

# Initial medical data preparation

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2022-08-03

## Prepare for initial analysis

```
set.seed(123)
library(lubridate)

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 4.2.1

library(randomForest)

## Warning: package 'randomForest' was built under R version 4.2.1
## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

library(dplyr)

##
## Attaching package: 'dplyr'

## The following object is masked from 'package:randomForest':
##
##     combine

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

```
## The following objects are masked from 'package:base':
##
## intersect, setdiff, setequal, union

library(rpart)
library(caret)

## Warning: package 'caret' was built under R version 4.2.1

## Loading required package: lattice

## Warning: package 'lattice' was built under R version 4.2.1

library(e1071)

## Warning: package 'e1071' was built under R version 4.2.1

library(corrplot)

## corrplot 0.92 loaded
```

## Functions to clean datasets

Read data sets from csv file

```
clean_dataset <- function() {
  datasetloc = "C:/Users/mavul/OneDrive/Desktop/Health care data.csv"
  if (file.exists(datasetloc)) {
    data <- read.csv(file=datasetloc, header = T)
  }
  return(data)
}
```

Partition #The data were partitioned into a test and training set using a 70/30 split

```
set.seed(100)
train <- sample(nrow(clean_dataset()), 0.7*nrow(clean_dataset()), replace = F
ALSE)
TrainSet <- clean_dataset()[train,]
TestSet <- clean_dataset()[~train,]
summary(TrainSet)
```

##	id	gender	dob	zipcode
##	Length:1400	Length:1400	Length:1400	Min. :10001
##	Class :character	Class :character	Class :character	1st Qu.:43221
##	Mode :character	Mode :character	Mode :character	Median :60612
##				Mean :62877
##				3rd Qu.:90008
##				Max. :94110
##	employment_status	education	marital_status	children
##	Length:1400	Length:1400	Length:1400	Min. :0.000
##	Class :character	Class :character	Class :character	1st Qu.:1.000
##	Mode :character	Mode :character	Mode :character	Median :2.000

```

##                                     Mean    :2.227
##                                     3rd Qu.:3.000
##                                     Max.    :7.000
##      ancestry      avg_commute    daily_internet_use available_vehicles
## Length:1400      Min.    :-2.47    Min.    :1.010    Min.    :0.000
## Class :character  1st Qu.:23.61    1st Qu.:4.070    1st Qu.:1.000
## Mode  :character  Median :30.39    Median :5.020    Median :2.000
##                                     Mean   :30.43    Mean   :5.009    Mean   :1.746
##                                     3rd Qu.:37.18    3rd Qu.:5.945    3rd Qu.:3.000
##                                     Max.    :63.73    Max.    :8.640    Max.    :4.000
## military_service  disease
## Length:1400      Length:1400
## Class :character  Class :character
## Mode  :character  Mode  :character
##
##
##

summary(TestSet)

##      id      gender      dob      zipcode
## Length:600    Length:600    Length:600    Min.    :10001
## Class :character  Class :character  Class :character  1st Qu.:43221
## Mode  :character  Mode  :character  Mode  :character  Median :60612
##                                     Mean   :64579
##                                     3rd Qu.:90008
##                                     Max.    :94110
## employment_status education    marital_status    children
## Length:600      Length:600      Length:600      Min.    :0.000
## Class :character  Class :character  Class :character  1st Qu.:1.000
## Mode  :character  Mode  :character  Mode  :character  Median :2.000
##                                     Mean   :2.358
##                                     3rd Qu.:3.000
##                                     Max.    :7.000
##      ancestry      avg_commute    daily_internet_use available_vehicles
## Length:600      Min.    : 4.63    Min.    :1.250    Min.    :0.000
## Class :character  1st Qu.:23.30    1st Qu.:3.938    1st Qu.:1.000
## Mode  :character  Median :29.91    Median :4.930    Median :2.000
##                                     Mean   :30.26    Mean   :4.958    Mean   :1.747
##                                     3rd Qu.:37.09    3rd Qu.:5.990    3rd Qu.:3.000
##                                     Max.    :61.66    Max.    :8.820    Max.    :4.000
## military_service  disease
## Length:600      Length:600
## Class :character  Class :character
## Mode  :character  Mode  :character
##
##
##

```

## Analysing the disease

The data set will predict the marital status with selected attributes that contributes to the analysis

```
disease_TrainSet <- select(TrainSet, gender, employment_status, education, marital_status, ancestry, disease)
disease_TestSet <- select(TestSet, gender, employment_status, education, marital_status, ancestry, disease)
disease_TrainSet$disease <- as.factor(disease_TrainSet$disease)
```

## Logistic Regression Model

The model was fit using a binomial logistic regression with the glm function in R, with family = binomial on the training data.

```
fit <- glm(disease~.,data=disease_TrainSet,family=binomial())
summary(fit)
```

```
##
## Call:
## glm(formula = disease ~ ., family = binomial(), data = disease_TrainSet)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3393   0.4403   0.5440   0.6441   1.0067
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.19000    0.37667   5.814 6.1e-09 ***
## gendermale         0.03196    0.14765   0.216 0.828649
## employment_statusretired -0.59919    0.16538  -3.623 0.000291 ***
## employment_statusstudent -0.40097    1.13363  -0.354 0.723564
## employment_statusunemployed -0.17617    0.28038  -0.628 0.529790
## educationhighschool -0.31052    0.20498  -1.515 0.129800
## educationhighschool 13.38707   723.39477   0.019 0.985235
## educationmasters    -0.12839    0.21414  -0.600 0.548810
## educationphd/md      0.08960    0.26839   0.334 0.738493
## educationphD/MD     14.00046   481.18170   0.029 0.976788
## marital_statussingle  0.31020    0.18310   1.694 0.090238 .
## ancestryBelgium     -0.21598    0.46794  -0.462 0.644394
## ancestryCzech Republic 0.16894    0.53153   0.318 0.750605
## ancestryDenmark     -0.83234    0.43726  -1.904 0.056972 .
## ancestryEngland      0.32945    0.50949   0.647 0.517882
## ancestryFinland     -0.40610    0.47259  -0.859 0.390165
## ancestryFrance       -0.33601    0.47969  -0.700 0.483638
## ancestryGermany      -0.21203    0.46892  -0.452 0.651142
## ancestryHungary      -0.40526    0.48217  -0.840 0.400631
## ancestryIreland      -0.05155    0.46598  -0.111 0.911906
## ancestryItaly        -0.35404    0.47117  -0.751 0.452413
```

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```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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```

##	2.5 %	97.5 %
## (Intercept)	1.49310795	2.981983016
## gendermale	-0.25786241	0.321451399
## employment_statusretired	-0.92785940	-0.278718811
## employment_statusstudent	-2.31644858	2.593249869
## employment_statusunemployed	-0.71917959	0.382573039
## educationhighschool	-0.70805338	0.096693127
## educationhighscool	-69.45973894	NA
## educationmasters	-0.54008833	0.301313496
## educationphd/md	-0.41765298	0.639333730
## educationphD/MD	-85.57307046	NA
## marital_statussingle	-0.04143041	0.677631890
## ancestryBelgium	-1.15214453	0.701580323
## ancestryCzech Republic	-0.86444750	1.250416462
## ancestryDenmark	-1.72198660	0.006793701
## ancestryEngland	-0.66860072	1.356370401
## ancestryFinland	-1.35123141	0.520177091
## ancestryFrance	-1.29176670	0.608895559
## ancestryGermany	-1.14995333	0.707492641
## ancestryHungary	-1.36593697	0.544167167
## ancestryIreland	-0.98383541	0.862453401
## ancestryItaly	-1.29647330	0.569533833
## ancestryNetherlands	-0.88319757	1.038468463
## ancestryPoland	-1.26989871	0.534913406
## ancestryPortugal	-0.89729025	1.023564349
## ancestryRussia	-1.77291681	-0.000330003

```
## ancestryScotland      -1.60667582  0.249496457
## ancestrySpain         -0.99118858  1.050582435
## ancestrySweden        -0.80919936  1.158627641
## ancestrySwitzerland   -1.41776928  0.322136248
## ancestryUkraine       -1.15273134  0.907692356
```

