

# Data Science II Final Project Analysis

Camille Okonkwo

## Contents

<b>Background</b>	<b>3</b>
<b>Data</b>	<b>3</b>
Data Preparation . . . . .	3
<b>Exploratory analysis and data visualization</b>	<b>6</b>
Descriptive Statistics . . . . .	6
Continuous Variable Visualization . . . . .	6
<b>Model training</b>	<b>9</b>
Logistic Regression . . . . .	9
Penalized Logistic Regression . . . . .	12
KNN . . . . .	13
PLS . . . . .	14
MARS . . . . .	15
GAM . . . . .	16
LDA . . . . .	19
QDA . . . . .	21
Naive Bayes (NB) . . . . .	22
CART . . . . .	78
Conditional Inference Trees (CIT) . . . . .	80
Random Forest . . . . .	82
AdaBoost . . . . .	83
Support Vector Machine: linear . . . . .	84
SVML: e1071 . . . . .	85
SVML: Radial Sigma . . . . .	86
SVML: radial cost . . . . .	87
<b>Results</b>	<b>88</b>
Model Comparison: Cross Validation Performance . . . . .	88
Test Data Performance . . . . .	101

```
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") # is depression discrete?

# 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

```
# when doing data exploration, should we do this on the entire dataset? do we need to create a random sample?

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

ds = t1kable(descriptive_table)
ds
```

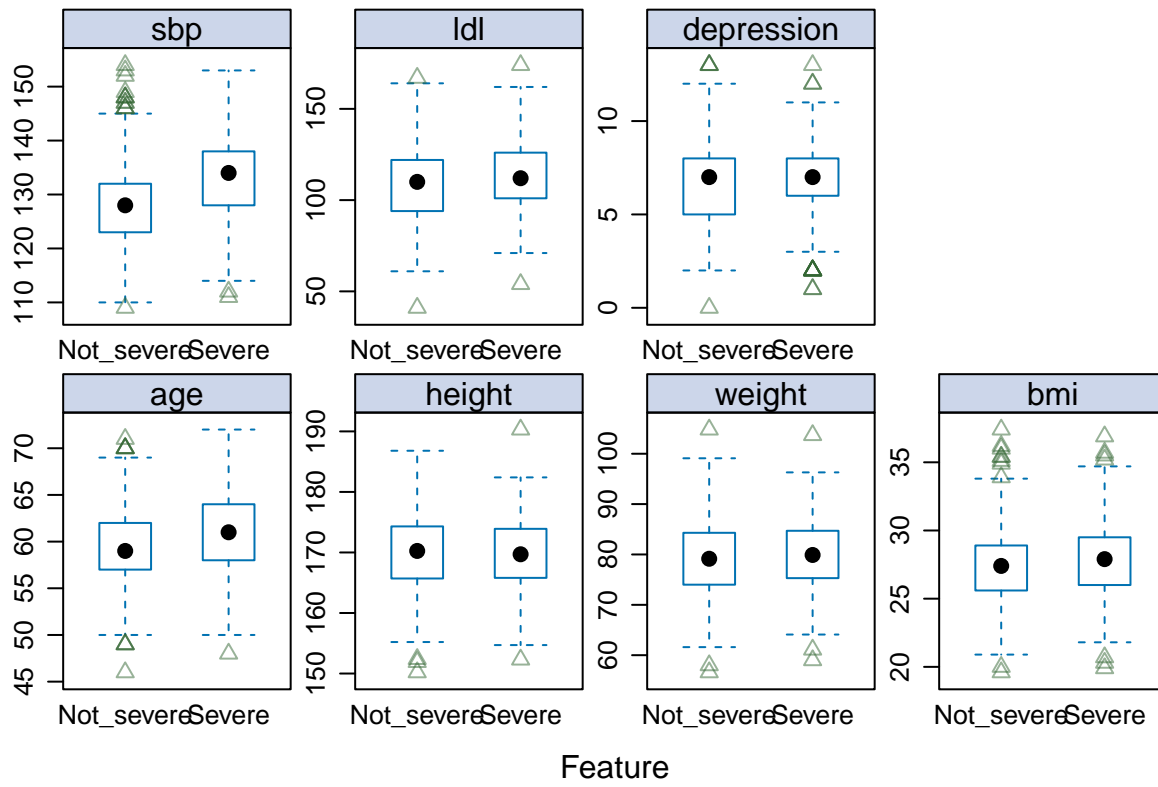
### Continuous Variable Visualization

```
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]





