130
## X558	0	167.0	86.0	30.8	0	1 131
## X559	0	173.8	75.5	25.0	0	1 136
## X560	0	171.8	71.1	24.1	0	1 132
## X561	0	166.2	93.1	33.7	0	1 137
## X562	0	168.8	78.2	27.5	0	0 127
## X563	0	165.7	75.8	27.6	0	0 129
## X564	0	179.1	87.0	27.1	0	0 124
## X565	1	167.8	85.8	30.5	0	0 128
## X566	0	182.6	85.6	25.7	0	1 136
## X567	0	180.5	90.6	27.8	0	0 125
## X568	0	167.4	77.0	27.5	0	1 143
## X569	0	171.9	78.6	26.6	0	1 134
## X571	0	168.1	72.2	25.5	0	0 119
## X573	0	166.5	86.8	31.3	0	1 142
## X574	1	168.5	74.3	26.2	0	0 117
## X575	0	151.9	69.2	30.0	0	0 110
## X576	0	164.0	86.0	32.0	0	1 142
## X577	0	173.3	75.3	25.0	0	0 127
## X579	0	168.5	86.6	30.5	0	0 126
## X580	0	163.6	82.3	30.7	0	0 125
## X582	0	180.8	74.4	22.7	0	0 122
## X584	1	171.1	69.2	23.6	0	1 137
## X587	0	163.2	68.5	25.7	0	1 136
## X588	0	168.5	83.7	29.5	0	1 136
## X589	0	165.3	90.4	33.1	0	1 139
## X591	0	178.9	72.9	22.8	0	0 118
## X592	0	162.1	79.6	30.3	0	0 122
## X593	1	182.2	82.0	24.7	0	0 117
## X594	0	171.4	68.4	23.3	0	1 141
## X597	0	165.1	87.8	32.2	1	0 125

## X598	1	178.0	87.9	27.8	1	0 124
## X600	0	172.9	83.7	28.0	0	0 128
## X601	0	176.1	69.3	22.4	1	0 127
## X602	0	173.7	86.5	28.7	0	0 124
## X603	0	158.5	65.8	26.2	0	0 130
## X604	0	167.1	83.5	29.9	0	0 122
## X605	0	161.7	74.1	28.4	0	1 136
## X606	0	161.3	78.6	30.2	0	1 131
## X609	0	170.4	70.4	24.2	0	1 145
## X610	0	177.1	86.5	27.6	0	1 135
## X611	0	155.3	83.7	34.7	0	0 115
## X613	0	173.8	81.5	27.0	1	1 137
## X614	0	178.9	93.5	29.2	1	1 135
## X615	0	166.4	69.1	24.9	0	0 120
## X617	0	172.0	97.0	32.8	0	1 132
## X618	0	174.3	70.1	23.1	0	0 119
## X619	0	159.1	68.5	27.1	1	1 132
## X620	1	169.2	80.9	28.3	0	0 113
## X623	1	173.2	73.5	24.5	0	1 134
## X624	0	177.5	83.6	26.5	0	0 129
## X625	0	168.5	80.2	28.2	1	0 130
## X626	0	176.3	83.4	26.8	0	1 139
## X628	0	162.1	81.0	30.8	1	1 134
## X629	0	164.7	74.3	27.4	1	0 118
## X630	0	163.1	82.6	31.0	1	0 130
## X631	0	174.0	66.1	21.8	0	1 131
## X632	0	163.6	66.5	24.8	1	0 129
## X633	0	182.4	86.1	25.9	1	0 130
## X634	1	169.6	76.1	26.4	0	0 130
## X635	1	176.2	79.0	25.5	0	0 130
## X636	0	164.3	73.5	27.2	0	0 128
## X637	0	180.5	90.4	27.7	0	0 128
## X638	0	165.9	85.9	31.2	0	0 116
## X640	1	162.7	77.9	29.4	0	1 132
## X641	0	168.3	79.5	28.1	0	0 126
## X642	0	162.0	82.4	31.4	0	0 129
## X643	0	165.1	78.4	28.8	0	0 115
## X644	0	167.1	77.4	27.7	0	0 118
## X645	0	163.8	75.7	28.2	0	1 137
## X646	0	161.6	81.6	31.3	0	0 125
## X648	0	167.1	80.0	28.6	0	0 127
## X649	0	169.0	83.1	29.1	0	0 123
## X650	0	172.5	77.8	26.1	0	0 123
## X652	0	165.8	83.4	30.4	0	1 132
## X654	0	178.3	90.9	28.6	0	1 135
## X655	0	164.5	72.7	26.9	0	1 151
## X656	1	169.5	76.8	26.7	0	1 133
## X657	0	175.0	66.0	21.6	0	0 120
## X658	0	162.3	82.0	31.1	0	1 134
## X659	0	171.0	72.1	24.7	0	0 127
## X660	1	162.2	92.6	35.2	0	1 138
## X661	0	181.0	72.5	22.1	0	1 143
## X663	0	177.2	82.4	26.2	0	0 129
## X664	0	179.5	80.4	25.0	1	1 135



## X665	0	168.7	79.8	28.1	0	1	134
## X666	0	170.8	94.1	32.2	0	0	130
## X667	0	161.1	94.0	36.2	0	1	142
## X668	0	157.1	71.0	28.7	0	0	127
## X669	0	163.1	76.7	28.9	0	1	134
## X670	0	186.7	80.9	23.2	0	1	135
## X673	0	171.9	90.1	30.5	0	1	142
## X674	0	178.5	90.4	28.4	0	0	127
## X675	0	176.1	80.7	26.0	0	0	130
## X676	0	167.8	73.8	26.2	1	1	139
## X677	0	166.2	78.1	28.3	0	0	127
## X678	0	166.7	79.7	28.7	0	1	131
## X679	0	178.4	86.3	27.1	0	1	136
## X680	0	168.7	87.3	30.7	0	1	137
## X681	0	168.0	86.5	30.7	1	1	147
## X682	0	170.5	84.7	29.1	0	1	134
## X683	0	171.7	84.2	28.6	0	0	127
## X684	0	178.5	85.0	26.7	0	1	136
## X685	0	166.9	83.8	30.1	0	0	123
## X686	0	169.2	74.8	26.1	0	0	119
## X687	0	170.1	85.0	29.4	0	1	132
## X688	0	171.4	86.1	29.3	1	1	136
## X690	0	161.9	71.2	27.2	0	0	130
## X691	0	161.1	83.9	32.3	0	0	130
## X692	0	172.4	81.5	27.4	0	1	136
## X693	0	180.0	81.7	25.2	0	1	140
## X694	0	169.8	80.9	28.1	0	0	127
## X697	1	175.4	80.0	26.0	0	0	127
## X698	0	167.5	68.1	24.3	0	1	138
## X699	0	168.1	78.8	27.9	0	0	118
## X700	1	176.4	95.8	30.8	0	0	129
## X701	0	170.3	74.8	25.8	0	1	139
## X702	0	166.1	76.9	27.9	0	0	126
## X703	0	175.0	84.4	27.6	0	0	130
## X705	1	184.1	73.9	21.8	0	0	123
## X706	0	170.4	80.5	27.7	1	0	123
## X707	0	169.9	74.1	25.7	1	1	139
## X708	0	169.5	65.3	22.7	0	0	126
## X709	0	156.6	70.8	28.9	0	0	129
## X710	0	178.3	82.7	26.0	1	1	143
## X711	0	169.5	86.5	30.1	0	1	144
## X712	1	157.3	78.8	31.9	0	0	120
## X713	0	170.4	77.2	26.6	1	0	121
## X714	0	176.3	75.6	24.3	0	0	123
## X715	0	159.5	69.2	27.2	1	0	127
## X716	0	169.5	75.7	26.3	0	0	116
## X717	0	171.5	83.8	28.5	0	1	132
## X718	1	182.7	85.4	25.6	0	0	123
## X719	0	170.5	65.6	22.6	1	0	125
## X720	1	172.2	72.1	24.3	0	1	136
## X721	0	168.5	82.7	29.1	0	0	125
## X722	0	170.7	80.0	27.5	1	1	133
## X724	0	168.7	71.0	25.0	0	0	124
## X725	1	178.2	83.1	26.2	0	0	128

## X726	0	174.1	78.0	25.7	0	1 143
## X730	1	174.6	79.2	26.0	0	0 127
## X731	0	177.0	88.9	28.4	1	1 133
## X732	0	172.8	85.8	28.7	0	1 135
## X734	0	174.3	89.4	29.4	0	1 138
## X735	0	178.3	77.6	24.4	1	0 130
## X737	0	178.5	81.3	25.5	0	0 117
## X738	0	165.6	74.0	27.0	0	0 130
## X739	0	182.8	66.7	20.0	0	0 120
## X740	0	165.4	90.1	33.0	0	1 147
## X744	0	178.9	87.1	27.2	0	1 132
## X745	0	171.6	75.6	25.7	0	1 134
## X746	0	179.6	85.2	26.4	1	1 139
## X747	0	173.2	84.0	28.0	0	0 123
## X748	0	165.7	79.6	29.0	0	1 134
## X749	0	175.2	70.9	23.1	1	1 135
## X751	0	171.3	70.4	24.0	0	0 121
## X752	1	163.5	85.7	32.1	0	1 141
## X753	0	173.9	74.4	24.6	0	1 136
## X754	1	169.1	95.6	33.5	0	0 126
## X757	0	170.2	76.4	26.4	0	0 124
## X758	0	179.2	83.3	25.9	0	0 128
## X759	0	177.2	88.0	28.0	0	0 109
## X761	1	171.7	88.0	29.8	0	0 115
## X762	0	168.7	73.0	25.6	0	0 124
## X763	0	171.6	87.8	29.8	0	1 132
## X764	0	170.0	80.5	27.9	0	1 138
## X765	0	179.8	86.3	26.7	1	1 136
## X766	0	177.2	72.4	23.0	0	0 113
## X767	0	167.0	91.5	32.8	0	1 138
## X768	0	163.1	78.2	29.4	0	0 129
## X769	0	170.2	73.3	25.3	0	0 129
## X770	1	162.1	80.7	30.7	0	0 125
## X772	0	167.7	64.1	22.8	0	1 133
## X773	0	163.9	78.2	29.1	1	1 131
## X774	0	168.4	71.5	25.2	0	1 137
## X775	0	164.7	75.5	27.9	0	0 125
## X776	0	170.3	78.6	27.1	0	0 122
## X777	0	161.6	75.9	29.1	1	1 132
## X778	0	165.5	74.6	27.2	1	0 125
## X779	0	180.6	83.3	25.5	0	1 134
## X780	0	155.2	71.3	29.6	0	0 128
## X781	0	164.0	74.3	27.6	0	1 132
## X784	0	171.8	83.2	28.2	0	0 121
## X786	1	173.7	74.2	24.6	1	0 127
## X787	1	169.7	97.8	33.9	0	0 124
## X788	0	161.5	68.9	26.4	0	0 119
## X789	0	166.5	94.8	34.2	1	0 124
## X790	0	174.6	88.2	28.9	0	0 129
## X791	0	169.4	64.8	22.6	0	1 136
## X792	0	178.7	64.9	20.3	0	1 143
## X794	0	176.8	75.3	24.1	0	0 119
## X795	1	168.5	78.6	27.7	0	0 129
## X796	0	172.0	79.0	26.7	0	1 146

## X797	0	168.5	77.1	27.2	0	1	131
## X798	1	174.0	86.1	28.4	0	0	124
## X799	0	162.0	79.2	30.2	0	0	118
## X800	0	163.0	74.6	28.1	1	1	148
## X801	0	175.8	73.3	23.7	0	1	152
## X802	0	176.3	77.6	25.0	0	0	124
## X803	1	168.6	91.9	32.3	0	0	127
## X804	0	171.3	74.0	25.2	0	0	125
## X805	0	171.2	80.8	27.6	0	1	134
## X807	0	161.8	65.6	25.1	0	1	132
## X808	0	164.1	75.2	27.9	1	1	134
## X809	0	170.2	82.4	28.4	0	0	127
## X810	0	171.2	86.1	29.4	1	0	111
## X812	0	165.0	96.3	35.4	1	0	125
## X813	1	168.2	78.9	27.9	0	1	131
## X814	0	170.9	84.6	29.0	0	0	130
## X815	0	170.5	65.5	22.5	0	0	121
## X816	0	171.1	76.7	26.2	0	0	122
## X817	0	163.9	78.5	29.2	0	1	140
## X818	0	175.6	89.1	28.9	0	1	144
## X820	0	178.1	62.2	19.6	1	0	117
## X821	0	182.4	79.5	23.9	0	1	138
## X822	1	173.1	81.9	27.3	0	1	131
## X823	0	178.1	81.2	25.6	0	1	136
## X824	0	171.3	85.4	29.1	0	0	122
## X825	0	181.7	85.1	25.8	0	1	133
## X826	0	167.2	76.8	27.5	1	1	132
## X830	0	169.8	81.5	28.2	0	1	133
## X831	0	174.3	86.7	28.5	0	0	128
## X832	0	152.4	86.8	37.4	0	0	122
## X833	0	164.5	71.2	26.3	0	0	122
## X834	0	159.8	81.5	31.9	0	1	142
## X836	0	178.9	84.7	26.5	0	1	133
## X837	0	172.0	70.4	23.8	0	0	130
## X838	0	160.0	70.5	27.5	0	0	128
## X839	1	165.7	80.4	29.3	0	0	128
## X840	1	172.4	82.0	27.6	0	1	132
## X841	0	176.3	86.3	27.8	0	1	136
## X842	0	164.2	83.8	31.1	0	0	120
## X843	0	163.9	73.1	27.2	0	0	117
## X844	0	172.6	62.3	20.9	0	0	126
## X847	0	163.0	71.3	26.8	0	1	141
## X848	0	172.5	90.6	30.4	1	0	122
## X849	0	164.8	72.2	26.6	0	1	140
## X850	1	169.7	84.4	29.3	0	0	112
## X851	0	169.9	74.6	25.8	0	1	134
## X852	0	168.7	73.4	25.8	0	0	130
## X853	0	171.5	82.6	28.1	1	0	126
## X854	0	156.1	69.7	28.6	0	1	146
## X855	0	160.7	90.2	34.9	0	0	124
## X856	0	169.1	69.4	24.3	0	0	121
## X857	0	169.1	76.4	26.7	0	0	130
## X858	0	161.0	80.4	31.0	0	0	130
## X859	0	178.7	75.5	23.6	0	1	132

## X860	0	172.4	81.7	27.5	0	1	131
## X861	0	165.3	74.8	27.4	0	0	130
## X862	0	174.2	86.3	28.4	0	0	118
## X864	0	160.2	71.9	28.0	0	0	123
## X865	0	168.6	76.5	26.9	0	0	128
## X866	0	167.5	73.4	26.1	0	0	127
## X867	0	173.4	80.7	26.8	0	1	138
## X868	0	167.0	81.2	29.1	0	0	119
## X869	0	180.4	79.7	24.5	0	1	136
## X870	0	165.0	67.0	24.6	0	0	118
## X871	0	166.0	77.1	28.0	0	1	135
## X872	1	163.7	71.6	26.7	0	0	130
## X873	0	166.8	77.5	27.9	1	1	136
## X874	1	165.9	67.6	24.6	0	0	128
## X875	0	167.8	79.3	28.2	0	0	120
## X877	1	170.7	83.9	28.8	0	0	125
## X878	0	172.2	70.2	23.7	0	0	127
## X879	0	177.8	90.0	28.5	0	0	125
## X880	0	178.0	82.9	26.2	0	0	128
## X881	0	171.1	86.2	29.5	0	1	132
## X882	0	173.3	70.3	23.4	0	0	120
## X883	0	158.5	86.5	34.4	0	0	130
## X884	0	166.4	89.1	32.2	0	1	135
## X885	0	180.6	93.1	28.5	1	1	133
## X886	0	163.5	73.5	27.5	1	1	145
## X887	0	181.9	79.2	23.9	0	1	132
## X888	0	166.2	78.3	28.3	0	0	130
## X889	0	165.0	78.5	28.9	0	0	126
## X890	0	171.4	71.1	24.2	1	0	116
## X891	0	165.9	68.8	25.0	1	1	137
## X892	0	177.5	87.5	27.8	0	1	137
## X894	0	175.6	81.7	26.5	0	0	129
## X895	0	169.8	80.2	27.8	0	0	121
## X897	0	175.1	74.1	24.2	0	0	130
## X899	0	175.6	74.8	24.3	0	0	127
## X900	0	155.7	74.6	30.8	0	0	122
## X901	0	169.9	80.7	28.0	0	1	150
## X902	0	169.6	90.2	31.3	0	0	128
## X903	0	165.7	82.7	30.1	0	0	129
## X904	0	172.3	76.2	25.7	0	1	132
## X905	0	186.8	83.2	23.8	0	1	138
## X906	0	170.7	83.3	28.6	0	0	122
## X907	0	169.9	84.5	29.3	0	0	127
## X908	0	175.8	80.3	26.0	0	1	133
## X909	0	174.3	93.8	30.9	0	0	127
## X910	0	165.9	84.9	30.9	0	1	145
## X911	0	171.6	82.8	28.1	0	0	124
## X913	0	173.3	73.4	24.4	0	1	134
## X916	0	162.5	82.8	31.4	0	0	125
## X917	0	163.6	88.2	32.9	0	1	145
## X918	0	164.6	79.9	29.5	0	0	119
## X919	0	172.0	94.5	31.9	0	1	139
## X920	0	164.8	82.2	30.3	0	0	123
## X921	0	162.9	75.4	28.4	0	1	149

## X922	0	167.3	79.4	28.3	1	1 140
## X924	0	179.0	99.1	30.9	1	0 118
## X925	0	177.2	93.1	29.7	0	0 126
## X926	0	165.8	75.6	27.5	0	0 110
## X927	0	163.4	78.5	29.4	1	0 129
## X929	0	173.6	77.7	25.8	1	1 143
## X932	0	170.7	81.3	27.9	1	1 139
## X933	0	173.2	74.7	24.9	0	0 130
## X935	0	175.0	73.1	23.8	0	1 139
## X936	0	175.6	89.3	29.0	0	1 145
## X937	0	174.2	84.5	27.8	0	1 140
## X939	0	170.1	86.4	29.9	0	1 153
## X940	0	168.3	77.8	27.5	0	0 128
## X941	0	159.3	73.0	28.8	0	1 138
## X942	0	171.9	83.2	28.2	0	0 130
## X943	0	171.6	84.7	28.8	0	1 139
## X945	0	180.7	80.8	24.7	0	0 130
## X946	0	165.5	80.0	29.2	0	1 137
## X948	0	162.9	74.7	28.2	0	1 135
## X949	0	172.5	76.9	25.9	0	0 122
## X950	0	173.6	74.7	24.8	0	0 112
## X951	1	176.2	84.5	27.2	0	0 119
## X953	0	164.5	84.3	31.1	0	0 125
## X954	1	171.7	74.9	25.4	0	1 137
## X955	0	183.7	89.5	26.5	0	0 124
## X956	0	169.2	64.4	22.5	1	0 128
## X957	0	173.1	71.4	23.8	0	1 135
## X958	0	162.9	70.2	26.5	0	1 142
## X959	0	164.1	67.4	25.0	0	0 128
## X960	1	176.8	78.3	25.0	0	0 113
## X961	0	168.8	86.1	30.2	1	1 133
## X962	0	174.5	90.4	29.7	0	1 134
## X963	0	160.1	78.6	30.7	0	0 123
## X964	0	169.3	83.2	29.0	0	0 122
## X965	0	168.7	81.8	28.8	0	1 131
## X966	0	172.4	83.5	28.1	0	0 125
## X968	0	168.9	91.4	32.0	1	1 132
## X969	0	168.9	76.9	27.0	0	1 138
## X970	0	176.0	85.3	27.6	0	1 135
## X971	0	171.4	68.5	23.3	0	0 122
## X972	0	174.0	76.2	25.2	0	0 127
## X973	0	163.7	73.2	27.3	0	0 120
## X974	0	170.2	67.7	23.4	0	1 148
## X975	0	171.8	90.2	30.6	0	1 131
## X976	0	168.3	79.3	28.0	0	0 125
## X977	0	179.7	92.9	28.8	0	0 123
## X978	0	169.7	82.4	28.6	0	0 122
## X979	0	162.5	83.7	31.7	0	1 149
## X980	0	170.7	76.5	26.3	0	1 132
## X981	0	167.7	83.2	29.6	0	0 123
## X982	0	156.7	74.8	30.5	0	1 136
## X983	0	164.9	74.8	27.5	0	1 140
## X984	1	168.5	76.5	26.9	0	0 120
## X985	0	165.9	84.8	30.8	0	1 132

## X986	0	170.1	74.2	25.6	0	0	117
## X987	0	159.9	73.3	28.7	0	0	121
## X988	0	176.0	81.7	26.4	0	0	112
## X989	0	172.5	84.4	28.4	0	0	125
## X990	0	159.9	78.0	30.5	0	0	128
## X991	0	170.2	89.0	30.7	1	0	129
## X992	1	172.2	85.6	28.9	0	0	117
## X993	0	164.7	83.5	30.8	0	0	129
## X994	0	174.4	73.1	24.1	0	0	130
## X995	0	167.5	75.3	26.9	1	1	132
## X996	0	174.7	80.9	26.5	1	1	131
## X997	1	169.7	73.3	25.4	0	1	135
## X998	0	164.7	72.5	26.7	0	1	133
## X999	0	174.3	82.5	27.2	0	1	137
##	ldl	vaccineVaccinated	depression				
## X1	95	1	5				
## X2	87	0	2				
## X3	139	1	5				
## X4	126	1	4				
## X6	99	1	9				
## X9	97	0	8				
## X10	111	0	8				
## X11	132	0	5				
## X12	103	0	4				
## X13	122	0	8				
## X14	97	0	6				
## X15	86	0	5				
## X17	117	0	10				
## X18	108	1	7				
## X19	133	1	8				
## X21	86	1	10				
## X22	127	1	5				
## X24	91	0	10				
## X25	119	0	7				
## X26	98	1	6				
## X27	115	0	6				
## X28	116	0	4				
## X29	95	0	7				
## X30	111	0	8				
## X31	67	1	7				
## X33	142	1	13				
## X36	84	1	10				
## X39	133	1	10				
## X40	118	1	9				
## X41	129	1	6				
## X42	114	1	7				
## X45	100	1	7				
## X46	98	1	8				
## X47	111	1	9				
## X49	117	1	7				
## X54	115	0	7				
## X56	139	1	6				
## X57	111	0	6				
## X59	89	1	4				

## X60	117	0	6
## X61	113	0	9
## X62	109	0	7
## X64	138	1	4
## X65	118	0	8
## X67	119	0	9
## X69	127	0	4
## X70	116	1	2
## X72	107	0	6
## X73	82	0	8
## X74	76	1	4
## X75	123	0	6
## X77	86	0	9
## X78	131	0	7
## X79	149	0	10
## X82	84	0	7
## X85	89	1	7
## X87	81	0	4
## X88	76	0	4
## X89	116	0	4
## X90	141	0	6
## X91	125	0	6
## X92	150	1	7
## X93	126	1	11
## X94	108	0	8
## X95	150	1	9
## X96	85	1	7
## X97	121	1	9
## X98	105	0	2
## X99	106	1	11
## X100	108	1	6
## X101	131	1	7
## X102	115	1	9
## X103	121	0	11
## X104	117	1	6
## X105	118	1	12
## X106	112	0	5
## X108	87	1	8
## X109	110	1	9
## X110	91	0	7
## X112	148	1	7
## X113	78	1	8
## X114	85	0	3
## X115	126	0	6
## X116	114	0	2
## X117	109	0	5
## X119	96	1	7
## X120	102	1	6
## X121	137	0	8
## X122	110	0	9
## X123	140	1	8
## X126	114	1	7
## X127	94	0	3
## X128	128	0	6

## X129 93	1	5
## X130 127	1	6
## X131 107	1	5
## X132 103	1	6
## X133 118	1	12
## X135 122	1	8
## X136 80	1	8
## X137 101	0	7
## X138 98	1	6
## X139 125	0	9
## X142 174	0	6
## X144 148	1	5
## X145 75	1	3
## X146 92	1	6
## X147 94	1	2
## X148 136	0	8
## X149 135	0	5
## X150 118	1	4
## X152 120	1	8
## X154 131	1	8
## X155 135	0	9
## X156 104	1	7
## X157 126	0	8
## X159 119	1	6
## X160 121	1	8
## X161 72	1	6
## X162 82	1	5
## X163 107	1	5
## X164 93	1	10
## X165 63	0	5
## X166 118	1	6
## X167 127	0	5
## X168 109	0	6
## X169 77	1	5
## X170 112	1	9
## X171 111	1	8
## X172 132	1	5
## X173 106	0	6
## X174 135	0	5
## X175 104	1	4
## X177 153	1	7
## X179 72	1	10
## X180 111	1	2
## X181 110	0	5
## X182 99	0	5
## X183 120	1	5
## X184 120	1	8
## X185 102	1	5
## X186 81	1	7
## X187 121	1	7
## X188 74	0	5
## X189 126	0	7
## X190 108	0	2
## X191 127	1	8



## X192 134	0	7
## X193 87	0	6
## X194 71	0	9
## X195 109	0	8
## X196 73	1	10
## X198 98	0	9
## X200 101	0	5
## X201 98	0	8
## X202 80	1	10
## X204 105	1	9
## X205 84	1	5
## X206 127	0	4
## X207 136	1	12
## X209 100	1	8
## X211 137	1	9
## X212 152	0	7
## X213 110	0	4
## X214 147	1	10
## X215 81	1	7
## X216 129	0	11
## X217 90	1	8
## X218 125	1	4
## X219 119	1	8
## X220 107	0	11
## X221 131	1	8
## X222 91	1	5
## X223 101	0	9
## X224 80	0	7
## X226 120	0	8
## X227 120	1	4
## X228 108	1	7
## X229 119	1	9
## X230 82	1	4
## X231 101	0	7
## X233 98	1	8
## X234 135	0	8
## X235 143	1	9
## X236 138	0	11
## X237 121	1	8
## X238 156	1	4
## X239 92	0	7
## X240 77	0	6
## X241 93	0	4
## X244 111	0	8
## X245 104	0	2
## X246 98	1	5
## X247 70	1	5
## X248 133	1	4
## X249 130	1	7
## X251 106	1	7
## X252 118	1	6
## X254 81	1	7
## X255 135	1	3
## X256 105	1	4

## X257 126	0	8
## X258 122	1	10
## X259 117	1	5
## X260 118	0	7
## X261 114	1	3
## X262 90	1	7
## X264 122	0	8
## X265 118	0	9
## X266 104	0	12
## X267 146	0	7
## X268 106	1	10
## X269 104	1	8
## X270 102	1	10
## X273 104	1	8
## X274 106	0	11
## X275 110	0	5
## X276 110	1	5
## X277 76	1	3
## X278 82	1	5
## X279 102	0	7
## X280 82	1	5
## X282 98	0	10
## X283 91	1	5
## X284 116	1	9
## X286 103	1	6
## X289 103	0	7
## X290 69	1	6
## X292 81	1	5
## X293 96	0	7
## X295 137	1	7
## X296 139	1	5
## X298 97	0	10
## X299 110	1	8
## X300 126	1	9
## X301 112	0	7
## X302 68	1	7
## X303 93	1	13
## X305 99	0	9
## X306 88	0	7
## X307 94	1	6
## X311 116	0	8
## X312 90	0	6
## X313 114	1	7
## X314 94	1	4
## X315 108	1	6
## X316 123	1	4
## X317 123	1	8
## X318 123	1	3
## X319 77	0	9
## X321 104	1	5
## X322 75	1	6
## X326 62	1	7
## X327 123	0	7
## X328 117	1	4

## X329 121	0	5
## X330 93	1	9
## X331 76	0	8
## X332 130	1	9
## X333 122	1	7
## X334 147	0	8
## X335 123	1	9
## X336 62	1	8
## X339 91	0	5
## X340 110	1	6
## X341 145	0	9
## X342 112	0	5
## X345 145	1	6
## X347 78	1	7
## X349 123	1	7
## X351 118	1	9
## X353 123	1	4
## X354 114	1	7
## X355 105	0	5
## X356 140	0	7
## X359 76	0	6
## X360 117	1	11
## X361 95	1	6
## X363 99	1	10
## X365 100	0	6
## X366 123	1	8
## X367 121	0	8
## X369 153	0	9
## X371 132	1	7
## X372 99	0	3
## X373 90	0	7
## X374 110	1	2
## X376 95	0	6
## X377 93	0	8
## X378 118	1	9
## X379 77	1	8
## X380 125	1	9
## X382 129	0	6
## X383 111	0	8
## X385 84	1	6
## X386 124	0	5
## X387 152	0	2
## X388 94	1	9
## X389 115	0	8
## X391 101	0	7
## X392 141	0	7
## X393 103	0	4
## X394 81	0	5
## X395 92	0	10
## X396 112	0	7
## X397 99	0	6
## X398 167	1	7
## X399 99	1	7
## X401 86	1	9

## X402 126	1	9
## X405 112	0	3
## X406 113	0	7
## X407 116	0	6
## X408 122	1	8
## X410 111	0	6
## X411 124	0	8
## X412 139	0	2
## X413 81	1	5
## X414 118	0	9
## X415 102	0	5
## X416 85	0	5
## X417 121	1	6
## X418 105	0	2
## X419 145	1	6
## X420 105	1	8
## X421 114	1	8
## X422 70	1	8
## X423 120	1	4
## X424 108	0	8
## X425 127	1	9
## X426 120	0	5
## X427 125	1	7
## X431 105	0	8
## X432 122	0	11
## X434 95	1	7
## X435 145	0	7
## X437 162	0	6
## X438 77	1	8
## X439 105	1	4
## X440 109	0	8
## X441 113	1	7
## X442 92	0	6
## X443 107	0	5
## X444 131	1	5
## X445 127	1	4
## X448 123	1	7
## X450 138	1	9
## X451 121	0	8
## X453 87	0	6
## X454 108	1	6
## X455 110	1	6
## X456 122	0	2
## X457 90	0	7
## X458 92	1	8
## X459 149	1	10
## X460 118	1	8
## X461 120	0	8
## X464 110	1	5
## X465 127	1	5
## X466 41	1	7
## X468 128	1	10
## X469 111	1	5
## X470 72	0	3

## X472 116	1	4
## X473 97	0	6
## X474 95	0	6
## X475 95	1	3
## X476 98	1	7
## X478 123	0	8
## X480 105	0	8
## X481 106	0	7
## X482 114	1	4
## X483 99	1	6
## X484 99	0	12
## X486 127	1	6
## X487 123	1	8
## X488 128	1	4
## X489 138	0	8
## X490 83	1	10
## X491 122	0	6
## X492 127	0	13
## X493 116	1	7
## X494 104	0	8
## X495 119	1	7
## X496 123	0	6
## X497 127	1	9
## X498 158	0	2
## X499 131	1	7
## X500 161	1	7
## X501 92	1	6
## X502 115	1	6
## X503 89	1	9
## X504 115	0	10
## X507 100	1	5
## X509 86	0	2
## X511 79	1	5
## X512 130	1	6
## X513 101	0	9
## X514 133	1	8
## X515 108	0	7
## X516 115	0	7
## X518 100	1	8
## X520 103	0	5
## X521 103	1	10
## X522 88	0	4
## X523 132	1	5
## X524 91	0	8
## X525 120	1	8
## X527 123	1	5
## X528 133	0	8
## X529 117	1	6
## X530 87	1	5
## X533 89	1	4
## X535 105	1	9
## X536 105	0	10
## X539 121	0	8
## X540 124	1	7

## X541 124	1	8
## X542 119	0	6
## X543 110	0	7
## X545 130	0	7
## X546 152	1	8
## X547 101	0	9
## X548 103	1	3
## X549 103	0	6
## X550 103	1	3
## X551 132	0	11
## X552 82	0	7
## X553 122	1	6
## X554 121	1	5
## X556 100	1	6
## X557 88	0	10
## X558 54	0	8
## X559 126	0	6
## X560 144	1	12
## X561 130	0	6
## X562 134	1	8
## X563 130	1	10
## X564 131	1	9
## X565 96	0	7
## X566 135	0	7
## X567 140	1	8
## X568 112	1	8
## X569 107	0	7
## X571 81	1	5
## X573 153	0	5
## X574 93	0	7
## X575 104	0	9
## X576 137	1	4
## X577 118	1	4
## X579 78	1	7
## X580 94	0	1
## X582 126	1	6
## X584 111	1	7
## X587 133	0	8
## X588 116	1	5
## X589 93	0	5
## X591 64	1	6
## X592 110	1	11
## X593 111	1	6
## X594 94	1	4
## X597 89	0	8
## X598 105	1	5
## X600 134	0	5
## X601 137	1	4
## X602 105	0	10
## X603 89	0	5
## X604 105	1	7
## X605 96	0	6
## X606 99	0	8
## X609 99	0	7

## X610 154	0	7
## X611 99	0	7
## X613 108	0	9
## X614 130	0	7
## X615 108	1	8
## X617 93	1	7
## X618 95	0	5
## X619 101	1	11
## X620 74	1	9
## X623 131	0	8
## X624 121	1	10
## X625 101	1	6
## X626 140	1	6
## X628 116	1	7
## X629 115	1	5
## X630 80	1	6
## X631 134	0	8
## X632 99	1	7
## X633 117	0	7
## X634 71	0	7
## X635 100	1	7
## X636 149	1	6
## X637 131	0	7
## X638 138	1	5
## X640 109	1	9
## X641 119	0	9
## X642 117	1	9
## X643 61	1	10
## X644 91	1	8
## X645 83	1	5
## X646 103	1	7
## X648 101	1	4
## X649 76	1	9
## X650 104	1	7
## X652 103	0	7
## X654 146	0	8
## X655 103	0	8
## X656 68	1	9
## X657 71	0	9
## X658 106	0	4
## X659 114	0	9
## X660 136	1	8
## X661 122	0	8
## X663 92	0	6
## X664 123	1	9
## X665 104	0	4
## X666 123	0	5
## X667 121	1	8
## X668 120	1	6
## X669 141	0	9
## X670 102	1	6
## X673 116	0	8
## X674 130	1	5
## X675 86	1	9

## X676 111	0	7
## X677 101	1	6
## X678 121	1	8
## X679 139	1	4
## X680 136	0	9
## X681 117	1	9
## X682 102	1	8
## X683 134	1	9
## X684 114	1	9
## X685 102	0	10
## X686 122	1	9
## X687 130	1	3
## X688 127	0	11
## X690 89	0	5
## X691 118	1	5
## X692 122	0	7
## X693 98	1	4
## X694 130	1	9
## X697 119	1	8
## X698 138	1	9
## X699 99	1	9
## X700 107	1	8
## X701 124	1	8
## X702 130	0	8
## X703 108	0	9
## X705 93	1	9
## X706 104	1	8
## X707 130	1	8
## X708 129	1	10
## X709 97	1	8
## X710 116	1	7
## X711 118	0	9
## X712 128	1	3
## X713 133	1	7
## X714 75	0	6
## X715 75	1	8
## X716 118	0	7
## X717 129	1	9
## X718 111	0	8
## X719 133	1	8
## X720 112	1	5
## X721 86	0	9
## X722 114	1	9
## X724 80	0	6
## X725 84	0	12
## X726 124	0	4
## X730 134	0	8
## X731 110	1	9
## X732 124	1	6
## X734 92	1	5
## X735 85	1	9
## X737 119	1	4
## X738 111	1	11
## X739 131	1	9



## X740 115	1	8
## X744 116	0	6
## X745 116	0	7
## X746 103	0	10
## X747 81	1	7
## X748 111	1	7
## X749 96	0	10
## X751 124	0	7
## X752 114	1	8
## X753 78	0	9
## X754 107	0	9
## X757 137	1	2
## X758 78	1	7
## X759 118	0	3
## X761 106	1	7
## X762 119	0	9
## X763 157	0	10
## X764 81	1	3
## X765 118	1	4
## X766 103	0	6
## X767 118	1	7
## X768 109	0	8
## X769 104	1	6
## X770 97	1	0
## X772 132	0	6
## X773 112	1	8
## X774 118	0	5
## X775 128	0	11
## X776 118	1	3
## X777 78	1	6
## X778 116	1	6
## X779 119	1	7
## X780 98	1	5
## X781 78	1	5
## X784 112	1	5
## X786 77	1	3
## X787 100	1	5
## X788 98	1	6
## X789 99	0	3
## X790 115	1	7
## X791 113	1	6
## X792 106	0	5
## X794 111	0	4
## X795 130	1	6
## X796 117	1	6
## X797 100	0	7
## X798 103	1	2
## X799 93	0	8
## X800 98	1	9
## X801 134	0	9
## X802 91	0	9
## X803 123	1	8
## X804 113	1	6
## X805 96	0	5

## X807 112	1	8
## X808 84	1	5
## X809 112	0	6
## X810 105	1	1
## X812 98	1	6
## X813 112	1	8
## X814 116	1	10
## X815 61	1	9
## X816 106	1	7
## X817 85	1	6
## X818 137	1	8
## X820 98	1	4
## X821 96	0	10
## X822 132	0	8
## X823 131	0	9
## X824 104	1	5
## X825 79	0	10
## X826 113	1	7
## X830 107	1	8
## X831 98	1	6
## X832 86	1	9
## X833 98	0	5
## X834 83	1	4
## X836 110	0	10
## X837 99	0	8
## X838 114	0	5
## X839 102	1	8
## X840 111	0	7
## X841 109	1	7
## X842 68	1	5
## X843 124	1	8
## X844 110	1	6
## X847 160	1	6
## X848 114	1	9
## X849 141	1	8
## X850 96	0	7
## X851 121	0	7
## X852 107	1	7
## X853 97	1	8
## X854 143	0	7
## X855 90	1	6
## X856 73	1	3
## X857 137	0	6
## X858 111	1	5
## X859 112	0	5
## X860 123	0	13
## X861 104	1	7
## X862 96	1	7
## X864 130	0	4
## X865 121	1	6
## X866 109	1	8
## X867 77	0	8
## X868 102	1	8
## X869 108	1	11

## X870 114	0	6
## X871 76	0	7
## X872 101	1	6
## X873 108	0	2
## X874 86	1	8
## X875 98	1	7
## X877 85	0	5
## X878 91	1	2
## X879 73	1	9
## X880 116	0	8
## X881 106	1	4
## X882 94	1	8
## X883 100	1	3
## X884 149	1	5
## X885 115	1	8
## X886 106	0	6
## X887 150	1	7
## X888 109	0	6
## X889 108	1	7
## X890 121	1	9
## X891 149	1	6
## X892 119	1	9
## X894 100	0	7
## X895 98	1	5
## X897 114	0	8
## X899 98	0	11
## X900 110	1	7
## X901 129	0	8
## X902 92	0	3
## X903 128	1	7
## X904 129	1	8
## X905 123	1	7
## X906 128	1	9
## X907 111	1	9
## X908 100	0	9
## X909 135	1	6
## X910 136	1	9
## X911 70	1	9
## X913 127	1	6
## X916 111	1	6
## X917 164	1	9
## X918 126	0	7
## X919 122	0	4
## X920 87	1	7
## X921 134	0	5
## X922 97	0	6
## X924 96	1	5
## X925 99	1	7
## X926 103	1	6
## X927 117	0	8
## X929 106	0	7
## X932 155	0	8
## X933 75	1	7
## X935 96	1	3