```
exp(coef(fit))
```

```
##              (Intercept)                gendermale
##      8.935227e+00                1.032472e+00
## employment_statusretired employment_statusstudent
##      5.492537e-01                6.696732e-01
## employment_statusunemployed educationhighschool
##      8.384750e-01                7.330646e-01
##      educationhighschool educationmasters
##      6.515256e+05                8.795114e-01
##      educationphd/md educationphD/MD
##      1.093741e+00                1.203159e+06
##      marital_statussingle ancestryBelgium
##      1.363698e+00                8.057475e-01
##      ancestryCzech Republic ancestryDenmark
##      1.184052e+00                4.350307e-01
##      ancestryEngland ancestryFinland
##      1.390197e+00                6.662430e-01
##      ancestryFrance ancestryGermany
##      7.146188e-01                8.089375e-01
##      ancestryHungary ancestryIreland
##      6.668019e-01                9.497524e-01
##      ancestryItaly ancestryNetherlands
##      7.018501e-01                1.080580e+00
##      ancestryPoland ancestryPortugal
##      7.033265e-01                1.065146e+00
##      ancestryRussia ancestryScotland
##      4.212932e-01                5.140393e-01
##      ancestrySpain ancestrySweden
##      1.016138e+00                1.183392e+00
##      ancestrySwitzerland ancestryUkraine
##      5.912699e-01                8.730862e-01
```

```
exp(confint(fit))
```

```
## Waiting for profiling to be done...
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
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```

```
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```

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```

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
```

	2.5 %	97.5 %
(Intercept)	4.450907e+00	19.7268966
gendermale	7.727015e-01	1.3791280
employment_statusretired	3.953992e-01	0.7567527
employment_statusstudent	9.862322e-02	13.3731621
employment_statusunemployed	4.871518e-01	1.4660520
educationhighschool	4.926022e-01	1.1015223
educationhighscool	6.823680e-31	NA



```
## educationmasters      5.826968e-01  1.3516330
## educationphd/md      6.585907e-01  1.8952177
## educationphD/MD      6.856267e-38      NA
## marital_statussingle  9.594161e-01  1.9692089
## ancestryBelgium      3.159585e-01  2.0169376
## ancestryCzech Republic 4.212842e-01  3.4917969
## ancestryDenmark      1.787108e-01  1.0068168
## ancestryEngland      5.124251e-01  3.8820773
## ancestryFinland      2.589212e-01  1.6823255
## ancestryFrance       2.747849e-01  1.8383999
## ancestryGermany      3.166515e-01  2.0288977
## ancestryHungary      2.551415e-01  1.7231727
## ancestryIreland      3.738744e-01  2.3689656
## ancestryItaly        2.734946e-01  1.7674429
## ancestryNetherlands  4.134587e-01  2.8248873
## ancestryPoland       2.808601e-01  1.7073004
## ancestryPortugal     4.076729e-01  2.7830970
## ancestryRussia       1.698369e-01  0.9996701
## ancestryScotland     2.005532e-01  1.2833790
## ancestrySpain        3.711353e-01  2.8593160
## ancestrySweden       4.452144e-01  3.1855585
## ancestrySwitzerland  2.422538e-01  1.3800728
## ancestryUkraine      3.157731e-01  2.4785962
```

```
#predict(fit, type="response")
#residuals(fit, type="deviance")
```

## Performance

Probabilities for the response variable based on the test data were assigned using the predict function.

```
#probs <- predict(fit, test, type = "response")
#pred <- predict(fit, newdata = TestSet)
#pred
```

## Confusion Matrix

```
#confusionMatrix(pred, TestSet$disease)
```

## Random forest model

Apply randomforest model

```
# Fine tuning parameters of Random Forest model
model2 <- randomForest(disease ~ ., data = disease_TrainSet, importance = TRUE)
model2

##
## Call:
## randomForest(formula = disease ~ ., data = disease_TrainSet, importance = TRUE)
```

```

nce = TRUE)
##                               Type of random forest: classification
##                               Number of trees: 500
## No. of variables tried at each split: 2
##
## OOB estimate of error rate: 83.29%
## Confusion matrix:
##                               Alzheimer's disease breast cancer diabetes endometriosis
is
## Alzheimer's disease          85          42          2
1
## breast cancer                31          30          0
1
## diabetes                    33          7          1
1
## endometriosis               10          15          2
0
## gastritis                   21          13          0
0
## heart disease               17          8          1
0
## HIV/AIDS                    9          8          0
0
## hypertension               52          34          0
1
## kidney disease              34          20          0
1
## multiple sclerosis          29          14          0
0
## prostate cancer             60          0          0
0
## schizophrenia               17          3          0
0
## skin cancer                 60          23          1
0
##                               gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease          1          2          1          31
## breast cancer                0          1          0          24
## diabetes                    0          1          1          10
## endometriosis               0          0          1          6
## gastritis                   0          0          1          12
## heart disease               0          0          0          8
## HIV/AIDS                    1          0          0          6
## hypertension               1          1          1          29
## kidney disease              0          1          1          13
## multiple sclerosis          1          1          0          6
## prostate cancer             0          0          1          7
## schizophrenia               2          0          0          7
## skin cancer                 0          0          1          17
##                               kidney disease multiple sclerosis prostate cancer

```

## Alzheimer's disease	5	2	37
## breast cancer	6	1	0
## diabetes	6	0	18
## endometriosis	6	0	0
## gastritis	2	0	14
## heart disease	4	0	22
## HIV/AIDS	4	0	21
## hypertension	12	1	43
## kidney disease	17	1	39
## multiple sclerosis	4	0	14
## prostate cancer	4	0	55
## schizophrenia	0	1	8
## skin cancer	7	0	41

##	schizophrenia	skin cancer	class.error
## Alzheimer's disease	0	23	0.6336207
## breast cancer	0	11	0.7142857
## diabetes	0	5	0.9879518
## endometriosis	0	5	1.0000000
## gastritis	2	5	1.0000000
## heart disease	0	4	1.0000000
## HIV/AIDS	1	2	1.0000000
## hypertension	1	21	0.8527919
## kidney disease	0	10	0.8759124
## multiple sclerosis	1	7	1.0000000
## prostate cancer	0	4	0.5801527
## schizophrenia	0	2	1.0000000
## skin cancer	0	17	0.8982036

*# Predicting on train set*

```
predTrain <- predict(model2, disease_TrainSet, type = "class")
```

*# Checking classification accuracy*

```
table(predTrain, disease_TrainSet$disease)
```

##	Alzheimer's disease	breast cancer	diabetes	endometriosis
## Alzheimer's disease	147	13	31	
## breast cancer	23	65	7	
## diabetes	1	0	9	
## endometriosis	0	0	0	
## gastritis	0	0	0	
## heart disease	2	0	0	
## HIV/AIDS	0	0	1	

```

1
## hypertension 17 13 9
7
## kidney disease 4 3 5
5
## multiple sclerosis 0 0 0
0
## prostate cancer 25 0 17
0
## schizophrenia 0 0 0
0
## skin cancer 13 11 4
5
##
## predTrain gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease 21 13 6 47
## breast cancer 12 9 9 20
## diabetes 0 0 0 0
## endometriosis 0 0 0 0
## gastritis 5 0 0 0
## heart disease 0 11 0 1
## HIV/AIDS 1 1 13 1
## hypertension 13 6 4 86
## kidney disease 1 2 1 3
## multiple sclerosis 0 0 0 0
## prostate cancer 12 18 16 28
## schizophrenia 1 0 0 0
## skin cancer 4 4 3 11
##
## predTrain kidney disease multiple sclerosis prostate cancer
## Alzheimer's disease 31 28 44
## breast cancer 18 15 0
## diabetes 0 0 0
## endometriosis 0 0 0
## gastritis 0 0 0
## heart disease 0 1 0
## HIV/AIDS 1 0 0
## hypertension 9 5 3
## kidney disease 35 2 0
## multiple sclerosis 0 6 0
## prostate cancer 34 14 83
## schizophrenia 0 0 0
## skin cancer 9 6 1
##
## predTrain schizophrenia skin cancer
## Alzheimer's disease 17 43
## breast cancer 3 19
## diabetes 0 0
## endometriosis 0 0
## gastritis 0 0

```

```

## heart disease 0 0
## HIV/AIDS 0 0
## hypertension 7 16
## kidney disease 0 6
## multiple sclerosis 1 0
## prostate cancer 7 36
## schizophrenia 3 0
## skin cancer 2 47

model2 <- na.omit(model2)

# Predicting on Validation set
predValid <- predict(model2, disease_TestSet, type = "class")

# Checking classification accuracy
mean(predValid == disease_TestSet$disease)

## [1] 0.1666667

table(predValid,disease_TestSet$disease)

##
## predValid Alzheimer's disease breast cancer diabetes endometri
osis
## Alzheimer's disease 43 14 15
7
## breast cancer 14 8 5
8
## diabetes 1 0 0
0
## endometriosis 0 0 0
0
## gastritis 0 0 0
0
## heart disease 0 0 0
0
## HIV/AIDS 1 1 0
1
## hypertension 8 7 10
5
## kidney disease 7 4 1
0
## multiple sclerosis 0 0 0
0
## prostate cancer 26 0 4
0
## schizophrenia 0 0 0
0
## skin cancer 7 6 1
0
##