## Model training

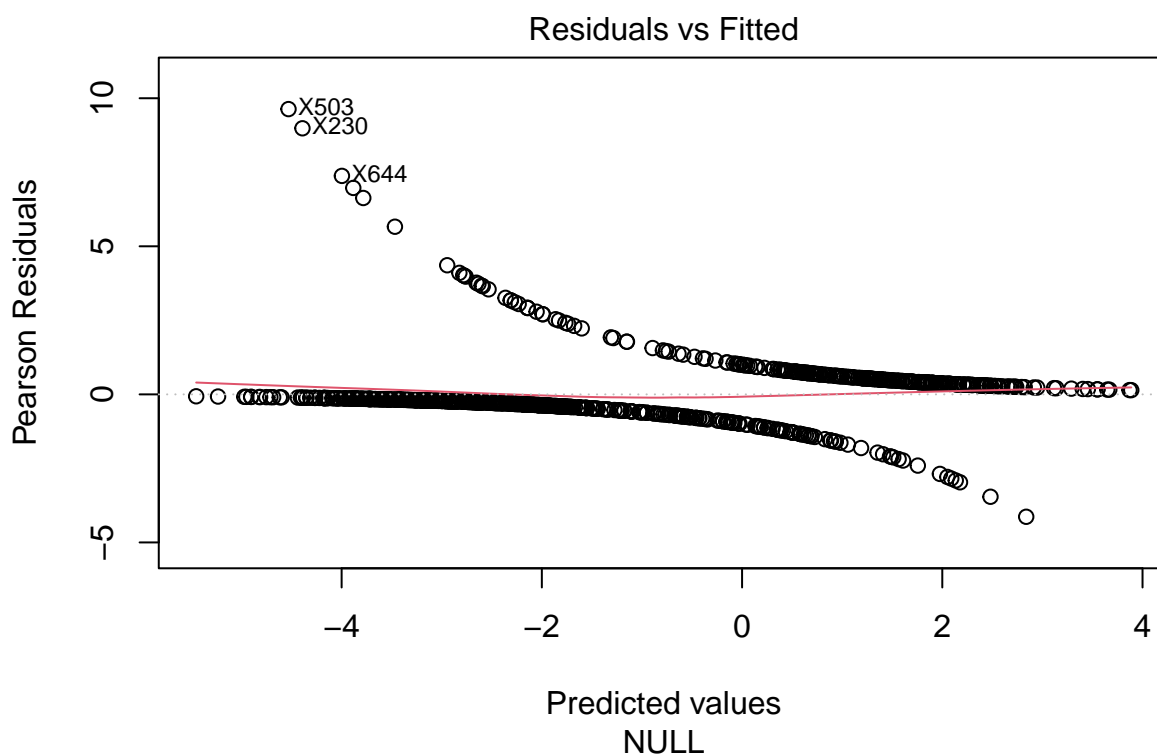
### Logistic Regression

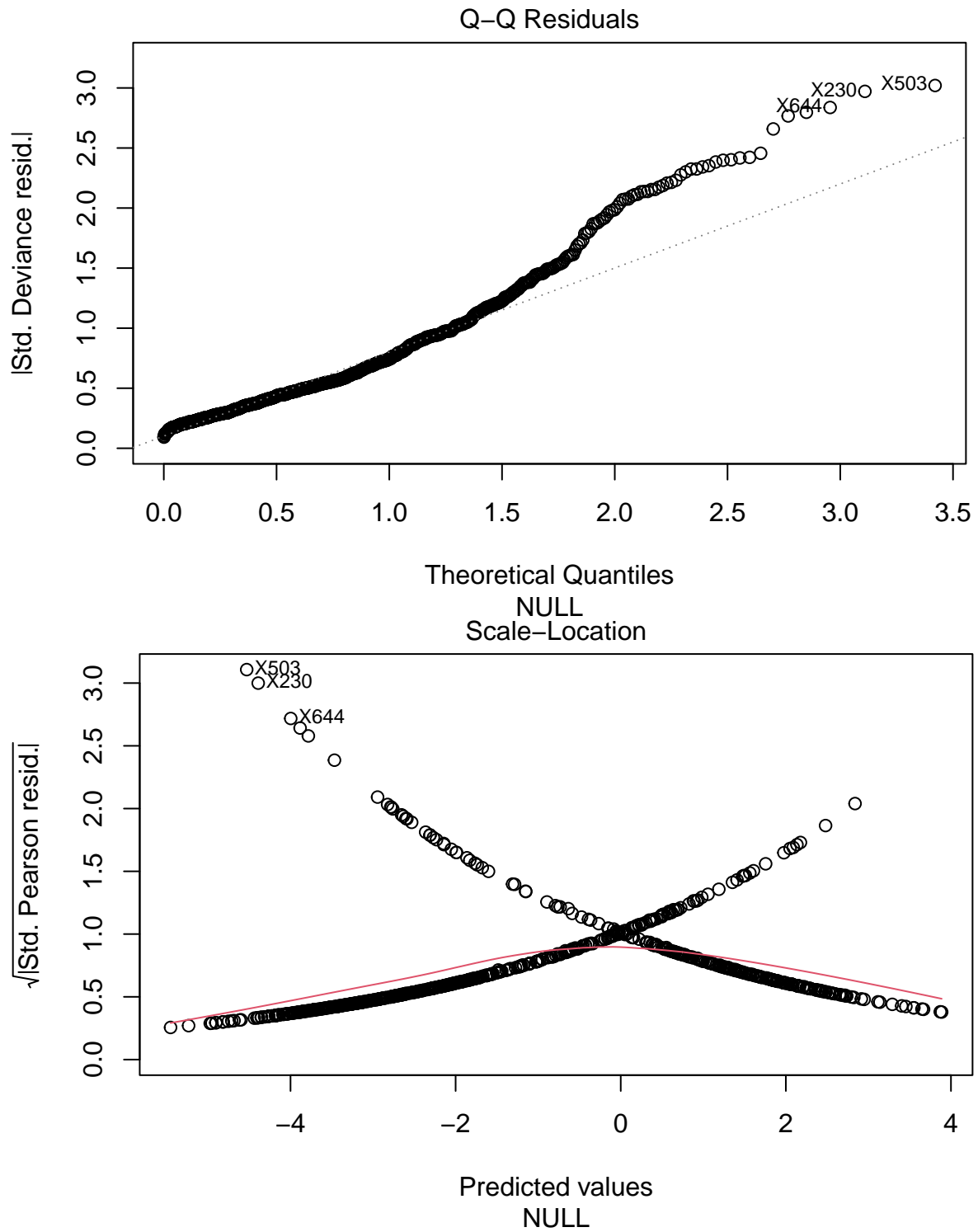
```
# setting a 10-fold cross-validation
ctrl = trainControl(method = "cv", number = 10,
                    summaryFunction = twoClassSummary,
                    classProbs = TRUE)

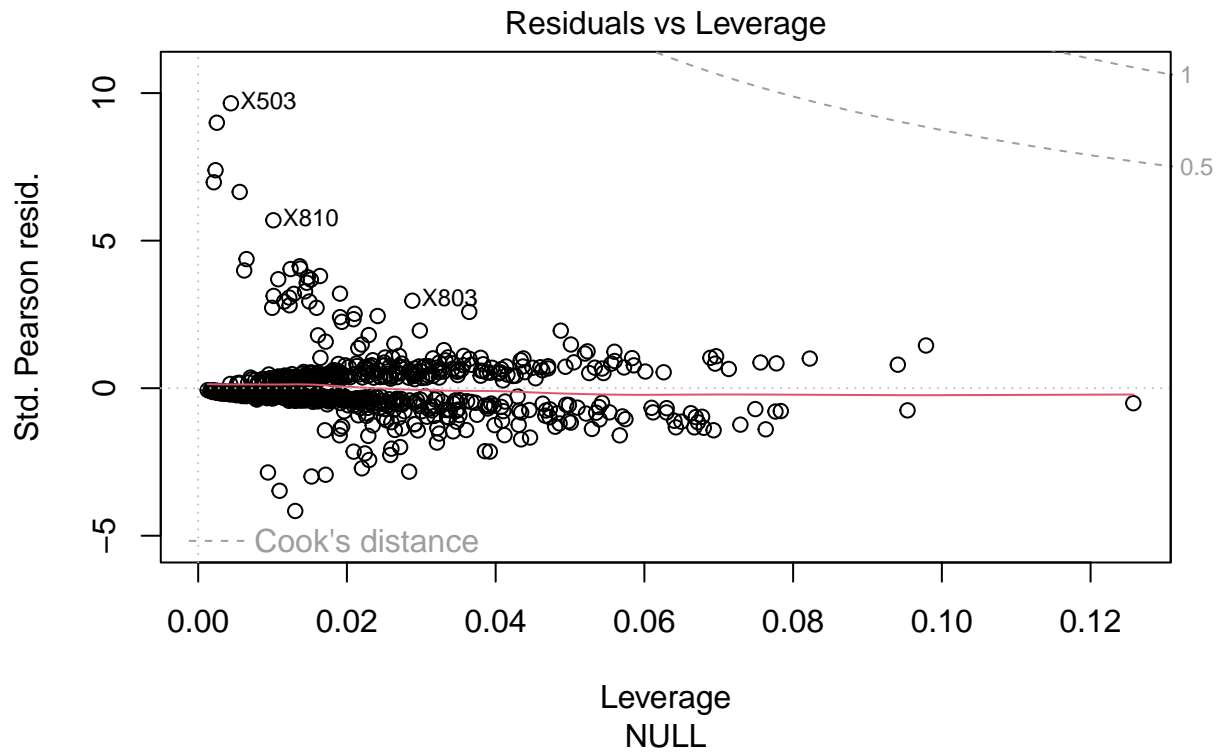
set.seed(2)

# logistic regression
model.glm = train(x = training_data[1:13],
                  y = training_data$severity,
                  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
```

## Penalized Logistic Regression

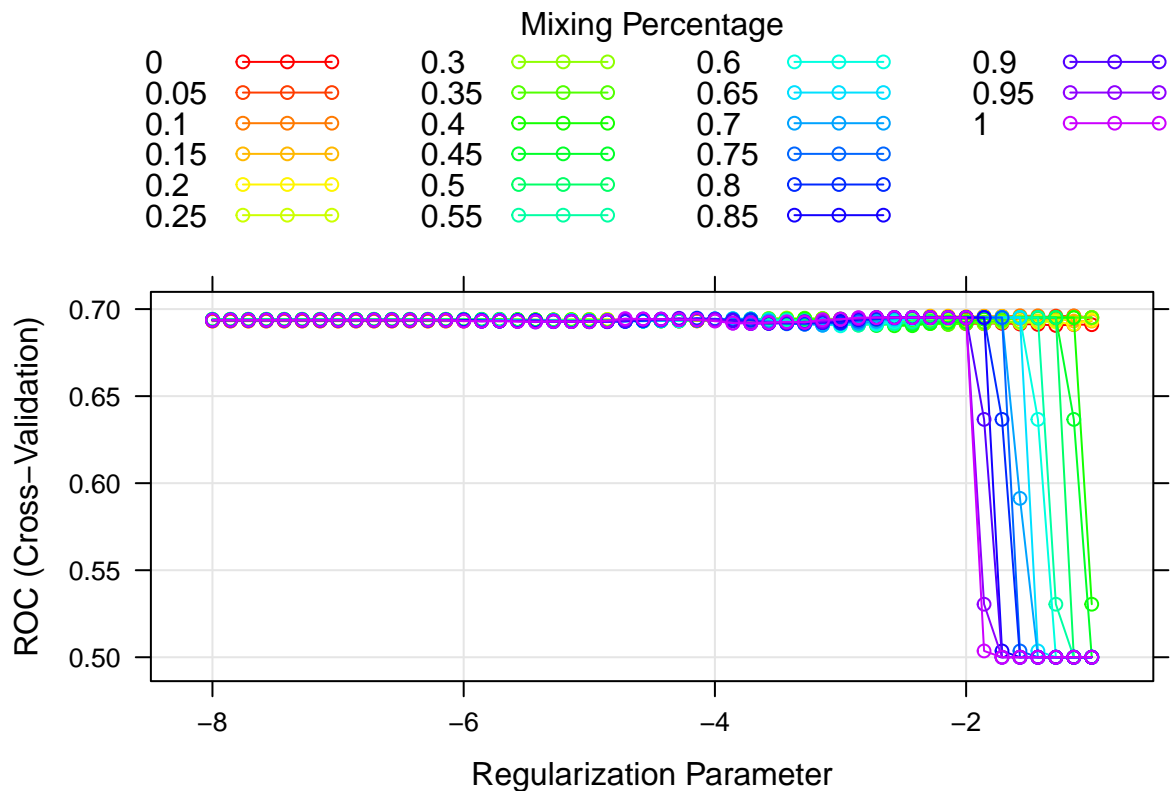
```
# penalized logistic regression - elastic net (need help)
glmnetGrid = expand.grid(.alpha = seq(0, 1, length = 21),
                        .lambda = exp(seq(-8, -1, length = 50)))

set.seed(2)
model.glmnet = train(x = training_data[1:13],
                     y = training_data$severity,
                     method = "glmnet",
                     tuneGrid = glmnetGrid,
                     metric = "ROC",
                     trControl = ctrl)

model.glmnet$bestTune
```

```
##      alpha      lambda
## 146    0.1 0.2077482
```