## X936 115	0	10
## X937 102	1	9
## X939 117	0	9
## X940 108	0	8
## X941 150	1	9
## X942 139	1	9
## X943 127	0	10
## X945 124	1	6
## X946 117	1	7
## X948 121	0	6
## X949 93	1	5
## X950 79	1	11
## X951 145	1	6
## X953 114	0	7
## X954 123	0	4
## X955 128	1	10
## X956 114	0	8
## X957 94	0	7
## X958 140	1	7
## X959 105	1	7
## X960 104	1	7
## X961 97	0	6
## X962 144	0	8
## X963 134	1	9
## X964 102	1	8
## X965 100	1	11
## X966 78	0	6
## X968 130	1	7
## X969 119	1	9
## X970 107	0	6
## X971 112	1	10
## X972 99	1	11
## X973 88	1	8
## X974 133	0	9
## X975 115	1	5
## X976 89	0	7
## X977 111	1	9
## X978 93	1	7
## X979 122	1	7
## X980 89	1	10
## X981 117	0	7
## X982 112	0	4
## X983 157	0	7
## X984 76	1	10
## X985 125	1	8
## X986 83	0	7
## X987 83	0	8
## X988 137	1	6
## X989 114	1	7
## X990 129	1	10
## X991 106	1	6
## X992 95	1	9
## X993 99	1	5
## X994 98	0	7

```

## X995 121          0          7
## X996 120          0          7
## X997 122          1          5
## X998 125          1          5
## X999 98           0          5
##
## $usekernel
## [1] TRUE
##
## $varnames
## [1] "age"          "genderMale"    "raceAsian"
## [4] "raceBlack"    "raceHispanic"  "smokingFormer_smoker"
## [7] "smokingCurrent_smoker" "height"        "weight"
## [10] "bmi"          "diabetesYes"   "hypertensionYes"
## [13] "sbp"          "ldl"           "vaccineVaccinated"
## [16] "depression"
##
## $xNames
## [1] "age"          "genderMale"    "raceAsian"
## [4] "raceBlack"    "raceHispanic"  "smokingFormer_smoker"
## [7] "smokingCurrent_smoker" "height"        "weight"
## [10] "bmi"          "diabetesYes"   "hypertensionYes"
## [13] "sbp"          "ldl"           "vaccineVaccinated"
## [16] "depression"
##
## $problemType
## [1] "Classification"
##
## $tuneValue
##      fL usekernel adjust
## 42  1      TRUE    3.4
##
## $obsLevels
## [1] "Not_severe" "Severe"
## attr(,"ordered")
## [1] FALSE
##
## $param
## list()
##
## attr("class")
## [1] "NaiveBayes"

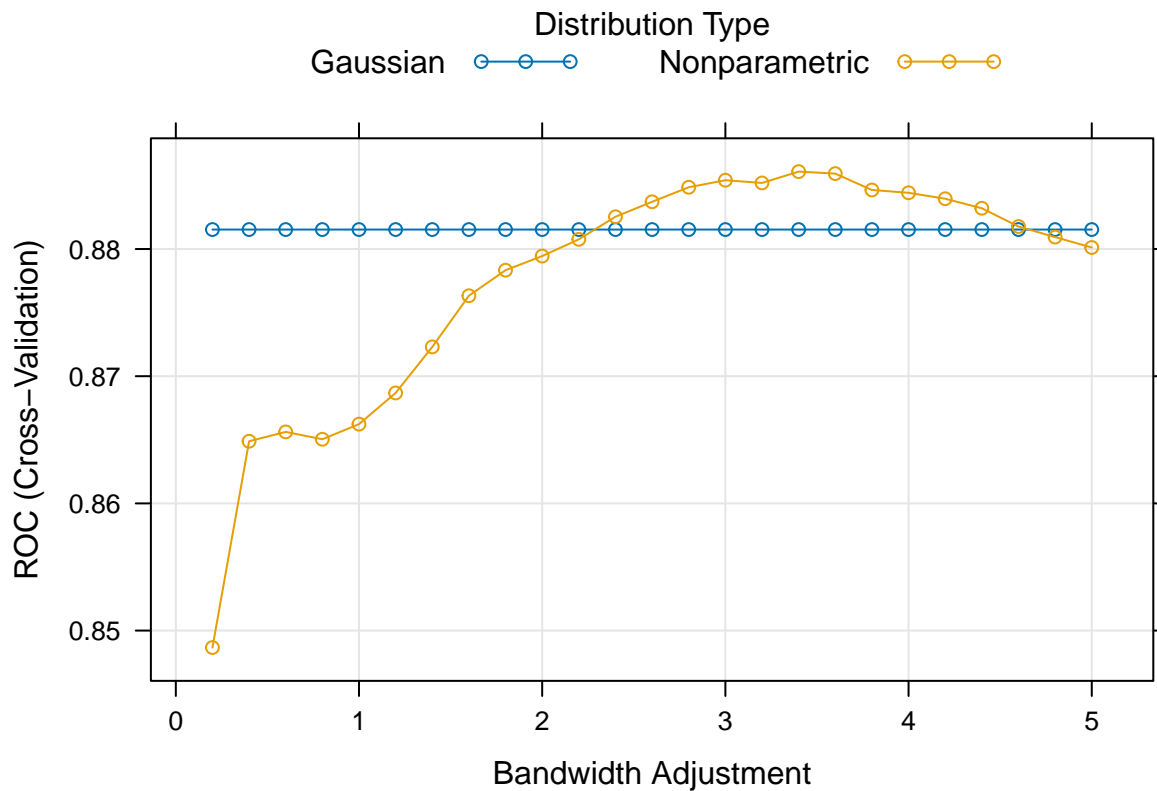
```

```
# NB scaled
```

```

set.seed(2)
scaled.model.nb = train(x = x.train.scaled,
                        y = y.train.scaled,
                        method = "nb",
                        tuneGrid = nbGrid,
                        metric = "ROC",
                        trControl = ctrl)
plot(scaled.model.nb)

```



```
scaled.model.nb$bestTune
```

```
## fL usekernel adjust
## 42 1 TRUE 3.4
```

```
scaled.model.nb$finalModel
```

```
## $apriori
## grouping
## Not_severe Severe
## 0.6425 0.3575
##
## $tables
## $tables$age
## $tables$age$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.7624
##
##      x      y
## Min. :-5.5527 Min. :1.391e-05
## 1st Qu.: -2.9546 1st Qu.: 2.190e-03
## Median :-0.3566 Median : 3.789e-02
## Mean :-0.3566 Mean : 9.613e-02
## 3rd Qu.: 2.2414 3rd Qu.: 1.865e-01
## Max. : 4.8394 Max. : 3.155e-01
##
## $tables$age$Severe
```

```
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.9474
##
##      x              y
## Min.   :-5.642222   Min.   :2.631e-05
## 1st Qu.: -2.824892   1st Qu.:2.076e-03
## Median :-0.007563   Median :3.324e-02
## Mean   :-0.007563   Mean    :8.865e-02
## 3rd Qu.: 2.809767   3rd Qu.:1.709e-01
## Max.    : 5.627096   Max.    :2.960e-01
##
##
## $tables$genderMale
## $tables$genderMale$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4394
##
##      x              y
## Min.   :-1.3183   Min.   :0.005056
## 1st Qu.: -0.4092   1st Qu.:0.065590
## Median : 0.5000   Median :0.296017
## Mean    : 0.5000   Mean    :0.274341
## 3rd Qu.: 1.4092   3rd Qu.:0.478500
## Max.    : 2.3183   Max.    :0.501583
##
## $tables$genderMale$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4928
##
##      x              y
## Min.   :-1.4783   Min.   :0.004163
## 1st Qu.: -0.4892   1st Qu.:0.054802
## Median : 0.5000   Median :0.249263
## Mean    : 0.5000   Mean    :0.252157
## 3rd Qu.: 1.4892   3rd Qu.:0.451335
## Max.    : 2.4783   Max.    :0.503657
##
##
## $tables$raceAsian
## $tables$raceAsian$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2184
```

```
##
##      x              y
## Min.   :-0.65534   Min.    :0.001356
## 1st Qu.: -0.07767   1st Qu.:0.058789
## Median : 0.50000   Median :0.115559
## Mean   : 0.50000   Mean    :0.431777
## 3rd Qu.: 1.07767   3rd Qu.:0.710201
## Max.    : 1.65534   Max.     :1.704901
##
## $tables$raceAsian$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.2273
##
##      x              y
## Min.   :-0.68188   Min.    :0.001102
## 1st Qu.: -0.09094   1st Qu.:0.056832
## Median : 0.50000   Median :0.096677
## Mean   : 0.50000   Mean    :0.422084
## 3rd Qu.: 1.09094   3rd Qu.:0.707112
## Max.    : 1.68188   Max.     :1.656538
##
##
## $tables$raceBlack
## $tables$raceBlack$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3518
##
##      x              y
## Min.   :-1.0555   Min.    :0.002552
## 1st Qu.: -0.2777   1st Qu.:0.070360
## Median : 0.5000   Median :0.244896
## Mean   : 0.5000   Mean    :0.320704
## 3rd Qu.: 1.2777   3rd Qu.:0.517906
## Max.    : 2.0555   Max.     :0.910590
##
## $tables$raceBlack$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3634
##
##      x              y
## Min.   :-1.090   Min.    :0.001981
## 1st Qu.: -0.295   1st Qu.:0.059468
## Median : 0.500   Median :0.203735
## Mean   : 0.500   Mean    :0.313730
## 3rd Qu.: 1.295   3rd Qu.:0.529073
```



```

## Max. : 2.090 Max. :0.925319
##
##
## $tables$raceHispanic
## $tables$raceHispanic$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2581
##
##      x      y
## Min. :-0.7743 Min. :0.001654
## 1st Qu.: -0.1372 1st Qu.:0.077879
## Median : 0.5000 Median :0.143643
## Mean : 0.5000 Mean :0.391457
## 3rd Qu.: 1.1372 3rd Qu.:0.651065
## Max. : 1.7743 Max. :1.398214
##
## $tables$raceHispanic$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3075
##
##      x      y
## Min. :-0.9224 Min. :0.001579
## 1st Qu.: -0.2112 1st Qu.:0.062210
## Median : 0.5000 Median :0.152821
## Mean : 0.5000 Mean :0.350712
## 3rd Qu.: 1.2112 3rd Qu.:0.597910
## Max. : 1.9224 Max. :1.157318
##
##
## $tables$smokingFormer_smoker
## $tables$smokingFormer_smoker$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4048
##
##      x      y
## Min. :-1.2145 Min. :0.003377
## 1st Qu.: -0.3572 1st Qu.:0.067287
## Median : 0.5000 Median :0.283394
## Mean : 0.5000 Mean :0.290960
## 3rd Qu.: 1.3572 3rd Qu.:0.460554
## Max. : 2.2145 Max. :0.699683
##
## $tables$smokingFormer_smoker$Severe
##
## Call:

```

```

## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4607
##
##      x              y
## Min.   :-1.382   Min.   :0.003094
## 1st Qu.: -0.441   1st Qu.:0.056076
## Median :  0.500   Median :0.244153
## Mean   :  0.500   Mean    :0.265065
## 3rd Qu.:  1.441   3rd Qu.:0.445425
## Max.    :  2.382   Max.    :0.619975
##
##
## $tables$smokingCurrent_smoker
## $tables$smokingCurrent_smoker$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.2673
##
##      x              y
## Min.   :-0.8019   Min.   :0.001728
## 1st Qu.: -0.1509   1st Qu.:0.077124
## Median :  0.5000   Median :0.151115
## Mean   :  0.5000   Mean    :0.383183
## 3rd Qu.:  1.1509   3rd Qu.:0.637338
## Max.    :  1.8019   Max.    :1.338499
##
## $tables$smokingCurrent_smoker$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3118
##
##      x              y
## Min.   :-0.9353   Min.   :0.001607
## 1st Qu.: -0.2177   1st Qu.:0.062239
## Median :  0.5000   Median :0.157377
## Mean   :  0.5000   Mean    :0.347555
## 3rd Qu.:  1.2177   3rd Qu.:0.592791
## Max.    :  1.9353   Max.    :1.137104
##
##
## $tables$height
## $tables$height$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.8988
##
##      x              y

```

```

## Min.      :-5.9452   Min.      :1.802e-05
## 1st Qu.: -3.0956   1st Qu.:1.898e-03
## Median : -0.2461   Median :3.268e-02
## Mean    : -0.2461   Mean    :8.765e-02
## 3rd Qu.:  2.6035   3rd Qu.:1.710e-01
## Max.     :  5.4531   Max.     :2.897e-01
##
## $tables$height$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.944
##
##      x              y
## Min.      :-5.7361   Min.      :1.709e-05
## 1st Qu.: -2.7614   1st Qu.:1.317e-03
## Median :  0.2133   Median :2.505e-02
## Mean     :  0.2133   Mean     :8.396e-02
## 3rd Qu.:  3.1880   3rd Qu.:1.602e-01
## Max.     :  6.1628   Max.     :2.979e-01
##
##
## $tables$weight
## $tables$weight$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.8869
##
##      x              y
## Min.      :-5.8049   Min.      :1.167e-05
## 1st Qu.: -2.8143   1st Qu.:1.169e-03
## Median :  0.1763   Median :2.415e-02
## Mean     :  0.1763   Mean     :8.351e-02
## 3rd Qu.:  3.1668   3rd Qu.:1.612e-01
## Max.     :  6.1574   Max.     :2.939e-01
##
## $tables$weight$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.9542
##
##      x              y
## Min.      :-5.6761   Min.      :1.826e-05
## 1st Qu.: -2.7052   1st Qu.:1.480e-03
## Median :  0.2658   Median :2.705e-02
## Mean     :  0.2658   Mean     :8.406e-02
## 3rd Qu.:  3.2368   3rd Qu.:1.608e-01
## Max.     :  6.2078   Max.     :2.935e-01
##

```

```
##
## $tables$bmi
## $tables$bmi$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.7902
##
##      x              y
## Min.   :-5.2714   Min.   :0.0000155
## 1st Qu.: -2.4599   1st Qu.:0.0017191
## Median :  0.3515   Median :0.0253085
## Mean   :  0.3515   Mean    :0.0888335
## 3rd Qu.:  3.1630   3rd Qu.:0.1671165
## Max.    :  5.9745   Max.    :0.3218230
##
## $tables$bmi$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.9424
##
##      x              y
## Min.   :-5.618   Min.   :2.766e-05
## 1st Qu.: -2.652   1st Qu.:2.009e-03
## Median :  0.315   Median :2.867e-02
## Mean   :  0.315   Mean    :8.419e-02
## 3rd Qu.:  3.282   3rd Qu.:1.585e-01
## Max.    :  6.248   Max.    :2.943e-01
##
##
## $tables$diabetesYes
## $tables$diabetesYes$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3137
##
##      x              y
## Min.   :-0.9410   Min.   :0.002137
## 1st Qu.: -0.2205   1st Qu.:0.073069
## Median :  0.5000   Median :0.198557
## Mean   :  0.5000   Mean    :0.346180
## 3rd Qu.:  1.2205   3rd Qu.:0.570623
## Max.    :  1.9410   Max.    :1.082367
##
## $tables$diabetesYes$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
```

```

## Data: xx (286 obs.); Bandwidth 'bw' = 0.3568
##
##      x              y
## Min.   :-1.0705   Min.   :0.00193
## 1st Qu.: -0.2853   1st Qu.:0.06001
## Median : 0.5000   Median :0.19888
## Mean   : 0.5000   Mean    :0.31763
## 3rd Qu.: 1.2853   3rd Qu.:0.53567
## Max.    : 2.0705   Max.    :0.94928
##
##
## $tables$hypertensionYes
## $tables$hypertensionYes$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.4203
##
##      x              y
## Min.   :-1.2610   Min.   :0.003773
## 1st Qu.: -0.3805   1st Qu.:0.066342
## Median : 0.5000   Median :0.289537
## Mean   : 0.5000   Mean    :0.283276
## 3rd Qu.: 1.3805   3rd Qu.:0.450622
## Max.    : 2.2610   Max.    :0.635073
##
## $tables$hypertensionYes$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.4716
##
##      x              y
## Min.   :-1.4149   Min.   :0.003319
## 1st Qu.: -0.4574   1st Qu.:0.055554
## Median : 0.5000   Median :0.246724
## Mean   : 0.5000   Mean    :0.260511
## 3rd Qu.: 1.4574   3rd Qu.:0.441410
## Max.    : 2.4149   Max.    :0.586568
##
##
## $tables$sbp
## $tables$sbp$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.7398
##
##      x              y
## Min.   :-4.8348   Min.   :0.0000253
## 1st Qu.: -2.3138   1st Qu.:0.0026191

```

```

## Median : 0.2071   Median :0.0363338
## Mean   : 0.2071   Mean    :0.0990708
## 3rd Qu.: 2.7281   3rd Qu.:0.1880096
## Max.   : 5.2490   Max.    :0.3372675
##
## $tables$sbp$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.9012
##
##      x              y
## Min.   :-5.0679   Min.    :4.602e-05
## 1st Qu.: -2.3990   1st Qu.:3.181e-03
## Median :  0.2699   Median :3.867e-02
## Mean   :  0.2699   Mean    :9.358e-02
## 3rd Qu.:  2.9388   3rd Qu.:1.768e-01
## Max.   :  5.6076   Max.    :3.105e-01
##
##
## $tables$ldl
## $tables$ldl$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.8996
##
##      x              y
## Min.   :-6.1520   Min.    :1.107e-05
## 1st Qu.: -3.2319   1st Qu.:1.429e-03
## Median : -0.3118   Median :2.945e-02
## Mean   : -0.3118   Mean    :8.553e-02
## 3rd Qu.:  2.6084   3rd Qu.:1.658e-01
## Max.   :  5.5285   Max.    :2.901e-01
##
## $tables$ldl$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.9185
##
##      x              y
## Min.   :-5.5604   Min.    :2.054e-05
## 1st Qu.: -2.6867   1st Qu.:1.417e-03
## Median :  0.1869   Median :2.713e-02
## Mean   :  0.1869   Mean    :8.691e-02
## 3rd Qu.:  3.0605   3rd Qu.:1.659e-01
## Max.   :  5.9341   Max.    :3.055e-01
##
##
## $tables$vaccineVaccinated

```

```

## $tables$vaccineVaccinated$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.3425
##
##      x          y
## Min.   :-1.0276   Min.   :0.002442
## 1st Qu.: -0.2638   1st Qu.:0.070760
## Median :  0.5000   Median :0.234795
## Mean   :  0.5000   Mean    :0.326552
## 3rd Qu.:  1.2638   3rd Qu.:0.530281
## Max.    :  2.0276   Max.    :0.950099
##
## $tables$vaccineVaccinated$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.3634
##
##      x          y
## Min.   :-1.090    Min.   :0.001981
## 1st Qu.: -0.295    1st Qu.:0.059468
## Median :  0.500    Median :0.203735
## Mean   :  0.500    Mean    :0.313730
## 3rd Qu.:  1.295    3rd Qu.:0.529073
## Max.    :  2.090    Max.    :0.925319
##
##
## $tables$depression
## $tables$depression$Not_severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (514 obs.); Bandwidth 'bw' = 0.8846
##
##      x          y
## Min.   :-5.9148   Min.   :1.263e-05
## 1st Qu.: -3.0539   1st Qu.:1.702e-03
## Median : -0.1929   Median :3.032e-02
## Mean   : -0.1929   Mean    :8.730e-02
## 3rd Qu.:  2.6680   3rd Qu.:1.682e-01
## Max.    :  5.5289   Max.    :2.969e-01
##
## $tables$depression$Severe
##
## Call:
## density.default(x = xx, adjust = ..1)
##
## Data: xx (286 obs.); Bandwidth 'bw' = 0.6955
##

```

```

##           x           y
## Min.      :-4.87558   Min.      :0.0000284
## 1st Qu.: -2.41626   1st Qu.: 0.0034250
## Median :  0.04307   Median : 0.0418612
## Mean    :  0.04307   Mean     : 0.1015527
## 3rd Qu.:  2.50240   3rd Qu.: 0.1898809
## Max.    :  4.96172   Max.     : 0.3422050
##
##
##
## $levels
## [1] "Not_severe" "Severe"
##
## $call
## NaiveBayes.default(x = x, grouping = y, usekernel = TRUE, fL = param$fL,
##   adjust = param$adjust)
##
## $x
##           age genderMale raceAsian raceBlack raceHispanic
## X1  -0.240265582           0           0           0           0
## X2  -1.403779294           1           0           0           0
## X3  -1.171076552           1           0           1           0
## X4  -0.240265582           0           0           0           0
## X6   0.923248131           1           0           0           0
## X9   1.621356358           0           0           0           0
## X10  1.388653616           1           0           0           0
## X11 -2.334590264           1           0           0           1
## X12  1.621356358           0           0           0           0
## X13  0.923248131           1           0           0           0
## X14  0.690545388           0           0           0           0
## X15 -1.636482037           0           0           0           1
## X17  0.225139903           1           0           0           0
## X18  0.457842646           0           0           0           0
## X19 -0.472968324           0           0           0           1
## X21 -0.472968324           1           0           0           0
## X22  0.690545388           0           0           1           0
## X24 -1.171076552           0           0           0           0
## X25  0.225139903           0           0           0           0
## X26  0.923248131           0           0           1           0
## X27  0.690545388           0           1           0           0
## X28 -0.240265582           0           0           0           0
## X29 -0.705671067           1           0           0           0
## X30  0.225139903           0           0           1           0
## X31  1.388653616           0           0           1           0
## X33  0.225139903           1           1           0           0
## X36 -0.938373809           1           0           1           0
## X39  0.690545388           1           0           1           0
## X40  0.923248131           0           0           0           0
## X41  1.155950873           1           0           0           0
## X42 -1.171076552           0           0           1           0
## X45 -0.007562839           1           0           1           0
## X46  0.457842646           1           0           0           0
## X47 -1.171076552           1           0           0           0
## X49  1.388653616           0           0           0           0

```



## X54	-0.007562839	1	0	1	0
## X56	0.225139903	1	0	0	0
## X57	0.457842646	1	1	0	0
## X59	0.457842646	1	0	0	0
## X60	-1.171076552	1	0	0	0
## X61	-3.265401234	1	0	0	0
## X62	0.690545388	1	0	0	0
## X64	1.388653616	0	0	0	0
## X65	-0.007562839	1	1	0	0
## X67	-0.472968324	0	0	0	1
## X69	1.155950873	0	0	0	0
## X70	0.225139903	0	0	0	0
## X72	-0.705671067	0	1	0	0
## X73	-0.472968324	0	0	0	1
## X74	-1.171076552	0	0	0	0
## X75	-0.240265582	0	0	0	0
## X77	1.155950873	0	0	0	1
## X78	1.388653616	1	0	0	0
## X79	0.923248131	0	0	1	0
## X82	-0.240265582	1	0	0	0
## X85	0.225139903	0	0	0	0
## X87	-0.938373809	1	1	0	0
## X88	-2.567293006	0	0	0	0
## X89	-1.171076552	1	0	0	0
## X90	-0.705671067	0	0	0	0
## X91	1.155950873	1	0	1	0
## X92	-0.007562839	0	0	0	0
## X93	0.923248131	0	0	0	0
## X94	-0.007562839	1	1	0	0
## X95	-0.705671067	0	0	0	0
## X96	-2.101887522	0	0	0	0
## X97	-0.007562839	0	0	0	0
## X98	1.388653616	0	0	0	0
## X99	0.923248131	0	1	0	0
## X100	0.923248131	0	0	0	0
## X101	-0.705671067	0	0	0	0
## X102	-0.240265582	0	0	0	0
## X103	0.225139903	1	0	1	0
## X104	-2.101887522	1	0	0	0
## X105	0.457842646	0	0	1	0
## X106	-0.705671067	1	0	0	0
## X108	-0.007562839	0	1	0	0
## X109	-2.101887522	0	0	0	0
## X110	-0.472968324	0	0	0	0
## X112	0.457842646	1	0	1	0
## X113	-1.636482037	0	0	0	0
## X114	-0.705671067	1	0	0	0
## X115	-0.938373809	1	1	0	0
## X116	0.457842646	1	0	0	0
## X117	0.923248131	1	0	0	1
## X119	0.457842646	1	0	0	0
## X120	-0.007562839	1	0	1	0
## X121	-0.240265582	0	0	1	0
## X122	-0.472968324	0	0	0	0

## X123	-1.403779294	1	0	0	0
## X126	0.690545388	1	0	0	0
## X127	-1.403779294	1	0	0	0
## X128	0.225139903	0	0	0	0
## X129	2.319464586	1	0	0	0
## X130	-0.007562839	0	0	0	0
## X131	-0.938373809	0	0	0	1
## X132	1.388653616	1	0	0	1
## X133	-0.705671067	0	1	0	0
## X135	1.388653616	0	0	0	1
## X136	0.923248131	1	1	0	0
## X137	-1.403779294	1	0	0	1
## X138	1.621356358	1	0	0	0
## X139	0.457842646	0	0	0	0
## X142	-0.705671067	0	0	0	1
## X144	1.621356358	0	1	0	0
## X145	-0.240265582	0	0	0	0
## X146	-1.636482037	1	0	1	0
## X147	0.923248131	1	0	0	0
## X148	0.225139903	0	0	0	1
## X149	0.225139903	0	0	0	1
## X150	-0.472968324	0	0	1	0
## X152	-1.171076552	0	0	0	0
## X154	-0.472968324	0	0	0	0
## X155	0.690545388	1	0	0	0
## X156	2.552167328	0	0	0	0
## X157	1.621356358	1	0	1	0
## X159	-0.007562839	0	0	0	1
## X160	-0.705671067	0	0	0	1
## X161	-0.240265582	1	0	0	0
## X162	-0.705671067	1	0	0	0
## X163	0.225139903	0	0	1	0
## X164	0.923248131	1	0	0	1
## X165	0.457842646	0	0	0	0
## X166	0.690545388	1	0	0	0
## X167	-1.403779294	0	0	1	0
## X168	-0.240265582	1	0	0	0
## X169	-0.938373809	0	0	0	0
## X170	0.457842646	1	0	0	0
## X171	-0.938373809	1	0	0	0
## X172	0.457842646	0	0	1	0
## X173	-0.705671067	0	0	0	0
## X174	-0.472968324	1	0	1	0
## X175	0.923248131	0	0	0	0
## X177	-0.472968324	0	0	0	0
## X179	-0.705671067	1	0	0	1
## X180	0.690545388	1	0	0	0
## X181	0.690545388	1	0	0	0
## X182	-1.636482037	1	0	0	0
## X183	-0.240265582	1	0	1	0
## X184	0.225139903	1	0	0	0
## X185	0.457842646	0	0	0	0
## X186	-1.403779294	1	0	1	0
## X187	1.155950873	0	0	0	0

## X188	-2.567293006	1	0	1	0
## X189	0.225139903	0	0	0	0
## X190	0.923248131	0	1	0	0
## X191	0.690545388	0	0	0	0
## X192	1.155950873	0	0	0	0
## X193	-2.334590264	1	0	1	0
## X194	2.784870071	0	0	0	0
## X195	-0.938373809	0	0	0	0
## X196	-0.705671067	0	0	0	0
## X198	0.457842646	0	0	0	0
## X200	-0.007562839	0	0	0	0
## X201	-0.240265582	1	0	0	0
## X202	-1.869184779	1	0	0	0
## X204	-0.240265582	1	0	0	0
## X205	-0.240265582	0	0	0	0
## X206	-0.705671067	1	0	0	0
## X207	2.086761843	0	0	0	0
## X209	1.155950873	0	0	0	1
## X211	-0.240265582	1	0	1	0
## X212	1.621356358	1	1	0	0
## X213	0.923248131	1	0	0	0
## X214	-0.007562839	1	0	1	0
## X215	-0.705671067	1	0	0	1
## X216	-0.007562839	0	0	1	0
## X217	-0.240265582	0	0	1	0
## X218	0.923248131	0	0	0	0
## X219	0.225139903	0	0	0	0
## X220	-0.007562839	0	0	0	0
## X221	0.690545388	0	0	0	0
## X222	-0.240265582	1	0	0	1
## X223	-0.007562839	0	0	0	0
## X224	1.621356358	0	0	0	1
## X226	1.621356358	1	0	1	0
## X227	1.388653616	1	0	1	0
## X228	-0.240265582	0	0	1	0
## X229	-0.472968324	1	0	0	0
## X230	-0.007562839	1	0	0	0
## X231	-0.472968324	1	0	0	0
## X233	0.457842646	1	0	1	0
## X234	-1.171076552	1	0	0	0
## X235	-0.472968324	1	0	0	0
## X236	0.457842646	0	1	0	0
## X237	-0.007562839	1	0	0	0
## X238	1.621356358	0	0	0	0
## X239	0.225139903	0	0	0	0
## X240	-0.938373809	0	0	0	0
## X241	-1.869184779	1	0	0	0
## X244	1.155950873	1	0	0	0
## X245	0.690545388	1	0	0	0
## X246	-0.938373809	1	0	0	1
## X247	-1.636482037	0	0	0	0
## X248	1.621356358	0	0	0	0
## X249	0.225139903	0	0	0	1
## X251	-0.240265582	1	0	0	0

## X252	-0.007562839	0	0	0	1
## X254	-0.938373809	0	0	0	0
## X255	-1.171076552	1	0	0	0
## X256	-1.403779294	0	0	1	0
## X257	0.690545388	0	0	0	1
## X258	0.225139903	0	0	1	0
## X259	0.225139903	0	0	0	0
## X260	-0.938373809	1	0	0	1
## X261	0.690545388	1	0	0	0
## X262	0.690545388	0	0	0	1
## X264	-0.472968324	0	0	0	0
## X265	1.388653616	1	0	0	0
## X266	0.457842646	1	1	0	0
## X267	0.923248131	0	0	0	1
## X268	-1.171076552	1	0	0	0
## X269	-0.007562839	1	0	0	0
## X270	-1.869184779	1	0	1	0
## X273	0.225139903	1	1	0	0
## X274	0.923248131	0	0	0	0
## X275	-1.636482037	1	0	0	0
## X276	0.690545388	0	0	1	0
## X277	-2.101887522	1	0	0	0
## X278	-0.938373809	0	0	0	0
## X279	-0.472968324	0	0	1	0
## X280	0.225139903	0	0	1	0
## X282	-0.240265582	1	0	0	0
## X283	-1.403779294	1	0	0	0
## X284	0.923248131	1	0	0	0
## X286	0.225139903	1	0	0	0
## X289	-0.007562839	1	0	0	0
## X290	-0.938373809	0	0	0	0
## X292	1.388653616	0	0	1	0
## X293	0.225139903	1	0	0	0
## X295	-0.472968324	1	0	0	0
## X296	-0.938373809	0	0	0	1
## X298	-0.007562839	0	0	0	0
## X299	-0.240265582	0	0	0	0
## X300	0.225139903	0	0	1	0
## X301	0.457842646	1	0	0	1
## X302	-0.472968324	0	0	0	0
## X303	0.923248131	0	1	0	0
## X305	-0.240265582	1	0	1	0
## X306	0.225139903	0	0	0	1
## X307	1.388653616	0	0	0	0
## X311	2.319464586	0	0	0	0
## X312	-0.240265582	0	0	0	0
## X313	2.086761843	1	0	0	0
## X314	-0.007562839	0	0	1	0
## X315	1.155950873	1	0	0	0
## X316	0.225139903	0	0	0	1
## X317	0.923248131	1	0	0	0
## X318	-1.171076552	0	0	0	0
## X319	-1.403779294	1	0	0	0
## X321	-1.171076552	1	0	0	0

## X322	-0.007562839	0	0	1	0
## X326	-0.240265582	0	0	1	0
## X327	0.923248131	1	0	0	0
## X328	-0.705671067	0	0	0	0
## X329	0.225139903	0	0	0	1
## X330	-1.171076552	0	0	0	0
## X331	-0.705671067	0	0	0	0
## X332	0.225139903	1	1	0	0
## X333	-0.007562839	1	0	1	0
## X334	0.457842646	0	0	0	0
## X335	0.225139903	0	0	0	0
## X336	-0.007562839	0	0	0	0
## X339	-0.007562839	1	0	0	1
## X340	-0.705671067	1	0	0	0
## X341	-0.240265582	1	0	0	0
## X342	-0.938373809	1	0	0	0
## X345	0.225139903	1	0	0	0
## X347	1.155950873	1	1	0	0
## X349	-0.007562839	0	0	0	0
## X351	-0.705671067	0	0	0	0
## X353	2.086761843	0	0	0	0
## X354	-0.938373809	1	0	0	0
## X355	-0.007562839	0	0	0	0
## X356	0.457842646	1	0	0	0
## X359	-0.007562839	0	0	0	0
## X360	1.854059101	1	0	0	0
## X361	0.923248131	0	0	0	0
## X363	-0.705671067	0	0	0	0
## X365	-1.636482037	1	0	0	0
## X366	-0.705671067	0	0	0	0
## X367	-0.007562839	0	0	0	0
## X369	-0.938373809	1	0	0	0
## X371	1.388653616	1	0	1	0
## X372	-0.240265582	0	0	0	0
## X373	1.155950873	0	0	0	0
## X374	-0.472968324	1	0	0	0
## X376	-0.240265582	1	0	0	0
## X377	-1.403779294	0	0	0	0
## X378	1.388653616	1	0	0	0
## X379	-1.869184779	1	0	0	0
## X380	-0.240265582	0	0	0	0
## X382	-0.705671067	0	0	0	0
## X383	-0.938373809	0	0	0	0
## X385	-0.007562839	0	0	1	0
## X386	-2.799995749	1	1	0	0
## X387	-0.007562839	0	0	0	0
## X388	1.388653616	1	0	0	0
## X389	-0.240265582	1	0	0	0
## X391	-1.869184779	1	0	0	0
## X392	0.457842646	1	0	0	0
## X393	-0.705671067	0	0	0	0
## X394	1.155950873	0	0	0	0
## X395	0.457842646	0	0	0	0
## X396	-0.705671067	0	0	0	1

## X397	-0.240265582	0	0	1	0
## X398	0.690545388	1	0	0	0
## X399	0.225139903	0	0	1	0
## X401	0.457842646	1	0	0	1
## X402	-0.705671067	1	0	0	0
## X405	0.225139903	1	0	0	0
## X406	0.457842646	1	0	0	1
## X407	-0.938373809	1	0	0	1
## X408	-1.171076552	0	0	0	0
## X410	1.621356358	1	0	0	0
## X411	0.457842646	1	0	0	1
## X412	0.923248131	1	0	1	0
## X413	0.225139903	0	0	0	0
## X414	-0.472968324	0	0	0	1
## X415	0.923248131	0	0	0	0
## X416	0.225139903	1	0	0	0
## X417	0.923248131	1	0	0	0
## X418	-0.240265582	0	0	0	0
## X419	-0.007562839	1	0	0	0
## X420	-1.869184779	1	0	0	0
## X421	1.388653616	1	0	0	0
## X422	-0.240265582	0	1	0	0
## X423	-0.007562839	0	0	0	1
## X424	0.690545388	1	0	1	0
## X425	-1.171076552	1	0	1	0
## X426	2.319464586	0	0	1	0
## X427	-0.007562839	0	0	1	0
## X431	-0.007562839	1	0	1	0
## X432	-0.938373809	1	0	0	0
## X434	-1.171076552	0	0	0	0
## X435	-0.472968324	0	0	0	0
## X437	2.086761843	0	1	0	0
## X438	-1.171076552	1	0	0	0
## X439	2.086761843	1	0	0	1
## X440	-0.007562839	0	0	0	0
## X441	-0.705671067	1	0	0	0
## X442	1.621356358	0	0	0	0
## X443	-0.705671067	1	0	0	0
## X444	1.155950873	1	0	0	1
## X445	-0.705671067	0	0	0	1
## X448	1.388653616	1	0	0	0
## X450	0.690545388	0	0	0	1
## X451	0.225139903	1	0	1	0
## X453	-0.938373809	0	0	0	0
## X454	0.457842646	0	0	1	0
## X455	-0.007562839	1	0	0	1
## X456	-0.007562839	1	0	0	0
## X457	0.225139903	0	0	0	0
## X458	-0.938373809	1	0	0	0
## X459	1.388653616	1	0	0	0
## X460	2.086761843	1	1	0	0
## X461	-0.705671067	1	0	1	0
## X464	0.923248131	0	0	0	0
## X465	1.854059101	0	0	0	1

## X466	-0.240265582	1	0	0	0
## X468	1.388653616	1	0	1	0
## X469	-0.240265582	0	0	0	1
## X470	0.225139903	0	0	0	0
## X472	0.225139903	0	0	1	0
## X473	0.457842646	0	0	0	0
## X474	0.690545388	0	0	0	0
## X475	0.457842646	1	0	0	0
## X476	-1.636482037	1	0	0	1
## X478	0.457842646	0	0	0	0
## X480	1.621356358	1	0	0	0
## X481	0.923248131	0	0	0	0
## X482	-0.472968324	1	0	0	0
## X483	0.923248131	1	1	0	0
## X484	-0.472968324	1	0	1	0
## X486	2.319464586	0	0	0	0
## X487	1.388653616	1	0	1	0
## X488	-0.938373809	0	0	0	0
## X489	2.319464586	1	0	0	0
## X490	0.690545388	1	0	0	0
## X491	1.155950873	0	0	0	0
## X492	-0.705671067	1	0	0	0
## X493	0.457842646	1	0	0	0
## X494	1.388653616	1	0	0	0
## X495	0.457842646	1	1	0	0
## X496	0.690545388	0	0	0	0
## X497	0.457842646	0	0	1	0
## X498	-0.705671067	1	0	0	0
## X499	-0.705671067	0	0	0	0
## X500	-0.007562839	1	0	1	0
## X501	0.457842646	1	0	1	0
## X502	1.388653616	1	0	0	0
## X503	-0.240265582	0	0	0	0
## X504	0.225139903	0	0	0	0
## X507	-0.240265582	0	0	0	0
## X509	-0.938373809	1	0	0	0
## X511	-0.472968324	1	0	0	0
## X512	1.854059101	0	0	0	0
## X513	-0.007562839	0	0	0	0
## X514	-0.705671067	0	0	0	0
## X515	-0.705671067	0	0	0	0
## X516	-0.007562839	1	0	0	0
## X518	-0.472968324	1	0	0	0
## X520	0.457842646	1	0	0	0
## X521	-0.472968324	1	0	0	0
## X522	0.225139903	0	0	0	0
## X523	-0.240265582	0	0	0	0
## X524	1.854059101	1	0	0	0
## X525	-0.240265582	0	0	0	0
## X527	-0.472968324	0	0	0	0
## X528	0.457842646	1	0	1	0
## X529	0.457842646	0	1	0	0
## X530	0.457842646	1	0	0	0
## X533	0.923248131	1	0	0	0