```

```
## predValid      gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease      10      10      2      31
## breast cancer      3      0      3      17
## diabetes      0      1      0      0
## endometriosis      0      0      0      0
## gastritis      0      0      0      0
## heart disease      0      1      0      2
## HIV/AIDS      0      0      0      2
## hypertension      3      1      5      11
## kidney disease      3      2      1      6
## multiple sclerosis      0      0      0      1
## prostate cancer      10      4      11      18
## schizophrenia      0      0      0      0
## skin cancer      1      4      6      13
```

```
##
## predValid      kidney disease multiple sclerosis prostate cancer
## Alzheimer's disease      19      14      15
## breast cancer      5      3      0
## diabetes      0      0      0
## endometriosis      0      0      0
## gastritis      0      0      0
## heart disease      1      0      1
## HIV/AIDS      0      0      0
## hypertension      8      4      3
## kidney disease      4      1      1
## multiple sclerosis      0      0      0
## prostate cancer      10      13      29
## schizophrenia      0      0      0
## skin cancer      1      1      0
```

```
##
## predValid      schizophrenia skin cancer
## Alzheimer's disease      6      29
## breast cancer      2      11
## diabetes      0      0
## endometriosis      0      1
## gastritis      0      0
## heart disease      0      1
## HIV/AIDS      1      0
## hypertension      1      3
## kidney disease      1      4
## multiple sclerosis      0      0
## prostate cancer      4      13
## schizophrenia      0      0
## skin cancer      0      4
```

*# To check important variables*

```
importance(model2)
```

```
##      Alzheimer's disease breast cancer diabetes endometriosis
s
```

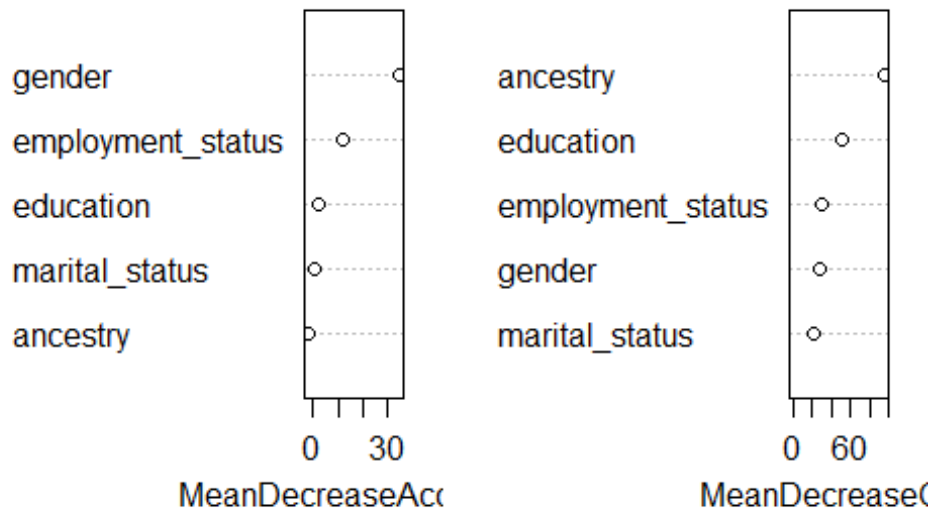
```

## gender          -0.3069681    28.0718616 -1.380107    7.8601294
4
## employment_status 8.8371133    -0.2679983  1.728054    -3.3498795
1
## education        -8.1680115    1.3234619  2.799283    -1.9265688
3
## marital_status   -0.8301061    -7.1404512  5.529093    -0.0408413
8
## ancestry         -4.4430299    -5.1554326  4.351547    -4.6347698
5
##
## gastritis heart disease HIV/AIDS hypertension
## gender          -3.092683    4.3303144  2.8995935    1.5726714
## employment_status -2.737173    -0.4860694  5.9254210    4.7360929
## education        -7.936120    2.2773281  4.0985963    0.4401083
## marital_status    0.690441    4.2159322 -0.3571497    1.8884930
## ancestry         -2.603470    -0.4569619  5.6758207    1.9357525
##
## kidney disease multiple sclerosis prostate cancer
## gender          10.428706    1.6532290    37.528819
## employment_status 9.456225    -5.7025661    1.454414
## education        8.865393    -1.5262814    2.838719
## marital_status    9.664055    -0.5272205    -6.919649
## ancestry         7.473705    -0.2640322    -7.662150
##
## schizophrenia skin cancer MeanDecreaseAccuracy
## gender          -7.7424957    5.196389    35.3158589
## employment_status 1.8606180    5.647893    12.0488859
## education        2.9206449    4.813521    1.8113220
## marital_status    -4.6329632    2.994119    0.9381829
## ancestry         -0.9734494    3.714359    -2.2621348
##
## MeanDecreaseGini
## gender          28.16827
## employment_status 30.39493
## education        50.73786
## marital_status    21.08354
## ancestry         96.29308

varImpPlot(model2)

```

model2



## Naive Bayes Model

```
NBclassifier = naiveBayes(disease~., data=disease_TrainSet)
print(NBclassifier)
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
## Alzheimer's disease      breast cancer      diabetes      endometr
iosis
##      0.16571429      0.07500000      0.05928571      0.032
14286
##      gastritis      heart disease      HIV/AIDS      hyperten
sion
##      0.05000000      0.04571429      0.03714286      0.140
71429
##      kidney disease multiple sclerosis      prostate cancer      schizoph
renia
##      0.09785714      0.05500000      0.09357143      0.028
57143
##      skin cancer
##      0.11928571
```



```

##
## Conditional probabilities:
##
##           gender
## Y           female      male
## Alzheimer's disease 0.4870690 0.5129310
## breast cancer       1.0000000 0.0000000
## diabetes            0.4337349 0.5662651
## endometriosis       1.0000000 0.0000000
## gastritis           0.4714286 0.5285714
## heart disease       0.3906250 0.6093750
## HIV/AIDS            0.4423077 0.5576923
## hypertension       0.5025381 0.4974619
## kidney disease      0.5109489 0.4890511
## multiple sclerosis  0.4545455 0.5454545
## prostate cancer     0.0000000 1.0000000
## schizophrenia       0.4250000 0.5750000
## skin cancer         0.4670659 0.5329341
##
##           employment_status
## Y           employed      retired      student      unemployed
## Alzheimer's disease 0.288793103 0.586206897 0.004310345 0.120689655
## breast cancer       0.390476190 0.485714286 0.009523810 0.114285714
## diabetes            0.313253012 0.530120482 0.012048193 0.144578313
## endometriosis       0.288888889 0.533333333 0.000000000 0.177777778
## gastritis           0.428571429 0.371428571 0.042857143 0.157142857
## heart disease       0.453125000 0.390625000 0.000000000 0.156250000
## HIV/AIDS            0.673076923 0.115384615 0.019230769 0.192307692
## hypertension       0.345177665 0.517766497 0.010152284 0.126903553
## kidney disease      0.489051095 0.364963504 0.007299270 0.138686131
## multiple sclerosis  0.363636364 0.493506494 0.025974026 0.116883117
## prostate cancer     0.381679389 0.488549618 0.000000000 0.129770992
## schizophrenia       0.350000000 0.500000000 0.075000000 0.075000000
## skin cancer         0.407185629 0.526946108 0.000000000 0.065868263
##
##           education
## Y           bachelors      highschool      highschool      masters
## Alzheimer's disease 0.508620690 0.245689655 0.000000000 0.159482759
## breast cancer       0.580952381 0.190476190 0.000000000 0.152380952
## diabetes            0.481927711 0.313253012 0.000000000 0.132530120
## endometriosis       0.533333333 0.222222222 0.000000000 0.111111111
## gastritis           0.500000000 0.242857143 0.000000000 0.157142857
## heart disease       0.531250000 0.203125000 0.000000000 0.218750000
## HIV/AIDS            0.346153846 0.307692308 0.038461538 0.192307692
## hypertension       0.548223350 0.208121827 0.000000000 0.126903553
## kidney disease      0.562043796 0.233576642 0.007299270 0.116788321
## multiple sclerosis  0.649350649 0.155844156 0.012987013 0.103896104
## prostate cancer     0.557251908 0.198473282 0.000000000 0.145038168
## schizophrenia       0.475000000 0.225000000 0.000000000 0.100000000
## skin cancer         0.556886228 0.185628743 0.000000000 0.137724551
##
##           education