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

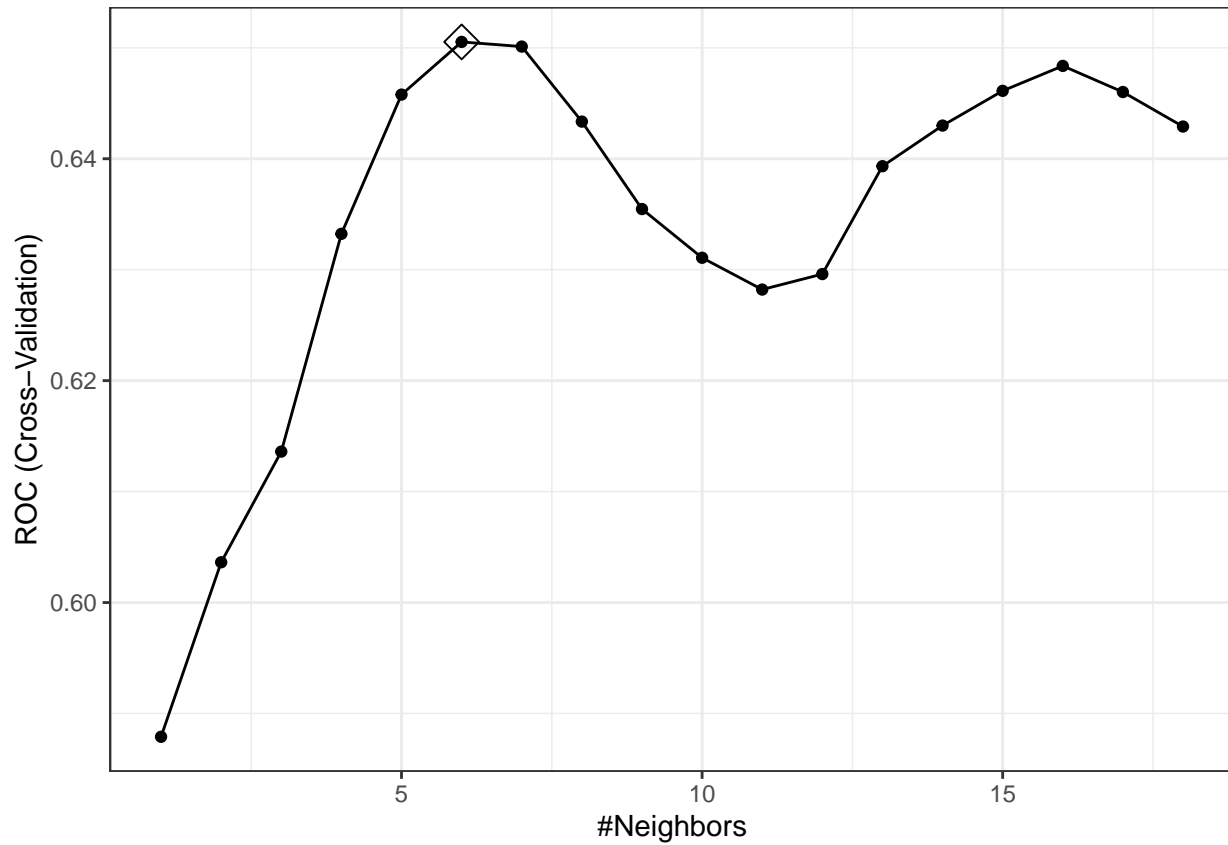


## KNN

```
set.seed(2)

model.knn = train(x.train, y.train,
  method = "knn",
  trControl = ctrl,
  tuneGrid = expand.grid(k = seq(from = 1, to = 18, by = 1)))

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

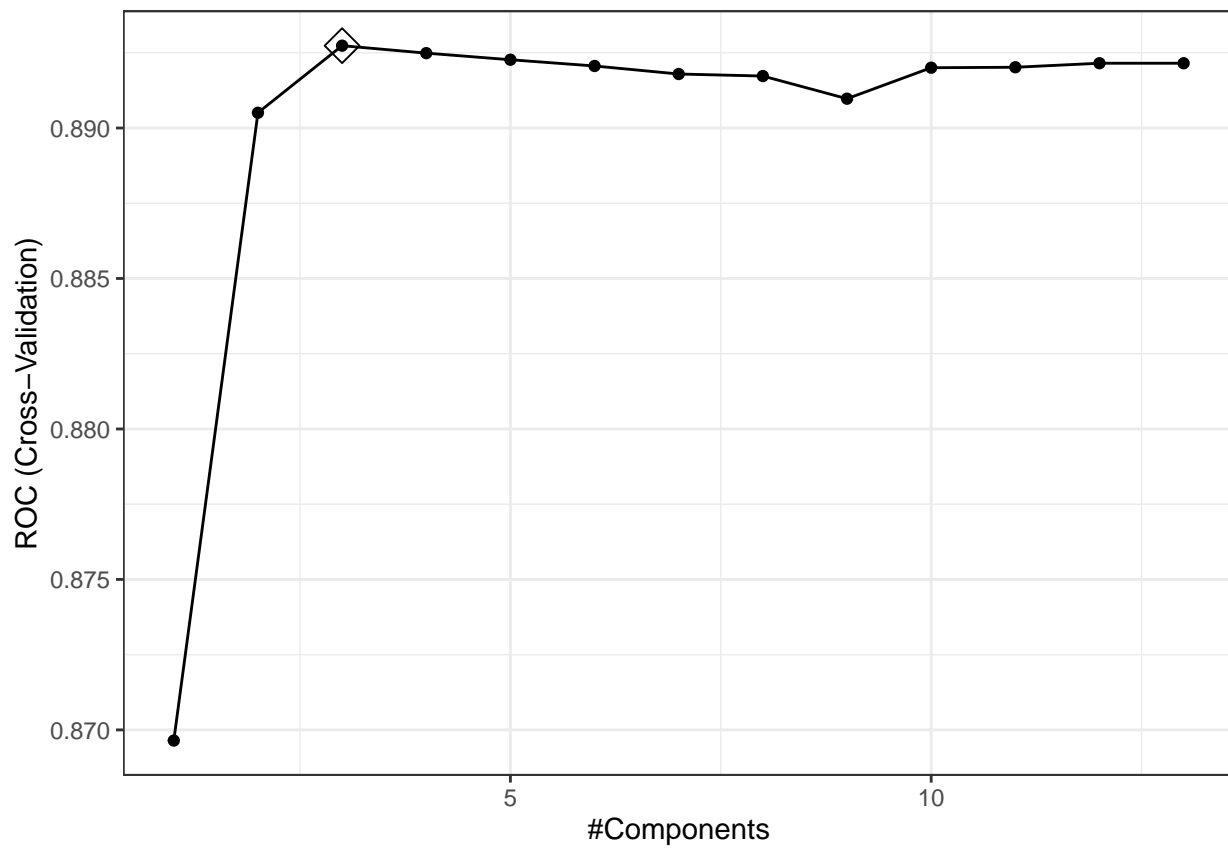


## PLS

```
set.seed(2)

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

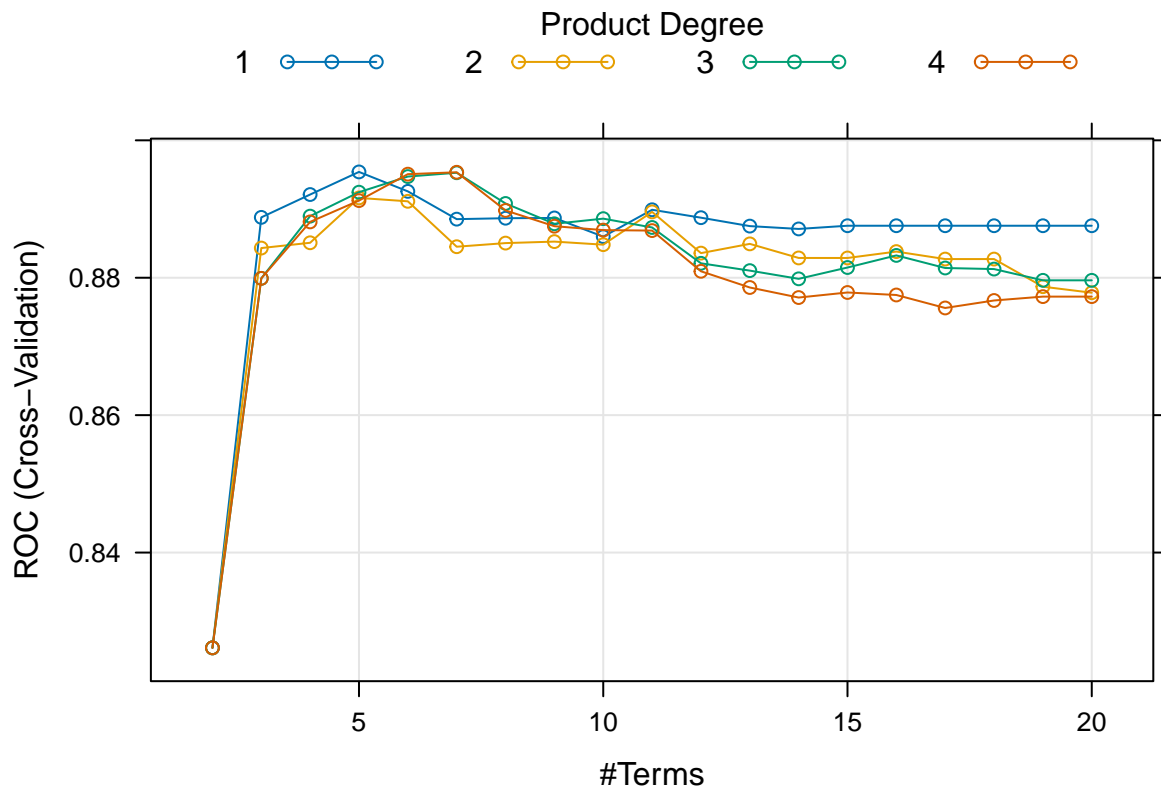
ggplot(model.pls, highlight = TRUE) + theme_bw()
```



## MARS

```
# MARS
set.seed(2)
model.mars = train(x = training_data[1:13],
  y = training_data$severity,
  method = "earth",
  tuneGrid = expand.grid(degree = 1:4,
    nprune = 2:20),
  metric = "ROC",
  trControl = ctrl)

plot(model.mars)
```



```
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
```

## GAM

```

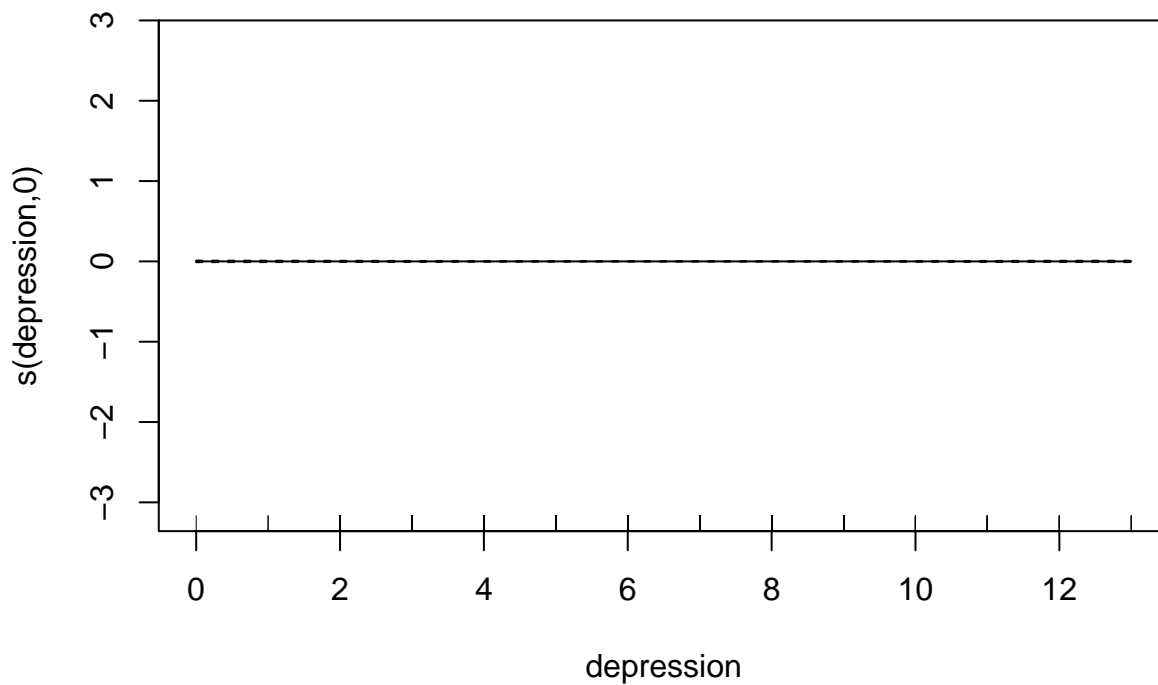
set.seed(2)