## X535	0.225139903	1	0	0	0
## X536	-0.240265582	1	0	0	0
## X539	-0.472968324	0	0	0	0
## X540	0.690545388	1	0	1	0
## X541	2.086761843	0	0	0	1
## X542	1.155950873	1	0	0	0
## X543	0.923248131	0	0	0	0
## X545	0.690545388	0	0	0	0
## X546	0.690545388	0	1	0	0
## X547	1.621356358	0	0	0	0
## X548	1.388653616	1	0	0	0
## X549	-1.403779294	1	0	0	0
## X550	-1.403779294	1	0	1	0
## X551	-1.403779294	1	0	1	0
## X552	0.457842646	0	0	0	0
## X553	1.388653616	0	0	0	0
## X554	0.457842646	1	0	0	1
## X556	0.225139903	0	0	0	0
## X557	-0.472968324	0	0	0	0
## X558	-0.705671067	1	0	0	0
## X559	1.155950873	1	0	0	0
## X560	-0.705671067	1	0	0	1
## X561	0.457842646	1	0	0	0
## X562	0.690545388	0	0	0	0
## X563	-0.472968324	1	0	0	0
## X564	-0.472968324	0	0	1	0
## X565	0.457842646	1	0	0	0
## X566	-1.636482037	0	0	0	0
## X567	-1.403779294	0	0	0	0
## X568	1.854059101	1	0	0	0
## X569	0.457842646	1	0	1	0
## X571	0.690545388	1	0	0	0
## X573	1.155950873	1	0	0	1
## X574	-0.240265582	1	0	0	1
## X575	-1.869184779	0	0	1	0
## X576	-0.240265582	1	0	0	0
## X577	0.225139903	1	0	0	0
## X579	-0.007562839	0	0	1	0
## X580	-1.403779294	0	0	0	1
## X582	0.457842646	0	0	0	0
## X584	0.923248131	1	0	0	0
## X587	-0.705671067	0	0	0	0
## X588	0.690545388	0	0	0	0
## X589	-0.938373809	1	0	0	0
## X591	-1.403779294	0	0	0	0
## X592	-0.007562839	0	0	1	0
## X593	-0.938373809	1	0	0	0
## X594	1.155950873	0	0	0	0
## X597	-0.938373809	0	0	0	1
## X598	-0.938373809	0	0	0	0
## X600	0.225139903	0	0	0	1
## X601	1.155950873	0	0	0	0
## X602	-0.472968324	0	0	0	0
## X603	0.690545388	0	0	0	0



## X604	-1.869184779	0	1	0	0
## X605	0.923248131	1	0	0	0
## X606	0.457842646	0	0	0	1
## X609	0.690545388	1	0	0	0
## X610	-0.472968324	1	0	0	0
## X611	-1.869184779	1	0	0	0
## X613	0.690545388	1	0	1	0
## X614	-0.472968324	0	0	0	0
## X615	-1.636482037	1	1	0	0
## X617	-0.705671067	1	0	0	1
## X618	-0.240265582	1	1	0	0
## X619	-0.705671067	0	0	0	0
## X620	-1.171076552	1	0	0	0
## X623	-0.240265582	0	0	0	0
## X624	0.225139903	0	0	0	0
## X625	-0.938373809	0	0	0	0
## X626	-0.472968324	0	0	0	0
## X628	2.319464586	1	0	1	0
## X629	-0.240265582	0	0	0	0
## X630	0.225139903	0	0	0	0
## X631	0.923248131	1	0	0	0
## X632	-0.240265582	0	0	0	0
## X633	-0.472968324	1	0	0	0
## X634	0.923248131	1	0	0	0
## X635	-1.171076552	1	0	0	0
## X636	-0.705671067	1	0	1	0
## X637	0.225139903	1	0	0	0
## X638	-0.938373809	0	0	1	0
## X640	-0.007562839	0	0	0	0
## X641	-0.472968324	0	0	0	0
## X642	-0.007562839	1	0	1	0
## X643	-2.334590264	1	0	0	1
## X644	-1.171076552	0	0	0	0
## X645	-1.403779294	1	0	0	1
## X646	-0.472968324	1	0	0	0
## X648	-1.171076552	1	0	0	0
## X649	-0.705671067	1	0	0	0
## X650	0.690545388	0	0	1	0
## X652	-0.472968324	0	0	0	0
## X654	0.923248131	0	0	0	0
## X655	1.854059101	1	0	0	0
## X656	-0.007562839	0	0	0	0
## X657	-0.938373809	1	0	0	0
## X658	0.225139903	1	0	1	0
## X659	-0.240265582	0	1	0	0
## X660	1.388653616	0	0	1	0
## X661	0.923248131	1	0	0	0
## X663	-0.472968324	0	1	0	0
## X664	0.225139903	1	0	0	0
## X665	0.225139903	0	0	0	0
## X666	-0.007562839	0	0	0	0
## X667	2.086761843	1	0	1	0
## X668	1.155950873	0	0	0	0
## X669	1.155950873	1	0	1	0

## X670	0.225139903	0	0	0	0
## X673	1.155950873	1	0	0	1
## X674	0.457842646	0	0	0	0
## X675	-1.869184779	0	0	0	0
## X676	-0.007562839	1	0	0	0
## X677	0.457842646	1	0	1	0
## X678	-0.240265582	1	0	0	1
## X679	0.690545388	1	0	1	0
## X680	-0.007562839	0	0	0	0
## X681	0.923248131	1	1	0	0
## X682	-0.705671067	0	0	1	0
## X683	-1.171076552	1	0	1	0
## X684	0.923248131	0	1	0	0
## X685	-0.705671067	0	0	1	0
## X686	-0.472968324	0	0	1	0
## X687	0.457842646	1	0	0	0
## X688	0.923248131	0	0	0	0
## X690	0.457842646	1	0	0	0
## X691	-1.869184779	0	0	0	0
## X692	-1.869184779	0	0	0	0
## X693	-0.007562839	0	0	0	0
## X694	0.457842646	0	1	0	0
## X697	-0.705671067	1	0	0	0
## X698	1.155950873	1	0	0	0
## X699	-0.938373809	1	0	0	0
## X700	-0.705671067	1	0	0	0
## X701	0.225139903	1	0	0	0
## X702	-0.472968324	1	1	0	0
## X703	0.690545388	1	0	0	0
## X705	-0.472968324	0	0	1	0
## X706	0.690545388	0	0	0	0
## X707	-0.705671067	1	0	0	0
## X708	-0.472968324	0	0	0	1
## X709	0.690545388	1	0	1	0
## X710	1.155950873	0	0	0	0
## X711	0.225139903	1	0	0	0
## X712	-0.472968324	0	0	0	0
## X713	-2.101887522	0	1	0	0
## X714	-1.171076552	0	1	0	0
## X715	-0.938373809	1	0	0	0
## X716	-0.705671067	0	0	0	0
## X717	0.457842646	1	0	0	0
## X718	-0.240265582	1	0	0	1
## X719	-0.240265582	1	0	1	0
## X720	0.457842646	0	0	0	0
## X721	-0.705671067	1	0	1	0
## X722	0.457842646	1	0	0	0
## X724	-2.334590264	0	0	0	0
## X725	-0.938373809	0	0	1	0
## X726	0.690545388	1	0	0	0
## X730	1.621356358	0	0	1	0
## X731	0.225139903	0	0	0	1
## X732	1.155950873	1	0	0	0
## X734	-0.705671067	1	0	0	0

## X735	-1.869184779	1	0	0	0
## X737	0.457842646	0	0	0	0
## X738	-0.938373809	0	0	1	0
## X739	-0.240265582	0	0	0	0
## X740	-0.938373809	0	0	0	0
## X744	-1.171076552	1	0	0	0
## X745	0.457842646	0	0	0	0
## X746	0.457842646	0	0	0	0
## X747	0.225139903	1	0	1	0
## X748	-1.403779294	1	0	0	0
## X749	0.690545388	0	0	0	0
## X751	-0.472968324	0	0	0	0
## X752	1.388653616	0	0	0	0
## X753	1.155950873	0	0	0	0
## X754	-0.472968324	1	1	0	0
## X757	0.923248131	1	0	0	0
## X758	-0.240265582	0	0	0	0
## X759	-0.472968324	1	0	1	0
## X761	1.155950873	0	0	1	0
## X762	0.457842646	0	0	0	0
## X763	0.457842646	0	1	0	0
## X764	1.621356358	1	0	0	0
## X765	0.923248131	1	0	1	0
## X766	-0.472968324	1	0	1	0
## X767	0.457842646	0	0	0	0
## X768	-0.472968324	0	0	0	0
## X769	0.225139903	1	0	0	0
## X770	1.155950873	1	0	0	0
## X772	-0.007562839	0	0	0	0
## X773	0.923248131	0	0	0	0
## X774	1.854059101	0	0	0	0
## X775	0.225139903	0	0	1	0
## X776	-0.240265582	0	0	0	0
## X777	0.225139903	1	1	0	0
## X778	1.388653616	1	0	0	0
## X779	0.690545388	1	0	0	0
## X780	0.225139903	0	0	0	0
## X781	2.086761843	1	0	0	0
## X784	-0.705671067	1	0	0	0
## X786	0.690545388	0	0	1	0
## X787	1.388653616	1	0	0	0
## X788	0.923248131	0	0	1	0
## X789	-0.938373809	0	0	1	0
## X790	-0.472968324	0	0	0	0
## X791	0.690545388	1	0	0	0
## X792	1.621356358	1	0	0	0
## X794	1.854059101	0	0	0	0
## X795	-1.171076552	1	0	1	0
## X796	0.225139903	0	0	0	0
## X797	-0.007562839	1	0	0	0
## X798	-0.472968324	1	0	0	0
## X799	-0.472968324	1	0	0	0
## X800	0.923248131	1	0	1	0
## X801	0.457842646	0	0	0	0

## X802	-2.334590264	1	0	0	0
## X803	-1.636482037	0	0	0	1
## X804	-1.171076552	0	0	0	0
## X805	-1.171076552	0	0	0	0
## X807	1.854059101	0	0	0	0
## X808	0.923248131	1	0	0	0
## X809	-0.472968324	1	0	0	0
## X810	-0.705671067	0	0	0	0
## X812	-0.705671067	0	0	0	0
## X813	0.923248131	0	0	1	0
## X814	0.457842646	1	0	0	0
## X815	-1.171076552	0	0	0	0
## X816	0.690545388	0	0	1	0
## X817	-0.007562839	1	0	0	0
## X818	0.225139903	1	0	0	0
## X820	0.225139903	1	0	0	0
## X821	-0.240265582	1	1	0	0
## X822	0.457842646	0	0	0	0
## X823	1.621356358	0	0	0	0
## X824	0.225139903	0	0	0	1
## X825	-1.171076552	1	0	0	1
## X826	0.923248131	0	0	1	0
## X830	0.690545388	1	0	0	0
## X831	-0.472968324	0	1	0	0
## X832	-1.171076552	0	0	0	0
## X833	-1.869184779	1	0	0	0
## X834	2.086761843	1	0	0	0
## X836	-0.938373809	0	0	1	0
## X837	-1.171076552	1	0	1	0
## X838	0.457842646	1	0	1	0
## X839	-1.636482037	1	0	0	0
## X840	-0.007562839	1	0	0	0
## X841	0.225139903	1	0	1	0
## X842	-0.938373809	1	0	0	0
## X843	-0.007562839	0	0	1	0
## X844	-0.705671067	0	0	0	0
## X847	2.319464586	1	0	0	0
## X848	0.457842646	0	1	0	0
## X849	-0.240265582	1	0	0	0
## X850	-0.472968324	0	0	0	1
## X851	0.923248131	1	0	0	0
## X852	-0.472968324	0	0	1	0
## X853	-1.403779294	1	0	0	0
## X854	1.854059101	0	0	0	0
## X855	-0.705671067	1	0	0	0
## X856	-2.567293006	0	0	1	0
## X857	0.225139903	0	0	0	0
## X858	-0.240265582	1	0	1	0
## X859	0.225139903	1	0	1	0
## X860	0.225139903	0	0	0	0
## X861	-0.938373809	0	0	0	0
## X862	-1.636482037	0	0	0	0
## X864	0.225139903	1	0	0	0
## X865	-1.636482037	0	0	0	0

## X866	0.923248131	1	0	1	0
## X867	-0.007562839	1	0	0	0
## X868	-0.240265582	1	0	0	0
## X869	-0.007562839	0	0	0	1
## X870	-0.938373809	0	0	0	0
## X871	0.690545388	0	0	0	0
## X872	-1.403779294	0	0	0	0
## X873	-0.938373809	0	0	1	0
## X874	-0.472968324	1	0	0	0
## X875	-0.705671067	1	0	1	0
## X877	0.923248131	0	0	0	0
## X878	-1.403779294	0	0	0	0
## X879	-0.240265582	0	0	0	0
## X880	0.457842646	1	0	1	0
## X881	-0.705671067	0	0	0	0
## X882	-0.007562839	0	1	0	0
## X883	-0.705671067	0	0	0	0
## X884	1.388653616	0	0	0	0
## X885	-0.240265582	0	0	1	0
## X886	0.225139903	0	0	0	0
## X887	1.155950873	1	0	0	0
## X888	1.155950873	1	0	0	0
## X889	1.155950873	1	0	0	1
## X890	-0.472968324	1	0	0	0
## X891	-0.472968324	0	0	0	0
## X892	-0.240265582	1	0	1	0
## X894	-0.007562839	0	0	0	1
## X895	0.923248131	1	0	1	0
## X897	-0.472968324	0	0	0	0
## X899	-0.472968324	1	0	0	0
## X900	-0.705671067	0	0	1	0
## X901	1.854059101	0	0	0	0
## X902	1.388653616	0	0	1	0
## X903	0.225139903	0	0	0	0
## X904	-0.705671067	0	0	0	0
## X905	0.225139903	0	0	0	0
## X906	-1.869184779	1	0	0	0
## X907	0.225139903	0	1	0	0
## X908	-0.705671067	1	0	0	0
## X909	-0.472968324	1	0	0	0
## X910	0.923248131	0	0	0	0
## X911	-1.403779294	0	0	1	0
## X913	-0.240265582	0	0	0	0
## X916	0.225139903	1	0	0	1
## X917	1.388653616	1	0	0	0
## X918	-1.171076552	0	0	0	0
## X919	-0.472968324	1	0	0	0
## X920	-1.403779294	1	0	0	0
## X921	2.319464586	0	0	0	0
## X922	0.690545388	1	0	0	0
## X924	-0.705671067	1	0	0	0
## X925	-1.171076552	0	0	0	0
## X926	-0.938373809	0	0	1	0
## X927	0.923248131	0	0	0	0

## X929	0.225139903	1	0	0	0
## X932	1.388653616	1	0	1	0
## X933	-0.705671067	1	0	0	0
## X935	1.155950873	0	0	0	0
## X936	0.690545388	1	0	0	0
## X937	-0.705671067	1	1	0	0
## X939	0.923248131	0	0	0	1
## X940	0.690545388	1	0	1	0
## X941	0.923248131	1	0	0	1
## X942	-0.240265582	0	0	1	0
## X943	-0.472968324	1	0	0	0
## X945	1.155950873	1	0	0	0
## X946	0.690545388	1	0	1	0
## X948	-0.472968324	0	0	0	0
## X949	-0.472968324	1	0	0	0
## X950	-2.334590264	0	0	0	0
## X951	-2.101887522	0	0	0	0
## X953	2.086761843	0	0	0	0
## X954	2.086761843	1	0	0	0
## X955	-0.240265582	0	0	0	0
## X956	0.457842646	1	0	0	0
## X957	-1.171076552	0	0	0	0
## X958	0.225139903	0	0	0	0
## X959	-1.403779294	0	0	0	0
## X960	-2.101887522	0	0	0	0
## X961	-0.938373809	0	0	1	0
## X962	0.690545388	1	0	0	1
## X963	0.690545388	1	0	0	0
## X964	1.155950873	1	0	0	0
## X965	-0.240265582	0	0	0	0
## X966	-0.938373809	1	0	1	0
## X968	-0.007562839	1	0	0	1
## X969	-0.007562839	1	0	0	0
## X970	-0.705671067	0	0	0	0
## X971	-1.636482037	0	0	0	0
## X972	-0.007562839	1	0	1	0
## X973	-1.171076552	0	0	0	0
## X974	1.388653616	1	0	0	0
## X975	-0.938373809	1	0	0	0
## X976	-0.472968324	1	0	0	0
## X977	-0.705671067	0	0	0	0
## X978	-0.240265582	1	0	0	0
## X979	1.621356358	0	0	0	0
## X980	-0.472968324	1	0	0	0
## X981	0.225139903	1	0	0	0
## X982	-0.938373809	0	0	1	0
## X983	1.388653616	1	0	1	0
## X984	-1.636482037	0	0	0	0
## X985	-0.240265582	1	0	1	0
## X986	-1.171076552	0	0	0	0
## X987	0.225139903	0	1	0	0
## X988	-2.101887522	1	0	1	0
## X989	-0.938373809	1	0	0	0
## X990	-0.938373809	0	0	0	1

##	X991	-1.171076552	0	0	1	0
##	X992	-0.705671067	1	0	1	0
##	X993	-0.240265582	0	0	0	0
##	X994	0.690545388	0	0	0	0
##	X995	-1.403779294	0	0	0	0
##	X996	-1.171076552	0	0	1	0
##	X997	-0.705671067	0	0	0	0
##	X998	0.457842646	1	0	0	0
##	X999	0.225139903	1	0	0	0
##		smokingFormer_smoker	smokingCurrent_smoker		height	weight
##	X1	1	0	0.0492639397	-0.650392519	
##	X2	1	0	0.1313021408	-0.512615737	
##	X3	1	0	0.4430473048	1.388703846	
##	X4	0	0	0.2789709027	-0.664170197	
##	X6	0	0	-0.1968506634	1.168260996	
##	X9	0	0	-0.2460735841	-0.402394312	
##	X10	0	0	0.0492639397	-0.884613047	
##	X11	1	0	0.4430473048	1.994921685	
##	X12	0	0	-0.0163666211	-0.760613944	
##	X13	0	0	1.8376967227	1.402481524	
##	X14	0	1	2.2150724476	-0.085507715	
##	X15	0	0	-0.2296659439	1.498925271	
##	X17	0	0	-1.6243153618	-0.843280013	
##	X18	0	0	0.4102320244	0.603376192	
##	X19	1	0	-1.3782007586	1.774478834	
##	X21	0	0	0.4922702254	0.878929755	
##	X22	0	0	0.3610091037	-0.250839853	
##	X24	0	0	-1.5422771607	-0.485060381	
##	X25	1	0	0.1148945006	0.851374399	
##	X26	0	0	-0.6234493089	-0.044174681	
##	X27	1	0	-0.0491819015	-1.449497851	
##	X28	0	0	-2.1985827691	-0.829502335	
##	X29	1	0	0.9680917915	-0.195729140	
##	X30	0	0	-0.5414111079	1.278482421	
##	X31	0	0	-0.6726722295	-0.622837163	
##	X33	0	0	0.9024612307	0.203823526	
##	X36	0	0	0.5086778656	-0.733058588	
##	X39	0	0	-1.1484937957	-2.041938011	
##	X40	0	0	-1.5750924411	-1.408164817	
##	X41	0	0	0.3610091037	-0.057952359	
##	X42	1	0	-0.7711180708	0.713597617	
##	X45	0	0	1.5259515587	0.479377089	
##	X46	1	0	0.4430473048	0.837596721	
##	X47	0	0	-1.1977167163	0.878929755	
##	X49	0	0	-0.6234493089	0.851374399	
##	X54	0	0	1.3454675164	-0.815724657	
##	X56	0	0	1.1321681936	3.496688602	
##	X57	1	0	0.7547924688	0.713597617	
##	X59	1	0	0.0820792202	0.451821733	
##	X60	0	1	0.3446014635	-1.862828195	
##	X61	0	0	0.5743084265	-0.209506818	
##	X62	1	0	1.0173147122	0.534487801	
##	X64	0	0	-0.3445194253	-0.801946978	
##	X65	0	1	-0.0655895417	-1.256610357	

## X67	1	0	0.0656715799	0.892707433
## X69	1	0	0.0000410191	0.258934239
## X70	1	0	1.8376967227	-0.333505922
## X72	0	0	-0.8859715523	0.176268170
## X73	0	0	-0.9187868327	-0.113063071
## X74	0	0	-1.0992708750	-1.642385345
## X75	1	0	0.0984868604	-1.587274633
## X77	1	0	0.3446014635	-1.132611254
## X78	1	0	1.4275057174	1.595369018
## X79	0	1	0.6399389873	0.231378882
## X82	0	0	-1.0992708750	-0.154396106
## X85	0	0	-0.9516021131	0.438044054
## X87	0	0	0.6563466275	0.148712813
## X88	0	0	1.7720661619	1.292260099
## X89	0	0	-0.1148124624	0.217601204
## X90	0	0	-0.3281117851	-0.388616634
## X91	0	0	0.0984868604	-0.195729140
## X92	0	0	-1.1484937957	-0.471282703
## X93	0	0	0.3281938233	-0.333505922
## X94	0	0	-0.3281117851	-0.402394312
## X95	0	0	1.0501299926	0.810041364
## X96	0	1	0.3774167439	-0.278395209
## X97	1	0	0.6727542677	-0.181951462
## X98	1	0	0.6727542677	0.506932445
## X99	1	0	0.3610091037	0.823819042
## X100	1	0	-0.4265576264	-0.967279116
## X101	0	0	0.8696459503	0.699819939
## X102	1	0	0.6891619080	0.754930652
## X103	0	0	0.2461556223	0.424266376
## X104	0	0	1.1157605534	1.168260996
## X105	0	0	-0.9023791925	-0.912168404
## X106	0	0	-0.7383027904	1.085594927
## X108	0	0	0.3774167439	0.258934239
## X109	0	0	-1.1156785152	-0.057952359
## X110	1	0	0.2789709027	0.121157457
## X112	1	0	-1.4110160390	-0.595281806
## X113	0	0	-1.5586848009	-0.636614841
## X114	0	0	0.5414931461	-0.526393416
## X115	0	0	-0.0655895417	0.493154767
## X116	1	0	0.4758625852	0.686042261
## X117	0	0	0.9844994317	1.319815456
## X119	0	0	-0.7711180708	-0.512615737
## X120	0	0	1.9033272836	2.559806488
## X121	0	0	1.8869196433	-0.278395209
## X122	1	0	2.1822571671	1.237149387
## X123	0	0	0.6399389873	-1.628607667
## X126	0	0	1.0009070720	2.132698466
## X127	0	0	1.8048814423	0.589598514
## X128	1	0	1.1157605534	1.347370812
## X129	0	0	-0.4593729068	-0.250839853
## X130	0	0	-2.1821751289	-1.614829989
## X131	1	0	0.1641174212	0.672264583
## X132	0	0	1.0829452730	1.264704743
## X133	1	0	-0.3773347057	-1.256610357



## X135	1	0	-0.5742263883	0.134935135
## X136	0	0	0.5414931461	0.603376192
## X137	0	0	-2.2970286104	-0.429949669
## X138	0	0	-0.1476277428	-0.374838956
## X139	1	0	0.0164486593	0.906485111
## X142	0	0	1.1321681936	0.258934239
## X144	0	0	0.4594549450	1.223371709
## X145	1	0	-0.7383027904	1.829589547
## X146	0	0	-0.4429652666	0.548265480
## X147	1	0	0.2625632625	-1.242832679
## X148	0	0	0.7547924688	1.195816352
## X149	0	0	1.5259515587	1.402481524
## X150	0	0	-1.5750924411	-0.967279116
## X152	0	0	0.8204230296	0.672264583
## X154	1	0	1.3946904370	-1.077500541
## X155	0	0	0.5414931461	-0.237062175
## X156	0	0	0.2625632625	0.355377986
## X157	0	1	1.2306140349	-0.953501438
## X159	0	0	0.2461556223	0.741152974
## X160	0	0	-0.7218951502	0.534487801
## X161	0	1	-1.4602389597	0.162490492
## X162	0	0	0.0328562995	0.534487801
## X163	0	1	-0.7054875100	-0.581504128
## X164	0	0	-0.8695639121	-0.030397002
## X165	0	1	1.7064356010	0.961595824
## X166	1	0	1.0501299926	0.644709227
## X167	1	0	-1.4110160390	0.851374399
## X168	1	0	0.6235313471	0.548265480
## X169	0	0	-0.2460735841	-0.691725553
## X170	0	0	0.6563466275	-0.085507715
## X171	0	0	-1.0008250338	-0.553948772
## X172	0	0	-1.1977167163	0.438044054
## X173	0	0	0.4922702254	1.319815456
## X174	0	0	0.7383848286	-0.181951462
## X175	0	0	-1.5915000813	-0.981056794
## X177	0	0	1.4931362783	0.134935135
## X179	1	0	-0.7711180708	2.284252926
## X180	1	0	0.5414931461	0.534487801
## X181	0	0	0.8204230296	0.410488698
## X182	1	0	0.0000410191	0.589598514
## X183	0	0	-0.4921881872	-1.573496954
## X184	0	0	1.5915821195	0.010936032
## X185	0	0	1.0501299926	-0.581504128
## X186	0	0	0.7055695482	1.416259203
## X187	0	0	-0.1640353830	-1.628607667
## X188	1	0	-2.0509140072	-0.030397002
## X189	0	1	0.3774167439	0.355377986
## X190	0	0	0.7055695482	-0.002841646
## X191	0	0	-1.4274236792	-0.140618428
## X192	1	0	-0.7711180708	-0.292172887
## X193	0	0	-0.4429652666	0.658486905
## X194	0	1	-0.6070416687	0.245156560
## X195	0	0	-1.2141243565	1.994921685
## X196	1	0	-0.7054875100	-2.014382655

## X198	0	0	0.6399389873	2.160253822
## X200	0	1	0.6563466275	0.341600307
## X201	1	0	0.9188688709	0.961595824
## X202	0	0	-0.6562645893	0.865152077
## X204	0	0	-0.4265576264	-0.429949669
## X205	0	0	1.3290598762	1.361148490
## X206	0	0	-0.5085958274	-0.126840749
## X207	0	0	-0.7218951502	0.768708330
## X209	0	0	-1.3617931184	-0.416171990
## X211	0	1	0.6399389873	-0.953501438
## X212	1	0	0.2133403418	0.975373502
## X213	1	0	0.6399389873	0.506932445
## X214	0	0	-0.1804430232	-1.091278219
## X215	0	0	-0.7875257110	-0.016619324
## X216	0	0	1.1157605534	0.093602101
## X217	1	0	0.2461556223	0.810041364
## X218	0	0	-1.3125701978	-0.939723760
## X219	0	1	0.0328562995	-0.719280910
## X220	0	0	0.4758625852	-0.664170197
## X221	0	0	-0.2624812243	0.699819939
## X222	1	0	-0.1148124624	1.085594927
## X223	0	0	-0.1968506634	-1.036167507
## X224	1	0	-0.3937423460	0.024713710
## X226	0	0	-0.2132583036	-0.733058588
## X227	0	0	-0.4265576264	1.044261893
## X228	0	0	-0.6234493089	-0.168173784
## X229	0	0	-0.5906340285	0.148712813
## X230	1	0	0.6727542677	-1.063722863
## X231	0	0	-0.0984048222	0.851374399
## X233	1	0	0.3774167439	-0.553948772
## X234	0	0	-1.1649014359	0.465599411
## X235	0	0	-0.2788888645	0.396711020
## X236	0	0	-2.5103279332	0.823819042
## X237	0	0	-1.4438313194	-1.063722863
## X238	0	1	0.4102320244	-0.540171094
## X239	0	0	-0.9516021131	-1.118833576
## X240	0	0	-1.4930542401	-0.030397002
## X241	0	0	0.1805250614	-0.057952359
## X244	0	0	0.1805250614	0.148712813
## X245	0	1	0.3938243842	-0.292172887
## X246	1	0	-0.8531562719	0.810041364
## X247	0	0	-0.7875257110	-0.030397002
## X248	0	0	1.3618751566	-0.788169300
## X249	0	0	-0.2624812243	-1.890383552
## X251	0	0	-2.1657674887	1.237149387
## X252	0	0	0.9516841513	1.058039571
## X254	0	0	0.1805250614	-0.016619324
## X255	0	0	-1.7063535628	-0.925946082
## X256	0	0	-0.4429652666	1.085594927
## X257	1	0	-0.9680097533	0.479377089
## X258	1	0	-0.4757805470	0.286489595
## X259	0	1	1.4275057174	-1.077500541
## X260	0	0	-1.3782007586	-1.022389829
## X261	1	0	-0.1312201026	-0.044174681

## X262	0	1	-2.1001369279	-1.477053207
## X264	0	0	-0.1640353830	-0.705503231
## X265	0	0	0.6891619080	-0.553948772
## X266	0	0	0.7055695482	0.796263686
## X267	0	0	-0.1640353830	0.148712813
## X268	0	0	1.2142063947	1.554035984
## X269	1	0	1.2470216751	1.182038674
## X270	1	0	-0.6398569491	1.099372605
## X273	0	0	-0.1148124624	-0.030397002
## X274	0	1	-0.9516021131	-1.339276426
## X275	0	0	-1.0336403142	-1.986827299
## X276	0	0	-0.9023791925	1.306037777
## X277	0	0	-1.1977167163	-0.595281806
## X278	0	0	-1.2961625576	-2.069493368
## X279	1	0	-1.1649014359	-1.807717483
## X280	0	0	1.2142063947	0.754930652
## X282	0	1	1.5095439185	-0.374838956
## X283	1	0	-0.3445194253	-1.849050517
## X284	0	0	0.4266396646	0.010936032
## X286	0	0	0.0656715799	1.595369018
## X289	0	1	0.9516841513	1.182038674
## X290	1	0	-0.4101499862	0.341600307
## X292	0	1	-3.2486717426	-2.951264769
## X293	1	0	1.5259515587	0.837596721
## X295	1	0	-0.4101499862	-1.504608564
## X296	0	0	0.5579007863	-0.085507715
## X298	0	0	-0.8039333512	-1.091278219
## X299	0	0	-0.6562645893	-0.746836266
## X300	0	0	0.3610091037	0.975373502
## X301	0	0	-0.6890798698	-0.347283600
## X302	0	0	0.4430473048	0.796263686
## X303	0	0	-0.6070416687	-0.677947875
## X305	1	0	-1.8047994041	0.424266376
## X306	0	0	0.0492639397	0.272711917
## X307	0	0	-0.9023791925	0.369155664
## X311	0	0	1.5423591989	0.479377089
## X312	0	0	-0.7711180708	-0.195729140
## X313	0	1	0.4922702254	1.719368122
## X314	0	0	2.4447794105	0.424266376
## X315	0	0	-1.8047994041	-0.168173784
## X316	1	0	-0.1804430232	-0.898390725
## X317	0	0	-0.3117041449	-2.014382655
## X318	0	0	-1.8376146845	-0.898390725
## X319	1	0	-0.1476277428	-0.733058588
## X321	0	1	1.7392508814	0.644709227
## X322	0	0	0.2625632625	1.430036881
## X326	0	0	1.4767286381	1.609146697
## X327	0	0	0.4266396646	2.325585960
## X328	1	0	-0.0984048222	1.030484215
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## X330	0	0	0.8040153894	0.562043158
## X331	1	0	-1.4766465999	-0.912168404
## X332	1	0	-1.4438313194	-0.733058588
## X333	0	0	-1.4930542401	-1.435720173

## X334	0	0 0.1477097810 -0.333505922
## X335	1	0 -0.4101499862 -0.829502335
## X336	1	0 -1.1156785152 -0.719280910
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## X340	0	1 -0.8039333512 -0.443727347
## X341	0	0 -1.8047994041 0.162490492
## X342	0	0 -0.6726722295 -1.559719276
## X345	0	0 1.0665376328 -0.898390725
## X347	0	0 -0.1968506634 -1.821495161
## X349	0	0 0.3774167439 0.989151180
## X351	1	0 -0.2624812243 0.300267273
## X353	0	0 0.3446014635 0.245156560
## X354	1	0 -0.0491819015 0.438044054
## X355	1	0 -0.9187868327 -1.890383552
## X356	0	1 -0.6398569491 -1.229055001
## X359	0	0 -0.8695639121 -3.144152263
## X360	1	0 -0.4593729068 0.107379779
## X361	0	0 -0.4757805470 0.148712813
## X363	0	0 -0.0491819015 0.190045848
## X365	0	0 -0.1968506634 1.650479731
## X366	0	0 0.3281938233 -0.912168404
## X367	1	0 0.6399389873 1.719368122
## X369	1	0 0.6235313471 1.085594927
## X371	0	0 -0.6562645893 -0.815724657
## X372	1	0 -0.3773347057 3.345134143
## X373	0	0 1.3126522360 0.741152974
## X374	1	0 0.4430473048 -1.256610357
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## X377	0	1 -2.9041112982 -1.959271942
## X378	0	0 -0.0327742613 -1.504608564
## X379	1	0 0.0164486593 -0.154396106
## X380	1	0 0.3117861831 1.815811869
## X382	0	1 -0.9023791925 -0.719280910
## X383	1	0 -0.8367486317 0.768708330
## X385	0	0 0.0820792202 -1.793939805
## X386	0	1 -0.8203409914 -0.237062175
## X387	0	0 0.1148945006 0.258934239
## X388	0	0 -0.2624812243 -0.278395209
## X389	0	0 0.7712001090 -1.242832679
## X391	0	0 -1.0008250338 -0.622837163
## X392	1	0 -0.3773347057 -0.002841646
## X393	1	0 0.8368306699 0.107379779
## X394	0	0 0.9188688709 0.465599411
## X395	0	0 1.3454675164 -0.168173784
## X396	0	1 1.5751744793 1.430036881
## X397	1	0 -0.6070416687 -0.154396106
## X398	0	0 -0.1640353830 -0.705503231
## X399	1	0 0.7219771884 -0.526393416
## X401	1	0 1.0993529132 -1.518386242
## X402	0	0 -0.7383027904 -1.614829989
## X405	0	0 0.4922702254 -0.057952359
## X406	0	0 0.7712001090 0.024713710
## X407	1	0 1.2142063947 0.920262789
## X408	1	0 0.5579007863 -0.540171094

## X410	1	0	-0.5414111079	-0.801946978
## X411	0	0	-1.5258695205	0.644709227
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## X413	0	1	0.2461556223	-0.388616634
## X414	0	0	0.0984868604	-0.581504128
## X415	0	0	0.4430473048	0.575820836
## X416	1	0	-0.9351944729	-1.931716586
## X417	0	0	-0.8695639121	-0.223284496
## X418	0	0	1.2306140349	0.961595824
## X419	1	0	1.3290598762	1.471369915
## X420	0	0	0.3117861831	-0.195729140
## X421	0	0	0.3938243842	-0.085507715
## X422	0	0	-0.2296659439	-0.967279116
## X423	0	0	-0.3609270655	0.810041364
## X424	0	0	-0.9516021131	0.024713710
## X425	0	0	0.5250855058	-0.223284496
## X426	0	0	2.2642953682	0.810041364
## X427	1	0	0.5743084265	-1.862828195
## X431	0	0	-0.6562645893	-0.223284496
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## X434	1	0	-0.2952965047	-0.843280013
## X435	0	0	0.8860535905	-0.540171094
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## X438	0	0	-0.3609270655	1.154483318
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## X440	1	0	0.2297479821	0.520710123
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## X445	1	0	-0.1148124624	0.851374399
## X448	1	0	0.9188688709	-0.237062175
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## X457	1	0	-0.0655895417	-0.126840749
## X458	0	0	-1.5094618803	0.534487801
## X459	1	0	1.4767286381	-0.278395209
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## X461	1	0	1.4603209979	0.203823526
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## X466	0	0	0.8696459503	-0.898390725
## X468	1	0	1.2142063947	-0.140618428
## X469	0	0	-0.6234493089	0.190045848
## X470	1	0	-0.7383027904	-0.622837163
## X472	1	0	-0.4921881872	0.396711020
## X473	0	0	1.1485758339	-0.485060381
## X474	0	1	0.9188688709	2.008699363
## X475	0	1	1.1977987545	0.686042261
## X476	0	1	1.3126522360	0.617153870

## X478	0	0	-0.1968506634	-0.181951462
## X480	1	0	0.2133403418	1.292260099
## X481	0	0	-0.3773347057	0.079824423
## X482	1	0	0.5250855058	2.711360948
## X483	0	0	-0.0491819015	-1.132611254
## X484	0	0	-1.3453854782	-0.912168404
## X486	0	0	1.1813911143	0.686042261
## X487	1	0	0.8204230296	0.562043158
## X488	1	0	0.3938243842	-1.366831782
## X489	0	0	0.6563466275	0.162490492
## X490	0	0	0.4266396646	-1.284165713
## X491	0	0	1.2634293153	-0.085507715
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## X495	1	0	-1.1156785152	-1.449497851
## X496	0	1	0.9024612307	-0.429949669
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## X500	0	0	-0.2460735841	-0.609059484
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## X502	0	0	1.9033272836	-0.429949669
## X503	0	0	3.3307919819	0.603376192
## X504	0	0	0.2461556223	-0.609059484
## X507	0	1	1.5751744793	-0.443727347
## X509	1	0	-1.9852834464	-0.609059484
## X511	0	0	-1.0828632348	0.892707433
## X512	0	1	-0.7218951502	-1.408164817
## X513	0	0	-0.3281117851	0.451821733
## X514	0	0	0.2625632625	-0.953501438
## X515	0	0	1.4767286381	0.562043158
## X516	0	0	-0.8367486317	-0.664170197
## X518	0	0	0.0820792202	-0.099285393
## X520	0	0	-0.2132583036	0.121157457
## X521	1	0	1.3290598762	0.575820836
## X522	1	0	0.0000410191	0.162490492
## X523	1	0	-0.6726722295	0.479377089
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## X525	0	0	0.3938243842	-0.912168404
## X527	0	1	-0.4265576264	-0.443727347
## X528	0	0	-0.1968506634	-2.813487987
## X529	1	0	-0.6398569491	-0.250839853
## X530	0	0	0.4430473048	-0.457505025
## X533	1	0	-0.3609270655	-0.374838956
## X535	1	0	0.8204230296	1.443814559
## X536	1	0	1.0173147122	0.754930652
## X539	1	0	-2.1821751289	-1.063722863
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## X541	0	0	-0.9351944729	0.630931548
## X542	1	0	-0.4921881872	0.479377089
## X543	0	0	-1.2797549173	-0.223284496
## X545	0	0	1.4439133577	-1.187721966
## X546	0	0	-0.0655895417	0.934040468