```

##	Y	phd/md	phD/MD		
##	Alzheimer's disease	0.086206897	0.000000000		
##	breast cancer	0.076190476	0.000000000		
##	diabetes	0.072289157	0.000000000		
##	endometriosis	0.133333333	0.000000000		
##	gastritis	0.071428571	0.028571429		
##	heart disease	0.046875000	0.000000000		
##	HIV/AIDS	0.096153846	0.019230769		
##	hypertension	0.111675127	0.005076142		
##	kidney disease	0.072992701	0.007299270		
##	multiple sclerosis	0.064935065	0.012987013		
##	prostate cancer	0.099236641	0.000000000		
##	schizophrenia	0.125000000	0.075000000		
##	skin cancer	0.119760479	0.000000000		
##					
##		marital_status			
##	Y	married	single		
##	Alzheimer's disease	0.7931034	0.2068966		
##	breast cancer	0.8000000	0.2000000		
##	diabetes	0.7590361	0.2409639		
##	endometriosis	0.7777778	0.2222222		
##	gastritis	0.7428571	0.2571429		
##	heart disease	0.5937500	0.4062500		
##	HIV/AIDS	0.6923077	0.3076923		
##	hypertension	0.7664975	0.2335025		
##	kidney disease	0.7153285	0.2846715		
##	multiple sclerosis	0.7272727	0.2727273		
##	prostate cancer	0.7175573	0.2824427		
##	schizophrenia	0.7500000	0.2500000		
##	skin cancer	0.7485030	0.2514970		
##					
##		ancestry			
##	Y	Austria	Belgium	Czech Republic	Denmark
##	Alzheimer's disease	0.04310345	0.05172414	0.03017241	0.08189655
##	breast cancer	0.06666667	0.04761905	0.05714286	0.03809524
##	diabetes	0.04819277	0.02409639	0.02409639	0.06024096
##	endometriosis	0.04444444	0.02222222	0.08888889	0.06666667
##	gastritis	0.10000000	0.02857143	0.01428571	0.05714286
##	heart disease	0.04687500	0.06250000	0.07812500	0.03125000
##	HIV/AIDS	0.03846154	0.05769231	0.03846154	0.00000000
##	hypertension	0.05076142	0.04568528	0.05076142	0.04568528
##	kidney disease	0.06569343	0.04379562	0.05839416	0.04379562
##	multiple sclerosis	0.02597403	0.05194805	0.02597403	0.07792208
##	prostate cancer	0.05343511	0.07633588	0.02290076	0.03816794
##	schizophrenia	0.05000000	0.05000000	0.05000000	0.02500000
##	skin cancer	0.04790419	0.08383234	0.05389222	0.04191617
##					
##	Y	ancestry			
##		England	Finland	France	Germany
##	ry				
##	Alzheimer's disease	0.03448276	0.05172414	0.04741379	0.05172414
##					0.047413

79						
##	breast cancer	0.04761905	0.03809524	0.04761905	0.02857143	0.047619
05						
##	diabetes	0.06024096	0.02409639	0.08433735	0.02409639	0.024096
39						
##	endometriosis	0.02222222	0.06666667	0.04444444	0.04444444	0.044444
44						
##	gastritis	0.05714286	0.01428571	0.04285714	0.05714286	0.014285
71						
##	heart disease	0.03125000	0.03125000	0.06250000	0.09375000	0.062500
00						
##	HIV/AIDS	0.03846154	0.07692308	0.00000000	0.07692308	0.076923
08						
##	hypertension	0.06598985	0.04060914	0.02538071	0.05076142	0.050761
42						
##	kidney disease	0.08029197	0.03649635	0.05109489	0.03649635	0.036496
35						
##	multiple sclerosis	0.07792208	0.05194805	0.07792208	0.02597403	0.077922
08						
##	prostate cancer	0.05343511	0.06870229	0.03053435	0.05343511	0.038167
94						
##	schizophrenia	0.05000000	0.02500000	0.00000000	0.10000000	0.025000
00						
##	skin cancer	0.05389222	0.04790419	0.05988024	0.05988024	0.041916
17						
##		ancestry				
## Y		Ireland	Italy	Netherlands	Poland	Portu
gal						
##	Alzheimer's disease	0.05172414	0.05172414	0.04310345	0.06034483	0.04310
345						
##	breast cancer	0.01904762	0.06666667	0.04761905	0.06666667	0.10476
190						
##	diabetes	0.10843373	0.08433735	0.07228916	0.07228916	0.02409
639						
##	endometriosis	0.06666667	0.02222222	0.02222222	0.04444444	0.00000
000						
##	gastritis	0.11428571	0.02857143	0.04285714	0.05714286	0.07142
857						
##	heart disease	0.07812500	0.09375000	0.06250000	0.04687500	0.01562
500						
##	HIV/AIDS	0.07692308	0.03846154	0.05769231	0.00000000	0.05769
231						
##	hypertension	0.05076142	0.02030457	0.05583756	0.08629442	0.06091
371						
##	kidney disease	0.04379562	0.05109489	0.05839416	0.05109489	0.04379
562						
##	multiple sclerosis	0.05194805	0.01298701	0.06493506	0.02597403	0.09090
909						
##	prostate cancer	0.04580153	0.09160305	0.05343511	0.03816794	0.07633
588						

##	schizophrenia	0.02500000	0.02500000	0.05000000	0.07500000	0.05000
000						
##	skin cancer	0.08383234	0.04790419	0.06586826	0.02994012	0.04790
419						
##		ancestry				
## Y		Russia	Scotland	Spain	Sweden	Switzerl
and						
##	Alzheimer's disease	0.07327586	0.05603448	0.03448276	0.03879310	0.07327
586						
##	breast cancer	0.06666667	0.01904762	0.02857143	0.04761905	0.06666
667						
##	diabetes	0.06024096	0.03614458	0.01204819	0.10843373	0.02409
639						
##	endometriosis	0.02222222	0.06666667	0.04444444	0.08888889	0.08888
889						
##	gastritis	0.01428571	0.02857143	0.01428571	0.11428571	0.07142
857						
##	heart disease	0.03125000	0.03125000	0.01562500	0.04687500	0.03125
000						
##	HIV/AIDS	0.01923077	0.07692308	0.05769231	0.05769231	0.07692
308						
##	hypertension	0.04060914	0.03045685	0.07106599	0.05583756	0.05583
756						
##	kidney disease	0.05109489	0.04379562	0.05839416	0.05109489	0.07299
270						
##	multiple sclerosis	0.03896104	0.07792208	0.03896104	0.02597403	0.05194
805						
##	prostate cancer	0.03816794	0.04580153	0.05343511	0.04580153	0.04580
153						
##	schizophrenia	0.10000000	0.00000000	0.15000000	0.02500000	0.10000
000						
##	skin cancer	0.02994012	0.02994012	0.04191617	0.05389222	0.05389
222						
##		ancestry				
## Y		Ukraine				
##	Alzheimer's disease	0.03448276				
##	breast cancer	0.04761905				
##	diabetes	0.02409639				
##	endometriosis	0.08888889				
##	gastritis	0.05714286				
##	heart disease	0.04687500				
##	HIV/AIDS	0.07692308				
##	hypertension	0.04568528				
##	kidney disease	0.02189781				
##	multiple sclerosis	0.02597403				
##	prostate cancer	0.03053435				
##	schizophrenia	0.02500000				
##	skin cancer	0.02395210				

## Performance

Probabilities for the response variable based on the test data were assigned using the predict function.

```
probs <- predict(fit, type = "response")
pred <- predict(fit, newdata = TestSet)
pred
```

##	7	8	9	10	14	19	
20							
##	1.2751480	2.1384476	1.7726179	1.7757150	2.2674994	1.4067777	1.99607
44							
##	22	24	25	27	33	39	
40							
##	2.3910580	1.7395332	2.2674994	2.4806032	1.0643005	0.6467856	0.75801
47							
##	41	43	44	45	46	49	
52							
##	1.7591920	1.3255753	1.6288563	1.7579081	2.1438841	1.6641972	0.87097
09							
##	54	57	58	60	68	71	
74							
##	1.8679219	1.6068155	1.6964746	1.6627590	2.0066189	1.3263748	1.64020
29							
##	75	80	84	86	89	93	
99							
##	1.7908262	2.0614740	1.1855444	1.7917053	1.7911478	1.9779680	1.99607
44							
##	103	104	108	111	112	113	1
17							
##	2.2089253	1.0891115	1.8334317	2.3583868	1.6539188	2.0776216	1.90365
06							
##	119	121	122	126	132	134	1
35							
##	1.1424398	2.2216358	0.8750230	1.2548008	0.9762352	0.7584680	1.17652
02							
##	138	139	140	141	148	151	1
52							
##	2.3580652	1.3961573	1.9779680	1.9170154	2.2379661	1.5245460	0.92835
14							
##	160	162	167	168	171	172	1
78							
##	1.4505382	1.3984728	1.1581396	1.4107290	1.4107290	2.0693918	1.53925
28							
##	181	185	188	189	190	191	1
95							
##	1.5712086	1.8700234	1.3576628	2.5952692	1.0470097	2.2850694	1.95220
77							
##	199	206	210	217	218	220	2