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

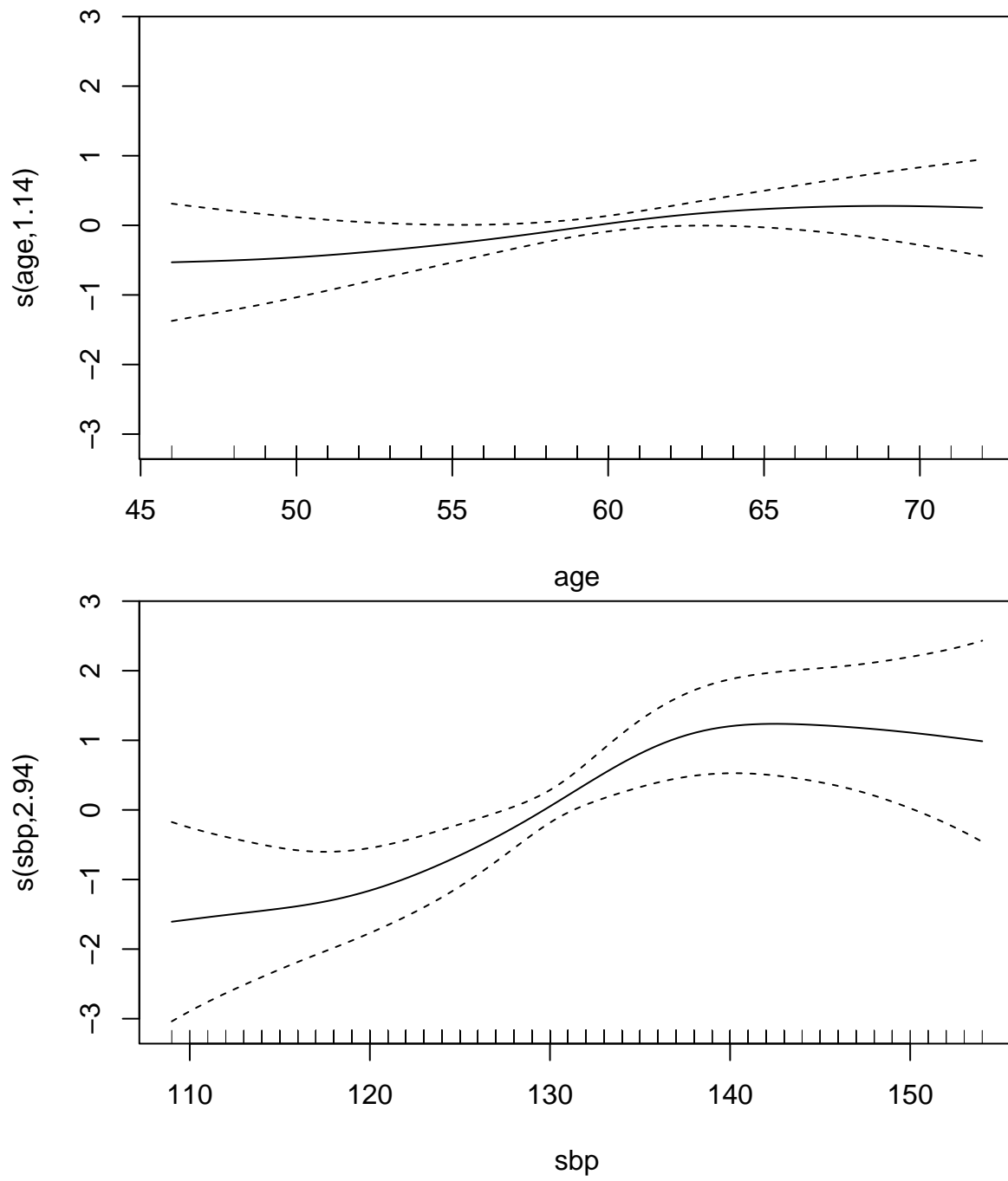
model.gam$finalModel

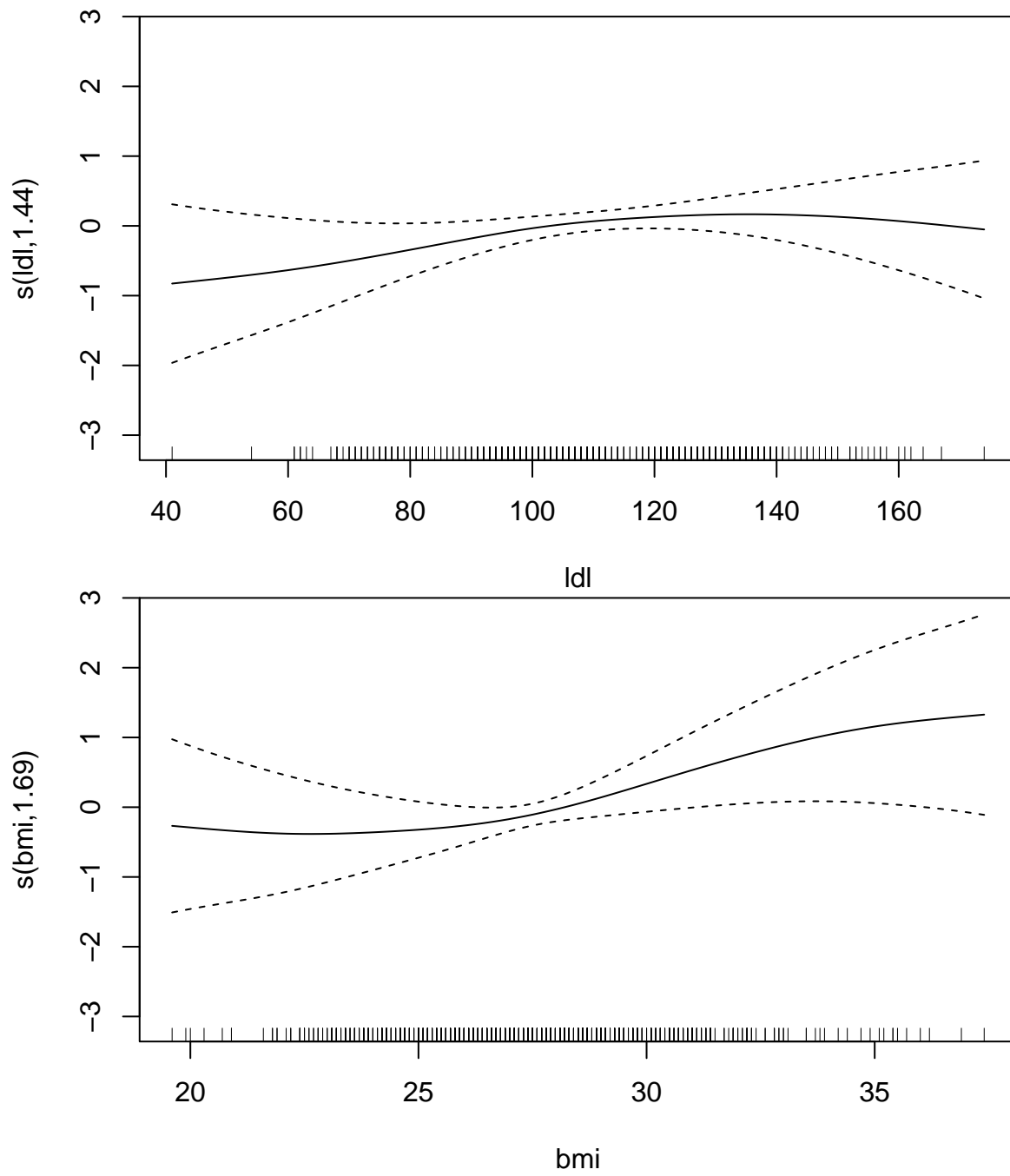
##
## Family: binomial
## Link function: logit
##
## Formula:
## .outcome ~ genderMale + raceAsian + raceBlack + raceHispanic +
##   smokingFormer_smoker + smokingCurrent_smoker + diabetesYes +
##   hypertensionYes + vaccineVaccinated + s(depression) + s(age) +
##   s(sbp) + s(ldl) + s(bmi) + s(height) + 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)

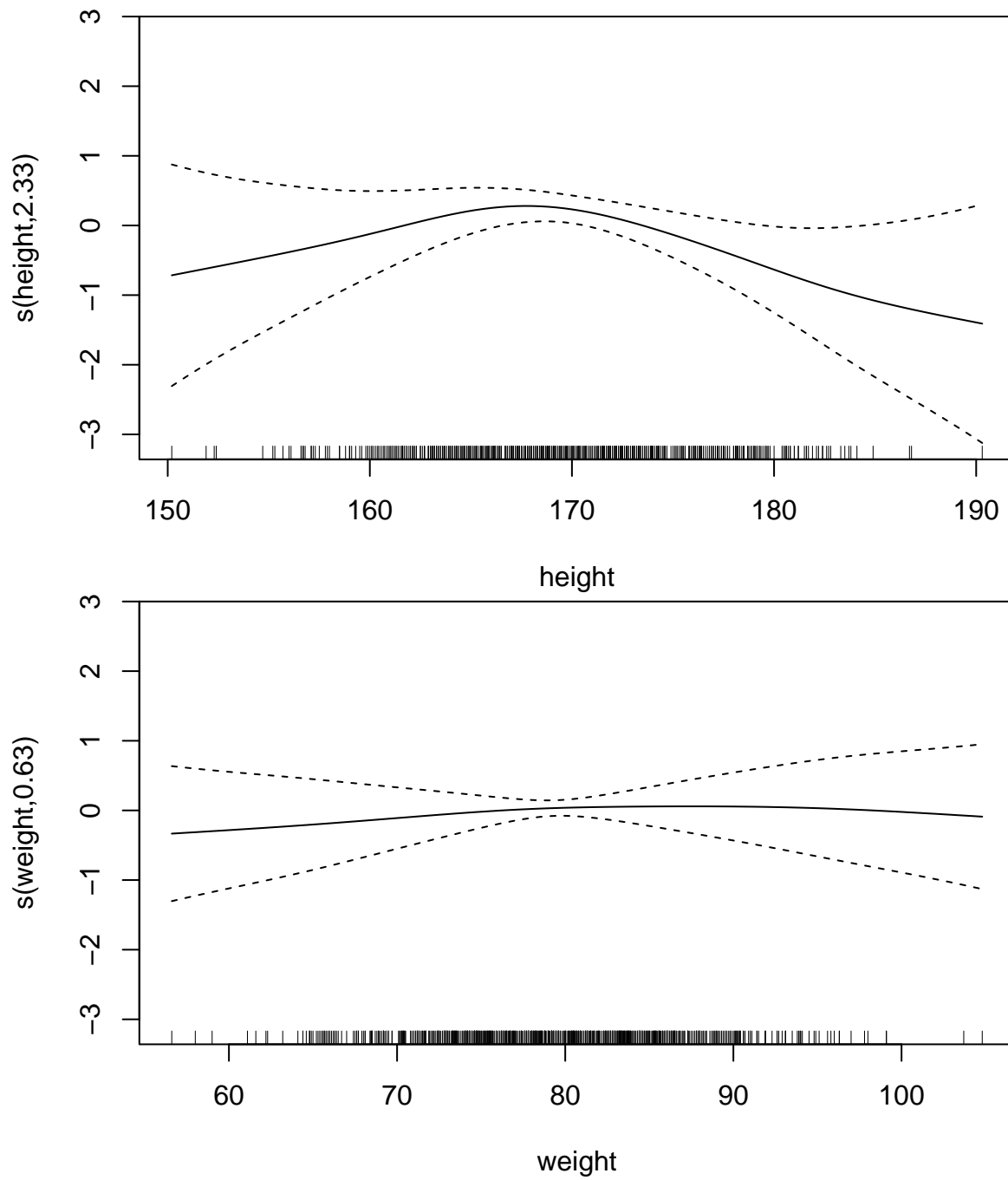
```











## 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
```