## X547	0	0	-1.0992708750	-0.471282703
## X548	1	0	-1.2633472771	-0.485060381
## X549	0	1	0.7055695482	1.126927962
## X550	1	0	-0.3773347057	-2.234825505
## X551	1	0	-2.0016910866	-1.807717483
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## X553	0	0	0.1148945006	1.016706536
## X554	0	0	-0.7218951502	-0.374838956
## X556	1	0	-0.1476277428	-1.036167507
## X557	1	0	1.9853654846	-0.650392519
## X558	0	0	-0.4921881872	0.906485111
## X559	0	0	0.6235313471	-0.540171094
## X560	1	0	0.2953785429	-1.146388932
## X561	1	0	-0.6234493089	1.884700259
## X562	1	0	-0.1968506634	-0.168173784
## X563	0	0	-0.7054875100	-0.498838059
## X564	0	0	1.4931362783	1.044261893
## X565	0	1	-0.3609270655	0.878929755
## X566	0	0	2.0674036857	0.851374399
## X567	0	0	1.7228432412	1.540258306
## X568	0	0	-0.4265576264	-0.333505922
## X569	1	0	0.3117861831	-0.113063071
## X571	1	0	-0.3117041449	-0.994834472
## X573	0	0	-0.5742263883	1.016706536
## X574	0	1	-0.2460735841	-0.705503231
## X575	0	0	-2.9697418591	-1.408164817
## X576	0	0	-0.9844173935	0.906485111
## X577	0	0	0.5414931461	-0.567726450
## X579	1	0	-0.2460735841	0.989151180
## X580	1	0	-1.0500479544	0.396711020
## X582	1	0	1.7720661619	-0.691725553
## X584	0	1	0.1805250614	-1.408164817
## X587	0	0	-1.1156785152	-1.504608564
## X588	1	0	-0.2460735841	0.589598514
## X589	0	0	-0.7711180708	1.512702950
## X591	0	0	1.4603209979	-0.898390725
## X592	1	0	-1.2961625576	0.024713710
## X593	0	1	2.0017731248	0.355377986
## X594	0	0	0.2297479821	-1.518386242
## X597	0	0	-0.8039333512	1.154483318
## X598	0	1	1.3126522360	1.168260996
## X600	1	0	0.4758625852	0.589598514
## X601	0	0	1.0009070720	-1.394387139
## X602	1	0	0.6071237069	0.975373502
## X603	1	0	-1.8868376051	-1.876605874
## X604	1	0	-0.4757805470	0.562043158
## X605	1	0	-1.3617931184	-0.733058588
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## X615	0	0	-0.5906340285	-1.421942495

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## X618	0	0	0.7055695482	-1.284165713
## X619	1	0	-1.7883917639	-1.504608564
## X620	0	1	-0.1312201026	0.203823526
## X623	0	1	0.5250855058	-0.815724657
## X624	0	0	1.2306140349	0.575820836
## X625	0	0	-0.2460735841	0.107379779
## X626	0	0	1.0337223524	0.548265480
## X628	0	0	-1.2961625576	0.217601204
## X629	0	0	-0.8695639121	-0.705503231
## X630	0	0	-1.1320861554	0.438044054
## X631	1	0	0.6563466275	-1.835272839
## X632	1	0	-1.0500479544	-1.780162127
## X633	0	0	2.0345884052	0.920262789
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## X635	0	1	1.0173147122	-0.057952359
## X636	1	0	-0.9351944729	-0.815724657
## X637	1	0	1.7228432412	1.512702950
## X638	0	0	-0.6726722295	0.892707433
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## X642	0	0	-1.3125701978	0.410488698
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## X644	0	0	-0.4757805470	-0.278395209
## X645	1	0	-1.0172326740	-0.512615737
## X646	0	0	-1.3782007586	0.300267273
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## X649	1	0	-0.1640353830	0.506932445
## X650	0	0	0.4102320244	-0.223284496
## X652	0	0	-0.6890798698	0.548265480
## X654	1	0	1.3618751566	1.581591340
## X655	1	0	-0.9023791925	-0.925946082
## X656	0	1	-0.0819971820	-0.361061278
## X657	0	0	0.8204230296	-1.849050517
## X658	1	0	-1.2633472771	0.355377986
## X659	0	0	0.1641174212	-1.008612151
## X660	0	1	-1.2797549173	1.815811869
## X661	1	0	1.8048814423	-0.953501438
## X663	0	0	1.1813911143	0.410488698
## X664	0	0	1.5587668391	0.134935135
## X665	1	0	-0.2132583036	0.052269066
## X666	1	0	0.1313021408	2.022477041
## X667	0	0	-1.4602389597	2.008699363
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## X670	0	0	2.7401169343	0.203823526
## X673	0	0	0.3117861831	1.471369915
## X674	0	0	1.3946904370	1.512702950
## X675	0	0	1.0009070720	0.176268170
## X676	0	0	-0.3609270655	-0.774391622
## X677	0	0	-0.6234493089	-0.181951462
## X678	1	0	-0.5414111079	0.038491388
## X679	0	0	1.3782827968	0.947818146
## X680	0	0	-0.2132583036	1.085594927



## X681	1	0	-0.3281117851	0.975373502
## X682	1	0	0.0820792202	0.727375295
## X683	0	0	0.2789709027	0.658486905
## X684	0	0	1.3946904370	0.768708330
## X685	0	0	-0.5085958274	0.603376192
## X686	0	0	-0.1312201026	-0.636614841
## X687	0	0	0.0164486593	0.768708330
## X688	1	0	0.2297479821	0.920262789
## X690	0	0	-1.3289778380	-1.132611254
## X691	0	0	-1.4602389597	0.617153870
## X692	0	0	0.3938243842	0.286489595
## X693	0	0	1.6408050402	0.314044951
## X694	1	0	-0.0327742613	0.203823526
## X697	0	1	0.8860535905	0.079824423
## X698	0	0	-0.4101499862	-1.559719276
## X699	0	0	-0.3117041449	-0.085507715
## X700	0	1	1.0501299926	2.256697569
## X701	0	0	0.0492639397	-0.636614841
## X702	0	0	-0.6398569491	-0.347283600
## X703	0	0	0.8204230296	0.686042261
## X705	0	1	2.3135182888	-0.760613944
## X706	0	0	0.0656715799	0.148712813
## X707	0	0	-0.0163666211	-0.733058588
## X708	0	0	-0.0819971820	-1.945494264
## X709	1	0	-2.1985827691	-1.187721966
## X710	1	0	1.3618751566	0.451821733
## X711	0	0	-0.0819971820	0.975373502
## X712	0	1	-2.0837292877	-0.085507715
## X713	0	0	0.0656715799	-0.305950565
## X714	1	0	1.0337223524	-0.526393416
## X715	0	0	-1.7227612030	-1.408164817
## X716	0	0	-0.0819971820	-0.512615737
## X717	0	0	0.2461556223	0.603376192
## X718	0	1	2.0838113259	0.823819042
## X719	0	0	0.0820792202	-1.904161230
## X720	0	1	0.3610091037	-1.008612151
## X721	0	0	-0.2460735841	0.451821733
## X722	0	0	0.1148945006	0.079824423
## X724	0	0	-0.2132583036	-1.160166610
## X725	0	1	1.3454675164	0.506932445
## X726	0	0	0.6727542677	-0.195729140
## X730	0	1	0.7547924688	-0.030397002
## X731	0	0	1.1485758339	1.306037777
## X732	0	0	0.4594549450	0.878929755
## X734	0	0	0.7055695482	1.374926168
## X735	0	0	1.3618751566	-0.250839853
## X737	0	0	1.3946904370	0.258934239
## X738	0	0	-0.7218951502	-0.746836266
## X739	1	0	2.1002189661	-1.752606770
## X740	1	0	-0.7547104306	1.471369915
## X744	0	0	1.4603209979	1.058039571
## X745	0	0	0.2625632625	-0.526393416
## X746	0	0	1.5751744793	0.796263686
## X747	1	0	0.5250855058	0.630931548

## X748	0	0	-0.7054875100	0.024713710
## X749	0	0	0.8532383101	-1.173944288
## X751	0	0	0.2133403418	-1.242832679
## X752	0	1	-1.0664555946	0.865152077
## X753	1	0	0.6399389873	-0.691725553
## X754	0	1	-0.1476277428	2.229142213
## X757	0	0	0.0328562995	-0.416171990
## X758	0	0	1.5095439185	0.534487801
## X759	0	0	1.1813911143	1.182038674
## X761	0	1	0.2789709027	1.182038674
## X762	0	0	-0.2132583036	-0.884613047
## X763	0	0	0.2625632625	1.154483318
## X764	0	0	0.0000410191	0.148712813
## X765	0	0	1.6079897598	0.947818146
## X766	1	0	1.1813911143	-0.967279116
## X767	0	0	-0.4921881872	1.664257409
## X768	1	0	-1.1320861554	-0.168173784
## X769	0	0	0.0328562995	-0.843280013
## X770	0	1	-1.2961625576	0.176268170
## X772	1	0	-0.3773347057	-2.110826402
## X773	0	0	-1.0008250338	-0.168173784
## X774	0	0	-0.2624812243	-1.091278219
## X775	0	0	-0.8695639121	-0.540171094
## X776	0	0	0.0492639397	-0.113063071
## X777	1	0	-1.3782007586	-0.485060381
## X778	0	0	-0.7383027904	-0.664170197
## X779	1	0	1.7392508814	0.534487801
## X780	1	0	-2.4282897321	-1.118833576
## X781	0	0	-0.9844173935	-0.705503231
## X784	0	0	0.2953785429	0.520710123
## X786	0	1	0.6071237069	-0.719280910
## X787	0	1	-0.0491819015	2.532251132
## X788	0	0	-1.3946083988	-1.449497851
## X789	0	0	-0.5742263883	2.118920788
## X790	0	0	0.7547924688	1.209594030
## X791	1	0	-0.0984048222	-2.014382655
## X792	0	0	1.4275057174	-2.000604977
## X794	0	0	1.1157605534	-0.567726450
## X795	0	1	-0.2460735841	-0.113063071
## X796	0	0	0.3281938233	-0.057952359
## X797	1	0	-0.2460735841	-0.319728243
## X798	0	1	0.6563466275	0.920262789
## X799	0	0	-1.3125701978	-0.030397002
## X800	0	0	-1.1484937957	-0.664170197
## X801	1	0	0.9516841513	-0.843280013
## X802	0	0	1.0337223524	-0.250839853
## X803	0	1	-0.2296659439	1.719368122
## X804	1	0	0.2133403418	-0.746836266
## X805	0	0	0.1969327016	0.190045848
## X807	0	0	-1.3453854782	-1.904161230
## X808	0	0	-0.9680097533	-0.581504128
## X809	1	0	0.0328562995	0.410488698
## X810	1	0	0.1969327016	0.920262789
## X812	1	0	-0.8203409914	2.325585960

## X813	0	1	-0.2952965047	-0.071730037
## X814	0	0	0.1477097810	0.713597617
## X815	0	0	0.0820792202	-1.917938908
## X816	0	0	0.1805250614	-0.374838956
## X817	0	0	-1.0008250338	-0.126840749
## X818	1	0	0.9188688709	1.333593134
## X820	0	0	1.3290598762	-2.372602287
## X821	0	0	2.0345884052	0.010936032
## X822	0	1	0.5086778656	0.341600307
## X823	1	0	1.3290598762	0.245156560
## X824	1	0	0.2133403418	0.823819042
## X825	0	0	1.9197349238	0.782486008
## X826	1	0	-0.4593729068	-0.361061278
## X830	0	0	-0.0327742613	0.286489595
## X831	1	0	0.7055695482	1.002928858
## X832	0	0	-2.8877036580	1.016706536
## X833	0	0	-0.9023791925	-1.132611254
## X834	1	0	-1.6735382824	0.286489595
## X836	0	0	1.4603209979	0.727375295
## X837	1	0	0.3281938233	-1.242832679
## X838	1	0	-1.6407230020	-1.229055001
## X839	0	1	-0.7054875100	0.134935135
## X840	0	1	0.3938243842	0.355377986
## X841	0	0	1.0337223524	0.947818146
## X842	0	0	-0.9516021131	0.603376192
## X843	1	0	-1.0008250338	-0.870835369
## X844	0	0	0.4266396646	-2.358824609
## X847	0	0	-1.1484937957	-1.118833576
## X848	0	0	0.4102320244	1.540258306
## X849	0	0	-0.8531562719	-0.994834472
## X850	0	1	-0.0491819015	0.686042261
## X851	1	0	-0.0163666211	-0.664170197
## X852	0	0	-0.2132583036	-0.829502335
## X853	0	0	0.2461556223	0.438044054
## X854	0	0	-2.2806209702	-1.339276426
## X855	1	0	-1.5258695205	1.485147593
## X856	0	0	-0.1476277428	-1.380609460
## X857	0	0	-0.1476277428	-0.416171990
## X858	0	0	-1.4766465999	0.134935135
## X859	0	0	1.4275057174	-0.540171094
## X860	0	0	0.3938243842	0.314044951
## X861	0	0	-0.7711180708	-0.636614841
## X862	1	0	0.6891619080	0.947818146
## X864	0	0	-1.6079077216	-1.036167507
## X865	1	0	-0.2296659439	-0.402394312
## X866	1	0	-0.4101499862	-0.829502335
## X867	0	0	0.5579007863	0.176268170
## X868	1	0	-0.4921881872	0.245156560
## X869	1	0	1.7064356010	0.038491388
## X870	0	0	-0.8203409914	-1.711273736
## X871	0	0	-0.6562645893	-0.319728243
## X872	0	1	-1.0336403142	-1.077500541
## X873	0	0	-0.5250034676	-0.264617531
## X874	0	1	-0.6726722295	-1.628607667

## X875	0	0	-0.3609270655	-0.016619324
## X877	0	1	0.1148945006	0.617153870
## X878	1	0	0.3610091037	-1.270388035
## X879	0	0	1.2798369555	1.457592237
## X880	0	0	1.3126522360	0.479377089
## X881	1	0	0.1805250614	0.934040468
## X882	1	0	0.5414931461	-1.256610357
## X883	1	0	-1.8868376051	0.975373502
## X884	0	0	-0.5906340285	1.333593134
## X885	0	0	1.7392508814	1.884700259
## X886	0	0	-1.0664555946	-0.815724657
## X887	0	0	1.9525502042	-0.030397002
## X888	0	0	-0.6234493089	-0.154396106
## X889	0	0	-0.8203409914	-0.126840749
## X890	0	0	0.2297479821	-1.146388932
## X891	1	0	-0.6726722295	-1.463275529
## X892	1	0	1.2306140349	1.113150283
## X894	0	0	0.9188688709	0.314044951
## X895	0	0	-0.0327742613	0.107379779
## X897	1	0	0.8368306699	-0.733058588
## X899	0	0	0.9188688709	-0.636614841
## X900	1	0	-2.3462515310	-0.664170197
## X901	1	0	-0.0163666211	0.176268170
## X902	0	0	-0.0655895417	1.485147593
## X903	0	0	-0.7054875100	0.451821733
## X904	1	0	0.3774167439	-0.443727347
## X905	1	0	2.7565245745	0.520710123
## X906	1	0	0.1148945006	0.534487801
## X907	0	0	-0.0163666211	0.699819939
## X908	1	0	0.9516841513	0.121157457
## X909	1	0	0.7055695482	1.981144006
## X910	1	0	-0.6726722295	0.754930652
## X911	0	0	0.2625632625	0.465599411
## X913	1	0	0.5414931461	-0.829502335
## X916	0	0	-1.2305319967	0.465599411
## X917	0	0	-1.0500479544	1.209594030
## X918	0	0	-0.8859715523	0.066046745
## X919	0	0	0.3281938233	2.077587753
## X920	1	0	-0.8531562719	0.382933342
## X921	0	0	-1.1649014359	-0.553948772
## X922	0	0	-0.4429652666	-0.002841646
## X924	0	0	1.4767286381	2.711360948
## X925	0	0	1.1813911143	1.884700259
## X926	1	0	-0.6890798698	-0.526393416
## X927	0	0	-1.0828632348	-0.126840749
## X929	0	0	0.5907160667	-0.237062175
## X932	0	0	0.1148945006	0.258934239
## X933	1	0	0.5250855058	-0.650392519
## X935	0	0	0.8204230296	-0.870835369
## X936	0	0	0.9188688709	1.361148490
## X937	0	0	0.6891619080	0.699819939
## X939	1	0	0.0164486593	0.961595824
## X940	1	0	-0.2788888645	-0.223284496
## X941	0	0	-1.7555764835	-0.884613047

## X942	0	0	0.3117861831	0.520710123
## X943	0	0	0.2625632625	0.727375295
## X945	0	0	1.7556585217	0.190045848
## X946	0	0	-0.7383027904	0.079824423
## X948	1	0	-1.1649014359	-0.650392519
## X949	0	0	0.4102320244	-0.347283600
## X950	0	0	0.5907160667	-0.650392519
## X951	0	1	1.0173147122	0.699819939
## X953	0	0	-0.9023791925	0.672264583
## X954	0	1	0.2789709027	-0.622837163
## X955	1	0	2.2478877280	1.388703846
## X956	0	0	-0.1312201026	-2.069493368
## X957	0	0	0.5086778656	-1.105055898
## X958	0	0	-1.1649014359	-1.270388035
## X959	0	0	-0.9680097533	-1.656163023
## X960	0	1	1.1157605534	-0.154396106
## X961	0	0	-0.1968506634	0.920262789
## X962	1	0	0.7383848286	1.512702950
## X963	1	0	-1.6243153618	-0.113063071
## X964	0	0	-0.1148124624	0.520710123
## X965	0	0	-0.2132583036	0.327822629
## X966	1	0	0.3938243842	0.562043158
## X968	0	0	-0.1804430232	1.650479731
## X969	1	0	-0.1804430232	-0.347283600
## X970	0	0	0.9844994317	0.810041364
## X971	0	0	0.2297479821	-1.504608564
## X972	1	0	0.6563466275	-0.443727347
## X973	1	0	-1.0336403142	-0.857057691
## X974	1	0	0.0328562995	-1.614829989
## X975	1	0	0.2953785429	1.485147593
## X976	0	0	-0.2788888645	-0.016619324
## X977	0	0	1.5915821195	1.857144903
## X978	0	0	-0.0491819015	0.410488698
## X979	0	0	-1.2305319967	0.589598514
## X980	1	0	0.1148945006	-0.402394312
## X981	1	0	-0.3773347057	0.520710123
## X982	1	0	-2.1821751289	-0.636614841
## X983	1	0	-0.8367486317	-0.636614841
## X984	0	1	-0.2460735841	-0.402394312
## X985	1	0	-0.6726722295	0.741152974
## X986	1	0	0.0164486593	-0.719280910
## X987	0	0	-1.6571306422	-0.843280013
## X988	0	0	0.9844994317	0.314044951
## X989	0	0	0.4102320244	0.686042261
## X990	1	0	-1.6571306422	-0.195729140
## X991	0	0	0.0328562995	1.319815456
## X992	0	1	0.3610091037	0.851374399
## X993	0	0	-0.8695639121	0.562043158
## X994	0	0	0.7219771884	-0.870835369
## X995	0	0	-0.4101499862	-0.567726450
## X996	1	0	0.7712001090	0.203823526
## X997	0	1	-0.0491819015	-0.843280013
## X998	1	0	-0.8695639121	-0.953501438
## X999	1	0	0.7055695482	0.424266376

##	bmi	diabetesYes	hypertensionYes	sbp	ldl
## X1	-0.63511852	0	0	-1.2354661	-0.76054208
## X2	-0.56203238	1	1	0.3953052	-1.15944958
## X3	0.89969033	0	0	-0.8591342	1.43344917
## X4	-0.81783386	0	0	-1.1100221	0.78522448
## X6	1.19203487	0	1	0.2698613	-0.56108833
## X9	-0.19660170	0	1	1.0225250	-0.66081520
## X10	-0.85437693	0	1	0.6461931	0.03727292
## X11	1.44783635	0	0	-0.2319145	1.08440510
## X12	-0.70820465	0	1	1.6497447	-0.36163458
## X13	-0.08697250	1	1	1.1479689	0.58577073
## X14	-1.51215215	0	0	-0.1064706	-0.66081520
## X15	1.55746555	0	1	0.1444173	-1.20931302
## X17	0.38808738	0	1	1.0225250	0.33645354
## X18	0.20537204	0	0	-0.2319145	-0.11231739
## X19	2.87301599	0	1	0.3953052	1.13426854
## X21	0.42463045	0	0	0.0189734	-1.20931302
## X22	-0.48894625	0	1	0.5207492	0.83508792
## X24	0.68043192	0	0	-0.7336903	-0.95999583
## X25	0.68043192	0	1	0.5207492	0.43618042
## X26	0.42463045	0	1	0.1444173	-0.61095177
## X27	-1.32943681	0	1	1.2734129	0.23672667
## X28	0.86314726	0	1	0.7716371	0.28659011
## X29	-0.85437693	0	1	0.7716371	-0.76054208
## X30	1.59400862	0	1	0.5207492	0.03727292
## X31	-0.12351557	0	1	0.1444173	-2.15671833
## X33	-0.45240318	0	0	0.0189734	1.58303948
## X36	-1.03709226	0	1	1.2734129	-1.30903989
## X39	-1.18326454	0	1	0.5207492	1.13426854
## X40	-0.23314477	0	1	0.3953052	0.38631698
## X41	-0.34277398	0	0	-0.7336903	0.93481479
## X42	1.26512101	0	0	-0.9845782	0.18686323
## X45	-0.63511852	0	1	0.6461931	-0.51122489
## X46	0.42463045	0	0	-0.2319145	-0.61095177
## X47	1.77672396	0	1	0.1444173	0.03727292
## X49	1.26512101	1	1	0.5207492	0.33645354
## X54	-1.58523828	0	0	-0.3573584	0.23672667
## X56	2.17869770	0	1	0.3953052	1.43344917
## X57	0.09574284	0	1	0.8970810	0.03727292
## X59	0.35154431	0	1	0.1444173	-1.05972270
## X60	-1.95066896	0	0	-1.1100221	0.33645354
## X61	-0.59857545	0	0	-0.6082463	0.13699979
## X62	-0.26968784	0	0	-0.7336903	-0.06245396
## X64	-0.52548931	1	1	2.9041842	1.38358573
## X65	-1.14672147	0	1	0.7716371	0.38631698
## X67	0.75351806	0	1	0.3953052	0.43618042
## X69	0.20537204	1	0	-0.6082463	0.83508792
## X70	-1.47560908	0	0	-1.1100221	0.28659011
## X72	0.82660419	1	0	-1.3609100	-0.16218083
## X73	0.57080272	0	1	0.2698613	-1.40876676
## X74	-0.81783386	0	0	-0.7336903	-1.70794739
## X75	-1.54869521	0	0	-1.7372419	0.63563417
## X77	-1.29289374	0	1	0.3953052	-1.20931302
## X78	0.35154431	0	1	0.6461931	1.03454167

## X79	-0.26968784	0	1	2.5278523	1.93208354
## X82	0.68043192	0	0	-1.9881298	-1.30903989
## X85	1.11894874	0	0	-0.7336903	-1.05972270
## X87	-0.34277398	0	0	-1.6117979	-1.45863020
## X88	-0.12351557	0	0	-1.6117979	-1.70794739
## X89	0.27845818	0	0	-1.2354661	0.28659011
## X90	-0.16005864	0	1	0.1444173	1.53317604
## X91	-0.26968784	0	0	-0.2319145	0.73536104
## X92	0.38808738	0	1	0.3953052	1.98194698
## X93	-0.56203238	0	1	2.2769645	0.78522448
## X94	-0.16005864	0	1	0.7716371	-0.11231739
## X95	-0.05042943	0	0	0.0189734	1.98194698
## X96	-0.52548931	0	0	-1.1100221	-1.25917645
## X97	-0.63511852	1	1	0.7716371	0.53590729
## X98	-0.05042943	0	1	1.2734129	-0.26190770
## X99	0.46117352	1	0	-1.3609100	-0.21204427
## X100	-0.59857545	0	1	0.2698613	-0.11231739
## X101	-0.01388637	0	0	-0.4828024	1.03454167
## X102	0.16882897	0	1	1.0225250	0.23672667
## X103	0.20537204	0	1	1.3988568	0.53590729
## X104	0.20537204	0	1	0.6461931	0.33645354
## X105	-0.23314477	0	1	0.2698613	0.38631698
## X106	1.59400862	0	0	-0.9845782	0.08713636
## X108	-0.05042943	0	0	-0.9845782	-1.15944958
## X109	0.79006113	0	1	0.6461931	-0.01259052
## X110	-0.08697250	0	0	-0.2319145	-0.95999583
## X112	0.49771658	1	0	-0.2319145	1.88222010
## X113	0.53425965	0	0	-0.9845782	-1.60822051
## X114	-0.85437693	0	0	-1.9881298	-1.25917645
## X115	0.49771658	1	0	-0.4828024	0.78522448
## X116	0.24191511	1	1	0.5207492	0.18686323
## X117	0.42463045	0	1	1.6497447	-0.06245396
## X119	0.05919977	0	0	-0.2319145	-0.71067864
## X120	0.79006113	0	0	-0.2319145	-0.41149802
## X121	-1.47560908	0	1	2.0260766	1.33372229
## X122	-0.45240318	0	0	-0.3573584	-0.01259052
## X123	-1.87758282	0	0	-1.7372419	1.48331260
## X126	1.11894874	0	0	-0.2319145	0.18686323
## X127	-0.70820465	0	0	-0.7336903	-0.81040552
## X128	0.35154431	0	1	2.6532963	0.88495135
## X129	0.05919977	0	1	1.9006326	-0.86026895
## X130	0.02265670	0	1	0.1444173	0.83508792
## X131	0.46117352	1	0	-0.9845782	-0.16218083
## X132	0.31500124	1	0	-1.4863540	-0.36163458
## X133	-0.92746306	0	0	-0.7336903	0.38631698
## X135	0.53425965	1	0	-0.4828024	0.58577073
## X136	0.13228591	0	0	-0.4828024	-1.50849364
## X137	1.41129328	0	0	-0.4828024	-0.46136145
## X138	-0.26968784	0	1	3.0296281	-0.61095177
## X139	0.79006113	0	1	0.1444173	0.73536104
## X142	-0.56203238	0	1	1.3988568	3.17866947
## X144	0.75351806	1	1	0.5207492	1.88222010
## X145	2.28832691	0	1	0.5207492	-1.75781083
## X146	0.82660419	0	0	-0.6082463	-0.91013239

## X147	-1.32943681	0	1	0.1444173	-0.81040552
## X148	0.49771658	0	0	-1.2354661	1.28385885
## X149	0.13228591	0	1	1.6497447	1.23399542
## X150	0.20537204	0	1	0.3953052	0.38631698
## X152	-0.01388637	1	0	0.0189734	0.48604386
## X154	-1.84103976	0	1	0.1444173	1.03454167
## X155	-0.59857545	1	1	0.2698613	1.23399542
## X156	0.13228591	0	1	0.1444173	-0.31177114
## X157	-1.65832442	0	1	1.6497447	0.78522448
## X159	0.46117352	1	0	-0.2319145	0.43618042
## X160	1.04586260	0	1	0.2698613	0.53590729
## X161	1.26512101	0	1	0.1444173	-1.90740114
## X162	0.46117352	0	0	-1.6117979	-1.40876676
## X163	-0.05042943	0	0	-0.4828024	-0.16218083
## X164	0.60734579	0	0	-0.4828024	-0.86026895
## X165	-0.34277398	0	0	-0.6082463	-2.35617208
## X166	-0.19660170	0	0	-0.2319145	0.38631698
## X167	1.92289623	0	1	0.6461931	0.83508792
## X168	0.02265670	1	1	0.1444173	-0.06245396
## X169	-0.48894625	1	0	-1.4863540	-1.65808395
## X170	-0.56203238	0	0	-0.7336903	0.08713636
## X171	0.20537204	0	0	-0.6082463	0.03727292
## X172	1.33820714	0	0	0.0189734	1.08440510
## X173	0.79006113	0	0	-1.2354661	-0.21204427
## X174	-0.67166159	0	1	0.1444173	1.23399542
## X175	0.20537204	0	1	0.2698613	-0.31177114
## X177	-0.92746306	0	1	0.5207492	2.13153729
## X179	2.76338679	0	0	-0.3573584	-1.90740114
## X180	0.05919977	0	1	2.4024084	0.03727292
## X181	-0.23314477	0	1	1.6497447	-0.01259052
## X182	0.53425965	0	0	-1.7372419	-0.56108833
## X183	-1.14672147	0	1	0.1444173	0.48604386
## X184	-1.07363533	1	1	1.9006326	0.48604386
## X185	-1.21980760	0	1	0.8970810	-0.41149802
## X186	0.71697499	0	0	-0.6082463	-1.45863020
## X187	-1.40252294	0	1	1.2734129	0.53590729
## X188	1.59400862	0	0	-1.8626858	-1.80767426
## X189	0.02265670	0	1	0.2698613	0.78522448
## X190	-0.52548931	1	1	1.5243008	-0.11231739
## X191	0.93623340	0	0	0.0189734	0.83508792
## X192	0.27845818	0	1	2.2769645	1.18413198
## X193	0.93623340	1	0	-0.7336903	-1.15944958
## X194	0.68043192	0	1	2.4024084	-1.95726458
## X195	2.90955906	0	0	-1.6117979	-0.06245396
## X196	-1.43906601	1	0	-0.8591342	-1.85753770
## X198	1.41129328	0	1	0.5207492	-0.61095177
## X200	-0.19660170	1	0	-0.9845782	-0.46136145
## X201	0.16882897	0	0	-0.1064706	-0.61095177
## X202	1.30166407	0	0	0.0189734	-1.50849364
## X204	-0.12351557	0	1	0.2698613	-0.26190770
## X205	0.24191511	0	0	-1.3609100	-1.30903989
## X206	0.24191511	0	1	0.5207492	0.83508792
## X207	1.26512101	1	1	1.0225250	1.28385885
## X209	0.60734579	0	0	-1.1100221	-0.51122489



## X211	-1.29289374	0	1	0.5207492	1.33372229
## X212	0.71697499	0	0	-0.2319145	2.08167385
## X213	-0.01388637	0	1	2.1515205	-0.01259052
## X214	-0.89091999	0	0	-1.7372419	1.83235667
## X215	0.57080272	0	0	-0.6082463	-1.45863020
## X216	-0.70820465	0	1	0.6461931	0.93481479
## X217	0.53425965	1	0	-0.7336903	-1.00985927
## X218	0.02265670	0	1	1.0225250	0.73536104
## X219	-0.70820465	0	1	0.5207492	0.43618042
## X220	-0.92746306	0	0	-0.9845782	-0.16218083
## X221	0.82660419	0	0	-0.9845782	1.03454167
## X222	1.08240567	0	0	-0.6082463	-0.95999583
## X223	-0.85437693	1	0	-1.1100221	-0.46136145
## X224	0.27845818	0	1	0.8970810	-1.50849364
## X226	-0.56203238	1	1	1.3988568	0.48604386
## X227	1.26512101	1	1	1.5243008	0.48604386
## X228	0.27845818	0	1	0.2698613	-0.11231739
## X229	0.57080272	1	0	-0.4828024	0.43618042
## X230	-1.40252294	0	0	-1.1100221	-1.40876676
## X231	0.82660419	0	0	-0.1064706	-0.46136145
## X233	-0.78129079	0	0	-0.7336903	-0.61095177
## X234	1.33820714	0	1	1.1479689	1.23399542
## X235	0.57080272	0	1	0.3953052	1.63290292
## X236	2.98264519	0	0	-0.3573584	1.38358573
## X237	0.02265670	0	0	-0.1064706	0.53590729
## X238	-0.78129079	0	1	1.2734129	2.28112760
## X239	-0.41586011	0	0	-0.9845782	-0.91013239
## X240	1.11894874	0	1	0.1444173	-1.65808395
## X241	-0.19660170	0	0	-1.2354661	-0.86026895
## X244	-0.01388637	0	0	-0.2319145	0.03727292
## X245	-0.56203238	0	0	0.0189734	-0.31177114
## X246	1.41129328	0	0	0.0189734	-0.61095177
## X247	0.53425965	0	1	0.2698613	-2.00712801
## X248	-1.58523828	0	0	-1.8626858	1.13426854
## X249	-1.58523828	0	1	1.0225250	0.98467823
## X251	3.09227440	0	1	0.3953052	-0.21204427
## X252	0.24191511	0	1	1.5243008	0.38631698
## X254	-0.16005864	0	0	-0.2319145	-1.45863020
## X255	0.38808738	0	1	0.5207492	1.23399542
## X256	1.33820714	0	0	-1.8626858	-0.26190770
## X257	1.19203487	0	1	1.3988568	0.78522448
## X258	0.60734579	0	0	-0.1064706	0.58577073
## X259	-1.87758282	0	0	-0.3573584	0.33645354
## X260	0.02265670	0	0	-0.2319145	0.38631698
## X261	0.02265670	0	0	-0.4828024	0.18686323
## X262	0.09574284	0	0	-0.4828024	-1.00985927
## X264	-0.56203238	0	1	0.2698613	0.58577073
## X265	-1.00054920	0	0	-0.8591342	0.38631698
## X266	0.20537204	0	0	-0.6082463	-0.31177114
## X267	0.24191511	0	1	1.0225250	1.78249323
## X268	0.46117352	0	1	0.3953052	-0.21204427
## X269	0.13228591	0	0	-0.2319145	-0.31177114
## X270	1.52092248	1	0	-1.9881298	-0.41149802
## X273	0.02265670	0	0	-0.8591342	-0.31177114

## X274	-0.59857545	0	1	0.5207492	-0.21204427
## X275	-1.18326454	0	0	-0.6082463	-0.01259052
## X276	1.95943930	0	0	-0.3573584	-0.01259052
## X277	0.31500124	1	0	-0.8591342	-1.70794739
## X278	-1.11017840	0	0	-0.9845782	-1.40876676
## X279	-0.92746306	1	1	0.3953052	-0.41149802
## X280	-0.19660170	0	0	-0.4828024	-1.40876676
## X282	-1.32943681	0	0	-0.9845782	-0.61095177
## X283	-1.51215215	0	0	-1.1100221	-0.95999583
## X284	-0.30623091	0	0	-0.8591342	0.28659011
## X286	1.37475021	0	0	-1.2354661	-0.36163458
## X289	0.35154431	0	0	-0.9845782	-0.36163458
## X290	0.60734579	0	0	-1.2354661	-2.05699145
## X292	-0.67166159	1	0	-0.9845782	-1.45863020
## X293	-0.34277398	0	0	-0.4828024	-0.71067864
## X295	-1.14672147	0	1	0.6461931	1.33372229
## X296	-0.48894625	0	0	-0.6082463	1.43344917
## X298	-0.48894625	0	1	0.1444173	-0.66081520
## X299	-0.23314477	0	0	-0.1064706	-0.01259052
## X300	0.60734579	0	1	0.5207492	0.78522448
## X301	0.16882897	1	0	-0.1064706	0.08713636
## X302	0.38808738	0	0	-0.6082463	-2.10685489
## X303	-0.23314477	0	0	-0.4828024	-0.86026895
## X305	1.84981009	0	1	0.1444173	-0.56108833
## X306	0.20537204	0	1	0.1444173	-1.10958614
## X307	1.00931953	0	0	-1.3609100	-0.81040552
## X311	-0.63511852	1	1	1.3988568	0.28659011
## X312	0.38808738	0	0	0.0189734	-1.00985927
## X313	1.15549180	0	1	1.3988568	0.18686323
## X314	-1.25635067	0	0	-0.4828024	-0.81040552
## X315	1.22857794	0	1	1.0225250	-0.11231739
## X316	-0.70820465	0	0	-0.1064706	0.63563417
## X317	-1.69486748	0	0	-0.6082463	0.63563417
## X318	0.49771658	0	0	-1.3609100	0.63563417
## X319	-0.59857545	0	0	-0.2319145	-1.65808395
## X321	-0.63511852	0	1	0.3953052	-0.31177114
## X322	1.08240567	0	0	-1.1100221	-1.75781083
## X326	0.31500124	0	0	-1.3609100	-2.40603551
## X327	1.74018089	0	1	0.6461931	0.63563417
## X328	1.00931953	0	0	-2.1135737	0.33645354
## X329	-0.26968784	1	0	-1.2354661	0.53590729
## X330	-0.08697250	0	0	-1.7372419	-0.86026895
## X331	0.20537204	0	0	-1.3609100	-1.70794739
## X332	0.35154431	0	1	1.0225250	0.98467823
## X333	-0.34277398	1	1	0.3953052	0.58577073
## X334	-0.41586011	0	1	1.1479689	1.83235667
## X335	-0.52548931	0	0	-0.3573584	0.63563417
## X336	0.13228591	0	1	0.7716371	-2.40603551
## X339	0.64388885	0	1	1.1479689	-0.95999583
## X340	0.16882897	0	0	-0.1064706	-0.01259052
## X341	1.59400862	1	1	0.6461931	1.73262979
## X342	-1.03709226	0	0	0.0189734	0.08713636
## X345	-1.51215215	0	1	0.3953052	1.73262979
## X347	-1.58523828	0	0	-0.4828024	-1.60822051

## X349	0.60734579	0	1	2.0260766	0.63563417
## X351	0.46117352	1	1	1.2734129	0.38631698
## X353	-0.05042943	0	1	0.5207492	0.63563417
## X354	0.42463045	0	0	-0.2319145	0.18686323
## X355	-1.18326454	0	0	-0.6082463	-0.26190770
## X356	-0.70820465	0	1	0.3953052	1.48331260
## X359	-2.42572884	1	1	0.2698613	-1.70794739
## X360	0.42463045	1	1	2.2769645	0.33645354
## X361	0.46117352	0	0	-0.8591342	-0.76054208
## X363	0.20537204	0	1	1.0225250	-0.56108833
## X365	1.66709475	0	0	-0.2319145	-0.51122489
## X366	-1.07363533	0	1	0.6461931	0.63563417
## X367	1.04586260	0	0	-1.1100221	0.53590729
## X369	0.49771658	0	1	1.0225250	2.13153729
## X371	-0.30623091	0	1	0.3953052	1.08440510
## X372	3.42116201	0	1	1.1479689	-0.56108833
## X373	-0.26968784	0	1	0.6461931	-1.00985927
## X374	-1.43906601	0	0	-0.8591342	-0.01259052
## X376	-1.36597987	0	0	-1.1100221	-0.76054208
## X377	0.20537204	0	1	0.5207492	-0.86026895
## X378	-1.36597987	0	1	0.8970810	0.38631698
## X379	-0.16005864	0	0	-1.3609100	-1.65808395
## X380	1.41129328	0	1	2.0260766	0.73536104
## X382	-0.05042943	0	1	0.1444173	0.93481479
## X383	1.33820714	0	0	-1.1100221	0.03727292
## X385	-1.73141055	0	1	0.1444173	-1.30903989
## X386	0.35154431	0	0	-1.9881298	0.68549761
## X387	0.13228591	0	1	0.6461931	2.08167385
## X388	-0.08697250	0	0	-1.6117979	-0.81040552
## X389	-1.62178135	1	0	-1.2354661	0.23672667
## X391	0.13228591	0	0	-1.4863540	-0.46136145
## X392	0.24191511	0	1	0.6461931	1.53317604
## X393	-0.48894625	0	0	-1.1100221	-0.36163458
## X394	-0.23314477	0	1	0.8970810	-1.45863020
## X395	-1.07363533	0	0	-0.7336903	-0.91013239
## X396	0.09574284	1	1	0.3953052	0.08713636
## X397	0.27845818	0	0	-0.6082463	-0.56108833
## X398	-0.56203238	0	1	0.1444173	2.82962541
## X399	-1.00054920	0	0	-0.1064706	-0.56108833
## X401	-2.06029816	1	1	1.3988568	-1.20931302
## X402	-1.03709226	0	0	-0.9845782	0.78522448
## X405	-0.41586011	0	0	-0.1064706	0.08713636
## X406	-0.52548931	0	1	0.7716371	0.13699979
## X407	-0.05042943	0	0	-1.3609100	0.28659011
## X408	-0.89091999	0	0	-0.9845782	0.58577073
## X410	-0.37931704	0	0	-0.2319145	0.03727292
## X411	1.84981009	0	1	0.5207492	0.68549761
## X412	-0.67166159	0	0	-0.6082463	1.43344917
## X413	-0.52548931	0	1	0.5207492	-1.45863020
## X414	-0.59857545	0	0	-0.4828024	0.38631698
## X415	0.16882897	0	0	0.0189734	-0.41149802
## X416	-1.21980760	0	1	1.2734129	-1.25917645
## X417	0.42463045	1	1	0.2698613	0.53590729
## X418	-0.05042943	0	0	-0.1064706	-0.26190770