31							
##	1.3266971	1.2464332	1.1847059	1.0150539	1.5490726	1.7754781	1.34440
43							
##	235	236	238	239	243	245	2
52							
##	1.2684055	2.2060103	2.3903426	1.8495793	1.2548008	0.7584680	2.07762
16							
##	260	265	269	271	275	280	2
84							
##	1.2388728	1.2675068	1.9740167	1.8359661	2.2379661	1.3433974	1.91793
00							
##	292	294	295	303	306	307	3
11							
##	0.7583363	1.2464332	2.2144080	1.7575627	1.9740167	0.9573070	1.75919
20							
##	312	319	320	323	326	330	3
31							
##	2.3583868	1.8494526	1.9054600	1.4107290	2.2147296	2.3644804	1.97369
51							
##	333	343	344	358	360	361	3
67							
##	1.2708286	1.9522077	2.7005424	2.3275696	1.5565018	1.6288563	1.38929
71							
##	368	369	370	373	377	379	3
80							
##	1.4806264	1.5192806	2.2850694	2.0454652	1.8700234	1.6618970	1.81585
65							
##	385	388	391	392	399	405	4
07							
##	1.8279262	1.1583679	1.5565018	1.1403384	1.6674466	1.1855444	1.72837
48							
##	414	415	417	424	426	427	4
38							
##	1.6858746	1.2548008	1.2355510	2.0862364	1.7591920	1.7847392	1.80147
59							
##	439	443	446	450	451	452	4
53							
##	1.2367713	1.6357751	0.8750230	1.4486706	1.3896186	1.0470097	1.33000
31							
##	462	475	483	485	491	494	4
96							
##	1.6964746	2.0454652	1.7808074	2.2156598	1.7757150	2.2305556	1.55650
18							
##	497	498	500	507	509	512	5
15							
##	0.9603072	2.1704034	1.2291423	1.4108641	2.4037685	2.2379661	2.39090
01							
##	524	525	531	533	534	539	5
40							
##	1.2175002	1.3748219	1.8493530	1.2166617	1.5392528	1.6387713	0.92535

12							
##	541	542	545	547	552	555	5
63							
##	1.8815351	2.2994552	1.5490726	1.5908068	1.5275462	15.6935962	1.46512
73							
##	565	569	570	572	579	580	5
81							
##	1.3263748	0.6148298	1.3575311	2.1781217	2.1019051	2.4486474	2.26000
69							
##	584	588	590	593	597	603	6
06							
##	1.9889338	1.6683046	2.5952692	0.6148298	1.7983775	1.7911478	1.81669
50							
##	607	613	615	617	618	622	6
24							
##	1.2612299	2.0862364	1.7978462	1.6850217	2.3429546	2.2379661	1.85399
56							
##	625	627	632	633	634	636	6
37							
##	1.7209288	1.8463299	1.6855530	2.2994552	1.4644254	1.5199825	1.96411
86							
##	652	658	675	676	677	678	6
83							
##	1.7169775	1.9578477	1.5650006	2.0542806	1.3539974	1.6850217	2.35894
43							
##	688	689	692	693	701	702	7
07							
##	2.0059725	0.9582057	2.7005424	1.6387713	1.5561802	2.0995273	16.26808
23							
##	715	716	718	719	721	722	7
25							
##	1.3961573	1.1583679	1.1855444	1.6288563	2.0059725	1.5908068	1.57120
86							
##	726	727	728	729	730	739	7
40							
##	1.9575254	0.4479467	2.1710664	1.4108641	1.6634953	2.1566807	1.78473
92							
##	741	745	746	748	749	760	7
61							
##	1.9779680	0.7548026	1.7169775	1.2459804	2.0225659	1.2292741	0.84807
16							
##	762	763	766	767	771	773	7
74							
##	1.5718716	0.8709709	0.7583363	2.4799461	1.6387713	1.8868449	1.85399
56							
##	777	779	787	790	791	792	8
07							
##	1.8356445	2.0199807	1.1583679	1.3787732	2.0636202	1.6227626	0.59799
18							
##	816	819	822	826	829	830	8

31							
##	1.9641186	1.5275462	1.6850217	1.6227626	2.2379661	1.7002604	1.55748
59							
##	834	836	845	847	848	855	8
59							
##	1.4742178	1.4943738	1.5712086	0.6299476	1.5675887	1.6555120	0.95730
70							
##	863	868	869	875	882	885	8
87							
##	1.0653240	0.8741845	2.5952692	1.5490726	2.2408811	1.2175002	2.39034
26							
##	888	889	890	891	892	901	9
11							
##	1.6677309	2.2527920	2.2219574	1.8380676	1.6994024	1.5245460	1.35399
74							
##	913	914	915	918	921	922	9
26							
##	1.3961573	1.3896186	1.6914298	1.9522077	1.2802854	1.8815351	1.28675
66							
##	930	932	933	934	938	950	9
51							
##	1.2802854	1.7395332	2.3910580	2.2850694	1.4107290	1.0653240	0.79042
38							
##	953	958	961	963	974	975	9
76							
##	2.2842165	1.9202519	2.1000637	1.0882730	2.1152446	1.4151788	1.33000
31							
##	979	990	991	992	1002	1007	10
10							
##	1.3745003	1.6227626	2.2600069	1.2471351	1.0972798	2.2619538	1.83375
33							
##	1015	1016	1017	1020	1023	1024	10
27							
##	1.7917053	1.5392528	2.2531136	1.2367713	1.4486706	1.8334317	1.49437
38							
##	1029	1032	1035	1037	1042	1049	10
54							
##	2.1883099	1.7983775	1.9960744	1.6393644	1.4108641	1.3753532	2.29945
52							
##	1055	1058	1060	1064	1066	1069	10
71							
##	1.5392528	1.6683046	1.6905311	2.0941005	1.6082471	1.4624181	1.75919
20							
##	1075	1076	1077	1080	1082	1086	10
87							
##	1.2708286	1.9415606	2.4805036	1.6683046	2.5162102	1.1847059	1.53925
28							
##	1090	1091	1093	1094	1096	1097	10
98							
##	1.7283748	0.9283514	1.1847059	1.4108641	1.9880249	2.3909001	1.26872



71							
##	1101	1110	1113	1114	1129	1130	11
34							
##	2.1900016	1.7591920	1.2287314	2.3749104	1.7847392	2.2138504	1.97209
68							
##	1137	1140	1144	1150	1151	1158	11
67							
##	1.6594740	1.0972798	1.9779680	1.8380676	1.2708286	2.1384476	0.44781
49							
##	1183	1185	1189	1192	1196	1201	12
03							
##	1.4873248	1.3266971	1.2548008	2.0099238	2.0910072	2.2850694	2.13844
76							
##	1204	1205	1206	1211	1214	1220	12
23							
##	1.3492742	0.9582057	0.8708391	1.8158565	1.8380676	1.7512742	2.23055
56							
##	1224	1231	1233	1237	1239	1240	12
43							
##	1.9880249	1.7664217	1.8356445	2.3589443	1.8815351	1.6563505	1.68830
63							
##	1250	1251	1254	1258	1260	1261	12
69							
##	2.4230138	2.0358067	0.9069788	2.1391106	2.0542806	1.0653240	1.63877
13							
##	1273	1276	1280	1281	1284	1289	12
91							
##	1.7352654	2.1818946	2.1597791	1.6313608	1.8380676	1.5754300	1.27430
94							
##	1294	1303	1309	1318	1319	1330	13
33							
##	1.9779680	2.1704034	0.4478149	0.9250296	1.7435223	1.5245460	2.37491
04							
##	1341	1343	1352	1353	1355	1359	13
60							
##	1.3787732	1.2166617	1.5925401	1.5712086	2.2531136	0.9573070	2.51944
67							
##	1369	1371	1375	1376	1377	1386	13
89							
##	2.0803787	1.1811707	1.5712086	2.1019051	1.6517556	1.5565018	1.23677
13							
##	1390	1404	1405	1406	1409	1410	14
12							
##	1.5810284	1.7597495	1.4949057	1.1847059	1.2131265	2.0776216	1.90420
82							
##	1413	1418	1423	1425	1426	1429	14
32							
##	1.9410030	1.4067777	1.7911478	1.7839007	1.7911478	1.2134481	1.56500
06							
##	1435	1436	1442	1443	1445	1446	14