## QDA

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

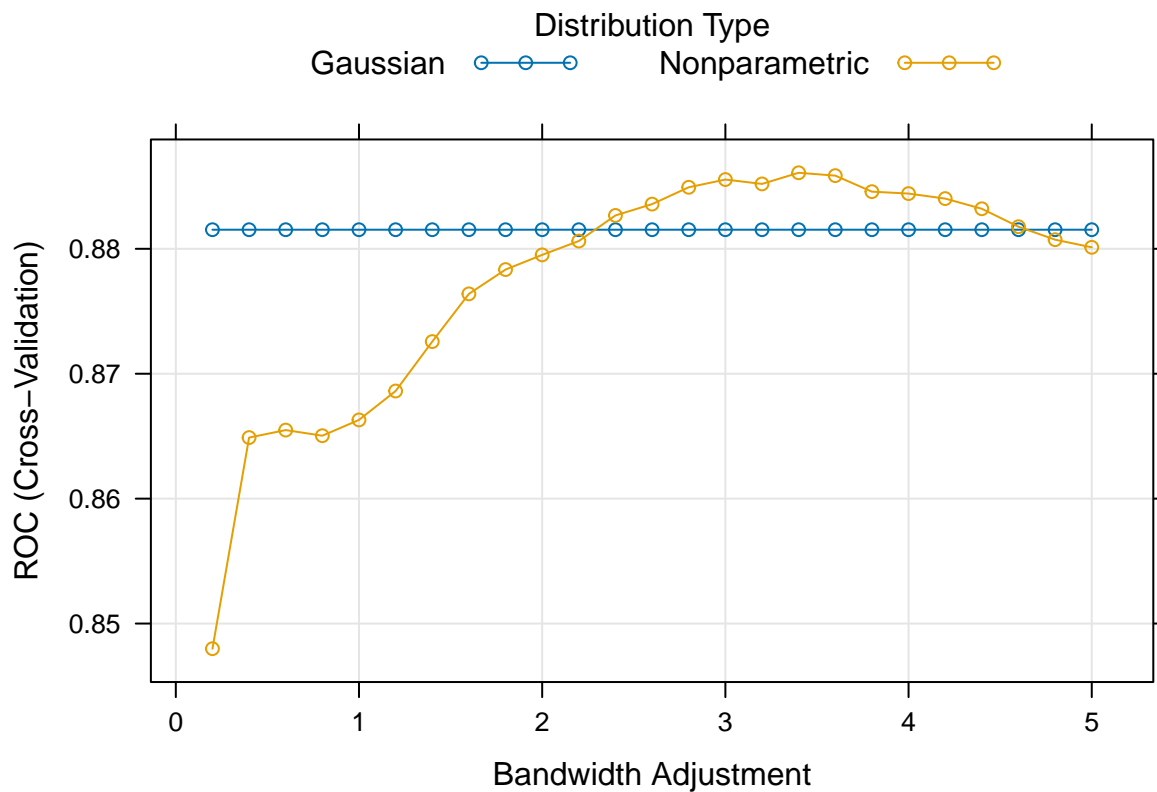
```
## Call:
## qda(x, grouping = y)
##
## Prior probabilities of groups:
## Not_severe      Severe
##      0.6425      0.3575
##
## Group means:
##               age genderMale  raceAsian raceBlack raceHispanic
## Not_severe 59.46887  0.5038911 0.06614786 0.2003891  0.09533074
## Severe    61.04545  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
```

## Naive Bayes (NB)

```
# how to tune 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	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	vaccine	Vaccinated	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

```

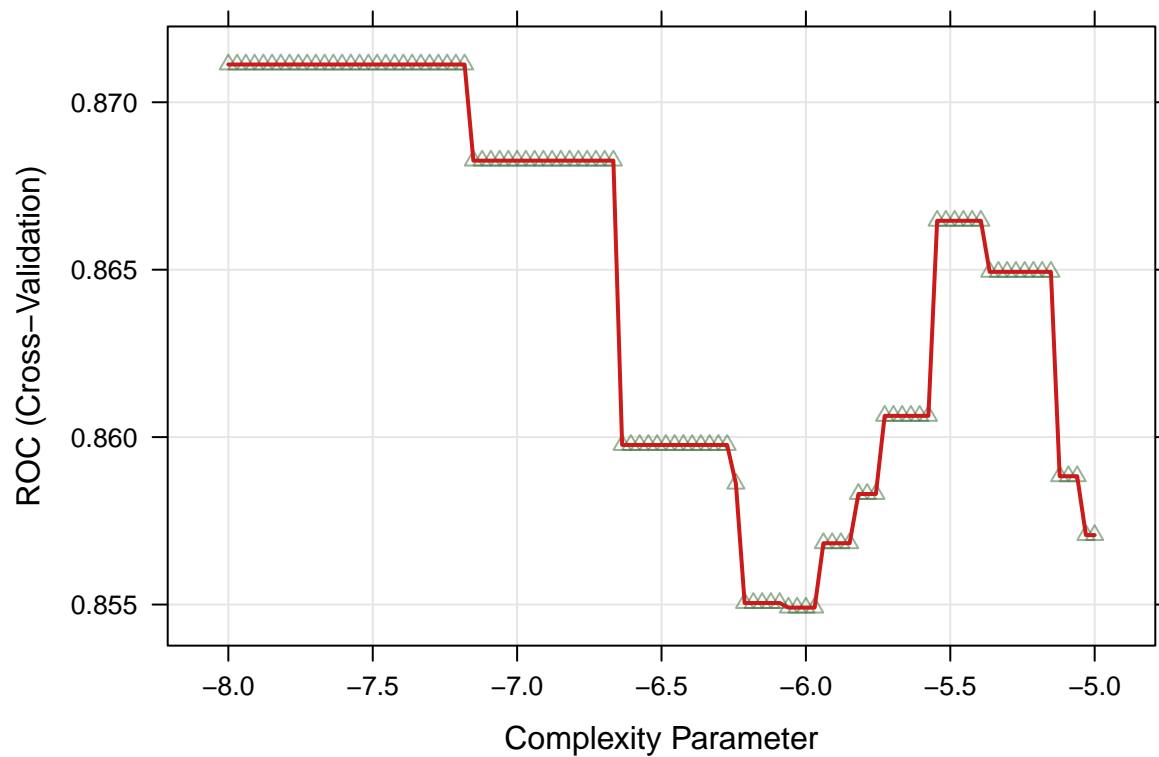
## X994  98          0          7
## X995 121          0          7
## X996 120          0          7
## X997 122          1          5
## X998 125          1          5
## X999  98          0          5
##
## $usekernel
## [1] TRUE
##
## $varnames
## [1] "age"          "genderMale"    "raceAsian"
## [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"

```

## CART

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

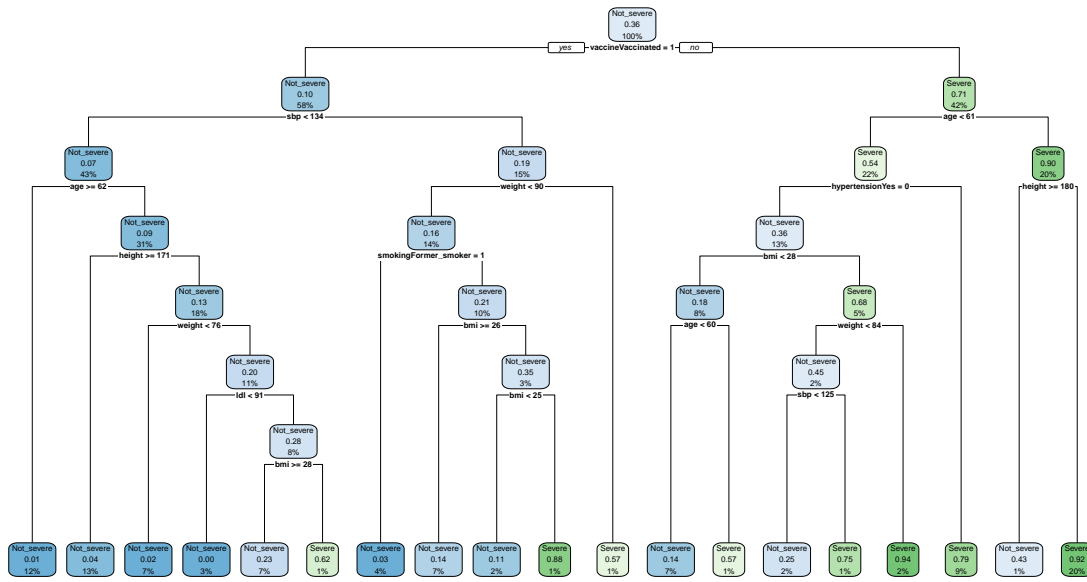
plot(model.cart, xTrans = log)
```



```
model.cart$bestTune
```