## X419	0.31500124	0	1	0.1444173	1.73262979
## X420	-0.41586011	0	1	0.2698613	-0.26190770
## X421	-0.37931704	1	0	-0.2319145	0.18686323
## X422	-0.74474772	0	0	-0.8591342	-2.00712801
## X423	1.00931953	0	0	-0.1064706	0.48604386
## X424	0.71697499	0	1	0.3953052	-0.11231739
## X425	-0.59857545	0	0	-1.8626858	0.83508792
## X426	-0.81783386	0	1	0.5207492	0.48604386
## X427	-2.06029816	0	0	0.0189734	0.73536104
## X431	0.24191511	0	1	0.6461931	-0.26190770
## X432	-0.89091999	0	1	0.7716371	0.58577073
## X434	-0.59857545	0	0	-0.9845782	-0.76054208
## X435	-1.11017840	0	0	-1.4863540	1.73262979
## X437	-2.79115952	0	1	1.7751887	2.58030823
## X438	1.33820714	0	0	0.0189734	-1.65808395
## X439	0.05919977	1	1	1.7751887	-0.26190770
## X440	0.27845818	0	0	-0.8591342	-0.06245396
## X441	-0.37931704	0	0	-1.1100221	0.13699979
## X442	-0.85437693	0	0	0.0189734	-0.91013239
## X443	-0.41586011	0	0	-1.3609100	-0.16218083
## X444	-1.69486748	1	0	0.0189734	1.03454167
## X445	0.86314726	0	0	-0.3573584	0.83508792
## X448	-0.85437693	0	1	1.2734129	0.63563417
## X450	0.79006113	0	1	0.3953052	1.38358573
## X451	0.35154431	0	0	-0.6082463	0.53590729
## X453	-0.59857545	1	0	-0.9845782	-1.15944958
## X454	0.57080272	0	1	0.5207492	-0.11231739
## X455	0.16882897	1	0	-0.3573584	-0.01259052
## X456	0.35154431	0	0	-0.7336903	0.58577073
## X457	-0.08697250	0	1	0.1444173	-1.00985927
## X458	1.70363782	0	1	0.1444173	-0.91013239
## X459	-1.21980760	0	1	0.6461931	1.93208354
## X460	-0.78129079	1	1	0.8970810	0.38631698
## X461	-0.81783386	1	0	-0.4828024	0.48604386
## X464	-1.03709226	0	1	2.1515205	-0.01259052
## X465	1.19203487	0	1	2.7787402	0.83508792
## X466	-1.40252294	1	0	-0.3573584	-3.45316770
## X468	-0.96400613	0	0	-0.7336903	0.88495135
## X469	0.60734579	0	1	0.2698613	0.03727292
## X470	-0.05042943	0	0	-0.8591342	-1.90740114
## X472	0.71697499	0	0	-0.2319145	0.28659011
## X473	-1.21980760	0	1	0.1444173	-0.66081520
## X474	1.08240567	0	0	-0.2319145	-0.76054208
## X475	-0.26968784	0	1	0.5207492	-0.76054208
## X476	-0.37931704	0	0	-1.2354661	-0.61095177
## X478	-0.05042943	0	1	0.8970810	0.63563417
## X480	0.97277646	0	0	0.0189734	-0.26190770
## X481	0.31500124	0	0	-0.1064706	-0.21204427
## X482	1.99598236	0	1	0.2698613	0.18686323
## X483	-1.03709226	0	1	0.2698613	-0.56108833
## X484	0.09574284	0	0	-0.6082463	-0.56108833
## X486	-0.23314477	0	1	1.0225250	0.83508792
## X487	-0.08697250	0	1	0.8970810	0.63563417
## X488	-1.51215215	1	0	-0.3573584	0.88495135

## X489	-0.34277398	0	1	1.0225250	1.38358573
## X490	-1.47560908	0	1	2.0260766	-1.35890333
## X491	-0.92746306	0	1	0.7716371	0.58577073
## X492	-0.26968784	1	1	1.0225250	0.83508792
## X493	-0.26968784	0	1	1.2734129	0.28659011
## X494	0.42463045	0	1	1.5243008	-0.31177114
## X495	-0.59857545	0	0	-0.1064706	0.43618042
## X496	-1.00054920	0	1	0.3953052	0.63563417
## X497	0.31500124	0	0	-0.3573584	0.83508792
## X498	0.38808738	0	1	0.1444173	2.38085448
## X499	-0.70820465	0	0	-0.8591342	1.03454167
## X500	-0.41586011	0	0	-0.8591342	2.53044479
## X501	0.13228591	0	1	0.3953052	-0.91013239
## X502	-1.62178135	0	1	1.0225250	0.23672667
## X503	-1.62178135	0	0	-1.4863540	-1.05972270
## X504	-0.74474772	0	0	-1.2354661	0.23672667
## X507	-1.43906601	0	0	-0.4828024	-0.51122489
## X509	0.93623340	0	0	0.0189734	-1.20931302
## X511	1.70363782	0	0	-1.1100221	-1.55835708
## X512	-0.85437693	0	1	0.5207492	0.98467823
## X513	0.64388885	0	1	0.3953052	-0.46136145
## X514	-1.07363533	0	0	-0.6082463	1.13426854
## X515	-0.56203238	1	0	0.0189734	-0.11231739
## X516	-0.01388637	1	1	0.1444173	0.23672667
## X518	-0.16005864	0	0	-0.8591342	-0.51122489
## X520	0.24191511	0	1	2.1515205	-0.36163458
## X521	-0.41586011	1	0	-1.1100221	-0.36163458
## X522	0.13228591	0	1	0.3953052	-1.10958614
## X523	0.93623340	0	0	-0.6082463	1.08440510
## X524	1.26512101	0	1	0.7716371	-0.95999583
## X525	-1.11017840	0	0	-1.8626858	0.48604386
## X527	-0.12351557	0	0	-0.7336903	0.63563417
## X528	-2.49881498	0	1	0.7716371	1.13426854
## X529	0.20537204	0	0	-0.4828024	0.33645354
## X530	-0.74474772	0	1	0.1444173	-1.15944958
## X533	-0.12351557	0	0	-0.4828024	-1.05972270
## X535	0.64388885	1	0	-0.8591342	-0.26190770
## X536	-0.08697250	0	1	0.1444173	-0.26190770
## X539	0.60734579	0	1	0.6461931	0.53590729
## X540	-1.87758282	0	0	-1.1100221	0.68549761
## X541	1.30166407	1	0	-0.2319145	0.68549761
## X542	0.79006113	0	1	2.6532963	0.43618042
## X543	0.75351806	0	1	0.6461931	-0.01259052
## X545	-1.95066896	0	1	1.0225250	0.98467823
## X546	0.89969033	0	0	-0.1064706	2.08167385
## X547	0.35154431	0	1	1.1479689	-0.46136145
## X548	0.46117352	0	0	0.0189734	-0.36163458
## X549	0.46117352	0	0	-0.9845782	-0.36163458
## X550	-1.84103976	0	0	-0.8591342	-0.36163458
## X551	-0.34277398	0	1	0.1444173	1.08440510
## X552	0.75351806	0	1	0.8970810	-1.40876676
## X553	0.82660419	0	1	0.8970810	0.58577073
## X554	0.16882897	0	1	1.0225250	0.53590729
## X556	-0.89091999	1	0	-0.7336903	-0.51122489

## X557	-1.84103976	1	0	0.0189734	-1.10958614
## X558	1.19203487	0	1	0.1444173	-2.80494301
## X559	-0.92746306	0	1	0.7716371	0.78522448
## X560	-1.25635067	0	1	0.2698613	1.68276635
## X561	2.25178384	0	1	0.8970810	0.98467823
## X562	-0.01388637	0	0	-0.3573584	1.18413198
## X563	0.02265670	0	0	-0.1064706	0.98467823
## X564	-0.16005864	0	0	-0.7336903	1.03454167
## X565	1.08240567	0	0	-0.2319145	-0.71067864
## X566	-0.67166159	0	1	0.7716371	1.23399542
## X567	0.09574284	0	0	-0.6082463	1.48331260
## X568	-0.01388637	0	1	1.6497447	0.08713636
## X569	-0.34277398	0	1	0.5207492	-0.16218083
## X571	-0.74474772	0	0	-1.3609100	-1.45863020
## X573	1.37475021	0	1	1.5243008	2.13153729
## X574	-0.48894625	0	0	-1.6117979	-0.86026895
## X575	0.89969033	0	0	-2.4899056	-0.31177114
## X576	1.63055169	0	1	1.5243008	1.33372229
## X577	-0.92746306	0	0	-0.3573584	0.38631698
## X579	1.08240567	0	0	-0.4828024	-1.60822051
## X580	1.15549180	0	0	-0.6082463	-0.81040552
## X582	-1.76795362	0	0	-0.9845782	0.78522448
## X584	-1.43906601	0	1	0.8970810	0.03727292
## X587	-0.67166159	0	1	0.7716371	1.13426854
## X588	0.71697499	0	1	0.7716371	0.28659011
## X589	2.03252543	0	1	1.1479689	-0.86026895
## X591	-1.73141055	0	0	-1.4863540	-2.30630864
## X592	1.00931953	0	0	-0.9845782	-0.01259052
## X593	-1.03709226	0	0	-1.6117979	0.03727292
## X594	-1.54869521	0	1	1.3988568	-0.81040552
## X597	1.70363782	1	0	-0.6082463	-1.05972270
## X598	0.09574284	1	0	-0.7336903	-0.26190770
## X600	0.16882897	0	0	-0.2319145	1.18413198
## X601	-1.87758282	1	0	-0.3573584	1.33372229
## X602	0.42463045	0	0	-0.7336903	-0.26190770
## X603	-0.48894625	0	0	0.0189734	-1.05972270
## X604	0.86314726	0	0	-0.9845782	-0.26190770
## X605	0.31500124	0	1	0.7716371	-0.71067864
## X606	0.97277646	0	1	0.1444173	-0.56108833
## X609	-1.21980760	0	1	1.9006326	-0.56108833
## X610	0.02265670	0	1	0.6461931	2.18140073
## X611	2.61721452	0	0	-1.8626858	-0.56108833
## X613	-0.19660170	1	1	0.8970810	-0.11231739
## X614	0.60734579	1	1	0.6461931	0.98467823
## X615	-0.96400613	0	0	-1.2354661	-0.11231739
## X617	1.92289623	0	1	0.2698613	-0.86026895
## X618	-1.62178135	0	0	-1.3609100	-0.76054208
## X619	-0.16005864	1	1	0.2698613	-0.46136145
## X620	0.27845818	0	0	-2.1135737	-1.80767426
## X623	-1.11017840	0	1	0.5207492	1.03454167
## X624	-0.37931704	0	0	-0.1064706	0.53590729
## X625	0.24191511	1	0	0.0189734	-0.46136145
## X626	-0.26968784	0	1	1.1479689	1.48331260
## X628	1.19203487	1	1	0.5207492	0.28659011

## X629	-0.05042943	1	0	-1.4863540	0.23672667
## X630	1.26512101	1	0	0.0189734	-1.50849364
## X631	-2.09684123	0	1	0.1444173	1.18413198
## X632	-1.00054920	1	0	-0.1064706	-0.56108833
## X633	-0.59857545	1	0	0.0189734	0.33645354
## X634	-0.41586011	0	0	0.0189734	-1.95726458
## X635	-0.74474772	0	0	0.0189734	-0.51122489
## X636	-0.12351557	0	0	-0.2319145	1.93208354
## X637	0.05919977	0	0	-0.2319145	1.03454167
## X638	1.33820714	0	0	-1.7372419	1.38358573
## X640	0.68043192	0	1	0.2698613	-0.06245396
## X641	0.20537204	0	0	-0.4828024	0.43618042
## X642	1.41129328	0	0	-0.1064706	0.33645354
## X643	0.46117352	0	0	-1.8626858	-2.45589895
## X644	0.05919977	0	0	-1.4863540	-0.95999583
## X645	0.24191511	0	1	0.8970810	-1.35890333
## X646	1.37475021	0	0	-0.6082463	-0.36163458
## X648	0.38808738	0	0	-0.3573584	-0.46136145
## X649	0.57080272	0	0	-0.8591342	-1.70794739
## X650	-0.52548931	0	0	-0.8591342	-0.31177114
## X652	1.04586260	0	1	0.2698613	-0.36163458
## X654	0.38808738	0	1	0.6461931	1.78249323
## X655	-0.23314477	0	1	2.6532963	-0.36163458
## X656	-0.30623091	0	1	0.3953052	-2.10685489
## X657	-2.16992737	0	0	-1.2354661	-1.95726458
## X658	1.30166407	0	1	0.5207492	-0.21204427
## X659	-1.03709226	0	0	-0.3573584	0.18686323
## X660	2.79992985	0	1	1.0225250	1.28385885
## X661	-1.98721203	0	1	1.6497447	0.58577073
## X663	-0.48894625	0	0	-0.1064706	-0.91013239
## X664	-0.92746306	1	1	0.6461931	0.63563417
## X665	0.20537204	0	1	0.5207492	-0.31177114
## X666	1.70363782	0	0	0.0189734	0.63563417
## X667	3.16536053	0	1	1.5243008	0.53590729
## X668	0.42463045	0	0	-0.3573584	0.48604386
## X669	0.49771658	0	1	0.5207492	1.53317604
## X670	-1.58523828	0	1	0.6461931	-0.41149802
## X673	1.08240567	0	1	1.5243008	0.28659011
## X674	0.31500124	0	0	-0.3573584	0.98467823
## X675	-0.56203238	0	0	0.0189734	-1.20931302
## X676	-0.48894625	1	1	1.1479689	0.03727292
## X677	0.27845818	0	0	-0.3573584	-0.46136145
## X678	0.42463045	0	1	0.1444173	0.53590729
## X679	-0.16005864	0	1	0.7716371	1.43344917
## X680	1.15549180	0	1	0.8970810	1.28385885
## X681	1.15549180	1	1	2.1515205	0.33645354
## X682	0.57080272	0	1	0.5207492	-0.41149802
## X683	0.38808738	0	0	-0.3573584	1.18413198
## X684	-0.30623091	0	1	0.7716371	0.18686323
## X685	0.93623340	0	0	-0.8591342	-0.41149802
## X686	-0.52548931	0	0	-1.3609100	0.58577073
## X687	0.68043192	0	1	0.2698613	0.98467823
## X688	0.64388885	1	1	0.7716371	0.83508792
## X690	-0.12351557	0	0	0.0189734	-1.05972270

## X691	1.74018089	0	0	0.0189734	0.38631698
## X692	-0.05042943	0	1	0.7716371	0.58577073
## X693	-0.85437693	0	1	1.2734129	-0.61095177
## X694	0.20537204	0	0	-0.3573584	0.98467823
## X697	-0.56203238	0	0	-0.3573584	0.43618042
## X698	-1.18326454	0	1	1.0225250	1.38358573
## X699	0.13228591	0	0	-1.4863540	-0.56108833
## X700	1.19203487	0	0	-0.1064706	-0.16218083
## X701	-0.63511852	0	1	1.1479689	0.68549761
## X702	0.13228591	0	0	-0.4828024	0.98467823
## X703	0.02265670	0	0	0.0189734	-0.11231739
## X705	-2.09684123	0	0	-0.8591342	-0.86026895
## X706	0.05919977	1	0	-0.8591342	-0.31177114
## X707	-0.67166159	1	1	1.1479689	0.98467823
## X708	-1.76795362	0	0	-0.4828024	0.93481479
## X709	0.49771658	0	0	-0.1064706	-0.66081520
## X710	-0.56203238	1	1	1.6497447	0.28659011
## X711	0.93623340	0	1	1.7751887	0.38631698
## X712	1.59400862	0	0	-1.2354661	0.88495135
## X713	-0.34277398	1	0	-1.1100221	1.13426854
## X714	-1.18326454	0	0	-0.8591342	-1.75781083
## X715	-0.12351557	1	0	-0.3573584	-1.75781083
## X716	-0.45240318	0	0	-1.7372419	0.38631698
## X717	0.35154431	0	1	0.2698613	0.93481479
## X718	-0.70820465	0	0	-0.8591342	0.03727292
## X719	-1.80449669	1	0	-0.6082463	1.13426854
## X720	-1.18326454	0	1	0.7716371	0.08713636
## X721	0.57080272	0	0	-0.6082463	-1.20931302
## X722	-0.01388637	1	1	0.3953052	0.18686323
## X724	-0.92746306	0	0	-0.7336903	-1.50849364
## X725	-0.48894625	0	0	-0.2319145	-1.30903989
## X726	-0.67166159	0	1	1.6497447	0.68549761
## X730	-0.56203238	0	0	-0.3573584	1.18413198
## X731	0.31500124	1	1	0.3953052	-0.01259052
## X732	0.42463045	0	1	0.6461931	0.68549761
## X734	0.68043192	0	1	1.0225250	-0.91013239
## X735	-1.14672147	1	0	0.0189734	-1.25917645
## X737	-0.74474772	0	0	-1.6117979	0.43618042
## X738	-0.19660170	0	0	0.0189734	0.03727292
## X739	-2.75461645	0	0	-1.2354661	1.03454167
## X740	1.99598236	0	1	2.1515205	0.23672667
## X744	-0.12351557	0	1	0.2698613	0.28659011
## X745	-0.67166159	0	1	0.5207492	0.28659011
## X746	-0.41586011	1	1	1.1479689	-0.36163458
## X747	0.16882897	0	0	-0.8591342	-1.45863020
## X748	0.53425965	0	1	0.5207492	0.03727292
## X749	-1.62178135	1	1	0.6461931	-0.71067864
## X751	-1.29289374	0	0	-1.1100221	0.68549761
## X752	1.66709475	0	1	1.3988568	0.18686323
## X753	-1.07363533	0	1	0.7716371	-1.60822051
## X754	2.17869770	0	0	-0.4828024	-0.16218083
## X757	-0.41586011	0	0	-0.7336903	1.33372229
## X758	-0.59857545	0	0	-0.2319145	-1.60822051
## X759	0.16882897	0	0	-2.6153495	0.38631698



## X761	0.82660419	0	0	-1.8626858	-0.21204427
## X762	-0.70820465	0	0	-0.7336903	0.43618042
## X763	0.82660419	0	1	0.2698613	2.33099104
## X764	0.13228591	0	1	1.0225250	-1.45863020
## X765	-0.30623091	1	1	0.7716371	0.38631698
## X766	-1.65832442	0	0	-2.1135737	-0.36163458
## X767	1.92289623	0	1	1.0225250	0.38631698
## X768	0.68043192	0	0	-0.1064706	-0.06245396
## X769	-0.81783386	0	0	-0.1064706	-0.31177114
## X770	1.15549180	0	0	-0.6082463	-0.66081520
## X772	-1.73141055	0	1	0.3953052	1.08440510
## X773	0.57080272	1	1	0.1444173	0.08713636
## X774	-0.85437693	0	1	0.8970810	0.38631698
## X775	0.13228591	0	0	-0.6082463	0.88495135
## X776	-0.16005864	0	0	-0.9845782	0.38631698
## X777	0.57080272	1	1	0.2698613	-1.60822051
## X778	-0.12351557	1	0	-0.6082463	0.28659011
## X779	-0.74474772	0	1	0.5207492	0.43618042
## X780	0.75351806	0	0	-0.2319145	-0.61095177
## X781	0.02265670	0	1	0.2698613	-1.60822051
## X784	0.24191511	0	0	-1.1100221	0.08713636
## X786	-1.07363533	1	0	-0.3573584	-1.65808395
## X787	2.32486997	0	0	-0.7336903	-0.51122489
## X788	-0.41586011	0	0	-1.3609100	-0.61095177
## X789	2.43449918	1	0	-0.7336903	-0.56108833
## X790	0.49771658	0	0	-0.1064706	0.23672667
## X791	-1.80449669	0	1	0.7716371	0.13699979
## X792	-2.64498725	0	1	1.6497447	-0.21204427
## X794	-1.25635067	0	0	-1.3609100	0.03727292
## X795	0.05919977	0	0	-0.1064706	0.98467823
## X796	-0.30623091	0	1	2.0260766	0.33645354
## X797	-0.12351557	0	1	0.1444173	-0.51122489
## X798	0.31500124	0	0	-0.7336903	-0.36163458
## X799	0.97277646	0	0	-1.4863540	-0.86026895
## X800	0.20537204	1	1	2.2769645	-0.61095177
## X801	-1.40252294	0	1	2.7787402	1.18413198
## X802	-0.92746306	0	0	-0.7336903	-0.95999583
## X803	1.74018089	0	0	-0.3573584	0.63563417
## X804	-0.85437693	0	0	-0.6082463	0.13699979
## X805	0.02265670	0	1	0.5207492	-0.71067864
## X807	-0.89091999	0	1	0.2698613	0.08713636
## X808	0.13228591	1	1	0.5207492	-1.30903989
## X809	0.31500124	0	0	-0.3573584	0.08713636
## X810	0.68043192	1	0	-2.3644616	-0.26190770
## X812	2.87301599	1	0	-0.6082463	-0.61095177
## X813	0.13228591	0	1	0.1444173	0.08713636
## X814	0.53425965	0	0	0.0189734	0.28659011
## X815	-1.84103976	0	0	-1.1100221	-2.45589895
## X816	-0.48894625	0	0	-0.9845782	-0.21204427
## X817	0.60734579	0	1	1.2734129	-1.25917645
## X818	0.49771658	0	1	1.7751887	1.33372229
## X820	-2.90078872	1	0	-1.6117979	-0.61095177
## X821	-1.32943681	0	1	1.0225250	-0.71067864
## X822	-0.08697250	0	1	0.1444173	1.08440510

## X823	-0.70820465	0	1	0.7716371	1.03454167
## X824	0.57080272	0	0	-0.9845782	-0.31177114
## X825	-0.63511852	0	1	0.3953052	-1.55835708
## X826	-0.01388637	1	1	0.2698613	0.13699979
## X830	0.24191511	0	1	0.3953052	-0.16218083
## X831	0.35154431	0	0	-0.2319145	-0.61095177
## X832	3.60387735	0	0	-0.9845782	-1.20931302
## X833	-0.45240318	0	0	-0.9845782	-0.61095177
## X834	1.59400862	0	1	1.5243008	-1.35890333
## X836	-0.37931704	0	1	0.3953052	-0.01259052
## X837	-1.36597987	0	0	0.0189734	-0.56108833
## X838	-0.01388637	0	0	-0.2319145	0.18686323
## X839	0.64388885	0	0	-0.2319145	-0.41149802
## X840	0.02265670	0	1	0.2698613	0.03727292
## X841	0.09574284	0	1	0.7716371	-0.06245396
## X842	1.30166407	0	0	-1.2354661	-2.10685489
## X843	-0.12351557	0	0	-1.6117979	0.68549761
## X844	-2.42572884	0	0	-0.4828024	-0.01259052
## X847	-0.26968784	0	1	1.3988568	2.48058135
## X848	1.04586260	1	0	-0.9845782	0.18686323
## X849	-0.34277398	0	1	1.2734129	1.53317604
## X850	0.64388885	0	0	-2.2390177	-0.71067864
## X851	-0.63511852	0	1	0.5207492	0.53590729
## X852	-0.63511852	0	0	0.0189734	-0.16218083
## X853	0.20537204	1	0	-0.4828024	-0.66081520
## X854	0.38808738	0	1	2.0260766	1.63290292
## X855	2.69030065	0	0	-0.7336903	-1.00985927
## X856	-1.18326454	0	0	-1.1100221	-1.85753770
## X857	-0.30623091	0	0	0.0189734	1.33372229
## X858	1.26512101	0	0	0.0189734	0.03727292
## X859	-1.43906601	0	1	0.2698613	0.08713636
## X860	-0.01388637	0	1	0.1444173	0.63563417
## X861	-0.05042943	0	0	0.0189734	-0.31177114
## X862	0.31500124	0	0	-1.4863540	-0.71067864
## X864	0.16882897	0	0	-0.8591342	0.98467823
## X865	-0.23314477	0	0	-0.2319145	0.53590729
## X866	-0.52548931	0	0	-0.3573584	-0.06245396
## X867	-0.26968784	0	1	1.0225250	-1.65808395
## X868	0.57080272	0	0	-1.3609100	-0.41149802
## X869	-1.11017840	0	1	0.7716371	-0.11231739
## X870	-1.07363533	0	0	-1.4863540	0.18686323
## X871	0.16882897	0	1	0.6461931	-1.70794739
## X872	-0.30623091	0	0	0.0189734	-0.46136145
## X873	0.13228591	1	1	0.7716371	-0.11231739
## X874	-1.07363533	0	0	-0.2319145	-1.20931302
## X875	0.24191511	0	0	-1.2354661	-0.61095177
## X877	0.46117352	0	0	-0.6082463	-1.25917645
## X878	-1.40252294	0	0	-0.3573584	-0.95999583
## X879	0.35154431	0	0	-0.6082463	-1.85753770
## X880	-0.48894625	0	0	-0.2319145	0.28659011
## X881	0.71697499	0	1	0.2698613	-0.21204427
## X882	-1.51215215	0	0	-1.2354661	-0.81040552
## X883	2.50758531	0	0	0.0189734	-0.51122489
## X884	1.70363782	0	1	0.6461931	1.93208354

## X885	0.35154431	1	1	0.3953052	0.23672667
## X886	-0.01388637	1	1	1.9006326	-0.21204427
## X887	-1.32943681	0	1	0.2698613	1.98194698
## X888	0.27845818	0	0	0.0189734	-0.06245396
## X889	0.49771658	0	0	-0.4828024	-0.11231739
## X890	-1.21980760	1	0	-1.7372419	0.53590729
## X891	-0.92746306	1	1	0.8970810	1.93208354
## X892	0.09574284	0	1	0.8970810	0.43618042
## X894	-0.37931704	0	0	-0.1064706	-0.51122489
## X895	0.09574284	0	0	-1.1100221	-0.61095177
## X897	-1.21980760	0	0	0.0189734	0.18686323
## X899	-1.18326454	0	0	-0.3573584	-0.61095177
## X900	1.19203487	0	0	-0.9845782	-0.01259052
## X901	0.16882897	0	1	2.5278523	0.93481479
## X902	1.37475021	0	0	-0.2319145	-0.91013239
## X903	0.93623340	0	0	-0.1064706	0.88495135
## X904	-0.67166159	0	1	0.2698613	0.93481479
## X905	-1.36597987	0	1	1.0225250	0.63563417
## X906	0.38808738	0	0	-0.9845782	0.88495135
## X907	0.64388885	0	0	-0.3573584	0.03727292
## X908	-0.56203238	0	1	0.3953052	-0.51122489
## X909	1.22857794	0	0	-0.3573584	1.23399542
## X910	1.22857794	0	1	1.9006326	1.28385885
## X911	0.20537204	0	0	-0.7336903	-2.00712801
## X913	-1.14672147	0	1	0.5207492	0.83508792
## X916	1.41129328	0	0	-0.6082463	0.03727292
## X917	1.95943930	0	1	1.9006326	2.68003510
## X918	0.71697499	0	0	-1.3609100	0.78522448
## X919	1.59400862	0	1	1.1479689	0.58577073
## X920	1.00931953	0	0	-0.8591342	-1.15944958
## X921	0.31500124	0	1	2.4024084	1.18413198
## X922	0.27845818	1	1	1.2734129	-0.66081520
## X924	1.22857794	1	0	-1.4863540	-0.71067864
## X925	0.79006113	0	0	-0.4828024	-0.56108833
## X926	-0.01388637	0	0	-2.4899056	-0.36163458
## X927	0.68043192	1	0	-0.1064706	0.33645354
## X929	-0.63511852	1	1	1.6497447	-0.21204427
## X932	0.13228591	1	1	1.1479689	2.23126416
## X933	-0.96400613	0	0	0.0189734	-1.75781083
## X935	-1.36597987	0	1	1.1479689	-0.71067864
## X936	0.53425965	0	1	1.9006326	0.23672667
## X937	0.09574284	0	1	1.2734129	-0.41149802
## X939	0.86314726	0	1	2.9041842	0.33645354
## X940	-0.01388637	0	0	-0.2319145	-0.11231739
## X941	0.46117352	0	1	1.0225250	1.98194698
## X942	0.24191511	0	0	0.0189734	1.43344917
## X943	0.46117352	0	1	1.1479689	0.83508792
## X945	-1.03709226	0	0	0.0189734	0.68549761
## X946	0.60734579	0	1	0.8970810	0.33645354
## X948	0.24191511	0	1	0.6461931	0.53590729
## X949	-0.59857545	0	0	-0.9845782	-0.86026895
## X950	-1.00054920	0	0	-2.2390177	-1.55835708
## X951	-0.12351557	0	0	-1.3609100	1.73262979
## X953	1.30166407	0	0	-0.6082463	0.18686323

## X954	-0.78129079	0	1	0.8970810	0.63563417
## X955	-0.37931704	0	0	-0.7336903	0.88495135
## X956	-1.84103976	1	0	-0.2319145	0.18686323
## X957	-1.36597987	0	1	0.6461931	-0.81040552
## X958	-0.37931704	0	1	1.5243008	1.48331260
## X959	-0.92746306	0	0	-0.2319145	-0.26190770
## X960	-0.92746306	0	0	-2.1135737	-0.31177114
## X961	0.97277646	1	1	0.3953052	-0.66081520
## X962	0.79006113	0	1	0.5207492	1.68276635
## X963	1.15549180	0	0	-0.8591342	1.18413198
## X964	0.53425965	0	0	-0.9845782	-0.41149802
## X965	0.46117352	0	1	0.1444173	-0.51122489
## X966	0.20537204	0	0	-0.6082463	-1.60822051
## X968	1.63055169	1	1	0.2698613	0.98467823
## X969	-0.19660170	0	1	1.0225250	0.43618042
## X970	0.02265670	0	1	0.6461931	-0.16218083
## X971	-1.54869521	0	0	-0.9845782	0.08713636
## X972	-0.85437693	0	0	-0.3573584	-0.56108833
## X973	-0.08697250	0	0	-1.2354661	-1.10958614
## X974	-1.51215215	0	1	2.2769645	1.13426854
## X975	1.11894874	0	1	0.1444173	0.23672667
## X976	0.16882897	0	0	-0.6082463	-1.05972270
## X977	0.46117352	0	0	-0.8591342	0.03727292
## X978	0.38808738	0	0	-0.9845782	-0.86026895
## X979	1.52092248	0	1	2.4024084	0.58577073
## X980	-0.45240318	0	1	0.2698613	-1.05972270
## X981	0.75351806	0	0	-0.8591342	0.33645354
## X982	1.08240567	0	1	0.7716371	0.08713636
## X983	-0.01388637	0	1	1.2734129	2.33099104
## X984	-0.23314477	0	0	-1.2354661	-1.70794739
## X985	1.19203487	0	1	0.2698613	0.73536104
## X986	-0.70820465	0	0	-1.6117979	-1.35890333
## X987	0.42463045	0	0	-1.1100221	-1.35890333
## X988	-0.41586011	0	0	-2.2390177	1.33372229
## X989	0.31500124	0	0	-0.6082463	0.18686323
## X990	1.08240567	0	0	-0.2319145	0.93481479
## X991	1.15549180	1	0	-0.1064706	-0.21204427
## X992	0.49771658	0	0	-1.6117979	-0.76054208
## X993	1.19203487	0	0	-0.1064706	-0.56108833
## X994	-1.25635067	0	0	0.0189734	-0.61095177
## X995	-0.23314477	1	1	0.2698613	0.53590729
## X996	-0.37931704	1	1	0.1444173	0.48604386
## X997	-0.78129079	0	1	0.6461931	0.58577073
## X998	-0.30623091	0	1	0.3953052	0.73536104
## X999	-0.12351557	0	1	0.8970810	-0.61095177
##	vaccineVaccinated	depression			
## X1		1		-0.90094190	
## X2		0		-2.31696060	
## X3		1		-0.90094190	
## X4		1		-1.37294814	
## X6		1		0.98708304	
## X9		0		0.51507680	
## X10		0		0.51507680	
## X11		0		-0.90094190	

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## X12      0 -1.37294814
## X13      0  0.51507680
## X14      0 -0.42893567
## X15      0 -0.90094190
## X17      0  1.45908927
## X18      1  0.04307057
## X19      1  0.51507680
## X21      1  1.45908927
## X22      1 -0.90094190
## X24      0  1.45908927
## X25      0  0.04307057
## X26      1 -0.42893567
## X27      0 -0.42893567
## X28      0 -1.37294814
## X29      0  0.04307057
## X30      0  0.51507680
## X31      1  0.04307057
## X33      1  2.87510798
## X36      1  1.45908927
## X39      1  1.45908927
## X40      1  0.98708304
## X41      1 -0.42893567
## X42      1  0.04307057
## X45      1  0.04307057
## X46      1  0.51507680
## X47      1  0.98708304
## X49      1  0.04307057
## X54      0  0.04307057
## X56      1 -0.42893567
## X57      0 -0.42893567
## X59      1 -1.37294814
## X60      0 -0.42893567
## X61      0  0.98708304
## X62      0  0.04307057
## X64      1 -1.37294814
## X65      0  0.51507680
## X67      0  0.98708304
## X69      0 -1.37294814
## X70      1 -2.31696060
## X72      0 -0.42893567
## X73      0  0.51507680
## X74      1 -1.37294814
## X75      0 -0.42893567
## X77      0  0.98708304
## X78      0  0.04307057
## X79      0  1.45908927
## X82      0  0.04307057
## X85      1  0.04307057
## X87      0 -1.37294814
## X88      0 -1.37294814
## X89      0 -1.37294814
## X90      0 -0.42893567
## X91      0 -0.42893567
## X92      1  0.04307057
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## X93	1	1.93109551
## X94	0	0.51507680
## X95	1	0.98708304
## X96	1	0.04307057
## X97	1	0.98708304
## X98	0	-2.31696060
## X99	1	1.93109551
## X100	1	-0.42893567
## X101	1	0.04307057
## X102	1	0.98708304
## X103	0	1.93109551
## X104	1	-0.42893567
## X105	1	2.40310174
## X106	0	-0.90094190
## X108	1	0.51507680
## X109	1	0.98708304
## X110	0	0.04307057
## X112	1	0.04307057
## X113	1	0.51507680
## X114	0	-1.84495437
## X115	0	-0.42893567
## X116	0	-2.31696060
## X117	0	-0.90094190
## X119	1	0.04307057
## X120	1	-0.42893567
## X121	0	0.51507680
## X122	0	0.98708304
## X123	1	0.51507680
## X126	1	0.04307057
## X127	0	-1.84495437
## X128	0	-0.42893567
## X129	1	-0.90094190
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## X131	1	-0.90094190
## X132	1	-0.42893567
## X133	1	2.40310174
## X135	1	0.51507680
## X136	1	0.51507680
## X137	0	0.04307057
## X138	1	-0.42893567
## X139	0	0.98708304
## X142	0	-0.42893567
## X144	1	-0.90094190
## X145	1	-1.84495437
## X146	1	-0.42893567
## X147	1	-2.31696060
## X148	0	0.51507680
## X149	0	-0.90094190
## X150	1	-1.37294814
## X152	1	0.51507680
## X154	1	0.51507680
## X155	0	0.98708304
## X156	1	0.04307057
## X157	0	0.51507680

## X159	1	-0.42893567
## X160	1	0.51507680
## X161	1	-0.42893567
## X162	1	-0.90094190
## X163	1	-0.90094190
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## X165	0	-0.90094190
## X166	1	-0.42893567
## X167	0	-0.90094190
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## X169	1	-0.90094190
## X170	1	0.98708304
## X171	1	0.51507680
## X172	1	-0.90094190
## X173	0	-0.42893567
## X174	0	-0.90094190
## X175	1	-1.37294814
## X177	1	0.04307057
## X179	1	1.45908927
## X180	1	-2.31696060
## X181	0	-0.90094190
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## X188	0	-0.90094190
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## X190	0	-2.31696060
## X191	1	0.51507680
## X192	0	0.04307057
## X193	0	-0.42893567
## X194	0	0.98708304
## X195	0	0.51507680
## X196	1	1.45908927
## X198	0	0.98708304
## X200	0	-0.90094190
## X201	0	0.51507680
## X202	1	1.45908927
## X204	1	0.98708304
## X205	1	-0.90094190
## X206	0	-1.37294814
## X207	1	2.40310174
## X209	1	0.51507680
## X211	1	0.98708304
## X212	0	0.04307057
## X213	0	-1.37294814
## X214	1	1.45908927
## X215	1	0.04307057
## X216	0	1.93109551
## X217	1	0.51507680
## X218	1	-1.37294814
## X219	1	0.51507680

## X220	0	1.93109551
## X221	1	0.51507680
## X222	1	-0.90094190
## X223	0	0.98708304
## X224	0	0.04307057
## X226	0	0.51507680
## X227	1	-1.37294814
## X228	1	0.04307057
## X229	1	0.98708304
## X230	1	-1.37294814
## X231	0	0.04307057
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## X234	0	0.51507680
## X235	1	0.98708304
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## X237	1	0.51507680
## X238	1	-1.37294814
## X239	0	0.04307057
## X240	0	-0.42893567
## X241	0	-1.37294814
## X244	0	0.51507680
## X245	0	-2.31696060
## X246	1	-0.90094190
## X247	1	-0.90094190
## X248	1	-1.37294814
## X249	1	0.04307057
## X251	1	0.04307057
## X252	1	-0.42893567
## X254	1	0.04307057
## X255	1	-1.84495437
## X256	1	-1.37294814
## X257	0	0.51507680
## X258	1	1.45908927
## X259	1	-0.90094190
## X260	0	0.04307057
## X261	1	-1.84495437
## X262	1	0.04307057
## X264	0	0.51507680
## X265	0	0.98708304
## X266	0	2.40310174
## X267	0	0.04307057
## X268	1	1.45908927
## X269	1	0.51507680
## X270	1	1.45908927
## X273	1	0.51507680
## X274	0	1.93109551
## X275	0	-0.90094190
## X276	1	-0.90094190
## X277	1	-1.84495437
## X278	1	-0.90094190
## X279	0	0.04307057
## X280	1	-0.90094190
## X282	0	1.45908927
## X283	1	-0.90094190