55							
##	1.9187685	1.8166950	1.4870416	1.0891115	2.0803787	1.3859532	1.97369
51							
##	1456	1457	1464	1466	1468	1469	14
70							
##	2.0862364	2.3909001	1.0653240	1.6539188	2.0862364	1.6889730	1.07909
72							
##	1476	1477	1480	1487	1492	1494	14
96							
##	1.5277001	1.4492281	1.9740167	1.3284763	1.0653240	1.2544792	1.91876
85							
##	1502	1507	1511	1512	1516	1521	15
23							
##	2.0769431	1.6858746	0.6467856	2.1397899	1.9522077	2.1704034	1.79114
78							
##	1526	1529	1535	1537	1538	1541	15
42							
##	1.3896186	1.8158565	1.1765202	1.0653240	1.4870416	0.5979918	2.26240
75							
##	1548	1551	1554	1557	1558	1559	15
62							
##	1.8598820	1.5446893	2.2379661	1.2459804	1.6634953	2.5002014	1.40677
77							
##	1564	1565	1568	1572	1574	1580	15
81							
##	1.9036506	2.0910072	2.2060103	2.5162102	2.2060103	2.0862364	1.98802
49							
##	1590	1592	1593	1594	1603	1604	16
06							
##	1.8337533	1.3665170	1.6068155	1.6546041	1.6645188	1.5192806	1.95072
43							
##	1610	1615	1616	1617	1622	1625	16
26							
##	1.5574859	1.8294804	2.3746729	1.2388728	1.7075774	2.2850694	1.87225
24							
##	1628	1630	1632	1635	1638	1640	16
42							
##	0.4478149	0.7583363	2.0099238	2.3429546	1.5995445	1.5712086	0.75833
63							
##	1643	1644	1646	1647	1650	1652	16
54							
##	0.6148298	1.6645188	1.7033096	1.2175002	2.0910072	1.2367713	15.96397
61							
##	1656	1658	1660	1664	1665	1667	16
68							
##	2.0699493	0.7904238	2.4924160	2.0693918	1.3576628	1.2708286	1.57892
69							
##	1671	1676	1683	1684	1688	1691	16
93							
##	2.3589443	0.4799024	2.3240308	1.6068155	1.8166950	1.2867566	1.88153

51							
##	1697	1699	1702	1703	1707	1710	17
15							
##	1.0643005	1.1843843	0.4158591	1.5712086	1.4107290	1.7985481	1.57892
69							
##	1716	1717	1719	1726	1736	1741	17
47							
##	2.4799461	1.1855444	1.9779680	0.9603072	1.8158565	1.4550858	1.75974
95							
##	1749	1750	1757	1759	1761	1766	17
70							
##	1.4870416	1.8294804	1.5810284	1.4550858	1.3266971	2.1095774	0.95730
70							
##	1774	1776	1777	1779	1788	1789	17
96							
##	2.5194467	1.7033096	2.0100589	0.7584680	1.9735164	1.3896186	1.32557
53							
##	1797	1800	1802	1807	1813	1814	18
15							
##	2.1818946	1.0972798	1.5712086	2.7010999	1.8859514	1.8205824	2.06471
06							
##	1818	1827	1829	1830	1831	1842	18
48							
##	0.7548026	1.8166950	2.0776216	2.5002014	2.1461659	2.3583868	1.06532
40							
##	1853	1856	1858	1860	1861	1865	18
69							
##	1.2364497	2.0803787	2.5194467	2.5514025	1.0365803	2.3275696	0.87083
91							
##	1870	1874	1876	1878	1881	1883	18
94							
##	1.8775838	1.3255753	1.7002604	1.4949057	1.3539974	0.4478149	1.97401
67							
##	1895	1897	1899	1900	1904	1905	19
07							
##	2.0484229	1.9755549	1.8155349	0.9061403	1.1855444	1.2166617	1.60570
89							
##	1908	1909	1911	1914	1922	1929	19
30							
##	1.7597495	1.2687271	1.5192806	1.6674466	2.0099238	1.1490832	1.40747
96							
##	1932	1935	1938	1940	1950	1951	19
55							
##	1.4880267	2.0040526	1.3300031	2.0199807	0.9262499	1.6858746	1.55740
05							
##	1958	1964	1973	1975	1977	1980	19
82							
##	2.2408811	2.1802232	2.0358067	1.9779680	2.5194467	1.8238190	1.57120
86							

```
##      1987      1988      1992      1996      1999
## 1.8158565 1.6858746 2.3903426 0.9688911 1.2166617
```

## Confusion Matrix

```
#confusionMatrix(pred, TestSet$disease)
```

## Random forest model

Apply random forest model

```
# Fine tuning parameters of Random Forest model
model2 <- randomForest(disease ~ ., data = disease_TrainSet, importance = TRUE)
model2

##
## Call:
## randomForest(formula = disease ~ ., data = disease_TrainSet, importance = TRUE)
##
##      Type of random forest: classification
##      Number of trees: 500
## No. of variables tried at each split: 2
##
##      OOB estimate of error rate: 83.57%
## Confusion matrix:
##
##      Alzheimer's disease breast cancer diabetes endometriosis
## Alzheimer's disease      83          39          1
## breast cancer           30          37          0
## diabetes                31           9          0
## endometriosis           13          13          1
## gastritis               21          14          0
## heart disease           15           9          0
## HIV/AIDS                7           8          0
## hypertension            59          32          0
## kidney disease          30          23          1
## multiple sclerosis       28          16          0
## prostate cancer         60           0          0
## schizophrenia            12           6          0
```

```

0
## skin cancer                63                22                1
1
##          gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease      0                4                0                28
## breast cancer            0                0                0                17
## diabetes                 0                0                1                8
## endometriosis           0                0                1                6
## gastritis                0                0                1                13
## heart disease            0                0                0                9
## HIV/AIDS                 1                0                1                3
## hypertension            1                1                1                24
## kidney disease           0                1                2                11
## multiple sclerosis       1                0                0                6
## prostate cancer          0                1                2                7
## schizophrenia            2                0                0                6
## skin cancer              0                1                1                16
##          kidney disease multiple sclerosis prostate cancer
## Alzheimer's disease      8                2                40
## breast cancer            8                1                0
## diabetes                 5                0                20
## endometriosis           4                0                0
## gastritis                1                0                15
## heart disease            4                0                22
## HIV/AIDS                 3                0                22
## hypertension            11               0                46
## kidney disease           14               3                39
## multiple sclerosis       3                0                16
## prostate cancer          2                1                55
## schizophrenia            0                1                10
## skin cancer              6                0                40
##          schizophrenia skin cancer class.error
## Alzheimer's disease      0                25  0.6422414
## breast cancer            0                12  0.6476190
## diabetes                 0                8  1.0000000
## endometriosis           0                7  1.0000000
## gastritis                2                3  1.0000000
## heart disease            0                4  1.0000000
## HIV/AIDS                 1                5  0.9807692
## hypertension            1                21  0.8781726
## kidney disease           0                11  0.8978102
## multiple sclerosis       1                6  1.0000000
## prostate cancer          0                3  0.5801527
## schizophrenia            0                3  1.0000000
## skin cancer              0                16  0.9041916

```

*# Predicting on train set*

```
predTrain <- predict(model2, disease_TrainSet, type = "class")
```

*# Checking classification accuracy*

```
table(predTrain, disease_TrainSet$disease)
```

```
##
## predTrain      Alzheimer's disease breast cancer diabetes endometri
osis
## Alzheimer's disease      137          14          32
11
## breast cancer           29          67          8
14
## diabetes                1           0          9
0
## endometriosis          1           0          1
3
## gastritis              0           0          0
0
## heart disease          1           0          0
0
## HIV/AIDS              0           0          1
1
## hypertension          14          9          5
5
## kidney disease         6           4          4
4
## multiple sclerosis     0           0          0
0
## prostate cancer        31          0          19
0
## schizophrenia          0           0          0
0
## skin cancer            12          11          4
7
##
## predTrain      gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease      20          14          4          48
## breast cancer           12          9          10          24
## diabetes                0           0          0          0
## endometriosis          0           0          1          0
## gastritis              6           0          0          0
## heart disease          0           8          0          0
## HIV/AIDS              1           1          13          1
## hypertension          11          5          2          73
## kidney disease         2           2          1          4
## multiple sclerosis     0           0          0          0
## prostate cancer        14          22          17          32
## schizophrenia          0           0          0          0
## skin cancer            4           3          4          15
##
## predTrain      kidney disease multiple sclerosis prostate cancer
## Alzheimer's disease      32          28          43
```

```

## breast cancer 19 14 0
## diabetes 0 0 0
## endometriosis 0 0 0
## gastritis 0 0 0
## heart disease 0 0 0
## HIV/AIDS 1 0 0
## hypertension 9 4 2
## kidney disease 34 3 0
## multiple sclerosis 0 6 0
## prostate cancer 35 16 85
## schizophrenia 0 0 0
## skin cancer 7 6 1
##
## predTrain schizophrenia skin cancer
## Alzheimer's disease 13 43
## breast cancer 6 19
## diabetes 0 0
## endometriosis 0 1
## gastritis 1 0
## heart disease 0 0
## HIV/AIDS 0 0
## hypertension 6 14
## kidney disease 0 6
## multiple sclerosis 1 0
## prostate cancer 9 35
## schizophrenia 2 0
## skin cancer 2 49

model2 <- na.omit(model2)

# Predicting on Validation set
predValid <- predict(model2, disease_TestSet, type = "class")

# Checking classification accuracy
mean(predValid == disease_TestSet$disease)

## [1] 0.165

table(predValid,disease_TestSet$disease)

##
## predValid Alzheimer's disease breast cancer diabetes endometri
osis
## Alzheimer's disease 39 13 17
9
## breast cancer 18 11 4
8
## diabetes 1 0 0
0
## endometriosis 0 0 0
0