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

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

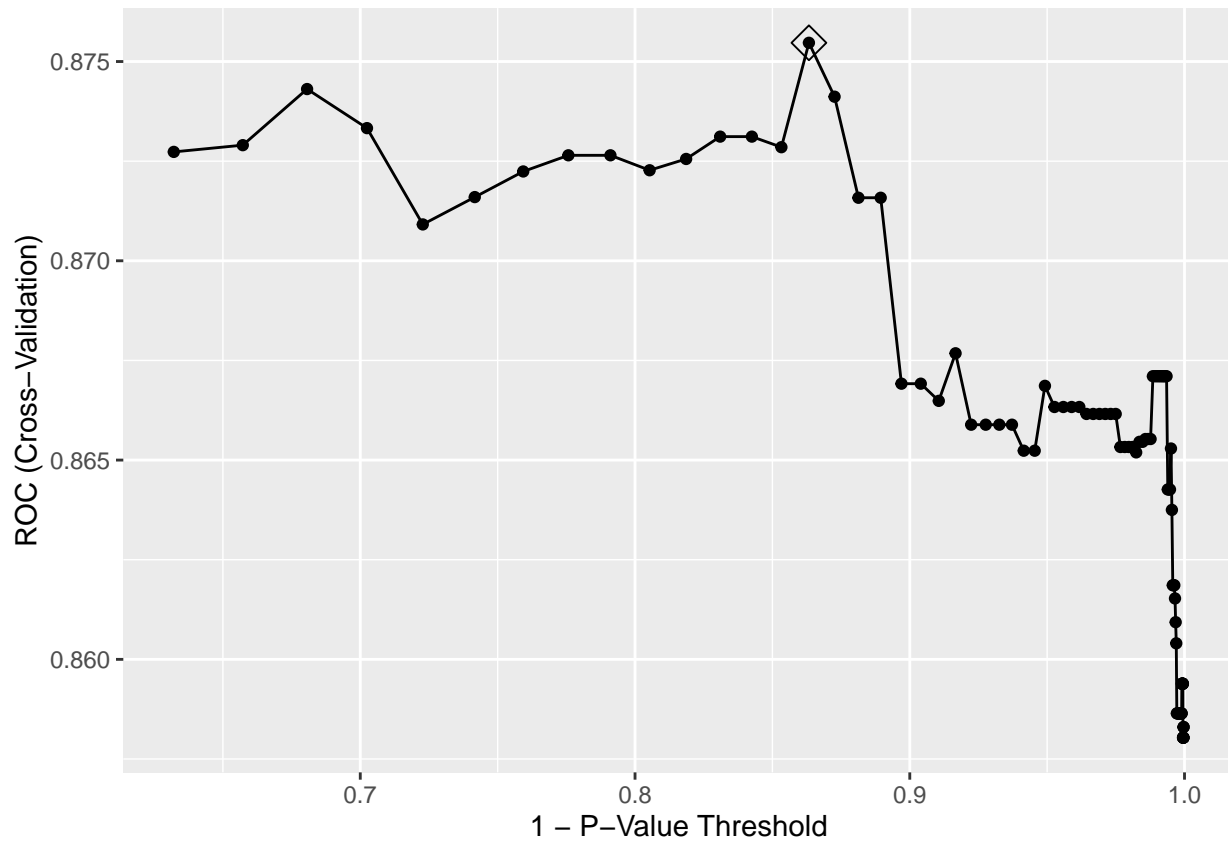


## Conditional Inference Trees (CIT)

```
set.seed(2)

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

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

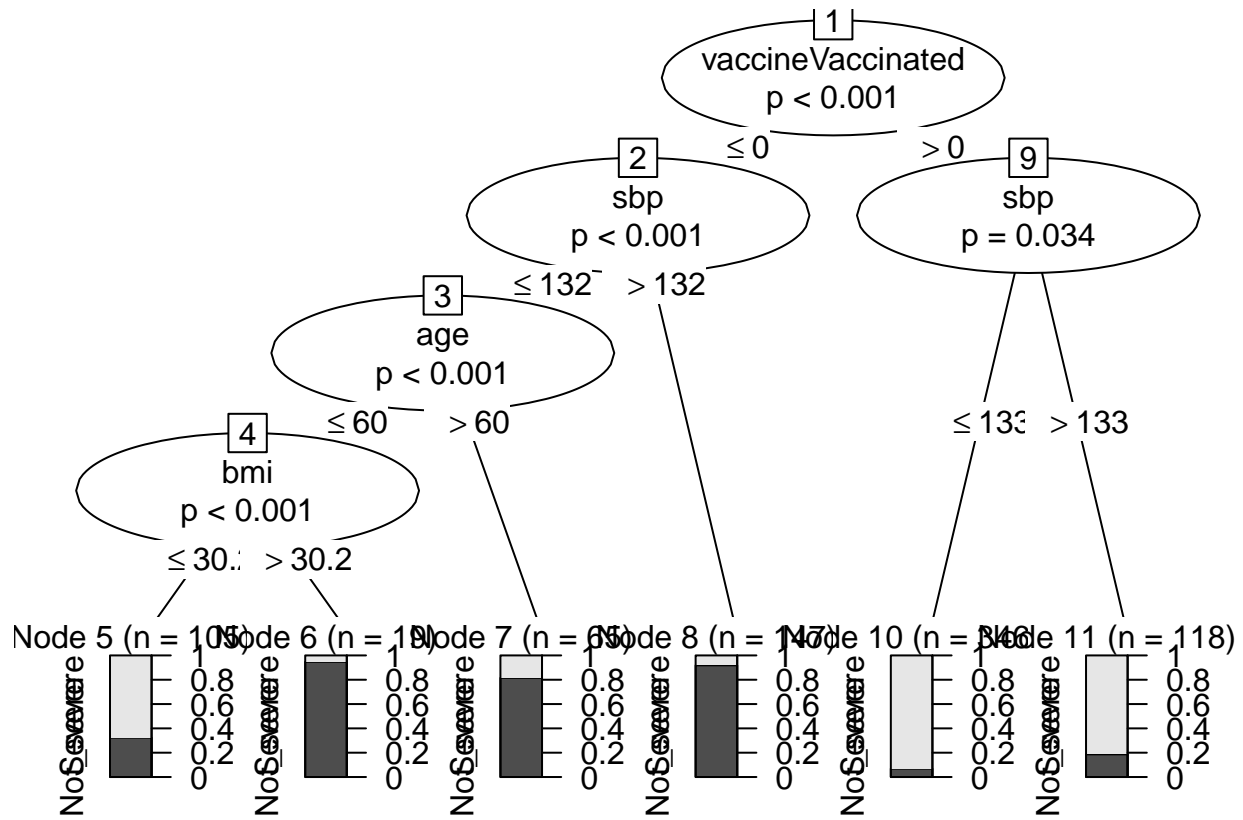


```
model.cit$bestTune
```

```
## mincriterion
## 15 0.8632908
```

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





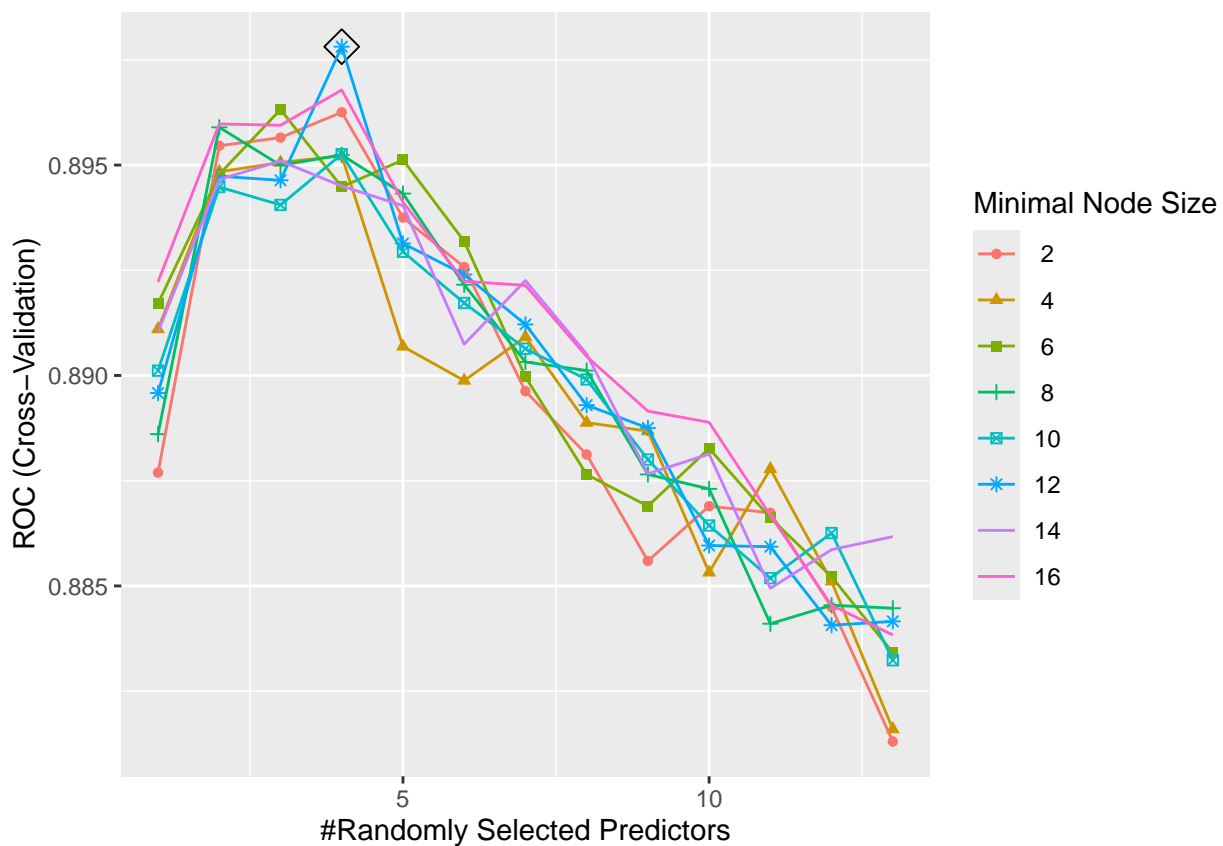
## Random Forest