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## X286	1	-0.42893567
## X289	0	0.04307057
## X290	1	-0.42893567
## X292	1	-0.90094190
## X293	0	0.04307057
## X295	1	0.04307057
## X296	1	-0.90094190
## X298	0	1.45908927
## X299	1	0.51507680
## X300	1	0.98708304
## X301	0	0.04307057
## X302	1	0.04307057
## X303	1	2.87510798
## X305	0	0.98708304
## X306	0	0.04307057
## X307	1	-0.42893567
## X311	0	0.51507680
## X312	0	-0.42893567
## X313	1	0.04307057
## X314	1	-1.37294814
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## X316	1	-1.37294814
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## X326	1	0.04307057
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## X328	1	-1.37294814
## X329	0	-0.90094190
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## X333	1	0.04307057
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## X335	1	0.98708304
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## X339	0	-0.90094190
## X340	1	-0.42893567
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## X355	0	-0.90094190
## X356	0	0.04307057
## X359	0	-0.42893567
## X360	1	1.93109551
## X361	1	-0.42893567

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## X365	0	-0.42893567
## X366	1	0.51507680
## X367	0	0.51507680
## X369	0	0.98708304
## X371	1	0.04307057
## X372	0	-1.84495437
## X373	0	0.04307057
## X374	1	-2.31696060
## X376	0	-0.42893567
## X377	0	0.51507680
## X378	1	0.98708304
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## X380	1	0.98708304
## X382	0	-0.42893567
## X383	0	0.51507680
## X385	1	-0.42893567
## X386	0	-0.90094190
## X387	0	-2.31696060
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## X392	0	0.04307057
## X393	0	-1.37294814
## X394	0	-0.90094190
## X395	0	1.45908927
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## X401	1	0.98708304
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## X405	0	-1.84495437
## X406	0	0.04307057
## X407	0	-0.42893567
## X408	1	0.51507680
## X410	0	-0.42893567
## X411	0	0.51507680
## X412	0	-2.31696060
## X413	1	-0.90094190
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## X415	0	-0.90094190
## X416	0	-0.90094190
## X417	1	-0.42893567
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## X421	1	0.51507680
## X422	1	0.51507680
## X423	1	-1.37294814
## X424	0	0.51507680
## X425	1	0.98708304
## X426	0	-0.90094190
## X427	1	0.04307057

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## X432	0	1.93109551
## X434	1	0.04307057
## X435	0	0.04307057
## X437	0	-0.42893567
## X438	1	0.51507680
## X439	1	-1.37294814
## X440	0	0.51507680
## X441	1	0.04307057
## X442	0	-0.42893567
## X443	0	-0.90094190
## X444	1	-0.90094190
## X445	1	-1.37294814
## X448	1	0.04307057
## X450	1	0.98708304
## X451	0	0.51507680
## X453	0	-0.42893567
## X454	1	-0.42893567
## X455	1	-0.42893567
## X456	0	-2.31696060
## X457	0	0.04307057
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## X459	1	1.45908927
## X460	1	0.51507680
## X461	0	0.51507680
## X464	1	-0.90094190
## X465	1	-0.90094190
## X466	1	0.04307057
## X468	1	1.45908927
## X469	1	-0.90094190
## X470	0	-1.84495437
## X472	1	-1.37294814
## X473	0	-0.42893567
## X474	0	-0.42893567
## X475	1	-1.84495437
## X476	1	0.04307057
## X478	0	0.51507680
## X480	0	0.51507680
## X481	0	0.04307057
## X482	1	-1.37294814
## X483	1	-0.42893567
## X484	0	2.40310174
## X486	1	-0.42893567
## X487	1	0.51507680
## X488	1	-1.37294814
## X489	0	0.51507680
## X490	1	1.45908927
## X491	0	-0.42893567
## X492	0	2.87510798
## X493	1	0.04307057
## X494	0	0.51507680
## X495	1	0.04307057
## X496	0	-0.42893567
## X497	1	0.98708304

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## X499	1	0.04307057
## X500	1	0.04307057
## X501	1	-0.42893567
## X502	1	-0.42893567
## X503	1	0.98708304
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## X507	1	-0.90094190
## X509	0	-2.31696060
## X511	1	-0.90094190
## X512	1	-0.42893567
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## X516	0	0.04307057
## X518	1	0.51507680
## X520	0	-0.90094190
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## X522	0	-1.37294814
## X523	1	-0.90094190
## X524	0	0.51507680
## X525	1	0.51507680
## X527	1	-0.90094190
## X528	0	0.51507680
## X529	1	-0.42893567
## X530	1	-0.90094190
## X533	1	-1.37294814
## X535	1	0.98708304
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## X542	0	-0.42893567
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## X545	0	0.04307057
## X546	1	0.51507680
## X547	0	0.98708304
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## X549	0	-0.42893567
## X550	1	-1.84495437
## X551	0	1.93109551
## X552	0	0.04307057
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## X554	1	-0.90094190
## X556	1	-0.42893567
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## X558	0	0.51507680
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## X569	0	0.04307057
## X571	1	-0.90094190
## X573	0	-0.90094190
## X574	0	0.04307057
## X575	0	0.98708304
## X576	1	-1.37294814
## X577	1	-1.37294814
## X579	1	0.04307057
## X580	0	-2.78896684
## X582	1	-0.42893567
## X584	1	0.04307057
## X587	0	0.51507680
## X588	1	-0.90094190
## X589	0	-0.90094190
## X591	1	-0.42893567
## X592	1	1.93109551
## X593	1	-0.42893567
## X594	1	-1.37294814
## X597	0	0.51507680
## X598	1	-0.90094190
## X600	0	-0.90094190
## X601	1	-1.37294814
## X602	0	1.45908927
## X603	0	-0.90094190
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## X605	0	-0.42893567
## X606	0	0.51507680
## X609	0	0.04307057
## X610	0	0.04307057
## X611	0	0.04307057
## X613	0	0.98708304
## X614	0	0.04307057
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## X617	1	0.04307057
## X618	0	-0.90094190
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## X625	1	-0.42893567
## X626	1	-0.42893567
## X628	1	0.04307057
## X629	1	-0.90094190
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## X633	0	0.04307057
## X634	0	0.04307057
## X635	1	0.04307057
## X636	1	-0.42893567
## X637	0	0.04307057

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## X645	1	-0.90094190
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## X652	0	0.04307057
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## X655	0	0.51507680
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## X657	0	0.98708304
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## X663	0	-0.42893567
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## X683	1	0.98708304
## X684	1	0.98708304
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## X686	1	0.98708304
## X687	1	-1.84495437
## X688	0	1.93109551
## X690	0	-0.90094190
## X691	1	-0.90094190
## X692	0	0.04307057
## X693	1	-1.37294814
## X694	1	0.98708304
## X697	1	0.51507680
## X698	1	0.98708304
## X699	1	0.98708304
## X700	1	0.51507680
## X701	1	0.51507680

## X702	0	0.51507680
## X703	0	0.98708304
## X705	1	0.98708304
## X706	1	0.51507680
## X707	1	0.51507680
## X708	1	1.45908927
## X709	1	0.51507680
## X710	1	0.04307057
## X711	0	0.98708304
## X712	1	-1.84495437
## X713	1	0.04307057
## X714	0	-0.42893567
## X715	1	0.51507680
## X716	0	0.04307057
## X717	1	0.98708304
## X718	0	0.51507680
## X719	1	0.51507680
## X720	1	-0.90094190
## X721	0	0.98708304
## X722	1	0.98708304
## X724	0	-0.42893567
## X725	0	2.40310174
## X726	0	-1.37294814
## X730	0	0.51507680
## X731	1	0.98708304
## X732	1	-0.42893567
## X734	1	-0.90094190
## X735	1	0.98708304
## X737	1	-1.37294814
## X738	1	1.93109551
## X739	1	0.98708304
## X740	1	0.51507680
## X744	0	-0.42893567
## X745	0	0.04307057
## X746	0	1.45908927
## X747	1	0.04307057
## X748	1	0.04307057
## X749	0	1.45908927
## X751	0	0.04307057
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## X753	0	0.98708304
## X754	0	0.98708304
## X757	1	-2.31696060
## X758	1	0.04307057
## X759	0	-1.84495437
## X761	1	0.04307057
## X762	0	0.98708304
## X763	0	1.45908927
## X764	1	-1.84495437
## X765	1	-1.37294814
## X766	0	-0.42893567
## X767	1	0.04307057
## X768	0	0.51507680
## X769	1	-0.42893567

## X770	1 -3.26097307
## X772	0 -0.42893567
## X773	1 0.51507680
## X774	0 -0.90094190
## X775	0 1.93109551
## X776	1 -1.84495437
## X777	1 -0.42893567
## X778	1 -0.42893567
## X779	1 0.04307057
## X780	1 -0.90094190
## X781	1 -0.90094190
## X784	1 -0.90094190
## X786	1 -1.84495437
## X787	1 -0.90094190
## X788	1 -0.42893567
## X789	0 -1.84495437
## X790	1 0.04307057
## X791	1 -0.42893567
## X792	0 -0.90094190
## X794	0 -1.37294814
## X795	1 -0.42893567
## X796	1 -0.42893567
## X797	0 0.04307057
## X798	1 -2.31696060
## X799	0 0.51507680
## X800	1 0.98708304
## X801	0 0.98708304
## X802	0 0.98708304
## X803	1 0.51507680
## X804	1 -0.42893567
## X805	0 -0.90094190
## X807	1 0.51507680
## X808	1 -0.90094190
## X809	0 -0.42893567
## X810	1 -2.78896684
## X812	1 -0.42893567
## X813	1 0.51507680
## X814	1 1.45908927
## X815	1 0.98708304
## X816	1 0.04307057
## X817	1 -0.42893567
## X818	1 0.51507680
## X820	1 -1.37294814
## X821	0 1.45908927
## X822	0 0.51507680
## X823	0 0.98708304
## X824	1 -0.90094190
## X825	0 1.45908927
## X826	1 0.04307057
## X830	1 0.51507680
## X831	1 -0.42893567
## X832	1 0.98708304
## X833	0 -0.90094190
## X834	1 -1.37294814



## X836	0	1.45908927
## X837	0	0.51507680
## X838	0	-0.90094190
## X839	1	0.51507680
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## X841	1	0.04307057
## X842	1	-0.90094190
## X843	1	0.51507680
## X844	1	-0.42893567
## X847	1	-0.42893567
## X848	1	0.98708304
## X849	1	0.51507680
## X850	0	0.04307057
## X851	0	0.04307057
## X852	1	0.04307057
## X853	1	0.51507680
## X854	0	0.04307057
## X855	1	-0.42893567
## X856	1	-1.84495437
## X857	0	-0.42893567
## X858	1	-0.90094190
## X859	0	-0.90094190
## X860	0	2.87510798
## X861	1	0.04307057
## X862	1	0.04307057
## X864	0	-1.37294814
## X865	1	-0.42893567
## X866	1	0.51507680
## X867	0	0.51507680
## X868	1	0.51507680
## X869	1	1.93109551
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## X871	0	0.04307057
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## X875	1	0.04307057
## X877	0	-0.90094190
## X878	1	-2.31696060
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## X882	1	0.51507680
## X883	1	-1.84495437
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## X886	0	-0.42893567
## X887	1	0.04307057
## X888	0	-0.42893567
## X889	1	0.04307057
## X890	1	0.98708304
## X891	1	-0.42893567
## X892	1	0.98708304
## X894	0	0.04307057

## X895	1	-0.90094190
## X897	0	0.51507680
## X899	0	1.93109551
## X900	1	0.04307057
## X901	0	0.51507680
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## X903	1	0.04307057
## X904	1	0.51507680
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## X907	1	0.98708304
## X908	0	0.98708304
## X909	1	-0.42893567
## X910	1	0.98708304
## X911	1	0.98708304
## X913	1	-0.42893567
## X916	1	-0.42893567
## X917	1	0.98708304
## X918	0	0.04307057
## X919	0	-1.37294814
## X920	1	0.04307057
## X921	0	-0.90094190
## X922	0	-0.42893567
## X924	1	-0.90094190
## X925	1	0.04307057
## X926	1	-0.42893567
## X927	0	0.51507680
## X929	0	0.04307057
## X932	0	0.51507680
## X933	1	0.04307057
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## X936	0	1.45908927
## X937	1	0.98708304
## X939	0	0.98708304
## X940	0	0.51507680
## X941	1	0.98708304
## X942	1	0.98708304
## X943	0	1.45908927
## X945	1	-0.42893567
## X946	1	0.04307057
## X948	0	-0.42893567
## X949	1	-0.90094190
## X950	1	1.93109551
## X951	1	-0.42893567
## X953	0	0.04307057
## X954	0	-1.37294814
## X955	1	1.45908927
## X956	0	0.51507680
## X957	0	0.04307057
## X958	1	0.04307057
## X959	1	0.04307057
## X960	1	0.04307057
## X961	0	-0.42893567
## X962	0	0.51507680

```

## X963      1  0.98708304
## X964      1  0.51507680
## X965      1  1.93109551
## X966      0 -0.42893567
## X968      1  0.04307057
## X969      1  0.98708304
## X970      0 -0.42893567
## X971      1  1.45908927
## X972      1  1.93109551
## X973      1  0.51507680
## X974      0  0.98708304
## X975      1 -0.90094190
## X976      0  0.04307057
## X977      1  0.98708304
## X978      1  0.04307057
## X979      1  0.04307057
## X980      1  1.45908927
## X981      0  0.04307057
## X982      0 -1.37294814
## X983      0  0.04307057
## X984      1  1.45908927
## X985      1  0.51507680
## X986      0  0.04307057
## X987      0  0.51507680
## X988      1 -0.42893567
## X989      1  0.04307057
## X990      1  1.45908927
## X991      1 -0.42893567
## X992      1  0.98708304
## X993      1 -0.90094190
## X994      0  0.04307057
## X995      0  0.04307057
## X996      0  0.04307057
## X997      1 -0.90094190
## X998      1 -0.90094190
## X999      0 -0.90094190
##
## $usekernel
## [1] TRUE
##
## $varnames
## [1] "age"           "genderMale"    "raceAsian"
## [4] "raceBlack"     "raceHispanic"  "smokingFormer_smoker"
## [7] "smokingCurrent_smoker" "height"        "weight"
## [10] "bmi"           "diabetesYes"   "hypertensionYes"
## [13] "sbp"           "ldl"           "vaccineVaccinated"
## [16] "depression"
##
## $xNames
## [1] "age"           "genderMale"    "raceAsian"
## [4] "raceBlack"     "raceHispanic"  "smokingFormer_smoker"
## [7] "smokingCurrent_smoker" "height"        "weight"
## [10] "bmi"           "diabetesYes"   "hypertensionYes"
## [13] "sbp"           "ldl"           "vaccineVaccinated"

```

```
## [16] "depression"
##
## $problemType
## [1] "Classification"
##
## $tuneValue
##      fL usekernel adjust
## 42  1      TRUE    3.4
##
## $obsLevels
## [1] "Not_severe" "Severe"
## attr("ordered")
## [1] FALSE
##
## $param
## list()
##
## attr("class")
## [1] "NaiveBayes"
```

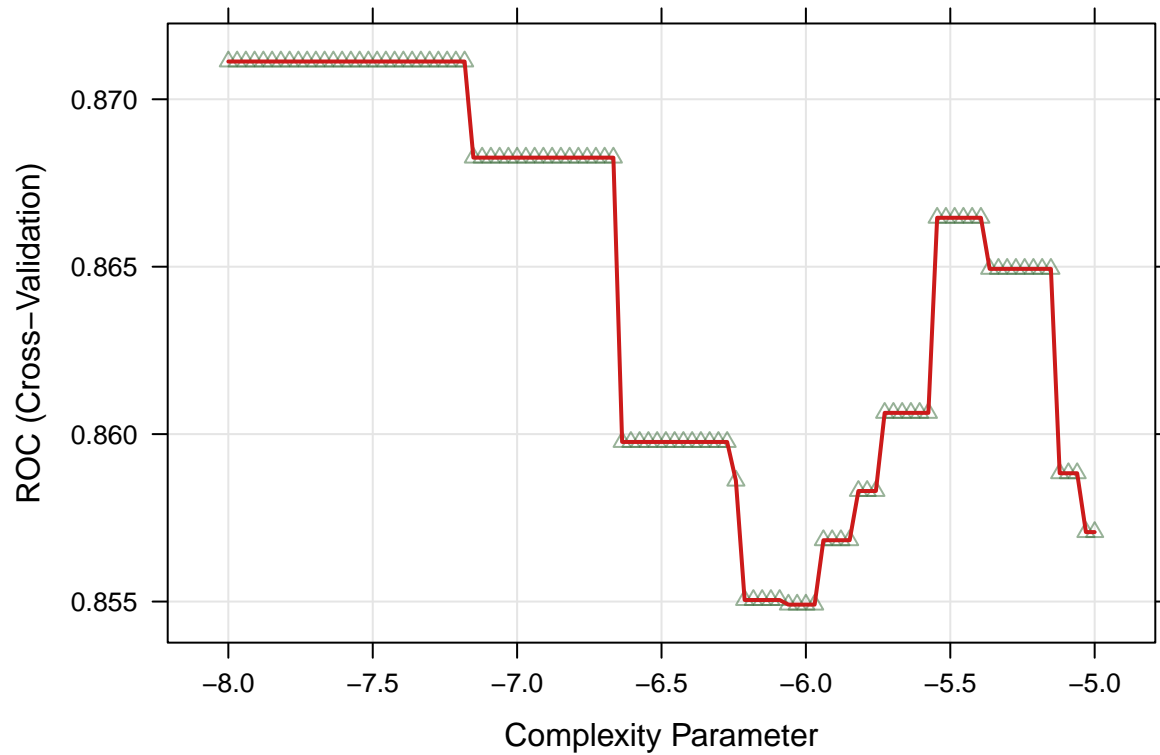
## CART

```

set.seed(2)
model.cart = train(x = x.train,
  y = y.train,
  method = "rpart",
  tuneGrid = data.frame(cp = exp(seq(-8,-5, len = 100))),
  trControl = ctrl,
  metric = "ROC")

plot(model.cart, xTrans = log)

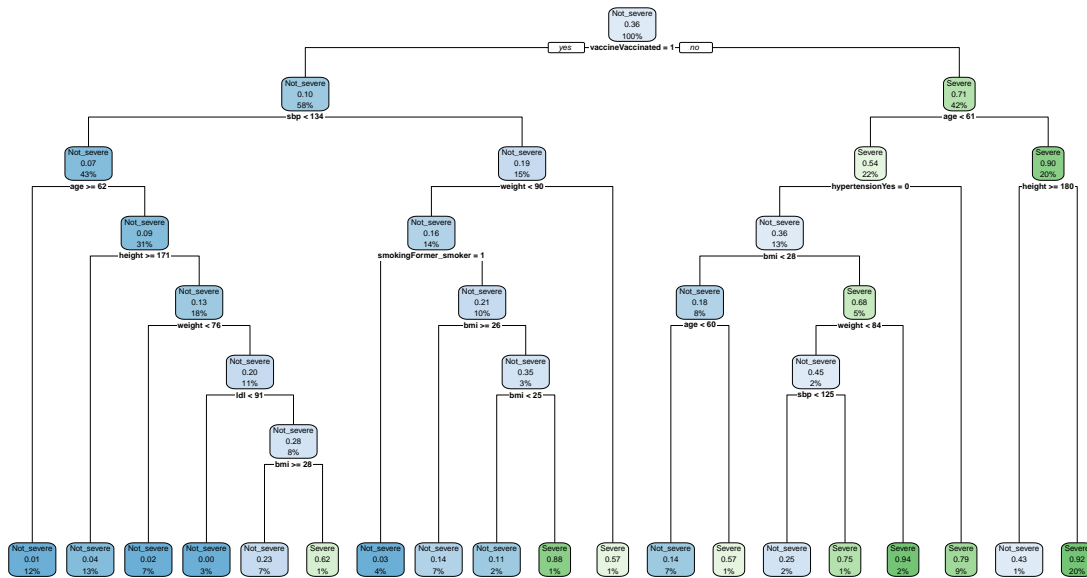
```



```
model.cart$bestTune
```

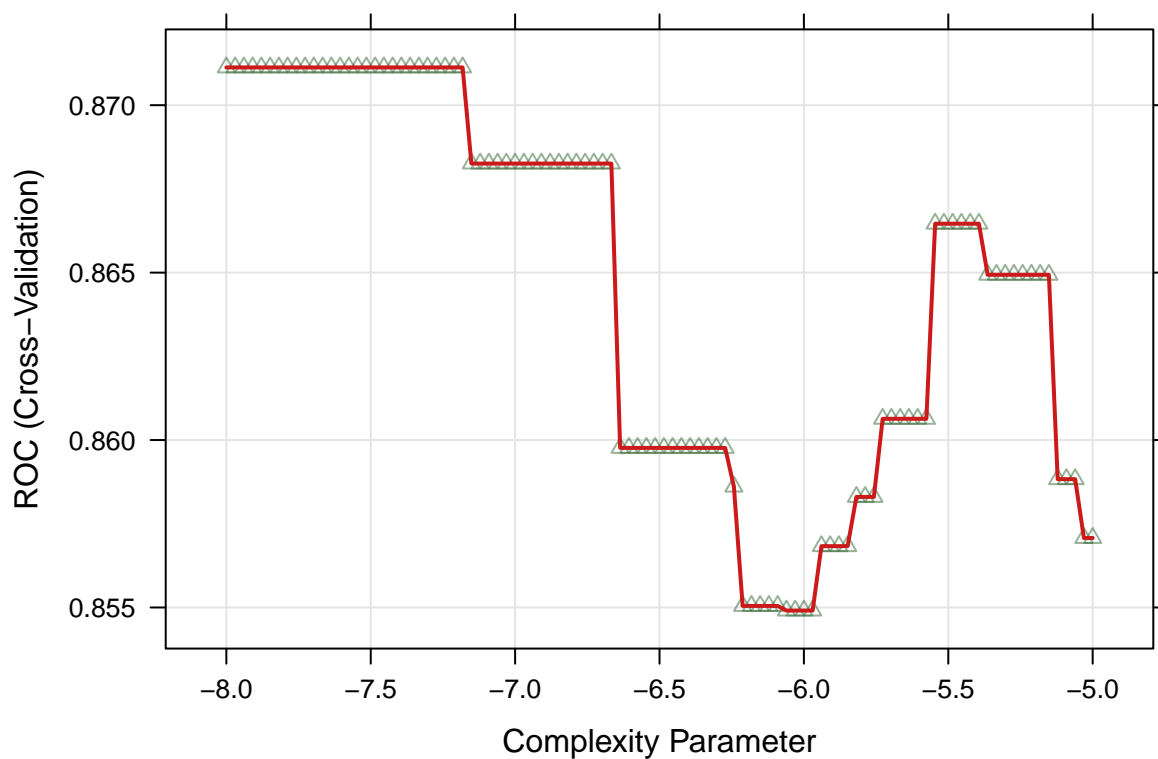
```
##          cp
## 28 0.0007602842
```

```
rpart.plot(model.cart$finalModel)
```



```
# CART scaled
set.seed(2)
scaled.model.cart = train(x = x.train.scaled,
                          y = y.train.scaled,
                          method = "rpart",
                          tuneGrid = data.frame(cp = exp(seq(-8,-5, len = 100))),
                          trControl = ctrl,
                          metric = "ROC")

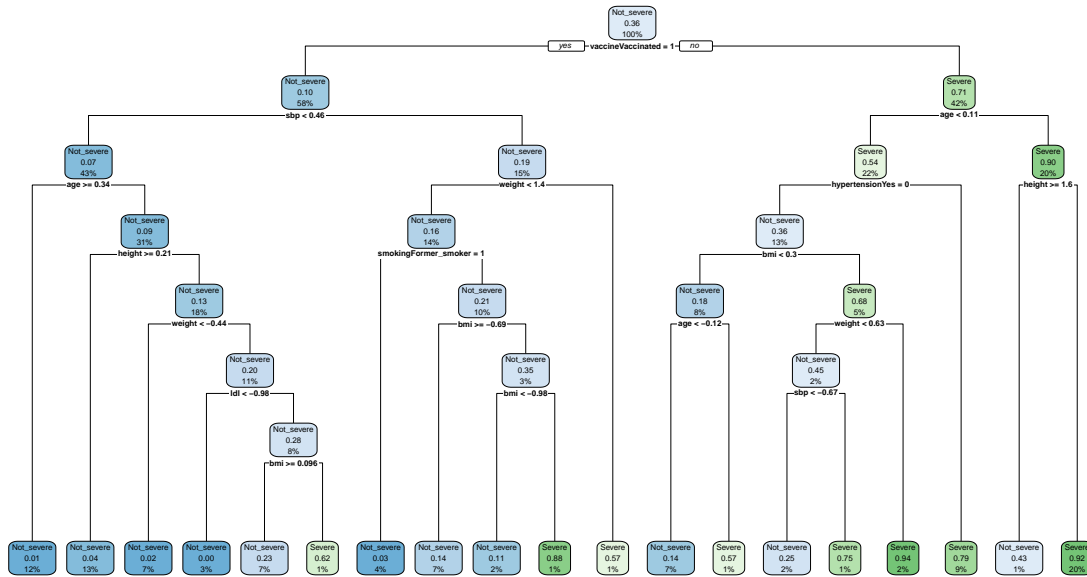
plot(scaled.model.cart, xTrans = log)
```



```
scaled.model.cart$bestTune
```

```
##                cp
## 28 0.0007602842
```

```
rpart.plot(scaled.model.cart$finalModel)
```



## Conditional Inference Trees (CIT)

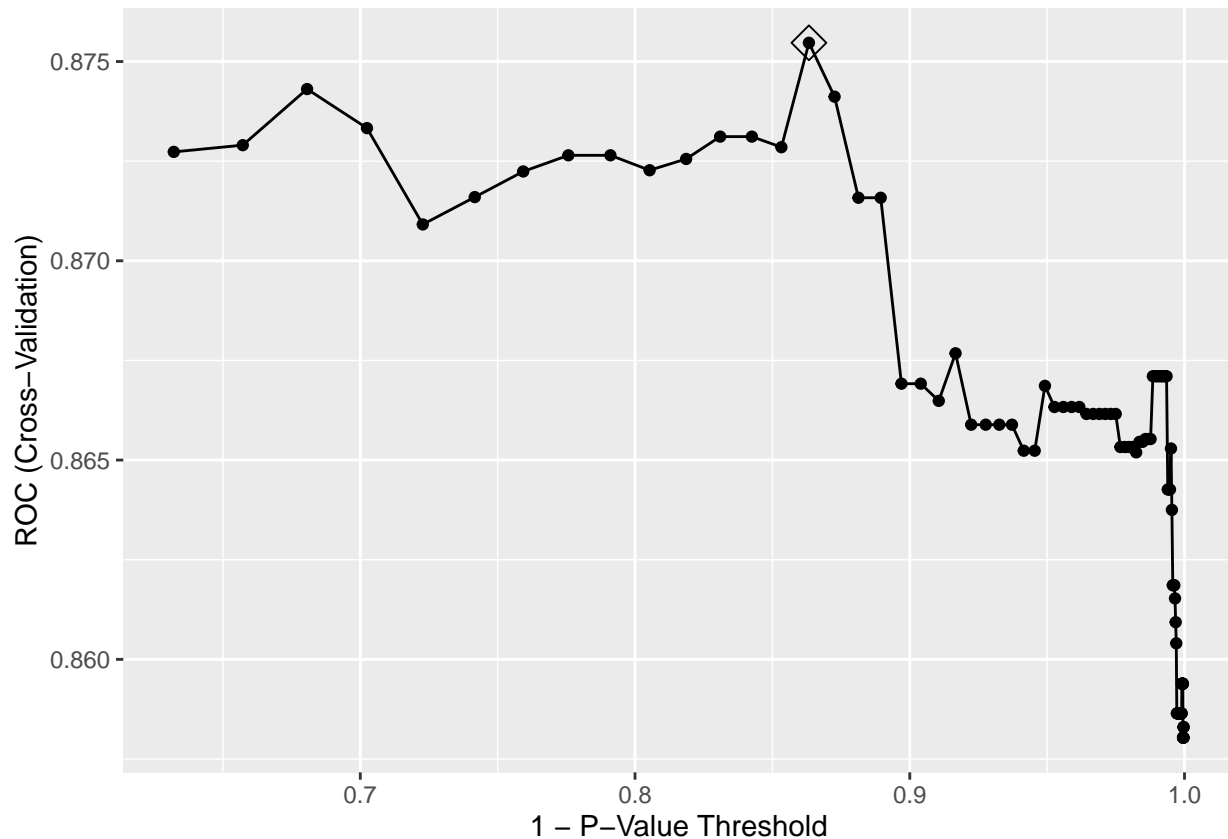
```

set.seed(2)

model.cit = train(x = x.train,
                  y = y.train,
                  method = "ctree",
                  tuneGrid = data.frame(mincriterion = 1-exp(seq(-8, -1, length = 100))),
                  trControl = ctrl)

ggplot(model.cit, highlight = TRUE)

```



```

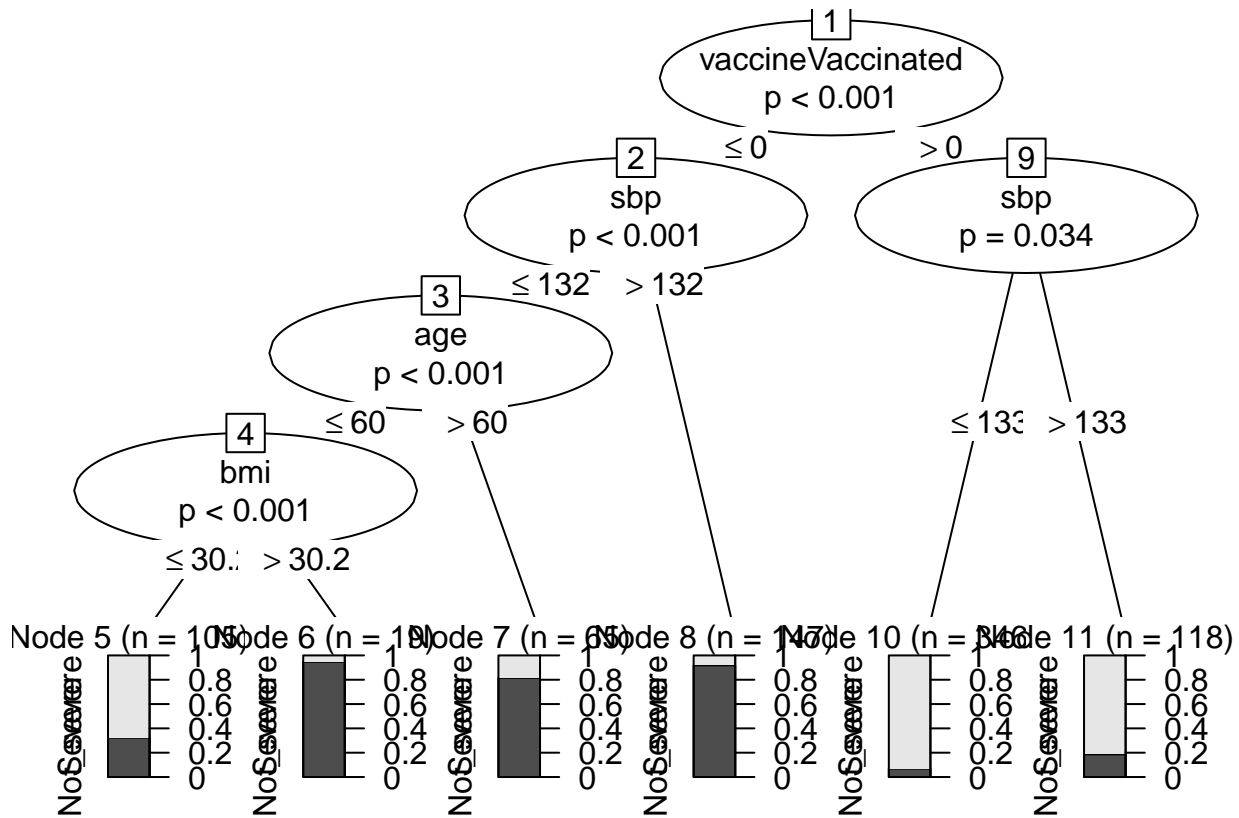
model.cit$bestTune

## mincriterion
## 15 0.8632908

plot(model.cit$finalModel)

```

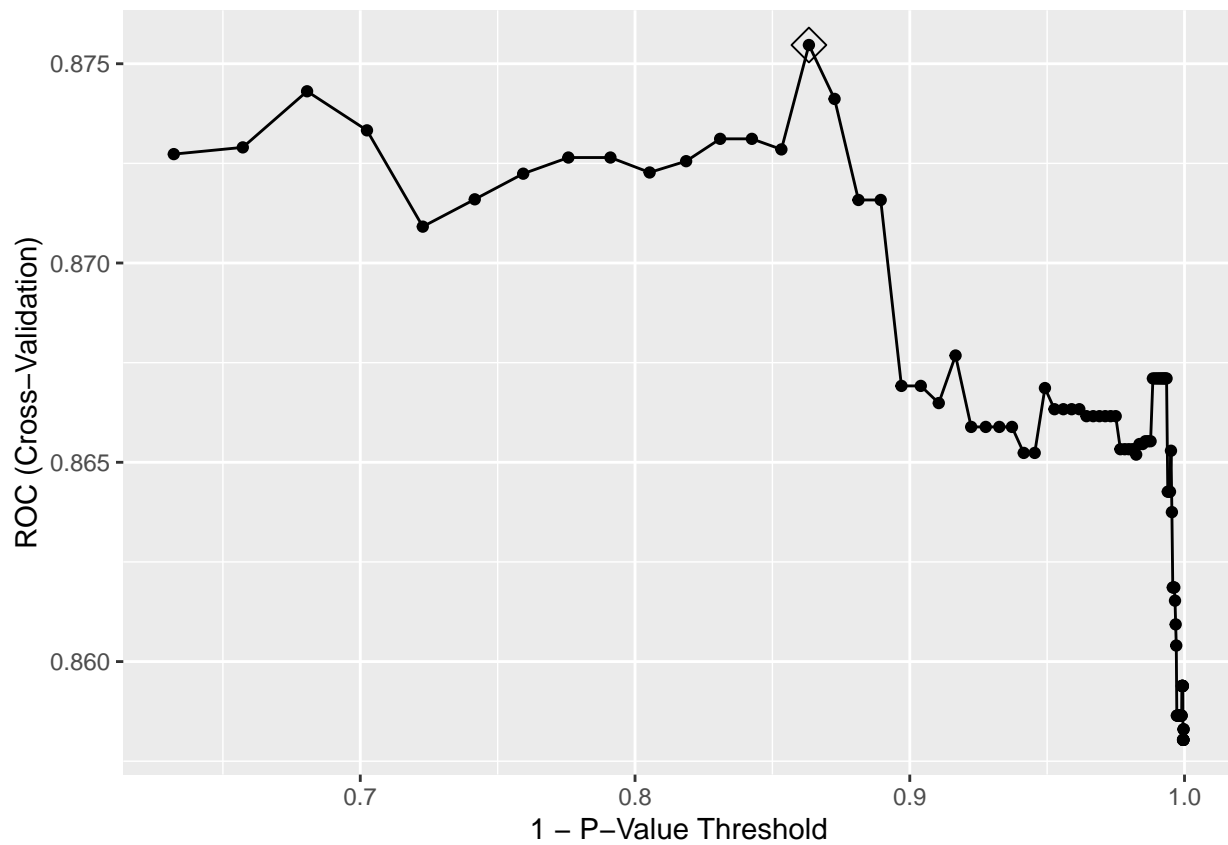




```
#CIT scaled
set.seed(2)

scaled.model.cit = train(x = x.train.scaled,
  y = y.train.scaled,
  method = "ctree",
  tuneGrid = data.frame(mincriterion = 1-exp(seq(-8, -1, length = 100))),
  trControl = ctrl)

ggplot(scaled.model.cit, highlight = TRUE)
```

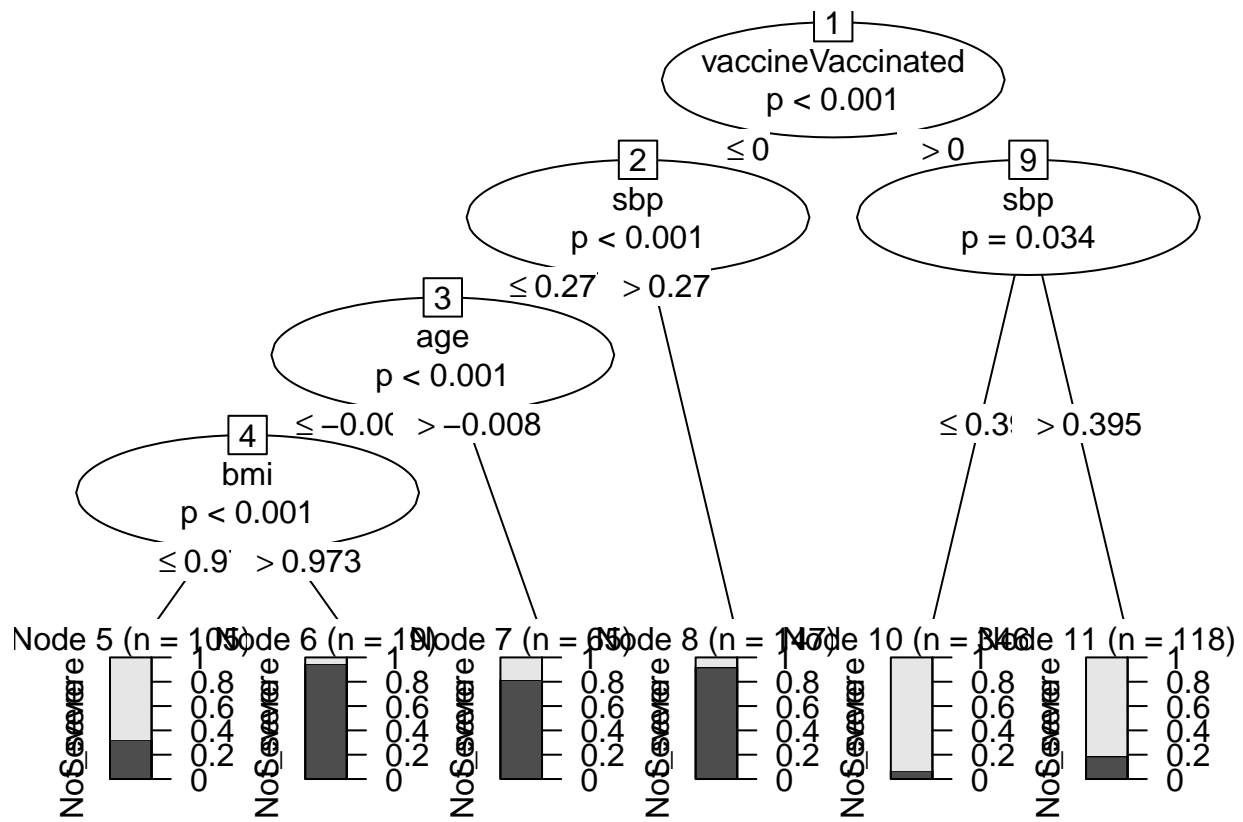


```
scaled.model.cit$bestTune
```

```
## mincriterion
```

```
## 15 0.8632908
```

```
plot(scaled.model.cit$finalModel)
```