```

```

## gastritis          0          0          0
0
## heart disease      0          0          0
0
## HIV/AIDS           1          1          0
1
## hypertension       6          4          9
2
## kidney disease     7          5          1
0
## multiple sclerosis 0          0          0
0
## prostate cancer    28         0          4
0
## schizophrenia      0          0          0
0
## skin cancer        7          6          1
1
##
## predValid          gastritis heart disease HIV/AIDS hypertension
## Alzheimer's disease 10          9          2          27
## breast cancer       3          1          3          21
## diabetes            0          1          0          0
## endometriosis       0          0          0          0
## gastritis           1          0          0          0
## heart disease       0          1          0          1
## HIV/AIDS            0          0          0          2
## hypertension        3          1          2          10
## kidney disease      3          2          1          6
## multiple sclerosis  0          0          0          1
## prostate cancer     9          4          12         20
## schizophrenia       0          0          0          0
## skin cancer         1          4          8          13
##
## predValid          kidney disease multiple sclerosis prostate cancer
## Alzheimer's disease 17          12          15
## breast cancer       8          5          0
## diabetes            0          0          0
## endometriosis       0          0          0
## gastritis           0          0          0
## heart disease       1          0          1
## HIV/AIDS            0          0          0
## hypertension        7          4          3
## kidney disease      4          2          1
## multiple sclerosis  0          0          0
## prostate cancer     10         12          29
## schizophrenia       0          0          0
## skin cancer         1          1          0
##
## predValid          schizophrenia skin cancer

```



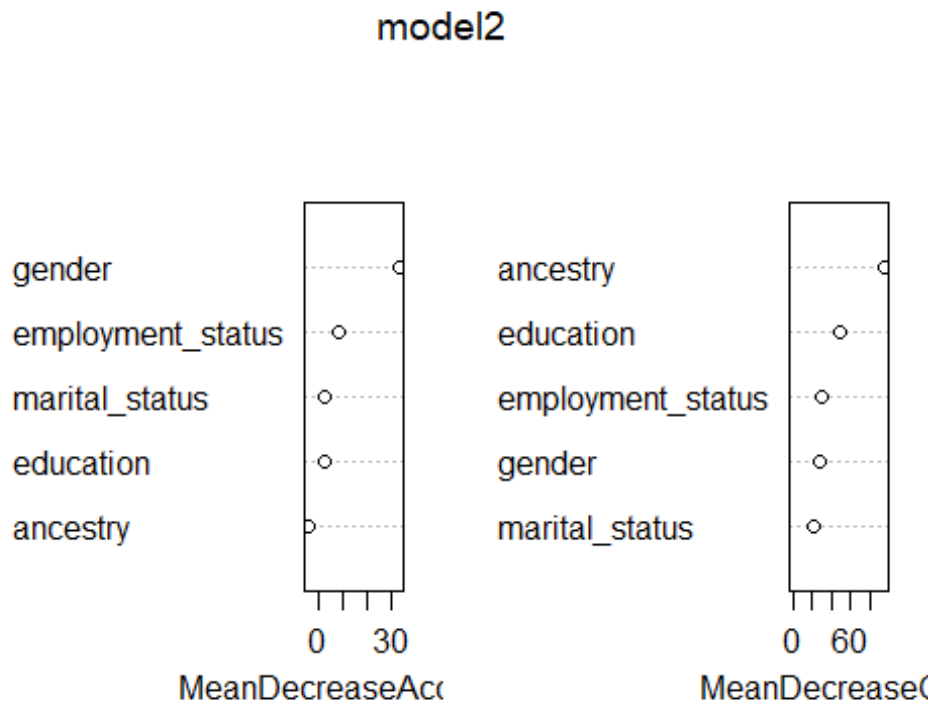
## Alzheimer's disease	6	27
## breast cancer	3	13
## diabetes	0	0
## endometriosis	0	1
## gastritis	0	1
## heart disease	0	1
## HIV/AIDS	1	1
## hypertension	0	3
## kidney disease	0	3
## multiple sclerosis	0	0
## prostate cancer	4	12
## schizophrenia	0	0
## skin cancer	1	4

*# To check important variables*  
importance(model2)

##	Alzheimer's disease	breast cancer	diabetes	endometriosis
## gender	-1.572030	29.337689	-2.372525	7.31396
## employment_status	8.261509	-3.560134	2.802048	-3.25048
## education	-7.859652	1.624276	3.229921	0.24609
## marital_status	-1.170440	-4.579872	6.081446	3.69514
## ancestry	-4.582599	-7.807351	5.144771	-2.21798
##	gastritis	heart disease	HIV/AIDS	hypertension
## gender	-0.7361897	1.920755	3.5379679	1.4733691
## employment_status	-1.4860458	-2.759647	4.9418385	2.9941151
## education	-6.0412280	2.067650	3.3755598	1.2388433
## marital_status	0.8802722	5.436578	-0.8679253	1.6938141
## ancestry	-1.4805477	-2.740245	2.7803375	0.2844226
##	kidney disease	multiple sclerosis	prostate cancer	
## gender	9.248339	1.999961	38.3640487	
## employment_status	10.049442	-9.329930	0.1440121	
## education	6.218238	-2.672903	4.7016289	
## marital_status	9.817900	-2.472035	-5.8784037	
## ancestry	3.755459	-1.120006	-5.9362590	
##	schizophrenia	skin cancer	MeanDecreaseAccuracy	
## gender	-7.290833	5.416934	33.929733	
## employment_status	2.122147	4.818350	8.330237	
## education	2.701801	4.801611	2.465961	
## marital_status	-5.176843	7.090811	2.618061	
## ancestry	-1.959080	3.297698	-4.563110	
##	MeanDecreaseGini			
## gender	27.81891			
## employment_status	29.50241			

```
## education          48.83914
## marital_status     21.16534
## ancestry           95.14737

varImpPlot(model2)
```



## Naive Bayes Model

```
NBclassifier = naiveBayes(disease~., data=disease_TrainSet)
print(NBclassifier)
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
## Alzheimer's disease      breast cancer      diabetes      endometr
iosis
##      0.16571429      0.07500000      0.05928571      0.032
14286
##      gastritis      heart disease      HIV/AIDS      hyperten
sion
##      0.05000000      0.04571429      0.03714286      0.140
71429
##      kidney disease      multiple sclerosis      prostate cancer      schizoph
```

```

renia
##          0.09785714          0.05500000          0.09357143          0.028
57143
##          skin cancer
##          0.11928571
##
## Conditional probabilities:
##          gender
## Y          female          male
## Alzheimer's disease 0.4870690 0.5129310
## breast cancer      1.0000000 0.0000000
## diabetes           0.4337349 0.5662651
## endometriosis      1.0000000 0.0000000
## gastritis          0.4714286 0.5285714
## heart disease      0.3906250 0.6093750
## HIV/AIDS           0.4423077 0.5576923
## hypertension       0.5025381 0.4974619
## kidney disease     0.5109489 0.4890511
## multiple sclerosis 0.4545455 0.5454545
## prostate cancer    0.0000000 1.0000000
## schizophrenia      0.4250000 0.5750000
## skin cancer        0.4670659 0.5329341
##
##          employment_status
## Y          employed          retired          student          unemployed
## Alzheimer's disease 0.288793103 0.586206897 0.004310345 0.120689655
## breast cancer      0.390476190 0.485714286 0.009523810 0.114285714
## diabetes           0.313253012 0.530120482 0.012048193 0.144578313
## endometriosis      0.288888889 0.533333333 0.000000000 0.177777778
## gastritis          0.428571429 0.371428571 0.042857143 0.157142857
## heart disease      0.453125000 0.390625000 0.000000000 0.156250000
## HIV/AIDS           0.673076923 0.115384615 0.019230769 0.192307692
## hypertension       0.345177665 0.517766497 0.010152284 0.126903553
## kidney disease     0.489051095 0.364963504 0.007299270 0.138686131
## multiple sclerosis 0.363636364 0.493506494 0.025974026 0.116883117
## prostate cancer    0.381679389 0.488549618 0.000000000 0.129770992
## schizophrenia      0.350000000 0.500000000 0.075000000 0.075000000
## skin cancer        0.407185629 0.526946108 0.000000000 0.065868263
##
##          education
## Y          bachelors          highschool          highschool          masters
## Alzheimer's disease 0.508620690 0.245689655 0.000000000 0.159482759
## breast cancer      0.580952381 0.190476190 0.000000000 0.152380952
## diabetes           0.481927711 0.313253012 0.000000000 0.132530120
## endometriosis      0.533333333 0.222222222 0.000000000 0.111111111
## gastritis          0.500000000 0.242857143 0.000000000 0.157142857
## heart disease      0.531250000 0.203125000 0.000000000 0.218750000
## HIV/AIDS           0.346153846 0.307692308 0.038461538 0.192307692
## hypertension       0.548223350 0.208121827 0.000000000 0.126903553
## kidney disease     0.562043796 0.233576642 0.007299270 0.116788321