```
# 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(severity ~ . ,
                 data = training_data,
                 method = "ranger",
                 tuneGrid = rf.grid,
                 trControl = ctrl)

model.rf$bestTune

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



## AdaBoost

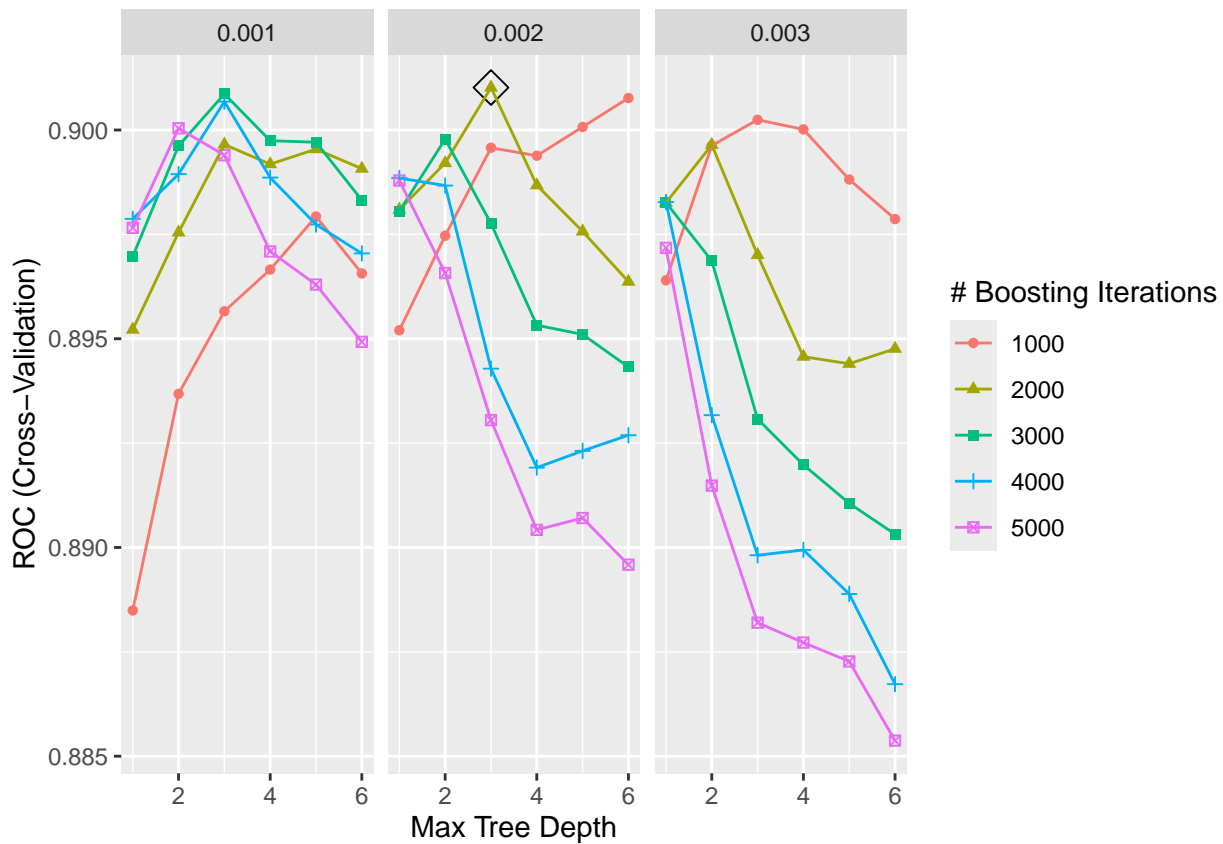
```
#Try more
gbmA.grid = expand.grid(n.trees = c(1000,2000,3000,4000,5000),
                        interaction.depth = 1:6,
                        shrinkage = c(0.001, 0.002, 0.003),
                        n.minobsinnode = 1)

set.seed(2)

model.gbmA = train(severity ~ . ,
                   training_data,
                   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)
```



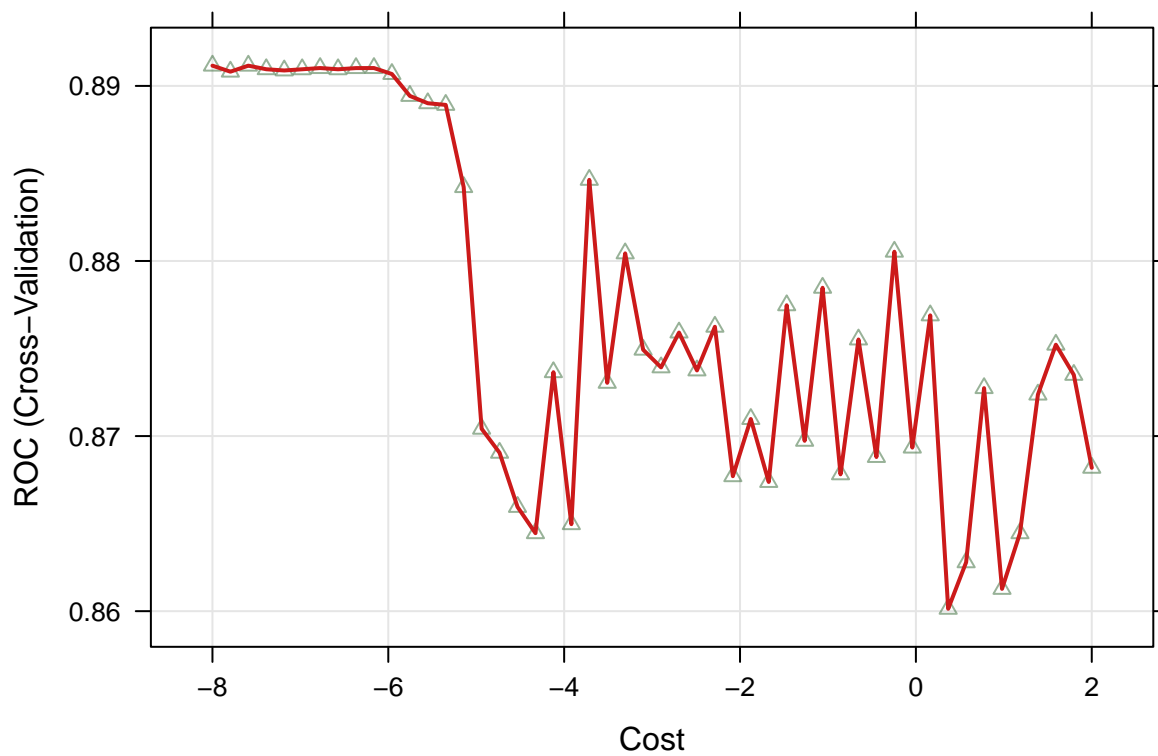
## Support Vector Machine: linear

```
set.seed(2)

model.svm1 = train(severity ~ . ,
  data = training_data,
  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)
```



## SVML: e1071

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

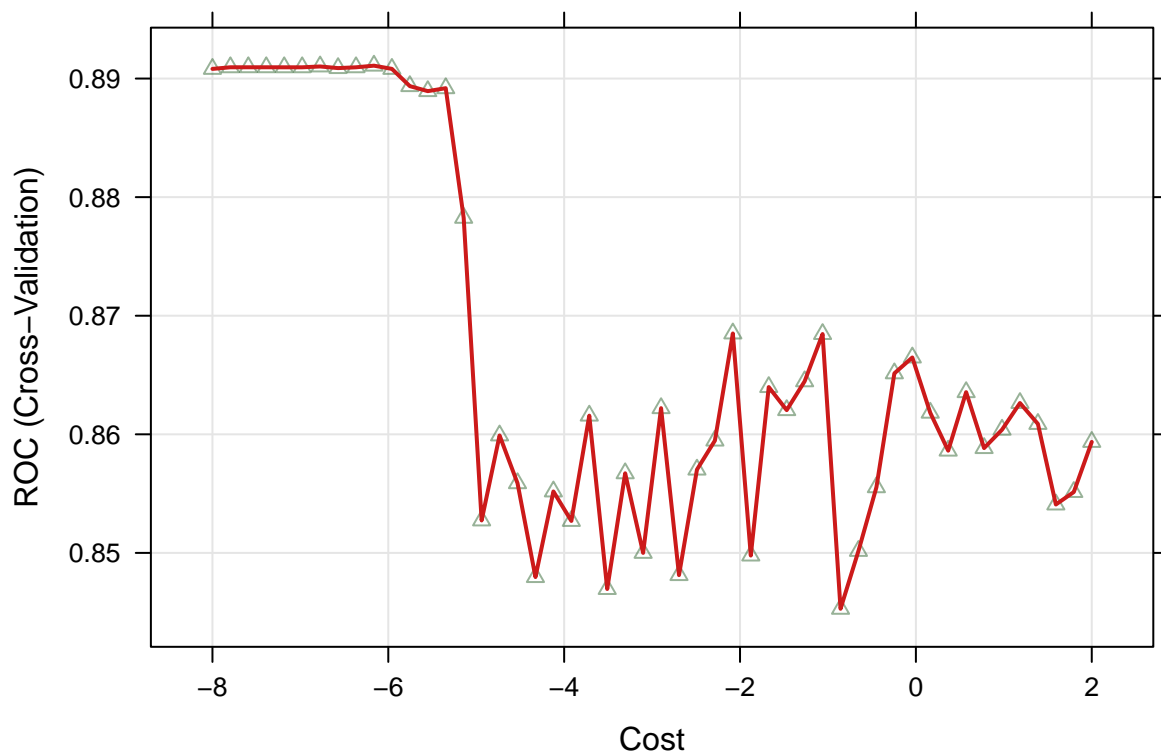
```
model.svm12 = train(severity ~ . ,
  data = training_data,
  method = "svmLinear2",
  tuneGrid = data.frame(cost = exp(seq(-8, 2, len = 50))),
  trControl = ctrl)
```

```
model.svm12$bestTune
```

```
##          cost
```

```
## 10 0.002105367
```

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



## SVML: 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(severity ~ . ,
                   data = training_data,
                   method = "svmRadialSigma",
                   tuneGrid = svmr.grid,
                   trControl = ctrl)
```

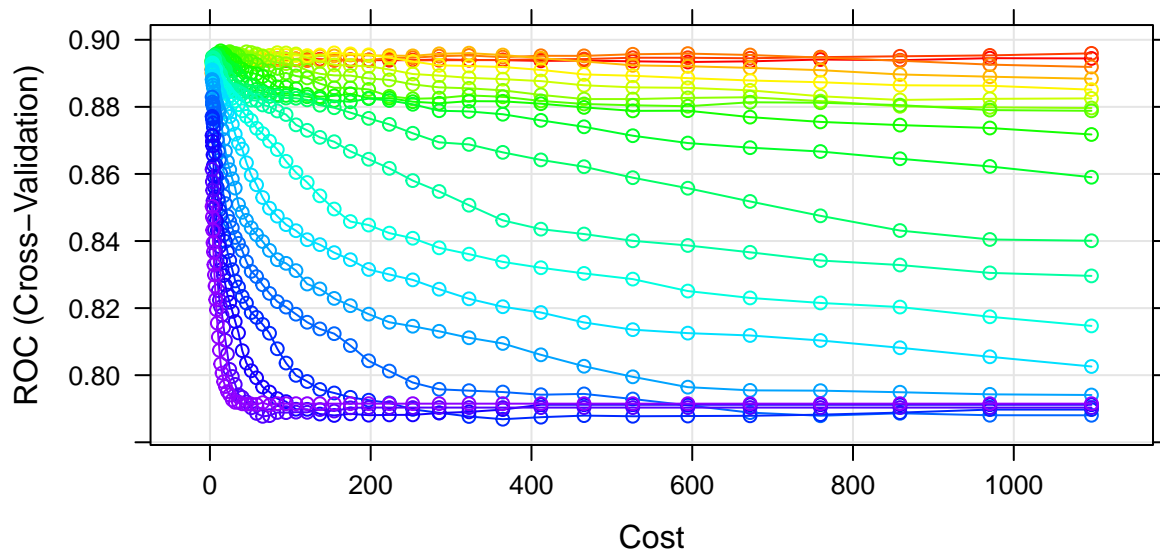
```
myCol = rainbow(25)
```