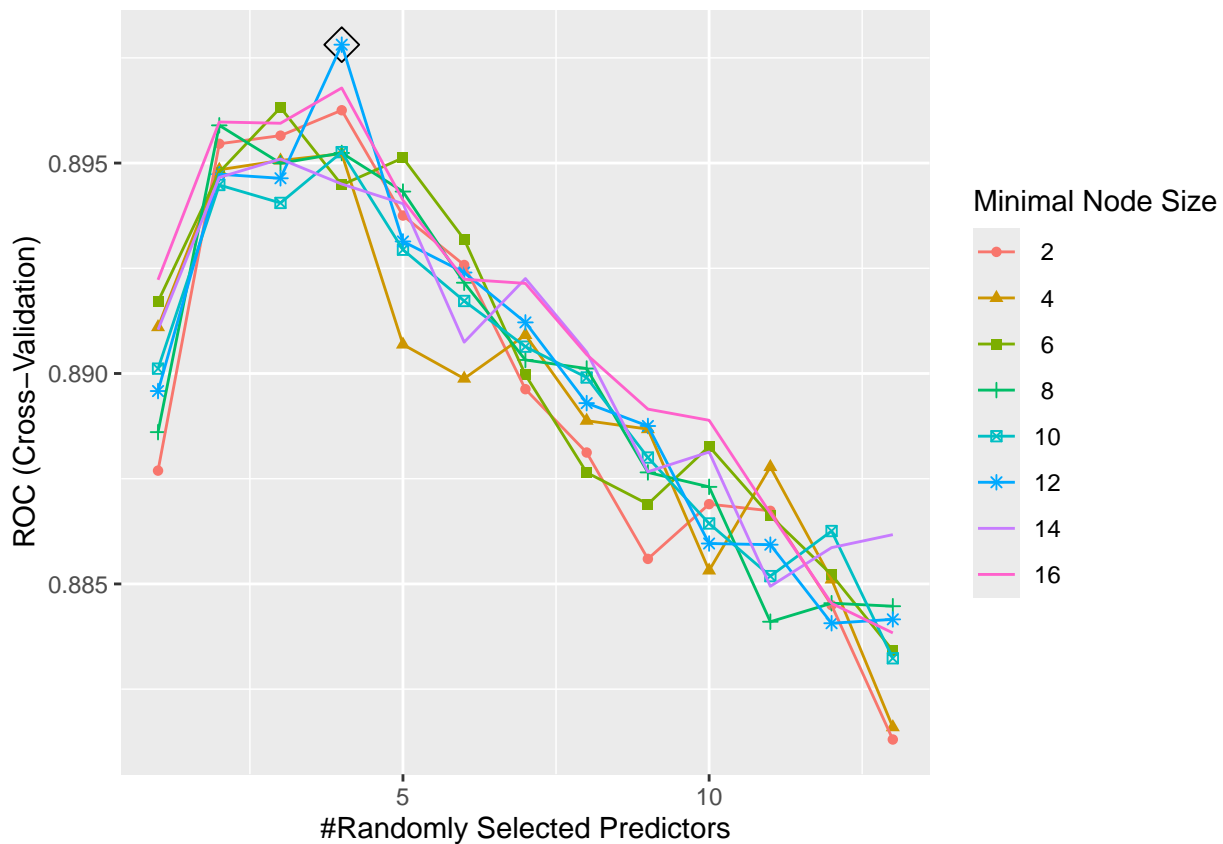
## Random Forest

```
# Try more if possible
rf.grid = expand.grid(mtry = 1:13,
                     splitrule = "gini",
                     min.node.size = seq(from = 2, to = 16, by = 2))

set.seed(2)
model.rf = train(x = x.train,
                 y = y.train,
                 method = "ranger",
                 tuneGrid = rf.grid,
                 trControl = ctrl)

model.rf$bestTune
```

```
##      mtry splitrule min.node.size
## 30      4      gini             12
ggplot(model.rf, highlight = TRUE)
```



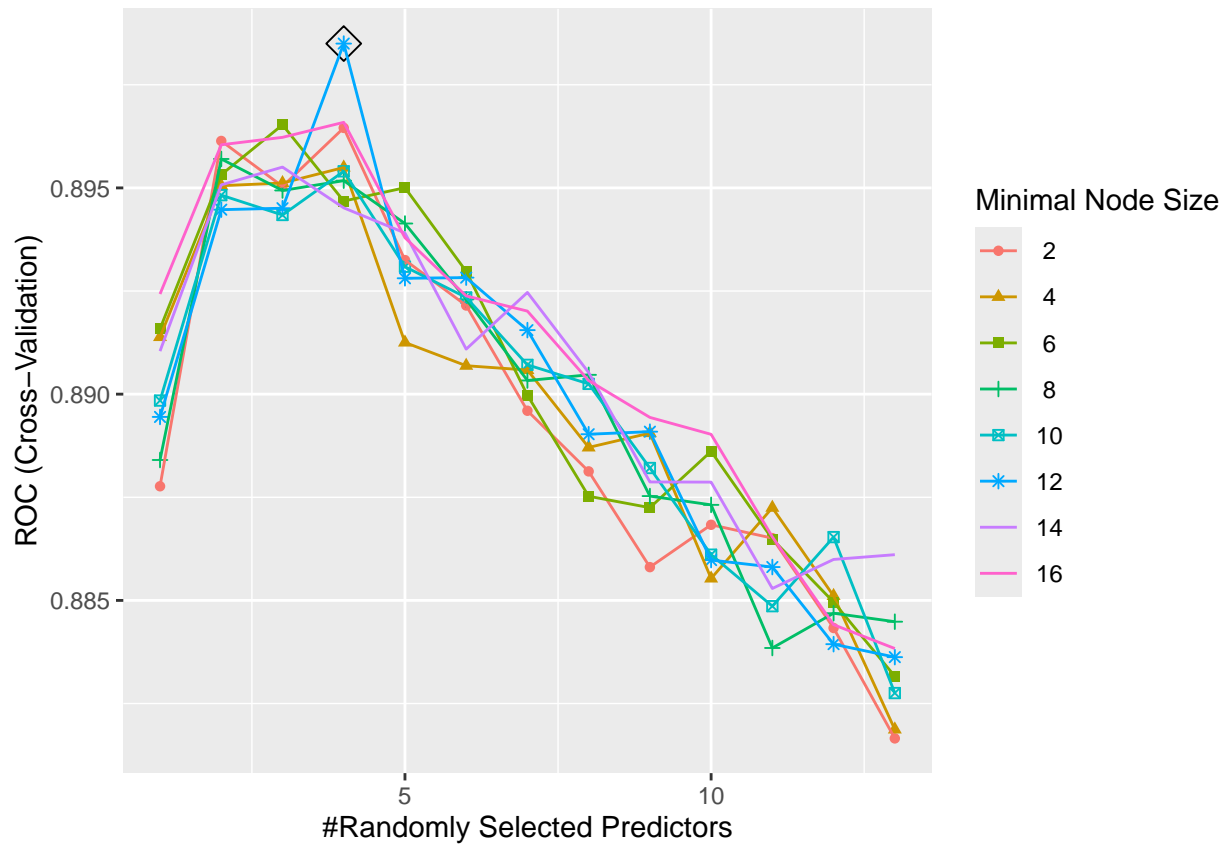
```
# RF scaled
set.seed(2)
scaled.model.rf = train(x = x.train.scaled,
                       y = y.train.scaled,
                       method = "ranger",
                       tuneGrid = rf.grid,
                       trControl = ctrl)

scaled.model.rf$bestTune
```

```
##      mtry splitrule min.node.size
```

```
## 30    4    gini      12
```

```
ggplot(scaled.model.rf, highlight = TRUE)
```



## AdaBoost

```
# Try more
gbmA.grid = expand.grid(n.trees = c(1000,2000,3000,4000,5000),
                        interaction.depth = 1:6,
                        shrinkage = c(0.001, 0.002, 0.003),
                        n.minobsinnode = 1)

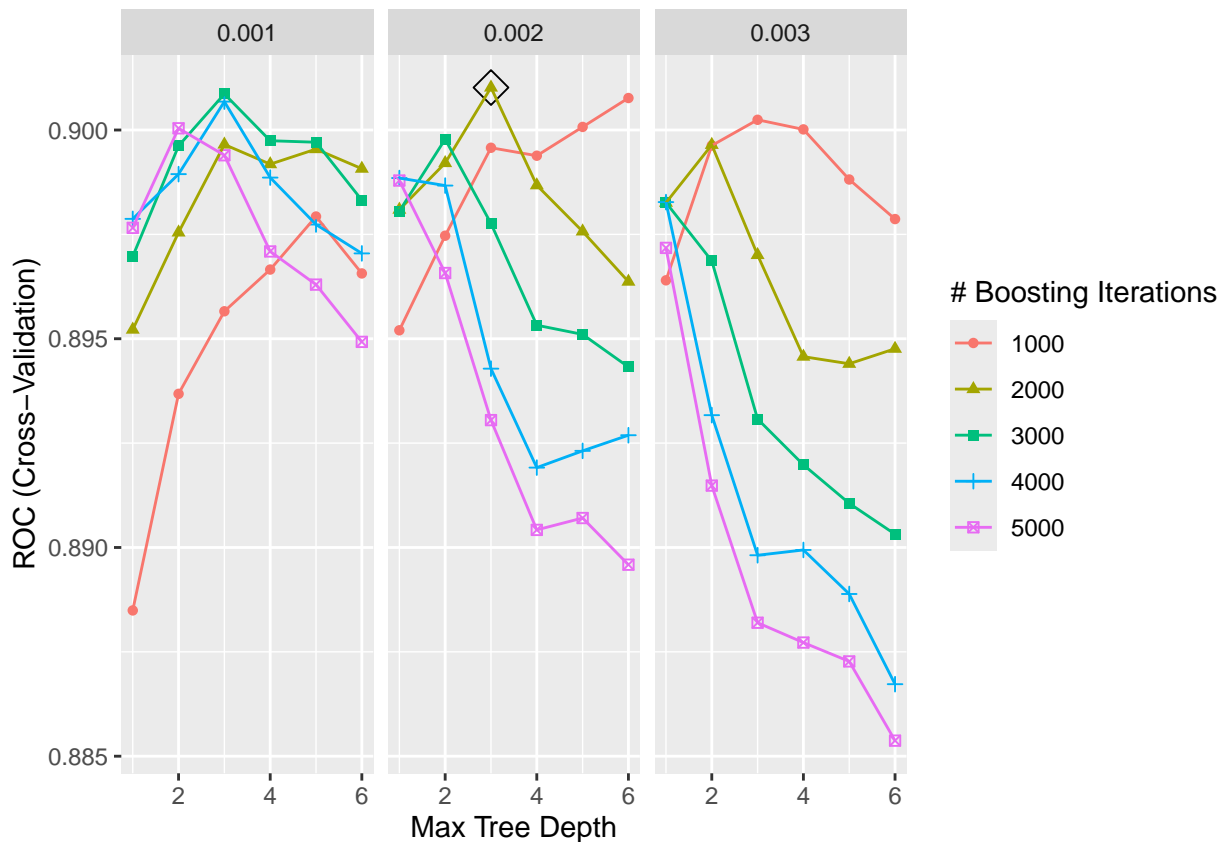
set.seed(2)

model.gbmA = train(x = x.train,
                   y = y.train,
                   tuneGrid = gbmA.grid,
                   trControl = ctrl,
                   method = "gbm",
                   distribution = "adaboost",
                   metric = "ROC",
                   verbose = FALSE)

model.gbmA$bestTune
```

```
##      n.trees interaction.depth shrinkage n.minobsinnode
## 42      2000                3      0.002                1
```

```
ggplot(model.gbmA, highlight = TRUE)
```

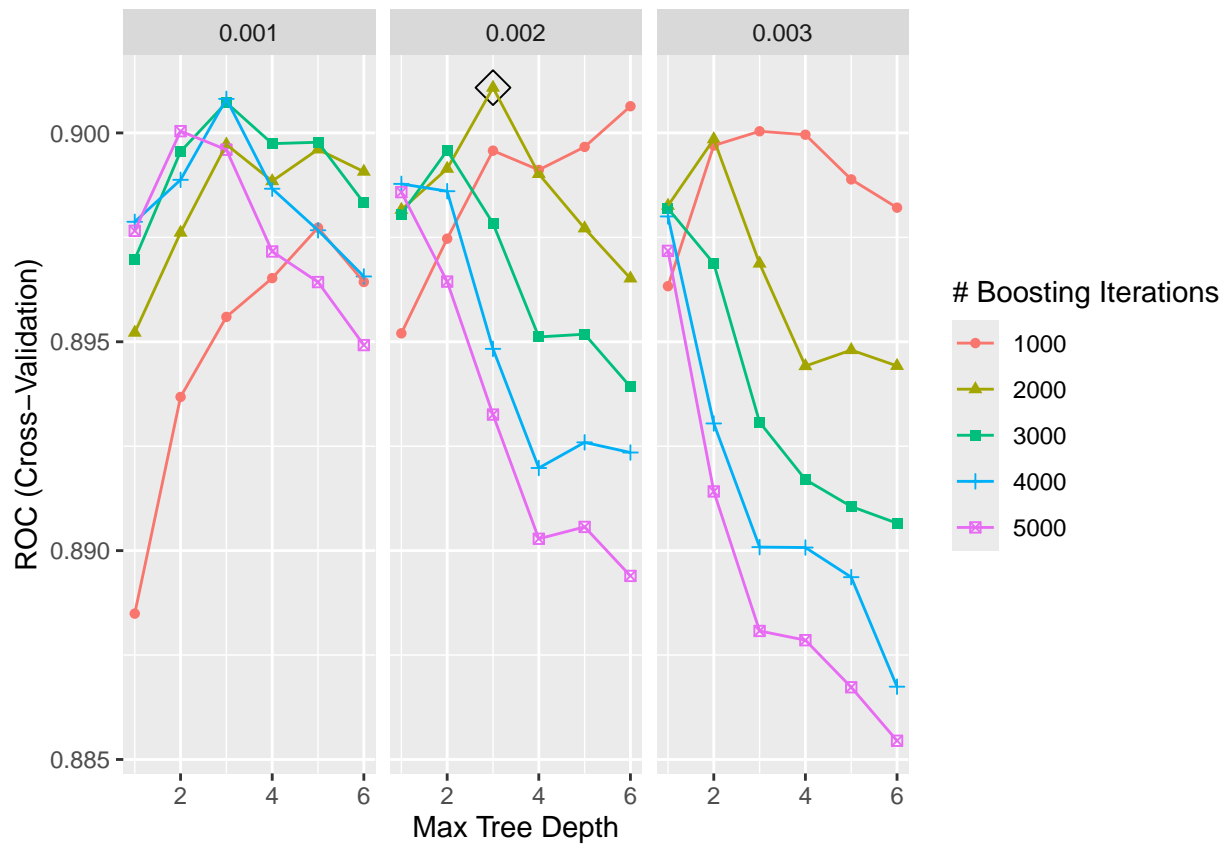


```
# boosted rf scaled
set.seed(2)
```

```
scaled.model.gbmA = train(x = x.train.scaled,
  y = y.train.scaled,
  tuneGrid = gbmA.grid,
  trControl = ctrl,
  method = "gbm",
  distribution = "adaboost",
  metric = "ROC",
  verbose = FALSE)
scaled.model.gbmA$bestTune
```

```
##      n.trees interaction.depth shrinkage n.minobsinnode
## 42      2000              3      0.002              1
```

```
ggplot(scaled.model.gbmA, highlight = TRUE)
```



## Support Vector Machine: linear

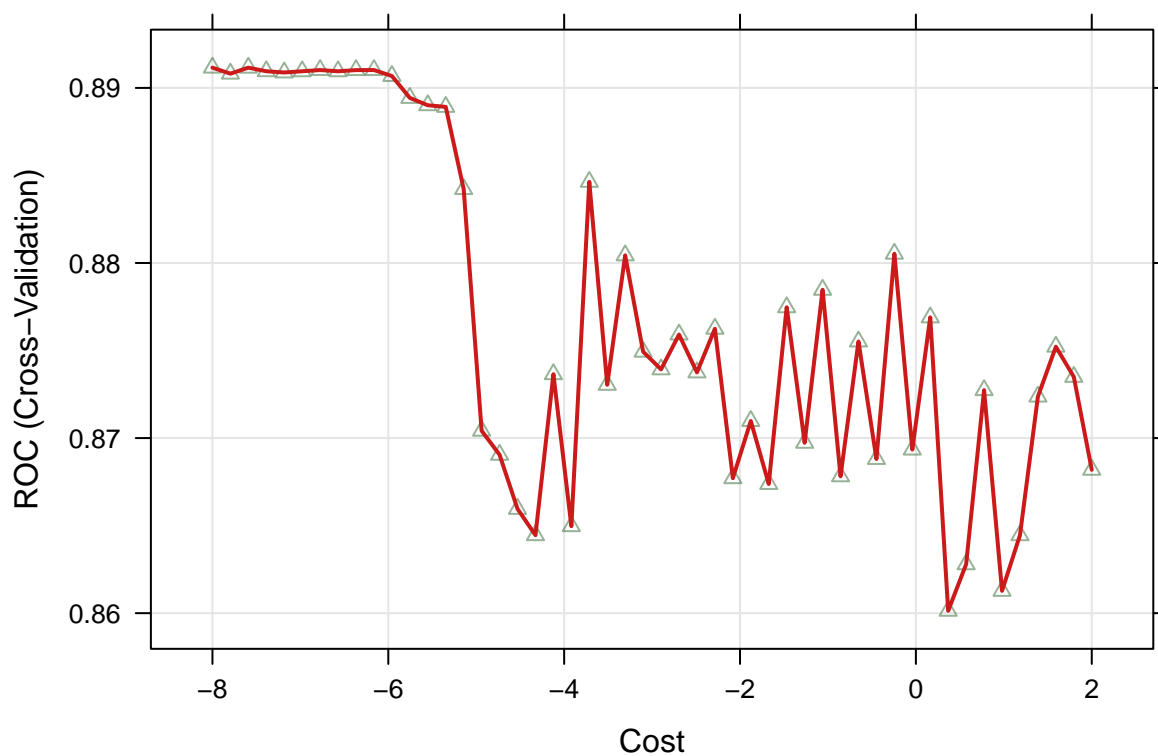
```
set.seed(2)

model.svm1 = train(x = x.train,
  y = y.train,
  method = "svmLinear",
  tuneGrid = data.frame(C = exp(seq(-8, 2, len = 50))),
  trControl = ctrl)

model.svm1$bestTune
```

```
##           C
## 1 0.0003354626
```

```
plot(model.svm1, highlight = TRUE, xTrans = log)
```



```
# SVM linear scaled
set.seed(2)

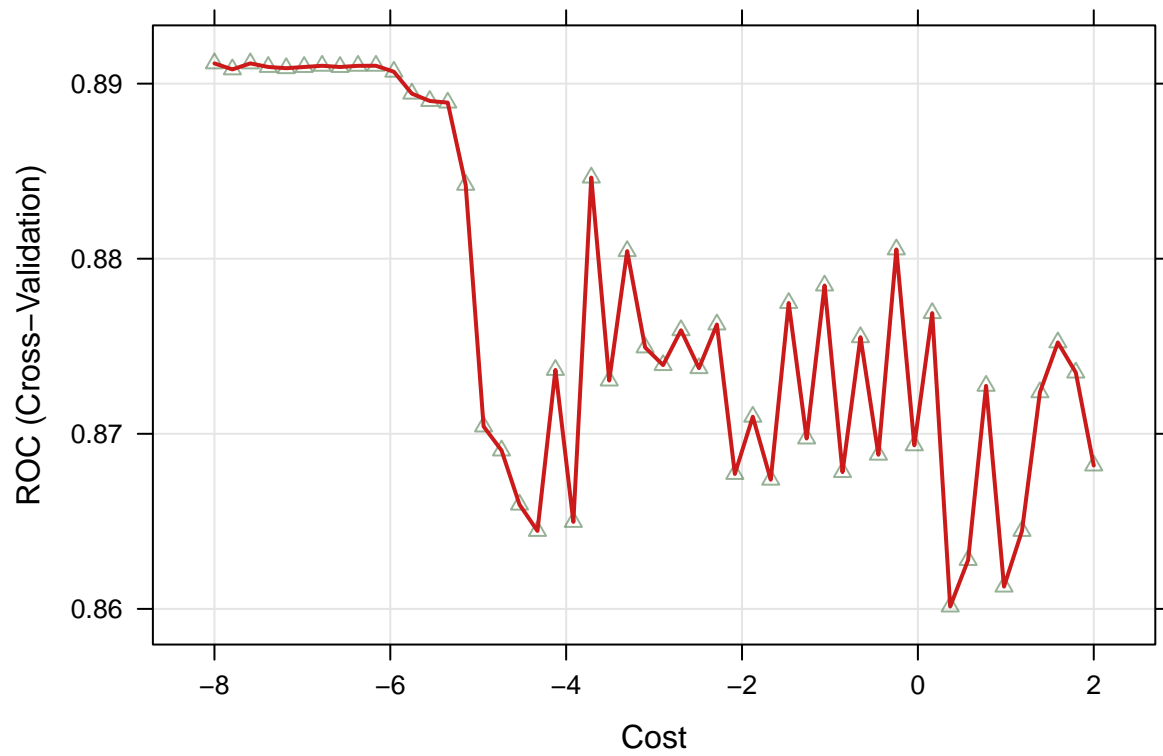
scaled.model.svm1 = train(x = x.train.scaled,
  y = y.train.scaled,
  method = "svmLinear",
  tuneGrid = data.frame(C = exp(seq(-8, 2, len = 50))),
  trControl = ctrl)

scaled.model.svm1$bestTune
```

```
##           C
## 1 0.0003354626
```



```
plot(scaled.model.svm1, highlight = TRUE, xTrans = log)
```



## SVML: e1071

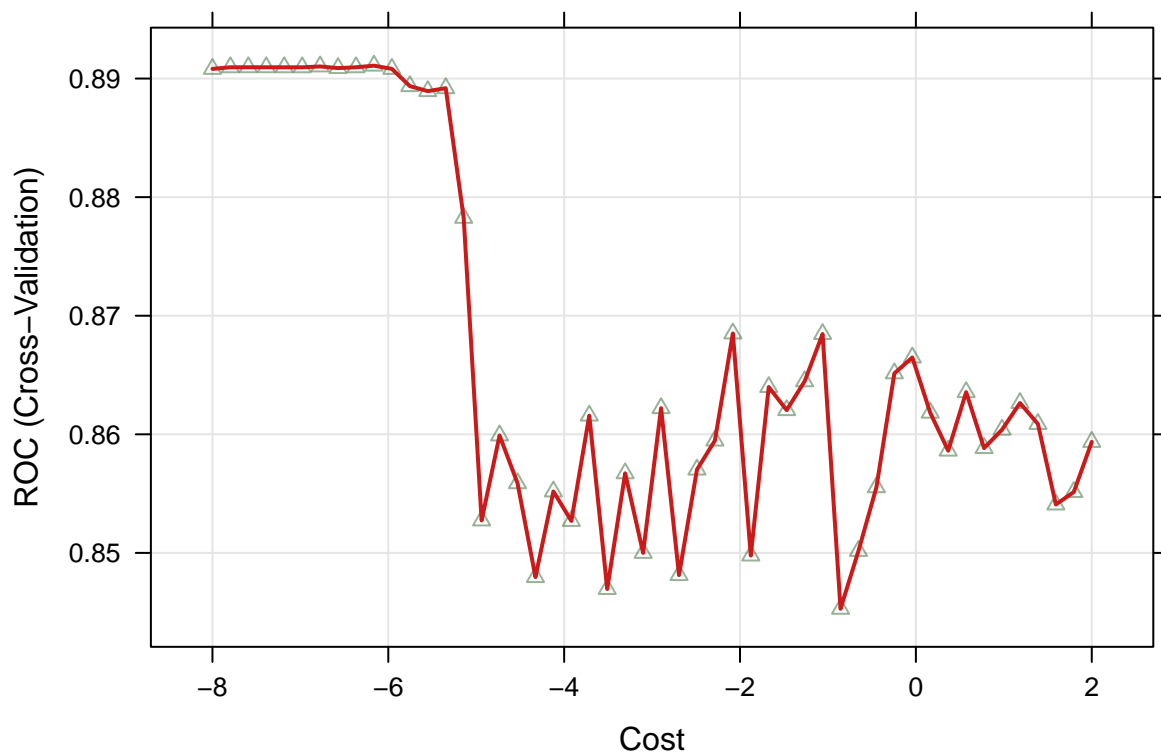
```
set.seed(2)

model.svm12 = train(x = x.train,
                    y = y.train,
                    method = "svmLinear2",
                    tuneGrid = data.frame(cost = exp(seq(-8, 2, len = 50))),
                    trControl = ctrl)

model.svm12$bestTune
```

```
##          cost
## 10 0.002105367
```

```
plot(model.svm12, highlight = TRUE, xTrans = log)
```



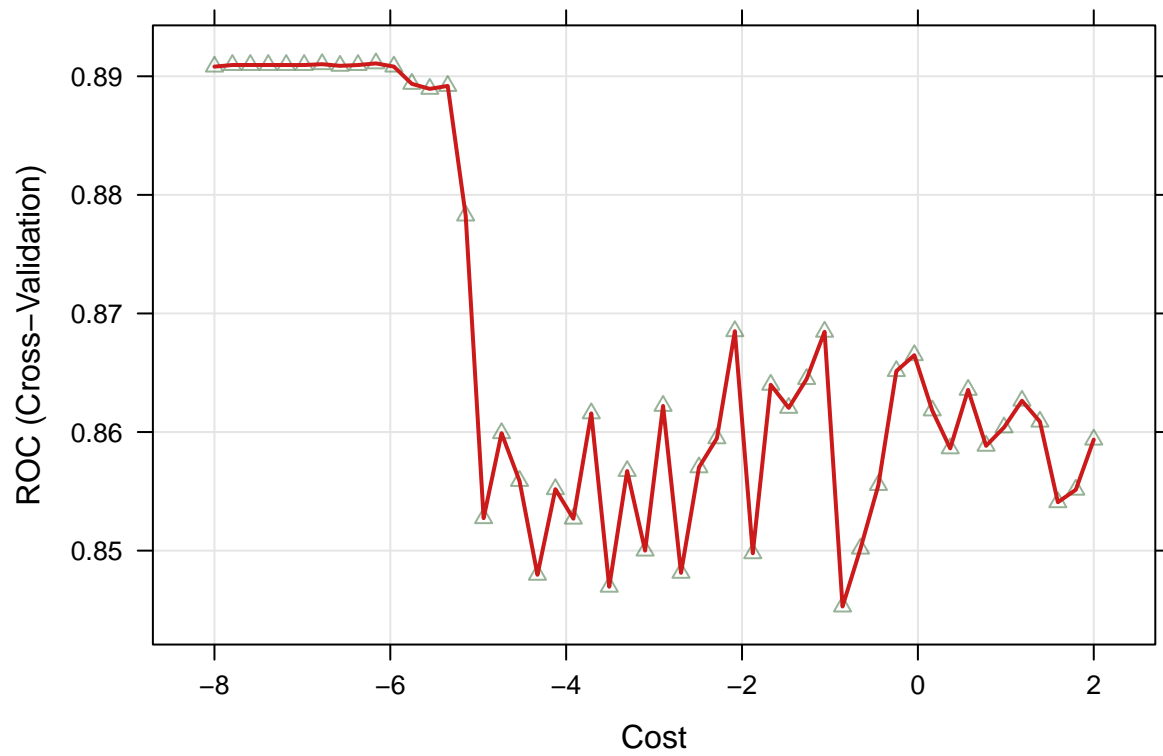
```
# SVML e1071 scaled
set.seed(2)

scaled.model.svm12 = train(x = x.train.scaled,
                           y = y.train.scaled,
                           method = "svmLinear2",
                           tuneGrid = data.frame(cost = exp(seq(-8, 2, len = 50))),
                           trControl = ctrl)

scaled.model.svm12$bestTune
```

```
##          cost
## 10 0.002105367
```

```
plot(scaled.model.svm12, highlight = TRUE, xTrans = log)
```



## SVML: Radial Sigma

```
svmr.grid = expand.grid(C = exp(seq(1, 7, len = 50)),
                        sigma = exp(seq(-8, -2, len = 20)))
```

```
# tunes over both cost and sigma
```

```
set.seed(2)
```

```
model.svmr = train(x = x.train,
                  y = y.train,
                  method = "svmRadialSigma",
                  tuneGrid = svmr.grid,
                  trControl = ctrl)
```

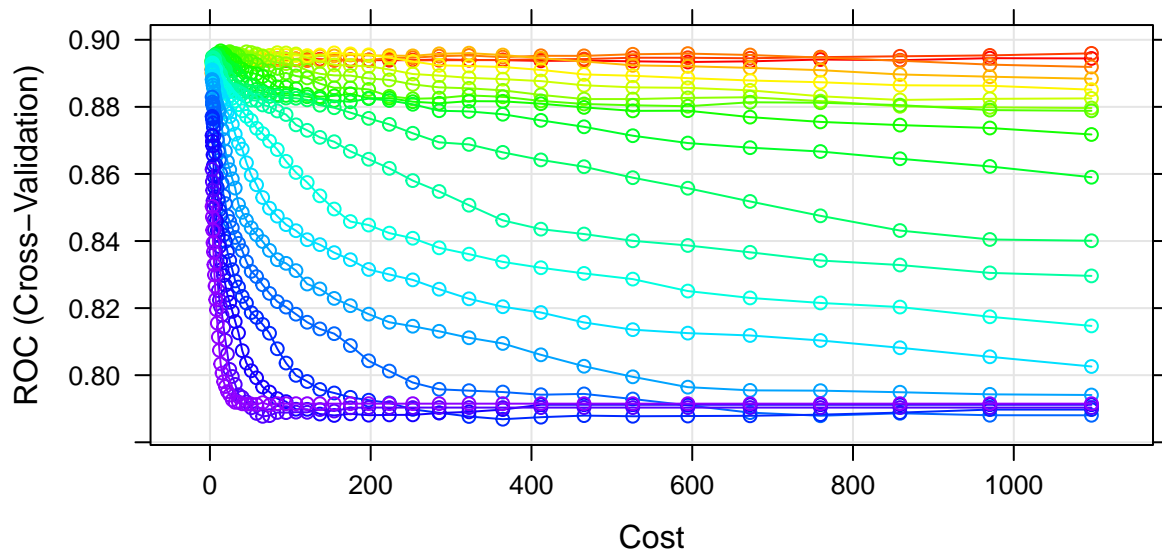
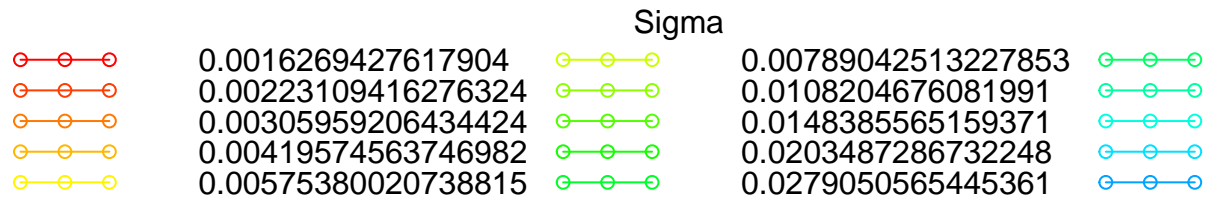
```
myCol = rainbow(25)
```

```
myPar = list(superpose.symbol = list(col = myCol),
             superpose.line = list(col = myCol))
```

```
model.svmr$bestTune
```

```
##          sigma          C
## 269 0.004195746 13.35428
```

```
plot(model.svmr, highlight = TRUE, par.settings = myPar)
```



```
# scaled model
```

```
set.seed(2)
```

```
scaled.model.svmr = train(x = x.train.scaled,
                          y = y.train.scaled,
                          method = "svmRadialSigma",
                          tuneGrid = svmr.grid,
```

```

trControl = ctrl)

myCol = rainbow(25)
myPar = list(superpose.symbol = list(col = myCol),
superpose.line = list(col = myCol))

scaled.model.svmr$bestTune

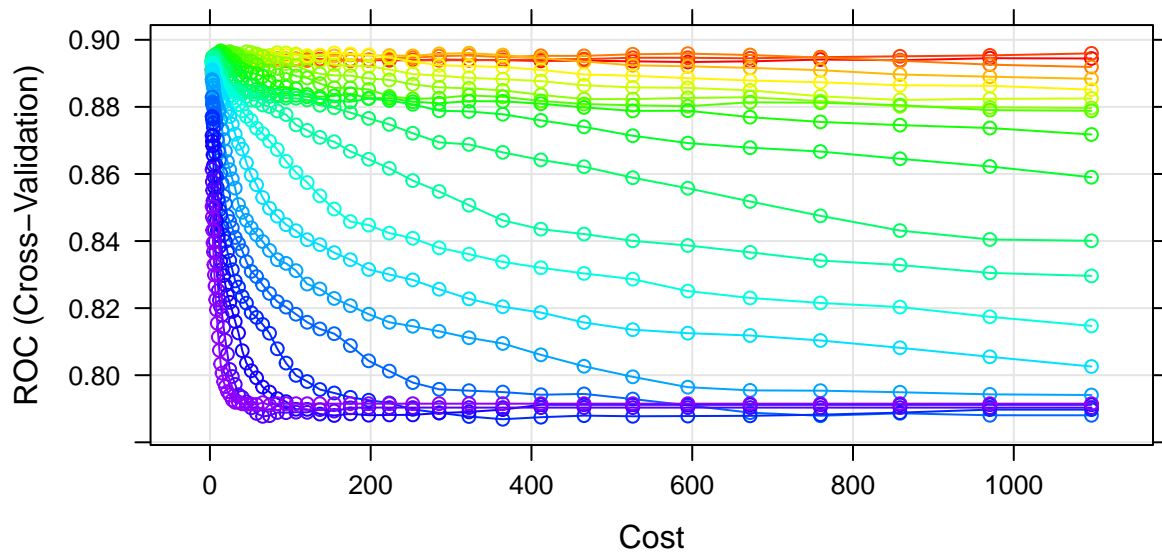
##          sigma          C
## 269 0.004195746 13.35428

plot(scaled.model.svmr, highlight = TRUE, par.settings = myPar)

```

Sigma

○ ○ ○ ○	0.0016269427617904	○ ○ ○ ○	0.00789042513227853	○ ○ ○ ○
○ ○ ○ ○	0.00223109416276324	○ ○ ○ ○	0.0108204676081991	○ ○ ○ ○
○ ○ ○ ○	0.00305959206434424	○ ○ ○ ○	0.0148385565159371	○ ○ ○ ○
○ ○ ○ ○	0.00419574563746982	○ ○ ○ ○	0.0203487286732248	○ ○ ○ ○
○ ○ ○ ○	0.00575380020738815	○ ○ ○ ○	0.0279050565445361	○ ○ ○ ○



## SVML: radial cost

```
set.seed(2)
```

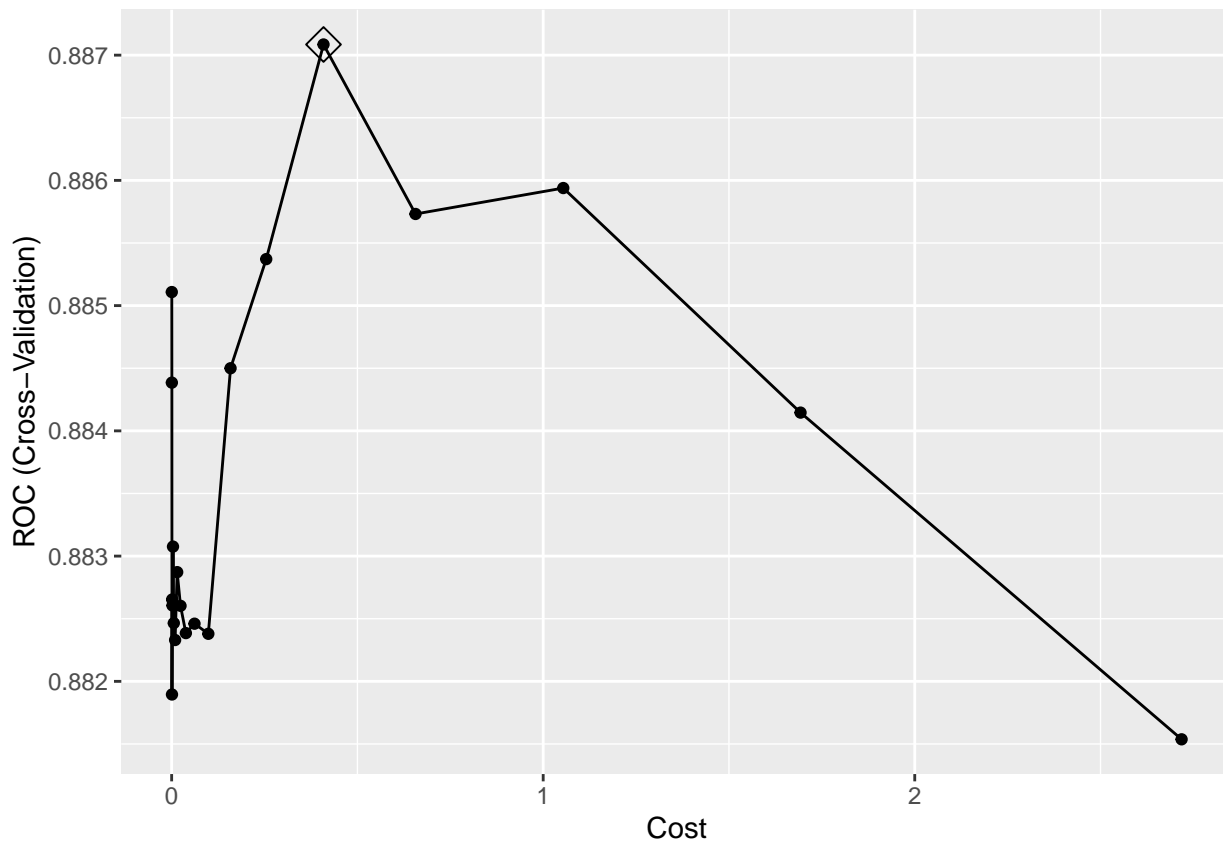
```
model.svmr2 = train(x = x.train,
                    y = y.train,
                    method = "svmRadialCost",
                    tuneGrid = data.frame(C = exp(seq(-8, 1, len = 20))),
                    trControl = ctrl)
```

```
## maximum number of iterations reached 1.184536e-05 1.182684e-05maximum number of iterations reached 1
```

```
model.svmr2$bestTune
```

```
##           C
## 16 0.4087151
```

```
ggplot(model.svmr2, highlight = TRUE, par.settings = myPar)
```



```
# scaled model
```

```
set.seed(2)
```