```

##	multiple sclerosis	0.649350649	0.155844156	0.012987013	0.103896104
##	prostate cancer	0.557251908	0.198473282	0.000000000	0.145038168
##	schizophrenia	0.475000000	0.225000000	0.000000000	0.100000000
##	skin cancer	0.556886228	0.185628743	0.000000000	0.137724551
##	education				
## Y		phd/md	phD/MD		
##	Alzheimer's disease	0.086206897	0.000000000		
##	breast cancer	0.076190476	0.000000000		
##	diabetes	0.072289157	0.000000000		
##	endometriosis	0.133333333	0.000000000		
##	gastritis	0.071428571	0.028571429		
##	heart disease	0.046875000	0.000000000		
##	HIV/AIDS	0.096153846	0.019230769		
##	hypertension	0.111675127	0.005076142		
##	kidney disease	0.072992701	0.007299270		
##	multiple sclerosis	0.064935065	0.012987013		
##	prostate cancer	0.099236641	0.000000000		
##	schizophrenia	0.125000000	0.075000000		
##	skin cancer	0.119760479	0.000000000		
##					
##	marital_status				
## Y		married	single		
##	Alzheimer's disease	0.7931034	0.2068966		
##	breast cancer	0.8000000	0.2000000		
##	diabetes	0.7590361	0.2409639		
##	endometriosis	0.7777778	0.2222222		
##	gastritis	0.7428571	0.2571429		
##	heart disease	0.5937500	0.4062500		
##	HIV/AIDS	0.6923077	0.3076923		
##	hypertension	0.7664975	0.2335025		
##	kidney disease	0.7153285	0.2846715		
##	multiple sclerosis	0.7272727	0.2727273		
##	prostate cancer	0.7175573	0.2824427		
##	schizophrenia	0.7500000	0.2500000		
##	skin cancer	0.7485030	0.2514970		
##					
##	ancestry				
## Y		Austria	Belgium	Czech Republic	Denmark
##	Alzheimer's disease	0.04310345	0.05172414	0.03017241	0.08189655
##	breast cancer	0.06666667	0.04761905	0.05714286	0.03809524
##	diabetes	0.04819277	0.02409639	0.02409639	0.06024096
##	endometriosis	0.04444444	0.02222222	0.08888889	0.06666667
##	gastritis	0.10000000	0.02857143	0.01428571	0.05714286
##	heart disease	0.04687500	0.06250000	0.07812500	0.03125000
##	HIV/AIDS	0.03846154	0.05769231	0.03846154	0.00000000
##	hypertension	0.05076142	0.04568528	0.05076142	0.04568528
##	kidney disease	0.06569343	0.04379562	0.05839416	0.04379562
##	multiple sclerosis	0.02597403	0.05194805	0.02597403	0.07792208
##	prostate cancer	0.05343511	0.07633588	0.02290076	0.03816794
##	schizophrenia	0.05000000	0.05000000	0.05000000	0.02500000

##	skin cancer	0.04790419	0.08383234	0.05389222	0.04191617	
##		ancestry				
## Y		England	Finland	France	Germany	Hunga
ry						
##	Alzheimer's disease	0.03448276	0.05172414	0.04741379	0.05172414	0.047413
79						
##	breast cancer	0.04761905	0.03809524	0.04761905	0.02857143	0.047619
05						
##	diabetes	0.06024096	0.02409639	0.08433735	0.02409639	0.024096
39						
##	endometriosis	0.02222222	0.06666667	0.04444444	0.04444444	0.044444
44						
##	gastritis	0.05714286	0.01428571	0.04285714	0.05714286	0.014285
71						
##	heart disease	0.03125000	0.03125000	0.06250000	0.09375000	0.062500
00						
##	HIV/AIDS	0.03846154	0.07692308	0.00000000	0.07692308	0.076923
08						
##	hypertension	0.06598985	0.04060914	0.02538071	0.05076142	0.050761
42						
##	kidney disease	0.08029197	0.03649635	0.05109489	0.03649635	0.036496
35						
##	multiple sclerosis	0.07792208	0.05194805	0.07792208	0.02597403	0.077922
08						
##	prostate cancer	0.05343511	0.06870229	0.03053435	0.05343511	0.038167
94						
##	schizophrenia	0.05000000	0.02500000	0.00000000	0.10000000	0.025000
00						
##	skin cancer	0.05389222	0.04790419	0.05988024	0.05988024	0.041916
17						
##		ancestry				
## Y		Ireland	Italy	Netherlands	Poland	Portu
gal						
##	Alzheimer's disease	0.05172414	0.05172414	0.04310345	0.06034483	0.04310
345						
##	breast cancer	0.01904762	0.06666667	0.04761905	0.06666667	0.10476
190						
##	diabetes	0.10843373	0.08433735	0.07228916	0.07228916	0.02409
639						
##	endometriosis	0.06666667	0.02222222	0.02222222	0.04444444	0.00000
000						
##	gastritis	0.11428571	0.02857143	0.04285714	0.05714286	0.07142
857						
##	heart disease	0.07812500	0.09375000	0.06250000	0.04687500	0.01562
500						
##	HIV/AIDS	0.07692308	0.03846154	0.05769231	0.00000000	0.05769
231						
##	hypertension	0.05076142	0.02030457	0.05583756	0.08629442	0.06091
371						
##	kidney disease	0.04379562	0.05109489	0.05839416	0.05109489	0.04379

562						
##	multiple sclerosis	0.05194805	0.01298701	0.06493506	0.02597403	0.09090
909						
##	prostate cancer	0.04580153	0.09160305	0.05343511	0.03816794	0.07633
588						
##	schizophrenia	0.02500000	0.02500000	0.05000000	0.07500000	0.05000
000						
##	skin cancer	0.08383234	0.04790419	0.06586826	0.02994012	0.04790
419						
##		ancestry				
## Y		Russia	Scotland	Spain	Sweden	Switzerl
and						
##	Alzheimer's disease	0.07327586	0.05603448	0.03448276	0.03879310	0.07327
586						
##	breast cancer	0.06666667	0.01904762	0.02857143	0.04761905	0.06666
667						
##	diabetes	0.06024096	0.03614458	0.01204819	0.10843373	0.02409
639						
##	endometriosis	0.02222222	0.06666667	0.04444444	0.08888889	0.08888
889						
##	gastritis	0.01428571	0.02857143	0.01428571	0.11428571	0.07142
857						
##	heart disease	0.03125000	0.03125000	0.01562500	0.04687500	0.03125
000						
##	HIV/AIDS	0.01923077	0.07692308	0.05769231	0.05769231	0.07692
308						
##	hypertension	0.04060914	0.03045685	0.07106599	0.05583756	0.05583
756						
##	kidney disease	0.05109489	0.04379562	0.05839416	0.05109489	0.07299
270						
##	multiple sclerosis	0.03896104	0.07792208	0.03896104	0.02597403	0.05194
805						
##	prostate cancer	0.03816794	0.04580153	0.05343511	0.04580153	0.04580
153						
##	schizophrenia	0.10000000	0.00000000	0.15000000	0.02500000	0.10000
000						
##	skin cancer	0.02994012	0.02994012	0.04191617	0.05389222	0.05389
222						
##		ancestry				
## Y		Ukraine				
##	Alzheimer's disease	0.03448276				
##	breast cancer	0.04761905				
##	diabetes	0.02409639				
##	endometriosis	0.08888889				
##	gastritis	0.05714286				
##	heart disease	0.04687500				
##	HIV/AIDS	0.07692308				
##	hypertension	0.04568528				
##	kidney disease	0.02189781				
##	multiple sclerosis	0.02597403				

##	prostate cancer	0.03053435
##	schizophrenia	0.02500000
##	skin cancer	0.02395210