```
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)
```



## SVML: radial cost

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

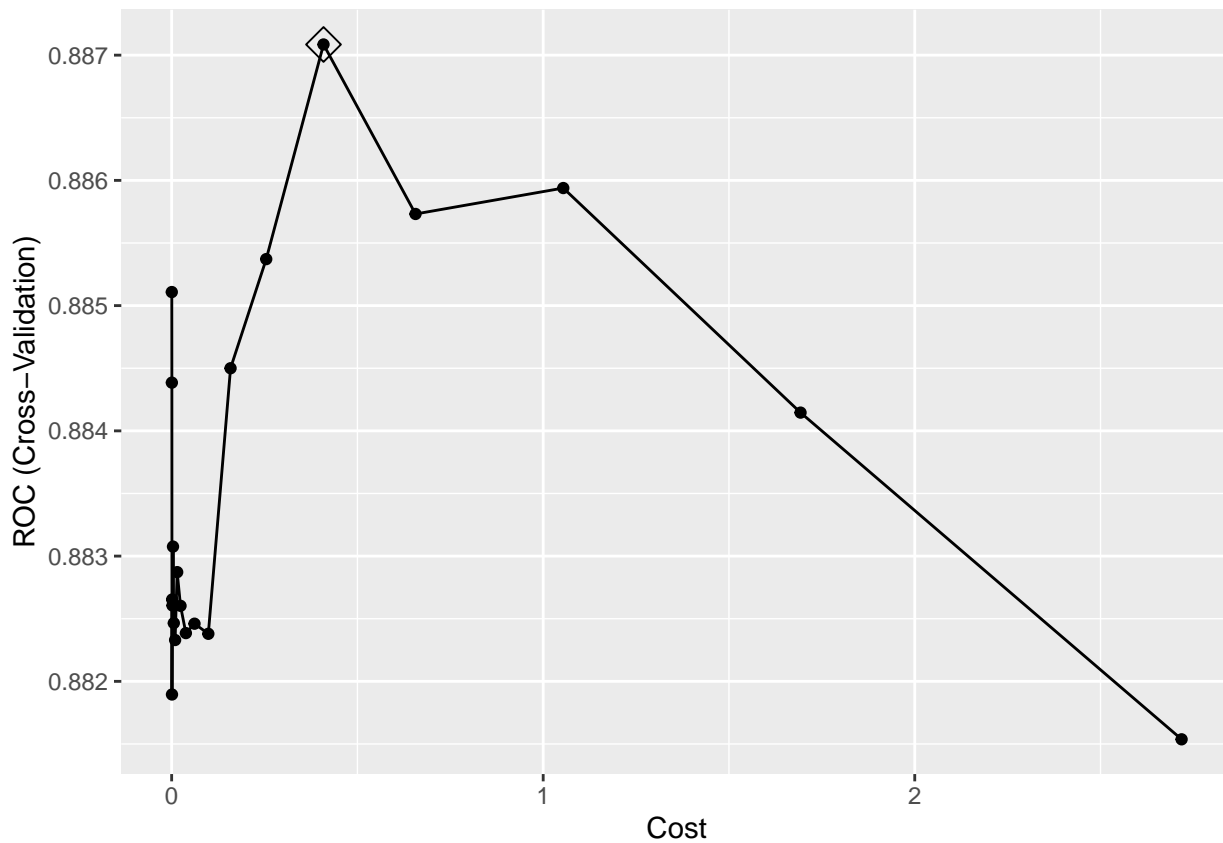
```
model.svmr2 = train(severity ~ . ,
  data = training_data,
  method = "svmRadialCost",
  tuneGrid = data.frame(C = exp(seq(-8, 1, len = 20))),
  trControl = ctrl)
```

```
## 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)
```



## 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
                     ))

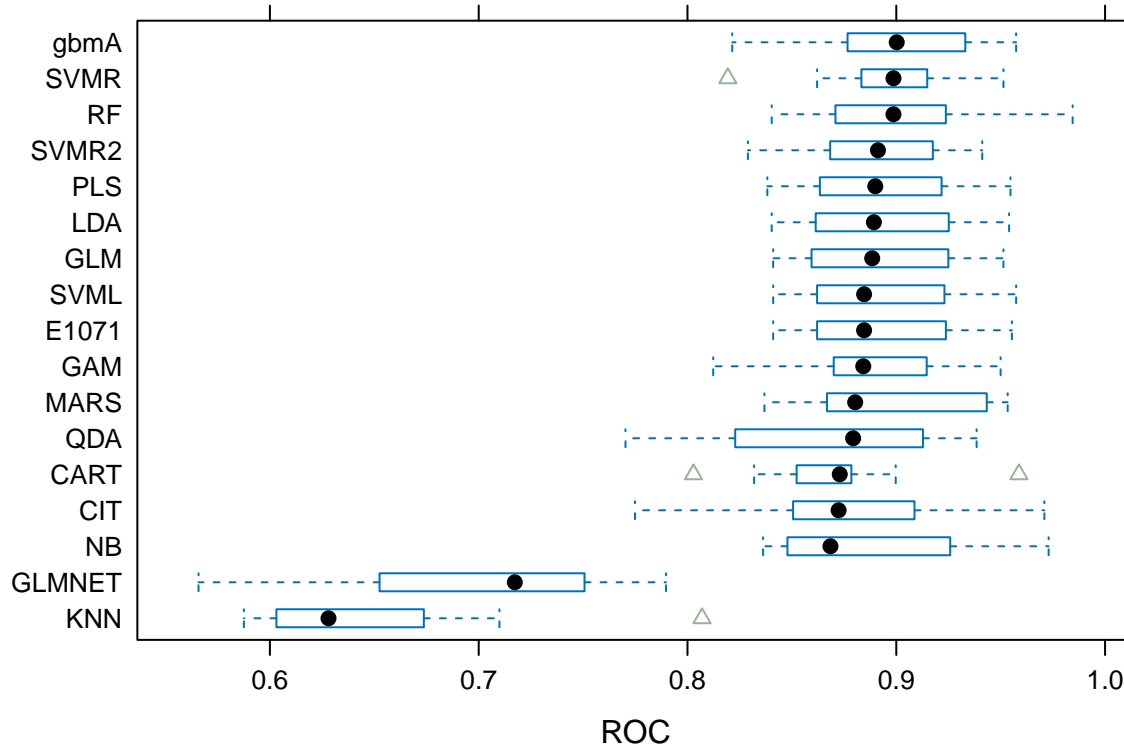
summary(res)
```

```
##
## 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    0.5658263 0.6652141 0.7172967 0.6961763 0.7462571 0.7897228    0
## KNN      0.5875350 0.6045609 0.6280788 0.6505299 0.6711704 0.8069642    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 0.9230769 0.9607843 0.9611614 0.9611614 0.9615385 1.0000000 0
## KNN 0.7115385 0.7364253 0.7843137 0.7921569 0.8195701 0.9411765 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 0.69827586 0.75431034 0.79064039 0.89562808 0.9642857 0
## GLMNET 0.0000000 0.06896552 0.07019704 0.07684729 0.09544335 0.1724138 0
## KNN 0.2142857 0.38269704 0.42118227 0.40443350 0.44827586 0.6206897 0
## PLS 0.6785714 0.76724138 0.82512315 0.82894089 0.89562808 0.9642857 0
## GAM 0.5862069 0.71674877 0.74137931 0.76243842 0.85190887 0.8928571 0
## MARS 0.6206897 0.69827586 0.73706897 0.76613300 0.84975369 0.9285714 0
## LDA 0.6785714 0.76724138 0.82512315 0.82894089 0.89562808 0.9642857 0
## QDA 0.5862069 0.69581281 0.72413793 0.76268473 0.86206897 0.9285714 0
## NB 0.3928571 0.49599754 0.56157635 0.56194581 0.61206897 0.7586207 0
## CART 0.6071429 0.66102217 0.71982759 0.72376847 0.75862069 0.8620690 0
## CIT 0.6071429 0.72413793 0.75431034 0.76588670 0.82758621 0.8928571 0
## RF 0.5862069 0.68996305 0.73706897 0.74802956 0.83620690 0.8965517 0
## SVM 0.6785714 0.80172414 0.86022167 0.84285714 0.89562808 0.9642857 0
## E1071 0.5172414 0.61607143 0.70689655 0.70997537 0.81711823 0.8620690 0
## SVMR 0.6428571 0.71674877 0.79310345 0.80073892 0.89562808 0.9642857 0
## SVMR2 0.6071429 0.70474138 0.77586207 0.78325123 0.89285714 0.8965517 0
## gbmA 0.5517241 0.69581281 0.73706897 0.74137931 0.81034483 0.9285714 0
```

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



```
# Cross-validation error
glm.predict = predict(model.glm, newdata = training_data)
# glmnet.predict = predict(model.glmn, newdata = x.train) # getting error?
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 = training_data)
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 = training_data)
cit.predict = predict(model.cit, newdata = training_data)
rf.predict = predict(model.rf, newdata = training_data)
svml.predict = predict(model.svml, newdata = training_data)
e1071.predict = predict(model.svml2, newdata = training_data)
svmr.predict = predict(model.svmr, newdata = training_data)
svmr2.predict = predict(model.svmr2, newdata = training_data)
gbmA.predict = predict(model.gbmA, newdata = training_data)

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

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  Not_severe Severe
## Not_severe      438     130
## Severe           76     156
##
##              Accuracy : 0.7425
##              95% CI : (0.7107, 0.7725)
##      No Information Rate : 0.6425
##      P-Value [Acc > NIR] : 9.156e-10
##
##              Kappa : 0.415
##
##      McNemar's Test P-Value : 0.0002219
##
##              Sensitivity : 0.8521
##              Specificity : 0.5455
##              Pos Pred Value : 0.7711
##              Neg Pred Value : 0.6724
##              Prevalence : 0.6425
##              Detection Rate : 0.5475
##      Detection Prevalence : 0.7100
##      Balanced Accuracy : 0.6988
##
##      '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 - 0.645
knn_CV_error = 1 - 0.7575
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
```

```
knn_CV_error
```

```
## [1] 0.2425
```

```
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.

## Test Data Performance

```
# test error: gbmA
gbmA.test = predict(model.gbmA, newdata = test_data)

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 = test_data)

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
```