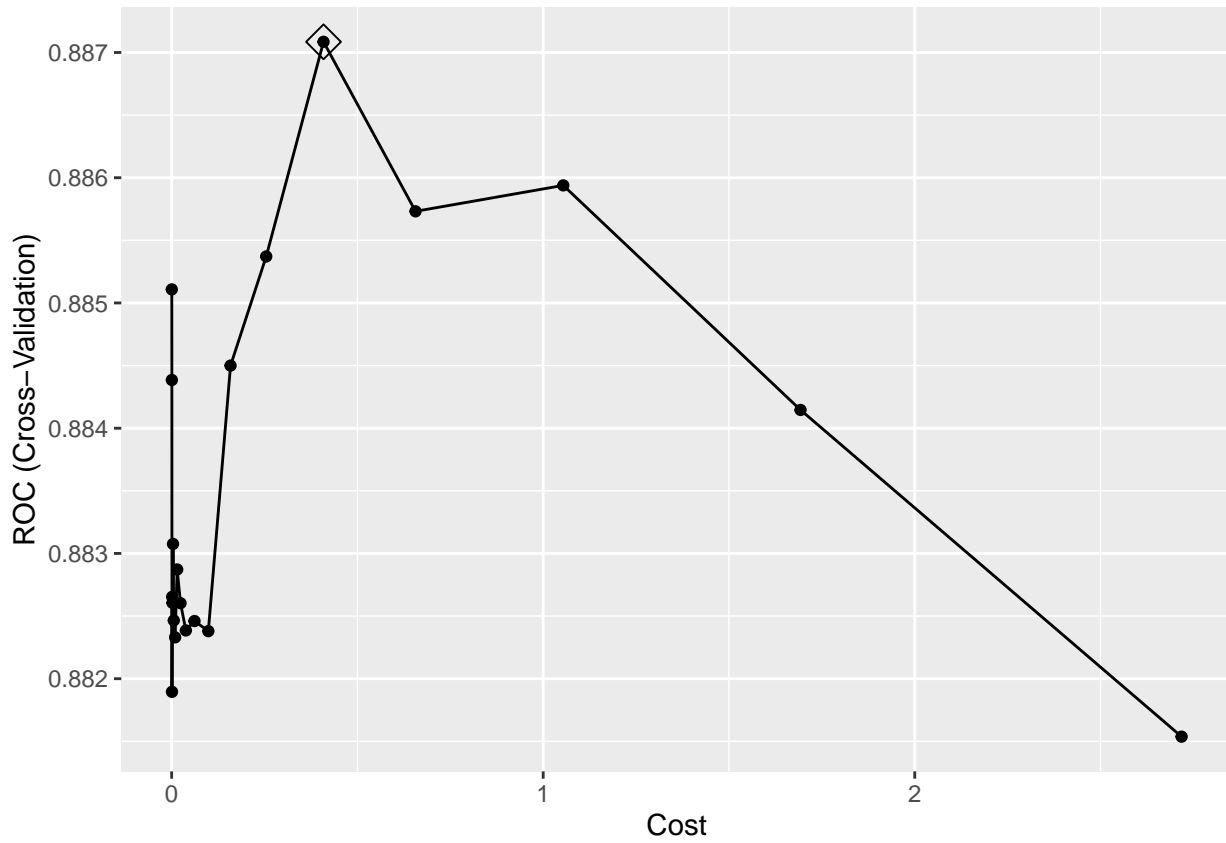
```
scaled.model.svmr2 = train(x = x.train.scaled,
                           y = y.train.scaled,
                           method = "svmRadialCost",
                           tuneGrid = data.frame(C = exp(seq(-8, 1, len = 20))),
                           trControl = ctrl)
```

```
## maximum number of iterations reached 1.184536e-05 1.182684e-05maximum number of iterations reached 1
```

```
scaled.model.svmr2$bestTune
```

```
##          C  
## 16 0.4087151
```

```
ggplot(scaled.model.svmr2, highlight = TRUE, par.settings = myPar)
```



## Results

### Model Comparison: Cross Validation Performance

```
res = resamples(list(GLM = model.glm,
                     GLMNET = model.glmn,
                     KNN = model.knn,
                     PLS = model.pls,
                     GAM = model.gam,
                     MARS = model.mars,
                     LDA = model.lda,
                     QDA = model.qda,
                     NB = model.nb,
                     CART = model.cart,
                     CIT = model.cit,
                     RF = model.rf,
                     SVML = model.svml,
                     E1071 = model.svml2,
                     SVMR = model.svmr,
                     SVMR2 = model.svmr2,
                     gbmA = model.gbmA
                     ))

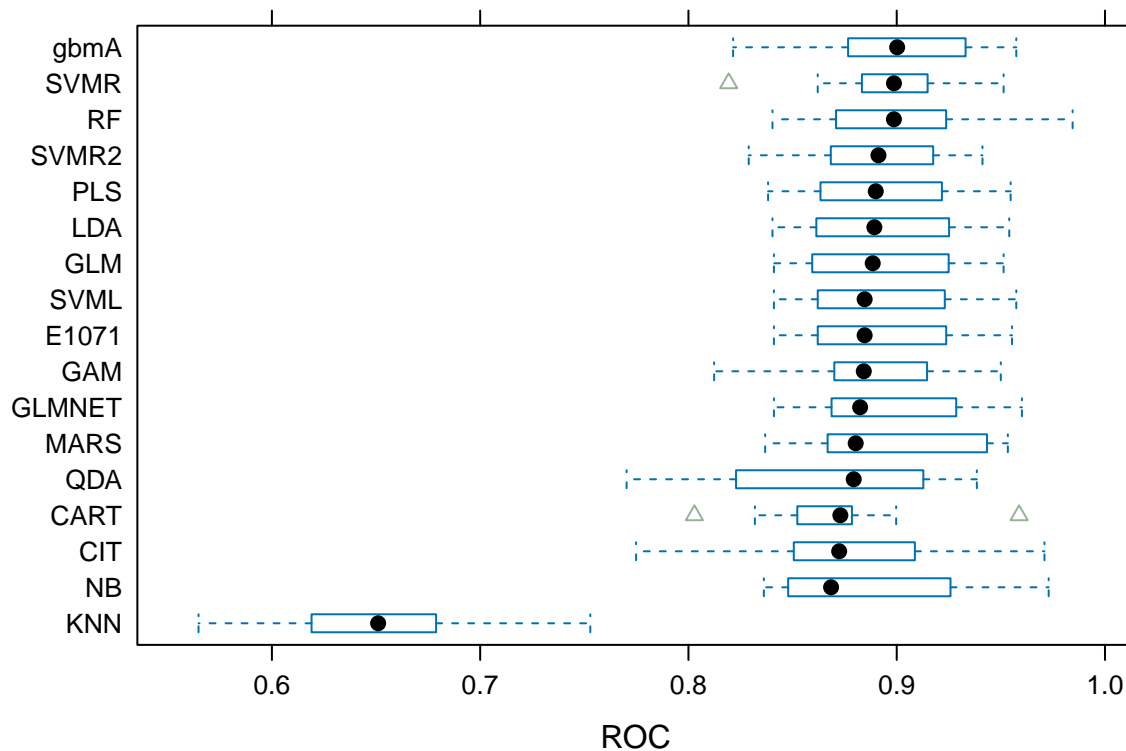
summary(res)
```

```
##
## Call:
## summary.resamples(object = res)
##
## Models: GLM, GLMNET, KNN, PLS, GAM, MARS, LDA, QDA, NB, CART, CIT, RF, SVML, E1071, SVMR, SVMR2, gbmA
## Number of resamples: 10
##
## ROC
##      Min.    1st Qu.    Median      Mean   3rd Qu.     Max. NA's
## GLM      0.8410364 0.8594164 0.8884762 0.8902533 0.9211279 0.9513185    0
## GLMNET    0.8410364 0.8705239 0.8824337 0.8946561 0.9271709 0.9601082    0
## KNN       0.5647759 0.6197361 0.6510080 0.6510491 0.6731696 0.7528736    0
## PLS       0.8382353 0.8653846 0.8899325 0.8927358 0.9192186 0.9546991    0
## GAM       0.8123249 0.8700265 0.8841817 0.8878412 0.9122597 0.9499662    0
## MARS      0.8368347 0.8678010 0.8803050 0.8954023 0.9367124 0.9533469    0
## LDA       0.8403361 0.8637268 0.8892694 0.8921525 0.9221443 0.9540230    0
## QDA       0.7703081 0.8323010 0.8793382 0.8685147 0.9055691 0.9384719    0
## NB        0.8362069 0.8484358 0.8684867 0.8860873 0.9237099 0.9729547    0
## CART      0.8028711 0.8556278 0.8729261 0.8711284 0.8778011 0.9587559    0
## CIT       0.7748599 0.8540285 0.8723739 0.8754698 0.9021152 0.9709263    0
## RF        0.8403361 0.8709822 0.8986526 0.8978131 0.9219717 0.9844490    0
## SVML      0.8410364 0.8627321 0.8845903 0.8911562 0.9204239 0.9574037    0
## E1071     0.8410364 0.8627321 0.8845903 0.8910873 0.9207640 0.9553753    0
## SVMR      0.8193277 0.8849469 0.8986646 0.8967070 0.9147678 0.9513185    0
## SVMR2     0.8289385 0.8689329 0.8912244 0.8870851 0.9168427 0.9411765    0
## gbmA      0.8214286 0.8774867 0.9002110 0.9010174 0.9329702 0.9574037    0
##
## Sens
##      Min.    1st Qu.    Median      Mean   3rd Qu.     Max. NA's
## GLM      0.8269231 0.8676471 0.8930995 0.8852187 0.9038462 0.9215686    0
```



```
## GLMNET 0.8846154 0.9264706 0.9607843 0.9435897 0.9615385 0.9803922 0
## KNN 0.7647059 0.8291855 0.8642534 0.8580694 0.8976244 0.9215686 0
## PLS 0.7647059 0.7901584 0.8640649 0.8461161 0.8970588 0.9038462 0
## GAM 0.8235294 0.8529412 0.8942308 0.8891026 0.9215686 0.9423077 0
## MARS 0.8235294 0.8486991 0.8738688 0.8773379 0.9171380 0.9230769 0
## LDA 0.7843137 0.7901584 0.8640649 0.8480769 0.8970588 0.9038462 0
## QDA 0.8039216 0.8438914 0.8725490 0.8715686 0.9033748 0.9230769 0
## NB 0.9038462 0.9411765 0.9607843 0.9572021 0.9615385 1.0000000 0
## CART 0.8076923 0.8627451 0.8834842 0.8872172 0.9278846 0.9607843 0
## CIT 0.8431373 0.8461538 0.9117647 0.8969080 0.9371229 0.9607843 0
## RF 0.8461538 0.9215686 0.9321267 0.9261312 0.9420249 0.9803922 0
## SVM 0.7058824 0.7730015 0.8039216 0.7974736 0.8260747 0.8461538 0
## E1071 0.8461538 0.8872549 0.9313725 0.9162519 0.9420249 0.9807692 0
## SVMR 0.8269231 0.8823529 0.8921569 0.8852187 0.9033748 0.9038462 0
## SVMR2 0.8269231 0.8725490 0.9019608 0.8891026 0.9033748 0.9230769 0
## gbmA 0.8461538 0.8829186 0.9215686 0.9144419 0.9371229 0.9803922 0
##
## Spec
## Min. 1st Qu. Median Mean 3rd Qu. Max. NA's
## GLM 0.6206897 0.6982759 0.7543103 0.7906404 0.8956281 0.9642857 0
## GLMNET 0.5172414 0.6071429 0.6483990 0.6713054 0.7241379 0.8571429 0
## KNN 0.1071429 0.2087438 0.2456897 0.2545567 0.3211207 0.4482759 0
## PLS 0.6785714 0.7672414 0.8251232 0.8289409 0.8956281 0.9642857 0
## GAM 0.5862069 0.7167488 0.7413793 0.7624384 0.8519089 0.8928571 0
## MARS 0.6206897 0.6982759 0.7370690 0.7661330 0.8497537 0.9285714 0
## LDA 0.6785714 0.7672414 0.8251232 0.8289409 0.8956281 0.9642857 0
## QDA 0.5862069 0.6958128 0.7241379 0.7626847 0.8620690 0.9285714 0
## NB 0.3928571 0.4959975 0.5615764 0.5619458 0.6120690 0.7586207 0
## CART 0.6071429 0.6610222 0.7198276 0.7237685 0.7586207 0.8620690 0
## CIT 0.6071429 0.7241379 0.7543103 0.7658867 0.8275862 0.8928571 0
## RF 0.5862069 0.6899631 0.7370690 0.7480296 0.8362069 0.8965517 0
## SVM 0.6785714 0.8017241 0.8602217 0.8428571 0.8956281 0.9642857 0
## E1071 0.5172414 0.6160714 0.7068966 0.7099754 0.8171182 0.8620690 0
## SVMR 0.6428571 0.7167488 0.7931034 0.8007389 0.8956281 0.9642857 0
## SVMR2 0.6071429 0.7047414 0.7758621 0.7832512 0.8928571 0.8965517 0
## gbmA 0.5517241 0.6958128 0.7370690 0.7413793 0.8103448 0.9285714 0
```

```
bwplot(res, metric = "ROC") # gbmA has highest median and mean ROC
```



```
# Cross-validation error
glm.predict = predict(model.glm, newdata = x.train)
glmnet.predict = predict(model.glmn, newdata = x.train)
knn.predict = predict(model.knn, newdata = x.train)
pls.predict = predict(model.pls, newdata = x.train)
gam.predict = predict(model.gam, newdata = x.train)
mars.predict = predict(model.mars, newdata = x.train)
lda.predict = predict(model.lda, newdata = x.train)
qda.predict = predict(model.qda, newdata = x.train)
nb.predict = predict(model.nb, newdata = x.train)
cart.predict = predict(model.cart, newdata = x.train)
cit.predict = predict(model.cit, newdata = x.train)
rf.predict = predict(model.rf, newdata = x.train)
svml.predict = predict(model.svml, newdata = x.train)
e1071.predict = predict(model.svml2, newdata = x.train)
svmr.predict = predict(model.svmr, newdata = x.train)
svmr2.predict = predict(model.svmr2, newdata = x.train)
gbmA.predict = predict(model.gbmA, newdata = x.train)

confusionMatrix(data = glm.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##               Reference
## Prediction  Not_severe Severe
## Not_severe      457      55
## Severe           57     231
##
##               Accuracy : 0.86
##               95% CI : (0.834, 0.8833)
```

```
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : <2e-16
##
##              Kappa : 0.6957
##
##      McNemar's Test P-Value : 0.9247
##
##              Sensitivity : 0.8891
##              Specificity : 0.8077
##              Pos Pred Value : 0.8926
##              Neg Pred Value : 0.8021
##              Prevalence : 0.6425
##              Detection Rate : 0.5713
##      Detection Prevalence : 0.6400
##      Balanced Accuracy : 0.8484
##
##      'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = glmnet.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      486      90
## Severe           28     196
##
##              Accuracy : 0.8525
##              95% CI : (0.826, 0.8764)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.6627
##
##      McNemar's Test P-Value : 1.96e-08
##
##              Sensitivity : 0.9455
##              Specificity : 0.6853
##              Pos Pred Value : 0.8437
##              Neg Pred Value : 0.8750
##              Prevalence : 0.6425
##              Detection Rate : 0.6075
##      Detection Prevalence : 0.7200
##      Balanced Accuracy : 0.8154
##
##      'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = knn.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
```

```

##      Not_severe      453      197
##      Severe          61      89
##
##              Accuracy : 0.6775
##              95% CI : (0.6439, 0.7098)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : 0.02065
##
##              Kappa : 0.2152
##
##      McNemar's Test P-Value : < 2e-16
##
##              Sensitivity : 0.8813
##              Specificity : 0.3112
##      Pos Pred Value : 0.6969
##      Neg Pred Value : 0.5933
##      Prevalence : 0.6425
##      Detection Rate : 0.5663
##      Detection Prevalence : 0.8125
##      Balanced Accuracy : 0.5963
##
##      'Positive' Class : Not_severe
##
confusionMatrix(data = pls.predict, reference = y.train)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      440      47
## Severe          74      239
##
##              Accuracy : 0.8488
##              95% CI : (0.822, 0.8729)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : <2e-16
##
##              Kappa : 0.6775
##
##      McNemar's Test P-Value : 0.0181
##
##              Sensitivity : 0.8560
##              Specificity : 0.8357
##      Pos Pred Value : 0.9035
##      Neg Pred Value : 0.7636
##      Prevalence : 0.6425
##      Detection Rate : 0.5500
##      Detection Prevalence : 0.6088
##      Balanced Accuracy : 0.8458
##
##      'Positive' Class : Not_severe
##

```

```
confusionMatrix(data = gam.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      463     54
## Severe           51    232
##
##              Accuracy : 0.8688
##              95% CI : (0.8434, 0.8914)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : <2e-16
##
##              Kappa : 0.7136
##
## Mcnemar's Test P-Value : 0.8453
##
##      Sensitivity : 0.9008
##      Specificity : 0.8112
##      Pos Pred Value : 0.8956
##      Neg Pred Value : 0.8198
##      Prevalence : 0.6425
##      Detection Rate : 0.5787
##      Detection Prevalence : 0.6462
##      Balanced Accuracy : 0.8560
##
##      'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = mars.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      457     60
## Severe           57    226
##
##              Accuracy : 0.8538
##              95% CI : (0.8273, 0.8775)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : <2e-16
##
##              Kappa : 0.6809
##
## Mcnemar's Test P-Value : 0.8533
##
##      Sensitivity : 0.8891
##      Specificity : 0.7902
##      Pos Pred Value : 0.8839
##      Neg Pred Value : 0.7986
##      Prevalence : 0.6425
##      Detection Rate : 0.5713
```

```
## Detection Prevalence : 0.6462
## Balanced Accuracy : 0.8397
##
## 'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = lda.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Not_severe Severe
## Not_severe      437      47
## Severe           77     239
##
##           Accuracy : 0.845
##           95% CI : (0.818, 0.8694)
## No Information Rate : 0.6425
## P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.6703
##
## Mcnemar's Test P-Value : 0.009207
##
##           Sensitivity : 0.8502
##           Specificity : 0.8357
## Pos Pred Value : 0.9029
## Neg Pred Value : 0.7563
## Prevalence : 0.6425
## Detection Rate : 0.5463
## Detection Prevalence : 0.6050
## Balanced Accuracy : 0.8429
##
## 'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = qda.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Not_severe Severe
## Not_severe      456      49
## Severe           58     237
##
##           Accuracy : 0.8662
##           95% CI : (0.8407, 0.8891)
## No Information Rate : 0.6425
## P-Value [Acc > NIR] : <2e-16
##
##           Kappa : 0.7109
##
## Mcnemar's Test P-Value : 0.4393
##
##           Sensitivity : 0.8872
```

```
##           Specificity : 0.8287
##           Pos Pred Value : 0.9030
##           Neg Pred Value : 0.8034
##           Prevalence : 0.6425
##           Detection Rate : 0.5700
##           Detection Prevalence : 0.6312
##           Balanced Accuracy : 0.8579
##
##           'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = nb.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  Not_severe Severe
## Not_severe      492    126
## Severe           22    160
##
##           Accuracy : 0.815
##           95% CI : (0.7863, 0.8413)
##           No Information Rate : 0.6425
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.562
##
## Mcnemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.9572
##           Specificity : 0.5594
##           Pos Pred Value : 0.7961
##           Neg Pred Value : 0.8791
##           Prevalence : 0.6425
##           Detection Rate : 0.6150
##           Detection Prevalence : 0.7725
##           Balanced Accuracy : 0.7583
##
##           'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = cart.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  Not_severe Severe
## Not_severe      474    44
## Severe           40    242
##
##           Accuracy : 0.895
##           95% CI : (0.8717, 0.9154)
##           No Information Rate : 0.6425
##           P-Value [Acc > NIR] : <2e-16
##
```

```
##                Kappa : 0.7707
##
## Mcnemar's Test P-Value : 0.7434
##
##          Sensitivity : 0.9222
##          Specificity : 0.8462
##          Pos Pred Value : 0.9151
##          Neg Pred Value : 0.8582
##          Prevalence : 0.6425
##          Detection Rate : 0.5925
##          Detection Prevalence : 0.6475
##          Balanced Accuracy : 0.8842
##
##          'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = cit.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      489      80
## Severe           25     206
##
##              Accuracy : 0.8688
##              95% CI : (0.8434, 0.8914)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.7016
##
## Mcnemar's Test P-Value : 1.365e-07
##
##          Sensitivity : 0.9514
##          Specificity : 0.7203
##          Pos Pred Value : 0.8594
##          Neg Pred Value : 0.8918
##          Prevalence : 0.6425
##          Detection Rate : 0.6112
##          Detection Prevalence : 0.7113
##          Balanced Accuracy : 0.8358
##
##          'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = rf.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      503      37
## Severe           11     249
##
```



```
##              Accuracy : 0.94
##              95% CI : (0.9212, 0.9554)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.8667
##
##      McNemar's Test P-Value : 0.000308
##
##              Sensitivity : 0.9786
##              Specificity : 0.8706
##      Pos Pred Value : 0.9315
##      Neg Pred Value : 0.9577
##              Prevalence : 0.6425
##      Detection Rate : 0.6288
##      Detection Prevalence : 0.6750
##      Balanced Accuracy : 0.9246
##
##      'Positive' Class : Not_severe
##
confusionMatrix(data = svm1.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      416      44
## Severe           98     242
##
##              Accuracy : 0.8225
##              95% CI : (0.7942, 0.8484)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.6291
##
##      McNemar's Test P-Value : 8.681e-06
##
##              Sensitivity : 0.8093
##              Specificity : 0.8462
##      Pos Pred Value : 0.9043
##      Neg Pred Value : 0.7118
##              Prevalence : 0.6425
##      Detection Rate : 0.5200
##      Detection Prevalence : 0.5750
##      Balanced Accuracy : 0.8277
##
##      'Positive' Class : Not_severe
##
confusionMatrix(data = e1071.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
```

```
##               Reference
## Prediction   Not_severe Severe
##   Not_severe      454     51
##   Severe          60     235
##
##               Accuracy : 0.8612
##               95% CI : (0.8353, 0.8845)
##   No Information Rate : 0.6425
##   P-Value [Acc > NIR] : <2e-16
##
##               Kappa : 0.7001
##
## Mcnemar's Test P-Value : 0.4477
##
##               Sensitivity : 0.8833
##               Specificity : 0.8217
##   Pos Pred Value : 0.8990
##   Neg Pred Value : 0.7966
##   Prevalence : 0.6425
##   Detection Rate : 0.5675
##   Detection Prevalence : 0.6312
##   Balanced Accuracy : 0.8525
##
##   'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = svmr.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##               Reference
## Prediction   Not_severe Severe
##   Not_severe      464     54
##   Severe          50     232
##
##               Accuracy : 0.87
##               95% CI : (0.8447, 0.8925)
##   No Information Rate : 0.6425
##   P-Value [Acc > NIR] : <2e-16
##
##               Kappa : 0.7161
##
## Mcnemar's Test P-Value : 0.7686
##
##               Sensitivity : 0.9027
##               Specificity : 0.8112
##   Pos Pred Value : 0.8958
##   Neg Pred Value : 0.8227
##   Prevalence : 0.6425
##   Detection Rate : 0.5800
##   Detection Prevalence : 0.6475
##   Balanced Accuracy : 0.8570
##
##   'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = svmr2.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      467     54
## Severe           47    232
##
##              Accuracy : 0.8738
##              95% CI : (0.8487, 0.896)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : <2e-16
##
##              Kappa : 0.7237
##
## Mcnemar's Test P-Value : 0.5505
##
##      Sensitivity : 0.9086
##      Specificity : 0.8112
##      Pos Pred Value : 0.8964
##      Neg Pred Value : 0.8315
##      Prevalence : 0.6425
##      Detection Rate : 0.5837
##      Detection Prevalence : 0.6512
##      Balanced Accuracy : 0.8599
##
##      'Positive' Class : Not_severe
##
```

```
confusionMatrix(data = gbmA.predict, reference = y.train)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      488     63
## Severe           26    223
##
##              Accuracy : 0.8888
##              95% CI : (0.8649, 0.9097)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : < 2.2e-16
##
##              Kappa : 0.7507
##
## Mcnemar's Test P-Value : 0.0001356
##
##      Sensitivity : 0.9494
##      Specificity : 0.7797
##      Pos Pred Value : 0.8857
##      Neg Pred Value : 0.8956
##      Prevalence : 0.6425
##      Detection Rate : 0.6100
```

```
##      Detection Prevalence : 0.6887
##      Balanced Accuracy : 0.8646
##
##      'Positive' Class : Not_severe
##
```

```
# 1 - accuracy
gbm_CV_error = 1 - 0.86
glmnet_CV_error = 1 - 0.825
knn_CV_error = 1 - 0.7425
pls_CV_error = 1 - 0.8488
gam_CV_error = 1 - 0.8688
mars_CV_error = 1 - 0.8538
lda_CV_error = 1 - 0.845
qda_CV_error = 1 - 0.8662
nb_CV_error = 1 - 0.815
cart_CV_error = 1 - 0.895
cit_CV_error = 1 - 0.8688
rf_CV_error = 1 - 0.94
svml_CV_error = 1 - 0.8225
e1071_CV_error = 1 - 0.8612
svmr_CV_error = 1 - 0.87
svmr2_CV_error = 1 - 0.8712
gbMA_CV_error = 1 - 0.8888
```

```
# CV error
gbm_CV_error
```

```
## [1] 0.14
```

```
glmnet_CV_error
```

```
## [1] 0.175
```

```
knn_CV_error
```

```
## [1] 0.2575
```

```
pls_CV_error
```

```
## [1] 0.1512
```

```
gam_CV_error
```

```
## [1] 0.1312
```

```
mars_CV_error
```

```
## [1] 0.1462
```

```
lda_CV_error
```

```
## [1] 0.155
```

```
qda_CV_error
```

```
## [1] 0.1338
```

```
nb_CV_error
```

```
## [1] 0.185
```

```
cart_CV_error
```

```
## [1] 0.105
```

```
cit_CV_error
```

```
## [1] 0.1312
```

```
rf_CV_error
```

```
## [1] 0.06
```

```
svml_CV_error
```

```
## [1] 0.1775
```

```
e1071_CV_error
```

```
## [1] 0.1388
```

```
svmr_CV_error
```

```
## [1] 0.13
```

```
svmr2_CV_error
```

```
## [1] 0.1288
```

```
gbMA_CV_error
```

```
## [1] 0.1112
```

The gbmA boosted model has the highest mean and median ROC value, based on the resampling summary. The random forest model, however, has the lowest cross-validation error, therefore is the model I choose.

## Scaled Model Performance

```
res2 = resamples(list(GLM = scaled.model.glm,
                      GLMNET = scaled.model.glmn,
                      KNN = scaled.model.knn,
                      PLS = scaled.model.pls,
                      GAM = scaled.model.gam,
                      MARS = scaled.model.mars,
                      LDA = scaled.model.lda,
                      QDA = scaled.model.qda,
                      NB = scaled.model.nb,
                      CART = scaled.model.cart,
                      CIT = scaled.model.cit,
                      RF = scaled.model.rf,
                      SVML = scaled.model.svml,
                      E1071 = scaled.model.svml2,
                      SVMR = scaled.model.svmr,
                      SVMR2 = scaled.model.svmr2,
                      gbmA = scaled.model.gbmA
                    ))

summary(res2)
```

```
##
## Call:
## summary.resamples(object = res2)
##
## Models: GLM, GLMNET, KNN, PLS, GAM, MARS, LDA, QDA, NB, CART, CIT, RF, SVML, E1071, SVMR, SVMR2, gbmA
## Number of resamples: 10
##
## ROC
```

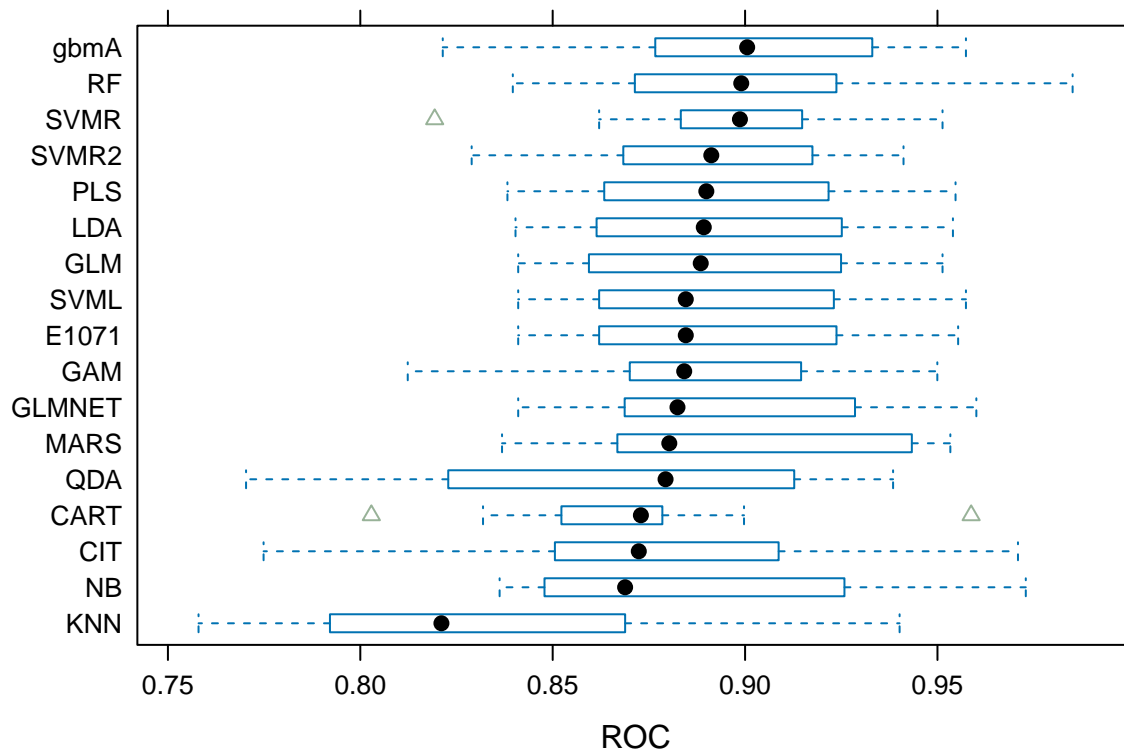
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
## GLM	0.8410364	0.8594164	0.8884762	0.8902533	0.9211279	0.9513185	0
## GLMNET	0.8410364	0.8705239	0.8824337	0.8946561	0.9271709	0.9601082	0
## KNN	0.7579576	0.7927719	0.8210784	0.8300805	0.8668528	0.9401623	0
## PLS	0.8382353	0.8653846	0.8899325	0.8927358	0.9192186	0.9546991	0
## GAM	0.8123249	0.8700265	0.8841817	0.8874978	0.9122597	0.9499662	0
## MARS	0.8368347	0.8678010	0.8803050	0.8954023	0.9367124	0.9533469	0
## LDA	0.8403361	0.8637268	0.8892694	0.8921525	0.9221443	0.9540230	0
## QDA	0.7703081	0.8323010	0.8793382	0.8685147	0.9055691	0.9384719	0
## NB	0.8362069	0.8484358	0.8688182	0.8860860	0.9235348	0.9729547	0
## CART	0.8028711	0.8556278	0.8729261	0.8711284	0.8778011	0.9587559	0
## CIT	0.7748599	0.8540285	0.8723739	0.8754698	0.9021152	0.9709263	0
## RF	0.8396359	0.8715673	0.8990027	0.8984987	0.9228471	0.9851251	0
## SVML	0.8410364	0.8627321	0.8845903	0.8911562	0.9204239	0.9574037	0
## E1071	0.8410364	0.8627321	0.8845903	0.8910873	0.9207640	0.9553753	0
## SVMR	0.8193277	0.8849469	0.8986646	0.8967070	0.9147678	0.9513185	0
## SVMR2	0.8289385	0.8689329	0.8912244	0.8870851	0.9168427	0.9411765	0
## gbmA	0.8214286	0.8774867	0.9005426	0.9010838	0.9329702	0.9574037	0

```
##
## Sens
```

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
--	------	---------	--------	------	---------	------	------

```
## GLM      0.8269231 0.8676471 0.8930995 0.8852187 0.9038462 0.9215686 0
## GLMNET   0.8846154 0.9264706 0.9607843 0.9435897 0.9615385 0.9803922 0
## KNN      0.8846154 0.9038462 0.9215686 0.9242459 0.9411765 0.9803922 0
## PLS      0.7647059 0.7901584 0.8640649 0.8461161 0.8970588 0.9038462 0
## GAM      0.8235294 0.8529412 0.8942308 0.8891026 0.9215686 0.9423077 0
## MARS     0.8235294 0.8486991 0.8738688 0.8773379 0.9171380 0.9230769 0
## LDA      0.7843137 0.7901584 0.8640649 0.8480769 0.8970588 0.9038462 0
## QDA      0.8039216 0.8438914 0.8725490 0.8715686 0.9033748 0.9230769 0
## NB       0.9038462 0.9411765 0.9607843 0.9572021 0.9615385 1.0000000 0
## CART     0.8076923 0.8627451 0.8834842 0.8872172 0.9278846 0.9607843 0
## CIT      0.8431373 0.8461538 0.9117647 0.8969080 0.9371229 0.9607843 0
## RF       0.8461538 0.9215686 0.9321267 0.9261312 0.9420249 0.9803922 0
## SVMML    0.7058824 0.7730015 0.8039216 0.7974736 0.8260747 0.8461538 0
## E1071    0.8461538 0.8872549 0.9313725 0.9162519 0.9420249 0.9807692 0
## SVMR     0.8269231 0.8823529 0.8921569 0.8852187 0.9033748 0.9038462 0
## SVMR2    0.8269231 0.8725490 0.9019608 0.8891026 0.9033748 0.9230769 0
## gbmA     0.8461538 0.8829186 0.9215686 0.9144419 0.9371229 0.9803922 0
##
## Spec
##          Min.    1st Qu.    Median      Mean    3rd Qu.      Max. NA's
## GLM      0.6206897 0.6982759 0.7543103 0.7906404 0.8956281 0.9642857 0
## GLMNET   0.5172414 0.6071429 0.6483990 0.6713054 0.7241379 0.8571429 0
## KNN      0.4642857 0.4959975 0.5615764 0.5522167 0.5825123 0.6551724 0
## PLS      0.6785714 0.7672414 0.8251232 0.8289409 0.8956281 0.9642857 0
## GAM      0.5862069 0.7167488 0.7413793 0.7624384 0.8519089 0.8928571 0
## MARS     0.6206897 0.6982759 0.7370690 0.7661330 0.8497537 0.9285714 0
## LDA      0.6785714 0.7672414 0.8251232 0.8289409 0.8956281 0.9642857 0
## QDA      0.5862069 0.6958128 0.7241379 0.7626847 0.8620690 0.9285714 0
## NB       0.3928571 0.4959975 0.5615764 0.5619458 0.6120690 0.7586207 0
## CART     0.6071429 0.6610222 0.7198276 0.7237685 0.7586207 0.8620690 0
## CIT      0.6071429 0.7241379 0.7543103 0.7658867 0.8275862 0.8928571 0
## RF       0.5862069 0.6899631 0.7370690 0.7480296 0.8362069 0.8965517 0
## SVMML    0.6785714 0.8017241 0.8602217 0.8428571 0.8956281 0.9642857 0
## E1071    0.5172414 0.6160714 0.7068966 0.7099754 0.8171182 0.8620690 0
## SVMR     0.6428571 0.7167488 0.7931034 0.8007389 0.8956281 0.9642857 0
## SVMR2    0.6071429 0.7047414 0.7758621 0.7832512 0.8928571 0.8965517 0
## gbmA     0.5517241 0.6958128 0.7370690 0.7413793 0.8103448 0.9285714 0
```

```
bwplot(res2, metric = "ROC")
```



## Test Data Performance

```
# test error: gbma
gbMA.test = predict(model.gbma, newdata = x.test)

confusionMatrix(data = gbMA.test,
                 reference = y.test,
                 )
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction  Not_severe Severe
```

```
## Not_severe      125     17
```

```
## Severe           10     48
```

```
##
```

```
##           Accuracy : 0.865
```

```
##           95% CI : (0.8097, 0.9091)
```

```
## No Information Rate : 0.675
```

```
## P-Value [Acc > NIR] : 5.597e-10
```

```
##
```

```
##           Kappa : 0.6835
```

```
##
```

```
## McNemar's Test P-Value : 0.2482
```

```
##
```

```
##           Sensitivity : 0.9259
```

```
##           Specificity : 0.7385
```

```
## Pos Pred Value : 0.8803
```

```
## Neg Pred Value : 0.8276
```



```

##           Prevalence : 0.6750
##           Detection Rate : 0.6250
##           Detection Prevalence : 0.7100
##           Balanced Accuracy : 0.8322
##
##           'Positive' Class : Not_severe
##
# 1 - accuracy
gbmA_test_error = 1 - 0.865
gbmA_test_error

## [1] 0.135
# test error: random forest
rf.test = predict(model.rf, newdata = x.test)

confusionMatrix(data = rf.test,
                  reference = y.test,
                  )

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  Not_severe Severe
## Not_severe      124      18
## Severe           11      47
##
##           Accuracy : 0.855
##           95% CI : (0.7984, 0.9007)
##           No Information Rate : 0.675
##           P-Value [Acc > NIR] : 4.95e-09
##
##           Kappa : 0.66
##
## Mcnemar's Test P-Value : 0.2652
##
##           Sensitivity : 0.9185
##           Specificity : 0.7231
##           Pos Pred Value : 0.8732
##           Neg Pred Value : 0.8103
##           Prevalence : 0.6750
##           Detection Rate : 0.6200
##           Detection Prevalence : 0.7100
##           Balanced Accuracy : 0.8208
##
##           'Positive' Class : Not_severe
##
# 1 - accuracy
rf_test_error = 1 - 0.855
rf_test_error

## [1] 0.145

```